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Self-Supervised Learning

Good-old-fashioned SSL

Sungjoon Choi, Korea University

kakaobrain

Introduction

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What is self-supervised learning?

Self-Supervised Learning

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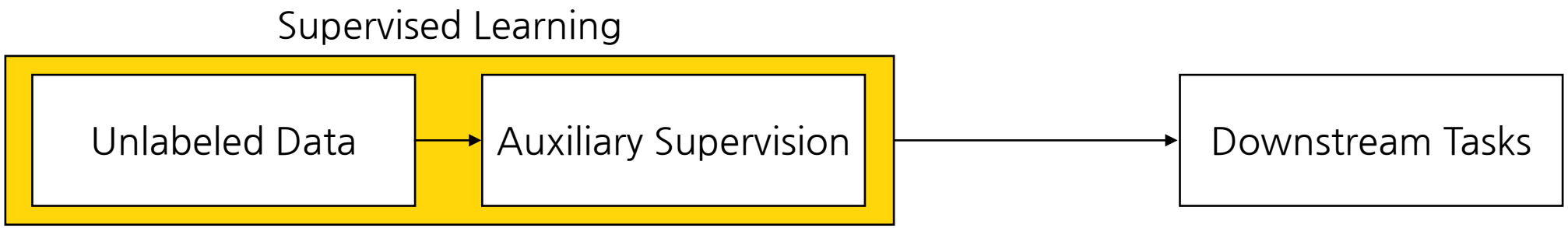

Caution

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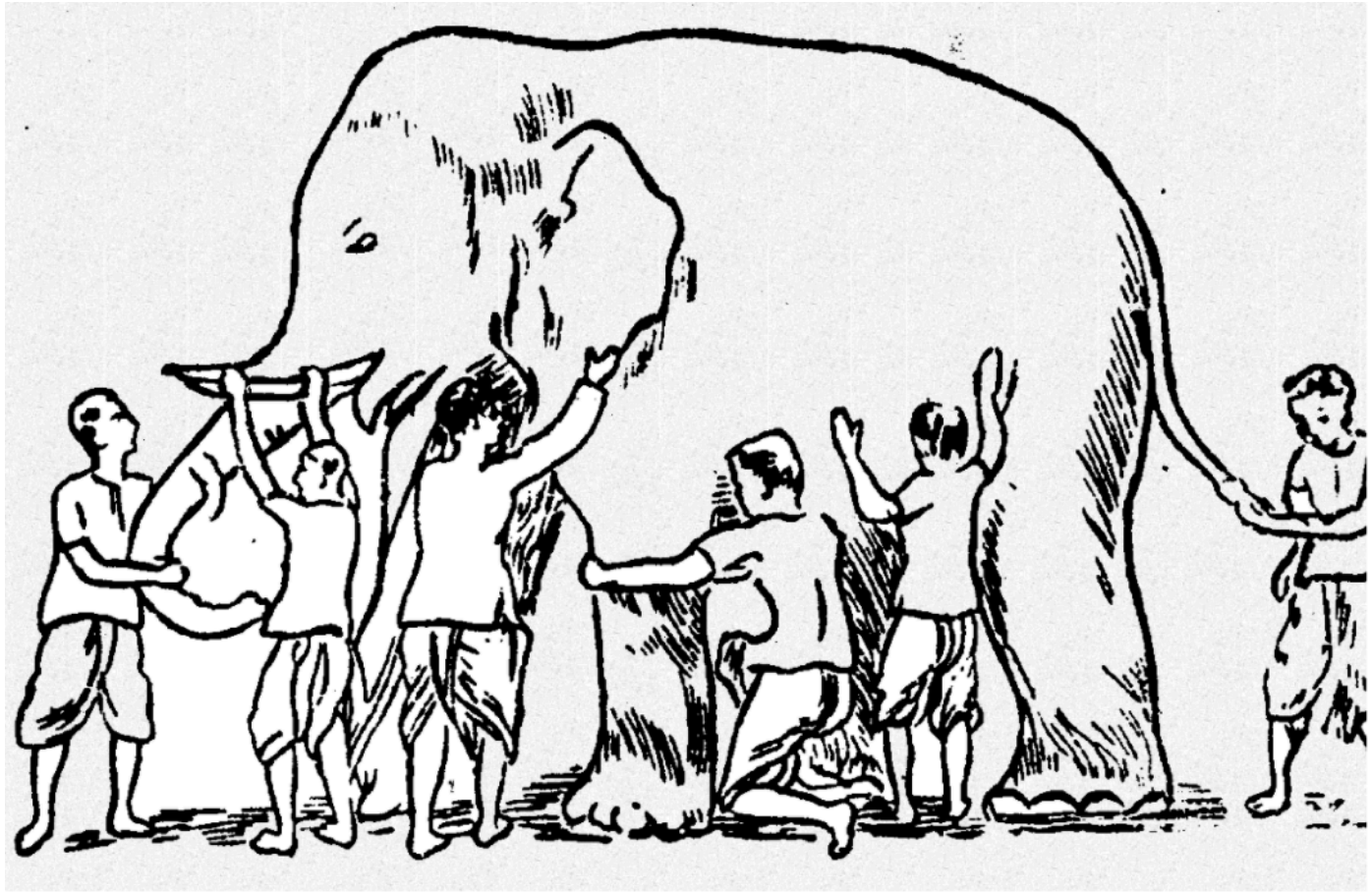

Contents

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Jigsaw

"Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles," 2017

Jigsaw Puzzles

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https://www.t3.com/news/where-to-buy-jigsaw-puzzles

Jigsaw Puzzle Reassembly

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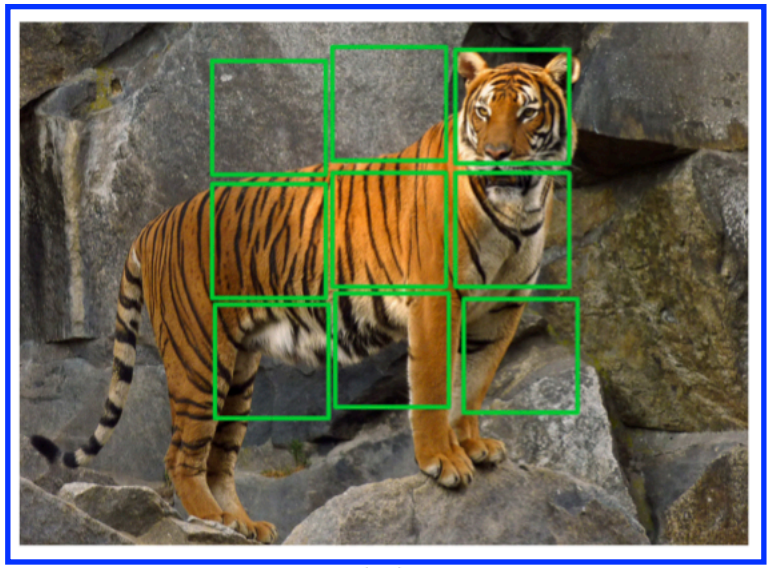
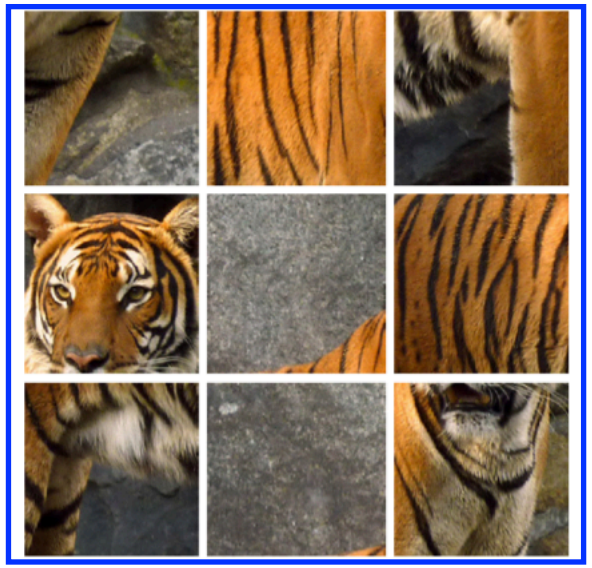
Select **patches** from an image



Shuffle **patches**



Reassemble **patches**

Context-Free Architecture

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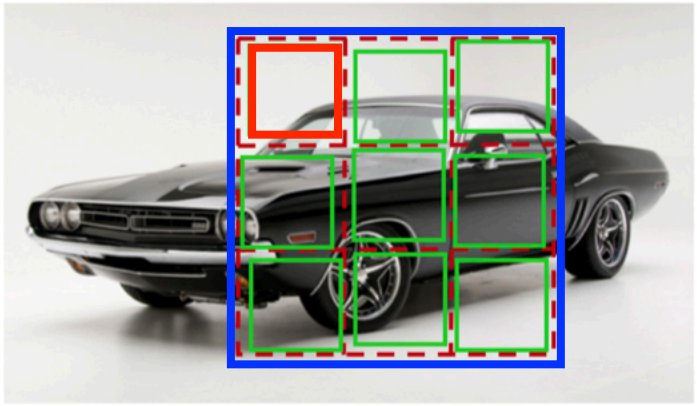
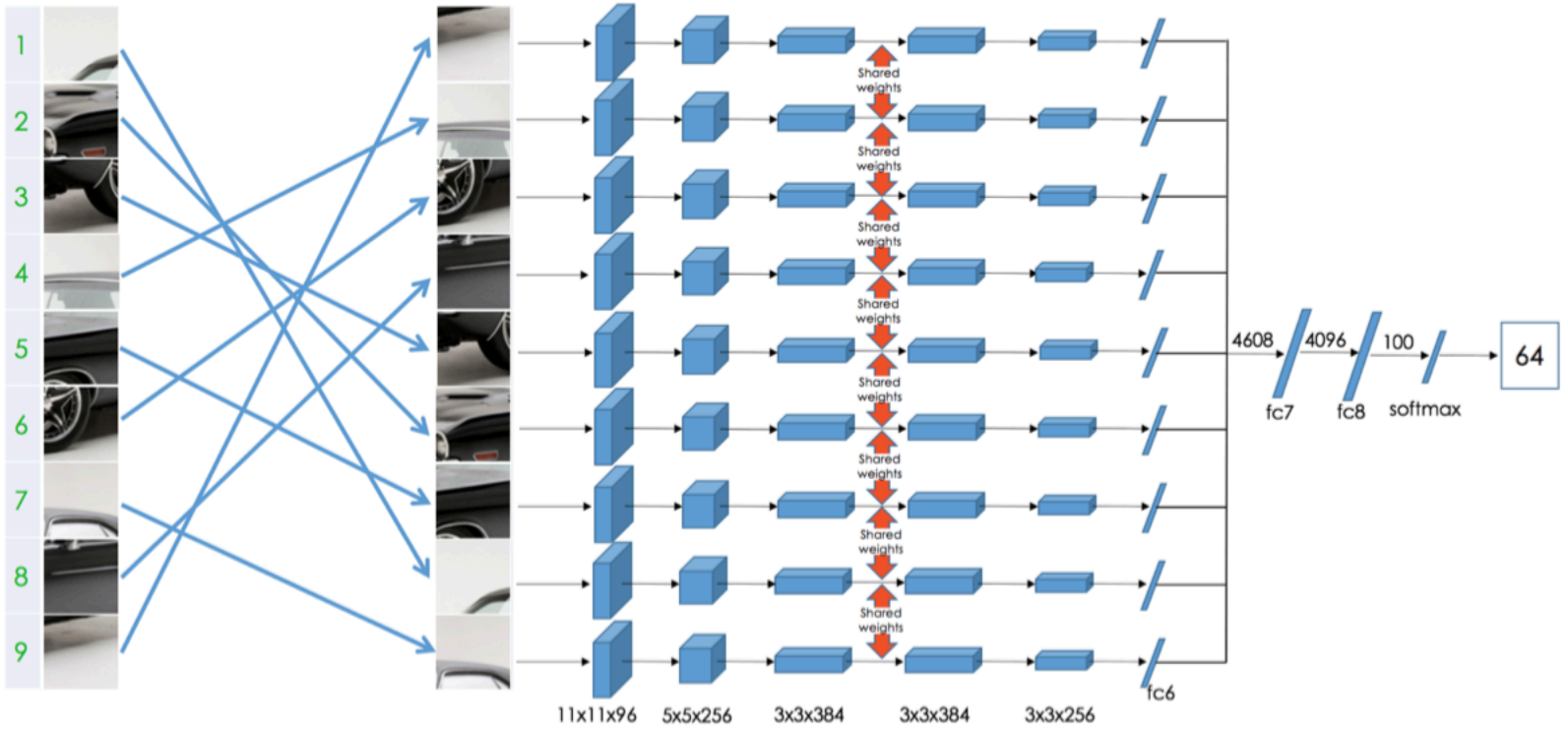


Permutation Set

index	permutation
64	9,4,6,8,3,2,5,1,7

Reorder patches according to the selected permutation



Given an image, context-free architecture randomly crop 225×225 **pixel window**, and randomly pick a 64×64 **pixel tiles** from each 75×75 pixel cell.

Context-Free Architecture

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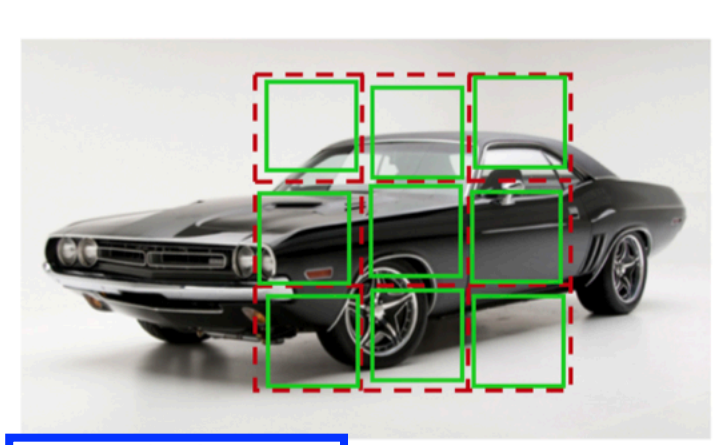

Permutation Set	
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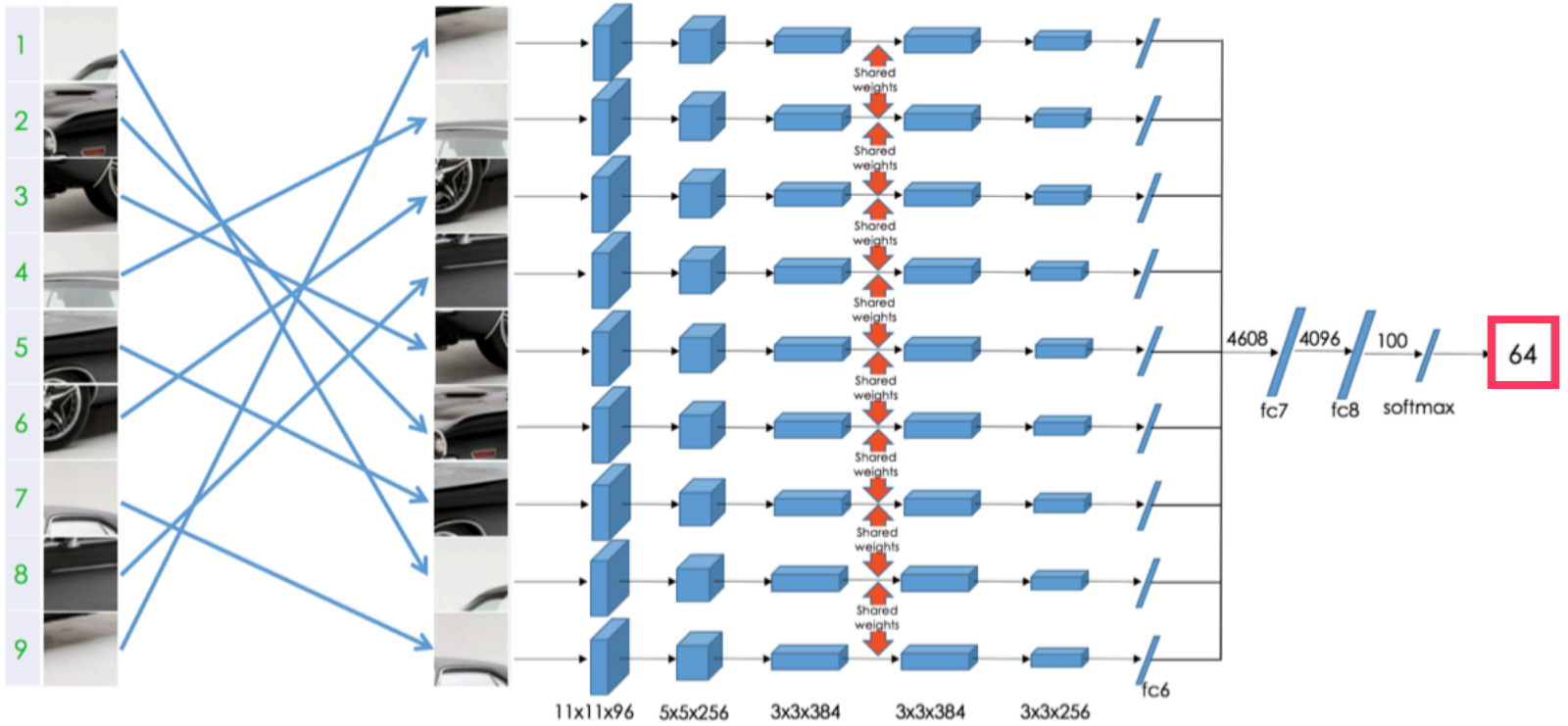

The number of total permutation is $9! = 362{,}880$. However, a subset of a possible permutation set is defined (of size 64) and cast the reassembly problem as a classification problem.

Context-Free Architecture

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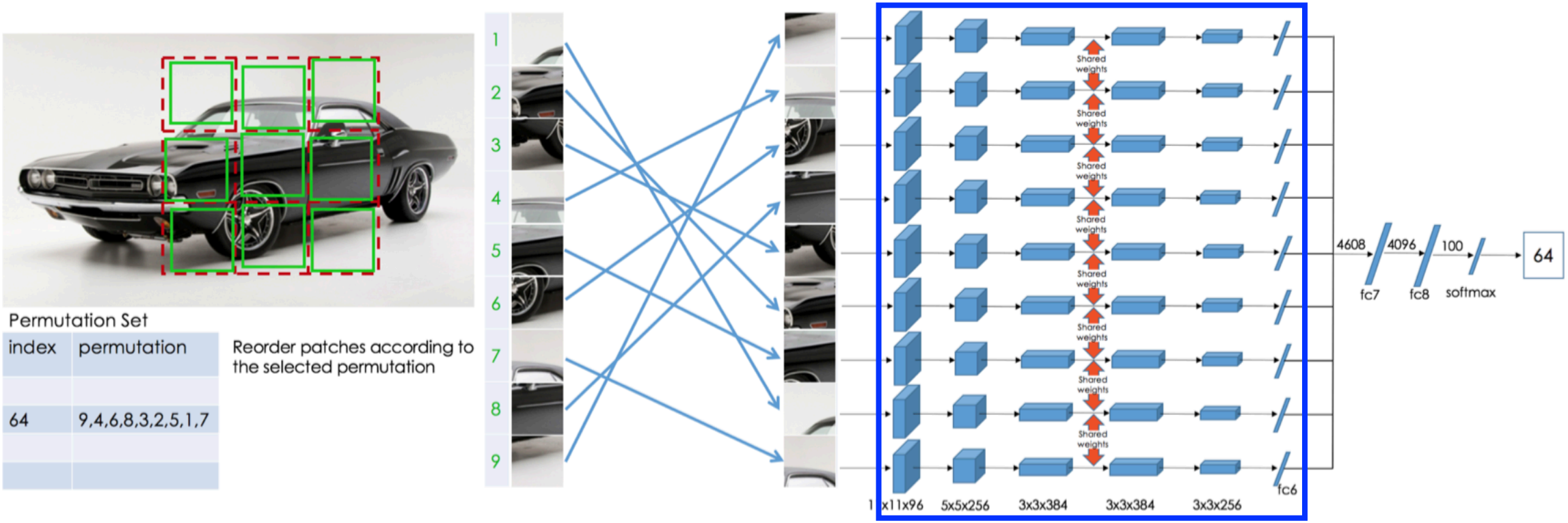

FCN utilizes AlexNet architecture with **weight-sharing** up-to the $fc6$ layer. Nine feature representation vectors are concatenated to predict the permutation class.

Image Retrieval

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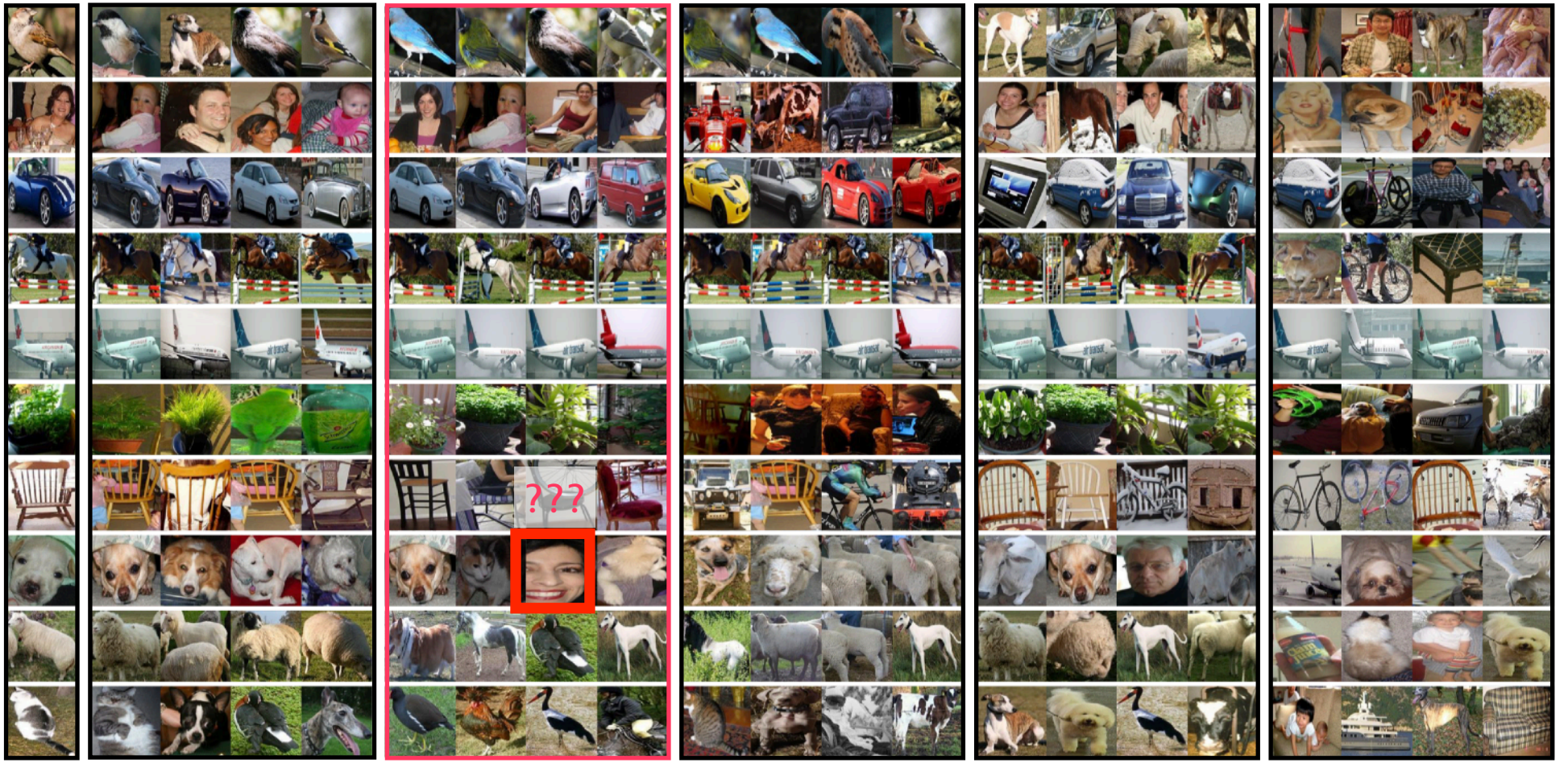

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BiGAN

"ADVERSARIAL FEATURE LEARNING," 2017

Generative Adversarial Net

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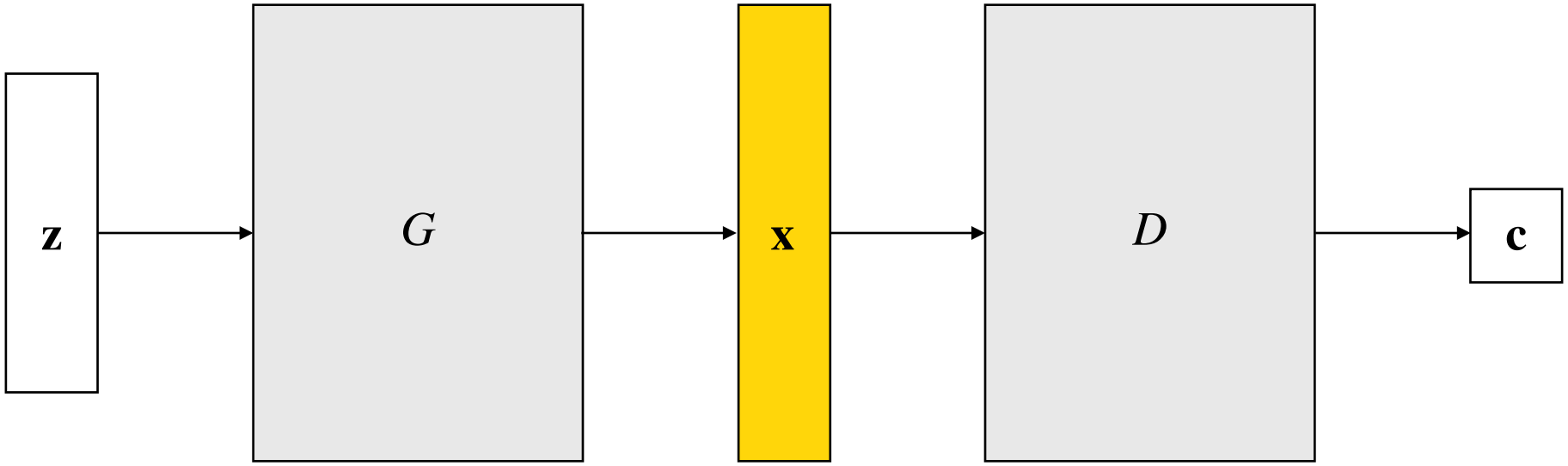

The objective of GAN is to minimize the distance between $p(\mathbf{x})$ and $G(\mathbf{z})$ where $\mathbf{z}$ follows a simple distribution.

Generative Adversarial Net

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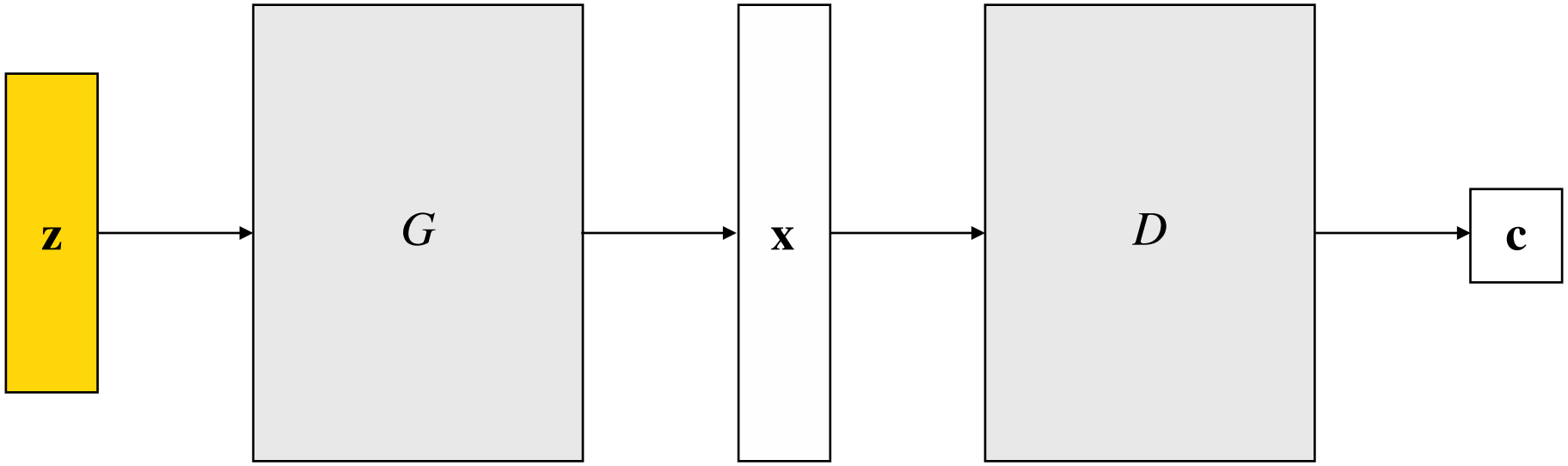
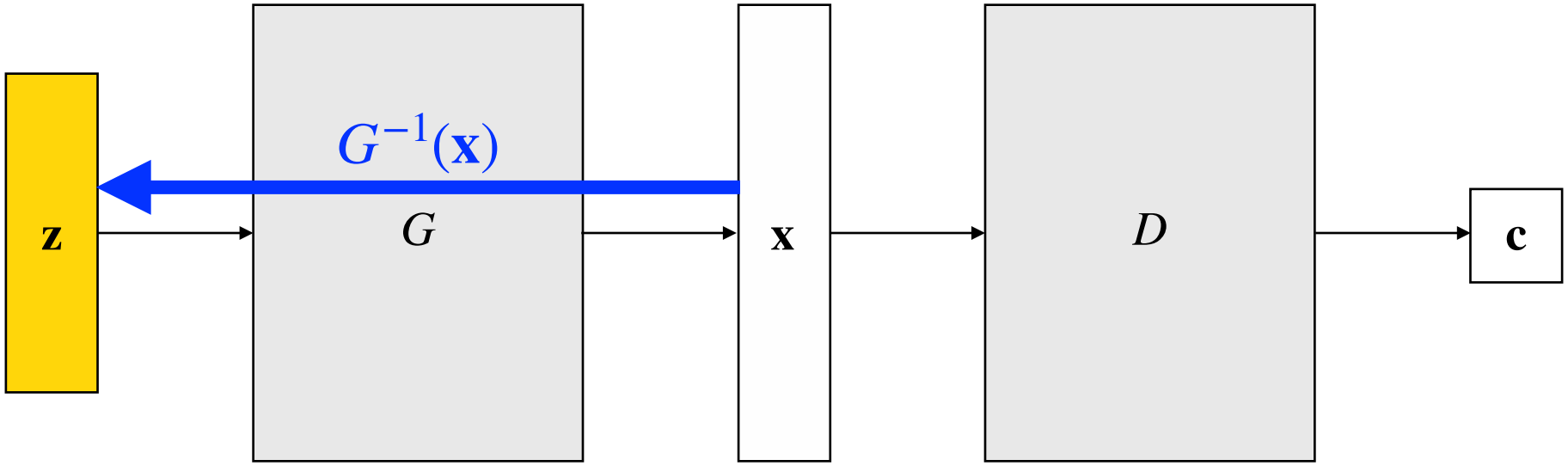


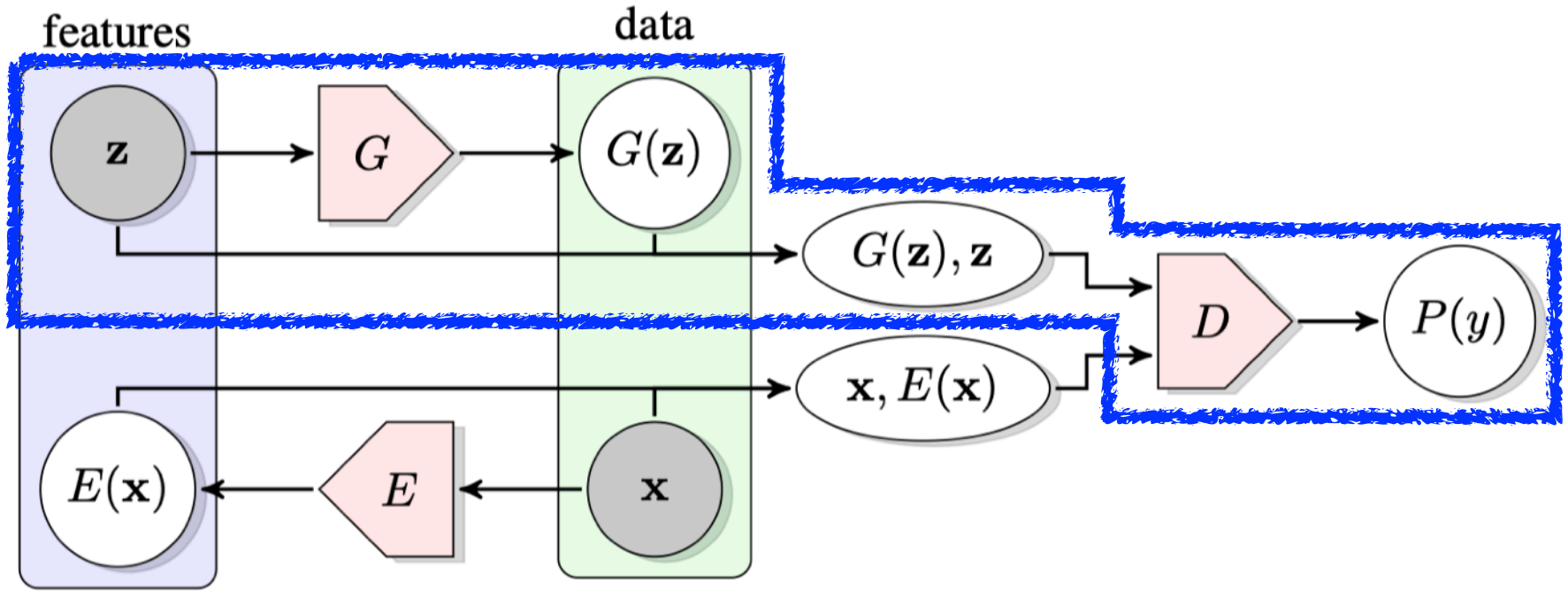
A latent vector $\mathbf{z}$ corresponds to an input $\mathbf{x}$, which can be thought as meaningful representation of $\mathbf{x}$.

Generative Adversarial Net



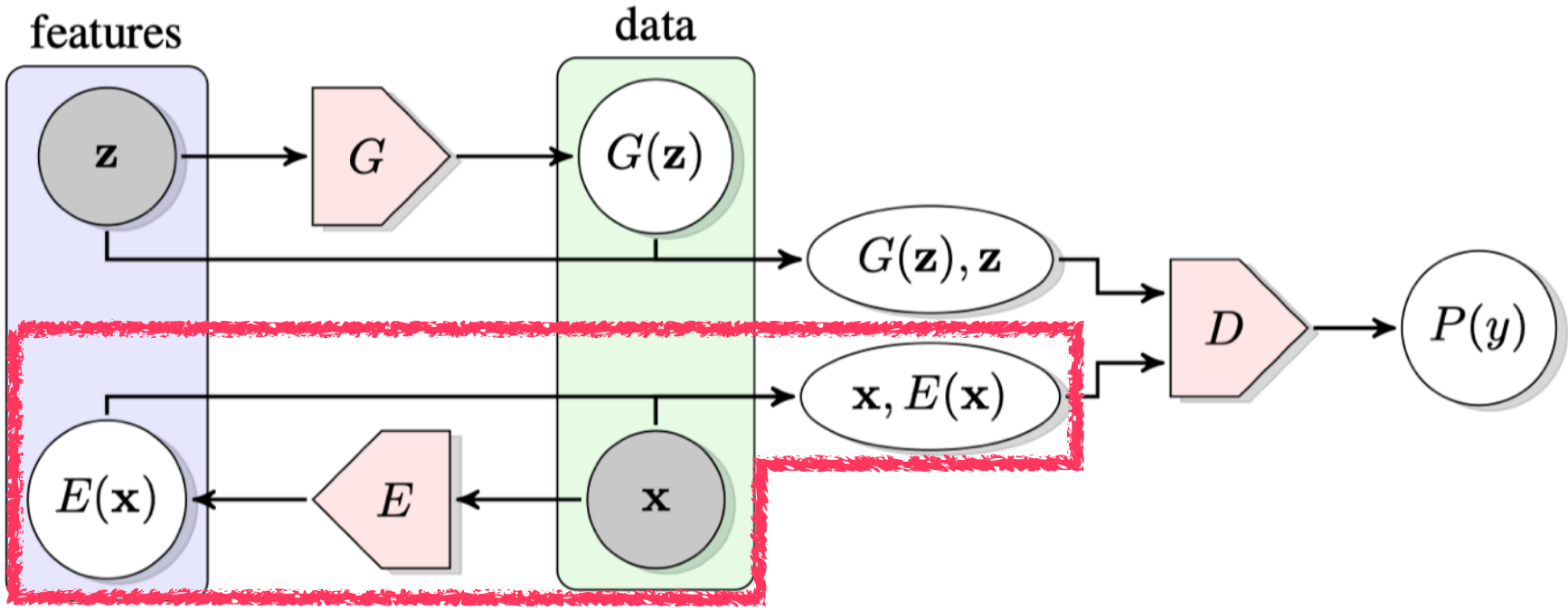
However, there is one remaining problem. G^{-1} does not exist in general.

Bidirectional GAN (BiGAN)



This part is the same as the original GAN

BiGAN



This part is newly added in BiGAN.

BiGAN

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The BiGAN training objective is defined as a minimax objective

$$\min_{G,E} \max_{D} V(D, E, G) \tag{2}$$

where

$$V(D, E, G) := \mathbb{E}_{\mathbf{x} \sim p_{\mathbf{X}}} \big[\underbrace{\mathbb{E}_{\mathbf{z} \sim p_E(\cdot|\mathbf{x})} [\log D(\mathbf{x}, \mathbf{z})]}_{\log D(\mathbf{x}, E(\mathbf{x}))} \big] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{Z}}} \big[\underbrace{\mathbb{E}_{\mathbf{x} \sim p_G(\cdot|\mathbf{z})} [\log (1 - D(\mathbf{x}, \mathbf{z}))]}_{\log(1 - D(G(\mathbf{z}), \mathbf{z}))} \big]. \tag{3}$$

The inputs of the **discriminator** are both $\mathbf{x}$ and $\mathbf{z}$, $D(\mathbf{x}, \mathbf{z})$, (the original discriminator only takes $\mathbf{x}$, i.e., $D(\mathbf{x})$).

BiGAN

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The newly added encoder maps an input $\mathbf{x}$ to a latent vector $\mathbf{z}$.

BiGAN

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To maximize $V(\cdot)$ w.r.t. $D(\cdot)$, the pair of a real image $\mathbf{x}$ and the encoded latent vector $\mathbf{z}' = E(\mathbf{x})$ gets higher value while the pair of a fake image $G(\mathbf{z})$ and the underlying latent vector $\mathbf{z}$ get lower values.

BiGAN

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To maximize $V(\cdot)$ w.r.t. $D(\cdot)$, the pair of a real image $\mathbf{x}$ and the encoded latent vector $\mathbf{z}' = E(\mathbf{x})$ gets higher value while the pair of a fake image $G(\mathbf{z})$ and the underlying latent vector $\mathbf{z}$ get lower values.

To minimize $V(\cdot)$ w.r.t. $E(\cdot)$, the encoder $E(\mathbf{x})$ mimics the inverse of $G(\mathbf{z})$, i.e., $G^{-1}(\mathbf{x})$.

BiGAN

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The BiGAN training objective is defined as a minimax objective

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An interesting idea of BiGAN is that the training objective of the encoder $E(\mathbf{x})$ is **NOT** directily minimizing $\|E\left(G(\mathbf{z})\right) - \mathbf{z}\|_2^2$.

Reconstruction

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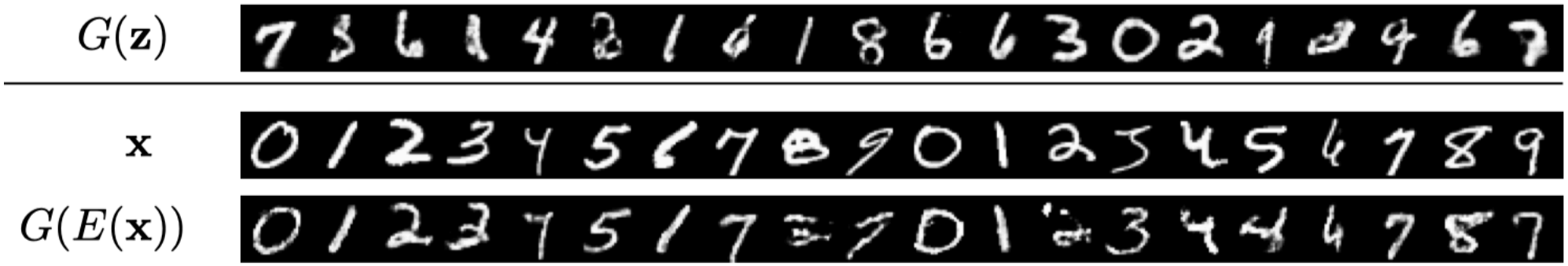

Reconstruction

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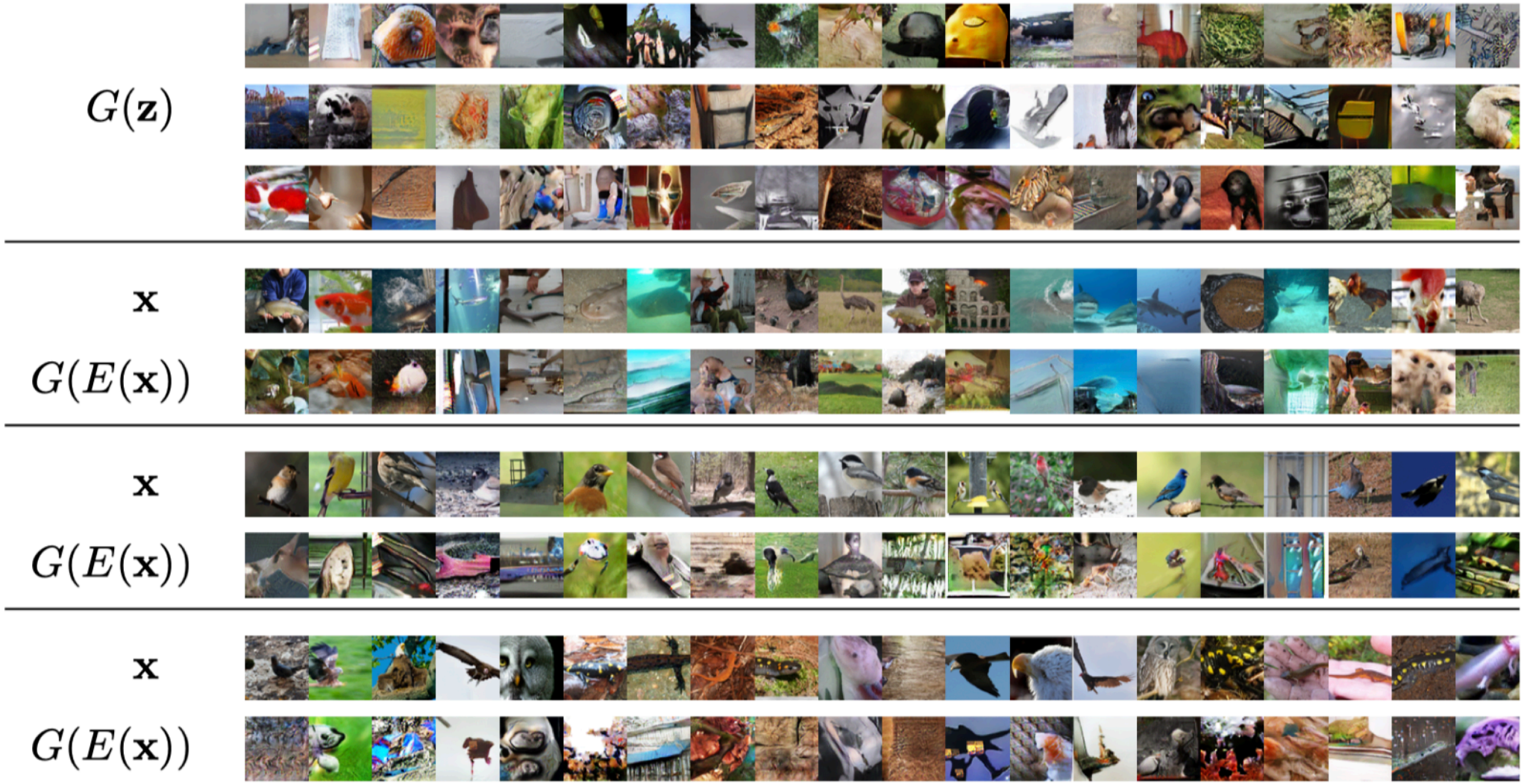

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RotNet

"UNSUPERVISED REPRESENTATION LEARNING BY PREDICTING IMAGE ROTATIONS," 2018

Intuition

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What kind of **supervision** can get out of these images?

Intuition

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

Predict the **rotated angle** of the original image!

Self-supervised Task

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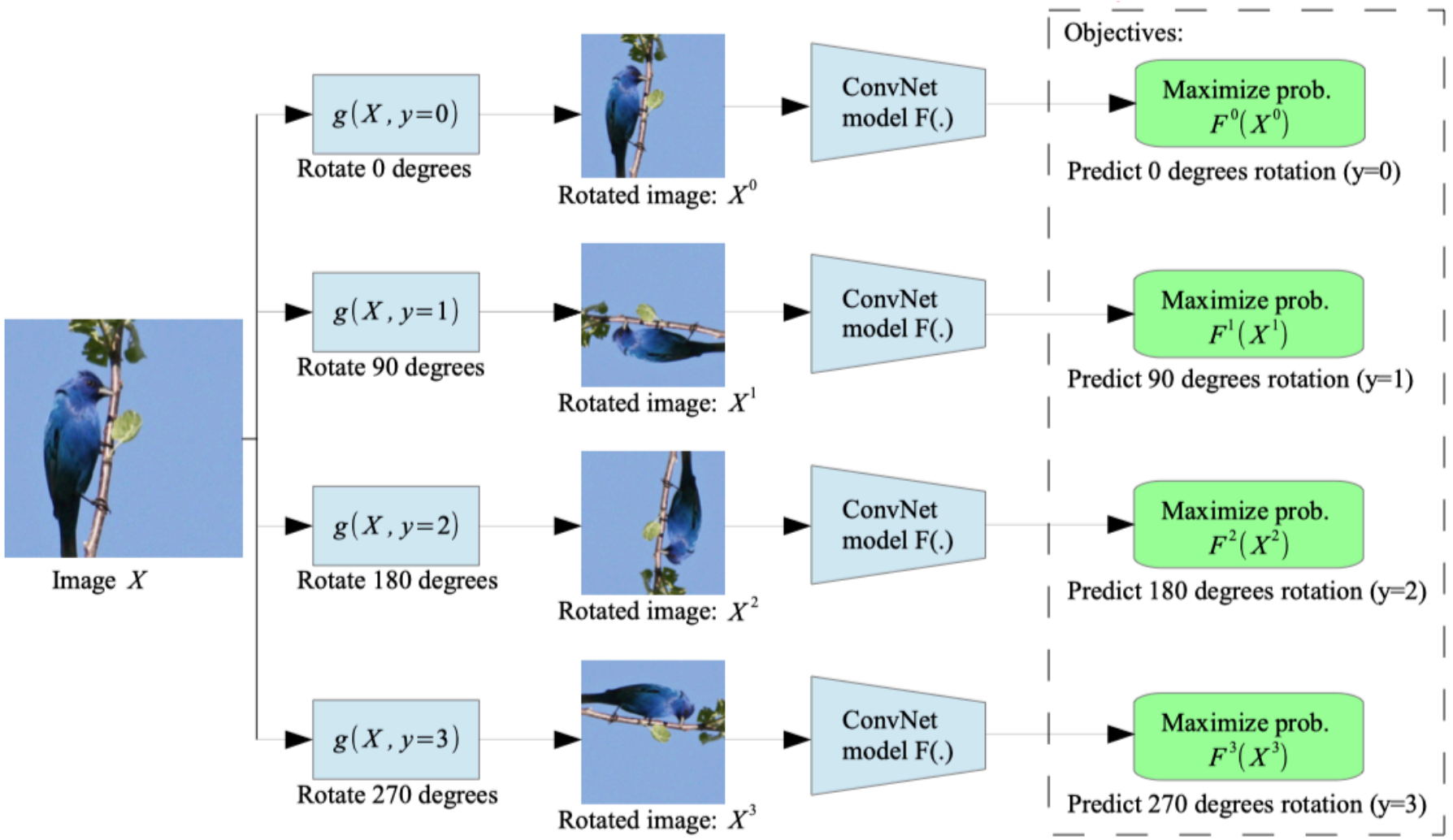

Attention Maps

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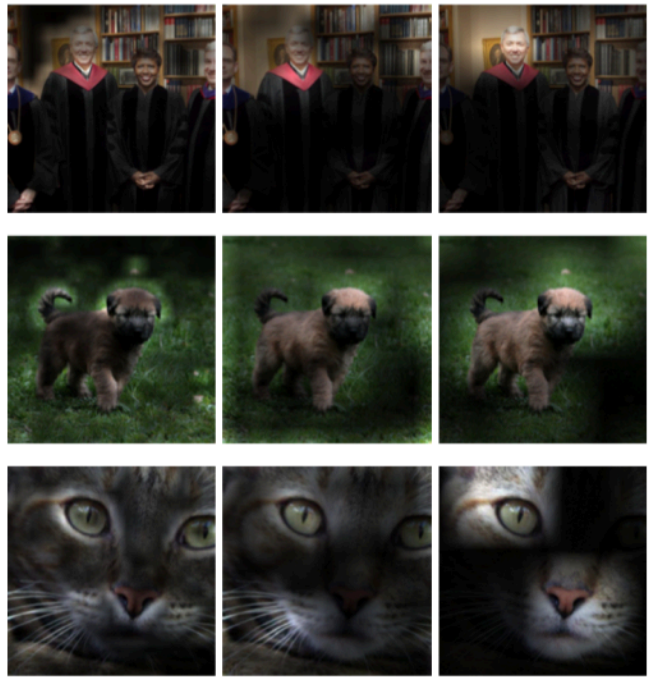
Input images on the models

Conv1 27 × 27 Conv3 13 × 13 Conv5 6 × 6

(a) **Attention maps of supervised model**



Conv1 27 × 27 Conv3 13 × 13 Conv5 6 × 6

(b) **Attention maps of our self-supervised model**

*Attention map is computed based on the magnitude of activations at each spatial cell.

Experiments

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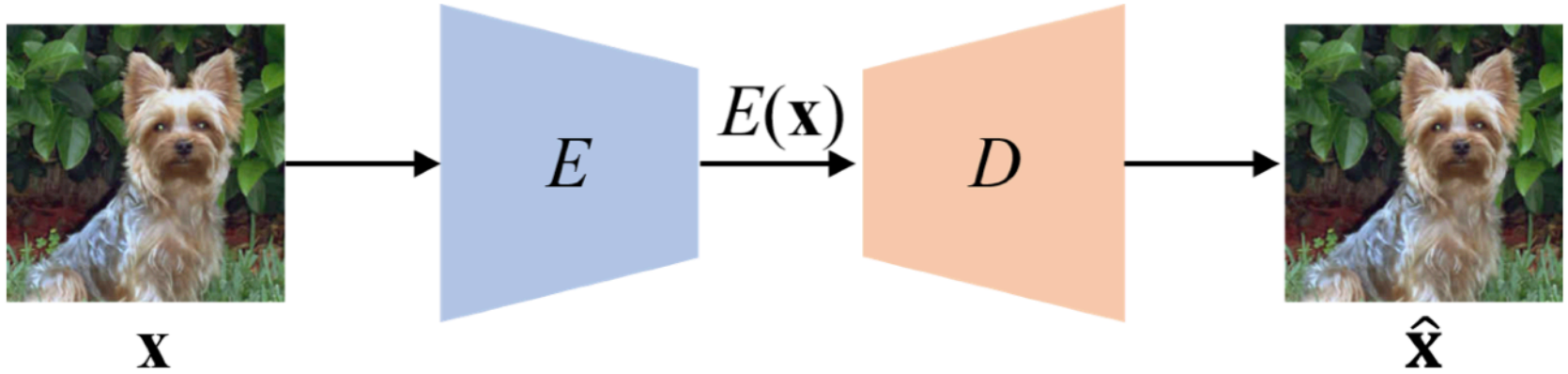
- Multiple experiments including unsupervised feature learning for
  - ImageNet classification
  - PASCAL classification
  - PASCAL detection
  - PASCAL segmentation
  - CIFAR-10 classification

Auto-Encoding Transformations

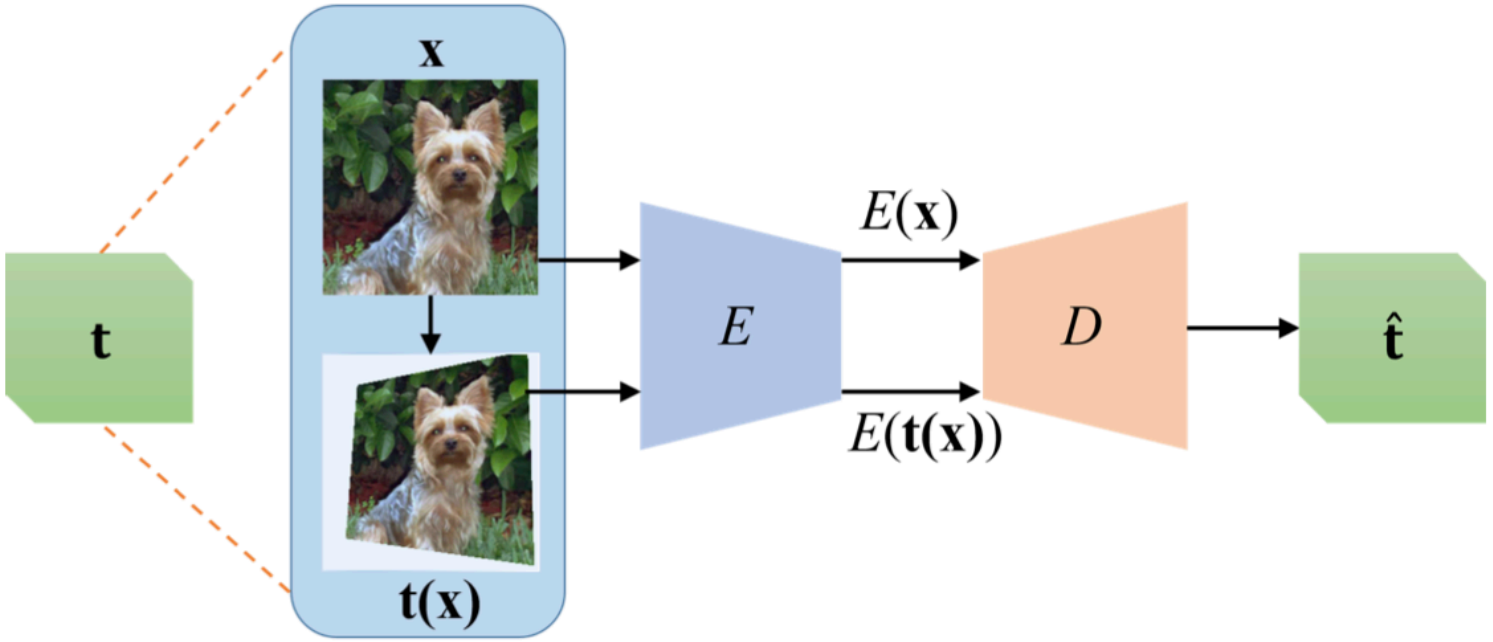
"AET vs. AED: Unsupervised Representation Learning by Auto-Encoding Transformations rather than Data," 2019

Auto-Encoders



Auto-Encoding Data (AED) has been widely used for unsupervised learning.

Auto-Encoding Transformation



This paper presents **auto-encoding transformation (AET)** as a mean of self-supervised learning.

Problem Formulation

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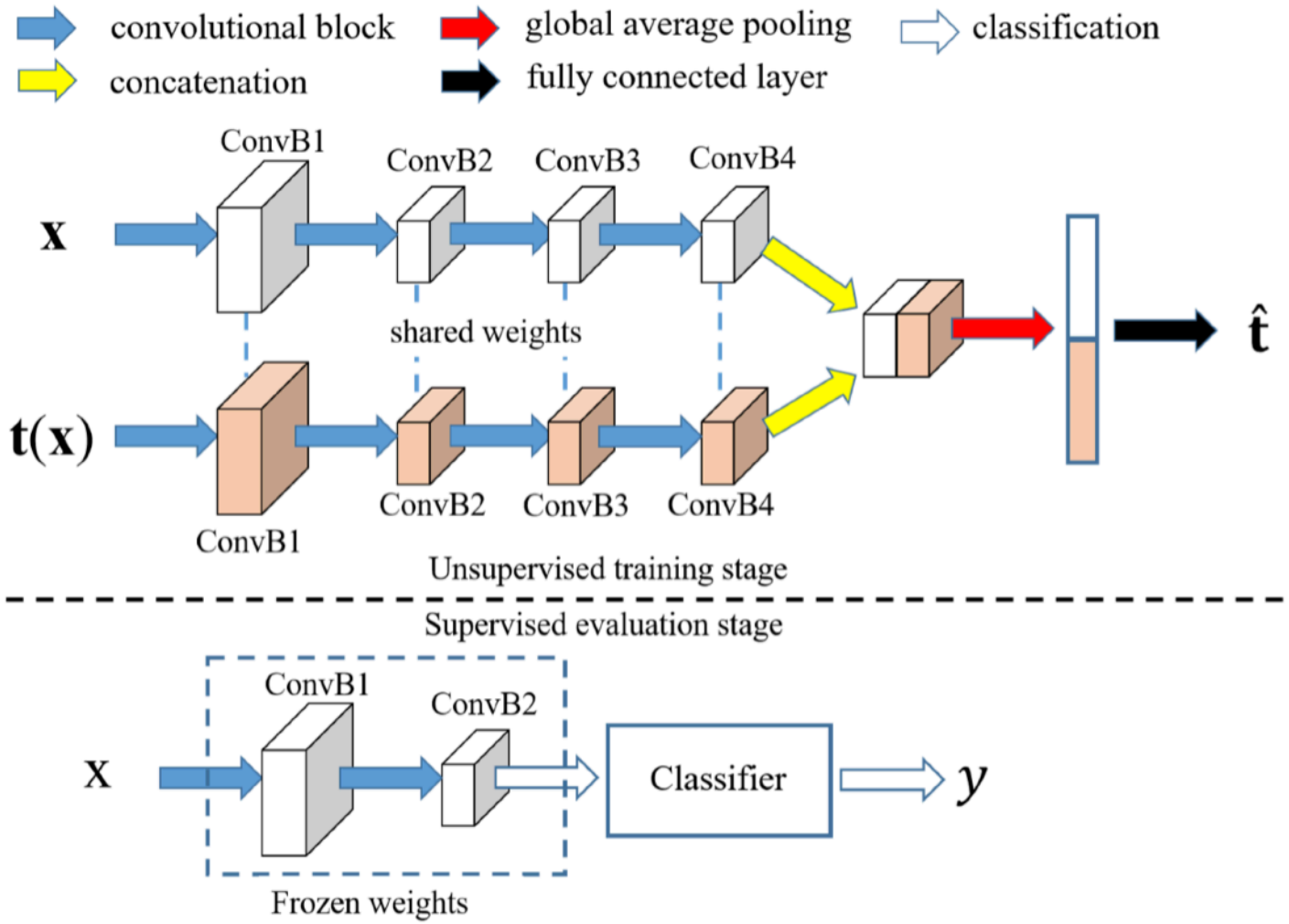
- **Encoder**
  - $E : \mathbf{x} \mapsto E(\mathbf{x})$ extracts the **representation** of a sample (image)
- **Transformation**
  - $\mathbf{t} : \mathbf{x} \mapsto \mathbf{t}(\mathbf{x})$ where a transformation is sampled from a distribution $\mathcal{T}$
  - The transform distribution $\mathcal{T} = \{\mathbf{t}_\theta | \theta \sim \Theta\}$ is parametrized by θ.
    - Projective and affine transformations: $M(\theta) \in \mathbb{R}^{3\times3}$ where the loss becomes $l(\mathbf{t}_\theta, \mathbf{t}_{\hat{\theta}}) = \frac{1}{2}\|M(\theta) - M(\hat{\theta})\|_2^2$
    - GAN-Induced transformations: $\mathbf{t}_\mathbf{z}(\mathbf{x}) = G(\mathbf{x}, \mathbf{z})$ where the loss becomes $l(\mathbf{t}_\mathbf{z} - \mathbf{t}_{\hat{\mathbf{z}}}) = \frac{1}{2}\|\mathbf{z} - \hat{\mathbf{z}}\|_2^2$
- **Decoder**
  - $D : \left[E(\mathbf{x}), E(\mathbf{t}(\mathbf{x}))\right] \mapsto \hat{t}$ **predicts the input transformation** from the original and transformed images.

Network Architectures



CIFAR-10

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Method	Error rate
Supervised NIN (Lower Bound)	7.20
Random Init. + conv (Upper Bound)	27.50
Roto-Scat + SVM [22]	17.7
ExamplarCNN [7]	15.7
DCGAN [26]	17.2
Scattering [21]	15.3
RotNet + FC [10]	10.94
RotNet + conv [10]	8.84
(Ours) AET-affine + FC	9.77
(Ours) AET-affine + conv	8.05
(Ours) AET-project + FC	**9.41**
(Ours) AET-project + conv	**7.82**

ImageNet (Top-1 Accuracy)

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Method	Conv4	Conv5
ImageNet Labels [3](Upper Bound)	59.7	59.7
Random [20] (Lower Bound)	27.1	12.0
Tracking [29]	38.8	29.8
Context [5]	45.6	30.4
Colorization [31]	40.7	35.2
Jigsaw Puzzles [19]	45.3	34.6
BiGAN [6]	41.9	32.2
NAT [3]	-	36.0
DeepCluster [4]	-	44.0
RotNet [10]	50.0	43.8
(Ours) AET-project	**53.2**	**47.0**

Reconstruction Results

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DeepCluster

"Deep Clustering for Unsupervised Learning of Visual Features," 2019

Clustering

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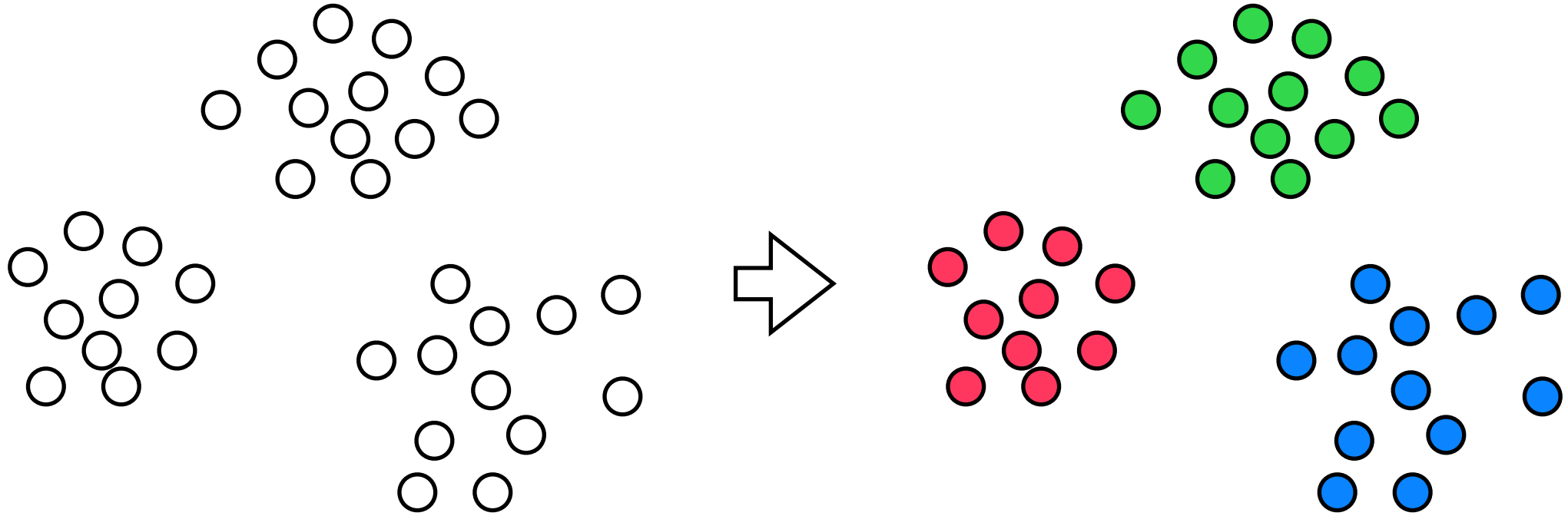

Conventional clustering methods work fairly well on **low-dimensional data** where **distance measures** can easily be defined and evaluated.

Distance Measure

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However, in high-dimensional space, computing distances between instances becomes **unintuitive**.

Deep Clustering

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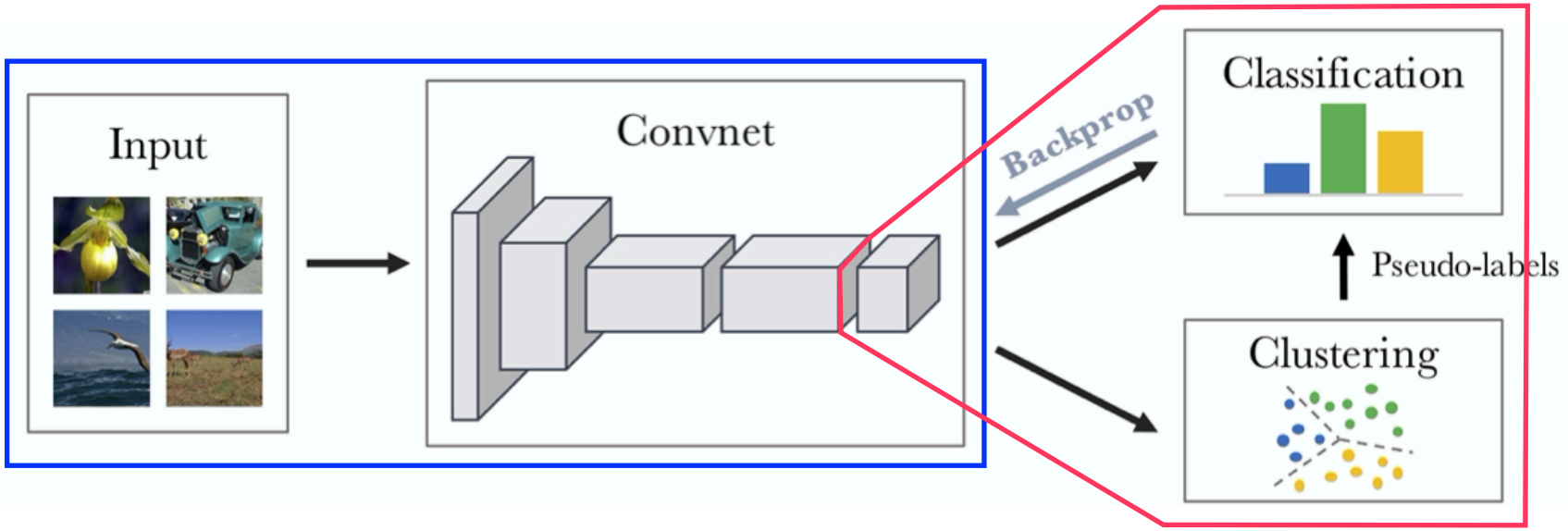

This paper combines the **representation learning power** of a Convnet with an **auxiliary learning objectives** from clustering results.

Deep Clustering

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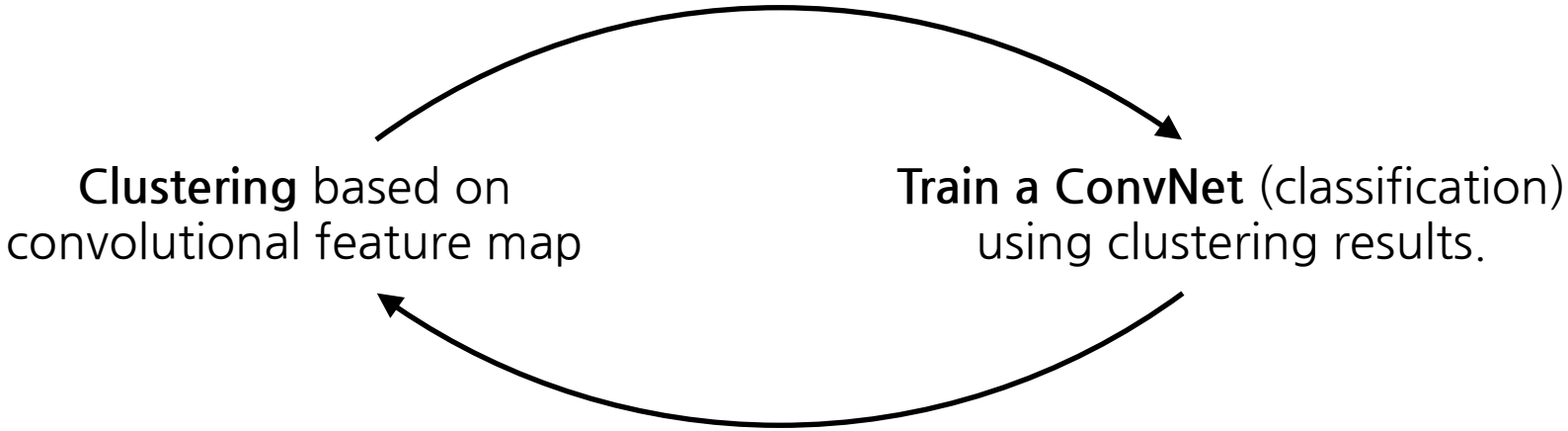

Results

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Method	ImageNet					Places				
	conv1	conv2	conv3	conv4	conv5	conv1	conv2	conv3	conv4	conv5
Places labels	–	–	–	–	–	22.1	35.1	40.2	43.3	44.6
ImageNet labels	19.3	36.3	44.2	48.3	50.5	22.7	34.8	38.4	39.4	38.7
Random	11.6	17.1	16.9	16.3	14.1	15.7	20.3	19.8	19.1	17.5
Pathak *et al.* [38]	14.1	20.7	21.0	19.8	15.5	18.2	23.2	23.4	21.9	18.4
Doersch *et al.* [25]	16.2	23.3	30.2	31.7	29.6	19.7	26.7	31.9	32.7	30.9
Zhang *et al.* [28]	12.5	24.5	30.4	31.5	30.3	16.0	25.7	29.6	30.3	29.7
BiGAN Donahue *et al.* [20]	17.7	24.5	31.0	29.9	28.0	21.4	26.2	27.1	26.1	24.0
Jigsaw Noroozi and Favaro [26]	**18.2**	28.8	34.0	33.9	27.1	23.0	32.1	35.5	34.8	31.3
Noroozi *et al.* [45]	18.0	**30.6**	34.3	32.5	25.7	**23.3**	**33.9**	36.3	34.7	29.6
Zhang *et al.* [43]	17.7	29.3	35.4	35.2	32.8	21.3	30.7	34.0	34.1	32.5
DeepCluster	12.9	29.2	**38.2**	**39.8**	**36.1**	18.6	30.8	**37.0**	**37.5**	**33.1**

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Single Image SSL

"A CRITICAL ANALYSIS OF SELF-SUPERVISION , WHAT WE CAN LEARN FROM A SINGLE IMAGE," 2020

Question

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Is self-supervision **able to exploit** the information contained in a large number of images in order to learn different parts of a neural network?

Findings

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1. **A single image** is sufficient, when combined with self-supervision and data augmentation, to learn the **first few layers** of standard deep network as well as using millions of images and full supervision.

2. For the deeper layers of the network, self-supervision remains inferior to supervision even if millions of images are used for training.

SSL Methods

- BiGAN ("ADVERSARIAL FEATURE LEARNING," 2017)
- RotNet ("UNSUPERVISED REPRESENTATION LEARNING BY PREDICTING IMAGE ROTATIONS," 2018)
- DeepCluster ("Deep Clustering for Unsupervised Learning of Visual Features," 2019)

Data

- **Baseline**: trained on d source images (e.g., $d = 1{,}281{,}167$ for ImageNet)
- **SSL methods**: $N \ll d$ source images (i.i.d. samples) and the remaining $d - N$ images are augmentations of the source images
  - N controls the **amount of information** in the training data, and if $N = 1$, we are using a single image for training.
- **Augmentations**: cropping, scaling, rotation, contrast changes, and adding noise

Real Samples

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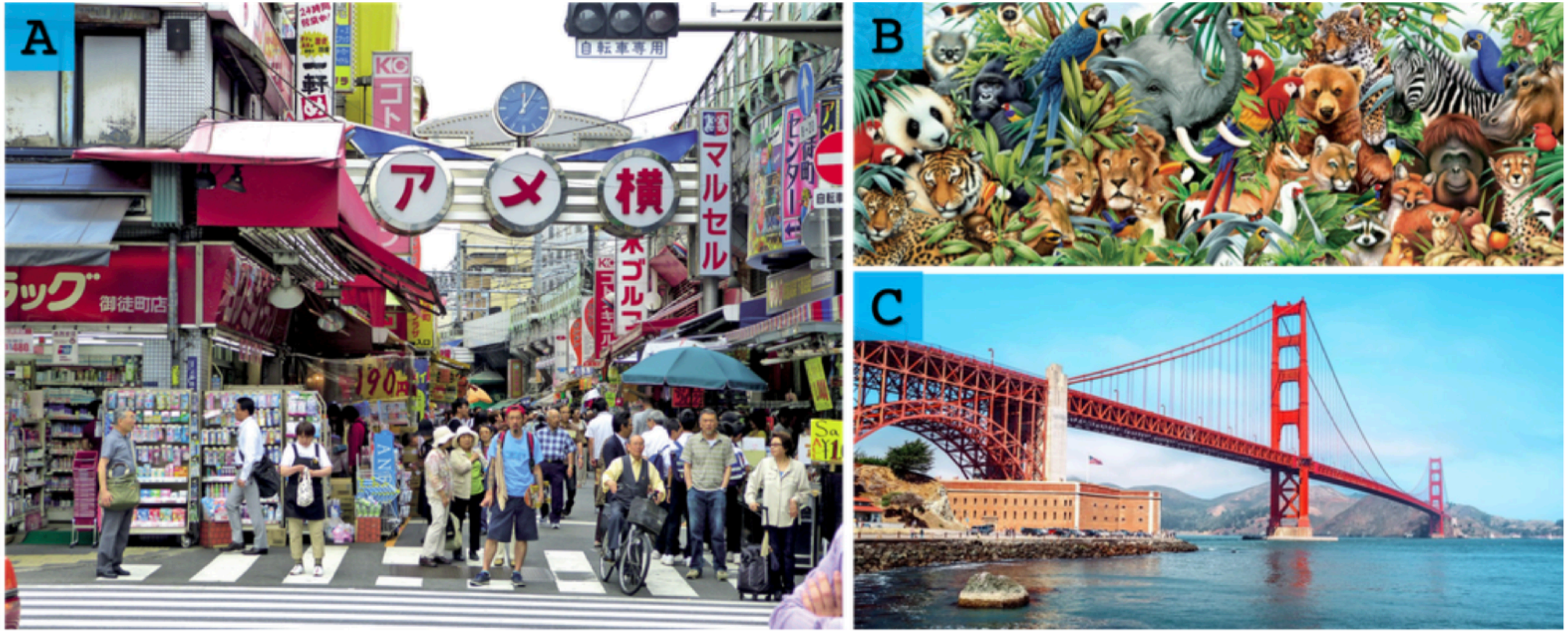

Image **A** and **B**: contain rich texture
Image **C**: ablates "crowdness" as it contains large areas covering no objects

Linear Probes

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Solve a difficult task such as ImageNet classification by training **a linear classifier** on top of pre-trained feature representations, which are kept fixed.

ImageNet

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	Method, Reference	#images	ILSVRC-12 conv1	conv2	conv3	conv4	conv5
(a)	Full-supervision‡	1,281,167	19.3	36.3	44.2	48.3	50.5
(b)	(Oyallon et al., 2017): Scattering	0	-	18.9	-	-	-
(c)	Random‡	0	11.6	17.1	16.9	16.3	14.1
(d)	(Krähenbühl et al., 2016):k-means‡	≈160	17.5	23.0	24.5	23.2	20.6
(e)	(Donahue et al., 2017): BiGAN‡	1,281,167	17.7	24.5	31.0	29.9	28.0
(f)	mono, Image A	1	20.4	30.9	33.4	28.4	16.0
(g)	mono, Image B	1	20.5	30.4	31.6	27.0	16.8
(h)	deka	10	16.2	16.5	16.5	13.1	7.5
(i)	kilo	1,000	16.1	17.7	18.3	17.6	13.5
(j)	(Gidaris et al., 2018): RotNet	1,281,167	18.8	31.7	38.7	38.2	36.5
(k)	mono, Image A	1	19.9	30.2	30.6	27.6	21.9
(l)	mono, Image B	1	17.8	27.6	27.9	25.4	20.2
(m)	deka	10	19.6	30.7	32.6	28.9	22.6
(n)	kilo	1,000	21.0	33.5	36.5	34.0	29.4
(o)	(Caron et al., 2018): DeepCluster	1,281,167	18.0	32.5	39.2	37.2	30.6
(p)	mono, Image A	1	20.7	31.5	32.5	28.5	21.0
(q)	mono, Image B	1	19.7	30.1	31.6	28.5	20.4
(r)	mono, Image C	1	18.9	29.2	31.5	28.9	23.5
(s)	deka	10	18.5	29.0	31.1	28.2	21.9
(t)	kilo	1,000	19.5	29.8	33.0	31.7	26.8

On lower layers, the performance gap between fully-supervised and self-supervised methods is small.

ImageNet

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(s)	deka	10	18.5	29.0	31.1	28.2	21.9
(t)	kilo	1,000	19.5	29.8	33.0	31.7	26.8

However, on higher layers, SSL methods show inferior performance.

Conclusion

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SSL with a single image can successfully capture the simplest image statistics (lower level features), but a gap exists with full supervision even when using larget datasets.

Conclusion

Good old fashioned SSL methods, more to come next week!

Thank You