Lecture 19:

Contrastive and Self-Supervised Visual Representations

CMSC 472/672 Computer Vision

UMBC

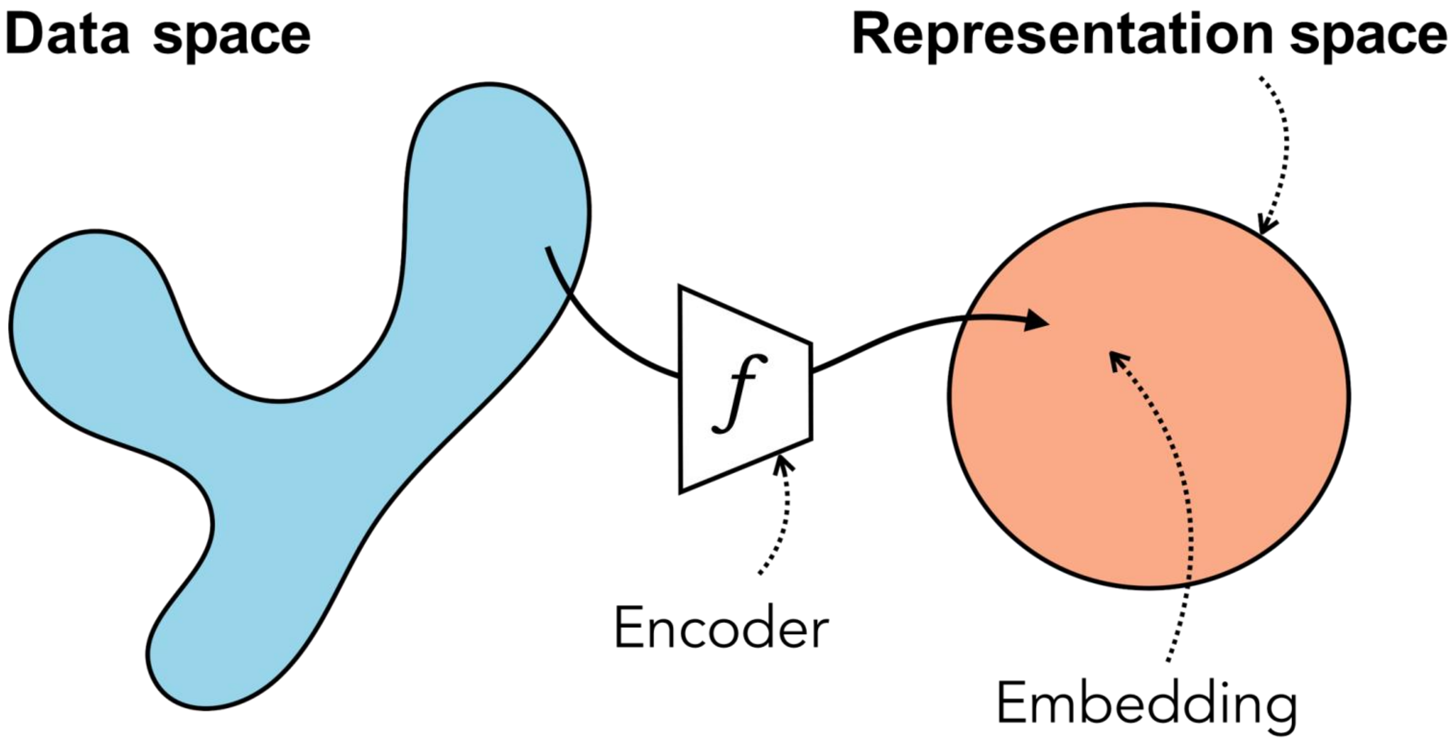
- Train a model on 1 million images ➔ label 1 million images
- Labels aren't magically given to you ➔ need human effort
- How much will it cost?

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

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

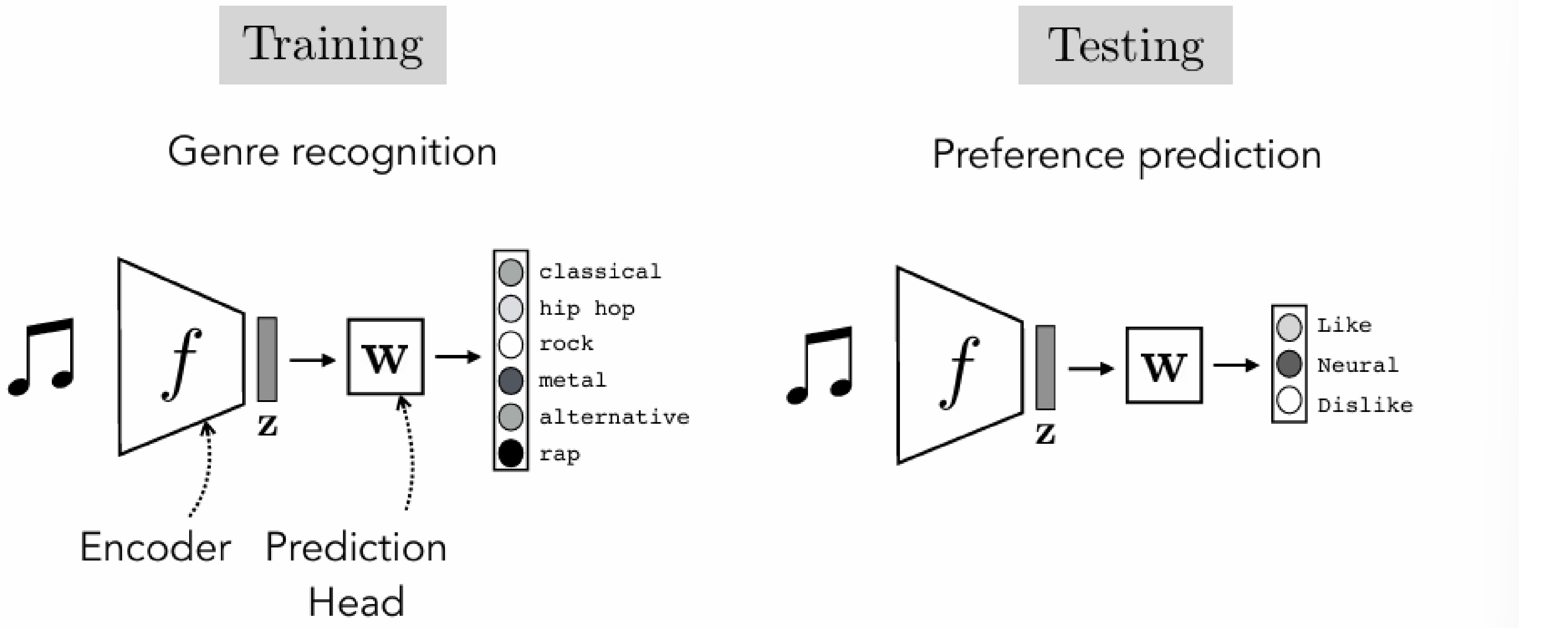
Recap: Representation Learning "x2vec"

- A representation of a data domain $\mathcal{X}$ is a function $f : \mathcal{X} \rightarrow \mathbb{R}^d$ (an encoder) that assigns a feature vector to each input in that domain.
- A representation of a datapoint is a vector $z \in \mathbb{R}^d$ with $z = f(x)$.



Why Learn Representations?

"Generally speaking, a good representation is one that makes a subsequent learning task easier."
- Goodfellow et al. "Deep Learning". 2016



Often, what we will be "tested" on is not what we were trained on.

Why Learn Representations?

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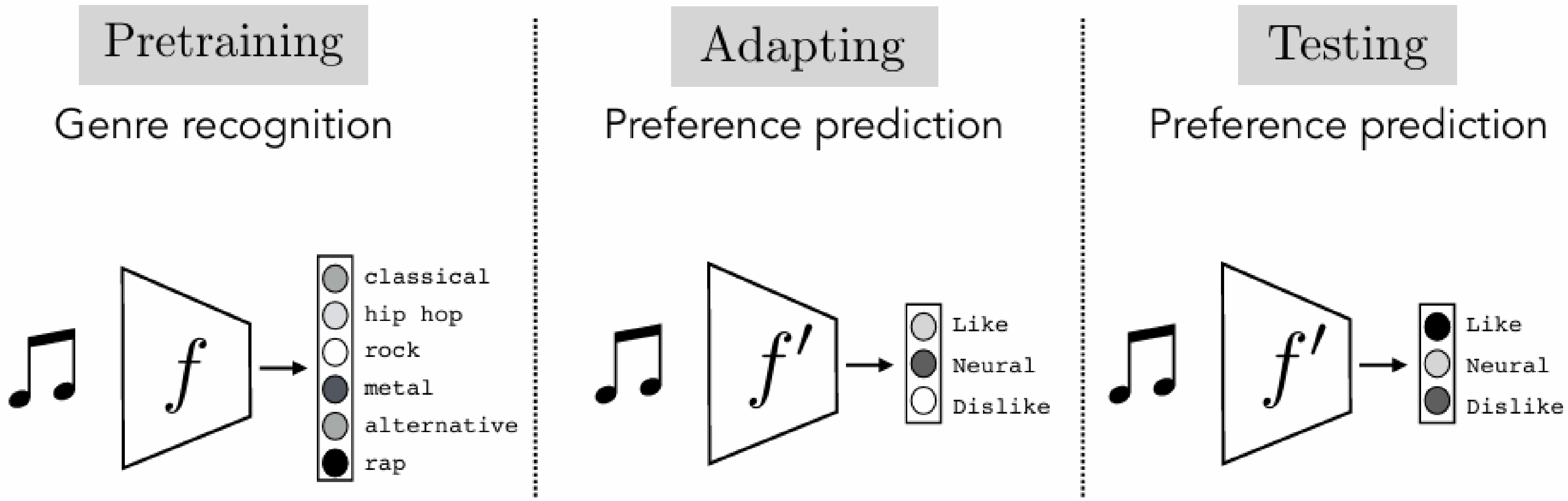


A lot of data

A little data

Learning from examples

(aka **supervised learning**)

Training data

$$\begin{matrix} \{x^{(1)}, y^{(1)}\} \\ \{x^{(2)}, y^{(2)}\} \\ \{x^{(3)}, y^{(3)}\} \\ \dots \end{matrix} \quad \rightarrow \quad \boxed{\text{Learner}} \quad \rightarrow \quad f : X \rightarrow Y$$

$$f^* = \arg\min_{f \in \mathcal{F}} \sum_{i=1}^{N} \mathcal{L}(f(\mathbf{x}^{(i)}), \mathbf{y}^{(i)})$$

Learning without examples

(includes **unsupervised learning / self-supervised learning**)

Data

$$\{x^{(1)}\}$$
$$\{x^{(2)}\}$$
$$\{x^{(3)}\}$$
$$\ldots$$

$\rightarrow$ Learner $\rightarrow$?

Learning without examples

(includes **unsupervised learning** / **self-supervised learning**)

Data

$\{x^{(1)}\}$
$\{x^{(2)}\}$
$\{x^{(3)}\}$
$\dots$

$\rightarrow$ Learner $\rightarrow$

Embeddings

Clusters

Metrics

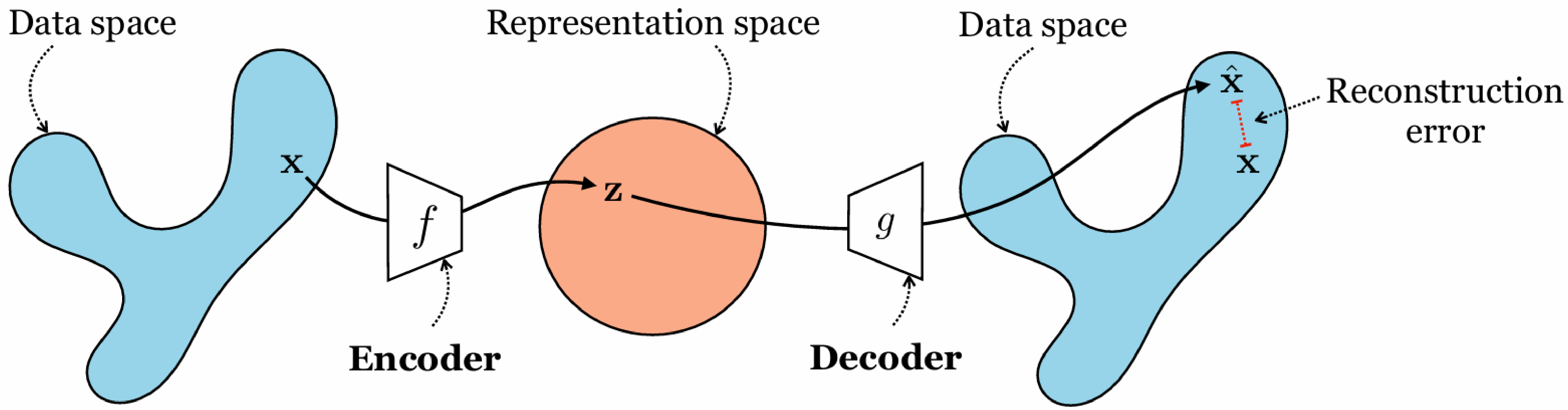
...

Two Basic Approaches:
(1) Compression (2) Prediction

Learning Method	**Learning Principle**	**Short Summary**
Autoencoding	Compression	Remove redundant information
Contrastive	Compression	Achieve invariance to viewing transformations
Clustering	Compression	Quantize continuous data into discrete categories
Future prediction	Prediction	Predict the future
Imputation	Prediction	Predict missing data
Pretext tasks	Prediction	Predict abstract properties of your data

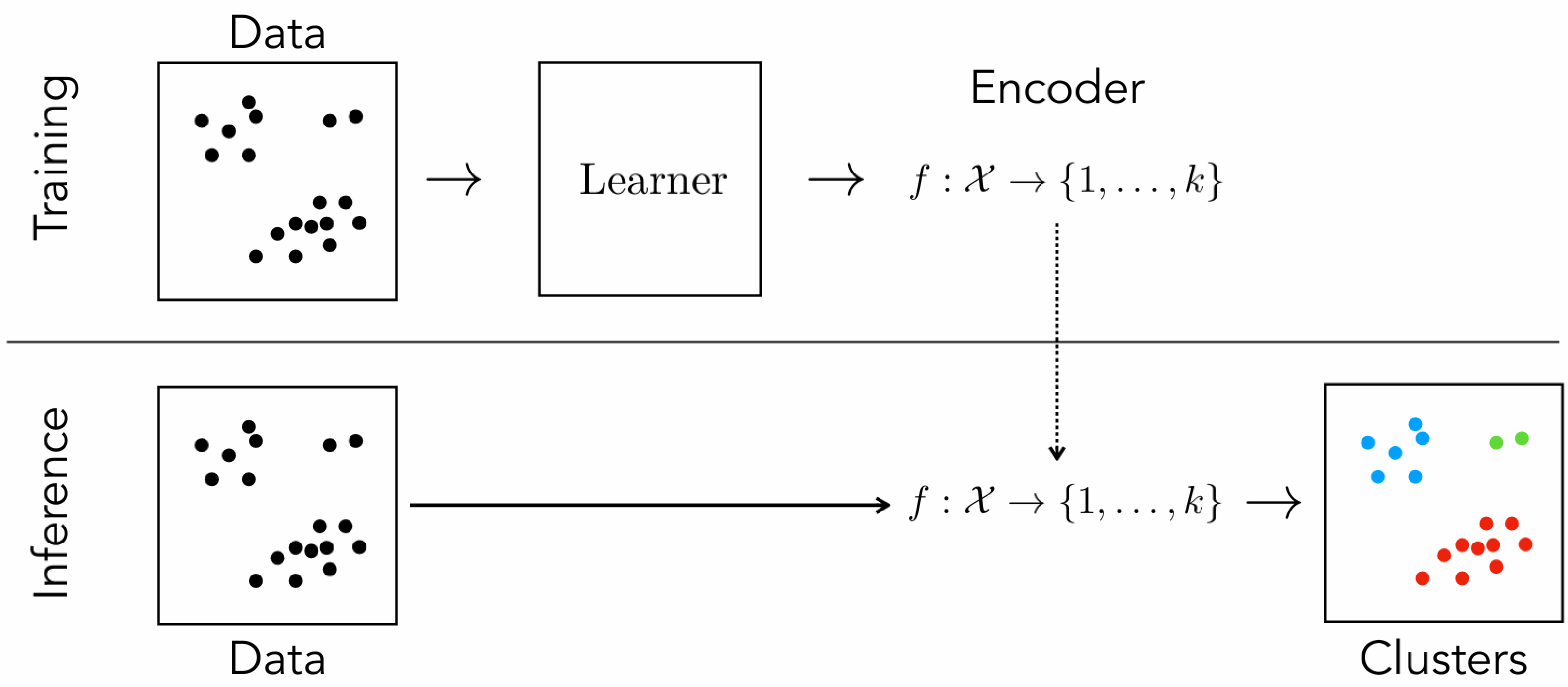
Some examples of the “Compression” Approach:

Recap: Autoencoder



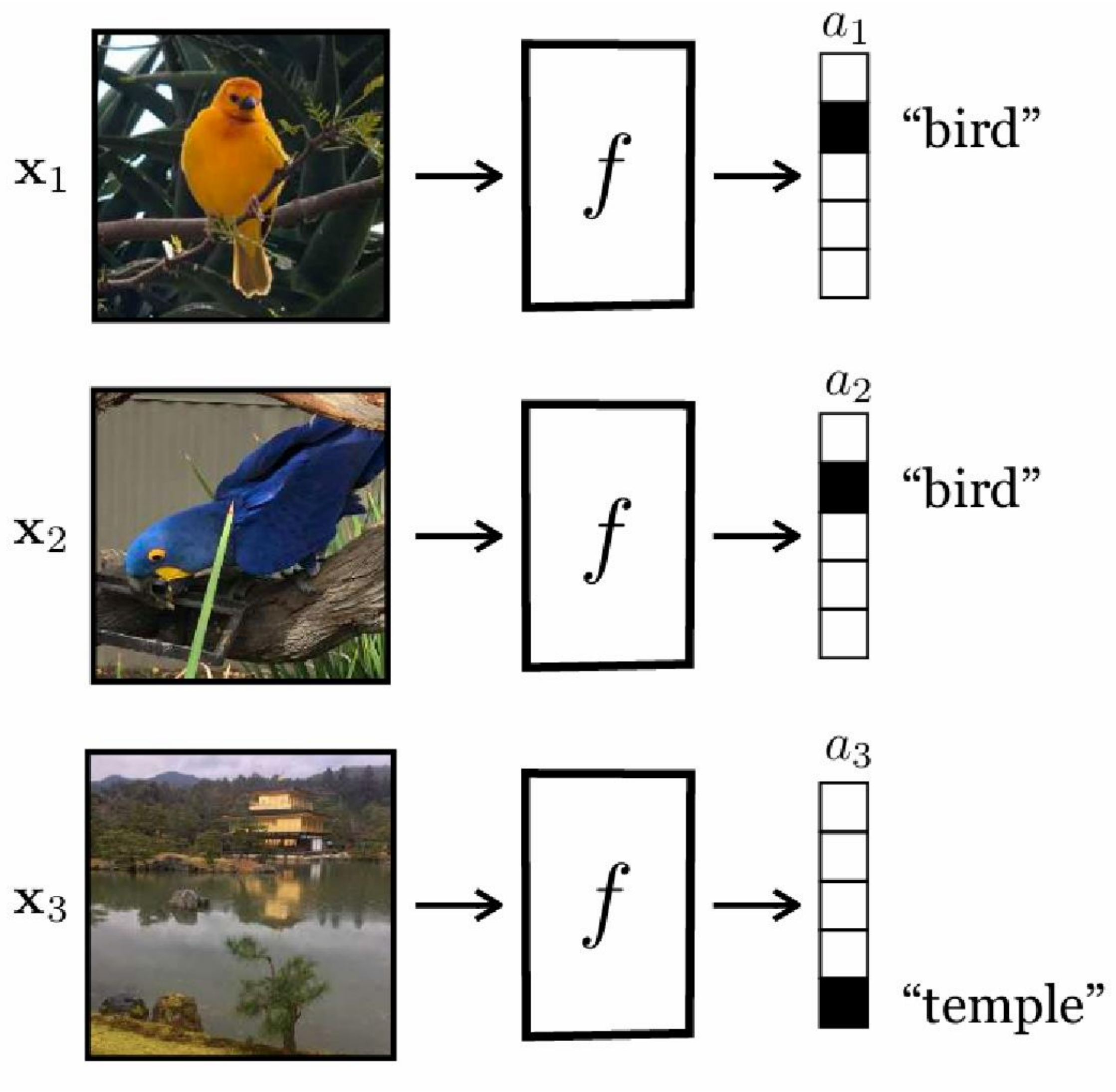
$$f^*, g^* = \arg\min_{f,g} \mathbb{E}_{\mathbf{x}} \|\mathbf{x} - g(f(\mathbf{x}))\|_2^2$$

Clustering



Training
Data
Learner
Encoder
$f : \mathcal{X} \to \{1, \dots, k\}$
Inference
Data
$f : \mathcal{X} \to \{1, \dots, k\}$
Clusters

Clustering

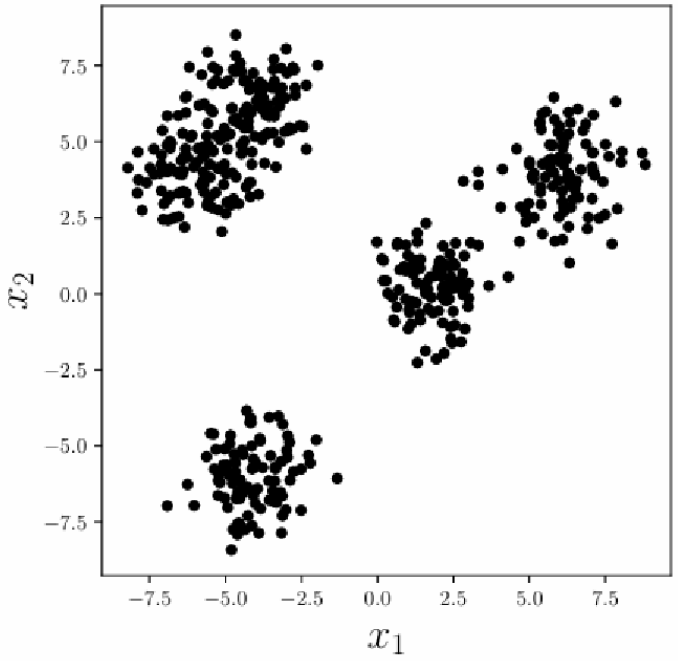


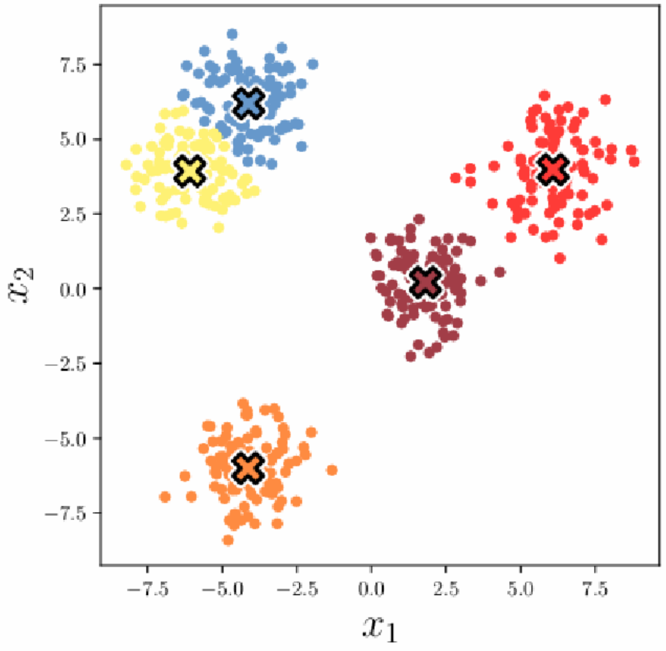
- What's the best representation that humans have come up with so far?
- Language!
- Words are the atoms of language
- Clustering is the problem of making up new words for things

Clustering Algorithm: k-means

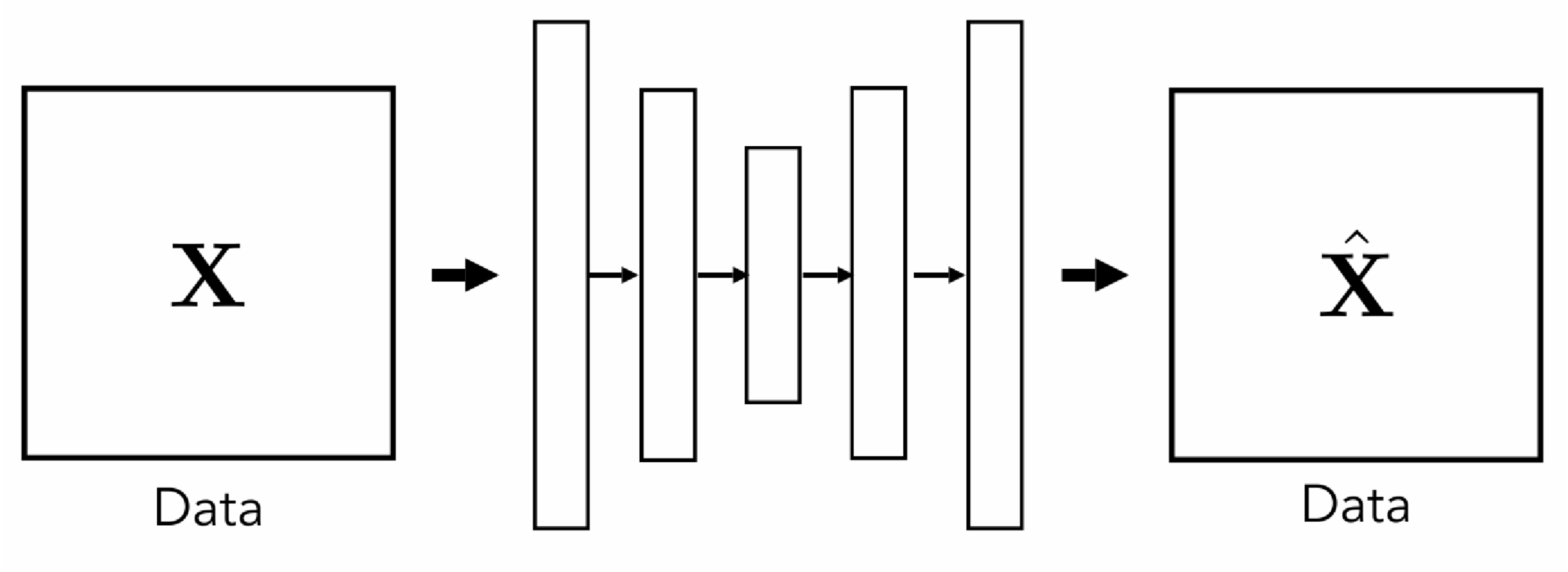
- Map datapoints to integers (i.e. cluster)

- In such a way that each datapoint is as close as possible to the mean of the cluster it is assigned to

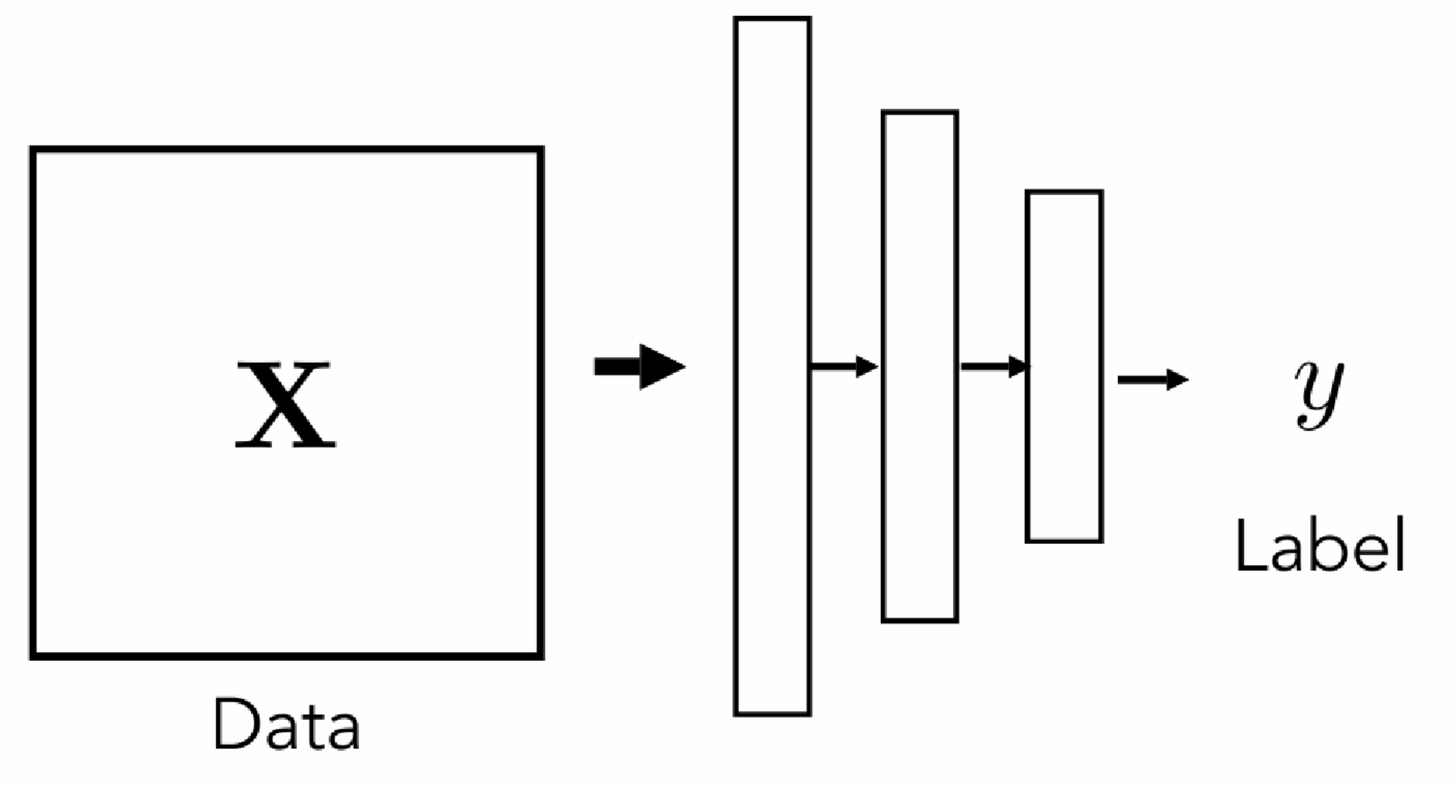




The "Compression" Approach



The "Prediction" Approach for Representation Learning



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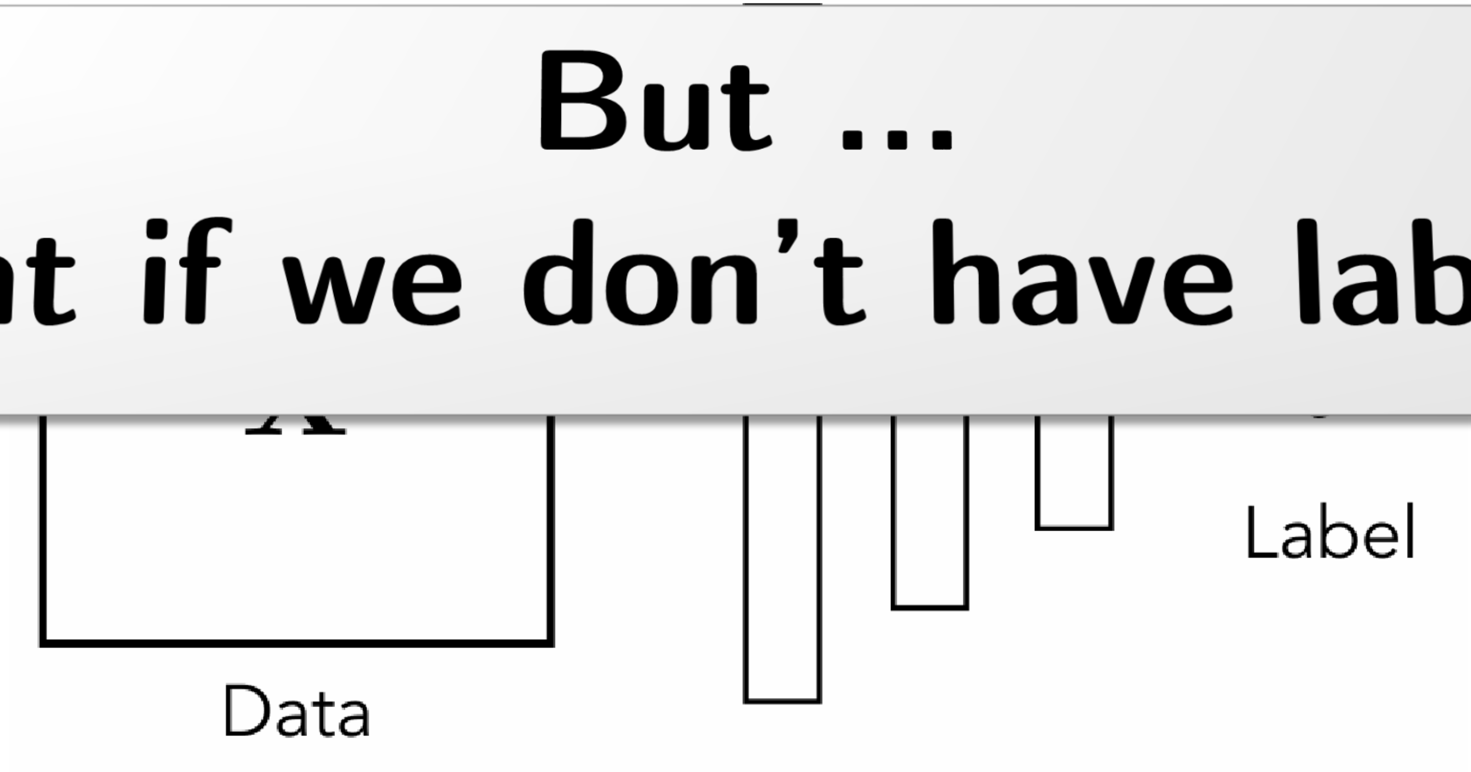
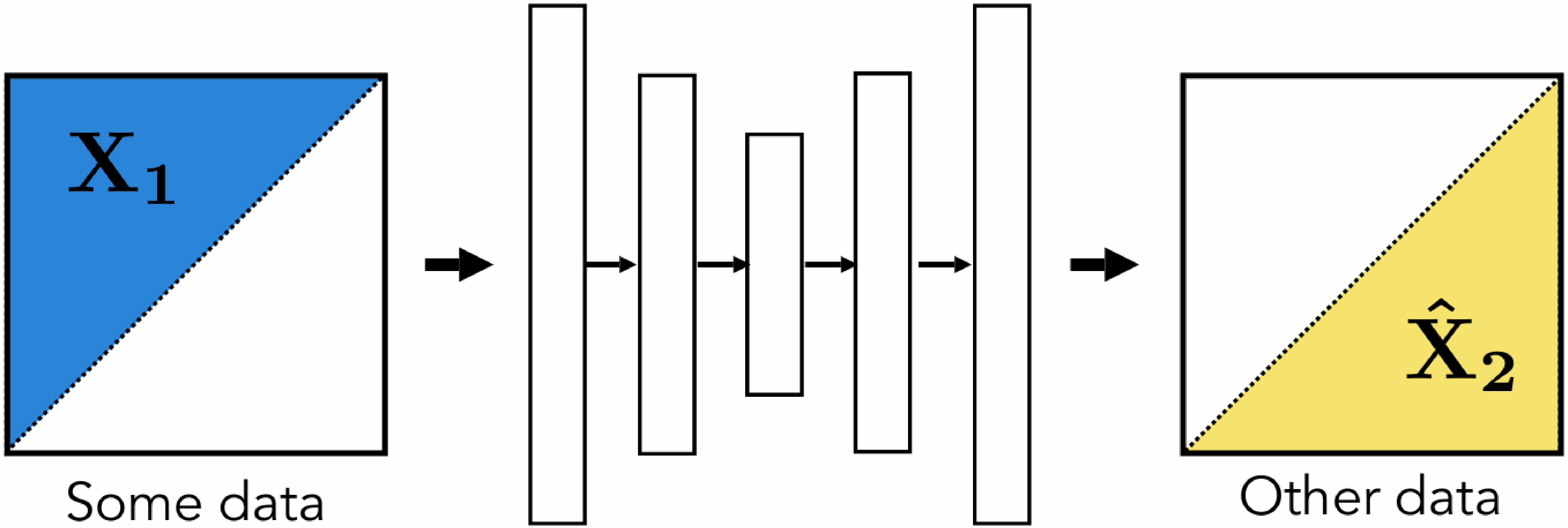


But ...
what if we don't have labels?

Data prediction
aka "self-supervised learning"



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.

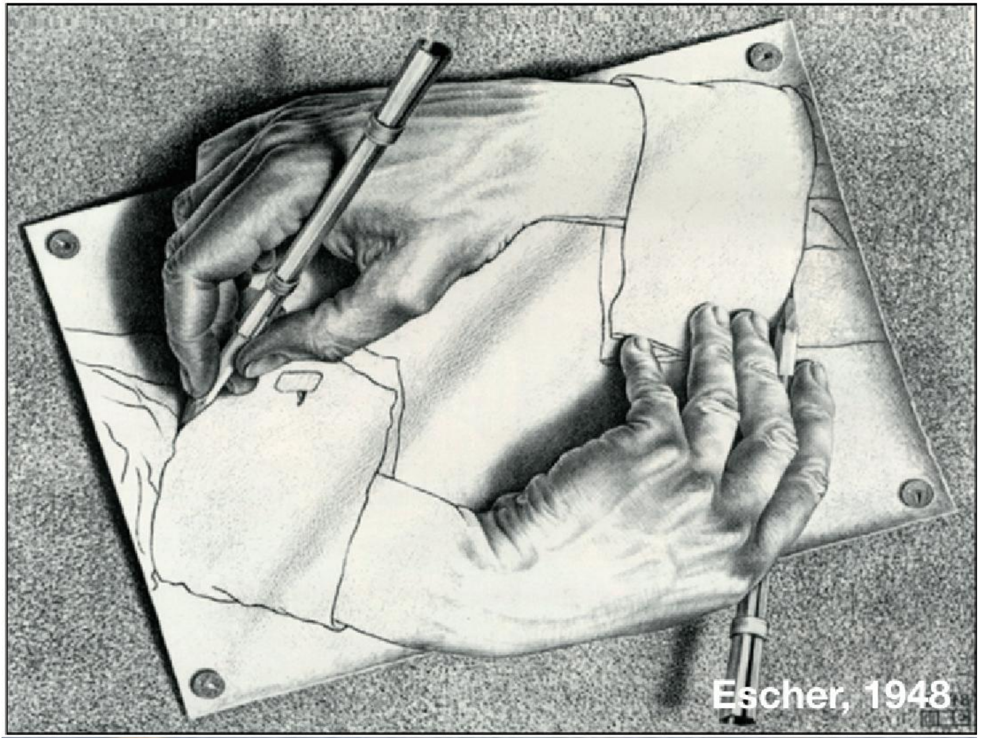
Self-Supervised Learning: A trick

- If you don't have labels, make labels.

- Convert "unsupervised" problem into "supervised"

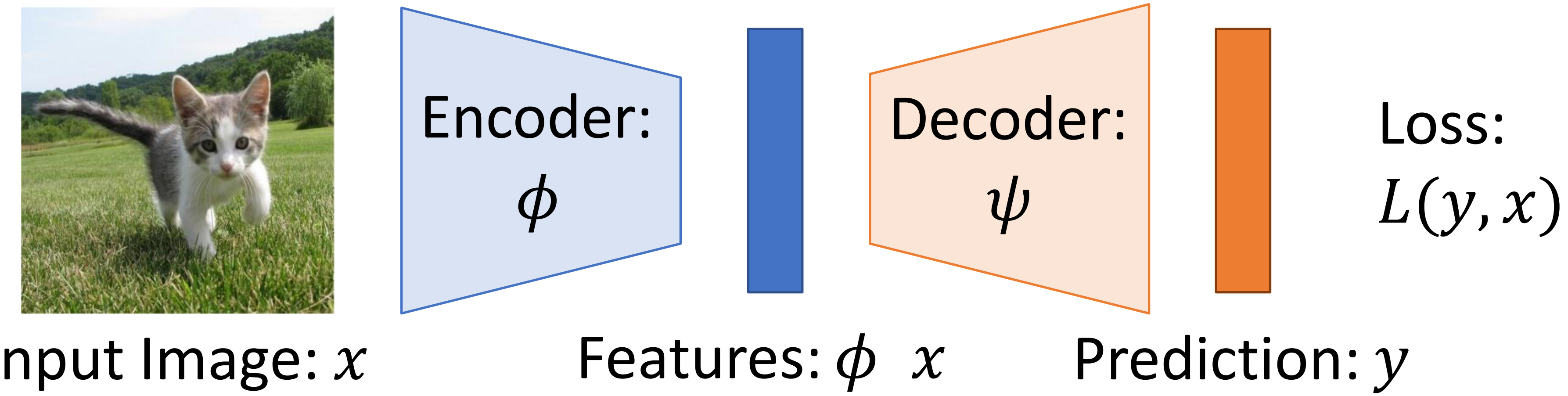
- Cook up labels (prediction targets) from the data itself
  - This is often called a "pretext" task

Claim:
Training a model for "pretext" task can lead to very good representations

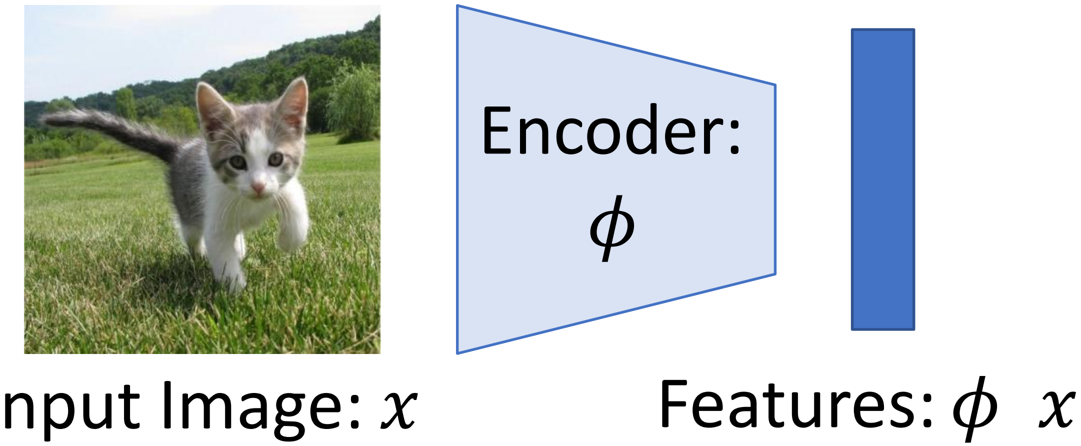


SSL: "Pretext then transfer"

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

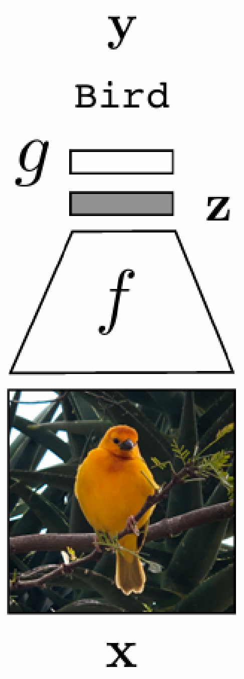
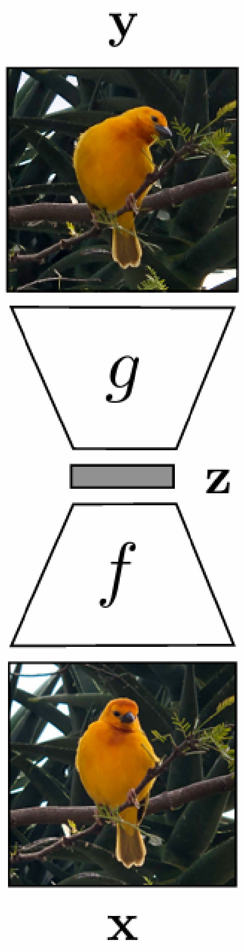
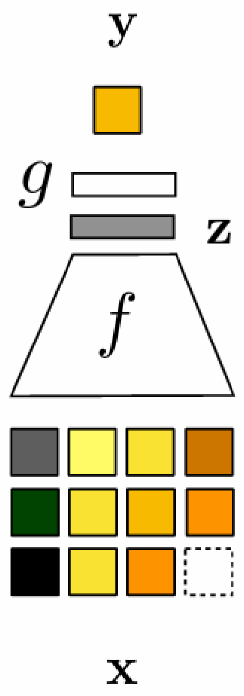


Step 2: Transfer encoder to downstream tasks via linear classifiers, KNN, finetuning



Downstream tasks: Image classification, object detection, semantic segmentation

Some Examples of Pretext Tasks

Pretext task:	Class prediction	Future frame prediction	Next pixel prediction
Model schematic:			

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:

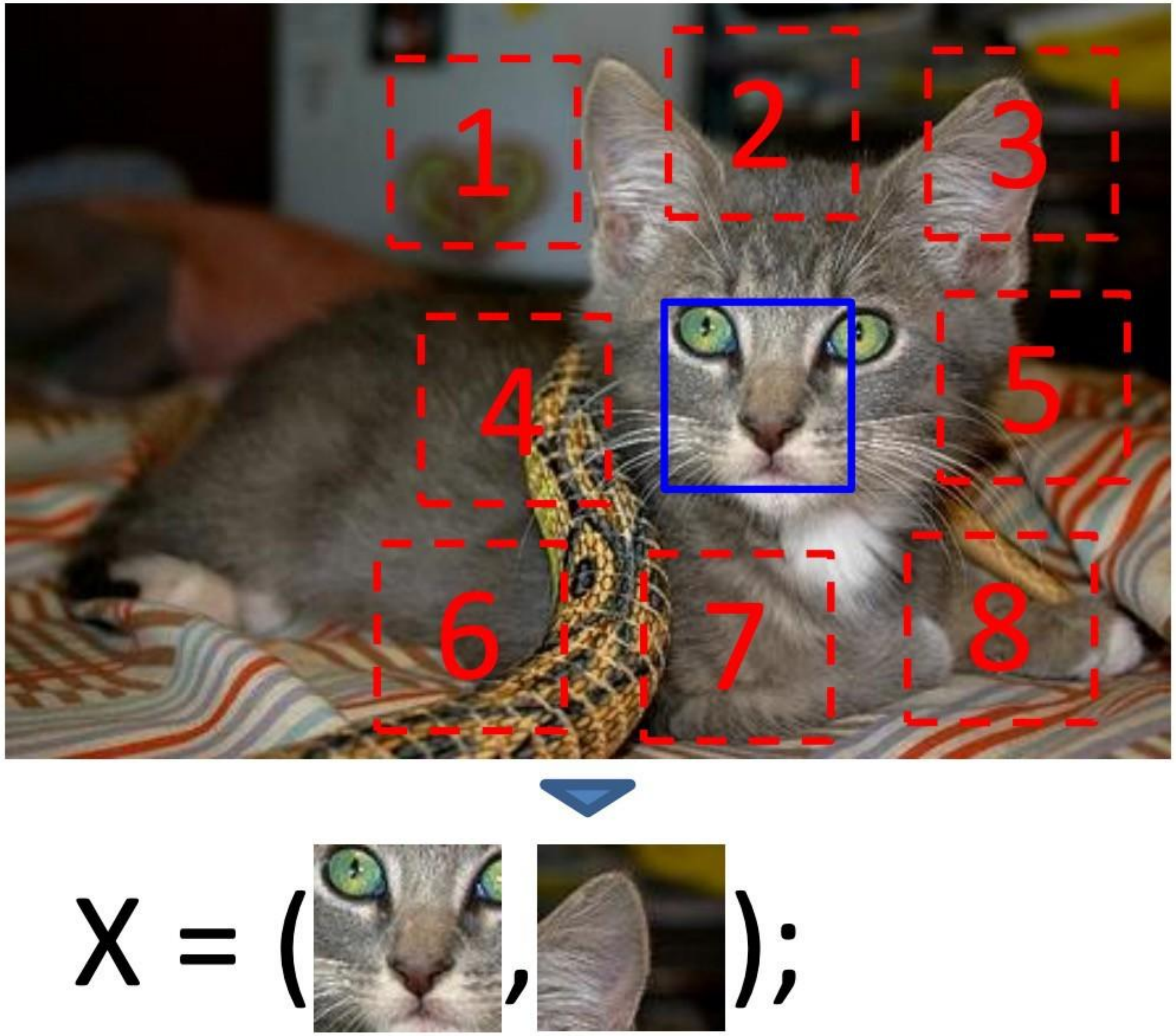
Use some signal in addition to RGB images

- Video
- 3D
- Sound
- Language

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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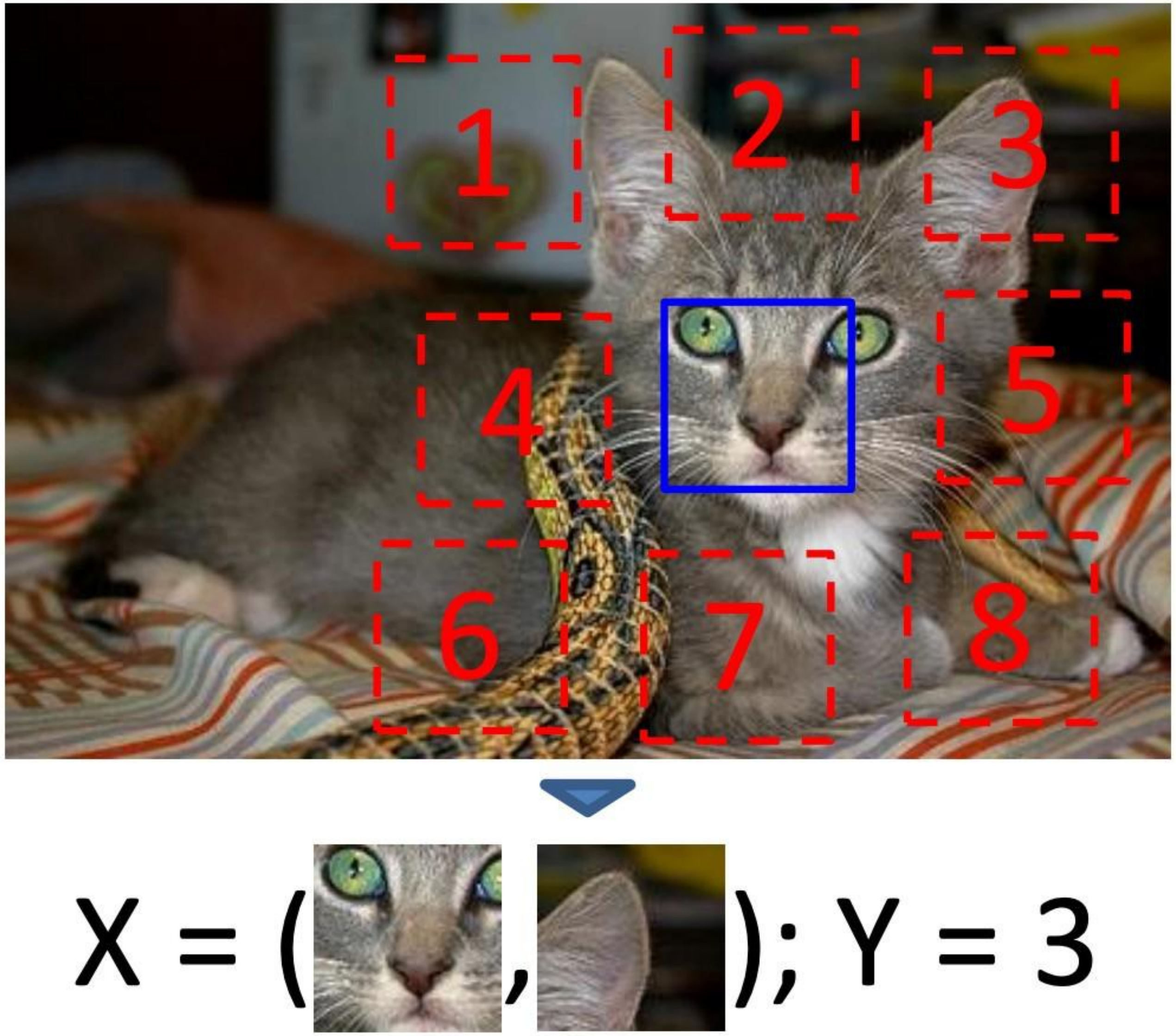

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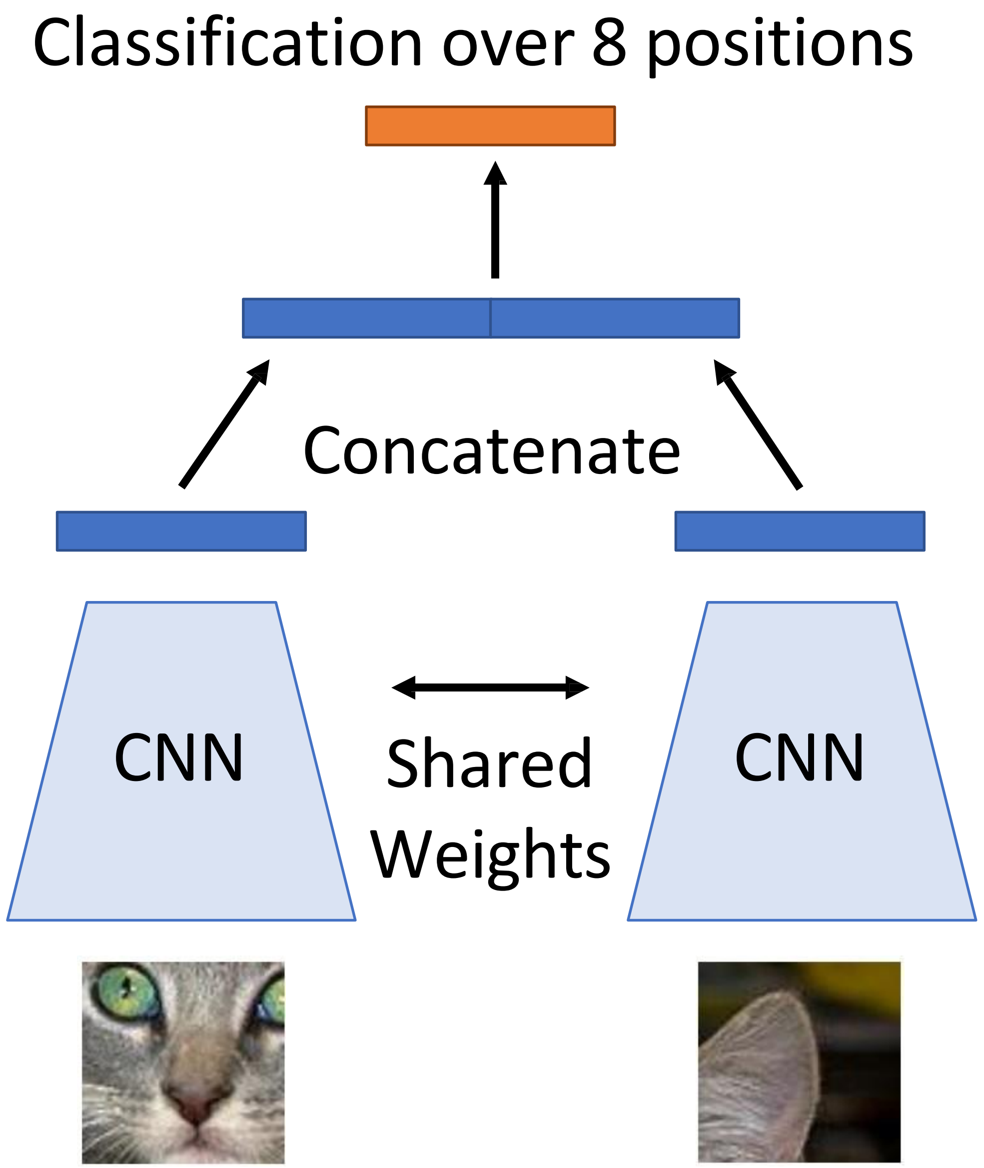

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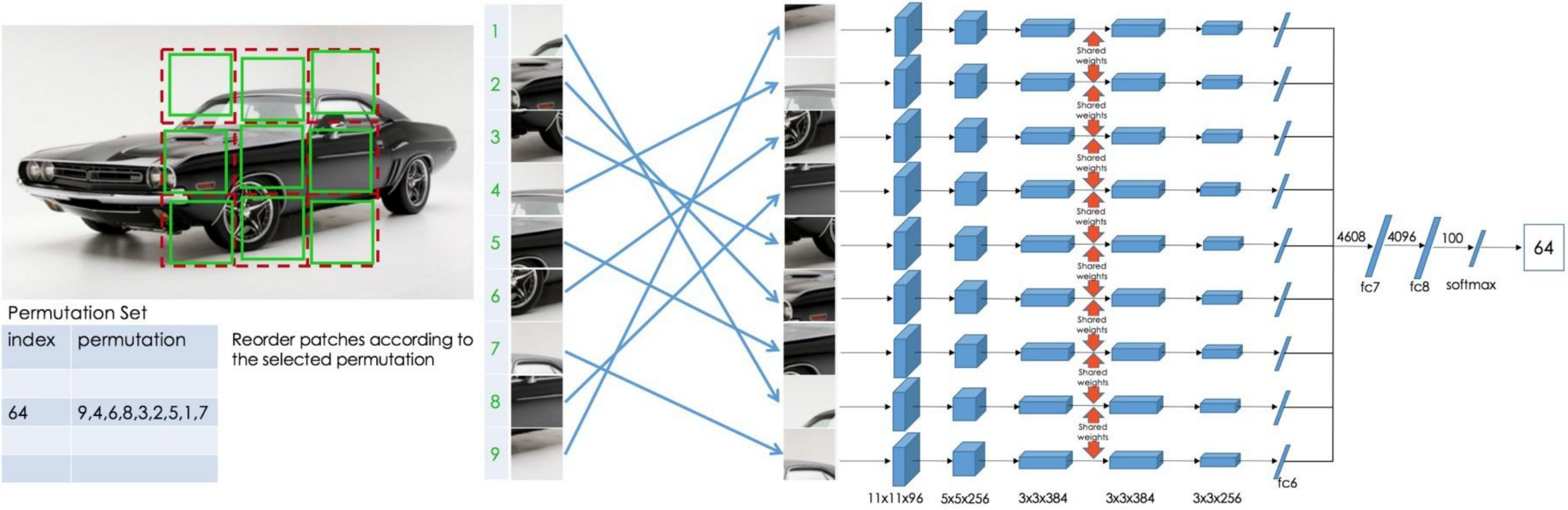
Extension: Solving Jigsaw Puzzles

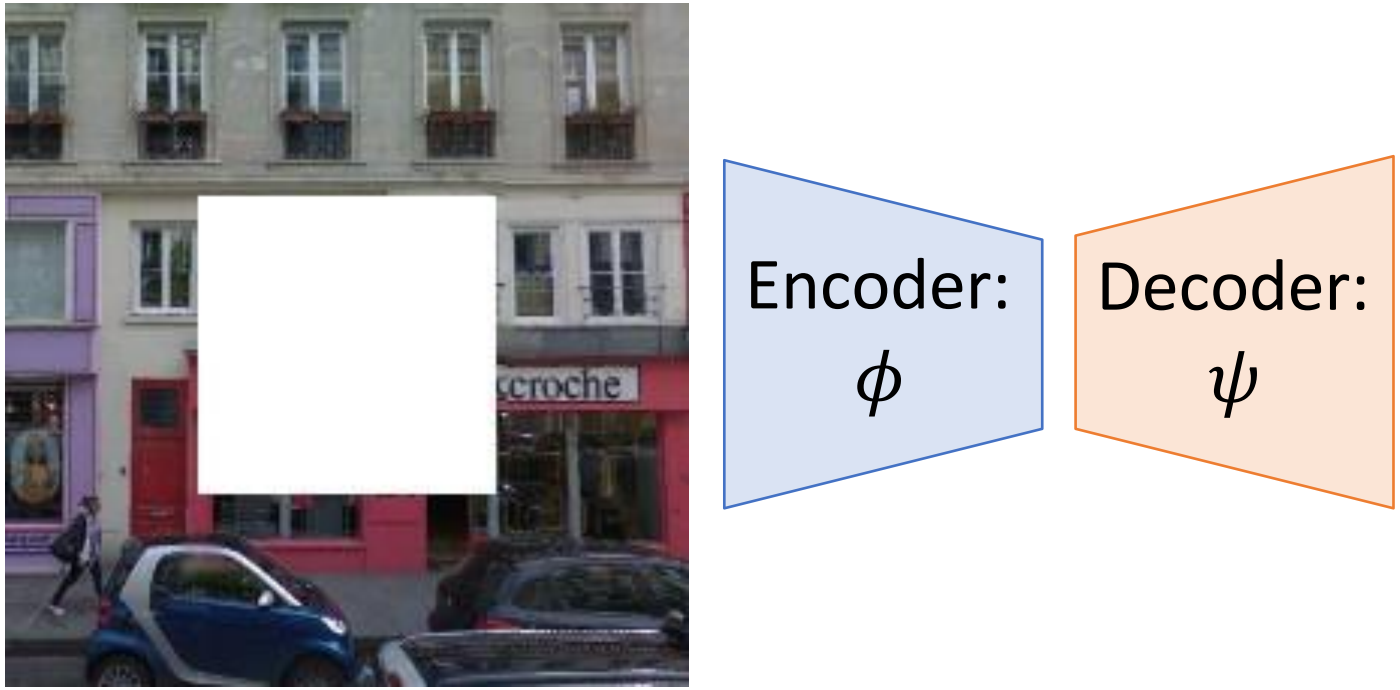
Rather than predict relative position of two patches, instead predict permutation to "unscramble" 9 shuffled patches



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

Context Encoders: Learning by Inpainting

Input Image

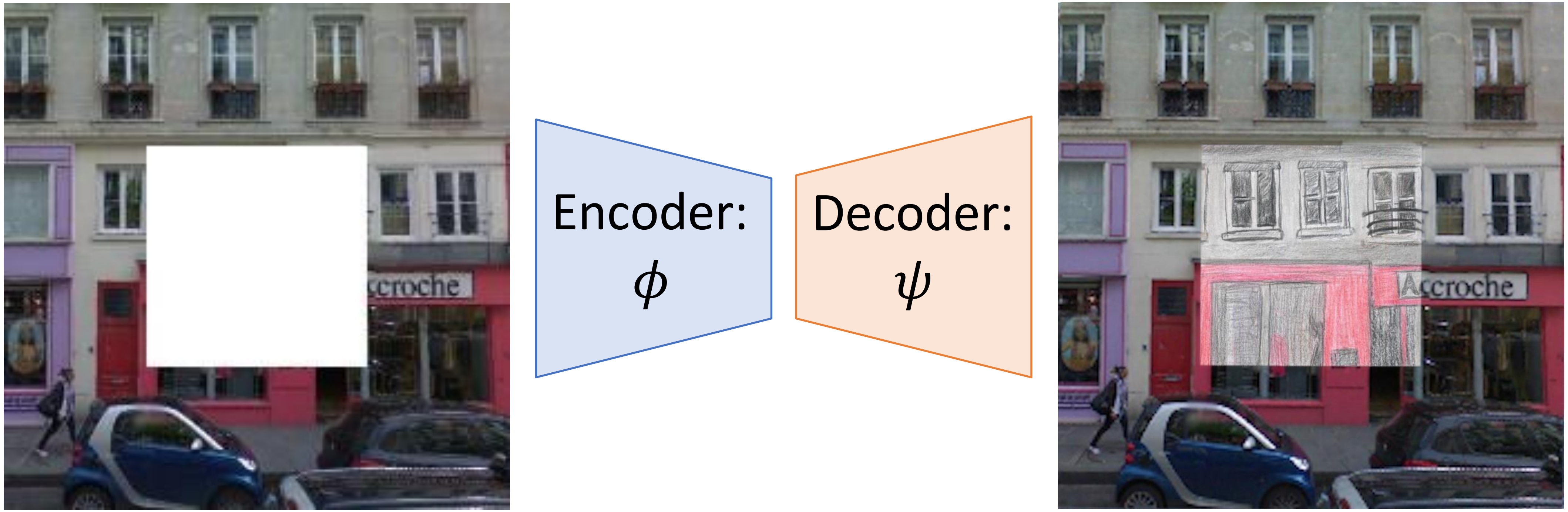


Pathak et al, “Context Encoders: Feature Learning by Inpainting”, CVPR 2016

Context Encoders: Learning by Inpainting

Input Image

Predict Missing Pixels

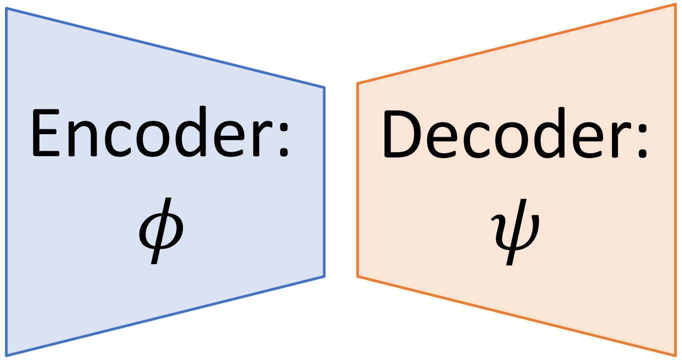


Human Artist

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

Context Encoders: Learning by Inpainting

Input Image



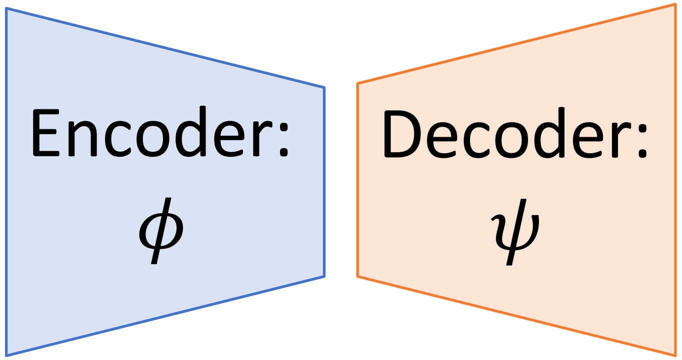
Predict Missing Pixels

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

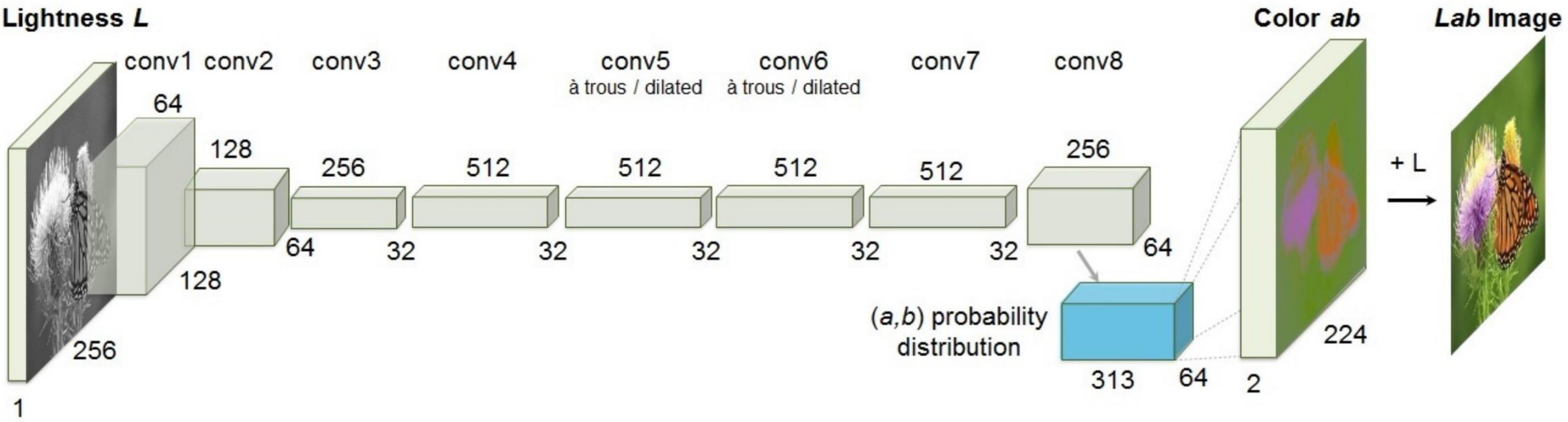
Intuition: A model must be able to identify objects to be able to colorize them

Input: Grayscale Image

Output: Color Image

Zhang et al, “Colorful Image Colorization”, ECCV 2016

Colorization



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

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

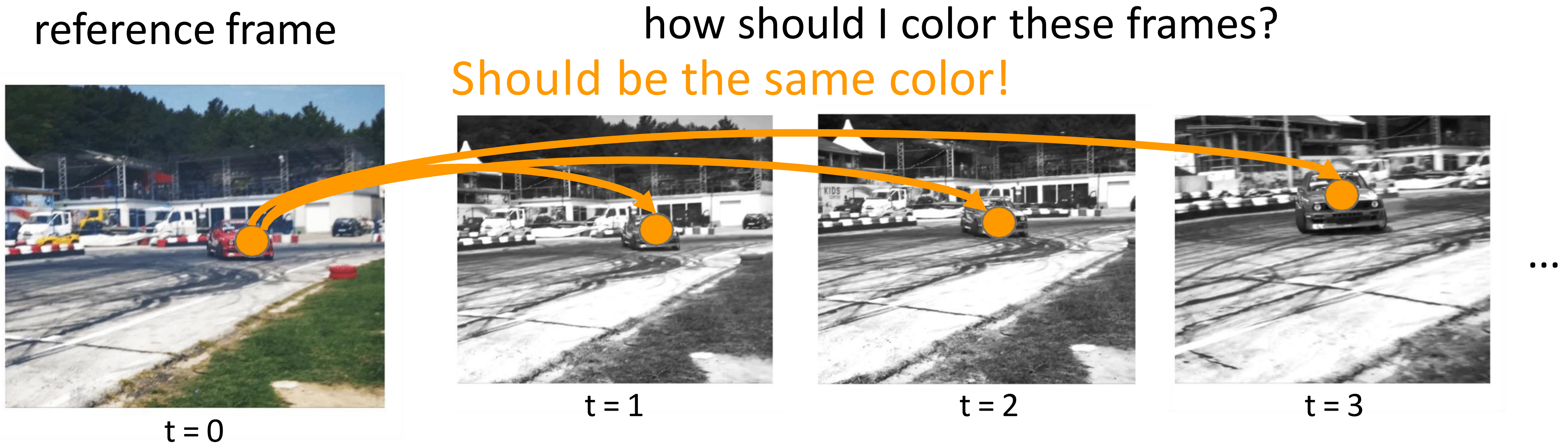
t = 3

...

Source: Vondrick et al., 2018

Pretext task: video coloring

Idea: model the temporal coherence of colors in videos

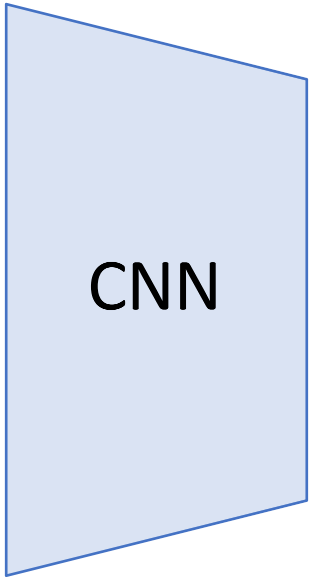


Hypothesis: learning to color video frames should allow model to learn to track regions or objects without labels!

Source: [Vondrick et al., 2018]

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
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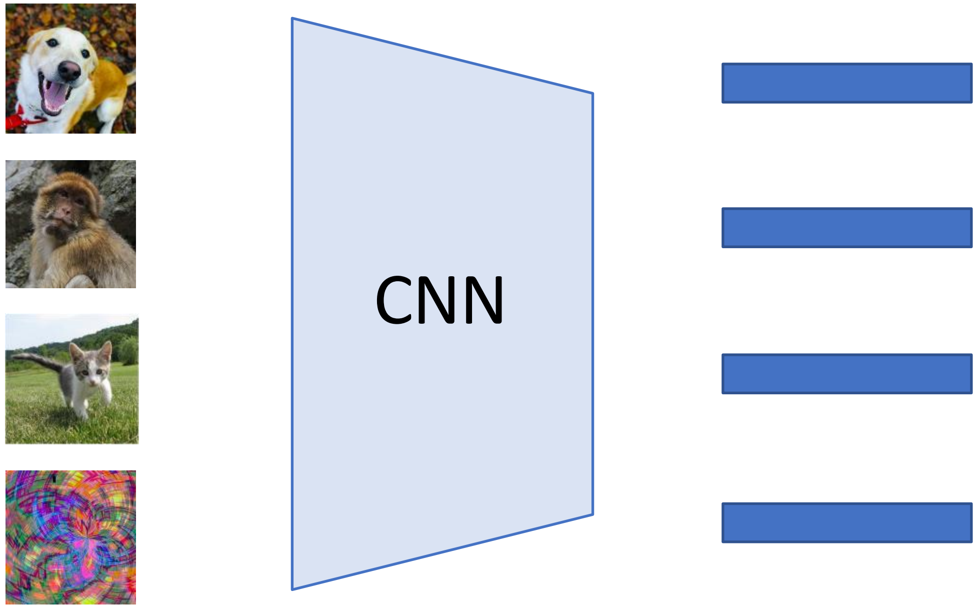

(2) Run many images through CNN, get their final-layer features

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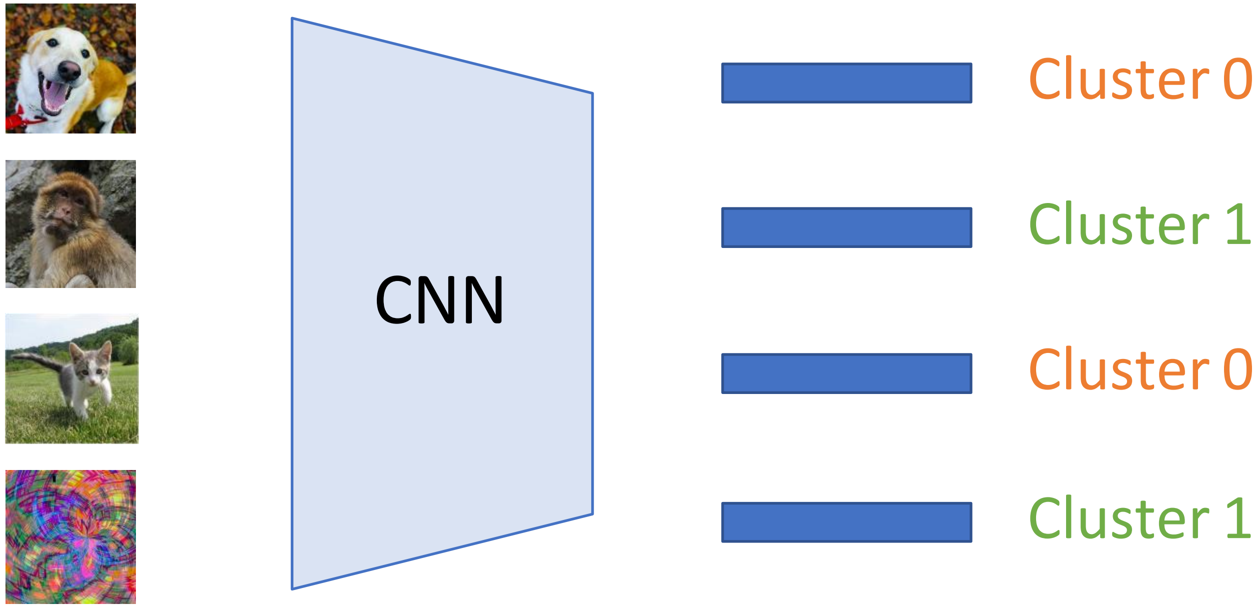

(3) Cluster the features with K-Means; record cluster for each feature

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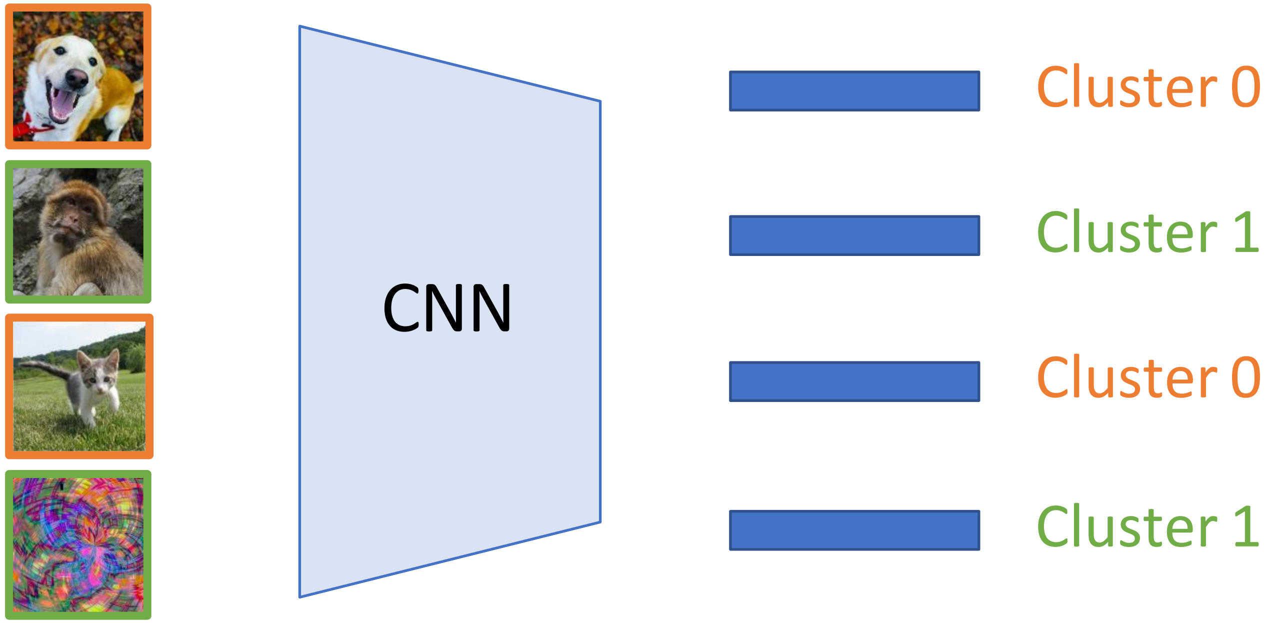

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(4) Use cluster assignments as pseudo-labels for each image; train the CNN to predict cluster assignments

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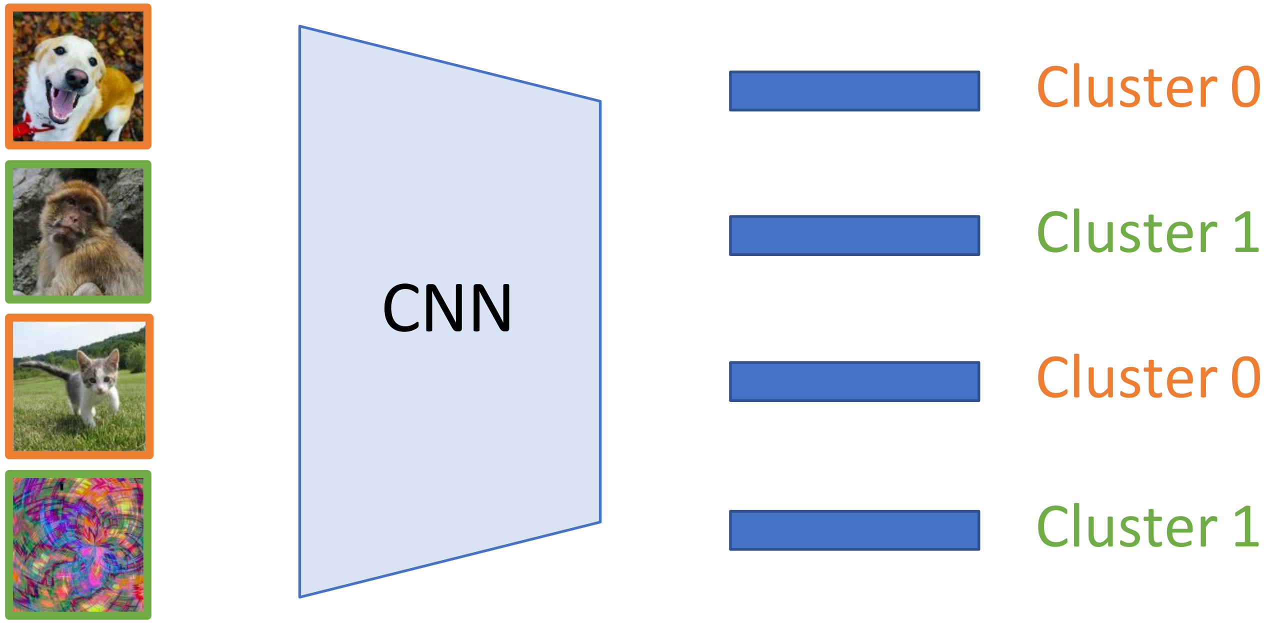

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(5) Repeat: GOTO (2)

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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

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

90

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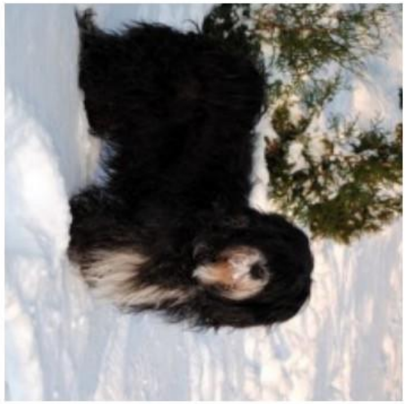
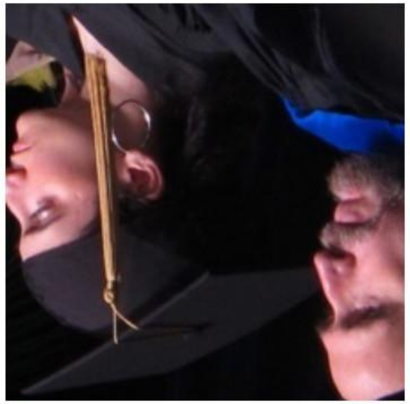


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Summary: pretext tasks via image transformations

- 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 via image transformations

- 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 !!!

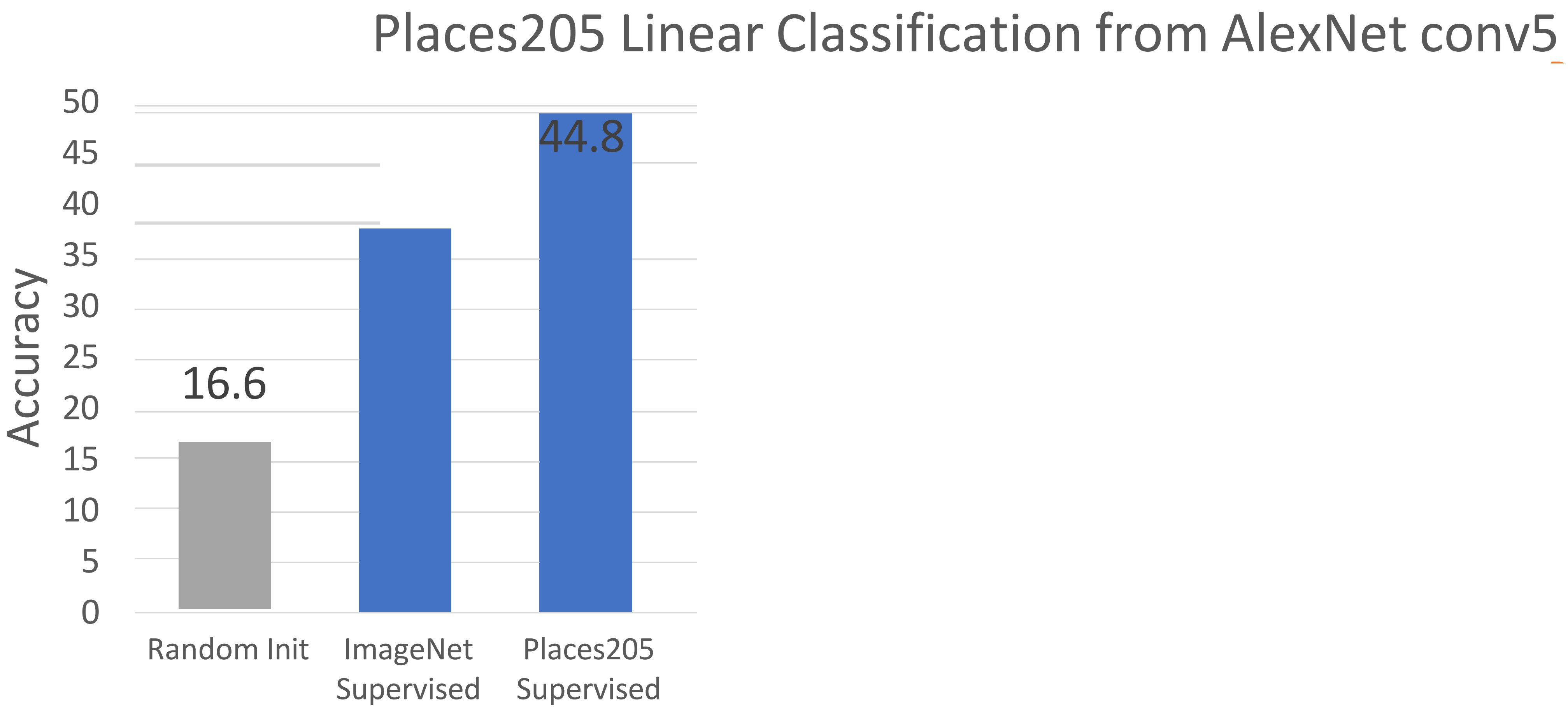
Many choices in experimental setup, huge variations from paper to paper:

- 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



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

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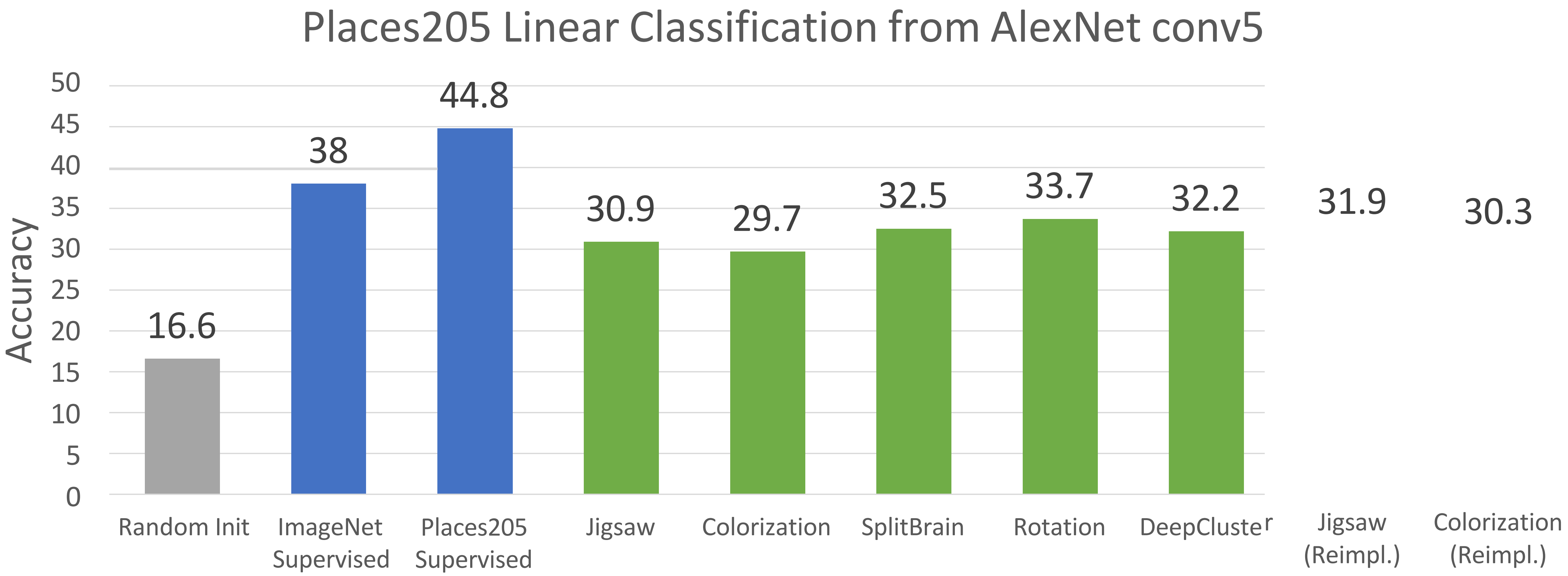

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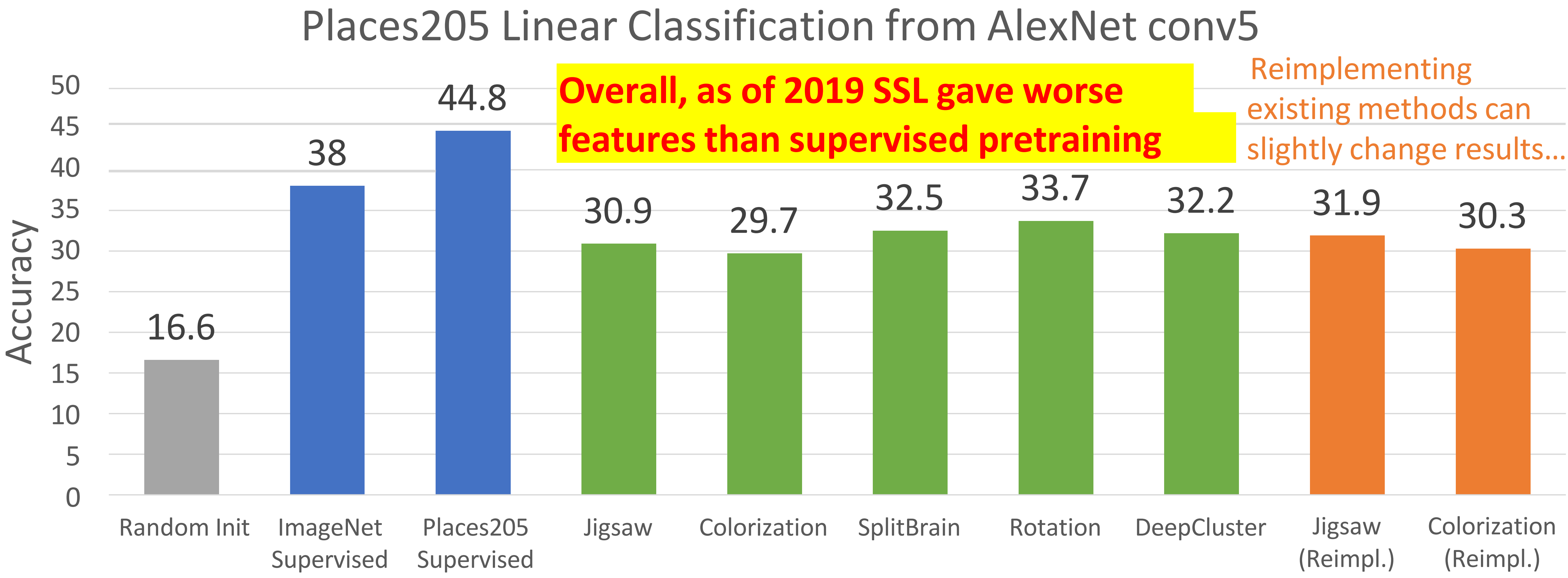

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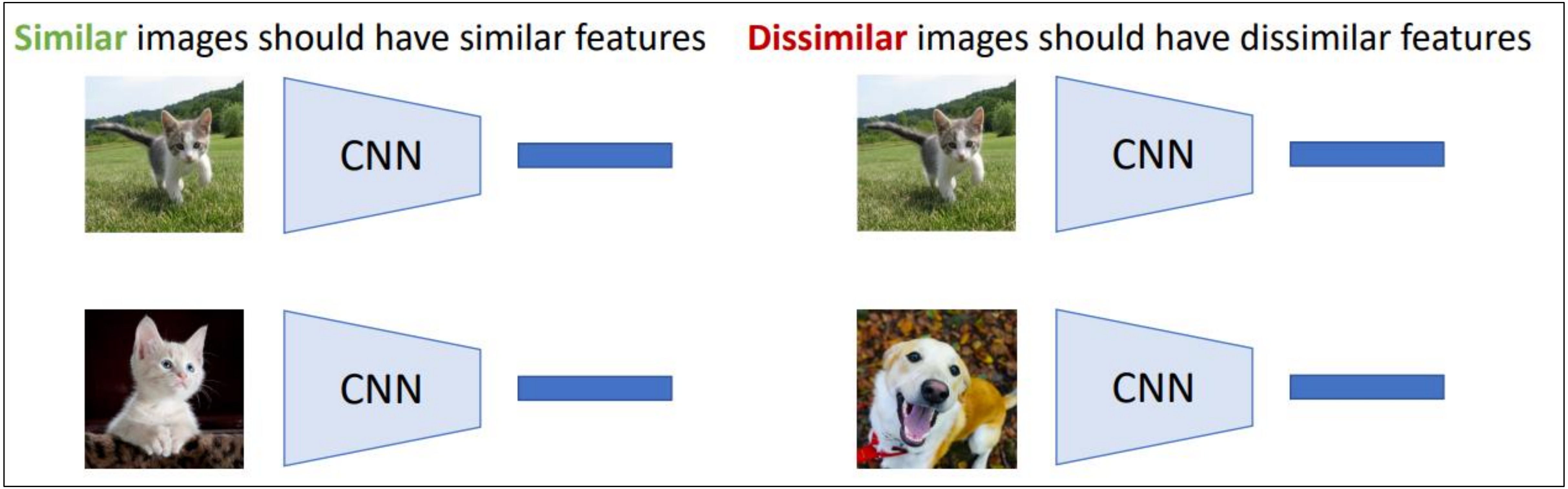
Let's take a step back ...

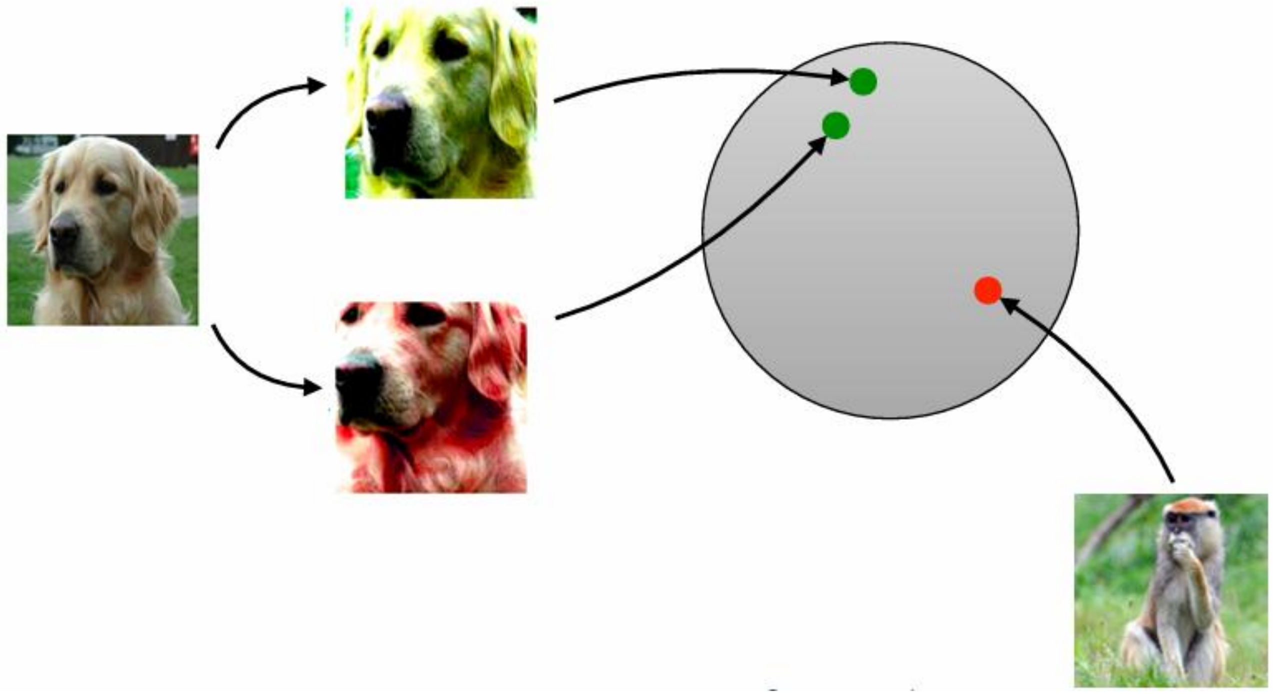
A simpler idea ...



Similarity based Representation Learning

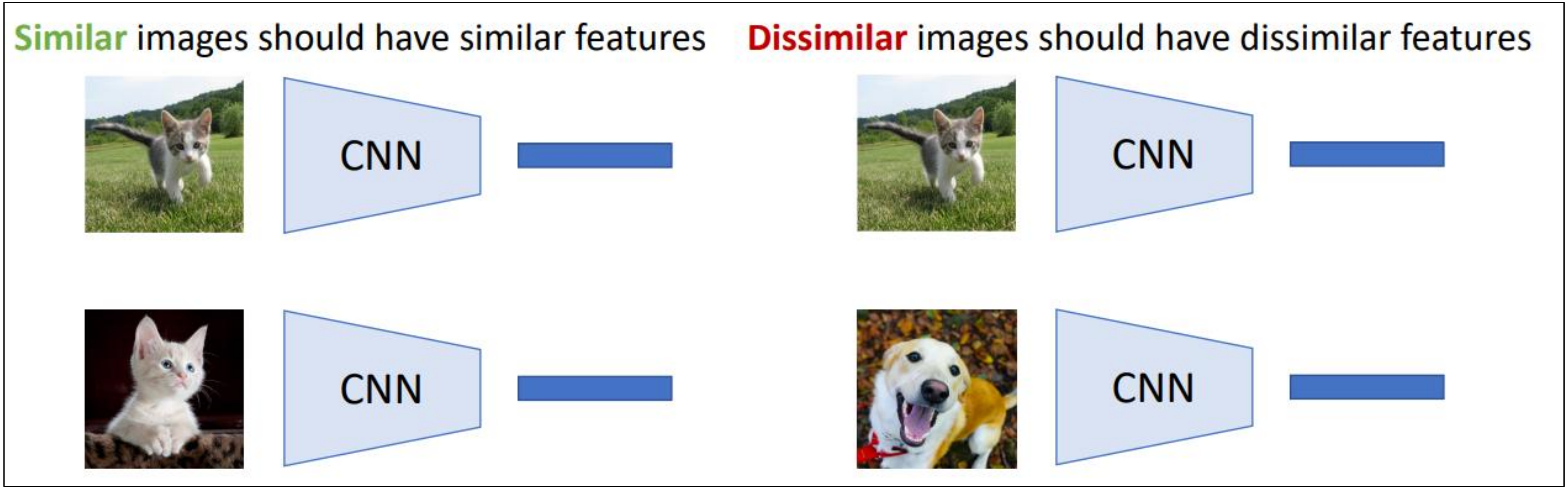
- Build representations via feedback in terms of similarity:

  pairs of similar / dissimilar inputs



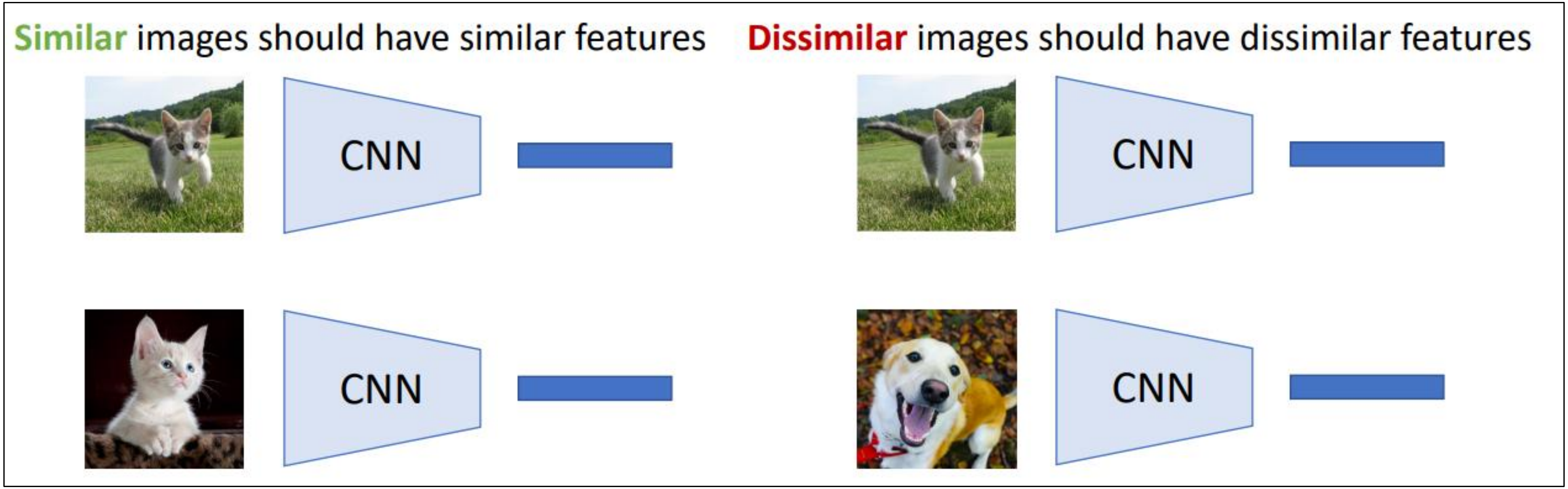
Contrastive Learning

Problem 1: How to compute similarity if we don't have labels for images?



Contrastive Learning

Problem 1: How to compute similarity if we don't have labels for images?
Solution? Euclidean Distance between features $\|\phi(x_1) - \phi(x_2)\|_2$



Contrastive Learning

Problem 1: How to compute similarity if we don't have labels for images?
Solution? Euclidean Distance between features $\|\phi(x_1) - \phi(x_2)\|_2$

Problem 2: Objective Function ?

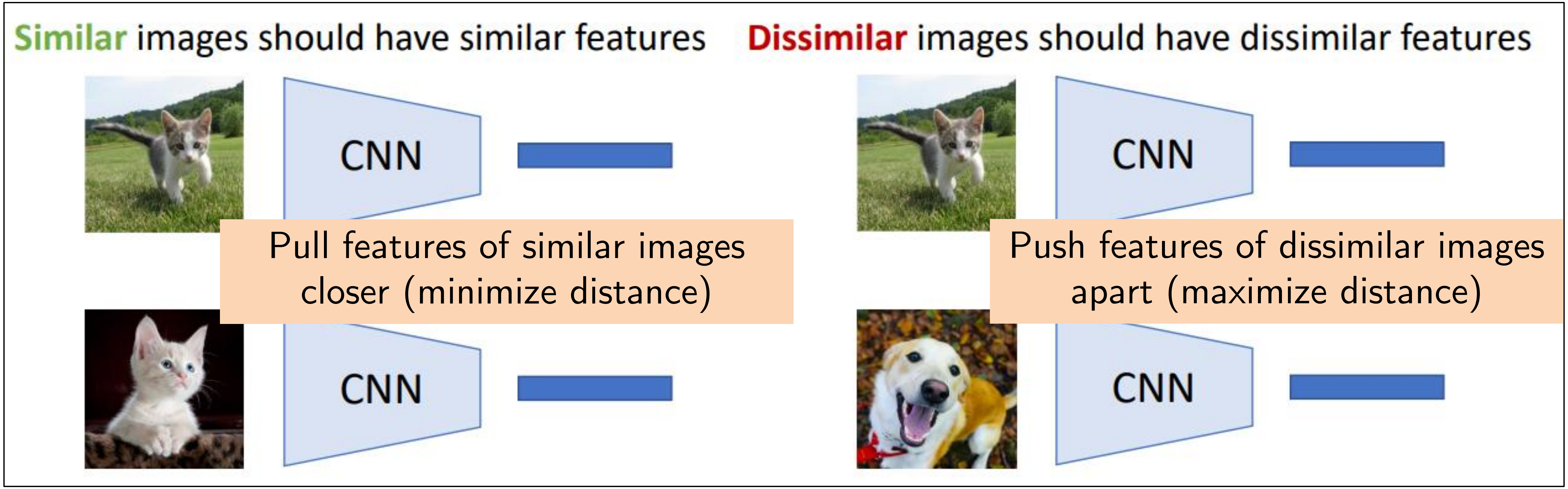
Similar images should have similar features

Dissimilar images should have dissimilar features

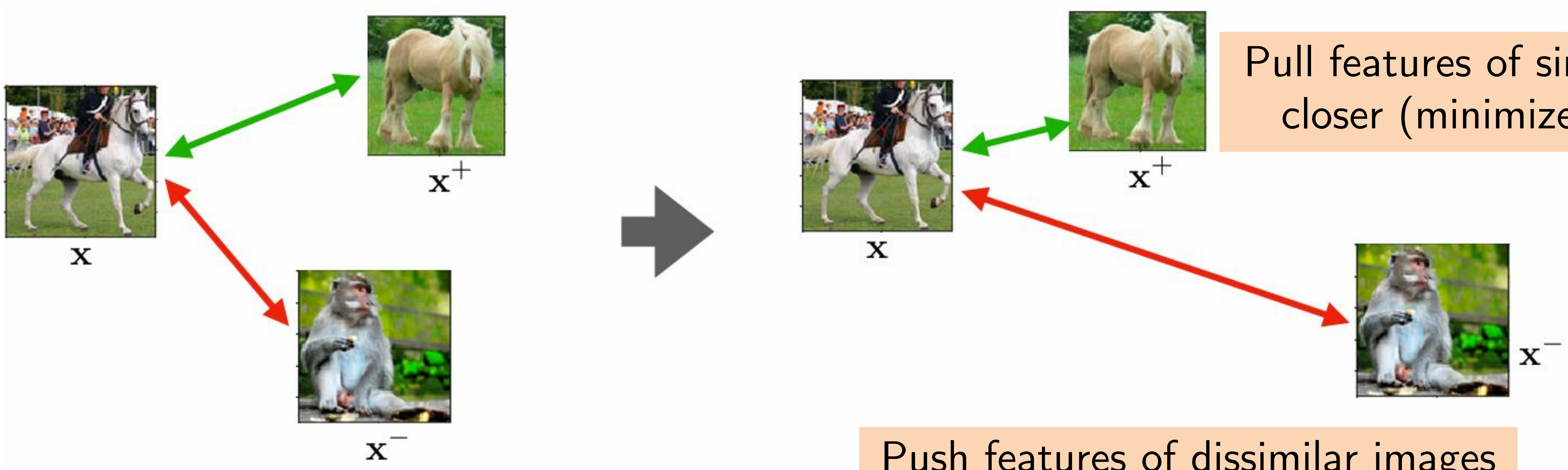
Contrastive Learning

Problem 1:	How to compute similarity if we don't have labels for images?
Solution?	Euclidean Distance between features $\|\phi(x_1) - \phi(x_2)\|_2$

Problem 2:	Objective Function ?



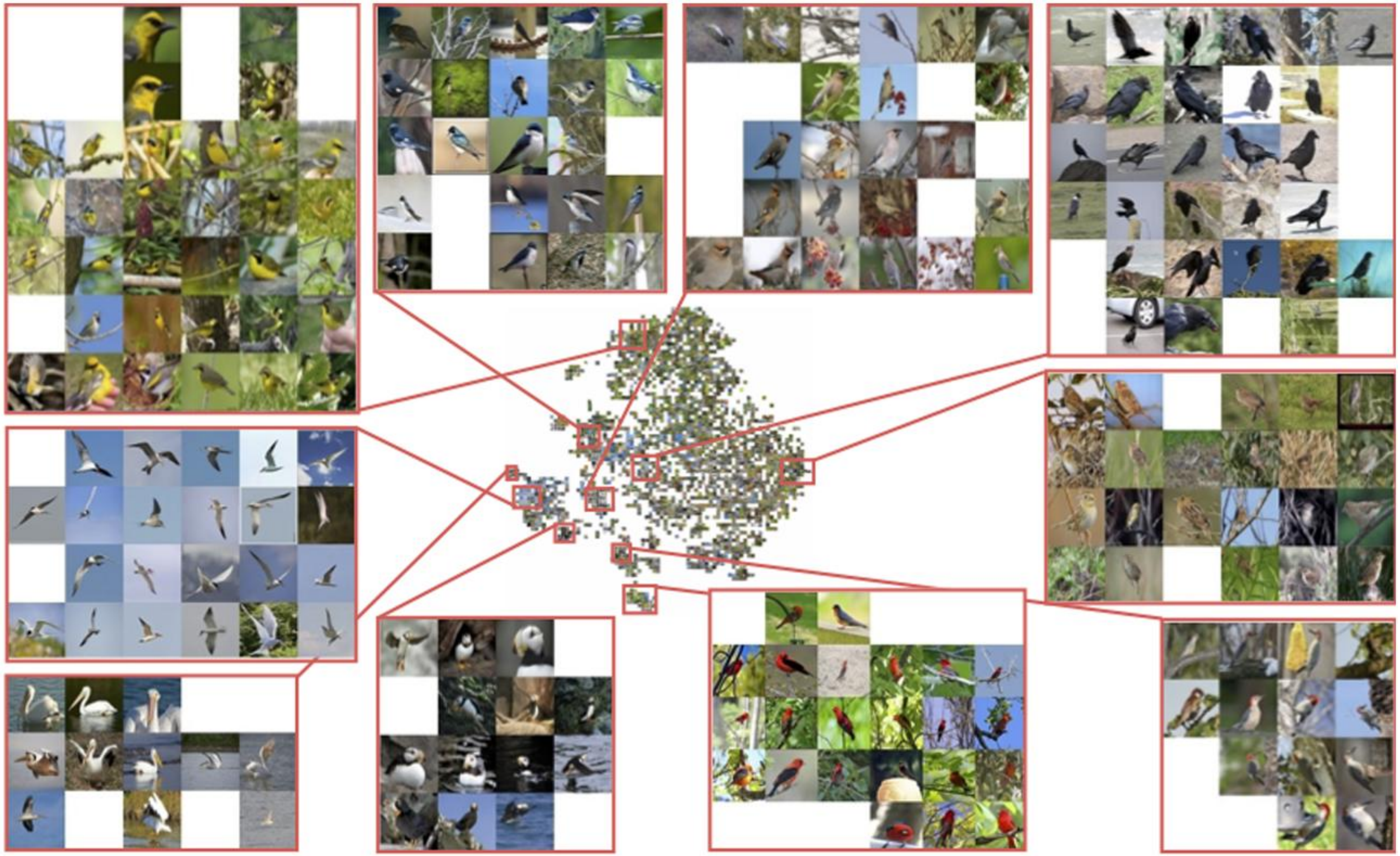
Examples of Contrastive Pairs



Pull features of similar images closer (minimize distance)

Push features of dissimilar images apart (maximize distance)

Examples of the Embedding Space



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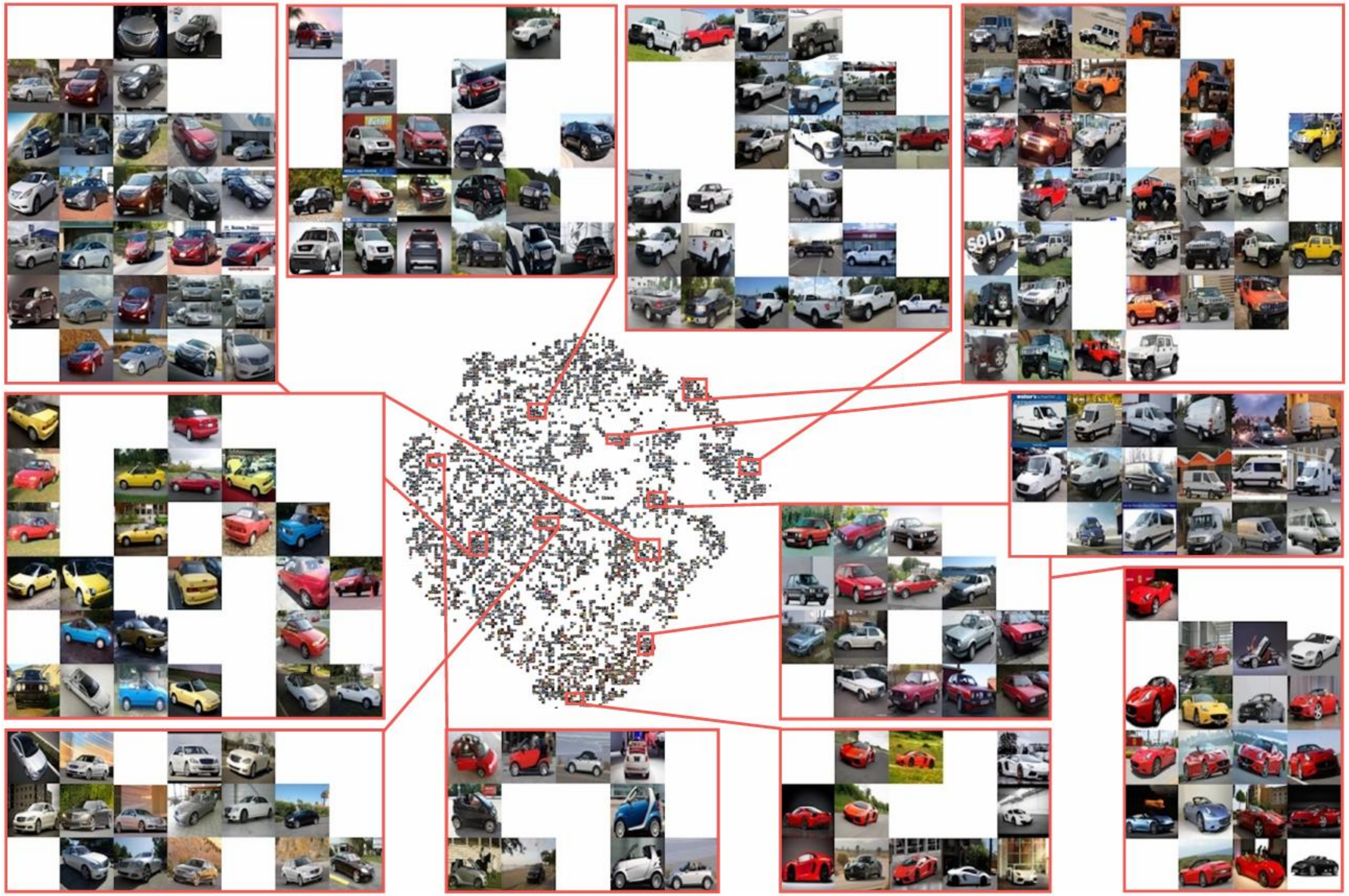
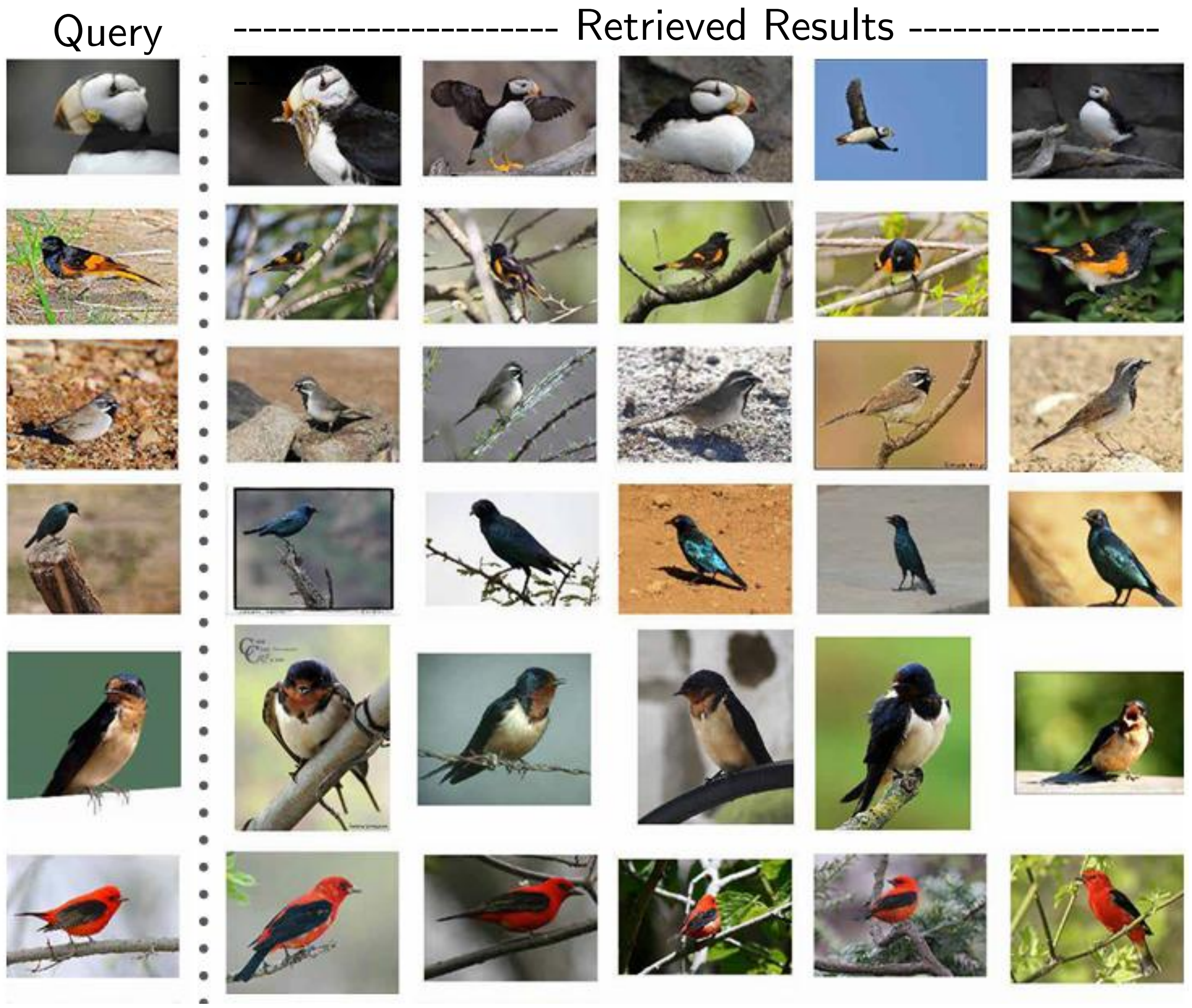


What can you do with this embedding space?

What can you do with this embedding space?

RETRIEVAL

- Given a query image (left column), find similar images
- All you have to do is find the nearest neighbors in the embedding space and return the results
- Embedding space now has a notion of "similarity"
  - Similar datapoints are neighbors
  - Dissimilar datapoints are not



results from Song et al. CVPR 2016

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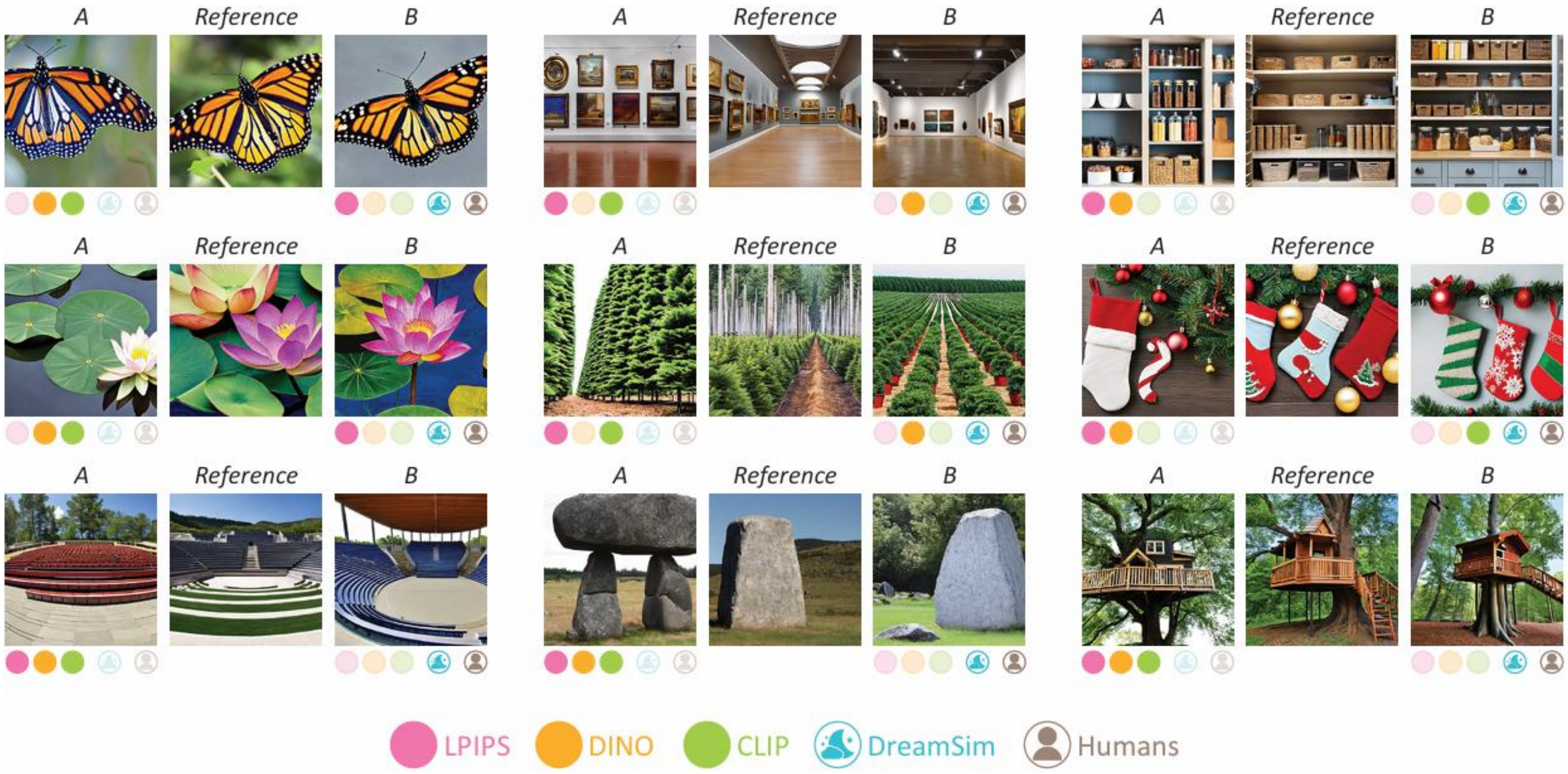
Figure 1: Example retrieval results on our *Online Products* dataset using the proposed embedding. The images in the first column are the query images.

results from Song et al. CVPR 2016

Challenges: “Similarity” is hard …
What makes an image “similar” ?



Similar in:

- Pose
- Perspective
- Foreground color
- Number of items
- Object shape

figure: Fu*, Tamir*, Sundaram* et al 2023

Where can we get pairs of similar and dissimilar images from?

Where can we get pairs of similar and dissimilar images from?

DATA AUGMENTATION

Contrastive Learning with Data Augmentation

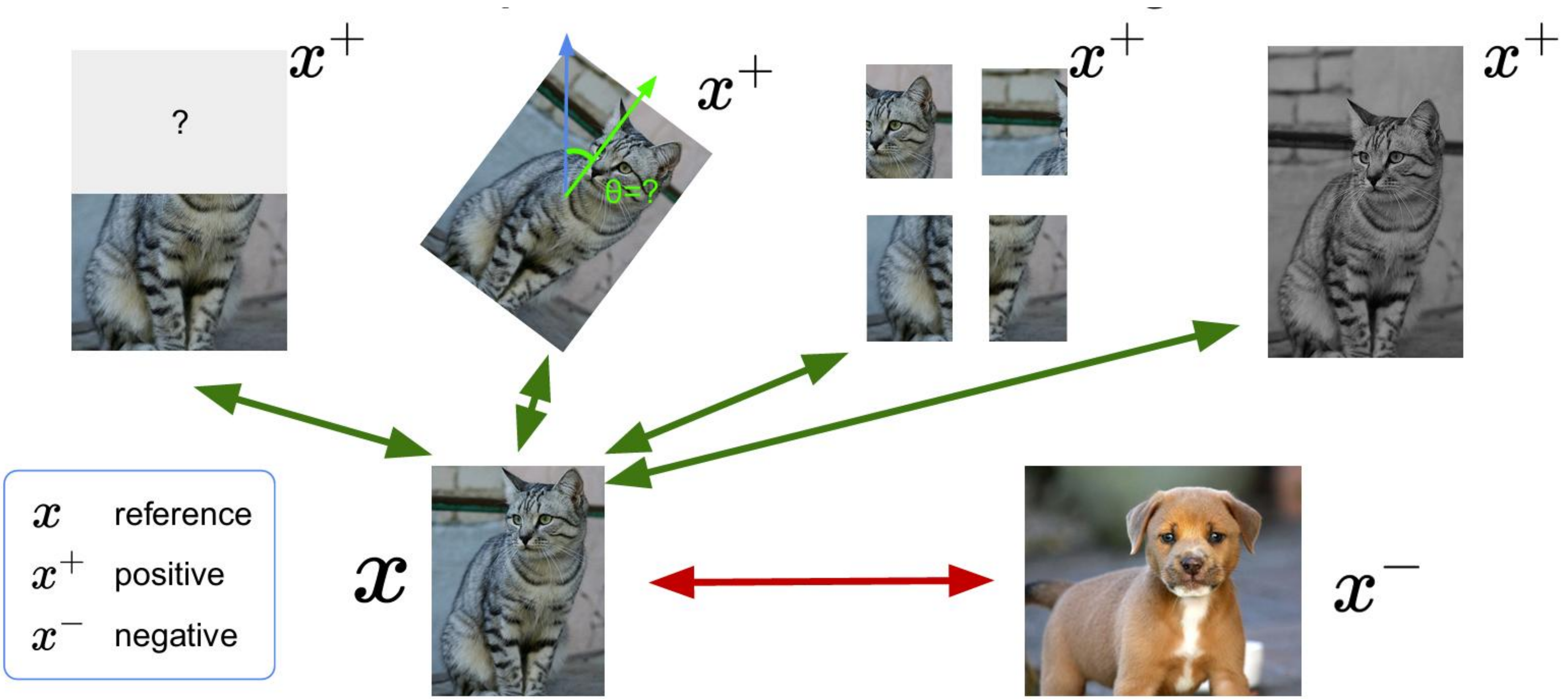


figure: Ranjay Krishna

Contrastive Learning Formulation

- We want:

$$\text{score}(f(x), f(x^+)) >> \text{score}(f(x), f(x^-))$$

x: reference sample; x^+ positive sample; x^- negative sample

- Objective:

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+))}{\exp(s(f(x), f(x^+)) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))} \right]$$

Loss function given 1 positive sample and N - 1 negative samples:

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x

x^+

x

x_1^-

x_2^-

x_3^-

...

Loss function given 1 positive sample and N - 1 negative samples:

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This seems familiar …

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This seems familiar …

Cross entropy loss for a N-way softmax classifier!

I.e., learn to find the positive sample from the N samples

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This seems familiar …

Cross entropy loss for a N-way softmax classifier!

I.e., learn to find the positive sample from the N samples

Very similar to a softmax classifier

We want to compare the reference image against all other positive and negative images.

We can exponentiate and normalize these scores like we did with the softmax classifier.

Contrastive Learning Loss

Loss function given 1 positive sample and N - 1 negative samples:

$$L = -\mathbb{E}_X \left[\log \frac{\exp(s(f(x), f(x^+))}{\exp(s(f(x), f(x^+)) + \sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))} \right]$$

Commonly known as the InfoNCE loss (van den Oord et al., 2018)

A *lower bound* on the mutual information between *f(x)* and *f(x^+)*

$$MI[f(x), f(x^+)] - \log(N) \geq -L$$

The larger the negative sample size (*N*), the tighter the bound

SimCLR: A Simple Framework for Contrastive learning

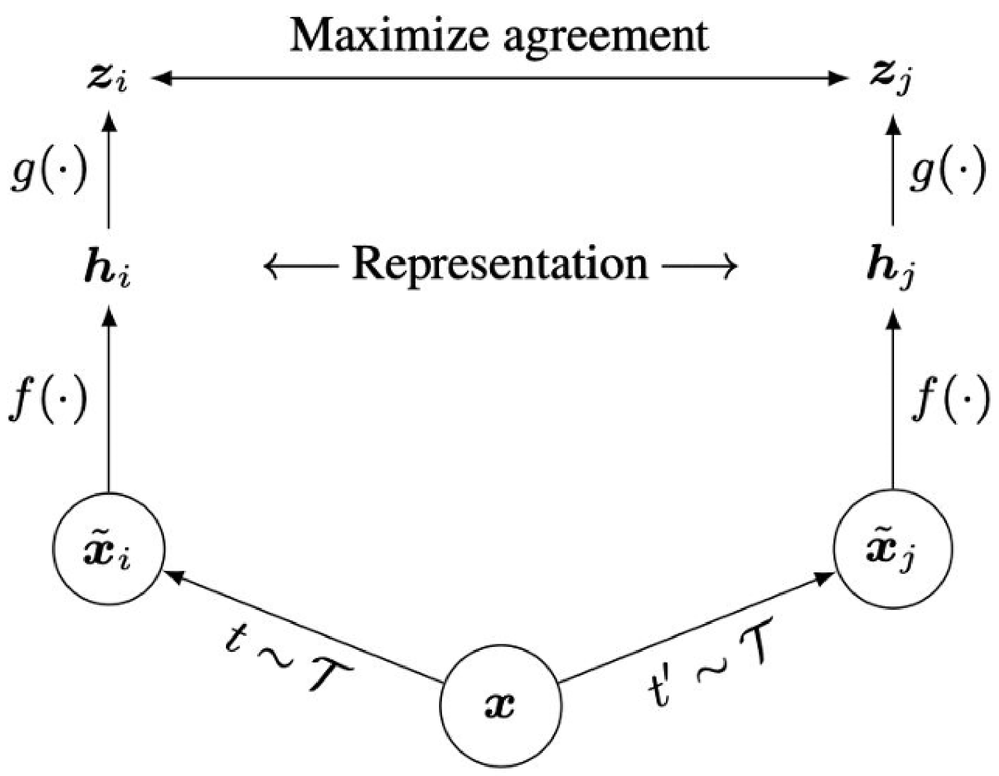
Cosine similarity as the score function:

$$s(u, v) = \frac{u^T v}{||u|| ||v||}$$

Use a projection network ***h(·)*** to project features to a space where contrastive learning is applied

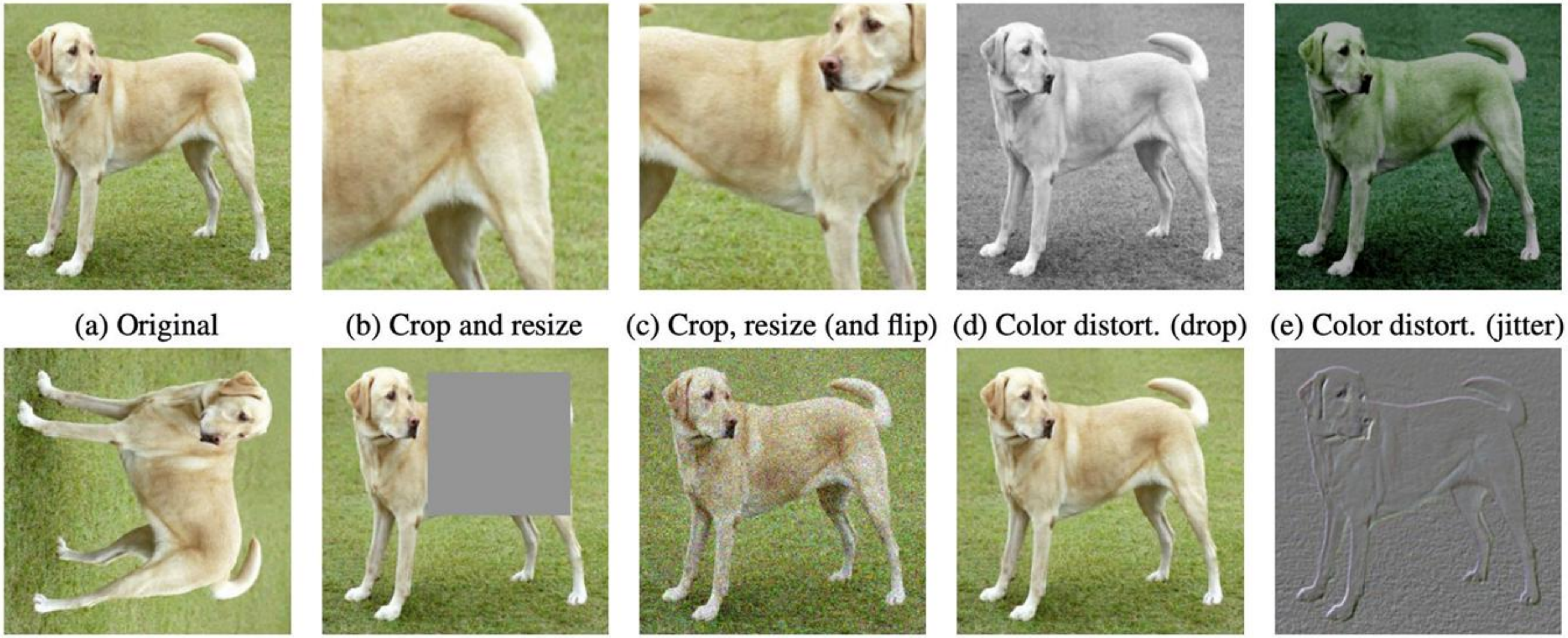
Generate positive samples through data augmentation:

- random cropping, random color distortion, and random blur.



Source: [Chen et al., 2020]

SimCLR: Data Augmentation Strategies



(a) Original (b) Crop and resize (c) Crop, resize (and flip) (d) Color distort. (drop) (e) Color distort. (jitter)

(f) Rotate $\{90°, 180°, 270°\}$ (g) Cutout (h) Gaussian noise (i) Gaussian blur (j) Sobel filtering

Source: [Chen et al., 2020]

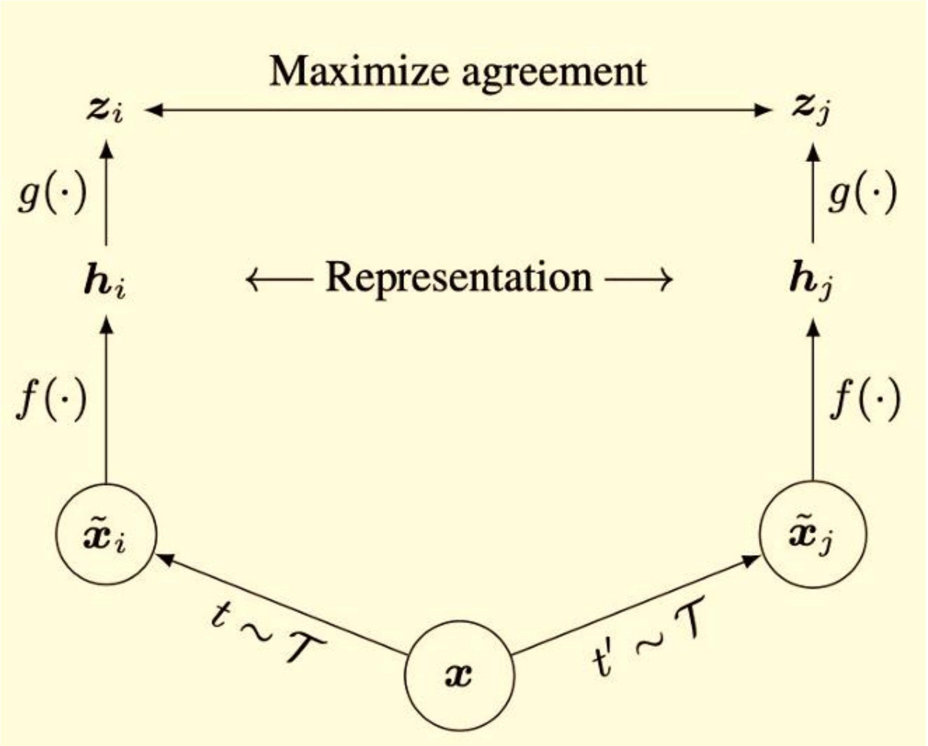
SimCLR: Algorithm Sketch

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
for sampled minibatch $\{\boldsymbol{x}_k\}_{k=1}^{N}$ **do**
  for all $k \in \{1, \ldots, N\}$ **do**
    draw two augmentation functions $t \sim \mathcal{T}$, $t' \sim \mathcal{T}$
    # the first augmentation
    $\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$ # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$ # projection
    # the second augmentation
    $\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$ # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$ # projection
  end for
  for all $i \in \{1, \ldots, 2N\}$ and $j \in \{1, \ldots, 2N\}$ **do**
    $s_{i,j} = \boldsymbol{z}_i^\top \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$ # pairwise similarity
  end for
  define $\ell(i,j)$ **as** $\ell(i,j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks f and g to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$

Generate a positive pair by sampling data augmentation functions

Iterate through and use each of the 2N sample as reference, compute average loss



InfoNCE loss:
Use all non-positive samples in the batch as x^-

Source: Chen et al., 2020

SimCLR Training

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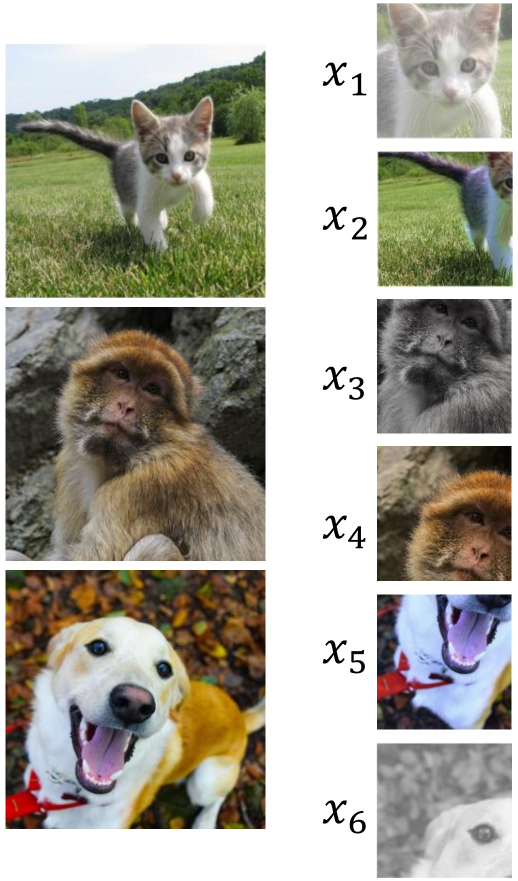
Chen et al, “A Simple Framework for Contrastive Learning of Visual Representations”, ICML 2020

SimCLR Training

Batch of N images

Two augmentations for each image



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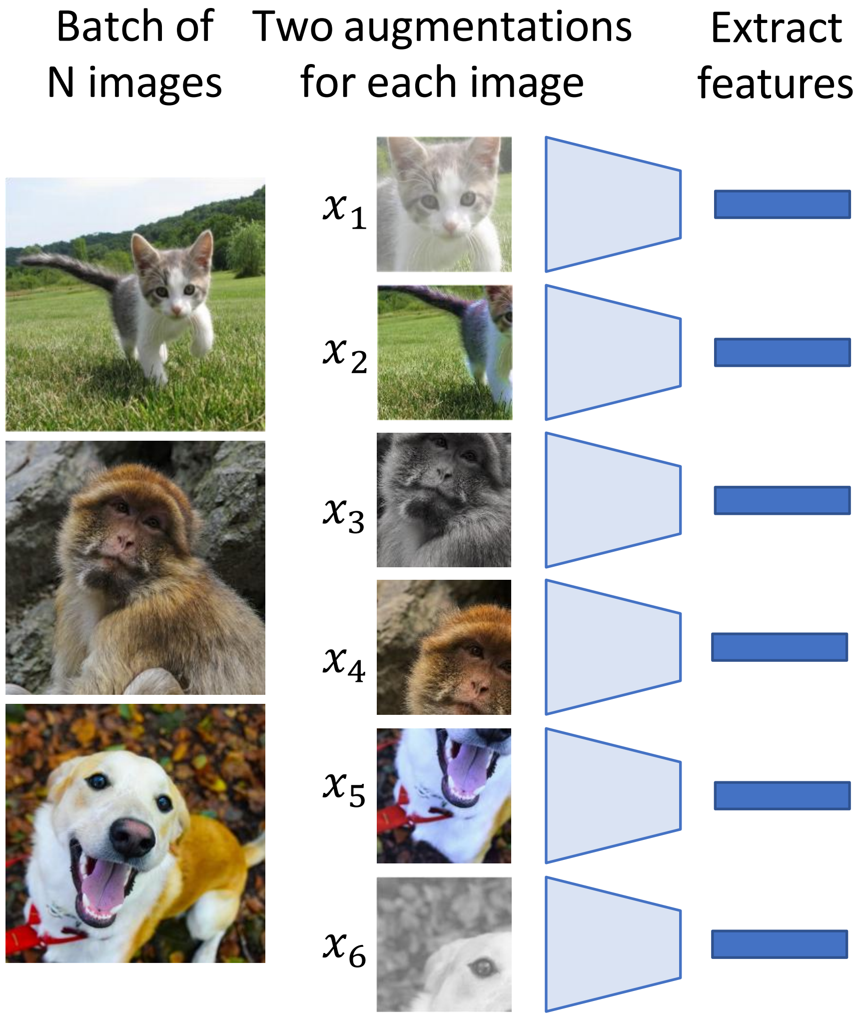

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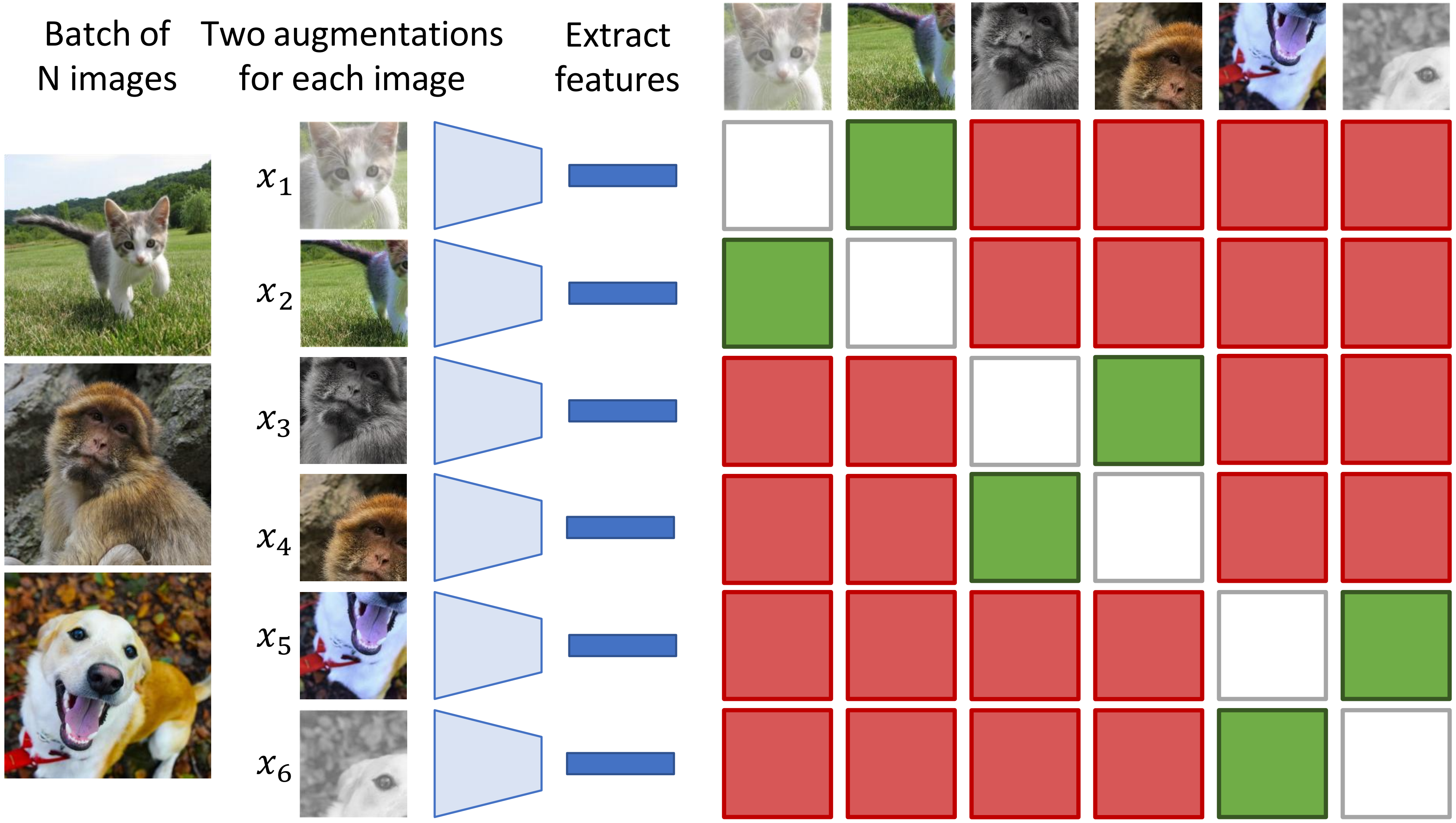

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(τ is a *temperature*)

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

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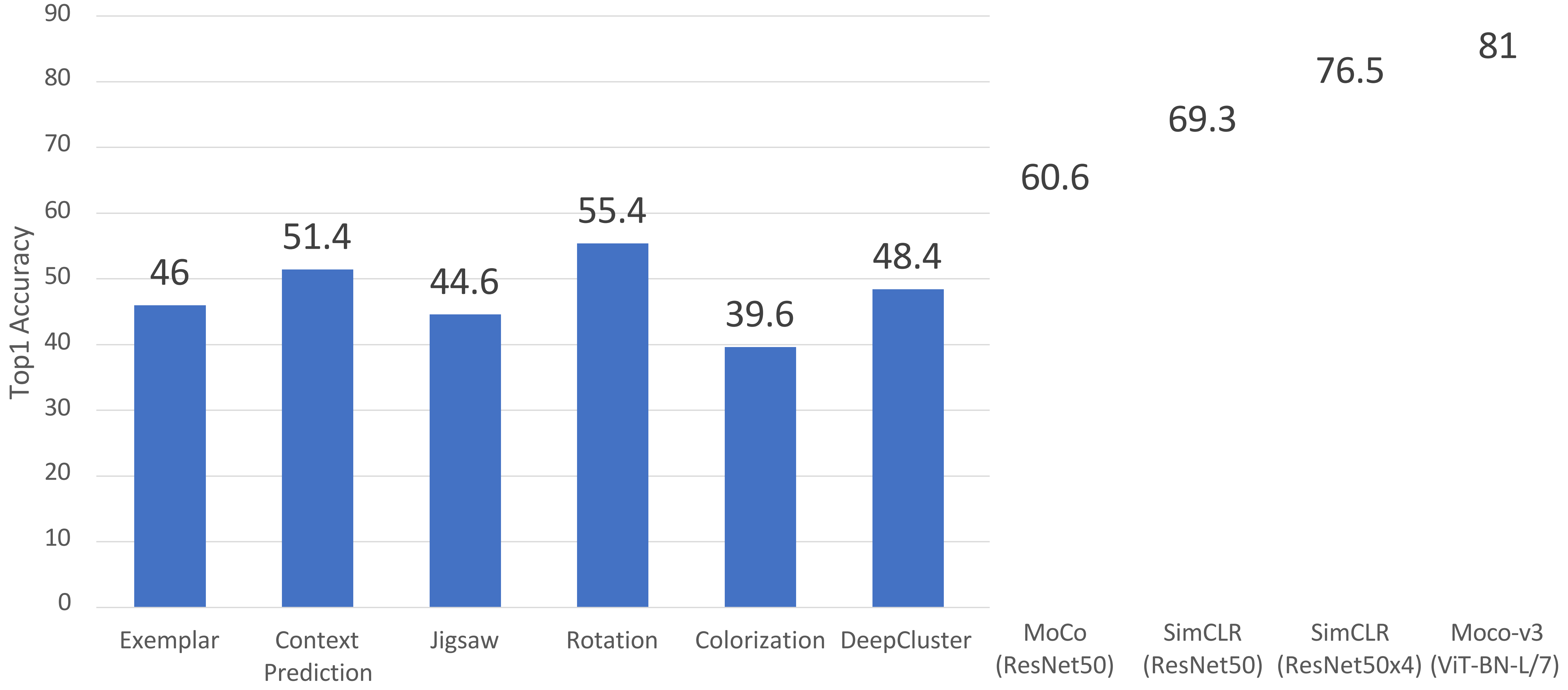
ImageNet Linear Classification from SSL Features



He et al, "Momentum Contrast for Unsupervised Visual Representation Learning", CVPR 2020
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Chen et al, "An Empirical Study of Training Self-Supervised Vision Transformers", ICCV 2021

(Lots of caveats here … different architectures, etc)

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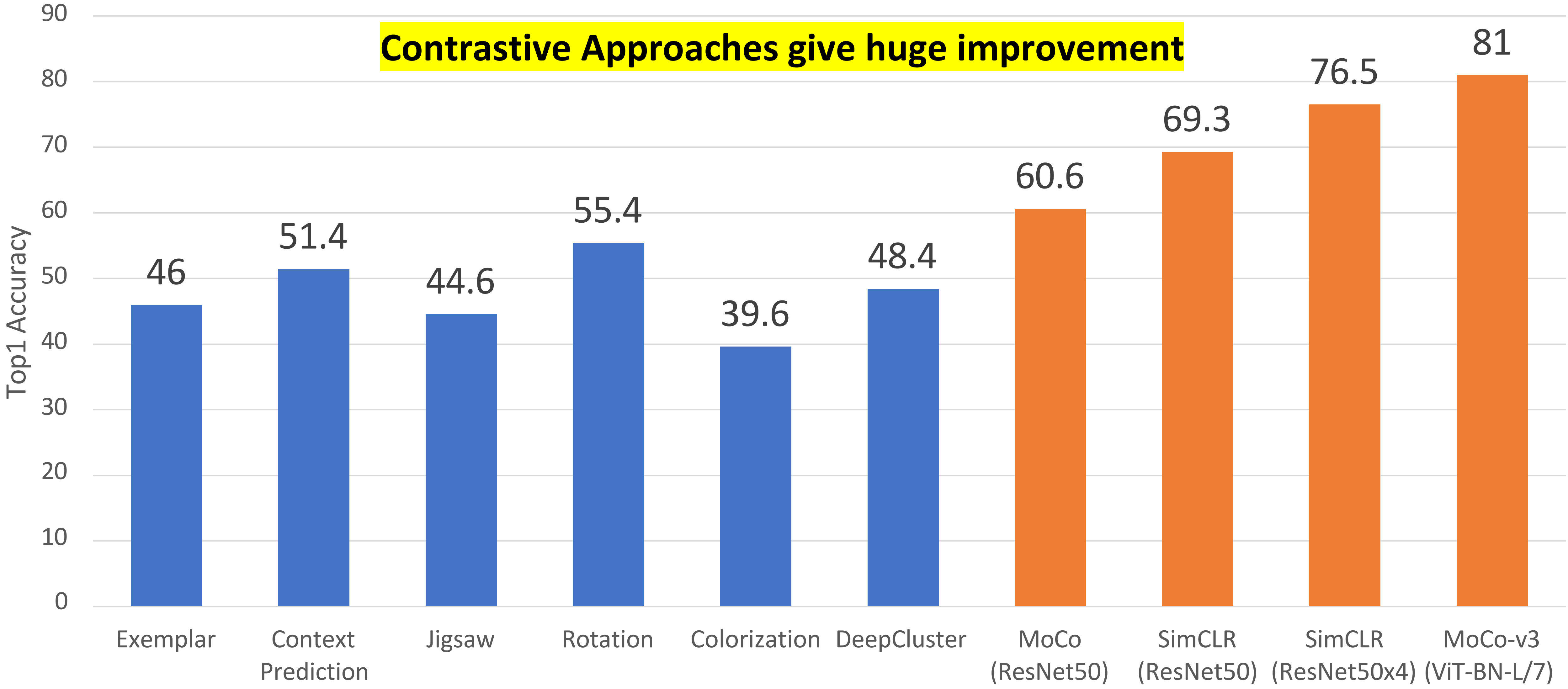

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(Lots of caveats here … different architectures, etc)

But how did you get the pretraining data?

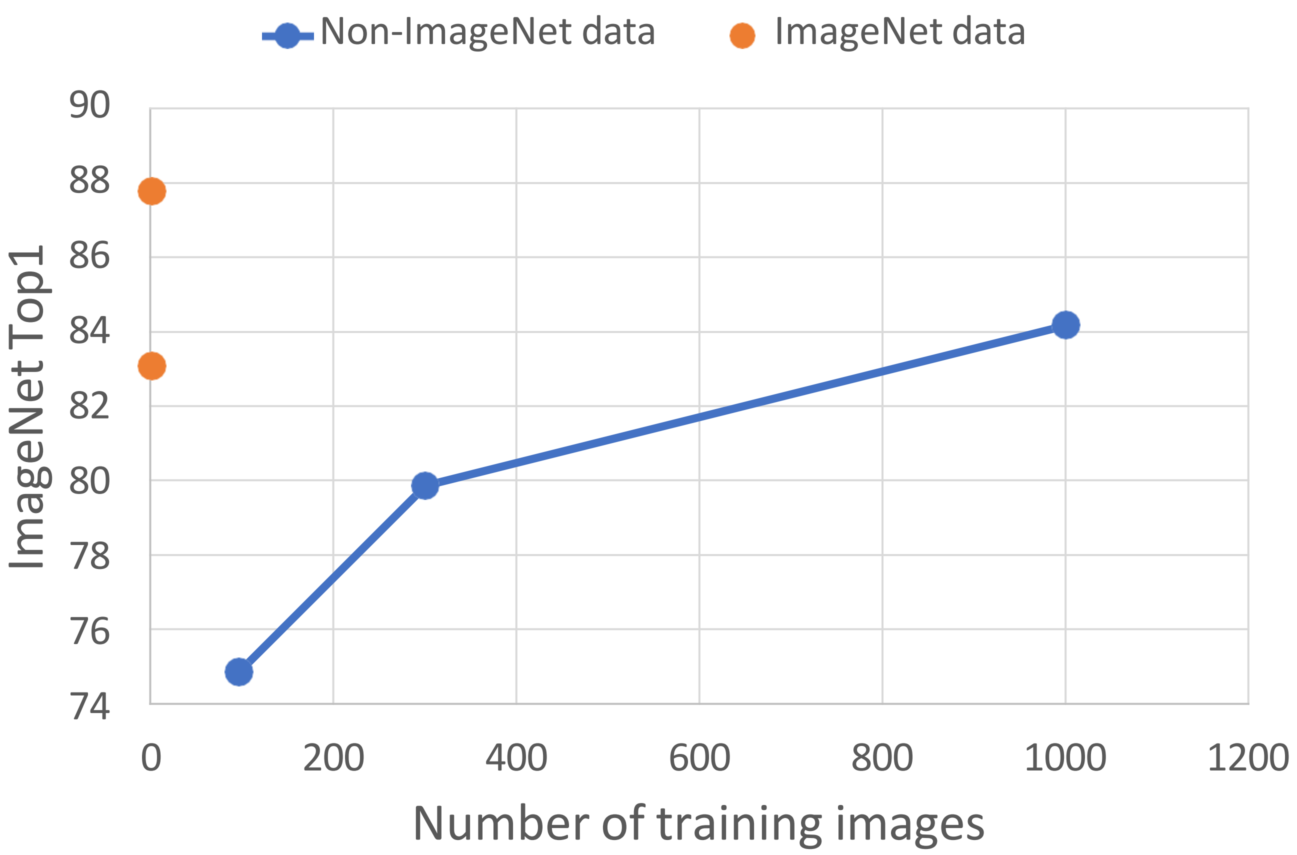
The motivation of SSL is scaling to large data that can't be labeled

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

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

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

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

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

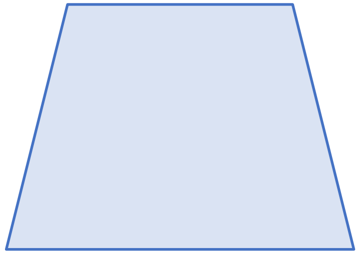
For now: Assume you can learn language representations

(I teach this in much detail on CMSC 475/675 Neural Networks)

Computer Vision

Image Features:

H x W x C

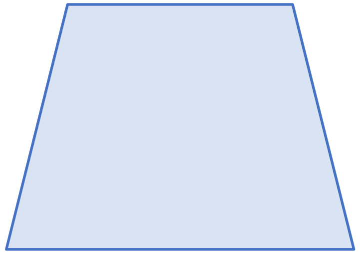


Input Image

Natural Language Processing

Word Features

L x C



A white and gray cat standing outside on the grass

Input Sentence (L words)

Contrastive Learning with Vision-Language Data

OpenAI

January 5, 2021 Milestone

CLIP: Connecting text and images

Contrastive Learning with Vision-Language Data

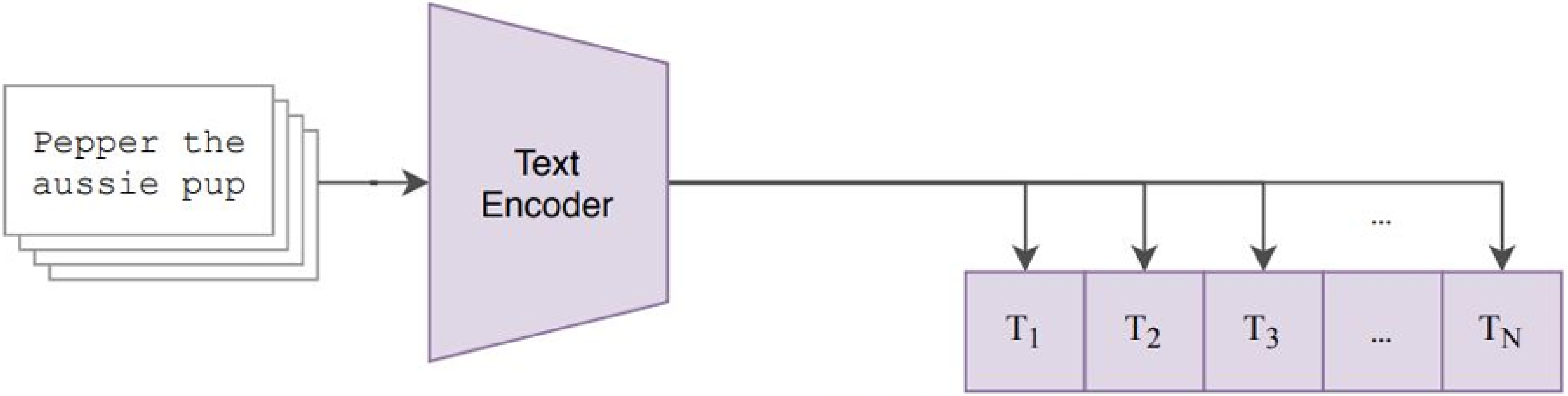
Learning Transferable Visual Models From Natural Language Supervision

Alec Radford [*1] Jong Wook Kim [*1] Chris Hallacy [1] Aditya Ramesh [1] Gabriel Goh [1] Sandhini Agarwal [1]
Girish Sastry [1] Amanda Askell [1] Pamela Mishkin [1] Jack Clark [1] Gretchen Krueger [1] Ilya Sutskever [1]

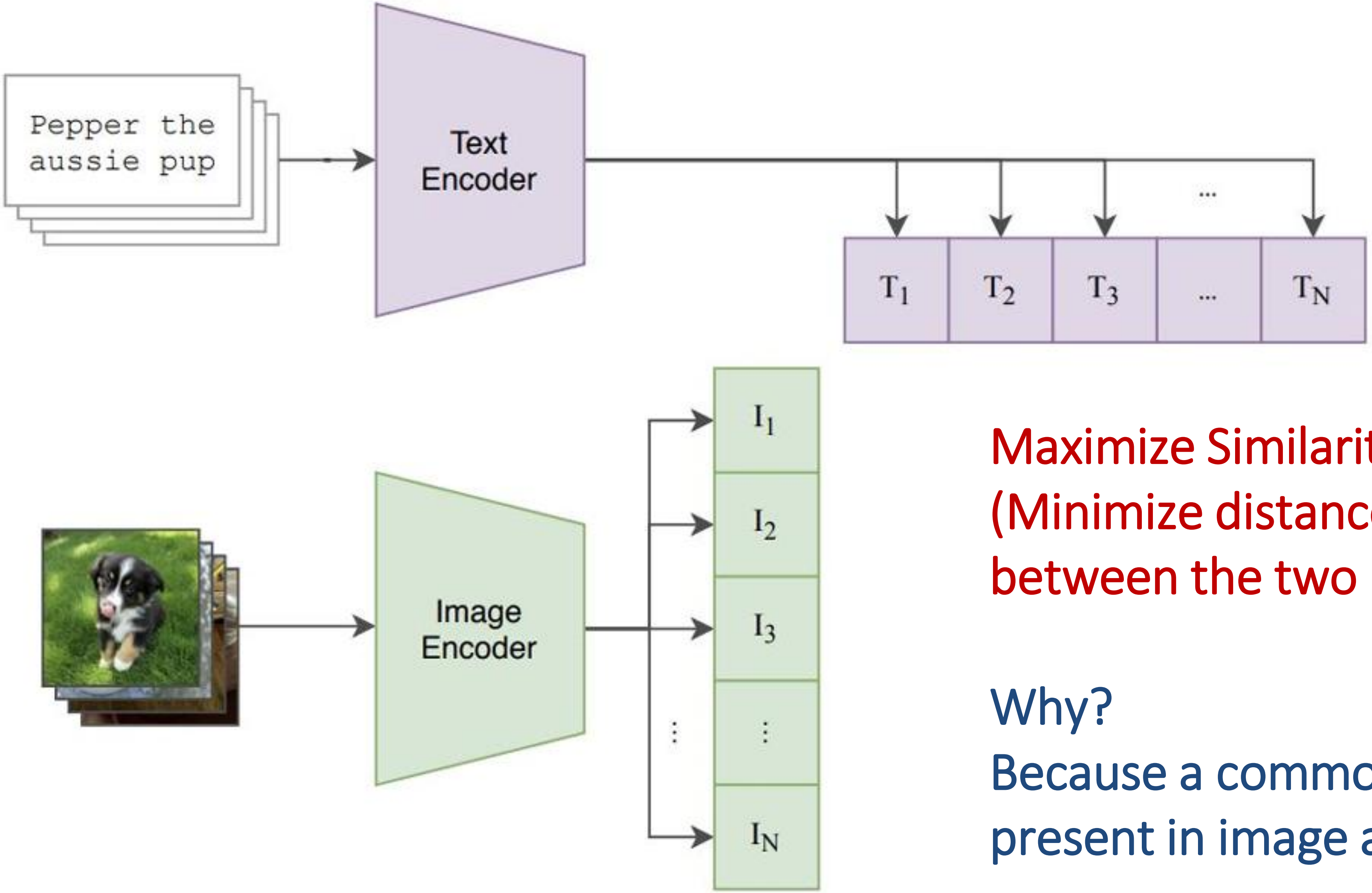
ICML | 2021

Thirty-eighth International Conference on
Machine Learning

Pepper the aussie pup


Pepper the
aussie pup
Text
Encoder
...
T_1
T_2
T_3
...
T_N

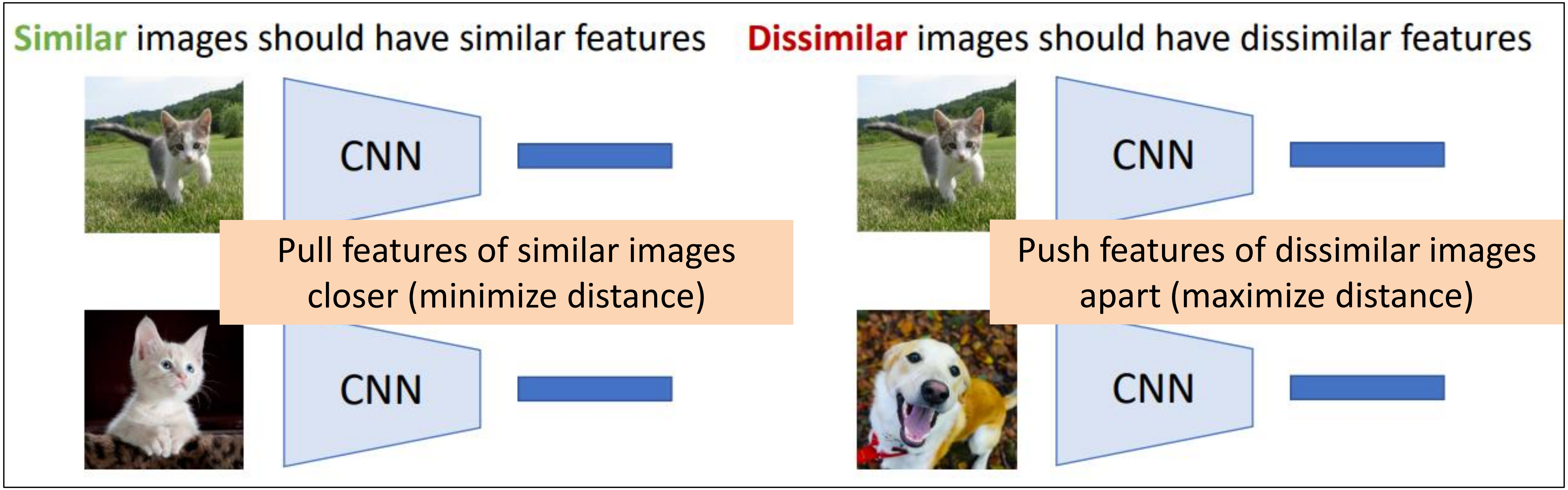
Goal: Do Contrastive Learning!



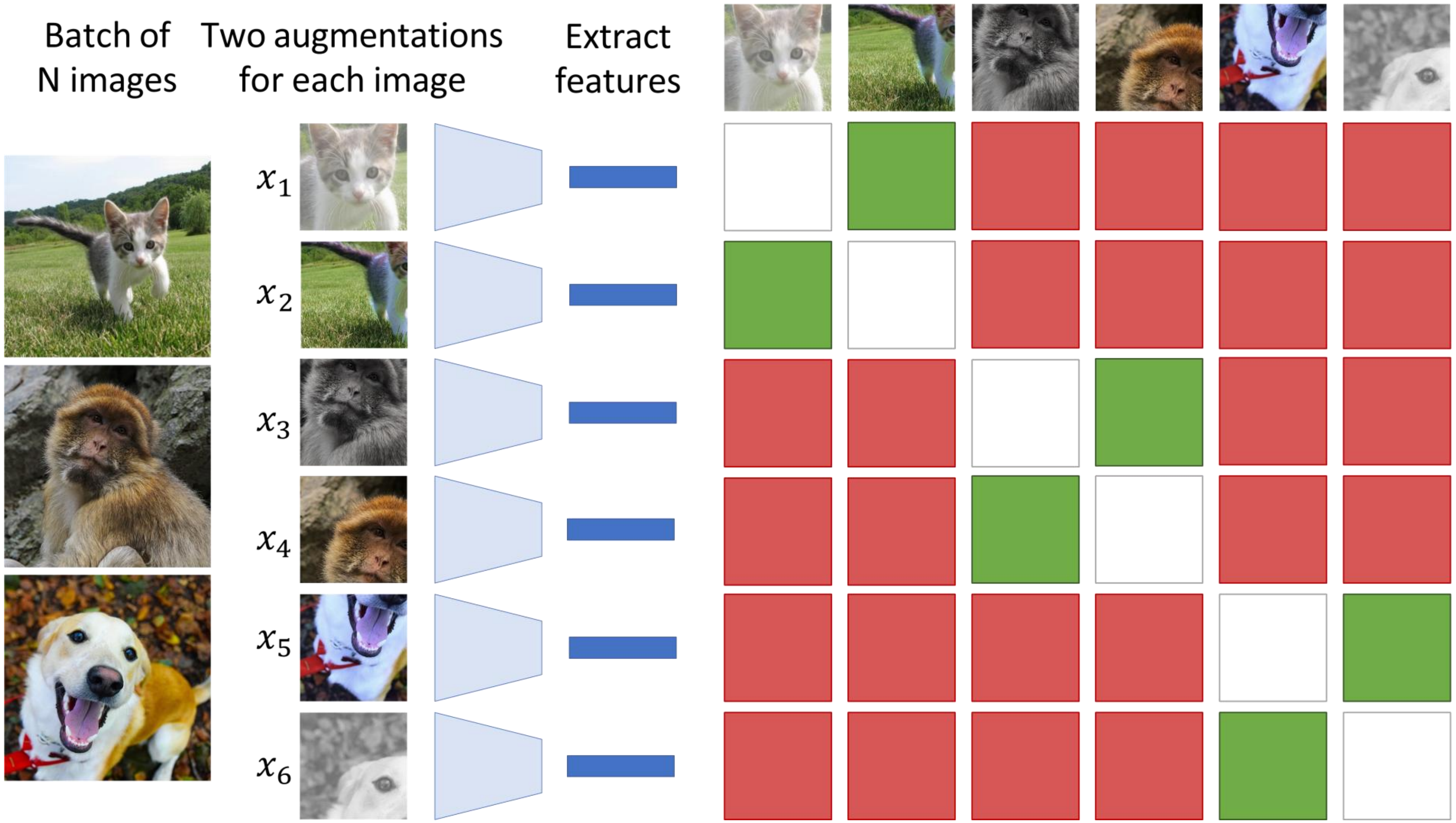
Maximize Similarity
(Minimize distance)
between the two representations

Why?
Because a common concept is present in image and sentence

Recall: Contrastive Learning (General Form)



Recall: Contrastive Learning (SimCLR)



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

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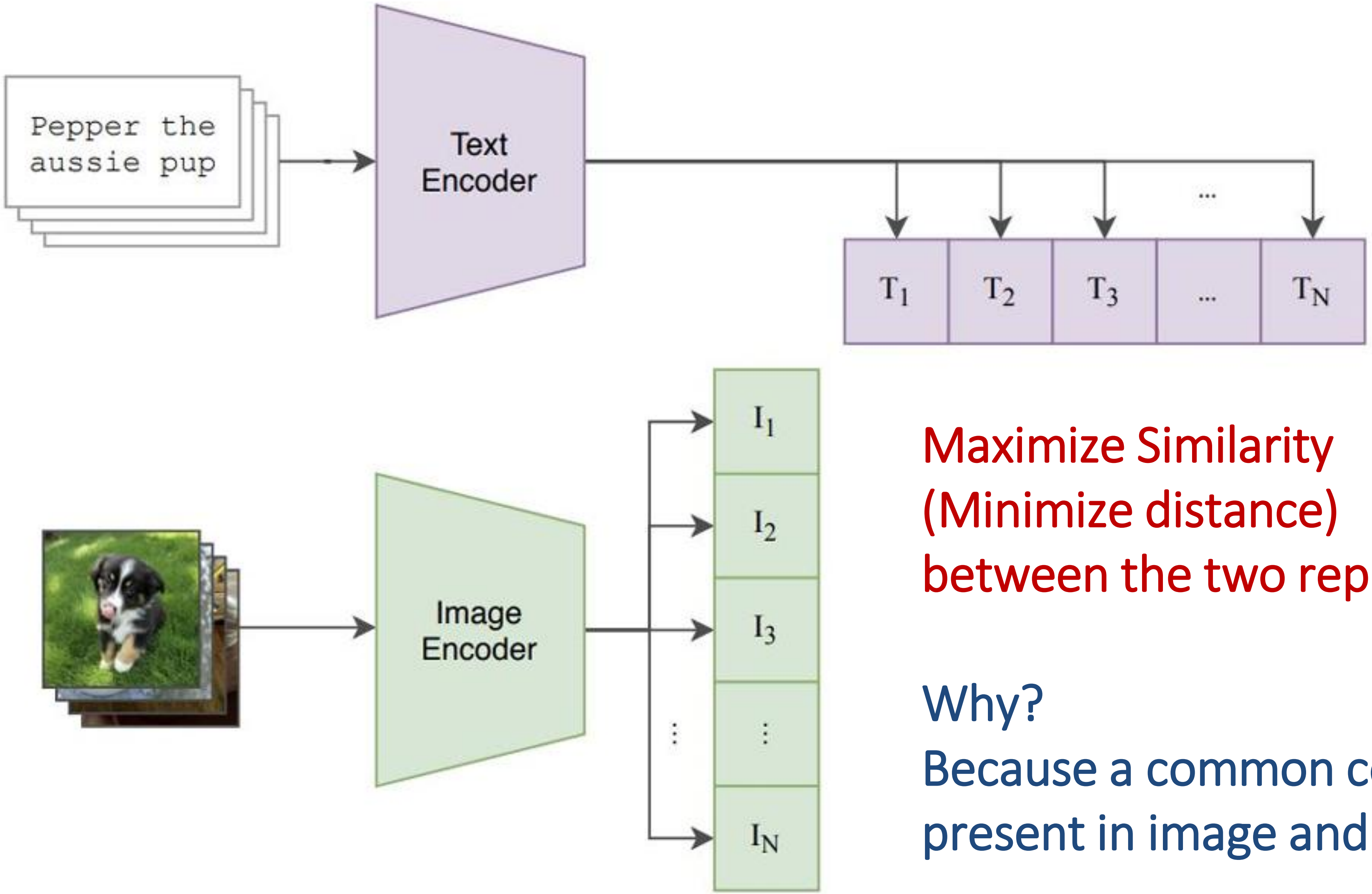

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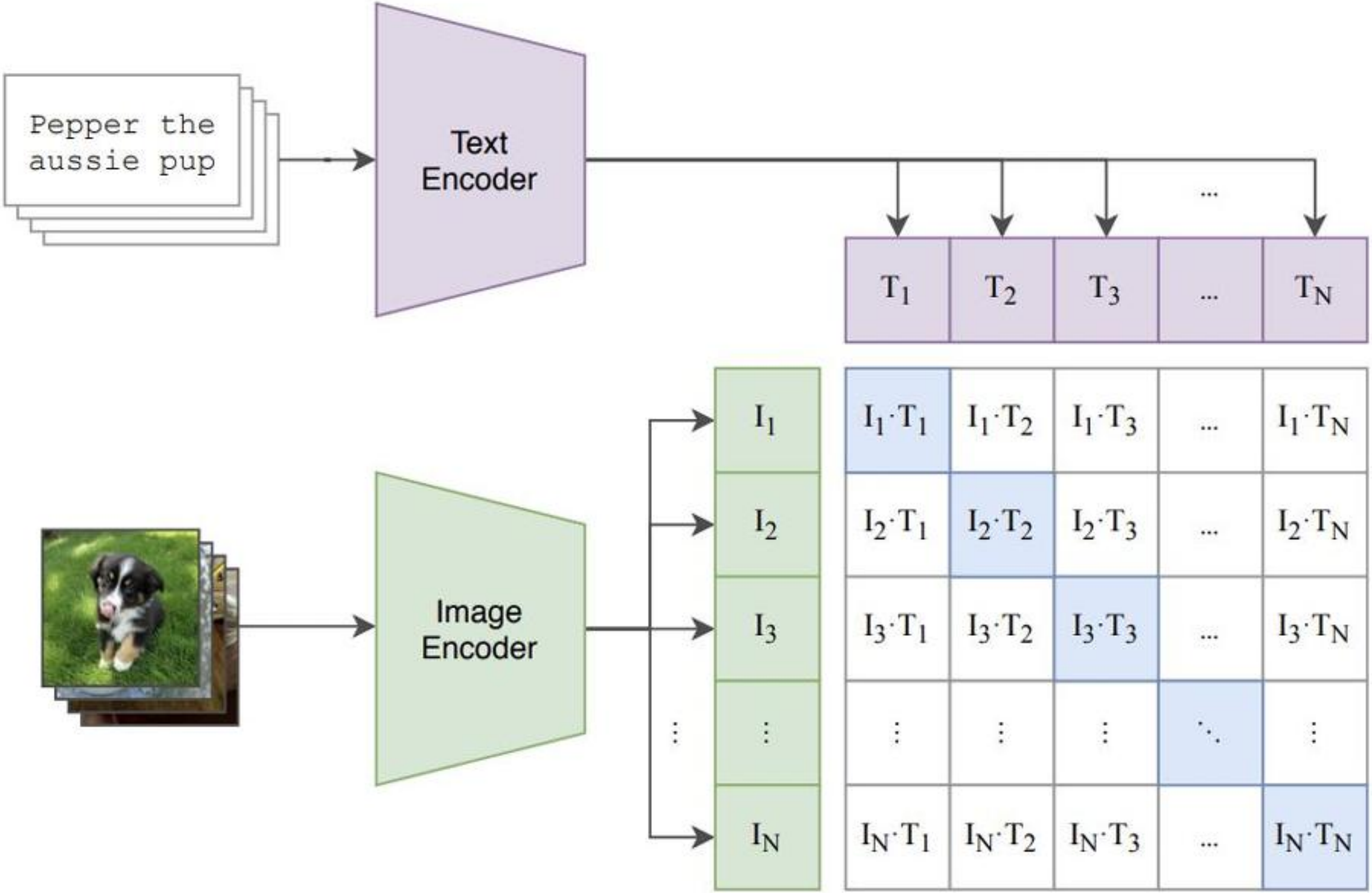
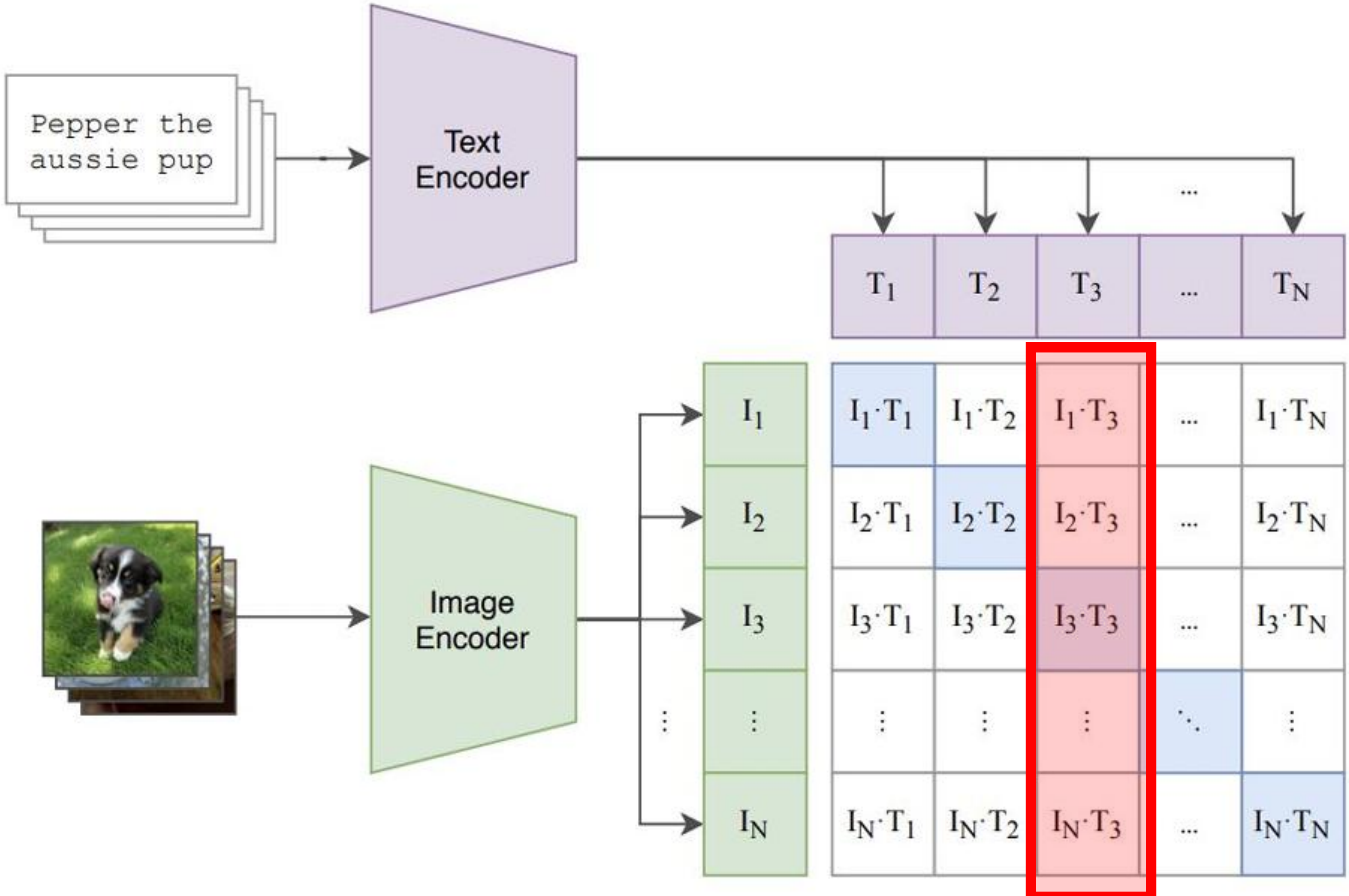
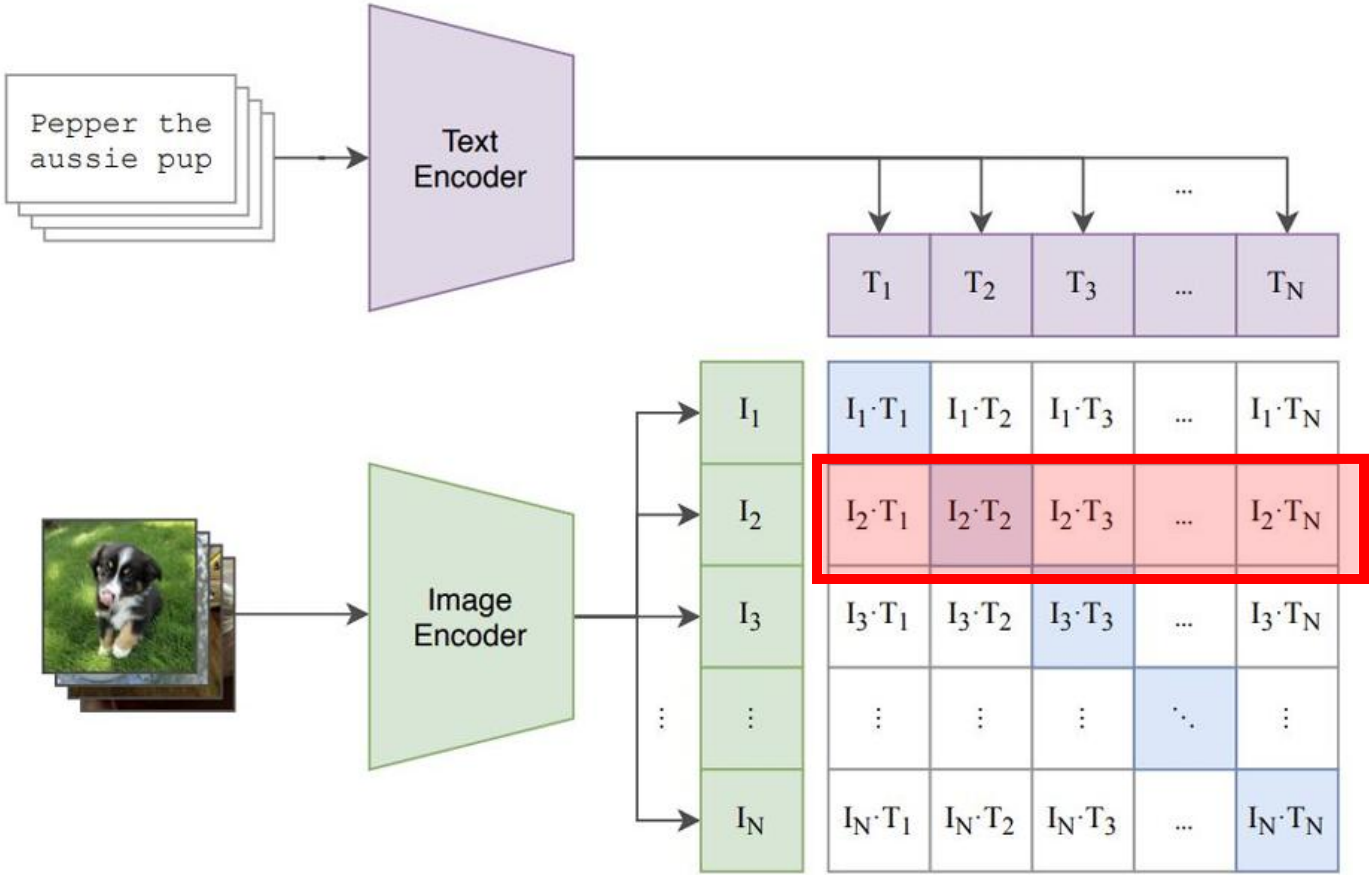


Pepper the aussie pup
Text Encoder
T_1 T_2 T_3 ... T_N
Image Encoder
I_1 I_2 I_3 ⋮ I_N
$I_1 \cdot T_1$ $I_1 \cdot T_2$ $I_1 \cdot T_3$ ... $I_1 \cdot T_N$
$I_2 \cdot T_1$ $I_2 \cdot T_2$ $I_2 \cdot T_3$ ... $I_2 \cdot T_N$
$I_3 \cdot T_1$ $I_3 \cdot T_2$ $I_3 \cdot T_3$ ... $I_3 \cdot T_N$
$I_N \cdot T_1$ $I_N \cdot T_2$ $I_N \cdot T_3$ ... $I_N \cdot T_N$



Pepper the aussie pup
Text Encoder
T_1 T_2 T_3 ... T_N
Image Encoder
I_1 I_2 I_3 ⋮ I_N
$I_1 \cdot T_1$ $I_1 \cdot T_2$ $I_1 \cdot T_3$ ... $I_1 \cdot T_N$
$I_2 \cdot T_1$ $I_2 \cdot T_2$ $I_2 \cdot T_3$ ... $I_2 \cdot T_N$
$I_3 \cdot T_1$ $I_3 \cdot T_2$ $I_3 \cdot T_3$ ... $I_3 \cdot T_N$
$I_N \cdot T_1$ $I_N \cdot T_2$ $I_N \cdot T_3$ ... $I_N \cdot T_N$


Pepper the aussie pup
Text Encoder
Image Encoder
T_1 T_2 T_3 ... T_N
I_1 I_2 I_3 ⋮ I_N
$I_1 \cdot T_1$ $I_1 \cdot T_2$ $I_1 \cdot T_3$ ... $I_1 \cdot T_N$
$I_2 \cdot T_1$ $I_2 \cdot T_2$ $I_2 \cdot T_3$ ... $I_2 \cdot T_N$
$I_3 \cdot T_1$ $I_3 \cdot T_2$ $I_3 \cdot T_3$ ... $I_3 \cdot T_N$
$I_N \cdot T_1$ $I_N \cdot T_2$ $I_N \cdot T_3$ ... $I_N \cdot T_N$

plane

car

dog

⋮

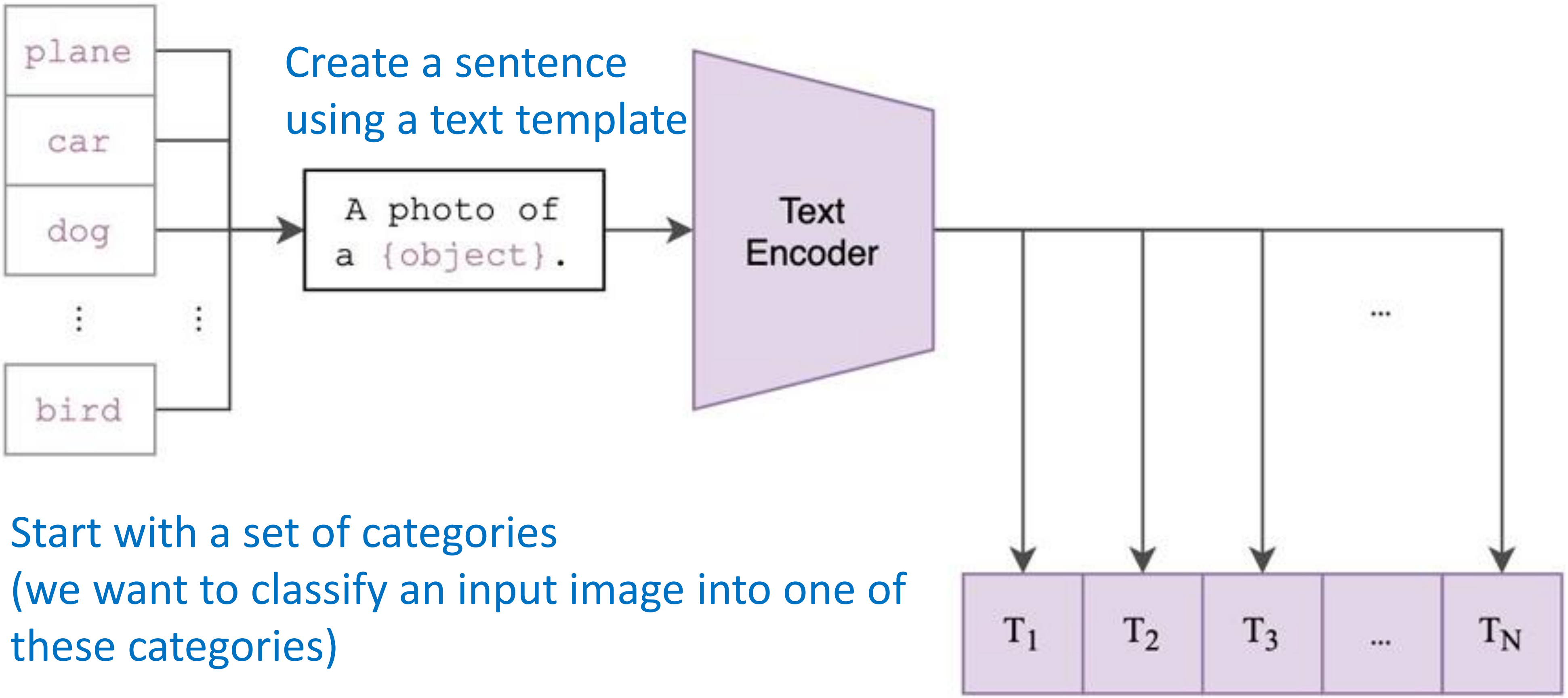
bird

Start with a set of categories
(we want to classify an input image into one of these categories)

Image Classification with CLIP

(so called "Zero-shot" classification)

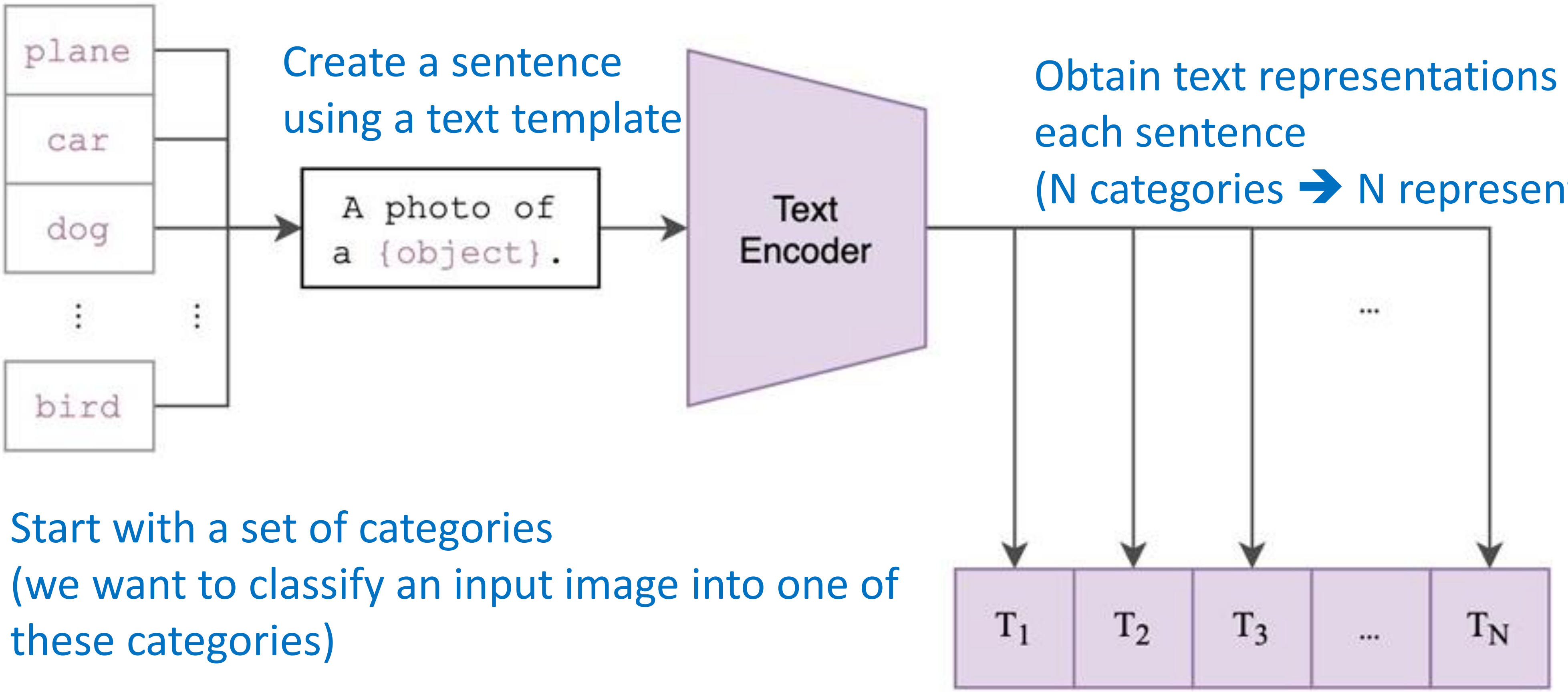
Create a sentence using a text template



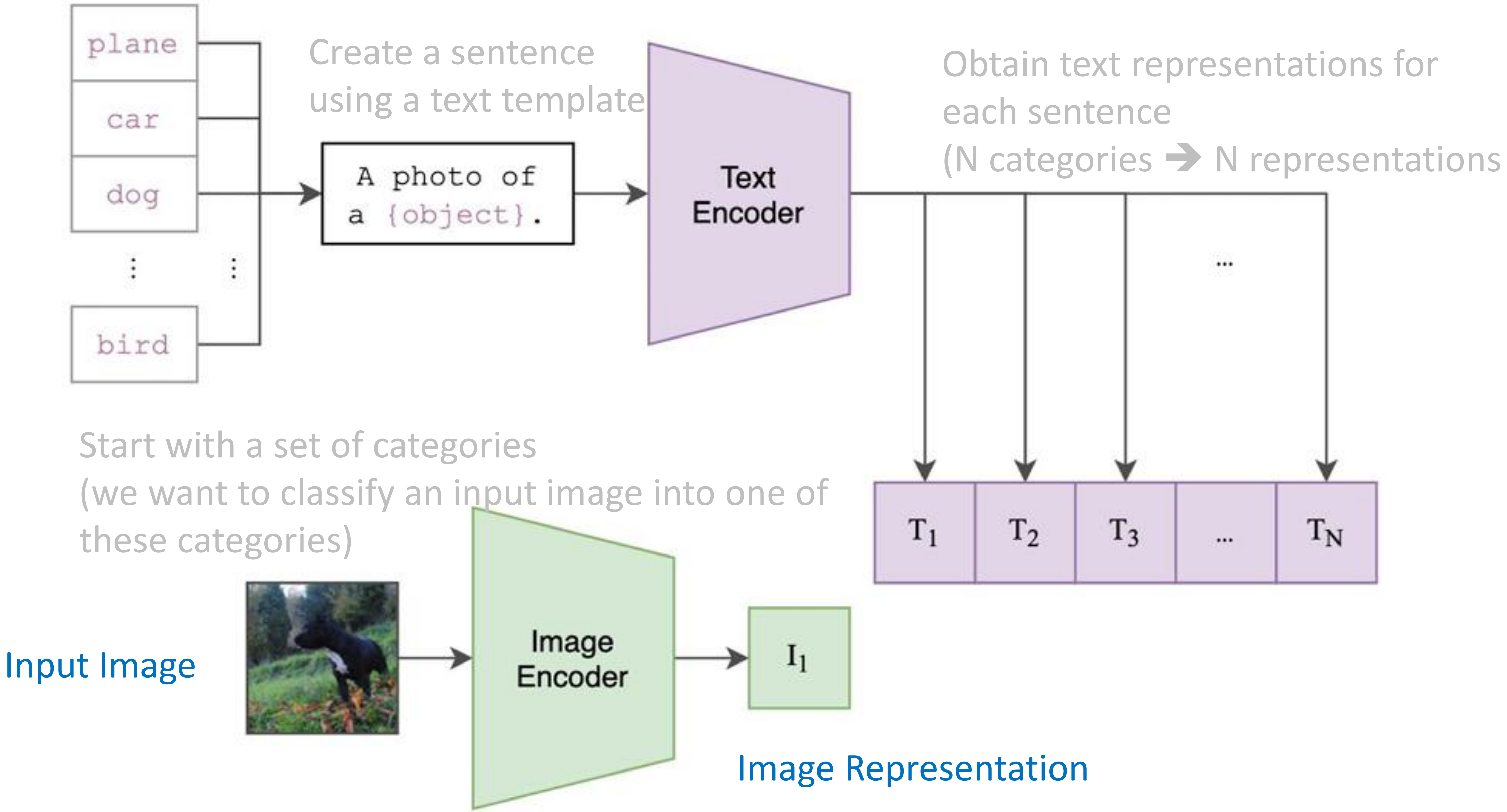
Start with a set of categories
(we want to classify an input image into one of these categories)

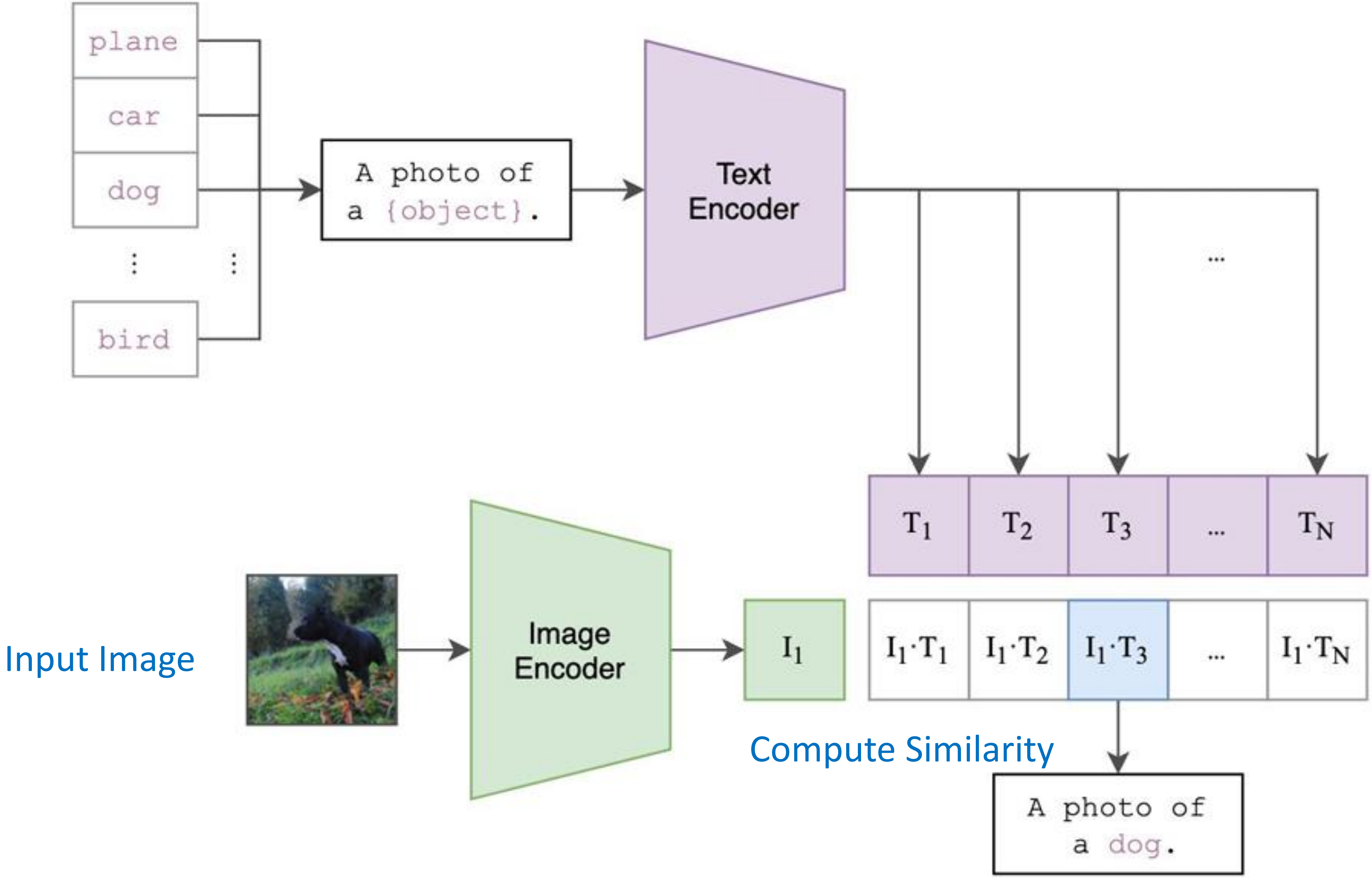
Create a sentence
using a text template

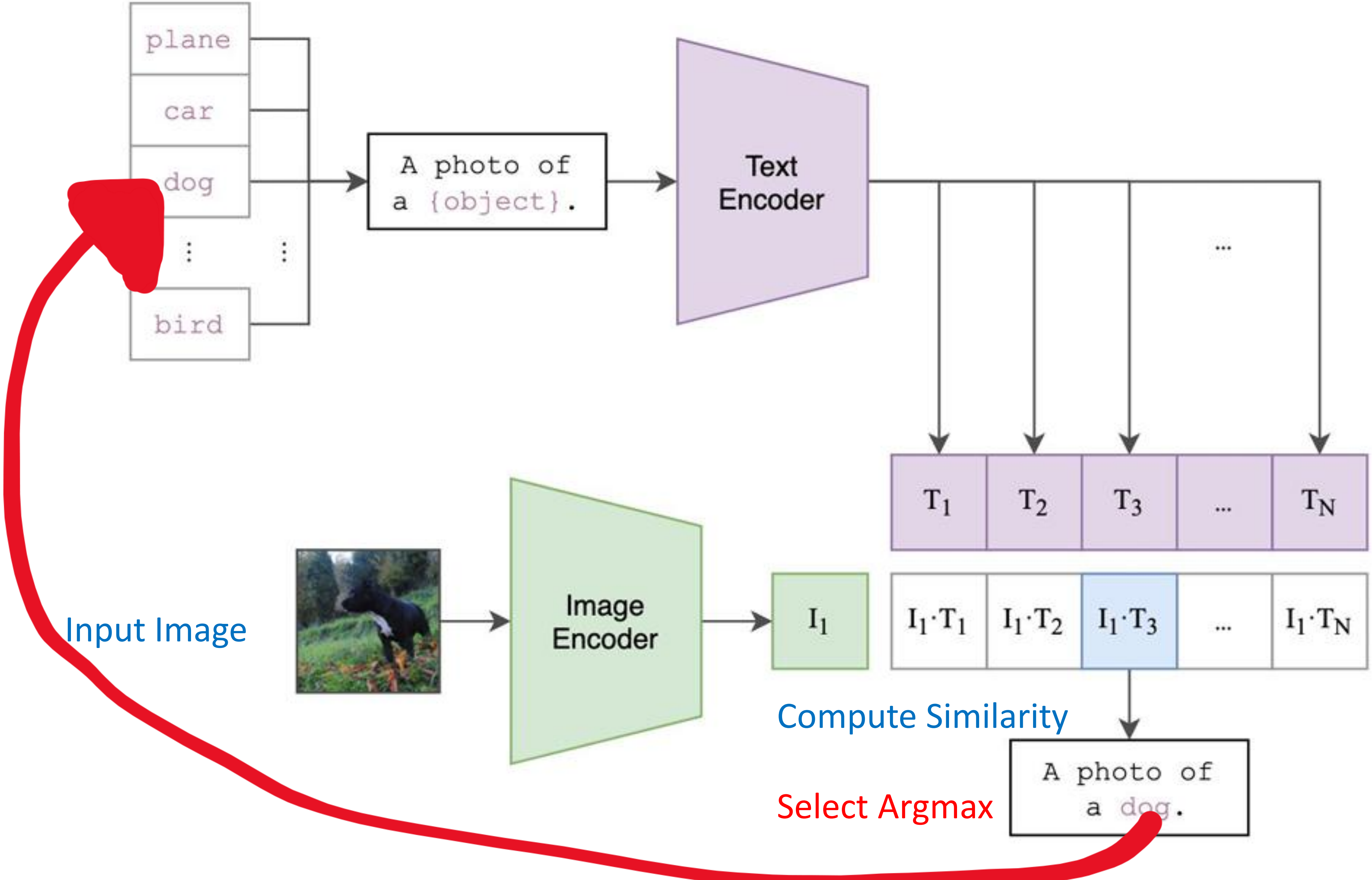
Obtain text representations for
each sentence
(N categories ➔ N representations)



Start with a set of categories
(we want to classify an input image into one of
these categories)

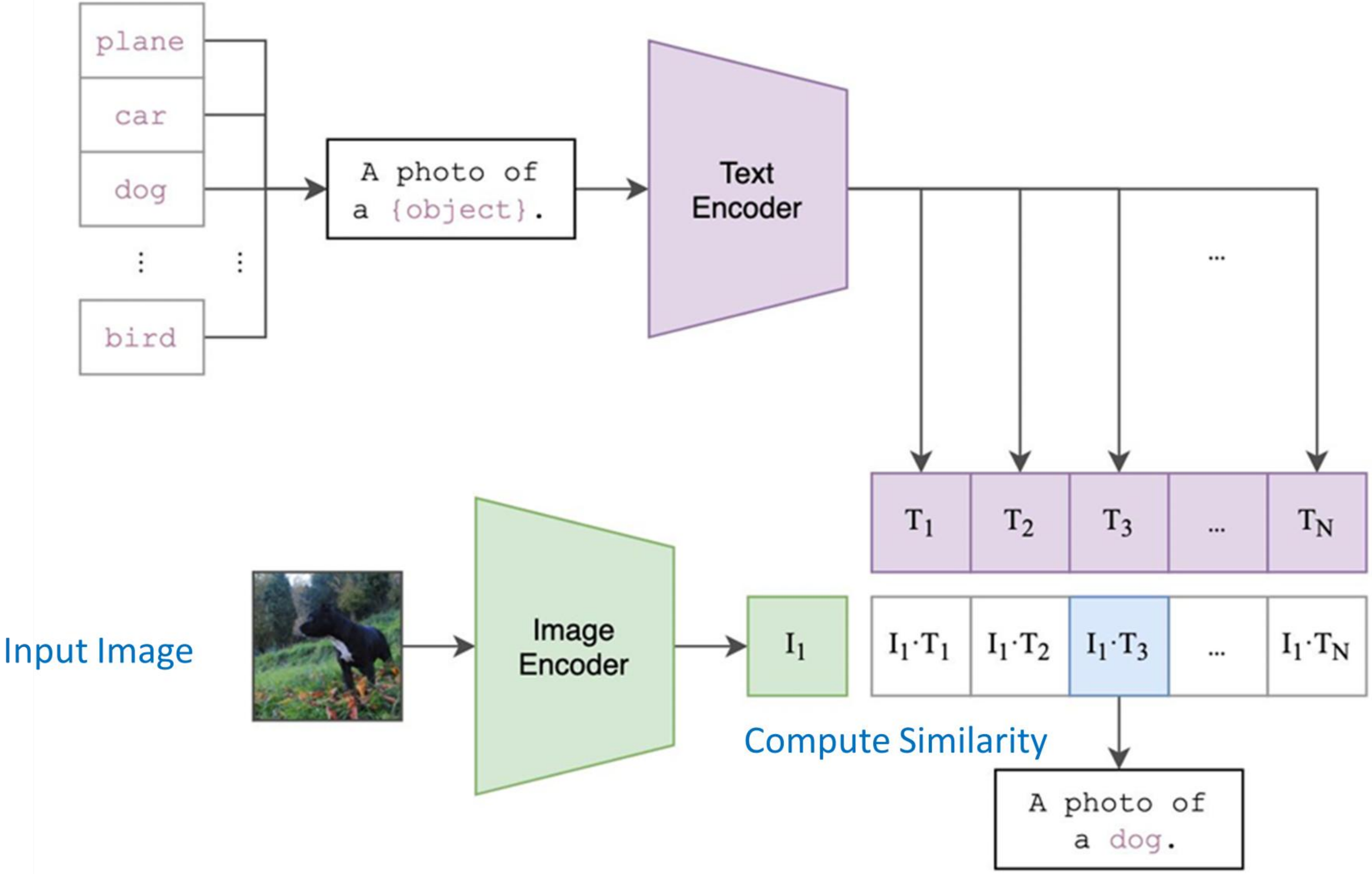

plane
car
dog
bird
Create a sentence
using a text template
A photo of
a {object}.
Text
Encoder
Obtain text representations for
each sentence
(N categories ➔ N representations
...
T1
T2
T3
...
TN
Start with a set of categories
(we want to classify an input image into one of
these categories)
Input Image
Image
Encoder
I1
Image Representation


plane
car
dog
bird
A photo of a {object}.
Text Encoder
T_1 T_2 T_3 ... T_N
Input Image
Image Encoder
I_1
$I_1 \cdot T_1$ $I_1 \cdot T_2$ $I_1 \cdot T_3$ ... $I_1 \cdot T_N$
Compute Similarity
A photo of a dog.



plane
car
dog
bird
A photo of a {object}.
Text Encoder
T1
T2
T3
...
TN
Input Image
Image Encoder
I1
I1·T1
I1·T2
I1·T3
...
I1·TN
Compute Similarity
Select Argmax
A photo of a dog.

CLIP: Zero-Shot Classification



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

Contrastive loss:
For each image, predict which sentence matches it.

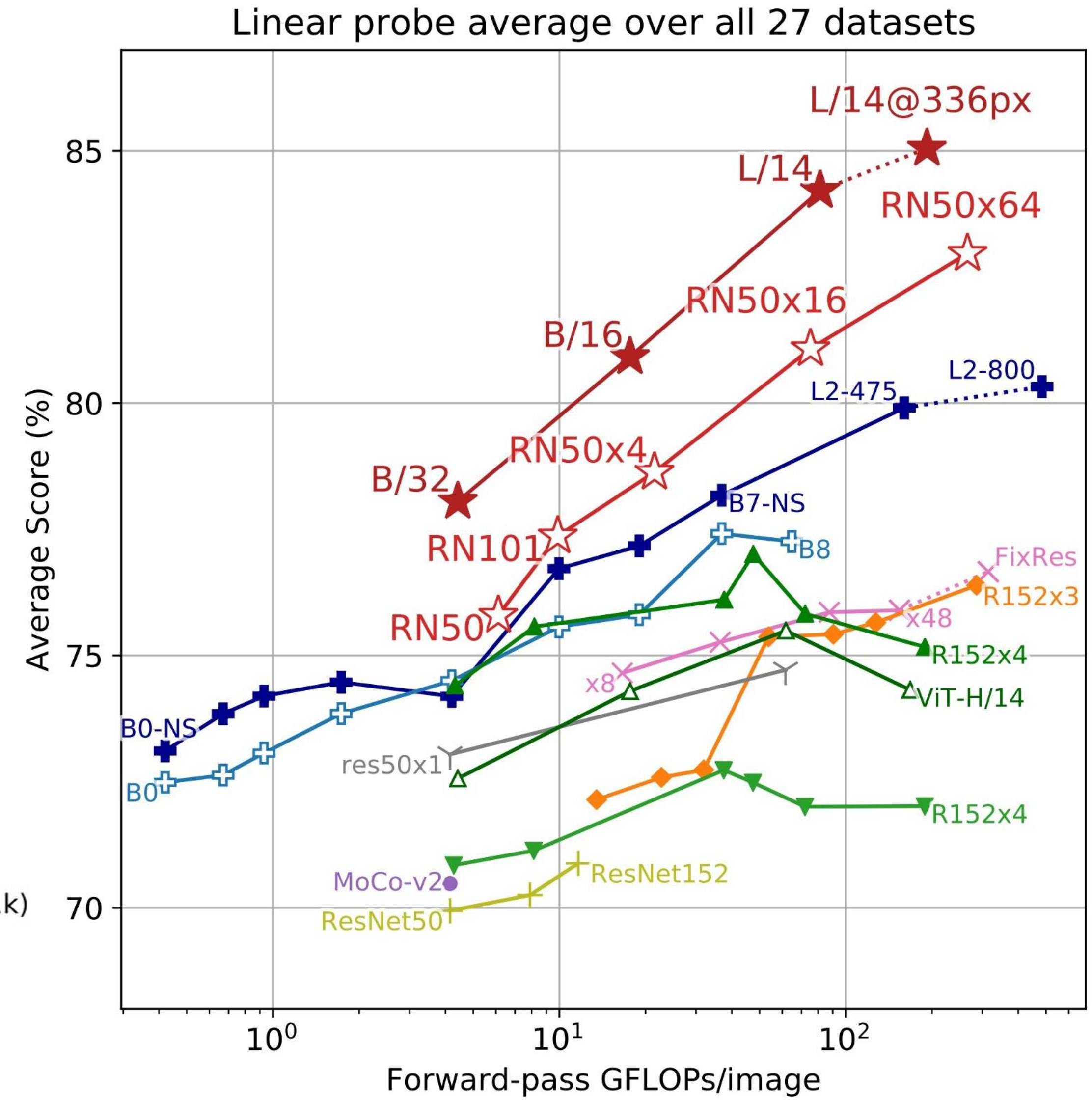
Large-scale training on 400M (image, text) pairs from the internet

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

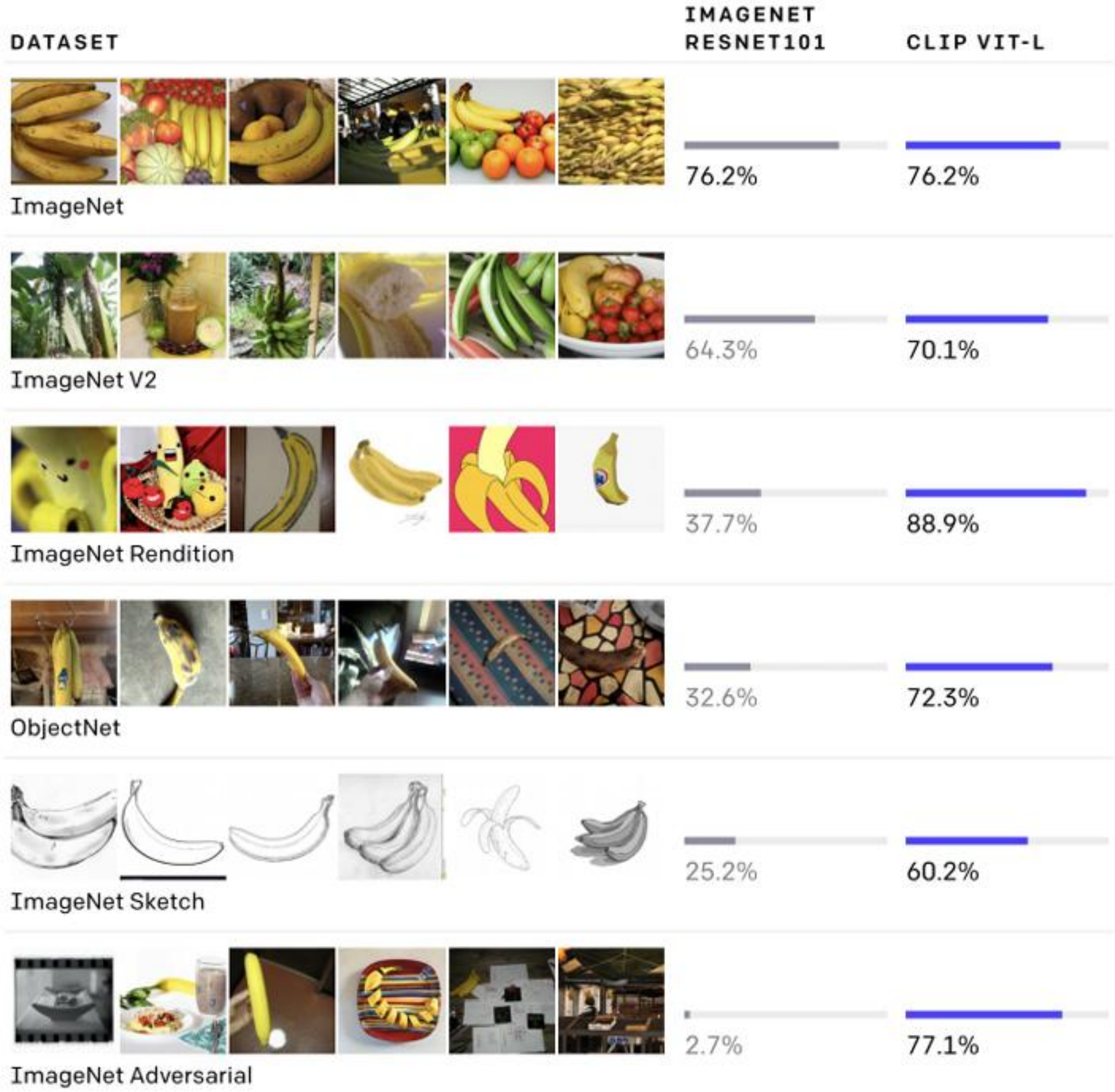
CLIP Performance

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 Details

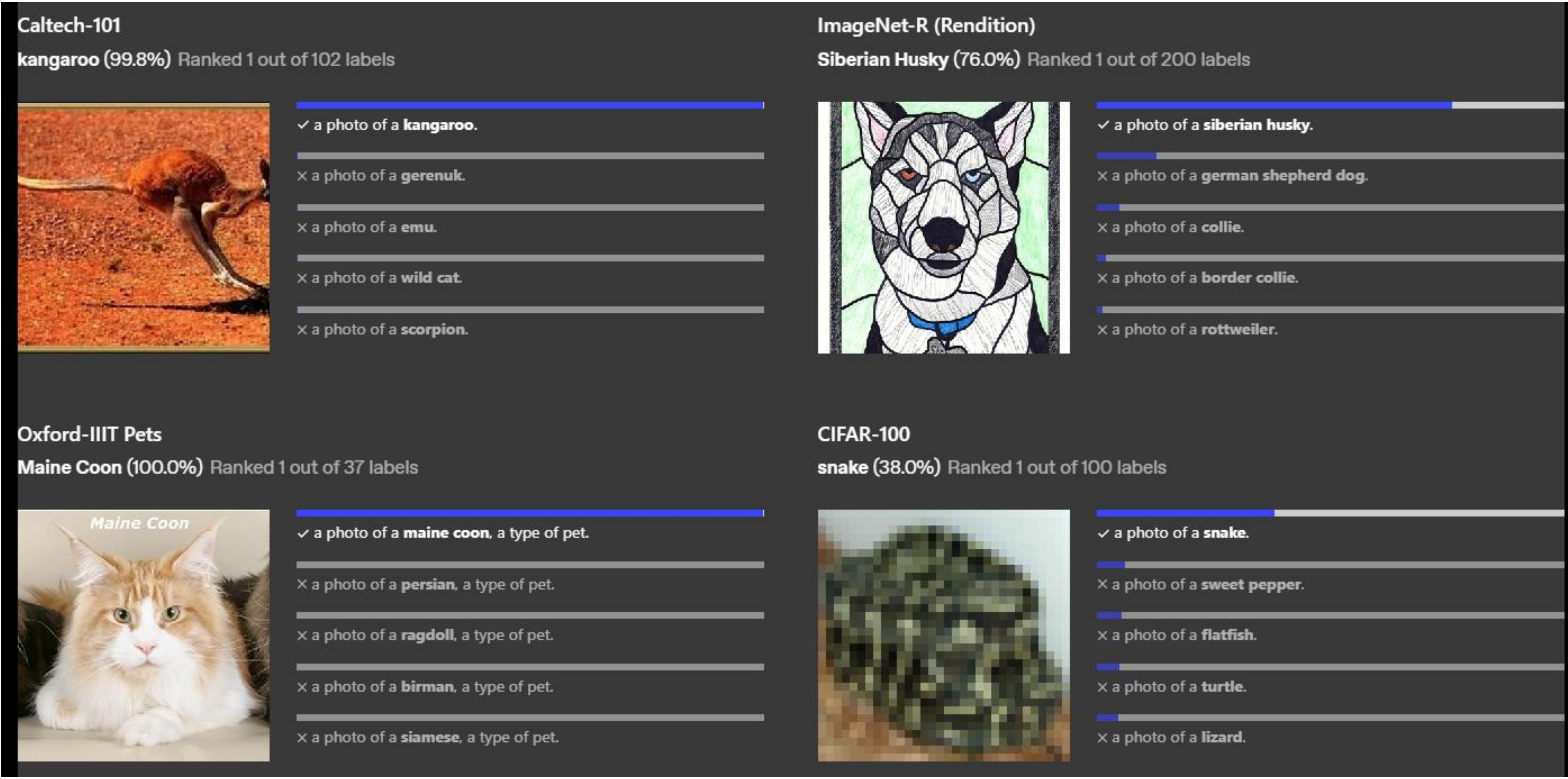
Training Details:

- Trained on 400M image-text pairs from the internet (i.e. without permissions a.k.a. stealing)

- Batch size of 32,768
- 32 epochs over the dataset
- Cosine learning rate decay

Architecture

- ResNet-based or ViT-based image encoder
- Transformer-based text encoder


Caltech-101
kangaroo (99.8%) Ranked 1 out of 102 labels
✓ a photo of a kangaroo.
× a photo of a gerenuk.
× a photo of a emu.
× a photo of a wild cat.
× a photo of a scorpion.
ImageNet-R (Rendition)
Siberian Husky (76.0%) Ranked 1 out of 200 labels
✓ a photo of a siberian husky.
× a photo of a german shepherd dog.
× a photo of a collie.
× a photo of a border collie.
× a photo of a rottweiler.
Oxford-IIIT Pets
Maine Coon (100.0%) Ranked 1 out of 37 labels
Maine Coon
✓ a photo of a maine coon, a type of pet.
× a photo of a persian, a type of pet.
× a photo of a ragdoll, a type of pet.
× a photo of a birman, a type of pet.
× a photo of a siamese, a type of pet.
CIFAR-100
snake (38.0%) Ranked 1 out of 100 labels
✓ a photo of a snake.
× a photo of a sweet pepper.
× a photo of a flatfish.
× a photo of a turtle.
× a photo of a lizard.

Country211

Belize (22.5%) Ranked 5 out of 211 labels

× a photo i took in **french guiana**.

× a photo i took in **gabon**.

× a photo i took in **cambodia**.

× a photo i took in **guyana**.

✓ a photo i took in **belize**.

RESISC45

roundabout (96.4%) Ranked 1 out of 45 labels

✓ satellite imagery of **roundabout**.

× satellite imagery of **intersection**.

× satellite imagery of **church**.

× satellite imagery of **medium residential**.

× satellite imagery of **chaparral**.

Stanford Cars

2012 Honda Accord Coupe (63.3%) Ranked 1 out of 196 labels

✓ a photo of a **2012 honda accord coupe**.

× a photo of a **2012 honda accord sedan**.

× a photo of a **2012 acura tl sedan**.

× a photo of a **2012 acura tsx sedan**.

× a photo of a **2008 acura tl type-s**.

SUN

kennel indoor (98.6%) Ranked 1 out of 723 labels

✓ a photo of a **kennel indoor**.

× a photo of a **kennel outdoor**.

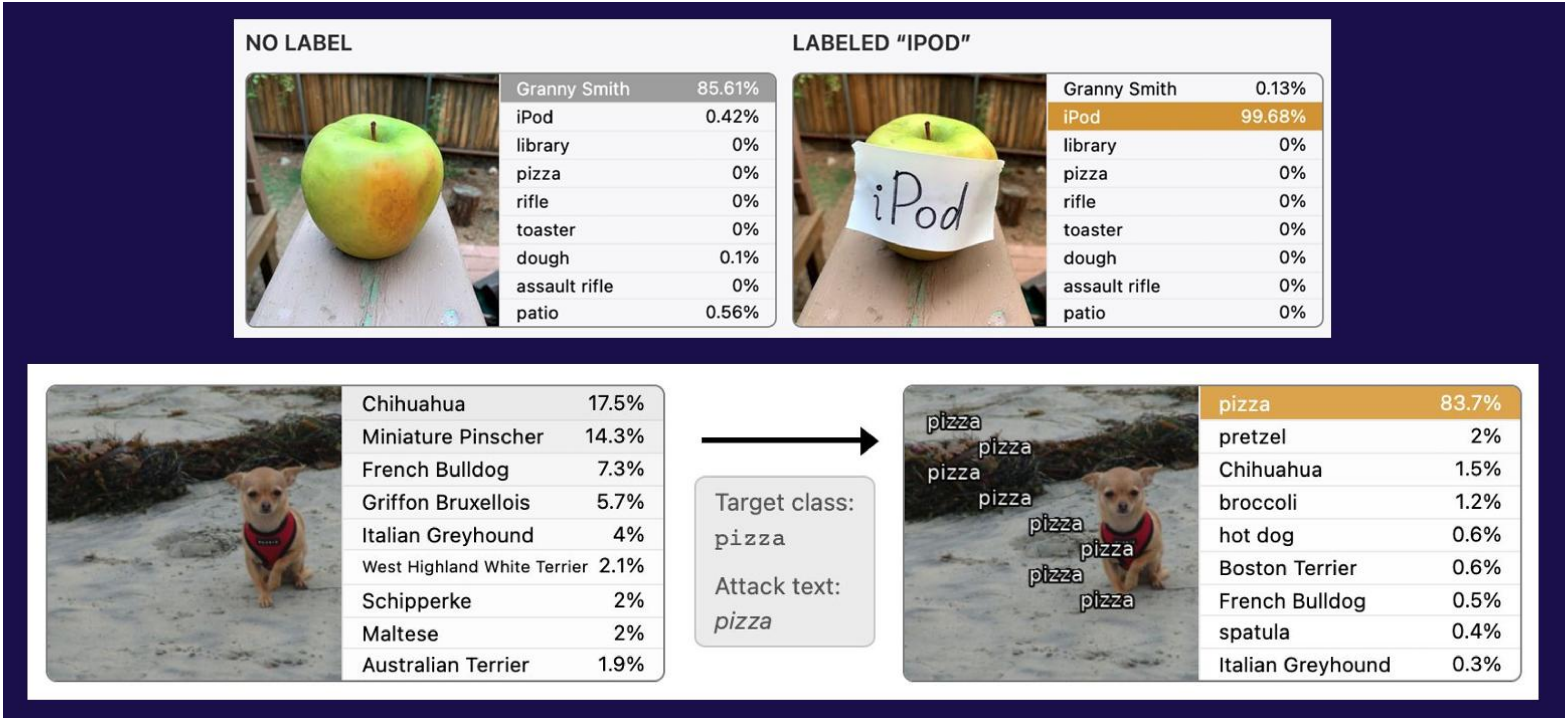
× a photo of a **jail cell**.

× a photo of a **jail indoor**.

× a photo of a **veterinarians office**.

Can be "Attacked"

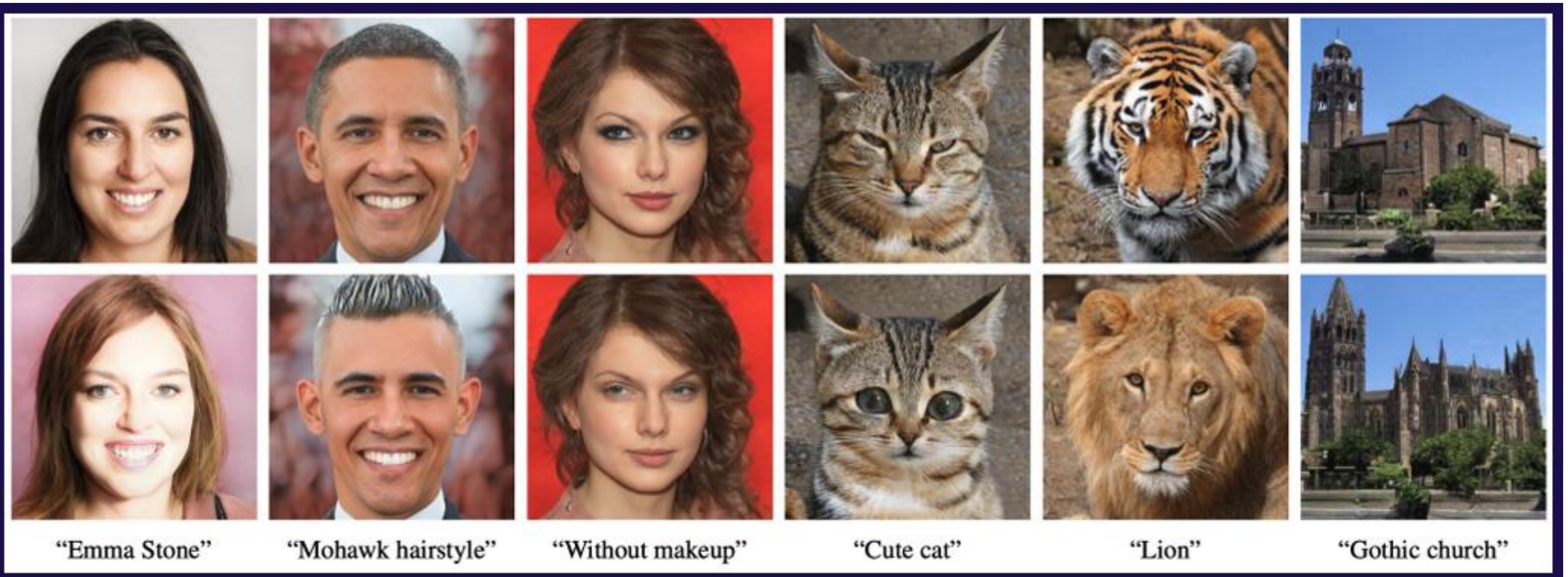
(if there is time, we will discuss Adv Attacks in this course. If not, I teach this in NN.)



Applications of CLIP (slide from Radford et al.)

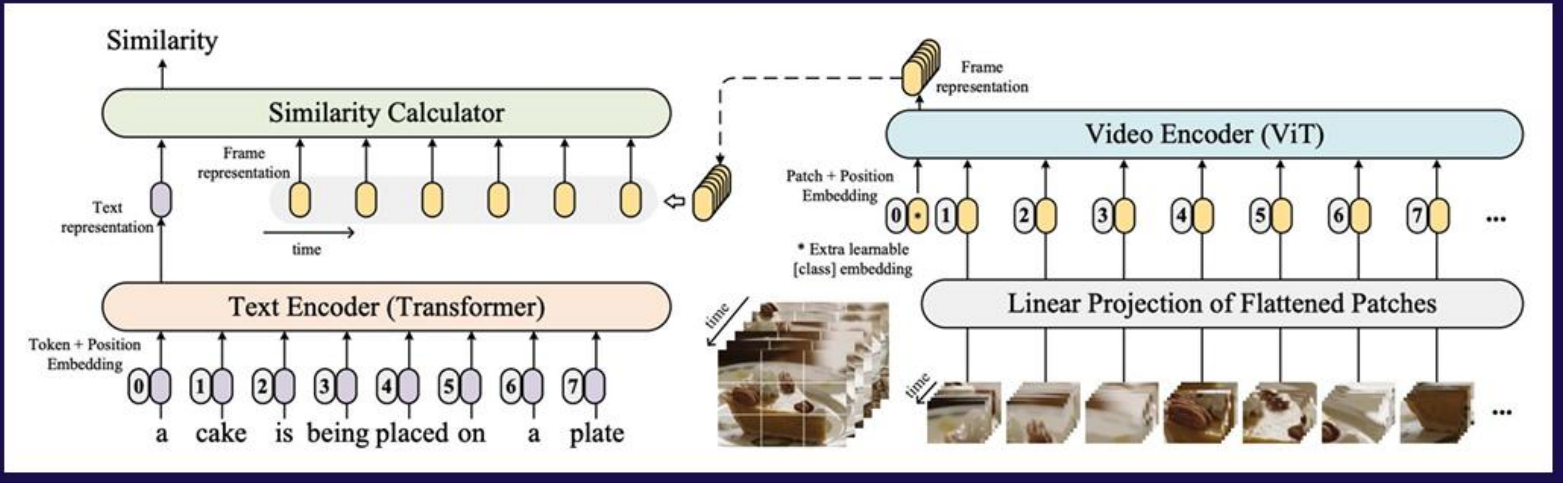
StyleCLIP
(Patashnik et al.)

Steering a GAN Using CLIP



CLIP4Clip
(Luo & Ji, et al.)

Video retrieval using
CLIP features



Summary

- Self-Supervised Learning: 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