Structure-Aware Face Clustering on a Large-Scale Graph with $10^7$ Nodes

Shuai Shen$^{1,2}$, Wanhua Li$^{1,2}$, Zheng Zhu$^{1,2}$, Guan Huang$^3$, Dalong Du$^3$, Jiwen Lu$^{1,2,*}$, Jie Zhou$^{1,2}$

$^1$ Department of Automation, Tsinghua University, China
$^2$ Beijing National Research Center for Information Science and Technology, China
$^3$ XForwardAI

{shens19,li-wh17}@mails.tsinghua.edu.cn; zhengzhu@tsinghua.edu.cn;
{guan.huang,dalong.du}@xforwardai.com; {lujiwen,jzhou}@tsinghua.edu.cn

Abstract

Face clustering is a promising method for annotating unlabeled face images. Recent supervised approaches have boosted the face clustering accuracy greatly, however their performance is still far from satisfactory. These methods can be roughly divided into global-based and local-based ones. Global-based methods suffer from the limitation of training data scale, while local-based ones are difficult to grasp the whole graph structure information and usually take a long time for inference. Previous approaches fail to tackle these two challenges simultaneously. To address the dilemma of large-scale training and efficient inference, we propose the STructure-AwaRe Face Clustering (STAR-FC) method. Specifically, we design a structure-preserved subgraph sampling strategy to explore the power of large-scale training data, which can increase the training data scale from $10^5$ to $10^7$. During inference, the STAR-FC performs efficient full-graph clustering with two steps: graph parsing and graph refinement. And the concept of node intimacy is introduced in the second step to mine the local structural information. The STAR-FC gets 91.97 pairwise F-score on partial MS1M within 310s which surpasses the state-of-the-art. Furthermore, we are the first to train on very large-scale graph with 20M nodes, and achieve superior inference results on 12M testing data. Overall, as a simple and effective method, the proposed STAR-FC provides a strong baseline for large-scale face clustering. Code is available at https://sstzal.github.io/STAR-FC/.

1. Introduction

Recent years have witnessed the great progress of face recognition [9, 29, 30, 39, 40, 43]. Large-scale datasets are an important factor in the success of face recognition and there is an increasing demand for larger-scale data. Face clustering [23, 31, 44, 50, 52, 53, 54] is a natural way to solve the data annotation problem so as to make better use of massive unlabeled data. Face clustering is also one possible approach to organize and file large volumes of real face images in social media or other application scenarios.

Recently a variety of efforts have been devoted to face clustering. Traditional unsupervised methods [16, 55] including K-Means [31] and DBSCAN [10] usually depend on some manually designed clustering strategies. They perform well on small datasets, however they are less effective when dealing with large-scale data as shown in Figure 1. Recent research trends [12, 44, 49, 51, 52] turn to the GCN-based supervised learning. These methods are performed based on the affinity graph and can be roughly divided into global-based and local-based ones according to whether their GCN input is the whole graph or not. The representative global-based method GCN-V+E [49] uses the entire graph for GCN training. As shown in Figure 1, it boosts the face clustering performance greatly compared with unsupervised methods, however the training data scale

Figure 1: Method comparison when training with different scales of data and testing on 12M data from WebFace42M [57]. The proposed STAR-FC can fully explore the power of large-scale training data. GCN-V+E fails to handle larger training graph while GCN-D’s performance is severely restricted due to the less consideration of the global structural information.
is limited by the GPU memory which makes it difficult to further explore the power of larger-scale training sets. Although local-based methods such as GCN-D [51] shown in Figure 1 don’t suffer from memory restrictions, its performance is limited since it lacks the comprehension of global graph structure. Besides, it organizes the data as overlapped local subgraphs which leads to inefficient inference.

For many computer vision tasks [7, 8, 11, 15, 26, 35], large-scale training data is one of the most important engines to promote the performance. With the emergence of some new large-scale benchmarks such as WebFace42M [57] whose data volume is ten times that of MS1M [13], we have more data available for training. Therefore, exploring the power of these rich training data is imperative. For testing, efficiency matters, we are therefore eager to perform full graph inference. Based on the above motivations, we propose a structure-aware face clustering method STAR-FC to address the dilemma of large-scale training and efficient inference. Specifically, we design a GCN [21] based on the KNN [6] affinity graph to estimate the edge confidence. Furthermore, a structure-preserved subgraph sampling strategy is proposed for larger-scale GCN training. During inference, we perform face clustering with two steps: graph parsing and graph refinement. In the second step, node intimacy is introduced to mine the local structural information for further refinement. In the inference process, the entire graph is taken as the input for efficiency.

The experiments demonstrate that with these structure-aware designs, the STAR-FC can not only perform sample-based training but also implement full-graph inference. With sample-based training, the training data scale can be increased by two orders of magnitude from $10^5$ to $10^7$ and beyond. As shown in Figure 1, with the increase of training data, our method has been consistently improved and finally achieves 95.1 pairwise F-score. Interestingly, we find that such sampling method does not lead to performance loss and brings some extra accuracy gain since it enhances the generalization of the model. In inference, with full-graph as input, the efficiency can be guaranteed. We achieve state-of-the-art face clustering results on partial MS1M within 310s. What’s more, we can complete inference on 12M data which provides a strong baseline for large-scale face clustering.

To summarize, we make the following contributions:

- The proposed STAR-FC achieves 91.97 F-score on partial MS1M within 310s. Moreover, we are the first to conduct large-scale training on 20M data which provides a strong baseline for large-scale face clustering.

2. Related Work

**Face Clustering.** Face clustering has been extensively studied as a classic task in machine learning. It provides an alternative way to exploit massive unlabeled data. Traditional algorithms including K-Means [31], spectral clustering [16], hierarchical clustering [55] and DBSCAN [10] laid a good theoretical foundation for clustering. However, they generally rely on simple data distribution assumptions thus are ineffective when dealing with real data. To improve the robustness in complex distributed face clustering, Lin et al. [28] proposed the proximity-aware hierarchical clustering. Zhu et al. [56] and Otto et al. [33] designed the rank-order connection metric. However, since [33, 56] did not establish the graph structure and lacked preliminary analysis for neighbor relations, they achieved poor results. Lin et al. [27] tried to measure density affinities between local neighborhoods. [37] modeled face clustering as a structured prediction problem using conditional random field.

Methods above make less use of supervised information in face clustering. More recently, the research trends turn to GCN-based supervised face clustering and have achieved impressive results [12, 44, 49, 50, 51, 52, 54]. These methods can be roughly divided into two categories: local-based face clustering [44, 51, 52] and global-based one [49]. In these local-based methods, Zhan et al. [52] designed a mediator network to aggregate information in the local graph. Wang et al. [44] predicted the linkage in an instance pivot subgraph. Yang et al. [51] generated a series of subgraphs as proposals and detected face clusters thereon. These methods pay more attention to local graph information and rely heavily on redundancy subgraph operations which limit their performance and lead to slow inference. Representative global-based method [49] took the entire graph as input and predicted the confidence and connectivity of all vertices. In [49], the holistic graph structure is better considered, however due to GPU memory limitation, it may be out of memory when dealing with larger training data. We therefore propose the STAR-FC to simultaneously tackle the challenges of large-scale training and efficient inference.

**Graph Convolutional Networks.** Graph Convolutional Networks (GCNs) [4, 36, 42, 45] extend the convolution idea of CNNs [5, 22, 34] to process non-Euclidean structured data. GCNs have shown impressive capability on various tasks [2, 21, 24, 25, 47, 48]. More recently, to improve GCN’s ability in handling larger-scale training graph, some GCN training algorithms have been proposed. GraphSAGE [14] traded off the performance and runtime via sam-
3. Methodology

3.1. Overview

To address the dilemma of large-scale training and efficient inference, we propose a structure-aware face clustering method. An overview of the proposed STAR-FC is shown in Figure 2. During training, the GCN-based edge confidence estimator is trained with the structure-preserved subgraph sampling strategy. We aim to approximate the full graph structure with the sampled subgraph and it retains most of the hard negative edges which contribute a lot for training. In this way, the potential of large-scale data can be fully unleashed. We specifically model the edge prediction as a binary classification problem and use the cross-entropy loss for supervising. During inference, we transform the face clustering into two steps: graph parsing and graph refinement. For graph parsing, we take the whole graph as the input of the trained GCN to estimate all edge confidence scores simultaneously. Then edges with low scores are removed and graph structures will become clearer. However, there still exist a few wrong connections. They have relatively high scores thus hard to be eliminated. To further refine the graph, we introduce the node intimacy for edge pruning again. After these two steps, face clusters are naturally formed by those connecting groups in the graph.

3.2. Large-Scale GCN Training

In this section, we detail the large-scale training process of the proposed STAR-FC.

**Design of the GCN.** In this step, we design a GCN-based edge confidence predictor on the basis of $K$NN affinity graph. We first get the feature matrix $F \in \mathbb{R}^{N \times D}$ with a trained ResNet-50, where $N$ is the number of face images and $D$ is the feature dimension. To build the $K$NN affinity graph, each sample can be treated as a node in the graph and is linked to its $K$ nearest neighbours [6]. The corresponding sparse symmetric adjacency matrix is $A \in \mathbb{R}^{N \times N}$.
Since the CNN is trained under the strong supervision of classification loss, the extracted features \( F \) actually contain rich identity information. However, due to intra-class variance and the fixed \( K \) value in KNN algorithm, the affinity graph may contain many wrong edge connections. We therefore try to directly predict the existence of the edges employing a GCN for propagating neighbor information. Following [44, 49], we use the more effective modified GCN as our backbone and the computational process of a \( L \)-layer modified GCN can be formulated as:

\[
F_{l+1} = \sigma \left( \left[ F_l^T, (\tilde{A}F_l)^T \right]^T W_l \right),
\]

where \( \tilde{A} = \tilde{D}^{-1} (A + I) \). \( \tilde{D} \) is a diagonal degree matrix with \( \tilde{D} = \sum_j \tilde{A}_{ij} \). \( F_l \) denotes the embeddings at \( l \)-th layer and \( F_0 \) is the input face features. \( W_l \in \mathbb{R}^{D_{in} \times D_{out}} \) is a learnable matrix that maps the embeddings to a new space. \( \sigma \) is a nonlinear activation and we use ReLU [32, 46] in this work. \( F_L \) indicates the output features of \( L \)-layer.

Since \( F_L \) aggregates many messages from the neighborhood and encode graph structural information, it is more suitable for the face clustering task. To predict the existence of the edges in the affinity graph, we design a binary classifier employing a 2-layer MLP [18] with the objective to minimize the cross-entropy loss between the predicted edge confidence and the ground-truth edge labels. Particularly, we take pair features corresponding to the edges in the affinity graph as the input of the MLP and get the two-dimension predicted edge confidence. The ground-truth label of an edge is 1 if the two nodes connected by this edge belong to the same class, otherwise it will be 0.

Under this simple supervision of binary signals, the distribution of the predicted confidence will appear as two sharp peaks approaching 0 and 1 as shown in Figure 3. Therefore, for inference we can use a single threshold \( \tau_k \) to effectively eliminate most of the wrong edges. This operation may lead to two types of misjudgments: (1) it may cut off a small number of real edges; (2) it may leave a few wrong connections hard to be identified via confidence. Since the original affinity graph is densely connected, the lost correct edges in the former case have a slight effect on the connectivity of the final graph. Those remaining wrong edges will be processed in the following procedure with node intimacy in Section 3.3.

Structure-Preserved Subgraph Sampling. Previous methods [49, 51] usually use 10% of MS1M (0.5M face images) [13] for GCN training. For global-based method [49] this has approximated to the memory threshold of a typical 1080Ti GPU. Although local-based methods [44, 51] can alleviate the GPU storage burden through local graph operation, they rely heavily on numerous overlapped subgraphs which severely affect their efficiency and accuracy.

Recent years have witnessed the success of large-scale training in many computer vision tasks [7, 8, 11, 15, 26, 35]. To fully explore the power of large-scale training data, we design a structure-preserved subgraph sampling (SPSS) strategy for GCN training. The edges in an affinity graph are mainly composed of two parts: dense intra-cluster connections and sparse connections between near clusters. Try to approximate the dense connections within clusters, our approach treats face clusters as the smallest sampling unit, different from previous methods [3, 14] which perform randomly sampling on nodes. To further model those inter-cluster connections, we extend the subgraph from the selected cluster to its neighbor clusters. On one hand, the sampled subgraphs preserve the important structural information of the full graph, i.e. the edge connections within the clusters and the connections between near clusters. On the other hand, many near clusters are sampled in a subgraph, and the edges between these near clusters can be treated as hard negative examples which can contribute a lot to the GCN training. Equipped with such a structure-preserved subgraph sampling strategy, our method can benefit from increasing training data. Interestingly, this sampling strategy does not lead to performance loss since the structural information of the whole graph is fully considered. Besides, the experimental results in Table 2 show that it brings further performance gain since the enhancement of generalization.

Algorithm 1 shows the details of the proposed SPSS. Given the training nodes reorganized in clusters, we randomly select \( M \) clusters from them as the sampling seeds. For each seed cluster, we extend to its \( N \) nearest neighbor clusters which are measured by the cosine similarity of the center. After this step, we can get a subgraph \( S_1 \) consists of \( M \times N \) clusters. To further strengthen the generalization, we introduce the cluster randomness (CR) strategy by randomly selecting \( K_1 \) clusters from \( S_1 \), and the sample randomness (SR) strategy by randomly selecting \( K_2 \) nodes from \( S_2 \). Then we rebuild the KNN affinity graph based on these sampled nodes to construct the subgraph \( S \).
3.3. Efficient Face Clustering Inference

This subsection shows how to perform efficient inference and get the final face clusters with the proposed STAR-FC in detail. Specifically, we transform the face clustering task into two steps: graph parsing and graph refinement.

Graph Parsing. In this step, we parse the built affinity graph preliminarily with the trained GCN. We feed the entire graph into the GCN and obtain all edge scores simultaneously. Figure 3 shows that the predicted scores are distributed in nearly two sharp peaks approaching 0 and 1. We can therefore perform simple but effective pruning with a single threshold \( \tau_1 \). A small number of correct edges may be cut off wrongly in this step. Whereas since the initial affinity graph is densely connected, this has a slight effect on the connectivity of the final clusters. After this step, most wrong connections are removed, and the graph structure has become clearer. However, there still exists a minority of false positive edges. To deal with these edges, we propose node intimacy in the second step trying to mine the local graph structure for further graph refinement.

Graph Refinement. The left false positive edges mistakenly connect different clusters, which may seriously affect the final clustering performance. These edges can not be removed directly using edge scores, we therefore try to identify them with node intimacy (NI).

The concept of node intimacy is inspired by the human familiarity. In human societies, two familiar people usually have many mutual friends. Extending this idea to the graph, we establish the concept of node intimacy. Particularly, given two nodes \( N_1 \) and \( N_2 \). There are \( n_1 \) edges connected to \( N_1 \) while \( n_2 \) edges connected to \( N_2 \) in all. Node \( N_1 \) and \( N_2 \) have \( k \) common neighbor nodes. We then calculate the NI between \( N_1 \) and \( N_2 \) as follows:

\[
NI = Aggregation \left( \frac{k}{n_1}, \frac{k}{n_2} \right),
\]

Common aggregation operations include mean, minimum and maximum. Comparison in Section 4.2 shows that the maximum function has the best performance. Figure 4 illustrates the NI on graph and shows the specific calculation.

We further implement the above calculation into a matrix operation. Given adjacency matrix \( A \in \mathbb{R}^{N \times N} \), the number of mutual neighbors of all node pairs is \( \hat{A} = AA \), with each element \( \hat{a}_{ij} \) in \( \hat{A} \) denoting the number of mutual neighbors for \( N_i \) and \( N_j \). Then the NI is formulated as:

\[
NI = \max ((\hat{A}^T sum_0)^T, \hat{A} sum_1), \quad (3)
\]

For inference, we use node intimacy to represent the edge score and remove those edges whose score is below \( \tau_2 \). After this step, we expect that most wrong connections have been removed. We can thus directly read the face clusters from the affinity graph.

Complexity Analysis. During inference, the main computation lies in the GCN and the node intimacy. Both of these calculations are sparse matrix multiplication, thus the complexity is \( O(|E|) \), where \( E \) denotes the edges in the affinity graph. For a KNN affinity graph with \( N \) nodes, we have \( |E| \leq KN \), thus the complexity increases linearly as the number of nodes in the graph increases.

4. Experiments

4.1. Experimental Settings

Datasets. We use MS1M [13] and a large face benchmark named WebFace42M [57] for training and testing in face clustering. We follow the noisy list provided in [9] to clean the MS1M, and the refined MS1M contains about 5.82M images from 85K identities. We follow the setting in [51] to partition MS1M [13] into 10 splits with
Figure 5: Pairwise F-score under different selections of two thresholds \( \tau_1 \) and \( \tau_2 \).

Table 1: Comparison between the naive and the NI-based pruning with different aggregation functions.

| Method        | Precision | Recall | \( F_P \) | \( F_B \) |
|---------------|-----------|--------|----------|----------|
| Naive Pruning | 92.83     | 74.24  | 82.50    | 80.93    |
| NI (mean)     | 94.21     | 84.97  | 89.35    | 87.58    |
| NI (min)      | 95.18     | 81.93  | 88.06    | 86.08    |
| NI (max)      | 95.50     | 85.91  | 90.45    | 88.06    |

Table 2: Comparison of different sampling strategies.

Selection of Thresholds. In our method, we refine the affinity graph with two steps involving two thresholds \( \tau_1 \) and \( \tau_2 \). In the first step, \( \tau_1 \) is used to process the GCN output edge scores, while in the second step \( \tau_2 \) is employed to prune the edges with low intimacy. We conduct experiments with different \( \tau_1 \), \( \tau_2 \). Results in Figure 5 show that \( \tau_1 = 0.7 \), \( \tau_2 = 0.72 \) is a suitable choice, we therefore adopt this setting in the following experiments.

Design of Node Intimacy. In our method, we transform the face clustering into two steps: graph parsing with a trained GCN and graph refinement with node intimacy (NI). In this subsection, we investigate the impact of NI for the final face clustering performance, and compare three designs of NI. For the naive pruning method in Table 1, face clusters are obtained with dynamic edge pruning [52] based on the edge scores predicted in the graph parsing step. Results in Table 1 show that compared with the naive pruning strategy, using node intimacy for further graph refinement can significantly boost the pairwise F-score from 82.5 to 90.45. This reveals the superiority of NI in dealing with face clustering problem. We further compare three different aggregation functions, i.e. mean, minimum and maximum for NI. Results in Table 1 show that the maximum strategy outperforms the other two methods. Therefore, we choose the maximum strategy in the following experiments.

Effect of Sampling Strategy. In the training process, we propose the structure-preserved subgraph sampling (SPSS) strategy. To add more randomness, We further introduce cluster randomness (CR) by randomly sampling partial clusters from the subgraph and sample randomness (SR) by randomly sampling some nodes from the subgraph. In this subsection, we study the effect of SPSS for GCN training. As shown in Table 2, for the non-sampling method (a), it needs to take the whole graph with about 500K nodes per batch for training which leads to high GPU memory consumption. Nevertheless, equipped with the struct-preserved subgraph sampling strategy, our method only uses a subgraph with about 10K nodes per batch for training, and we achieve 91.21 pairwise F-score which is comparable with the non-sampling method with less GPU memory usage. This interesting performance gain demonstrates that our sampling strategy successfully preserves most structure message of the whole graph. Moreover, adding the cluster and sample randomness to the SPSS can further improve the pairwise F-score from 91.21 to 91.97. We argue that

Algorithms. We evaluate the performance of our approach on both face clustering and face recognition tasks. For face clustering, we adopt the commonly used metric Pairwise F-score (\( F_P \)) and BCubed F-score (\( F_B \)) [1]. For face recognition, we use different proportions of pseudo-label data along with 1 part labeled data to train the face recognition model and then test the rank-1 face identification accuracy on MegaFace challenge 1 with 1M distractors.

Implementation Details. The affinity graph is built by KNN algorithm [6] with \( K = 80 \) for MS1M [13] and \( K = 30 \) for WebFace42M [57]. For structure-preserved subgraph sampling, we set \( M = 2 \) (the number of cluster seeds), \( N = 750 \) (the number of the sampled near clusters for each seed), \( K_1 = 1300 \) (parameter in CR) for MS1M and \( M = 4 \), \( N = 1100 \), \( K_1 = 4000 \) for WebFace42M, then set \( K_2 = 90\% \) (parameter in SR) for both datasets.

4.2. Ablation Study

All models in this subsection are trained with the part0_train and tested on the part1_test in MS1M.
Table 3: Comparison on face clustering when training with 0.5M face images and testing with different numbers of unlabeled face images. All results are obtained on the MS1M dataset. The proposed STAR-FC consistently outperforms other face clustering baselines on different scale of testing data.

| Method / Metrics | 1.74M | 2.89M | 4.05M | 5.21M |
|------------------|-------|-------|-------|-------|
|                  | $F_P$ | $F_B$ | $F_P$ | $F_B$ | $F_P$ | $F_B$ | $F_P$ | $F_B$ |
| K-Means [31]     | 73.04 | 75.20 | 69.83 | 72.34 | 67.90 | 70.57 | 66.47 | 69.42 |
| HAC [38]         | 54.40 | 69.53 | 11.08 | 68.62 | 1.40  | 67.69 | 0.37  | 66.96 |
| DBSCAN [10]      | 63.41 | 66.53 | 52.50 | 66.26 | 45.24 | 44.87 | 44.94 | 44.74 |
| ARO [33]         | 8.78  | 12.42 | 7.30  | 10.96 | 6.86  | 10.50 | 6.35  | 10.01 |
| CDP [31]         | 70.75 | 75.82 | 69.51 | 74.58 | 68.62 | 73.62 | 68.06 | 72.92 |
| L-GCN [44]       | 75.83 | 81.61 | 74.29 | 80.11 | 73.70 | 79.33 | 72.99 | 78.60 |
| GCN-D [51]       | 83.76 | 83.99 | 81.62 | 82.00 | 80.33 | 80.72 | 79.21 | 79.71 |
| GCN-V+E [49]     | 84.04 | 82.84 | 82.10 | 81.24 | 80.45 | 80.09 | 79.30 | 79.25 |
| STAR-FC          | 88.28 | 86.26 | 86.17 | 84.13 | 84.70 | 82.63 | 83.46 | 81.47 |

Table 4: Methods comparison on face clustering performance and inference time. All models are trained with part0_train (0.5M images) from MS1M and tested with part1_test (0.5M images) from MS1M. The STAR-FC significantly outperforms the state-of-the-arts, and can control the inference time within 310s.

| Method      | Precision | Recall | $F_P$ | Time  |
|-------------|------------|--------|-------|-------|
| K-Means     | 52.52      | 70.45  | 60.18 | 11.5h |
| DBSCAN      | 72.88      | 42.46  | 53.50 | 110s  |
| HAC         | 66.84      | 70.01  | 68.39 | 12.7h |
| ARO         | 81.10      | 7.30   | 13.34 | 1650s |
| CDP         | 80.19      | 70.47  | 75.01 | 140s  |
| L-GCN       | 74.38      | 83.51  | 78.68 | 5208s |
| GCN-D+S     | 98.24      | 75.93  | 85.66 | 3700s |
| GCN-V+E     | 92.56      | 83.74  | 87.93 | 690s  |
| DA-Net      | 95.88      | 85.87  | 90.60 | 329s  |
| STAR-FC     | 96.20      | 88.10  | 91.97 | 310s  |

The introduction of randomness enhances the generalization of the trained model. These experimental results prove the ability of our method to handle large-scale training effectively. With the proposed SPSS, we can break through the limitation of the size of the training set and achieve excellent face clustering performance.

4.3. Face Clustering on MS1M

Table 3 and Table 4 show the comparison on face clustering. All results in Table 4 are obtained on the MS1M dataset with part0_train as the training set and part1_test as the testing set, and the inference time is obtained following the experimental configuration in [49]. In Table 3 we further show the face clustering performance on different numbers of unlabeled data. Results in Table 4 show that the proposed STAR-FC outperforms other clustering baselines consistently. Moreover, since all modules in the STAR-FC use full graph operation and parallel matrix computing, it can perform efficient inference within 310s. For fair comparison with DA-Net [12], this time does not include the time of computing KNN graph, and the total inference time including computing KNN is 435s which can be accelerated with parallel GPUs. Results in Table 3 show that our method can keep superior performance when dealing with larger-scale inference. What’s more, compared with the representative clustering method GCN-V+E [49], our method boosts the $F_P$ significantly from 79.3 to 83.46 and improves the $F_B$ from 79.25 to 81.47.

We further use these pseudo-labeled data to train face recognition models and investigate the performance gain brought by these extra pseudo-labeled training data. We follow the experiment setting in [49, 51], and use labeled data and various amounts of unlabeled data with pseudo-label to train the face recognition models. Figure 6 shows the rank-1 face identification accuracy on MegaFace [20] with 1M distractors. As shown in Figure 6, extra unlabeled training data with pseudo-label brings continuous performance gain for face recognition. Owing to the superior performance in face clustering, our method achieves higher recognition accuracies than other face clustering baselines. With extra 5.21M unlabeled data, our method improves the recognition performance on MegaFace from 58.2% to 79.26%.

4.4. Face Clustering on WebFace42M

In this subsection, we first compare the face clustering performance of different methods on the WebFace42M and then explore the training upper bound of the STAR-FC. Recent years have witnessed the success of large-scale training in many computer vision tasks. Large-scale training data is one of the key engines for the performance gain. To verify the capacity of the proposed method to handle large-scale graph, we conduct more experiments on the million-scale face benchmark WebFace42M [57]. We randomly select 4M samples from the dataset as labeled data for training and take 4M, 8M and 12M samples respectively as unlabeled data for testing. There is no identities overlap between the training set and the testing set. We reproduce a
### Table 5: Comparison on face clustering when training with 4M face images and testing with different numbers of unlabeled data from the WebFace42M. Inference time on 12M testing data is shown in the right-most column. GCN-V+E [49] fails to perform training on 4M data due to out-of-memory, so we don’t show it in this table. HAC [38] is able to train on large-scale data, however it fails to perform large-scale inference with 12M testing data. The proposed STAR-FC achieves superior results on different testing settings and can complete inference on 12M data within 1.7h.

| Method / Metrics | 4M | 8M | 12M | Time |
|------------------|----|----|-----|------|
| K-Means [31]     | 95.99 | 90.50 | 65.80 | 78.29 | 92.20 | 49.91 | 64.34 | 76.47 | 88.75 | 49.69 | 63.71 | 75.04 | 2h |
| HAC [38]         | 98.25 | 59.76 | 74.31 | 85.46 | 96.55 | 58.98 | 73.23 | 84.57 | 85.57 | 43.76 | 57.91 | 76.38 | 3h |
| DBSCAN [10]      | 94.77 | 44.12 | 60.21 | 77.87 | 89.97 | 43.55 | 58.69 | 77.02 | 85.57 | 43.76 | 57.91 | 76.38 | 3h |
| ARO [33]         | 99.34 | 62.83 | 76.98 | 88.83 | 98.44 | 62.01 | 76.09 | 88.66 | 97.49 | 62.34 | 76.05 | 88.60 | 4h |
| GCN-D [51]       | 98.05 | 52.54 | 68.42 | 71.47 | 96.47 | 51.82 | 67.42 | 71.24 | 95.08 | 53.70 | 68.63 | 72.39 | 8h |
| STAR-FC          | 96.77 | 94.00 | 95.36 | 94.93 | 93.95 | 93.99 | 93.97 | 94.77 | 90.86 | 94.06 | 92.43 | 94.63 | 1.7h |

![Figure 6: Rank-1 face identification accuracy on MegaFace with 1M distractors. The X-axis indicates the ratio of unlabeled to labeled data. The point where ratio is 0 indicates that only a split of labeled data is used for training. The upper bound is trained using data with ground-truth labels.](image.png)

Figure 6: Rank-1 face identification accuracy on MegaFace with 1M distractors. The X-axis indicates the ratio of unlabeled to labeled data. The point where ratio is 0 indicates that only a split of labeled data is used for training. The upper bound is trained using data with ground-truth labels.

### Table 6: Face clustering performance of the STAR-FC with different scales of training data from the WebFace42M and testing on 12M unlabeled data from the WebFace42M.

| Training set | Pre | Recall | F_P | Pre | Recall | F_B | NMI |
|--------------|-----|--------|-----|-----|--------|-----|-----|
| 0.4M         | 96.7 | 84.6   | 90.2 | 99.6 | 75.9   | 86.1 | 97.8 |
| 4M           | 90.9 | 94.1   | 92.4 | 99.0 | 90.7   | 94.6 | 99.1 |
| 12M          | 95.4 | 92.9   | 94.2 | 99.4 | 88.3   | 93.5 | 99.0 |
| 20M          | 97.8 | 92.5   | 95.1 | 99.4 | 88.1   | 93.4 | 99.0 |

5. Conclusion

In this paper, we have proposed a structure-aware face clustering method STAR-FC which addresses the dilemma of large-scale training and efficient inference. A structure-preserved subgraph sampling method is introduced to explore the power of larger-scale training data, and it can achieve satisfactory performance with less GPU memory usage. Moreover, a two-step graph refinement strategy with full-graph operation is developed to perform efficient inference. For the first time, a face clustering model is trained on a very large-scale graph with $10^7$ nodes, thus provide a strong baseline for large-scale face clustering. Our method is promising to perform excellently when a larger training set appears.

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References

[1] Enrique Amigó, Julio Gonzalo, Javier Artiles, and Felisa Verdejo. A comparison of extrinsic clustering evaluation metrics based on formal constraints. *IR*, 2009. 6

[2] Rianne van den Berg, Thomas N Kipf, and Max Welling. Graph convolutional matrix completion. *arXiv:1706.02263*, 2017. 2

[3] Jie Chen, Tengfei Ma, and Cao Xiao. FastGCN: fast learning with graph convolutional networks via importance sampling. In *ICLR*, 2018. 3, 4

[4] Wei-Lin Chiang, Xuanqing Liu, Si Si, Yang Li, Samy Bengio, and Cho-Jui Hsieh. Cluster-GCN: An efficient algorithm for training deep and large graph convolutional networks. In *KDDM*, 2019. 2

[5] François Chollet. Xception: Deep learning with depthwise separable convolutions. In *CVPR*, 2017. 2

[6] Thomas Cover and Peter Hart. Nearest neighbor pattern classification. *TIF*, 1967. 2, 3, 6

[7] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *CVPR*, 2009. 2, 4

[8] Jiakang Deng, Jia Guo, Tongliang Liu, Mingming Gong, and Stefanos Zafeiriou. Sub-center ArcFace: Boosting face recognition by large-scale noisy web faces. In *ECCV*, 2020. 2, 4

[9] Jiakang Deng, Jia Guo, Niannan Xue, and Stefanos Zafeiriou. ArcFace: Additive angular margin loss for deep face recognition. In *CVPR*, 2019. 1, 5

[10] Martin Ester, Hans-Peter Kriegel, Jörg Sander, Xiaowei Xu, et al. A density-based algorithm for discovering clusters in large spatial databases with noise. In *SIGKDD*, 1996. 1, 2, 7, 8

[11] Ross Girshick. Fast R-CNN. In *ICCV*, 2015. 2, 4

[12] Senhui Guo, Jing Xu, DaPeng Chen, Chao Zhang, Xiaogang Wang, and Rui Zhao. Density-aware feature embedding for face clustering. In *CVPR*, 2020. 1, 2, 7

[13] Yandong Guo, Lei Zhang, Xuyiao Hu, Xiaodong He, and Jianfeng Gao. MS-Celeb-1M: A dataset and benchmark for large-scale face recognition. In *ECCV*, 2016. 2, 4, 5, 6, 11

[14] Will Hamilton, Zhitao Ying, and Jure Leskovec. Inductive representation learning on large graphs. In *NeurIPS*, 2017. 2, 4

[15] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016. 2, 4

[16] Jeffrey Ho, Ming-Hsang Yang, Jongwoo Lim, Kuang-Chih Lee, and David Kriegman. Clustering appearances of objects under varying illumination conditions. In *CVPR*, 2003. 1, 2

[17] Paul Jaccard. The distribution of the flora in the alpine zone. *New phytologist*, 1912. 11

[18] Anil K Jain, Jianchang Mao, and K Moidin Mohiuddin. Artificial neural networks: A tutorial. *Computer*, 1996. 4

[19] Jeff Johnson, Matthijs Douze, and Hervé Jégou. Billion-scale similarity search with GPUs. *TBD*, 2019. 8

[20] Ira Kemelmacher-Shlizerman, Steven M Seitz, Daniel Miller, and Evan Brossard. The MegaFace Benchmark: 1 million faces for recognition at scale. In *CVPR*, 2016. 6, 7

[21] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. In *ICLR*, 2017. 2

[22] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. ImageNet classification with deep convolutional neural networks. In *NerulIPS*, 2012. 2

[23] Peizhao Li, Han Zhao, and Hongfu Liu. Deep fair clustering for visual learning. In *CVPR*, 2020. 1

[24] Han Zhao, Yiwei Duan, Jiwen Lu, Jianjiang Feng, and Jie Zhou. Graph-based social relation reasoning. In *ECCV*, 2020. 2

[25] Han Zhao, Yiwei Duan, Jiwen Lu, Jianjiang Feng, and Jie Zhou. Graph-based kinship reasoning network. In *ICME*, 2020. 2

[26] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft COCO: Common objects in context. In *ECCV*, 2014. 2, 4

[27] Wei-An Lin, Jun-Cheng Chen, Carlos D Castillo, and Rama Chellappa. Deep density clustering of unconstrained faces. In *CVPR*, 2018. 2

[28] Wei-An Lin, Jun-Cheng Chen, and Rama Chellappa. A proximity-aware hierarchical clustering of faces. In *FG*, 2017. 2

[29] Weiyang Liu, Yandong Wen, Zhiding Yu, Ming Li, Bhiksha Raj, and Le Song. Sphereface: Deep hypersphere embedding for face recognition. In *CVPR*, 2017. 1

[30] Weiyang Liu, Yandong Wen, Zhiding Yu, and Meng Yang. Large-margin softmax loss for convolutional neural networks. In *ICML*, 2016. 1

[31] Stuart Lloyd. Least squares quantization in pcm. *TIP*, 1982. 1, 2, 7, 8

[32] Vinod Nair and Geoffrey E Hinton. Rectified linear units improve restricted boltzmann machines. In *ICML*, 2010. 4

[33] Charles Otto, Dayong Wang, and Anil K Jain. Clustering millions of faces by identity. *TPAMI*, 2017. 2, 7, 8, 11

[34] Omkar M Parkhi, Andrea Vedaldi, and Andrew Zisserman. Deep face recognition. *BMVC*, 2015. 2

[35] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster R-CNN: Towards real-time object detection with region proposal networks. In *NeurIPS*, 2015. 2, 4

[36] Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne Van Den Berg, Ivan Titov, and Max Welling. Modeling relational data with graph convolutional networks. In *EWSIC*, 2018. 2

[37] Yichun Shi, Charles Otto, and Anil K Jain. Face clustering: representation and pairwise constraints. TIFS, 2018. 2

[38] Robin Sibson. Slink: an optimally efficient algorithm for the single-link cluster method. *The Computer Journal*, 1973. 7, 8

[39] Yi Sun, Yuheng Chen, Xiaogang Wang, and Xiaoou Tang. Deep learning face representation by joint identification-verification. In *NeurIPS*, 2014. 1

[40] Yaniv Taigman, Ming Yang, Marc’Aurelio Ranzato, and Lior Wolf. Deepface: Closing the gap to human-level performance in face verification. In *CVPR*, 2014. 1

[41] Taffee T Tanimoto. Elementary mathematical theory of classification and prediction. 1958. 11

[42] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. In *ICLR*, 2018. 2

[43] Hao Wang, Yitong Wang, Zheng Zhou, Xing Ji, Dihong Yang, Yi, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *ICCV*, 2009. 6, 7

[44] Yaniv Taigman, Ming Yang, Marc’Aurelio Ranzato, and Lior Wolf. Deepface: Closing the gap to human-level performance in face verification. In *CVPR*, 2014. 1
Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu. Cosface: Large margin cosine loss for deep face recognition. In CVPR, 2018.

[44] Zhongdao Wang, Liang Zheng, Yali Li, and Shengjin Wang. Linkage based face clustering via graph convolution network. In CVPR, 2019.

[45] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqiang Zhang, and S Yu Philip. A comprehensive survey on graph neural networks. TNNLS, 2020.

[46] Bing Xu, Naiyan Wang, Tianqi Chen, and Mu Li. Empirical evaluation of rectified activations in convolutional network. arXiv:1505.00853, 2015.

[47] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. A comprehensive survey on graph neural networks. TNNLS, 2020.

[48] Sijie Yan, Zhizhong Li, Yuanjun Xiong, Huahan Yan, and Dahua Lin. Convolutional sequence generation for skeleton-based action synthesis. In ICCV, 2019.

[49] Sijie Yan, Yuanjun Xiong, and Dahua Lin. Spatial temporal graph convolutional networks for skeleton-based action recognition. In AAAI, 2018.

[50] Lei Yang, Dapeng Chen, Xiaohang Zhan, Rui Zhao, Chen Change Loy, and Dahua Lin. Learning to cluster faces via confidence and connectivity estimation. In CVPR, 2020.

[51] Lei Yang, Xiaohang Zhan, Dapeng Chen, Junjie Yan, Chen Change Loy, and Dahua Lin. Learning to cluster faces on an affinity graph. In CVPR, 2019.

[52] Xiaohang Zhan, Zhiwei Liu, Junjie Yan, Dahua Lin, and Chen Change Loy. Consensus-driven propagation in massive unlabeled data for face recognition. In ECCV, 2018.

[53] Xiaohang Zhan, Jiahao Xie, Zhiwei Liu, Yew-Soon Ong, and Chen Change Loy. Online deep clustering for unsupervised representation learning. In CVPR, 2020.

[54] Yaobin Zhang, Weihong Deng, Mei Wang, Jiani Hu, Xian Li, Dongyue Zhao, and Dongchao Wen. Global-Local GCN: Large-scale label noise cleansing for face recognition. In CVPR, 2020.

[55] Ming Zhao, Yong Wei Teo, Siliang Liu, Tat-Seng Chua, and Ramesh Jain. Automatic person annotation of family photo album. In ICIVR, 2006.

[56] Chunhui Zhu, Fang Wen, and Jian Sun. A rank-order distance based clustering algorithm for face tagging. In CVPR, 2011.

[57] Zheng Zhu, Guan Huang, Jiankang Deng, Yun Ye, Junjie Huang, Xinzhe Chen, Jiagang Zhu, Tian Yang, Jiwen Lu, Da- long Du, and Zhou Jie. Webface260M: A benchmark unveiling the power of million-scale deep face recognition. In CVPR, 2021.
A. Effect of Graph Parsing

| Method                               | Pre  | Recall | $F_P$ |
|--------------------------------------|------|--------|-------|
| only graph refinement                | 91.84| 70.87  | 80.00 |
| only graph parsing                   | 92.83| 74.24  | 82.50 |
| graph parsing+graph refinement       | 95.50| 85.91  | 90.45 |

Table 7: Method comparison with different inference strategies. Train with the part0_train and test on the part1_test in MS1M [13].

In the proposed STAR-FC, we transform the face clustering task into two steps: **graph parsing** and **graph refinement**. The graph parsing step is based on a GCN edge confidence estimator, while the graph refinement step is based on the node intimacy (NI). In our paper, we have proved that these two steps are indispensable. Here we conduct more experiments to further demonstrate that clustering faces with a single step does not work well.

In Table 7 we compare the pairwise F-score under three different inference strategies. The **only graph refinement** method means that we directly perform pruning with NI on the KNN graph. In **only graph parsing** method, face clusters are obtained by dynamic edge pruning [52] based on the GCN predicted edge scores. As shown in Table 2, face clustering with single step achieves poor performance. We have analyzed the disadvantage of the **only graph parsing** method in the paper. Here we mainly discuss the poor performance of the **only graph refinement** method. We argue that since there exist lots of wrong connections in the initial KNN graph, different clusters are also densely linked and the NI of negative neighbor may be very high. So the NI is difficult to work well on this graph. Therefore, performing graph parsing to get a relatively clear graph structure before employing the NI-based pruning is indispensable, and the combination of these two steps can achieve superior 90.45 pairwise F-score.

B. Comparing the NI with Jaccard similarity

Jaccard similarity coefficient is a statistic used for calculating the similarity and diversity of sample sets. Following the symbols defined in Sec.3.3, Jaccard [17, 41] $\frac{k}{n_1+n_2-k}$, while NI = $\max(\frac{k}{n_1}, \frac{k}{n_2})$. NI considers the attributes of two nodes respectively then uses max aggregation for judgment while Jaccard ignores the difference between the two nodes. As shown in Figure 7, A and B should be in the same cluster. Since A has many neighbors and B has a few, Jaccard gets a low score leading to misjudgment while NI can handle this case well. Therefore NI is more suitable for intimacy measures. In the added ablation study, the $F_P$ of Jaccard and NI are 88.39 and 91.97, respectively.

C. More details on the SPSS

We use visualization to explain how SPSS works more vividly. Figure 8 illustrates the graph structure. (a) is the whole graph. (b) and (c) show the subgraph sampled in random way and SPSS respectively. Nodes with the same color belong to the same class. (c) preserves both the intra-cluster links and the hard negative edges between near clusters. These two types of edges in (c) approximate the structure of edges in (a). However the negative edges in (b) are mostly with low similarity that contribute less for training (Sec.3.2). Compared with the whole graph training (90.45 $F_P$), training with SPSS does not lead to performance loss and brings some extra accuracy gain (91.97 $F_P$), which further indicates that the global structure is preserved.

D. Discussion

In this section, we discuss core differences between some representative face clustering methods and the proposed STAR-FC.

L-GCN [44] predicts the linkage within some selected subgraphs. It relies heavily on a mass of subgraphs. Since there exist many overlapped neighbors in these subgraphs, it suffers from heavily redundant calculations which is a big drag on the inference speed. Besides, such local graph operations lack the comprehension of global graph structure which limits its performance upper bound. GCN-D [51] formulates face clustering as a detection and segmentation problem based on the affinity graph. However, it has the same problem as the L-GCN. It generates a large number of cluster proposals thus leading to inefficient inference. By contrast, the proposed STAR-FC performs face clustering inference based on the full-graph operation which can satisfy both efficiency and accuracy. ARO [33] computes the
top-k nearest neighbors for each face in the dataset and performs face clustering based on the approximate rank-order metric. However, it lacks the parsing of the initial structure information. The coarse top-k nearest neighbors may contain a number of negative samples and the order of images may be far from the exact one, thus the effect of the rank-order metric will be greatly damaged. In the proposed STAR-FC, we use the edge scores predicted by the GCN to parse the graph in advance, therefore most wrong connections can be removed and the NI can work better on this graph with clearer structure. And the importance of graph parsing has been proved in Table 2. GCN-V+E [49] obtains face clusters through predicting the vertex confidence and edge connectivity. It takes the entire graph as input for GCN training. Due to the limitation of GPU memory, it is hard to handle larger-scale training set. The proposed STAR-FC proposes the structure-preserved subgraph sampling strategy to address this challenge and is able to explore larger-scale training data.