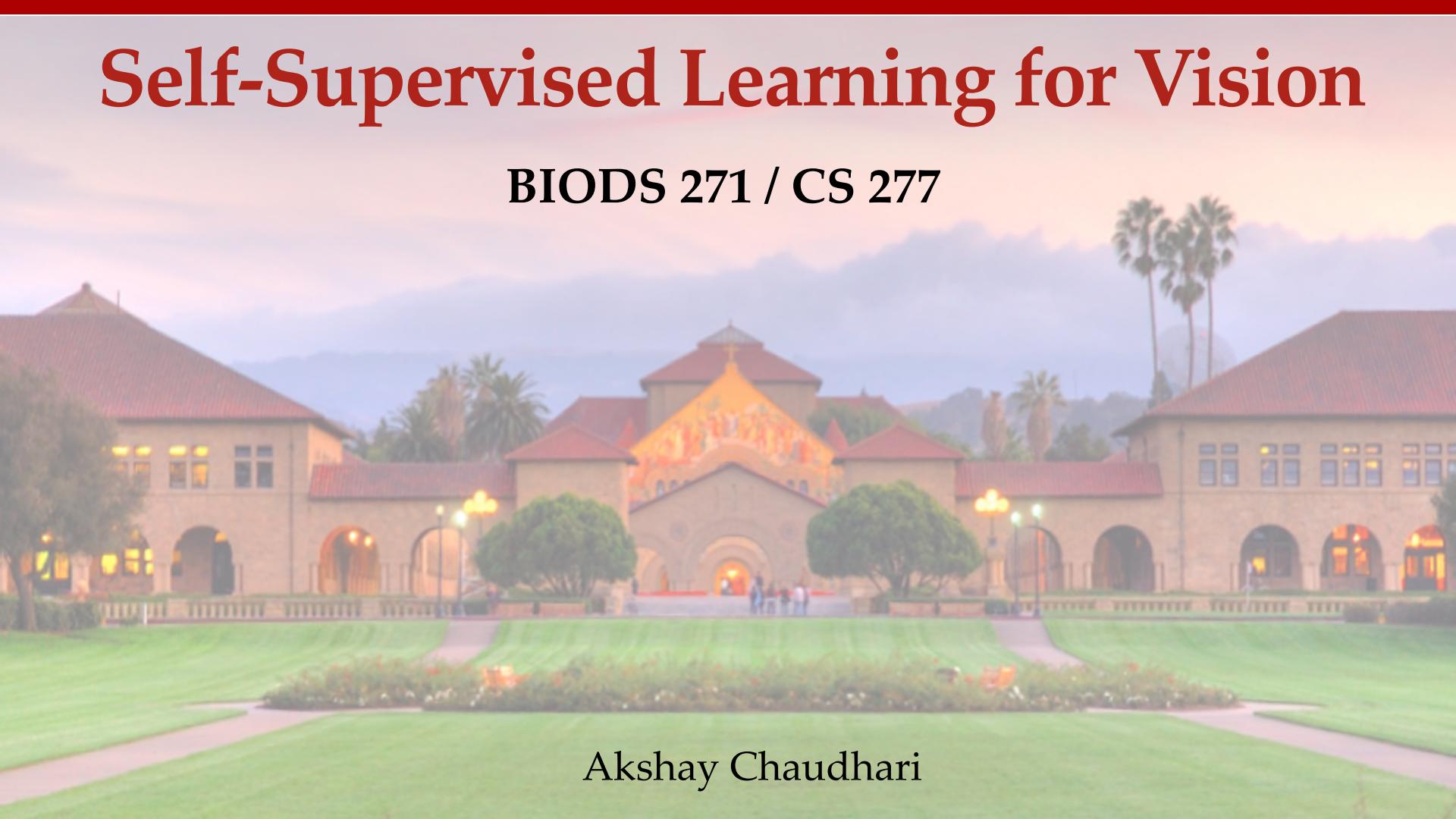


Self-Supervised Learning for Vision

BIODS 271 / CS 277

A blurred background image of the Stanford University quad at dusk. The image shows the main building with its iconic mosaic on the dome, surrounded by palm trees and other buildings. The sky is a soft pink and blue, and the grass in the foreground is a vibrant green.

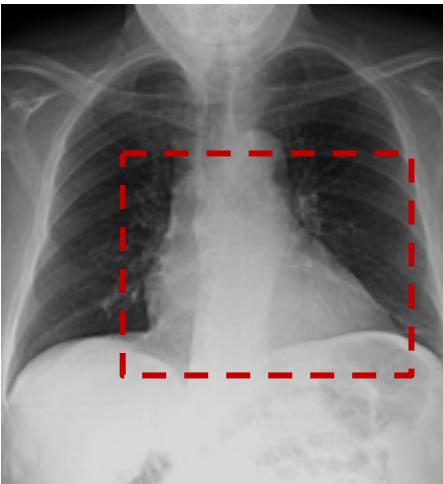
Akshay Chaudhari

Data Enables Solving Medical Problems

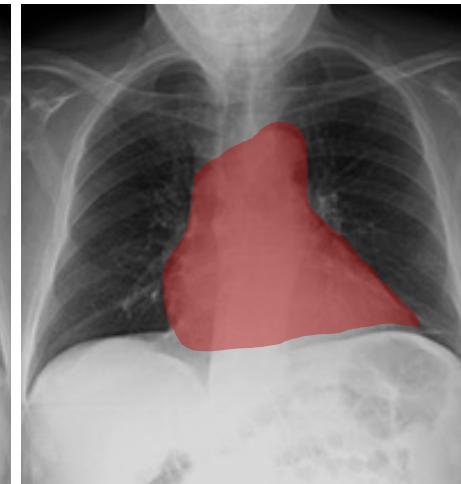
Classification



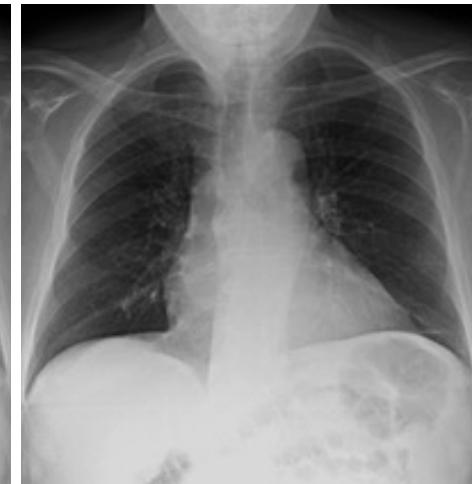
Detection



Segmentation



Regression



✓: Cardiomegaly

Ejection
Fraction: 49%

Supervised Learning

IM = Image
L = Label

IM1	IM2	IM3
IM4	IM5	IM6
IM7	IM8	IM9

+

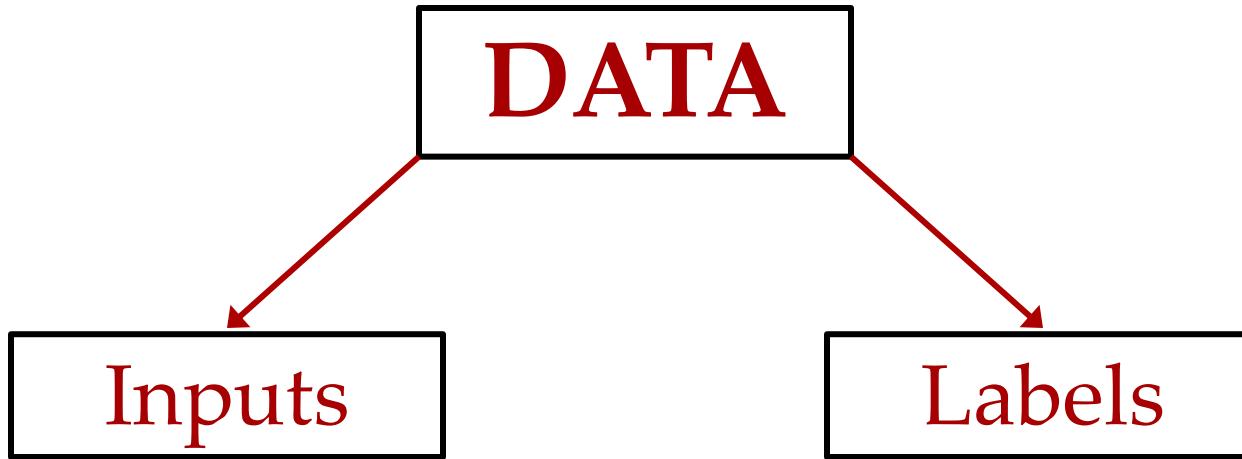
L1	L2	L3
L4	L5	L6
L7	L8	L9

= Model!

( , Dog)

( , Cat)

( , Hot Dog)



Dog

Cat

Hot Dog

...

and so on...

Label-Starved Learning

IM = Image
L = Label

IM1	IM2	IM3
IM4	IM5	IM6
IM7	IM8	IM9

+

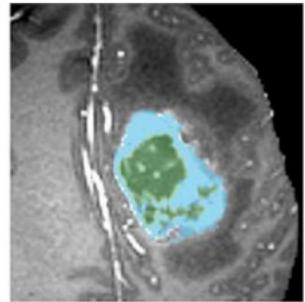
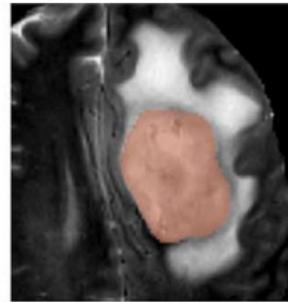
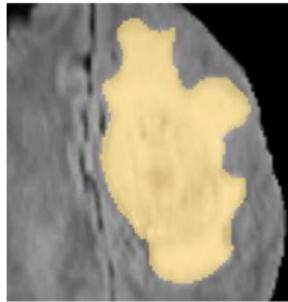
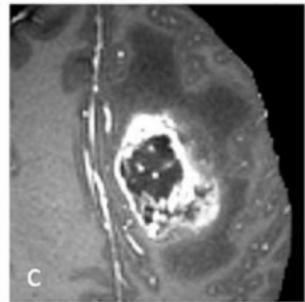
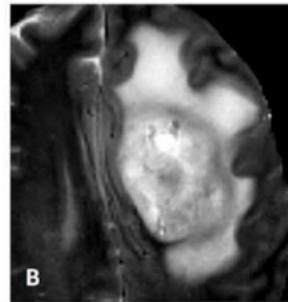
L1	L2	L3
L4	L5	L6
L7	L8	L9

=

No
Model!



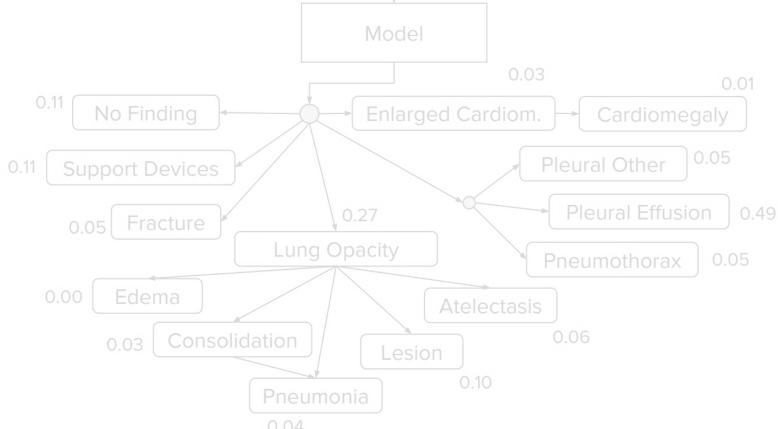
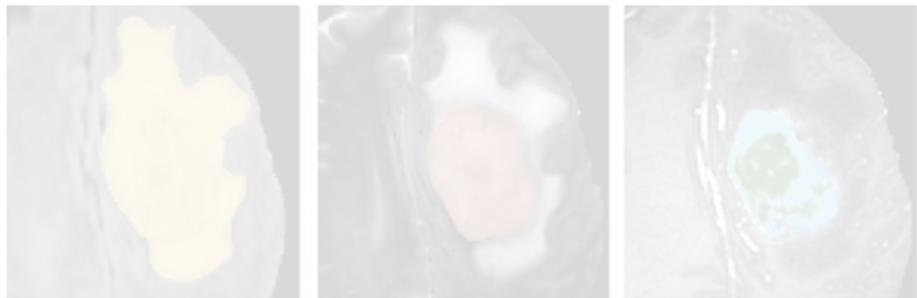
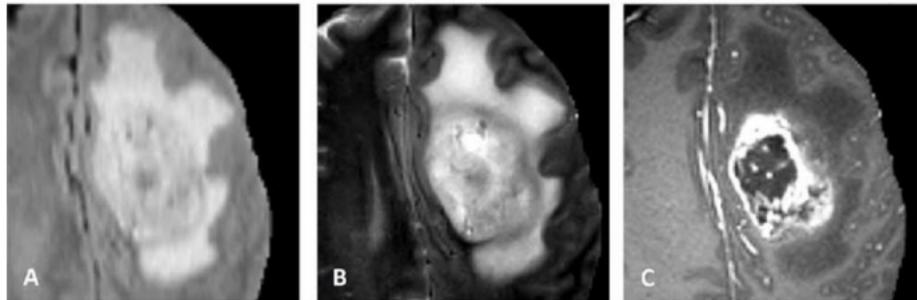
Example Labels in Medical Imaging



[1] Irwin et al. CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison. AAAI. 2019

[2] Menze et al. The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). IEEE TMI. 2015

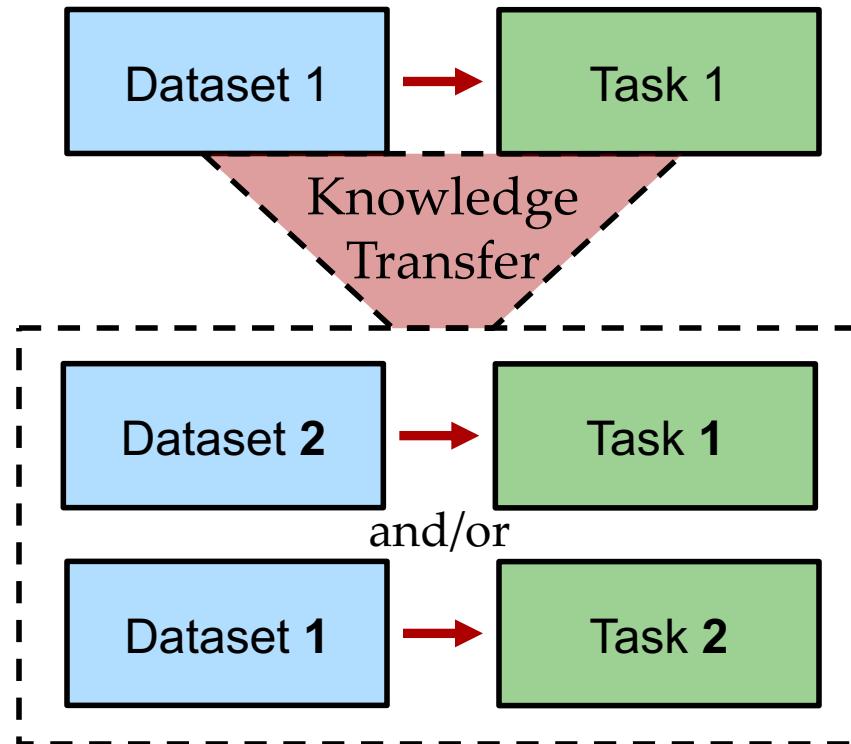
Example Labels in Medical Imaging



[1] Irwin et al. CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison. AAAI. 2019

[2] Menze et al. The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). IEEE TMI. 2015

Transfer Learning



Beyond Supervised Learning

- Semi-Supervised Learning

Step 1:

IM1	IM2
IM4	IM5



L1	L2
L4	L5

= Model 1

Step 2:

IM3		
IM6		
IM7	IM8	IM9

Model 1



PL3		
PL6		
PL7	PL8	PL9

= Dataset 2

Step 3:

IM1	IM2	IM3
IM4	IM5	IM6
IM7	IM8	IM9



L1	L2	PL3
L4	L5	PL6
PL7	PL8	PL9

= Model 2

Semi-Supervised Learning: Self-Training

Self-Training Terminology

- **Teacher Network:** Network that creates pseudo labels
- **Student Network:** Network that learns using pseudo labels

Terminology

- **Self-Training:** When student network is same/larger sized than teacher network
- **Knowledge Distillation:** When student network is smaller than teacher network

Noisy Student Self Training



ImageNet (**14M** examples)



JFT (**300M** examples)

	ImageNet top-1 acc.	ImageNet-A top-1 acc.
Prev. SOTA	86.4%	61.0%
Ours	88.4%	83.7%

Large accuracy gain for
adversarial examples

Adversarial Examples

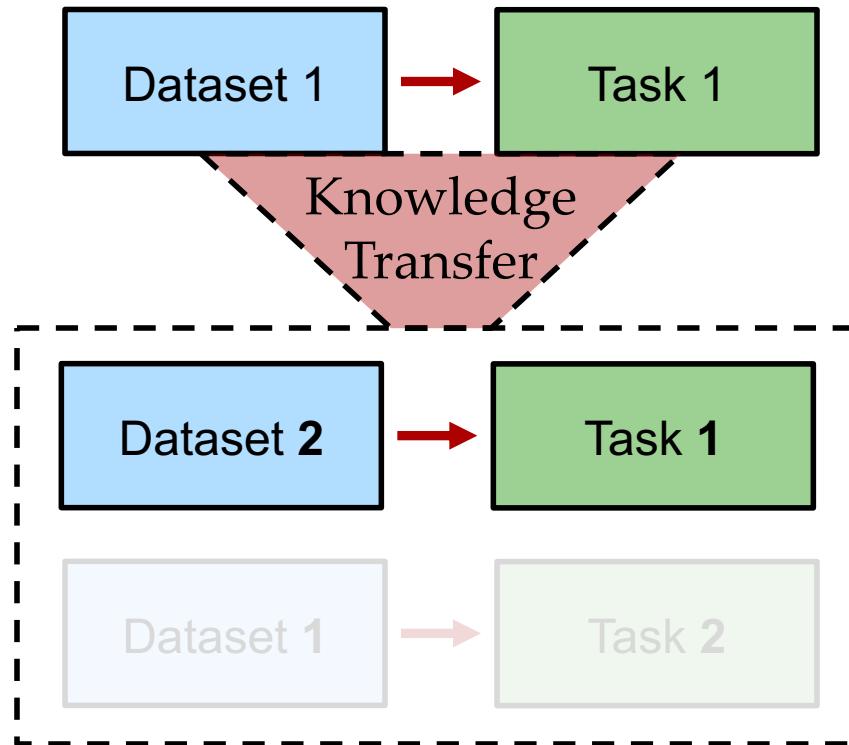
ImageNet-A



ImageNet-O



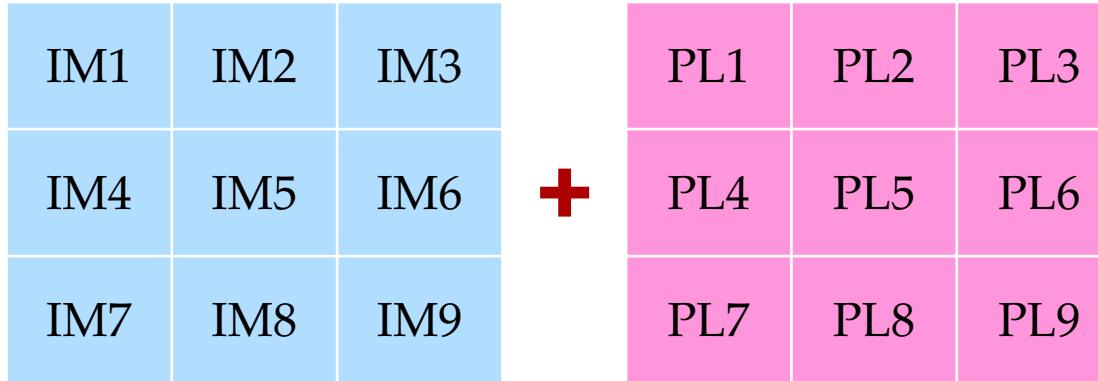
Semi-Supervised Transfer Learning



Self- Supervised Learning

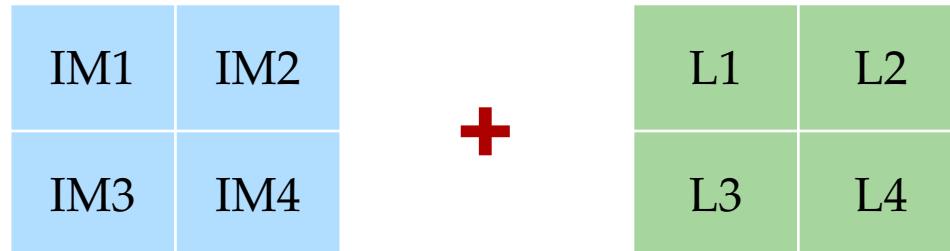
IM = Image
PL = Pseudolabel
L = Label

Step 1:



= Pretrained Model

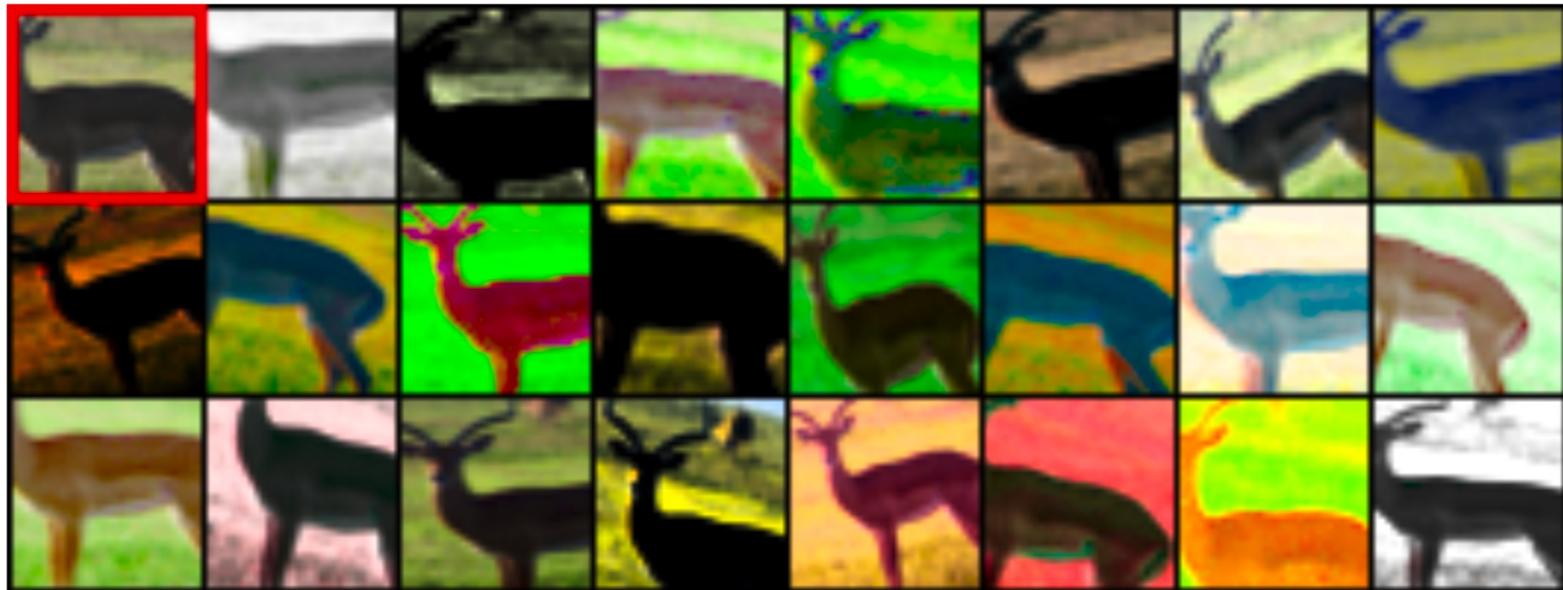
Step 2:



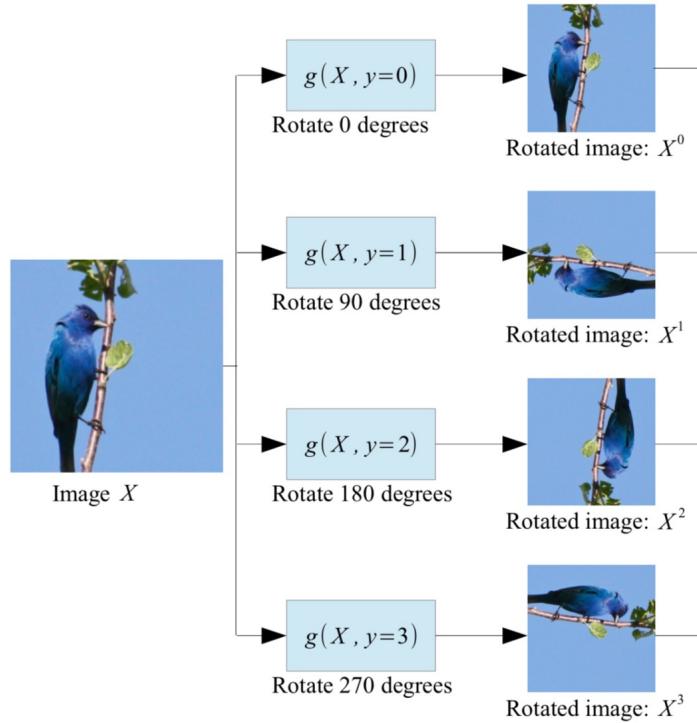
= Model!

Pretext Tasks

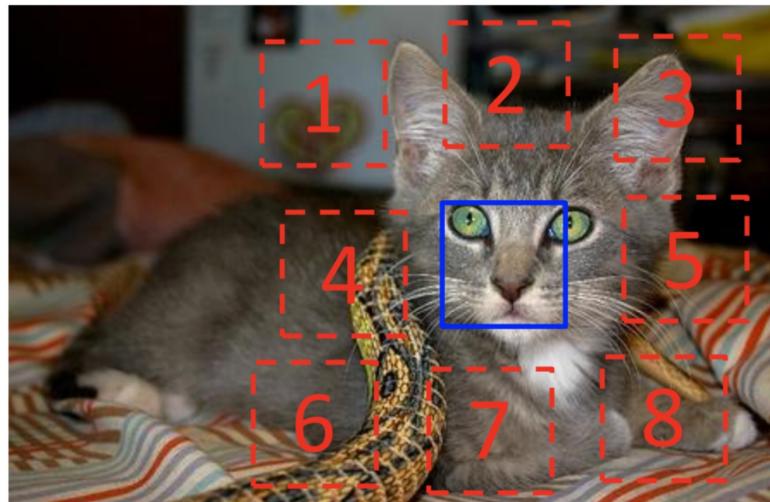
- Exemplar images



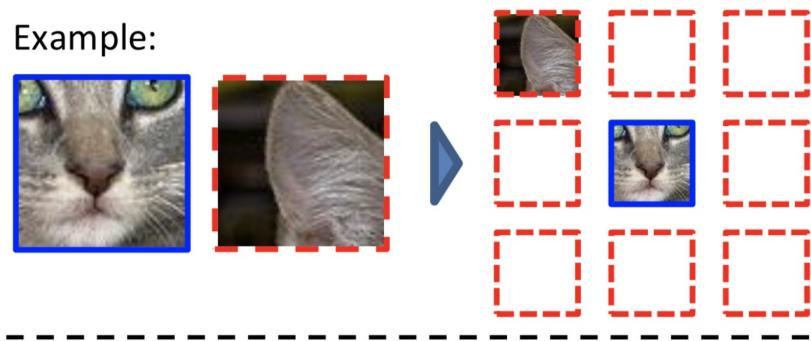
Pretext Tasks - Rotation



Pretext Tasks - Patching



Example:



What Position Does the Blue Square Occupy?

1	2	3
4	5	6
7	8	9



?

Image Inpainting

BERT Pretraining

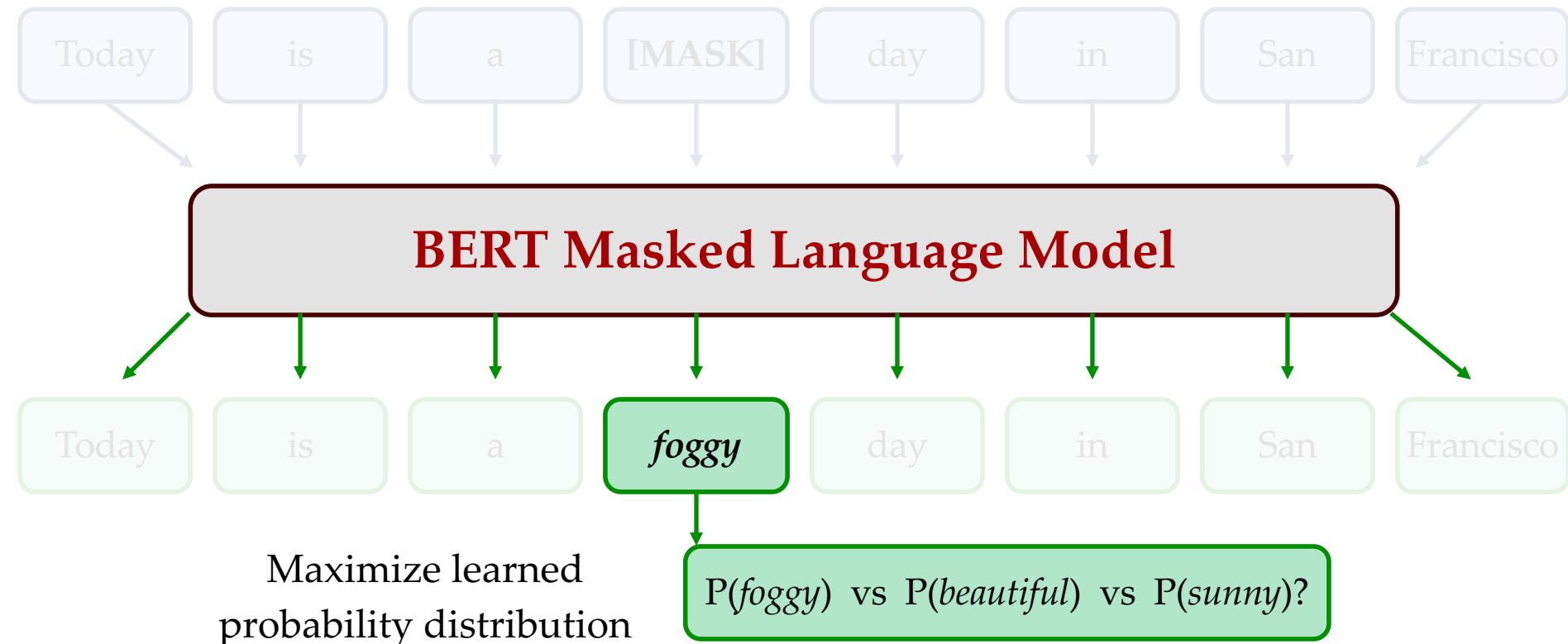
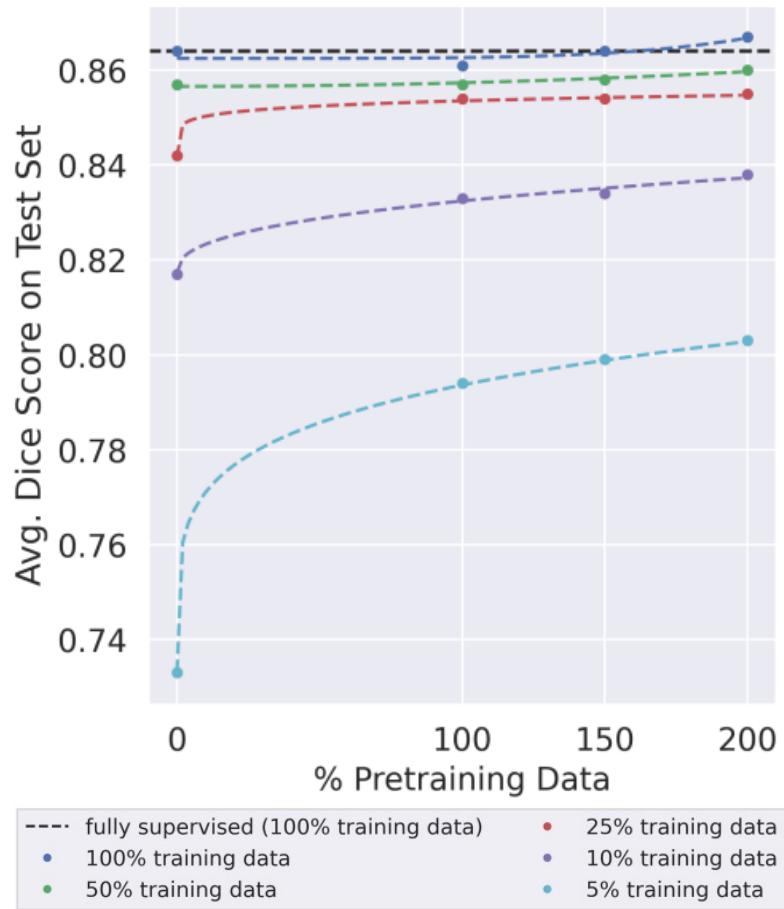
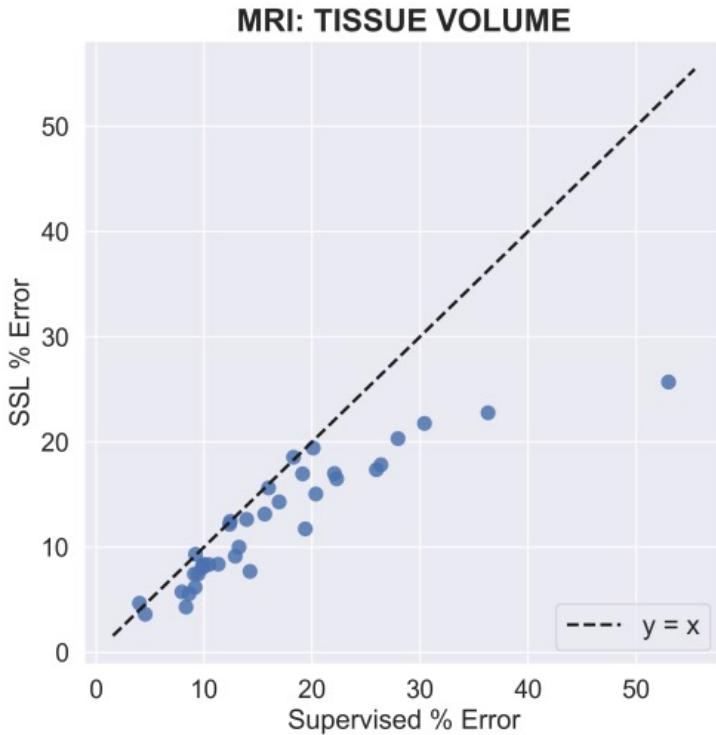
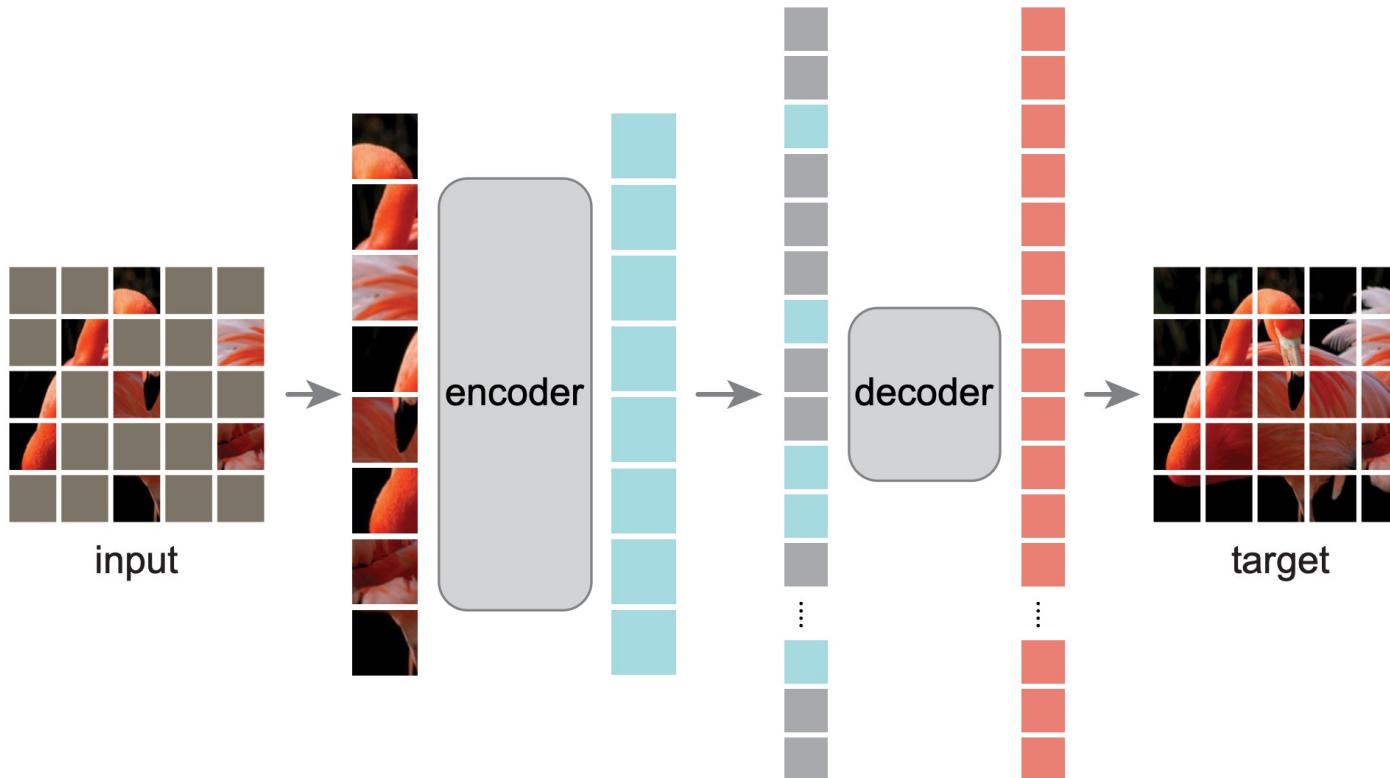


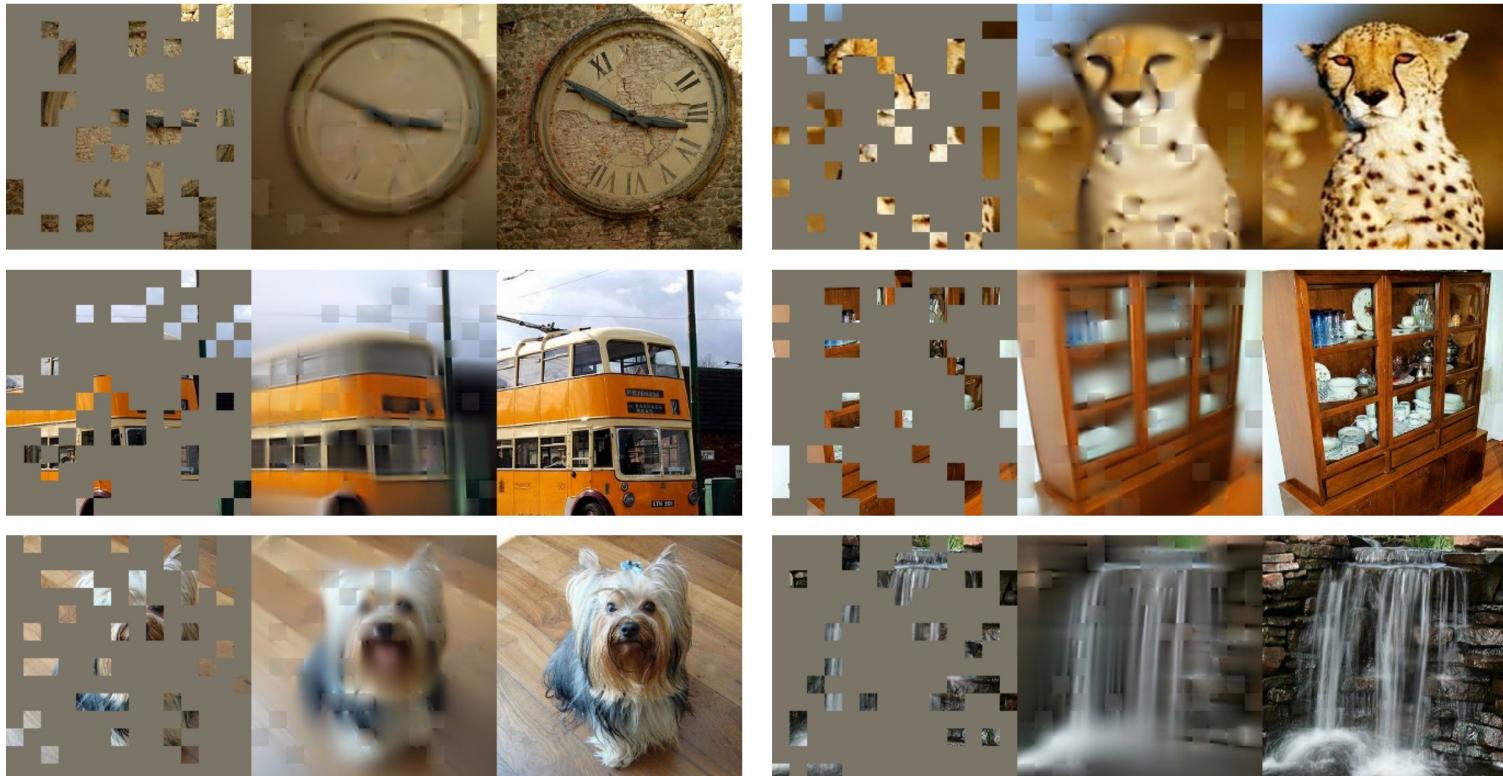
Image SSL Benefits



Latest Self-Supervised Learning



Latest Self-Supervised Learning



Contrastive Learning

Match the correct animal



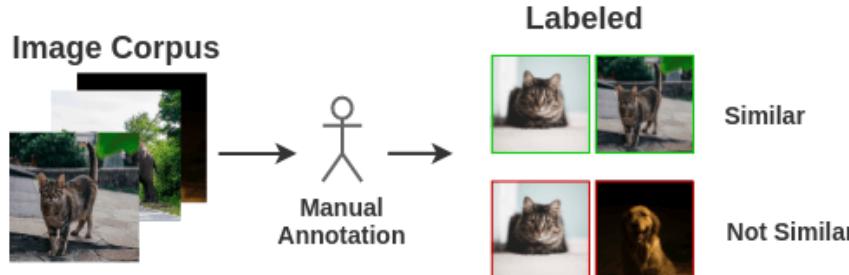
Contrastive Learning

Need similar and different examples

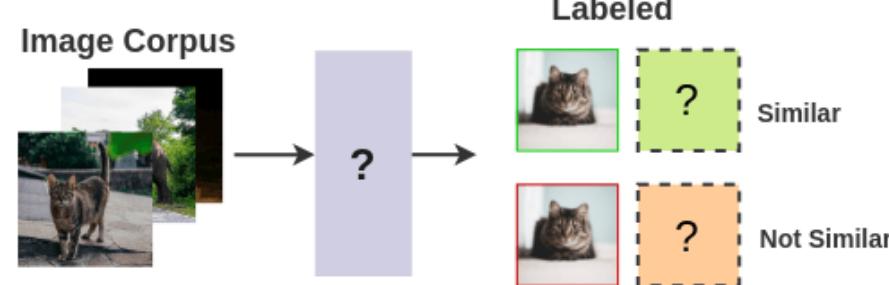


similarity(, **)**

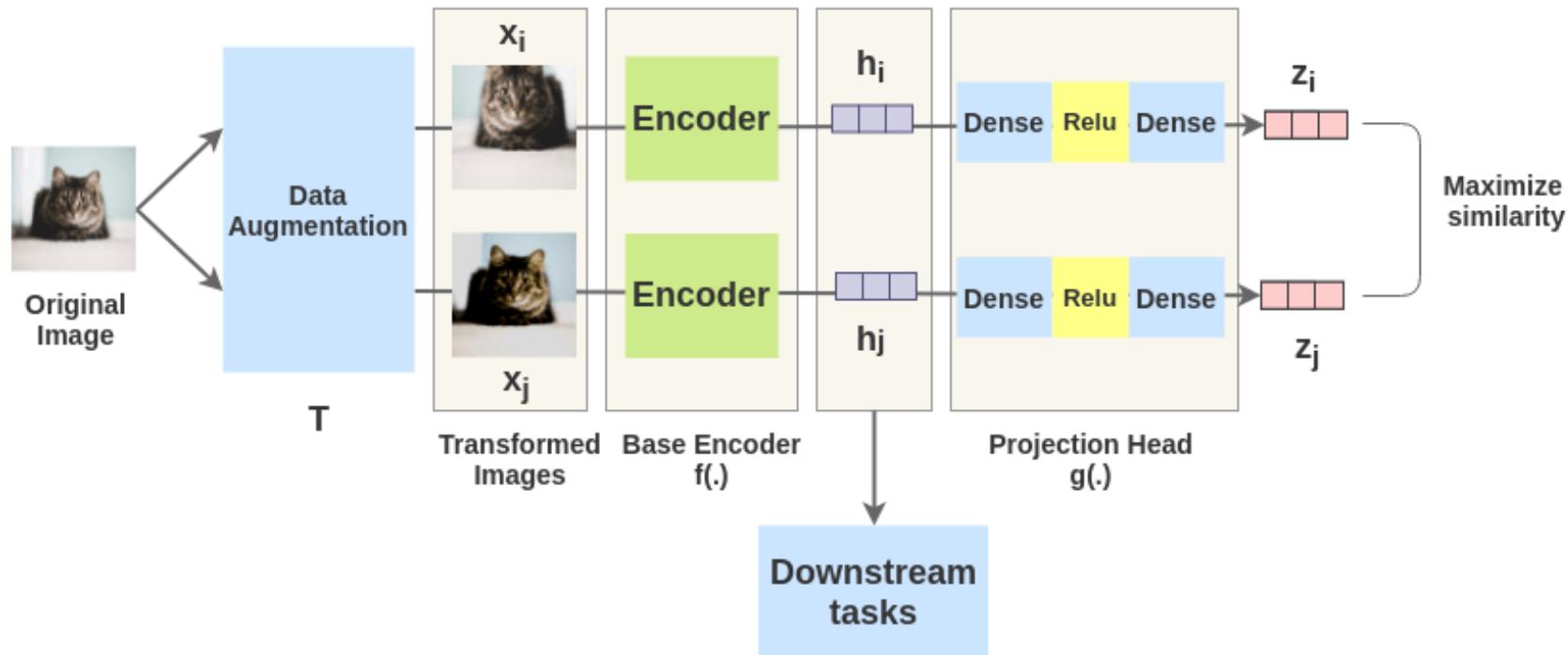
Supervised Approach



How can we automatically generate pairs?



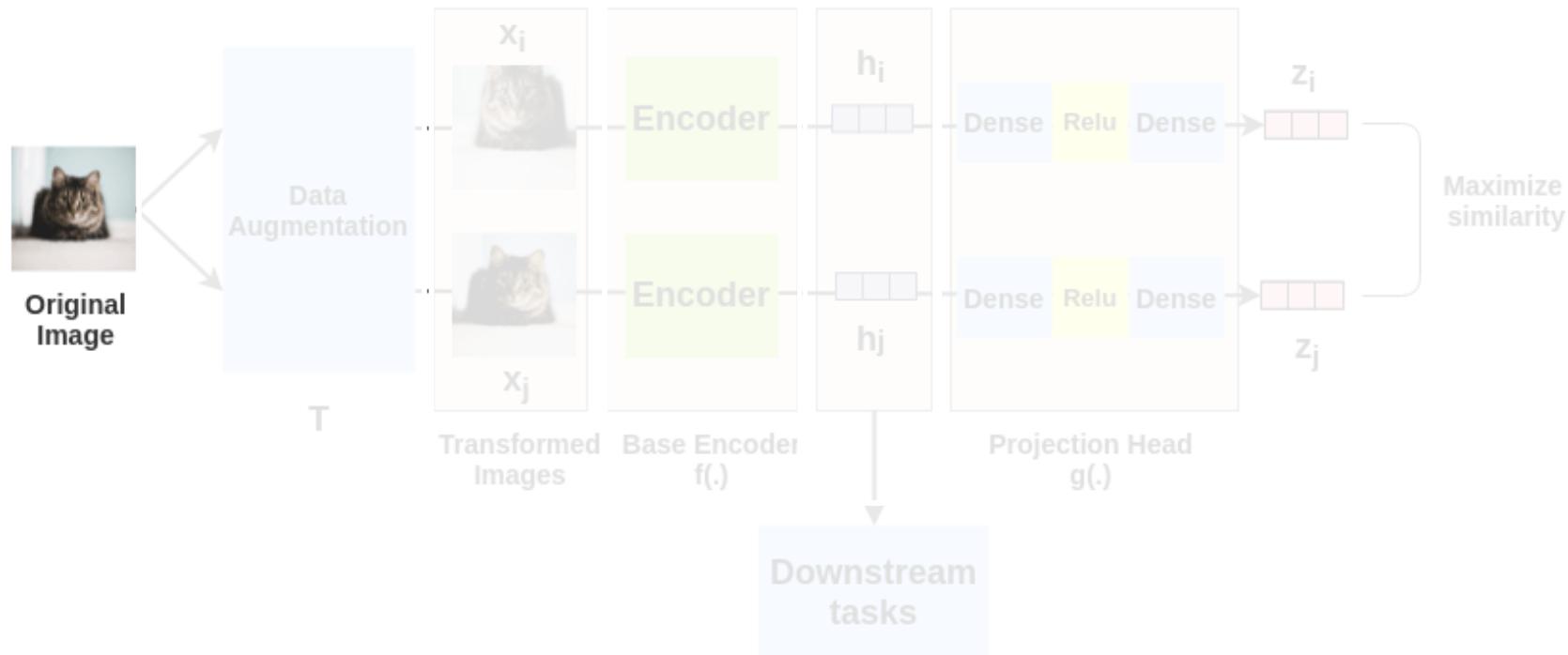
Contrastive Learning



[1] Chaudhary A. The Illustrated SimCLR Framework. <https://amitness.com/2020/03/illustrated-simclr/> 2020.

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

Contrastive Learning



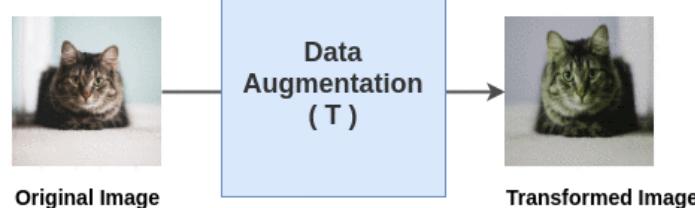
[1] Chaudhary A. The Illustrated SimCLR Framework. <https://amitness.com/2020/03/illustrated-simclr/> 2020.

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

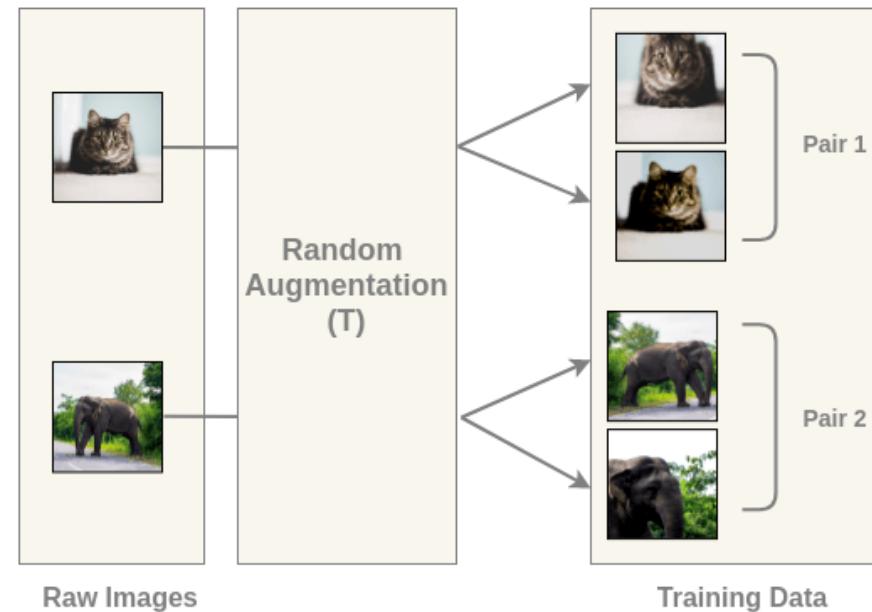
Contrastive Learning

Preparing similar pairs in a batch

Random Transformation



Batch Size
 $N = 2$



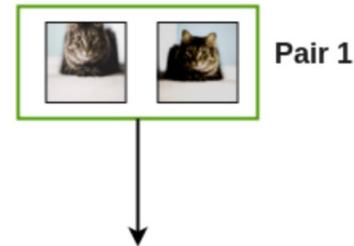
[1] Chaudhary A. The Illustrated SimCLR Framework. <https://amitness.com/2020/03/illustrated-simclr/> 2020.

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

Contrastive Learning

Similarity Calculation of Augmented Images

$$\text{similarity}(\mathbf{x}_i, \mathbf{x}_j) = \text{cosine similarity}(\mathbf{z}_i, \mathbf{z}_j)$$



Softmax =

$$\frac{e^{\text{similarity}(\mathbf{x}_i, \mathbf{x}_j)}}{e^{\text{similarity}(\mathbf{x}_i, \mathbf{x}_j)} + e^{\text{similarity}(\mathbf{x}_i, \mathbf{x}_k)} + e^{\text{similarity}(\mathbf{x}_i, \mathbf{x}_l)}}$$

Pairwise cosine similarity

[1] Chaudhary A. The Illustrated SimCLR Framework. <https://amitness.com/2020/03/illustrated-simclr/> 2020.

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

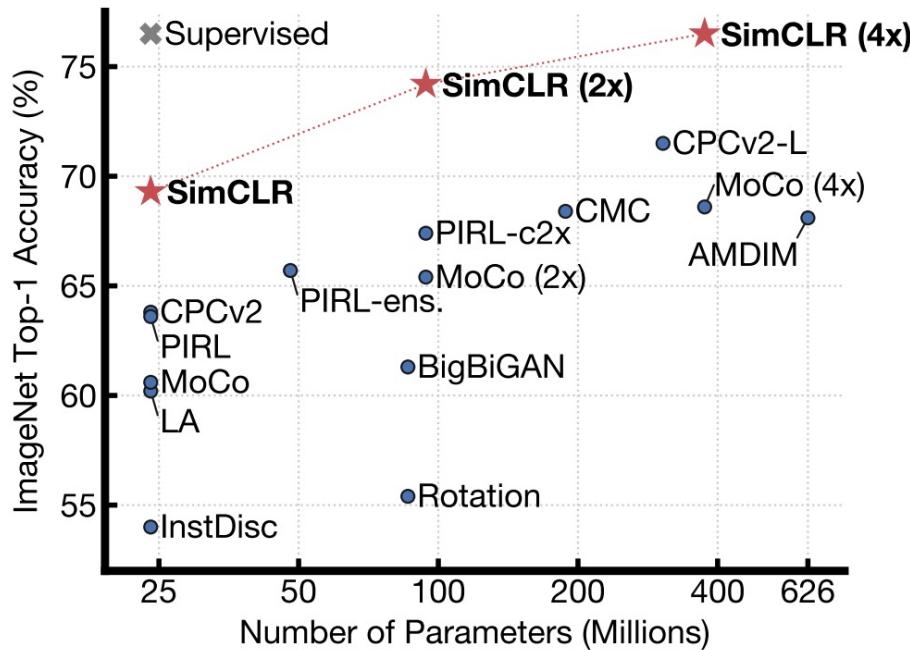
Noise Contrastive Estimation Loss

- Compute over both pairs to account for asymmetry

$$l(i, j) = -\log \frac{\exp(s_{i,j})}{\sum_{k=1}^{2N} l_{[k \neq i]} \exp(s_{i,k})}$$

$$l(\begin{array}{|c|c|}\hline \text{cat} & \text{cat} \\\hline\end{array}) = -\log \left(\frac{e^{\text{similarity}(\begin{array}{|c|c|}\hline \text{cat} & \text{cat} \\\hline\end{array})}}{e^{\text{similarity}(\begin{array}{|c|c|}\hline \text{cat} & \text{cat} \\\hline\end{array})} + e^{\text{similarity}(\begin{array}{|c|c|}\hline \text{cat} & \text{elephant} \\\hline\end{array})} + e^{\text{similarity}(\begin{array}{|c|c|}\hline \text{cat} & \text{bear} \\\hline\end{array})}} \right)$$

SimCLR Technique



- Large batch size requirements
- Long training times
- Heuristic data augmentations

SimCLR Augmentations



(a) Original



(b) Crop and resize



(c) Crop, resize (and flip)



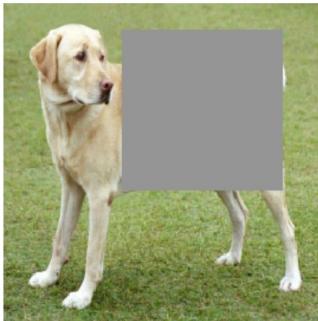
(d) Color distort. (drop)



(e) Color distort. (jitter)



(f) Rotate $\{90^\circ, 180^\circ, 270^\circ\}$



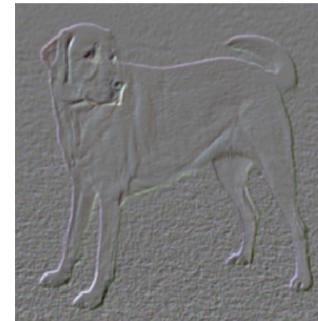
(g) Cutout



(h) Gaussian noise

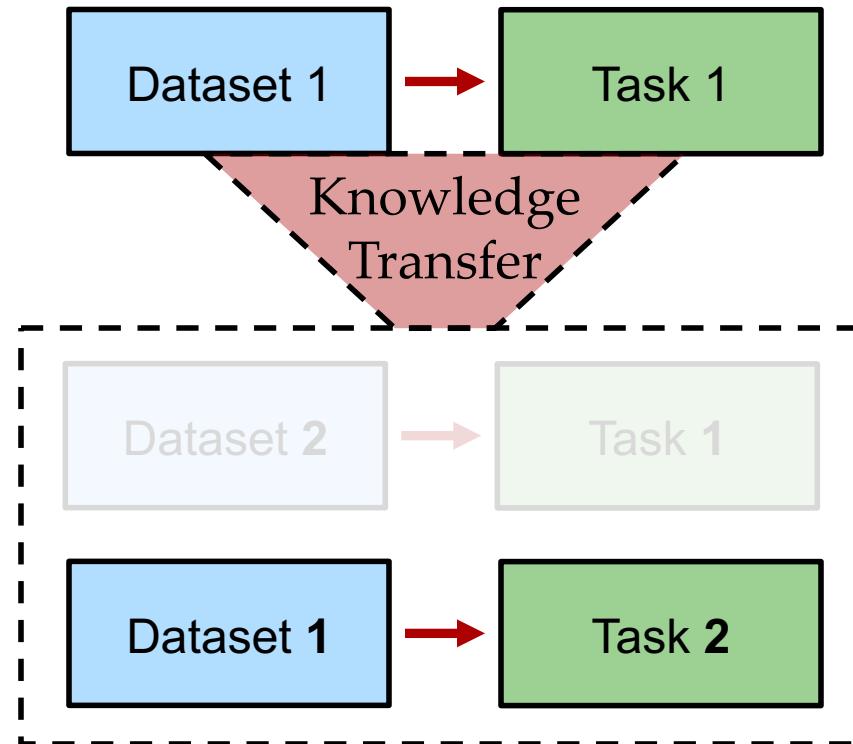


(i) Gaussian blur

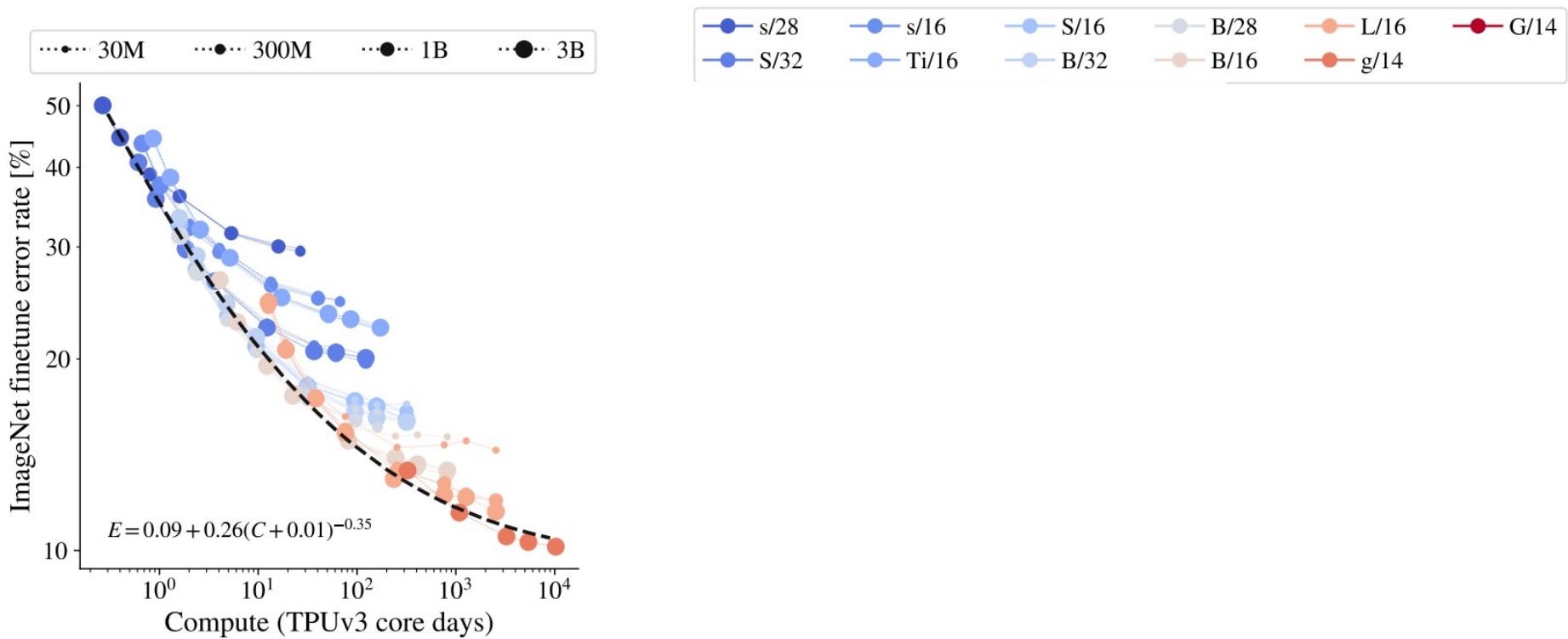


(j) Sobel filtering

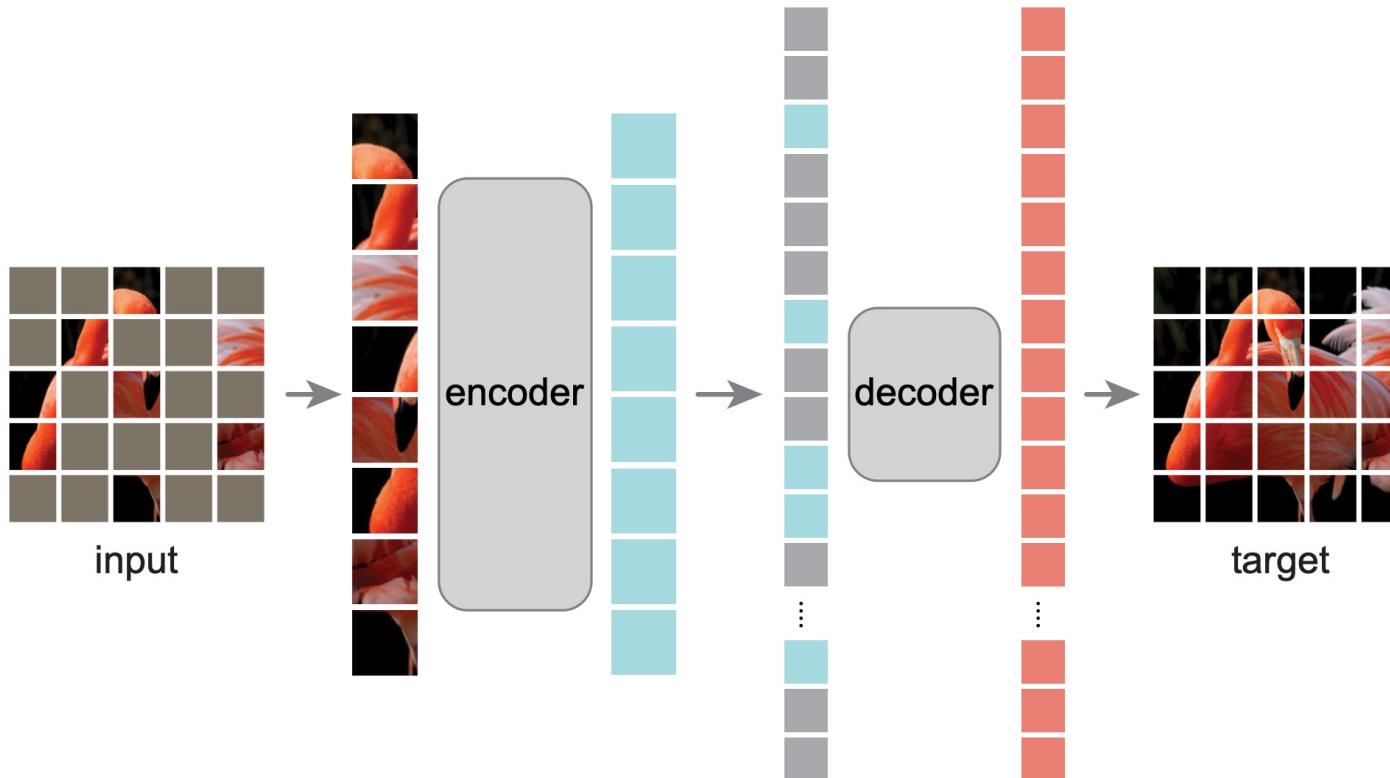
Transfer Learning



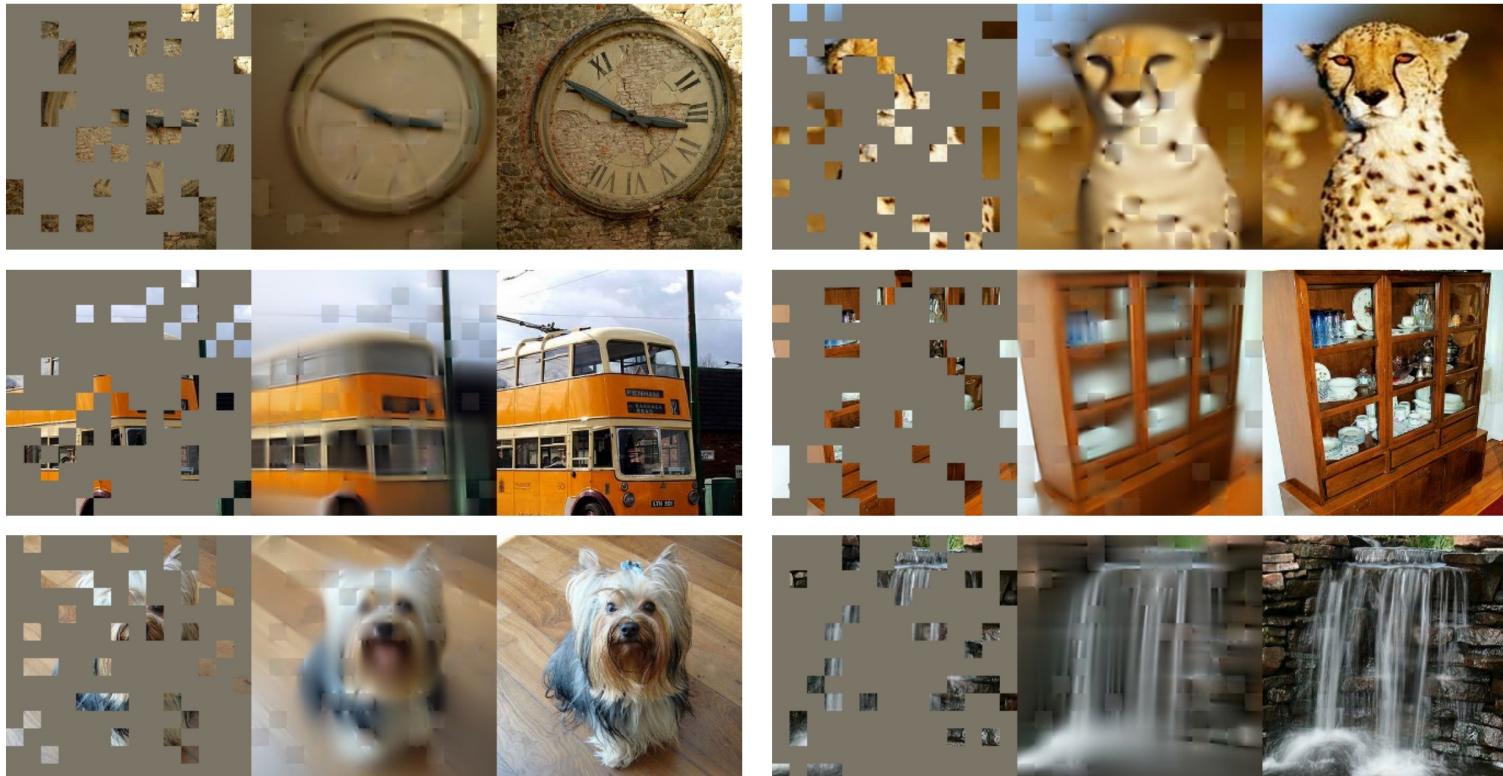
Benefits of Scaling



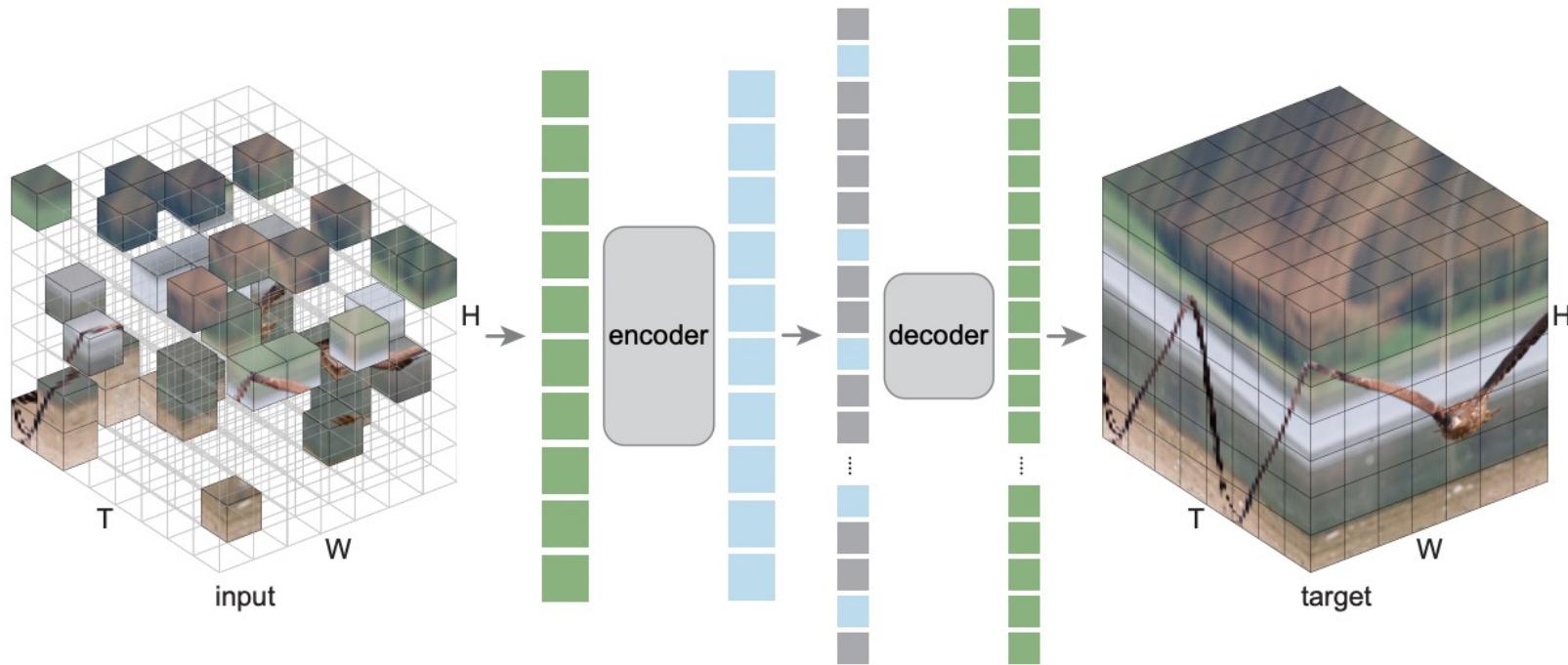
Latest Self-Supervised Learning



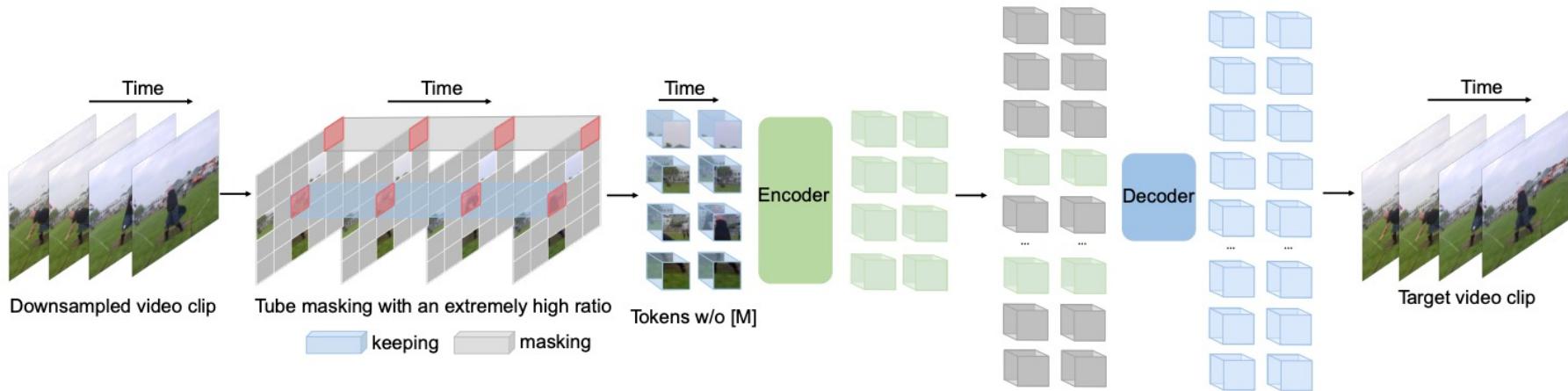
Latest Self-Supervised Learning



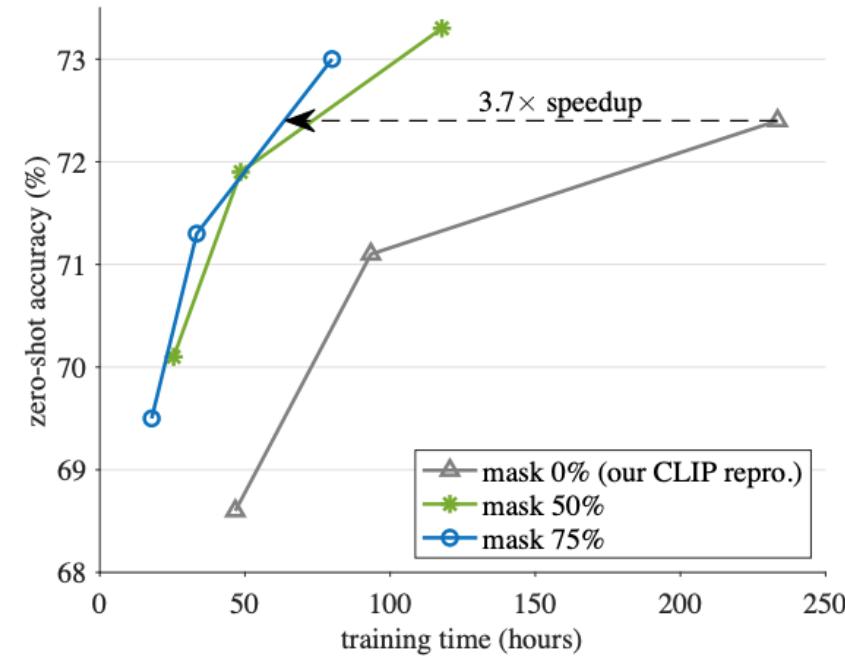
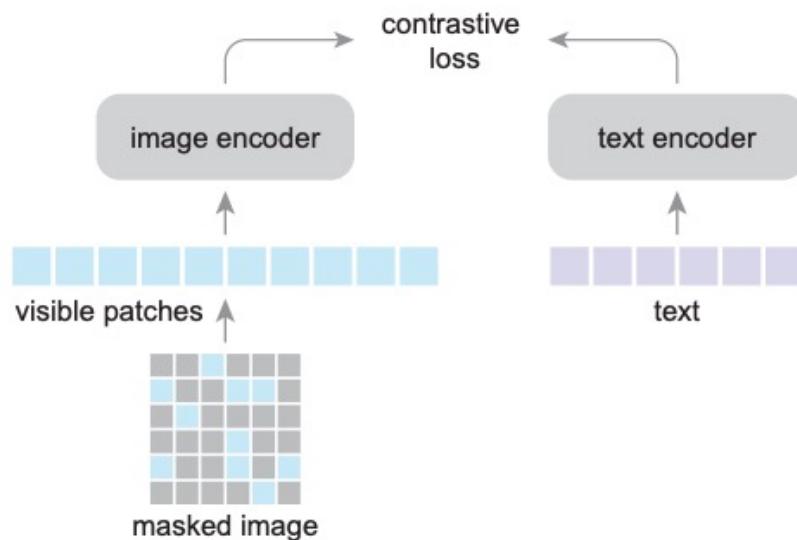
Extensions of Prior Approaches



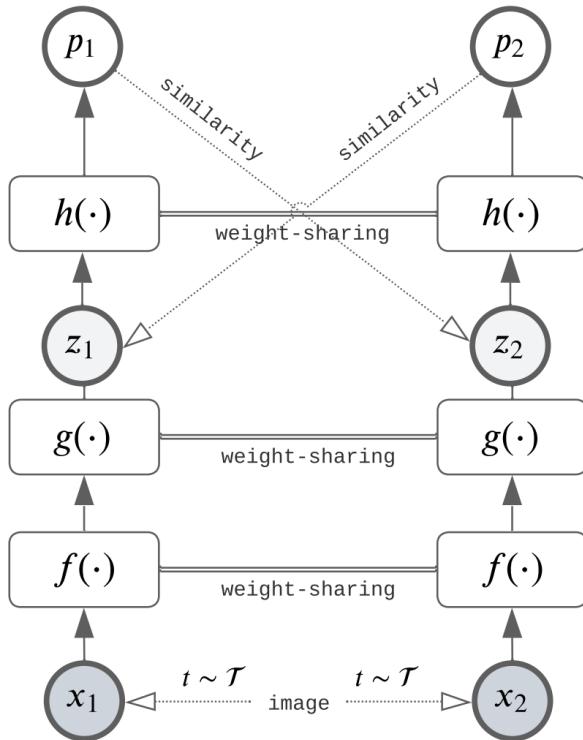
Tube Masking for Video MAE



Masking for Multi-Modal Learning



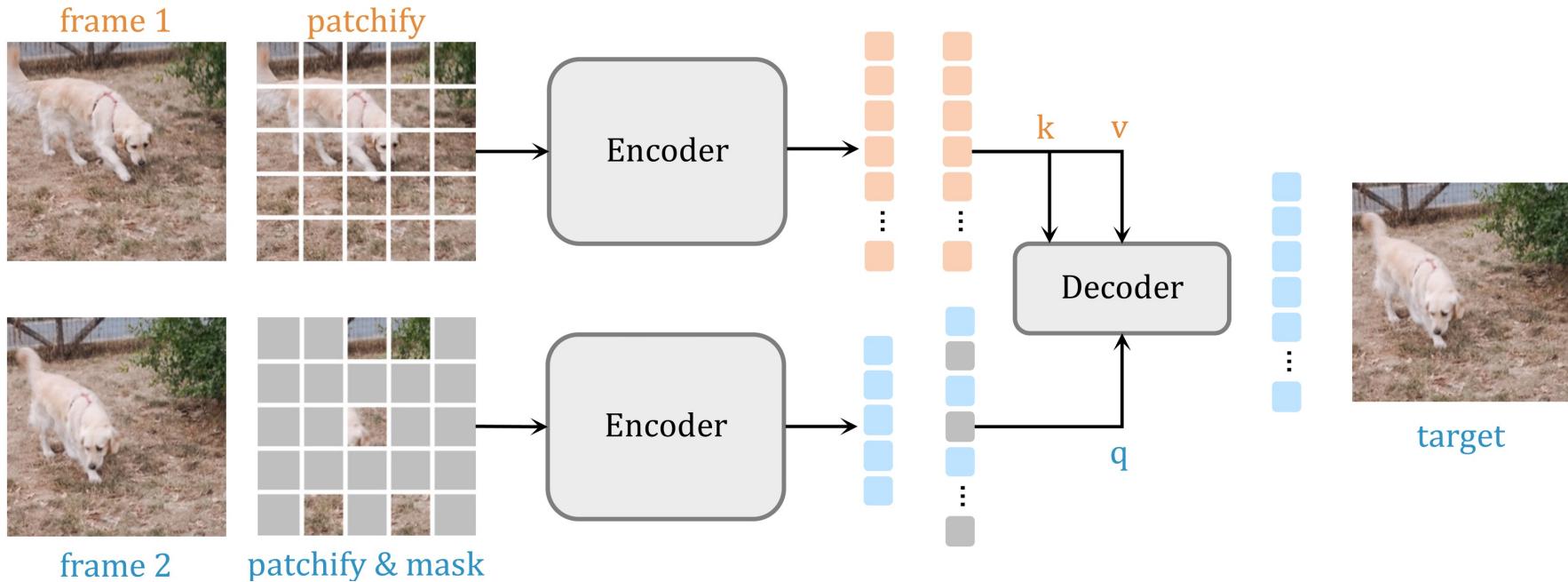
Adaptations to Medical Imaging



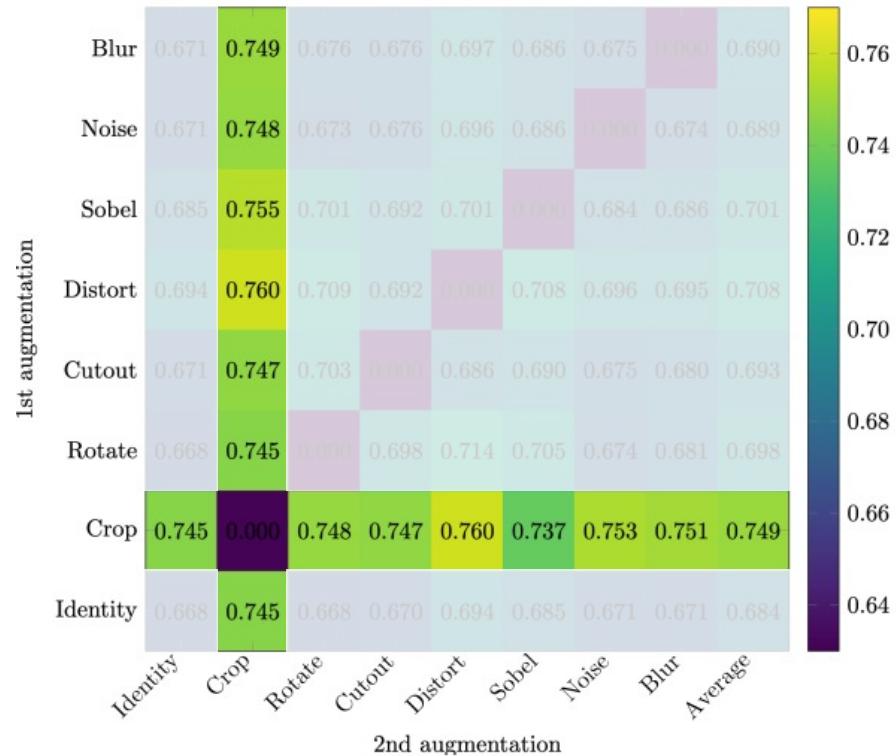
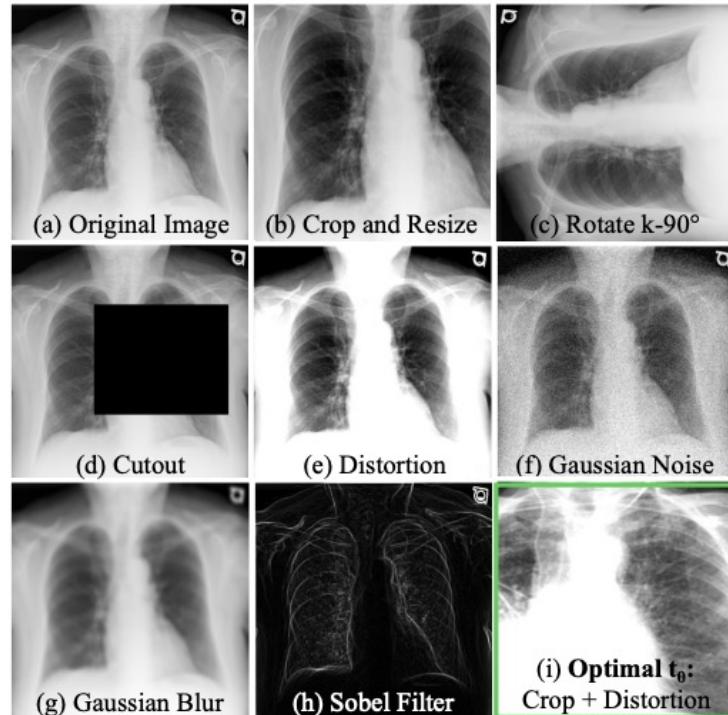
- Architectures inspired by the SimSiam method
- X = Image
- F = Image Encoder
- G, H = MLP projectors
- Z = latent representation
- P = latent representation predictors

$$\mathcal{L} = -\frac{1}{2} \left(\frac{p_1}{\|p_1\|_2} \cdot \frac{z_2}{\|z_2\|_2} \right) - \frac{1}{2} \left(\frac{p_2}{\|p_2\|_2} \cdot \frac{z_1}{\|z_1\|_2} \right)$$

Siamese Masked Autoencoders



Augmentations for Medical Imaging



Suggested Reading

A Simple Framework for Contrastive Learning of Visual Representations

Ting Chen¹ Simon Kornblith¹ Mohammad Norouzi¹ Geoffrey Hinton¹

Masked Autoencoders Are Scalable Vision Learners

Kaiming He^{*,†} Xinlei Chen^{*} Saining Xie Yanghao Li Piotr Dollár Ross Girshick

^{*}equal technical contribution [†]project lead

Facebook AI Research (FAIR)

Questions?

akshaysc@stanford.edu

