



# Computer Vision; Image Classification; Data-efficient Learning

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# Self-training with Noisy Student improves ImageNet classification

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

- 1: Learn teacher model  $\theta_*^t$  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

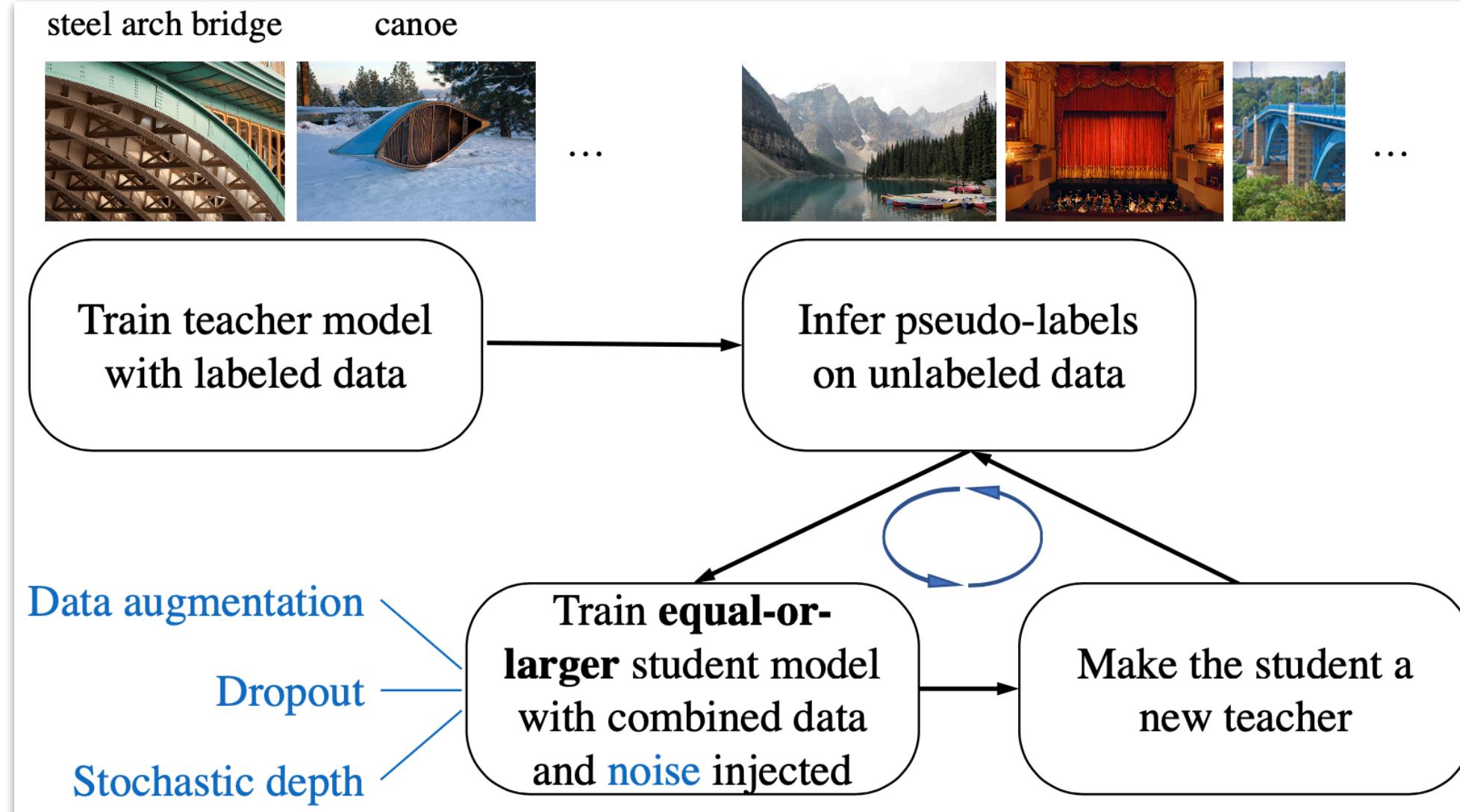
$$\tilde{y}_i = f(\tilde{x}_i, \theta_*^t), \forall i = 1, \dots, m$$

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

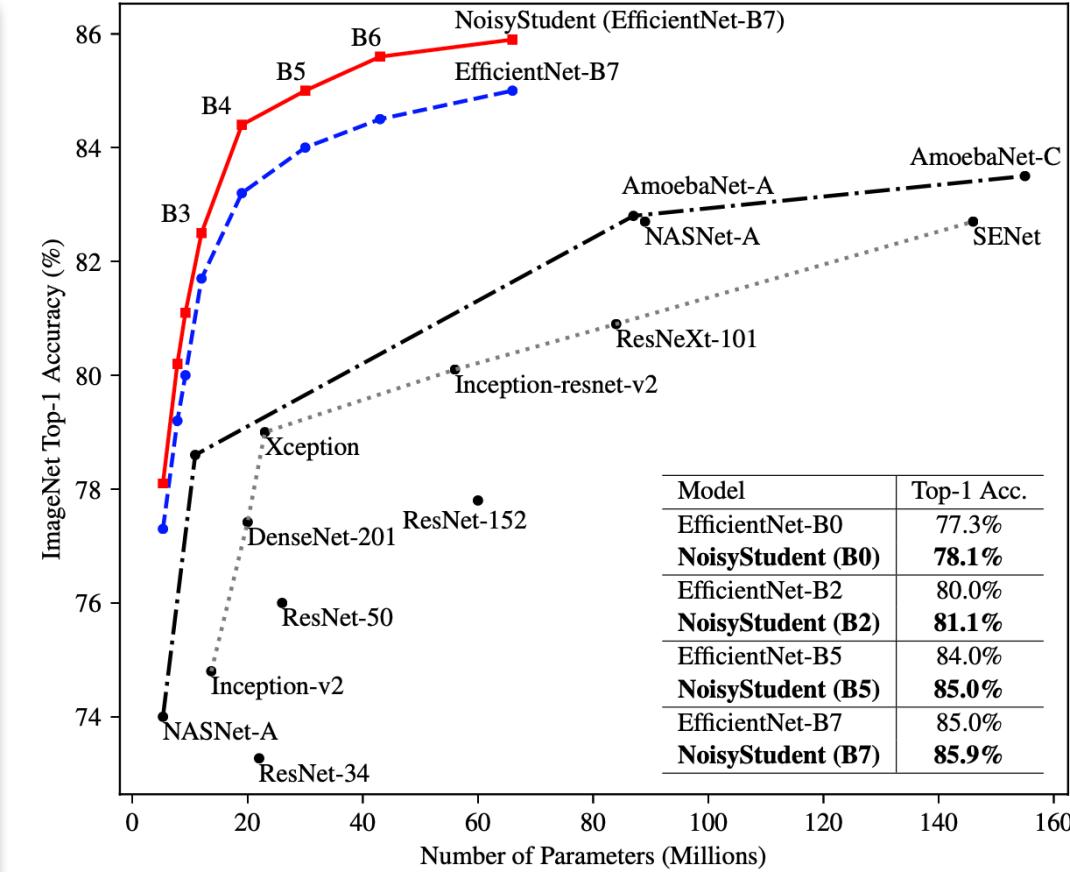
$$\frac{1}{n} \sum_{i=1}^n \ell(y_i, f^{noised}(x_i, \theta^s)) + \frac{1}{m} \sum_{i=1}^m \ell(\tilde{y}_i, f^{noised}(\tilde{x}_i, \theta^s))$$

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

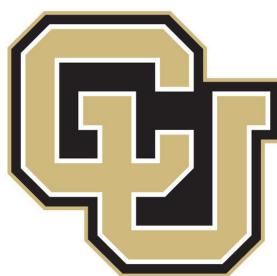
	ImageNet top-1 acc.	ImageNet-A top-1 acc.	ImageNet-C mCE	ImageNet-P mFR
Prev. SOTA	86.4%	61.0%	45.7	27.8
NoisyStudent	<b>88.4%</b>	<b>83.7%</b>	<b>28.3</b>	<b>12.2</b>



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).



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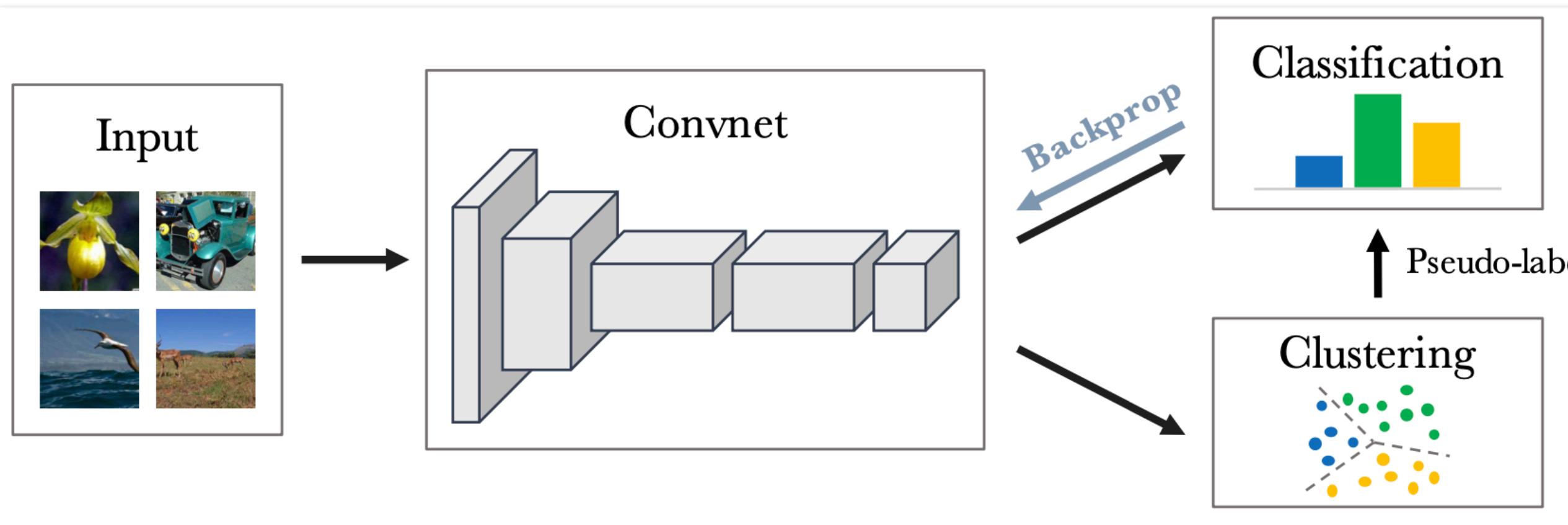
# Deep Clustering for Unsupervised Learning of Visual Features

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.

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

Problem setup: Find parameters  $\theta^*$  such that the convnet mapping  $f_{\theta^*}$  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

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

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

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

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

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

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

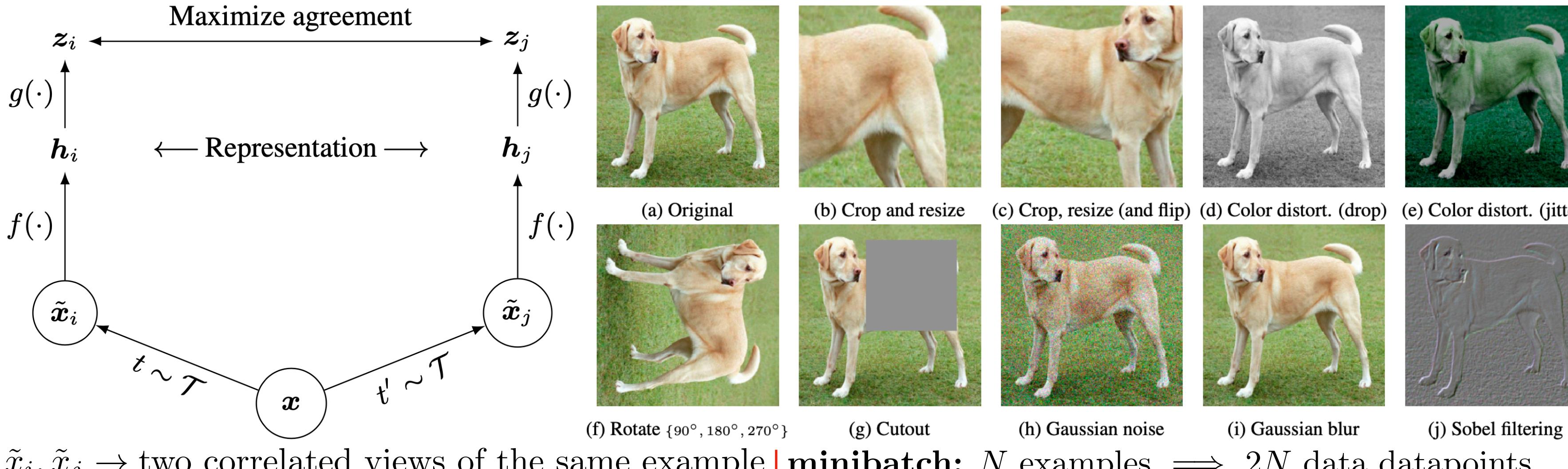
Sample images based on a uniform distribution over the classes, or pseudo-labels.

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 <sup>†</sup>	53.2	35.8 <sup>†</sup>	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		Method	Oxford5K		Paris6K	
		AlexNet	VGG-16	AlexNet	VGG-16		Oxford5K	Paris6K	Oxford5K	Paris6K
	ImageNet labels	56.8	67.3				72.4	81.5		
	Random	47.8	39.7				6.9	22.0		
	Doersch <i>et al.</i> [13]	51.1	61.5				35.4	53.1		
	Wang and Gupta [63]	47.2	60.2				42.3	58.0		
	Wang <i>et al.</i> [64]	–	63.2							
	DeepCluster	<b>55.4</b>	<b>65.9</b>				<b>61.0</b>	<b>72.0</b>		

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

# A Simple Framework for Contrastive Learning of Visual Representations



## 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

$$z_i = g(h_i) = W^2 \sigma(W^1 h_i)$$

ReLU

## 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

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

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

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
<i>Linear evaluation:</i>												
SimCLR (ours)	<b>76.9</b>	<b>95.3</b>	80.2	48.4	<b>65.9</b>	60.0	61.2	<b>84.2</b>	<b>78.9</b>	89.2	<b>93.9</b>	<b>95.0</b>
Supervised	75.2	95.7	81.2	56.4	64.9	<b>68.8</b>	<b>63.8</b>	83.8	<b>78.7</b>	92.3	94.1	94.2
<i>Fine-tuned:</i>												
SimCLR (ours)	<b>89.4</b>	<b>98.6</b>	<b>89.0</b>	<b>78.2</b>	<b>68.1</b>	<b>92.1</b>	<b>87.0</b>	<b>86.6</b>	<b>77.8</b>	92.1	<b>94.1</b>	97.6
Supervised	88.7	98.3	88.7	77.8	67.0	91.4	<b>88.0</b>	86.5	<b>78.8</b>	<b>93.2</b>	94.2	<b>98.0</b>
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
<i>Methods using ResNet-50:</i>				
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	<b>69.3</b>	<b>89.0</b>

## 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	<b>76.5</b>	<b>93.2</b>

## Semi-supervised learning on ImageNet

Method	Architecture	Label fraction	
		1%	10%
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

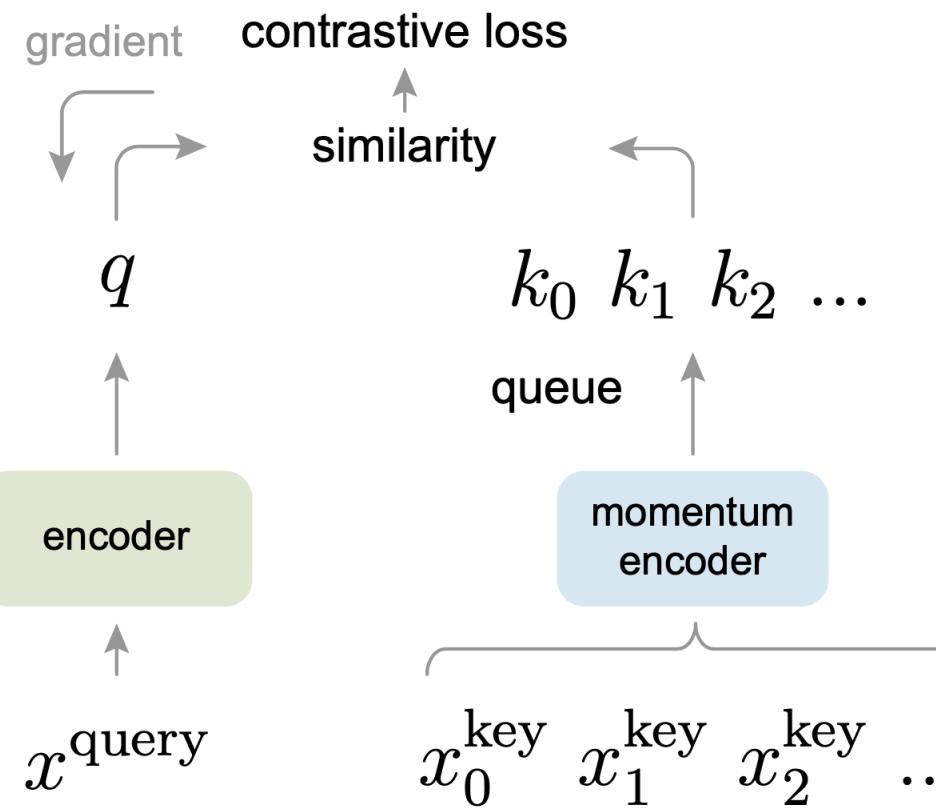
## Methods using representation learning only:

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×)	<b>85.8</b>	<b>92.6</b>



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# Momentum Contrast for Unsupervised Visual Representation Learning



**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

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

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

$$\mathcal{L}_q = -\log \frac{\exp(q \cdot k_+ / \tau)}{\sum_{i=0}^K \exp(q \cdot k_i / \tau)}$$

InfoNCE (noise-contrastive estimation) loss

$\tau \rightarrow$  temperature hyper-parameter

$q = f_q(x^q)$  query sample

$k = f_k(x^k)$  encoder network

**Momentum Contrast (MoCo)**

- ① dynamic
  - ② large
  - ③ consistent dictionary
- dictionary as queue

The current mini-batch is enqueue 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 <sub>50</sub>	AP	AP <sub>75</sub>
random init.	60.2	33.8	33.1
super. IN-1M	81.3	53.5	58.8
<b>MoCo</b> IN-1M	81.5 (+0.2)	55.9 ( <b>+2.4</b> )	62.6 ( <b>+3.8</b> )
<b>MoCo</b> IG-1B	82.2 ( <b>+0.9</b> )	57.2 ( <b>+3.7</b> )	63.7 ( <b>+4.9</b> )

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: Nx1
    k = f_k.forward(x_k) # keys: Nx1
    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

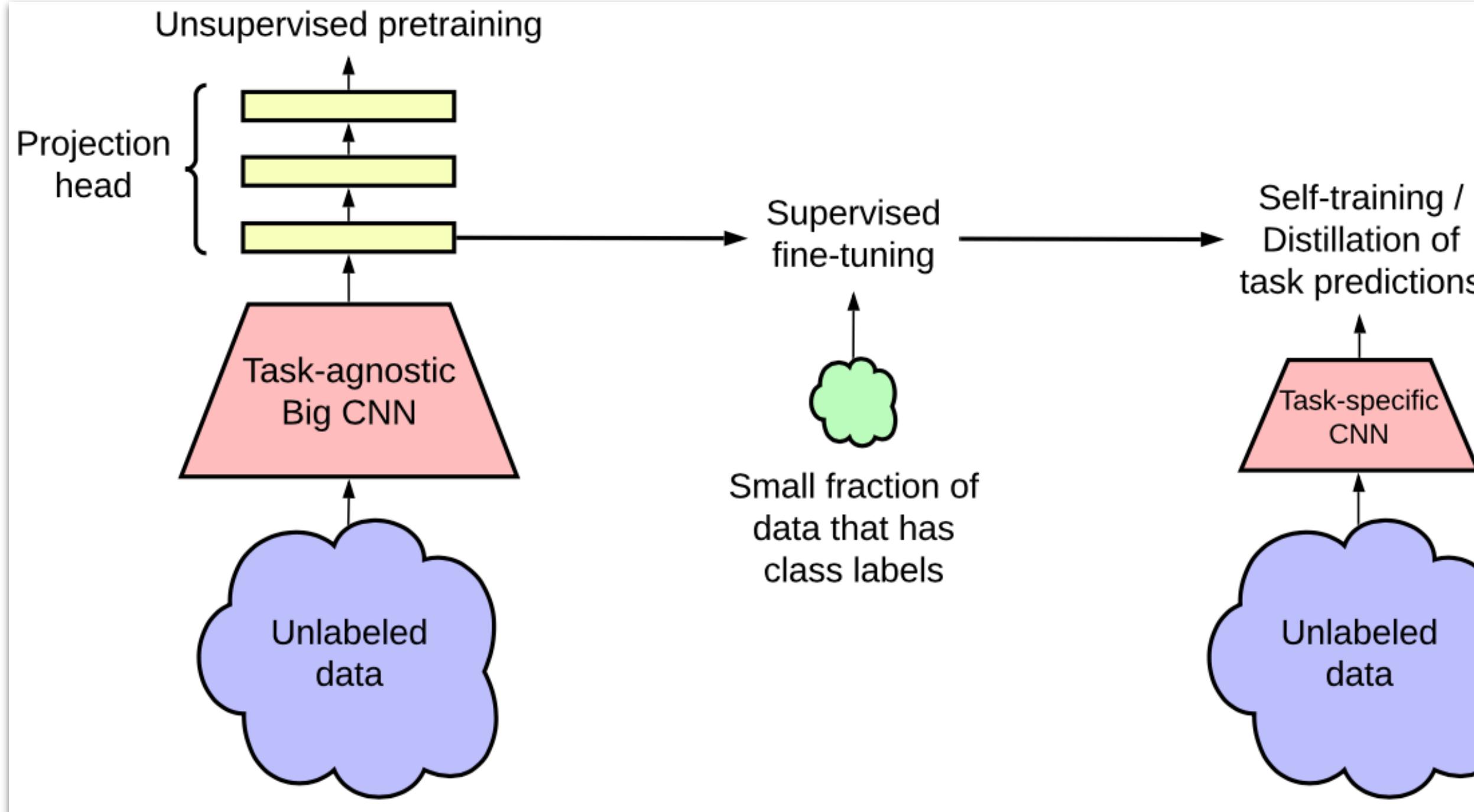
```

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



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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)

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

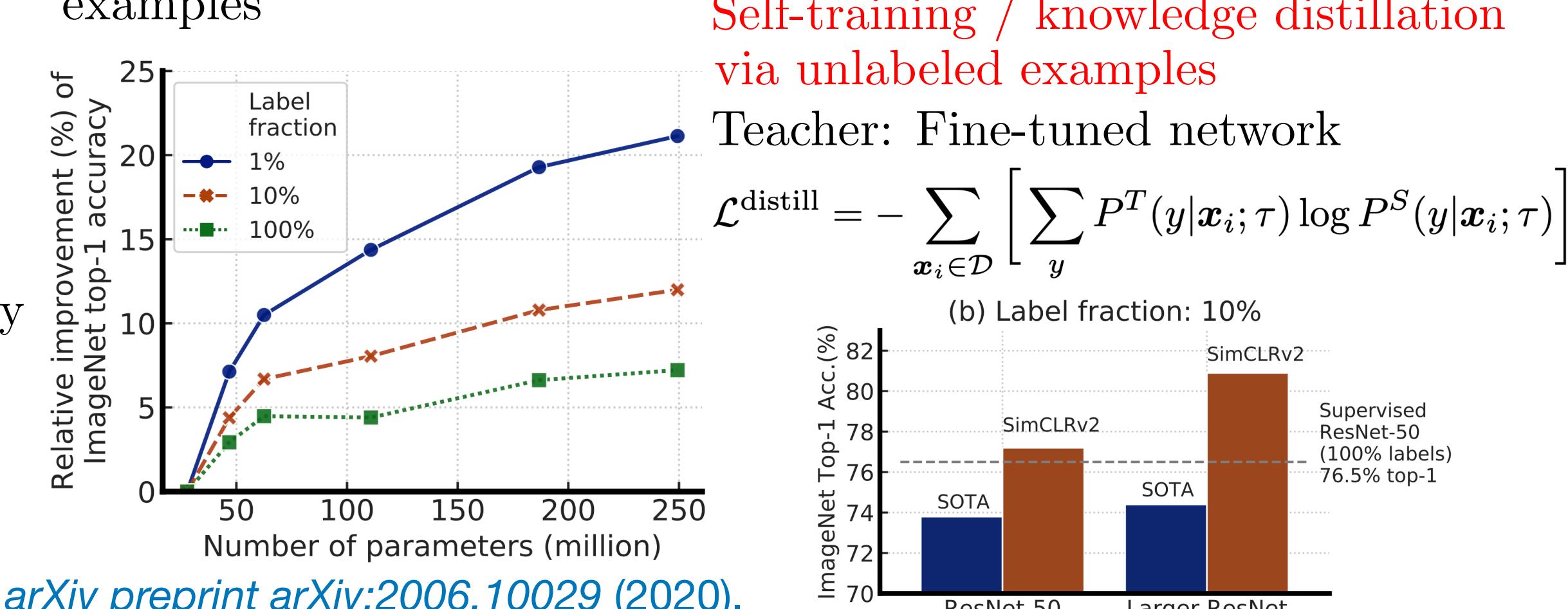
$z_{2k-1}, z_{2k} = g(h_{2k-1}), g(h_{2k}) \rightarrow$  used for contrastive loss  
 $g \rightarrow$  non-linear transformation network (MLP projection head)  
 $i, j \rightarrow$  positive examples (i.e., augmented from the same image)

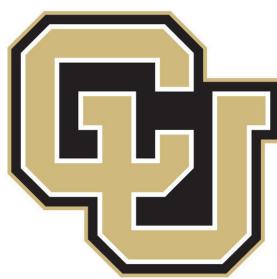
$$\ell_{i,j}^{\text{NT-Xent}} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(z_i, z_k)/\tau)}$$

**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





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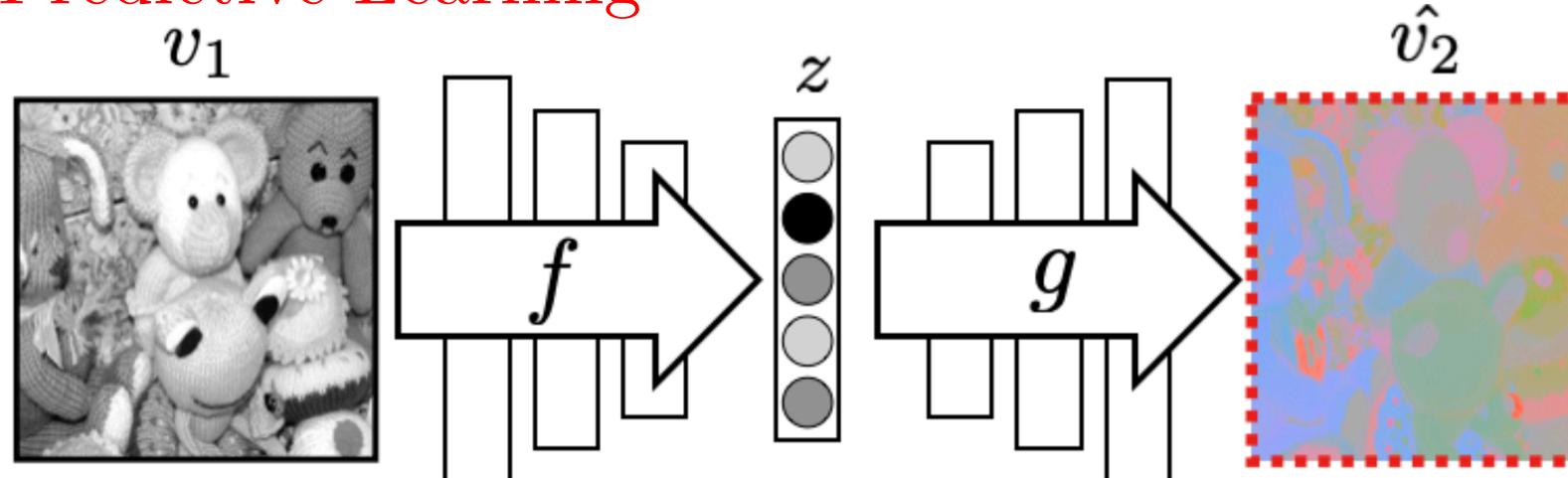
# Contrastive Multiview Coding

A “dog” can be seen, heard and felt!

$V_1, V_2, \dots, V_M \rightarrow$  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  $v_1$

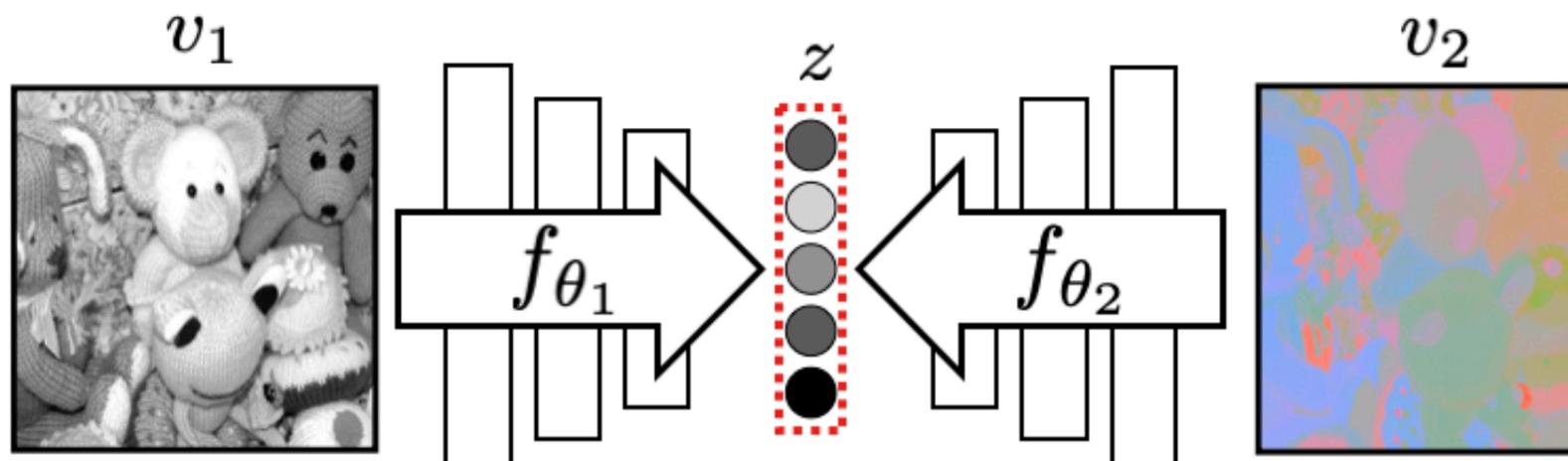
$z \rightarrow$  latent variables

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

Independence assumption between elements or pixels

$p(v_2|v_1) = \prod_i p(v_{2i}|v_1)$  of  $v_2$  given  $v_1$ !

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  $S = \{x, y_1, y_2, \dots, y_k\}$  that contains  $k$  negative samples

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

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

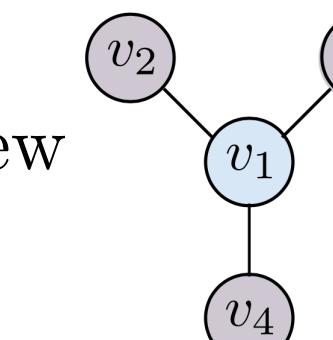
Connecting to Mutual Information

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

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

Contrastive Learning with More Than Two Views

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



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

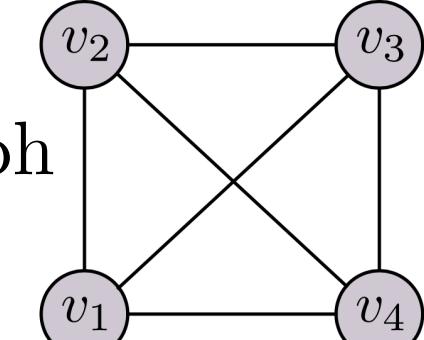


Image Views

luminance (L channel), chrominance (ab channel)

Video Views

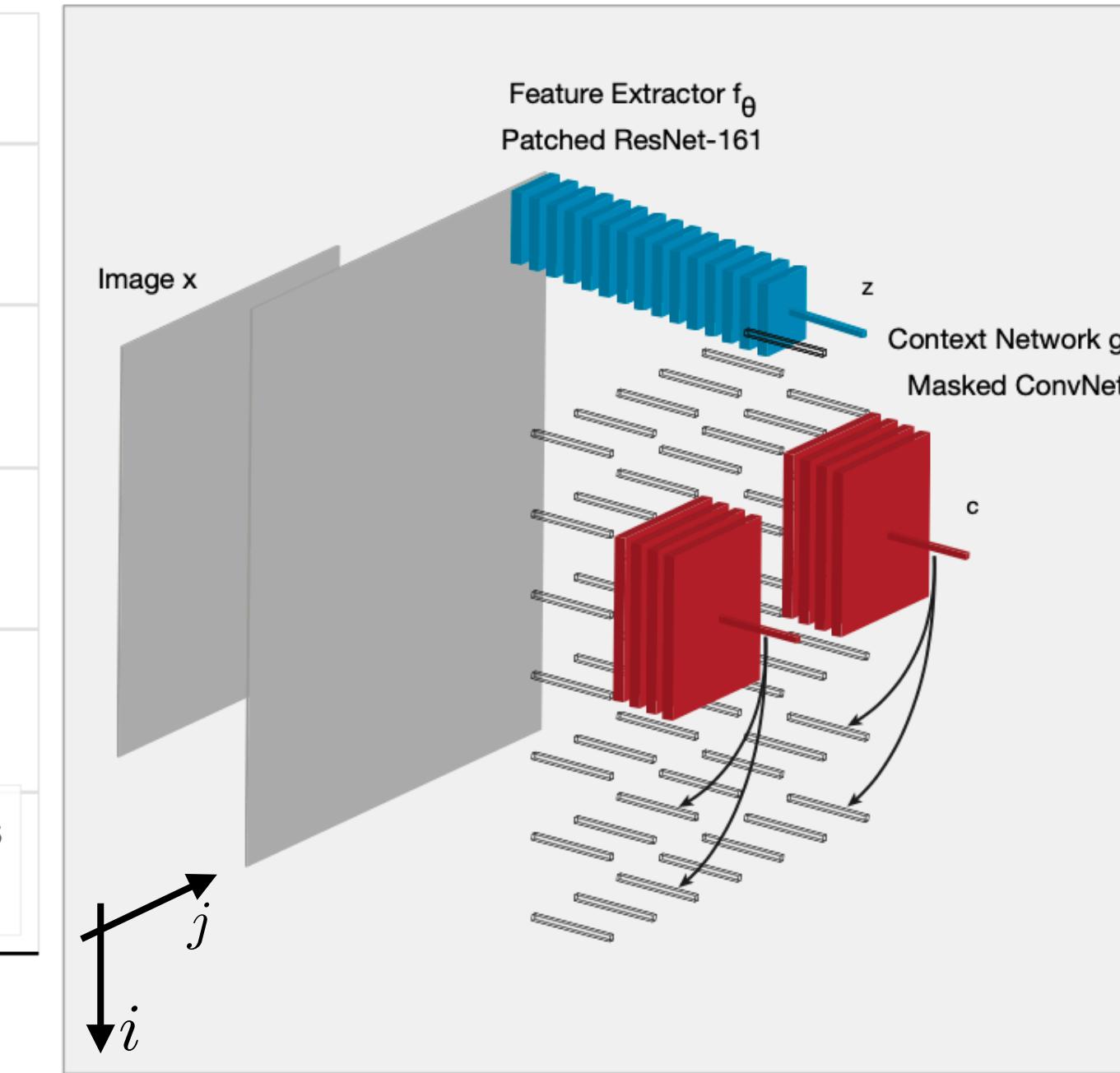
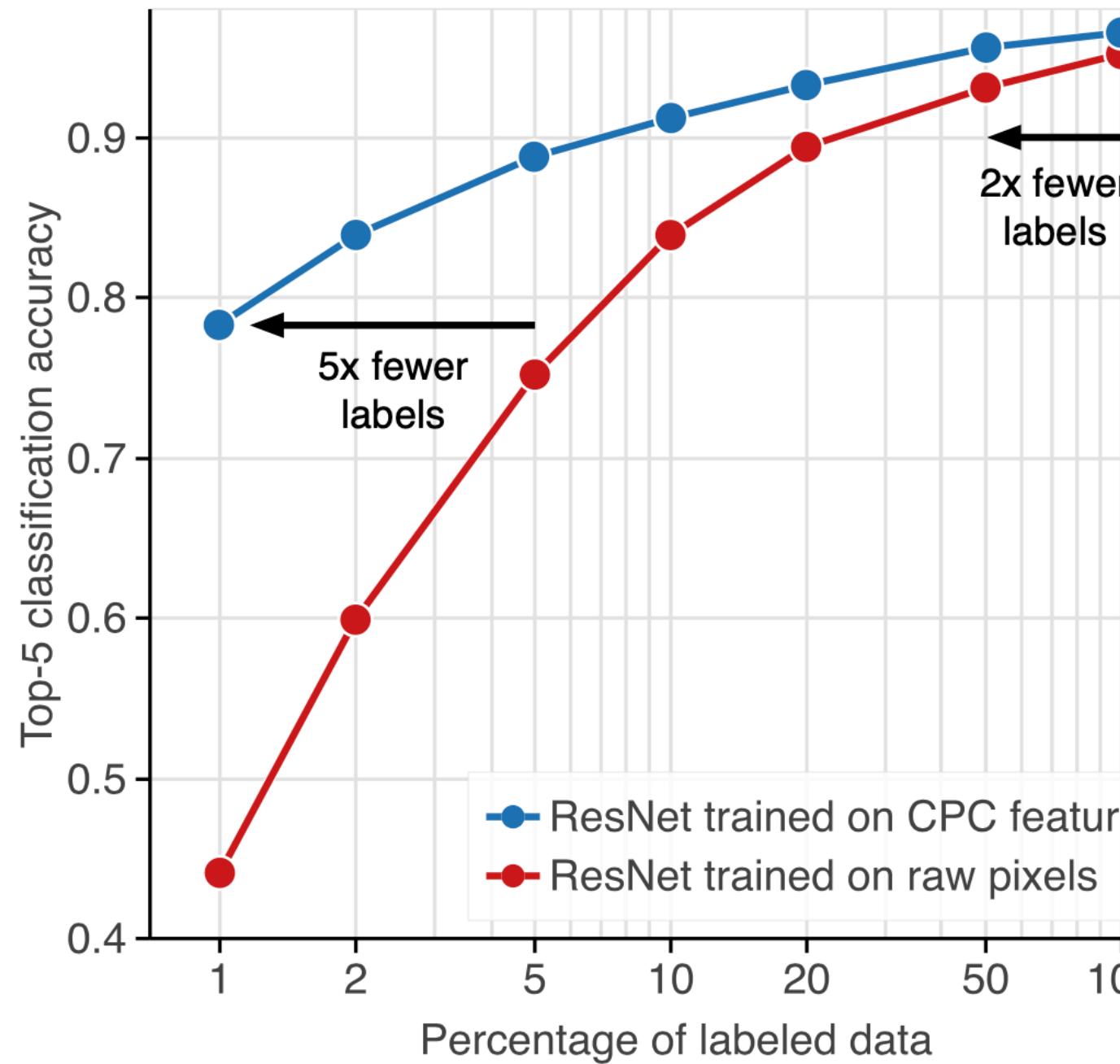
$i_t \rightarrow$  image at time  $t$ ,  $i_{t+k} \rightarrow$  neighboring frame,  $f_t \rightarrow$  optical flow (10 frames centered at time  $t$ )  
 $(i_t, i_{t+k}), (i_t, f_t) \rightarrow$  two separate contrastive learning objectives

Multiple Image Views

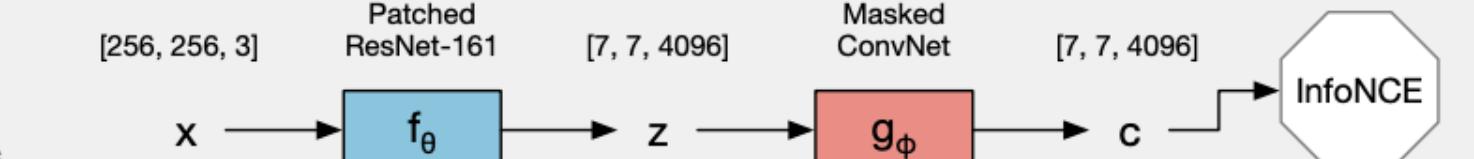
luminance (L channel), chrominance (ab channel), depth, surface normal, and semantic labels



# Data-Efficient Image Recognition with Contrastive Predictive Coding



**Self-supervised pre-training**  
100% images; 0% labels



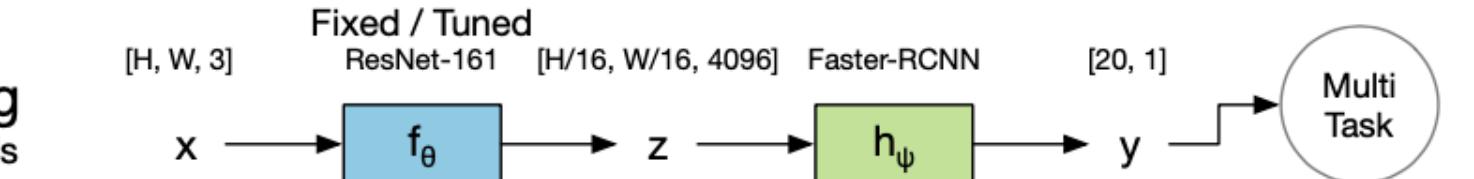
**Linear classification**  
100% images and labels



**Efficient classification**  
1% to 100% images and labels



**Transfer learning**  
100% images and labels



**Supervised training**  
1% to 100% images and labels



$\{x_{i,j}\} \rightarrow$  a grid of overlapping patches dividing each input image  
 $i, j \rightarrow$  location of the patch

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

↳ neural network

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

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

↳ feature vectors that lie above  $i, j$

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

$k \rightarrow$  prediction length

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

– 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.

InfoNCE (Noise Contrastive Estimation)

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

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



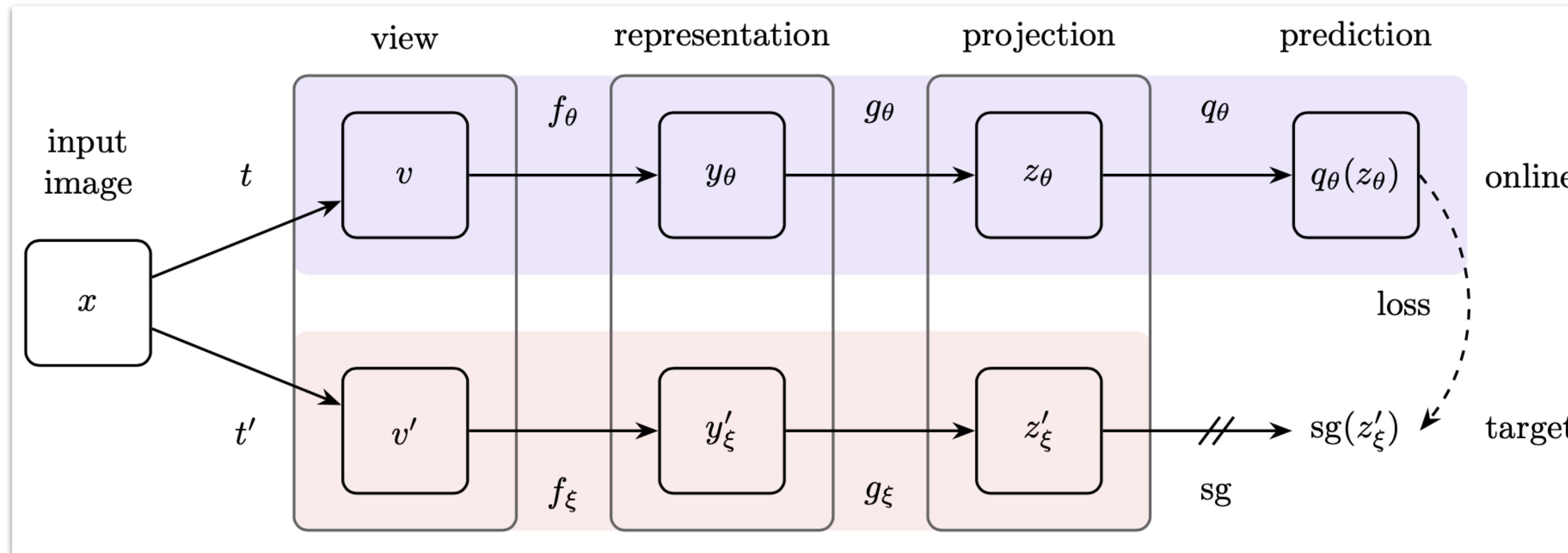
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# Bootstrap your own latent: A new approach to self-supervised Learning

Bootstrap Your Own Latent (BYOL)

Self-supervised image representation learning without using negative pairs! (★)

Learn a representation  $y_\theta$  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 (★)

$\theta \rightarrow$  online parameters

$\xi \rightarrow$  parameters of the target network

$\xi \leftarrow \tau\xi + (1 - \tau)\theta$  (★)

$\mathcal{D} \rightarrow$  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

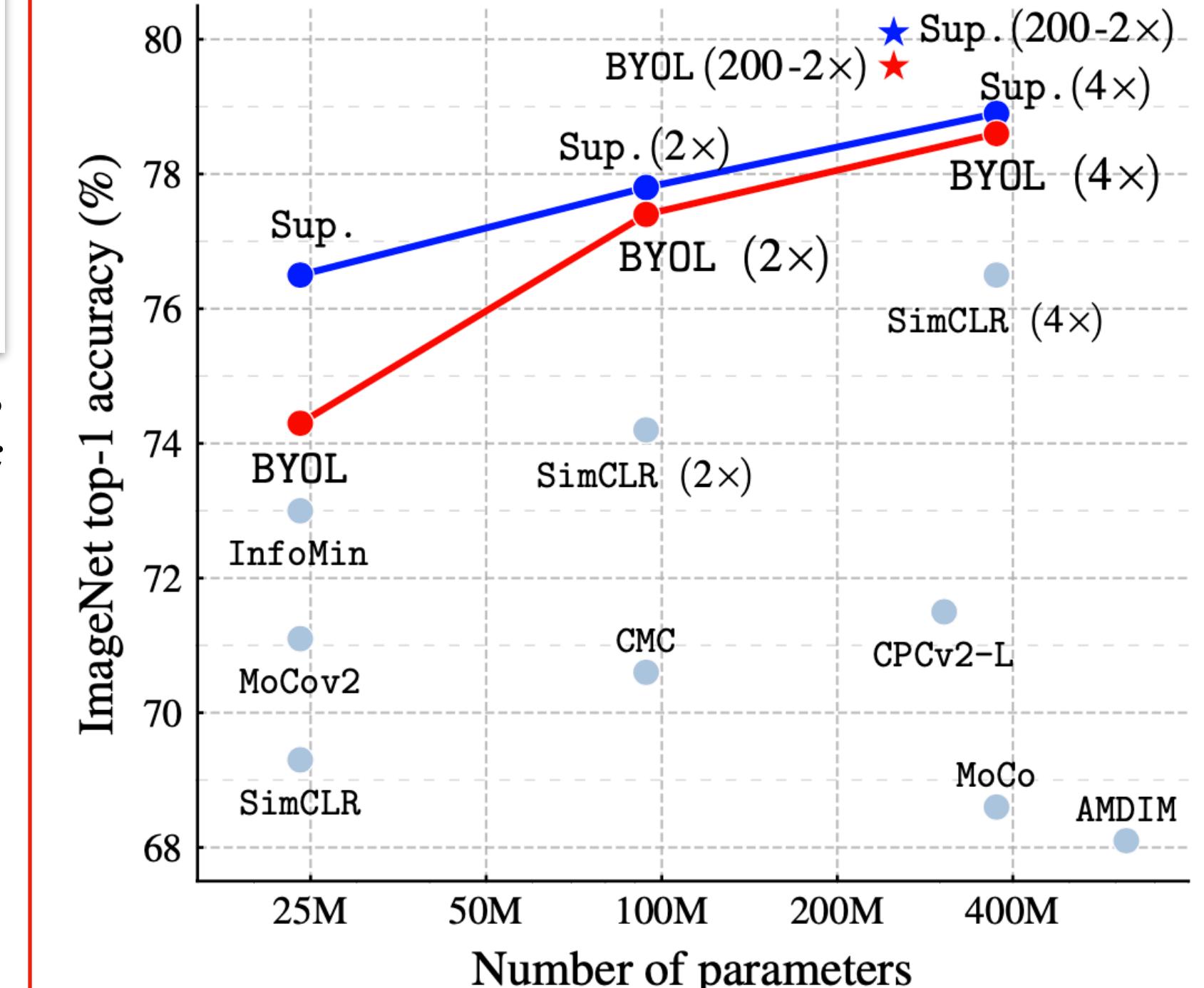
$v = t(x), v' = t'(x) \rightarrow$  two augmented views from  $x$   
 $t \sim \mathcal{T}, t' \sim \mathcal{T}'$   
 $y_\theta = f_\theta(v) \rightarrow$  representation  
 $z_\theta = g_\theta(y_\theta) \rightarrow$  projection  
 $y'_\xi = f'_\xi(v') \rightarrow$  target representation  
 $z'_\xi =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

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

$$\mathcal{L}_{\text{BYOL}} = \mathcal{L}_{\theta, \xi} + \tilde{\mathcal{L}}_{\theta, \xi}$$

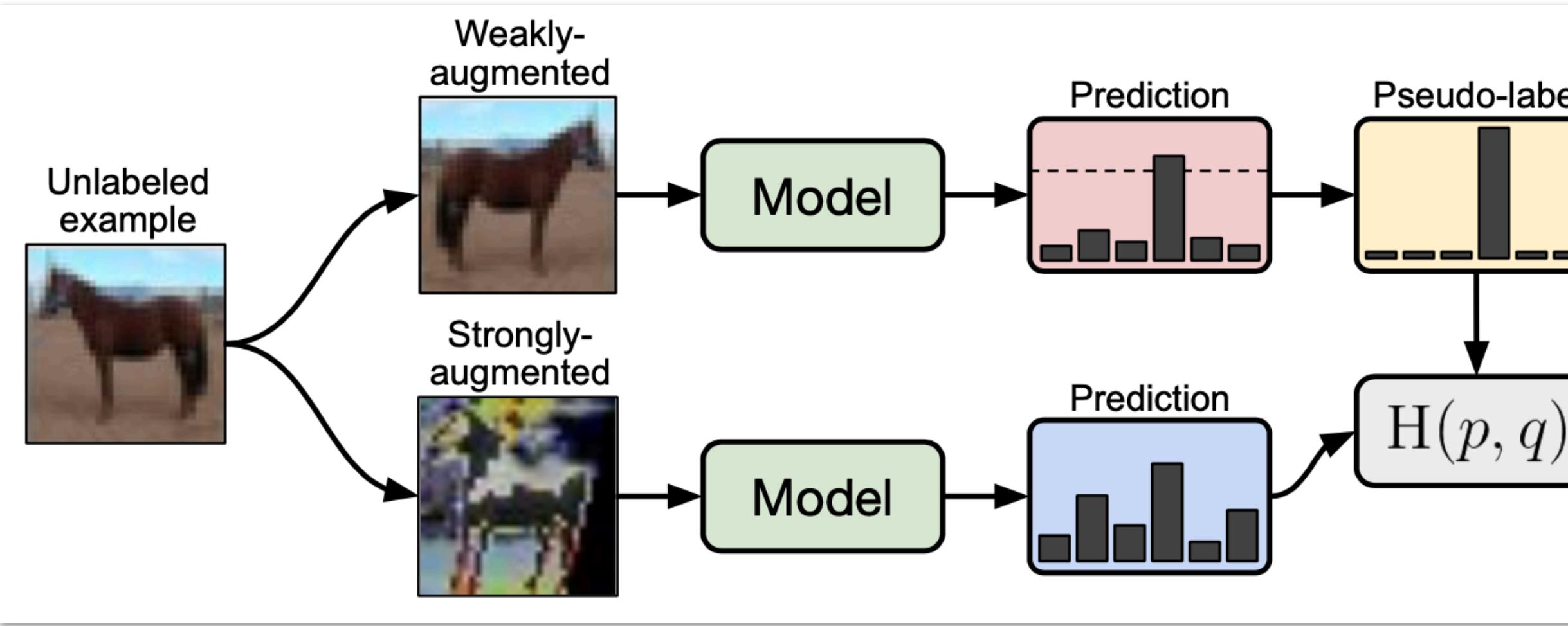
feeding  $v'$  to the online network and  $v$  to the target network

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.



# FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence

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



$L \rightarrow$  number of classes

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

$x_b \rightarrow$  training example

$p_b \rightarrow$  one-hot-labels

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

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

$p_m(y|x) \rightarrow$  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**

$\mu B$

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

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

**Extensions of the consistency regularization idea**

- using an adversarial transformation in place of  $\alpha$
- 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**

$$q_b = p_m(y|u_b)$$

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

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

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

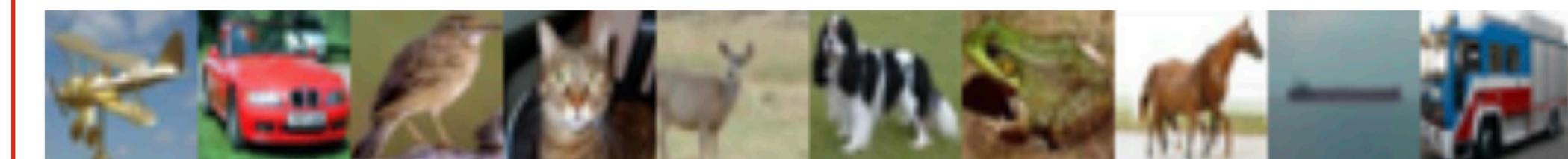
**FixMatch**

$\ell_s \rightarrow$  supervised loss

$\ell_u \rightarrow$  unsupervised loss

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

$$q_b = p_m(y | \alpha(u_b)) \quad \hat{q}_b = \arg \max(q_b) \rightarrow \text{pseudo-label} \quad \ell_s + \lambda_u \ell_u$$



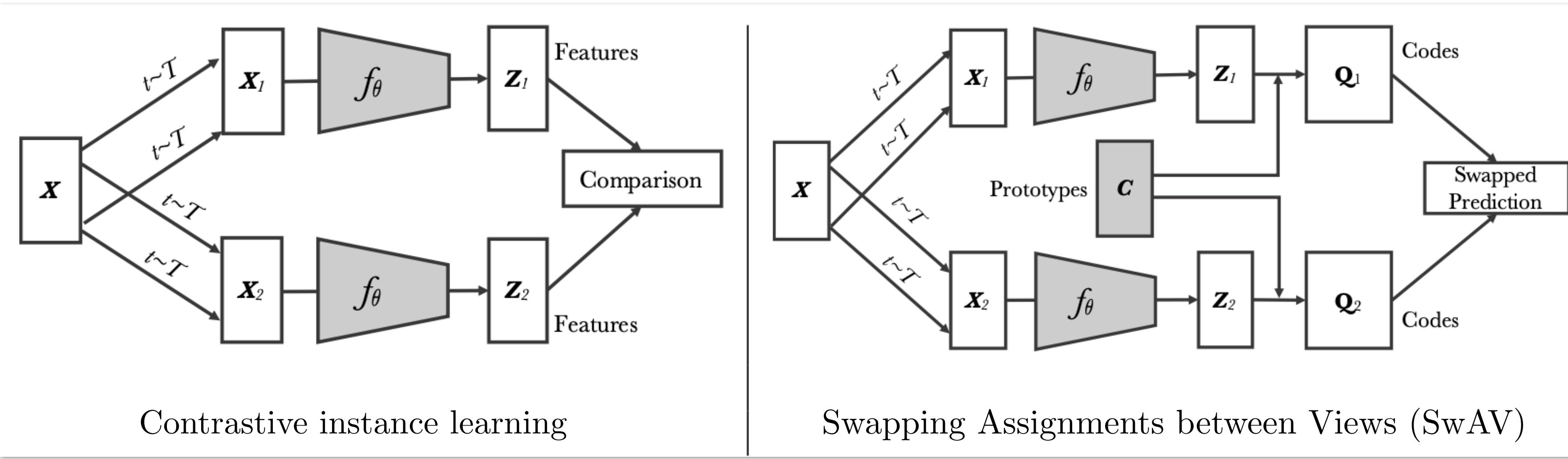
FixMatch reaches 78% CIFAR-10 accuracy using only above 10 labeled images.

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



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# Unsupervised Learning of Visual Features by Contrasting Cluster Assignments



Contrastive instance learning

Swapping Assignments between Views (SwAV)

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

$\{c_1, \dots, c_K\} \rightarrow$  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  $q$

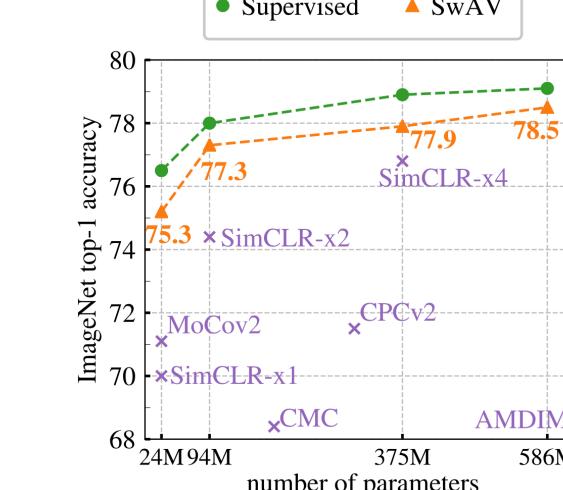
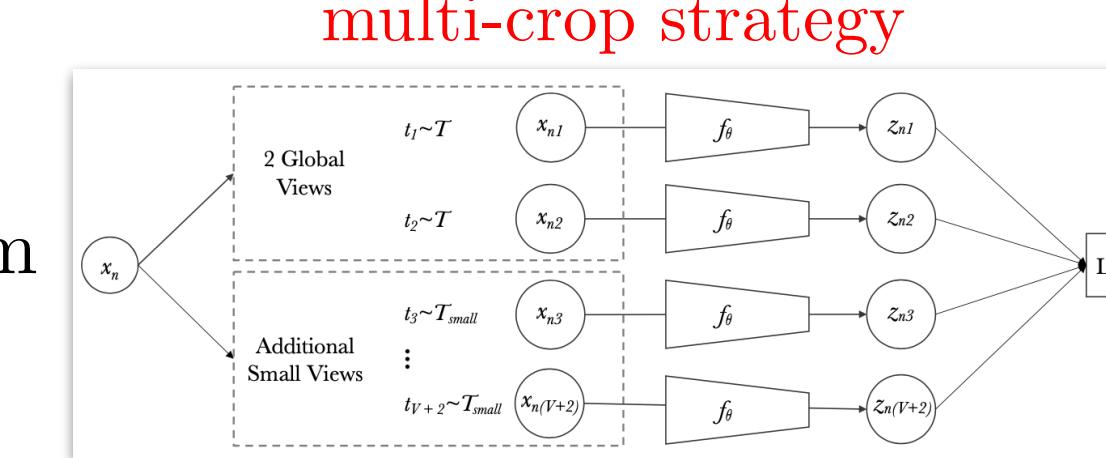
## Online Clustering

$t \sim \mathcal{T} \rightarrow$  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



Swapped prediction problem

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

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

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

$$- \log \sum_{k=1}^K \exp\left(\frac{\mathbf{z}_{nt}^\top \mathbf{c}_k}{\tau}\right) - \log \sum_{k=1}^K \exp\left(\frac{\mathbf{z}_{ns}^\top \mathbf{c}_k}{\tau}\right)$$

Minimized with respect to the prototypes  $C$  and the parameters  $\theta$

Computing codes online

Trivial solution: every image having the same code  
 $Z = [z_1, \dots, z_B] \rightarrow B$  feature vectors

$B \rightarrow$  mini-batch size

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

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

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

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

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

Three iterations of iterative Sinkhorn-Knopp algorithm!

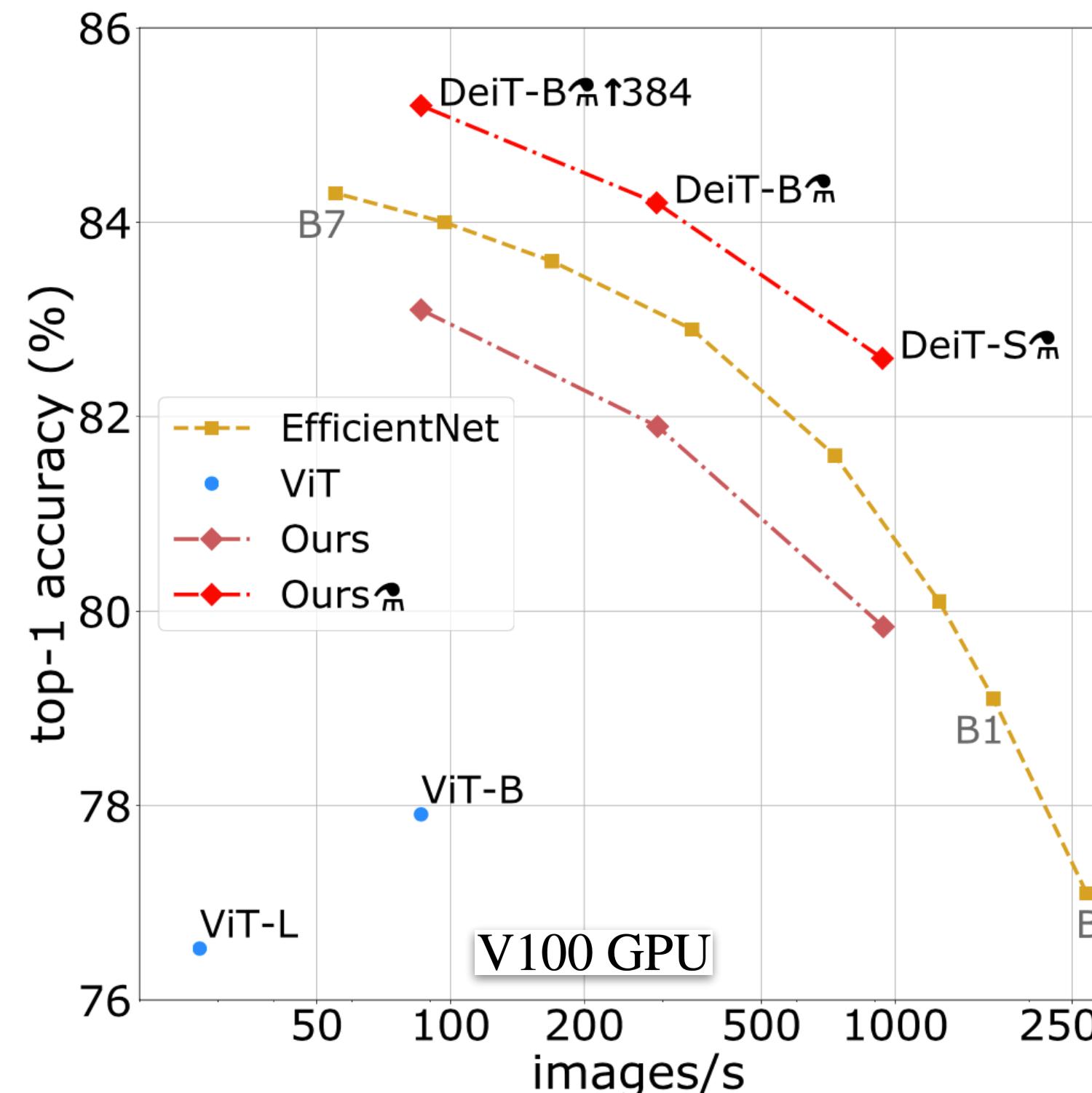


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# Training Data-Efficient Image Transformers & Distillation Through Attention

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

⇒  $N$  (sequence length) changes

⇒ need to adapt positional encodings (use bicubic interpolation)

Pre-training	Fine-tuning	Rand-Augment				Stoch. Depth	Repeated Aug.	Exp. Moving Avg.	pre-trained 224	fine-tuned 384
		AutoAug	Mixup	CutMix	Erasing					
adamw	adamw	✓	✗	✓	✓	✓	✓	✗	81.8 $\pm$ 0.2	83.1 $\pm$ 0.1
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)

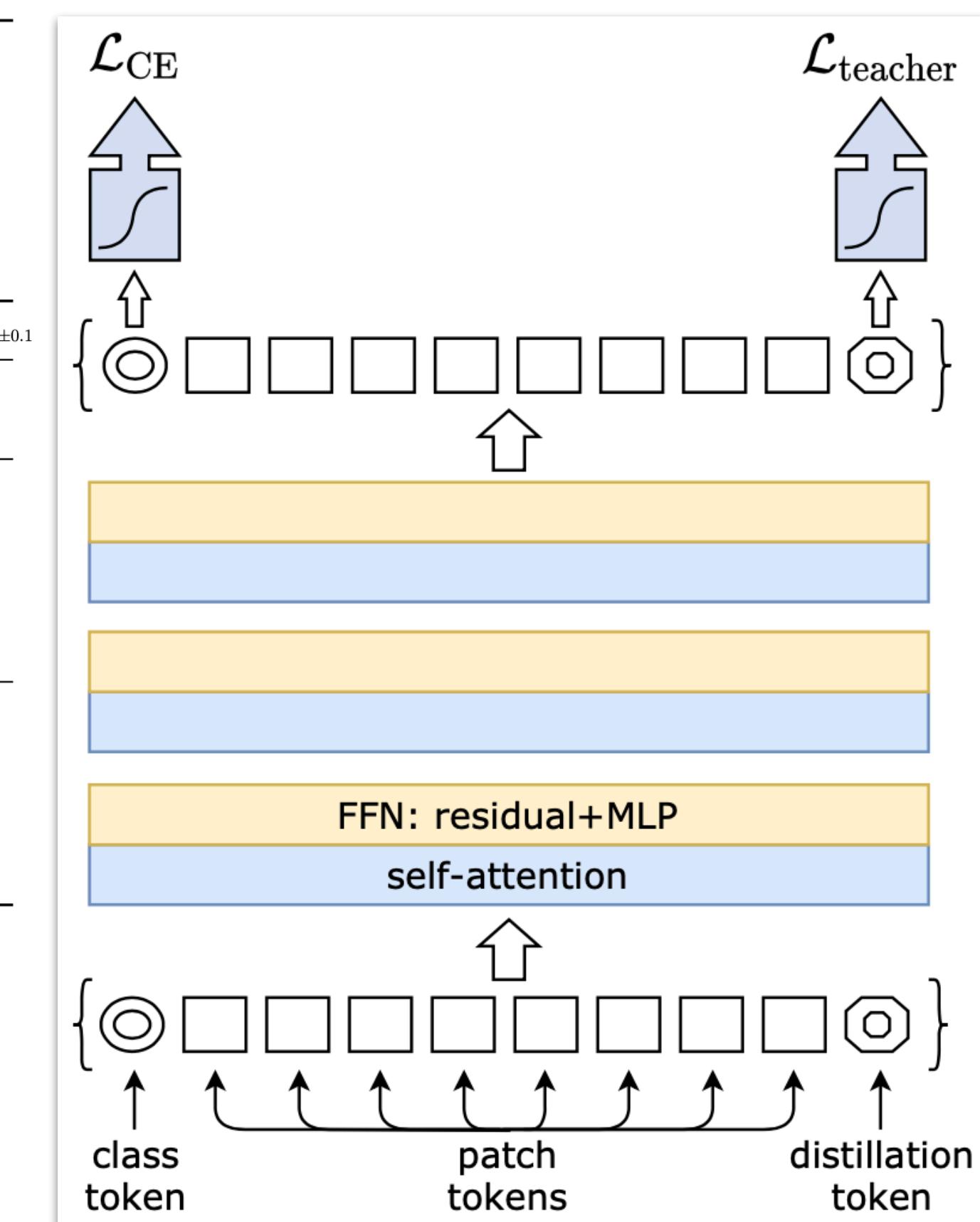
## Soft Distillation

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

$\psi \rightarrow \text{softmax}$

$\tau \rightarrow \text{temperature}$

$Z_s, Z_t \rightarrow \text{student and teacher logits}$



## Hard-label Distillation

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

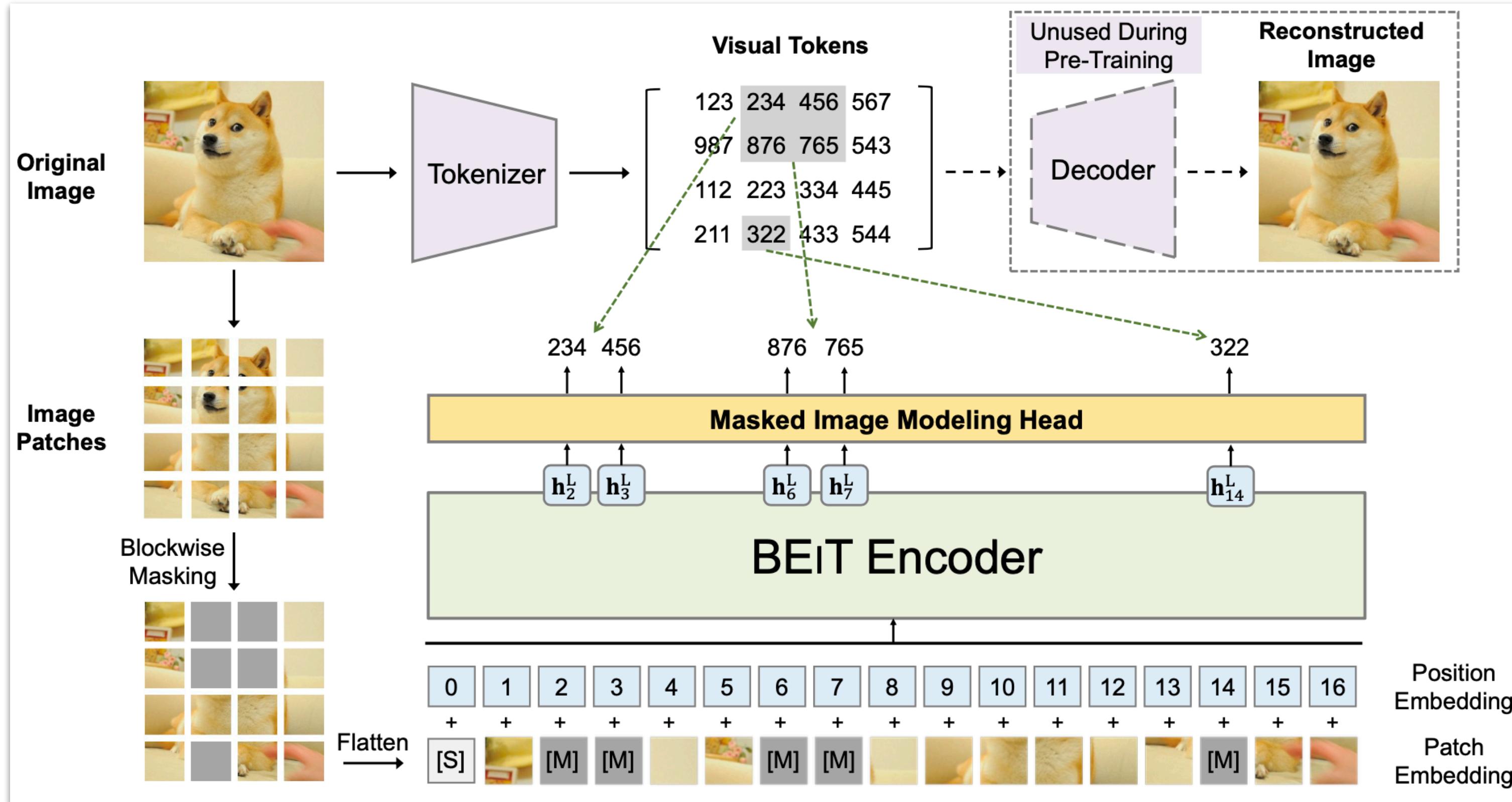
$$\begin{aligned} \mathcal{L}_{\text{global}}^{\text{hardDistill}} = & \frac{1}{2} \mathcal{L}_{\text{CE}}(\psi(Z_s), y) \\ & + \frac{1}{2} \mathcal{L}_{\text{CE}}(\psi(Z_s), y_t) \end{aligned}$$



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# BEiT: BERT Pre-Training of Image Transformers

## Bidirectional Encoder representation from Image Transformers



### Visual Token

image tokenizer (discrete variational autoencoder)

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

$\mathcal{V} = \{1, \dots, |\mathcal{V}|\} \rightarrow$  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).

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

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

Gumbel-softmax relaxation

---

### Algorithm 1 Blockwise Masking

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**Input:**  $N (= h \times w)$  image patches

**Output:** Masked positions  $\mathcal{M}$

$$\mathcal{M} \leftarrow \{\}$$

**repeat**

$$s \leftarrow \text{Rand}(16, 0.4N - |\mathcal{M}|)$$

$$r \leftarrow \text{Rand}(0.3, \frac{1}{0.3})$$

$$a \leftarrow \sqrt{s \cdot r}; b \leftarrow \sqrt{s/r}$$

$$t \leftarrow \text{Rand}(0, h - a); l \leftarrow \text{Rand}(0, w - b)$$

$$\mathcal{M} \leftarrow \mathcal{M} \cup \{(i, j) : i \in [t, t + a], j \in [l, l + b]\}$$

**until**  $|\mathcal{M}| > 0.4N$

$\triangleright$  Masking ratio is 40%

**return**  $\mathcal{M}$

---

Models	CIFAR-100	ImageNet
<i>Training from scratch (i.e., random initialization)</i>		
ViT <sub>384</sub> (Dosovitskiy et al., 2020)	48.5*	77.9
DeiT (Touvron et al., 2020)	n/a	81.8
<i>Supervised Pre-Training on ImageNet-1K (using labeled data)</i>		
ViT <sub>384</sub> (Dosovitskiy et al., 2020)	87.1	77.9
DeiT (Touvron et al., 2020)	90.8	81.8
<i>Self-Supervised Pre-Training on ImageNet-1K (without labeled data)</i>		
iGPT-1.36B <sup>†</sup> (Chen et al., 2020a)	n/a	66.5
ViT <sub>384</sub> -JFT300M <sup>‡</sup> (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	<b>83.2</b>
<i>Self-Supervised Pre-Training, and Intermediate Fine-Tuning on ImageNet-1K</i>		
BEiT (ours)	<b>91.8</b>	<b>83.2</b>

Top-1 accuracy of image classification



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# Questions?

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