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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

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

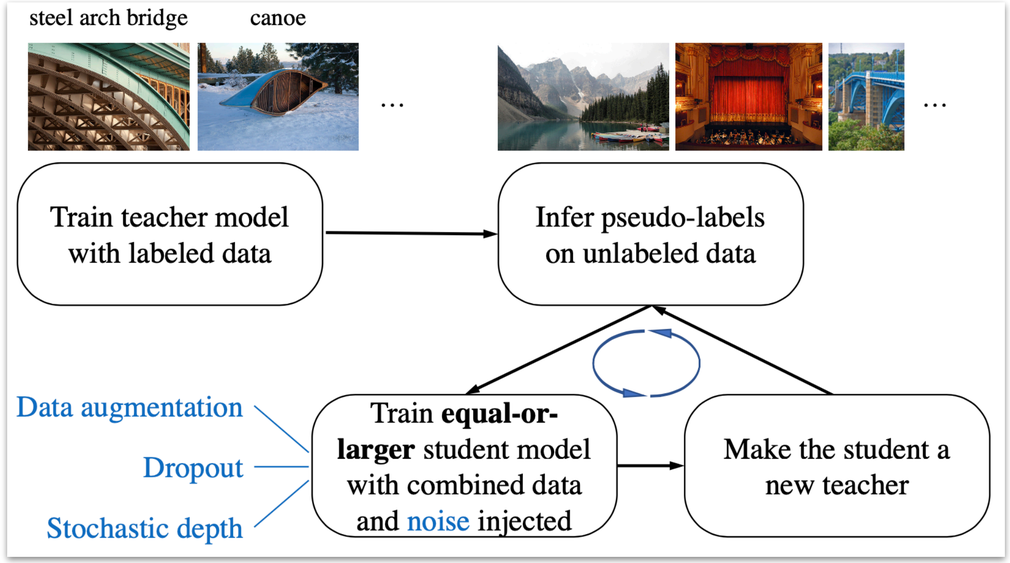
$$\tilde{y}_i = f(\tilde{x}_i, \theta_*^t), \forall i = 1, \cdots, m$$

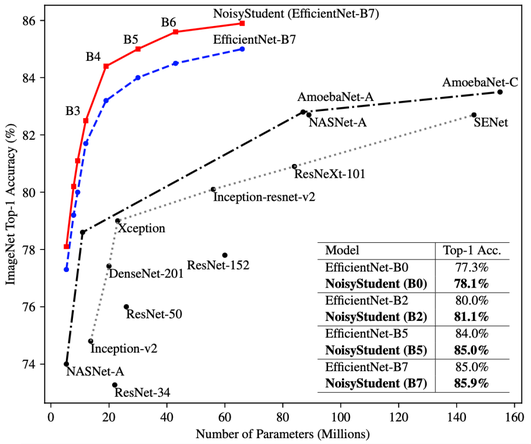
3: Learn an **equal-or-larger** student model θ_*^s which minimizes the cross entropy loss on labeled images and unlabeled images with **noise** added to the student model

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

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**



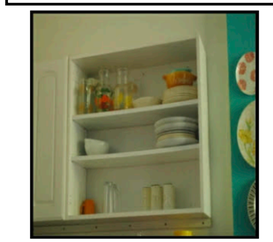


ImageNet-C and ImageNet-P test sets include images with common corruptions and perturbations such as blurring, fogging, rotation and scaling. ImageNet-A test set consists of difficult images that cause significant drops in accuracy to state-of-the-art models. These test sets are considered as "robustness" 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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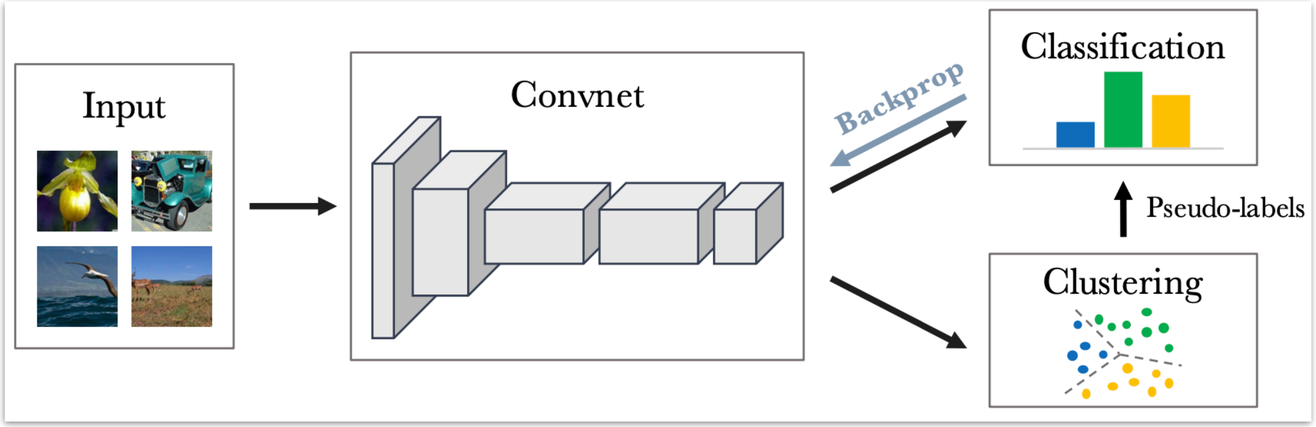
Key observation: A multilayer perceptron classifier on top of the last convolutional layer of a random AlexNet achieves 12% in accuracy on ImageNet while the chance is at 0.1%.
This is because a convolutional structure gives a strong prior.
$\{x_1, \ldots, x_N\} \rightarrow$ training set of N images
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 $f_\theta(x_n)$

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

$\ell \rightarrow$ 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

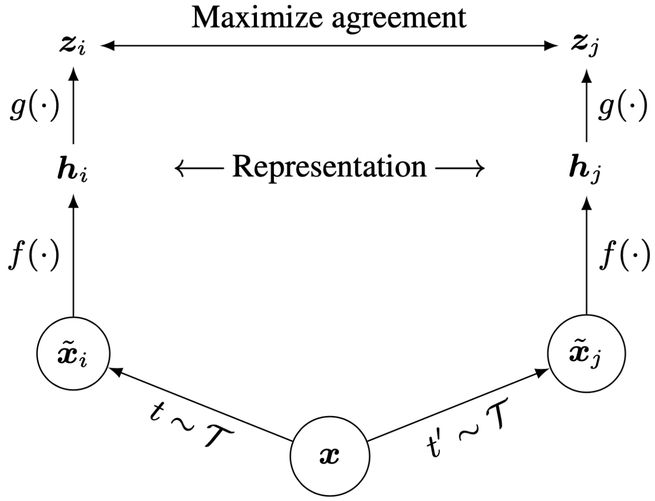
Method	AlexNet	VGG-16
ImageNet labels	56.8	67.3
Random	47.8	39.7
Doersch *et al.* [13]	51.1	61.5
Wang and Gupta [63]	47.2	60.2
Wang *et al.* [64]	–	63.2
DeepCluster	**55.4**	**65.9**

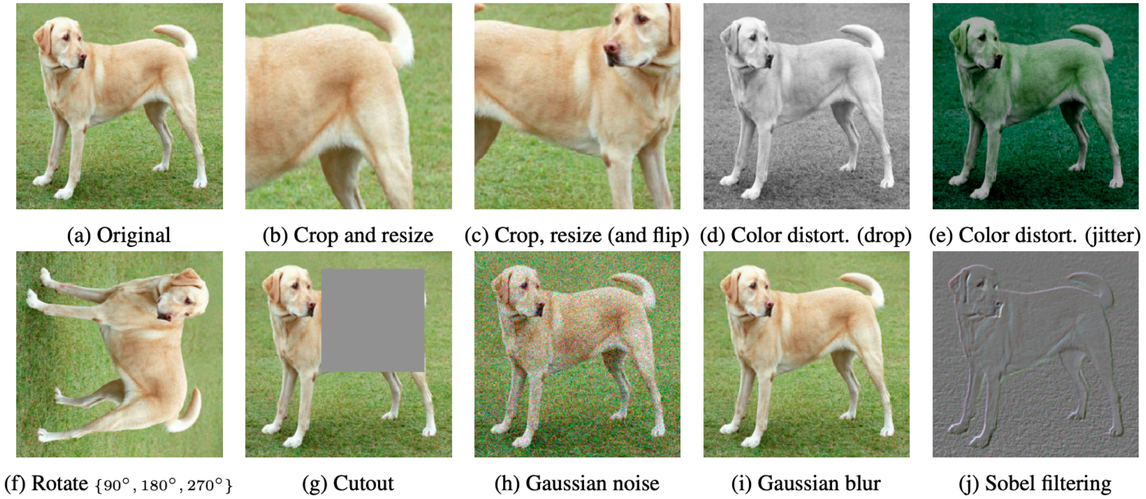
mAP on instance-level image retrieval on Oxford and Paris dataset with a VGG-16

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





$\tilde{x}_i, \tilde{x}_j \rightarrow$ 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

$z_i = g(h_i) = W^2\sigma(W^1 h_i)$ (σ: 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 $\Longrightarrow$ $2N$ 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

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

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 (Top 5) 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×)	**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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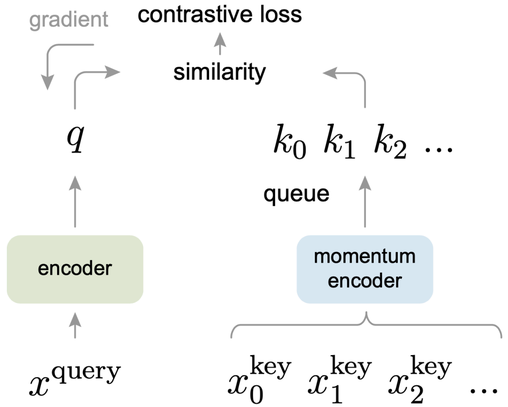


Keys (tokens): samples from the data (e.g., images or patches) represented by an encoder network

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

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

InfoNCE (noise-contrastive estimation) loss

$\tau \rightarrow$ temperature hyper-parameter

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

encoder network

$k = f_k(x^k)$

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)

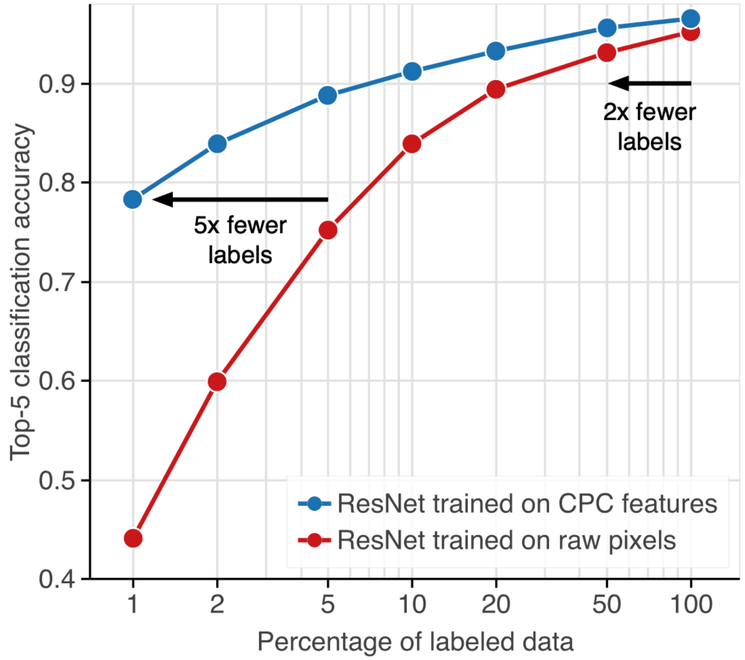
Algorithm 1 Pseudocode of MoCo in a PyTorch-like style.

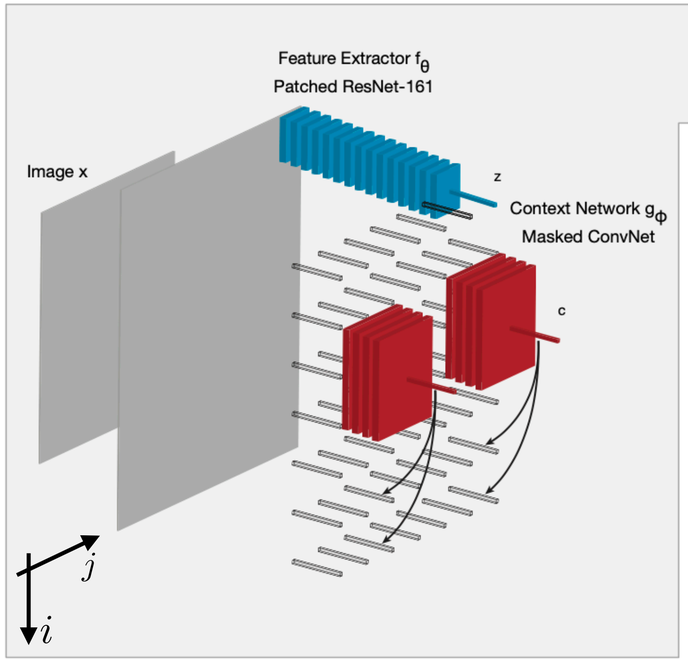
```
# f_q, f_k: encoder networks for query and key
# queue: dictionary as a queue of K keys (CxK)
# m: momentum
# t: temperature

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
```

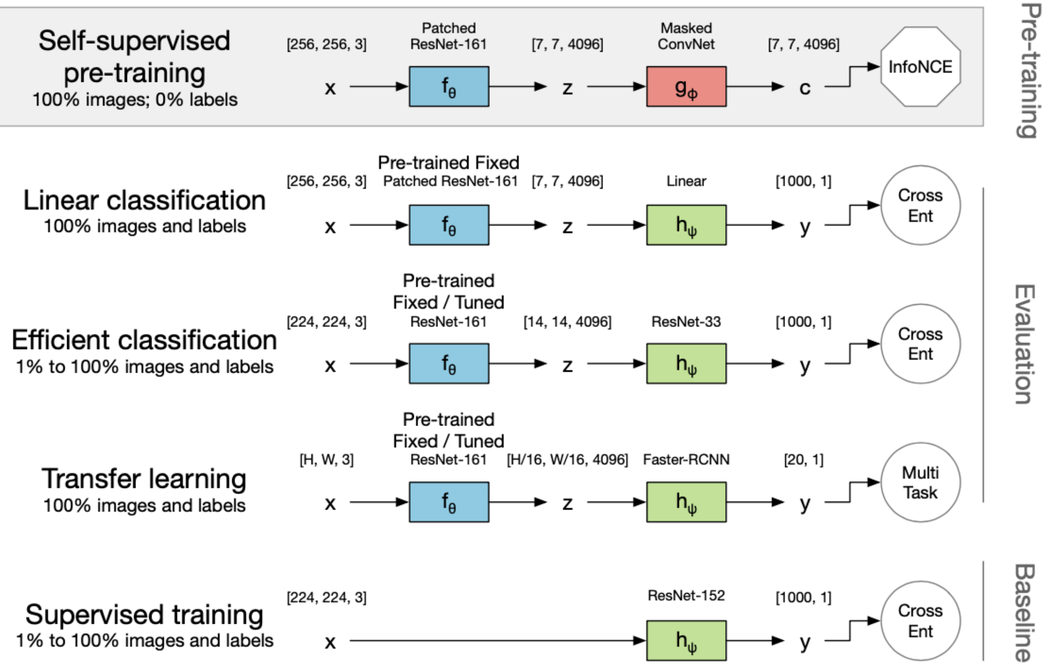
bmm: batch matrix multiplication; mm: matrix multiplication; cat: concatenation.

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

Data-Efficient Image Recognition with Contrastive Predictive Coding







$\{x_{i,j}\} \rightarrow$ 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)

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

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.

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Questions?