

Web-Scale Training for Face Identification

Yaniv Taigman, Ming Yang, Marc'Aurelio Ranzato

Facebook AI Research
Menlo Park, CA 94025, USA
{yaniv, mingyang, ranzato}@fb.com

Lior Wolf

Tel Aviv University
Tel Aviv, Israel
wolf@cs.tau.ac.il

Abstract

Scaling machine learning methods to massive datasets has attracted considerable attention in recent years, thanks to easy access to ubiquitous sensing and data from the web. Face recognition is a task of great practical interest for which (i) very large labeled datasets exist, containing billions of images; (ii) the number of classes can reach tens of millions or more; and (iii) complex features are necessary in order to encode subtle differences between subjects, while maintaining invariance to factors such as pose, illumination, and aging. We present an elaborate pipeline that consists of a crucial network compression step followed by a new bootstrapping scheme for selecting a challenging subset of the dataset for efficient training of a higher capacity network. By using this approach, we are able to greatly improve face recognition accuracy on the widely used LFW benchmark. Moreover, as performance on supervised face verification (1:1) benchmarks saturates, we propose to shift the attention of the research community to the unsupervised Probe-Gallery (1:N) identification benchmarks. On this task, we bridge between the literature and the industry, for the first time, by directly comparing with the state of the art Commercially-Off-The-Shelf system and show a sizable leap in performance. Lastly, we demonstrate an intriguing trade-off between the number of training samples and the optimal size of the network.

1 Introduction

Face recognition is among the most successful computer vision applications and the most widely studied problems in machine learning, computer vision, psychology and cognitive science. Performance improvements in recent years have been staggering, and automatic recognition systems cope much better today with the challenges of the field than they did just a few years ago. These challenges are well documented and include changing illumination, pose and facial expression of the subject, occlusion, variability of facial features due to aging, and more. In the past, impressive performance was only demonstrated for carefully registered face images that did not exhibit much variability, a set up commonly referred to as *constrained conditions*. The performance on the *unconstrained* setting where there is no control nor knowledge about any of these nuisance variables affecting the appearance of the subject is now quickly catching up.

Current state-of-the-art methods for unconstrained face recognition and verification (the task of predicting whether two face images belong to the same person or not) [21, 2, 19] employ a similar protocol: they use a fairly large collection of images to learn a robust representation or metric, and then they perform transfer learning to predict the identity or the similarity between two face images. These methods are trained on hundreds of thousands or a few million images and recognize up to a few thousand different subjects. This is orders of magnitude bigger than what was ever attempted in the past, yet two or three orders of magnitude smaller than the actual datasets available today! The questions we aim to address in this paper are: **How can we further scale up face recognition methods? How do we cope computationally with almost infinite data? Do we still benefit by using even larger datasets?** In addition, as the datasets scale up, there is a growing need to construct compact representations that are still able to retain information about the subtle details that constitute the identity of people. Doing so while learning to distinguish among an unconstrained number of identities seems counter intuitive. However, as we show, it is important to keep the learned representation compact even as the number of training samples becomes virtually unlimited.

Our starting point is the DeepFace architecture [21], which, based on recent advances in deep learning, is currently leading the performance charts on the LFW benchmark. The DeepFace network has roughly 100 million parameters and produces more than 4000 features to describe a single image. Scaling the training of such a network to a dataset with almost half a billion images is a major challenge. We propose a novel pipeline that handles two necessary axis of such training: (i) controlling the capacity of the network, and (ii) selecting a representative subset of the large training set.

First, we compress the network by adding a bottleneck to reduce its feature dimensionality in a discriminative manner. Then, for a large subset of the identities in the large dataset, we train independent linear classification models on top of the size-reduced representation. Using a cosine similarity between the learned hyperplanes, we select a subset of the training set that is highly challenging. Lastly, we retrain using a network of a higher capacity. This process greatly reduces the size of the dataset, yet provides the network with many cases that are very challenging to discriminate. Through this efficient bootstrapping procedure we greatly improve verification performance on a widely used benchmark dataset, the LFW dataset [9]. We then turn our attention to the 1:N identification problem, in which the image is identified out of a gallery of N persons.

While the usage of verification datasets has advanced the field of computer vision greatly, the 1:N scenario is much more directly related to face identification applications. For instance, vendor tests, e.g., [6], focus on 1:N protocols. As a result, the community lost the ability to directly compare academic contributions to the most prominent commercial systems. By making use of a recently proposed 1:N benchmarks built on top of the LFW images [1], we are able to demonstrate, for the first time, a sizable performance gap over such systems.

Our contribution can be summarized as follows: (i) we provide a pipeline for scaling up face recognition systems, which is shown to outperform baseline alternatives; (ii) we propose a new bootstrapping method for subsampling a large dataset; (iii) we show that the network based representations can (and should) be greatly compressed leading to an actual gain in accuracy and (iv) we go beyond face verification and compare the *identification* performance of our system to one of the best commercial systems available today.

Working with faces provides a unique opportunity to work with practically an unrestricted amount of data. It provides insights into the practices that would be employed when other computer vision domains become as plentiful, such as non-intuitive relations between sample size and network capacity. We conjecture that many of the findings of this work also apply to generic object recognition and other large scale systems.

2 State Of The Art

The U.S. National Institute of Standards and Technology (NIST) publicly reports every several years its internal benchmark on face recognition; systems taking part in the competition are developed by leading commercial vendors as well as academic institutions. For instance, in the MBE 2010 report [6], the three top-ranked Commercial Off The Shelf (COTS) correctly matched probed faces against a large collection (“gallery” in the commonly used terminology) of 1.6 million identities with an 82%-92% accuracy rate. In another test, the leading system could help identify one of the two suspected Boston bombers out of a gallery composed of one million subjects [10].

The datasets used by [6, 10] are not publicly available, and therefore it is hard to compare the performance of academic systems on the same benchmarks. Fortunately, the same COTS system was recently tested [1] on a 1:N identification benchmark constructed using the images of the public Labeled Faces in the Wild (LFW) [9] dataset. On this benchmark, the rank-1 accuracy of the COTS system dropped to about 56% [1], even though the gallery has only a couple of thousands identities. This finding demonstrates that although constrained face recognition has reached impressive accuracy, the unconstrained one is still far from being solved. Since most existing face recognition applications are unconstrained, advancing our ability to process face images in this setting is key for the successful widespread use of face recognition technology.

Face *verification*, which is the task of determining whether two face images belong to the same subject, has greatly advanced in recent years, especially in the unconstrained setting. In fact, a recent work [21] reported nearly human level performance on the LFW verification task using the DeepFace system, but no test is reported on the probe-gallery identification task. In this work, we

consider a convolutional neural network system of the same architecture as DeepFace and investigate ways to scale its training and capacity up and improve performance in probe-gallery protocols.

Scaling up face recognition is a non-trivial challenge. The baseline DeepFace system [21] has about 100 million parameters to start with. It is very hard to distribute efficiently [7, 11]. It produced features that are lower dimensional than engineered features [2] but still contain several thousand dimensions; and it needs massive amounts of data to generalize well [12, 20]. There is simply no known method to effectively train such a large system on billions of images with millions of labels, using thousands of features. In the machine learning literature, several methods have been proposed to deal with very large datasets. The simplest method is to randomly down-sample the dataset, which is a clearly sub-optimal approach. A more suitable alternative is to employ bootstrapping procedures that aim at focusing on the hardest cases ignoring or down-weighting the easy ones, like in boosting [5]. Our approach is, in essence, a bootstrapping one since we focus the training effort on a cleverly selected subset of the samples that are hard to classify. However, the selection process is made much more efficient than in standard bootstrapping because we do not need to first evaluate each training sample in order to perform our selection.

There are also several ways to cope with the large dimensionality of the feature space. There are both unsupervised methods to compress features, like PCA or hashing based methods [18], and supervised methods [16]. It is commonly believed that compression of features leads to impoverished recognition accuracy because many discriminative details are lost in the process. Surprisingly, we show that this is not the case when this compression is performed discriminatively. In fact, when the learned features are used for another task/dataset (transfer learning) there might be a sizable gain in performance.

Finally, several approaches have been proposed to deal with a very large number of categories. In face recognition, each subject is a class and the system has to recognize among up to several millions of them. The standard approach is to train a multinomial logistic regression classifier whose computation scales linearly with the number of classes. Following methods proposed for language modeling [15], the logistic regression classifier can be made more efficient by factorizing the probability distribution using a tree (with a learned or predefined hierarchy). An entirely different approach is to replace the log-loss with a ranking loss, like in wsabie [23]. This requires the evaluation of only one incorrect label (as opposed to the whole set of labels) for every training sample. While this latter approach is significantly more efficient, we show empirically that using the standard log-loss remains practical even for 10^5 classes.

3 Architecture

In this section, we describe the framework that we used in our experiments starting with the initial face representation, which was trained similarly to DeepFace [21], and then the design of a bootstrapping algorithm which utilizes a compressed representation to effectively generate the second iteration of learning, leading to the final face representation.

3.1 DeepFace Representation

A total of 4 million face images belonging to 4,000 anonymized identities (classes), were aligned using a 3D model and used in learning an *initial* face representation, based on a deep convolutional neural network. As shown in Figure 1, the network consists of two convolutional layers with a single max-pooling layer in between (C1-M2-C3), followed by three locally-connected layers L4-L5-L6, without weight sharing, and two fully-connected layers F7-F8. The output of F8 is fed to a 4000-way softmax which produces a distribution over the class labels. Denote by $o_i(x)$ the i -th output of the network on a given input x , the probability assigned to the i -th class is the output of the softmax function: $p_i(x) = \exp(o_i(x)) / \sum_j \exp(o_j(x))$. The $ReLU(a) = \max(0, a)$ nonlinearity [4] is applied after every layer (except for F8) and optimization is done through stochastic gradient descent and standard back-propagation [17, 14], minimizing the cross-entropy loss. If k is the index of the true label for a given input x , the loss associated with this sample is: $L(x) = -\log p_k(x)$. Once trained, the representation used is the normalized feature vector of layer F7 [21].

Deepface was shown to achieve good generalization and reduce the risk of overfitting when training through the use of a dataset of a few million faces. However, the association between the size of the training dataset and the obtained test accuracies beyond that size was left largely unexplored.

As we show in the experiments, to fully utilize the benefits of scaling up the training set by more than two orders of magnitude requires new methods. These include network compression, semantic bootstrapping, and retraining a larger capacity network that is initialized using the compressed network.

3.2 Representation Compression

Compressing serves two purposes. First, it allows to more efficiently access and process a corpus containing billions of face images. Second, and perhaps unintuitively, it increases performance when the representation is used for transfer learning. We achieve compression by retraining the very same network (in a supervised way) but with a narrower bottleneck at layer F7 (i.e., using fewer features). We do not apply any (unsupervised) dimensionality reduction algorithm to the original representations. Directly training the modified networks with the smaller F7 layers was effective when reducing the original dimension of 4096 to 2048 or 1024. For smaller dimensions, the training error stopped decreasing early on. However, we note a useful property: by pre-loading the weights of the initial network, except for the last layer, we were able to learn much smaller embeddings effectively, as further detailed in the experiment section. Remarkably, a bottleneck of 256 dimensions not only provided favorable scaling properties that enabled us to scale the experiment by an order of magnitude, but also yielded a comparable if not better accuracy than the initial one, see Sec. 4. Further analysis of this regularization is discussed in Sec. 3.5.

3.3 Semantic Bootstrapping

Next, we leverage the compressed representation to train on a much larger dataset. Having a larger dataset at our disposal, we search for impostor samples to be used in our second round of training, as normally done in bootstrapping. The most basic method would be to sample a large pool of face representations, each represented by the compact feature, and select the nearest neighbors from other identities (“impostors”). However, we show that a significant improvement in scalability and reliability can be obtained by working in the space of linear models, trained discriminatively on top of these compressed representations, as opposed to directly work on these compressed features.

As a first step, we represent each class by a single classifier, i.e., for each identity, we learn a hyperplane trained in a binary classification setting of one-vs-all, where the positive instances (representations) are of the same identity and the negatives are randomly chosen. Since each identity in our dataset is associated with an average of 50 face images, working with these linear models, instead of the underlying instances, enables us to scale the exploration of impostor identities by another order of magnitude. In terms of efficiency, training such linear models is highly distributable, very efficient when using compact features, and takes around 0.1 seconds per each core.

In addition to being more scalable, this semantic distance (i) performs better than instance-based bootstrapping and (ii) is more robust to human labeling error of the ground-truth. The latter is verified by training, similarly to [21] a pair-wise similarity metric, given by a Siamese network on 4M nearest neighbor pair instances, belonging either to the same class or not (=impostors), and obtained substantially worse results than the baseline system. We noticed that many of the pairs sampled, in particular those that are labeled as the ‘same’ identity, contained a large amount of noise due to human labeling error. This observation is also consistent with the fact that the initial representation machine is already on-par with humans w.r.t. pair-wise verification performance.

The dataset at our disposal contains 10 million anonymized models belonging to roughly 50 times more images. This is to be compared to around 4000 identities and 4 million images (DB_1) in [21]. In order to select a challenging subset of our dataset, we randomly select 100 identities, as seeds, among the 10 million models. For each seed, we search for the 1000 nearest models, where the similarity between any two models h_1, h_2 is defined as the cosine of the angle between the associated hyperplanes: $S(h_1, h_2) = \langle h_1, h_2 \rangle / (\|h_1\| \|h_2\|)$. The union of all images of all retrieved identities constitutes the new bootstrapped dataset DB_2 , containing 55,000 identities overall.

In terms of efficiency, evaluating the distance between each seed and a gallery pool of 10^7 hyperplanes reduces to a matrix-multiplication $W s_i$ where W is a matrix of $10^7 \times 256$ and seed $s_i \in R^{256}$. The run time of this step on a single server is about 1 second per seed query.

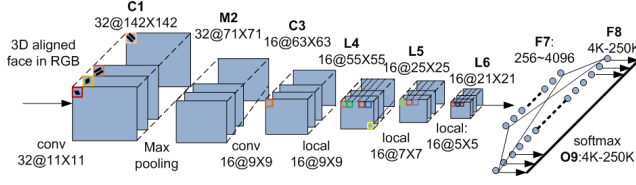


Figure 1: **The initial network architecture.** A front end of convolutional, pooling, convolutional layers is followed by three locally connected layers and two fully connected layers.

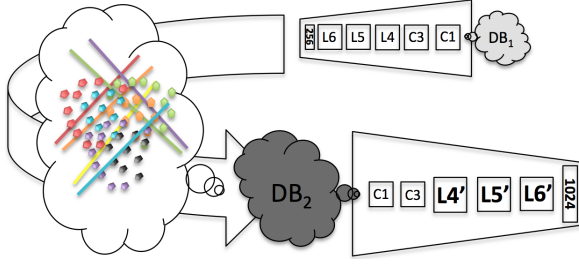


Figure 2: **The bootstrapping method.** An initial 256D-compressed representation trained on DB_1 is used to find the semantically-nearest identities of randomly picked 100 seeds, in a large pool of pre-trained hyper-planes. The union of all 100 groups of selected identities define the bootstrapped dataset DB_2 . A larger capacity network with enlarged locally-connected layers and a 1024D representation is then trained.

3.4 Final Network Architecture

DB_2 is a challenging dataset, where our objective is to train feature representation that can discriminate between the new selected identities. As we show in Sec 4, only when scaling the capacity of the initial network, we are able to do so convincingly.

Specifically, we pre-load C1 and C2 layers from the initial network, and double the number of filters of each locally-connected layer from 16 to 32. In addition, we enlarge the representation layer F7 from 256 to 1024. All new layers, except for C1 and C2, are randomly initialized and trained on DB_2 , with the same algorithm as before. The two first convolutional layers C1 and C2 are merely feature extractors, which include less than 1% of the overall weights. Empirically, we found that fixing these layers did not affect performance while speeding up training considerably. The subsequent stages employ more complicated features, however in contrast to boosting and cascaded architectures [22], we end up with a single classifier and are interested in learning representations that are useful for transfer learning. Figure 2 visualizes the process.

3.5 Trade-offs Between Sample Size and Regularization for Transfer Learning

Intuitively, the more samples we have, the higher dimension we can afford our representation to be. However, we observe empirically that decreasing the representation size is beneficial and the overall performance follows a trade-off curve in which there is a relatively low optimal size, even if the number of training samples is virtually unlimited. The reason is that we learn our representation in one domain (the massive face set) and test it on another (LFW images), where no training is performed. An illustration of this situation is depicted in Figure 3. The size of the representation layer F7 serves as a regularizer since it reduces the capacity of the network. In the illustration, we model it as a regularization parameter β . The higher β is, the smaller the network. Four paths are drawn: The dashed line in Figure 3(a) describes the effect of increasing the number of samples. The solid path in Figure 3(a) describes the effect of reducing the regularization term when the sample size is limited. The solid line in Figure 3(b) is similar but assumes that the sample size is virtually infinite. Finally, the dashed line in Figure 3(b) describes what would happen as the regularization decreases if we'd be learning with unlimited samples on the target domain (ideal case). Assuming that the target domain and the source domain tend to be modeled more similarly by lower-capacity models, decreasing regularization, even when perfectly learning the source domain, results in the learned representation drifting away from the ideal representation for the target domain. This trade-off between the sample size in the source domain and the optimal regularization does not appear, as far as we know, in the literature. More generally, the study of transfer learning where there are no training samples (labeled or unlabeled) in the target domain, is still under-treated despite its immediate implications to the field of representation learning.

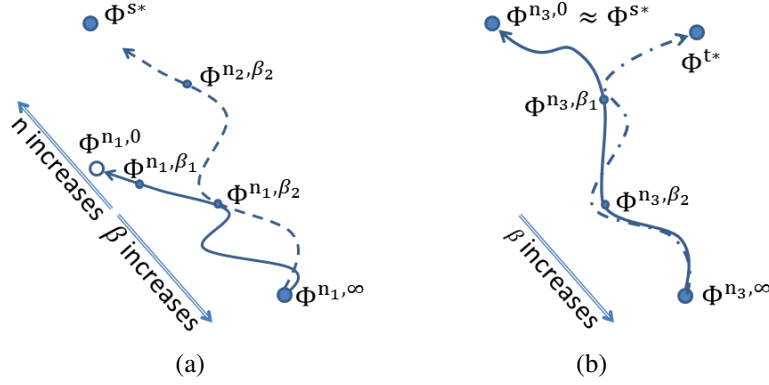


Figure 3: Illustration of the trade-off between the regularization parameter β and the number of samples n . (a) Trade-off between the regularization parameter and the number of training samples. (b) Representation is learned in the source domain and transferred to the target domain. In both illustrations $\beta_1 < \beta_2$, $n_1 < n_2 < n_3$. Φ^{S*} , Φ^{t*} are the representations that minimize the expected loss for the probability distributions of the source domain s and the target domain t , respectively. Φ^{n_i, β_j} is the learned representation for a fixed sample of size n_i using a regularization parameter of β_j . $\Phi^{n_i, 0}$ minimizes the empirical loss for a fixed sample of size n_i (no regularization). $\Phi^{n_i, \infty}$ is the representation learned when the regularization is very large ($\beta = \infty$). The solid paths in (a) and (b) describe the path of learned representations ϕ as β decreases for a fixed sample. The dashed line in (a) describes the path as the number of samples increases. These three paths describe the learning in the source domain. The dashed path in (b) describes a hypothetical representation learned in the target domain as the regularization parameter is decreased (in our application no learning is performed in the target domain). While an increase in the training size in the source domain might improve performance in that domain, it could actually decrease performance in the target domain. Assuming that the two domains are well behaved in the sense that solutions learned separately in each domain are closer to each other for a higher regularization term, it might be beneficial to increase regularization as the number of samples used to train the source domain increases.

4 Experiments

We evaluate the learned representations on cropped¹ images of the Labeled Faces in the Wild (LFW) public dataset [9], using multiple protocols. The LFW dataset consists of 13,233 web photos of 5,749 celebrities, and is commonly used for benchmarking face verification. In this work, we focus on two new Probe-Gallery *unsupervised* protocols proposed in [1] (the original splits are used):

1. A closed set identification task, where the gallery set includes 4,249 identities, each with only a single example, and the probe set includes 3,143 faces belonging to the same set of identities. The performance is measured by the Rank-1 identification accuracy.
2. An open set identification task, where not all probe faces have a true mate in the gallery. The gallery includes 596 identities, each with a single example, and the probe set include 596 genuine probes and 9,491 impostor ones. Here the performance is measured by the Rank-1 Detection and Identification Rate (DIR), which is the fraction of genuine probes matched correctly in Rank-1 at a 1% False Alarm Rate (FAR) of impostor probes that are not rejected.

As the verification protocol, we follow the LFW unrestricted protocol [8] (which uses only the same-not-same labels), and similarly to [21] train a kernel SVM (with $C=1$) on top of the χ^2 -distance vectors derived from the computed representations. For the open and closed set identification experiments we simply use the cosine similarity (normalized dot product). **A critical difference** between the LFW verification protocols and the Probe-Gallery ones is that the latter do not permit training on the LFW dataset. They therefore demonstrate how face recognition algorithms perform on an unseen data distribution, as close as possible to real-life applications. Also, as pointed out in [1], the Probe-Gallery protocols correspond to many challenging practical scenarios, such as retrieval [10]. The importance of such protocols as tools that differentiate face recognition methods based on performance is confirmed by our results, since methods that exhibit very similar results on the LFW verification protocol display large performance gaps on the Probe-Gallery ones, as shown in Table 1.

¹Using the biased [13] background to improve performance is not in the scope of this work.

Dimension	4096	1024	512	256	128	64	32	16	8
Verification	97.00	96.72	96.78	97.17	96.42	96.10	94.50	92.75	89.42
Rank-1	60.9	64.9	67.4	72.3	69.1	66.5	39.6	23.2	7.00
Rank-10	78.7	83.9	85.2	90.4	88.8	87.7	70.8	52.9	24.7
DIR @ 1%	41.9	44.7	46.1	46.3	44.1	36.7	12.2	5.37	0.33

Table 1: Performance on the three protocols, when varying the dimensionality of the representations. Performance is measured in terms of the verification accuracy (%) of the *unrestricted* verification protocol, Rank-1 and rank-10 accuracy (%) on the Closed Set, and the DIR (%) at 1% FAR on the Open Set.

Training set	Random 108K			Random 250K			Bootstrapped 55K		
Dimension	256	512	1024	256	512	1024	1024	256+	1024+
Verification	97.35	97.62	96.90	96.33	97.10	97.67	97.57	97.58	98.00
Rank-1	69.7	68.1	70.2	59.6	74.0	74.9	75.9	77.0	82.1
Rank-10	88.5	87.8	90.1	86.0	91.7	90.9	91.1	91.7	93.7
DIR @ 1%	51.3	46.5	51.0	38.1	54.7	58.7	56.2	57.6	59.2

Table 2: Performance of the three protocols on different training sets. The two rightmost columns (denoted by 256+ and 1024+) report results using the architecture discussed in Sec. 3.4.

4.1 Compressed Representations

We first evaluate different compressed representations, all utilizing the initial face representation system, with sizes ranging from 4096 dimensions down to 8. These networks were retrained as described in Sec. 3.2 on the 4 million images associated with 4,000 random identities used in [21].

Table 1 shows that compression improves generalization considerably. With only 256 dimensions, the obtained Rank-1 accuracy stands on 72.3% on the Closed Set protocol, and DIR 46.3% at 1% FAR on the Open Set, and greatly outperforms the original 4096D representation. Note however, that the difference in the verification protocol remains within a 1% range when compressing the 4096 dimensions down to 64, and either due to performance saturation and/or the type of benchmark, differences in face recognition capabilities are not captured well.

4.2 Bootstrapped Representations

We now compare the representation learned on the 55K bootstrapped identities (4.5M faces) with those learned from randomly selected 108K identities (3.2M faces) and even 250K identities (7.5M faces), as shown in Table 2. We note that: (i) The deep neural network (DNN) can benefit from additional amount of training data, *e.g.*, 250K identities, boost the recognition performance over those trained on 4K identities in Table 1. (ii) The bootstrapped training set of 55K identities, although 5 times smaller than the biggest training set used, delivers better Probe-Gallery performance. (iii) An even larger improvement is obtained when the locally-connected layers (L4-L5-L6) are expanded as described in Sec. 3.4, and the extended 256D and 1024D representations (denoted as 256+ and 1024+) generalize better than their unmodified counterparts. Larger networks were also attempted but failed to improve performance, *e.g.* 2048+ reduced Rank-1 accuracy by 4.21% on the closed set.

4.3 Comparison with the State-of-the-art

The state of the art COTS face recognition system, as evaluated by NIST in [6], and diligently benchmarked by [1] on the LFW open and closed set protocols provides a unique insight as to how well our system compares to the best commercial system available. The authors of [1] have also employed an additional vendor that rectifies non-frontal images by employing 3D face modeling and improved the results of the baseline **COTS-s1** system, the combined system is denoted **COTS-s1+s4**. For further comparison we have evaluated the publicly available LFW high dimensional LBP features of [3], denoted as **BLS**, which are published online in their raw format, *i.e.* *before* applying the prescribed supervised metric learning method. Finally, in order to push our results further, we fuse all of the models we trained in this work by simply concatenating their features, and report a slight improvement, denoted as **Fusion**.

Method	DeepFace [21]	BLS [3]*	COTS- s1 [1]	COTS- s1+s4 [1]	1024+	Fusion
Verification	97.35	93.18	-	-	98.00	98.37
Rank-1	64.9	18.1	56.7	66.5	82.1	82.5
DIR @ 1%	44.5	7.89	25	35	59.2	61.9

Table 3: Comparison to state of the art that includes the COTS method and 2 recent methods, in terms of the Probe-Gallery’s Rank-1 accuracy (%) on the Closed Set, the DIR at 1% FAR on the Open Set, as well as the verification protocol. *For [3] only the published raw features are used and not the full system. The full system achieves 95.17% on the verification task. For both COTS the verification performance was not reported.

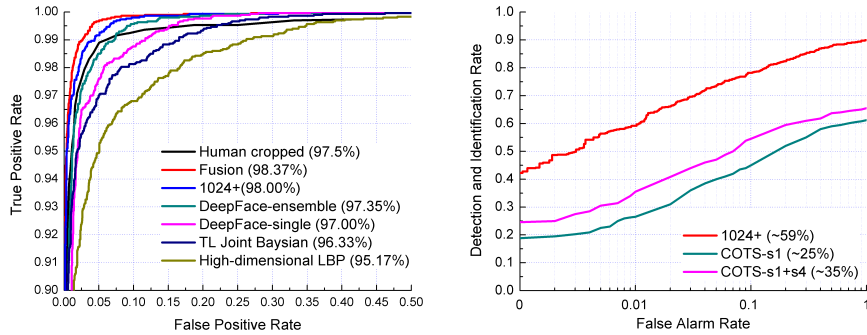


Figure 4: **Left:** The ROC curves on the face verification unrestricted protocol. **Right:** The DIR vs. FAR curves on the Open Set protocol. As mentioned above, for identification, training on LFW images is not permitted as it invalidates the comparison to baselines; had we jointly fit a multi-class linear svm to the gallery, the best model would achieve 69% DIR @ 1% on the open set. Best viewed in color. The ordinate scales are different. COTS graphs were reconstructed from [1].

Table 3 and Figure 4 summarize these results. Our best method lowers the state of the art miss rate on the closed set protocol by 57%, and by 45%, at the same precision level, on the open set protocol. The error in the verification protocol is reduced by 38% over the state of the art.

5 Discussion

Face recognition is unlike any other visual perception domain in that there is more explicitly tagged data available than the current methods can make use of. Many of the algorithms suggested in the past only benefit marginally from an additional increase in the size of the training set since their capacity is limited by a specific hypothesis space. For example, metric learning techniques are often constrained to learn a mahalanobis distance. Deep networks instead are able to meet capacity demands of any size, however, they are limited by practical considerations such as training time and memory. Therefore, the study of multi-GPU and cloud computing methods to distribute computation is of a great importance. In this work, we take a different approach and look into the problem of efficiently constructing challenging subsets of the training set. We show that such sampling can be done most effectively by considering not the samples themselves but instead the classifiers that are used to model each sample. The result is a highly challenging training set that is enriched in training opportunities that address the inherent challenges of face recognition.

Understanding the trade-offs involved with determining the representation dimensionality is extremely important. We provide insights into two such effects: controlling the network capacity to allow good generalization in transfer learning; and increasing the capacity to the best use of carefully constructed challenging training sets. Lastly, our work is unique in that it allows a direct comparison of commercial systems to those published in the academic literature, in the domain most frequently used to benchmark commercial retrieval systems. Despite years of development and careful engineering invested in commercial systems, deep learning systems trained on massive face datasets seem to greatly outperform.

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