SphereFace: Deep Hypersphere Embedding for Face Recognition

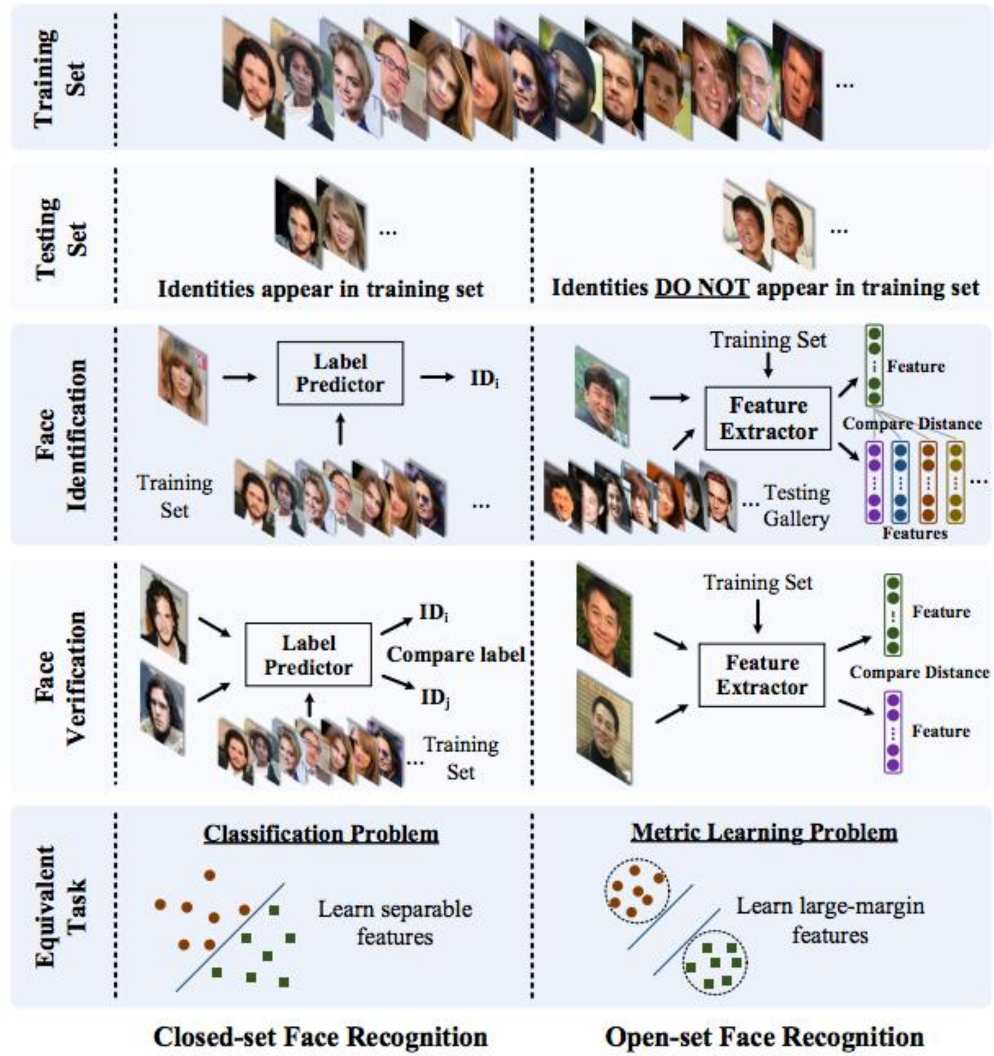
Weiyang Liu, Yandong Wen, Zhiding Yu, Ming Li,
Bhiksha Raj, and Le Song.

College of Computing
Georgia Institute of Technology

What is the key to open-set face recognition?

Open-set face recognition

- Face identities do not appear simultaneously on training set and testing set.
- Requires more generalization power than close-set face recognition.
- Essentially, it can be viewed as a metric learning problem.



Prevailing methods for deep face recognition

Deep-ID network (CUHK)

- Combine the softmax loss and the contrastive loss to learn discriminative face representation.

FaceNet (Google)

- Use Triplet loss to supervise the network learning, but require very large amount of data. (200 million face images)

Things in common

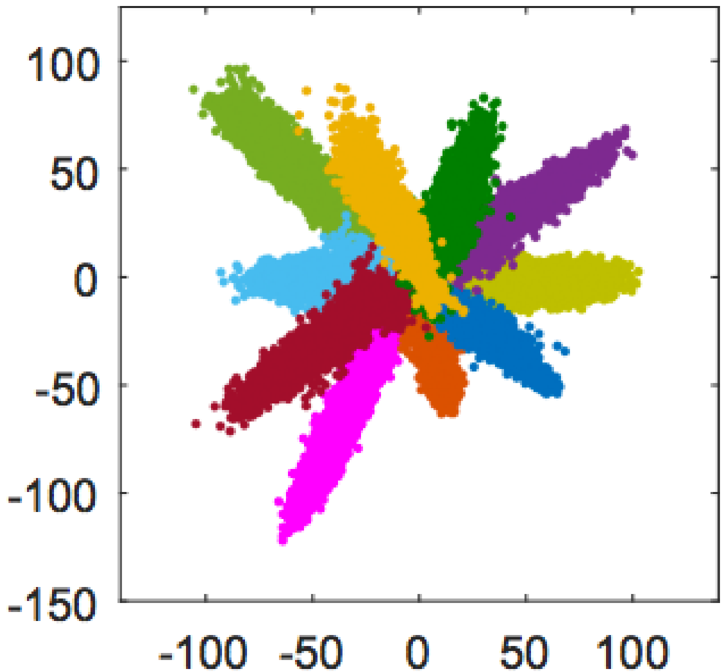
- They all explicitly treat the open-set face recognition problem as metric learning problem, since contrastive loss and triplet loss are both originally used in metric learning.

Drawbacks

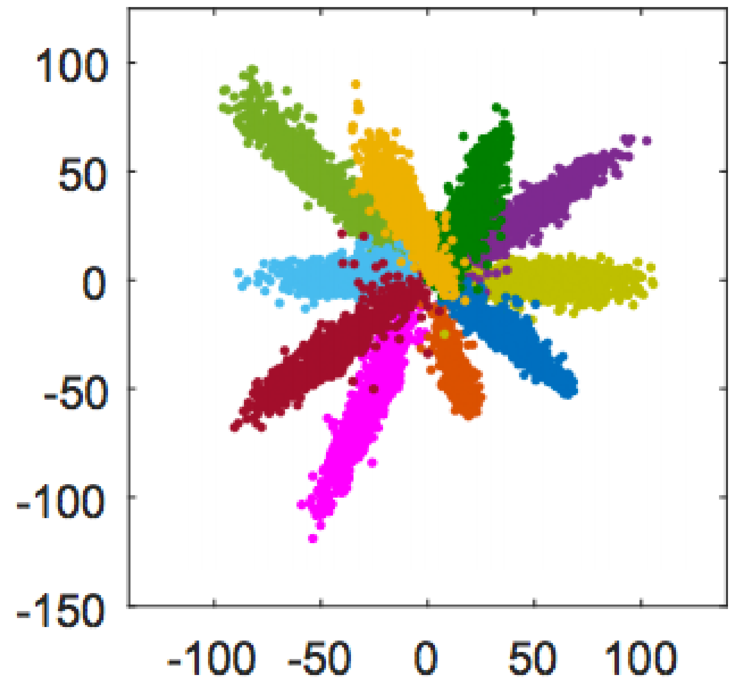
- Deep-ID network combines the softmax loss and contrastive loss, but these two losses produces totally different feature distribution.
- FaceNet requires large amount of data. It is computationally expensive

Softmax loss learns angularly distributed features

Softmax loss can naturally learn angularly distributed features, so it will not be naturally motivated to incorporate any Euclidean losses.



Training set



Testing set

A motivating binary classification example

- Softmax computes the probability for two classes as

$$p_1 = \frac{\exp(\boldsymbol{W}_1^T \boldsymbol{x} + b_1)}{\exp(\boldsymbol{W}_1^T \boldsymbol{x} + b_1) + \exp(\boldsymbol{W}_2^T \boldsymbol{x} + b_2)} \quad (1)$$

$$p_2 = \frac{\exp(\boldsymbol{W}_2^T \boldsymbol{x} + b_2)}{\exp(\boldsymbol{W}_1^T \boldsymbol{x} + b_1) + \exp(\boldsymbol{W}_2^T \boldsymbol{x} + b_2)} \quad (2)$$

- The decision boundary produced by softmax loss is

$$(\boldsymbol{W}_1 - \boldsymbol{W}_2)\boldsymbol{x} + b_1 - b_2 = 0$$

- To achieve angular decision boundary, the weights for the final FC layer is in fact useless. So we will first normalize the weights and zero out the biases.
- To further introduce angular margin, we propose to make the decision more difficult.

Loss Function	Decision Boundary
Softmax Loss	$(\boldsymbol{W}_1 - \boldsymbol{W}_2)\boldsymbol{x} + b_1 - b_2 = 0$
Modified Softmax Loss	$\lVert\boldsymbol{x}\rVert(\cos\theta_1 - \cos\theta_2) = 0$
A-Softmax Loss	$\lVert\boldsymbol{x}\rVert(\cos m\theta_1 - \cos\theta_2) = 0$ for class 1 $\lVert\boldsymbol{x}\rVert(\cos\theta_1 - \cos m\theta_2) = 0$ for class 2

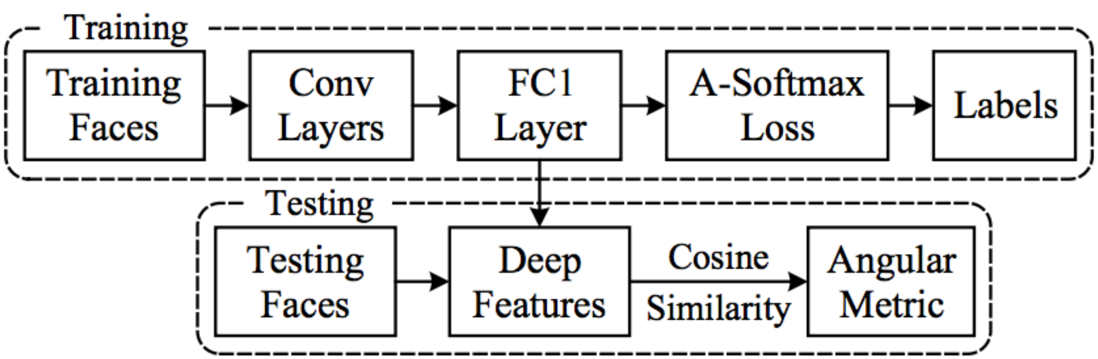
SphereFace Algorithm

The angular softmax (A-Softmax) loss is defined as

$$L_{\text{ang}} = \frac{1}{N}\sum_i -\log\left(\frac{e^{\|\boldsymbol{x}_i\|\psi(\theta_{y_i,i})}}{e^{\|\boldsymbol{x}_i\|\psi(\theta_{y_i,i})} + \sum_{j\neq y_i} e^{\|\boldsymbol{x}_i\|\cos(\theta_{j,i})}}\right)$$

where $\psi(\theta_{y_i,i}) = (-1)^k \cos(m\theta_{y_i,i}) - 2k$, $\theta_{y_i,i} \in [\frac{k\pi}{m}, \frac{(k+1)\pi}{m}]$ $k \in [0, m-1]$ eter m is to control the margin size. Larger m gives larger margin.

The learning and inference pipeline of SphereFace:

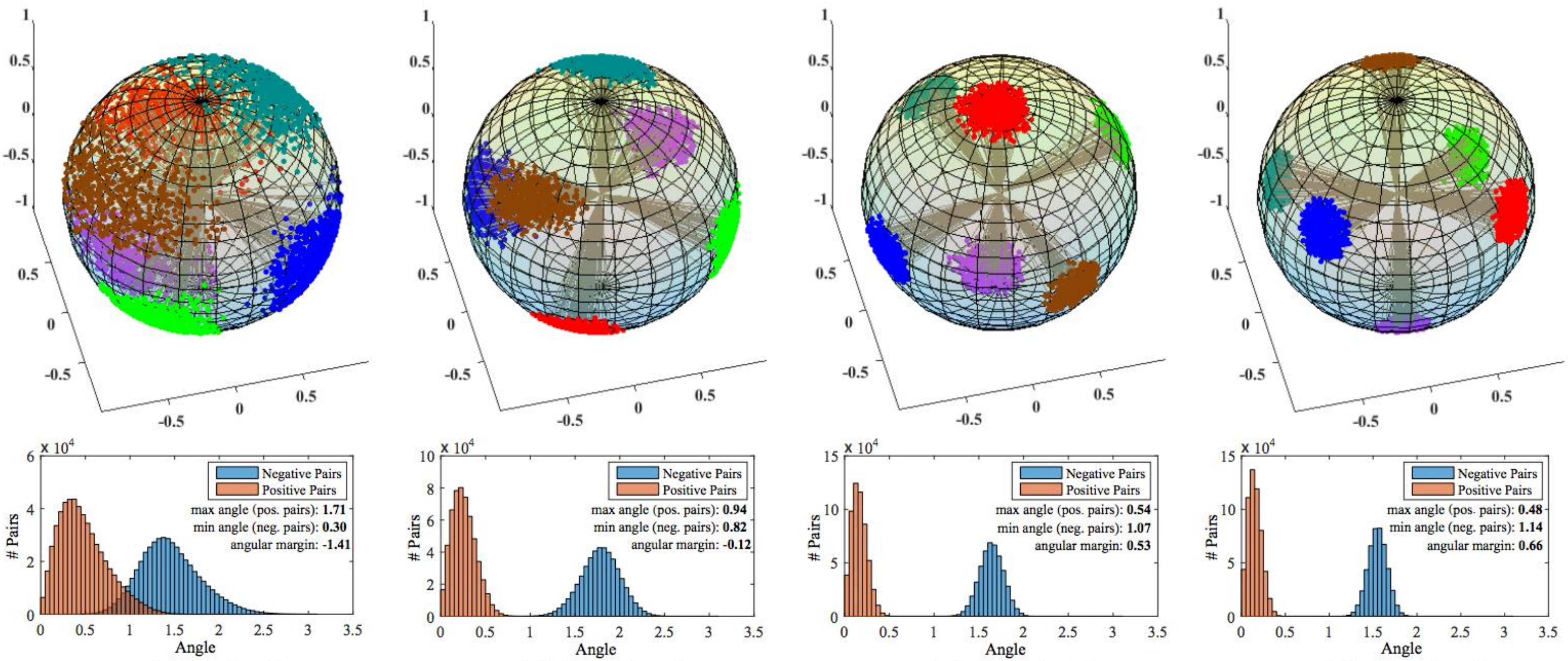


It is the same as traditional CNN framework, so it is extremely simple and compatible with any advanced network architecture such as VGG, ResNet. But with the proposed angular softmax loss, the learned features will be much more discriminative.

SphereFace feature visualization

3D feature visualization.

The SphereFace features are very discriminative in the angular space.



A-Softmax (m=1) A-Softmax (m=2) A-Softmax (m=3) A-Softmax (m=4)

Experiments

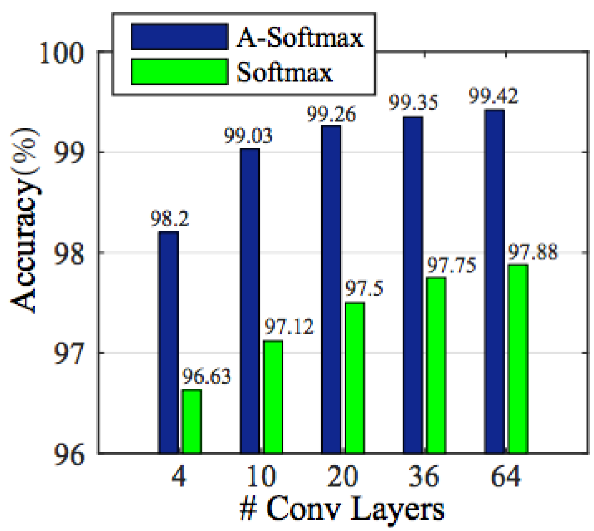
Exploratory study

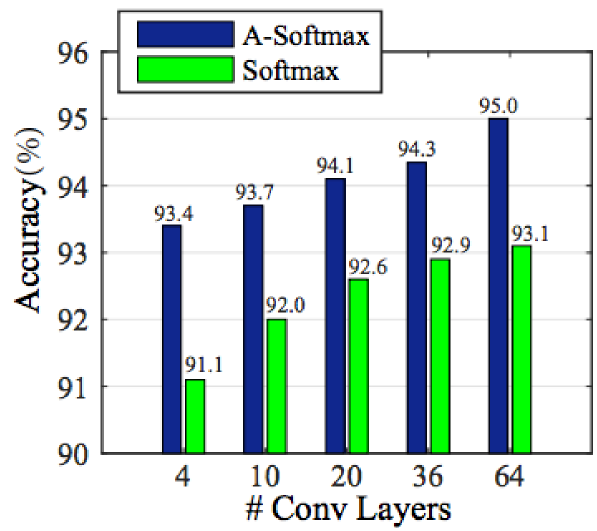
- How m affects the performance

  The verification accuracy on LFW dataset

Dataset	Original	m=1	m=2	m=3	m=4
LFW	97.88	97.90	98.40	99.25	**99.42**
YTF	93.1	93.2	93.8	94.4	**95.0**

- How the number of convolution layers affect the performance





Performance on LFW and YTF dataset

Both LFW and YTF are widely used open-set face recognition benchmarks.

Method	Models	Data	LFW	YTF
DeepFace [30]	3	4M*	97.35	91.4
FaceNet [22]	1	200M*	**99.65**	95.1
Deep FR [20]	1	2.6M	98.95	**97.3**
DeepID2+ [27]	1	300K*	98.70	N/A
DeepID2+ [27]	25	300K*	99.47	93.2
Baidu [15]	1	1.3M*	99.13	N/A
Center Face [34]	1	0.7M*	99.28	94.9
Yi et al. [37]	1	WebFace	97.73	92.2
Ding et al. [2]	1	WebFace	98.43	N/A
Liu et al. [16]	1	WebFace	98.71	N/A
Softmax Loss	1	WebFace	97.88	93.1
Softmax+Contrastive [26]	1	WebFace	98.78	93.5
Triplet Loss [22]	1	WebFace	98.70	93.4
L-Softmax Loss [16]	1	WebFace	99.10	94.0
Softmax+Center Loss [34]	1	WebFace	99.05	94.4
SphereFace	1	WebFace	**99.42**	**95.0**

Among all the methods trained on the publicly available WebFace dataset, we achieve the current best performance and significantly outperforms the #2 performance.

Megaface Challenge

Megaface challenge is one of the most difficult face recognition competition. SphereFace ranked #1 from Nov. 2016 to Jan. 2017.

- SphereFace achieves this performance using only publicly available small-scale dataset, while the other commercial algorithms use private and large-scale datasets.

Method	protocol	Rank1 Acc.	Ver.
NTechLAB - facenx large	Large	73.300	85.081
Vocord - DeepVo1	Large	**75.127**	67.318
Deepsense - Large	Large	74.799	**87.764**
Shanghai Tech	Large	74.049	86.369
Google - FaceNet v8	Large	70.496	86.473
Beijing FaceAll_Norm_1600	Large	64.804	67.118
Beijing FaceAll_1600	Large	63.977	63.960
Deepsense - Small	Small	**70.983**	**82.851**
SIAT_MMLAB	Small	65.233	76.720
Barebones FR - cnn	Small	59.363	59.036
NTechLAB - facenx_small	Small	58.218	66.366
3DiVi Company - tdvm6	Small	33.705	36.927
Softmax Loss	Small	54.855	65.925
Softmax+Contrastive Loss [26]	Small	65.219	78.865
Triplet Loss [22]	Small	64.797	78.322
L-Softmax Loss [16]	Small	67.128	80.423
Softmax+Center Loss [34]	Small	65.494	80.146
SphereFace (single model)	Small	**72.729**	**85.561**
SphereFace (3-patch ensemble)	Small	**75.766**	**89.142**