

# Momentum Contrast for Unsupervised Visual Representation Learning

Kaiming He   Haoqi Fan   Yuxin Wu   Saining Xie   Ross Girshick

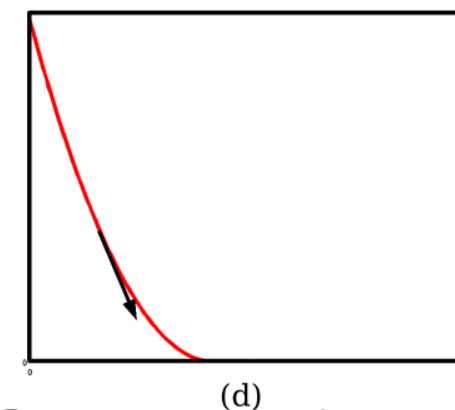
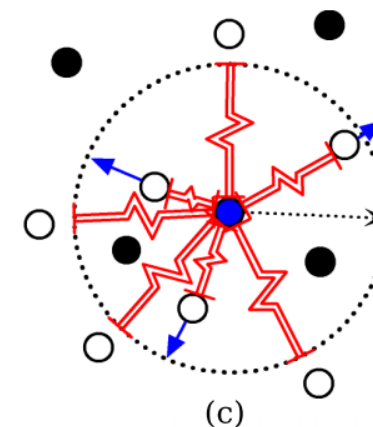
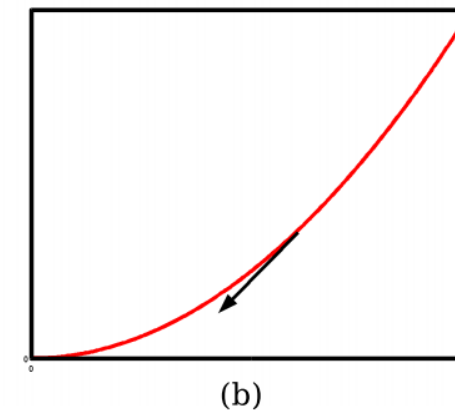
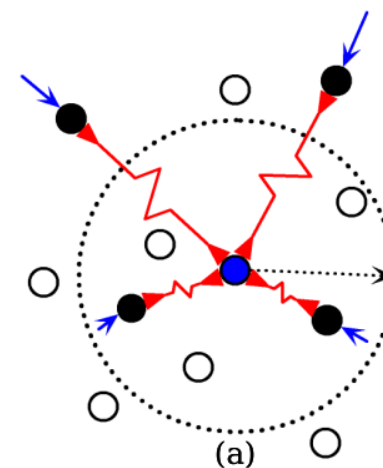
Facebook AI Research (FAIR)

Hanqing Chao

# Contrastive Learning

- $Y = 0$  if  $X_1$  and  $X_2$  are deemed similar
- $Y = 1$  if they are deemed dissimilar

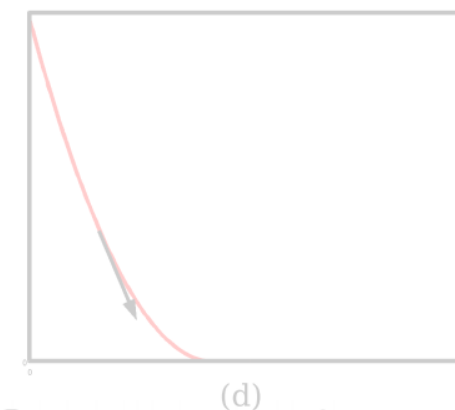
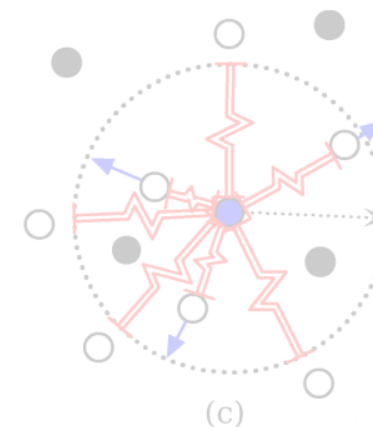
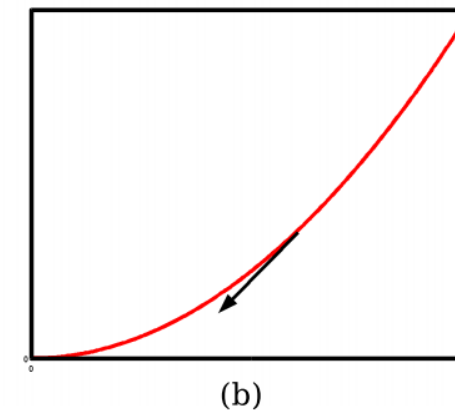
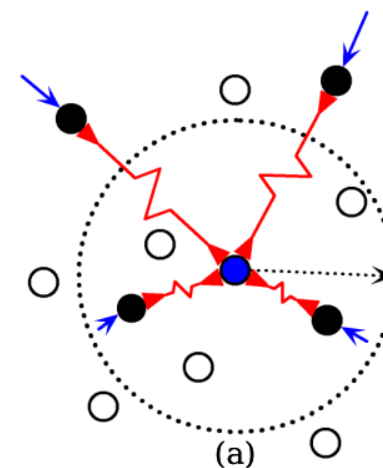
$$L(W, Y, \vec{X}_1, \vec{X}_2) = (1 - Y) \frac{1}{2} (D_W)^2 + (Y) \frac{1}{2} \{ \max(0, m - D_W) \}^2$$



# Contrastive Learning

- $Y = 0$  if  $X_1$  and  $X_2$  are deemed similar
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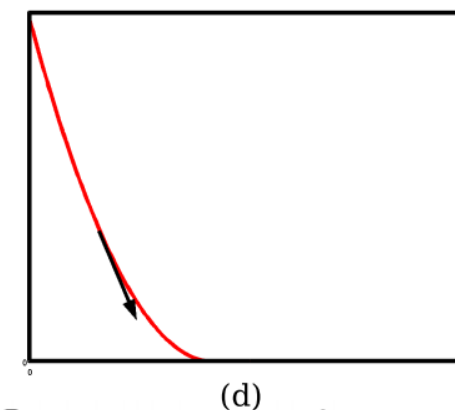
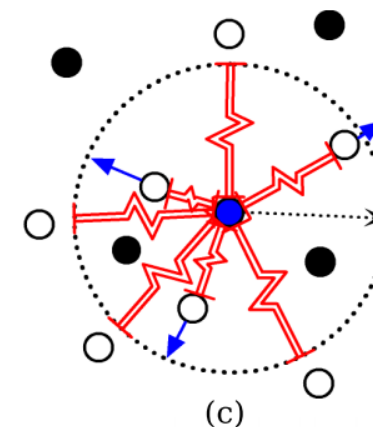
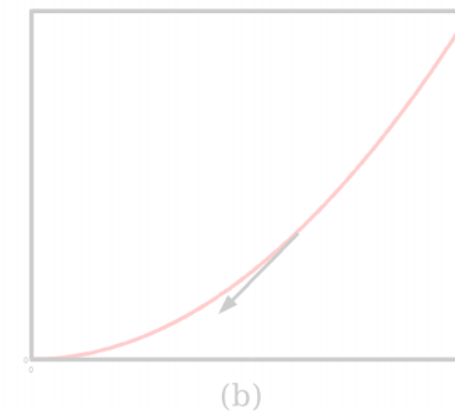
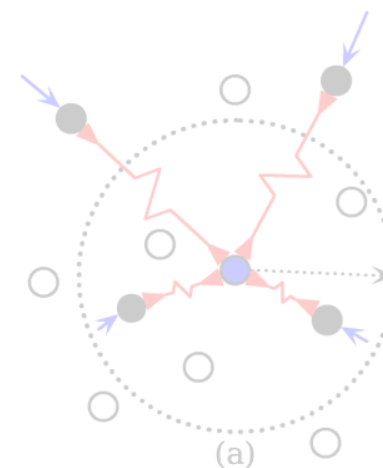
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# Contrastive Learning

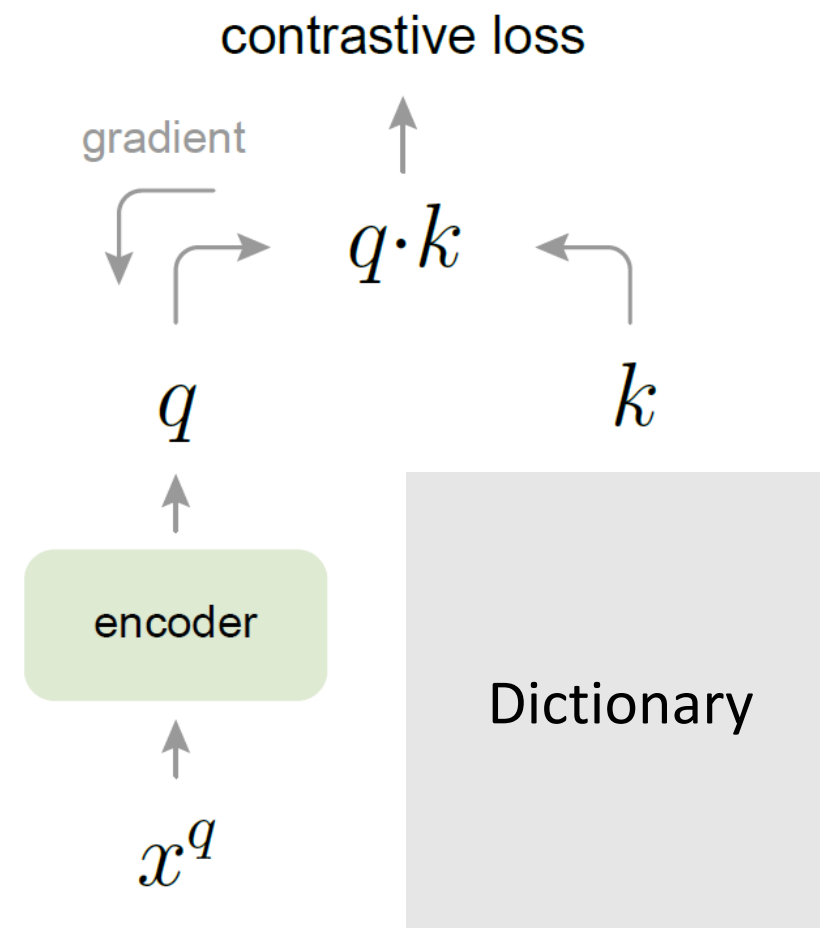
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$$L(W, Y, \vec{X}_1, \vec{X}_2) = (1 - Y) \frac{1}{2} (D_W)^2 + (Y) \frac{1}{2} \{ \max(0, m - D_W) \}^2$$



# Dictionary Learning

- Goal: train encoder
- To make it work, we have to find a way to establish the dictionary
- Two key properties:
  - CONSISTENCY
  - LARGE: covers a rich set of samples



# Pretext task

## Unsupervised learning:

With a dataset like ImageNet,

Regarding each picture as a class

Positive: if a pair of sample is generated from a same picture

Negative: otherwise

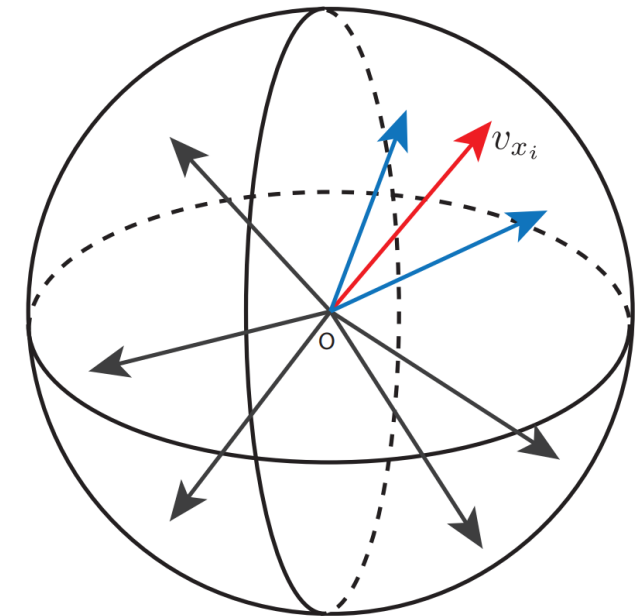
# NCE

$$L(W, Y, \vec{X}_1, \vec{X}_2) = (1 - Y) \frac{1}{2} (D_W)^2 + (Y) \frac{1}{2} \{ \max(0, m - D_W) \}^2$$

## Softmax:

Too much parameters

$$-\frac{1}{M} \sum_{i=1}^M \log \frac{e^{\boxed{W_{y_i}^T} f(\mathbf{x}_i) + b_{y_i}}}{\sum_{j=1}^C e^{W_j^T f(\mathbf{x}_i) + b_j}}$$



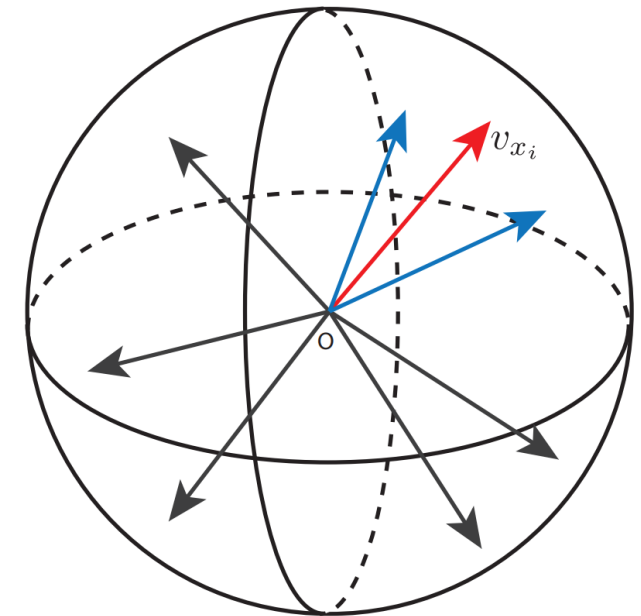
# NCE

$$L(W, Y, \vec{X}_1, \vec{X}_2) = (1 - Y) \frac{1}{2} (D_W)^2 + (Y) \frac{1}{2} \{ \max(0, m - D_W) \}^2$$

## Noise-contrastive estimation:

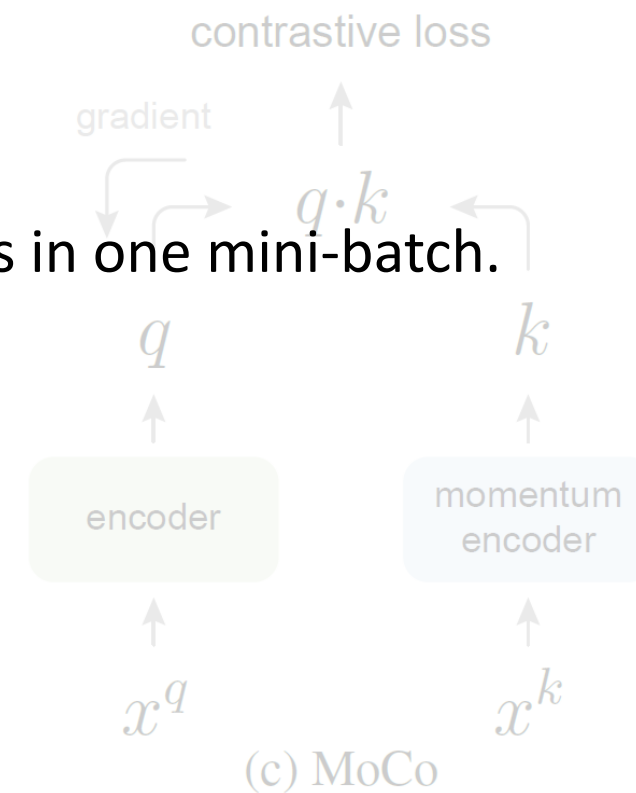
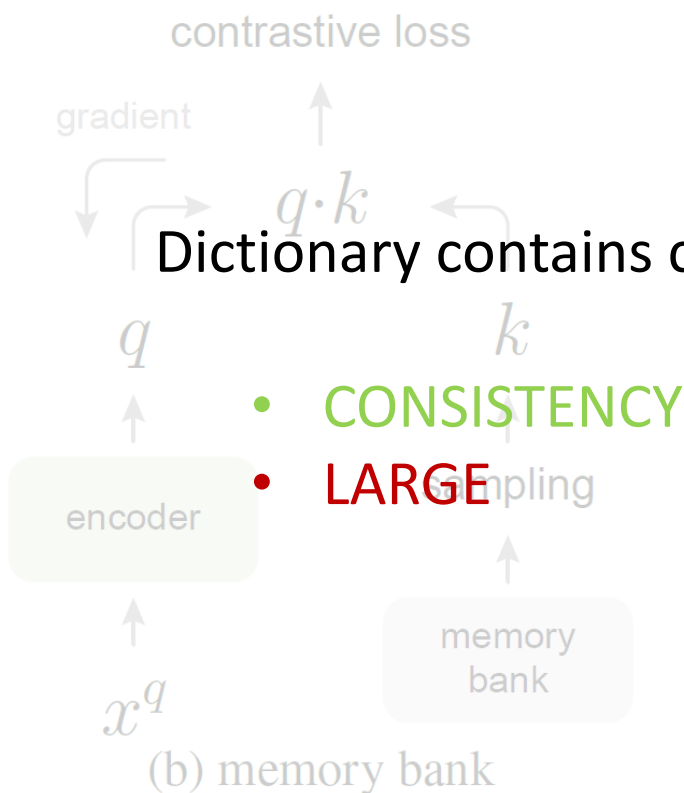
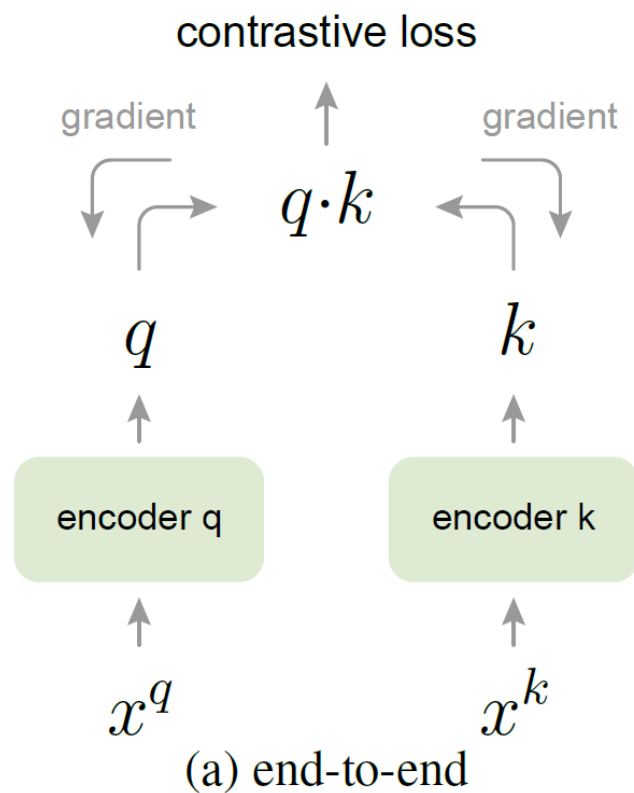
$$\mathcal{L}_q = -\log \frac{\exp(q \cdot k_+ / \tau)}{\sum_{i=0}^K \exp(q \cdot k_i / \tau)}$$

Using K negative samples with 1 positive sample





# Dictionary Learning



# Dictionary Learning

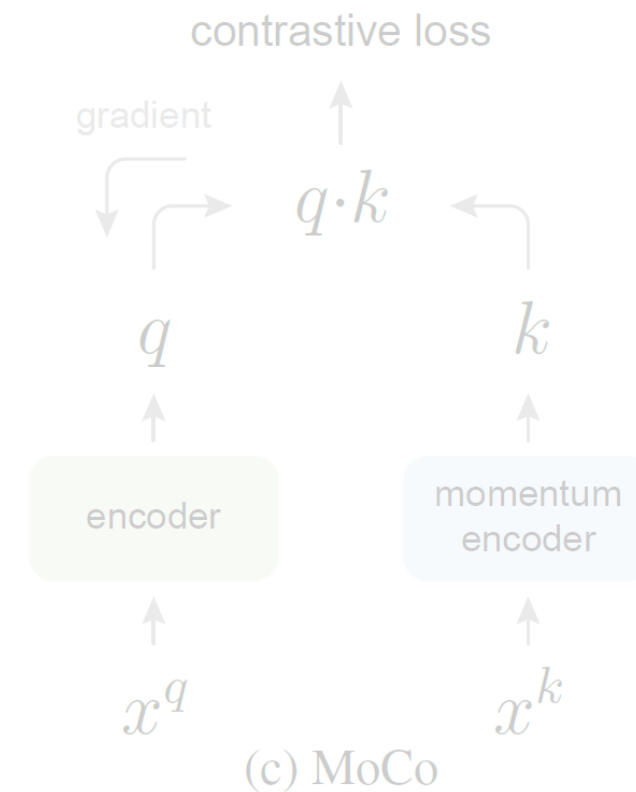
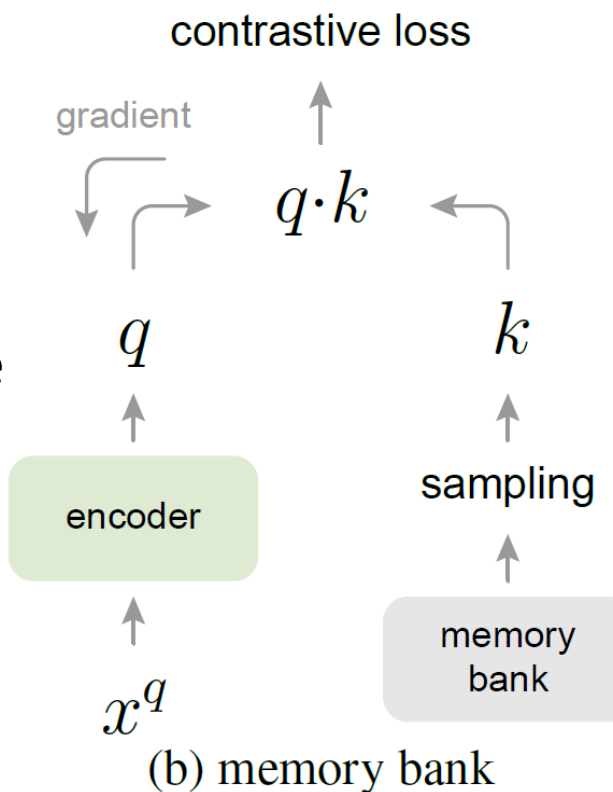
Dictionary contains all cases

Keys are updated when the sample is calculated by the encoder

- **CONSISTENCY**

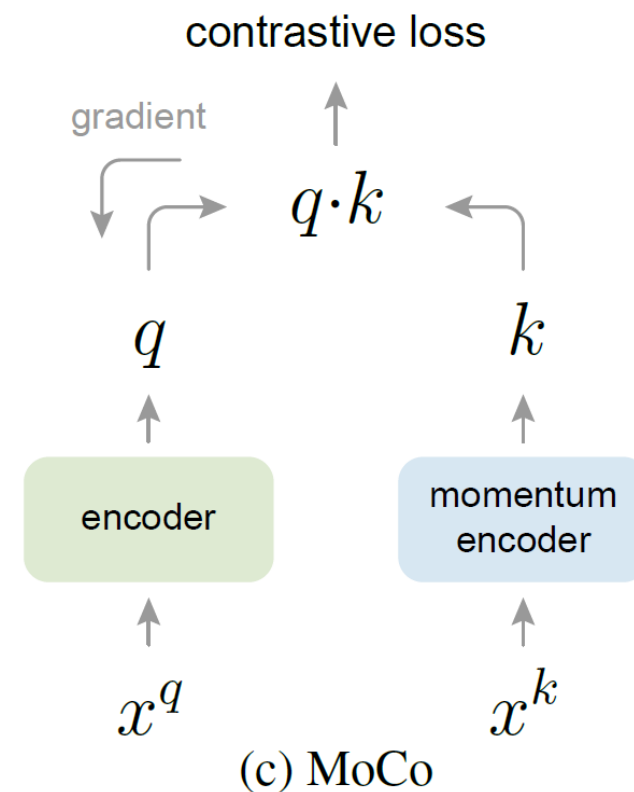
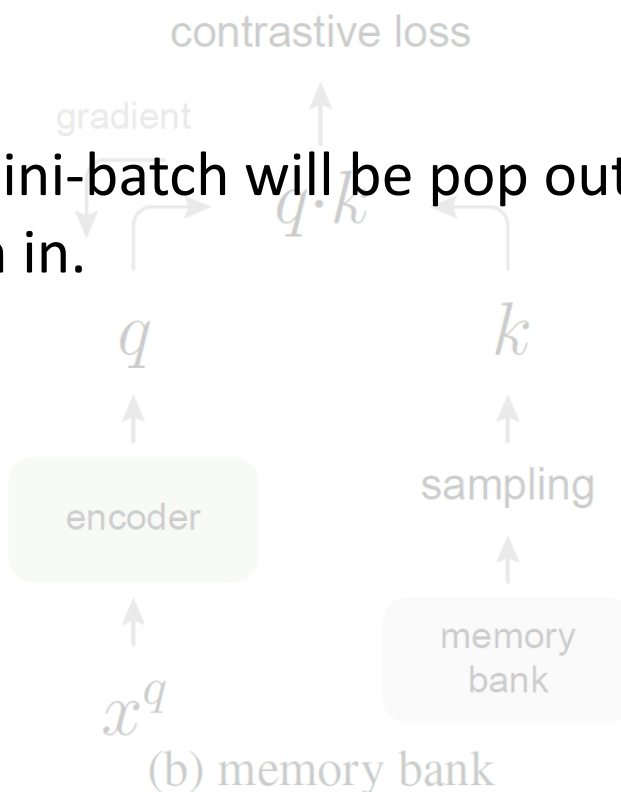
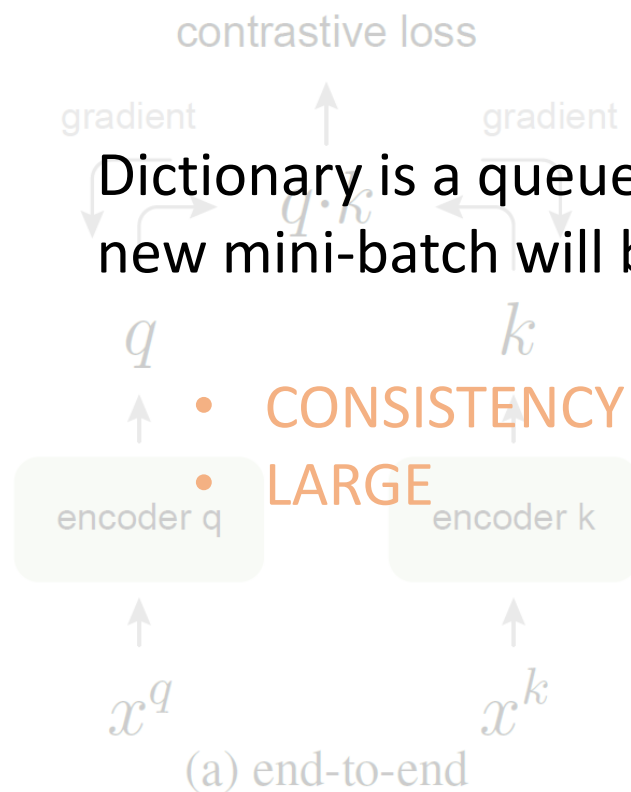
- **LARGE**

(a) end-to-end

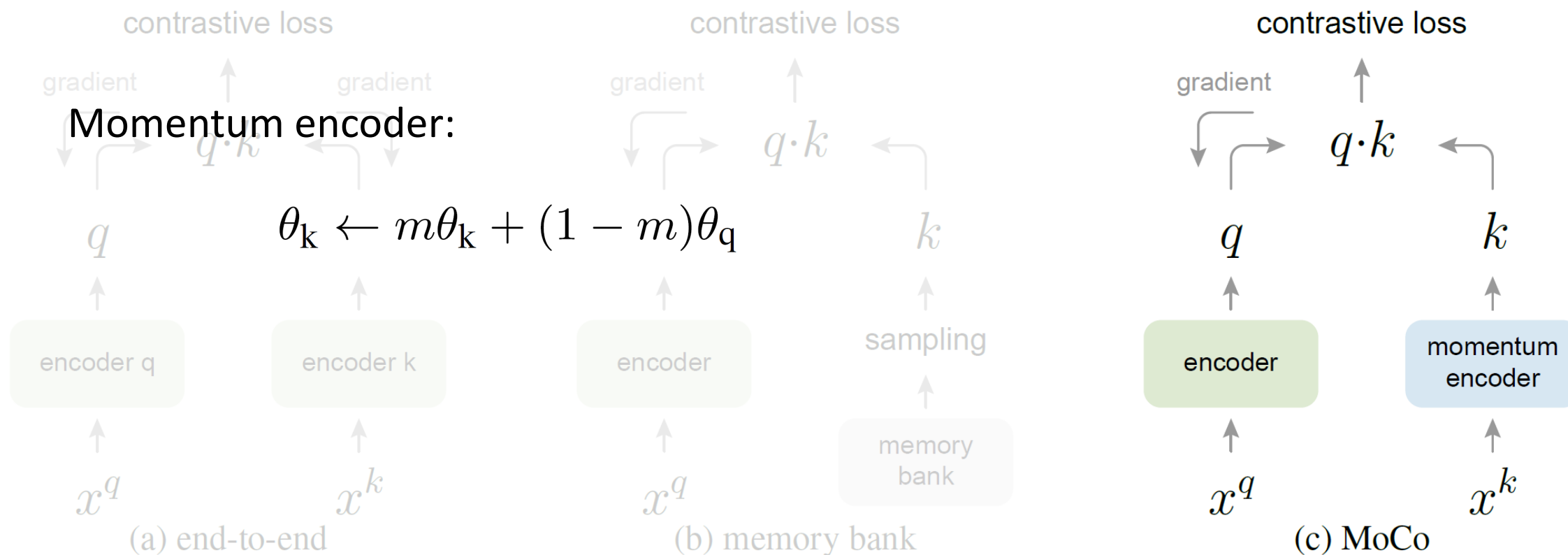


# Dictionary Learning

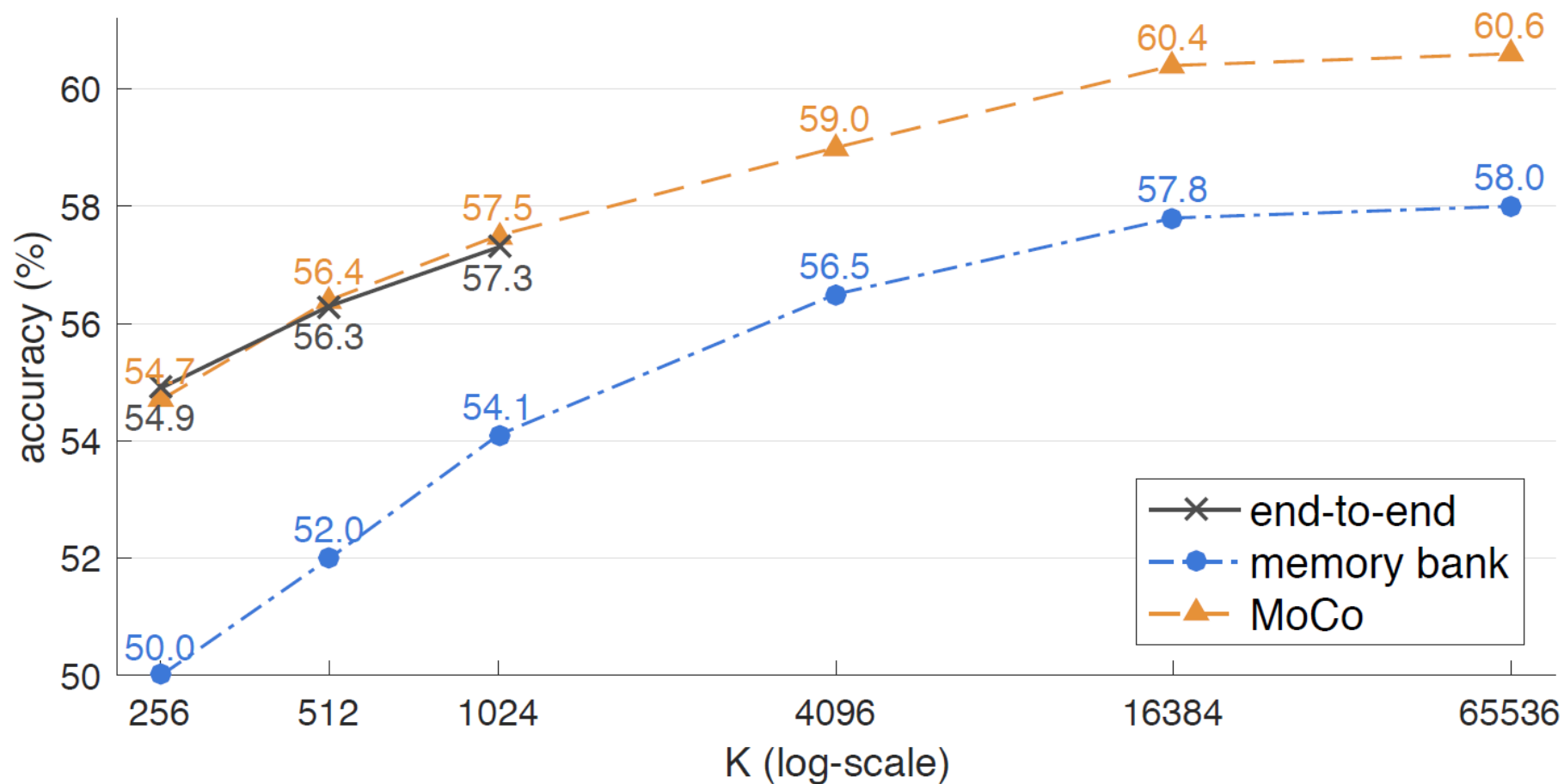
Dictionary is a queue, old mini-batch will be pop out, new mini-batch will be push in.



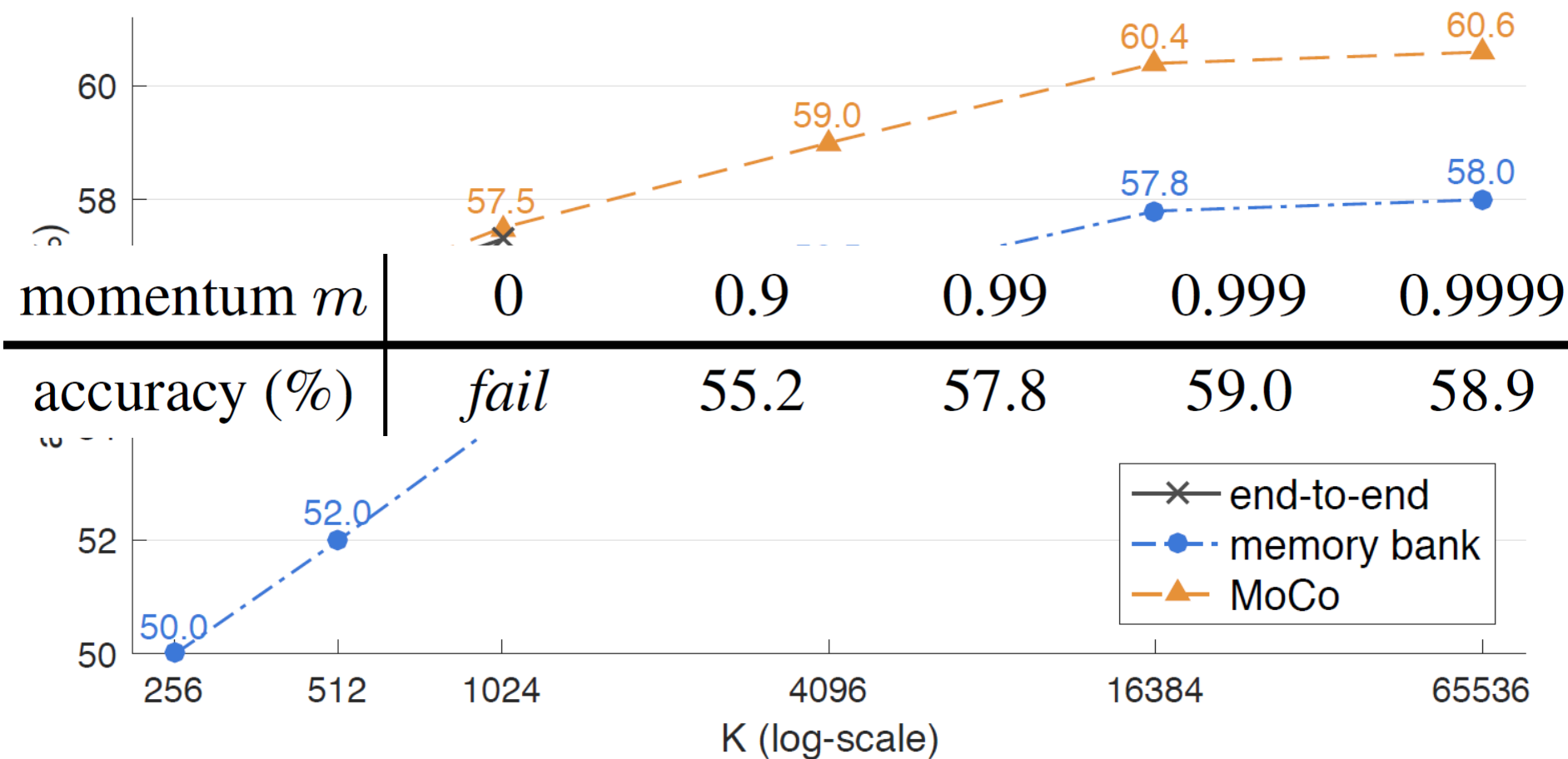
# Dictionary Learning



# ImageNet



# Momentum



# Object Detection

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

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

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

(b) Faster R-CNN, R50-C4

# Object Detection

pre-train	AP <sub>50</sub>					AP	AP <sub>75</sub>	
	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)



# COCO

pre-train	AP <sup>bb</sup>	AP <sup>bb</sup> <sub>50</sub>	AP <sup>bb</sup> <sub>75</sub>	AP <sup>mk</sup>	AP <sup>mk</sup> <sub>50</sub>	AP <sup>mk</sup> <sub>75</sub>
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
<b>MoCo</b> 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)
<b>MoCo</b> 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

AP <sup>bb</sup>	AP <sup>bb</sup> <sub>50</sub>	AP <sup>bb</sup> <sub>75</sub>	AP <sup>mk</sup>	AP <sup>mk</sup> <sub>50</sub>	AP <sup>mk</sup> <sub>75</sub>
36.7	56.7	40.0	33.7	53.8	35.9
40.6	61.3	44.4	36.8	58.1	39.5
40.8 (+0.2)	61.6 (+0.3)	44.7 (+0.3)	36.9 (+0.1)	58.4 (+0.3)	39.7 (+0.2)
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 <sup>bb</sup>	AP <sup>bb</sup> <sub>50</sub>	AP <sup>bb</sup> <sub>75</sub>	AP <sup>mk</sup>	AP <sup>mk</sup> <sub>50</sub>	AP <sup>mk</sup> <sub>75</sub>
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
<b>MoCo</b> 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)
<b>MoCo</b> 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

AP <sup>bb</sup>	AP <sup>bb</sup> <sub>50</sub>	AP <sup>bb</sup> <sub>75</sub>	AP <sup>mk</sup>	AP <sup>mk</sup> <sub>50</sub>	AP <sup>mk</sup> <sub>75</sub>
35.6	54.6	38.2	31.4	51.5	33.5
40.0	59.9	43.1	34.7	56.5	36.9
40.7 (+0.7)	60.5 (+0.6)	44.1 (+1.0)	35.4 (+0.7)	57.3 (+0.8)	37.6 (+0.7)
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

# Thanks !