Class imbalance and Metric Learning

Charles Ollion - Olivier Grisel

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- 2-1000 classes ; 1000+ samples per class

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What if I have 1M classes and 10 samples / class?

Outline

Multi-labeling and Sampling strategies

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Metric Learning and siamese networks

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Triplet Loss and advanced techniques

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Dealing with Imbalance

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Evaluation must be very rigorous (the test set should represent the **true distribution** of data and labels)

Multilabel classification

Build a **binary classifier for each class** but with shared activations on hidden layers. Easily adapted from classic classification:

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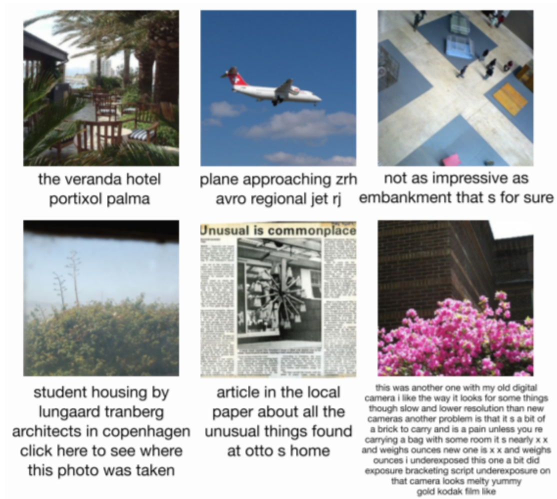
Problem : costly to label images exhaustively for ALL possible tags

Weak supervision



Joulin, Armand, et al. "Learning visual features from large weakly supervised data." ECCV, 2016

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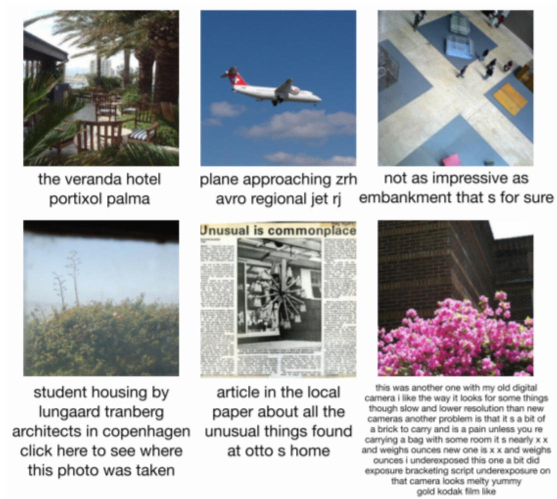

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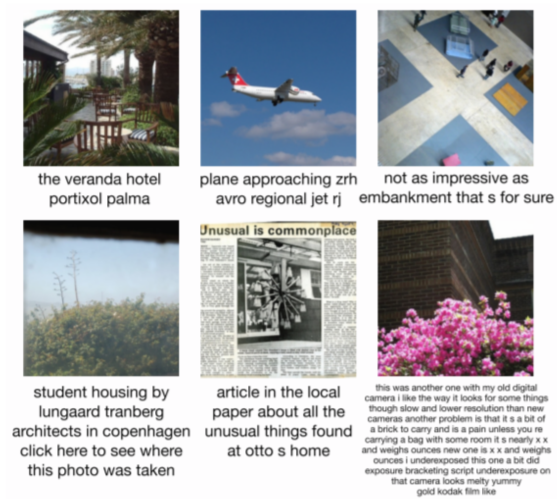

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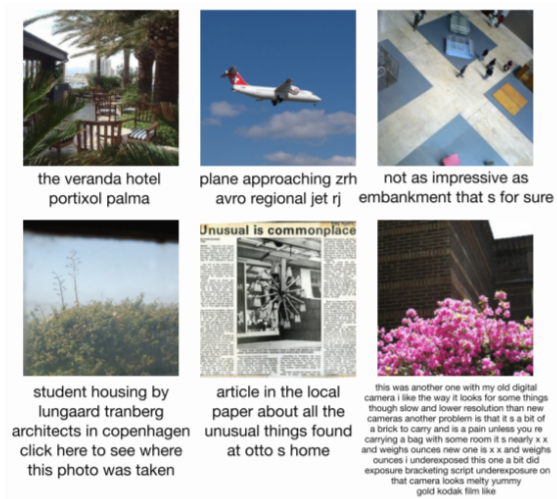

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- After stopword removal, **importance sampling** of positive labels
- Do not compute the full softmax, **randomly sample negatives**

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Weak supervision

Mahajan, Dhruv, et al. "Exploring the Limits of Weakly Supervised Pretraining." Technical Report, 2018

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Inference tricks

You may train with a **softmax**, and do multilabel inference with a **sigmoid**

Garrigues, P., Farfade, S., Izadinia, H., Boakye, K., & Kalantidis, Y. (2016). Tag prediction at flickr: a view from the darkroom. NIPS workshop on large scale CV 2016

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Measure **precision/recall** per class on a fully labeled test set.

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Metric Learning & Siamese networks

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Mahalanobis distance Metric Learning may be used to build distances, but are limited to linear projections, which won't be enough for fine-grained image analysis

Weinberger, Kilian Q., John Blitzer, and Lawrence K. Saul. "Distance metric learning for large margin nearest neighbor classification." Advances in neural information processing systems. 2006.

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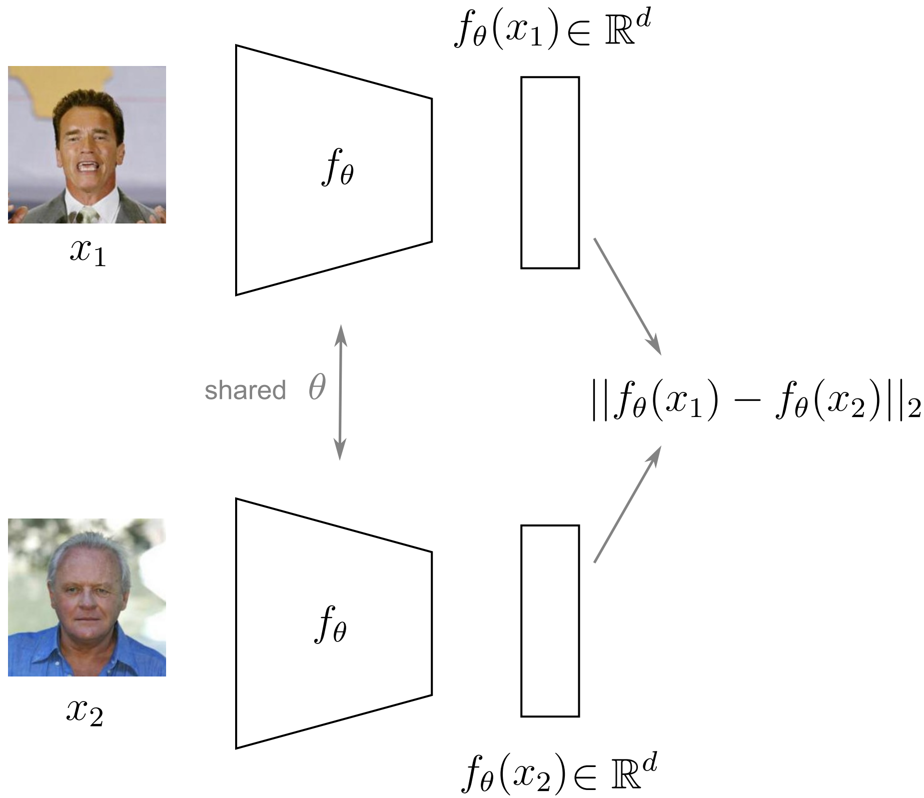
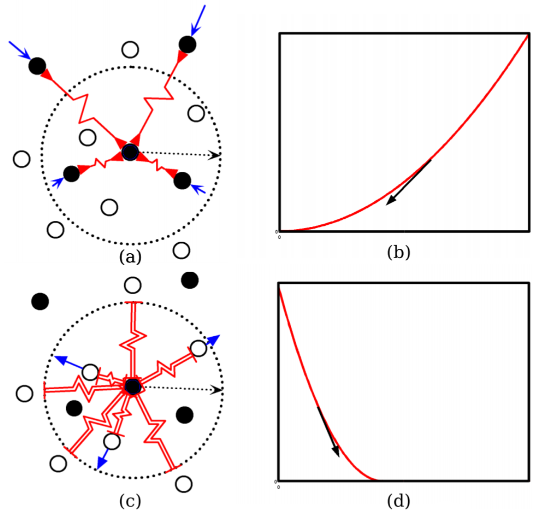
Training f_θ is also called **representation learning**

Siamese networks



Chopra, Sumit, Raia Hadsell, and Yann LeCun. "Learning a similarity metric discriminatively, with application to face verification." CVPR 2005.

Loss function



Contrastive loss: Pushes together same class pairs, and further away different class ones, up to a margin.

$$L_{\text{contrastive}}(Y, D) = \frac{1}{2}(1 - Y)D^2 + \frac{1}{2}Y \max\,(0, m - D)^2$$

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Alternative loss functions

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Simpler:regression after cosine similarity

Training

- sample positive pairs (x_i, x_j), with (i, j) of same class
- sample negative pairs (x_i, x_j), with (i, j) of different classes

Taigman et. al., 2014. DeepFace closing the gap to human level performance

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Important to **craft batches carefully** (balance positive and negative, group positives together). Many negatives are *easy* (closer than margin) & don't contribute to the loss.

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YouTube Faces Database

3,425 videos of 1,595 different people averaging 181 frames per video

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Cars196, CUB200, Online Products

16,185 images of 196 classes of cars

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120,053 images, 22,634 Online Products (classes) from eBay.com. 5.3 images per class

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α **margin** typically small positive number $(0.2, 0.5, \cdot)$

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- Sample a minibatch of triplets $\{(x^a, x^+, x^-)_i\}$
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- Compute the gradients through the 3 networks
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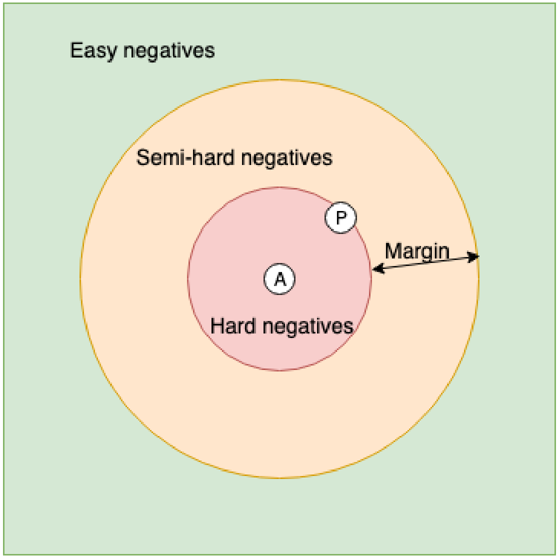

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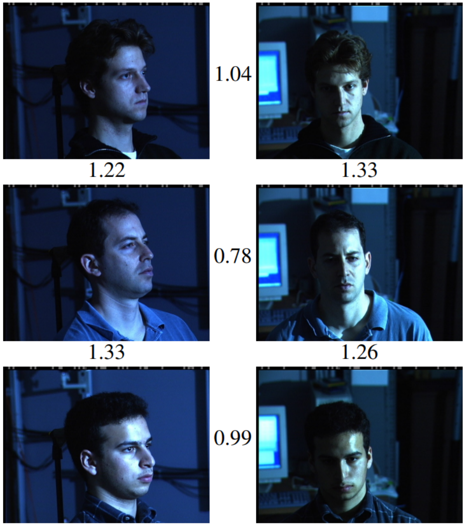
Triplets results



Schroff, Florian, et al. Facenet: A unified embedding for face recognition and clustering, CVPR 2015. = hard negative mining and semi hard

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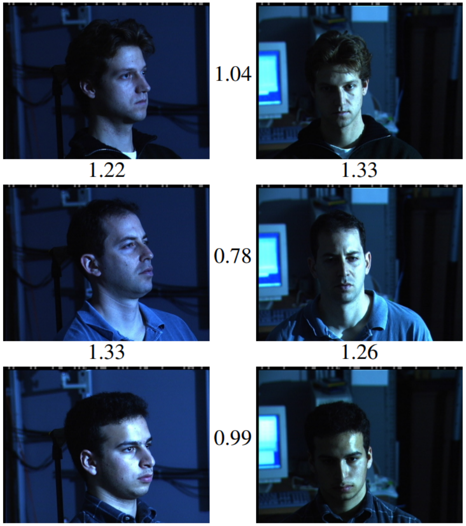
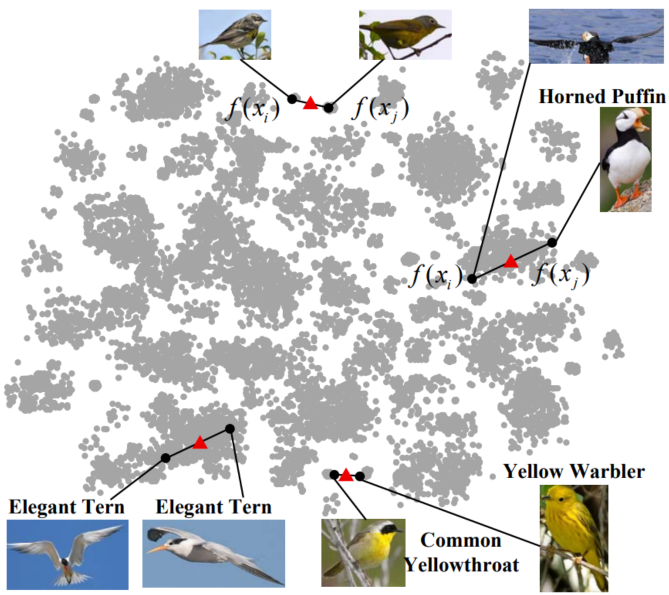
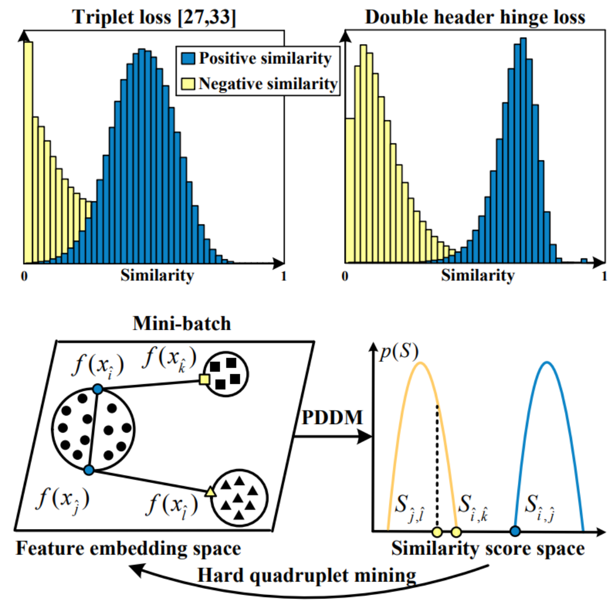


- A threshold is computed on test set (1.2)
- Best model achieves 99.6% verification accuracy on LFW
- Face alignment is critical!

Schroff, Florian, et al. Facenet: A unified embedding for face recognition and clustering, CVPR 2015. = hard negative mining and semi hard

Quadruplet loss





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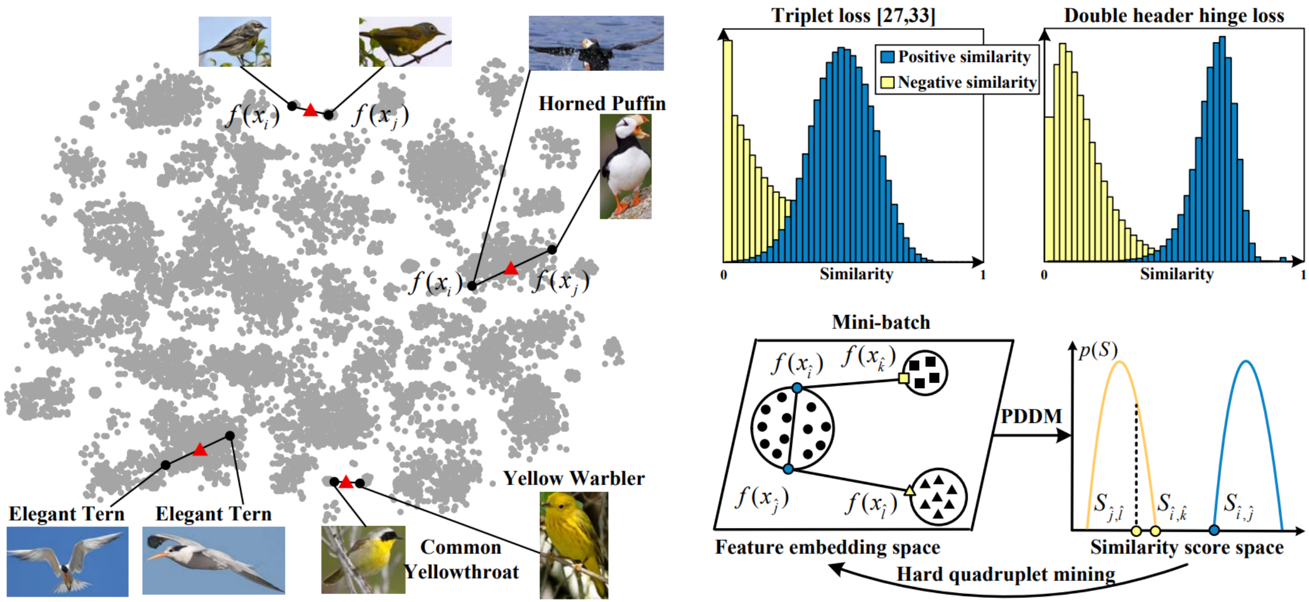

intraclass distance in a high-density region may be larger than the **interclass distance** in low-density regions

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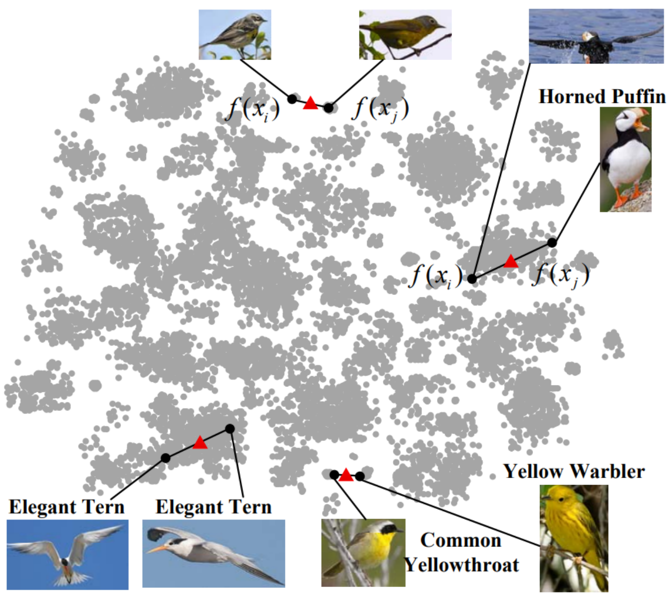

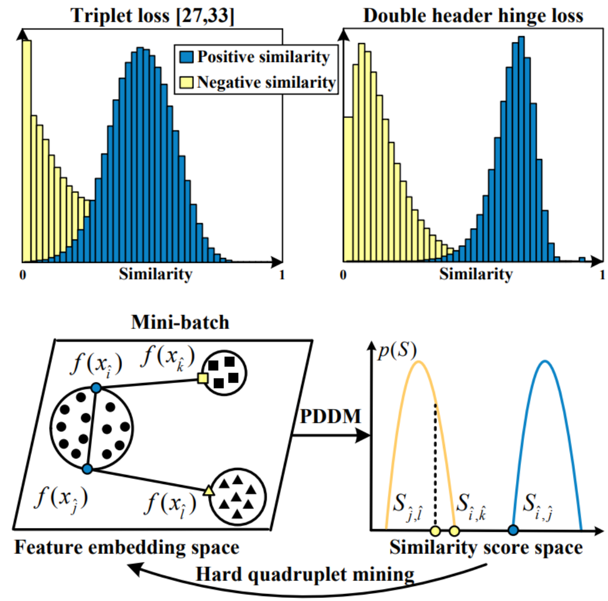

Position-Dependent Deep Metric (PDDM) depends on two points + position of mean (red triangle)

Huang, Chen, et al. Local similarity-aware deep feature embedding, NIPS 2016

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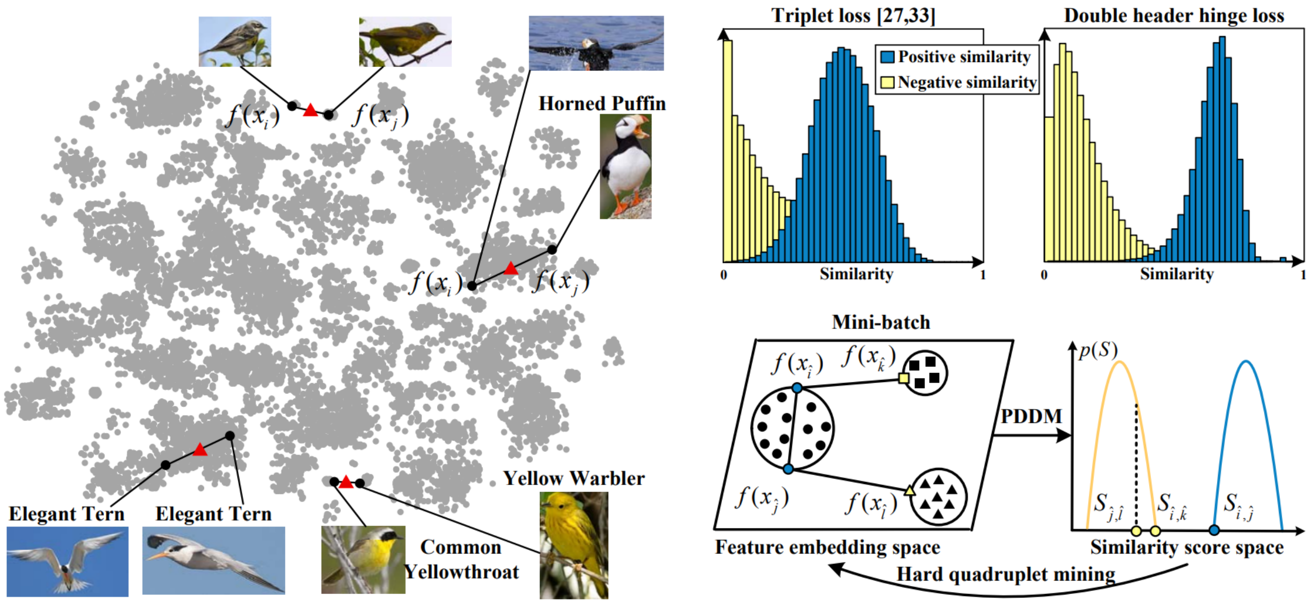

Sample a hard quadruplet (i, j) most dissimilar positive sample, and k and l are hard negatives

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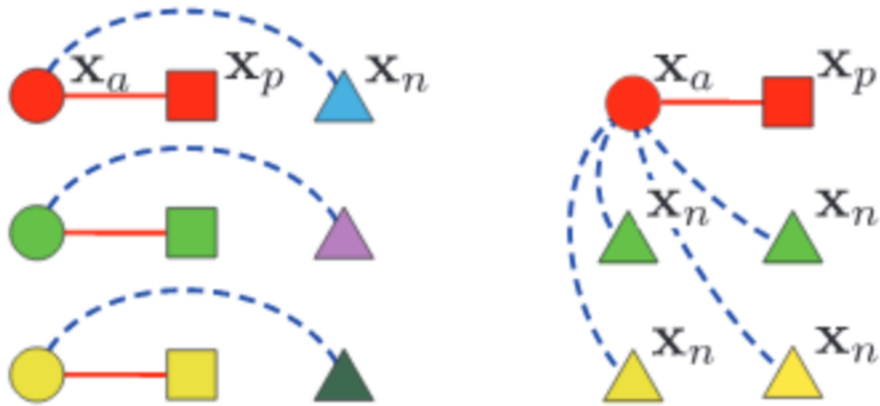
N-pair loss



- Generalization of triplets to n-uplets
- Samples pair of similar examples, negatives are all other samples in the batch

Sohn, Kihyuk. "Improved Deep Metric Learning withMulti-class N-pair Loss Objective", NIPS 2016

Results

	CUB-200-2011						CARS196					
K	1	2	4	8	16	32	1	2	4	8	16	32
Contrastive [1]	26.4	37.7	49.8	62.3	76.4	85.3	21.7	32.3	46.1	58.9	72.2	83.4
Triplet [27, 33]	36.1	48.6	59.3	70.0	80.2	88.4	39.1	50.4	63.3	74.5	84.1	89.8
LiftedStruct [29]	47.2	58.9	70.2	80.2	89.3	93.2	49.0	60.3	72.1	81.5	89.2	92.8
PDDM+Triplet	50.9	62.1	73.2	82.5	91.1	94.4	46.4	58.2	70.3	80.1	88.6	92.6
PDDM+Quadruplet	**58.3**	**69.2**	**79.0**	**88.4**	**93.1**	**95.7**	**57.4**	**68.6**	**80.1**	**89.4**	**92.3**	**94.9**

Metric: **Recall @K**

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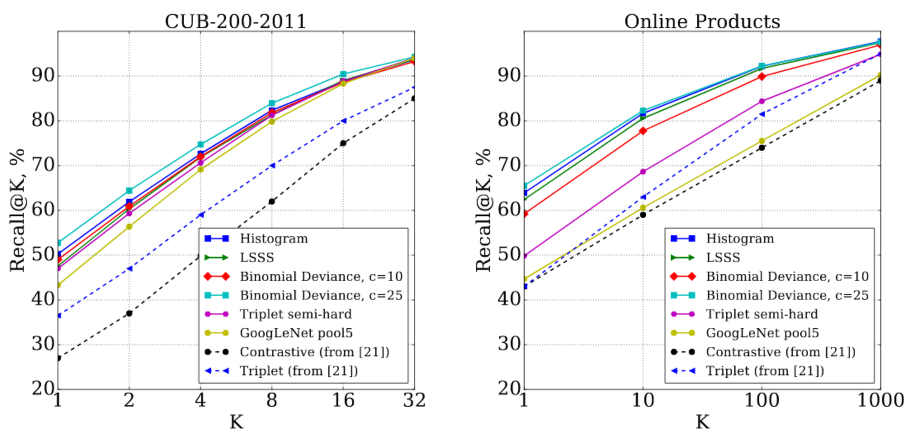
Triplet [27, 33]	36.1	48.6	59.3	70.0	80.2	88.4	39.1	50.4	63.3	74.5	84.1	89.8
LiftedStruct [29]	47.2	58.9	70.2	80.2	89.3	93.2	49.0	60.3	72.1	81.5	89.2	92.8
PDDM+Triplet	50.9	62.1	73.2	82.5	91.1	94.4	46.4	58.2	70.3	80.1	88.6	92.6
PDDM+Quadruplet	**58.3**	**69.2**	**79.0**	**88.4**	**93.1**	**95.7**	**57.4**	**68.6**	**80.1**	**89.4**	**92.3**	**94.9**

Metric: **Recall @K**



Getting started

Available open source implementations / pretrained models:

- Openface https://cmusatyalab.github.io/openface/
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Commercial recognition systems are trained on a large datasets like 10/100 million images

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Beforehand, precompute representations of your 10 photos

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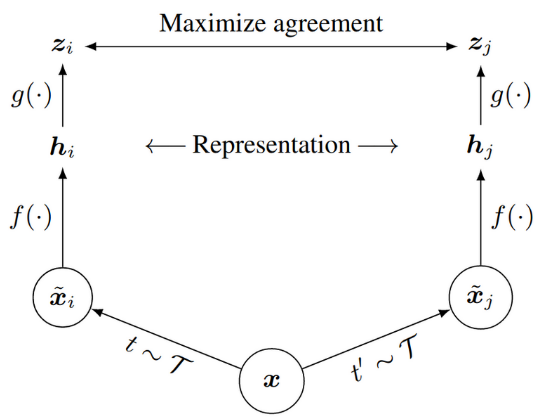
Deploying Verification models e.g. Iphone FaceID:

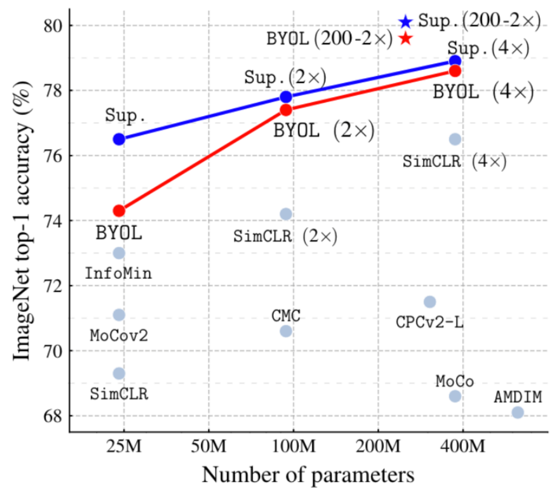
Beforehand, precompute representations of your 10 photos

At test time, compute representation of the photo, then compute similarities with the 10 representations

If a similarity is within a predefined threshold then Unlock!

Self-supervised learning





[SimCLR](#) uses a contrastive loss on pairs of heavily augmented images vs independent images in the batch.

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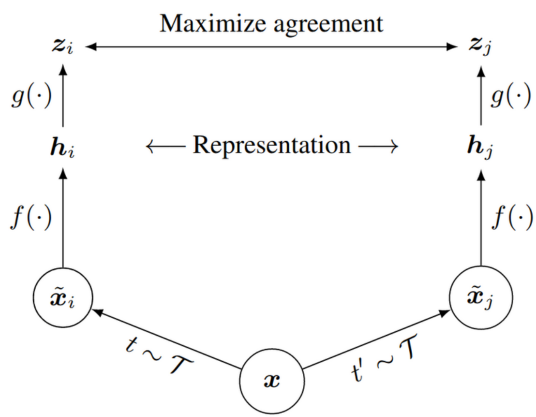

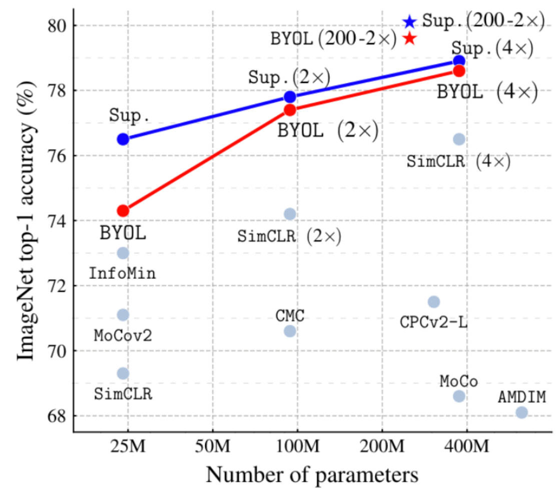

SimCLR uses a contrastive loss on pairs of heavily augmented images vs independent images in the batch.

BYOL can even do away with the negative terms with an asymmetric architecture.

Take Aways on classification

- For most cases, use a **classifier with softmax**
- If you have many classes, and/or strong class imbalance use **representation learning**
- both can give useful embeddings for clustering / low shot learning

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Use of **simulations** for generating data esp localisation / segmentation data (GTA V...)

Lab 09: back here in 15 min!