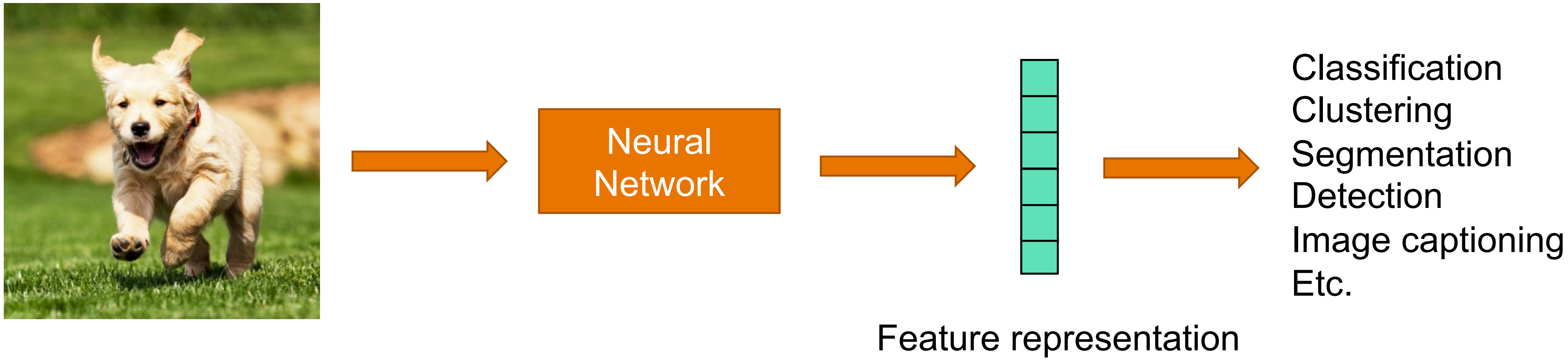
THE UNIVERSITY OF TEXAS AT DALLAS

Visual Representation Learning

CS 6384 Computer Vision
Professor Yapeng Tian
Department of Computer Science

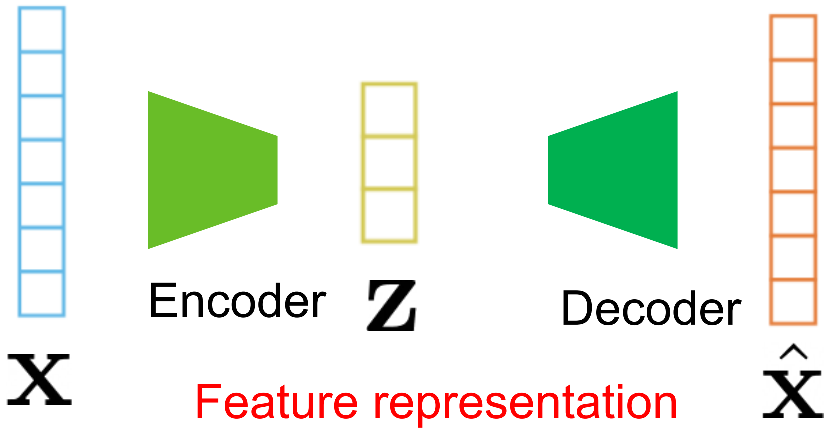
Slides borrowed from Professor Yu Xiang

Learning Visual Representations

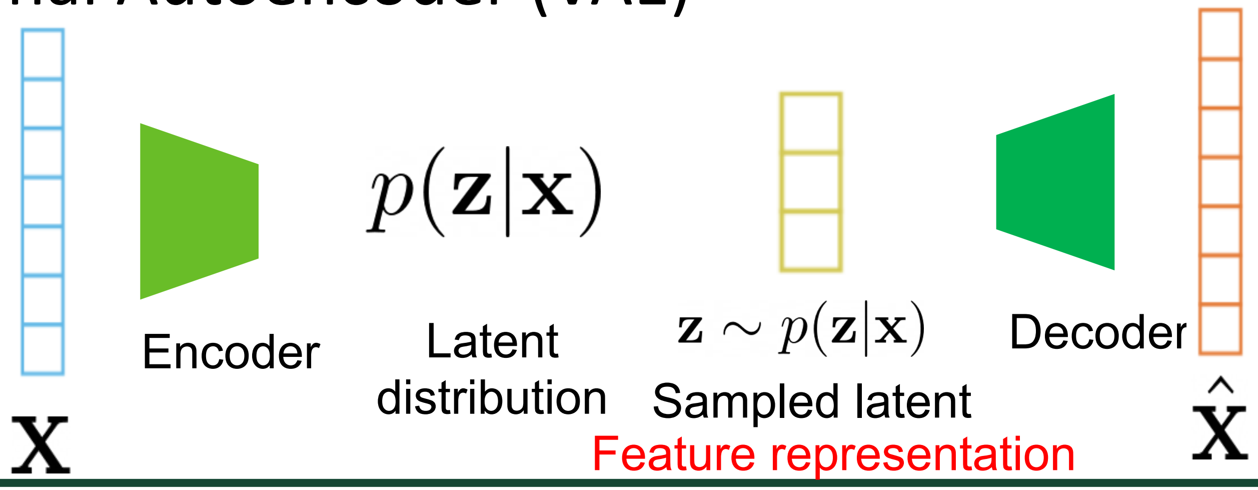


Generative Models

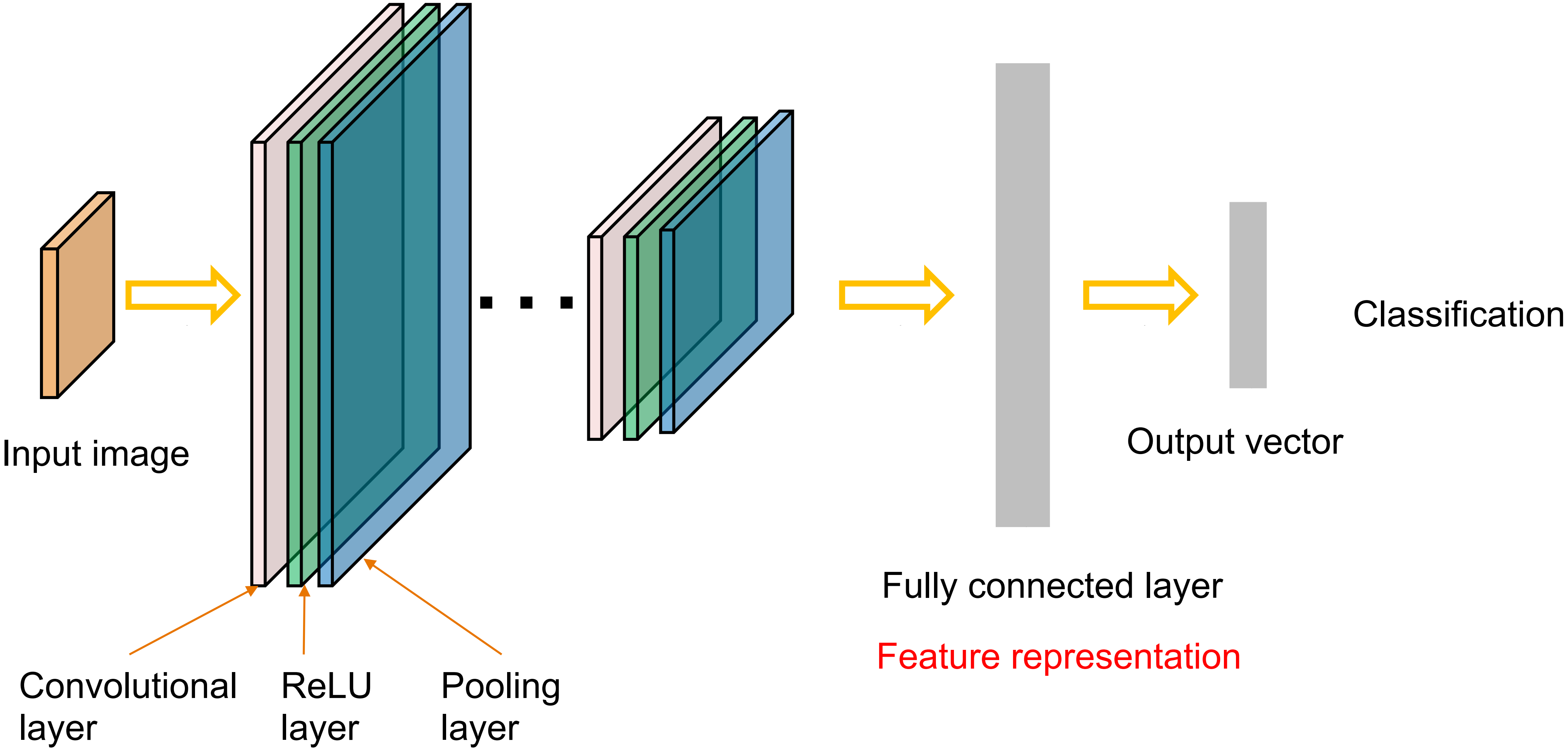
Autoencoder



Variational Autoencoder (VAE)



Discriminative Models (Supervised Learning)



Supervised Representation Learning

Train neural networks for image classification

Use internal features in the network as feature representations

Applications

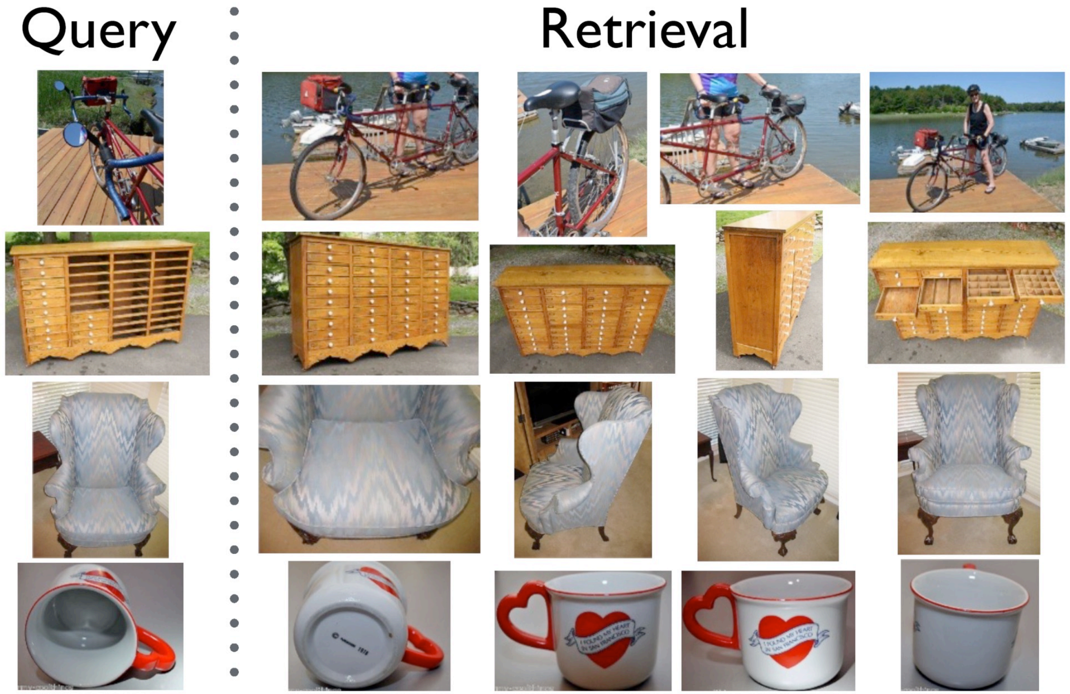
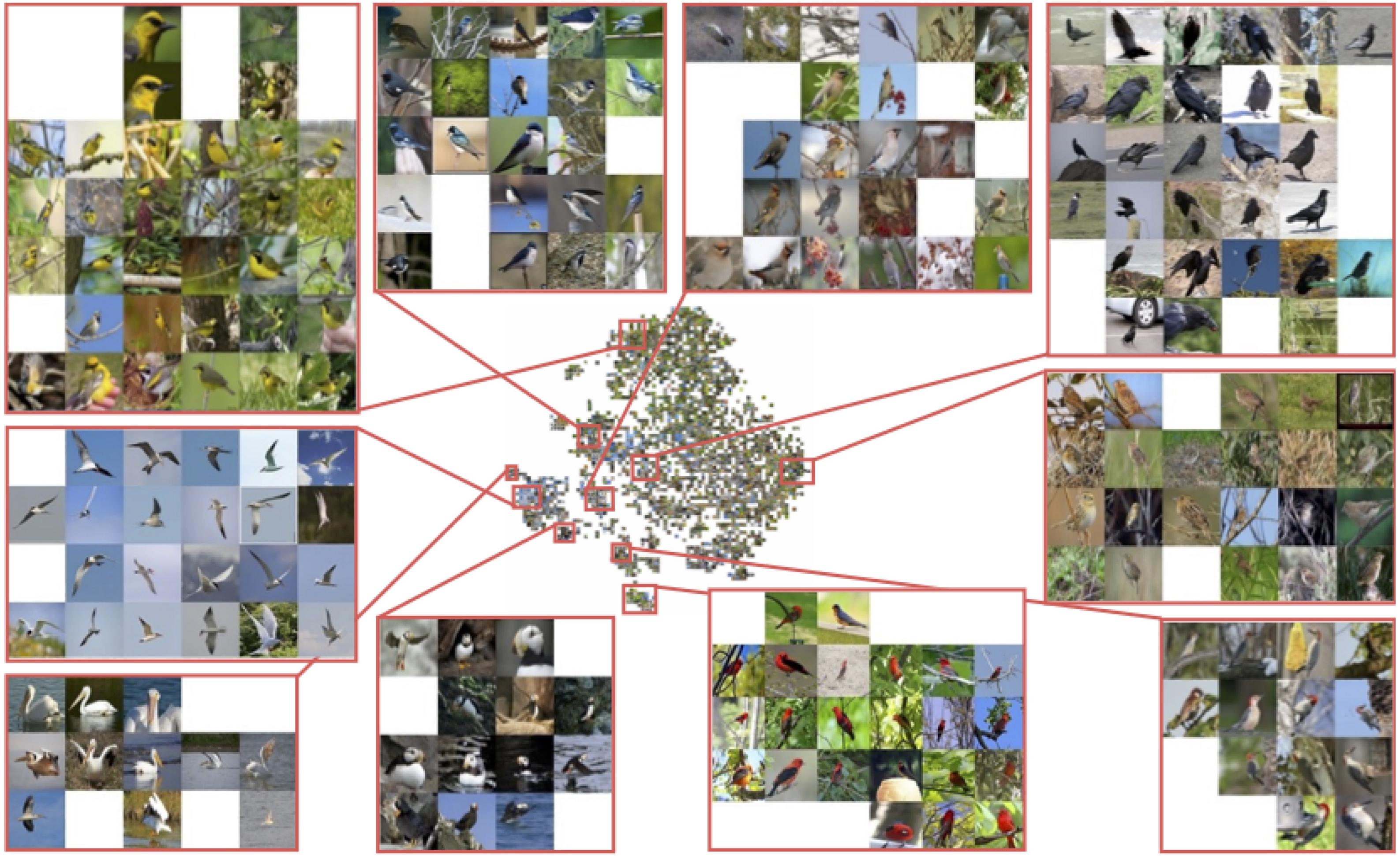


Image retrieval

Deep Metric Learning via Lifted Structured Feature Embedding. Song et al., CVPR, 2016.

Supervised Representation Learning

Image clustering



Deep Metric Learning via Lifted Structured Feature Embedding. Song et al., CVPR, 2016.

t-Distributed Stochastic Neighbor Embedding (t-SNE)

L.J.P. van der Maaten and G.E. Hinton. **Visualizing High-Dimensional Data Using t-SNE**. *Journal of Machine Learning Research* 9(Nov):2579-2605, 2008.

Supervised Representation Learning

Training with classification loss functions

- E.g., cross-entropy loss

Can we have better loss functions for representation learning?

Deep metric learning

- Learning distance metrics with neural networks

Distance metrics

L1 distance

$$D(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^{N} |x_i - y_i|$$

L2 distance

$$D(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2}$$

Cosine distance

$$D(\mathbf{x}, \mathbf{y}) = 1 - \underbrace{\frac{\mathbf{x} \cdot \mathbf{y}}{||\mathbf{x}|| \, ||\mathbf{y}||}}_{\text{Cosine similarity}}$$

Deep Metric Learning

$$\mathbf{x} \longrightarrow \boxed{\text{Neural Network}} \longrightarrow f(\mathbf{x})$$

Feature representation

$$D(\mathbf{x}_1, \mathbf{x}_2) = D(f(\mathbf{x}_1), f(\mathbf{x}_2))$$

L2 distance $D(\mathbf{x}_1, \mathbf{x}_2) = \|f(\mathbf{x}_1) - f(\mathbf{x}_2)\|_2$

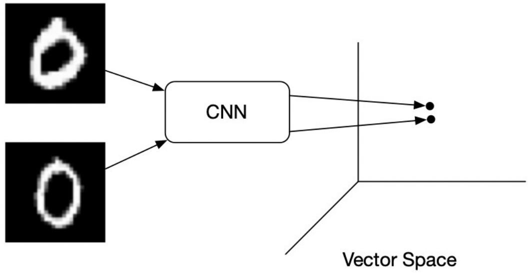
Learning the distance metric is equivalent to learning the feature representation

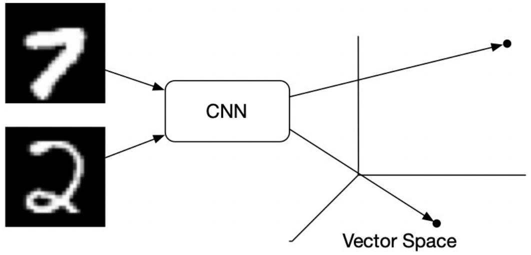
Contrastive Loss

Use positive pairs and negative pairs

$\mathbf{x}_1 \rightarrow$ Neural Network $\rightarrow f(\mathbf{x}_1)$

$\mathbf{x}_2 \rightarrow$ Neural Network $\rightarrow f(\mathbf{x}_2)$





Positive pair $f(\mathbf{x}_1)$ $f(\mathbf{x}_2)$ should be close

$D(\mathbf{x}_1, \mathbf{x}_2)$ small

Negative pair $f(\mathbf{x}_1)$ $f(\mathbf{x}_2)$ should be far

$D(\mathbf{x}_1, \mathbf{x}_2)$ large

Learning a Similarity Metric Discriminatively, with Application to Face Verification. Chopra et al., CVPR, 2005.

Contrastive Loss

Training data $\{(\mathbf{x}_i, \mathbf{x}_j, y_{ij})\}$

$$y_{ij} = \begin{cases} 1 & \text{if positive pair} \\ 0 & \text{if negative pair} \end{cases}$$

(a) Contrastive embedding

$$J = \frac{1}{m} \sum_{(i,j)}^{m/2} y_{i,j} D_{i,j}^2 + (1 - y_{i,j}) \left[\alpha - D_{i,j}\right]_+^2$$

margin

$$[x]_+ = \max(0, x)$$

m: number of images in a batch

Learning a Similarity Metric Discriminatively, with Application to Face Verification. Chopra et al., CVPR, 2005.

Contrastive Loss

Compute Gradient

$$J = \frac{1}{m} \sum_{(i,j)}^{m/2} y_{i,j} D_{i,j}^2 + (1 - y_{i,j}) \left[\alpha - D_{i,j}\right]_+^2$$

$$\frac{\partial J}{\partial D_{i,j}} = \frac{2}{m} \left(y_{i,j} D_{i,j} - (1 - y_{i,j}) [\alpha - D_{i,j}]_+ \right)$$

$$D_{i,j} = \| f(\mathbf{x}_i) - f(\mathbf{x}_j) \|_2 \qquad \frac{\partial D_{i,j}}{\partial f(\mathbf{x}_i)} = \frac{f(\mathbf{x}_i) - f(\mathbf{x}_j)}{\| f(\mathbf{x}_i) - f(\mathbf{x}_j) \|}$$

$\mathbf{x}_i \longrightarrow$ Neural Network $\longrightarrow f(\mathbf{x}_i)$

$\longleftarrow$ Gradients $\longleftarrow \dfrac{\partial J}{\partial f(\mathbf{x}_i)}$

Triplet Loss

Use a triplet (anchor, positive, negative)

(b) Triplet embedding

$$J = \frac{3}{2m} \sum_{i}^{m/3} \left[D_{ia,ip}^2 - D_{ia,in}^2 + \alpha \right]_+$$

$$D_{ia,ip} = ||f(\mathbf{x}_i^a) - f(\mathbf{x}_i^p)|| \qquad D_{ia,in} = ||f(\mathbf{x}_i^a) - f(\mathbf{x}_i^n)||$$

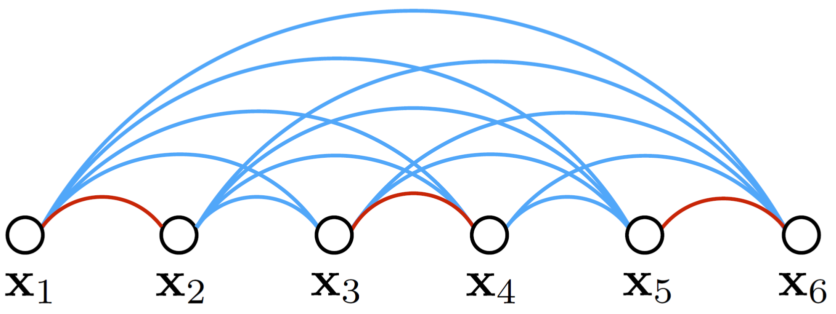
FaceNet: A Unified Embedding for Face Recognition and Clustering. Schroff et al., CVPR, 2015.

Lifted Structured Loss

Consider all positive pairs and negative pairs in a mini-batch

$$J = \frac{1}{2|\widehat{\mathcal{P}}|} \sum_{(i,j)\in\widehat{\mathcal{P}}} \max\left(0,\ J_{i,j}\right)^2$$

$$J_{i,j} = \max\left(\max_{(i,k)\in\widehat{\mathcal{N}}} \alpha - D_{i,k},\ \max_{(j,l)\in\widehat{\mathcal{N}}} \alpha - D_{j,l}\right) + D_{i,j}$$



(c) Lifted structured embedding

Hard negative

Distance for the negative pair

Distance for the positive pair

Relaxed loss $\tilde{J}_{i,j} = \log\left(\sum_{(i,k)\in\mathcal{N}} \exp\{\alpha - D_{i,k}\} + \sum_{(j,l)\in\mathcal{N}} \exp\{\alpha - D_{j,l}\}\right) + D_{i,j}$

Deep Metric Learning via Lifted Structured Feature Embedding. Song et al., CVPR, 2016.

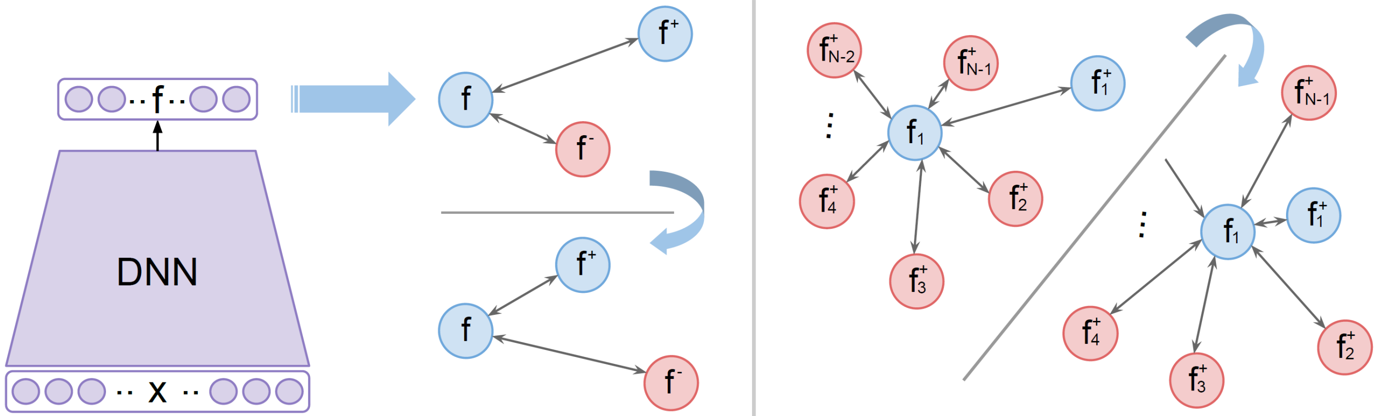
Multi-class N-pair Loss

Use a positive pair and N-1 negative ones and $\{\mathbf{x}, \mathbf{x}^+, \mathbf{x}_1^-, \dots, \mathbf{x}_{N-1}^-\}$

$$\mathcal{L}_{\text{N-pair}}(\mathbf{x}, \mathbf{x}^+, \{\mathbf{x}_i^-\}_{i=1}^{N-1}) = \log\left(1 + \sum_{i=1}^{N-1} \exp(f(\mathbf{x})^\top f(\mathbf{x}_i^-) - f(\mathbf{x})^\top f(\mathbf{x}^+))\right)$$

$$= -\log \frac{\exp(f(\mathbf{x})^\top f(\mathbf{x}^+))}{\exp(f(\mathbf{x})^\top f(\mathbf{x}^+)) + \sum_{i=1}^{N-1} \exp(f(\mathbf{x})^\top f(\mathbf{x}_i^-))}$$

Softmax for multi-class classification



Improved Deep Metric Learning with Multi-class N-pair Loss Objective. Kihyuk Sohn, NeurIPS, 2016

InfoNCE (Noise Contrastive Estimation) Loss

Similar to multi-class N-pair Loss

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

Query q

Positive k+

Negatives ki

(K+1)-way softmax classification

Motivated from identifying targets from noisy data

Supervised Representation Learning

Use class labels to specify positive pairs and negative pairs

Loss functions

- Contrastive loss
- Triplet loss
- Lifted structured loss
- N-pair loss
- InfoNCE

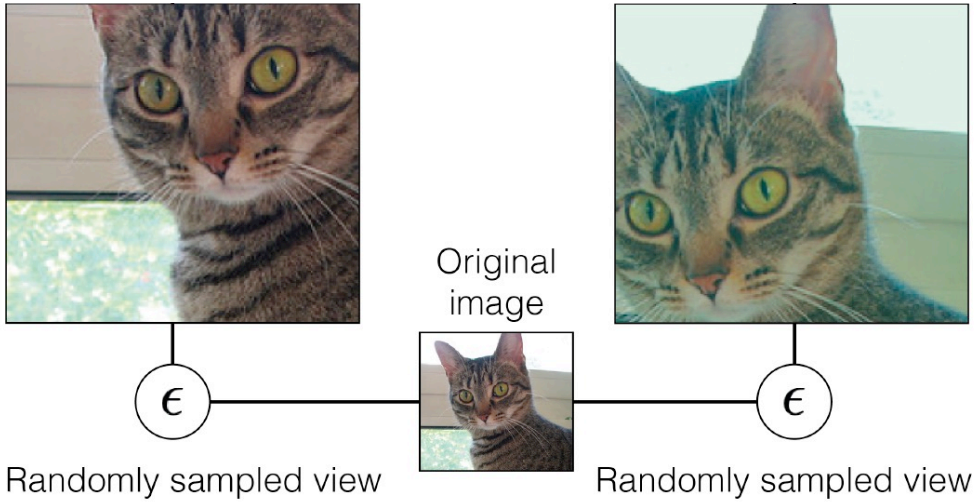
Consider more relationships in a mini-batch is better

Unsupervised/Self-supervised Representation Learning

Pretext tasks

- Tasks designed for feature learning
- Not the final tasks

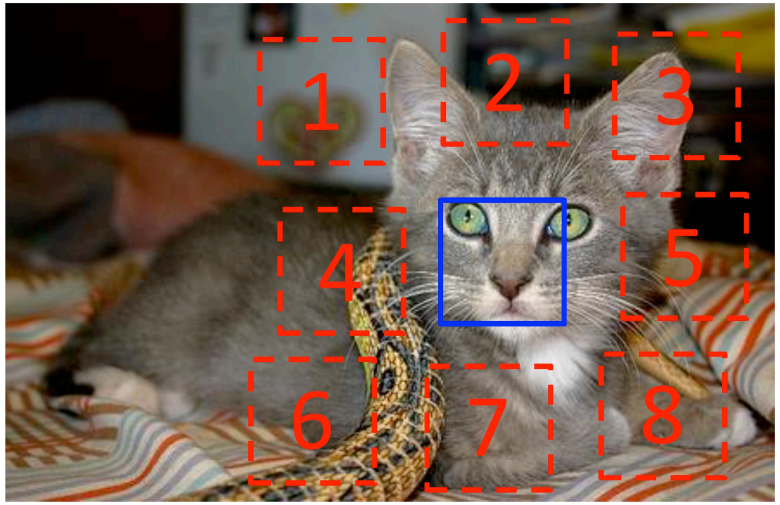
Positive pairs from different views of the same image



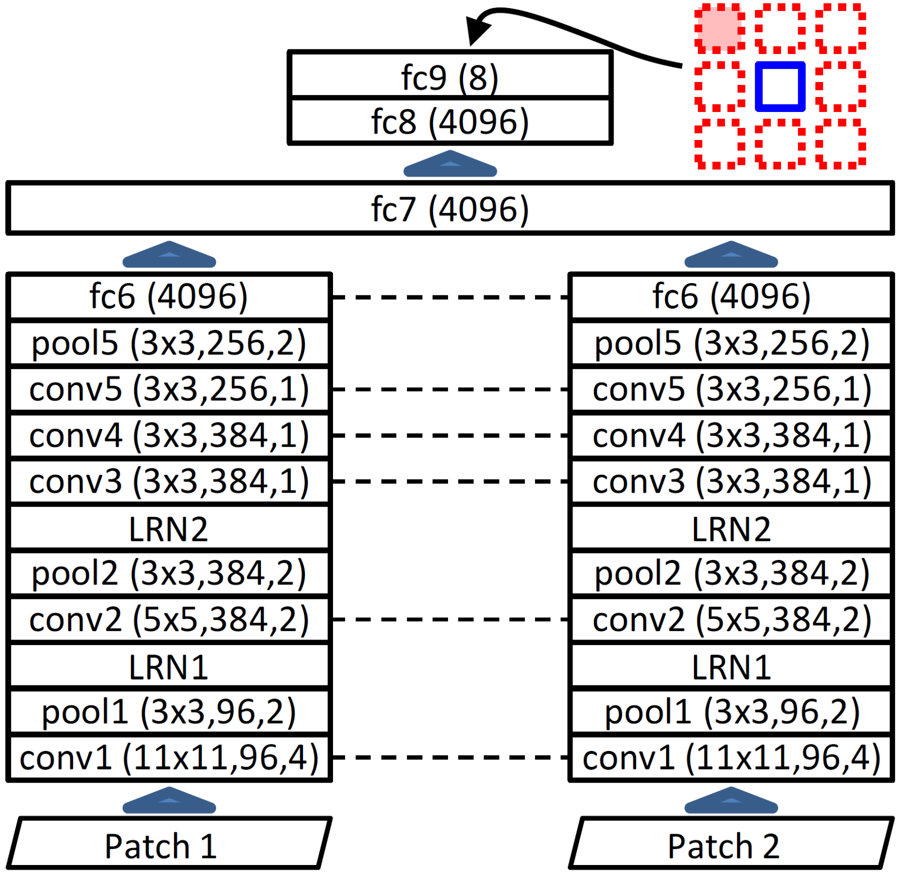
Learning Representations by Maximizing Mutual Information Across Views. Bachman et al., NeurIPS, 2019

Unsupervised/Self-supervised Representation Learning

Pretext task: context prediction



X = (); Y = 3

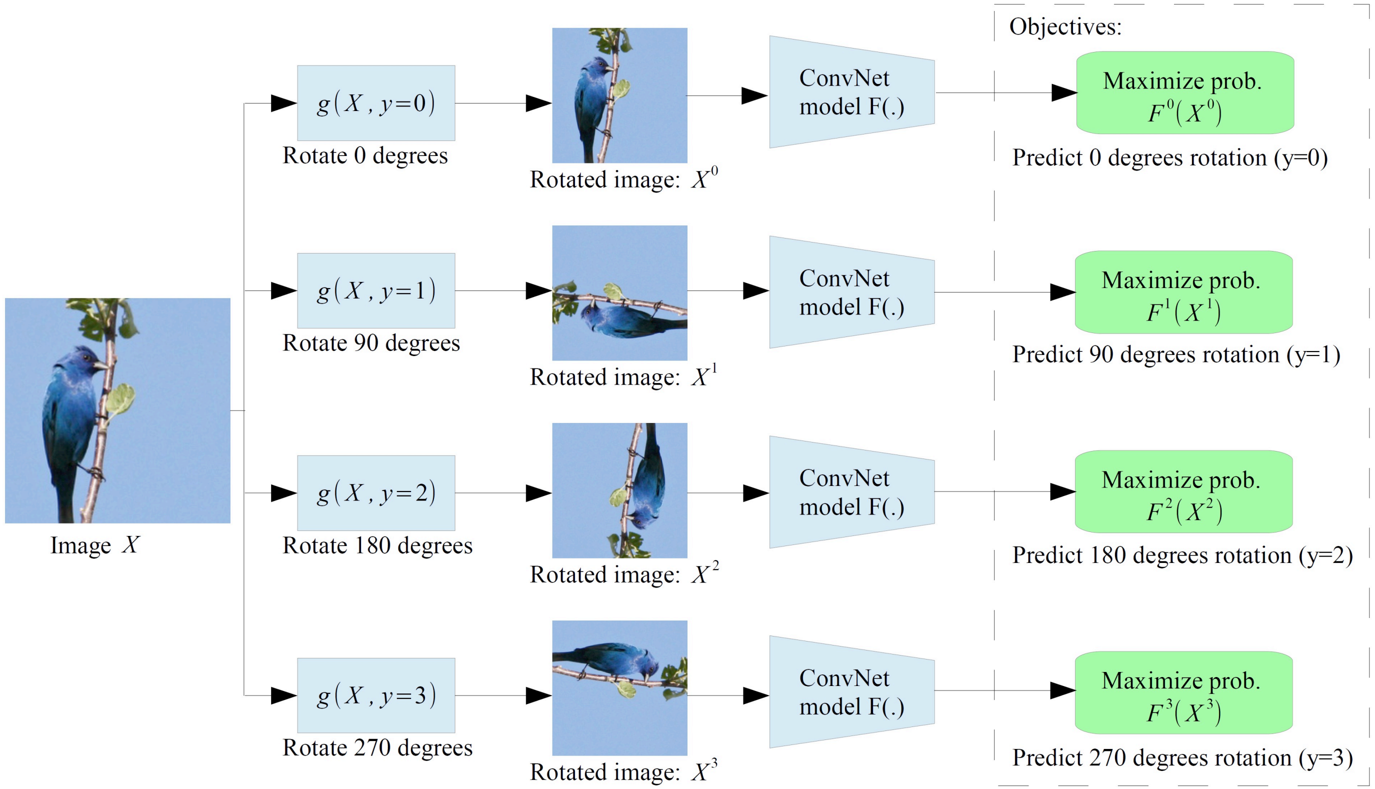


Feature representation

Unsupervised Visual Representation Learning by Context Prediction. Doersch, et al., ICCV, 2015

Unsupervised/Self-supervised Representation Learning

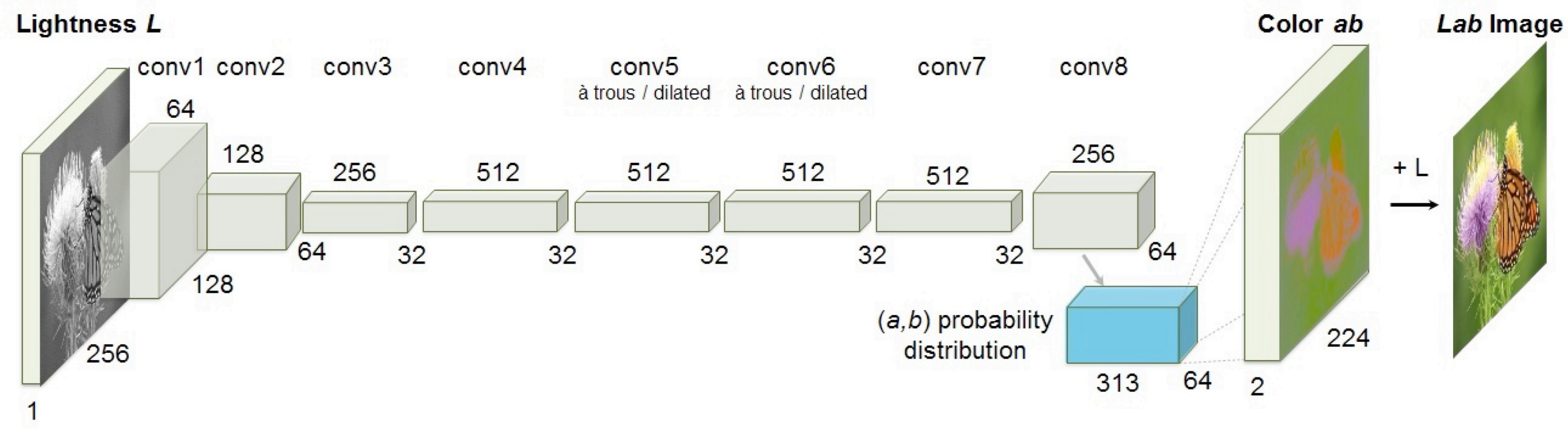
Pretext task: rotation prediction



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

Unsupervised/Self-supervised Representation Learning

Pretext task: colorization



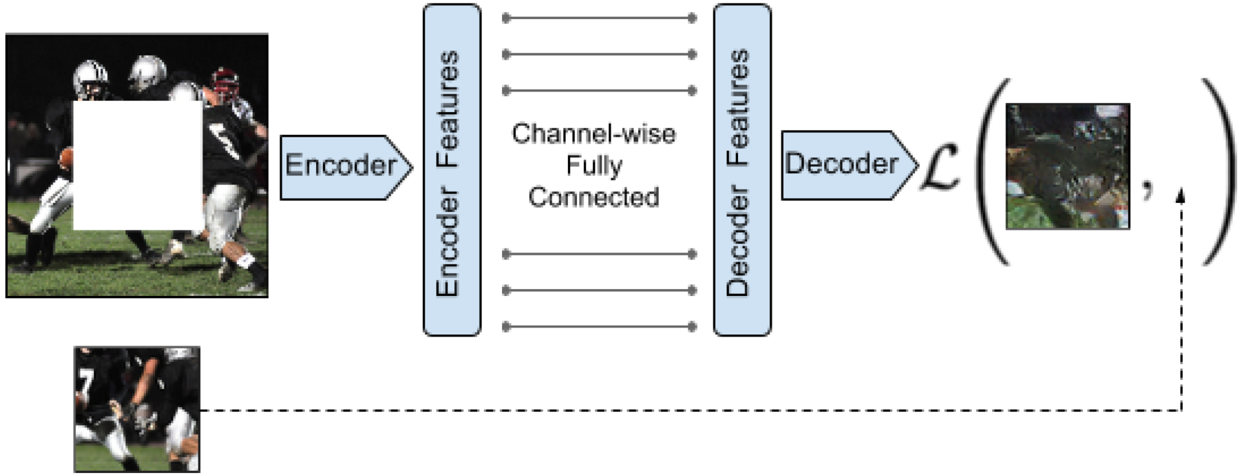
Colorful Image Colorization. Zhang, et al., ECCV, 2016

Unsupervised/Self-supervised Representation Learning

Pretext task: inpainting

(a) Input context (b) Human artist

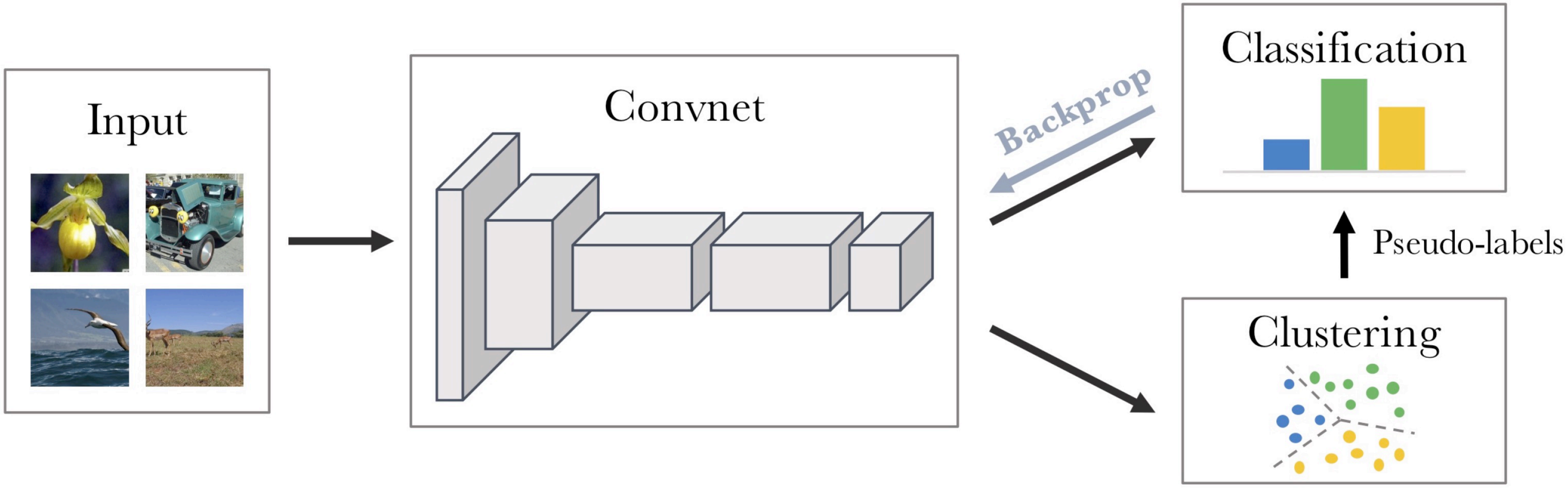
(c) Context Encoder ($L2$ loss) (d) Context Encoder ($L2$ + Adversarial loss)



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

Unsupervised/Self-supervised Representation Learning

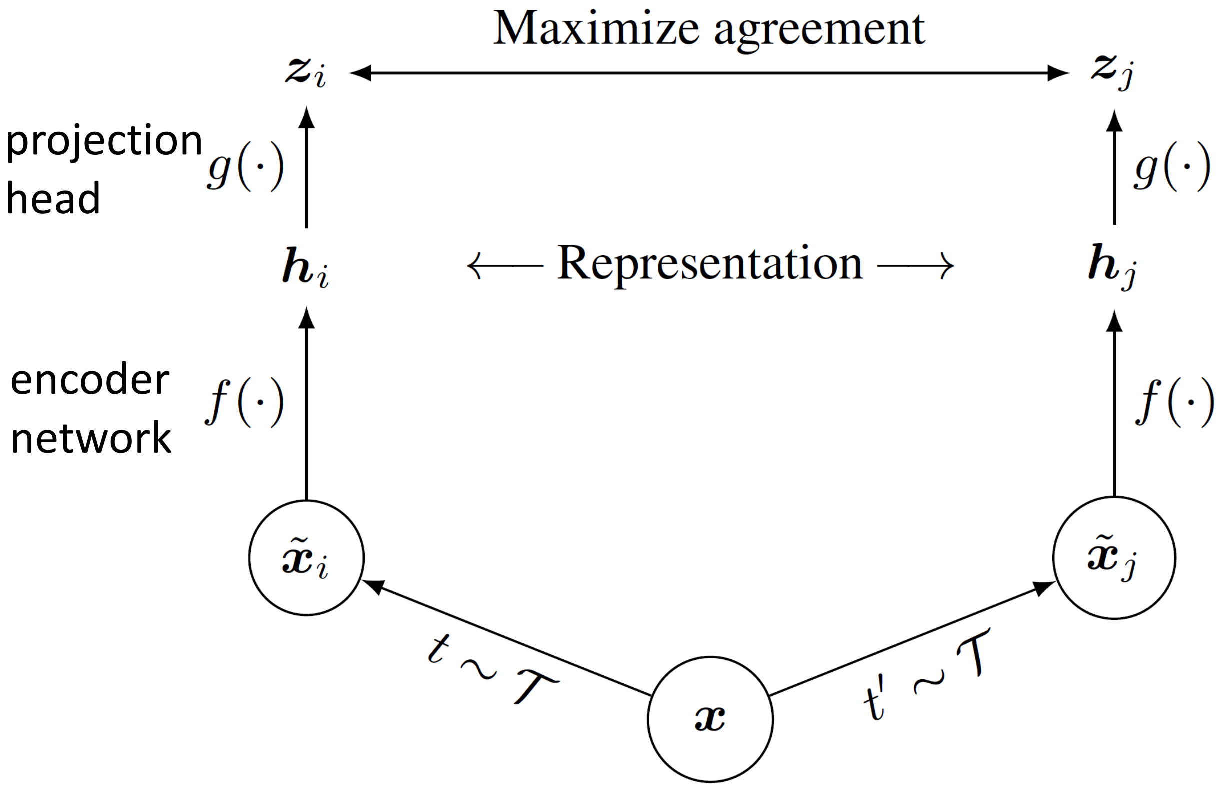
Pretext task: clustering



Deep Clustering for Unsupervised Learning of Visual Features. Caron et al., ECCV, 2018

SimCLR

A simple framework for contrastive learning of visual representations



Loss function

$$\ell_{i,j} = -\log \frac{\exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$

for a positive pair of examples (i, j)

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

SimCLR

Transformations

(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

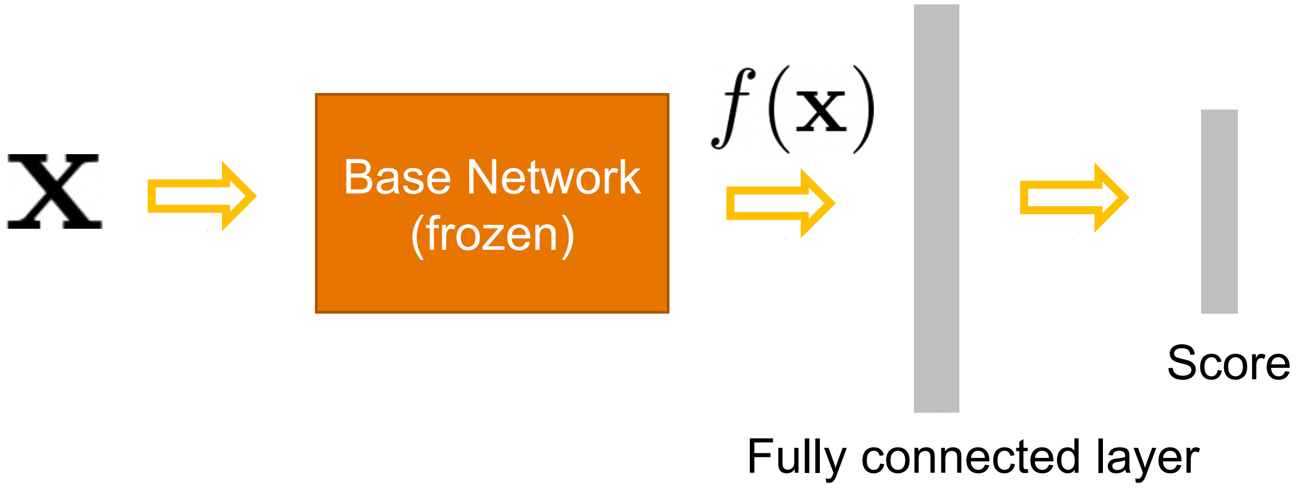
A Simple Framework for Contrastive Learning of Visual Representations. Chen et al., ICML, 2020

SimCLR

After training, keep the encoder network $\boldsymbol{h}_i = f(\tilde{\boldsymbol{x}}_i) = \mathrm{ResNet}(\tilde{\boldsymbol{x}}_i)$

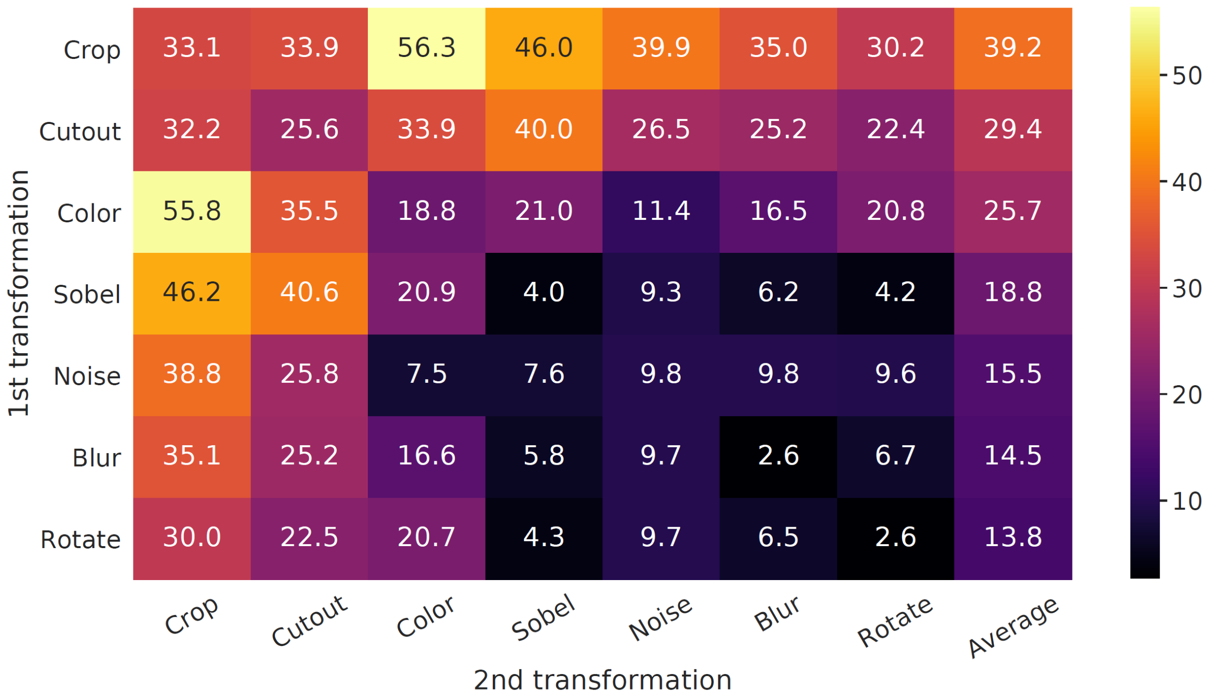
Linear evaluation protocol for classification

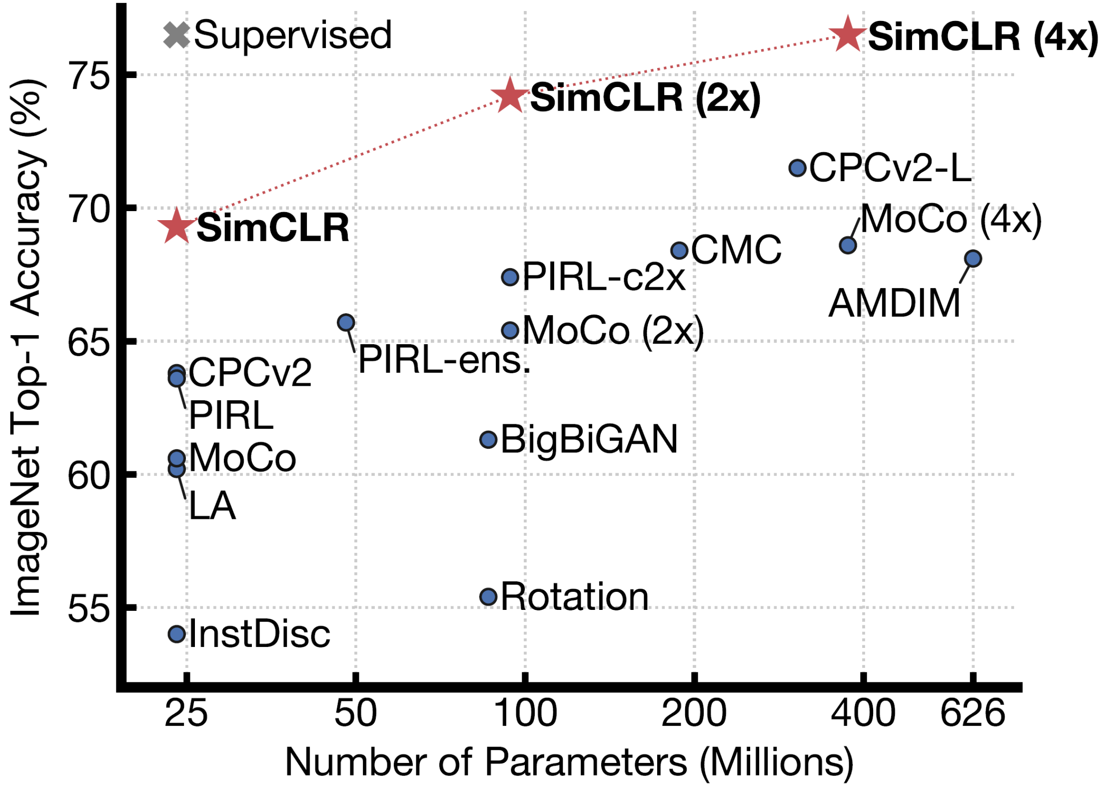
- A linear classifier is trained on top of the frozen base network



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

SimCLR





ImageNet top-1 accuracy

2x, 4x: more channels in ResNet

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

SimCLR

https://github.com/google-research/simclr

Summary: Visual Representation Learning

Generative models

- Autoencoder
- VAE
- GAN

Discriminative models

- Supervised learning
  - Training with image classification
  - Deep metric learning
- Unsupervised/self-supervised learning
  - Use pretext tasks
  - Metric learning loss functions

Further Reading

Learning a Similarity Metric Discriminatively, with Application to Face Verification, 2005 http://yann.lecun.com/exdb/publis/pdf/chopra-05.pdf

FaceNet: A Unified Embedding for Face Recognition and Clustering, 2015 https://arxiv.org/abs/1503.03832

Deep Metric Learning via Lifted Structured Feature Embedding, 2016 https://arxiv.org/abs/1511.06452

Improved Deep Metric Learning with Multi-class N-pair Loss Objective, 2016 https://papers.nips.cc/paper/2016/file/6b180037abbebea991d8b1232f8a8ca9-Paper.pdf

Learning Representations by Maximizing Mutual Information Across Views, 2019 https://arxiv.org/pdf/1906.00910.pdf

A Simple Framework for Contrastive Learning of Visual Representations, 2020 https://arxiv.org/abs/2002.05709