Introduction to Deep Learning Theory

FaceID: Evolution of Loss function

Aleksandr Petiushko

MIPT
RAIRI

February 16, 2023

AP

Content

AP

Feature engineering

- Initially the Machine Learning machinery was targeted at **feature engineering** (or extraction, or discovery)
  - Mapping f from arbitrary object $o \in O$ to its unified feature space representation $x \in X \subseteq \mathbb{R}^D$: $f : O \to X$
- Suppose we have m objects $\Rightarrow$ can construct training dataset X^m
- On top of that representation (usually a *linear*) a classifier is learned (e.g., SVM): $a(w, X^m) = \operatorname{sign} g(x, w) = \operatorname{sign}\langle x, w\rangle$

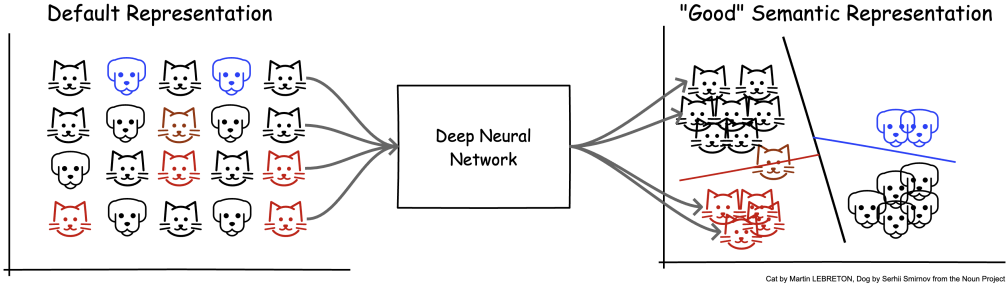
AP

Representations Learning

- Main goal: to have objects representations rich and descriptive:
  - Representations of objects from the same class are better *to be close* (according to some metric, e.g., Euclidean) in the feature space
  - Representation of objects from different classes are better to *lie far* from each other (according to some metric)
- Sometimes the initial features $x \in X$ are not suited enough for this task
- For this purpose, additional mapping h from X into some additional representation space $R \subseteq \mathbb{R}^N$: $h : X \to R$
- The learning of this additional mapping h is called **Representation Learning**

AP

Representation spaces illustration[1]



[1]Image credit: blog.fastforwardlabs.com

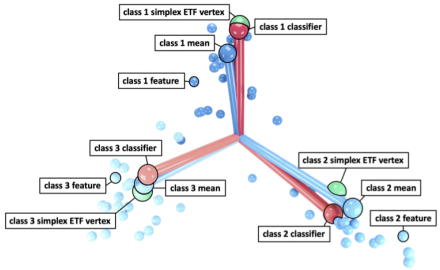
Representation for classification

- Suppose the representation of input $x \in \mathbb{R}^D$ is done by function (e.g., Neural Net-based) $h(x) \in \mathbb{R}^N$
- Our goal is to classify x based on its representation $h(x)$ into one of K classes: $Y = \{0, \ldots, K-1\}$
- For this purpose, we need to project the (learned) representation into K *logits*, that later will be used as the inputs to SoftMax (and corresponding SoftMax loss) to produce probabilities
  - Logits are defined by $l = W * h(x) + b$, where W is the projection matrix $K \times N$, $b \in \mathbb{R}^K$ (often $b = 0$)
  - Output probabilities are $q = SoftMax(l) = SoftMax(W * h(x) + b)$
  - Linear classifier is $\arg\max_{c \in Y} SoftMax(l)_c \Leftrightarrow \arg\max_{c \in Y} \langle W_c, h(x) \rangle + b_c$, where W_i is the i-th row of W

AP

Neural Collapse

- Recently it was found that in the terminal stage of training of any deep learning classifier (with Cross-Entropy loss) in the overparametrization regime, when ER is already zero but ERA is not, the average representations $h(x)$ tend to group around each class center
  - And even coincide up to rescaling to linear classifiers W_i
- This phenomena is called **Neural Collapse**, initially it was discovered for classifiers[2], and later found for regression too[3]



[2] V. Papyan et al. "Prevalence of neural collapse during the terminal phase of deep learning training." 2020.

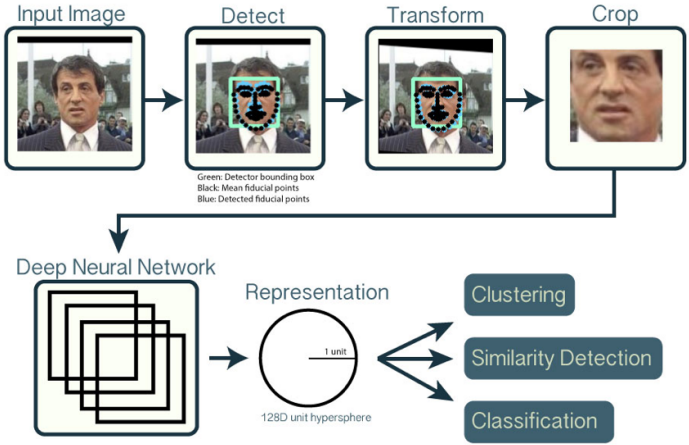
[3] X. Y. Han et al. "Neural collapse under mse loss: Proximity to and dynamics on the central path." 2021.

Face Recognition: Verification vs Identification

1. Two main Face Recognition tasks: Verification and Identification (FaceID)
2. **Verification**: check if the input face is the same as the original one
3. **Identification**: find the identity from the ID dataset, or report the absence
4. "*FaceID*" on phones is actually Verification
5. FaceID is much harder than Verification
6. Nowadays the number of IDs in the ID dataset is $\sim 1B$, and the training dataset can contain $\sim 10M$ of IDs
7. It makes FaceID one of the most challenging applications of Representation Learning techniques

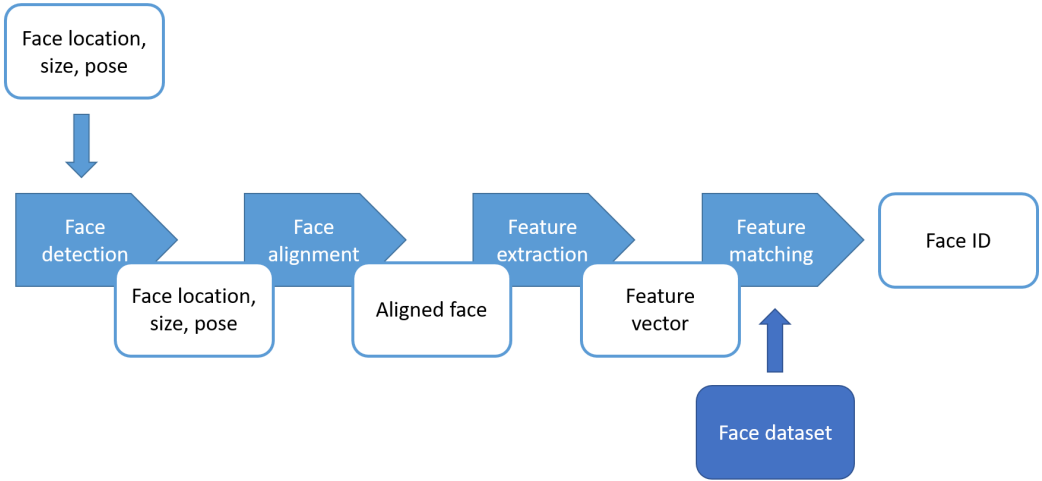
AP

FaceID common pipeline



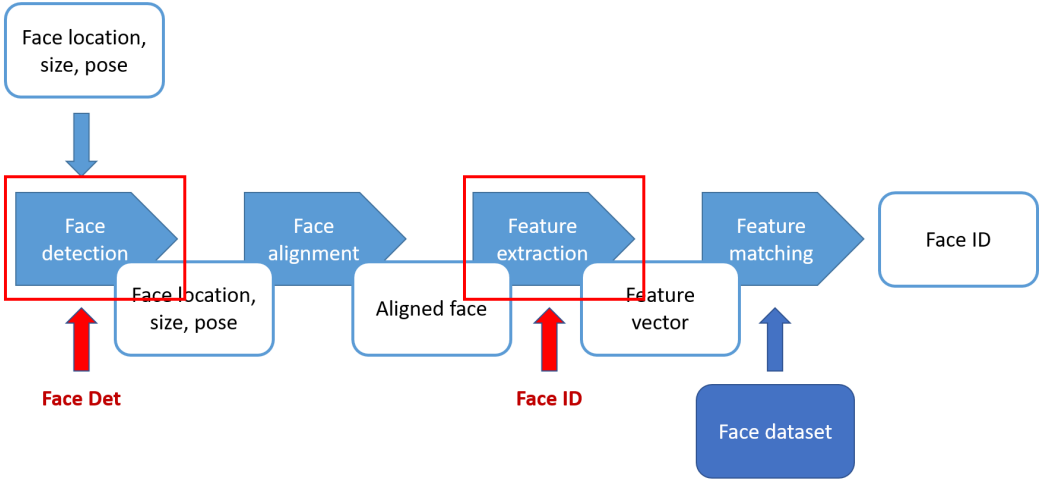
AP

FaceDet and FaceID



AP

FaceDet and FaceID



AP

FaceID task

FaceID

- Initially task formulation – Face Classification: assigning an input to a predefined class
- Later the task evolved to few-shot learning: very similar, but classes are known only during inference (not during training)
- Anyway, both are based on a simple classification task

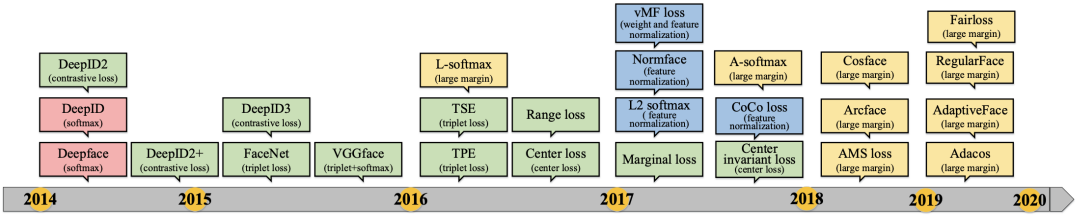
FaceID task

- **Classification**: Given K classes (IDs) and input face x, find the closest class $\arg\max_{i \in \{0,\dots,K-1\}} \langle W_i, h(x) \rangle + b_i$
- **Identification**: Given the dataset of m ID representations $H = (h_0, \dots, h_{m-1})$ input face x, find the closest ID based on some similarity function $s : \mathbb{R}^N \times \mathbb{R}^N \to \mathbb{R}$: $\arg\max_{i \in \{0,\dots,m-1\}} s(h(x), h_i)$ or report the absence if $max_{i \in \{0,\dots,m-1\}} s(x, h_i) < \theta$

AP

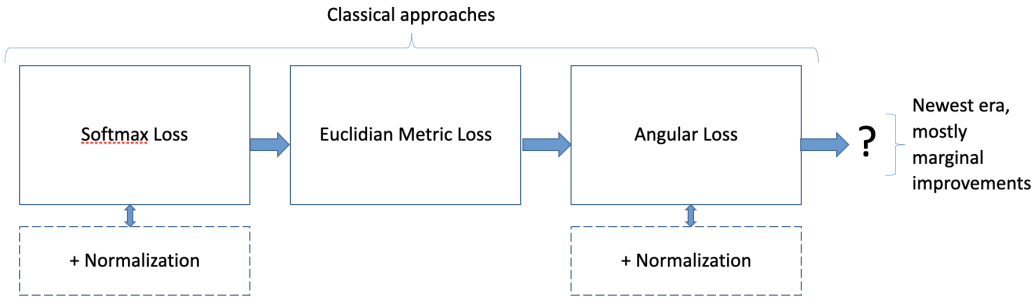
Historical overview

Evolution of losses to overview[4]:



[4]M. Wang et al. "Deep face recognition: A survey." 2018.

FaceID loss evolution: lecture scope



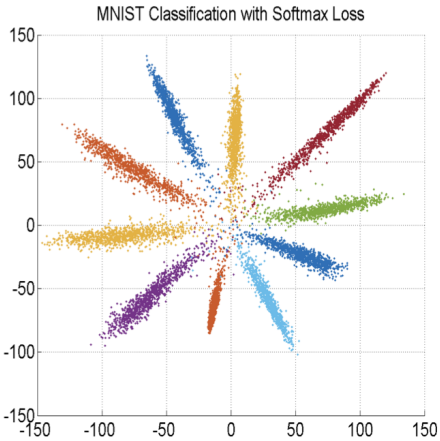
AP

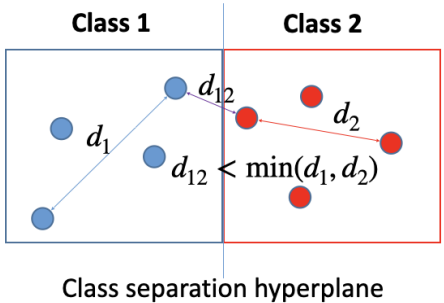
Softmax Loss

- In FaceID community, "*SoftMax (SM) Loss*" == Cross-entropy
- SM loss was the first loss type used for the FaceID task
  - Some examples are: DeepFace[5], DeepID[6]
- In comparison to usual classification, here we have a larger number of classes
  - Class == person ID
  - Usually it is apprx 10-100K classes and even more (e.g., in surveillance applications)
- Intra-class variation can be bigger than inter-class difference

[5] Y. Taigman et al. "Deepface: Closing the gap to human-level performance in face verification." 2014.
[6] Yi Sun et al. "Deep learning face representation from predicting 10,000 classes." 2014.

Softmax Loss: illustration



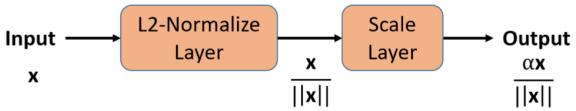


AP

L_2-SoftMax[7]

- Often cosine similarity is used: $s(x, y) = \frac{\langle h(x), h(y) \rangle}{||h(x)||_2 ||h(y)||_2}$
- It causes some discrepancy between training loss (SM) and testing procedure, and it is empirically shown that best results are for the representations with high L_2-norm
- Idea: introduce scale layer h' on top of representations $h(x)$ with one learnable parameter α so as: $h'(x) = \frac{\alpha h(x)}{||h(x)||_2}$
- The training loss:

$$L_{SM} = -\frac{1}{m} \sum_{i=0}^{m-1} \log \frac{e^{\langle W_{y_i}, h(x_i) \rangle + b_{y_i}}}{\sum_{j=1}^{K} e^{\langle W_j, h(x_i) \rangle + b_j}} \quad s.t. ||h(x_i)||_2 = \alpha \quad \forall i = 0, \ldots, m-1$$



[7] Rajeev R. et al. "L2-constrained softmax loss for discriminative face verification" 2017.

L_2-SoftMax: results

- Learned α usually tends to be quite large ($\Rightarrow$ L_2-constraint is relaxed) $\Rightarrow$ use it as an upper bound
- Fixing α to a small value leaves the hypersphere a small raduis and less surface to spread the centroids
- Assuming the number of classes K to be lower than twice the representation dimension N, we can distribute the classes on a hypersphere of dimension N such that any two class centers are at least $\frac{\pi}{2}$ apart
- It leads to $p = \frac{e^{\alpha}}{e^{\alpha} + \sum_{j=1}^{K-2} e^{0} + e^{-\alpha}} \approx \frac{e^{\alpha}}{e^{\alpha} + K - 2} \Rightarrow$ the lower bound to have allowable accuracy p is $\alpha_{low} = \log \frac{p(K-2)}{1-p}$
- In practice, fixed α closer to α_{low} is preferred for smaller datasets, and more close to learned α for larger ones (e.g., 10-100)

AP

NormFace[8]: further normalization

- Consider the case of no bias term: $\arg\max_{i\in\{0,\dots,K-1\}}\langle W_i, h(x)\rangle$
- Simple Proposition: for any $s > 1$,

$$\max_{i\in\{0,\dots,K-1\}} \frac{e^{\langle W_i, sh(x)\rangle}}{\sum_{j=0}^{K-1} e^{\langle W_j, sh(x)\rangle}} \geq \max_{i\in\{0,\dots,K-1\}} \frac{e^{\langle W_i, h(x)\rangle}}{\sum_{j=0}^{K-1} e^{\langle W_j, h(x)\rangle}}$$

- It means that scaling the dot product $\langle W_i, h(x)\rangle$ makes the probability of class bigger
- Let's normalize both projection W_i **and** representation $h(x)$ by scaling factor l: $h'(x) = l\frac{h(x)}{||h(x)||_2}$, $W_i'(x) = l\frac{W_i(x)}{||W_i(x)||_2}$
- At the same time, the following Proposition is true: for the Neural Collapse case, the lower bound on SM loss with normalized projections and representations is $\log(1 + (K-1)e^{-\frac{K}{K-1}l^2})$

Exercise: Prove these Propositions.

[8] F. Wang et al. "Normface: L2 hypersphere embedding for face verification." 2017.

NormFace: training

- Taking into account the above Propositions, it makes sense to put a large l
- Also, omitting bias term b makes the training procedure as close as possible to the testing procedure with similarity function $s(x, W_i) = \frac{\langle h(x), W_i \rangle}{||h(x)||_2 ||W_i||_2}$
- And the final proposal is not to fix a large l, but to have the single parameter $s = l^2$ a learnable one so as the final loss is the following:

$$L_{SM'} = -\frac{1}{m} \sum_{i=0}^{m-1} \log \frac{e^{s\langle W'_{y_i}, h'(x_i) \rangle}}{\sum_{j=1}^{K} e^{s\langle W'_j, h'(x_i) \rangle}}$$

AP

CoCo Loss[9]: centroids

- Suppose we are using scaled representations: $h'(x) = \alpha \frac{h(x)}{||h(x)||_2}$
- Idea: instead of using learned W_i in the SoftMax, let's use the corresponding normalized centroids:

$$c_j = \frac{\sum_{i=0}^{m-1} \delta_j(y_i) h'(x_i)}{\sum_{i=0}^{m-1} \delta_j(y_i)}, \quad c'_j = \frac{c_j}{||c_j||_2}, \quad j = 0, \ldots, K-1$$

- CoCo loss:

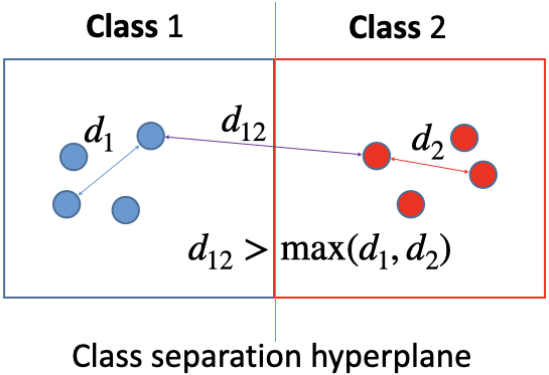
$$L_{CoCo} = -\frac{1}{m} \sum_{i=0}^{m-1} \log \frac{e^{s\langle c'_{y_i}, h'(x_i)\rangle}}{\sum_{j=0}^{K-1} e^{s\langle c'_j, h'(x_i)\rangle}}$$

Exercise. Given the upper bound for $L_{CoCo} < \epsilon$, prove the lower bound on $\alpha > \frac{1}{2} \log \frac{K-1}{e^{\epsilon}-1}$

[9] Yu Liu et al. "Rethinking feature discrimination and polymerization for large-scale recognition." 2017.

Euclidean Metric Loss

- **Goal**: to increase inter-class difference and to decrease intra-class variance based not on probabilities, but on embeddings itself
  - Some examples are: DeepID2 (contrastive)[10], FaceNet (triplet)[11]



[10] Yi Sun et al. "Deep learning face representation by joint identification-verification." 2014.
[11] F. Schroff et al. "Facenet: A unified embedding for face recognition and clustering." 2015.

Contrastive Learning[13]

- Setting: Face Verification
- Labeling: $y_{ij} = 0$ means that pair of faces (x_i, x_j) from different persons, $y_{ij} = 1$ means that pairs of faces from the same person
- Measure of 'closeness': Euclidean distance on top of face representations $s(x_i, x_j) = ||h(x_i) - h(x_j)||_2$
- Empirical observations:
  - Need a sort of Hinge Loss for different IDs (no need to make their representations going to infinity)
  - No need in Hinge Loss for the same IDs (otherwise the representations will be concentrated near the margin boundary)
  - Need a margin to have non-trivial representations (w/o collapse)[12]

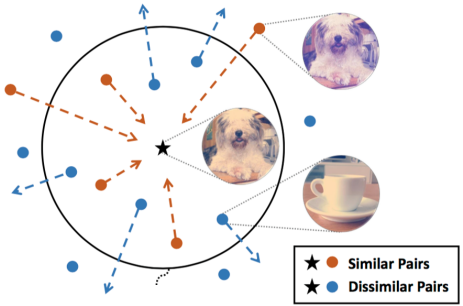
[12] Y. LeCun et al. "A tutorial on energy-based learning." 2006.

[13] S. Chopra et al. "Learning a similarity metric discriminatively, with application to face verification." 2005.

Max Margin Contrastive Loss

- Denote as $m > 0$ the margin for 'negative' (e.g. from different ID) pair of faces
- The final loss for the pair (x_i, x_j) is:

$$L_{MMC}(x_i, x_j) = \frac{1}{2} y_{ij} \cdot s(x_i, x_j)^2 + \frac{1}{2}(1 - y_{ij}) \cdot \max(0, m - s(x_i, x_j))^2$$



AP

Marginal Loss[14]: one non-linearity with two margins

- Let's concentrate on the farthest intra-class samples and the nearest inter-class samples to compute a margin loss:

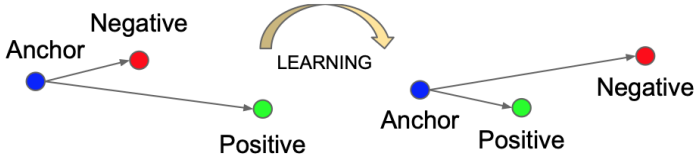
$$L_M = \frac{1}{m^2 - m} \sum_{i<j} \max\left(0, \xi - y_{ij}\left(\theta - \left|\left|\frac{h(x_i)}{||h(x_i)||_2} - \frac{h(x_j)}{||h(x_j)||_2}\right|\right|_2^2\right)\right)$$

  - where $y_{ij} = +1$ if representations from the same ID and $y_{ij} = -1$ vise versa
  - θ: threshold for distinguishing whether representations are from the same class
  - ξ: error margin for the classification hyperplane

[14] J. Deng et al. "Marginal loss for deep face recognition." 2017.

Triplets instead of pairs

- For contrastive learning, we concentrated on pairs: 'positive' representations should be as close as possible and 'negative' should be not closer than a predefined threshold
- And these distances (as well as thresholds) are absolute ones
- But actually we need for every input representation (called 'anchor') to be closer to the positive embedding than to the negative one: relative difference of distances



AP

Triplet Loss

- In FaceNet[15] the concept of triplets was used to define the Triplet Loss:

$$L_T = \frac{1}{m} \sum_{i=0}^{m-1} \max\left(0, ||h(x_i^a) - h(x_i^p)||_2^2 - ||h(x_i^a) - h(x_i^n)||_2^2 + \alpha\right)$$

  - $x_i = x_i^a$: anchor, input face
  - x_i^p: positive face (of the same ID as x_i^a)
  - x_i^n: negative face (of the different ID from x_i^a)
  - all representations are normalized: $||h(x)||_2 = 1$
  - α: hyperparameter for margin (0.2 used)

[15] F. Schroff et al. "Facenet: A unified embedding for face recognition and clustering." 2015.

Triplet selection process

- Crucial how to construct triplets (mostly negative examples) for Triplet loss

Easy triplets

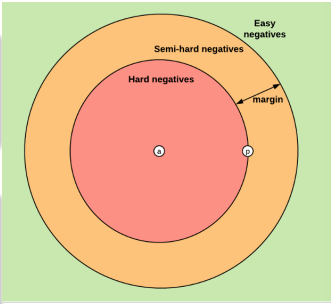
Triplets with zero loss, i.e.
$||h(x_i^a) - h(x_i^p)||_2^2 + \alpha < ||h(x_i^a) - h(x_i^n)||_2^2$

Hard triplets (used for FaceNet)

Triplets where the negative is closer to the anchor than the positive, i.e. $||h(x_i^a) - h(x_i^n)||^2 < ||h(x_i^a) - h(x_i^p)||^2$

Semi-hard triplets

Triplets where the negative is not closer to the anchor than the positive, but still having the non-zero loss, i.e.
$||h(x_i^a) - h(x_i^p)||_2^2 < ||h(x_i^a) - h(x_i^n)||_2^2 < ||h(x_i^a) - h(x_i^p)||_2^2 + \alpha$



AP

Better triplets

- Idea: to project the representations (even as a post-processing!) from arbitrary FaceID NN and to learn these projection matrices T: $h'(x) = T * h(x)$
- TSE[16] approach:

$$L_{TSE} = \frac{1}{m} \sum_{i=0}^{m-1} \max\left(0, \alpha + \langle h'(x_i^a), h'(x_i^n) \rangle - \langle h'(x_i^a), h'(x_i^p) \rangle\right)$$

- TPE[17] approach:

$$L_{TPE} = -\frac{1}{m} \sum_{i=0}^{m-1} \log \frac{e^{\langle h'(x_i^a), h'(x_i^p) \rangle}}{e^{\langle h'(x_i^a), h'(x_i^p) \rangle} + e^{\langle h'(x_i^a), h'(x_i^n) \rangle}}$$

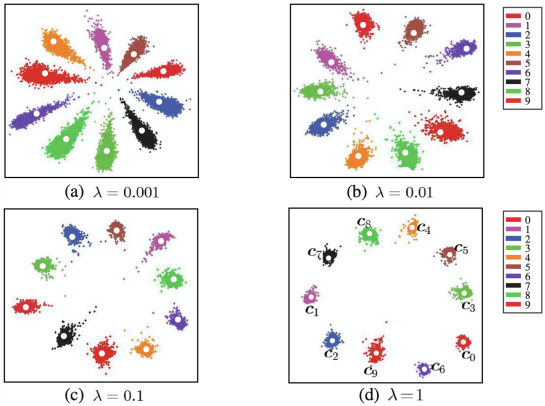
- Empirical observation: very unstable

[16] S. Sankaranarayanan et al. "Triplet similarity embedding for face verification." 2016.

[17] S. Sankaranarayanan et al. "Triplet probabilistic embedding for face verification and clustering." 2016.

Center loss[18]

- Idea: to reduce intra-variance
- Additional loss term:
  $L_C = \frac{1}{2}\sum_{i=0}^{m-1} ||h(x_i) - c_{y_i}||_2^2$
- Centers $c_i, i = 0, \ldots, K-1$ can be initialized with W_i and updated later with the fine-tuning process
- Final loss is $L_{SM} + \lambda L_c$

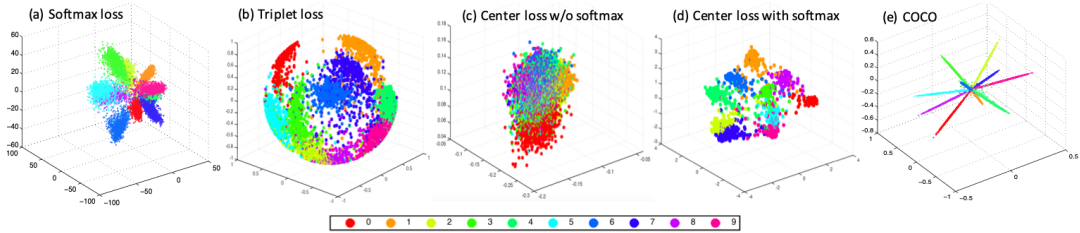


(a) $\lambda = 0.001$ (b) $\lambda = 0.01$

(c) $\lambda = 0.1$ (d) $\lambda = 1$

[18] Y. Wen et al. "A discriminative feature learning approach for deep face recognition." 2016.

SM-based and some metric-based losses comparison

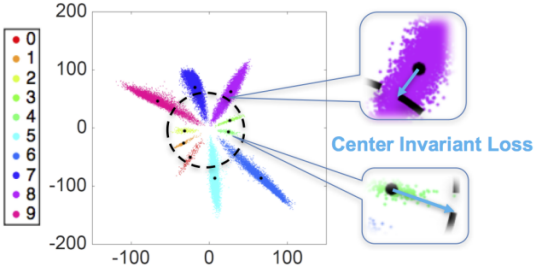


AP

Imbalance problem: Center Invariant (CI) Loss[19], Range (R) Loss[20]

- CI Idea: normalize (implicitly) class centers
- Done by additional loss term to Center Loss
- R Idea: minimize intra-class volume **and** maximize inter-class distance
- $L_{R_{intra}} = \sum_{i=0}^{K-1} \frac{r}{\sum_{j=1}^{r} \frac{1}{D_i^j}}$, where D_i^j is the j-th largest pairwise representation distance inside class i
- $L_{R_{inter}} = \max(0, m - \min_{i<j} ||c_i - c_j||_2^2)$

$$L_{CI} = \frac{1}{4} \sum_{i=0}^{m-1} \left(||c_{y_i}||_2^2 - \frac{1}{K} \sum_{j=0}^{K-1} ||c_j||_2^2 \right)$$

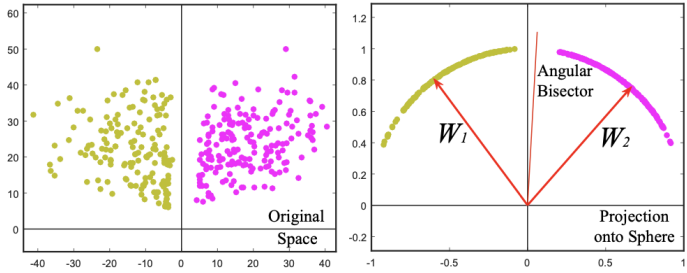


[19] Yue Wu et al. "Deep face recognition with center invariant loss." 2017.

[20] X. Zhang et al. "Range loss for deep face recognition with long-tailed training data." 2017.

Angular Loss

- **Goal**: to perform the separation not in Euclidean space of embeddings, but in the space of embedding angles θ
  - Some examples are: L-Softmax[21], A-Softmax (SphereFace)[22], AM-Softmax[23] (CosFace[24])



[21] W. Liu et al. "Large-margin softmax loss for convolutional neural networks." 2016.
[22] W. Liu et al. "Sphereface: Deep hypersphere embedding for face recognition." 2017.
[23] F. Wang et al. "Additive margin softmax for face verification." 2018.
[24] H. Wang et al. "Cosface: Large margin cosine loss for deep face recognition." 2018.

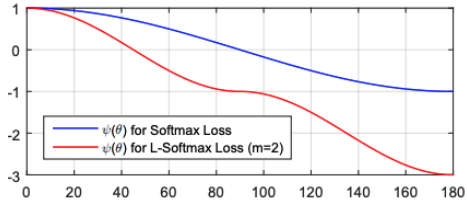
L-Softmax[25] idea

- Let's omit bias term b and reformulate the logit l: $l_i = \langle W_i, h(x) \rangle = \|W_i\| \, \|h(x)\| \cos\theta_i$, where $\theta_i \in [0, \pi]$ is the angle between projection vector W_i and representation $h(x)$
- So SM loss becomes $L_{SM}(x_i) = -\log \frac{e^{\|W_{y_i}\| \|h(x_i)\| \cos\theta_{y_i}}}{\sum_j e^{\|W_j\| \|h(x_i)\| \cos\theta_j}}$
- For binary classification with the correct class 1, the original SM forces $\langle W_1, h(x) \rangle > \langle W_2, h(x) \rangle$, i.e. $\|W_1\| \, \|h(x)\| \cos\theta_1 > \|W_2\| \, \|h(x)\| \cos\theta_2$
- Idea: let's do the task even harder: $\|W_1\| \, \|h(x)\| \cos m\theta_1 > \|W_2\| \, \|h(x)\| \cos\theta_2$, $\theta_1 \in [0, \frac{\pi}{m}]$, $m \in \mathbb{N}$
- In this case we'll automatically get the needed $\|W_1\| \, \|h(x)\| \cos\theta_1 > \|W_2\| \, \|h(x)\| \cos\theta_2$
  - just because $\|W_1\| \, \|h(x)\| \cos\theta_1 \geq \|W_1\| \, \|h(x)\| \cos m\theta_1 > \|W_2\| \, \|h(x)\| \cos\theta_2$

[25] W. Liu et al. "Large-margin softmax loss for convolutional neural networks." 2016.

L-Softmax

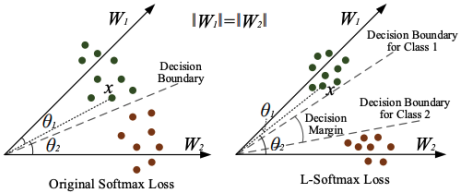
- The new L-SM: $L_{L-SM}(x_i) = -\log \frac{e^{\|W_{y_i}\|\|h(x_i)\|\psi(\theta_{y_i})}}{e^{\|W_{y_i}\|\|h(x_i)\|\psi(\theta_{y_i})} + \sum_{j \neq y_i} e^{\|W_j\|\|h(x_i)\|\cos\theta_j}}$
  - Where $\psi(\theta) = \cos m\theta, \theta \in [0, \frac{\pi}{m}]$,
  - $\psi(\theta) = D(\theta), \theta \in (\frac{\pi}{m}, \pi]$, $D(\frac{\pi}{m}) = \cos m\frac{\pi}{m}$, $D(\theta)$ – monotonically decreasing function
  - Let's use $\psi(\theta) = (-1)^k \cos m\theta - 2k, \theta \in [\frac{k\pi}{m}, \frac{(k+1)\pi}{m}], k \in [0, m-1]$
  - In practice authors provided the relaxed strategy ($SM \to L-SM$) gradually reducing parameter λ from a large value (1000) to a small value (5):
    $\psi(\theta) = \frac{(-1)^k \cos m\theta - 2k + \lambda\cos\theta}{\lambda+1}, \theta \in [\frac{k\pi}{m}, \frac{(k+1)\pi}{m}], k \in [0, m-1]$



AP

L-Softmax: decision rule

- Suppose the norms of projection vectors are the same: $\|W_1\| = \|W_2\| \Rightarrow$ the initial SM rule is $\theta_1 < \theta_2$ (case $\|W_1\| \neq \|W_2\|$ is more complicated, but generally similar)
- For the L-SM case, it means $m\theta_1 < \theta_2$
  - And the same for the second class: $m\theta_2 < \theta_1$
- Suppose α is the angle between W_1 and W_2. It leads to the following:
  - Decision boundary for the class 1: $m\theta_1 = \theta_2$, $\theta_1 + \theta_2 = \alpha \Rightarrow \theta_1 = \alpha\frac{1}{m+1}$
  - Decision boundary for the class 2: $\theta_2 = \alpha\frac{1}{m+1}$
- Note: decision boundaries are different for classes 1 and 2 (cf. to SM)
- Decision margin is $\alpha_M = \alpha - (\theta_1 + \theta_2) = \alpha\frac{m-1}{m+1}$ (e.g. if $\alpha = 180°, m = 2 \Rightarrow \alpha_M = 60°$)
- Recall: SVM margin



AP

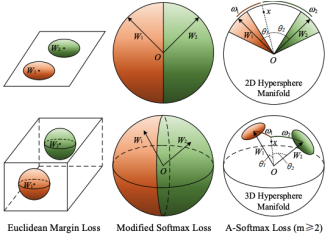
A-Softmax[27]: normalization

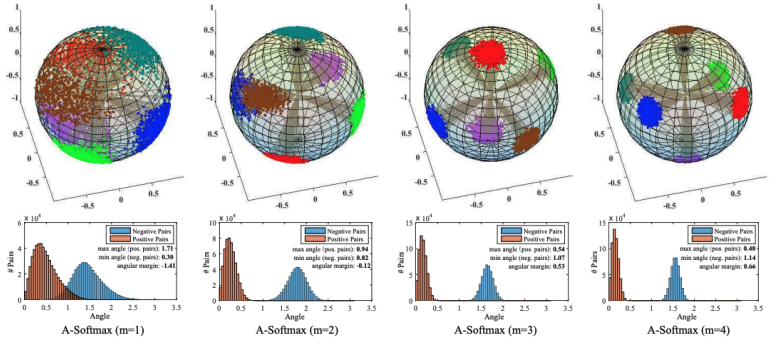
- Explicitly normalize projection vectors $\|W_i\| = 1$ and zero biases $b_i = 0 \quad \forall i$: it is called '**Modified SM Loss**'
- Introduce angular margin ($m\theta$): '**A-SM Loss**'
- Binary case:
  - Max intra-class angle is $\alpha_{intra} = \frac{\alpha}{m-1} + \frac{\alpha}{m+1}$ (depending on whether the representation is lying inside or outside angle α)
  - Min inter-class angle is $\alpha_{inter} = \alpha\frac{m-1}{m+1}$
  - $\alpha_{intra} \leq \alpha_{inter} \Rightarrow m \geq 2 + \sqrt{3}$
- For multi-class case $m \geq 3$[26]
  - For experiments makes sense to use $m = 4$

[26] Prove it (use assumption of W_i uniform distribution)

[27] W. Liu et al. "Sphereface: Deep hypersphere embedding for face recognition." 2017.

A-Softmax: illustration



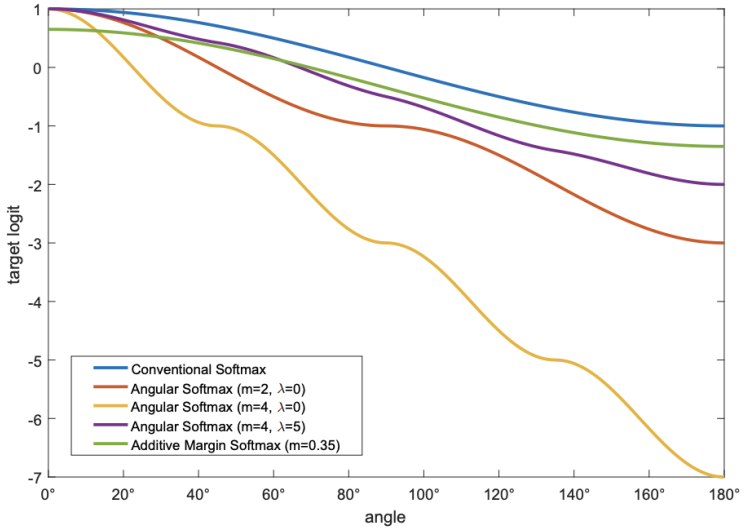


AM-Softmax[28]

- Additive Margin SM idea: add margin, but additive (not multiplicative) and outside of $\cos\theta$: $\psi(\theta) = \cos\theta - m$
- Normalization: like NormFace, normalize both representations $h(x)$ and projection W_i and scale both of them to l, so as $s = l^2 = \|W_i'\| \, \|h'(x)\|$
- AM Loss: $L_{AM-SM}(x_i) = -\log \frac{e^{s\psi(\theta_{y_i})}}{e^{s\psi(\theta_{y_i})} + \sum_{j \neq y_i} e^{s\cos\theta_j}}$
- In practice: use $s = 30, m = 0.4$, no any relaxation strategy (no hyperparam λ)

[28] F. Wang et al. "Additive margin softmax for face verification." 2018.

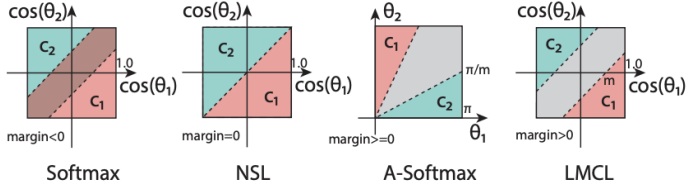
AM-Softmax: visualization



AP

CosFace[30]

- The very same idea as for AM-SoftMax, but with a grain of theory
- Lower bound of SM Loss is $-\log P \geq \log(1 + (K-1)e^{-\frac{K}{K-1}s})$ (refer to NormFace) $\Rightarrow$ $s \geq \frac{K}{K-1} \log \frac{P(K-1)}{1-P}$
- Bounds for cosine margin: $0 \leq m \leq \frac{K}{K-1}$[29] (in practice $m = 0.35$ was used)

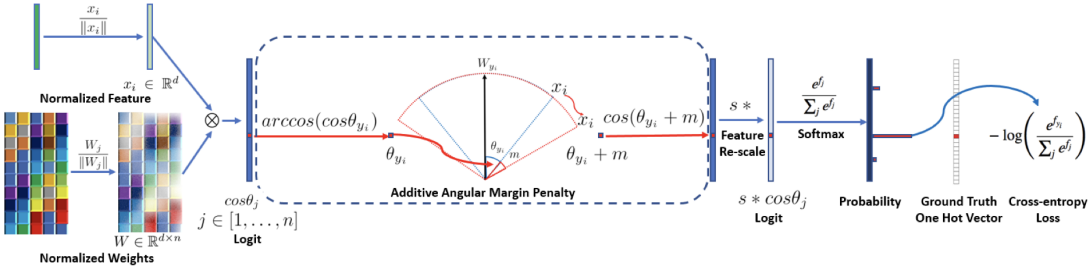


[29] Prove it. Hint: use $0 \leq m \leq 1 - \max_{i \neq j} W_i W_j$

[30] H. Wang et al. "Cosface: Large margin cosine loss for deep face recognition." 2018.

Arcface: best of Angular Losses

- Arcface[31] is most probably the most successful implementation of Angular Loss idea



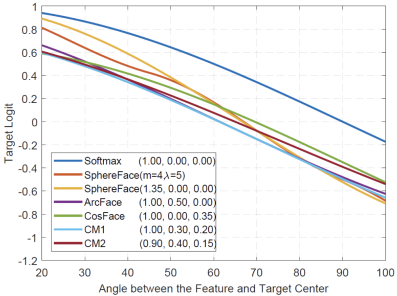
[31] J. Deng et al. "Arcface: Additive angular margin loss for deep face recognition." 2019.

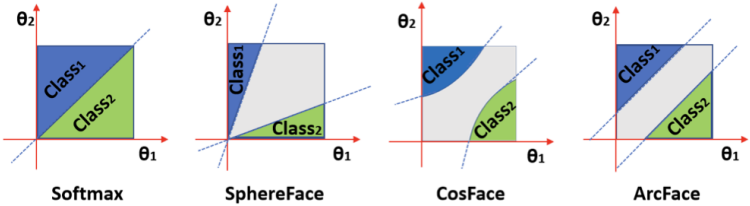
Arcface: details

- Idea: additive margin **inside** $\cos\theta$: $\psi(\theta) = \cos(\theta + m)$ (in practice $m = 0.5$ is used)
- **ArcFace** Loss: $L_{Arcface}(x_i) = -\log \frac{e^{s\psi(\theta_{y_i})}}{e^{s\psi(\theta_{y_i})} + \sum_{j \neq y_i} e^{s\cos\theta_j}}$ (in practice $s = 64$ is used)
- And the final step: let's combine all margins!
- The function for **Combined Margin** Loss: $\psi(\theta) = \cos(m_1\theta + m_2) - m_3$

AP

Final Loss comparison





AP

Takeaway notes

1. Representations learned are one of the most valuable outcomes of Deep Learning and Neural Nets in particular
2. Given the correct representation, the final classifier is (surprise!) just a usual linear discriminate function
3. Normalization of representation and projection vector is important
4. Metric learning is unstable, but can be really inevitable (for Contrastive learning w/o labels)
5. Angular-based margins now are the major and dominant forms of separation for representations (angular analogy of SVM)
6. Overviewing the historical perspective, we can better understand the reasoning behind the design choices

AP

Thank you!