Unsupervised Learning of Face Representations

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Abstract—We present an approach for unsupervised training of CNNs in order to learn discriminative face representations. We mine supervised training data by noting that multiple faces in the same video frame must belong to different persons and the same face tracked across multiple frames must belong to the same person. We obtain millions of face pairs from hundreds of videos without using any manual supervision. Although faces extracted from videos have a lower spatial resolution than those which are available as part of standard supervised face datasets such as LFW and CASIA-WebFace, the former represent a much more realistic setting, e.g. in surveillance scenarios where most of the faces detected are very small. We train our CNNs with the relatively low resolution faces extracted from video frames collected, and achieve a higher verification accuracy on the benchmark LFW dataset cf. hand-crafted features such as LBPs, and even surpasses the performance of state-of-the-art deep networks such as VGG-Face, when they are made to work with low resolution input images.

Keywords-face representations, unsupervised learning, face datasets, face verification

I. INTRODUCTION

Recent advances in deep convolutional neural networks, e.g. Krizhevsky et al. [9], coupled with availability of large annotated datasets, have led to impressive results on supervised image classification. While the annotated datasets available are of the order of millions of images, annotation beyond a point is infeasible, especially to the scale of billions of images and videos available on the Internet currently. To leverage this vast amount of visual data, albeit without any annotations, the community is starting to look towards unsupervised learning methods for learning generic image representations [3], [4], [10], [22]. The general idea is to obtain some form of weakly supervised data and then train a system to make predictions of these meta-classes from the originally unannotated images, e.g. Huang et al. [7] use a discriminative clustering method to mine attributes and then learn a CNN based similarity to capture the presence of attributes in the images while Wang et al. [27] propose to derive similar and dissimilar patches via motion information and then learn a CNN based similarity, conceptualy close to the former method. These methods have shown good promise for the general task of image representation learning.

In the present paper, we focus on a particular but very important subset of images, that of human faces, and investigate unsupervised learning of representations for the same.

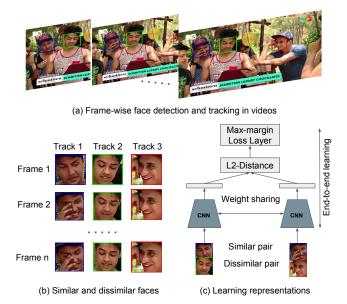


Figure 1. Overview of our approach. (a) Given a video, we perform framewise face detection followed by the temporal tracking of those faces across different frames. (b) Based on the observation that multiple faces in the same frame must belong to different persons and the same face tracked across multiple frames must belong to the same person, we generate a set of similar and dissimilar face pairs. (c) We use these face pairs to train a Siamese network using max-margin loss that learns discriminative face representations.

We study if unsupervised learning can compete with handcrafted features as well as with supervised learning based methods, for the specific and limited case of human face images. Given the availability of large amount of human centered data on the Internet, we investigate whether having a large corpus of such videos with challenging appearance variations makes it possible to learn a meaningful face representation which can be used out-of-the-box for face verification in the wild. Also, do the representations improve when they are fine-tuned on the current, application and domain conditioned set of faces? In particular, since getting very high resolution data is impractical so far, in real life scenarios like surveillance etc., we focus on lower resolution face images. We show that using a simple observation that faces in the same frame have to be of different persons (barring rare exceptions of reflections etc.) and those which are associated via tracking across different frames are of the same person, we train a CNN based similarity function. We then used this pre-trained network to obtain the representations of novel features for face verification on novel

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datasets. We also finetune these representations on the given task and show how the performance changes. As a summary, the main contributions of our paper are as follows. (i) We collect a large-scale dataset of 5M face pairs with similar and dissimilar labels by tracking YouTube videos. The dataset is shown to have faces in a wide variety of scale, pose, illumination, expression and occlusion conditions, thereby making it challenging source of data for facial analysis research. (ii) We present a method to learn discriminative, deep CNN based facial representations using the above dataset. In contrast with other state-of-the-art facial representations, we do not use even a single identity label for learning our representations. Rather, we rely on weak annotations of similarity and dissimilarity of faces to train our network. (iii) We perform extensive empirical studies and demonstrate the effectiveness of the representations that we learn by comparing them with hand-crafted features (LBP) as well as state-of-the-art VGG-Face descriptor in the domain of low-resolution input images. We also do ablation studies and report the importance of the different parametric choices involved.

II. RELATED WORK

Supervised image classification has seen rapid progress recently, starting from the seminal works of Krizhevsky *et al.* [9]. While the progress has been less stellar for the unsupervised counterparts, the field has been active in studying such methods as well [1], [3], [6], [10], [12]. Particularly in computer vision, there have been numerous attempts at learning representations using, e.g., videos [11], [21], [28], [4], [16], [23] As some representative works, Wang *et al.* [27] mine thousands of unlabelled videos to track objects in order to learn effective representations. Masi *et al.* [15] uses low-level motion cues to perform motion-based segmentation of objects in videos which are then used as ground truth for training CNNs. Liang *et al.* [13] uses an Image-Net pre-trained CNN as initialization followed by semi-supervised learning in videos for object detection.

The progress, in the specific domain of human faces, has also been dominated by supervised face recognition methods based on deep neural networks. The DeepID series of networks [24] were trained using two types of supervisory signals - a Softmax loss that learns to separate interpersonal variations and a pairwise verification loss that learns intra-personal variations. These networks were trained using identity labeled images from the CelebFaces+ [14] dataset. The training using Softmax loss was done using a randomly sampled set of 8192 identities and 200k pairs from the remaining 1985 identities were used for learning the verification model. Similarly, [17] poses face recognition as an N-way classification problem where N = 2600. They collect a identity labelled dataset of 2.6M face images with the help of popular image search engines. The authors then train their networks using a Softmax loss to learn identitydiscriminative face representations. On the other hand, [18] and [25] use weak annotations in terms of either triplets or (non-)matching pairs to train deep network to learn representations that discriminate between similar and dissimilar face pairs. While [25] uses 4 million face images belonging to 4k identities, the dataset collected in [18] consists of 200 million training images. Although our work also makes use of weak annotations in the form of (dis)similar pairs, unlike all the methods discussed here, we do not use a single identity label in the process of generating our training pairs.

Curating large-scale, identity labeled face datasets poses challenges in scaling. As a testimony to this fact, the biggest supervised face datasets have been collated by organizations such as Google [18] and Facebook [25] and are not accessible to the research community. This raises a very pertinent question - is it really necessary to use millions of identity labeled face images to learn discriminative representations? Masi et al. [15] tackle this problem by augmenting labelled datasets by synthesizing face images in challenging appearance variations. A complimentary approach to deal with the same challenge is to develop methods and systems to leverage the large amounts of unsupervised video data, freely available on the internet – we explore this approach here. Both [27] and [2] and used motion information to obtain supervision of similar and dissimilar patches (based on objects or faces, respectively. Since, like us, Cinbis et al. [2] work with faces, we point out the following differences between our work and them. While their scope of application is quite narrow, i.e. learning cast-specific metrics for TV videos, we are interested in whether we can learn meaningful face representations without having to rely on supervision in terms of face identities. We work with end to end pipelines for learning representation, while they have hand designed features. We work at a significantly larger scale; while they had 3 videos (episodes) with ~ 650 manually annotated tracks, we work with 850 videos with 1904 automatically formed tracks giving a total of 5×10^6 mined similar and dissimilar face pairs. Similarly, the number of identities they had were 8, while here we have order of hundreds. Also, they acknowledge (Sec. 3.2) that their set of dissimilar pairs is heavily biased towards a few pairs of actors who coappear frequently, while we have taken specific measures to mitigate such a scenario by doing cross-pairings between faces collected from widely different genres of videos. Finally, they worked with high quality broadcast videos whereas we work with unconstrained YouTube videos, and study low resolution face analysis and, while they used significant manual annotations, large majority of the steps are automatic in our case and here our method is scalable.

Recently, there also has been an interest towards learning face representations using low resolution images. Hermann et al. [5] train networks on input image sizes of 32×32 by combining face images from multiple data sources including surveillance videos–which are a very large and relevant

Dataset	Id	# Faces	Face size		Ratio
Dataset	Iu	# Faces	mean	median	Katio
LFW [8]	\checkmark	13k	113	113	$1.7 \times$
TSFT [19]	\checkmark	32k	121	109	$1.8 \times$
VGG-Face [17]	\checkmark	2.6M	125	108	$1.9 \times$
CelebA [14]	×	220k	152	145	$2.3 \times$
Ours	×	1.36M	67	56	ref.

Table I

Face sizes (mean and median) across different datasets – both supervised and unsupervised, i.e. with and without identity labels resp. ("Id" column). The "Ratio" column gives the relative mean face size with respect to the mean face size in our dataset.

area for face identification applications. All images in their dataset, however, have been manually annotated with identity labels, posing scalability challenges. We aim to learn low resolution face representations without manual identity level annotations.

III. OVERVIEW

Our goal is to train deep convolutional neural networks to learn face representations using videos downloaded from the internet. High-performing, state-of-the-art systems rely on massive amounts of high-resolution, identity-labeled face images for learning discriminative face representations. Table I shows the statistics of different face datasets being used, most of the existing datasets use faces of sizes upwards of $\sim 120 \times 120$. As an example, VGG-Face network [17] was trained on 2.6 million face images annotated with identity labels from a set of N = 2600 celebrity identities with an input image size of 224×224 . They posed face recognition as an N-way classification problem and trained their network architecture using a standard classification (Softmax) loss. The ℓ_2 -normalized output of the last fully connected layer was then used as a face descriptor which was further finetuned on the LFW training set.

We work with a large set of internet videos, i.e. they do not provide us with any strong supervision in the form of identity labels for faces. This rules out the possibility of using a set-up similar to VGG-Face and learning identitywise discriminative representations. However, we exploit the temporal supervision that is implicit in videos to generate weak annotations in terms of similar and dissimilar (wrt. identity) face pairs. Figure 1 gives an illustration of our overall approach, which we explain in detail below. Instead of using identity labeled face images, we train our CNNs by using the generated pairs of faces. The visual representations that we learn embeds similar face pairs closer in the feature space than dissimilar faces using a max-margin loss function that learns to separate similar and dissimilar pairs by a specified margin. We now give the details of all the different steps involved.

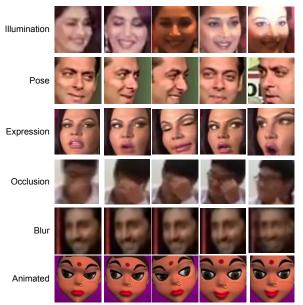


Figure 2. Some samples showing the rich amount of variations in terms of pose, occlusion, illumination, expression etc. in the dataset that we have captured

IV. MINING FACE PAIRS FROM VIDEOS

We now describe the data collection process that we used to mine face pairs via face detection and tracking in videos. A key observation is that all pairs of faces that are detected in a single video frame must belong to different identities (barring rare exceptions such as reflections in mirrors) and hence contribute to the set of dissimilar face pairs. Similarly, by tracking a face across multiple frames we can obtain face images belonging to the same identity which helps us generate our set of similar face pairs. By processing thousands of videos in this fashion, we were able to generate a dataset of more than 5 million face pairs as follows.

A. YouTube Videos

To construct our dataset we downloaded videos from YouTube - a popular video sharing site. Since our aim was to detect faces in order to generate a set of face pairs, we chose the genres of videos in such a manner so as to maximize the number of faces appearing in each video frame– genres which have a lot of people appearing in them and at the same time instants, and with high number of faces appearing in any given video frame. Keeping this in mind, we looked at videos of news debate shows, TV series where multiple actors are part of a majority of the scenes, discussion panels with several panelists, reality shows where participation is usually in the form of teams/groups and celebrity interview shows. We manually created a list of search keywords on the basis of the above criteria for genre selection and downloaded 850 videos from YouTube.

Given a video, we then wanted to detect faces and subsequently track the faces over time to generate the desired set of similar and dissimilar face pairs.

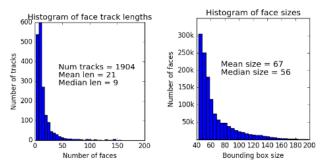


Figure 3. Histogram of track lengths and face sizes (square bounding box) in the proposed dataset collected in an unsupervised fashion from videos. The average face size and track length is 67 pixels and 21 faces respectively.

B. Face Detection

We used the implementation of the Viola-Jones (VJ) face detector [26] that is available as part of the OpenCV library for detecting faces. Every 10th frame of a given video was sampled and a combination of face detectors trained on frontal and profile faces was applied to detect faces that appear in the frames. The face detectors were configured to output only high-confidence detections at the cost of missing out on some faces. There were some cases of false positive detections which were removed manually (approximately 10-12% of the total face detections were false positives).

C. Face Tracking

Given the location of detected faces (if any) in each of the sampled video frames, the next step was to generate face tracks. Face tracking was done using a tracking-by-detection framework with a temporal association of face bounding boxes across frames. For each detected face in a given frame, we checked if there was an overlap between its bounding box with that of any face in the previously sampled frames. If there was an overlap, the current face was added to the existing track (if there are multiple overlaps, we added it to the track corresponding to the face with the maximum overlap). Otherwise, a new face track was started for the given face detection. A face track was marked to have ended when no new bounding boxes were added for 5 consecutive sampled frames. As a post-processing step, all face tracks with less than 5 faces were discarded. This rather simple and conservative tracking strategy ensured that we got only high quality similar face pairs, which is eventually what the tracking was supposed to achieve.

D. Dataset Statistics

After processing all the 850 videos with a total running time of about 70 hours, we detected a total of 1.36M faces and generated 1904 face tracks. The distribution of face track length (number of faces in a track) as well as the distribution of face sizes (square bounding box as detected by the VJ detector) are shown in Figure 3. Given the faces detected in a single frame as well as the face tracks, we generated a set of more than 5 million similar and dissimilar face pairs.

850
70 h
1.36 M
1904
2.5 M
2.5 M
5 M

Table II STATISTICS OF THE PROPOSED UNSUPERVISED FACE PAIRS DATASET THAT WAS COLLECTED FROM VIDEOS.

Table IV-D shows the statistics of the constructed face pairs dataset. A comparison of the face sizes in our dataset in Table I shows that faces detected from video frames are of much lower spatial resolution than those available as part of identity-labeled face datasets such as LFW, CelebA etc. The mean face size as detected by the VJ detector in our dataset is 67 pixels whereas it is 113 pixels for LFW and goes up to 152 pixels in the case of CelebA. This fact plays an important role in designing our CNN architecture which is discussed in Section V. Qualitatively, as shown in Figure 2, the dataset is able to capture a rich amount of variations in challenging conditions of pose, illumination, expression, resolution and occlusion etc., making it an apt source for learning face representations.

V. LEARNING FACE REPRESENTATIONS

The previous section described how we generated similar and dissimilar face pairs from unlabeled videos. In this section, we discuss our framework that uses those millions of face pairs and learns discriminative face representations.

A. Network Architecture

We designed a Siamese network which consists of two base networks which share parameters and whose architectures (convolutional layers) are similar to the VGG-Face network [17]. The VGG-Face network was trained using images of size 224×224 . As shown in Figure 3 and Table I, the face sizes in our dataset are constrained by the video quality and are much smaller than 224×224 . Therefore, we trained our networks for input resolutions of 64×64 and 128×128 . As a consequence of this change in resolution of input images, the sizes of the FC layers were also changed appropriately. Instead of 4096-d, we have 1024-d FC layers, and cf. the architecture of [17] which consisted of 38M parameters, our networks have 17 million and 24 million parameters, for the 64 and 128 sized networks, respectively. The final output (of the last FC layer) of both our nets is a 1024-d feature vector that is the learned representation of the face in the feature space.

B. Max-margin Loss Function

If x is an input to the CNN, let $\phi(\mathbf{x})$ be the output of the last FC layer. The function $\phi(.)$ is parameterized by the weights and biases of the CNN. We define the distance between two faces x_1 and x_2 in the learned representation space as the square of the L2 distance between their descriptors, i.e.

$$D^{2}(\mathbf{x_{1}}, \mathbf{x_{2}}) = \|\phi(\mathbf{x_{1}}) - \phi(\mathbf{x_{2}})\|_{2}^{2}$$
(1)

Our goal was to learn visual representations such that similar face pairs are closer together in the representation space and dissimilar face pairs are far apart. This objective guided our choice of the loss function that we used for training. Formally, let $\mathcal{T} = \{(\mathbf{x_i}, \mathbf{x_j}, y_{ij})\}$ be the dataset where $y_{ij} = 1$ if $\mathbf{x_i}$ and $\mathbf{x_j}$ are similar face pairs and $y_{ij} = -1$ otherwise. Then, the loss function can be defined as follows,

$$L(\mathcal{T}) = \sum_{\mathcal{T}} \max\left\{0, m - y_{ij}(b - D^2(\mathbf{x}_i, \mathbf{x}_j))\right\}.$$
 (2)

Where, $D(\mathbf{x_i}, \mathbf{x_j})$ is the distance as defined in Eq. 1. Minimization of this margin-maximizing loss encourages the distance between pairs of faces of same (different) person to be less (greater) than the bias b by a margin of m.

C. Fine-tuning Using Supervised Metric Learning

Supervised fine-tuning of descriptors using the target dataset has been shown to be very effective for faces [20]. Using the max-margin loss as described in Eq. 2, the CNN learns discriminative representations for faces by training over data from the (unsupervised) face pairs dataset. Since we wished to report pair matching (face verification) accuracies on the benchmark LFW dataset, we used training pairs from LFW to fine-tune our descriptors using metric learning. This was done by learning low dimensional projections with a discriminative objective function. Therefore, the fine-tuning served two purposes - (a) it reduced the dimensionality of the learned representations, making it suitable for large datasets, and (b) further enhanced the discrimination capability of the features upon projection.

Formally, the aim was to learn a linear projection $W \in \mathbb{R}^{p \times d}$, $p \ll d$ which projects the representations learned by our network $\phi(\mathbf{x}) \in \mathbb{R}^d$ to low dimensional projections $W\phi(\mathbf{x}) \in \mathbb{R}^p$. This was done such that the square of the Euclidean distance between faces *i* and *j* in the projected space, given by the equation

$$D_W^2(\phi_i, \phi_j) = \|W\phi_i - W\phi_j\|_2^2,$$
(3)

is smaller than a learned threshold $b \in \mathbb{R}$ by a (fixed) margin of m, if i and j are of the same person, and larger otherwise.

The objective is similar to the one which we used to train our deep network. Such fine-tuning using metric learning is equivalent to supervised learning of another FC layer on top of the unsupervised representations learned by our CNN. There is one difference – while training the deep network, both the bias and the margin were fixed whereas while finetuning, only the margin is fixed and the bias is a parameter which is learned.

Input Images

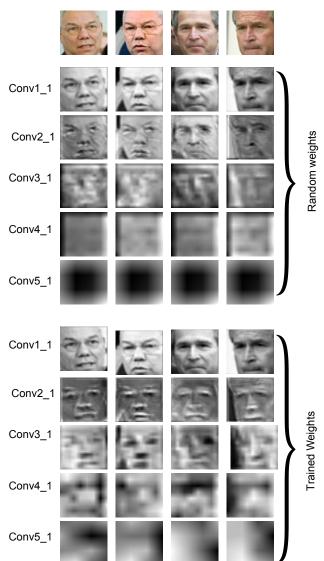


Figure 4. Visualization of the activations of the 1st filter for 5 Conv. layers at different depths for 4 input images from LFW. A qualitative comparison between our trained network and a network with random weights shows the discriminative abilities of the weights learned by our network especially at the deeper layers.

VI. EXPERIMENTS

We now present the experiments we did to validate our method. We first give the training details, followed by results with unsupervised representations learnt by the networks. We then give the results when the unsupervised representations are fine-tuned on the current task. We also give ablation studies, showing the importance of difference choices.

A. Training Details

The training dataset comprises of 2.5M similar and dissimilar face pairs each. Apart from pairing faces that were

	No fine-tuning done (accuracy EER AUC)		Fine-tuned on LFW (accuracy EER AUC)	
$\text{Descriptors} \downarrow \text{Image sizes} \rightarrow$	64×64	128×128	64×64	128×128
LBP	64.60 35.40 70.79	64.60 35.39 70.39	70.18 29.82 78.14	72.44 27.56 79.82
VGG-Face (Random)	60.54 39.46 64.97	61.55 38.45 65.72	65.02 34.98 70.65	65.34 34.66 71.64
VGG-Face (Supervised)	62.38 37.62 67.21	62.55 37.45 67.43	66.00 34.00 72.08	66.34 33.67 73.03
Proposed face representations	71.48 28.53 78.78	71.48 28.51 78.40	73.22 26.78 80.57	72.20 27.79 80.29

Table III

FACE VERIFICATION ACCURACIES FOR DIFFERENT DESCRIPTORS ACROSS DIFFERENT INPUT IMAGE SIZES: (I) HAND-CRAFTED FEATURES – *LBP*, (II) A NETWORK (WITH THE SAME ARCHITECTURE AS OURS) INITIALIZED WITH RANDOM WEIGHTS – *VGG-Face (Random)*, (III) THE VGG-FACE NETWORK [17] PRE-TRAINED NETWORK MADE TO OPERATE IN A LOW-RESOLUTION SETTING – *VGG-Face (Supervised)*, AND (IV) PEOPOSED METHOD.

detected in the same video frame, we increased the number of dissimilar face pairs by taking arbitrary subsets of faces detected from widely different genres of videos and pairing them up. For example, the video of a TV reality show based in another country is highly likely to have a mutually exclusive set (in terms of identities) of actors/participants than a popular Hollywood TV series. We found such forms of cross-pairings to be an effective way to increase the size of the dataset.

Unsupervised Training Implementation. We trained two networks with different input resolutions -64×64 and 128×128 using backpropoation and SGD with a batchsize of 32 image pairs and a learning rate of 0.01. For regularization, we set the weight-decay parameter to 0.0005 and also do Batch-Normalization after every convolutional and FC layer. The bias and margin of the max-margin loss (*b* and *m* in Eq. 2) were set to 1.0 and 0.5 respectively. All implementations related to training of the CNNs were done using Torch and the networks were trained on 12 GB NVIDIA GeForce TitanX GPUs.

For validation, we kept aside a set of 6400 similar and dissimilar face pairs each as our validation set (this was disjoint from our training set). We monitored the training of our CNN using face matching accuracies on the validation set with the bias of the loss function as a threshold. A (dis)similar face pair in the val set is said to be correctly matched if the distance between their descriptors is (greater) less than the threshold.

Hard-mining. We trained the networks until the validation accuracy began to saturate and then performed hard-mining of the training pairs. During hard-mining, we computed the distances between the learned descriptors of all face pairs in the training set. Those (dis)similar pairs whose distances are greater (lesser) than b(+) - m were classified as "hard pairs" which meant that they would accrue a loss as per our max-margin loss module. After hard-mining, training was resumed only on the "hard pairs". This enabled the CNN to learn more robust representations.

The hard-mining process was performed after 28k iterations and 50k iterations for the 64×64 and the 128×128 net respectively. Post hard-mining, 28.07% and 16.18% of the original set of 5M face pairs were classified as "hard" for the 64×64 and 128×128 net respectively. Both networks were subsequently trained on the reduced set of hard-mined pairs for 3 more epochs.

Data Augmentation. Similar to [17], we performed data augmentation during training. We scaled the input images to a slightly larger size by keeping the aspect ratio same and then proceeded to take crops of the desired input size from all the 4 corners and the center resulting in 5 different images. We also performed a horizontal flip for each of the face crops to get a total of 10 data augmented versions of a single image. These augmentations were applied randomly and independently to each image of any given face pair during training. In total, we trained the 64×64 and 128×128 networks for a total of 150k iterations and 125k iterations respectively (for a batch size of 32 and dataset size of 5M face pairs, this corresponds to 0.8 and 1 epoch respectively.).

B. Results with Unsupervised Representations

We refer to the representations learned by our network after training on the face pairs dataset as "unsupervised representations". In this section, we demonstrate the effectiveness of the unsupervised representations using both qualitative and quantitative experiments.

Qualitative Results. We sampled four images from the LFW dataset – 2 images each belonging to 2 identities and visualized the activations of 5 convolutional layers at different depths for all the 4 images. Figure 4 shows a qualitative comparison between the activations for two networks: (a) initialized with random weights and (b) trained using unsupervised face pairs data (both the nets have 64×64 sized inputs). It can be observed from Figure 4 that the random weights CNN has very low discriminative power as evident from its activations from the deeper convolutional layers (Conv4_1 and Conv5_1) which are similar for all the 4 inputs. On the other hand, our trained network has been able to learn weights which enable it to discriminate between images.

LFW Dataset. Quantitatively, we report face verification (pair matching) accuracies on the benchmark LFW dataset. The dataset comprises of 13,233 face images from 5,749

identities. We used the Viola-Jones detector [26] to detect faces in the LFW images. The average face size (square bounding box) of the faces is 113 pixels (Figure I). The cropped faces were then resized to the desired input size $(64 \times 64 \text{ or } 128 \times 128)$. For the purpose of pair-wise face matching, the LFW dataset provides 6000 face pairs that are divided into 10 identity exclusive sets (folds). In addition to the verification accuracies, we also report the area under the ROC curve (AUC) and the Equal Error Rate (EER) metric which is defined as the error rate when the false positive and the false negative rates are equal as per the ROC curve. The EER metric is independent of any threshold. All reported figures (Table III) were averaged across the 10 folds.

Another noteworthy fact is that we did not use the aligned version of the LFW dataset as the images in the aligned dataset are all grayscale and our CNNs were trained on RGB images. Also, we did not perform any sort of facial alignment (other than face detection and cropping) on the LFW images. We felt that operating in the space of non-aligned, "in-the-wild" face images is a more realistic setting. The same principles are also reflected in our training set which has been shown to posses a wide variety of challenging imaging conditions (Figure 2).

Quantitative Results. The output of the last FC layer of our network was L2-normalized and treated as the learned (unsupervised) representation of the input face image. In fact, we took equal-sized crops from all 4 corners and the center of the input image, horizontally flipped each of the 5 crops and took the average of all the 10 descriptors as the descriptor of the input face image. Our CNN, trained using unsupervised face pairs of size 64×64 , was able to achieve an accuracy of 71.475% on the verification task. For the net with an input size of 128×128 , the accuracy was 71.483%. We expect the accuracies to go up with the size of the dataset, with diminishing returns. We observed this in intermediate results while training our networks. For example, after training for 10k iterations (which corresponds to a dataset size of 0.3M image pairs), the LFW verification rate is 63.35%. This increases to 64.65%, 66.92% and 68.28% for 0.64M, 1.28M and 1.6M face pairs. The final verification accuracy that we get using our entire dataset of 5M training image pairs is 71.48%.

Baseline. We compared the above accuracies with LBP features (hand-crafted features), a network with randomly initialized weights and the VGG-Face network that has been trained using supervised data (Table III). For LBP, we used the grayscale variants of the LFW images and kept the cell size as 16×16 . This led to 928-d and 3712-d LBP descriptors for 64×64 and 128×128 input images respectively. To simulate low-resolution input setting for the VGG-Face network trained using supervised data [17], we first down-sampled the cropped LFW faces to either 64×64 or 128×128 and then up-sampled them to the expected input

size of 224×224^1 .

Our network trained on unsupervised data was consistently able to outperform all the others by a significant margin. In comparison to the 71.475% verification accuracy of our unsupervised network (64×64 input size), a network with random weights gave an accuracy of only 60.536% whereas LBP features gave 64.6% verification accuracy. The accuracy of the VGG-Face network trained using identity-labeled (supervised) data was only 62.844%. Our experiments thus demonstrate that the performance of the nets trained on high-resolution (labeled) input faces drops drastically when they are made to operate on a low-resolution setting. These trends are similar to the ones observed in [5] where the authors have made similar comparisons. We also plot and compare the ROC curves in Figure 5 for our network and the baselines (please refer to the Appendix).

C. Results with Fine-tuned Representations

We also fine-tuned the unsupervised representations learned by our network using training image pairs from the target dataset - LFW. For generating image pairs, we used the "unrestricted" setting as mentioned by the dataset providers [8]. The accuracies that we report in Table III under the heading "Supervised (Fine-tuned)" are all 10-fold cross-validated.

For fine tuning, we initialized the projection matrix $W \in \mathbb{R}^{p \times d}$ using small random values sampled from a zero-mean Gaussian distribution with $\sigma = 0.01$. The margin was set to 0.5 (the bias is a learned parameter). The learning rate was set to 0.01 and decreased by a factor of 1.2 after every epoch. As expected, there was an increase in the verification accuracies after fine-tuning across all different types of feature descriptors and input image sizes. In the case of our unsupervised representations, as given in Table III, the accuracies increased from 71.475% to 73.220% for 64×64 net and from 71.483% to 72.204% for the 128×128 net.

D. Ablation Studies

We performed some ablation studies, the details of which can be found in the Appendix.

VII. DISCUSSION AND CONCLUSION

We presented a method to learn discriminative, deep CNN based face representations using a dataset of 5M face pairs and without using a single identity label. Our net, trained on unsupervised data, was able to achieve a verification rate of 71.48% on the benchmark LFW dataset with low-resolution input images of size 64×64 . This perormance is superior to both hand-crafted features, i.e. LBP (64.6%) as well as

¹We also considered training the VGG-Face net from scratch using lowresolution versions of the training images used in [17]. However, the images in the training set are provided in the form of web URLs and ~25% of the image URLs were unavailable.

CNNs (62.38%) trained on supervised data in comparable low-resolution settings. Further, upon fine-tuning unsupervised representations using max-margin metric learning on the annotated training images from the LFW dataset, the accuracies for the target task of face verification increased to 73.22%. We also performed empirical experiments to study the effect of (a) descriptor size of the fine-tuned representations and (b) amount of supervised training used during fine-tuning on the verification accuracies. We found that increasing the dimensionality of the representations leads to better accuracies – using a 1000 - d fine-tuned descriptor, we were able to push the verification rates up to 74.13%. Similarly, using larger amounts of supervised data also boosted performance. Our work is the first attempt at using unsupervised learning methods in the limited, but nevertheless important domain of face images. We believe that it brings forth newer opportunities to leverage the vast amounts of human-centric multimedia data on the Internet for designing CNN based facial representations.

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REFERENCES

- [1] Y. Bengio, A. Courville, and P. Vincent. Representation learning: A review and new perspectives. *IEEE transactions* on pattern analysis and machine intelligence, 2013.
- [2] R. G. Cinbis, J. Verbeek, and C. Schmid. Unsupervised metric learning for face identification in tv video. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2011.
- [3] C. Doersch, A. Gupta, and A. A. Efros. Unsupervised visual representation learning by context prediction. In *Proceedings* of the IEEE International Conference on Computer Vision, 2015.
- [4] R. Goroshin, J. Bruna, J. Tompson, D. Eigen, and Y. LeCun. Unsupervised learning of spatiotemporally coherent metrics. In *Proceedings of the IEEE International Conference on Computer Vision*, 2015.
- [5] C. Herrmann, D. Willersinn, and J. Beyerer. Low-resolution convolutional neural networks for video face recognition. In Advanced Video and Signal Based Surveillance (AVSS), 2016 13th IEEE International Conference on, pages 221–227. IEEE, 2016.
- [6] G. E. Hinton and R. R. Salakhutdinov. Reducing the dimensionality of data with neural networks. *science*, 313(5786):504–507, 2006.
- [7] C. Huang, C. Change Loy, and X. Tang. Unsupervised learning of discriminative attributes and visual representations. In *CVPR*, 2016.
- [8] G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller. Labeled faces in the wild: A database for studying face recognition in unconstrained environments. Technical report, Technical Report 07-49, University of Massachusetts, Amherst, 2007.
- [9] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *NIPS*, 2012.

- [10] Q. V. Le. Building high-level features using large scale unsupervised learning. In *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*, pages 8595–8598. IEEE, 2013.
 [11] Q. V. Le, W. Y. Zou, S. Y. Yeung, and A. Y. Ng. Learn-
- [11] Q. V. Le, W. Y. Zou, S. Y. Yeung, and A. Y. Ng. Learning hierarchical invariant spatio-temporal features for action recognition with independent subspace analysis. In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 3361–3368. IEEE, 2011.
- [12] H. Lee, R. Grosse, R. Ranganath, and A. Y. Ng. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In *Proceedings of the 26th annual international conference on machine learning*, pages 609–616. ACM, 2009.
- [13] X. Liang, S. Liu, Y. Wei, L. Liu, L. Lin, and S. Yan. Towards computational baby learning: A weakly-supervised approach for object detection. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 999–1007, 2015.
- [14] Z. Liu, P. Luo, X. Wang, and X. Tang. Deep learning face attributes in the wild. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2015.
- [15] I. Masi, A. T. Trážğn, T. Hassner, J. T. Leksut, and G. Medioni. Do we really need to collect millions of faces for effective face recognition? In *European Conference on Computer Vision*, pages 579–596. Springer, 2016.
- [16] H. Mobahi, R. Collobert, and J. Weston. Deep learning from temporal coherence in video. In *Proceedings of the 26th Annual International Conference on Machine Learning*, pages 737–744. ACM, 2009.
- [17] O. M. Parkhi, A. Vedaldi, and A. Zisserman. Deep face recognition. In *BMVC*, 2015.
- [18] F. Schroff, D. Kalenichenko, and J. Philbin. Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 815–823, 2015.
- [19] G. Sharma and P. Perez. Latent max-margin metric learning for comparing video face tubes. In *Computer Vision and Pattern Recognition (CVPR) Workshops*, 2015.
- [20] K. Simonyan, O. M. Parkhi, A. Vedaldi, and A. Zisserman. Fisher vector faces in the wild. In *BMVC*, 2013.
- [21] N. Srivastava, E. Mansimov, and R. Salakhutdinov. Unsupervised learning of video representations using lstms. In *ICML*, pages 843–852, 2015.
- [22] N. Srivastava and R. R. Salakhutdinov. Multimodal learning with deep boltzmann machines. In Advances in neural information processing systems, pages 2222–2230, 2012.
- [23] D. Stavens and S. Thrun. Unsupervised learning of invariant features using video. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 1649–1656. IEEE, 2010.
- [24] Y. Sun, X. Wang, and X. Tang. Deeply learned face representations are sparse, selective, and robust. In *Proceedings* of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2892–2900, 2015.
- [25] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf. Deepface: Closing the gap to human-level performance in face verification. In *CVPR*, 2014.
- [26] P. Viola and M. Jones. Rapid object detection using a boosted cascade of simple features. In *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on.* IEEE, 2001.
- [27] X. Wang and A. Gupta. Unsupervised learning of visual representations using videos. In *ICCV*, 2015.
- [28] W. Y. Zou, A. Y. Ng, S. Zhu, and K. Yu. Deep learning of invariant features via simulated fixations in video. In *NIPS*, volume 3, page 6, 2012.

Appendix

A. Ablation Studies

We also performed some ablation studies to understand the effect of different parameters of the fine-tuning process. In particular, we studied the effect of the size of the projection dimension, p and the amount of supervised LFW data (as measured by the number of LFW face pairs used for fine-tuning) on the verification accuracies. We discuss some of the results in this section.

Projection Dimension. We ran experiments to see the effect of change in the projection dimension on the verification accuracies. Specifically, we varied p (with d = 1024) while learning the projection matrix $W \in \mathbb{R}^{p \times d}$ for the network trained on our face pairs dataset and having an input image size of 64×64 . In Table IV, the accuracies are shown to increase with an increase in the size of the projection dimension.

Proj. Dim.	Input image s Acc.	$ize = 64 \times 64$ AUC
p = 128	73.18	80.30
p = 256	73.22	80.57
p = 512	74.00	81.41
p = 1000	74.13	81.66

Table IV EFFECT OF THE DIMENSIONALITY OF THE FINE-TUNED DESCRIPTORS ON VERIFICATION ACCURACIES.

Amount of Supervised Data. In Table V, we report verification accuracies by varying the amount of supervised LFW face pairs data used for fine-tuning the unsupervised representations. The trends show that using larger amounts of training data improves performance.

# Face Pairs	Input image size = 64×64			
	Acc.	AUC		
1k	70.89	78.62		
2k	71.75	79.40		
5k	73.49	80.38		
10k	73.22	80.57		
20k	73.85	81.13		

Table V EFFECT OF THE AMOUNT OF SUPERVISED DATA DURING METRIC LEARNING ON THE VERIFICATION ACCURACIES

B. ROC Curves

We plot ROC curves for face verification on the LFW dataset. We compare our unsupervised representations with two baselines – LBP (hand-crafted features) and representations from the VGG-Face [17] network trained using supervised (identity labeled) dataset. Figure 5 shows the ROC curves for our (unsupervised) representations and the baselines.

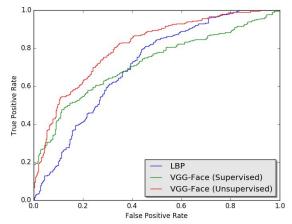


Figure 5. ROC Curves for verification on the LFW dataset