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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Metric Learning and siamese networks

Triplet Loss and advanced techniques

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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:

```
# ...
x = Convolution2D(2048, 3)(x)
x = GlobalAveragePooling2D()(x)
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Problem : costly to label images exhaustively for ALL possible tags

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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Score reflects the posterior of a tag being present in an image, e.g. $p(dog|image)$

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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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A verification system can be implemented as a similarity measure. If it's really good, useful for recognition.

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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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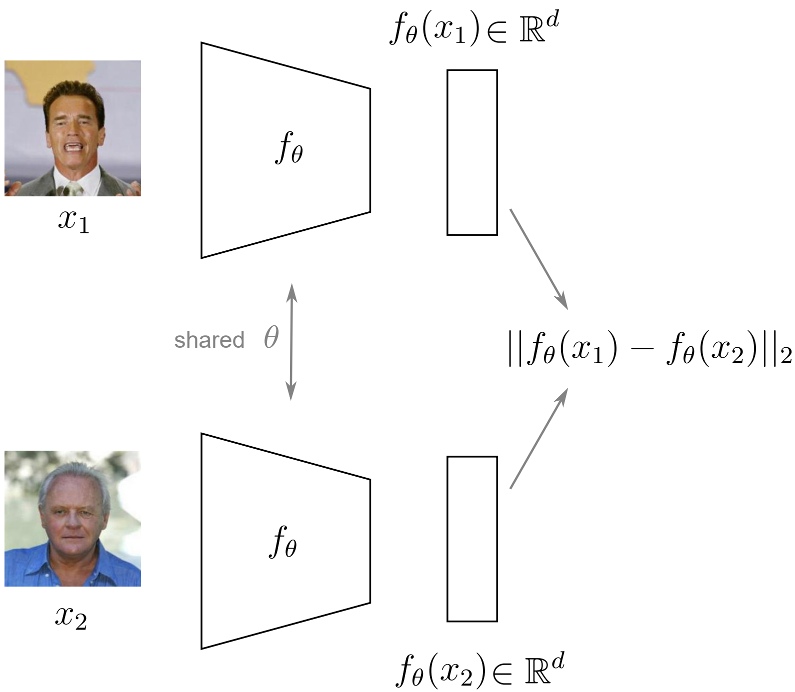
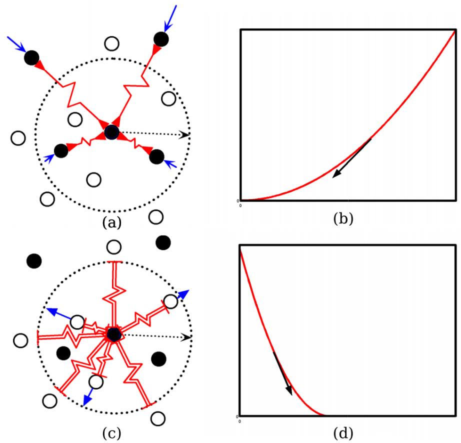
Training f_θ is also called **representation learning**

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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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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Dataset Face verification

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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

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

Triplet Loss

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We compute f_θ for each of these 3 images

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

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minimize $||f(x^a) - f(x^+)||_2 - ||f(x^a) - f(x^-)||_2 + \alpha$

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$$l(x^a, x^+, x^-) =$$

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- Sample a minibatch of triplets $\{(x^a, x^+, x^-)_i\}$
- Forward pass on all 3 networks using f_θ
- Compute $\sum_i l((x^a, x^+, x^-)_i)$

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Hard negative sampling

After a few epochs, If (x^a, x^+, x^-) are chosen randomly, it will be easy to satisfy the inequality.

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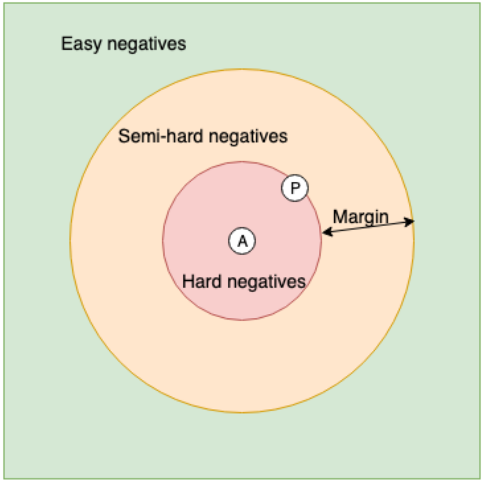

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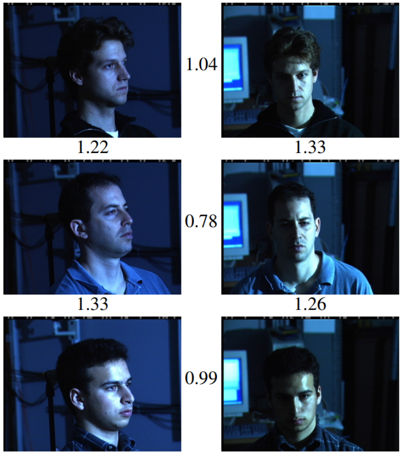

Schroff, Florian, et al. Facenet: A unified embedding for face recognition and clustering, CVPR 2015. = hard negative mining and semi hard

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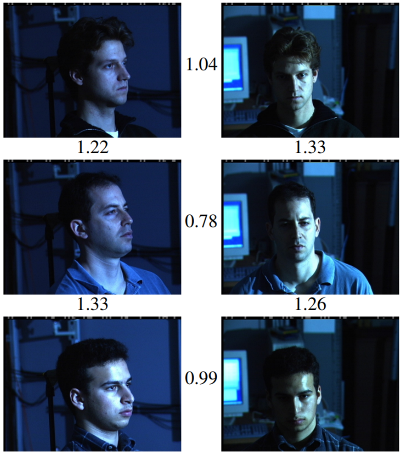

- A threshold is computed on test set (1.2)
- Best model achieves 99.6% verification accuracy on LFW
- Face alignment is critical!

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Model in production

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Build as light as possible model, both in terms of memory footprint and computing cost

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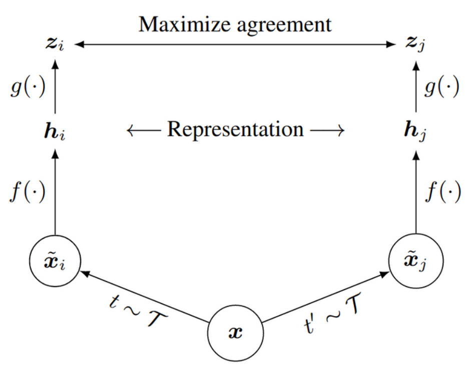
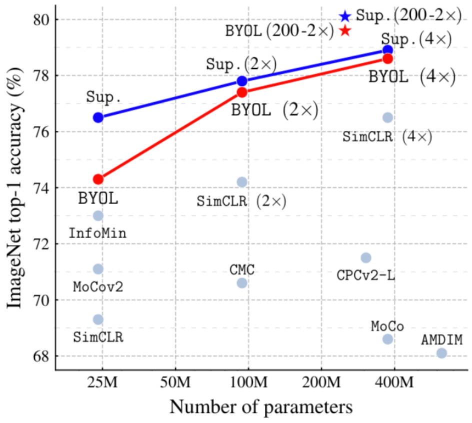
At test time, compute representation of the new photo, then compute similarities with the 10 representations

If a similarity is within a predefined threshold then Unlock!

Self-supervised learning





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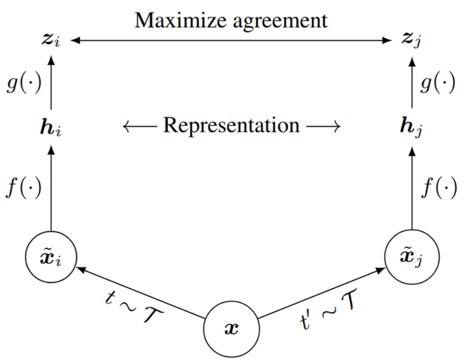

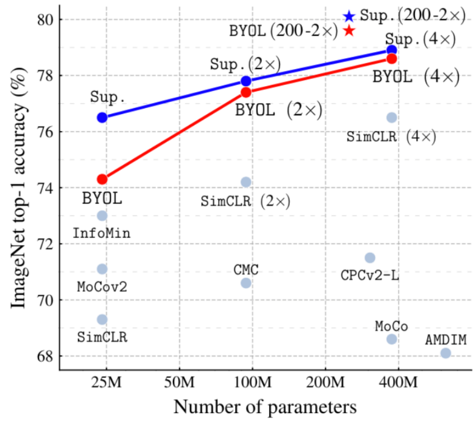

[SimCLR](#) uses a contrastive loss on pairs of heavily augmented images vs independent images in the batch.

[BYOL](#) and [data2vec](#) can even do away with the negative terms.

Take Aways on classification

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- Use **ImageNet pre-trained features** in most cases
- If you have many many unlabeled images, self-supervised learning can be an alternative
- Very active area of research!