

1 **Sizes of Permanent Campsite Communities Reflect Constraints on Natural Human Communities**

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Abstract

Both small-scale human societies and personal social networks have a characteristic hierarchical structure with successively inclusive layers of 15, 50, 150, 500 and 1500 individuals. It has been suggested that these values represent a set of natural social attractors or ‘sweet spots’ in organisational terms. We exploited the new phenomenon of permanent (i.e. residential) campsites to ask whether these values are present in the size distribution of the numbers of residents in these naturally small-scale communities. In two separate datasets of different grain, we find consistent evidence for sites with 50, 150, 500 and maybe 1500 residents. We infer that these reflect numerical sizes at which communities may in some way be socially optimal. Our data do not allow us to say why this pattern emerges, but the consistency of the results, and the fact that the predetermined sizes of permanent campsites adhere to this pattern, suggests that it may arise from the limits on the number of relationships that make an effective community.

Keywords natural community size, human communities, permanent campsites, social brain hypothesis

1. Introduction

Hunter-gatherer communities typically occur in quite specific sizes that form a hierarchically scaled series of natural groupings of approximately 50, 150, 500 and 1500 individuals, with a scaling ratio of approximately 3 (Zhou, Sornette, Hill, & Dunbar, 2005; Hamilton, Milne, Walker, Burger, & Brown, 2007; Lehmann et al. 2014). These groupings correspond, respectively, to communities that are conventionally labelled as bands (or overnight camp groups), communities (or clans), mega-bands and tribes (Lehmann et al. 2014). Data from Facebook, twitter, email and massive multiplayer online games suggest that this same grouping pattern and scaling ratio occurs even in online environments (Pollet et al. 2011; Gonçalves et al. 2011; Haerter et al. 2012; Fuchs et al. 2014; Dunbar et al. 2015; Arnabaldi et al. 2015). These structural features of communities turn out to mirror the internal structure of personal social networks (Hill & Dunbar, 2003; Zhou et al., 2005; Sutcliffe et al. 2012), and are similar to the layering pattern found in animal species that live in complex societies (Hill et al. 2008).

Quite why social communities and networks should have the values and scaling ratio they do is, as yet, unclear. However, the core value of ~150 fits with the predictions of the social brain hypothesis (Dunbar 1992, 1993). Since we know from a series of neuroimaging studies in humans that individual differences in the size of personal social networks are correlated with the volume of core brain regions associated with the mentalising circuit, notably in the prefrontal cortex (Lewis et al. 2011; Powell et al. 2012, 2014; Kanai et al. 2012), it is likely that this reflects a real cognitive constraint of some kind. If so, it implies that these numbers are relatively fixed and are likely to reappear in many different social contexts.

In recent years, a new movement in German housing has emerged: elderly people, in particular, give up their regular housing (mostly rented apartments) and move to permanent camping sites, where little villages/communities emerge naturally, often equipped with amenities like pubs or nurseries (Soares 2013). In many such cases, the accommodation involves mobile homes, and is probably similar

to the trailer park phenomenon in the USA. Purportedly, the main reasons for this are the low cost of such locations, compared to the increasing price of regular housing, combined with the communality or sense of community they provide. This unusual process of contemporary small-scale natural community formation provides us with a unique opportunity to test the hypothesis that there are natural grouping sizes for such communities.

We collated data on community sizes at permanent campsites in Germany and ask whether the same kind of patterns that have been found in hunter-gatherer societies are also evident in these. We considered two datasets: a small dataset for which we established exact numbers of residents and a large dataset for which only the number of 'camping pitches' was available (which we used to estimate maximum community size). We ask two questions of the data. First, does the actual number of residents on these camp sites exhibit peaks in frequency that correspond to the layers of natural human communities and personal social networks? In effect, we view these campsites as a form of joiner-leaver game in which individuals or families join or leave the community depending on whether they find its size socially congenial. Such decisions may, of course, be complex and involve many factors, but by focussing on the end product (the census size of camps) we observe the cumulative outcome of many such decisions over time. Second, using the larger dataset, we ask whether campsite owners design their sites with these numbers in mind. The null hypothesis in this case is that, all else equal, site sizes should be distributed with an arbitrary mean and variance reflecting the area and funding available to establish sites. At worst, there should be no particular pattern and all sizes of sites might be equally represented. We assume that site owners would like to maximise the number of residents they have, but they might be intuitively aware that some community sizes are most attractive; hence, they might adjust the number of pitches they allow in the light of this, but if they do we imagine they are likely err on the high side to allow flexibility for more solo (as opposed to family) units.

As the baseline for comparison in both cases, we use the groupings identified for hunter-gatherer communities, as given by Lehmann et al. (2014), since these provide both means and variance statistics for all layers between 50 and 1500. Lehmann et al. (2014) give values of 42.8 ± 18.0 SD, 127.3 ± 43.8 , 566.6 ± 166.2 and 1727.9 ± 620.6 , respectively, for the four layers, which are numerically very similar to those obtained by Hamilton et al. (2007) using a different dataset. The differences between these values and the nominal layers of 50-150-500-1500 largely reflect ecological conditions: for example, band sizes average approximately 35 in ecologically stressed high latitude hunter-gatherers but approximately 50 in low latitude populations (Binford 2001).

It is important to be clear that the question we are asking is not whether the same kind of structured layering as has been found in human social organisations or personal social networks also occurs in these campsites, but rather whether the number of residents, and even the number of pitches, is dictated by this layering pattern across the range of camps. In other words, do these layers in some sense represent ‘sweet spots’ in organisation size that are preferred because they work better socially? To establish whether the same kinds of layerings occur *within* communities, we would need data of a very different kind (namely, data on interaction frequencies: e.g. Dunbar et al. 2015). Similarly, we cannot address the question of whether sites of particular size are socially optimal since we do not have data on either community longevity or residents’ satisfaction ratings. Our concern, rather, is whether the number of residents on permanent campsites favours particular values, and, secondarily, whether site owners opt for particular sizes when deciding how many pitches to allow. We cannot say anything about why people choose to live in communities of particular sizes, but simply ask whether or not they do. It is also important to emphasise that we are only concerned with individuals who live permanently on these sites and who regard the campsite as their main residence for legal purposes (as is now permitted in Germany). We are not concerned with temporary campers, who in any case invariably occupy a different part of the campsite from permanent campers.

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110 2. Methods

111 Lists of camping sites in Germany which allow permanent camping were derived from online
112 sources (www.mobilheim-forum.de, www.lebenaufdemcampingplatz.de, and www.camping.info). We
113 used these sites to estimate camping community size in two separate ways. Most of these sites also
114 offered camping places for temporary campers, in addition to permanent residents. On most campsites,
115 temporary and permanent camping areas are separate. We are concerned here only with the
116 permanent camping places.

117 First, 53 camping sites that were referred to on the forums of the first two webpages or found
118 via the search functionality of the third webpage were contacted directly and the number of residents
119 on the site was obtained from the site office. Some could not provide us with the exact number of
120 permanent campers, but only the number of permanent pitches that were occupied. In these cases, we
121 asked the administrator to estimate the average number of campers per pitch on the site (this number
122 consistently was either 2, 2.5 or 3 campers per pitch), and an average figure of 2.5 was then used to
123 estimate the number of permanent campers at the site. The average for the number of people per pitch
124 for those sites that provided this information was 2.39 ($SD = 0.39$, range 1-3, $N=25$). Second, we used a
125 dataset from a camping guide containing 1216 camping sites which gave the number of permanent
126 camping pitches at each site (ADAC, 2014). From these, 1123 offered at least one permanent camping
127 pitch. We used the average number of 2.5 campers per permanent camping pitch to estimate the
128 maximum total number of permanent campers possible at the site.

129 We attempt to detect the clusters by two different methods: (i) we fit different distributions to
130 the data and test if a composite of distributions is a likely candidate, and (ii) we apply a clustering
131 algorithm to the data and test if the means and layers are similar to the layer sizes observed in other
132 datasets.

To find a fit to the distribution, we use the method of maximum likelihood similar to Clauset and colleagues (2009). As our data comprise positive integers, we treat distributions in a discrete manner. This involves normalising the distribution by

$$\sum_{k=0}^{k_{\min}} \rho_k + \sum_{k=k_{\min}}^{\infty} p_k = 1,$$

where p_k is the distribution we are interested in for the variable k and ρ_k is the distribution below some minimum value for that variable k_{\min} in case the distribution p_k is only exhibited in the tail. We next numerically maximise the log of the likelihood to estimate the parameters for different distributions. The numerical maximisation is implemented with the scipy (v0.17.1) library in Python. We then compute the Akaike Information Criterion (AIC) for each of the candidate models (Akaike 1974), and identify the model with the lowest value of the AIC as being the most likely of the candidate models.

We tested the following models: power law, Gaussian, log-normal, geometric, compound Poisson and compound negative binomial distributions (noting again that these are treated in a discrete manner). In the case of the last two, we treat the data as being made up of 1 to n distributions, and calculate the AIC for each n , stopping when we reach a local minimum to give the optimal n . If the distribution is best fitted by one of these composite distributions, then the estimates for the means from the maximum likelihood parameters give the mean layer sizes.

We also apply a clustering algorithm to the data. To find the optimal number of clusters, we use the method of goodness of variance fit, also known as Jenks natural breaks optimisation (Jenks 1967). This is an iterative process that moves values between clusters until the variance within each cluster is minimised. A goodness of fit value is calculated for different numbers of clusters. A goodness of fit of 1.0 can only be attained when there is zero within-class variation, which will typically be the case when the number of clusters is the same as the sample size. Here we follow Coulson (1987) and take a value of

0.85 as the threshold. The advantage of using the Jenks algorithm over other clustering techniques is that it is designed for one-dimensional data such as we have here.

The data can be found at <https://osf.io/v8jaf/>.

3. Results

Figure 1a plots the frequency distribution of the number of actual permanent residents at the 53 camping sites which provided this information. The distribution is highly skewed with a long right tail and a geometric mean of 97.5. A log-transformation yields a more normalised distribution (Figure 1b). For illustration, the values at 15, 50, 150 and 500 are superimposed as solid vertical lines on Figure 1b. The binning in Figure 1 is, of course, somewhat arbitrary (albeit determined by the SPSS software), and not of particular significance of itself, although the correspondence between the peaks and the theoretical values is striking nonetheless. The more important issue is whether the data themselves exhibit any kind of structure.

The AIC values using maximum likelihood estimates to the distributions described above are reported in Table 1. The two most likely candidates are a compound of 5 Poisson distributions and a compound of 4 negative binomial distributions, the latter receiving the most support. The means for the compound Poisson distribution are 16.2, 56.4, 139.6, 350.0 and 677.2, while for the compound negative binomial the means at each peak calculated from the parameter estimates are 47.3, 136.4, 349.8 and 759.5.

Table 1. The Akaike Information Criteria (AIC) for the candidate models applied to each dataset. The lower the AIC value, the more likely the candidate model is. Values in bold are the most likely candidates for that dataset.

Model	Small dataset ($n = 53$)	Large dataset ($n = 1123$)
Power law	749.4	17390.0
Discrete normal	700.8	15396.7
Log-normal	668.0	15193.3
Geometric	677.5	15145.3
Poisson	14590.1	327200.0
Negative binomial	678.4	15157.8
Compound Poisson	614.8	46579.9
Compound negative binomial	558.4	12809.4

We also use the Jenks algorithm as described above to detect clusters in the data. This finds five clusters with means at 42.0 (23 cases), 139.6 (17 cases), 350 (5 cases), 623 (5 cases) and 1075 (3 cases), with a scaling ratio of 2.33. The first three of these are remarkably close to the estimates from the compound negative binomial distribution, and individually not significantly different from the equivalent values of 42.8, 127.3, 566.6 and 1727.9 given by the hunter-gatherer data (if we allow that the 350 and 623 are essentially picking up the same grouping level, with an average of 486.5) ($Z=-0.04$, $Z=-0.28$, $Z=-0.34$ and $Z=-1.05$; $0.968 \geq p \geq 0.297$).

We next apply the same method to the larger campsite dataset. Although the values we have in this case are maximum possible community sizes and not actual number of residents, nonetheless we can ask whether or not they exhibit a similar patterning to the smaller dataset. Figure 2a plots the distribution of estimated maximum residential capacity in the 1123 campsites, and Figure 2b plots this on a log-transformed scale. The geometric mean is 177.8. Once again, the dashed vertical lines indicate communities of 15, 50, 150 and 500 individuals. From the maximum likelihood approach we find that a

compound negative binomial is also the most likely of the candidate models (Table 1). This has means at 72.2, 233.6, 438.2 and 936.4. The Jenks algorithm also has an optimised value of four clusters which have means of 107.4 (628 cases), 369.2 (324 cases), 825.4 (142 cases) and 1622.9 (29 cases), with a scaling ratio of 2.55. The values in the Jenks case are larger than those for the compound negative binomial, but in both cases the cluster means are larger in this dataset than in the small dataset.

4. Discussion

We examined the size distribution of communities in what was, in effect, a natural experiment created by the provision of permanent pitches at a large number of German campsites. The distributions are highly skewed in both the datasets we had available, but their geometric means (~98 and ~178) straddle the value of 150 observed for natural human networks (and are within the natural range of variation for this value: Hill & Dunbar 2003). Partitioning the datasets into what seem to be natural sub-clusters suggests an even closer fit, with peaks at ~140 and ~107 for the small and large datasets, respectively. There is considerable evidence for the existence of a natural community size of approximately 150 in both ethnographic (Dunbar 2008; Alberti 2014) and online (Pollet et al. 2011; Gonçalves et al. 2011; Haerter et al. 2012; Fuchs et al. 2014) environments, and the fact that the average camp community size in the present samples is in this same area adds support to the claim that this is an optimal or preferred community size. More generally, analysis of the sub-structuring patterns in both datasets suggests peaks at values that approximate the observed social layering values of 50, 150 and 500 observed in natural communities.

Not too surprisingly, the fit is rather better for the number of actual residents than it is for the maximum residential capacity: the latter will inevitably be driven by the site owners' economic interest in maximising the number of residents, whereas the former is the outcome of a conventional joiner-leaver game in which individuals decide whether a particular community provides an appropriate social

environment. Camp owners should always want to have more pitches available than they think they can fill, partly because they will want the flexibility to allow more single occupants and in part because it will always be to their financial advantage to have a few extra people on their site (providing these don't exceed any optimal limit by too many and so disturb the community's equanimity). Nonetheless, the fact both datasets are in broad agreement suggests that campsite owners must have in their minds a sense of what the ideal size is. It seems that these particular community sizes are in some way socially optimal, and act as attractors when individuals, couples or families decide to join or leave a community. It would be particularly illuminating to observe the conditional frequencies with which individuals joined and left communities so as to test the hypothesis that joining rates are higher on the downside of each number and leaving rates higher on the upside.

The hierarchically inclusive layered structuring of both natural communities and personal social networks is a consequence of a combination of cognitive limits on the number of relationships that can be maintained at a given emotional intensity and the time available to maintain such relationships (Roberts & Dunbar 2011a, 2011b; Sutcliffe et al. 2012; Miritello et al. 2013; Roberts et al. 2014; Saramäki et al. 2014), with very characteristic frequencies of interaction for each layer that are in fact mirrored even in the online world (Dunbar et al. 2015; Arnabaldi et al. 2015). We might expect the camp communities to be organised in the same way. Although outside the scope of the present study, obvious predictions to test are: (1) that average contact frequencies among camp members are higher in the smaller campsites than in the larger ones and (2) that large camp sites are divided into sub-communities that interact within themselves especially frequently and between themselves only rarely. To test this, we would need data on interaction frequencies between individuals within the set of permanent residents. Such data would require detailed interviews that we are not able to carry out, although in principle this could be done.

The existence of this apparently natural structuring to communities raises the question as to the functional significance of these layers. Whether the layers have functional properties or are simply an emergent property of how relationships are organised remains to be resolved, though some adaptive functions have been suggested for the various layers (Sutcliffe et al. 2012; Lehmann et al. 2014). Even so, it seems that while specific functions can be ascribed to the different layers, there is some inflexibility in the numbers of individuals on whom one can draw for these functions, suggesting that there may be intrinsic constraints on layer size that require more detailed investigation. These ‘sweet spots’ may arise because they allow natural communities to grow within them. Thus, 50 individuals may represent a natural social grouping (in the world of personal social networks, it is the set of individuals that provides the bulk of one’s regular social contacts and all of one’s emotional and economic support: Sutcliffe et al. 2012; Roberts et al. 2014) and functional communities must either be of this size or some multiple of this so as to allow several such self-contained communities to co-exist.

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Legends to Figures

Fig. 1 (a) Frequency distribution of actual permanent residents at the 45 camping sites in Germany which provided numbers of actual permanent campers and (b) with number of residents \log_{10} -transformed. The solid vertical lines demarcate values of 15, 50, 150 and 500; the dashed lines identify the cluster means identified by the compound negative binomial.

Fig. 2 (a) Frequency distribution of maximum number of residents for the 1123 campsites from the camping guide (assuming an average number of 2.5 campers per pitch) and (b) with maximum number of residents \log_{10} -transformed. The solid vertical lines demarcate values of 15, 50, 150 and 500; the dashed lines identify the cluster means identified by the compound negative binomial.