Momentum Contrast for Unsupervised Visual Representation Learning

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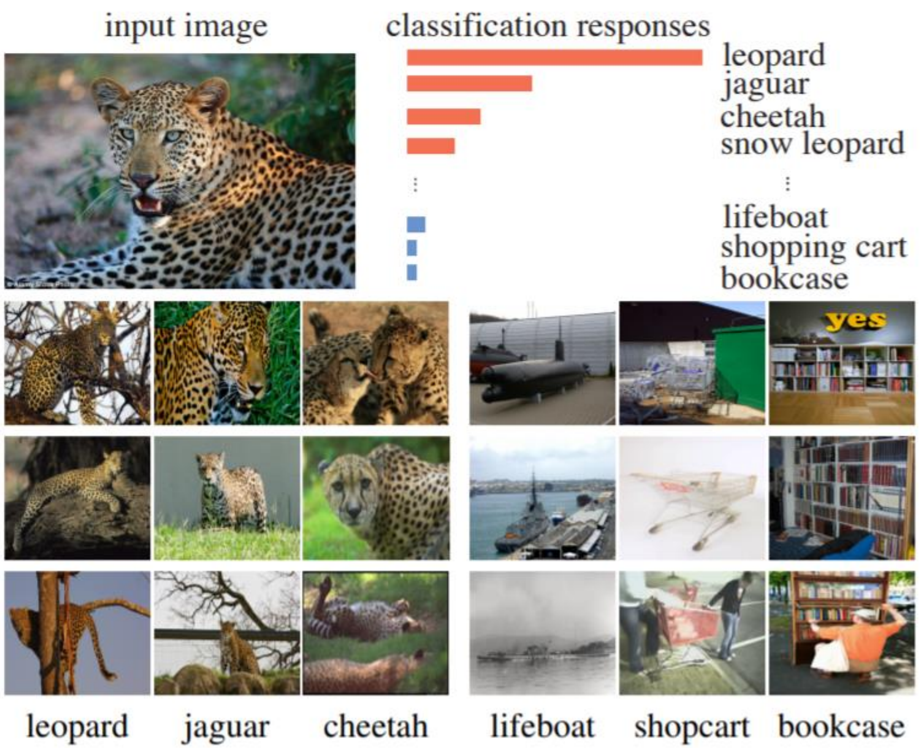
2020.03.19

Prerequisite

Unsupervised Feature Learning via Non-Parametric Instance Discrimination

Motivation



- A classifier can automatically <u>dis cover apparent similarity</u> among semantic categories, <u>without se mantic annotation.</u>

- Can we learn a good feature rep resentation that captures appare nt <u>similarity among instances, in stead of classes</u>, by merely askin g the feature to be discriminativ e of individual instances?

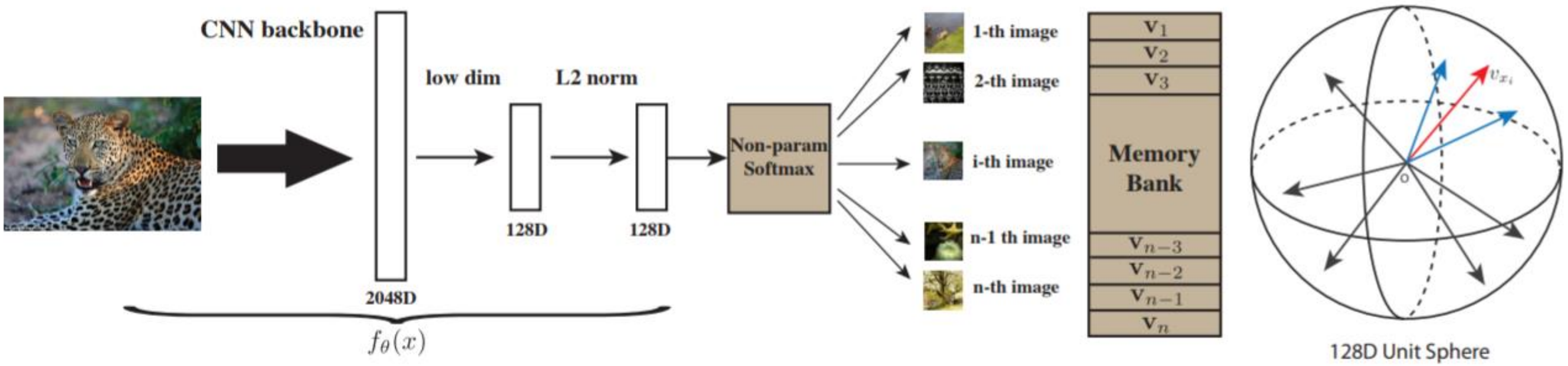
- Unsupervised learning setting에서 feature를 학습하고 transfer 함으로써 downstream task의 성능을 높이고자 하는 게 목표

Prerequisite

Unsupervised Feature Learning via Non-Parametric Instance Discrimination

Method

Memory Bank = instance dictionary



$$P(i|\mathbf{v}) = \frac{\exp\left(\mathbf{w}_i^T \mathbf{v}\right)}{\sum_{j=1}^{n} \exp\left(\mathbf{w}_j^T \mathbf{v}\right)} \qquad P(i|\mathbf{v}) = \frac{\exp\left(\mathbf{v}_i^T \mathbf{v}/\tau\right)}{\sum_{j=1}^{n} \exp\left(\mathbf{v}_j^T \mathbf{v}/\tau\right)}$$

<u>Computational cost</u>

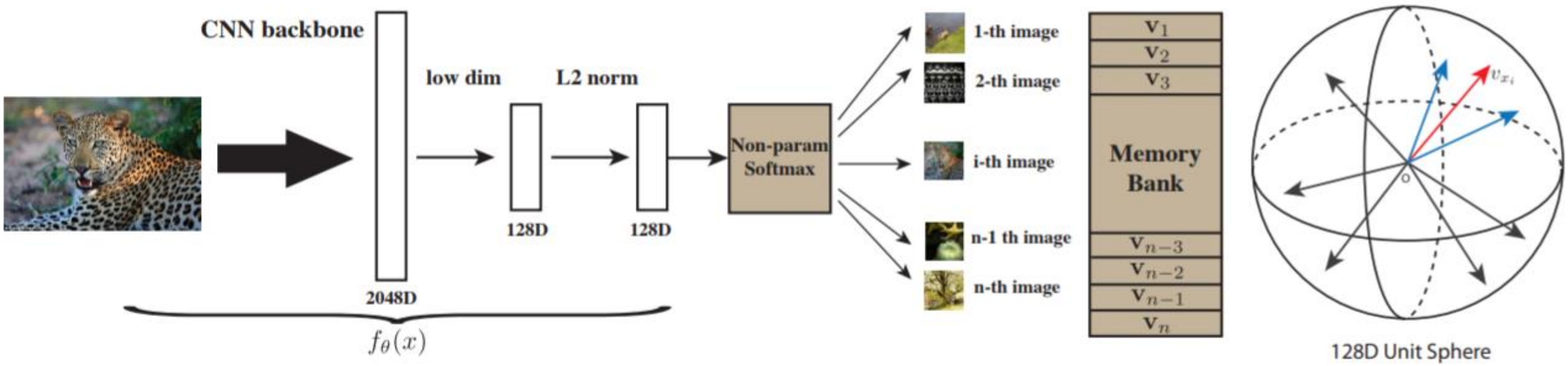
Negative contrastive estimation(NCE) performs binary classification task that is to <u>discriminate between data samples and noise samples</u>.

Prerequisite

Unsupervised Feature Learning via Non-Parametric Instance Discrimination

NCE

Memory Bank : instances dictionary



$$P(i|\mathbf{v}) = \frac{\exp(\mathbf{v}^T \mathbf{f}_i / \tau)}{Z_i}$$

$$Z_i = \sum_{j=1}^{n} \exp\left(\mathbf{v}_j^T \mathbf{f}_i / \tau\right)$$

Monte Carlo approximation:

$$Z \simeq Z_i \simeq n E_j \left[\exp(\mathbf{v}_j^T \mathbf{f}_i / \tau)\right] = \frac{n}{m} \sum_{k=1}^{m} \exp(\mathbf{v}_{j_k}^T \mathbf{f}_i / \tau)$$

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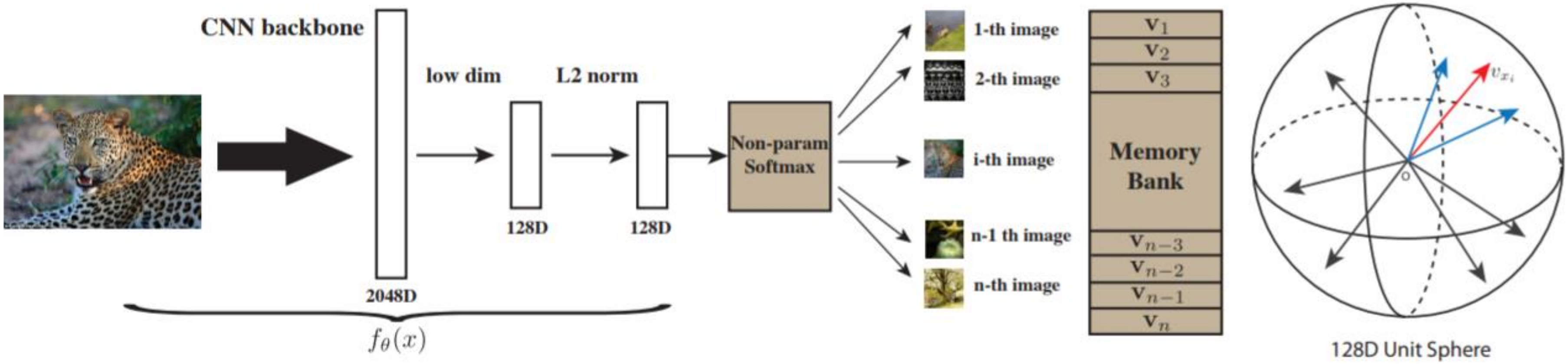
NCE

Memory Bank : instances dictionary



$$P(i|\mathbf{v}) = \frac{\exp(\mathbf{v}^T \mathbf{f}_i/\tau)}{Z_i}$$

Noise distribution : $P_n = 1/n$

$$h(i, \mathbf{v}) := P(D = 1|i, \mathbf{v}) = \frac{P(i|\mathbf{v})}{P(i|\mathbf{v}) + mP_n(i)}$$

Induced by posterior probability

$$J_{NCE}(\boldsymbol{\theta}) = -E_{P_d}\left[\log h(i, \mathbf{v})\right] \\ -m \cdot E_{P_n}\left[\log(1 - h(i, \mathbf{v}'))\right]$$

<u>**Consistency problem**</u>

Prerequisite

Unsupervised learning vs Self-supervised learning

In unsupervised learning, you try to find some 'structure' (clusters, densities, latent representation) in the entire while using their original form.

In self-supervised learning, you try to learn the 'dynamics' of the data at its raw level. Popular self-supervised learning, i.e image colorization uses only the gray-scale (part of the data is withheld) version and try to predict its colors.

Motivation

- 앞서 설명한 논문 : Unsupervised 방식으로 image를 embedding vector로 encoding 하도록 학습
- NLP에서 Unsupervised 방식으로 mask 처리된 단어를 embedding vector로 encoding 하도록 학습
- 왜 vision은 아직 supervised pre-training 을 많이 쓸까?

NLP vs Computer vision

- The reason may stem from differences in their respective signal spaces.

  Language tasks have discrete signal spaces(words, sub-word units, etc.) for building tokenized dictionaries.

  The raw signal of computer vision is in continuous, high-dimensional space unlike words.

Motivation

- The authors hypothesize that it is desirable to build dictionaries that are :
  1. Large
  2. Consistent

- A main purpose of unsupervised learning is to pre-train representation that can be transferred to downstream tasks by fine-tuning.
- They show that in 7 downstream tasks related to detection or segment ation.
- MoCo unsupervised pre-training can surpass its ImageNet supervised c ounter part, in some cases by nontrivial margins.

Method

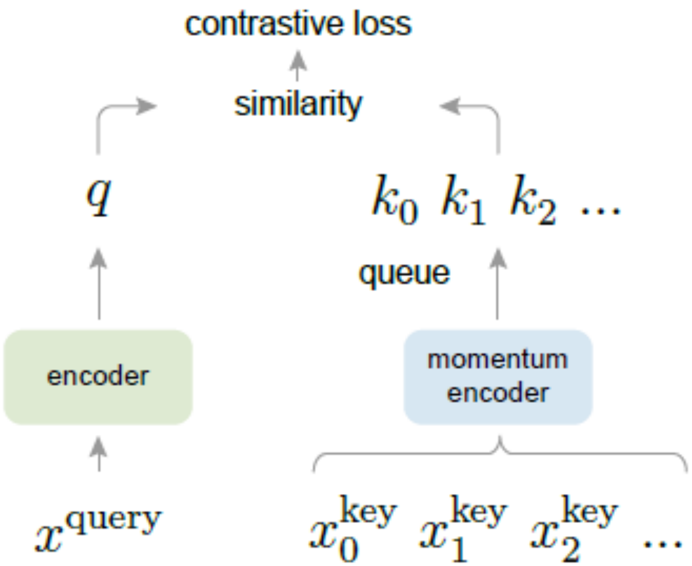
Algorithm 1 Pseudocode of MoCo in a PyTorch-like style.

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

Initialize queue / K=4096, C=128

```
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.



InfoNCE

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

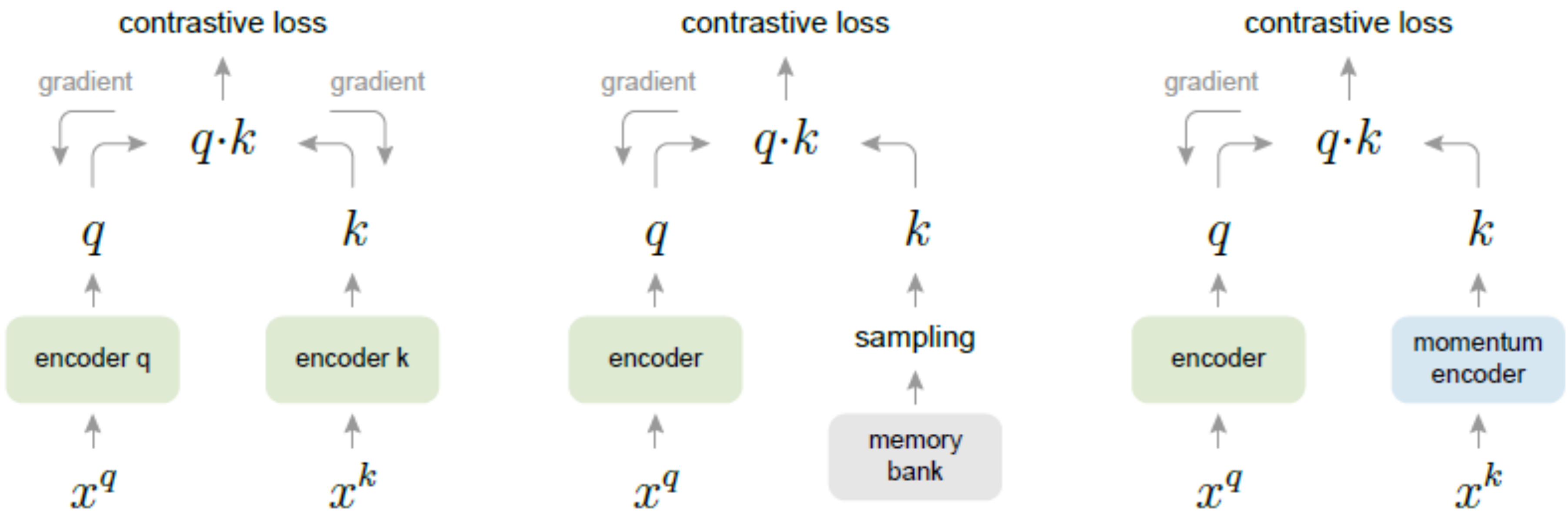
Momentum update

$$\theta_{\mathrm{k}} \leftarrow m\theta_{\mathrm{k}} + (1-m)\theta_{\mathrm{q}}$$

aug : color jittering, horizontal flip, grayscale

Method

Comparison with existing method

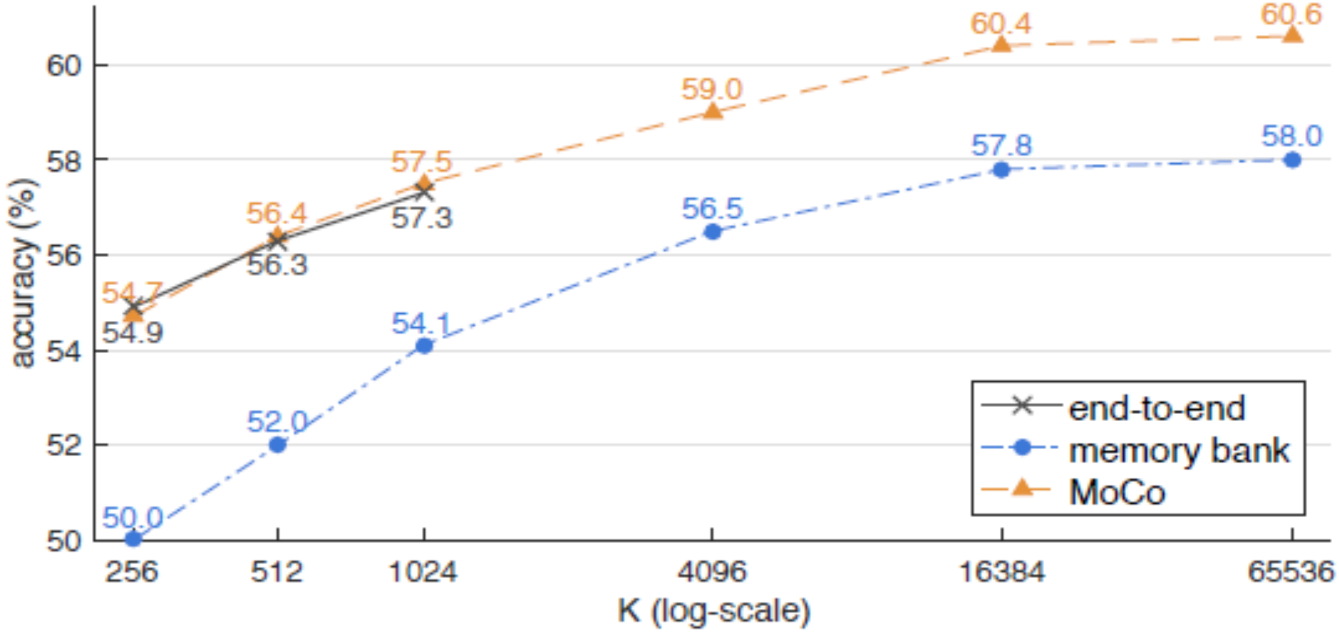


(a) end-to-end (b) memory bank (c) MoCo

Experiments

Ablation: contrastive loss mechanisms.

$$\theta_{\mathrm{k}} \leftarrow m\theta_{\mathrm{k}} + (1-m)\theta_{\mathrm{q}}$$

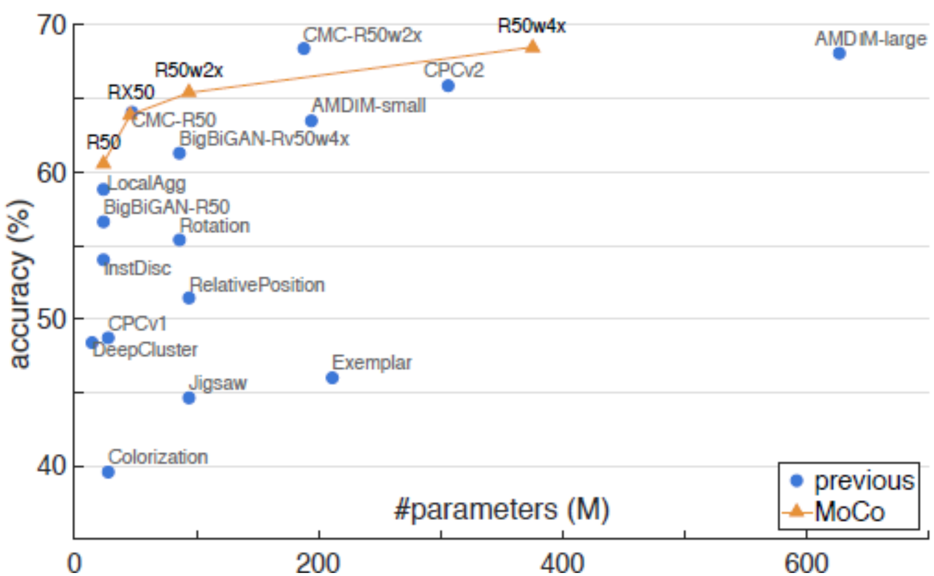


Ablation: momentum. The table below shows ResNet-50 accuracy with different MoCo momentum values (m in Eqn.(2)) used in pre-training ($K = 4096$ here) :

momentum m	0	0.9	0.99	0.999	0.9999
accuracy (%)	*fail*	55.2	57.8	59.0	58.9

Experiments

Comparison with previous results under the linear classification on ImageNet.



method	architecture	#params (M)	accuracy (%)
Exemplar [15]	R50w3×	211	46.0 [36]
RelativePosition [11]	R50w2×	94	51.4 [36]
Jigsaw [43]	R50w2×	94	44.6 [36]
Rotation [17]	Rv50w4×	86	55.4 [36]
Colorization [62]	R101*	28	39.6 [12]
DeepCluster [3]	VGG [51]	15	48.4 [4]
BigBiGAN [14]	R50	24	56.6
	Rv50w4×	86	61.3
methods based on contrastive learning follow:			
InstDisc [59]	R50	24	54.0
LocalAgg [64]	R50	24	58.8
CPC v1 [44]	R101*	28	48.7
CPC v2 [33]	$R170^*_{wider}$	303	65.9
CMC [54]	$R50_{L+ab}$	47	$64.1^\dagger$
	$R50w2\times_{L+ab}$	188	$68.4^\dagger$
AMDIM [2]	$AMDIM_{small}$	194	$63.5^\dagger$
	$AMDIM_{large}$	626	$68.1^\dagger$
MoCo	R50	24	60.6
	RX50	46	63.9
	R50w2×	94	65.4
	R50w4×	375	**68.6**

Experiments

PASCAL VOC Object Detection

Ablation : backbones

pre-train	AP_{50}	AP	AP_{75}
random init.	58.0	32.8	32.5
super. IN-1M	81.5	53.6	58.9
MoCo IN-1M	81.1 (−0.4)	53.8 (+0.2)	58.6 (−0.3)
MoCo IG-1B	81.6 (+0.1)	54.8 (+1.2)	60.3 (+1.4)

(a) Faster R-CNN, R50-**dilated-C5**

pre-train	AP_{50}	AP	AP_{75}
random init.	52.5	28.1	26.2
super. IN-1M	80.8	52.0	56.5
MoCo IN-1M	81.4 (+0.6)	55.2 (+3.2)	61.2 (+4.7)
MoCo IG-1B	82.1 (+1.3)	56.2 (+4.2)	62.3 (+5.8)

(b) Faster R-CNN, R50-C4

Ablation : contrastive loss mechanisms

	R50-dilated-C5			R50-C4		
pre-train	AP_{50}	AP	AP_{75}	AP_{50}	AP	AP_{75}
end-to-end	77.8	50.1	53.8	79.7	53.0	57.9
memory bank	79.6	51.9	56.3	80.3	53.9	58.9
MoCo	**81.1**	**53.8**	**58.6**	**81.4**	**55.2**	**61.2**

Ablation : Comparison with previous results

	AP_{50}					AP	AP_{75}	
pre-train	RelPos, by [12]	Multi-task [12]	Jigsaw, by [24]	LocalAgg [64]	**MoCo**	**MoCo**	Multi-task [12]	**MoCo**
super. IN-1M	74.2	74.2	70.5	74.6	74.4	42.4	44.3	42.7
unsup. IN-1M	66.8 (−7.4)	70.5 (−3.7)	61.4 (−9.1)	69.1 (−5.5)	74.9 (+0.5)	46.6 (+4.2)	43.9 (−0.4)	50.1 (+7.4)
unsup. IN-14M	-	-	69.2 (−1.3)	-	75.2 (+0.8)	46.9 (+4.5)	-	50.2 (+7.5)
unsup. YFCC-100M	-	-	66.6 (−3.9)	-	74.7 (+0.3)	45.9 (+3.5)	-	49.0 (+6.3)
unsup. IG-1B	-	-	-	-	75.6 (+1.2)	47.6 (+5.2)	-	51.7 (+9.0)

Experiments

COCO Object Detection and Segmentation

pre-train	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}	AP^{mk}	AP^{mk}_{50}	AP^{mk}_{75}
random init.	31.0	49.5	33.2	28.5	46.8	30.4
super. IN-1M	38.9	59.6	42.7	35.4	56.5	38.1
MoCo IN-1M	38.5 (−0.4)	58.9 (−0.7)	42.0 (−0.7)	35.1 (−0.3)	55.9 (−0.6)	37.7 (−0.4)
MoCo IG-1B	38.9 (0.0)	59.4 (−0.2)	42.3 (−0.4)	35.4 (0.0)	56.5 (0.0)	37.9 (−0.2)

(a) Mask R-CNN, R50-**FPN**, **1**× schedule

pre-train	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}	AP^{mk}	AP^{mk}_{50}	AP^{mk}_{75}
random init.	36.7	56.7	40.0	33.7	53.8	35.9
super. IN-1M	40.6	61.3	44.4	36.8	58.1	39.5
MoCo IN-1M	40.8 (+0.2)	61.6 (+0.3)	44.7 (+0.3)	36.9 (+0.1)	58.4 (+0.3)	39.7 (+0.2)
MoCo IG-1B	41.1 (+0.5)	61.8 (+0.5)	45.1 (+0.7)	37.4 (+0.6)	59.1 (+1.0)	40.2 (+0.7)

(b) Mask R-CNN, R50-**FPN**, **2**× schedule

pre-train	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}	AP^{mk}	AP^{mk}_{50}	AP^{mk}_{75}
random init.	26.4	44.0	27.8	29.3	46.9	30.8
super. IN-1M	38.2	58.2	41.2	33.3	54.7	35.2
MoCo IN-1M	38.5 (+0.3)	58.3 (+0.1)	41.6 (+0.4)	33.6 (+0.3)	54.8 (+0.1)	35.6 (+0.4)
MoCo IG-1B	39.1 (+0.9)	58.7 (+0.5)	42.2 (+1.0)	34.1 (+0.8)	55.4 (+0.7)	36.4 (+1.2)

(c) Mask R-CNN, R50-**C4**, **1**× schedule

pre-train	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}	AP^{mk}	AP^{mk}_{50}	AP^{mk}_{75}
random init.	35.6	54.6	38.2	31.4	51.5	33.5
super. IN-1M	40.0	59.9	43.1	34.7	56.5	36.9
MoCo IN-1M	40.7 (+0.7)	60.5 (+0.6)	44.1 (+1.0)	35.4 (+0.7)	57.3 (+0.8)	37.6 (+0.7)
MoCo IG-1B	41.1 (+1.1)	60.7 (+0.8)	44.8 (+1.7)	35.6 (+0.9)	57.4 (+0.9)	38.1 (+1.2)

(d) Mask R-CNN, R50-**C4**, **2**× schedule

Experiments

More Downstream Tasks

pre-train	COCO keypoint detection AP^{kp}	AP^{kp}_{50}	AP^{kp}_{75}
random init.	65.9	86.5	71.7
super. IN-1M	65.8	86.9	71.9
MoCo IN-1M	66.8 (+1.0)	87.4 (+0.5)	72.5 (+0.6)
MoCo IG-1B	66.9 (+1.1)	87.8 (+0.9)	73.0 (+1.1)

pre-train	COCO dense pose estimation AP^{dp}	AP^{dp}_{50}	AP^{dp}_{75}
random init.	39.4	78.5	35.1
super. IN-1M	48.3	85.6	50.6
MoCo IN-1M	50.1 (+1.8)	86.8 (+1.2)	53.9 (+3.3)
MoCo IG-1B	50.6 (+2.3)	87.0 (+1.4)	54.3 (+3.7)

pre-train	LVIS v0.5 instance segmentation AP^{mk}	AP^{mk}_{50}	AP^{mk}_{75}
random init.	22.5	34.8	23.8
super. IN-1M†	24.4	37.8	25.8
MoCo IN-1M	24.1 (−0.3)	37.4 (−0.4)	25.5 (−0.3)
MoCo IG-1B	24.9 (+0.5)	38.2 (+0.4)	26.4 (+0.6)

pre-train	Cityscapes instance seg.		Semantic seg. (mIoU)	
	AP^{mk}	AP^{mk}_{50}	Cityscapes	VOC
random init.	25.4	51.1	65.3	39.5
super. IN-1M	32.9	59.6	74.6	74.4
MoCo IN-1M	32.3 (−0.6)	59.3 (−0.3)	75.3 (+0.7)	72.5 (−1.9)
MoCo IG-1B	32.9 (0.0)	60.3 (+0.7)	75.5 (+0.9)	73.6 (−0.8)