Addressing the data challenge: Transfer learning and semi-supervised learning

The data challenge

- Fundamentally, neural networks need a lot of data
- Why?
  - Lots of parameters
  - Deeper, bigger models are better in CV, and they all have many more parameters
- Large datasets are problematic
  - Expensive to collect
  - Expensive to curate
  - Expensive to label
  - Associated issues of bias

The “fundamental law” of neural networks

- Neural networks must be trained on a large dataset
- If not enough labeled data for target task, then what?
  - Unlabeled data from target domain: *Self-supervised learning*
  - Labeled + Unlabeled data for target task: *Semi-supervised learning*
  - Labeled data from a related problem domain: *Few-shot / transfer learning*

Learning from unlabeled data: Self-supervised learning

- Two classes of approaches

- *Pretext*-based learning
  - Design a “pretext” task that leads to good features

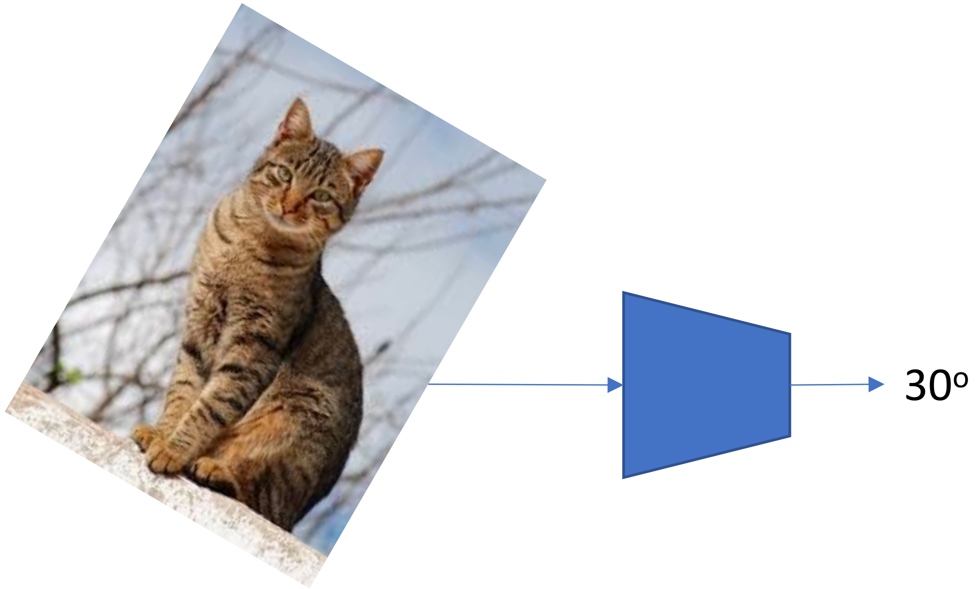
- *Contrastive* learning
  - Spread images out in feature space

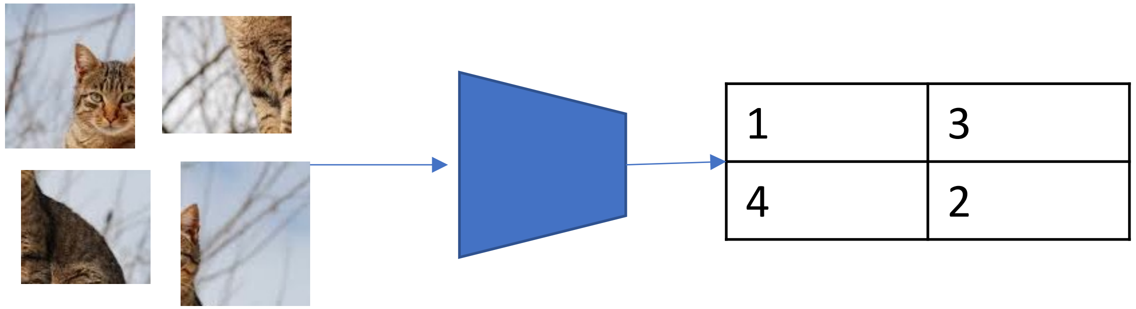
Classical unsupervised learning

- PCA (Principal Components Analysis)
  - Reduces dimensionality
  - But is a linear approach

Pretext tasks

- Transform input, task network with predicting transformation



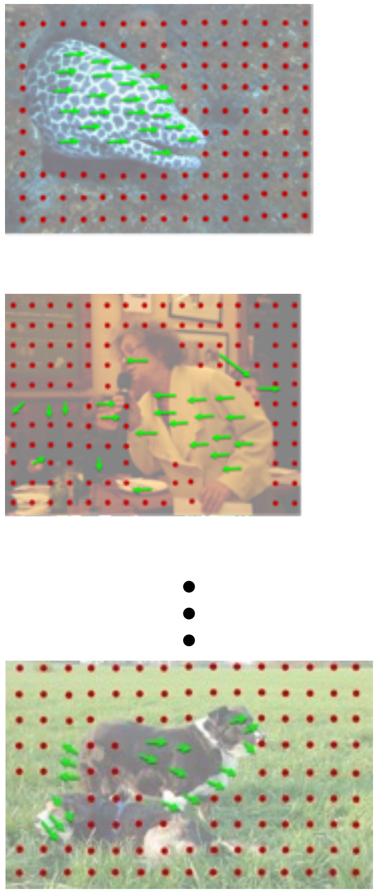


Pretext tasks

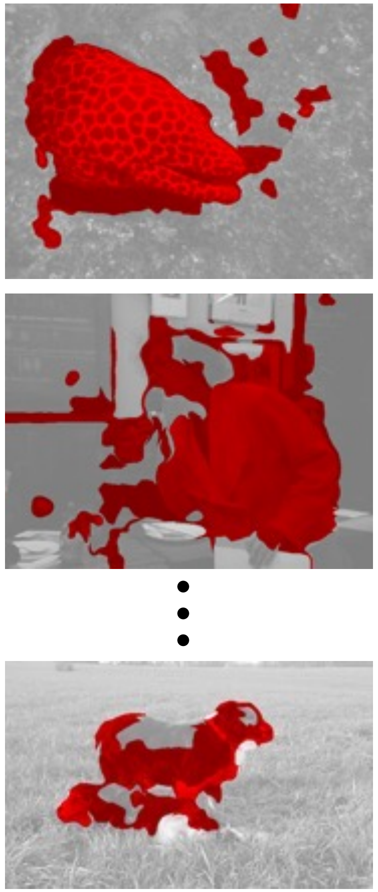
- Remove data, then task network with predicting it

Pretext tasks

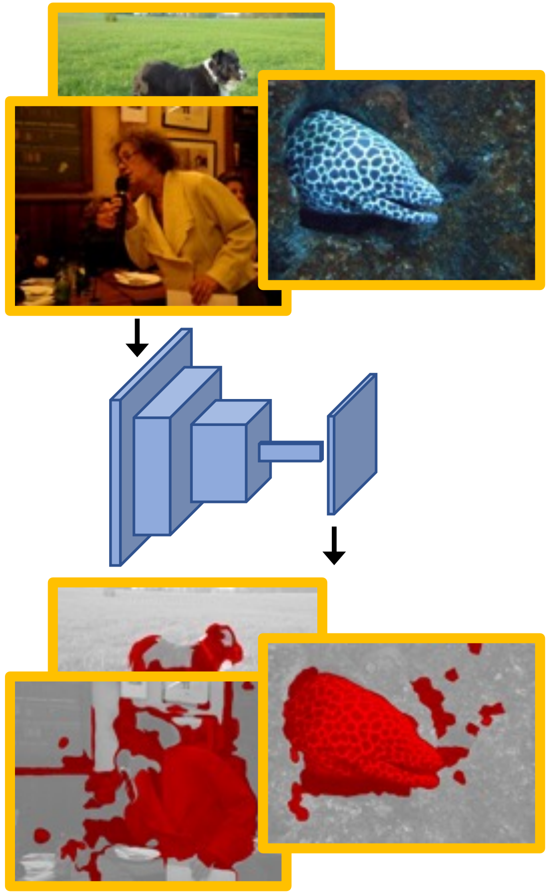
- Use some source with additional data
- E.g. videos



1. Collect videos



2. Segment using motion



3. Train ConvNet

Pathak, Deepak, et al. "Learning Features by Watching Objects Move." *CVPR*. Vol. 1. No. 2. 2017.

Ego-motion ↔ vision: view prediction

After moving:

Slide credit: Dinesh Jayaraman

Approach idea: Ego-motion equivariance

Training data

Unlabeled video + motor signals

Learn

Equivariant embedding

organized by ego-motions

Pairs of frames related by similar ego-motion should be related by same feature transformation

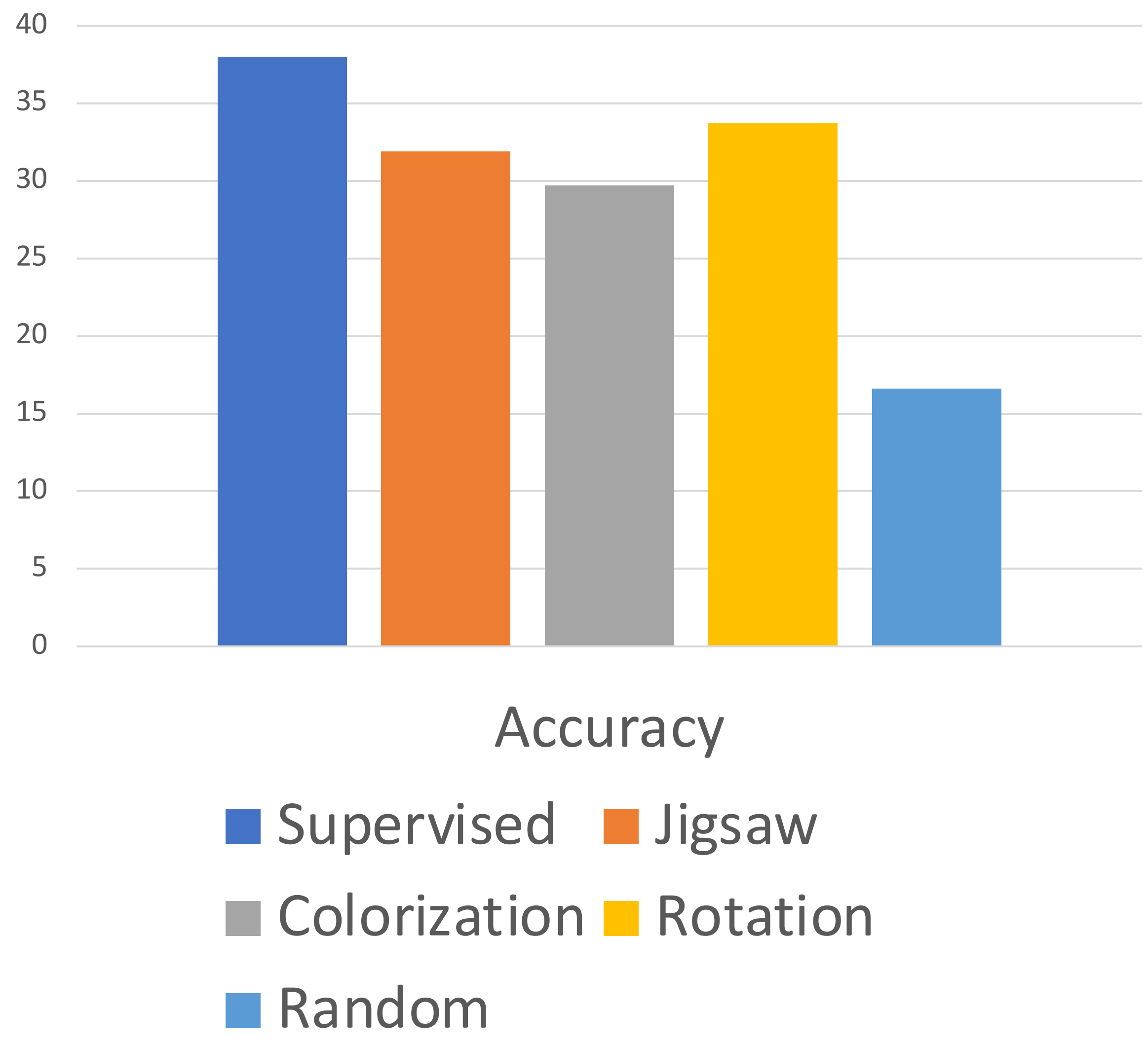
Slide credit: Dinesh Jayaraman

Self-supervision from multimodal data

Owens et al, CVPR 2016

Comparison

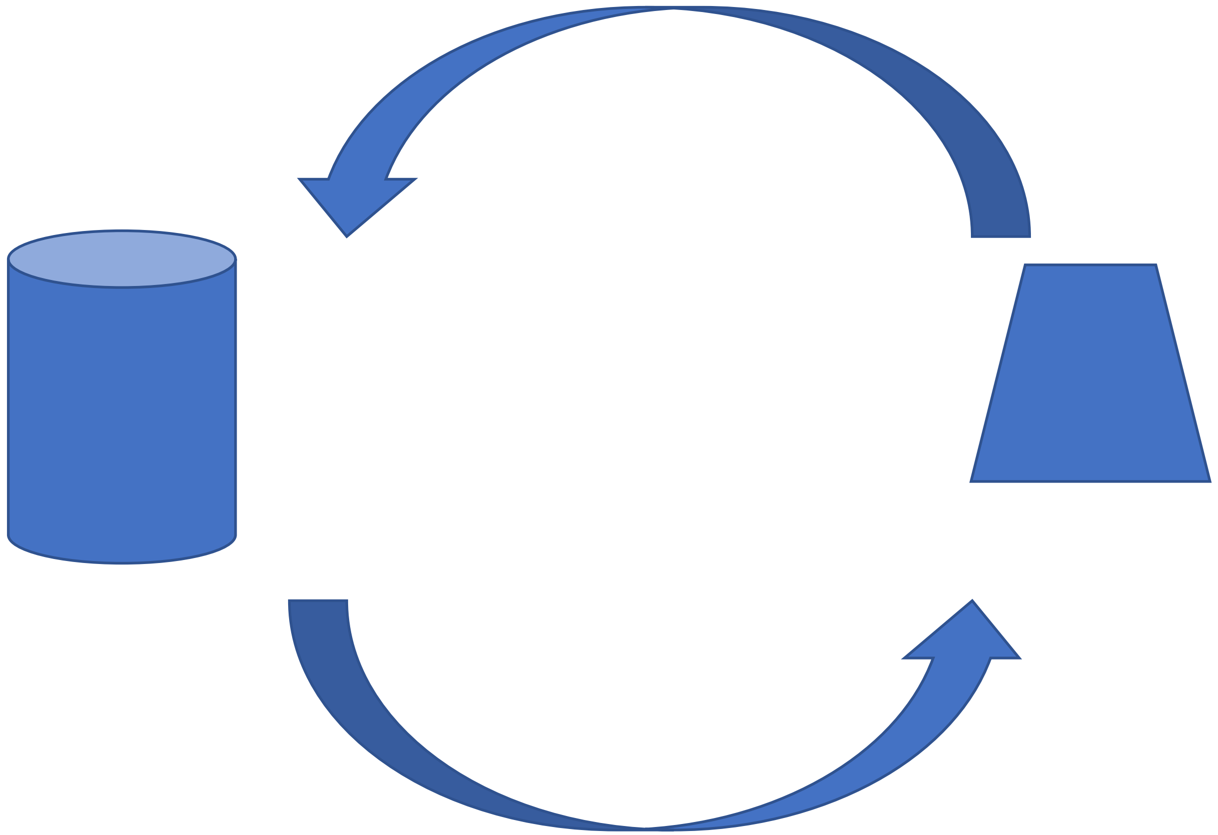
- Train on ImageNet w/o labels
- Use features to train linear classifier on scene classification (Places205)



Contrastive learning

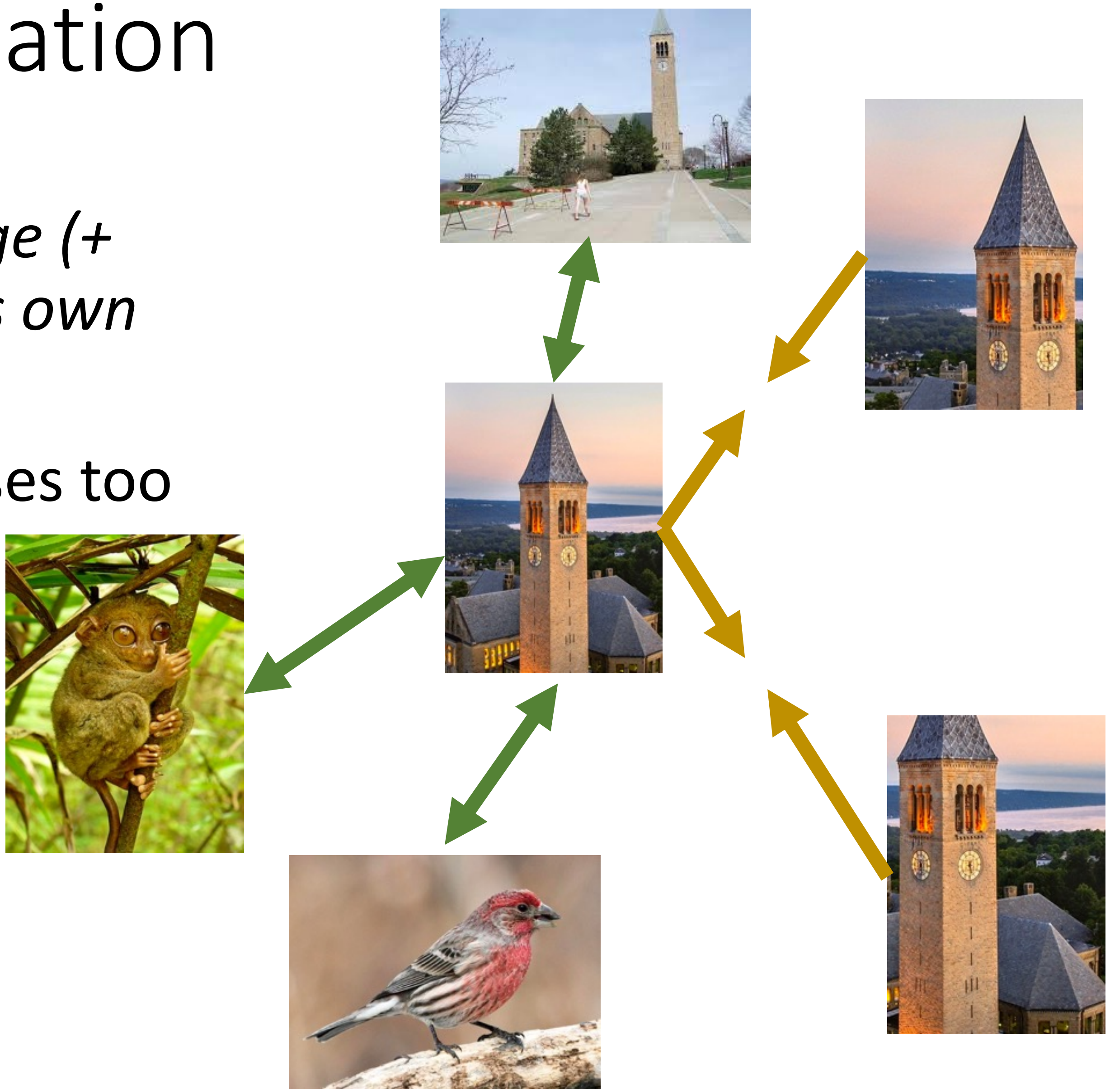
- Training for classification is great!
- However, no class labels ☹
- Idea: let data define the classes

DeepCluster



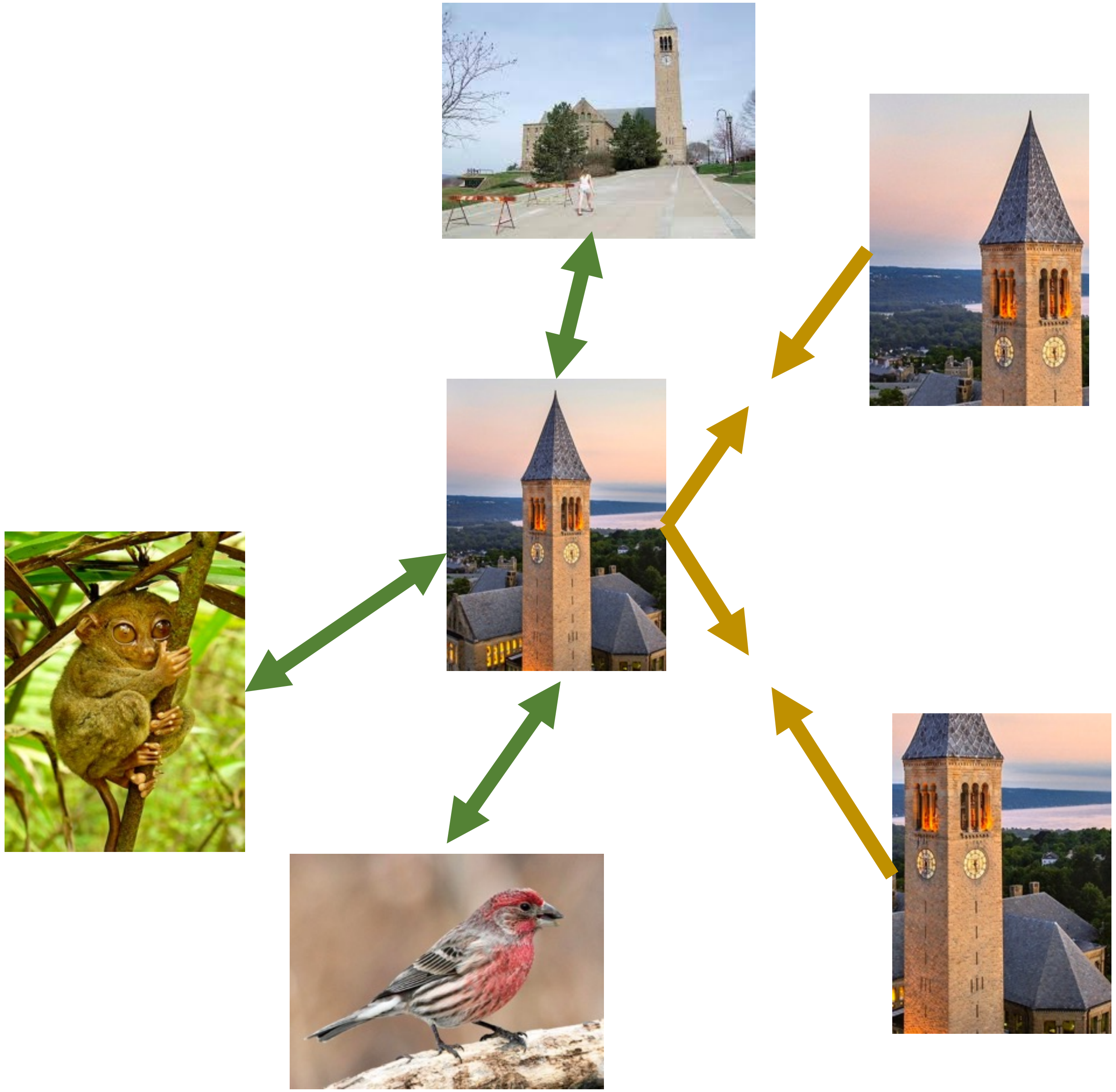
Instance Discrimination

- Simpler idea: *let each image (+ data augmentations) be its own class*
- Challenge: number of classes too many!



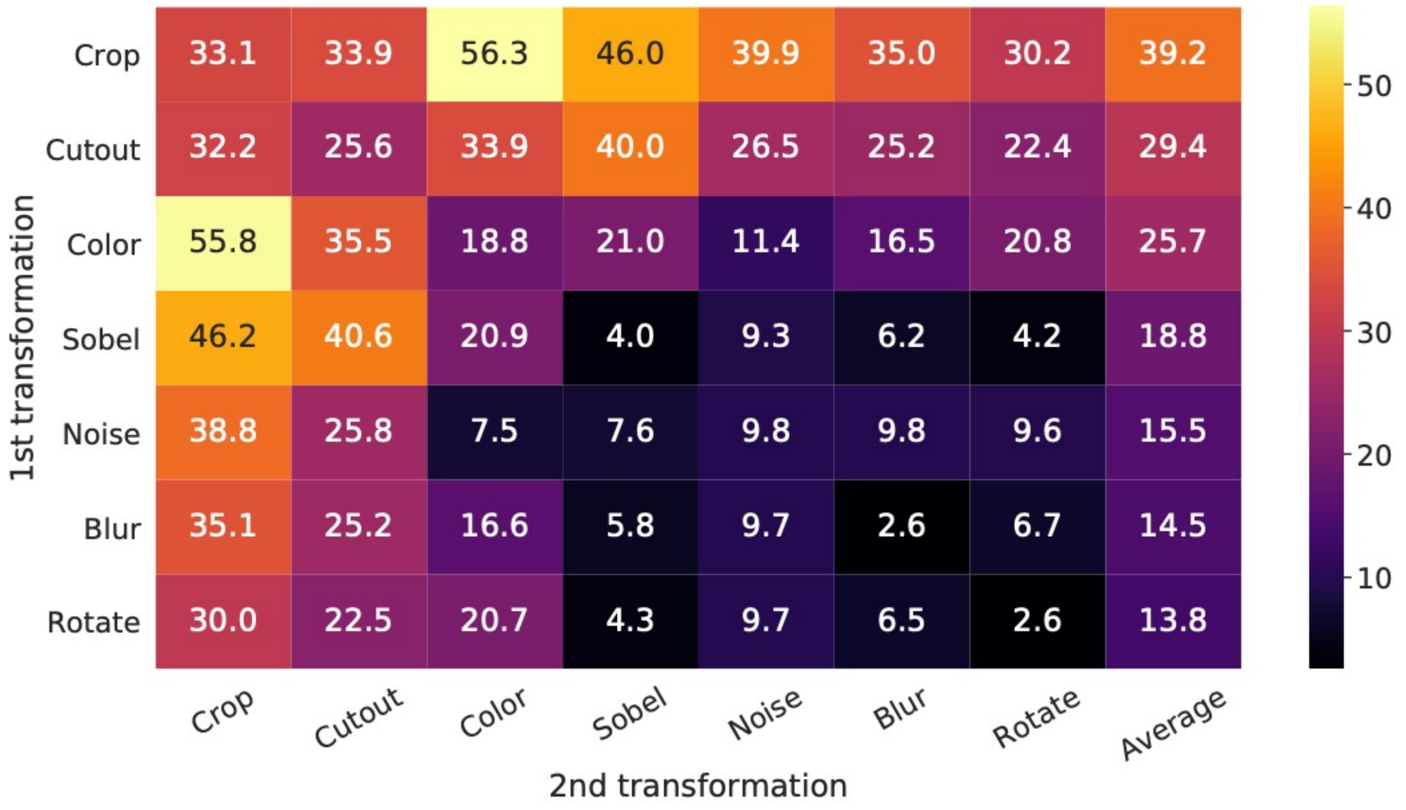
SimCLR

- Sample a batch of images $x_1, \ldots, x_n$
- Augment each to produce $x_{n+1}, \ldots, x_{2n}$
- Loss = $-\log \sum_i \frac{e^{-d(x_i, x_{i+n})}}{\sum_{k \neq i} e^{-d(x_k, x_i)}}$

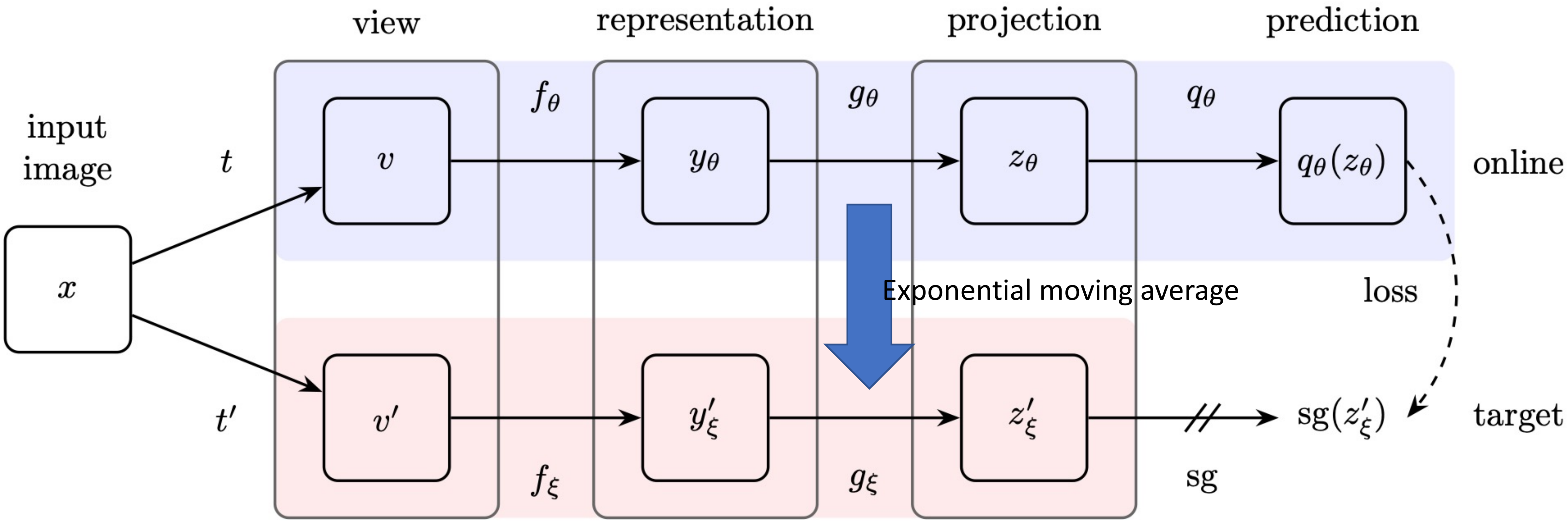


Why does this work?

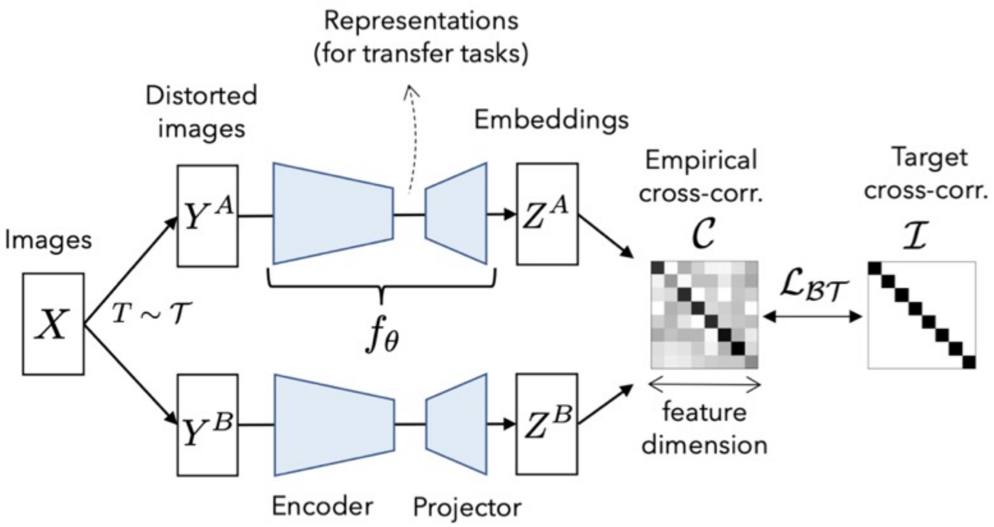
- Data augmentation?



Curioser and curioser



Why does this work



- Simple mechanism:
- *Spread images out in feature space while ensuring invariance to augmentation*

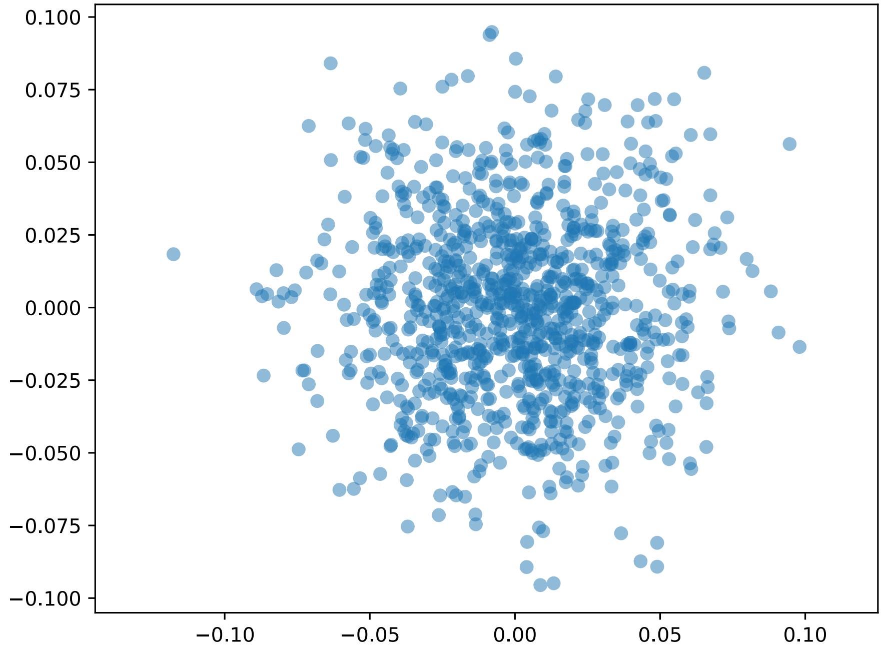
- Current techniques appear to be as good as supervised training
- But need much longer training, large datasets

Classical unsupervised learning

- Unsupervised learning is *old*
- Even with handcrafted features, some feature transformations are necessary
- E.g.: *spurious correlations between features* cause problems doing learning
  - If a car is always seen on a road, then learning algorithm may latch on to the road

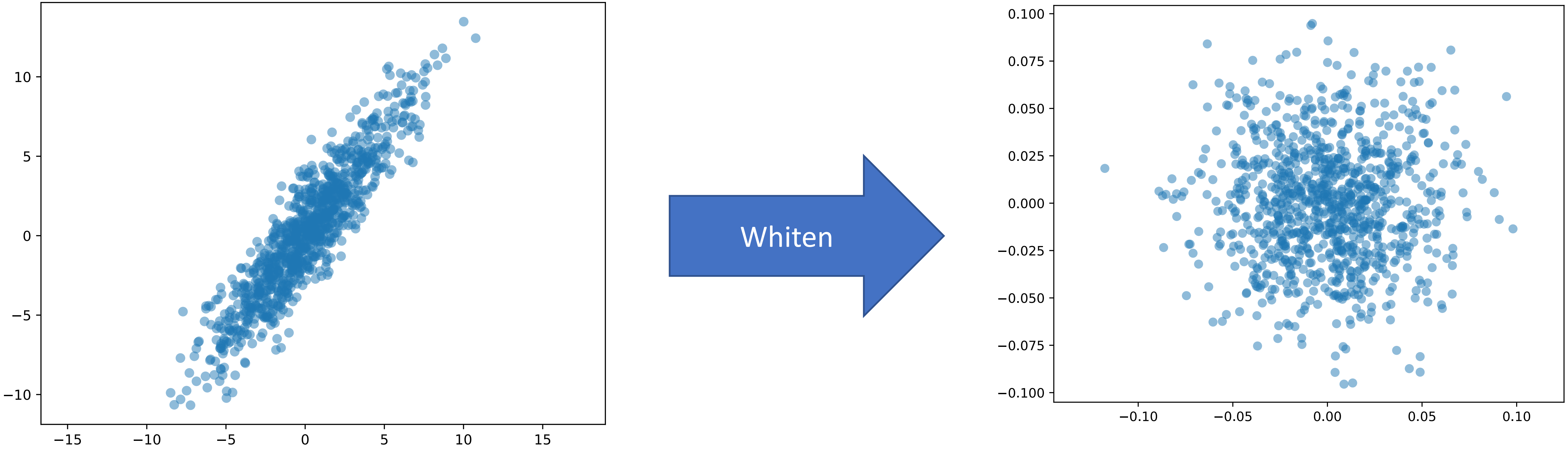
Classical unsupervised learning

- Typically want features to be *independent* and *uncorrelated*
- What do uncorrelated features look like?
- If each feature dimension is normally distributed, and features are all independent
  - Multivariate Gaussian with identity covariance!



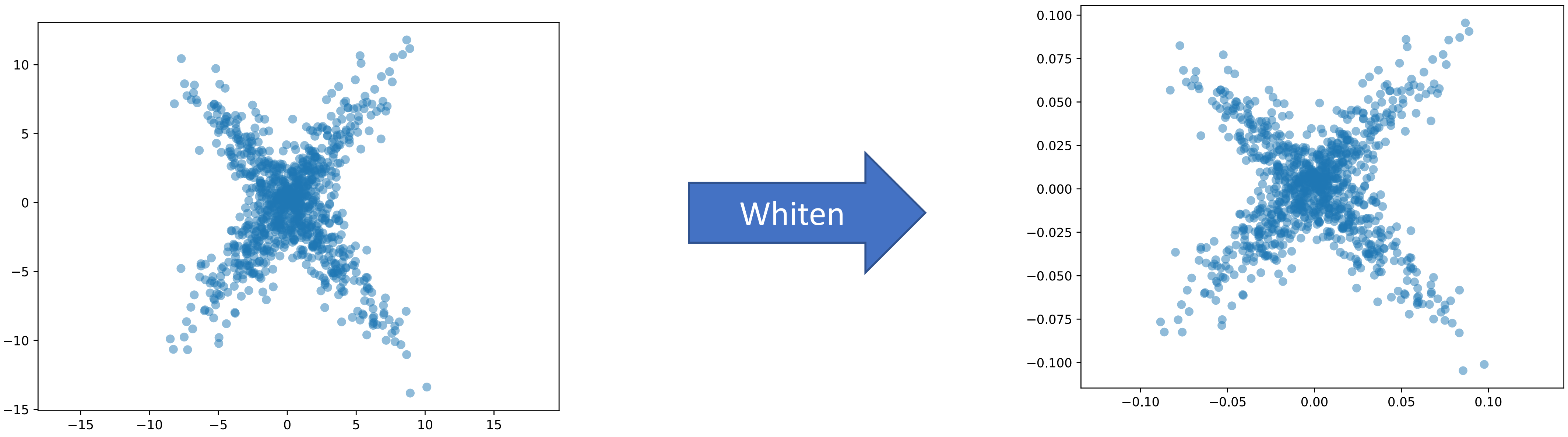
Classical unsupervised learning

- Whitening
  - Linear transformation to make the data have identity covariance
  - Closely related to LDA (Linear discriminant analysis), one of the earliest classification algorithm



Classical unsupervised learning

- But classical whitening is limited by linear transforms
  - Will remove only first order correlations



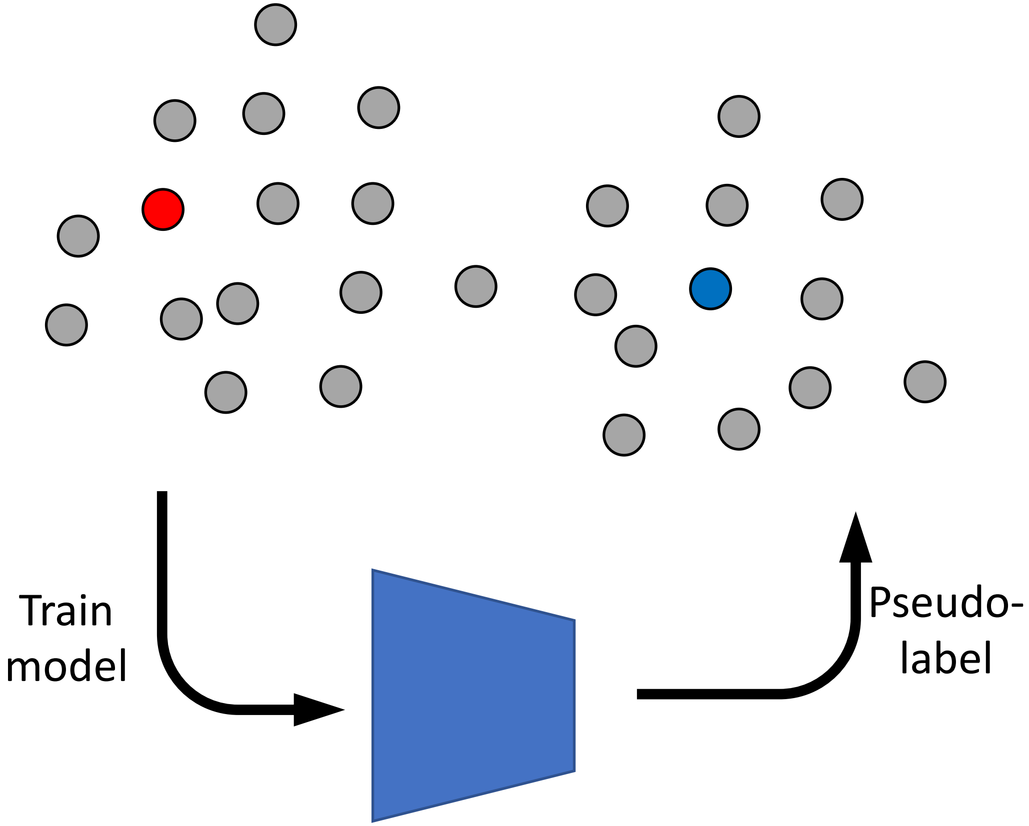
Deep unsupervised learning

- Key question: can we get a deep network to remove all correlations?
- Has been the subject of study for many years
- Contrastive learning turns out to be very good at this!

Semi-supervised learning

- What if we have both labeled and unlabeled data?
- E.g., dataset only partially labeled

Semi-supervised learning I – Self-training / Psuedo-labeling



Semi-supervised learning II – Entropy minimization

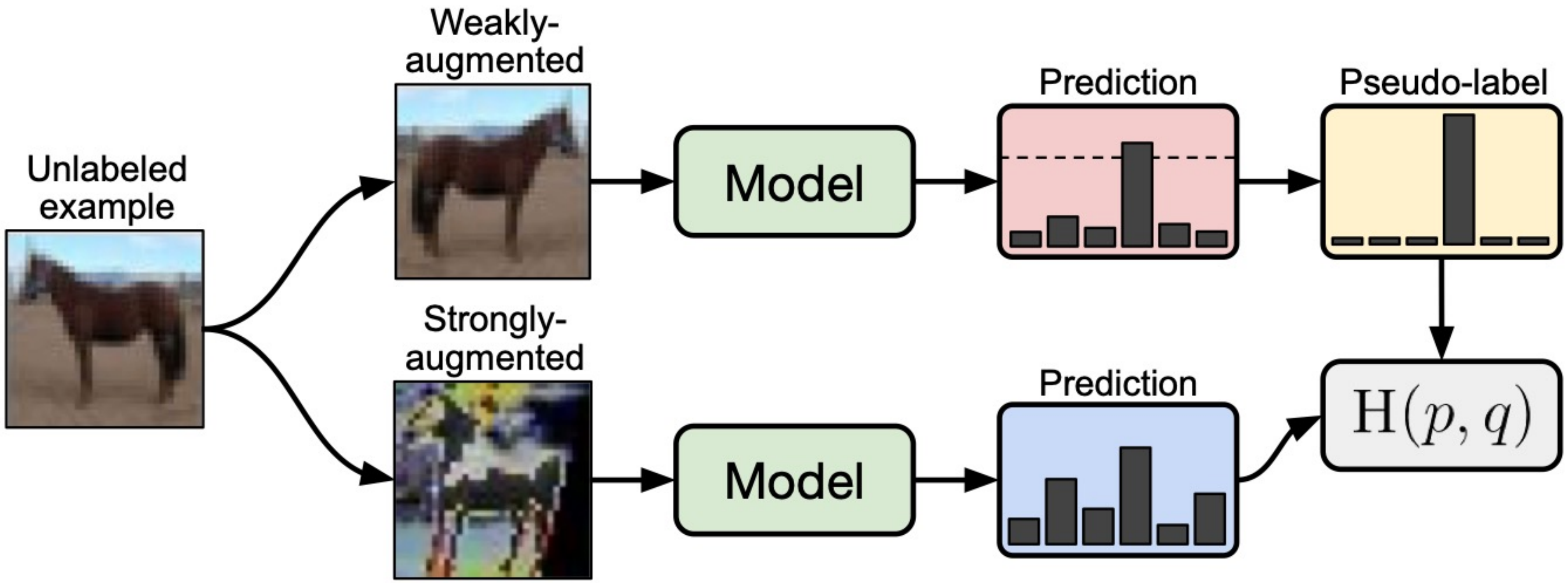
- Loss function on labeled examples: standard negative log likelihood
- Loss function on unlabeled examples: *entropy*
  - $H(p) = -\sum_i p_i \log p_i$
  - Entropy is high when probabilities are uniform
  - Minimize entropy → encourage classifier to be more confident

Semi-supervised learning III – Consistency regularization

- Loss on unlabeled images: *consistency* between predictions on augmented versions

$$l_{\mathcal{U}}^{\mathrm{TS}} = \sum_{j=1}^{n-1} \sum_{k=j+1}^{n} \|\mathbf{f}^j(T^j(\mathbf{x}_i)) - \mathbf{f}^k(T^k(\mathbf{x}_i))\|_2^2$$

Semi-supervised learning IV - FixMatch



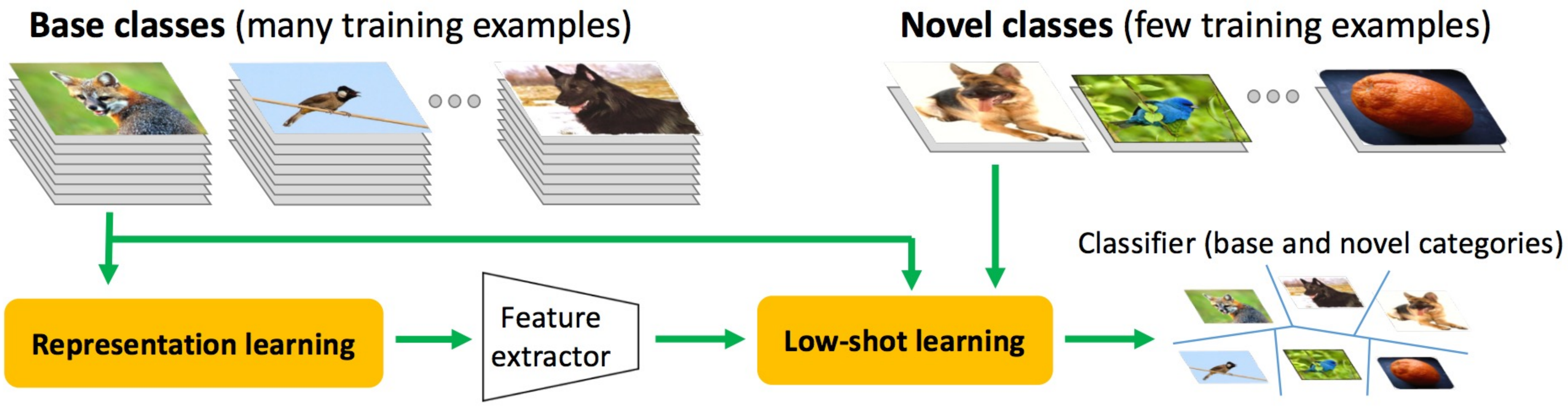
Semi-supervised learning V – S4L

- Simple idea: use *self-supervised loss* on unlabeled data
- “Self-supervision for semi—upervised learning”

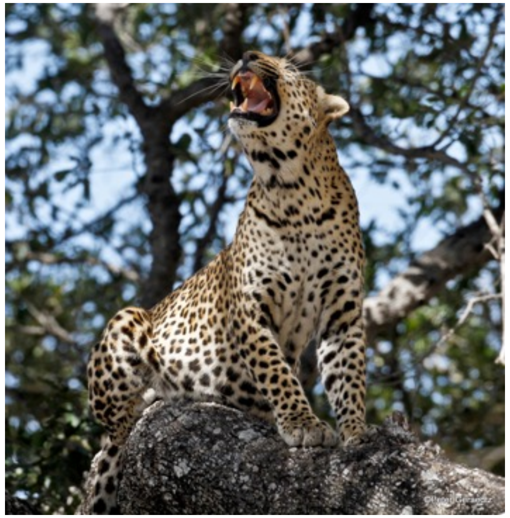
Limitations of semi-supervised learning

- Still needs at least 10s of examples per class
- Need unlabeled data

Few-shot learning



The challenge: Intra-class variation



“Train set”

Philippine Tarsier

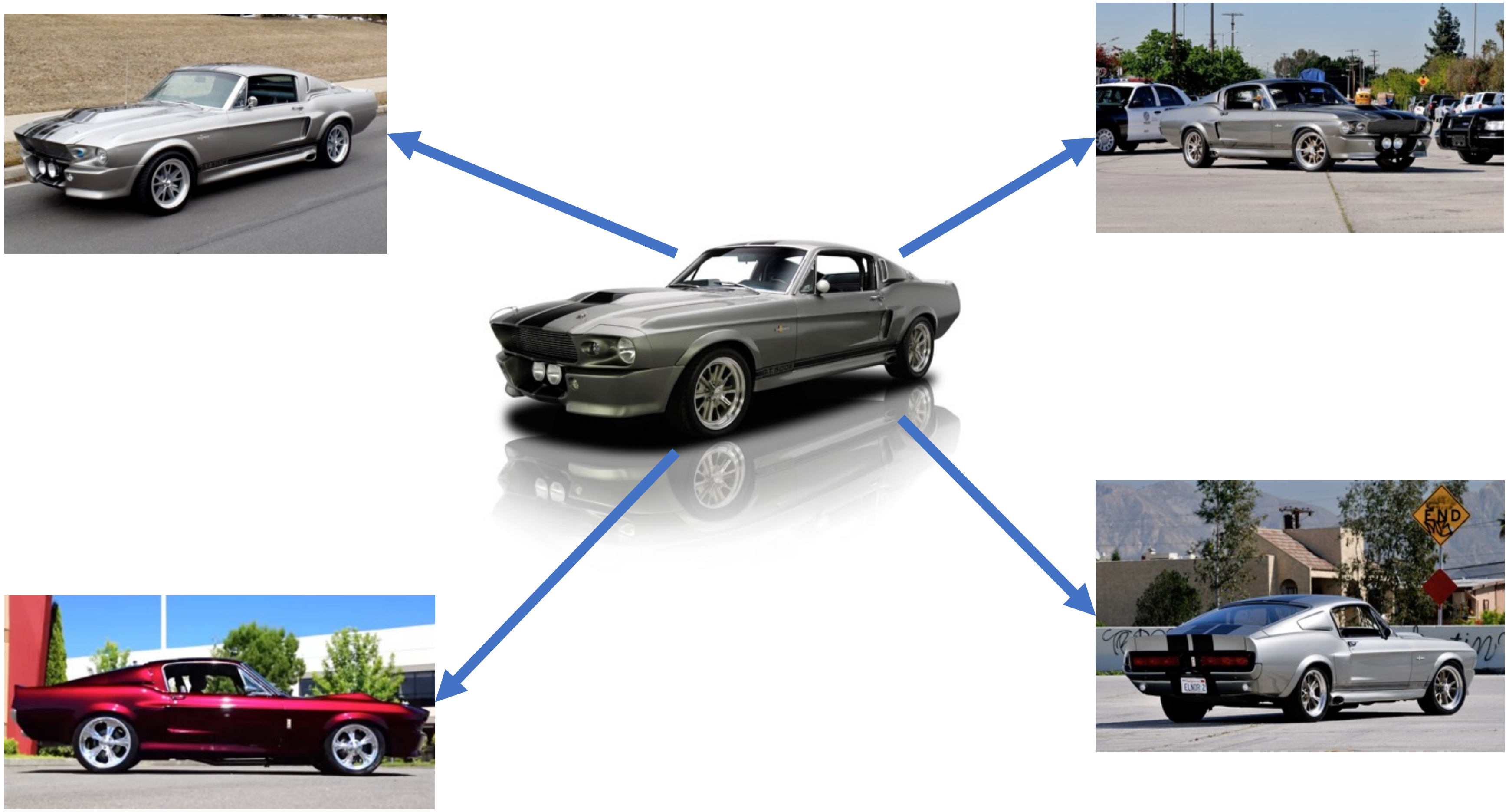
“Test set”

Philippine Tarsier

Mouse lemur

Beaver

Key cue: shared modes of variation



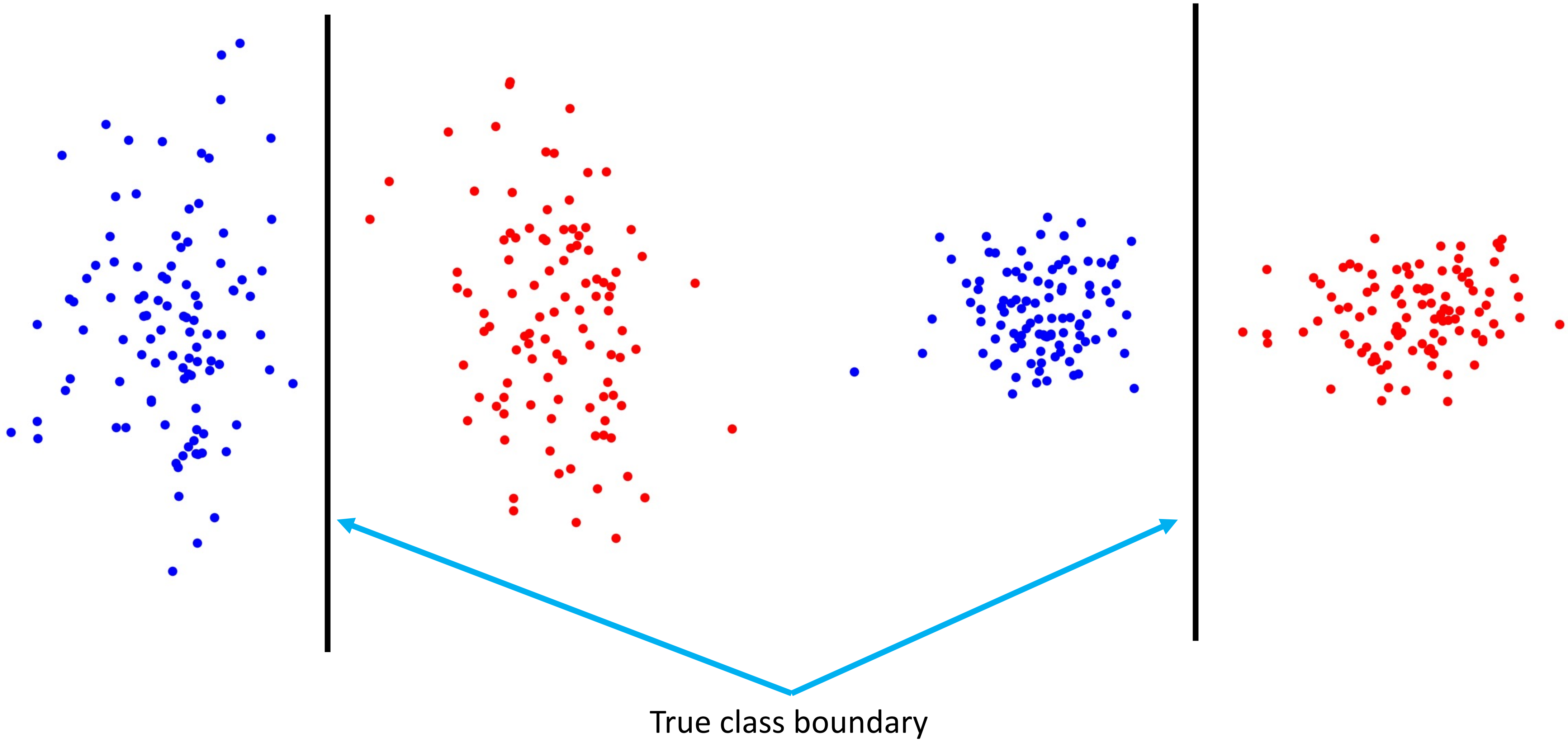
How do humans do this?

Bird, grey color, long beak, long legs, black markings on head,...

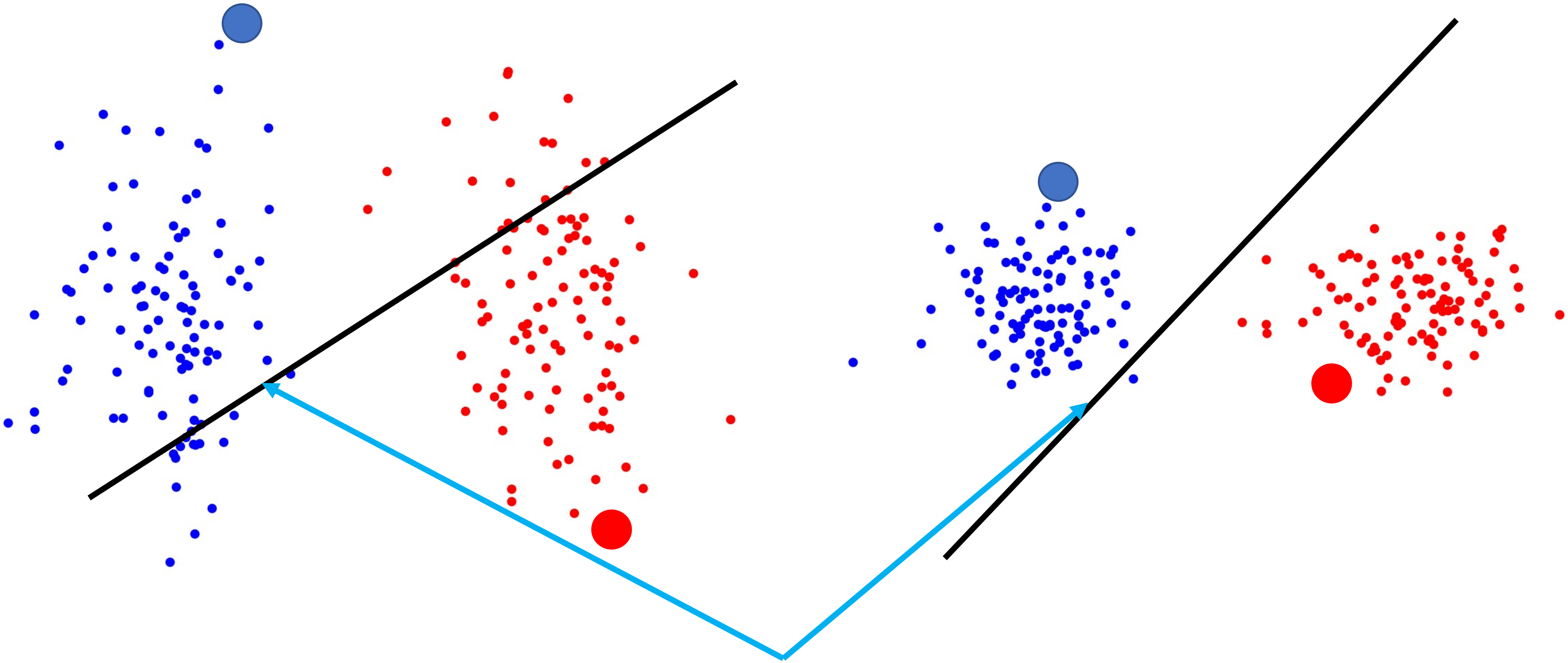
More invariant representations

Inductive biases during learning

Better representations: metric learning



Better representations: metric learning



“One-shot” class boundary

Metric learning

- Pull same-class pairs closer and different-class pairs apart
- Contrastive loss (DrLIM)
  - $= d(x, x')^2 \ \ if \ y = y'$
  - $= \ \max\left(0, m \ - d(x, x')\right)^2 if \ y \neq y'$
- Triplet loss
  - $= \max(d(x, x_+) - d(x, x_-) + \gamma, 0)$

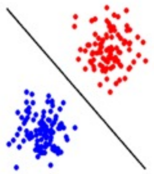
Dimensionality reduction by learning an invariant mapping. *Raia Hadsell, Sumit Chopra, Yann LeCun.*
Computer Vision and Pattern Recognition (CVPR), 2006

Meta-learning

- Given:

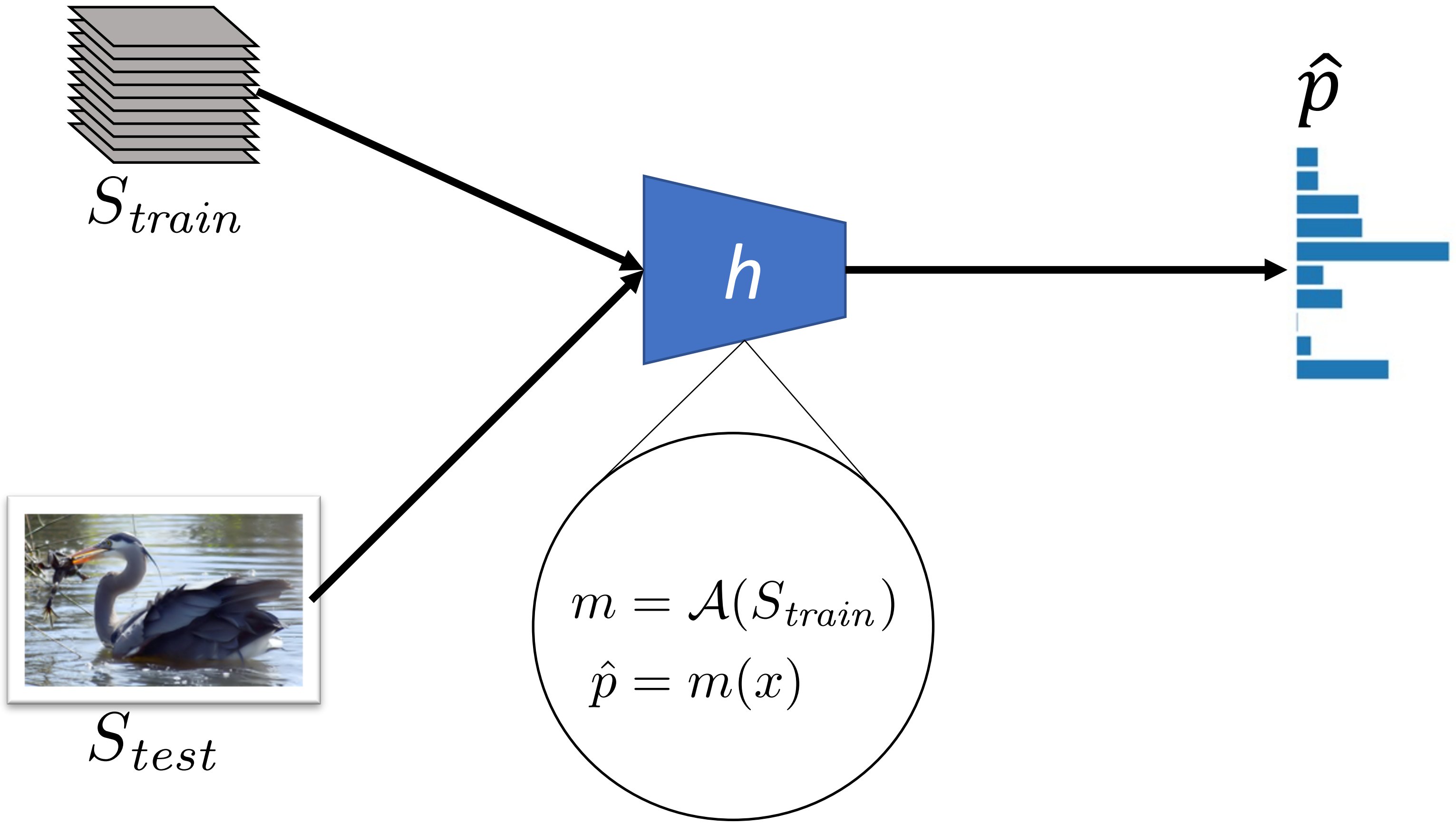
Small training set
(few training examples)

- Produce:

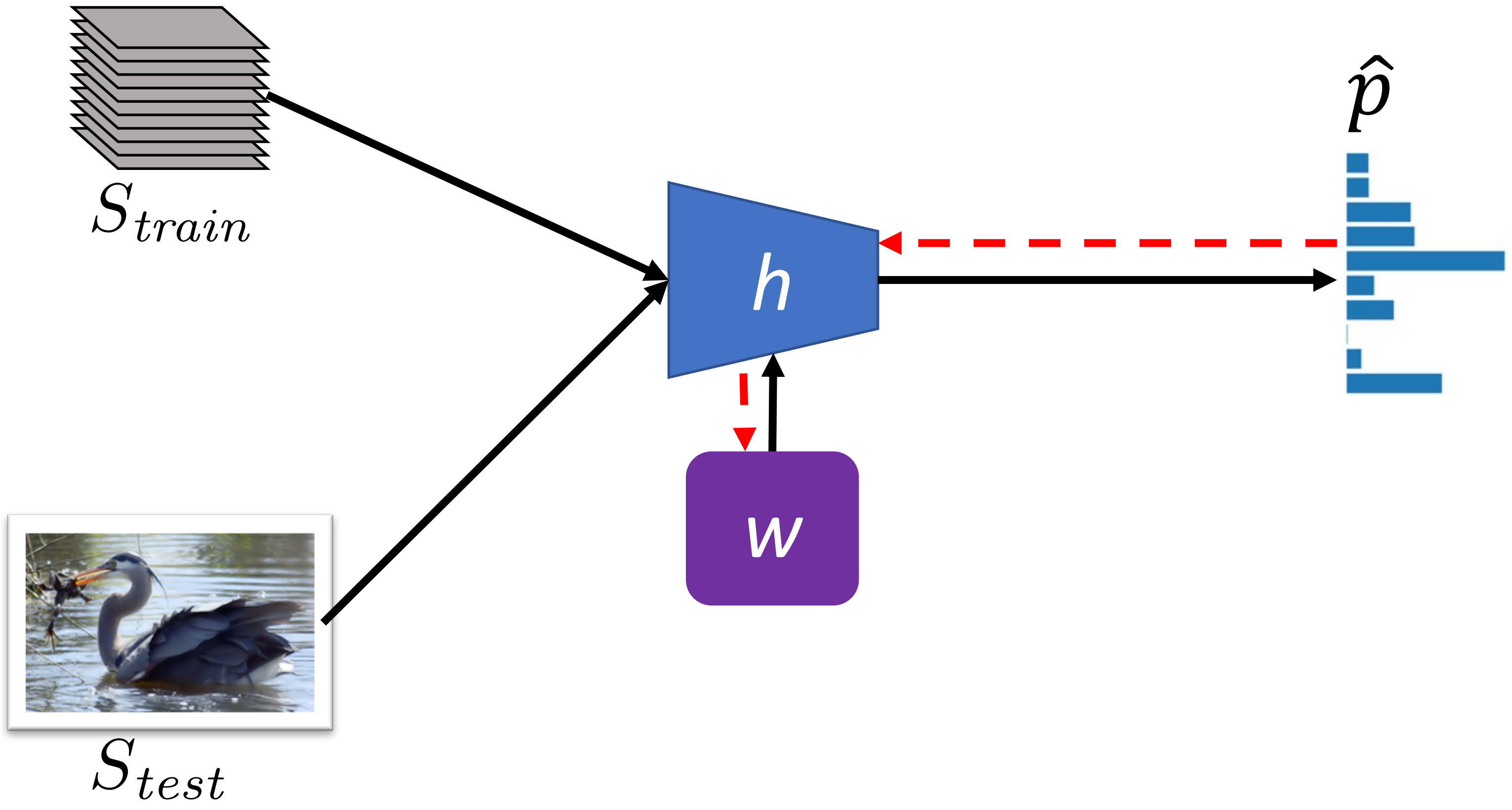


- Idea: Make this a learnable function!

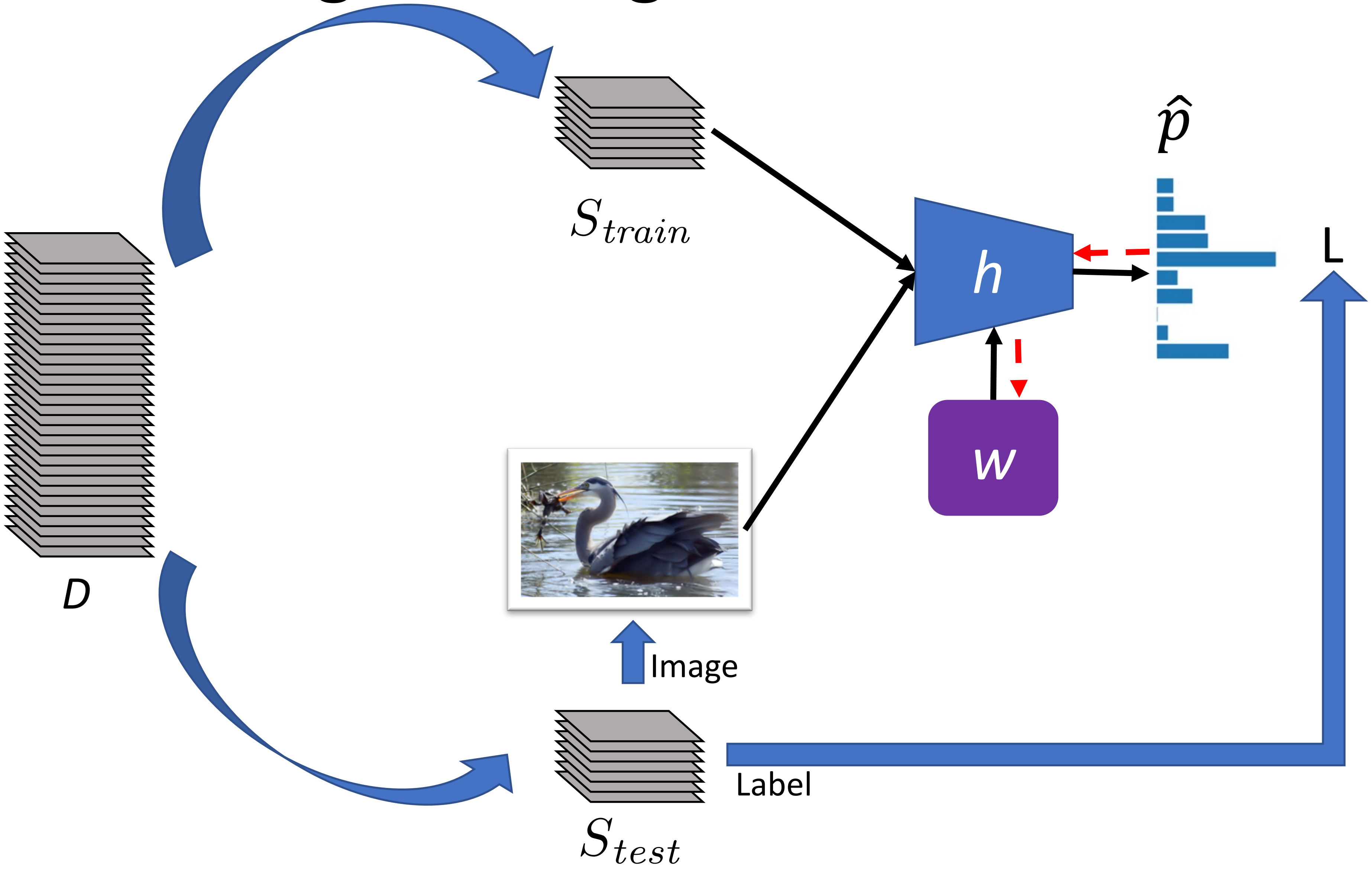
Meta-learning



Meta-learning



Meta-learning: training



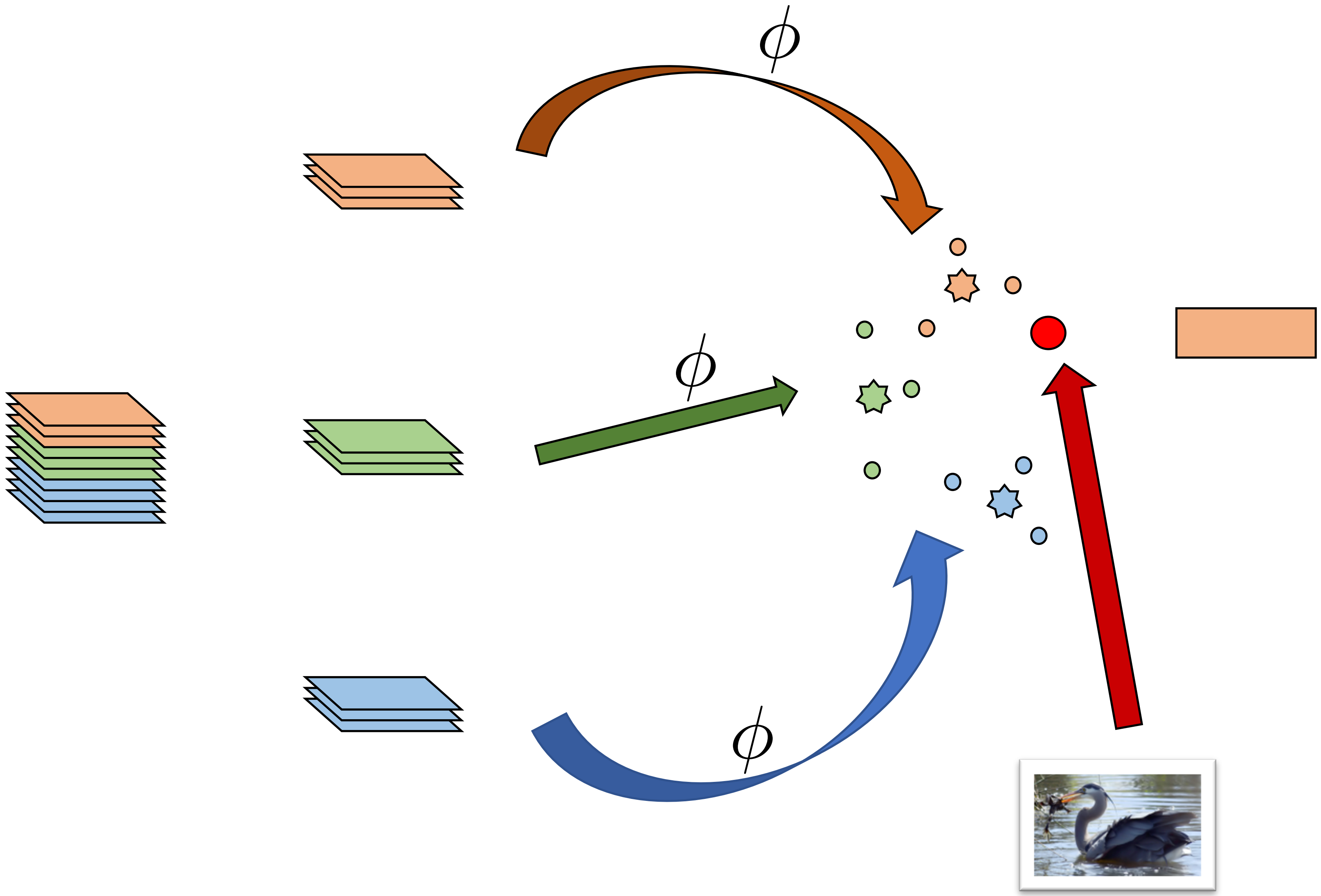
An army of meta-learners

- Vinyals, Oriol, et al. "Matching networks for one shot learning." *NIPS*. 2016.
- Ravi, Sachin, and Hugo Larochelle. "Optimization as a model for few-shot learning." *ICLR,* 2017.
- Snell, Jake, Kevin Swersky, and Richard Zemel. "Prototypical networks for few-shot learning." *NIPS*. 2017.
- Finn, Chelsea, Pieter Abbeel, and Sergey Levine. "Model-agnostic meta-learning for fast adaptation of deep networks." *ICML.* 2017.

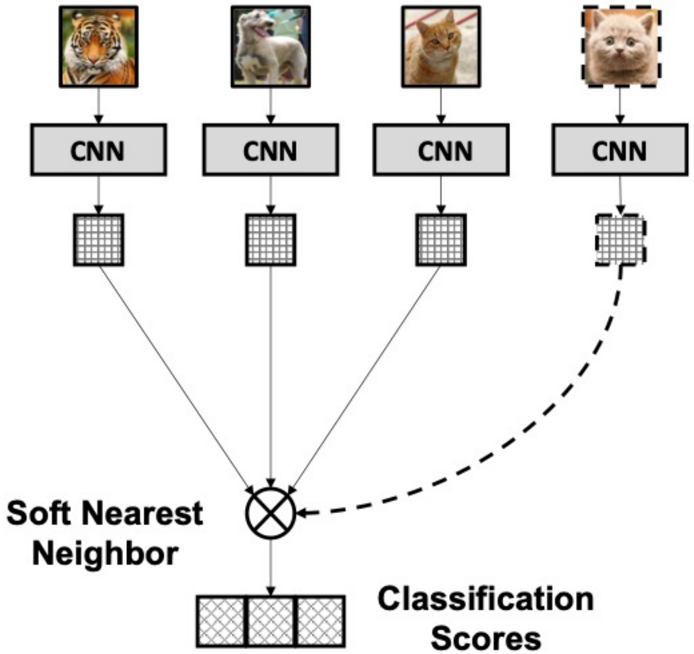
Meta-learning : MAML

- Given training set S, query example q, need function $h(S, q\ ; \boldsymbol{w})$
- Idea:
  - $\boldsymbol{w}$ is initialization of neural network
  - h does a few SGD steps using S and then classifies q
  - Backpropagating through h is difficult but can be done

Meta-learning: Prototypical Networks



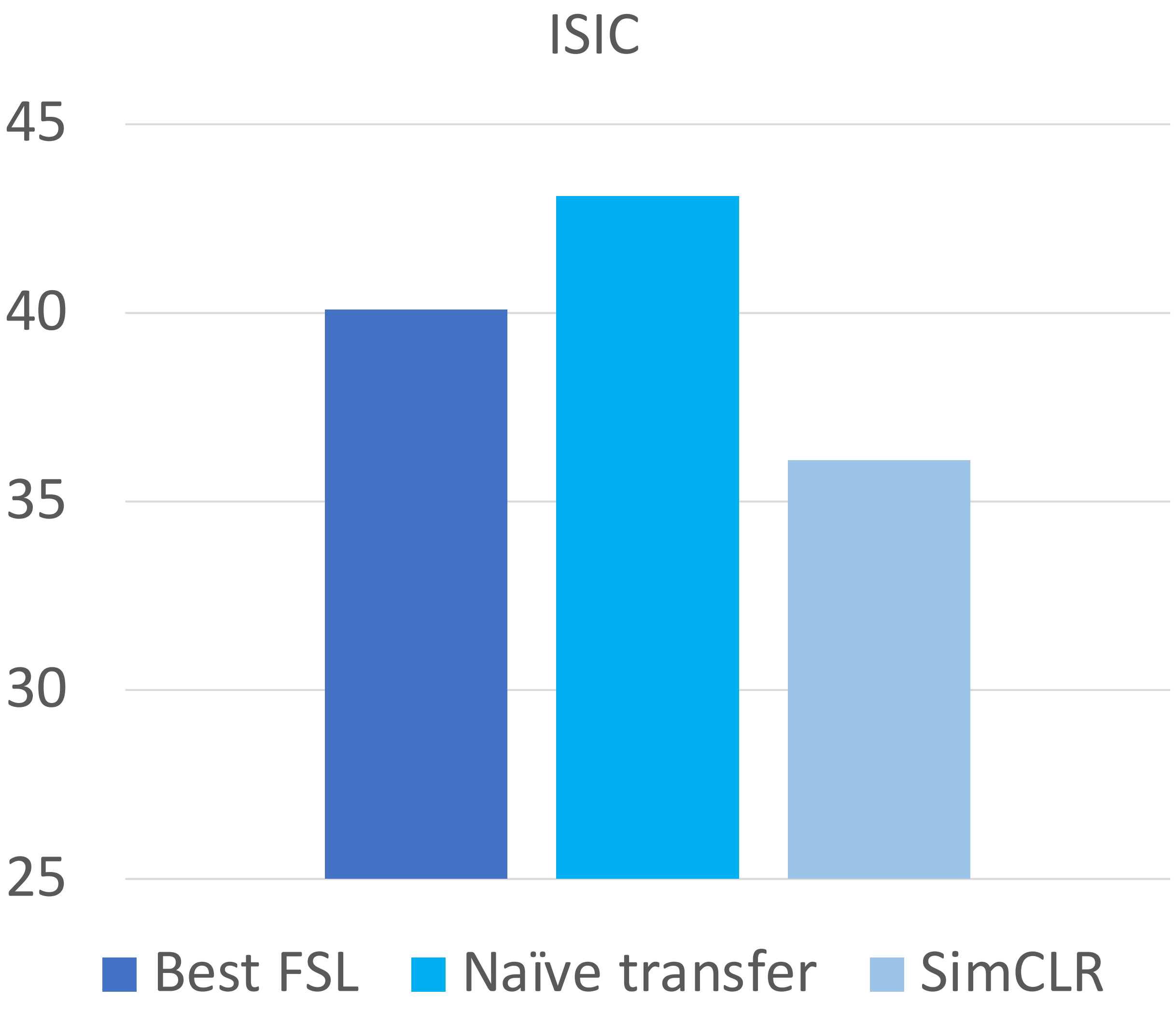
Meta-learning: FEAT

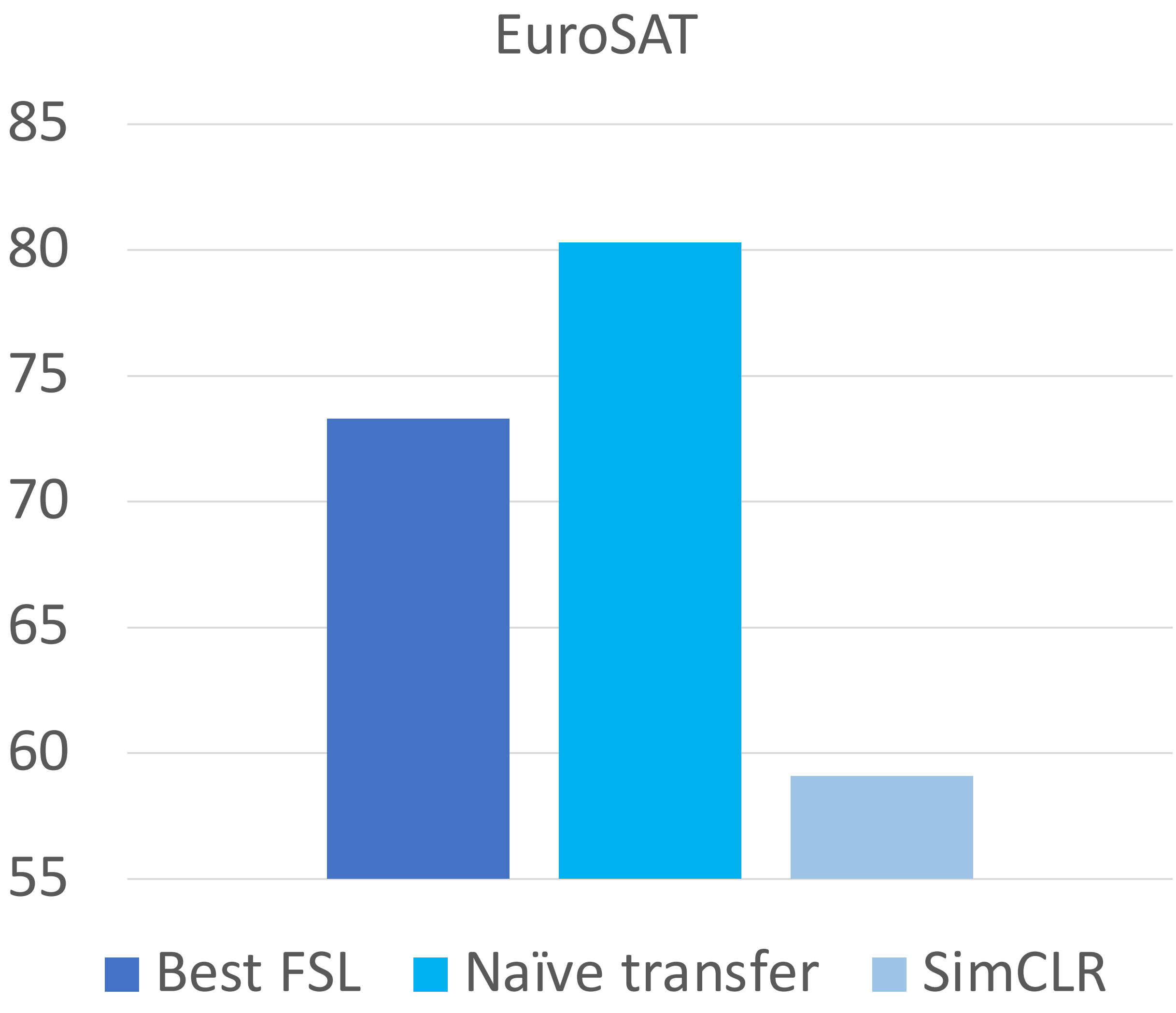


(a) Instance Embedding

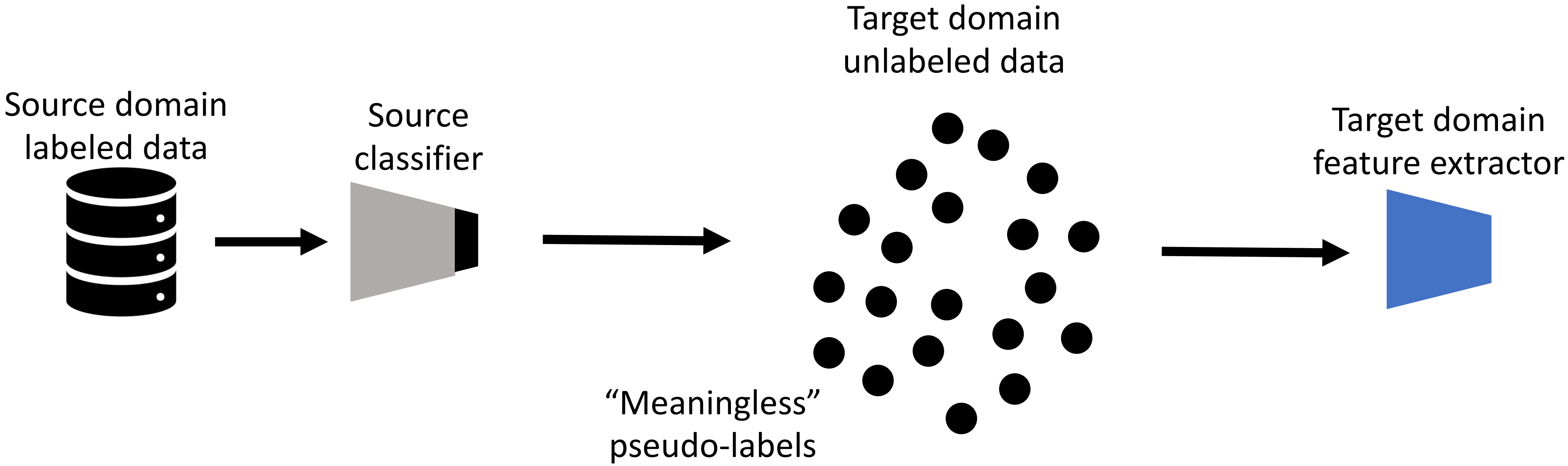
Meta-learning: FRN

Transfer vs self-supervision vs few-shot on new domains





A magic ingredient



Step 1: Train classifier in source domains

Step 2: Pseudo-label target domain unlabeled data

Step 3: Use pseudo-labels + self-supervision to train target domain features

The magic of self-training in 3 steps

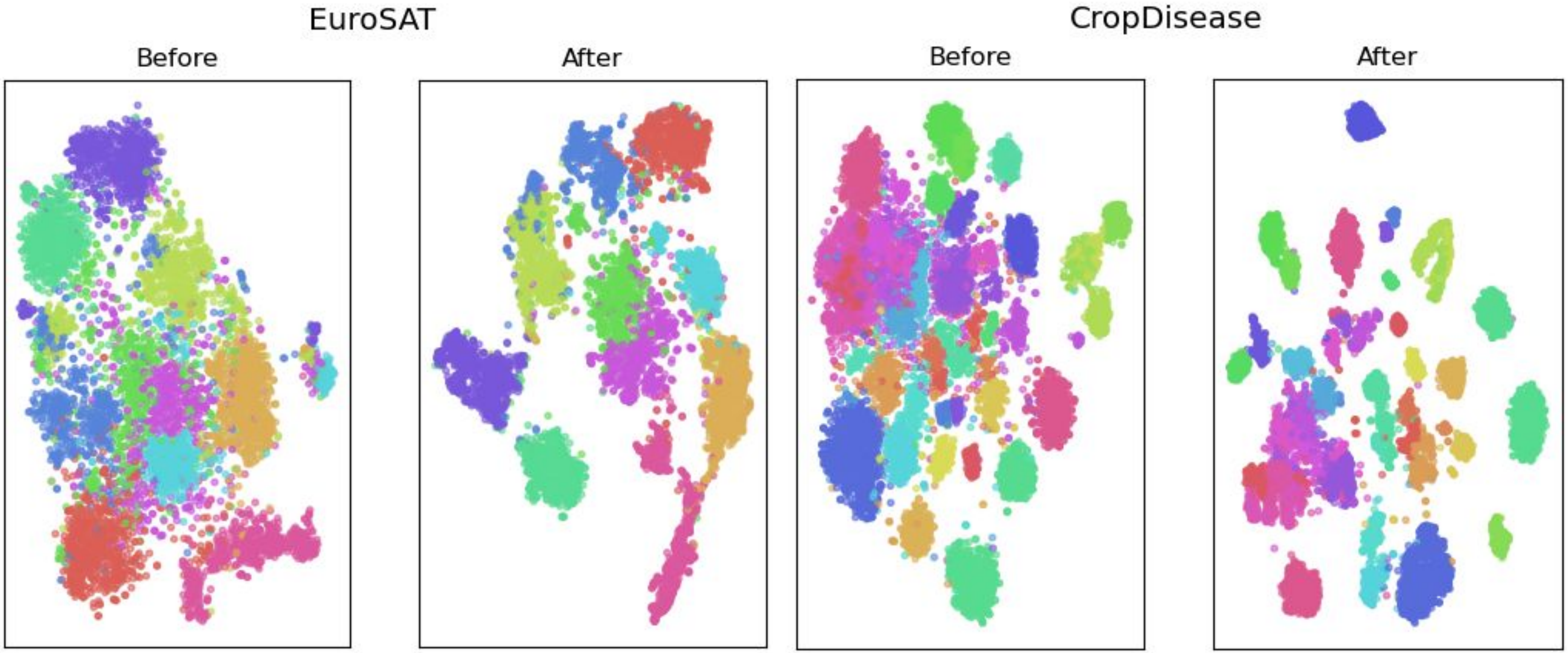
1. Pre-train convnet on source domain (ImageNet)

2. Use pre-trained convnet on unlabeled data from target domain to get pseudolabels

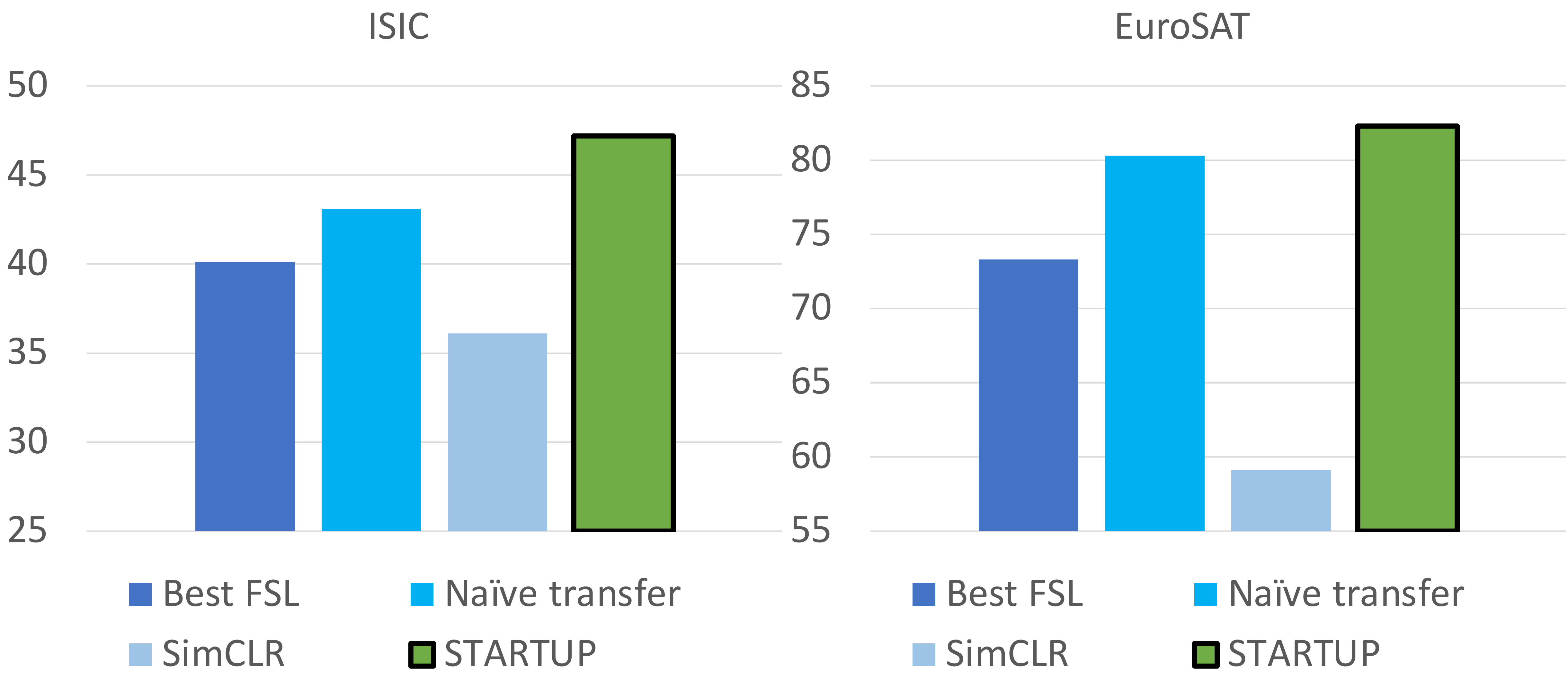
3. Use pseudo-labels to train target domain representation (+SimCLR as potential aux. loss)

Self **T**raining for **A**dapting **R**epresentations **T**o **U**nseen **P**roblems (under review)

STARTUP – what does it do?



STARTUP


ISIC
50
45
40
35
30
25
Best FSL
Naïve transfer
SimCLR
STARTUP
EuroSAT
85
80
75
70
65
60
55
Best FSL
Naïve transfer
SimCLR
STARTUP

Why does STARTUP work?

- Induced grouping can be still meaningful in the target domain
  - STARTUP performance correlated with this

- Training with induced grouping forces network to learn domain-specific features

Phoo, Cheng Perng, and Bharath Hariharan. "Self-training for Few-shot Transfer Across Extreme Task Differences." *ICLR, 2021.*