

Compact Deep Aggregation for Set Retrieval

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Abstract. The objective of this work is to learn a compact embedding of a set of descriptors that is suitable for efficient retrieval and ranking, whilst maintaining discriminability of the individual descriptors. We focus on a specific example of this general problem – that of retrieving images containing multiple faces from a large scale dataset of images. Here the set consists of the face descriptors in each image, and given a query for multiple identities, the goal is then to retrieve, in order, images which contain all the identities, all but one, etc.

To this end, we make the following contributions: first, we propose a CNN architecture – *SetNet* – to achieve the objective: it learns face descriptors and their aggregation over a set to produce a compact fixed length descriptor designed for set retrieval, and the score of an image is a count of the number of identities that match the query; second, we show that this compact descriptor has minimal loss of discriminability up to two faces per image, and degrades slowly after that – far exceeding a number of baselines; third, we explore the speed vs. retrieval quality trade-off for set retrieval using this compact descriptor; and, finally, we collect and annotate a large dataset of images containing various number of celebrities, which we use for evaluation and will be publicly released.

1 Introduction

Suppose we wish to retrieve all images in a very large collection of personal photos that contain a particular set of people, such as a group of friends or a family. Then we would like the retrieved images that contain all of the set to be ranked first, followed by images containing subsets, e.g. if there are three friends in the query, then first would be images containing all three friends, then images containing two of the three, followed by images containing only one of them. We would also like this retrieval to happen in real time.

This is an example of a *set retrieval problem*: each image contains a set of elements (faces in this case), and we wish to order the images according to a query (on multiple identities) such that those images satisfying the query completely are ranked first (i.e. those images that contain all the identities of the query), followed by images that satisfy all but one of the query identities, etc. An example of this ranking is shown in Fig. 1 for two queries.

We can operationalize this by scoring each face in each photo of the collection as to whether they are one of the identities in the query. Each face is represented by a fixed length vector, and identities are scored by logistic regression classifiers. But, consider

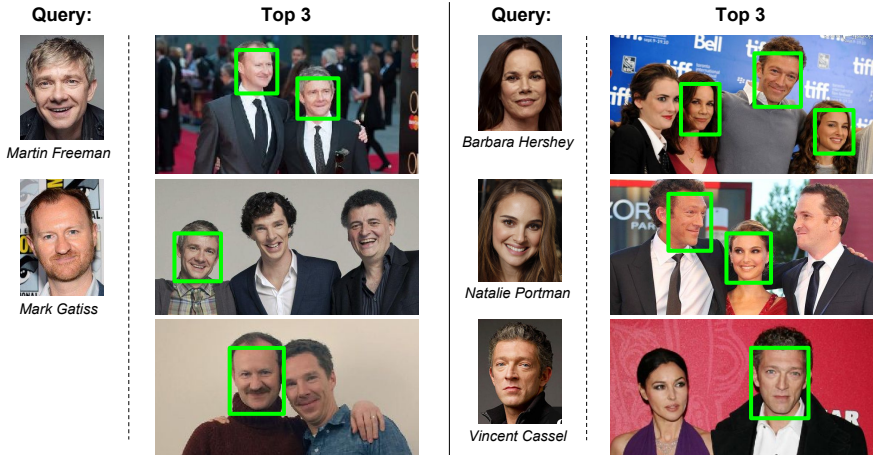


Fig. 1: **Images ranked using set retrieval for two example queries.** The query faces are given on the left of each example column, together with their names (only for reference). Left: a query for two identities; right: a query for three identities. The first ranked image in each case contains all the faces in the query. Lower ranked images partially satisfy the query, and contain progressively fewer faces of the query. The results are obtained using the compact set retrieval descriptor generated by the SetNet architecture, by searching over 200k images of the *Celebrity Together* dataset introduced in this paper.

the situation where the dataset is very large, containing millions or billions of images each containing multiple faces. In this situation two aspects are crucial for real time retrieval: first, that all operations take place in memory (not reading from disk), and second that an efficient algorithm is used when searching for images that satisfy the query. The problem is that storing a fixed length vector for each *face* in memory is prohibitively expensive at this scale, but this cost can be significantly reduced if a fixed length vector is only stored for each *set of faces* in an image (since there are far fewer images than faces). As well as reducing the memory cost this also reduces the run time cost of the search since fewer vectors need to be scored.

So, the question we investigate in this paper is the following: can we aggregate the *set of vectors* representing the multiple faces in an image into a *single vector* with little loss of set-retrieval performance? If so, then the cost of both memory and retrieval can be significantly reduced as only one vector per *image* (rather than one per *face*) have to be stored and scored.

Although we have motivated this question by face retrieval it is quite general: there is a set of elements, each element is represented by a vector of dimension D , and we wish to represent this set by a single vector of dimension D' , where $D' = D$ in practice, without losing information essential for the task. Of course, if the total number of elements in all sets, N , is such that $N \leq D$ then this certainly can be achieved provided that the set of vectors are orthogonal. However, we will consider the situation

commonly found in practice where $N \gg D$, e.g. D is small, typically 128 (to keep the memory footprint low), and N is in the thousands.

We make the following contributions: first, we introduce a trainable CNN architecture for the set-retrieval task that is able to learn to aggregate face vectors into a fixed length descriptor in order to minimize interference, and also is able to rank the face sets according to how many identities are in common with the query using this descriptor. To do this, we propose a paradigm shift where we draw motivation from image retrieval based on local descriptors. In image retrieval, it is common practice to aggregate all local descriptors of an image into a fixed-size image-level vector representation, such as bag-of-words [25] and VLAD [12]; this brings both memory and speed improvements over storing all local descriptors individually. We generalize this concept to set retrieval, where instead of aggregating local interest point descriptors, set element descriptors are pooled into a single fixed-size set-level representation. For the particular case of face set retrieval, this corresponds to aggregating face descriptors into a set representation. The novel aggregation procedure is described in Sec. 2 where compact set-level descriptors are trained in an end-to-end manner using a ResNet-50 [8] as the base CNN.

Our second contribution is to introduce a dataset annotated with multiple faces per images. In Sec. 3 we describe a pipeline for automatically generating a labelled dataset of pairs (or more) of celebrities per image. This *Celebrity Together* dataset contains around 200k images with more than half a million faces in total. It will be publicly released.

The performance of the set-level descriptors is evaluated in Sec. 4. We first ‘stress test’ the descriptors by progressively increasing the number of faces in each set, and monitoring their retrieval performance. We also evaluate retrieval on the *Celebrity Together* dataset, where images contain a variable number of faces, with many not corresponding to the queries, and explore efficient algorithms that can achieve immediate (real-time) retrieval on very large scale datasets.

Note, although we have grounded the set retrieval problem as faces, the treatment is quite general: it only assumes that dataset elements are represented by vectors and the scoring function is a scalar product. We return to this point in the conclusion.

1.1 Related work

To the best of our knowledge, this paper is the first to consider the set retrieval problem. However, the general area of image retrieval has an extensive literature that we build on here.

One of the central problems that has been studied in large scale image instance retrieval is how to condense the information stored in multiple local descriptors such as SIFT [16], into a single compact vector to represent the image. This problem has been driven by the need to keep the memory footprint low for very large image datasets. An early approach is to cluster descriptors into visual words and represent the image as a histogram of word occurrences – bag-of-visual-words [25]. Performance can be improved by aggregating local descriptors within each cluster, in representations such as Fisher Vectors [13, 20] and VLAD [12]. In particular, VLAD – ‘Vector of Locally Aggregated Descriptors’ by Jégou et al. [12] and its improvements [2, 5, 14] was used

to obtain very compact descriptions via dimensionality reduction by PCA, considerably reducing the memory requirements compared to earlier bag-of-words based methods [18, 22, 25]. VLAD has superior ability in maintaining the information about individual local descriptors while performing aggressive dimensionality reduction.

VLAD has recently been adapted into a differentiable CNN layer, NetVLAD [1], making it end-to-end trainable. We incorporate a modified form of the NetVLAD layer in our SetNet architecture. An alternative, but related, very recent approach is the memory vector formulation of [10], but we have not employed it here as it has not been made differentiable yet.

Another strand of research we build on is category level retrieval, where in our case the category is a face. This is another classical area of interest with many related works [4, 21, 28, 30, 32]. For the case of faces, the feature vector is produced from the face region using a CNN trained to classify or embed faces [19, 24, 27].

Also relevant are works that explicitly deal with sets of vectors. Kondor and Jebara [15] developed a kernel between vector sets by characterising each set as a Gaussian in some Hilbert space. However, their set representation cannot currently be combined with CNNs and trained in an end-to-end fashion. Recently, Zaheer et al. [31] investigate permutation-invariant objective functions for operating on sets, although their method boils down to average pooling of input vectors, which we compare to as a baseline. Rezatofighi et al. [7] consider the problem of predicting sets, i.e. having a network which outputs sets, rather than our case where a set of elements is an input to be processed and described with a single vector.

2 SetNet – a CNN for set retrieval

As described in the previous section, using a single fixed-size vector to represent a set of vectors is a highly appealing approach due to its superior speed and memory footprint over storing a descriptor-per-element. In this section, we propose a CNN architecture, *SetNet*, for the end-task of set retrieval. There are two objectives:

1. To learn the element descriptors together with the aggregation in order to minimise the loss in face classification performance between using individual descriptors for each face, and an aggregated descriptor for the set of faces. This is achieved by training the network for this task, using an architecture combining ResNet for the individual descriptors together with NetVLAD for the aggregation.
2. To be able to rank the images using the aggregated descriptor in order of the number of faces in each image that correspond to the identities in the query. This is achieved by scoring each face using a logistic regression classifier. Since the score of each classifier lies between 0 and 1, the score for the image can simply be computed as the sum of the individual scores, and this summed score determines the ranking function.

As an example of the scoring function, if the search is for two identities and an image contains faces of both of them (and maybe other faces as well), then the ideal score for each relevant face would be one, and the sum of scores for the image would be two. If an image only contains one of the identities, then the sum of the scores would be one. The images with higher summed scores are then ranked higher and this naturally orders the images by the number of faces it contains that satisfy the query.

To deploy the set level descriptor for retrieval in a large scale dataset, there are two stages:

Offline: SetNet is used to compute face descriptors for each face in an image, and aggregate them to generate a set-vector representing the image. This procedure is carried out for every image in the dataset, so that each image is represented by a single vector.

At **run-time**, to search for an identity, a face descriptor is computed for the query face using SetNet, and a logistic regression classifier used to score each image based on the scalar product between its set-vector and the query face descriptor. Searching with a set of identities amounts to summing up the image scores of each query identity.

2.1 SetNet architecture

In this section we introduce our CNN architecture, designed to aggregate multiple element (face) descriptors into a single fixed-size set representation. The *SetNet* architecture (Fig. 2) conceptually has two parts: (i) each face is passed through a feature extractor network separately, producing one descriptor per face; (ii) the multiple face descriptors are aggregated into a single compact vector using a modified NetVLAD layer, followed by a trained dimensionality reduction. At training time, we add a third part which emulates the run-time use of logistic regression classifiers. All three parts of the architecture are described in more detail next.

Feature extraction. The first part is a modified ResNet-50 [8] chopped after the global average pooling layer. The ResNet-50 is modified to produce 128-D vectors in order to keep the dimensionality of our feature vectors relatively low (we have not observed a significant drop in face recognition performance from the original 2048-D descriptors). The modification is implemented by adding a fully-connected (FC) layer of size 2048×128 after the global average pooling layer in the original ResNet, in order to obtain a lower dimensional face descriptor (full details of the architecture are given in the supplementary material). In this part, individual element descriptors (x_1, \dots, x_F) are obtained from ResNet, where F is the number of faces in an image.

Feature aggregation. Face features are aggregated into a single vector V using a NetVLAD layer (illustrated in Fig. 3, and described below in Sec. 2.2). The NetVLAD layer is slightly modified by adding an additional L2-normalization step – the total contribution of each face descriptor to the aggregated sum (i.e. its weighted residuals) is L2-normalized in order for each face descriptor to contribute equally to the final vector; this procedure is an adaptation of residual normalization [5] of the vanilla VLAD to NetVLAD. The NetVLAD-pooled features are reduced back to 128-D by means of a fully-connected layer followed by batch-normalization [9], and L2-normalized to produce the final set representation v_{set} .

Training block. At training time, an additional logistic regression loss layer is added to mimic the run-time scenario where a logistic regression classifier is used to score each image based on the scalar product between its set-vector and the query face descriptor. Note, SetNet is used to generate both the set-vector and the face descriptor. Sec. 2.3 describes the appropriate loss and training procedure in more detail.

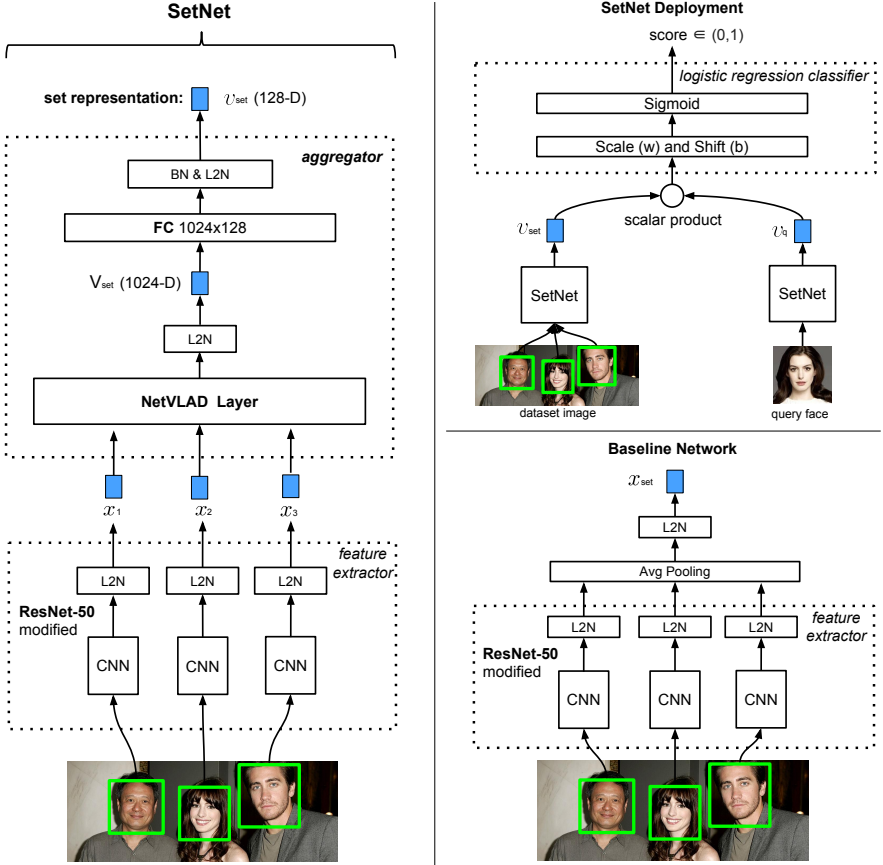


Fig. 2: **SetNet architecture and training.** **Left:** SetNet – features are extracted from each face in an image using a modified ResNet-50. They are aggregated using a modified NetVLAD layer into a single 1024-D vector which is then reduced to 128-D via a fully connected dimensionality reduction layer, and L2-normalized to obtain the final image-level compact representation. **Right (top):** at test time, a query descriptor, v_q , is obtained for each query face using SetNet (the face is considered as a single-element set), and the dataset image is scored by a logistic regression classifier on the scalar product between the query descriptor v_q and image set descriptor v_{set} . The final score of an image is then obtained by summing the scores of all the query identities. **Right (bottom):** the baseline network has the same feature extractor as SetNet, but the feature aggregator uses an average-pooling layer, rather than NetVLAD.

2.2 NetVLAD trainable pooling

NetVLAD has been shown to outperform sum and max pooling for the same vector dimensionality, which makes it perfectly suited for our task. Here we provide a brief overview of NetVLAD, for full details please refer to [1].

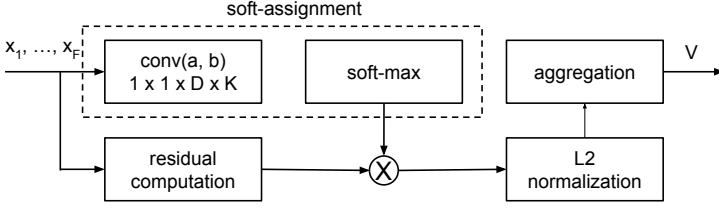


Fig. 3: **NetVLAD layer.** Illustration of the NetVLAD layer [1], corresponding to equation (1), and slightly modified to perform L2-normalization before aggregation; see Sec. 2.2 for details.

For F D -dimensional input descriptors $\{x_i\}$ and a chosen number of clusters K , NetVLAD pooling produces a single $D \times K$ vector V (for convenience written as a $D \times K$ matrix) according to the following equation:

$$V(j, k) = \sum_{i=1}^F \frac{e^{a_k^T x_i + b_k}}{\sum_{k'} e^{a_{k'}^T x_i + b_{k'}}} (x_i(j) - c_k(j)) \quad (1)$$

where $\{a_k\}$, $\{b_k\}$ and $\{c_k\}$ are trainable parameters for $k \in [1, 2, \dots, K]$. The first term corresponds to the soft-assignment weight of the input vector x_i for cluster k , while the second term computes the residual between the vector and the cluster centre. Finally, the vector is L2-normalized.

2.3 Loss function and training procedure

In order to achieve the two objectives outlined at the beginning of Sec. 2, a Multi-label logistic regression loss is used. Suppose a particular training image contains F faces, and the mini-batch consists of faces for P identities. Then in a forward pass at training time, the descriptors for the F faces are aggregated into a single feature vector, v_{set} , using the SetNet architecture, and a face descriptor, v_f , is computed using SetNet for each of the faces of the P identities. The training image is then scored for each face f by applying a logistic regressor classifier to the scalar product $v_{set}^T v_f$, and the score should ideally be one for each of the F identities in the image, and zero for the other $P - F$ faces. The loss measures the deviation from this ideal score, and the network learns to achieve this by maintaining the discriminability for individual face descriptors after aggregation.

In detail, incorporating the loss is achieved by adding an additional layer at training time which contains a logistic regression loss for each of the P training identities, and is trained together with the rest of the network.

Multi-label logistic regression loss. For each training image (set of faces), the value of the loss is:

$$-\sum_{f=1}^P y_f \log(\sigma(w(v_f^T v_{set}) + b)) + (1 - y_f) \log(1 - \sigma(w(v_f^T v_{set}) + b)) \quad (2)$$

where $\sigma(s) = 1/(1 + \exp(-s))$ is a logistic function, P is the number of face descriptors (the size of the mini-batches at training), and w and b are the scaling factor and shifting bias respectively of the logistic regression classifier, and y_f is a binary indicator whether face f is in the image or not. Note that multiple y_f 's are equal to 1 if there are multiple faces which correspond to the identities in the image.

2.4 Implementation details

This section gives full details of the training procedure, including how the network is used at run-time to rank the dataset images given query examples.

Training data. The network is trained using faces from the training partition of the VGGFace2 dataset [3]. This consists of 8631 identities, with on average 360 face samples for each identity.

Balancing positives and negatives. For each training image (face set) there are many more negatives (the $P - F$ identities outside of the image set) than positives (identities in the set), i.e. most y_f 's in eq. (2) are equal to 0 with only a few 1's. To restore balance, the contributions of the positives and negatives to the loss function is down-weighted by their respective counts.

Initialization and pre-training. A good (and necessary) initialization for the network is obtained as follows. The face feature extraction block is pretrained for single face classification on the VGGFace2 Dataset [3] using softmax loss. The NetVLAD layer, with $K = 8$ clusters, is initialized using k-means as in [1]. The fully-connected layer, used to reduce the NetVLAD dimensionality to 128-D, is initialized by PCA, i.e. by arranging the first 128 principal components into the weight matrix. Finally, the entire SetNet is trained for face aggregation using the Multi-label logistic regression loss (Sec. 2.3).

Training details. Training requires face set descriptors computed for each image, and query faces (which may or may not occur in the image). The network is trained on synthetic face sets which are built by randomly sampling identities (e.g. two identities per image). For each identity in a synthetic set, two faces are randomly sampled (from the average of 360 for each identity): one contributes to the set descriptor (by combining it with samples of the other identities), the other is used as a query face, and its scalar product is computed with all the set descriptors in the same mini-batch. In our experiments, each mini-batch contains 84 faces. Stochastic gradient descent is used to train the network (implemented in MatConvNet [29]), with weight decay 0.001, momentum 0.9, and an initial learning rate of 0.001 for pre-training and 0.0001 for fine-tuning; the learning rates are divided by 10 in later epochs.

Training faces are resized such that the smallest dimension is 256 and random 224×224 crops are used as inputs to the network. To further augment the training faces, random horizontal flipping and up to 10 degree rotation is performed. At test time, faces are resized so that the smallest dimension is 224 and the central crop is taken.

Dataset retrieval. Suppose we wish to retrieve images containing multiple query faces (or a subset of these). First, a face descriptor is produced by *SetNet* for each query face. The face descriptors are then used to score a dataset image for each query identity, followed by summing the individual logistic regression scores to produce the final



Fig. 4: **Example images of the *Celebrity Together* Dataset.** Note that only those celebrities who appear in the VGG Face Dataset are listed, as the rest are labelled as ‘unknown’. (a) Amy Poehler, Anne Hathaway, Kristen Wiig, Maya Rudolph. (b) Bingbing Fan, Blake Lively. (c) Kat Dennings, Natalie Portman, Tom Hiddleston. (d) Kathrine Narducci, Naturi Naughton, Omari Hardwick, Sinqua Walls. Additional examples of the dataset images are given in the supplementary material.

image score. A ranked list is obtained by sorting the dataset images in non-increasing score order. In the case where multiple face examples are available for a query identity, the multiple descriptors produced by *SetNet* are simply averaged and L2-normalized to form a richer descriptor for that query identity.

3 ‘Celebrity Together’ dataset

A new dataset, *Celebrity Together*, is collected and annotated. It contains images that portray multiple celebrities simultaneously (Fig. 4 shows a sample), making it ideal for testing set retrieval methods. Unlike the other face datasets, which exclusively contain individual face crops, *Celebrity Together* is made of full images with multiple labelled faces. It contains 194k images and 546k faces in total, averaging 2.8 faces per image. The image collection and annotation procedures are explained next.

The dataset is created with the aim of containing multiple people per image, which makes the image collection procedure much more complex than when building a single-face-per-image dataset, such as [19]. The straightforward strategy of [19], which involves simply searching for celebrities on an online image search engine, is inappropriate: consider an example of searching for Natalie Portman on Google Image Search – *all* top ranked images contain only her and no other person. Here we explain how to overcome this barrier to collect images with multiple celebrities in them.

Search string selection. We use the list of 2622 celebrities from the VGG Face Dataset [19] and aim to download images containing at least two celebrities each. Since it is inappropriate to query internet image search engines for single celebrities, here we explain how to obtain sets of celebrities to search for. A straightforward approach would be to query for all pairs of celebrities; assuming top 100 images are downloaded for each query, this would result in 300 million images, which is clearly prohibitively time-consuming to download and exhaustively annotate. We use the fact that only a small portion of the name pairs is actually useful as not all pairs of celebrities have photos taken together. To obtain a list of plausible celebrity pairs, we consider each celebrity as a “seed” in turn. For each seed-celebrity, a search is performed for ‘seed-celebrity and’ to obtain a list of images of the seed-celebrity together with another person. The meta information associated with these images (image caption in Google Image Search) is then scanned for other celebrity names, producing a list of (seed-celebrity, celebrity-friend) pairs.

No. faces / image	2	3	4	5	>5
No. images	113k	43k	19k	9k	10k

Table 1: **Distribution of faces / image.**

No. celeb / image	1	2	3	4	5	>5
No. images	88k	89k	12k	3k	0.7k	0.3k

Table 2: **Distribution of annotations / image.**

Image download and filtering. The list of celebrity pairs is used to query Google Image Search and download the images, which are then filtered using the meta information to contain both queried celebrities, and a face detector [17] is used to filter out images which contain fewer than two faces. De-duplication is performed using the method of [19], and images in common with the VGG Face Dataset [19] are removed as well.

Image annotation. Since the same list of celebrities is used as in the VGG Face Dataset [19], we use the pre-trained Deep Face CNN [19] to aid with annotation. Combining the very confident CNN classifications with our prior belief of who is depicted in the image (i.e. the query terms), results in many good quality automatic annotations which further decreases the manual annotation effort and costs. Remaining images are annotated manually using Mechanical Turk. Full details of the annotation procedure are provided in the supplementary material. Note that not all faces in the dataset correspond to the 2622 queried celebrities, and these are labelled as “unknown” people, but are kept in the dataset as distractors; 41% of all faces are distractors. Table 1 shows the breakdown of the total number of faces appearing in each image, while Table 2 shows the same breakdown but for celebrities (i.e. people with known identities).

4 Experiments and results

In this section we investigate three aspects: first, in Sec. 4.1 we study the performance of different models (SetNet and baselines) as the number of faces per image in the dataset is increased. Second, we compare the performance of SetNet and the best baseline model on the real-world *Celebrity Together* dataset in Sec. 4.2. Third, the trade-off between time complexity and set retrieval quality is investigated in Sec. 4.3.

Note, in all the experiments, there is no overlap between the query identities used for testing and the identities used for training the network, as the VGG Face Dataset [19] (used for testing, e.g. for forming the *Celebrity Together* dataset) and the VGGFace2 Dataset [3] (used for training) share no common identities.

Evaluation protocol. We use Normalized Discounted Cumulative Gain (nDCG) to evaluate set retrieval performance, as it can measure how well images containing *all* the query identities and also *subsets* of the queries are retrieved. For this measurement, images have different relevance, not just a binary positive/negative label; the relevance of an image is equal to the number of query identities it contains. We report nDCG@10 and nDCG@30, where nDCG@N is the nDCG for the ranked list cropped at the top *N* retrievals. nDCGs are written as percentages, so the scores range between 0 and 100.

4.1 Stress test

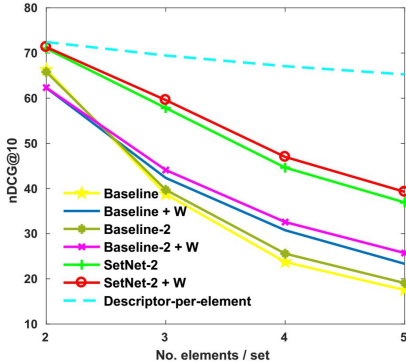
In this test, we aim to investigate how different models perform with increasing number of faces per set (image) in the test dataset. The effects of varying the number of faces per set used for training are also studied.

Test dataset synthesis. To this end, a base dataset with 64k face sets of 2 faces each is synthesized, using only the face images of labelled identities in the *Celebrity Together* dataset. A random sample of 100 sets of 2 identities are used as queries, taking care that the two queried celebrities do appear together in some dataset face sets. To obtain four datasets of varying difficulty, 0, 1, 2 and 3 distractor faces per set are sampled from the unlabelled face images in *Celebrity Together* Dataset, taking care to include only true distractor people, i.e. people who are not in the list of labelled identities in the *Celebrity Together* dataset. Therefore, all four datasets contain the same number of face sets (64k) but have a different number of faces per set, ranging from 2 to 5. Importantly, by construction, the relevance of each set to each query is the same across all four datasets, which makes the performance numbers comparable across them.

Methods. The *SetNet* models are trained as described in Sec. 2.4, where the suffix '-2' or '-3' denotes whether 2- or 3-element sets are used during training. For baselines, the optional suffix '+W' indicates whether the face descriptors have been whitened and L2-normalized before aggregation; whereas for *SetNet*, '+W' means that the set descriptors are whitened. For example, *SetNet-2+W* is a model trained with 2-element sets and whitening. Baselines follow the same naming convention, and use ResNet-50 with average-pooling (i.e. the same feature extractor network, data augmentation, optional whitening, etc.), where the architectural difference from the *SetNet* is that the aggregator block is replaced with average-pooling followed by L2-normalization (as shown in Fig. 2). The baselines are trained in the same manner as *SetNet*. The exceptions are *Baseline* and *Baseline+W*, which simply use ResNet-50 with average-pooling, but no training. For reference, an upper bound performance (*Descriptor-per-element*, see Sec. 4.3 for details) is also reported, where no aggregation is performed and all descriptors for all elements are stored. In this test, one randomly sampled face example per query identity is used to query the dataset. The experiment is repeated 10 times using different face examples, and the nDCG scores are averaged.

Results. From the results in Fig. 5 it is clear that *SetNet-2+W* and *SetNet-3+W* outperform all baselines. A similar trend also happens for nDCG@30; results for this are included in the supplementary material. As expected, the performance of all models decreases as the number of elements per set increases due to larger cross-element interference. However, *SetNet+W* deteriorates more gracefully (the margin between it and the baselines increases), demonstrating that our training makes *SetNet* learn representations which minimise the interference between elements. The set training is beneficial for all architectures, as *Baseline-2+W* and *Baseline-3+W* achieve better results than *Baseline+W* which is not trained for set retrieval.

Whitening improves the performance for all architectures when there are more than 2 elements per set, which is a somewhat surprising result since adding whitening only happens after the network is trained. However, using whitening is common in the retrieval community as it is usually found to be very helpful [2, 11], but has also been used



(a)

Scoring model	2/set	3/set	4/set	5/set
Baseline	66.3	38.8	23.7	17.5
Baseline-2	65.8	39.7	25.6	19.0
Baseline-3	65.9	39.4	24.8	18.4
SetNet-2	71.0	57.7	44.6	36.9
SetNet-3	71.9	57.9	44.7	37.0
Baseline + W	62.3	42.3	30.8	23.3
Baseline-2 + W	62.3	44.1	32.6	25.7
Baseline-3 + W	62.1	44.0	32.3	25.6
SetNet-2 + W	71.3	59.5	47.0	39.3
SetNet-3 + W	71.8	59.8	47.1	39.3
Desc-per-element	72.4	69.4	67.1	65.3

(b)

Fig. 5: **Stress test comparison of different models.** There are 100 query sets, each with two identities. (a) nDCG@10 for different number of elements (faces) per set (image) in the test dataset. (b) Table of nDCG@10 of stress test. Columns corresponds to the four different test datasets defined by the number of elements (faces) per set.

recently to improve CNN representations [23, 26]. It is likely that whitening before aggregation is beneficial also because it makes descriptors more orthogonal to each other, which helps to reduce the amount of information lost by aggregation. However, *SetNet* gains much less from whitening, which may indicate that it learns to produce more orthogonal face descriptors. In the supplementary material we investigate the orthogonality of descriptors further by analysing the Gram matrix computed on the identities in the VGG Face Dataset. We observe that SetNet produces even more orthogonal descriptors than the whitened baselines.

It is also important to note that, as illustrated by Fig. 5b, the cardinality of the sets used for training does not affect the performance much, regardless of the architecture. Therefore, training with a set size of 2 or 3 is sufficient to learn good set representations which generalize to larger sets.

4.2 Evaluating on the Celebrity Together dataset

Here we evaluate the SetNet performance on the full *Celebrity Together* dataset.

Test dataset. The dataset is described in Sec. 3. To increase the retrieval difficulty, random 355k distractor images are sampled from the MS-Celeb-1M Dataset [6], as before taking care to include only true distractor people. The sampled distractor sets are constructed such that the number of faces per set follows the same distribution as in the *Celebrity Together* dataset. The statistics of the resultant test dataset are shown in Table 3. There are 1000 test queries, formed by randomly sampling 500 queries containing two celebrities and 500 queries containing three celebrities, under the restriction that the queried celebrities do appear together in some dataset images.

Experimental setup and baseline. In this test we consider two scenarios: first, where only one face example is available for each query identity, and second, where three face

	Celebrity Together	Dist. from MS1M	Total
Images	194k	355k	549k
Faces	546k	1M	1546k

Table 3: **Number of images and faces in the test dataset.**

The test dataset consists of the *Celebrity Together* dataset and distractor images from the MS-Celeb-1M dataset [6].

Scoring model	N_{ex}	N_{qd}	nDCG@10	nDCG@30
Baseline-2 + W	1	Q	50.0	49.4
SetNet-3 + W	1	Q	59.1	59.4
SetNet-3 + W w/ query avg.	1	1	58.7	59.4
Baseline-2 + W	3	Q	56.6	56.0
SetNet-3 + W	3	Q	63.8	64.1
SetNet-3 + W w/ query avg.	3	1	62.9	64.1

Table 4: **Set retrieval performance on the test set.** Q is the number of identities in the query. There are 500 queries with $Q = 2$, and 500 with $Q = 3$. N_{ex} is the number of available face examples for each identity. N_{qd} is the number of descriptors actually used for querying.

examples per query identity are available. In the second scenario, for each query identity, three extracted face descriptors are averaged and L2-normalized to form a single enhanced descriptor which is then used to query the dataset. In both scenarios the experiment is repeated 10 times using different face examples for each query identity, and the nDCG score is averaged. The best baseline from the stress test (Sec. 4.1) *Baseline-2+W*, is used as the main comparison method.

Results. Table 4 shows that *SetNet-3+W* outperforms the best baseline for all performance measures by a large margin. Particularly impressive is the boost when only one face example is available for each query identity, where *Baseline-2+W* is beaten by 9.1% and 10.0% at nDCG@10 and nDCG@30 respectively. The results demonstrate that our trained aggregation method is indeed beneficial since it is designed and trained end-to-end exactly for the task in hand. The improvement is also significant for the second scenario where three face examples are available for each query identity, namely an improvement of 7.2% and 8.1% over the baseline. Fig. 1 shows the top 3 retrieved images out of 549k images for two examples queries using SetNet (images are cropped for better viewing). The supplementary material contains many more examples.

Query averaging. We also investigate a more efficient method to query the database for multiple identities. Namely, we average the descriptors of all the query identities to produce a single descriptor which represents all query identities, and query with this single descriptor. In the second scenario, when three face examples are available for each query identity, all of the descriptors are simply averaged to a single descriptor. With this query representation we obtain a slightly lower nDCG@10 compared to the original method shown in Table 4 (62.9 vs 63.8), and the same nDCG@30 (64.1). However, as will be seen in the next section, this drop can be nullified by re-ranking, making *query averaging* an attractive method due to its efficiency.

4.3 Efficient set retrieval

Our SetNet approach stores a single descriptor-per-set making it very fast though with potentially sacrificed accuracy. This section introduces alternatives and evaluates trade-offs between set retrieval quality and retrieval speed. To evaluate computational efficiency formally with the big-O notation, let Q , F and N be the number of query

Scoring method	N_r	Without query averaging				With query averaging			
		nDCG@10	nDCG@30	Timing	Speedup	nDCG@10	nDCG@30	Timing	Speedup
Desc-per-set	-	59.1	59.4	0.11s	57.5×	58.7	59.4	0.01s	635×
Desc-per-set + Re.	100	76.5	70.1	0.13s	48.8×	76.4	70.1	0.03s	212×
Desc-per-set + Re.	1000	84.2	80.0	0.20s	31.8×	84.1	80.0	0.10s	63.5×
Desc-per-set + Re.	2000	85.3	81.4	0.28s	22.7×	85.3	81.4	0.18s	35.3×
Desc-per-element	-	85.4	81.7	6.35s	-	-	-	-	-

Table 5: **Retrieval speed vs quality trade-off with varied number of re-ranking images.** Retrieval performance, average time required to execute a set query and speedup over *Desc-per-element* are shown for each method. ‘Re.’ denotes re-ranking. The evaluation is on the 1000 test queries and on the same full dataset with distractors as in Sec. 4.2.

identities, average number of faces per dataset image, and the number of dataset images, respectively, and let the face descriptor be D -dimensional. Recall that our SetNet produces a compact set representation which is also D -dimensional, and $D = 128$ throughout.

Descriptor-per-set (SetNet). Storing a single descriptor per set is very computationally efficient as ranking only requires computing a scalar product between Q query D -dimensional descriptors and each of the N dataset descriptors, passing them through a logistic function, followed by scoring the images by the sum of similarity scores, making this step $O(NQD)$. For the more efficient *query averaging* where only one query descriptor is used to represent all the query identities, this step is even faster with $O(ND)$. Sorting the scores is $O(N \log N)$. Total memory requirements are $O(ND)$.

Descriptor-per-element. Set retrieval can also be performed by storing all element descriptors, requiring $O(NFD)$ memory. An image can be scored by obtaining all $Q \times F$ pairs of (query-identity, image-face) scores and finding the optimal assignment by considering it as a maximal weighted matching problem in a bipartite graph. Instead of solving the problem using the Hungarian algorithm which has computational complexity that is cubic in the number of faces and is thus prohibitively slow, we use a greedy matching approach which is $O(QF \log(QF))$ per image. Therefore, the total computational complexity is $O(NQFD + NQF \log(QF) + N \log N)$. For our problem, we do not find any loss in retrieval performance compared to optimal matching, while being $7\times$ faster.

Combinations by re-ranking. Borrowing ideas again from image retrieval [22, 25], it is possible to combine the speed benefits of the faster methods with the accuracy of the slow descriptor-per-element method by using the former for initial ranking, and the latter to re-rank the top N_r results. The computational complexity is then equal to that of the fast method of choice, plus $O(N_r QFD + N_r QF \log(QF) + N_r \log N_r)$.

Experimental setup. The performance is evaluated on the 1000 test queries and on the same full dataset with distractors as in Sec. 4.2. N_r is varied in this experiment to demonstrate the trade-off between accuracy and retrieval speed. For the descriptor-per-element method, we use the Baseline + W features. In the supplementary material we also discuss a naive approach of pre-tagging the dataset with a list of identities.

Results. Table 5 shows set retrieval results for the various methods together with the time it takes to execute a set query. The full descriptor-per-element approach is the most accurate one, but also prohibitively slow for most uses, taking more than 6 seconds to execute a query. The descriptor-per-set (i.e. SetNet) approach with query averaging is blazingly fast with only 0.01s per query using one descriptor to represent all query identities, but sacrifices retrieval quality to achieve this speed. However, using SetNet for initial ranking followed by re-ranking achieves good results without a significant speed hit – the accuracy almost reaches that of the full slow descriptor-per-element, while being more than $35\times$ faster. Furthermore, by combining *desc-per-set* and *desc-per-element* it is possible to choose the trade-off between speed and retrieval quality, as appropriate for specific use cases. For a task where speed is crucial, *desc-per-set* can be used with few re-ranking images (e.g. 100) to obtain a $212\times$ speedup over the most accurate method (*desc-per-element*). For an accuracy-critical task, it is possible to re-rank more images while maintaining a reasonable speed.

5 Conclusion

We have considered a new problem of set retrieval, discussed multiple different approaches to tackle it, and evaluated them on a specific case of searching for sets of faces. Our learnt compact set representation, produced using the SetNet architecture and trained in a novel manner directly for the set retrieval task, beats all baselines convincingly. Furthermore, due to its high speed it can be used for fast set retrieval in large image datasets. The set retrieval problem has applications beyond multiple faces in an image. For example, a similar situation would also apply for the task of video retrieval when the elements themselves are images (frames), and the set is a video clip or shot.

We have also introduced a new dataset, *Celebrity Together*, which can be used to evaluate set retrieval performance and to facilitate research on this new topic. The dataset will be released publicly.

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Compact Deep Aggregation for Set Retrieval

– Supplementary Material –

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The supplementary material provides additional details over the main paper on several aspects. First, in Sec. 1, we give details on the modification of the ResNet-50 [2] to output 128-D feature vectors. Second, in Sec. 2, we describe in more detail the collection and annotation procedure of ‘Celebrity Together’ Dataset, including additional example images of the dataset. In Sec. 3, we provide additional results for the stress test (nDCG@30). In Sec. 4, further analysis is given on the orthogonality of descriptors. Sec. 5 describes pre-tagging, which is another approach for set retrieval. In Sec. 6, we give implementation details on the testing retrieval speed. Lastly, we show a number of retrieval examples from the test set in Sec. 7.

1 ResNet Modification

The modification (as shown in Fig. 1) is implemented by adding a fully-connected (FC) layer of size 2048×128 after the global average pooling layer in the original ResNet, such that the size of the output feature vector of the modified ResNet is 128-D instead of 2048-D. This additional fully-connected layer essentially acts as a dimensionality reduction layer if we consider the input 2048-D feature vector as a stack of feature maps of spatial size 1×1 . This modification introduces around 260k extra weights to the network, and we do not observe a prominent drop in the face classification performance using an output of compact 128-D features compared to the original 2048-D features.

It is important to note that training the ResNet-50 128-D network on the VGGFace2 dataset [1] provides a very strong baseline (referred to as *Baseline* in the stress test in the main paper). Although the objective of this paper is not face classification, to demonstrate the performance of this baseline network, we test it on the public IARPA Janus Benchmark A (IJB-A dataset) [3]. Specifically, we follow the same test procedure for the 1:N Identification task described in [1]. In terms of the true positive identification rate (TPIR), it achieves 0.975, 0.993 and 0.994 for the top 1, 5 and 10 ranking respectively, which is on par with the state-of-the-art networks in [1].

2 ‘Celebrity Together’ Dataset Collection and Annotation

In this section, we explain in detail how to collect images with multiple labeled celebrities.

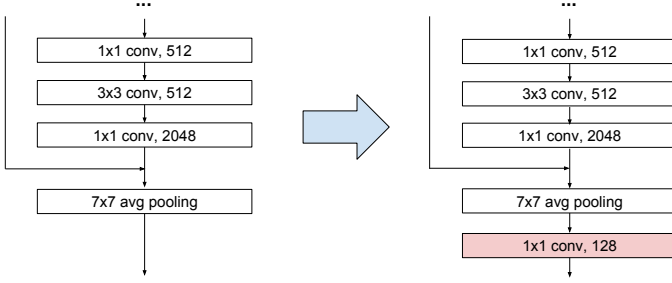


Fig. 1: **Modification of ResNet-50.** The modification is highlighted in red, where an extra fully-connected layer is added after the global average pooling layer to output 128-D features.

Query selection. In order to acquire celebrity name pairs, we first perform a search by using ‘seed-celebrity and’, and then scan the meta information for other celebrity names to produce a list of (seed-celebrity, celebrity-friend) pairs. However, one important procedure which is not included in the main paper is that some celebrity may have a strong connection to one or more particular celebrities, which could prevent us from obtaining a diverse list of celebrity friends. For instance, almost all the top 100 images returned by ‘Beyoncé and’ are with her husband Jay Z. Therefore, to prevent such celebrity friends dominating the top returned results, a secondary search is conducted by explicitly removing pairs found by the first-round search, i.e. the query term now is ‘seed-celebrity and -friend1 -friend2 ...’, where friend1, friend2 .. are those found in the first search. We do not perform more searches after the second round, as we find that the number of new pairs obtained in the third-round search is minimal.

Image download and filtering. Once the name pairs are obtained, we download the images and meta information from the image search engine, followed by name scanning again to remove false images. Face detection is performed afterwards to further refine the dataset by removing images with fewer than two faces.

De-duplication. Removal of near duplicate images is performed using the same method as [4], and images in common with the VGG Face Dataset [4] are removed as well.

Image annotation. Each face in each image is assigned to one of 2623 classes: 2622 celebrity names used to collect the dataset, or a special “unknown person” label if the person is not on the predefined celebrity list; the “unknown” people are used as distractors.

As the list of celebrities is the same as that used in the VGG Face Dataset [4], we use the pre-trained VGG-Face CNN [4] to aid with annotation by using it to predict the identities of the faces in the images. Combining the very confident CNN classifications with our prior belief of who is depicted in the image (i.e. the query terms), results in many good quality automatic annotations, which further decreases the manual annotation effort and costs. But choosing thresholds for deciding which images need annotation can



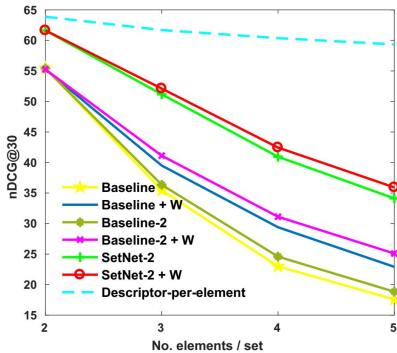
Fig. 2: **Example images of the ‘Celebrity Together’ Dataset.** (a) Anil Kapoor, Irrfan Khan. (b) Cory Monteith, Kevin McHale, Mark Salling. (c) Martin Freeman, Mackenzie Crook. (d) Takeshi Kaneshiro, Qi Shu. (e) Helena Christensen, Karolina Kurkova, Miranda Kerr. (f) Adam Levine, Blake Shelton, CeeLo Green. (g) Aamir Khan, John Abraham, Ranbir Kapoor. (h) Amanda Seyfried, Anne Hathaway, Hugh Jackman.

be tricky, as we need to consider two cases: (i) if a face in an image belongs to one of the query names used for downloading that image, or (ii) if the face does not belong to the query names. The two cases require very different thresholds, as explained in the following.

Identities in the query text. We first consider the case where the predicted face (using VGG-Face) matches the corresponding query words for downloading that image. In this case, there is a very strong prior that the predicted face is correctly labelled as the predicted celebrity was explicitly searched for. Therefore, if the face is scored higher than 0.2 by the CNN, it is considered as being correctly labelled, otherwise it is sent for human annotation. As another way of including low scoring predictions, if one of the query names is ranked within top 5 out of the 2622 celebrities by the CNN, the face is also sent for annotation. A face that does not pass any of the automatic or manual annotation requirements, is considered to be an “unknown” person.

Identities not in the query text. The next question is: if a face is predicted to be one of the 2622 celebrities with a high confidence (CNN score) but it does not match any query celebrities, can we automatically label it as a celebrity without human annotation? In this situation, the CNN is much less likely to be correct as the predicted celebrity was not explicitly searched for. Therefore, it has to pass a much stricter CNN score threshold of 0.8 in order to be considered to be correctly labelled without need for manual annotation. On the other hand, empirically we find that a prediction scored below 0.4 is always wrong, and is therefore automatically assigned the “unknown” label. The remaining case, a face with score between 0.4 and 0.8, should be manually annotated, but to save time and human effort we simply remove the image from the dataset.

Additional example images from the dataset are displayed in Fig. 2.



(a)

Scoring model	2/set	3/set	4/set	5/set
Baseline	55.5	35.5	23.0	17.6
Baseline-2	55.4	36.3	24.6	18.8
Baseline-3	55.3	35.9	23.9	18.3
SetNet-2	61.6	51.1	40.9	34.1
SetNet-3	61.5	51.2	41.0	34.2
Baseline + W	55.2	39.5	29.4	22.9
Baseline-2 + W	55.3	41.1	31.1	25.1
Baseline-3 + W	55.2	41.0	30.9	25.0
SetNet-2 + W	61.6	52.1	42.4	35.9
SetNet-3 + W	61.2	52.2	42.5	36.0
Desc-per-element	63.9	61.7	60.4	59.3

(b)

Fig. 3: **Stress test comparison of nDCG@30 of different models.** Columns corresponds to the four different test datasets defined by the number of elements (faces) per set.

3 Additional results for stress test

In this section, nDCG@30 for the stress test in the main paper are reported. As can be seen in Fig. 3, nDCG@30 generally follows a similar trend to nDCG@10: SetNet outperforms all the baselines by a large margin and, moreover, the gap increases as the number of elements per set increases.

4 Descriptor orthogonality

A whitening transformation decorrelates each dimension of the descriptors, and consequently descriptors will interfere less when added to each other. We expect SetNet to automatically learn such behaviour in order to minimize the interference between descriptors after aggregation. To verify this, we compute the gram matrix of 2622 identities in the VGG Face Dataset for both the baseline models and SetNet, and measure the deviation G_{dif} between the computed gram matrix and an identity matrix. G_{dif} is defined as equation (1).

$$G_{dif} = \|G - I\|_{Frob} \quad (1)$$

where G is the gram matrix and I is the identity matrix.

G_{dif} is computed in four steps: first, 100 faces are randomly sampled for each identity in VGG Face Dataset, and a feature vector for each face sample is extracted from the network; second, a mean descriptor for each identity is obtained by averaging the 100 descriptors followed by L2-normalization; third, the gram matrix is computed by taking the scalar product between the mean descriptors of each possible pair of identities, i.e. gram matrix is of size 2622×2622 . Finally, G_{dif} is computed as the Frobenius norm of the difference of the gram matrix and an identity matrix of the same size. We compute G_{dif} using non-whitened and whitened features of the best baseline network,

Model	Not whitened	Whitened
Baseline-2	416	297
SetNet-3	282	276

Table 1: **Difference between gram matrix and identity matrix G_{dif} .** The gram matrix is computed over 2622 identities in VGG Face Dataset.

Baseline-2, and SetNet. Notably, both networks are trained on VGGFace2 dataset [1], and their corresponding whitening transformation are also computed on VGGFace2 dataset; whereas in this test, all the identities are from the VGGFace dataset[4]. An identity matrix means all the considered identities are orthogonal to each other; therefore a smaller G_{dif} corresponds to more orthogonal descriptors.

As Table 1 shows, whitening reduces G_{dif} for both *Baseline-2* and *SetNet-3*; especially for *Baseline-2*. More importantly, SetNet without whitening has even smaller G_{dif} than the whitened baseline. Therefore, from Table 1 we can see that SetNet learns to produce more discriminative descriptors, which is beneficial for set retrieval with descriptor-per-set approach.

5 Pre-tagging Baseline

This approach pre-tags all the dataset images offline with a closed-dictionary of known identities by deeming a person to appear in the image if the classification score is larger than a threshold. Set retrieval is then performed by ranking images based on the intersection between the query and image tags. Pre-tagging seems straightforward, however, it suffers from two large limitations; first, it is very constrained as it only supports querying for a fixed set of identities which has to be predetermined at the offline tagging stage. Second, it relies on making hard decisions when assigning an identity to a face, which is expected to perform badly, especially in terms of recall. In our test, by using descriptors of *Baseline* + W , pre-tagging achieves 65.7% and 68.6% for nDCG@10 and nDCG@30. It is significantly lower than the results of SetNet even with only 100 re-ranking images (i.e. 76.5% and 70.1% for nDCGs) in Table 5 in the main paper. Therefore, since our descriptor-per-set + re-ranking method achieves vastly superior performance as well as allowing querying for novel identities, it is strongly preferred over pre-tagging.

6 Speed Test Implementation

The retrieval speed is measured as the mean over all 1000 test query sets. The test is implemented in Matlab, and the measurements are carried out on a Xeon E5-2667 v2/3.30GHz, with only a single thread.

7 Retrieval Examples

To visualize the performance of the set retrieval system, the top ranked 5 images (ordered column-wise) for several queries are shown in Fig. 4, 5, 6 (images are cropped for displaying purposes in order to see the faces better). Notably, the $\text{nDCG}@5$ (the quality of the top 5 retrievals) is equal to 1 for all examples, meaning that images are correctly ranked according to the size of their overlap with the query set.

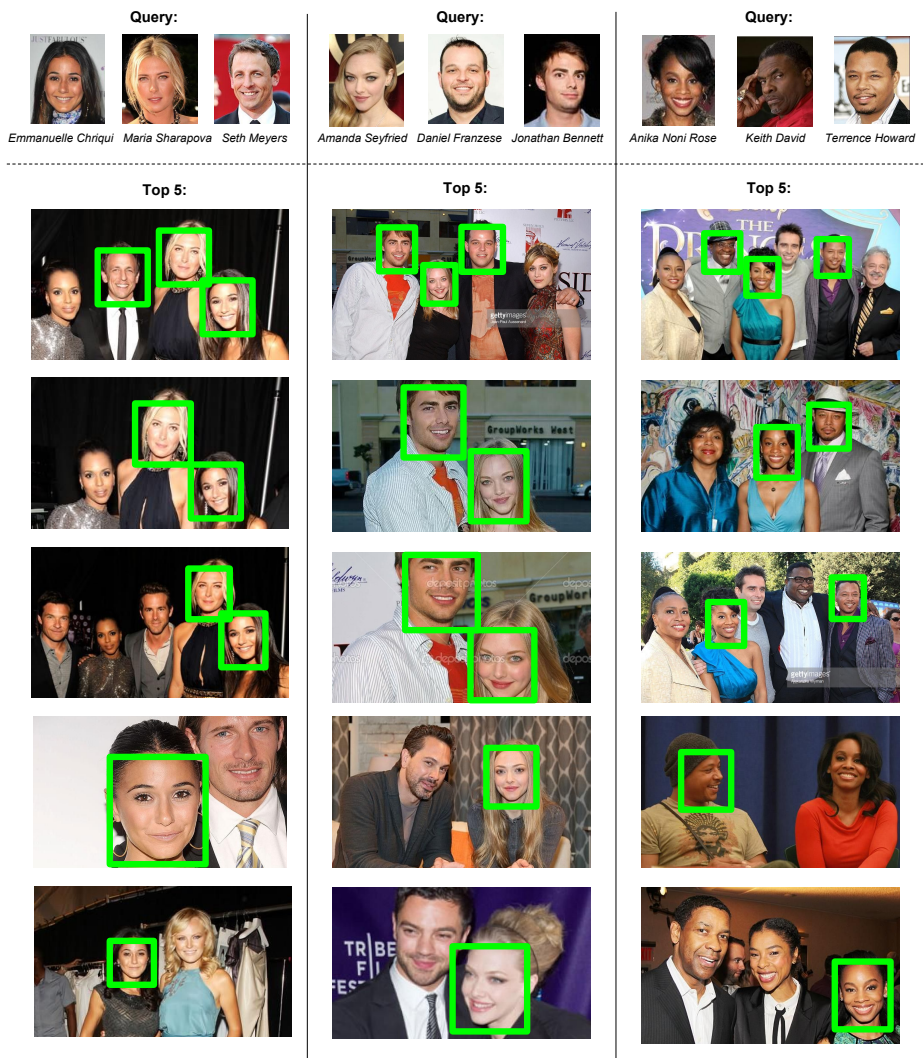


Fig. 4: **Top 5 ranked images returned by the SetNet based descriptor-per-set retrieval.** The query identities are highlighted by green bounding boxes.

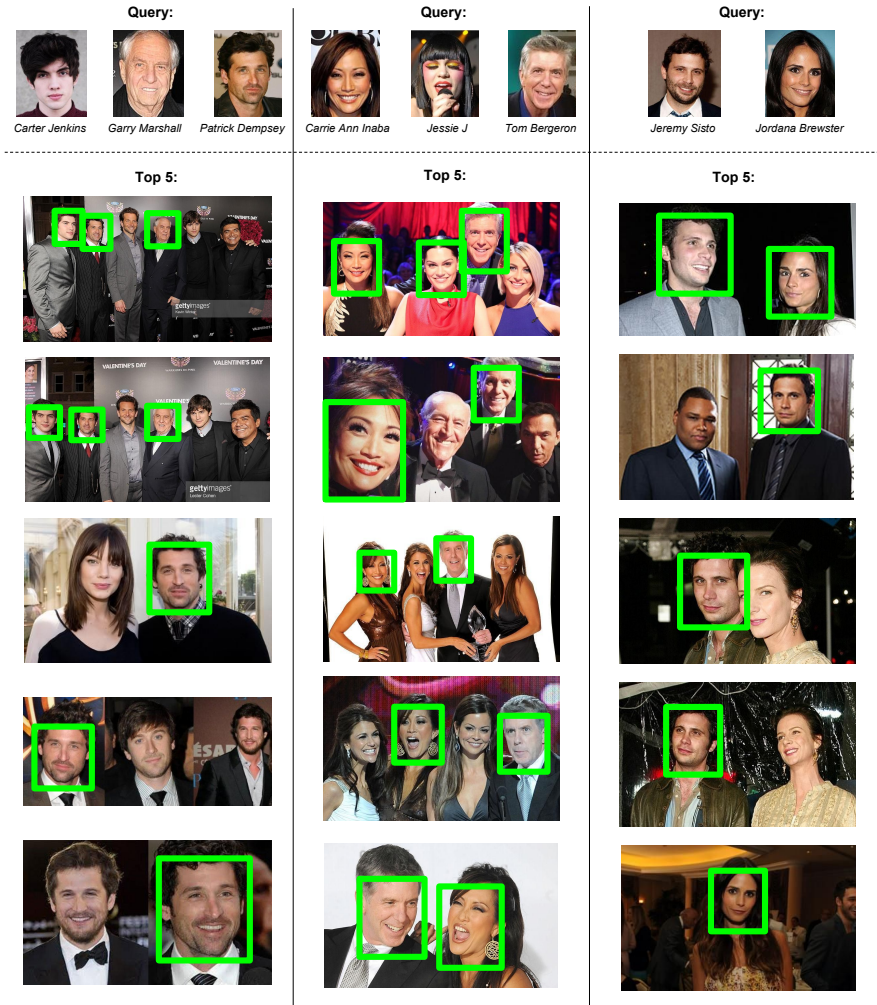


Fig. 5: Top 5 ranked images returned by the SetNet based descriptor-per-set retrieval. The query identities are highlighted by green bounding boxes.

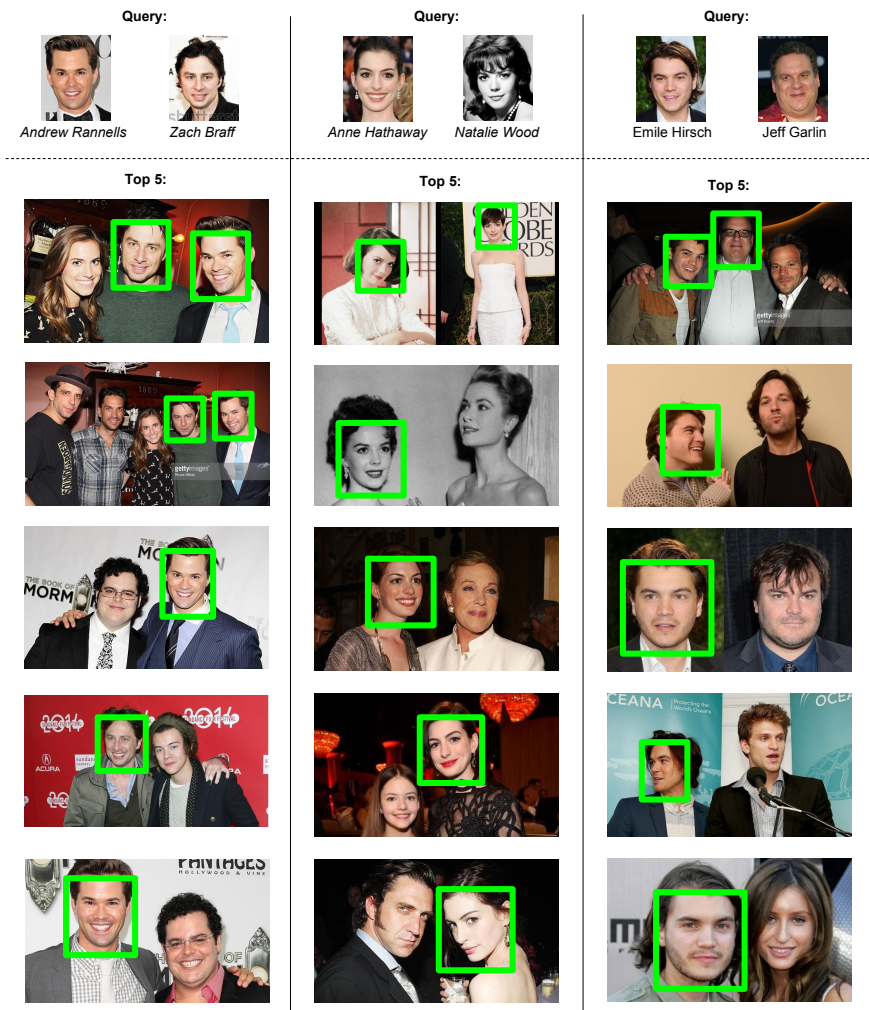


Fig. 6: **Top 5 ranked images returned by the SetNet based descriptor-per-set retrieval.** The query identities are highlighted by green bounding boxes.

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