

Abstract

- We propose a novel loss function called Max-Margin Loss that benefits from set-based information by drawing inter-class margins. It maximizes the maximum possible inter-class margin that is calculated by SVMs. It implicitly pushes all the samples towards correct side of the margin with a vector perpendicular to the hyperplane and a strength inversely proportional to the distance to the hyperplane.
- We review existing set-based DML approaches and evaluate them and their combinations together with Max-Margin Loss and Softmax Loss
- We build a framework where such functions can operate jointly with sample-based ones and investigate the strategies to maintain set information during training

Overview of Set-based Learning Framework

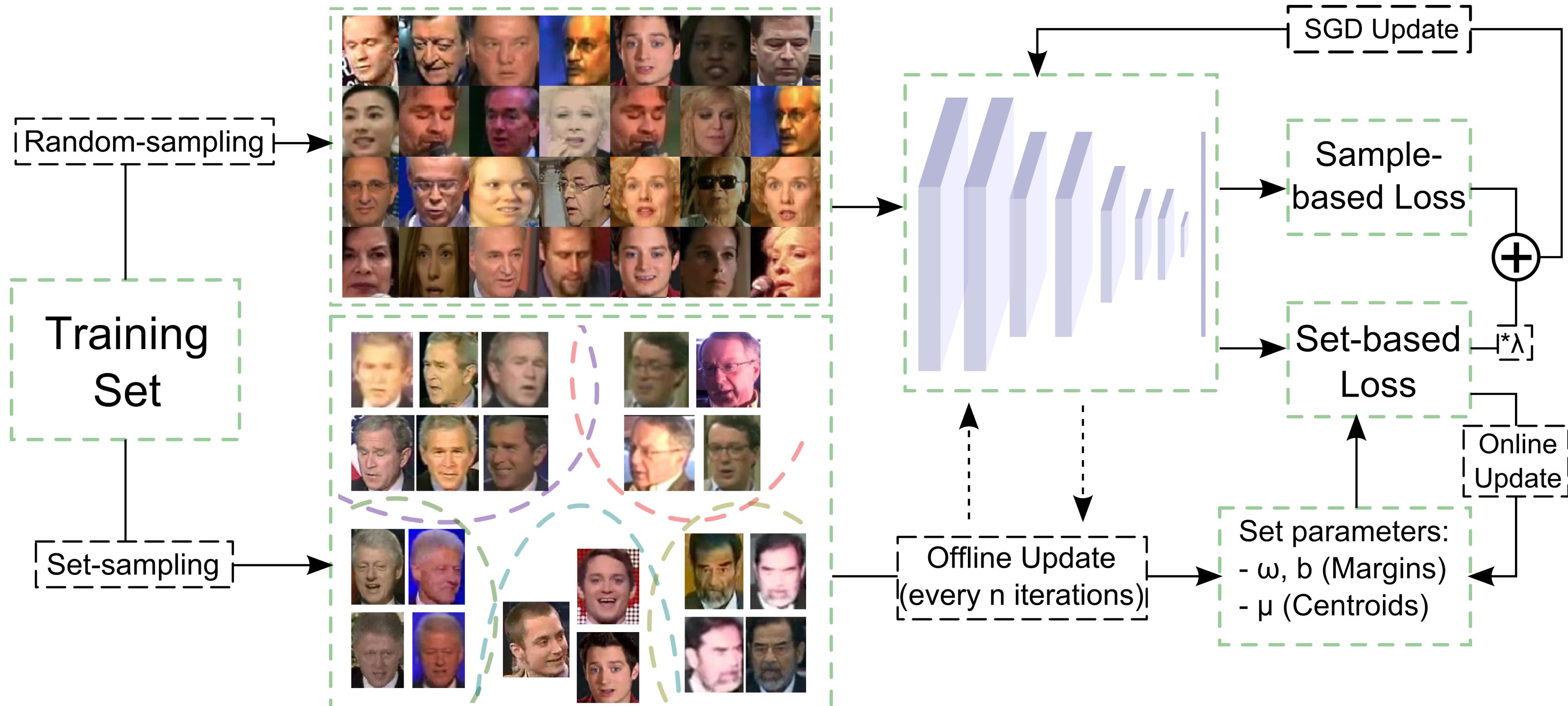


Figure 1: Random batch of face images are sampled from the training set to train a CNN with sample-based loss function (i.e., Softmax).
Offline Update: In every n iterations, set of face images are sampled that consist significant amount of images from each identities and fed into the network while training is paused. Resulting feature vectors are used to calculate set parameters whose way is specific to set-based loss used.
Online Update: While the training is going, set parameters are updated with a small weight by the parameters calculated with current random batches.

Related Work

- Sample-based DML methods (e.g., Softmax, Contrastive, Triplet, LSE, Quadruplet Losses)
- Set-based DML methods
 - Center Loss [4]: Biased centroid estimation and Do not tolerate intra-class variation
 - Magnet Loss [3] : Not combinatorial with other functions
- SVM based Deep Learning [5] : Penalizes only slack variables

Max-Margin Loss

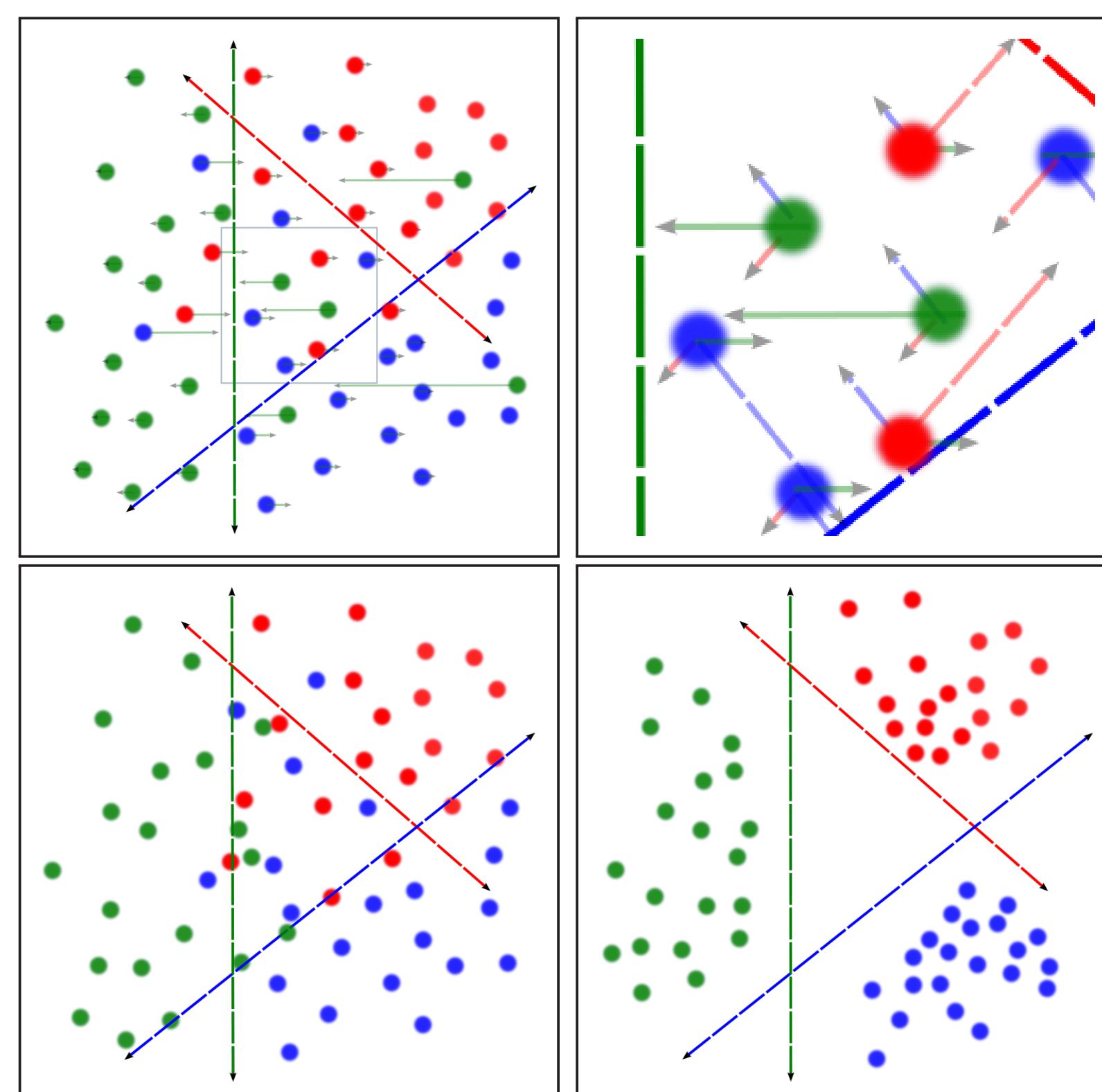


Figure 2: (top-left) First, good embedding is used to calculate separating hyperplanes. The loss applies to all samples by green plane is indicated with arrows. (bottom-left) After one update for only green plane. (bottom-right) After many iteration, almost convergence.

The loss is computed by the following formula:

$$\mathcal{L}_M = \lambda_M \sum_{i=1}^n \sum_{j=1}^m \frac{1 - \delta(y_i=j)}{m-1} e^{-\frac{\delta(y_i=j)(w_j^T x_i + b)}{\|w_j\|_2}}$$

where separating hyperplane for j th class is defined as $w_j^T x + b = 0$ and $\delta(\text{condition})$ equals to 1 if the condition is satisfied and -1 otherwise.

Embedding of 3 Identities

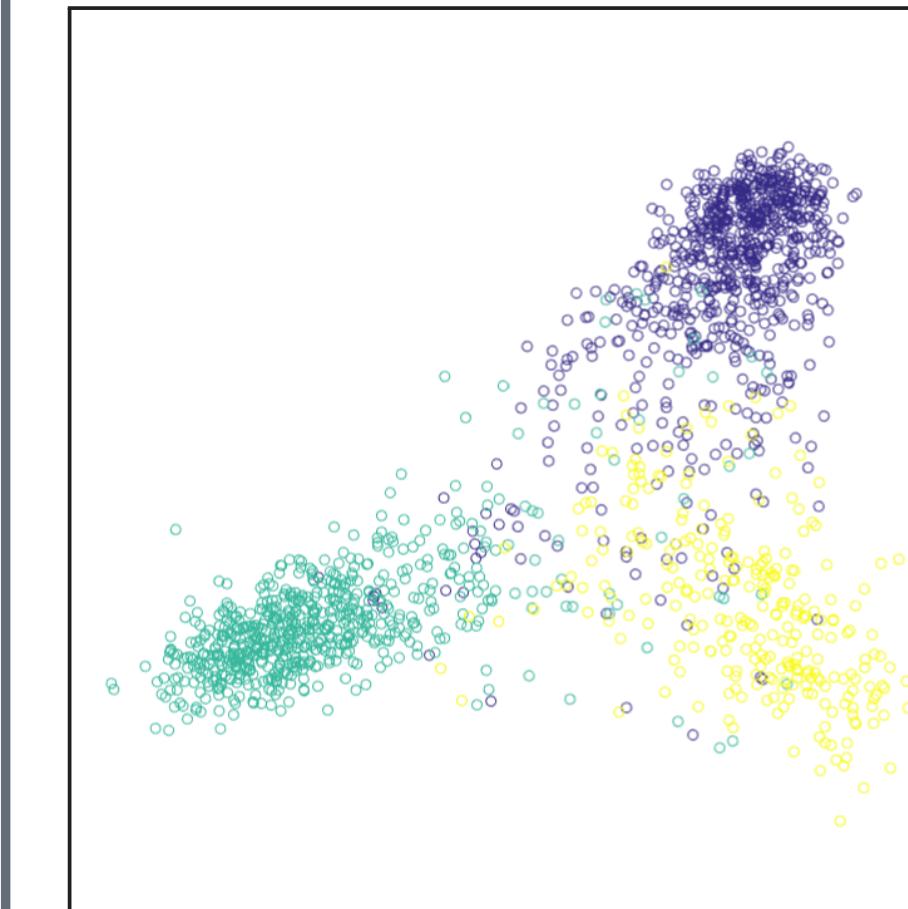


Figure 3: Softmax Loss Alone

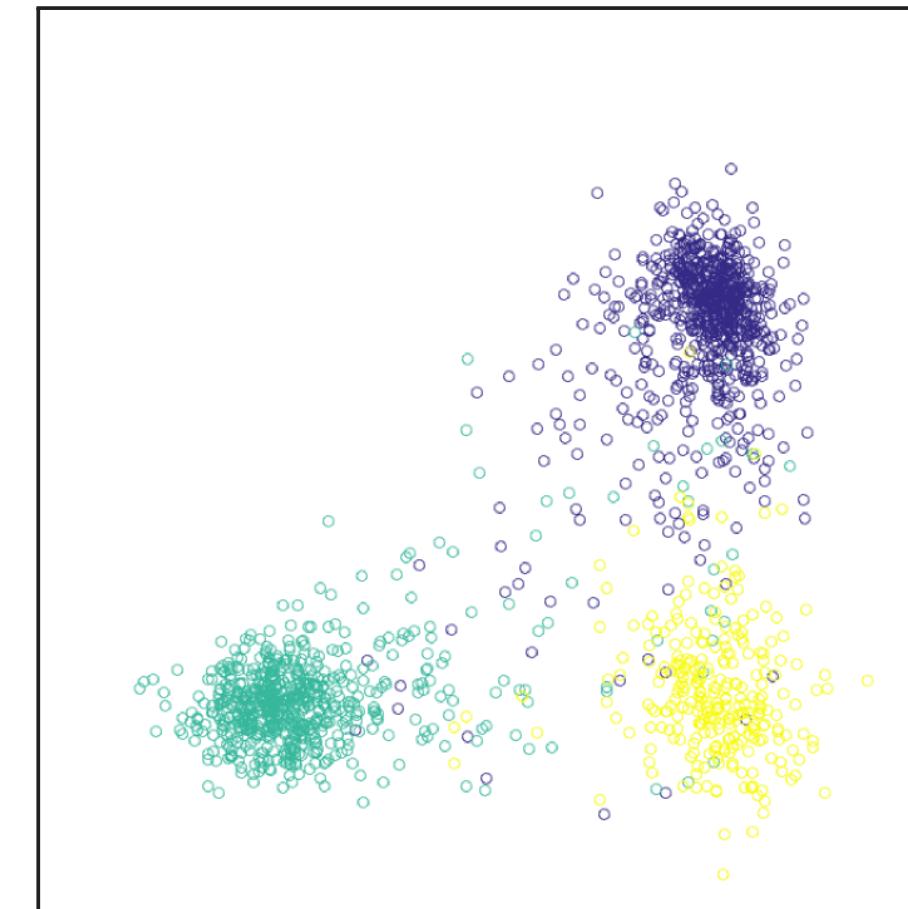


Figure 4: Softmax & Center L.

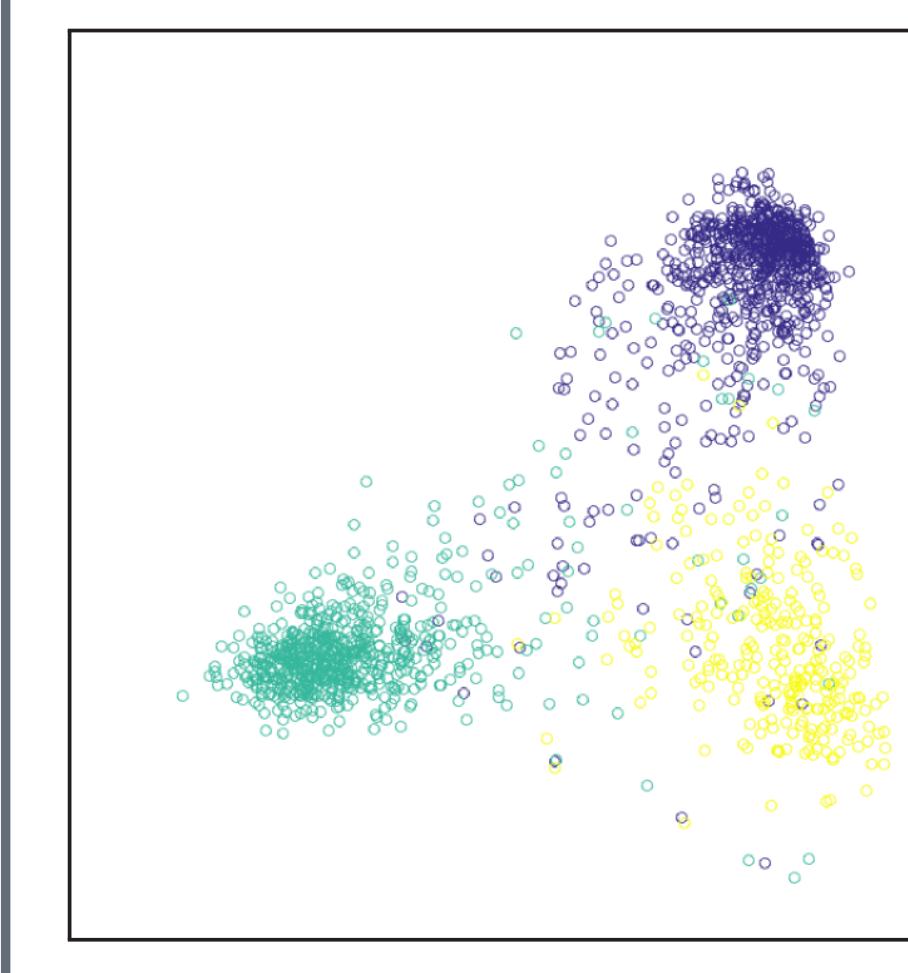


Figure 5: Softmax & Pushing L.

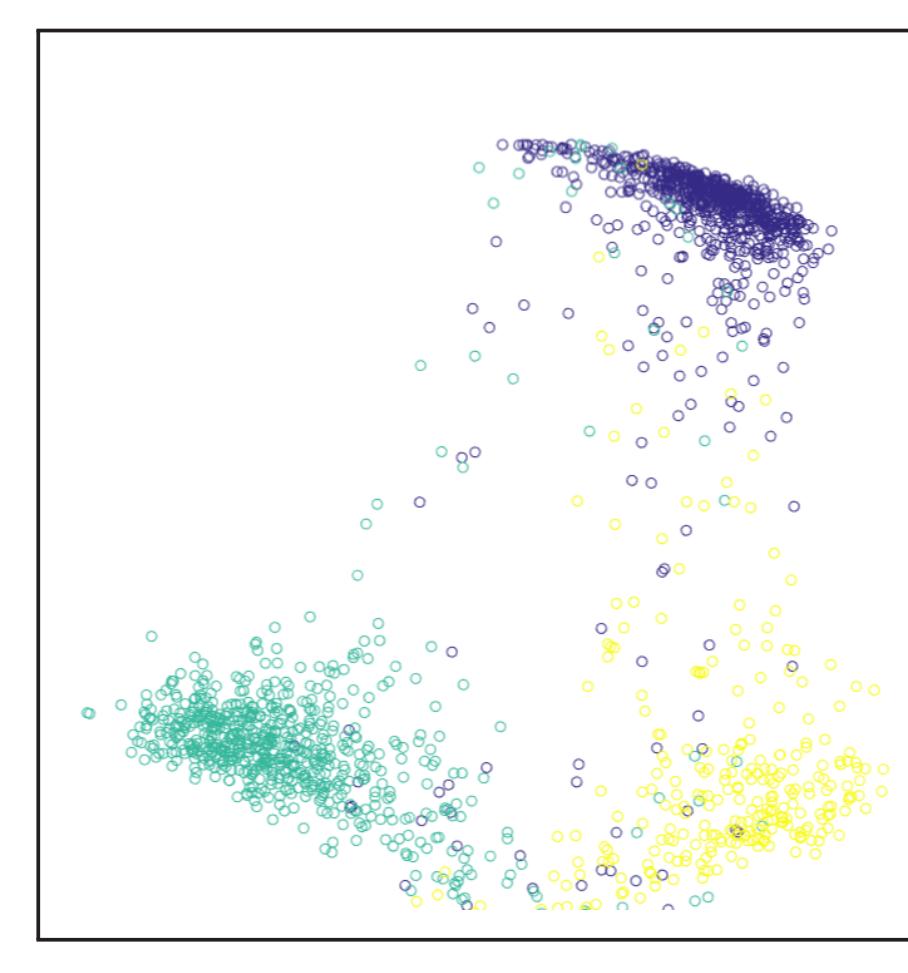


Figure 6: Soft. & Max-Margin L.

Comparison of Set-based Losses

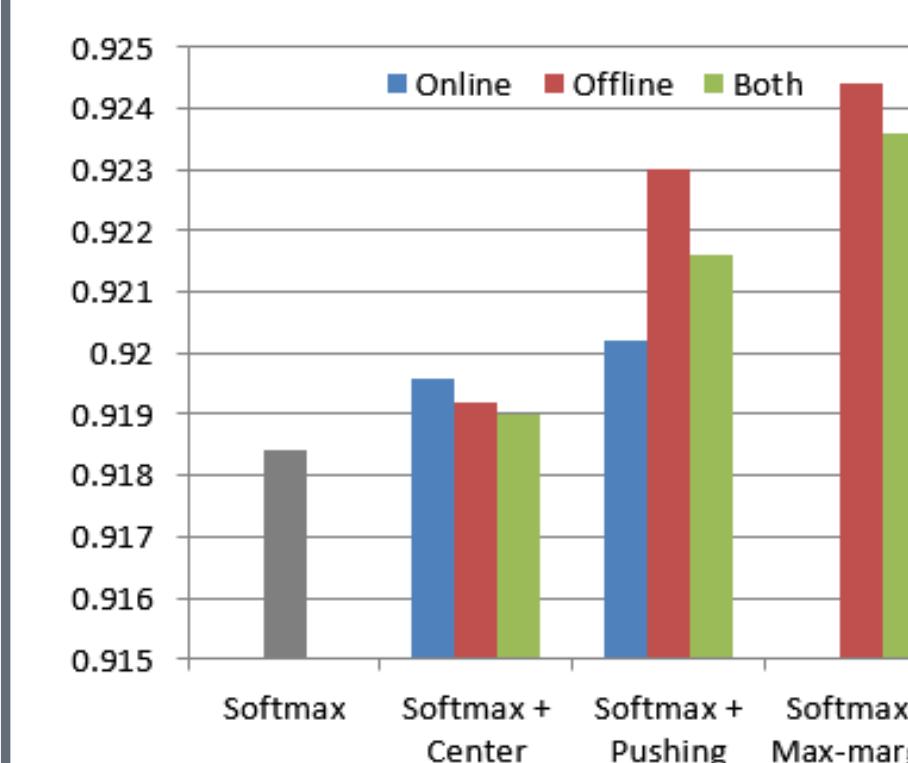


Figure 7: Accuracies on YTF

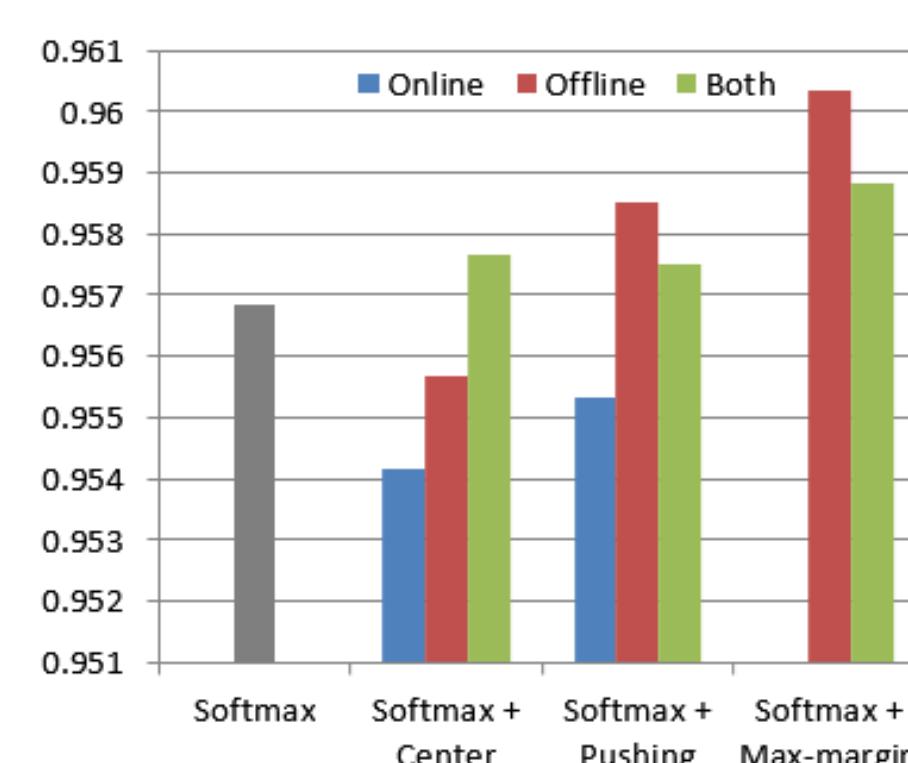


Figure 8: Accuracies on LFW

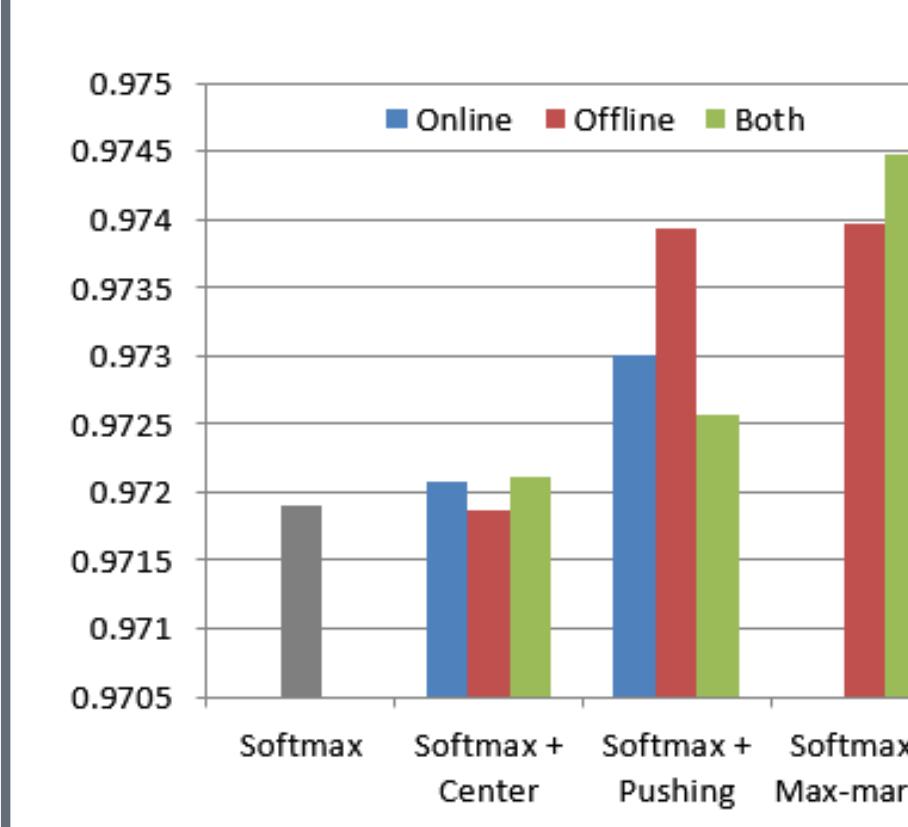


Figure 9: AUC on YTF

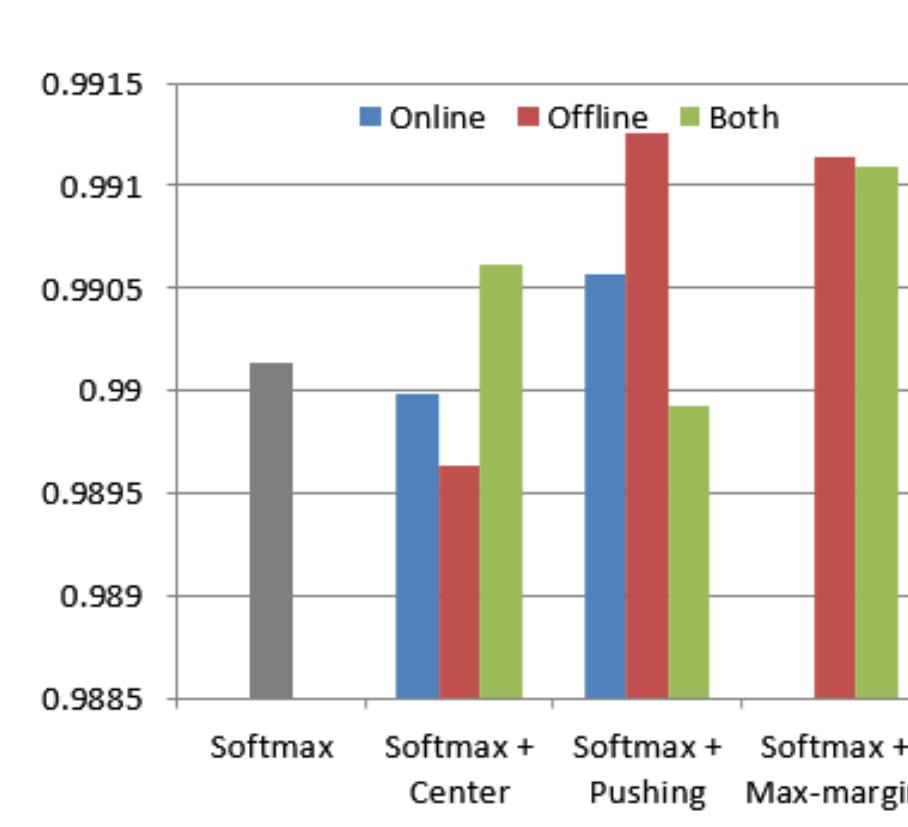


Figure 10: AUC on LFW

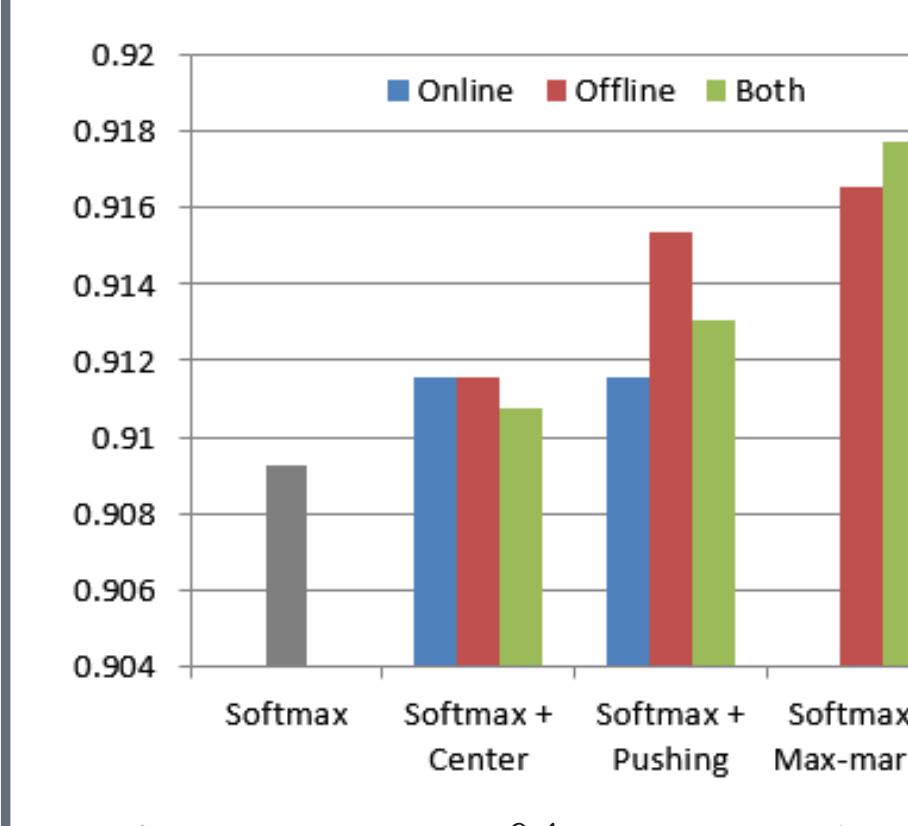


Figure 11: 100%- EER on YTF

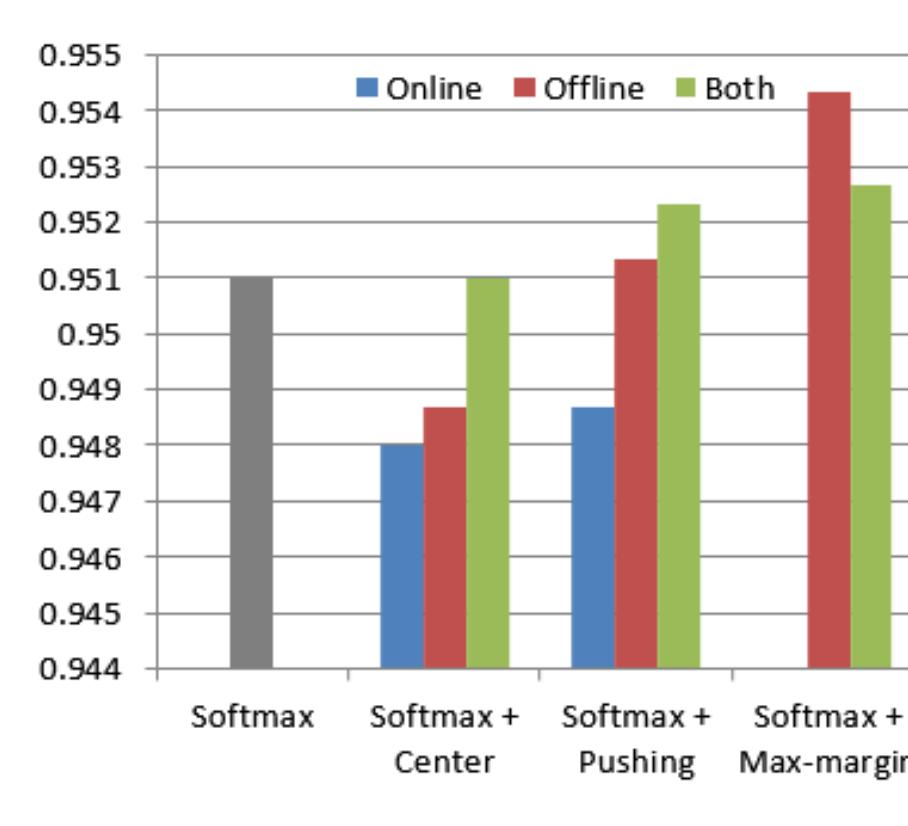


Figure 12: 100%- EER on LFW

Comparison to State-of-the-art

Method	#Training Images	#Ids	Input Size	Network (#Params.)	FT on YTF or LFW	Accuracy on YTF (%)	Accuracy on LFW (%)
DeepFace [1]	4.4M	4,030	152×152	AlexNet(120M)	No	91.4	97.35
VGG Face [2]	2.62M	2,622	224×224	VGG(138M)	Yes	97.3	98.95
VGG Face [2]	2.62M	2,622	224×224	VGG(138M)	No	91.6	-
$\mathcal{L}_S + \mathcal{L}_M$	0.83M	2,558	96×96	NNS1(26M)	No	92.44	96.03