Self-Supervised Learning

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Most slides have been adapted from:

Fei Fei Li and colleagues lectures, cs231n, Stanford

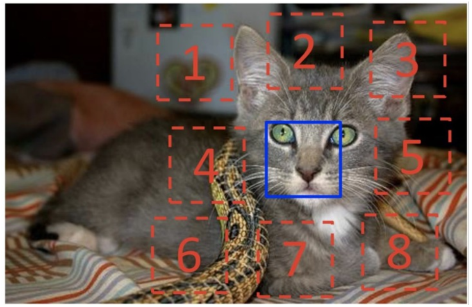
Generative vs. Self-supervised Learning

- Both aim to learn from data without manual label annotation.
- Generative learning aims to model **data distribution** $p_{data}(x)$, e.g., generating realistic images.
- Self-supervised learning methods solve “pretext” tasks that produce **good features** for downstream tasks.
    - Learn with supervised learning objectives, e.g., classification, regression.
    - Labels of these pretext tasks are generated *automatically*

Self-supervised learning

Today's lecture

computer vision



Doersch et al., 2015

robot / reinforcement learning

Dense Object Net (Florence and Manuelli et al., 2018)

language modeling

Language Models are Few-Shot Learners

Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*

Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam Girish Sastry

Amanda Askell Sandhini Agarwal Ariel Herbert-Voss Gretchen Krueger Tom Henighan

Rewon Child Aditya Ramesh Daniel M. Ziegler Jeffrey Wu Clemens Winter

Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

Benjamin Chess Jack Clark Christopher Berner

Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

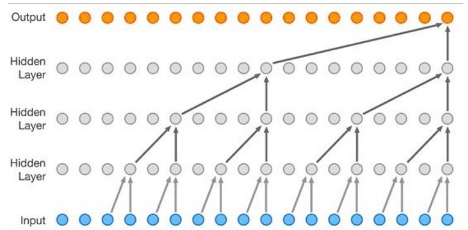
OpenAI

Abstract

Recent work has demonstrated substantial gains on many NLP tasks and benchmarks by pre-training on a large corpus of text followed by fine-tuning on a specific task. While typically task-agnostic in architecture, this method still requires task-specific fine-tuning datasets of thousands or tens of thousands of examples. By contrast, humans can generally perform a new language task from only a few examples or from simple instructions – something which current NLP systems still largely struggle to do. Here we show that scaling up language models greatly improves task-agnostic, few-shot performance, sometimes even reaching competitiveness with prior state-of-the-art fine-tuning approaches. Specifically, we train GPT-3, an autoregressive language model with 175 billion parameters, 10x more than any previous non-sparse language model, and test its performance in the few-shot setting. For all tasks, GPT-3 is applied without any gradient updates or fine-tuning, with tasks and few-shot demonstrations specified purely via text interaction with the model. GPT-3 achieves strong performance on many NLP datasets, including translation, question-answering, and cloze tasks, as well as several tasks that require on-the-fly reasoning or domain adaptation, such as unscrambling words, using a novel word in a sentence, or performing 3-digit arithmetic. At the same time, we also identify some datasets where GPT-3's few-shot learning still struggles, as well as some datasets where GPT-3 faces methodological issues related to training on large web corpora. Finally, we find that GPT-3 can generate samples of news articles which human evaluators have difficulty distinguishing from articles written by humans. We discuss broader societal impacts of this finding and of GPT-3 in general.

GPT3 (Brown, Mann, Ryder, Subbiah et al., 2020)

speech synthesis



Wavenet (van den Oord et al., 2016)

...

Self-supervised pretext tasks

Example: learn to predict image transformations / complete corrupted images

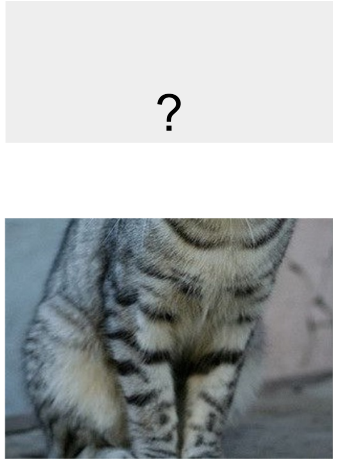
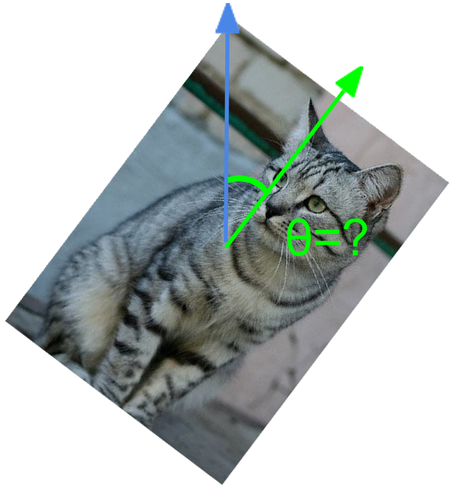
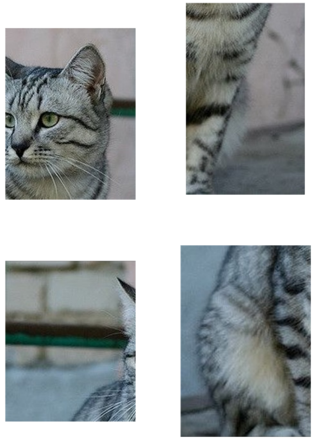


image completion



rotation prediction



“jigsaw puzzle”

colorization

1. Solving the pretext tasks allow the model to learn good features.
2. We can automatically generate labels for the pretext tasks.

How to evaluate a self-supervised learning method?

We usually don't care about the performance of the self-supervised learning task, e.g., we don't care if the model learns to predict image rotation perfectly.

Evaluate the learned feature encoders on downstream *target tasks*

Today’s Agenda

Pretext tasks from image transformations

- Rotation, rearrangement, coloring

Contrastive representation learning

- Intuition and formulation
- Instance contrastive learning: SimCLR and MOCO
- More recent methods

Generative algorithms

- Masked Image Modeling

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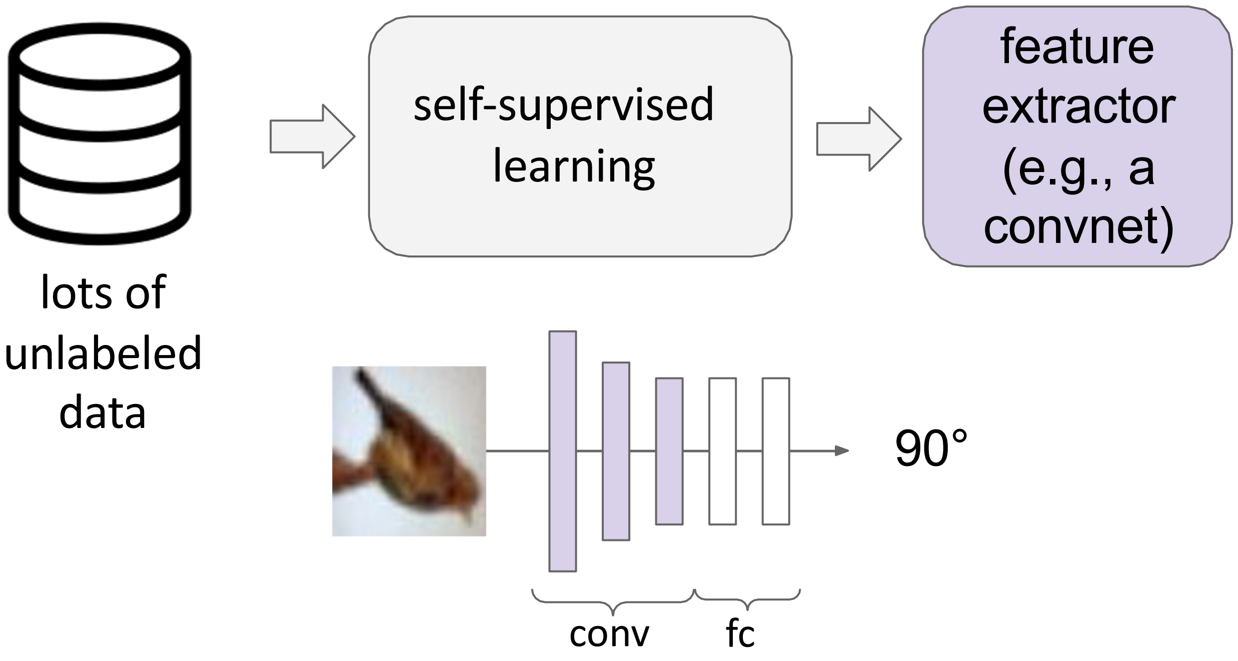
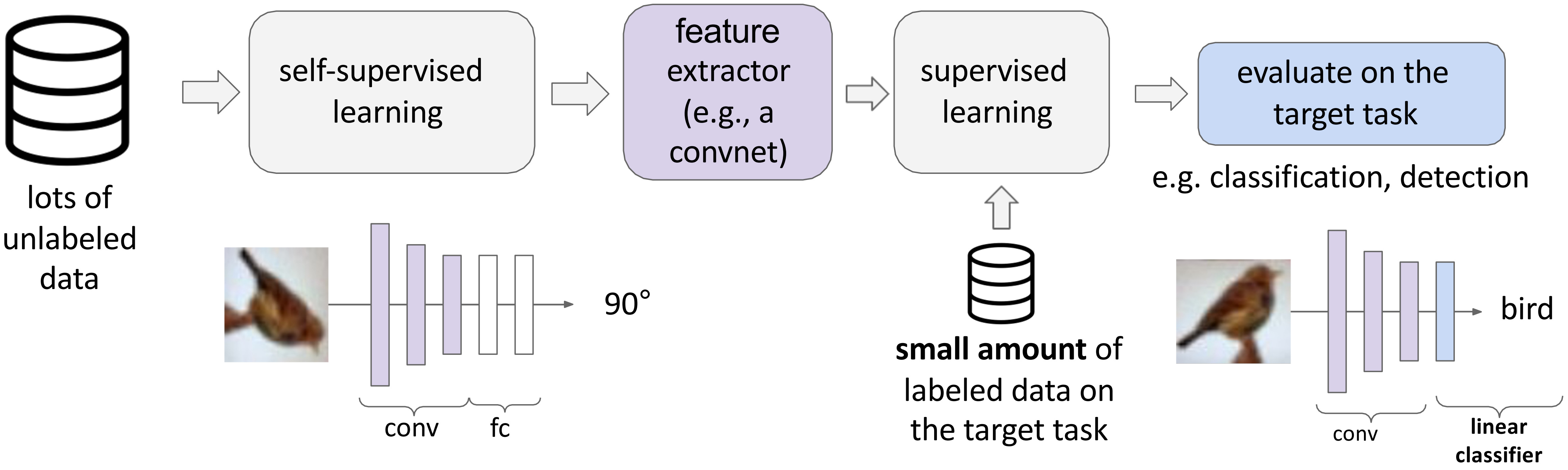
How to evaluate a self-supervised learning method?



1. Learn good feature extractors from self-supervised pretext tasks, e.g., predicting image rotations

[Gidaris et al. Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018]

How to evaluate a self-supervised learning method?

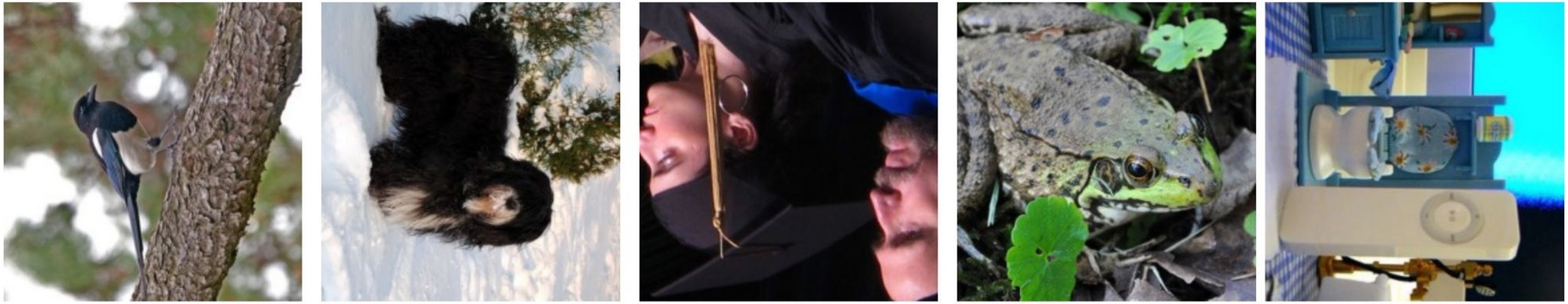


1. Learn good feature extractors from self-supervised pretext tasks, e.g., predicting image rotations

2. Attach a shallow network on the feature extractor; train the shallow network on the target task with small amount of labeled data

[Gidaris et al. Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018]

Pretext task: predict rotations

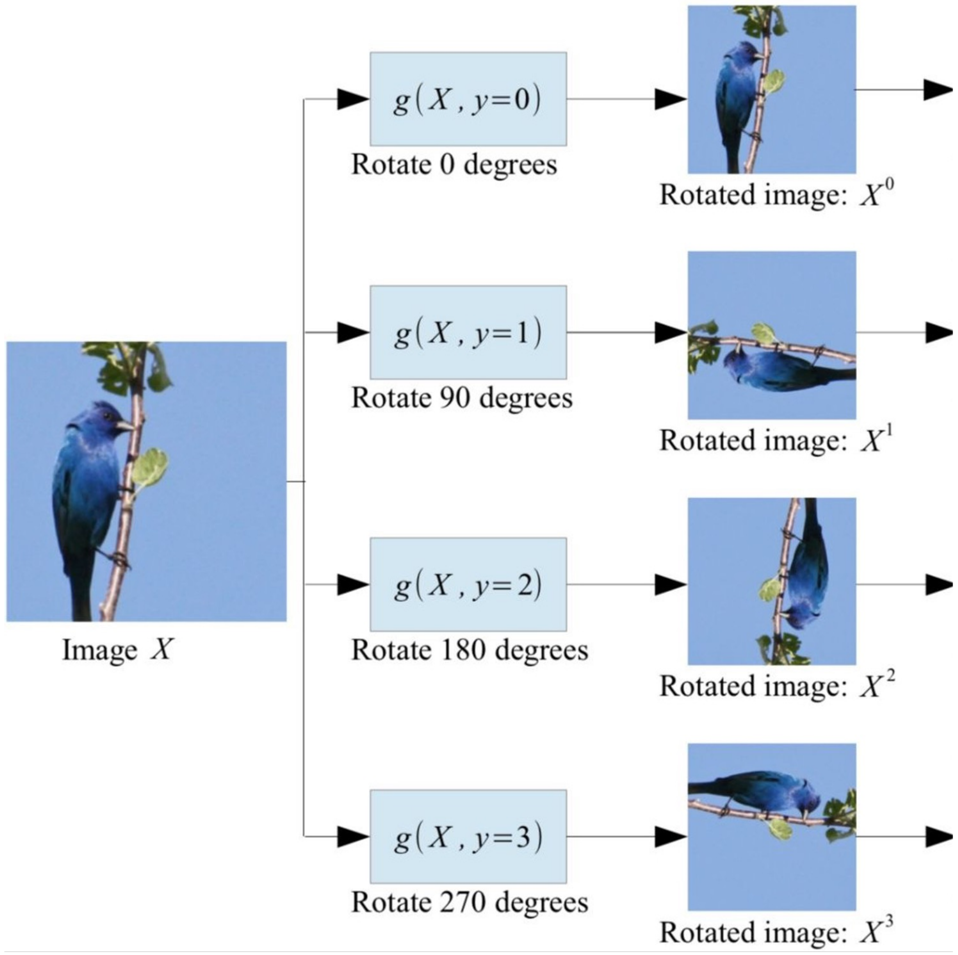


90° rotation | 270° rotation | 180° rotation | 0° rotation | 270° rotation

Hypothesis: a model could recognize the correct rotation of an object only if it has the "visual commonsense" of what the object should look like unperturbed.

Gidaris et al. Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018

Pretext task: predict rotations

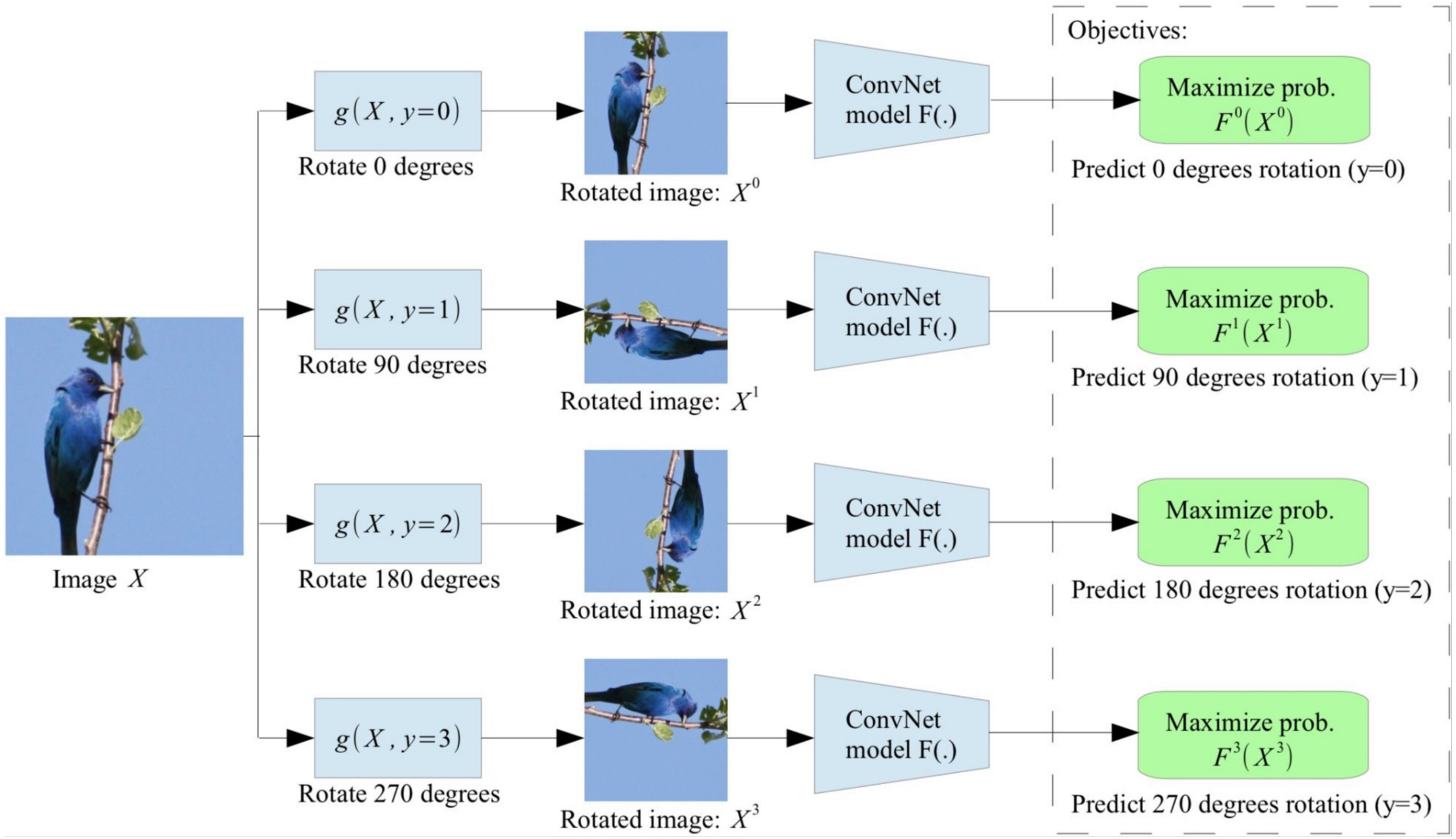


Self-supervised learning by rotating the entire input images.

The model learns to predict which rotation is applied (4-way classification)

[Gidaris et al. Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018]

Pretext task: predict rotations



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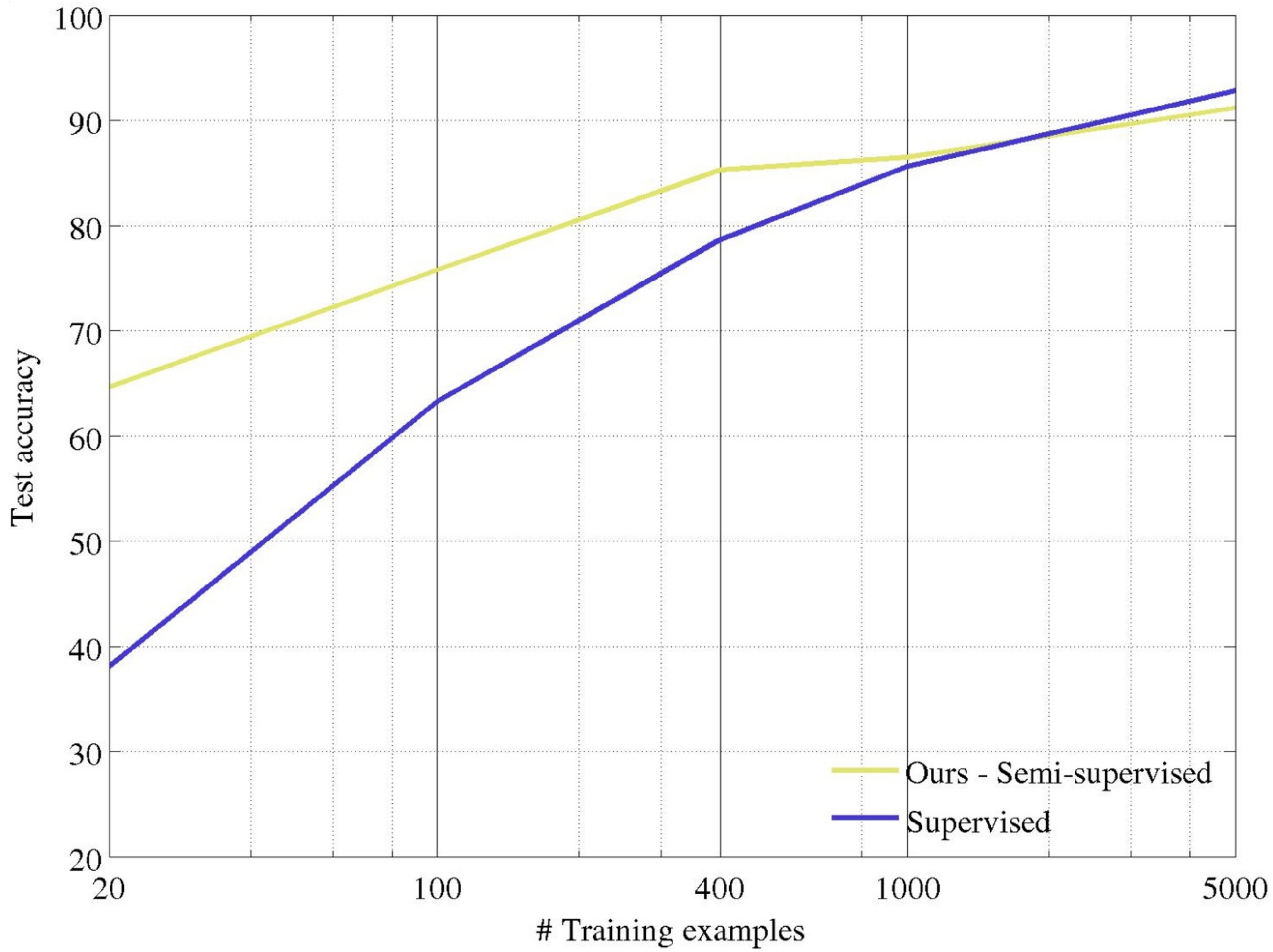
[Gidaris et al. Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018]()

Evaluation on semi-supervised learning



Self-supervised learning on **CIFAR10** (entire training set).

Freeze conv1 + conv2 Learn **conv3 + linear** layers with subset of labeled CIFAR10 data (classification).

[Gidaris et al. Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018]

Transfer learned features to supervised learning

	Classification (%mAP)		Detection (%mAP)	Segmentation (%mIoU)
Trained layers	fc6-8	all	all	all
ImageNet labels	78.9	79.9	56.8	48.0
Random		53.3	43.4	19.8
Random rescaled Krähenbühl et al. (2015)	39.2	56.6	45.6	32.6
Egomotion (Agrawal et al., 2015)	31.0	54.2	43.9	
Context Encoders (Pathak et al., 2016b)	34.6	56.5	44.5	29.7
Tracking (Wang & Gupta, 2015)	55.6	63.1	47.4	
Context (Doersch et al., 2015)	55.1	65.3	51.1	
Colorization (Zhang et al., 2016a)	61.5	65.6	46.9	35.6
BIGAN (Donahue et al., 2016)	52.3	60.1	46.9	34.9
Jigsaw Puzzles (Noroozi & Favaro, 2016)	-	67.6	53.2	37.6
NAT (Bojanowski & Joulin, 2017)	56.7	65.3	49.4	
Split-Brain (Zhang et al., 2016b)	63.0	67.1	46.7	36.0
ColorProxy (Larsson et al., 2017)		65.9		38.4
Counting (Noroozi et al., 2017)	-	67.7	51.4	36.6
(Ours) RotNet	**70.87**	**72.97**	**54.4**	**39.1**

Pretrained with full ImageNet supervision

No pretraining

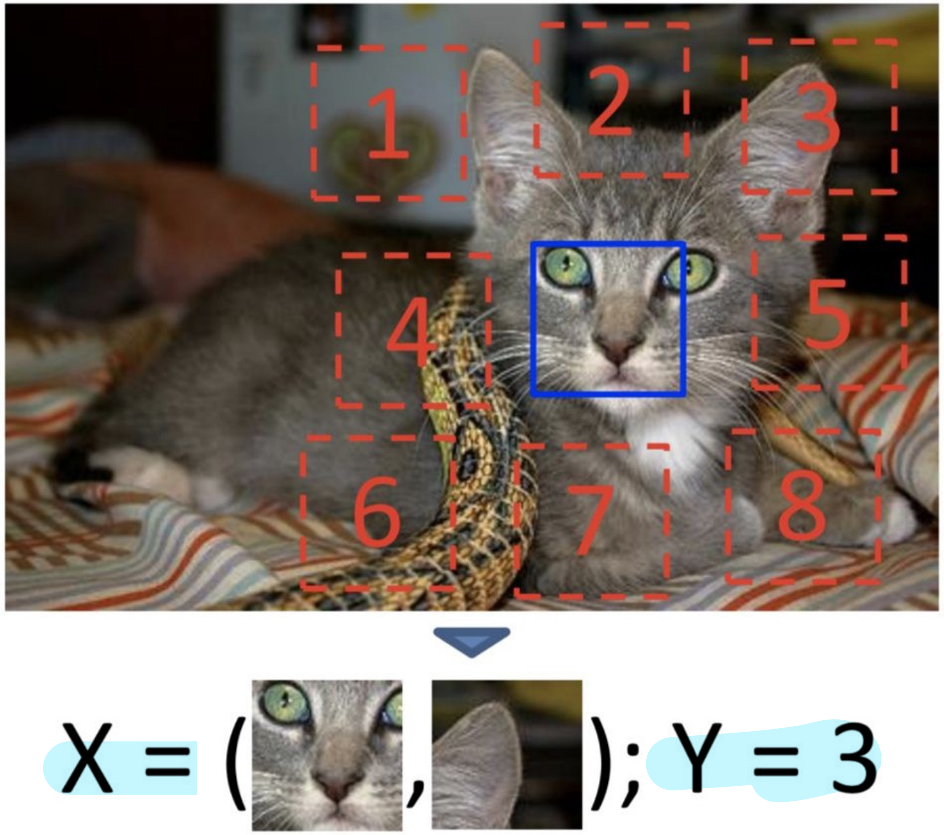
Self-supervised learning with rotation prediction

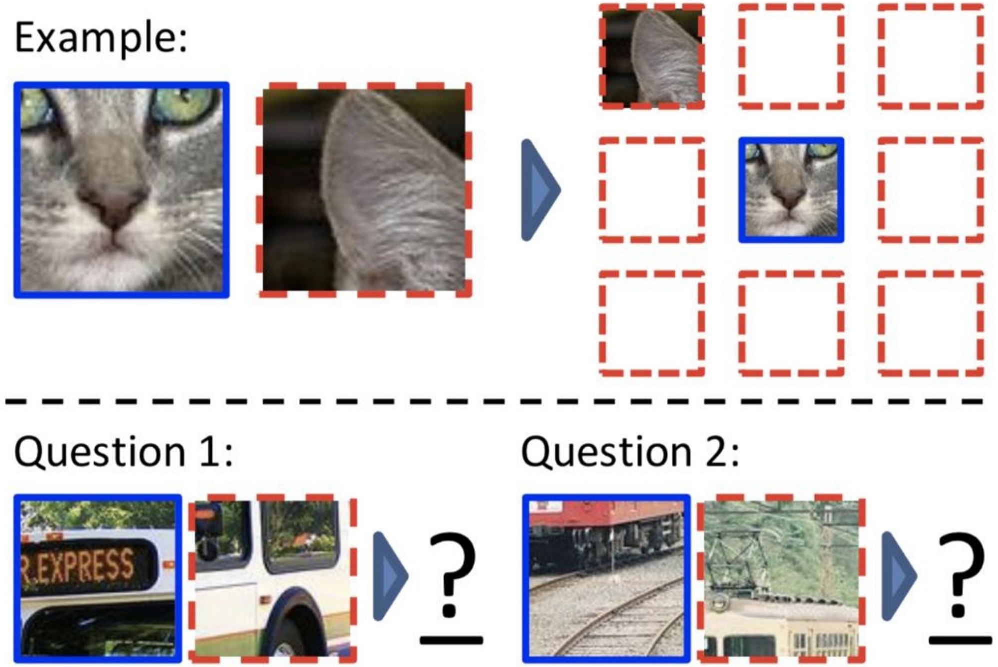
Self-supervised learning on **ImageNet** (entire training set) with AlexNet.

Finetune on labeled data from **Pascal VOC 2007**.

Gidaris et al. Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018

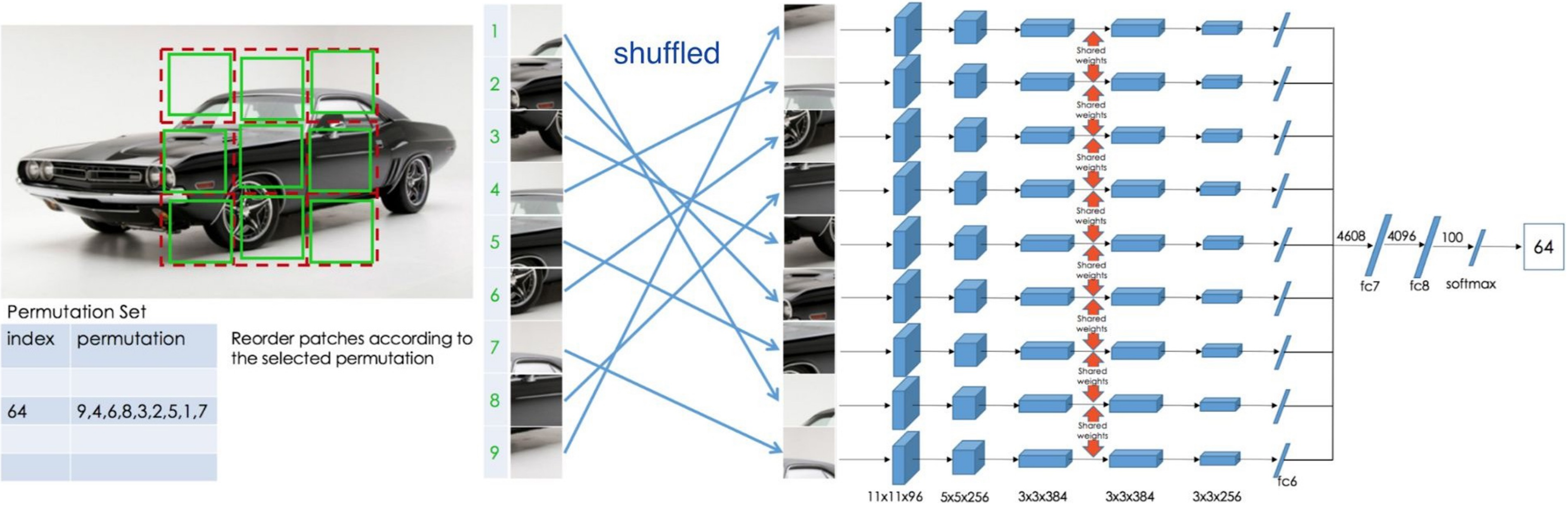
Pretext task: predict relative patch locations





[Doersch et al., Unsupervised Visual Representation Learning by Context Prediction, 2015](#)

Pretext task: solving "jigsaw puzzles"



Noroozi & Favaro, Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles, 2016

Transfer learned features to supervised learning

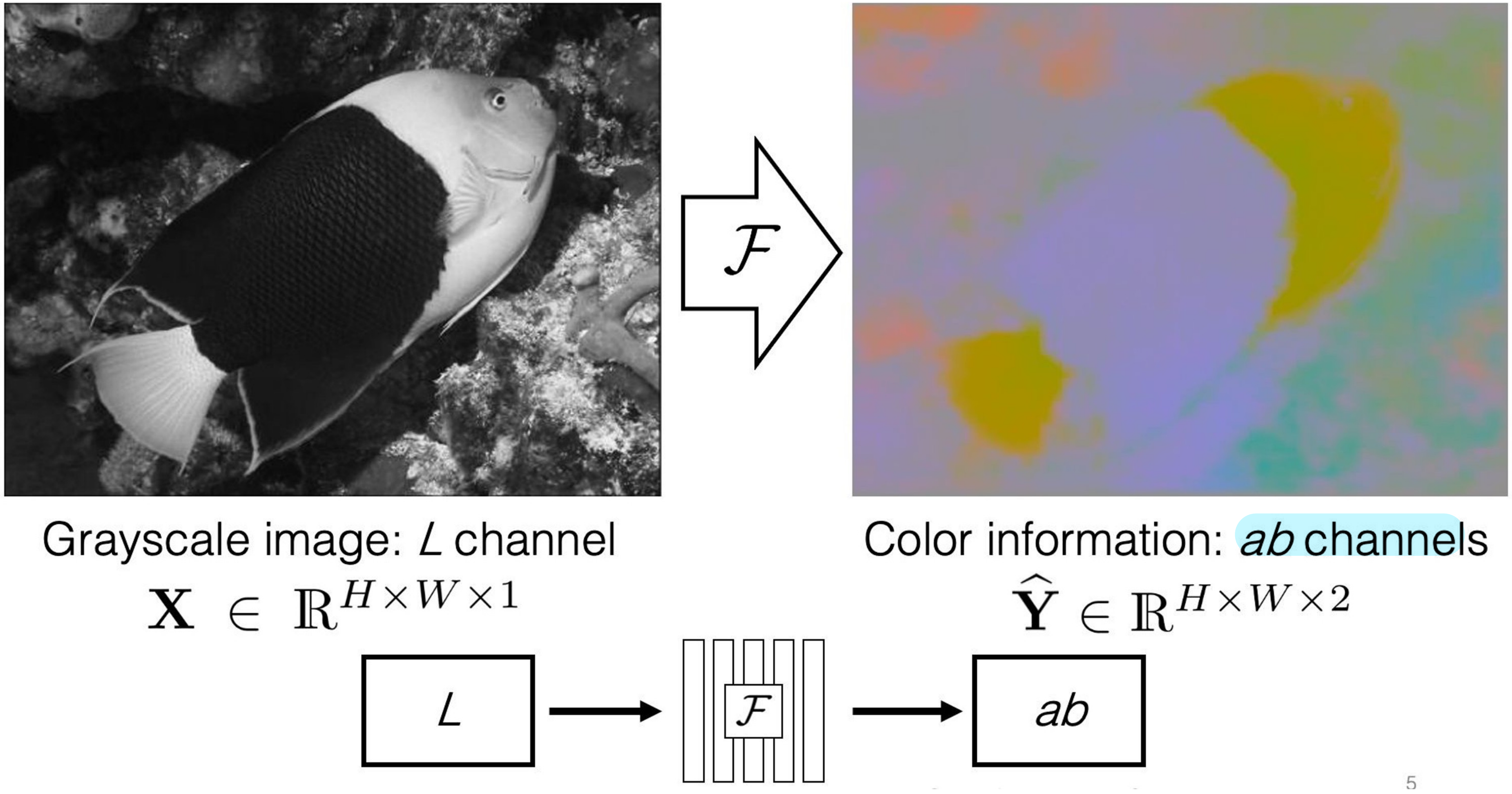
Table 1: Results on PASCAL VOC 2007 Detection and Classification. The results of the other methods are taken from Pathak *et al.* [30].

Method	Pretraining time	Supervision	Classification	Detection	Segmentation
Krizhevsky*et al.* [25]	3 days	1000 class labels	**78.2%**	**56.8%**	**48.0%**
Wang and Gupta[39]	1 week	motion	58.4%	44.0%	-
Doersch *et al.* [10]	4 weeks	context	55.3%	46.6%	-
Pathak *et al.* [30]	14 hours	context	56.5%	44.5%	29.7%
Ours	2.5 days	context	**67.6%**	**53.2%**	**37.6%**

"Ours" is feature learned from solving image Jigsaw puzzles (Noroozi & Favaro, 2016). Doersch et al. is the method with relative patch location

Noroozi & Favaro, Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles, 2016

Pretext task: image coloring



[Zhang, Isola & Efros, Colorful Image Colorization, 2016]

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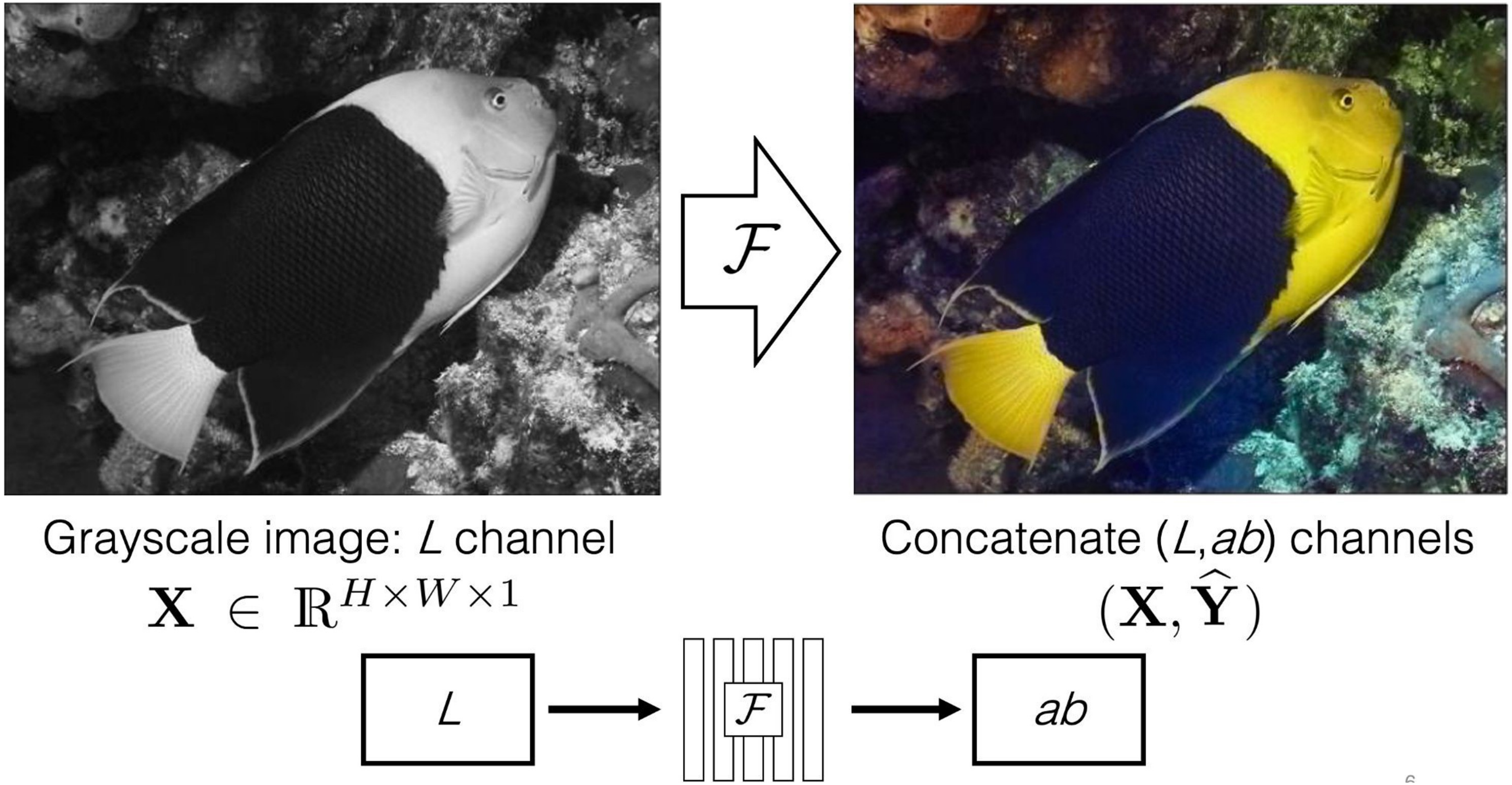


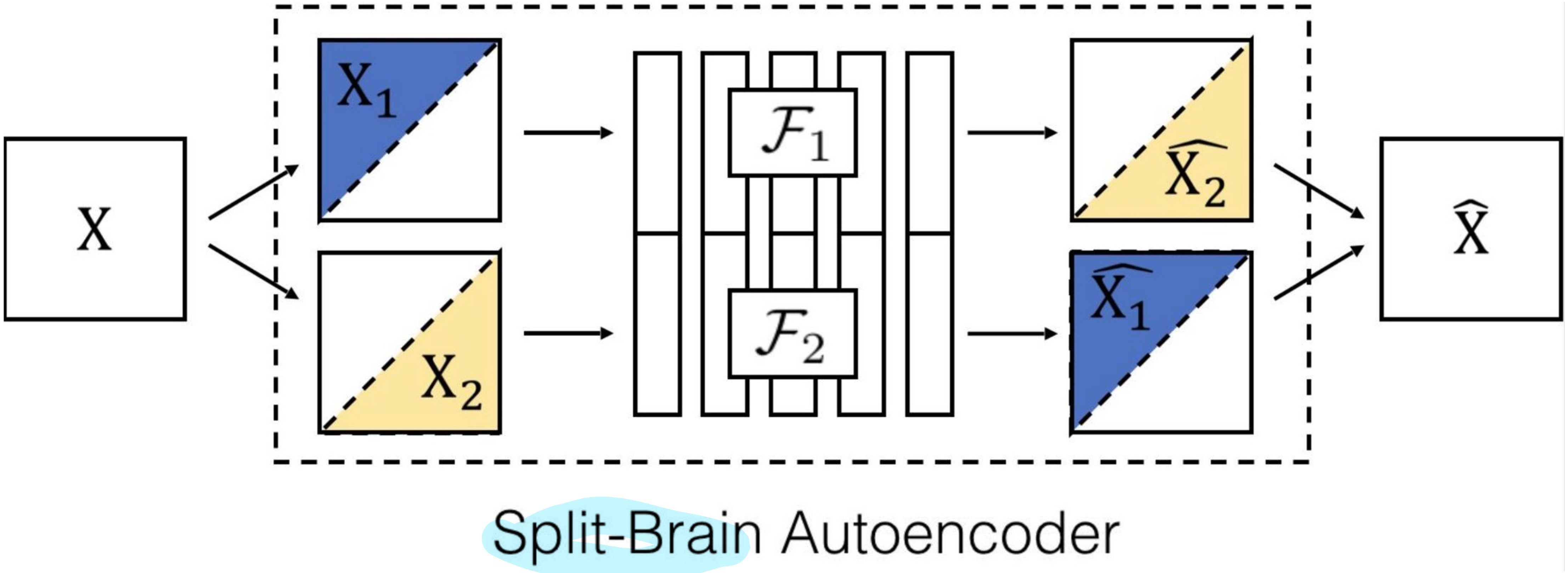
Zhang, Isola & Efros, Colorful Image Colorization, 2016

Pretext task: image coloring

Zhang, Isola & Efros, Colorful Image Colorization, 2016

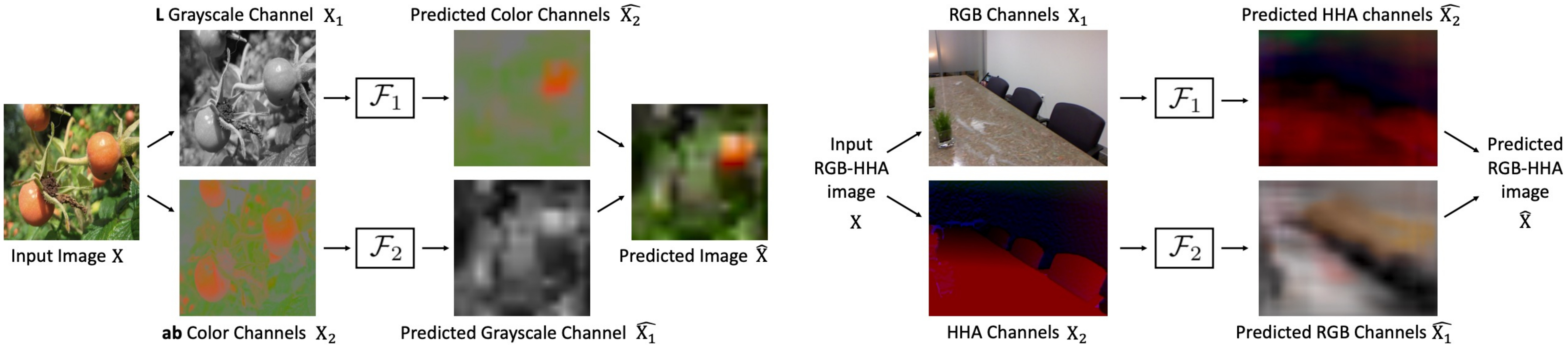
Learning features from colorization: Split-brain

Idea: cross-channel predictions



Zhang, Isola & Efros, Split-Brain Autoencoders: Unsupervised Learning by Cross-Channel Prediction, CVPR 2017

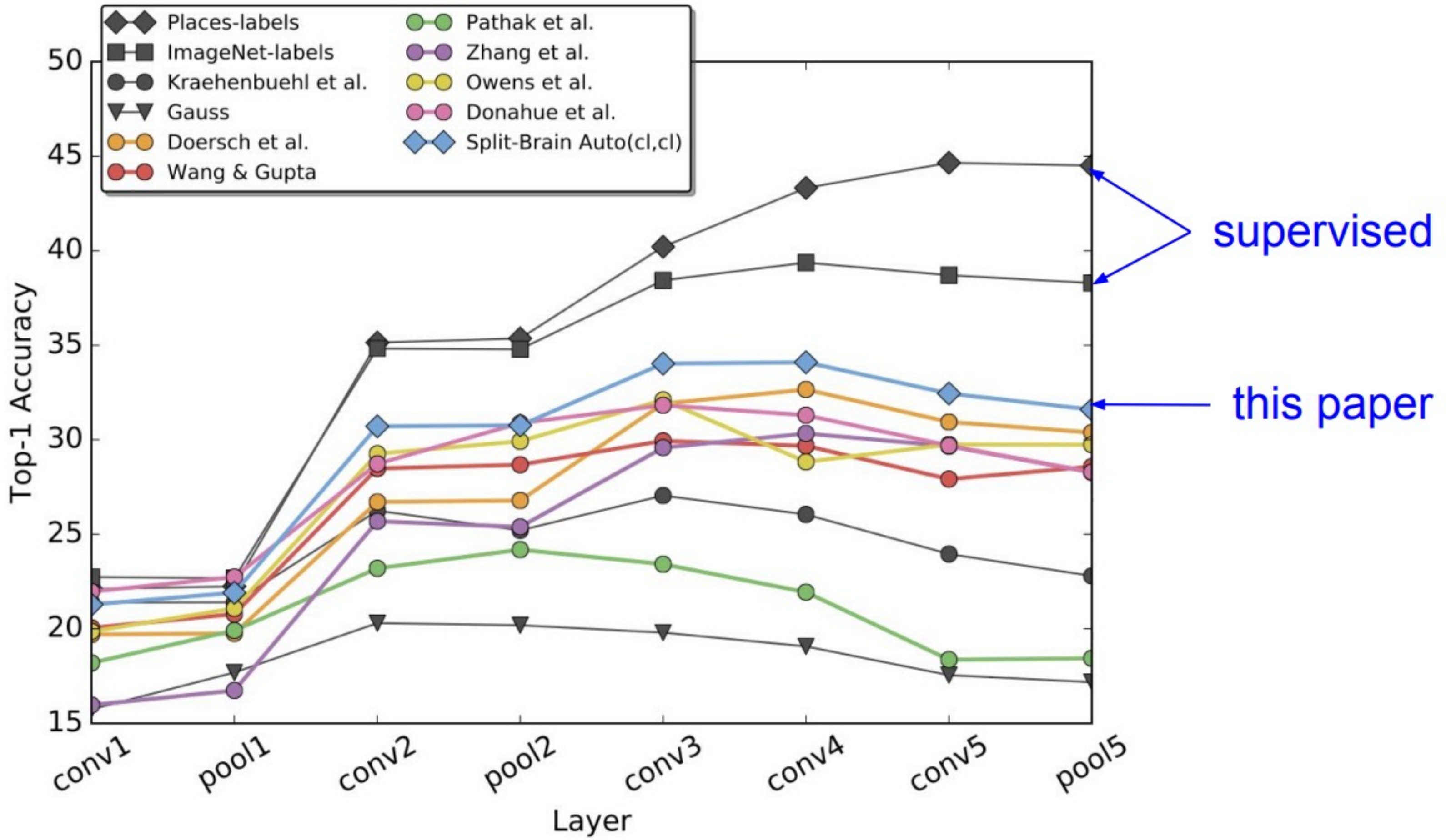
Learning features from colorization: Split-brain



(a) ***Lab* Images** (b) **RGB-D Images**

[Zhang, Isola & Efros, Split-Brain Autoencoders: Unsupervised Learning by Cross-Channel Prediction, CVPR 2017]

Transfer learned features to supervised learning



Self-supervised learning on ImageNet (entire training set).

Use concatenated features from F1 and F2

Labeled data is from the Places (Zhou 2016).

[Zhang, Isola & Efros, Split-Brain Autoencoders: Unsupervised Learning by Cross-Channel Prediction, CVPR 2017]

Summary: pretext tasks from image transformations

- Pretext tasks focus on “visual common sense”, e.g., predict rotations, inpainting, rearrangement, and colorization.
- The models are forced learn good features about natural images, e.g., semantic representation of an object category, in order to solve the pretext tasks.
- We don’t care about the performance of these pretext tasks, but rather how useful the learned features are for downstream tasks (classification, detection, segmentation).

Summary: pretext tasks from image transformations

- Pretext tasks focus on “visual common sense”, e.g., predict rotations, inpainting, rearrangement, and colorization.
- The models are forced learn good features about natural images, e.g., semantic representation of an object category, in order to solve the pretext tasks.
- We don’t care about the performance of these pretext tasks, but rather how useful the learned features are for downstream tasks (classification, detection, segmentation).
- Problems:
    1. coming up with individual pretext tasks is tedious
    2. the learned representations may not be general.

Pretext tasks from image transformations

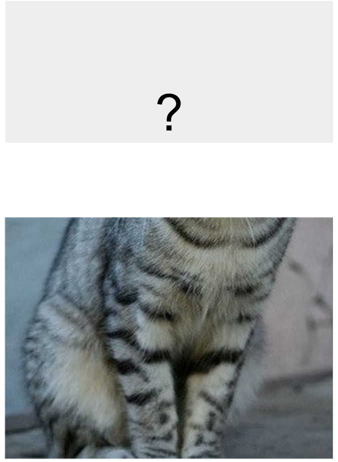
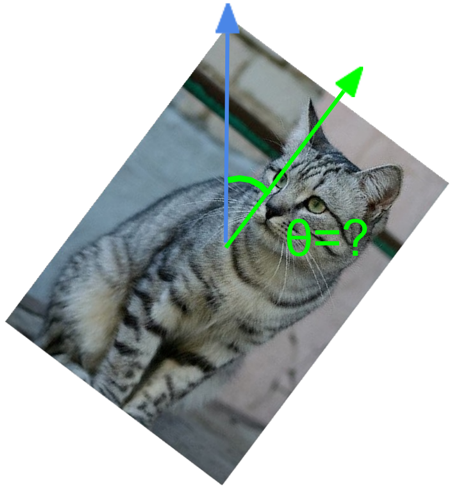
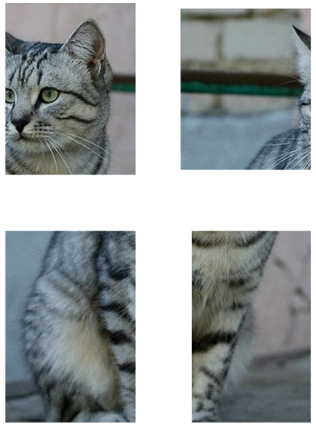


image completion



rotation prediction



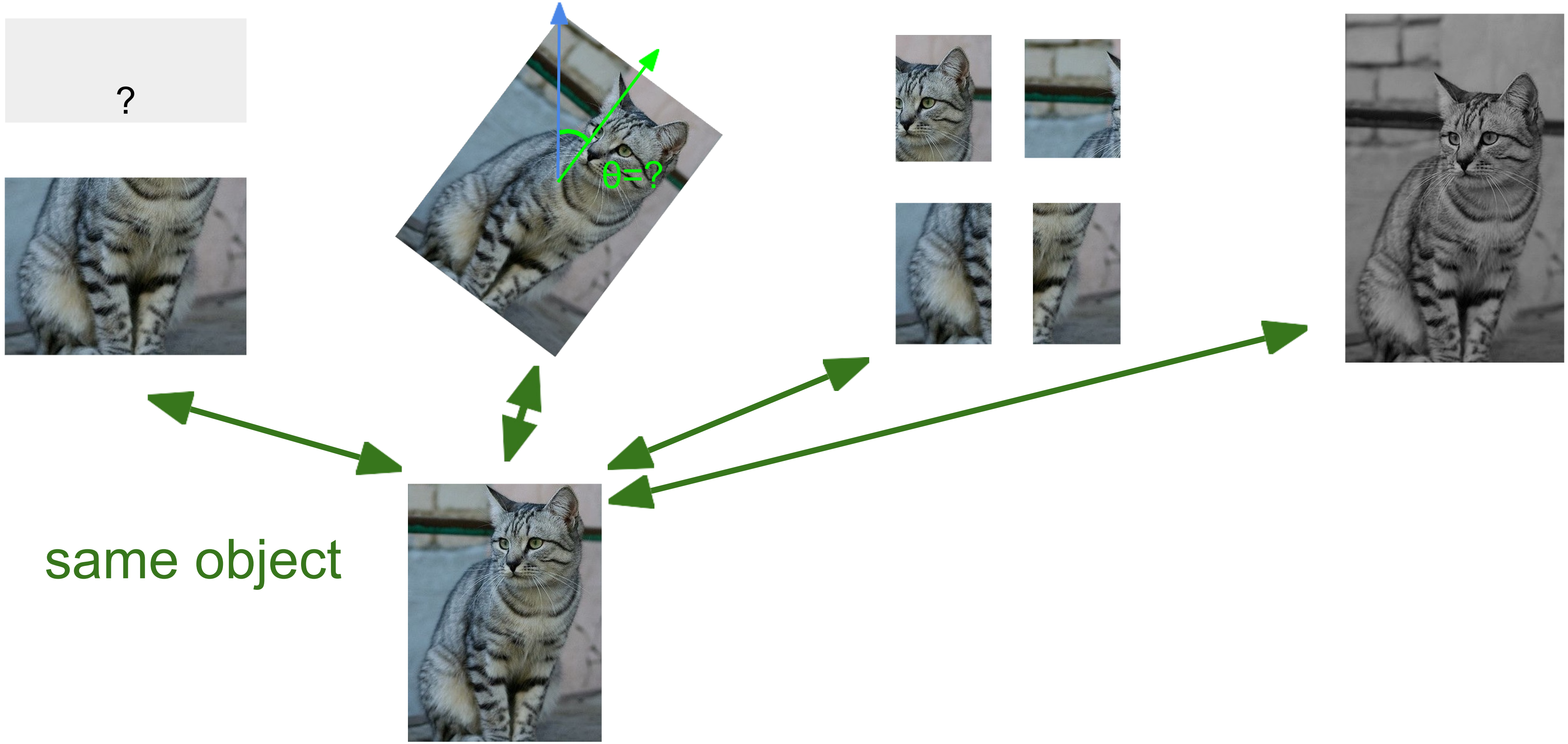
"jigsaw puzzle"

colorization

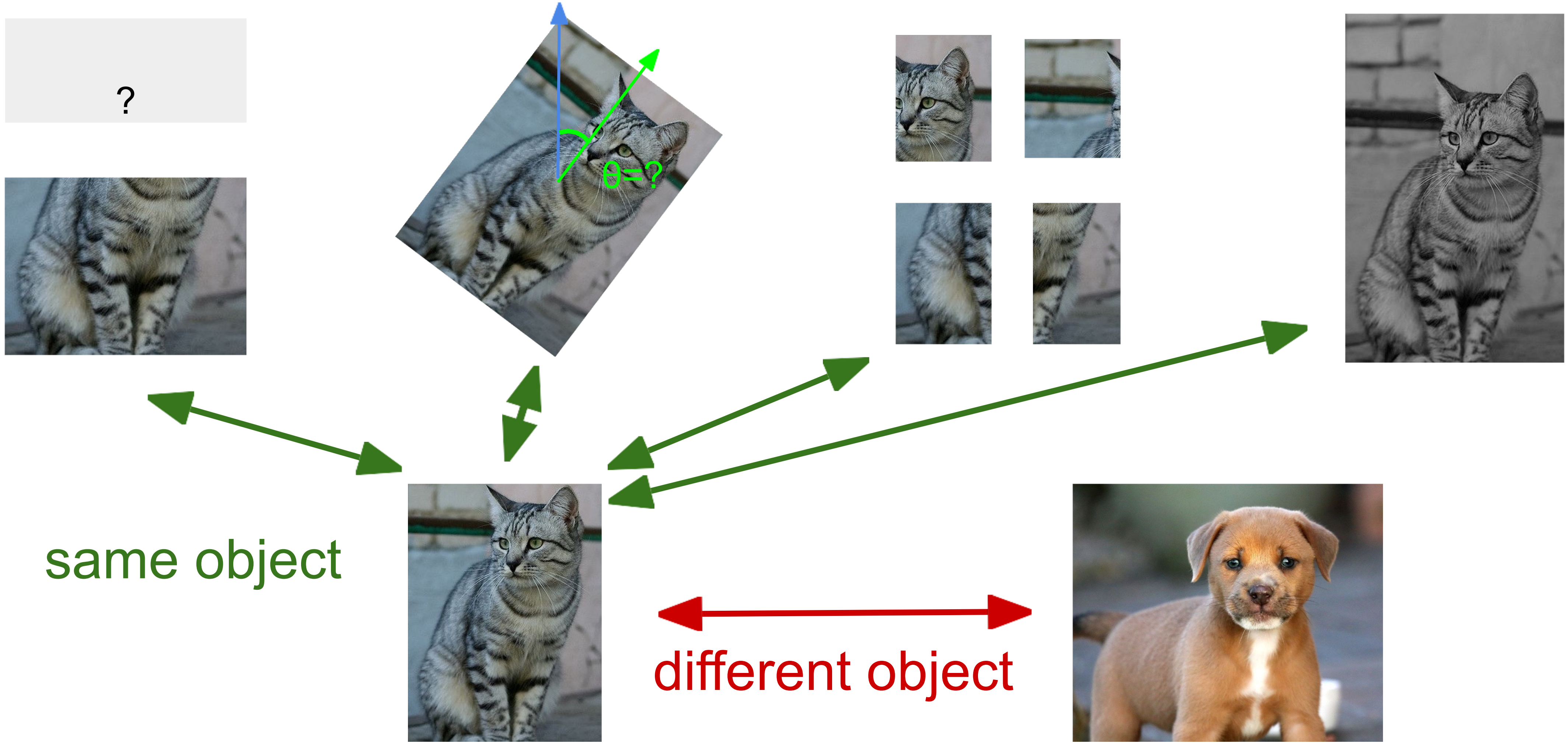
Learned representations may be tied to a specific pretext task!

Can we come up with a more general pretext task?

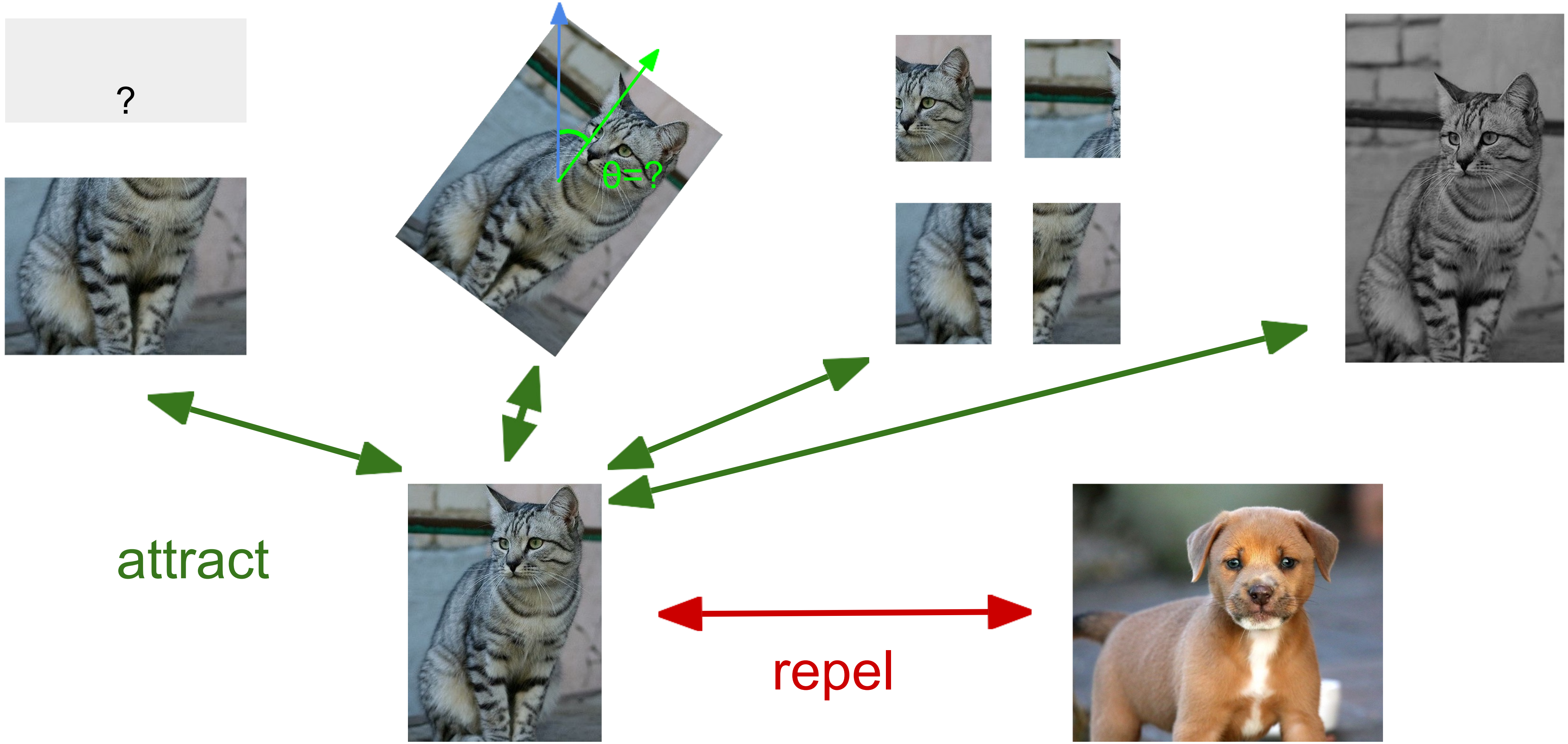
A more general pretext task?



A more general pretext task?



Contrastive Representation Learning



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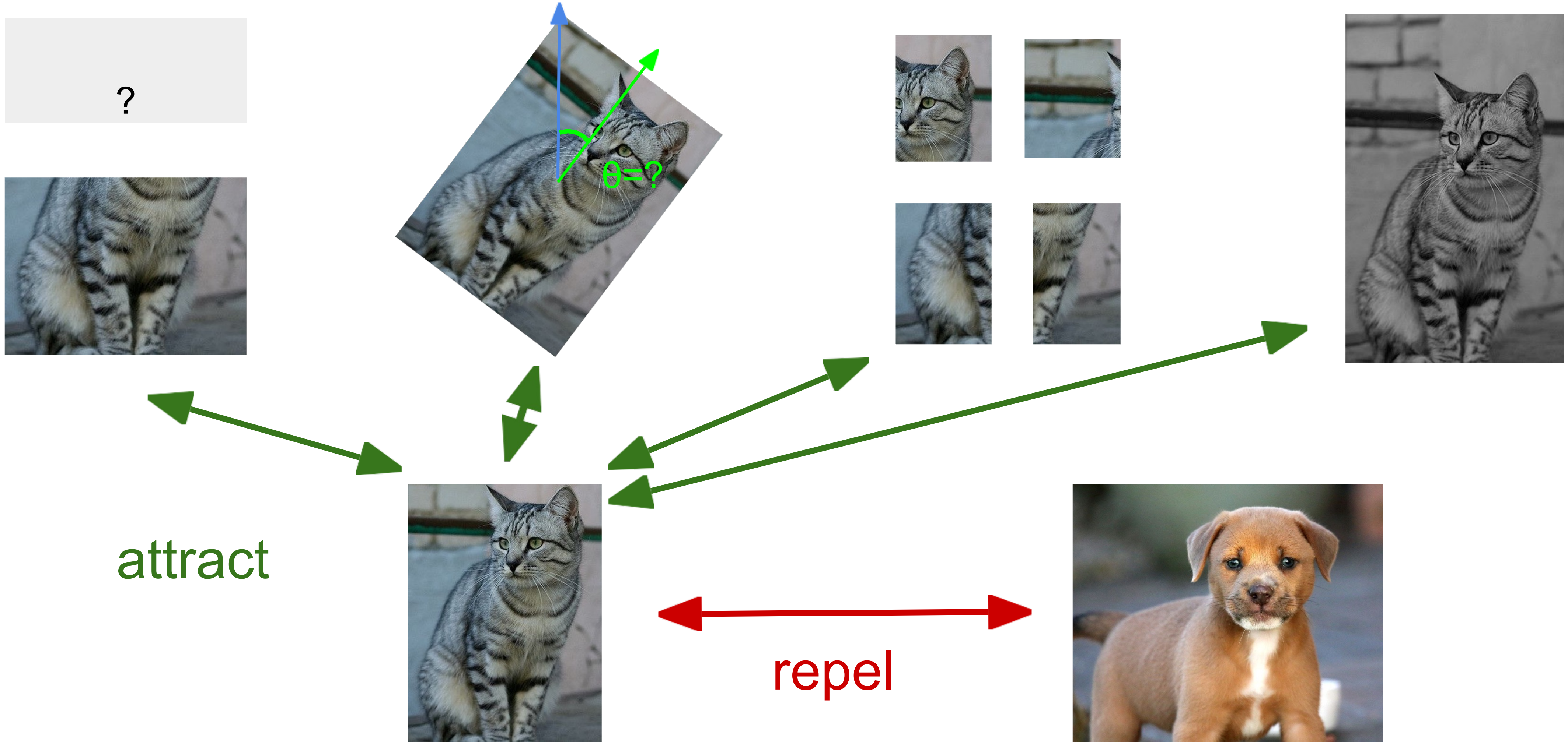

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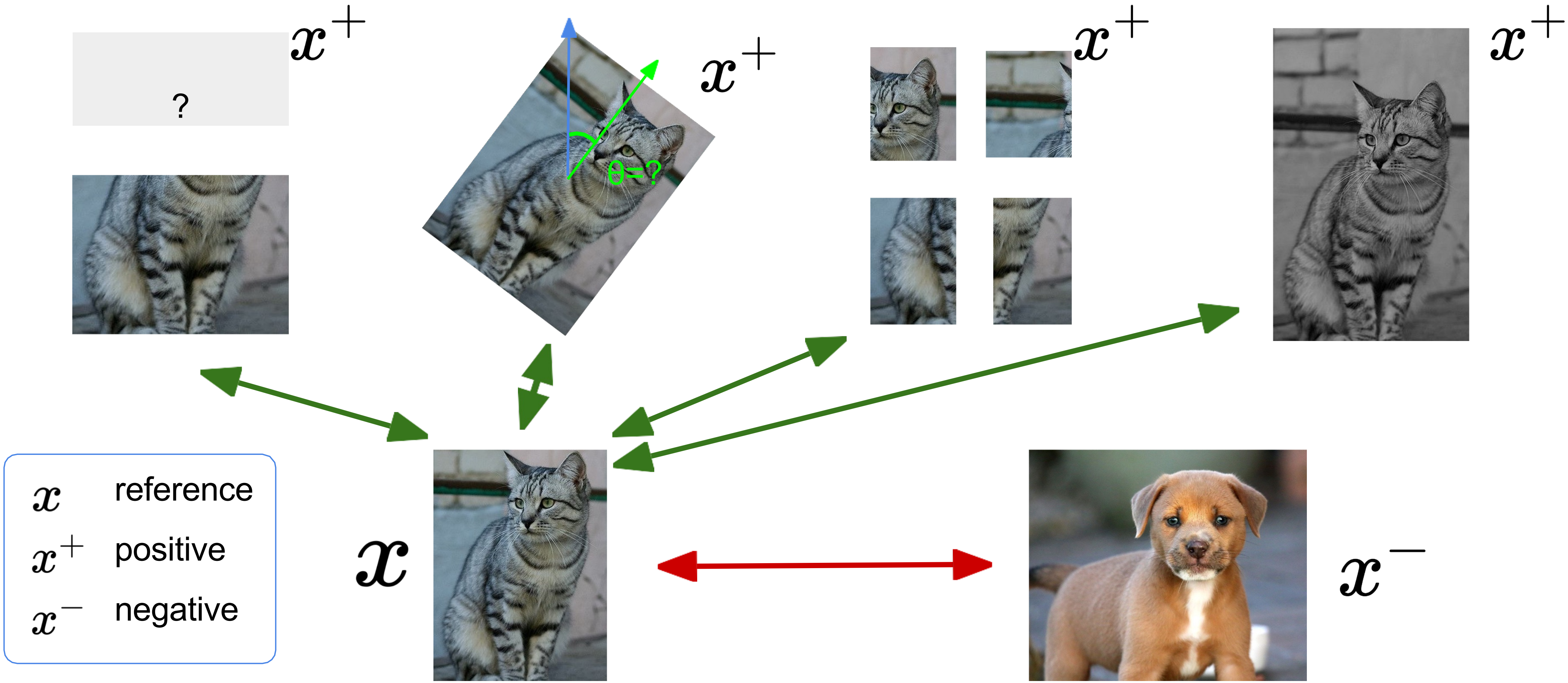

A formulation of contrastive learning

What we want:

$$\text{score}(f(x), f(x^+)) >> \text{score}(f(x), f(x^-))$$

x: reference sample; x^+ positive sample; x^- negative sample

Given a chosen score function, we aim to learn an **encoder function** *f* that yields high score for positive pairs (x,x^+) and low scores for negative pairs (x,x^-).

A formulation of contrastive learning

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+))}{\exp(s(f(x), f(x^+)) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))} \right]$$

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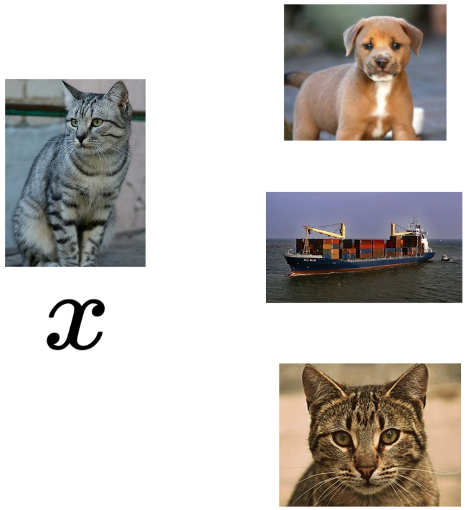
x x^+



x

x_1^-

x_2^-

x_3^-

...

A formulation of contrastive learning

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+)))}{\underbrace{\exp(s(f(x), f(x^+)))}_{\text{score for the positive pair}} + \underbrace{\sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-)))}_{\text{score for the N-1 negative pairs}}} \right]$$

This seems familiar …

Cross entropy loss for a N-way softmax classifier!
i.e., learn to find the positive sample from the N samples

A formulation of contrastive learning

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+))}{\exp(s(f(x), f(x^+)) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))} \right]$$

Commonly known as the InfoNCE loss (van den Oord et al., 2018) A *lower bound* on the mutual information between *f(x)* and *f(x⁺)*

$$MI[f(x), f(x^+)] - \log(N) \geq -L$$

The larger the negative sample size (*N*), the tighter the bound

Detailed derivation: Poole et al., 2019

SimCLR: A Simple Framework for Contrastive Learning

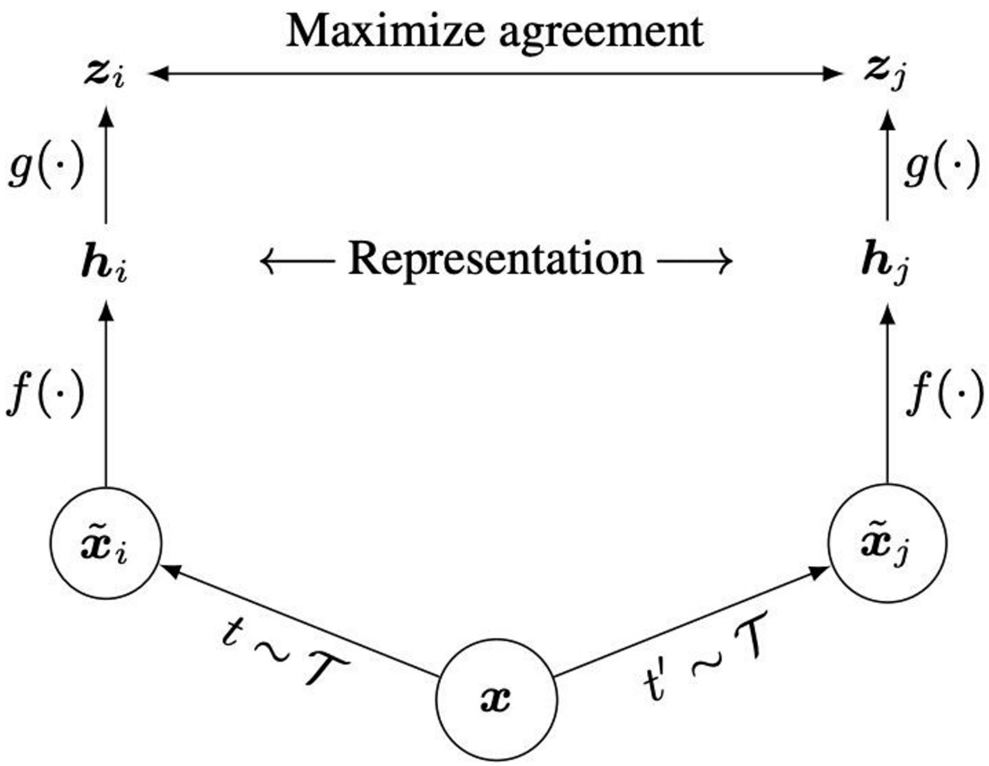
Cosine similarity as the score function:

$$s(u, v) = \frac{u^T v}{||u||||v||}$$

Use a projection network $g(\cdot)$ to project features to a space where contrastive learning is applied

Generate positive samples through data augmentation:

- random cropping, random color distortion, and random blur.



Chen et al., A Simple Framework for Contrastive Learning of Visual Representations, 2020

SimCLR: generating positive samples from

(a) Original (b) Crop and resize (c) Crop, resize (and flip) (d) Color distort. (drop) (e) Color distort. (jitter)

(f) Rotate $\{90°, 180°, 270°\}$ (g) Cutout (h) Gaussian noise (i) Gaussian blur (j) Sobel filtering

[Chen et al., A Simple Framework for Contrastive Learning of Visual Representations, 2020]

SimCLR

Generate a positive pair by sampling data augmentation functions

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
for sampled minibatch $\{\boldsymbol{x}_k\}_{k=1}^{N}$ **do**
  for all $k \in \{1, \ldots, N\}$ **do**
    $\boxed{\text{draw two augmentation functions } t \sim \mathcal{T}, t' \sim \mathcal{T}}$
    # the first augmentation
    $\boxed{\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)}$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$ # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$ # projection
    # the second augmentation
    $\boxed{\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)}$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$ # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$ # projection
  end for
  for all $i \in \{1, \ldots, 2N\}$ and $j \in \{1, \ldots, 2N\}$ **do**
    $s_{i,j} = \boldsymbol{z}_i^\top \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$ # pairwise similarity
  end for
  define $\ell(i,j)$ **as** $\ell(i,j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks f and g to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$

Chen et al., 2020

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InfoNCE loss:
Use all non-positive samples in the batch as x^-

Chen et al., 2020

SimCLR

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
for sampled minibatch $\{\boldsymbol{x}_k\}_{k=1}^{N}$ **do**
  for all $k \in \{1, \ldots, N\}$ **do**
    draw two augmentation functions $t \sim \mathcal{T}$, $t' \sim \mathcal{T}$
    # the first augmentation
    $\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$ # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$ # projection
    # the second augmentation
    $\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$ # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$ # projection
  end for
  for all $i \in \{1, \ldots, 2N\}$ and $j \in \{1, \ldots, 2N\}$ **do**
    $s_{i,j} = \boldsymbol{z}_i^\top \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$ # pairwise similarity
  end for
  define $\ell(i,j)$ **as** $\ell(i,j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks f and g to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$

Generate a positive pair by sampling data augmentation functions

Iterate through and use each of the 2N sample as reference, compute average loss

InfoNCE loss:
Use all non-positive samples in the batch as x^-

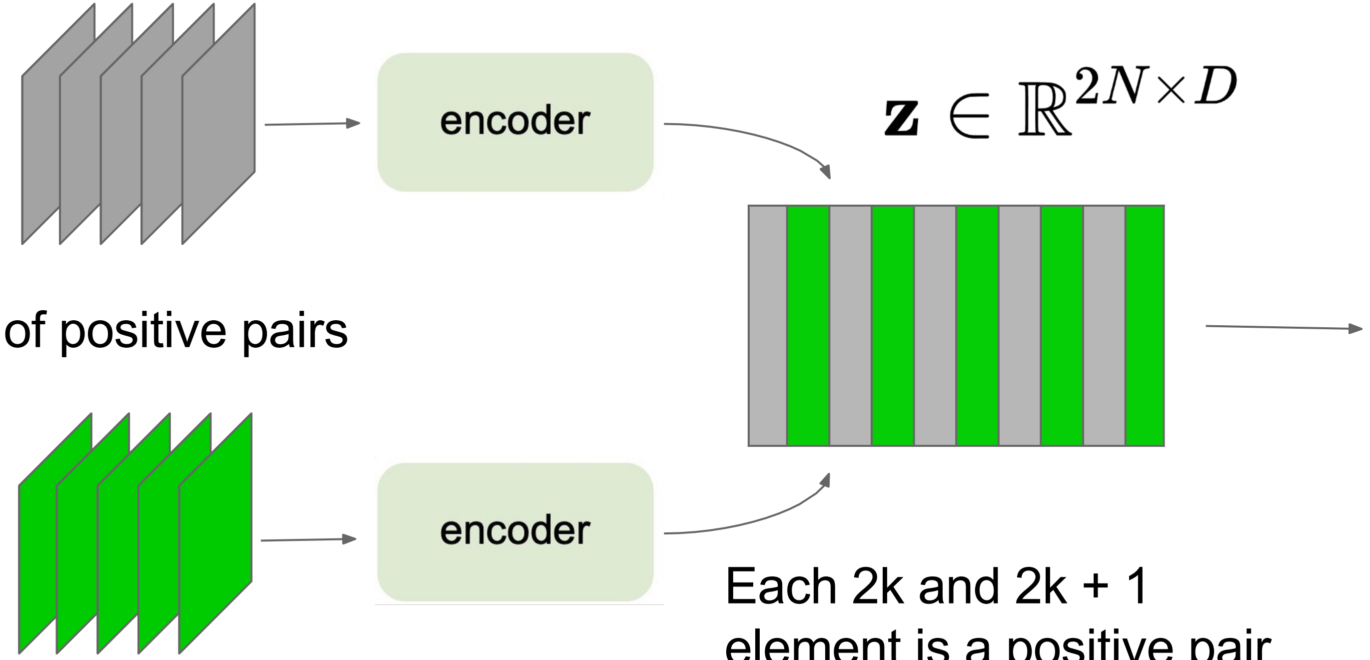
Chen et al., 2020

SimCLR: mini-batch training

$$s_{i,j} = \frac{z_i^T z_j}{||z_i|| \, ||z_j||}$$

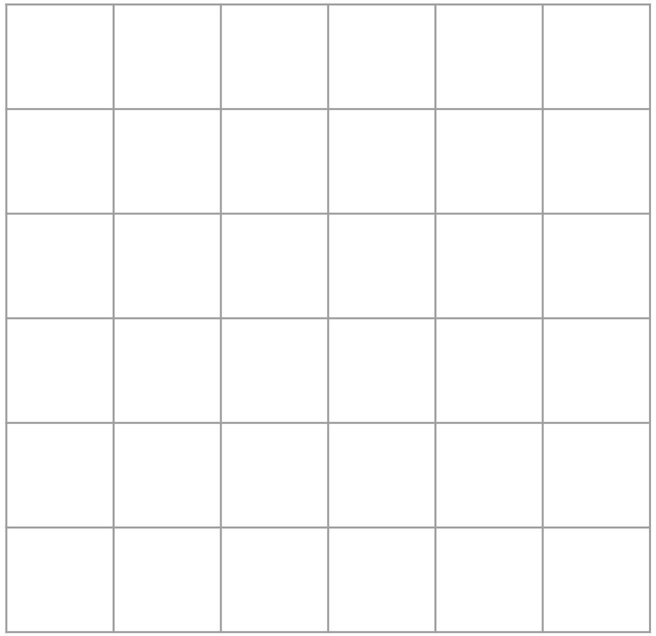
"Affinity matrix"

$\mathbf{z} \in \mathbb{R}^{2N \times D}$



list of positive pairs

Each 2k and 2k + 1
element is a positive pair

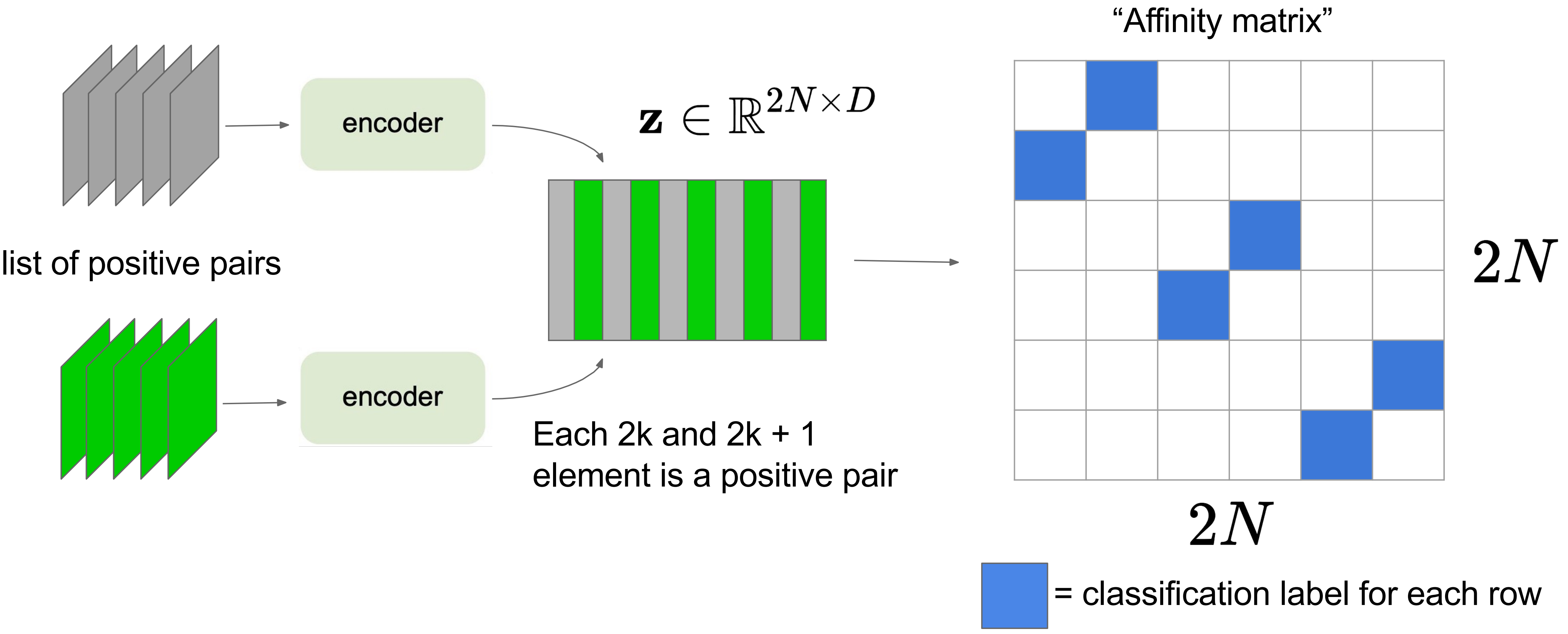


$2N$

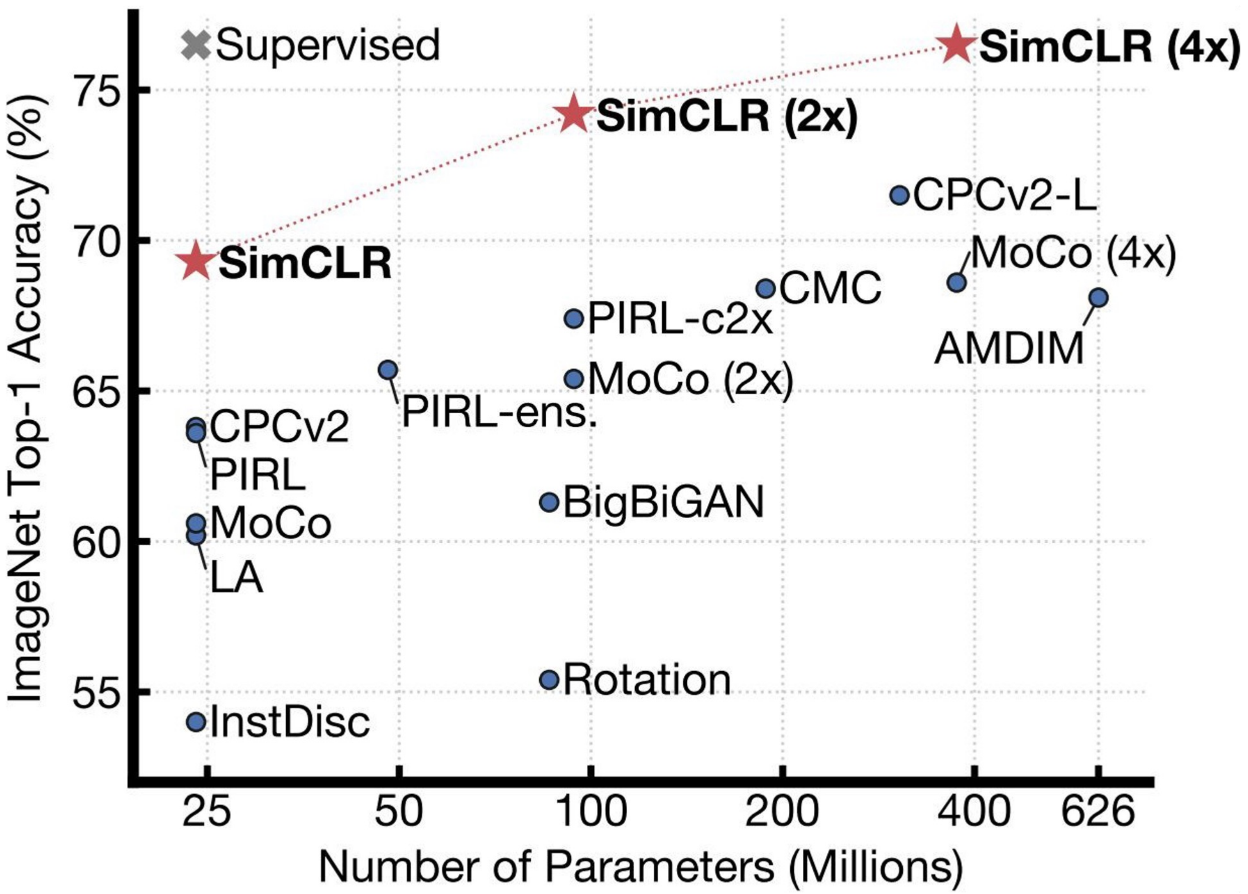
$2N$

SimCLR: mini-batch training

$$s_{i,j} = \frac{z_i^T z_j}{||z_i|| \, ||z_j||}$$



Training linear classifier on SimCLR features



Train feature encoder on **ImageNet** (entire training set) using SimCLR.

Freeze feature encoder, train a linear classifier on top with labeled data.

Chen et al., A Simple Framework for Contrastive Learning of Visual Representations, 2020

Semi-supervised learning on SimCLR features

Method	Architecture	Label fraction 1%	10%
		Top 5	
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**

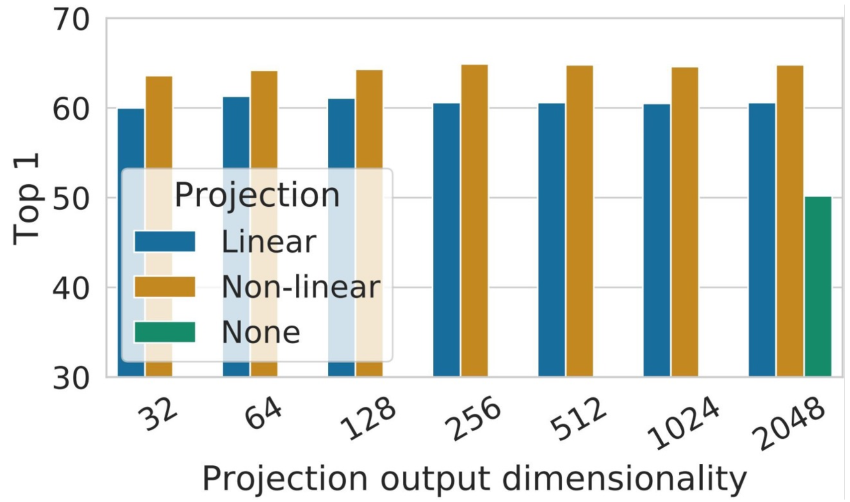
Table 7. ImageNet accuracy of models trained with few labels.

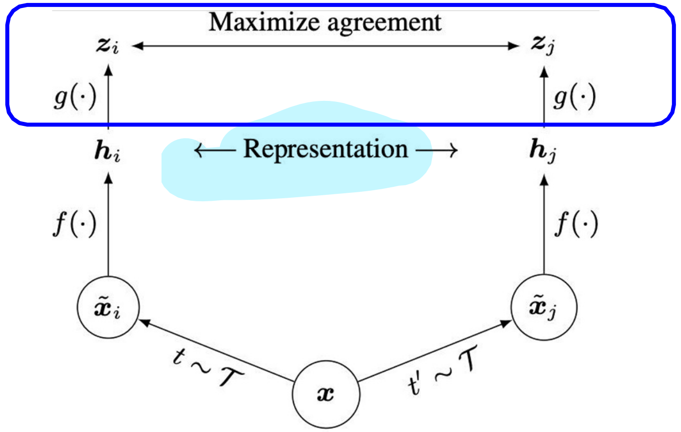
Train feature encoder on **ImageNet** (entire training set) using SimCLR.

Finetune the encoder with 1% / 10% of labeled data on ImageNet.

Chen et al., A Simple Framework for Contrastive Learning of Visual Representations, 2020

SimCLR design choices: projection head





Linear / non-linear projection heads improve representation learning.

A possible explanation:

- contrastive learning objective may discard useful information for downstream tasks
- representation space z is trained to be invariant to data transformation.
- by leveraging the projection head **g(·)**, more information can be preserved in the **h** representation space

Chen et al., A Simple Framework for Contrastive Learning of Visual Representations, 2020

SimCLR design choices: large batch size

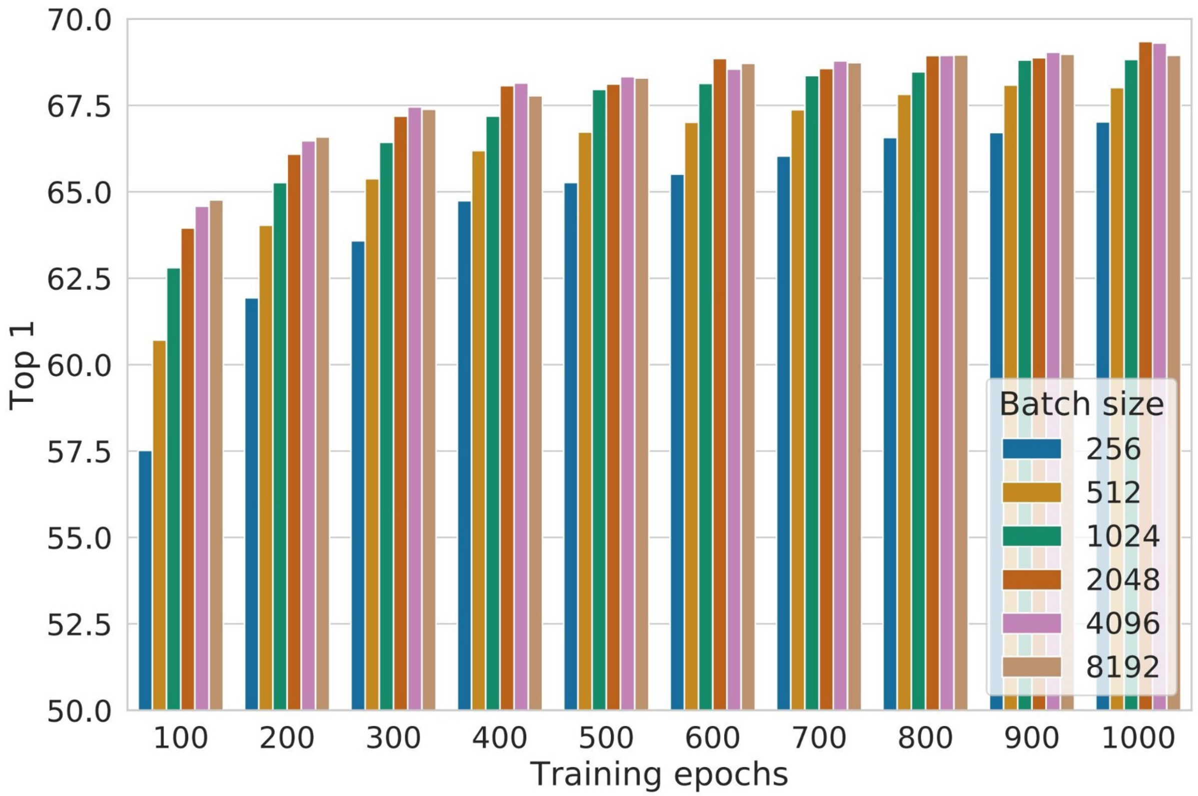


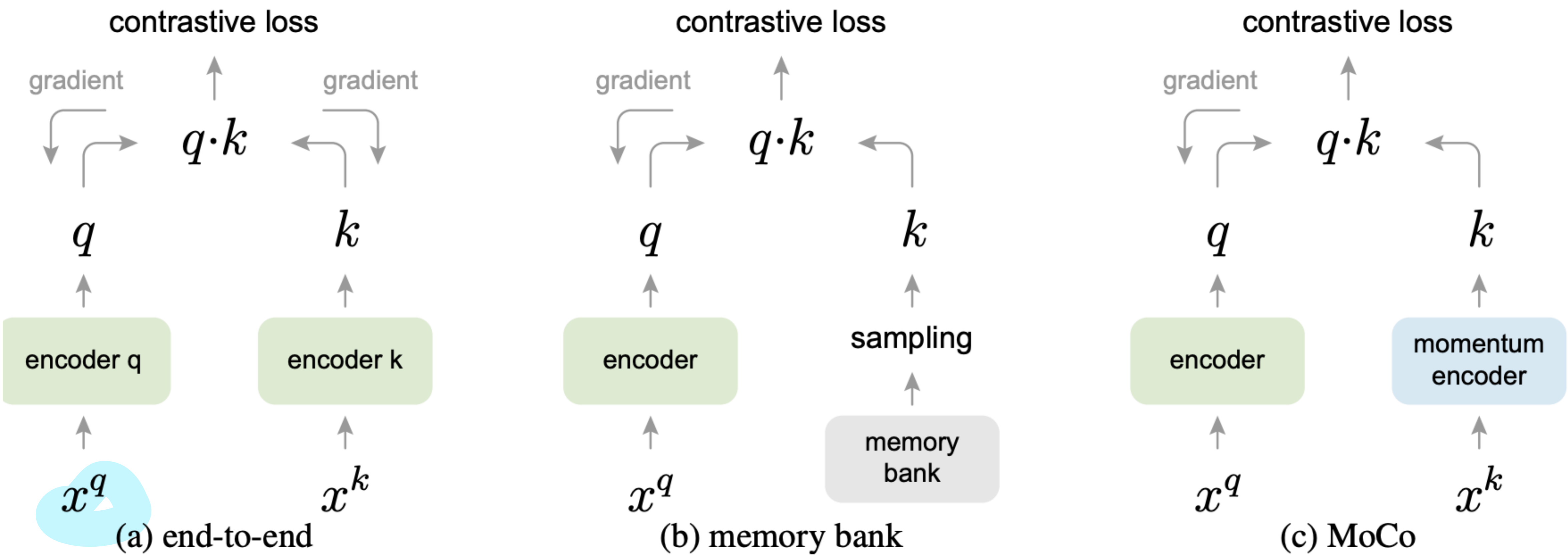
Figure 9. Linear evaluation models (ResNet-50) trained with different batch size and epochs. Each bar is a single run from scratch.[10]

Large training batch size is crucial for SimCLR!

Large batch size causes large memory footprint during backpropagation: requires distributed training on TPUs (ImageNet experiments)

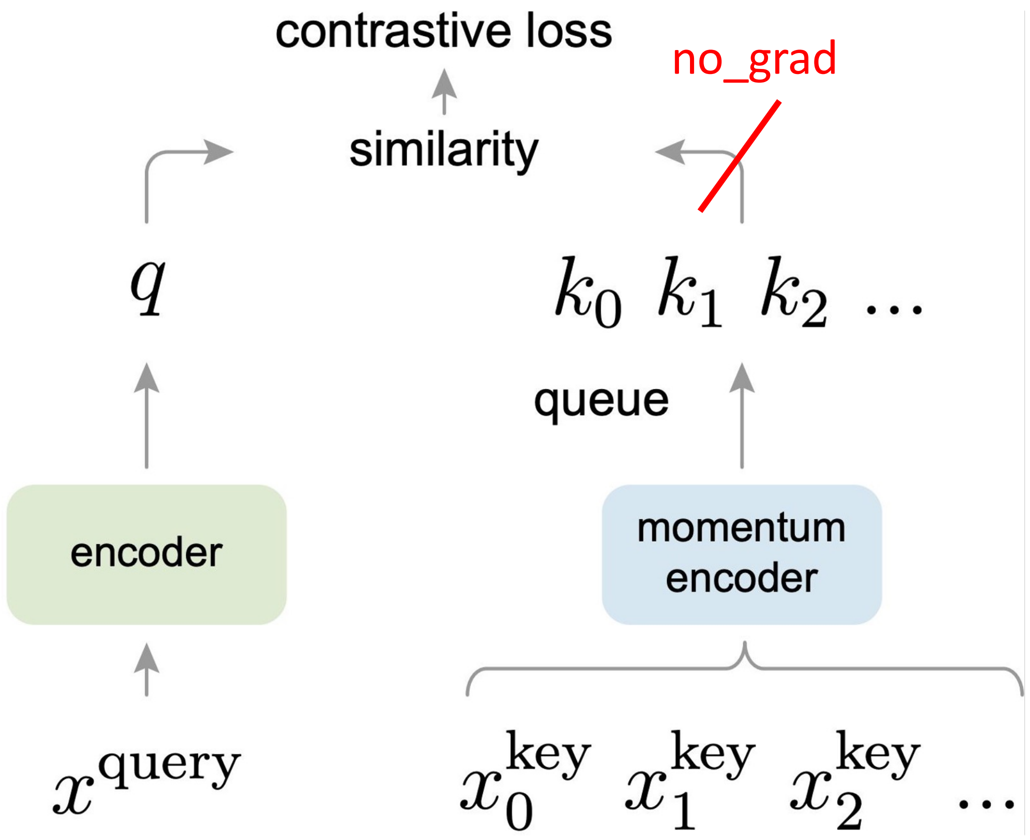
[Chen et al., A Simple Framework for Contrastive Learning of Visual Representations, 2020](#)

Momentum Contrastive Learning (MoCo)



[He et al., Momentum Contrast for Unsupervised Visual Representation Learning, 2020]

Momentum Contrastive Learning (MoCo)

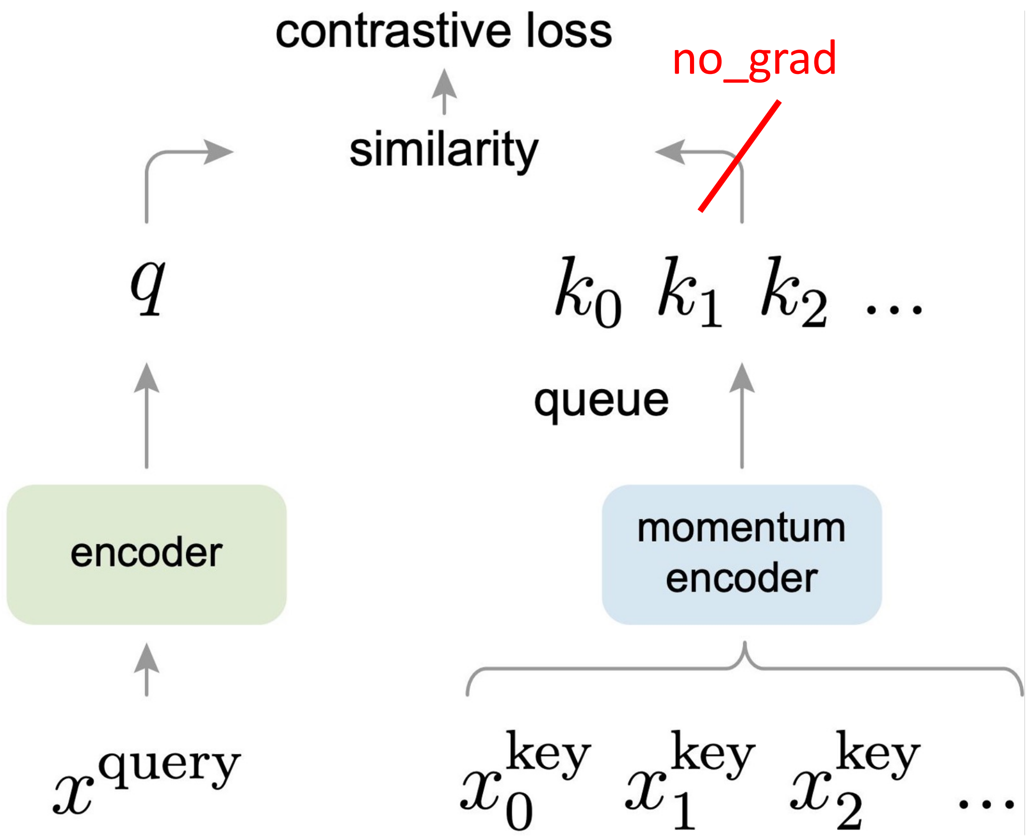


Key differences to SimCLR:

- Keep a running queue of keys (negative samples).
- Compute gradients and update the encoder only through the queries.
- Decouple min-batch size with the number of keys: can support a large number of negative samples.

He et al., 2020

Momentum Contrastive Learning (MoCo)



Key differences to SimCLR:

- Keep a running queue of keys (negative samples).
- Compute gradients and update the encoder only through the queries.
- Decouple min-batch size with the number of keys: can support a large number of negative samples.
- The key encoder is slowly progressing through the momentum update rules:
$$\theta_{\mathrm{k}} \leftarrow m\theta_{\mathrm{k}} + (1-m)\theta_{\mathrm{q}}$$

He et al., Momentum Contrast for Unsupervised Visual Representation Learning, 2020

MoCo

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.

Generate a positive pair by sampling data augmentation functions

No gradient through the positive sample

Use the running queue of keys as the negative samples

InfoNCE loss

Update f_k through momentum

Update the FIFO negative sample queue

He et al., 2020

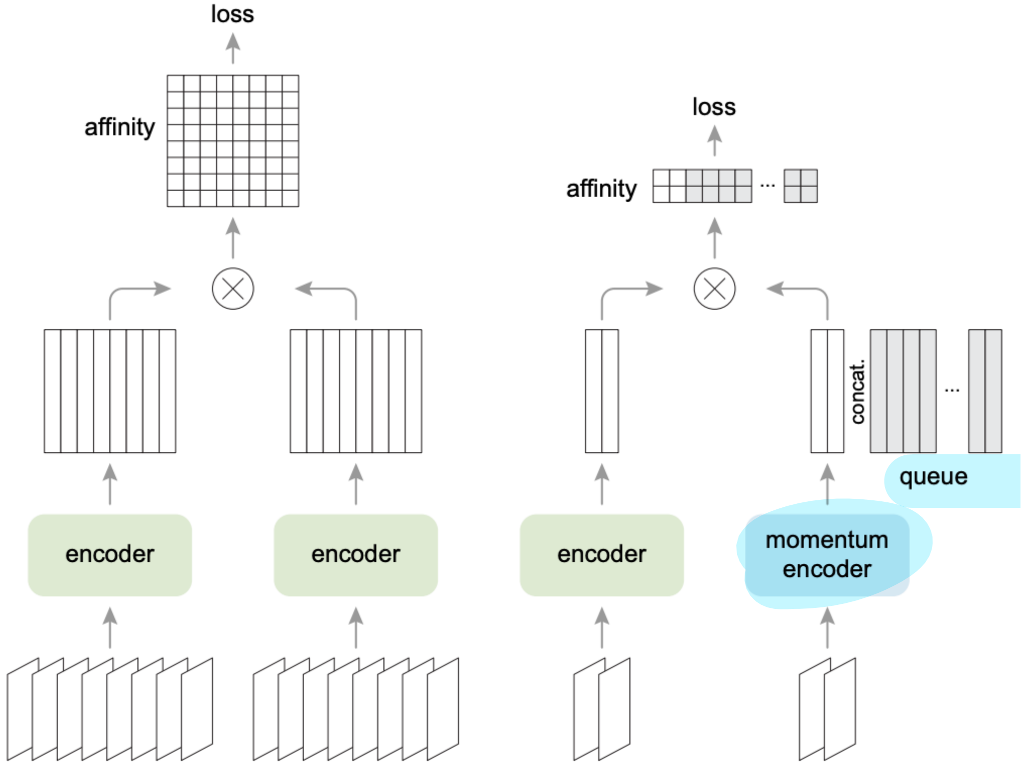
"MoCo V2"

Improved Baselines with Momentum Contrastive Learning

Xinlei Chen Haoqi Fan Ross Girshick Kaiming He
Facebook AI Research (FAIR)

A hybrid of ideas from SimCLR and MoCo:

- **From SimCLR**: non-linear projection head and strong data augmentation.
- **From MoCo**: momentum-updated queues that allow training on a large number of negative samples (no TPU required!).



(a) end-to-end (b) Momentum Contrast

[Chen et al., Improved Baselines with Momentum Contrastive Learning, 2020]

MoCo vs. SimCLR vs. MoCo V2

case	unsup. pre-train MLP	aug+	cos	epochs	ImageNet acc.	VOC detection 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.

Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.

[Chen et al., Improved Baselines with Momentum Contrastive Learning, 2020]

MoCo vs. SimCLR vs. 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).

Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.
- Decoupling mini-batch size with negative sample size allows MoCo-V2 to outperform SimCLR with smaller batch size (256 vs. 8192).

Chen et al., Improved Baselines with Momentum Contrastive Learning, 2020

MoCo vs. SimCLR vs. MoCo V2

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.

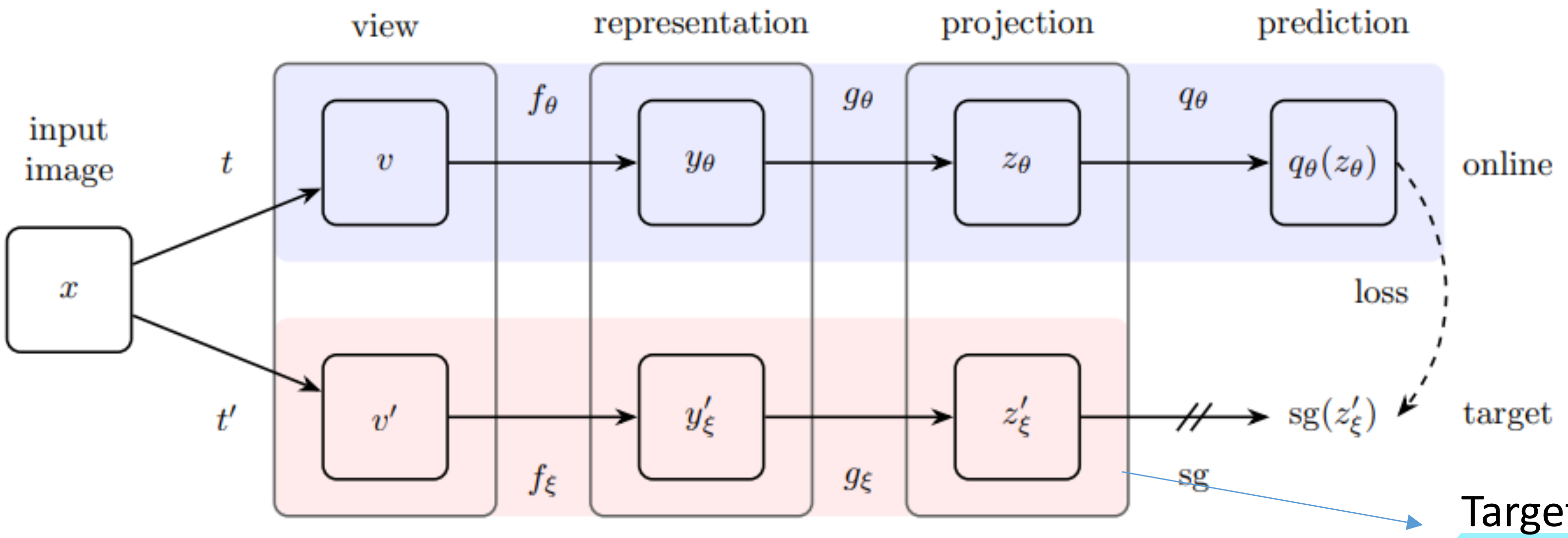
Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.
- Decoupling mini-batch size with negative sample size allows MoCo-V2 to outperform SimCLR with smaller batch size (256 vs. 8192).
- … all with much smaller memory footprint! ("end-to-end" means SimCLR here)

Chen et al., Improved Baselines with Momentum Contrastive Learning, 2020

BYOL: Bootstrap Your Own Latent

- Doesn't need negative pairs
- Uses two networks (online and target), that interact and learn from each other



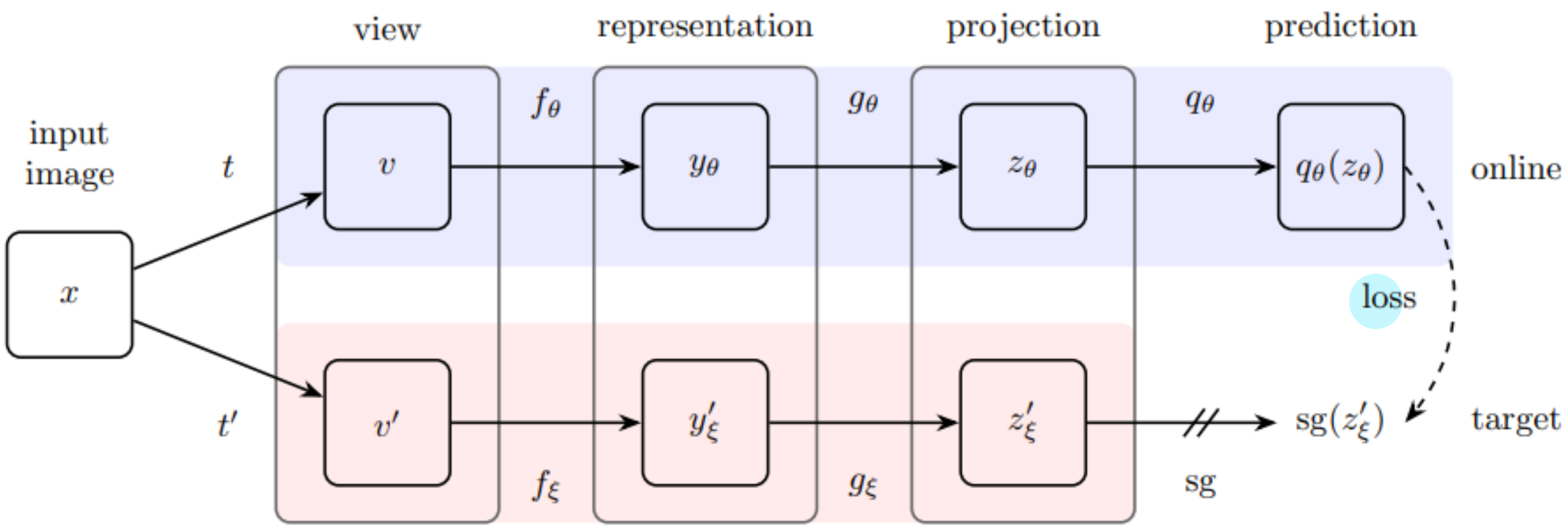
Target network: slow-moving average of the online parameters

- Addition of a predictor to the online network
  - making the architecture asymmetric
- Using the target network encourages encoding more and more information within the online projection and avoids collapsed solutions

J.B. Grill et al., Bootstrap Your Own Latent, 2020

BYOL: Bootstrap Your Own Latent

- Doesn't need negative pairs
- Uses two networks (online and target), that interact and learn from each other



$$\overline{q_\theta}(z_\theta) \triangleq q_\theta(z_\theta)/\|q_\theta(z_\theta)\|_2$$

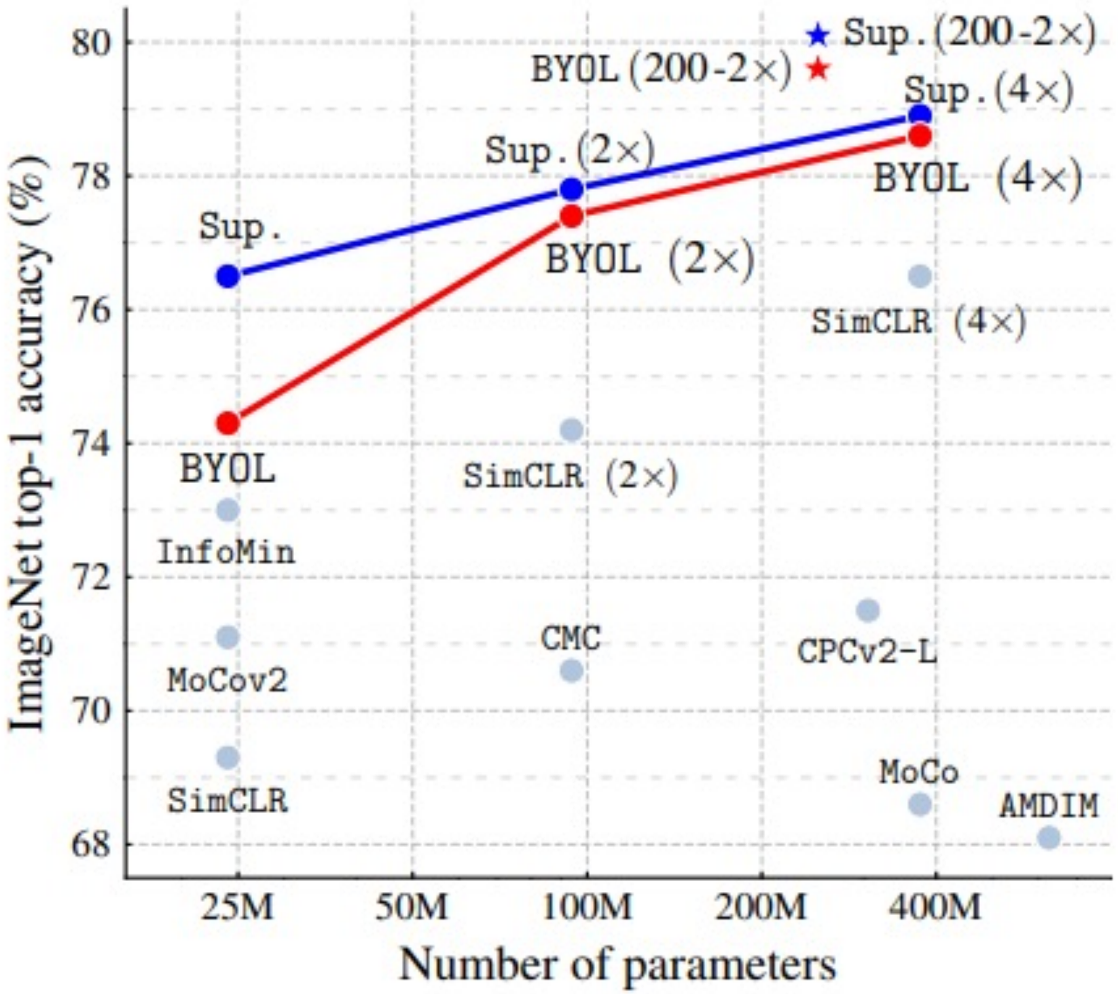
$$\overline{z}'_\xi \triangleq z'_\xi/\|z'_\xi\|_2$$

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

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

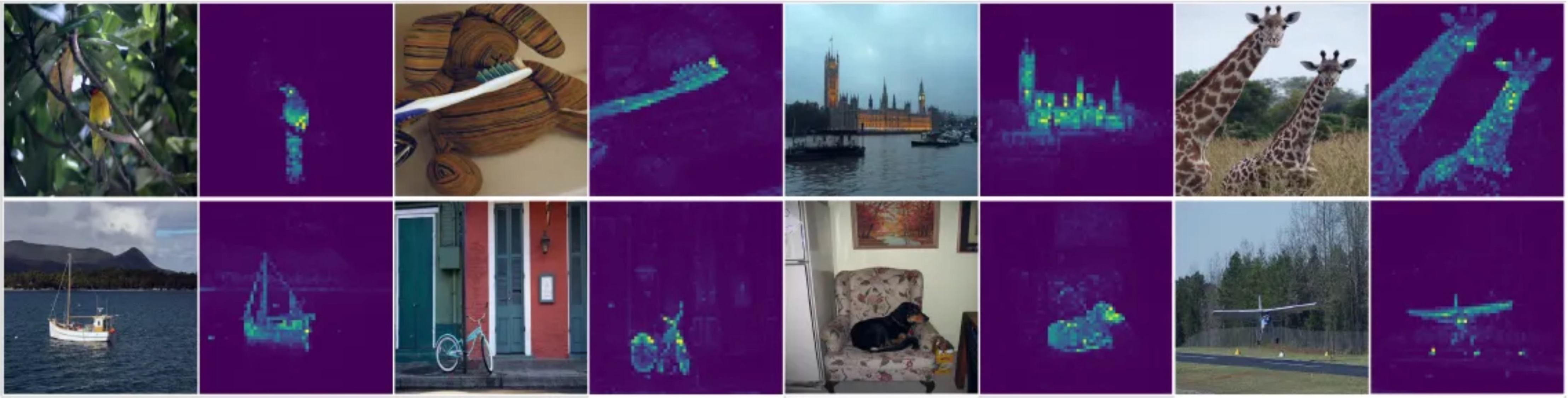
[J.B. Grill et al., Bootstrap Your Own Latent, 2020](#)

BYOL: Results



[J.B. Grill et al., Bootstrap Your Own Latent, 2020]

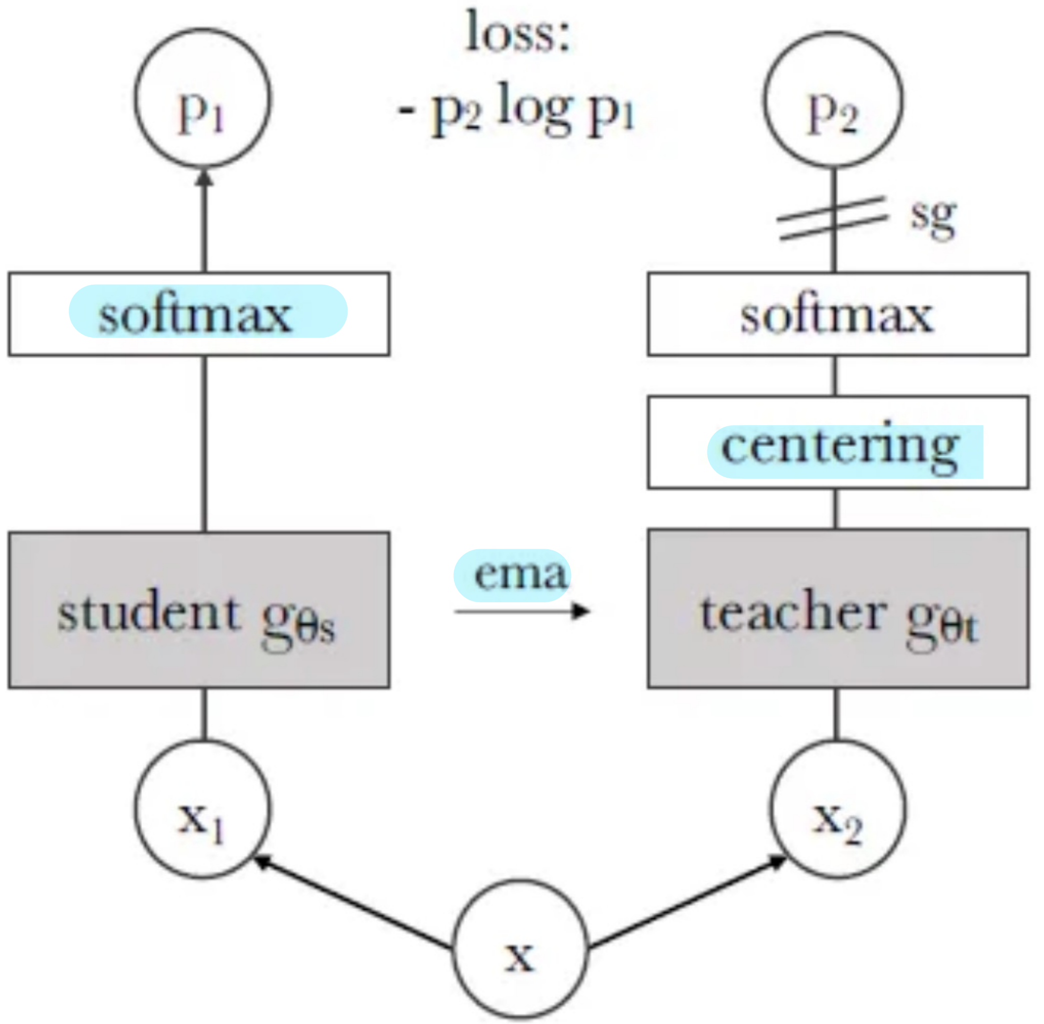
DINO



Caron et al., Emerging Properties in Self-Supervised Vision Transformers, 2022

DINO

- DINO is inspired from BYOL



[Caron et al., Emerging Properties in Self-Supervised Vision Transformers, 2022]()

DINO

	Method	Mom.	SK	MC	Loss	Pred.	k-NN	Lin.
1	DINO	✓	✗	✓	CE	✗	72.8	76.1
2		✗	✗	✓	CE	✗	0.1	0.1
3		✓	✓	✓	CE	✗	72.2	76.0
4		✓	✗	✗	CE	✗	67.9	72.5
5		✓	✗	✓	MSE	✗	52.6	62.4
6		✓	✗	✓	CE	✓	71.8	75.6
7	BYOL	✓	✗	✗	MSE	✓	66.6	71.4
8	MoCov2	✓	✗	✗	INCE	✗	62.0	71.6
9	SwAV	✗	✓	✓	CE	✗	64.7	71.8

SK: Sinkhorn-Knopp, MC: Multi-Crop, Pred.: Predictor
CE: Cross-Entropy, MSE: Mean Square Error, INCE: InfoNCE

[Caron et al., Emerging Properties in Self-Supervised Vision Transformers, 2022]

Summary: Contrastive Representation Learning

A general formulation for contrastive learning:

$$\text{score}(f(x), f(x^+)) >> \text{score}(f(x), f(x^-))$$

InfoNCE loss: N-way classification among positive and negative samples

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+))}{\exp(s(f(x), f(x^+)) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))} \right]$$

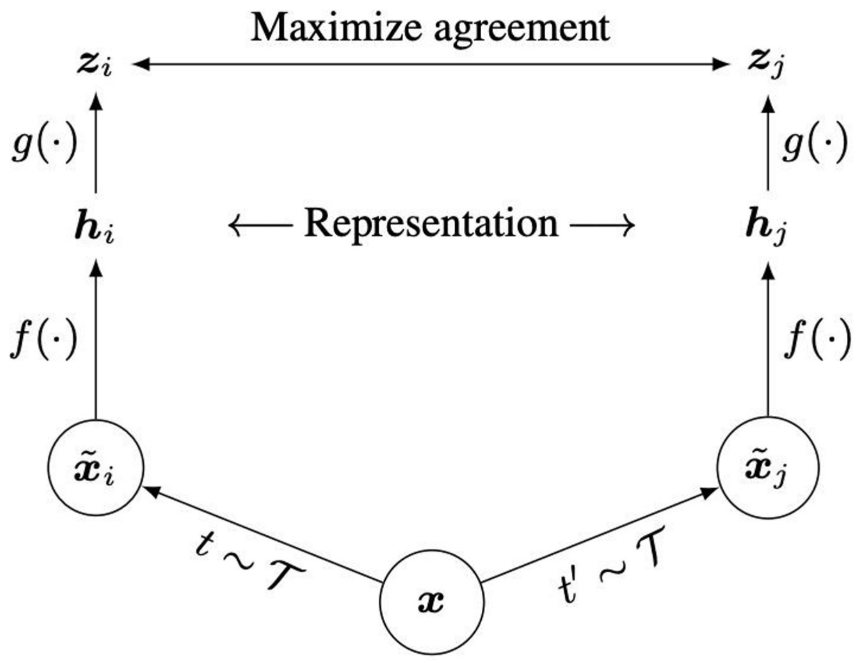
Commonly known as the InfoNCE loss (van den Oord et al., 2018)
A *lower bound* on the mutual information between *f(x)* and *f(x⁺)*

$$MI[f(x), f(x^+)] - \log(N) \geq -L$$

Summary: Contrastive Representation Learning

SimCLR: a simple framework for contrastive representation learning

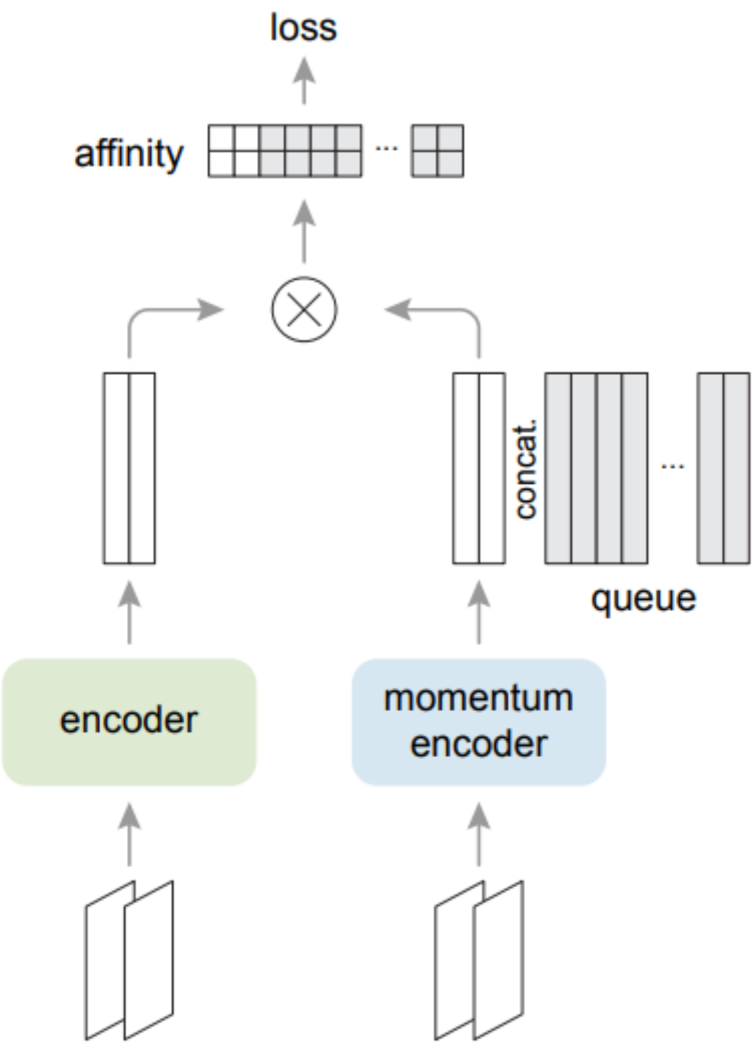
- **Key ideas**: non-linear projection head to allow flexible representation learning
- Simple to implement, effective in learning visual representation
- Requires large training batch size to be effective; large memory footprint



Summary: Contrastive Representation Learning

MoCo (v1, v2): contrastive learning using momentum sample encoder

- Decouples negative sample size from minibatch size; allows large batch training without TPU
- MoCo-v2 combines the key ideas from SimCLR, i.e., nonlinear projection head, strong data augmentation, with momentum contrastive learning

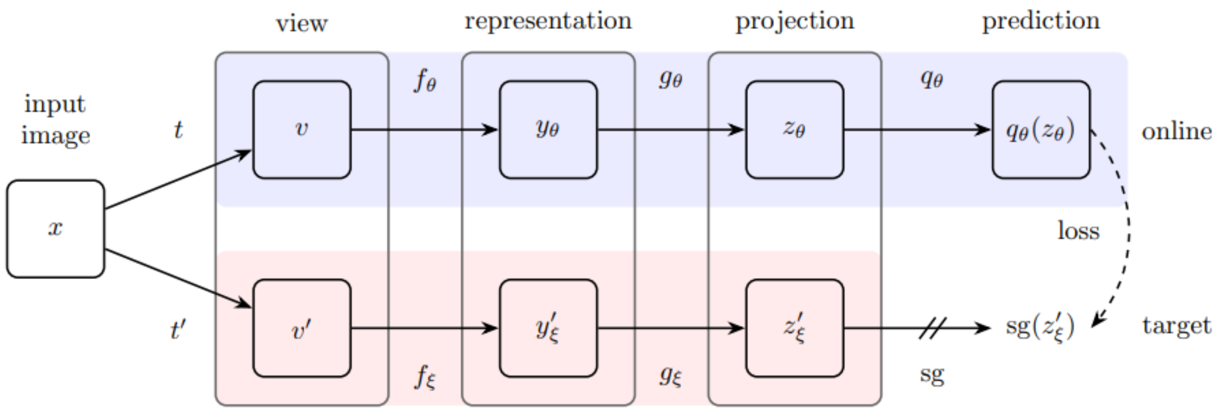


Summary: Self-Supervised Approaches w.o. negative pairs

Self-supervised learning without utilizing negative pairs

- Doesn't need large minibatch size

BYOL



Today's Agenda

Pretext tasks from image transformations

- Rotation, rearrangement, coloring

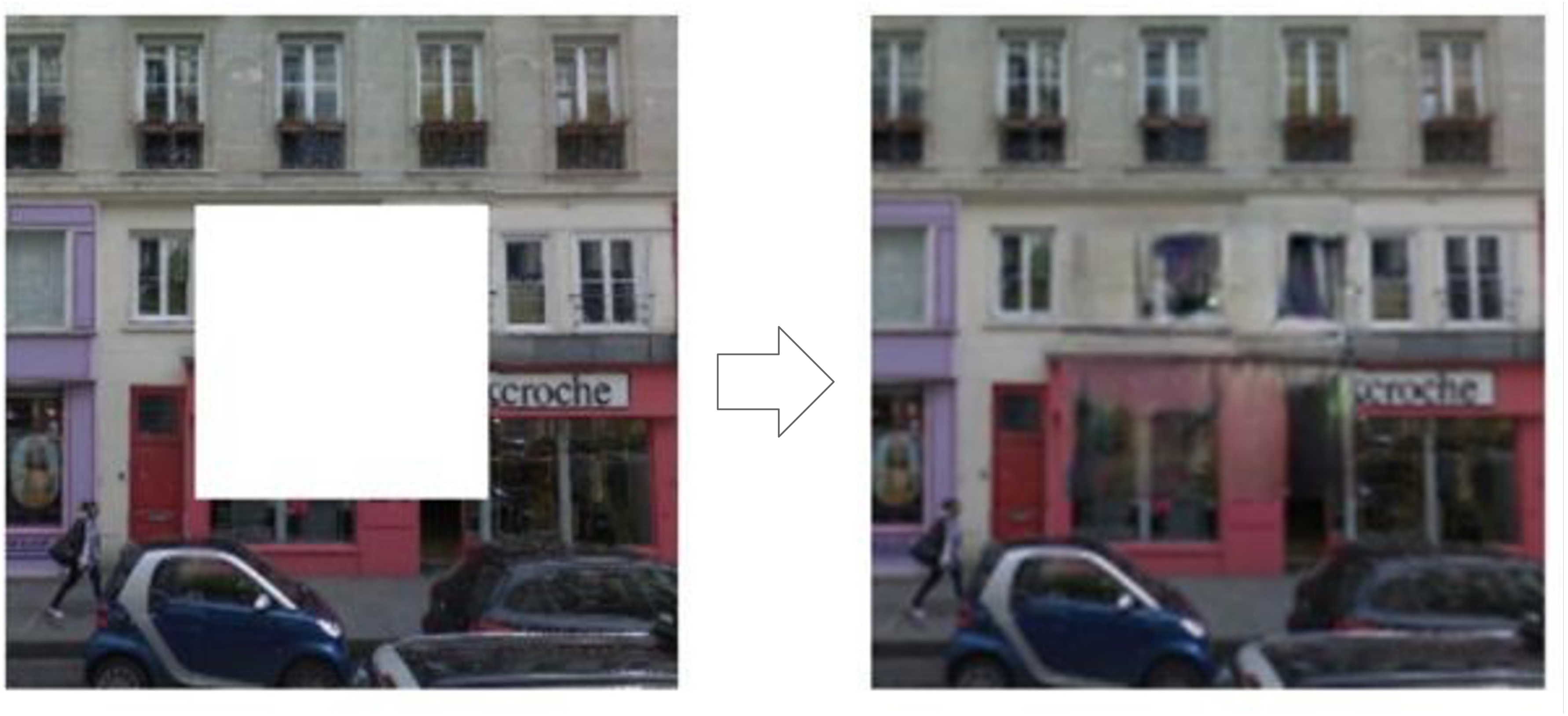
Contrastive representation learning

- Intuition and formulation
- Instance contrastive learning: SimCLR and MOCO
- More recent methods

Generative algorithms

- Pretext impainting task
- Masked Image Modeling

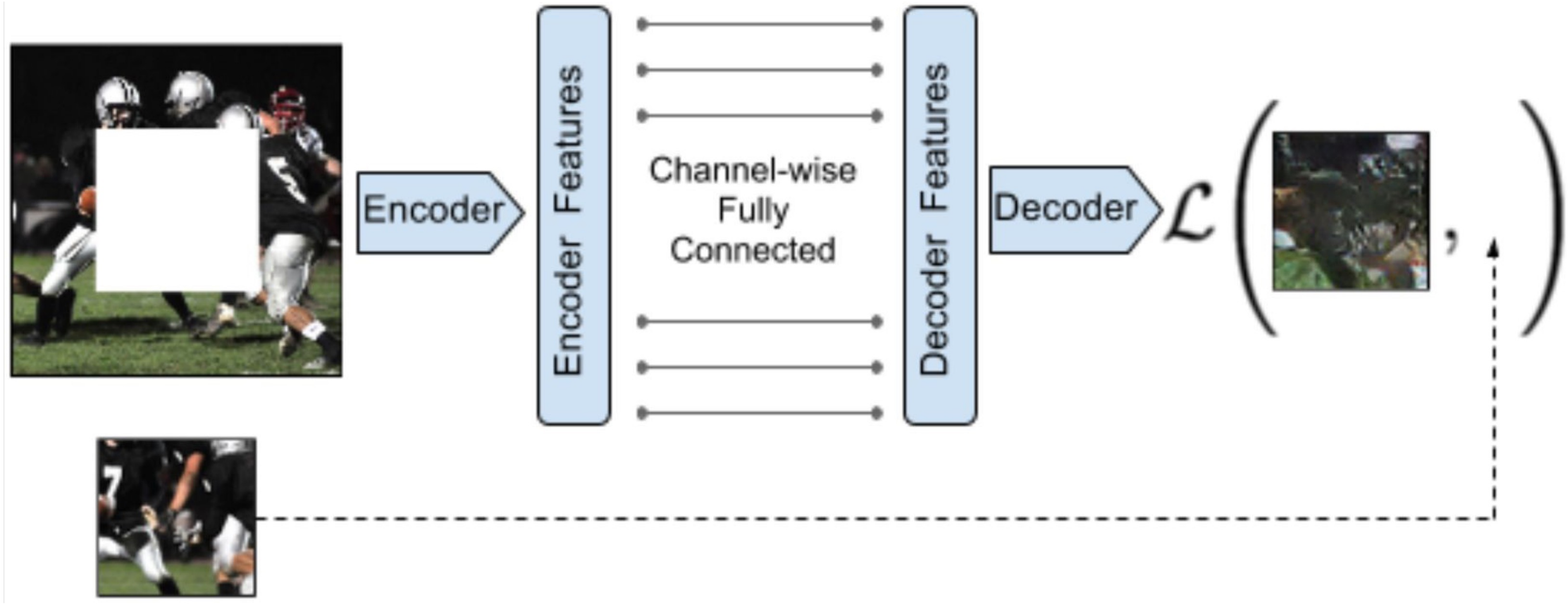
Pretext task: predict missing pixels (inpainting)



Context Encoders: Feature Learning by Inpainting (Pathak et al., 2016)

[Pathak et al., Context Encoders: Feature Learning by Inpainting, 2016]

Learning to inpaint by reconstruction



Learning to reconstruct the missing pixels

[Pathak et al., Context Encoders: Feature Learning by Inpainting, 2016](#)

Inpainting evaluation

Input (context)

reconstruction

Pathak et al., Context Encoders: Feature Learning by Inpainting, 2016

Learning to inpaint by reconstruction

Loss = reconstruction + adversarial learning

$$L(x) = L_{recon}(x) + L_{adv}(x)$$

$$L_{recon}(x) = ||M * (x - F_\theta((1 - M) * x))||_2^2$$

$$L_{adv} = \max_D \mathbb{E}[\log(D(x))] + \log(1 - D(F((1 - M) * x)))]$$

Adversarial loss between “real” images and *inpainted images*

[Pathak et al., Context Encoders: Feature Learning by Inpainting, 2016](#)

Inpainting evaluation

Input (context) reconstruction adversarial recon + adv

Pathak et al., Context Encoders: Feature Learning by Inpainting, 2016

Transfer learned features to supervised learning

Pretraining Method	Supervision	Pretraining time	Classification	Detection	Segmentation
ImageNet [26]	1000 class labels	3 days	78.2%	56.8%	48.0%
Random Gaussian	initialization	< 1 minute	53.3%	43.4%	19.8%
Autoencoder	-	14 hours	53.8%	41.9%	25.2%
Agrawal *et al.* [1]	egomotion	10 hours	52.9%	41.8%	-
Wang *et al.* [39]	motion	1 week	58.7%	47.4%	-
Doersch *et al.* [7]	relative context	4 weeks	55.3%	46.6%	-
Ours	context	14 hours	56.5%	44.5%	30.0%

Self-supervised learning on ImageNet training set, transfer to classification (Pascal VOC 2007), detection (Pascal VOC 2007), and semantic segmentation (Pascal VOC 2012)

Pathak et al., Context Encoders: Feature Learning by Inpainting, 2016

Masked Image Modeling (MIM)

- MIM leverages co-occurrence relationships among image patches as supervision signals

- Masking certain patches of the original image and subsequently recovering the masked information.
  - MIM represents a variant of the denoising AE (DAE) emphasizing the importance of a robust representation that remains resilient to input noise.

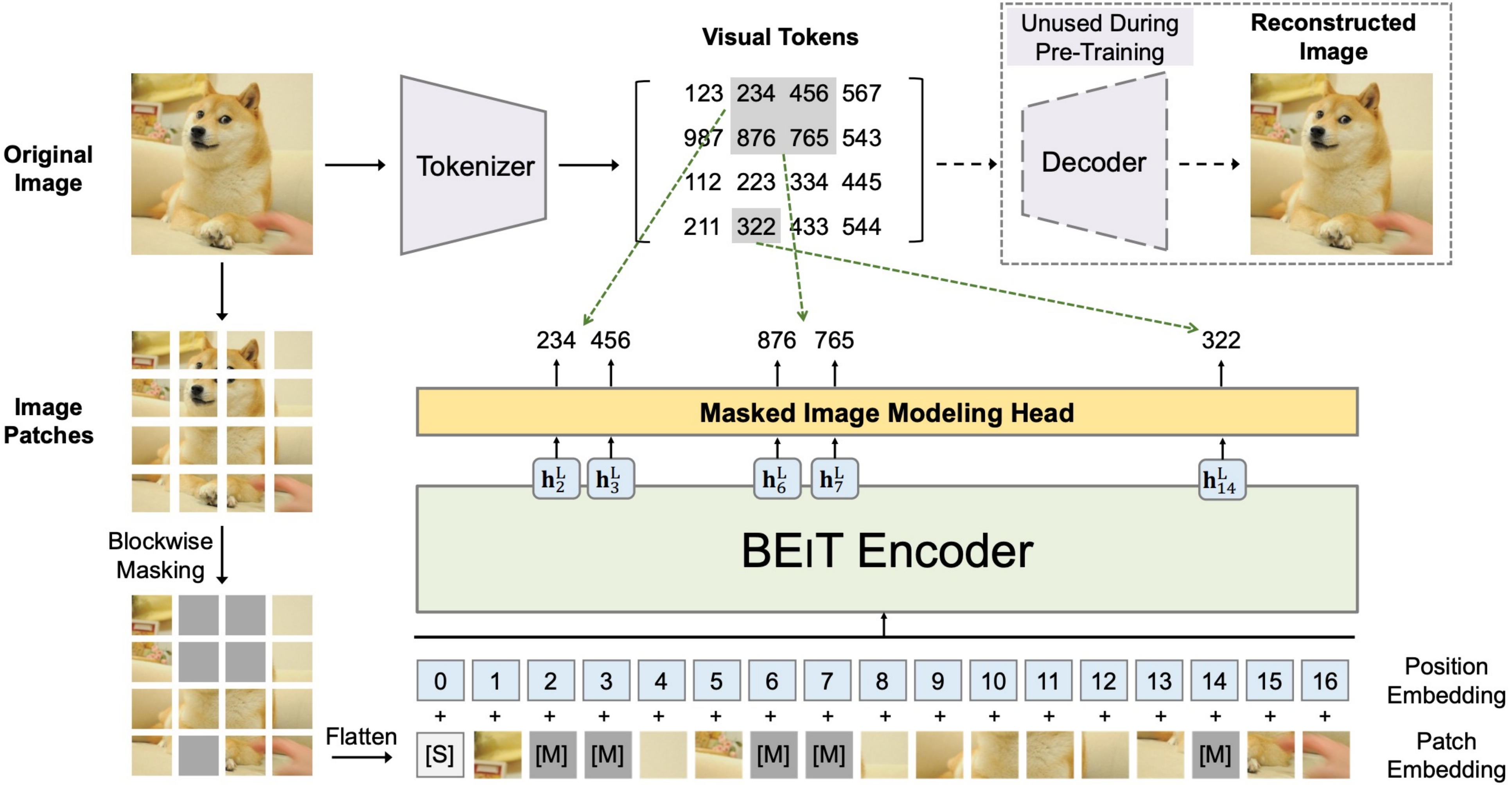
Masked Image Modeling (MIM)

- Low-level targets: treats the task as a regression problem with the original pixels as its target
  - Masked Autoencoder (MAE)

- High-level targets: breaks down the input image into discrete visual tokens, and then randomly masks a subset of the image patches
  - BEiT

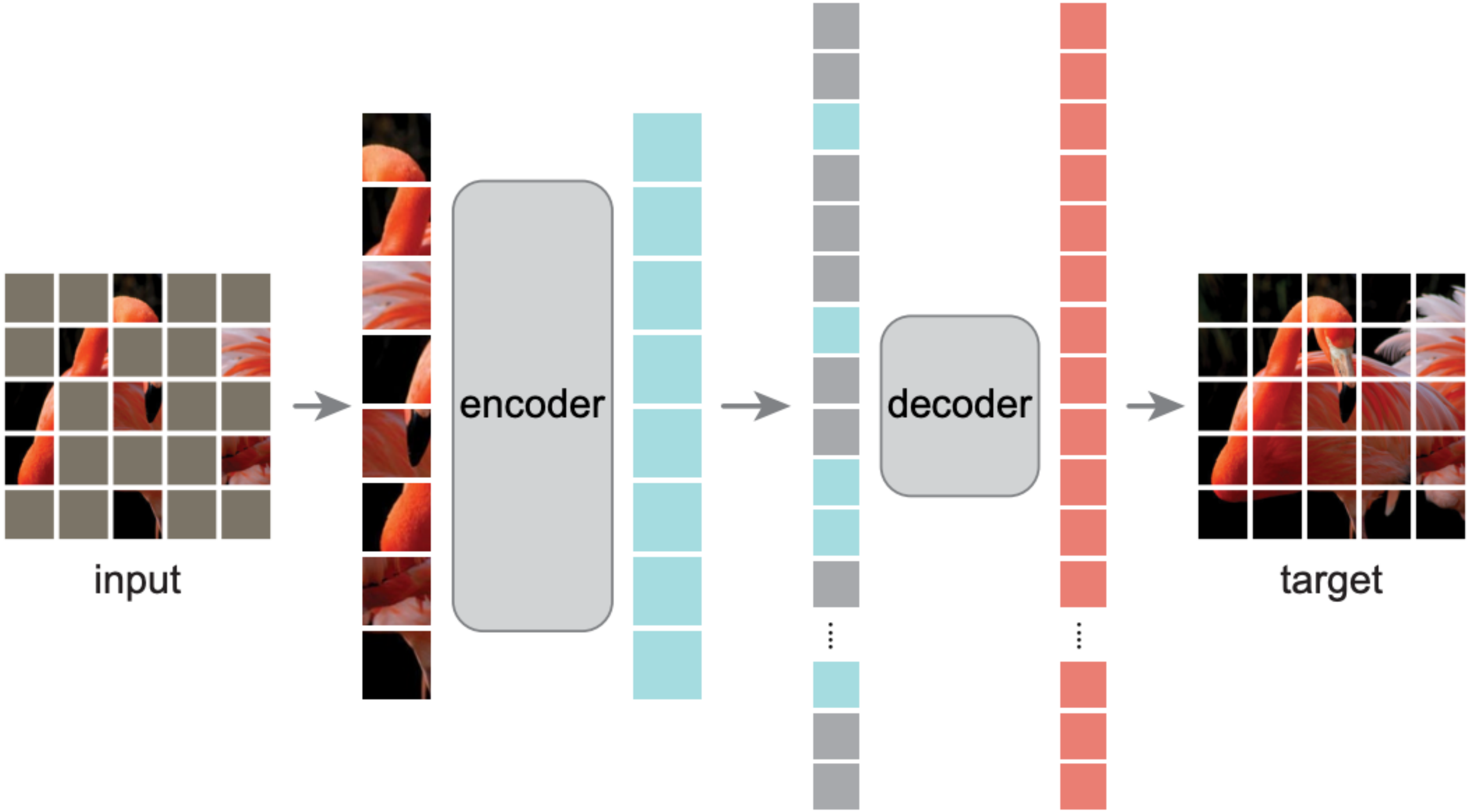
BEiT

- Bidirectional Encoder representation from Image Transformers



[Bao et al., BEIT: BERT Pre-Training of Image Transformers, 2022](#)

Masked Auto-Encoder (MAE)



He et al., Masked Autoencoders Are Scalable Vision Learners, 2021

Masked Auto-Encoder (MAE)

- Comparisons with previous results on ImageNet1K.

method	pre-train data	ViT-B	ViT-L	ViT-H	ViT-H_{448}
scratch, our impl.	-	82.3	82.6	83.1	-
DINO [5]	IN1K	82.8	-	-	-
MoCo v3 [9]	IN1K	83.2	84.1	-	-
BEiT [2]	IN1K+DALLE	83.2	85.2	-	-
MAE	IN1K	83.6	85.9	86.9	**87.8**

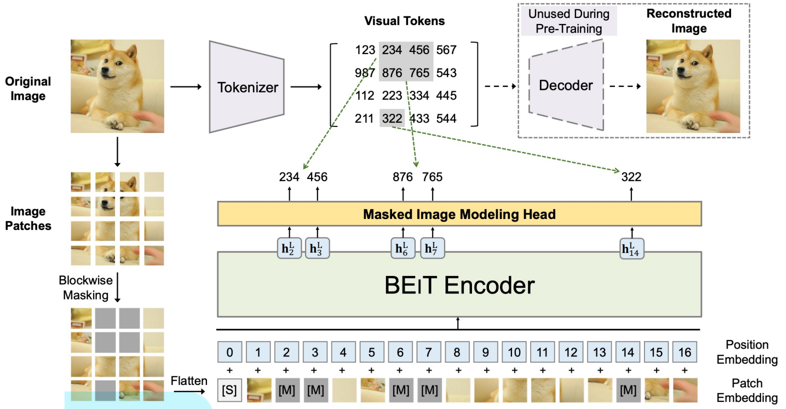
Bao et al., BEIT: BERT Pre-Training of Image Transformers, 2022

Summary: Masked Image Modeling

Autoencoder based models: a variant of the denoising AE

High-Level Targets

BEiT



Low-Level Targets

MAE