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Background

Metric Learning = Distance Metric Learning = “Similarity” Learning

(maximize the inter-class variations and minimize the intra-class variations)

Common method for face recognizing

Comparing to kNN, k-means, SVM:

Focus on the data characteristics of the task rather than data themselves, more robust

Comparing to classical classification network:

No need for manually adding new classes and training the network again

(CVPR2021)SetMargin loss applied to deep keystroke biometrics with circle packing interpretation

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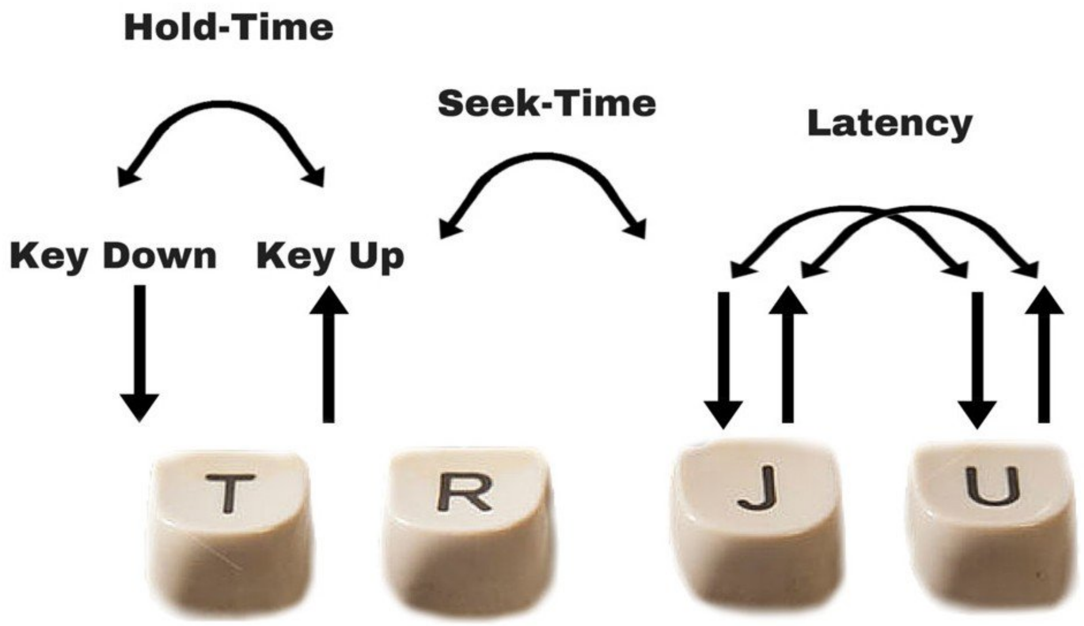
Keystroke biometrics

Keystroke biometrics : the behavior of typing

Keystroke biometric systems : fixed-text and free-text(classes used in learning and inference are disjoint)

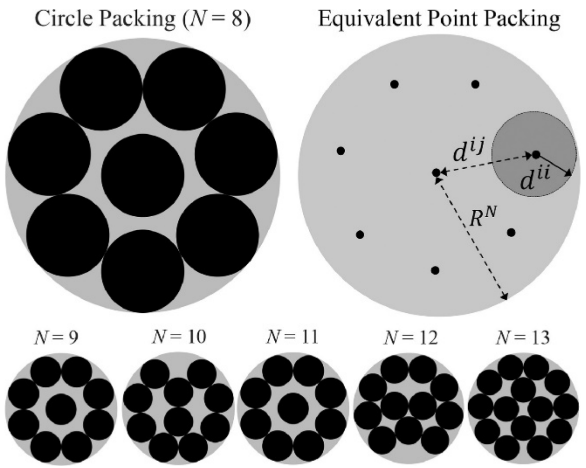


Motivation and Contribution

1. The performance in free-text scenarios × in the fixed-text √ during the last decade
2. More recently, the availability of large scale databases with millions of keystroke samples → in free-text scenarios √
3. Improve further the state-of-the-art results of deep keystroke biometrics
4. Introduce a new loss function for free-text (instead of prevailing fixed-text)
5. Identify the membership of the input data to a class unseen during learning

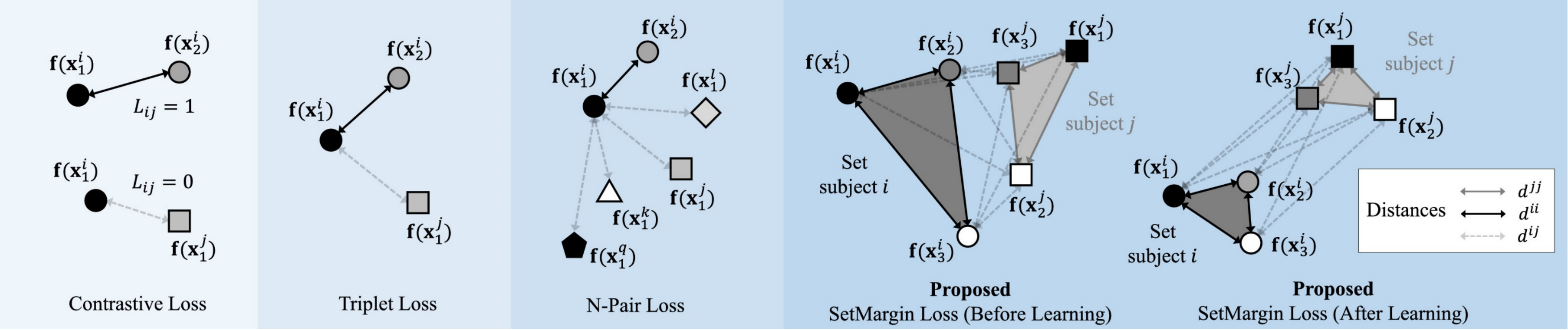
The Circle Packing problem for DML

1. The minimum distance between circles is maximized
2. Thus minimize the radius of the outer circle
3. →Point Packing problem by replacing circles by their centers
4. Specially useful in open-set classification problems : maximize inter-class distances (for new classes)



Method(SM-L)

1. pairs of sets instead of pairs of samples
2. SetMargin Contrastive Loss (SM-CL) and SetMargin Triplet Loss (SM-TL)



Method(SM-L)

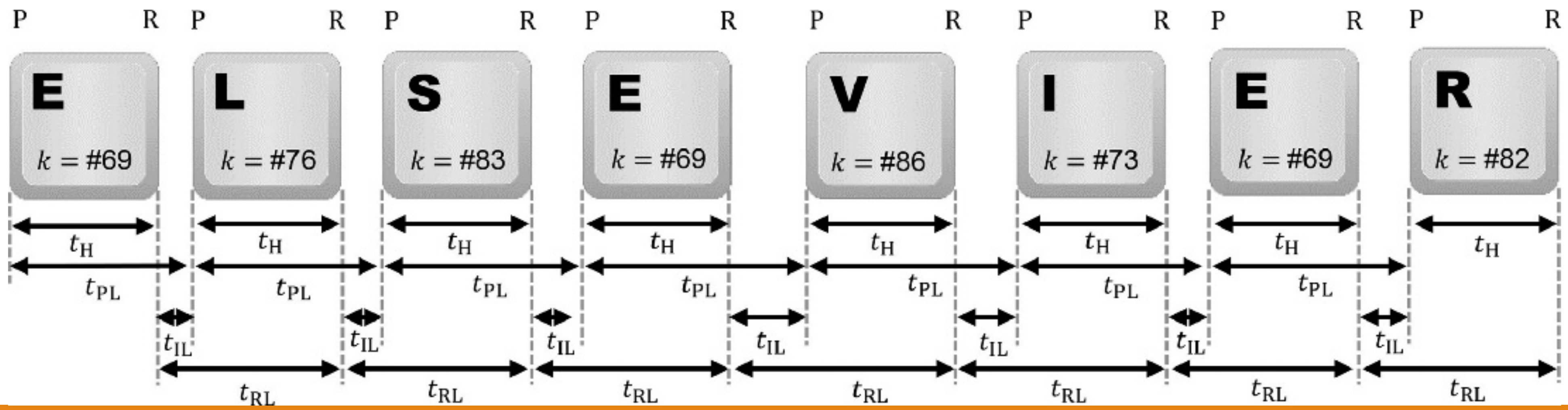
1. pairs of sets instead of pairs of samples
2. SetMargin Contrastive Loss (SM-CL) and SetMargin Triplet Loss (SM-TL)

$$\mathcal{L}_{SM-CL} = \sum_{k=1}^{G^i} \sum_{q=k+1}^{G^i} \frac{d^2\left(\mathbf{x}_k^i, \mathbf{x}_q^i\right)}{2} + \beta \sum_{k=1}^{G^i} \sum_{q=1}^{G^j} \frac{\max^2\left\{0, \alpha - d\left(\mathbf{x}_k^i, \mathbf{x}_q^j\right)\right\}}{2}$$

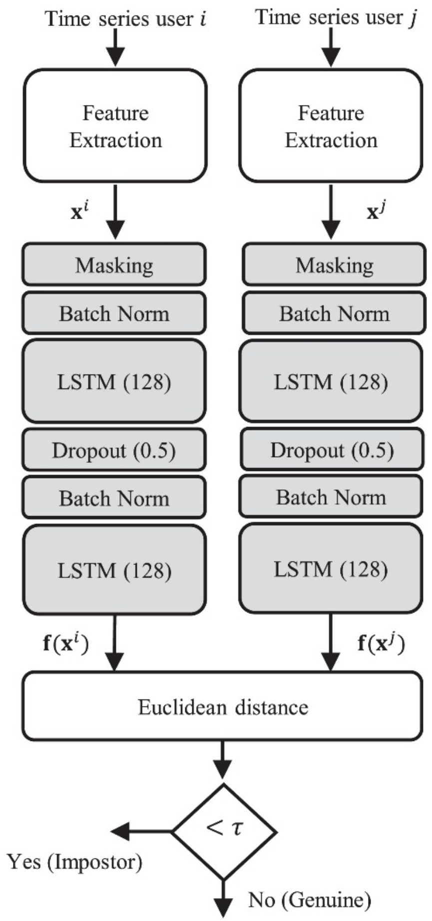
$$\mathcal{L}_{SM-TL} = \sum_{k=1}^{G^i} \sum_{q=k+1}^{G^i} \sum_{l=1}^{G^j} \left(\max\left\{0, d^2\left(\mathbf{x}_k^i, \mathbf{x}_q^i\right) - d^2\left(\mathbf{x}_k^i, \mathbf{x}_l^j\right) + \alpha\right\} + \max\left\{0, d^2\left(\mathbf{x}_k^j, \mathbf{x}_q^j\right) - d^2\left(\mathbf{x}_k^j, \mathbf{x}_l^i\right) + \alpha\right\}\right)$$

Dataset

1. Aalto University Dataset that comprises keystroke sequences from 168,000 subjects
2. All subjects in the database completed 15 sessions with a different sentence in each session(each sentence 3~70 words)
3. Input (adjusted) : Hold Latency(t_H), Inter-key Latency(t_{IL}), Release Latency(t_{RL}), Press Latency(t_{PL}), and the keycodes(cut the end or add zero pad, 50 words heuristically)



Framework(TypeNet)



Additionally, each LSTM layer has a dropout rate of 0.2.

Batch: 256 set pairs (random)

Epoch: 500 batches per

Converge: 40 epochs

Output: array (size 128)

Distance between two keystroke sequences:

$$d_{i,j} = \frac{1}{T} \sum_{g=1}^{T} \left\| \mathbf{f}\left(\mathbf{x}_g^i\right) - \mathbf{f}\left(\mathbf{x}_q^j\right) \right\|$$

Experiment

Method	Rank-1	Rank-5	Rank-20
Digraph [8]	0.5%	0.9%	1.2%
POHMM [6]	6.1%	10.3%	13.8%
TypeNet: *Contrastive Loss* [7]	17.8%	31.5%	38.9%
TypeNet: *DeepLDA* [40]	34.2%	63.2%	84.2%
TypeNet: *Softmax*	37.9%	64.9%	84.4%
TypeNet: *Triplet Loss* [10]	38.2%	68.2%	88.5%
TypeNet: *Quadruplet Loss* [12]	38.6%	68.7%	87.9%
TypeNet: *N-Pair Loss* [11]	38.7%	67.7%	87.0%
TypeNet: *SM-CL, G=3*	31.0%	59.9%	82.7%
TypeNet: *SM-CL, G=6*	37.5%	67.0%	86.8%
TypeNet: *SM-CL, G=9*	36.7%	65.8%	86.3%
TypeNet: *SM-TL, G=3*	39.4%	68.3%	88.1%
TypeNet: *SM-TL, G=6*	45.8%	73.9%	91.0%
TypeNet: *SM-TL, G=9*	45.3%	72.4%	89.5%

Method	EER
Digraph [8]	43.1%
POHMM [6]	24.7%
TypeNet: *Contrastive Loss* [7]	5.40%
TypeNet: *DeepLDA* [40]	4.21%
TypeNet: *Softmax*	10.8%
TypeNet: *Triplet Loss* [10]	2.20%
TypeNet: *Quadruplet Loss* [12]	2.33%
TypeNet: *N-Pair Loss* [11]	2.51%
TypeNet: *SM-CL, G=6*	2.42%
TypeNet: *SM-TL, G=6*	1.85%

(CVPR2021) Triplet Contrastive Learning for Brain Tumor Classification

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Motivation

1. Learning robust deep embeddings for brain tumor type classification given a segmented tumor image
2. the recent progress in learning efficient embeddings for face recognition and retrieval
3. leverage three techniques : contrastive learning for pre-training, data augmentation over rare cases, and triplet loss for learning efficient embeddings

The unique challenge in brain tumor MRI datasets

1. The scarcity of labelled data
2. The unlabeled MRI scans are generally more readily available

Method

1. Pre-train the model using a contrastive learning module(SimCLR) adapted for MRI scans
2. Artificially increase the size of the labelled dataset by incorporating a rare-case data augmentation module to generate new data for rare tumor classes
3. Apply triplet loss for training the final model to learn efficient embeddings

Dataset(labeled)

1. a labelled dataset acquired by (Anonymous Company), which contains 27 different classes of T2-weighted brain MRI scans
2. In total, 4,962 different MRI scans, split to 70% training, 10% validation, 20% testing
3. Each MRI scan example is resized to 128x128 pixels, with a depth component of size 12

Type	Train	Val	Test
0	662	94	189
1*	37	5	10
2	162	23	46
3	342	48	97
4	163	23	46
5	231	32	65
6	140	19	39
7*	32	4	8
8*	7	1	2

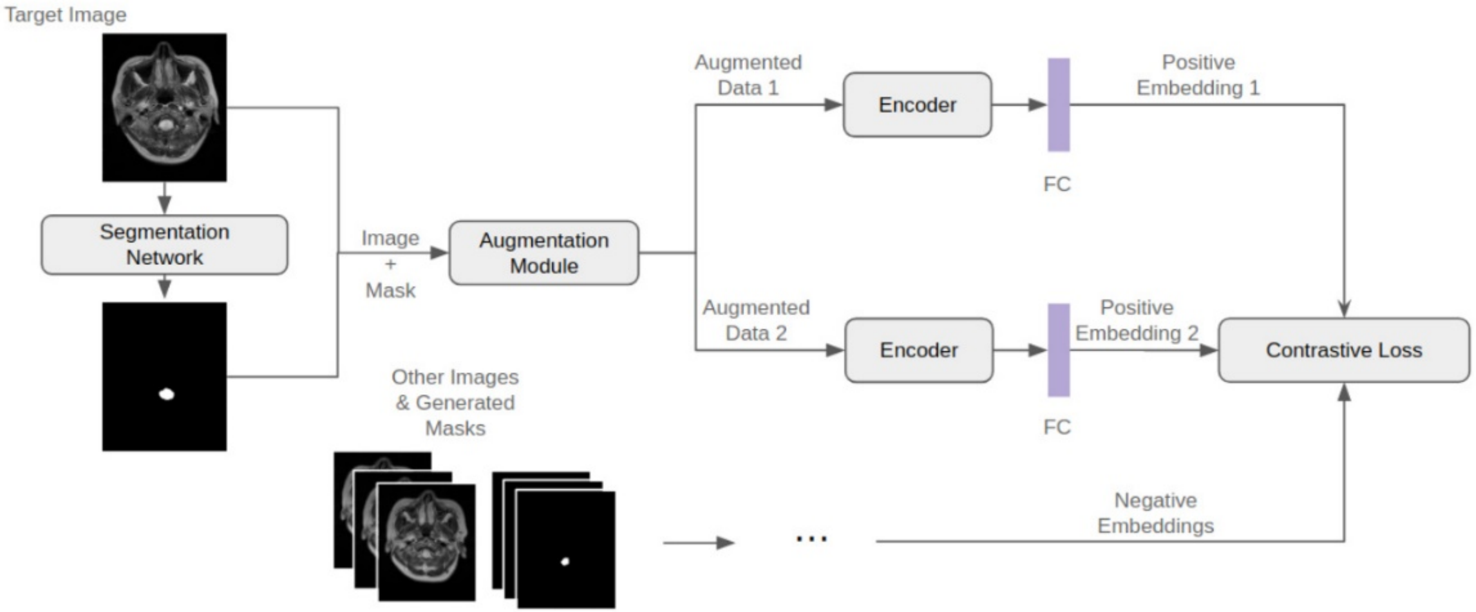
Type	Train	Val	Test
9	120	17	34
10*	38	5	10
11*	32	4	8
12*	32	4	9
13*	21	3	6
14	61	8	17
15*	8	1	2
16*	5	1	1
17	101	14	28

Type	Train	Val	Test
18*	35	5	10
19*	27	3	7
20*	29	3	7
21*	16	2	4
22	64	8	17
23	642	91	183
24	161	23	46
25	201	28	57
26	124	17	35
Total	3493	486	983

Dataset(unlabeled)

1. a separate unlabeled dataset (lacking both ground truth tumor classes and segmentation masks) for evaluating our contrastive pre-training approach
2. It consists of around 22K randomly selected MRI tumor images with unknown labels
3. use a separate pre-trained model to generate pseudo segmentation masks for these labels

Framework(Contrasive pre-training)



1. data augmentation module adjusted to MRI images

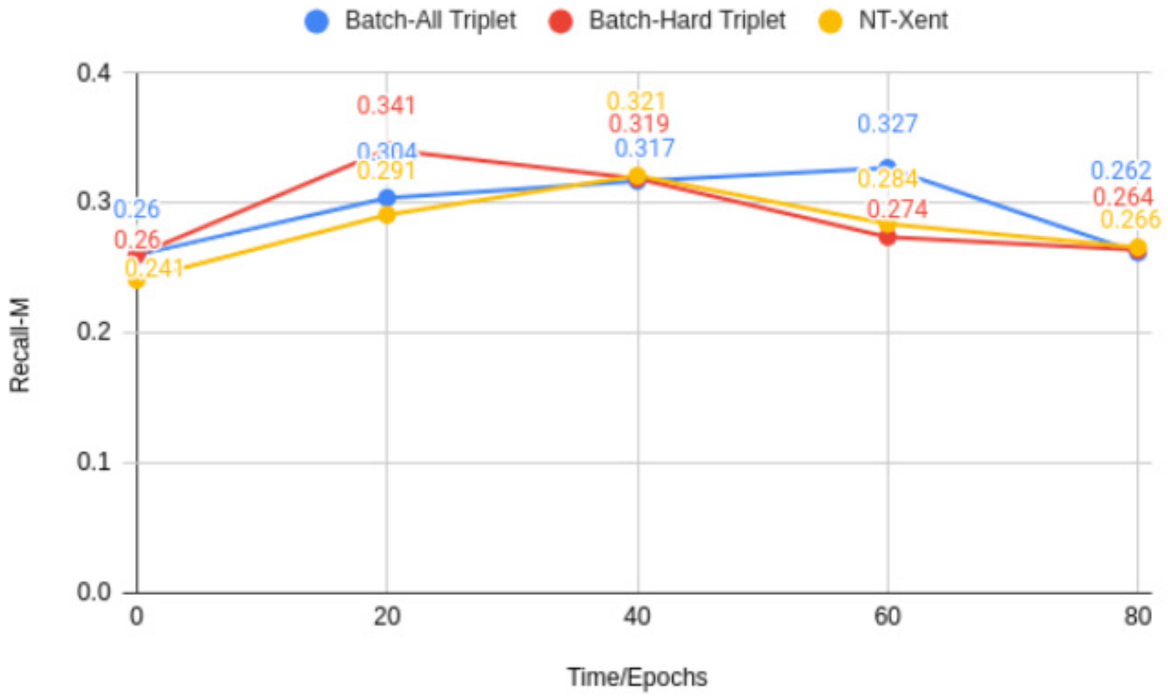
2. a pseudo ground truth segmentation mask using a pre-trained tumor segmentation model

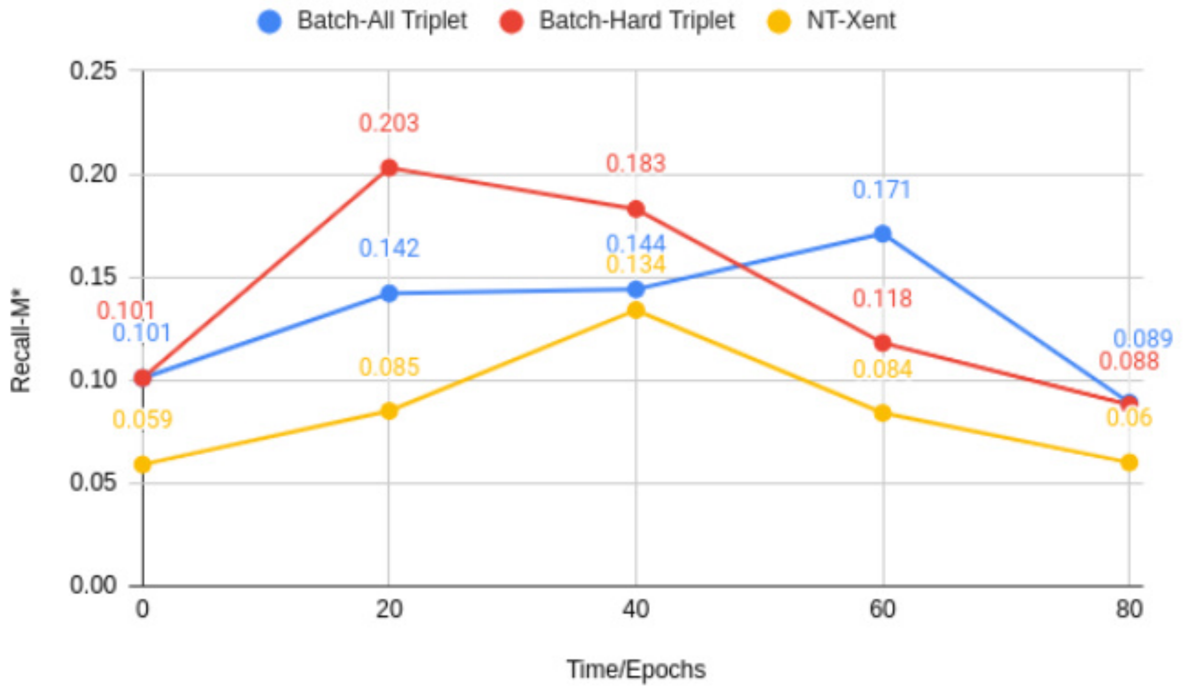
3. Add loss: Batch-Hard Triplet Loss and Batch-All Triplet Loss

$$L_{BH} = \sum_{t}^{T} \sum_{k}^{K} \left(\max_{j=1..K} \left\| E^{t,k} - E^{t,j} \right\| - \min_{\substack{i=1..T \\ j=1..K \\ i \neq t}} \left\| E^{t,k} - E^{i,j} \right\| + \alpha \right)$$

$$L_{BA} = \sum_{t}^{T} \sum_{k}^{K} \sum_{i \neq t}^{T} \sum_{j \neq k}^{K} \left\| E^{t,k} - E^{i,j} \right\| + \alpha$$

Experiment


Batch-All Triplet
Batch-Hard Triplet
NT-Xent
0.4
0.3
0.2
0.1
0.0
Recall-M
0.26
0.26
0.241
0.341
0.304
0.291
0.321
0.319
0.317
0.327
0.284
0.274
0.262
0.264
0.266
0
20
40
60
80
Time/Epochs


Batch-All Triplet
Batch-Hard Triplet
NT-Xent
0.25
0.20
0.15
0.10
0.05
0.00
Recall-M*
0.101
0.101
0.059
0.203
0.142
0.085
0.183
0.144
0.134
0.171
0.118
0.084
0.089
0.088
0.06
0
20
40
60
80
Time/Epochs

Experiment

Contrastive Loss	**Augment**	**Training Loss**	**Recall**$_\mu$	**Recall**$_M$	**Recall**$^*_M$	**Rank-5**	**Acc**$_{\text{clf}}$
-	-	CrossEntropy	0.435	0.241	0.0588	0.561	0.440
-	-	Interval [15]	0.458	0.233	0.022	0.590	0.463
NT-Xent	-	CrossEntropy	**0.511**	0.291	0.0849	0.610	0.505
-	Yes	CrossEntropy	0.391	0.244	0.0901	0.649	0.398
NT-Xent	Yes	CrossEntropy	**0.502**	0.284	0.0821	0.574	0.501
BATriplet	-	CrossEntropy	0.433	0.245	0.0495	0.555	0.417
BHTriplet	-	CrossEntropy	0.498	0.269	0.103	0.583	0.502
-	-	BHTriplet	0.414	0.260	0.101	0.667	-
-	Yes	BHTriplet	0.491	0.338	0.168	**0.705**	-
NT-Xent	-	BHTriplet	0.177	0.0562	0.011	0.427	-
BATriplet	-	BHTriplet	0.465	0.304	0.142	0.681	-
BHTriplet	-	BHTriplet	0.465	**0.341**	**0.203**	0.696	-
BATriplet	Yes	BHTriplet	0.484	0.295	0.0978	**0.704**	-
BHTriplet	Yes	BHTriplet	0.478	0.299	0.118	0.695	-

Thanks