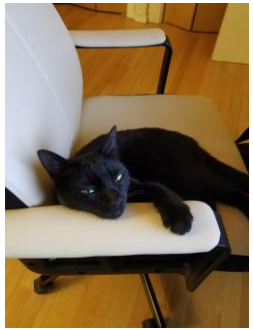
MATHÉMATIQUES ET INFORMATIQUE
Sciences
Université Paris Cité

Cours 5 : Image representations
Self-Supervised Learning

Support de cours adapté de
« CS231n: Deep Learning for Computer Vision, **Stanford - Spring 2022** »,
http://cs231n.stanford.edu/

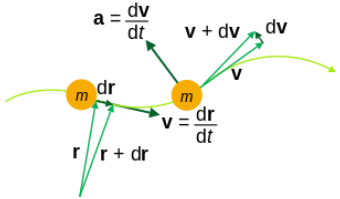
Representations

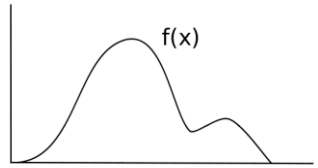
Things...

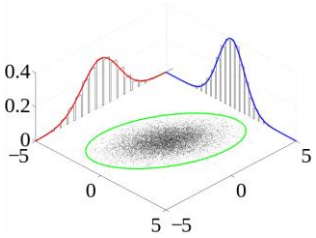


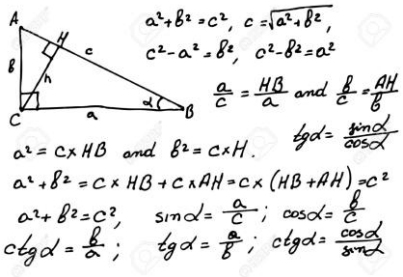
My heart beats as if the world is dropping, you may not feel the love but i do its a heart breaking moment of your life. enjoy the times that we have, it might not sound good but one thing it rhymes it might not be romantic but i think it is great,the best rhyme i've ever heard.

Our Knowledge...









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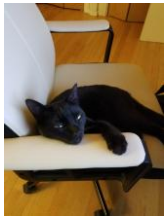


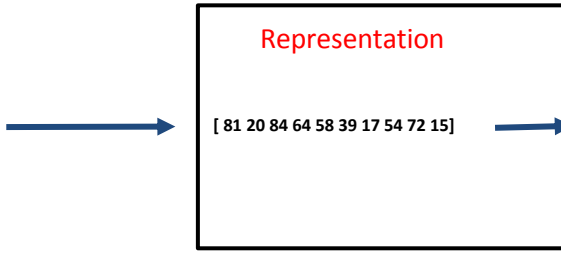
I dare not speak of what I have done. Such twisted thoughts overtook my mind and now I am sorry to say that *I have done the deed.* I have murdered the King of Scotland, King Duncan.

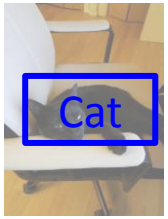
After naming me the *Worthy Thane of Cawdor,* this is how I repay him. I have betrayed him in the most unimaginable way a person possibly could, and I've been disloyal to him, just like I have to Banquo, whom I have lost as a dear friend. I wish that I had never done such a treacherous thing, as I am afraid that *I shall sleep no more.*

I was waiting anxiously for my Lady to sound the bell that called me to do the deed. But before she did, a symbol of the supernatural appeared before my eyes. *The dagger of the mind* captured me and the handle was to my hand yet I couldn't grasp it, but *I could see thee still.* I knew not whether to follow or to discard it from my eyes, but the *false creation* remained.

As I stepped closer to Duncan's room, I thought that I would panic and freeze, but when I got nearer, a sickening thought made me feel like I was doing the right thing! As soon as I heard the bell I knew that it was the bell summoning me.

I heard him pleading as the dagger pierced through his skin,





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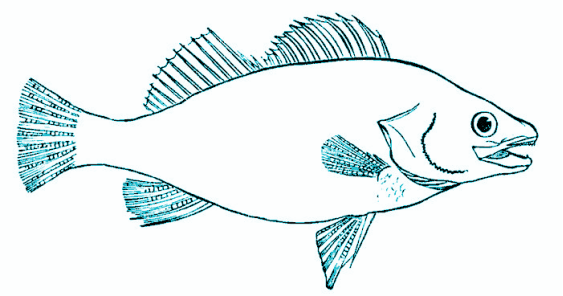
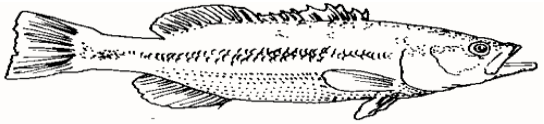


~12 lbs



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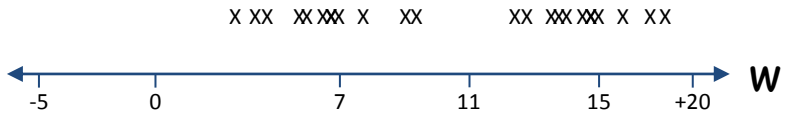
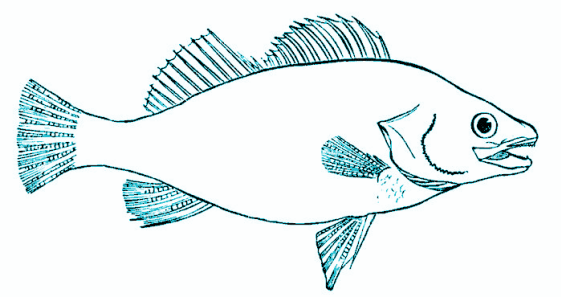
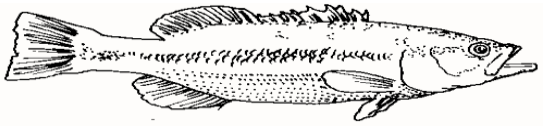


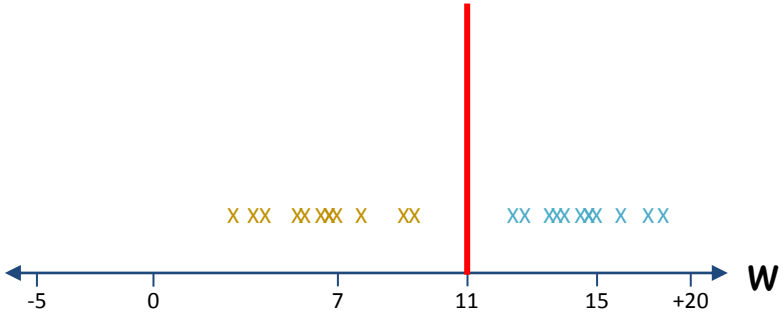
Representations



~12 lbs



~8 lbs



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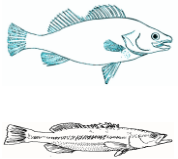
~8 lbs



Representation

Weight (w)

Mathematical Model (Classifier)

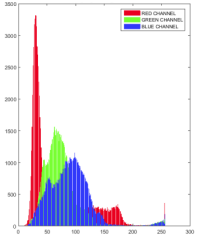
w>11

Type A

Type B

Handcrafted image representation

Represent these cats for a cat detector!



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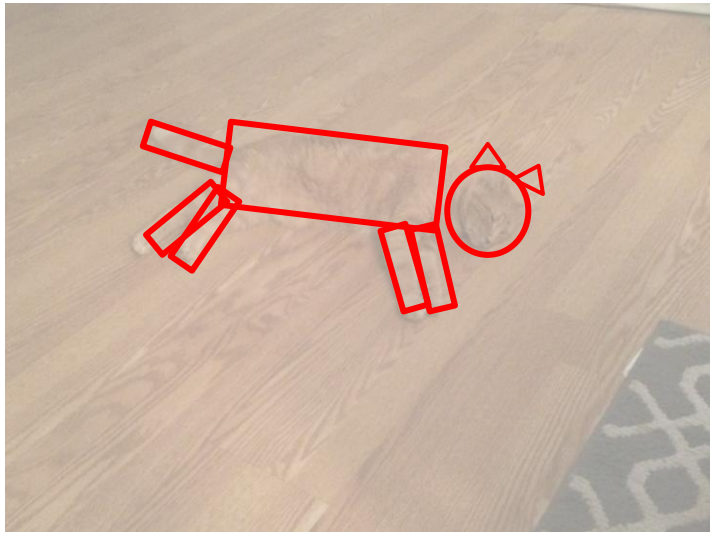

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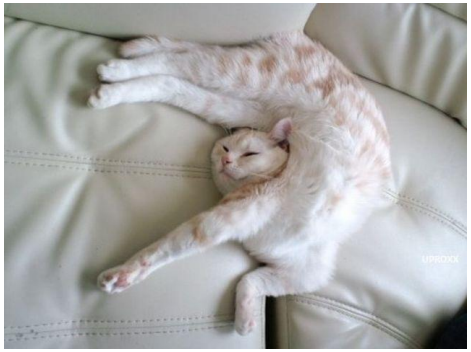

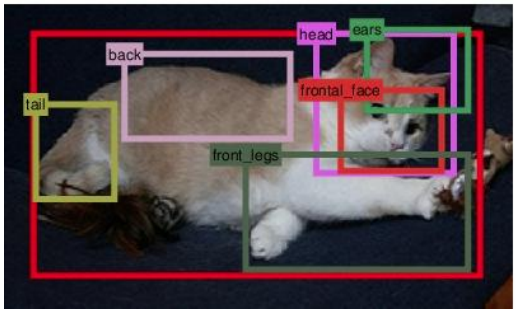

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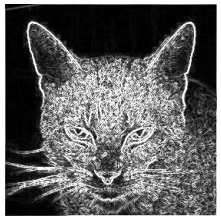
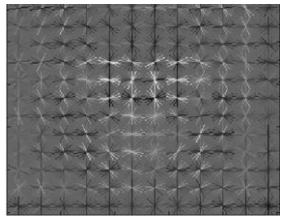
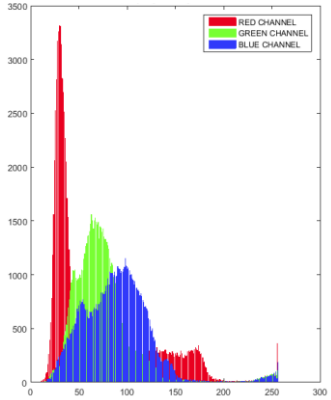
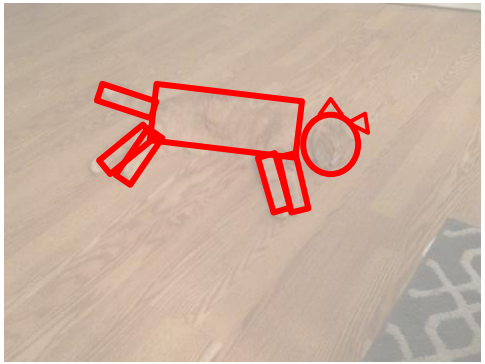




Handcrafted image representation

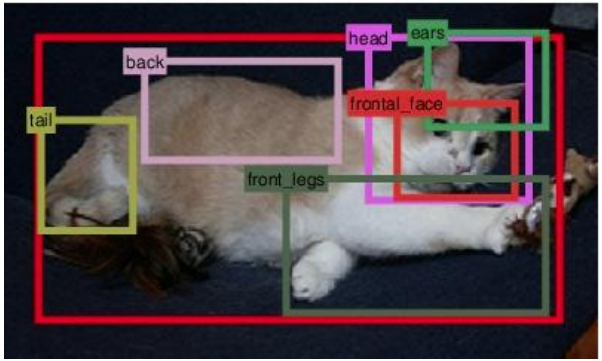
Color Histograms

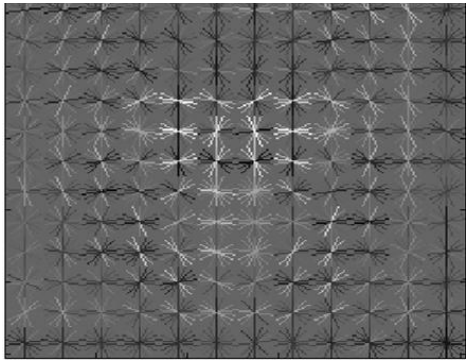




Models based Shapes

Deformable Part based Models (DPM)





Histogram of Gradients (HOG)

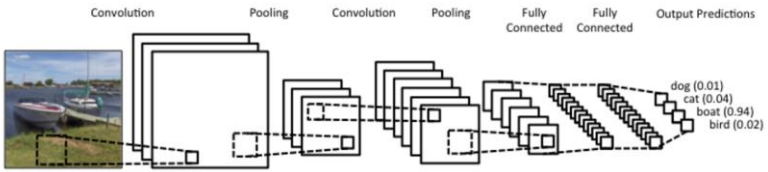
Handcrafted image representation

- Was the only way for a long time.
- (almost) Worked for many great applications:
  - Image Retrieval, Structure-from-motion, Face detection, Identification, etc
- Why alternatives?
  - Can’t quite find the discriminative signature for a problem.
  - Discriminative signature can be found, but hard to approach programmatically.
  - Too many contributing factors to the problem.
    - Fusion non-trivial. Rule-based fusion outruled.
    - Fusion of contributing factors itself a comparably complex representation problem.

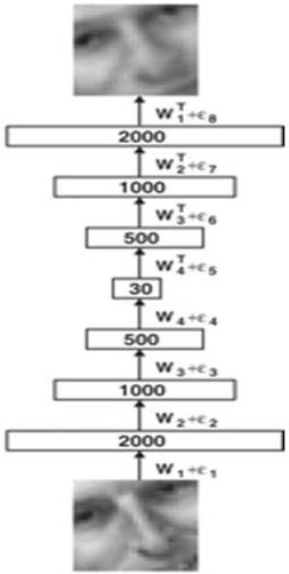
Why a sad image?

Representation learning: 2 main approaches

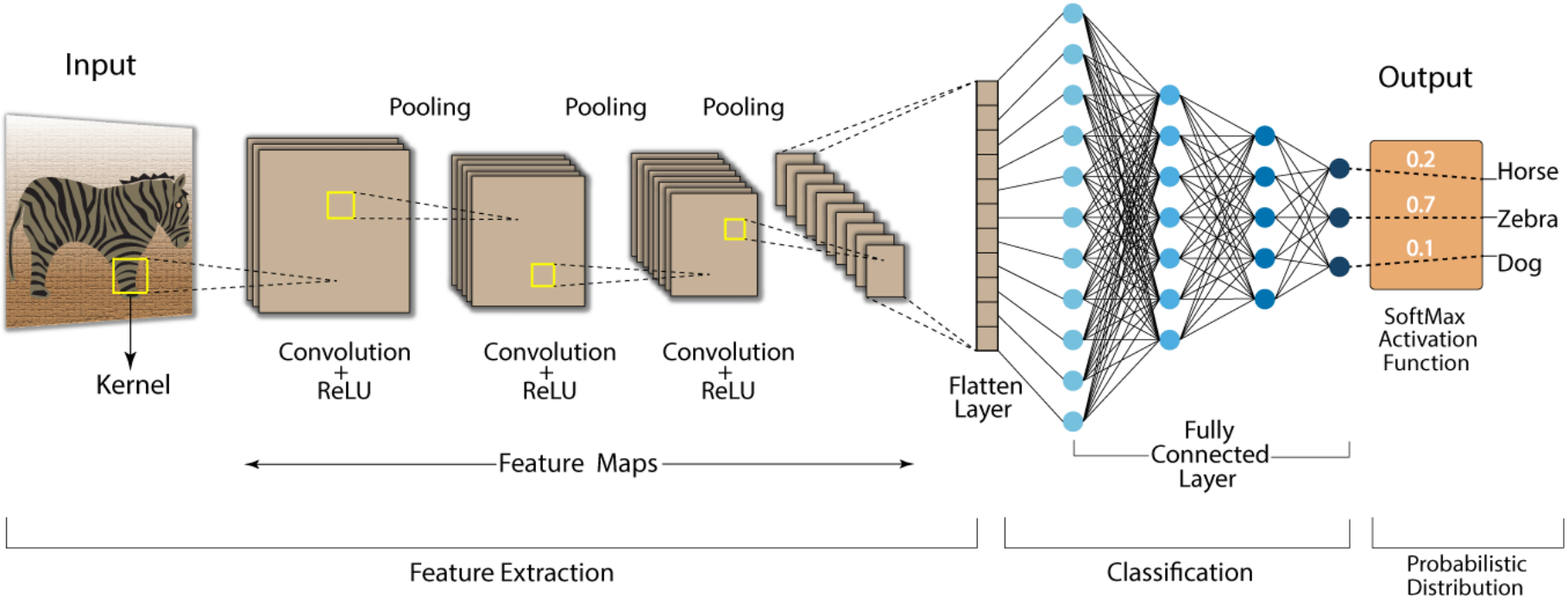
- Supervised
  - Representation constrained on task(s).



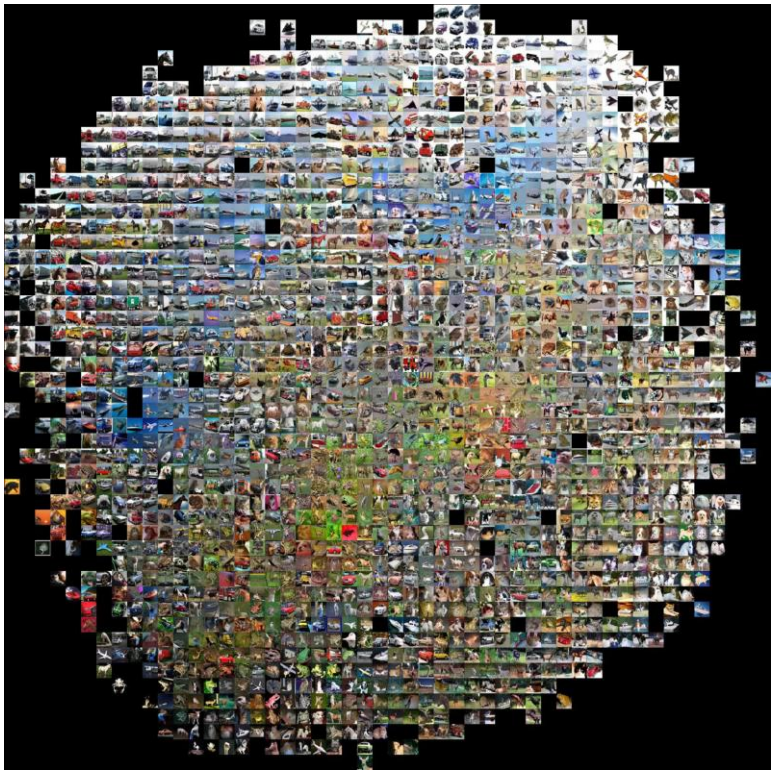
- Unsupervised
  - Representation constrained on reconstruction.

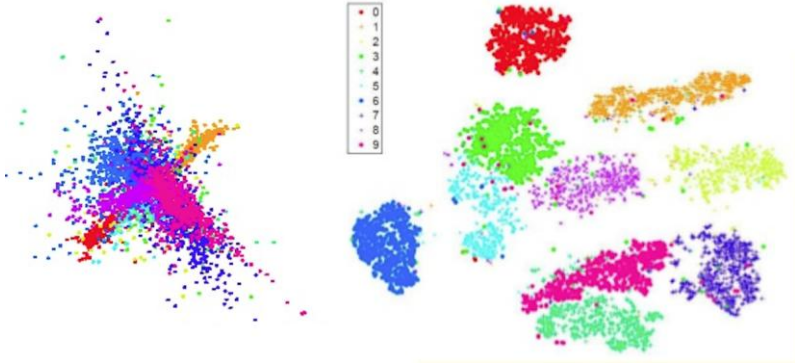


Supervised approaches



Visualization





Embedding

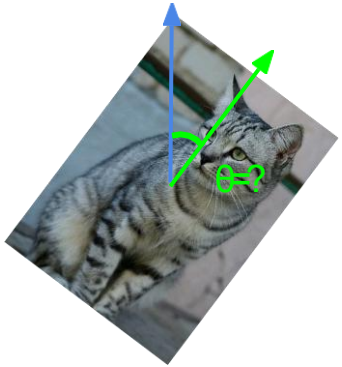
Self-supervised Learning

- Aim to learn from data without manual label annotation.
- Self-supervised learning methods solve “pretext” tasks that produce **good features** for downstream tasks.
  - Learn with supervised learning objectives, e.g., classification, regression.
  - Labels of these pretext tasks are generated *automatically*

Self-supervised pretext tasks

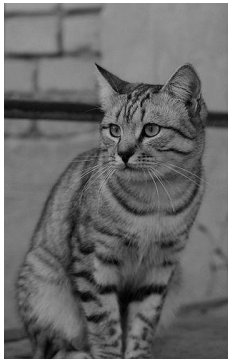
Example: learn to predict image transformations / complete corrupted images

image completion



rotation prediction

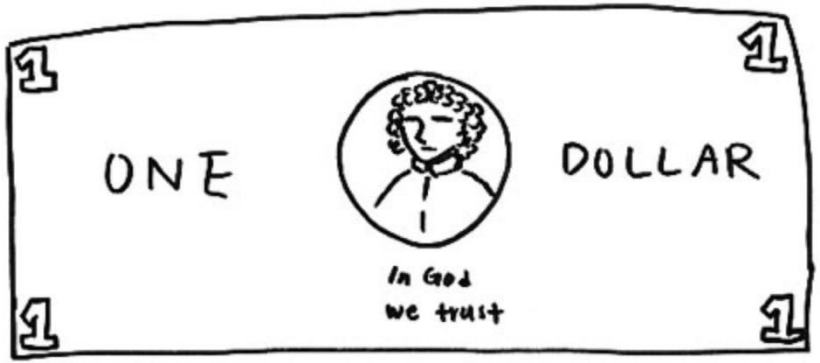
“jigsaw puzzle”



colorization

1. Solving the pretext tasks allow the model to learn good features.
2. We can automatically generate labels for the pretext tasks.

Generative vs. Self-supervised Learning



Left: Drawing of a dollar bill from memory. Right: Drawing subsequently made with a dollar bill present. Image source: Epstein, 2016

Learning to generate pixel-level details is often unnecessary; learn high-level semantic features with pretext tasks instead

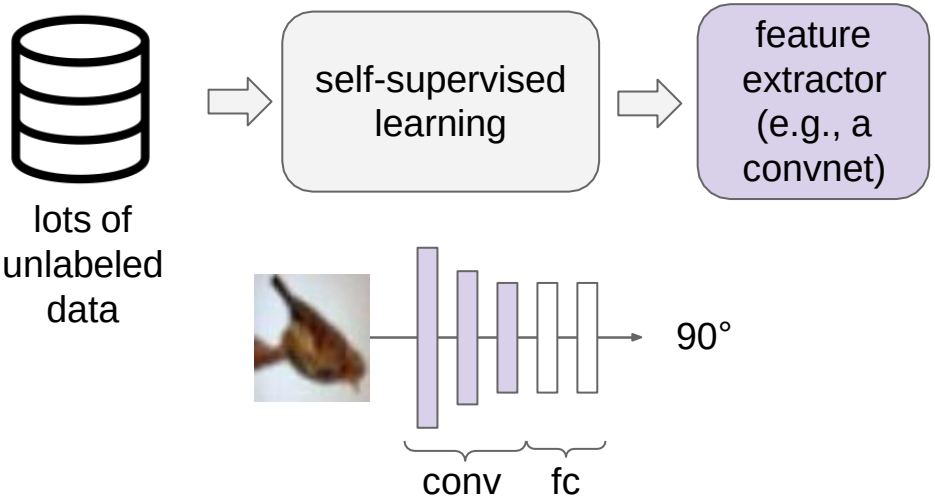
Source: Anand, 2020

How to evaluate a self-supervised learning method?

We usually don’t care about the performance of the self-supervised learning task, e.g., we don’t care if the model learns to predict image rotation perfectly.

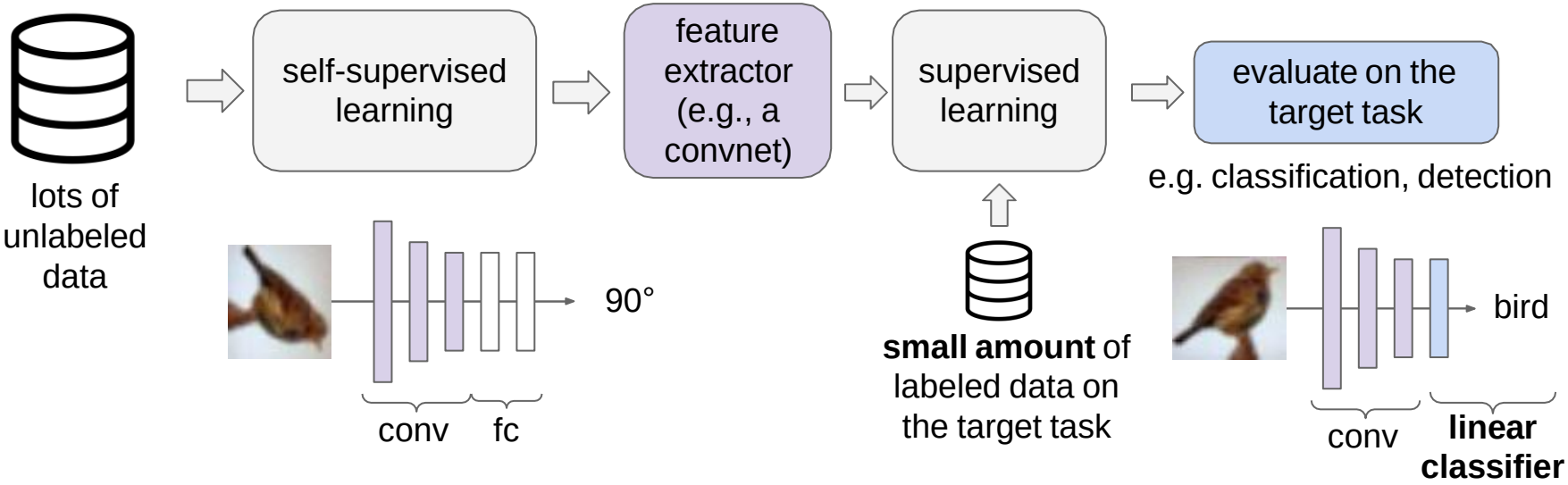
Evaluate the learned feature encoders on downstream *target tasks*

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?



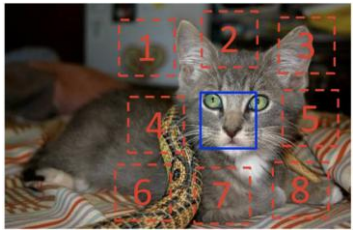
1. Learn good feature extractors from self-supervised pretext tasks, e.g., predicting image rotations

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

Today's lecture

computer vision



Doersch et al., 2015

robot / reinforcement learning

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

language modeling

Language Models are Few-Shot Learners

Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*

Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam Girish Sastry

Amanda Askell Sandhini Agarwal Ariel Herbert-Voss Gretchen Krueger Tom Henighan

Rewon Child Aditya Ramesh Daniel M. Ziegler Jeffrey Wu Clemens Winter

Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

Benjamin Chess Jack Clark Christopher Berner

Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

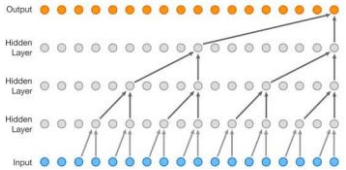
OpenAI

Abstract

Recent work has demonstrated substantial gains on many NLP tasks and benchmarks by pre-training on a large corpus of text followed by fine-tuning on a specific task. While typically task-agnostic in architecture, this method still requires task-specific fine-tuning datasets of thousands or tens of thousands of examples. By contrast, humans can generally perform a new language task from only a few examples or from simple instructions – something which current NLP systems still largely struggle to do. Here we show that scaling up language models greatly improves task-agnostic, few-shot performance, sometimes even reaching competitiveness with prior state-of-the-art fine-tuning approaches. Specifically, we train GPT-3, an autoregressive language model with 175 billion parameters, 10x more than any previous non-sparse language model, and test its performance in the few-shot setting. For all tasks, GPT-3 is applied without any gradient updates or fine-tuning, with tasks and few-shot demonstrations specified purely via text interaction with the model. GPT-3 achieves strong performance on many NLP datasets, including translation, question-answering, and cloze tasks, as well as several tasks that require on-the-fly reasoning or domain adaptation, such as unscrambling words, using a novel word in a sentence, or performing 3-digit arithmetic. At the same time, we also identify some datasets where GPT-3's few-shot learning still struggles, as well as some datasets where GPT-3 faces methodological issues related to training on large web corpora. Finally, we find that GPT-3 can generate samples of news articles which human evaluators have difficulty distinguishing from articles written by humans. We discuss broader societal impacts of this finding and of GPT-3 in general.

GPT3 (Brown, Mann, Ryder, Subbiah et al., 2020)

speech synthesis



Wavenet (van den Oord et al., 2016)

...

Today’s Agenda

Pretext tasks from image transformations

- Rotation, inpainting, rearrangement, coloring

Contrastive representation learning

- Intuition and formulation
- Instance contrastive learning: SimCLR and MOCO
- Sequence contrastive learning: CPC

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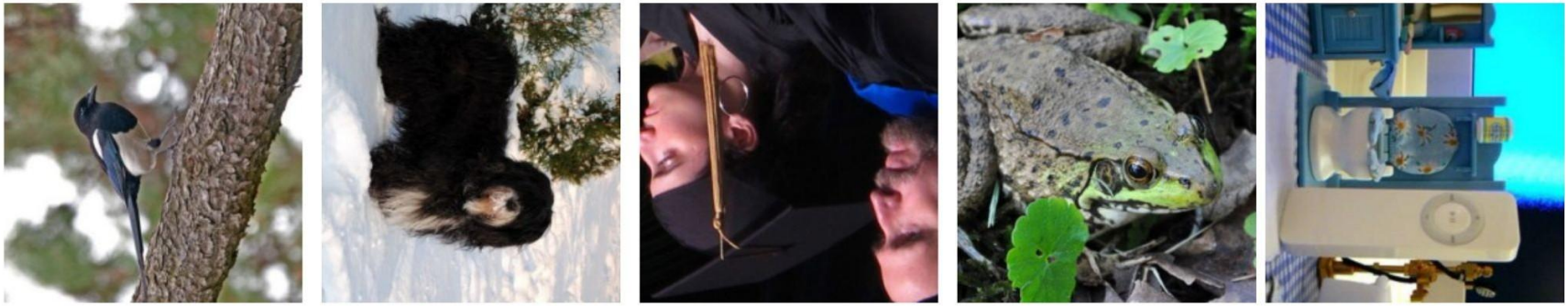
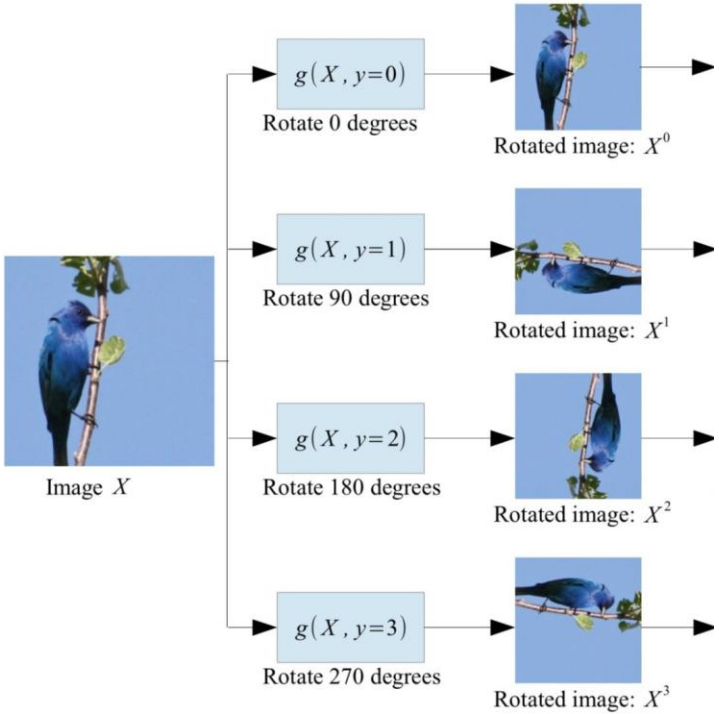
Pretext task: predict rotations



Hypothesis: a model could recognize the correct rotation of an object only if it has the “visual commonsense” of what the object should look like unperturbed.

(Image source: Gidaris et al. 2018)

Pretext task: predict rotations

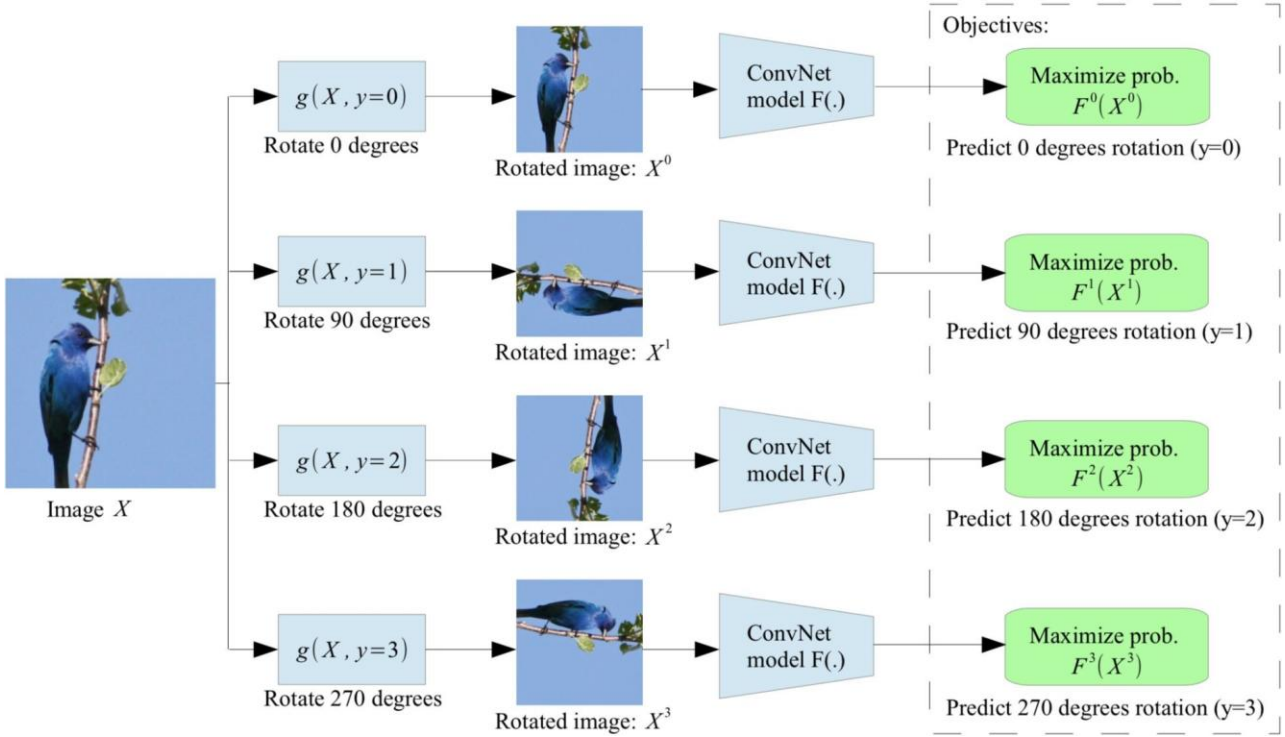


Self-supervised learning by rotating the entire input images.

The model learns to predict which rotation is applied (4-way classification)

(Image source: Gidaris et al. 2018)

Pretext task: predict rotations

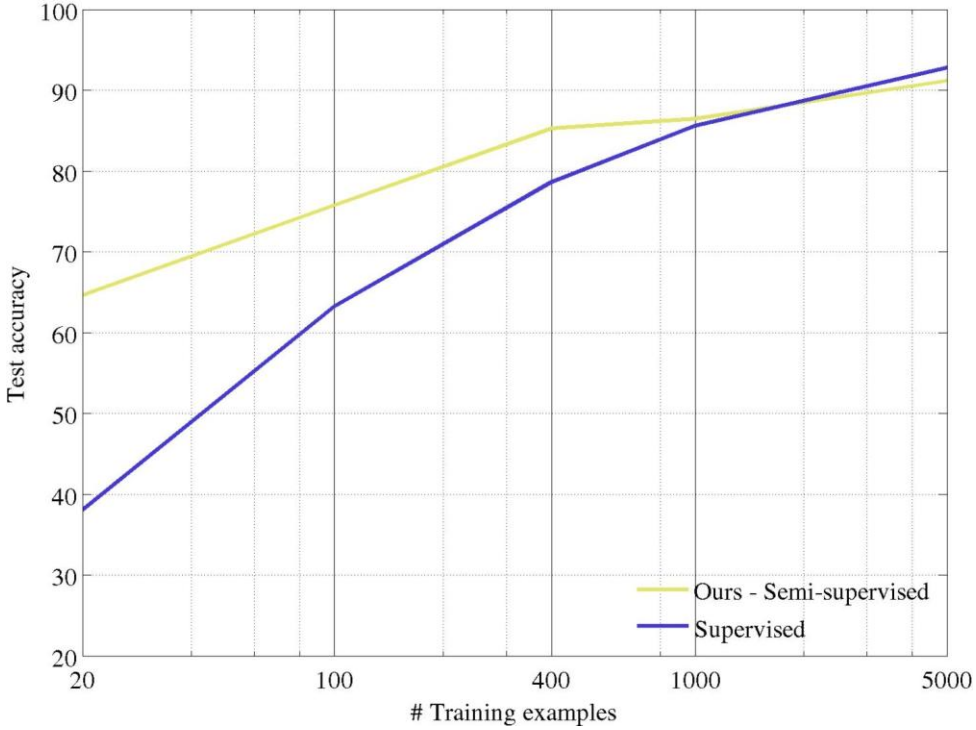


Self-supervised learning by rotating the entire input images.

The model learns to predict which rotation is applied (4-way classification)

(Image source: Gidaris et al. 2018)

Evaluation on semi-supervised learning



Self-supervised learning on **CIFAR10** (entire training set).

Freeze conv1 + conv2
Learn **conv3 + linear** layers with subset of labeled CIFAR10 data (classification).

(Image source: Gidaris et al. 2018)

Transfer learned features to supervised learning

	Classification (%mAP)		Detection (%mAP)	Segmentation (%mIoU)
Trained layers	fc6-8	all	all	all
ImageNet labels	78.9	79.9	56.8	48.0
Random		53.3	43.4	19.8
Random rescaled Krähenbühl et al. (2015)	39.2	56.6	45.6	32.6
Egomotion (Agrawal et al., 2015)	31.0	54.2	43.9	
Context Encoders (Pathak et al., 2016b)	34.6	56.5	44.5	29.7
Tracking (Wang & Gupta, 2015)	55.6	63.1	47.4	
Context (Doersch et al., 2015)	55.1	65.3	51.1	
Colorization (Zhang et al., 2016a)	61.5	65.6	46.9	35.6
BIGAN (Donahue et al., 2016)	52.3	60.1	46.9	34.9
Jigsaw Puzzles (Noroozi & Favaro, 2016)	-	67.6	53.2	37.6
NAT (Bojanowski & Joulin, 2017)	56.7	65.3	49.4	
Split-Brain (Zhang et al., 2016b)	63.0	67.1	46.7	36.0
ColorProxy (Larsson et al., 2017)		65.9		38.4
Counting (Noroozi et al., 2017)	-	67.7	51.4	36.6
(Ours) RotNet	**70.87**	**72.97**	**54.4**	**39.1**

Pretrained with full ImageNet supervision

No pretraining

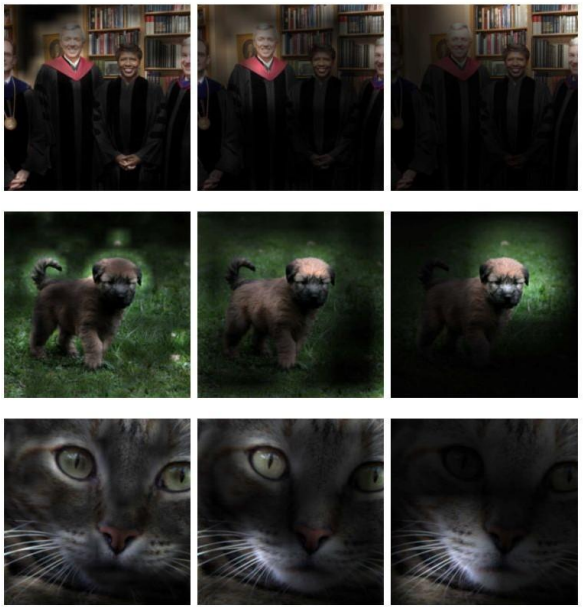
Self-supervised learning with rotation prediction

Self-supervised learning on **ImageNet** (entire training set) with AlexNet.

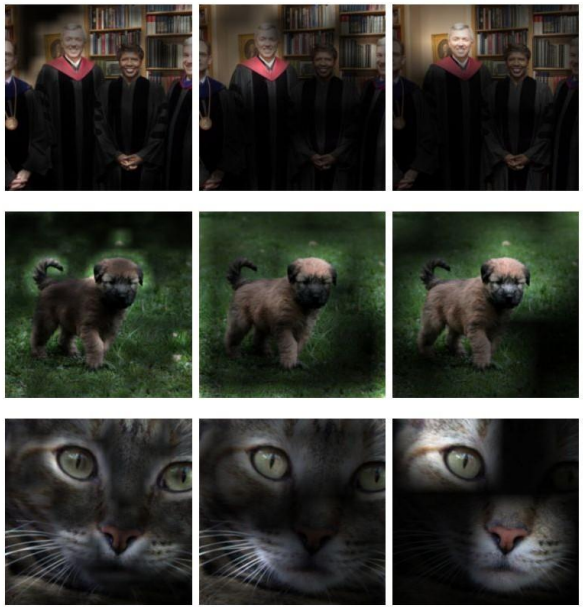
Finetune on labeled data from **Pascal VOC 2007**.

source: Gidaris et al. 2018

Visualize learned visual attentions



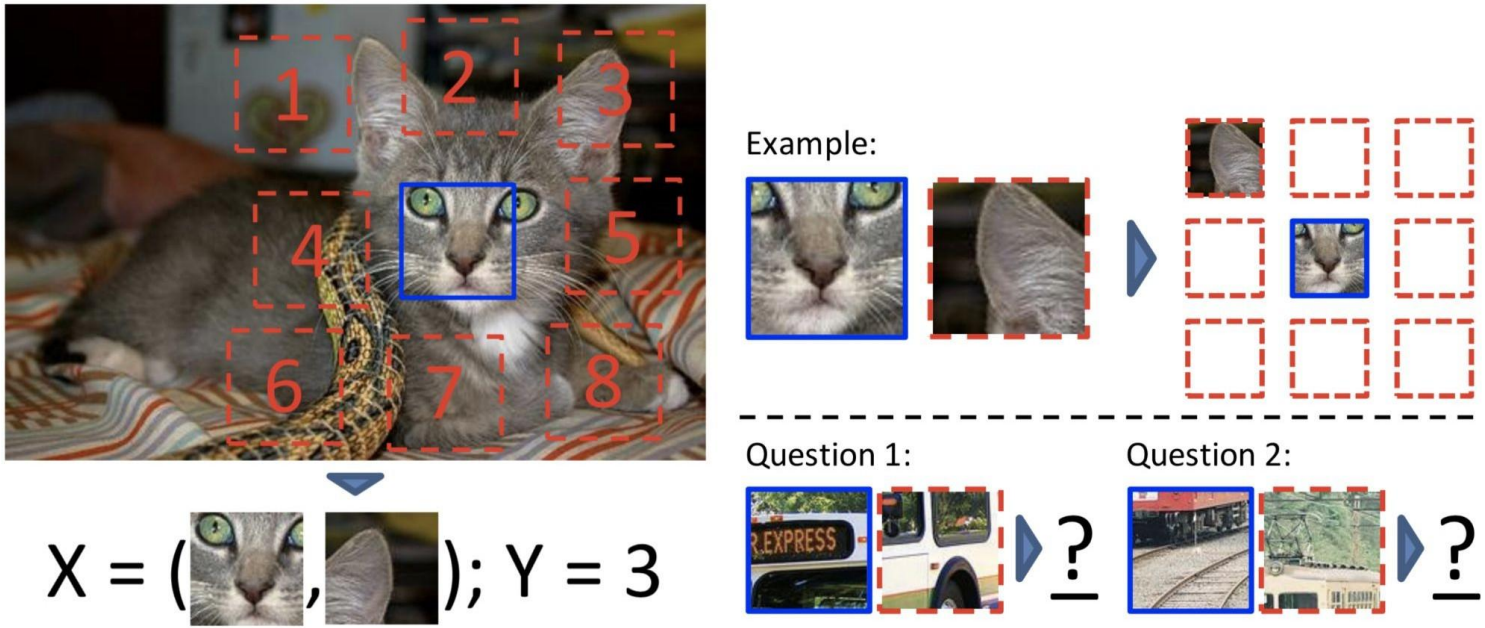
(a) **Attention maps of supervised model**



(b) **Attention maps of our self-supervised model**

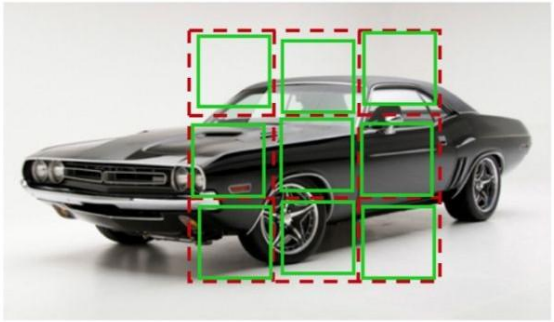
(Image source: Gidaris et al. 2018)

Pretext task: predict relative patch locations



(Image source: Doersch et al., 2015)

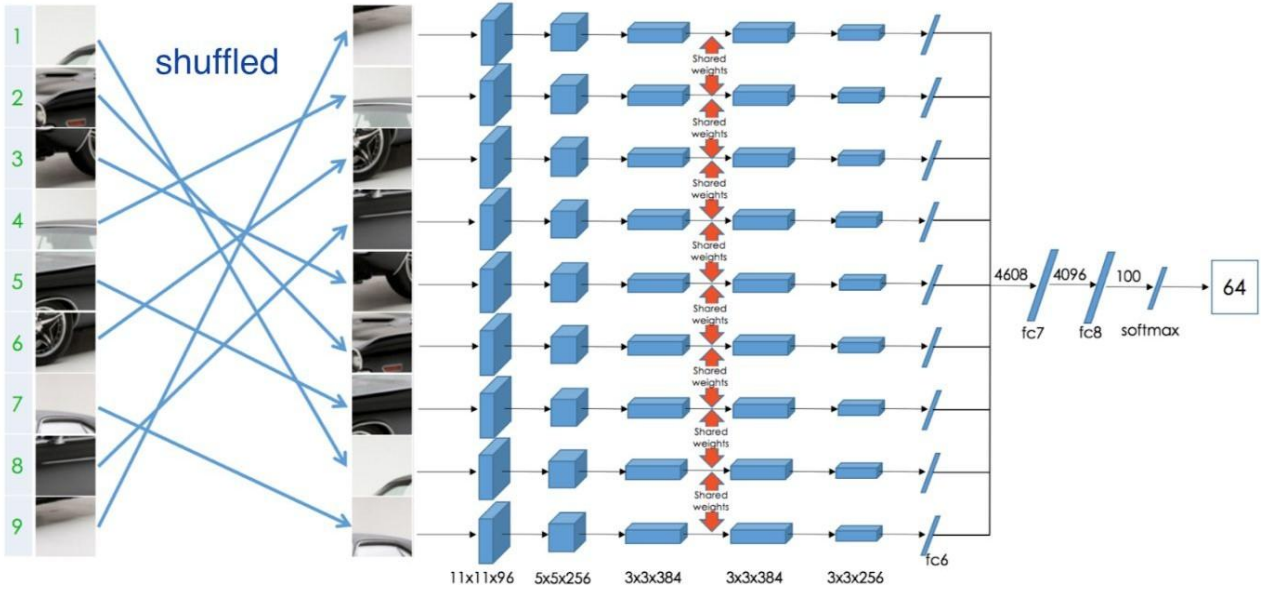
Pretext task: solving “jigsaw puzzles”



Permutation Set

index	permutation
64	9,4,6,8,3,2,5,1,7

Reorder patches according to the selected permutation



(Image source: Noroozi & Favaro, 2016)

Transfer learned features to supervised learning

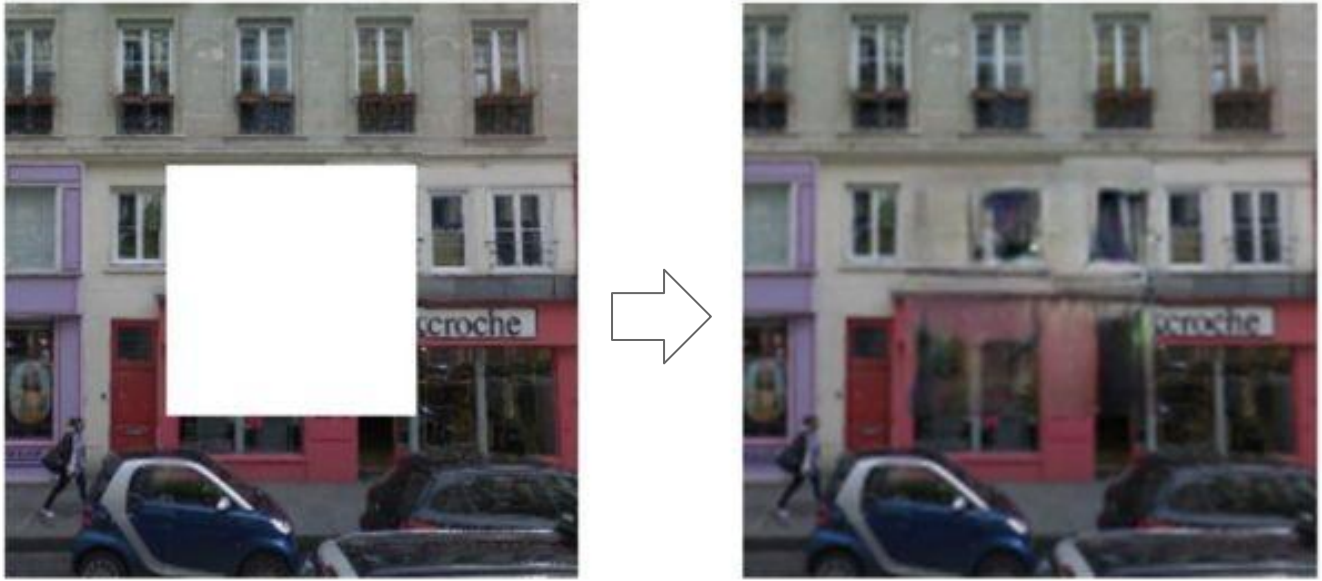
Table 1: Results on PASCAL VOC 2007 Detection and Classification. The results of the other methods are taken from Pathak *et al.* [30].

Method	Pretraining time	Supervision	Classification	Detection	Segmentation
Krizhevsky*et al.* [25]	3 days	1000 class labels	**78.2%**	**56.8%**	**48.0%**
Wang and Gupta[39]	1 week	motion	58.4%	44.0%	-
Doersch *et al.* [10]	4 weeks	context	55.3%	46.6%	-
Pathak *et al.* [30]	14 hours	context	56.5%	44.5%	29.7%
Ours	2.5 days	context	**67.6%**	**53.2%**	**37.6%**

"Ours" is feature learned from solving image Jigsaw puzzles (Noroozi & Favaro, 2016). Doersch et al. is the method with relative patch location

(source: Noroozi & Favaro, 2016)

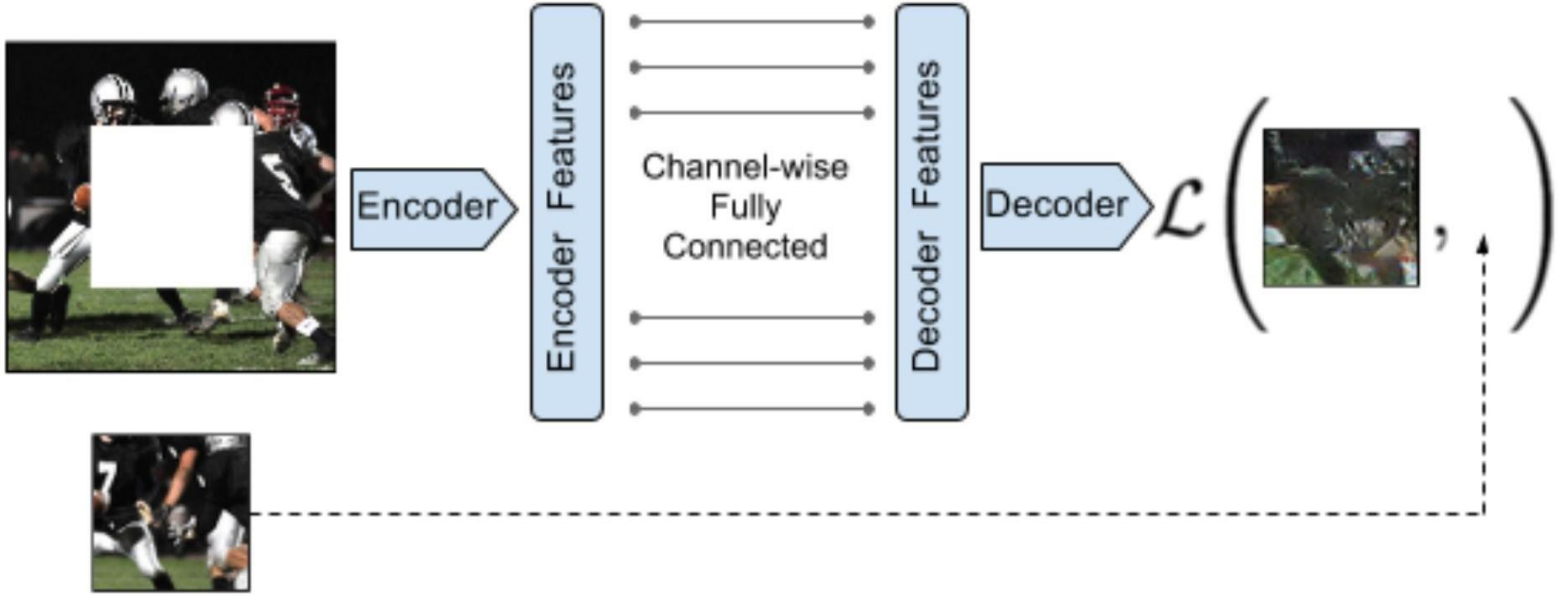
Pretext task: predict missing pixels (inpainting)



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

Source: Pathak et al., 2016

Learning to inpaint by reconstruction



Learning to reconstruct the missing pixels

Source: Pathak et al., 2016

Inpainting evaluation

Input (context)

reconstruction

Source: [Pathak et al., 2016]

Learning to inpaint by reconstruction

Loss = reconstruction + adversarial learning

$$L(x) = L_{recon}(x) + L_{adv}(x)$$

$$L_{recon}(x) = ||M * (x - F_\theta((1 - M) * x))||_2^2$$

$$L_{adv} = \max_D \mathbb{E}[\log(D(x))] + \log(1 - D(F((1 - M) * x)))]$$

Adversarial loss between “real” images and *inpainted images*

Source: Pathak et al., 2016

Inpainting evaluation

Input (context) reconstruction adversarial recon + adv

Source: Pathak et al., 2016

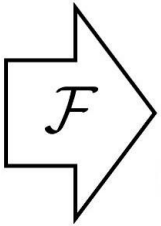
Transfer learned features to supervised learning

Pretraining Method	Supervision	Pretraining time	Classification	Detection	Segmentation
ImageNet [26]	1000 class labels	3 days	78.2%	56.8%	48.0%
Random Gaussian	initialization	< 1 minute	53.3%	43.4%	19.8%
Autoencoder	-	14 hours	53.8%	41.9%	25.2%
Agrawal *et al.* [1]	egomotion	10 hours	52.9%	41.8%	-
Wang *et al.* [39]	motion	1 week	58.7%	47.4%	-
Doersch *et al.* [7]	relative context	4 weeks	55.3%	46.6%	-
Ours	context	14 hours	56.5%	44.5%	30.0%

Self-supervised learning on ImageNet training set, transfer to classification (Pascal VOC 2007), detection (Pascal VOC 2007), and semantic segmentation (Pascal VOC 2012)

Source: Pathak et al., 2016

Pretext task: image coloring

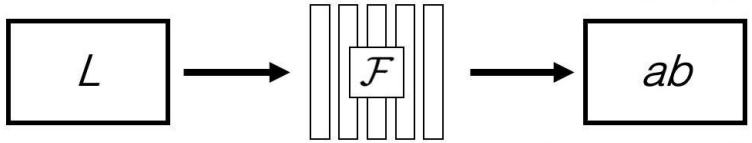


Grayscale image: *L* channel

$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$

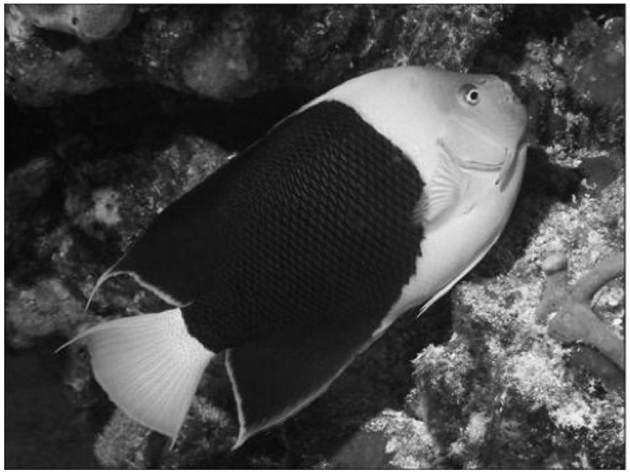
Color information: *ab* channels

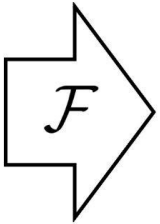
$\hat{\mathbf{Y}} \in \mathbb{R}^{H \times W \times 2}$



Source: Richard Zhang / Phillip Isola

Pretext task: image coloring



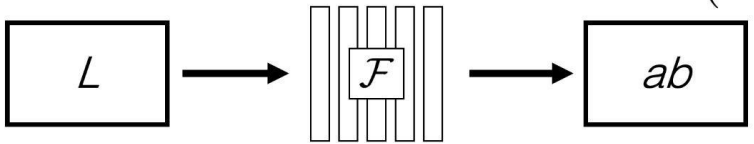


Grayscale image: *L* channel

$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$

Concatenate (*L*,*ab*) channels

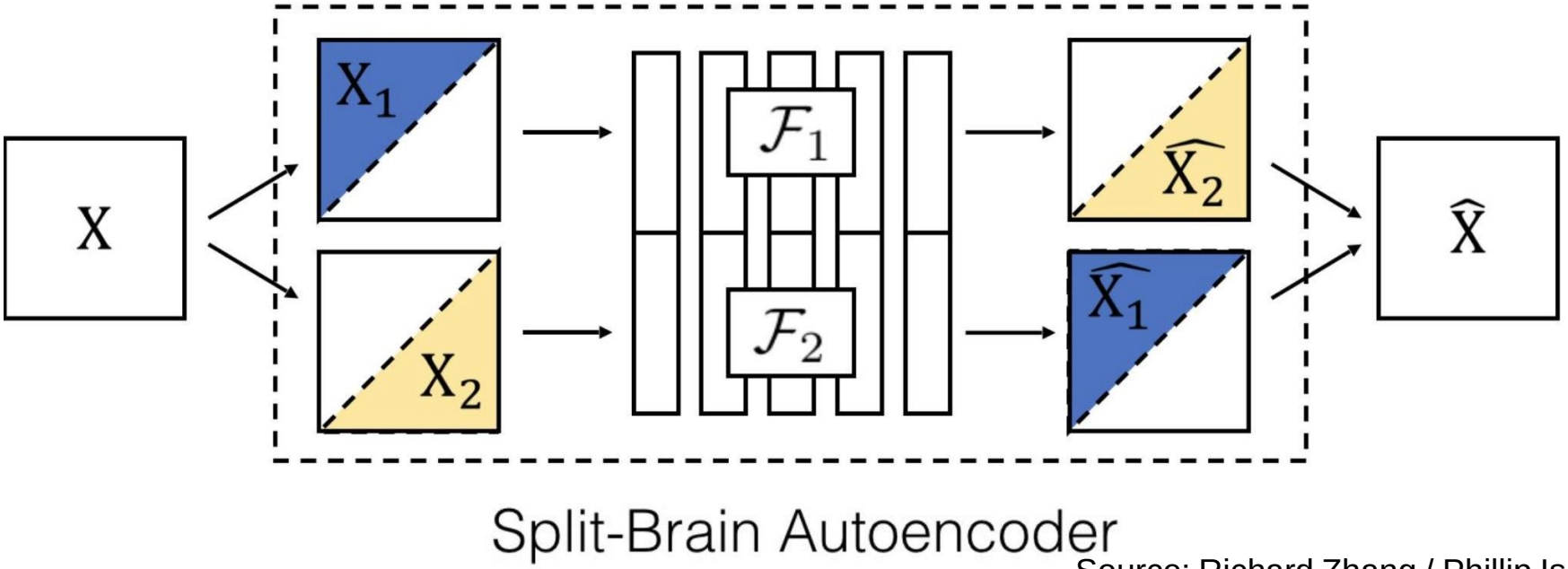
$(\mathbf{X}, \hat{\mathbf{Y}})$



Source: Richard Zhang / Phillip Isola

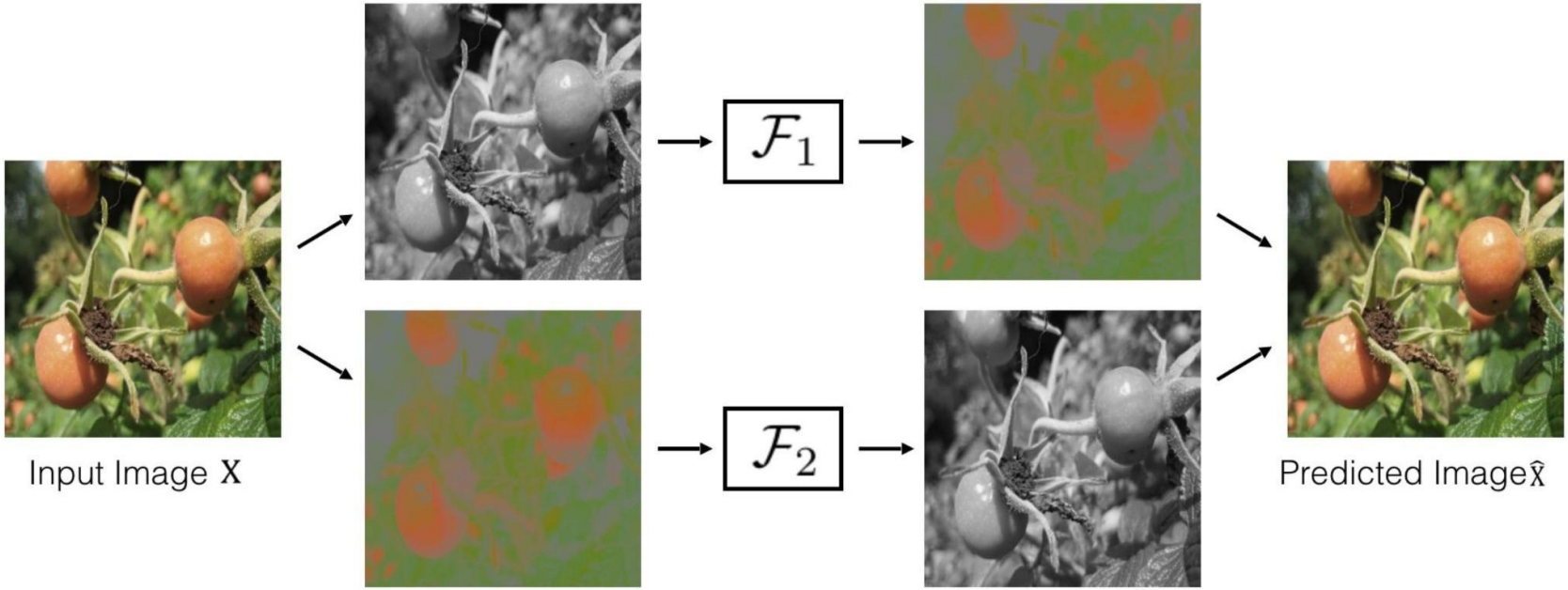
Learning features from colorization: Split-brain Autoencoder

Idea: cross-channel predictions



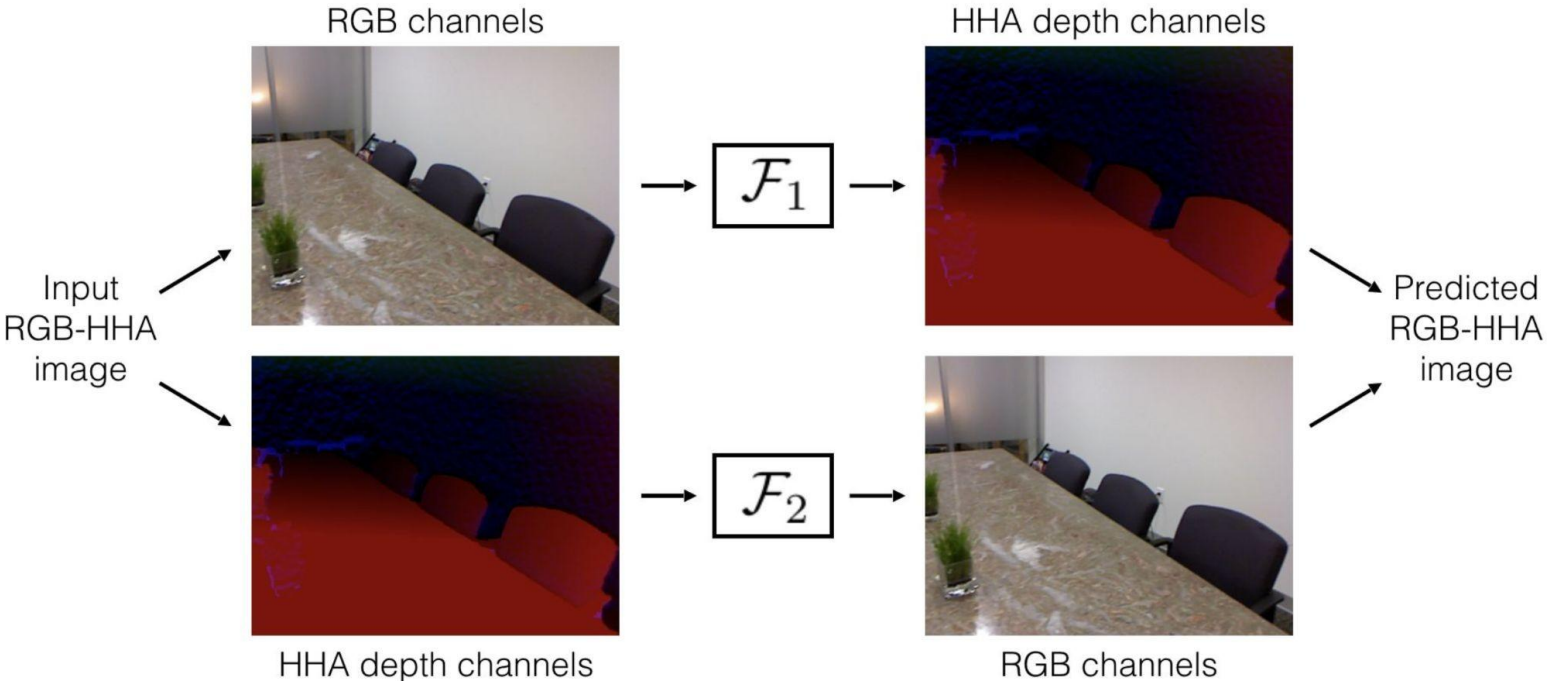
Source: Richard Zhang / Phillip Isola

Learning features from colorization: Split-brain Autoencoder



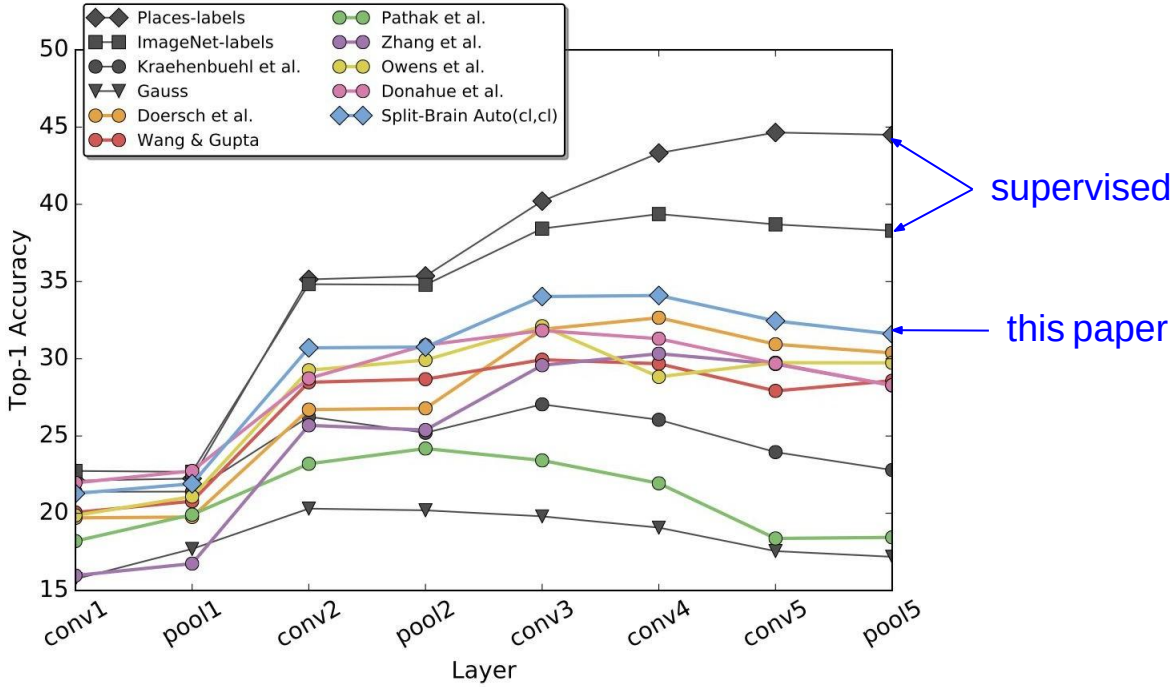
Source: Richard Zhang / Phillip Isola

Learning features from colorization: Split-brain Autoencoder



Source: Richard Zhang / Phillip Isola

Transfer learned features to supervised learning



Self-supervised learning on **ImageNet** (entire training set).

Use *concatenated features* from F_1 and F_2

Labeled data is from the **Places** (Zhou 2016).

Source: Zhang et al., 2017

Pretext task: image coloring

Source: Richard Zhang / Phillip Isola

Pretext task: image coloring

Source: Richard Zhang / Phillip Isola

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

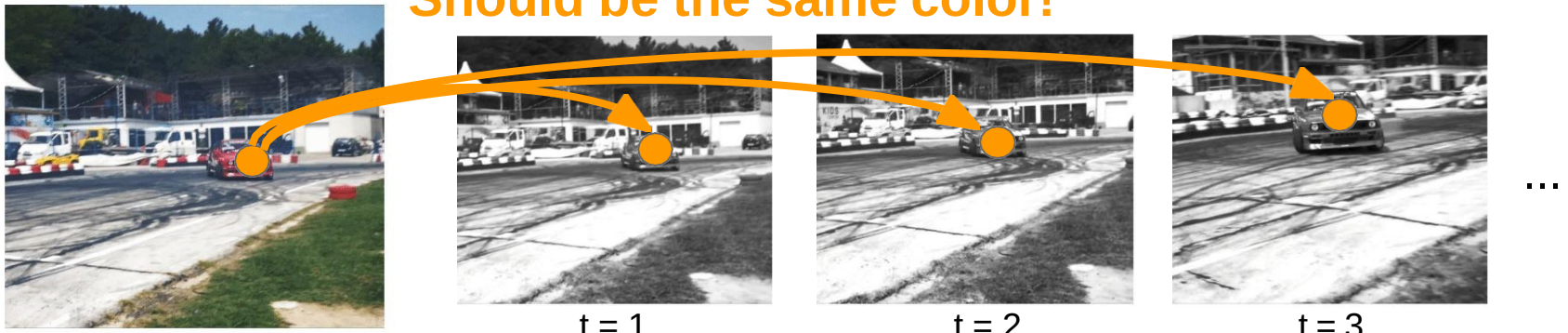
Pretext task: video coloring

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

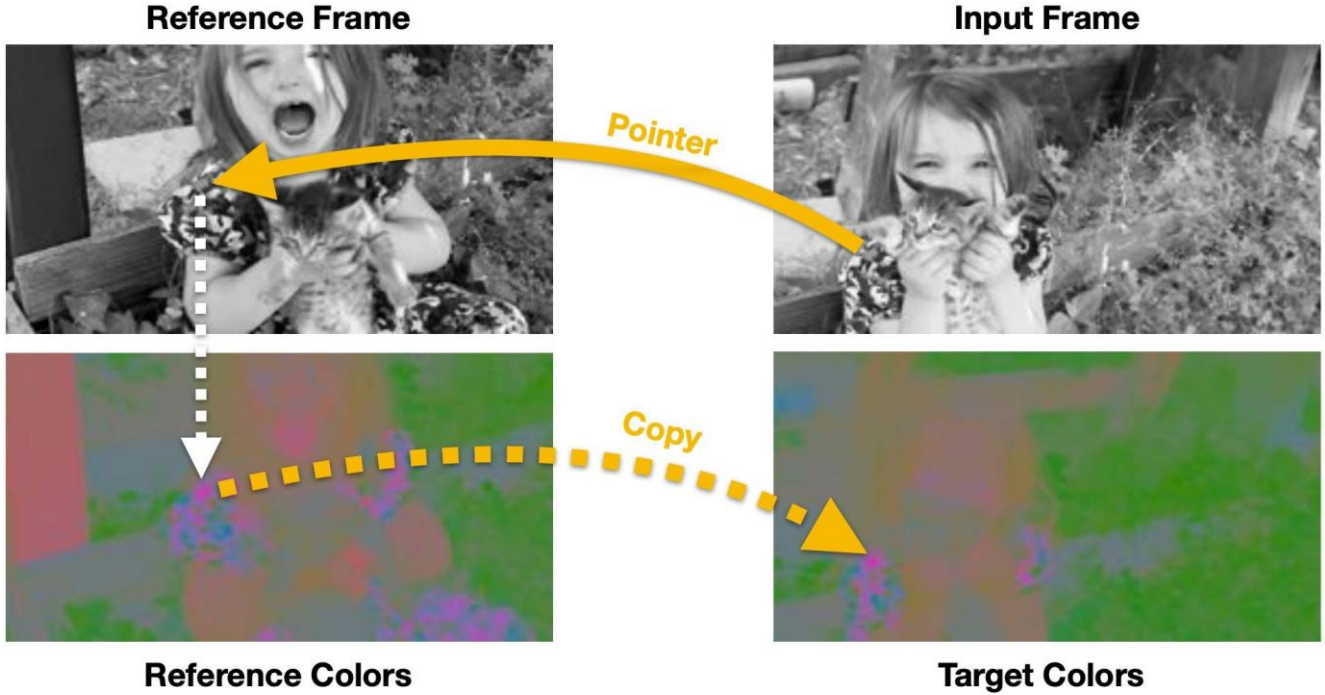
t = 3

...

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



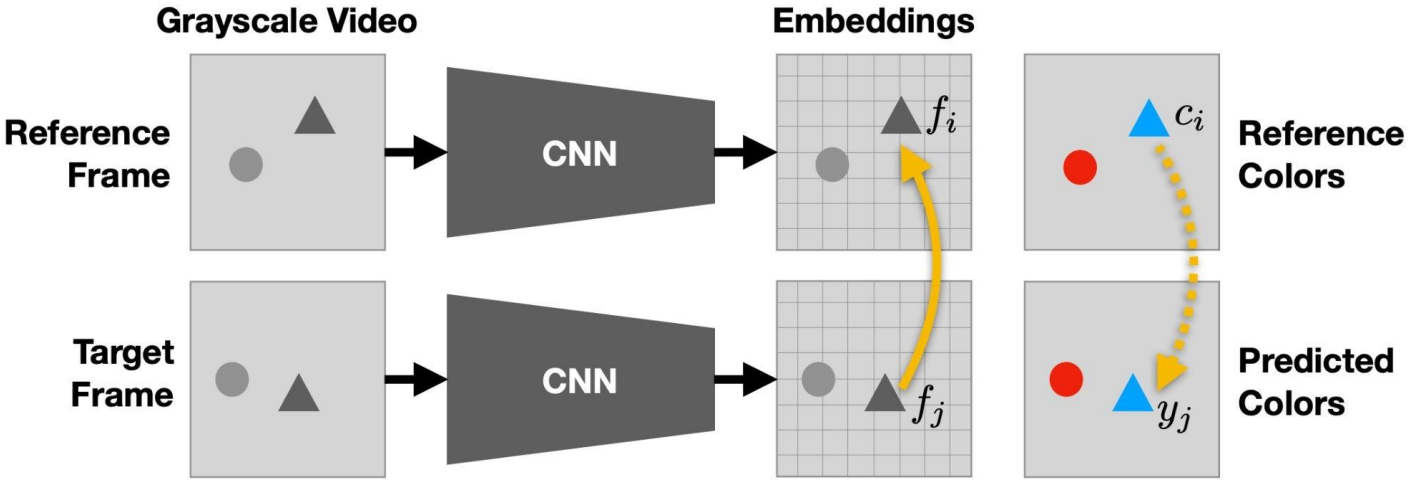
Learning objective:

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

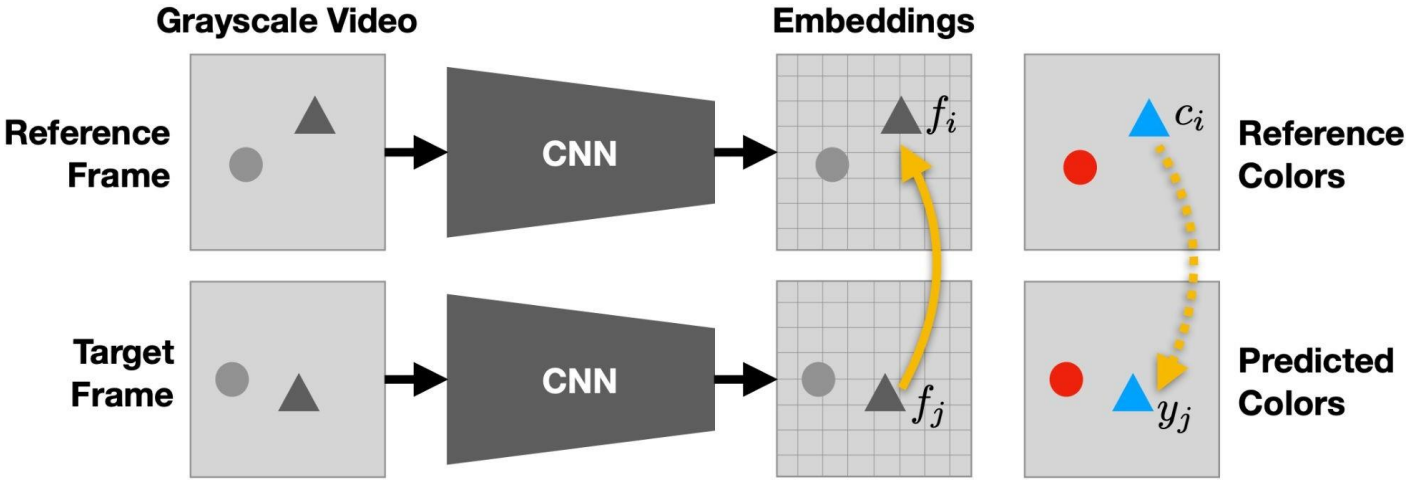


attention map on the reference frame

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

Source: Vondrick et al., 2018

Learning to color videos



attention map on the reference frame

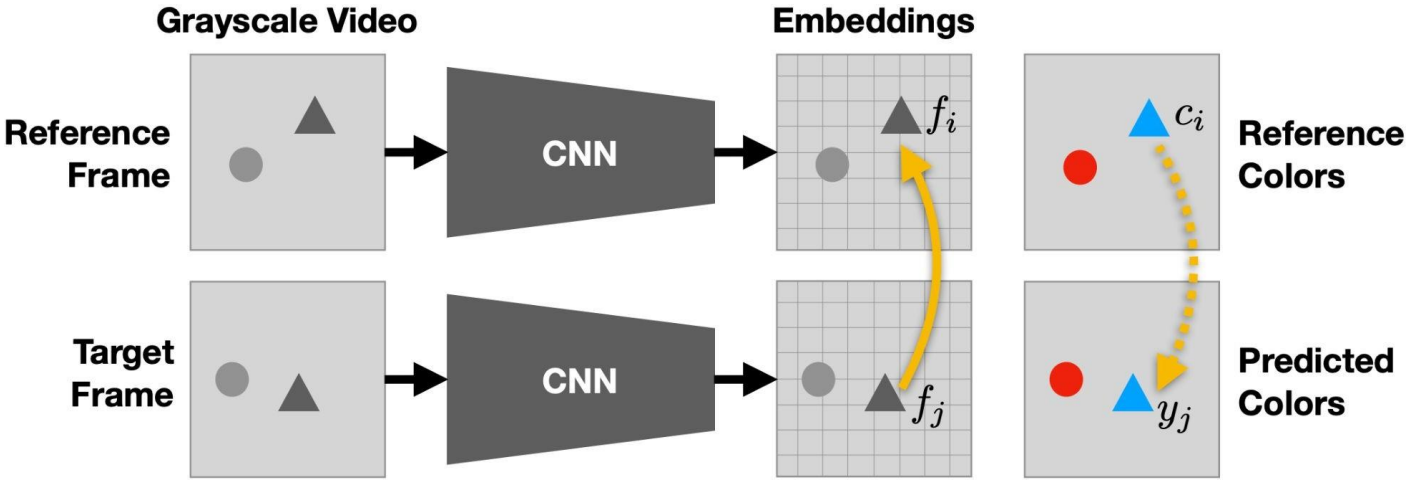
$$A_{ij} = \frac{\exp\left(f_i^T f_j\right)}{\sum_k \exp\left(f_k^T f_j\right)}$$

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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predicted color = weighted sum of the reference color

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

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

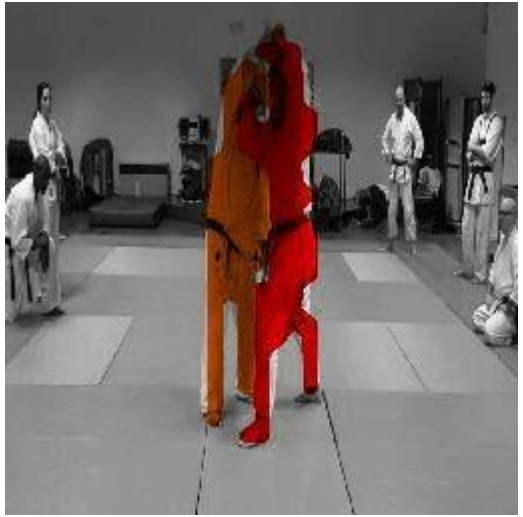
target frames (gray)

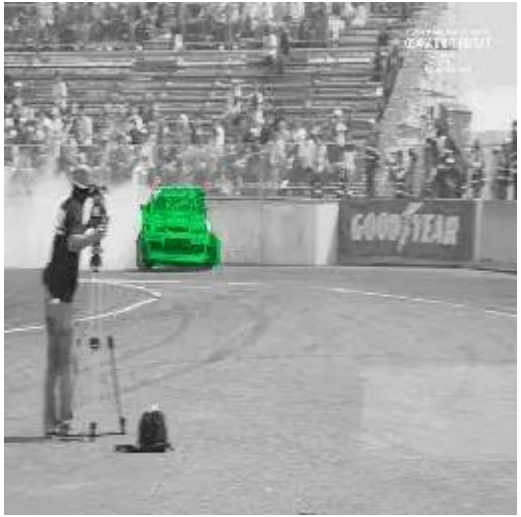
predicted color

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

Summary: pretext tasks from image transformations

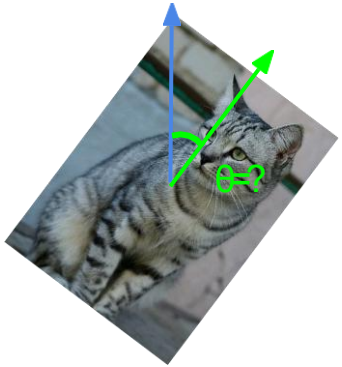
- Pretext tasks focus on “visual common sense”, e.g., predict rotations, inpainting, rearrangement, and colorization.
- The models are forced learn good features about natural images, e.g., semantic representation of an object category, in order to solve the pretext tasks.
- We don’t care about the performance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

Summary: pretext tasks 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 don’t 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, and 2) the learned representations may not be general.

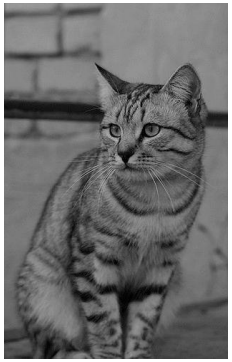
Pretext tasks from image transformations

image completion



rotation prediction

“jigsaw puzzle”

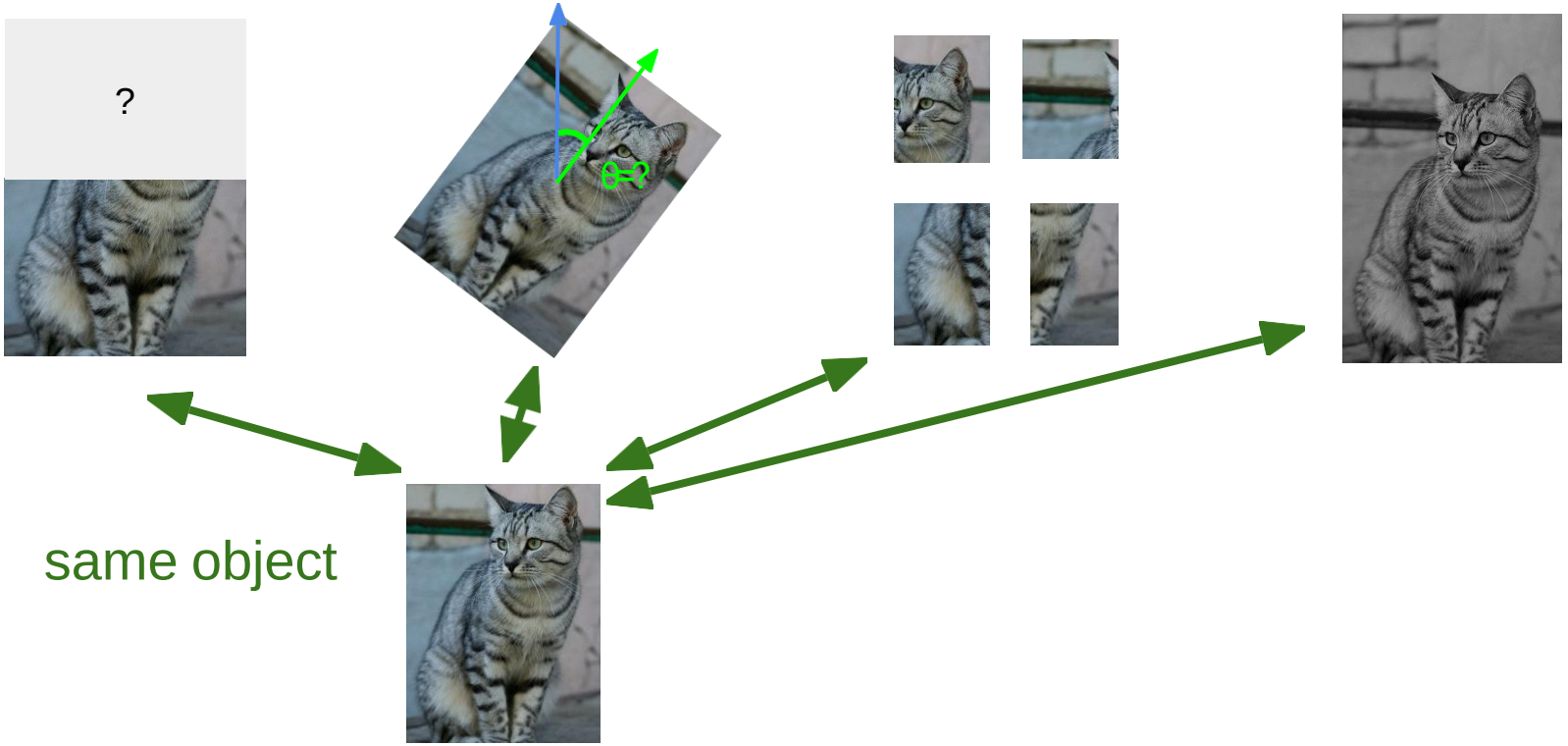


colorization

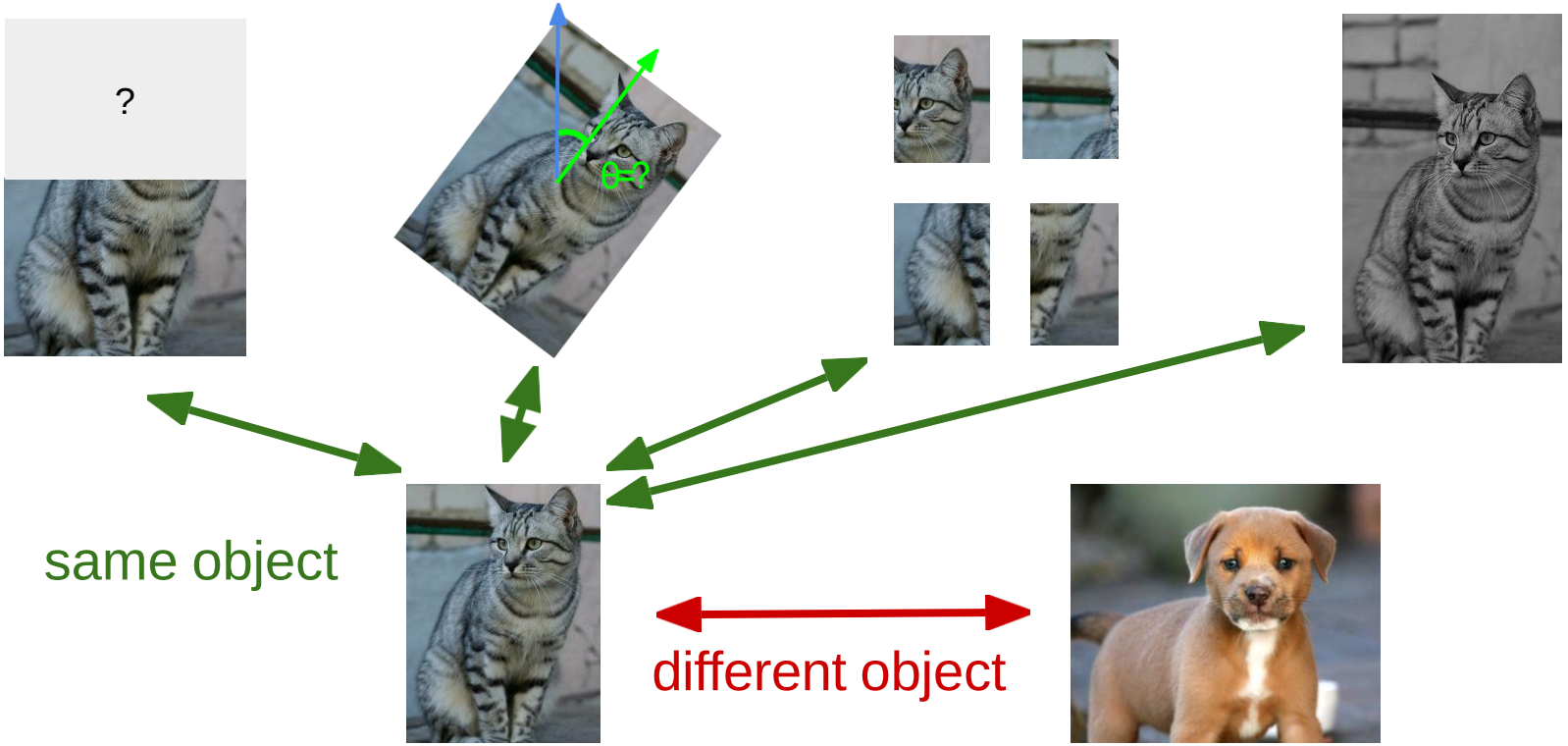
Learned representations may be tied to a specific pretext task!

Can we come up with a more general pretext task?

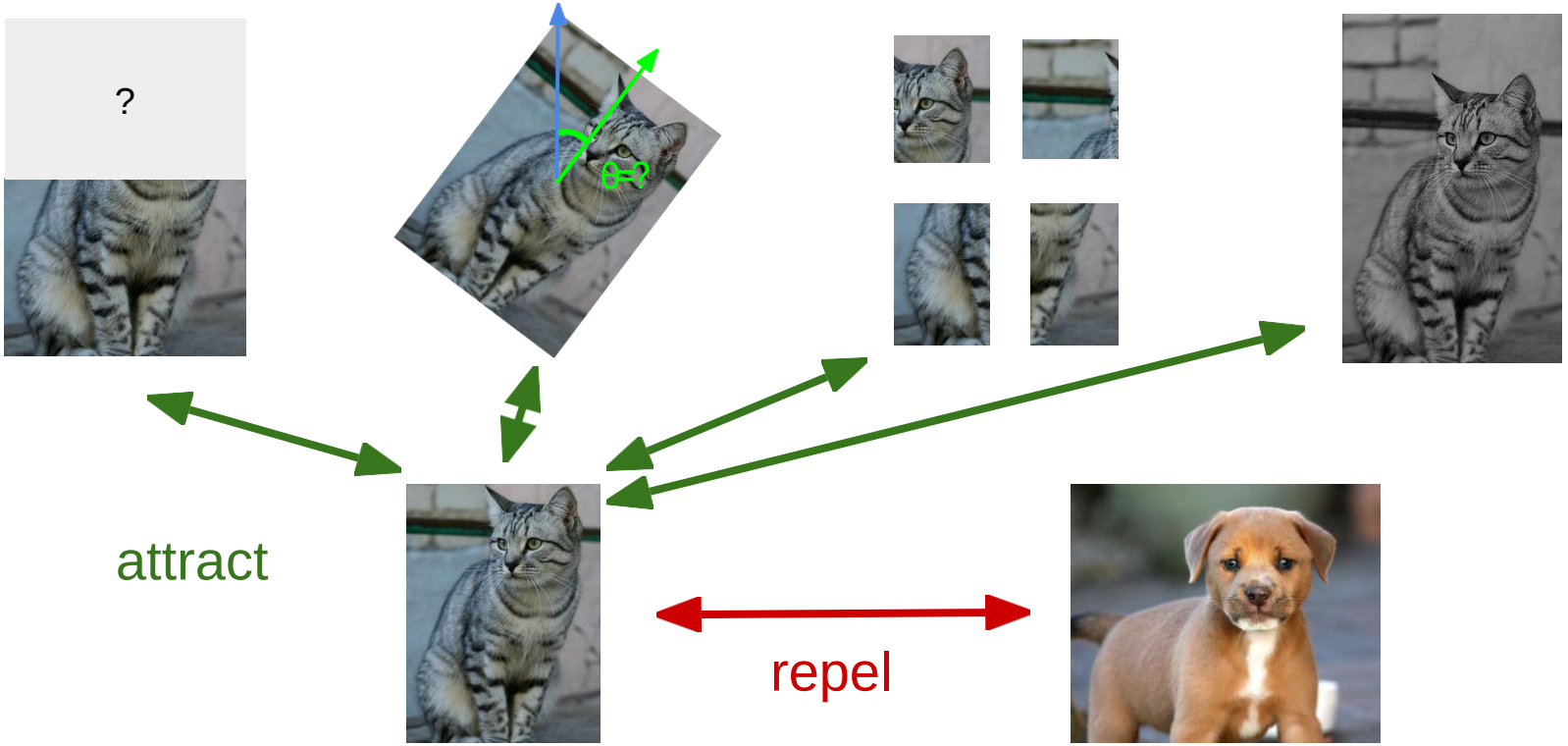
A more general pretext task?



A more general pretext task?



Contrastive Representation Learning



Today’s Agenda

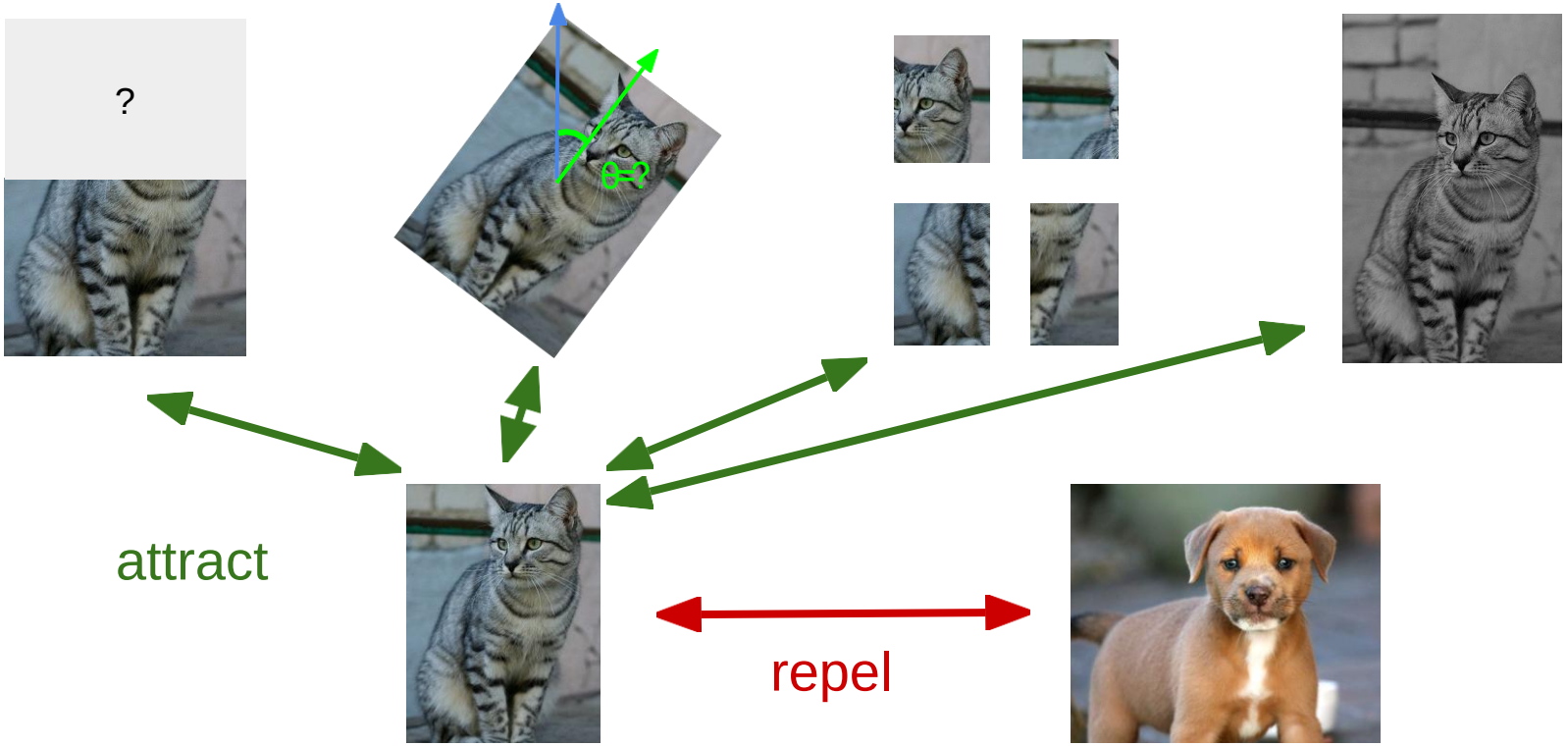
Pretext tasks from image transformations

- Rotation, inpainting, rearrangement, coloring

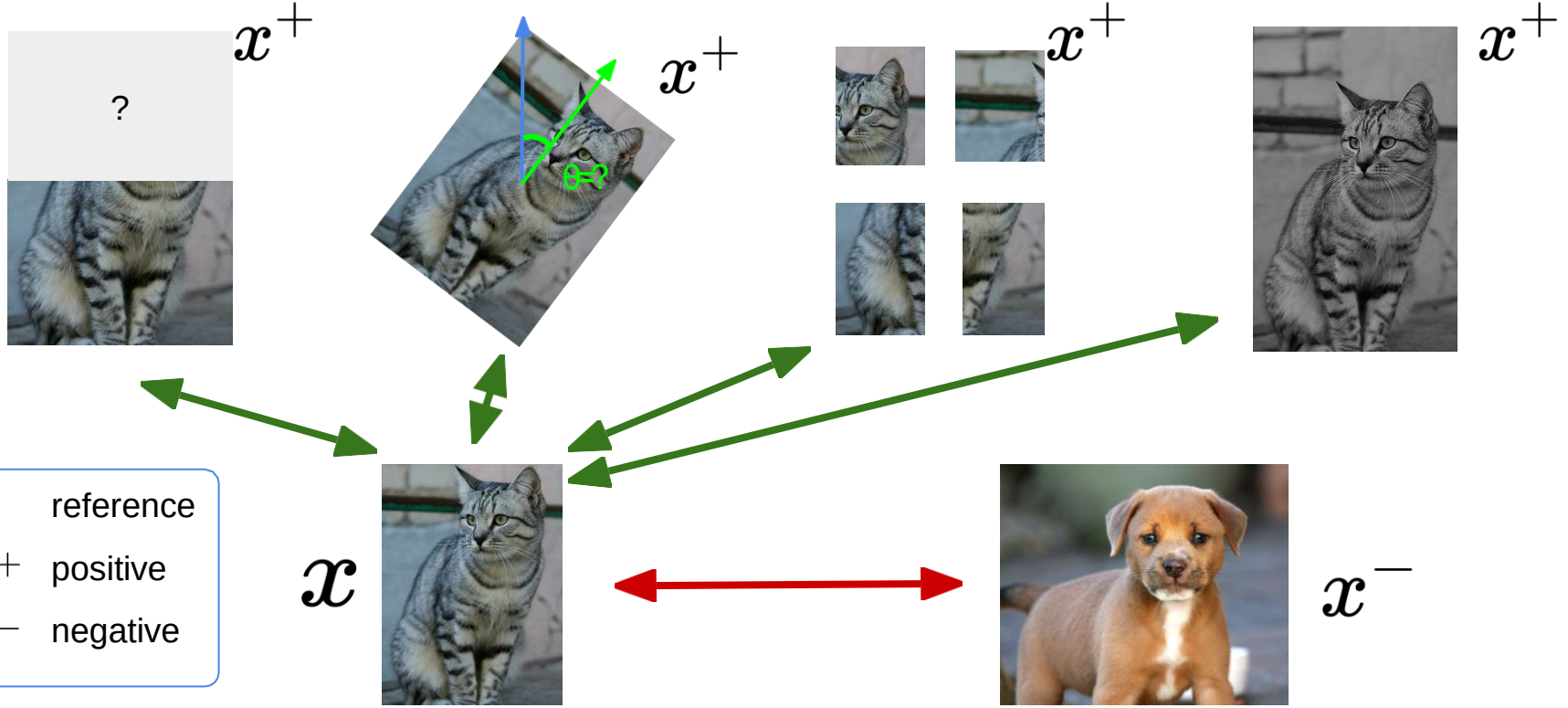
Contrastive representation learning

- Intuition and formulation
- Instance contrastive learning: SimCLR and MOCO
- Sequence contrastive learning: CPC

Contrastive Representation Learning



Contrastive Representation Learning



A formulation of contrastive learning

What we want:

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

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

Given a chosen score function, we aim to learn an **encoder function** *f* that yields high score for positive pairs (x, x^+) and low scores for negative pairs (x, x^-).

A formulation of contrastive learning

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

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

A formulation of contrastive learning

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

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

x

x^+

x

x_1^-

x_2^-

x_3^-

...

A formulation of contrastive learning

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

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

score for the positive pair

score for the N-1 negative pairs

This seems familiar …

A formulation of contrastive learning

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

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

score for the positive pair

score for the N-1 negative pairs

This seems familiar …

Cross entropy loss for a N-way softmax classifier!

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

A formulation of contrastive learning

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

Detailed derivation: Poole et al., 2019

SimCLR: A Simple Framework for Contrastive Learning

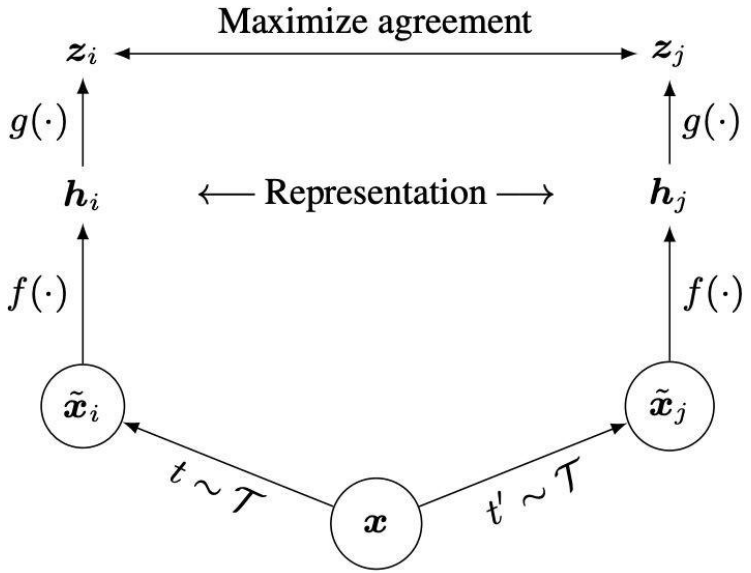
Cosine similarity as the score function:

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

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

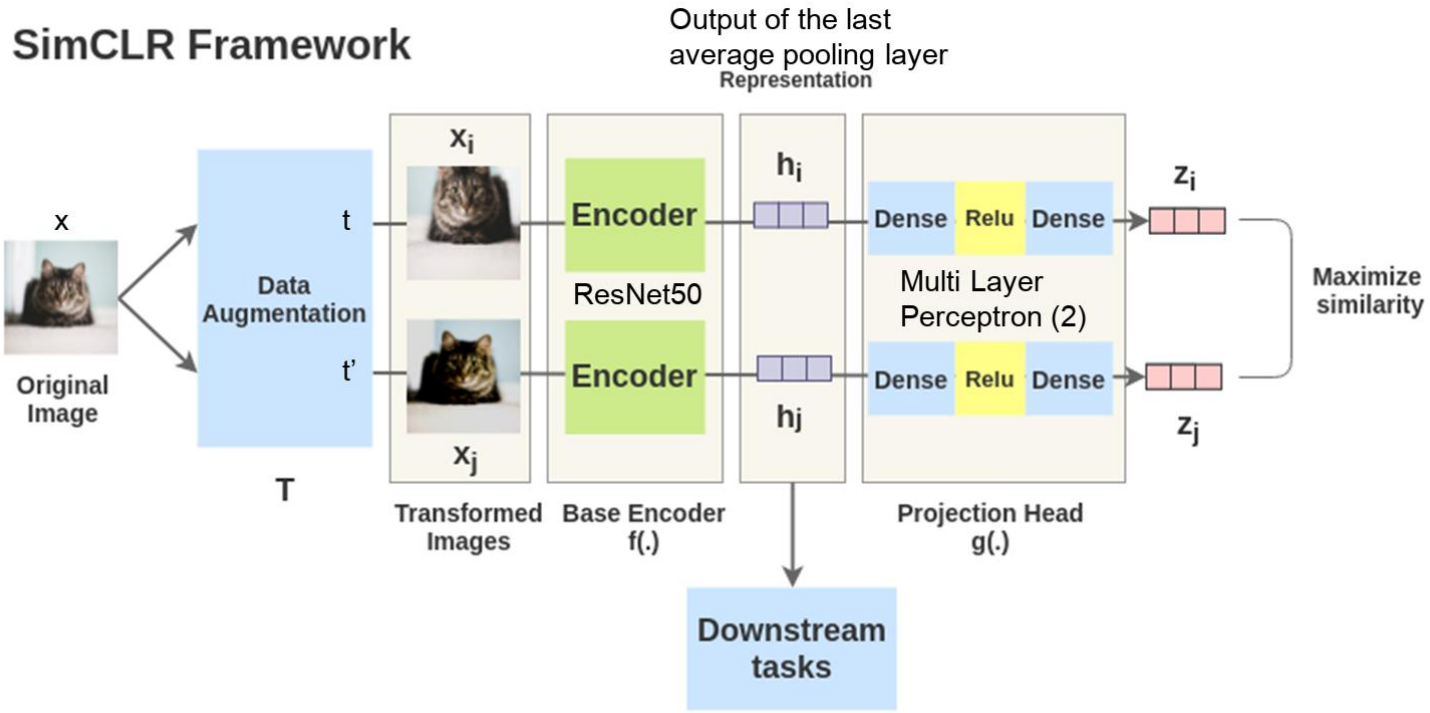
Generate positive samples through data augmentation:

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

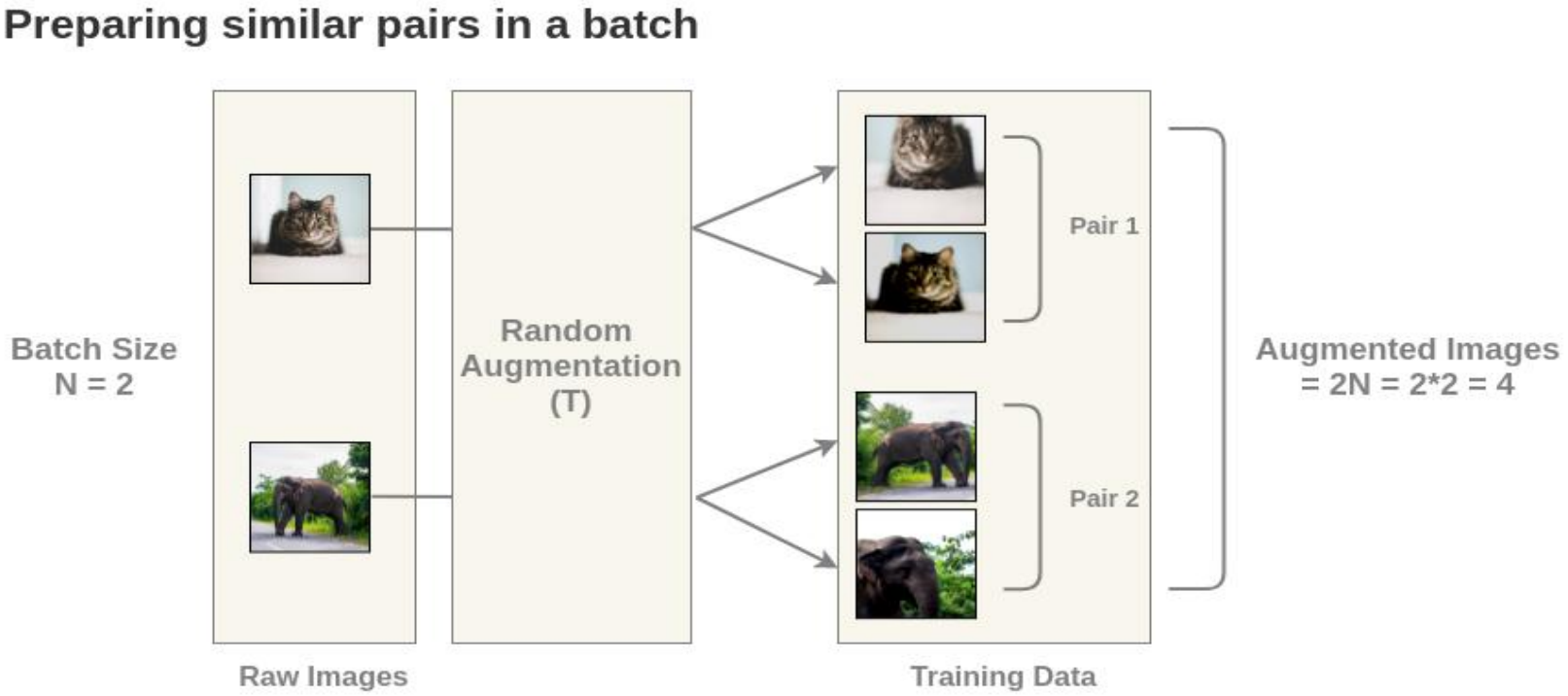


Source: [Chen et al., 2020]

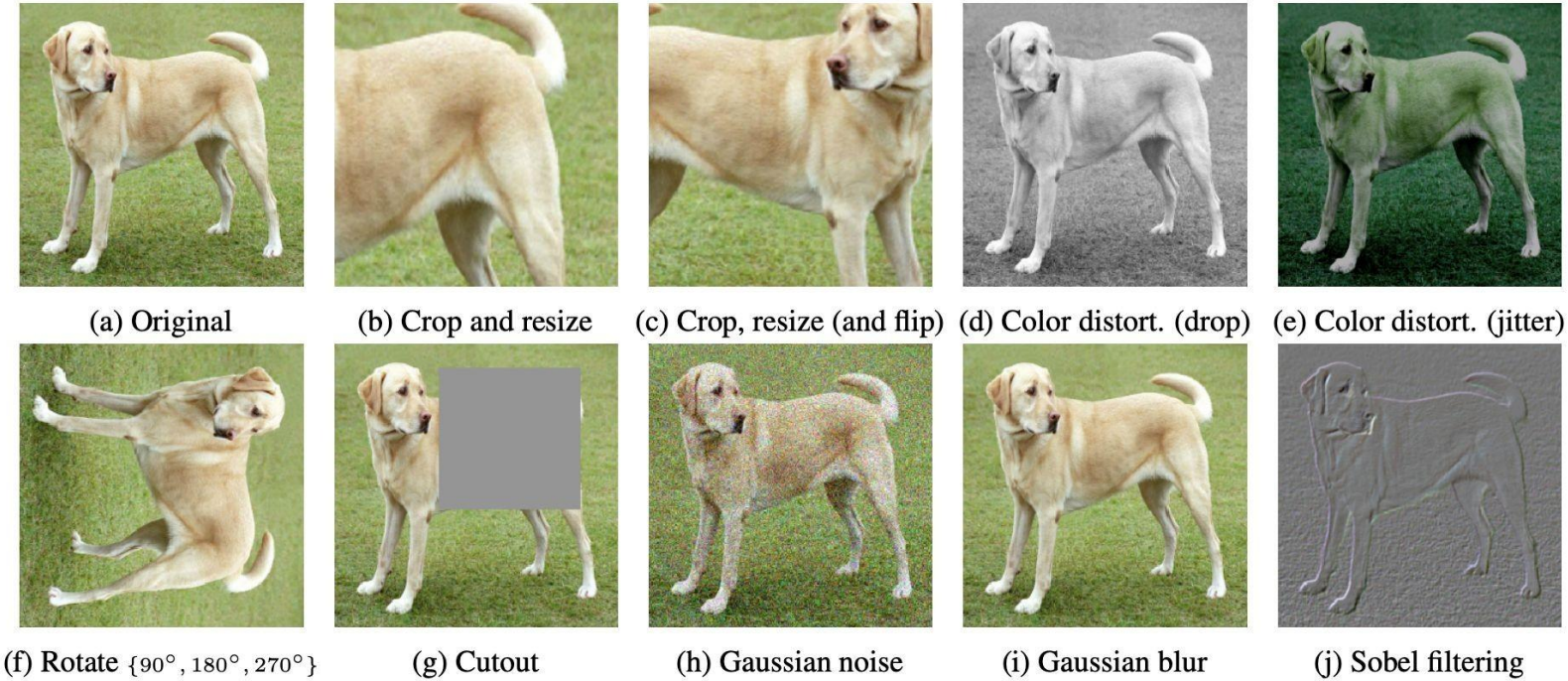
SimCLR: A Simple Framework for Contrastive Learning



SimCLR: A Simple Framework for Contrastive Learning



SimCLR: generating positive samples from data augmentation

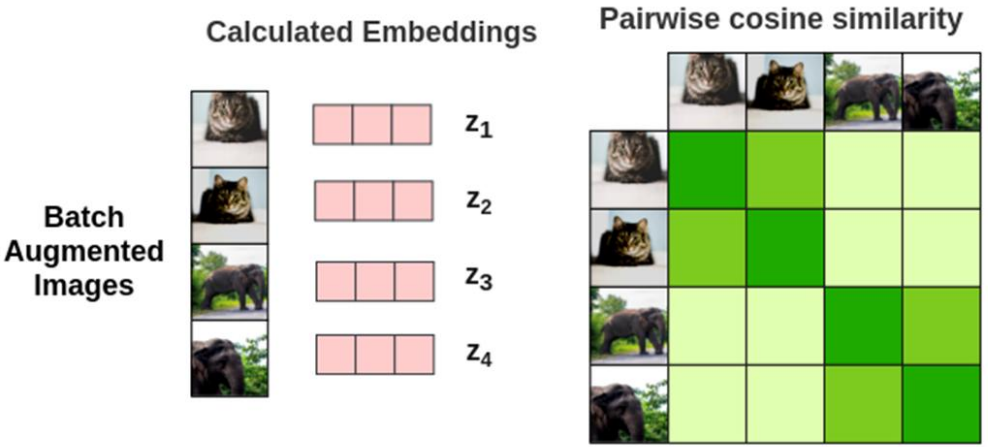


(a) Original (b) Crop and resize (c) Crop, resize (and flip) (d) Color distort. (drop) (e) Color distort. (jitter)

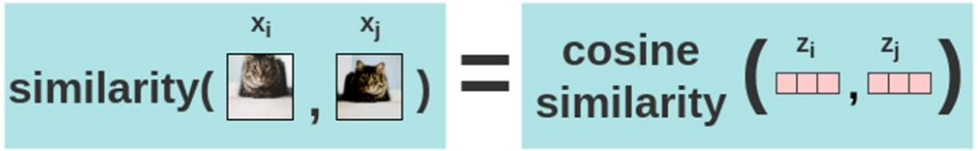
(f) Rotate $\{90°, 180°, 270°\}$ (g) Cutout (h) Gaussian noise (i) Gaussian blur (j) Sobel filtering

Source: [Chen et al., 2020]

SimCLR: mini-batch training



Similarity Calculation of Augmented Images

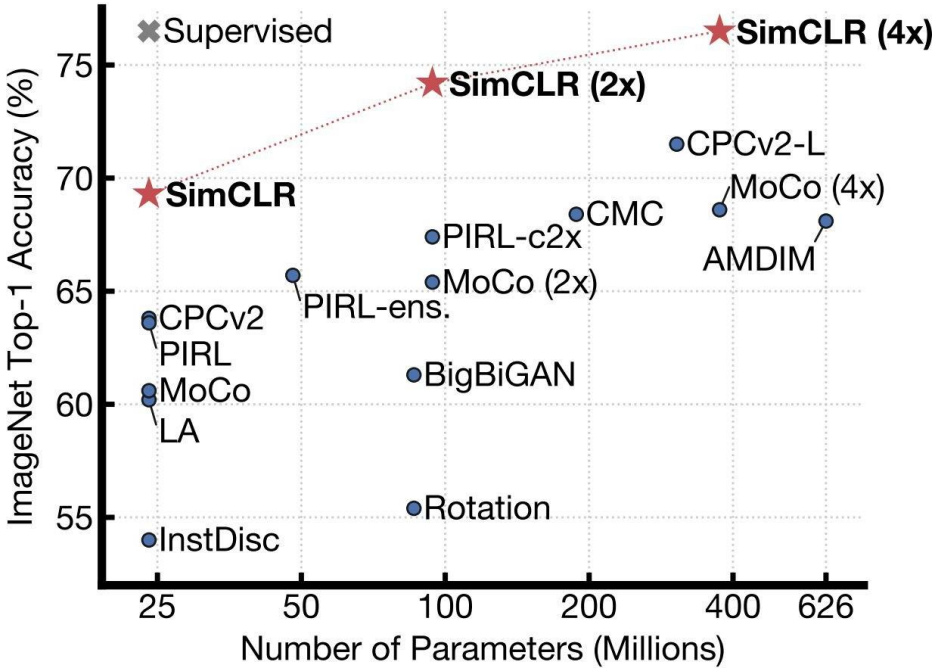


$$s_{i,j} = \frac{z_i^T z_j}{(\tau ||z_i|| ||z_j||)}$$

τ = temperature hyperparameter. It can scale the input and widen the range [-1, 1] of cosine similarity

||z|| = vector norm

Training linear classifier on SimCLR features



Train feature encoder on **ImageNet** (entire training set) using SimCLR.

Freeze feature encoder, train a linear classifier on top with labeled data.

Source: [Chen et al., 2020]

Semi-supervised learning on SimCLR features

Method	Architecture	Label fraction 1%	Label fraction 10%
		Top 5	Top 5
Supervised baseline	ResNet-50	48.4	80.4
Methods using other label-propagation:			
Pseudo-label	ResNet-50	51.6	82.4
VAT+Entropy Min.	ResNet-50	47.0	83.4
UDA (w. RandAug)	ResNet-50	-	88.5
FixMatch (w. RandAug)	ResNet-50	-	89.1
S4L (Rot+VAT+En. M.)	ResNet-50 (4×)	-	91.2
Methods using representation learning only:			
InstDisc	ResNet-50	39.2	77.4
BigBiGAN	RevNet-50 (4×)	55.2	78.8
PIRL	ResNet-50	57.2	83.8
CPC v2	ResNet-161(*)	77.9	91.2
SimCLR (ours)	ResNet-50	75.5	87.8
SimCLR (ours)	ResNet-50 (2×)	83.0	91.2
SimCLR (ours)	ResNet-50 (4×)	**85.8**	**92.6**

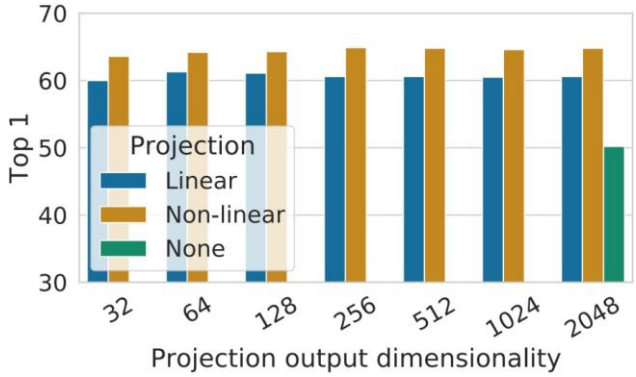
Table 7. ImageNet accuracy of models trained with few labels.

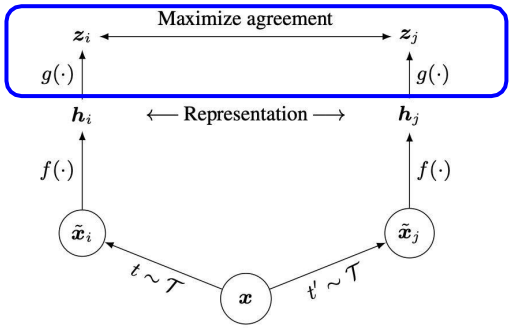
Train feature encoder on **ImageNet** (entire training set) using SimCLR.

Finetune the encoder with 1% / 10% of labeled data on ImageNet.

Source: [Chen et al., 2020]

SimCLR design choices: projection head





Linear / non-linear projection heads improve representation learning.

A possible explanation:

- contrastive learning objective may discard useful information for downstream tasks
- representation space ***z*** is trained to be invariant to data transformation.
- by leveraging the projection head **g(□)**, more information can be preserved in the **h** representation space

Source: Chen et al., 2020

SimCLR design choices: large batch size

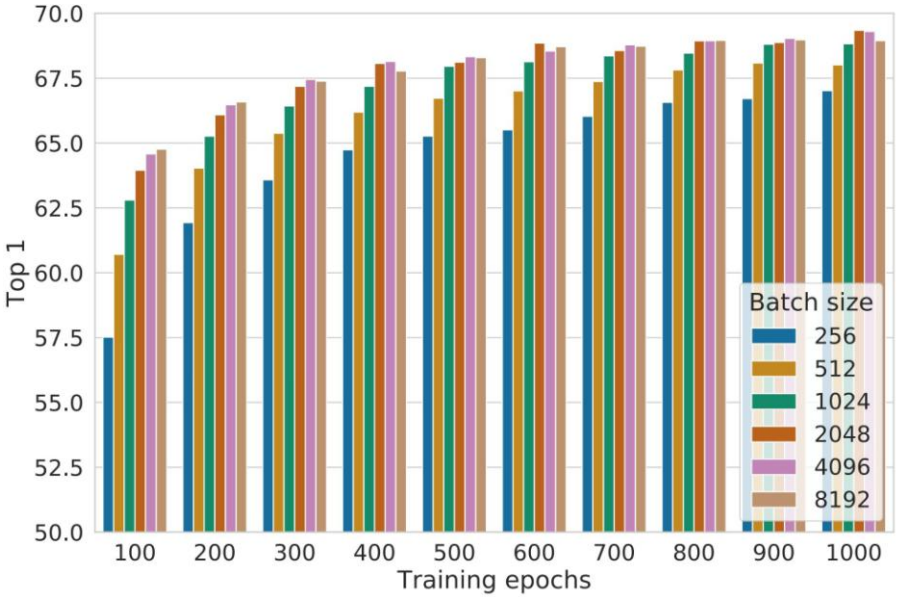


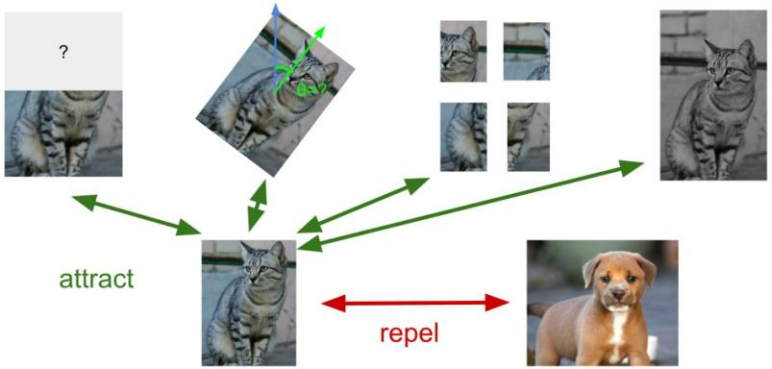
Figure 9. Linear evaluation models (ResNet-50) trained with different batch size and epochs. Each bar is a single run from scratch.[10]

Large training batch size is crucial for SimCLR!

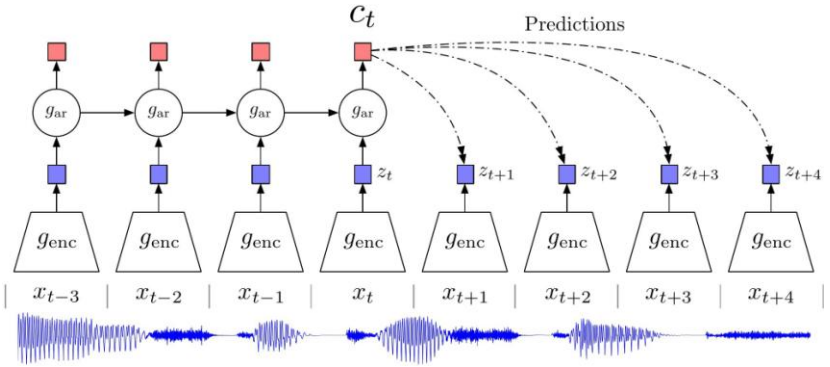
Large batch size causes large memory footprint during backpropagation: requires distributed training on TPUs (ImageNet experiments)

Source: Chen et al., 2020

Instance vs. Sequence Contrastive Learning



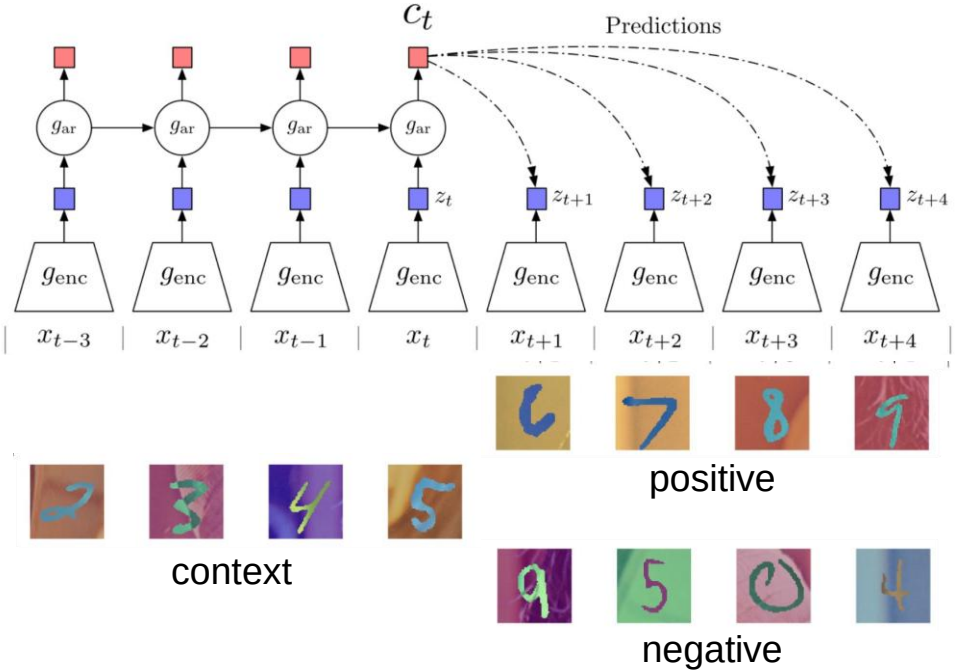
Instance-level contrastive learning:
contrastive learning based on
positive & negative instances.
Examples: SimCLR, MoCo



Source: van den Oord et al., 2018

Sequence-level contrastive learning:
contrastive learning based on
sequential / temporal orders.
Example: **Contrastive Predictive Coding (CPC)**

Contrastive Predictive Coding (CPC)



Contrastive: contrast between “right” and “wrong” sequences using contrastive learning.

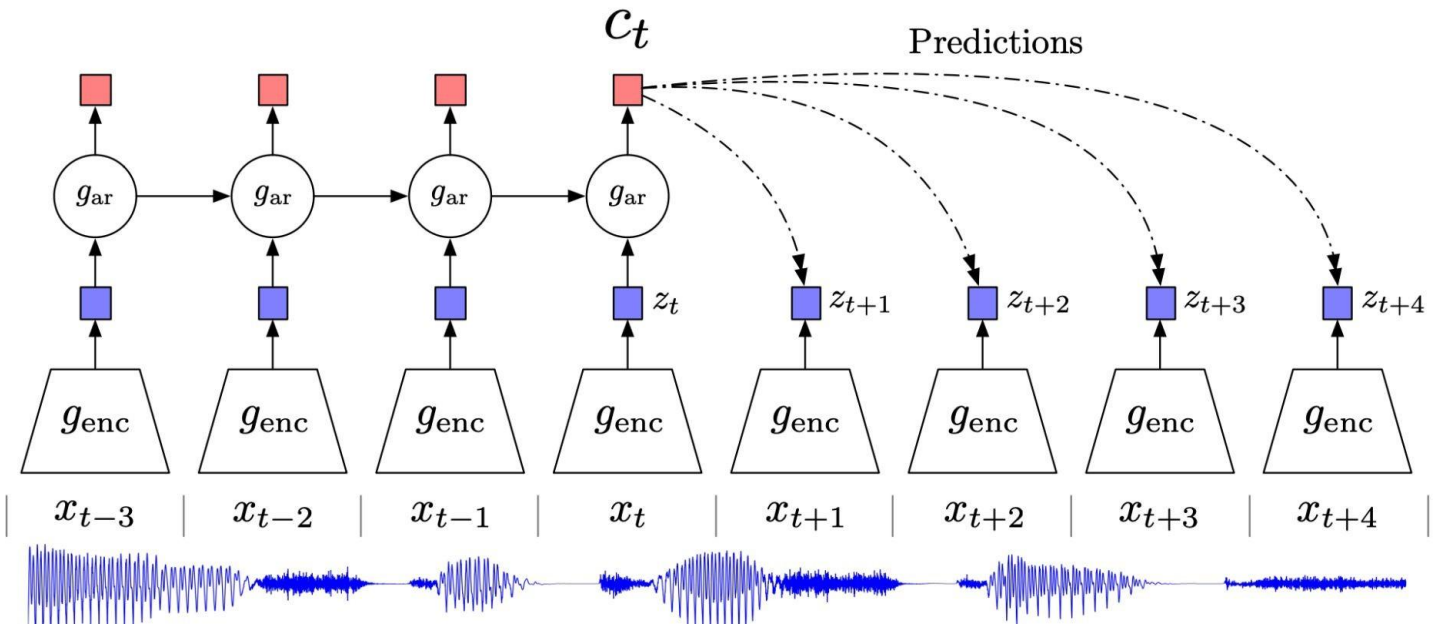
Predictive: the model has to predict future patterns given the current context.

Coding: the model learns useful feature vectors, or “code”, for downstream tasks, similar to other self-supervised methods.

Figure source

Source: van den Oord et al., 2018,

CPC example: modeling audio sequences



Source: [van den Oord et al., 2018](),

CPC example: modeling audio sequences

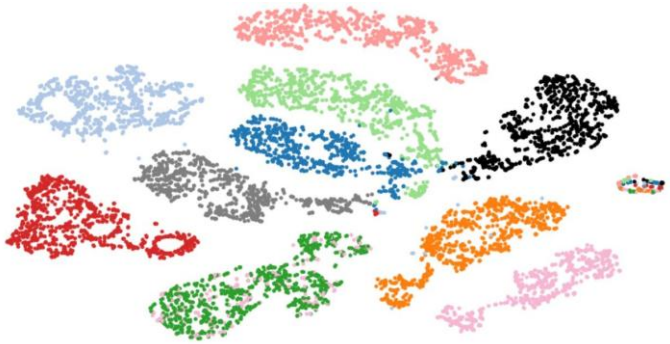


Figure 2: t-SNE visualization of audio (speech) representations for a subset of 10 speakers (out of 251). Every color represents a different speaker.

Method	ACC
Phone classification	
Random initialization	27.6
MFCC features	39.7
CPC	64.6
Supervised	74.6
Speaker classification	
Random initialization	1.87
MFCC features	17.6
CPC	97.4
Supervised	98.5

Linear classification on trained representations (LibriSpeech dataset)

Source: van den Oord et al., 2018,

Summary: Contrastive Representation Learning

A general formulation for contrastive learning:

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

InfoNCE loss: N-way classification among positive and 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)

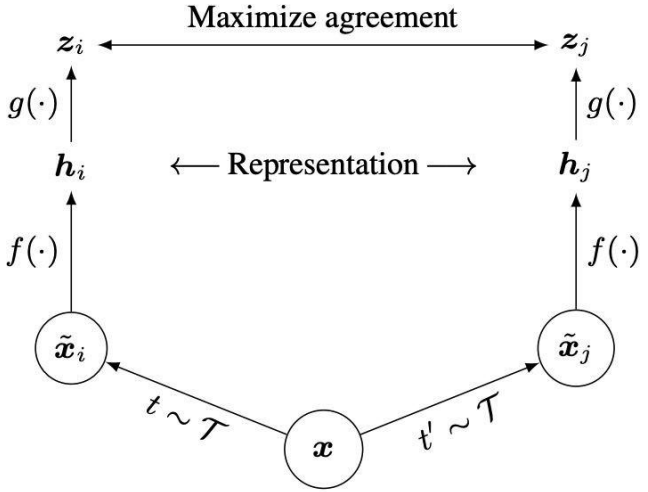
A *lower bound* on the mutual information between *f(x)* and *f(x⁺)*

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

Summary: Contrastive Representation Learning

SimCLR: a simple framework for contrastive representation learning

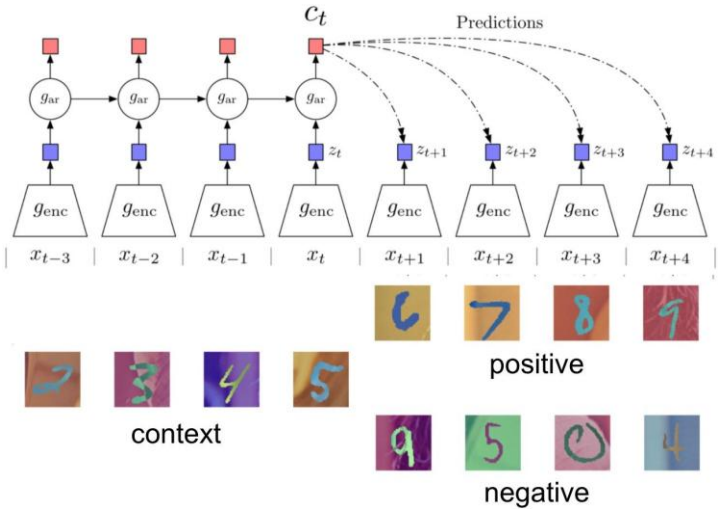
- **Key ideas**: non-linear projection head to allow flexible representation learning
- Simple to implement, effective in learning visual representation
- Requires large training batch size to be effective; large memory footprint



Summary: Contrastive Representation Learning

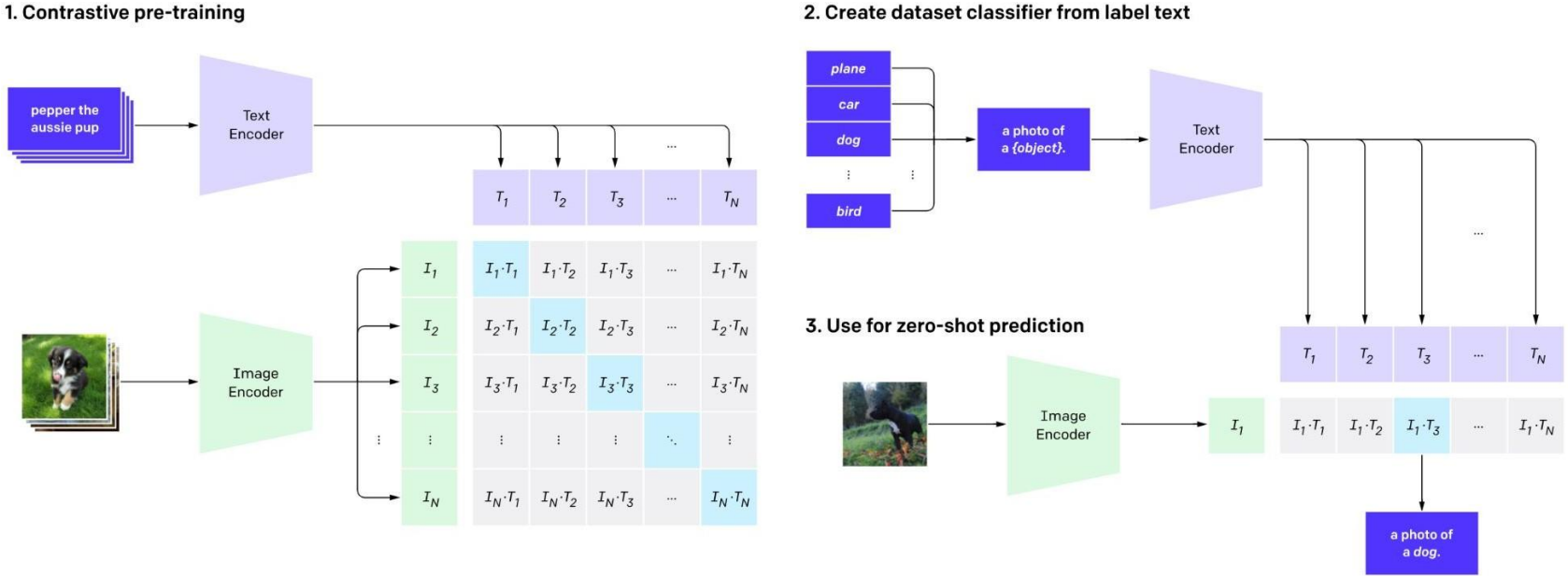
CPC: sequence-level contrastive learning

- Contrast “right” sequence with “wrong” sequence.
- InfoNCE loss with a time-dependent score function.
- Can be applied to a variety of learning problems, but not as effective in learning image representations compared to instance-level methods.



Other examples

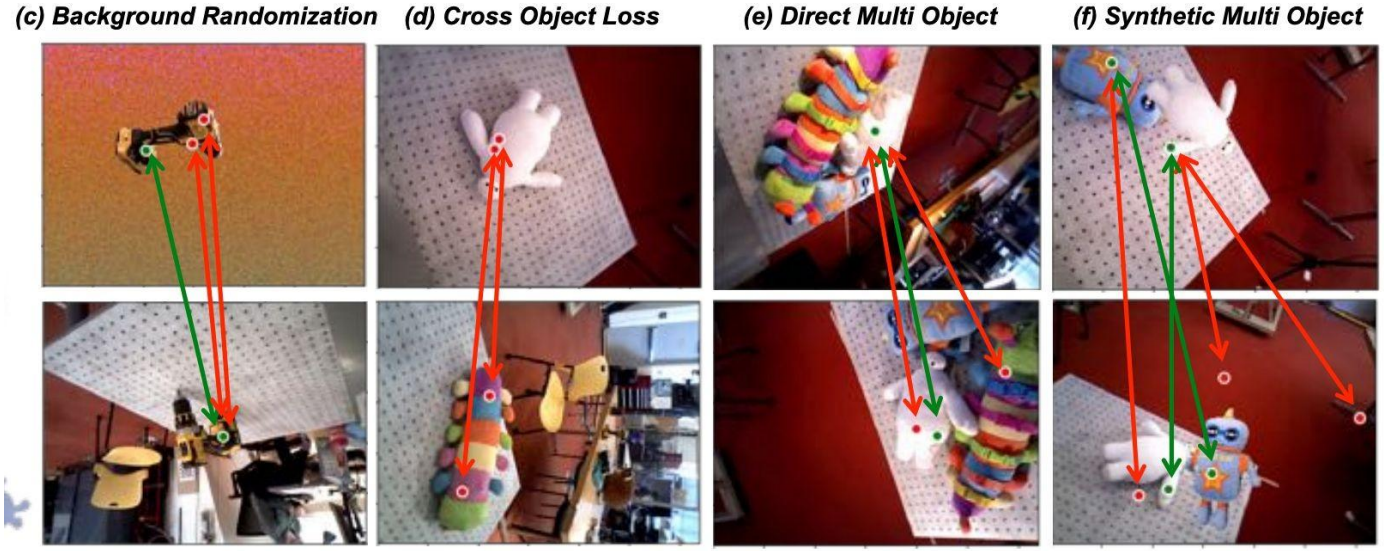
Contrastive learning between image and natural language sentences



CLIP (*Contrastive Language–Image Pre-training*) Radford *et al.*, 2021

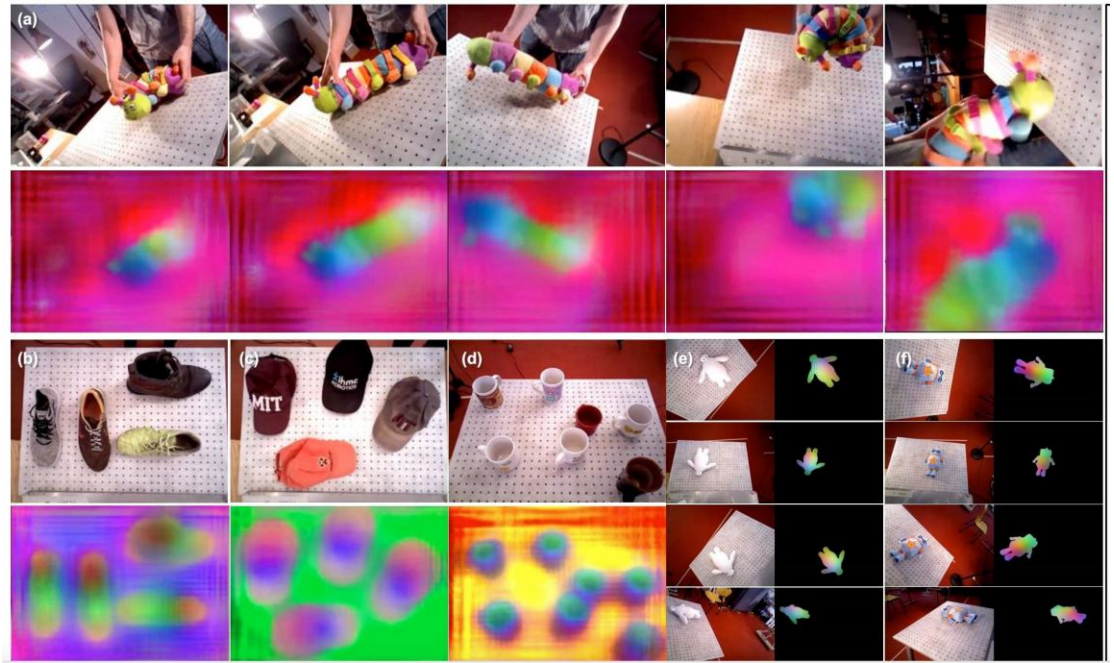
Other examples

Contrastive learning on pixel-wise feature descriptors



Dense Object Net, Florence et al., 2018

Other examples



Dense Object Net, Florence et al., 2018

Self-Supervised Learning

General idea: pretend there is a part of the data you don't know and train the neural network to predict that.