Multi-Face: Self-supervised Multiview Adaptation for Robust Face Clustering in Videos

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Abstract. Robust face clustering is a key step towards computational understanding of visual character portrayals in media. Face clustering for long-form content such as movies is challenging because of variations in appearance and lack of large-scale labeled video resources. However, local face tracking in videos can be used to mine samples belonging to same/different persons by examining the faces co-occurring in a video frame. In this work, we use this idea of self-supervision to harvest large amounts of weakly labeled face tracks in movies. We propose a nearest-neighbor search in the embedding space to mine hard examples from the face tracks followed by domain adaptation using multiview shared subspace learning. Our benchmarking on movie datasets demonstrate the robustness of multiview adaptation for face verification and clustering. We hope that the large-scale data resources developed in this work can further advance automatic character labeling in videos.

Keywords: video character labeling; self-supervision; multiview correlation

1 Introduction

Media is created by humans, for humans: to tell stories that educate, entertain, inform, market products or call us to action. When we watch a commercial, TV show or film, the onscreen characters shape our point of view by providing a window into the narrative. These characters advance the plot and play a vital role in effective storytelling [1]. Advances in machine learning can help automatically identify who, where and when to further our understanding of character portrayals and behaviors in media content. Character-level analysis offers numerous applications for an array of stakeholders: from content creators and curators to media scholars and consumers. Consider video streaming platforms which are able to tailor recommendations based on the cast of characters and the settings in which they appear [2]. Social media scholars and content creators can easily research TV and film trends and use character on-screen presence to shed light on a variety of relevant topics such as diversity and inclusion in casting [3]. This research can also directly influence other fields such as understanding social interactions in videos [4] and automatic video captioning [5].

A first step toward developing such tools is the ability to automatically identify the characters in the visual modality i.e., the who. This is a difficult task
because characters are often portrayed with varying degrees of complexity with respect to appearance and design in different media forms (e.g., automatic character labeling in animated content [6]). In this paper, we focus on live-action content where a person’s face is used as a primary feature of identification. This is typically achieved through a two-step process: face detection to localize the face of a person in a frame and then group all the detected faces to recognize a person irrespective of where and how they appear in the content. Recent advances in face detection can localize faces with near-perfect precision, even in extreme conditions of illumination and pose [7]. Similarly, advances in learning face representations (embeddings) and rich face datasets (e.g., [8,9]) have provided powerful features to identify a person by their face.

However, face recognition in videos in the absence of domain-matched training data remains a challenging problem. In TV shows and movies, we need to robustly identify the characters in the presence of multiple visual distractors such as changes in appearance, background imagery, facial expression, size (resolution), view points (pose), illumination, partial detection (occlusion), and in some cases, age [10]. We provide a few examples of visual distractors in Figure 1 from one of the movies in our dataset. This task is further complicated in long-form content such as movies where different characters occur at varying frequencies and an exemplar of a character is not always available. In this setup, effective face recognition not only requires face representations which remain robust to visual distractors, but possibly unsupervised methods such as clustering to accurately identify every character in a given video. This is the main focus of this work with movie videos as our domain-of-interest.

Face recognition in videos is typically performed at the track-level. Unlike photo albums or image datasets, the temporal nature of videos can be used to group consecutive face detections into face tracks using simple heuristics based on the detection overlap [11] agnostic to the face identity. Face tracking offers an effective way to mine different instances of the same person (must-link constraints). Multiple faces occurring in a given video frame can be assumed to belong to different characters, that provides a set of face tracks that belong to different persons (cannot-link constraints). This process exploits the co-occurring

Fig. 1. Visual distractors associated with three prominent characters from a movie in our dataset. The images in the first column are exemplars taken from the IMDb page.
nature of faces in videos, both spatially and temporally, and does not require additional supervision; hence the term *self-supervised*. In the context of video face clustering in video, self-supervision was explored by several past papers to obtain robust domain-specific face representations to specific domains (e.g., [12,13]) as well as using the must-link and cannot-link constraints to improve face clustering [14,15].

In this paper, we use the ideas of self-supervision to contribute toward two critical aspects of face clustering in movies: (1) addressing the lack of domain-matched training data and (2) adapting deep face representations learnt from static images for face tracks mined from movies. First, we address the lack of domain-matched training data by mining all instances of co-occurring faces in movie video frames to obtain cannot-link face tracks, and subsequently must-link instances within the individual face tracks. Using this procedure, for a dataset of 240 Hollywood movies released between 2014–2016, we were able to obtain over 169,000 face tracks consisting of a total of 10 million face images with weak labels at a movie-level (i.e., whether two faces belong to the same person or not). We have made this data publicly available for the benefit of the wider research community.

Second, using these face tracks as training data, we explore triplet loss [8,12] and multiview correlation [16] based methods to adapt pre-trained face embeddings in order to improve face recognition in movies. For this purpose, we propose an offline method based on nearest-neighbor search in the embedding space, to identify hard-positives and hard-negatives for each face track, i.e., maximally distant must-link faces and minimally distant cannot-link faces respectively.

Finally, in order to benchmark the performance of the proposed adaptation methods for face clustering in videos, we consider publicly available datasets for three movies and a TV show [12,15,17] that have been widely used for benchmarking in related work. As part of this effort, we obtained character labels in-house for two other movies which include a more racially diverse cast of characters. For all six videos, we also annotate face quality labels (See Figure 1) to evaluate the performance of different methods in the presence of visual distractors. Our experimental results with face verification and clustering and error analysis demonstrate the benefit of using self-supervised adaptation techniques to improve character labeling in videos.

2 Related Work

2.1 Automatic character labeling in videos and data resources

Some earlier works [17,18,19] have explored the use of aligning speaker names available in movie screenplays with subtitles to obtain character labels for a given timestamp. Character identification was then framed as a matching problem between the faces detected in a movie frame and the names extracted from the screenplay-subtitle alignment. While screenplay-based methods are effective in identifying at least the speaking/named characters in a video, approaches
based on subtitles failed to scale due to the lack of accurate screenplays as well as inaccurate subtitle alignment [20,21]. Additional sources for supervised matching of characters have also been explored, such as, using IMDb images for TV series labeling [22]. While effective for some TV series, these methods fail to generalize for movies. For example, in Figure 1, the differences between a character’s appearance in an IMDb-curated image vs actual appearance in the movie, are very noticeable.

Recently, supervised deep representations of faces (e.g., [8,23,24,25,26]) have proven to be powerful and discriminative of a person’s identity, thereby reducing the need for additional sources of supervision. While methods such as [27,28] developed track-level face embeddings, simply averaging the embeddings of all the faces in a track offers robust face representations for downstream tasks such as face clustering [29]. These representations are typically trained on large labeled datasets that consist of static images mined from web search or photo albums. As such, we have to consider the domain mismatch of the training data while directly applying these representations to cluster faces in domains such as TV/movies [12].

While other datasets such as YouTube Faces (YTFaces [30]) have provided labeled face tracks from videos, they are relatively smaller in size (about 3500 face tracks, 1500 identities) and the source videos have fewer visual distractors (e.g., video interviews of celebrities). In addition, manually assigning character labels to face tracks from videos can be an expensive process. Thus, in our work, we simply mine a large number of face tracks from movie videos and use the co-occurring nature of faces, either spatially or temporally, to provide weak labels at a movie level. These face tracks provide domain-matched training data to adapt face embeddings learnt from static images. This method of “harvesting” weakly-labeled data with no supervision has been used previously to generate positive/negative samples for object recognition [31].

2.2 Self-supervision and metric-learning for adaptation

Self-supervision for face clustering in videos generally involves tracking faces locally in a video to obtain must-link face constraints and using the co-occurring faces in frame to generate cannot-link face constraints. In related work, these ideas have been effectively used both for feature adaptation (e.g., [14,30,32]) and for setting up constraint-based clustering [15,29,33]. The pairwise constraints mined through self-supervision were used to modify a distance matrix so as to satisfy the constraints [34]. Along similar lines, unsupervised logistic discriminative learning (ULDML [14]) was proposed to learn a metric such that must-link faces are closer to each other and the cannot-link faces are further apart in the feature space. Hidden Markov random field models (HMRF [32,33]) were also used to cluster faces by iteratively associating face tracks with the available constraints as the initial starting point.

A key insight with respect to pairwise constraints is that, if all the must-link and cannot-link face pairs in a video are known, the constraint matrix is low-rank. This property was effectively used to improve face clustering by learning
low-rank subspace representation \[29,35\]. Matrix completion was also used to impute the unknown pairwise constraints while jointly optimizing subspace representations \[15\]. A semi-supervised method leveraging the low-rank structure was proposed to jointly detect and cluster faces in a video \[30\]. More recently, face representations trained on datasets such as VggFace2 were adapted using track-level distances in the embedding space with methods based on contrastive and triplet loss (e.g., \[13\]) as well as linear discriminant analysis (LDA \[37\]). The effectiveness of the triplet loss for adaptation was further improved by identifying samples in must-link faces that are maximally distant (hard-positives) and cannot-link face that are nearby in the embedding space (hard-negatives) \[13\].

In this paper, we study the benefit of adapting face representations on the face tracks mined from movies. In addition to studying the benefit of triplet loss adaptation on the subset of hard-positives and negatives, we also explore multi-view correlation (MvCorr \[16\]) which can obtain the shared information across multiple faces with visual distractors. MvCorr has been shown to offer state-of-the-art performance for speaker clustering in the domain of speaker recognition \[38\] capturing information regarding the person’s identity irrespective of the spoken utterance. However, it has not been explored for face clustering. Analogous to speaker recognition, the hard-positives we extract from face tracks readily include faces of the same person in different views with respect to pose, illumination and occlusion. This makes MvCorr an appealing alternative to contrastive and triplet loss objectives for feature adaptation.

3 Methods

3.1 Self-supervised harvesting of movie face tracks

As described in Sec.2, we use the ideas of self-supervision to harvest co-occurring movie face tracks that can provide weak must-link and cannot-link face labels at the movie level. For this task, we used a dataset of 240 movies (24 fps video frame rate, 720x1280 resolutions) released between 2014–2016 that were purchased in-house. The movie titles and related details are provided in the supplementary materials, S1. First, we performed face detection and local tracking using Google’s API obtained with an academic license\[1\]. The face tracking used here was developed using simple heuristics based on analyzing the intersection-of-union of the successive bounding boxes of the detected faces \[39\]. Since our goal was to extract face tracks for one person appearing in different conditions such as pose, illumination, etc., we limited our search to face tracks that were at least 1s long (24 faces). For the set of 240 movies, this resulted in a total of 335,845 face tracks with 1389.9 ± 760.3 face tracks per movie.

In order to further limit the search space of face tracks, we only considered those tracks which co-occur with at least one other face track. Across all movies, on an average, 45.1 ± 21.2% of the face tracks had at least one co-occurring track. This statistic is consistent with the range of 35 – 70% reported by Sharma et.al

\[1\] Neven Vision fR\(^{TM}\) API
This process reduced the number of face tracks to 169,201 with an average of 726.2 ± 704.4 face tracks per movie. All the faces within a track provided must-link faces that can be used as positive samples (different face samples of the same person). Similarly, each face track overlapped with at least one other face track in time thus providing cannot-link face tracks to be used as negative samples (faces from different persons). Among these face tracks, we had a total of 10.2 million faces with an average of 63.3 ± 79.2 faces per track sampled at 24 fps. Overall, the number of cannot-link face tracks for a given track ranged between 1–94 with an average of 5.2 ± 9.1 per track. Of these, 43% of face tracks had only a single cannot-link track. We use this set of 169K harvested face tracks for all adaptation experiments in this work.

### 3.2 Mining hard-positive and hard-negatives

Many face clustering works which have used must-link and cannot-link constraints have emphasized the need for hard example mining to improve robustness of face representations to visual distractors (e.g., [26]). The goal here is to identify samples belonging to the same person which are further apart in the embedding space (hard-positives) and samples belonging to different persons that are close to each other (hard negatives). Hard example mining has been studied extensively in computer vision literature for tasks such as object recognition (e.g., [40]). In the context of face clustering, mining hard-positive and hard-negative faces in an embedding space can be easily achieved by identifying the pairs of face samples that yield maximum and minimum distance respectively [13]. However, face clustering is performed at the track-level where we average the embeddings of all the faces in a track to provide a robust representation. Thus, we propose a nearest-neighbor based approach to identify the hard-positive and hard-negative tracklets.

Let $\mathbf{H} = [\mathbf{h}_1, \ldots, \mathbf{h}_N] \in \mathbb{R}^{d \times N}$ be the $d$-dimensional embeddings from $N$ samples in a face track. Let $\mathbf{D}$ be the $N \times N$ pairwise distance matrix. First, we identify a pair of must-link faces that are maximally distant in the embedding space. That is,

$$(\mathbf{h}_a, \mathbf{h}_{p_1}) = (\mathbf{h}_i, \mathbf{h}_j) \quad \text{s.t.} \quad i, j = \arg \max_{i,j=1,\ldots,N} \mathbf{D}_{i,j}$$

where $\mathbf{h}_a$ and $\mathbf{h}_{p_1}$ are the anchor and positive face sample. Next, we construct a tracklet for $\mathbf{h}_a$ by finding its $k$-nearest neighbors, $\mathbf{H} = [\tilde{\mathbf{h}}_1, \ldots, \tilde{\mathbf{h}}_k] \in \mathbb{R}^{d \times k}$ which is a subset of columns from the matrix $\mathbf{H}$. The embedding for the anchor tracklet, $\mathbf{v}_a$, is obtained by averaging all the face embeddings of its nearest neighbors. That is, $\mathbf{v}_a = \frac{1}{k} \sum_{i=1}^{k} \tilde{\mathbf{h}}_k$. Similarly, we find the tracklet $\mathbf{v}_{p_1}$ corresponding to $\mathbf{h}_{p_1}$ by finding its $k$-nearest neighbors in the $d \times (n-k)$ matrix constructed by removing the the columns of $\mathbf{H}$ from $\mathbf{H}$.

Our proposed method can be used iteratively to mine more hard-positives. We summarize the method: (1) Identify the farthest face embedding $\mathbf{h}_{p_1}$ with respect to $\mathbf{h}_a$ from the remaining columns in $\mathbf{H}$, (2) find the $k$-nearest neighbors
for $h_{p_i}$, and average them to obtain $v_{p_i}$ (3) remove the nearest neighbors of $h_{p_i}$ from the matrix $H$. The number of hard-positives to be mined can be controlled by choosing an appropriate value for $k$. For example, if we need five tracklets from a face track of $N$ frames, we set $k = \lceil \frac{N}{5} \rceil$. Note that our choice of $k$ ensures that all tracklets are of same length and that all faces in a track are used up. Constructing tracklets of varying length is a focus of our future work.

Typically, for triplet loss based systems, a pair of hard-positives is sufficient. However, we also explore MvCorr which was shown to be effective for three or more hard-positive samples [38]. Hence, we mine three hard-positives for every face track by setting the number of neighbors $k = \lceil \frac{N}{3} \rceil$. Thus, we obtain a set of three hard-positive embeddings ($v_a, v_{p_1}, v_{p_2}$) for every face-track in the harvested data. These embeddings are additionally normalized to have a unit $l_2$ norm. Figure 2 shows an example of the hard-positive tracklets mined using the nearest-neighbor approach. Notice that while constructing hard-positive tracklets, we do not incorporate temporal constraints. This allows us to form tracklets by considering faces that are similar in the embedding space but may not be sequential in a face track as shown in Figure 2.

In order to mine hard-negative samples, we consider the set of face tracks that co-occur with each track in our data. Let $\{v_{n_i} : 1 \leq i \leq c\}$ be the corresponding track-averaged $d$-dimensional embeddings where $c$ is the number of co-occurring tracks. We choose the track embedding $v_{n_i}$ that has the shortest distance to the anchor $v_a$. Thus we mine one hard-negative set $(v_a, v_q)$ per track with $v_q = \arg \min_{i=1:c} d(v_a, v_{n_i})$, where $d$ is a distance metric. In all our experiments, we used normalized Euclidean distance for $d$ and the implementation of KDTree algorithm in scikit-learn [41] for nearest neighbor search.

### 3.3 Feature adaptation using multi-view shared subspace learning

In this section, we briefly describe the multiview correlation objective (MvCorr) [16, 38] which aims to capture the shared information across multiple views of the data by considering the between- and within-view variances. This method only requires the multiple views of the data to be sampled by observing the same event and does not need additional labels for training. In our case, the face
samples with different visual distractors can be considered as multiple views of a person’s facial identity. Since we can readily use the must-link constraints from the harvested face tracks as multi-view data, MvCorr is well suited for our task of learning robust face representations.

Consider $N$ samples of $d$-dimensional features of the same face under $M$ different views. Let $X_l \in \mathbb{R}^{D \times N}$, $l = 1, \ldots, M$, be the data matrix for the $l$-th view with columns as features. The multi-view correlation matrix $\mathbf{A}$ is formulated as the normalized ratio of the sum of between-view covariances $\mathbf{R}_B$ and sum of within-view covariances $\mathbf{R}_W$ for $M$ views as follows:

$$\mathbf{A} = \frac{1}{M-1} \frac{\mathbf{R}_B}{\mathbf{R}_W} = \frac{\sum_{l=1}^{M} \sum_{k=1, k \neq l}^{M} \bar{X}_l (\bar{X}_k)^\top}{(M-1) \sum_{l=1}^{M} \bar{X}_l (\bar{X}_l)^\top}$$

where $\bar{X}_* = X_* - \mathbb{E}(X_*)$ are mean-centered data matrices. The common scaling factor $(N-1)^{-1}M^{-1}$ in the ratio is omitted.

Our objective is to estimate a shared subspace, $\mathbf{V} \in \mathbb{R}^{d \times d}$ such that the multi-view correlation is maximized. Formally:

$$\rho(M) = \max_{\mathbf{V}} \frac{1}{D(M-1)} \frac{\text{tr}(\mathbf{V}^\top \mathbf{R}_B \mathbf{V})}{\text{tr}(\mathbf{V}^\top \mathbf{R}_W \mathbf{V})}$$

where $\text{tr}(\cdot)$ denotes the trace of a matrix. The subspace $\mathbf{V}$ can be estimated by solving the generalized eigenvalue problem to simultaneously diagonalize $\mathbf{R}_B$ and $\mathbf{R}_W$. Hence, the MvCorr objective is the average of the ratio of eigenvalues of between-view and within-view covariances. In other words, if $\mathbf{R}_W$ is invertible, then we wish to find the a transformation matrix $\mathbf{V}$ that maximizes the spectral norm of $\mathbf{R}_W^{-1} \mathbf{R}_B$, thus accounting for both the between-view and within-view variabilities associated with the multiple views of data.

We use neural networks to scale MvCorr for complex datasets similar to the work in [38] where each view of the data is input to an identical neural network without sharing any weights across the $M$ networks. The multiview shared representation is the output of the last layer of the individual networks. Since the last layer activations are maximally correlated across the networks we only need to use one of the $M$ networks to extract embeddings during inference [16].

4 Experiments and Results

4.1 Benchmarking dataset

The goal of this work is to improve character labeling for videos by adapting pre-trained face embeddings to a large dataset of rich, weakly-labeled face tracks harvested from movies. In order to benchmark our adaptation methods, we used a dataset of six videos (five movies and a TV show episode).

We started with two popular benchmark datasets, the movie Notting-Hill (NH) [29], and an episode from season 5 of the TV series, Buffy the Vampire Slayer (BFF, [17]). We also used two other movies, Dumb and Dumber To
Table 1. Details of the benchmarking dataset with track-level character labels

| Movie (year) | No. faces | No. tracks | No. characters | Tracks/character (min, max) | % Frontal tracks |
|--------------|-----------|------------|----------------|-----------------------------|------------------|
| ALN (2014)   | 70210     | 1880       | 10             | (16, 491)                  | 41.1             |
| BFF (1997)   | 47870     | 634        | 12             | (17, 112)                  | 16.3             |
| DD2 (2014)   | 152908    | 2361       | 10             | (12, 557)                  | 24.9             |
| HF (2016)    | 101438    | 1902       | 24             | (8, 283)                   | 47.3             |
| MT (2014)    | 53450     | 875        | 10             | (14, 254)                  | 28.2             |
| NH (1999)    | 154625    | 2121       | 12             | (18, 585)                  | 21.9             |

(DD2) and Maleficent (MT) whose face labels were released in [15]. In addition, we considered two other movies About Last Night (ALN) and Hidden Figures (HF) purchased in-house because these movies have a more racially diverse casting and complement existing benchmarking resources.

A summary of the benchmark dataset is shown in Table 1. For all videos, we performed face detection and tracking as described in Sec. 3.1. Although labels are publicly available for four videos, we obtained in-house annotations for all six videos separately because the number of faces detected by our system was significantly different than those reported in the corresponding papers. For example, Sharma et al., [13] reported 39263 faces detected for BFF. However, we detected about 8000 more faces (See Table 1, row 2).

For character labeling, we used the names listed on the IMDb casting page corresponding to the TV/movie. Character labels were manually assigned at the face-track level by two human annotators independently and ties were resolved by a third person. The number of characters were limited to cover at least 99% of all detected faces. We chose not to use the metric of face tracks per character since the number of faces per track has high variance. Among the videos we considered, HF had the highest number of characters at 24. The number of face tracks per character varied widely within a movie. For example, in HF, the least frequent character has only eight face tracks while the most commonly appearing character had 283 tracks (See Table 1).

While manually labeling face tracks we also obtained qualitative labels for six visual distractors at the face-track level for error analysis. A few exemplars of the face quality labels are shown in Figure 1. The quality of face tracks were labeled along six dimensions: whether all faces in a track facing the viewer (frontal; F); at least one face in a track is facing sideways (profile; P); blurry; B; wearing glasses (G); partial face detection or occluded (O); and poor lighting condition (L). We found that on average, only 30% of all face tracks were completely frontal facing in this dataset (See Table 1). These annotations along with the track-level character labels will be made publicly available.
4.2 Face verification experiments

We evaluate the performance of some of the best performing methods proposed for face verification over the past decade \cite{8,9,24,26} in order to choose the best embeddings for adaptation. Additional information on pre-processing and implementation details are included in supp. materials S2.

**Baseline models:** We use the following supervised methods to extract face embeddings and baseline their face verification performance. For all methods, we used the publicly available code and pre-trained models for feature extraction.

- **FaceNet** \cite{8} was trained using triplet loss and Inception-v1 architecture. We used the model trained on the VggFace2.
- **SphereFace** \cite{24} is a metric-learning method which combines the ideas of cross-entropy and angular margin loss to improve classification. It maximizes the angle between cannot-link faces while minimizing the angle between must-link faces. We used the model trained on CASIA WebFace \cite{42} in our experiments.
- **VggFace2** \cite{9} is a ResNet-50 neural network trained on the large-scale VggFace2 dataset for the task of face classification. These embeddings have shown state-of-the-art face verification and clustering performance for standard datasets such as IJB-B \cite{43}. Finally, **probabilistic face embeddings (PFE)** \cite{26} model different faces of the same person as multivariate Gaussian distributions where the mean captures information about the identity. This is enforced by minimizing a negative log-likelihood loss in a neural-network framework trained on MSCeleb-1M \cite{44}.

**Verification setup:** We first perform face verification experiments on IJB-B to ensure that the pre-trained models show performance comparable to that reported in their papers (See supp. materials S3 for performance details on IJB-B). We use the verification setup described in \cite{9}. Next, we evaluate all the models for the face verification task at the track level for YTFaces \cite{30}, which consists of videos from Youtube with character labels. We report results averaged across the standard 10-fold split\footnote{YTFaces splits: \url{www.cs.tau.ac.il/wolf/ytfaces/}} as shown in the ROC curves in Figure 3a. VggFace2 embeddings out performed other methods that we considered here. For the benchmarking dataset, we generate verification pairs by exhaustively
Fig. 4. Distribution of Euclidean distances of the hard-positives and hard-negatives with respect to anchor points in our dataset. Smaller distance between the embeddings is desired for positives and larger distance for negatives.

mining all combinations of face tracks using the character labels. As shown in Figure 3b, while the performance of FaceNet and VggFace2 models was similar to that of YTFaces, SphereFace and PFE models performed worse for movie videos. The FaceNet and VggFace2 models were both trained on the VggFace2 which may have contributed to the robustness for face verification in movie videos.

4.3 Feature adaptation

Existing deep learning-based feature adaptation methods for face clustering have primarily focused on contrastive loss (siamese networks, e.g., [13]) or triplet loss (e.g., [12]). Thus, in order to compare the performance of MvCorr adaptation, we train a triplet-network using the hard-positives and hard-negatives.

Implementation and network architectures: For triplet loss based adaptation, we used the improved triplet (ImpTriplet) loss shown to improve face clustering in videos [12]. Canonical triplet loss systems (e.g., [8]) only push the negative sample $v_q$ away from the anchor, $v_a$ but do not push $v_q$ away from the positive samples $v_p$. This problem is addressed by ImpTriplet by pulling the anchor closer to the positive as well the pushing the anchor away from the negative. The system parameters (margin and regularization terms) were chosen to be the same as in [12]. We used a publicly available code\(^3\) to implement this loss.

The network architecture for ImpTriplet consists of three sub-networks. Each sub-network is a fully connected network (FCN) with identical architecture and shared weights. Following our experiments in Sec. 4.2, we used the 512-dimensional VggFace2 embeddings averaged across the faces in anchor, positive and negative tracklets as input. For architecture search, we considered three FCN sub-network configurations:

$C1$: \text{INP}[(512)] \rightarrow \text{FC}[512], \text{DO}(0.2) \rightarrow \text{FC}[256]$

$C2$: \text{INP}[(512)] \rightarrow \text{FC}[1024], \text{DO}(0.2) \rightarrow \text{FC}[512]$

\(^3\) ImpTriplet code: github.com/manutdzou/Strong_Person_ReID_Baseline
Table 2. Comparison of face verification performance with adaptation averaged across all videos in the benchmarking dataset

| Method          | PFE [26] | FaceNet [8] | VggFace2 [9] | +ImpTriplet | +MvCorr |
|-----------------|----------|-------------|---------------|-------------|---------|
| TPR @ 0.1FPR    | 82.6 ± 1.6 | 90.2 ± 3.5 | 92.5 ± 1.7    | 91.4 ± 2.0  | 93.7 ± 1.2 |

C3: \text{INP}[(512)] \rightarrow \text{FC}[1024], \text{DO}(0.2) \rightarrow \text{FC}[512], \text{DO}(0.2) \rightarrow \text{FC}[256]

where \text{INP} = \text{Input}, \text{FC} = \text{Fully connected layer with ReLu/sigmoid activation followed by batch normalization and} [\cdot] \text{ indicates the number of nodes in the layer. A dropout (DO) of 0.2 was added for all intermediate FC layers.}

For the MvCorr adaptation, we set the number of multiple views to three and used the anchor \(v_a\) and two hard-positives, \(v_{p1}, v_{p2}\) as the three inputs to the network. Although the three sub-networks in MvCorr have the same architecture, the weights are not shared between them unlike ImpTriplet. The training code for MvCorr was obtained from [38] and we explored the architectures \(C1–C3\) for fair comparison with ImpTriplet adaptation.

**Training and model choice:** All adaptation experiments were conducted on the 169K tracks harvested from the 240 movies. For the training set, we used the data mined for each track from 180 movies resulting in 126,435 samples each for hard-positives and hard-negatives. The remaining 42,766 samples were used as the validation set. Both adaptation networks were trained with a batch size of 1024 using SGD (momentum=0.9, decay=1e−6) with a learning rate of 0.001 for ImpTriplet and 0.01 for MvCorr. To determine model convergence, we applied early stopping criteria (stop training if the loss on the validation set at the end of a training epoch did not decrease by 10−3 for 5 consecutive epochs). All models were implemented in TensorFlow\(^4\) and trained on GeForce GTX 1080 Ti GPU. Of the \(C1–C3\) configurations, we chose \(C2\) for ImpTriplet and \(C1\) for MvCorr as they showed the smallest loss on the validation set at convergence. Increasing the model size over \(C3\) and changing the embedding size from 256 to 128 or 1024 did not further improve the loss. All configurations showed slightly better performance with ReLu over sigmoid activation.

**Adaptation results:** Our experimental results on face verification (See Sec. 4.2 YTFaces) showed that pre-trained VggFace2 embeddings outperform other baseline methods. Thus, we restrict all our adaptation and clustering experiments to VggFace2 embeddings as the initial input. First, we examine the distribution of the Euclidean distance for all the hard-positive and hard-negative embedding pairs in our validation set of 60 movies without any adaptation. The distribution of the pairwise distances is shown in Figure 4a. As expected, the distribution of the distances is skewed right, indicating that they are farther apart in general. For hard-positives, we expect smaller pairwise distance and the distribution to skew left. However, for the face tracks mined, the distribution is fairly uniform in the range 0.6–1. This result suggests the domain-mismatch that we may incur for the direct application of these embeddings for movies as they

\(^4\) TensorFlow 2.1: tensorflow.org
were pre-trained on images from the web. It also emphasizes the effectiveness of our nearest-neighbor based hard example mining in identifying difficult samples in the embedding space.

Next, we examine the distribution of hard example distributions for ImpTriplet and MvCorr adaptation. As shown in Figure 4b–c, both models skew the hard-positive distances further to the left compared to VggFace2 without adaptation. This suggests that both methods help reduce the distances between the hard-positives as desired. Furthermore, MvCorr skews the distribution of hard-negative distances further to the right than ImpTriplet, pushing the cannot-link faces further apart.

A possible drawback of the adaptation methods is that they transform the embedding space to optimize for the distances between hard examples while losing the discriminability of the input embeddings. In other words, they could overfit to the adaptation dataset. To test this, we repeat the face verification experiments for the six videos using the adapted VggFace2 embeddings as features. We report TPR at 0.1 FPR averaged across all videos as the performance metric. As shown in Table 2, the performance of ImpTriplet is comparable to that of VggFace2 whereas MvCorr performs slightly better than VggFace2.

### 4.4 Face clustering and multiview adaptation

To test the applicability of our system for automatic character labeling in videos, we compare the unsupervised clustering performance for VggFace2 embeddings with and without adaptation.

For fair comparison with past works [12,45], we use hierarchical agglomerative clustering (HAC [41]) and assume the number of desired clusters (unique characters) to be known. However, in practice, the number of unique characters in a movie is often not available. Hence we also experiment with affinity propagation clustering (AP [46]) which does not require the number of clusters before running the algorithm. Similar to the k-medoids algorithm, AP first finds representative exemplars to cluster all the points in the dataset. The number of exemplars determine the number of clusters.

We evaluate the performance using several clustering metrics: homogeneity, completeness, V-measure, purity and accuracy. In Table 3, we report the V-measure for hierarchical agglomerative clustering (HAC) and affinity propagation (AP).

| Method       | ALN | BFF | DD2 | HF  | MT  | NH  | Mean (OCI) |
|--------------|-----|-----|-----|-----|-----|-----|------------|
| VggFace2     | 83.2| 95.3| 82.6| 76.7| 88.6| 79.5| 84.3 (1.0) |
| HAC          | 81.2| 96.6| 83.9| 78.0| 89.7| 81.1| 85.1 (1.0) |
| + impTriplet | 86.8|     | 97.6| 85.7| 82.2| 92.1| 84.0 (1.0) |
| + MvCorr     |     |     |     |     |     |     | 88.1 (1.0) |
| VggFace2     | 56.3| 76.9| 57.1| 65.9| 67.5| 59.5| 63.9 (5.2) |
| AP           | 57.4| 77.9| 58.8| 67.7| 68.9| 60.6| 65.2 (6.0) |
| + impTriplet | 60.4| 84.3| 60.1| 70.1| 69.6| 62.0| 67.7 (6.7) |
Table 4. Comparison of average clustering accuracy with state-of-the-art

|        | uLDML [14] | HMRF [33] | WBSLRR [29] | Zhang'19 [45] | TSiam [13] | +MvCorr |
|--------|------------|-----------|-------------|---------------|------------|---------|
| BFF    | 41.6       | 50.3      | 62.7        | 92.1          | 92.5       | 97.7    |
| NH     | 73.2       | 84.4      | 96.3        | **99.0**      | -          | 96.3    |

measure scores on the benchmarking dataset. Comparison with respect to other metrics, as well as a detailed error analysis with respect to face quality labels is presented in the supp. materials S4 and S5. For both HAC and AP, we achieve nearly 3% improvement using ImpTriplet and 4% improvement using MvCorr (See Table 3). The V-measure scores for MvCorr were significantly better than VggFace2 across all videos in our dataset. In contrast to HAC, the V-measure scores for AP were low, but it yields clusters which are nearly 100% pure where multiple clusters may belong to the same character. We quantify this by reporting the over-clustering index [6] which is the average number of clusters assigned to a character (the mean OCI across all movies is shown in Table 3); mean OCI for HAC is 1 because the number of clusters is provided to the clustering algorithm. Our future work will focus on assessing recent methods such as ball clustering [47] developed for unknown number of clusters.

Finally, we compare the HAC performance for clustering characters in BFF and NH to the results reported in existing works. It is important to note that although the number of characters in our dataset is greater, the comparison metric is mean clustering accuracy which is generally robust to these differences. As shown in Table 4 our proposed approach is comparable to the state-of-the-art methods for the two videos.

4.5 Conclusion

In this work, we used the notion of self-supervision in videos to harvest large amounts of weakly-labeled face data from movies. Using these face tracks, we adapted face embeddings trained on web images for such long-form content. We proposed a nearest-neighbor approach to search for hard examples in the embedding space and explored triplet loss and multiview correlation based feature adaptation. Our experimental results and error analysis suggest that learning the information shared across faces of the same person with different visual distractors can offer robust representations for face clustering in movies. Hence, the term Multi-Face. The weakly labeled face tracks harvested across 240 movies as well the benchmarking dataset developed in-house will be made publicly available. We hope that these resources help advance the research of automatic character labeling in videos and understanding character portrayals in media content.

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5 Significance testing: permutation test $n = 10^5$, $p = 0.007$
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