Momentum Contrast for Unsupervised Visual Representation Learning

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Outline

Abstract

✓ Momentum Contrast (MoCo) for unsupervised visual representation learning

✓ A dynamic dictionary with queue and a moving-averaged encoder

→ Large & consistent dictionary

→ Contrastive unsupervised learning을 용이하게

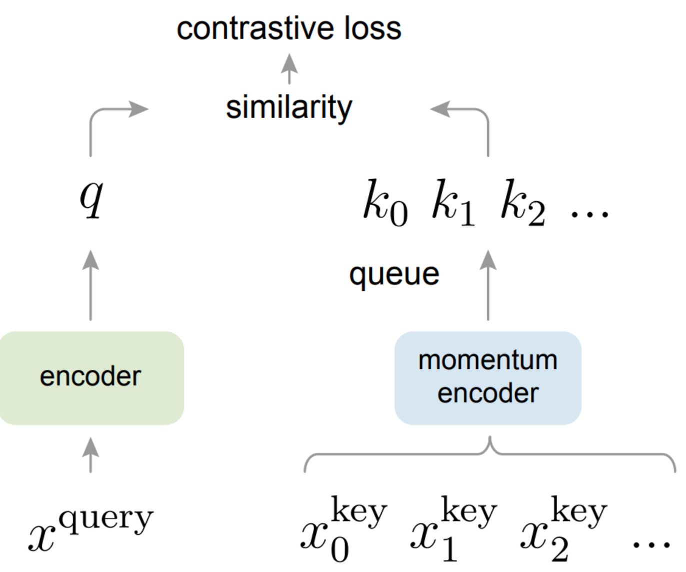
✓ Representation → downstream task good

✓ Supervised pre-training in 7 tasks on PASCAL VOC, COCO, and others와 비교

Introduction

- ✓ Unsupervised representation learning은 자연어처리 분야에서 성공적인 연구
    - ✓ 하지만 여전히 computer vision에서는 supervised learning이 지배적
    - ∵ continuous, high-dimensional space 그리고 구조적이지 않은 데이터 → dictionary building이 쉽지 않음
- ✓ 최근 연구에서 contrastive loss 접근법을 활용한 unsupervised visual representation이 좋은 성과
- ✓ 1. Large : 다양한 negative pair 확보→ 좋은 feature
- ✓ 2. Consistent : 일관된 표현을 위해 느리게 update 되는 key encoder
- ✓ *"MoCo는 contrastive learning을 위해 dynamic dictionary를 building하는 메커니즘, 다양한 pretext task에 사용됨"*

Introduction



← Samples, keys

Positive Sample : 1개
Negative Sample : 나머지

Figure 1. Momentum Contrast (MoCo) trains a visual representation encoder by matching an encoded query q to a dictionary of encoded keys using a contrastive loss. The dictionary keys $\{k_0, k_1, k_2, ...\}$ are defined on-the-fly by a set of data samples. The dictionary is built as a queue, with the current mini-batch enqueued and the oldest mini-batch dequeued, decoupling it from the mini-batch size. The keys are encoded by a slowly progressing encoder, driven by a momentum update with the query encoder. This method enables a large and consistent dictionary for learning visual representations.

Method

- ✓ Contrastive Learning as Dictionary Look-up
  - ✓ Dictionary look-up task를 위한 encoder를 학습시키는 것
  - ✓ k_+ : q에 match 되는 single key
  - ✓ $\{k_0, k_1, k_2 \dots\}$: 나머지 negative samples
  - ✓ τ : hyper parameter
  - ✓ InfoNCE

이미지 유사도 측정

$$\mathcal{L}_q = -\log \frac{\exp(q \cdot k_+ / \tau)}{\sum_{i=0}^{K} \exp(q \cdot k_i / \tau)} \qquad (1)$$

Method

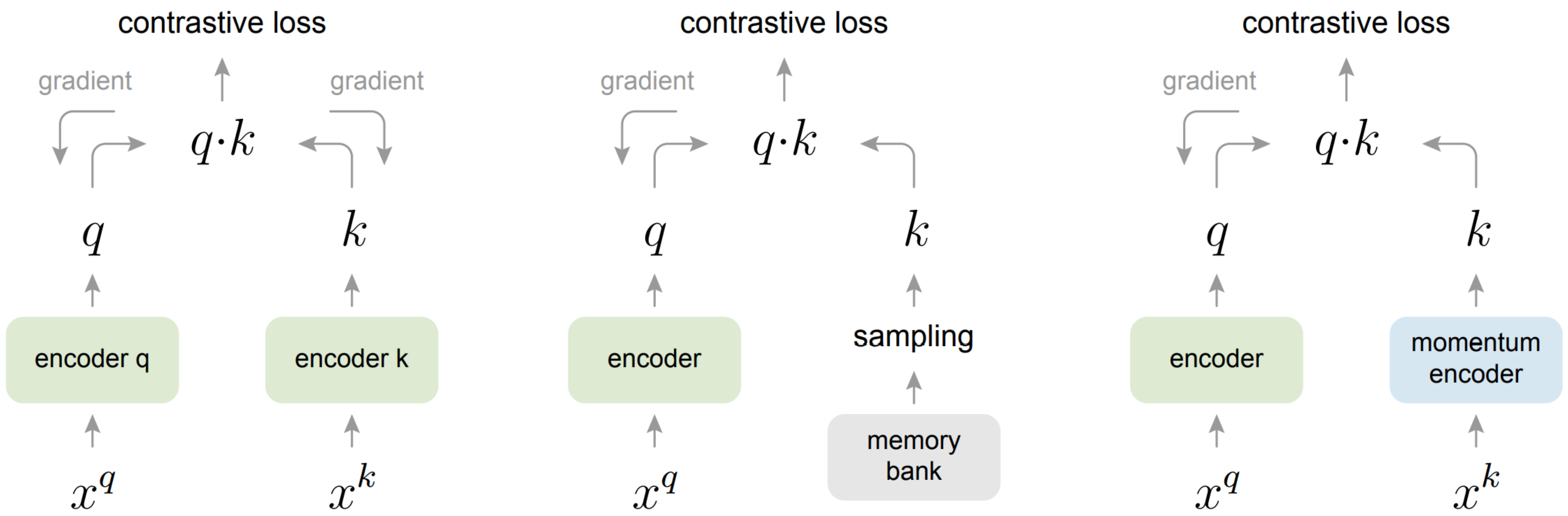
- ✓ Momentum Contrast
  - ✓ Contrastive learning ← 이미지와 같은 high-dimensional continuous input에 대해 discrete dictionary를 만들기위해
  - ✓ Key encoder update → Sampling → “dynamic dictionary”
  - ✓ Dictionary as a queue : current mini-batch to the dictionary, the oldest mini-batch is removed (→ consistency 유지)

Method

- ✓ Momentum Contrast
  - ✓ Momentum update
  - ✓ Large dictionary → queue 사용 → key encoder update 어려움 → encoder copy (q → k)
    → poor result (consistency x) → ***momentum update 제안***
  - ✓ $$\theta_{\mathrm{k}} \leftarrow m\theta_{\mathrm{k}} + (1-m)\theta_{\mathrm{q}}. \qquad (2) \qquad m \in [0, 1)$$
  - ✓ M값이 클수록 better (m = 0.999 default)

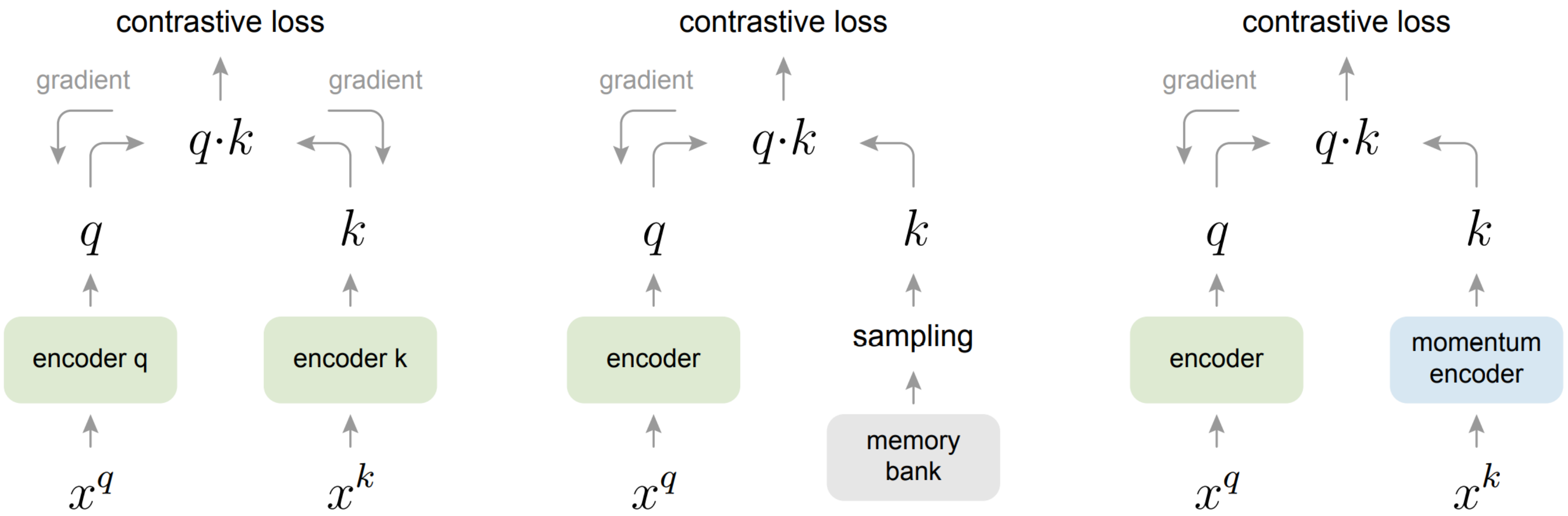
Method

- ✓ Momentum Contrast
  - ✓ Relations to previous mechanisms (dictionary size, consistency)



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

Method



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

- Dictionary = samples = 현재 mini batch
- GPU memory size에 따른 제약
- Key consistency

- Enqueue, dequeue 과정 → memory save
- Key consistency (slowly updated)

- Sample = randomly sampled
- No back-propagation
- Key consistency x

Method

- ✓ Pretext Task
  - ✓ Contrastive learning → 다양한 pretext tasks → “instance discrimination”
  - ✓ Query - k_+ : positive pair
  - ✓ Query - 나머지 : negative pair
- ✓ ResNet as the encoder
  - ✓ Output dimension : 128
  - ✓ L2 norm → representation
  - ✓ τ : 0.07
  - ✓ Data augmentation : color jittering, random horizontal flip, random grayscale conversion …

Method

- ✓ Shuffling BN
  - ✓ BN → good representation 학습 방해
  - ✓ Pretext task cheat 하는 경향, low-loss solution을 쉽게 찾음 ← information leak

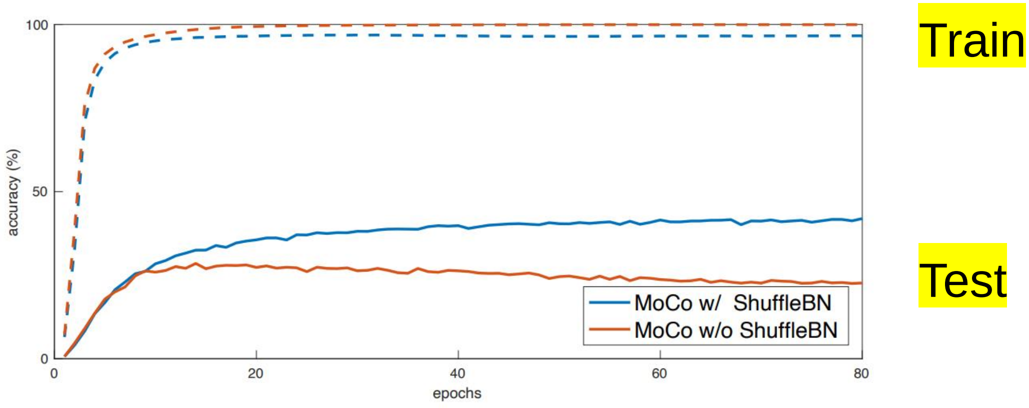
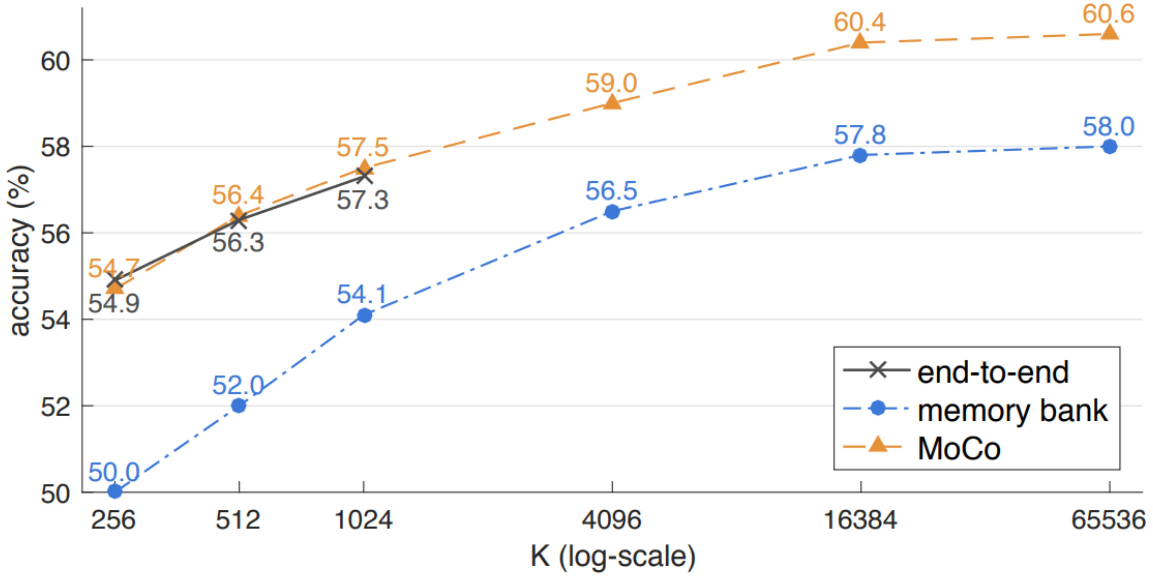


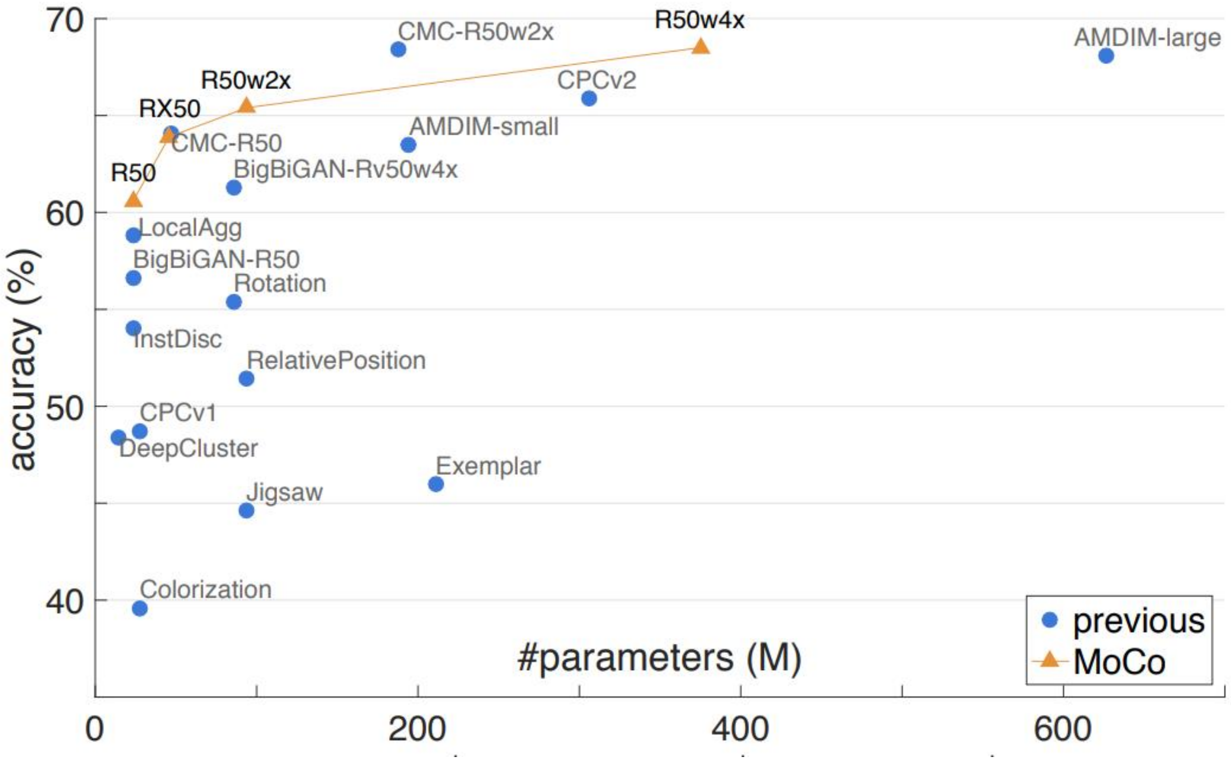
Figure A.1. **Ablation of Shuffling BN**. *Dash*: training curve of the pretext task, plotted as the accuracy of $(K+1)$-way dictionary lookup. *Solid*: validation curve of a kNN-based monitor [61] (not a linear classifier) on ImageNet classification accuracy. This plot shows the first 80 epochs of training: training longer without shuffling BN overfits more.

Experiments



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

Experiments



Comparison under the linear classification protocol on ImageNet

Experiments

pre-train	AP_{50}	AP	AP_{75}
random init.	64.4	37.9	38.6
super. IN-1M	81.4	54.0	59.1
MoCo IN-1M	81.1 (−0.3)	54.6 (**+0.6**)	59.9 (**+0.8**)
MoCo IG-1B	81.6 (+0.2)	55.5 (**+1.5**)	61.2 (**+2.1**)

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

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**)

(b) Faster R-CNN, R50-**C4**

Table 2. **Object detection fine-tuned on PASCAL VOC** `trainval07+12`. Evaluation is on `test2007`: AP_{50} (default VOC metric), AP (COCO-style), and AP_{75}, averaged over 5 trials. All are fine-tuned for 24k iterations (~23 epochs). In the brackets are the gaps to the ImageNet supervised pre-training counterpart. In green are the gaps of at least **+0.5** point.

	R50-dilated-C5			R50-C4		
pre-train	AP_{50}	AP	AP_{75}	AP_{50}	AP	AP_{75}
end-to-end	79.2	52.0	56.6	80.4	54.6	60.3
memory bank	79.8	52.9	57.9	80.6	54.9	60.6
MoCo	**81.1**	**54.6**	**59.9**	**81.5**	**55.9**	**62.6**

Table 3. **Comparison of three contrastive loss mechanisms** on PASCAL VOC object detection, fine-tuned on `trainval07+12` and evaluated on `test2007` (averages over 5 trials). All models are implemented by us (Figure 3), pre-trained on IN-1M, and fine-tuned using the same settings as in Table 2.

Discussion and Conclusion

- ✓ Positive results of unsupervised learning
- ✓ MoCo가 실용적이고, 다른 pretext task에 대해 유용하기를 기대

MoCo v2

SimCLR

1) Large batch size
2) MLP projection head
3) Strong data augmentation

MoCo v2

SimCLR

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MoCo v2

1) Large batch size
2) MLP projection head
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MoCo v2

case	unsup. pre-train				ImageNet	VOC detection		
	MLP	aug+	cos	epochs	acc.	AP_{50}	AP	AP_{75}
supervised					76.5	81.3	53.5	58.8
MoCo v1				200	60.6	81.5	55.9	62.6
(a)	✓			200	66.2	82.0	56.4	62.6
(b)		✓		200	63.4	82.2	56.8	63.2
(c)	✓	✓		200	67.3	**82.5**	57.2	63.9
(d)	✓	✓	✓	200	67.5	82.4	57.0	63.6
(e)	✓	✓	✓	**800**	**71.1**	**82.5**	**57.4**	**64.0**

Table 1. **Ablation of MoCo baselines**, evaluated by ResNet-50 for (i) ImageNet linear classification, and (ii) fine-tuning VOC object detection (mean of 5 trials). "**MLP**": with an MLP head; "**aug+**": with extra blur augmentation; "**cos**": cosine learning rate schedule.

τ	0.07	0.1	0.2	0.3	0.4	0.5
w/o MLP	60.6	**60.7**	59.0	58.2	57.2	56.4
w/ MLP	62.9	64.9	**66.2**	65.7	65.0	64.3

MoCo v2

case	MLP	aug+	cos	epochs	batch	ImageNet acc.
	unsup. pre-train					
MoCo v1 [6]				200	256	60.6
SimCLR [2]	✓	✓	✓	200	256	61.9
SimCLR [2]	✓	✓	✓	200	8192	66.6
MoCo v2	✓	✓	✓	200	256	**67.5**
results of ***longer*** *unsupervised training follow:*						
SimCLR [2]	✓	✓	✓	1000	4096	69.3
MoCo v2	✓	✓	✓	800	256	**71.1**

Table 2. **MoCo *vs.* SimCLR**: ImageNet linear classifier accuracy (**ResNet-50, 1-crop 224×224**), trained on features from unsupervised pre-training. "aug+" in SimCLR includes blur and stronger color distortion. SimCLR ablations are from Fig. 9 in [2] (we thank the authors for providing the numerical results).

mechanism	batch	memory / GPU	time / 200-ep.
MoCo	256	**5.0G**	**53 hrs**
end-to-end	256	7.4G	65 hrs
end-to-end	4096	93.0G†	n/a

Table 3. **Memory and time cost** in 8 V100 16G GPUs, implemented in PyTorch. †: based on our estimation.

References

[Paper]

He, K., Fan, H., Wu, Y., Xie, S., & Girshick, R. (2020). Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 9729-9738).

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[Review]

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Q & A

Thank you ☺