Topic 7: Self-Supervised Learning

CMSC 491/691 Robust Machine Learning

UMBC

Some slides from Justin Johnson

Supervised vs Unsupervised Learning

Supervised Learning

- Data: (x, y) pairs
  - x: input, y: true label
- Goal: Learn mapping $f: x \rightarrow y$
- Approaches: ERM, Decision Trees, Naïve Bayes, …
- Tasks: Classification, Regression

Unsupervised Learning

- Data: Only x
  - Just inputs, no labels!
- Goal: Learn some "underlying hidden structure" of the data … somehow
- Approaches: clustering, dimensionality reduction, density estimation …
- Tasks: Generative Models

Supervised Learning is Expensive ...

- Train a model on 1 million images → label 1 million images
- Labels aren't magically given to you → need human effort
- How much will it cost?

(1,000,000 images)	(Small to medium sized dataset)
× (10 seconds/image)	(Fast annotation)
× (1/3600 hours/second)	
× ($15 / hour)	(Minimum wage)
× (3 annotators / image)	(for consensus / removing noise)

= ~ $125k without considering overhead / admin costs …

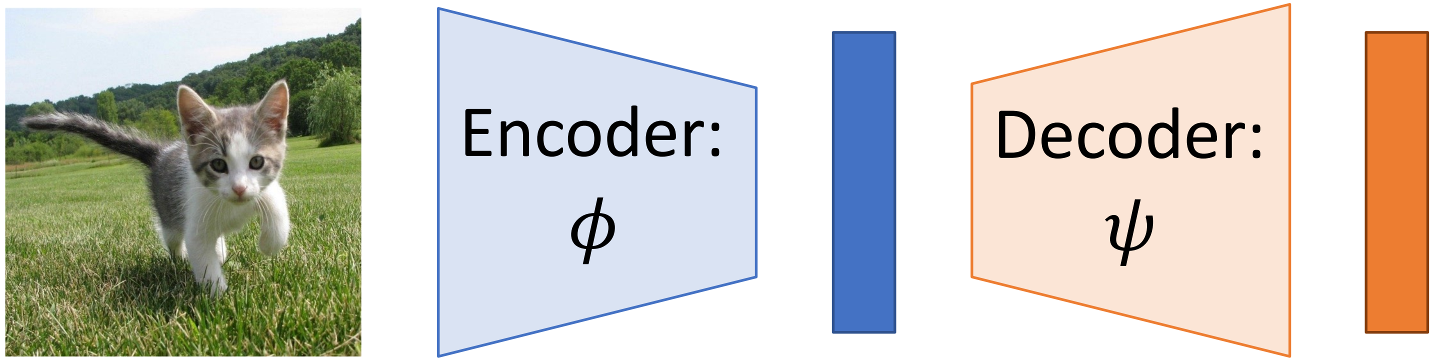
Self-Supervised Learning

Build methods that learn from "raw" data (inputs only) — no labels!

- **Unsupervised Learning:** older terminology ... model isn't told what to predict
- **Self-Supervised Learning:** model is trained to predict *some natural occurring signal* rather than predicting labels
- **Semi-Supervised Learning:** train jointly with some labeled data and a lot of unlabeled data.

SSL: “Pretext then transfer”

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



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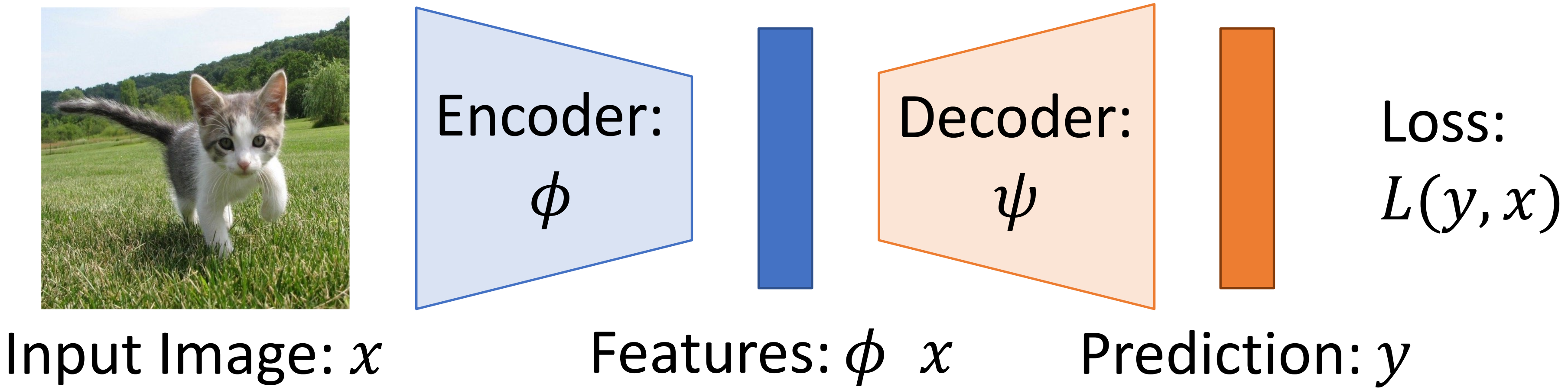
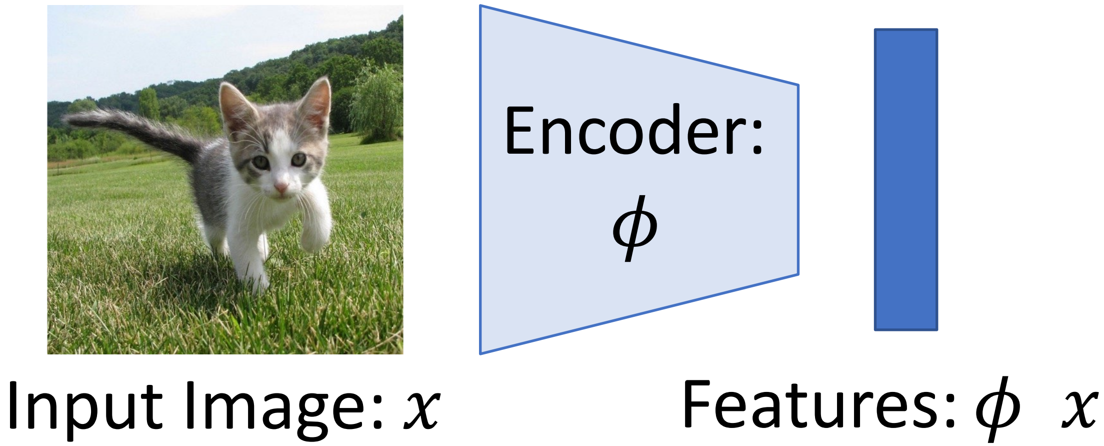


Step 2: Transfer encoder to downstream tasks via linear classifiers, KNN, finetuning

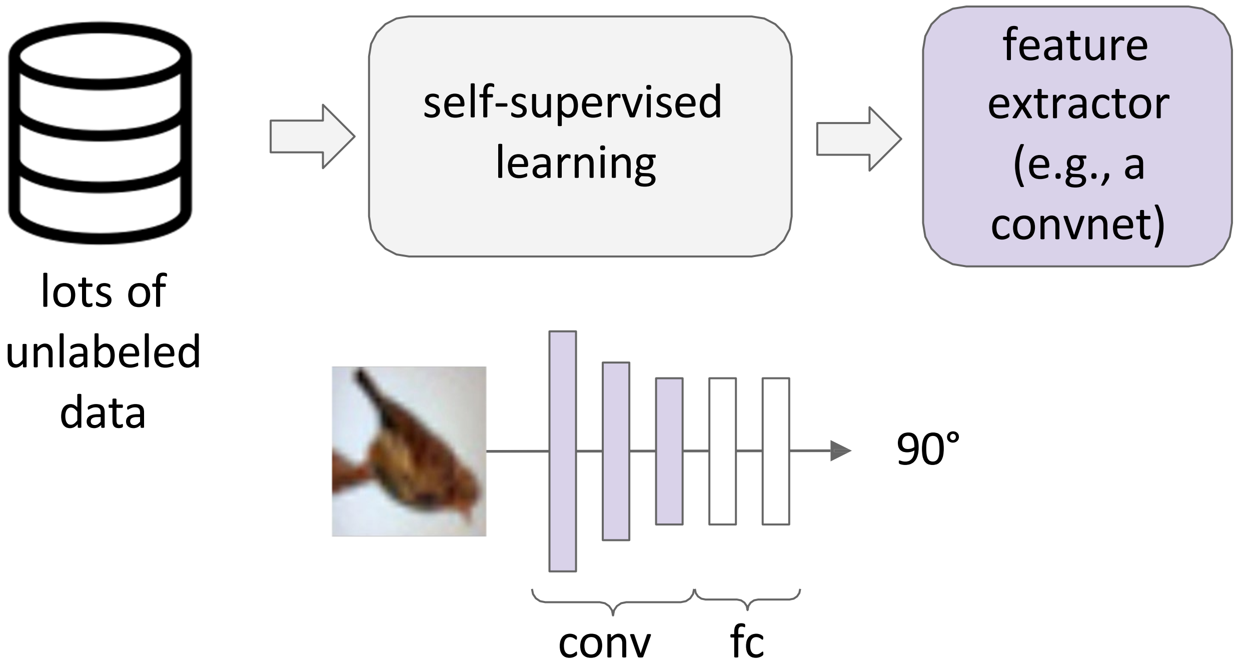


Downstream tasks:
Image classification,
object detection,
semantic segmentation

How to evaluate a self-supervised learning method?

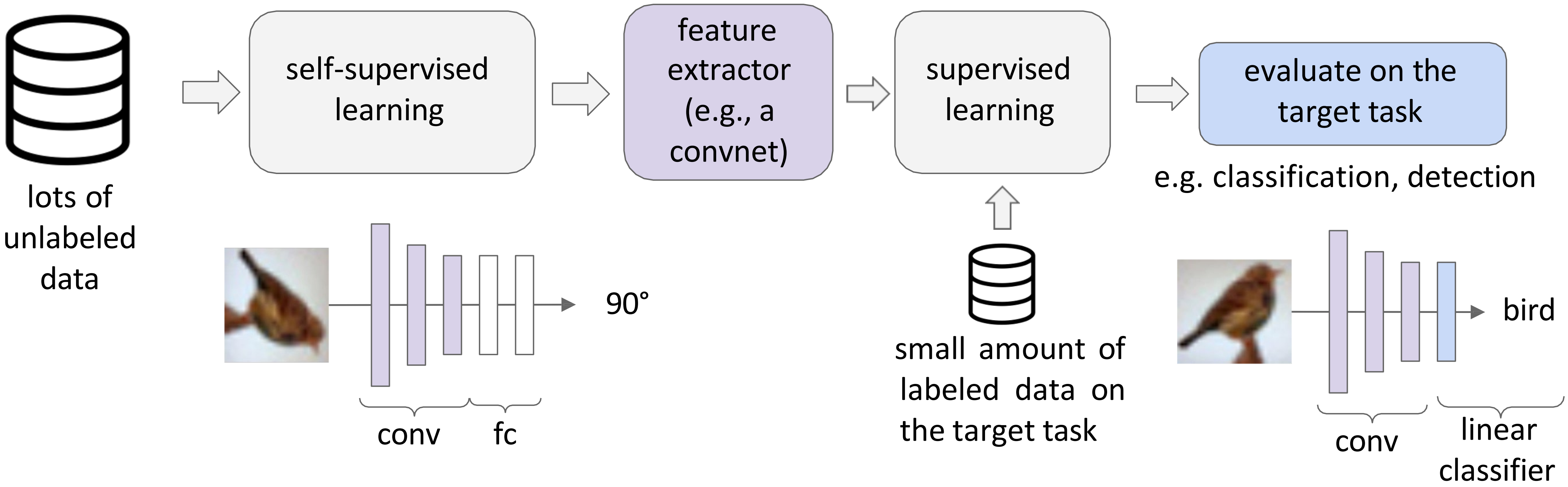
- **Pretext Task Performance**
  - Measure how well the model performs on the task it was trained on without labels.
- **Representation Quality**
  - Evaluate the quality of the learned representations
    - *Linear Evaluation Protocol:* Train a linear classifier on the leaerned representations;
    - *Clustering:* Measure clustering performance;
    - *t-SNE:* Visualize the representations to assess their separability.)
- **Robustness and Generalization**
  - Test how well the model generalizes to different datasets and is robust to variations.
- **Computational Efficiency**
  - Assess the efficiency of the method in terms of training time and resource requirements.
- **Transfer Learning and Downstream Task Performance**
  - Assess the utility of the learned representations by transferring them to a downstream supervised task.

How to evaluate a self-supervised learning method?



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

How to evaluate a self-supervised learning method?

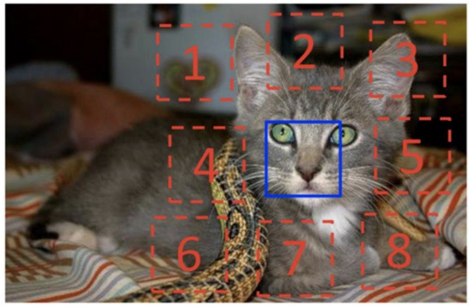


1. Learn good feature extractors from self-supervised pretext tasks, e.g., predicting image rotations

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

Broader picture

computer vision



Doersch et al., 2015

robot / reinforcement learning

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

language modeling

GPT-4 Technical Report

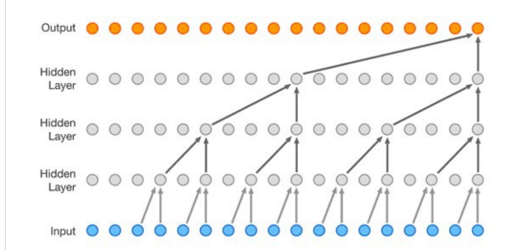
OpenAI*

Abstract

We report the development of GPT-4, a large-scale, multimodal model which can accept image and text inputs and produce text outputs. While less capable than humans in many real-world scenarios, GPT-4 exhibits human-level performance on various professional and academic benchmarks, including passing a simulated bar exam with a score around the top 10% of test takers. GPT-4 is a Transformer-based model pre-trained to predict the next token in a document. The post-training alignment process results in improved performance on measures of factuality and adherence to desired behavior. A core component of this project was developing infrastructure and optimization methods that behave predictably across a wide range of scales. This allowed us to accurately predict some aspects of GPT-4's performance based on models trained with no more than 1/1,000th the compute of GPT-4.

GPT-4 (OpenAI 2023)

speech synthesis



Wavenet (van den Oord et al., 2016)

...

Examples of 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 signal in addition to RGB images

- Video
- 3D
- Sound
- Language

Quick Introduction to Autoencoders

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

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

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

$H < D$

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

Sparse Autoencoder

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

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

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

$[0, 0, 1, 0, 0, 0, 1, 0]$

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

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

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

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

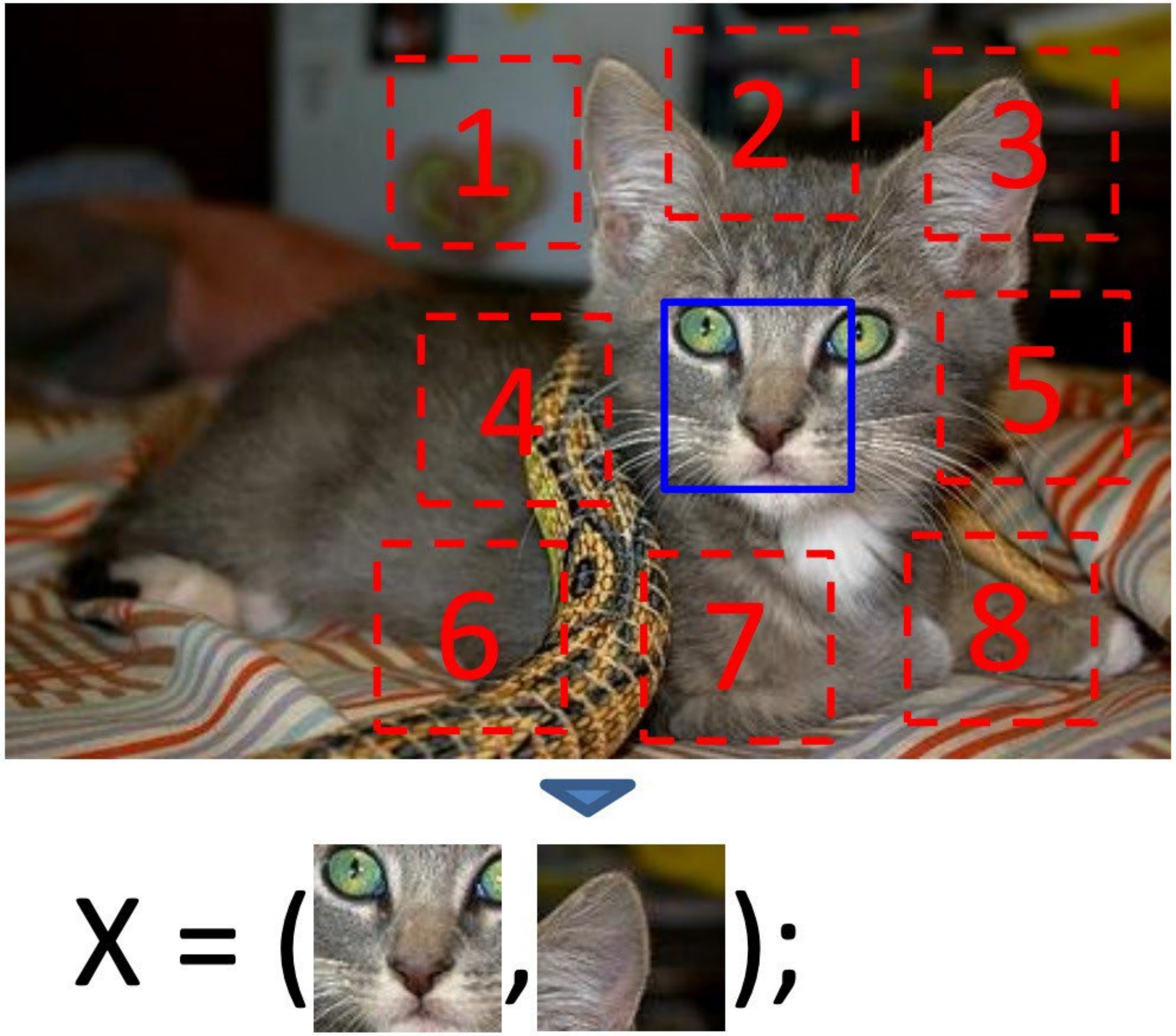
Reconstructed Image: $\hat{x} \in \mathbb{R}^D$

'incent 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.
<u>Discriminative</u> 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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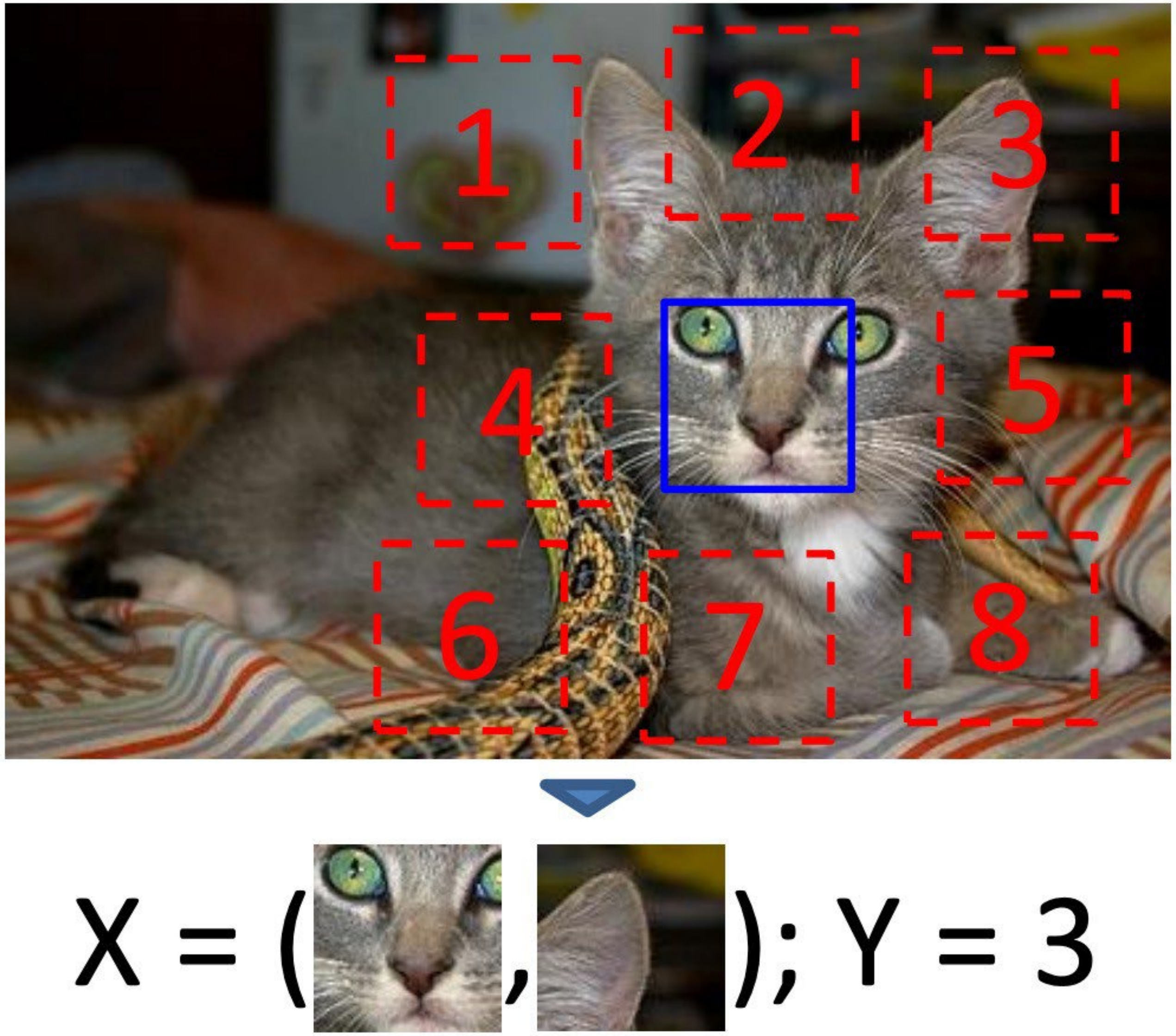

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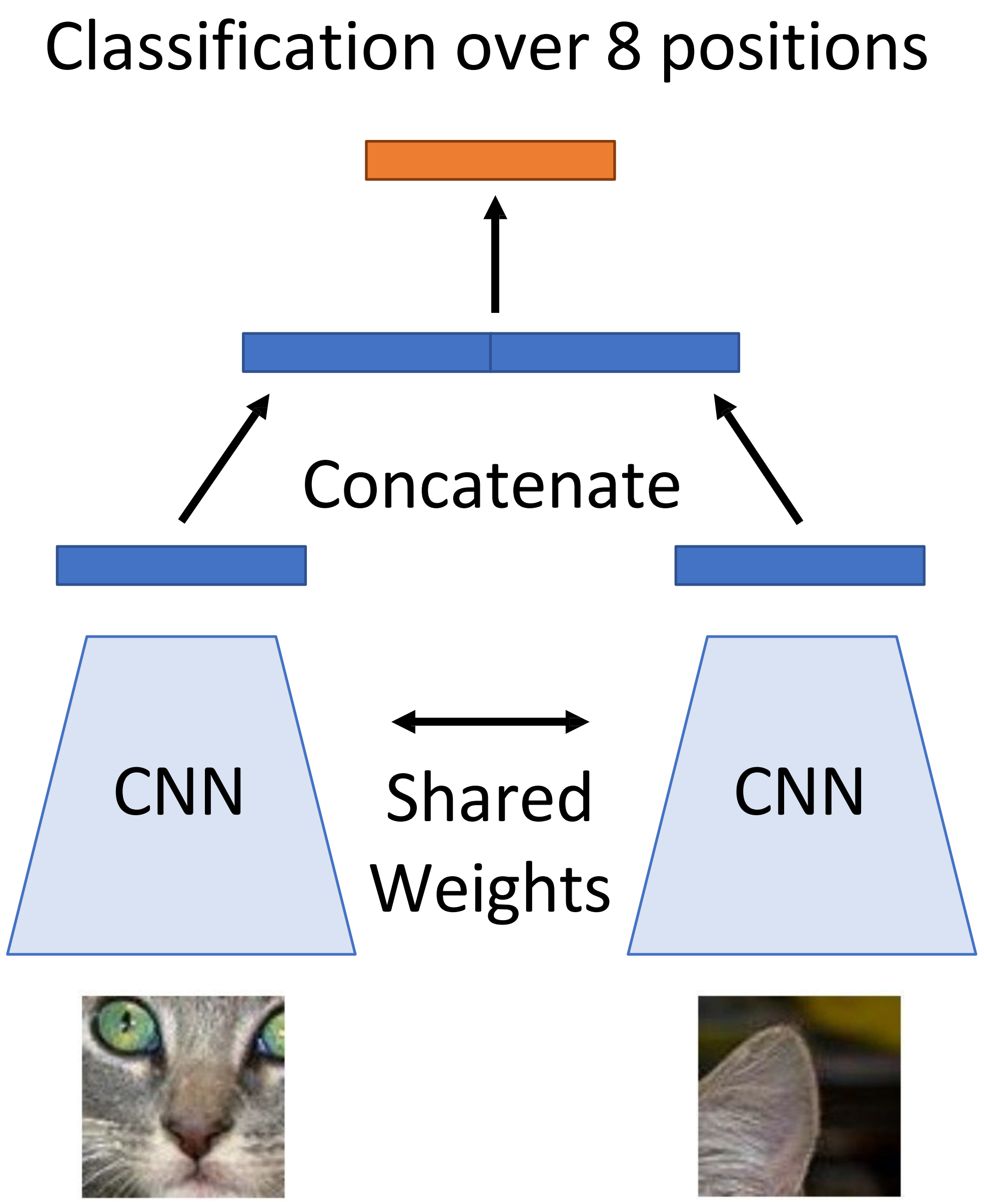

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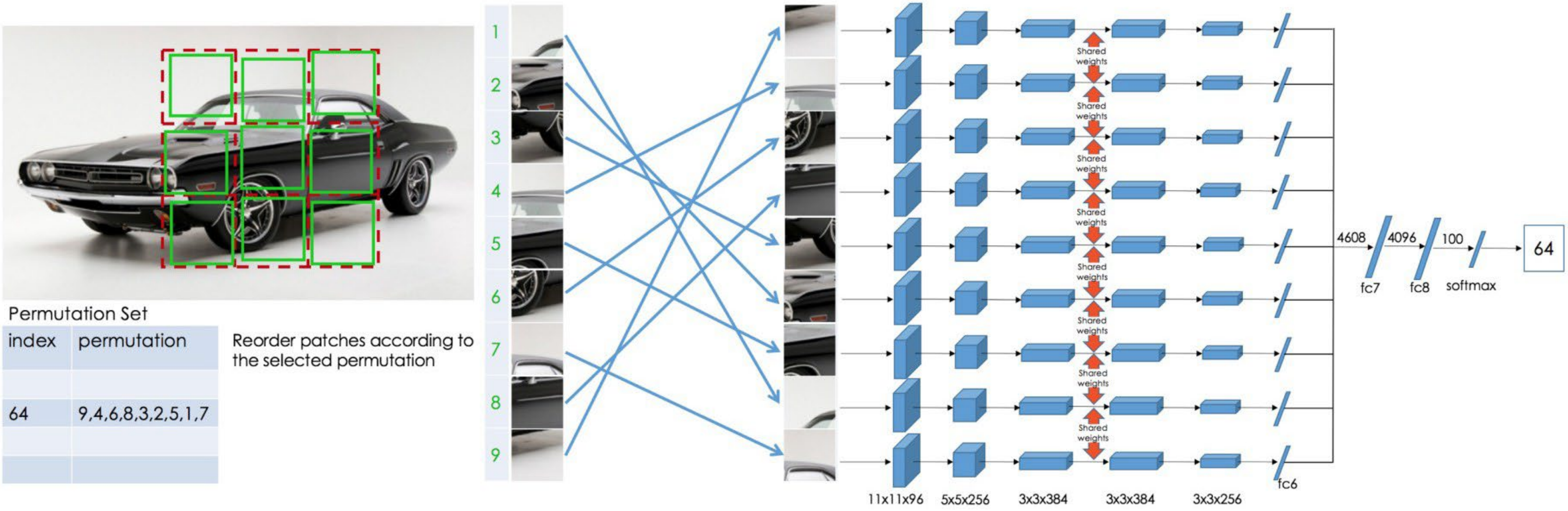
Extension: Solving Jigsaw Puzzles

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

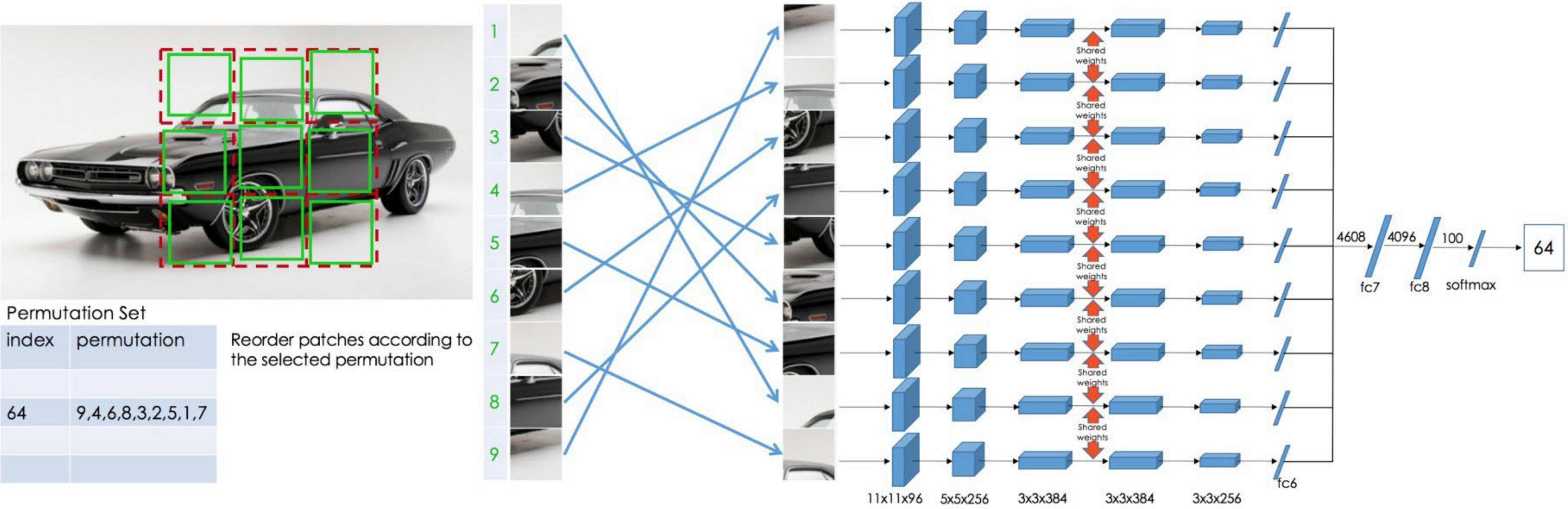


Noroozi and Favoro, “Unsupervised learning of visual representations by solving jigsaw puzzles”, ECCV 2016

Extension: Solving Jigsaw Puzzles

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

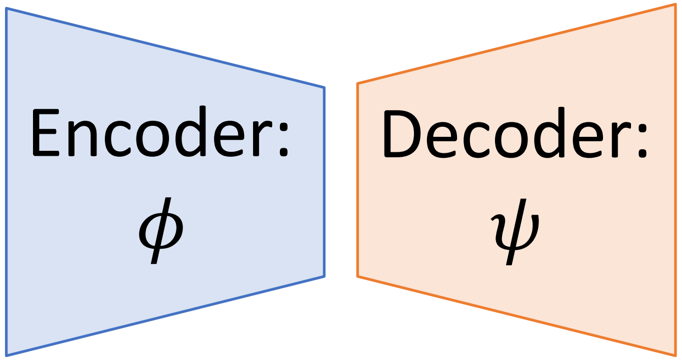
Rather than predict relative position of two patches, instead predict permutation to “unscramble” 9 shuffled patches



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

Context Encoders: Learning by Inpainting

Input Image

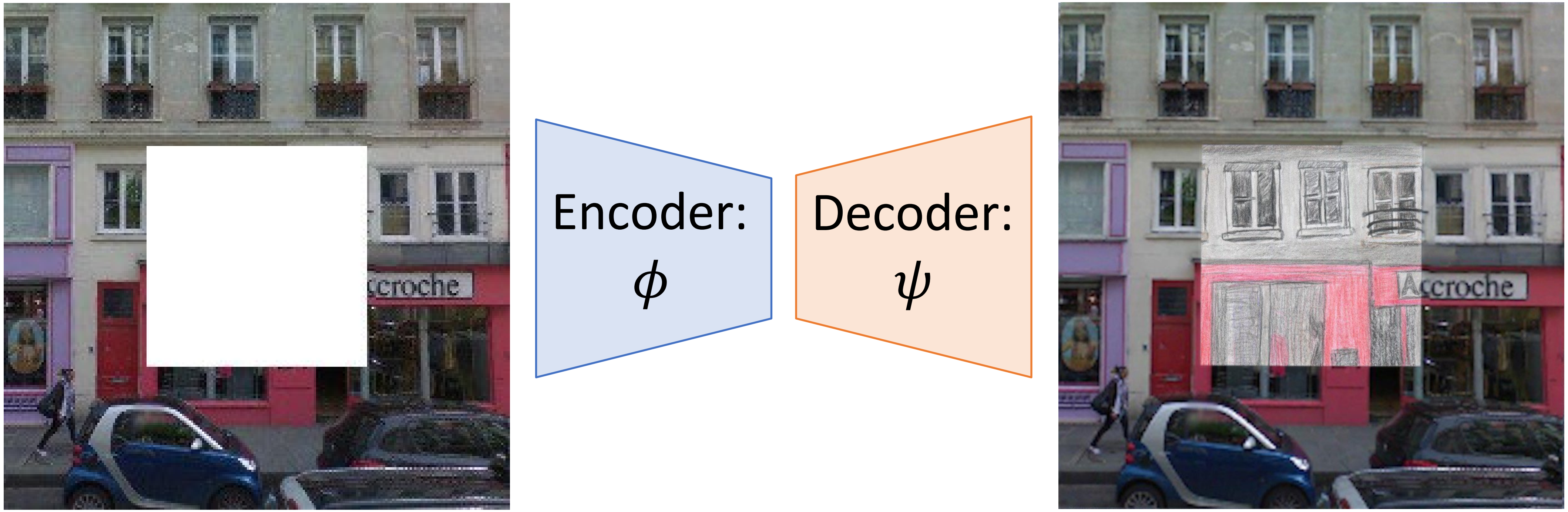


Pathak et al, “Context Encoders: Feature Learning by Inpainting”, CVPR 2016

Context Encoders: Learning by Inpainting

Input Image

Predict Missing Pixels



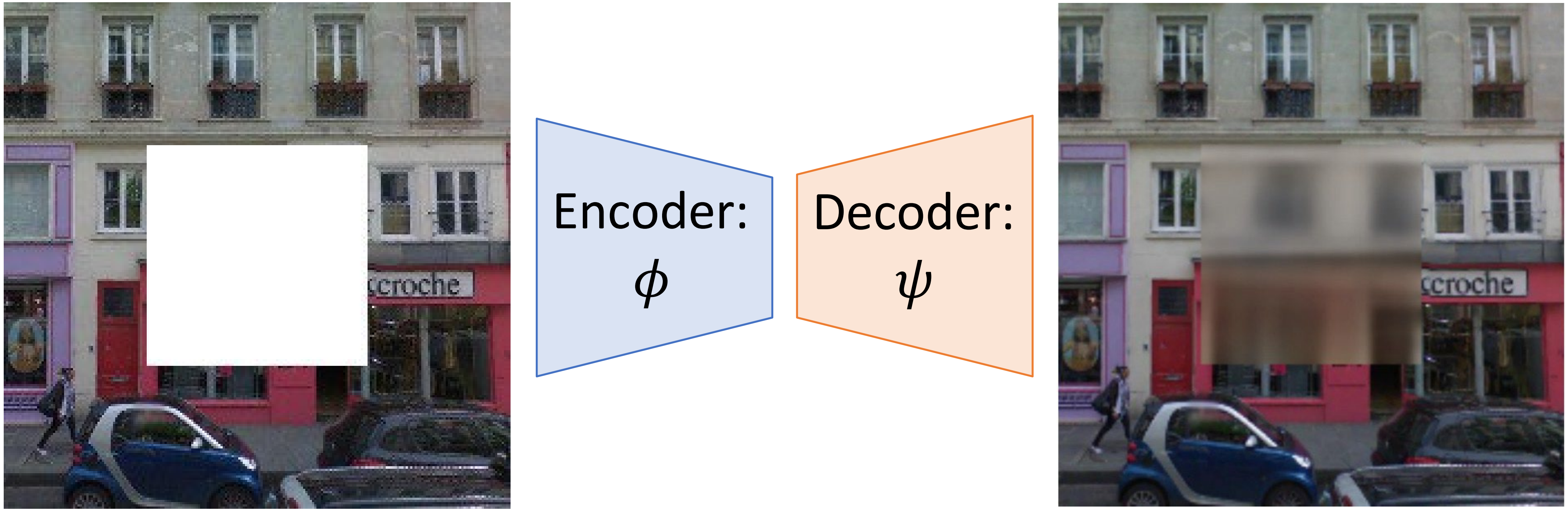
Human Artist

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

Context Encoders: Learning by Inpainting

Input Image

Predict Missing Pixels



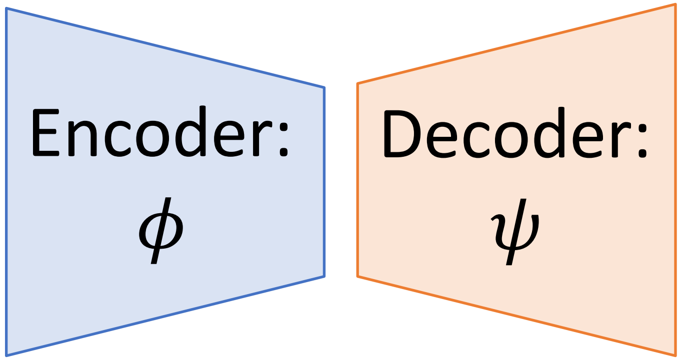
L2 Loss

(Best for feature learning)

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

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

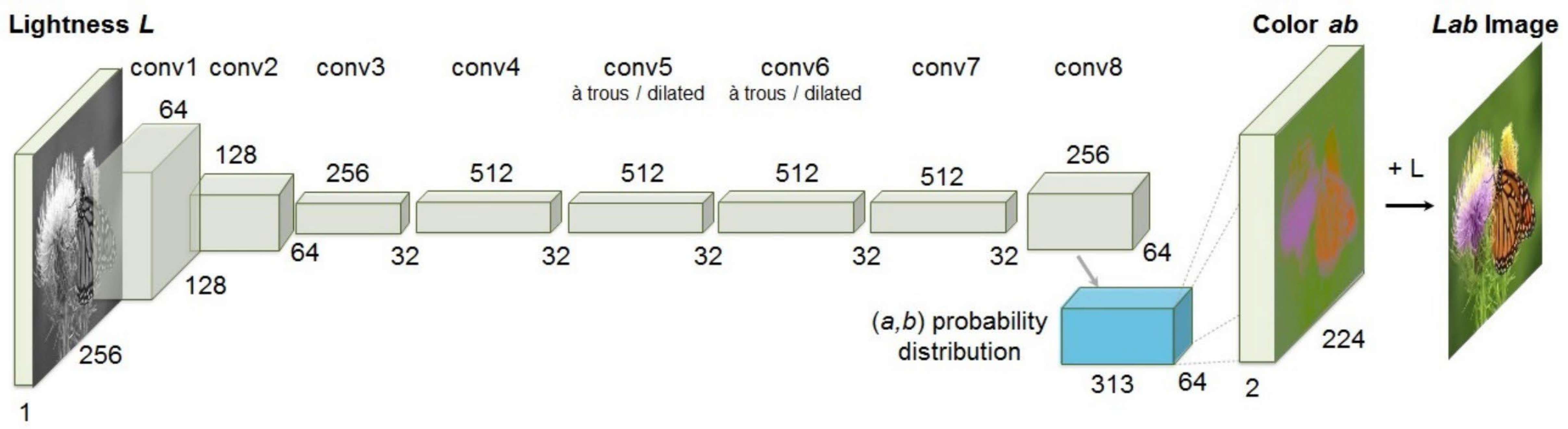
Intuition: A model must be able to identify objects to be able to colorize them

Input: Grayscale Image

Output: Color Image

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

Colorization



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Pretext task: video coloring

Idea: model the temporal coherence of colors in videos

reference frame

how should I color these frames?

t = 0

t = 1

t = 2

t = 3

...

Source: [Vondrick et al., 2018]

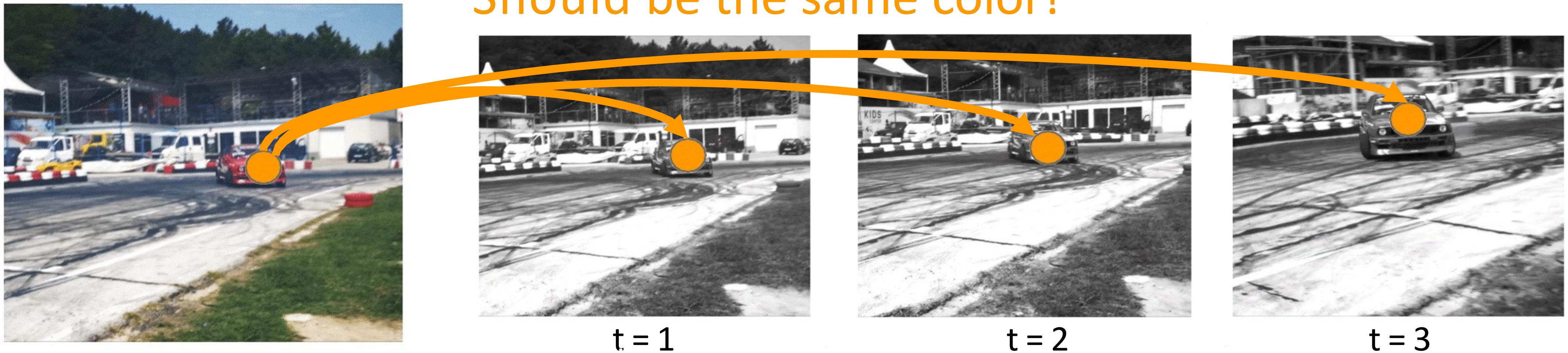
Pretext task: video coloring

Idea: model the temporal coherence of colors in videos

reference frame

how should I color these frames?

Should be the same color!



t = 0

t = 1

t = 2

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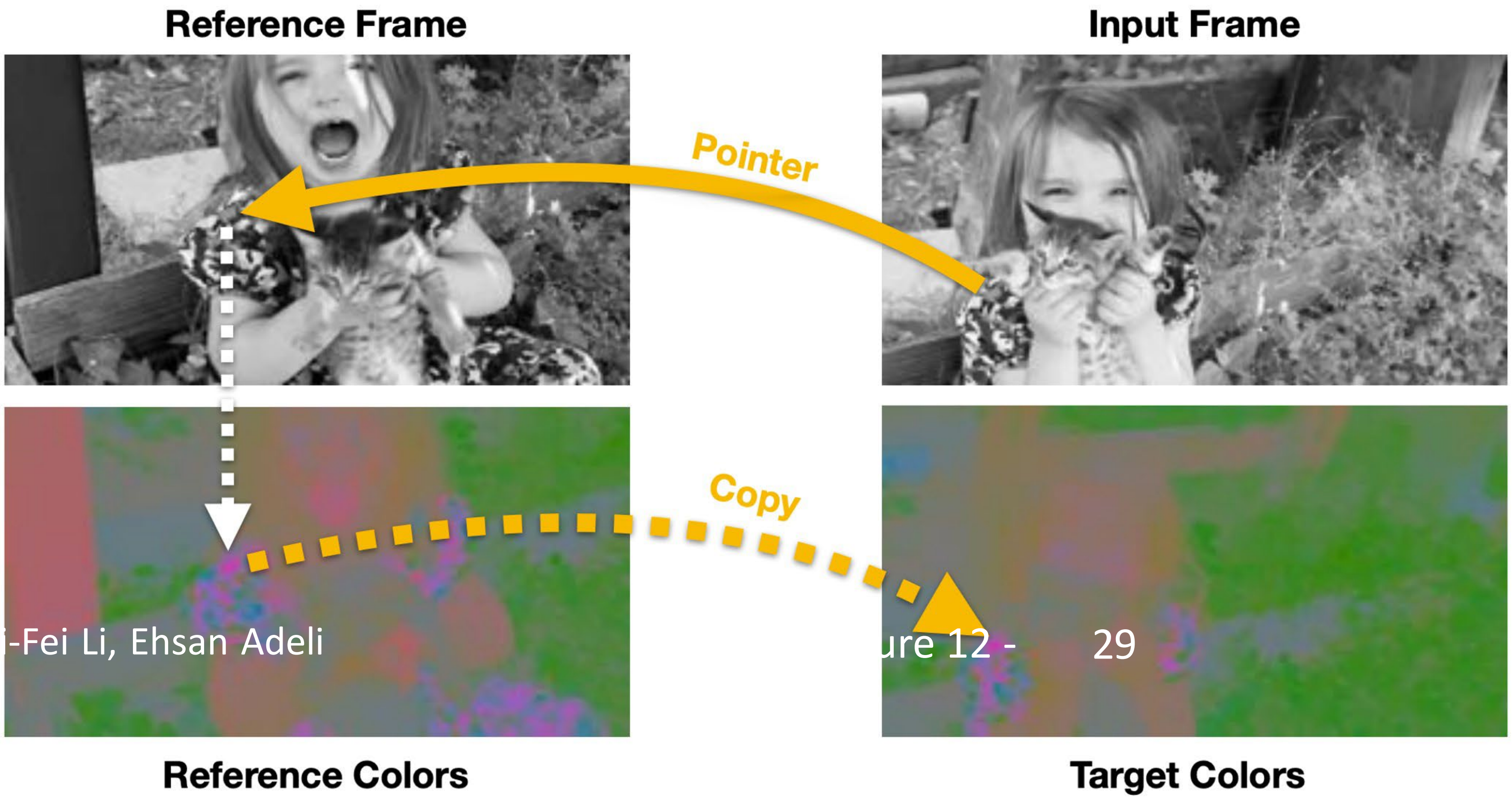
...

Hypothesis: learning to color video frames should allow model to learn to track regions or objects without labels!

Source: [Vondrick et al., 2018]

Learning to color videos



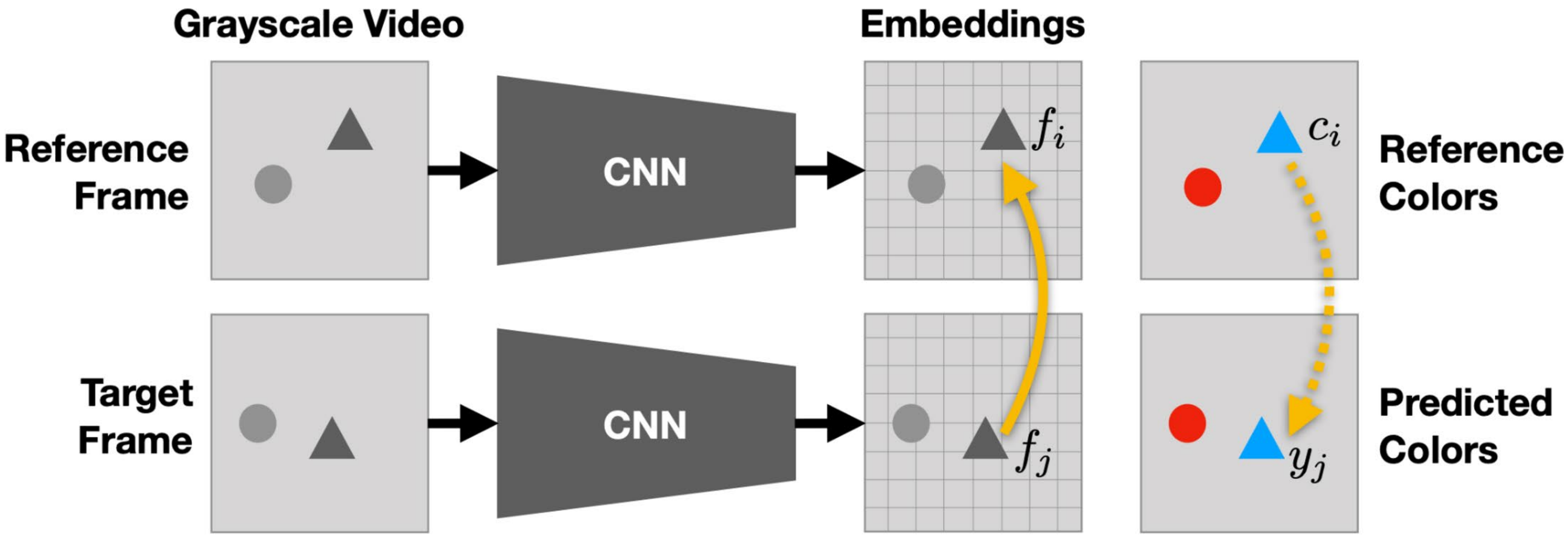
Learning objective:

Establish mappings between reference and target frames in a learned feature space.

Use the mapping as "pointers" to copy the correct color (LAB).

Source: [Vondrick et al., 2018]

Learning to color videos

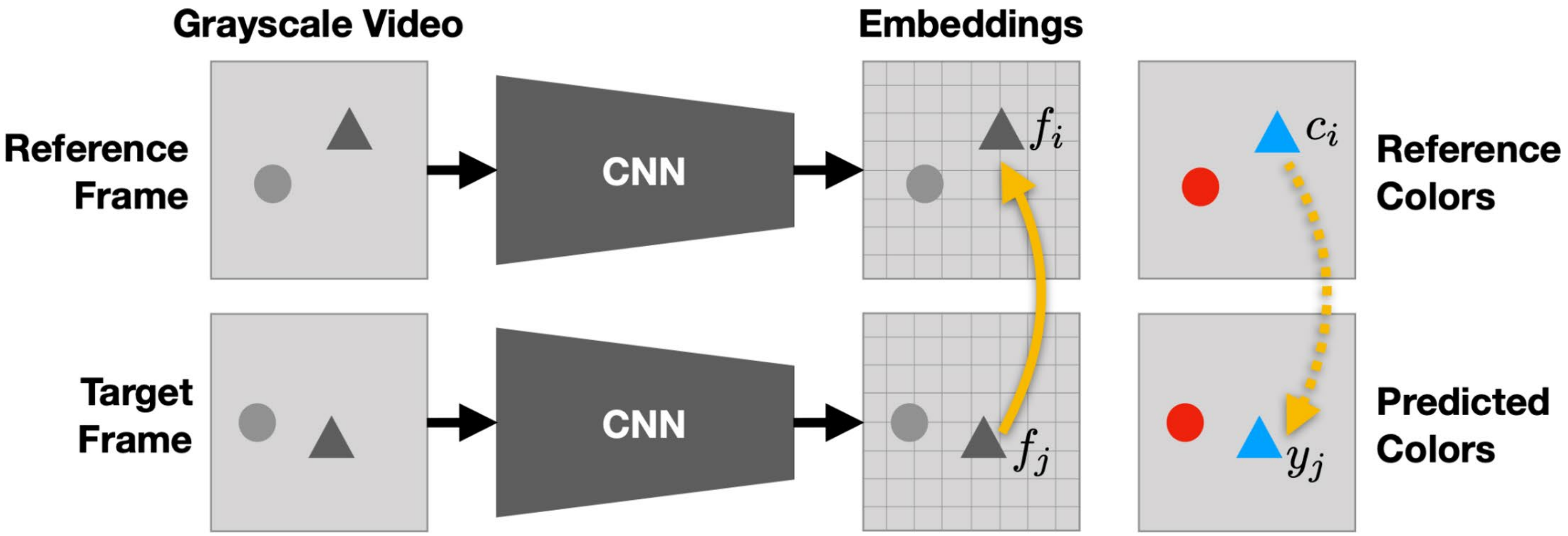


attention map on the reference frame

$$A_{ij} = \frac{\exp\left(f_i^T f_j\right)}{\sum_k \exp\left(f_k^T f_j\right)}$$

Source: [Vondrick et al., 2018]

Learning to color videos



attention map on the reference frame

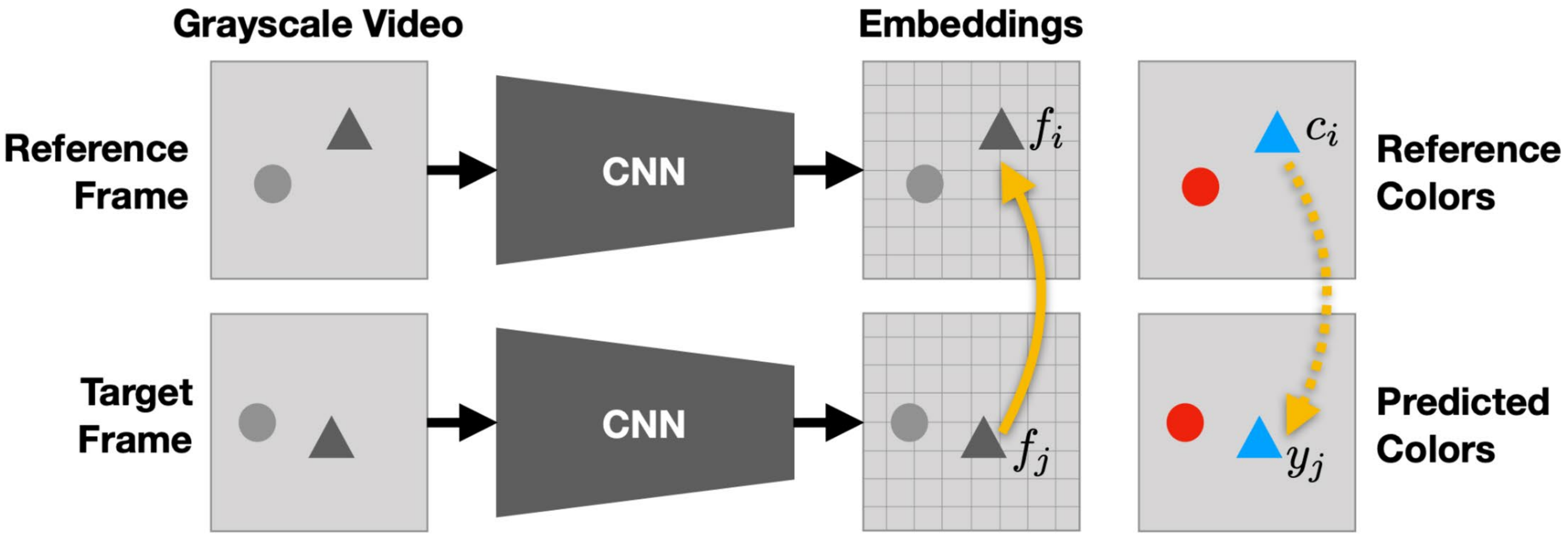
$$A_{ij} = \frac{\exp\left(f_i^T f_j\right)}{\sum_k \exp\left(f_k^T f_j\right)}$$

predicted color = weighted sum of the reference color

$$y_j = \sum_i A_{ij} c_i$$

Source: [Vondrick et al., 2018]

Learning to color videos



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$$y_j = \sum_i A_{ij} c_i$$

loss between predicted color and ground truth color

$$\min_\theta \sum_j \mathcal{L}\left(y_j, c_j\right)$$

Source: [Vondrick et al., 2018]

Colorizing videos (qualitative)

reference frame | target frames (gray) | predicted color

Source: [Google AI blog post]

Colorizing videos (qualitative)

reference frame

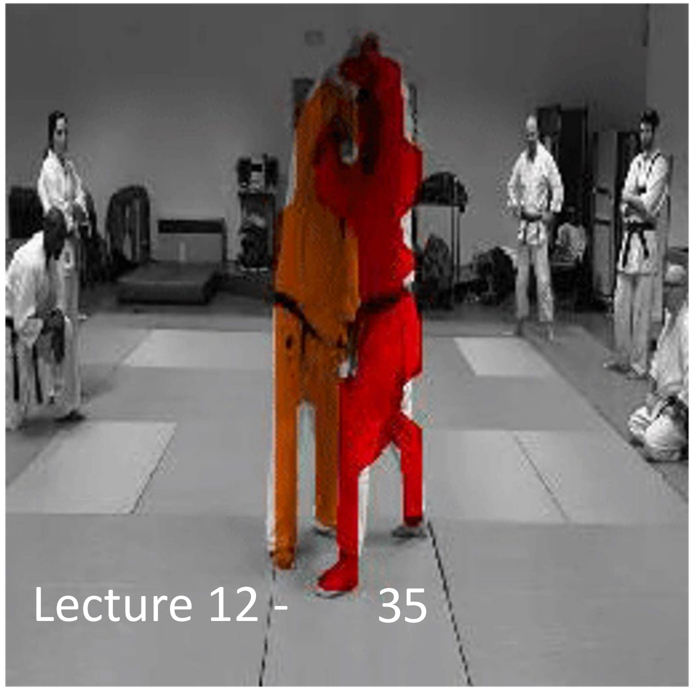
target frames (gray)

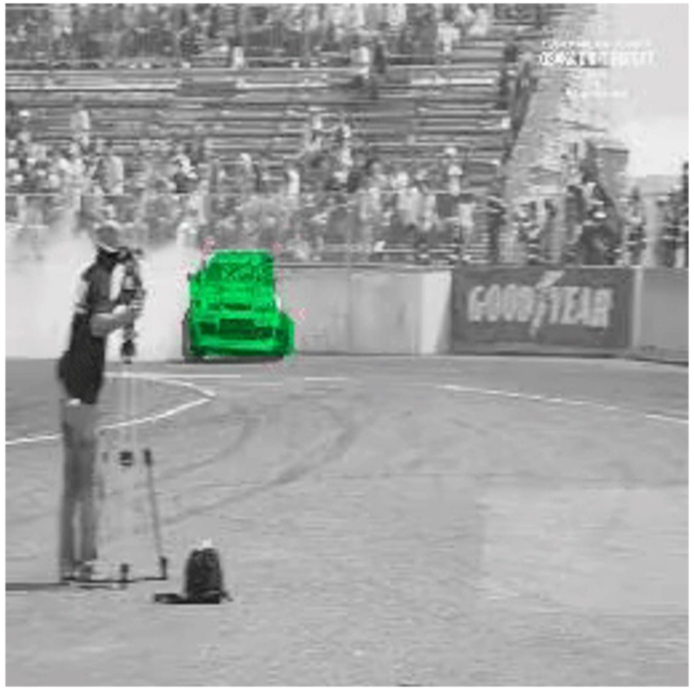
predicted color

Source: [Google AI blog post]

Tracking emerges from colorization

Propagate segmentation masks using learned attention

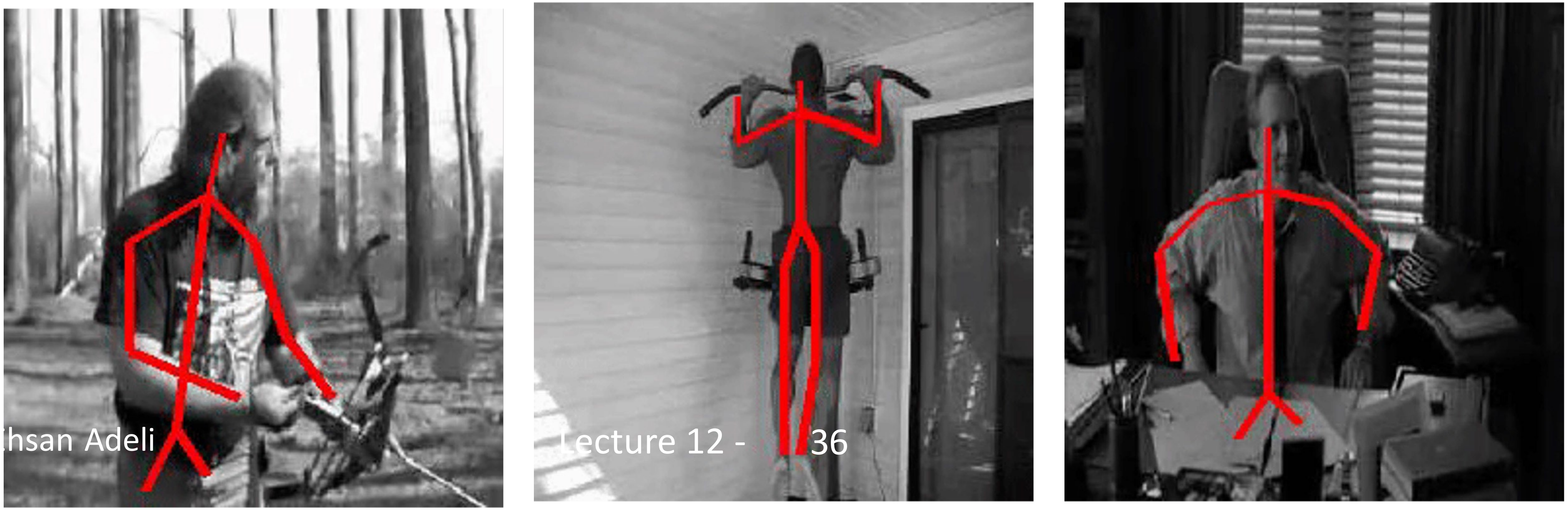




Source: [Google AI blog post]

Tracking emerges from colorization

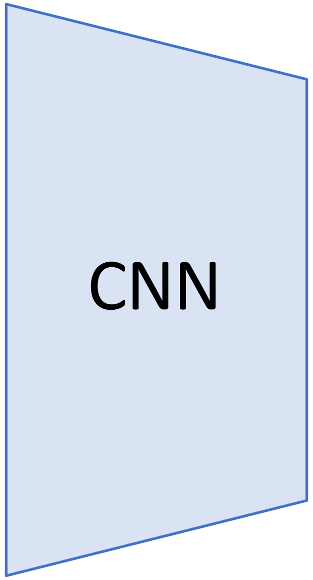
Propagate pose keypoints using learned attention



Source: Google AI blog post

Deep Clustering

(1) Randomly initialize a CNN



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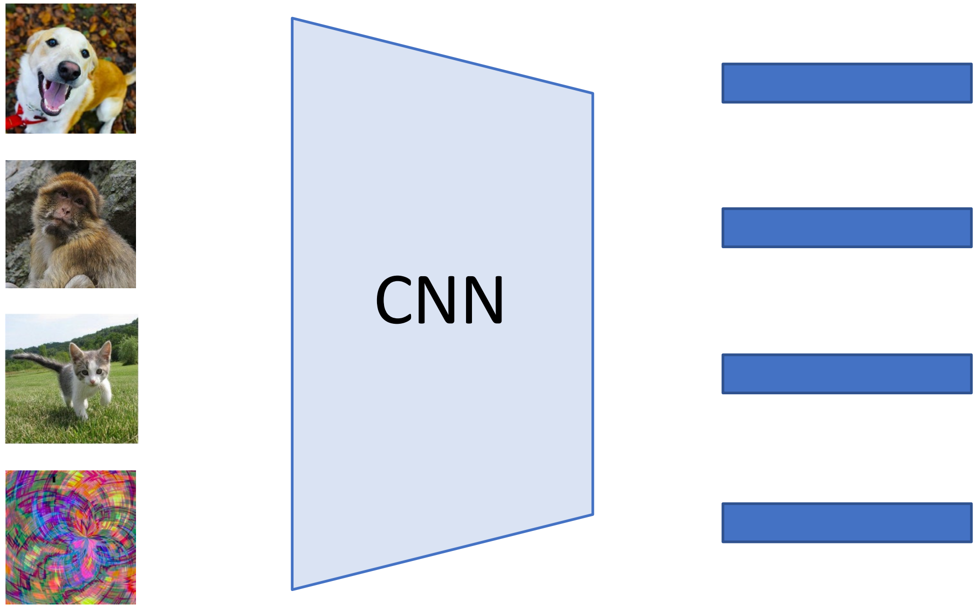

(2) Run many images through CNN, get their final-layer features

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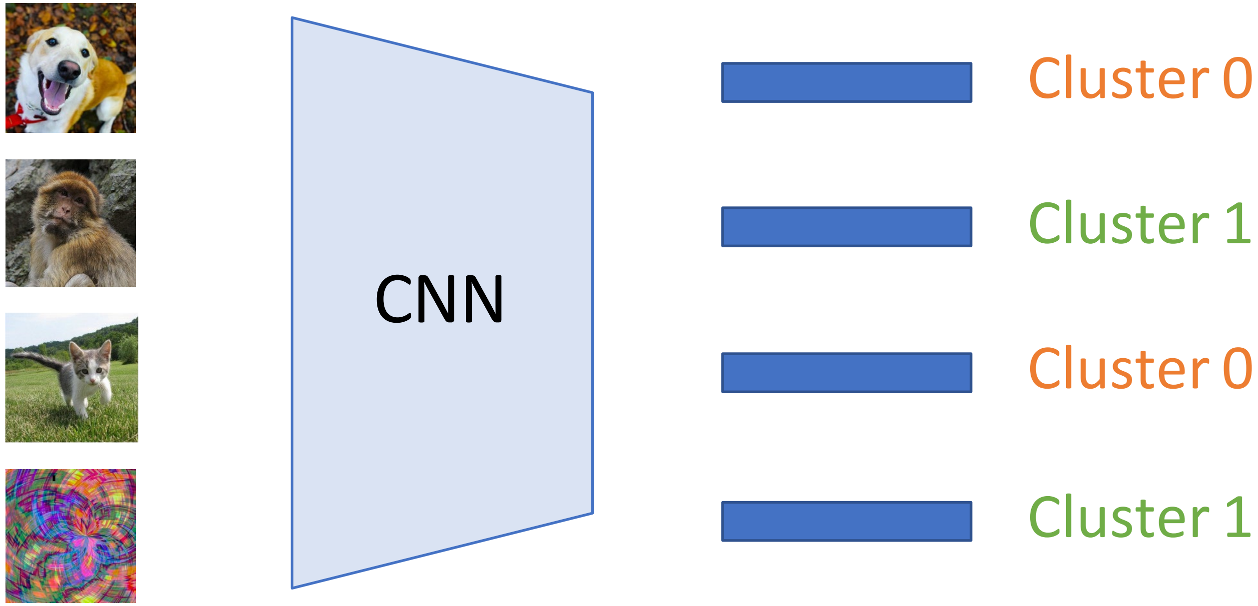

(3) Cluster the features with K-Means; record cluster for each feature

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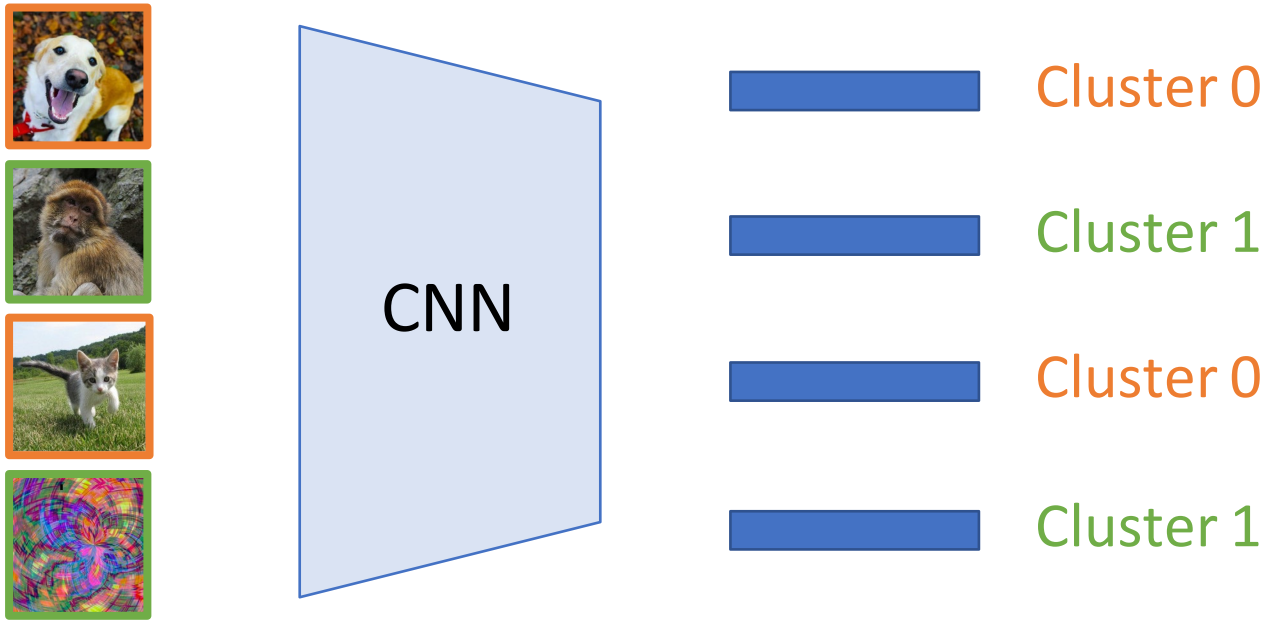

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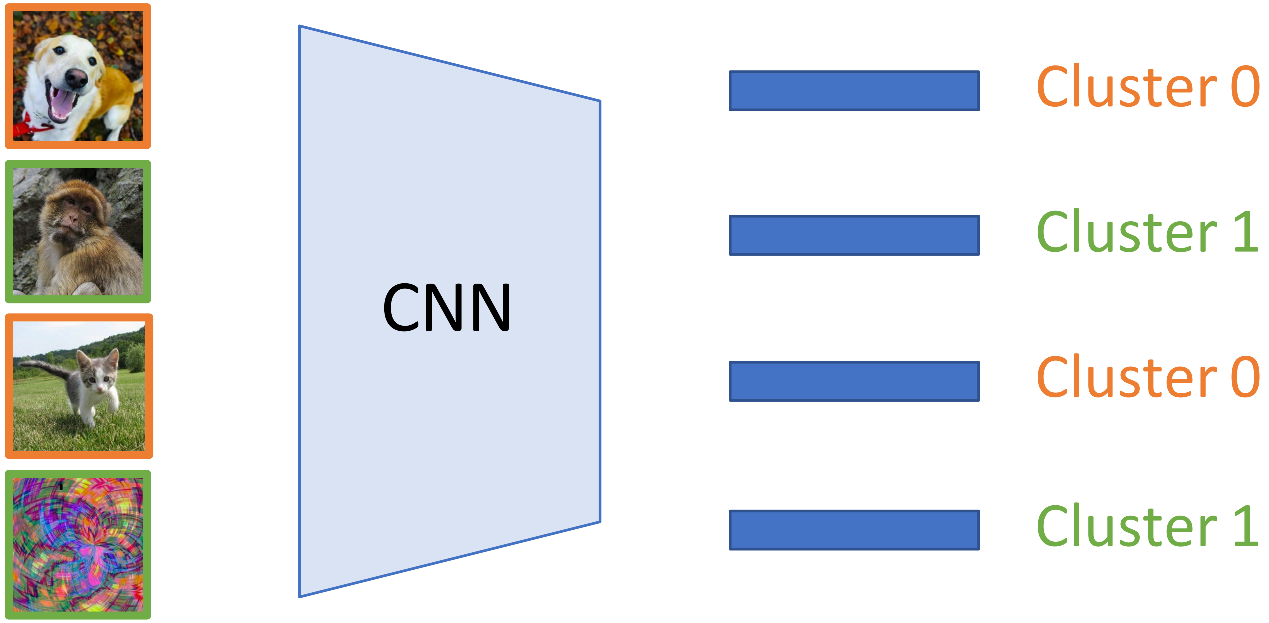

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(5) Repeat: GOTO (2)

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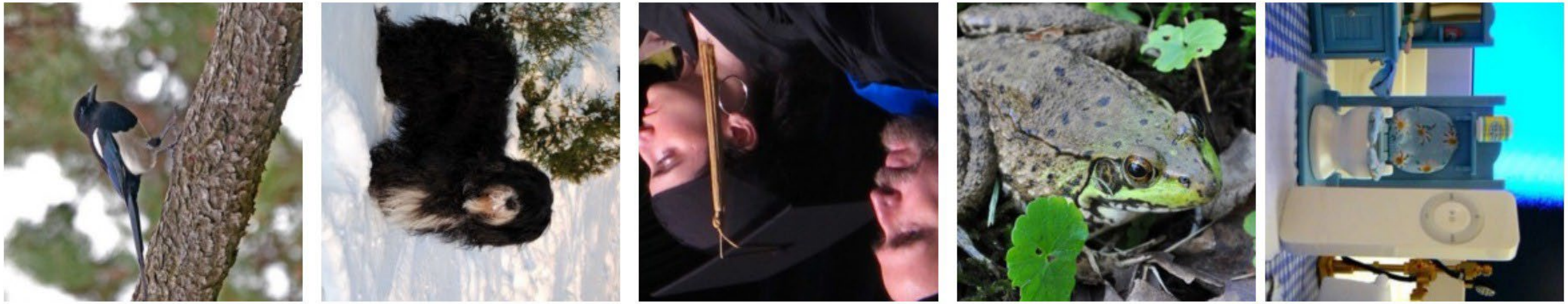
RotNet: Predict Rotation

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



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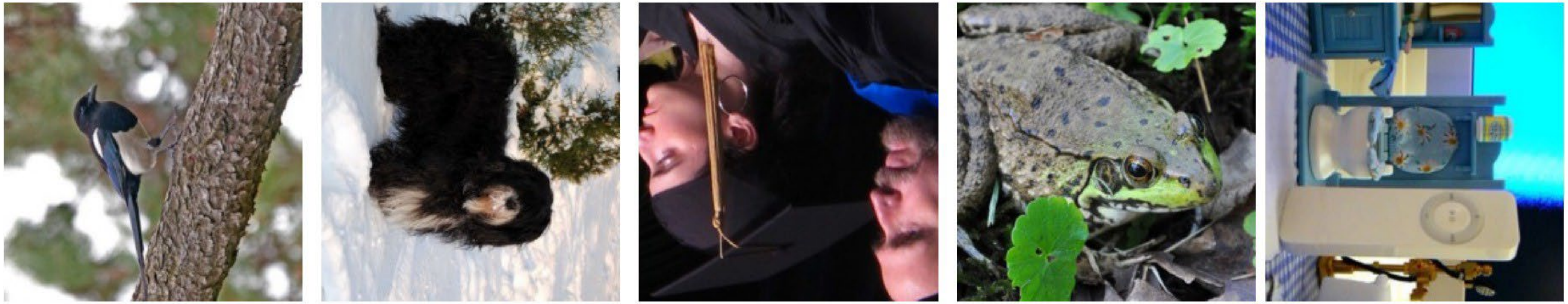

90

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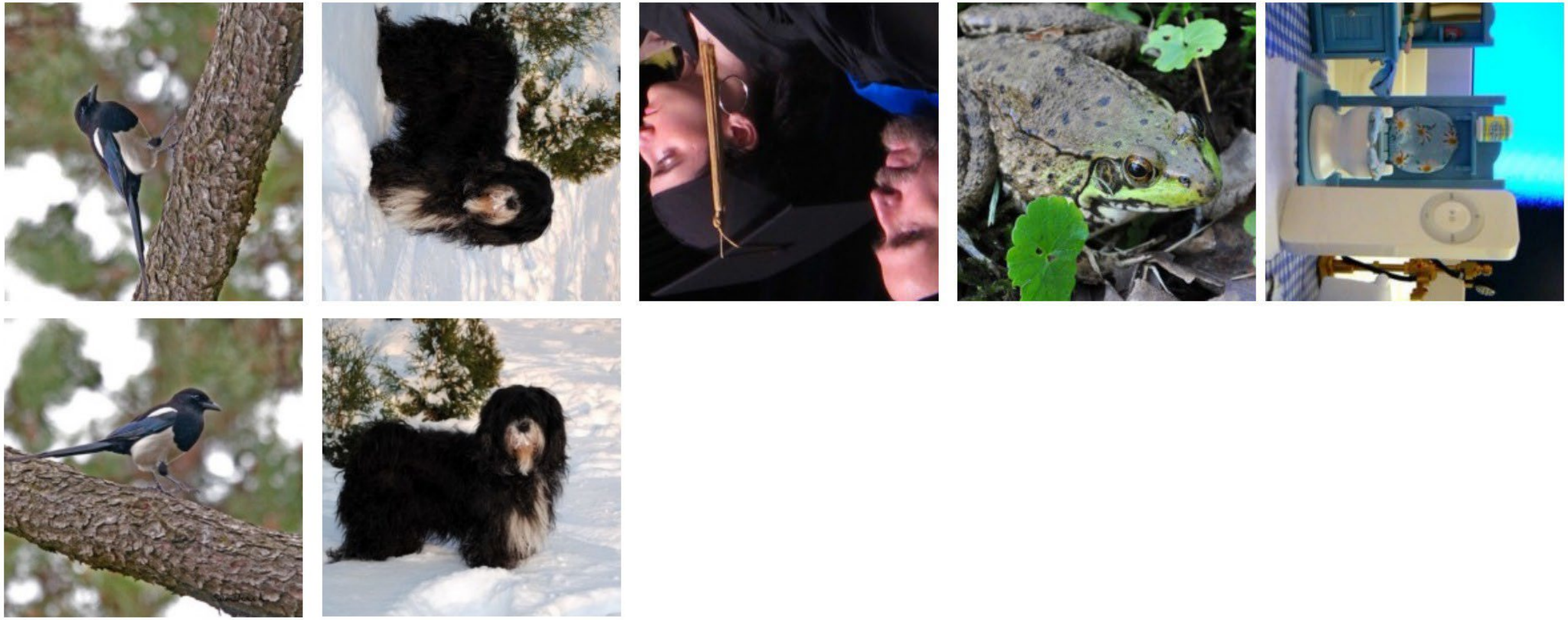

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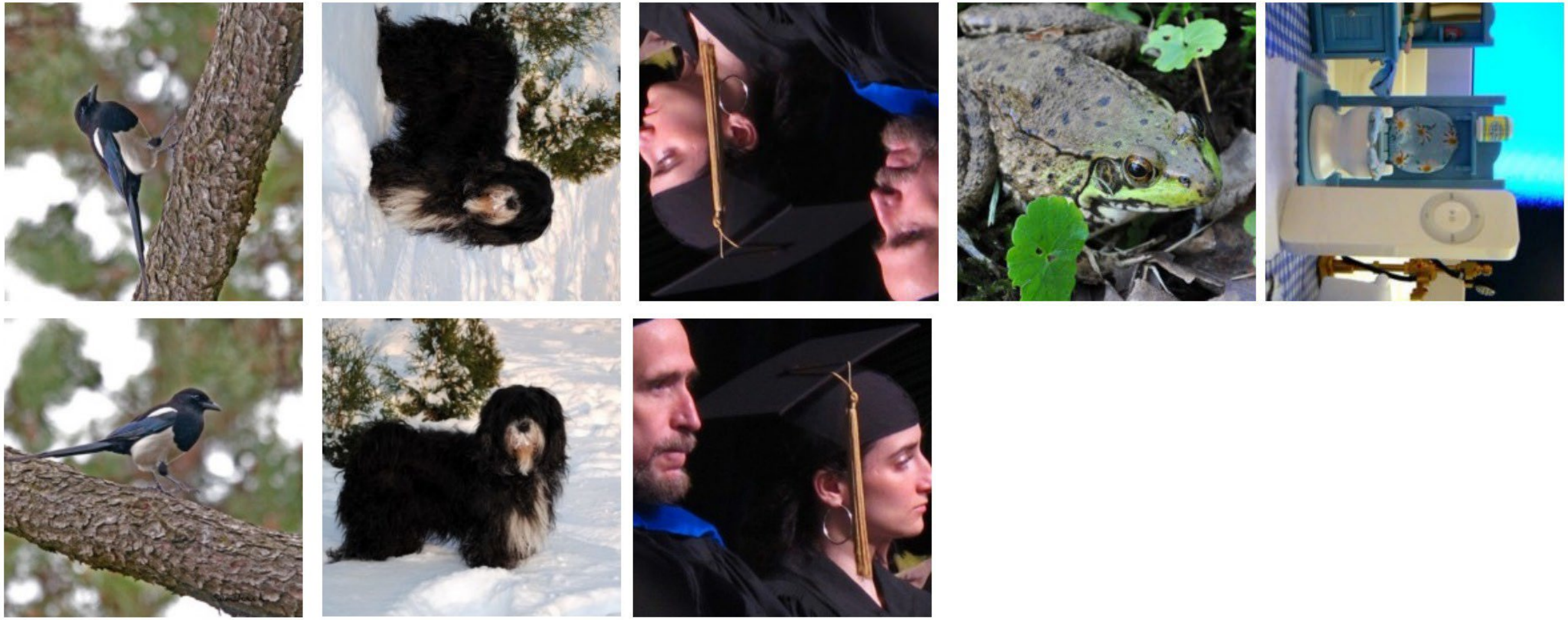

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90 270 180 0 270

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Summary: pretext tasks from image transformations

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

Summary: pretext tasks

- Pretext tasks focus on “visual common sense”
  - e.g., predict rotations, inpainting, rearrangement, and colorization.
- We often do not care about the performance of these pretext tasks
  - but rather how useful the learned features are for downstream tasks (classification, detection, segmentation).
- Problems:
  - (1) coming up with individual pretext tasks is tedious
  - (2) the learned representations may not be general.

Which SSL Method is best?

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

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

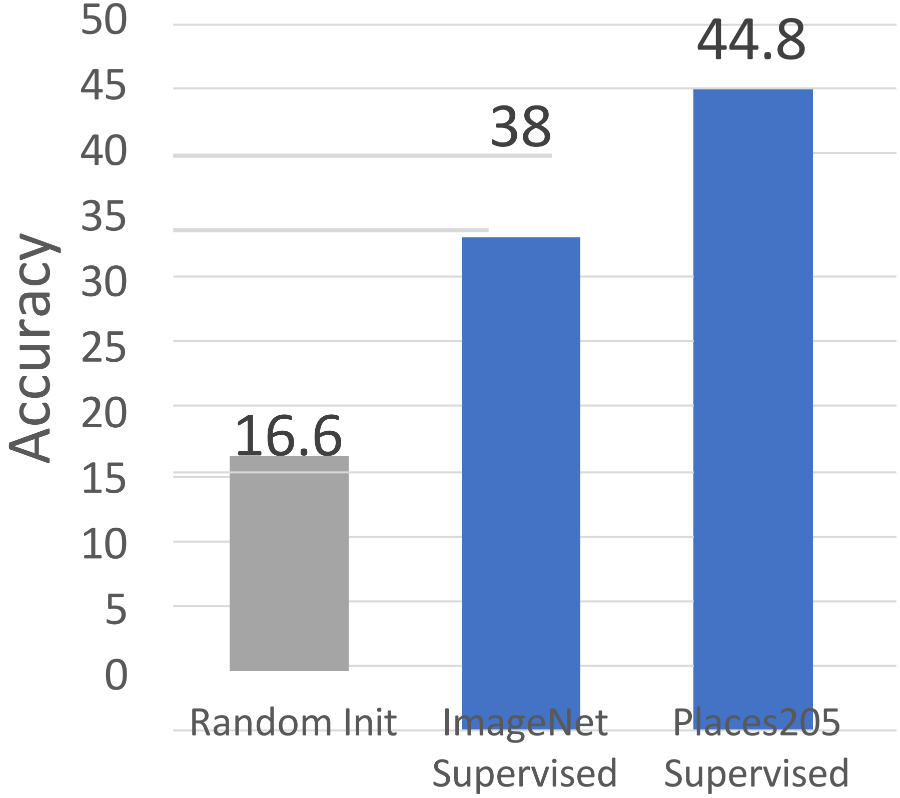
- CNN architecture? AlexNet, ResNet50, something else?
- Pretraining dataset? ImageNet, or something else?
- Downstream task? ImageNet classification, detection, something else?
- Pretraining hyperparameters? Learning rates, training iterations, data augmentation?

- 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? which layer? 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

Places205 Linear Classification from AlexNet conv5



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

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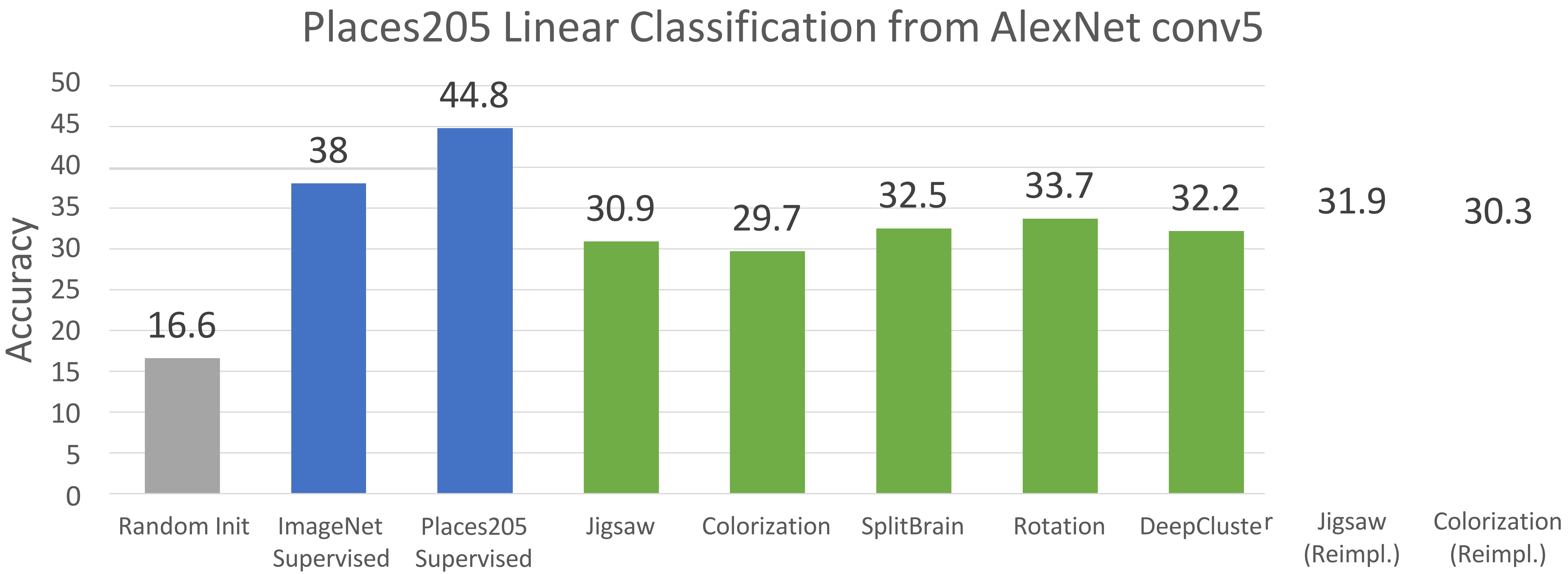

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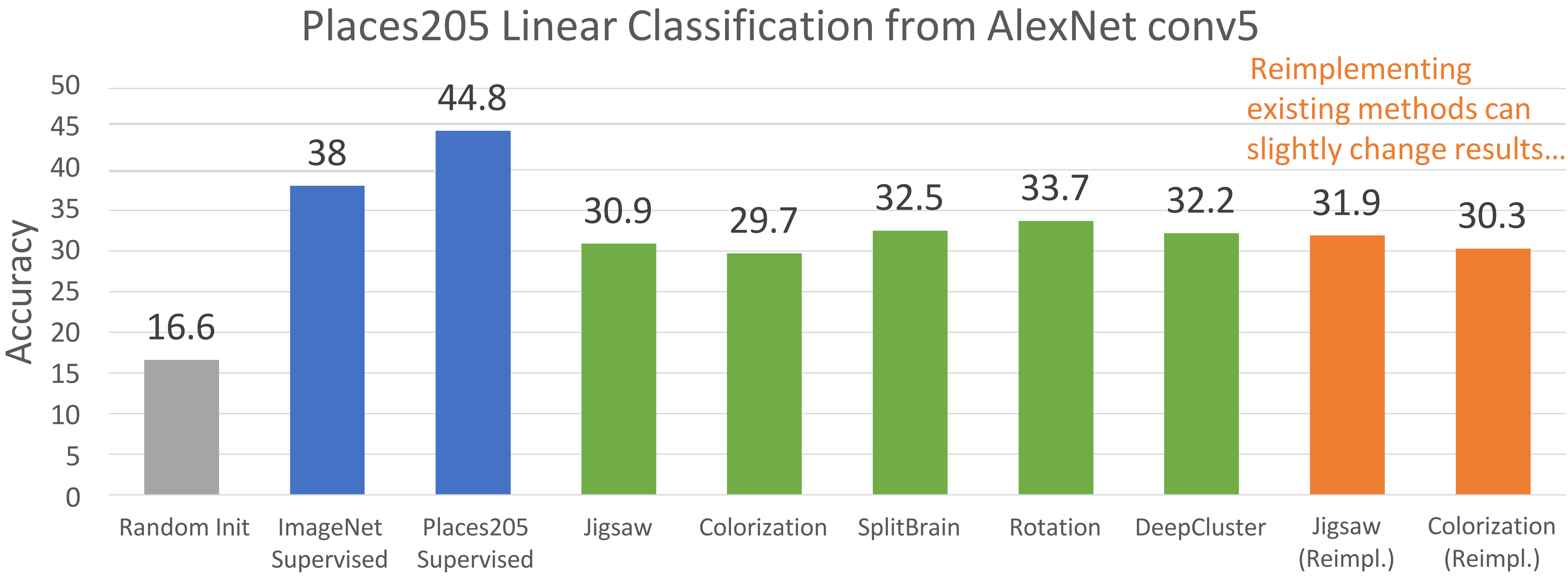

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Which SSL Method is best?

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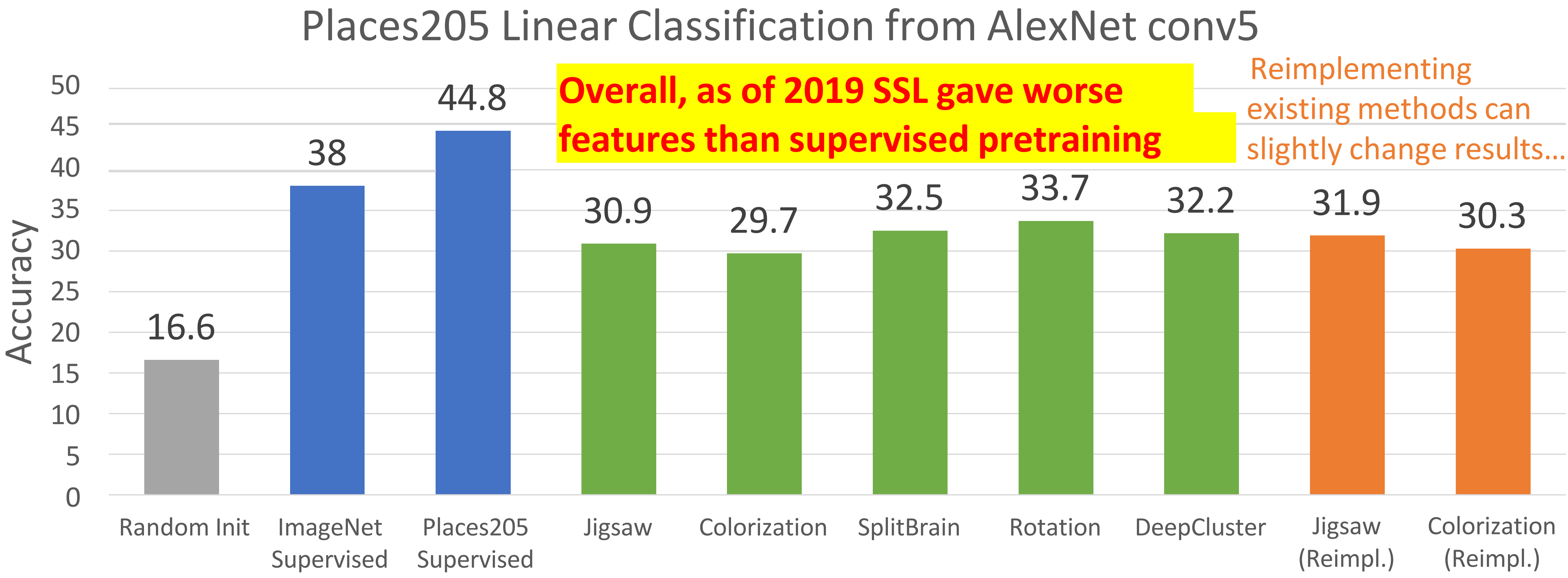
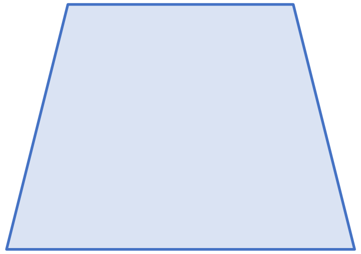


Goyal et al, "Scaling and Benchmarking Self-Supervised Visual Representation Learning", ICCV 2019

Self-Supervised Learning for Natural Language

Computer Vision

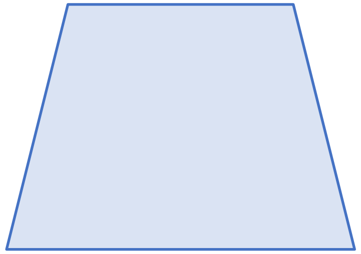
Image Features:
H x W x C



Input Image

Natural Language Processing

Word Features
L x C

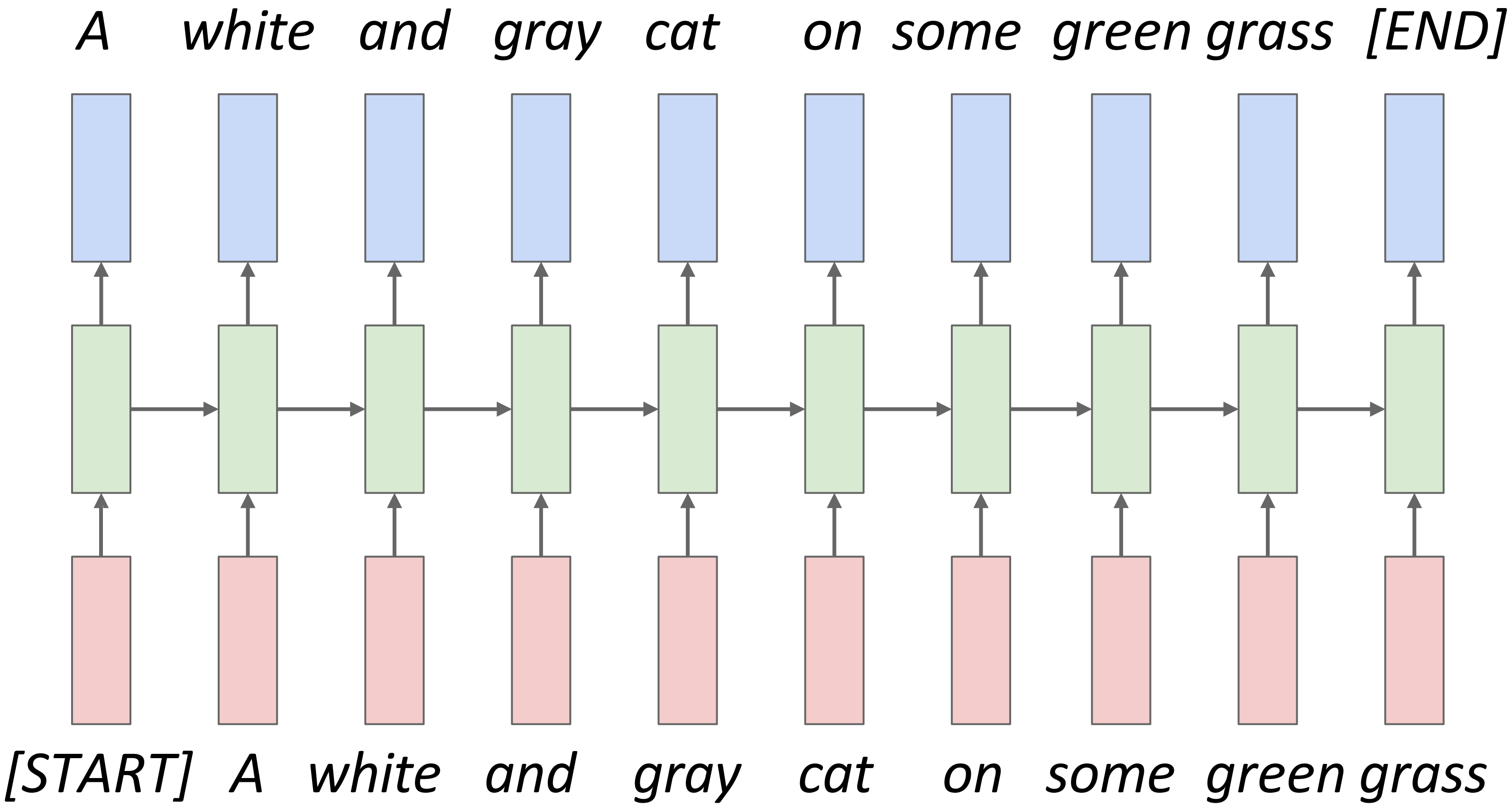


A white and gray cat standing outside on the grass

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!

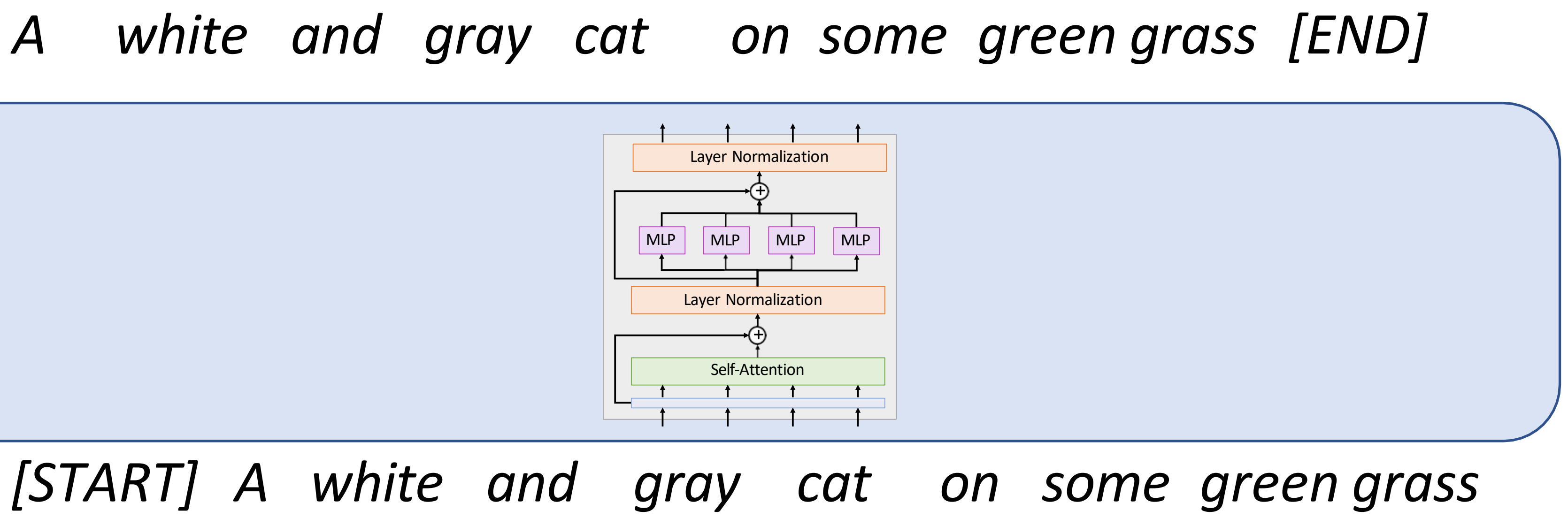


Peters et al, "Deep contextualized word representations", NAACL 2018

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!



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

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!

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

Exemplar CNN: Invariance to Data Augmentation

Quiz: What is this?

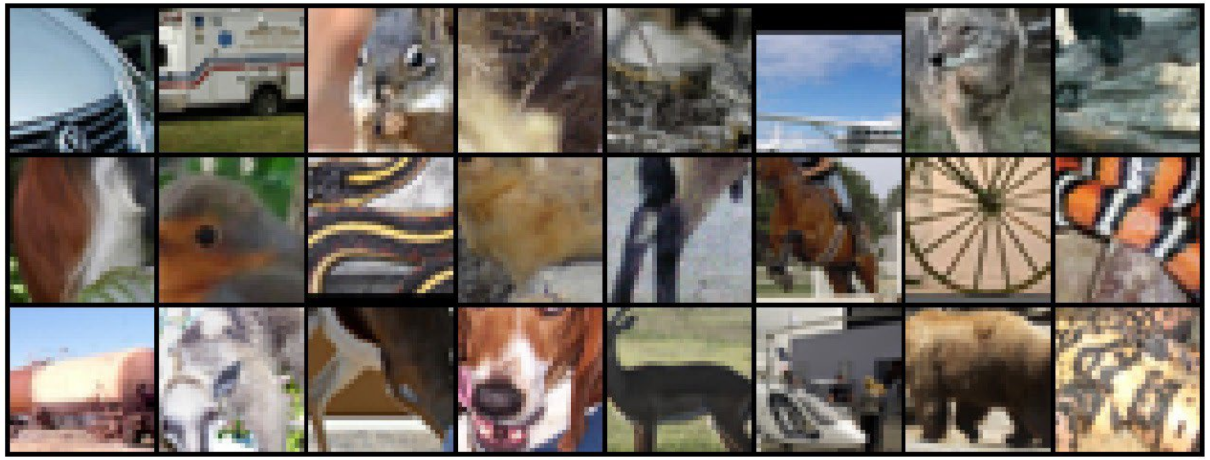
Different data augmentations (scale, shift, color jitter) of the same initial image patch

Answer: Deer!

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

Exemplar CNN: Invariance to Data Augmentation

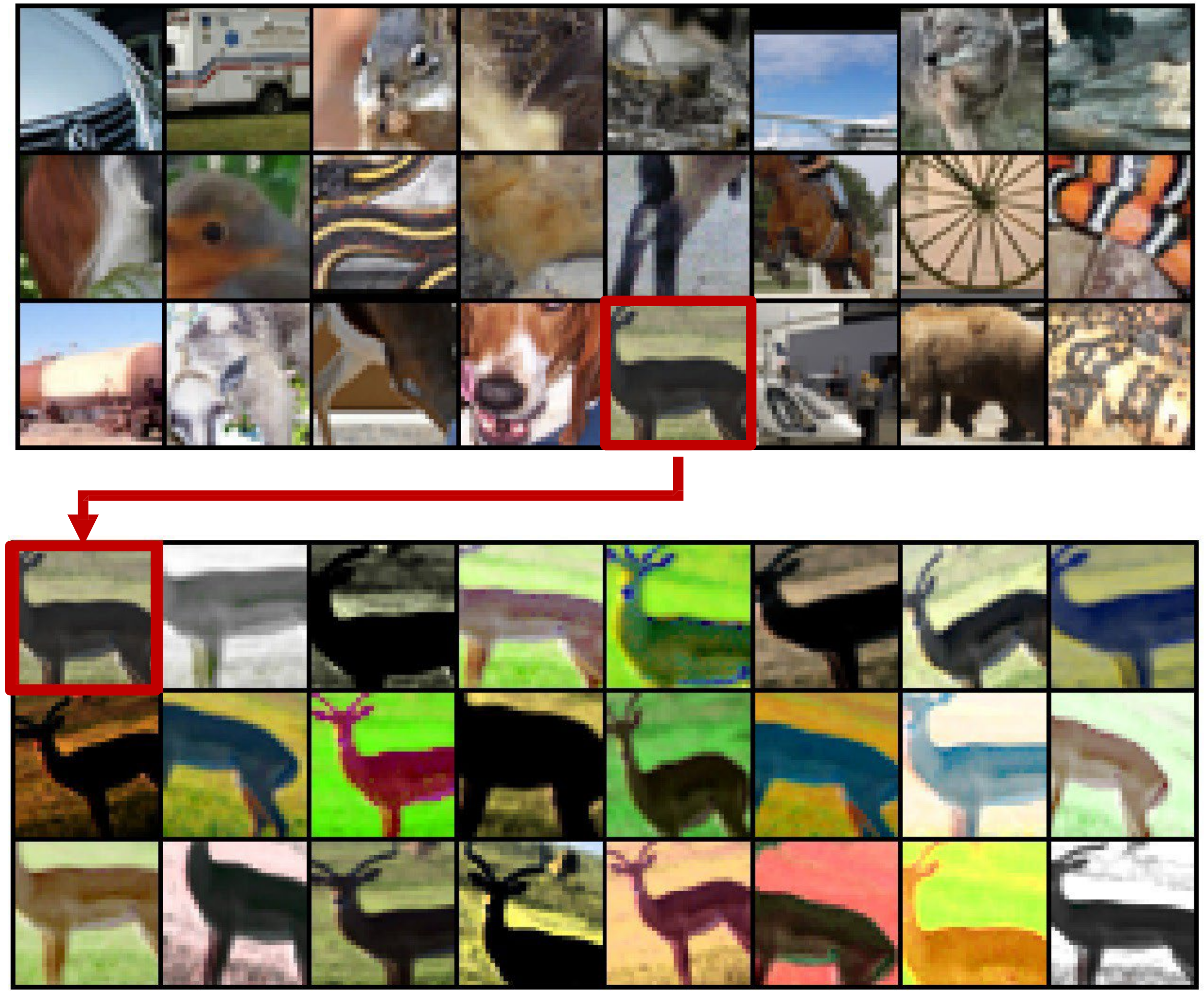
Given an initial dataset of N image patches



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

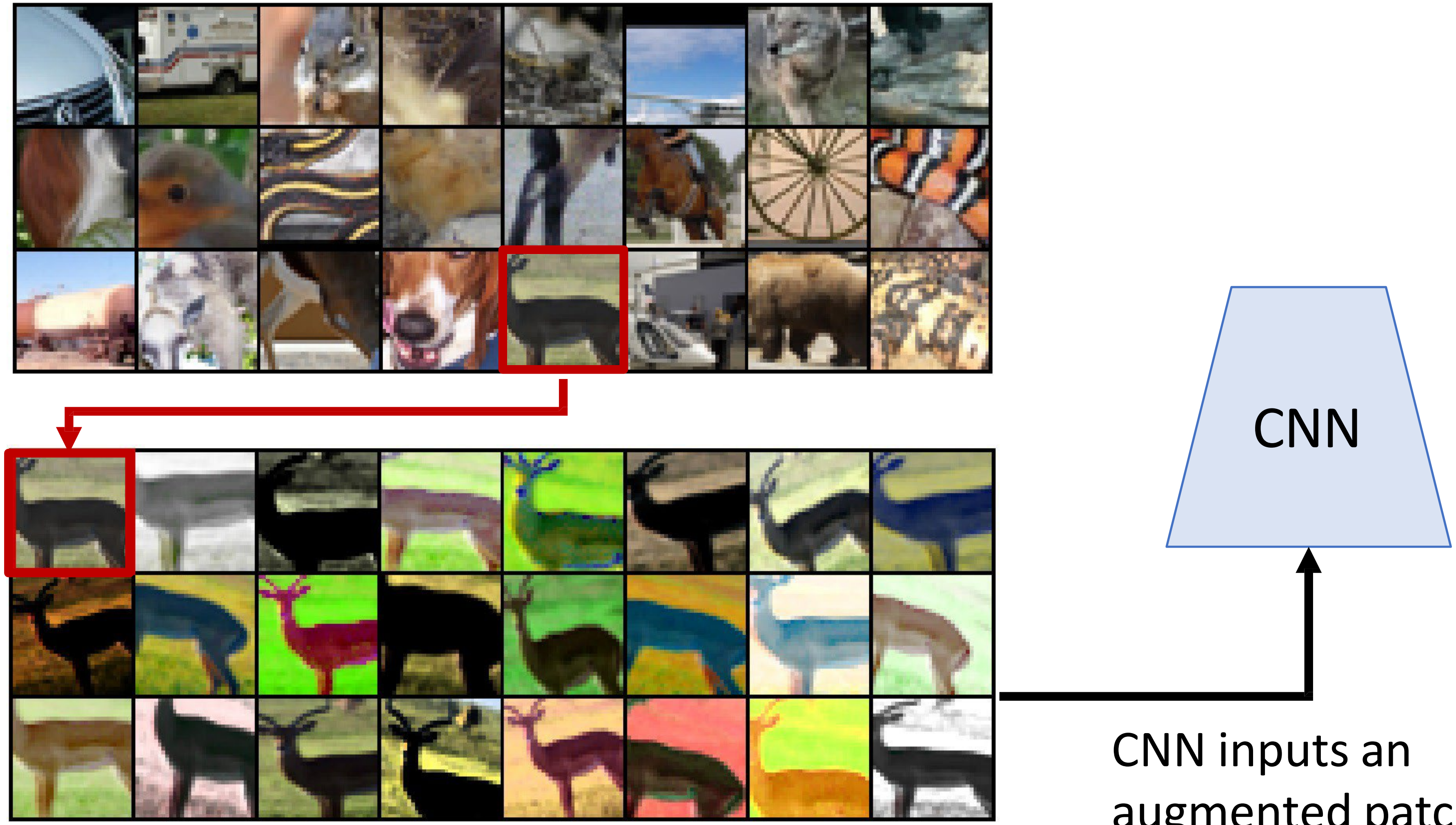


Sample K different augmentations for each; now have K*N total patches

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



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

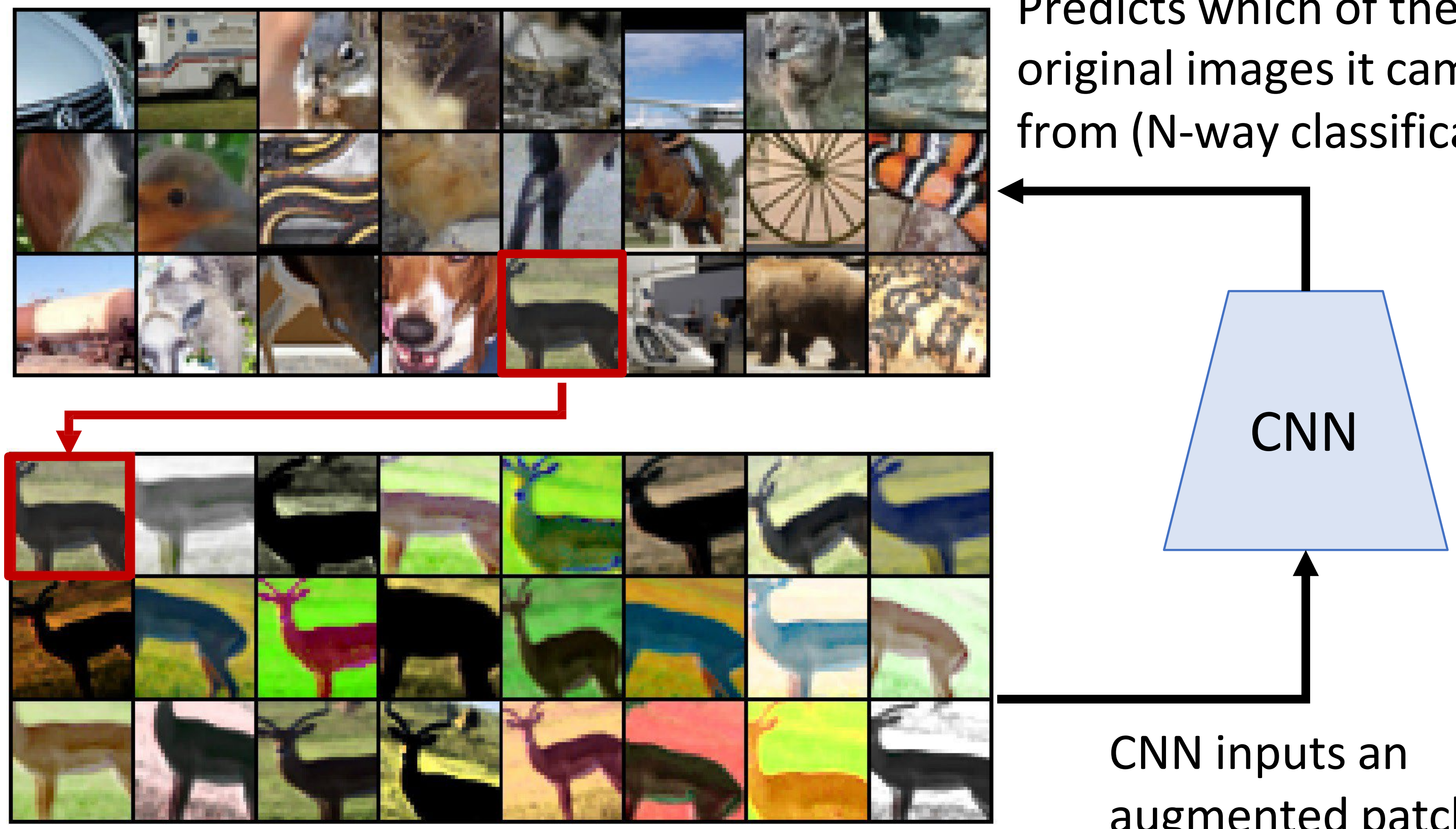
CNN inputs an augmented patch

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

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



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

CNN inputs an augmented patch

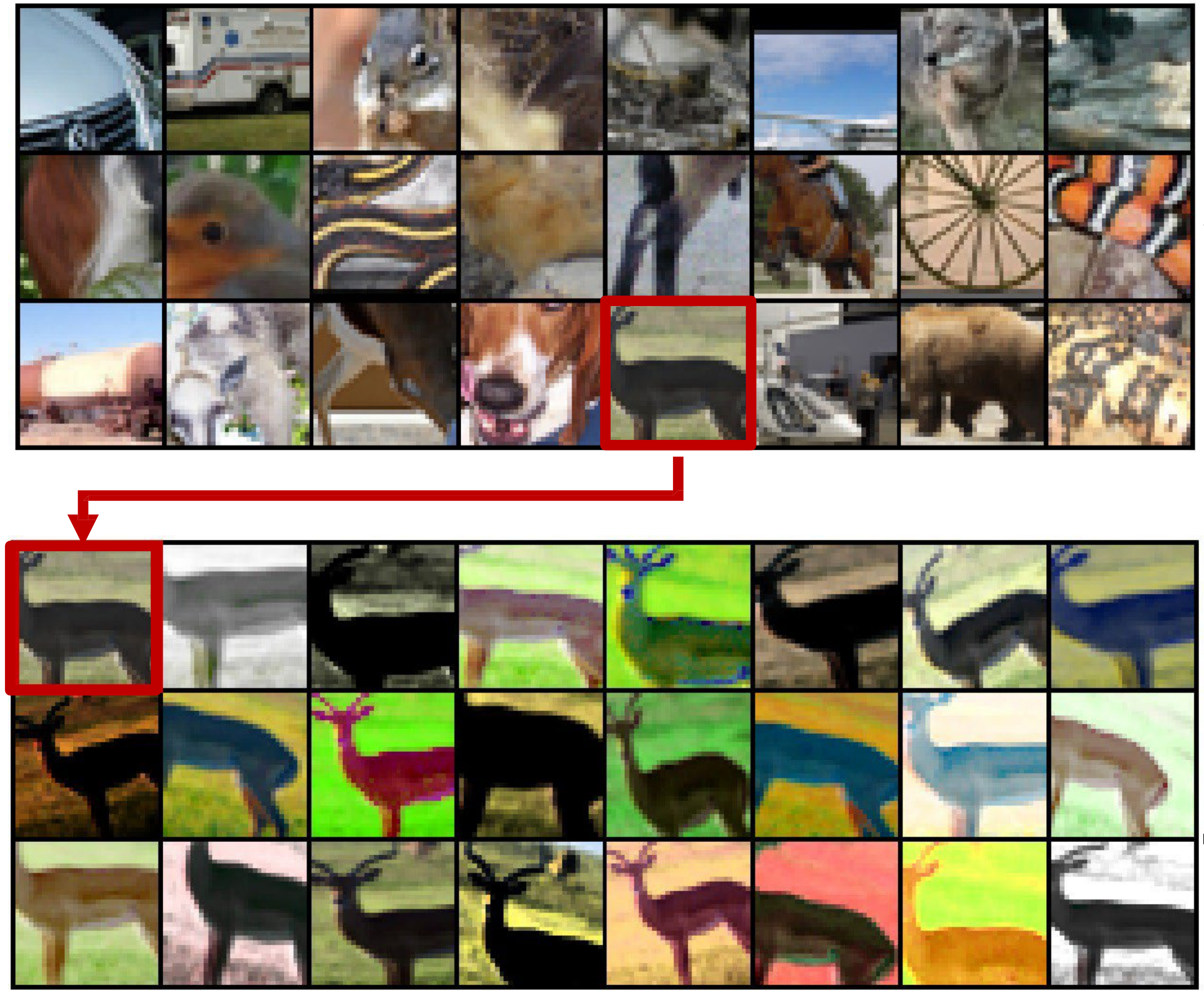
Dosovitskiy et al, "Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks"

Exemplar CNN: Invariance to Data Augmentation

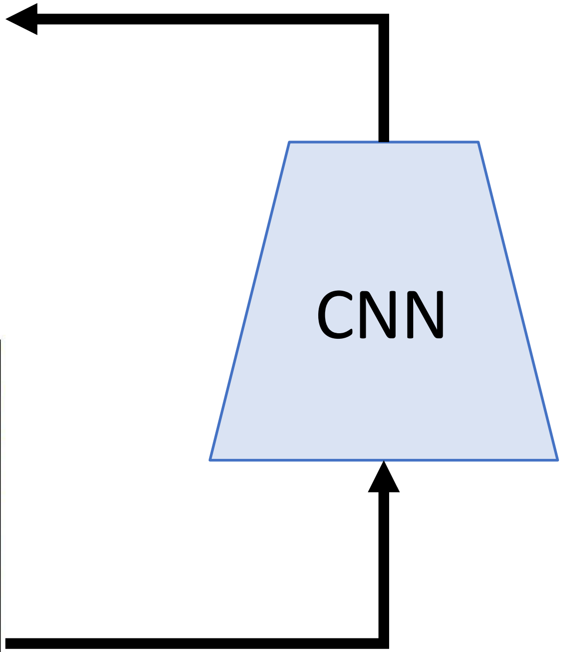
Given an initial dataset of N image patches

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



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

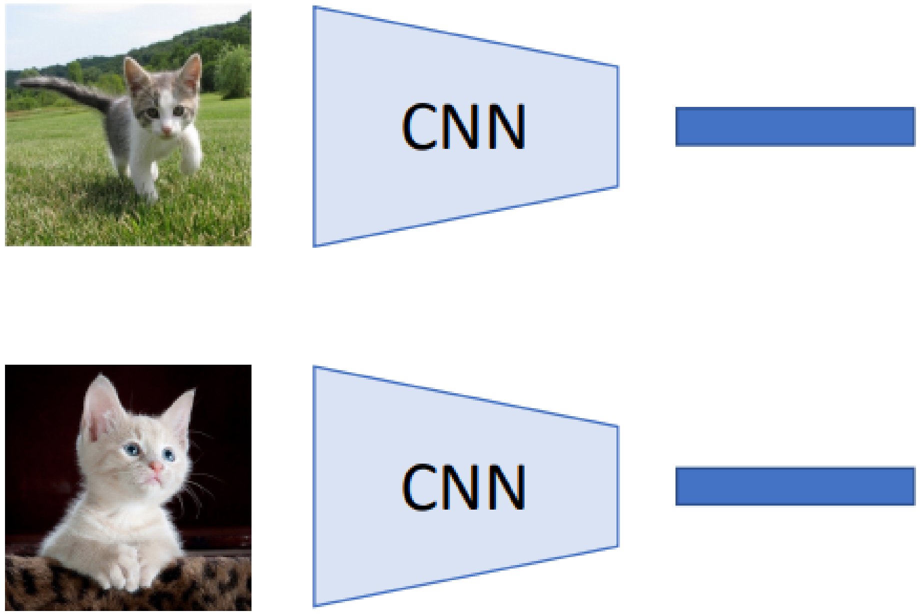


CNN inputs an augmented patch

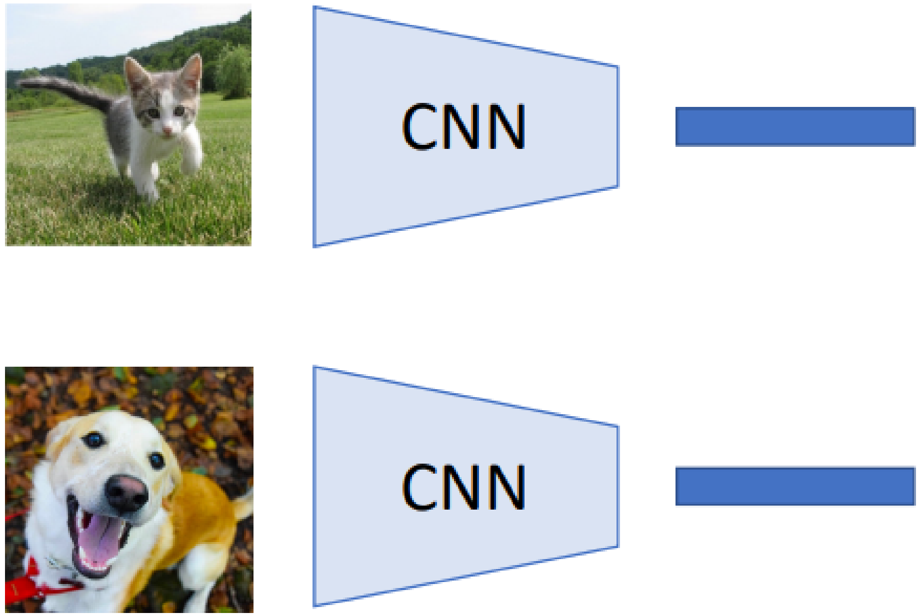
Dosovitskiy et al, “Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks”

Let's take a step back ...

Similar images should have similar features



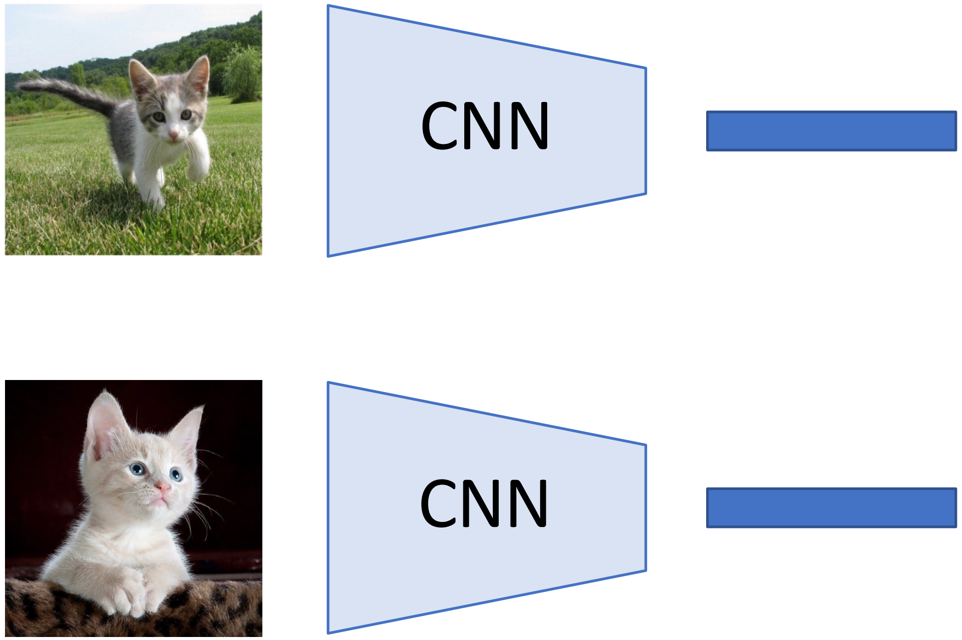
Dissimilar images should have dissimilar features



Contrastive Learning

we know whether some pairs of images are similar or dissimilar

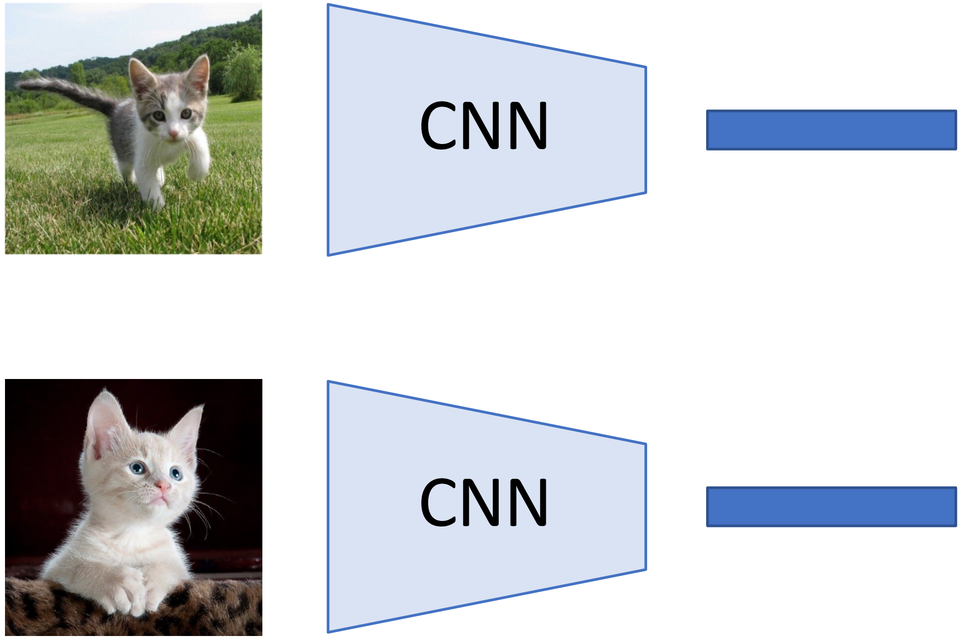
Similar images should have similar features



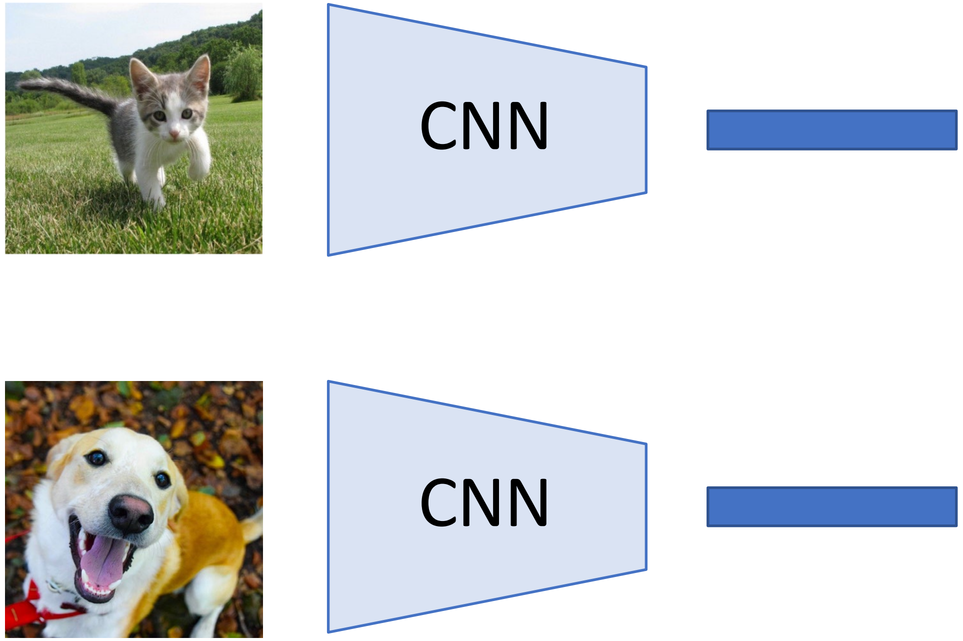
Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning

Similar images should have similar features



Dissimilar images should have dissimilar features



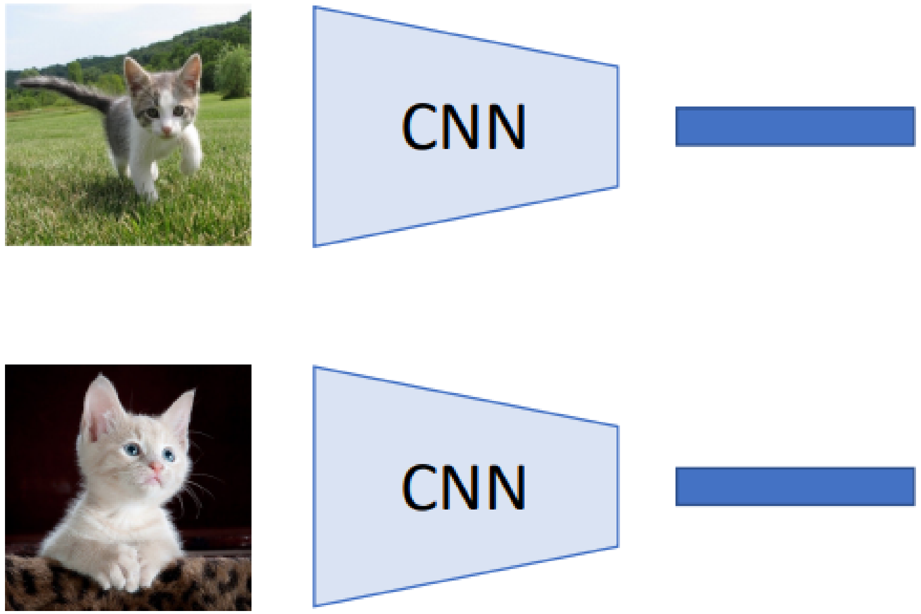
Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning

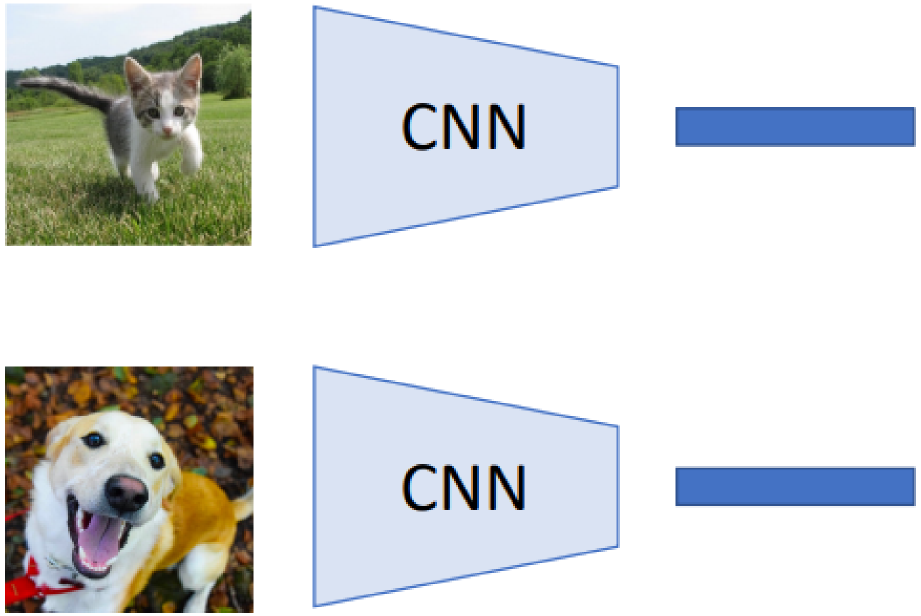
Assume we don't have labels for images, but we know whether some pairs of images are **similar** or **dissimilar**

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



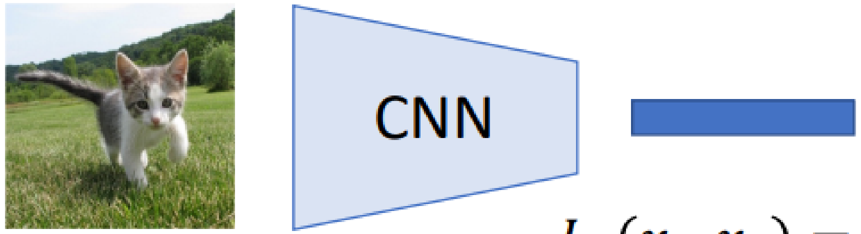
Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning

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

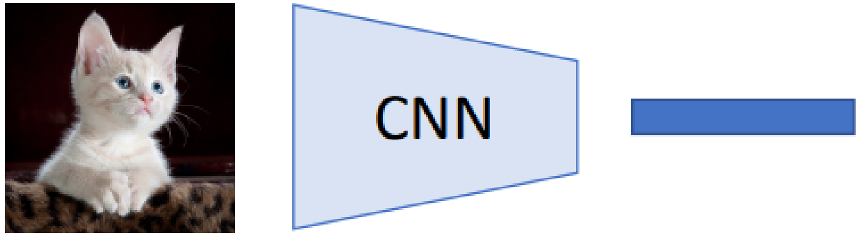
Let $\mathrm{d} = ||\phi(x_1) - \phi(x_2)||_2$ be the Euclidean distance between features for two images

Similar images should have similar features

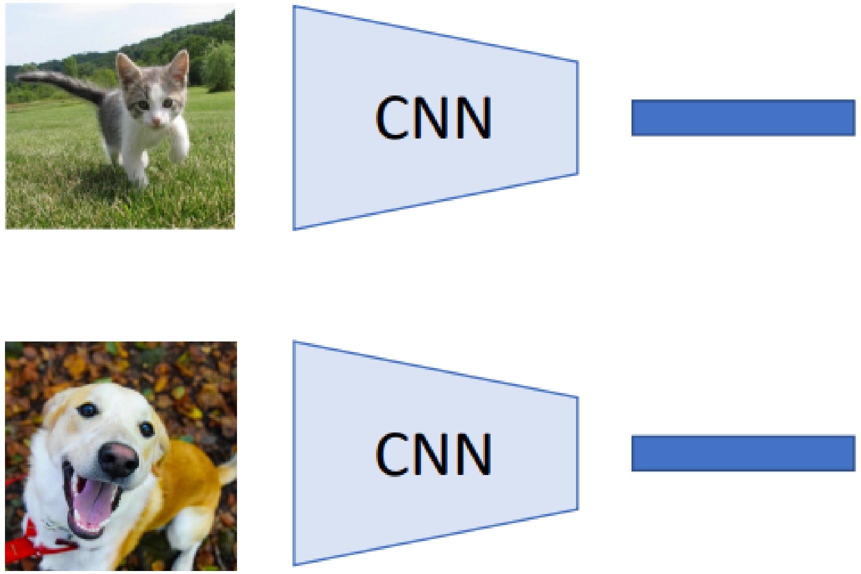


$$L_S(x_1, x_2) = d^2$$

Pull features together



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

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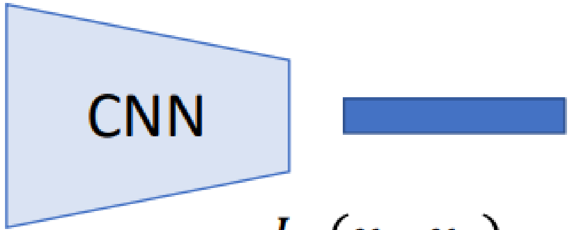
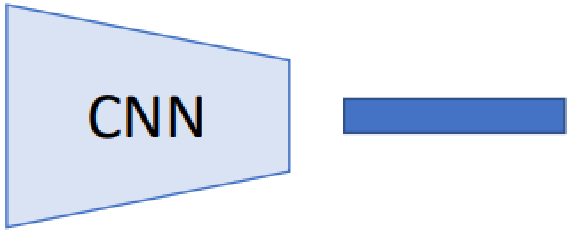
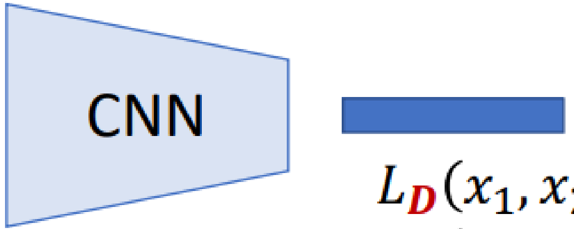


$L_S(x_1, x_2) = d^2$

Pull features together

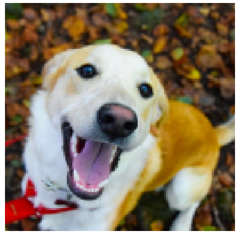
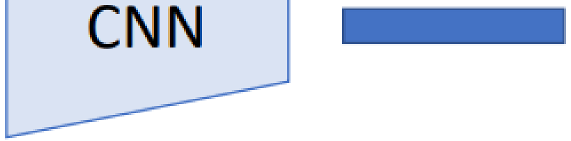



Dissimilar images should have dissimilar features

$L_D(x_1, x_2)$
$= \max(0, m - d)^2$

Push features apart (up to margin m)

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

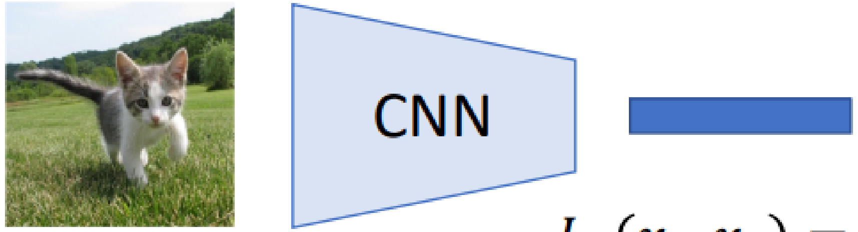
Problem: Where to get positive and negative pairs?

Contrastive Learning

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

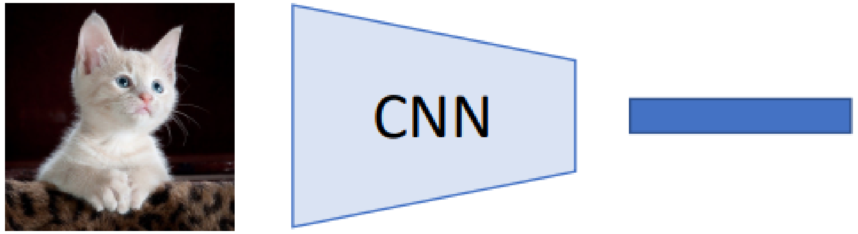
Let $\mathrm{d} = ||\phi(x_1) - \phi(x_2)||_2$ be the Euclidean distance between features for two images

Similar images should have similar features

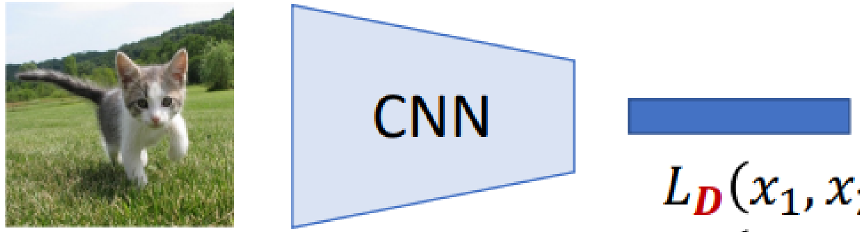


$L_S(x_1, x_2) = d^2$

Pull features together



Dissimilar images should have dissimilar features

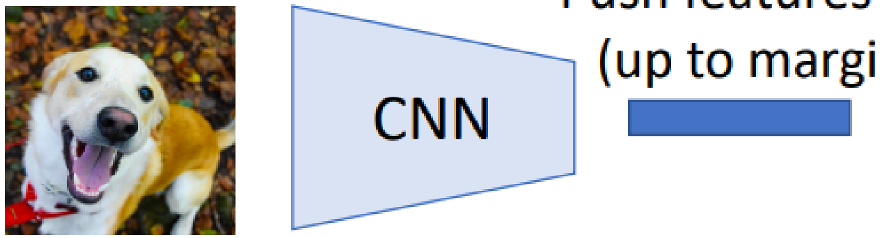


$L_D(x_1, x_2)$

$= \max(0, m - d)^2$

Push features apart

(up to margin m)

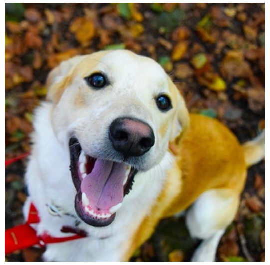


Hadsell et al, "Dimensionality Reduction by Learning and Invariant Mapping", CVPR 2006

Contrastive Learning 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
Hjelm et al, “Learning deep representations by mutual information estimation and maximization”, ICLR 2019
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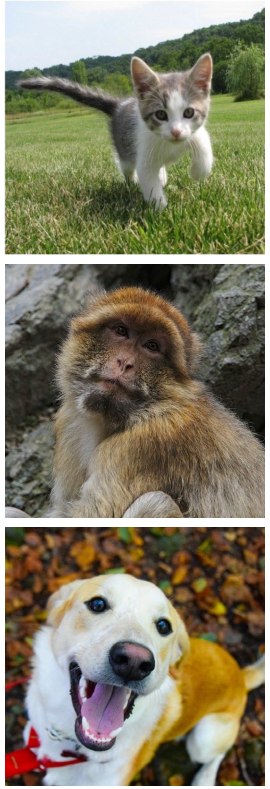
He et al, “Momentum Contrast for Unsupervised Visual Representation Learning”, CVPR 2020
Chen et al, “A Simple Framework for Contrastive Learning of Visual Representations”, ICML 2020

Contrastive Learning with Data Augmentation

Batch of N images



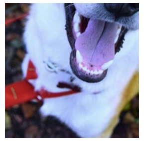
Two augmentations for each image

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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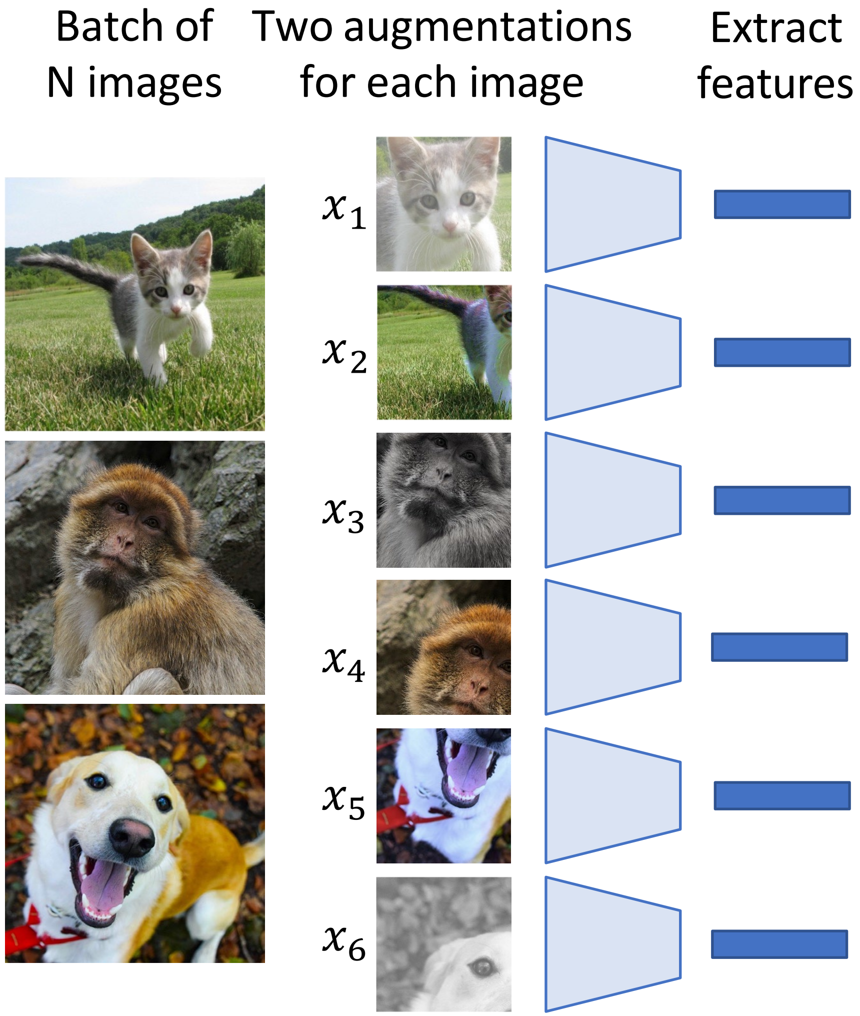
Contrastive Learning with Data Augmentation



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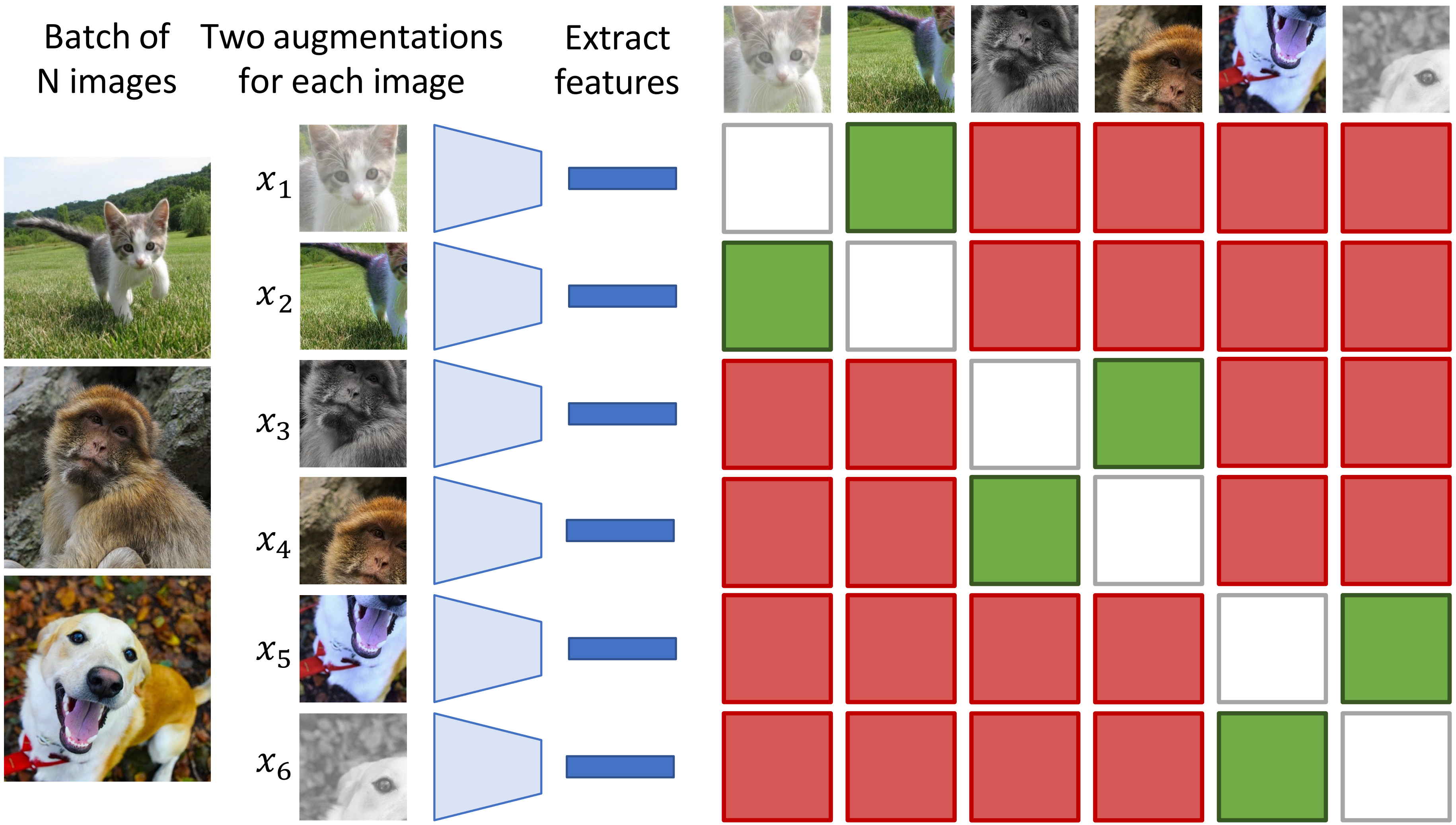
Contrastive Learning with Data Augmentation

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



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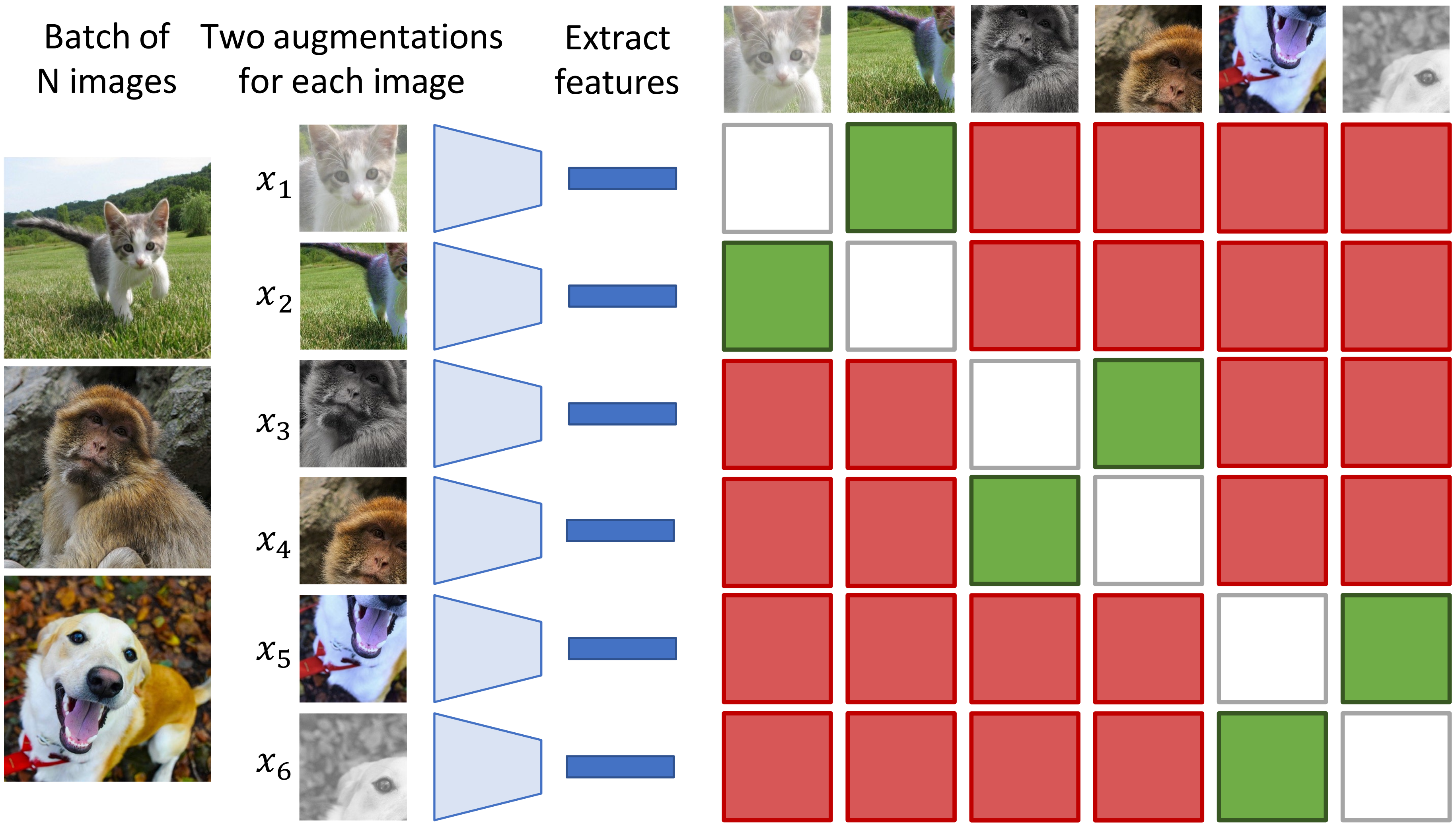
Contrastive Learning with Data Augmentation



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

Similarity between x_i and x_j:

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

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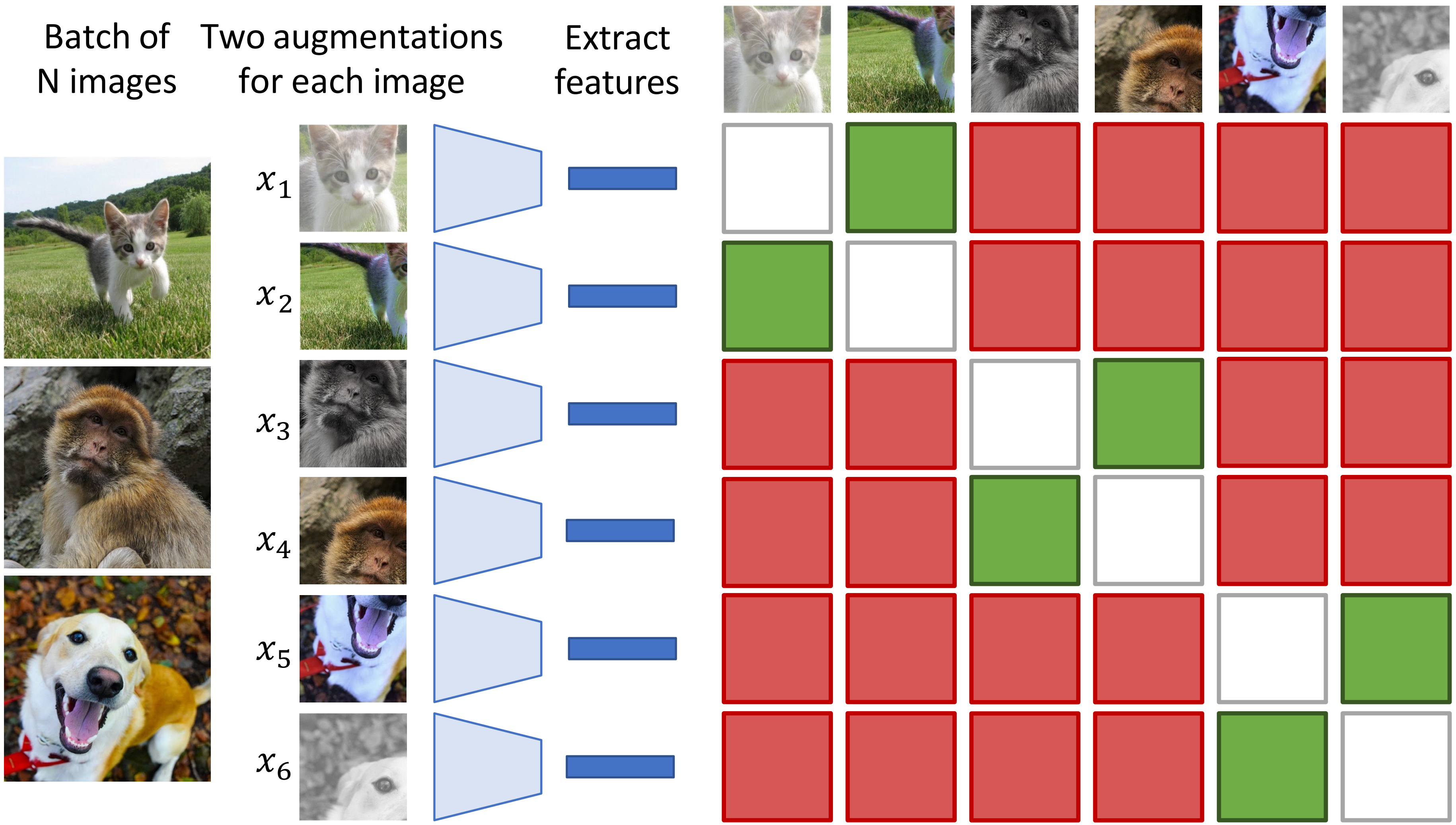
Contrastive Learning with Data Augmentation



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

Similarity between x_i and x_j:

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

If (x_i, x_j) is a positive pair, then loss for x_i is:

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

(τ is a *temperature*)

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
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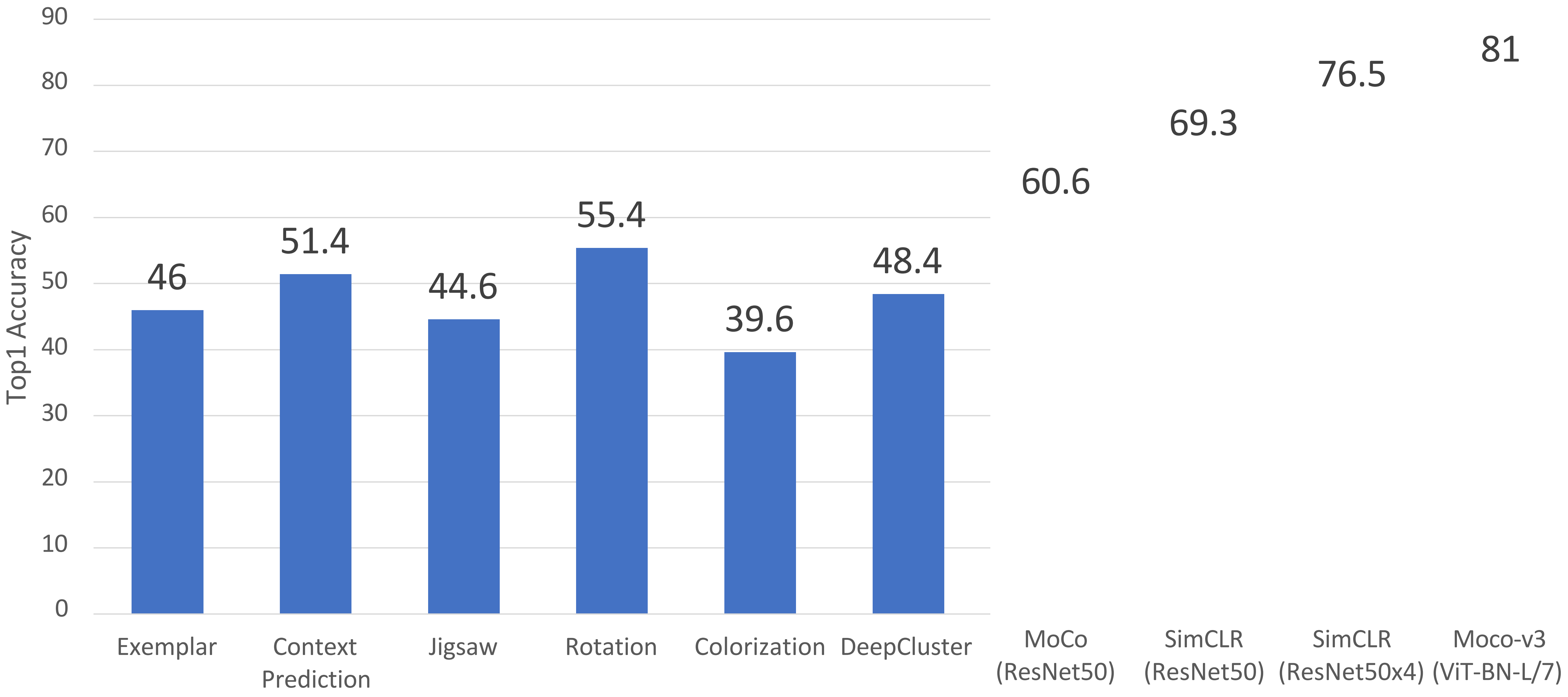
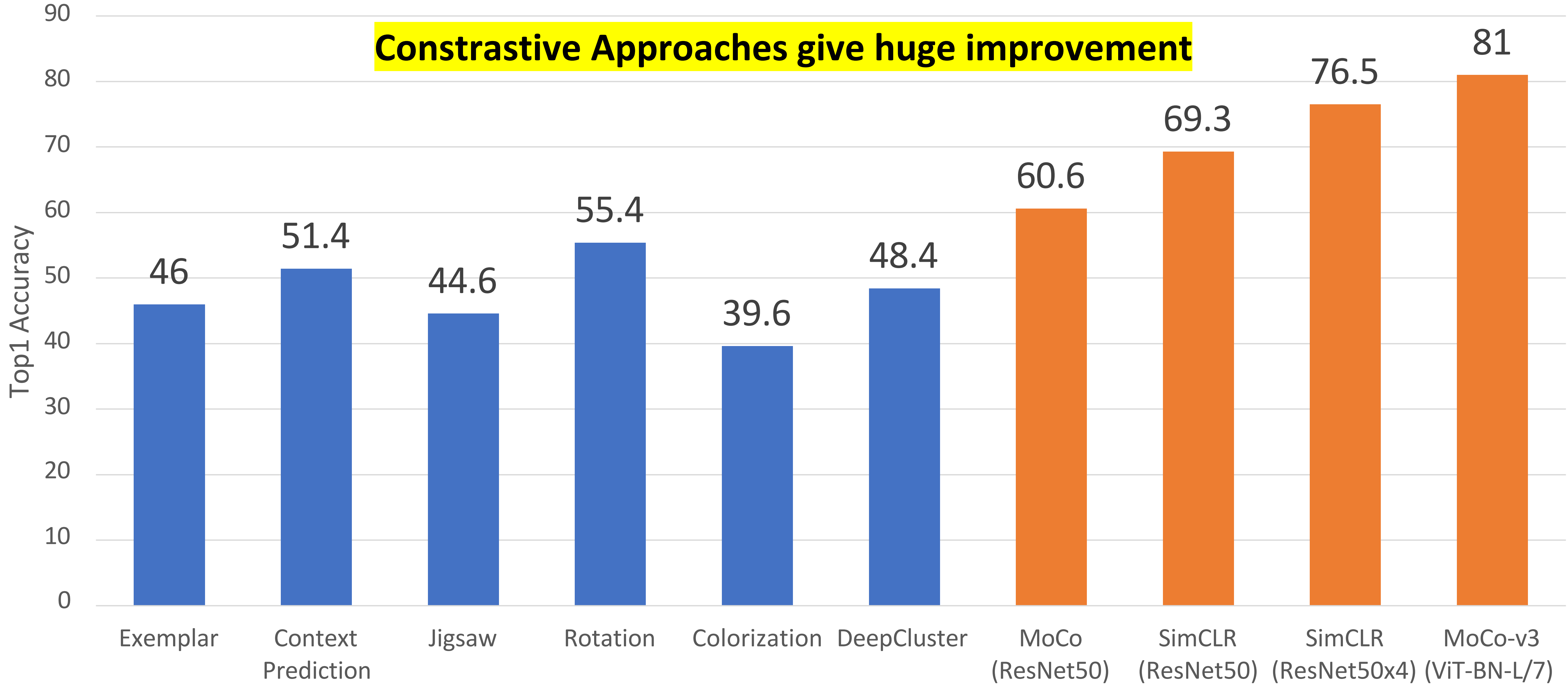
ImageNet Linear Classification from SSL Features



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, "An Empirical Study of Training Self-Supervised Vision Transformers", ICCV 2021

(Lots of caveats here … different architectures, etc)

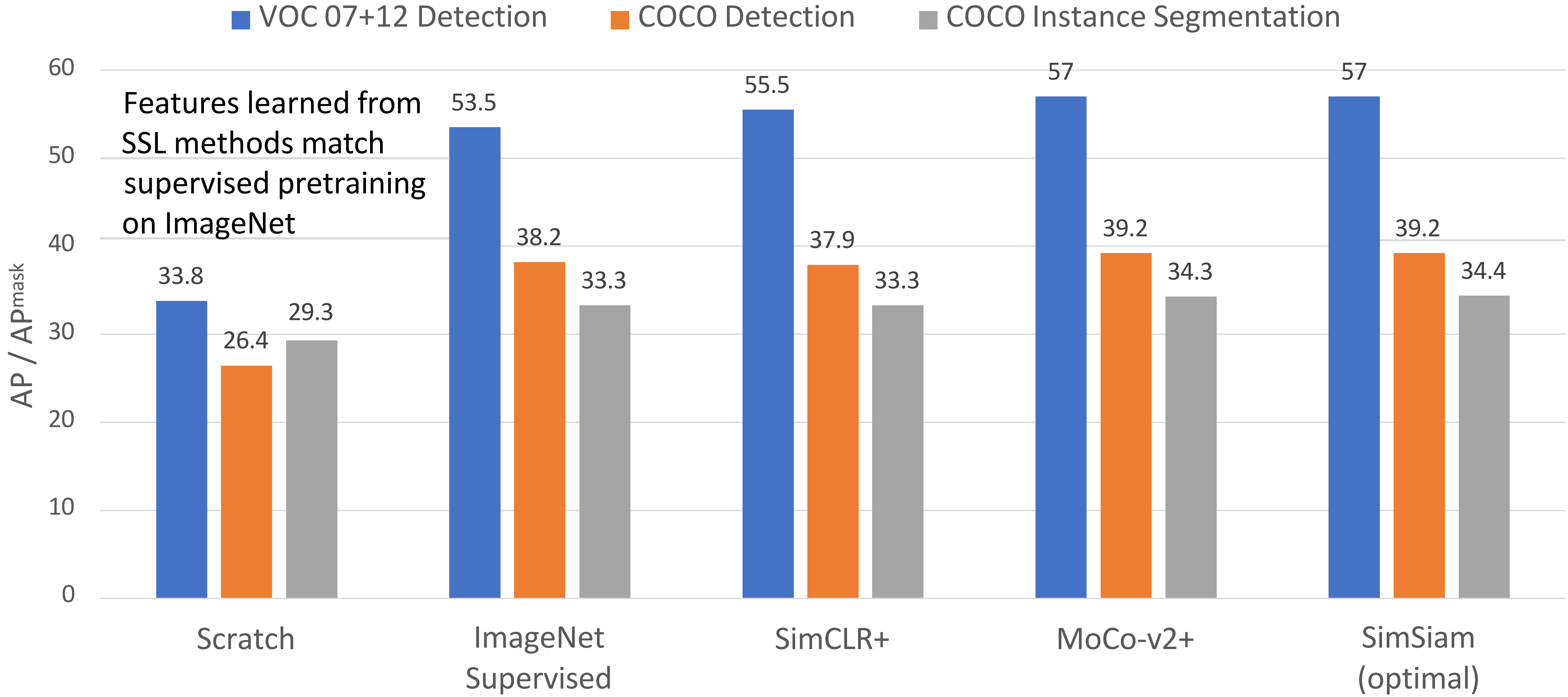
ImageNet Linear Classification from SSL Features



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, "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

But how did you get the pretraining data?

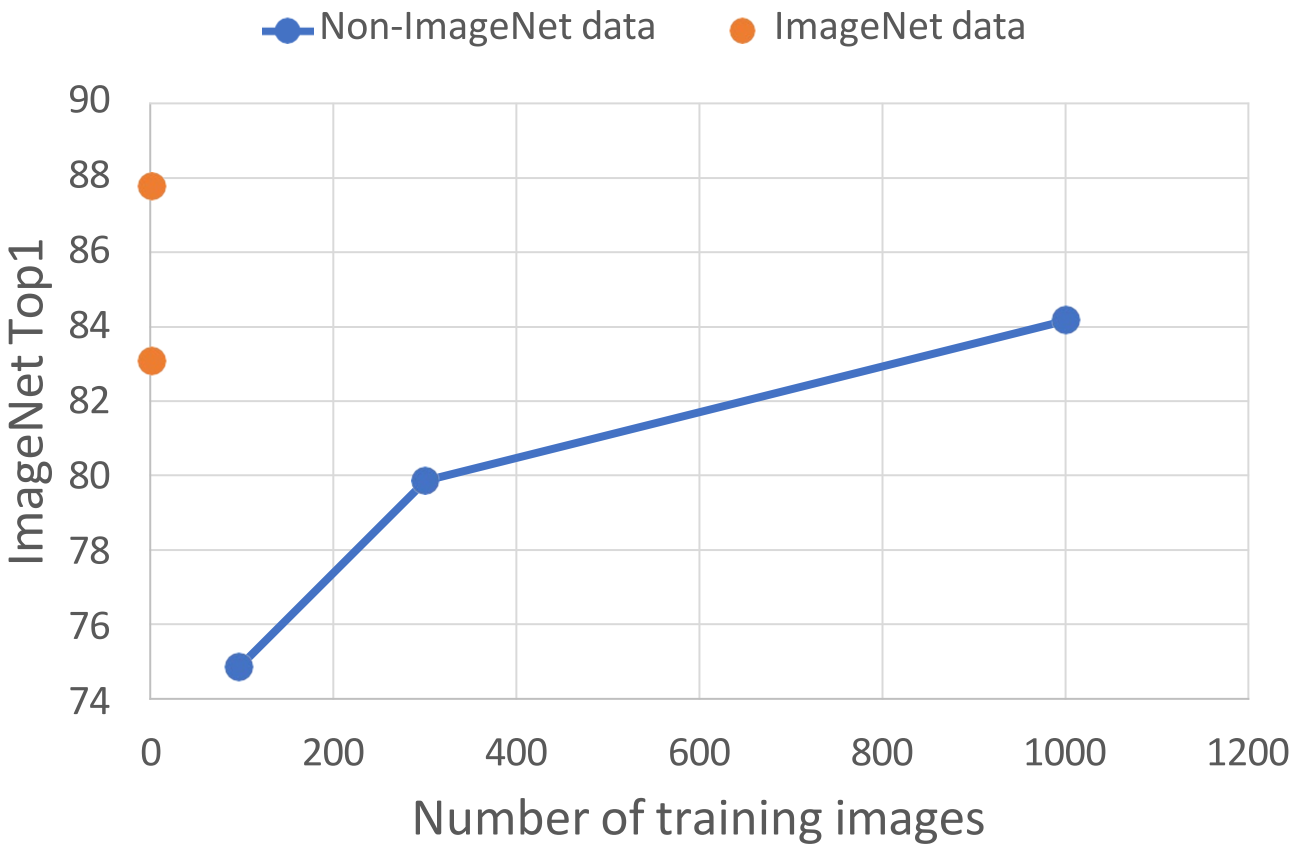
The motivation of SSL is scaling to large data that can't be labeled

Most papers pretrain on (unlabeled) ImageNet, then evaluate on ImageNet!

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

Self-Supervised Learning on larger datasets hasn't been as successful as NLP

Idea: What if we go beyond isolated images?



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
Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021
Goyal et al, "Self-supervised Pretraining of Visual Features in the Wild", arXiv 2021
He et al, "Masked Autoencoders are Scalable Vision Learners", arXiv 2021

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
Wang et al, “Unsupervised Learning of Visual Representations using Videos”, ICCV 2015
Pathak et al, “Learning Features by Watching Objects Move”, CVPR 2017

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Sound: Image with audio track from video

Owens et al, “Ambient Sound Provides Supervision for Visual Learning”, ECCV 2016
Arandjelovic and Zisserman, “Look, Listen and Learn”, ICCV 2017

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3D: Image with depth map or point cloud

Xie et al, “PointContrast: Unsupervised Pre-training for 3D Point Cloud Understanding”, ECCV 2020
Zhang et al, “Self-supervised pretraining of 3D features on any point-cloud”, CVPR 2021

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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

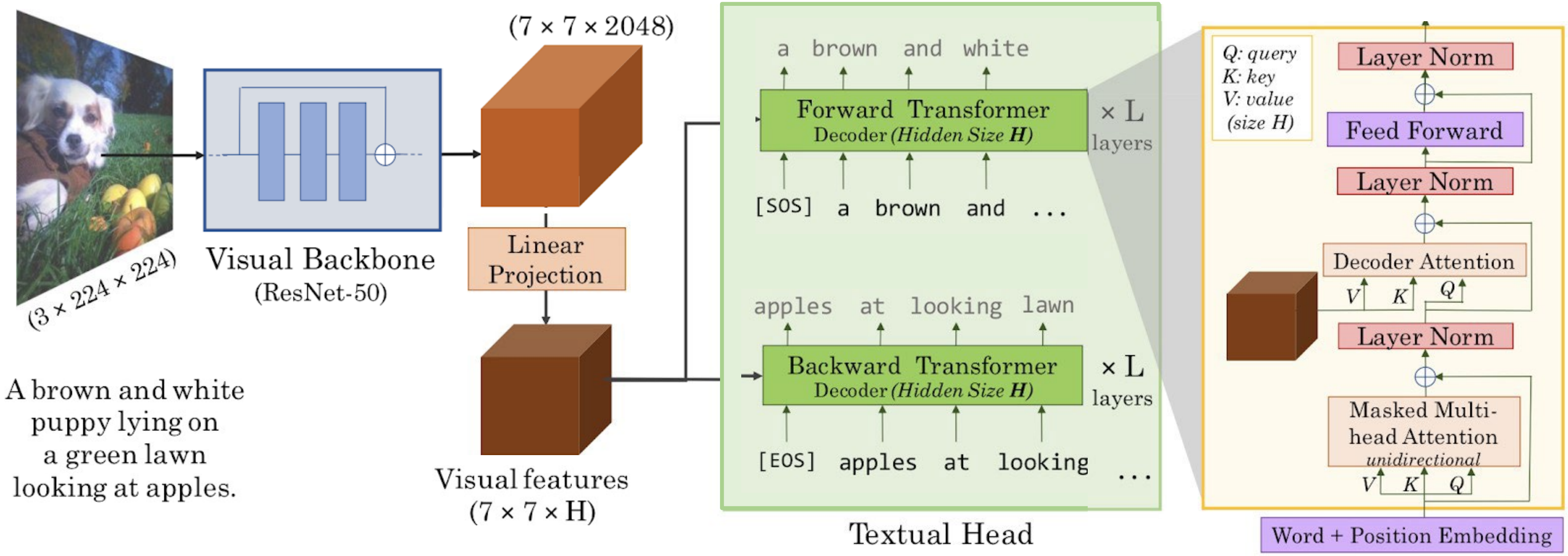
a black and orange cat is resting on a keyboard and yellow back scratcher

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

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

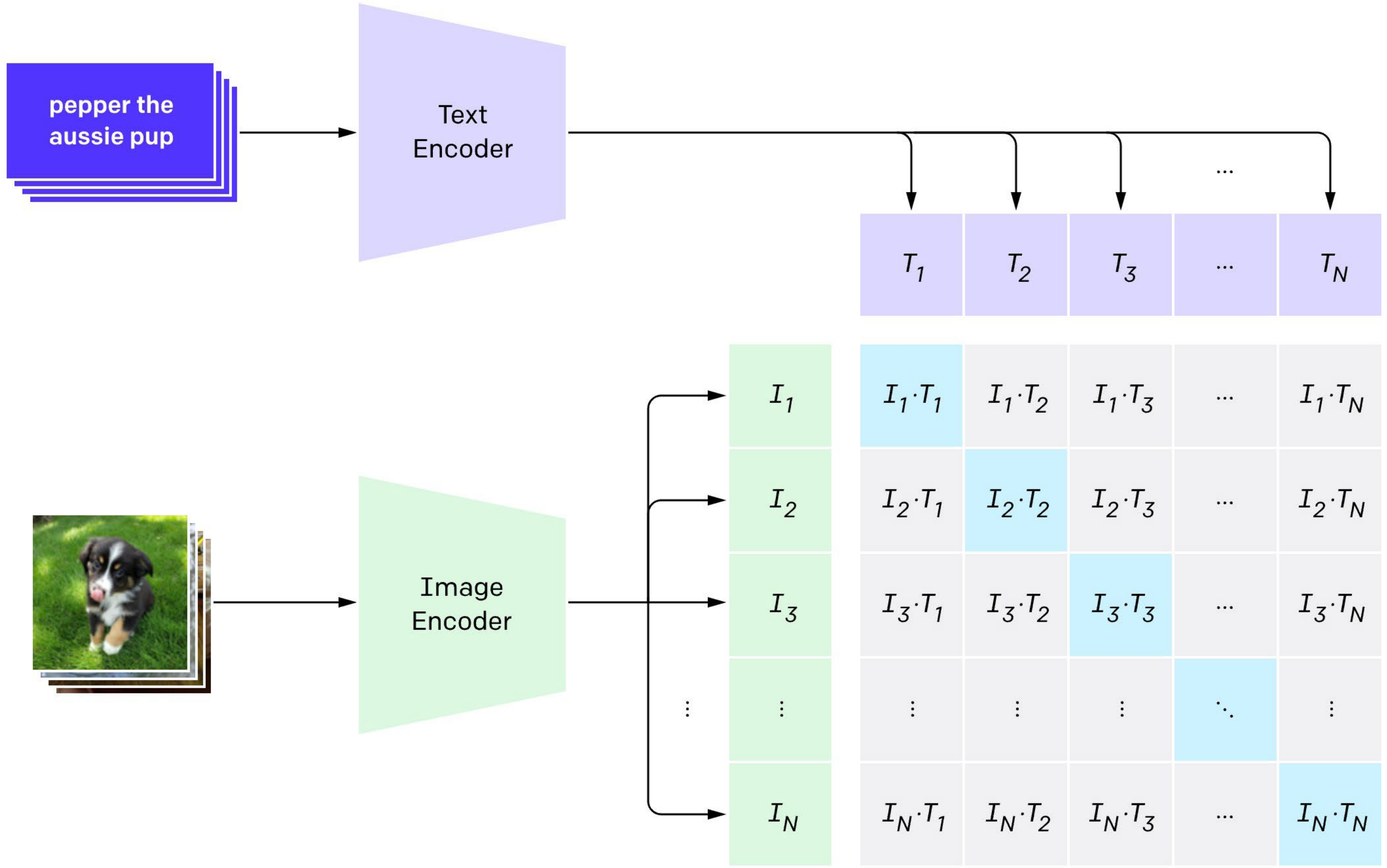
3. **Scalability**: Non-experts can easily caption images; data can also be collected from the web at scale

Generating Captions



Desai and Johnson, “Desai and Johnson, “VirTex: Learning Visual Representations from Textual Annotations”, CVPR 2021

Matching Images and Text

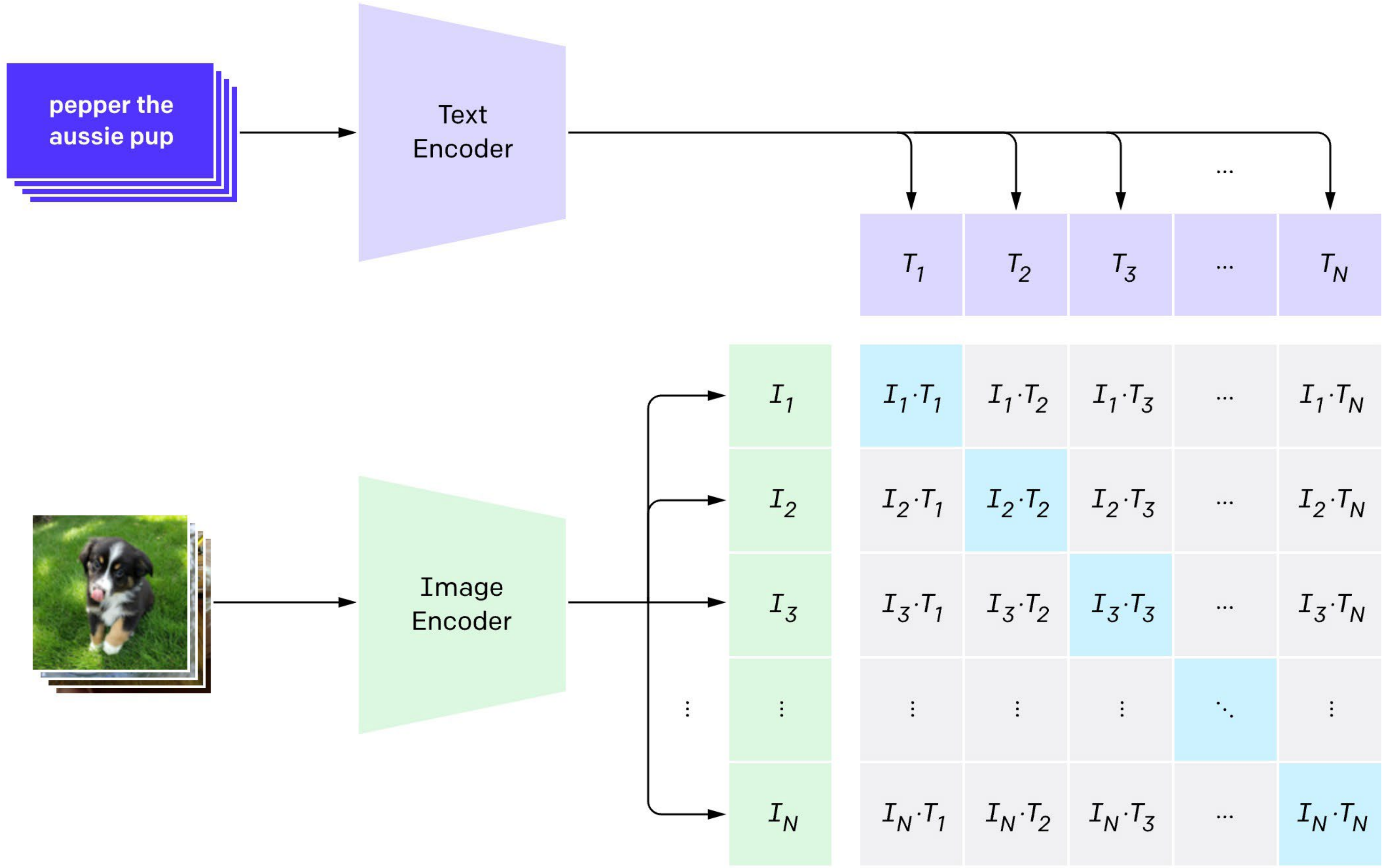


Contrastive loss: Each image predicts which caption matches

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



Contrastive loss: Each image predicts which caption matches

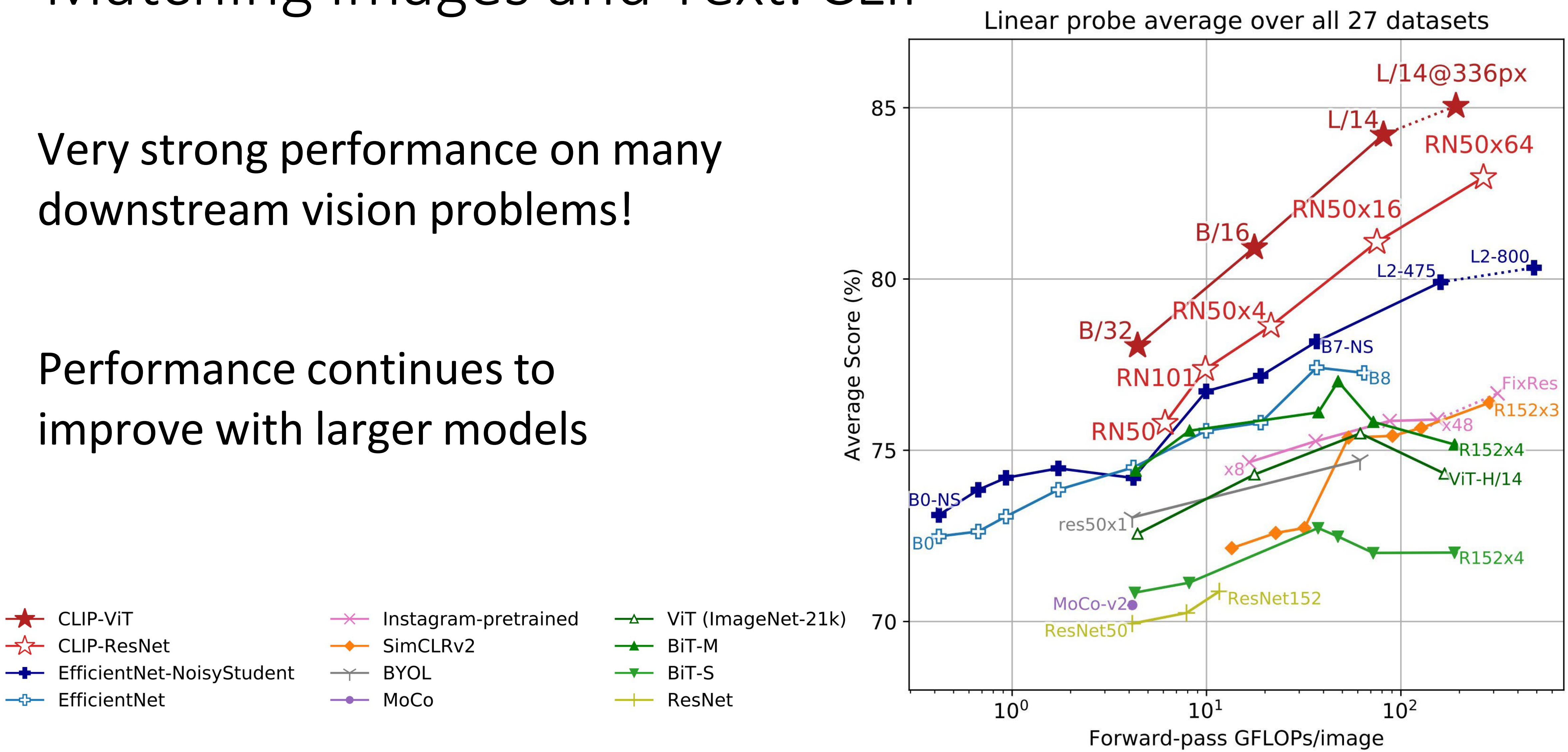
Large-scale training on 400M (image, text) pairs from the internet

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

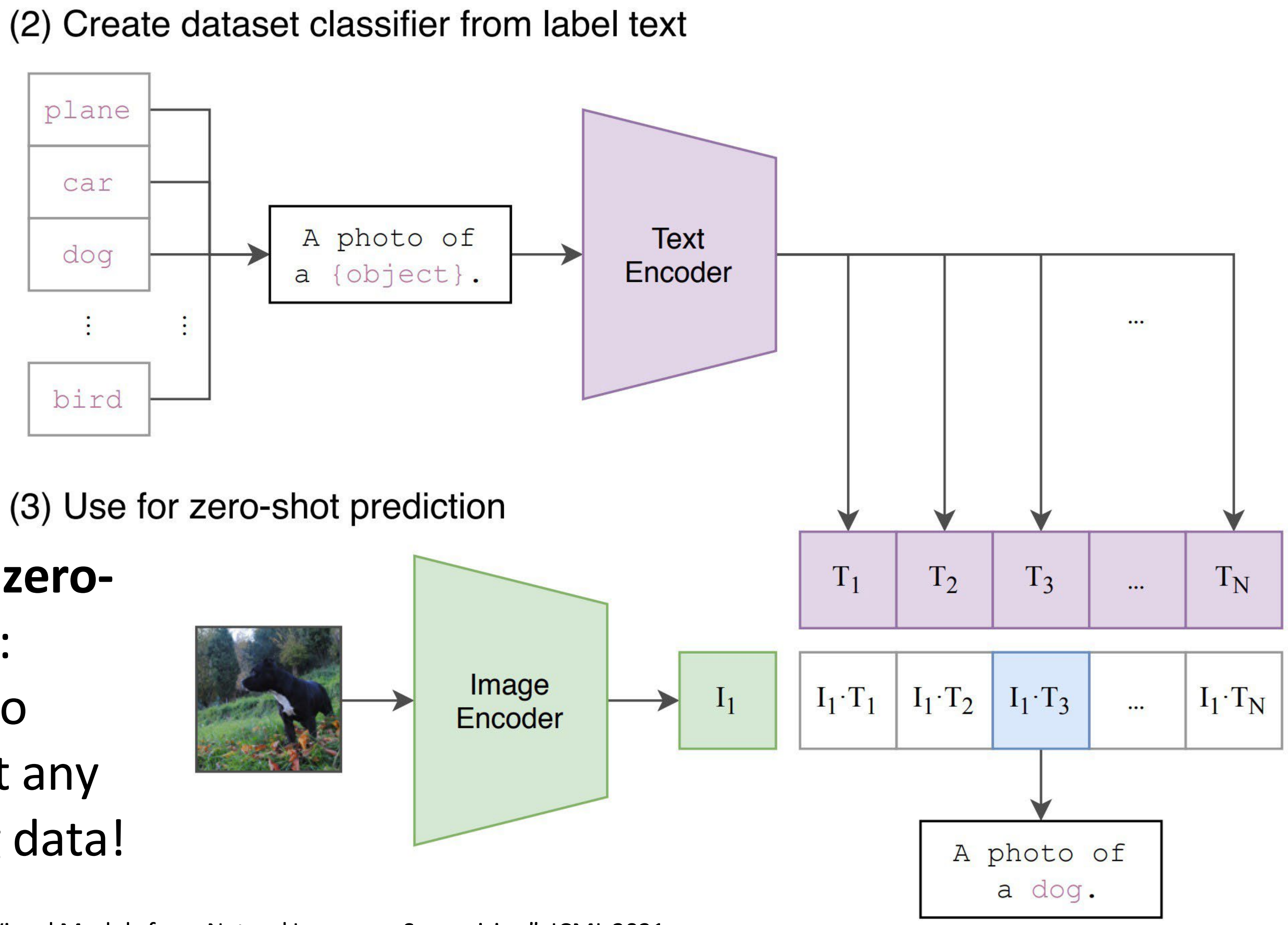
Very strong performance on many downstream vision problems!

Performance continues to improve with larger models



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

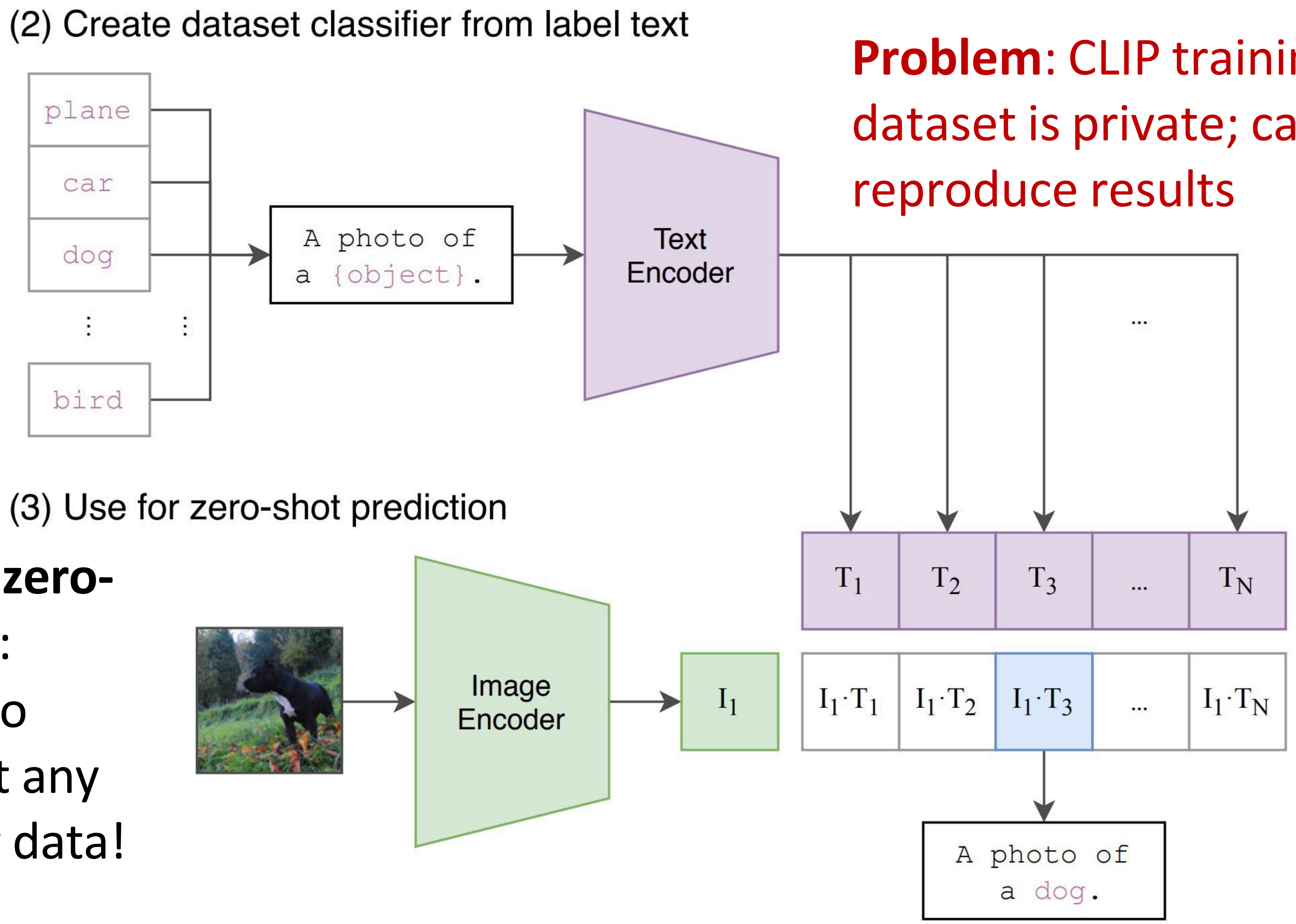
CLIP: Zero-Shot Classification



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

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

CLIP: Zero-Shot Classification



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

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

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

RedCaps: Images and Captions from Reddit

r/birdpics: male northern cardinal | **r/crafts:** my mom tied this mouse | **r/itookapicture:** itap of the taj mahal | **r/perfectfit:** this lemon in my drink | **r/shiba:** mlem!

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 aims to scale up training 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
- Multimodal SSL with vision + language has been very successful