Lecture 22:
Self-Supervised Learning

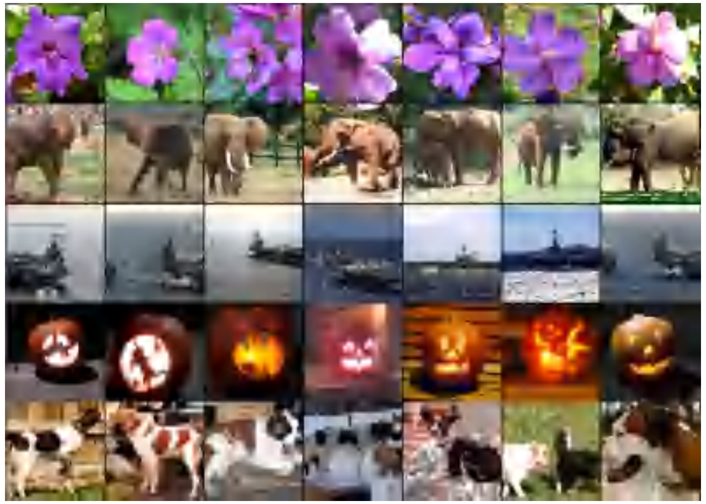
Reminder: A5

Recurrent networks, attention, Transformers

Due on **Tuesday 4/12**, 11:59pm ET

Last Time: Visualizing and Understanding CNNs

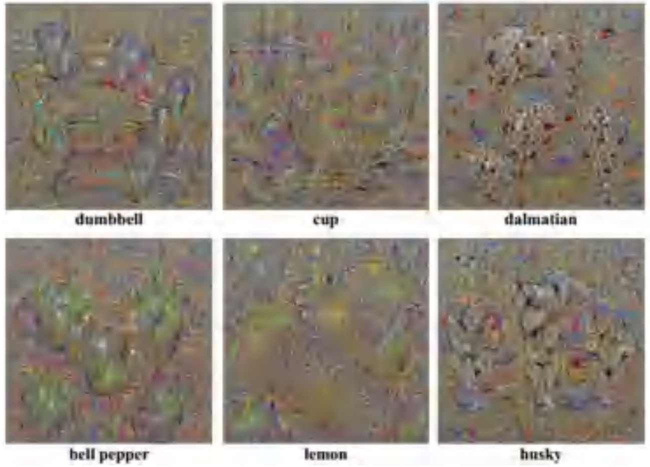
Nearest Neighbor



Maximally Activating Patches

(Guided) Backprop

Synthetic Images via Gradient Ascent



Feature Inversion

Last Time: Making Art with CNNs

DeepDream

Style Transfer

Today: Self-Supervised Learning

Recall: Supervised vs Unsupervised Learning

Supervised Learning

Data: (x, y)

x is data, y is label

Goal: Learn a *function* to map x -> y

Examples: Classification, regression, object detection, semantic segmentation, image captioning, etc.

Unsupervised Learning

Data: x

Just data, no labels!

Goal: Learn some underlying hidden *structure* of the data

Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.

Problem: Supervised Learning is Expensive!

Assume you want to label 1M images. How much will it cost?

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(1,000,000 images)	(Small to medium sized dataset)
× (10 seconds/image)	(Fast annotation)
× (1/3600 hours/second)	
× ($15 / hour)	(Low wage paid to annotator)

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= $41,667	

(Other assumptions: one annotator per image, no benefits / payroll tax / crowdsourcing fee for annotators; not accounting for time to set up tasks for annotators, etc. Real costs could easily be 3x this or more)

Problem: Supervised Learning is Expensive!

Assume you want to label **1B** images. How much will it cost?

(1,000,000,000 images)	(Large dataset)
$\times$ (10 seconds/image)	(Fast annotation)
$\times$ (1/3600 hours/second)	
$\times$ (\$15 / hour)	(Low wage paid to annotator)
= **\$41,666,667**	

(Other assumptions: one annotator per image, no benefits / payroll tax / crowdsourcing fee for annotators; not accounting for time to set up tasks for annotators, etc. Real costs could easily be 3x this or more)

Problem: Supervised Learning is Not How We Learn

Babies don't get supervision for everything they see!

Solution: Self-Supervised Learning

Lets build methods that learn from ”raw” data – no annotations required

Unsupervised Learning: Model isn’t told what to predict. Older terminology, not used as much today.

Self-Supervised Learning: Model is trained to predict some naturally-occurring signal in the raw data rather than human annotations.

Solution: Self-Supervised Learning

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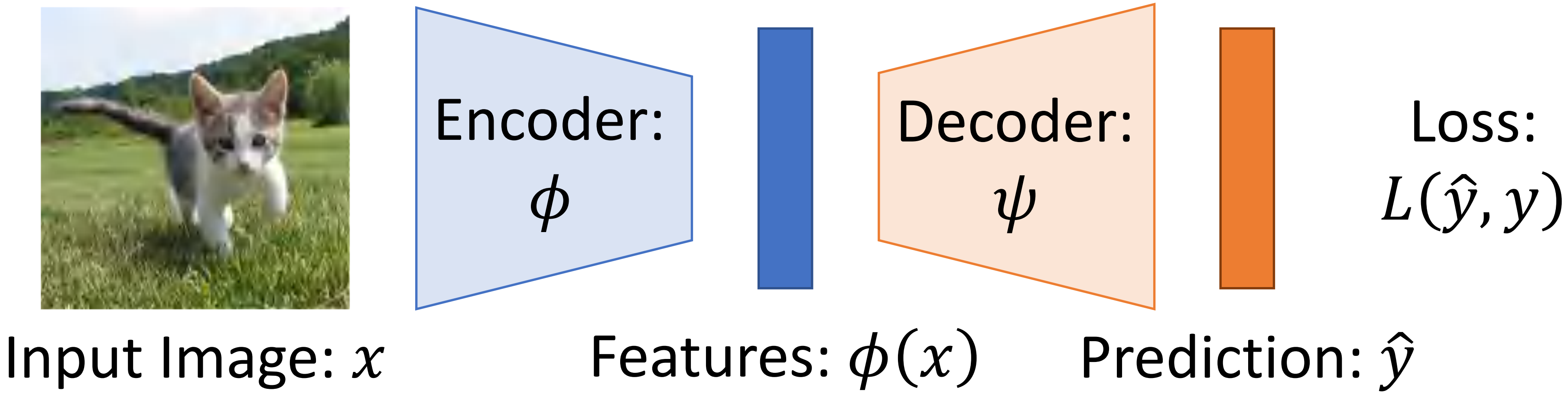
Semi-Supervised Learning: Train jointly with some labeled data and (a lot) of unlabeled data.

Self-Supervised Learning: Pretext then Transfer

Step 1: Pretrain a network on a pretext task that doesn't require supervision



Self-Supervised Learning: Pretext then Transfer

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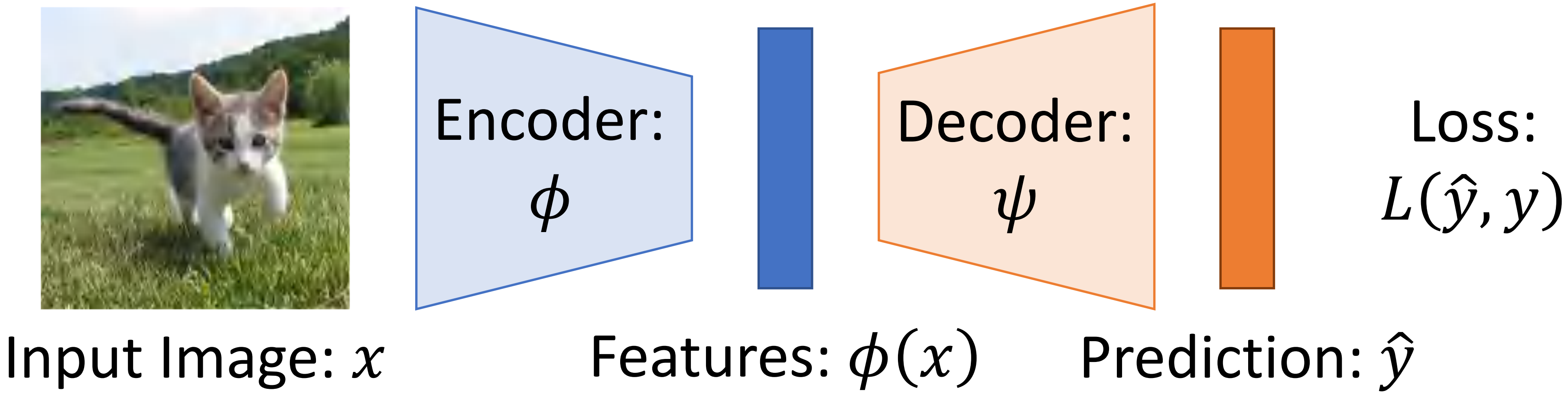
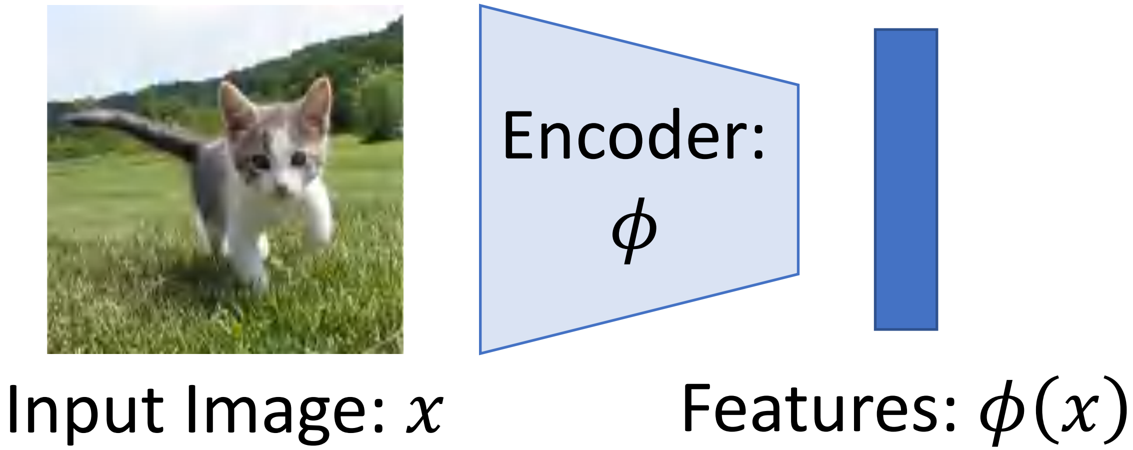


Step 2: Transfer encoder to downstream tasks via linear classifiers, KNN, finetuning



Downstream tasks: Image classification, object detection, semantic segmentation

Self-Supervised Learning: Pretext then Transfer

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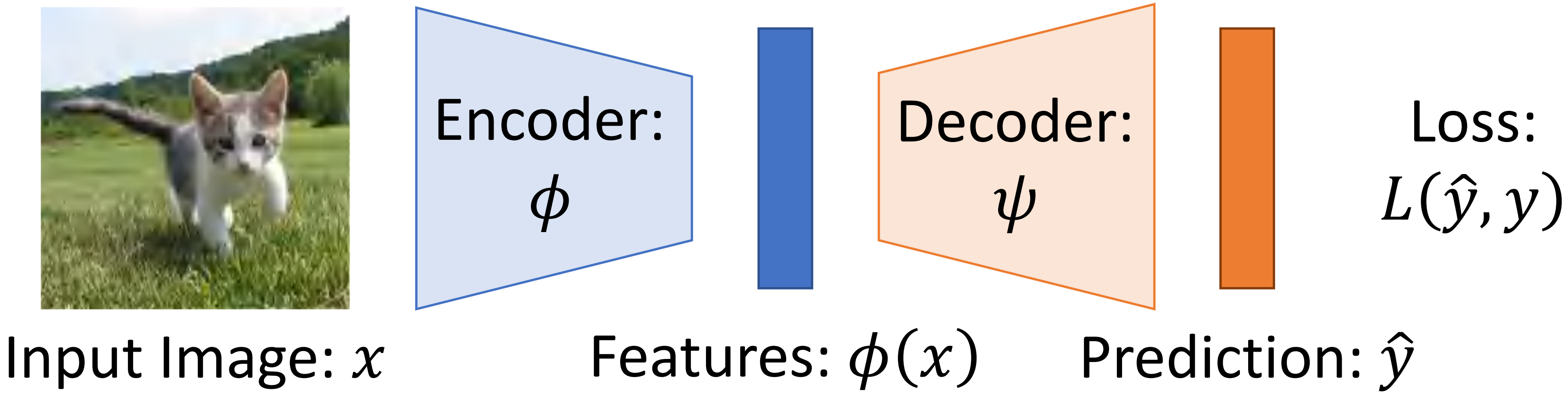

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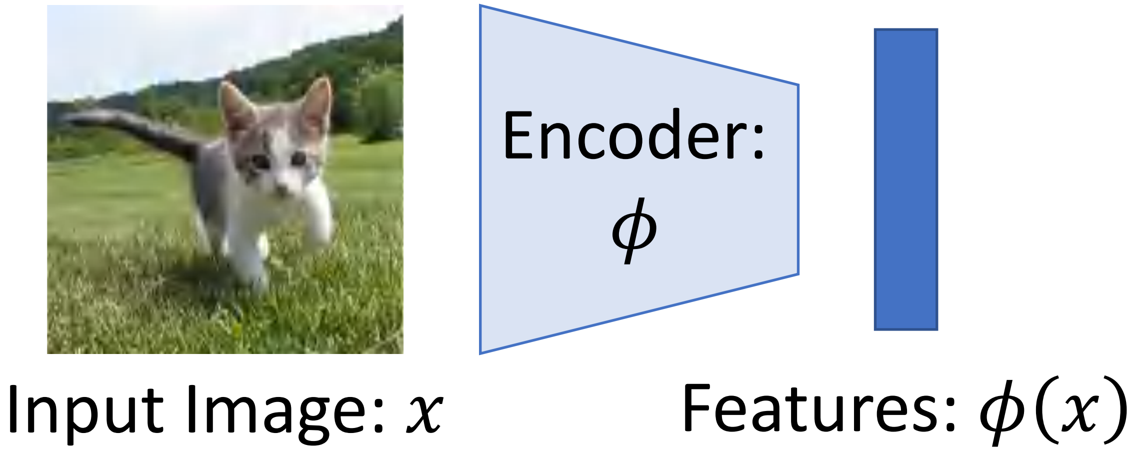


Goal: Pretrain + Transfer does better than supervised pretraining, and better than directly training on downstream

Self-Supervised Learning: Pretext Tasks

Generative: Predict part of the input signal
- Autoencoders (sparse, denoising, masked)
- Autoregressive
- GANs
- Colorization
- Inpainting

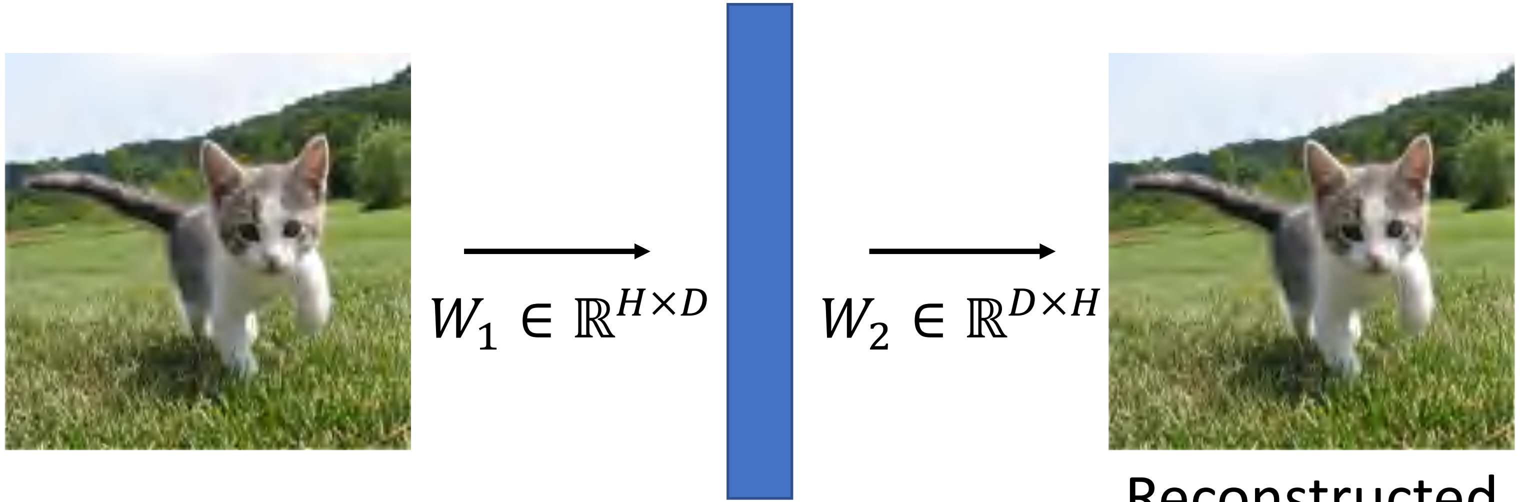
Discriminative: Predict something about the input signal
- Context prediction
- Rotation
- Clustering
- Contrastive

Multimodal: Use some additional signal in addition to RGB images
- Video
- 3D
- Sound
- Language

Recall: Autoencoder

Autoencoder tries to reconstruct inputs. Hidden layer (hopefully) learns good representations. <u>Generative</u> pretraining task!

$$L(x) = R(x, \hat{x}) = \|x - \hat{x}\|_2^2$$



$W_1 \in \mathbb{R}^{H \times D}$ $W_2 \in \mathbb{R}^{D \times H}$

Input Image: $x \in \mathbb{R}^D$

Hidden Layer: $\mathrm{h} \in \mathbb{R}^H$

Reconstructed Image: $\hat{x} \in \mathbb{R}^D$

Lee et al, "Efficient Sparse Coding Algorithms", NeurIPS 2006; Ranzato et al, "Efficient Learning of Sparse Representations with an Energy-Based Model", NeurIPS 2006; Lee et al, "Sparse deep belief net models for visual area V2", NeurIPS 2007; Ng, "Sparse Autoencoder", CS294A Lecture Notes

Recall: Autoencoder

Autoencoder tries to reconstruct inputs. Hidden layer (hopefully) learns good representations

$$L(x) = R(x, \hat{x}) \\ = \|x - \hat{x}\|_2^2$$

H < D is the only thing forcing non-trivial hidden representations…

Input Image:
$x \in \mathbb{R}^D$

$\xrightarrow{\quad}$ $W_1 \in \mathbb{R}^{H \times D}$

Hidden Layer:
$\mathrm{h} \in \mathbb{R}^H$

$\xrightarrow{\quad}$ $W_2 \in \mathbb{R}^{D \times H}$

Reconstructed Image:
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Sparse Autoencoder

Train an autoencoder to **reconstruct inputs** with **sparse activations** (mostly 0). Many ways to implement sparsity penalties!

$$L(x) = R(x, \hat{x}) + \lambda S(h)$$
$$= \|x - \hat{x}\|_2^2 + \lambda \|h\|_1$$

$W_1 \in \mathbb{R}^{H \times D}$

Hidden Layer: 0 0 1 0 0 0 1 0

$W_2 \in \mathbb{R}^{D \times H}$

Input Image: $x \in \mathbb{R}^D$

Hidden Layer: $h \in \mathbb{R}^H$

Reconstructed Image: $\hat{x} \in \mathbb{R}^D$

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Denoising Autoencoder

Train an autoencoder to reconstruct noisy inputs (pixels randomly set to zero)

$$L(x) = R(x, \hat{x}) = \|x - \hat{x}\|_2^2$$

Input Image: $x \in \mathbb{R}^D$

Corrupted Image: $x \in \mathbb{R}^D$

$W_1 \in \mathbb{R}^{H \times D}$

Hidden Layer: $\mathrm{h} \in \mathbb{R}^H$

$W_2 \in \mathbb{R}^{D \times H}$

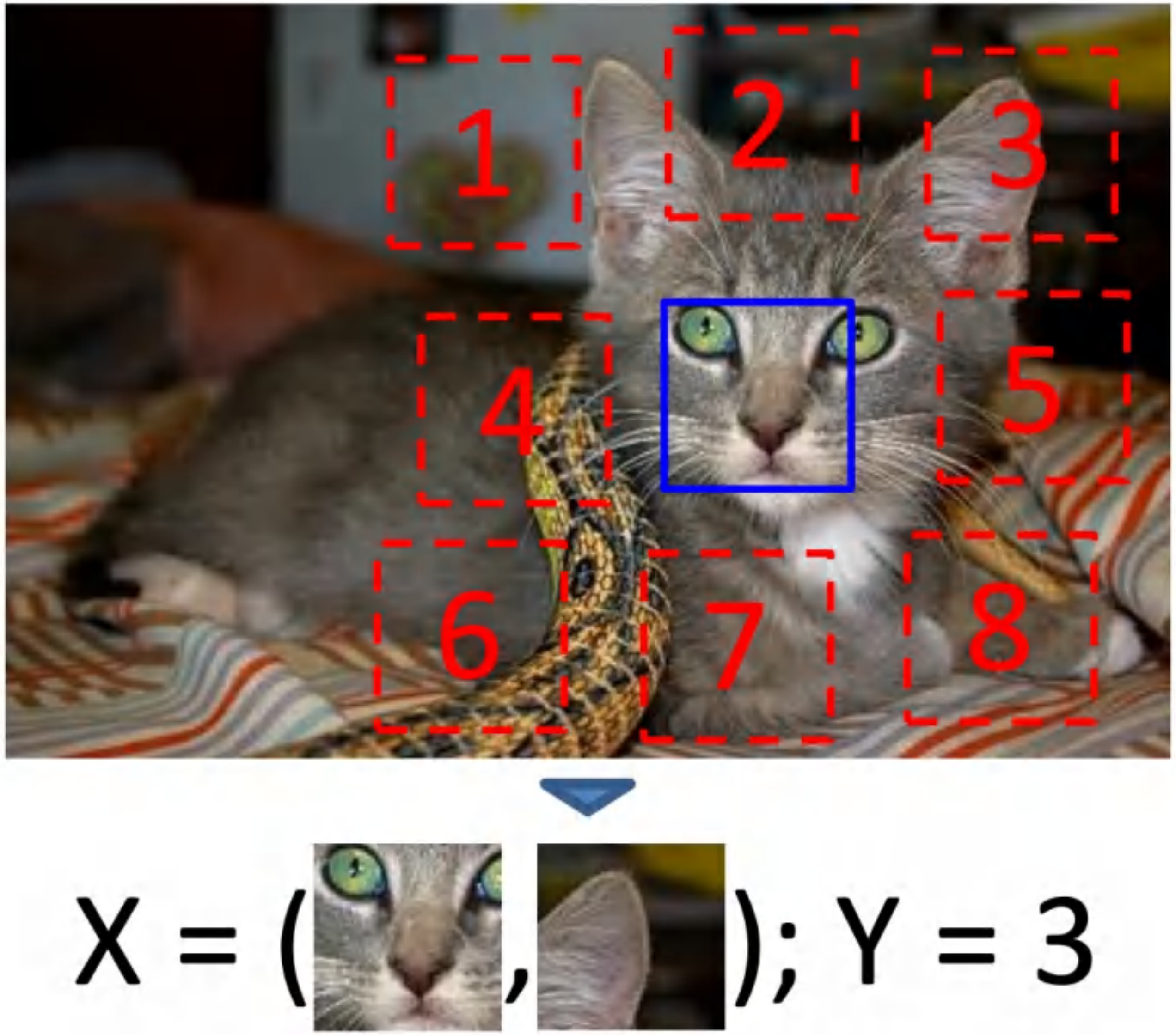
Reconstructed Image: $\hat{x} \in \mathbb{R}^D$

Vincent et al, "Extracting and Composing Robust Features with Denoising Autoencoders", ICML 2008

Context Prediction

Model predicts relative location of two patches from the same image.
Discriminative pretraining task

Intuition: Requires understanding objects and their parts



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

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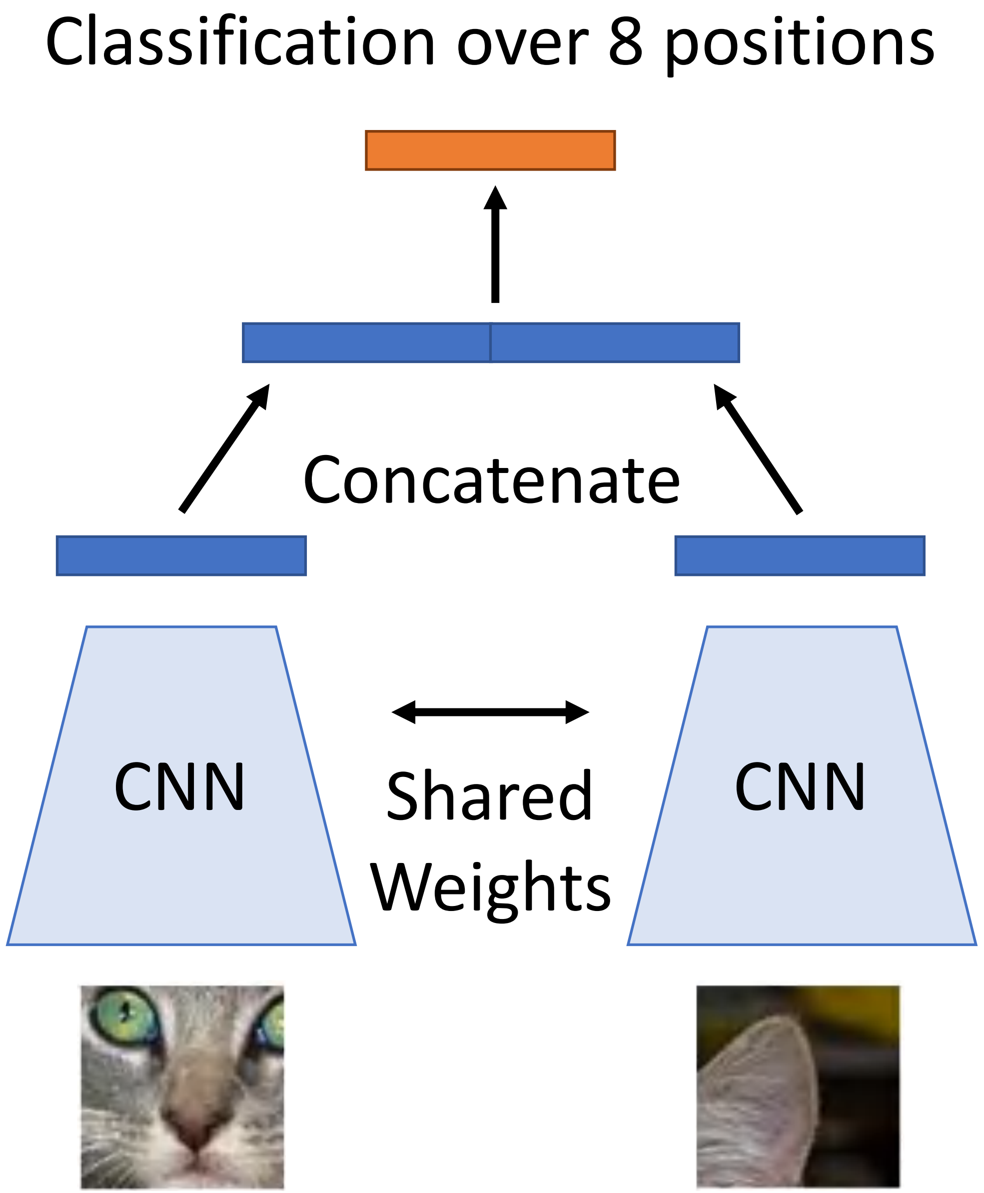

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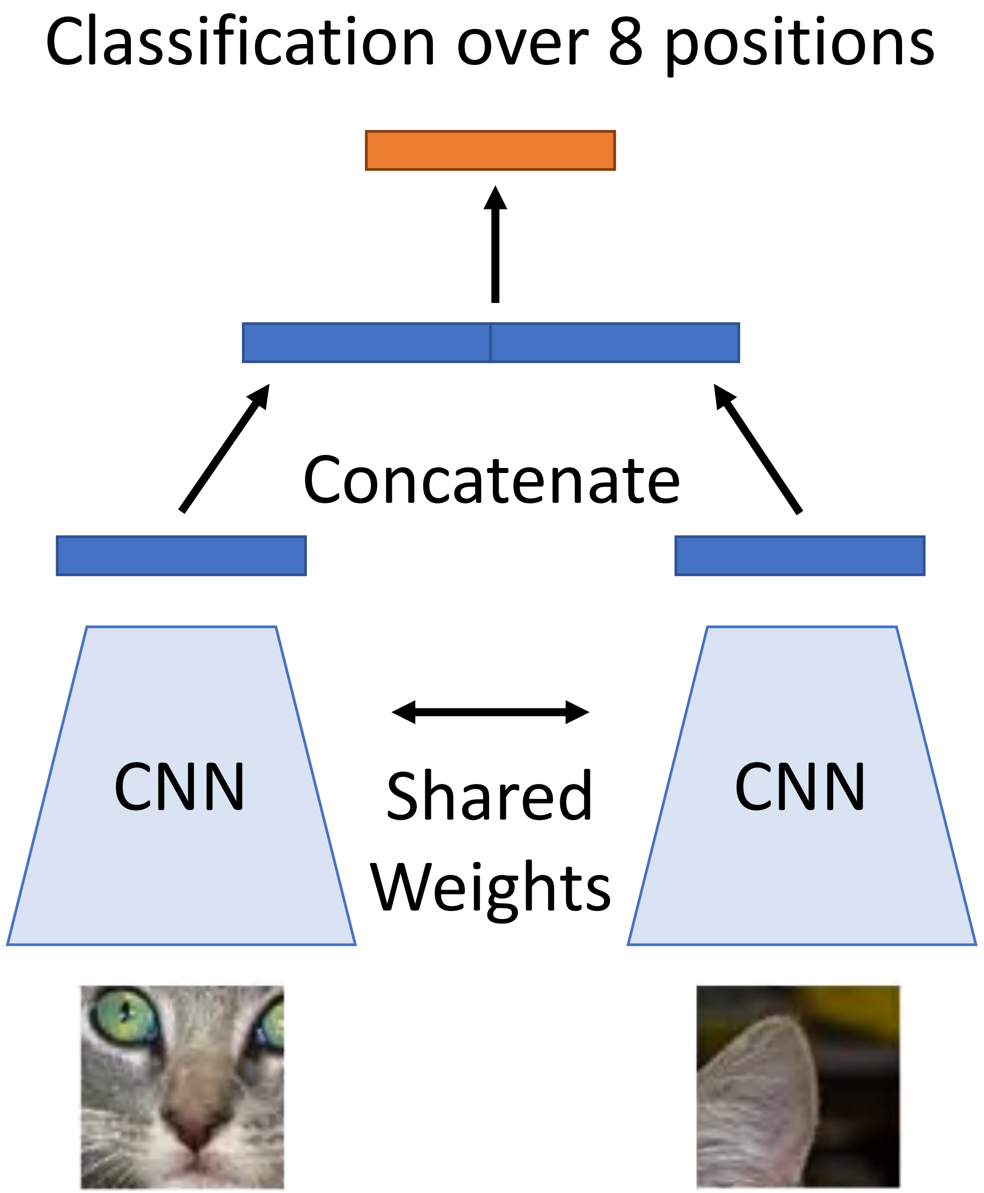
Model predicts relative location of two patches from the same image. Discriminative pretraining task

Intuition: Requires understanding objects and their parts

Two networks with shared weights sometimes called a ”Siamese network” – but I don’t really like this term



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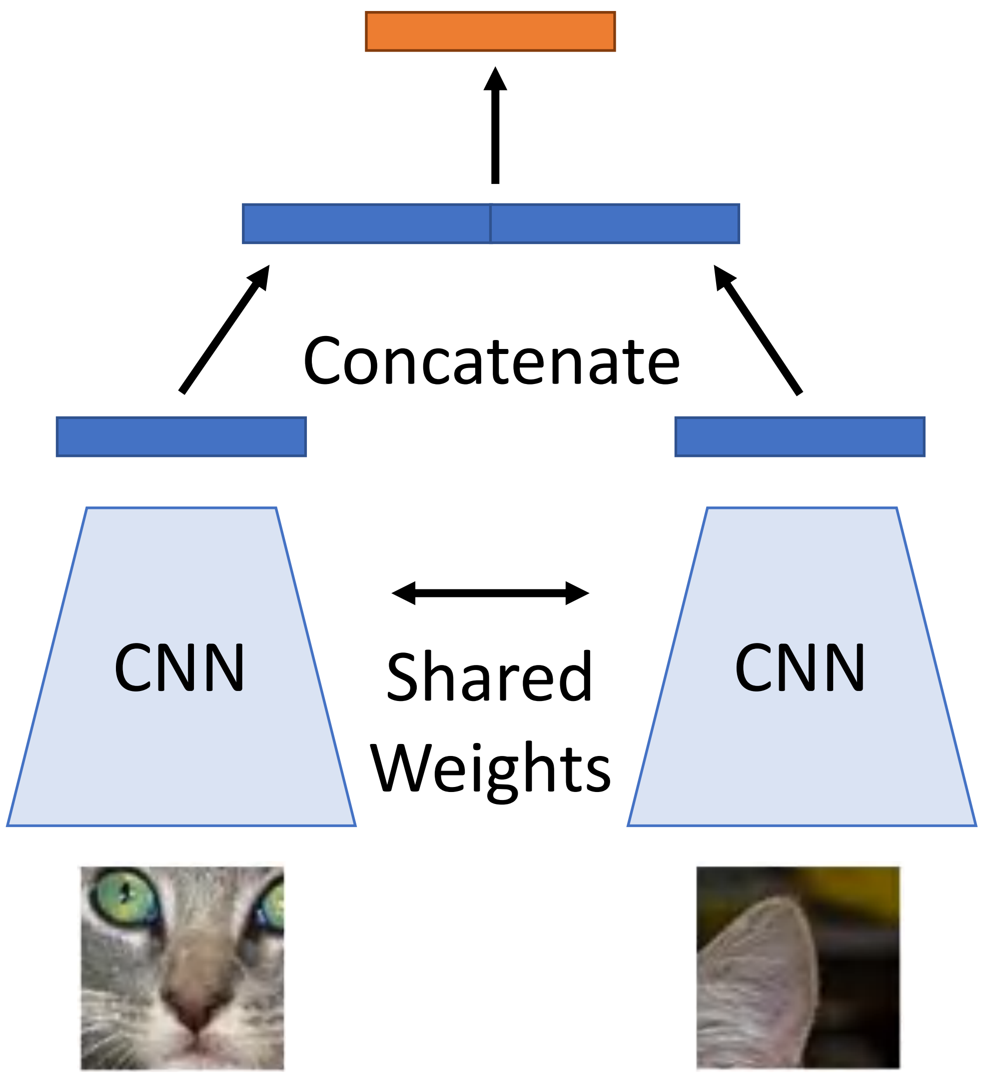
"For experiments, we use a ConvNet trained on a K40 GPU for approximately four weeks."



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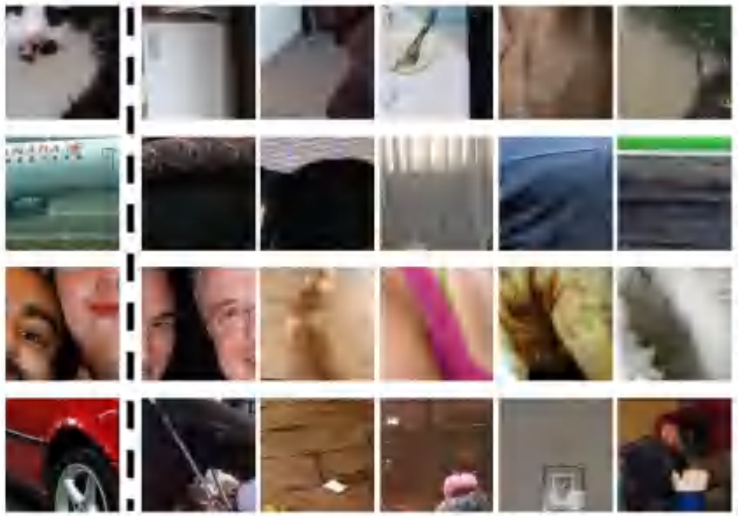
Context Prediction: Nearest Neighbors in Feature Space

Input Patch

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

Context Prediction: Nearest Neighbors in Feature Space

Input Patch Random Init



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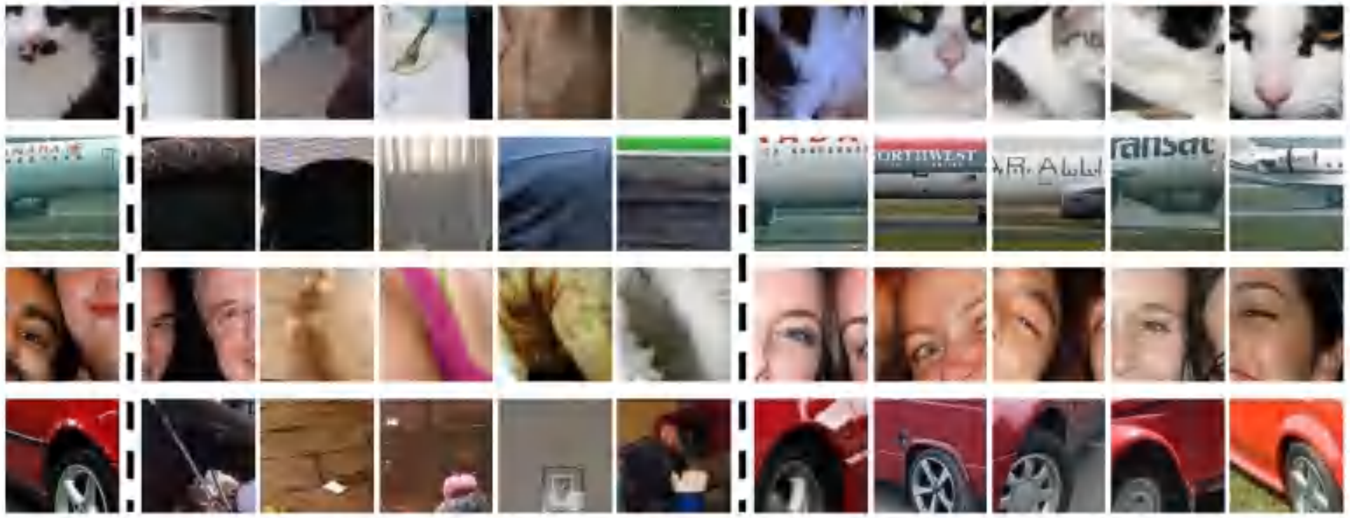
Context Prediction: Nearest Neighbors in Feature Space

Input Patch Random Init Supervised AlexNet



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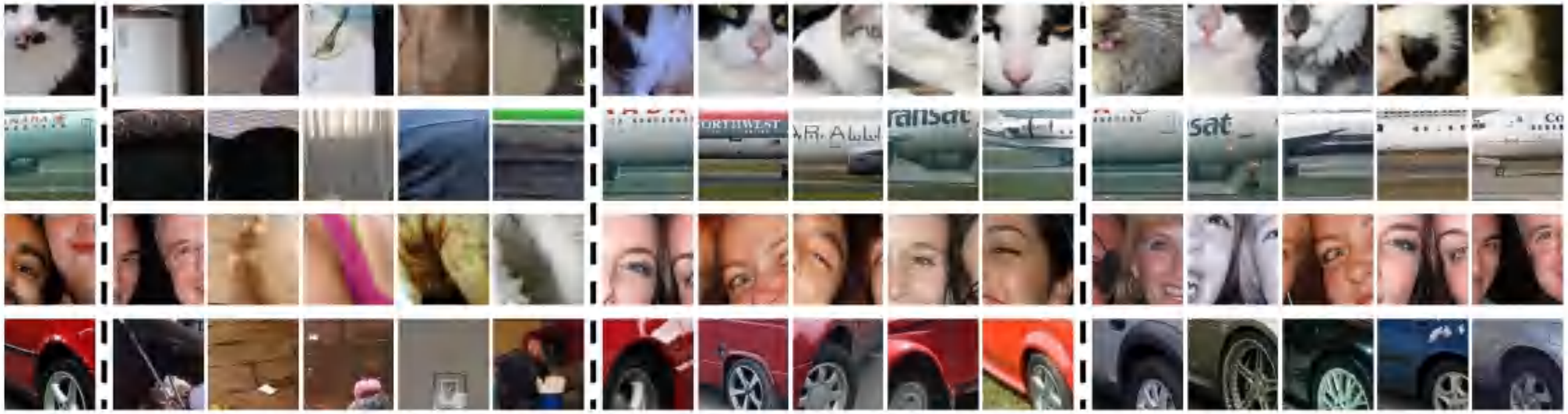
Context Prediction: Nearest Neighbors in Feature Space

Input Patch   Random Init   Supervised AlexNet   Their Features

Works well! Similar to AlexNet



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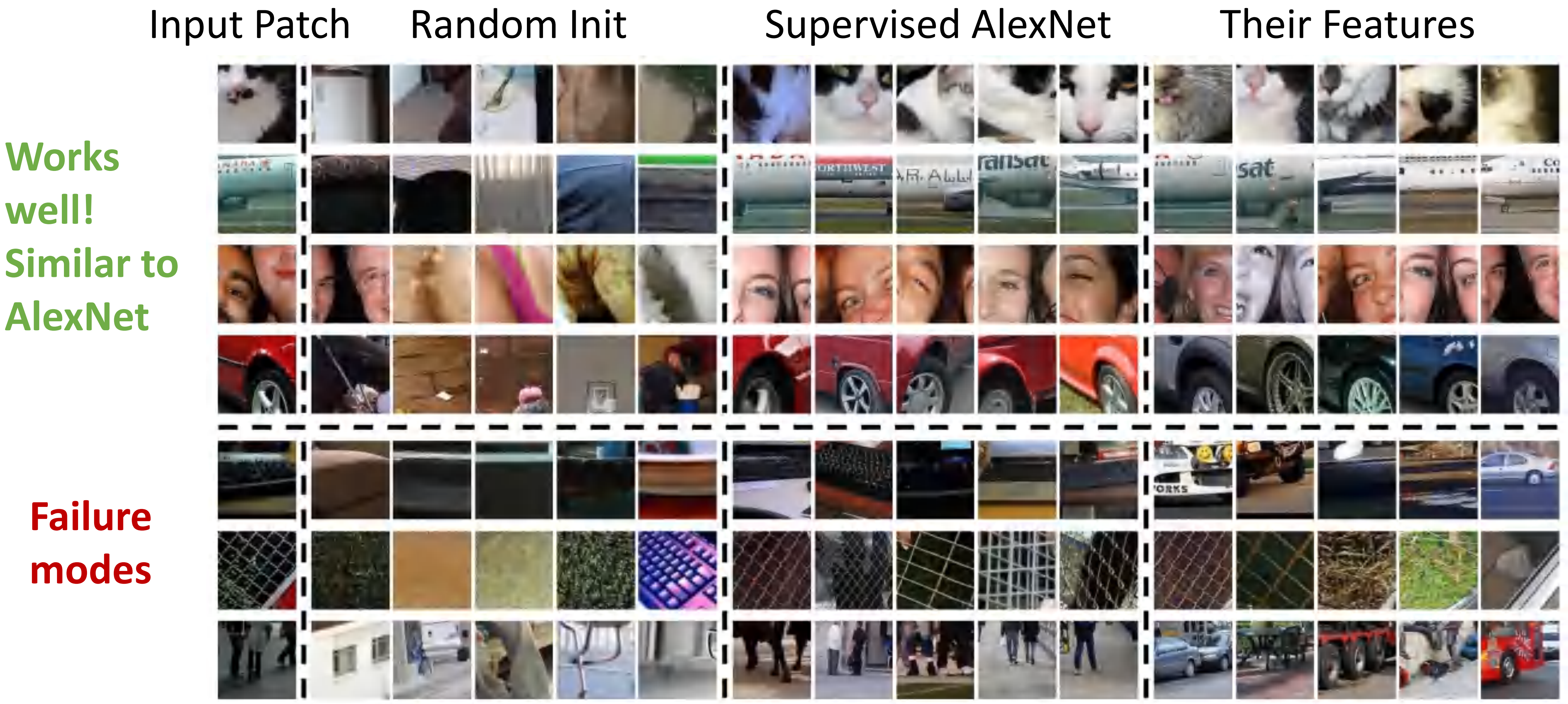

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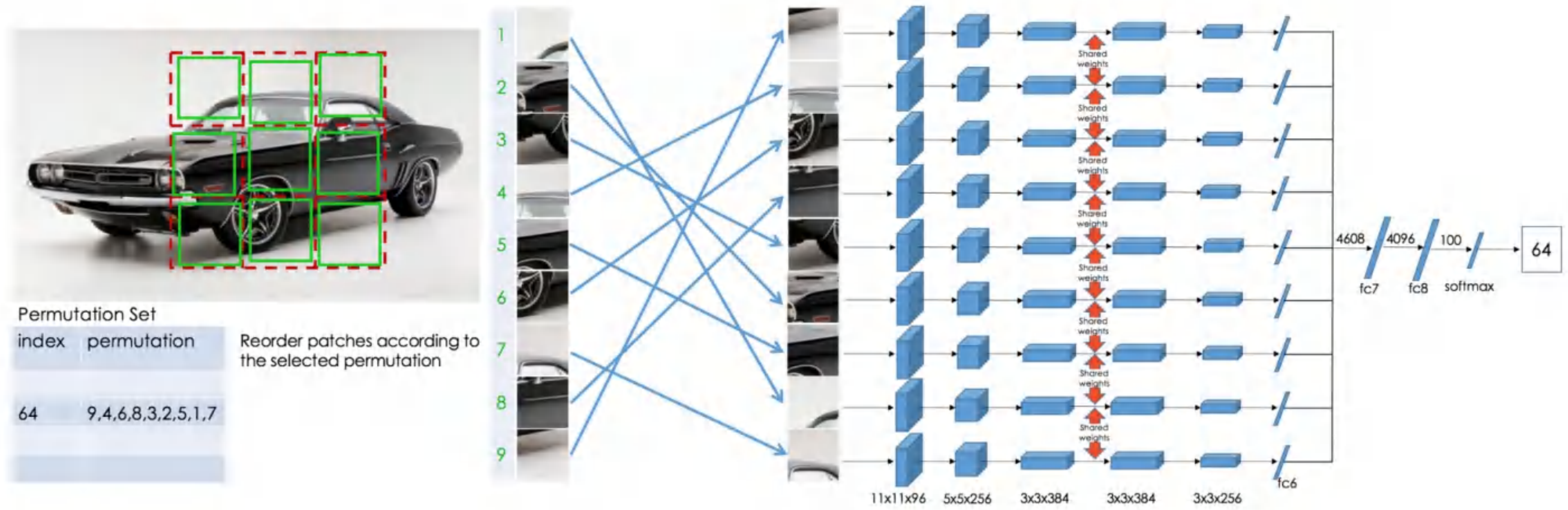
Extension: Solving Jigsaw Puzzles

Rather than predict relative position of two patches, instead predict permutation to "unscramble" 9 shuffled patches

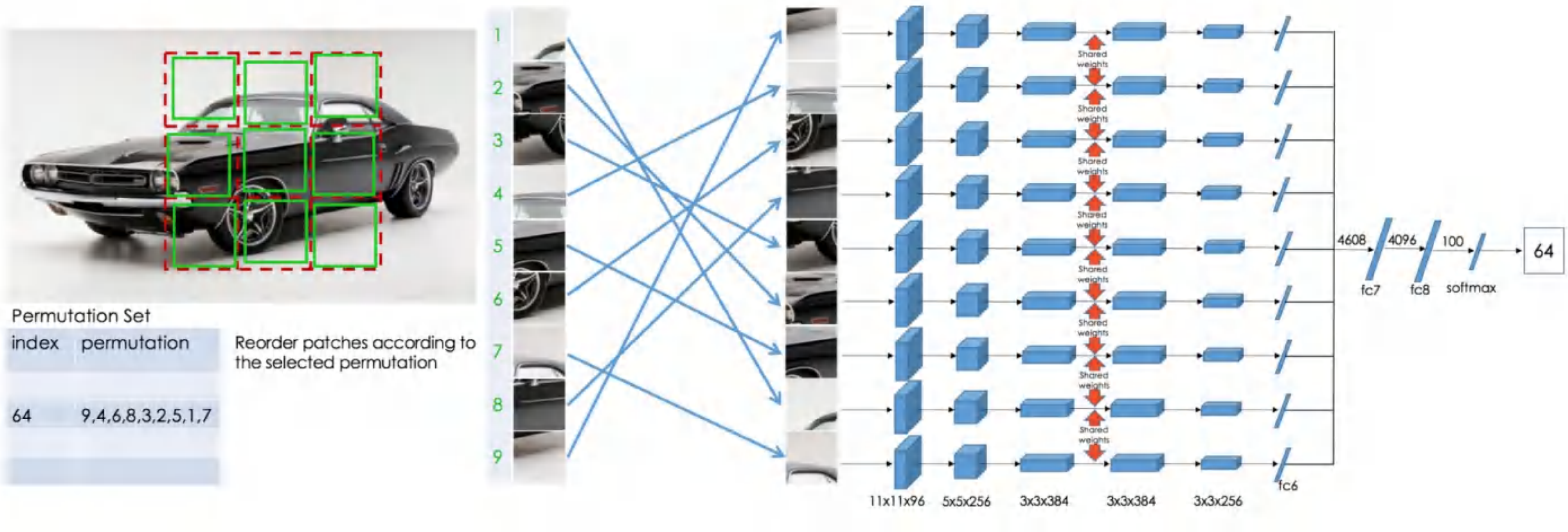


Noroozi and Favoro, "Unsupervised learning of visual representations by solving jigsaw puzzles", ECCV 2016

Extension: Solving Jigsaw Puzzles

Problem: These methods only work on patches, not whole images!

Rather than predict relative position of two patches, instead predict permutation to "unscramble" 9 shuffled patches



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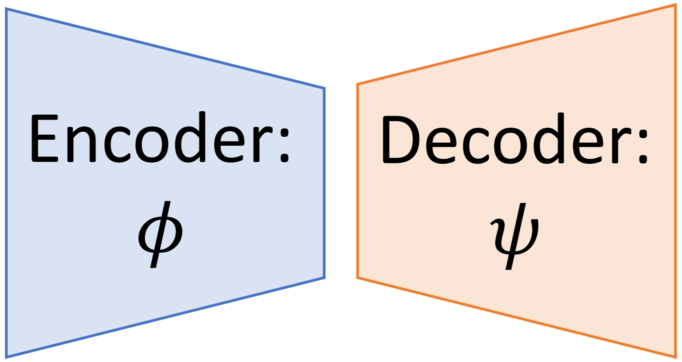
Context Encoders: Learning by Inpainting

Input Image



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

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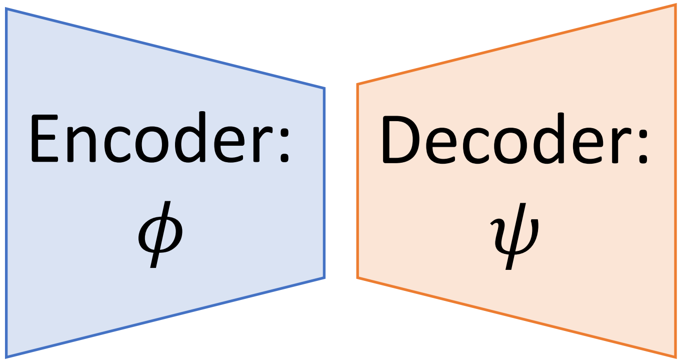


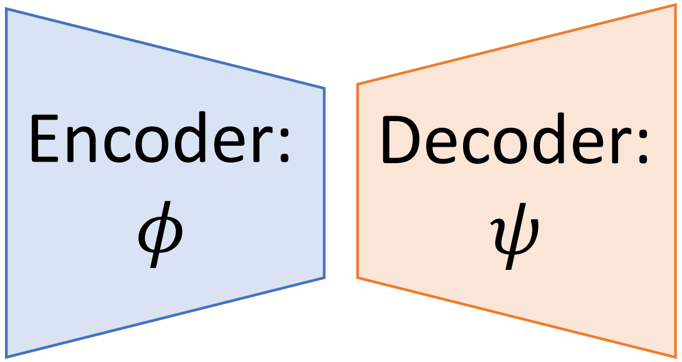
Predict Missing Pixels

Human Artist

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

Context Encoders: Learning by Inpainting

Input Image



Predict Missing Pixels

L2 Loss

(Best for feature learning)

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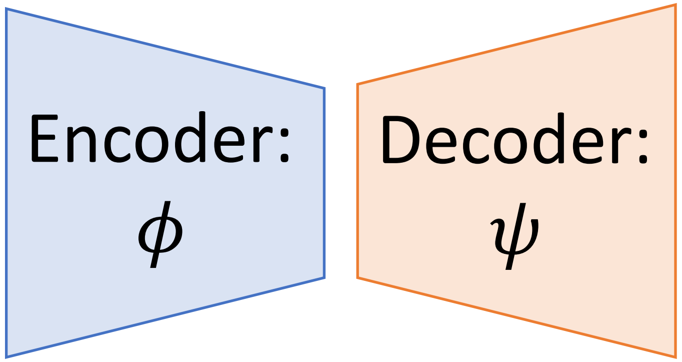
Context Encoders: Learning by Inpainting

Input Image



Predict Missing Pixels

L2 + Adversarial Loss
(Best for nice images)

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

Colorization

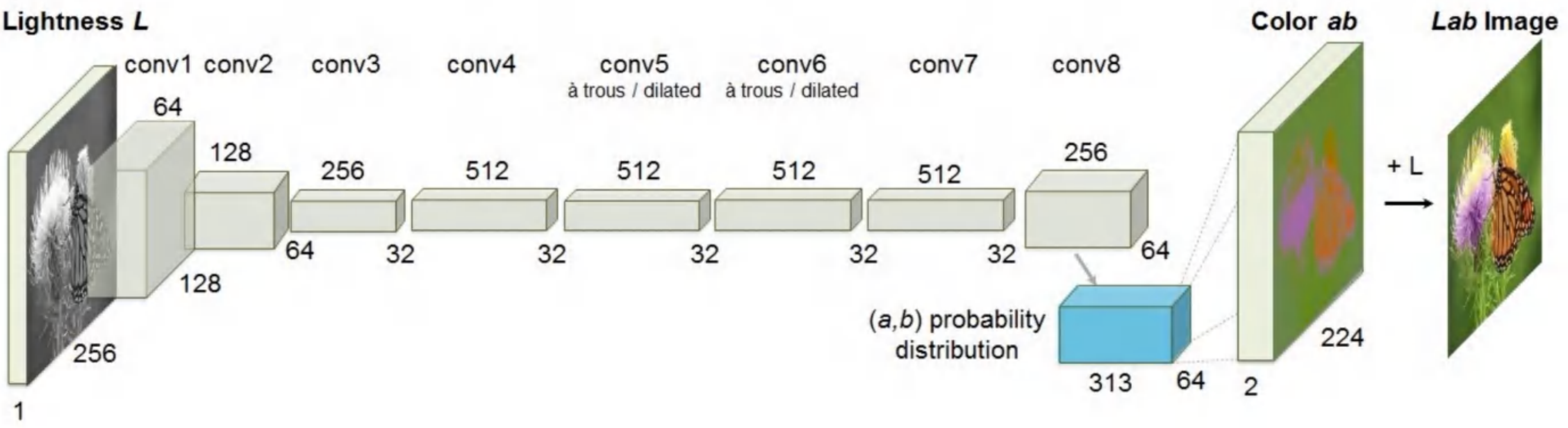
Intuition: A model must be able to identify objects to be able to colorize them

Input: Grayscale Image

Output: Color Image

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

Colorization



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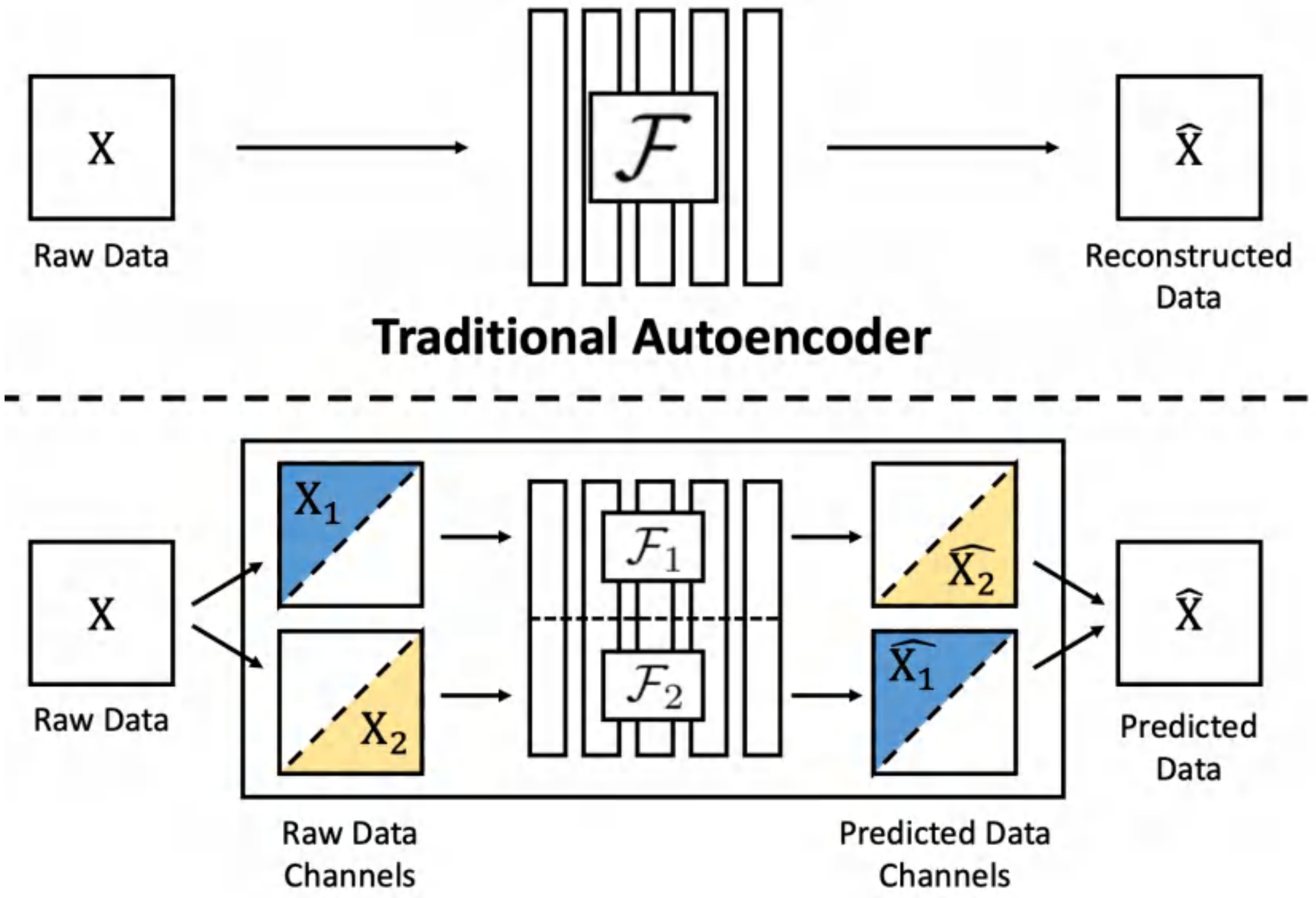
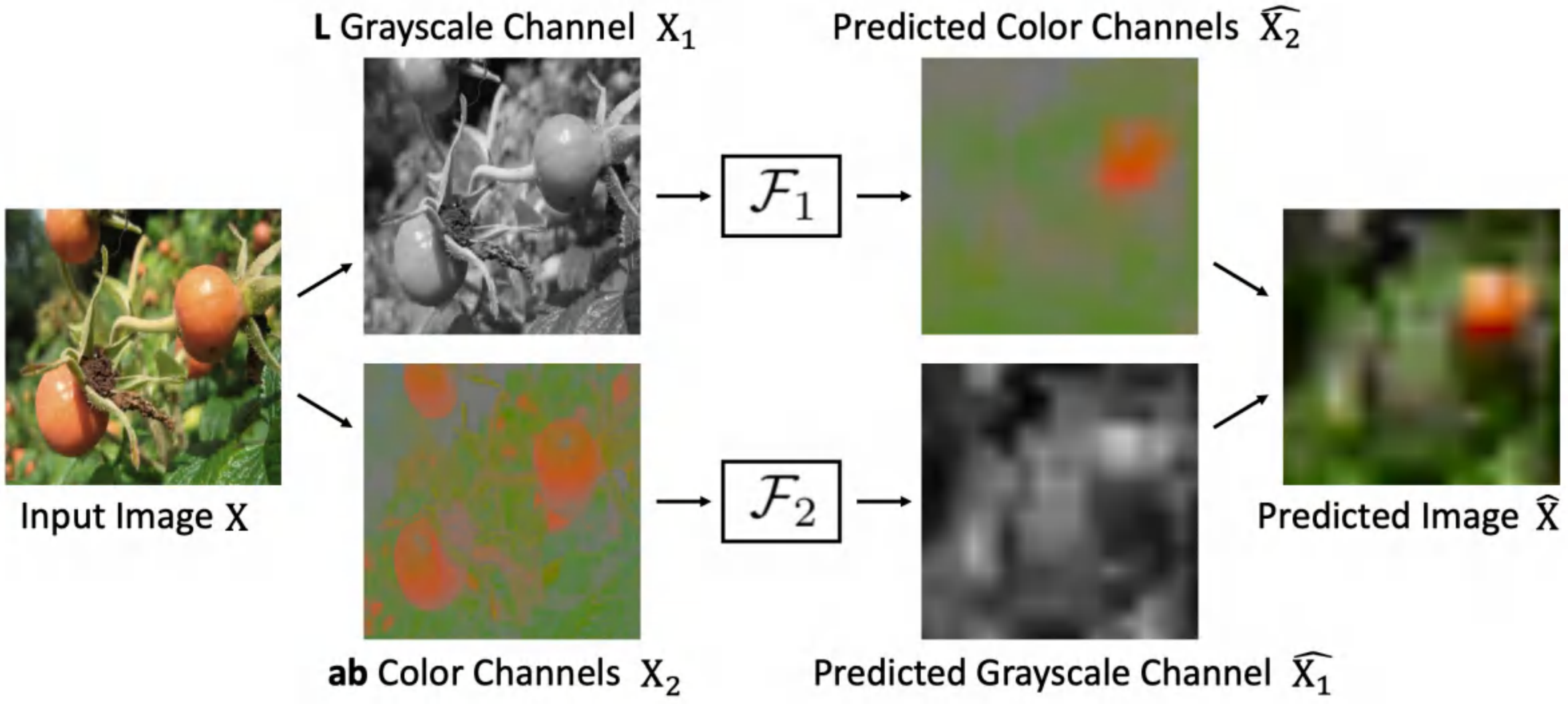
Colorization Extension: Split-Brain Autoencoder



Zhang et al, "Split-Brain Autoencoders: Unsupervised Learning by Cross-Channel Prediction", CVPR 2017

Colorization Extension: Split-Brain Autoencoder



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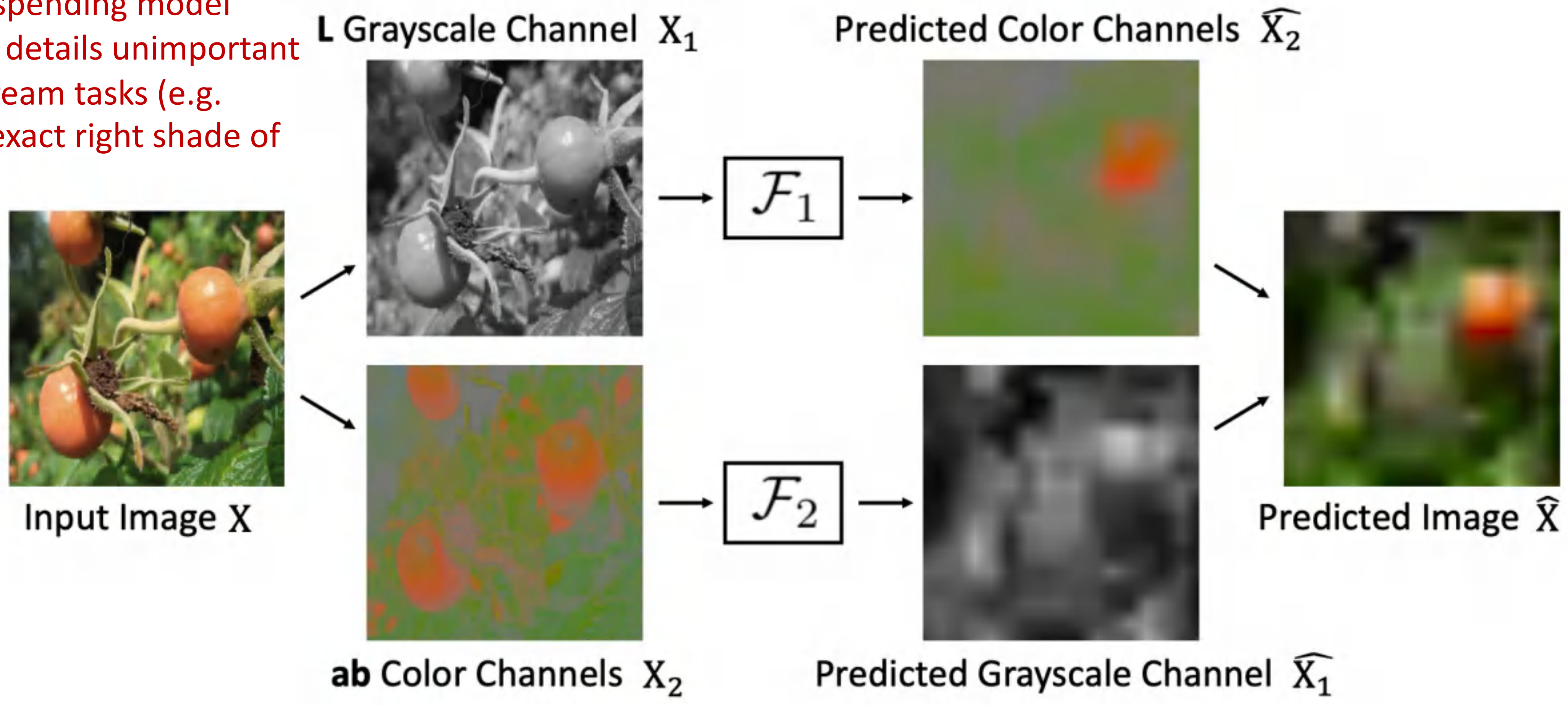
Colorization Extension: Split-Brain Autoencoder

Concern: Generative pretexts encourage spending model capacity on details unimportant for downstream tasks (e.g. regressing exact right shade of orange)



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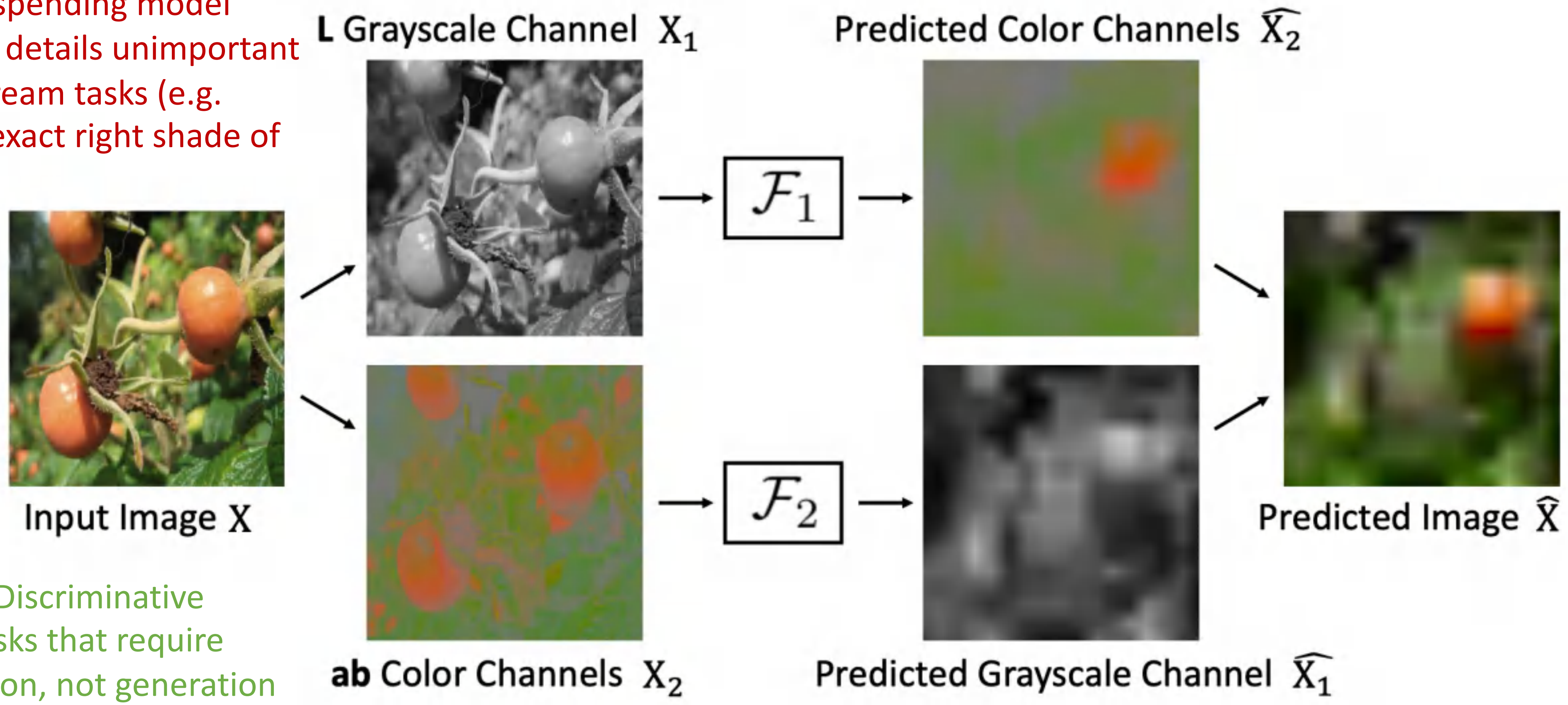
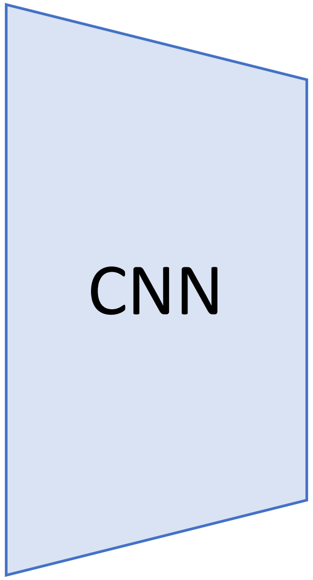


Solution: Discriminative pretext tasks that require classification, not generation

Zhang et al, "Split-Brain Autoencoders: Unsupervised Learning by Cross-Channel Prediction", CVPR 2017

Deep Clustering

(1) Randomly initialize a CNN



Caron et al, “Deep Clustering for Unsupervised Learning of Visual Features”, ECCV 2018
Caron et al, “Unsupervised Pre-Training of Image Features on Non-Curated Data”, ICCV 2019
Yan et al, “ClusterFit: Improving Generalization of Visual Representations”, CVPR 2020
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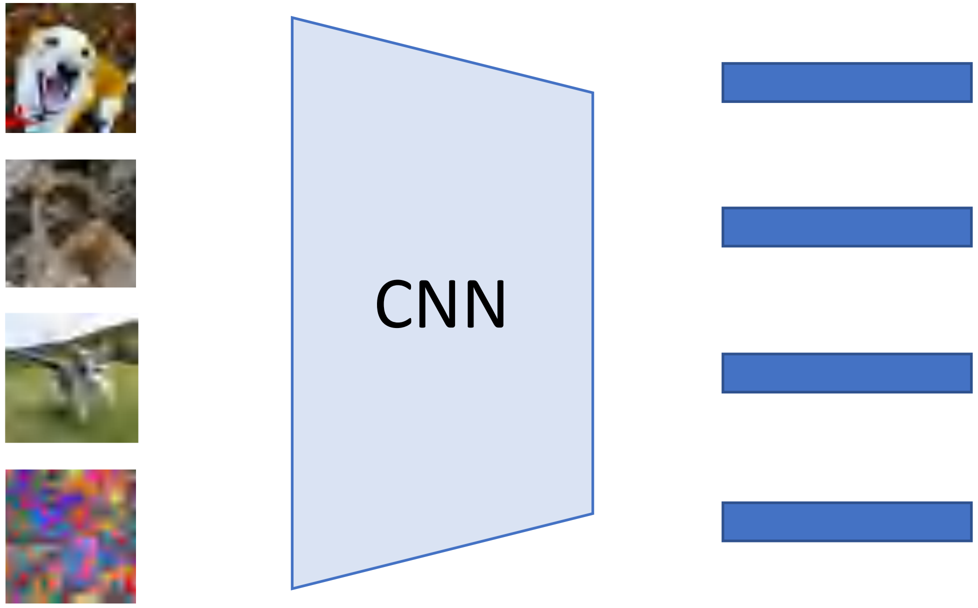

(2) Run many images through CNN, get their final-layer features

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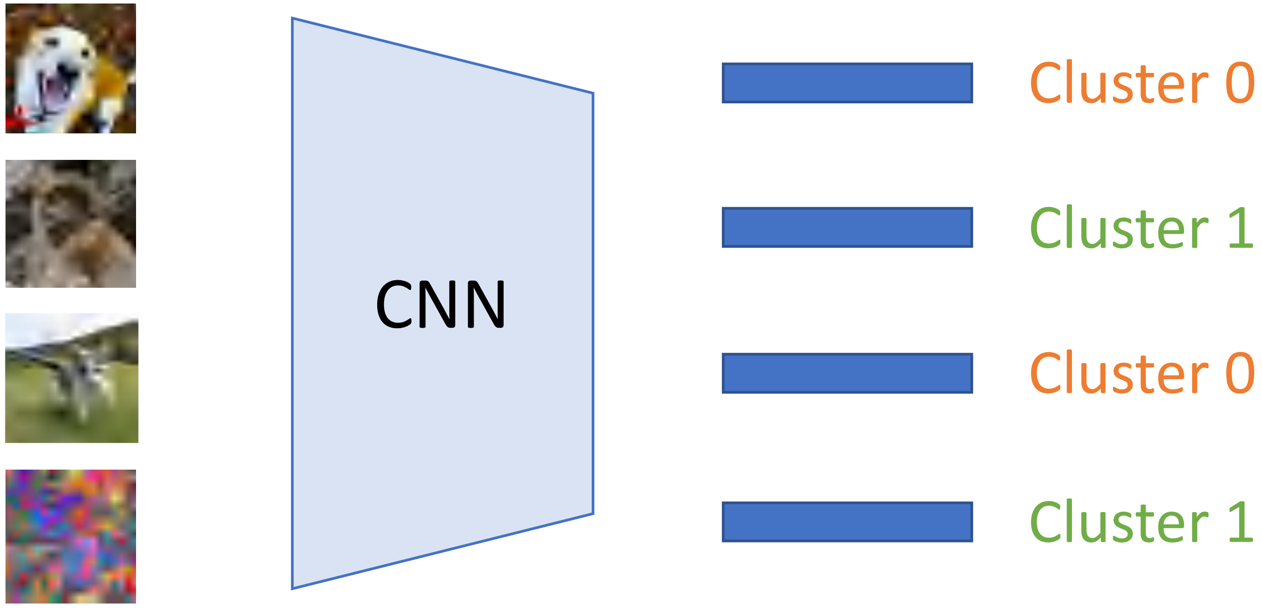

(3) Cluster the features with K-Means; record cluster for each feature

(2) Run many images through CNN, get their final-layer features

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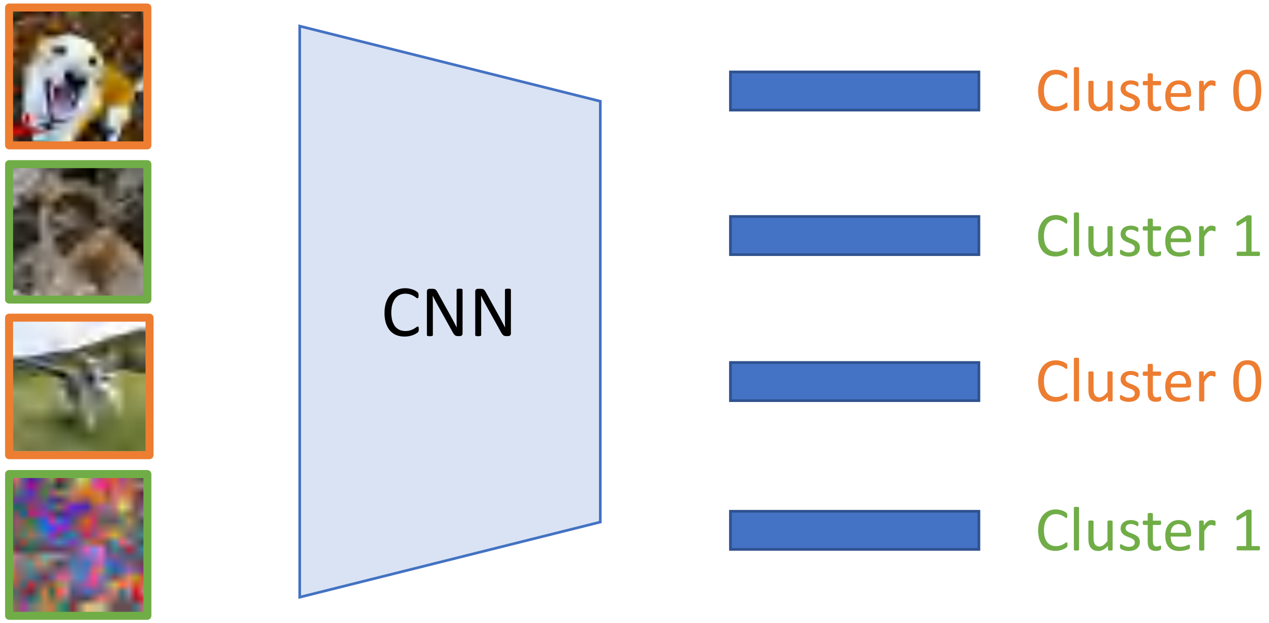

(3) Cluster the features with K-Means; record cluster for each feature

(4) Use cluster assignments as pseudo-labels for each image; train the CNN to predict cluster assignments

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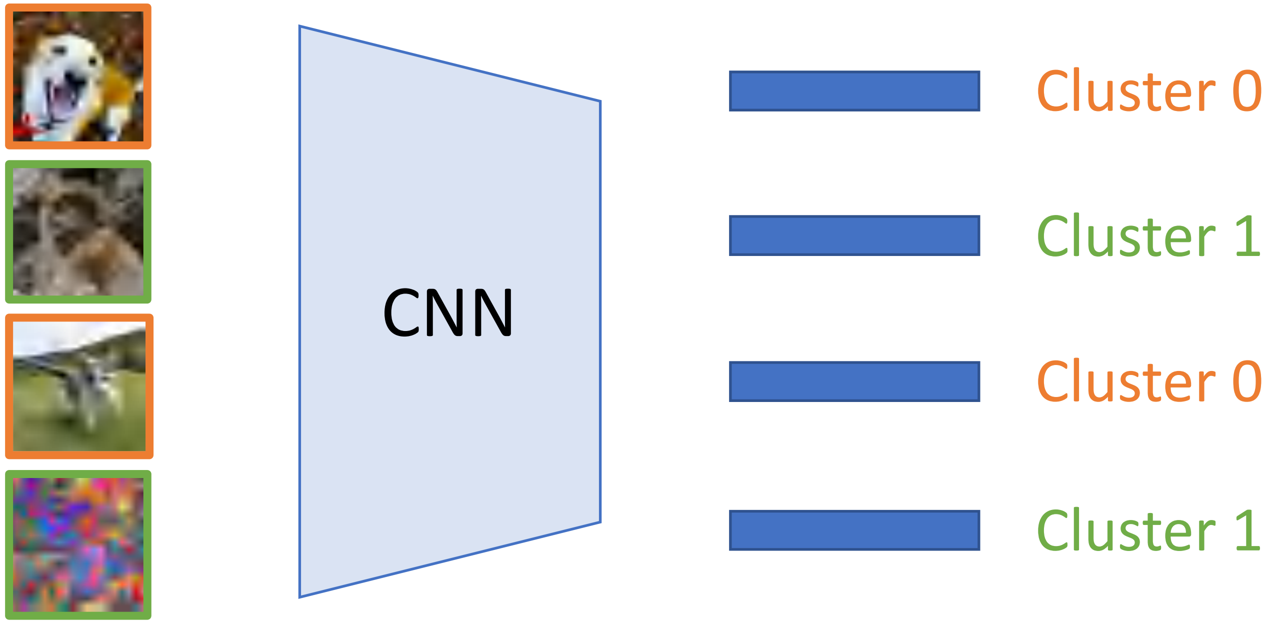

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(5) Repeat: GOTO (2)

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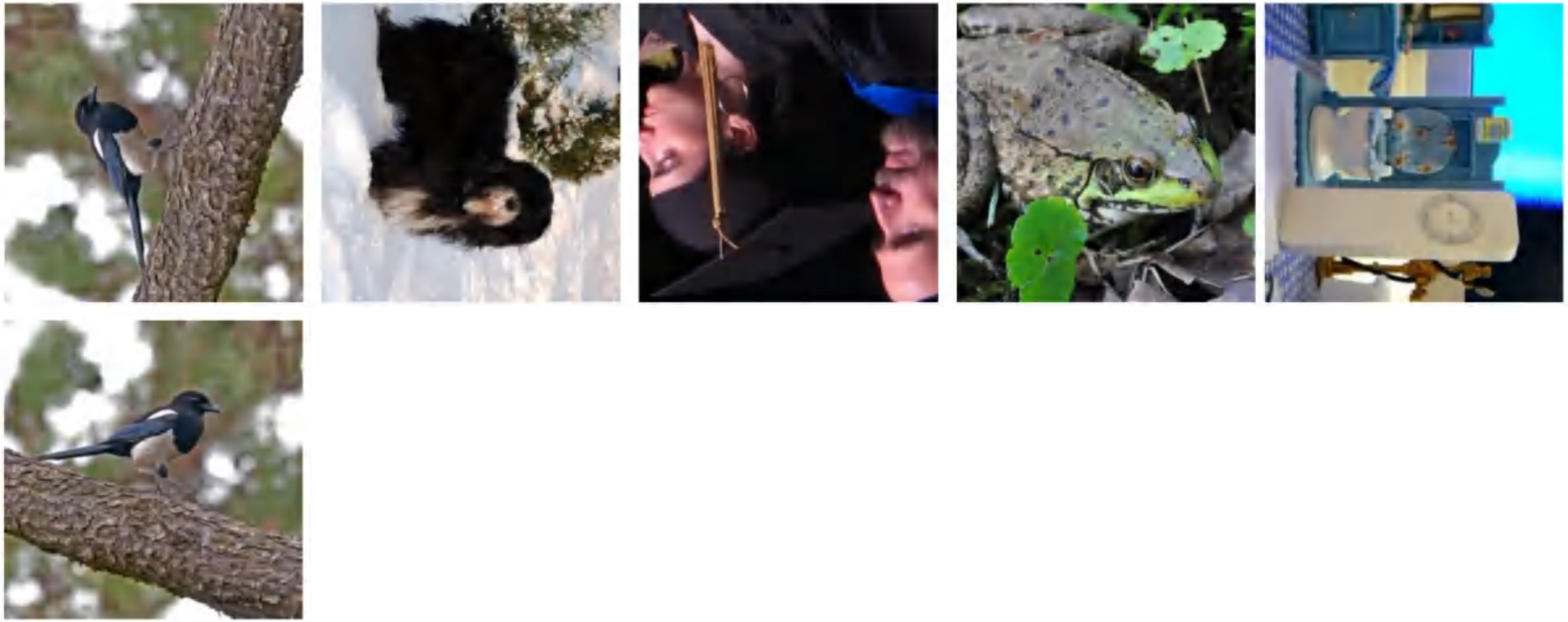
RotNet: Predict Rotation

4-way classification task: How much was each image rotated? (0, 90, 180, or 270 degrees)

Gidaris et al, “Unsupervised representation learning by predicting image rotations”, ICLR 2018

RotNet: Predict Rotation

4-way classification task: How much was each image rotated? (0, 90, 180, or 270 degrees)



90

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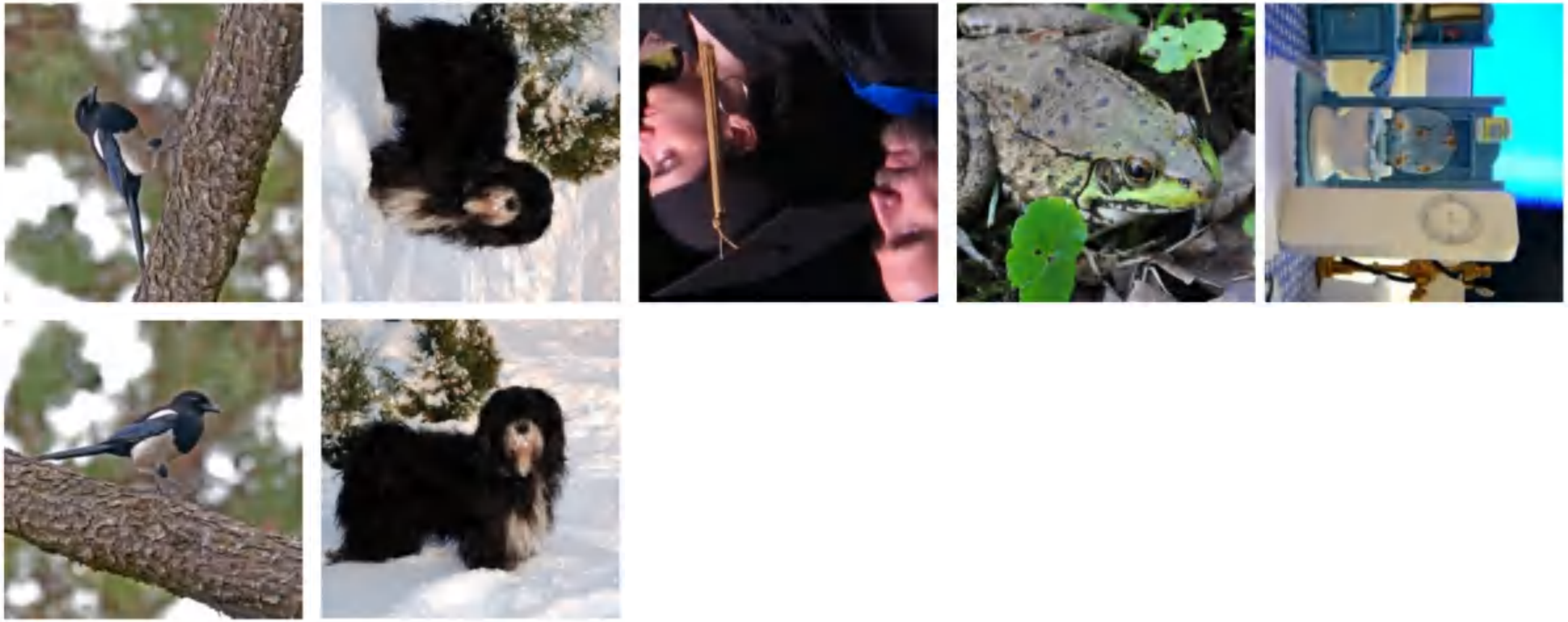

90 270

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RotNet: Predict Rotation

4-way classification task: How much was each image rotated? (0, 90, 180, or 270 degrees)

90 270 180

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90 270 180 0

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RotNet: Predict Rotation

4-way classification task: How much was each image rotated? (0, 90, 180, or 270 degrees)

90 | 270 | 180 | 0 | 270

Gidaris et al, “Unsupervised representation learning by predicting image rotations”, ICLR 2018

Which SSL Method is best?

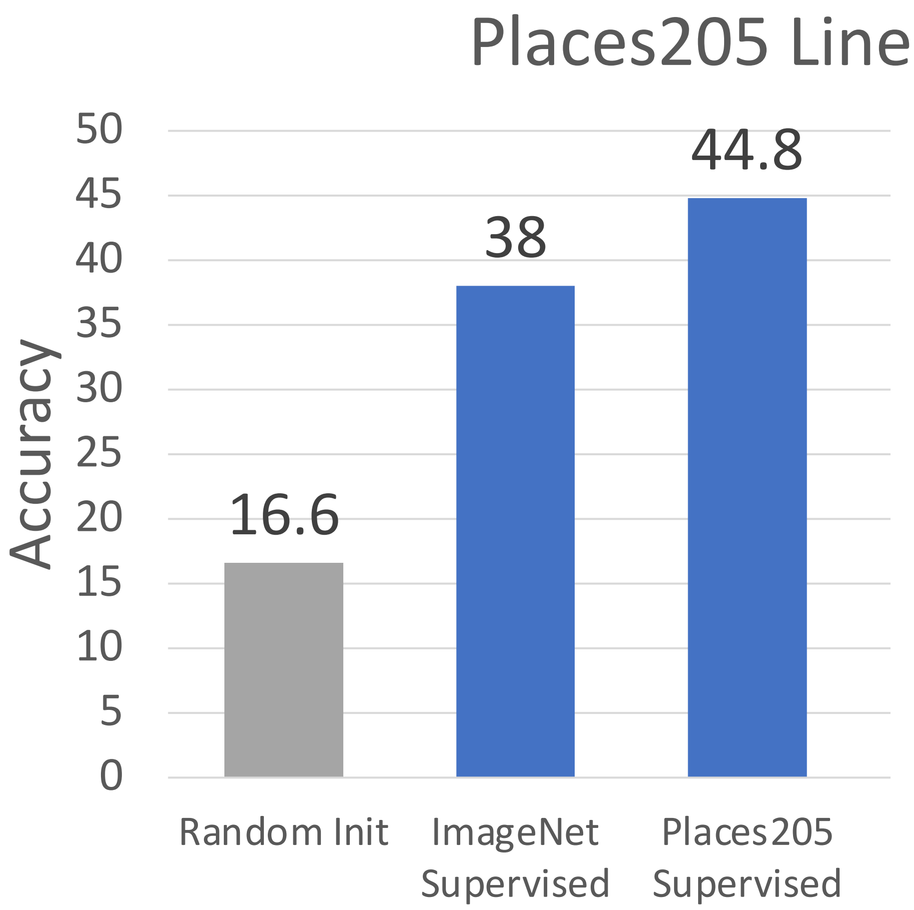
Fair evaluation of SSL methods is very hard! No theory, so we need to rely on experiment

Many choices in experimental setup, huge variations from paper to paper:

- CNN architecture? AlexNet, ResNet50, something else?
- Pretraining dataset? ImageNet, or something else?
- Downstream task? ImageNet classification, detection, something else?
- Pretraining hyperparameters? Learning rates, training iterations, data augmentation?
- Transfer learning protocol?
    - Linear probe? From which layer? How to train linear models? SGD, something else? Transfer learning hyperparameters? Data augmentation or BatchNorm during transfer learning?
    - Fine-tune? From which layer? Architecture of “head” you attach? Linear or nonlinear? Fine-tuning hyperparameters?
    - KNN? What value of K? Normalization on features?

Which SSL Method is best?

Some papers have tried to do fair comparisons of many SSL methods



Goyal et al, "Scaling and Benchmarking Self-Supervised Visual Representation Learning", ICCV 2019

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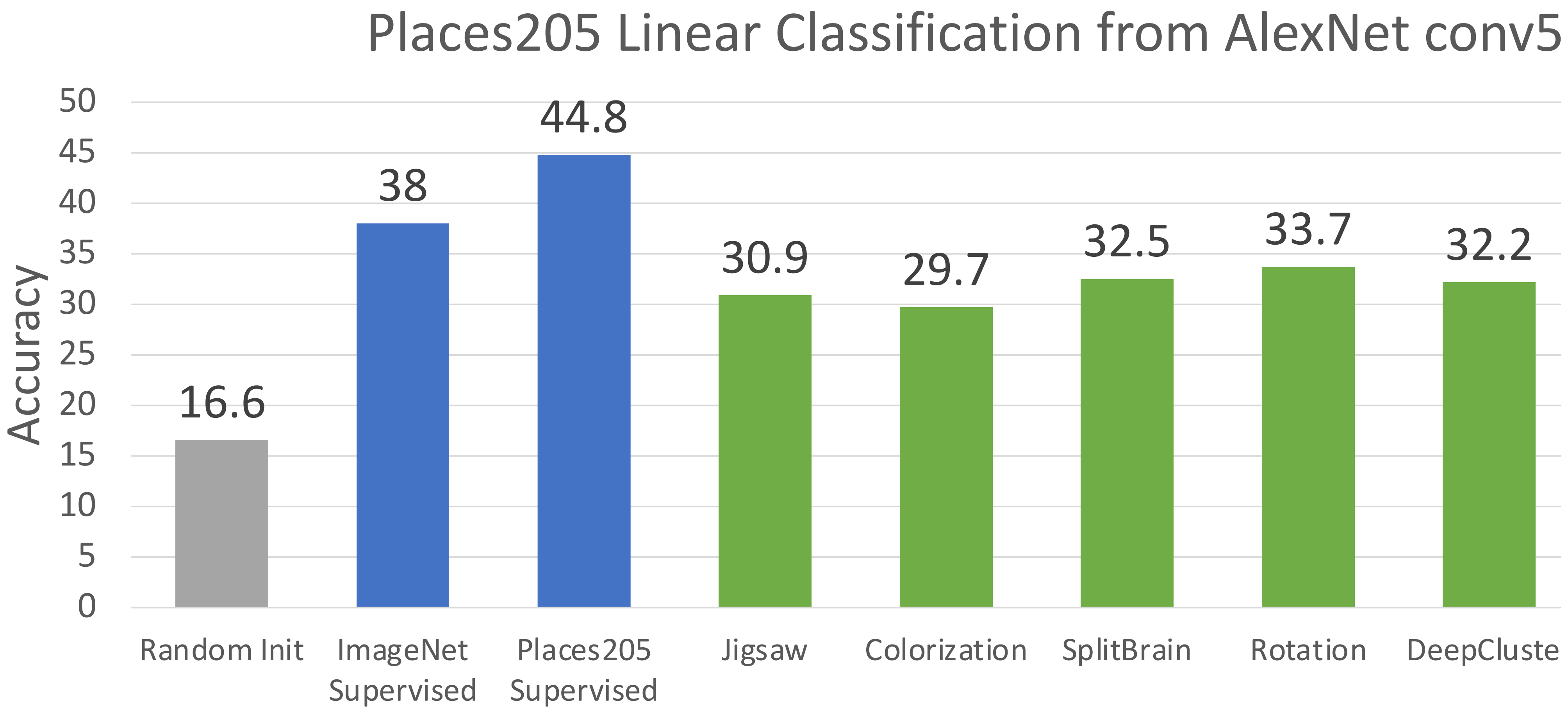

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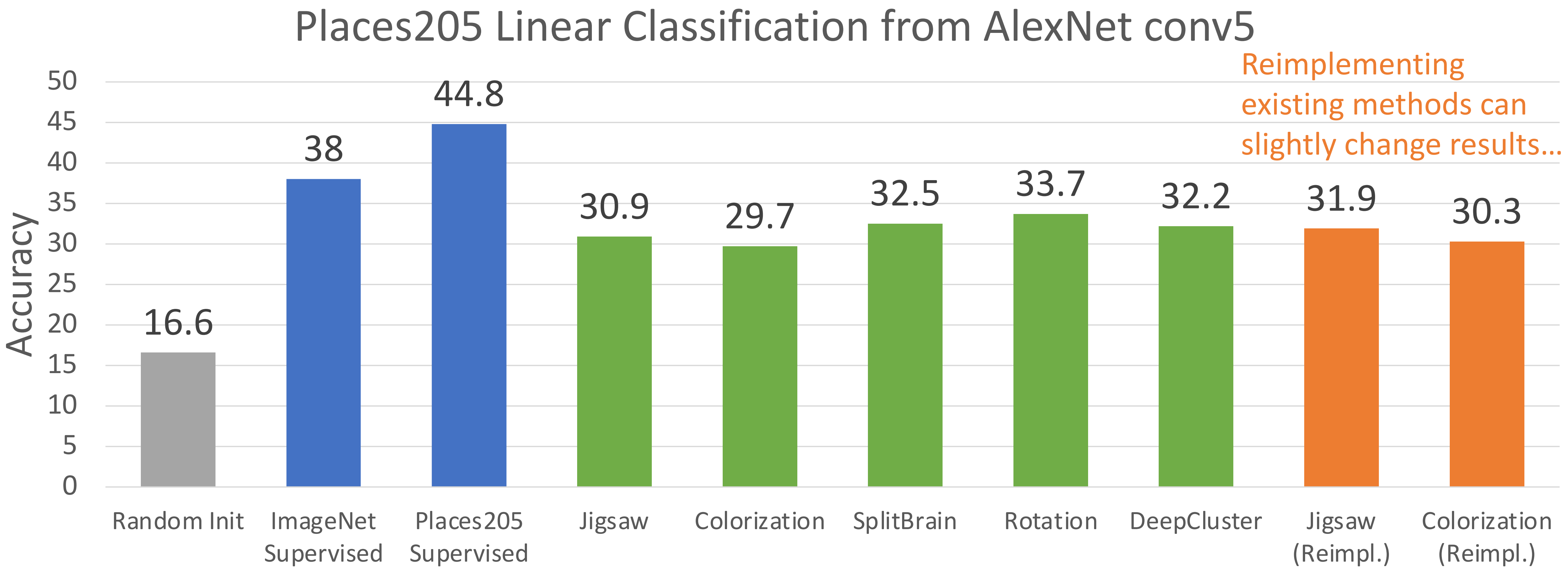

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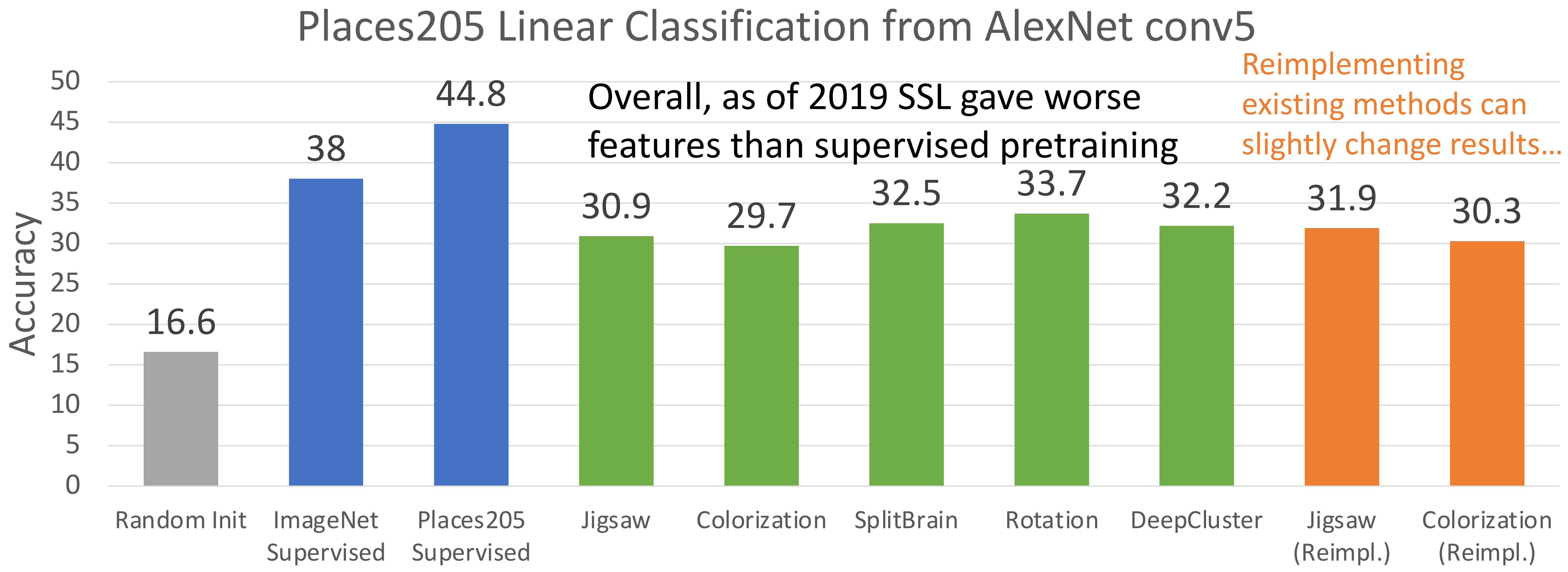
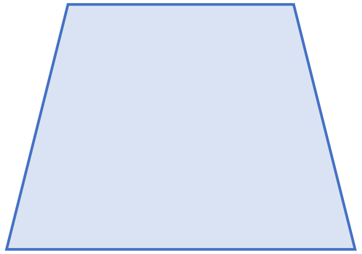


Goyal et al, "Scaling and Benchmarking Self-Supervised Visual Representation Learning", ICCV 2019

Self-Supervised Learning for Natural Language

Computer Vision

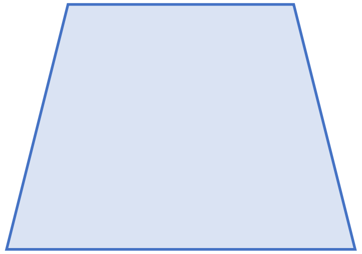
Image Features:
H x W x C



Input Image

Natural Language Processing

Word Features
L x C

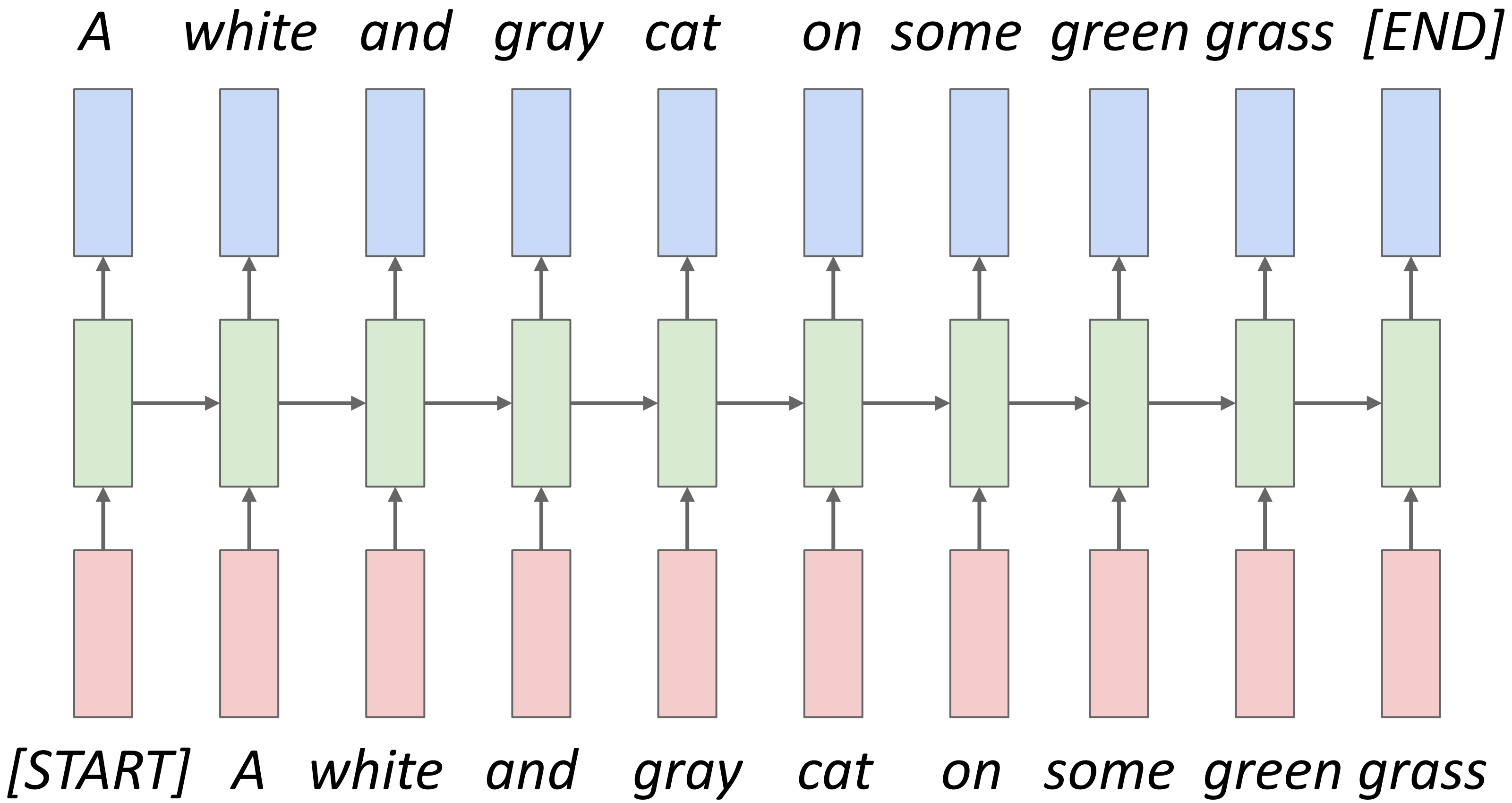


A white and gray cat standing outside on the grass

Input Sentence (L words)

Self-Supervised Learning for Natural Language

RNN language models train on raw text – no human labels required!
Their hidden states give features that transfer to many downstream tasks!



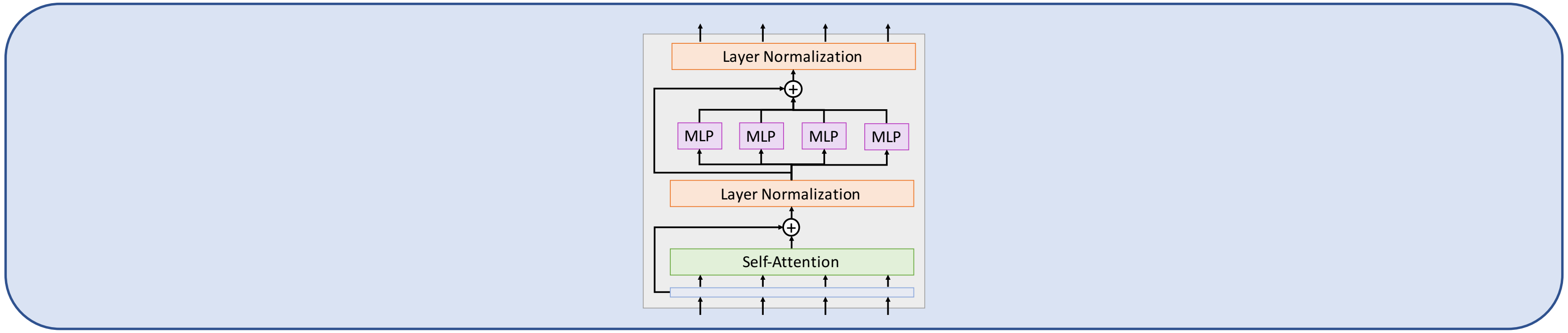
Peters et al, "Deep contextualized word representations", NAACL 2018

Self-Supervised Learning for Natural Language

Transformer-based language models work even better! Can scale up to very large datasets, and give extremely powerful features that transfer to downstream tasks

Wildly successful: larger models, larger datasets give better features that improve performance on many downstream NLP tasks. The dream of SSL made real!

A white and gray cat on some green grass [END]



[START] A white and gray cat on some green grass

Radford et al, "Language models are unsupervised multitask learners", 2019
Brown et al, "Language Models are Few-Shot Learners", arXiv 2020
Rae et al, "Scaling Language Models: Methods, Analysis, & Insights from Training Gopher", arXiv 2021

This Week: Pathways Language Model (PaLM)

Transformer with 118 layers, 48 heads, d_model=18,432, 540B parameters
Dataset: 780 billion tokens; trained on 6144 TPU-v4 chips

Bigger models trained on more data tend to give better downstream task performance

Model	Avg NLG	Avg NLU
GPT-3 175B	52.9	65.4
GLaM 64B/64E	58.4	68.7
PaLM 8B	41.5	59.2
PaLM 62B	57.7	67.3
PaLM 540B	63.9	74.7

NLG = Natural Language Generation (8 benchmarks)

NLU = Natural Language Understanding (21 benchmarks

Chowhery et al, "PaLM: Scaling Language Models with Pathways", 2022

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NLG = Natural Language Generation (8 benchmarks)

NLU = Natural Language Understanding (21 benchmarks

How can we achieve this success in vision?
Intensified interest in SSL since ~2018

Chowhery et al, “PaLM: Scaling Language Models with Pathways”, 2022

Exemplar CNN: Invariance to Data Augmentation

Quiz: What is this?

Dosovitskiy et al, "Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks"

Exemplar CNN: Invariance to Data Augmentation

Quiz: What is this?

Answer: Deer!

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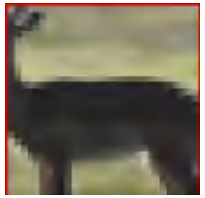


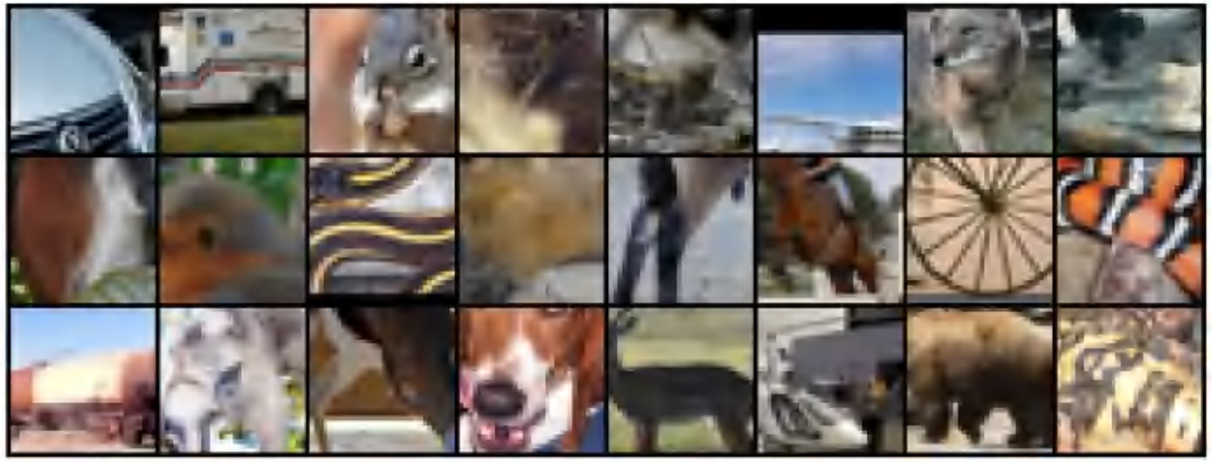
Different data augmentations (scale, shift, color jitter) of the same initial image patch

Answer: Deer!

Dosovitskiy et al, "Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks"

Exemplar CNN: Invariance to Data Augmentation

Given an initial dataset of N image patches



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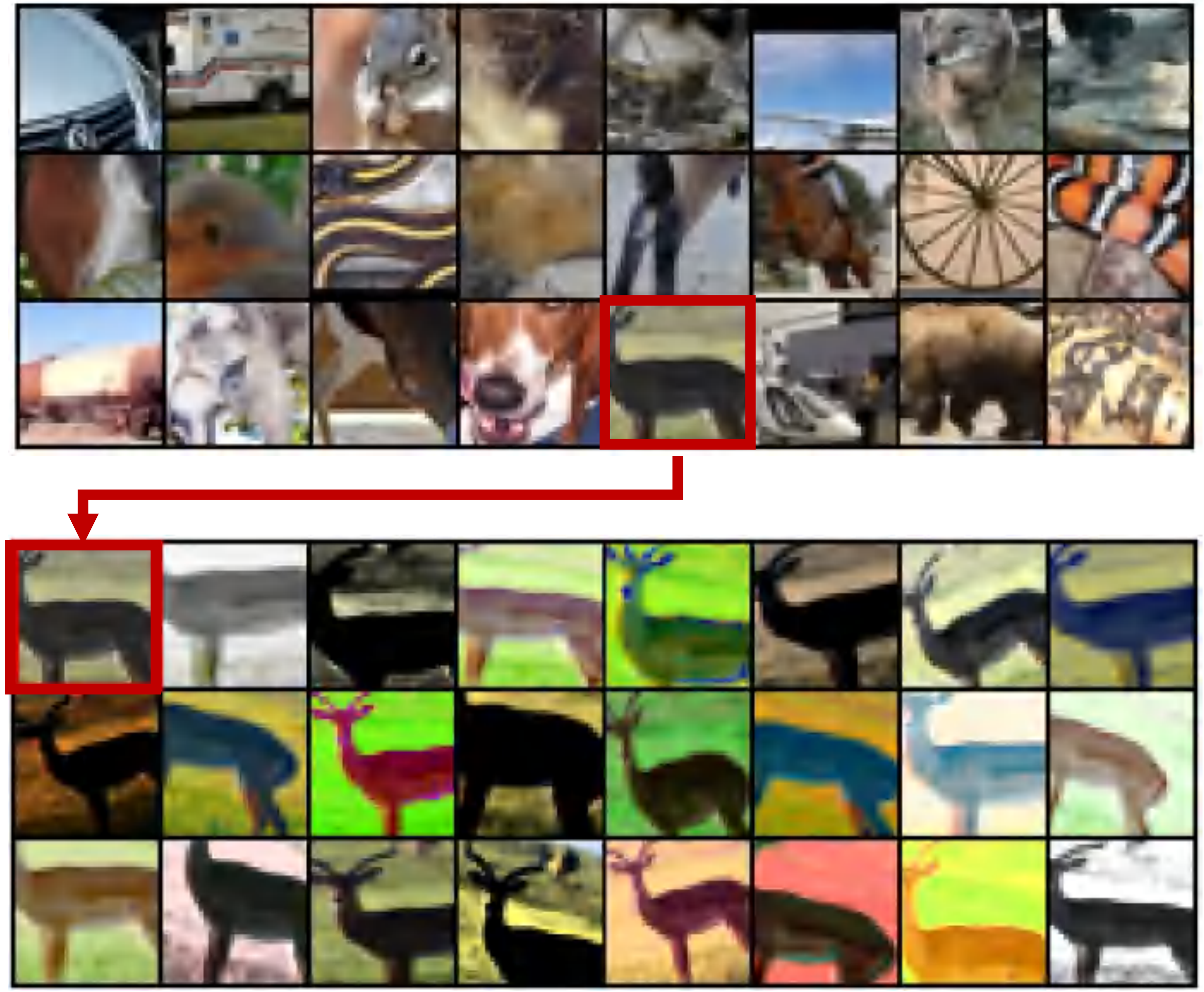
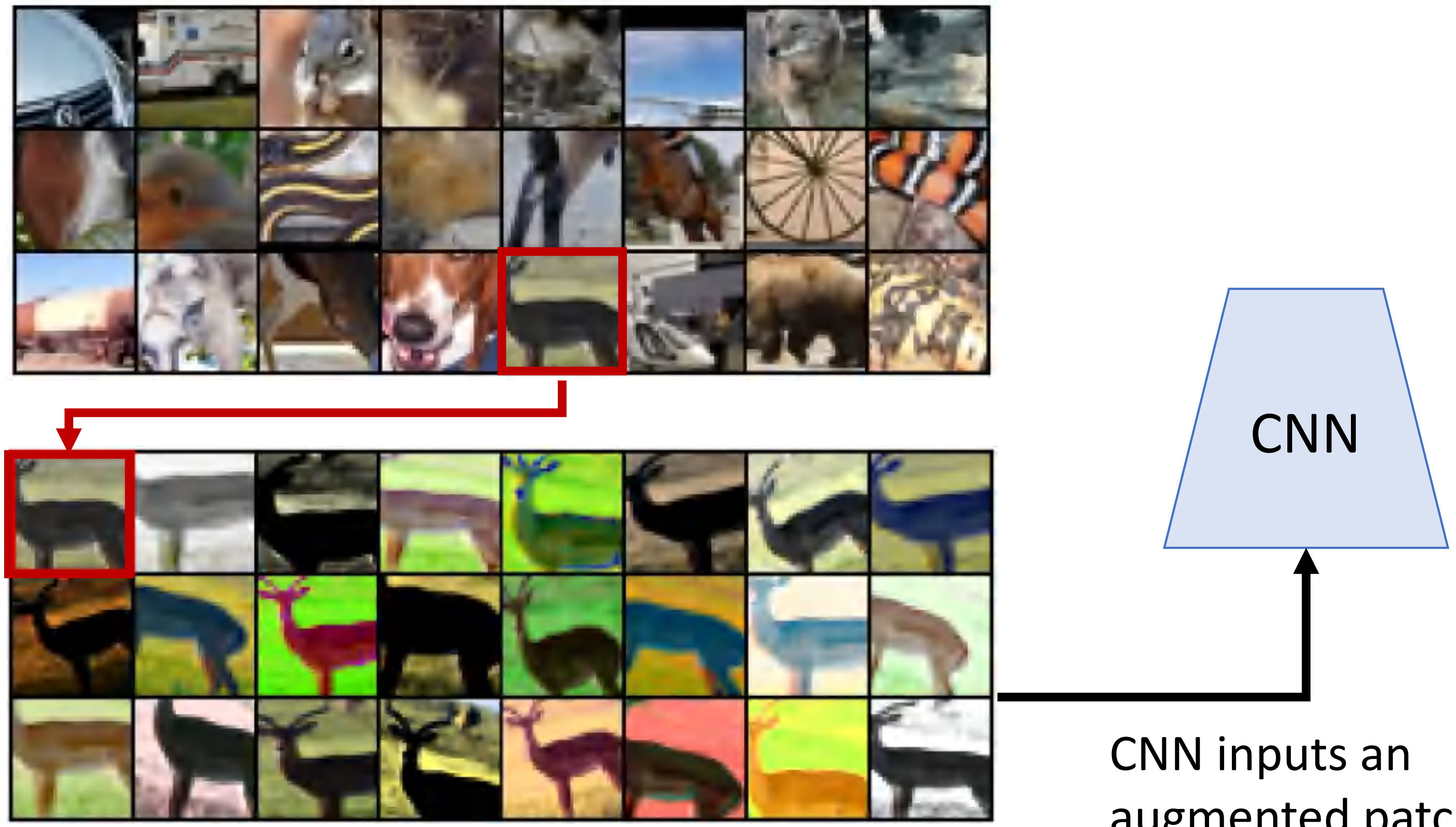


Sample K different augmentations for each; now have K*N total patches

Dosovitskiy et al, "Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks"

Exemplar CNN: Invariance to Data Augmentation

Given an initial dataset of N image patches



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CNN inputs an augmented patch

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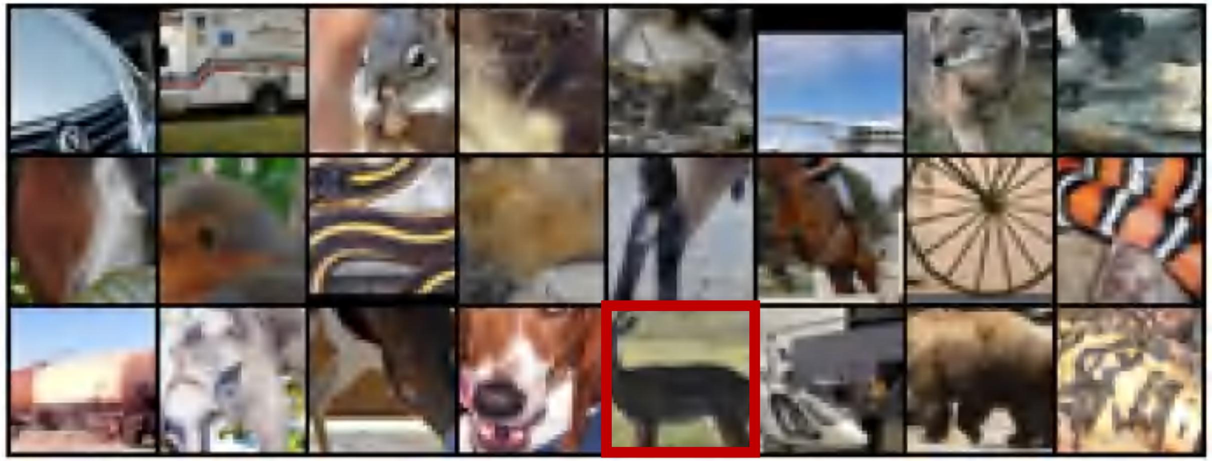
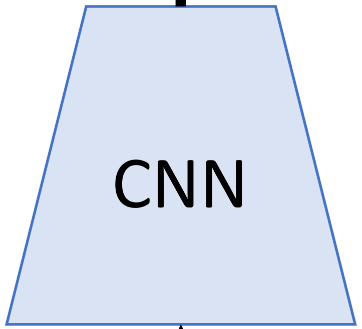
Exemplar CNN: Invariance to Data Augmentation

Given an initial dataset of N image patches



Predicts which of the N original images it came from (N-way classification)



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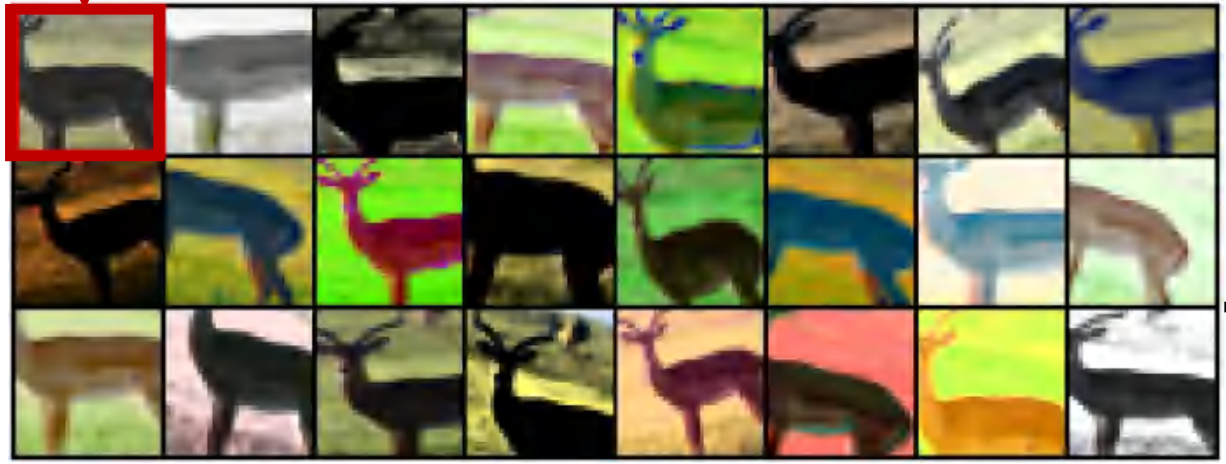

CNN inputs an augmented patch

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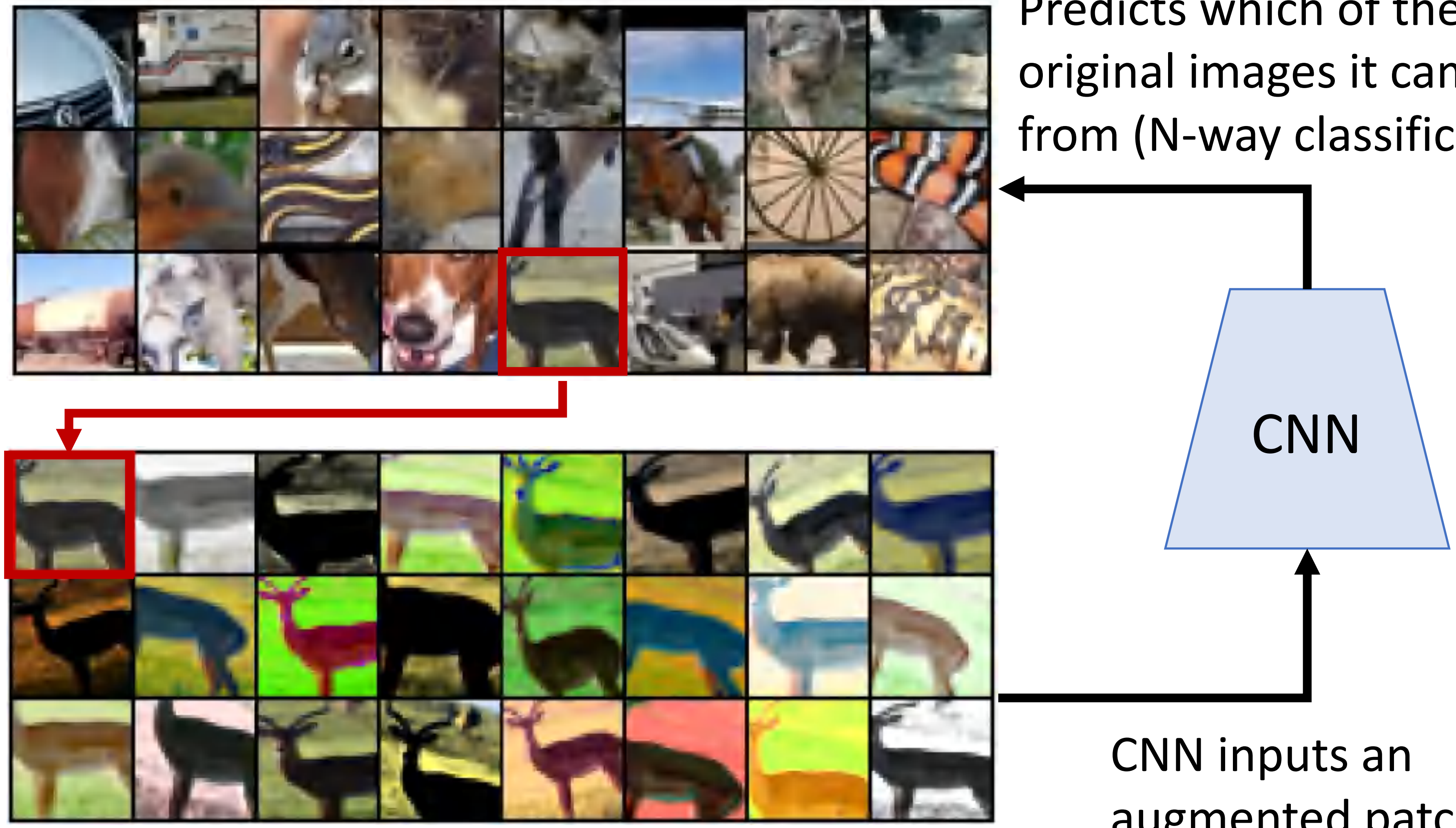
Exemplar CNN: Invariance to Data Augmentation

Given an initial dataset of N image patches

Problem: number of parameters in final layer depends on N; hard to scale

Sample K different augmentations for each; now have K*N total patches



Dosovitskiy et al, “Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks”

Contrastive Learning

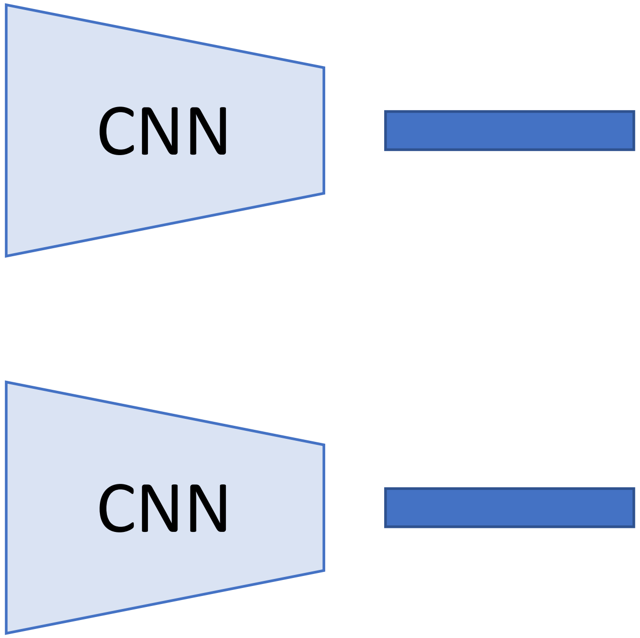
Assume we don't have labels for images, but we know whether some pairs of images are **similar** or **dissimilar**

Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning

Assume we don't have labels for images, but we know whether some pairs of images are **similar** or **dissimilar**

Similar images should have similar features



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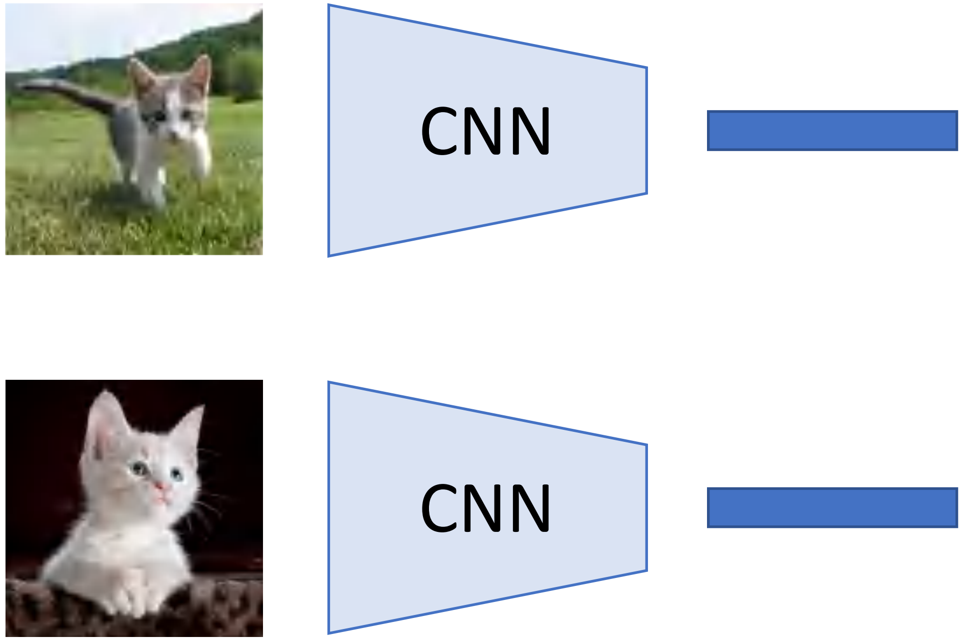
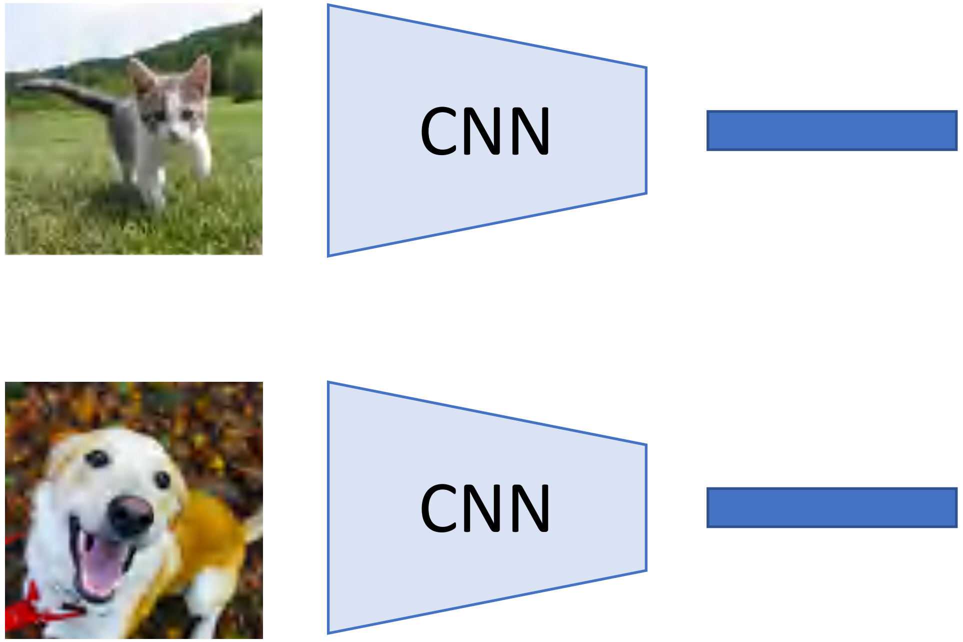


Dissimilar images should have dissimilar features



Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning

Assume we don't have labels for images, but we know whether some pairs of images are **similar** or **dissimilar**

Let $\mathrm{d} = ||\phi(x_1) - \phi(x_2)||_2$ be the Euclidean distance between features for two images

Similar images should have similar features

Dissimilar images should have dissimilar features

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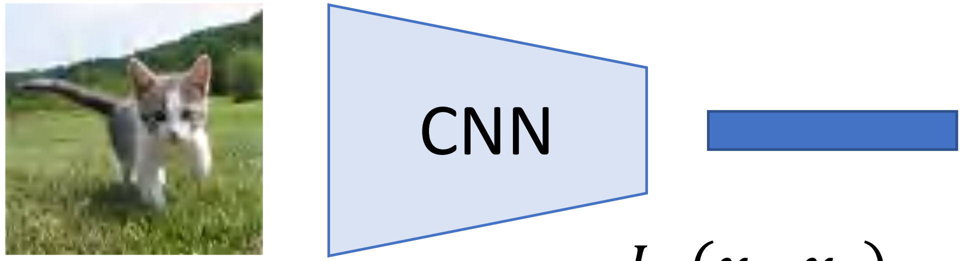
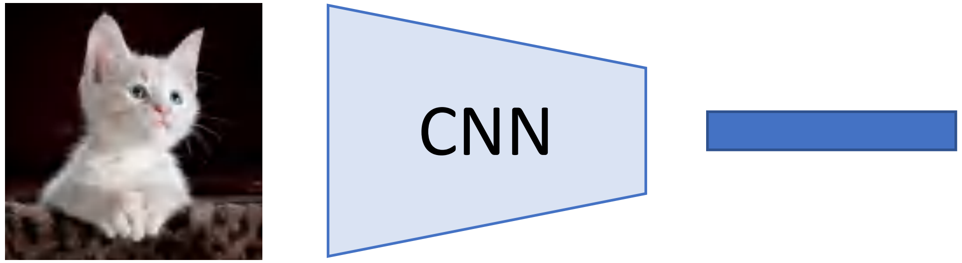


$$L_S(x_1, x_2) = d^2$$

Pull features together



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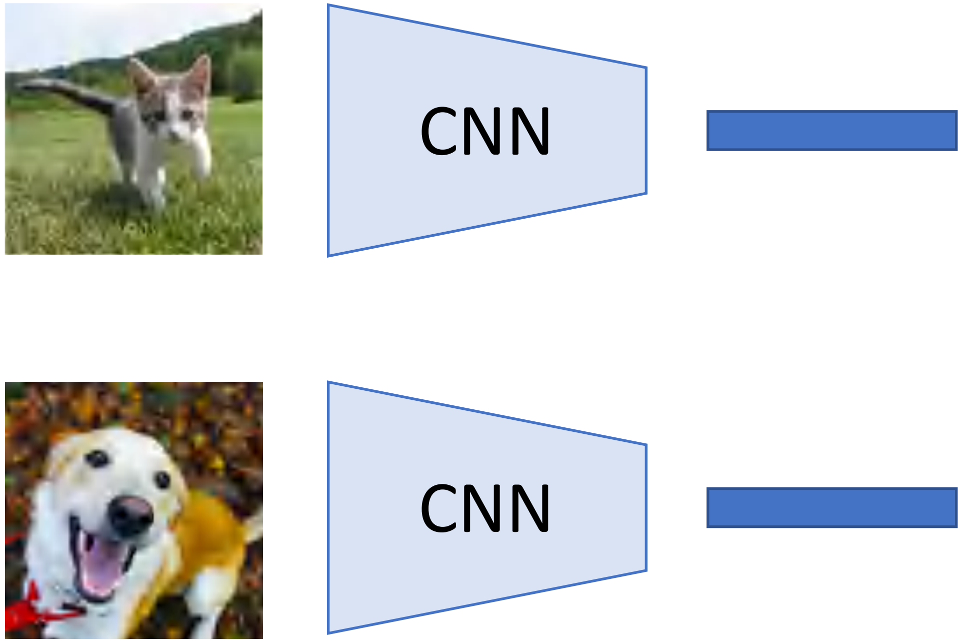

Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning

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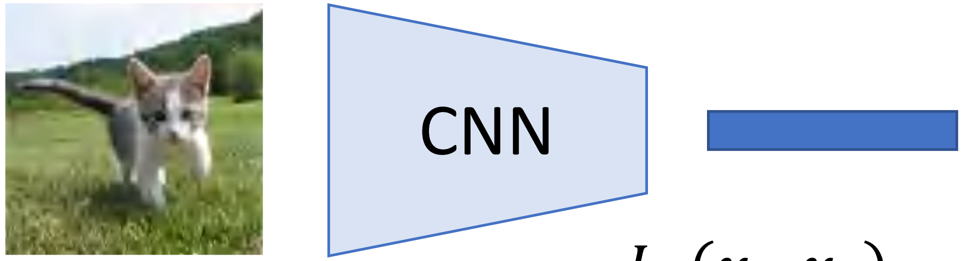
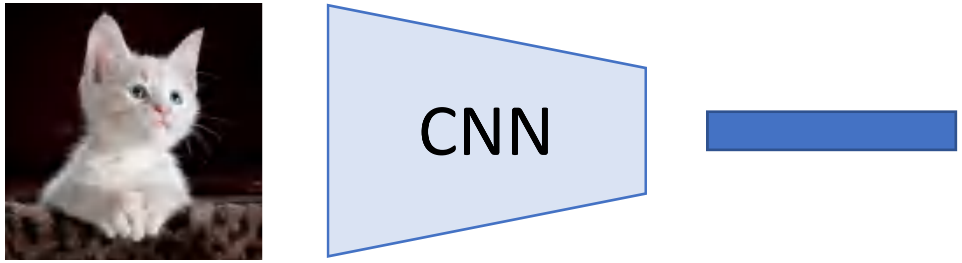
Similar images should have similar features

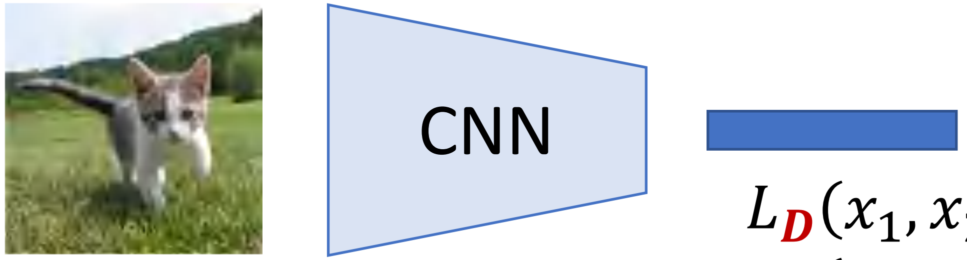


$L_{\boldsymbol{S}}(x_1, x_2) = d^2$

Pull features together

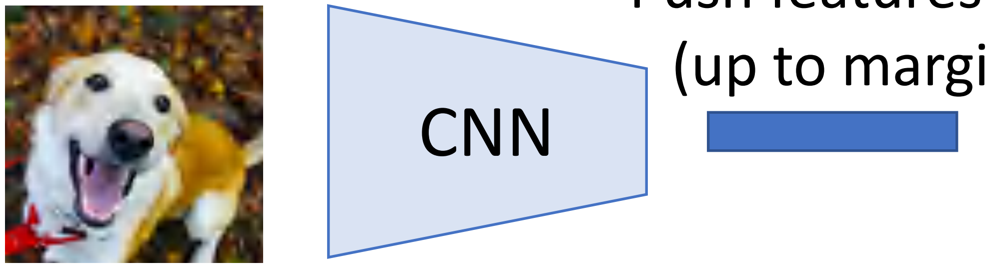


Dissimilar images should have dissimilar features



$L_{\boldsymbol{D}}(x_1, x_2)$
$= \max(0, m - d)^2$

Push features apart (up to margin m)



Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning

Problem: Where to get positive and negative pairs?

Assume we don't have labels for images, but we know whether some pairs of images are **similar** or **dissimilar**

Let $\mathrm{d} = ||\phi(x_1) - \phi(x_2)||_2$ be the Euclidean distance between features for two images

Similar images should have similar features

CNN

$L_{\boldsymbol{S}}(x_1, x_2) = d^2$

Pull features together

CNN

Dissimilar images should have dissimilar features

CNN

$L_{\boldsymbol{D}}(x_1, x_2)$
$= \max(0, m - d)^2$

Push features apart (up to margin m)

CNN

Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning with Data Augmentation

Batch of
N images

Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006
Wu et al, "Unsupervised Feature Learning by Non-Parametric Instance-Level Discrimination", CVPR 2018
Van den Oord et al, "Representation Learning with Contrastive Predictive Coding", NeurIPS 2018
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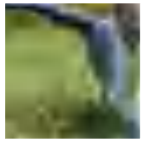
He et al, "Momentum Contrast for Unsupervised Visual Representation Learning", CVPR 2020
Chen et al, "A Simple Framework for Contrastive Learning of Visual Representations", ICML 2020

Contrastive Learning with Data Augmentation

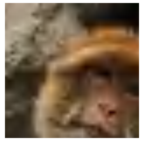
Batch of N images

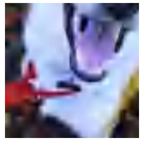
Two augmentations for each image

x_1 

x_2 

x_3 

x_4 

x_5 

x_6 

Hadsell et al, “Dimensionality Reduction by Learning and Invariant Mapping”, CVPR 2006
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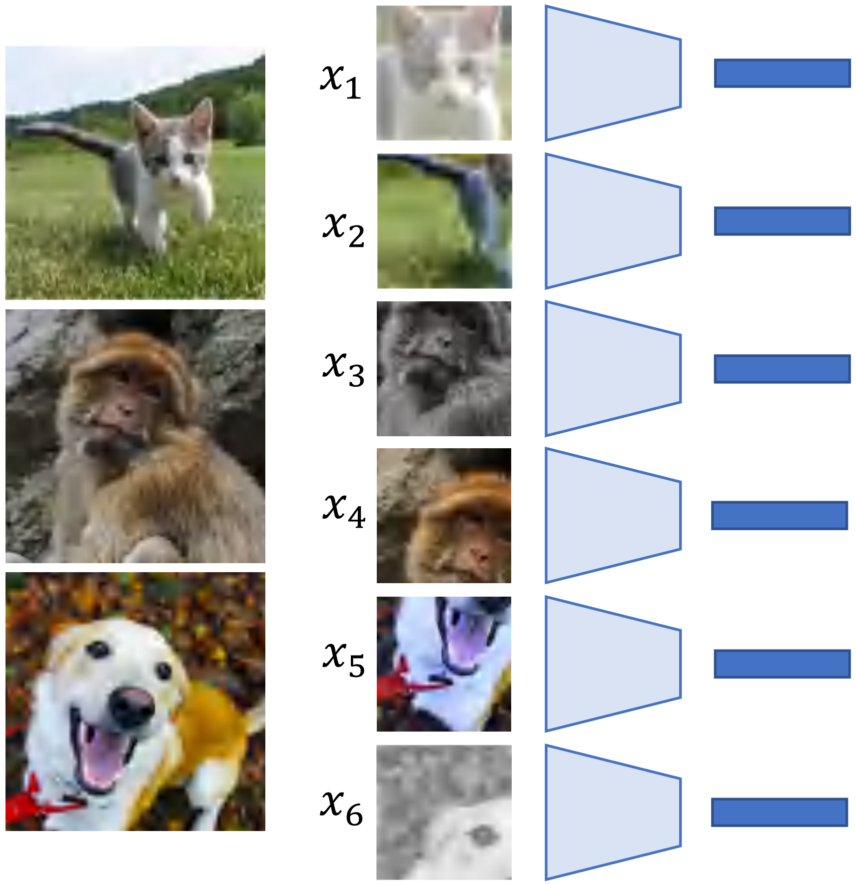
Contrastive Learning with Data Augmentation

Batch of N images | Two augmentations for each image | Extract features



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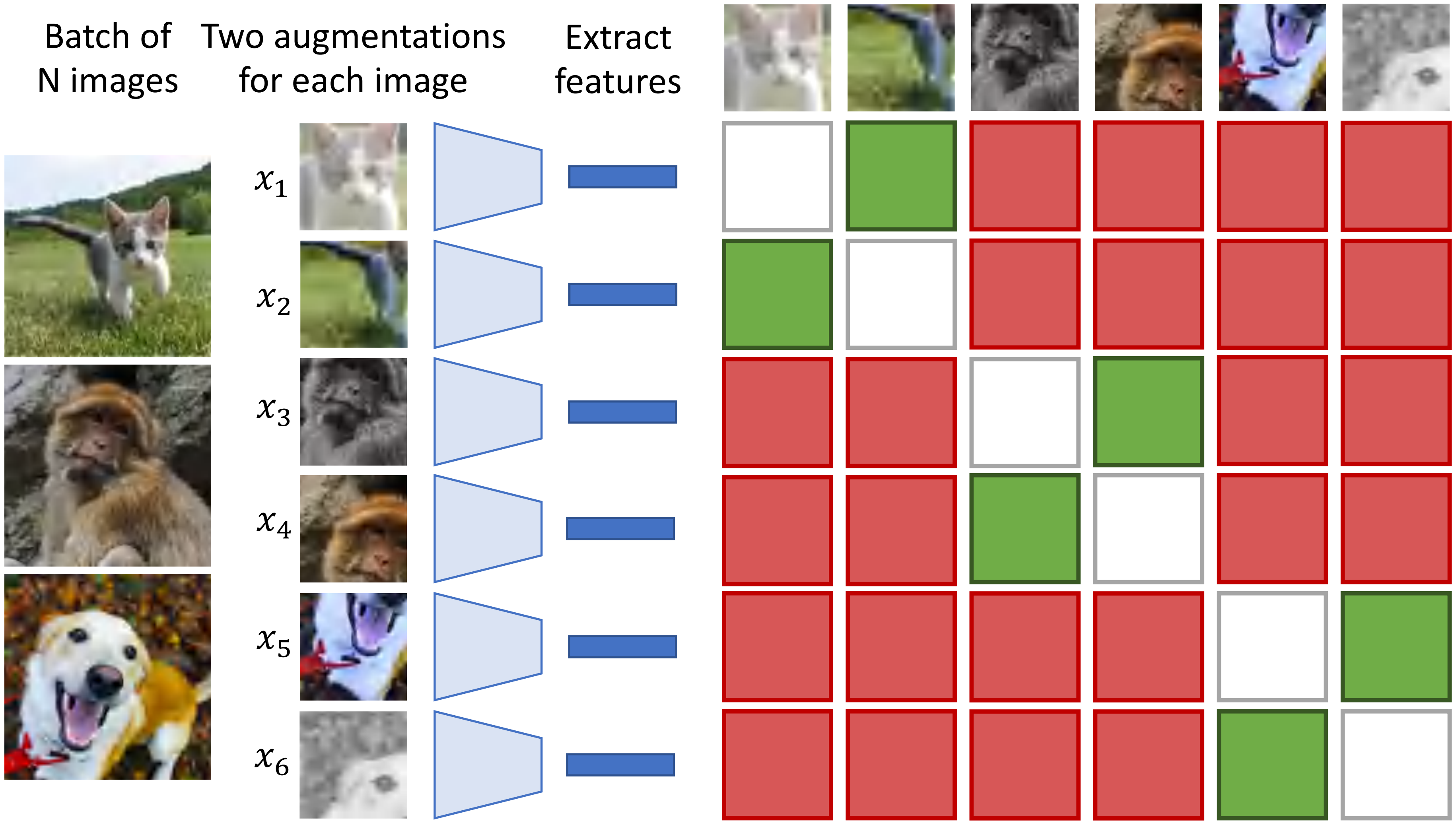
Contrastive Learning with Data Augmentation



Each image tries to predict which of the *other* 2N-1 images came from the same original image

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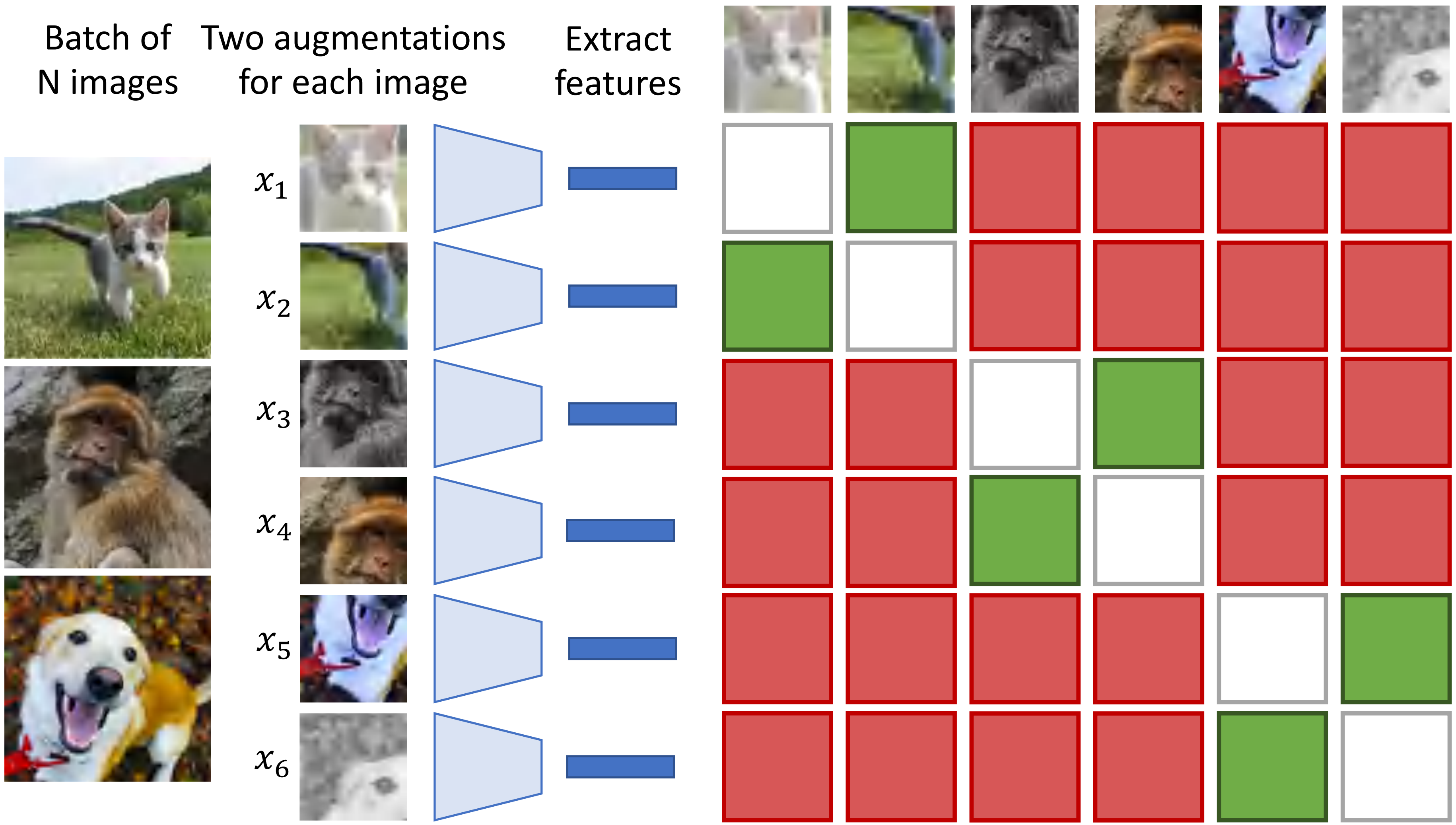
Contrastive Learning with Data Augmentation



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$$s_{i,j} = \frac{\phi(x_i)^T \phi(x_j)}{\|\phi(x_i)\| \cdot \|\phi(x_i)\|}$$

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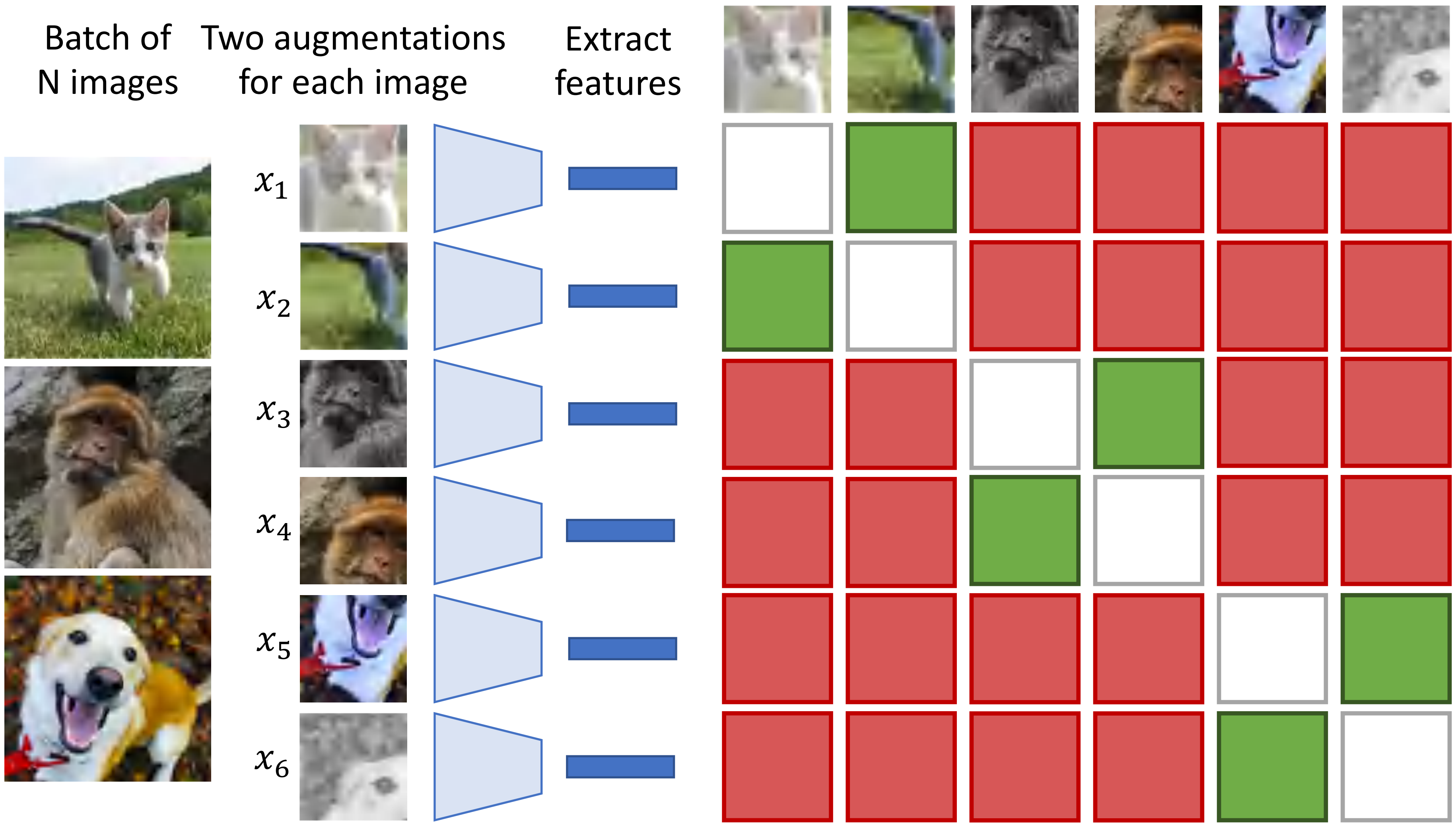
Contrastive Learning with Data Augmentation



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$$L_i = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{\substack{k=1 \\ k \neq i}}^{2N} \exp(s_{i,k}/\tau)}$$

(τ is a *temperature*)

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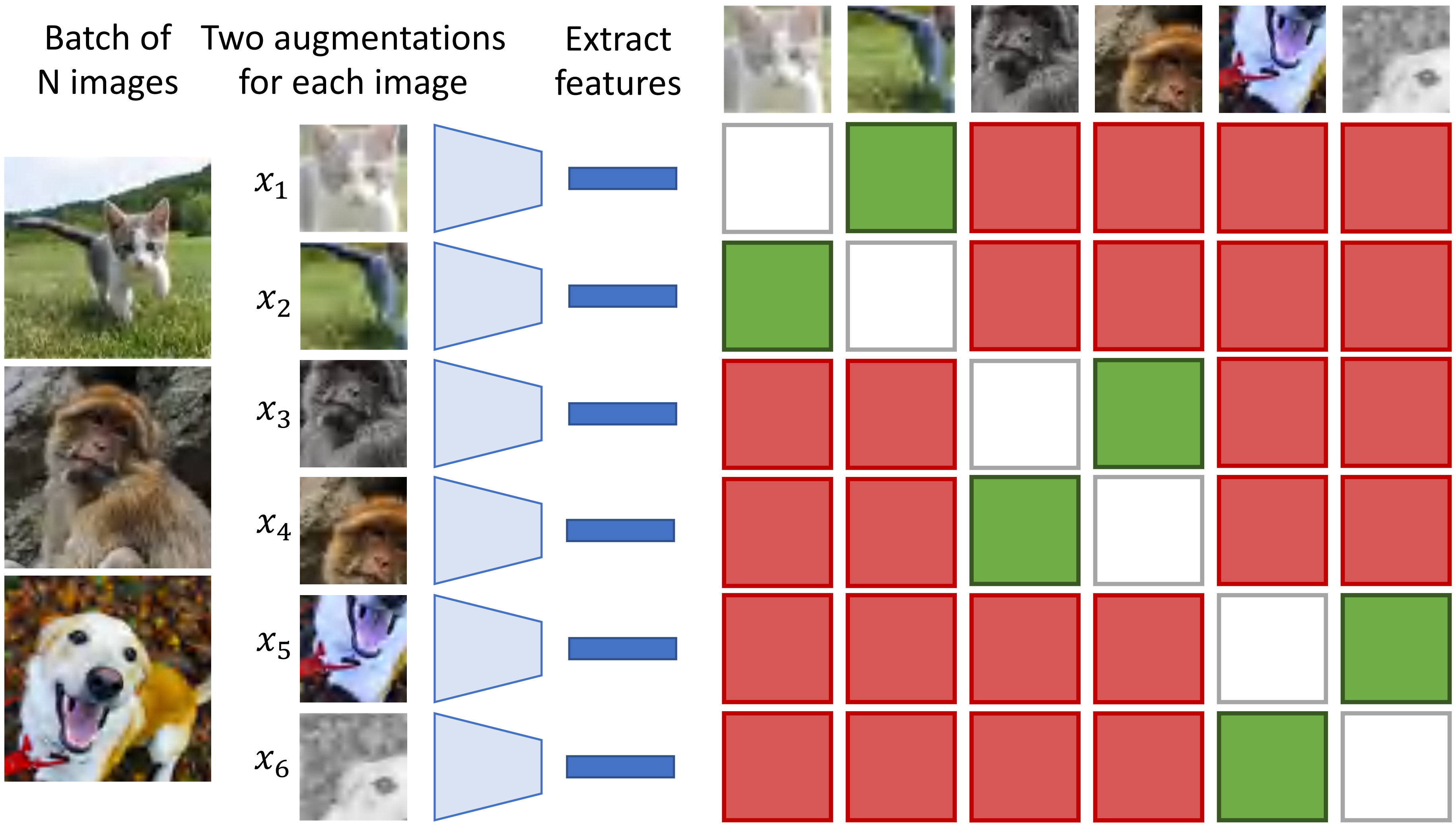
Contrastive Learning with Data Augmentation



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Interpretation: Cross-entropy loss over the other 2N-1 elements in the batch!

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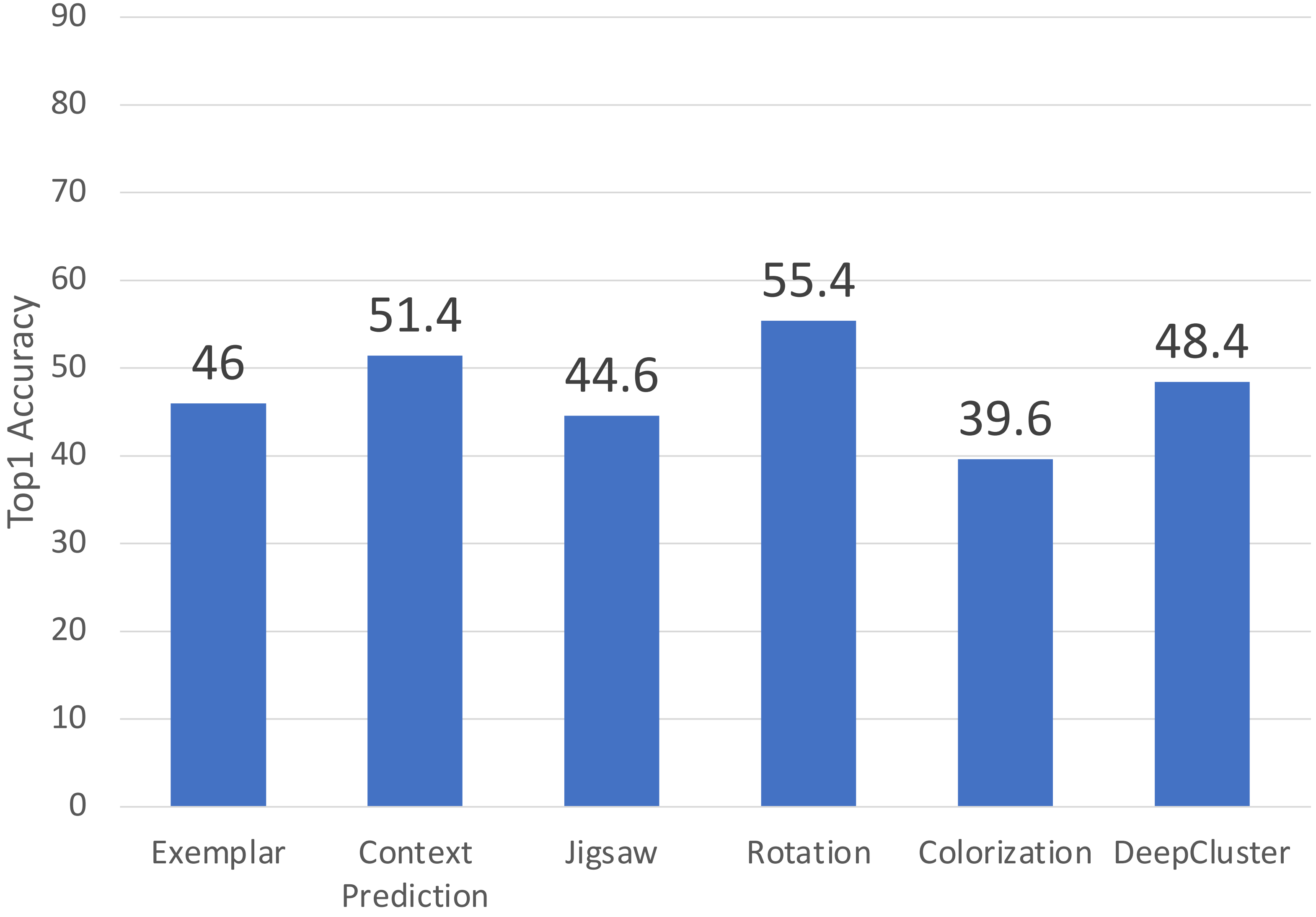
ImageNet Linear Classification from SSL Features



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(Lots of caveats here … different architectures, etc)

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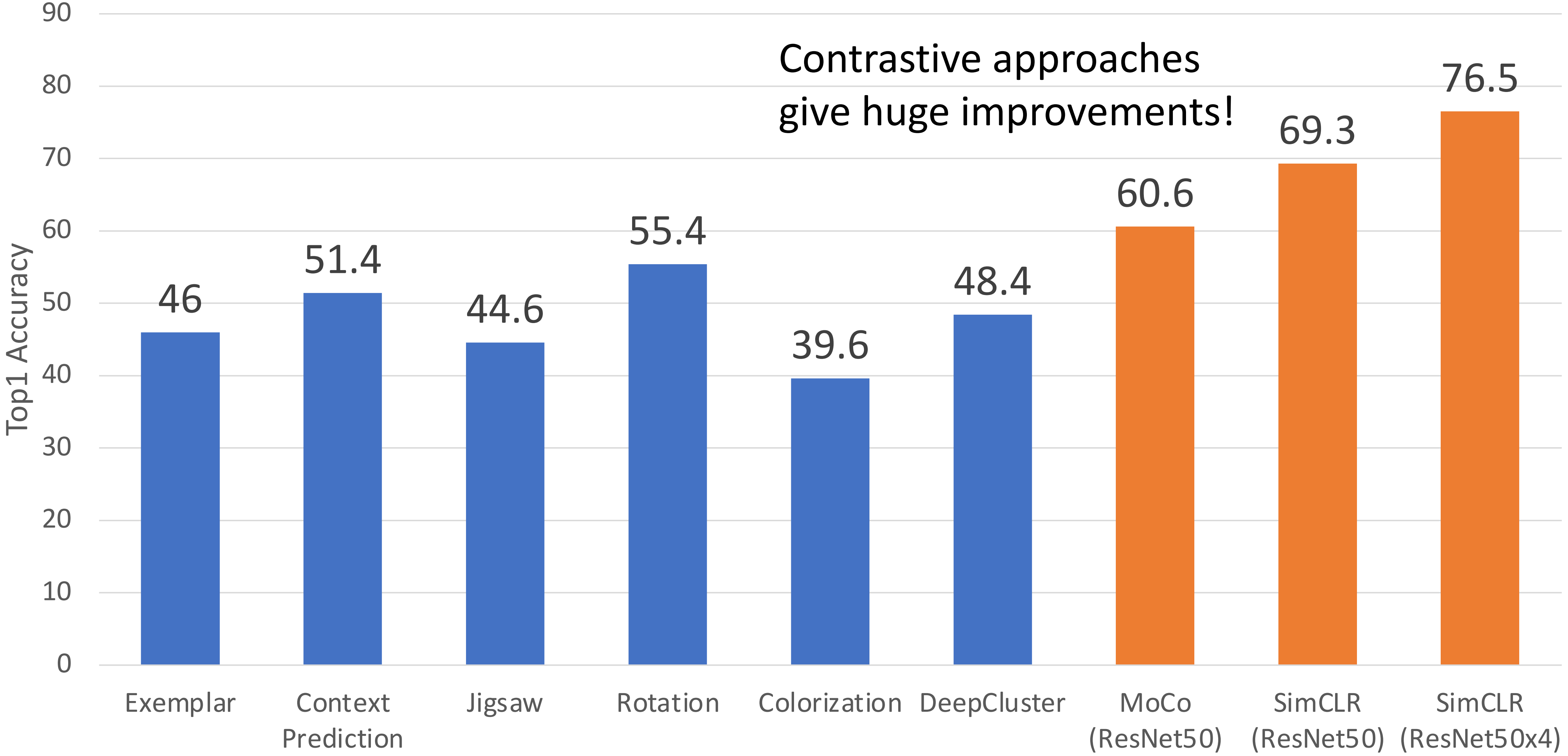

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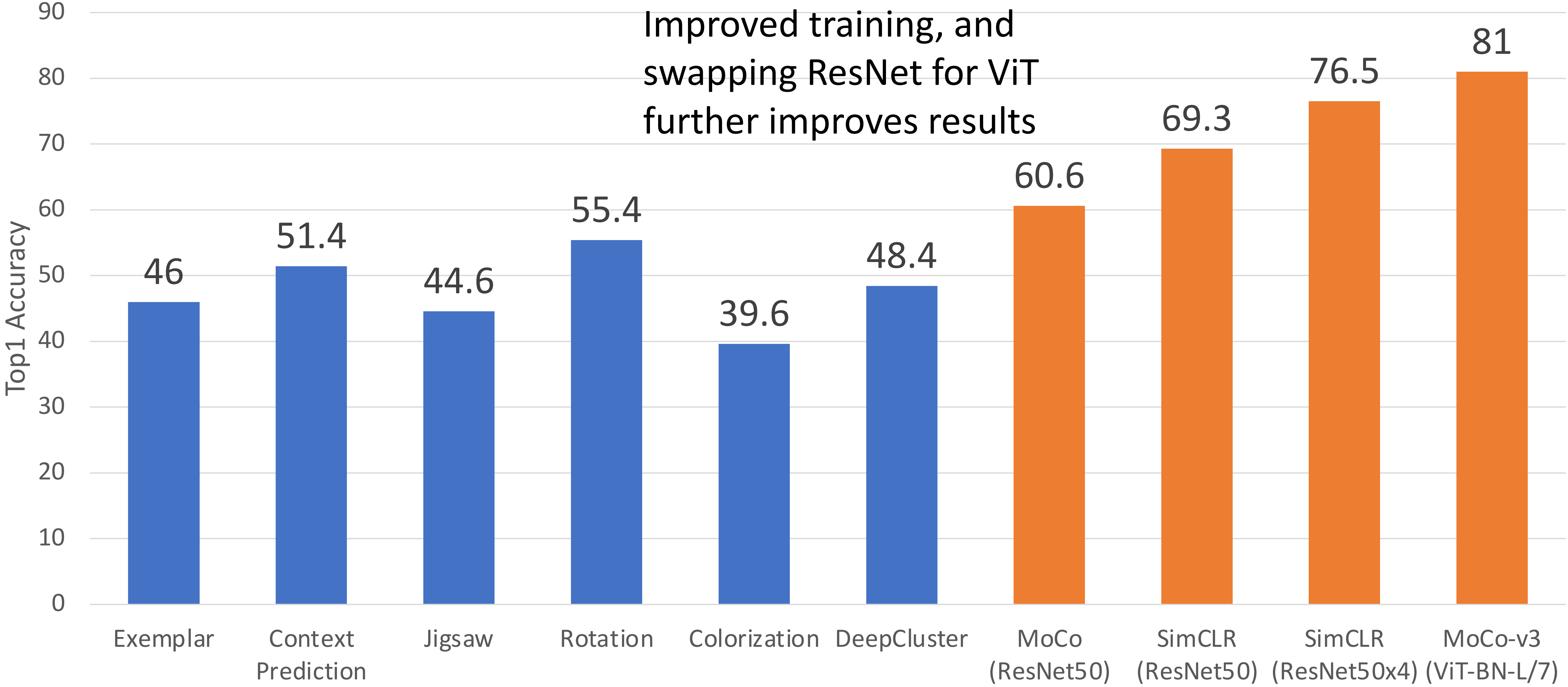

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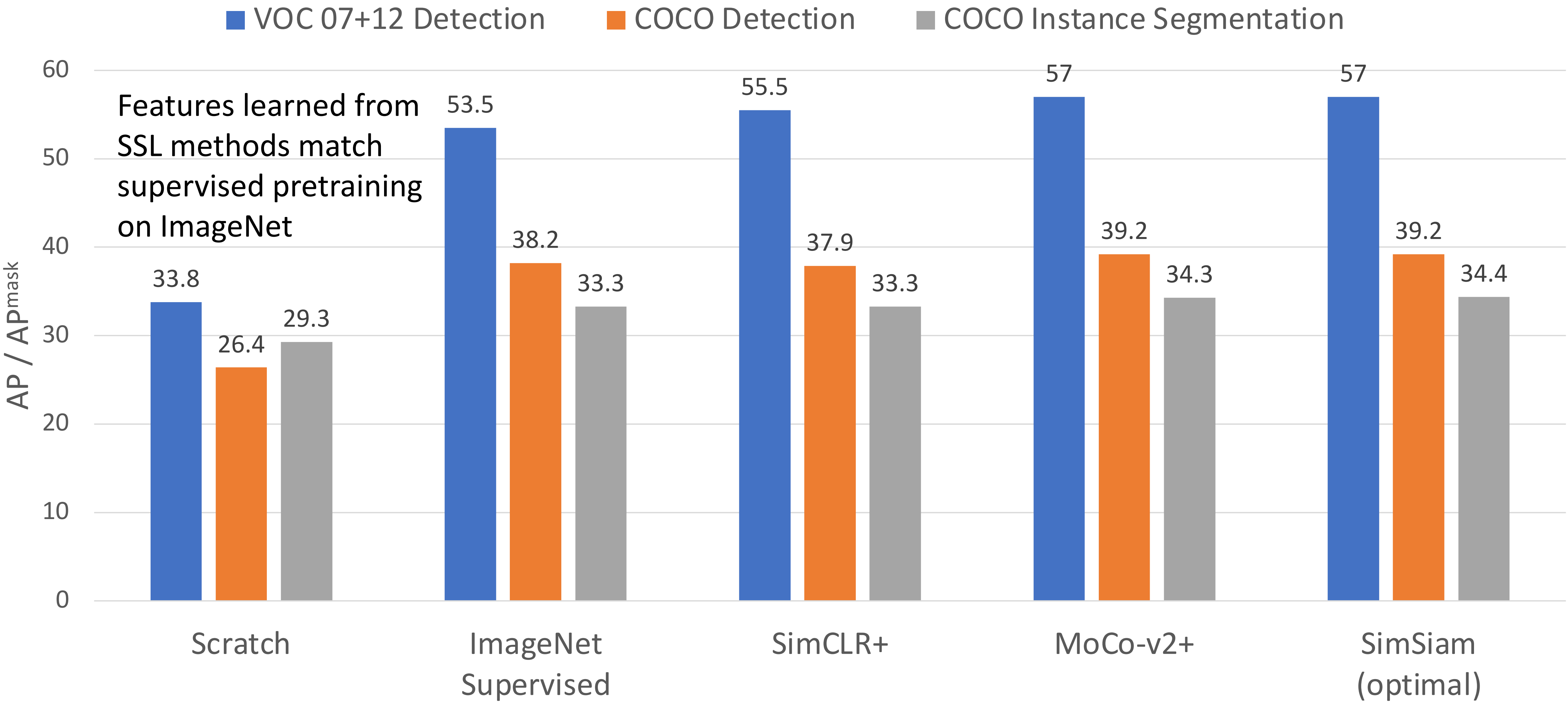
Chen et al, “A Simple Framework for Contrastive Learning of Visual Representations”, ICML 2020
Chen et al, “An Empirical Study of Training Self-Supervised Vision Transformers”, ICCV 2021

(Lots of caveats here … different architectures, etc)

Contrastive SSL Pretraining then Finetuning on Detection



He et al, "Momentum Contrast for Unsupervised Visual Representation Learning", CVPR 2020
Chen et al, "A Simple Framework for Contrastive Learning of Visual Representations", ICML 2020
Chen et al, "Improved Baselines with Momentum Contrastive Learning", arXiv 2020
Chen and He, "Exploring simple Siamese representation learning", CVPR 2021

Masked Autoencoders (MAE)

A ~~new~~ old method dethrones contrastive learning? Denoising Autoencoder with Vision Transformer

He et al, “Masked Autoencoders are Scalable Vision Learners”, CVPR 2022

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Divide image into nonoverlapping patches, discard most of them

input

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Encode remaining patches with a ViT

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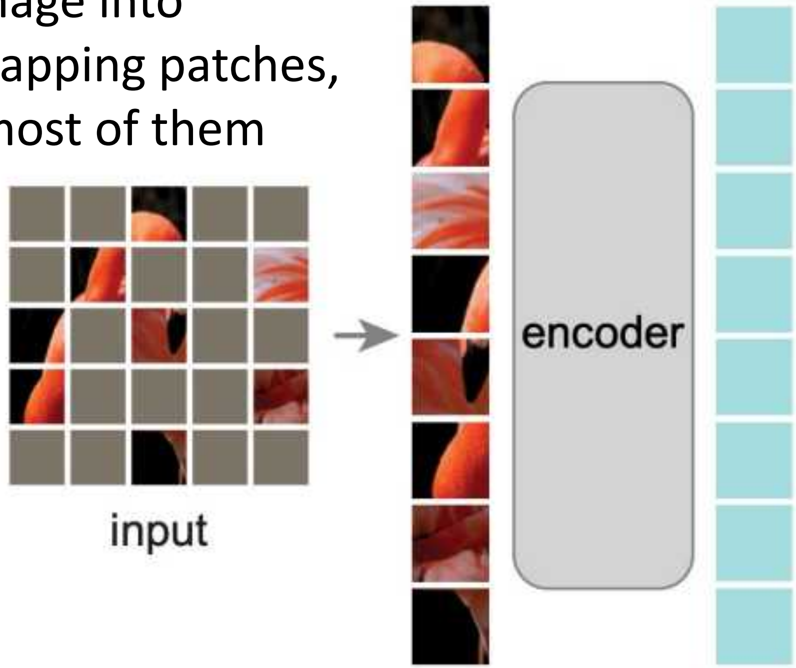

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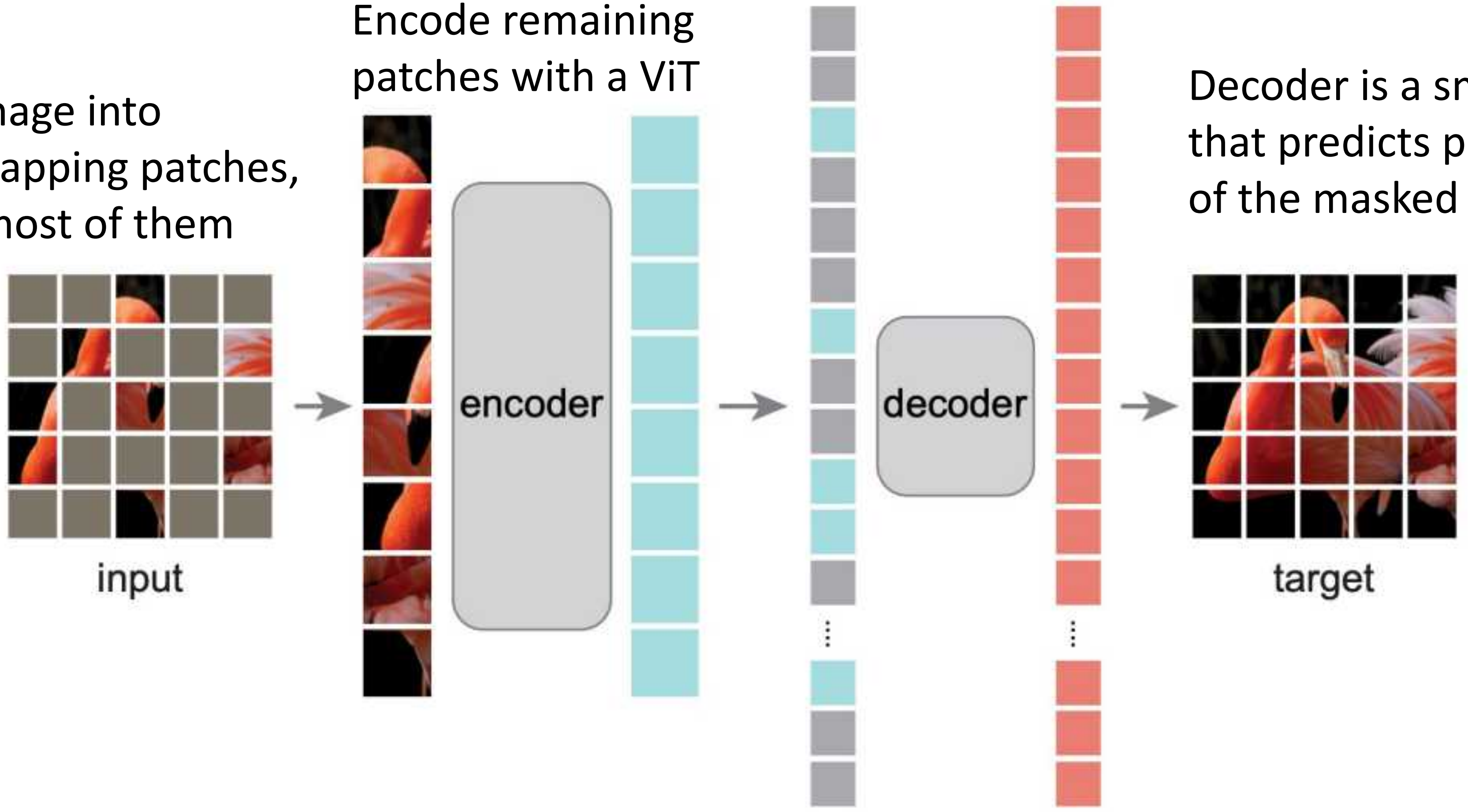
Encode remaining patches with a ViT

Decoder is a small ViT that predicts pixel values of the masked patches



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Masked Autoencoders (MAE): Reconstructions

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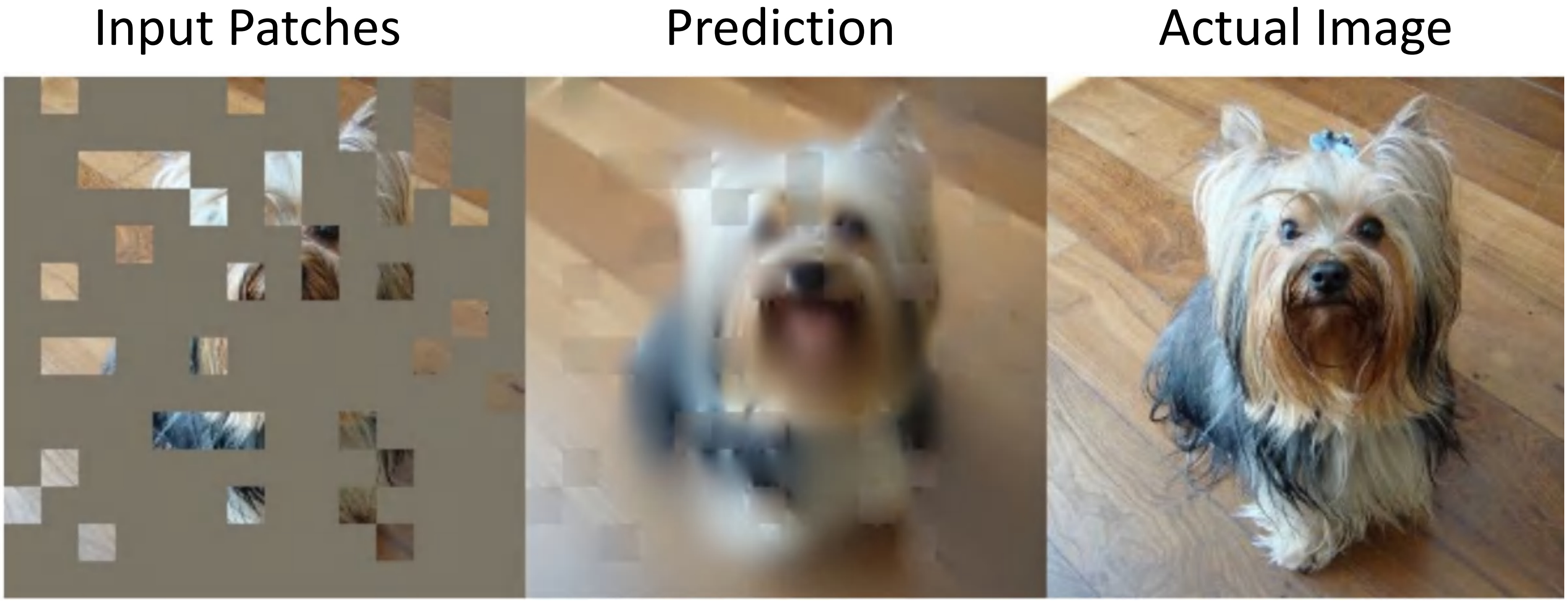
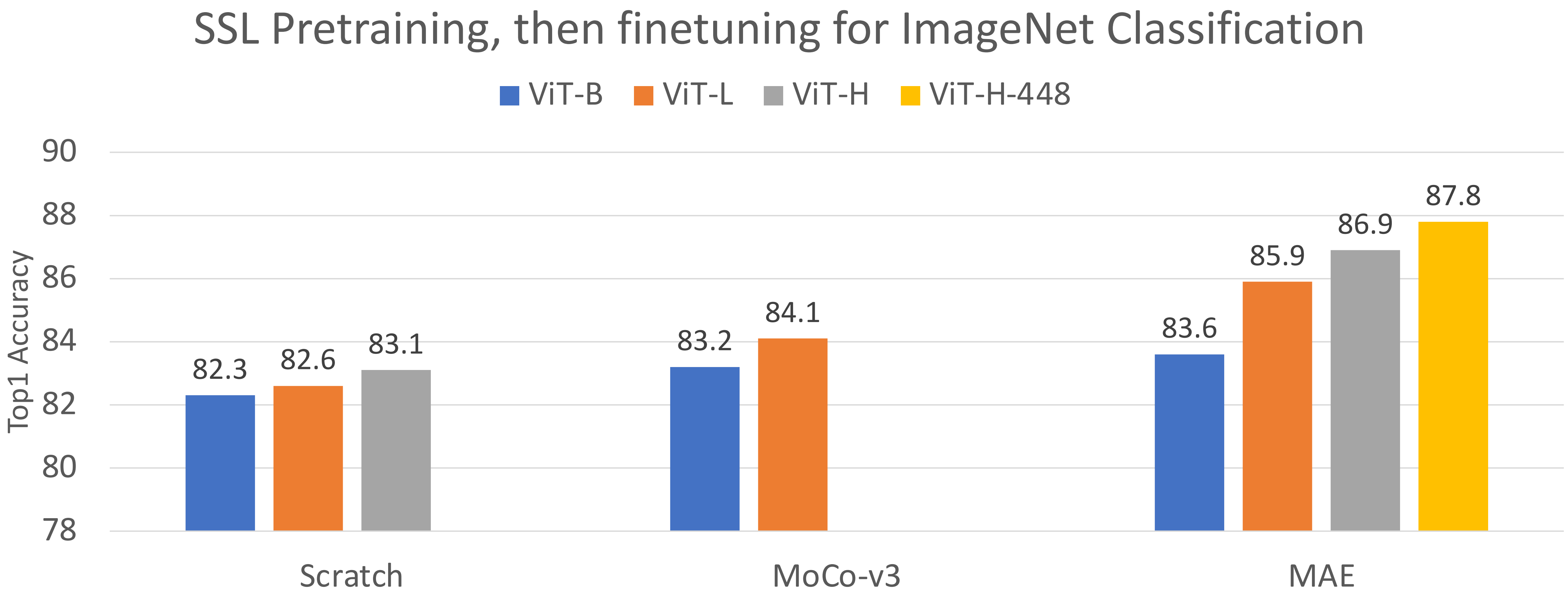


He et al, "Masked Autoencoders are Scalable Vision Learners", CVPR 2022

Masked Autoencoders (MAE): Reconstructions

Input Patches | Prediction | Actual Image

He et al, "Masked Autoencoders are Scalable Vision Learners", CVPR 2022



MAE Pretraining outperforms training from scratch, and allows scaling to larger ViT models

He et al, “Masked Autoencoders are Scalable Vision Learners”, CVPR 2022

A rant about data…

The motivation of SSL is scaling to large data that can't be labeled

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Unlabeled ImageNet is still curated: single object per image, balanced classes

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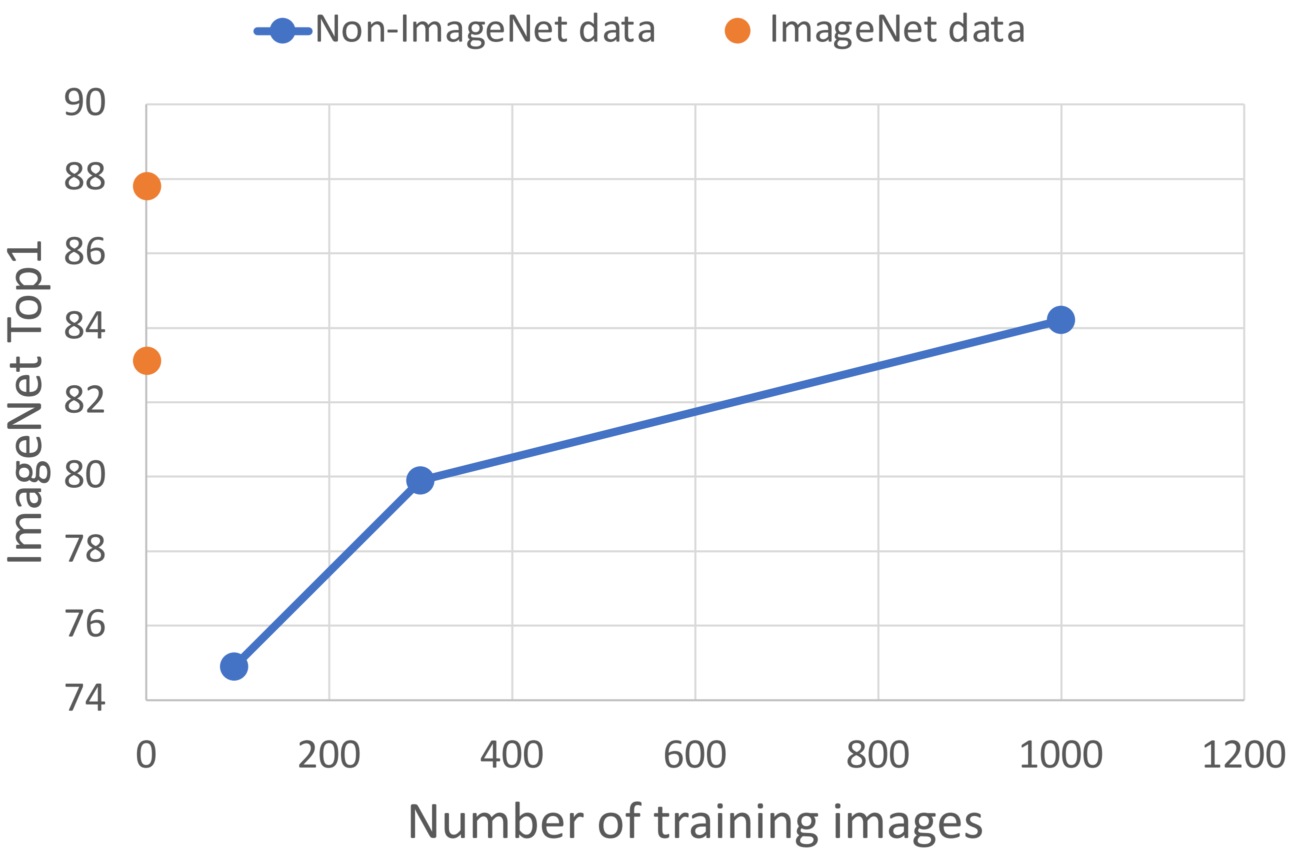

Caron et al, "Unsupervised pre-training of images features on non-curated data", ICCV 2019
Chen et al, "Big self-supervised models are strong semi-supervised learners", NeurIPS 2020
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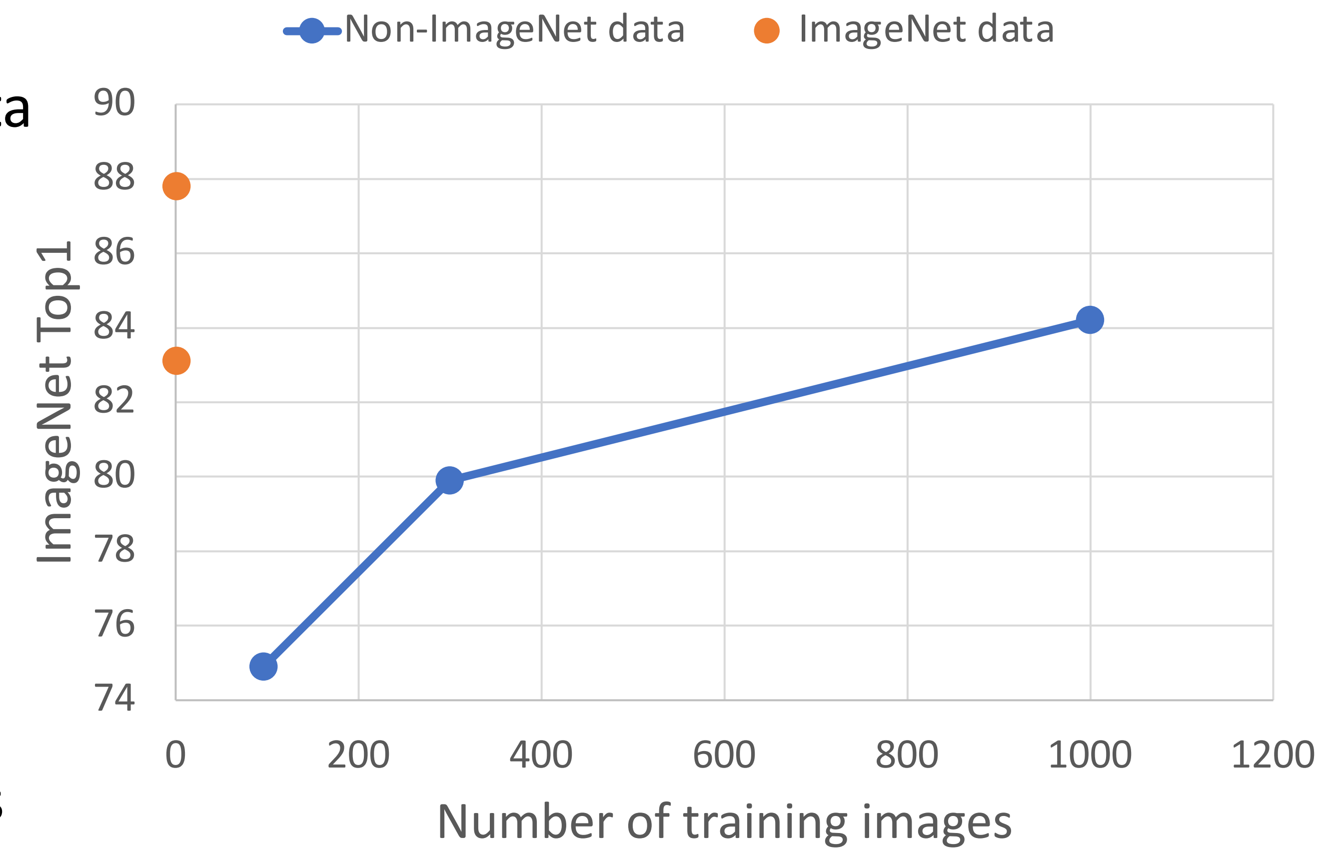
Idea: What if we go beyond isolated images?



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Multimodal Self-Supervised Learning

Don't learn from isolated images -- take images together with some **context**

Video: Image together with adjacent video frames

Agrawal et al, "Learning to See by Moving", ICCV 2015
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Language: Image with natural-language text

Sariyildiz et al, “Learning Visual Representations with Caption Annotations”, ECCV 2020
Desai and Johnson, “VirTex: Learning Visual Representations from Textual Annotations”, CVPR 2021
Radford et al, “Learning Transferable Visual Models form Natural Language Supervision”, ICML 2021
Jia et al, “Scaling up Visual and Vision-Language Representation Learning with Noisy Text Supervision”, ICLR 2021
Desai et al, “RedCaps: Web-curated Image-Text data created by the people, for the people”, NeurIPS 2021

Why Language?

Large dataset of
(image, caption)

a dog with his head out the window of the car

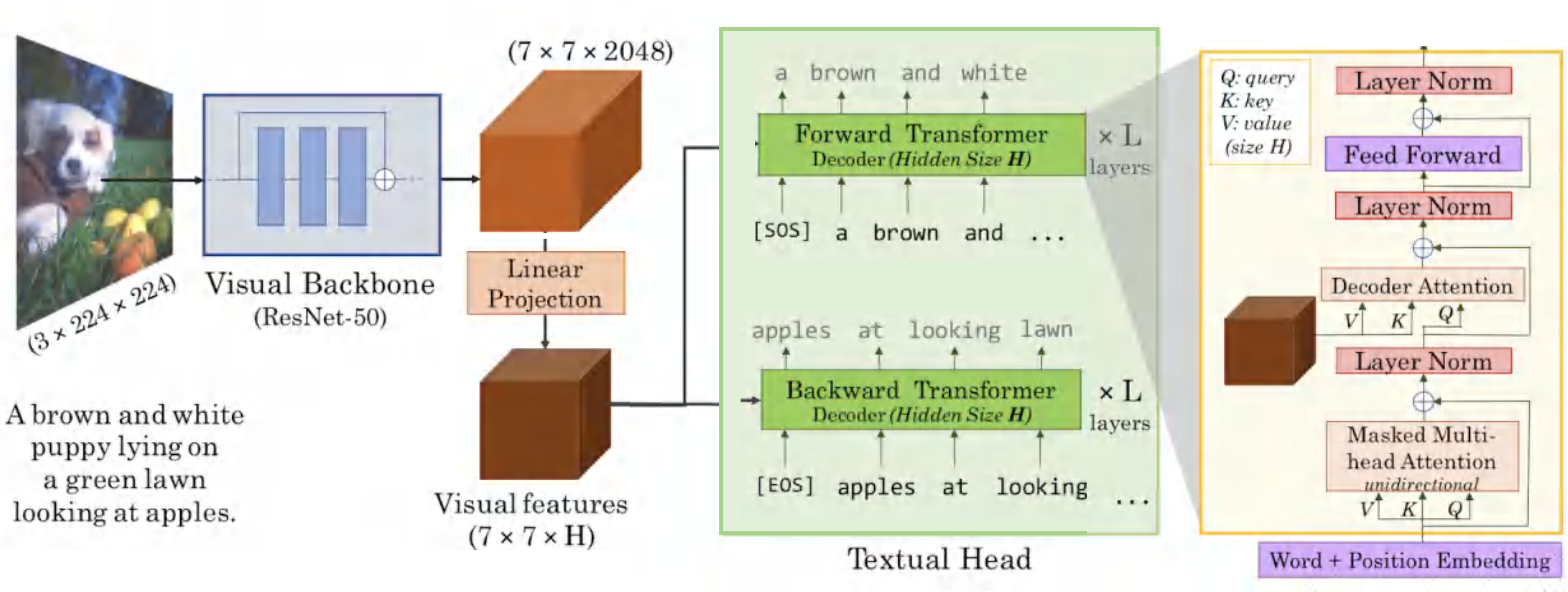
a black and orange cat is resting on a keyboard and yellow back scratcher

1. **Semantic density**: Just a few words give rich information

2. **Universality**: Language can describe any concept

3. **Scalability**: Non-experts can easily caption images; data can also be collected from the web at scale

Generating Captions



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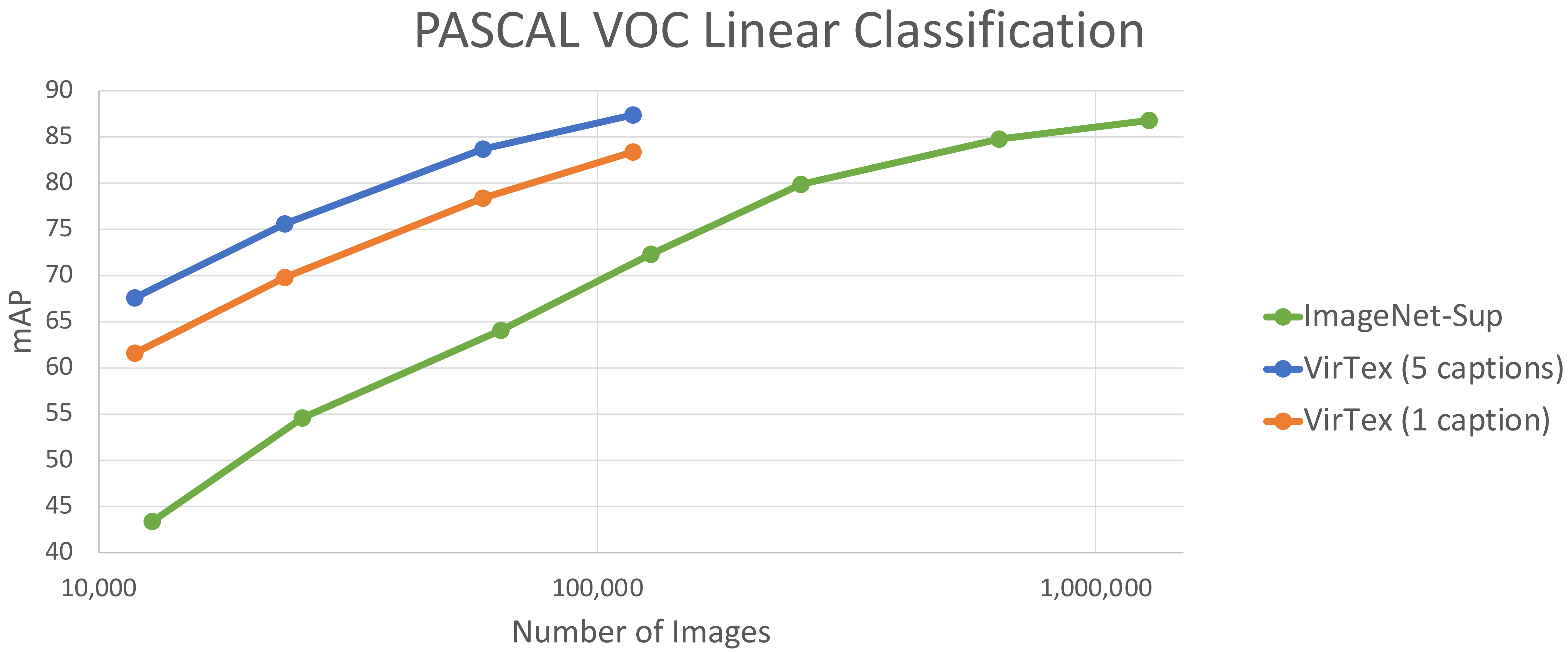

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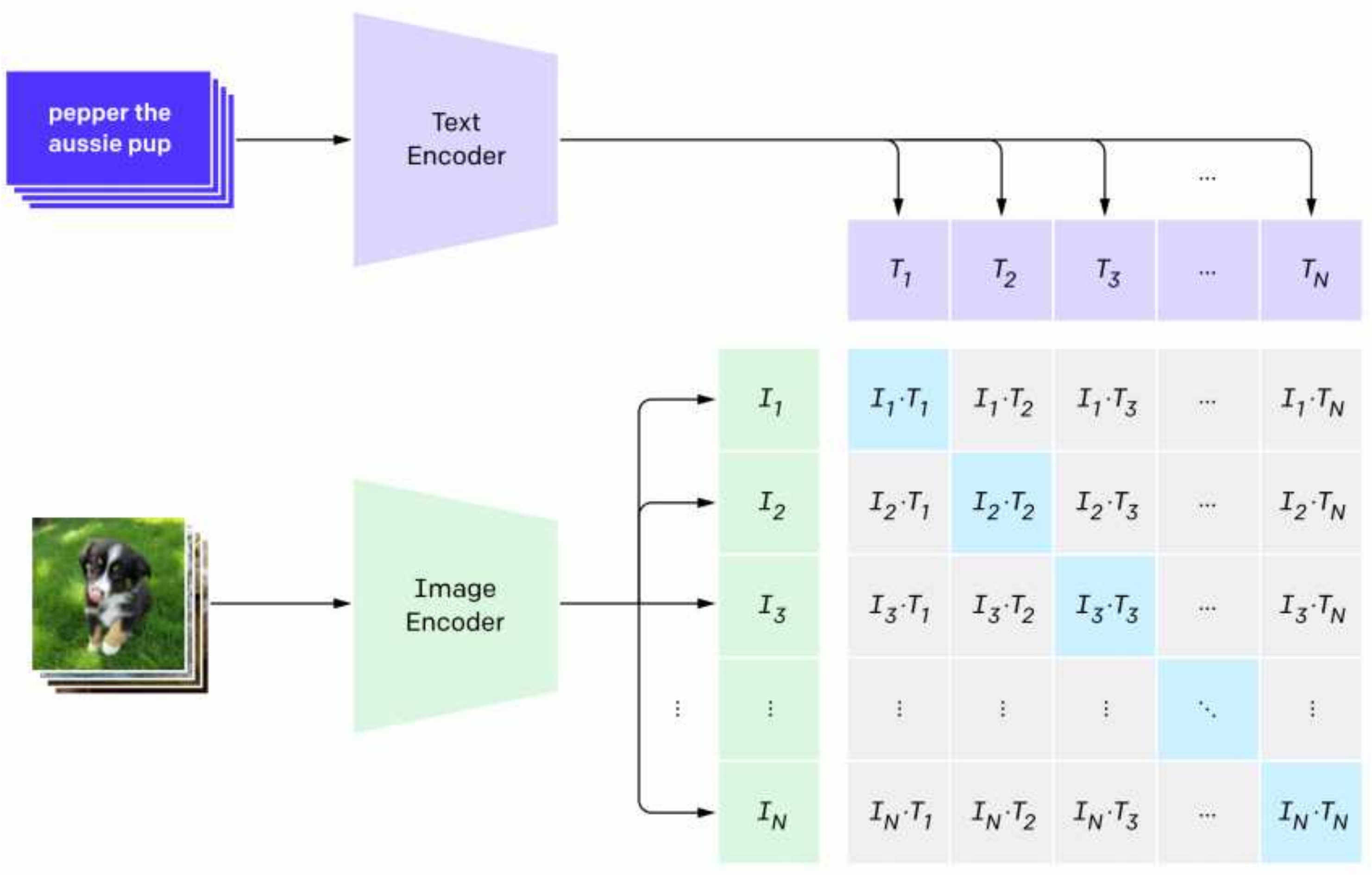
Matching Images and Text



Contrastive loss: Each image predicts which caption matches

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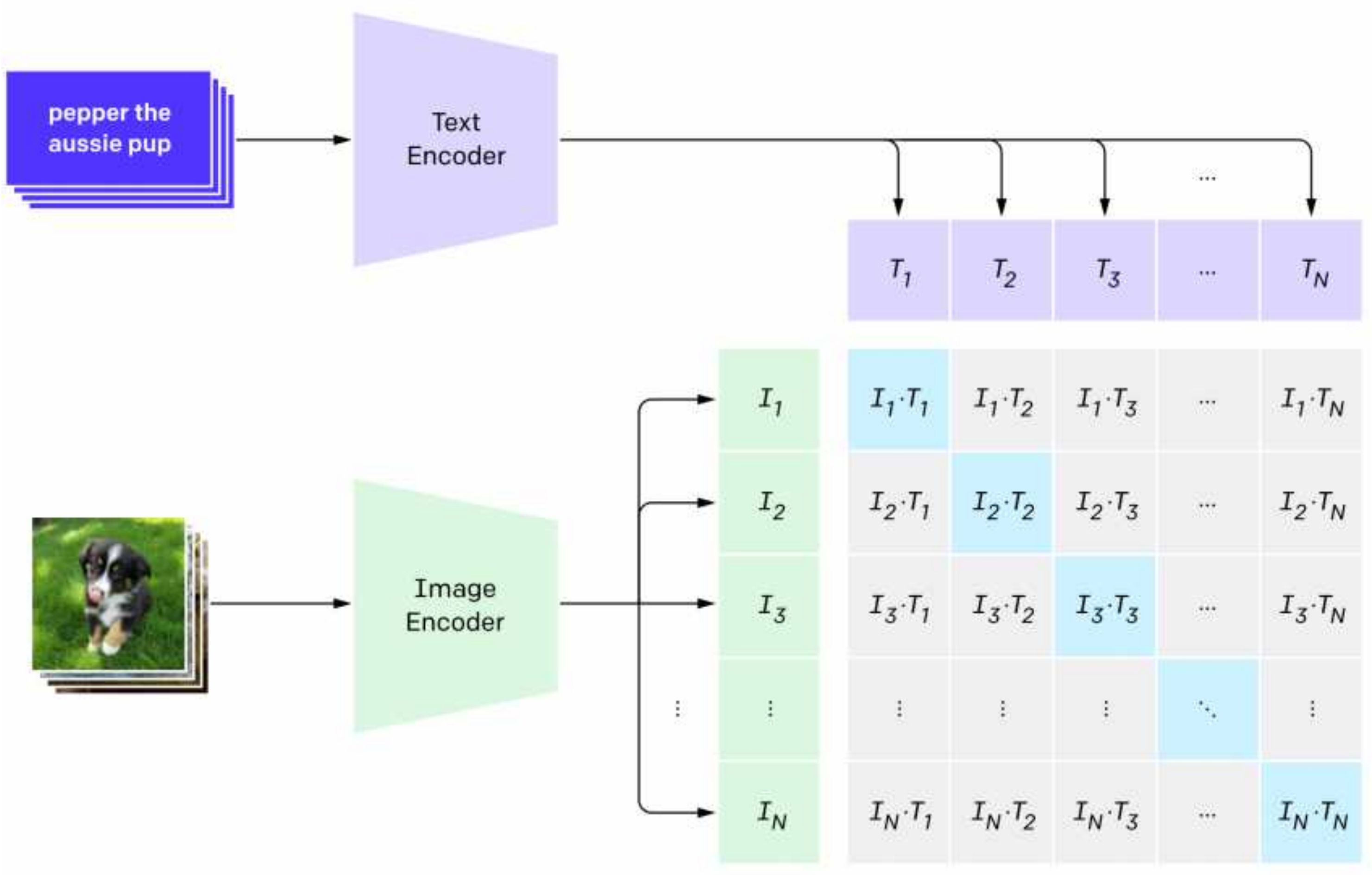
Matching Images and Text: CLIP



Contrastive loss: Each image predicts which caption matches

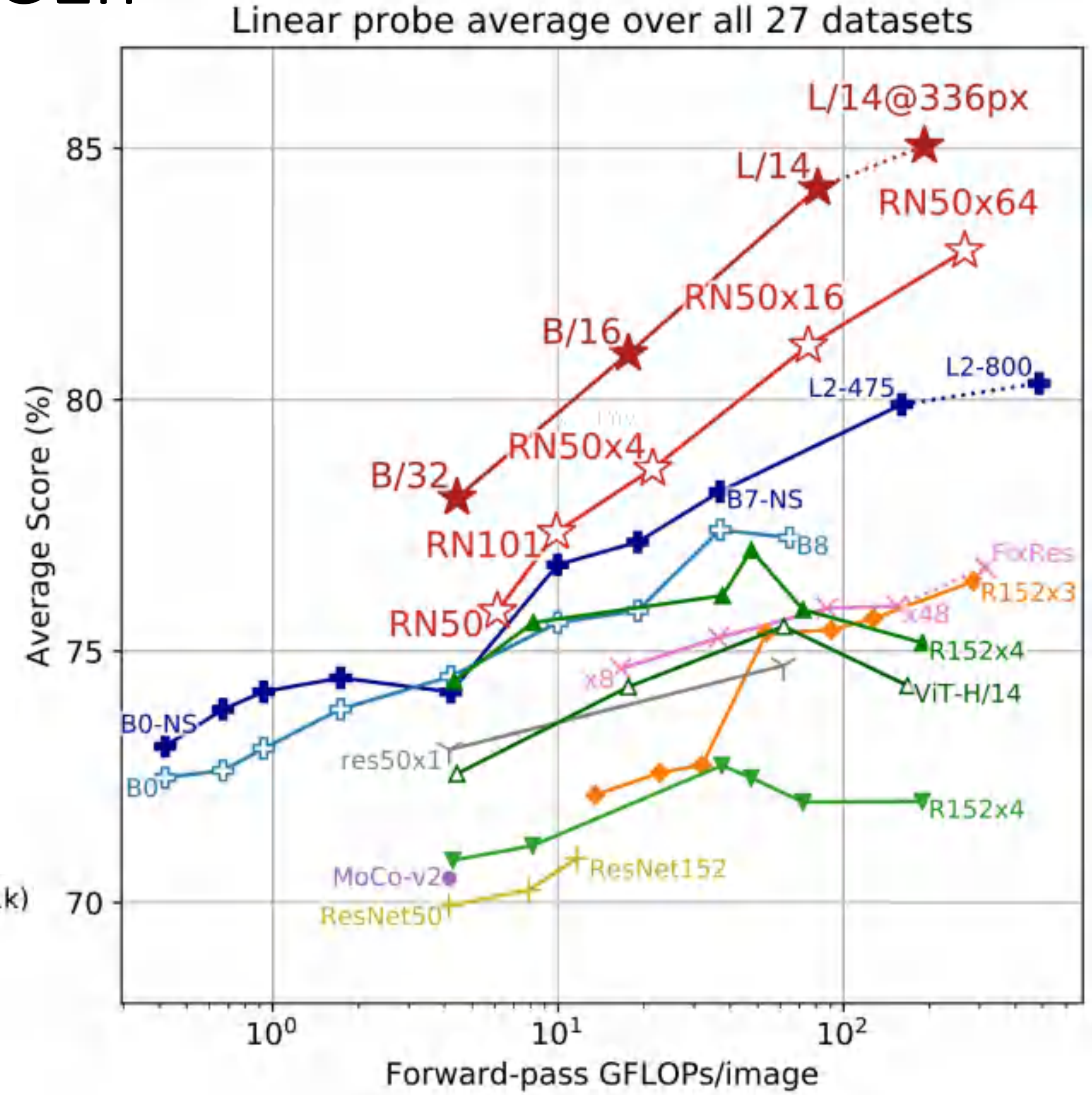
Large-scale training on 400M (image, text) pairs from the internet

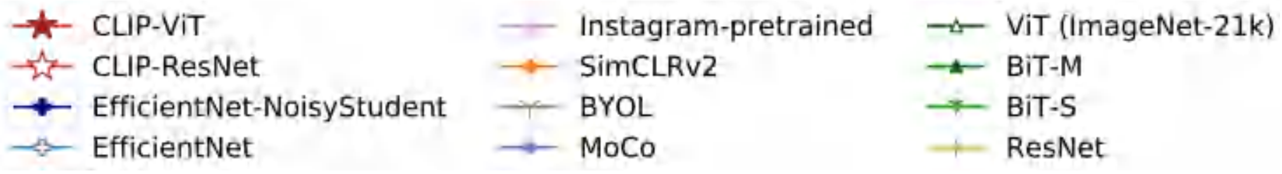
Radford et al, "Learning Transferable Visual Models form Natural Language Supervision", ICML 2021
Jia et al, "Scaling up Visual and Vision-Language Representation Learning with Noisy Text Supervision", ICLR 2021

Matching Images and Text: CLIP

Very strong performance on many downstream vision problems!

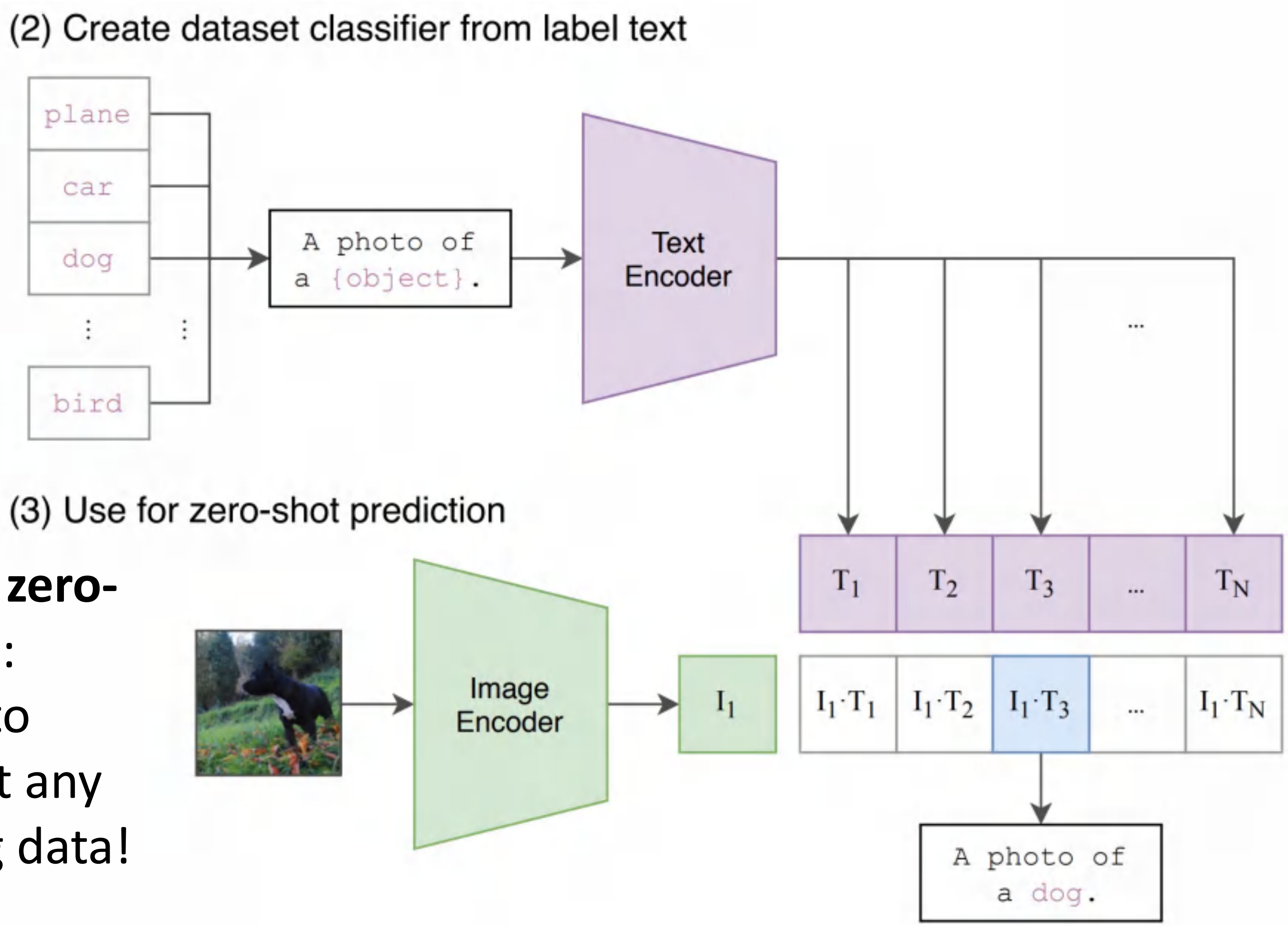
Performance continues to improve with larger models





Radford et al, "Learning Transferable Visual Models form Natural Language Supervision", ICML 2021

CLIP: Zero-Shot Classification



Language enables **zero-shot classification**: Classify images into categories without any additional training data!

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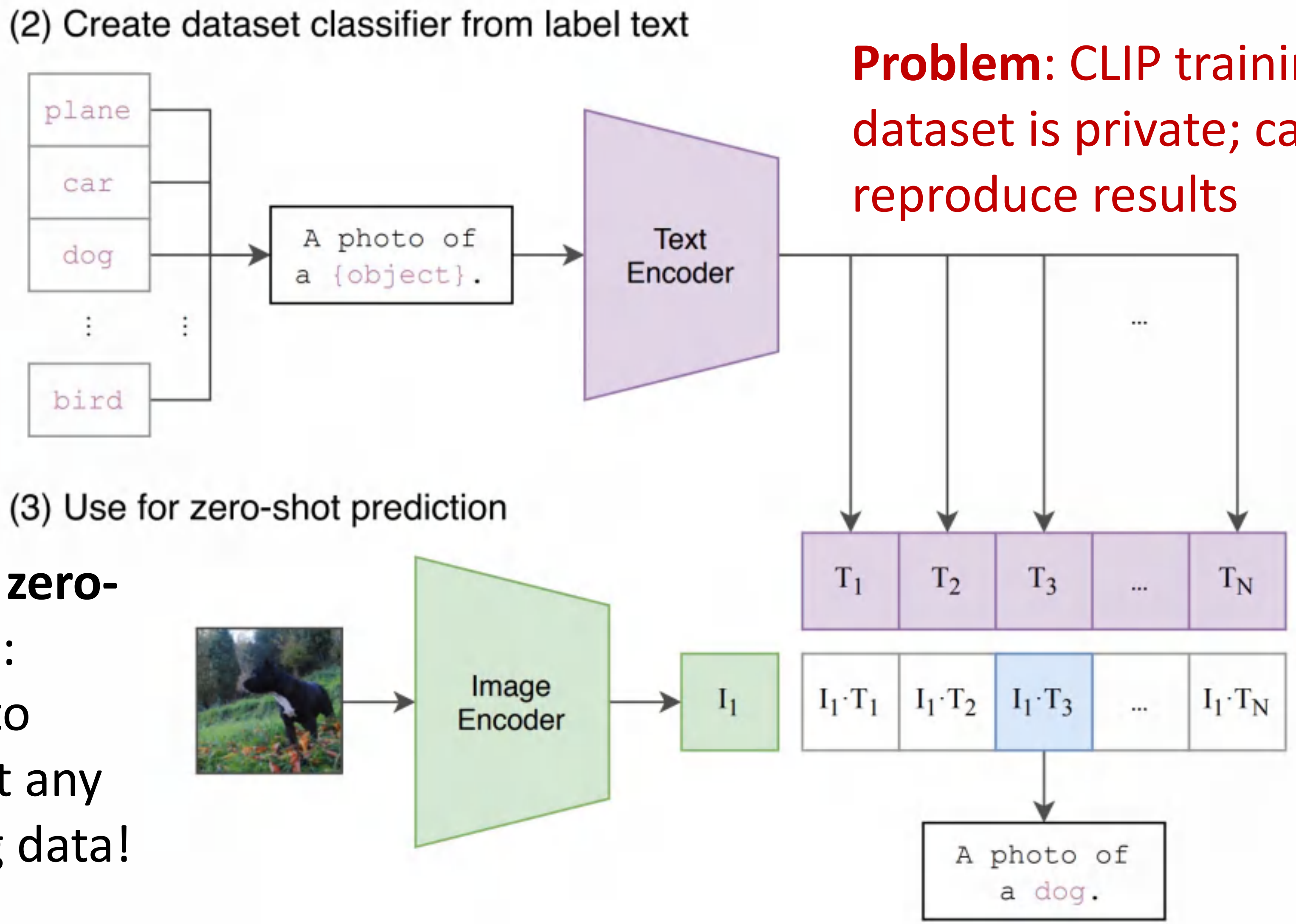

Problem: CLIP training dataset is private; can't reproduce results

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RedCaps: Images and Captions from Reddit

Data from 350 manually-chosen subreddits
12M high-quality (image, caption) pairs

Desai, Kaul, Aysola, and Johnson, NeurIPS Datasets & Benchmarks Track, 2021

Summary

Self-Supervised Learning (SSL) aims to scale up to larger datasets without human annotation

First train for a **pretext** task, then **transfer** to **downstream** tasks

Many pretext tasks: context prediction, jigsaw, colorization, clustering, rotation

SSL has been wildly successful for language

Intense research on SSL in vision; current best are contrastive, masked autoencoding

Multimodal SSL uses images together with additional context

Multimodal SSL with vision + language has been very successful; seems very promising!

Next Time:
3D Vision