Computer Vision; Image Classification; Data-efficient Learning

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– un/self/semi-supervised learning

– representation learning and/or label propagation

Self-training with Noisy Student improves ImageNet classification

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Require: Labeled images $\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$ and unlabeled images $\{\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_m\}$.

1: Learn teacher model θ_*^t which minimizes the cross entropy loss on labeled images

$$\frac{1}{n}\sum_{i=1}^{n} \ell(y_i, f^{noised}(x_i, \theta^t))$$

2: Use an unnoised teacher model to generate soft or hard pseudo labels for unlabeled images

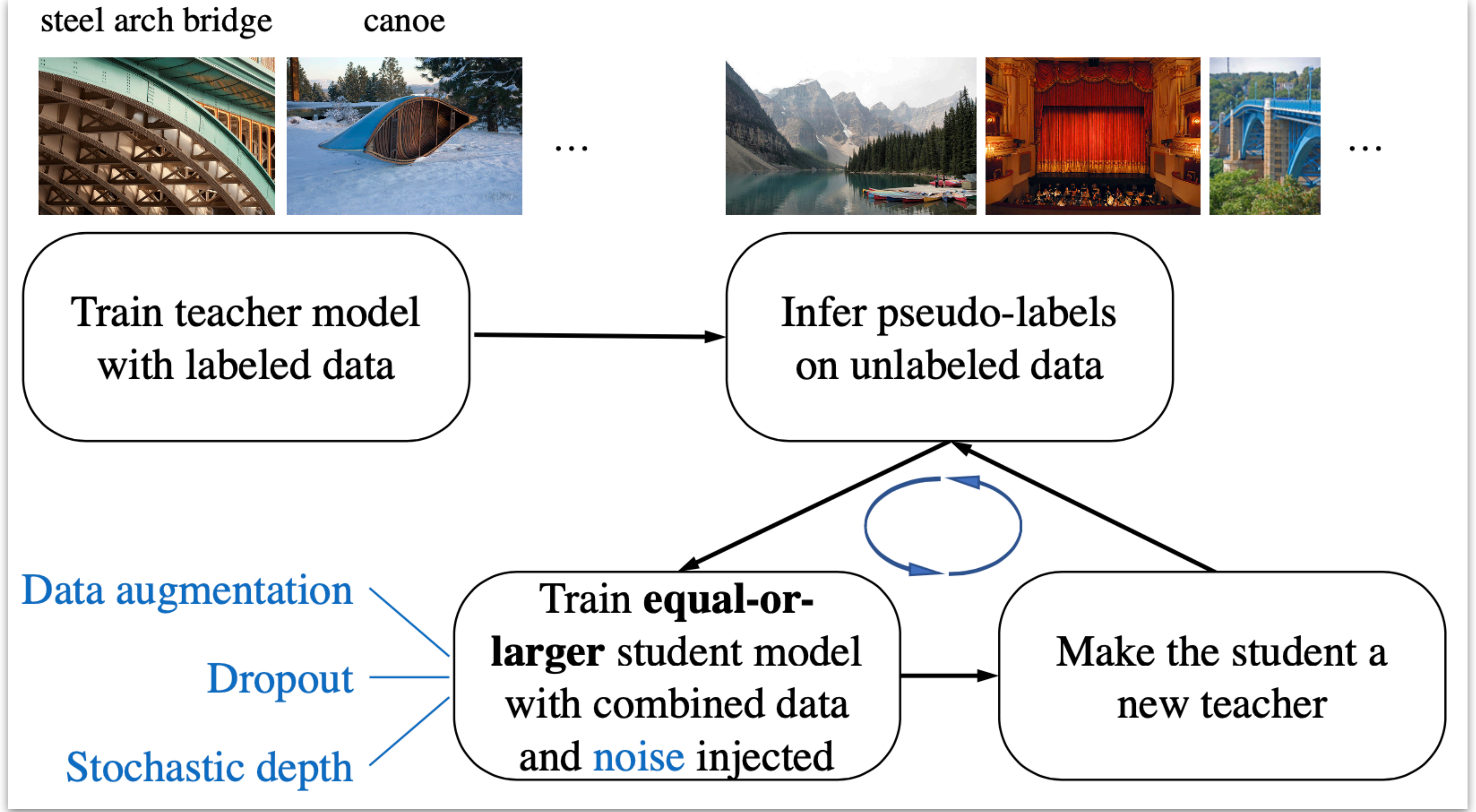
$$\tilde{y}_i = f(\tilde{x}_i, \theta_*^t), \forall i = 1, \cdots, m$$

3: Learn an **equal-or-larger** student model θ_*^s which minimizes the cross entropy loss on labeled images and unlabeled images with **noise** added to the student model

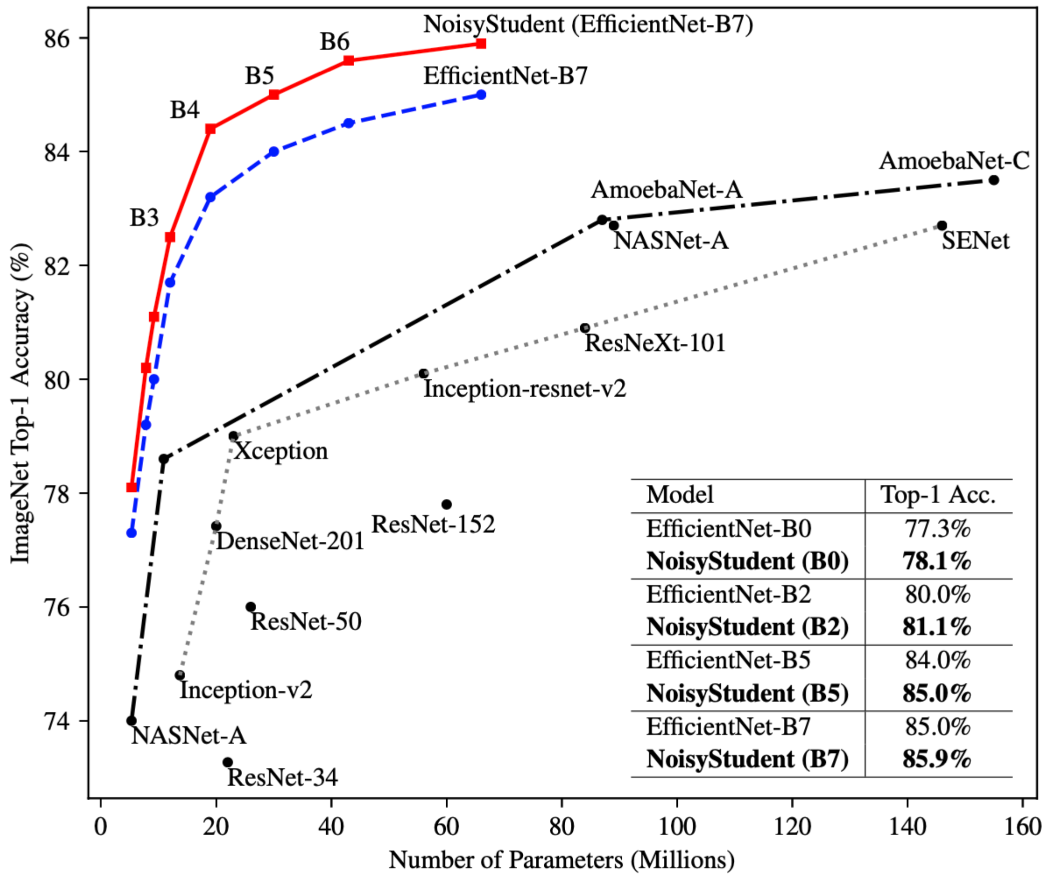
$$\frac{1}{n}\sum_{i=1}^{n} \ell(y_i, f^{noised}(x_i, \theta^s)) + \frac{1}{m}\sum_{i=1}^{m} \ell(\tilde{y}_i, f^{noised}(\tilde{x}_i, \theta^s))$$

4: Iterative training: Use the student as a teacher and go back to step 2.

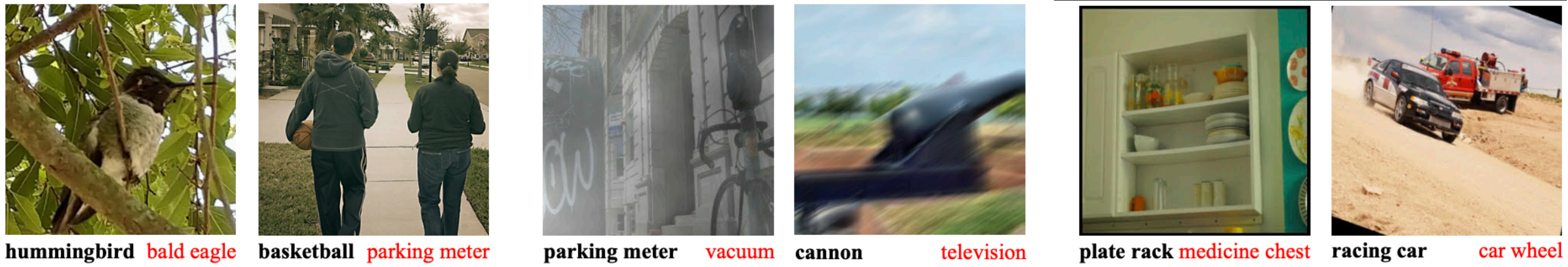
	ImageNet top-1 acc.	ImageNet-A top-1 acc.	ImageNet-C mCE	ImageNet-P mFR
Prev. SOTA	86.4%	61.0%	45.7	27.8
NoisyStudent	**88.4%**	**83.7%**	**28.3**	**12.2**



ImageNet-C and ImageNet-P test sets include images with common corruptions and perturbations such as blurring, fogging, rotation and scaling. ImageNet-A test set consists of difficult images that cause significant drops in accuracy to state-of-the-art models. These test sets are considered as “robustness” benchmarks.



mCE (mean corruption error) is the weighted average of error rate on different corruptions, with AlexNet’s error rate as a baseline (lower is better). mFR (mean flip rate) measures the model's probability of flipping predictions under perturbations with AlexNet as a baseline (lower is better).



(a) ImageNet-A (b) ImageNet-C (c) ImageNet-P

Xie, Qizhe, et al. "Self-training with noisy student improves imagenet classification." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020.

Deep Clustering for Unsupervised Learning of Visual Features

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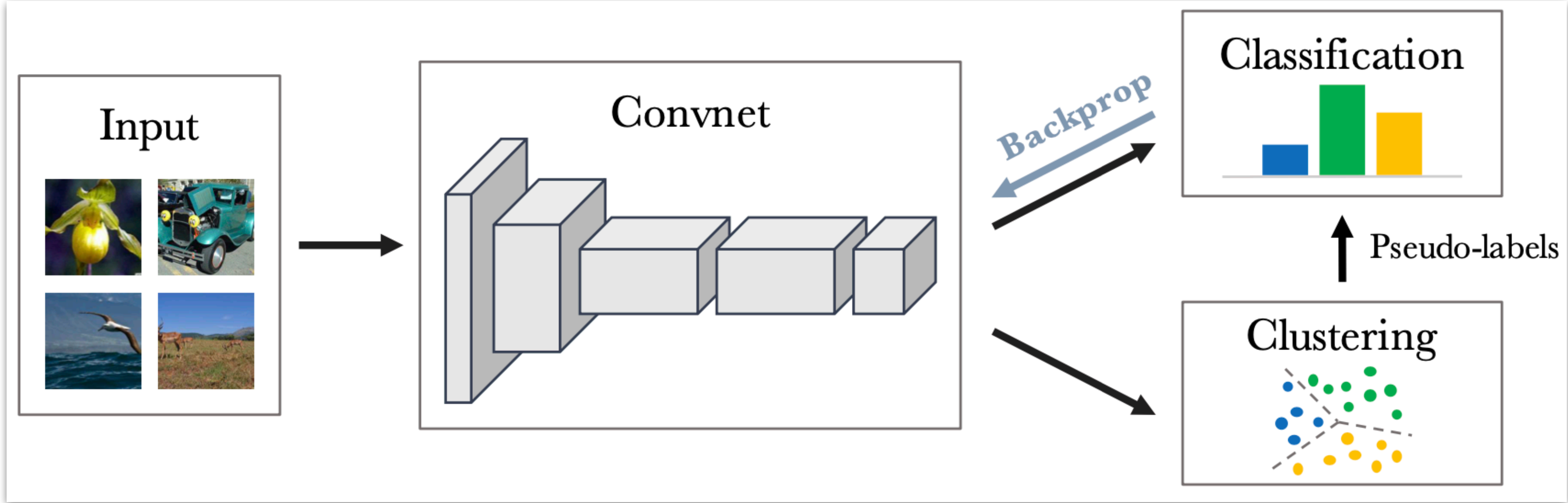
Key observation: A multilayer perceptron classifier on top of the last convolutional layer of a random AlexNet achieves 12% in accuracy on ImageNet while the chance is at 0.1%.

This is because a convolutional structure gives a strong prior.

$\{x_1, \ldots, x_N\} \rightarrow$ training set of N images

Problem setup: Find parameters θ^* such that the convnet mapping f_{θ^*} produces good general-purpose features (representations).



k-means: cluster the features $f_\theta(x_n)$ into k distinct groups

$C \in \mathbb{R}^{d \times k} \rightarrow$ centroid matrix

$y_n \rightarrow$ cluster assignment of each image

$$\min_{C \in \mathbb{R}^{d \times k}} \frac{1}{N} \sum_{n=1}^{N} \min_{y_n \in \{0,1\}^k} \|f_\theta(x_n) - C y_n\|_2^2 \quad \text{such that} \quad y_n^\top 1_k = 1.$$

$y_n^* \rightarrow$ optimal assignment (pseudo label)

$C^* \rightarrow$ optimal centroid matrix (not used)

$g_W \rightarrow$ parametrized classifier on top of the features $f_\theta(x_n)$

$$\min_{\theta, W} \frac{1}{N} \sum_{n=1}^{N} \ell\left(g_W\left(f_\theta(x_n)\right), y_n\right)$$

multinomial logistic loss

Avoiding Trivial Solutions

Empty clusters:

An optimal decision boundary is to assign all of the inputs to a single cluster.

When a cluster becomes empty, randomly select a non-empty cluster and use its centroid with a small random perturbation as the new centroid for the empty cluster. Then reassign the points belonging to the non-empty cluster to the two resulting clusters.

Trivial parametrization:

Unbalanced number of images per cluster

Sample images based on a uniform distribution over the classes, or pseudo-labels.

PASCAL VOC transfer tasks		Classification		Detection		Segmentation	
Method	Training set	FC6-8	ALL	FC6-8	ALL	FC6-8	ALL
Best competitor	ImageNet	63.0	67.7	43.4†	53.2	35.8†	37.7
DeepCluster	ImageNet	72.0	73.7	51.4	55.4	43.2	45.1
DeepCluster	YFCC100M	67.3	69.3	45.6	53.0	39.2	42.2

Pascal VOC 2007 object detection

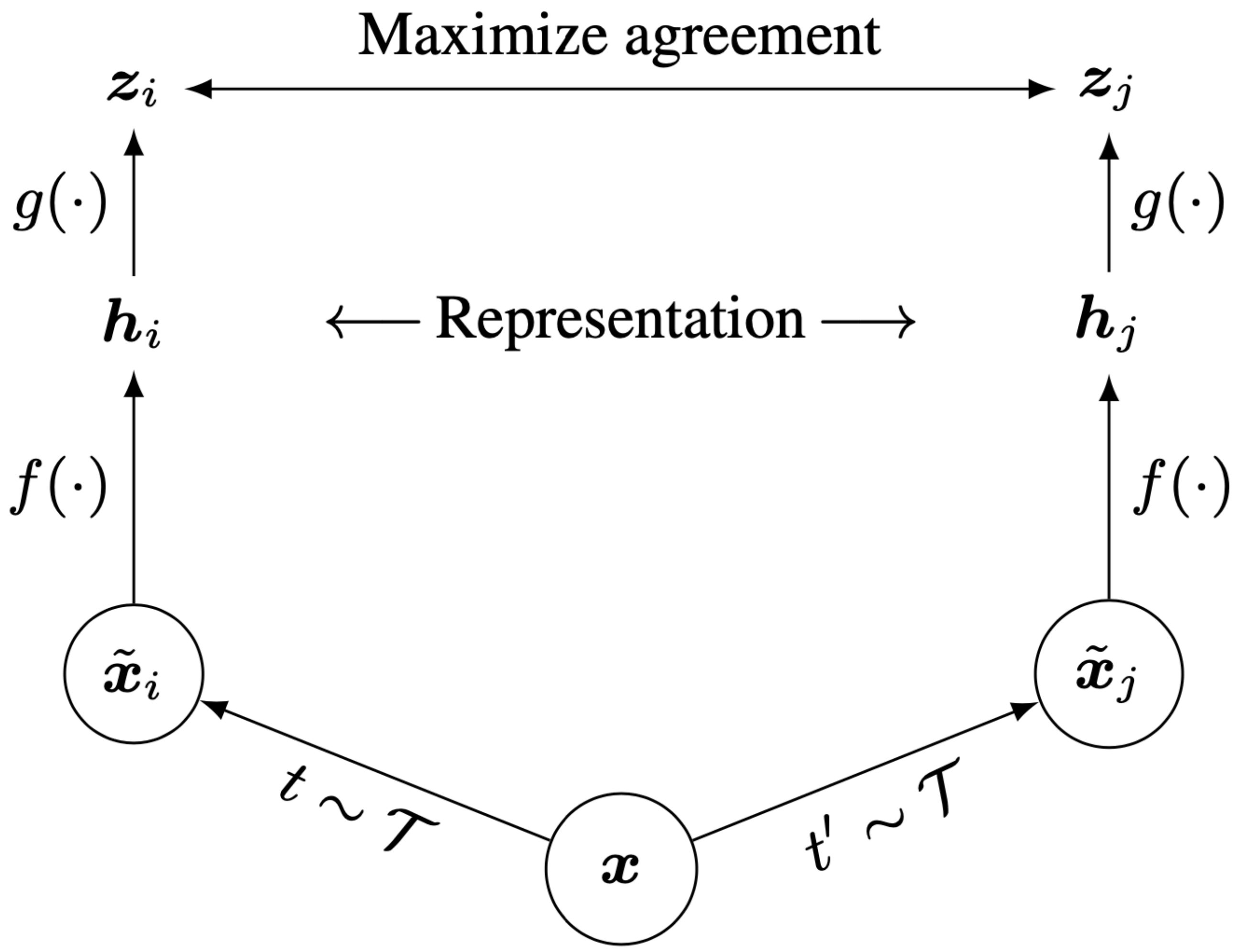
Method	AlexNet	VGG-16
ImageNet labels	56.8	67.3
Random	47.8	39.7
Doersch *et al.* [13]	51.1	61.5
Wang and Gupta [63]	47.2	60.2
Wang *et al.* [64]	–	63.2
DeepCluster	**55.4**	**65.9**

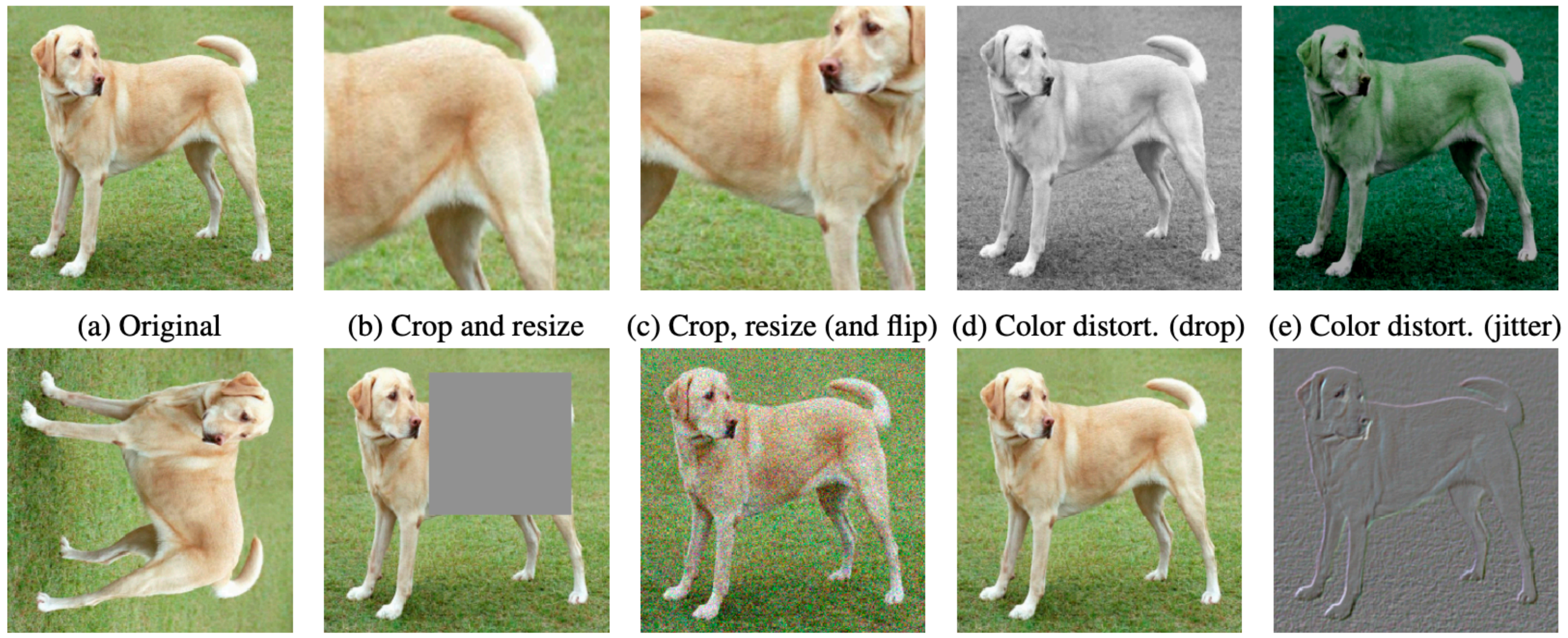
mAP on instance-level image retrieval on Oxford and Paris dataset with a VGG-16

Method	Oxford5K	Paris6K
ImageNet labels	72.4	81.5
Random	6.9	22.0
Doersch *et al.* [13]	35.4	53.1
Wang *et al.* [64]	42.3	58.0
DeepCluster	**61.0**	**72.0**

Caron, Mathilde, et al. "Deep clustering for unsupervised learning of visual features." *Proceedings of the European Conference on Computer Vision (ECCV)*. 2018.

A Simple Framework for Contrastive Learning of Visual Representations





(a) Original (b) Crop and resize (c) Crop, resize (and flip) (d) Color distort. (drop) (e) Color distort. (jitter)

(f) Rotate $\{90°, 180°, 270°\}$ (g) Cutout (h) Gaussian noise (i) Gaussian blur (j) Sobel filtering

$\tilde{x}_i, \tilde{x}_j \rightarrow$ two correlated views of the same example

Data Augmentation

Random cropping and resizing to the original size
Random color distortions
Random Gaussian blur

Base Encoder

$h_i = f(\tilde{x}_i) = \text{ResNet}(\tilde{x}_i)$

$h_i \in \mathbb{R}^d \rightarrow$ output after average pooling layer

Projection Head

$z_i = g(h_i) = W^2 \underbrace{\sigma}_{\text{ReLU}}(W^1 h_i)$

Contrastive Loss

Contrastive Prediction Task: Given a set $\{\tilde{x}_k\}$ including a positive pair of examples $\tilde{x}_i$ and $\tilde{x}_j$, identify $\tilde{x}_j$ in $\{\tilde{x}_k\}_{k \neq i}$ for a given $\tilde{x}_i$.

minibatch: N examples $\implies 2N$ data datapoints

Given a positive pair, treat the other $2(N-1)$ augmented examples as negatives

$\text{sim}(u, v) = u^T v / \|u\| \|v\| \rightarrow$ cosine similarity

$$\ell_{i,j} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(z_i, z_k)/\tau)}$$

NT-Xent Loss (normalized temperature-scaled cross entropy loss)

$\tau \rightarrow$ temperature

The final loss is computed over all positive pairs (i, j) & (j, i).

Transfer learning performance

	Food	CIFAR10	CIFAR100	Birdsnap	SUN397	Cars	Aircraft	VOC2007	DTD	Pets	Caltech-101	Flowers
Linear evaluation:												
SimCLR (ours)	**76.9**	**95.3**	80.2	48.4	**65.9**	60.0	61.2	**84.2**	**78.9**	89.2	**93.9**	**95.0**
Supervised	75.2	**95.7**	**81.2**	**56.4**	64.9	**68.8**	**63.8**	83.8	**78.7**	**92.3**	**94.1**	94.2
Fine-tuned:												
SimCLR (ours)	**89.4**	**98.6**	**89.0**	**78.2**	**68.1**	**92.1**	**87.0**	**86.6**	**77.8**	92.1	**94.1**	97.6
Supervised	88.7	98.3	**88.7**	**77.8**	67.0	91.4	**88.0**	86.5	**78.8**	**93.2**	**94.2**	**98.0**
Random init	88.3	96.0	81.9	**77.0**	53.7	91.3	84.8	69.4	64.1	82.7	72.5	92.5

Self-supervised learning on ImageNet

Method	Architecture	Param (M)	Top 1	Top 5
Methods using ResNet-50:				
Local Agg.	ResNet-50	24	60.2	-
MoCo	ResNet-50	24	60.6	-
PIRL	ResNet-50	24	63.6	-
CPC v2	ResNet-50	24	63.8	85.3
SimCLR (ours)	ResNet-50	24	**69.3**	**89.0**
Methods using other architectures:				
Rotation	RevNet-50 (4×)	86	55.4	-
BigBiGAN	RevNet-50 (4×)	86	61.3	81.9
AMDIM	Custom-ResNet	626	68.1	-
CMC	ResNet-50 (2×)	188	68.4	88.2
MoCo	ResNet-50 (4×)	375	68.6	-
CPC v2	ResNet-161 (∗)	305	71.5	90.1
SimCLR (ours)	ResNet-50 (2×)	94	74.2	92.0
SimCLR (ours)	ResNet-50 (4×)	375	**76.5**	**93.2**

Semi-supervised learning on ImageNet

Method	Architecture	Label fraction 1%	10%
		Top 5	
Supervised baseline	ResNet-50	48.4	80.4
Methods using other label-propagation:			
Pseudo-label	ResNet-50	51.6	82.4
VAT+Entropy Min.	ResNet-50	47.0	83.4
UDA (w. RandAug)	ResNet-50	-	88.5
FixMatch (w. RandAug)	ResNet-50	-	89.1
S4L (Rot+VAT+En. M.)	ResNet-50 (4×)	-	91.2
Methods using representation learning only:			
InstDisc	ResNet-50	39.2	77.4
BigBiGAN	RevNet-50 (4×)	55.2	78.8
PIRL	ResNet-50	57.2	83.8
CPC v2	ResNet-161(∗)	77.9	91.2
SimCLR (ours)	ResNet-50	75.5	87.8
SimCLR (ours)	ResNet-50 (2×)	83.0	91.2
SimCLR (ours)	ResNet-50 (4×)	**85.8**	**92.6**

Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." *arXiv preprint arXiv:2002.05709* (2020).

Momentum Contrast for Unsupervised Visual Representation Learning

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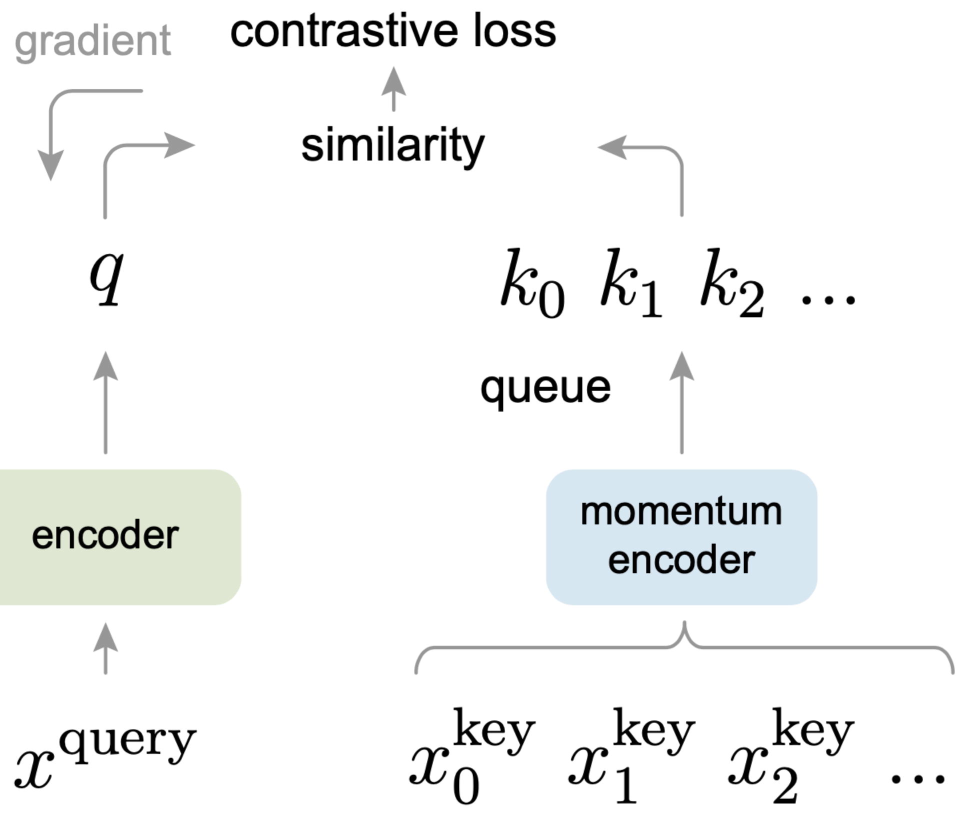

Keys (tokens): samples from the data (e.g., images or patches) represented by an encoder network

Unsupervised Learning: dictionary look-up

```
An encoded "query" should be
similar to its matching "key"
and dissimilar to others
```

Instance discrimination task

A query matches a key if they are encoded views (e.g., different crops) of the same image

Contrastive learning

$q \rightarrow$ encoded query

$\{k_0, k_1, \ldots\} \rightarrow$ set of encoded samples (keys of a dictionary)

$k_+ \rightarrow$ the single key in the dictionary that matches q

$$\underbrace{\mathcal{L}_q}_{\text{InfoNCE (noise-contrastive estimation) loss}} = -\log \frac{\exp(q \cdot k_+ / \tau)}{\sum_{i=0}^{K} \exp(q \cdot k_i / \tau)}$$

$\tau \rightarrow$ temperature hyper-parameter

$q = \underbrace{f_q}_{\text{encoder network}}(x^q)$ query sample

$k = f_k(x^k)$

Momentum Contrast (MoCo)

① dynamic ② large ③ consistent dictionary

dictionary as queue

```
The current mini-batch is enqueued to the dictionary,
and the oldest mini-batch in the queue is removed
```

$\theta_k \rightarrow$ parameters of f_k

$\theta_q \rightarrow$ parameters of f_q

$\theta_k \leftarrow m\theta_k + (1-m)\theta_q, m \in [0,1), m = 0.999$

$\theta_q \rightarrow$ updated by backprop

Object detection fine-tuned on PASCAL VOC

pre-train	AP_{50}	AP	AP_{75}
random init.	60.2	33.8	33.1
super. IN-1M	81.3	53.5	58.8
MoCo IN-1M	81.5 (+0.2)	55.9 (+2.4)	62.6 (+3.8)
MoCo IG-1B	82.2 (+0.9)	57.2 (+3.7)	63.7 (+4.9)

Faster R-CNN

ImageNet-1M (IN-1M), Instagram-1B (IG-1B), super. (supervised)

Algorithm 1 Pseudocode of MoCo in a PyTorch-like style.

```
# f_q, f_k: encoder networks for query and key
# queue: dictionary as a queue of K keys (CxK)
# m: momentum
# t: temperature

f_k.params = f_q.params # initialize
for x in loader: # load a minibatch x with N samples
   x_q = aug(x) # a randomly augmented version
   x_k = aug(x) # another randomly augmented version

   q = f_q.forward(x_q) # queries: NxC
   k = f_k.forward(x_k) # keys: NxC
   k = k.detach() # no gradient to keys

   # positive logits: Nx1
   l_pos = bmm(q.view(N,1,C), k.view(N,C,1))

   # negative logits: NxK
   l_neg = mm(q.view(N,C), queue.view(C,K))

   # logits: Nx(1+K)
   logits = cat([l_pos, l_neg], dim=1)

   # contrastive loss, Eqn.(1)
   labels = zeros(N) # positives are the 0-th
   loss = CrossEntropyLoss(logits/t, labels)

   # SGD update: query network
   loss.backward()
   update(f_q.params)

   # momentum update: key network
   f_k.params = m*f_k.params+(1-m)*f_q.params

   # update dictionary
   enqueue(queue, k) # enqueue the current minibatch
   dequeue(queue) # dequeue the earliest minibatch
```

bmm: batch matrix multiplication; mm: matrix multiplication; cat: concatenation.

He, Kaiming, et al. "Momentum contrast for unsupervised visual representation learning." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020.

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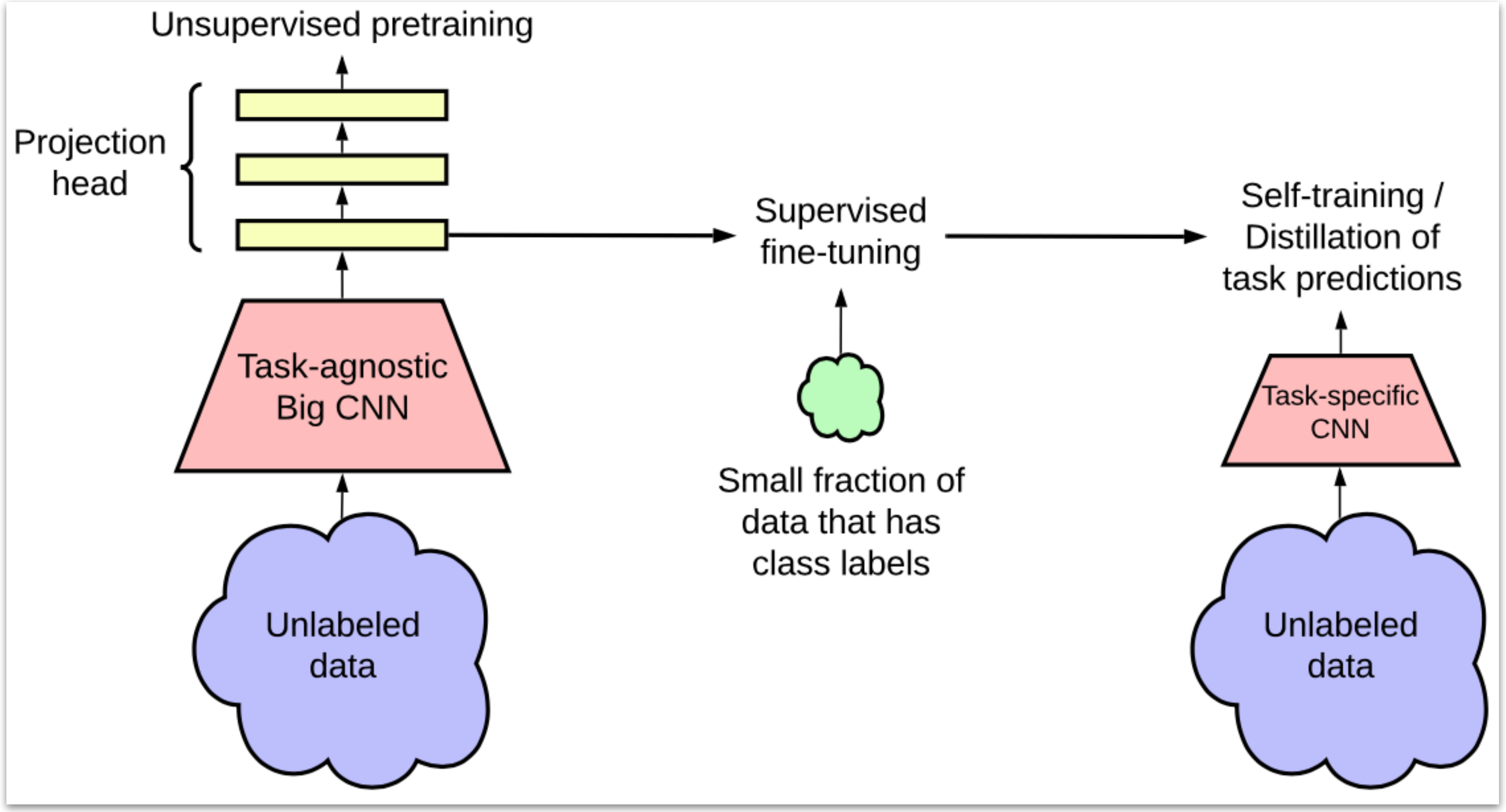
Big Self-Supervised Models are Strong Semi-Supervised Learners



Learning from few labeled examples

(1) unsupervised or self-supervised pretraining

(2) supervised fine-tuning, and

(3) distillation using unlabeled data

Self-supervised pretraining with SimCLRv2

$x_{2k-1}, x_{2k} \rightarrow$ two views of the same example augmented twice in a randomly sampled mini-batch of images

augmented twice using random crop, color distortion and Gaussian blur

$h_{2k-1}, h_{2k} = f(x_{2k-1}), f(x_{2k})$

$f \rightarrow$ encoder network (e.g., ResNet)

$z_{2k-1}, z_{2k} = g(h_{2k-1}), g(h_{2k}) \rightarrow$ used for contrastive loss

$g \rightarrow$ non-linear transformation network (MLP projection head)

$i, j \rightarrow$ positive examples (i.e., augmented from the same image)

$$\ell_{i,j}^{\text{NT-Xent}} = -\log \frac{\exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$

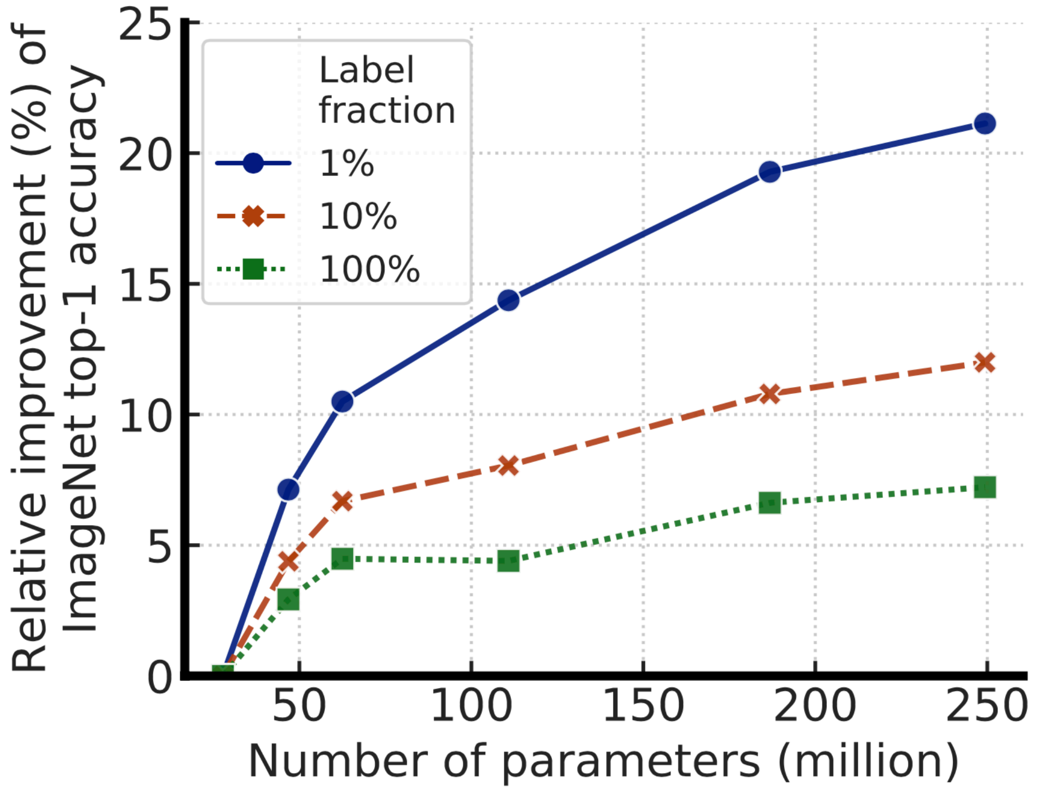
Improvements

(1) Larger ResNet models
ResNet-152(3×+SK)
SK → selective kernels (a channel-wise attention mechanism)

(2) Making g deeper and fine-tuning from a middle layer of g (instead of discarding g entirely)

(3) Incorporate the memory mechanism from MOCO
A memory network (with a moving average of weights for stabilization) whose output will be buffered as negative examples

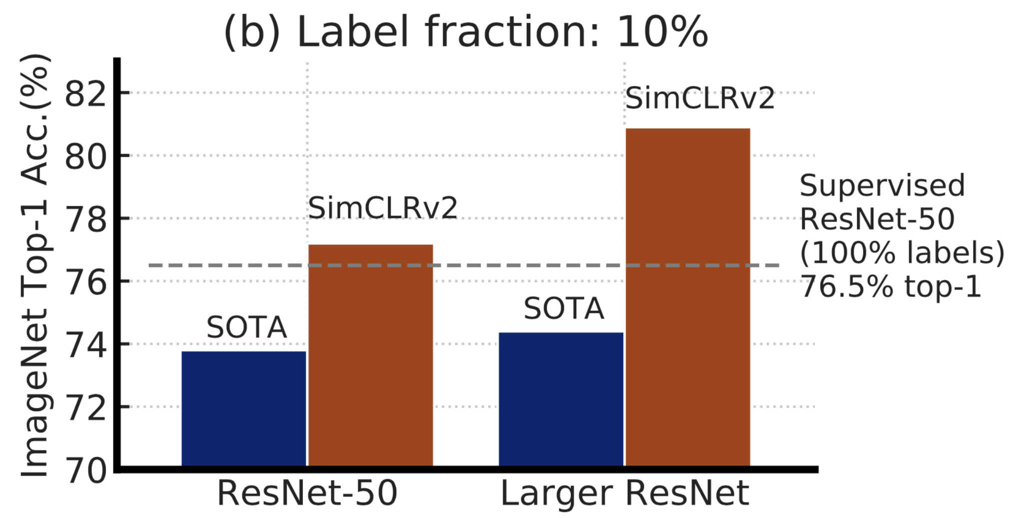
Bigger models yield larger gains when fine-tuning with fewer labeled examples



Self-training / knowledge distillation via unlabeled examples

Teacher: Fine-tuned network

$$\mathcal{L}^{\text{distill}} = -\sum_{\boldsymbol{x}_i \in \mathcal{D}} \left[\sum_y P^T(y|\boldsymbol{x}_i;\tau) \log P^S(y|\boldsymbol{x}_i;\tau) \right]$$



Chen, Ting, et al. "Big self-supervised models are strong semi-supervised learners." *arXiv preprint arXiv:2006.10029* (2020).

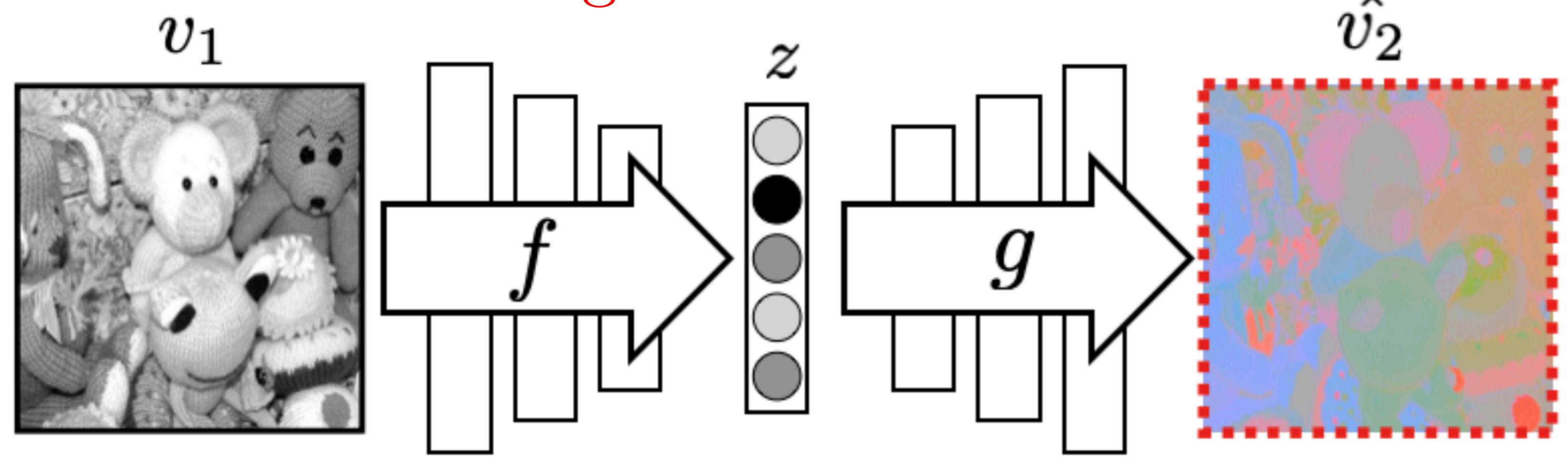
Contrastive Multiview Coding

A "dog" can be seen, heard and felt!

$V_1, V_2, \ldots, V_M \rightarrow$ a collection of M views of the data

$v_i \sim \mathcal{P}(V_i) \rightarrow$ a random variable representing samples

Predictive Learning



$V_1, V_2 \rightarrow$ two views of a dataset (e.g., luminance and chrominance)

$z = f(v_1) \rightarrow$ encoder

$\hat{v}_2 = g(z) \rightarrow$ decoder

prediction of v_2 given v_1

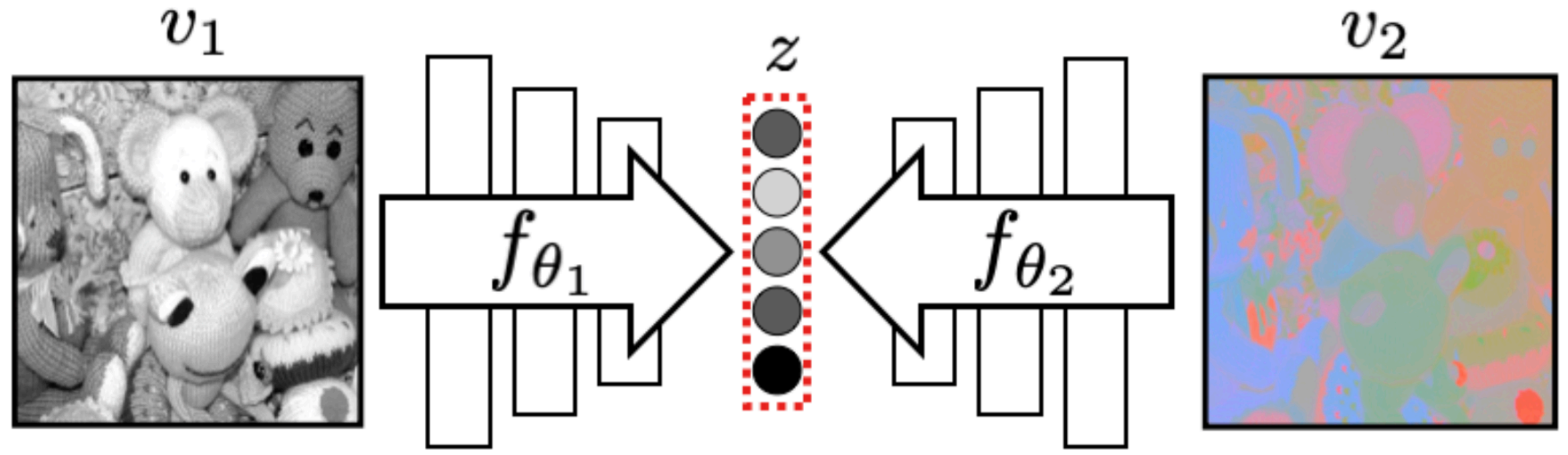
$z \rightarrow$ latent variables

Bring $\hat{v}_2$ close to $v_2 \rightarrow$ objective function (L_1 or L_2)

Independence assumption between elements or pixels of v_2 given v_1!

$p(v_2|v_1) = \Pi_i p(v_{2i}|v_1)$

Contrastive Learning with Two Views



$\{v_1^i, v_2^i\}_{i=1}^N \rightarrow$ collection of samples from V_1 and V_2

$x = \{v_1^i, v_2^i\} \rightarrow$ positives (congruent pairs), $x \sim p(v_1, v_2) \rightarrow$ joint distribution

$y = \{v_1^i, v_2^j\} \rightarrow$ negatives (incongruent pairs), $y \sim p(v_1)p(v_2) \rightarrow$ product of marginals

Select a single positive sample x out of a set $S = \{x, y_1, y_2, \ldots, y_k\}$ that contains k negative samples

$$\mathcal{L}_{contrast} = -\mathop{\mathbb{E}}_{S}\left[\log \frac{h_\theta(x)}{h_\theta(x) + \sum_{i=1}^{k} h_\theta(y_i)}\right]$$

$$h_\theta(\{v_1, v_2\}) = \exp\left(\frac{f_{\theta_1}(v_1) \cdot f_{\theta_2}(v_2)}{\|f_{\theta_1}(v_1)\| \cdot \|f_{\theta_2}(v_2)\|} \cdot \frac{1}{\tau}\right)$$

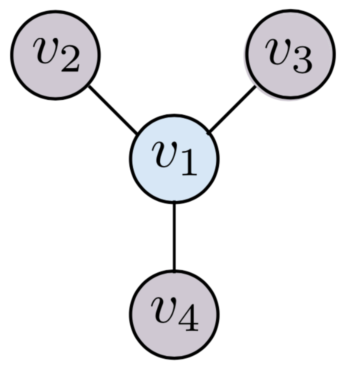
Connecting to Mutual Information

$$h_\theta^*(\{v_1, v_2\}) \propto \frac{p(z_1, z_2)}{p(z_1)p(z_2)} \propto \frac{p(z_1|z_2)}{p(z_1)} \rightarrow \text{point-wise mutual information}$$

$$I(v_i; v_j) \geq I(z_i; z_j) \geq \log(k) - \mathcal{L}_{contrast}$$

Contrastive Learning with More Than Two Views

$$\mathcal{L}_C = \sum_{j=2}^{M} \mathcal{L}(V_1, V_j) \rightarrow \text{core view}$$



$$\mathcal{L}_F = \sum_{1 \leq i < j \leq M} \mathcal{L}(V_i, V_j) \rightarrow \text{full graph}$$

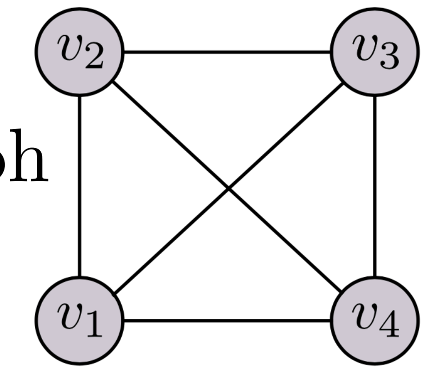


Image Views

luminance (L channel), chrominance (ab channel)

Video Views

$i_t \rightarrow$ image at time t, $i_{t+k} \rightarrow$ neighboring frame, $f_t \rightarrow$ optical flow (10 frames centered at time t)

$(i_t, i_{t+k}), (i_t, f_t) \rightarrow$ two separate contrastive learning objectives

Multiple Image Views

luminance (L channel), chrominance (ab channel), depth, surface normal, and semantic labels

Tian, Yonglong, Dilip Krishnan, and Phillip Isola. "Contrastive multiview coding." Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XI 16. Springer International Publishing, 2020.

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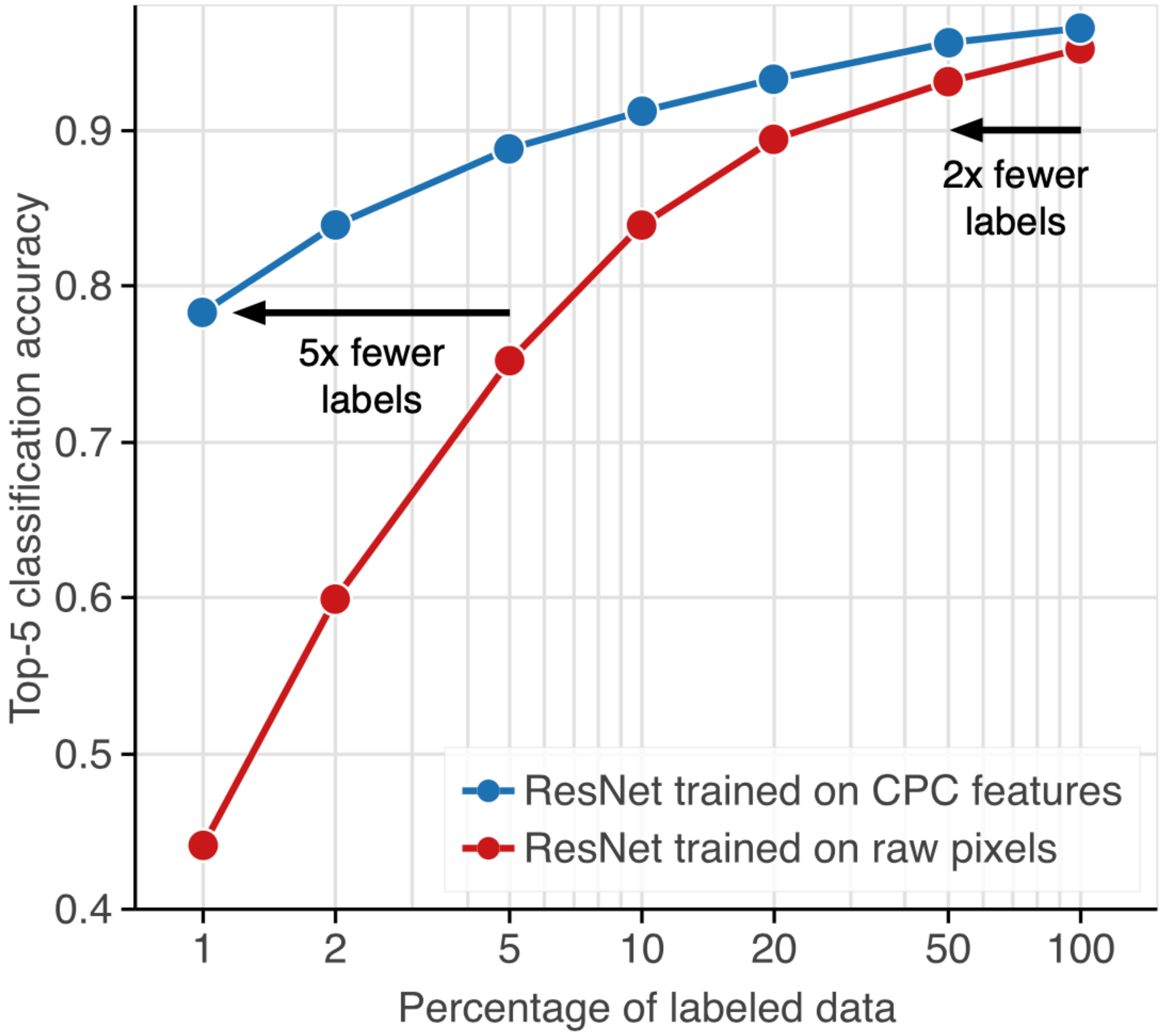
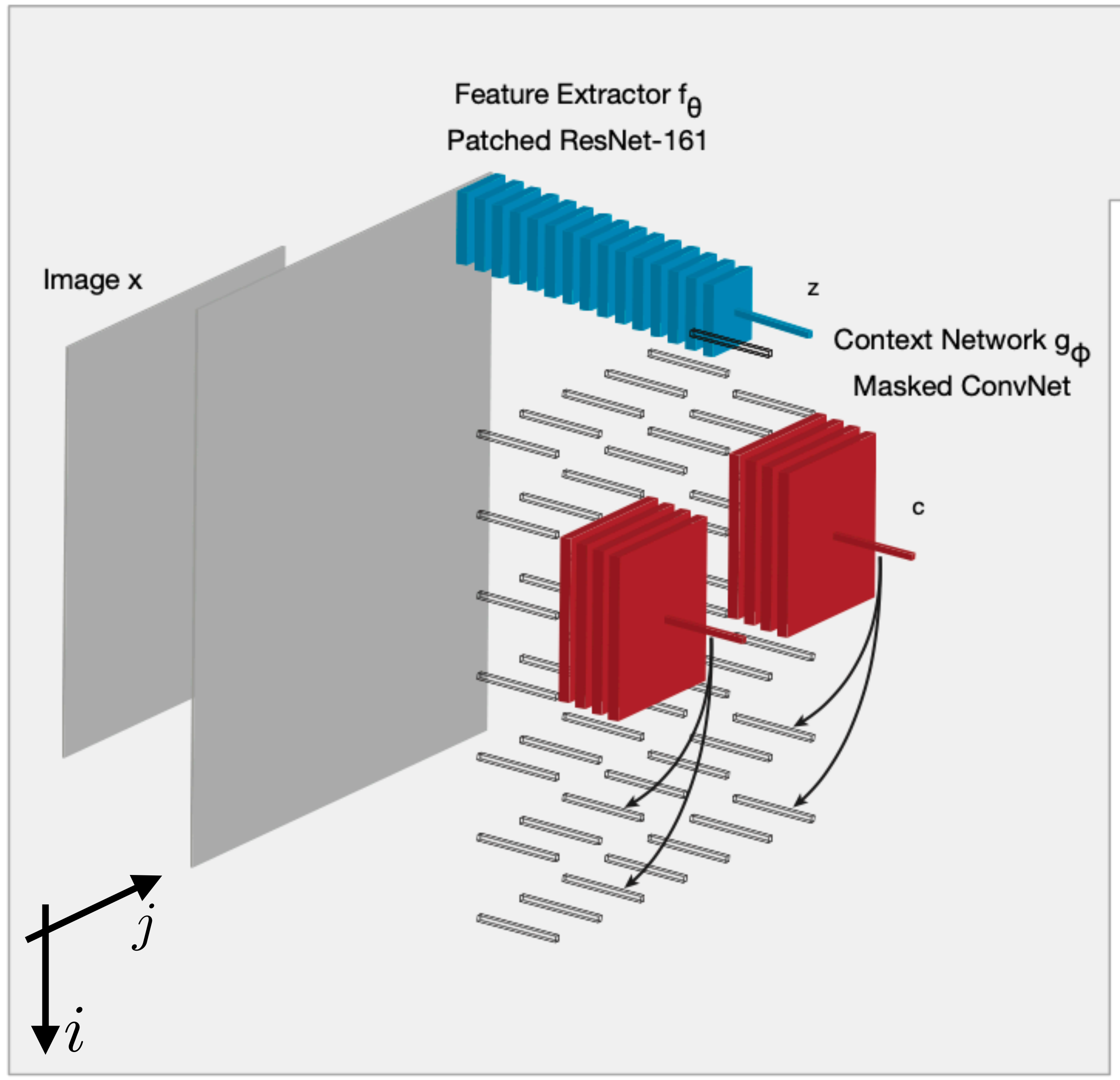
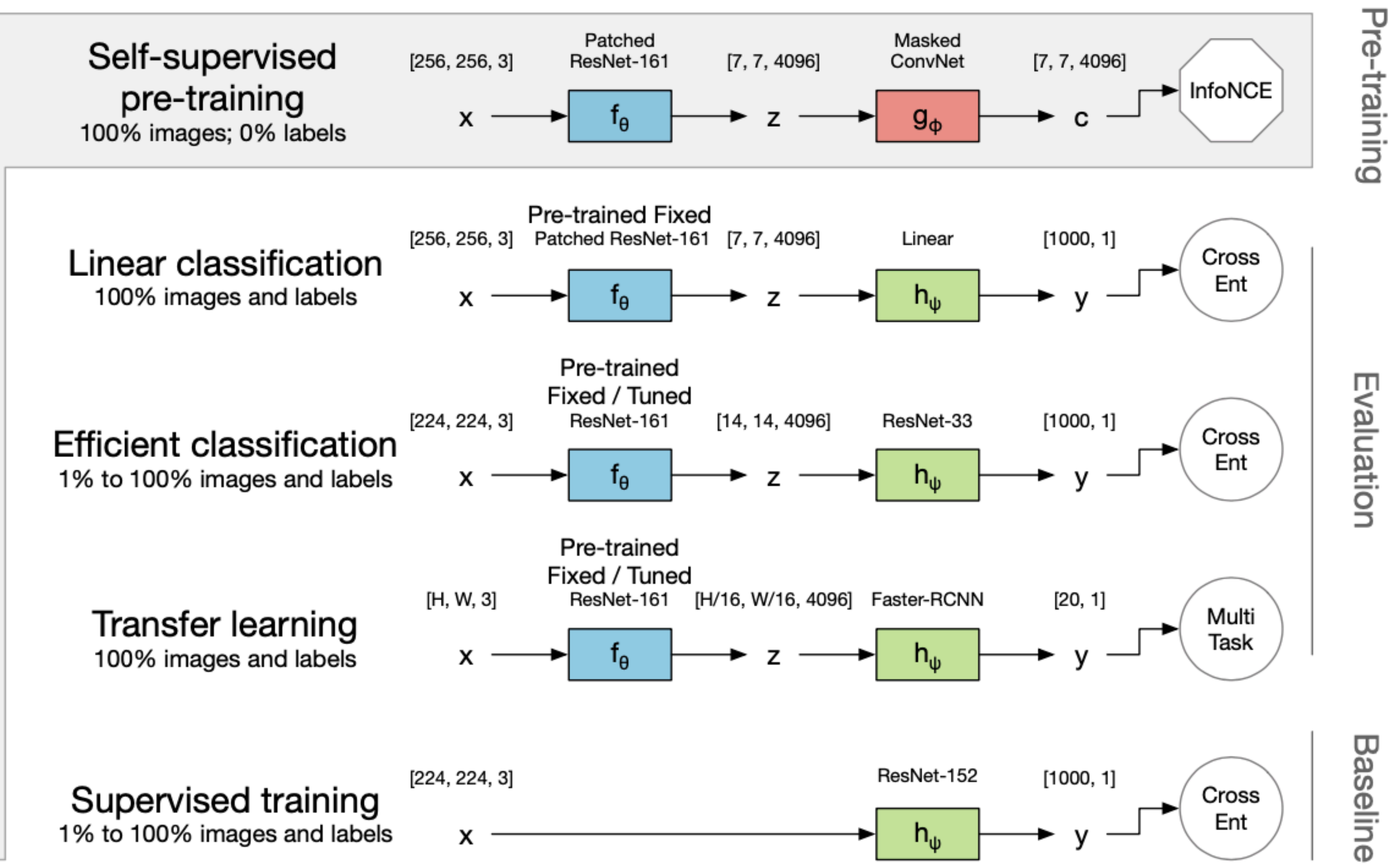
Data-Efficient Image Recognition with Contrastive Predictive Coding







$\{x_{i,j}\} \to$ a grid of overlapping patches dividing each input image

$i, j \to$ location of the patch

$z_{i,j} = f_\theta(x_{i,j}) \to$ encoded patch

neural network

$g_\phi \to$ masked convolutional network (applied to the grid of feature vectors)

$c_{i,j} = g_\phi(\{z_{u,v}\}_{u \leq i,v}) \to$ context vector

feature vectors that lie above i, j

$z_{i+k,j} \to$ "future" feature vectors to be predicted from current context vector $c_{i,j}$

$k \to$ prediction length

$\hat{z}_{i+k,j} = W_k c_{i,j}$

prediction matrix

Correctly recognize the target $z_{i+k,j}$ among a set of randomly sampled feature vectors $\{z_l\}$ from the dataset (i.e., other locations in the image and other images in the mini-batch)

$$\mathcal{L}_{\text{CPC}} = -\sum_{i,j,k} \log p(\boldsymbol{z}_{i+k,j} | \hat{\boldsymbol{z}}_{i+k,j}, \{\boldsymbol{z}_l\})$$

$$= -\sum_{i,j,k} \log \frac{\exp(\hat{\boldsymbol{z}}_{i+k,j}^T \boldsymbol{z}_{i+k,j})}{\exp(\hat{\boldsymbol{z}}_{i+k,j}^T \boldsymbol{z}_{i+k,j}) + \sum_l \exp(\hat{\boldsymbol{z}}_{i+k,j}^T \boldsymbol{z}_l)}$$

InfoNCE (Noise Contrastive Estimation)

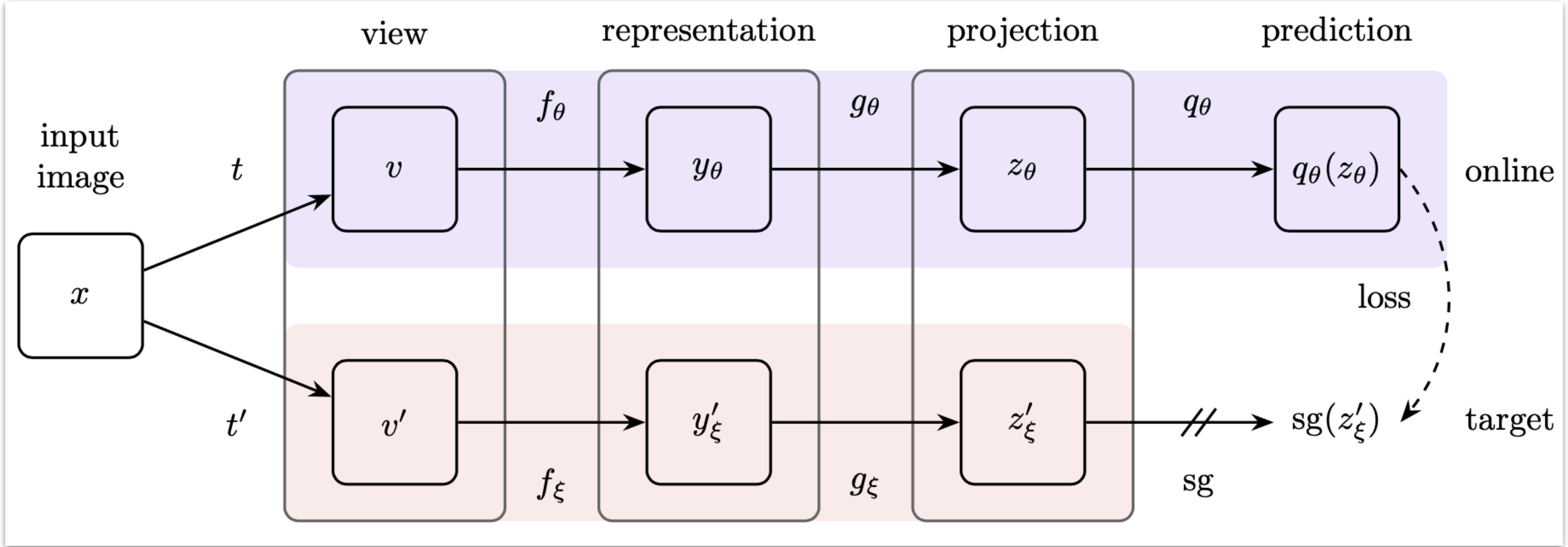
– increase depth & width – layer normalization – making predictions in all four directions – extensive patch-based data augmentation

Henaff, Olivier. "Data-efficient image recognition with contrastive predictive coding." *International Conference on Machine Learning*. PMLR, 2020.

Bootstrap your own latent: A new approach to self-supervised Learning

Boulder

Bootstrap Your Own Latent (BYOL)
Self-supervised image representation learning without using negative pairs! ($\star$)
Learn a representation y_θ which can be used for downstream tasks!



Three stages of the online network:
1. $f_\theta \rightarrow$ encoder
2. $g_\theta \rightarrow$ projector
3. $q_\theta \rightarrow$ predictor ($\star$)

$\theta \rightarrow$ online parameters
$\xi \rightarrow$ parameters of the target network
$\xi \leftarrow \tau\xi + (1-\tau)\theta$ ($\star$)
$\mathcal{D} \rightarrow$ set of images
$x \sim \mathcal{D} \rightarrow$ an image sampled uniformly from $\mathcal{D}$
$\mathcal{T}, \mathcal{T}' \rightarrow$ two distributions of image augmentations

$v = t(x), v' = t'(x) \rightarrow$ two augmented views from x
$t \sim \mathcal{T}, t' \sim \mathcal{T}'$
$y_\theta = f_\theta(v) \rightarrow$ representation
$z_\theta = g_\theta(y_\theta) \rightarrow$ projection
$y'_\xi = f'_\xi(v') \rightarrow$ target representation
$z'_\xi = g'_\xi(y'_\xi) \rightarrow$ target projection
$q_\theta(z_\theta) \rightarrow$ prediction of z'_ξ
$\bar{q}_\theta(z_\theta), \bar{z}'_\xi \rightarrow l_2$ normalized

$$\mathcal{L}_{\theta,\xi} \triangleq \left\|\overline{q_\theta}(z_\theta) - \bar{z}'_\xi\right\|_2^2 = 2 - 2 \cdot \frac{\langle q_\theta(z_\theta), z'_\xi \rangle}{\left\|q_\theta(z_\theta)\right\|_2 \cdot \left\|z'_\xi\right\|_2}$$

$$\mathcal{L}^{\mathrm{BYOL}}_{\theta,\xi} = \mathcal{L}_{\theta,\xi} + \widetilde{\mathcal{L}}_{\theta,\xi}$$

feeding v' to the online network and v to the target network

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While this objective admits collapsed solutions, e.g., outputting the
same vector for all images, the paper empirically shows that BYOL does
not converge to such solutions. It hypothesizes (see Section 3.2) that
the combination of (i) the addition of a predictor to the online network
and (ii) the use of a slow-moving average of the online parameters as
the target network encourages encoding more and more information within
the online projection and avoids collapsed solutions.
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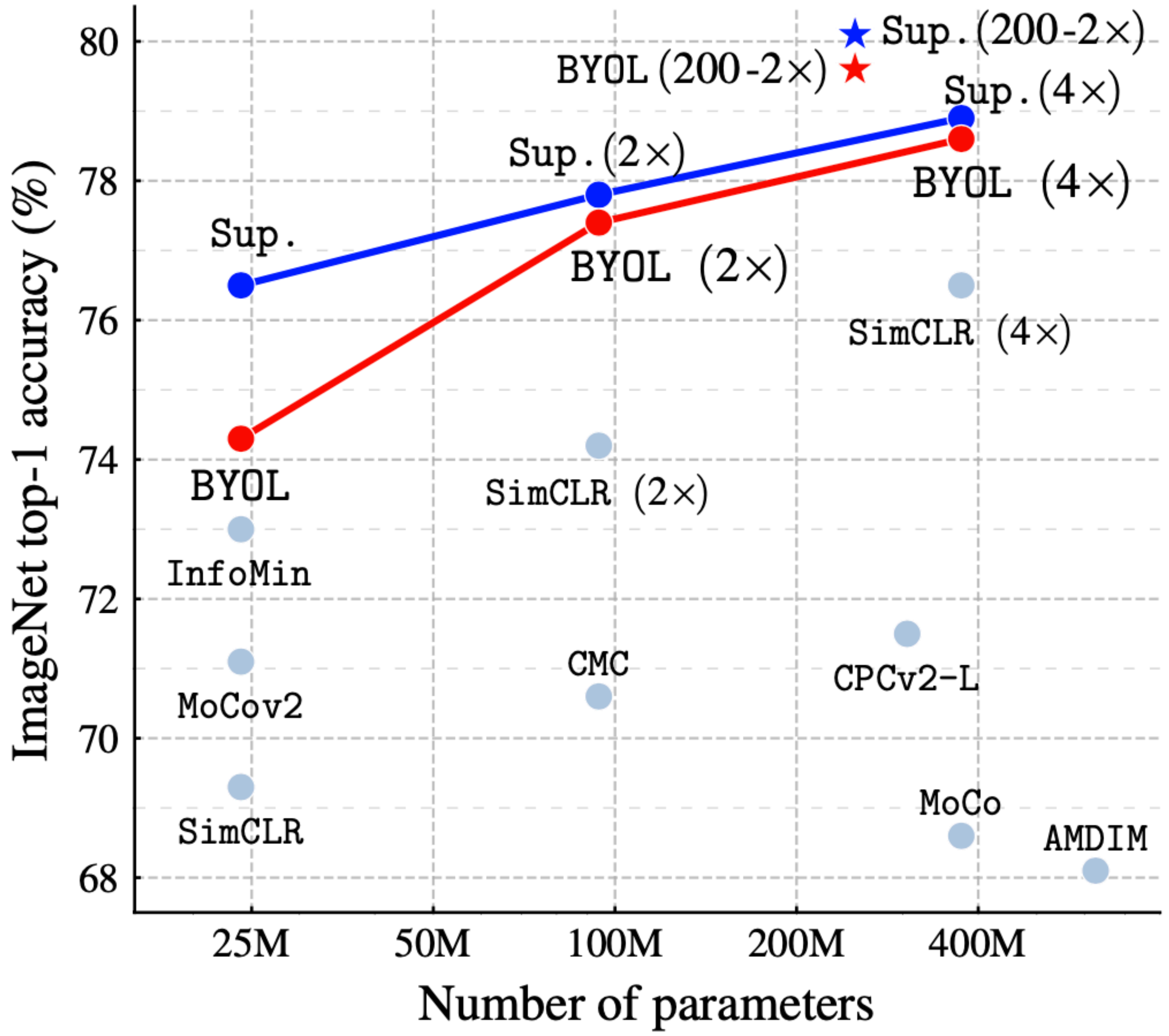
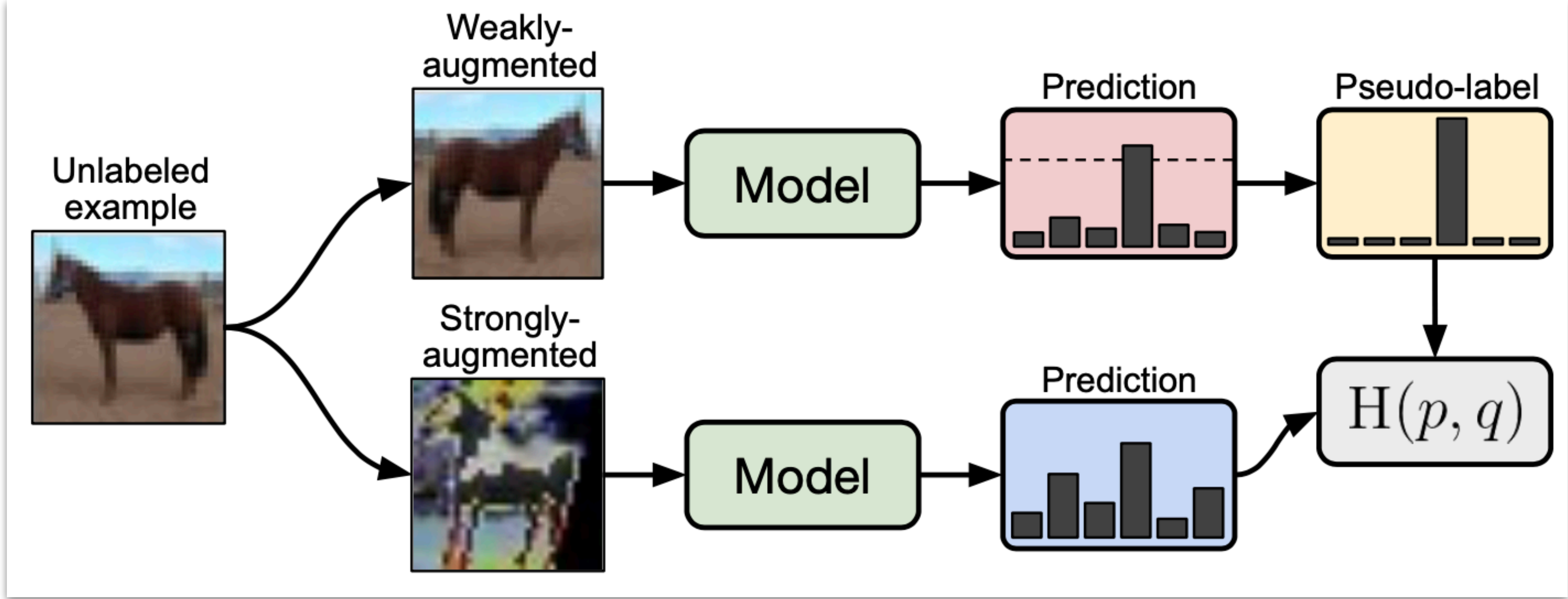


Grill, Jean-Bastien, et al. "Bootstrap your own latent: A new approach to self-supervised learning." *arXiv preprint arXiv:2006.07733* (2020).

FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence

Boulder

Semi-Supervised Learning (SSL): Leveraging unlabeled data to improve a model's performance



$L \rightarrow$ number of classes

$\mathcal{X} = \{(x_b, p_b) : b = 1, \ldots, B\} \rightarrow$ batch of B labeled examples

$x_b \rightarrow$ training example

$p_b \rightarrow$ one-hot-labels

$\mathcal{U} = \{u_b : b = 1, \ldots, \mu B\} \rightarrow$ batch of μB unlabeled examples

$\mu \rightarrow$ determines the relative size of $\mathcal{X}$ and $\mathcal{U}$

$p_{\mathrm{m}}(y|x) \rightarrow$ predicted class distribution produced by the model for input x

$H(p, q) \rightarrow$ cross-entropy between two probability distributions p and q

$\mathcal{A}(\cdot) \rightarrow$ strong augmentation (autoaugment/randaugment + cutout)

$\alpha(\cdot) \rightarrow$ weak augmentation (flip and shift)

Consistency Regularization

$$\sum_{b=1}^{\mu B} \|p_{\mathrm{m}}(y|\,\alpha(u_b)) - p_{\mathrm{m}}(y|\,\alpha(u_b))\|_2^2$$ $\rightarrow$ both α and p_{m} are stochastic functions, so the two terms in this equation will indeed have different values

Extensions of the consistency regularization idea

– using an adversarial transformation in place of α

– using a running average or past model predictions for one invocation of p_{m}

– using a cross-entropy loss in place of the squared l^2 loss

– using stronger forms of augmentation

Pseudo-labeling

$$q_b = p_{\mathrm{m}}(y|u_b)$$

predefined threshold

$$\frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}(\max(q_b) \geq \tau)\, \mathrm{H}(\hat{q}_b, q_b)$$

$\hat{q}_b = \arg\max(q_b) \rightarrow$ one-hot (hard-label)

encourages model predictions to be low-entropy (i.e., high-confidence) on unlabeled data

FixMatch

$\ell_s \rightarrow$ supervised loss

$\ell_u \rightarrow$ unsupervised loss

$$\ell_s = \frac{1}{B} \sum_{b=1}^{B} \mathrm{H}(p_b, p_{\mathrm{m}}(y \mid \alpha(x_b)))$$

$$\ell_u = \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}(\max(q_b) \geq \tau)\, \mathrm{H}(\hat{q}_b, p_{\mathrm{m}}(y \mid \mathcal{A}(u_b)))$$

$q_b = p_{\mathrm{m}}(y \mid \alpha(u_b))$ $\quad$ $\hat{q}_b = \arg\max(q_b) \rightarrow$ pseudo-label $\quad$ $\ell_s + \lambda_u \ell_u$

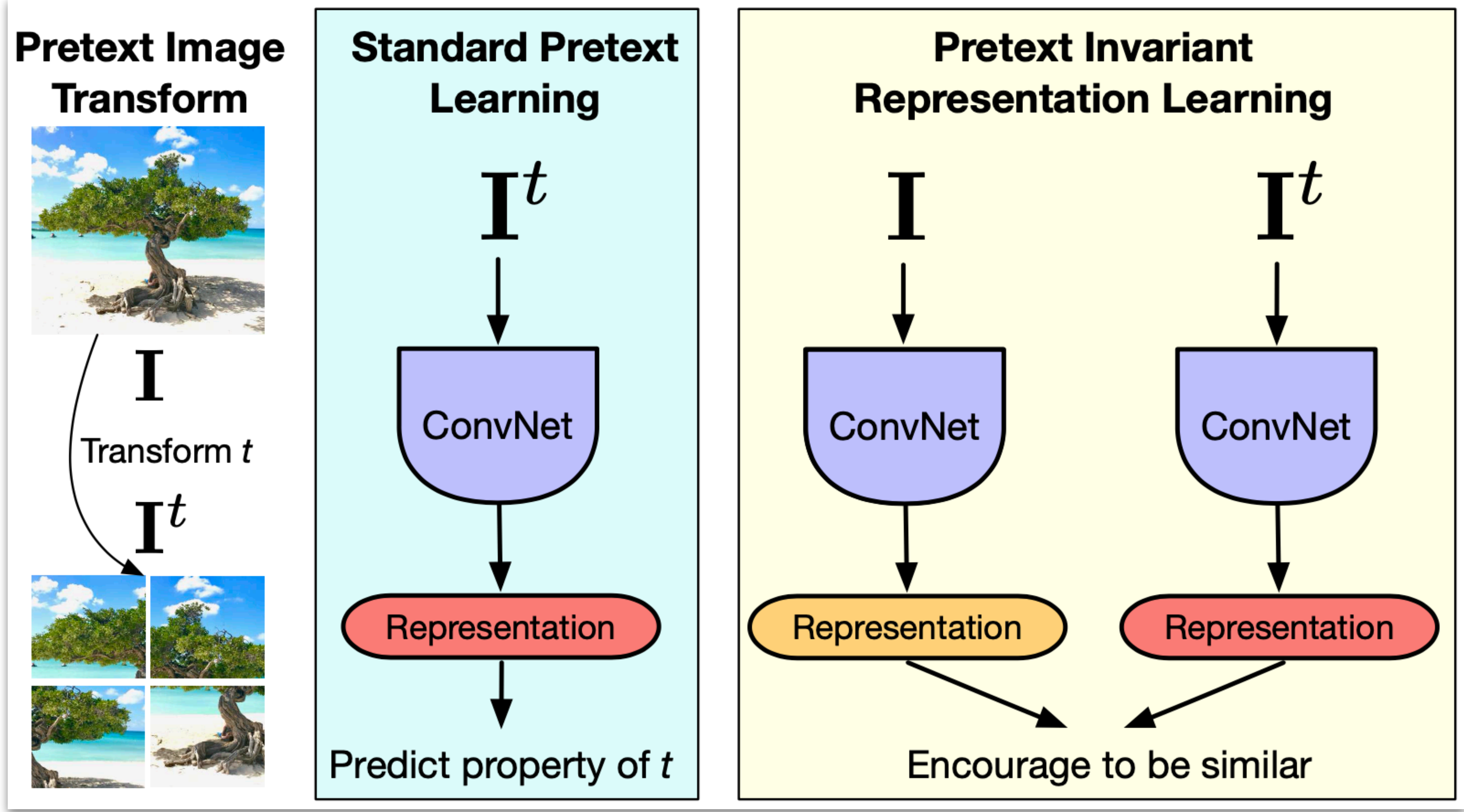
FixMatch reaches 78% CIFAR-10 accuracy using only above 10 labeled images.

Sohn, Kihyuk, et al. "Fixmatch: Simplifying semi-supervised learning with consistency and confidence." *arXiv preprint arXiv:2001.07685* (2020).

Self-Supervised Learning of Pretext-Invariant Representations

Boulder

Pretext-Invariant Representation Learning (PIRL)



$\mathcal{D} = \{I_1, \ldots, I_{|\mathcal{D}|}\} \rightarrow$ image dataset

$I_n \in \mathbb{R}^{H \times W \times C}$

$\mathcal{T} \rightarrow$ set of image transformations (e.g., reshuffling of image patches, image rotation, etc.)

$\phi_\theta(\cdot) \rightarrow$ CNN

$v_I = \phi_\theta(I) \rightarrow$ image representation

$I^t = t(I) \rightarrow$ image I after the transformation $t \in \mathcal{T}$

$$\ell_{co}(\theta; \mathcal{D}) = \mathbb{E}_{t \sim p(\mathcal{T})} \left[\frac{1}{|\mathcal{D}|} \sum_{\mathbf{I} \in \mathcal{D}} L_{co}\left(\mathbf{v_I}, z(t)\right) \right]$$

$\rightarrow$ Many pretext tasks (e.g., solving jigsaw puzzles) lead to representations that are covariant with image transformations

$z \rightarrow$ a function that measures some properties of transformation t

Make representations invariant under transformations $t \in \mathcal{T}$

$$\ell_{inv}(\theta; \mathcal{D}) = \mathbb{E}_{t \sim p(\mathcal{T})} \left[\frac{1}{|\mathcal{D}|} \sum_{\mathbf{I} \in \mathcal{D}} L\left(\mathbf{v_I}, \mathbf{v_{I^t}}\right) \right]$$

L measures the similarity between two image representations

Loss Function

$(I, I^t) \rightarrow$ "positive" pair

$N \rightarrow$ number of corresponding "negative" pairs (computing features from other images $I' \neq I$)

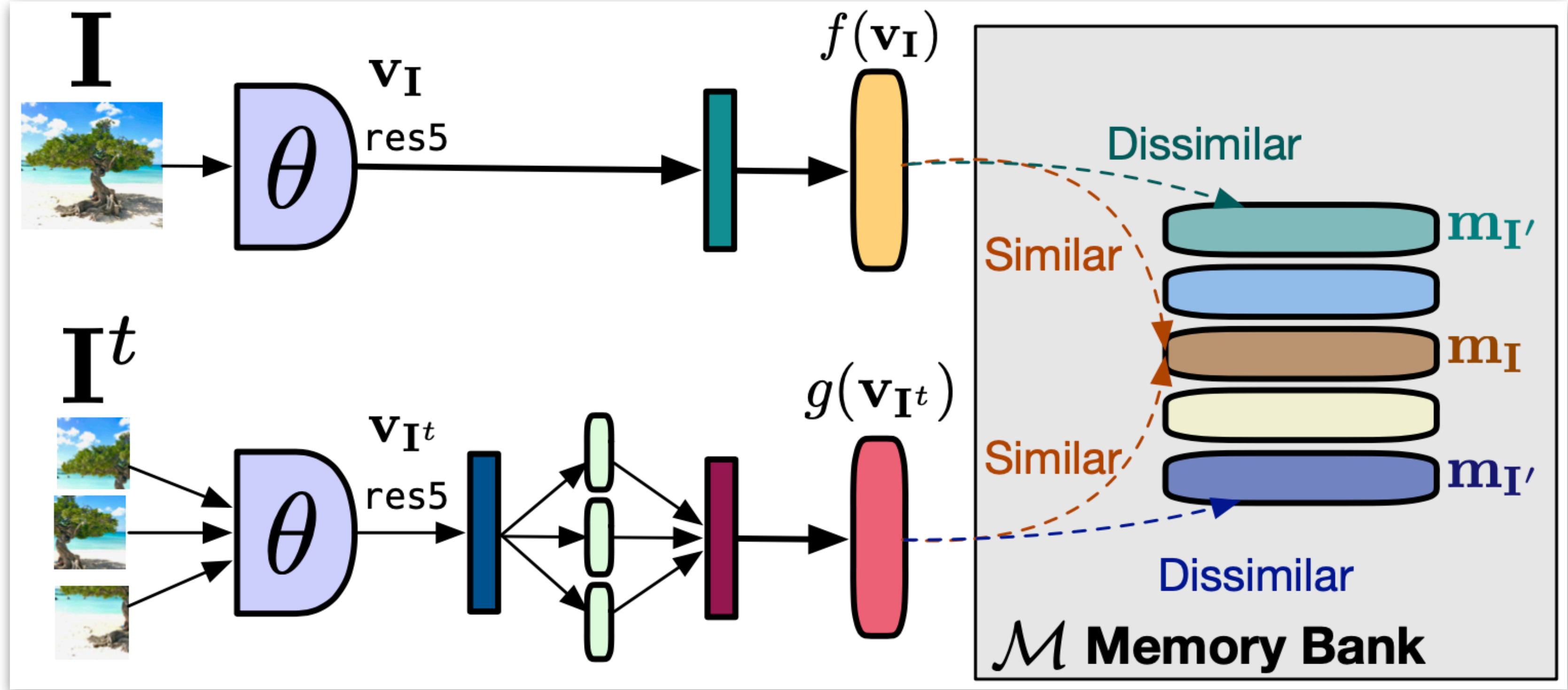
$$h(\mathbf{v_I}, \mathbf{v_{I^t}}) = \frac{\exp\left(\frac{s(\mathbf{v_I}, \mathbf{v_{I^t}})}{\tau}\right)}{\exp\left(\frac{s(\mathbf{v_I}, \mathbf{v_{I^t}})}{\tau}\right) + |\mathcal{D}_N| / |\mathcal{D}|}$$

$\rightarrow$ probability of the binary event that (I, I_t) originates from data distribution

$s(\cdot, \cdot) \rightarrow$ cosine similarity

$$L_{\text{NCE}}\left(\mathbf{I}, \mathbf{I}^t\right) = -\log\left[h\left(f(\mathbf{v_I}), g(\mathbf{v_{I^t}})\right)\right] - \sum_{\mathbf{I}' \in \mathcal{D}_N} \log\left[1 - h\left(g(\mathbf{v}_\mathbf{I}^t), f(\mathbf{v_{I'}})\right)\right]$$

L_{NCE}: noise contrastive estimator

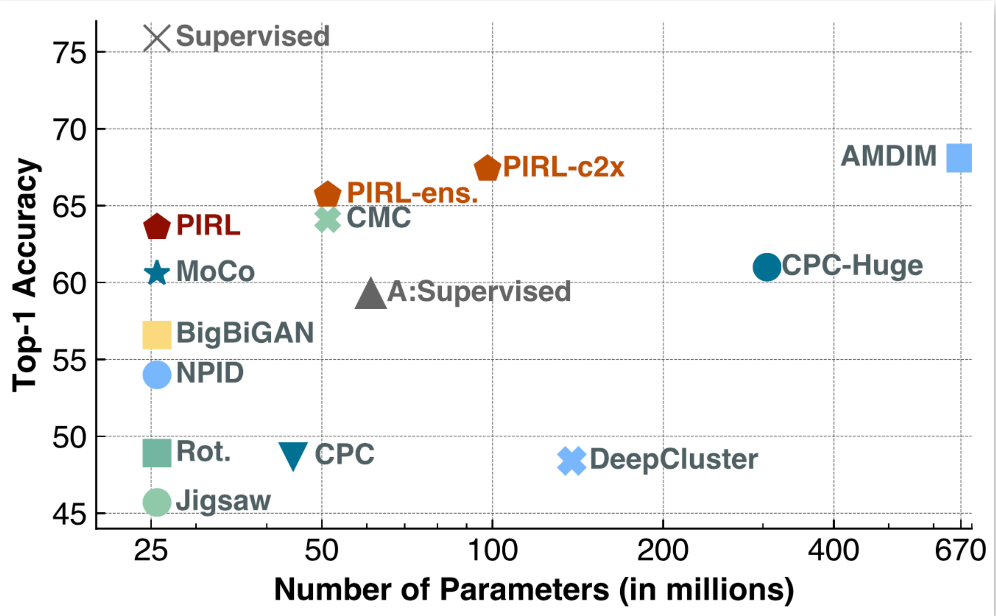


$f, g \rightarrow$ two different heads

$m_I \rightarrow$ exponential moving average of feature representations $f(v_I)$

Final loss function

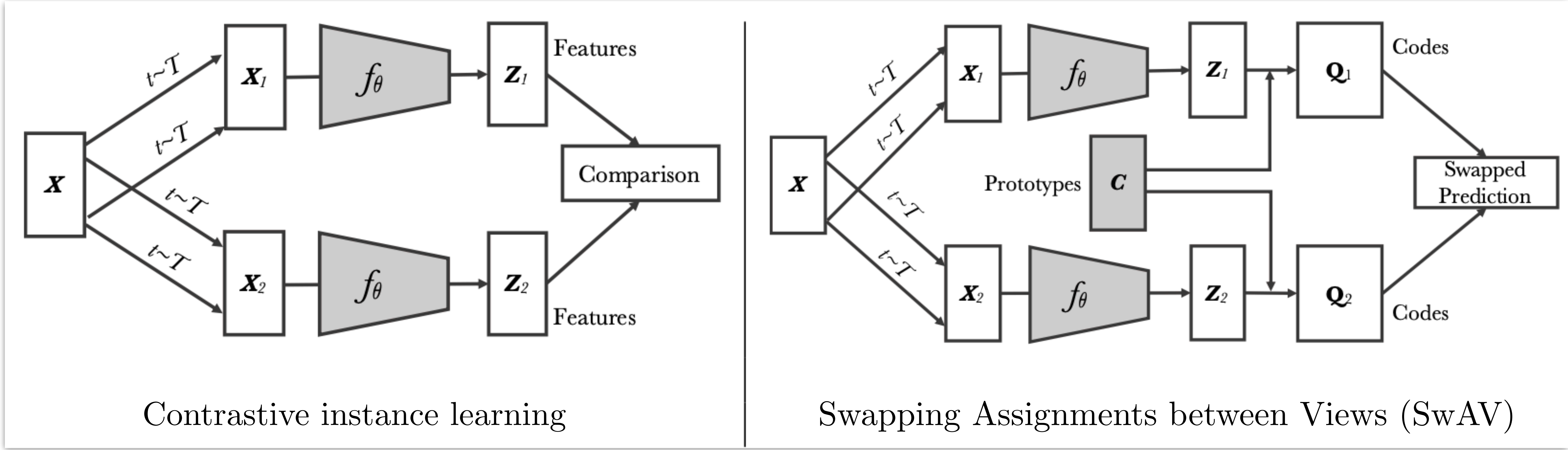
$$L\left(\mathbf{I}, \mathbf{I}^t\right) = \lambda L_{\text{NCE}}(\mathbf{m_I}, g(\mathbf{v_{I^t}})) + (1 - \lambda) L_{\text{NCE}}(\mathbf{m_I}, f(\mathbf{v_I})).$$



Misra, Ishan, and Laurens van der Maaten. "Self-supervised learning of pretext-invariant representations." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020.

Unsupervised Learning of Visual Features by Contrasting Cluster Assignments

Boulder



Swapped prediction problem

$$\ell(\mathbf{z}_t, \mathbf{q}_s) = -\sum_k \mathbf{q}_s^{(k)} \log \mathbf{p}_t^{(k)}$$

$$\mathbf{p}_t^{(k)} = \frac{\exp\left(\frac{1}{\tau}\mathbf{z}_t^\top \mathbf{c}_k\right)}{\sum_{k'} \exp\left(\frac{1}{\tau}\mathbf{z}_t^\top \mathbf{c}_{k'}\right)}$$

$$-\frac{1}{N}\sum_{n=1}^{N}\sum_{s,t\sim\mathcal{T}}\left[\frac{1}{\tau}\mathbf{z}_{nt}^\top \mathbf{C}\mathbf{q}_{ns} + \frac{1}{\tau}\mathbf{z}_{ns}^\top \mathbf{C}\mathbf{q}_{nt} - \log\sum_{k=1}^{K}\exp\left(\frac{\mathbf{z}_{nt}^\top \mathbf{c}_k}{\tau}\right) - \log\sum_{k=1}^{K}\exp\left(\frac{\mathbf{z}_{ns}^\top \mathbf{c}_k}{\tau}\right)\right]$$

Minimized with respect to the prototypes C and the parameters θ

DeepCluster (offline) v.s. SwAV (online)

Offline: requires a pass over the entire dataset to form image "codes" (i.e., cluster assignments)

$z_t, z_s \rightarrow$ two image features from two different augmentations of the same image

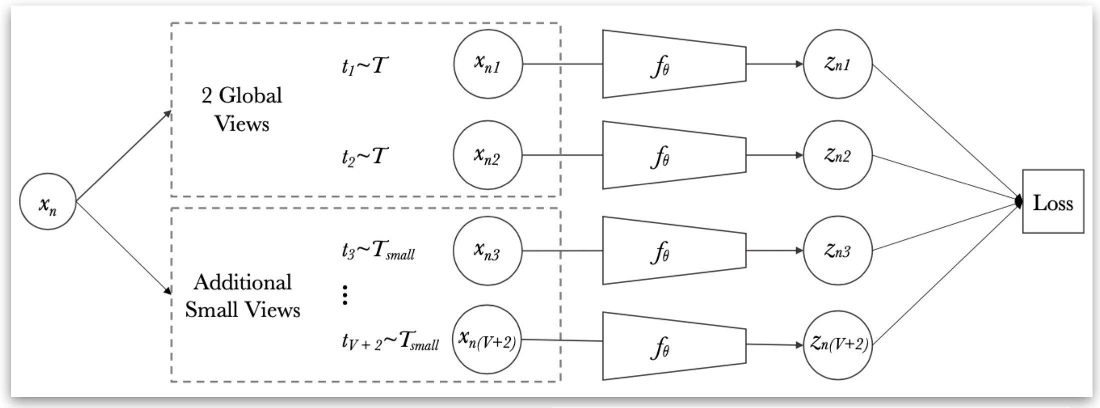
$\{c_1, \ldots, c_K\} \rightarrow$ set of K prototypes

$q_t, q_s \rightarrow$ codes (matching z_t, z_s to the set of K prototypes)

$L(z_t, z_s) = \ell(z_t, q_s) + \ell(z_s, q_t) \rightarrow$ "swapped" prediction problem

$\ell(z, q) \rightarrow$ measures the fit between features z and a code q

multi-crop strategy



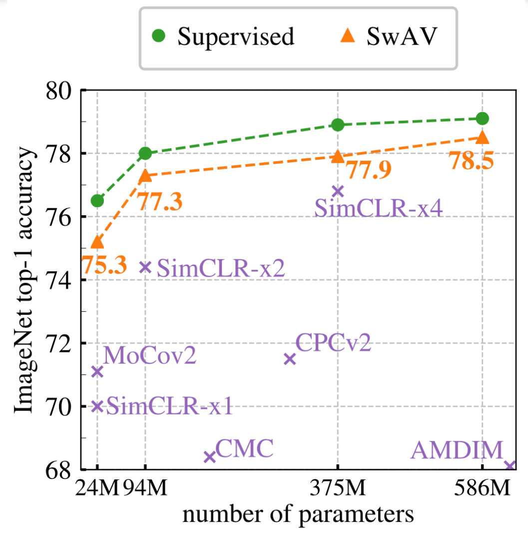
Online Clustering

$t \sim \mathcal{T} \rightarrow$ transformation t sampled from the set of image augmentations $\mathcal{T}$

$x_{nt} \rightarrow$ augmented view of image x_n transformed by t

$$z_{nt} = \frac{f_\theta(x_{nt})}{\|f_\theta(x_{nt})\|_2} \rightarrow \text{image features}$$

$q_{nt} \rightarrow$ code computed by mapping z_{nt} to a set of K trainable prototype vectors



Computing codes online

Trivial solution: every image having the same code

$Z = [z_1, \ldots, z_B] \rightarrow B$ feature vectors

$B \rightarrow$ mini-batch size

$Q = [q_1, \ldots, q_B] \rightarrow$ codes

$$\max_{\mathbf{Q}\in\mathcal{Q}} \operatorname{Tr}\left(\mathbf{Q}^\top \mathbf{C}^\top \mathbf{Z}\right) + \varepsilon H(\mathbf{Q})$$

$H(\mathbf{Q}) = -\sum_{ij} \mathbf{Q}_{ij} \log \mathbf{Q}_{ij} \rightarrow$ entropy

$$\mathcal{Q} = \left\{\mathbf{Q} \in \mathbb{R}_+^{K\times B} \mid \mathbf{Q}\mathbf{1}_B = \frac{1}{K}\mathbf{1}_K, \mathbf{Q}^\top \mathbf{1}_K = \frac{1}{B}\mathbf{1}_B\right\}$$

Enforce that on average each prototype is selected at least B/K times in the batch

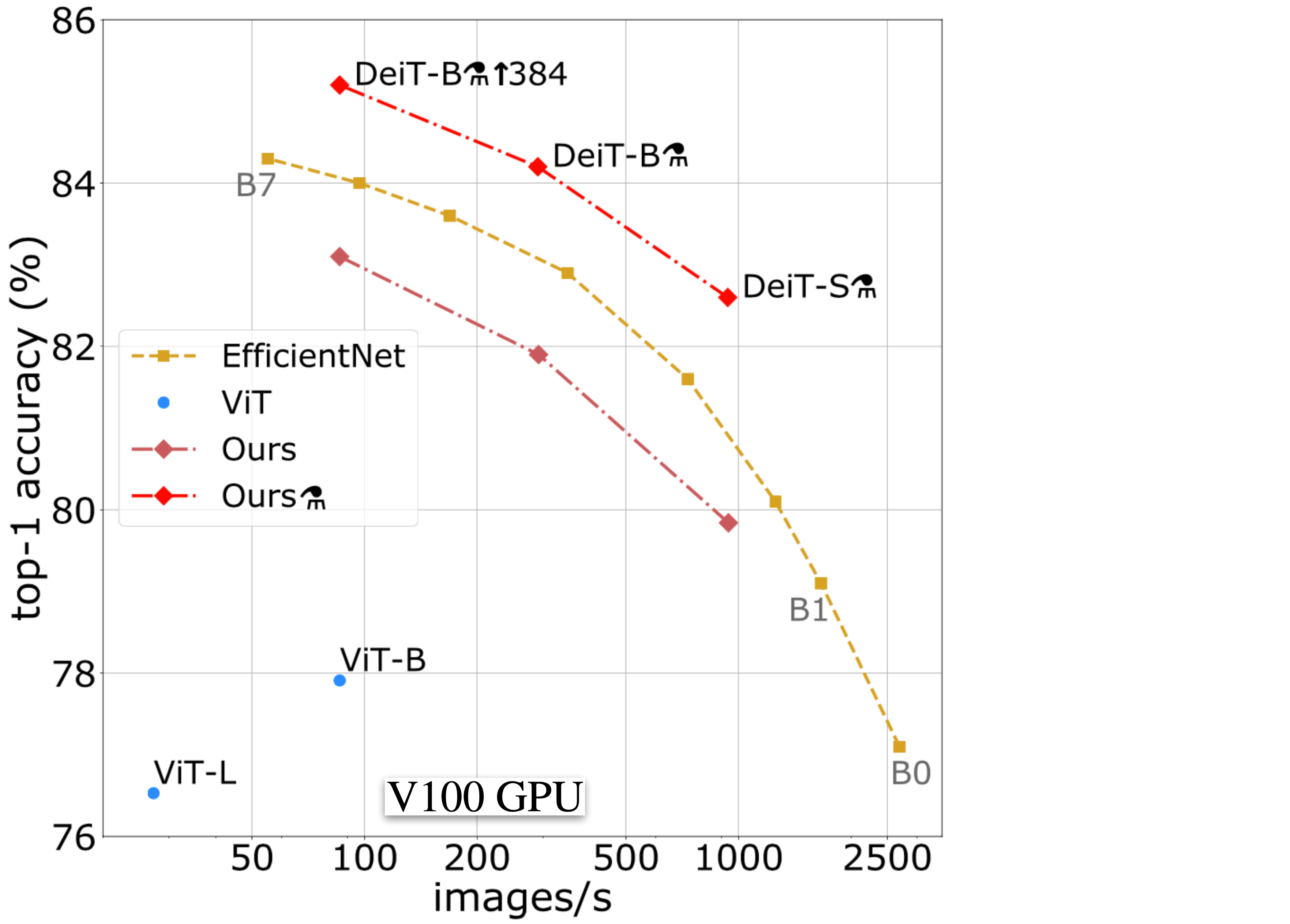
Three iterations of iterative Sinkhorn-Knopp algorithm!

Caron, Mathilde, et al. "Unsupervised learning of visual features by contrasting cluster assignments." *arXiv preprint arXiv:2006.09882* (2020).

Training Data-Efficient Image Transformers & Distillation Through Attention

DeiT: Data-Efficient Image Transformers

ImageNet Data Only (No External Data such as JFT-300M)



⚗ → models trained with our transformer-specific distillation

Fixing the positional encoding across resolutions

Use a lower training resolution and fine-tune the network at a larger resolution

Keep the image patch sizes the same

$\implies$ N (sequence length) changes

$\implies$ need to adapt positional encodings (use bicubic interpolation)

Pre-training	Fine-tuning	Rand-Augment	AutoAug	Mixup	CutMix	Erasing	Stoch. Depth	Repeated Aug.	Dropout	Exp. Moving Avg.	pre-trained 224	fine-tuned 384
adamw	adamw	✓	✗	✓	✓	✓	✓	✓	✗	✗	$81.8_{\pm0.2}$	$83.1_{\pm0.1}$
SGD	adamw	✓	✗	✓	✓	✓	✓	✓	✗	✗	74.5	77.3
adamw	SGD	✓	✗	✓	✓	✓	✓	✓	✗	✗	81.8	83.1
adamw	adamw	✗	✗	✓	✓	✓	✓	✓	✗	✗	79.6	80.4
adamw	adamw	✗	✓	✓	✓	✓	✓	✓	✗	✗	81.2	81.9
adamw	adamw	✓	✗	✗	✓	✓	✓	✓	✗	✗	78.7	79.8
adamw	adamw	✓	✗	✓	✗	✓	✓	✓	✗	✗	80.0	80.6
adamw	adamw	✓	✗	✗	✗	✓	✓	✓	✗	✗	75.8	76.7
adamw	adamw	✓	✗	✓	✓	✗	✓	✓	✗	✗	4.3*	0.1
adamw	adamw	✓	✗	✓	✓	✓	✗	✓	✗	✗	3.4*	0.1
adamw	adamw	✓	✗	✓	✓	✓	✓	✗	✗	✗	76.5	77.4
adamw	adamw	✓	✗	✓	✓	✓	✓	✓	✓	✗	81.3	83.1
adamw	adamw	✓	✗	✓	✓	✓	✓	✓	✗	✓	81.9	83.1

Distillation through attention

Teacher Model: A strong image classifier (e.g., RegNetY ConvNet)

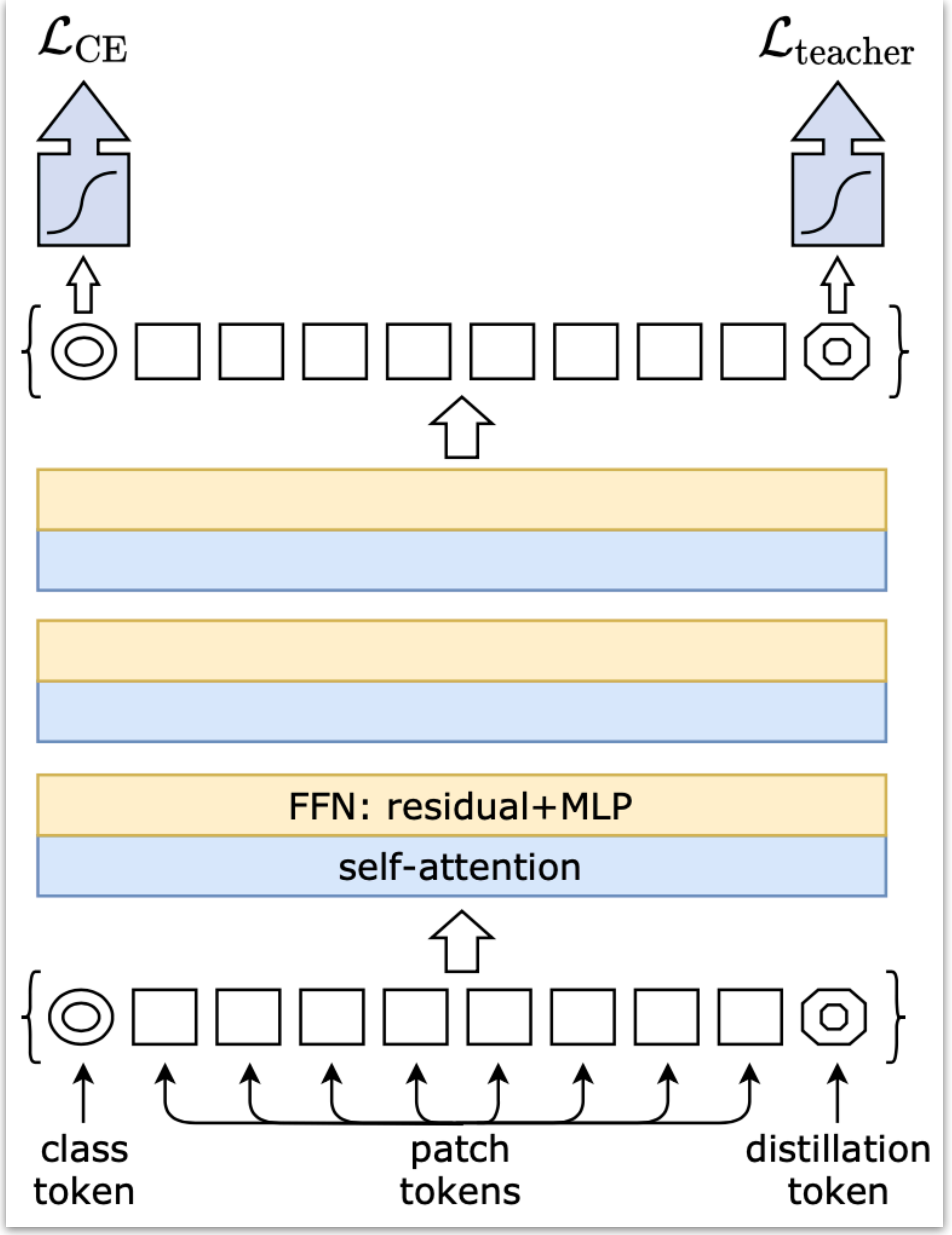
Soft Distillation

$$\mathcal{L}_{\text{global}} = (1-\lambda)\mathcal{L}_{\text{CE}}(\psi(Z_s), y) + \lambda\tau^2 \text{KL}(\psi(Z_s/\tau), \psi(Z_t/\tau))$$

$\psi \rightarrow$ softmax

$\tau \rightarrow$ temperature

$Z_s, Z_t \rightarrow$ student and teacher logits



Hard-label Distillation

$$y_t = \text{argmax}_c Z_t(c)$$

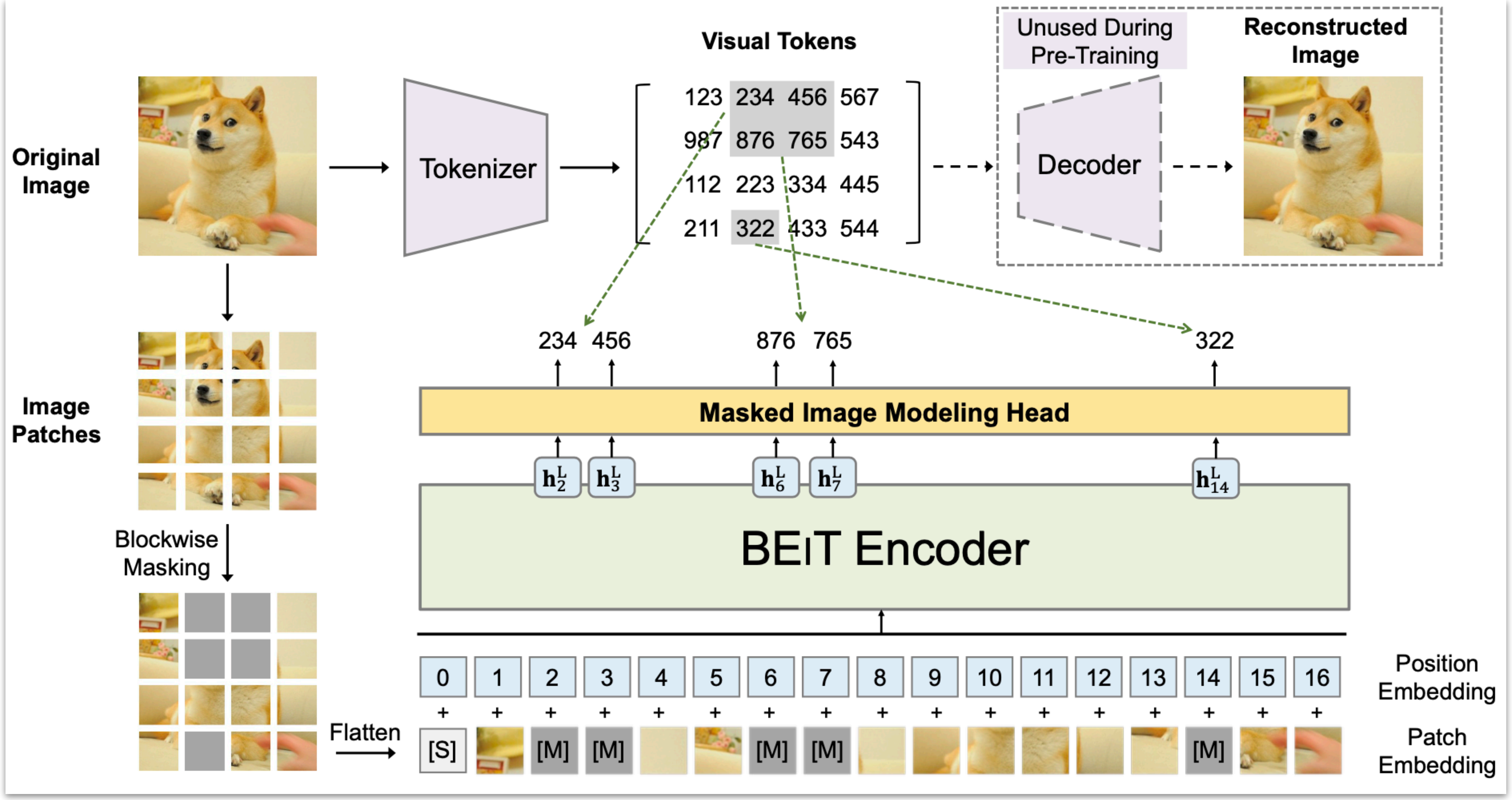
$$\mathcal{L}_{\text{global}}^{\text{hardDistill}} = \frac{1}{2}\mathcal{L}_{\text{CE}}(\psi(Z_s), y) + \frac{1}{2}\mathcal{L}_{\text{CE}}(\psi(Z_s), y_t)$$

Touvron, Hugo, et al. "Training data-efficient image transformers & distillation through attention." *International Conference on Machine Learning*. PMLR, 2021.

BEIT: BERT Pre-Training of Image Transformers

Boulder

Bidirectional Encoder representation from Image Transformers



$p_\psi(x|z) \rightarrow$ decoder (reconstruct the input image x based on the visual tokens z)

$$\max_{\phi,\psi} \mathbb{E}_{z\sim q_\phi(z|x)}[\log p_\psi(x|z)] - \mathrm{KL}[q_\phi(z|x) \parallel p(z)]$$

Gumbel-softmax relaxation

Algorithm 1 Blockwise Masking

Input: $N(= h \times w)$ image patches
Output: Masked positions $\mathcal{M}$
$\mathcal{M} \leftarrow \{\}$
repeat
  $s \leftarrow \mathrm{Rand}(16, 0.4N - |\mathcal{M}|)$ ▷ *Block size*
  $r \leftarrow \mathrm{Rand}(0.3, \frac{1}{0.3})$ ▷ *Aspect ratio of block*
  $a \leftarrow \sqrt{s \cdot r}; b \leftarrow \sqrt{s/r}$
  $t \leftarrow \mathrm{Rand}(0, h-a)\ ; l \leftarrow \mathrm{Rand}(0, w-b)$
  $\mathcal{M} \leftarrow \mathcal{M} \bigcup \{(i,j) : i \in [t, t+a), j \in [l, l+b)\}$
until $|\mathcal{M}| > 0.4N$ ▷ *Masking ratio is 40%*
return $\mathcal{M}$

Models	CIFAR-100	ImageNet
Training from scratch (i.e., random initialization)		
ViT_{384} (Dosovitskiy et al., 2020)	48.5*	77.9
DeiT (Touvron et al., 2020)	n/a	81.8
Supervised Pre-Training on ImageNet-1K (using labeled data)		
ViT_{384} (Dosovitskiy et al., 2020)	87.1	77.9
DeiT (Touvron et al., 2020)	90.8	81.8
Self-Supervised Pre-Training on ImageNet-1K (without labeled data)		
iGPT-1.36B† (Chen et al., 2020a)	n/a	66.5
ViT_{384}-JFT300M‡ (Dosovitskiy et al., 2020)	n/a	79.9
DINO (Caron et al., 2021)	91.7	82.8
MoCo v3 (Chen et al., 2021)	87.1	n/a
BEIT (ours)	90.1	**83.2**
Self-Supervised Pre-Training, and Intermediate Fine-Tuning on ImageNet-1K		
BEIT (ours)	**91.8**	**83.2**

Top-1 accuracy of image classification

Visual Token

image tokenizer (discrete variational autoencoder)

tokenize $x \in \mathbb{R}^{H\times W\times C}$ into $z \in \mathcal{V}^{h\times w}$

$\mathcal{V} = \{1, \ldots, |\mathcal{V}|\} \rightarrow$ vocabulary containing discrete token indices

https://github.com/openai/DALL-E

$q_\phi(z|x) \rightarrow$ tokenizer (maps image x into discrete tokens z according to a visual codebook/vocabulary)

Bao, Hangbo, Li Dong, and Furu Wei. "BEiT: BERT Pre-Training of Image Transformers." *arXiv preprint arXiv:2106.08254* (2021).

Questions?