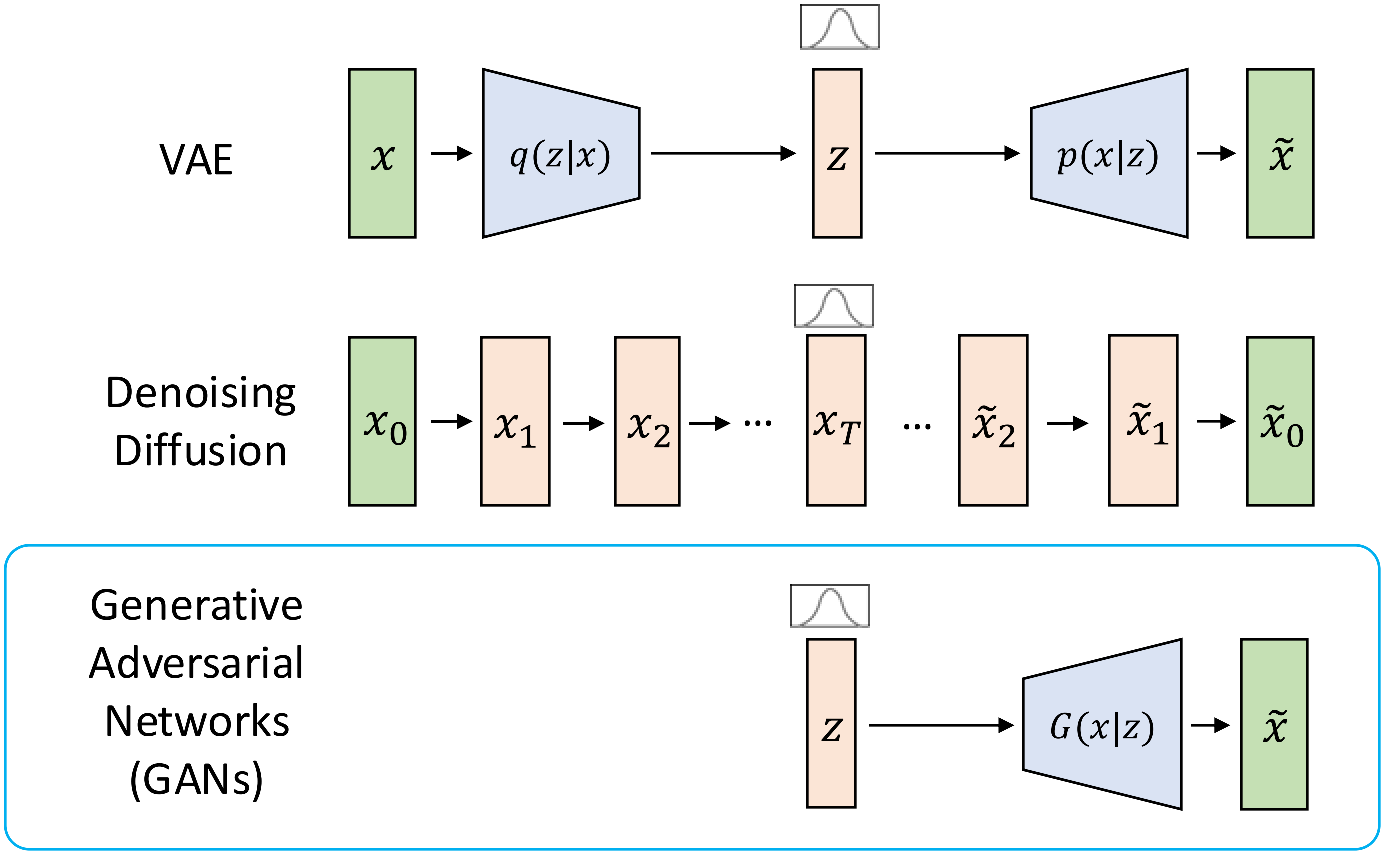
CS 4644/7643: Lecture 19
Danfei Xu

Topics:

- Self-supervised Learning
  - **Pretext task from image transformation**
  - **Contrastive learning**
- 3D Vision

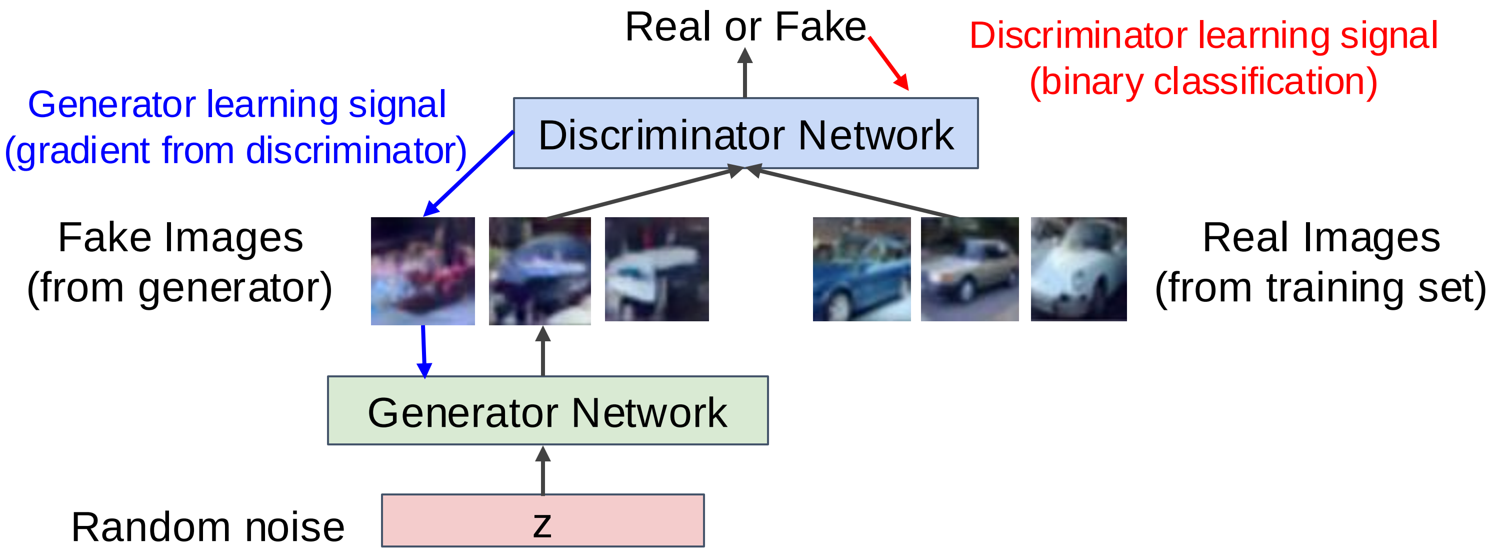
GANs: Learning generate samples directly



Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Discriminator network: try to distinguish between real and fake images
Generator network: try to fool the discriminator by generating real-looking images



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Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Discriminator network: try to distinguish between real and fake images
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Train jointly in **minimax game**

Discriminator outputs likelihood in (0,1) of real image

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

Classify all real images as real

Classify all generated images as fake

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Generator: learn to fool discriminator. Minimize $\log(1 - p_{\theta_d}(x_{gen}))$

Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Alternate between:

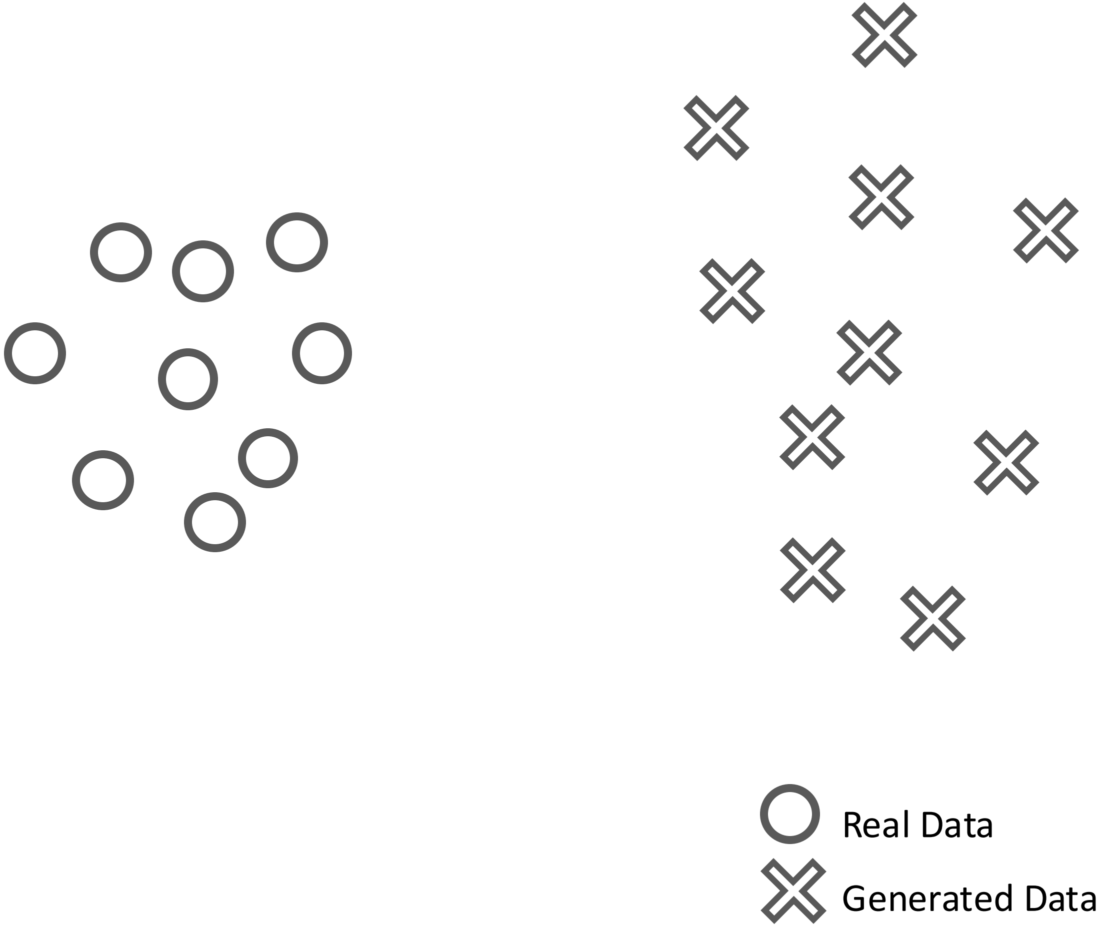
1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

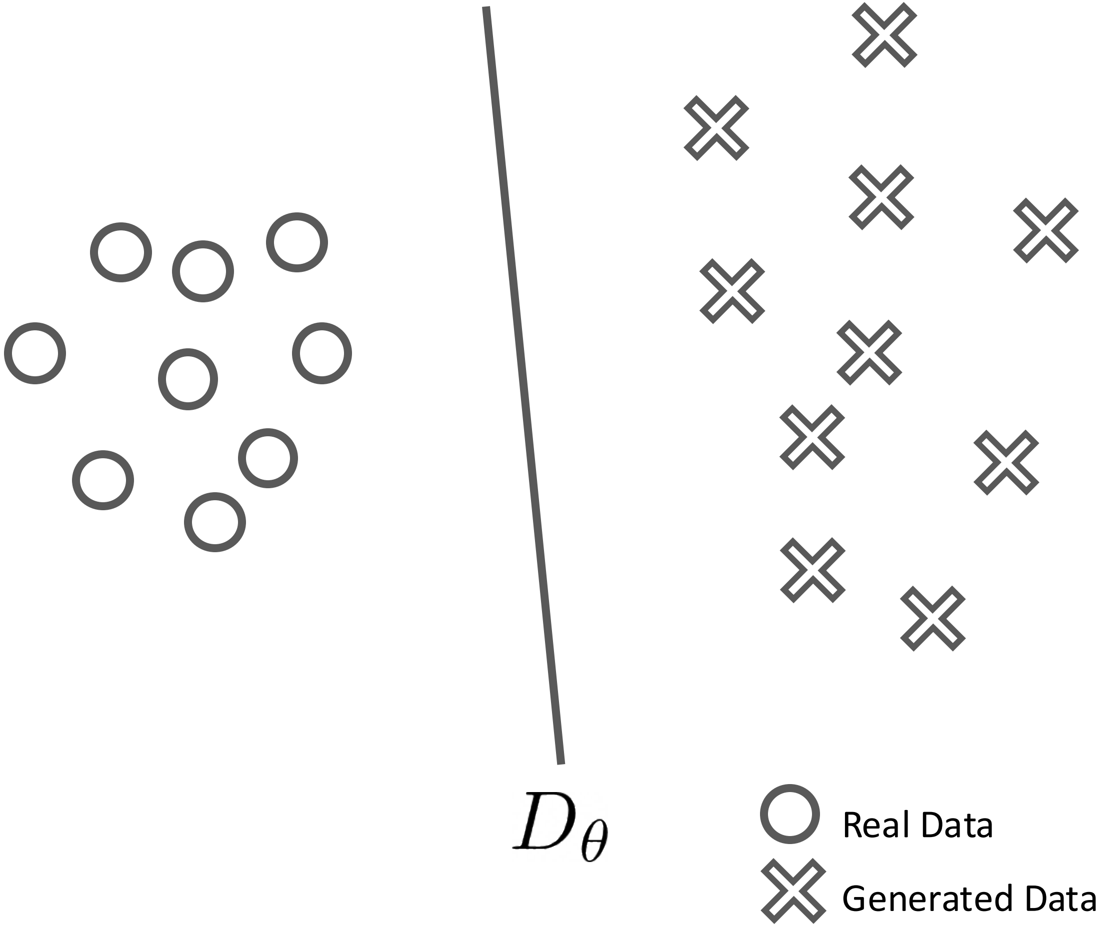
2. **Gradient descent** on generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

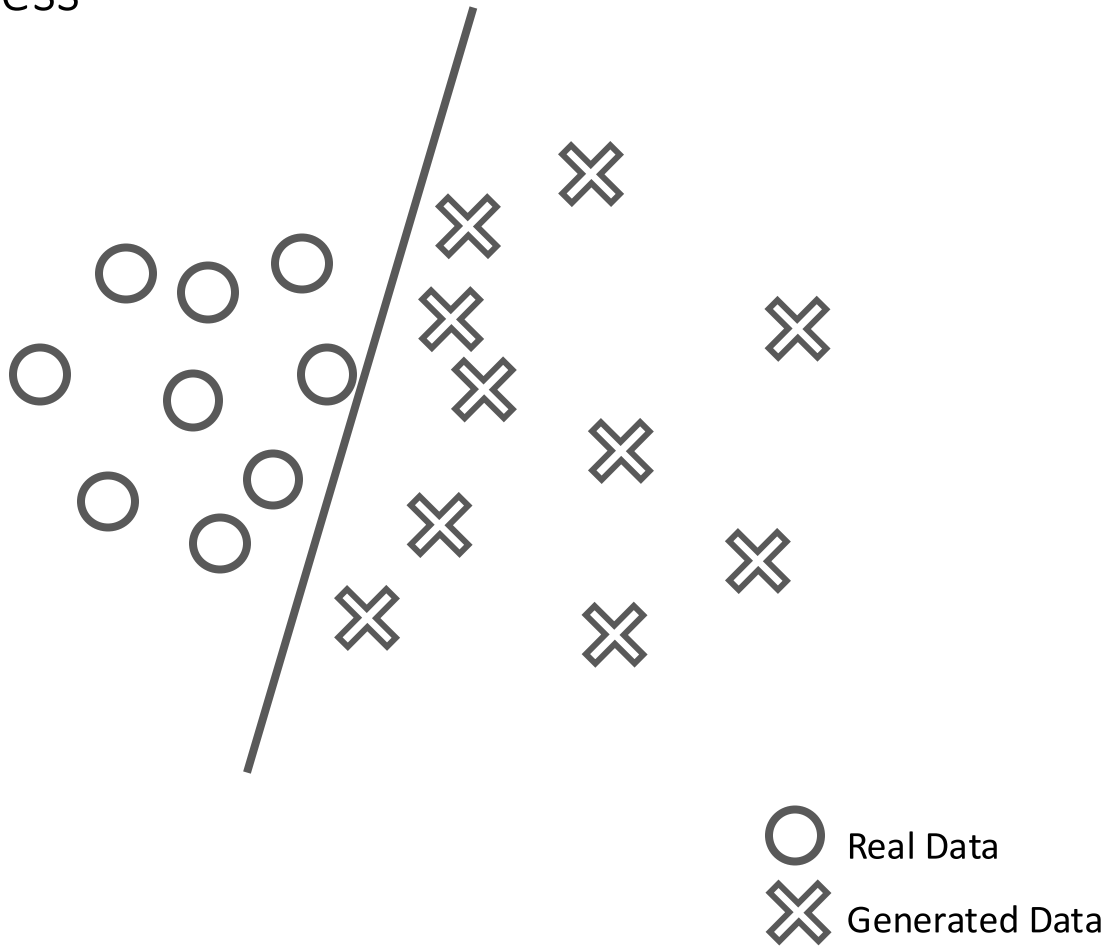
GAN Learning Process



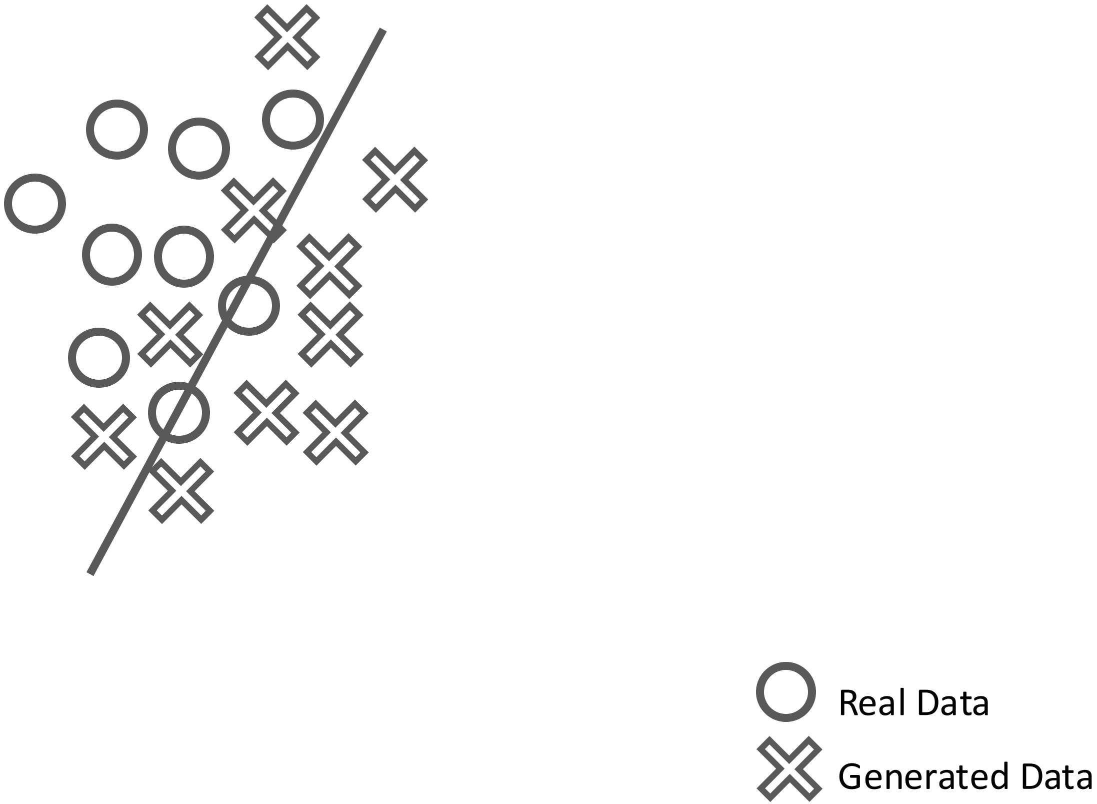
GAN Learning Process



GAN Learning Process



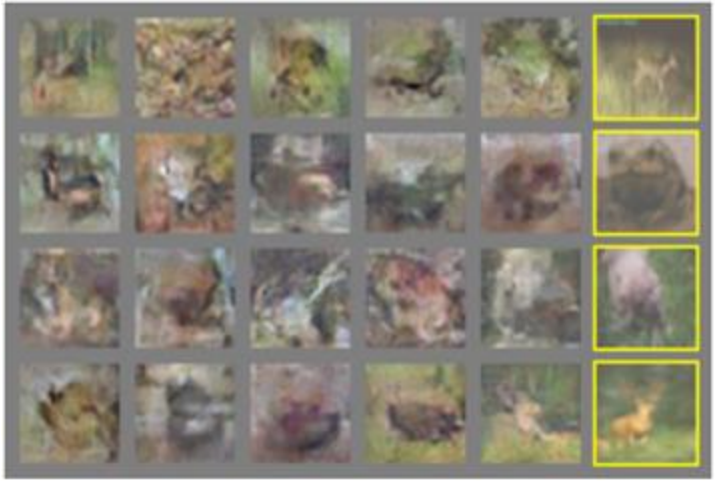
GAN Learning Process



Generative Adversarial Nets

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Generated samples (CIFAR-10)



Nearest neighbor from training set

Generative Adversarial Nets: Convolutional Architectures

Generator is an upsampling network with fractionally-strided convolutions
Discriminator is a convolutional network

Architecture guidelines for stable Deep Convolutional GANs

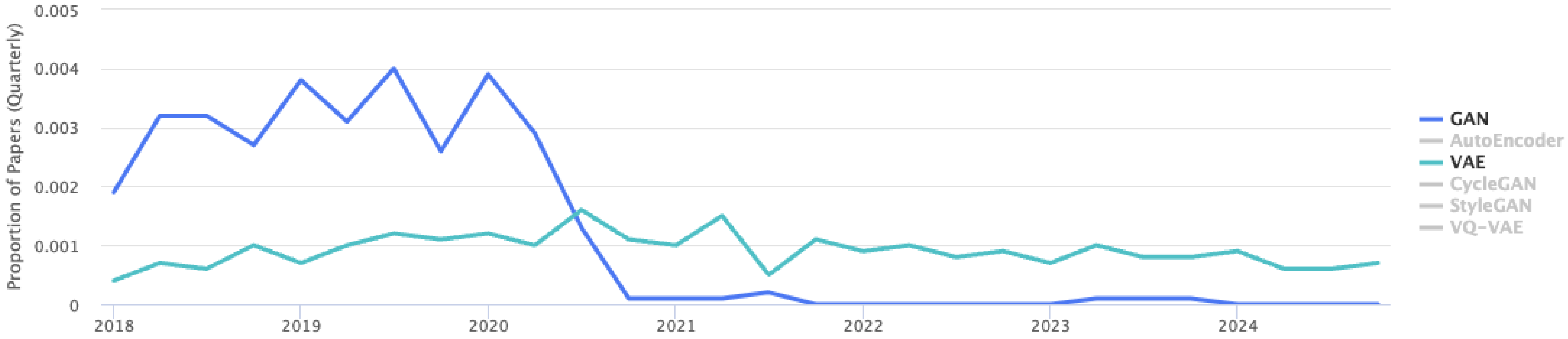
- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

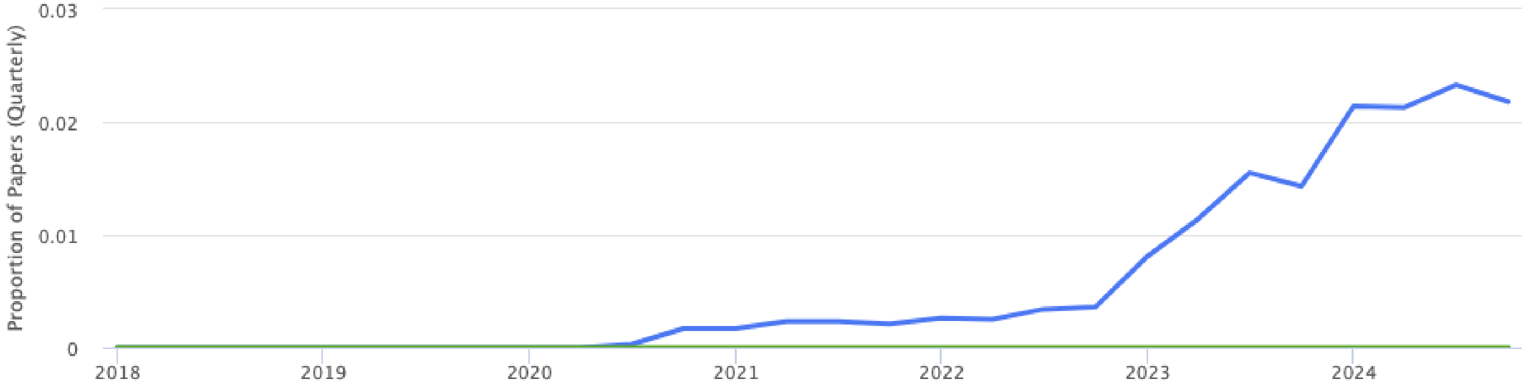
Radford et al, “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks”, ICLR 2016

2019: BigGAN

Brock et al., 2019

GANs were popular …





Source: https://paperswithcode.com

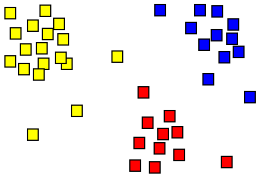
Supervised Learning

- Train Input: $\{X, Y\}$
- Learning output: $f: X \rightarrow Y$, $P(y|x)$
- e.g. classification

Sheep
Dog
Cat
Lion
Giraffe

Unsupervised Learning

- Input: $\{X\}$
- Learning output: $P(x)$
- Example: Clustering, density estimation, generative modeling



Reinforcement Learning

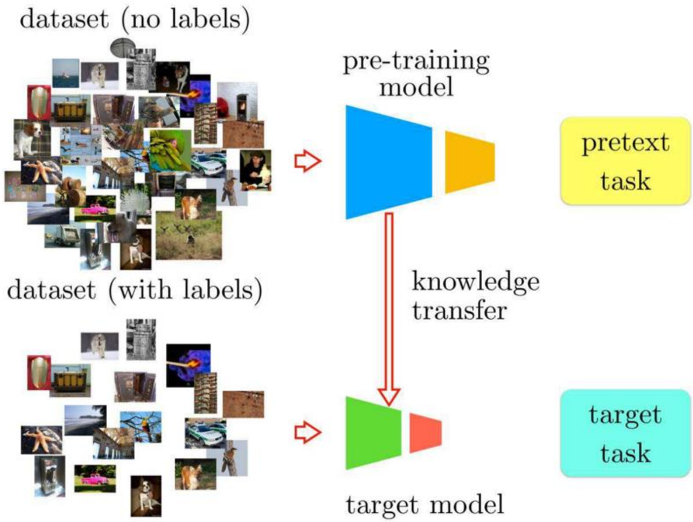
- Evaluative feedback in the form of **reward**
- No supervision on the right action

Self-Supervised Learning:
Create your own supervision

Self-supervised Learning

In short: still supervised learning, with two important distinctions:

1. Learn from labels generated *autonomously* instead of human annotations.
2. The goal is to learn *good representations* for *other target tasks*.



Source: Noroozi *et al.*, 2018

Self-supervised pretext tasks

Example: learn to predict image transformations / complete corrupted images

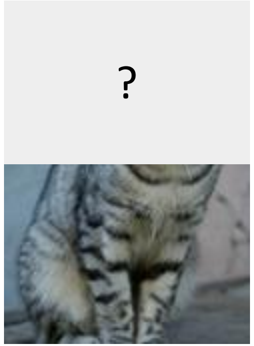
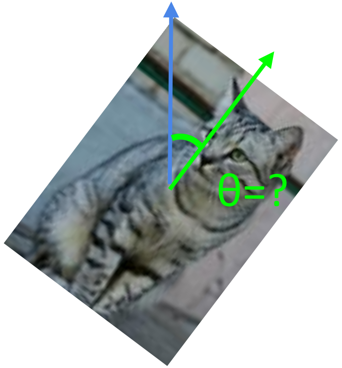


image completion



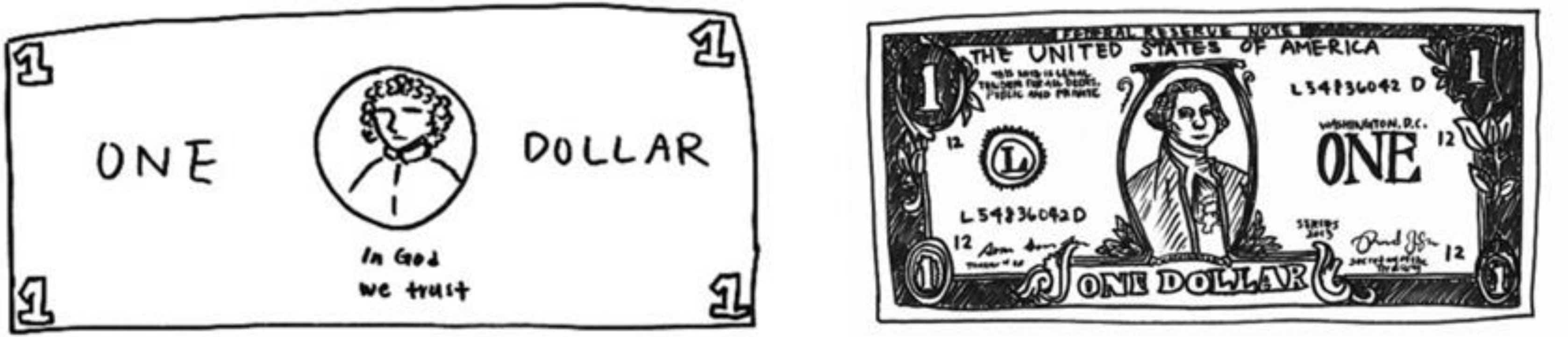
rotation prediction

“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

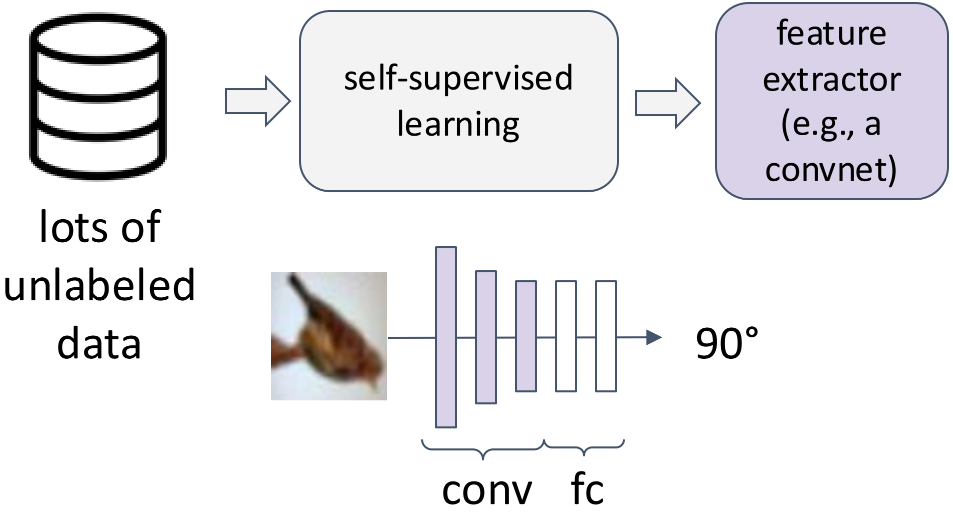


Left: Drawing of a dollar bill from memory. Right: Drawing subsequently made with a dollar bill present. Image source: [Epstein, 2016]

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

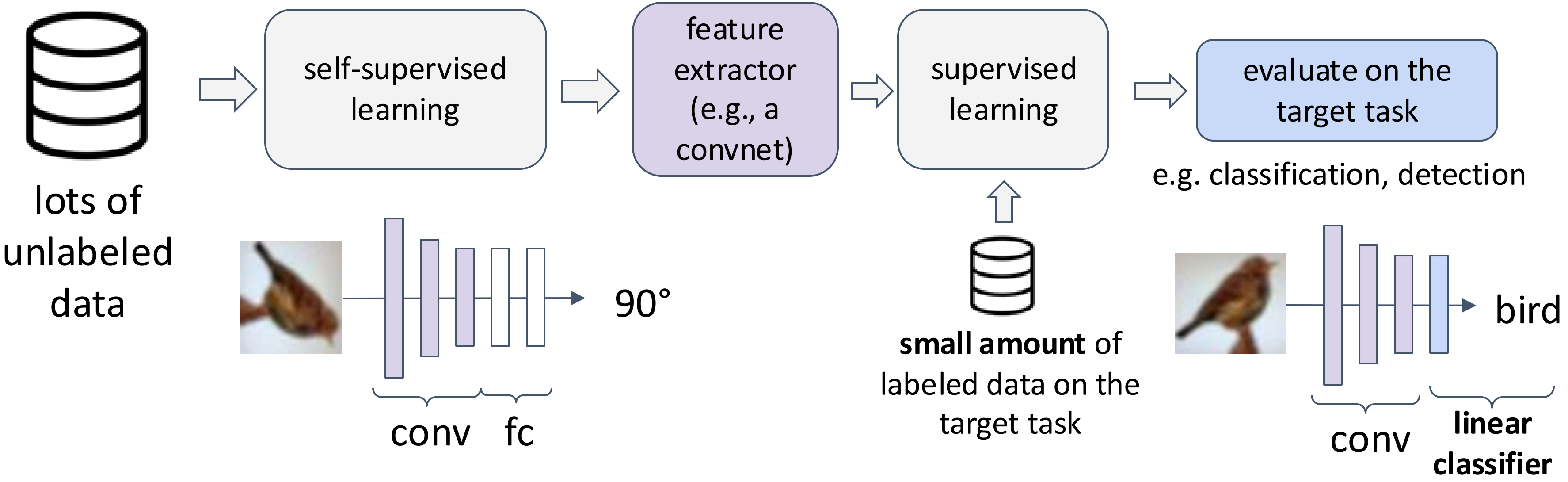
Source: [Anand, 2020]

How to evaluate a self-supervised learning method?



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

How to evaluate a self-supervised learning method?



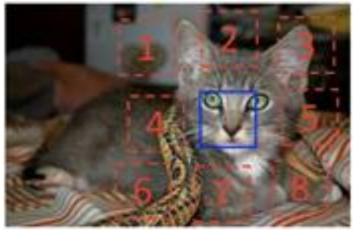
1. Learn good feature extractors from self-supervised pretext tasks, e.g., predicting image rotations

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

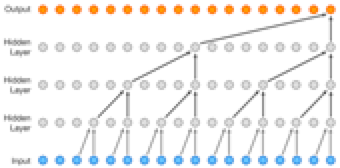
Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*
Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam Girish Sastry
Amanda Askell Sandhini Agarwal Ariel Herbert-Voss Gretchen Krueger Tom Henighan
Rewon Child Aditya Ramesh Daniel M. Ziegler Jeffrey Wu Clemens Winter
Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray
Benjamin Chess Jack Clark Christopher Berner
Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

OpenAI

Abstract

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

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Pretext tasks from image transformations

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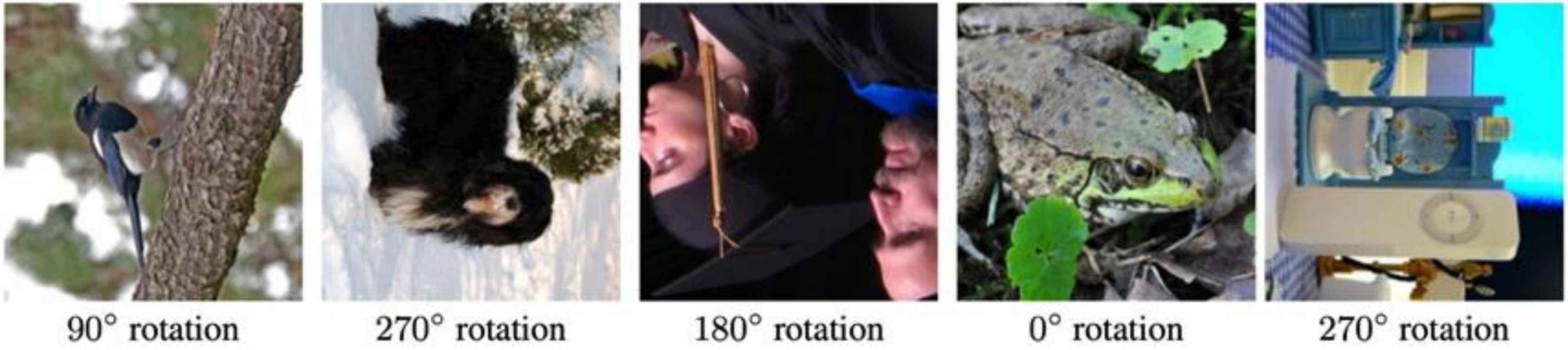
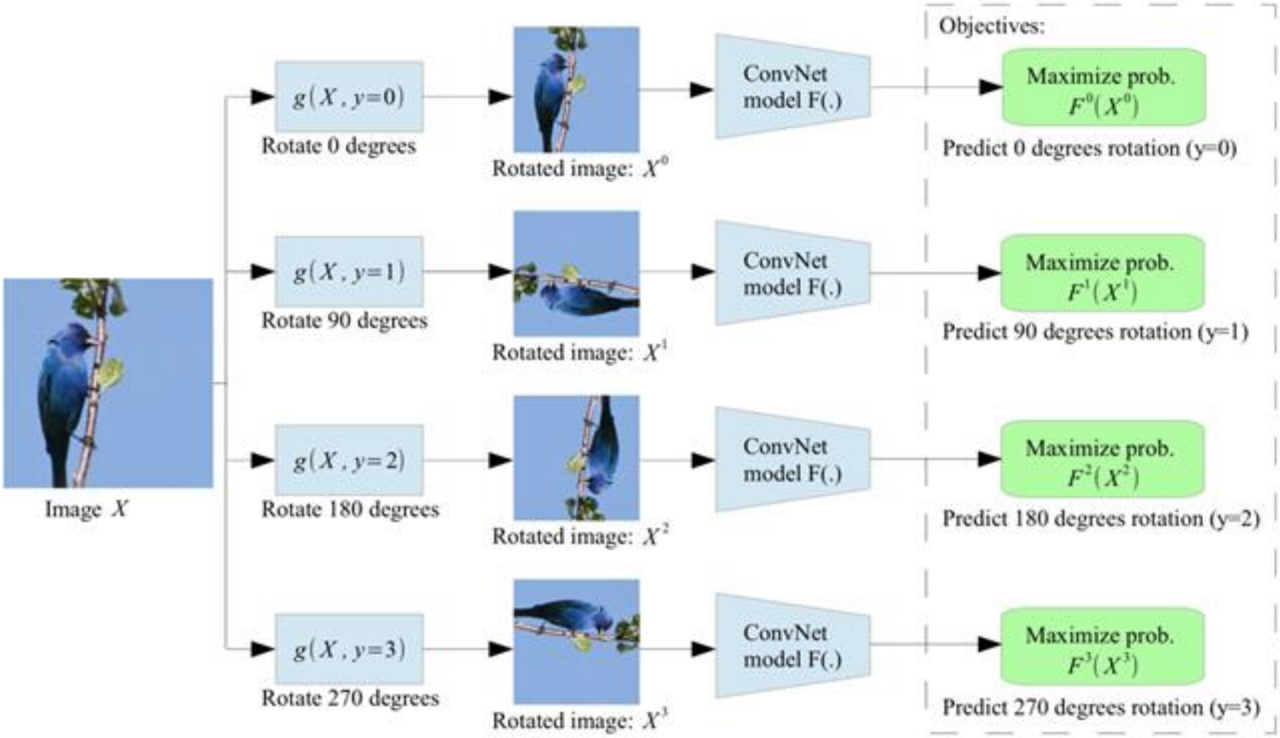
Pretext task: predict rotations



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

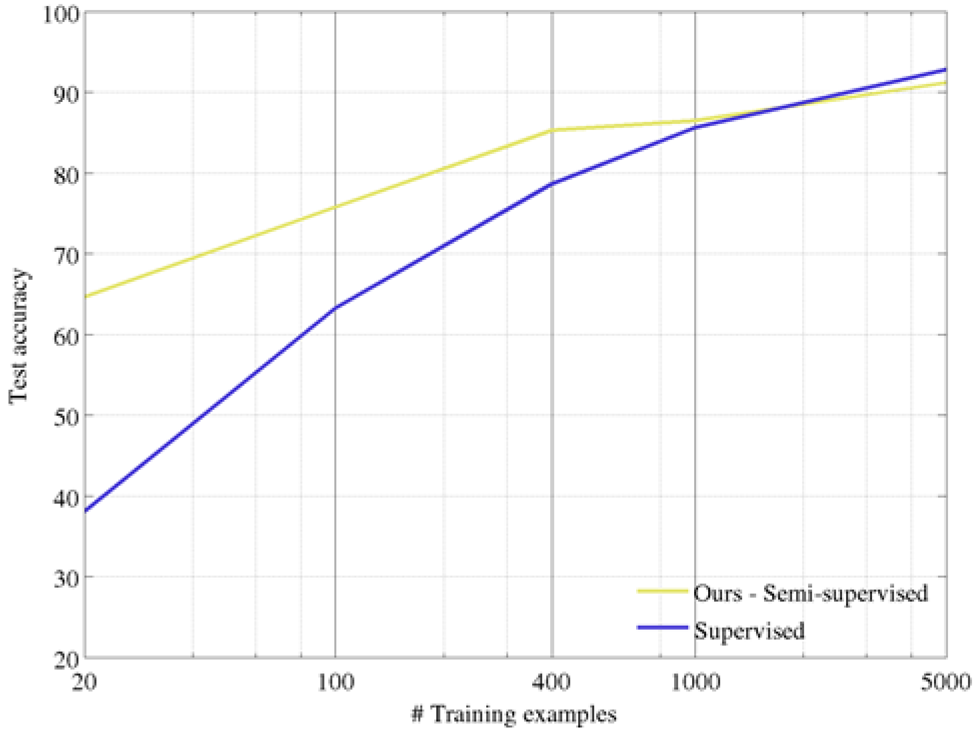


Self-supervised learning by rotating the entire input images.

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

(Image source: Gidaris et al. 2018)

Evaluation on semi-supervised learning

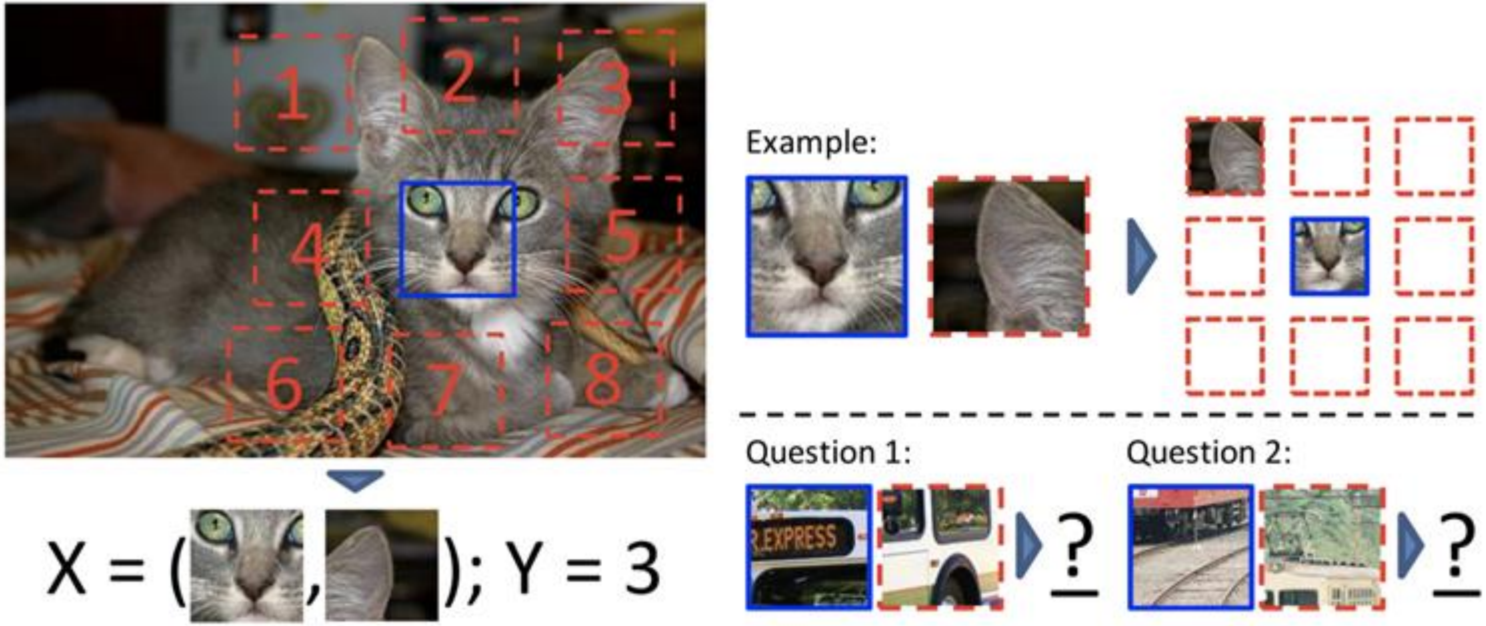


Self-supervised learning on **CIFAR10** (entire training set).

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

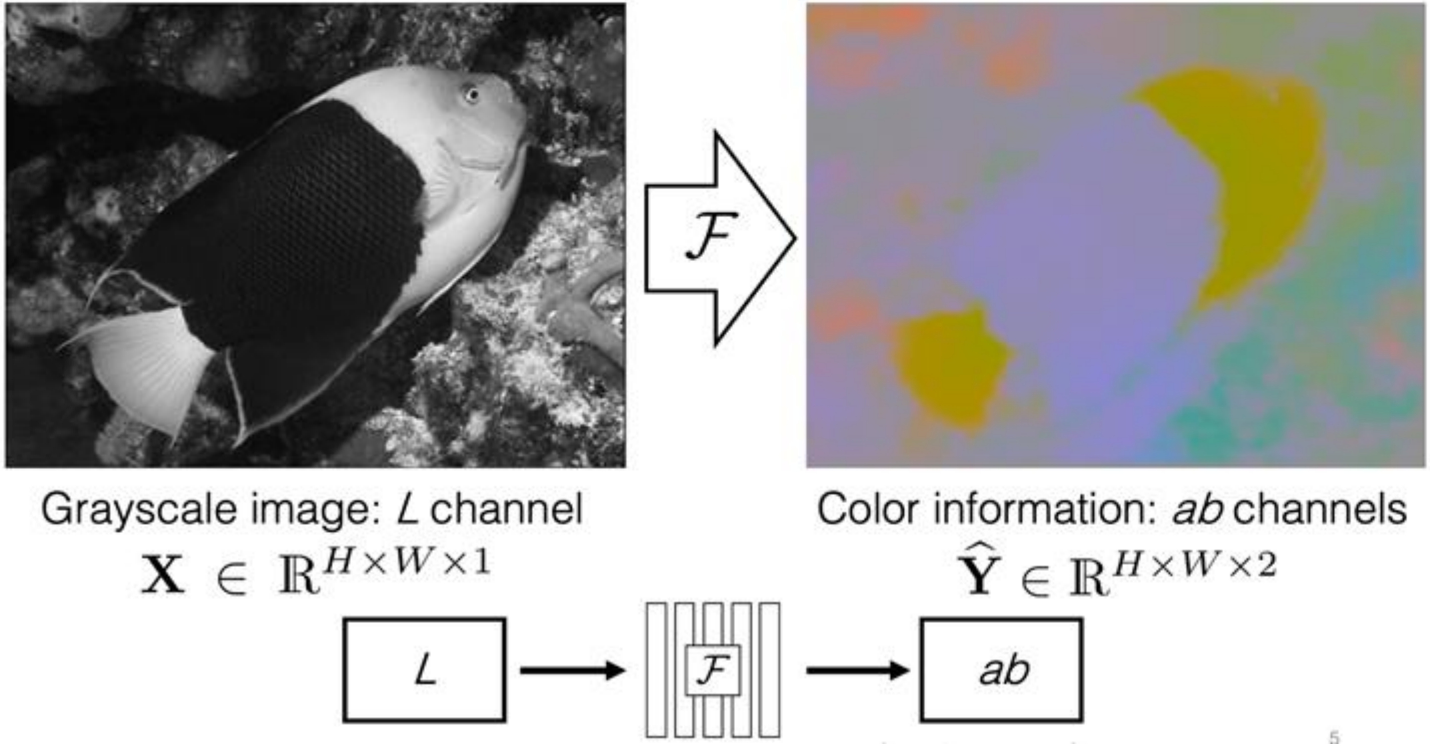
(Image source: [Gidaris et al. 2018](#))

Pretext task: predict relative patch locations



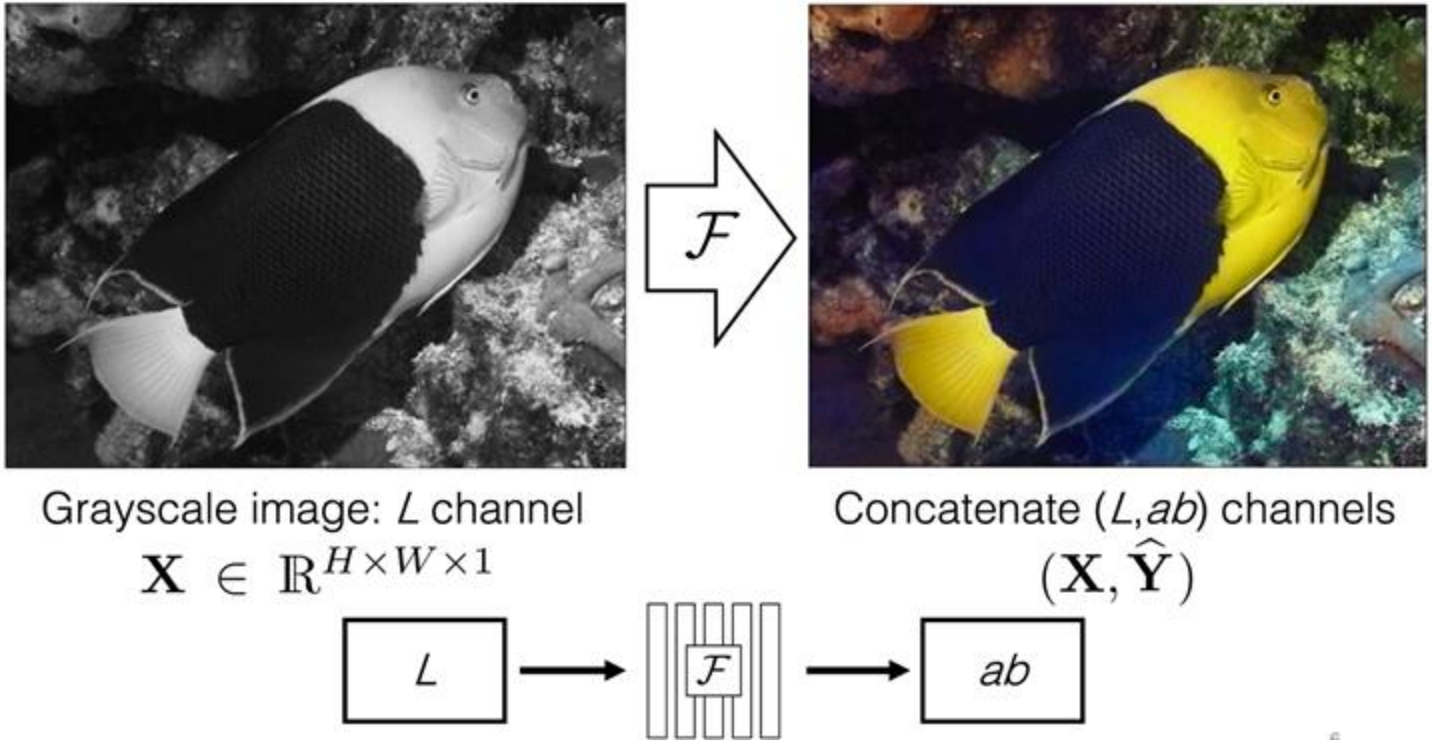
(Image source: [Doersch et al., 2015](https://arxiv.org/abs/1505.05192))

Pretext task: image coloring



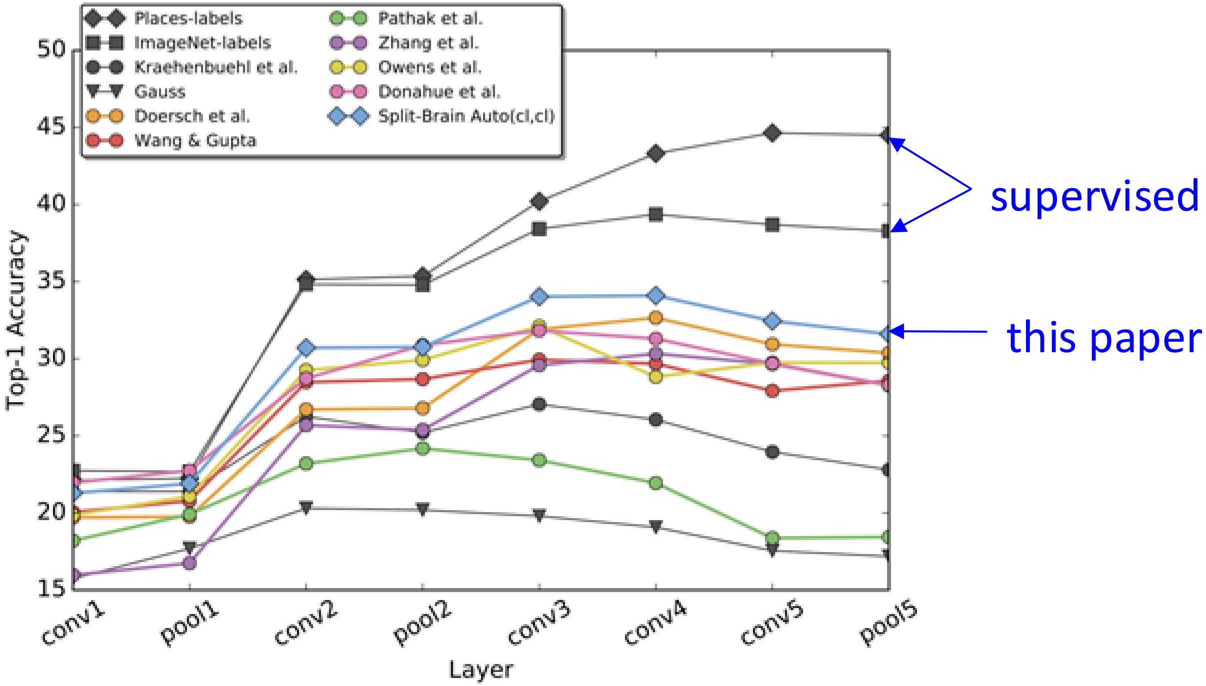
Source: Richard Zhang / Phillip Isola

Pretext task: image coloring



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: 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

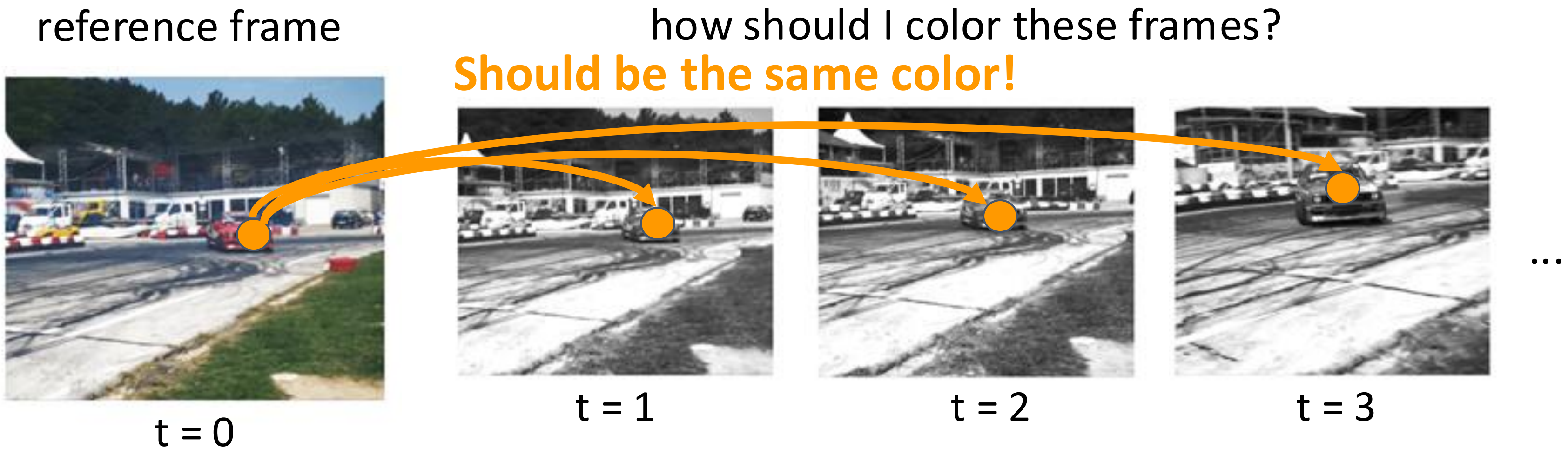
t = 3

...

Source: [Vondrick et al., 2018]

Pretext task: video coloring

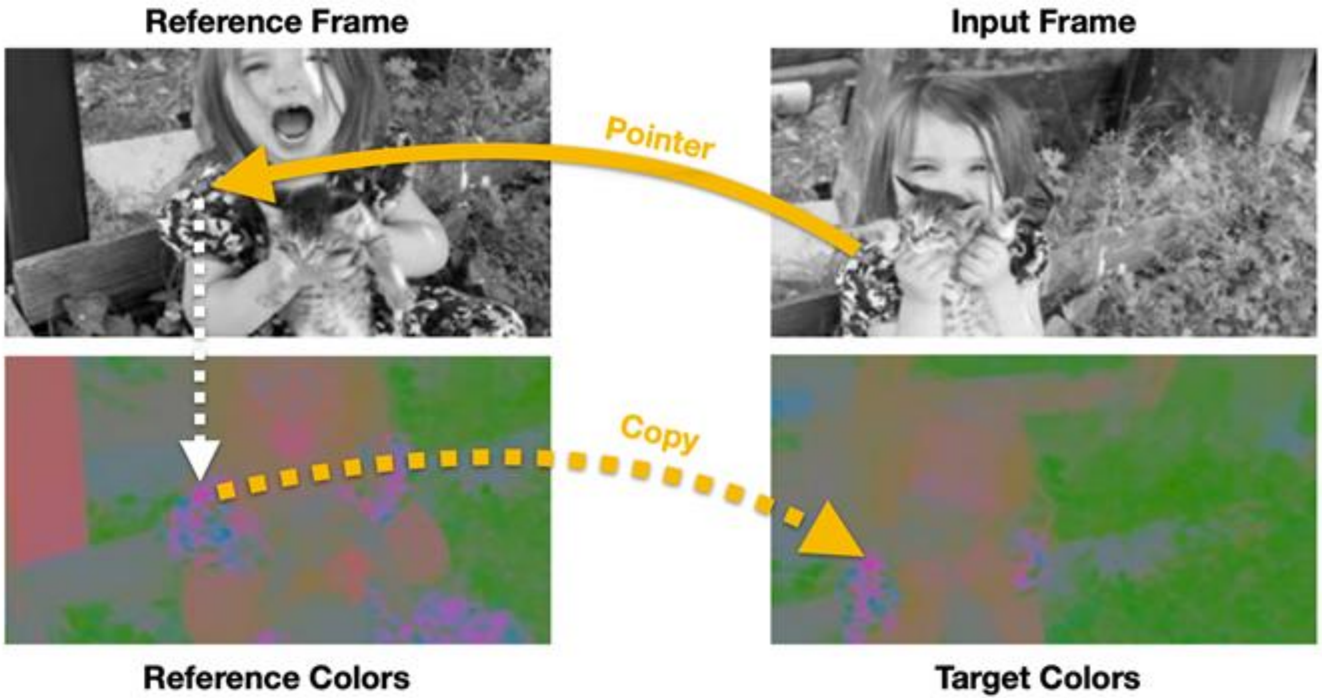
Idea: model the *temporal coherence* of colors in videos



Hypothesis: learning to copy colors from reference to future video frames should allow model to learn to track regions or objects without labels!

Source: [Vondrick et al., 2018]

Learning to color videos



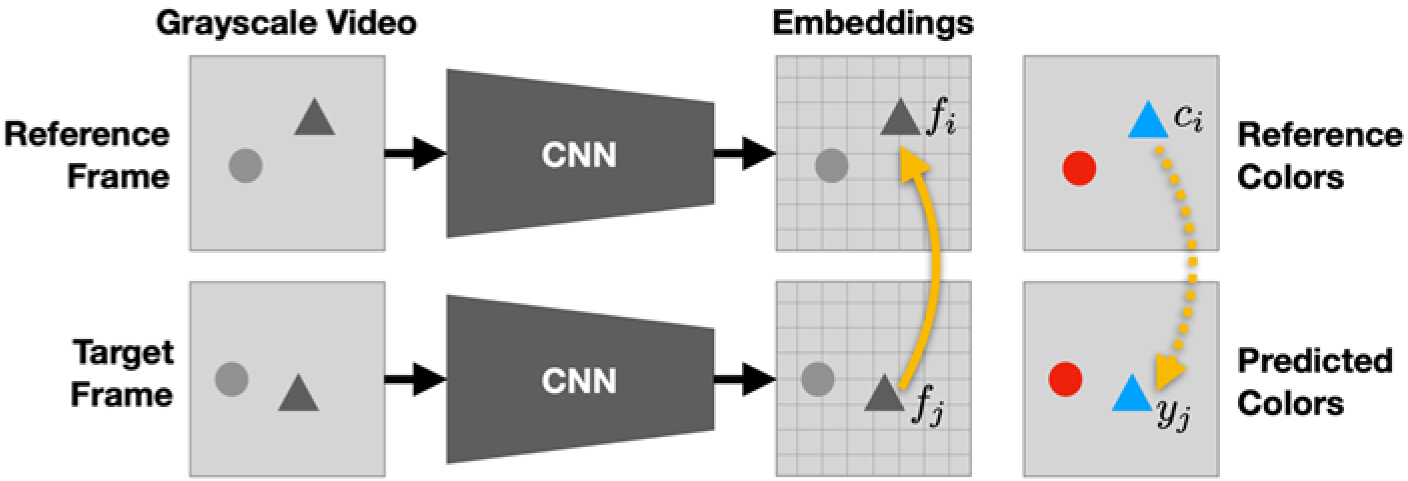
Learning objective:

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

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

Source: [Vondrick et al., 2018]

Learning to color videos

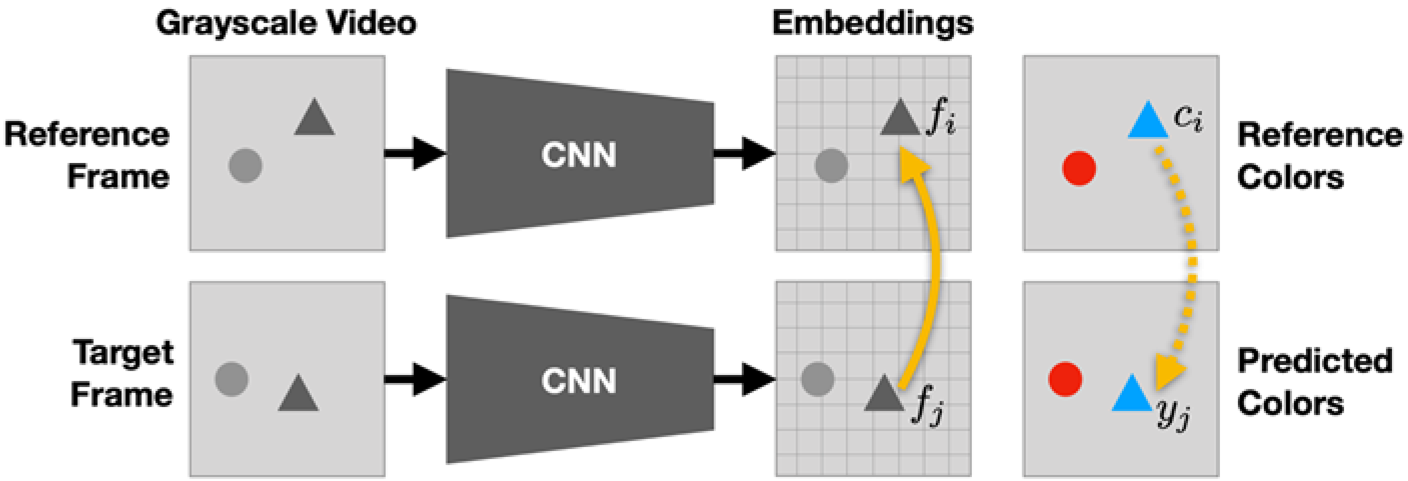


attention map on the reference frame

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

Source: [Vondrick et al., 2018]

Learning to color videos



attention map on the reference frame

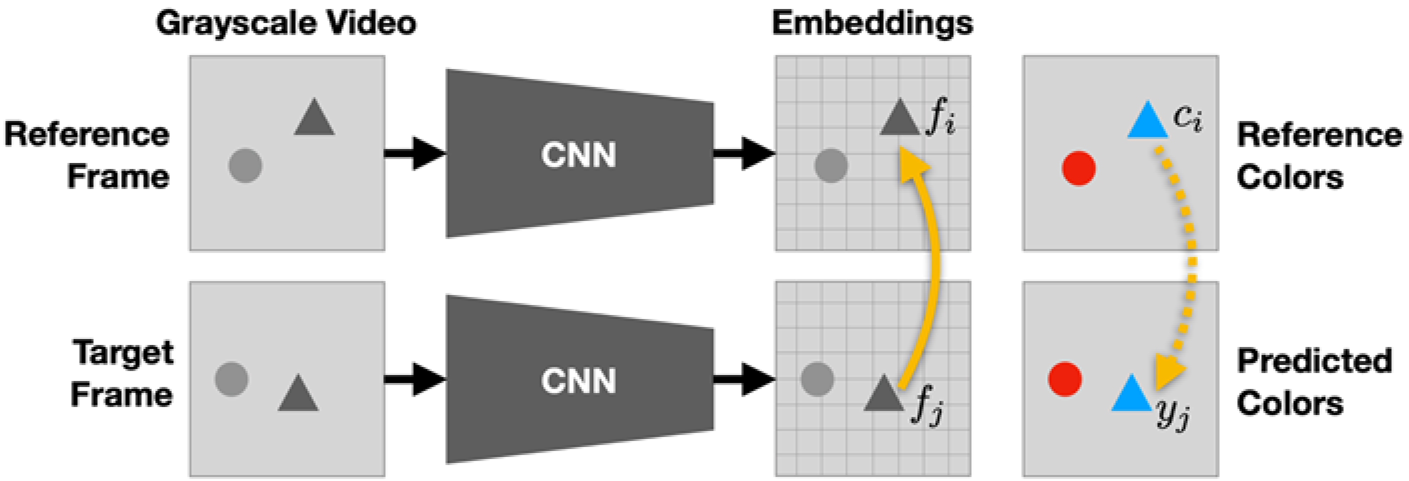
$$A_{ij} = \frac{\exp\left(f_i^T f_j\right)}{\sum_k \exp\left(f_k^T f_j\right)}$$

predicted color = weighted sum of the reference color

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

Source: [Vondrick et al., 2018]

Learning to color videos



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

loss between predicted color and ground truth color

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

Source: [Vondrick et al., 2018]

Colorizing videos (qualitative)

reference frame

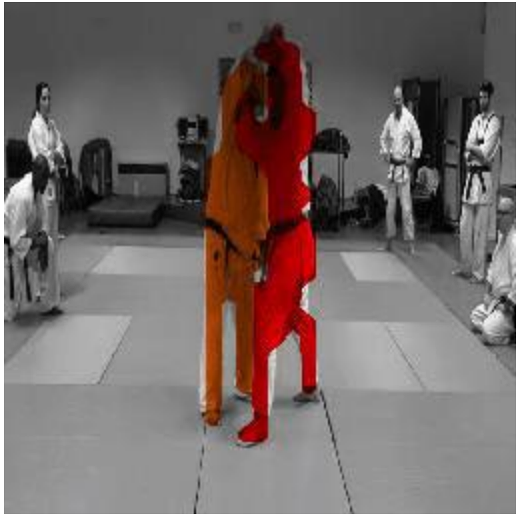
target frames (gray)

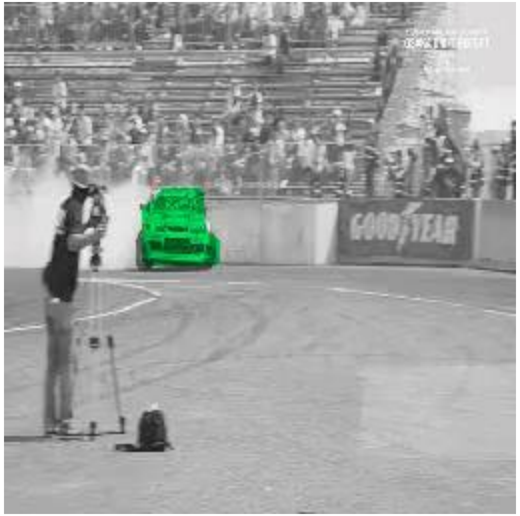
predicted color

Source: [Google AI blog post]

Tracking emerges from colorization

Propagate segmentation masks using learned attention

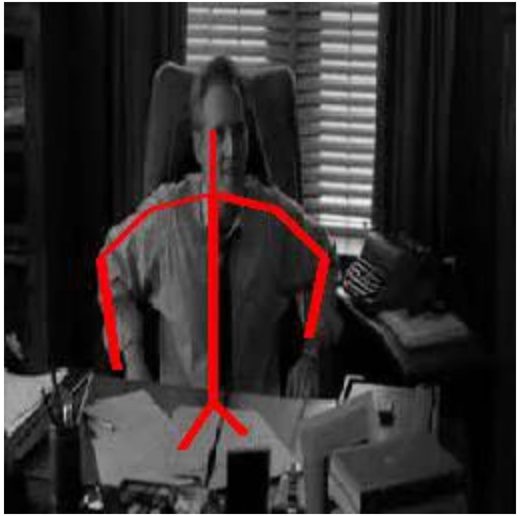




Source: [Google AI blog post]

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

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- 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

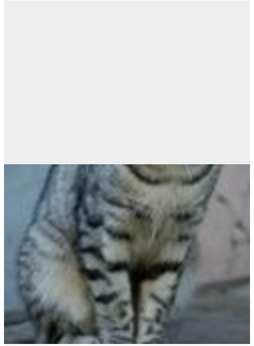


image completion

rotation prediction

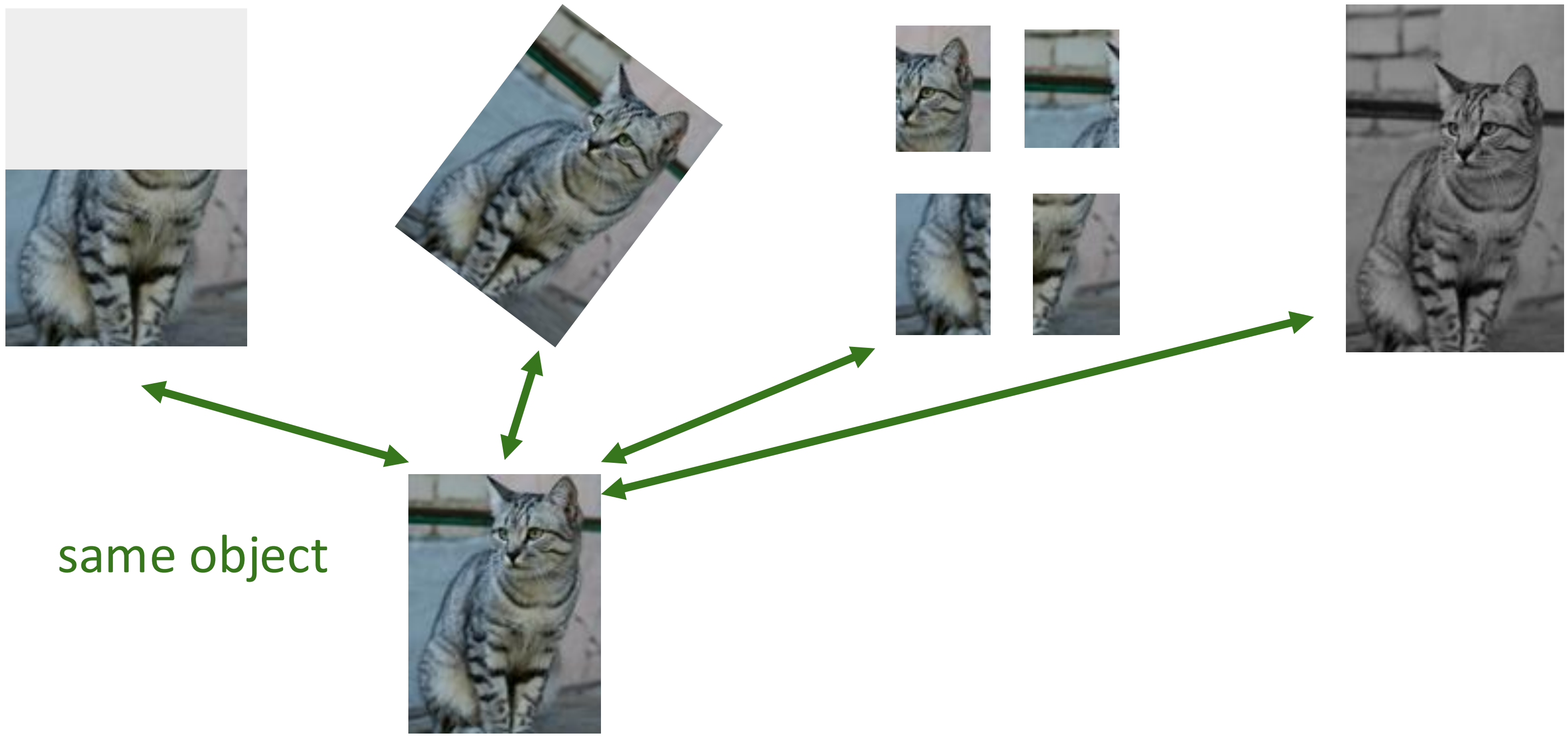
“jigsaw puzzle”

colorization

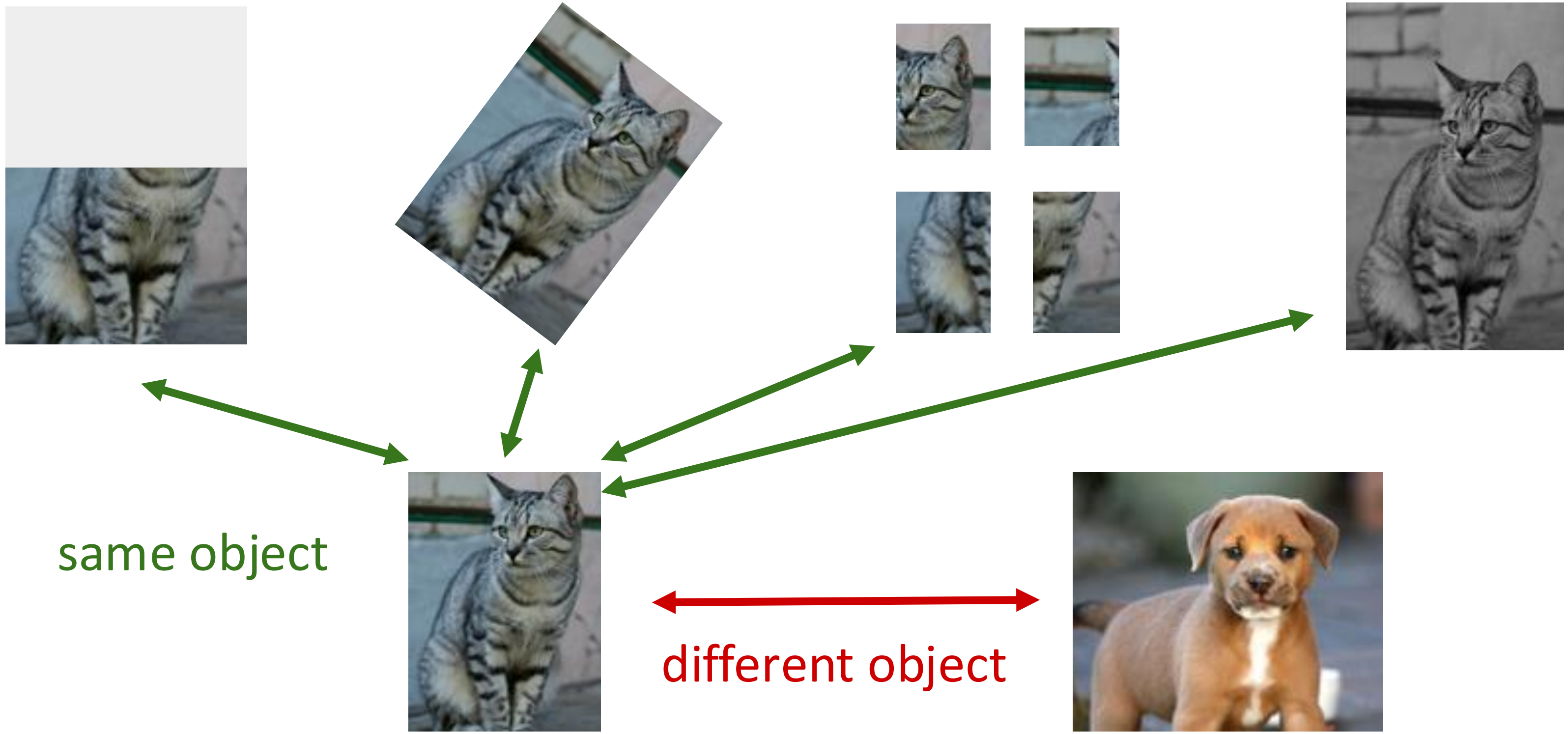
Learned representations may be tied to a specific pretext task!

Can we come up with a more general pretext task?

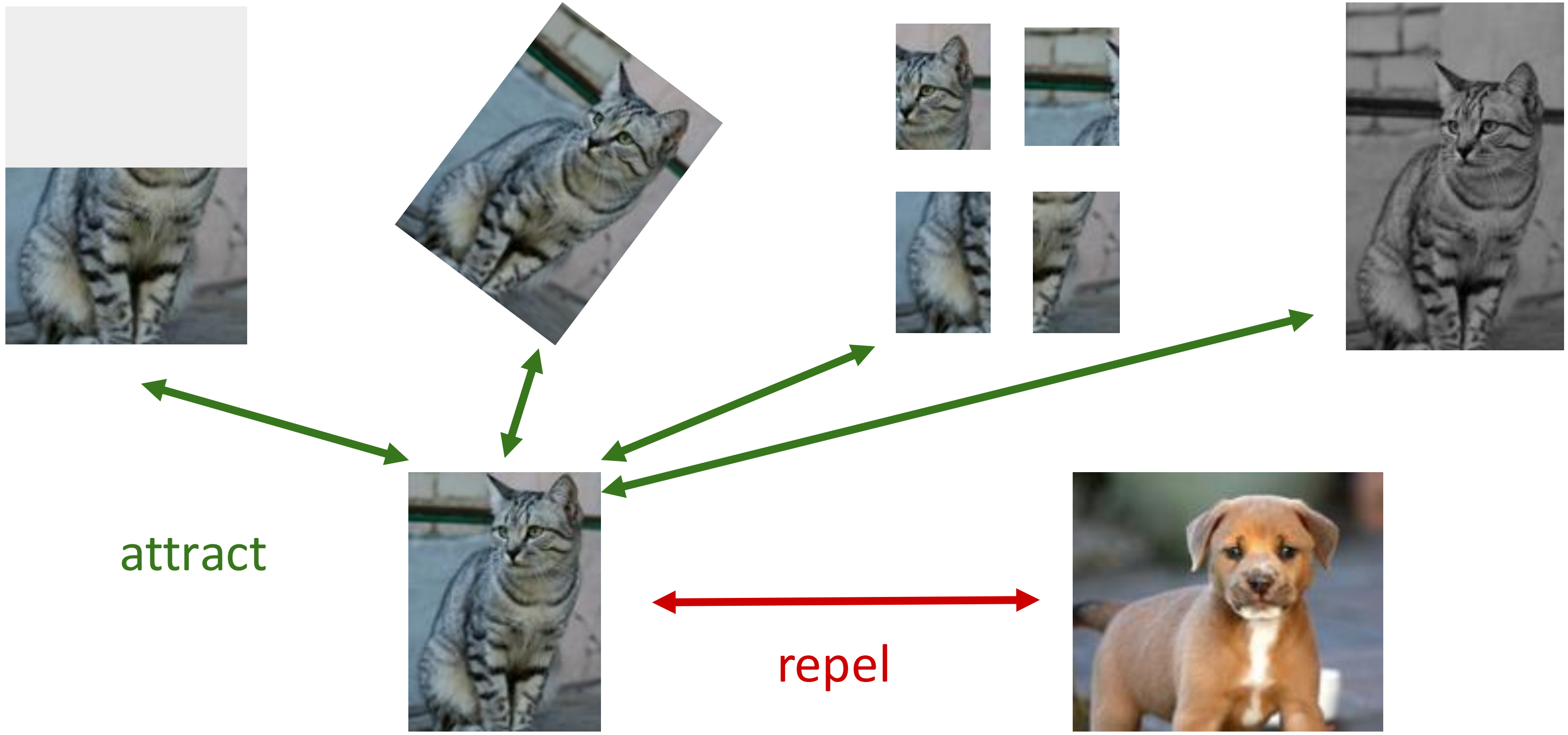
A more general pretext task?



A more general pretext task?



Contrastive Representation Learning



Today's Agenda

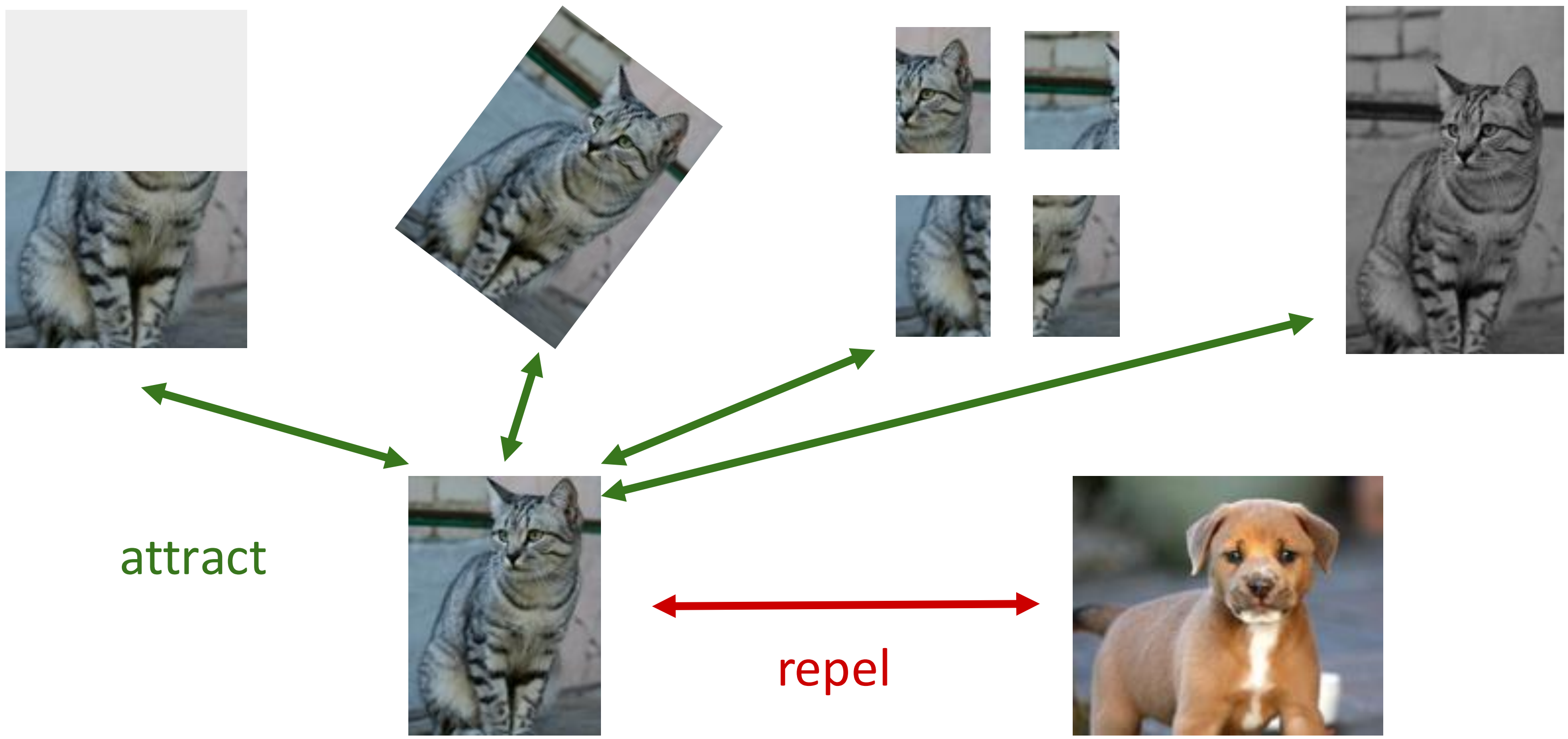
Pretext tasks from image transformations

- Rotation, inpainting, rearrangement, coloring

Contrastive representation learning

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

Contrastive Representation Learning



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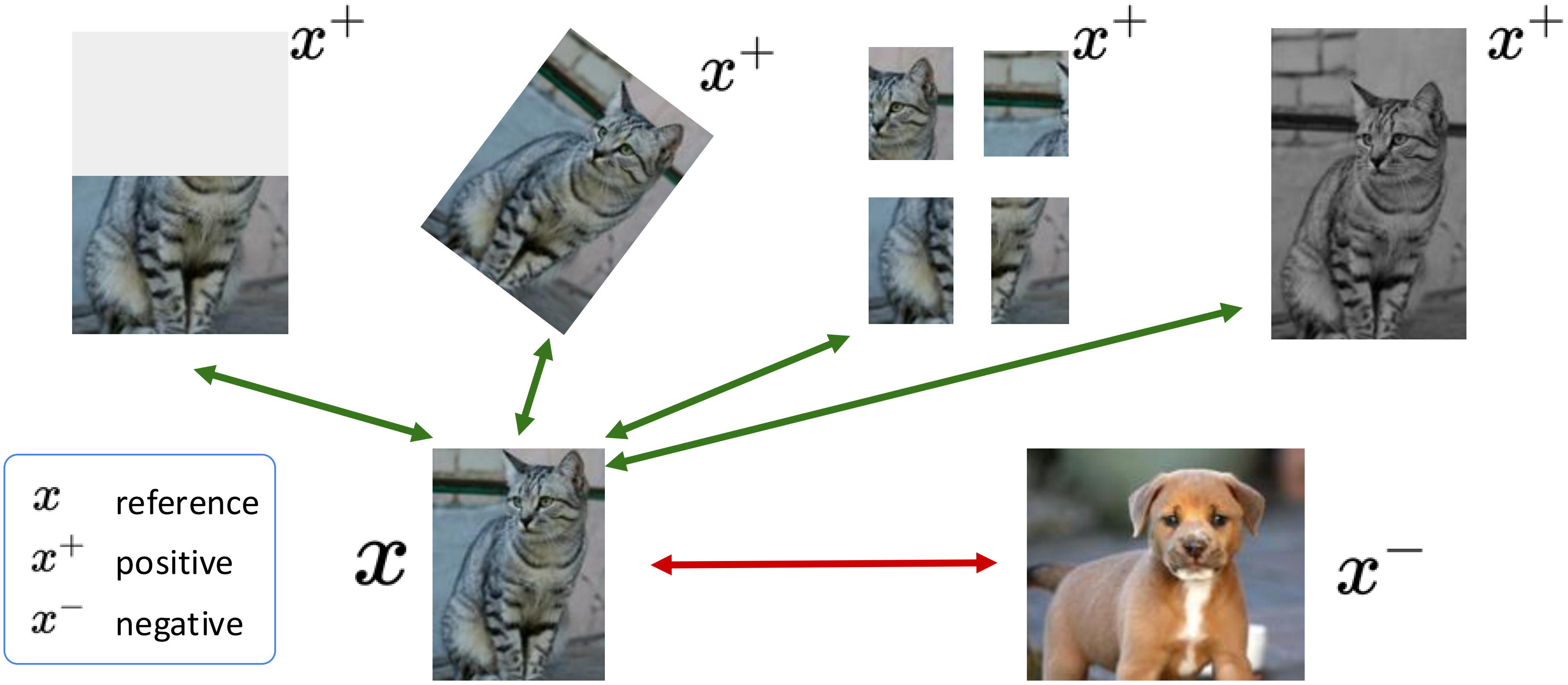
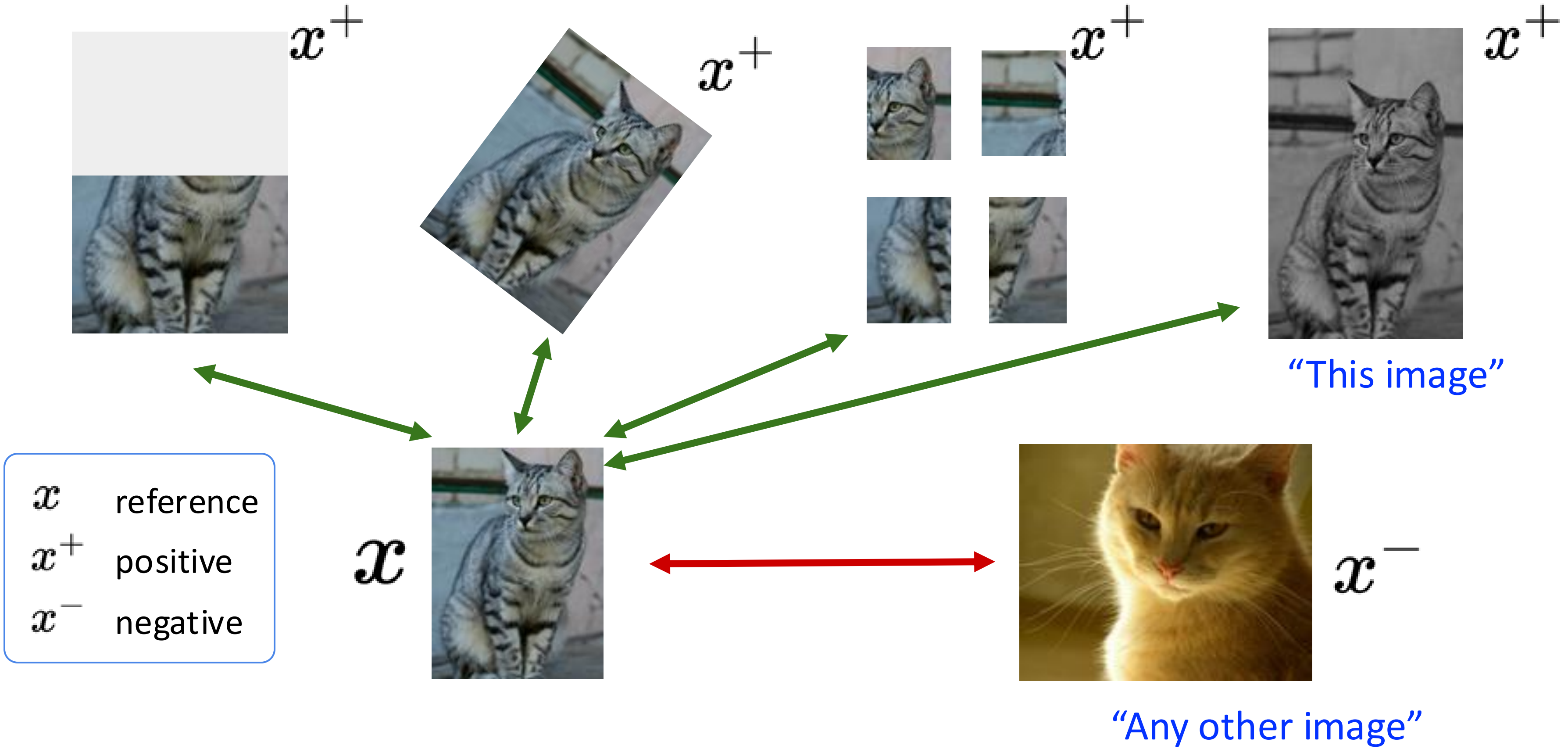


Contrastive Representation Learning



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

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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:

$$L = -\mathbb{E}_X \left[\log \frac{\overline{\exp(s(f(x), f(x^+))}}{\underbrace{\exp(s(f(x), f(x^+))}_{\text{score for the positive pair}} + \underbrace{\sum_{j=1}^{N-1} \exp(s(f(x), f(x_j^-))}_{\text{score for the N-1 negative pairs}}} \right]$$

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

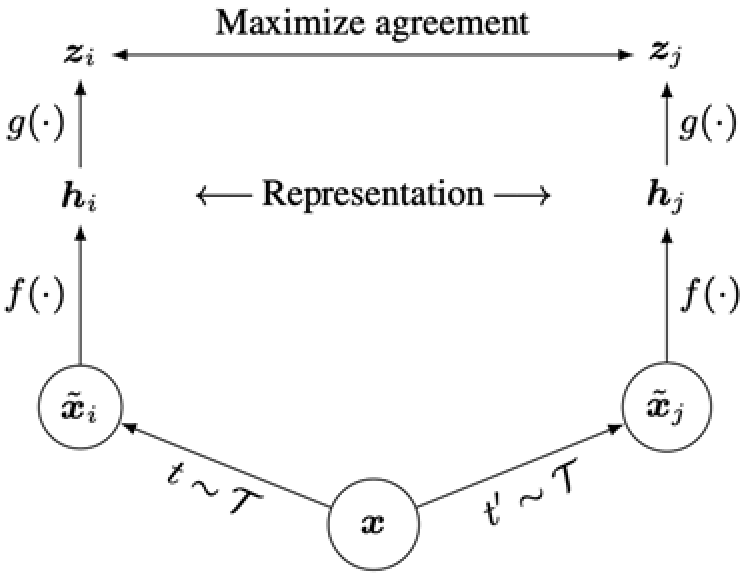
Cosine similarity as the score function:

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

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

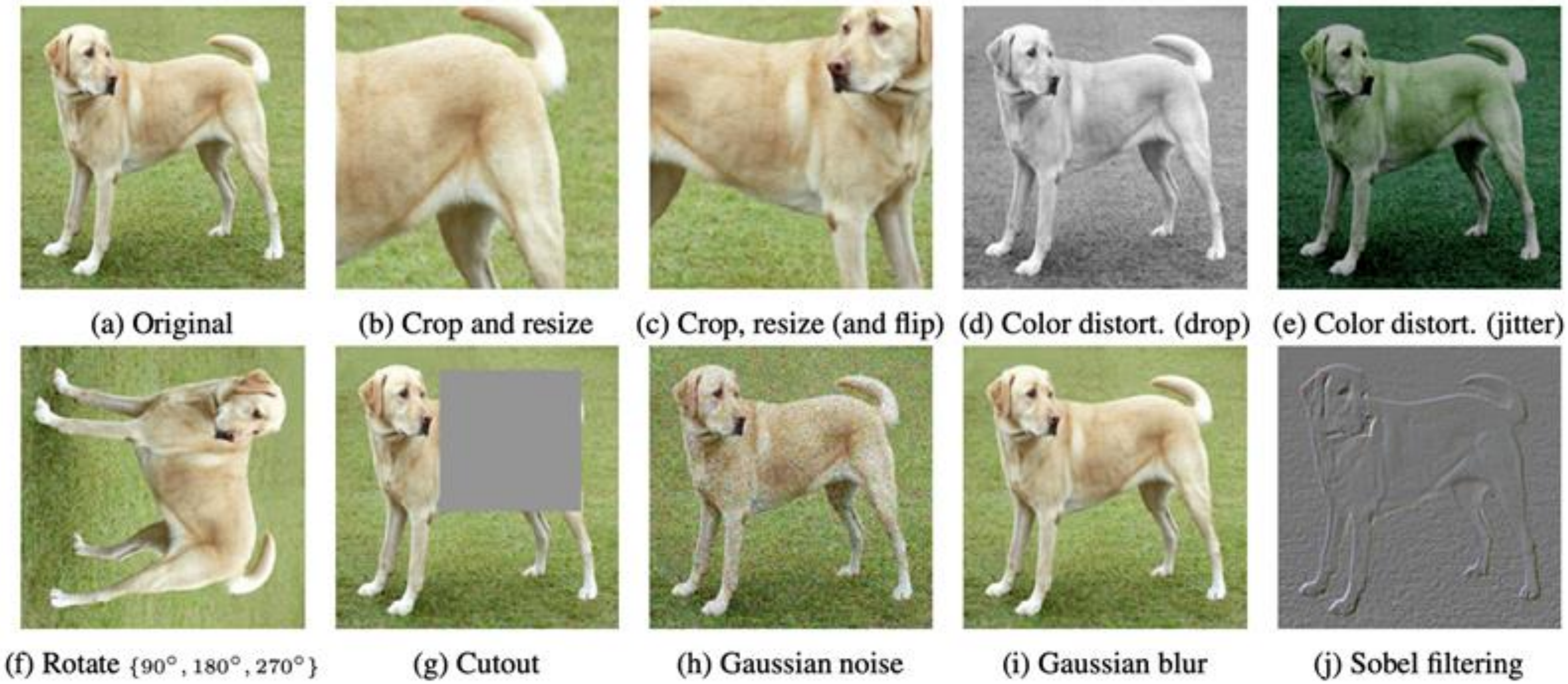
Generate positive samples through data augmentation:

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



Source: [Chen et al., 2020]()

SimCLR: generating positive samples from data augmentation



Source: [Chen et al., 2020]

SimCLR

Generate a positive pair by sampling data augmentation functions

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 $g(\cdot)$

Source: Chen et al., 2020

SimCLR

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
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Generate a positive pair by sampling data augmentation functions

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

Source: [Chen et al., 2020]

SimCLR

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
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    $s_{i,j} = \boldsymbol{z}_i^{\top} \boldsymbol{z}_j / (\lVert \boldsymbol{z}_i \rVert \lVert \boldsymbol{z}_j \rVert)$ # pairwise similarity
  end for
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  update networks f and g to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$

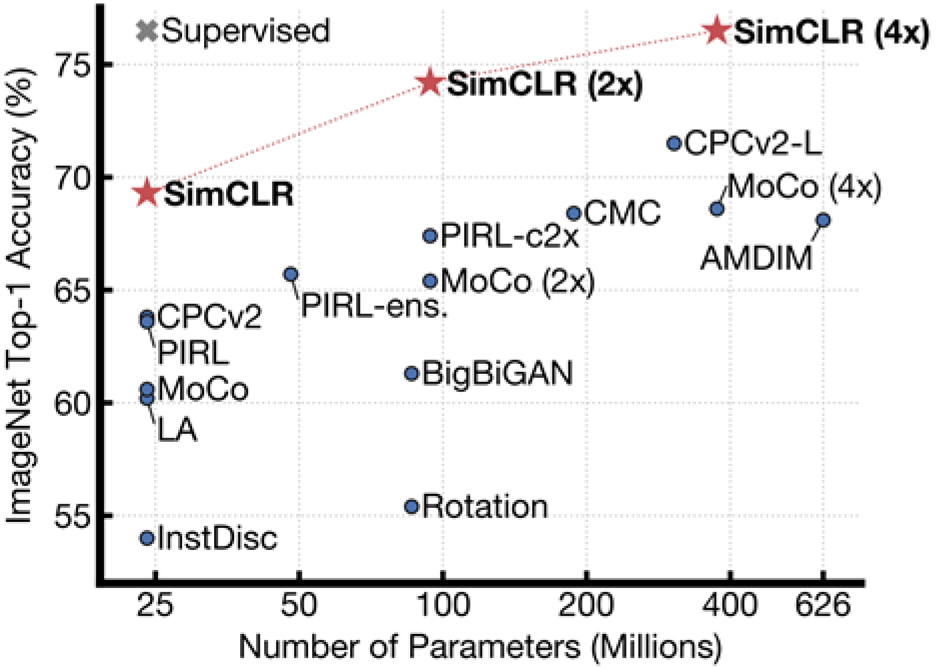
Generate a positive pair by sampling data augmentation functions

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]

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%	10%
		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**

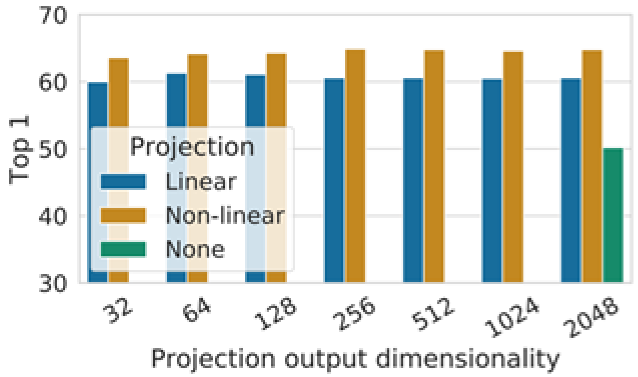
Table 7. ImageNet accuracy of models trained with few labels.

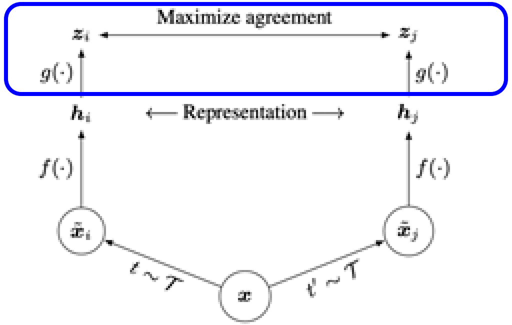
Train feature encoder on **ImageNet** (entire training set) using SimCLR.

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

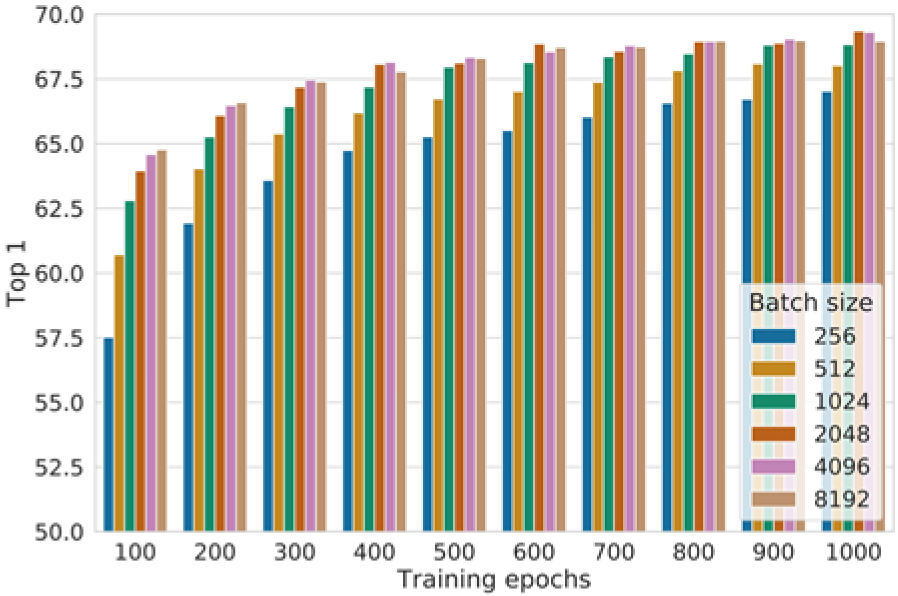


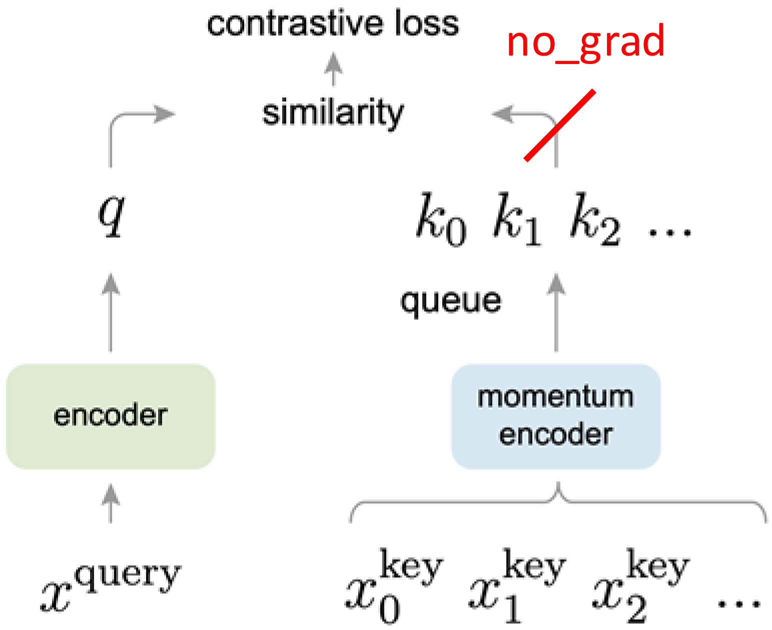
Figure 9. Linear evaluation models (ResNet-50) trained with different batch size and epochs. Each bar is a single run from scratch.[10]

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]

Momentum Contrastive Learning (MoCo)

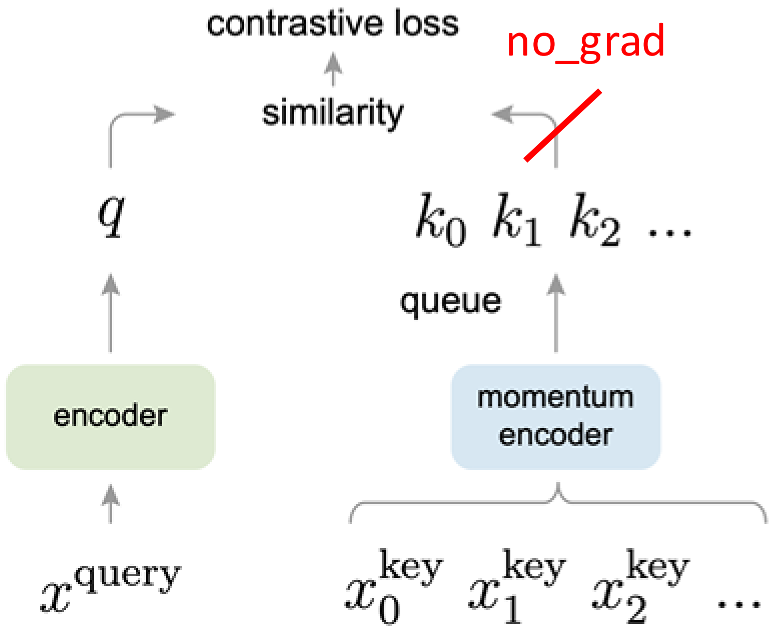


Key differences to SimCLR:

- Keep a running queue of keys (negative samples).
- Compute gradients and update the encoder only through the queries.
- Decouple min-batch size with the number of keys: can support a large number of negative samples.

Source: He et al., 2020

Momentum Contrastive Learning (MoCo)



Key differences to SimCLR:

- Keep a running queue of keys (negative samples).
- Compute gradients and update the encoder only through the queries.
- Decouple min-batch size with the number of keys: can support a large number of negative samples.
- The key encoder is slowly progressing through the momentum update rules:

$$\theta_{\mathrm{k}} \leftarrow m\theta_{\mathrm{k}} + (1-m)\theta_{\mathrm{q}}$$

Source: He et al., 2020

MoCo

Algorithm 1 Pseudocode of MoCo in a PyTorch-like style.

```
# f_q, f_k: encoder networks for query and key
# queue: dictionary as a queue of K keys (CxK)
# m: momentum
# t: temperature

f_k.params = f_q.params # initialize
for x in loader: # load a minibatch x with N samples
    x_q = aug(x) # a randomly augmented version
    x_k = aug(x) # another randomly augmented version

    q = f_q.forward(x_q) # queries: NxC
    k = f_k.forward(x_k) # keys: NxC
    k = k.detach() # no gradient to keys

    # positive logits: Nx1
    l_pos = bmm(q.view(N,1,C), k.view(N,C,1))

    # negative logits: NxK
    l_neg = mm(q.view(N,C), queue.view(C,K))

    # logits: Nx(1+K)
    logits = cat([l_pos, l_neg], dim=1)

    # contrastive loss, Eqn.(1)
    labels = zeros(N) # positives are the 0-th
    loss = CrossEntropyLoss(logits/t, labels)

    # SGD update: query network
    loss.backward()
    update(f_q.params)

    # momentum update: key network
    f_k.params = m*f_k.params+(1-m)*f_q.params

    # update dictionary
    enqueue(queue, k) # enqueue the current minibatch
    dequeue(queue) # dequeue the earliest minibatch
```

bmm: batch matrix multiplication; mm: matrix multiplication; cat: concatenation.

Generate a positive pair by sampling data augmentation functions

No gradient through the positive sample

Use the running queue of keys as the negative samples

InfoNCE loss

Update f_k through momentum

Update the FIFO negative sample queue

Source: He et al., 2020

“MoCo V2”

Improved Baselines with Momentum Contrastive Learning

Xinlei Chen Haoqi Fan Ross Girshick Kaiming He
Facebook AI Research (FAIR)

A hybrid of ideas from SimCLR and MoCo:

- **From SimCLR**: non-linear projection head and strong data augmentation.
- **From MoCo**: momentum-updated queues that allow training on a large number of negative samples (no TPU required!).

Source: [Chen et al., 2020]

MoCo vs. SimCLR vs. MoCo V2

case	unsup. pre-train				ImageNet	VOC detection		
	MLP	aug+	cos	epochs	acc.	AP_{50}	AP	AP_{75}
supervised					76.5	81.3	53.5	58.8
MoCo v1				200	60.6	81.5	55.9	62.6
(a)	✓			200	66.2	82.0	56.4	62.6
(b)		✓		200	63.4	82.2	56.8	63.2
(c)	✓	✓		200	67.3	**82.5**	57.2	63.9
(d)	✓	✓	✓	200	67.5	82.4	57.0	63.6
(e)	✓	✓	✓	**800**	**71.1**	**82.5**	**57.4**	**64.0**

Table 1. **Ablation of MoCo baselines**, evaluated by ResNet-50 for (i) ImageNet linear classification, and (ii) fine-tuning VOC object detection (mean of 5 trials). "**MLP**": with an MLP head; "**aug+**": with extra blur augmentation; "**cos**": cosine learning rate schedule.

Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.

Source: [Chen et al., 2020]

MoCo vs. SimCLR vs. MoCo V2

case	unsup. pre-train MLP	aug+	cos	epochs	batch	ImageNet acc.
MoCo v1 [6]				200	256	60.6
SimCLR [2]	✓	✓	✓	200	256	61.9
SimCLR [2]	✓	✓	✓	200	8192	66.6
MoCo v2	✓	✓	✓	200	256	**67.5**
*results of **longer** unsupervised training follow:*						
SimCLR [2]	✓	✓	✓	1000	4096	69.3
MoCo v2	✓	✓	✓	800	256	**71.1**

Table 2. **MoCo *vs.* SimCLR**: ImageNet linear classifier accuracy (**ResNet-50, 1-crop 224×224**), trained on features from unsupervised pre-training. "aug+" in SimCLR includes blur and stronger color distortion. SimCLR ablations are from Fig. 9 in [2] (we thank the authors for providing the numerical results).

Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.
- Decoupling mini-batch size with negative sample size allows MoCo-V2 to outperform SimCLR with smaller batch size (256 vs. 8192).

Source: [Chen et al., 2020]

MoCo vs. SimCLR vs. MoCo V2

mechanism	batch	memory / GPU	time / 200-ep.
MoCo	256	**5.0G**	**53 hrs**
end-to-end	256	7.4G	65 hrs
end-to-end	4096	93.0G†	n/a

Table 3. **Memory and time cost** in 8 V100 16G GPUs, implemented in PyTorch. †: based on our estimation.

Key takeaways:

- Non-linear projection head and strong data augmentation are crucial for contrastive learning.
- Decoupling mini-batch size with negative sample size allows MoCo-V2 to outperform SimCLR with smaller batch size (256 vs. 8192).
- … all with much smaller memory footprint! ("end-to-end" means SimCLR here)

Source: Chen et al., 2020

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)

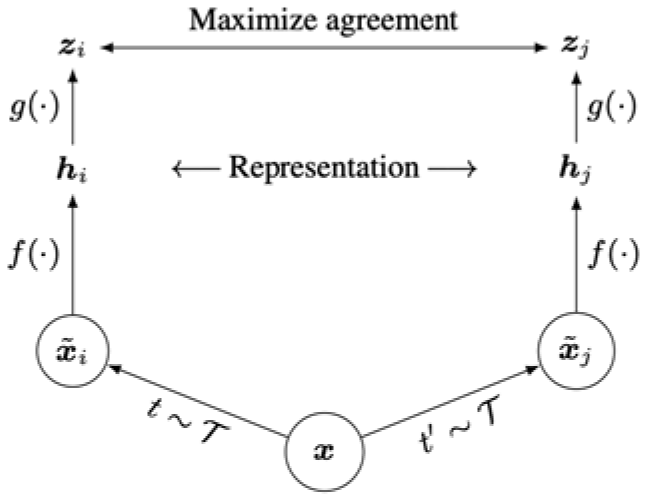
A *lower bound* on the mutual information between *f(x)* and *f(x⁺)*

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

Summary: Contrastive Representation Learning

SimCLR: a simple framework for contrastive representation learning

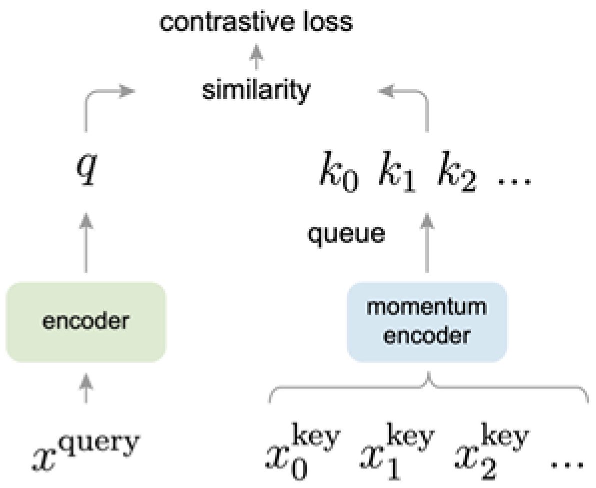
- **Key ideas**: non-linear projection head to allow flexible representation learning
- Simple to implement, effective in learning visual representation
- Requires large training batch size to be effective; large memory footprint



Summary: Contrastive Representation Learning

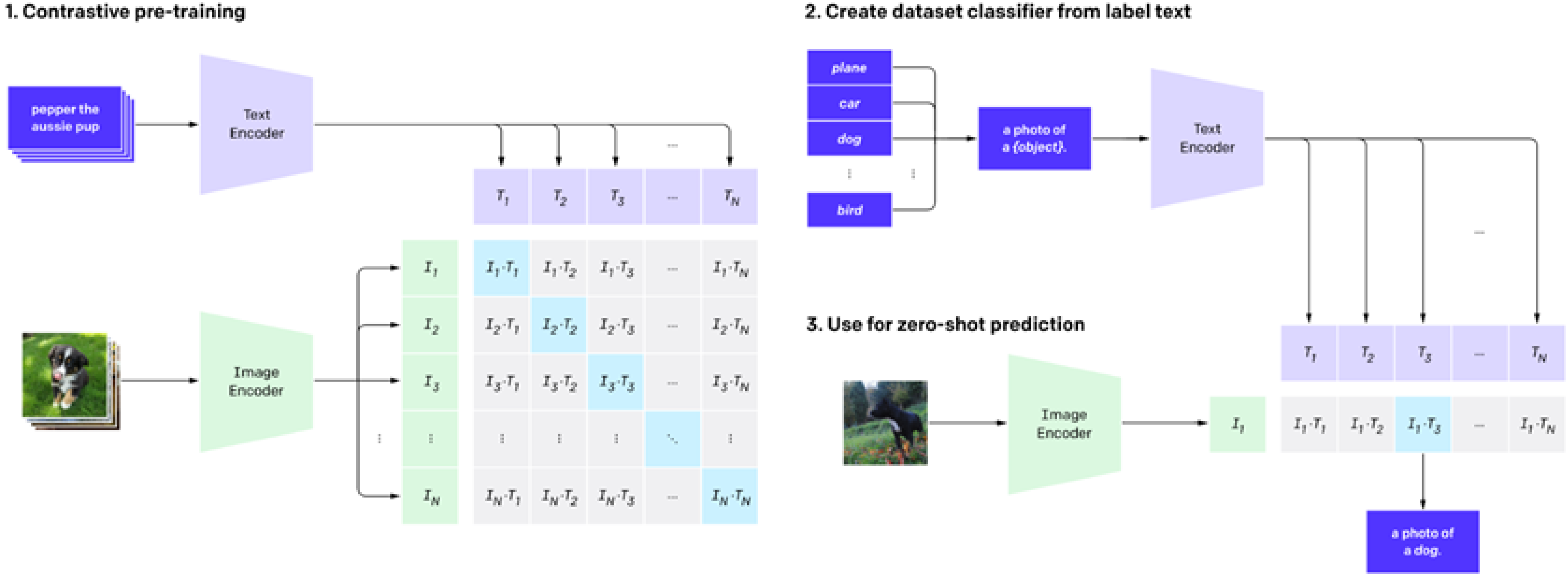
MoCo (v1, v2): contrastive learning using momentum sample encoder

- Decouples negative sample size from minibatch size; allows large batch training without TPU
- MoCo-v2 combines the key ideas from SimCLR, i.e., nonlinear projection head, strong data augmentation, with momentum contrastive learning



Other examples

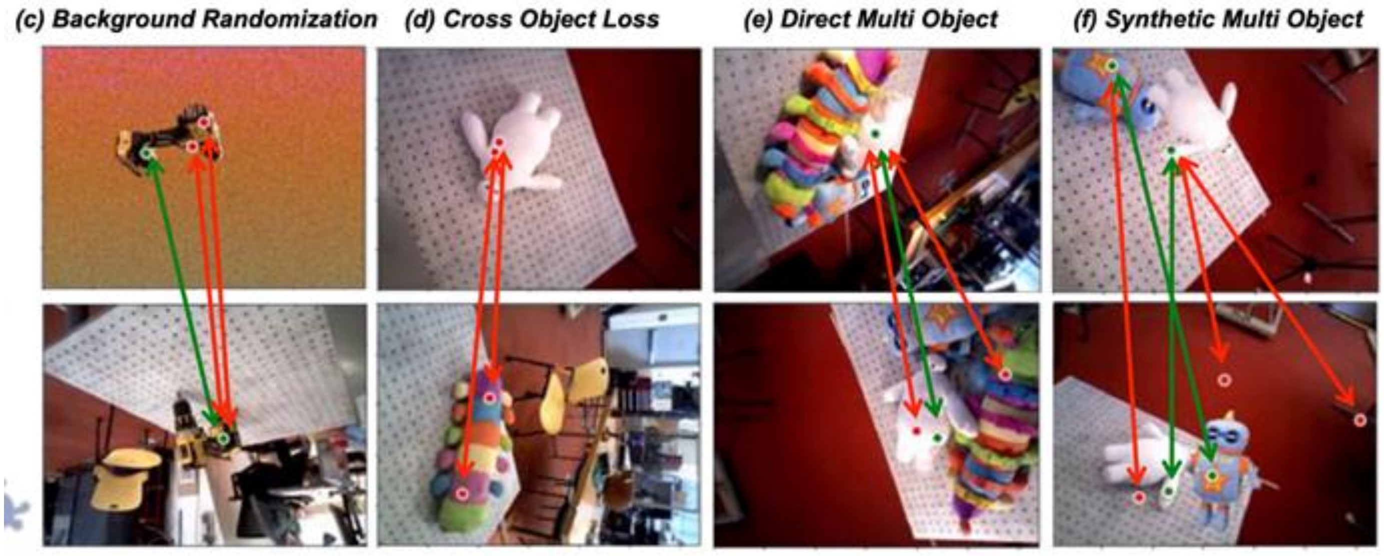
Contrastive learning between image and natural language sentences



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

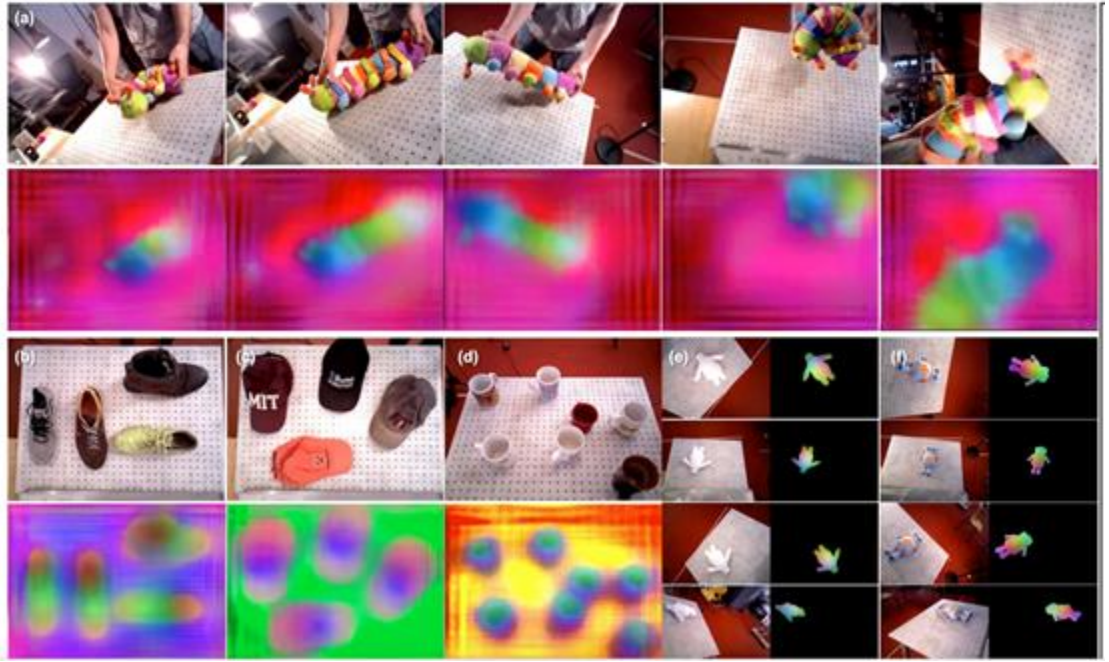
Other examples

Contrastive learning on pixel-wise feature descriptors



Dense Object Net, Florence et al., 2018

Other examples

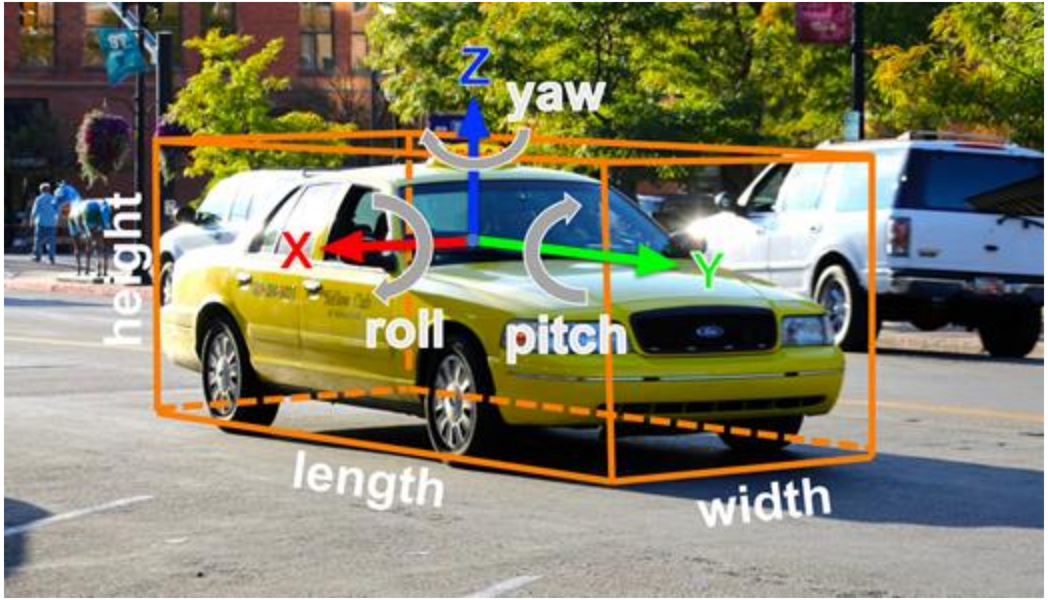


Dense Object Net, Florence et al., 2018

3D Vision with Deep Neural Networks:

A very very short lecture

3D Object Detection



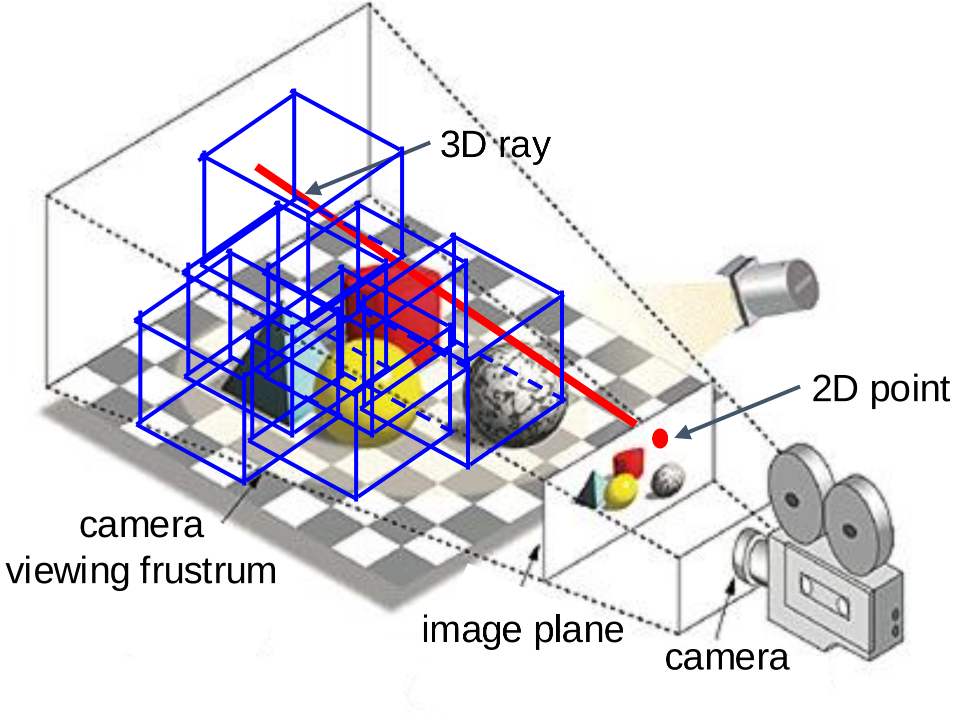
2D Object Detection:
2D bounding box
(x, y, w, h)

3D Object Detection:
3D oriented bounding box
(x, y, z, w, h, l, r, p, y)

Simplified bbox: no roll & pitch

Much harder problem than 2D object detection!

3D Object Detection: Simple Camera Model



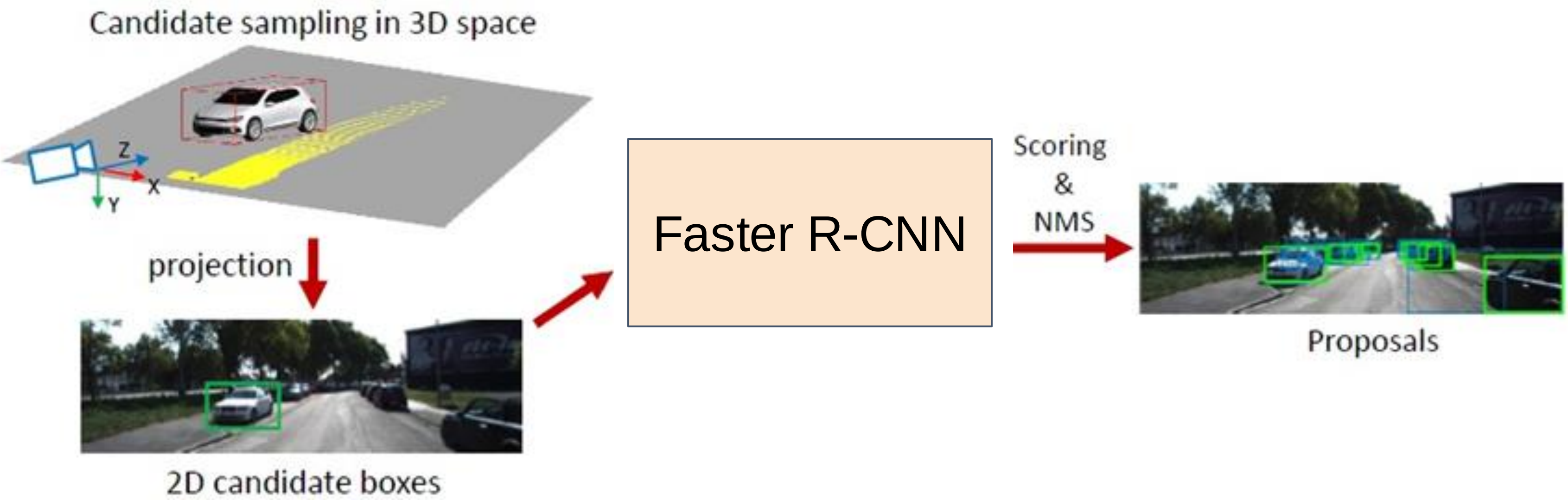
A point on the image plane corresponds to a **ray** in the 3D space

A 2D bounding box on an image is a **frustrum** in the 3D space

Localize an object in 3D:
The object can be anywhere in the **camera viewing frustrum**!

Image source: https://www.pcmag.com/encyclopedia_images/_FRUSTUM.GIF

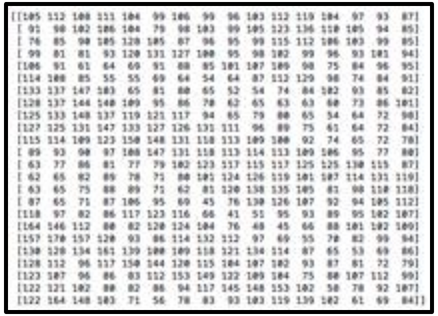
3D Object Detection: Monocular Camera



- Same idea as Faster RCNN, but proposals are in 3D
- 3D bounding box proposal, regress 3D box parameters + class score

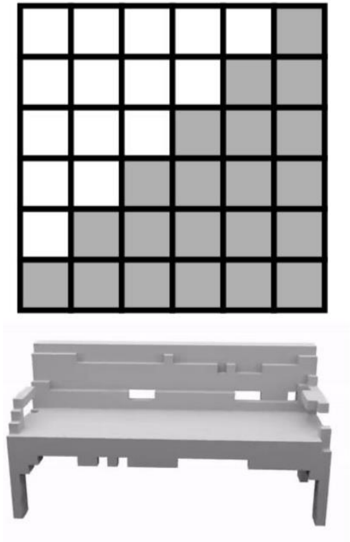
Chen, Xiaozhi, Kaustav Kundu, Ziyu Zhang, Huimin Ma, Sanja Fidler, and Raquel Urtasun. "Monocular 3d object detection for autonomous driving." CVPR 2016.

How to Represent 3D Data?

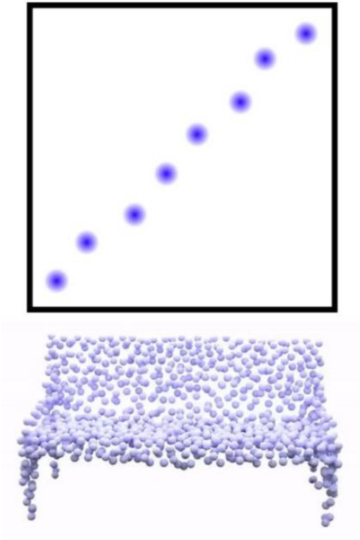


?

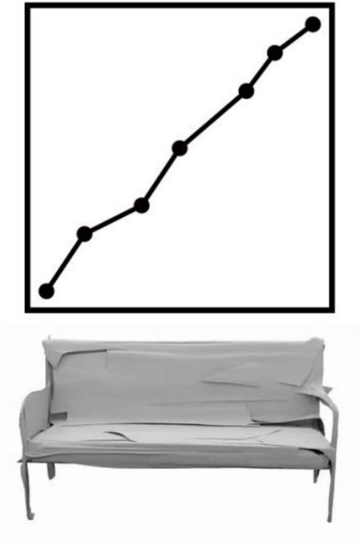
3D Representations



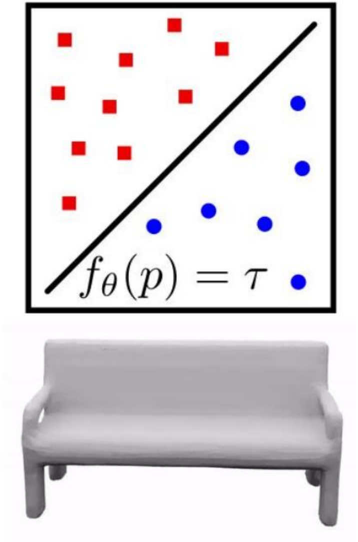
Occupancy Grid
[h, w, l]



Point Cloud
[num_pts, 3]



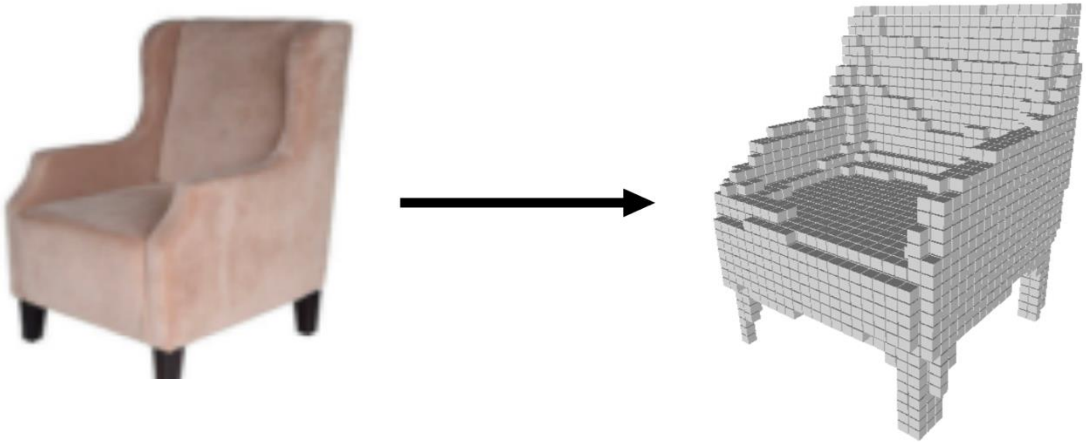
Surface Mesh
(edge list, face list, vertex list)



Implicit Functions
(x, y, z -> d)

Figure credit: Autonomous Vision Group

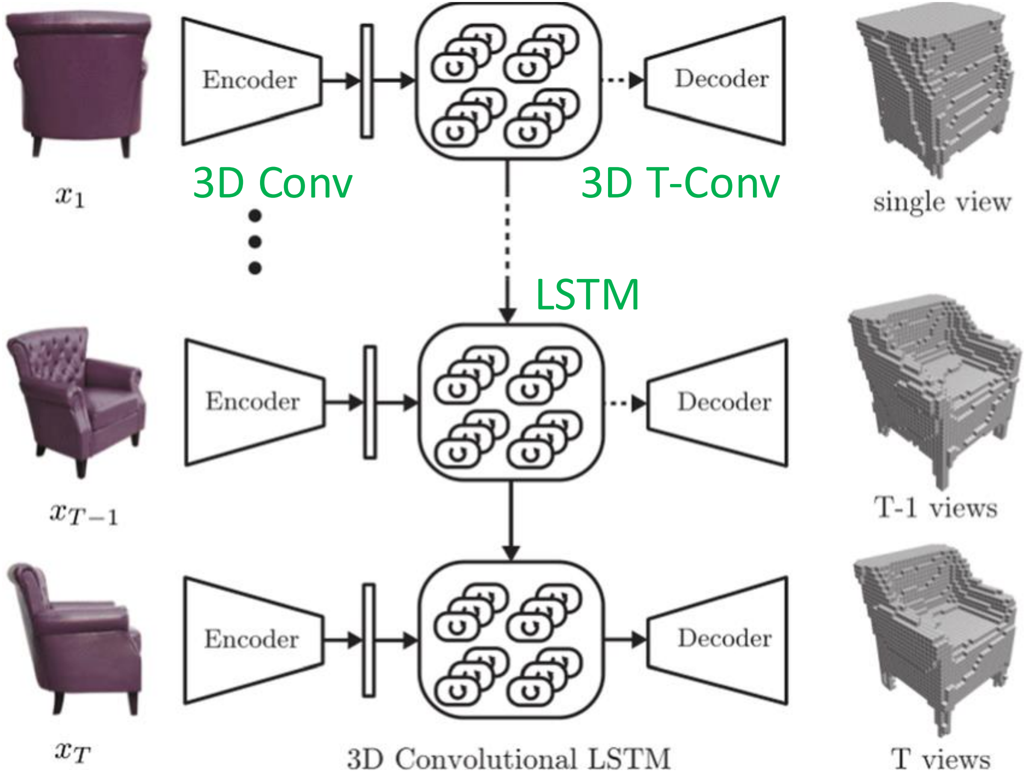
3D Occupancy Grid



Represent the “occupancy” of objects in 3D space with a 3D voxel grid

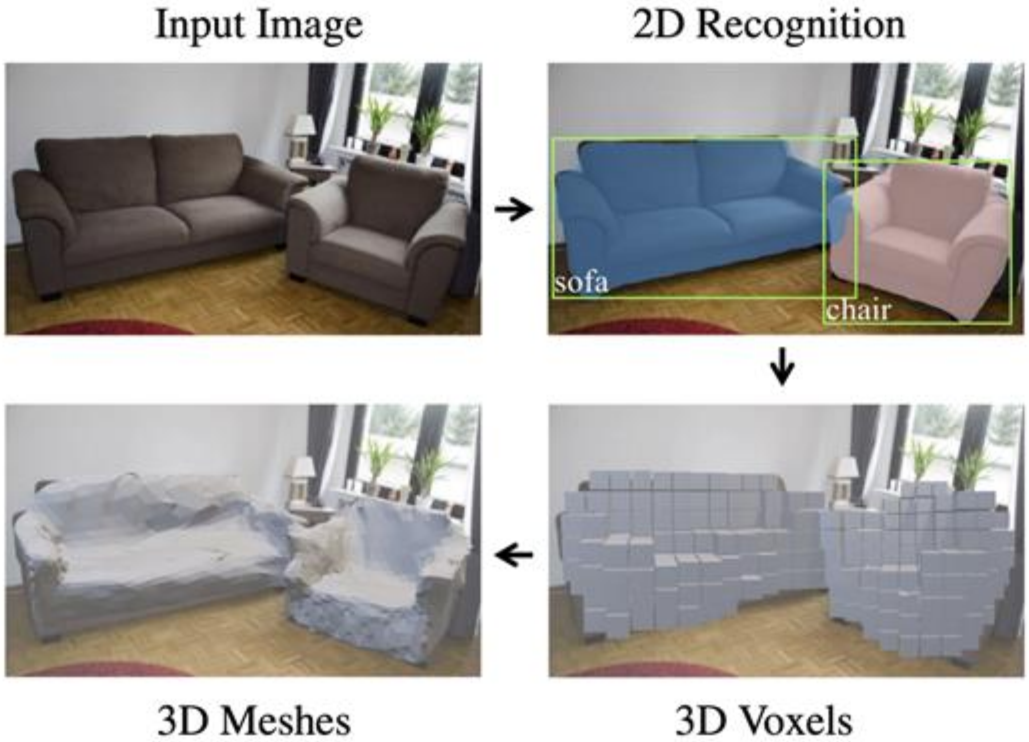
- $V \in \{0, 1\}^{[H,W,L]}$
- Just like segmentation in Masked-RCNN, but in 3D!
- Conceptually simple
- Not trivial to scale to high-resolution shapes

Predicting 3D Voxel Grid with 3D ConvNet



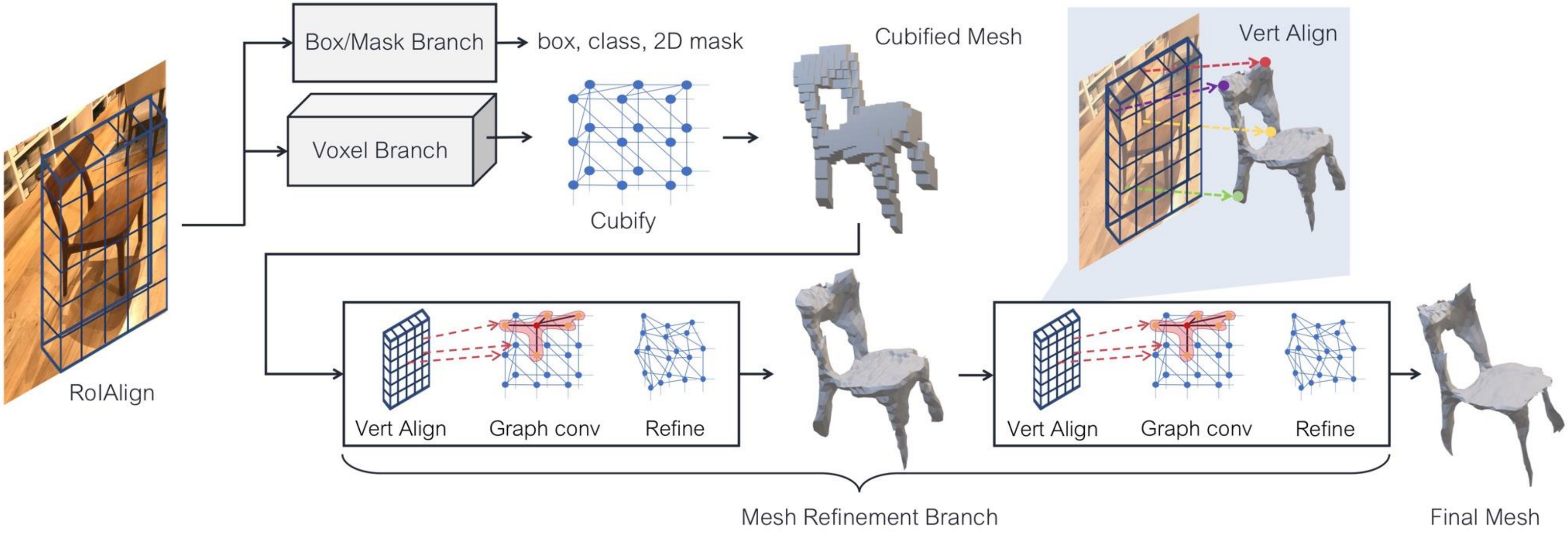
Cho et al. 2016, 3D-R2N2: A Unified Approach for Single and Multi-view 3D Object Reconstruction

Detection + Reconstruction: Mesh R-CNN



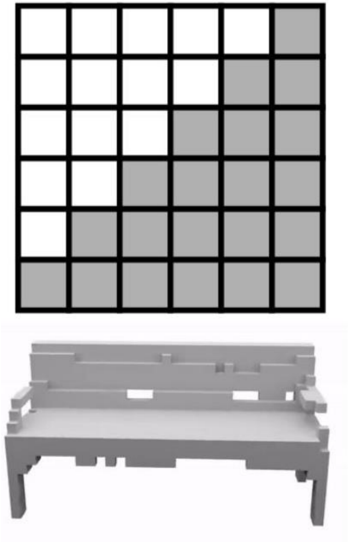
Gkioxari et al., Mesh RCNN, ICCV 2019

Detection + Reconstruction: Mesh R-CNN

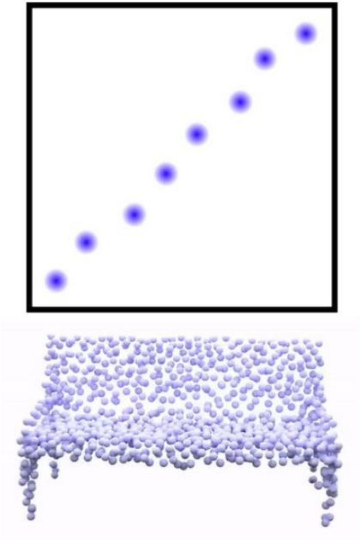


Gkioxari et al., Mesh RCNN, ICCV 2019

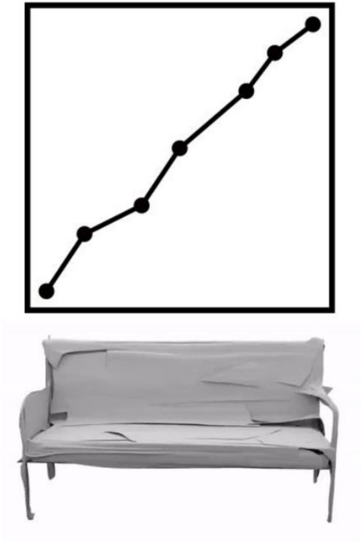
3D Representations



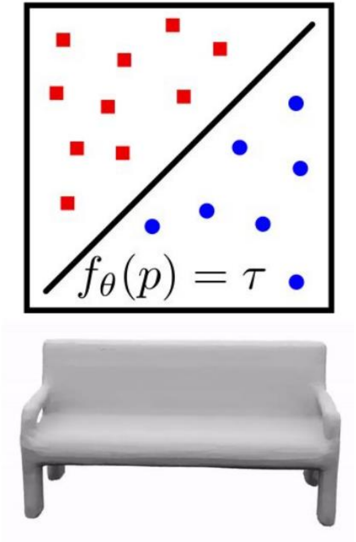
Occupancy Grid
[h, w, l]



Point Cloud
[num_pts, 3]



Surface Mesh
(edge list, face list, vertex list)

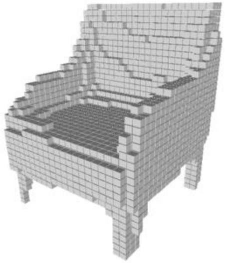


Implicit Functions
(x, y, z -> d)

Figure credit: Justin Johnson

What is an implicit representation for 3D data?

Example: representing a 3D occupancy grid



Explicit: A tensor of **3D voxel grid** $V \in \{0, 1\}^{[H,W,L]}$

Implicit: A **function** that maps locations to occupancies

$$F_\theta : x, y, z \rightarrow \{0, 1\}$$

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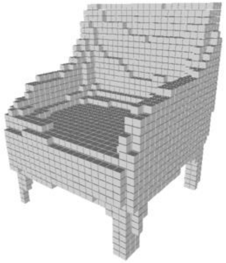

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Implicit representation describes 3D shapes using **mathematical functions** rather than explicit voxels, points, or mesh.

Example: Signed Distance Function

$$F_\theta:\ \mathbb{R}^3 \to \mathbb{R}$$

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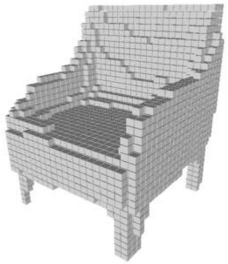

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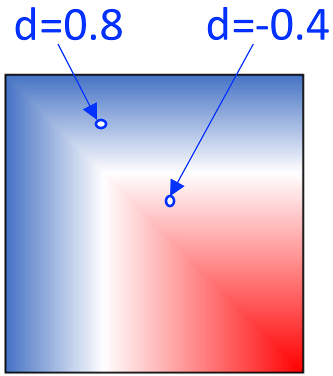
Example: Signed Distance Function

$$F_\theta:\ \mathbb{R}^N \to \mathbb{R}$$



SDF distance map

How far is a point from the nearest surface, and is the point *inside or outside* of the shape?

Can we represent more than just geometry?

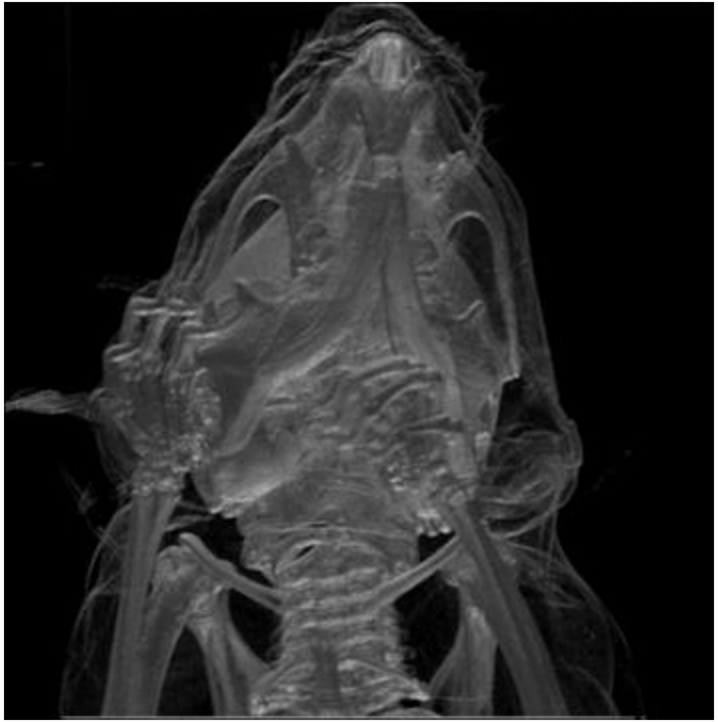
Implicit 3D Representation: Beyond Geometry

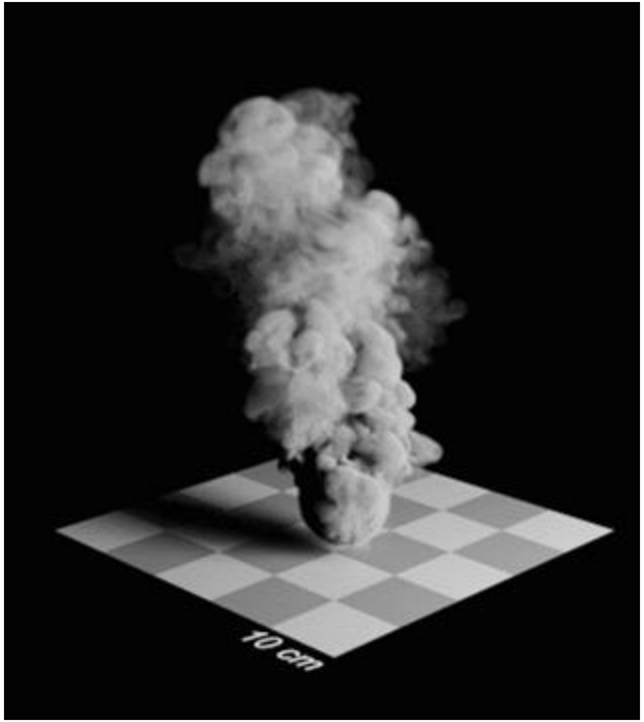
$$f_\theta(viewpoint) = Image$$

Goal: Learn an implicit 3D representation function that maps any camera viewpoint to full RGB images

Can we implicitly represent a full 3D scene, including its fine-grained geometry (e.g., surface occupancy) and appearance?

Basics: Volume Rendering

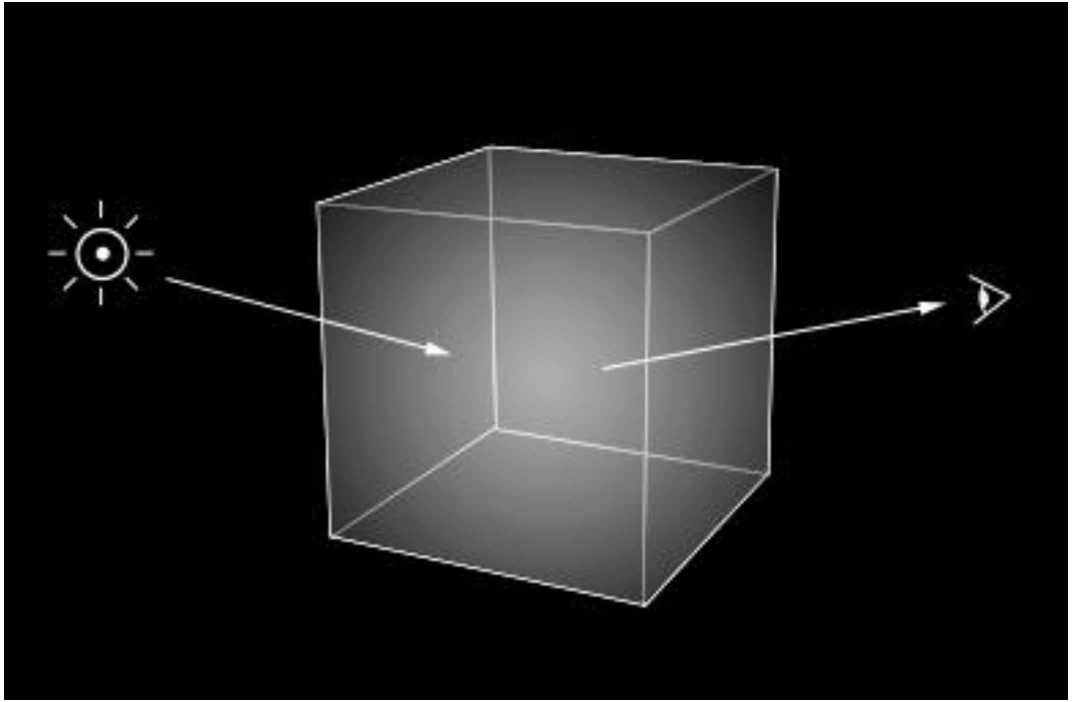




https://en.wikipedia.org/wiki/Volume_rendering

https://coronarenderer.freshdesk.com/support/solutions/articles/12000045276-how-to-use-the-corona-volume-grid-

Volume Rendering: Scene Representation



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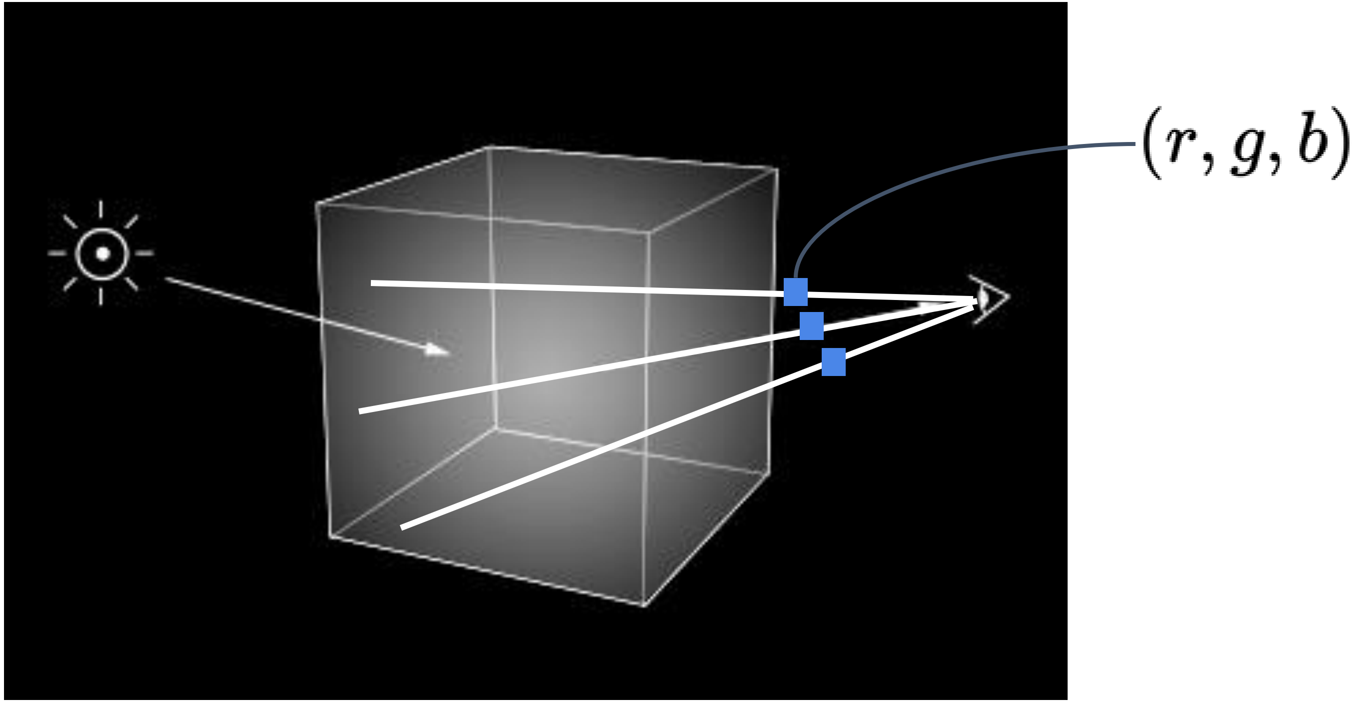
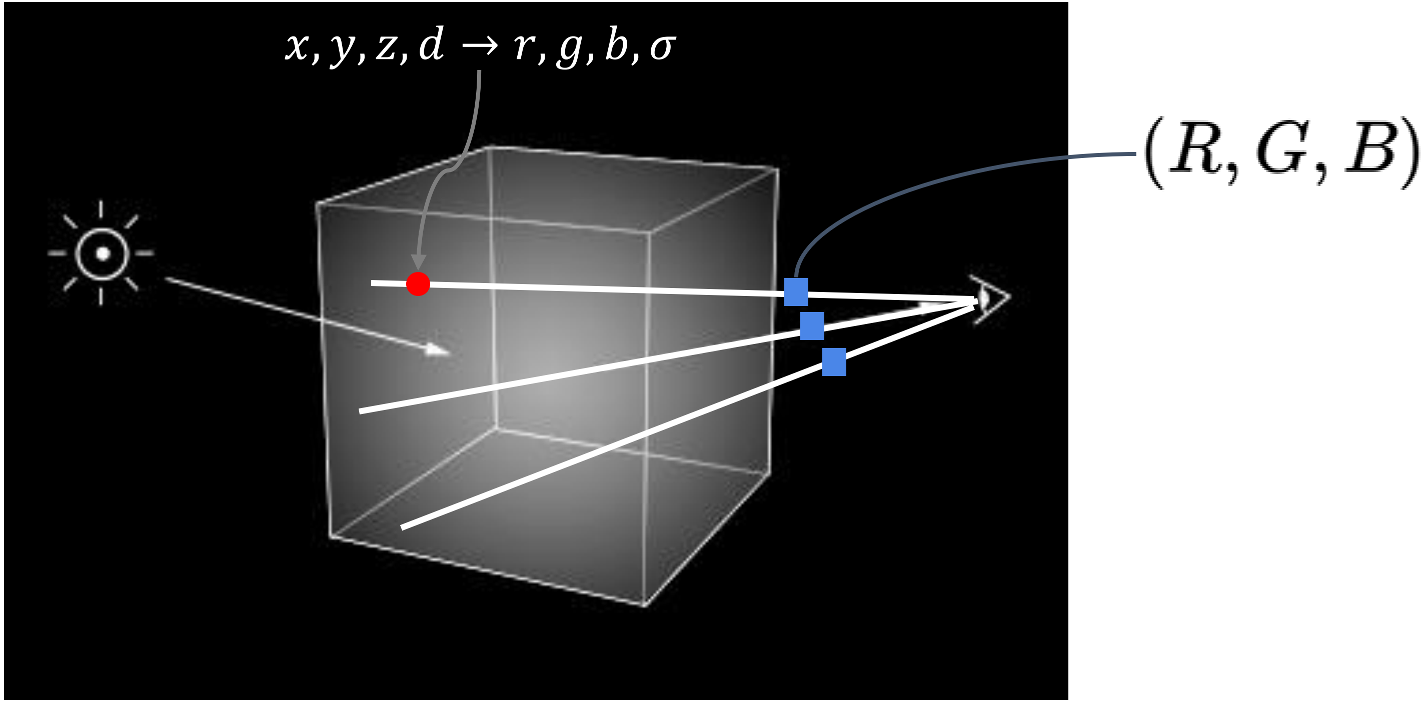


Volume Rendering: Scene Representation

Each location (x, y, z) emits certain color r, g, b when viewed with direction d.
We represent point occupancy continuously as density d.



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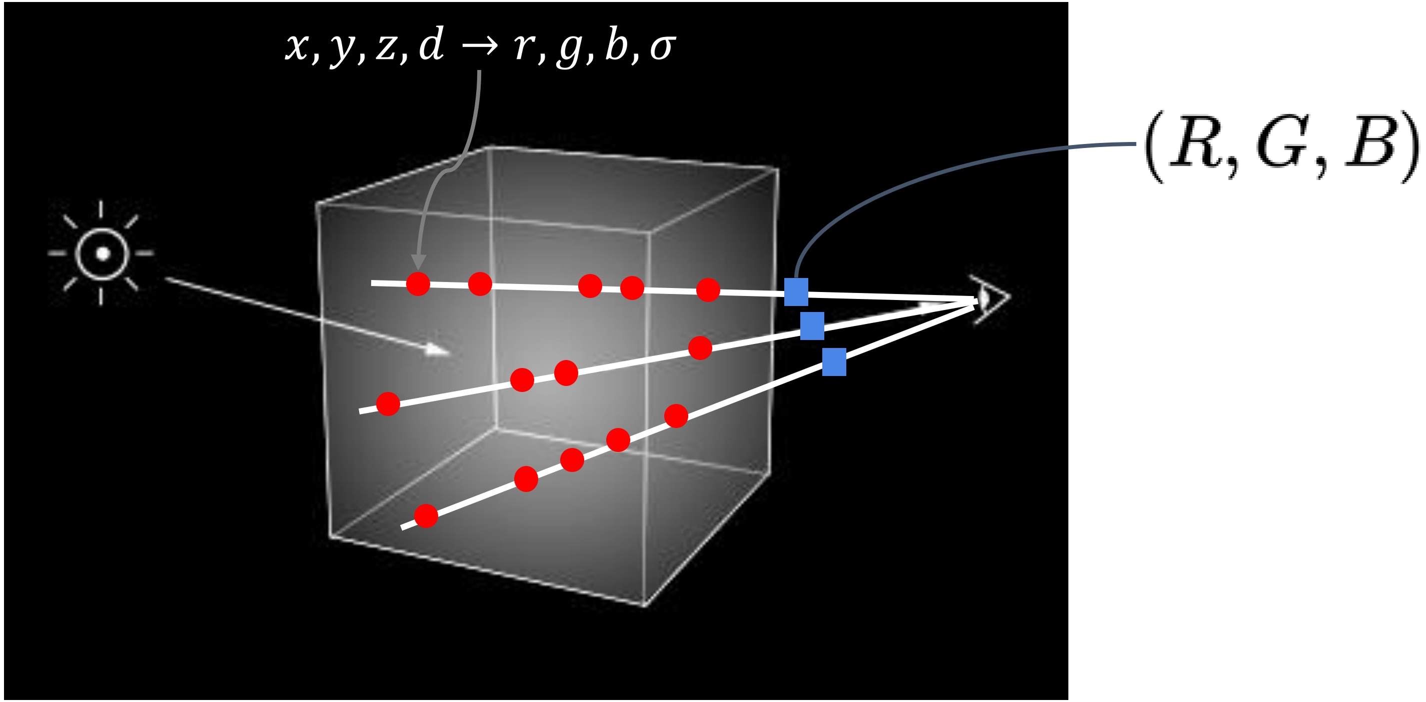
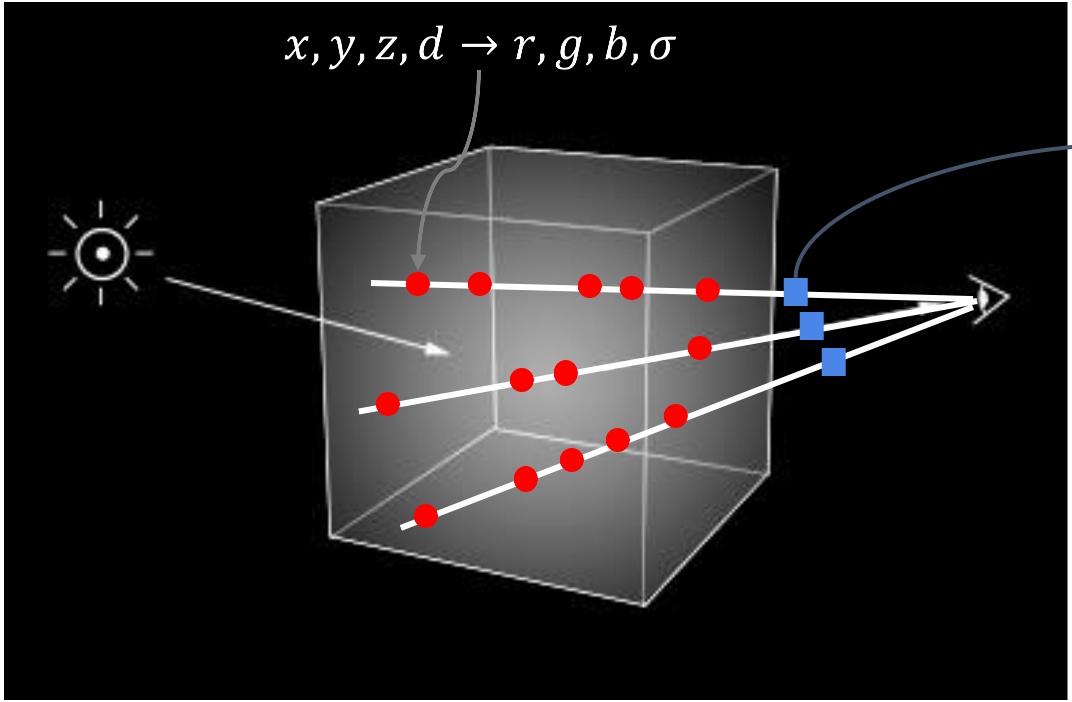
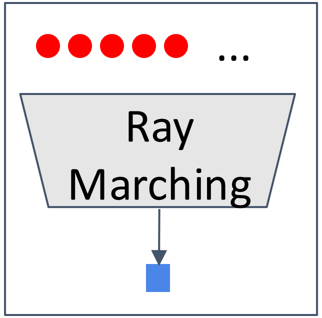


Volume Rendering: Ray Marching

Ray Marching: Integrate color and density of points along a ray (via discretization) to render an RGB value. Render many points -> An image!

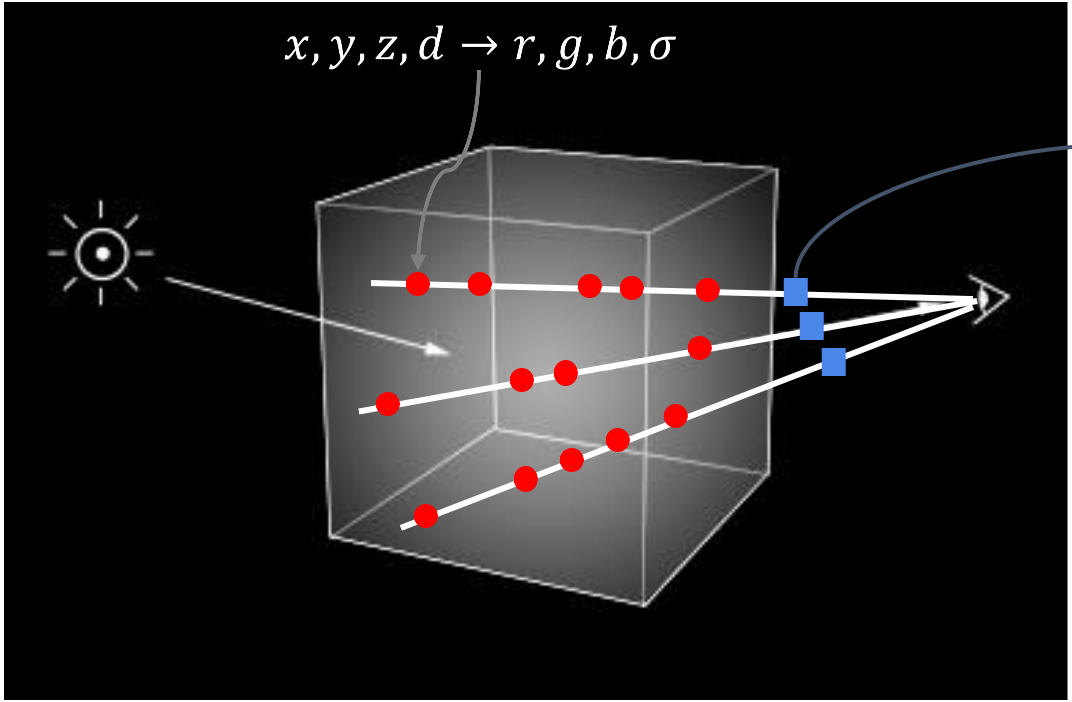


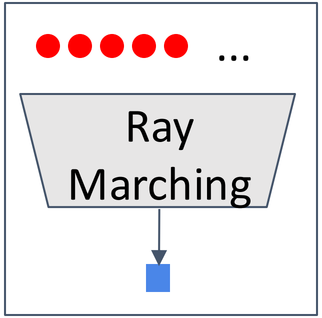


This is Differentiable!

Volume Rendering: Ray Marching

Neural Radiance Field (NeRF): Train a neural network to represent the ray marching volume rendering function: $F_\theta(x, y, z, d) = (r, g, b, \sigma)$. **Each NN encodes a 3D scene.**





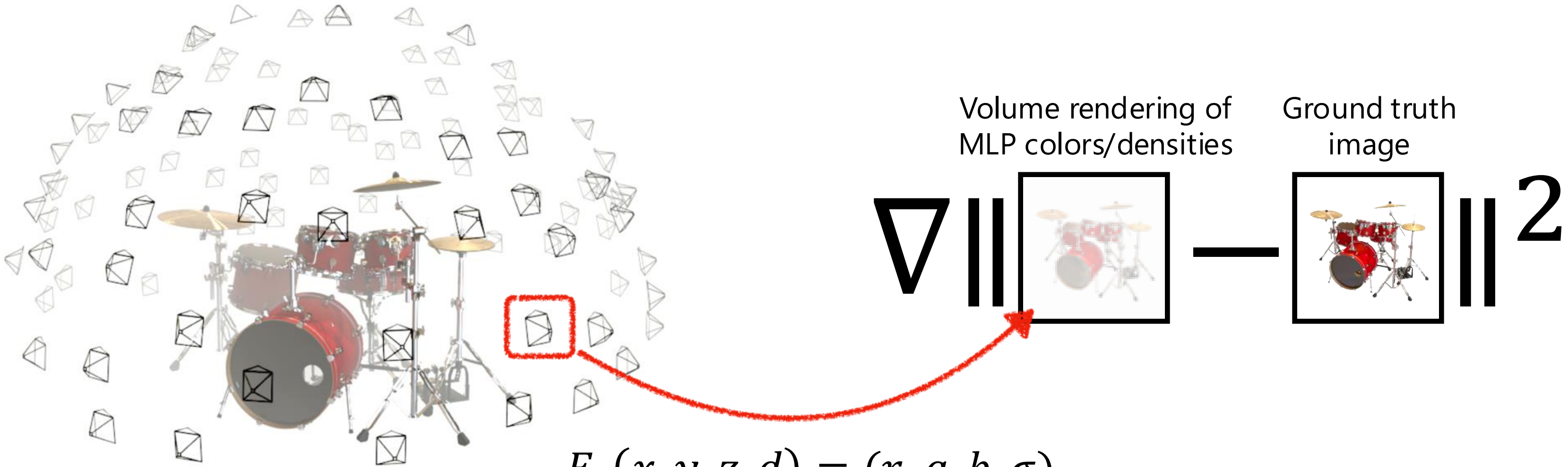
This is Differentiable!

NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis

Ben Mildenhall[1*] Pratul P. Srinivasan[1*] Matthew Tancik[1*]
Jonathan T. Barron[2] Ravi Ramamoorthi[3] Ren Ng[1]

[1]UC Berkeley [2]Google Research [3]UC San Diego

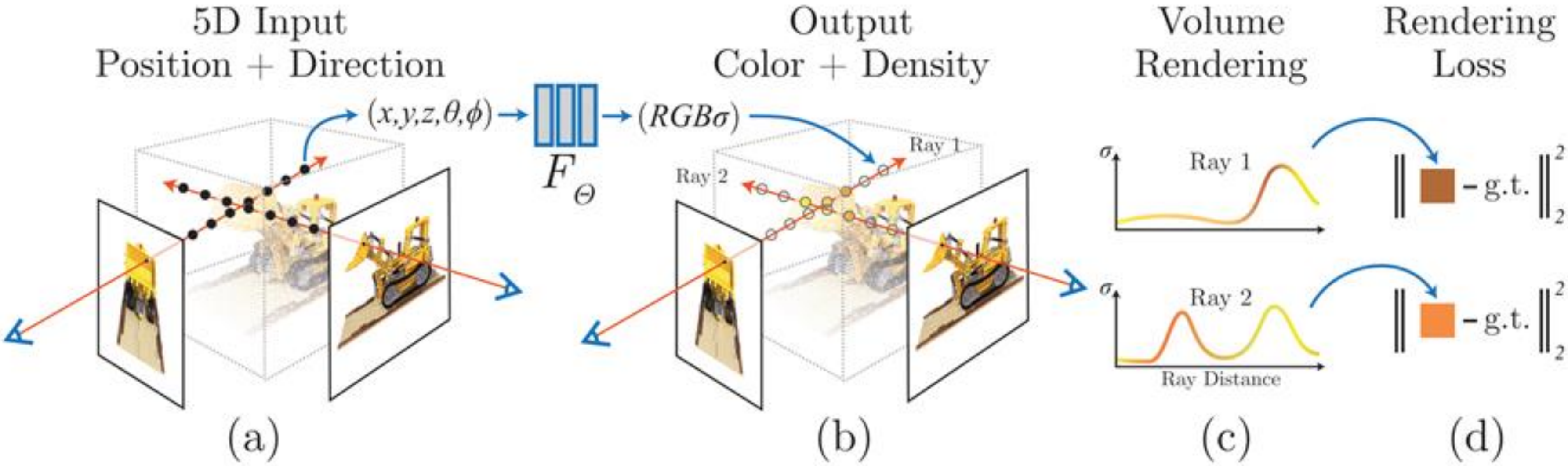
Train a Single Neural Network to Reproduce the Ground Truth Images of a Scene



$$F_\theta(x, y, z, d) = (r, g, b, \sigma)$$

Adapted from material from Pratul Srinivasan

NeRF Overview



NeRF: Optimization

The volume density $\sigma(\mathbf{x})$ can be interpreted as the differential probability of a ray terminating at an infinitesimal particle at location $\mathbf{x}$. The expected color $C(\mathbf{r})$ of camera ray $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$ with near and far bounds t_n and t_f is:

$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{r}(t))\mathbf{c}(\mathbf{r}(t), \mathbf{d})dt\,, \text{ where } T(t) = \exp\left(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))ds\right). \quad (1)$$

Solution: Numerically estimate the integral (quadrature).

1. Discretize the ray into bins.
2. Sample point in each bin.
3. Compute numerical integration.

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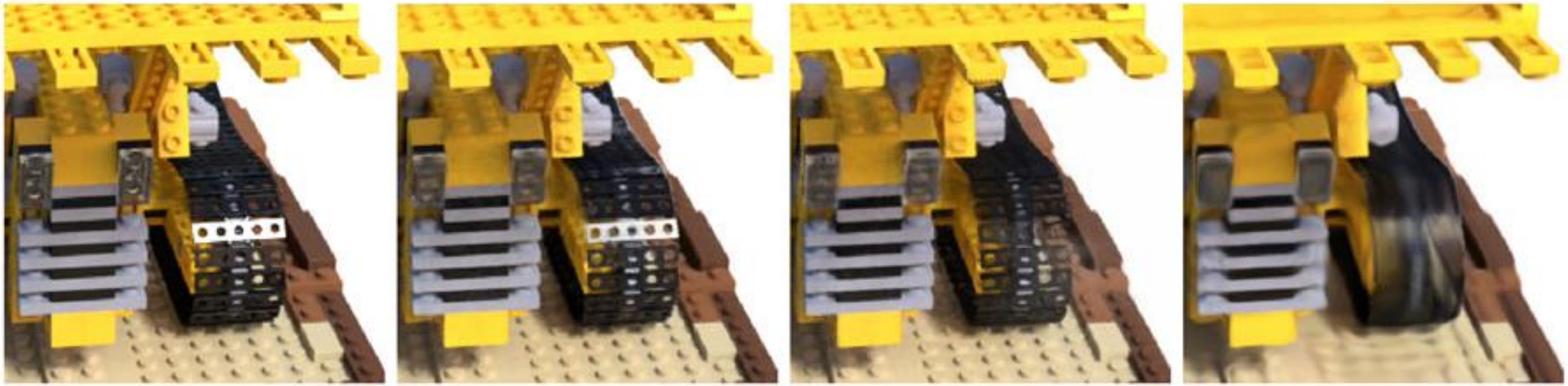
$$\hat{C}(\mathbf{r}) = \sum_{i=1}^{N} T_i(1 - \exp(-\sigma_i\delta_i))c_i\,, \text{ where } T_i = \exp\left(-\sum_{j=1}^{i-1} \sigma_j\delta_j\right)$$

Key Insight 1: Positional Encoding

Challenge: Having F_θ operate directly on (x, y, z, d) performs poorly.

Solution: Positional encoding

$$\gamma(p) = \left(\sin(2^0\pi p), \cos(2^0\pi p), \cdots, \sin(2^{L-1}\pi p), \cos(2^{L-1}\pi p)\right)$$



Ground Truth | Complete Model | No View Dependence | No Positional Encoding

Key Insight 2: Hierarchical Volume Rendering

Challenge: Waste of compute on empty space.

Solution: coarse-to-fine prediction.

$$\hat{C}_c(\mathbf{r}) = \sum_{i=1}^{N_c} w_i c_i \,, \qquad w_i = T_i(1 - \exp(-\sigma_i \delta_i)) \,. \tag{5}$$

Normalizing these weights as $\hat{w}_i = w_i / \sum_{j=1}^{N_c} w_j$ produces a piecewise-constant PDF along the ray. We sample a second set of N_f locations from this distribution using inverse transform sampling, evaluate our "fine" network at the union of the first and second set of samples, and compute the final rendered color of the ray $\hat{C}_f(\mathbf{r})$ using Eqn. $\boxed{3}$ but using all $N_c + N_f$ samples. This procedure allocates more

NeRF encodes convincing view-dependent effects using directional dependence

Slide credit: Noah Snavely

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NeRF encodes detailed scene geometry with occlusion effects

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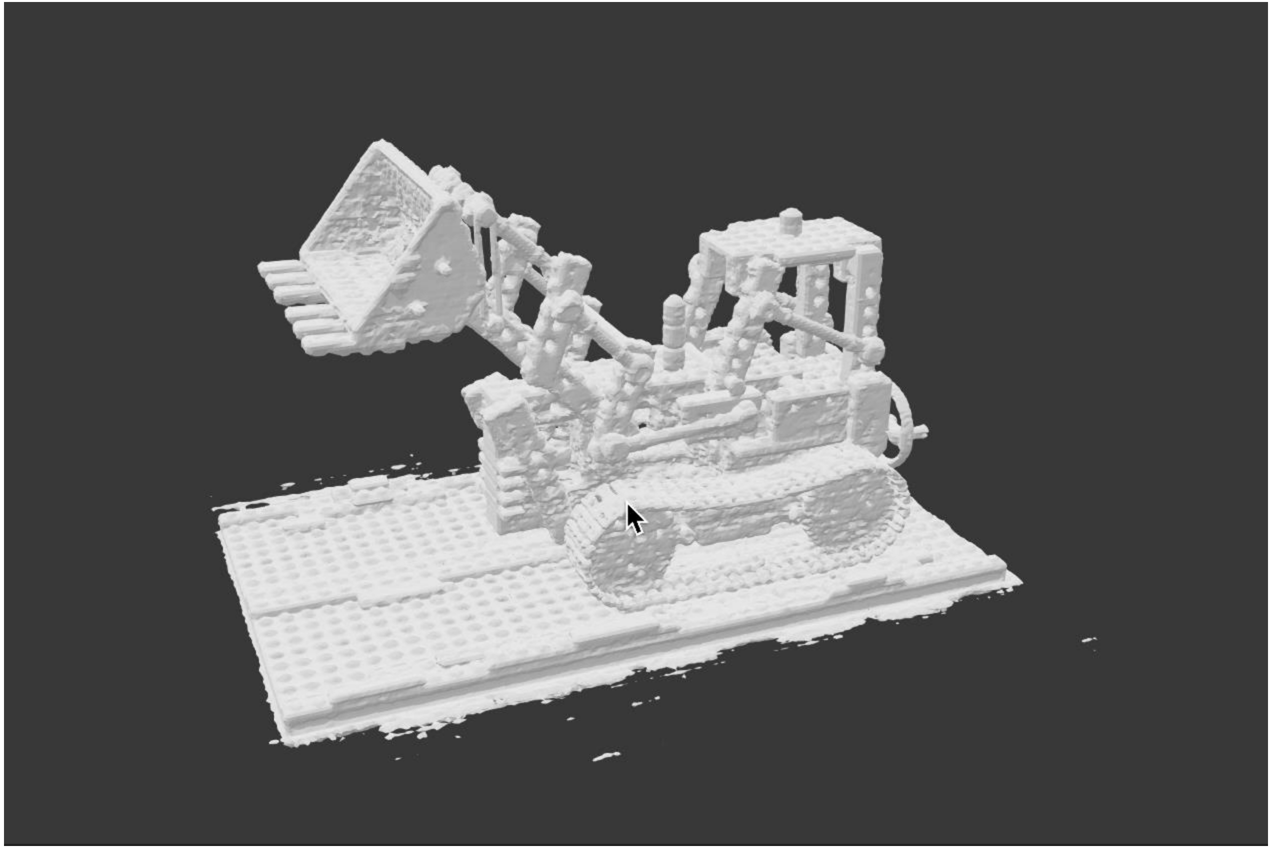
NeRF encodes detailed scene geometry



Slide credit: Noah Snavely

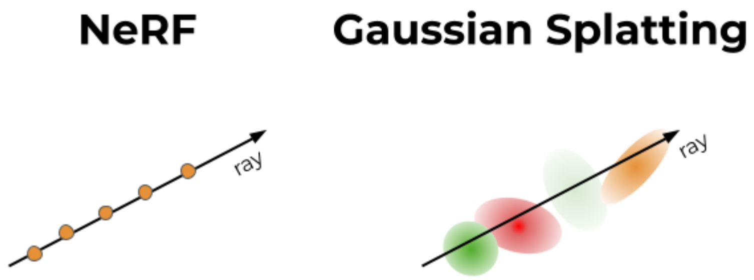
Space vs. Time Tradeoff

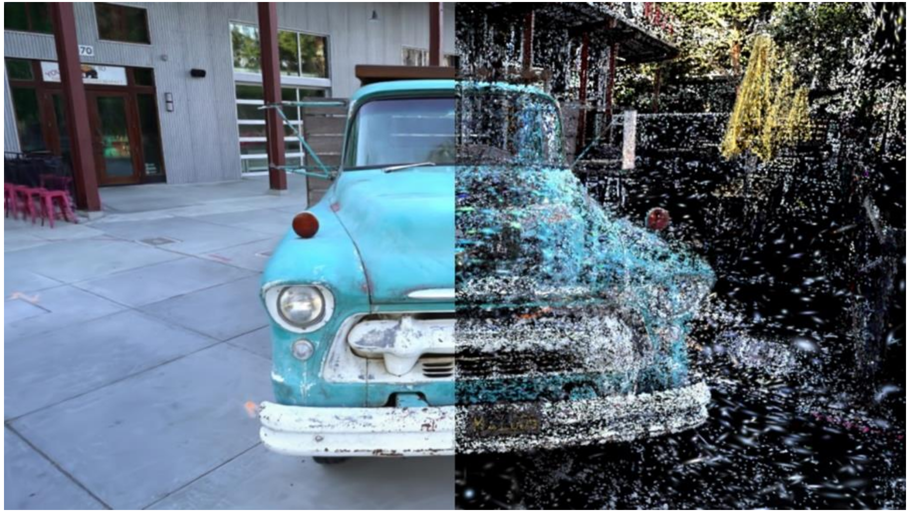
The biggest practical tradeoffs between these methods are time versus space. All compared single scene methods take at least 12 hours to train per scene. In contrast, LLFF can process a small input dataset in under 10 minutes. However, LLFF produces a large 3D voxel grid for every input image, resulting in enormous storage requirements (over 15GB for one "Realistic Synthetic" scene). Our method requires only 5 MB for the network weights (a relative compression of 3000× compared to LLFF), which is even less memory than the *input images alone* for a single scene from any of our datasets.

3D Gaussian Splatting (Kerbl and Kopanas et al., 2023)

Key idea: 3D Gaussians as an **explicit representation** of a scene

- Train Gaussian blobs via inverse rendering (similar to NeRF)
- Store scene as Gaussian blobs instead of neural network weights (NeRF)
- Much faster during inference, but takes a lot of space to store





Summary: 3D Representation and Neural Rendering

- Representation matters a lot for 3D computer vision tasks (detection, reconstruction, etc.)
- 3D Voxels are intuitive representation of space but struggles with high-resolution shape and large scenes
- Implicit function emerge as a new paradigm in representing scenes with Neural Networks
- Neural volume rendering: represent scenes implicit as point-direction to color-density neural networks. Photorealistic rendering, slow to train and evaluate
- More recent works on trading off space and time