

Stellar Kinematics, Morphology and Local Environment of Galaxies with Integral Field Spectroscopy



Mark Thomas Graham
Wadham College
University of Oxford

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To my wife Lisa,
for her unending love and support.

Statement of Originality

I carried out the work presented in this thesis at the Department of Astrophysics, University of Oxford between October 2015 and April 2019, under the supervision of Prof. Michele Cappellari. It was funded by a Science Technology Facilities Council Studentship Grant Code ST/N504233/1. I hereby declare that no part of this thesis has been accepted or is currently being submitted, for any degree or diploma or certificate or any other qualification at this University or elsewhere. This thesis is the result of my own work unless otherwise specified. Funding for the Sloan Digital Sky Survey IV has been provided by the Alfred P. Sloan Foundation, the U.S. Department of Energy Office of Science, and the Participating Institutions. SDSS acknowledges support and resources from the Center for High-Performance Computing at the University of Utah. The SDSS website is www.sdss.org.

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Abstract

In this thesis, I study the stellar angular momentum within one effective radius, λ_{Re} of a few thousand galaxies and consider how this property relates to other galaxy properties such as stellar mass, optical morphology and environment. I make use of data from the Sloan Digital Sky Survey's (SDSS) Mapping Nearby Galaxies at Apache Point Observatory (MaNGA) survey which is a large integral field spectroscopic survey. I classify early-type galaxies (ETGs) as slow rotators if $\lambda_{Re} < 0.08 + 0.25\epsilon$ and $\epsilon < 0.4$, where ϵ is the galaxy flattening, and as fast rotators if otherwise. I present the (λ_{Re}, ϵ) diagram for about 2300 galaxies and provide the first conclusive evidence that fast and slow rotator ETGs form a bimodality in angular momentum suggesting that they are kinematically distinct populations. I show that they also form a bimodality in other properties such as stellar mass and kinematic morphology, which I attribute as being a direct consequence of the existence of two ETG formation channels, a gas rich (wet) accretion channel which produces FRs and a gas poor (dry) merger channel which produces SRs.

I investigate the hypothesis that massive SRs have built up their stellar mass and decreased their angular momentum as a result of experiencing multiple dry minor mergers by studying their environment. By running a new group-finder algorithm on a large galaxy catalogue containing spectroscopic and photometric observations, I find the neighbouring galaxies for about 4600 MaNGA galaxies. For all neighbours that satisfy the criteria for massive SRs ($M \geq 2 \times 10^{11} \text{ M}_{\odot}$ and $\epsilon < 0.4$), I assign an angular momentum classification based on optical morphology to achieve a complete, volume-limited sample of about 14,000 galaxies.

Using this sample, I reproduce the kinematic morphology-density (kT- Σ) relation for massive SRs, finding that they are about six times more abundant in the dense centres of clusters compared to the field. I show that when the kT- Σ relation is derived from multiple clusters, the individual

cluster trends are washed out. I account for this smoothing effect by defining a relative density estimator, Σ^{rel} , that measures number density relative to the cluster/group peak density. I show that the kT - Σ^{rel} relation is a better predictor of the abundance of massive SRs than the kT - Σ relation. I find that these environmental trends persist at fixed stellar mass, although they are subtle because stellar mass is the main driver for slow rotation. I also present schematics for 10 large galaxy clusters highlighting the location of the massive SRs. In all cases, the density peaks contain at least one massive SR, while FRs are distributed evenly throughout the cluster. I conclude that these results provide definitive proof that the progenitors of modern-day massive SRs formed rapidly at high redshift in dense environments before accreting a significant fraction of their stellar mass via dry minor mergers. Finally, I suggest potential avenues for follow-up.

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Chapter 1

Introduction

[Astronomy] shows you exactly how a star is formed; nothing else can be so pretty! A cluster of vapor, the cream of the milky way, a sort of celestial cheese, churned into light.

Benjamin Disraeli
Tancred

1.1 A brief history of galaxy rotation observations

Almost 100 years ago, our view of the Universe was transformed by the pioneering work of Edwin Hubble. He was motivated by the Great Debate between Harlow Shapley and Heber Curtis who disagreed on the distance and intrinsic size of “nebulae” which are extended objects. Between 1922 and 1926, Hubble observed approximately 400 of these nebulae with the largest telescope in existence at the time. During this time, he observed a number of a special type of star called a Cepheid variable in the Andromeda galaxy (“nebula”). Cepheid variables obey a tight scaling relation between the luminosity and the time between observed pulses (Leavitt’s Law; e.g. Breger & Bregman, 1975). Hence, the distance to the galaxy which hosts the star can be accurately determined by comparing the apparent magnitude with the absolute magnitude, as determined from the pulsation period (Sandage, 1958; Tammann & Sandage, 1968; Sandage & Tammann, 1971; Riess et al., 2009). The first “nebula” that Hubble was able to place outside the Milky Way using Cepheid variables was NGC 6822 (Hubble, 1925). Using this technique, Hubble unambiguously confirmed that almost all other “nebulae”, including the nearby Andromeda “nebula”, are in fact galaxies external to our Milky Way galaxy (Hubble, 1929a,b; Hubble & Humason, 1931).

Hubble recognised that galaxies could be classified into two main types, called ellipticals and spirals, which represent a continuum of galaxy morphology (Hubble, 1926). (About 3% of the sample were deemed to be irregular and not easily classified into the two main classes.) Later, an intermediate type dubbed ‘lenticular’ galaxies were added as they appear disk-like, like spiral galaxies, but are smooth and featureless, like elliptical galaxies. Hubble arranged these galaxy types into the now-classic “tuning fork” diagram (Figure 1.1; Hubble, 1936), where the ellipticals, which lie along the handle, are separated from spirals by lenticular galaxies (S0s) which lie where the handle meets the two prongs. Spirals are separated according to whether or not they possess a bar at the centre. Although it was not Hubble’s intention, the tuning fork was sometimes interpreted as an evolutionary sequence leading to the idea that ellipticals and S0s are early-type galaxies (ETGs), while spirals and irregular galaxies are known as late-type galaxies (LTGs). Nowadays, galaxy morphologies are routinely classified by “citizen scientists” as part of the groundbreaking Galaxy Zoo project (Lintott et al., 2008, 2011; Willett et al., 2013). The Galaxy Zoo catalogue contains morphologies for almost a million galaxies (Lintott et al., 2011) and so provides a powerful resource for studying galaxy evolution (e.g. Bamford et al., 2009; Skibba et al., 2009) as well as discovering new objects (e.g. Cardamone et al., 2009).

1.1.1 First observational evidence of a dichotomy in elliptical properties

Even before the work of Hubble, it was known that galaxies rotate (Slipher, 1913). Initially, it was assumed that the observed flattening of elliptical galaxies in particular is caused by their intrinsic rotation. A number of dynamical models were developed describing elliptical galaxies as axisymmetric, isotropic stellar systems rotating in equilibrium (Gott, 1973, 1975; Larson, 1975; Wilson, 1975). The models predicted very high rotation velocities compared to the velocity dispersion, and the model isophotes and rotation curves were found to be in good agreement with observations. However, the field was radically changed as a result of observations by Bertola & Capaccioli (1975) who obtained the first rotation curve of an elliptical galaxy (NGC 4697) by obtaining the spectra of Ca II lines. At the time, it was more challenging to accurately measure absorption lines for elliptical galaxies compared to spirals, partly due to the drop in luminosity with radius. Bertola & Capaccioli (1975) combined information about the circular velocity obtained from the rotation curve with analytical forms for the mass and angular momentum within a cylinder, to show that the angular momentum content per unit mass of NGC 4697 is between 5 and

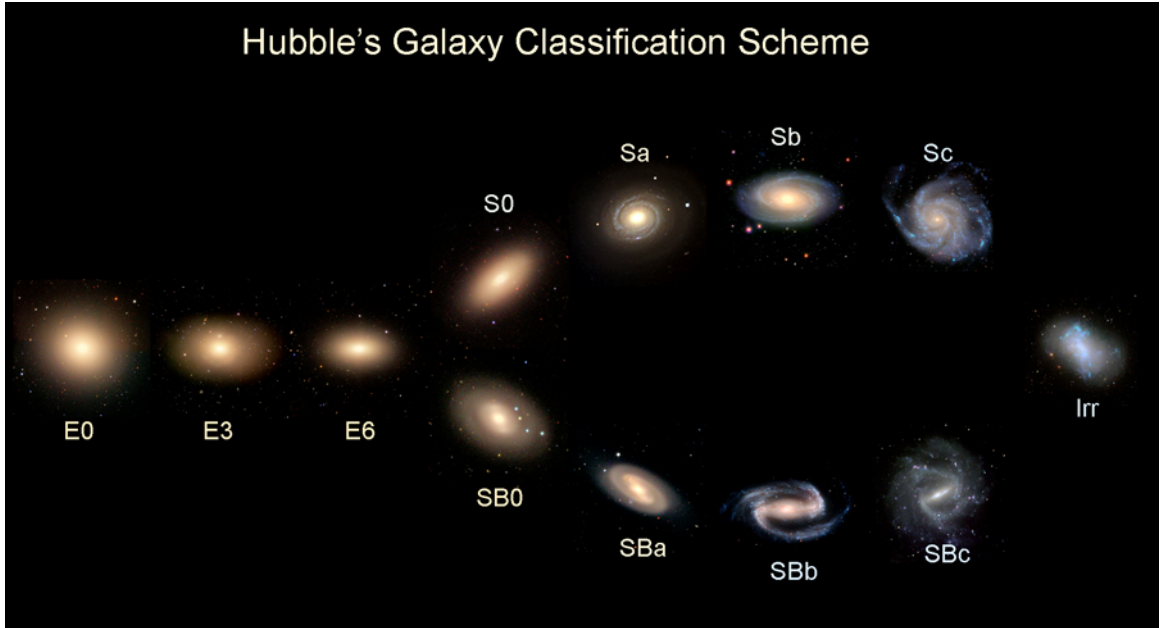


Figure 1.1: **Hubble’s “tuning fork” diagram with Sloan Digital Sky Survey images.** Elliptical galaxies are placed left to right in order of increased flattening. The diagram splits into two arms, one barred and another unbarred, with disk galaxies placed in order of decreasing bulge-to-total ratio from left to right. At the far right is an irregular galaxy. Credit to John Kormendy.

30 times smaller than spirals from Takase & Kinoshita (1967). NGC 4697 was chosen for the study because it appears flattened (E5 according to Sandage, 1961), and was observed to have a high velocity dispersion $\sigma = 310 \text{ km s}^{-1}$ (King & Minkowski, 1966).

In light of the discovery that elliptical galaxies have lower angular momentum than spiral galaxies, Binney (1976) suggested that if the observed flattening of elliptical galaxies is not due to their rotation, it must be caused by a dissipative phase during formation. In this phase, the primordial gas cools, loses kinematic energy and sinks towards the centre of the gravitational potential of the dark matter halo, thereby moving to a lower energy state (Benson, 2010). Dissipation naturally results in the spreading of disks because the total energy of the system reduces, while angular momentum is conserved (Lynden-Bell & Kalnajs, 1972; Kormendy & Kennicutt, 2004). The initial result from NGC 4697 was corroborated by observations of the rotation of 12 more giant elliptical galaxies by Illingworth (1977), and later by Schechter & Gunn (1979). All of these galaxies showed rotational velocities that were approximately 25% – 50% of the velocity dispersion. By comparing V/σ ratios for galaxies and models of similar ellipticity on the now-classic $(V/\sigma, \epsilon)$ diagram, Illing-

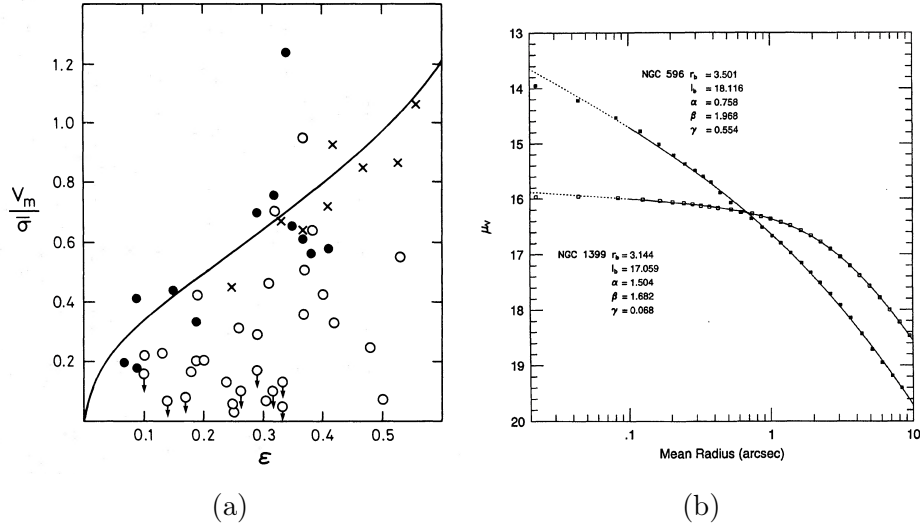


Figure 1.2: **Dichotomy in properties of elliptical galaxies.** **Left:** One of the earliest examples of the $(V/\sigma, \epsilon)$ diagram. Faint ellipticals are shown as filled black circles while bright ellipticals are shown as open circles. Galaxy bulges are indicated with a cross. The solid line is the prediction for V/σ as a function of ϵ for an isotropic rotator (Binney, 1978). Taken from Davies et al. (1983). **Right:** Surface brightness profiles for two ETGs, NGC 720 and NGC 1399. NGC 720 shows a power-law (cuspy) profile, while NGC 1399 shows a deficit in the nuclear region (core). Taken from Lauer et al. (1995).

worth (1977) showed that elliptical galaxies only have between one and two thirds the rotational velocity required to support the flattening, as was assumed by the models, and that they are consistently dominated by random motion to a greater degree than the oblate galaxy models suggest.

Binney (1978) showed that the lower V/σ ratio for giant ellipticals can be explained if the velocity ellipsoid is allowed to be anisotropic i.e. the equality $\sigma_R = \sigma_z = \sigma_\phi$ does *not* hold, where σ_R , σ_z and σ_ϕ are the stellar velocity dispersion in the radial, vertical and tangential directions respectively (in cylindrical coordinates). Later observations included low-luminosity ellipticals (Davies et al., 1983) as well as the bulges of barred (Kormendy, 1982) and unbarred galaxies (Kormendy & Illingworth, 1982; see Figure 1.2). This sample of galaxies and bulges were found to be consistent with the oblate, isotropic ($\sigma_R = \sigma_z = \sigma_\phi$), axisymmetric models of Binney (1978). Moreover, it was shown that V/σ tends to decrease with increasing absolute luminosity, albeit with large intrinsic scatter. This was an indication that the kinematic structure of elliptical galaxies depends on their stellar mass. Davies et al. (1983) suggested that mergers could play a role in growing the stellar mass and altering the kinematic structure of ETGs.

The fact that some elliptical galaxies rotate faster than others suggests that there are two types of elliptical galaxy, one which is diskly and one which is intrinsically spheroidal. However, ellipticals appear to be very homogeneous in their morphology and so any signs that betray the true kinematic nature of ellipticals must not be readily apparent. One possible measurement to make is of the shape of contours of constant surface brightness (isophotes). The usual method is to fit an ellipse and then measure deviations from the ellipse for a range of radii (see sec 2.3 of Cappellari, 2016; hereafter C16). Carter (1987) was the first to find evidence of deviations along the major axis, suggesting weak disks in four rapidly rotating elliptical galaxies (including NGC 4697). Nieto et al. (1988) concluded that between 30% to 50% of genuine ellipticals are in fact diskly, oblate and nearly isotropic rotators. Bender (1988a) combined published data on the shapes of elliptical isophotes (Jedrzejewski, 1987; Bender et al., 1987, 1988) along with rotation curve measurements for 17 elliptical galaxies to show that rotationally supported ellipticals were essentially diskly (isophotes are stretched along the major axis), while galaxies which are supported by random motions have boxy isophotes (isophotes are squashed along the major axis). Bender (1988a) concluded that the diskly elliptical galaxies consist of a spheroidal component flattened due to rotation with nearly isotropic velocity ellipsoids, and a weak disk component (Rix & White, 1990; Rix et al., 1999). They also concluded that the diskly elliptical galaxies form a continuous sequence along with S0 galaxies and spirals where the bulge-to-disk ratio varies along the sequence, indicating a common formation mechanism. On the other hand, boxy elliptical galaxies were thought to be flattened due to anisotropy in the velocity dispersion, and many were found to have active radio and X-ray emission (Bender et al., 1987, 1989).

Along with the shape of the isophotes, elliptical galaxies were also found to show a dichotomy in the surface brightness profiles. At large radii, elliptical galaxies show a smooth power-law profile increasing in magnitude towards the nuclear region. The high resolution provided by the Hubble Space Telescope allowed the profiles to be measured in the cores of nearby elliptical galaxies, a task that requires a resolution of better than one tenth of an arcsec. Elliptical galaxies were found to belong to one of two types (Jaffe et al., 1994; Ferrarese et al., 1994; Lauer et al., 1995): those which show a continuation of the power-law profiles towards the galaxy centre, and those that show a shallower slope in the nuclear region (right panel of Figure 1.2). The latter is known as a core nuclear profile. This collection of characteristics of elliptical galaxies motivated Kormendy & Bender (1996) to propose a revision to the Hubble diagram which orders elliptical galaxies by the shape of their isophotes, rather

than the ellipticity which is strongly affected by inclination. A dichotomy could be found in global and core galaxy properties in that boxy ellipticals are giant, slowly rotating galaxies with cores and are anisotropic and triaxial, while disk ellipticals are normal/low-luminosity ellipticals that rotate rapidly and are nearly isotropic, oblate and possess a power-law nuclear surface brightness profile. While it was clear that the disk ellipticals are related to S0s and spirals, it was unclear as to whether disk ellipticals transition smoothly into boxy ellipticals (see sec. 2.4 of C16).

1.1.2 The era of integral field spectroscopy

While the sequence of Kormendy & Bender (1996) is more physically motivated than the Hubble sequence, it is still based on photometry which does not necessarily encode galaxy kinematics with complete accuracy. As reviewed by C16 (see sec. 3.1), photometry has two fundamental limitations in that subarcsecond resolution is required to accurately measure the inner slope of the surface brightness profile, and that measurements of the deviations from elliptical isophotes require galaxies to be close to edge-on in order to be seen. Clearly these two limitations greatly restrict the utility of the photometric classification given that only a finite number of galaxies are close enough to observe the cores, of which only a small fraction will be edge on.

Coincidentally in the mid-1990s, the new technology of integral field spectroscopy (IFS) was coming into use (see Allington-Smith, 2006 for a review). Since then, IFS has completely transformed our view of galaxy kinematics. Rather than use the time scanning approach where a slit is moved across the face of an extended object, IFS takes only a single exposure to collect the light. IFS consists of two components: an integral field unit (IFU) which obtains spectra from across a two-dimensional plane, and a spectrograph. The data from an IFU takes the form of two spatial dimensions and one dimension corresponding to wavelength, and these three dimensions are bundled into a “datacube”. A datacube can be understood in two ways: It is both a spectra at every pixel (spaxel) and an image of the galaxy at every wavelength. One of the early integral field spectrographs was TIGER (Bacon et al., 1995) based at the Canada-France-Hawaii Telescope. TIGER formed the blueprint for the hugely successful SAURON spectrograph on the 4.2-metre William Herschel Telescope (Bacon et al., 2001). The spectrograph was designed using a lenslet array configuration where microlenses are arranged on a regular grid. The beam from each lens is directed onto a grism and the resulting spectra are imaged by the detector. One advantage of using a lenslet array is that the filling factor can be 100% (Bacon et al., 2001). SAURON had a larger field of view than TIGER (≈ 1350 square arcsec

compared to 100 square arcsec) and so was able to probe the kinematics on a global scale. A survey of 48 nearby ETGs was conducted as part of the SAURON survey (de Zeeuw et al., 2002) providing stellar and gas kinematics as well as maps of emission line strengths pertaining to the stellar populations.

1.1.3 Extracting stellar kinematics from IFS data

Emsellem et al. (2004) presented kinematic maps of velocity and velocity dispersion for the SAURON sample as well as additional higher order parameters (see below). The kinematics were obtained using the Penalised PiXel Fitting routine **pPXF**¹ (Cappellari & Emsellem, 2004; Cappellari, 2017), which has since become a popular spectral fitting tool that is widely used by the community. **pPXF** fits the observed spectra in each pixel (spectral channel) with a linear combination of stellar templates taken from a stellar library. It works on the principle that the observed spectrum is a convolution of the individual stellar spectra and the line-of-sight velocity distribution (LOSVD) due to the random motions of the stars along the LOS. The stars are assumed to belong to a set of single stellar populations (SSP), each specified by an age and metallicity with the assumption that all stars in the galaxy belong to one of these SSPs. In reality, there will be a spread in these values for a given stellar population, but as stars are formed in clusters rather than in isolation, the above assumption is valid. Only a single fit is required to find the linear combination of SSPs that can match the observed stellar spectra. The standard functional form used to describe the LOSVD is the set of Gauss-Hermite polynomials (Gerhard, 1993; van der Marel & Franx, 1993). The first four terms in the series are the velocity V , velocity dispersion σ , h_3 and h_4 . h_3 and h_4 describe the asymmetric and symmetric deviations from a Gaussian (skew and kurtosis) respectively. All parameters are fitted simultaneously using least-square optimisation. Where the signal-to-noise ratio (S/N) is low, an adjustable penalty term can be applied to the χ^2 to bias the solution to a more Gaussian shape when higher order moments are unconstrained by the data. In this case, a deviation from a Gaussian will only be accepted if the residuals between the fit and the data are reduced.

The stellar kinematics are rarely derived on a pixel-by-pixel basis. In some cases, it is not desirable to fit low S/N data for a single spaxel as the higher order moments, which are important for revealing subtle kinematic features, can be overpowered by the noise. The usual solution to this problem is simply to bin nearby spaxels to

¹<http://purl.org/cappellari/software>

increase the flux. One strategy would be to bin the spaxels in annuli of increasing radius and thickness (as the surface brightness typically falls off with radius). While the flux will be boosted as a result, the S/N may not be constant. In order to achieve a constant minimum S/N threshold, Cappellari & Copin (2003) developed an adaptive spatial binning technique for integral field data that uses Voronoi tessellations. The bins are arbitrary in shape and enclose a constant flux. Where the flux in a given pixel exceeds the minimum threshold, for example in the bulge, the bins can simply enclose a single pixel. Otherwise, the flux is summed from the pixels contained within each bin and the stellar kinematics are derived as described above.

1.1.4 Kinematic morphology

Prior to the SAURON survey, little was known about the variety of kinematic morphologies exhibited by ETGs. A handful of galaxies were known to have rotation about the minor axis (Wagner et al., 1988) and a few galaxies showed evidence of kinematically decoupled cores (KDC; Bender, 1988b; Moellenhoff & Bender, 1989; Statler, 1991; Balcells & Carter, 1993), where the core shows rotation that is disconnected from the global galaxy rotation. However, a full suite of kinematic morphologies was revealed with the SAURON data by Emsellem et al. (2007). Now ETGs could be classified by their kinematic morphology (Figure 1.3) rather than their Hubble morphology (ellipticity). While this can be done by eye, Krajnović et al. (2006) developed KINEMETRY as a tool to quantify kinematic morphology. KINEMETRY is a generalisation of surface photometry to the higher order moments of the LOSVD. The zeroth order moment of the LOSVD, which is flux, has even parity in that it is symmetrical about a given axis. In surface photometry, the flux is assumed to be constant within ellipses of radius R centred on the galaxy centre. The first order moment is velocity and is of odd parity (V flips sign about the minor axis). KINEMETRY makes the assumption that V varies with the cosine of the azimuthal angle from the projected major axis, while σ is assumed to be constant with azimuthal angle. For regularly rotating galaxies, this assumption is very well justified and can describe the moments of the LOSVD with remarkable accuracy (sec. 3.2, C16). Signals in the higher order moments are a sign of kinematic features, and can be used to assign galaxies into classes of kinematic morphology.

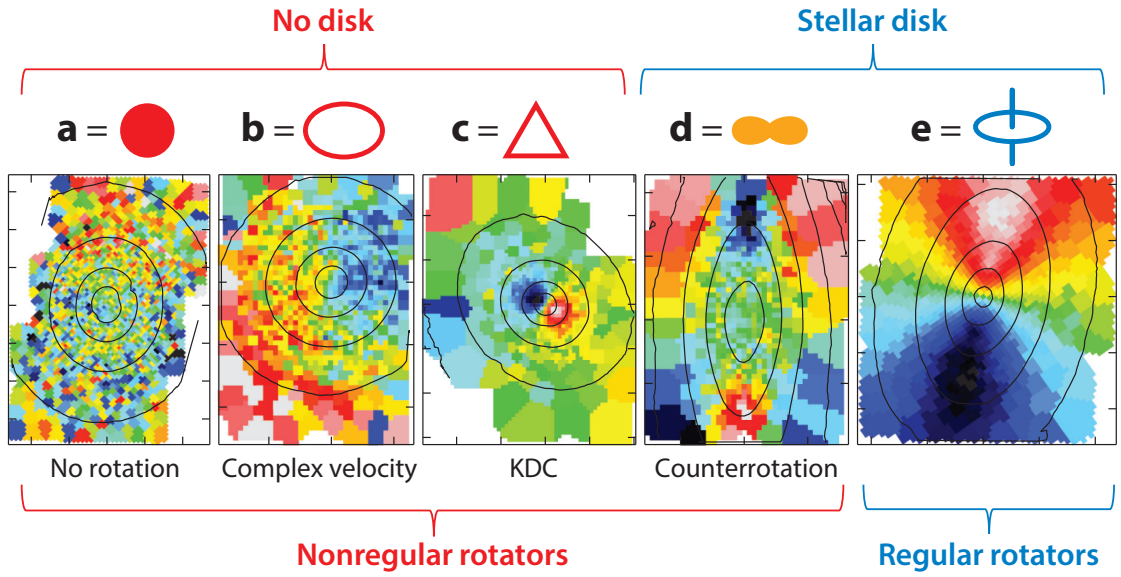


Figure 1.3: **Kinematic morphology of ETGs.** Each panel shows a velocity map corresponding to a particular kinematic morphology. Yellow/red/grey pixels indicate redshifted motion relative to the systemic velocity of the galaxy, shown in green, while light/dark blue pixels indicate the relative blueshifted motion. The non-regular rotators are split into four categories: non-rotators, complex rotators, kinematically decoupled cores and counter-rotators. All other galaxies are regular rotators which exhibit a characteristic hourglass velocity map. Slowly rotating galaxies appear as one of the left three panels (no disk), while fast rotators by definition have a stellar disk.

1.1.5 Quantifying galaxy rotation

Integral field data allows a more robust determination of V/σ to be estimated that relates directly to the tensor virial theorem, which itself relates the kinetic and potential energy tensors in a stellar system (Binney, 2005; sec. 4.8.3 of Binney & Tremaine, 2008). Cappellari et al. (2007) applied the revised formalism of Binney (2005) to integral field data to obtain (eq. 10)

$$\frac{\langle V^2 \rangle}{\langle \sigma^2 \rangle} \approx \left(\frac{V}{\sigma} \right)_e^2 \equiv \frac{\sum_{n=1}^N F_n V_n^2}{\sum_{n=1}^N F_n \sigma_n^2}, \quad (1.1)$$

where V and σ are weighted by luminosity in the summations within $1R_e$ before the ratio is taken. While this is more robust than the traditional V/σ ratio calculated from a single slit, Emsellem et al. (2007) recognised that it is not sensitive to the kinematic morphology. For example, two galaxies in the SAURON sample, NGC 3379 and 5813, have the same V/σ as calculated using Eq. (1.1) but have completely different kinematic morphologies (regular rotator vs KDC with no global rotation). The drawback of V/σ is that it has no knowledge of the spatial distribution and so can fail to distinguish between clear cases such as these. Emsellem et al. (2007) proposed a new parameter, λ_R , that retains the essence of V/σ while taking the spatial structure of the stellar kinematics into account. λ_R is more closely related to the angular momentum as it considers the distance of a spaxel from the galaxy centre. Its form can be derived from the spin parameter of Peebles (1971) as was done by Emsellem et al. (2007). Here I briefly introduce the spin parameter of Peebles (1971) before summarising the thought process of Emsellem et al. (2007), also described in appendix A of the same.

Peebles (1971) defined the dimensionless spin parameter

$$\lambda = \frac{J|E|^{1/2}}{GM^{5/2}}, \quad (1.2)$$

where J , E and M are the total angular momentum, total energy (including kinetic and potential) and total mass (dark matter and baryons) of the protogalaxy (G is Newton's constant). λ measures the degree of rotational support in a system as it relates the ratio between the centrifugal acceleration $g_c \sim v_c^2/r$ to the gravitational acceleration $g \sim GM/r^2$:

$$\sqrt{\frac{g_c}{g}} \sim \sqrt{\frac{v_c^2}{r} \frac{r^2}{GM}} = M_d r_d v_c \sqrt{\frac{GM^2}{r} \frac{1}{G^2 M^5}} \sim \frac{J|E|^{1/2}}{GM^{5/2}} = \lambda \quad (1.3)$$

where the angular momentum $J = 2M_d r_d v_c$ and the binding energy is $E = -GM^2/2r$ (Mo et al., 1998). M_d and r_d are the disk mass and scale length respectively, and v_c is the circular velocity. Peebles (1971) used linear perturbation theory to derive a value of λ for the Milky Way of about 0.1. Subsequent analyses of cosmological N -body simulations showed typical values to be in the range 0.02-0.08 (Efstathiou & Jones, 1979; Barnes & Efstathiou, 1987; Zurek et al., 1988). Initially λ was assumed to be the same for the dark matter and the baryons (Fall & Efstathiou, 1980; Fall, 1983; Mo et al., 1998), and this was shown to be the case in numerical (van den Bosch et al., 2002) and N -body/hydrodynamical simulations (Zavala et al., 2008). Hahn et al. (2010) found the orientations of the spin vectors of the gaseous and stellar disks and the inner part of the dark matter halo to be aligned within about 20° , although van den Bosch et al. (2002) found a poorer alignment. The distribution of λ is well described by a lognormal (Warren et al., 1992; van den Bosch et al., 2002; Vitvitska et al., 2002; D’Onghia & Navarro, 2007; Hernandez et al., 2007) and is independent of halo mass (Macciò et al., 2007), redshift and cosmology (Lemson & Kauffmann, 1999).

The main purpose of λ_R is to quantify the relative contribution of ordered motion to random motion in a galaxy. Hence, it should measure the total specific angular momentum $J/M \sim \langle R|V| \rangle^2$ where R is the distance to the centre (assumed to be the location of the spin axis). The absolute value is taken as only the speed is of interest and not the direction. The total energy in the system is captured by the second velocity moment via the scalar virial relation: $E \sim -M\langle V^2 + \sigma^2 \rangle/2$. Finally, GM in the denominator of Eq. (1.3) is related to the potential energy via $\sim -WR/M \sim 2ER/M \sim \langle R(V^2 + \sigma^2) \rangle$. The $\langle \rangle$ notation indicates that the flux-weighted average is taken. After some rearrangement and approximations, the final form for the observational spin parameter is Emsellem et al. (2007)

$$\lambda_R = \frac{\langle R|V| \rangle}{\langle R\sqrt{V^2 + \sigma^2} \rangle}. \quad (1.4)$$

λ_R tends towards unity as σ tends to zero, and will drop close to zero when σ becomes large compared to V . The fact that λ_R contains the modulus of the velocity means that there will be a floor set by the random noise present in the IFS data (see fig. B1 of Emsellem et al., 2007).

λ_R is performed on the IFS data as a sum over pixels within a predefined aperture. Emsellem et al. (2007) calculated λ_R within a range of radii up to about one effective

²For the sake of simplicity, we leave out scalar constants which account for the effect of viewing angle (Franx, 1988). See appendix A of Emsellem et al. (2007) for a complete discussion.

radius. λ_R tends to zero as R approaches zero simply because V is taken with respect to the systemic velocity of the galaxy, which is zero at the centre, and σ generally increases towards the galaxy centre. The profiles of λ_R flatten beyond about $1 R_e$ and so λ_R within this radius, λ_{R_e} , is taken as the standard.

λ_{R_e} is a projected quantity and so is dependent on the inclination (Emsellem et al., 2007). But in a companion paper, Cappellari et al. (2007) showed that the fast/slow rotator classification is robust to projection effects and thus represents an intrinsic characteristic. It is in principle possible to deproject the observed λ_{R_e} to the intrinsic one for axisymmetric disks but this would require highly accurate knowledge of the inclination. Jesseit et al. (2009) compared the apparent angular momentum from an N -body simulation with $\langle R|V| \rangle$ and found the two to be in excellent agreement in an absolute sense. However, when both are normalised to the edge-on value and the viewing angle is varied between edge-on and face-on, they present different behaviours. λ_{R_e} declines much slower towards face-on than $\langle R|V| \rangle$ because $\langle V \rangle$ and $\langle \sigma \rangle$ both decline as $\sin i$ where i is the inclination.

1.1.6 λ_{R_e} as a discriminant between fast and slow rotators

As λ_{R_e} is essentially a proxy for kinematic morphology, it seems natural to substitute the $(V/\sigma, \epsilon)$ diagram for a $(\lambda_{R_e}, \epsilon)$ diagram. A galaxy is defined as a fast or slow rotator depending on where it falls on the $(\lambda_{R_e}, \epsilon)$ diagram. In Emsellem et al. (2007), a simple demarcation line of $\lambda_{R_e} = 0.1$ was used to separate fast and slow rotators. They based the value of 0.1 on the shapes of the λ_{R_e} profiles out to $1R_e$, where the profile is obtained by calculating λ_R within ellipses with radii in the range $0 \lesssim R \leq R_e$. Galaxies with $\lambda_{R_e} \leq 0.1$ show essentially flat profiles in λ_R , while all other galaxies show rising profiles of λ_R with increasing R (see their fig. 2). The rising profiles are a result of regular rotation: As R increases, V and σ increase and decrease respectively, and so λ_R also increases. In contrast, galaxies with $\lambda_{R_e} < 0.1$ show irregular rotation and hence λ_R is essentially independent of R in these galaxies. $\lambda_{R_e} = 0.1$ was also shown to separate galaxies where the kinematic major axis (parallel to the direction of maximum velocity along the line of sight) is aligned with the photometric major axis (i.e. regular, fast rotators) from galaxies where these two axes are arbitrarily misaligned (non-regular, slow rotators; see fig. 4 of Emsellem et al., 2007).

A separation at $\lambda_{R_e} = 0.1$ was defined using the SAURON sample of 48 ETGs. The follow-up to SAURON was the pioneering ATLAS^{3D} survey (Cappellari et al., 2011a) which was a multi-wavelength effort combined with IFS. With the availability of λ_{R_e} measurements obtained from ATLAS^{3D} stellar kinematics for 260 ETGs, Emsellem

et al. (2011) revised the demarcation line with an added dependence on ϵ : $\lambda_{Re} = 0.31\sqrt{\epsilon}$. This empirical separation was designed to best separate regular rotators from non-regular rotators on the (λ_{Re}, ϵ) diagram: galaxies with $\lambda_{Re} \geq 0.31\sqrt{\epsilon}$ were defined as fast rotators, while those with $\lambda_{Re} < 0.31\sqrt{\epsilon}$ were defined as slow rotators. The ellipticity dependence was included because in the ATLAS^{3D} sample, they found that λ_{Re} generally increases with increasing ϵ , and that this applies to regular and non-regular rotators alike.

More recently, the CALIFA survey (Sánchez et al., 2012) observed ~ 600 galaxies of all morphological types at low redshift ($z < 0.03$) with a single IFU to provide kinematic maps of velocity and velocity dispersion as well as properties of the stellar population and ionised gas. CALIFA provided (λ_{Re}, ϵ) values for 300 galaxies comprising the largest homogeneous census of λ_{Re} at the time (Falcón-Barroso et al., 2015). A tight connection between spiral galaxies and FR ETGs was observed, but a dependence on bulge size was also observed, with Sa and Sb galaxies exhibiting high λ_{Re} , and Sc and Sd galaxies showing lower values. While ATLAS^{3D} and CALIFA provided a large homogeneous sample of nearby galaxies, their main limitation was the availability of only one single IFU, meaning that only one galaxy could be observed at once, making the possibility of larger surveys unlikely.

The first IFU survey capable of observing more than one galaxy simultaneously with IFS was The Sydney-AAO Multi-object Integral field spectrograph survey (SAMI; see Croom et al., 2012 for details about the spectrograph and Fogarty et al., 2015 for details about the survey). SAMI utilises 13 IFUs identical in size and shape (hexabundles containing 61 fibres each) with the aim of mapping 3400 nearby galaxies ($z < 0.095$; primary sample; Bryant et al., 2015). Using 488 galaxies from the SAMI survey, Cortese et al. (2016) found that, rather than galaxies forming two distinct channels on the $j_\star - M_\star$ plane as found by Fall (1983) and Romanowsky & Fall (2012), galaxies form a continuous sequence whereby a galaxy’s position on the $j_\star - M_\star$ plane, where $j_\star = J_\star/M_\star$ is correlated with morphology and Sérsic index (Sérsic, 1963, 1968). The same result has been found in hydrodynamical simulations (Lagos et al., 2017) using a number of proxies for galaxy morphology. These results may suggest that the formation of spheroids and disks is a continuous process rather than being fundamentally different in nature.

Already with the SAURON survey, Cappellari et al. (2007) noted that slow rotators “tend to be fairly round ($\epsilon \lesssim 0.3$)” but the sample was still quite small for significant conclusions. The roundness of slow rotators is more apparent from ATLAS^{3D} (fig. 6 of Emsellem et al., 2011), but Emsellem et al. (2011) still considered the much

flatter 2σ galaxies, the counter-rotating disks, as belonging to the same class. These galaxies are intrinsically flat but can have low λ_{Re} due to the presence of two disks rotating in opposite directions. These counter-rotating disks show a different distribution on the (λ_{Re}, ϵ) diagram to the other non-regular rotators (see Figure 1.4). C16 used realistic galaxy models (Cappellari, 2008) to show the structural continuity between 2σ galaxies and fast rotators (see sec. 3.5.3 of C16). C16 introduced a maximum ellipticity $\epsilon = 0.4$ so that any galaxy that is flatter than E4 cannot be a genuine slow rotator, regardless of λ_{Re} . C16 also revised the demarcation line of Emsellem et al. (2011) to better account for the fact that λ_{Re} has a floor at about 0.02-0.05 which is set by the noise in the stellar kinematics. As ϵ tends towards zero, $0.31\sqrt{\epsilon}$ also tends to zero, and so very round slow rotators could potentially be misclassified as fast rotators (because λ_{Re} cannot reach zero due to noise). By combining data from the ATLAS^{3D} (Emsellem et al., 2011) and SAMI-Pilot (Fogarty et al., 2015) surveys, C16 found that $\lambda_{Re} = 0.08 + 0.25\epsilon$ separates regular and non-regular rotators with minimal overlap (see Figure 1.4). I use this definition in this work.

1.2 From observations to models: relating observable quantities to galaxy dynamics

It is an inescapable fact that we only have one viewing angle for each galaxy from our location here on Earth. Furthermore, all but a handful of galaxies are too far away to resolve individual stars and so it is not possible (or in fact necessary) to measure velocities for individual stars. Instead, we obtain the LOSVD integrated across a finite aperture. Specifically, we obtain the mean velocity along the line of sight $\langle v_{\text{LOS}} \rangle$ as well as the velocity dispersion σ_{LOS} from the width of absorption lines. The challenge is to infer the dynamical structure of galaxies from this limited information. Fortunately, a great deal of effort has gone into solving this problem, and so in this section, I provide a brief review about how we relate observational quantities to physical ones, which can then be used to construct galaxy models.

1.2.1 The collisionless Boltzmann equation

The fundamental equation of stellar dynamics is the collisionless Boltzmann equation (CBE; eq. 4-13 BT87):

$$\frac{\delta f}{\delta t} + \mathbf{v} \cdot \nabla f - \nabla \Phi \cdot \frac{\delta f}{\delta \mathbf{v}} = 0, \quad (1.5)$$

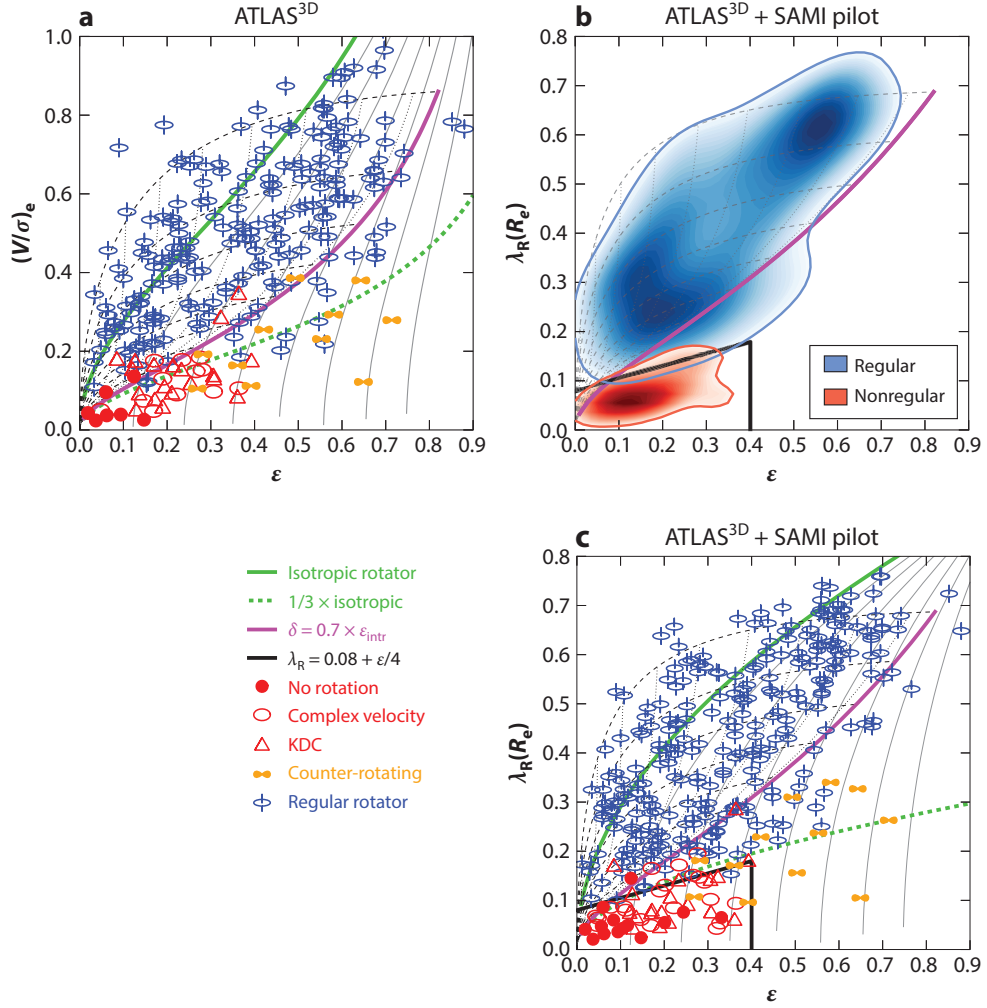


Figure 1.4: **ETG angular momentum as a function of apparent flattening.** **a:** The classic $(V/\sigma, \epsilon)$ diagram. The points are the $(V/\sigma, \epsilon)$ values for the ATLAS^{3D} ETGs taken from Emsellem et al. (2011). Each point is coloured according to its kinematic morphology as given in the legend. The theoretical edge-on predictions for isotropic and anisotropic rotators are shown as solid green and magenta lines respectively. The solid grey lines show how the green solid line changes with increasing anisotropy δ as given by eq. (14) of C16. The dashed grey lines trace how a galaxy with a given edge-on ellipticity moves from the magenta line (eq. (11) of C16; Cappellari et al., 2007) across the diagram as the viewing angle is varied towards face-on. **b:** The $(\lambda_{R_e}, \epsilon)$ diagram first introduced in Emsellem et al. (2007). The magenta line is the same as in **a** but it has been transformed into the $(\lambda_{R_e}, \epsilon)$ plane using eq. (B1) of Emsellem et al. (2007). The distributions for regular and non-regular rotators are smoothed with a Gaussian kernel. The data comes from Emsellem et al. (2011) and Fogarty et al. (2015). The solid black lines are the revised boundary between SRs and FRs of eq. (10) of C16. In particular the upper limit, $\lambda_{R_e} = 0.08 + 0.25\epsilon$, was motivated by this distribution. **c:** The points are the data that are smoothed in **b**. In this diagram, it becomes clear that only the counter-rotating disks occupy $\epsilon \geq 0.4$ and $\lambda_{R_e} \lesssim 0.2$ motivating the need for a boundary at $\epsilon = 0.4$ between SRs and FRs. Taken from C16.

or more explicitly,

$$\frac{\delta f}{\delta t} + \sum_{i=1}^3 \left(v_i \frac{\delta f}{\delta x_i} - \frac{\delta \Phi}{\delta x_i} \frac{\delta f}{\delta v_i} \right) = 0. \quad (1.6)$$

The CBE is analogous to the fluid equation where the conserved quantity is the phase space density (or distribution function) f . f simply describes the probability of a star appearing in a small, six-dimensional volume $d^3\mathbf{x}d^3\mathbf{v}$ at time t . The CBE states that the density of stars in a volume of phase-space is constant, implying that as the density of stars increases, the stellar velocity dispersion also increases. The assumption is that the stars are collisionless, which is a valid assumption because the distances between stars are orders of magnitude larger than the sizes of the stars themselves, and also because the relaxation timescale (which is the timescale on which two-body interactions become important) is about nine orders of magnitude larger than the orbital timescale (~ 250 Myr for the Milky Way). It also assumes that stars cannot be created or destroyed (a fact we know not to be true from stellar evolution). Specifically, the CBE states that the rate at which mass enters the volume element $d^3\mathbf{x}d^3\mathbf{v}$ is the same as the rate at which mass leaves the element. Eq. (1.5) only applies in the steady state where a stellar system has reached equilibrium i.e. the virial theorem is satisfied and $df/dt = 0$.

1.2.2 The axisymmetric Jeans equations

As already mentioned, Eq. (1.5) is fundamental to stellar dynamics as it describes the motions of stars within galaxies, and yet it is impossible to solve since there are an infinite number of solutions (e.g. Cappellari, 2008). However, if the galaxy is assumed to be axisymmetric, then the potential Φ and the distribution function f are constant with angle ϕ . Hence, some of the terms in Eq. (1.5) become zero if the CBE is rewritten in cylindrical coordinates (R, z, ϕ) (eq 4-17 BT87):

$$v_R \frac{\partial f}{\partial R} + v_z \frac{\partial f}{\partial z} + \left(\frac{v_\phi^2}{R} - \frac{\partial \Phi}{\partial R} \right) \frac{\partial f}{\partial v_R} - \frac{\partial \Phi}{\partial z} \frac{\partial f}{\partial v_z} - \frac{v_R v_\phi}{R} \frac{\partial f}{\partial v_\phi} = 0. \quad (1.7)$$

At this point, it becomes useful to take moments of the CBE in order to attempt to solve it. This will allow us to define a series of equations called the Jeans equations (Jeans, 1922) which relate the densities of stars to their position, velocity, velocity dispersion and the gravitational potential of the galaxy. The first order Jeans equation describes the velocity of the stellar system and is obtained as:

$$n \langle v_i \rangle = \int v_i f d^3\mathbf{v} \quad (1.8)$$

where n is the number (luminosity) density and $\langle v_i \rangle$ is the local expectation value of v_i ³. If we multiply Eq. (1.8) by v_R and v_z in turn, then integrate over velocity space, we arrive at the two axisymmetric Jeans equations (Jeans, 1922; eq. 4-29 a, c, BT87):

$$n \frac{\langle v_R^2 \rangle - \langle v_\phi^2 \rangle}{R} + \frac{\partial n \langle v_R^2 \rangle}{\partial R} + \frac{\partial n \langle v_R v_z \rangle}{\partial z} = -n \frac{\partial \Phi}{\partial R} \quad (1.9)$$

$$n \frac{\langle v_R v_z \rangle}{R} + \frac{\partial n \langle v_z^2 \rangle}{\partial z} + \frac{\partial n \langle v_R v_z \rangle}{\partial R} = -n \frac{\partial \Phi}{\partial z}, \quad (1.10)$$

where $n \langle v_i v_j \rangle$ is defined as:

$$n \langle v_i v_j \rangle = \int v_i v_j f d^3 \mathbf{v} \quad (1.11)$$

There is a third Jeans equation obtained by substituting v_i for v_ϕ in Eq. (1.8), but all its terms are zero for the axisymmetric case.

The Jeans equations in the form given in Eqs. (1.9) and (1.10) are solvable, but rather than provide a unique solution, they provide a family of possible solutions, and so they are useless in the form above. One way to solve the equations would be to specify the shape and orientation of the velocity ellipsoid, defined by $\langle v_R^2 \rangle$, $\langle v_z^2 \rangle$ and $\langle v_R v_z \rangle$, at every point in the meridional plane (i.e. a plane at constant ϕ ; see fig. 1 of Cappellari, 2008). As noted by Cappellari (2008), a common choice is to assume that the velocity ellipsoid is circular in the meridional plane, meaning that $\langle v_R^2 \rangle = \langle v_z^2 \rangle$. Cappellari (2008) instead allowed for an ellipsoid that is flattened in the z -direction (the ellipsoid is anisotropic), as this was found to be the case in real galaxies (Cappellari et al., 2007). Another assumption that simplifies the equations is that the velocity ellipsoid is aligned with the cylindrical coordinate system. In this case, the radial and vertical motions are completely independent implying that $\langle v_R v_z \rangle = 0$. If the anisotropy is defined by $\langle v_R^2 \rangle = b \langle v_z^2 \rangle$, the Jeans equations simplify to (eqs. 8 and 9 of Cappellari, 2008):

$$n \frac{b \langle v_z^2 \rangle - \langle v_\phi^2 \rangle}{R} + \frac{\partial b n \langle v_z^2 \rangle}{\partial R} = -n \frac{\partial \Phi}{\partial R} \quad (1.12)$$

$$\frac{\partial n \langle v_z^2 \rangle}{\partial z} = -n \frac{\partial \Phi}{\partial z}, \quad (1.13)$$

These equations are considerably simpler than Eq. (1.7), and can be solved if one specifies n and hence the potential Φ . In this case, Eq. (1.12) and Eq. (1.13) become

³Explicitly, $\langle v_i \rangle = \langle v_i(\mathbf{x}) \rangle = \int v_i(\mathbf{x}) f(\mathbf{x}, \mathbf{v}) d^3 \mathbf{v}$

(Eqs. 10 and 11 of Cappellari, 2008):

$$n\langle v_\phi^2 \rangle(R, z) = b \left[R \frac{\partial n\langle v_z^2 \rangle}{\partial R} + n\langle v_z^2 \rangle \right] + Rn \frac{\partial \Phi}{\partial R} \quad (1.14)$$

$$n\langle v_z^2 \rangle(R, z) = \int_z^\infty n \frac{\partial \Phi}{\partial z} dz. \quad (1.15)$$

To specify the number density n , Cappellari (2008) used the Multi-Gaussian Expansion (MGE) method of Emsellem et al. (1994) which accurately describes galaxy surface brightness profiles as a linear sum of Gaussians each described by the σ , the axial ratio q and the position angle ϕ . The inclination needs to be taken into account as we observe the LOS velocity v_{LOS} . The general expression for the second moment of the velocity component along the line of sight, Σv_{LOS}^2 , is given by eq. (28) of Cappellari (2008). The Jeans Anisotropic Modelling (JAM) method fits Σv_{LOS}^2 to the observed second velocity moment $V_{\text{rms}} \equiv \sqrt{V^2 + \sigma^2}$. The only free parameters in JAM are the anisotropy β_z (see subsection 1.2.3), the inclination and the total mass-to-light ratio (M/L) (Cappellari, 2008, 2016).

JAM gives a prediction of the intrinsic second velocity moment $\langle v_\phi^2 \rangle$ in the tangential direction ϕ (Cappellari, 2008, 2016). However, $\langle v_\phi^2 \rangle$ is a combination of an ordered component and a random component,

$$\langle v_\phi^2 \rangle = \langle v_\phi \rangle^2 + \sigma_\phi^2, \quad (1.16)$$

and one needs to make assumptions about how to split $\langle v_\phi^2 \rangle$. However, it turns out that on average the velocity ellipsoid of real galaxies tends to be oblate i.e. $\sigma_\phi = \sigma_R$ (fig. 2, Cappellari et al., 2007). In this case, the velocity can be obtained as

$$\langle v_\phi \rangle = \sqrt{\langle v_\phi^2 \rangle - \sigma_R^2}. \quad (1.17)$$

Cappellari (2016) found that with the assumption of an oblate ellipsoid, the observed V can be predicted by the models with no scaling required (Figure 1.5). This remarkable agreement, which is not yet understood, suggests that regularly rotating ETGs do have (nearly) oblate velocity ellipsoids. Therefore, the only parameter required to describe the shape of the velocity ellipsoid is β_z .

1.2.3 The anisotropy parameter

The anisotropy parameter β_z describes the flattening of the velocity ellipsoid in the z -direction. However, it is seen in the models that β_z does not span this value for all

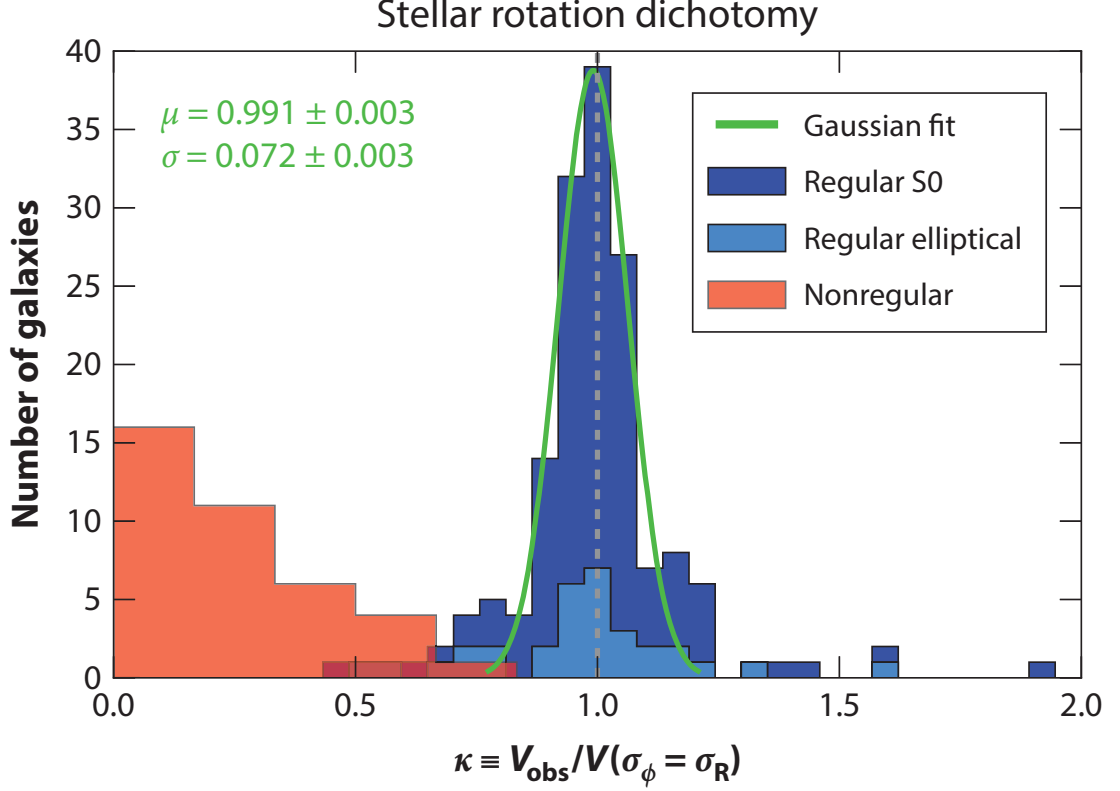


Figure 1.5: **Stellar rotation dichotomy.** The x -axis is the ratio κ between the observed velocity field, V_{obs} , and the velocity field predicted using the JAM method, assuming that the velocity ellipsoid is oblate and aligned with the cylindrical coordinate system, $V(\sigma_{\phi} = \sigma_R)$. The values are extracted from model A of Cappellari et al. (2013a). The histograms for regular S0s and regular elliptical galaxies peak at about $\kappa = 1$ (μ of a Gaussian fit to the blue histograms is equal to 0.991) with remarkably little scatter ($\sigma = 0.072$), proving that the assumption of an oblate velocity ellipsoid is valid for regular rotator ETGs. In contrast, the histogram for the non-regular rotators is skewed towards zero with a tail extending out to about $\kappa \approx 0.75$, suggesting that JAM over-predicts the velocity field in all cases. Clearly, the assumptions for regular rotators cannot be applied to non-regular (slow) rotators. The fact that the blue and red histograms barely overlap suggests a dichotomy in stellar rotation, rather than a smooth transition. Taken from C16.

regular rotators, but is restricted below a value that depends on the intrinsic ellipticity ϵ_{intr} as (eq. 11 of C16, Cappellari et al., 2007)

$$\delta \approx \beta_z = 0.7 \times \epsilon_{\text{intr}}. \quad (1.18)$$

Eq. (1.18) defines what appears to be an approximate limit to the maximum anisotropy permitted as a function of ϵ_{intr} : the flatter a galaxy, the flatter the velocity ellipsoid can be. As ϵ_{intr} is directly related to V/σ , the anisotropy of regular rotators is also related to V/σ . These relationships are encapsulated in the theoretical prediction for an edge-on galaxy, as given by Binney (2005) (Eq. 14, C16):

$$\frac{\langle V^2 \rangle}{\langle \sigma^2 \rangle} = \frac{(1 - \delta)\Omega(e) - 1}{\alpha(1 - \delta)\Omega(e) + 1}, \quad (1.19)$$

where (eq. 15, C16)

$$\Omega(e) = \frac{0.5[(\arcsine)/\sqrt{1 - e^2} - e]}{e - (\arcsine)\sqrt{1 - e^2}}, \quad (1.20)$$

and

$$e = \sqrt{1 - (1 - \epsilon_{\text{intr}})^2}. \quad (1.21)$$

The parameter α depends on the shape of the galaxy's velocity curve and radial luminosity profile (eq. 27, Binney, 2005), and was found to take a fixed value $\alpha \approx 0.15$ in real galaxies (Cappellari et al., 2007). Eq. (1.20) is a measure of the ratio of the potential of the system in the plane of the galaxy compared to perpendicular to the plane and Eq. (1.21) is merely a conversion between the intrinsic ellipticity and the eccentricity.

Eq. (1.19) is equivalent to the luminosity weighted V/σ within $1R_e$ (eq. 13, C16),

$$\frac{\langle V^2 \rangle}{\langle \sigma^2 \rangle} \approx \left(\frac{V}{\sigma} \right)_e^2. \quad (1.22)$$

The minimum effective V/σ as a function of ϵ_{intr} can be predicted by setting $\delta = 0.7\epsilon_{\text{intr}}$ in Eq. (1.19).

The above equations give a prediction for $(V/\sigma)_e$ and ϵ for the edge-on case. A galaxy's position on the $(V/\sigma, \epsilon)$ diagram depends on its inclination. The projected values for V/σ and ϵ are (sec. 4.3, BT87)

$$\left(\frac{V}{\sigma} \right)_e^{\text{obs}} = \left(\frac{V}{\sigma} \right)_e \frac{\sin i}{\sqrt{1 - \delta \cos^2 i}}, \quad (1.23)$$

and

$$\epsilon = 1 - \sqrt{1 + \epsilon_{\text{intr}}(\epsilon_{\text{intr}} - 2) \sin^2 i}, \quad (1.24)$$

respectively.

Cappellari (2008) followed standard practice by defining the anisotropy parameter $\beta_z \equiv 1 - \langle v_z^2 \rangle / \langle v_R^2 \rangle = 1 - 1/b$ (sec. 4.3, BT87). If the shape of the velocity ellipsoid is constant everywhere inside the galaxy, then the anisotropy becomes (Cappellari et al., 2007)

$$\beta_z = 1 - \left(\frac{\sigma_z}{\sigma_R} \right)^2. \quad (1.25)$$

1.3 Galaxy formation theory

Our understanding of the Universe is driven by observations. However, it is essential to produce models and simulations that can replicate the properties of individual galaxies or galaxy populations as a whole. A synergy of these two strands of astrophysics leads to a theoretical understanding of the Universe and its components. In this section, I review our current understanding of galaxy formation which is a culmination of 100 years of effort by the astronomical community. I base my discussion on the reviews by Somerville & Davé (2015) and Naab & Ostriker (2017).

1.3.1 Λ -CDM Cosmology

The prevailing cosmological theory of today is the Lambda-Cold Dark Matter (Λ -CDM) model. It states that just $\sim 5\%$ of the total energy content of the Universe is made up of baryonic matter (Planck Collaboration et al., 2016). The remaining constituents are collisionless dark matter ($\sim 27\%$), which is invisible and acts purely through gravitation, and dark energy ($\sim 68\%$), which is responsible for the accelerating expansion of the Universe as evidenced by the apparent dimming of Type Ia supernova (Riess et al., 1998). The local expansion rate of the Universe is determined observationally to be about $H_0 = 70 \text{ km s}^{-1}$ (Planck Collaboration et al., 2016), where H_0 is known as Hubble’s constant. To explain the large-scale structure that we observe, it is often enough to neglect baryonic physics and simply consider the dark matter. A useful picture to have in mind is the one proposed by Somerville & Davé (2015) where the dark matter field can be imagined as a mountain range with smaller peaks embedded within larger peaks forming a very craggy structure. These peaks arise as a result of small density fluctuations in the early Universe which grow over time via gravitational instabilities. Once a region of dark matter reaches a critical density, it collapses and decouples from the general expansion. These collapsed regions of dark matter are called halos, and they are found in N -body simulations to grow hierarchically, such that the largest halos grow from smaller “building blocks”

(Davis et al., 1985; Efstathiou et al., 1985; Bertschinger & Gelb, 1991; Lacey & Cole, 1993; Springel, 2005, see Figure 1.6 for an illustration of a state-of-the-art cosmological simulation).

1.3.2 The growth of galaxies

Galaxies are thought to follow one of two major growth channels (C16). The first, and vastly more common one, is the fast rotator channel which I describe first. Afterwards, I describe the much rarer slow rotator channel following the argument laid out in sec. 7.2 of C16.

Dark matter halos are the sites where galaxies are formed. The primordial gas, composed of hydrogen, helium and lithium, sinks to the centre of the halo potential well (White & Rees, 1978; White & Frenk, 1991). In contrast to the dark matter, the gas is collisional and so it can dissipate its energy via radiative cooling. As the gas collapses, it becomes shocked (Bertschinger, 1985; Tozzi & Norman, 2001). The gas then cools via a number of processes, but primarily via bremsstrahlung emission (free-free emission between gas particles), in places where the gas is hotter than $T \approx 10^7 K$ (Hoyle, 1953). Once the gas has cooled sufficiently, it loses pressure support and collapses further, conserving specific angular momentum in the process (Mestel, 1963). The gas initially gets its angular momentum from interactions with neighbouring protogalaxies. As proposed by Hoyle (1951), protogalaxies acquire their angular momentum as a result of tidal torques from nearby protogalaxies (see Jones, 1976 for a review on contemporary alternative theories). These protogalaxies are unlikely to be spherically symmetric and so their quadrupole moment will be coupled to the tidal field produced by neighbouring galaxies (Peebles, 1969). This coupling creates a velocity shear that naturally results in rotation. The magnitude of the torque depends on the magnitude of the misalignment.

Energy dissipation in the scenario where mass and angular momentum are conserved (Fall & Efstathiou, 1980) naturally leads to the formation of disk-like structures (Abadi et al., 1990; Kormendy & Bender, 1996) as it tends to reduce the kinematic energy in the direction parallel to the spin axis (Cappellari et al., 2007). The disk is supported by rotation and can accrete more cold gas along filaments (cold mode accretion; Kereš et al., 2005; Dekel et al., 2009) while conserving the spin. Provided the disk remains in relative isolation, it can remain a spiral galaxy. The preferred environment of galaxies is the group environment, so spirals can easily accrete gas or experience minor mergers. These interactions tend to drive gas towards the centre which feeds the central supermassive black hole which in turn increases the velocity

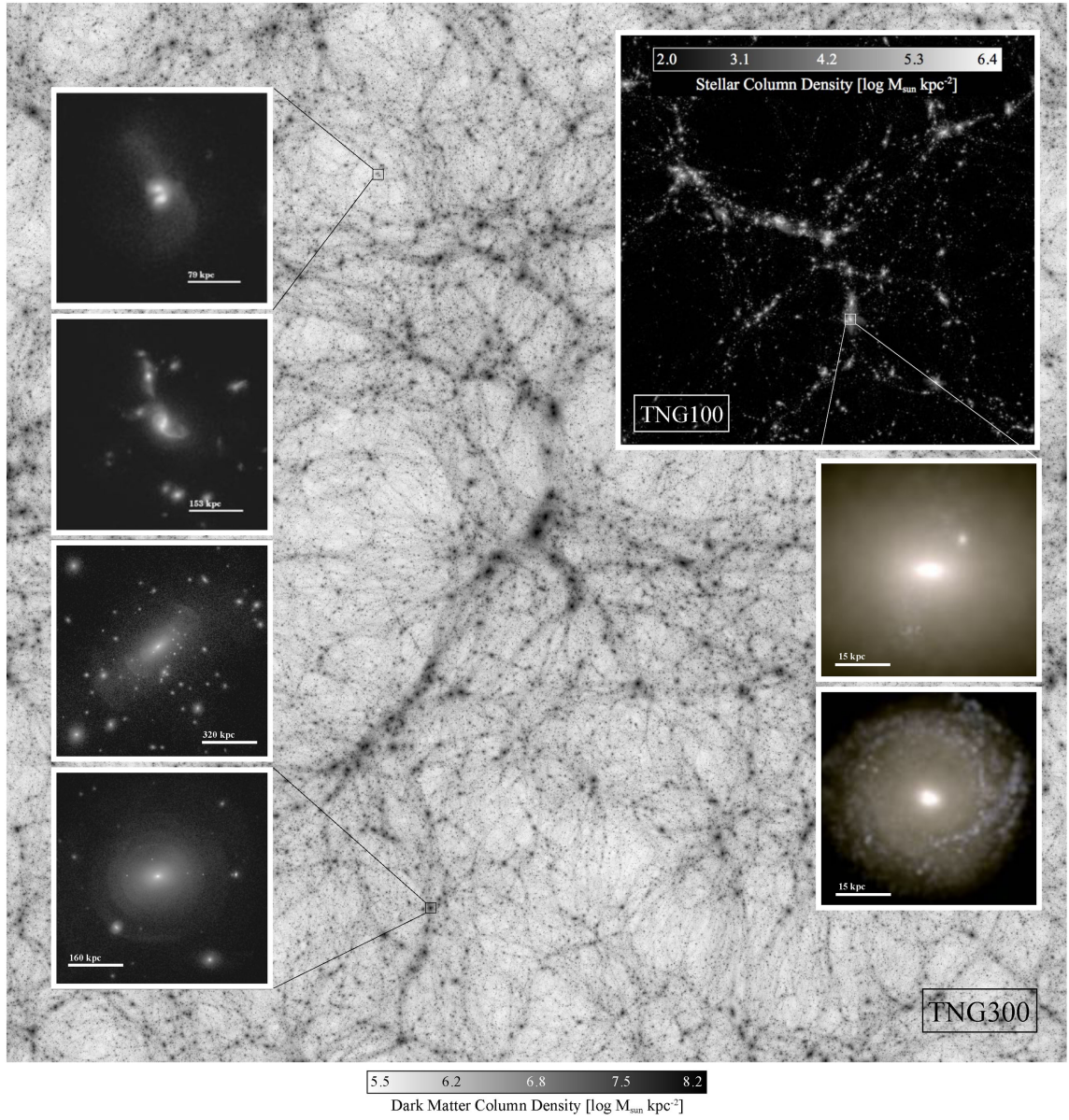


Figure 1.6: **Cosmological magnetohydrodynamical simulation from IllustrisTNG.** The main panel shows the dark matter column density along the line of sight within a volume with sides of length 300 Mpc across (TNG300) at $z = 0$. In the larger inset, the stellar column density is shown within a smaller volume of sides 100 Mpc across (TNG100). The densities in the TNG300 and TNG100 panels only show the projected column density for a third of each volume. The panels on the left show the projected stellar mass density for two examples of galaxy-galaxy interactions from the TNG300 simulation as well as two examples of massive ETGs which exhibit shells indicative of a recent merger event. The two panels on the bottom right show the stellar light of two massive face-on galaxies ($M \geq 10^{11} M_{\odot}$) from the higher resolution TNG100 simulation. Taken from Pillepich et al. (2018).

dispersion and grows the bulge (Magorrian et al., 1998). Bulge growth can increase the chances of the galaxy having its star formation quenched (Somerville et al., 2008; Kormendy & Ho, 2013, C16).

In the early stages of the Universe, some of the dark matter halos that condensed out of the dark matter fields were larger than average. These halos acquired gas faster than smaller mass halos and were also able to attract larger amounts of gas thanks to their large gravitational potentials. Simulations have shown that for halos above a critical mass of $\sim 10^{12} M_{\odot}$, the cooling timescale for the shocked gas is longer than the Hubble time and so it cannot contribute to disk growth (Kereš et al., 2005; Dekel & Birnboim, 2006). Instead, the gas is heated by feedback from the active galactic nucleus (AGN) of the galaxy in the halo which serves to quench the star formation (see Urry & Padovani, 1995 and Fabian, 2012). The hot gas has been observed in the X-ray (Bender et al., 1989; Mathews & Brighenti, 2003; Kormendy et al., 2009; Sarzi et al., 2013) and seen in simulations due to artificial feedback from the AGN (Negri et al., 2014; Ciotti et al., 2017; Choi et al., 2017; Eisenreich et al., 2017). These massive and passive galaxies are the progenitors of the modern day slow rotators. They sit at rest near the centre of mass of the group halo surrounded by mostly star-forming galaxies.

In the hierarchical framework, the group halos merge to form larger groups and clusters. The central galaxies are able to sink to the centre of the merged halo due to dynamical friction, and hence are able to merge efficiently due to their lower relative velocities. This contrasts with the lower mass galaxies in the group which have higher relative velocities and so are much less likely to merge. Because the two merged galaxies only contain a stellar component (as the gas is either not present or dynamically unimportant), the merger is collisionless and therefore dissipationless (or “dry”). This means that the stellar angular momentum of the luminous matter is not conserved but instead is redistributed out into the halo. The supermassive black holes from each progenitor form a binary at the centre of the remnant and scatter stars out of the nucleus via three-body interactions. Over time, a deficit in a nuclear light profile forms (i.e. a “core”; Lauer, 1985). The remnant is therefore a massive core slow rotator dominated by velocity dispersion. Slow rotators accrete about 50-90% of their stellar mass via mergers with satellites (Khochfar et al., 2011). This scenario is supported by observations of brightest cluster galaxies (BCGs) that show they were fainter at $z = 1$ compared to $z = 0$, which suggests that they have accreted mass since $z = 1$ and grown their luminosity, rather than dimmed due to an ageing stellar

population (Aragon-Salamanca et al., 1998). As such, they grow in size much more rapidly than the fast rotator ETGs (C16).

These two formation pathways are illustrated in Figure 1.7a. The depiction moves from the initial conditions to the group environment. The slow rotators have already formed in the group environment. The groups merge into a larger single halo and over time, the massive slow rotators from each progenitor halo merge to form a single massive SR. In Figure 1.7b, I show three schematics for three large clusters which highlight the positions of the massive SRs in each cluster. The observations agree remarkably well with the theoretical depiction given in Figure 1.7a.

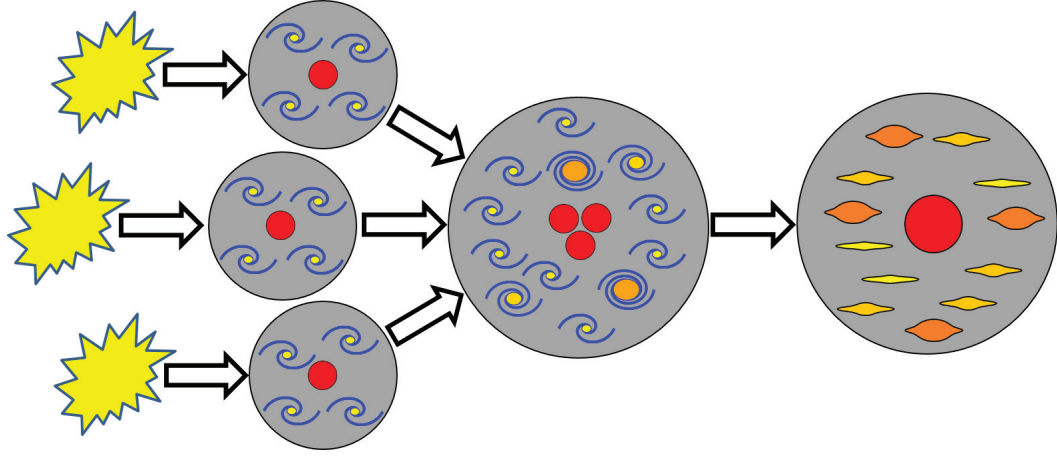
1.4 The Mapping Nearby Galaxies at Apache Point Observatory survey

MaNGA (Mapping Nearby Galaxies at Apache Point Observatory; Bundy et al., 2015) is a large-scale integral-field spectroscopic survey currently operating during the fourth phase of the SDSS (Sloan Digital Sky Survey). Hence, before I describe the MaNGA survey in detail, I introduce the SDSS.

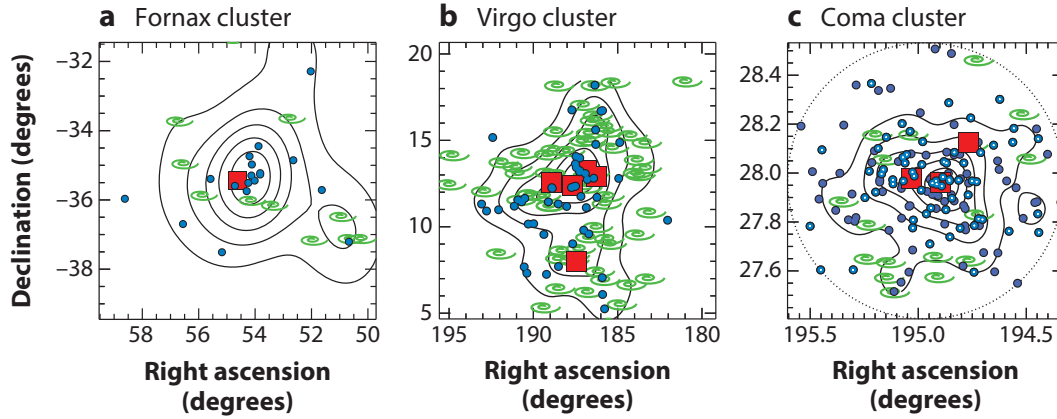
1.4.1 The Sloan Digital Sky Survey

The SDSS (York et al., 2000) is a pioneering feat of imaging and electronics and is arguably the most successful astronomical survey in existence. It has been running for almost two decades and has revolutionised our view of the Universe. It has produced high-precision maps of the large-scale structure of the Universe, which have provided important constraints on the role of dark matter, dark energy and structure formation (e.g. Blanton & Moustakas, 2009). The survey is based principally at the dedicated Sloan Foundation 2.5 metre telescope located at Apache Point Observatory in New Mexico (Gunn et al., 2006; Figure 1.8). To date, it has covered 14,555 square degrees of the sky mostly in the Northern hemisphere (about a third of the celestial sphere).

The SDSS is currently in its fourth phase, SDSS-IV (Blanton et al., 2017), and has three projects running concurrently sharing telescope time. One of these projects, the Apache Point Observatory Galactic Evolution Experiment 2 (APOGEE-2) is an extension of an earlier survey of the same name (Majewski et al., 2017) aimed at observing thousands of Milky Way stars with high resolution in the near-infrared. The second project is the extended Baryon Oscillation Spectroscopic Survey (eBOSS; Dawson et al., 2016), which aims to observe large-scale structure beyond the redshift of



(a)



(b)

Figure 1.7: (a) **Hierarchical formation of massive SRs.** At first, the most massive dark matter halos collapse, and the baryonic matter falls in to the potential well. The massive progenitors of the core slow rotators (red circles) are at rest at the centre of the group halo while star forming galaxies populate the rest of the halo. As groups merge, the core slow rotators efficiently sink to the centre of the cluster potential well due to their low relative velocities with respect to the constituent group halos. Over time, they merge into a single massive slow rotator. The spirals are quenched due to ram-pressure stripping and gas starvation, and their bulges grow as a result. However, they are unlikely to merge due to their large relative velocities. (b) **SRs, FRs and spirals in three nearby clusters.** Each panel shows a cluster where each galaxy is either a core SR (red square), FR ETG (blue circle) or a spiral galaxy (green spiral). The contours are kernel density estimates of the density field. The clear tendency for core SRs to occupy the centres of clusters can be seen. Both figures are taken from C16.

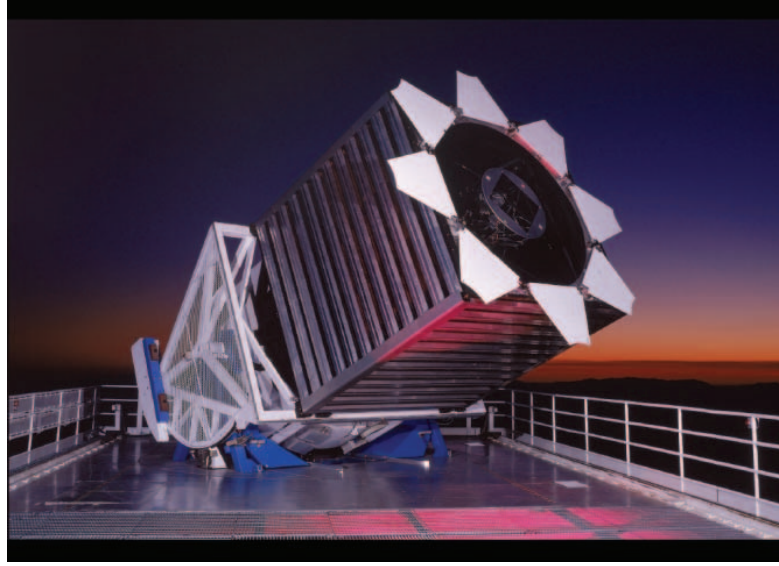


Figure 1.8: **Image of the SDSS telescope at sunset.** Taken from Gunn et al. (2006)

the main SDSS survey to provide a better understanding of dark matter, dark energy and neutrinos. The third project is MaNGA which I leave to the next subsection.

The photometric imaging camera has 30 charge-coupled device (CCD) detectors and is placed at the focal plane of the Sloan telescope (Gunn et al., 1998). The CCDs are arranged in an array of five rows, each containing six CCDs. Each row is covered by one of the five SDSS photometric colours in the order *riuzg*. During the original survey, the telescope moved constantly along great circles on the sky so that each object spent about a minute in each filter before moving onto the next. The *u* filter peaks at a wavelength of $3500 \text{ \AA}$, while the *z* filter is a near-infrared filter centred at $9100 \text{ \AA}$. The five filters cover the entire visible part of the spectrum, although the throughput is not constant across the wavelength range (Gunn et al., 1998). In fact, the *r*-band has the highest sensitivity and is centred at a wavelength of $6250 \text{ \AA}$. The field of view of the telescope is 3° on the sky which is crucial for a large-area survey.

An ingenious feature of the SDSS is that imaging and spectroscopy are carried out at the same telescope (Figure 1.8). To switch from imaging to spectroscopic observations, the imaging camera is removed from the focal plane and is replaced by an aluminium plate. The plate has about 1000 holes drilled into it where each hole corresponds to the location of the light path of a particular target on the focal plane. (Not all objects are MaNGA objects as MaNGA shares its dark time with APOGEE-2.) Small optical fibres are *manually* placed into the holes before the plate

is fixed onto the focal plane, and each fibre connects to one of two spectrographs. The plates are mounted within a cartridge that also houses the fibre feeding system that leads to the spectrographs (Smee et al., 2013). Each fibre is 0.2 mm in diameter corresponding to 3 arcsec on the sky, and adjacent fibres cannot be placed closer than 55 arcsec on the sky. The SDSS has two spectrographs each with two cameras split about a wavelength of about 6000 Å. The spectral range covers the entire visible spectrum from about 3600 - 10300 Å, resulting in a typical resolving power $R \sim 2000$ (Smee et al., 2013; Law et al., 2015). The original spectrographs were upgraded to accommodate the BOSS (Dawson et al., 2013), and so they are known as the BOSS spectrographs and remain active on the telescope. Up to nine plates can be observed every night, meaning that spectra for about 9000 targets can be obtained in one night. The original legacy survey was completed in 2008, with the final imaging taken in 2009, and was released as part of SDSS Data Release 8 (Aihara et al., 2011). A complete summary of the technical details of the survey is given in York et al. (2000).

1.4.2 Introducing MaNGA

The SDSS has obtained accurate redshifts for about 2 million objects with single-fibre spectroscopy, but a single fibre does not capture light from the whole galaxy. Galaxies are extended objects and so there is much to be gained by obtaining spectra for the rest of the galaxy. As discussed earlier, single slits also do not capture all the information about a galaxy. Integral field spectroscopy allows spectra across the two-dimensional face of a galaxy to be obtained using bundles of optical fibres. MaNGA (Bundy et al., 2015) is certainly not the first survey to use IFS, but it is truly the first that manages to combine the power and scope of a large sky survey with the high information content that an IFU provides. At completion, MaNGA will have observed at least 10,000 galaxies in the nearby Universe with IFS (with the possibility of adding more thanks to additional time as a result of rescheduling) which is more than three times its current competitor SAMI (Croom et al., 2012). MaNGA’s overall goal is to understand the life cycle of present day galaxies by “seeking the physical origin of the mechanisms” (Bundy et al., 2015) that govern galaxy birth (formation, gas accretion), life (star formation activity, merging) and death (quenching).

1.4.3 Instrumentation

The core component of MaNGA is the IFUs themselves (Figure 1.9; see Drory et al., 2015 for a complete description and Law et al., 2015 for details on the observing

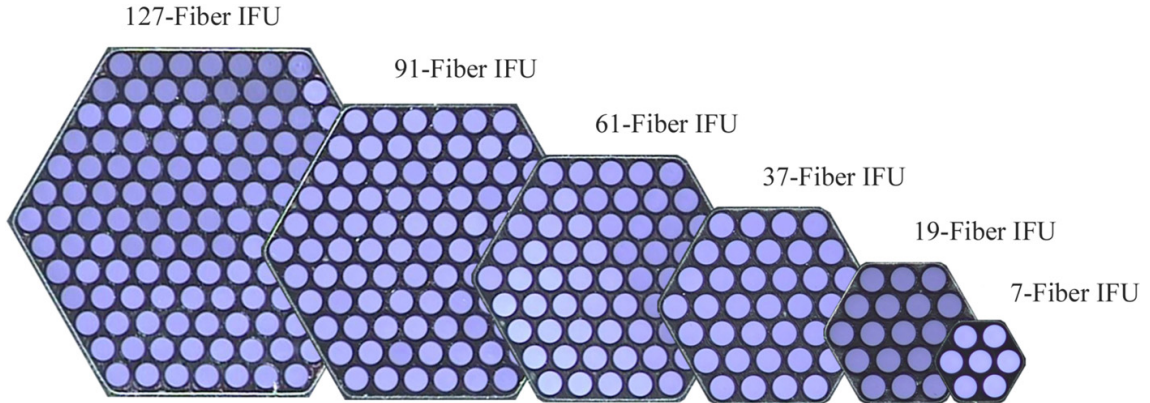


Figure 1.9: **Images of the MaNGA IFUs from Bundy et al. (2015).** Each blue circle is an optical fibre, and each hexagon is an IFU (the harness is not shown). All but the smallest IFU are used for science, while the smallest IFU is used only to observe standard stars for spectrophotometric calibration.

strategy). The observing setup is similar to the one used for the main SDSS spectroscopic survey, in that the harnesses that house the IFU ferrules are manually plugged into holes which were previously drilled into plates and correspond to targets on the sky. The fibres within each IFU are arranged into a hexagonal bundle (“hexabundle”) which allows the fibres to be packed to a very high density in order to optimise the available space on the detector. The spatial resolution is set by the 2 arcsec diameter of each fibre, subtending a physical distance of ~ 2 kpc at $z \sim 0.05$. MaNGA has 1423 fibres split between 17 IFUs of various different sizes (Figure 1.9). The two smallest IFUs contain 19 fibres each, while there are five IFUs that contain 127 fibres each. In between, there are four 37-fibre IFUs, four 61-fibre IFUs and two 91-fibre IFUs. Each IFU is assigned to a galaxy depending on its angular size on the sky. The harnesses each contain one of these IFUs, as well as between two and eight fibres to be used for sky subtraction. There are four more harnesses that each contain three mini-IFUs themselves consisting of seven fibres and three sky fibres. These IFUs are used for observing standard stars for spectrophotometric calibration (Yan et al., 2016a). MaNGA has six cartridges that it shares with the APOGEE-2 survey. It takes about 10 minutes to switch each cartridge for another one.

All IFUs are subject to the fact that there are gaps between each fibre (e.g. Sánchez et al., 2012; Sharp et al., 2015). This means that a point source will change its shape depending on whether it happens to fall directly onto a fibre or in the small gap between fibres (Law et al., 2015). A process called dithering is used to account for this effect, and involves moving the IFU by a small fraction of the fibre size. MaNGA

uses a triangular dithering pattern where the IFUs are moved between exposures. Dithering vastly decreases the variation of the point source function and maintains the circularity of point sources across the IFU (see fig. 5 of Law et al., 2015).

1.4.4 Target selection

The targets for MaNGA have been selected at low redshift ($0.01 < z < 0.15$) to follow a flat distribution across the full stellar mass range ($10^9 M_{\odot} - 10^{12} M_{\odot}$), using the absolute magnitude in SDSS i -band, M_i , as a proxy for stellar mass to remove any bias from stellar population models (Bundy et al., 2015). The MaNGA sample consists of three distinct subsets: the Primary, Secondary and Colour-Enhanced sample. One of the survey targets for MaNGA is to observe all galaxies in the Primary sample out to $\sim 1.5R_e$ and all galaxies in the Secondary sample out to $\sim 2.5R_e$. Therefore, the Secondary sample contains galaxies that are systematically at higher redshifts for a given M_i than the Primary sample. The Colour-Enhanced sample is designed to fill in gaps in the colour-magnitude plane (Bell et al., 2004; Baldry et al., 2004), covering low-mass red galaxies and high-mass blue galaxies for example. No cuts are made on colour, morphology or environment such that the galaxies observed by MaNGA are fully representative of the local galaxy population.

The galaxies in MaNGA were taken from the NASA-Sloan Atlas (NSA; Blanton et al., 2011; see subsection 2.1.3) which provided the parent catalogue. Details of how specific galaxy targets are chosen are given in Yan et al. (2016b) and Wake et al. (2017). Briefly, a process called tiling is used to decide which parts of the sky will actually be observed from the DR7 footprint. Tiles of 7 deg^2 are overlaid on the sky and allowed to overlap. Out of a total of about 1800 tiles, about 600 will be observed. The final tiles are chosen based on whether they are observable during specific observing runs and can achieve a high S/N due to a long exposure, as well as if they overlap with other imaging surveys. At the beginning of each night, a simulation tool attempts to find the best possible tiles to observe, taking into account the survey requirements as well as the current hardware setup (including which plates are already drilled and available to observe with for example).

1.4.5 MaNGA Data Pipeline

The MaNGA pipeline is split into two parts. The first of these is the Data Reduction Pipeline (DRP; Law et al., 2016), which itself is split into two stages. The first of these is the 2D stage that extracts the spectra for each fibre from the CCD image.

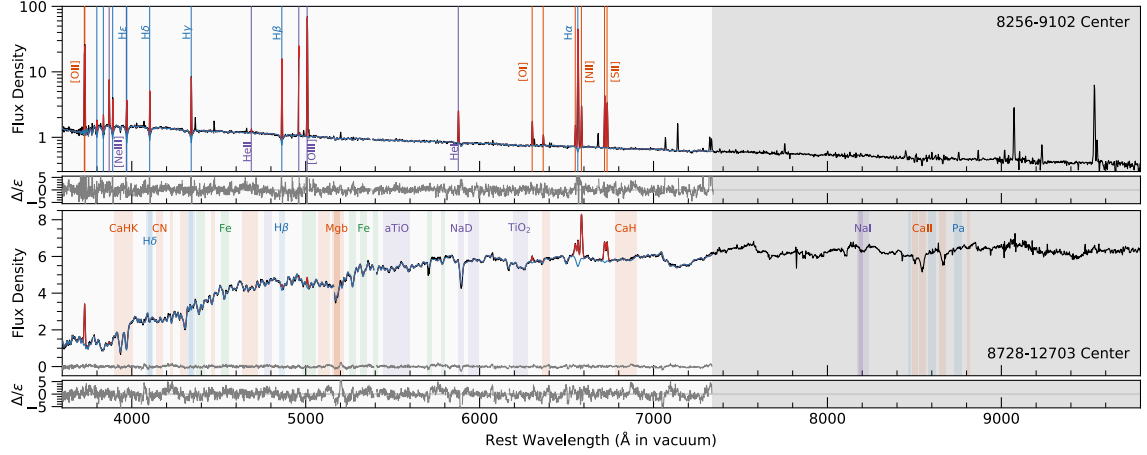


Figure 1.10: **MaNGA spectral fitting.** Observed spectra (black) for the central spaxel for two galaxies given in the corner of each panel. The best-fitting DAP model spectra fitted using the stellar continuum and emission lines are shown in red, and the stellar-continuum-only fits are shown in blue. Flux densities are plotted in units of 10^{-17} erg/s/cm²/Å/spaxel. The residuals are shown in grey. The grey region at $\lambda \gtrsim 7300$ is not covered by the MILES templates and so is not fitted. Emission lines are shown and labelled accordingly. Taken from Westfall et al. (2019)

Initially, the calibration exposures are processed and then used to calibrate the science exposures. The background sky is subtracted from the spectra of each individual fibre and the 12 mini-bundles are used to determine the flux calibration. The result is a FITS file containing 1423 rows corresponding to the 1423 fibres for a single exposure. Masks are applied to each fibre to indicate problems such as cosmic rays, missing fibres, bad sky subtraction etc. The second part of the DRP is a 3D stage that constructs a regularised grid from the individual exposures known as a data cube. The data cubes can also have masks indicating problems such as foreground stars or low fibre coverage for example. The final data products are ready for science applications and have a median spatial resolution of 2.54 arcsec and a median spectral resolution $\sigma = 72$ km s⁻¹, although the latter varies with wavelength (Law et al., 2016).

The second part of the MaNGA pipeline is the Data Analysis Pipeline (DAP; Westfall et al., 2019). The DAP performs spectral modelling among other analyses to produce data products that are intended for specific science applications. In particular, the DAP measures stellar kinematics, emission-line properties (kinematics, fluxes and equivalent widths) and spectral indices used to determine the age and metallicity of stellar populations. I focus on the stages of the DAP that are relevant to this work.

At first, the DAP checks the flags that were assigned by the DRP and excludes spaxels accordingly. It also calculates the signal-to-noise ratio which is then used by

the binning scheme to bin spaxels. The DAP uses a few different binning schemes including Voronoi binning (Cappellari & Copin, 2003) which bins the spaxels to a minimum S/N of 30. The DAP uses pPXF (Cappellari & Emsellem, 2004; Cappellari, 2017) to extract the stellar kinematics using the MILES stellar library (Sánchez-Blázquez et al., 2006; Falcón-Barroso et al., 2011) which covers just over half of the MaNGA wavelength range (3600 - 7400 Å; see Figure 1.10) and has a spectral resolution of 2.5 Å (Beifiori et al., 2011). Instead of fitting stars individually in the MILES stellar library, pPXF fits a set of 49 clusters of stellar spectra from the MILES stellar library, known internally as MILES-THIN, to the absorption-line spectra. The clusters are determined by a hierarchical clustering method and each cluster contains a number of stellar spectra with similar properties. Each datacube contains 4563 spectral slices covering the full MaNGA wavelength range. The kinematics are fitted to the observed velocities before being adjusted to the systemic velocity of the galaxy. In this thesis, I use the MAPS files which contain DAP measured properties. I extract the mean velocity and velocity dispersion for each Voronoi bin, as well as the bin coordinates (in RA and Dec). At each pixel, I obtain the median signal (corresponding to flux) so that the surface brightness is measured across the field of view at a constant resolution.

1.5 Thesis Summary

This thesis proceeds as follows. In chapter 2, I discuss the samples and measurements of galaxy properties used throughout this thesis. In particular, I perform some important quality control tests and derive a correction to account for seeing effects. In chapter 3, I illustrate the statistical properties of fast and slow rotators using a large sample of about 2300 galaxies, and I draw conclusions on their formation based on these results. In chapter 4, I develop a new group finder algorithm that is optimised for the study of the local galaxy environment. I use this algorithm in chapter 5 to construct a large volume-limited group catalogue of about 14,000 galaxies with complete angular momentum classifications. In chapter 6, I use the aforementioned catalogue to undertake an extensive and detailed study focussing on the influence of local galaxy environment on galaxy kinematic structure. Finally, I discuss the key results of my work and suggest potential avenues for future work.

Chapter 2

Data: samples, quality control and tests

May the wind under your wings
bear you where the sun sails and
the moon walks.

*J.R.R. Tolkien
The Hobbit or
There and Back Again*

2.1 Data Samples

2.1.1 MaNGA IFU observations

The data used in this chapter and chapter 3 are taken from the fifth MaNGA Product Launch (MPL-5; July 2016), an incremental internal data release. The spectra for MPL-5 were released to the public as part of the SDSS Data Release 14 (DR14; SDSS Collaboration et al., 2017). MPL-5 contains stellar and gas kinematics for 2722 galaxies. A small number of galaxies were observed with more than one IFU bringing the total number of data cubes to 2774.

2.1.2 Cross referencing with the 2MASS XSC

We cross-reference the MaNGA sample with the Two Micron All-Sky Survey Extended Source Catalog (2MASS XSC⁴; Skrutskie et al., 2006). Our focus is the near-infrared J and K_S bands which are most sensitive to old stellar populations that form the dominant baryonic mass component of galaxies. The near-infrared is also unobscured

⁴<http://irsa.ipac.caltech.edu/>

by dust extinction allowing the distribution of stellar populations to be revealed. Of the 2722 MaNGA galaxies in MPL-5, 2270 galaxies ($\sim 83\%$) were matched by ra and dec to within 5 arcsec of a near-infrared source. The remaining $\sim 17\%$ are too faint in the near-infrared to be included in the XSC. They are found in the 2MASS Point Source Catalog but lack any 2D photometric parameters such as ϵ .

For each matched target, we record the axis ratio (`sup_ba`), the apparent magnitude in K_S band (`k_m_ext`) and the major axis of the isophote enclosing half the total galaxy light in J band (`j_r_eff`). Half-light (or effective) radii are a poorly defined empirical quantity for low signal-to-noise (S/N) images, as they formally require the knowledge of galaxy fluxes out to infinite radii. For this reason, we use an empirical relation to calibrate the semi-major axis with respect to `j_r_eff`. This relation is defined by Cappellari (2013) (see also Krajnović et al., 2018) to be $R_e^{\text{maj}} = 1.61 \times \text{j_r_eff}$ where 1.61 is a best-fit factor used to match the 2MASS effective radii to the RC3 catalogue (de Vaucouleurs et al., 1991). (A previous relation used in Cappellari et al. (2011a) took $R_e^{\text{maj}} = \text{MEDIAN}(\text{j_r_eff}, \text{h_r_eff}, \text{k_r_eff})$ where `h_r_eff` is the same quantity in H band etc. However, this definition of R_e^{maj} required a factor of 1.7 to match RC3.) As noted by Cappellari (2013), J band is preferable over other bands as it has a higher signal-to-noise ratio. The circularised 2MASS effective radius is then $R_e = R_e^{\text{maj}} \times \sqrt{\text{sup_ba}}$.

2.1.3 NSA optical data

The target selection for MaNGA was taken from the NASA-Sloan Atlas⁵ (NSA) which is based on SDSS imaging (Blanton et al., 2011). The version of the catalogue used for MaNGA is v1_0_1, a summary of which was released as part of DR14⁶. Many relevant quantities are stored in a companion catalogue to each MPL; for MPL-5, we use `drpall-v2_1_2`. Along with the full NSA catalogue, companion FITS files are also available containing images in the SDSS *ugriz* bands. For each galaxy, we use the following quantities from the NSA catalog: the redshift (`z_dist`) estimated using the peculiar velocity model of Willick et al. (1997), the stellar mass derived from the K-correction (`mass`, Blanton & Roweis, 2007) as well as parameters derived from a 2D Sérsic fit (Blanton et al., 2011). These are the 50% light (effective) radius along the major axis (`sersic_th50`), the angle (East of North) of the major axis (`sersic_phi`), the axis ratio (`sersic_ba`) and the Sérsic index n (`sersic_n`).

⁵<http://www.nsatlas.org>

⁶<http://www.sdss.org/dr15/manga/manga-target-selection/nsa/>

As the 2MASS XSC is incomplete for the MaNGA sample, we need to ensure that the NSA R_e measurements are at the same scale as the XSC R_e , which are in turn scaled to match RC3. The 2MASS catalogue is accurate over all radii above ~ 5 arcsec, below which the effects due to the 2.5 arcsec PSF (FWHM) are dominant. At small radii, the NSA is more accurate than 2MASS due to the small 1.3 arcsec PSF (FWHM) (Stoughton et al., 2002). We find that there is a systematic offset between the NSA and XSC values of R_e , due to differences in depth of photometry, as well as a deviation from a one-to-one correlation at low radii, due to the different PSFs of the two catalogues.

In order to bring the NSA R_e to the same RC3 scale as our 2MASS-derived $R_e^{2\text{MASS}}$ values, we find the smallest $R_e^{2\text{MASS}}$ above which $R_e^{2\text{MASS}} \propto R_e^{\text{NSA}}$ i.e. the slope is equal to one within the errors. We find that for $R_e^{2\text{MASS}} > 7.5$ arcsec, $R_e^{2\text{MASS}} = 1.17 R_e^{\text{NSA}}$. We apply this scale factor to all R_e^{NSA} including those at low radii where there is not a one-to-one correlation with 2MASS. These scaling ensures that all our R_e are consistent with the sizes adopted in both the RC3 and ATLAS^{3D} catalogues, so they can be compared in an absolute sense.

2.2 Method and data analysis

In this section, we describe our methods for extracting the stellar kinematics from the MaNGA data, as well as our process of determining the parameters of the half-light ellipse. We introduce the spin parameter λ_{R_e} which acts as a proxy for the stellar angular momentum within the half-light ellipse and is sensitive to the kinematic morphology which we classify. We also derive stellar mass estimates from apparent K_S band magnitudes from the 2MASS XSC using distance estimates derived from the NSA redshift. In order to produce a *clean sample* of galaxies on which to base our final results, we perform a number of quality control steps. As part of this, we run a number of simulations to allow us to assess how an intrinsic velocity dispersion of 0 km s^{-1} affects λ_{R_e} after necessarily correcting for the instrumental dispersion. We discuss our method for returning from the MaNGA selection function to a volume-limited sample. Finally, we introduce our approximate analytic correction that can be used to correct λ_{R_e} for atmospheric seeing.

2.2.1 Determination of the half-light ellipse

For each galaxy, we require robust and accurate parameters of the half-light ellipse in order to calculate λ_{R_e} . The half-light ellipse is defined as an ellipse which covers the

same area as the half-light circle, i.e. a circle containing half of the visible light of a galaxy with a radius equal to the effective radius. Even though the NSA and 2MASS XSC catalogues provide parameters for the half-light ellipse, neither are individually suitable for covering the wide range of galaxy sizes in the MaNGA sample. Rather than seeking a combination of the two, we measure our own values for effective radius, ellipticity and position angle.

2.2.1.1 Multi-Gaussian Expansion method

We start by fitting the NSA r band photometry for each galaxy using the Multi-Gaussian Expansion (MGE) method (Emsellem et al., 1994; Cappellari, 2002). MGEs are an efficient way of describing the surface brightness and morphology of galaxies. They consist of a sum of two dimensional Gaussians each described by three parameters: the dispersion σ , the axial ratio q and the luminosity L (see Eq. 9 in Cappellari et al., 2013a). For all MaNGA galaxies, we use 12 Gaussians which we find is more than sufficient to successfully describe the photometry. We use the Python version of the `mge_fit_sectors` package¹ described in Cappellari (2002).

Before starting the fitting procedure, we subtract the sky background measured using `measure_sky`⁷. Simply, the routine fits a second degree polynomial Ax^2+Bx+C to a logarithmic histogram of the flux in pixels. The sky level is calculated as $-0.5B/A$ where A and B are the coefficients of the fitted polynomial. This is equivalent to fitting a Gaussian to the original fluxes and finding the peak, but the pixels are weighted differently. Once the sky background is subtracted, we fit an ellipse with an area (number of pixels) equal to $\pi R_e^{\text{NSA}^2}$ to the largest connected group of pixels in the NSA r band photometry using `find_galaxy`⁸ in the `mge_fit_sectors` package. To ensure we are fitting to the correct target in the NSA cutout (size $\sim 2''/\sim 10R_e$ FOV), we restrict our search field to $2R_e^{\text{maj}}$ (from 2MASS or NSA) or the size of the IFU, whichever is larger.

The photometry is divided into sectors linearly spaced in eccentric anomaly using `sectors_photometry`, and the MGE fit is performed on the sectors using `mge_fit_sectors`. Once we have the parameters of the MGE, we convert the total counts (TotalCounts) of each Gaussian into peak surface brightness C_0 using Eq. (1) from Cappellari (2002),

$$C_0 = \frac{\text{TotalCounts}}{2\pi\sigma^2q_{\text{obs}}}, \quad (2.1)$$

⁷<https://gist.github.com/jiffyclub/1310947#file-msky-py>

⁸We use the keyword `fraction` where $\text{fraction} = \pi R_e^2/N$ where N is the total number of pixels in the image.

where q_{obs} is the axial ratio of each Gaussian. To make the fit independent of distance, we convert σ into units of arcsec.

Finally, we determine the semi-major axis of the isophotal contour containing half the MGE luminosity using the routine `mge_half_light_isophote`¹ which implements steps (i) to (iv) found before Equation 12 in Cappellari et al. (2013a). In short, the routine constructs a synthetic galaxy image from the MGE and finds the surface brightness enclosed by a number of different isophotes each with different radii. To save computing time, the routine only considers one quadrant as 2D Gaussians naturally have symmetry about both axes. By using linear interpolation, the routine finds the isophote that encloses half the surface brightness. The semi-major axis is then the x -coordinate of that isophote. The ellipticity of the isophote is also determined by the same routine using Eq. (12) of Cappellari et al. (2013a). We also obtain the photometric position angle Ψ_{phot} and the central coordinates of the half-light ellipse for each target galaxy.

2.2.1.2 Effective radius

Given that we use the same SDSS photometry, in the same r band, we follow Cappellari et al. (2013a) by scaling the (circular) R_e^{MGE} by an empirical factor of 1.35 in order to make our R_e^{MGE} measurements comparable to ATLAS^{3D} (see fig. 7 of Cappellari et al., 2013a). In Figure 2.1a, we plot the correlation between our R_e^{MGE} measurements against $R_e^{2\text{MASS}}$ calculated in subsection 2.1.2 for galaxies which are found in the XSC. We find the best-fit correlation using the `lts_linefit`¹ program described in Section 3.2 of Cappellari et al. (2013a). The procedure combines the robust Least Trimmed Squares (LTS) technique of Rousseeuw & Van Driessen (2006) into a least-squares fitting algorithm. The routine starts by assuming an intrinsic scatter of zero. It then selects a subset of data points that when fit with a linear relation minimises the χ^2 (see Eq. 6 of Cappellari et al., 2013a). The whole process is then repeated assuming a different intrinsic scatter. Once all the variables settle, the best fit linear relation is found. In order to reduce covariance between the slope and intercept, and also to reduce uncertainty in the intercept, we perform the fit about a pivot x_0 which is equal to the median value of x (also see Eq. 6 of Cappellari et al., 2013a). We use this method in all similar plots in this thesis.

By applying the 1.35 factor, Cappellari et al. (2013a) found that the MGE R_e measurements agree remarkably well with R_e measurements from 2MASS and RC3 combined, considering that the two sources are independent. In Figure 2.1a, we find a similar correlation with a slope of one within the errors. We note the higher level

of scatter, likely due to the combination of a larger sample and the larger distances involved. However, we reiterate that both the best-fitting slope and intercept are very close to one, confirming the tight agreement between R_e^{MGE} , which in our case is measured from the r band photometry, and $R_e^{2\text{MASS}}$, which is taken from fits to the surface brightness in J band.

We note that for a small number ($\sim 4\%$) of galaxies, nearby foreground stars and/or low surface brightness can result in inaccurate fits from the MGE. In the first case, the fit can be found to be very round and centred not on the coordinates of the galaxy, indicating that a foreground star dominates the fit. In the second case, the surface brightness can fail to be sufficiently above that of the sky background in which case the MGE fit fails. For these cases, instead of using R_e^{MGE} , we use $R_e^{2\text{MASS}}$ if this value is greater than 7.5 arcsec (i.e. the cutoff found in subsection 2.1.3), and R_e^{NSA} if $R_e^{2\text{MASS}}$ is less than 7.5 arcsec.

2.2.1.3 Ellipticity

We compare our values for the ellipticity determined using the MGE method with those taken from the NSA in Figure 2.1b. We find that although the slope is less than one, the best-fit line passes very close to the origin. The likely reason for the slope to be less than one is that our ellipticity is measured within the 1 R_e isophotes, while NSA is globally fitted. As galaxies tend to be rounder near the centre, this likely explains the small systematic difference. Our aim is to use the MGE ellipticity for all galaxies. For the $\sim 4\%$ of galaxies for which the MGE fits are inaccurate, we measure ϵ using `find_galaxy`, which fits directly to the photometry, and compare with ϵ taken from the NSA. If the galaxy falls within 2.6Δ of the best-fit line in Figure 2.1b where Δ is the intrinsic scatter, then the `find_galaxy` value is taken. Otherwise, the NSA ellipticity calculated from the axis ratio (see subsection 2.1.3) is taken.

2.2.2 Proxy for specific angular momentum and effective velocity dispersion

We measure the luminosity-weighted stellar angular momentum λ_R using Eq. (1) from Emsellem et al. (2007), reproduced here,

$$\lambda_R \equiv \frac{\langle R|V| \rangle}{\langle R\sqrt{V^2 + \sigma^2} \rangle} = \frac{\sum_{n=1}^N F_n R_n |V_n|}{\sum_{n=1}^N F_n R_n \sqrt{V_n^2 + \sigma_n^2}} \quad (2.2)$$

where the summation is performed over N pixels within the radius R . F_n , V_n and σ_n are the flux, projected velocity and velocity dispersion of the n th pixel respectively.

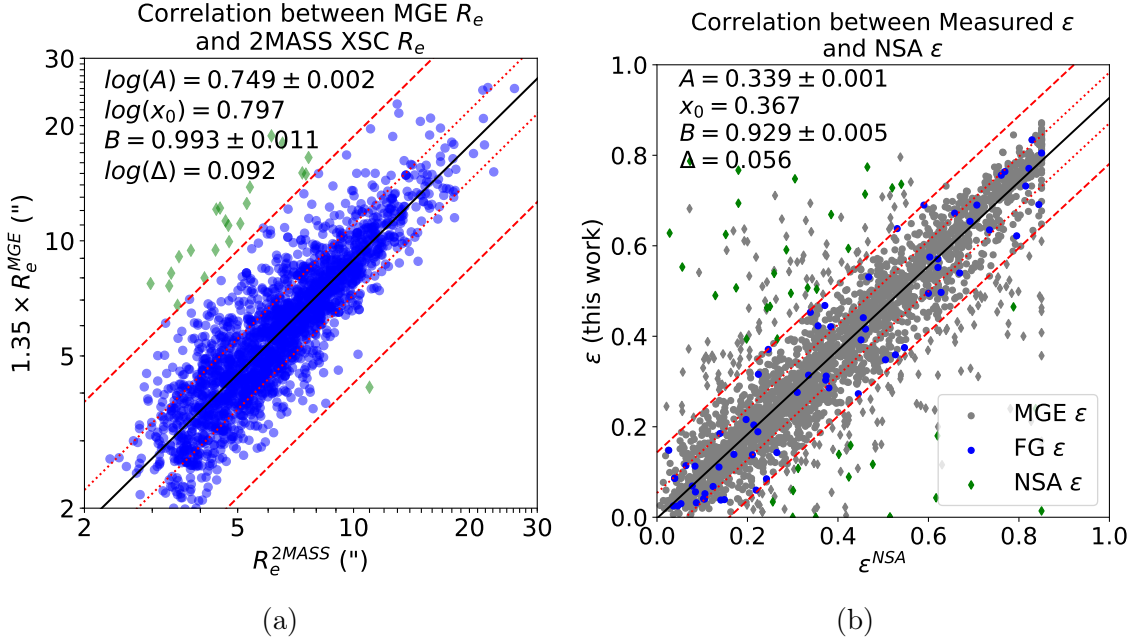


Figure 2.1: (a) **Comparison between effective radii measured from MGE fits to the SDSS NSA r -band photometry and the same quantity derived from fits to the J band luminosity from 2MASS XSC.** The parameters of the best fitting line are shown. The red dotted and dashed lines are Δ and 3.5Δ from the best fit line, where Δ is the intrinsic scatter. Galaxies which are not included in the fit are shown as green diamonds. (b) **Correlation between measured half-light ellipticity from the SDSS NSA r -band photometry and the half-light ellipticity recorded in the NSA catalogue.** For all galaxies, we aim to use the ellipticity measured from the MGE (grey). If for a particular galaxy this measurement is not possible (likely due to nearby foreground stars or low surface brightness), we use either ϵ measured using `find_galaxy` (blue) or the NSA catalog value (lime green) depending on how far the point is from the best-fit line. We make this cut at 2.6Δ from the best fit line, corresponding to 99% of points for a Gaussian and indicated by the outer red-dashed lines. Points which are not included in the fit are shown as diamonds.

As V and σ are binned, the binned values are replicated for each pixel belonging to each bin. The quantity $\sqrt{V_n^2 + \sigma_n^2}$ is proportional to mass and ensures that λ_R is normalised. The fact that R is present on both the numerator and denominator means that λ_R is dimensionless.

We also estimate the effective velocity dispersion, σ_e within $1 R_e$ from the projected second velocity moment using Equation 29 from Cappellari et al. (2013a),

$$\langle v_{\text{rms}}^2 \rangle_e = \langle v^2 + \sigma^2 \rangle_e \equiv \frac{\sum_{n=1}^N F_n (V_n^2 + \sigma_n^2)}{\sum_{n=1}^N F_n}, \quad (2.3)$$

where the summation is performed analogously to the calculation of λ_{R_e} . In the ATLAS^{3D} works, σ_e is measured from the integrated spectra within the half-light ellipse. However, here we calculate σ_e as $\langle v_{\text{rms}}^2 \rangle_e^{\frac{1}{2}}$ in order to fully take advantage of the IFS data available to us. σ_e is found to be approximately equal to $\langle v_{\text{rms}}^2 \rangle_e^{\frac{1}{2}}$ within the random errors (Cappellari et al., 2013a). Since σ_e is defined as an observed (projected) quantity, we do not attempt to deproject the velocities.

2.2.3 Kinematic properties

We measure the kinematic position angle Ψ_{kin} using `fit_kinematic_pa`¹. The method is described in Appendix C of Krajnović et al. (2006). Briefly, the routine generates a number of symmetrised models of the data by averaging values over four quadrants such that $V'(x, y) = [V(x, y) + V(x, -y) - V(-x, y) - V(-x, -y)]/4$ where V' denotes the model velocity field and V denotes the observed velocity field. The best-fit position angle Ψ_{kin} is the angle that minimises the χ^2 difference between the model and the data. The kinematic misalignment is then $\Psi_{\text{mis}} = \Psi_{\text{kin}} - \Psi_{\text{phot}}$.

Kinematic classifications were judged from the maps by eye by MTG following the five kinematic groups introduced in Section 3.2.2 of Krajnović et al. (2011). Here, however, we perform a purely qualitative classification from the map following the illustration in fig. 4 of C16, rather than using KINEMETRY (Krajnović et al., 2006). Each galaxy is either a regular or non-regular rotator. A regular rotator exhibits an hourglass-shaped velocity map. Of the non-regular rotators, there are four sub-categories: non-rotators (NRs; showing no overall rotation), complex rotators (CRs; showing non-regular rotation), kinematically decoupled cores (KDCs; showing a rotating core that is small compared to the galaxy which itself is non-rotating), and counter-rotators (“ 2σ ” galaxies; showing an inner region that is rotating in an opposite direction to the global rotation, see Figure 1.3). The alternate motion in counter-rotating galaxies results in two peaks in the velocity dispersion, hence the name “ 2σ ”.

We flag galaxies that are either ongoing mergers, or close pairs making the galaxy boundaries indeterminate. We also flag galaxies with bad kinematic data or galaxies that do not fit into the categories mentioned (see subsection 2.2.5).

The two most likely border cases for classifying non-regular rotators are between non-rotators/complex rotators and KDCs/ 2σ galaxies. For the first case (i.e. NR/CR), both classes typically have disordered rotation. We make the distinction that the absolute maximum velocity within the half-light ellipse is $|V_{\max}| \lesssim 30 \text{ km s}^{-1}$ for NRs, whereas for CRs, $|V_{\max}| \gtrsim 30 \text{ km s}^{-1}$. The arbitrary cutoff of 30 km s^{-1} is not a physical distinction but is purely driven by data quality and thus serves as an approximate boundary for distinguishing between the two classes. For the second case (i.e. KDC/ 2σ), we require that 2σ galaxies show either two strong peaks in σ along the major axis, or clear counter-rotation and high σ at the counter-rotation boundary. All other cases are KDCs. Although the definition of KDC given above specifies that there should be no large scale rotation, we allow for some small ($\sim 30 \text{ km s}^{-1}$) regular rotation at larger scales. Most border cases, including those not described here, were verified by MC.

2.2.4 Stellar mass derived from 2MASS absolute K_S band magnitude

The stellar mass values in the NSA are derived using the K-correction to calculate rest-frame luminosities before applying a colour-dependent mass-to-light ratio (Blanton & Roweis, 2007). Because these estimates are dependent on stellar population models, we estimate the stellar mass using an empirical relation which is calibrated to ATLAS^{3D} dynamical models and is based on the absolute K_S band magnitude, M_{K_S} (Cappellari, 2013, Eq. 2):

$$\log_{10} M_*^{2\text{MASS}} \approx 10.58 - 0.44 \times (M_{K_S} + 23), \quad (2.4)$$

where the stellar mass $M_*^{2\text{MASS}}$ is approximately equal to the dynamical mass M_{JAM} . The dynamical mass is a good measure of the stellar mass because the dark matter fraction within one effective radius is typically small (for example, Cappellari et al. (2013a) found a fraction of 15% for a range of stellar masses), and so the total mass, as probed by the dynamics, can be assumed to be close to the stellar mass. As noted by Cappellari (2013), Eq. (2.4) is for ETGs only. However, it is not thought to vary significantly for spirals/S0s as the mass-to-light ratios in K_S band differ by less than $\sim 50\%$ for spirals and ETGs (Williams et al., 2009). We calculate M_{K_S} from m_{K_S} using the luminosity distance estimated from the NSA heliocentric redshift.

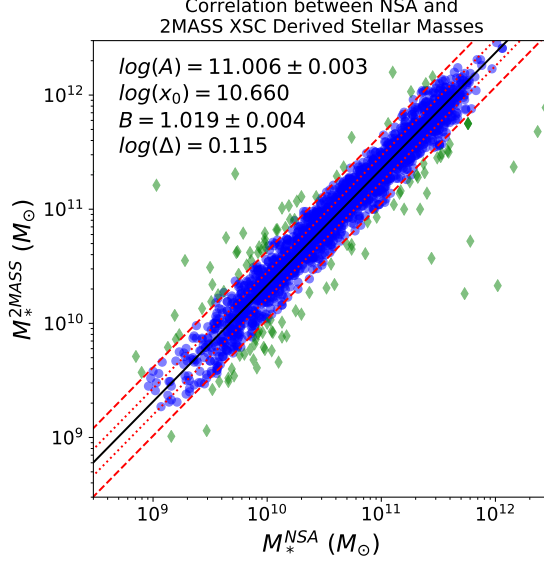


Figure 2.2: **Correlation between the stellar mass estimated from apparent K_S band magnitudes from the 2MASS XSC and the stellar mass derived from the K-correction tabulated in the NSA.** The red dashed lines indicate the 2.6Δ region where Δ is the intrinsic scatter. Points which are outside the 2.6Δ region are not included in the fit and are shown as green diamonds.

In order not to exclude the $\sim 17\%$ of galaxies that are not in the 2MASS XSC, we estimate the value that would be obtained using Eq. (2.4) assuming the NSA value which we have for all galaxies. We find that there is a tight one-to-one correlation between the two catalogues with a best-fitting relation $M_*^{2MASS} = 2.22 M_*^{NSA 1.019}$ (see Figure 2.2). There is a non-trivial scale factor of 2.22 which is due in part to different assumptions in the initial mass function (IMF). For both the NSA stellar masses and the ATLAS^{3D} dynamical modelling, the stellar mass is calculated as a product of the mass-to-light ratio (M/L) and the stellar luminosity. In calculating the stellar M/L from the stellar population models, Blanton & Roweis (2007) assume a Chabrier IMF (Chabrier, 2003), whereas the masses obtained from dynamical modelling (which are assumed by Cappellari (2013) to represent the stellar mass) are found to be consistent with an IMF mass normalisation which varies systematically as a function of galaxy σ from that of a Chabrier to heavier than a Salpeter (1955) IMF (Cappellari et al., 2012). Updated trends are given by Posacki et al. (2015) and Li et al. (2017). For reference, Bernardi et al. (2010) quote a factor 1.78 between the stellar M/L predicted by a Chabrier and a Salpeter IMF.

2.2.5 Quality control

For the *whole sample* of 2722 galaxies, we can in principle calculate λ_{R_e} for each one and place them on the $(\lambda_{R_e}, \epsilon)$ diagram. However, in practice, there are a number of reasons where this is not possible or sensible. In this section, we describe our methods for achieving a *clean sample* of MaNGA galaxies to use in our final results. We list the six criteria which we then expand on in turn. We intentionally leave out the number of affected galaxies to simplify the discussion. Instead, we provide a summary table at the end of the subsection (see Table 2.1).

We exclude galaxies that fall into the following criteria:

1. are identified to be a merger or part of a close pair,
2. are flagged as having bad or unclassifiable kinematics or morphology,
3. have more than 10% of spaxels within the half-light ellipse flagged by the MaNGA DRP as DONOTUSE,
4. have been classified as a FR but have a misalignment between the kinematic and photometric major axes that is greater than 30° (except for when $\epsilon < 0.4$, see section 2.3),
5. have more than 50% of pixels within the half-light ellipse with $\sigma_* = 0$ where σ_* is the intrinsic velocity dispersion (except for disks, see section 2.4),
6. have R_e^{maj} small enough that $\sigma_{\text{PSF}}/R_e^{\text{maj}} > 1$ (see section 2.5).

We exclude galaxies identified to be mergers or in close pairs as often the half-light ellipse is difficult to define photometrically. If the galaxies are interacting through a merger process and are close enough to lie within the field of view of the IFU, then the velocity and velocity dispersion maps are usually too chaotic to measure a meaningful value of λ_{R_e} . Apart from mergers or close pairs, there are some galaxies for which the kinematic structure does not conform to the categories outlined in subsection 2.2.3. These are not the border cases between the adopted kinematic classifications, but are kinematics which are affected by foreground stars for example. We also perform our own morphological classification using the SDSS true colour image for each galaxy in the MaNGA sample according to the Hubble scheme, i.e. ellipticals, S0s, spirals and irregular galaxies (Hubble, 1926, 1936; Sandage, 1961). We distinguish edge-on spirals from S0s as having a dust lane that extends across the disk. We also separate face-on S0s from ellipticals by considering the galaxy edge. If the edges are (well)

defined, then we classify the galaxy as an S0. If the surface brightness decreases to the sky level, then we classify the galaxy as an elliptical. We exclude galaxies where the classification is ambiguous or not possible.

In section 2.5, we present a correction to account for the distortion due to atmospheric seeing. The correction is largest for small galaxies with $R_e^{\text{maj}} \approx \sigma_{\text{PSF}}$ where σ_{PSF} is the width of the Gaussian PSF of the 2.5-metre Sloan telescope. The correction becomes inaccurate for galaxies small enough such that $R_e^{\text{maj}} < \sigma_{\text{PSF}}$. We also exclude galaxies where more than 10% of spaxels within the half-light ellipse have been flagged by the MaNGA DRP with a `MANGA_DRP3PIXMASK` value of 1024, indicating that a particular spaxel is unsuitable for science (see Table B11 of Law et al., 2016). The `MANGA_DRP3PIXMASK` also contains masks indicating dead fibres, lack of coverage and foreground stars, but these are not sufficient to render a spaxel unsuitable for science purposes.

Regarding criterion (v), FRs are known to be aligned to within 10° whereas SRs are naturally misaligned (Emsellem et al., 2007; Krajnović et al., 2011). Here, we define SRs to be galaxies that lie within the region where $\lambda_{R_e} < 0.08 + \epsilon/4$ and $\epsilon < 0.4$ (C16, Eq. 19). The requirement that SRs should be rounder than $\epsilon = 0.4$ is useful to exclude counter-rotating disks that are physically related to FRs (section 3.4.3 of C16) but also have low values of λ_{R_e} . In section 2.3, we show that for FRs rounder than $\epsilon = 0.4$, our measurement of λ_{R_e} within a randomly orientated half-light ellipse is underestimated at most by 0.1 when compared to an ellipse that is aligned with the major axis. For this reason, we include misaligned FRs with $\epsilon < 0.4$.

Finally, we exclude elliptical and irregular galaxies where the fraction of pixels within the half-light ellipse with $\sigma_* = 0$ is greater than 50%. We choose this cut based on the simple test described in section 2.4, where we show that for a reasonable estimate of the noise in the instrumental dispersion, the intrinsic value of λ_{R_e} can be recovered to within 0.1 provided that the maximum velocity and velocity dispersion are $\gtrsim 50$ and $\gtrsim 25 \text{ km s}^{-1}$ respectively. As we assume the noise in the instrumental dispersion to be random with a Gaussian distribution, the maximum fraction of pixels with $\sigma_* = 0$ is 50%, and hence we exclude galaxies without disks where we observe a higher fraction.

Having applied these steps to the *whole sample*, we arrive at a *clean sample* containing all the surviving galaxies. These galaxies have complete photometric and kinematic data as well as morphological and kinematical classifications. We give the number of galaxies removed due to each criterion in Table 2.1. For MPL-5, 2286

Table 2.1: The number of galaxies not included in the *clean sample* due to the reasons outlined in subsection 2.2.5. Column 1 lists each criteria according to the list found at the beginning of subsection 2.2.5, and column 2 list the total number of galaxies that have been flagged due to each criterion. Column 3 lists the number of galaxies not already excluded due to previous criteria and column 4 lists the cumulative number of galaxies excluded.

Criterion	Total No. of Galaxies	No. Not Already Excluded	Cumulative No.
(i)	171	0	171
(ii)	106	96	267
(iii)	4	3	270
(iv)	109	82	352
(v)	97	56	408
(vi)	62	28	436

galaxies remain forming the *clean sample* which we use in all results unless specified otherwise.

2.2.6 Volume correction and kernel smoothing

The MaNGA sample is designed to have a roughly flat distribution in absolute i -band magnitude, M_i , as a proxy for stellar mass. However, as detailed in the survey design paper (Yan et al., 2016b), the range in redshift at which a galaxy with a given M_i can be observed varies systematically with M_i . Hence the survey is volume-limited at a given M_i . The minimum redshift is set by the angular size of the IFU bundles (the galaxy has to fit onto the detector), and the maximum redshift is set in order to maintain a constant number density of galaxies in each M_i bin (Wake et al., 2017). As a result, the brightest, largest galaxies are sampled at a higher redshift than the dimmest, smallest galaxies. In order to correct the MaNGA sample to a volume-limited sample, we weight each galaxy based on the volume it occupies.

In order to visualise the effect of correcting the MaNGA sample to a volume-limited sample, we “smooth” the galaxy distribution using a weighted kernel density estimation (KDE) routine⁹ (Scott, 2015; Silverman, 1986, see Figure 3.4b for an example). Each data point is replaced by a 2D Gaussian, the amplitude of which can be weighted according to the volume correction. At any location on the diagram, the

⁹We use a modified version (<https://gist.github.com/tillahoffmann/f844bce2ec264c1c8cb5>) of the scipy implementation in Python (<http://docs.scipy.org/doc/scipy/reference/index.html>).

total density is a linear combination of each Gaussian. The result is a 2D probability density field. To eliminate regions of low density extending out to ∞ , we restrict the smoothed regions within 80% probability contours, unless otherwise stated.

2.3 Misaligned Fast Rotators

In our sample, we find a large number of FRs with misalignments greater than 30° . Many of these are barred spirals or S0s. For cases where the bar is misaligned with the photometric major axis of the galaxy (and R_e^{circ} is a similar scale to the size of the bar), `find_galaxy` will fit to the bar. This implies that both the ellipticity and position angle are not representative of the galaxy as a whole.

Another case where our measurement of the misalignment might not reflect the intrinsic misalignment is for near face-on axisymmetric galaxies with low (apparent) ϵ . As described by Krajnović et al. (2011), the position angle is essentially degenerate when ϵ is low, and so the orientation of the ellipse is not well defined meaning that λ_{R_e} only has a weak dependency on Ψ_{phot} . We check whether the NSA measurement of the position angle is more robust against the effect of bars and find that for barred galaxies with $\Psi_{\text{mis}} > 30^\circ$, NSA is comparable to `find_galaxy`.

If we vary by eye the `FRACTION` parameter in `find_galaxy` for 143 galaxies, as was carried out by Hongyu Li, we are able to find a more accurate position angle. To determine whether we should include the galaxies that are still affected after performing this step, we take 181 barred spiral galaxies and S0s (all regular rotators) with $\Psi_{\text{mis}} > 30^\circ$ and measure λ_{R_e} rotating the half-light ellipse with position angles between 0° and 175° in steps of 5° . As expected, we find that the maximum change in λ_{R_e} increases with ϵ . For galaxies with $\epsilon < 0.4$, more than 90% decrease by less than $\lambda_{R_e} = 0.1$ when measuring λ_{R_e} within an ellipse with minimal misalignment compared with maximal misalignment. Hence, the maximum expected decrease in λ_{R_e} due to an incorrect position angle for galaxies with $\epsilon < 0.4$ is 0.1. For this reason, we include misaligned fast rotators with $\epsilon < 0.4$.

As detailed in Table 2.1, we exclude 56 galaxies based on this criterion. About half of these lie below the magenta line in Figure 3.1a and so by performing this step, we are reducing the contamination from galaxies where the measured λ_{R_e} is too low. However, we are including 220 FRs with $\epsilon < 0.4$ which may bias us towards more face-on galaxies. Certainly for $\epsilon < 0.2$, the degeneracy in Ψ_{phot} means that we cannot exclude these galaxies based on misalignment. A quick test shows that by *not*

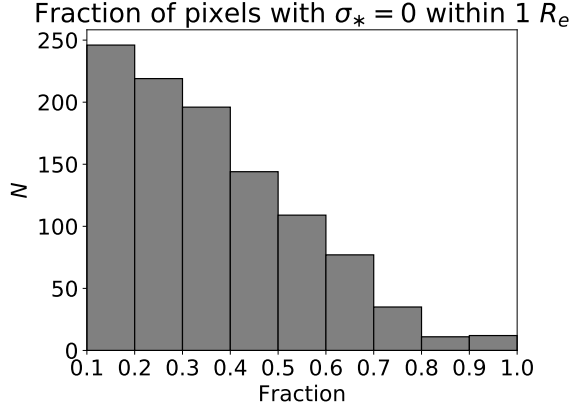


Figure 2.3: Histogram indicating the number of galaxies N in MPL-5 with at least 10% of pixels within $1 R_e$ with $\sigma_* = 0 \text{ km s}^{-1}$.

including the 220 FRs mentioned here, our conclusions remain the same, albeit with slightly different statistics.

2.4 λ_{R_e} in the low σ_* regime

The observed stellar velocity dispersion σ_{obs} must be corrected for the instrumental resolution σ_{inst} of the spectrograph. The correction is applied in quadrature as

$$\sigma_* = \sqrt{\sigma_{\text{obs}}^2 - \sigma_{\text{inst}}^2} \quad (2.5)$$

where σ_* is the corrected, intrinsic velocity dispersion. While this is a necessary step to recover the true velocity dispersion, a caveat arises from the fact that it is entirely possible that at a S/N of 10, the error in σ_{obs} can be as much as 20% (Penny et al., 2016), leading to a situation where $\sigma_{\text{obs}} < \sigma_{\text{inst}}$. Numerically, this leads to an unphysical value of σ_* in Eq. (2.5). We stress that these unphysical values do not indicate any problem with the data or any failure of the kinematic extraction. They simply imply that the dispersion at those locations is quite low with respect to σ_{inst} (typically $\sigma_* \lesssim \sigma_{\text{inst}}/2$), but a more accurate σ_* value cannot be determined, due to noise and uncertainties in σ_{inst} . One option is simply to set σ_* of the affected pixels to be zero. This may not be entirely satisfactory as it is clear that σ_* must be very low at these pixels, but not necessarily equal to zero. Moreover, in the summation over all pixels within $1 R_e$, the contribution of these pixels to the summation is the same at the denominator and numerator. The result is an inflated value of the intrinsic $\lambda_{R_e}^{\text{true}}$.

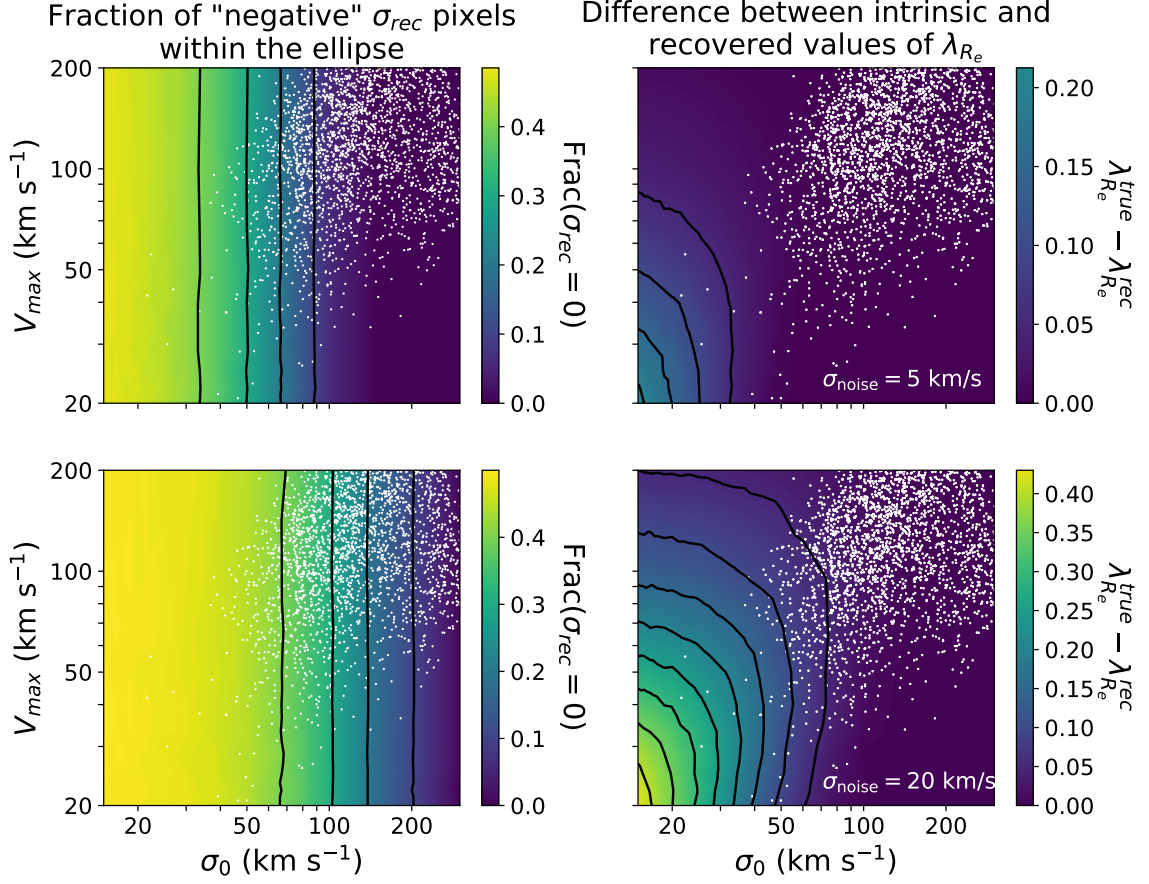


Figure 2.4: **Top row:** On the left, we plot the fraction of pixels within the half-light ellipse with $\sigma_{\text{rec}} = 0$ km s⁻¹, indicated by the colour map, for the 200 models in the grid. When performing the σ correction, we assume that the instrumental resolution is described by a Gaussian with a width of $\sigma = 5$ km s⁻¹. The black vertical lines are contours of constant fraction at values of 0.1, 0.2, 0.3 and 0.4. On the right, we plot on the same axes the difference between the *intrinsic* $\lambda_{R_e}^{\text{true}}$ and the *recovered* $\lambda_{R_e}^{\text{rec}}$. The contours now trace constant values of $\lambda_{R_e}^{\text{true}} - \lambda_{R_e}^{\text{rec}} = 0.05, 0.1, 0.15$ and 0.2 . For both panels in the top row, the colours are scaled to the equivalent panel in the bottom row. In all panels, we plot the maximum velocity against maximum velocity dispersion within the half light ellipse for MPL-5 galaxies (white points). **Bottom row:** The same except we increase the width of the instrumental noise to $\sigma = 20$ km s⁻¹. The contours on the left are at values of 0.1, 0.2, 0.3, and 0.4. The contours on the right are at values of 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35 and 0.4.

For MPL-5, there are approximately 1000 galaxies which have more than 10% of pixels with $\sigma_* = 0$ within $1 R_e$ (see Figure 2.3). In order to assess whether to trust $\lambda_{R_e}^{\text{true}}$ for the affected galaxies, we take a simple galaxy model and add noise to simulate the measurement errors and the uncertainties in the instrumental resolution before attempting to recover the intrinsic $\lambda_{R_e}^{\text{true}}$ (i.e. without noise). For our galaxy model, we assume the circular velocity to be Eq. (16) from Hernquist (1990), reproduced here:

$$V_c = \frac{\sqrt{GM}r}{r+s} \quad (2.6)$$

where M is the total mass, r is the radius and s is the scale length. V_c is equal to V_{max} when $r = s$. We note that the assumed velocity profile applies to regular rotators only. However, the effect we are studying is not likely to affect non-regular rotators which typically have high σ_* , and so our assumption is valid. We assume the intrinsic velocity dispersion takes the form $\sigma_* = \sigma_0/(r+s)$ where σ_0 is the velocity dispersion at the galaxy centre. To estimate the surface brightness, we use the example MGE given in the `test_jam_axi_rms` function which can be found in the `jam_axi_rms` routine, part of the JAM package¹. The flux is given by the `jam_axi_rms` function, for which we assume an inclination of 60° . Finally, we assume $R_e = 1.8153s$ (Hernquist, 1990, Eq. 38) where $s = 40$ arcsec (corresponding to 3.2 kpc at the assumed distance of the Virgo Cluster i.e. 16.5 Mpc) and $\epsilon = 0.4$.

We take a grid of 200 models parameterised by $(V_{\text{max}})_i = 200/i \text{ km s}^{-1}$ where $1 \leq i \leq 10$ and $(\sigma_0)_j = 300/j \text{ km s}^{-1}$ where $1 \leq j \leq 20$. For each model in the grid, we calculate the intrinsic $\lambda_{R_e}^{\text{true}}$ using intrinsic values of the velocity dispersion σ_* . We apply the correction in reverse to calculate the observed velocity dispersion, σ_{obs} . We then add random Gaussian noise $N(\mu, \sigma_{\text{noise}})$ where $\mu = 0 \text{ km s}^{-1}$ and $\sigma_{\text{noise}} = 5$ and 20 km s^{-1} to simulate the uncertainty in the instrumental resolution:

$$\sigma_{\text{obs}} = \sqrt{\sigma_*^2 + \sigma_{\text{inst}}^2} + N(\mu, \sigma_{\text{noise}}), \quad (2.7)$$

where σ_{inst} is the instrumental resolution. For MaNGA, we take σ_{inst} to be the median value of 72 km s^{-1} (Law et al., 2016). We note that σ_{inst} does have a dependence on wavelength (see Figure 18 of Law et al., 2016) which we ignore for this approximate test. To recover the intrinsic velocity dispersion, σ_{rec} , from the observed velocity dispersion (as is done for MaNGA using Eq. (2.5)), we apply the instrumental correction to the noisy data:

$$\sigma_{\text{rec}} = \sqrt{\sigma_{\text{obs}}^2 - \sigma_{\text{inst}}^2}. \quad (2.8)$$

We calculate the recovered $\lambda_{R_e}^{\text{rec}}$ using σ_{rec} and compare with $\lambda_{R_e}^{\text{true}}$ calculated with σ_* . Our results are shown in Figure 2.4. We find that for all values of σ_0 and V_{max} , $\lambda_{R_e}^{\text{rec}}$ *underestimates* $\lambda_{R_e}^{\text{true}}$. This seems at first to be counter-intuitive, since σ_{rec} can take a value of zero, whereas σ_* can never equal zero (in the models). Hence, we would expect that $\lambda_{R_e}^{\text{rec}} > \lambda_{R_e}^{\text{true}}$ if this was the only effect. However, we find that the random *positive* noise added at $r \approx 0$ where $\sigma \approx \sigma_0$ gives a larger contribution to *lowering* $\lambda_{R_e}^{\text{rec}}$ than the pixels at large r with $\sigma_* = 0 \text{ km s}^{-1}$ which serve to *inflate* $\lambda_{R_e}^{\text{rec}}$. We find that the regime where $\lambda_{R_e}^{\text{true}} - \lambda_{R_e}^{\text{rec}} > 0.1$ for low instrumental noise of $\sigma_{\text{noise}} = 5 \text{ km s}^{-1}$ is $\sigma_0 \lesssim 25 \text{ km s}^{-1}$ and $V_{\text{max}} \lesssim 50 \text{ km s}^{-1}$. For higher noise where $\sigma_{\text{noise}} = 20 \text{ km s}^{-1}$, this region expands to $\sigma_0 \lesssim 50 \text{ km s}^{-1}$ and $V_{\text{max}} \lesssim 100 \text{ km s}^{-1}$. However, this level of noise is extreme and is expected to be much larger than any realistic instrumental noise.

As the noise we are adding is randomly positive and negative about the mean, the maximum percentage of pixels in the simulations where $\sigma_{\text{rec}} = 0 \text{ km s}^{-1}$ is 50%. Therefore, we exclude MaNGA galaxies where the fraction of pixels with $\sigma_* = 0 \text{ km s}^{-1}$ is greater than 50%. The exception to this cut are disk galaxies (i.e. galaxies determined in subsection 2.2.5 to be spirals or S0s) which intrinsically can have low velocity dispersion but also high circular velocities meaning that they occupy the top region of Figure 2.4. Hence, we are confident in the accuracy of λ_{R_e} for disk galaxies regardless of the fraction of pixels with $\sigma_* = 0 \text{ km s}^{-1}$.

2.5 Analytic correction to account for atmospheric seeing

As the distances probed by large-scale, ground-based IFU surveys increase, it is becoming necessary to account for atmospheric seeing when measuring a quantity that is derived from the LOSVD, such as λ_{R_e} . At the spatial resolution of the PSF, the LOSVD is smeared out such that values measured for V and σ are converged towards the mean (zero and $\bar{\sigma}$ for V and σ respectively). The overall effect is that the observed value of λ_{R_e} is *lower* than the intrinsic value (i.e. without seeing). At larger distances, both the apparent sizes of galaxies and the spatial resolution decrease, and therefore atmospheric seeing effects become more important. D’Eugenio et al. (2013) investigated the effect of reduced spatial resolution on λ_{R_e} . By “reobserving” kinematic models of SAURON data using KINEMETRY (Krajnović et al., 2006) at the distance of the galaxy cluster A1689 (~ 50 times the average distance of the SAURON

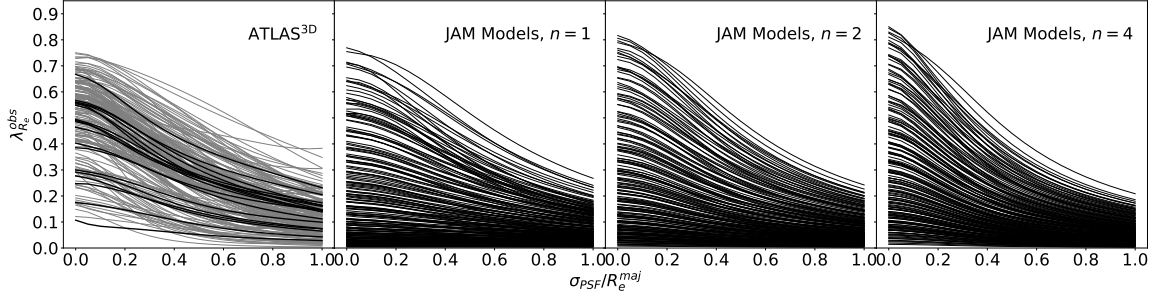


Figure 2.5: The first panel shows profiles of $\lambda_{R_e}^{\text{obs}}$ as a function of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$ for 18 galaxies in the `small_a3d` subsample (black) and 165 galaxies in the `large_a3d` subsample (grey). The remaining panels show the same for 540 JAM Models with Sérsic indices of $n = 1, 2$ and 4 shown as indicated. Each value of $\lambda_{R_e}^{\text{obs}}$ is measured at intervals of 0.05 in $\sigma_{\text{PSF}}/R_e^{\text{maj}}$. Constant errors are assumed in $\lambda_{R_e}^{\text{obs}}$.

survey), they found they could approximate λ_{R_e} by using all available spaxels to measure $\lambda_R(\text{IFU})$, before applying a correction based on R_e . van de Sande et al. (2017) simulated the effect of seeing on ATLAS^{3D} kinematics, which, being very nearby, can be assumed to be unaffected by seeing, in order to provide an estimate for the error on λ_{R_e} measurements. They found that the impact is strongest for small galaxies ($R_e \sim \text{PSF}$) with $\lambda_{R_e} > 0.2$, with a median decrease of 0.08 when the PSF is 3 arcsec at FWHM. Finally, Greene et al. (2018) took a subset of 50 galaxies in MaNGA that have at least four beams within R_e with radial coverage out to $1.5R_e$, and degraded the resolution so that the PSF was a constant fraction of R_e that matched the typical resolution of the whole MaNGA sample. They found that λ_{R_e} decreased by up to 0.075 for $\lambda_{R_e} < 0.2$, and up to 0.125 for $\lambda_{R_e} > 0.2$. While these tests provide a useful indication of the errors due to atmospheric effects, it remains difficult to correct λ_{R_e} on an galaxy-by-galaxy basis without an analytic correction.

In this section, we derive such a correction by simulating the effect of seeing on the kinematics of galaxy models using the Jeans Anisotropic Modelling method (JAM; Cappellari, 2008).

2.5.1 Derivation of the beam smearing correction

The two key quantities of interest are the size of the PSF, here quantified by $\sigma_{\text{PSF}} = \text{FWHM}_{\text{PSF}}/2.355$, and the size of the galaxy, quantified here by the semi-major axis, R_e^{maj} . Since the effect we are interested in is significant for large σ_{PSF} and small R_e^{maj} , we choose our correction to be a function of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$. We choose the semi-major axis rather than the circular effective radius for the simple reason that the correction correlates with R_e^{maj} much better than with R_e . This is due to the fact that for very

elliptical galaxies or models, the circular radius can be as much as three times smaller than the semi-major axis. By defining the ratio with respect to the semi-major axis, the correction depends only on the angular size and not inclination.

There is also a secondary dependence on the Sérsic index in that the exact nature of the “blurring” effect depends on the concentration of the galaxy. To account for this, we derive a secondary correction as a function of Sérsic index and $\sigma_{\text{PSF}}/R_e^{\text{maj}}$.

2.5.2 Velocity moment convolution

In order to measure how λ_{R_e} varies due to the size of the PSF, we use general formulas to convolve the first and second velocity moments and the surface brightness Σ of all galaxies and models with the same circular Gaussian PSF (e.g. Equations 51-53 of Emsellem et al., 1994):

$$\Sigma_{\text{obs}} = \Sigma \otimes \text{PSF}, \quad (2.9)$$

$$[\overline{v_{\text{los}}}]_{\text{obs}} = \frac{(\Sigma \overline{v_{\text{los}}}) \otimes \text{PSF}}{\Sigma_{\text{obs}}}, \quad (2.10)$$

$$[\overline{v_{\text{los}}^2}]_{\text{obs}} = \frac{(\Sigma \overline{v_{\text{los}}^2}) \otimes \text{PSF}}{\Sigma_{\text{obs}}}, \quad (2.11)$$

where $\otimes$ represents convolution. We measure λ_{R_e} for the convolved quantities using Eq. (2.2) substituting F , V and σ for these three quantities.

There is a separate effect whereby the “blurring” of the visual image causes the observed flattening to be circularised. As a result, ϵ is also lowered due to beam smearing. However, we do not correct ϵ for this effect as doing so would require an *intrinsic* measurement of the effective radius. From Eq. (2.9), it is clear that the surface brightness becomes more extended with an increasing PSF, and hence the effective radius is also a function of the PSF. Hence, it is impossible to correct ϵ before correcting R_e . This argument nullifies the need for an ϵ correction as ϵ can then be measured within the intrinsic R_e . Furthermore, in the practical sense, ϵ is generally measured directly from photometry which is likely either already deconvolved (as in our case when using MGEs or the NSA which uses Sérsic models), or has a small enough PSF that this effect is small. In the case of λ_{R_e} , this circular argument does not apply as ϵ does not depend on λ_{R_e} . In any case, the effect due to the circularisation of the ellipse is likely to be much smaller than the uncertainties in our approximate correction.

2.5.3 JAM and ATLAS^{3D} kinematics

We model the first and second velocity moments, V and $V_{\text{RMS}} \equiv \sqrt{V^2 + \sigma^2}$ respectively, by using the Jeans Anisotropic Modelling (JAM) method (Cappellari, 2008). The use of this method is justified by the fact that the resulting models were shown to provide quite realistic descriptions of the kinematics of real galaxies as a function of a single physical parameter (e.g. Figure 10 of C16). Given the surface brightness (i.e. a MGE) and two parameters (the inclination and the anisotropy $\beta_z \equiv 1 - (\sigma_z/\sigma_R)^2$ where σ_z is the velocity dispersion in the z direction and σ_R is the velocity dispersion in the R direction), the method provides a solution to the Jeans equations (Jeans, 1922) assuming axisymmetry. Using simulated kinematics from JAM models brings a significant advantage in that there are no border effects.

We generate 1080 models with a range of intrinsic ellipticities ($0.1 \leq \epsilon_{\text{intr}} \leq 0.94$), inclinations ($10^\circ \leq i \leq 90^\circ$ where 90° is edge-on) and Sérsic indices ($1 \leq n \leq 6$). This range of parameters should cover “normal” late-type disks. We use a Sérsic profile to describe the stellar mass surface density as a function of radius. We fit the Sérsic profile using the MGE fitting method and software `mge_fit_1d`¹ by Cappellari (2002) to find the surface density and the dispersion σ_j of each Gaussian in the unconvolved MGE. We calculate Eqs. 2.9-2.11 assuming a self-consistent model whereby the same Gaussians are used to describe the surface brightness and the potential. For all models, we assume a semi-major axis R_e^{maj} of 10 arcsec and an axisymmetric galaxy potential. We assume a distance of 41.2 Mpc (approximate maximum distance in ATLAS^{3D}) and an anisotropy parameter $\beta_z = 0.7 \times \epsilon_{\text{intr}}$ (Cappellari et al., 2007).

Although we derive our correction purely from JAM models, we repeat the same method using kinematics from the ATLAS^{3D} survey. The targets of the survey are much closer than the MaNGA galaxies ($\gtrsim 100$ Mpc), and so can be considered to be unaffected by seeing. We measure $\lambda_{R_e}^{\text{true}}$ (i.e. without any convolution) within the half-light ellipse using the published values for ϵ (Table B1 from Emsellem et al., 2011), photometric PA (Table D1 from Krajnović et al., 2011) and effective radius (Table 1 from Cappellari et al., 2013a) for all the ATLAS^{3D} galaxies. We are able to reproduce the published values of λ_{R_e} from Emsellem et al. (2011) to within about 0.1 for 247/257 of the ATLAS^{3D} galaxies. We therefore exclude 10 galaxies: five due to foreground star(s) (*IC0676*, *NGC2679*, *NGC4478*, *NGC4684*, *NGC5770*), two due to border effects (*UGC6014*, *UGC03960*), one due to the presence of a foreground star and a companion galaxy (*NGC5846*), one due to high velocity and velocity dispersion at the bulge (*NGC4486A*) and one due to an unknown reason (*NGC3032*).

We then remove 50/247 galaxies which are not regular rotators, as the correction is calibrated using JAM models which only describe regular rotators. Finally, we remove 14/197 galaxies which lie outside the range $0.5 \leq n \leq 6.5$, where n are the values for the Sérsic index obtained from single fits to 1D light profiles and are found in Table C1 of Krajnović et al. (2013a). We split the remaining 183 galaxies into two samples, the `small_a3d` sample and the `large_a3d` sample. The `small_a3d` sample contains 18 galaxies which have 100% coverage¹⁰ within the half-light ellipse and contain no jumps in V or σ within the half-light ellipse that may affect the convolution. These galaxies are: *NGC0502*, *NGC2592*, *NGC2778*, *NGC3457*, *NGC3458*, *NGC3648*, *NGC3674*, *NGC4255*, *NGC4262*, *NGC4283*, *NGC4377*, *NGC4434*, *NGC4660*, *NGC5507*, *NGC5845*, *NGC6278*, *UGC04551* and *UGC06062*. The `large_a3d` sample contains the other 165 surviving galaxies. For both subsamples, we convolve the galaxy MGEs, surface brightness and the first two velocity moments with Gaussian PSFs ranging from 0 to R_e^{maj} as described above.

2.5.4 Sérsic-dependent generalised Moffat function

For each JAM model and ATLAS^{3D} galaxy, we obtain profiles for “observed” values of λ_{R_e} , i.e. $\lambda_{R_e}^{\text{obs}}$, as a function of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$ (see Figure 2.5). To describe the JAM profiles analytically, we adopt a generalised form of the Moffat function (Moffat, 1969), which is widely used to provide an analytic description of the PSF¹¹:

$$gM_n(\sigma_{\text{PSF}}/R_e^{\text{maj}}) = \left[1 + \left(\frac{\sigma_{\text{PSF}}/R_e^{\text{maj}}}{a_n} \right)^{c_n} \right]^{-b_n}, \quad (2.12)$$

where our generalised Moffat (gMoffat) reduces to the Moffat for $c_n = 2$. Our choice for the gMoffat is arbitrary in that it provides a simple function which approximates the observed variations with few free parameters.

We find the coefficients for our gMoffat function by minimising the least square of the residuals between the data and the function. The coefficients a_n , b_n and c_n are specific to the Sérsic index n . This fact is clearly illustrated by the different profile shapes in Figure 2.5. However, rather than tabulating best-fitting coefficients for each Sérsic index which would limit the usability and accuracy of the correction, we find that we can approximate the correction at all n between 1 and 6 by multiplying the

¹⁰We define the coverage to be the fraction of the half-light ellipse covered by spaxels, and is calculated as $N_{\text{pix}}\Delta x^2/(\pi R_e^2)$ where N_{pix} is the number of pixels within the half-light ellipse, Δx is the pixel size in arcsec, and R_e is the circularised effective radius.

¹¹The Moffat function is similar to a Gaussian except with larger tails.

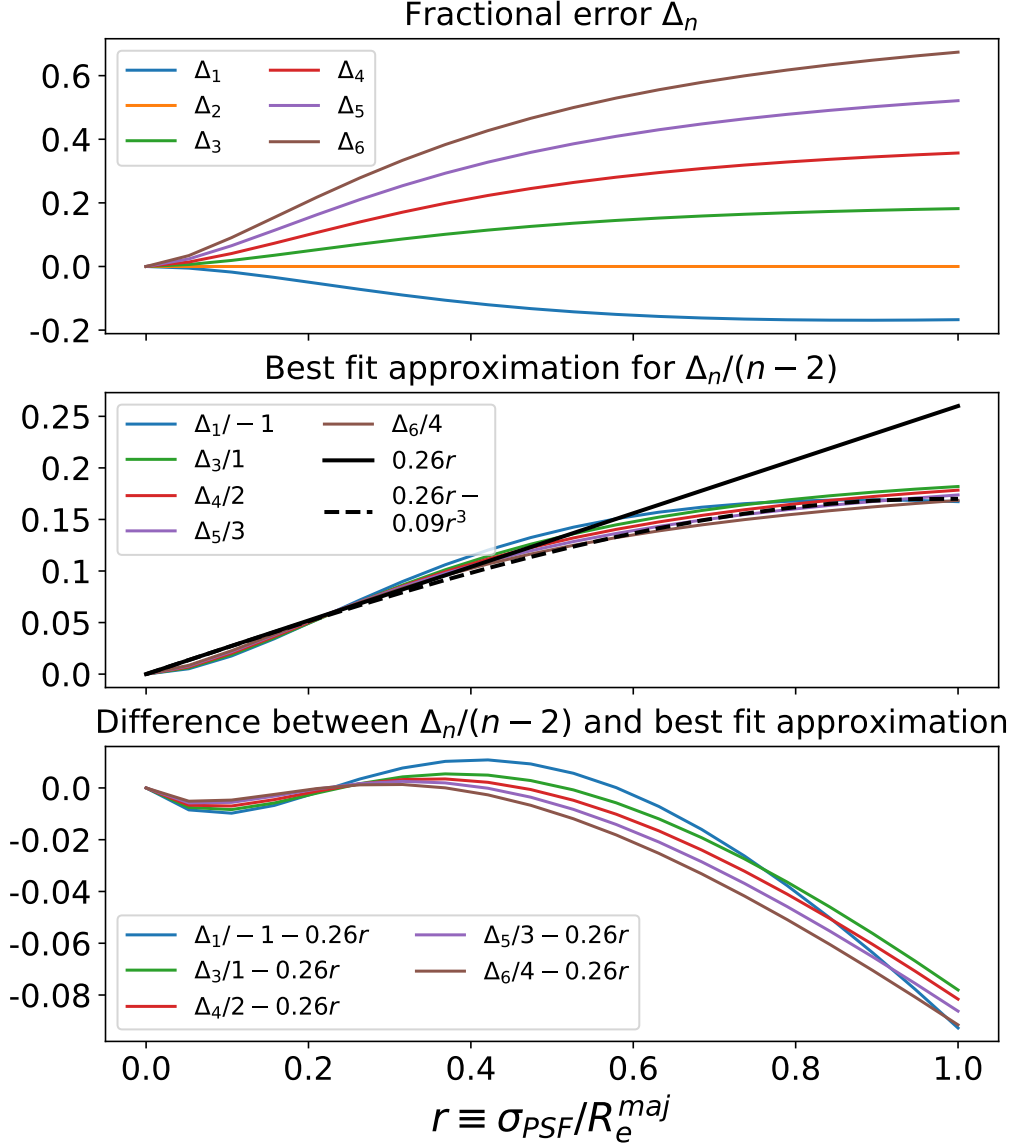


Figure 2.6: **Top:** For a constant value of $\lambda_{R_e}^{\text{true}}$, we plot Δ_n , i.e. Eq. (2.13), for each Sérsic-specific gMoffat function gM_n as a function of r where $r \equiv \sigma_{\text{PSF}}/R_e^{\text{maj}}$. **Middle:** We divide each Δ_n (apart from Δ_2) in the top panel by $(n-2)$ to bring each curve to the same scale (i.e. Δ_3). Two fits are shown: a cubic fit shown as the black dashed line, and a linear fit, shown as the black solid line. **Bottom:** We plot the difference between each $\Delta_n/(n-2)$ in the middle panel and the linear fit.

gMoffat derived from $n = 2$ JAM models by a factor $f_n(\sigma_{\text{PSF}}/R_e^{\text{maj}})$. While there is nothing particularly special about $n = 2$, it is used as it gives the best results in the following analysis.

In order to find the functional form of f_n , we first find the coefficients a_n , b_n and c_n for each Sérsic index by fitting Eq. (2.12) using the JAM models with the corresponding Sérsic index from $n = 1$ to $n = 6$. We then compare each of the six Sérsic-*specific* gMoffat functions using fractional errors, i.e.

$$\Delta_n = \frac{gM_2(\sigma_{\text{PSF}}/R_e^{\text{maj}})}{gM_n(\sigma_{\text{PSF}}/R_e^{\text{maj}})} - 1, \quad (2.13)$$

as shown in the top panel of Figure 2.6. We find that Δ_n takes the same form as a function of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$ for $n = 1$ to $n = 6$ (apart from $n = 2$ where $\Delta_2 = 0$). This non-trivial fact allows us to scale Δ_n by $1/(n-2)$ to match Δ_3 (see the middle panel of Figure 2.6).

While there does not exist a simple mathematical function that accurately describes $\Delta_n/(n-2)$, we find that we can approximate the scaled curves by fitting a straight line using `lts_linefit` (see the solid black line in the middle panel of Figure 2.6). Clearly, this simple linear fit becomes inaccurate at $\sigma_{\text{PSF}}/R_e^{\text{maj}} \gtrsim 0.5$ (see the bottom panel of Figure 2.6) for all curves shown. While the addition of a cubic term does more accurately describe each curve (see the dashed black line in the middle panel of Figure 2.6), we find that in practice, adopting the simple linear fit does not significantly affect the accuracy of the correction overall, considering that this effect is well within the errors of the approximate correction itself. Moreover, the fraction of galaxies in the *clean sample* small enough to have $\sigma_{\text{PSF}}/R_e^{\text{maj}} \gtrsim 0.5$ is 0.6%.

The final function form for the Sérsic-*dependent* gMoffat function is

$$\lambda_{R_e}^{\text{mod}} = \lambda_{R_e}^{\text{true}} gM_2 \left(\frac{\sigma_{\text{PSF}}}{R_e^{\text{maj}}} \right) f_n \left(\frac{\sigma_{\text{PSF}}}{R_e^{\text{maj}}} \right), \quad (2.14)$$

where

$$gM_2 \left(\frac{\sigma_{\text{PSF}}}{R_e^{\text{maj}}} \right) = \left[1 + \left(\frac{\sigma_{\text{PSF}}/R_e^{\text{maj}}}{0.47} \right)^{1.76} \right]^{-0.84}, \quad (2.15)$$

and

$$f_n \left(\frac{\sigma_{\text{PSF}}}{R_e^{\text{maj}}} \right) = \left[1 + (n-2) \left(0.26 \frac{\sigma_{\text{PSF}}}{R_e^{\text{maj}}} \right) \right]^{-1}, \quad (2.16)$$

where $\lambda_{R_e}^{\text{mod}}$ and $\lambda_{R_e}^{\text{true}}$ are the model (“observed”) and true (“intrinsic”) values of λ_{R_e} , $\sigma_{\text{PSF}} = \text{FWHM}_{\text{PSF}}/2.355$, R_e^{maj} is the semi-major axis and n is the Sérsic index. The

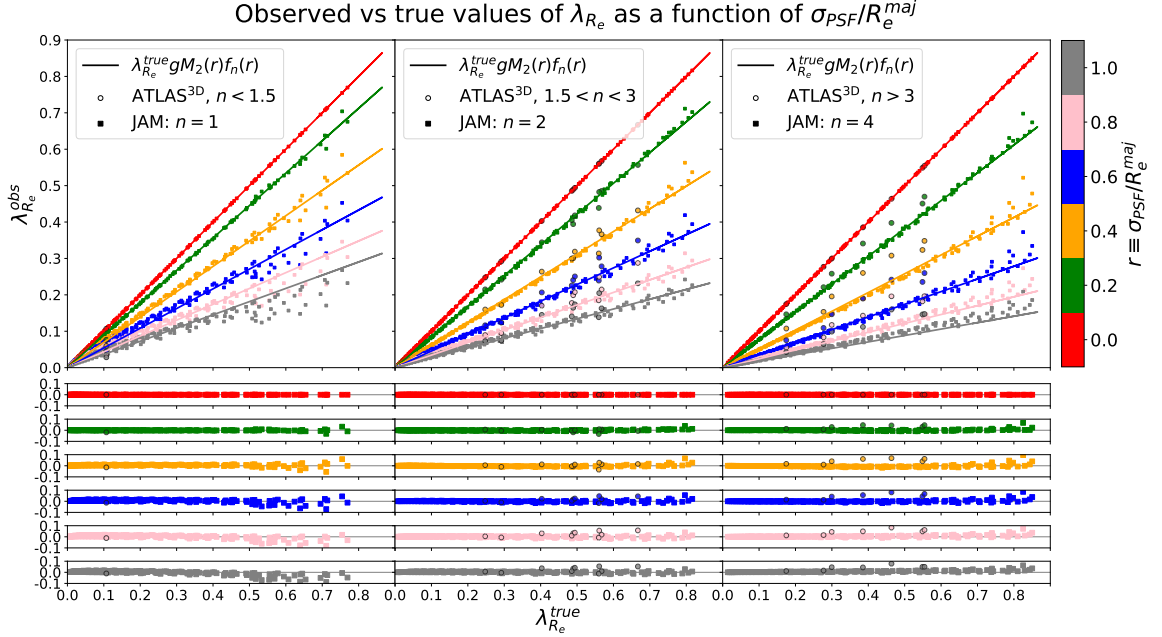


Figure 2.7: The best-fitting generalised Moffat (gMoffat) function describing how λ_{R_e} changes with increasing $\sigma_{\text{PSF}}/R_e^{\text{maj}}$ for Sérsic indices $n = 1$, $n = 2$ and $n = 4$ (left to right). The gMoffat fit is shown as the solid lines for values of $\sigma_{\text{PSF}}/R_e^{\text{maj}} = 0, 0.2, 0.4, 0.6, 0.8, 1$ indicated by the colourbar. The points are the data for which the model is fit at the same ratios. ATLAS^{3D} galaxies are shown by the large circles whereas the JAM models are shown by small squares. The six lower panels for each column indicate the residuals (data - model) for each ratio, where the model is shown as the grey horizontal line at $y = 0$.

function gM_2 is a generalised form of the Moffat function (Moffat, 1969), and f_n is an empirical function required to model the dependence on the Sérsic index. It is the best-fitting function that describes the observed behaviour with the fewest number of variables. Six linear slices for $n = 1, 2$ and 4 are shown in Figure 2.7. The residuals between the JAM data and the correction are largely due to inclination effects. We supplement the JAM data with a subsample of 18 galaxies from the ATLAS^{3D} survey, which are assumed to be unaffected by seeing.

2.5.5 Application and error analysis

Eq. (2.14) satisfies three physical boundary conditions:

1. $\lim_{\sigma_{\text{PSF}} \rightarrow 0} \lambda_{R_e}^{\text{mod}} = \lambda_{R_e}^{\text{true}},$

¹¹22680 points = 1080 models $\times$ 21 values of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$. To save computing time, we select a random sample of 3000 points from which to estimate the density field.

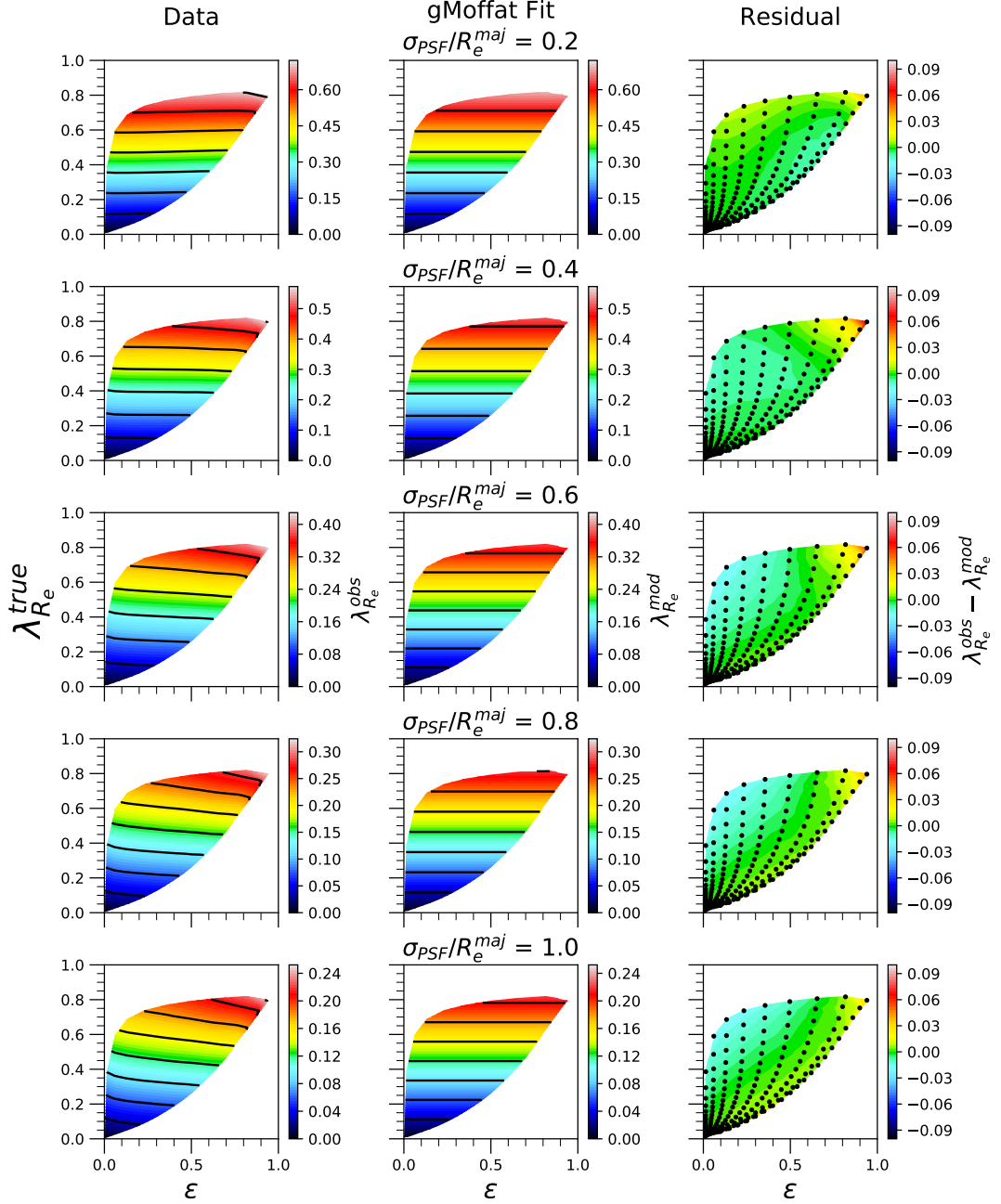


Figure 2.8: Plots showing the observed values of λ_{R_e} from the JAM models, the model given by Eq. (2.14) and the residuals on the $(\lambda_{R_e}^{\text{true}}, \epsilon)$ plane for $n = 2$. **Left:** Values of $\lambda_{R_e}^{\text{obs}}$, indicated by the colourbar, shown for five values of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$, indicated for each row. The points with positions $(x, y) = (\epsilon, \lambda_{R_e}^{\text{true}})$ are hidden in this column, but are shown in the right-hand column. **Middle:** The best-fitting gMoffat function where values are calculated using Eq. (2.14). The colourbar ranges are the same as in the left column to allow for direct comparison. **Right:** Residuals, i.e. the difference between the data and the model, for each value of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$. The black points are the $n = 2$ JAM models and the colourbar is fixed for all rows between -0.1 and 0.1.

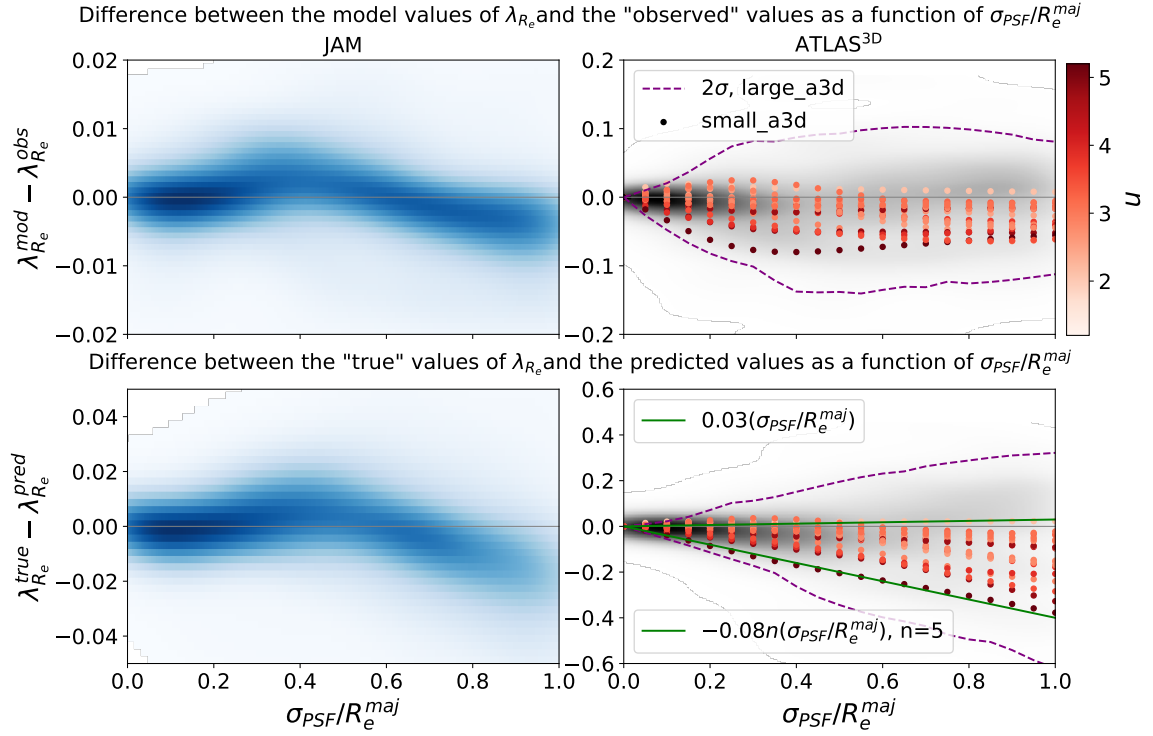


Figure 2.9: **Top Left:** Difference between the model λ_{R_e} ($\lambda_{R_e}^{\text{mod}}$) for JAM predicted by Eq. (2.14) and the “observed” (i.e. convolved) λ_{R_e} ($\lambda_{R_e}^{\text{obs}}$) as a function of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$. The 22680 points are smoothed using the KDE method described in subsection 2.2.6¹¹. The model is indicated by the horizontal grey line where $\lambda_{R_e}^{\text{mod}} - \lambda_{R_e}^{\text{obs}} = 0$. **Top Right:** The same as top left except for the **small_a3d** subsample, shown as circles coloured according to n , and the **large_a3d** subsample, shown as a smoothed grey density field. The purple dashed lines indicate the inner 95% ($\sim 2\sigma$) of the **large_a3d** subsample. **Bottom Left:** The difference between the true values of λ_{R_e} ($\lambda_{R_e}^{\text{true}}$) and the values predicted by inverting Eq. (2.14) ($\lambda_{R_e}^{\text{pred}}$) as a function of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$. The grey horizontal line indicates where the model accurately predicts the true (corrected) values of λ_{R_e} . **Bottom Right:** The same as bottom left except for the **small_a3d** and **large_a3d** subsamples. The purple dashed lines are as top right. The green lines are approximate linear fits to the outermost tracks of the **small_a3d** subsample. The lower limit has an approximate linear dependence on n , shown here for $n = 5$. The equations are shown in the legend, and can be used to predict the error in $\lambda_{R_e}^{\text{pred}}$ as a function of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$.

$$2. \lim_{\sigma_{\text{PSF}} \rightarrow \infty} \lambda_{R_e}^{\text{mod}} = 0,$$

$$3. \lim_{\lambda_{R_e}^{\text{true}} \rightarrow 0} \lambda_{R_e}^{\text{mod}} = 0.$$

For $0 \leq \sigma_{\text{PSF}}/R_e^{\text{maj}} \leq 1$, Eq. (2.14) is well determined, whereas for $\sigma_{\text{PSF}}/R_e^{\text{maj}} > 1$, the function plateaus such that

$$\lambda_{R_e}^{\text{mod}}(\sigma_{\text{PSF}}/R_e^{\text{maj}} = 1) \approx \lambda_{R_e}^{\text{mod}}(\sigma_{\text{PSF}}/R_e^{\text{maj}} = \infty). \quad (2.17)$$

This imposes an upper limit on our correction above which the function is too uncertain. Hence, we only define (and apply) our correction within the range $0 \leq \sigma_{\text{PSF}}/R_e^{\text{maj}} \leq 1$.

There is a low level of intrinsic scatter in the JAM models that can be seen in the residuals between the data and the model (e.g. Figure 2.7). This intrinsic scatter is due to inclination effects. For each JAM model with intrinsic ellipticity ϵ_{intr} , we incline the model between $i = 90^\circ$ and $i = 10^\circ$. The LOSVD is dependent on inclination, but the Gaussian used to describe the PSF is always circular, and hence the effects due to convolution are dependent on inclination. As a result, the correction is most accurate at intermediate inclinations of $i \sim 50^\circ$ as can be seen in Figure 2.8. However, as the scatter is less than 10% for $\lambda_{R_e}^{\text{true}} \gtrsim 0.05$ (and ~ 0 as $\lambda_{R_e}^{\text{true}}$ approaches 0), the correction can be considered valid for all inclinations.

Since Eq. (2.14) does not include an ϵ term, we are assuming that there is no trend in ϵ . We check that this is the case by plotting the data from the JAM models, the model prediction and the difference between the two on the $(\lambda_{R_e}, \epsilon)$ plane for $n = 2$ (see Figure 2.8). We find that there is a slight trend in the data at $\sigma_{\text{PSF}}/R_e^{\text{maj}} \gtrsim 0.5$ whereby for a given $\lambda_{R_e}^{\text{true}}$, $\lambda_{R_e}^{\text{obs}}$ is higher for higher ϵ . This trend is observed for all n in our range. The consequence is that the model prediction $\lambda_{R_e}^{\text{mod}}$ is slightly higher than $\lambda_{R_e}^{\text{obs}}$ for lower ϵ , and vice versa (see the right column of Figure 2.8). However, the magnitude of this effect is low considering that the disagreement between the data and the model is ~ 0.03 over the $(\lambda_{R_e}, \epsilon)$ plane.

In order to assess the accuracy of Eq. (2.14) when predicting $\lambda_{R_e}^{\text{true}}$ from observed values of $\lambda_{R_e}^{\text{obs}}$, we directly compare the true, unconvolved values of $\lambda_{R_e}^{\text{true}}$ with values predicted by Eq. (2.14) i.e. $\lambda_{R_e}^{\text{pred}}$. We apply our correction at the same ratios of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$ and the same sample of JAM models used to derive Eq. (2.14), as well as the two ATLAS^{3D} subsamples. In the bottom part of Figure 2.9, we plot the difference between $\lambda_{R_e}^{\text{true}}$ and $\lambda_{R_e}^{\text{pred}}$ for the JAM models (left) and the two ATLAS^{3D} subsamples (right). We find that Eq. (2.14) is able to predict $\lambda_{R_e}^{\text{true}}$ to within 0.02 for the vast majority of JAM models. The scatter is due to a combination of inclination

effects described above, as well as the range of Sérsic indices used. The turnover at $\sigma_{\text{PSF}}/R_e^{\text{maj}} \sim 0.5$ is due to the linear approximation we adopted to keep the correction simple. The accuracy remains better than ~ 0.04 for all ratios.

We fit the outermost tracks on the lower right of Figure 2.9 for the `small_a3d` subsample with an approximate linear fit to estimate the error as a function of $\sigma_{\text{PSF}}/R_e^{\text{maj}}$ when applying the correction to real galaxies. We find that the correction essentially gives an upper limit for the true value of λ_{R_e} . The lower limit has an approximate linear dependence on n . As the errors are not a function of $\lambda_{R_e}^{\text{obs}}$, it is entirely possible that the lower limit is below $\lambda_{R_e}^{\text{obs}}$, in which case $\lambda_{R_e}^{\text{obs}}$ itself provides the lower limit.

In subsection 3.1.1, we apply our beam correction to our sample of MaNGA galaxies (e.g. Figure 3.1b). In doing so, we note that 15 galaxies overshoot i.e. $\lambda_{R_e}^{\text{true}} > 1$. Almost all of these galaxies have high $\lambda_{R_e}^{\text{obs}}$ values greater than 0.8. We note that our JAM models shown in Figure 2.8 reach a maximum $\lambda_{R_e}^{\text{true}} = 0.8$ and hence we do not have any data above this range. This is likely a coincidence, as each $\lambda_{R_e}^{\text{obs}}$ profile is essentially a scaled version of every other profile for constant n , as can be seen in Figure 2.5. This fact is what allows the correction to be as accurate as it is for the range of $\lambda_{R_e}^{\text{true}}$. While there is no reason to expect that this should change significantly above $\lambda_{R_e}^{\text{true}} > 0.8$, it may be the case that there are some border effects at $\lambda_{R_e}^{\text{true}} \sim 1$ for which we do not have data for. However, as discussed in subsection 3.1.1, there are other sources of error that need to be considered for these particular galaxies.

In practice, one will only have single values for $\sigma_{\text{PSF}}/R_e^{\text{maj}}$ and $\lambda_{R_e}^{\text{obs}}$ for any given galaxy. The correction relies on the assumption that if one were to measure $\lambda_{R_e}^{\text{obs}}$ using an arbitrary number of telescopes with IFS capabilities, each with different PSFs, the resulting profile will exactly follow Eq. (2.14) (assuming of course that there are no systematic differences between telescopes other than the size of the PSF). As mentioned above, we derive our correction from JAM models with 100% coverage within the half-light ellipse. While it is likely the correction is less accurate for galaxies without 100% coverage (for example the `large_a3d` subsample), there is no reason to refrain from using the correction in this case because the accuracy of Eq. (2.14) does not depend in a well-defined way on the coverage. Moreover, the most likely reason for a galaxy to have incomplete coverage is when the effective radius is large compared to the beam size, in which case the change in λ_{R_e} due to the correction is likely to be small.

However, the correction is likely to be inaccurate for galaxies outside of the range

$0.5 \leq n \leq 6.5$ as the correction is calibrated for about that range¹². Finally, as the JAM method can only describe regular rotators (ETGs and spirals), the correction is only valid for regular rotators. We find that the correction does not describe well the profiles of non-regular ATLAS^{3D} galaxies. Furthermore, non-regular rotators have intrinsically low $\lambda_{R_e} \sim 0.2$ and so the effect due to seeing is small. Hence, in all our results where we apply the beam correction, we only correct λ_{R_e} values for regular rotator ETGs and spirals, leaving non-regular rotators unchanged.

2.5.6 Summary

In summary, the Sérsic-*dependent* gMoffat function provides an approximate but accurate description of the behaviour observed in Figure 2.5 for a range of JAM models with Sérsic indices from $n = 1$ to $n = 6$. At constant $\sigma_{\text{PSF}}/R_e^{\text{maj}}$ and n , Eq. (2.14) is a linear function of $\lambda_{R_e}^{\text{true}}$ (see Figure 2.7). The correction is applicable only for regular rotators where $R_e^{\text{maj}} \geq \sigma_{\text{PSF}}$ (as described in subsection 2.2.5) and $0.5 \leq n \leq 6.5$. In subsection 3.1.1, we apply our correction to observed values of λ_{R_e} . For a given galaxy, the intrinsic λ_{R_e} corrected for seeing is given by solving Eq. (2.14) for $\lambda_{R_e}^{\text{true}}$. The error in the value of $\lambda_{R_e}^{\text{true}}$ is given by $[+0.03(\sigma_{\text{PSF}}/R_e^{\text{maj}}), -0.08n(\sigma_{\text{PSF}}/R_e^{\text{maj}})]$ (see Figure 2.9). In the case that $\lambda_{R_e}^{\text{true}} - 0.08n(\sigma_{\text{PSF}}/R_e^{\text{maj}}) < \lambda_{R_e}^{\text{obs}}$, which can happen for low $\lambda_{R_e}^{\text{obs}}$, then the value of $\lambda_{R_e}^{\text{obs}}$ itself provides the lower limit. We find that for regular rotators in the *clean sample*, the mean error is $[0.005, -0.041]$ and the median error is $[0.004, -0.027]$.

To facilitate the application of our correction, we provide a `Python` code that calculates Eqs. 2.2 and 2.14 as well as Eq. (2.3) for stellar kinematic data. The code is available at this address: https://github.com/marktgraham/lambdaR_e_calc.

¹²We extend the applicable range from $1 \leq n \leq 6$ to $0.5 \leq n \leq 6.5$ for the simple reason that the NSA values for n start at 0.5.

Chapter 3

SDSS-IV MaNGA: Stellar angular momentum of 2286 galaxies: unveiling the bimodality of massive galaxy properties

Ultimately, education in its real sense is the pursuit of truth. It is an endless journey through knowledge and enlightenment.

A.P.J. Abdul Kalam

3.1 Results and discussion

Here we present our results for the 2286 galaxies in the *clean sample*. We present the (λ_{Re}, ϵ) diagram both with and without the beam correction and classified by kinematic morphology, Hubble morphology, stellar mass and σ_e . We also show the kinematic misalignment as a function of ϵ , including some galaxies that are not in the *clean sample*. Finally, we present the mass-size relation for the *clean sample*, classifying for Hubble and kinematic morphology as well as the fast/slow classification. All the quantities required to reproduce these plots are given in Table 3.1.

3.1.1 Stellar angular momentum

The MaNGA survey is designed such that each internal data release (MPL-5 etc.) contains observations for a representative subset of the complete sample of $\sim 10,000$

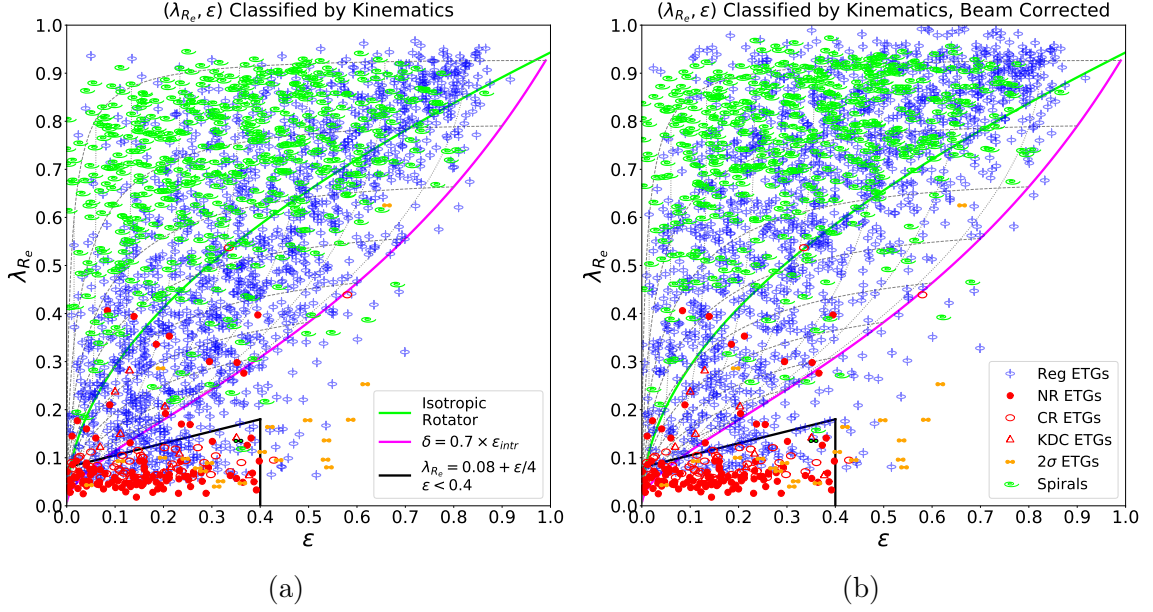


Figure 3.1: (a) **The $(\lambda_{R_e}, \epsilon)$ diagram labelled by kinematic morphology.** The points are the *observed* $(\lambda_{R_e}, \epsilon)$ values for the 2286 galaxies that form the *clean sample*. We label the ETGs according to the kinematic classes detailed in subsection 2.2.3, where “Reg” = regular rotator, “NR” = non-rotator, “CR” = complex rotator, “KDC” = kinematically decoupled core and “2 σ ” = counter-rotating disk. All spirals (apart from MaNGA-ID 1-236144, see text) are regular rotators and so they are not labelled kinematically. MaNGA-ID 1-236144 is shown as a lime-green 2 σ galaxy with black edges. The thick green line is the prediction for an edge-on ($i = 90^\circ$) isotropic rotator from Binney (2005) (see Eq. 14 in C16), and the magenta line is the edge-on relation from Cappellari et al. (2007) (see Eq. 11 in C16). The thin dotted lines show how the magenta line changes at different inclinations ($\Delta i = 10^\circ$), while the black dashed lines trace how galaxies with a particular value of ϵ_{intr} at $i = 90^\circ$ move across the diagram with changing inclination. Finally, the black lines at the lower-left corner define the region occupied by SRS: $\lambda_{R_e} < 0.08 + \epsilon/4$, $\epsilon < 0.4$ (see Eq. (19) in C16). (b) The same as (a) except that the beam correction has been applied to regular ETGs and spirals using Eq. (2.14). Out of 2286, 15 galaxies have a value of $\lambda_{R_e}^{\text{true}} > 1$ and hence 2271 galaxies remain in this version of the diagram.

galaxies. This means that any initial results we draw from a subset of ~ 2300 galaxies should be indicative of the full sample. Figure 3.1a shows the $(\lambda_{R_e}, \epsilon)$ diagram classified by kinematic morphology. Each point is a single galaxy in the *clean sample*. There are some galaxies for which we have more than one kinematic observation with different IFUs. For these cases, we plot the λ_{R_e} value derived from the kinematic maps which have the lowest error in Ψ_{kin} (or in some cases the lowest misalignment if the error is the same).

We apply our beam correction given in section 2.5 to values of λ_{R_e} for regular rotator ETGs and spirals, shown in Figure 3.1b. For the rest of this thesis, we consider the beam-corrected version to be the “true” diagram. We find the mean and median increase in λ_{R_e} due to the beam correction for regular rotator ETGs and spirals to be 0.09 and 0.07 respectively.

There are 15 galaxies that, once beam-corrected, overshoot $\lambda_{R_e} = 1$ and therefore are not shown in the right-hand side of Figure 3.1b. The beam corrected values are affected by errors in $\lambda_{R_e}^{\text{obs}}$, σ_{PSF} , R_e^{maj} (i.e. R_e and ϵ), and n . Yan et al. (2016b) estimated the uncertainty on $\lambda_{R_e}^{\text{obs}}$ by generating 100 random normal distributions for V and σ according to the measurement errors on both quantities, and computed λ_{R_e} for each (see their sec. 8.4 and fig. 29). For $\lambda_{R_e} \sim 0.1$, the error is within 0.05 but can be as high as ~ 0.08 for $\lambda_{R_e} > 0.5$. The error in σ_{PSF} is less than 10% (Law et al., 2016) and it is possible that the Sersic index can have systematic uncertainties of ± 2 . Finally, as described in subsection 2.1.2 and shown in Figure 2.1a, effective radii are poorly defined and can easily have uncertainties of a few arcseconds. Hence, a combination of these errors can result in large errors in the beam-corrected λ_{R_e} which are impossible to quantify. A value of $\lambda_{R_e} > 1$ can only be as a result of these errors and hence we remove these galaxies.

Before this work, there was much debate on whether there is a continuum of galaxy properties on the $(\lambda_{R_e}, \epsilon)$ plane, or if there is a dichotomy with a break between slow and fast rotators. A dichotomy was claimed using dynamical models (Figure 1.5), but the same was not apparent in the $(\lambda_{R_e}, \epsilon)$ diagram itself. Thanks to the large number statistics provided by MaNGA, we are able for the first time to provide unambiguous evidence of a bimodality between fast and slow rotators, which can be seen in Figure 3.1b.

We compare Figure 3.1b with Figure 1.4 which plots values for 340 ETGs from ATLAS^{3D} (Emsellem et al., 2011) and the SAMI Pilot survey (Fogarty et al., 2015). In both diagrams, the non-regular rotators cluster in the SR region (indicated by the black lines), while the majority of regular ETGs and, in our case nearly all spirals,

occupy the FR regime, with almost all of the population lying above the empirical relation for edge-on galaxies (magenta line). In our work, there are a small number of regular ETGs in the SR region which are not seen in C16. Although these galaxies have ordered rotation, the maximum rotation velocity within the half-light ellipse is $\sim 30 - 50 \text{ km s}^{-1}$. Since σ is high (see Figure 3.6a), these galaxies have a low value of λ_{Re} . While most non-rotators lie within the SR regime, a small population lies in the FR regime. Many of these galaxies, especially above $\lambda_{Re} \sim 0.3$, are either face on disks with no overall rotation, or irregular galaxies. In some of these cases, λ_{Re} has been inflated due to the low dispersion found in these galaxies (see section 2.4). Another effect to consider is the standard $|V|$ effect in the summation over pixels when calculating λ_{Re} as illustrated in Figure B1 of Emsellem et al. (2007). In theory, a perfectly noisy velocity map should result in $\lambda_{Re} = 0$ if the sign of V were taken into account. However, the absolute V in Eq. (2.2) prevents λ_{Re} lying below about 0.025. It is likely that this effect contributes to the high λ_{Re} seen in these galaxies. The counter-rotating ETGs occupy similar regions in both diagrams with the exception of one at $\lambda_{Re} \sim 0.6$. We note that these galaxies are more difficult to recognise in MaNGA than they were in ATLAS^{3D} due to the lower spatial resolution (both due to larger distances and to larger fibres compared to smaller lenslets), and this implies that some will be visually classified as regular rotators.

We note that our kinematic classification applies only to ETGs and not to spirals as, by nature, all spirals are regular rotators. However, we find one galaxy (MaNGA-ID 1-236144, Plate-IFU 8980-12703) that has a clear dust lane indicative of spiral structure, but also has a discernible counter-rotating core, suggesting that this galaxy is in fact a 2σ galaxy. It is possible that the dust lane is in fact gas accreted after formation, and may itself be counter rotating. Furthermore, this galaxy appears in the SR region. However, as the galaxy is edge-on, it is impossible to rule out spiral structure.

While there are more outliers in Figure 3.1b than can be seen in C16, their small number compared to the size of the sample allows us to treat these galaxies as noise. In order to highlight the bimodality without first classifying by any galaxy property, we split the (λ_{Re}, ϵ) diagram into a grid with cells 0.05×0.05 in size. We then colour-code each cell by the number of points within that cell as shown in Figure 3.2 for ETGs only. We only show ETGs at first as this is the class of galaxies that visually appear homogeneous, and hence require IFS observations in order to separate them in terms of angular momentum. We include a histogram of λ_{Re} with bin widths of 0.05. We also apply an adaptive KDE routine to the original unbinned values (i.e. not the

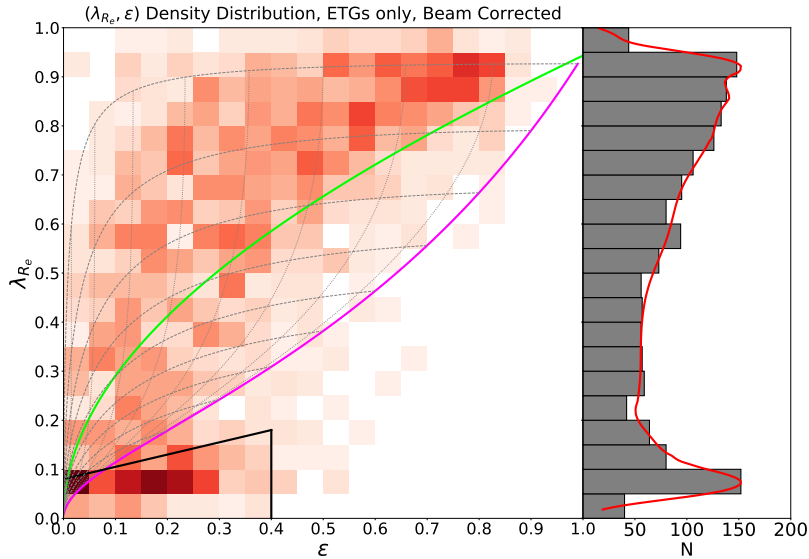


Figure 3.2: **Left:** The beam-corrected (λ_{Re}, ϵ) diagram for ETGs only colour coded by the number of points in a grid with cells of size 0.05×0.05 . Dark red indicates a high density of points while pale red indicates a low density of points. The black, magenta, green and dashed lines are the same as in Figure 3.1a. **Right:** A histogram of λ_{Re} collapsed along the x -axis. The red curve is a one-dimensional smoothing of the individual data points using an adaptive KDE routine.

histogram) which allows for local variations in the kernel size to give a smoothed 1D distribution. Using an adaptive kernel is advantageous in that it preserves density information on a range of scales. We use the Python implementation¹³ of the method outlined in Shimazaki & Shinomoto (2010). All three measures of density agree qualitatively with the conclusion that slow and fast rotators form distinct galaxy populations on the (λ_{Re}, ϵ) diagram with local maxima within and outside the SR region respectively. However, there is a non-zero density of points at $\lambda_{Re} \sim 0.3$ which constitutes a minimum between the two distributions. For this reason, the observed bimodality does not necessarily imply a dichotomy, which is however indicated by the dynamical models (see Figure 1.5). The bimodality in λ_{Re} does correspond to a bimodality in the intrinsic ϵ_{intr} (see Weijmans et al., 2014, Figure 8 and Foster et al., 2017, Figure 5) which is unavailable to us without accurate inclinations. In Figure 3.3, we include spirals and irregular galaxies which can be distinguished by visual morphology from ETGs.

We note in passing that there is a lower density of points in the region bound by the green and magenta lines for $\epsilon > 0.4$ than has been seen in previous studies such as ATLAS^{3D} and CALIFA. It is possible that there could be some circularisation

¹³<https://github.com/cooperlab/AdaptiveKDE>

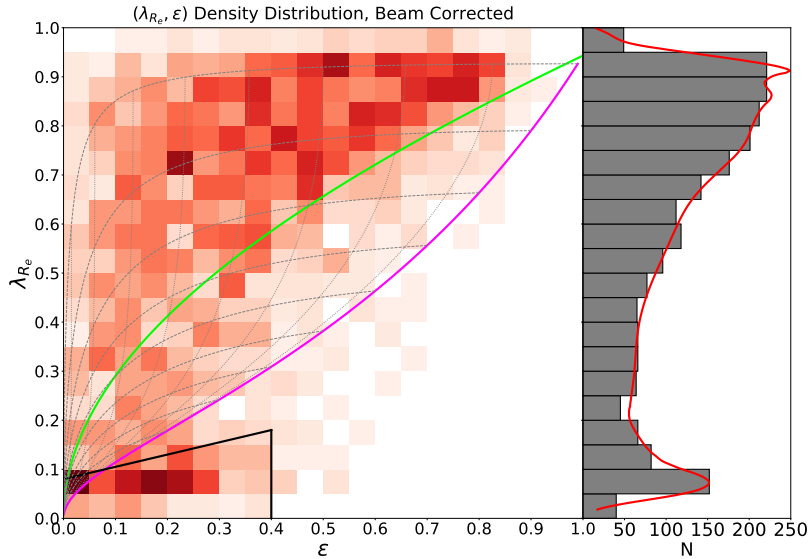


Figure 3.3: The same as Figure 3.2 except that spirals are included.

of the ellipticity due to seeing and lower spatial sampling, which in principle should be corrected for, but maybe not fully. As MaNGA galaxies are more distant than ATLAS^{3D} and CALIFA, this may explain what we observe. Even if we include all 2722 galaxies in the *whole sample*, we do not see an increase in number density in this region.

In Figure 3.4a, we show the $(\lambda_{R_e}, \epsilon)$ diagram classified by morphology. In Figure 3.4b, we smooth the points using a KDE routine, applying the appropriate volume weighting to each data point. In doing this, we recover the distribution as would be obtained from a volume-limited sample. For ellipticals, there is a discernible difference between the position of the peak of the smoothed distribution and the highest density of points in the raw data. This is because the MaNGA selection function, which samples galaxies with a flat distribution in stellar mass, selects a higher fraction of massive SR galaxies than would be observed in a random, volume-limited sample. Hence, massive elliptical SRs are down-weighted. We show both the unweighted and weighted distributions as both are valid representations of the galaxies in the MaNGA sample.

We compare Figure 3.4a and Figure 3.4b with fig. 15 of C16 which shows 666 spirals and ETGs taken from different surveys: 260 ETGs from ATLAS^{3D} (Emsellem et al., 2011), 300 (mostly) spirals from CALIFA (Falc3n-Barroso et al., 2015) and ~ 100 (mostly) ETGs from SAMI (Fogarty et al., 2015). Elliptical galaxies occupy similar regions in fig. 15 of C16 and Figure 3.4a and Figure 3.4b with a maximum λ_{R_e} of 0.5 and ~ 0.8 respectively, and a maximum ellipticity of 0.4. The strongest

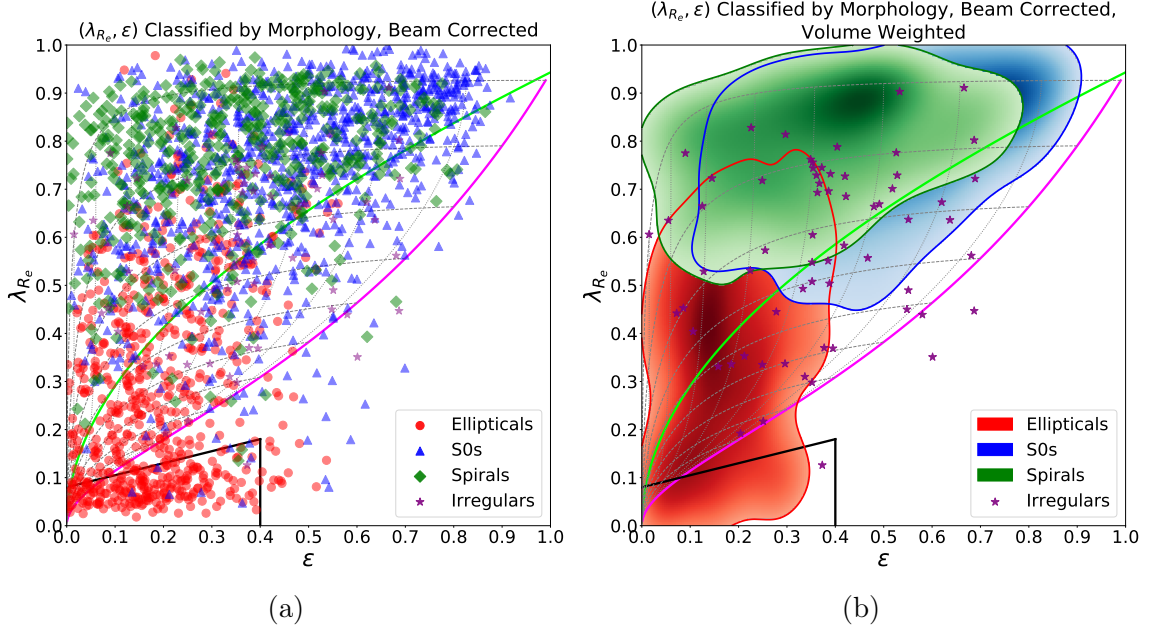


Figure 3.4: (a) **The beam-corrected $(\lambda_{R_e}, \epsilon)$ diagram colour coded by Hubble morphology.** Each morphology is given in the legend. The black, magenta, green and dashed lines are the same as in Figure 3.1a. (b) The same as (a) except that ETGs and spirals (i.e. excluding irregular galaxies) are smoothed and volume weighted using the method described in subsection 2.2.6.

concentration of ellipticals in Figure 3.4b is at $(\lambda_{R_e}, \epsilon) = (0.125, 0.4)$ which is higher than C16, who finds the peak to be at $(\lambda_{R_e}, \epsilon) = (0.1, 0.15)$. The higher peak in our work is a direct effect of the volume weighting as the highest density of points is closer to the SR boundary.

While there is good agreement on the distribution of spiral galaxies, there are many spiral galaxies above $\lambda_{R_e} = 0.9$ which are not seen in fig. 15 of C16. The lack of spirals with $\epsilon < 0.2$ in fig. 15 of C16 is due to the sample selection of CALIFA which omits very round and very flat spirals from their sample (Walcher et al., 2014). However, the lower and right-hand-side extent of both distributions agree to about 0.1. There are few spirals flatter than $\epsilon = 0.75$ because for very flat discs ($\epsilon \sim 0.8$), it is difficult to verify the presence of spiral arms without a clear dust lane present. Therefore, it is possible that many edge-on spirals will be misclassified as S0s. ATLAS^{3D}, CALIFA and SAMI are all at a lower redshift than MaNGA ($z < 0.01$, $z < 0.03$ and $z < 0.095$ respectively) and so are less likely to suffer from the same bias. In our work, the peak(s) of the distribution are at slightly lower ϵ and higher λ_{R_e} . We find that many galaxies with a beam corrected $\lambda_{R_e} > 0.9$ have a high fraction of low σ pixels, with a mean of 32%. However, as many of these intrinsically have low σ , we are confident in

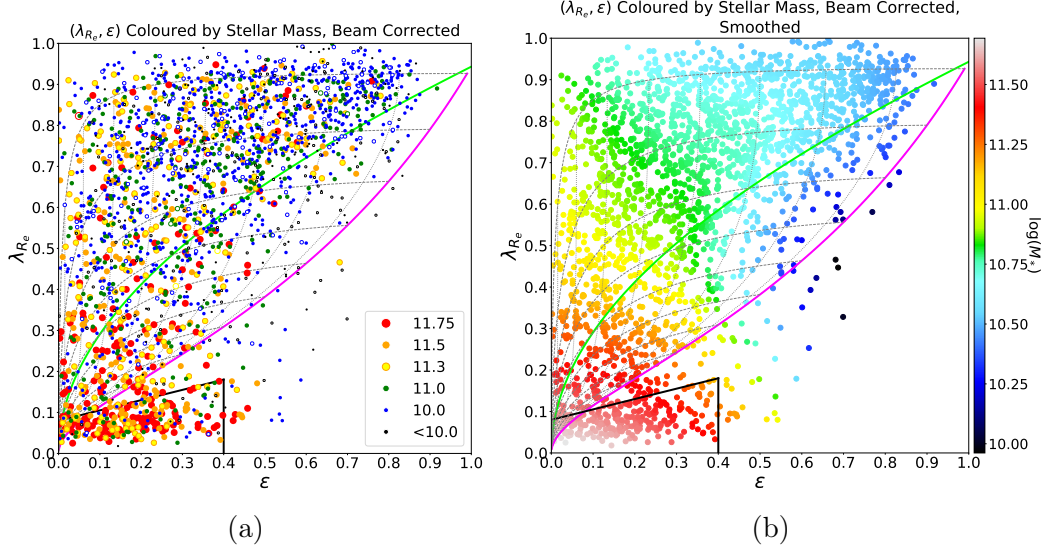


Figure 3.5: (a) **The beam-corrected (λ_{Re}, ϵ) diagram colour coded by $\log(M_*)$.** The values for each colour are indicated in the legend in $\log(M_\odot)$. If a galaxy is found in the 2MASS XSC, the stellar mass is calculated using Eq. (2.4) and the point is shown as a filled circle. Otherwise, we use a best fit to calculate the 2MASS stellar mass from the NSA stellar mass (see Figure 2.2). These galaxies are indicated with a hollow circle and are almost exclusively found in the lowest three mass bins. The lines are the same as in Figure 3.1a. (b) The same as (a) except that all colours have been LOESS smoothed. The colours are indicated by the colourbar.

their λ_{Re} . There is less agreement between Figure 3.4b and fig. 15 of C16 for S0s. In our work, we find S0s have about 0.3 higher λ_{Re} on average and are flatter by about 0.1 in ϵ . Irregular galaxies are randomly distributed throughout the diagram, but all lie in the FR region. Figure 3.4b agrees qualitatively with Cortese et al. (2016) who found that λ_{Re} is on average lower for elliptical galaxies than spirals and S0s.

The (λ_{Re}, ϵ) diagram coloured by intervals of stellar mass is shown in Figure 3.5a. While the majority of the most massive galaxies ($M > 10^{11.75} M_\odot$) are in the SR region, a significant number are in the FR region. Galaxies with $M > 10^{11} M_\odot$ are evenly distributed across the diagram. To highlight the overall trend, we also show a smoothed version of the same diagram using the `cap_loess_2d`¹ routine of Cappellari et al. (2013b), which implements the multivariate, locally weighted regression (LOESS) algorithm of Cleveland & Devlin (1988). The technique is able to find the best-fitting two-dimensional surface on the (x, y) plane that describes the mean values of a third variable (i.e. z). The smoothed plot reveals the underlying trend where the stellar mass decreases with increasing λ_{Re} and ϵ . We note that the absolute range in the LOESS smoothed diagram is less than what is shown in Figure 3.5a.

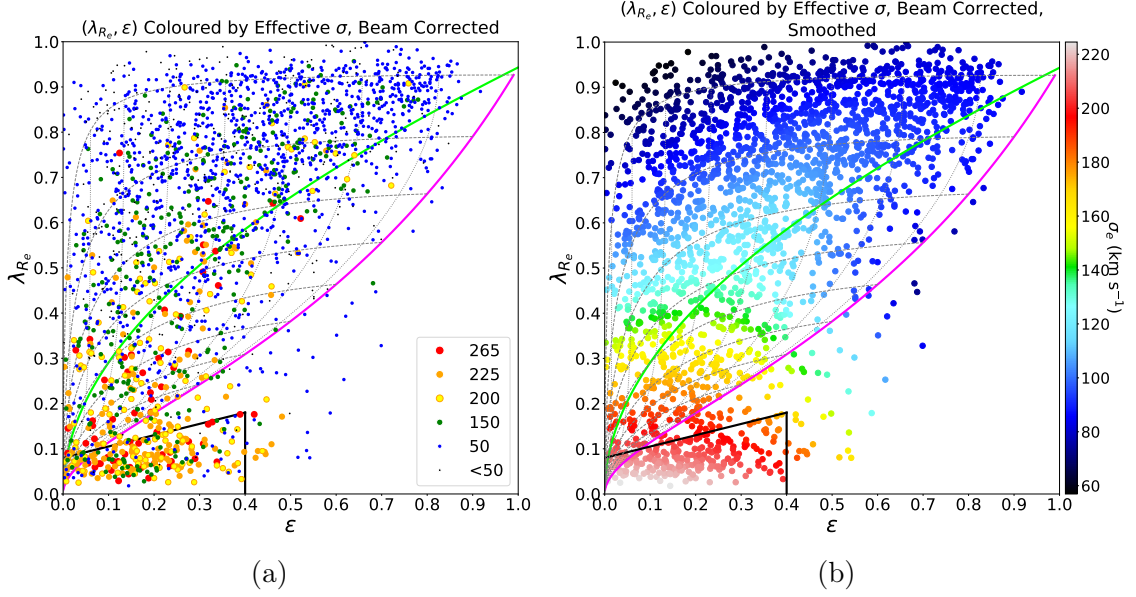


Figure 3.6: (a) **The beam-corrected $(\lambda_{R_e}, \epsilon)$ diagram colour coded by σ_e where each bin in σ_e is indicated in km s^{-1} .** The black, magenta, green and dashed lines are the same as in Figure 3.1a. (b) The same as (a) except that all colours have been LOESS smoothed. The colours are indicated by the colourbar.

We compare Figure 3.5a with Figure 3.6a which is colour-coded by the luminosity-weighted effective velocity dispersion, σ_e , within the half-light ellipse. We find that σ_e performs significantly better at differentiating between regions on the $(\lambda_{R_e}, \epsilon)$ diagram than stellar mass, with fewer outliers for a clearer transition between high/low σ_e and slow/fast rotators. There is no clear trend (by eye) between the stellar mass and λ_{R_e} in the FR region. There are a large number of galaxies more massive than the critical mass (yellow, orange and red) which are uniformly distributed throughout the FR region up to the highest λ_{R_e} . However, (almost) all high σ galaxies are concentrated in the low λ_{R_e} region of FRs and at high λ_{R_e} , (almost) all galaxies have low σ (black, blue and green). σ_e correlates positively with bulge mass fraction or central mass density (Cappellari et al., 2013b; C16) such that a larger bulge fraction results in a higher ratio of random to ordered motion within the effective radius. Therefore, a high value of σ_e corresponds to a lower value of λ_{R_e} . We also show the LOESS smoothed version in Figure 3.6b. σ_e correlates strongly with λ_{R_e} and, in contrast with the stellar mass, only has a weak dependence on ϵ .

We compare Figure 3.6a with fig. 1 of Falc3n-Barroso et al. (2015) which shows the $(\lambda_{R_e}, \epsilon)$ diagram classified by morphology, using the bulge fraction classifier for spirals. We note that there is some disagreement between the two diagrams as their results seem to imply that some Sc and Sd galaxies can have a lower λ_{R_e} than Sa or

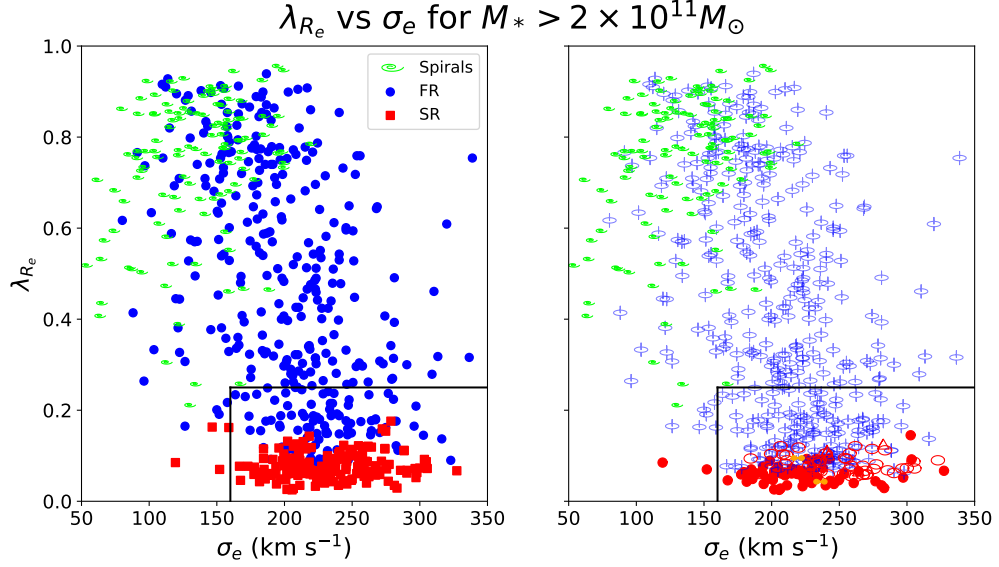


Figure 3.7: **Correlation between λ_{R_e} and σ_e for galaxies more massive than $2 \times 10^{11} M_{\odot}$.** The region enclosed by the black solid lines indicates where SRs with a core nuclear profile are likely to be found. **Left:** Galaxies are separated into fast and slow rotators. **Right:** Galaxies are classified by kinematic morphology as in Figure 3.1b.

Sb galaxies. In fact, we only find a few galaxies that overlap with their low λ_{R_e} , high ϵ Sc and Sd galaxies, and certainly not in a similar fraction. (Counter-rotating galaxies have S0 classification and they generally have $\lambda_{R_e} \lesssim 0.2$.) By using σ_e in place of Sa, Sb, Sc and Sd classifications, we can rule out the population of Sd galaxies with low λ_{R_e} seen in Falcón-Barroso et al. (2015).

To illustrate the relationship between λ_{R_e} and σ_e more explicitly, we follow Figure 7 of Krajnović et al. (2013b). Krajnović et al. (2013b) defined an area on the $(\lambda_{R_e}, \sigma_e)$ plane which cleanly separates core and core-less SRs. In Figure 3.7, we plot the same quantities selecting only galaxies that lie above the critical mass of $2 \times 10^{11} M_{\odot}$ (see subsection 3.1.3). We find that all but four SRs lie within the region corresponding to core galaxies (i.e. $\sigma_e > 160 \text{ km s}^{-1}$, $\lambda_{R_e} < 0.25$), while the majority of FRs and nearly all spirals lie outside this region. Although we cannot say for certain without obtaining higher resolution photometry from HST for example, the best candidates for true dry merger relics are the high-mass SRs found inside the ‘core’ region in Figure 3.7. (In any case, the distances involved are too great to resolve the cores even if they do exist in these galaxies.)

3.1.2 Kinematic misalignment

Figure 3.8 illustrates the kinematic misalignment for galaxies in the *clean sample*. We also include galaxies that are not in the *clean sample*, but have classifiable kinematics that fall into the categories described in subsection 2.2.3 (i.e. are not part of mergers or close pairs, and do not have flagged kinematics). To remove any potential bias between positive and negative misalignments, we symmetrise the diagram about $\Psi_{\text{mis}} = 0$. The population of disks at high $|\Psi_{\text{mis}}|$ and low ϵ are not necessarily intrinsically misaligned, as described in subsection 2.2.5, but are most likely due to uncertain or inaccurate Ψ_{phot} .

There is a strong peak of disk galaxies centred around $\Psi_{\text{mis}} = 0$. We find that 83.7% of regular ETGs and 84.5% of spiral galaxies are aligned within 10° . This is in good agreement with Krajnović et al. (2011) who suggest that 80% of all regular ETGs lie within $|\Psi_{\text{mis}}| = 10^\circ$. While we note that our accuracy is generally lower due to the larger distances, this is offset by the larger numbers providing a powerful statistical measurement. C16 measured the 1σ rms scatter in misalignment to be 4° for the combined ATLAS^{3D} and SAMI Pilot survey. If we consider only regular ETGs with $\epsilon \geq 0.4$ in the *clean sample*, we find the 1σ rms scatter to be 4.2° . The agreement between the two is impressive considering that we measure the photometric position angle at R_e , whereas C16 used the photometric position angle measured at $3R_e$. If we consider spirals in the *clean sample* with $\epsilon \geq 0.4$, then the 1σ rms scatter is 6.0° .

We also show the same diagram but for SRs only, and we include a histogram of the distribution to highlight overdensities. While there is some uniformity in the distribution of SRs between $\Psi_{\text{mis}} = \pm 90^\circ$, we find very interesting evidence for a peak in the distribution for a misalignment of $\pm 90^\circ$. This is the misalignment one would expect for prolate galaxies. Previous evidence of 90° misalignment exists. For example, Krajnović et al. (2011) found misalignments of $\sim \pm 90^\circ$ (see their Figure 8), but made no statement about mass. Simulations have found that the fraction of prolate galaxies increases with stellar mass (Li et al., 2018a; Ebrova & Łokas, 2017). While some claims exist that prolate galaxies may be more numerous at large mass (Emsellem, 2016; Tsatsi et al., 2017), those studies have very small statistics and cannot make any claims about the intrinsic shape distribution. Moreover, the fact that we find a peak at $\pm 90^\circ$ does not by itself imply any of the galaxies are necessarily prolate, as 90° misalignment can be expected in triaxial galaxies too (e.g. Franx et al., 1991). However, the large sample of SRs in the MaNGA sample makes it possible to reveal the excess at $\pm 90^\circ$ for the first time. This interesting result is discussed further in Li et al. (2018c).

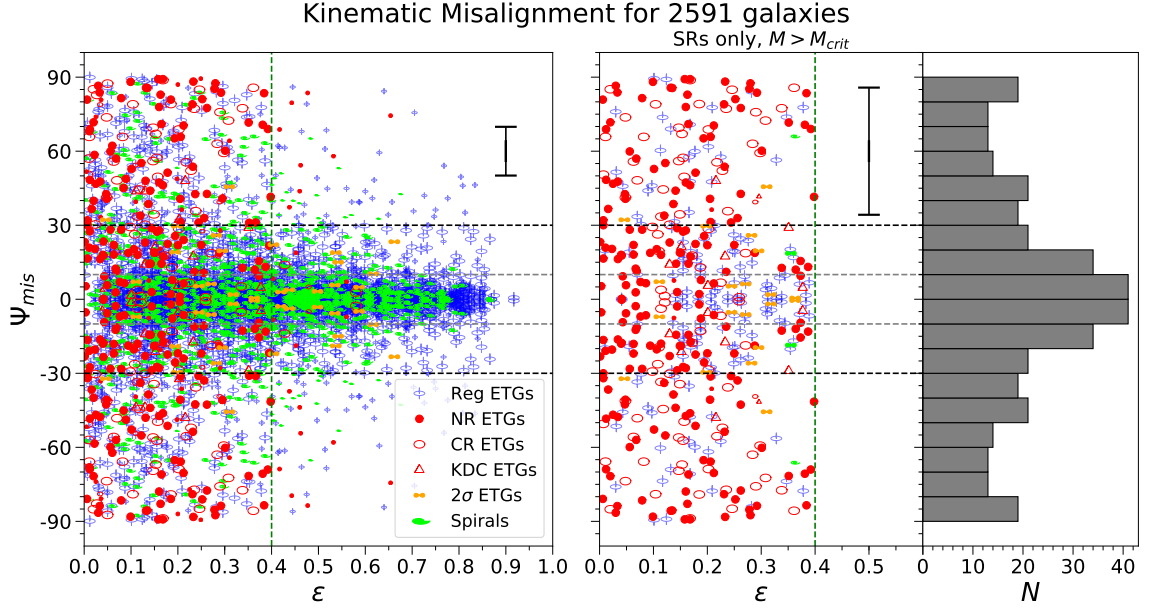


Figure 3.8: **Left:** Misalignment Ψ_{mis} between the photometric axis Ψ_{phot} and the kinematic axis Ψ_{kin} as a function of ϵ for all galaxies that are not mergers/close pairs and otherwise have classifiable kinematics. Galaxies that are not in the *clean sample* and do not appear in the other figures in this section are indicated here by a smaller symbol. Each galaxy has been symmetrised to appear above and below the zero line to remove any potential bias between positive and negative misalignments. The vertical dashed green line indicates the $\epsilon < 0.4$ criterion for SRs. The black horizontal dashed lines indicate the cut-off at $|\Psi_{mis}| = 30^\circ$ above which we discard FRs that are flatter than $\epsilon = 0.4$ (criterion (v) in subsection 2.2.5). The horizontal grey dashed lines indicate the more stringent limit of $|\Psi_{mis}| = 10^\circ$ (Emsellem et al., 2007). The mean error for all galaxies in the *clean sample* is indicated. **Right:** The same selection as left except that only SRs more massive than M_{crit} diagram are shown. A histogram of the distribution is shown to the right of the scatter plot.

3.1.3 Mass-size relation

Figure 3.9 shows the kinematic mass-size relation for galaxies in the *clean sample*, using the same kinematic classification as in Figure 3.1b. We use R_e^{maj} as it is far less dependent on inclination than R_e (Cappellari et al., 2013a). This is particularly important for a sample like ours, which includes a large population of disk galaxies (spirals and FRs). We compare the left-hand side of Figure 3.9 with fig. 21 of C16 which shows the mass-size diagram separately for galaxies in the field and two large clusters. In both the field and the Virgo and Coma Clusters, there exists a critical mass $M_{\text{crit}} \approx 2 \times 10^{11} M_{\odot}$ above which core SRs dominate while FRs and spiral galaxies are essentially absent. In Figure 3.9, we confirm this characteristic mass where 73.1% of SRs lie above M_{crit} (however some SRs below M_{crit} are unlikely to be genuine core SRs, see discussion below), while 77.0% of FRs and 76.2% of spirals lie below M_{crit} . Of the ETGs that lie above M_{crit} , 31.7% are SRs (25.8% including spirals). We also show the fraction of SRs ($F(\text{SR})$) and non-regular rotators ($F(\text{Non-Reg})$) in bins of width $\log(M_*) = 0.25$. We find that below M_{crit} , both fractions are less than about 0.1, while above M_{crit} , both fractions are above 0.1. (The spikes at low mass are due to low number statistics). The result is unchanged if spirals are included.

There are exceptions on both sides. A greater fraction of FRs lie above M_{crit} in Figure 3.9 than in fig. 21 of C16. This may still be consistent with C16 when one considers that the MaNGA sample is dominated by the field environment, and the separation in mass between fast and slow rotator is cleaner in a cluster environment (see Cappellari et al., 2011b for Virgo, Houghton et al., 2013 for Coma, Cappellari, 2013 for Virgo and Coma, D'Eugenio et al., 2013 for Abell 1689, Scott et al., 2014 for Fornax and Brough et al., 2017 for eight clusters observed with SAMI). Another source of the massive FRs could be major mergers in circular orbits. It has been shown in simulations of binary major mergers (Bois et al., 2011) and cosmological simulations (Naab et al., 2014; Li et al., 2018a) that gas-rich major mergers in circular orbits can preserve or even spin-up the merger remnants (Lagos et al., 2018). Hence, it is possible that these massive galaxies could be in a cluster environment, having built up their mass through mergers. Therefore, the left panel of Figure 3.9 is qualitatively consistent with the left panel of fig. 21 in C16, but we have vastly superior number statistics.

Recent studies have argued that there is no significant dependence of λ_{R_e} on environment at fixed stellar mass (Brough et al., 2017; Greene et al., 2017; Oliva-Altamirano et al., 2017; Veale et al., 2017b). These results may be superficially

interpreted as implying that environment is not important for the formation of slow rotators. And in this way they may appear in contrast with clear observations, from better resolved IFS data, that the massive slow rotators are only found near the peak density of clusters or groups (Cappellari et al., 2011b; Cappellari, 2013; D'Eugenio et al., 2013; Houghton et al., 2013; Scott et al., 2014; see a review of this topic in sec. 5 of C16). But actually, even fig. 11 from Brough et al. (2017) of SAMI observations, which likely represent the current state-of-the art in terms of sample size and environment sampled, shows that slow rotators are rare and they are essentially *all* massive and *all* lie near the peak overdensities, in agreement with previous studies. It is currently unclear whether the SAMI results of Brough et al. (2017) are in tension with the MaNGA results of Greene et al. (2017), or whether the differences are due to the larger environmental ranges sampled by SAMI. But overall, all these observations seems consistent with a picture in which the formation of slow rotators is driven by mass growth via dry mergers in groups (as reviewed in sec. 7 of C16). We study this interesting aspect in chapter 6.

There are also a few non-regular rotators at the low mass end (see the right-hand side of Figure 3.9). Of this population, those which lie inside the SR region are smaller in size than those which lie outside. This population of low mass SRs also existed in ATLAS^{3D} (see fig. 8 of Cappellari et al., 2013b), but none of those galaxies have a core in the surface brightness profile (see Appendix A in Krajnović et al., 2013b), suggesting that those galaxies in ATLAS^{3D} are not genuine dry merger relics. It is likely these low mass SRs shown in Figure 3.9 would disappear if we showed only SRs with cores as in C16, but as mentioned above, we cannot observe all of them with the resolution of HST. Some galaxies visually identified as KDCs are likely to be inclined 2σ (counter-rotating) galaxies. Compared with true KDCs which show ordered rotation within the core but no overall rotation on a global scale, these galaxies have rising velocity profiles out to the borders, indicating a counter-rotating disc. However, these galaxies show no obvious peaks in velocity dispersion and so cannot be classified as 2σ galaxies. Aside from these examples, some of the low-mass non-rotators are face-on discs with low σ_e . These galaxies appear as the FR non-rotators in Figure 3.1b. We find that the fraction of galaxies with masses less than $5 \times 10^{10} M_\odot$ that are either non-rotators, complex rotators or KDCs (i.e. not regular rotators or counter-rotating discs) is $\sim 1\%$ which can be expected with a large sample of galaxies.

In Figure 3.9, we provide linear relations using `lts_linefit` for SRs with $M \geq M_{\text{crit}}$ (dashed red), FR ETGs (dashed blue) and FR spirals (dashed green). We also

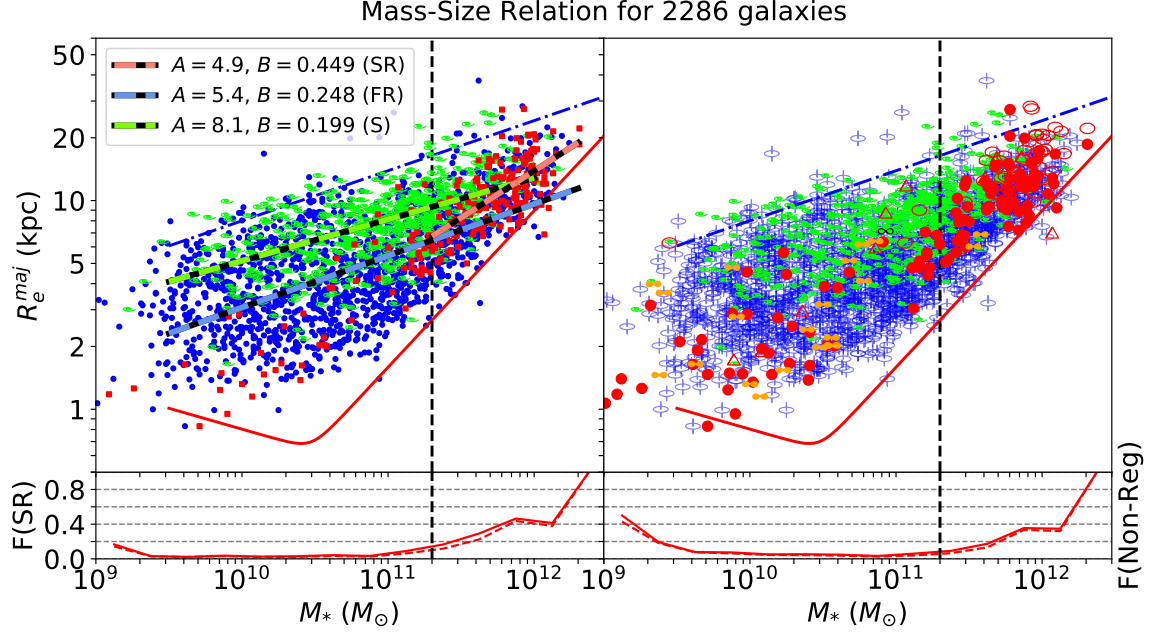


Figure 3.9: **Top Left:** The mass-size relation for galaxies in the *clean sample* classified by spirals and fast/slow ETGs where the symbols are as in Figure 3.7. The galaxies are enclosed between two regimes: the red line, defined by eq. 4 of Cappellari et al. (2013b), is known as the Zone of Exclusion (Burstein et al., 1997) which is an empirically determined boundary on the fundamental plane, and fig. 9 (dashed blue) of Cappellari et al. (2013b) which defines an empirical upper limit to galaxy size as a function of stellar mass. The effective radius in kpc is calculated from the effective radius in arcsec using the angular diameter distance (Hogg, 1999): $R_e[\text{kpc}] = R_e[\text{arcsec}] \times D_A[\text{Mpc}]/206.265$. SRs are expected to lie above $2 \times 10^{11} M_\odot$ (vertical dashed black line) if they possess a ‘core’ surface brightness profile. Overplotted are fits to FR ellipticals and S0s (dashed blue), FR spirals (dashed green) and SRs with $M \geq M_{\text{crit}}$ (dashed red). Each relation is shown in the legend where A is the intercept at $M_* = 10^{11} M_\odot$ and B is the slope. The errors in A are all ± 0.1 and the errors in B are ± 0.01 apart from the red SR relation where the error is ± 0.04 . **Top Right:** The same relation classified by visual kinematic morphology. The symbols are as in Figure 3.1b. **Bottom Left:** The fraction of slow rotators compared to the total i.e. $F(\text{SR}) = N_{\text{SR}}/[N_{\text{SR}} + N_{\text{FR}}]$ where N_{SR} is the number of SRs, as a function of stellar mass. The fraction is calculated in bins of width $\log(M_*) = 0.25$. The solid red line does not include spirals whereas the dashed red line does include spirals. **Bottom Right:** The fraction of non-regular rotators compared to the total i.e. $F(\text{Non-Reg}) = N_{\text{Non-Reg}}/[N_{\text{Non-Reg}} + N_{\text{Reg}}]$, as a function of stellar mass. As bottom left, the solid red line does not include spirals whereas the dashed red line does include spirals.

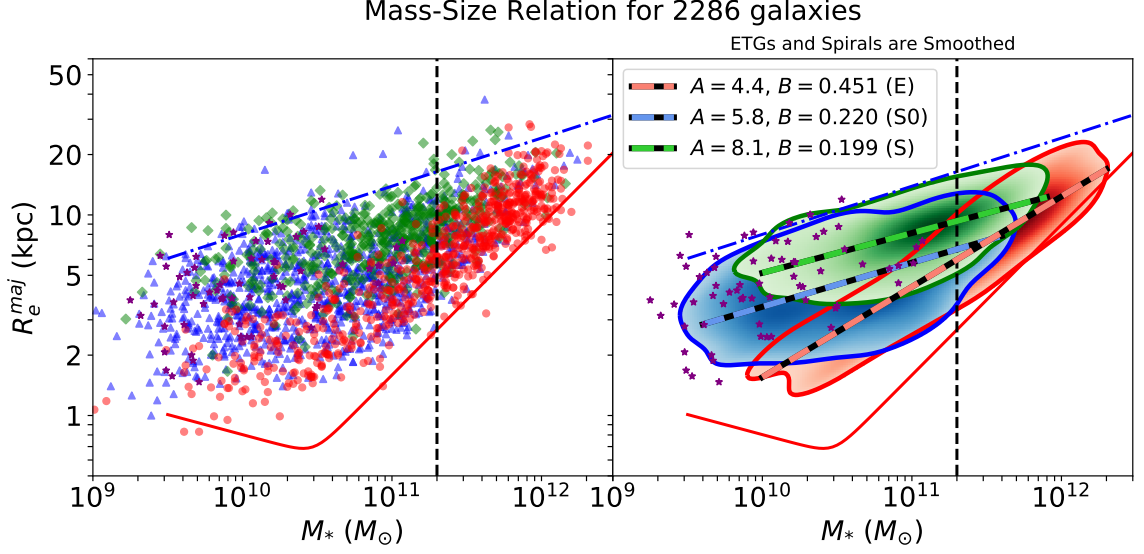


Figure 3.10: **Left:** The mass-size relation for galaxies in the *clean sample* classified by visual morphology. The symbols are the same as in Figure 3.4a. **Right:** The same as left except ETGs and spirals are smoothed. Overplotted are fits for each major galaxy population (i.e. not irregulars) with each relation given in the legend. The errors in A are all ± 0.1 and the errors in B are all ± 0.01 .

compare relations (not shown) from the GAMA survey for $z = 0$ disks and spheroids (Lange et al., 2016) with similar populations in our work. We fit FR ellipticals and FR disks (i.e. spirals and S0s) separately below M_{crit} , and SRs above M_{crit} using eq. 2 from Lange et al. (2016),

$$R_e = A \left(\frac{M_*}{10^{10} M_\odot} \right)^B, \quad (3.1)$$

where R_e is the effective radius in kpc and M_* is the stellar mass. We find that the best-fit relation for SRs with $M \geq M_{\text{crit}}$ has a slope of 0.449 ± 0.039 which is steeper than the Lange et al. (2016) $z = 0$ spheroid relation ($B = 0.263$) but not as steep as the Lange et al. (2016) elliptical, $M > 10^{10} M_\odot$ relation ($B = 0.643$). However, the slope is very close to that found by Lange et al. (2015) for ETGs ($B = 0.46$). The FR spheroids have a slope $B = 0.293 \pm 0.018$ which is similar to that of the Lange et al. (2016) $z = 0$ spheroids ($B = 0.263$), while the FR disks have a slightly shallower slope ($B = 0.201 \pm 0.011$) than the Lange et al. (2016) $z = 0$ disks ($B = 0.274$).

Finally, we show the mass-size relation coloured by morphology (Figure 3.10). We include relations for ellipticals, S0s and spirals of all masses. Ellipticals lie almost parallel to the solid-red line (eq. 4 of Cappellari et al., 2013b) while spirals and S0s lie almost parallel with the dashed blue line (fig. 9 of Cappellari et al., 2013b). All

irregular galaxies lie below $10^{11} M_{\odot}$ with the majority at lower masses still. Here we compare relations (not shown) for ellipticals with $M > 10^{10} M_{\odot}$ and for disks, i.e. spirals and S0s, at all masses with the analogous relations from Lange et al. (2016). We find that ellipticals in our work have a similar slope ($B = 0.485 \pm 0.009$) to that of SRs given above and hence is less steep than the $M > 10^{10} M_{\odot}$ elliptical relation from Lange et al. (2016). The slope of our disk relation, $B = 0.249 \pm 0.008$, agrees well with the Lange et al. (2016) $z = 0$ disk relation. However, our effective radii are generally measured from MGE fitting, while Lange et al. (2016) used bulge-disk decompositions to derive R_e , and so our results are unlikely to agree in all cases.

3.2 Conclusions

We have measured the stellar angular momentum parameterised by λ_{R_e} from the kinematics of 2286 galaxies in the MaNGA sample, the largest sample with IFS observations to date. For the first time, we see a clear bimodality in galaxy properties between slow and fast rotators which may result from fundamental differences in their formation history. The bimodality we see in the $(\lambda_{R_e}, \epsilon)$ diagram is necessarily a strict lower limit to the intrinsic bimodality we would observe in that same diagram if all galaxies were edge-on. This would be true even in noiseless galaxies due to the effect of inclination. However, in our sample, noise does play a role in weakening the observed bimodality. This means that if we could deproject all galaxies and remove all noise, we would dramatically sharpen the separation between the fast and slow rotators. In this case, the histogram in Figure 3.2 would most likely look more similar to fig. 11 in C16, but with much better statistics.

The majority of regular rotators and spirals occupy the fast rotator region on the $(\lambda_{R_e}, \epsilon)$ diagram. There is a large concentration of non-rotating galaxies in the slow rotator region and all non-rotators are rounder than E4. If we consider only galaxies with a mass greater than $2 \times 10^{11} M_{\odot}$, there is a sharp cutoff in effective velocity dispersion and λ_{R_e} associated with a core surface brightness profile. These galaxies are the best candidates for the genuine dry merger relics.

The strongest concentration of elliptical galaxies is on the upper boundary of the SR region. However, when weighted by volume, these galaxies are down-weighted as they are rare in a random volume of the Universe. There is a strong concentration of spirals and S0s at $\lambda_{R_e} \sim 0.9$ which is higher than seen in previous samples. This is caused by a combination of effects due to the instrumental resolution (i.e. unresolved σ) and the spatial resolution (i.e. the MaNGA PSF). As shown in section 2.4, λ_{R_e}

Table 3.1: Table containing all the quantities and properties required to plot all the figures in section 6.2. Column (1) is the MaNGA-ID associated with a unique MaNGA galaxy and Column (2) indicates whether the galaxy given in Column (1) is in the *clean sample* as decided by the criteria given at the beginning of subsection 2.2.5. Column (3) lists the Hubble classification determined visually by MTG and MC (see subsection 2.2.5, U = unclassified, M/CP = merger or close pair) and Column (4) lists the kinematic classification (F = flagged) described in subsection 2.2.3. Column (5) lists the circular effective radius given in log units which is taken from either the MGE fit (subsection 2.2.1.1), the 2MASS XSC (subsection 2.1.2) or the NSA catalogue (subsection 2.1.3) as described in subsection 2.2.1.2. Column (6) lists the semi-major axis given in physical log units and calculated using the angular diameter distance (see Figure 3.9) estimated from the redshift given in Column (15). These two radii are given in log units as they have constant relative errors. Column (7) gives the FWHM of the PSF in arcsec taken from `drpall-v2_1_2` and Column (8) lists λ_{R_e} corrected for the PSF given in Column (7) using Eq. (2.14). Columns (9) and (10) list the final ϵ and photometric position angle Ψ_{phot} , defined as East of North, taken from either the MGE fit, the photometric fit from `find_galaxy` or the NSA catalogue (see Figure 2.1b and subsection 2.2.1.3). For 143 galaxies, the measured Ψ_{phot} is replaced by a more accurate value supplied by HL (see section 2.3). Column (11) lists the kinematic position angle Ψ_{kin} East of North and column (12) lists the error in Ψ_{kin} . Column (13) lists $\log(M_*)$ either calculated from the absolute K_S using Eq. (2.4), or taken from the NSA catalogue and scaled to 2MASS (see Figure 2.2). Column (14) lists the effective velocity dispersion in log units calculated using Eq. (2.3). Finally, columns (15) and (16) list the redshift and Sérsic index taken from the NSA catalogue. Only the first 10 rows are shown.

MaNGA-ID	Clean Sample?	Hubble Group	Kinematic Classification	$\log(R_e^{\text{circ}})$ (")	$\log(R_e^{\text{maj}})$ (kpc)	PSF (")	$\lambda_{R_e}^{\text{true}}$ (8)	ϵ (9)	Ψ_{phot} (") (10)	Ψ_{kin} (") (11)	Error in Ψ_{kin} (") (12)	$\log(M_*)$ (13)	$\log(\sigma_e)$ (km s ⁻¹) (14)	z (15)	n (16)
12-98126	Y	E	R	0.699	0.417	2.6	0.793	0.342	154.8	153.0	5.5	10.38	1.747	0.0209	4.4
12-84674	N	U	R	0.934	0.996	2.6	0.788	0.054	99.5	110.0	8.0	11.11	1.691	0.0579	1.7
12-193481	N	M/CP	R	0.831	0.891	2.6	0.400	0.510	153.3	4.5	3.2	11.34	2.102	0.0406	2.2
12-84731	Y	S0	R	1.080	0.941	2.5	0.801	0.709	125.1	128.0	3.2	10.44	1.850	0.0193	0.9
12-84627	Y	S0	R	0.831	1.121	2.6	0.926	0.592	34.7	41.5	2.8	11.21	2.068	0.0648	1.0
12-84620	Y	S0	R	0.650	0.301	2.6	0.627	0.240	75.8	64.5	14.0	9.81	1.621	0.0193	2.2
12-49536	Y	S0	R	0.548	0.314	2.6	0.745	0.546	10.8	5.0	9.8	10.03	1.605	0.0194	2.8
12-193534	N	I	NR	0.684	0.384	2.6	0.332	0.438	137.7	175.0	48.2	9.49	1.543	0.0185	1.3
12-84670	Y	E	NR	0.545	0.858	2.5	0.025	0.034	141.8	125.5	81.2	11.84	2.313	0.1108	6.0
12-180451	N	E	F	0.348	0.134	2.6	0.800	0.095	158.1	137.0	0.5	9.30	2.501	0.0290	0.9

is accurate to within ~ 0.1 when $\sigma_{\text{max}} \gtrsim 25 \text{ km s}^{-1}$ for low instrumental noise. We find that the effective velocity dispersion σ_e and kinematic morphology are the galaxy properties that give the cleanest separation between slow and fast rotators, as opposed to visual morphology and stellar mass. We find many more high-mass fast rotators than in previous studies (e.g. Cappellari, 2013). This is likely due to MaNGA sampling a larger and more representative sample of the Universe than previous studies, which had a disproportionately high number of cluster satellite galaxies. However, it could also be due to gas-rich major mergers on circular orbits that preserve the spin of the merger remnant.

We also measure the misalignment between the photometric major axis and the kinematic axis for 2547 galaxies with kinematics that can be visually classified using the scheme described in subsection 2.2.3. We find that $\sim 80\%$ of regular ETGs and spiral galaxies are aligned within 10° . There is a large range of misalignments for slow rotators as expected from a triaxial distribution. Thanks to the large number of galaxies in the MaNGA sample, we are able for the first time to resolve a peak at $\Psi_{\text{mis}} = \pm 90^\circ$, indicating minor axis rotation. This interesting result is discussed further in Li et al. (2018c).

Finally, we plot the mass-size relation for the MaNGA sample. For ETGs, we find a tight agreement between the *quantitative* measurement of slow/fast rotator and the *qualitative* classification of the kinematic morphology (regular/non-regular rotator), further highlighting the bimodality in galaxy properties. In chapter 6, we will look at the dependence that galaxy mass has on environment, using the large number statistics that the MaNGA sample provides.

Chapter 4

A group finder algorithm optimised for the study of local galaxy environment

The surest sign that intelligent life exists elsewhere in the universe is that it has never tried to contact us.

*Bill Watterson
Calvin and Hobbes*

4.1 Introduction

It has been known since the first large-scale galaxy surveys that galaxies are not randomly distributed throughout the Universe, but are preferentially found in groups and clusters. This structure traces the underlying dark matter distribution which cannot be observed directly. Moreover, many galaxy properties depend on the local environment, including morphology and colour (Blanton et al., 2005; Blanton & Moustakas, 2009). Therefore, it is of great interest to produce accurate and reliable group catalogues of nearby galaxies with which to study the properties of galaxies as a function of environment. While the first spectroscopic galaxy survey (CfA1 Redshift Survey; Huchra & Geller, 1982; Geller & Huchra, 1983) only used a single slit to obtain the redshift, more recent surveys use multi-slit or fibre-optic spectrographs to observe hundreds of thousands of galaxies with spectroscopy. Notable examples are the Two Degree Field Galaxy Redshift Survey (2dFGRS; Colless et al., 2001), the Galaxy And Mass Assembly survey (GAMA; Driver et al., 2009, 2011) and the SDSS (see York et al., 2000 for a technical summary, Gunn et al., 2006 for a summary of the SDSS telescope, Smee et al., 2013 for a description of the spectrographs and Blanton

et al., 2017 for a summary of SDSS-IV). Collectively, these surveys have provided the basis for studying galaxy environments across huge samples.

The availability of such large datasets allows the opportunity to produce galaxy group catalogues. Many catalogues have been produced by various research teams using data from one or more of these surveys. Although some catalogues have been based purely on data from the 2dFGRS (Merchán & Zandivarez, 2002; Eke et al., 2004; Yang et al., 2005) or the GAMA survey (G3Cv7, Robotham et al., 2011), the most productive survey for group catalogues has been the SDSS. Most significant data releases have been complemented by a group catalogue based on the spectroscopic sample, including DR2 (Miller et al., 2005), DR3 (Merchán & Zandivarez, 2005), DR4 (Yang et al., 2007, updated to DR7), DR5 (Tago et al., 2008), DR7 (Tago et al., 2010; Muñoz-Cuartas & Müller, 2012), DR8 (Tempel et al., 2012), DR10 (Tempel et al., 2014) and DR12 (Tempel et al., 2017).

The power of these catalogues lies in their scope for studying galaxy properties across large samples to obtain powerful statistical results. However, they are almost always based on the friends-of-friends (FoF) method to assign galaxies to groups (Huchra & Geller, 1982; Davis et al., 1985). This simple method uses a linking metric to assign particles to halos and as such is a frequent choice for assigning galaxies to halos in dark matter simulations (Eke et al., 2004; Tempel et al., 2016; see Knebe et al., 2013 for a review). The linking metric is usually defined to be a constant fraction of the mean particle separation. For magnitude-limited surveys (like the SDSS spectroscopic survey), the linking length varies with z to account for the change in the luminosity function with z (Huchra & Geller, 1982). One potential issue with the FoF method is that groups can end up being joined by thin bridges, which may not be desirable (or even harmful). Yang et al. (2005) combined the FoF method with an iterative procedure that first estimates the location, mass and radius of dark matter halos based on the galaxy distribution, before assigning galaxies to those halos and recomputing the halos. Miller et al. (2005) used a spherical aperture and information about the galaxy colours to identify clusters based on the probability of obtaining the observed galaxy distribution randomly.

Another independent method for estimating the underlying probability density function of some discrete data is the kernel-density estimation (KDE) method (Parzen, 1962). The premise behind this approach is that by replacing particles/galaxies of zero size by kernels of non-zero size, a continuous probability density function can be obtained across the coordinate space. To find clumps or groups in the particle distribution, all one needs to do is locate local maxima in the density function. There

are a number of algorithms which assign particles/galaxies to groups based on the density field, although the details of the method can vary somewhat between them. However, there are no group catalogues currently available that are based on redshift surveys and use the KDE method. See Knebe et al. (2013) for a complete review of group-finder algorithms used in galaxy simulations.

Our ultimate goal is to study the environment of MaNGA galaxies in as much detail as possible. To this end, we have paid great attention to obtaining an accurate catalogue of galaxies and galaxy groups. A key advantage of the sample of galaxies observed by the MaNGA survey is that it is small enough that the neighbours of MaNGA galaxies can be assessed visually. We take the opportunity to develop an algorithm that assigns galaxies to groups based on the underlying galaxy distribution, with the intention of identifying groups that match what one might conclude from looking at the galaxy distribution by eye.

This chapter is split as follows. In section 4.3, we present a new group-finder algorithm, TD-ENCLOSER¹⁴, which adapts features of previous algorithms and is suitable for sample sizes of up to $\sim 10^5$ particles. We focus on providing a simple routine that provides a careful treatment of small groups and cropping outliers from large groups. In subsection 4.2.1, we summarise previous group finder algorithms. We use the “hill-climbing” method but only consider directions where a galaxy is known to exist. We also adapt parameters from the HOP method of Eisenstein & Hut (1998), hereafter EH96. We then test our algorithm on a mock galaxy catalogue to demonstrate its operation and effectiveness (section 4.4).

In chapter 5, we use TD-ENCLOSER to find the nearest neighbours to MaNGA galaxies. The set of neighbours that we find depends on the MaNGA galaxy, and if MaNGA galaxies are local to each other, then the same intrinsic groups may be found multiple times but with slight differences between each set. Ultimately we want to construct a group catalogue for MaNGA galaxies where each MaNGA galaxy lives in a well-defined environment. This requires us to select unique environments for each MaNGA galaxy, which we achieve in section 4.5.

¹⁴The name TD-ENCLOSER encapsulates the general idea behind our algorithm in that it considers galaxies by their density in descending order i.e. Top Down (TD). ENCLOSER refers to the fact that the algorithm finds the group that encloses a particular galaxy. As the algorithm was developed with a specific astronomical application in mind, we give it an unofficial acronym in the spirit of so many other acronyms in astronomy: Top Down-Efficient loCaL neighbOur SEarchER.

4.2 KDE-based clustering

4.2.1 Previous KDE-based group finder algorithms

There are many algorithms present in the literature that use a kernel density estimator to group particles into clusters. Many of these were optimised for N -body dark matter simulations and hence deal with $\mathcal{O}(10^6)$ particles. The first to be developed was DENMAX (Bertschinger & Gelb, 1991; Gelb & Bertschinger, 1994) which uses an interpolation of the particle distribution to define a regular rectangular grid. Particles slide from their original locations towards a nearby dense grid cell with a force that is proportional to the local gradient (i.e. the particles follow a fluid equation). All particles that settle at the same peak are considered to be part of the same halo. Particles at the edges are clipped using an energy constraint (by comparing a particle’s kinetic and potential energy at different timestamps). Spline Kernel Interpolative Denmax (SKID; Weinberg et al., 1997) is an updated version of DENMAX that employs a spline kernel interpolation with a variable kernel size, rather than a regular grid of uniform kernel size. The densities are only measured at the particle locations, and particles then move in the same way as DENMAX towards density peaks. The HOP method (Eisenstein & Hut, 1998; EH96) is inspired by SKID in that densities are only calculated at particle locations. However, instead of particles following the density field via a fluid equation, particles “hop” to the densest neighbour within the nearest N_{hop} neighbours. Particles hop until they reach the densest particle, and all particles that hop to the same particle are assigned to the same halo. A set of six parameters (not including the kernel bandwidth) are used to merge groups and clip outliers.

DENCLUE (Hinneburg et al., 1998; Hinneburg & Gabriel, 2007) is another KDE-based group finder algorithm. From a given particle, the algorithm climbs hills defined by the density field, and assigns all particles that climb to the same hill to the same cluster. This method has the advantage of many density-based methods in that there is a unique result regardless of the order in which particles are considered. DENCLUE 2.0 (Hinneburg & Gabriel, 2007) includes a variable step size to reduce the number of iterations by considering the local gradients, without compromising on accuracy. It also has a noise threshold which is used to discount local maxima which fail to reach this threshold. However, the algorithm does not set a minimum threshold for particles to be considered as members of a cluster, and so a cluster can have members with density ≈ 0 .

If limitations due to computing power or sample size were not an issue, then the precise and formal way to find groups would be to start from a particular galaxy and

find the direction of maximal gradient in the density field. After moving a certain step size in that direction, the search would be repeated until the galaxy reaches a point where all gradients are negative. A helpful picture to have in mind is if the field were overturned so that peaks became valleys, then the galaxy would roll down in the direction of the steepest downwards slope, rather like a rain drop, before stopping at the bottom of the valley where all gradients are positive. We note that a similar method already exists and is known as “mean-shifting” or “mode-seeking” (e.g. Cheng, 1995, see Carreira-Perpiñán, 2015 for a review). In this method, a kernel is placed over a point and is shifted towards the direction where the density (number of points) increases within the kernel (defined by the mean-shift vector). While the “rain drop” method would be the most rigorous solution to this problem, there are two drawbacks to implementing it computationally.

Firstly, the step size should be sensitive to the gradient so that a steeper gradient encourages a larger step size, as in Hinneburg & Gabriel (2007). This can be fairly straightforward to implement based on the equations of motion in a potential for example. However, this will be inefficient for points which are far away from the peak/valley, as the gradient will be small. The second obstacle is optimising the search for the direction of steepest gradient. Once the particle has *initially* found this direction, the search can be limited to $\phi \pm \Delta\phi$, where ϕ is the current direction of the steepest gradient and $\Delta\phi$ is the field of view (width of an arc). While this works in principle, the path to the top of the peak/bottom of the valley has the potential to be much longer than the distance travelled as the crow flies, especially if the topology is complex.

One option to simplify this is to roll down *from* peaks in the density and tag all particles that are met along the way. Here, the search stops at the foot of the hill where all gradients are positive. This approach requires prior knowledge of the location of the peaks but can, in theory, be more efficient than the method described above. Instead of moving from multiple points to a single location, this method moves outward from a single location assigning particles to the peak along the way. This “hill-down” approach was first applied in HD-DENCLUE by Xie et al. (2007) with the intention of finding groups of connected points in medical imaging data (see also Xie et al., 2010). In their approach, the data are finely gridded and all points on the grid are added to the cluster with each successive step down the hill. The edge (foot) of the cluster is defined where the absolute value of the gradient falls below a predefined noise threshold. While this method works well for millions of particles (as is the case

for imaging data), it becomes inefficient for smaller samples of a few hundred particles because all directions need to be searched from the point of view of the peak.

A similar approach was taken by Springel et al. (2001) who combined the FoF method with a “top-down” method that can identify the background density field and substructure in a dark matter simulation. Their algorithm, called **SUBFIND**, sorts particles by their density and then “rebuilds” the particle distribution by adding them to halos in order of decreasing density. Particles are only assigned to one subhalo so that they do not contribute to the mass of the parent halo, but Springel et al. (2001) find that this does not affect the parent halo a great deal as the substructure is usually at a scale that is small compared to the parent halo.

4.2.2 A top-down approach to KDE-based clustering

All of these algorithms have been optimised for millions of particles and hence are appropriate for producing group catalogues based on the dark matter distribution. However, we are interested in simply grouping galaxies together and obtaining directly observable relations and are not concerned with the dark matter distribution. As we are only focussing on the neighbours local to a specific sample of galaxies (the MaNGA galaxies), we do not need to consider large numbers of galaxies. Moreover, we would like to be able to detect all group sizes from two upwards. We would also like to be able to differentiate nearby peaks rather than merge them, which can happen with the **HOP** method for example (see fig. 1 of EH96).

Our approach is to combine a “top-down” method with a hill climbing method so that it is efficient for sample sizes of a few hundred to a thousand particles. To keep our algorithm as simple as possible, we will only consider straight lines between points, ignoring the surface topology. By considering galaxies in order of their density from highest to lowest, we can identify the peaks before attracting galaxies towards those peaks. Hence, rather than sliding or hopping from a particular galaxy, we take a “top-down” approach where we move out from regions of high density to low density.

4.3 Description of TD-ENCLOSER

4.3.1 Definition of algorithm parameters

The algorithm we present here is similar to **SUBFIND** in that it considers galaxies by their density in decreasing order, but its function is an adaptation of the **HOP** method of EH96. However, while there are some similarities, we have a different goal in

Algorithm 1: TD-ENCLOSER: Finds group enclosing a target galaxy.

Data: $\{\mathbf{x}, \mathbf{y}\}$ coordinates in physical units (Mpc) for N galaxies *relative* to the target galaxy at $(0, 0)$
Input: $\sigma_{\text{ker}} = 0.3$ Mpc, $\rho_{\text{outer}} = 1.6$, $\rho_{\text{saddle}} = 4$, $\rho_{\text{peak}} = 4.8$, $N_{\text{merge}} = 4$ (defaults).
Result: $\{\mathbf{x}, \mathbf{y}\}$ coordinates for N galaxies where N is the richness of the group that encloses the target galaxy.

- 1 Set N to be the number of coordinate pairs.
- 2 Construct coarse regular grid C_g .
- 3 **for** $i = 1$ **to** N **do**
- 4 Add 2D Gaussian kernel of standard deviation σ_{ker} , amplitude 1 and centre $(\mathbf{x}_i, \mathbf{y}_i)$ to C_g .
- 5 Interpolate coarse grid C_g using a 2D spline interpolator: $s = \text{spline}(C_g)$.
- 6 **if** $s(0, 0) < \rho_{\text{outer}}$ **then return** // Target galaxy is isolated.
- 7 **else** // Target galaxy must be in a group.
- 8 Evaluate s at $\{\mathbf{x}, \mathbf{y}\}$ to obtain density ρ at each galaxy location: $\rho = s(\mathbf{x}, \mathbf{y})$.
- 9 Remove all galaxies where $\rho < \rho_{\text{outer}}$. // These galaxies are isolated.
- 10 Set N to the number of (remaining) coordinate pairs.
- 11 Set $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}$ to be an array of shape $(N, 4)$ which will hold information about a galaxy's enclosing peak, namely (x^P, y^P) coordinates and density ρ^P of its central galaxy, and peak number P .
- 12 Sort $\mathbf{x}, \mathbf{y}$ and ρ by ρ in descending order such that $\rho[1] > \rho[2] > \rho[3] \dots$
- 13 # First pass
- 14 Assign galaxy with density $\rho[1]$ to peak 1: $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}[1, :] \leftarrow (1, \mathbf{x}[1], \mathbf{y}[1], \rho[1])$.
- 15 Set N_P to be the number of peaks: $N_P \leftarrow 1$. // Only 1 peak exists at this point.
- 16 **for** $i = 2$ **to** N **do**
- 17 Select unique rows (peaks) from $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}$ where $P \geq 1$:
 $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}_u \leftarrow \{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}[P \geq 1, :]$. // Only select identified peaks.
- 18 Sort $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}_u$ in order of increasing distance from $(\mathbf{x}_i, \mathbf{y}_i)$.
- 19 **while** $(j \leq N_P) \wedge (j \leq 10)$ **do** // Only consider at most the 10 nearest peaks.
- 20 Check if the gradient of the connecting line between the galaxy at location $(\mathbf{x}_i, \mathbf{y}_i)$ and the peak at location $(\mathbf{x}_j^P, \mathbf{y}_j^P)$ changes sign or increases monotonically:
 $\text{mono} \leftarrow \text{MonotonicIncrease}(\mathbf{x}_i, \mathbf{y}_i, \mathbf{x}_j^P, \mathbf{y}_j^P, s, \rho_{\text{cap}} = \rho_j^P, \epsilon = -0.1)$.
- 21 **if** $\text{mono} = \text{True}$ **then** // Assign galaxy to existing peak.
- 22 $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}[i, :] \leftarrow \{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}_u[j, :]$; **break**
- 23 **else** $j \leftarrow j + 1$ // Move on to next peak.
- 24 **if** $\text{mono} = \text{False}$ **then** // Galaxy cannot be added to any existing peak.
- 25 Assign galaxy to be the central galaxy of a new peak:
 $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}[i, :] \leftarrow (N_P + 1, \mathbf{x}[i], \mathbf{y}[i], \rho[i])$, $N_P \leftarrow N_P + 1$
- 26 # Second pass
- 27 **for** $i = 1$ **to** N **do**
- 28 **if** $(\rho_{\text{outer}} \leq \rho_i < \rho_{\text{saddle}}) \wedge (\rho_i^P \geq \rho_{\text{peak}})$ **then**
- 29 Sort $\{\mathbf{x}, \mathbf{y}, \rho\}$ in order of increasing distance from $(\mathbf{x}_i, \mathbf{y}_i)$.
- 30 Set ρ_{max} to be the maximum density of the nearest $N_{\text{merge}} - 1$ neighbours.
- 31 **if** $(\rho_i + \rho_{\text{max}})/2 < \rho_{\text{saddle}}$ **then**
- 32 Eject galaxy from group: $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}[i, :] \leftarrow (0, \mathbf{x}[i], \mathbf{y}[i], \rho[i])$
- 33 # Third pass
- 34 Select galaxies that have been ejected from their original peaks in the SP:
 $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}' \leftarrow \{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}[(\rho_{\text{outer}} \leq \rho < \rho_{\text{saddle}}) \wedge (P = 0), :]$,
 $\{\mathbf{x}, \mathbf{y}, \rho\}' \leftarrow \{\mathbf{x}, \mathbf{y}, \rho\}[(\rho_{\text{outer}} \leq \rho < \rho_{\text{saddle}}) \wedge (P = 0), :]$.
- 35 Set N' to be the number of rows (galaxies) in $\{\mathbf{x}, \mathbf{y}, \rho\}'$.
- 36 Assign galaxy with density $\rho'[1]$ to peak $N_P + 1$: $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}'[1, :] \leftarrow \{N_P + 1, \mathbf{x}'[1], \mathbf{y}'[1], \rho'[1]\}$.
- 37 Set N'_P to be the number of new peaks added in the TP: $N'_P \leftarrow 1$.
- 38 **for** $i = 2$ **to** N' **do**
- 39 Select unique rows (peaks) from $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}'$ where $P > N_P$:
 $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}'_u \leftarrow \{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}'[P > N_P, :]$. // Do not consider peaks from FP.
- 40 Sort $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}'_u$ by distance from $(\mathbf{x}'_i, \mathbf{y}'_i)$.
- 41 $\text{mono} \leftarrow \text{MonotonicIncrease}(\mathbf{x}_i, \mathbf{y}_i, \mathbf{x}'_j, \mathbf{y}'_j, s, \rho_{\text{cap}} = 0, \epsilon = -0.01)$
- 42 **while** $(j \leq N'_P) \wedge (j \leq 10)$ **do**
- 43 **if** $\text{mono} = \text{True}$ **then** $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}'[i, :] \leftarrow \{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}'_u[j, :]$; **break**.
- 44 **else** $j \leftarrow j + 1$
- 45 **if** $\text{mono} = \text{False}$ **then** $\{\mathbf{P}, \mathbf{x}^P, \mathbf{y}^P, \rho^P\}'[i, :] \leftarrow (N'_P + 1, \mathbf{x}'[i], \mathbf{y}'[i], \rho'[i])$, $N'_P \leftarrow N'_P + 1$
- 46 Select only galaxies which lie in the same peak as the target galaxy.

Algorithm 2: MonotonicIncrease: Checks if the gradient of a line remains above a (small) threshold ϵ along the entire length of the line.

```

Data:  $x_0, y_0, x_1, y_1, s$ 
Input:  $\rho_{\text{cap}} = 0, \epsilon = -0.1$ 
Result: mono
# Sample line along intervals with spacing 1% of its total length.
1 Set  $\rho^{\text{mid}}$  to be an array of length 101.
2 for  $i = 0$  to 100 do
3    $x^{\text{mid}} \leftarrow x_0 + (x_1 - x_0)i/100$ 
4    $y^{\text{mid}} \leftarrow y_0 + (y_1 - y_0)i/100$ 
5    $\rho_i^{\text{mid}} \leftarrow s(x^{\text{mid}}, y^{\text{mid}})$  // Calculate density at the  $i$ th element.
6 for  $i = 0$  to 99 do
7    $\rho_{\text{diff}} \leftarrow \rho_{\text{mid}, i+1} - \rho_{\text{mid}, i}$ 
8   if  $[(\rho_{\text{cap}} \geq 0) \wedge (\rho_{\text{mid}, i+1} \leq \rho_{\text{cap}})] \vee (\rho_{\text{cap}} = 0)$  then
9     if  $\rho_{\text{diff}} \geq \epsilon$  then mono  $\leftarrow$  True // If gradient does not fall below  $\epsilon$ .
10    else mono  $\leftarrow$  False; break
11 return mono

```

mind to EH96, namely that we want to identify small scale group environments in detail, while HOP was designed for N -body simulations of order 10^6 particles. EH96 solved two key problems regarding the separation of halos from their surroundings as well as the merging of groups by introducing six tunable parameters. Despite the added complexity, they showed that the result was insensitive to all but five of those parameters. We adopt four of these parameters, and adapt three of them to our specific requirements. Another similarity between our algorithm and the one of EH96 is that we make three passes of the data, although the manner in which our passes operate differ.

Now, we give details of the parameters that we adopt from EH96 (they used δ to denote density but we use ρ instead, as δ can also represent a difference):

- ρ_{outer} : This is the minimum density required for a galaxy to be considered as part of a group. By setting this parameter, EH96 prevent particles in underdense regions from joining groups. We retain this functionality of ρ_{outer} in this work. This is the only parameter found by EH96 to have a significant impact on the final group distribution.
- ρ_{saddle} : This is a second contour level which, if $\rho_{\text{saddle}} \neq \rho_{\text{outer}}$, can be used to separate two peaks which are joined by a thin bridge where $\rho \geq \rho_{\text{outer}}$. It could also be used to join two peaks which are separated by a local minimum where $\rho \geq \rho_{\text{saddle}}$. Our algorithm considers the density field rather than only the galaxies and so we do not need to separate nearby peaks within ρ_{saddle} as they will not be joined in the first place. However, we use ρ_{saddle} to exclude outliers from groups based on the density of one of their local neighbours.

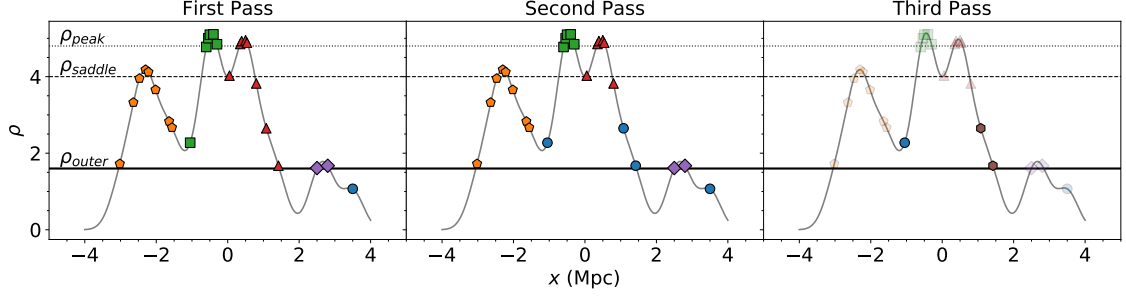


Figure 4.1: One-dimensional visualisation of the group finder algorithm TD-ENCLOSER introduced in this section. The points in the three panels are identical and each point represents a galaxy. Galaxies belonging to the same group as coloured accordingly. The contour levels from bottom up are ρ_{outer} (solid), ρ_{saddle} (dashed) and ρ_{peak} (dotted). The outcome of the first pass is shown in the first panel, where galaxies are assigned to groups based only on the contour morphology, shown as the grey curve. In the second pass, outliers are disconnected from their groups based on the density of their $N_{\text{merge}} - 1$ neighbours and are tagged as isolated. In the third pass, each ejected galaxy is assigned to a new group. All galaxies which were not clipped in the second pass are shown as faint to indicate that they are considered to be absent in the third pass.

- N_{merge} : In EH96, this parameter is used to merge two nearby groups. If a particle and one of its nearest N_{merge} neighbours are in different groups, then a boundary pair is defined between the particle and the densest of the N_{merge} nearest neighbours. If the density of the boundary pair, defined to be the mean of the density of the two particles, is greater or equal to ρ_{saddle} , then the two groups are merged. We use N_{merge} and ρ_{saddle} in a similar way to eject galaxies which lie far enough below ρ_{saddle} . Specifically, we eject galaxies if the mean between their density and the maximum density of their $N_{\text{merge}} - 1$ neighbours is less than ρ_{saddle} . Hence, this decision is determined by the local galaxy distribution and ρ_{saddle} is effectively a blurred boundary.
- ρ_{peak} : In EH96, if the density ρ of a peak is such that $\rho_{\text{outer}} \leq \rho < \rho_{\text{peak}}$, then the peak is only considered as part of a subgroup and is attached to a larger group with $\rho > \rho_{\text{peak}}$. Here, we would like to detect small groups which may not have the density required to reach ρ_{peak} . However, we do use ρ_{peak} to decide whether to disconnect outliers from groups using ρ_{saddle} and N_{merge} .

The final parameter is the kernel size σ_{ker} although this parameter is general to all KDE-based methods and is not specific to EH96.

Table 4.1: Table listing the relevant information about the example galaxies shown in Figure 4.1. Galaxies are numbered from left to right as given in Column (1). Column (2) gives the position along the x axis in Mpc and Column (3) gives the density δ at each galaxy. Column (4) lists the density rank for each galaxy with column (1) being the galaxy with the highest density. Columns (5), (6) and (7) give the group number that each galaxy belongs to after the first, second and third passes respectively. A value of zero indicates that a galaxy is isolated.

Galaxy No. (1)	x (Mpc) (2)	ρ (3)	Rank (4)	Group No. (1 st pass) (5)	Group No. (2 nd pass) (6)	Group No. (3 rd pass) (7)
1	-3.02	1.723	21	3	3	3
2	-2.64	3.325	16	3	3	3
3	-2.47	3.953	13	3	3	3
4	-2.30	4.183	10	3	3	3
5	-2.22	4.120	11	3	3	3
6	-2.02	3.657	15	3	3	3
7	-1.64	2.831	17	3	3	3
8	-1.56	2.669	18	3	3	3
9	-1.05	2.274	20	1	0	0
10	-0.60	4.775	9	1	1	1
11	-0.54	5.003	3	1	1	1
12	-0.50	5.096	2	1	1	1
13	-0.40	5.105	1	1	1	1
14	-0.30	4.846	8	1	1	1
15	0.05	4.026	12	2	2	2
16	0.35	4.853	7	2	2	2
17	0.39	4.929	5	2	2	2
18	0.50	4.950	4	2	2	2
19	0.54	4.886	6	2	2	2
20	0.80	3.822	14	2	2	2
21	1.08	2.651	19	2	0	5
22	1.42	1.673	22	2	0	5
23	2.50	1.612	24	4	4	4
24	2.80	1.672	23	4	4	4
25	3.50	1.070	25	0	0	0

4.3.2 Algorithm methodology

In what follows, we explain the methodology behind TD-ENCLOSER, referring to the pseudocode given in algorithm 1 by line number (e.g. **line 1**) and the one-dimensional visualisation shown in Figure 4.1. In algorithm 1, we only give the minimum amount of information required to implement the algorithm, leaving finer details to the text. To allow the reader to follow the decision making process, we have provided in Table 4.1 values for position along the x -axis and ρ (height) for each example galaxy in Figure 4.1, as well as the group assignments at each pass. In our discussion, we use the default parameters which we introduce fully in subsection 4.3.3. These are: $\sigma_{\text{ker}} = 0.3$ Mpc, $\rho_{\text{outer}} = 1.6$, $\rho_{\text{saddle}} = 4$, $\rho_{\text{peak}} = 4.8$ and $N_{\text{merge}} = 4$. Finally, we use one-based indexing in algorithm 1, so that $\mathbf{x}[1]$ is the first element of the array $\mathbf{x}$.

4.3.2.1 Setting up the grid

The first step is to construct a two-dimensional coarse grid ($\mathbf{C}_g$) that covers the extent of the galaxy distribution (**line 2**). The spacing between grid elements is a compromise between resolution and computational power. To set the spacing, we assume that we only need a box 20 by 20 Mpc in size centred on the target galaxy (although there is no requirement that the box should be square). The spacing needs to be at the very least smaller than the kernel size which by default is 0.3 Mpc. However, it needs to be a small fraction of σ_{ker} because the density field should be independent of the position of the grid on the sky. If the spacing is equal to σ_{ker} , then the result will differ dramatically if the grid becomes offset by $\sigma_{\text{ker}}/2$ for example. We find that if the spacing is about $0.2\sigma_{\text{ker}}$, then the contour morphology of the density field remains unchanged regardless of any offset. For simplicity, we choose the grid size to be 301^2 giving a spacing of $20/300 \approx 0.0666$ Mpc. We choose 301 rather than 300 to ensure that a grid element is placed at the centre where the target galaxy lives.

4.3.2.2 Calculating the density field

We calculate the density field by placing two-dimensional circular Gaussians,

$$\hat{f}(x, y) = \exp \left[\frac{1}{2} [x - \mathbf{X}, y - \mathbf{Y}]^T \cdot \Sigma^{-1} \cdot (x - \mathbf{X}, y - \mathbf{Y}) \right], \quad (4.1)$$

at each galaxy location (x, y) , where Σ is the covariance matrix $\begin{pmatrix} \sigma_{\text{ker}}^2 & 0 \\ 0 & \sigma_{\text{ker}}^2 \end{pmatrix}$, and $(\mathbf{X}, \mathbf{Y})$ are the grid coordinates (**line 3**). The contribution from each kernel at

each grid element is added to the density field (**line 4**). We do not use an adaptive kernel as this would produce unwanted substructure in dense groups (where the kernel is smaller to allow greater resolution) or group together galaxies which are isolated (because the kernel size increases in areas of lower density). The radial profile of the kernel does not have an effect on the end result and hence we choose to use a Gaussian kernel. We estimate the density field on a grid rather than the galaxy positions themselves to maintain a constant resolution across the field. We perform a two-dimensional interpolation of the density field¹⁵ (**line 5**), which allows us to calculate the density field at any location within the extent of the grid.

As with many group finder algorithms, there are potential edge effects being close to the boundary of the density field. It may be the case that the density at galaxies close to the edge will be underestimated, and so the algorithm may potentially miss groups at the boundary, leading to inconsistent clustering. However, as long as the boundary is at least twice the expected maximum group radius from a particular galaxy, then these effects will not affect the clustering near to the target galaxy.

4.3.2.3 Checking for isolation

Before running the main body of TD-ENCLOSER, we check to see if the target galaxy is isolated (**line 6**). If so, then the target galaxy cannot be part of a group, and so there is no need to proceed. Hence, TD-ENCLOSER terminates at this point, and the computing time is reduced. This would happen if the target galaxy were galaxy 25 in Figure 4.1. If $\rho \geq \rho_{\text{outer}}$ for the target galaxy, then TD-ENCLOSER proceeds as described below (**line 7**).

4.3.2.4 Finding peaks in the first pass

The first step in the first pass is to obtain the density at each galaxy by evaluating the spline interpolation at each galaxy location (**line 8**). We then automatically assign all isolated galaxies to be in groups of one member each (in essence removing them from the dataset; **line 9**). For each of the N remaining galaxies with $\rho \geq \rho_{\text{outer}}$ (**line 10**), we track which peak it belongs to as well as the position and density of the central galaxy (**line 11**). Before proceeding, we sort the N galaxies by their density in descending order, so that we consider the galaxies at the peak densities first (Rank = 1, 2, ...) before adding nearby galaxies to the peaks (**line 12**). We then assign the galaxy at the densest peak to be the central galaxy of Group 1, as this is the

¹⁵We use the SciPy implementation `RectBivariateSpline`.

only possible outcome for this galaxy (line 13). In our example, we assign galaxy 13 (Rank = 1) of density ρ_{13} to be the central galaxy of Group 1. In this discussion, we use the term “peak” to describe a local maximum in the density field and the term “group” to refer to the galaxies that lie at a particular peak. There is a one-to-one correspondence between them i.e. Group 1 lies at peak 1.

We now enter a loop which loops over each of the remaining $N - 1$ galaxies where $\rho_{\text{outer}} \leq \rho < \rho_{13}$ (line 15). For each galaxy, we loop over all existing peaks (line 16) in order of increasing distance from the galaxy (line 17). We assume that a galaxy will not be able to join a more distant peak than the tenth nearest peak, and so if there are more than 10 peaks, we only consider the nearest 10 (line 18). The first galaxy we encounter in the loop in our example is galaxy 12 (Rank = 2). To decide whether or not to assign galaxy 12 to Group 1, which is the only existing group at this point, we check if the connecting line between galaxies 12 and 13 increases monotonically. Our assumption is that if it does increase monotonically in ρ , then galaxies 12 and 13 belong to the same group. However, we do require the whole length of the line to increase monotonically for the following reason. The local maxima in the density field will almost certainly not be at the location of any galaxy. However, we do not know the density field at “every” location within the grid and so we do not know the *precise* locations of each local maxima. Instead, we only have knowledge of the galaxy that is closest to each local maxima by virtue of their high density ρ . Since we do not know in which direction the true local maxima lies with respect to the nearest galaxy, we have to treat the galaxy as if it is at the *precise* location of the maxima. This means that when we move along the connecting line between two galaxies from low to high density (e.g. from galaxy 12 to galaxy 13), we stop when we reach the density of the upper galaxy (e.g. ρ_{13}) for the *first* time.

We describe this check for monotonic increase in algorithm 2. First, we obtain the density ρ at 101 equally spaced intervals along the line, where the spacing is equivalent to 1% of the length of the line (lines 1-5 of algorithm 2). We then iterate over each element starting from the low density end (i.e. the location of the galaxy of which we are deciding whether or not to assign to the peak; line 6). For each iteration, we calculate the difference between the element and the next one (lines 7). If the difference does not drop below $\epsilon = -0.1$, then the gradient of the line at the element is positive, and the algorithm moves on to the next element. We allow the gradient to go slightly negative (a difference of $\epsilon = -0.1$) to essentially account for noise in the density field. After some tests, we realised that some galaxies were being cut off from the peak even though the gradient was essentially flat to within

10%. This could happen if a density contour happened to lie in parallel with the direction of the connecting line for example. We do not consider ϵ as a free parameter as it merely represents the uncertainty in the gradient. If the difference between each element does not fall below ϵ up until ρ_{cap} is reached, then we consider the two galaxies to be connected and part of the same peak (lines 9-10). On the other hand, if the difference does drop below ϵ , then the two galaxies are not connected, and the main body of TD-ENCLOSER proceeds. In the following text, we represent these two outcomes with either $\text{MonotonicIncrease}(x_b, y_b, x_a, y_a, \text{spline} = s, \rho_{\text{cap}} = \rho_a, \epsilon = -0.1) = \text{True}$ or $\text{MonotonicIncrease}(x_b, y_b, x_a, y_a, \text{spline} = s, \rho_{\text{cap}} = \rho_a, \epsilon = -0.1) = \text{False}$ respectively, where x_b and y_b are the coordinates for galaxy b (the low density galaxy).

In our example, we find that for galaxies 12 (Rank = 2) and 13 (Rank = 1), $\text{MonotonicIncrease}(x_{12}, y_{12}, x_{13}, y_{13}, \text{spline} = s, \rho_{\text{cap}} = \rho_{13}, \epsilon = -0.1) = \text{True}$ (line 19). The same is true for galaxy 11 (Rank = 3), and hence galaxies 12 and 11 are assigned to Group 1. However, $\text{MonotonicIncrease}(x_{18}, y_{18}, x_{13}, y_{13}, \text{spline} = s, \rho_{\text{cap}} = \rho_{13}, \epsilon = -0.1) = \text{False}$ (line 23), and hence galaxy 18 (Rank = 4) cannot be part of the same density peak as galaxy 13. Galaxy 18 is then designated as the central galaxy of Group 2 (line 24). We repeat this step until all galaxies above ρ_{outer} are assigned to groups/peaks (line 15).

4.3.2.5 Ejecting outliers in the second pass

Since the only requirement for assigning a galaxy to a peak in the first pass is that the connecting line between the galaxy and the peak increases monotonically up until a predetermined level, galaxies are assigned to peaks regardless of their distance from the peak. Hence, there may be outliers at the “foot” of the peak. Hence, we use a second pass to decide whether or not to eject those outliers. For each galaxy, we check if the density of the central galaxy of its enclosing group has reached ρ_{peak} (Groups 1 and 2 in our example) and if the density of the galaxy satisfies $\rho_{\text{outer}} \leq \rho < \rho_{\text{saddle}}$ (line 26). For each of these galaxies (line 25), we use the density of one of the nearest $N_{\text{merge}} - 1$ neighbours to decide if the galaxy should be removed from the group. Specifically, we take the maximum density from the nearest $N_{\text{merge}} - 1$ neighbours (line 28) and consider if the mean of this density and the density of the galaxy in question is less than ρ_{saddle} (line 29). If so, then the galaxy is clipped from the peak (line 30). Hence, ρ_{saddle} is not a rigid boundary but is in fact blurred according to the local galaxy distribution. By setting $\rho_{\text{peak}} > \rho_{\text{saddle}}$, we ensure that the second pass does not affect groups which just reach ρ_{saddle} , and hence only groups with dense

peaks will be clipped. For example, if $\rho_{\text{peak}} = \rho_{\text{saddle}}$, then Group 3 would be clipped. However, as the peak only just reaches ρ_{saddle} , only the central three galaxies would remain unclipped and hence Group 3 would be split up even though it is a clearly defined peak.

4.3.2.6 Cleaning up in the third pass

Once the second pass is completed, we use a third pass to attempt to group together the galaxies that were ejected during the second pass. If we do not have a “clean up” step, then we will be left with many isolated galaxies in potentially dense environments above ρ_{outer} . We keep the method of the third pass identical to that of the first pass, but with three key differences. Firstly, we wish to prevent these galaxies from being reassigned to their original groups. Hence, we restrict the available neighbours to only those galaxies which have been ejected from groups in the second pass (line 31). Secondly, we lift the cap from the first pass that prevents galaxies on opposite sides of a peak from missing each other (line 38). In this case, we have the opposite situation to the first pass where we do *not* want outliers forming very broad but low density peaks which encompass other (higher density) peaks. Hence, it is necessary to relax this rule here and require that the connecting line increases along its full length. Finally, we decrease the magnitude of the noise threshold by a factor of 10 to give $\epsilon = -0.01$ so that galaxies cannot form groups over long distances.

In our one-dimensional example, the first galaxy to be considered in the third pass is galaxy 21. As far as this galaxy is concerned, there are no other peaks and hence it becomes the central galaxy of a new group (line 33). Galaxy 9 is the next to be considered. For galaxy 9, `MonotonicIncrease`($x_9, y_9, x_{21}, y_{21}, \text{spline} = s, \rho_{\text{cap}} = \rho_{21}, \epsilon = -0.01$) = *True*, but galaxies 9 and 21 are clearly not connected (see right panel of Figure 4.1). Hence this is why the cap that is present in the first pass is lifted in the third pass, so that `MonotonicIncrease`($x_9, y_9, x_{21}, y_{21}, \text{spline} = s, \rho_{\text{cap}} = 0, \epsilon = -0.01$) = *False* (line 42). Thus, galaxy 9 becomes an isolated galaxy where $\rho > \rho_{\text{outer}}$ (line 38). Finally, `MonotonicIncrease`($x_{22}, y_{22}, x_{21}, y_{21}, \text{spline} = s, \rho_{\text{cap}} = 0, \epsilon = -0.01$) = *True* (line 40). These two galaxies make up a galaxy pair where the separation is (marginally) larger than σ_{ker} . This is indeed possible, but in practice, we find that the separation between a pair of galaxies is rarely larger than about $1.3\sigma_{\text{ker}}$.

4.3.3 Specifying default parameter values

Now we have described TD-ENCLOSER, we describe our best choices for the five free parameters. A common choice for the bandwidth, σ_{ker} , is a “rule-of-thumb” estimation known as Scott’s rule¹⁶ (Scott 1992). However, this choice depends on the number of data points which in our case is not a constant. Furthermore, we wish to have a physically motivated value for σ_{ker} . We first inspect by eye and deduce empirically which value best describes the galaxy distribution. For small values ($\sigma_{\text{ker}} \sim 0.1$ Mpc), we find that galaxies struggle to form groups, and if large groups do form, then unphysical substructure appears. For large values ($\sigma_{\text{ker}} \sim 0.5$ Mpc), then groups which are clearly distinct from each other merge to form larger groups which are not likely to be physically bound. We settle on a value of $\sigma_{\text{ker}} = 0.3$ Mpc.

We follow EH96 by defining the three contour levels in terms of ρ_{outer} . ρ_{outer} must be greater than one (in order to exclude isolated galaxies) and less than two (so that galaxy pairs are not missed)¹⁷. To set ρ_{outer} , we consider a pair of galaxies separated by a distance D , one of which is the target galaxy. If $D = \sigma_{\text{ker}}$, then the total density at the target galaxy is very close to 1.6¹⁸, regardless of the kernel size. Hence, we set $\rho_{\text{outer}} = 1.6$ so that we detect pairs of galaxies which are closer than the kernel size. This assumes that the pair is in isolation which is an unrealistic scenario. However, a Gaussian with amplitude 1 at a distance $D = 3\sigma_{\text{ker}} = 0.9$ Mpc measures only ~ 0.01 at $D = 0$ and hence will only contribute about that much to the density at the pair¹⁹. Having defined the two parameters that will affect the group assignments the most, we use the default recommendations suggested by EH96 for the remaining three parameters. These are: $\rho_{\text{saddle}} = 2.5\rho_{\text{outer}}$, $\rho_{\text{peak}} = 3\rho_{\text{outer}}$ and $N_{\text{merge}} = 4$.

4.4 Testing TD-ENCLOSER performance

4.4.1 Parameter sensitivity

4.4.1.1 Mock catalogue

TD-ENCLOSER has four free parameters compared with their six parameters of HOP (not including σ_{ker}), but unlike other density-based algorithms, our result *does* depend on

¹⁶BW= $n^{-1/6}$ for two-dimensional data where n is the number of points.

¹⁷ ρ_{outer} only needs to be smaller than the minimum group richness that one wishes to be sensitive to.

¹⁸ $e^0 + e^{\frac{-(-\sigma_{\text{ker}})^2}{2\sigma_{\text{ker}}^2}} = 1 + e^{-0.5} = 1.60653\dots$

¹⁹In any case, our approximation of 1.6 is about 0.6% smaller than the exact value so these two effects essentially cancel out.

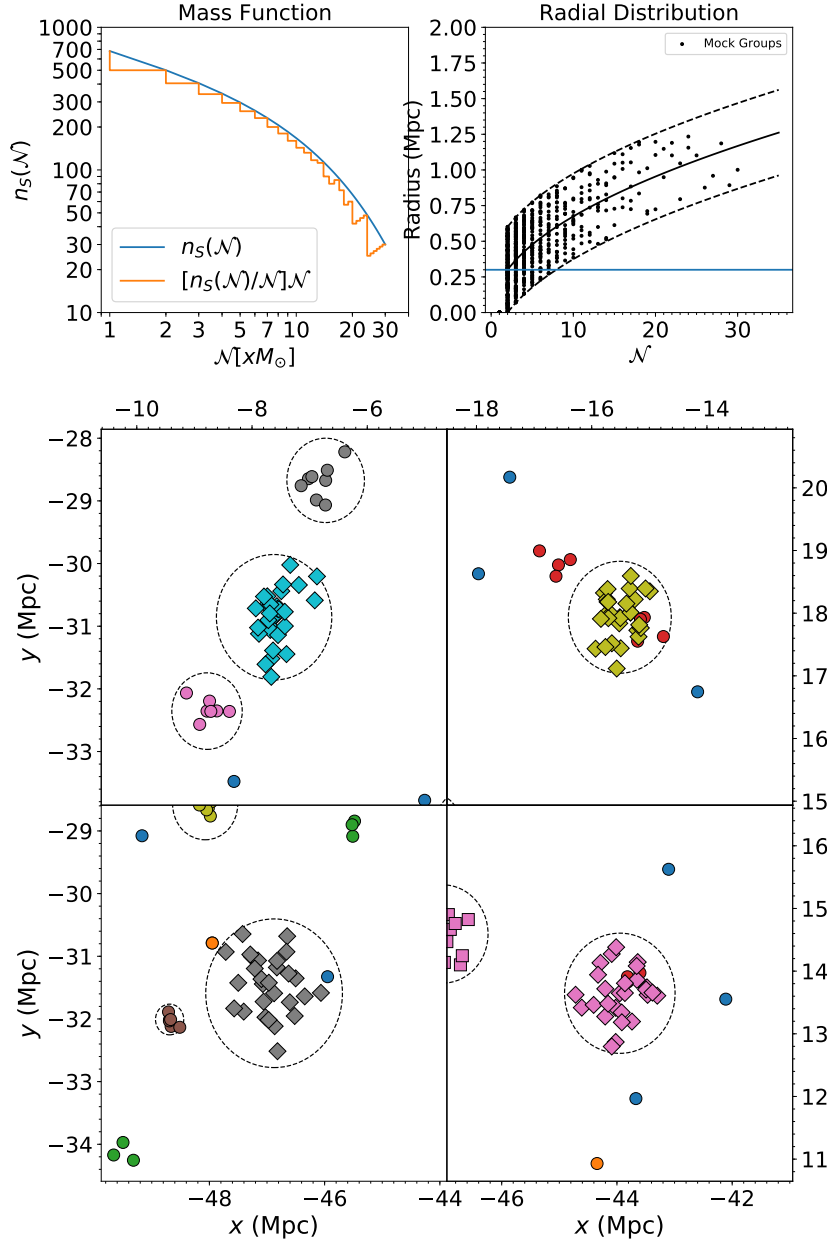


Figure 4.2: **Top left:** The mass function which defines our mock catalogue. The blue curve is Eq. (4.2) and the orange curve is the final mass distribution. At each value of $\mathcal{N}$, the orange curve is the number of galaxies contained within the maximum integer number of groups with size $\mathcal{N}$ allowed by the blue curve (see text). **Top right:** Radial size of groups as a function of group membership. The black points are the mock galaxies and are bound by the dashed black lines. The blue horizontal line marks the chosen σ_{ker} : only pairs where the two galaxies are closer than about this value are grouped as pairs by TD-ENCLOSER. **Bottom:** We show the four largest groups in the mock catalogue. Around each group of five or more members, the maximum radius is shown as a dashed circle. Each group is identified by a colour and marker.

the order in which particles are considered. We perform similar tests to EH96 to show how our results depend on our choice of parameters. Rather than use a particular distribution of galaxies, we randomly generate a mock galaxy catalogue within a box 100 Mpc across. To make our test as simple as possible, we assume each mock galaxy has the same mass x . With this assumption, we use a Schechter function to sample the group membership²⁰ (see the top left panel in Figure 4.2). To scale the Schechter function, we choose a maximum group size of 30 members. We arrive at this number by roughly comparing with the group catalogue of Tempel et al. (2017) (their Table 2). We then define our mass function $n_S(\mathcal{N})$ as:

$$n_S(\mathcal{N}) = A 10^{(\alpha+1)(\mathcal{N}-\mathcal{N}_0)} e^{-10^{(\mathcal{N}-\mathcal{N}_0)}} \quad (4.2)$$

where $\alpha = -1.35$, $\mathcal{N}$ is the group membership and A is a scale factor. We choose our break $\mathcal{N}_0$ to be 15 as it is simply half the maximum allowed group size. We use a scale factor $A \approx 282.5$ ²¹ so that $n_S(30) = 30$ i.e. a group of 30 members has a mass of 30 in units of x . However, the statement $n_S(\mathcal{N}) = \mathcal{N}$ is only true for $\mathcal{N} = 30$ due to the shape of the function. As we require integer numbers of groups with membership $\mathcal{N}$, we take the number of groups with membership $\mathcal{N}$ as $\lfloor n_S(\mathcal{N})/\mathcal{N} \rfloor$ where $\lfloor \rfloor$ denotes floor.

To populate the box, we generate $(x_{\text{grp}}, y_{\text{grp}})$ coordinates for each *group* from a random uniform distribution within the limits of the box. For each group with $\mathcal{N}_{\text{mem}} > 1$, we assign a radius $r = \sqrt{\mathcal{N}/7\pi} + f_r$ where f_r is randomly chosen from a uniform distribution with range $[-0.3, 0.3]$ (see the top right panel of Figure 4.2). We choose 7 as an empirical factor so that roughly 50% of galaxy pairs are separated by 0.3 Mpc or less (so as to be picked up by TD-ENCLOSER). Clearly this simple prescription assumes that the area of a group is proportional to its membership. For each group, we sample relative $(x_{\text{gal}}, y_{\text{gal}})$ coordinates for $\mathcal{N}$ galaxies between $[-r, r]$. The final coordinate for a given galaxy is then $(y_{\text{grp}} + x_{\text{gal}}, y_{\text{grp}} + y_{\text{gal}})$.

In the lower panel of Figure 4.2, we show the four largest groups in our mock catalogue. Each group with five or more members is enclosed by a circle with a radius equal to the maximum radius allowed for each group. This panel highlights why we neither want nor need to recover the input distribution with TD-ENCLOSER. Firstly, as the coordinates of both galaxies and groups are randomly chosen, it is likely that some groups will overlap and become a single group, or even some isolated

²⁰If a group has 30 members where each member is identical and has a mass of x , then the group will have a mass of $30x$.

²¹ $A = 30/0.10618 = 282.53908$ to five significant figures.

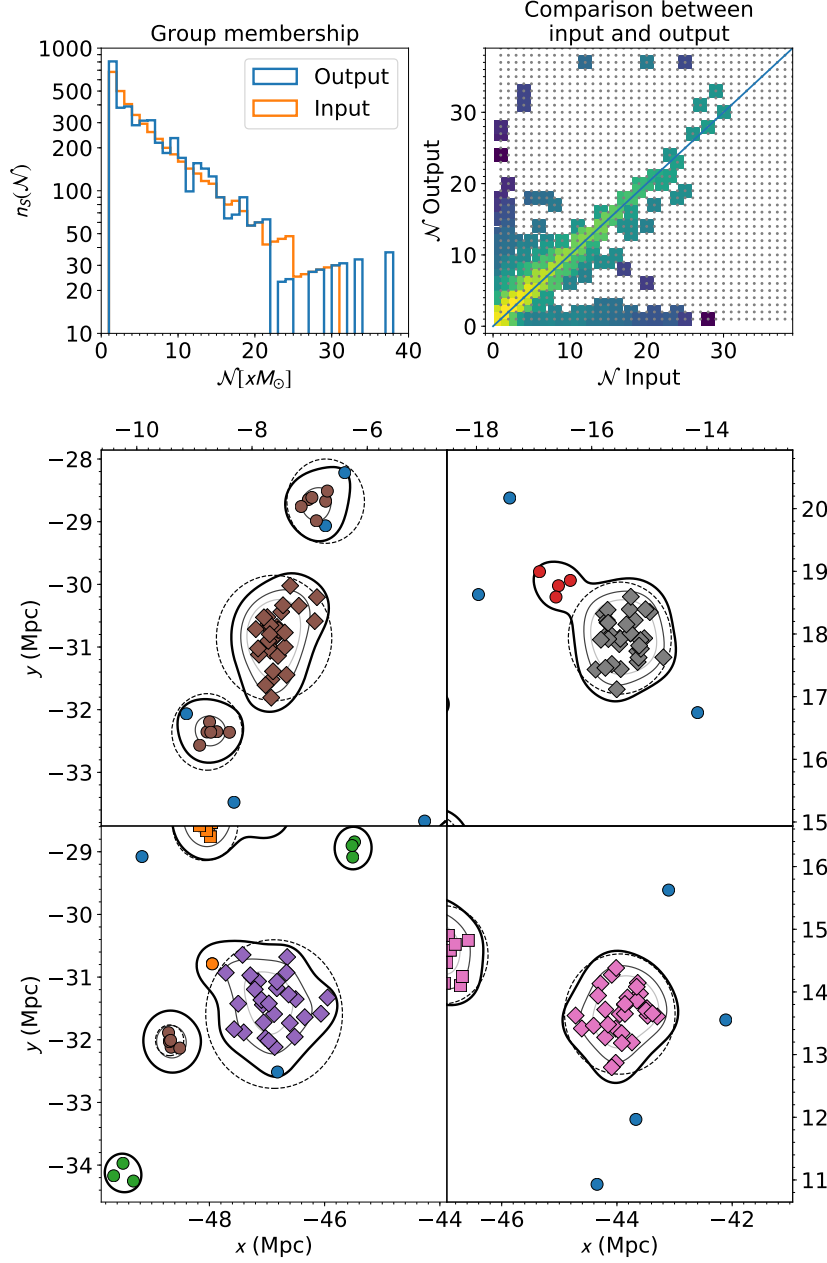


Figure 4.3: **Bottom:** The same as the bottom panel of Figure 4.2 except that galaxies are coloured according to the groups which they have been assigned by TD-ENCLOSER. The contours are ρ_{outer} (black), $2.5\rho_{\text{outer}} = \rho_{\text{saddle}}$ (dark grey) and $4\rho_{\text{outer}}$ (light grey). Isolated galaxies are shown as blue circles and galaxy pairs are shown as orange circles. The colours continue in sequence, and the marker indicates the group size in multiples of 10: circles are between 1 and 10, squares are between 11 and 20, diamonds are between 21 and 30 and triangles are between 31 and 40.

galaxies might lie embedded within another group. TD-ENCLOSER does not know the true input distribution. In fact, we would rather that not all groups are simple isolated circular objects, but actually reflect the real Universe, where larger groups can have substructure. Furthermore, we have programmed TD-ENCLOSER to sensibly clip outliers, and so some galaxies from large groups may be detached from their original groups.

Nevertheless, it is still useful to compare the mass function of the input with the mass function determined using the default parameters, even if individual galaxies are not in similar groups in both. As shown in Figure 4.3, the “recovered” mass function is not too dissimilar from the input mass function. The discrepancies are due to the reasons outlined above. In particular, the mass of individual galaxies is less in the “recovered” mass function compared to the input mass function, while the mass in galaxy pairs is greater in the “recovered” mass function compared to the input mass function. This is because our radial size prescription was calibrated such that approximately half of all galaxy pairs lie have a separation smaller than 0.3 Mpc (see top right panel of Figure 4.2). Hence, we expect fewer galaxy pairs and more isolated galaxies in the “recovered” distribution according to our prescription.

4.4.1.2 Testing parameter sensitivity

In order to check how the group assignments depend on each parameter, we vary the parameters σ_{ker} , ρ_{saddle} , ρ_{peak} and N_{merge} in turn and rerun TD-ENCLOSER on the mock catalogue. We do not perturb the values by a large amount because there are restrictions on each parameter, but also because we already have a good idea about what the default values should be. For example, we have already found $\sigma_{\text{ker}} = 0.3$ Mpc gives the most faithful representation of the true galaxy distribution. We know from EH96 that ρ_{outer} does have a significant effect on the result and hence we do not vary this parameter at all. For the other three parameters, there are stricter constraints. ρ_{saddle} cannot be equal to ρ_{outer} if it is to clip outliers effectively, and in practice, it should be at least $2\rho_{\text{outer}}$. ρ_{peak} must not be equal (or even very close) to ρ_{saddle} regardless of the value of ρ_{saddle} as this will split groups unnecessarily. We suggest that $\rho_{\text{peak}} - \rho_{\text{saddle}} \geq 0.25\rho_{\text{outer}}$ as a minimum separation. Finally, N_{merge} must be greater than or equal to two, as at least two galaxies are required to calculate a mean. In the following test, we keep to these limits so that TD-ENCLOSER can operate as desired. If the results depend only weakly on each parameter, we can be confident in our ability to effectively assign galaxies to groups.

4.4.1.3 Test results

The results of our test are shown in Figure 4.4, where for each panel, we change one parameter keeping all others the same. To indicate which parameter we are varying, we use the notation $[\text{vary}(P)]$ where P is the parameter that is *not* set to the default value. If all parameters are set to the default values, then we use the shorthand $[\text{default}]$. Rather than show the mass function as in Figure 4.3, we take the *difference* between the group richness $\mathcal{N}$ determined using the default parameters ($\mathcal{N}^{[\text{default}]}$) and the perturbed parameters ($\mathcal{N}^{[\text{vary}(P)]}$) for each mock galaxy, and compute the histogram for all mock galaxies. This is *not* the same as comparing the *input* from Figure 4.2 with the *output* from Figure 4.3, as here we are comparing the *output* using different values for the free parameters. To give a complete picture, we could replace the x and y axis in the top-right panel of Figure 4.3 with $\mathcal{N}^{[\text{default}]}$ and $\mathcal{N}^{[\text{vary}(P)]}$ respectively. However, this would give us eight panels to present, two for each parameter. Instead, we show the difference in the richness distribution with varying parameters. The result is Figure 4.4, where each panel corresponds to a parameter, and each panel contains two histograms corresponding to each value we choose.

We go through each panel of Fig. 4.4 in turn. Each histogram can be interpreted in the following way: if a single galaxy is near a group of 20 galaxies when $\sigma_{\text{ker}} = 0.3$, then when $\sigma_{\text{ker}} = 0.4$, it becomes part of a new group of 21 members. In this case, $\mathcal{N}^{[\text{vary}(\sigma_{\text{ker}})]} = \mathcal{N}^{[\text{default}]} + 1$ for 20 galaxies, and $\mathcal{N}^{[\text{vary}(\sigma_{\text{ker}})]} = \mathcal{N}^{[\text{default}]} + 20$ for one galaxy.

4.4.1.4 Varying σ_{ker}

We select $\sigma_{\text{ker}} = 0.2$ and 0.4 Mpc. As expected, setting $\sigma_{\text{ker}} = 0.2$ Mpc generally results in galaxies forming smaller groups in the first pass compared to $\sigma_{\text{ker}} = 0.3$ Mpc. A small fraction of galaxies ($\sim 1\%$) join larger groups due to the fact that by using a smaller kernel, some groups that would have reached ρ_{peak} when $\sigma_{\text{ker}} = 0.3$ would not have reached ρ_{peak} when $\sigma_{\text{ker}} = 0.2$. Hence, these groups would not have been clipped in the second pass with $\sigma_{\text{ker}} = 0.2$ and therefore the galaxies which were clipped when $\sigma_{\text{ker}} = 0.3$ have appeared to join a larger group, even though the kernel size has decreased. However, this occurrence is rare because ρ_{peak} is close to ρ_{saddle} . Conversely, setting $\sigma_{\text{ker}} = 0.4$ Mpc results in more galaxies residing in larger groups compared to the default choice. Here, about 2% of galaxies join smaller groups because they are clipped when $\sigma_{\text{ker}} = 0.4$ but not when $\sigma_{\text{ker}} = 0.3$, and hence belong to a smaller group even though the kernel size has increased. The result is most sensitive

to this parameter out of the four parameters as evidenced by the lower height of each peak at $\mathcal{N}^{[\text{vary}(\sigma_{\text{ker}})]} - \mathcal{N}^{[\text{default}]} = 0$ (indicating no change) and the broad distribution. For $\sigma_{\text{ker}} = 0.2$ and 0.4 Mpc, 95% of galaxies change group membership by less than 15 and 9 members respectively.

4.4.1.5 Varying ρ_{saddle}

We select $\rho_{\text{saddle}} = 3.6$ and 4.4 . A value of $\rho_{\text{saddle}} = 3.6$ tends to increase group sizes (and reduce the number of groups) as some galaxies are less likely to be clipped in the second pass than when $\rho_{\text{saddle}} = 4$. This makes sense conceptually as all groups above ρ_{peak} essentially grow and absorb nearby groups. A very small fraction of galaxies move to smaller groups which occurs when a small group is split up and one part joins a nearby large group and the other part then forms a small group. In total, 95% of galaxies change group membership by less than 3. Choosing a value of $\rho_{\text{saddle}} = 4.4$ means that galaxies are more likely to be clipped from their original groups. Again, 95% of galaxies change group membership by less than 3.

4.4.1.6 Varying ρ_{peak}

We select $\rho_{\text{peak}} = 4.4$ and 5.2 . As seen in the third panel of Fig. 4.4, this is the parameter that the group membership is the least sensitive to. This is because varying ρ_{peak} only changes *which* groups are clipped in the second pass and doesn't have any bearing on how *much* those groups are clipped. By lowering ρ_{peak} , more groups are clipped. If ρ_{peak} is increased compared to the default value, then fewer groups are clipped. In total, 95% of galaxies do not change group membership at all.

4.4.1.7 Varying N_{merge}

We select $N_{\text{merge}} = 2$ and 8 . Using $N_{\text{merge}} = 2$, galaxies at the fringe of ρ_{saddle} are more likely to be clipped during the second pass compared with $N_{\text{merge}} = 4$. Hence, groups are more likely to be split up into a large subgroup and one or more smaller subgroups (extended blue tail in the fourth panel). Using $N_{\text{merge}} = 6$ means that galaxies are less likely to be clipped (extended red tail in the fourth panel). Because this parameter is only relevant in the second pass, and then only when a group reaches ρ_{peak} , the sensitivity of the result on N_{merge} is less than that of σ_{ker} and ρ_{saddle} , and only slightly more than ρ_{peak} . This can be seen as 95% of galaxies change membership by 4 or less when $N_{\text{merge}} = 2$, and by 1 or zero when $N_{\text{merge}} = 6$.

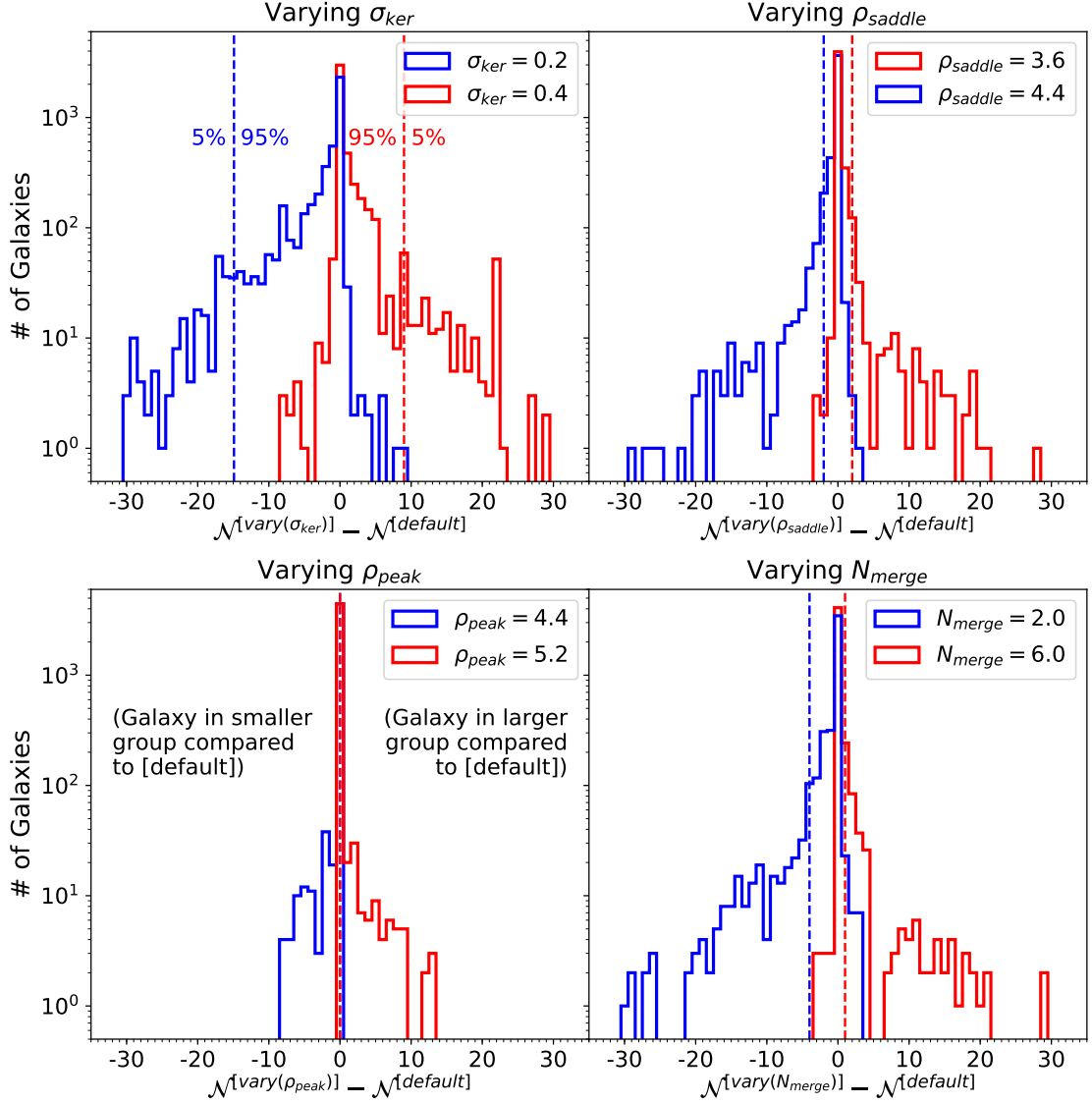


Figure 4.4: Histograms illustrating how the group membership depends on the free parameters of TD-ENCLOSER. In each panel, a single parameter is changed from the default value to two different values either side of the default, corresponding to the two histograms in each panel. In each panel, the x -axis is the *difference* between the richness of the group a particular *galaxy* belongs to using the *perturbed* parameters, and the richness of the group using the *default* parameters.

4.4.2 TD-ENCLOSER running speed

Finally, we assess the speed of TD-ENCLOSER. As TD-ENCLOSER is designed to only consider the local environment close to a “target” galaxy, it is not optimised for large sample sizes. We find that the elapsed time t in seconds depends on the sample size N as $\log(t) = 1.09 \log(N) - 2.55$, taking approximately 5 seconds to iterate through 1000 galaxies using a late 2013 iMac computer. We check to see if the speed varies with different choices in the parameters. We find that for $N \gtrsim 100$, choosing parameters that reduce the number of galaxies to consider in the second and third passes decreases the performance time. Of these, choosing a lower ρ_{saddle} gives the largest reduction in speed because fewer galaxies are clipped. Choosing a larger N_{merge} also reduces the number of galaxies to be clipped. Finally, by choosing a higher ρ_{peak} , fewer groups are clipped in the second pass, although the improvement is minor overall.

Choosing values that increases the number of galaxies to be considered after the first pass increases the time taken. The most significant increase is seen with ρ_{saddle} , where an increase of 10% in ρ_{saddle} results in a 10% increase in calculation time. Decreasing N_{merge} by a factor of two compared to the default value only results in a 5% increase in performance time, and there is almost no change with ρ_{peak} . ρ_{saddle} produces the biggest changes overall to performance time.

4.5 Accounting for group multiplicity

As discussed at the end of section 4.1, we will likely find many duplicates of the same intrinsic group when we run TD-ENCLOSER on a set of neighbouring galaxies that changes depending on which MaNGA galaxy is the target galaxy. Suppose that a given galaxy group contains four MaNGA galaxies, $[M_1, M_2, M_3, M_4]$, where each MaNGA galaxy (e.g. M_1) plays host to its own set of neighbours (e.g. S_1). Hence, we will find four sets, one for each MaNGA galaxy. Of course, we did not know beforehand that this group would be found four times, although we could have predicted it by finding the four MaNGA galaxies in advance. In the case that they are identical, we can randomly select one of the groups to represent all four. However, we may be presented with a case where not all sets are equal. In fact, it is possible that not all four MaNGA galaxies will appear in all four sets. In another example, a MaNGA galaxy can appear on the outskirts of a large cluster with hundreds of member galaxies, but can also appear as a small group. In these cases, we choose a subset to represent the intrinsic groups so that each MaNGA galaxy appears only once in our catalogue. We achieve this aim using the following steps:

1. We select N_1 MaNGA galaxies which are contained within set S_1 .
2. We select N_2 sets that contain at least one of the MaNGA galaxies belonging to set S_1 . N_2 may be larger than N_1 .
3. We select N_3 MaNGA galaxies that are found in the N_2 set identified in step 2.
4. If $N_3 > N_1$, then we repeat steps 1. - 3. selecting the set of N_3 MaNGA galaxies which are found in set N_2 . If $N_3 = N_1$, we move onto step 5.
5. We select all sets that are larger than half the maximum richness, $\mathcal{N}_{\max}$, of the final sets. This step ensures we are likely to select duplicates or variations of the same large group, deselecting nearby small groups and isolated galaxies that are otherwise connected to the large group.
6. Of the subset of sets that satisfy $\mathcal{N} > \mathcal{N}_{\max}/2$, we calculate the median redshift of the host galaxies in the subset.
7. We select the set S_M which encloses/is hosted by the MaNGA galaxy with the median redshift and assign this set to the final selection. If there are more than one MaNGA galaxies at the median redshift, we randomly select one.
8. We remove *all* sets which contain the same *MaNGA* galaxies as set S_M from our final selection.
9. If there are remaining sets that do not share any MaNGA galaxies in common with set S_M , we randomly *non-unique* galaxies within the remaining sets²², and repeat step 8.
10. We repeat step 9. until all MaNGA galaxies are assigned to one set only.

We illustrate this selector algorithm in Figure 4.5. We start with set S_1 and find that it hosts five MaNGA galaxies (step 1.). We then check all other sets and find five more sets that contain at least one of these five MaNGA galaxies (step 2.). Two of these (sets S_5 and S_6) contain MaNGA galaxies that are not found in set S_1 , and so we search for all sets that contain these new MaNGA galaxies (step 3.). We find four new sets that do not contain any of the original five MaNGA galaxies, but are

²²Consider four sets: $[M_1, M_2, M_3]$, $[M_1]$, $[M_2]$ and $[M_3]$. If we randomly select by set, then the set containing three MaNGA galaxies has only a 25% chance of being selected. If we choose by MaNGA galaxy and select its enclosing set, then the set containing three MaNGA galaxies has a 50% chance of being selected. We choose to select using the latter method in step 9.

linked to set S_1 by a chain of MaNGA galaxies (step 4.). As we do not find any more sets containing these new MaNGA galaxies, the tree stops growing here.

Following step 4. above, we select all sets that are richer than half the maximum richness. In this example, set S_5 is the richest set with 56 members, and so we select sets S_1 , S_5 , S_6 , S_8 and S_{10} . Of these five sets, we select the set with the median redshift, which in this case is set S_{10} (steps 6. and 7.). This is the first set to make the final selection. We deselect all sets that share at least one MaNGA galaxy in common with set S_{10} , namely sets S_5 , S_7 and S_8 (step 8.). We randomly select one of the remaining sets, which happens to be set S_1 (step 9.). The only remaining set that doesn't share any MaNGA galaxies in common with set S_1 is set S_9 , and so the final selection contains sets S_1 , S_9 and S_{10} (step 10.). We could also select sets S_2 , S_3 , S_4 , S_6 , S_9 in step 9., in which case the final selection would be slightly different.

There are a few alternative ways we could use to select the representative set(s). For example, we could take the largest set found as that is most likely to contain all of the MaNGA galaxies. However, that may bias us towards larger groups. We could also randomly select the representative set from all possible sets, but that may select a small set instead of a larger set just by chance. For a large *group* with many MaNGA galaxies, we may miss a substantial fraction of the group if we were to select MaNGA galaxies with high velocity relative to the group centre, as galaxies at the other velocity extreme would be missed. Therefore, by choosing a set based on the median redshift of the MaNGA galaxies, we expect the cylinder to encompass the “true” velocity extent of the group.

It is possible that some MaNGA galaxies won't make it into the final selection, depending on the exact galaxy configuration in three dimensional space. If we take our earlier example of four MaNGA galaxies, but split them into three sets of $[M_1, M_2, M_3]$ and one set of $[M_2, M_3, M_4]$, then according to our random selection, M_4 is likely to be excluded. We find that out of nearly 4600 galaxies, about 3% don't make it into the final selection. These galaxies will essentially only live in small groups, and so we do not expect any bias to come from this.

4.6 Conclusions

In section 4.3, we introduced a new group finder algorithm (TD-ENCLOSER) which has some features in common with the HOP method of EH96 (see algorithm 1), but is based on an entirely different method. Its main function is to assign galaxies to regions of high density, before clipping outliers and forming new groups from those outliers

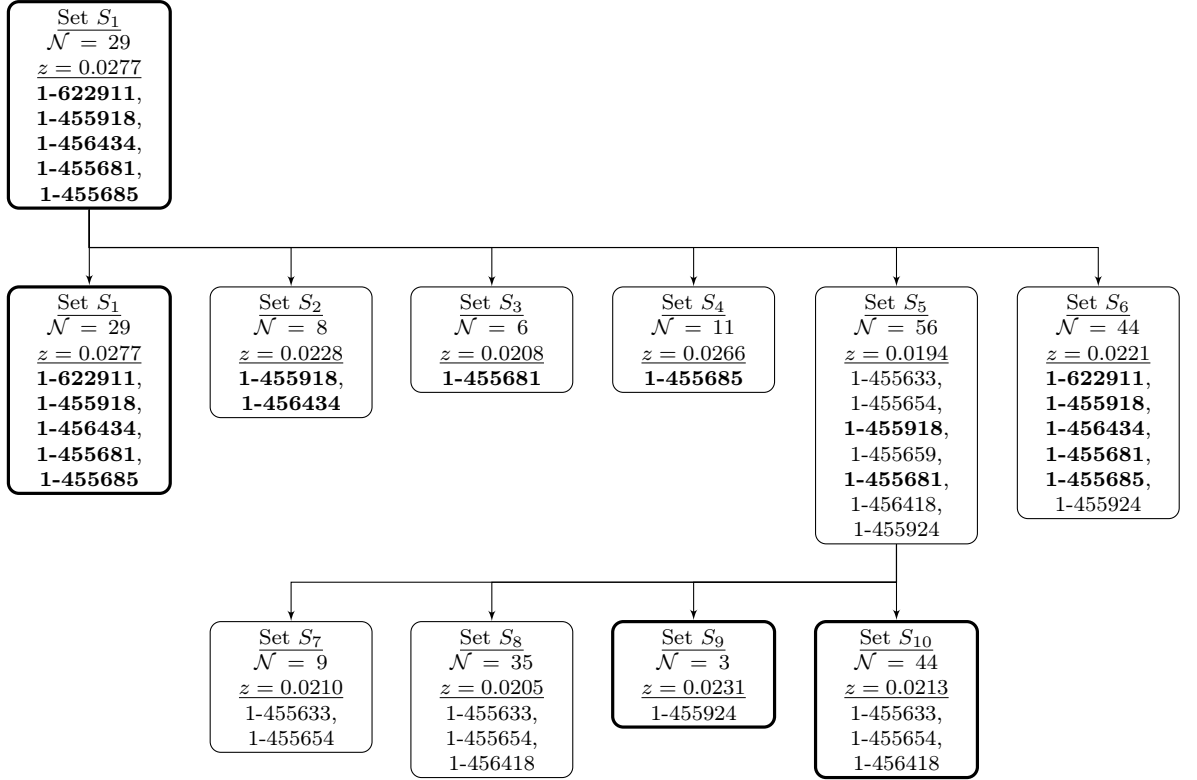


Figure 4.5: **Finding unique groups.** Here we show an example where 10 galaxy sets are connected by a network of MaNGA galaxies. For each set, we give the richness $\mathcal{N}$ and the redshift of the “host” MaNGA galaxy. The starting set is set S_1 , and its member galaxies are emphasised in bold. The final representative sets selected by the selector are set S_1 , S_9 and S_{10} which are indicated by thick borders. These three sets do not share any MaNGA galaxies but may share galaxies not in MaNGA. This example has many possible solutions (see the text for details).

(Figure 4.1). TD-ENCLOSER is different to most other group-finder algorithms in that it is used to discover which group encloses a particular galaxy of interest. It is not designed to produce large group catalogues of hundreds of thousands of galaxies but can be used to obtain the local galaxy distribution. It works on the simple assumption that the gradient along a one-dimensional straight line between two points encodes the local two-dimensional topology. If the gradient of the connecting line between a galaxy and a nearby peak does not fall below a small noise threshold ϵ , and if the galaxy is in a sufficiently dense environment, then we assign the galaxy to that peak. If the galaxy satisfies the threshold to be in a group but is sufficiently far enough from the peak to be near the outskirts, it is ejected from the peak after which it seeks to join a new, smaller group. As with any algorithm, there will inevitably be anomalies, especially when the contour topology is complex. However, TD-ENCLOSER has already been used on thousands of real life cases (see chapter 5 for an overview and section 6.7 for a few key examples) and has been thoroughly checked for reliability.

In section 4.4, we tested TD-ENCLOSER on a mock catalogue of galaxies using a Schechter mass function (Schechter, 1976) to define the group membership (Figure 4.2). While we did not aim to reproduce exactly the input distribution, we found that we could match the input mass function with reasonable accuracy (top left panel of Figure 4.3). The reason for the discrepancy is that many pairs are broken up (by design) and a small percentage of individual galaxies can dramatically change their group membership (top right panel of Figure 4.3). We found that of the four parameters where we have some freedom to choose the default values, TD-ENCLOSER is reasonably insensitive to all but one of them (Figure 4.4). Again, individual galaxies can change group membership dramatically depending on the choice of parameters, but the fraction of galaxies with large changes in group membership is small. The highest sensitivity is towards σ_{ker} , which is a known feature of KDE methods. We checked the speed of operation and found that it increases linearly with the sample size. The parameter that introduces the most variation is ρ_{saddle} where a variation of 10% results in a similar change in performance time.

In preparation for the task of constructing the group catalogue in chapter 5, we have developed a simple procedure to select one or more representative groups of a set of duplicates linked by MaNGA galaxies (see section 4.5). We select representative sets using knowledge about the group size while incorporating a random selection to ensure we are not biased towards any particular sets.

Chapter 5

SDSS-IV MaNGA: Complete census of massive slow-rotator early-type galaxy candidates and their environment in a volume-limited sample

A person who never made a mistake
never tried anything new.

Albert Einstein

5.1 Introduction

Observations of galaxy clusters with IFS have revealed that there are tight relations between galaxy kinematic morphology and location within clusters (C16). This kinematic-morphology density (kT- Σ) relation (Cappellari et al., 2011b) is an update to the classic morphology relation of Dressler (1980), where instead of separating early-type galaxies (ETGs) by the traditional Hubble morphology i.e. S0s and ellipticals (Hubble, 1926, 1936; Sandage, 1961), ETGs are separated according to their angular momentum as revealed by their stellar kinematics obtained with IFS. ETGs can be robustly classified as fast or slow rotators by considering a proxy for the specific stellar angular momentum λ_{R_e} within the half-light radius R_e and the galaxy apparent flattening ϵ (Emsellem et al., 2007, 2011; Cappellari, 2016). The two classes of ETG are thought to be the end result of two distinct formation channels (C16), and we have already shown observational evidence in subsection 3.1.1 that they form a bimodality in galaxy properties, rather than a smooth continuum.

Previous studies of the kT - Σ relation fall into two categories:

1. Three, very nearby and well-studied clusters were mapped in detail with IFS producing a complete census of SRs. These three clusters were the Fornax (Scott et al., 2014) and Virgo (Cappellari et al., 2011b) clusters as well as the central part of the Coma (Houghton et al., 2013) cluster. Schematics for these clusters are presented in Figure 1.7b where the genuine dry merger relics, i.e. core SRs above a critical mass of $M_{\text{crit}} \geq 2 \times 10^{11} M_{\odot}$ (Cappellari, 2013), are highlighted.
2. Large-scale IFS surveys have mapped large numbers of clusters and groups, but with only very sparse coverage. This “incomplete” approach was started by Houghton et al. (2013); D’Eugenio et al. (2013) and Scott et al. (2014) and was later extended by Brough et al. (2017) with data from SAMI (Croom et al., 2012) and by Greene et al. (2017) with MaNGA data (Bundy et al., 2015). Both surveys encompass a broad range of environments from clusters and groups to the field and provide up to two orders of magnitude more galaxies than the dedicated cluster observations.

Here, we try for the first time to combine the strength of both approaches by mapping a large number of groups and clusters while making a complete census of the massive SRs in those clusters. Such a census would allow us to explore the generality of the clear result seen in Figure 1.7b where the massive SRs are seen to lie at the centres of clusters, or in some cases at a secondary peak within clusters.

We base our study around a sample of about 4600 galaxies observed by the MaNGA survey. The survey targets galaxies in the redshift range $0.01 \leq z \leq 0.15$ and has a flat selection in stellar mass, making it the best sample currently available for studying massive SRs, with about 1200 ETGs above M_{crit} . The nearest competitor, the MASSIVE survey, only has about 100 galaxies above $M \sim 10^{11.5} M_{\odot}$, while MaNGA has nearly 900 ETGs in the same mass range. SAMI only has a handful of galaxies in the same mass range (e.g. Brough et al., 2017). The targets for the MaNGA survey are taken from the NASA-Sloan Atlas (NSA; Blanton et al., 2011) and so we could rely on the NSA to finding neighbouring galaxies of MaNGA galaxies. However, the NSA is not complete (section 5.2) and so we decide to supplement it with the SDSS photometric catalogue (Stoughton et al., 2002; hereafter S02). However, the photometric catalogue does not present a comparable level of accuracy to the NSA, and so in section 5.2 we “clean” up the catalogue using some empirical

criteria for selecting clean photometry that cannot otherwise be selected by using the flags generated by the SDSS imaging pipeline (S02).

As we require stellar mass estimates for all galaxies in our combined catalogue, we use dynamical mass estimates for MaNGA galaxies to estimate the stellar mass from the absolute luminosity in the SDSS r -band. (subsection 5.3.2). In subsection 5.3.3, we describe our method for finding galaxy groups that contain MaNGA galaxies using the group finder algorithm, TD-ENCLOSER, which is described in detail in chapter 4. Finally, we identify candidate massive slow rotators in a redshift-limited sample and quantify our performance by performing the same classification on MaNGA galaxies where we know the true fast/slow classification (section 5.4).

5.2 Cleaning up the SDSS photometric catalogue

In the case of MaNGA, there are two potential sources of incompleteness which may hamper any attempt to undertake a study of the kT - Σ relation in a way that emulates the detailed studies of nearby clusters. The first is a direct consequence of the limited scope of the SDSS spectroscopic sample. Spectroscopy provides an accurate redshift estimate, and hence the location of galaxies with spectroscopic observations is well-defined in three dimensions. The disadvantage of spectroscopic observations is that they are time consuming and are limited to the brightest galaxies at higher redshifts. The SDSS spectroscopic sample is at least 95% complete above an apparent magnitude of 17.77 mag in the r -band. This results in a difference of a factor of 250 in the minimum intrinsic luminosity that is possible to observe between $z = 0.01$ and $z = 0.15$ for example. This change in the luminosity function with redshift means that the low-mass neighbours of galaxies at the higher redshifts within the SDSS would not be observed with spectroscopy. Furthermore, the finite size of the fibres means that it is not possible to obtain spectroscopic redshifts for two galaxies if the distance between them is less than 55 arcsec on the sky (a case which is referred to as a fibre collision, see Blanton et al., 2003). This effect is particularly enhanced in dense cluster regions (and for close pairs) and so it presents a serious problem for detailed studies of cluster environment with spectroscopy. In total, about 6% of all objects that are identified by the bespoke SDSS imaging pipeline (S02) to be galaxies *and* are brighter than $m_r = 17.77$ mag are not observed with spectroscopy (Strauss et al., 2002), although this fraction was recently estimated by Lazo et al. (2018) to be 7.2%.

One possible way to overcome this incompleteness would be to apply a weighting to the group luminosity or richness (multiplicity) as a function of redshift as was done

by Tempel et al. (2012). While it would be possible to weight other parameters such as the projected surface density $\Sigma_n \equiv n/(\pi D_n^2)$, which considers the proximity D_n of the nearest n th neighbour to a galaxy, it would not be possible to recover the intrinsic environment of these galaxies at $z \sim 0.1$. To gain the most information about how a galaxy is affected by its environment, the optimal strategy is to actually *observe* its environment, rather than look at trends as a function of a suitable parameter such as Σ_n .

Here we take an entirely different approach by combining the SDSS spectroscopic sample with the photometric catalogue obtained with imaging (Gunn et al., 2006; York et al., 2000). For our spectroscopic sample, we use the final version of the NASA Sloan Atlas (v1_0_1), released as part of DR13 (SDSS Collaboration et al., 2016). The NSA is an improvement on the standard SDSS pipeline with better sky subtraction for larger galaxies and a better treatment of deblending (Blanton et al., 2011). It contains spectroscopic and photometric data for 636,394 galaxies below $z \approx 0.15$. The SDSS DR12 photometric catalogue (SDSS Collaboration et al., 2015) is 95% complete for point sources at magnitudes brighter than $m_r = 22.2$ (S02) and as a result, it is two orders of magnitude larger than the spectroscopic sample. By combining the NSA with the photometric catalogue in a robust way, we can construct a large galaxy catalogue that doesn't suffer from the same selection effects and biases that the NSA does.

5.2.1 Summary of the SDSS imaging pipeline

The SDSS imaging pipeline is the powerhouse of the photometric catalogue and performs object detection, deblending and flagging (S02). Objects are initially detected above 200σ where σ is the local sky level after the global sky background has been subtracted. Afterwards, the image is smoothed at the level of the PSF ($1''.2 - 2''.3$ at full-width at half maximum) and objects are then detected above 5σ . After detection, the objects are “grown” in increments equal to the size of the PSF. Objects are deblended if multiple individual peaks, including the original peak, are detected across the five SDSS *ugriz* bands. These multiple peaks are referred to as “children” of the “parent” (original), and the parent is considered obsolete from then on.

The pipeline uses a simple criterion to separate stars (which are point-like) and galaxies (which are extended objects). Each object has a **psfMag** quantity, which is the flux within a Gaussian model of the PSF centred on the object (see sec. 4.4.5.2 of S02), and a **cModelMag** quantity, which is the magnitude from a fit produced from a linear combination of the de Vaucouleurs (de Vaucouleurs, 1948) and exponential

Sérsic (1968) fits. If `psfMag` is large enough compared to `cModelMag`, then the object is classified as a star (see sec. 4.4.6.1 of S02).

The pipeline has been improved since Data Release 1 (SDSS Collaboration et al., 2003) to better deal with unusual cases (such as foreground stars). However, S02 acknowledged that the automatic star-galaxy separation has a 95% accuracy rate at $m_r = 21$ mag and, as there are 2×10^8 objects in the SDSS DR12, there are likely to be objects which on closer inspection appear to be misclassified. In our assessment, we find many objects that have been classified by the imaging pipeline to be galaxies with clean photometry, but actually appear to the naked eye to have a different appearance. In this section, we describe two such cases (subsection 5.2.3 and subsection 5.2.4). At first, we use colour, magnitude and half-light radius to classify objects. We also include the error in photometric redshift as this error correlates with the error in flux (subsection 5.2.5). Finally, we show that our criteria are independent of the SDSS flags assigned by the pipeline. Before we present our findings, we describe how we obtain a clean selection of objects from the photometric catalogue.

5.2.2 Initial selection from the database

We obtain a clean sample of objects that have been classified as galaxies from the SDSS DR12²³ photometric catalogue (SDSS Collaboration et al., 2015) using the following SQL query on CasJobs:

```
SELECT g.ra, g.dec, g.petroR50_r,
       g.petroMag_u, g.petroMagErr_u, g.petroMag_g, g.petroMagErr_g,
       g.petroMag_r, g.petroMagErr_r, g.petroMag_i, g.petroMagErr_i,
       g.petroMag_z, g.petroMagErr_z, g.expAB_r,
       pz.z, pz.zErr, pz.photoErrorClass, pz.nnCount
FROM GalaxyTag AS g
JOIN Photoz AS pz
ON g.ObjID = pz.ObjID
WHERE
    g.type = 3                                # (1)
    AND g.clean = 1                            # (2)
    AND (g.calibStatus_r & 1) != 0            # (3)
```

²³The latest data release is DR15 (SDSS Collaboration et al., 2018) which contains identical imaging to DR12.

For each object, we select the RA and Dec coordinates, the Petrosian half-light radius in the r -band `petroR50_r` (Petrosian, 1976), the apparent magnitude and errors from the Petrosian fit in the $ugriz$ bands (`petroMag_u`, `petroMagErr_u` etc.), the axial ratio of an exponential fit to the r -band (`expAB_r`), the redshift and redshift error (`z`, `zErr`) as well as two quantities related to the redshift (`photoErrorClass` and `nnCount`; see subsection 5.2.5).

Objects can be detected more than once if they lie in regions where two or more scans overlap. To avoid selecting duplicates, we only select objects in the `GalaxyTag` database, which contains objects which have been classified as “primary”. `g.type = 3` only selects objects that have been classified as galaxies by the automatic pipeline (see subsection 5.2.1). The pipeline generates flags for each object in the catalogue. To aid the user in quickly selecting objects with clean photometry, a shortcut is available that is designed to select only objects which have reliable photometry. The shortcut, which can be applied using (2) and (3) in the SQL query, is described on the SDSS website²⁴, but here we briefly summarise its function. Each selection below is made in the r -band which has the best signal-to-noise of the five SDSS bands.

The function of `g.clean = 1` is to:

- only select objects which do not suffer from deblending problems in the r -band.
- check if there have been substantial interpolation issues in the r -band. If so, the object has too few good pixels to estimate the photometric errors from and so the errors may be underestimated (S02).
- ensures that objects are detected in the first pass where the image is only smoothed to the level of the PSF. (Many objects that are first detected after 2×2 or 4×4 pixel binning are not astrophysical objects or scattered light from stars.)
- check that objects are not saturated as the photometry can be inaccurate.
- check if an object has a valid radial profile, otherwise the photometric quantities are likely to be unreliable.

An extra criterion is that `calibStatus_r` flag is set to true, indicating that the calibration in the r -band is successful. The flags are described in detail in the Early Data Release paper (S02). By applying the recommended shortcut, the objects obtained are not affected by any of these issues. Of the objects that satisfy these criteria, we

²⁴http://www.sdss.org/dr12/algorithms/photo_flags_recommend/

find two populations, one faint and one bright, which appear erroneous. We suggest simple empirical criteria that are defined using the photometry and can be used to remove these objects. To obtain a test catalogue, we run the above query within a region of sky defined by $200^\circ \leq \text{RA} \leq 210^\circ$ and $30^\circ \leq \text{Dec} \leq 40^\circ$.

5.2.3 Removing spurious faint objects

In the photometric catalogue, we find many objects that have unusual colours. We also find many objects which have been incorrectly fitted with an unrealistically large radius which produces an artificial overestimation of the total magnitude and consequently are recorded to be much brighter than they appear. We suspect they are likely to be reddened galaxies at high redshift. To exclude these and other unusual objects, we examine the distribution of objects on a colour-colour plane using various combinations of the five SDSS *ugriz* bands. We use the four traditional SDSS colours, $u - g$, $g - r$, $r - z$ and $i - z$, as well as $g - i$ to provide a fifth colour. We find that the vast majority of galaxies lie close to a peak in the five-dimensional colour space (see the top panels in Figure 5.1). The peaks of the colour distributions are roughly between 0-2 suggesting that the fluxes in both bands are comparable. The location of the peaks agrees broadly with that found by Hansson et al. (2012) who studied a smaller, brighter sample of SDSS galaxies. However, we find a significant population of outliers which can extend out to extreme parts of the parameter space. Many of these objects are detected in one band but are undetected in another band. We find that many of these objects are in fact artifacts (see the images in Figure 5.1).

We use the distribution of objects in the five-parameter colour space to define empirical criteria for selecting clean objects:

$$\begin{aligned}
-2 &\leq u - g \leq 15 \\
0 &\leq g - r \leq 3 \\
-1 &\leq r - i \leq 2 \\
-1 &\leq i - z \leq 2 \\
0 &\leq g - i \leq 3
\end{aligned} \tag{5.1}$$

In Figure 5.1, we plot various combinations of the five colour criteria for all galaxies that satisfy the other selection criteria in this section. Rather than choosing to keep a specific percentile of objects, we simply use the density peaks to define our criteria. We ensure that each boundary is far enough from the peak so as only

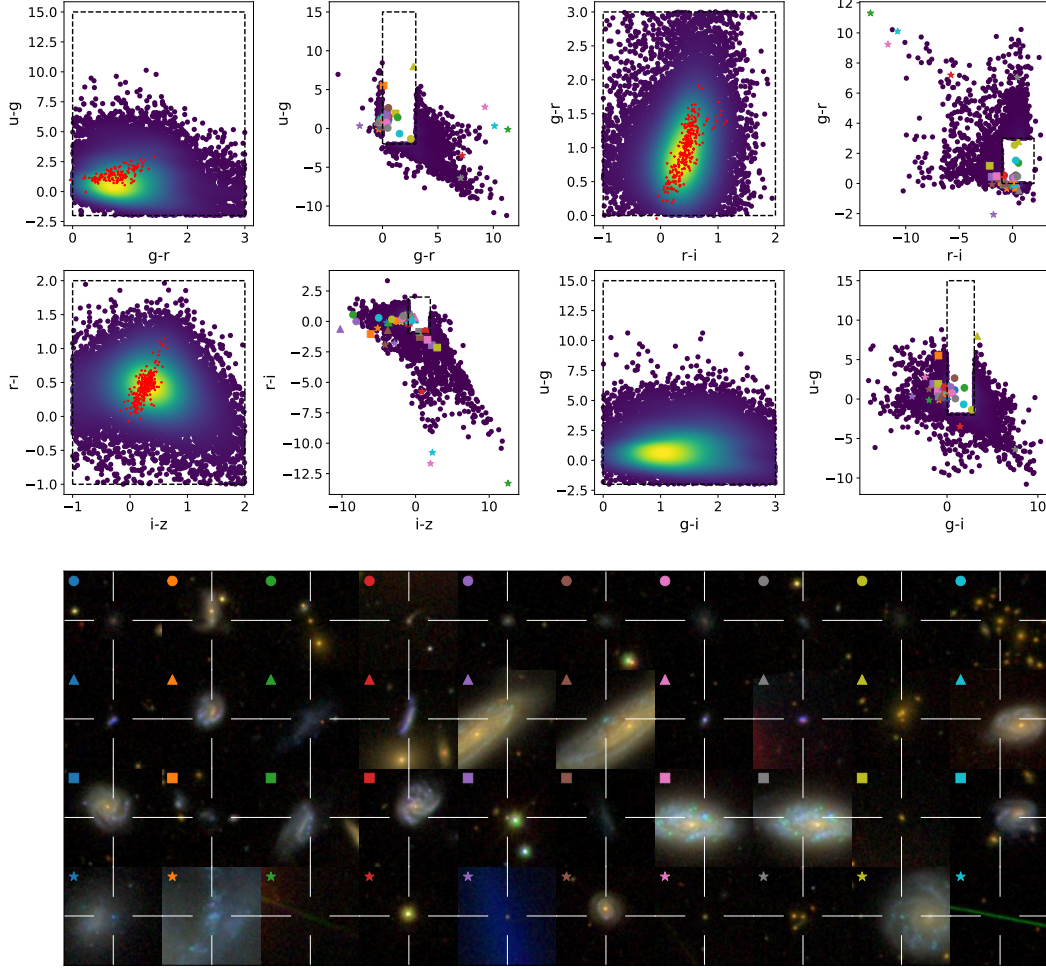


Figure 5.1: **Upper:** Colours of objects in the photometric catalogue with $R_{r,\text{Petro}} \leq 10''$. In the first two panels (i.e. top left), we plot $u - g$ versus $g - r$ for 20,000 randomly selected objects of all magnitudes within a 10×10 degree patch of the sky. Of these two panels, the first contains all objects that fall within the bounding box indicated by the dashed lines, and the second contains all objects that fall outside this box. Each point is coloured by the density estimated using a KDE. In both panels, the colour scale is identical. The remaining three sets of panels plot the same for different colour combinations: $g - r$ v $r - i$, $r - i$ v $i - z$ and $u - g$ v $g - i$. Note that the objects that appear inside/outside each box are not necessarily the same in all panels. In some of the panels, we plot colours for about 300 galaxies from Newberg et al. (1999) (red crosses). **Lower:** Optical images from the SDSS for 40 randomly chosen objects that fail to satisfy all the colour-colour criteria, and hence lie outside *at least* one of the boxes. Each object has a coloured marker associated with it which can be used to match the object to the four wide-view panels in the upper section. Cross-hairs are included to indicate the centre to guide the eye.

to clip outliers. We only keep photometric objects that satisfy *all* of these colour criteria. For $15 \leq m_r < 18$, at least $\sim 99\%$ of objects satisfy these criteria, while for $14 \leq m_r < 15$ and $18 \leq m_r < 19$, this fraction is $\sim 97\%$. For bins $13 \leq m_r < 14$ and $19 \leq m_r < 20$, $\sim 96\%$ and $\sim 93\%$ survive the colour cut respectively. The errors in u -band are greater than the other bands because the flux calibration is accurate to 2% in this band compared to the other bands (Padmanabhan et al., 2008), and so we have a relaxed criteria for this band. These empirical criteria exclude unusual objects with only a minimal chance of removing genuine galaxies. To illustrate this in Figure 5.1, we overplot galaxies from Newberg et al. (1999) who measured the photometric properties of different celestial objects using the SDSS photometry (see Fan, 1999 for simulations). For each combination of colours, the peak is strongly centred cleanly inside the bounding box. There is structure outside the bounding boxes which correspond to different types of object (see Hansson et al., 2012 for some examples).

We randomly select 40 objects which fail to satisfy at least one of the criteria in Eq. (5.1) and show images in Figure 5.1. Overall, we find that some of the objects are faint, while others are duplicates of objects or cases where it is ambiguous where the brightest part of the object is. In a small number of cases, objects that have genuine close neighbours in a cluster environment ($\lesssim 5$ arcsec) are excluded on the basis of their $i - z$ colour. Our colour criteria are chosen purely to exclude as many outliers as possible while keeping as many genuine galaxies as possible. As the selection is empirical, we acknowledge that it is not perfect. However, as the vast majority of objects are not close to the boundaries, the chances of a normal galaxy being unfairly excluded are very small.

As an aside, the $u - r$ colour is used to separate galaxies into a red and blue sequence (Strateva et al., 2001; Baldry et al., 2004). A colour of $u - r \approx 2$ is used as a divider, and in the $(g - r, u - g)$ plane, there are two peaks either side of the diagonal line. However, in the first panel in Figure 5.1 comparing $g - r$ with $u - g$, there is only one peak visible. The dividing line varies as a function of absolute magnitude (Baldry et al., 2004) and moves towards bluer colours with decreasing flux. As the number counts of galaxies increases with decreasing flux, faint galaxies vastly outnumber bright galaxies in Figure 5.1. As faint galaxies tend to be in the blue sequence, only this peak is visible. To check, we replot $g - r$ vs $u - g$ for $m_r < 18$ (not shown) and find the peak corresponding to the red sequence. However, we note that we are not comparing like for like as we do not have absolute magnitudes for

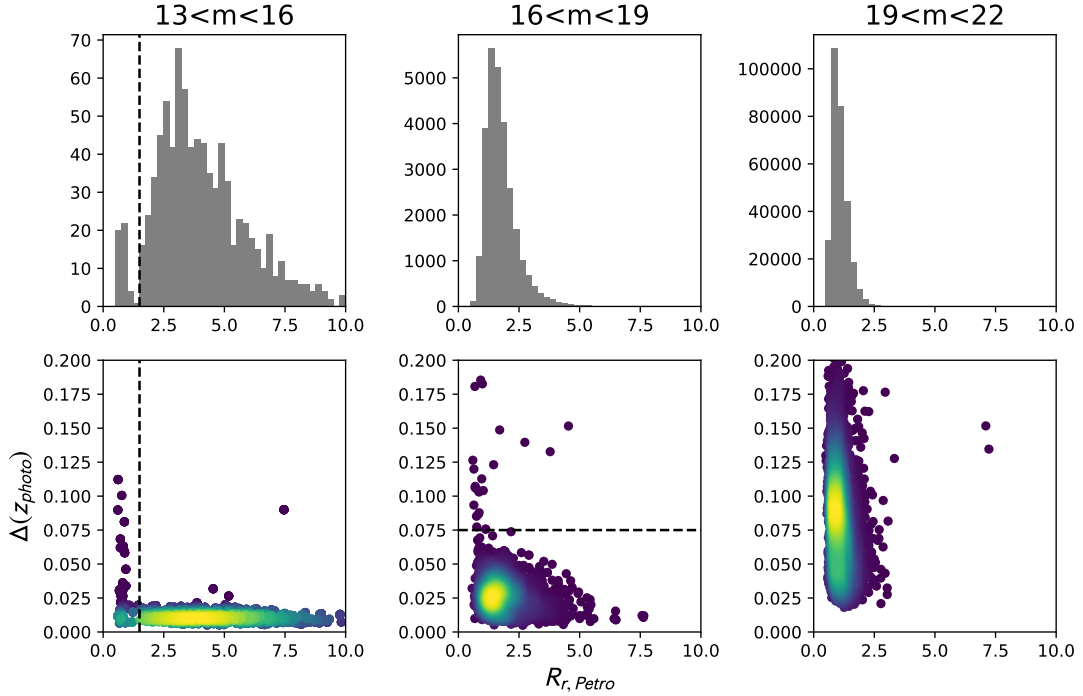


Figure 5.2: **Top:** The distribution of the Petrosian r -band half-light radius $R_{r,\text{Petro}}$ for three magnitude bins. The vertical line in the first panel indicates a cut in radius. **Bottom:** The error in photometric redshift versus $R_{r,\text{Petro}}$ for each magnitude bin. In the left and middle panel, we show the region where we exclude galaxies ($R_{r,\text{Petro}} < 1.5$ arcsec and $z_{\text{err}} > 0.075$ respectively). The density of points is indicated by the colourmap.

these galaxies, and we do not attempt to separate galaxies into red and blue using the $u - r$ colour.

We note that Lazo et al. (2018) have also attempted to clean the SDSS photometric catalogue using colour criteria. They adopted a visual classification approach not dissimilar to the one used here to eliminate artifacts and spurious objects. They find a slightly higher incompleteness of 7.2% than the 6% quoted by S02.

5.2.4 Removing spurious bright objects

In the top-left panel of Figure 5.2, we plot the distribution for the Petrosian radius in the r -band, $R_{r,\text{Petro}}$, for bright objects that have been classified by the pipeline to be galaxies and satisfy all the clean photometry cuts *and* our empirical colour cuts. We find two peaks, one major and one minor, separated at approximately $R_{r,\text{Petro}} = 1.5$ arcsec. In Figure 5.4, we show images for a random selection of the objects in the minor peak: These objects resemble stars in their appearance. We test the hypothesis

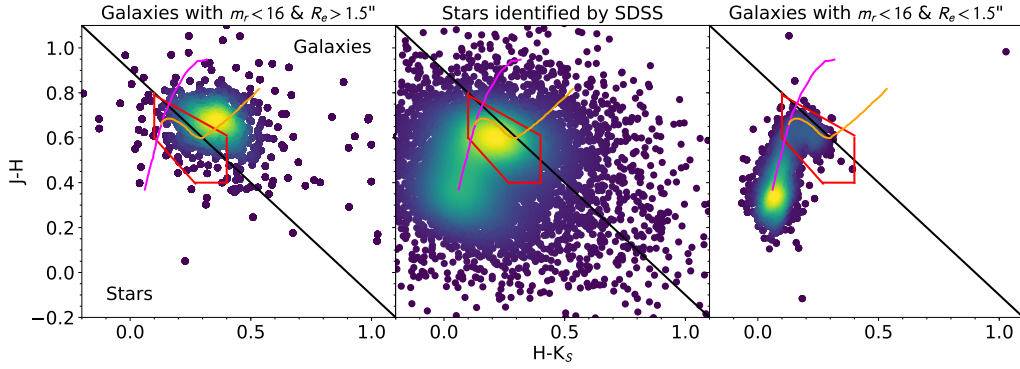


Figure 5.3: $J - H$ versus $H - K_S$ infrared colours from the 2MASS PSC for objects that satisfy our colour cuts. **Left:** $J - H$ versus $H - K_S$ for objects larger than 1.5 arcsec and brighter than $m_r = 16$. Each point is coloured by the density estimated using a KDE. The solid black line indicates the dividing line between galaxies and stars ($J - K_S = 0.9$). The magenta and orange tracks indicate where K0 and M0 dwarf stars appear and are taken from Bessell & Brett (1988). The region bound by the red lines is the “red dwarf box” from Lépine & Gaidos (2011). The $J - K_S$ colours for the majority of these objects are consistent with the infrared colours of galaxies. **Middle:** The same for objects identified as stars by the SDSS imaging pipeline. The $J - K_S$ colours of these objects are consistent with the infrared colours of stars. The dominant peak corresponds to sub-dwarfs. **Right:** The same for objects identified as galaxies by the SDSS imaging pipeline. The infrared colours of these objects are almost exclusively consistent with the infrared colours of stars. The sharp peak corresponds to K0 dwarf stars.

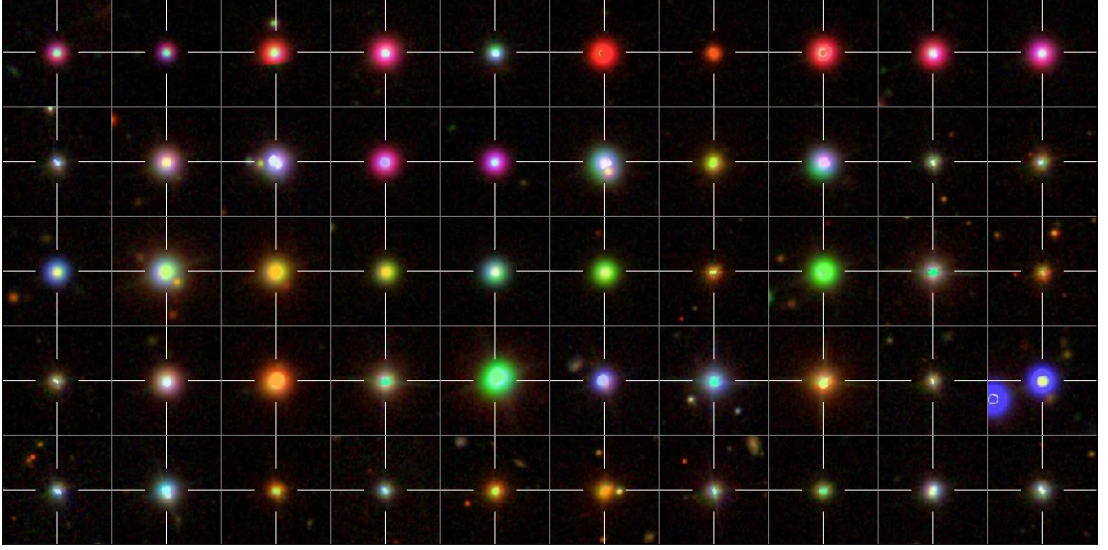


Figure 5.4: Optical images from the SDSS of objects which are smaller than $R_{\text{r,Petro}} = 1.5''$, brighter than $m_r = 16$ and are found in the 2MASS PSC. All of these objects lie in the bottom-right panel of Figure 5.3 and their infrared colours are consistent with stars.

that the two peaks correspond to galaxies and stars by obtaining magnitudes in the J , H and K_s infrared bands from the Two Micron All-Sky Survey (2MASS) Point Source Catalogue (PSC; Skrutskie et al., 2006). It is known that different stellar populations occupy different regions on the $(J - H, H - K_s)$ plane (see Fig. 1 of Koornneef, 1983 and Fig. A3 of Bessell & Brett, 1988). Furthermore, $J - K_s = 0.9$ has been found to be a good discriminant for stars and galaxies, as galaxies are generally redder than this value in the infrared, although bulgeless spirals can have $J - K_s \sim 0.8$ (Jarrett et al., 2003). Interstellar reddening can make stars appear to have reddened $J - K_s$ colours, but as we are not observing through the Galactic plane, we do not expect this effect to be strong.

To investigate the reliability of this simple criterion, we compare the infrared colours $J - H$ and $H - K_s$ for objects that have been classified as galaxies, are brighter than $m_r = 16$ mag, and have $R_{\text{r,Petro}} \geq 1.5''$ (left panel of Figure 5.3). We find that the peak in the distribution is placed cleanly above the demarcation line with only a small fraction lying below the line. We repeat the exercise for objects which have been classified as stars by the SDSS pipeline and find that the overall majority have $J - K_s < 0.9$ (middle panel of Figure 5.3). Finally, we take the objects that have been classified as galaxies and are brighter than $m_r = 16$ mag, but resemble stars ($R_{\text{r,Petro}} < 1.5$ arcsec) and find that they in fact peak at $J - K_s \approx 0.3 - 0.4$, with very few appearing on the side pertaining to galaxies (right panel of Figure 5.3).

Their location of the peak matches the track belonging to the K0 dwarf stars on the diagram (magenta line; Bessell & Brett, 1988) and the distribution also follows that occupied by M0 stars (orange line). These are predominantly red stars (see Figure 5.4) which may explain why they were missed by the pipeline. The peak in the distribution of stars which the pipeline *did* identify correctly lies within the “red dwarf box” of Lépine & Gaidos (2011) (red box).

We conclude that these objects are indeed stars and should be removed from any photometric galaxy catalogue. Hence, for $m_r < 16$, we require that all objects have $R_{r,\text{Petro}} \geq 1.5''$. We cannot repeat this exercise for $m_r \gtrsim 16$ for two main reasons. Firstly, galaxies with fainter apparent magnitudes are likely to be at further distances and hence will have smaller angular size (e.g. the right panel of Figure 5.2). Secondly, the magnitude limit of 2MASS prevents us from getting measurements of the infrared colours for faint objects. However, we do not think that many nearby bright stars will be faint enough to lie in this magnitude range, and hence we are confident that we are not missing many other stars.

In the next subsection, we describe the photometric redshift estimates which we use as part of our criteria.

5.2.5 Photometric redshift estimates

Photometric redshifts were estimated for all $\sim 2 \times 10^8$ objects in the photometric catalogue by Beck et al. (2016). They used an empirical local linear regression technique along with a supervised machine learning algorithm to find patterns in a filtered training set of objects with spectroscopic redshifts. Each photometric object was assigned to a class which allows a predefined maximum for the error in the r -band magnitude as well as in the $g - r$, $r - i$ and $i - z$ colours (see their Table 2). Photometric objects were matched to spectroscopic galaxies in a five dimensional colour-magnitude parameter space using the photometric colour and magnitudes. Galaxies which are close in the parameter space are assumed to be close in redshift. The redshift estimates that are obtained for the photometric objects follow a one-to-one relationship with the redshifts of the training set up until $z \approx 0.6$ (four times our maximum redshift) beyond which the accuracy worsens rapidly (see their fig. 3). We follow Aragon-Calvo et al. (2015) and only keep redshifts with `nnCount` ≥ 95 . A lower value of `nnCount` indicates that the galaxy does not overlap well with the training set in colour-magnitude space²⁵. The reliability of a given galaxy’s redshift estimate can

²⁵<https://www.sdss.org/dr12/algorithms/photo-z/>

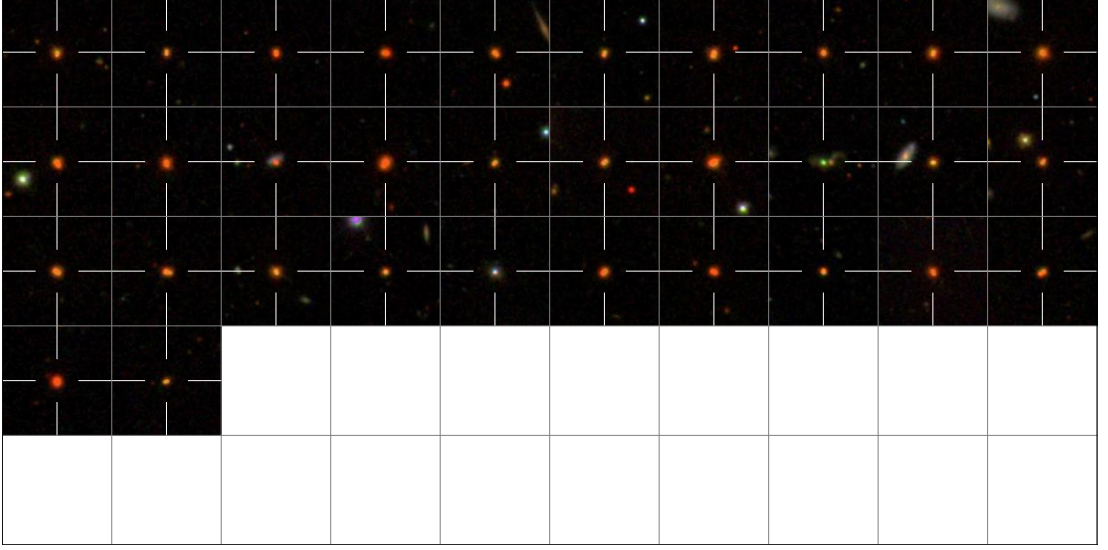


Figure 5.5: Optical images from the SDSS for all objects with $16 \leq m_r < 19$, $\Delta z_{\text{phot}} > 0.075$ and $R_{r,\text{Petro}} < 1.5$ arcsec. Almost all of them appear to be stars with red optical colours.

also be assessed by consulting the `photoErrorClass` parameter. A value of 1 is the best, while a value of 7 is the worst. This parameter is positive if the galaxy is within the bounding box of its 100 nearest neighbours, and negative if otherwise (because it is an outlier). It is recommended only to keep estimates with class 1 (see footnote 25). However we also include classes -1, 2 and 3 (see footnote 25) as the bias for these classes is close enough to class 1 (see Table 3 of Beck et al., 2016).

We check the next magnitude bin $16 < m_r \leq 19$ and find that there are some outliers which have an error in the photometric redshift $\Delta(z_{\text{phot}}) \geq 0.075$ (middle panel of Figure 5.2). We find that these are red and appear to be stars (see Figure 5.5), so we also exclude this small number of objects.

In Figure 5.6, we plot the fraction of objects which do not satisfy these two criteria as a function of apparent r -band magnitude. We find that at magnitudes brighter than $m_r \approx 20$, this fraction is less than 1%. (The fraction increases towards the bright end as well but for different reasons.) This fraction increases smoothly with decreasing flux until it reaches almost 100% at the 95% completeness limit for point sources ($m_r = 22.2$ mag). We also give the redshift where the apparent magnitude m_r corresponds to an absolute luminosity $M_r = -18$ mag (see subsection 5.3.2).

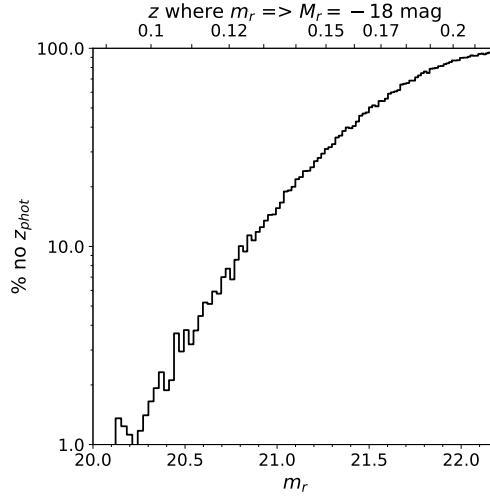


Figure 5.6: The fraction of galaxies that do not satisfy the two photometric redshift criteria as a function of apparent r -band magnitude (bottom axis). On the top axis, we give the redshift where the apparent magnitude on the bottom axis corresponds to an absolute magnitude $M_r = -18$ mag (see subsection 5.3.2).

5.2.6 Comparison with SDSS flags

Apart from selecting the type corresponding to galaxies and applying the recommended shortcut for selecting clean photometry, we have not used any other flags from the SDSS pipeline. It is important to check that we are not missing any crucial flags, as well as make sure that our cuts in photometry cannot also be obtained by simply using one or more of the SDSS flags (and hence are independent of the SDSS flags).

In Figure 5.7, we give a visual representation of the distribution of the flags in the r -band for different photometric selections. Each line corresponds to a particular flag and the length of each bar corresponds to the fraction of objects that have this flag set equal to *True*. In all panels, **BINNED1** and **CANONICAL CENTER** are set to *True* for all objects as a result of the **clean** shortcut. All flags which are deselected by the **clean** shortcut are absent from these objects. It is clear that while there are noticeable differences in each distribution, the overall distribution of flags does not change as a result of our photometric selections, confirming that our selections are indeed independent of the SDSS flags.

As many of the flags are not critical for clean photometry, any differences between the panels for these flags can be ignored (such as **BAD RADIAL**). One flag we do check is **NOPETRO_BIG**. This flag is set when the Petrosian radius is larger than the extracted radial profile, and can happen for faint objects with low signal-to-noise. In the left

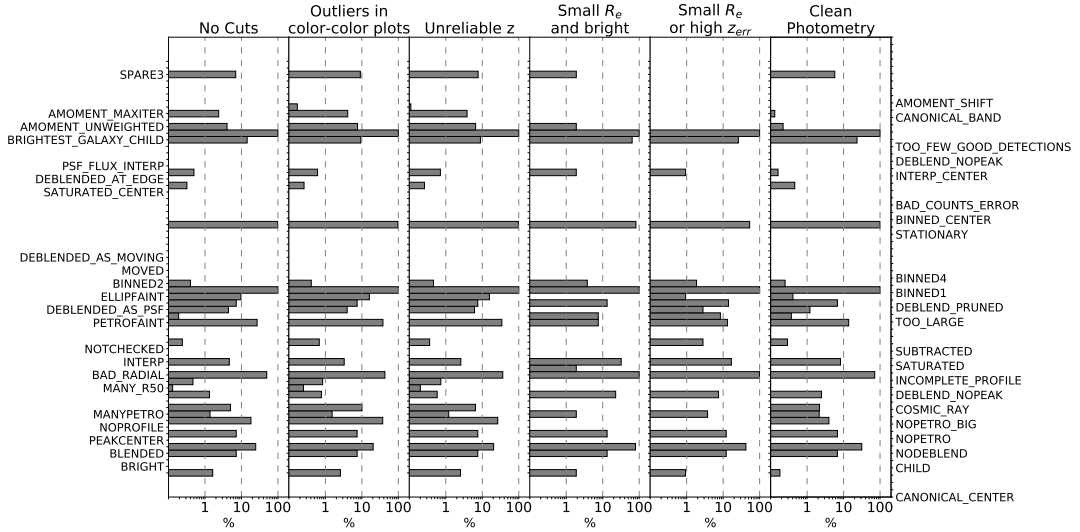


Figure 5.7: **Flags assigned to objects by the SDSS imaging pipeline.** Each bar counts the fraction of objects that have the corresponding flag set in the r -band. Each panel has different selection criteria indicated by each title. The final panel has all selection criteria applied.

panel of Figure 5.8, we plot the Petrosian apparent r -band magnitude versus the Petrosian half-light radius for all objects in our 10 square degree test field that have `NOPETRO_BIG` set equal to *True*. The majority of objects are small and faint, but there is a tail which extends to large radii and bright magnitudes. This is because these objects are intrinsically faint and have low signal-to-noise, but the radial fit has become very extended, and hence the quoted magnitudes are overestimated as a result. About 98% of all objects with $R_{r,\text{Petro}} > 10$ have the `NOPETRO_BIG` flag set equal to *True* confirming that the flag is very efficient at finding these objects. However, as stated, the vast majority of objects with this flag set to *True* are small and faint, and hence are likely to be intrinsically small and faint. Hence, discarding all objects with this flag may not be desirable.

In the right panel of Figure 5.8, we plot the same quantities for the subset of objects in the left panel that satisfy our colour criteria. We find that using the colour criteria is almost as effective at removing the tail as `NOPETRO_BIG`. However, our criteria leave a clean sample of galaxies at the faint end, although only about a third of the objects remain. Note that the factor of three decrease between the top and bottom panels does *not* reflect the overall reduction due to the colour cut, as the majority of these objects are fainter than 20 – 21 mag, which are more affected than brighter magnitudes, and these objects all have `NOPETRO_BIG` set, which is not true for all objects.

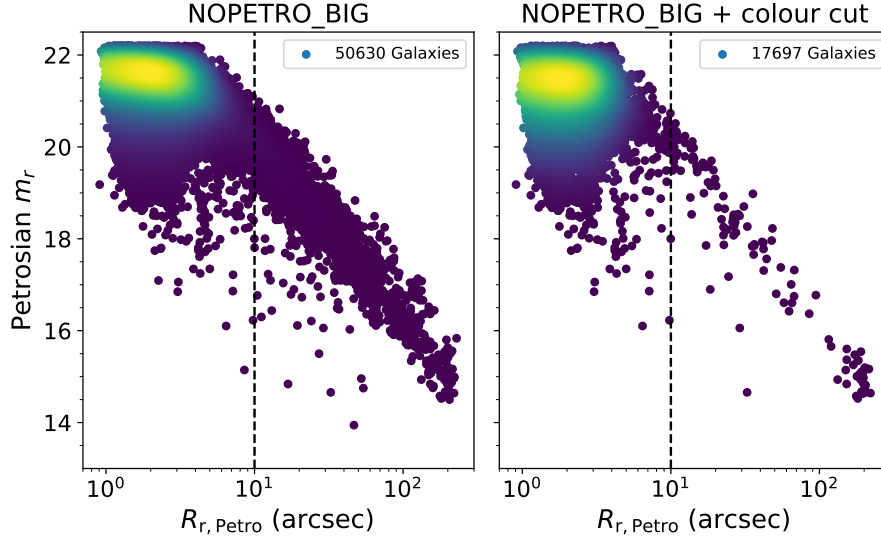


Figure 5.8: **Left:** m_r versus $R_{r,\text{Petro}}$ for all galaxies in our 10x10 degree field with the NOPETRO_BIG flag set in the r -band. The colour indicates the density of points and the number of galaxies are given in the legend. **Right:** The same except galaxies which fail to satisfy the colour-colour cut are not shown. About 35% of the galaxies in the left plot remain in the right plot.

As a result, we do not apply the NOPETRO_BIG flag to exclude objects in the tail as our colour criteria take care of this with reasonable accuracy. Just to be complete, we exclude all objects larger than $R_{r,\text{Petro}} = 10$ arcsec which will not in any way discard the general population (see Figure 5.2).

5.2.7 Summary

Here we summarise the criteria we use to obtain a clean photometric sample. They are given alongside the reasons for applying those criteria.

1. `type = 3` corresponding to ‘galaxy’ as determined by the SDSS pipeline. This ensures that point-like stars are not included.
2. Clean photometry tagged with `clean = 1` and `calibStatus_r & 1) ≠ 0`. These are recommended to select clean photometry.
3. Five colour criteria given in Eq. (5.1). This is to exclude some stars and other unusual objects (such as patches of spiral arms/cosmic rays etc.).
4. $R_{r,\text{Petro}} \leq 10$. This is to discard any objects where the fit in the r -band has failed and have not been removed by the colour criteria (see Figure 5.8).

5. For $m_r < 16$, we require that $R_{\text{petro},r} \geq 1.5$. This is to exclude nearby K stars which have not been classified as stars by the imaging pipeline due to their extended appearance.
6. For $16 \leq m_r < 19$, we require that $R_{\text{petro},r} \geq 1.5$ *or* $\Delta z_{\text{phot}} \leq 0.075$. This is also to exclude a small fraction of stars as in the previous cut.

Our only other criteria we use are `photoErrorClass` = [-1, 1, 2, 3] & `nnCount` ≥ 95 . We exclude galaxies if they do not satisfy this criteria as their redshift estimates are too uncertain. We find that these galaxies constitute about 10% of the population at $m_r \approx 21$ mag and 50% at $m_r \approx 21.5$ mag.

5.3 Compiling the MaNGA group catalogue

In the previous section, we cleaned the SDSS photometric catalogue using empirical criteria. By combining this catalogue with the NSA, we have a magnitude limited sample of galaxies at all redshifts within MaNGA.

5.3.1 MaNGA data

In this chapter, we use data from MPL-7 (compared with MPL-5 in chapter 3) which contains data for 4597 unique galaxies and was released internally to the collaboration in Spring 2018. MPL-7 is identical to the MaNGA content of SDSS DR15 (SDSS Collaboration et al., 2018). As in chapter 3, we make use of stellar kinematics provided by the Data Analysis Pipeline (DAP; Westfall et al., 2019) which is a fully-automated procedure that uses pPXF (Cappellari & Emsellem, 2004; Cappellari, 2017) to derive the stellar and gas kinematics from the stellar spectra. We obtain measurements for stellar mass, ϵ , λ_{R_e} etc. for all MaNGA galaxies using the method described in detail in section 2.2. (For a complete list of quantities that we extract, see Table 3.1.)

5.3.2 A new mass-luminosity relation

Ultimately our aim is to produce a complete catalogue which includes classifications of all candidate SRs. For this classification we will not use kinematics alone, but also stellar mass, because it was shown that genuine dry merger relics are essentially absent below a characteristic stellar mass $M_{\text{crit}} = 2 \times 10^{11} M_{\odot}$ (see C16 for a review of this evidence). For this reason we need to estimate well calibrated stellar masses for each galaxy.

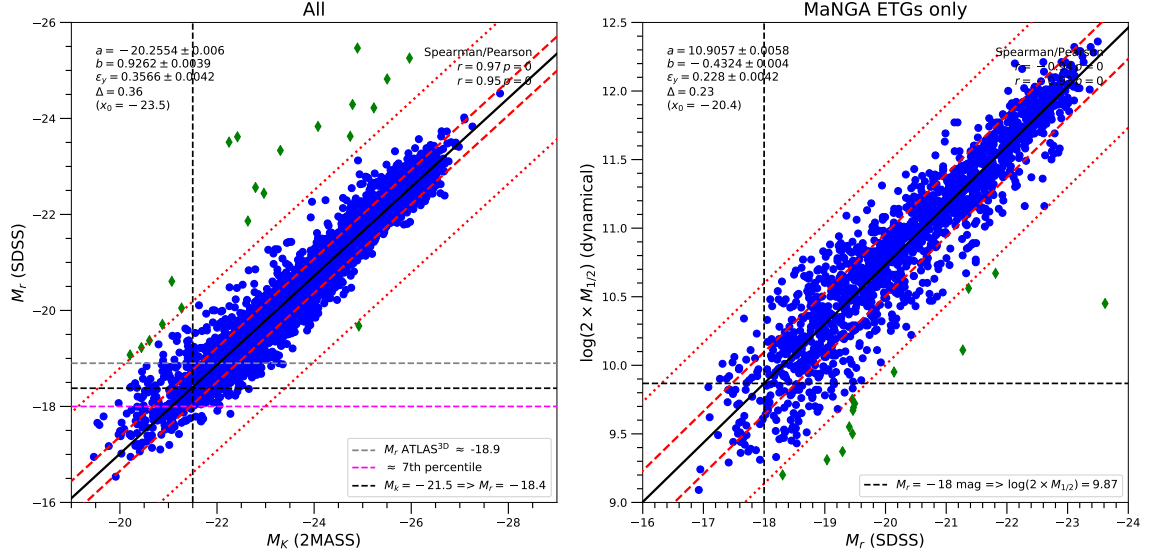


Figure 5.9: **Dynamical mass-luminosity relation.** *Top:* We plot the luminosity in the 2MASS K_s band and the SDSS r -band for 3813 MaNGA galaxies of all morphologies which have 2MASS XSC photometry. *Bottom:* We plot the dynamical mass-luminosity relationship for 1576 ETGs from MPL-5.

For the NSA, the stellar mass is calculated by multiplying the rest-frame absolute luminosities, calculated using the K-correction, with a colour-dependent M/L ratio (Blanton & Roweis, 2007). However, we have no such estimate for the photometric catalogue. Dynamical masses correlate linearly with absolute K_s -band magnitudes (Cappellari, 2013) obtained from the 2MASS Extended Source Catalogue (XSC; Skrutskie et al., 2006), but we do not have access to the XSC photometry for all sources as the sensitivity of 2MASS is not the same as the SDSS. We do however have r -band apparent magnitudes for all sources from the SDSS combined catalogue, and so we fit a new relation using absolute luminosities in the r -band. Of course, in general, galaxies of a given stellar mass can have a range of r -band luminosities, as their mass-to-light ratio (M/L) varies with σ rather than mass alone. However this M/L variation is dramatically reduced around and above M_{crit} (e.g. fig. 22 of C16), which is the mass we use for selecting massive SRs. This ensures that although our stellar masses will not be very precise at the lower masses, they will be quite accurate for massive galaxies, ensuring a reliable rejection of non-massive galaxies.

Before we fit M_r to the stellar mass, we first find the M_r corresponding to the ATLAS^{3D} limit $M_{K_s} = -21.5$ so that we are comparable to the ATLAS^{3D} survey, which represents the benchmark of IFU surveys. To do this, we use `lts_linefit`¹ described in section 3.2 of Cappellari et al. (2013a) (see subsection 2.2.1.2 for a

brief description) to fit M_r as a function of M_{K_s} for 3813 galaxies from MPL-7 which are in the 2MASS XSC (see left panel of Figure 5.9). We find that there is an almost one-to-one correlation between the two luminosities with only a handful of outliers outside of 5Δ . In the ATLAS^{3D} survey paper, $M_{K_s} = -21.5$ was found to correspond approximately to $M_r = -18.9$ (Cappellari et al., 2011a). In our relation, we find that $M_{K_s} = -21.5$ corresponds to $M_r \approx -18.4$ (we have about a factor 10 more galaxies). However, we find that about 13% of MaNGA galaxies lie below this limit, and so we choose a fainter limit of $M_r = -18$, below which only $\sim 8\%$ of MaNGA galaxies lie.

We fit a new mass-luminosity relation using the half-light mass estimated from realistic galaxy models made using the Jeans Anisotropic Modelling (JAM) method of Cappellari (2008) for 1576 ETGs in MaNGA tabulated in Table A1 of Li et al. (2018b). We correlate the M_r luminosities to the M_{JAM} stellar masses, as was done for the K_s -band by Cappellari (2013). The advantage of using JAM dynamical mass estimates instead of stellar population values to transform our r -band luminosities is that the former do not suffer from the uncertain normalisation of about a factor two which is likely due to the systematic variation of the initial mass function with mass (van Dokkum & Conroy, 2010; Cappellari et al., 2012).

This relation is shown in the right panel of Figure 5.9. We compare our slope of -0.4324 with that of Cappellari (2013) (-0.4449) and find that they are very similar. There is an offset between the different bands of about 3 mag, but this is purely due to the offset seen in the top panel of Figure 5.9. From this relation, we find that we are complete down to a stellar mass $M \approx 7.4 \times 10^9 M_\odot$. If instead we use spirals, we find a slightly shallower slope (-0.355), nevertheless we apply the ETG relation to all galaxies.

In Figure 5.10, we show the distribution of galaxy fluxes with redshift for $0.01 \lesssim z \leq 0.15$. Two sequences can be seen in the MaNGA distribution (blue) corresponding to the Primary and Secondary samples (subsection 1.4.4). The black points are galaxies from the NSA which are brighter than $m_r = 17.77$ mag. Beyond $z \approx 0.0325$, the NSA is not complete in the luminosity function down to $M_r = -18$ mag. The combined photometric and NSA catalogue is complete out to $z = 0.15$.

5.3.3 Finding neighbours of MaNGA galaxies

As we are interested in the environment of MaNGA galaxies specifically, we use the MaNGA galaxies as our starting point. For this we need to find a volume-limited mass-selected sub-sample of SDSS galaxies which includes the MaNGA galaxies. We

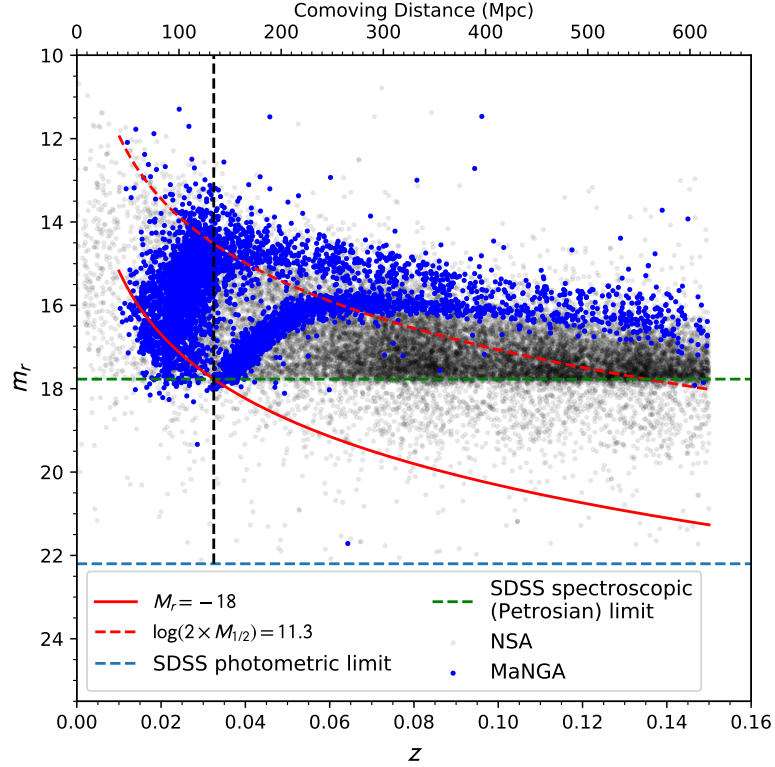


Figure 5.10: **NSA completeness as a function of redshift.** We plot the apparent magnitude and z distributions of NSA (black) and MaNGA (blue) galaxies. The primary and secondary MaNGA samples are visible as two separate streams. The completeness limits for the NSA and the photometric sample are shown as green and blue dashed lines respectively. We also plot the apparent magnitude corresponding to $M_r = -18$ mag (solid red), and the absolute magnitude corresponding to M_{crit} from the right panel of Figure 5.9 (dashed red). The vertical dashed line at $z \approx 0.0325$ indicates below which redshift the NSA is complete down to $M_r = -18$.

repeat the method outlined below once for each MaNGA galaxy in our sample, meaning we find one set of neighbours for each MaNGA galaxy. We refer to each starting MaNGA galaxy as the “host” galaxy of its set of neighbours to differentiate it from other potential MaNGA galaxies that may be enclosed within the same set.

5.3.3.1 Excluding interlopers using redshift

For each MaNGA galaxy, we select galaxies from the catalogue which lie within a cylinder with radius equal to 10 comoving Mpc centred on the MaNGA galaxy. We remove photometric objects that coincide with stars within 2 arcsec. For duplicate galaxies i.e. galaxies that appear in both the NSA and the photometric catalogue, we discard the entry from the photometric catalogue as the spectroscopic redshift is much more accurate. The remaining objects constitute the neighbouring galaxies. The height h of the cylinder along the line of sight is by default 600 km s^{-1} ($\Delta V = 300 \text{ km s}^{-1}$) to be consistent with Cappellari et al. (2011b). However, we extend this up to $\Delta V = 3000 \text{ km s}^{-1}$ for MaNGA galaxies that lie in large clusters with high velocity dispersion.

The peculiar velocity ΔV_{neigh} between two galaxies assumed to be at the same cosmological redshift z_{cosm} is (see Eq. (9) of Hogg, 1999 or Eq. 10 of Cappellari, 2017)

$$\Delta V_{\text{neigh}} = V_{\text{neigh}} - V_{\text{MaNGA}} = \left(\frac{z_{\text{neigh}} - z_{\text{MaNGA}}}{1 + z_{\text{MaNGA}}} \right) c, \quad (5.2)$$

where c is the speed of light in km s^{-1} . By comparing the difference between z_{neigh} and z_{MaNGA} with $1 + z_{\text{MaNGA}}$, Eq. (5.2) states that the velocity difference between two redshifts depends on the cosmological redshift. Baldry, 2018 makes the case that $\ln(z)$ is a more natural distance indicator because a velocity measurement is effectively a shift on a logarithmic wavelength scale, as galaxy spectra are binned linearly with $\ln(\lambda)$ (e.g. Tonry & Davis, 1979; Cappellari, 2017). If we instead define ΔV_{neigh} as

$$\Delta V_{\text{neigh}} = V_{\text{neigh}} - V_{\text{MaNGA}} = [\ln(1 + z_{\text{neigh}}) - \ln(1 + z_{\text{MaNGA}})]c, \quad (5.3)$$

then the cosmological and peculiar velocities add linearly, without the need to “deredshift” from the cosmological redshift. When the peculiar velocities are of order 100 km s^{-1} , then Eq. (5.2) and Eq. (5.3) are equivalent to within 1 km s^{-1} (see fig. 1 of Baldry, 2018). As we are free to use either definition, we choose to use Eq. (5.3) as it is mathematically more elegant than Eq. (5.2).

For the spectroscopic neighbours, we could simply check that $|\Delta V_{\text{neigh}}| \leq \Delta V$. However, this would not work for photometric galaxies as we need to check if the

photometric redshift errors, converted to velocity, overlap with the cylinder. Hence, we use a more general function,

$$f_{\text{overlap}}(V_{\text{min}}, V_{\text{max}}, \Delta V) = \begin{cases} 1, & \text{if } V_{\text{min}} \leq \Delta V/2 \text{ and } V_{\text{max}} \geq -\Delta V/2 \\ 0, & \text{otherwise} \end{cases} \quad (5.4)$$

where V_{min} and V_{max} are the lower and upper velocity limits and $f_{\text{overlap}} = 1$ corresponds to an overlapping galaxy. To satisfy $f_{\text{overlap}} = 1$, a galaxy needs only to overlap with the cylinder and not $V = 0 \text{ km s}^{-1}$ corresponding to the MaNGA galaxy itself. For galaxies in the NSA, V_{min} is equal to V_{max} within our precision of $\sim 30 \text{ km s}^{-1}$. In contrast, photometric galaxies can easily have velocity errors that are much larger than the height of the cylinder. However, we have no reason to exclude these galaxies on the basis of large errors in redshift. If we were to estimate the local density using only the spectroscopic catalogue, we would grossly underestimate the number density of the high redshift galaxies in our sample, which are the most massive and most likely to be SRs.

Here we quantify the probability that a given photometric galaxy will actually lie within a given cylinder. We assume that the errors on the photometric redshifts provided in Beck et al. (2016) are reliable. We also assume that the likelihood of a galaxy lying within its error bounds is uniform. In fact, this likelihood is a Gaussian centred on the most likely value, but as our discussion is only approximate, this assumption is not critical. For a cylinder with $\Delta V = 300 \text{ km s}^{-1}$, the probability of overlap is at best about 20%²⁶ but could be as low as $\sim 0.01\%$ ²⁷. It is possible that for the few groups where the cylinder is extended in velocity, the probability of overlap can equal 100%. However, the probability of *multiple* photometric galaxies lying in a single cylinder rapidly approaches zero as the number of photometric galaxies increases.

5.3.3.2 Excluding interlopers using luminosity

Clearly, it makes little sense to include galaxies with only a photometric redshift with large errors that happens to overlap with the cylinder, especially if they are at high redshift. We can improve the selection and further eliminate interlopers by assuming that if they are at the redshift of the MaNGA galaxy, their apparent magnitude should be such that their absolute magnitude satisfies our minimum luminosity of $M_r = -18$

²⁶For a minimum $z_{\text{err}} = 0.005$ for photometric galaxies, $P(\text{overlap}) \approx 0.001/0.005 = 20\%$ assuming maximal overlap and $\Delta V/c \approx 0.001$.

²⁷For $z_{\text{err}} = 0.2$ for photometric galaxies, $P(\text{overlap}) \approx 0.001 * 0.01/0.2 = 0.005\%$ assuming 1% of the cylinder overlaps and $\Delta V/c \approx 0.001$.

mag. In essence, we move each galaxy from its recorded photometric redshift to the redshift of the MaNGA galaxy, which it must be at if it is to be bound to the same dark matter halo. Galaxies at high redshift that are brought forward will decrease in luminosity (and stellar mass), and vice versa. To quantify the effectiveness of this extra quality control step, we select N_{overlap} photometric galaxies that overlap with cylinders spaced at regular redshift intervals between $z = 0.01$ and $z = 0.15$. At each redshift, we calculate the fraction of N_{overlap} galaxies that survive the luminosity cut i.e. $M_r \leq -18$ mag assuming they are at the redshift of the cylinder. We find that this fraction increases linearly with redshift regardless of the height of cylinder (see lower left panel of Figure 5.11). As expected, increasing h from $\sim 300 \text{ km s}^{-1}$ to $\sim 3000 \text{ km s}^{-1}$ only increases the fraction of surviving galaxies by at most $\sim 5\%$. Only about 5% of galaxies survive the luminosity cut at $z \sim 0.01$ compared with $\sim 80\%$ at $z \sim 0.15$.

We also compare the redshift and apparent magnitude distributions (and their corresponding errors) as a function of redshift before and after applying the luminosity cut (see middle and right panels right of Figure 5.11). We find that by applying the luminosity cut, we automatically select galaxies which (1) are lower in redshift and (2) are brighter and so therefore they have (3) smaller errors in redshift and (4) in apparent magnitude. After the luminosity cut, the median z of surviving galaxies increases linearly with z , and the error also generally increases with z . The apparent magnitude increases linearly with $\log(z)$ and the magnitude errors remain roughly constant with a slight upturn beyond about $z \sim 0.1$. Hence, applying the luminosity cut is crucial for us to obtain a cleaner sample of galaxies than would be achieved with just the velocity cut.

5.3.4 Constructing the group catalogue

For each MaNGA galaxy, we find the surviving neighbours that satisfy all our criteria i.e. the clean photometric selection as well as the velocity and luminosity cuts. We then run the group finder algorithm TD-ENCLOSER, presented in chapter 4, using each set of surviving neighbours as input. We then find the subset of galaxies which *encloses* each MaNGA galaxy i.e. we find all galaxies that belong to the same density peak as the MaNGA galaxy. These galaxies constitute a *set of neighbours* which are “hosted” by the MaNGA galaxy. We do not call these *groups* (yet) for the following reason. As some MaNGA galaxies will be physically close to other MaNGA galaxies (especially at low redshift), some of these *sets* will be duplicates of the same intrinsic *groups*. We do not know in advance which sets will be duplicates. We account for

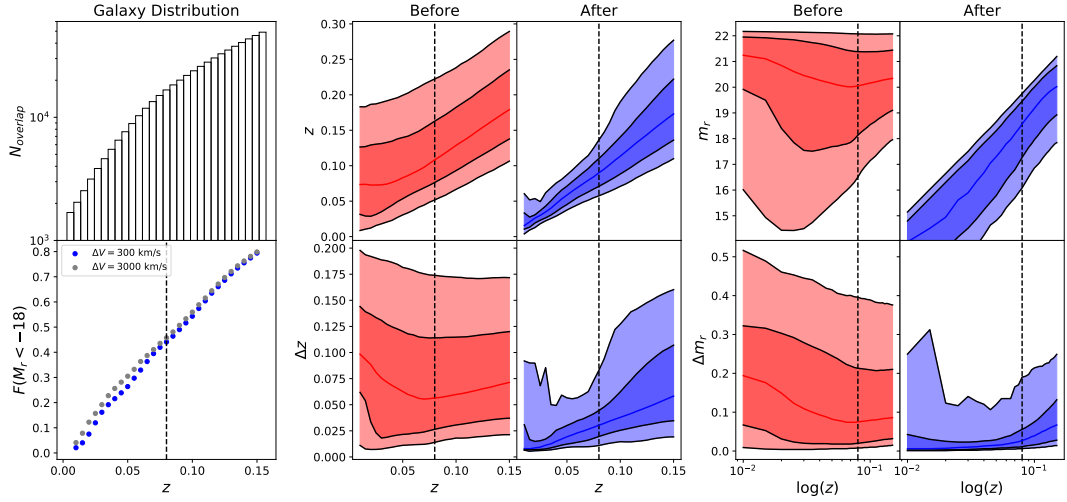


Figure 5.11: **Applying the luminosity cut.** **Left:** We plot $F(M_r \leq -18)$ as a function of redshift for galaxies in the photometric sample. At each redshift z , the fraction is calculated as the number of galaxies that overlap with a redshift cylinder with height $z = 0.002$ centred on z and satisfy our minimum absolute magnitude $M_r = -18$ assuming they are at redshift z divided by the total number of galaxies that overlap at redshift z . Hence, the number of galaxies in each z bin is not constant. **Right:** In the upper left set of two panels, we plot the redshift distribution of galaxies that overlap the redshift cylinder centred at each z before (red, left) and after (blue, right) the luminosity cut is applied. The median is shown as the thick coloured line and the inner 1σ and 2σ percentiles are shown as shaded regions. The upper right set of panels is the same for the apparent magnitude distribution. The bottom sets of panels illustrate the corresponding error distributions. For the right set of plots, we show the x -axis as a logarithmic scale as the apparent magnitude increases as a function of $\log(z)$. In all panels, the upper redshift limit of the volume-limited sample is indicated with a dashed vertical line (see subsubsection 5.3.4.3).

this duplicity in section 4.5 where we present a simple procedure to remove duplicates sets. However, we only apply this procedure after completing the task outlined below, namely the visual classification of galaxies, as we do not know which duplicates will be removed.

5.3.4.1 Environmental measures

At this point, we have a group catalogue with which we can study galaxy environment. In this subsection, we introduce the parameters we will use for our science analysis presented in section 6.2.

There are a variety of different methods found in the literature that are designed to quantify galaxy environment. Muldrew et al. (2012) compared two broad groups of measures, one based on the distance to the n th nearest neighbour, and another based on the number of galaxies enclosed within a fixed aperture. Their analysis concluded that the methods based on the n th nearest neighbour are better probes of the local density, while aperture based methods are more sensitive to the large scale density. Moreover, Cappellari et al. (2011b) found that galaxy morphology is affected more by the projected number density Σ_3 compared to a more distant measure such as Σ_{10} . Nearest neighbour methods have also been used by a number of other studies to study galaxy morphology as a function of environment (e.g. Baldry et al., 2006; Park & Hwang, 2009; Tonnesen & Cen, 2012; Etherington & Thomas, 2015; Goddard et al., 2017; Brough et al., 2017; Greene et al., 2017; Schaefer et al., 2017; Lee et al., 2018). Here we focus on the projected number density $\Sigma_3 = 3/(\pi D_3^2)$ where D_3 is the projected comoving distance in Mpc of the third nearest neighbour to a galaxy.

Another commonly used parameter is the mass of the dark matter halo that hosts a group of galaxies. The halo mass is the only halo property to correlate with local galaxy density to the first order (Lemson & Kauffmann, 1999; Haas et al., 2012) and can be measured accurately in dark matter simulations. We do not have access to halo masses, but we take advantage of the halo mass-richness relation (e.g. Becker et al., 2007; Rozo et al., 2009; Shen et al., 2014) which allows the group richness $\mathcal{N}$ to be used as a proxy. Finally, for each galaxy, we measure the projected comoving distance to the galaxy at the centre of the group as determined by TD-ENCLOSER, D_{cen} . We do not choose the most massive galaxy to be the central galaxy. Instead, we designate the galaxy that lies at the peak of the density field to be the central galaxy, so that we do not bias the measurement in any way. The ETG fraction is known to correlate with the cluster-centric radius (Whitmore & Gilmore, 1991; Whitmore et al., 1993; Hansen et al., 2009), and hence it would be logical to expect

that the fraction of massive SRs would also vary as a function of D_{cen} . As we also do not have virial radii to hand, we consider both the physical group-centric radius D_{cen} and the group-centric radius normalised to the 90th percentile, which is less affected by outliers than the 100th percentile.

Although it has been established that the abundance of SRs is larger at the centre of clusters, Cappellari et al. (2011b) showed that the SR fraction $F(\text{SR})$ is not a simple function of Σ_3 , unlike for the classic T- Σ relation. In fact, outside Virgo, $F(\text{SR})$ was found to be nearly independent of Σ_3 . The lack of a universal $f_{\text{SR}} - \Sigma_3$ relation was also found when studying different galaxy clusters. The clearest example can be seen in fig. 7 of Scott et al. (2014) which compares $F(\text{SR})$ for the Coma, Virgo and Fornax clusters as well as the ATLAS^{3D} field sample. At a fixed number density $\log(\Sigma_3) \approx 2 \text{ Mpc}^{-2}$, SRs can either be absent or constitute one third of all ETGs. For the eight clusters in the SAMI cluster sample (Brough et al., 2017), $F(\text{SR})$ can vary between clusters by up to 20% for a given overdensity. By averaging $F(\text{SR})$ profiles from multiple clusters to produce a single kT- Σ relation, we risk washing out the clear trends seen in the $F(\text{SR})$ profiles for individual clusters. In light of this, we define the *relative* number density $\Sigma_3^{\text{rel}} = \Sigma_3 / \Sigma_3^{\text{max}}$ where Σ_3^{max} is the maximum Σ_3 for a given cluster. (We maintain the subscript 3 for clarity, but this parameter can be calculated for any n as Σ_n^{rel} .) By this definition, a galaxy at the peak of the number density will have $\log(\Sigma_3^{\text{rel}}) = 0$, and all other galaxies will have $\log(\Sigma_3^{\text{rel}}) < 0$. In this way, all clusters are shifted to a common baseline. Houghton (2015) already suggested that the fraction of elliptical galaxies depends on the relative local density within a cluster, but this has not yet been investigated for massive SRs. One possible interpretation of $\log(\Sigma_3^{\text{rel}})$ is that it is a distance indicator, where the distance metric is number density. In this way, it is analogous to the projected distance D_{cen} , which can also be considered as a relative estimator (i.e. relative to the central galaxy). However clusters are not spherically symmetric, but contain substructure, and for this reason Σ_3^{rel} and D_{cen} measure different slightly physical quantities.

5.3.4.2 Achieving a volume-limited sample

While the MaNGA selection function is ideal for studying massive slow rotators as it allows for many massive galaxies to be observed, it is by design not a volume-limited sample. MaNGA does not have a dedicated cluster programme²⁸ and so this

²⁸There is an ancillary programme for the Coma cluster which we do not consider as it uses different observing strategies. See Gu et al., 2018 for a description and SDSS Collaboration et al., 2016 for a complete list of ancillary programmes.

poses a challenge in how to interpret the kT - Σ relation when the MaNGA sample only contains arbitrarily chosen members of multiple distinct clusters or groups. It would not make sense to obtain the kT - Σ relation for a cluster with only partial observations with IFS, because our results will be affected by major selection biases that are difficult to correct for. Moreover, the results would not be comparable with single cluster studies or volume limited surveys. It is trivial to correct for the volume represented by every galaxy, producing a volume-weighted sample, by duplicating each MaNGA galaxy N times where N is inversely proportional to the size of the volume in which the galaxy would still be observed by MaNGA. However this will produce an artificial sample which does not reflect the real Universe. Small galaxy groups are much more numerous in the Universe than large groups or galaxy clusters. The mass-environment degeneracy means that MaNGA will observe galaxies in large groups more frequently than if the sample was a random, volume-limited sample. For example, we are very unlikely to observe low mass fast rotators in groups of 50 members because they are much more likely to be isolated or live in small groups.

A simple but non-trivial solution would be to take all galaxies in a cluster or group for which we do not have stellar kinematics and make an educated guess using the optical morphology as to the angular momentum classification (fast or slow rotator). This would work for spiral galaxies which form a parallel sequence to fast rotators and so the presence of spiral arms immediately rules out of the possibility of a galaxy being a SR. Unfortunately, there is a substantial lack of a one-to-one correspondence between the stellar kinematics and optical morphology of ETGs. In fact, two-thirds of galaxies classified as elliptical (i.e. spheroidal) are in fact fast rotators, which intrinsically are axisymmetric disk galaxies and would appear flattened if viewed edge on (Cappellari et al., 2011b).

Thankfully, fast and slow rotators are not defined solely in terms of angular momentum, which is only obtainable with stellar kinematics, but also in terms of stellar mass and ϵ (Cappellari, 2013, 2016). The slow rotators are thought to be the relics of dry mergers and as such they are expected to be massive compared to fast rotators, which form by accretion of cold gas, and are also products of gas-rich (wet) mergers (Cappellari, 2016). Observationally, galaxies classified as slow rotators using stellar kinematics have been shown to dominate above a critical mass of $2 \times 10^{11} = 10^{11.3} M_{\odot}$ as was initially pointed out by Emsellem et al. (2011) and reinforced by Cappellari et al. (2013b) (see their fig. 14) in ATLAS^{3D}. This characteristic was later confirmed by Veale et al. (2017a) with MASSIVE, Greene et al. (2017) with MaNGA, Brough et al. (2017) with SAMI as well as in subsection 3.1.3. Lower mass galaxies appear

to be a qualitatively different class of objects and follow different formation channels (e.g. C16). If a merger remnant is less massive than the critical mass, then its progenitors must not be fully quenched and in this case, the disk can remain stable and the merger remnant is a fast rotator ETG. For this reason it makes sense to exclude lower mass galaxies when studying massive slow rotators as a homogenous class. The dry merger channel is violent and disrupts the stellar disk as a result of the redistribution of angular momentum from within $1R_e$ out into the galaxy halo. Hence, the slow rotator merger remnants are intrinsically round and so would appear round from any viewing angle. Therefore, any ETG that is less massive than $\log(M) = 11.3$ or appears to be flatter than $\epsilon = 0.4$ (an empirical demarcation line that was proposed by C16 and strongly confirmed in chapter 3) cannot by definition be a genuine dry merger relic (i.e. a slow rotator). Hence, we only have to visually classify the subset of galaxies that satisfy $M \geq M_{\text{crit}}$ and $\epsilon < 0.4$.

5.3.4.3 Choosing a maximum redshift limit

Ideally, we would like to be able to visually classify all the potential SRs in all sets of neighbours. However, there are three main reasons why we would not want to classify galaxies up to the maximum redshift of MaNGA ($z = 0.15$):

1. At high redshifts ($z \gtrsim 0.1$), it is more difficult to classify galaxies visually as the resolution is poorer compared to lower redshifts.
2. As the completeness of the spectroscopic sample declines with redshift, the accuracy of the galaxy groups and hence the reliability of any statistical measurement also decreases (see Figure 5.10).
3. The MaNGA survey preferentially observes galaxies at lower redshifts ($z \lesssim 0.05$: see Figure 5.10), and hence the fraction of confirmed fast (or slow) rotators compared to the total will be greater for a redshift-limited subsample than for the whole sample.

It is therefore necessary to specify an intermediate redshift between the MaNGA limits ($0.01 \leq z \leq 0.15$) below which we classify galaxies. However, an important constraint on this redshift is that the brightest and most massive galaxies in MaNGA are observed at the higher redshifts, and so the majority of *confirmed* slow rotators will be at the higher redshifts (see Figure 5.10). Moreover, the reduction in sample size may mean that our number statistics become poorer as a result. In short, whichever redshift we choose to define as a upper limit for our subsample will be a compromise

between resolution and accuracy of both the groups and the angular momentum (case for low z), and number statistics and number of confirmed slow rotators (case for high z). We find that roughly half ($\sim 43\%$) of all *confirmed* massive slow rotators in MaNGA lie below the redshift midpoint ($z = 0.08$) and so we choose this redshift to define the upper limit of our volume-limited sample.

To summarise, we only classify the angular momentum of galaxies which satisfy $M \geq M_{\text{crit}}$ and $\epsilon < 0.4$ and lie in sets hosted by MaNGA galaxies which lie at a redshift $z \leq 0.08$. We describe our classification method in detail in section 5.4. We do not classify galaxies in sets that lie beyond $z = 0.08$. In section 5.5, we present the group catalogue. In our catalogue, we include *MaNGA* galaxies in the redshift range $0.08 < z \leq 0.15$ for reference, but we do not use these galaxies for any science.

5.3.4.4 Comparison with Yang et al. 2007 group catalogue

Now that we have constructed our group catalogue, we compare our volume-limited sample catalogue with a well-established one. We choose the Yang et al. (2007) catalogue updated to SDSS DR7 due to its popularity and the fact that it is based on SDSS (we use the one based on Petrosian magnitudes and sample II which supplements SDSS redshifts with additional redshifts from other surveys). It also extends to $z = 0.09$ which is beyond the limit of our volume-limited sample. We first match galaxies to groups using NYU_ID, and then calculate the richness for each group in the catalogue (as this is not provided). We then match each galaxy in our group catalogue to the one in the Yang et al. (2007) catalogue using RA and Dec coordinates. We find that $\sim 32\%$ of the galaxies in our catalogue do not have a match within 5 arcsec in the Yang et al. (2007) catalogue, of which $\sim 75\%$ only have a photometric redshift, and not a spectroscopic one. For each matched galaxy in our catalogue, we now have a richness for its enclosing group from this work ($\mathcal{N}^{\text{TW}}$), and its enclosing group from Yang et al. (2007) ($\mathcal{N}^{\text{Yang}}$).

We plot the richness distributions for $\mathcal{N}^{\text{TW}}$ and $\mathcal{N}^{\text{Yang}}$ on the left hand side of Figure 5.12. We find that while they are comparable overall, we tend to find larger groups more frequently than Yang et al. (2007), who conversely find more isolated galaxies than we do. Our group memberships are slightly biased towards larger groups as can be seen in the right hand side of Figure 5.12, where we compare $\mathcal{N}^{\text{TW}} - \mathcal{N}^{\text{Yang}}$ for individual galaxies.

It is also useful to compare halo masses, as this is a standard parameter of group catalogues. To estimate the halo mass for the groups in our catalogue, we use the halo-richness relation of Shen et al. (2014) (see their Eq. 2 and Figure 2) which estimates

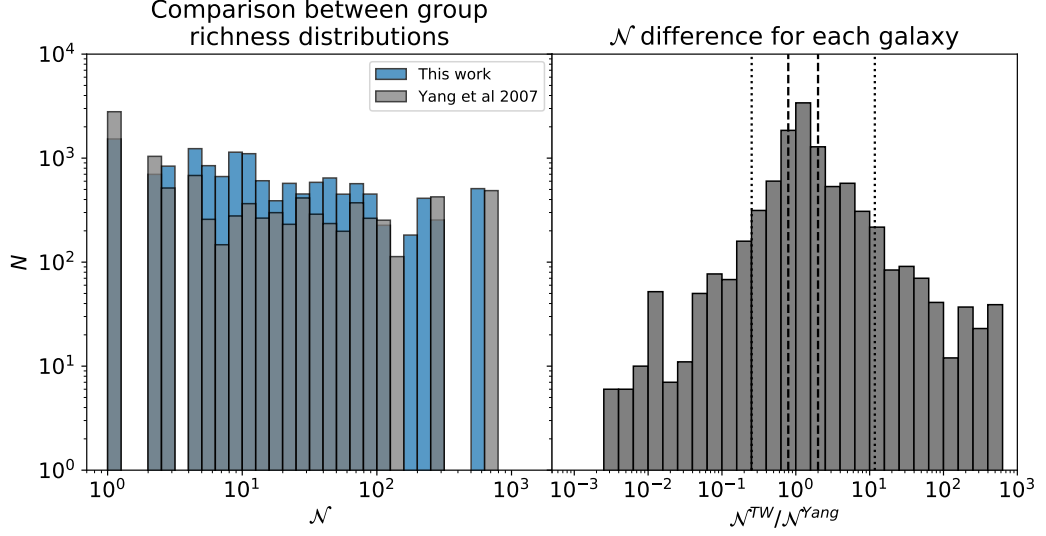


Figure 5.12: **Comparing group richness.** **Left:** For galaxies which are in our catalogue and have a group assigned in the Yang et al. (2007) DR7 catalogue, we plot the richness distribution from our catalogue in blue, and the richness distribution from the Yang et al. (2007) catalogue in grey. The bins are evenly spaced in log units. **Right:** For each galaxy present in both catalogues, we calculate N^{TW}/N^{Yang} and compute the histogram for all galaxies. The dashed and dotted lines indicate the inner 50% and 90% respectively.

halo masses using abundance matching considering only galaxies with $M_r < -19.5$. We choose their relation to be consistent as it is based on the same group catalogue of Yang et al. (2007). Instead of using M_r , we estimate the stellar mass corresponding to $M_r = -19.5$ using the relation shown in Figure 5.9 to be $10^{10.5} M_\odot$. (Shen et al., 2014 have an alternate relation, given in their Eq. B3, which is calibrated for galaxies above this stellar mass but we do not expect any significant changes when using this relation due to its similarity to their Eq. 2.) The relation is a broken power-law where the halo mass $M_{\text{halo}}^{\text{Shen}}$ is calculated from the number of galaxies with $M_r < -19.5$, or in our case $M \geq 10^{10.5} M_\odot$.

We compare our estimated halo mass with the halo mass given in the Yang et al. (2007) catalogue ($M_{\text{halo}}^{\text{Yang}}$) in Figure 5.13. We allow for the error in log units to be 0.3 for both catalogues otherwise the fit is not successful, likely due to the discrete nature of our halo masses (as they are calculated from a discrete group richness). We measure the slope and scatter of the distribution using `LTS_LINEFIT`. We find that while there is a large amount of scatter, the slope is not far from one, and the intercept at the pivot is almost identical to the pivot value itself, suggesting that there is little to no offset between the two halo mass estimates. The broad agreement

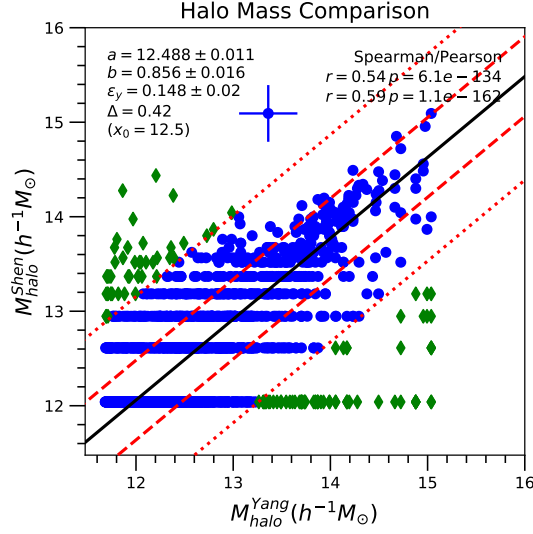


Figure 5.13: **Comparing cluster mass.** On the x-axis, we plot the halo mass from the Yang et al. (2007) catalogue, $M_{\text{halo}}^{\text{Yang}}$, and on the y-axis, we plot the halo mass for our group catalogue estimated using Eq. 2 of Shen et al. (2014). As with similar plots in this thesis, the best fitting relation is calculated using `LTS_LINEFIT`. The errorbars along each axis are shown in the upper middle of the plot (where no real galaxy lies).

between our estimated halo masses and those of Yang et al. (2007) gives confidence that the accuracy of our group finder algorithm and method is sufficient.

Finally, we compare which groups and clusters we have in common with Yang et al. (2007). We find that while very few groups match up entirely, about 2000 ($\sim 55\%$) of our groups (including isolated galaxies) have all their members present in the Yang et al. (2007) catalogue split between multiple groups, although almost all of these have $\mathcal{N} < 10$ in our catalogue. Of the largest 10 groups in our catalogue which we find to have at least about 90 galaxies each, seven have at least 50% of the members present in the Yang et al. (2007) catalogue, while the remaining three have between 30% and 50% present (again split between different groups in the Yang et al. (2007) catalogue). About 100 groups with $\mathcal{N} \lesssim 15$ do not have any members present in the Yang et al. (2007) catalogue. All groups with $\mathcal{N}$ in our catalogue have at least 20% of their members in the Yang et al. (2007) catalogue. Comparing the content of two group catalogues is challenging, as even if two overlapping groups have the same $\mathcal{N}$ in both catalogues, the member galaxies may not be the same set of galaxies.

5.4 Selecting the slow rotator candidates

Before we classify galaxies without stellar kinematics as fast or slow rotators, it is crucial to understand how accurately we can make the classification. Cappellari et al. (2011b) found that only one third of elliptical galaxies are genuinely spheroidal (slow rotators) and that two thirds are in fact misclassified face-on disks (fast rotators). However, they did not take into account the stellar mass or ellipticity criteria that we enforce here. Can we use the extra criteria to improve the accuracy rate for slow rotators? The MaNGA sample is ideally suited for answering this question as it contains a large number of high-mass galaxies compared to a volume limited sample of the same sample size (Wake et al., 2017).

5.4.1 Visual classification using morphological features

We answer the above question by guessing the angular momentum classification of 581 MaNGA galaxies that satisfy the SR criteria ($\log(M) \geq 11.3$ and $\epsilon < 0.4$), and compare our guesses to the true classifications obtained using λ_{R_e} . In our test, we look out for known characteristic signatures: SRs are massive ellipticals with a bright bulge and an extended stellar halo (e.g. Schombert, 1986). All disk-related features such as bars and rings are absent, although they can possess shells which are indicative of a recent dry merger event. In contrast, the majority of FRs exhibit disk-like features with only a handful appearing morphologically indistinct from SRs.

Before we quantify our rate of success, we present a random selection of 160 MaNGA ETGs that are *confirmed* SRs and FRs (see Figure 5.14, Figure 5.15 for true-colour images and Figure 5.16, Figure 5.17 for velocity maps). To aid our comparison, we split up the MaNGA ETGs into five redshift bins and randomly select 32 galaxies in each bin. For each galaxy, we give the MaNGA-ID, the redshift and our guess (S/F). While it is obvious which of these galaxies are *not* SRs, there are a substantial number of false positives (FRs incorrectly classified as SRs). From the images, it becomes clear why we decided to limit this classification to $z \leq 0.08$: it is harder to pick out the defining morphological features pertaining to FRs and SRs when z is large.

5.4.2 Quantifying rate of success

In Figure 5.18a, we plot $\lambda_{R_e} - (0.25\epsilon + 0.08)$, which is the vertical distance from the upper limit for SRs, as a function of stellar mass for MaNGA galaxies of all morphologies that satisfy the SR criteria (i.e. $\log(M) \geq 11.3$, $\epsilon < 0.4$). All galaxies

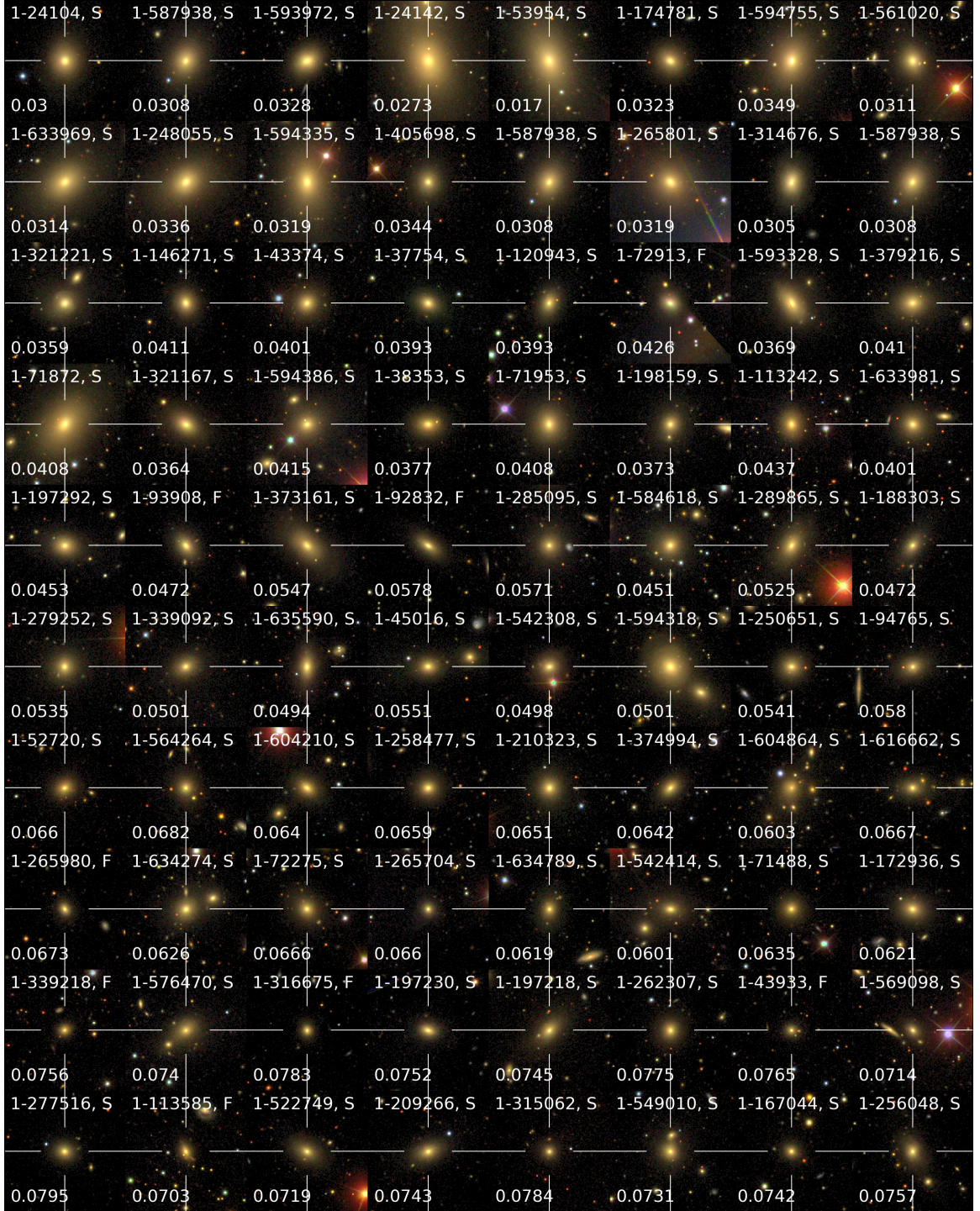


Figure 5.14: **Confirmed slow rotators.** We show SDSS optical images for 80 randomly selected confirmed SRs. We select galaxies in five redshift bins with redshift increasing from the top downwards. The .jpg images have been adjusted to better highlight the faint outer envelopes that are characteristic of SRs. For each galaxy, we give the MaNGA-ID and the guess (upper left) and the redshift (lower left).

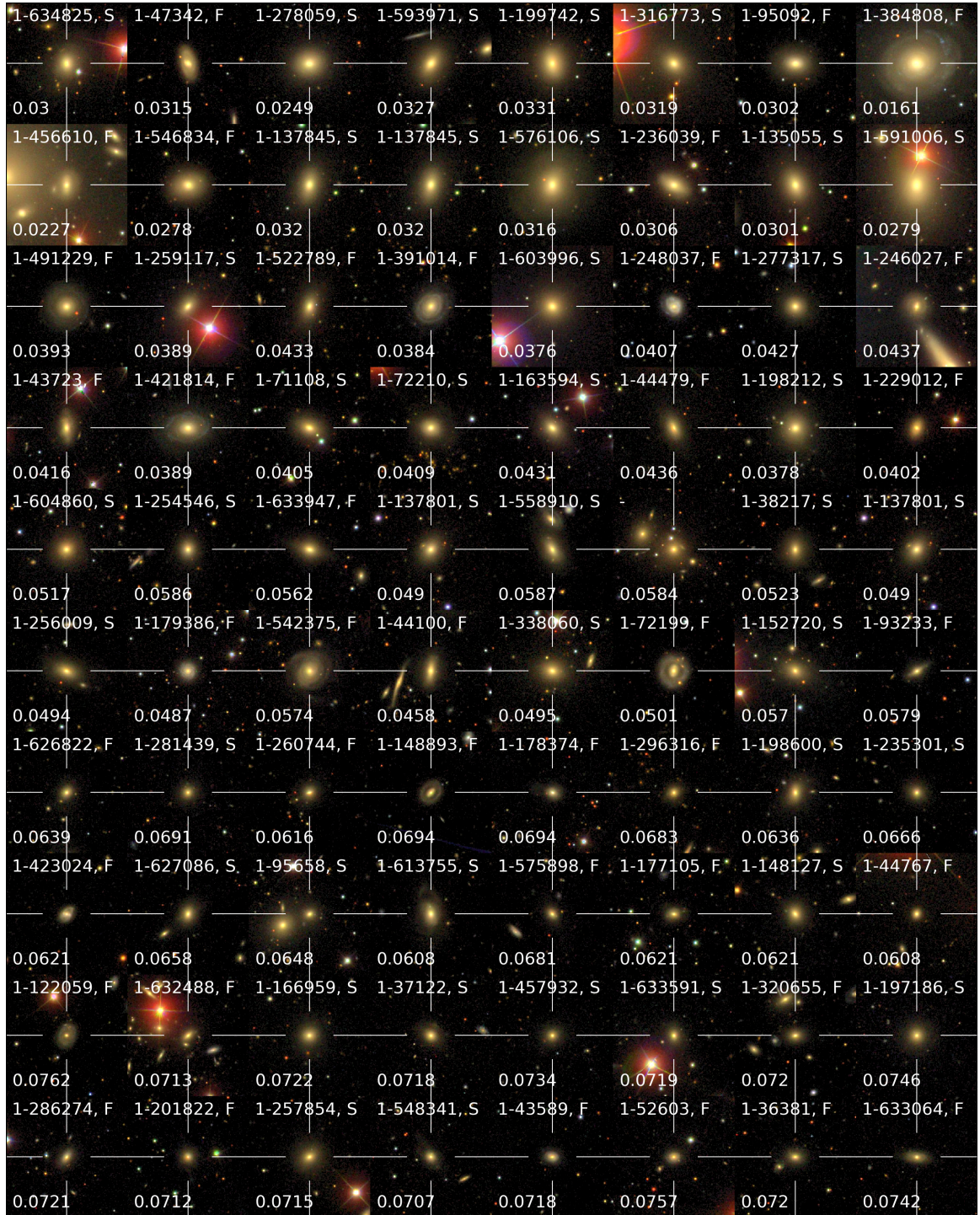


Figure 5.15: **Confirmed fast rotators.** The same as Figure 5.14 except for ETGs which have been confirmed as fast rotators.

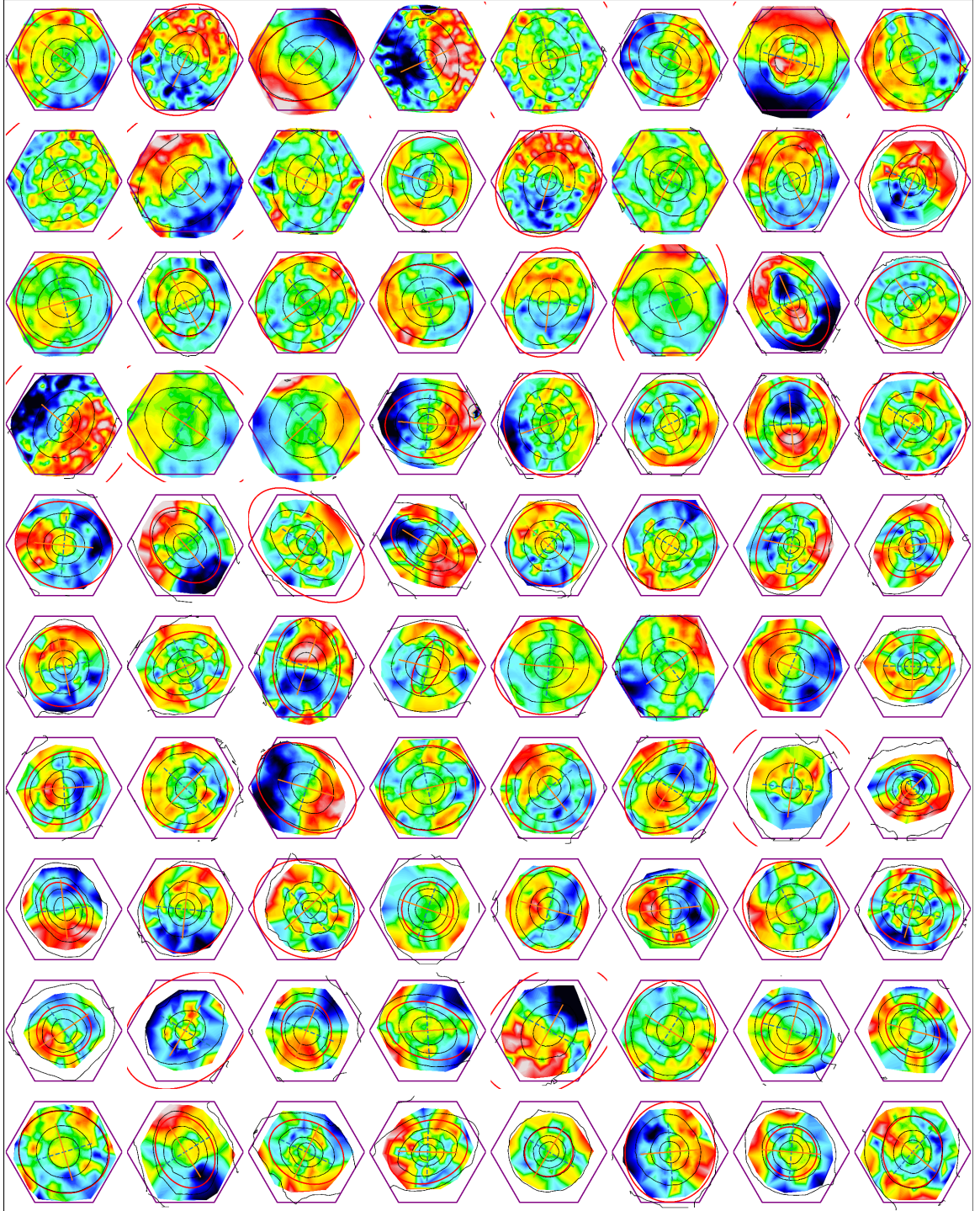


Figure 5.16: **Slow rotator kinematics.** For each galaxy in Figure 5.14, we plot the velocity map from the MaNGA stellar kinematics. Velocities are red and blue shifted according to their colour and green if they are at the mean velocity i.e. zero. The red ellipse indicates the half-light ellipse with an area equal to πR_e^2 . In many cases, there is little sign of rotation. If the maximum speed is less than 30 km s^{-1} , then we fix the colourmap to range between -30 and $+30 \text{ km s}^{-1}$.

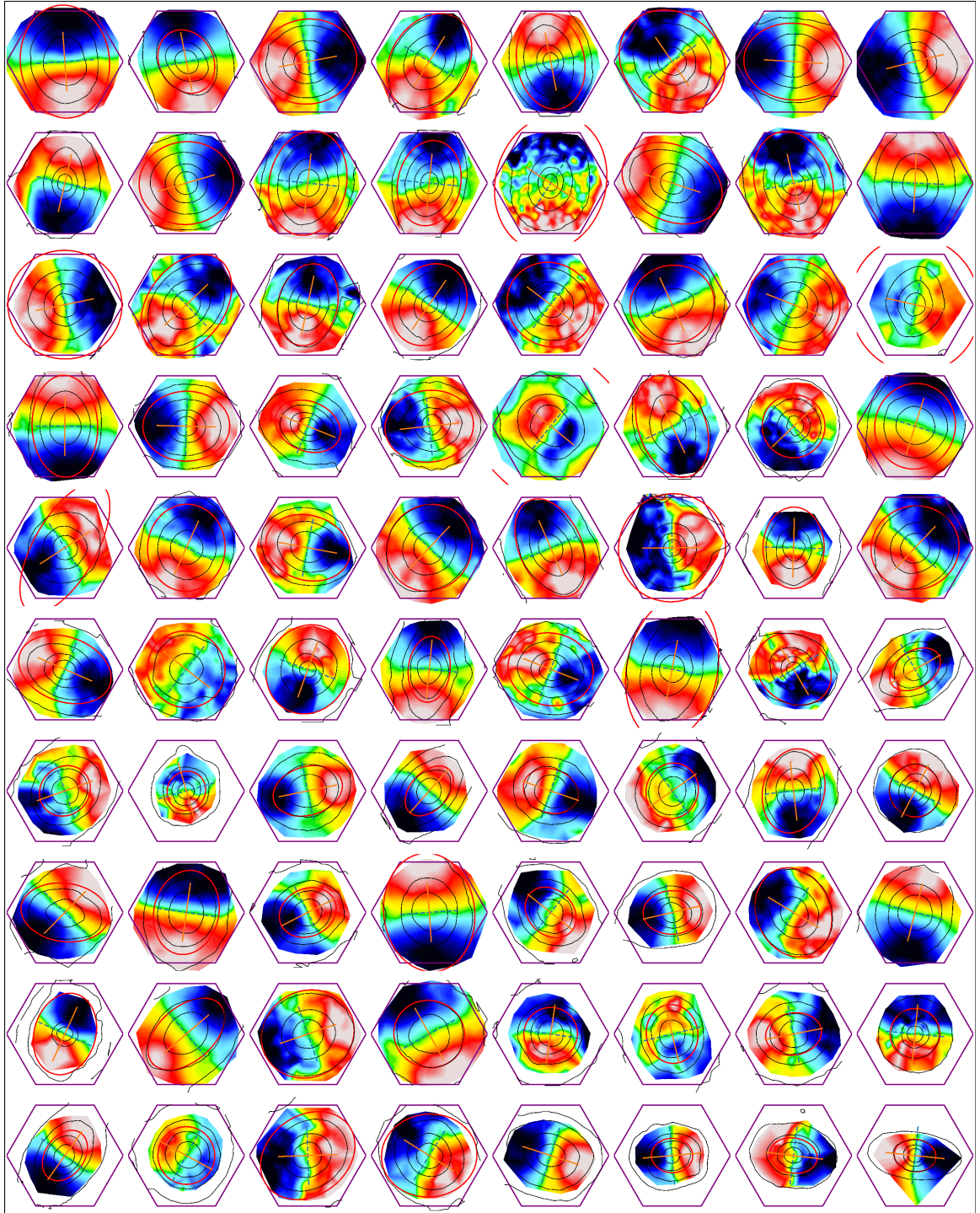


Figure 5.17: **Fast rotator kinematics.** The same as Figure 5.16 except for fast rotators. In almost all cases, the characteristic hourglass velocity field is clearly visible.

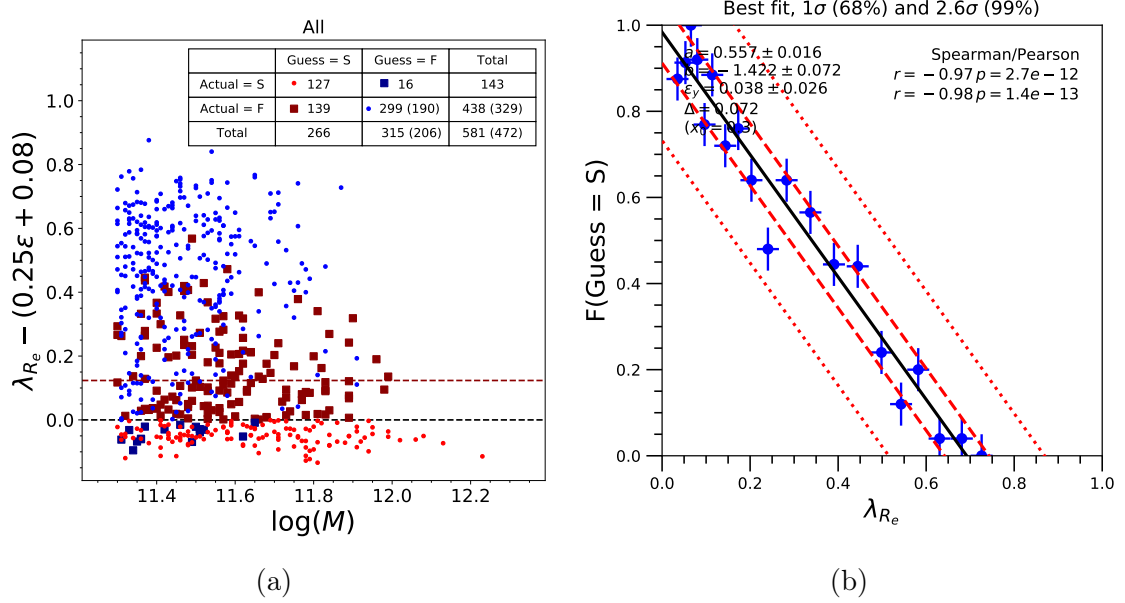


Figure 5.18: *Left: Quantifying success rates.* We plot the vertical distance from the upper SR limit as a function of stellar mass for all MaNGA galaxies which satisfy the SR photometric criteria i.e. $\log(M) \geq 11.3$ and $\epsilon < 0.4$. The sample is split into four subsamples: true positives (red circles), true negatives (blue circles), false positives (dark red squares) and false negatives (dark blue squares). The confusion matrix is given in the upper right and details the number of galaxies in each subsample. Where two numbers are given, the number in brackets is for ETGs only, and the number outside the brackets includes late types. The black horizontal dashed line indicates the SR boundary and separates positives (below) from negatives (above). The dark red horizontal dashed line indicates the median vertical distance for the false positives. *Right: Estimating λ_{Re} by eye.* We plot the fraction of galaxies classified visually as slow rotators regardless of whether they are confirmed as slow rotators or not. The parameters of the linear fit are shown.

that lie above and below the dashed line are *confirmed* FRs and SRs respectively. All blue points (dark squares and light circles) have been classified *by eye* as FRs, and the red equivalent have been visually classified as SR *candidates*. We also give the confusion matrix for the sample which contains our key result: Crucially, the number of false negatives is only 16 out of a total of 581 galaxies. The fact that this number is so small is pivotal for the accuracy of our angular momentum classification for two key reasons. Firstly, it means that 127/143 ($\sim 89\%$) of *confirmed* SRs are visually classified as such. Hence, we are confident that we miss only one in ten genuine massive SRs. Secondly, and more importantly, *given a guess of FR*, we are correct for 299 out of 315 cases, giving us a success rate of $\sim 95\%$. If we consider only ETGs, this fraction drops slightly to 190/206 ($\sim 92\%$). This means that if we classify 100 galaxies as FRs, then only 5 will have incorrect classifications (and will actually be SRs). Furthermore, this *only* applies to galaxies with $11.3 \leq \log(M) \lesssim 11.7$. Above this approximate upper limit in stellar mass, we are able to classify FRs with very high accuracy, and we also do not miss any genuine SRs.

On the contrary, of the 266 galaxies we classify as SRs, only 127 are actually SRs, which means that *given a guess of SR*, we are only correct in $\sim 48\%$ of cases. One reason for this is that all SRs have the morphological features described in subsection 5.4.1, but not all galaxies with those features are necessarily SRs. Another reason is that we take into account the stellar mass in making our classifications. The SR fraction is a strong function of stellar mass, and so the more massive a galaxy, the more likely we are to classify it as a SR if it has the required morphology. Reassuringly, 50% of the false positives are within $+0.125$ of the upper limit for SRs ($\lambda_{Re} = 0.08 + 0.25\epsilon$; see Figure 5.18a) which, given that λ_{Re} has errors of about 0.05 in this λ_{Re} regime (Yan et al., 2016b), means that we are able to classify galaxies that have a non-negligible chance of actually being in the SR regime. In fact, the fraction of false positives decreases linearly with increasing λ_{Re} with surprisingly small scatter (Figure 5.18b), and very few galaxies with $\lambda_{Re} > 0.5$ are guessed as SRs. This implies that the eye is able to qualitatively estimate the velocity dispersion in ETGs with remarkable accuracy.

There is the caveat that the fractions quoted above are not for a volume weighted sample. However, because we are only considering massive galaxies, the volume weighting has a minimal effect. Nevertheless, we also give the volume weighted percentages. Our misclassification rate for SRs increases from $\sim 11\%$ to $\sim 26\%$ for the volume weighted sample because the SRs that are guessed as FRs are lower than $\log(M) \approx 11.7$ in stellar mass and so they are relatively upweighted. Hence, we miss

one in four in the volume weighted sample. Crucially, given a guess of FR, we are still correct in $\sim 95\%$ of all cases ($\sim 93\%$ for ETGs only) even for the volume weighted sample. Unfortunately, our true positive rate decreases from $\sim 48\%$ to $\sim 39\%$ after applying the volume weighting. As previously mentioned, the volume weighted sample is constructed artificially by duplicating galaxies, and of course no two galaxies in the Universe are identical. Hence, there is some uncertainty on the volume-weighted true positive rate that is difficult to quantify.

Finally, as an aside, we check to see if we have improved on the two-thirds misclassification rate for *elliptical* galaxies as quoted in Cappellari et al. (2011b). Only two MaNGA galaxies were classified as SR but not as elliptical galaxies (i.e. S0s), and so the fraction is essentially the same as quoted above. Therefore, we have been able to improve on the misclassification rate for SRs given in Cappellari et al. (2011b).

As an aside, the two galaxies which were separately classified as S0s and SRs, 1-594069 and 1-156062, illustrate the difficulty in classifying galaxies with morphology. Both these galaxies were classified on separate occasions to be disk (S0) and spheroidal (SR) by MG. However, this only happened for $\sim 1\%$ of MaNGA galaxies that were guessed to be SRs and so the classifications are in general very consistent.

5.4.3 Example candidates

In Figure 5.19, we present a random selection of the 262 galaxies we visually classify as SRs. All these galaxies share morphological characteristics with the SRs in Figure 5.14, but one half will actually turn out to be FRs if/when stellar kinematics become available. Figure 5.20 shows a random selection of the 203 FR candidates. The majority of these are unambiguous in their classification since they possess disk-like features. A handful appear to be ellipticals but are deemed to either be too elongated or likely to contain disks.

5.4.4 Catalog statistics

In Table 5.1, we summarise the number of galaxies in each sample. We only consider galaxies in unique groups that have been selected using the algorithm described in section 4.5. This means that no MaNGA galaxy can appear more than once in our catalogue, but galaxies that are not in MaNGA can be duplicated.

Sample A consists of all groups in the MaNGA redshift range ($0.01 \leq z \leq 0.15$). There are 4597 unique MaNGA galaxies in MPL-7, but only 4430 in our catalogue. This is because of our random group selection process that selects representative

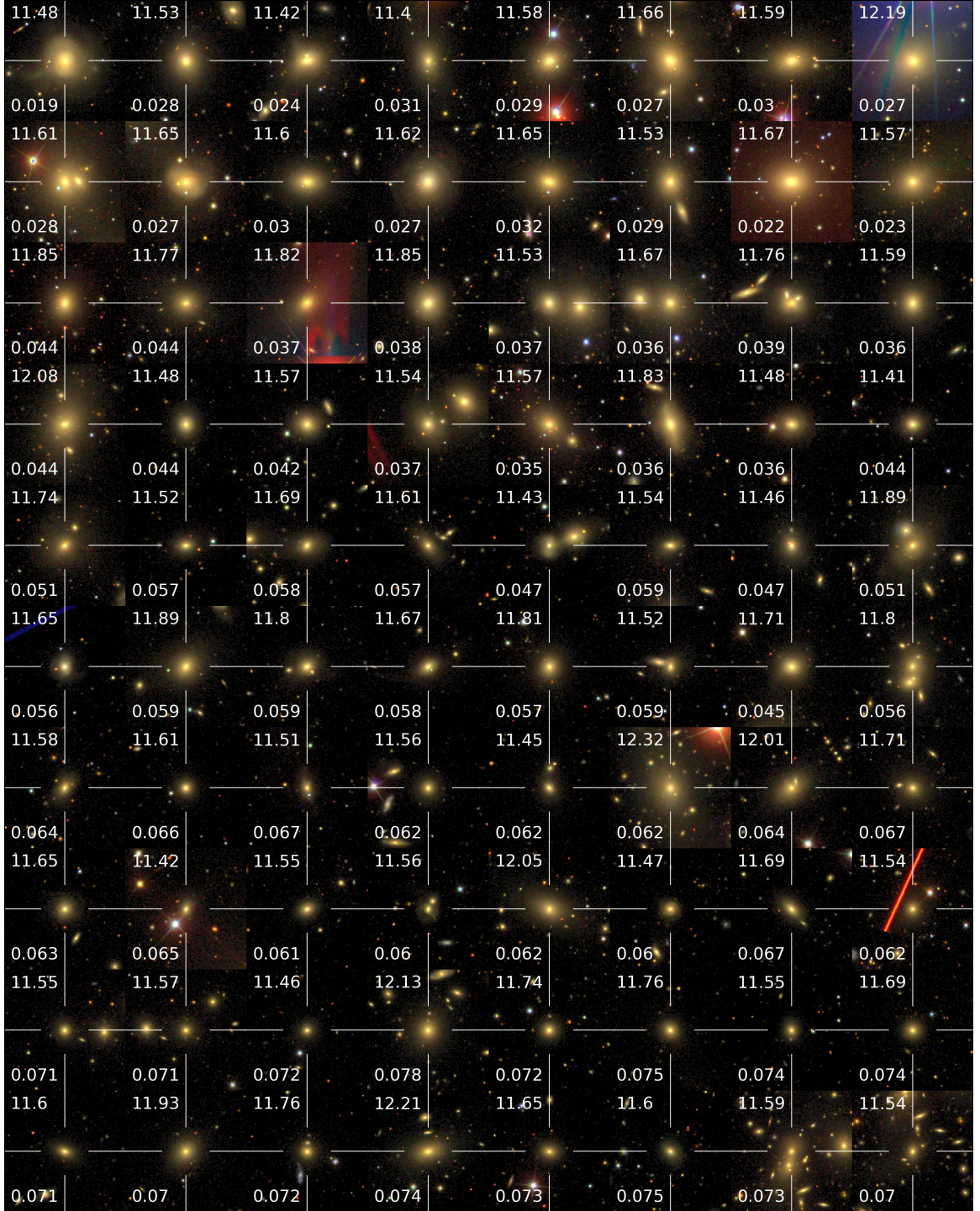


Figure 5.19: **Slow rotator candidates.** We show SR candidates using the same bins as Figure 5.14 etc. For each galaxy, we give the stellar mass (upper left) and the redshift (lower left) as we take these into account when assigning a classification. According to our analysis of the MaNGA sample, about half of these galaxies will be confirmed as FRs if we were able to obtain stellar kinematics (see text).

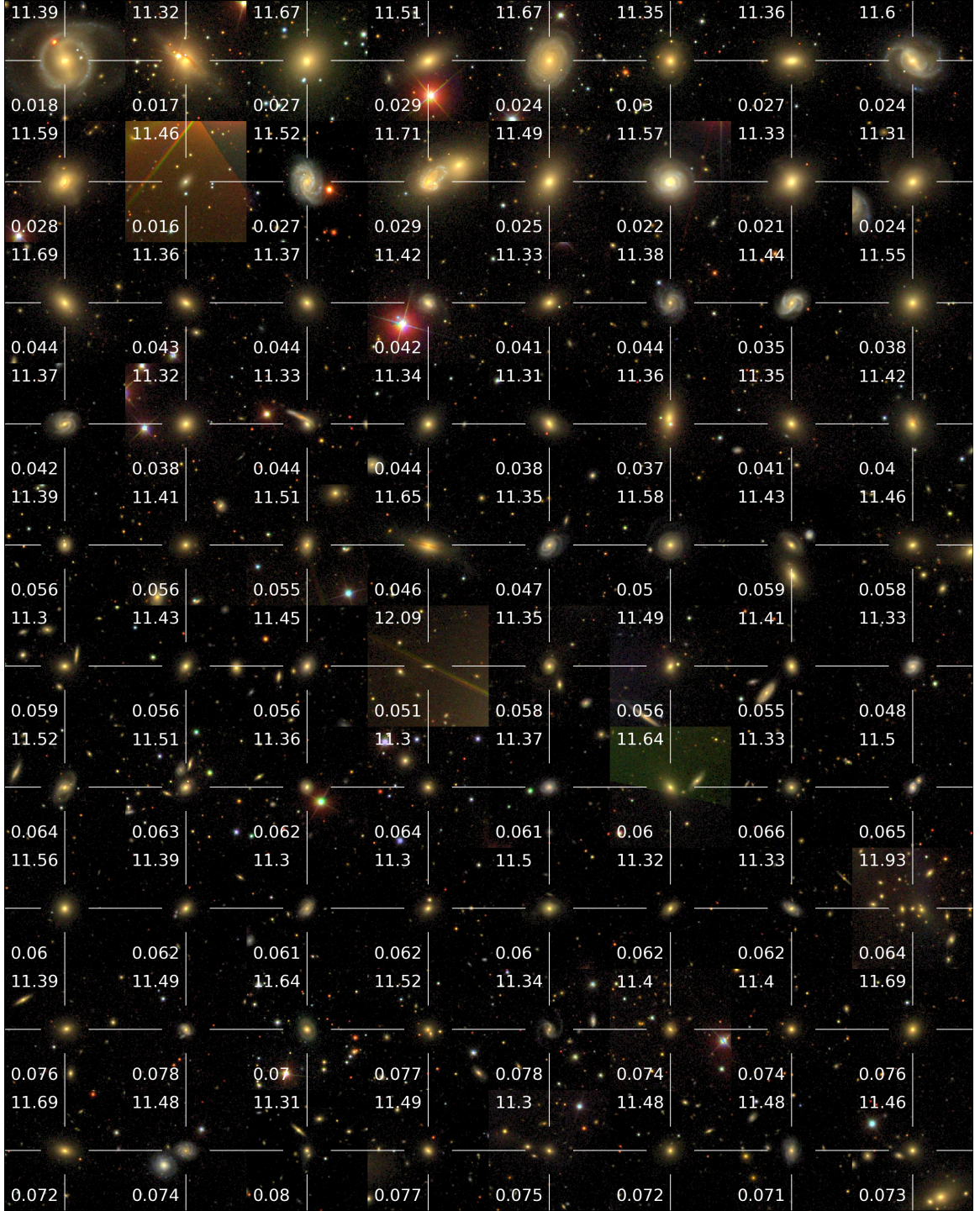


Figure 5.20: **Fast rotator candidates.** The same as Figure 5.19 except for galaxies which we have classified as FRs. According to our analysis of the MaNGA sample, only about 6% of these galaxies will be confirmed as SRs with observations of the stellar kinematics.

Table 5.1: Table containing the numbers of galaxies in the various samples used in this work, which are labelled in Column (1). Column (2) lists the criteria used to define the sample given in Column (1), and Column (3) gives the number of total number of galaxies in each sample. Columns (4) and (5) give the number of MaNGA galaxies of all morphologies and ETGs respectively. Column (6) lists the number of galaxies which are not in MaNGA that are contained in our catalogue. This column is split up into those with spectroscopic (Column (7)) and photometric (Column (8)) redshifts. The groups that make up each sample have been selected using our group selector algorithm (see section 4.5). As such, the MaNGA galaxies in each sample are unique, but of the galaxies which are not in MaNGA, there may be a small number of duplicates.

Sample	Criteria	Total	MaNGA		Non-MaNGA		
(1)	(2)	(3)	Total (4)	ETGs (5)	Total (6)	Spectroscopic z (7)	Photometric z (8)
A	All	17300	4460	3168	12840	8177	4663
B	A & $z \leq 0.08$	14093	3891	2761	10202	6683	3519
C	B & $\log(M_*) \geq 11.3$	1594	812	588	782	749	33
D	C & $\epsilon < 0.4$	1169	616	479	553	529	24
E	D & ROT = S	345	174	154	171	171	0

groups from duplicate sets (see section 4.5). As discussed in subsection 5.3.4.3, we limit our volume-limited sample with complete angular momentum classifications to $z \leq 0.08$, which we refer to in Table 5.1 as Sample B. By introducing a lower maximum redshift, we only reduce our sample size by $\sim 18.5\%$ and so we do not significantly compromise on number statistics.

Next, we define Sample C to be a subsample contained within Sample B that itself only contains galaxies more massive than M_{crit} . About 20.9% of MaNGA galaxies that are in Sample B also lie in Sample C, whereas only $\sim 7.7\%$ of non-MaNGA galaxies satisfy the mass threshold. This is unsurprising since MaNGA has a flat selection in stellar mass, while massive galaxies are much rarer in the general population. Above M_{crit} , the redshift accuracy is much higher than for the whole sample, where only $\sim 2.1\%$ of galaxies above the mass limit have photometric redshifts.

We also define the sample which we classify using our visual method (Sample D). The number of MaNGA galaxies is given as 616 which is slightly higher than the MaNGA sample used in subsection 5.4.1. This number includes mergers and galaxies with flagged kinematics. We do not use λ_{R_e} or ϵ for merging galaxies to quantify the angular momentum because one or both of these can be inaccurate for a merger. Hence, we classify the merger galaxy centred in the IFU as a fast or slow rotator using

Table 5.2: Table containing the results of our visual classification test. All the quantities required to plot Figure 5.18a and calculate the confusion matrix are given. Column (1) is the MaNGA-ID, Column (2) is the confirmed classification from the λ_{R_e} diagram, Column (3) is the visual classification, and Columns (4) and (5) are the y and x axes of Figure 5.18a respectively. Only the first 10 rows are shown.

MaNGA ID	Confirmed Classification	Visual Classification	$\lambda_{R_e} - (0.25\epsilon + 0.08)$	Stellar Mass log(M)
(1)	(2)	(3)	(4)	(5)
1-178828	F	F	0.369	11.52
1-384808	F	F	0.291	11.42
1-53954	S	S	-0.1198	11.32
1-456984	F	F	0.088	11.54
1-593929	S	S	-0.049	11.48
1-604022	F	F	0.657	11.32
1-456610	F	F	0.3848	11.47
1-256293	F	F	0.5875	11.33
1-278059	F	S	0.2932	11.3
1-392067	F	F	0.512	11.33

the same technique as described in subsection 5.4.1. Because we do not know the true angular momentum for merging galaxies, we do not include them in our training set. However, we do not exclude them from our catalogue on that basis. It is shown that in total, we classify 553 candidates using our visual method.

Finally, we define Sample E which only contains confirmed and candidate SRs. Of these galaxies, $\sim 49.6\%$ are candidates of which $\sim 52\%$ are misclassified. In total, about a quarter of SRs in our catalogue will be misclassified. None of the galaxies in Sample E have photometric z so their proximity to MaNGA galaxies is robust.

5.5 Conclusions

In this chapter, we have produced a volume-limited sample of about 14000 galaxies with complete estimates for stellar mass, ellipticity and angular momentum. This is the largest sample of its kind available in the literature and has been checked for quality and reliability. In section 5.2, we introduced four new criteria for selecting a sample of galaxies with clean photometry that are independent from the flags provided by the SDSS imaging pipeline. The first of these criteria are limits in five colours that effectively clip outliers with unusual colours (see Figure 5.1). We find that most objects that are clipped are faint and can have inaccurate photometric measurements due to fitting errors. However, a small fraction of excluded objects are in galaxy clusters. We also examine the nature of very bright objects with small Petrosian radii using infrared colours from the 2MASS PSC and find that they are in fact

foreground stars (Figure 5.3). The stars are extended and so were missed by the SDSS pipeline, which is optimised to classify point sources as stars (Figure 5.4). We suggest that for the bright end ($m_r < 16$), a minimum value of $R_{r,\text{Petro}} = 1.5$ arcsec should be enforced (Figure 5.2). Of course, these objects could also be removed on the basis of their $J - K_S$ colour, but having equivalent criteria defined using just the SDSS photometric quantities negates the need to consult the 2MASS PSC. For the range $16 < m_r \leq 19$, a maximum error in z_{phot} should be limited to 0.075 (Figure 5.5).

We took the photometric redshifts that were estimated by Beck et al. (2016) for all objects that were classified as galaxies. We adopted a selection criteria that only accepts redshifts with a certain degree of accuracy and reliability. In Figure 5.6, we showed that galaxies with photometric redshifts that do not satisfy these criteria only constitute a significant fraction fainter than $m_r \approx 20.2$ mag. We confirm that our new criteria are independent of the r -band flags provided by the SDSS pipeline and so cannot be recreated using only these flags (Figure 5.7). One particular flag, `NOPEYRO_BIG`, is assigned to objects where the signal-to-noise ratio is small and hence the fit is extended out to unphysically large radii. We find that our colour criteria almost eliminates the objects with very large radii, but ignores the objects that have the flag but are *intrinsically* faint and actually have small $R_{r,\text{Petro}}$ (Figure 5.8). Hence, by applying our criteria along with the criteria recommended for clean photometry (see subsection 5.2.2), a clean photometric galaxy sample can be obtained.

We estimate the stellar mass for all galaxies in the combined NSA/photometric catalogue by fitting M_r to the dynamical masses from MaNGA (Figure 5.9). In Figure 5.10, we show that our combined sample is complete down to a stellar mass of about $7.4 \times 10^9 M_\odot$ for $z \leq 0.15$. To improve the selection and remove potential interlopers with large photometric redshifts, we make the important assumption that all neighbours of a MaNGA galaxy should have an absolute luminosity that satisfies the minimum stellar mass ($M_r \leq -18$), assuming all neighbours are at the redshift of the MaNGA galaxy. By making this assumption, we are able to exclude a large fraction of interlopers that overlap in redshift but would not satisfy our luminosity threshold if they are, in fact, bound to the halo containing the MaNGA galaxy (Figure 5.11).

From each set of surviving galaxies that surrounds each MaNGA galaxy, we find the group enclosing the galaxy using the new algorithm `TD-ENCLOSER` (chapter 4) which is optimised for obtaining the local galaxy environment. Because of the decreasing accuracy of the groups with increasing z due to the higher fraction of photometric galaxies, we limit our final sample to groups below $z = 0.08$ (see subsubsection 5.3.4.2). For all galaxies in the catalogue which are not observed with MaNGA, we assign

angular momentum classifications using a novel visual classification method (subsection 5.4.1). We test our method on a sample of 581 galaxies that satisfy the mass and shape criteria for genuine SRs (see Figure 5.14, Figure 5.15 for true-colour images and Figure 5.16, Figure 5.17 for velocity maps of a random selection). We find that we can determine which galaxies are FRs with an accuracy of $\sim 94\%$ (Figure 5.18a). However, we are only correct in about half of all cases where we guess a galaxy to be a SR. This is a slight improvement on the SR positive identification rate of 34% for ETGs found in ATLAS^{3D}. A surprising result is that the eye is qualitatively able to estimate the velocity dispersion in galaxies, as the majority of galaxies we incorrectly identify as SRs are close to the SR boundary (see Figure 5.18b). Crucially, we always correctly identify SRs if they are more massive than about $10^{11.7} M_{\odot}$. The galaxies which we classify as SRs should be considered as SR *candidates* and would make good targets for future observations with IFS (see Figure 5.19 and Figure 5.20 for candidate SRs and FRs respectively).

This last set of results regarding the visual classification of FRs and SRs is the most significant advance to come out of this work, as it opens up the possibility for environmental studies of galaxy angular momentum where only partial IFU observations have been made. The high accuracy of FR classification for massive, round galaxies has potential implications for visual classification of galaxies in general, as it suggests that the presence of ordered disk rotation across populations is easily detectable by eye. An interesting point not already mentioned is that of the 206 ETGs that were classified as FRs, 62% were classified by eye to be ellipticals. If the ‘elliptical’ classification is intended to mean ‘spheroidal’, then it is perhaps surprising that more than half of all massive, round ETGs are classified as such, considering that FRs are disk. We have demonstrated that it is possible to positively identify FRs by eye, but not SRs with any certainty. It would be instructive to investigate the possibility of using machine learning models to improve the SR classification rate by replicating the method used here on visual data, as the potential would be enormous if SRs could be identified with reasonable accuracy without the requirement for IFS observations (although IFS is necessary to confirm λ_{Re}).

In Table 5.3, Table 5.4 and Table 5.5, we tabulate a small portion of our group catalogue. In chapter 6, we use this catalogue to conduct the largest study of galaxy kinematics and the kT- Σ relation to date. The high level of accuracy overall for our angular momentum classifications, combined with its large scope, makes our catalogue the benchmark for future studies of this kind, and has the potential to provide powerful constraints on galaxy evolution.

Table 5.3: Table containing the group characteristics. Column (1) gives the group number and Column (2) gives the group richness. Column (3) gives the group radius equal to the 90th percentile of D_{cen} . Columns (4) and (5) give the coordinates of the central galaxy of the group and Column (6) gives the redshift of the host MaNGA galaxy (see section 4.5). Only the first 30 rows are shown.

Group Number (1)	Group Richness $\mathcal{N}$ (2)	90th % (Mpc) (3)	RA ($^{\circ}$) (4)	DEC ($^{\circ}$) (5)	Redshift of host galaxy (6)
1	1	0.0	230.50746	43.53234	0.0205
2	1	0.0	231.3607	43.1699	0.0575
3	1	0.0	229.52558	42.74584	0.0403
4	1	0.0	230.15302	41.96044	0.0645
5	3	0.347	231.20531	42.17256	0.0188
6	1	0.0	230.57438	42.28702	0.0179
7	1	0.0	230.59834	43.36778	0.1105
8	1	0.0	232.16734	43.02268	0.0286
9	1	0.0	231.47876	41.90977	0.0227
10	1	0.0	231.57732	41.29463	0.0309
11	1	0.0	231.6067	42.35403	0.028
12	1	0.0	230.23367	42.77554	0.0183
13	3	0.238	232.16464	42.43981	0.0751
14	1	0.0	229.24684	42.59826	0.0405
15	1	0.0	232.01387	42.81367	0.0916
16	1	0.0	205.07482	26.34956	0.0284
17	1	0.0	206.47067	26.77516	0.0299
18	4	0.388	205.47557	27.0626	0.0289
19	1	0.0	205.53997	27.57037	0.0288
20	1	0.0	205.04477	26.84104	0.0318
21	4	0.347	203.93349	26.11623	0.067
22	1	0.0	205.00799	26.9789	0.0275
23	2	0.075	205.26734	27.69384	0.0285
24	3	0.372	203.78377	25.49544	0.0267
25	1	0.0	204.51286	26.33821	0.0261
26	1	0.0	204.69273	26.49877	0.0295
27	1	0.0	204.88484	27.10715	0.0324
28	5	0.446	204.60071	26.77924	0.029
29	1	0.0	317.94353	9.27749	0.0395
30	7	0.755	317.04129	11.3196	0.0715

Table 5.4: Table containing the relevant information for the MaNGA galaxies in our sample. Descriptions for columns 1-16 are found in the caption of Table 3.1. Column 17 is the final group number that the MaNGA galaxy appears in and can be used to match up with Table 5.3. Columns 18, 19, 20, 21 and 22 are $\log(\Sigma_3)$, $\log(\Sigma_3^{\text{rel}})$, $\log(\Sigma_{10})$, D_{cen} , $D_{\text{cen}}^{\text{norm}}$ respectively. Only the first 30 rows are shown.

MaNGA-ID	Clean Sample?	Hubble Group	Kinematic Classification	$\log(P_{\text{pec}})$ ($''$)	$\log(R_{\text{maj}})$ (kpc)	PSF ($''$)	$\lambda_{\text{H}\alpha}^{\text{true}}$ ($''$)	ϵ	Ψ_{phot} ($^\circ$)	Ψ_{kin} ($^\circ$)	Error in Ψ_{kin} ($^\circ$)	$\log(M_*)$ (13)	$\log(\sigma_e)$ (km s $^{-1}$)	z	n	Group Number	$\log(\Sigma_3)$ Mpc^{-2}	$\log(\Sigma_3^{\text{rel}})$ Mpc^{-2}	$\log(\Sigma_{10})$ Mpc^{-2}	D_{cen} Mpc	$D_{\text{cen}}^{\text{norm}}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
12-98126	Y	E	R	0.692	0.4	2.6	0.731	0.337	138.5	152.0	6.0	10.36	1.841	0.0205	4.4	1	-0.984	0.0	-0.854	0.0	0.0
12-84674	N	U	R	0.939	0.996	2.5	0.77	0.048	100.6	110.5	8.2	11.1	1.799	0.0575	1.7	2	-0.23	0.0	-0.275	0.0	0.0
12-193481	N	M/CP	R	0.775	0.739	2.6	0.425	0.25	24.9	165.5	12.5	11.33	2.111	0.0403	2.2	3	-0.755	0.0	-0.655	0.0	0.0
12-84731	Y	S0	R	1.105	0.924	2.5	0.756	0.608	114.6	128.0	3.5	10.41	1.882	0.0187	0.9	3548	0.786	-0.951	0.051	0.689	1.073
12-84627	Y	S0	R	0.806	1.09	2.6	0.88	0.586	40.5	42.0	3.8	11.2	2.108	0.0645	1.0	4	0.124	0.0	0.139	0.0	0.0
1-322159	N	S0	R	0.649	0.29	2.6	0.344	0.235	77.9	58.0	15.0	9.78	1.897	0.0188	2.2	5	0.278	-0.033	-0.049	0.265	0.764
1-199287	N	S0	R	0.551	0.307	2.6	0.697	0.547	10.5	6.5	10.8	10.01	1.624	0.0189	2.8	3548	1.544	-0.193	0.035	0.101	0.157
1-322172	Y	I	2S	0.682	0.371	2.6	0.201	0.444	134.7	121.5	89.8	9.45	1.63	0.0179	1.3	6	0.196	0.0	-0.125	0.0	0.0
12-84670	Y	E	NR	0.544	0.855	2.5	0.024	0.032	111.7	68.5	89.8	11.84	2.314	0.1105	6.0	7	-0.456	0.0	-0.606	0.0	0.0
12-180451	N	E	F	0.342	0.13	2.6	-0.990	0.121	143.5	-999.0	-999.0	9.3	-999.0	0.0286	0.9	8	-0.49	0.0	-0.706	0.0	0.0
12-84617	N	E	R	0.529	0.31	2.6	0.169	0.423	65.6	11.0	43.0	9.49	1.916	0.0227	1.6	9	-1.107	0.0	-0.806	0.0	0.0
12-84726	Y	S0	R	0.641	0.515	2.7	0.567	0.315	96.7	126.5	27.8	9.53	1.772	0.0309	1.1	10	-0.892	0.0	-1.076	0.0	0.0
12-180432	Y	S	R	0.83	0.678	2.6	0.649	0.364	128.2	137.0	3.5	10.98	1.992	0.028	1.5	11	-0.425	0.0	-0.645	0.0	0.0
12-84665	Y	S0	R	0.772	0.516	2.6	0.481	0.548	15.3	28.5	3.8	9.98	1.925	0.0183	0.8	12	-0.189	0.0	0.016	0.0	0.0
12-84677	Y	E	R	0.79	1.006	2.6	0.701	0.25	123.6	106.5	3.0	11.71	2.185	0.0751	3.1	13	0.136	-0.111	0.293	0.036	0.151
12-84660	Y	S	R	0.834	0.831	2.6	0.711	0.348	67.1	73.0	1.8	10.92	1.785	0.0405	2.4	14	-0.762	0.0	-0.749	0.0	0.0
12-84679	Y	E	R	0.766	1.082	2.5	0.156	0.32	50.6	52.5	8.0	11.83	2.439	0.0916	6.0	15	-0.475	0.0	-0.435	0.0	0.0
12-192120	Y	S0	R	0.747	0.866	2.3	0.522	0.193	120.8	143.0	6.2	11.25	2.149	0.0612	1.2	-999	-999.0	-999.0	-999.0	-999.0	-999.0
12-129612	Y	S	R	0.879	0.958	2.3	0.899	0.775	13.6	13.5	1.5	11.05	2.071	0.0284	1.8	16	0.17	0.0	0.436	0.0	0.0
1-458515	N	S0	R	1.007	0.944	2.3	0.922	0.522	15.1	15.0	2.0	10.88	2.012	0.0299	0.8	17	-0.624	0.0	-0.421	0.0	0.0
1-458396	Y	S	R	1.057	0.938	2.3	0.902	0.418	151.3	171.5	1.5	11.17	2.061	0.0289	1.3	18	0.747	0.0	-0.012	0.144	0.371
12-129629	Y	S0	R	0.882	1.108	2.3	0.262	0.263	56.0	119.0	28.2	11.1	1.928	0.0762	4.7	2543	1.251	-1.036	1.113	1.061	0.801
12-110746	Y	E	R	0.358	0.161	2.3	0.219	0.174	16.4	9.5	20.0	10.31	2.065	0.0288	4.9	19	-0.008	0.0	-0.299	0.0	0.0
12-129608	Y	S0	R	0.394	0.34	2.3	0.881	0.481	14.2	23.5	10.0	10.06	1.772	0.0318	2.2	20	-0.687	0.0	-0.767	0.0	0.0
12-129446	Y	S0	R	0.77	0.911	2.3	0.754	0.138	145.2	156.5	3.0	11.5	2.076	0.067	2.0	21	0.628	-0.084	0.549	0.081	0.233
12-192149	Y	S0	R	0.593	0.589	2.3	0.791	0.689	45.6	52.0	10.0	10.18	1.888	0.0275	1.2	22	-0.339	0.0	-0.234	0.0	0.0
12-110756	Y	S0	R	0.555	0.595	2.2	0.961	0.728	136.1	162.5	23.5	9.92	1.74	0.0285	0.5	23	0.303	0.0	-0.136	0.083	1.107
12-129601	Y	S0	R	0.649	0.467	2.3	0.42	0.144	24.2	6.0	4.0	11.01	2.217	0.0304	5.2	-999	-999.0	-999.0	-999.0	-999.0	-999.0
12-129434	Y	S0	R	0.679	0.483	2.4	0.514	0.289	148.5	144.5	13.5	9.51	1.9	0.0267	0.9	24	0.099	-0.434	-0.14	0.0	0.0
12-192116	Y	I	R	0.879	0.656	2.3	0.368	0.233	101.5	172.0	9.0	9.4	1.754	0.0261	2.5	25	-0.321	0.0	-0.022	0.0	0.0

Table 5.5: Table containing the characteristics for all galaxies in our group catalogue that are not in the MaNGA sample. For each galaxy, columns (1) gives its enclosing group number and columns (2) and (3) give the RA and Dec from the combined NSA+SDSS catalogue Columns (4) - (8) give $\log(\Sigma_3)$, $\log(\Sigma_3^{\text{rel}})$, $\log(\Sigma_{10})$, D_{cen} and $D_{\text{cen}}^{\text{norm}}$ which are all measured in this work. Columns (9) and (10) list the redshift and redshift error respectively from the combined catalogue, and Columns (11) and (12) give the absolute magnitude and error in magnitude respectively. Column (13) gives the stellar mass in log units calculated using the relation shown in Figure 5.9. Column (14) gives the ellipticity ϵ taken from the combined NSA+SDSS catalogue and Column (15) gives the angular momentum classification. This classification is S for galaxies which have been visually classified as SRs and satisfy the criteria for SRs, and F otherwise. Finally, Column (16) gives the object name from the HyperLEDA catalogue (Paturel et al., 2003) if there is a match. Only the first 20 rows are shown.

Group Number (1)	RA ($^{\circ}$) (2)	DEC ($^{\circ}$) (3)	Σ_3 (Mpc^{-2}) (4)	Σ_3^{rel} (Mpc^{-2}) (5)	Σ_{10} (Mpc^{-2}) (6)	D_{cen} (Mpc) (7)	$D_{\text{cen}}^{\text{norm}}$ (8)	Redshift z (9)	Redshift error Δz (10)	Absolute Magnitude M_r (11)	Magnitude error ΔM_r (12)	$\log(M)$ (13)	Ellipticity ϵ (14)	Angular Momentum (15)	Object Name (16)
6	231.05952	42.39746	0.311	0.0	-0.054	0.368	1.061	0.0186	0.0	-19.86	0.2	10.64	0.61	F	PGC054995
15	232.16464	42.43981	0.136	-0.111	0.289	0.0	0.0	0.1727	0.1098	-18.59	0.916	10.11	0.18	F	-
15	232.21886	42.42426	0.247	0.0	0.304	0.289	1.214	0.0751	0.0	-19.83	0.2	10.63	0.26	F	SDSSJ152852.52+422527.3
21	205.47557	27.0626	0.595	-0.152	-0.04	0.0	0.0	0.0287	0.0	-18.52	0.2	10.08	0.84	F	PGC1796683
21	205.54325	26.8366	0.42	-0.327	-0.045	0.493	1.271	0.029	0.0	-18.82	0.2	10.21	0.2	F	PGC1789796
25	203.93349	26.11623	0.712	0.0	0.483	0.0	0.0	0.0677	0.0	-21.12	0.2	11.17	0.42	F	PGC1763246
25	203.96621	26.11137	0.454	-0.258	0.561	0.153	0.441	0.0641	0.0225	-18.6	0.034	10.11	0.27	F	-
25	203.84106	26.10623	0.509	-0.203	0.299	0.43	1.239	0.075	0.0101	-20.68	0.223	10.98	0.35	F	PGC1762840
27	205.26734	27.69384	0.281	-0.022	-0.118	0.0	0.0	0.0286	0.0	-19.68	0.2	10.57	0.51	F	PGC1815439
29	203.69127	25.44989	0.156	-0.377	-0.138	0.199	0.535	0.0264	0.0	-18.25	0.2	9.97	0.53	F	PGC1736968
29	203.77524	25.71026	0.533	0.0	-0.102	0.415	1.116	0.0485	0.0296	-18.23	0.008	9.96	0.43	F	-
34	204.00071	26.77924	1.282	0.0	-0.015	0.0	0.0	0.0291	0.0	-19.17	0.2	10.35	0.41	F	PGC048203
34	204.60445	26.74248	1.051	-0.231	-0.022	0.077	0.173	0.0285	0.0	-22.07	0.2	11.57	0.18	S	IC4314
34	204.53374	26.86278	0.788	-0.494	0.041	0.223	0.5	0.0287	0.0	-18.78	0.2	10.19	0.4	F	PGC1790602
37	317.04129	11.3196	0.394	-0.071	0.261	0.0	0.0	0.0522	0.0364	-18.57	1.816	10.1	0.45	F	-
37	317.03331	11.3562	0.436	-0.029	0.164	0.184	0.244	0.0713	0.0	-20.96	0.2	11.1	0.49	F	PGC1392380
37	317.15099	11.38284	0.394	-0.071	0.314	0.621	0.823	0.0755	0.0196	-19.02	0.048	10.29	0.65	F	-
37	316.99296	11.18472	0.396	-0.069	0.313	0.703	0.931	0.0442	0.0342	-19.93	0.006	10.67	0.7	F	-
37	317.06798	11.16976	0.312	-0.153	0.383	0.747	0.989	0.1268	0.0563	-19.3	0.011	10.4	0.93	F	-
37	317.16755	11.412	0.21	-0.255	0.207	0.767	1.016	0.0714	0.0	-20.62	0.2	10.96	0.8	F	PGC1393205

Chapter 6

SDSS-IV MaNGA: New benchmark for the connection between stellar angular momentum and environment: a study of about 900 groups/clusters

The beginning of knowledge is the discovery of something we do not understand.

Frank Herbert

6.1 Introduction

It has long been understood that the optical morphology of galaxies is related to their local environment (Hubble & Humason, 1931; Zwicky, 1942; Sandage, 1961; Oemler, 1974; Melnick & Sargent, 1977). In a seminal paper, Dressler (1980) observed the morphology and position of 6000 galaxies in 55 rich clusters and showed for the first time that there is a fundamental correlation between optical morphology and local projected number density of galaxies. In particular, the spiral population diminishes with increasing local density whereas the fraction of early-type galaxies (ETGs; ellipticals and S0s) increases with increasing local density. This now classic morphology-density relation has been shown to extend to sparser environments (Postman & Geller, 1984; Helsdon & Ponman, 2003; Goto et al., 2003), and it is found to be already established by $z = 1$ (Dressler et al., 1997; Postman et al., 2005; Smith et al., 2005). The morphology-density relation is believed to be universal, although there is evidence to suggest that the relationship between morphology and clustercentric

radius is a more fundamental relation (Whitmore & Gilmore, 1991; Whitmore et al., 1993).

Within ETGs, ellipticals are significantly more clustered than S0s (Dressler, 1980). In fact, the shallow increase in the S0 fraction with increasing local density mirrors the decrease in the spiral fraction suggesting that spirals are transformed into S0s with increasing frequency as the local density increases. Various mechanisms have been proposed to explain this transformation, including ram pressure stripping (e.g. Gunn & Gott, 1972; Abadi et al., 1999; van der Wel et al., 2010), harassment (Moore et al., 1996), starvation/strangulation (Larson et al., 1980; Dekel & Birnboim, 2006) and tidal interactions (e.g. Park et al., 2007; see Boselli & Gavazzi, 2006 for a review on quenching mechanisms of late type galaxies); although it is unclear which mechanisms dominate in groups (Smethurst et al., 2017) and clusters (Taranu et al., 2014; Boselli et al., 2016). Mergers are also thought to play a role, although galaxy interactions are more likely to take place in the group environment compared to a cluster environment (Martínez & Muriel, 2006a; Zabludoff & Mulchaey, 1998; Hashimoto & Oemler, 2000; Wilman et al., 2005; Martínez & Muriel, 2006b). There is plenty of evidence to suggest that some S0s are the product of gas-rich (wet) major/minor mergers (Barnes, 2002; Springel & Hernquist, 2005; Robertson et al., 2006; Hopkins et al., 2009; Moster et al., 2011; Querejeta et al., 2015), as the gas is able to dissipate kinetic energy while also conserving its mass and specific angular momentum. The process of dissipation encourages disks to form (Fall & Efstathiou, 1980; Abadi et al., 1990; Kormendy & Bender, 1996), as it tends to reduce the kinetic energy in the direction parallel to the spin axis (Cappellari et al., 2007).

As a result of the development of integral field spectroscopy (IFS), it has become clear that the S0/elliptical classification of ETGs, which is intended to separate disks and spheroids, is strongly affected by inclination, and in fact two-thirds of all spheroids are actually misclassified face-on, axisymmetric disks (Cappellari et al., 2011b). A more robust classification is based on the specific stellar angular momentum within one effective radius, denoted λ_{Re} , which is obtained from observations of the stellar kinematics made possible with IFS (Emsellem et al., 2007, 2011). A recent revision to the classification scheme defines ETGs as slow rotators if they have low λ_{Re} as a result of highly disordered stellar motions *and* appear round as quantified by the ellipticity within $1R_e$, $\epsilon \equiv 1 - b/a$ where a and b are the semi-major and semi-minor axes respectively (C16). All other ETGs (and all spirals) are classified as fast rotators which collectively form a homogenous family of axisymmetric disk galaxies that are supported by rotation and show a range of bulge-to-total ratios (see C16 for a review).

In subsection 3.1.1, we used a sample of about 2300 galaxies with IFS data of all morphological types to show, without any ambiguity, that fast and slow rotators form two distinct galaxy populations separated by a clean break in angular momentum. They are not a single population within which ETGs transition smoothly from fast to slow rotation. This dichotomy is consistent with previous expectations based on much smaller galaxy samples (C16). Fast and slow rotators are also distinct in stellar mass and the orientation of the spin axis. SRs are generally massive whereas FRs appear at all masses (Cappellari, 2013; Figure 3.9). In FRs the spin axis is perpendicular to the disk, but in SRs, the spin axis is randomly orientated (Krajnović et al., 2008, 2011; Fogarty et al., 2015, Figure 3.8) as a result of their triaxiality (Weijmans et al., 2014; Foster et al., 2017; Li et al., 2018c). The fact that fast and slow rotators form a dichotomy in a number of properties suggests that they have followed separate evolutionary channels.

The fact that the fast/slow classification is based on galaxy *structure* prompted Cappellari et al. (2011b) to update the classical morphology-density relation into a *kinematic* morphology-density relation (hereafter kT- Σ relation), where ETGs are split according to their angular momentum content. They used the pioneering volume-limited ATLAS^{3D} survey of 871 nearby galaxies (Cappellari et al., 2011b) of all morphological types to study the kT- Σ relation for the first time. The sample included the Virgo cluster, which meant it was possible to compare galaxy populations across over four orders of magnitude in number density, from the field to the dense core of Virgo. They found that the linear *decrease* of spirals mirrors the linear *increase* in fast rotator ETGs, a result that is consistent with the classical morphology-density relation (Dressler, 1980). This linear trend breaks inside the core of Virgo (galaxy surface density of $\sim 200 \text{ Mpc}^{-2}$), where spirals dramatically decrease in number. Cappellari et al. (2011b) concluded that different processes act in the cluster core to transform spirals into FRs, such as ram-pressure stripping which strips the cold gas as well as prevents cold gas accretion.

On the other hand, SRs only appear in any significant fraction in the density bin corresponding to the core of Virgo. Cappellari et al. (2011b) attributed this increase to the high frequency of close encounters and minor mergers that galaxies now lying in the centre of clusters undergo during their evolution, compared to the field. A prerequisite for SR formation is that the merger must be gas-poor i.e. a dry merger (Jesseit et al., 2009; Bois et al., 2010, 2011; Hoffman et al., 2010; Li et al., 2018a; Penoyre et al., 2017). In this scenario, dissipation is not possible as the system is dominated by a collisionless stellar component.

The relics of dry mergers can be distinguished from other elliptical galaxies by the presence of a flux deficit in the nuclear region of the surface brightness profile (Faber et al., 1997). This is the reason why the fast/slow rotator dichotomy essentially traces the separation between galaxies with a core and the rest (Ferrarese et al., 1994; Lauer et al., 1995, 2005; Kormendy et al., 2009) as shown by Lauer (2012), Krajnović et al. (2013b) (page 23) and Krajnović (2019). Cores are thought to arise as a consequence of a merger between two galaxies each containing a supermassive black hole that sinks to the centre of the merger remnant via dynamical friction to form a binary (Faber et al., 1997; Volonteri et al., 2003; Trujillo et al., 2004). Successive three-body interactions between stars and the resulting binary eject a stellar mass roughly equivalent to the total mass of the binary (Ebisuzaki et al., 1991; Milosavljević & Merritt, 2001). The angular size of these cores is a small fraction compared to the galaxy and are only resolvable with HST imaging (Crane et al., 1993; Lauer et al., 1995; Faber et al., 1997). Fortunately, Cappellari (2013) found that the stellar mass of genuine core SRs exceeds a critical stellar mass of $M_{\text{crit}} = 2 \times 10^{11} M_{\odot} = 10^{11.3} M_{\odot}$. Enforcing this criterion allows one to remove “spurious” SRs, namely SRs likely not formed through multiple dry mergers, like for example 2σ galaxies (see page 2 of Krajnović et al., 2011) in large surveys where HST imaging is not available.

Although massive SRs dominate in the centres of clusters, they are not completely absent in the field. Cappellari (2013) presented the mass-size relation for the ATLAS^{3D} field sample and found 10 examples of massive core SRs. Cappellari (2013) suggested that they form in galaxy groups at high redshifts and sink to the centre of the dark matter halo of the group via dynamical friction (Chandrasekhar, 1943; White, 1976; Kashlinsky, 1986). These halos merge with other nearby halos in a hierarchical way (White & Rees, 1978; White & Frenk, 1991; De Lucia et al., 2012). As the massive SRs are essentially at rest within each subhalo and they have a large collisional cross-section, they are able to merge on radial orbits (Ramírez & de Souza, 1998; Boylan-Kolchin et al., 2006; Von Der Linden et al., 2007). In contrast, the FRs and spirals have lower masses, small collisional cross-sections and higher relative velocities, and so are much less likely to merge (C16). Hence, the track on the mass-size relation followed by massive SRs is steeper ($R \propto M$) than for FRs, as they follow different evolutionary paths (C16, Figure 3.9). Scott et al. (2014) note that this hierarchical scenario is more realistic than one where SRs are drawn to the centres of clusters by dynamical friction alone. They showed that for a mass-matched sample, SRs are more biased to denser environments compared to FRs. If dynamical friction were indeed the cause, then we would expect SRs and FRs of similar masses

to follow the same distribution with respect to local density, given that dynamical friction is only a function of the stellar mass and not the internal kinematic structure of galaxies.

Two challenging aspects of studying galaxy trends as a function of environment are that (1) environment has a similar effect on galaxy properties as mass, and (2) many galaxy properties are driven by stellar mass. In fact, the two effects are separable (Peng et al., 2010) and the classical morphology-density relation has been observed at fixed stellar mass (Bamford et al., 2009). However, the scarcity of massive SRs in a volume limited sample means that a similar study using the kinematic classification scheme requires very large numbers of galaxies. Now, we are in the era of massive IFS surveys. One of these is the SAMI (Croom et al., 2012; Bryant et al., 2015) survey of 3000 galaxies in the Southern hemisphere. SAMI has a dedicated cluster sample (Fogarty et al., 2014; Owers et al., 2017; Brough et al., 2017) which makes it ideal for studying stellar kinematics of cluster galaxies (Fogarty et al., 2015). The second IFS survey currently in operation is the MaNGA survey (Bundy et al., 2015) operating as part of SDSS-IV (Blanton et al., 2017). MaNGA aims to observe 10,000 galaxies with IFS across six years (Yan et al., 2016b). Its unique selection function allows it to observe many more massive galaxies than a volume limited survey, thus making it ideal for studying diverse galaxy populations (Wake et al., 2017). Another survey that is relevant to this work is the MASSIVE survey (Ma et al., 2014) which targets very massive galaxies ($M \gtrsim 10^{11.5} M_{\odot}$) for a volume limited sample and is designed to complement the ATLAS^{3D} survey ($M \lesssim 10^{11.5} M_{\odot}$).

Three separate groups have studied the kT- Σ relation at fixed stellar mass using data from the MaNGA (Greene et al., 2017), SAMI (Brough et al., 2017) and MASSIVE (Veale et al., 2017b) surveys and they have found very little or no correlation between a galaxy’s angular momentum and the local galaxy density. These results have been corroborated by Choi et al. (2018), who separated galaxies in the Horizon-AGN simulation by cluster, groups and field and found very little trend in λ_{R_e} with the number density at fixed stellar mass. These results have been interpreted as evidence that the kT- Σ relation is in fact driven by segregation of stellar mass, whereby the most massive galaxies sink to the centre of the potential well of galaxy groups and clusters and so find themselves at the highest densities *as a result* of their stellar mass (Brough et al., 2017). In actual fact, there is no clear reason why such a trend should exist, because by only considering galaxies in a certain mass bin, the resulting subsample is naturally restricted in terms of the environment. One possible interpretation of these results is that dense environments are not required to form slow

rotators. This may seem to be in tension with the results from nearby clusters, which clearly illustrates that massive core SRs have a distinctly different spatial distribution to FRs and spirals (Cappellari, 2013; D’Eugenio et al., 2013; Houghton et al., 2013; Scott et al., 2014; Cappellari, 2016). However, these two different conclusions are not necessarily inconsistent, as they merely represent two alternative ways of looking at the same problem.

It should be noted that Lee et al. (2018) studied the relationship between galaxy spin and small- and large-scale environment for a sample of $\sim 1500 - 1800$ MaNGA galaxies. They found that galaxy spin is insensitive to the large-scale environment as probed by a background mass density of 20 nearby galaxies. However, they found some evidence that λ_{R_e} for late-type galaxies is sensitive to the distance to the nearest neighbour (small scale environment), if the neighbours are early-type galaxies. They suggest that their results indicate that hydrodynamical interactions can play a part in reducing the spin of regular rotators. However, they make no conclusions about the distribution of fast and slow rotators with respect to their environment.

Up until now, studies have fallen into two camps: detailed studies of a few individual clusters with complete kinematic observations, including the Fornax, Coma and Virgo clusters, or extensive studies with the MaNGA, SAMI and MASSIVE surveys of many clusters each with incomplete kinematic classifications (although SAMI does have a cluster sample). In this chapter, we try to combine the strengths of both approaches by studying many clusters, each with complete kinematic classifications in order to gain valuable insight into the role of environment in galaxy transformation and kinematic structure.

We base our analysis on stellar kinematics of about 4500 galaxies released as part of the MaNGA Product Launch 7 (MPL-7) internal data release. MaNGA is “agnostic” to environment (see Smethurst et al., 2018), meaning that any selection in environment, if present, arises indirectly as a result of the other selection criteria (for example stellar mass). MaNGA does not target specific clusters, apart from one ancillary programme (Gu et al., 2018), and so galaxies are selected from multiple distinct groups. Hence, we do not have complete stellar kinematic observations for any clusters which play host to MaNGA galaxies. To overcome this, we have developed a novel method to assign angular momentum classifications to all galaxies for which we do not have stellar kinematics, which we describe in detail in subsection 5.4.1. As a result, we have a sample of about 14,000 galaxies in groups of $z \leq 0.08$ of which $\sim 98.8\%$ have accurate angular momentum classifications. These are galaxies which either (1) have stellar kinematic observations, (2) do not satisfy the criteria for

genuine SRs ($\log(M) < 11.3$ or $\epsilon \geq 0.4$) and so by definition must be FRs, or (3) have been visually classified as FRs with 94% accuracy. The remaining $\sim 1.2\%$ (about 200 galaxies) satisfy the criteria for genuine SRs ($\log(M) \geq 11.3$ and $\epsilon < 0.4$) and have been visually classified as SRs. However, for this specific case, the classification is only accurate about half the time. This is the largest sample of its kind and will provide the basis for the in-depth study of angular momentum and environment that we present here.

In section 6.7, we present schematics for ten clusters in our sample, highlighting the locations of the massive SRs in particular. In section 6.2, we study the environmental properties of galaxies for all group sizes taken from our catalogue. We also compare with previous works by attempting to reproduce their results using similar methodologies (section 6.3). Finally, in section 6.4, we describe the powerful technique of Bayesian logistic regression that allows us to explore the abundance of massive SRs in a three dimensional parameter space without binning the data.

6.2 Results

We start by updating the (λ_{Re}, ϵ) diagram for about 4000 galaxies in MPL-7. This sample is nearly twice as large than the one we presented in subsection 3.1.1. We then present the results from our complete kinematic study.

6.2.1 Stellar angular momentum of about 4000 galaxies

We update Figure 3.1b for a sample of 4003 galaxies which we present in Figure 6.1. We apply the correction introduced in section 2.5 to account for the effect on λ_{Re} due to the atmospheric seeing. This correction was tested by Harborne et al. (2019) on realistic galaxy models with a range of bulge-to-total mass ratios and Sérsic indices and which are completely independent of the JAM models used to derive the correction. They generated 1425 simulated observations from their models according to the SAMI specifications and measured λ_{Re} for a range of seeing conditions. They found that the atmospheric correction does a good job in recovering the intrinsic λ_{Re} with no systematic deviations for a range of PSF widths (see their fig. 10). They also confirmed the level of scatter seen in Figure 2.9 due to the inclination.

The upper envelope does not extend as high in Figure 6.1 compared to Figure 3.1b. In short, the reason for the discrepancy is because here we use a fixed value for the correction required to obtain the astrophysical velocity dispersion, σ_{corr} of 40 km s^{-1} , whereas in section 2.2, we use the value provided by the DAP, which has a median

value of $\sigma_{\text{corr}} = 51 \text{ km s}^{-1}$ for MPL-5. We do not use σ_{corr} provided for MPL-7 for the reasons outlined below.

For MPL-5, the DAP calculated σ_{corr} as a quadrature difference:

$$\sigma_{\text{corr}}^{\text{MPL-5}} = \sqrt{(\sigma_{\text{inst}}^{\text{MaNGA}})^2 - (\sigma_{\text{inst}}^{\text{MILES}})^2} \quad (6.1)$$

where $\sigma_{\text{inst}}^{\text{MaNGA}}$ and $\sigma_{\text{inst}}^{\text{MILES}}$ are the instrumental resolution of the MaNGA spectra and the MILES templates respectively (e.g. Bershady et al., 2010; Westfall et al., 2011). Typically, $\sigma_{\text{inst}}^{\text{MaNGA}} \sim 72 \text{ km s}^{-1}$ (Law et al., 2016) and $\sigma_{\text{inst}}^{\text{MILES}} \sim 50 \text{ km s}^{-1}$ (Sánchez-Blázquez et al., 2006; Falcón-Barroso et al., 2011), leading to a correction $\sigma_{\text{corr}}^{\text{MPL-5}} \approx 52 \text{ km s}^{-1}$. The method used to calculate $\sigma_{\text{corr}}^{\text{MPL-7}}$ for MPL-7 is described in sec. 7.1.5 of Westfall et al. (2019). Briefly, the DAP fits pPXF (Cappellari & Emsellem, 2004; Cappellari, 2017) to the MILES template and the galaxy spectra obtaining σ for both. The quadrature difference between R_{MaNGA}^{-2} and R_{template}^{-2} where $R = \lambda/\Delta\lambda$ is calculated for each wavelength channel. All quadrature differences are summed and the sum is multiplied by a factor proportional to the number of wavelength channels fitted by pPXF. In this way, the average instrumental resolution is taken across all wavelength channels. This method was tested on galaxy models and real galaxies and was found to be more robust (Westfall, private communication) than using Eq. (6.1). In particular, the correction obtained using the latter method is expected to be a few km s^{-1} less than the old method used in MPL-5, meaning that the *intrinsic* σ_* would be higher.

Unfortunately, we find this not to be the case when comparing $\sigma_{\text{corr}}^{\text{MPL-7}}$ with $\sigma_{\text{corr}}^{\text{MPL-5}}$. We find $20 \lesssim \sigma_{\text{corr}}^{\text{MPL-7}} \lesssim 60 \text{ km s}^{-1}$ with a median of $\sim 30 \text{ km s}^{-1}$ compared with $45 \lesssim \sigma_{\text{corr}}^{\text{MPL-5}} \lesssim 80 \text{ km s}^{-1}$ with a median of $\sim 50 \text{ km s}^{-1}$. Although we know that $\sigma_{\text{corr}}^{\text{MPL-5}}$ is not exactly equal to the true velocity dispersion correction because $\sigma_{\text{inst}}^{\text{MaNGA}}$ is generally not well-defined, we also know that $\sigma_{\text{corr}}^{\text{MPL-7}}$ is definitely further from the truth. If we assume that the expected instrumental resolution of MPL-7 is 65 km s^{-1} (Belfiore, private communication), then the expected correction for MPL-7 is $\sigma_{\text{corr}}^{\text{MPL-7}} = \sqrt{65^2 - 50^2} \sim 40 \text{ km s}^{-1}$. This was found to be the case for the MaNGA stellar library MaStar (Yan et al., 2018; Shetty, private communication).

By using a fixed correction $\sigma_* = \sqrt{\sigma_{\text{obs}}^2 - 40^2}$, we can neatly explain why we observe a lower FR envelope in Figure 6.1 compared to Figure 3.1b. We can also explain why we observe a peculiar gap between the magenta line and the isotropic rotator line (green) in Figure 3.1b. In subsection 3.1.1, we attribute this gap to the possible circularisation of the ellipticity due to seeing or perhaps the larger distances in MaNGA compared to ATLAS^{3D} and CALIFA, which have better quality data.

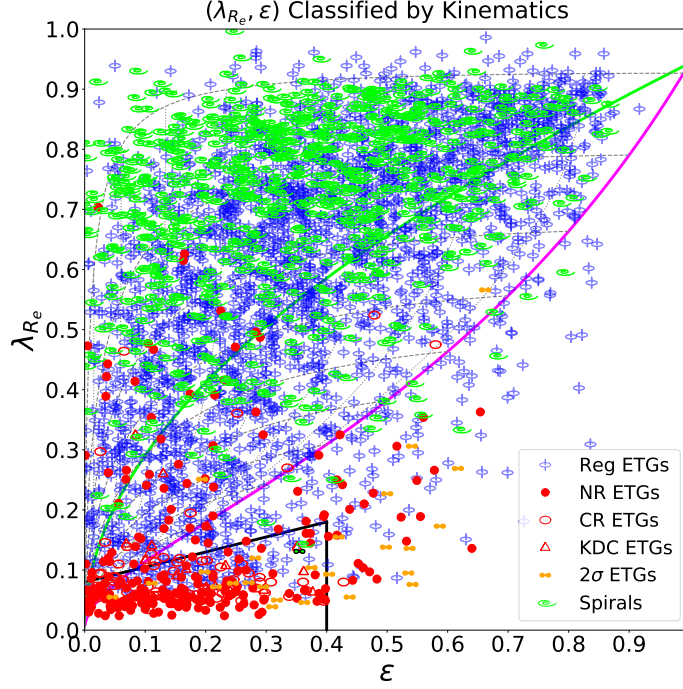


Figure 6.1: $(\lambda_{R_e}, \epsilon)$ **diagram for about 4000 galaxies.** We plot the proxy for specific stellar angular momentum λ_{R_e} and the ellipticity ϵ for 4003 galaxies in MPL-7. The lines and symbols are the same as in Figure 3.1a. All points outside the SR region have been corrected for atmospheric seeing using Eq. (2.14).

We now understand that λ_{R_e} was overestimated due to an overestimation of σ_{corr} which was brought to our attention with the development of the new, more robust correction. More work has been done since the release of MPL-7 to understand this complex issue.

We only plot 4003 galaxies in Figure 6.1, but there are 4597 galaxies in MPL-7. About 600 galaxies do not satisfy the quality control criteria given in subsection 2.2.5 and so their λ_{R_e} and/or ϵ are not deemed to be accurate enough to place on the $(\lambda_{R_e}, \epsilon)$ diagram. Many of these galaxies are mergers or have flagged kinematics for example. For these galaxies, we classify them as fast or slow rotators using the method from section 5.4 as well as the stellar kinematics. Because we do have the stellar kinematics for these galaxies, we do not consider them to be affected by the misclassification bias because we have extra information from the kinematics.

6.2.2 Results from a volume-limited sample of about 14000 galaxies

The MaNGA survey selection is agnostic to environment, meaning that while the survey has no selection in environment, the flat selection in stellar mass means that the number of dense environments will be higher than for a volume limited sample. There is nothing special about the groups in our catalogue, or in other words, there is no reason why the galaxy groups contained in this sample should be different from any other groups which do not enclose any MaNGA galaxies (and therefore are not presented here).

6.2.2.1 $F(\text{SR})$ vs $\log(\Sigma_3)$

In Figure 6.2, we present $\mathcal{N}$ vs $\log(\Sigma_3)$ for 14093 galaxies. Each point corresponds to a galaxy, but in places where the density of blue points is too high, we simply draw a line. All the points on the same horizontal line do not necessarily belong to the same group; they simply share the same group richness $\mathcal{N}$. Galaxies are coloured red or salmon if they are SRs (MaNGA = C16 box criterion, non-MaNGA = visual classification and $\epsilon < 0.4$) *and* have a stellar mass greater than M_{crit} . We separate SRs that lie in groups of four or larger (red) from those that are either isolated or lie in pairs or triplets (salmon). This is purely because Σ_3 includes galaxies from nearby groups when $\mathcal{N} \leq 3$, and so there is a large shift in the $\log(\Sigma_3)$ distribution between $\mathcal{N} = 3$ and $\mathcal{N} = 4$. (Later on we change the separation for a different reason.) All other galaxies are coloured blue.

First, we consider the x -axis histogram in Figure 6.2, namely the kT- Σ relation for massive SRs. In all cases, $F(\text{SR})$ is defined as the fraction of massive SRs compared to all galaxies i.e. $F(\text{SR}) = N(\text{SR})/[N(\text{SR}) + N(\text{FR})]$ where $N(\text{FR})$ is the number of galaxies which are *not* massive SRs i.e. are FRs or are less massive than M_{crit} but are classified as a SR with kinematics. In general, $F(\text{SR})$ increases from $\sim 1\%$ at low number density to $\sim 7\%$ at high number density. We are close to the value of 4% reported by Cappellari et al. (2011b) for $F(\text{SR})$ in the field (compared to all galaxies). For ETGs only, Houghton et al. (2013) and Cappellari et al. (2011b) find a fraction of 15% if the fraction is defined as $N(\text{SR})/N(\text{FR})$ (where FR does not include spirals). We do not have access to Hubble morphologies for all galaxies in our sample, and so cannot confirm this fraction. However, as we are consistent with Cappellari et al. (2011b) for all galaxies (including spirals), we have every reason to agree with the 15% fraction for ETGs in the field.

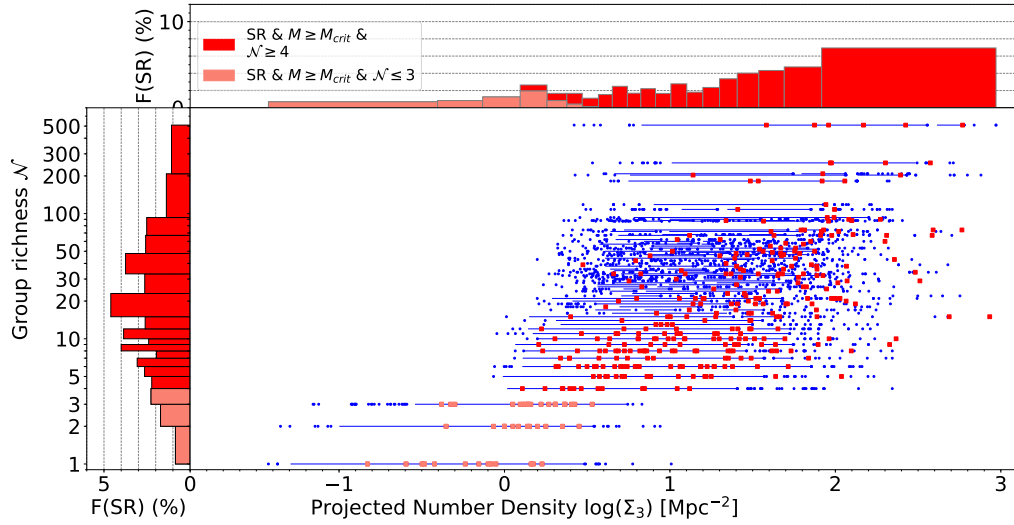


Figure 6.2: **Kinematic morphology-density relation.** We plot group richness $\mathcal{N}$ as a function of $\log \Sigma_3$ for all galaxies in our sample. The y -axis is shown as a logarithmic scale for visual purposes. Each horizontal line corresponds to a single group richness. In the lower half of the diagram, there will be multiple groups on a single line, whereas for the upper half, there will be between one to a few groups on a single line. For $1 \leq \mathcal{N} \leq 3$, $\log(\Sigma_3)$ necessarily includes galaxies which lie in the field or in nearby groups. Massive SRs in these groups are coloured salmon, while massive SRs in groups of $\mathcal{N} \geq 4$ are coloured red. FRs are coloured blue and in places where the density of blue points is too high, we instead show a thin line. The medians for the blue and red/salmon population for $\mathcal{N}$ and $\log(\Sigma_3)$ are shown as blue and red dashed lines respectively. We do not include isolated galaxies for the horizontal median as there are roughly equal numbers of blue points just on the $\mathcal{N} = 1$ line compared to $\mathcal{N} > 1$. We also plot the $F(\text{SR})$ histograms along both axes, with the salmon population separated from the red population.

However, we can confidently rule out a fraction of 15% for $2 \lesssim \log(\Sigma_3) \lesssim 3$ as was claimed by Houghton et al. (2013). We can do this because spirals are nearly absent in this regime and so we are essentially only considering ETGs (Cappellari et al., 2011b). We also have very good number statistics with about 700 galaxies in each Σ_3 bin. In section 6.7, we present schematics for the most massive clusters in our sample. In some cases, we combine clusters which are geographically adjacent, but in Figure 6.2, we keep them separate. The largest cluster in our sample is the Coma cluster, which occupies the top line at $\mathcal{N} \approx 500$ in Figure 6.2. There are six massive SRs, only one of which is a candidate. The total $F(\text{SR})$ for all galaxies in Coma is 1%, while for the highest density bin, $F(\text{SR})$ is approximately $4/200 = 2\%$. The difference between this fraction and the 15% fraction quoted by Houghton et al. (2013) for all densities cannot be attributed to the fact that Houghton et al. (2013) considered SRs of all masses, since the number of (non dry merger relic) SRs below M_{crit} is small. Hence, we can confidently rule out a constant fraction $F(\text{SR})$ of 15% *in clusters*.

There is a small bump at $\log(\Sigma_3) \approx 0.3$ corresponding to the number density where the $\mathcal{N} \leq 3$ and $\mathcal{N} \geq 4$ overlap. Indeed, the two coloured histograms should be considered separately. There is a very weak trend for $\mathcal{N} \leq 3$ which implies that $F(\text{SR})$ for isolated galaxies, galaxy pairs or triplets somehow depends on the distance to the nearest galaxy or group. Assigning galaxies to groups is not a solved problem. Our group-finder algorithm, described in chapter 4, clips outliers from the edge of groups which then go on to form new, smaller groups. However, the number density is unchanged and so we find a few small groups which are close to nearby, denser groups. This artificially causes the slight bump at $\log(\Sigma_3) \approx 0.3$.

6.2.2.2 $F(\text{SR})$ vs $\mathcal{N}$

We plot the fraction of massive SRs as a function of group richness $\mathcal{N}$ as a histogram along the y -axis in Figure 6.2. The fraction increases from 1% for isolated galaxies (comparable to the 2% reported by Cappellari et al., 2011b) to $\sim 6\%$ for $\mathcal{N} \approx 10 - 30$. Beyond $\mathcal{N} = 30$, the fraction decreases to about 1 – 2% at $\mathcal{N} \approx 200 - 500$. Each bin contains at least 500 galaxies and so the measurement is of high accuracy. The fact that a peak exists at intermediate $\mathcal{N}$ suggests that there is an optimal group size where the process which facilitates the formation of SRs is at its most efficient. There is a chance that the height of this peak is more pronounced by virtue of the fact that our groups are not selected at random, but are only in our study because they contain MaNGA galaxies. Since the MaNGA galaxies are flat in stellar mass, we may have

more groups with SRs at a given $\mathcal{N}$ than for a volume limited sample. However, as already discussed, the groups themselves are not special in any way and so we are confident that the peak is real. If we calculate the fraction of *groups* which contain at least one massive SR as a function of $\mathcal{N}$, we find that this fraction increases roughly linearly from 1% for $\mathcal{N} = 1$ to about 100% for $\mathcal{N} \approx 30$. All groups with 32 members or more contain at least one massive SR.

6.2.2.3 F(SR) vs $\log(\Sigma_3^{\text{rel}})$

As discussed in subsubsection 5.3.4.1, the fraction of SRs at a given $\log(\Sigma_3)$ is not a constant, but can vary by up to about 33%. We defined a new parameter Σ_3^{rel} which shifts all clusters to a common baseline such that the galaxy at the peak density has a value of $\log(\Sigma_3^{\text{rel}}) = 0 \text{ Mpc}^{-2}$. Clearly, this does not make sense for individual galaxies or galaxies in small groups, and so we only calculate F(SR) as a function of $\log(\Sigma_3^{\text{rel}})$ for groups with 10 or more members as indicated in Figure 6.3. There is a clear difference between F(SR) as a function of $\log(\Sigma_3^{\text{rel}})$ compared to $\log(\Sigma_3)$. For the seven bins where $\log(\Sigma_3^{\text{rel}}) \gtrsim -0.5 \text{ Mpc}^{-2}$, F(SR) fluctuates between 5% and 10%. For all other bins, F(SR) is less than 3% and for $\log(\Sigma_3^{\text{rel}}) \lesssim -1 \text{ Mpc}^{-2}$, the fraction is less than about 1%. The striking variability in F(SR) above and below $\Sigma_3^{\text{rel}} \sim -0.5 \text{ Mpc}^{-2}$ reflects what we see by eye (see section 6.7). At the locations of peak density in groups and clusters, the fraction of galaxies that are massive SRs is a factor of 5-10 higher than in regions which are underdense compared to the peak.

The red histogram ($\mathcal{N} \geq 4$) steadily increases from $\log(\Sigma_3) \approx 0.1$ up to the maximum number density, in agreement with previous results. The kT- Σ relation presented here is an upper limit, as some of the galaxies we identify as SRs will inevitably be misclassified. However, another source of uncertainty to consider is that due to the errors in ellipticity and λ_{R_e} , although the latter only applies to galaxies with λ_{R_e} measurements. To simulate the effect due to random errors, we randomly perturb ϵ values for all galaxies 100 times within an error $\Delta\epsilon$, which can be calculated from Figure 2.1b as $2.6 \times 0.056/\sqrt{2} \sim 0.1$. For MaNGA galaxies only, we randomly perturb λ_{R_e} within $\Delta\lambda_{R_e}$. For each dataset, we select all galaxies that satisfy the SR criteria. Galaxies which lie close to the border of the SR region risk becoming FRs and vice versa. The uncertainty in λ_{R_e} due to random noise in V, σ etc. is illustrated in fig. 29 of Yan et al. (2016b) where $\Delta\lambda_{R_e}$ is shown as a function of λ_{R_e} . We fit the 2σ percentiles by eye to be $\Delta\lambda_{R_e} = 0.02 + 0.08\lambda_{R_e}$. Clearly this breaks down at $\lambda_{R_e} \sim 1$ as random errors will not push λ_{R_e} above 1. However, this is only a crude fit that needs only to be realistic for low λ_{R_e} values near the SR regime. We add

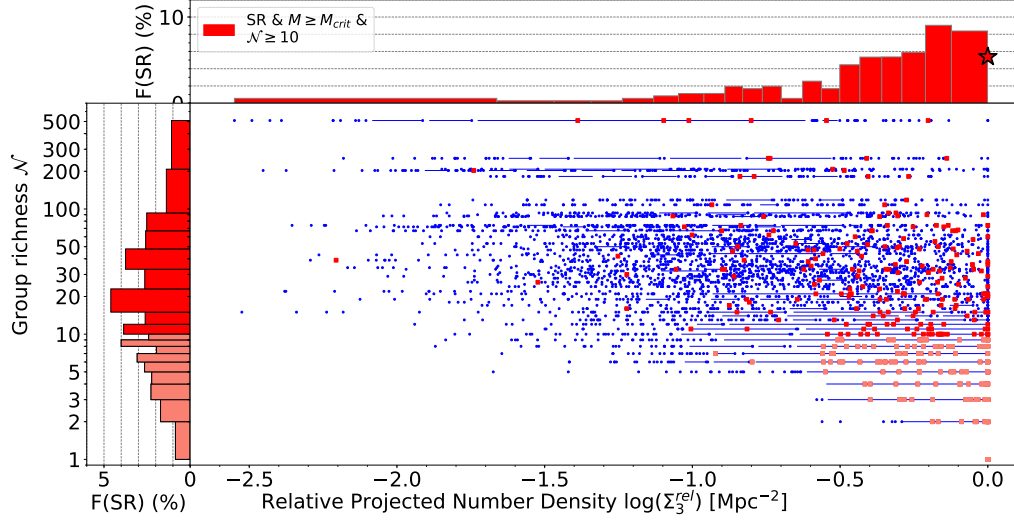


Figure 6.3: **Relative number density.** The same as Figure 6.2 except that the x -axis now shows the relative number density $\log(\Sigma_3^{\text{rel}})$. Unlike Fig. 6.2, groups with $\mathcal{N} < 10$ are distinguished from $\mathcal{N} \geq 10$. The histogram along the x -axis only considers groups with $\mathcal{N} \geq 10$ to avoid contamination from small groups and isolated galaxies. The red star shows the fraction for galaxies with $\log(\Sigma_3^{\text{rel}}) = 0$ and $\mathcal{N} \geq 10$.

an extra source of error due to the beam smearing correction (see Eq. (2.14)). As discussed in section 2.5, the correction gives an upper limit to the true value of λ_{R_e} . We find that the mean error in the $-\lambda_{R_e}$ direction for MPL-5 is 0.03 (see Table 3.1). Hence, our random error on λ_{R_e} is $[(+)(0.02 + 0.08\lambda_{R_e}), -(0.05 + 0.08\lambda_{R_e})]$.

In the left hand side panel of Figure 6.4, we show the uncertainty in the $\text{kT}-\Sigma_3^{\text{rel}}$ relation due to random measurement errors. For galaxies not in MaNGA, we only consider errors in ellipticity, assuming that the stellar mass and all visual classifications are correct. (The way to simulate the errors in λ_{R_e} for these galaxies would be to classify them as FRs or SRs with 100 independent classifiers using Galaxy Zoo citizen scientists for example. However, this visual classification is not accurate for SRs.) The 2σ error in $F(\text{SR})$ is less than 0.8% across all $\log(\Sigma_3^{\text{rel}})$. In the right hand side panel of Figure 6.4, we randomly assign 52% of all candidate massive SRs to be FRs as well as calculate the measurement errors as before. We recalculate $F(\text{SR})$ for each of the 100 iterations and find that as expected, $F(\text{SR})$ decreases when we account for the misclassification. In the highest density bin, $F(\text{SR})$ decreases by up to a factor of two which is unsurprising considering that massive galaxies are mostly found at high densities. Despite this uncertainty, we can still conclude that there is a trend in $F(\text{SR})$ with $\log(\Sigma_3^{\text{rel}})$ with a factor ~ 5 in variation between the two density extremes.

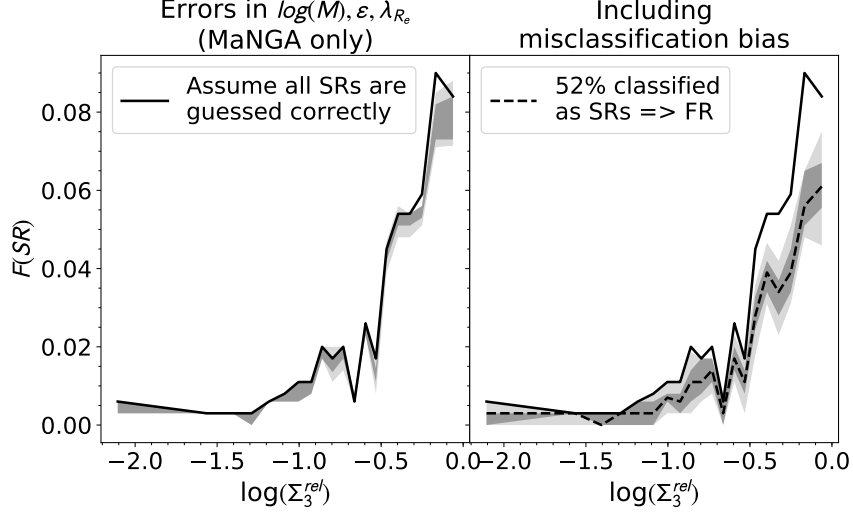


Figure 6.4: **Uncertainty in the kT- Σ relation.** *Left:* In black, we plot the same relation seen in the upper histogram of Figure 6.2. In dark and light grey, we plot the inner 68th and 95th percentiles for the fractions in each bin from 100 perturbed samples (see the text). *Left:* The black line is the same as left, and the black dotted line is the 50th percentile now assuming that 48% of the SR *candidates* are misclassified and are therefore FRs. Again we show the 68th and 95th inner percentiles. Here we also include the errors shown on the left hand side.

6.2.2.4 F(SR) vs D_{cen}

There is a close relationship between $\log(\Sigma_3^{\text{rel}})$ and D_{cen} because by definition, the density peaks are close to the centres of groups, and the number density is on average expected to fall off with radial distance from the centre. In Figure 6.5, we plot $F(\text{SR})$ as a function of the projected distance from the group centre, D_{cen} . We find that for $D_{\text{cen}} \lesssim 0.12$ Mpc (the first two bins), $F(\text{SR})$ is about 11-14%. The fraction drops dramatically beyond $D_{\text{cen}} \sim 0.12$ Mpc after which it settles at about 1% beyond $D_{\text{cen}} \sim 0.5$ Mpc. This trend is even stronger than the one seen in Figure 6.3 and reveals that massive SRs are strongly biased towards the central ~ 100 kpc of clusters.

6.2.2.5 F(SR) vs $D_{\text{cen}}^{\text{norm}}$

Finally, we normalise the groups to the 90th percentile to bring all groups to a comparable scale in terms of group radius (Figure 6.6). We find that the $F(\text{SR})$ - $D_{\text{cen}}^{\text{norm}}$ relation is less skewed but looks similar overall to the D_{cen} relation from Figure 6.5. Here we conclude that within the inner 20% of the group/cluster radius, the fraction of galaxies that are massive SRs is at least 8%. Outside the same radius, the fraction is less than 4% for all bins.

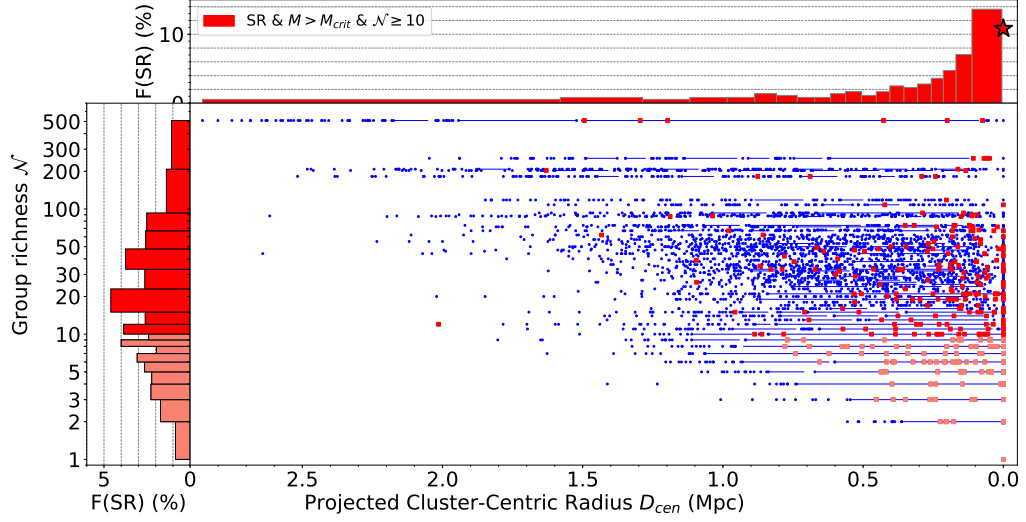


Figure 6.5: **Projected clustercentric distance.** The same as Figure 6.3 but now considering the projected comoving clustercentric distance. The red star shows the fraction for galaxies with D_{cen} and $\mathcal{N} \geq 10$.

6.2.3 Disentangling stellar mass and environment

Here, we examine the relationship between stellar mass and environment using our relative density estimator. In Figure 6.7, we plot $F(\text{SR})$ as a function of $\log(\Sigma_3^{\text{rel}})$ for intervals of fixed stellar mass. Each bin in stellar mass contains about 200 galaxies, and each density bin contains about 40 galaxies. We calculate the error in $F(\text{SR})$ in the same way as in the right panel of Figure 6.4 i.e. we include the misclassification bias. In all but one stellar mass bin, we see an increase in $F(\text{SR})$ within about $\log(\Sigma_3^{\text{rel}}) \approx -0.5 \text{ Mpc}^{-2}$. Within the errors, the mass interval $11.5 \leq \log(M) < 11.66$ does not show a strong trend, but $F(\text{SR})$ at $\log(\Sigma_3^{\text{rel}}) \approx 0$ is about a factor of two greater than at $\log(\Sigma_3^{\text{rel}}) \approx -1.5 \text{ Mpc}^{-2}$ for the same mass bin. The increase in $F(\text{SR})$ with stellar mass is clearly visible from the difference between the $F(\text{SR})$ profiles for each stellar mass bin.

By comparing the mass-size diagram for the ATLAS^{3D} field sample with the same for the Coma cluster, Cappellari (2013) highlighted the difference between massive SRs in the field and in cluster environments. The extent and the stellar mass of the two BCGs of Coma compared to lower mass core SRs provides evidence that the growth of SRs takes place within the cluster environment. The growth is not “within” the cluster, but only takes place for the galaxies that end up at the centres of clusters. The process must be hierarchical as in Figure 1.7a. However, only one cluster was available at the time to support this argument. Now we have enough data to be able

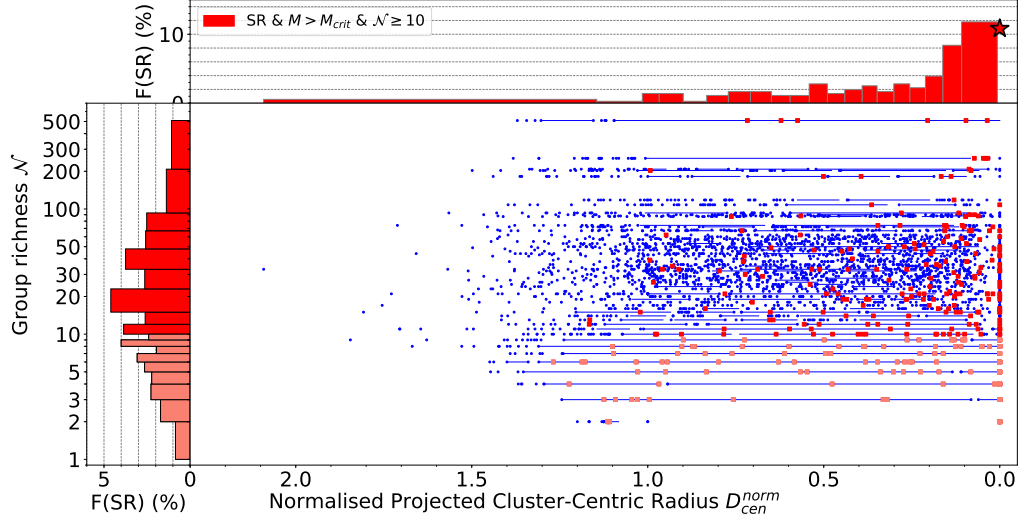


Figure 6.6: **Normalised projected clustercentric distance.** The same as Figure 6.5 except that projected distances are normalised to the 90th percentile. The red star shows the fraction for galaxies with $D_{\text{cen}}^{\text{norm}}$ and $\mathcal{N} \geq 10$.

to investigate the mass distribution of SRs and FRs as a function of environment with good number statistics.

In Figure 6.8, we plot the stellar mass distribution for SRs with $M \geq M_{\text{crit}}$ (red) as a function of environment (dotted, dashed and solid curves). All other galaxies are contained within the blue curves for the same environments. We find no significant differences between the blue curves suggesting that the stellar mass distribution of FRs and spirals doesn't change as a function of environment. One clear difference is that the peak is more defined for FRs and spirals in clusters compared to the field environment. On the other hand, there is a systematic shift in the SR stellar mass distribution from the field towards the cluster regime. This is consistent with the hierarchical formation scenario where clusters are built up from the mergers of groups, and in parallel the central SRs also build their stellar mass via dry mergers (C16). Note that Figure 6.8 is not showing that the frequency of SRs is a result of the changing stellar mass distribution, as the red curve is only for massive SRs in the first place. The only free variable in Figure 6.8 is environment.

We do not attempt to produce the mass-size relation as a function of environment as we do not have consistent radii across all galaxies. For galaxies in the NSA, but not in MaNGA, we only have Petrosian radii, whereas we measure R_e directly from the photometry (see subsection 2.2.1.1). The SDSS Petrosian radii are numerically similar to R_e but are defined in a completely different way. Moreover, there can easily

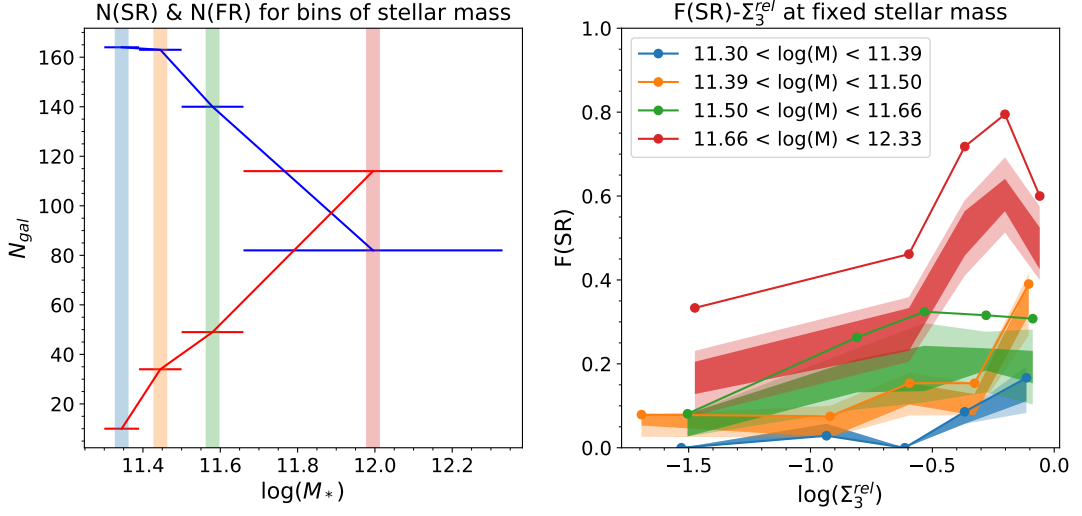


Figure 6.7: **$F(SR)$ vs Σ_3^{rel} at fixed stellar mass.** *Left:* Stellar mass distribution of SRs and FRs above M_{crit} . Each bin has equal numbers of galaxies. *Right:* For each bin shown at top, we plot the $F(SR)$ as a function of $\log(\Sigma_3^{rel})$. We also show each relation including the errors in λ_{Re} and ϵ as well as accounting for the misclassification bias.

be deblending issues in a dense cluster environment and so the radii are not reliable in the regime where we would require them to be accurate in order to observe the steep trend seen in Cappellari (2013) and Figure 3.9.

At this point, we have not mentioned anything about possible edge effects where galaxies are close to the boundary of the SDSS footprint (see Berlind et al., 2006 where the footprint was much smaller). It is possible that if galaxies are close to the edge, then a portion of its enclosing group could be missing from the catalogue. To assess the frequency of such a scenario, we select a random sample of 50,000 photometric objects that lie within a square of width 10 Mpc centred on each MaNGA galaxy, regardless of their redshift. We also select spectroscopic galaxies within the box that lie within a velocity difference of $\pm 3000 \text{ km s}^{-1}$ from each MaNGA galaxy. While the footprint is only well traced by the photometric catalogue which comes from imaging, the spectroscopic galaxies are useful to assess the local density of the MaNGA galaxy. (This analysis is only approximate so we don't use the groups here.) We divide up the squares into 25 smaller squares each with sides 2 Mpc in length. We simply count the number of objects in each squares and count how many squares have 5% or less of the maximum number of objects in any one square. If 5 or more squares are sufficiently underpopulated, we visually inspect the footprint. We find about 200 MaNGA galaxies ($\sim 5\%$) are close to the edge of the footprint. It is

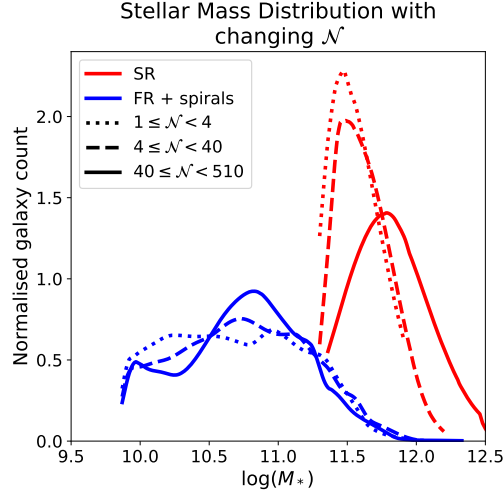


Figure 6.8: **Stellar mass distributions as a function of environment.** We plot probability distributions for massive SRs in red and all other galaxies in blue. We split each population into environment bins representing the field (dotted), group environments (dashed) and clusters (solid). We truncate the blue curves below the completeness limit of $\log(M) = 9.87$.

non-trivial to estimate what fraction of these galaxies are actually affected, since some will be in genuinely sparse environments (about half of all MaNGA galaxies are isolated). Nevertheless, we redo the figures presented in this section without the groups enclosing these galaxies, and find that our conclusions are unchanged.

6.3 Comparison with other work

With the large sample that MaNGA provides, we are able to separate MaNGA galaxies into bins of stellar mass and still retain sufficiently large numbers in each bin to detect meaningful signals which are not affected by random errors in environmental parameters. We now use the MaNGA sample for which we have λ_{R_e} to make comparisons with the work of three other studies which have claimed that once stellar mass has been accounted for, there are no residual trends with either the angular momentum proxy λ_{R_e} or the fraction of slow rotators as a function of environment. We have already provided clear evidence that Σ_3 cannot be used to accurately predict the abundance of massive SRs which is highly sensitive to the cluster morphology. Similarly, the fraction of massive SRs is not a simple function of group richness. While we do not necessarily have access to the same datasets or parameters, we can nevertheless still make a qualitative comparison in order to “test our machinery”.

We choose not to use the volume-weighted sample, which is equivalent to a volume-limited survey, because massive SRs are vastly outnumbered by FRs in such a sample. Moreover, large weights are given to very unusual objects and so our statistics will be dominated by these objects. The weights are defined in terms of redshift, as galaxies which are observed at low redshifts are upweighted and vice versa. However, as the MaNGA selection function requires that galaxies of increasing luminosity (and therefore stellar mass) are observed at higher redshifts, the weights also depend on stellar mass. Hence, the range of possible weights is restricted for bins of fixed mass, and so for the regime where genuine SRs exist, the effect of using the volume weighted sample is in any case minimal.

6.3.1 Comparison with Veale et al. 2017

In Figure 6.9, we aim to reproduce fig. 8 from Veale et al. (2017b) which was used to argue for the absence of strong trends in angular momentum with three different environmental parameters. We keep the same mass bins, simply for direct comparison, despite the fact that the middle mass bin ($10.9 < \log(M_*) < 11.7$) straddles the critical mass above which SRs are dominant. This implies that the Veale et al. (2017b) sample includes some galaxies that are likely “spurious” SR, in the sense of not being dry merger relics. Furthermore, the number counts are not equally shared between these three stellar mass bins, which means that the uncertainty is not the same for each bin.

We do not share any environmental parameters with Veale et al. (2017b). Instead of the halo mass, we use the group richness $\mathcal{N}$ as a proxy. In place of the luminosity density within the 10th nearest neighbour, we use the projected surface density within the 10th nearest neighbour, $\log(\Sigma_{10})$. We compare values of $\log(\Sigma_{10})$ (units of Mpc^{-2}) and $\log(\nu_{10})$ (units of $L_{\odot K} \text{Mpc}^{-3}$) from table 2 of Cappellari et al. (2011b) and find that they vary almost linearly with reasonable amounts of scatter. We do not have an equivalent for the overdensity δ_g , which measures environmental density on large scales of a few Mpc and is related to the halo mass (Veale et al., 2017b). Instead, we swap δ_g for $\log(\Sigma_3)$ which is our local density estimator. However, this means that the middle columns of our plots are not directly comparable, as they probe completely different scales. For the three mass bins (referred here as low-mass, intermediate-mass and high-mass bins), we plot λ_{R_e} as a function of the three environmental parameters (upper panels of Figure 6.9). Although Veale et al. (2017b) calculated the mean for

three environment bins (referred here as low-density, intermediate-density and high-density bins), we choose to calculate the median which is less affected by outliers. We also plot $F(\text{SR})$ for each bin in density and stellar mass (lower panels of Figure 6.9).

We fail to detect any strong trends in λ_{R_e} as a function of either of the three environmental parameters for the lowest mass bin. However, for the intermediate mass bin, there is a visible trend in that λ_{R_e} decreases with environmental density. Perhaps the strongest trend is seen in the median for the intermediate-mass distribution as a function of $\log(\Sigma_3)$. There is a similar trend in the highest mass bin but it is slightly weaker. However, the dominance of stellar mass is clearly visible, as the difference *between* the median lines is much greater than the gradient of the lines themselves. Each distribution is highly asymmetric and the inner $1\sigma/2\sigma$ percentiles would be far from the median lines if we were to show them. (For the sake of clarity, we omit these lines.) As the slope of the gradients are upper limits, they would be even weaker for a volume weighted sample.

There is a marked difference in the histograms of $F(\text{SR})$ as a function of environment between the stellar mass bins (but not between the three environmental parameters which show similar distributions). First we consider the bottom left panels of our Figure 6.9 and fig. 8 of Veale et al. (2017b). Our results show some general similarity. Veale et al. (2017b) find an increase of $\sim 20\%$ for $F(\text{SR})$ between the low-mass halos and high-mass halos. In our data, we see a $\sim 30\%$ for $F(\text{SR})$ for comparable environments. For the intermediate- and low-mass bins, Veale et al. (2017b) find a constant $F(\text{SR})$ as a function of halo mass. We agree for the lower-mass bin, and we find a slight increase $F(\text{SR})$ as a function of halo mass for the intermediate mass bin.

Next, we consider the bottom right panels of both figures. The trends for the high mass bin are not unlike those seen for M_{halo} , in that we see a $\sim 30\%$ increase in $F(\text{SR})$ between bins of low and high density, where Veale et al. (2017b) see a $\sim 20\%$ for a similar regime. For the intermediate mass bin, we actually find a shallower trend compared to Veale et al. (2017b). Meanwhile, we agree on the slightly decreasing trend for the lowest mass bin. However, as previously mentioned, these are not the relics of dry mergers but are low-mass galaxies that are slowly rotating.

Finally, we consider the middle bottom panel of Figure 6.9. We see a strong increase in $F(\text{SR})$ of $\sim 40\%$ between the low and high density (Σ_3) bin. The trends for the intermediate- and low-mass bins are similar to the Σ_{10} $F(\text{SR})$ histograms. The lack of high-mass galaxies at $\log(\Sigma_3) \gtrsim 2$ in MaNGA can be explained as a result of

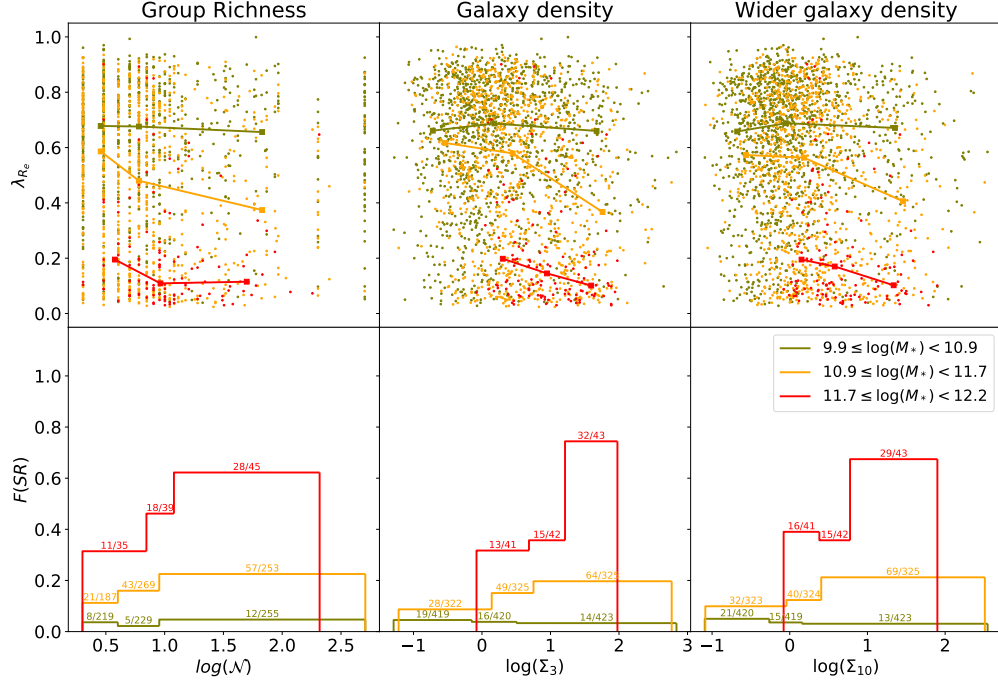


Figure 6.9: **Comparison with Veale et al. (2017b).** *Top:* We plot λ_{Re} as a function of $\log(\mathcal{N})$ (left), $\log(\Sigma_3)$ (middle) and $\log(\Sigma_{10})$ (right). As in fig. 8 of Veale et al. (2017b), we split the sample into bins of stellar mass: $9.9 \leq \log(M) < 10.9$ (green), $10.9 \leq \log(M) < 11.7$ (olive) and $11.7 \leq \log(M) < 12.2$ (red). For each environmental parameter, we plot the median λ_{Re} for bins of equal number. *Bottom:* The same as above except for the fraction of SRs, f_{slow} . We give the number of SRs and total galaxies in each bin.

the fact that there is an intrinsic maximum density that massive galaxies which are large in radius can find themselves.

Overall, we find stronger increasing trends for $F(SR)$ as a function of environment for the highest mass bin compared to those found by Veale et al. (2017b). We conclude from Figure 6.9 that for massive galaxies, environment *does* influence the abundance of dry merger relics (see section 6.5).

The histograms are relatively unaffected by the volume weighting because in fixed stellar mass bins, the weights will not vary greatly. As a result, the net effect of switching to the volume-weighted sample is that $F(SR)$ decreases largely uniformly across all parameters by up to 20%. The trends themselves are preserved and so we would draw the same conclusions for the volume-weighted MaNGA sample.

6.3.2 Comparison with Greene et al. 2017

Greene et al. (2017) studied the fraction of SRs in a sample of 538 ETGs ($M \geq$

$10^{10} M_{\odot}$) taken from the MPL-5 sample as a function of normalised cluster radius. They used the group catalogue of Yang et al. (2007) based on SDSS DR7 that assigns galaxies to groups using a friends-of-friends algorithm before assigning a halo mass based on the total galaxy luminosity and refining using an iterative procedure. Hence, they had estimates for the virial radii of each cluster which we do not have. To make a comparable study, we take the radius of each group to be the 90% percentile, as opposed to the maximum which may be affected by outliers. Greene et al. (2017) used $\log(\Sigma_5)$ which is not identical but is tightly correlated with $\log(\Sigma_3)$ which we use here. In the top panels of Figure 6.10, we show the fraction of SRs as a function of $D_{\text{cen}}^{\text{norm}}$ (left) and $\log(\Sigma_3)$ (right) for four subsamples: All ETGs, all ETGs in groups with $\mathcal{N} \geq 10$, ETGs less massive than M_{crit} , and ETGs more massive than M_{crit} . We note that we use a different mass cut, and specifically we use M_{crit} , which defines the minimum mass of genuine dry-merger SRs and is more physically motivated than the two used by Greene et al. (2017).

We find that $F(\text{SR})$ for the low mass sample is less than 10% for all values of $D_{\text{cen}}^{\text{norm}}$, but we stress that these are essentially mis-classified SRs (such as face-on counter-rotating disks), so their trend is not very meaningful. We show it simply to be consistent with Greene et al. (2017). For the high mass sample, the fraction increases from about 20% at the group boundary to $\sim 45\%$ at the group centre. This is in clear contrast with that shown in fig. 2 of Greene et al. (2017) where there is essentially no trend with normalised group radius. Although we show the relation for all galaxies in all groups, $D_{\text{cen}}^{\text{norm}}$ is essentially meaningless for small groups ($D_{\text{cen}}^{\text{norm}} = 0$ for isolated galaxies). Hence, we also show the relation considering only groups with 10 or more members as in Figure 6.6 etc. Unsurprisingly, this relation lies between the low-mass and high-mass relation, and show an increasing trend with decreasing $D_{\text{cen}}^{\text{norm}}$. All the trends with $D_{\text{cen}}^{\text{norm}}$ become flatter with volume weighting (apart from the low-mass trend which is already flat without volume weighting), with only the high-mass bin retaining any noticeable trend.

There is a strong linear trend visible for the high mass sample where $F(\text{SR})$ increases from $\sim 15\%$ to $\sim 50\%$ for massive MaNGA SRs between $\log(\Sigma_3) \approx -0.2$ and $\log(\Sigma_3) \approx 2.2 \text{ Mpc}^{-2}$. This trend contrasts with that seen in fig. 1 of Greene et al. (2017) where $F(\text{SR})$ is constant as a function of Σ_5 within the errors. $\log(\Sigma_3)$ is restricted for $\mathcal{N} \geq 10$ (see Figure 6.2), and here we do not see any strong trend for all galaxies for these groups. However, this is because high-mass galaxies are greatly outnumbered by low-mass galaxies.

To check that we are not affected by the MaNGA selection function, we plot $F(\text{SR})$ for the volume-limited sample using the same selection criteria in the bottom two panels of (Figure 6.10). We find qualitatively the same result with a slight reduction in $F(\text{SR})$ for the high mass sample.

6.3.3 Comparison with Brough et al. 2017

Finally, we carry out a comparable analysis to that shown in Fig. 11 of Brough et al. (2017) which looks at the mean deprojected λ_{R_e} for fixed density as a function of stellar mass, and at fixed stellar mass as a function of density. The deprojection is achieved by assuming that the demarcation line between FRs and SRs used in Emsellem et al. (2011), $\lambda_{R_e} = 0.31\sqrt{\epsilon}$, approximately separates ETGs by their *intrinsic* edge-on angular momentum. λ_{R_e} certainly should not be interpreted without knowledge of ϵ (as we have done in subsection 6.3.1), but as more data have become available, the demarcation line has been refined (see Figure 6.1 and C16). Furthermore, Brough et al. (2017) deproject SRs which are not intrinsically axisymmetric and so the deprojection is not meaningful for these galaxies. (Even if we observed all SRs “edge-on” i.e. $\epsilon \sim 0.3 - 0.4$, we would still observe low λ_{R_e} .) Finally, it is clear that deprojecting galaxies of low ϵ and high λ_{R_e} using $1/\sqrt{\epsilon}$ will result in unphysical values (see Greene et al., 2017 and fig. 6 of Lee et al., 2018).

In Figure 6.1, we plot how the edge-on ($i = 90^\circ$) theoretical (magenta) line changes as a function of inclination (Binney, 2005, Cappellari et al., 2007, C16). We also plot lines which show how a galaxy with a given $(\lambda_{R_e}^{\text{intr}}, \epsilon^{\text{intr}})$ at $i = 90^\circ$ moves across the diagram as the inclination progresses towards face on ($i = 0^\circ$; Cappellari et al. (2007)). We could use these lines to deproject λ_{R_e} and ϵ to the intrinsic values for FRs. However, the inclination is generally undefined due to measurement errors in ϵ , and measurement errors of ~ 0.05 in λ_{R_e} can easily change the deprojected $\lambda_{R_e}^{\text{intr}}$ by a larger amount, especially at low ϵ . Finally, the functional forms that predict the magenta line and its projections are at a far higher precision than is generally required, especially considering the measurement errors.

In light of this, we derive a simple empirical function that can predict the deprojected value of λ_{R_e} to within an accuracy of about 0.05. For all SRs or galaxies with $\epsilon \geq 0.4$, we assume that the observed λ_{R_e} is the edge-on one, and we do not correct for any inclination effects. For FRs rounder than $\epsilon = 0.4$, we calculate the edge-on,

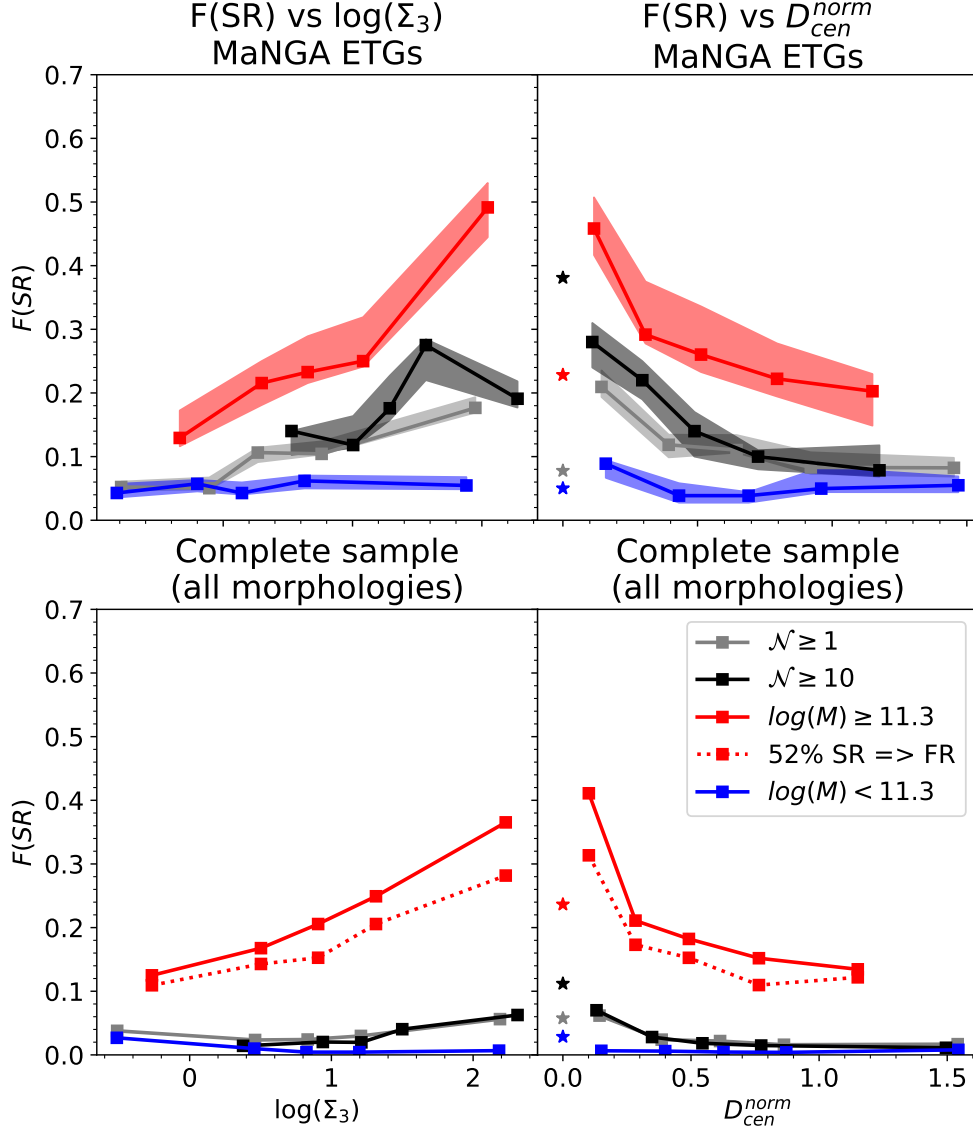


Figure 6.10: **Comparison with Greene et al. (2017).** *Top Left:* $F(\text{SR})$ as a function of $\log(\Sigma_3)$. We show trends for all galaxies (grey) galaxies in groups of 10 or more members (black) and galaxies more and less massive than M_{crit} (red and blue respectively) for all group memberships. Each subsample is split up into five bins of equal numbers of galaxies. *Top Right:* $F(\text{SR})$ as a function of $D_{\text{cen}}^{\text{norm}}$ normalised to the 90th percentile for MaNGA ETGs only. The stars correspond to the values at $D_{\text{cen}}^{\text{norm}} = 0$ for each subsample. *Bottom Left:* As top left except for the complete volume-limited sample (all morphologies). As this sample contains SR candidates, we randomly assign FR classifications to 52% of our SR candidates (dashed-red). *Bottom Right:* As top right except for the complete sample (all morphologies).

intrinsic $\lambda_{R_e}^{\text{intr}}$ using an empirical correction for inclination

$$\lambda_{R_e}^{\text{intr}} - \lambda_{R_e} = 0.16 \exp \left[-\frac{(\lambda_{R_e} - 0.4)^2}{0.04} \right] x + 0.2x^2, \quad (6.2)$$

where

$$x = \frac{0.4 - \epsilon}{0.4}, \quad (6.3)$$

and ϵ and λ_{R_e} are the apparent ellipticity and beam corrected stellar angular momentum parameter respectively.

Equation 6.2 has two components on the right hand side. The first component models the change in λ_{R_e} as a function of ϵ and λ_{R_e} . The form is a Gaussian which is scaled according to ϵ , and peaks at $\lambda_{R_e} = 0.4$, which is roughly where the inclination lines are at their maximum gradient. The change is greatest at intermediate λ_{R_e} and falls off towards the two extremes of $\lambda_{R_e} = 0$ and $\lambda_{R_e} = 1$. When $\epsilon = 0$ and $\lambda_{R_e} = 0.4$, the change in λ_{R_e} due to this component is simply 0.16. The second component, proportional to x^2 , models the change in λ_{R_e} as a function of ϵ , assuming that the increase in λ_{R_e} is proportional to the square of the fractional distance x from $\epsilon = 0.4$ in the range $0 \leq \epsilon \leq 0.4$. In other words, when $\epsilon = 0$ i.e. maximum distance from $\epsilon = 0.4$, the component evaluates to 0.08, and when $\epsilon = 0.4$, the component evaluates to zero.

We illustrate Equation 6.2 in Figure 6.11, where we plot the apparent $(\lambda_{R_e}, \epsilon)$ and deprojected $(\lambda_{R_e}^{\text{intr}}, \epsilon^{\text{intr}})$ for 15 mock galaxies. We do not calculate ϵ^{intr} but simply match it with the value of $\lambda_{R_e}^{\text{intr}}$. (We do this purely for illustration as we are not interested in obtaining ϵ^{intr} .) We can assess the performance of the inclination correction by comparing the distance along the magenta line between each coloured square to its corresponding inclination track (grey dashed lines). We find that the correction can predict $\lambda_{R_e}^{\text{intr}}$ to within about 0.05 which is sufficiently accurate for our purposes. The function was calibrated using the 15 mock galaxies shown, and so performs as intended when $\epsilon \geq 0.05$. The accuracy will decrease below $\epsilon \geq 0.05$ where small shifts in λ_{R_e} or ϵ can would result in large shifts in the deprojected values, but we expect the accuracy to still be within about 0.1 for this ϵ range.

In the upper panel of Figure 6.12, we plot $\log(\lambda_{R_e}^{\text{intr}})$ calculated using Equation 6.2 as a function of stellar mass for the MaNGA sample. We also plot the median and inner 1σ percentiles of $\log(\lambda_{R_e}^{\text{intr}})$ for the lower and upper $\log(\Sigma_3)$ quartiles, shown as blue and red lines respectively. For the low density bin, there is essentially no trend in the intrinsic λ_{R_e} as a function of stellar mass, which is to be expected if there are by definition no environmental effects for galaxies in regions of low density. We do

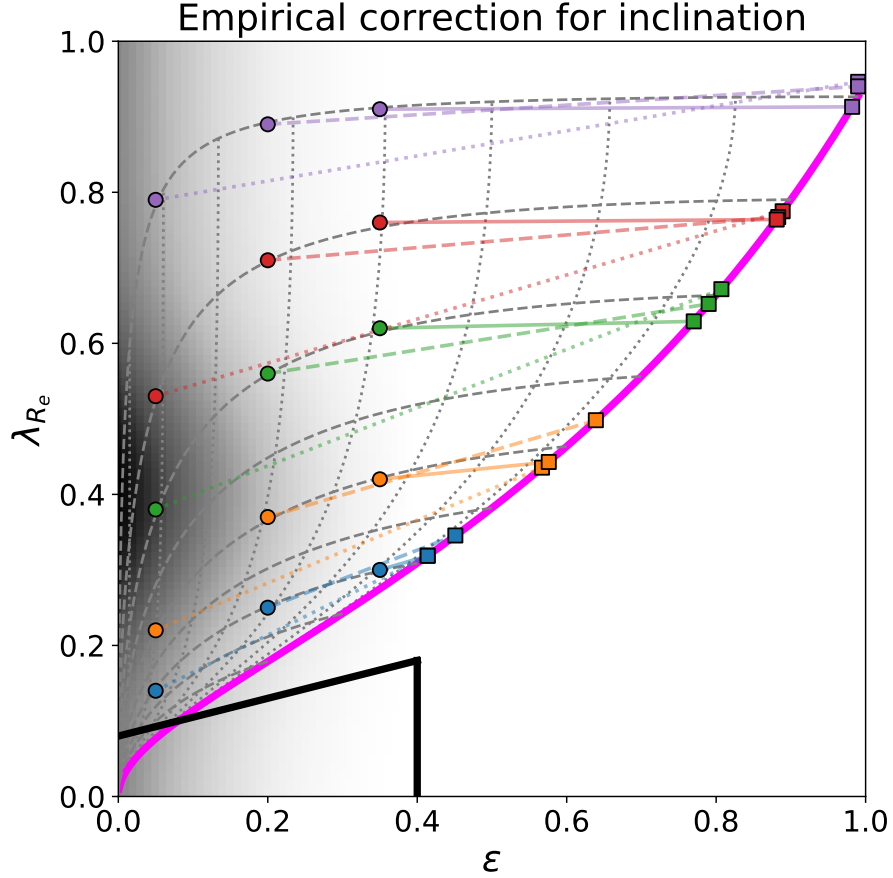


Figure 6.11: **Correcting for inclination.** Illustration of our empirical inclination correction (Equation 6.2). The magenta, black and grey dashed lines are the same as in Figure 6.1. The coloured circles are the apparent positions for 15 mock galaxies. The colours correspond to a particular intrinsic ϵ^{intr} to guide the eye. For each colour, three values of ϵ are chosen as 0.05, 0.2 and 0.35, and λ_{Re} is chosen so that the point lies on one of the ϵ^{intr} inclination tracks. The inclination corrected locations are shown as coloured squares, and each pair of points is joined by a line of the same colour. We do not calculate ϵ^{intr} but simply match up the corresponding value on the magenta line. The black shaded region indicates the magnitude of the inclination correction at each position on the plane. The peak is centred at $(\lambda_{Re}, \epsilon) = (0.4, 0)$, and there is no correction for galaxies flatter than E4.

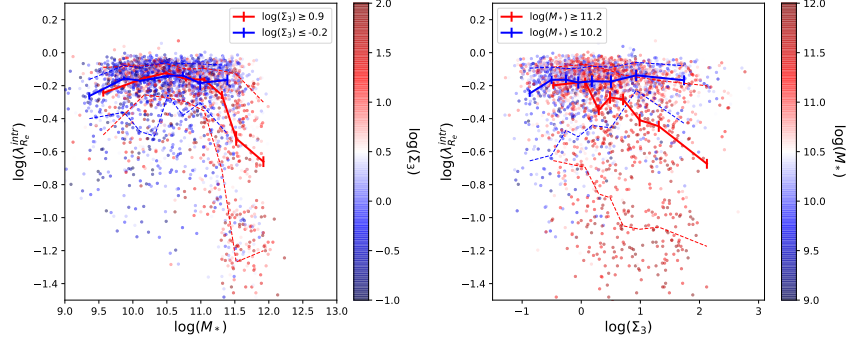


Figure 6.12: **Comparison with Brough et al. (2017).** *Left:* Log of the inclination corrected $\lambda_{R_e}^{\text{intr}}$ corrected using Equation 6.2 as a function of stellar mass for the MaNGA sample. The colours of the points correspond to $\log(\Sigma_3)$ as shown in the colourbar. The red and blue solid lines are the median $\log(\lambda_{R_e}^{\text{intr}})$ for the upper and lower 25th density percentiles. The lower and upper limits of the upper and lower percentiles respectively are indicated in the colour bar by two solid black lines. For each density percentile, we indicate the extent of the inner 1σ percentile of the distribution with dashed lines. *Right:* Same as above except that the independent variable is the surface density and the colours indicate the stellar mass as shown in the colourbar.

not observe the dip in $\log(\lambda_{R_e}^{\text{intr}})$ seen in the low density-high stellar mass bin in Veale et al. (2017b). This is simply because very few galaxies of masses greater than the critical mass for SRs reside in low density environments. We do confirm the sharp downward trend for the high density bin at $M \approx M_{\text{crit}}$, which is the mass above which genuine dry-mergers slow rotators start appearing (C16).

In the lower panel of the same figure, we plot $\log(\lambda_{R_e}^{\text{intr}})$ as a function of $\log(\Sigma_3)$ for the lower and upper quartiles in stellar mass. We find no trend in the lower mass quartile as expected. However, we see a decrease in the median $\lambda_{R_e}^{\text{intr}}$ for the high mass bin as $\log(\Sigma_3)$ increases. The distribution in $\log(\lambda_{R_e}^{\text{intr}})$ for this stellar mass quartile is highly asymmetric, however it is clear that the frequency of galaxies with $\lambda_{R_e} \approx 0.1$ increases with increasing Σ_3 as evidenced by the distribution of the points themselves. We have a larger sample than Brough et al. (2017) and a robust estimate of Σ_3 so we are able to reveal trends that have previously been missed. Furthermore, we have a more accurate inclination correction that does not overestimate $\lambda_{R_e}^{\text{intr}}$ at low ϵ . In retrospect, it would have been better to produce this plot using Σ_3^{rel} instead of Σ_3 , as the red median line in the lower panel of Figure 6.12 would be stronger (compare Figure 6.2 with Figure 6.3). However, we would have to reduce the sample size to groups of 10 members or larger so we would have to compromise on accuracy.

6.4 Bayesian logistic regression

The kT- Σ relation allows us to quantify the probability that a given galaxy will be a massive SR, $P(\text{SR})$, as a function of local number density. However, the scope of our sample, including its size and completeness, allows us for the first time to investigate $P(\text{SR})$ in a multi-dimensional parameter space. As in most cases, we would naively use ordinary linear regression to fit $P(\text{SR})$ as a function of D_{cen} for example. However, our raw unbinned data is actually in the form of ones and zeros ($1 = \text{SR} \ \& \ M \geq M_{\text{crit}}$, $0 = \text{FR or } M < M_{\text{crit}}$) as a function of our dependent variables, and so the distribution is not normally distributed. As we are interested in obtaining probabilities which can only take values between zero and one, linear regression is not suitable.

In order to answer the question “*What is the probability of a massive galaxy being a SR as a function of $\log(\Sigma_3^{\text{rel}})$, $\mathcal{N}$ etc.?*”, we must turn to logistic regression, which is a special case of generalised linear model (GLM; Nelder & Wedderburn, 1972). If we want to quantify our uncertainty in the answer to the above question, we must use *Bayesian* logistic regression (see Hilbe, 2016 for a practical overview).

6.4.1 Definition of generalised linear models

Generalised linear models (GLM) were first developed by Nelder & Wedderburn (1972) and popularised by McCullagh & Nelder (1983, 1989) (see Hilbe et al., 2017 for an excellent review on the application of GLMs and Bayesian inference on astrophysical data). GLMs are useful as they allow for a response variable (Y) to have an error distribution taken from the exponential family of distributions, which includes Gaussian, Poisson, Binomial etc. (Hardin & Hilbe, 2012). A random response variable Y may be expressed as (eq. 5.1, Hilbe et al., 2017):

$$Y \sim f(\mu, a(\phi), V(\mu)), \quad (6.4)$$

$$g(\mu) = \eta, \quad (6.5)$$

$$\eta \equiv \mathbf{x}^T \beta = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k \quad (6.6)$$

In this formalism, f is a response variable distribution from the exponential family, μ is the mean of the response variable, ϕ is the exponential family dispersion parameter in the dispersion function $a(\phi)$, $V(\mu)$ is the variance function, η is the linear predictor, $\mathbf{x} = \{x_1, x_2, \dots, x_k\}$ is the vector of the explanatory variables (predictors) and $\beta = \{\beta_1, \beta_2, \dots, \beta_k\}$ is the vector of the predictor coefficients. $g(\mu)$ is the link function which connects the mean μ to the predictor: $\mu = g^{-1}(\mathbf{X}^T \beta)$. The linear predictor $\mathbf{X}^T \beta$ “predicts” the expected value $E(Y)$ (i.e. mean) via the link function g . The link

function varies *linearly* with the predicted values, rather than assuming the response function itself varies linearly. In linear regression, a constant change in the predictor leads to a constant change in the response variable (i.e. a *linear-response* model). Hence, linear regression with Gaussian errors is just a special case of GLM where the expected value is $E(Y) = g(\mu) = \mu$ i.e. the link function is μ itself.

6.4.1.1 Logistic regression

As noted by de Souza et al. (2015) and de Souza et al. (2016), GLM techniques have seldom been used in astronomical studies (see Raichoor & Andreon, 2012, 2014; de Souza et al., 2016; Huppenkothen et al., 2017; Lin et al., 2018 for examples of logistic regression in astronomy). Here, we concentrate on logistic regression which is used when the response variable is taken from the Bernoulli distribution. The Bernoulli distribution is a discrete probability distribution of a random variable which can take either a value of one with probability p (probability of success), or a value of zero with probability $1 - p$. The Bernoulli distribution is a special case of the Binomial distribution $\binom{n}{p} p^y (1 - p)^{n-y}$ where y is the number of successes and n is the number of trials. For the Bernoulli distribution, $n = 1$ and so the distribution is simply $p^y (1 - p)^{1-y}$. As with all link functions in GLM, the link function can be derived directly from the distribution. For the Bernoulli distribution, the natural link function is the logit function which defines the logistic model (Hilbe et al., 2017):

$$g(p) = \text{logit}(p) = \log\left(\frac{p}{1-p}\right). \quad (6.7)$$

Qualitatively, the logit function is the log of the odds and can take values between $-\infty$ and $+\infty$ for $0 \leq p \leq 1$. Odds themselves are simply a different way of expressing probabilities ($p = 0.8 \rightarrow p/(1 - p) = 4$ so the odds of success are 4 to 1). Eq. (6.7) can be fit to the linear predictors with linear regression using the errors defined by the variance function:

$$\text{Var}(Y) = V(\mu) = V(g^{-1}(\mathbf{X}\beta)) \quad (6.8)$$

To transform the predicted odds back into probabilities, we need the inverse of the logit function (Eq. (6.7)), which is the logistic function (hence the term *logistic regression*):

$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x + \dots + \beta_k X_k)}} \quad (6.9)$$

6.4.1.2 Bayesian regression

To understand the uncertainties in the logistic regression model, it is useful to use Bayesian inference to provide probability distributions for each fitted parameter. Bayes' theorem formally states that (e.g. eqs. 3.10 and 3.11, Hilbe et al., 2017):

$$p(\text{model}|\text{data}) \propto p(\text{data}|\text{model})p(\text{model}) \equiv L(\text{model})\pi(\text{model}) \quad (6.10)$$

i.e. the posterior probability distribution of the model given the data is proportional to the product of the probability of the data given the model (likelihood of the model) and the probability of the model (prior belief of the model parameters). In order to obtain $p(\text{model}|\text{data})$, we must first obtain expressions for the likelihood and priors. The likelihood in our case is the Bernoulli probability distribution function:

$$L_i = p(x_i)^{y_i}(1 - p(x_i))^{1-y_i}. \quad (6.11)$$

We substitute Eq. (6.9) into Eq. (6.11) to obtain

$$L_i = \left(\frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip})}} \right)^{y_i} \quad (6.12)$$

$$\times \left(1 - \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip})}} \right)^{(1-y_i)} \quad (6.13)$$

where p is the total number of parameters. As individual measurements are assumed to be independent from each other, the likelihood for n total measurements is

$$L = \prod_{i=1}^n L_i \quad (6.14)$$

In order to let the data speak for themselves, we use a non-informative normal prior for each parameter β i.e. $\beta_j \sim N(\mu_j, \sigma_j^2)$. The most common choice for μ is zero and σ is usually large enough to remain non-informative (i.e. 1000).

The posterior distribution can now be estimated using Bayes theorem:

$$P = L \times \prod_{j=1}^p \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left\{ -\frac{1}{2} \left(\frac{\beta_j - \mu_j}{\sigma_j} \right)^2 \right\} \quad (6.15)$$

where the latter part of the expression is the normal distribution for the β parameters. In most cases, it is impossible to calculate the posterior analytically so a Markov-Chain Monte Carlo (MCMC) is typically used to sample from the posterior. We use PyMC3²⁹ (Salvatier et al., 2016) which contains the entire suite of methods required to

²⁹<https://github.com/pymc-devs/pymc3>

set up the logistic regression model and sample the posterior probability distribution. PyMC3 makes use of Hamiltonian Monte Carlo (HMC) which makes use of knowledge of the gradient of the posterior distribution to inform the next random jump. This has the advantage of converging quicker than standard MCMC routines which do not know anything about the gradient and therefore the likely locations of local maxima. HMC uses equations which are analogous to those that describe the motion of a particle in a potential. However, HMC requires two predefined parameters, a step size ϵ and number of steps L (Hoffman & Gelman, 2014) which can affect the efficiency of the algorithm. To alleviate the need for these two parameters, PyMC3 uses the No-U-Turn Sampler (NUTS) extension (Hoffman & Gelman, 2014) which tunes ϵ on the fly using adaptive techniques (Andrieu & Thoms, 2008). Hoffman & Gelman (2014) provided a new technique that stops the MCMC when no significant improvements will be made. Hence, there are no user-defined parameters required to obtain an estimate of the posterior.

6.4.2 Model selection

PyMC3 allows the user to define a model that the user predicts will best fit the data. Whichever model we use, it must be the simplest model that can best describe the data. The stellar mass is an obvious parameter to include since the probability of a galaxy being a slow rotator is a strong function of stellar mass. We also need to include the group richness because a cluster environment is very different to a group environment and we have shown that the abundance of massive SRs varies as a function of $\mathcal{N}$ (e.g. Figure 6.2). Finally, we choose our relative density estimator Σ_3^{rel} as it accurately predicts the abundance of SRs in groups and clusters (Figure 6.3). We could also choose D_{cen} (Figure 6.5) which also accurately predicts massive SR abundances, but it is measured relative to a fixed point, whereas Σ_3^{rel} is coordinate free.

To define our model, we examine $F(\text{SR})$ as a function of these three parameters. We assume that in the stellar mass range of genuine SRs, $F(\text{SR})$ increases linearly with $\log(M)$ (e.g. left panel of Figure 3.9). The distribution of $F(\text{SR})$ as a function of $\mathcal{N}$ is very skewed towards low $\mathcal{N}$ and is poorly sampled at high $\mathcal{N}$, and so we take the logarithm of $\mathcal{N}$. It is clear from Figure 6.2 and similar figures that $F(\text{SR})$ does not vary linearly with $\log(\mathcal{N})$, but is peaked at intermediate values. Hence, any function that can describe this behaviour needs to have a positive gradient at low $\log(\mathcal{N})$ and a smoothly decreasing gradient as $\log(\mathcal{N})$ increases. The simplest function that can provide a better fit is a second order polynomial $a \log(\mathcal{N}) + b \log(\mathcal{N})^2$, where $a > 0$

and $b < 0$. The gradient of this curve is $a + 2b \log(\mathcal{N})$ and so the parameter a sets the gradient at $\log(\mathcal{N}) = 0$ while b sets the *rate of change* of the gradient (or equivalently the width of the peak). The location of the turnover is where the gradient is equal to zero as given by $-a/(2b)$.

We have already shown how $F(\text{SR})$ varies with Σ_3^{rel} at fixed stellar mass (Figure 6.7). As we mentioned in section 6.5, the massive SRs are not always at the peak density, especially in the most massive clusters, because close pairs can lie closer together than the spatial extent of the massive SRs. Hence, to properly model the trends seen in Figure 6.7, we choose the same functional form that we use for $\log(\mathcal{N})$. We assume that the three variables are independent of each other and so we simply construct our model using an additive form:

$$\log \left[\frac{P(\text{SR})}{1 - P(\text{SR})} \right] = \beta_0 + \beta_1 \log(\mathcal{N}) + \beta_2 [\log(\mathcal{N})]^2 + \beta_3 \log(\Sigma_3^{\text{rel}}) + \beta_4 \log(\Sigma_3^{\text{rel}})^2 + \beta_5 (\log(M_*) - 11.3) \quad (6.16)$$

where $\beta_0, \beta_1 \dots$ are the fitted parameters. $P(\text{SR})$ can only take values between zero and one for all possible inputs.

Our coverage from the data will not be uniform across our parameter space. For example, $\log(\Sigma_3^{\text{rel}})$ only takes a single value for isolated galaxies, and is not meaningful for small $\mathcal{N}$. Hence, we do not include groups with $1 \leq \mathcal{N} \leq 3$ in our analysis. We account for the misclassification bias by randomly assigning 53% of all SRs which do not have stellar kinematics to be FRs.

6.4.3 Results

In Table 6.1, we tabulate the best fitting parameters of Eq. (6.16), and in Figure 6.13, we present the posterior distribution of Eq. (6.16). In each panel, we fix two of the variables and vary the remaining one. Each column pertains to a particular variable, and in each row, one of the fixed variables are held constant, while the other variable takes one of three values. For each set of fixed values, we draw 200 samples for each parameter values from the posterior distribution, and plot Eq. (6.16).

The key result is that the abundance of SRs depends on all three parameters. The distributions for this high mass subset are qualitatively similar to the ones seen for $F(\text{SR})$ for the whole volume-limited sample (see section 6.2). $P(\text{SR})$ is highest for

Table 6.1: Table giving the values of the best-fitting coefficients from Eq. (6.16).

Coefficient	β_0	β_1	β_2	β_3	β_4	β_5
Value	-3.656	2.481	-0.758	-0.915	-0.200	3.656

intermediate $\mathcal{N}$, maximum $\log(\Sigma_3^{\text{rel}})$ and high stellar mass. The parameter space is filled without any knowledge of the physical meaning. Unsurprisingly, the strongest trend is that of $P(\text{SR})$ as a function of stellar mass, evidenced by the large value of β_5 compared to the other coefficients (see Table 6.1). We also see a clear trend in $\log(\Sigma_3^{\text{rel}})$ that was already seen in Figure 6.7. Here however, the trend is seen at fixed values of stellar mass, rather than at fixed intervals. The fact that β_2 and β_4 take similar values shows that the width of the polynomials in the left and middle columns of Figure 6.13 are similar, but with different turning points specified by β_1 and β_3 . β_0 is merely an intercept which defines $P(\text{SR})$ for an isolated galaxy with $\log(M_*) = 11.3$ (i.e. when $\log(\mathcal{N})$, $\log(\Sigma_3^{\text{rel}})$ and $\log(M_*) - 11.3$ are all equal to zero) to be $\sim 2.4\%$.

We check for covariance between each parameter (not including β_0) in order to assess if there are any degeneracies between independent parameters. We take 5000 samples from the posterior distribution, and plot each pair of values in the corresponding panel in Figure 6.15. We measure the linearity of each distribution using the Pearson correlation coefficient r , which can take values between -1 (negative correlation) and 1 (positive correlation), where a value of zero indicates no correlation. We also measure the p -value which is the probability of finding each r value if there was no correlation (i.e. $r = 0$). By convention, a p -value of less than 0.05 means the correlation is statistically significant.

The only strong linearity is found between β_1 and β_2 , and also between β_3 and β_4 , which is to be expected as the spread represents the family of polynomials that fit $\log(\mathcal{N})$ and $\log(\Sigma_3^{\text{rel}})$ respectively. There is some covariance for pairs β_3 - β_1 , β_3 - β_2 , β_4 - β_1 and β_4 - β_2 , indicating some degeneracy. However, neither of these correlations are particularly strong and so $\log(\mathcal{N})$ and $\log(\Sigma_3^{\text{rel}})$ are sufficiently independent. There is no significant covariance between M_* and either $\log(\mathcal{N})$ or $\log(\Sigma_3^{\text{rel}})$.

One of the key advantages of using logistic regression is that the model is fit to the data directly without the need to bin the data beforehand. Eq. (6.16) predicts the probability that a given galaxy is a SR as a function of three input parameters. In other words, it also predicts the *fraction* of massive SRs within three dimensional bins. To illustrate this, we calculate $P(\text{SR})$ using the best-fitting parameters from Table 6.1, and assign MaNGA galaxies to bins of $P(\text{SR})$. In Figure 6.16, we show

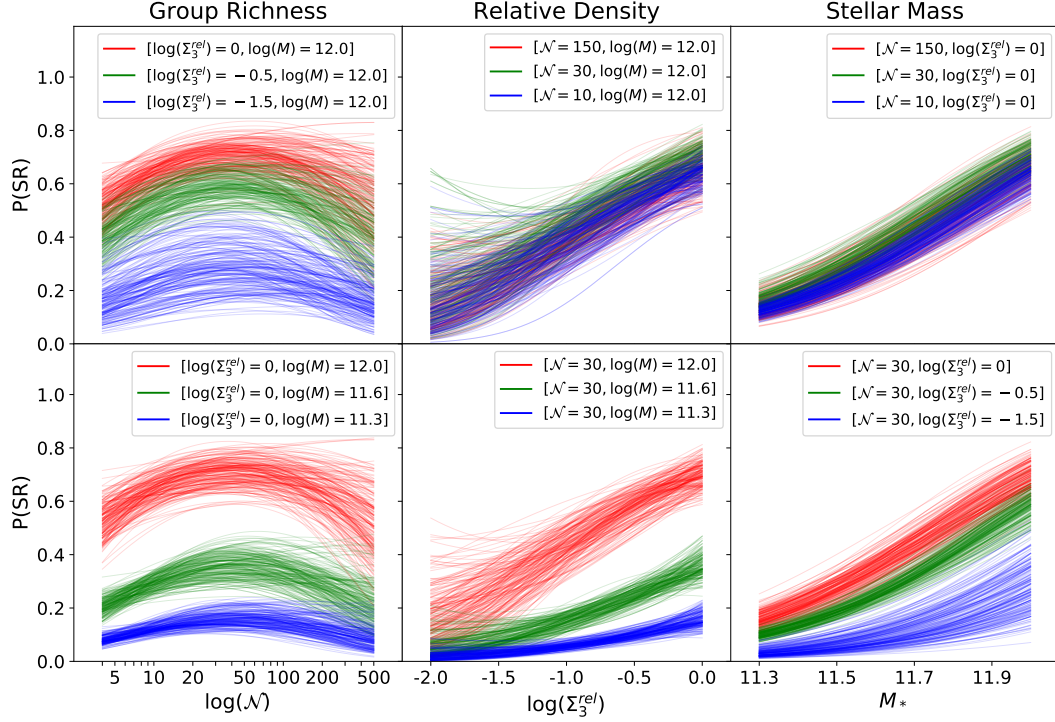


Figure 6.13: **Posterior distribution for the probability of a massive galaxy being a SR.** In the left column, we plot the probability of a galaxy with $M \geq M_{\text{crit}}$ being a SR as a function of $\log(\mathcal{N})$ where $\mathcal{N}$ is the richness of the group to which the galaxy belongs. Each set of coloured tracks is for a particular set of fixed values for $\log(\Sigma_3^{\text{rel}})$ and $\log(M_*)$ indicated in the legend. Each set contains 200 curves where the parameters for each curve are randomly drawn from the posterior distributions shown in Figure 6.14 and substituted into Eq. (6.16). In each row, we show three sets corresponding to two values of one of the two fixed parameters. For example, in the top-left panel, we choose three values of $\log(\Sigma_3^{\text{rel}})$. From left to right, the dependent variables are $\log(\mathcal{N})$, $\log(\Sigma_3^{\text{rel}})$ and $\log(M_*)$.

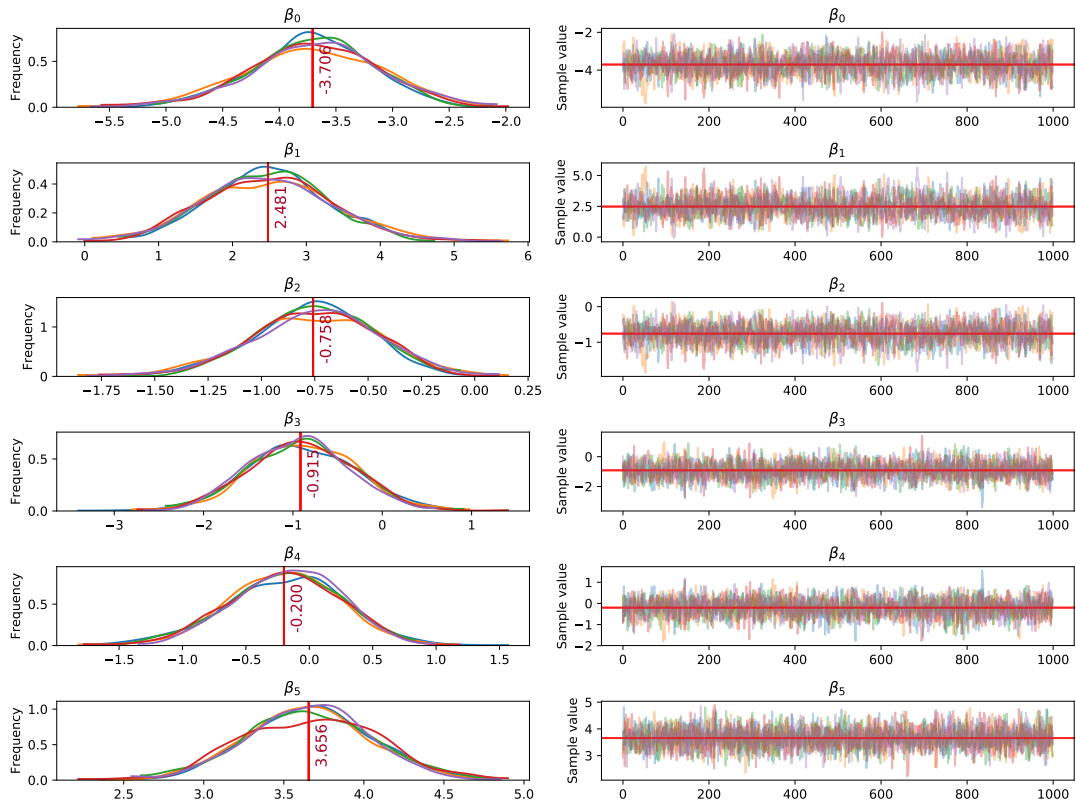


Figure 6.14: **Posterior distributions for the model parameters.** For each parameter (row), we plot the posterior distributions (left) estimated from the MCMC of PyMC3. The traces are stable (right) indicating that the MCMC has settled on the most likely values for each parameter. The MCMC is run five times and a mean parameter value is taken from the mean of these five runs. 3000 samples are drawn in total but we only show the last 1000 samples drawn for each run.

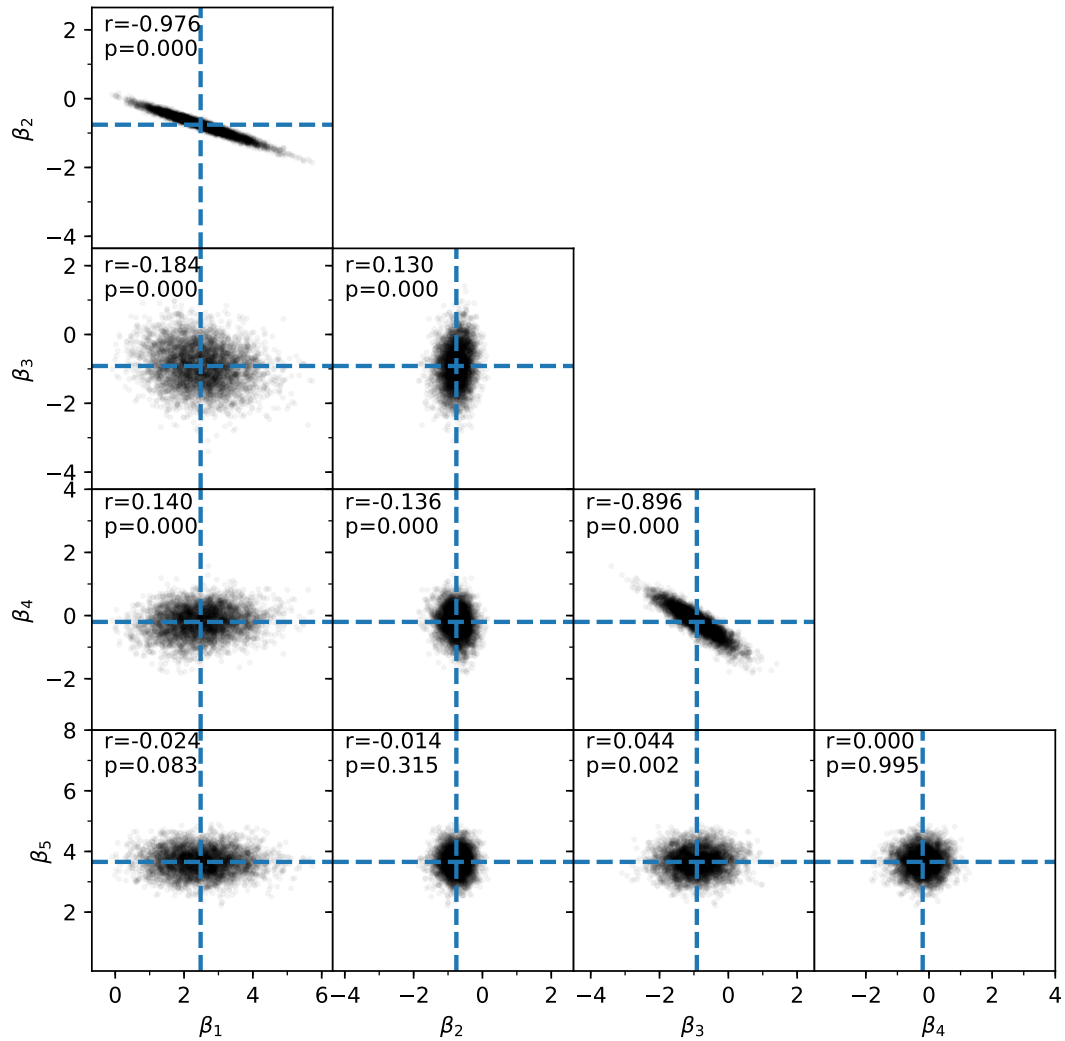


Figure 6.15: **Covariance between parameters.** In each panel, we plot the pair of values for two parameters (not including β_0) for each of the 1000 samples taken from the posterior distribution. We plot the mean parameter values as a dashed blue line. In the top left of each panel, we give the Pearson correlation coefficient r , and its associated p -value.

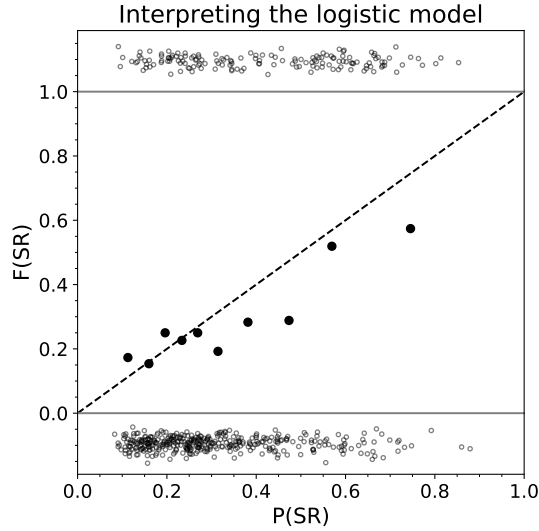


Figure 6.16: **Interpreting the logistic regression model.** The x -axis is $P(\text{SR})$ calculated using Eq. (6.16). The points below zero and above one on the y axis correspond to all FRs and SRs (both candidate and confirmed) which are more massive than M_{crit} in the complete sample respectively. The position of each point along the x -axis is given by its probability of being a SR. The points are randomly scattered in the vertical direction to highlight the density of points. For bins of equal numbers in $P(\text{SR})$, we calculate the *fraction* of SRs in each bin (black filled circles). We also plot a one-to-one line for guidance. This plot shows that the logistic model correctly predicts the fraction of SRs in bins of $P(\text{SR})$, and the fact that there are no significant deviations from linearity suggests that our model is suitable.

the fraction of SRs in each bin of $P(\text{SR})$. We find that there is a linear relationship between the two variables suggesting that the model is a good fit to the data.

6.5 Discussion

The results presented in this chapter allow us for the first time to provide a fully consistent picture of different results on the importance of environment in influencing the internal kinematics of galaxies.

1. Our main conclusion is that the prevalence of massive SRs is closely related to the density *relative* to the peak density of their enclosing clusters, and is not predicted accurately by the absolute galaxy surface density Σ_3 .
2. As a result of the previous point, combining multiple clusters in a single kT - Σ relation effectively washes out the individual $F(\text{SR})$ profiles that are clearly observed within clusters.

3. At fixed stellar mass, there *is* a dependence of $F(\text{SR})$ on the environment as traced by Σ_3^{rel} .
4. The mean of the stellar mass distribution for core SRs increases from the field to group environments and on to cluster environments. The same cannot be said for the mass distribution of FR ETGs and spirals.

Our results are fully consistent with the evolutionary picture outlined in sec. 6 of C16. The BCGs of Coma and the other clusters in our sample (see section 6.7) are strongly biased towards the densest regions of each particular cluster which encloses them. The fact that the mass of the BCG depends on the cluster richness suggests that the evolutionary history of the most massive SRs is closely linked to the formation of their enclosing clusters. When two clusters merge, the massive SRs also merge on radial orbits and increase their mass and size dramatically. The FRs (and spirals) are unlikely to merge due to their relative velocities.

We observe a peak in the distribution of SRs as a function of group richness. This presence of such a peak at intermediate richness is in agreement with the accepted view that galaxy groups, rather than more massive clusters, are the most likely environments for galaxy interactions to occur because the velocity dispersion of the group is near that of the velocities of the galaxies themselves (Martínez & Muriel, 2006a; Zabludoff & Mulchaey, 1998; Hashimoto & Oemler, 2000; Wilman et al., 2005; Martínez & Muriel, 2006b). Groups of 20 or 30 members are the progenitors of the massive clusters, and as the SRs merge, their frequency decreases.

We are able to reproduce the kT - Σ relation for SRs where in general, the fraction of galaxies in bins of density that are massive SRs increases with increasing local number density (Figure 6.2). Our relation is the first to only count SRs if their stellar mass is greater than $\log(M) = 11.3$, which has been shown to effectively separate genuine core SRs from galaxies that exhibit low angular momentum for other reasons, such as slowly-rotating low-mass irregular galaxies (Cappellari, 2013; see Figure 3.9). The genuine SRs are believed to be the true dry merger relics and would show a core surface brightness profile (Krajnović et al., 2013b, C16, Krajnović, 2019) if we had HST imaging for those galaxies. Thus, it is crucial that we do not include low mass SRs when calculating $F(\text{SR})$, as they cannot have formed by dry mergers.

We find that $F(\text{SR})$ is only a weak function of Σ_3 , increasing by at most only 5% across a decade of increasing number density. In contrast, $F(\text{SR})$ jumps by about 15% between the ATLAS^{3D} field sample and the core of Virgo, although Cappellari et al. (2011b) did not specify a minimum critical mass to define SRs. The difference

between $F(\text{SR})$ as a function of Σ_3 (Figure 6.2) and $F(\text{SR})$ as a function of Σ_3^{rel} (Figure 6.3) is striking. In general, the massive SRs show a clear preference towards the densest regions of their respective clusters, regardless of the group richness. We have confirmed the hypothesis outlined in subsection 5.3.4.1 regarding the fact that $F(\text{SR})$ profiles for individual clusters can be smoothed out and flattened when combined with other clusters. In fact, this effect is seen to be strong in our case as we have hundreds of groups where the maximum local number density between groups can vary considerably.

The peak in the $F(\text{SR})$ - $\log(\Sigma_3^{\text{rel}})$ relation appears to not be at $\log(\Sigma_3^{\text{rel}}) = 0$ precisely, but is offset at about $\log(\Sigma_3^{\text{rel}}) = -0.2$. This is because in some case, the peak density in a cluster is not at the most massive ETG, but is in a compact group of low mass galaxies, which can reach separations which are comparable to the extent (angular size) of the most massive galaxies. However, we find that this only affects the most massive ETGs which are also the largest (see Figure 6.7), as more lightweight SRs are smaller in size, and so do tend to live at the peak density. Hence, the slight offset of the peak seen in $\log(\Sigma_3^{\text{rel}})$ is likely an observational artifact. Furthermore, as the clusters are projected, we would likely find that the massive SRs are genuinely sitting at the peak density if we were to view the cluster from all possible viewing angles.

As expected, Figure 6.5 looks qualitatively similar to Figure 6.3, given that in some sense, D_{cen} is also a relative measurement (comparing each galaxy with the central galaxy where $D_{\text{cen}} = 0$). In fact, $F(\text{SR})$ as a function of D_{cen} is even more skewed towards the minimum value than Σ_3^{rel} , suggesting that the projected distance is a better predictor of the abundance of massive SRs than even Σ_3^{rel} . Indeed, the median distance for the massive SRs is less than 0.2 Mpc compared with nearly 0.6 Mpc for the FRs. Unlike friends-of-friends methods which choose the most luminous galaxy to be the centre of the group, our centre is taken as the peak of the underlying galaxy distribution and so is independent of the stellar mass. The fact that the peak is close to zero indicates the robustness of the $F(\text{SR})$ - D_{cen} relation shown here.

In subsection 6.2.3, we investigate the hypothesis that the $\text{kT}-\Sigma$ relation is a result of the changing stellar mass distribution with environment by calculating $F(\text{SR})$ for bins of $\log(\Sigma_3^{\text{rel}})$ at fixed stellar mass intervals (Figure 6.7). We find that $F(\text{SR})$ generally increases with relative density although each trend is not particularly strong. However, the presence of such a trend again rules out the scenario where SRs are at the cluster cores simply as a result of dynamical friction. If dynamical friction were

indeed the cause, then we would expect the $F(\text{SR})$ profiles to be flat, as dynamical friction is only dependent on the stellar mass (Scott et al., 2014).

We also extend the analysis of Cappellari (2013) who compared the mass-size distributions of SRs and FRs in the field and in the Coma cluster. In Figure 6.8, we compare the stellar mass distributions in the field, group and cluster environments for SRs above M_{crit} and all other galaxies. The systematic increase in the SR stellar mass distribution from the field to the cluster supports the hypothesis that clusters are built up in a hierarchical formation process from smaller groups, as this growth is mirrored in the merging of SRs initially at rest at the centre of the subcluster potentials (Cappellari, 2016). The FRs do not experience the same broad shift in stellar mass as they are less likely to merge due to their high relative velocities within the cluster. If massive SRs grow by dry mergers during the hierarchical build-up of groups and clusters, we should expect the probability of being a SR to be closely linked to stellar mass, because galaxy mass cannot disappear and all the stellar mass that was added to a galaxy during its evolution will be easily detected observationally. We would also expect a dependence on environment, but this trend should be weaker because:

- Environment is more difficult to reliably measure empirically and clusters/groups are not easy to define observationally.
- Galaxies move inside clusters, especially during merging of groups, and do not simply sit still at the centre of clusters.
- A massive SR could have merged with perhaps all of its nearby neighbours so that it would appear to be in a low-density environment (or even isolated) in the present day. Hence, galaxies that formed in a high density environment may sometimes be observed in lower density ones at a later stage of their evolution.

These three effects will act to wash out any environmental trend. Overall, the trends with mass and environment we observe are consistent with the overall picture described in C16. They are also in excellent agreement with results from numerical simulations (Choi et al., 2018).

In section 6.3, we attempted to replicate the results published by three independent studies on the effect of environment on stellar angular momentum. All three studies account for the degeneracy between stellar mass and environment by investigating trends at fixed intervals of stellar mass. While there is nothing wrong with this approach, the results can be open to interpretation, considering that the errors tend

to increase when the sample size is reduced. We do not suffer from this problem due to our large sample size. Furthermore, the flat selection in stellar mass is what allows us to sample a wide range in environment of over four orders of magnitude in number density. Combining the clear trends seen in Figure 6.9, Figure 6.10 and Figure 6.12, we conclude that the fraction of SRs *does* increase with Σ_3 at fixed mass, but that the trends are only valid if the mass interval is above M_{crit} . The most robust trend is seen in the bottom left panel of Figure 6.10 where we show $F(\text{SR})$ as a function of Σ_3 for massive galaxies in the complete, volume-limited sample. The clear increase of $F(\text{SR})$ with increasing local density is strong evidence that environment does affect the likelihood of a galaxy being a SR. The trend is robust against our misclassification bias.

Finally, we use the powerful technique of Bayesian logistic regression to summarise the main results of section 6.2. We fit the model given in Eq. (6.16) to the unbinned data to find $F(\text{SR})$ as a function of $\mathcal{N}$, Σ_3^{rel} and $\log(M)$. The dominance of stellar mass is readily apparent, but there are clear trends in $\mathcal{N}$ and $\log(\Sigma_3)$ also.

6.6 Conclusions

We have presented results from the largest complete study of galaxy angular momentum and environment to date. About one third of our sample have MaNGA stellar kinematic observations, which itself represents the largest homogenous sample with stellar kinematics (Figure 6.1), and of the remaining two-thirds, only about 2% have uncertain angular momentum classifications, meaning that the sample overall is robust.

As a starting point, we reproduce the kT- Σ relation by calculating the fraction of galaxies that are classified as SRs *and* are more massive than a critical stellar mass of $2 \times 10^{11} M_{\odot}$, $F(\text{SR})$, in bins of $\log(\Sigma_3)$ where Σ_3 is a projected local density estimator. These galaxies are the relics of violent dry merger events experienced by their progenitors as a result of being embedded at the centres of the most massive dark matter halos at the time of their formation. Indeed, we see a clear trend where $F(\text{SR})$ increases with increasing local density (Figure 6.2).

In subsection 5.3.4.1, we introduced a new parameter Σ_3^{rel} which is a *relative* density estimator. Our motivation for defining a density that is relative to the peak of the group or cluster is that the formation of core SRs is inextricably linked to the formation of the clusters themselves. The maximum density achieved in clusters increases with the cluster richness (Figure 6.2) and so the individual $F(\text{SR})$ profiles for

each cluster are smoothed out if combined into a single kT- Σ relation as we have done in Figure 6.2. We recalculate $F(\text{SR})$ as a function of Σ_3^{rel} and find that the massive SR distribution is skewed more towards the *peak* densities rather than simply *high* densities (Figure 6.3). Hence, we find clear evidence that core SRs, which are the relics of dry merger events and are selected here to be above a critical stellar mass of $2 \times 10^{11} M_\odot$, are strongly biased towards the dense cores of clusters and groups. This conclusion agrees with what we see by eye for individual clusters section 6.7 and is one of the key results from this work. Because about a quarter of all SRs will be misclassified (see section 5.4), we check to see if the trend with Σ_3^{rel} remains after taking this into account. We find that while the trend becomes weaker, it does not disappear completely (Figure 6.4). In total, the uncertainty in $F(\text{SR})$ is less than about 1.5% due to measurement and classification errors.

We also investigate $F(\text{SR})$ as a function of distance to the centre of the cluster (Figure 6.5) and normalised cluster-centric radius (Figure 6.6) for the complete sample and find stronger trends than those based on Σ_3 and Σ_3^{rel} . This may suggest that the distance to the group centre is a better predictor of the abundance of massive SRs than density-based estimators.

As Σ_3^{rel} is a more fundamental parameter than Σ_3 , we investigate the hypothesis that the kT- Σ^{rel} relation is simply a result of dynamical friction, where the most massive galaxies sink to the bottom of the potential well due to their stellar mass. In Figure 6.7, we calculate the fraction of SRs in four bins of stellar mass ($M \geq M_{\text{crit}}$) and find that in all bins, $F(\text{SR})$ increases with increasing Σ^{rel} . The trend deviates from flatness within the errors and so we can confidently rule out the dynamical friction hypothesis. We also studied the stellar mass distribution of massive SRs and FRs as a function of group richness (proportional to halo mass) in Figure 6.8. If the large galaxy clusters are built up from smaller groups as is predicted by hierarchical structure formation, and if the present-day SRs were always at the centres of the “building blocks”, then we would expect to see an increase in the stellar mass of massive SRs with increasing group richness. This is exactly what we see in Figure 6.8 supporting the above hypothesis. The FRs (including spirals) do not show a similar increase which is consistent with the idea that they do not follow the dry merger channel and are unlikely to merge in the cluster environment.

Finally, we aim to reproduce the results of previous studies that did not find a trend of angular momentum with environment at fixed stellar mass (section 6.3). We do find evidence for such a trend, and because we have better statistics than the previous studies did thanks to our large sample size and completeness, we are confident

that these trends do exist. However, we are in some cases limited by the fact that in order to investigate trends as a function of λ_{Re} , we must restrict ourselves to the MaNGA sample which is not a volume weighted sample. We could weight the MaNGA sample by volume but this tends to amplify unusual objects at the expense of massive SRs. However, we see evidence for the same trends in the volume-weighted sample when we simply consider $F(SR)$, which of course is related to λ_{Re} .

Our analysis has focused on the relatively nearby Universe ($z \leq 0.08$) and so a natural extension to this work would be to target clusters at high redshift with the next generation of IFUs. Our hypothesis suggests that the core SRs are formed at early times and so the progenitor clusters of present day clusters should display similar morphologies to the ones in our sample. Filling in these gaps will provide an important constraint on galaxy evolution models and the theory of slow rotator formation.

6.7 Complete census of massive slow rotators in ten large galaxy clusters

Galaxy interactions leave imprints in the motions of their stars, and so observing the two-dimensional stellar kinematics allows us to uncover their formation process (C16). slow rotators, which have stellar orbits dominated by random motions, are thought to be the fossil relics of a sequence of multiple gas-poor mergers, in an environment where the cold gas required to form new stars is nearly absent (Emsellem et al., 2007, 2011; Naab & Burkert, 2003; Naab et al., 2014). Indeed, observations of a handful of nearby galaxy clusters have indicated that slow rotators are preferentially found in the gas-poor, dense cores of clusters, which themselves must form by merging of smaller groups (Cappellari, 2013; Houghton et al., 2013; Scott et al., 2014; Brough et al., 2017). However, the generality of this result and connection between kinematics and environment is currently unclear, as recent studies have suggested that, at given stellar mass, the environment does not influence the formation of slow rotators (Brough et al., 2017; Veale et al., 2017b; Greene et al., 2017). Here we address this issue by combining a careful quality-assessed sample selection with two-dimensional stellar kinematics from a large galaxy survey and a novel photometric classification approach where kinematics are unavailable. We obtain the first complete census of the location of massive slow rotators in ten large clusters enclosing: in all cases, slow rotators are extremely rare and generally trace the clusters density peaks. This re-

sult unambiguously establishes that massive slow rotators are the relics of violent hierarchical cluster formation.

We conduct the first complete census of kinematic morphology for a subsample of 2007 galaxies taken from the catalogue presented in chapter 5 of about 14,000 galaxies (approximate minimum stellar mass $M \gtrsim 7.4 \times 10^9 M_\odot$, redshift $z \lesssim 0.08$). The galaxies in this subsample of 2007 galaxies are assigned to a cluster using the robust local neighbour finder TD-ENCLOSER (chapter 4). All of the galaxies have photometric properties such as apparent magnitude, and 1636 ($\sim 82\%$) have spectroscopic redshifts. 193 galaxies ($\sim 10\%$) in the sample have stellar kinematics obtained by the MaNGA survey (Bundy et al., 2015)), and a further 25 galaxies in the Coma cluster have integral-field kinematics obtained by with other instruments (23 from SWIFT; Thatte et al., 2006; Houghton et al., 2013 and two from the MASSIVE survey Veale et al., 2017a; Ene et al., 2018). Galaxies can be robustly separated into fast and slow rotators (FR and SR) using a proxy for specific stellar angular momentum λ_{R_e} , derived from the stellar kinematics, the apparent flattening ϵ and the stellar mass. Of the remaining 1791 galaxies for which we do not have stellar kinematics, only 123 ($\sim 7\%$) satisfy the criteria for SRs: $M_* \geq M_{\text{crit}} \equiv 2 \times 10^{11} M_\odot$ and $\epsilon < 0.4$. We classify the galaxies in this small subset as SR/FR *candidates* according to their visual morphology. We showed that one can guess an early type galaxy (ETG) that is more massive than M_{crit} to be a FR with $\sim 92\%$ accuracy, and so of the 1964 *total* FRs in the sample, we expect just *nine* ($\sim 0.5\%$) to be misclassified, as all galaxies less massive than M_{crit} are by definition fast rotators (C16). Hence, we can be certain that almost *all* galaxies classified as FRs in our sample are *genuine* FRs. On the other hand, given a guess of SR, we are correct in just under half of all cases ($\sim 48\%$), meaning that the lower and upper limit for the number of massive SRs per cluster is given by the number of confirmed and confirmed + candidate SRs respectively.

In Figures 1 and 2, we present the on-sky projections for our cluster sample, clearly highlighting the location of the massive SRs. The key result is that the central part of *every* cluster has *at least* one massive SR, and almost all massive SRs that are not in the centres are associated with substructure (e.g. Abell 2065). Abell 2197 is known to have a bimodal galaxy distribution (Rines et al., 2002), and Abell 1775 is known to have multiple components (Oegerle et al., 1995; Kopylov & Kopylova, 2009; Zhang et al., 2011); in these cases, a massive SR exists at each density peak. In cases where clusters appear elongated and are relaxing post merger, the SRs are aligned with the orientation of the cluster major axis, suggesting they sit at the bottom of the

potential well in their respective subclusters (e.g. Abell 2167 (Marini et al., 2004), Abell 2161 (Rines & Diaferio, 2006), Abell 2079 and Abell 1314 (Wilber et al., 2018)).

Our results are in good agreement with early indications for three clusters (see Figure 1.7b) using data compiled from observations of the Virgo (Cappellari et al., 2011a), Fornax (Scott et al., 2014) and Coma (Houghton et al., 2013) clusters. Our results are consistent with the theoretical viewpoint that the progenitors of present-day core SRs formed at the centres of the most massive haloes early in the history of the Universe, and experienced successive dry (gas-poor) mergers as a result of merging with other galaxy groups. We are also consistent with results from eight clusters in the Southern sky (Brough et al., 2017) which show that in general, the most massive ETGs with low angular momentum are found in the dense cluster core. However, that study was based on very incomplete coverage of the clusters. Moreover, the same study, along with two other recent studies (Veale et al., 2017b; Greene et al., 2017) have shown that at *fixed stellar mass*, there is little or no trend in the observed angular momentum or the fraction of SRs with environment.

If present-day massive SRs did form by hierarchical merging, then we should indeed observe the stellar mass to be the main driver of slow rotation in galaxies since stellar mass cannot disappear and can be easily be determined observationally. We would still expect to see a trend with environment as the frequency of minor mergers must increase with increasing galaxy density. However, we would expect this trend to be weaker than the one with stellar mass because the environment is non-trivial and challenging to measure reliably and the boundaries of clusters and groups are not easy to define. Moreover, massive ellipticals “slosh” about within clusters (Barbosa et al., 2018), especially during or after mergers of group haloes (Randall et al., 2010), and so may appear in lower density environments in a later stage as a result. Finally, it is possible that a present-day SR may have accreted a large proportion of its neighbours and so may appear to be in a low-density environment or even in isolation. These effects conspire to wash out the dependence of angular momentum on environment for SRs at low redshift which constitute the evolutionary end points. However, if taken at face value, the lack of such a trend implies that the environment *itself* has little to no effect on the formation of SRs.

One crucial aspect of massive SRs is that they are intrinsically rare, making up between 21-35 ($\sim 1\% - 2\%$) of the galaxies in our cluster sample. Thus, they are vastly outnumbered by FRs and spirals and so any trends for subsamples containing galaxies less massive than M_{crit} will be driven by these galaxies. Indeed, FRs are necessary in order to build up the number density in the cores of clusters and so on average, only

one in four galaxies will be a SR at a given number density. These aspects should be taken into account when interpreting trends at fixed stellar mass. Furthermore, we have used a larger sample with groups of 10 or more members to show that massive SRs are biased towards the densest regions of groups and clusters *particular to each cluster*. In other words, the fraction of SRs is *not* an absolute function of number density, but *is* a function of the *relative* number density compared to the maximum in each cluster. This means that by combining multiple clusters in a single kinematic morphology-density relation, the profiles of increasing $F(\text{SR})$ with number density, which represent what we see by eye, are smoothed out.

Our study has provided the first complete view of the relationship between kinematic morphology, which encodes the fossil record of a galaxy’s formation mechanism, and environment, which strongly influences a galaxy’s evolution. We have shown that within the cluster environment, massive SRs are almost non-existent beyond about 0.5 Mpc from the cluster centre or local overdensity. Hierarchical formation predicts that the most massive clusters, such as the ones presented here, are built up from smaller groups. The fact that the distribution of massive SRs in present-day clusters is concentrated towards the density peaks provides conclusive evidence that the progenitor haloes (“building blocks”) each contained massive SRs or passive FRs at their centres. The results of this study provide a unique benchmark for future theoretical studies of galaxy formation and present a challenge to cosmological simulations which must be able to reproduce what we see by eye.

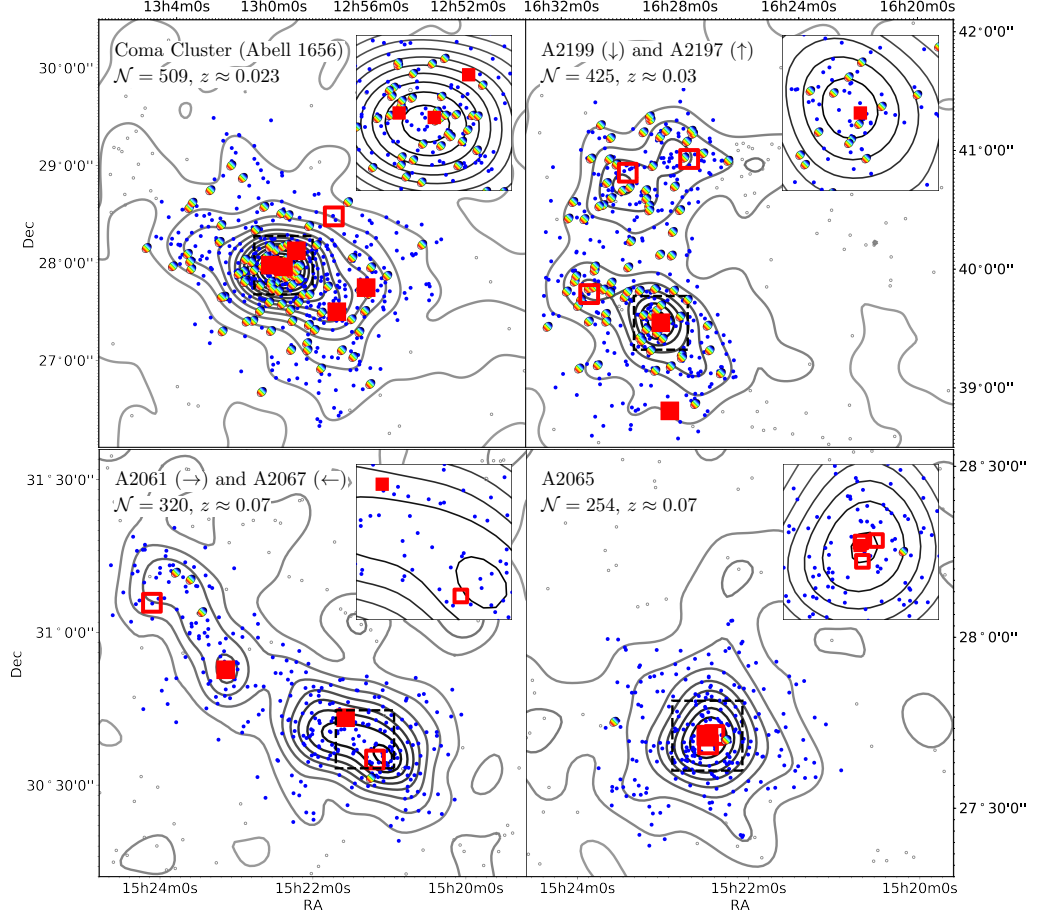


Figure 6.17: **Galaxy clusters where at least one galaxy has been observed with kinematics.** Massive SRs are shown as red squares, and are filled if they are confirmed SRs with stellar kinematics and $M > M_{\text{crit}}$, and unfilled if they are candidate SRs with $M > M_{\text{crit}}$. Miniature velocity maps indicate FRs with stellar kinematics (or SR and $M < M_{\text{crit}}$), and blue points indicate candidate FRs (or SR and $M < M_{\text{crit}}$). The contour levels indicate increasing density with increasing opacity. Galaxies which are not cluster members are shown as grey unfilled circles. The square has an area equal to 1 Mpc^2 and is centred on the densest peak in the field of view. A close up of the region within the square is shown in the inset. For each cluster, we give the designation, number of members $\mathcal{N}$ and approximate redshift. *Top Left:* The Coma Cluster (A1656). We supplement our classifications with published classifications (Houghton et al., 2013; Veale et al., 2017a; Ene et al., 2018), including the three SRs at the core. *Top Right:* A2197 (top) and A2199 (bottom). Abell 2197 has a bimodal velocity distribution and is considered to be two clusters, A2197W and A2197E, which may be interacting (Rines et al., 2002). *Bottom Left:* A2061 (lower right) and A2067 (upper left). This pair of clusters is in the Corona Borealis Supercluster (Postman et al., 1988; Marini et al., 2004; Pearson et al., 2014) (CBS) and is likely to be bound as the velocity difference is only $\sim 600 \text{ km s}^{-1}$ (Rines & Diaferio, 2006). *Bottom Right:* A2065. Part of the CBS.

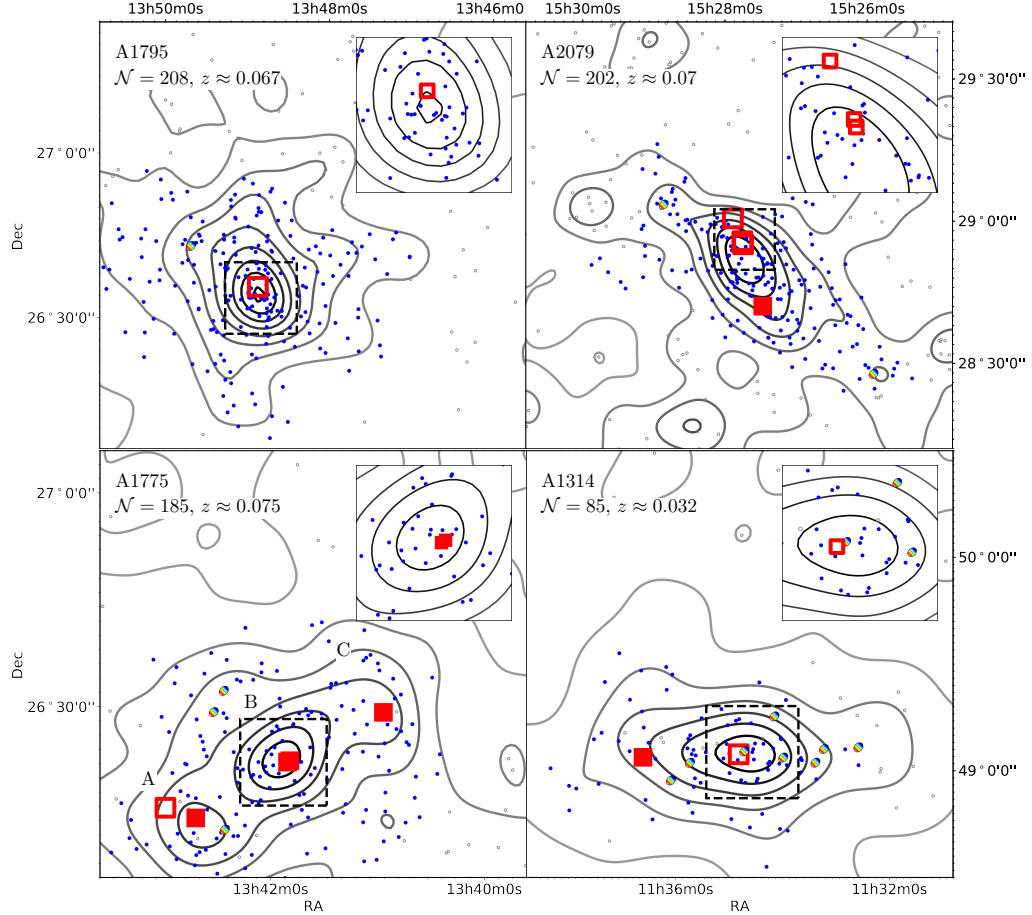


Figure 6.18: The same as Figure 6.17. *Top Left*: A1795 (van Breugel et al., 1984; Buote & Tsai, 1996; Fabian et al., 2001; Kokotanekov et al., 2018). This cluster lies within the Boötes supercluster. *Top right*: A2079. This cluster is located within the CBS. *Bottom Left*: A1775. This cluster has three components which are labelled (Oegerle et al., 1995; Kopylov & Kopylova, 2009; Zhang et al., 2011). The two BCGs of A1775B appear to be very close but the easternmost of the pair is closer in redshift to A1775A (Kopylov & Kopylova, 2009). A1775A and A1775B may be interacting as suggested by X-ray observations of the hot gas (Andersson et al., 2009). *Bottom Right*: A1314. This low-mass cluster has a disturbed morphology and is likely to be merging (Wilber et al., 2018).

Chapter 7

Discussion

Two roads diverged in a wood, and
I—, I took the one less traveled by,
And that has made all the
difference.

Robert Frost

In this chapter, I briefly summarise the results of this work, and suggest potential opportunities for follow-up study.

7.1 Summary of results

In this thesis, I have studied the stellar kinematics of nearby galaxies, which represent the product of around 13 billion years of galaxy evolution, in order to gain an understanding of their internal structure and make conclusions about their formation history. The focal point of my work has been the stellar angular momentum within one effective radius, λ_{Re} , which is related to many galaxy properties such as stellar mass and morphology. The larger distances of the MaNGA targets compared to previous surveys has required me to address observational challenges. In section 2.4, I showed that the error in λ_{Re} introduced by assuming that the intrinsic velocity dispersion $\sigma_* = 0$ when the observed velocity dispersion σ_{obs} is lower than the instrumental resolution σ_{inst} (as can happen at low S/N) is minimal. I also showed that the λ_{Re} of FRs with arbitrary misalignment due to bars or degeneracy in the position angle is not substantially affected for $\epsilon < 0.4$, and thus these galaxies could be included in the *clean sample* of galaxies for which λ_{Re} is deemed to be accurate (see section 2.3). Finally, I addressed the problem of the smoothing effect of the velocity fields due to the finite PSF which had previously only been accounted for in an approximate way (D'Eugenio et al., 2013; van de Sande et al., 2017; Greene et al., 2018). In section 2.5,

I used the JAM method (Cappellari, 2008) to derive an analytical correction that can be applied to any FR to obtain the λ_{R_e} that would be observed if there was no seeing.

I used a large sample of about 2300 galaxies with MaNGA stellar kinematics to show for the first time that FRs and SRs form a bimodality in galaxy properties. The results presented in chapter 3 refute the notion that massive SRs constitute a sub-population of FR ETGs, and reinforce the theoretical viewpoint that two dominant channels of galaxy formation exist. In chapter 5, I constructed a large galaxy catalogue using the group-finder algorithm TD-ENCLOSER (chapter 4) that contains essentially complete information about the angular momentum classifications of all galaxies in the catalogue. I used this catalogue to show that core SRs occupy very different spatial distributions in clusters and groups compared to FRs (chapter 6). The high level of completeness as well as the large scope of the catalogue provide additional certainty to our conclusions. These results are fully consistent with the theoretical hypothesis outlined in subsection 1.3.2, in which the environment of SRs plays a fundamental role in determining their present-day properties.

7.2 Suggestions for future work

In this section, I will touch upon some potential avenues for follow-up on the work presented in this thesis and discuss some of the open questions.

Ground-based IFS surveys such as MaNGA are reaching the limit in terms of what is achievable from the ground. Already at $z \approx 0.1$, it is only possible to obtain stellar kinematics in large numbers for the most massive and largest galaxies with today's suite of instruments. The follow-up to MaNGA is Hector (Bland-Hawthorn, 2015) which will be based at the Anglo-Australian Telescope (AAT) and aims to observe 100,000 galaxies with IFS, which is a factor 10 times larger than the MaNGA sample. Hector will have about twice the spectral resolution of MaNGA allowing sensitive measurements of the higher order moments h_3 and h_4 and which will improve observations in galaxies of low σ .

However, to really understand the formation pathways of massive SRs, it is necessary to observe massive galaxies at intermediate and high redshifts. Many IFU surveys have been conducted at the epoch of peak star formation ($1 \lesssim z \lesssim 3$; Hopkins & Beacom, 2006; Madau & Dickinson, 2014) including SINS (Cresci et al., 2009), MASSIV (Contini et al., 2012), KMOS^{3D} (Wisnioski et al., 2015) and KROSS (Stott et al., 2016). At these redshifts, it is only possible to measure the kinematics of ionised gas, but a significant fraction of galaxies are star forming and building up their stellar

mass and so are rich in gas. The gas forms clumpy disks with high σ where the sites of intense star formation are located (Epinat et al., 2012; Förster Schreiber et al., 2009; Swinbank et al., 2012; for a complete review, see Conselice, 2014.)

Galaxies have been observed at intermediate redshifts ($0.2 \lesssim z \lesssim 0.7$) with high resolution single-object IFUs such as MUSE-HDFS (Contini et al., 2016) and are seen to be mostly rotation-dominated in the gas component. The Tully-Fisher relation, which relates the maximum rotation speed of a disk to its luminosity, has been observed in these redshifts suggesting that stellar disks are already well established by this point. Thus, the FR formation channel is well sampled at different redshifts.

Much less is known about the formation channel taken by present-day massive SRs from observations. SRs are expected to quench earlier and more rapidly than FRs (Smethurst et al., 2017) and so are expected to deplete their gas reservoirs more quickly. Therefore, it is much more challenging to observe SRs with gas kinematics. Guérou et al. (2017) were the first to observe stellar kinematics at intermediate redshifts ($0.2 \lesssim z \lesssim 0.8$), using MUSE on the VLT to observe a sample of 17 mostly late-type, rotation dominated galaxies. They found that σ_{gas} roughly increases in a 1:1 relationship with σ_{stellar} , suggesting that the gas is not dominated by shocks or turbulence at these redshifts for galaxies in their sample. Their stellar mass range was too low to probe the mass range of core SRs ($M \lesssim 10^{10.5} \text{ M}_{\odot}$).

According to the theoretical framework outlined in subsection 1.3.2, the progenitors of present-day massive SRs should already be established at high redshift after an intense period of star formation followed by rapid quenching by AGN feedback. Their growth is predicted to be dominated by minor mergers at intermediate redshifts (Naab & Ostriker, 2009) by which point they should already be reaching the stellar masses required for a core nuclear profile (Figure 7.1). Thus, it should also be possible to observe SRs at intermediate redshifts, but they have not been targeted as of yet. It would be insightful to carry out a survey in the style of MASSIVE (Ma et al., 2014) but for intermediate redshifts. Such a survey will allow us to put constraints on the formation epoch of SRs: merger rates are expected to peak at about $1 \lesssim z \lesssim 2$ and so we would expect the progenitors of present-day massive SRs to be in dense environments at these redshifts. The next generation of multi-object spectrographs with adaptive optics will be able to probe this mass range at $z \approx 1$. These instruments include MOSAIC on the European-Extremely Large Telescope (Hammer et al., 2014) and HARMONI on the VLT (Arribas et al., 2010).

There is still much to be learned about the evolution of massive SRs at the low redshift regime with IFS. The star formation and accretion history of massive galaxies

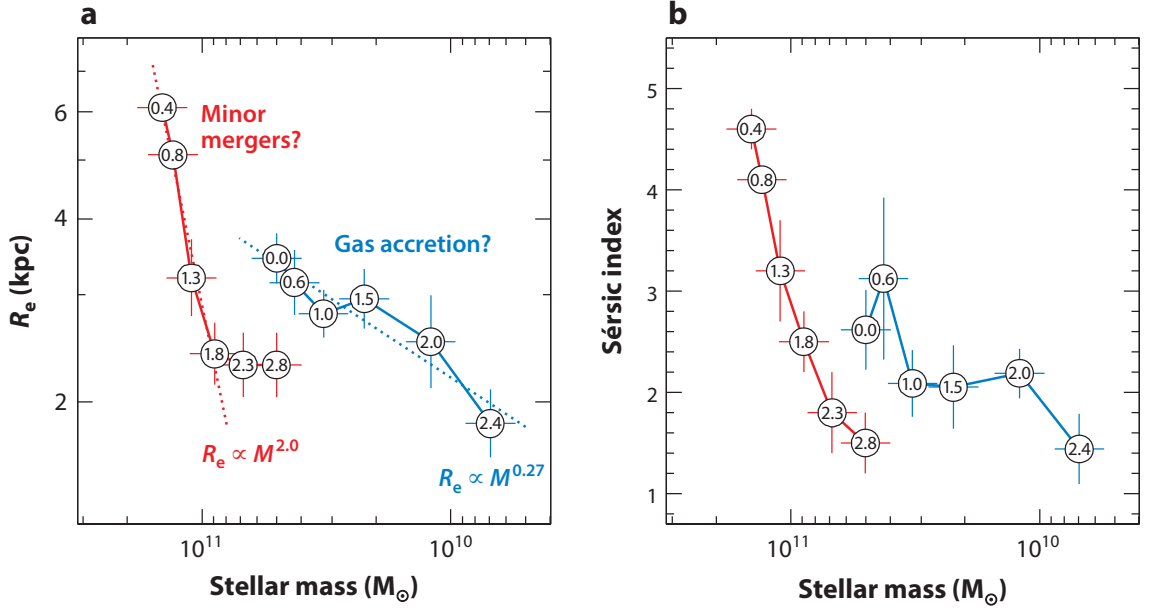


Figure 7.1: **Size and surface brightness profile redshift evolution for the fast and slow rotator channels.** The numbers inside each circle indicate the redshift. The red channel tracks the progenitor of a massive galaxy ($M \sim 3 \times 10^{11} M_\odot$) while the blue channel tracks the progenitor for an intermediate mass galaxy ($M \sim 5 \times 10^{10} M_\odot$). Taken from C16.

can be uncovered by studying their spatially-resolved age and metallicity. The ratio of α elements to Fe gives information about the relative contribution of Type II supernovae, which occur when a massive star explodes at the end of its life, and Type Ia supernovae, which are the evolutionary end-points of less massive stars (Thomas et al., 2005 and references therein). The $[\alpha/\text{Fe}]$ ratio can be used as a diagnostic for reconstructing the star formation history, as a high $[\alpha/\text{Fe}]$ ratio indicates a rapid timescale for star formation. It is well known that $[\alpha/\text{Fe}]$ increases with stellar mass as well as the global metallicity, $[\text{Z}/\text{H}]$ and stellar age (McDermid et al., 2015). These three stellar population parameters are also found to vary with radius within ETGs (e.g. Kuntschner et al., 2010; La Barbera et al., 2012; González Delgado et al., 2015; Boardman et al., 2017; Martín-Navarro et al., 2018; Parikh et al., 2019). Such radial gradients are consistent with the general consensus that massive ETGs form “inside-out” in a two stage process where the core forms in an intense starburst at high redshift, while the outskirts are predominantly built up over time via minor mergers (e.g. Oser et al., 2012). This scenario is supported by cosmological simulations (e.g. Zhao et al., 2003; Diemand et al., 2007; Cook et al., 2009; Oser et al., 2010).

The study of radial gradients as a function of environment has been thus far limited

to samples of a few hundred galaxies. Goddard et al. (2017) and Zheng et al. (2017) studied a sample of about 750-1000 MaNGA galaxies and found that the environment does not play a significant role on the age or metallicity gradients. To build up a full picture of galaxy transformation, it will be necessary to study galaxy populations in a multi-dimensional parameter space with dimensions of stellar mass, environment, angular momentum and population parameters such as age and metallicity.

Cosmological hydrodynamical simulations such as Illustris (Vogelsberger et al., 2014; Pillepich et al., 2018), EAGLE (Schaye et al., 2015) and HORIZON-AGN (Dubois et al., 2016) are crucial for testing theoretical hypotheses. However, there are still some challenges to overcome before simulations fully converge with the observations. In particular, SRs in simulations tend to be too flat, rarely reaching rounder than $\epsilon \approx 0.1$ (e.g. Naab et al., 2014; Penoyre et al., 2017; Schulze et al., 2018), whereas our observations show a strong peak of non-rotators at $\epsilon = 0 - 0.1$ (e.g. Figure 3.1b). It is not yet fully understood why this discrepancy exists although it is likely to be related to the spatial resolution. It is also challenging for simulations to generate galaxies of low and high masses in a consistent way as well as realistically model complex cluster environments (see Borgani & Kravtsov, 2011 for a review). My work sets the benchmark for simulations in that they must be able to reproduce what we see in nature.

Finally, an interesting observation that has only become apparent in my work is the apparent lack of non-rotating SRs in the upper right corner of the (λ_{Re}, ϵ) diagram at about $(\lambda_{Re}, \epsilon) \approx (0.15, 0.35)$ (see Figure 3.1b and Figure 6.1). The density of non-rotating SRs falls off from a peak at $\epsilon \approx 0$ towards $\epsilon \approx 0.3 - 0.4$ (see Li et al., 2018c). This is consistent with the result that genuine core SRs are mostly triaxial-oblate in shape with a possible minor population of triaxial-prolate objects (Li et al., 2018c). However, there seems to be no upturn in λ_{Re} for the apparently flatter SRs. The SR region on the (λ_{Re}, ϵ) is empirical (C16) as were all other previous SR/FR boundaries (Emsellem et al., 2007, 2011). λ_{Re} naturally rises with increasing ϵ for axisymmetric FRs and so the upper SR boundary of C16 also rises with ϵ . It is therefore intriguing that the original SAURON criteria for SRs of $\lambda_{Re} < 0.1$ (now combined with $\epsilon < 0.4$) seems to be a better fit to the data. This observation is even more intriguing when we realise that the sample in Figure 6.1 is almost two orders of magnitude larger than SAURON (Emsellem et al., 2007). It remains a puzzle as to why the non-rotating SRs do not reach $\lambda_{Re} \approx 0.15$ at $\epsilon \approx 0.35$. Higher quality observations with forthcoming IFU surveys may be able to shed light on this interesting aspect as well as the formation of massive SRs in general.

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