LESS DATA

Deep Learning for Computer Vision

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https://arthurdouillard.com/deepcourse

Few-Shot Learning

Few-Shots Learning

[LFW: Labeled Face in the Wild]

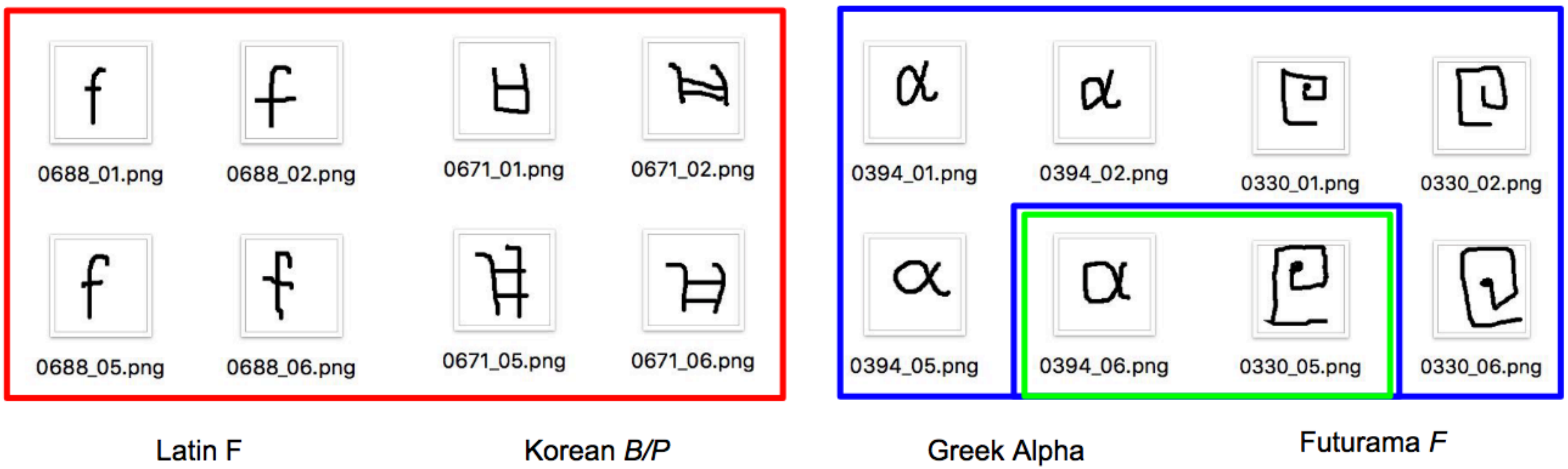
[Omniglot]

[Kaggle's Humpback Whale identification]

Few-Shots Learning

1. Learn to classify the few labeled samples in the **background set**
2. With a a few labeled samples in **support set**, classify the **query set**

Training: Testing:



Number of labeled samples / class in background set: **K-shots**

Number of classes in query set: **N-ways**

Metric Learning

A huge, potentially growing number of classes.

Less than a dozen labeled samples per class.

Discriminative model is impossible.

What if we learn a metric instead?

Metric Learning

Distance:

$$d(x_1, x_2) = \|f(x_1) - f(x_2)\|_2 \in \mathbb{R}^+$$

Similarity:

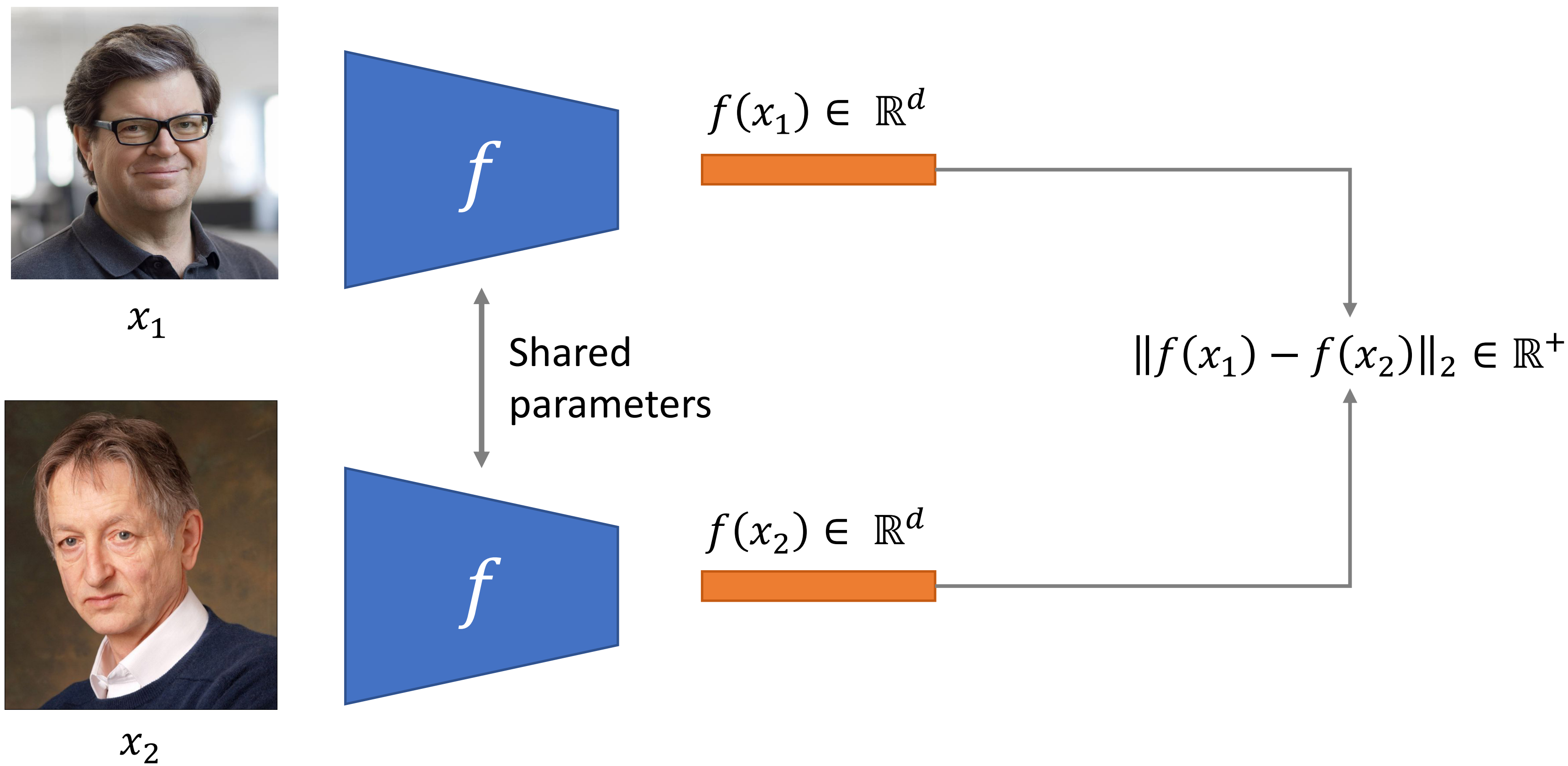
$$s(x_1, x_2) = \cos\big(f(x_1), f(x_2)\big) \in [-1, +1]$$

With $f(x) \in \mathbb{R}^d$ a features extractor (e.g. ConvNet).

Given two images of the class, we want:
- Minimize distance
- Maximize similarity

Given two images of different classes, we want:
- Maximize distance
- Minimize similarity

Siamese Network

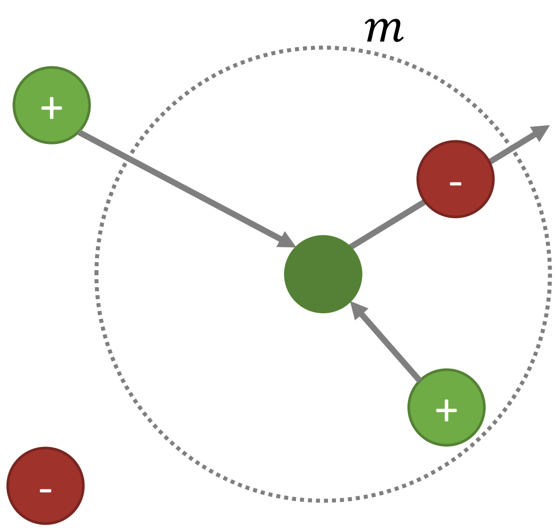


[Chopra et al. CVPR 2005]

Contrastive Loss

$$\boldsymbol{D} = \|f(x_1) - f(x_2)\|_2 \in \mathbb{R}^+$$

$$\mathcal{L}_{contrastive}(\boldsymbol{y}, \boldsymbol{D}) = \frac{1}{2}(1 - \boldsymbol{y})\boldsymbol{D}^2 + \frac{1}{2}\boldsymbol{y}\max(m - \boldsymbol{D}, 0)^2$$



Weaknesses of Pairwise Models

- The margin m may be hard to tune, especially because distributions can change through training

- A double-margin may improve to avoid collapsing all positive samples together

- Try to learn an absolute distance between images

Triplet Network

We want to learn **relative distance** between samples

Given an anchor x_a, we want to have a small distance with a positive (same class) x_+:

$$\min \|f(x_a) - f(x_+)\|_2$$

And maximize with a negative (different class) x_-:

$$\max \|f(x_a) - f(x_-)\|_2$$

Therefore:

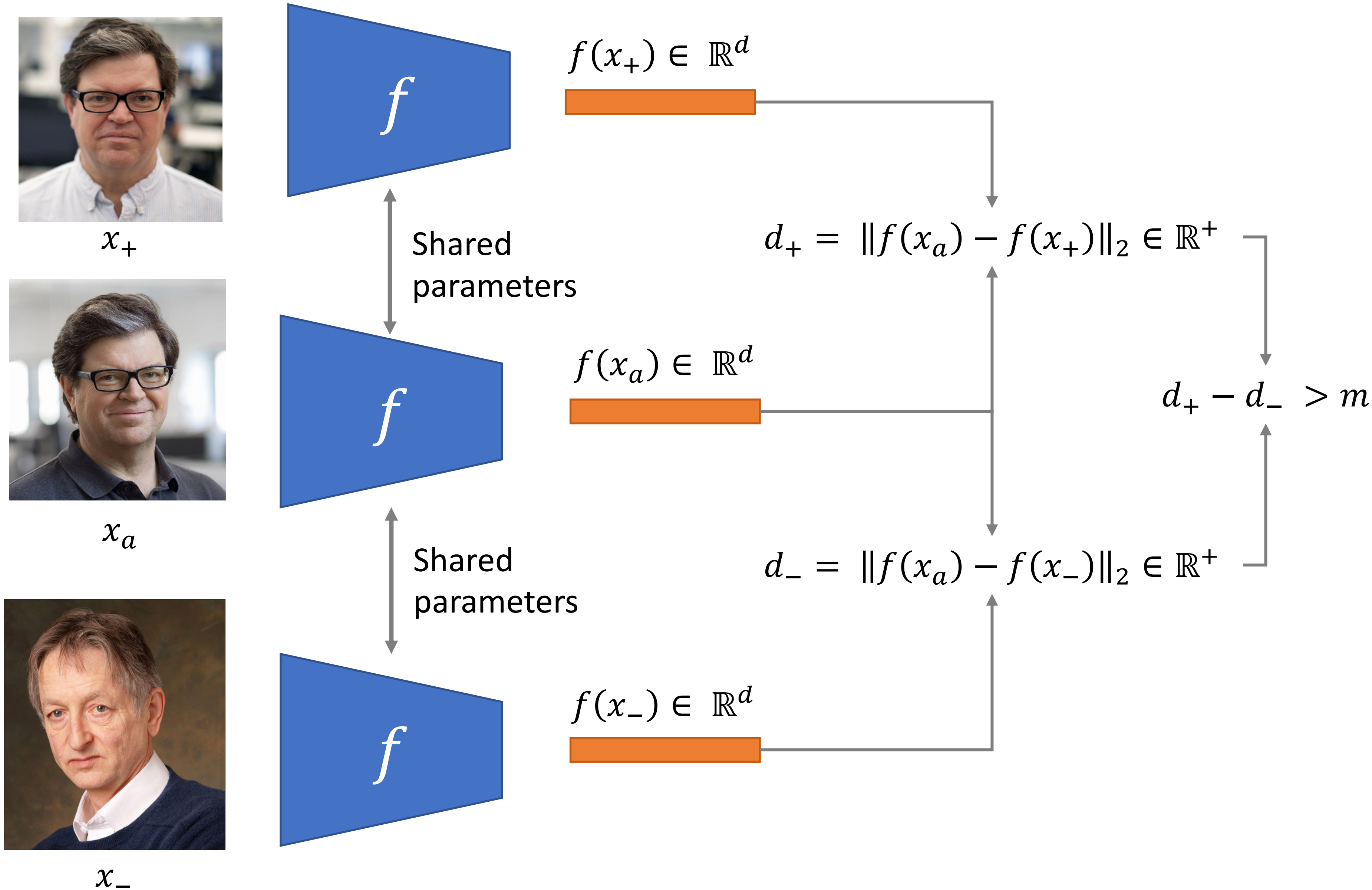
$$\|f(x_a) - f(x_+)\|_2 \; > \; \|f(x_a) - f(x_-)\|$$
$$\|f(x_a) - f(x_+)\|_2 \; - \|f(x_a) - f(x_-)\| \; > 0$$

Add a margin m to ensure extra separability:

$$\|f(x_a) - f(x_+)\|_2 \; - \|f(x_a) - f(x_-)\| \; > m$$

[Hoffer et al. SIMBAD 2015]

Triplet Network



Hard Negative Mining

Most triplets are easy.

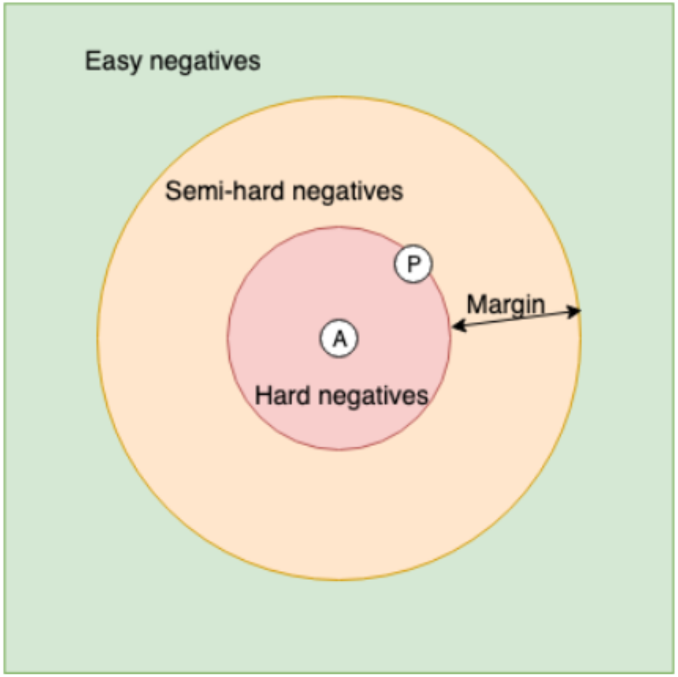
We want to sample either:

Hard negatives:

$$\|f(x_a) - f(x_+)\|_2 > \|f(x_a) - f(x_-)\| + m$$

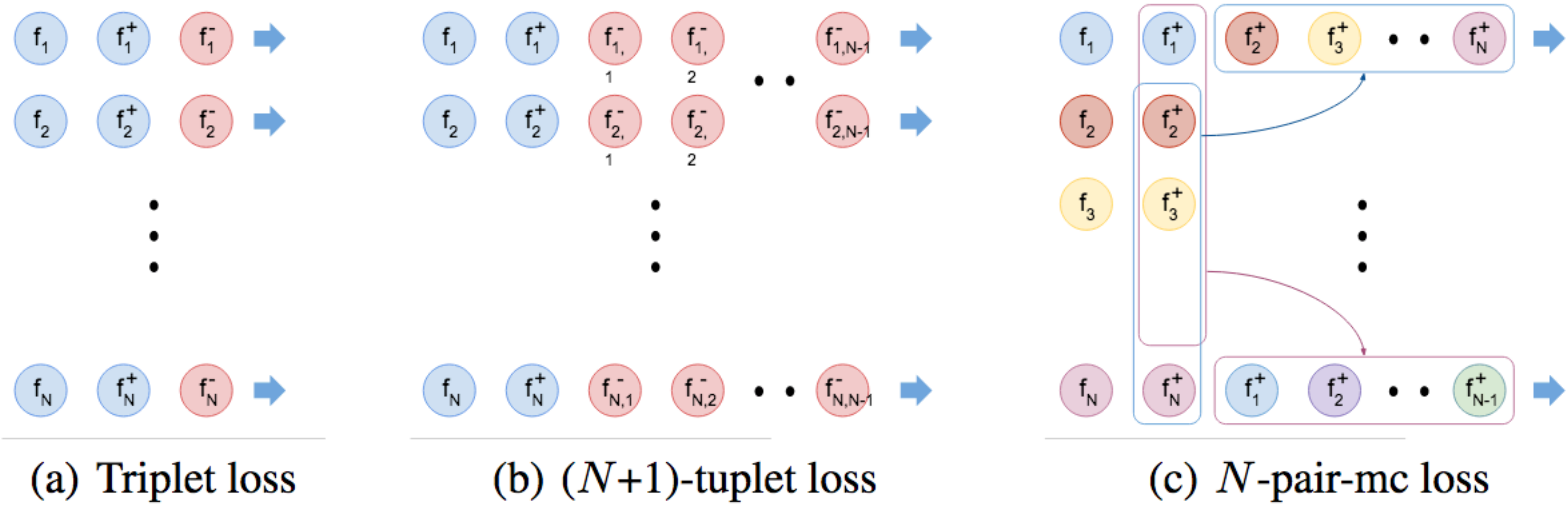
Semi-Hard negatives:

$$\|f(x_a) - f(x_+)\|_2 > \|f(x_a) - f(x_-)\|$$



Pretty much essential to have SotA performance!

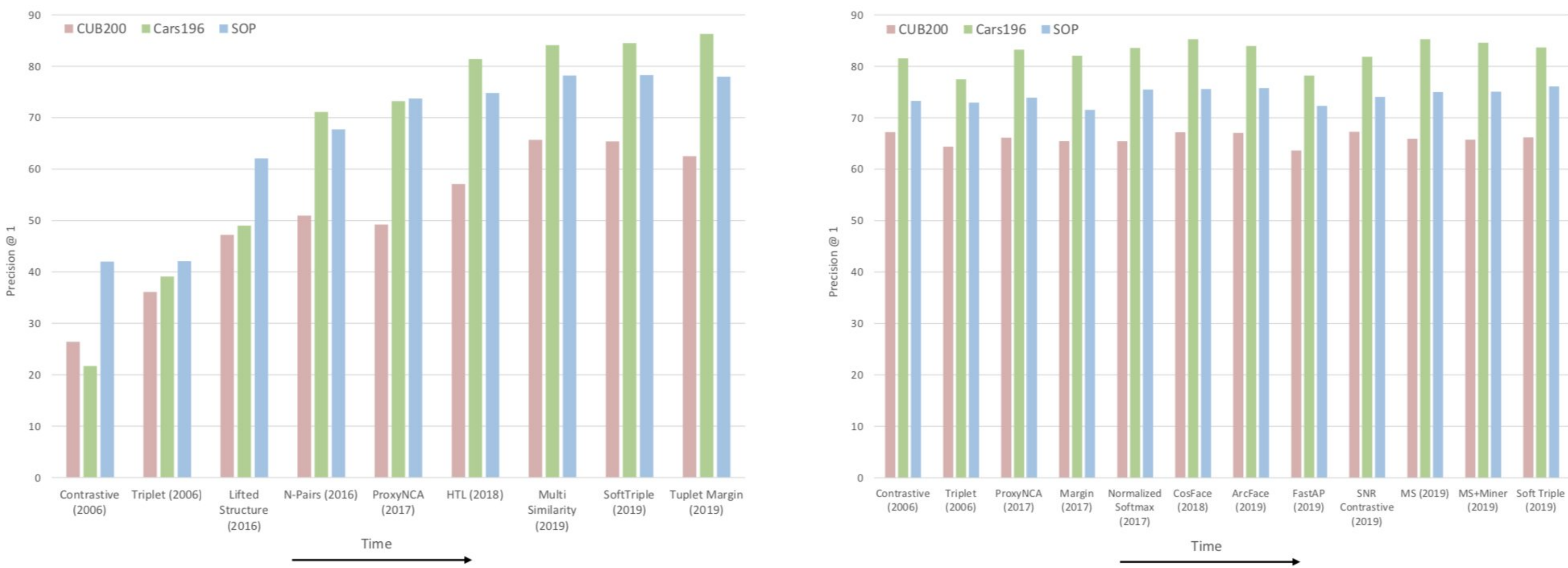
N-Pairs



Efficient generalization of Triplet networks that uses the whole batch.

[Sonh, NeurIPS 2016]

Troubles in Metric Learning…



(a) The trend according to papers

(b) The trend according to reality

Fig. 4. Papers versus Reality: the trend of Precision@1 of various methods over the years.

The gain of more recent Metric Learning models <u>may</u> come from:

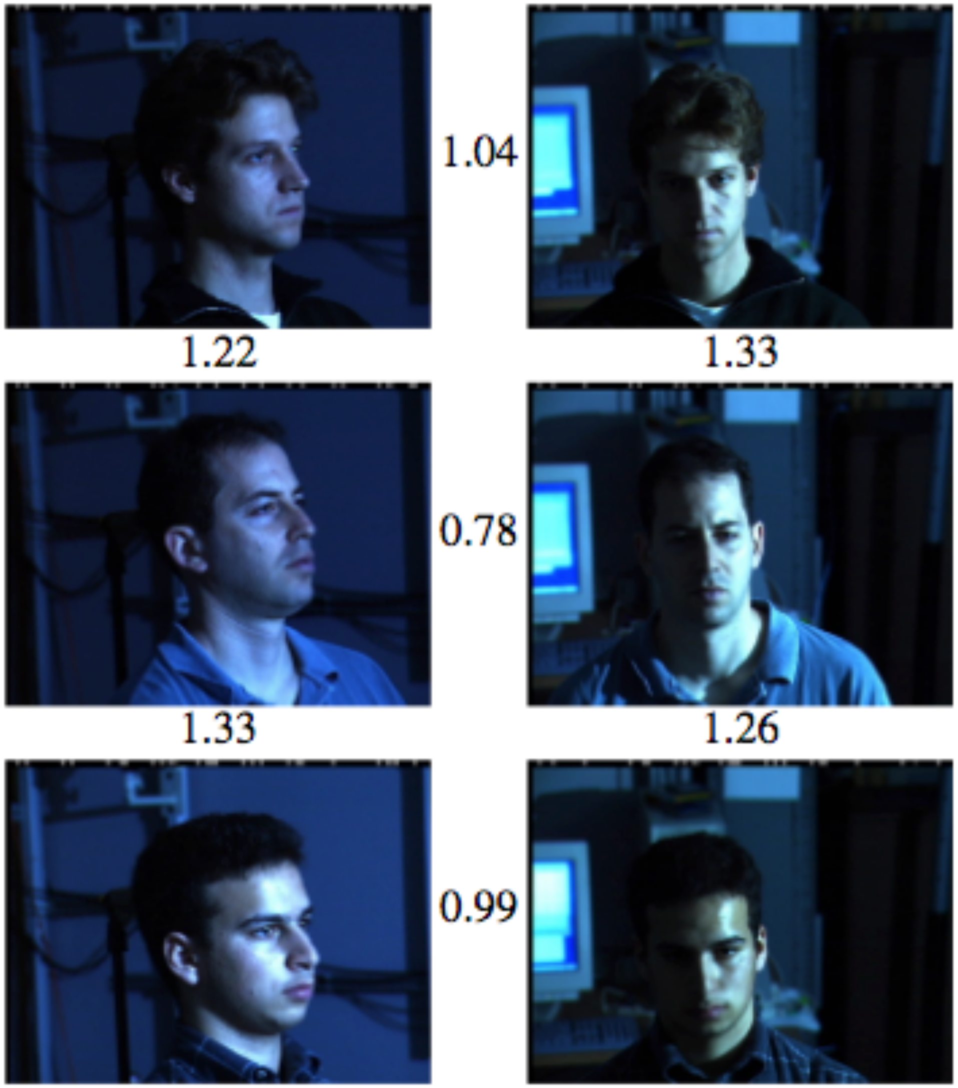
- Better backbone
- Better hyperparameters tuning
- Better data augmentation

[Musgrave et al. arXiv 2020]

FaceNet

Triplet Network with semi-hard negative mining.

Pretty much solved the LFW dataset.



Distance between pairs

[Schroff et al. CVPR 2015]

Meta-Learning MAML

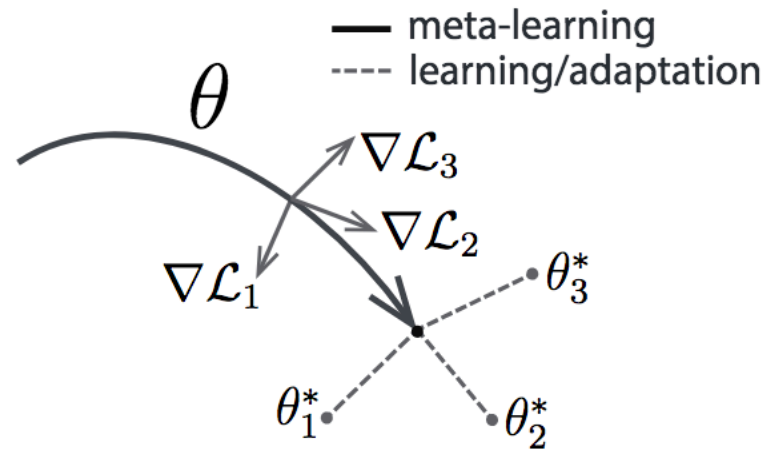
Learning to learn:

→ Given a few samples can learn faster

Outer and inner loop:

- Inner loop learns to classify well a few labeled samples.
- Outer loop learns to have good weights for the inner loop.

During inference, perform only inner loop.



Algorithm 1 Model-Agnostic Meta-Learning

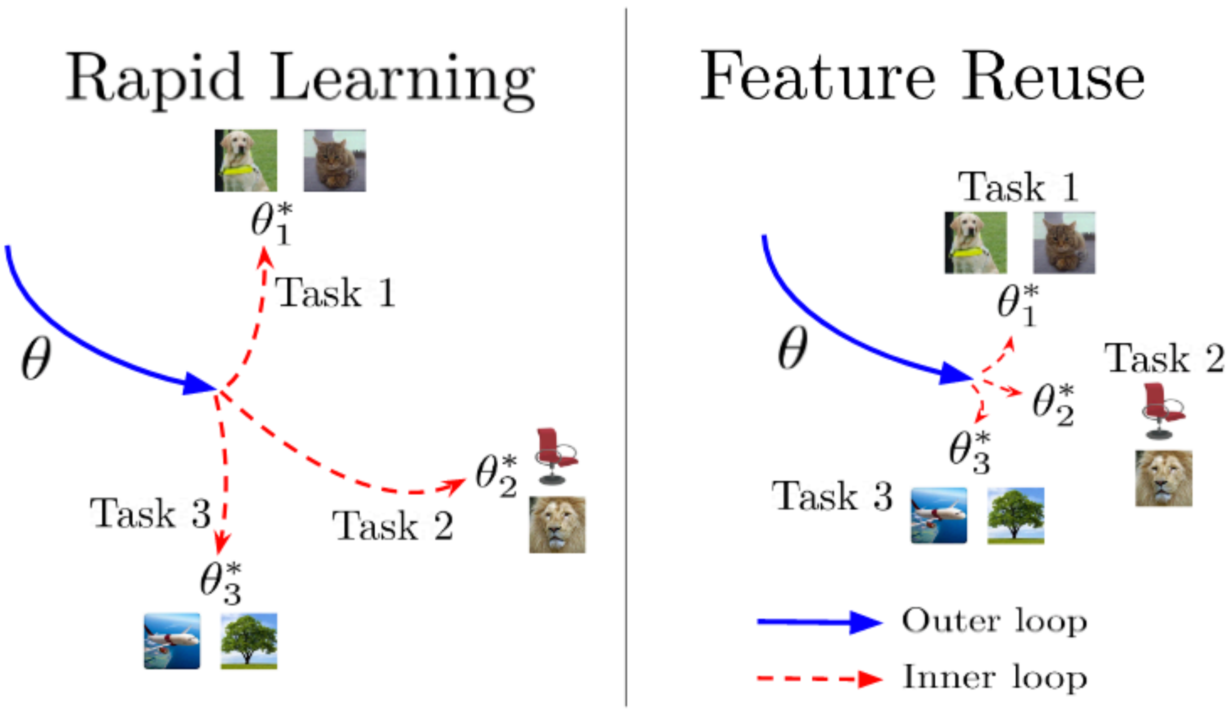
Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters
randomly initialize θ
while not done **do**
  Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$
  for all $\mathcal{T}_i$ **do**
    Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples
    Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
  end for
  Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$
end while

[Finn et al. ICML 2017]

Meta-Learning MAML

Does MAML *really* learns to learn (**rapid learning**)?

More probably it manages to learn features that generalize well (**feature reuse**)



[Raghu et al. ICLR 2020]

Self-Supervised Learning

(also Unsupervised Learning)

Setting

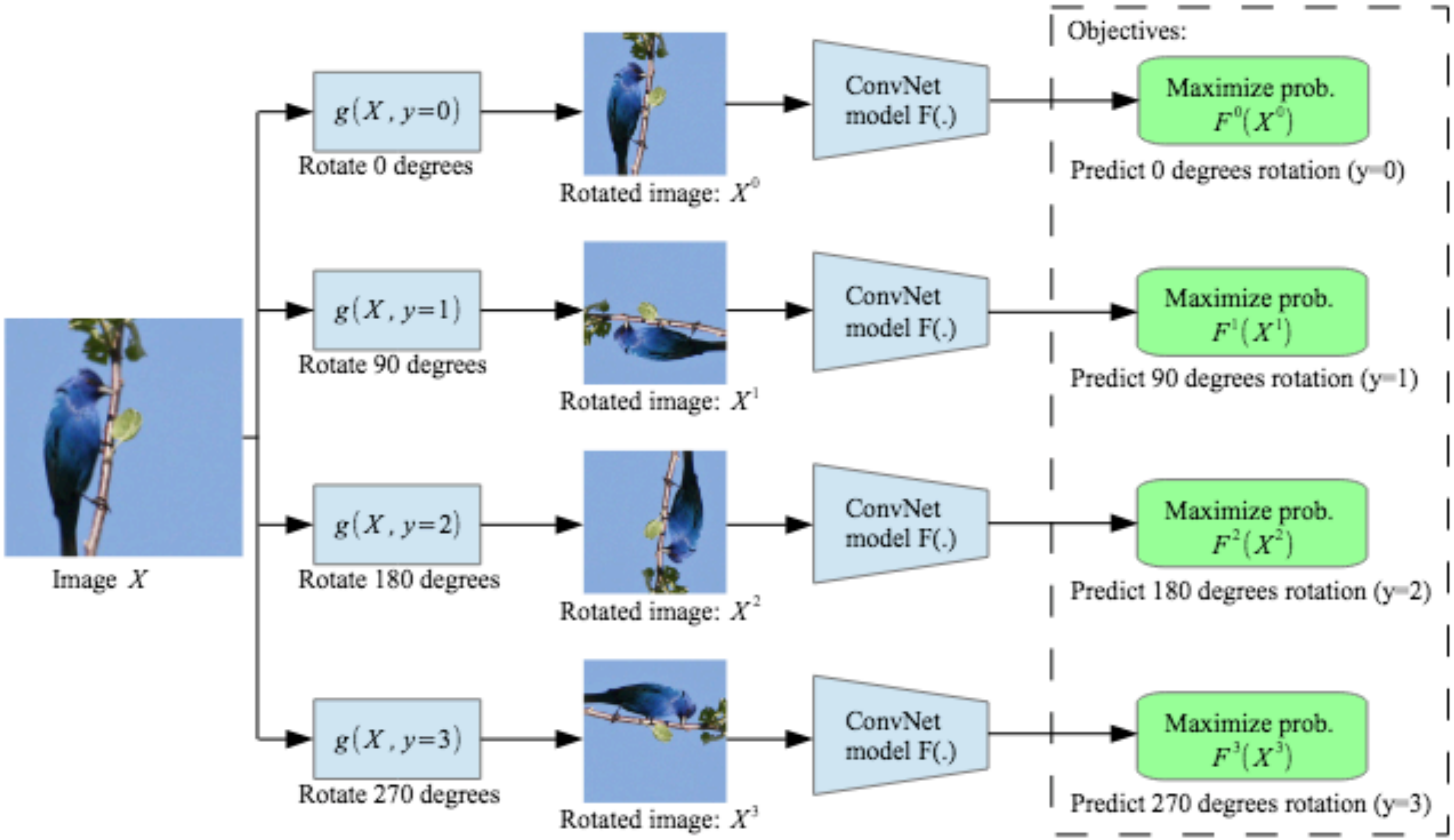
1. Learn a backbone with a lot of **unlabeled data** using a self-designed objective

2. Freeze the backbone
3. Learn a classifier on top of it on labeled data.

→ Evaluate how much the learned representation (features extracted by ConvNet) is useful.

It can be useful to have a good model pretraining in order to do transfer learning later.

Rotation

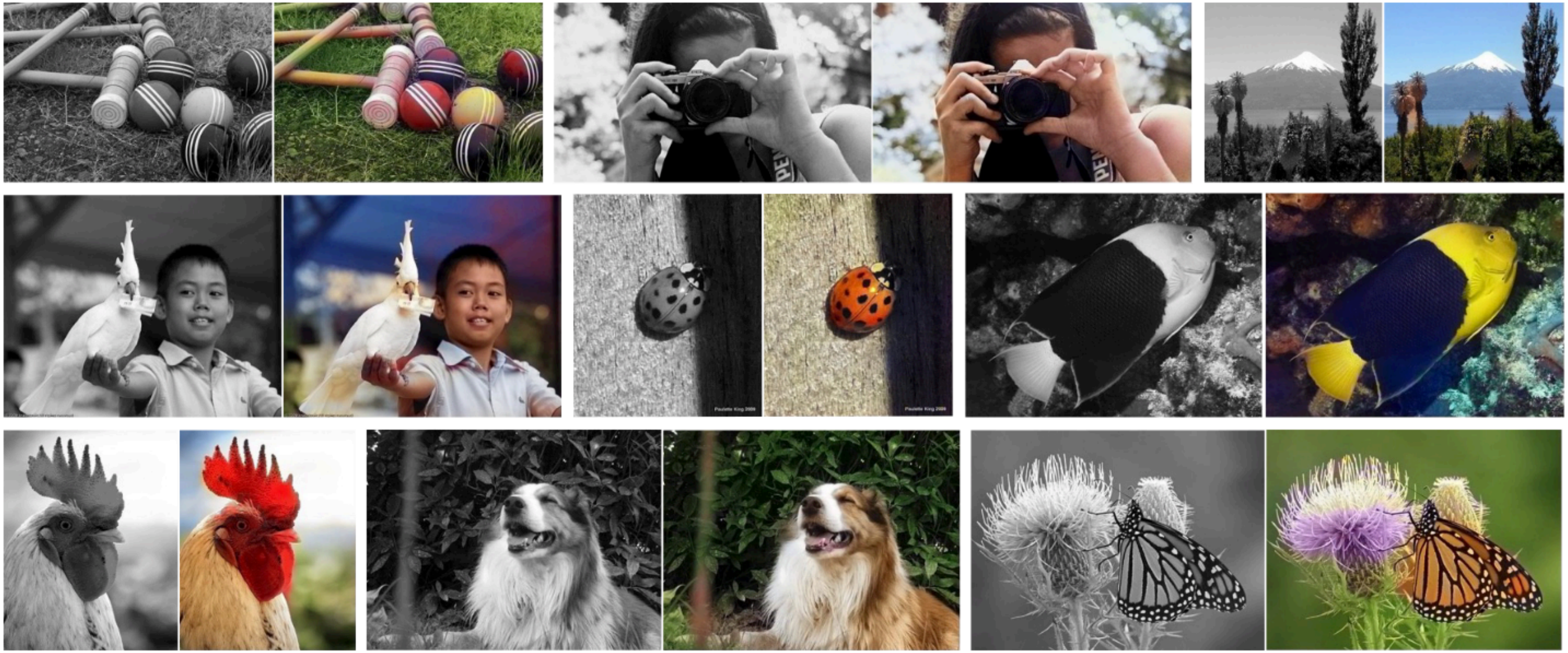


Learn what is the rotation applied.

→ Thus it must learn what is the structure of the visual world.

[Gidaris et al. ICLR 2018]

Colorization

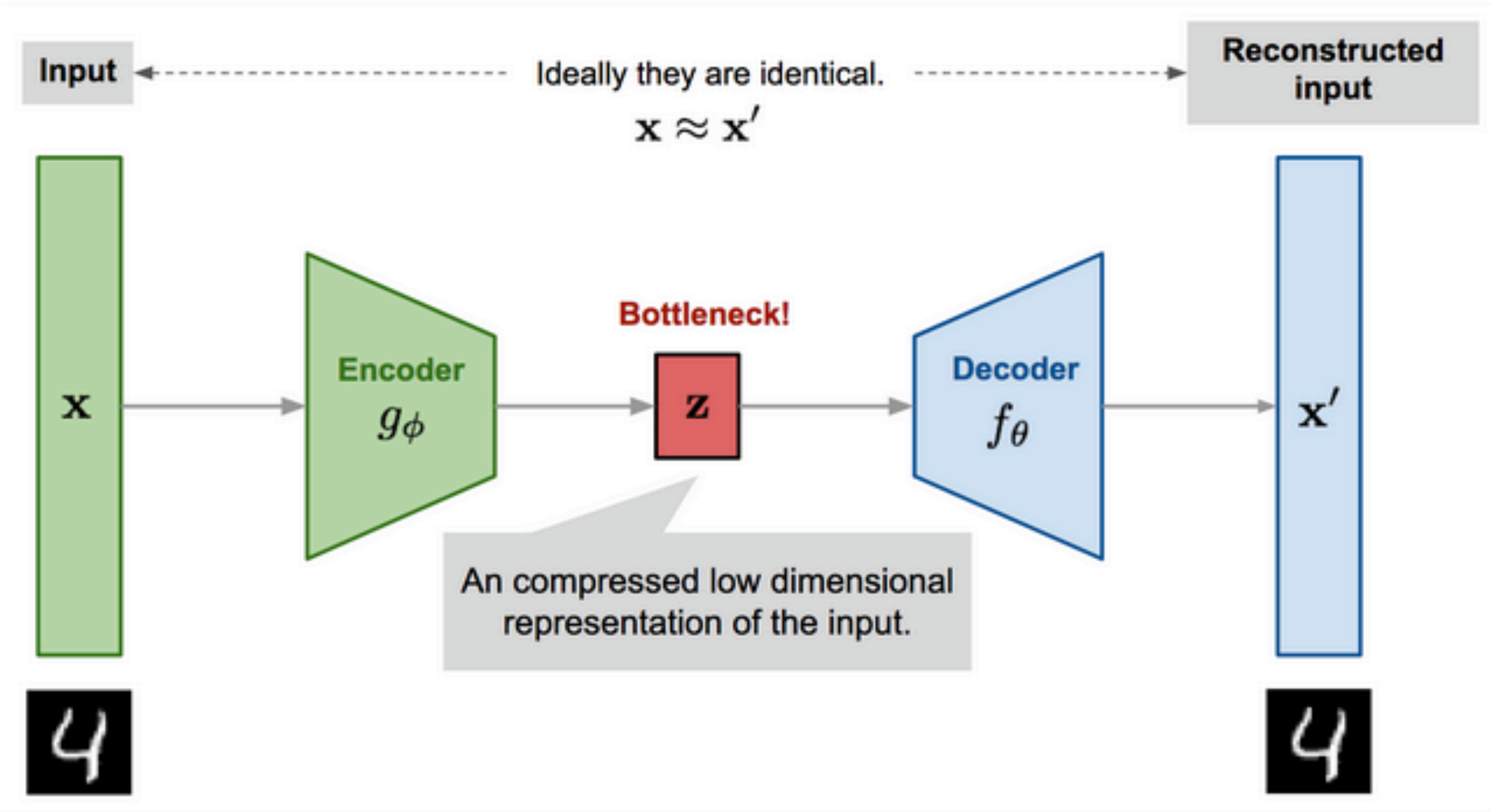


Learns to predict the colors from "*grayscale*" images.

→ Regression problem
→ Done in the LAB space instead of RGB

[Zhang et al. ECCV 2018]

Auto-Encoder



Compress an image and then reconstruct it.

→ Similarly to method of dimensionality reduction like PCA
→ It must only keep important features.

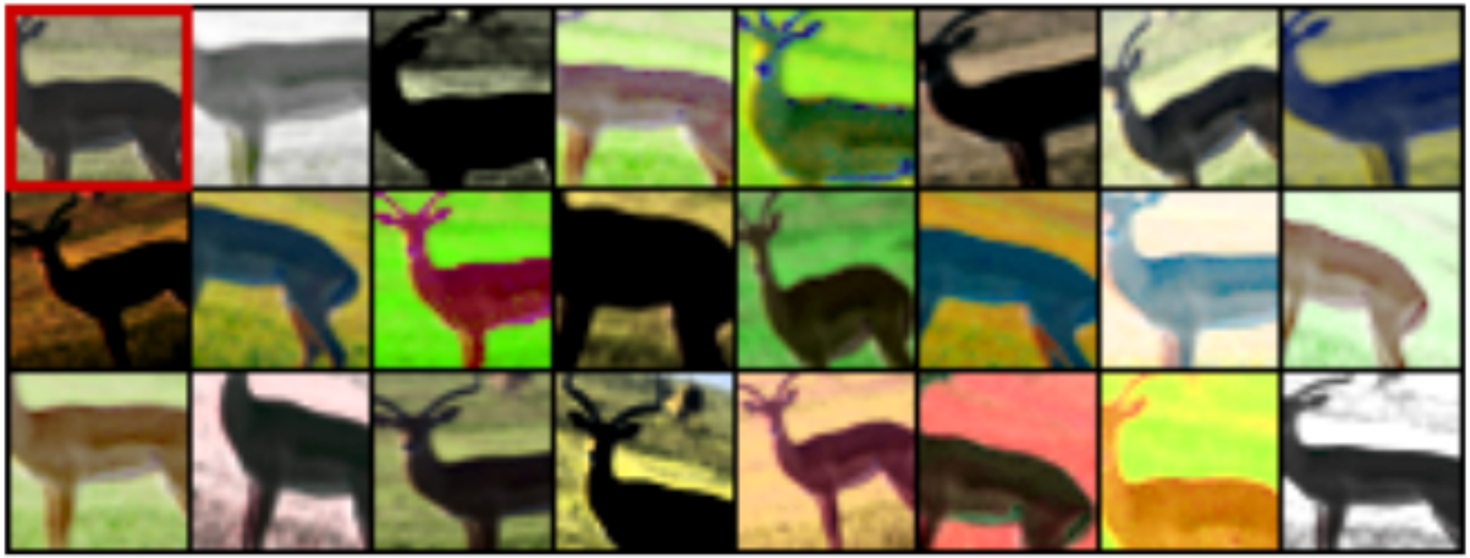
Image from the excellent blog of Lilian Weng.

Constrastive

Each image is considered as a class.

New samples of this "class" are generated with heavy data augmentation.

Trained with usual softmax + cross-entropy.



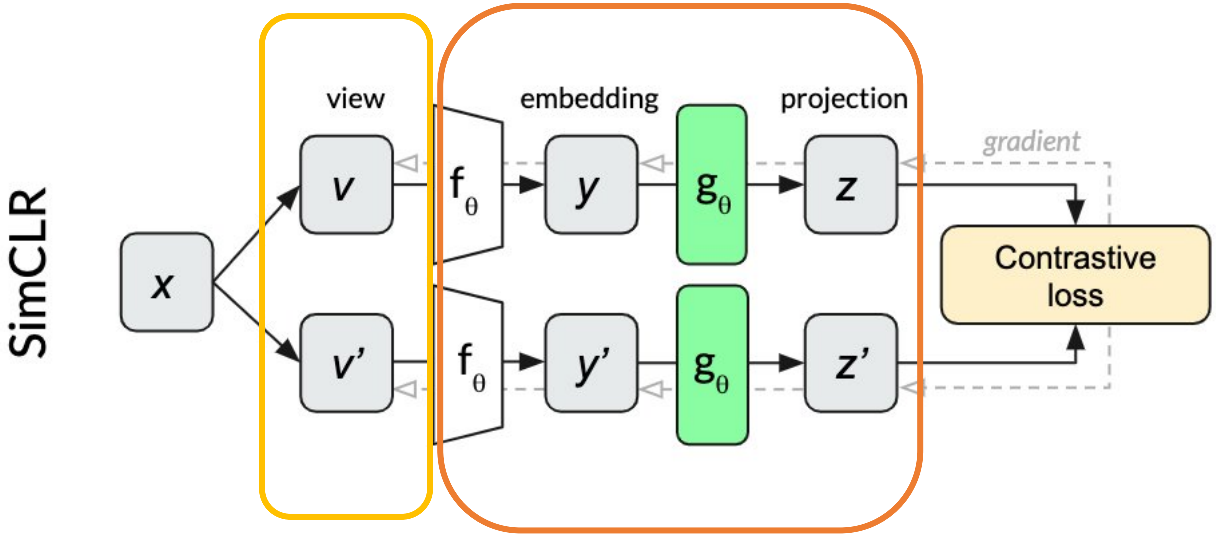
Most of future self-supervised models also try to:

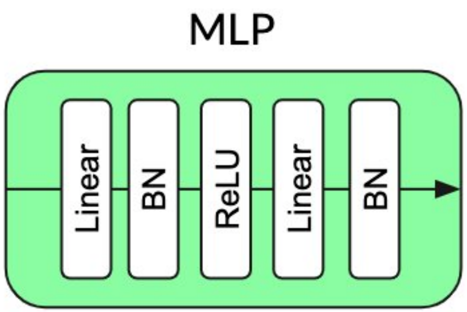
- Bring together the same image augmented differently
- Push away all others images

[Dosovitskiy et al. NeurIPS 2014]

SimCRL

Batch of images is augmented
twice differently





Extract features with ConvNet f_θ,
then project it with a small MLP
to produce $z \in \mathbb{R}^d$

Alternative version of the constrastive loss.
→ Bring together the same image augmented differently
→ Push away all others images of the batch

$$-\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$$

[Chen et al. ICML 2020], image from Raffin's twitter thread.

SimCRL

Alternative version of the constrastive loss.
→ Bring together the same image augmented differently
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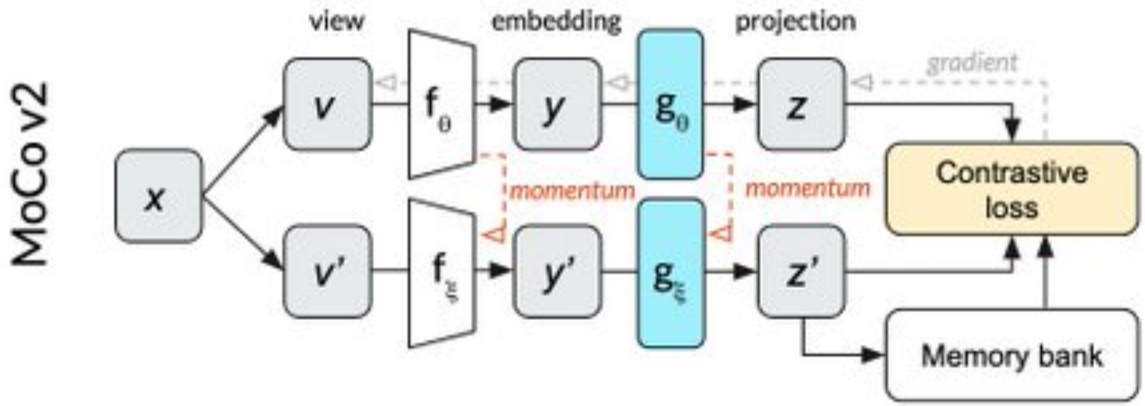
$$-\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k\neq i]} \exp(s_{i,k}/\tau)}$$

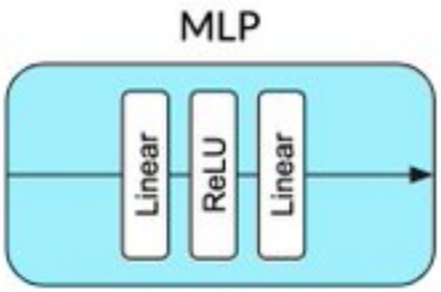
It needs a very large batch size >= 1024!

The MLP that does the projection is essential.
→ Learns useful transformations for the contrastive task
→ But it discarded during the finetuning phase

[Chen et al. ICML 2020]

MoCo



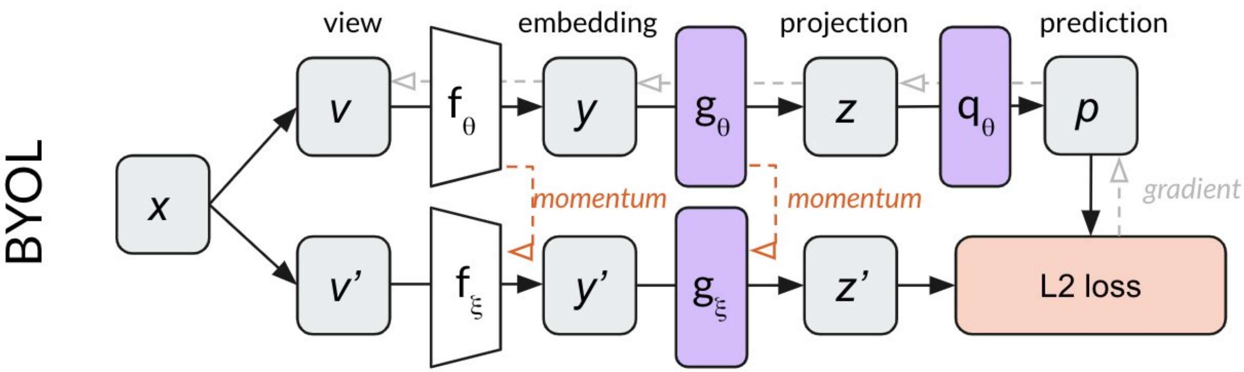


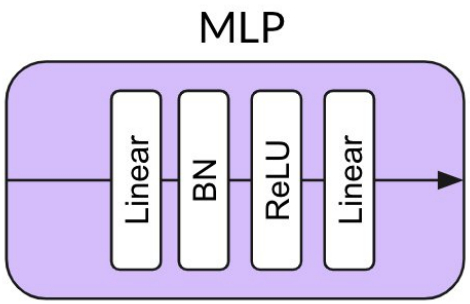
Reduces the need of large batch size with a **memory bank**:
→ Stores previously computed projections z'
→ Means more negative in the contrastive loss

The gradient is backpropagated only through one version of the network:
→ The other network is, as in RL, a **target network**
→ It is updated with momentum $\theta_t \leftarrow \alpha\ \theta_t + (1-\alpha)\ \theta_s$
→ Enforce stability in the memory bank representations

[Chen et al. arXiv 2020], image from Raffin's twitter thread.

BYOL





L2 distance between **only positive examples**, **not negative examples are used**!

Why does the representation do not collapse?
→ Meaning only producing a zero vector for any input would minimize the loss

Still an active area of research, but some intuitions:
→ Asymmetrical architecture with another MLP q_θ
→ Momentum for the target network

[Grill et al. NeurIPS 2020] but extremely similar to Mean Teacher [Tarvainen and Valpola, NeurIPS 2017], image from Raffin's twitter thread.

What do we actually need for self-supervision?

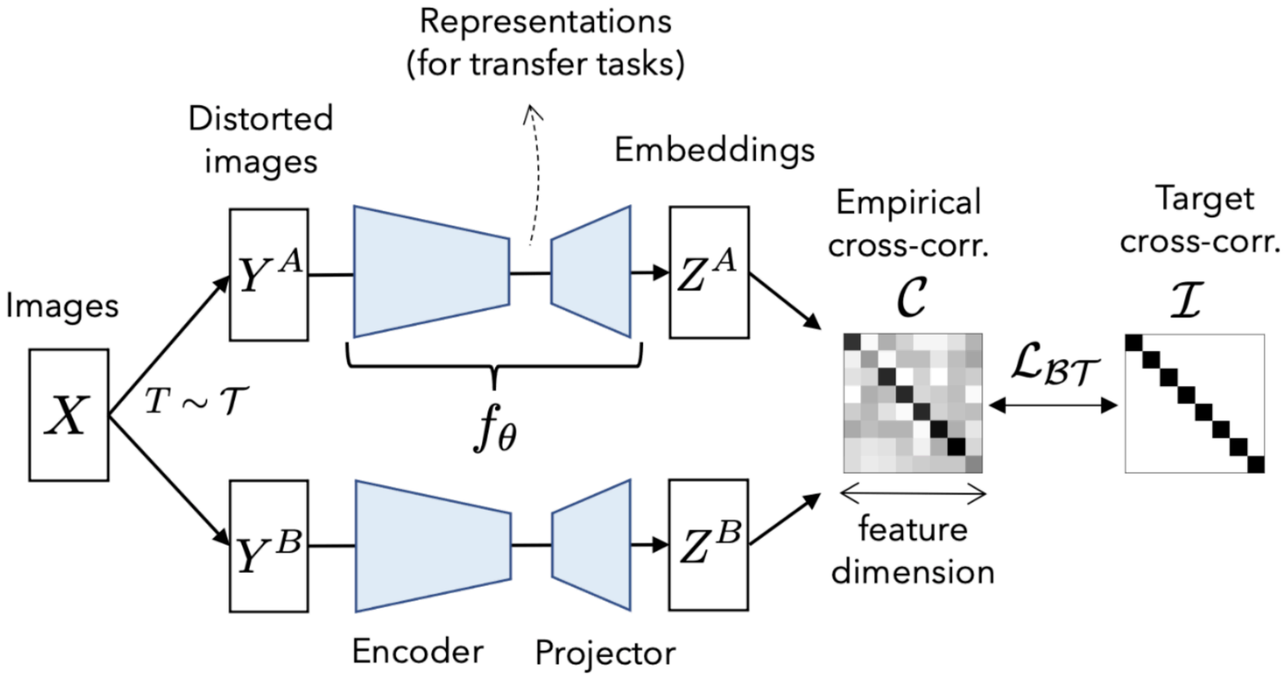
Invariance to transformations:

→ Two augmentations of the same image should produce the same representation

Disentangling of the dimensions:

→ Each dimension of the representation should encode a different info

Barlow Twins



Cross-correlation along the batch dimension:

$$\mathcal{C}_{ij} \triangleq \frac{\sum_b z^A_{b,i} z^B_{b,j}}{\sqrt{\sum_b \left(z^A_{b,i}\right)^2} \sqrt{\sum_b \left(z^B_{b,j}\right)^2}}$$

$$\mathcal{L}_{\mathcal{BT}} \triangleq \underbrace{\sum_i (1 - \mathcal{C}_{ii})^2}_{\text{invariance term}} + \lambda \underbrace{\sum_i \sum_{j \neq i} {\mathcal{C}_{ij}}^2}_{\text{redundancy reduction term}}$$

Invariance to transformations:

→ First term forces each dimension i from both views to be very correlated (+1) despite the views were generated by different transformations

Disentangling of the dimensions:

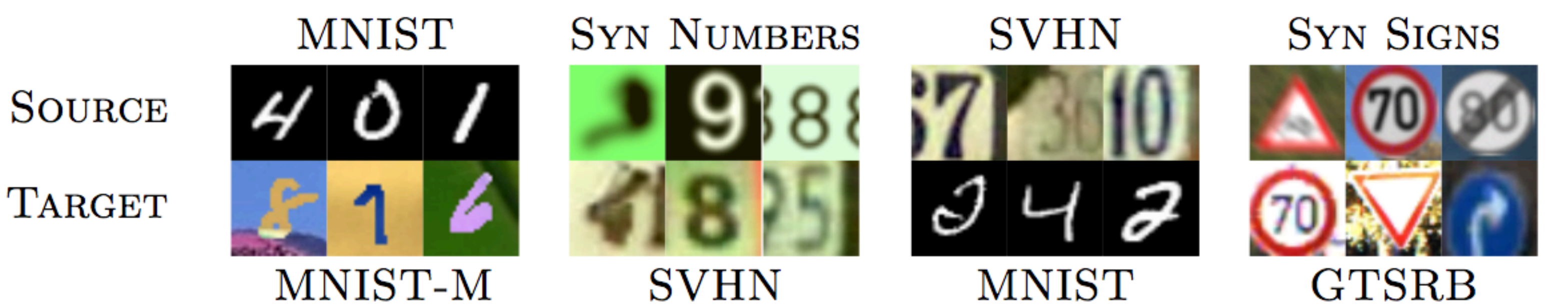
→ Second term forces each dimension i to be orthogonal (0) with dimension $j \neq i$ so that each dimension encodes a different information, aka no collapse

[Zbontar and Jing et al. ICML 2021]

Domain Adaptation

Setting

- Source domain/dataset is fully labeled
- Target domain/dataset is unlabeled
- Both represent the same classes
- Huge discrepancy in the pixels distribution

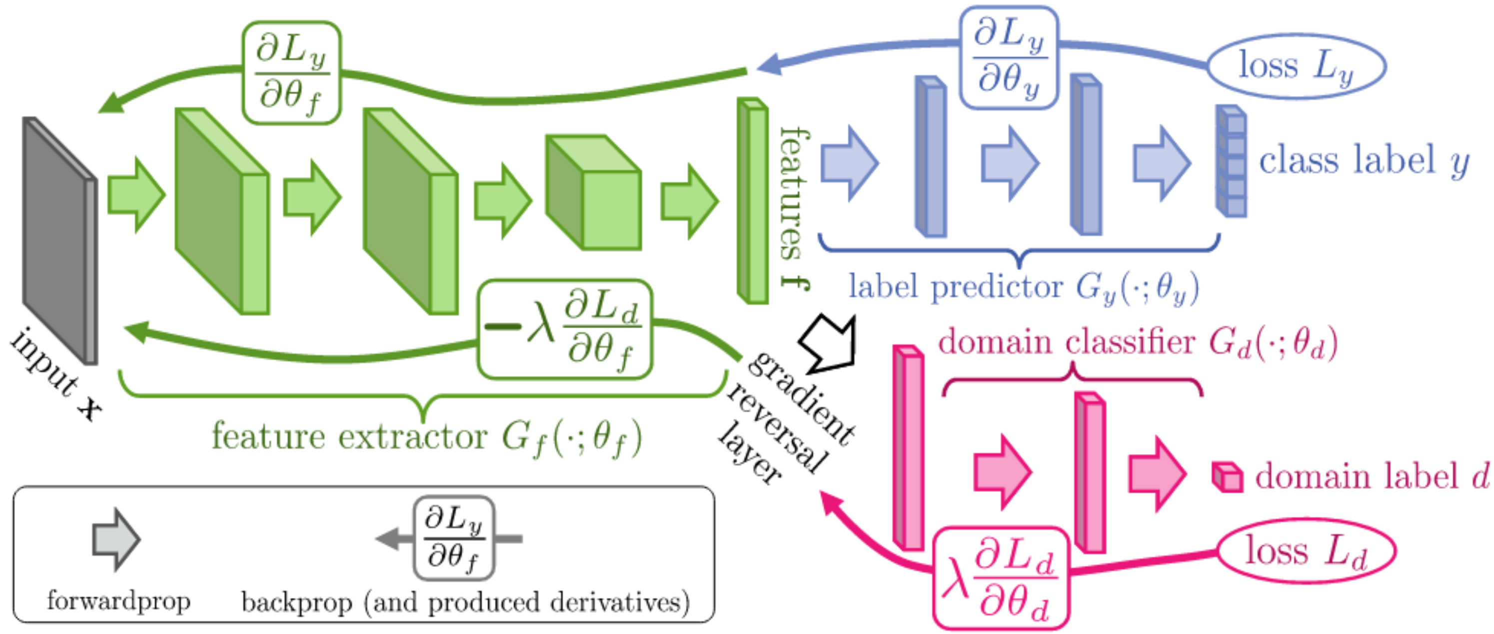


Source Domain

GTA5 (yes the game)

Target Domain

Cityscapes

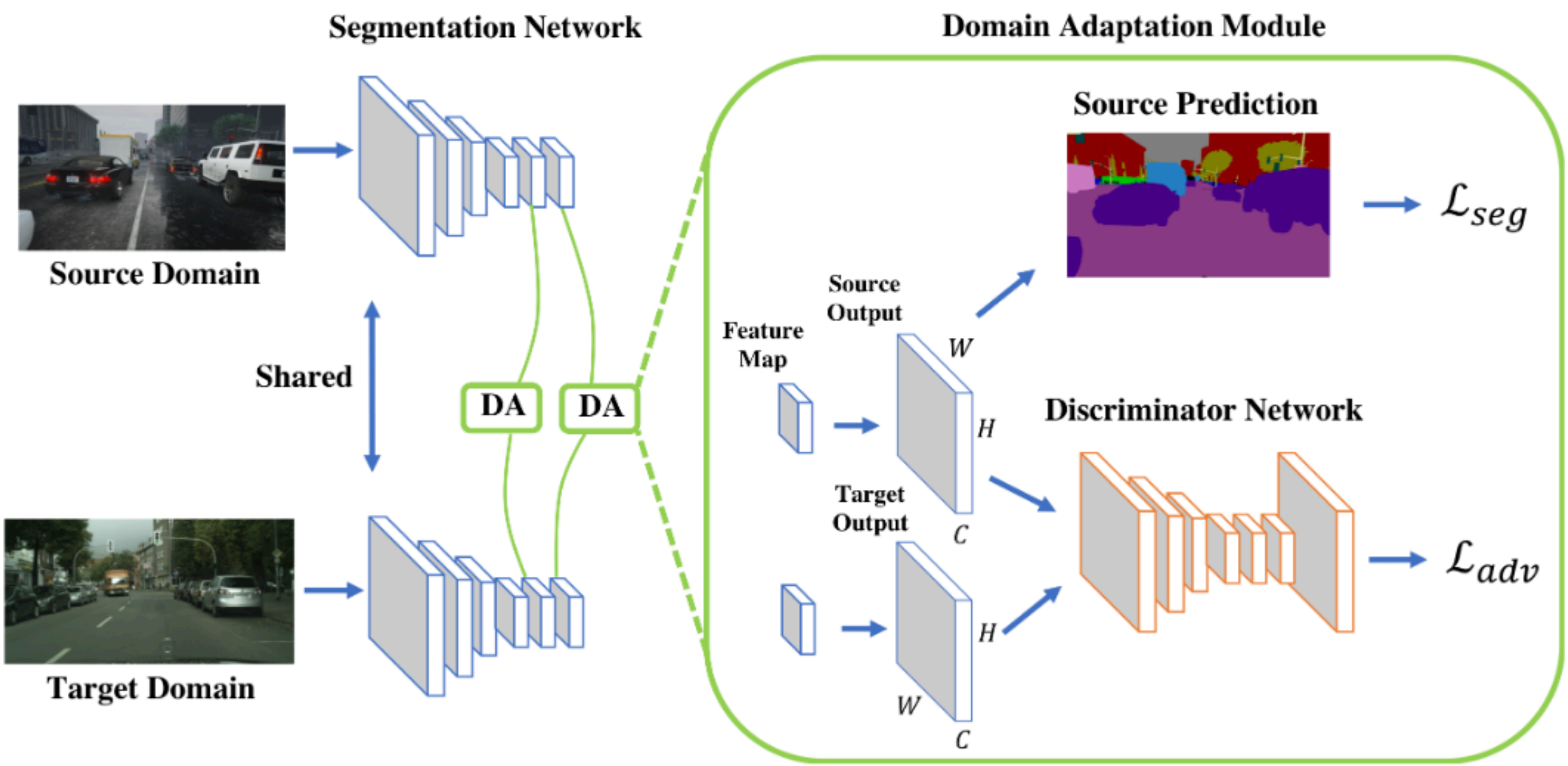


Gradient Reversal Layer (GRL) forces the **ConvNet** to maximize the loss of the **Domain Classifier**.

→ Force to learn domain agnostic features

[Ganin et al. JMLR 2015]

AdaptSegNet



- Train the Discriminator on the probabilities of the source and target without the gradient flowing backward
- Train the Segmentation Network on source for classification and also force the discriminator to predict source given target images

$$\max_{\mathbf{D}} \min_{\mathbf{G}} \mathcal{L}(I_s, I_t). \qquad \mathcal{L}(I_s, I_t) = \mathcal{L}_{seg}(I_s) + \lambda_{adv}\mathcal{L}_{adv}(I_t)$$

[Tsai et al. CVPR 2018]

Two key ideas

Two key ideas for domain adaption in segmentation:

1. **Adversarial loss** forcing a similar representation for both source and target domains

2. **Pseudo-labeling** to generates labels for the unlabeled target domain

Other Problems

Not covered in this lecture

Zero-shot Learning:
→ Not a single image of the class to predict, but access to metadata
→ *Ex: understand a Wikipedia description to classify a never-seen before animal*

Semi-Supervised:
→ A few amount (~10%) of the data is labeled, while the remaining is unlabeled but present
→ Most of the recent self-supervision literature took a lot of inspiration from it
→ Often solved with contrastive, weights averaging, and pseudo-labeling with consistency

Weak supervision:
→ Labels are imperfect
→ *Ex: training a model to predict the hashtag on Instagram photos*

Small break,
then coding session!