So Far

Few-shot learning via meta-learning

Problem: Given data from $\mathcal{T}_1, \ldots, \mathcal{T}_n$, solve new task $\mathcal{T}_{\text{test}}$ more quickly / proficiently / stably

Methods: black-box, optimization-based, non-parametric

What if you don't have a lot of tasks?

What if you ***only*** have **one batch** of **unlabeled data**?

This Lecture

Unsupervised representation learning for few-shot learning

Part I: Contrastive learning

Part II (next time): Reconstruction-based methods

Relation to meta-learning.

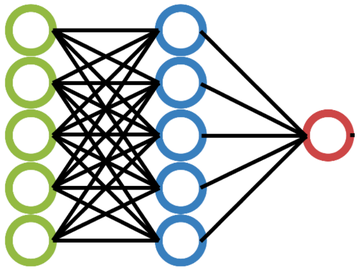
Goals for the lecture:

- Understand **contrastive learning**: intuition, design choices, how to implement
- How contrastive learning relates to meta-learning

Unsupervised Pre-Training Set-Up

Diverse unlabeled dataset $\{x_i\}$

Unsupervised pre-training



Pre-trained model

Fine-tuning

Labeled $\mathcal{D}_j^{tr}$

Goal: Get predictor for task $\mathcal{T}_j$

Key Idea of Contrastive Learning

Similar examples should have **similar representations**

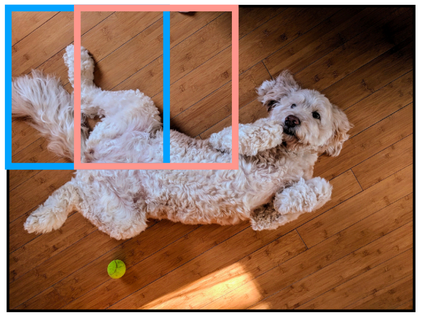
Examples with the same class label

(Requires labels, related to Siamese nets, ProtoNets)

Augmented versions of the example

(flip & crop)

Nearby image patches



Nearby video frames

van den Oord, Li, Vinyals. CPC. 2018

Chen, Kornblith, Norouzi, Hinton. SimCLR. ICML 2020

Dog credit to Maggie & Luke

Key Idea of Contrastive Learning

Similar examples should have **similar representations**

Similar representations

Similar representations

Question: Why not simply minimize difference between representations?

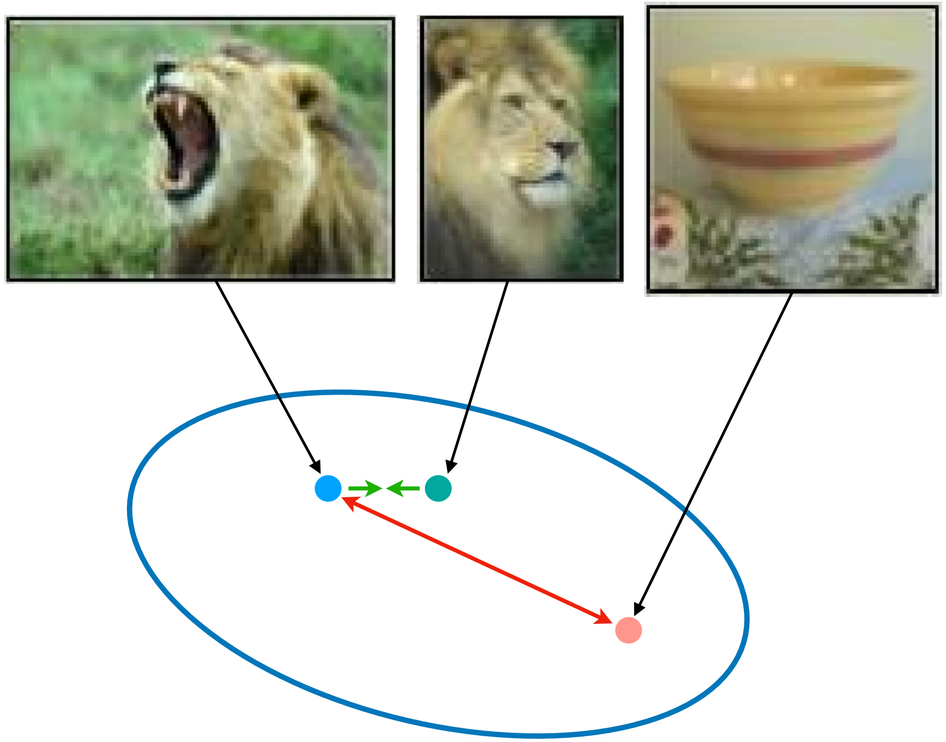
$$\min_{\theta} \sum_{(x_i,x_j)} \|f_\theta(x_i) - f_\theta(x_j)\|^2$$

Need to both **compare** & ***contrast***!

Key Idea of Contrastive Learning

Similar examples should have **similar representations**

Need to both **compare** & *contrast*!



Embedding space $f_\theta(x)$

Bring together representations of similar examples.

Push apart representations of differing examples.

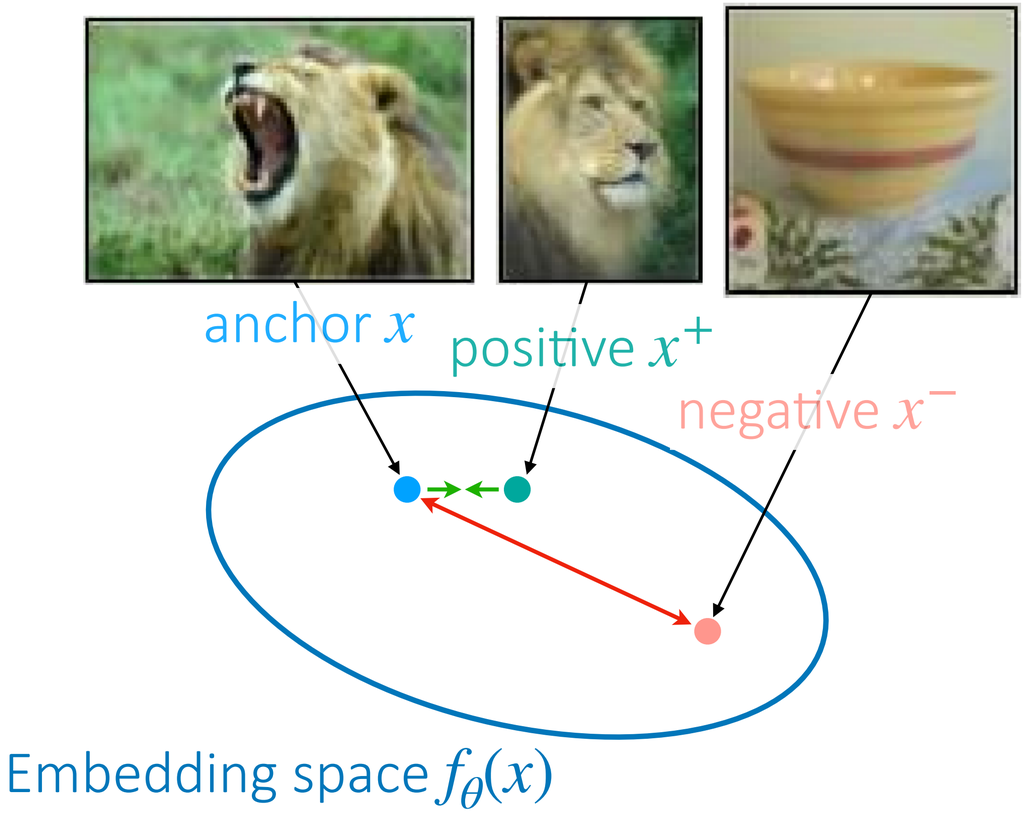
Key design choices:

1. Implementation of contrastive loss
2. Choosing what to compare/contrast

Contrastive Learning Implementation

Similar examples should have **similar representations**

Need to both **compare** & *contrast*!



V1. Triplet loss:

$$\min_\theta \sum_{(x,x^+,x^-)} \max\left(0,\ \|f_\theta(x) - f_\theta(x^+)\|^2 - \|f_\theta(x) - f_\theta(x^-)\|^2 + \epsilon\right)$$

Compare to **Siamese networks**:

Classify (x, x') as same class if $\|f(x) - f(x')\|^2$ is small.

Key difference: learns a metric space, not just a classifier

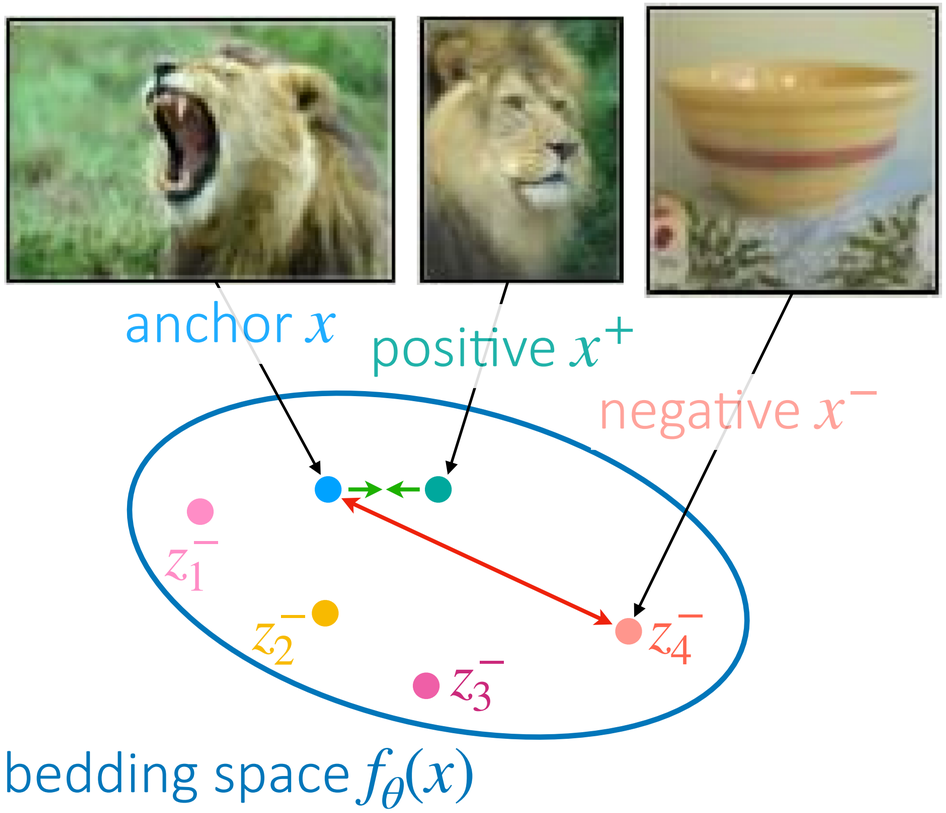
Challenge: need to find difficult negatives.

Schroff, Kalenichenko, Philbin. CVPR 2015

Contrastive Learning Implementation

Similar examples should have **similar representations**

Need to both **compare** & *contrast*!



V2. From binary to N-way classification:

$$\mathscr{L}_{\text{N-way}}(\theta) = -\sum_{z} \log \frac{\exp(-d(z, z^+))}{\sum_i \exp(-d(z, z_i^-))}$$

- generalization of triplet loss to multiple negatives

Sohn. N-Pair Loss Objective. NIPS 2016

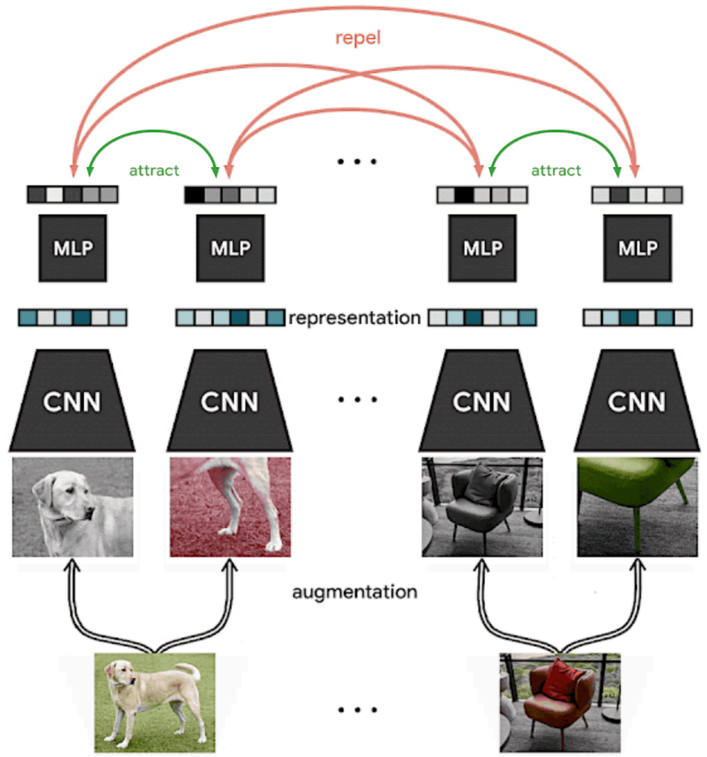
Chen, Kornblith, Norouzi, Hinton. SimCLR. ICML 2020

Contrastive Learning Implementation

SimCLR Algorithm

Unsupervised Pre-Training

1. Sample minibatch of examples $x_1, \ldots, x_N$
2. **Augment** each example twice to get $\tilde{x}_1, \ldots, \tilde{x}_N, \tilde{x}'_1, \ldots, \tilde{x}'_N$
3. **Embed examples** with f_θ to get $\tilde{z}_1, \ldots, \tilde{z}_N, \tilde{z}'_1, \ldots, \tilde{z}'_N$
4. Compute all **pairwise distances** $d(z_i, z_j) = -\dfrac{z_i^T z_j}{\|z_i\| \|z_j\|}$
5. **Update** θ w.r.t. loss $\mathscr{L}_{\text{N-way}}(\theta) = -\sum_i \log \dfrac{\exp(-d(\tilde{z}_i, \tilde{z}'_i))}{\sum_{j \neq i} \exp(-d(\tilde{z}_i, \tilde{z}_j))}$



After Pre-Training: train classifier on top of representation or fine-tune entire network.

Chen, Kornblith, Norouzi, Hinton. SimCLR. ICML 2020

Performance of Contrastive Learning

ImageNet Classification Results

Method	Architecture	Label fraction (Top 5) 1%	10%
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.

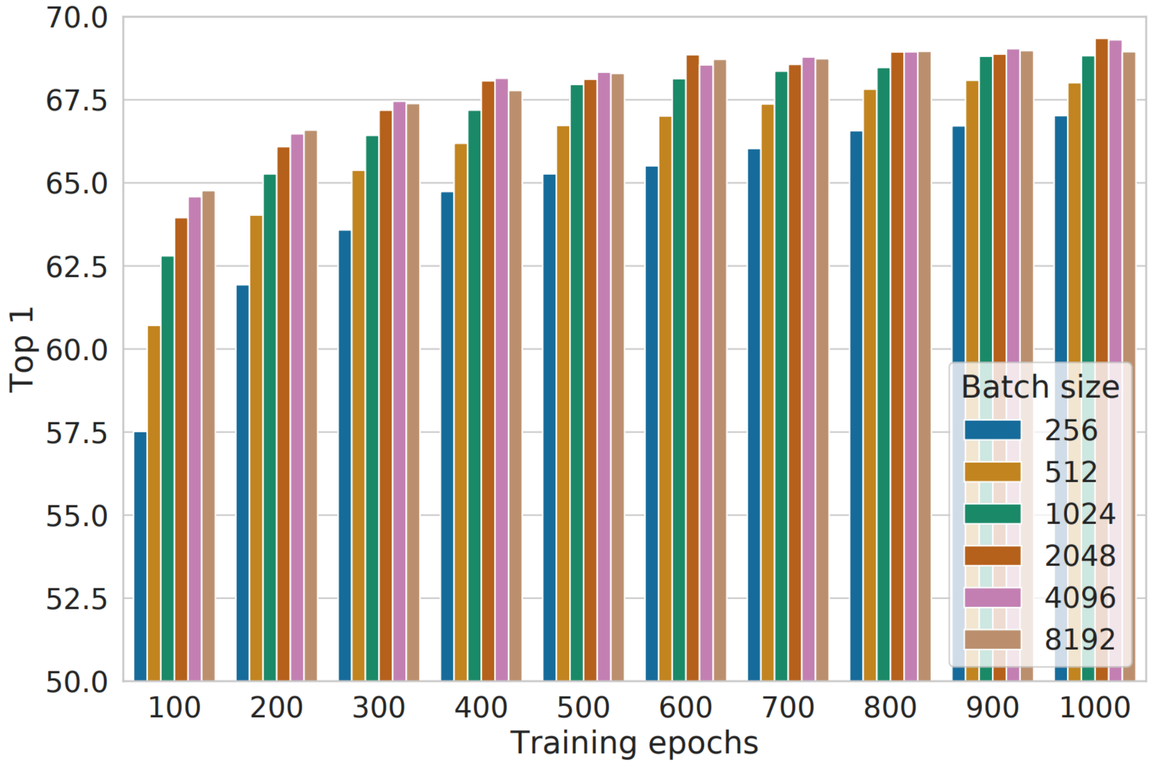
1% labels: ~12.8 images/class

- Substantial improvements over training from scratch
- Improvements over other methods, especially in 1% label setting

Chen, Kornblith, Norouzi, Hinton. SimCLR. ICML 2020

Performance of Contrastive Learning

Effect of Batch Size & Number of Training Epochs



- Important to train for longer (~600+ epochs)
- Requires **large batch size**

Chen, Kornblith, Norouzi, Hinton. SimCLR. ICML 2020

Why does contrastive learning need a large batch size?

Interpretation of loss: classifying augmented example from rest of dataset

$$\mathscr{L}_{\text{N-way}}(\theta) = -\sum_{i} \log \frac{\exp(-d(\tilde{z}_i, \tilde{z}_i'))}{\sum_{j \neq i} \exp(-d(\tilde{z}_i, \tilde{z}_j))}$$ <— summation over entire dataset

Intuition: Closest z will dominate the denominator, can be missed when subsampling

Mathematically?

Why does contrastive learning need a large batch size?

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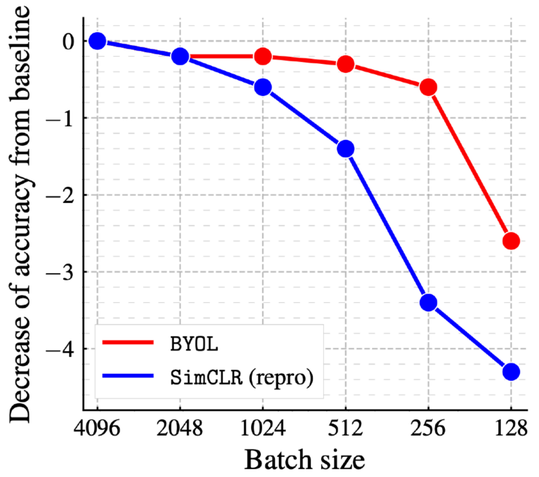
Intuition: Closest z will dominate the denominator, can be missed when subsampling

Mathematically: Minimizing a lower-bound.

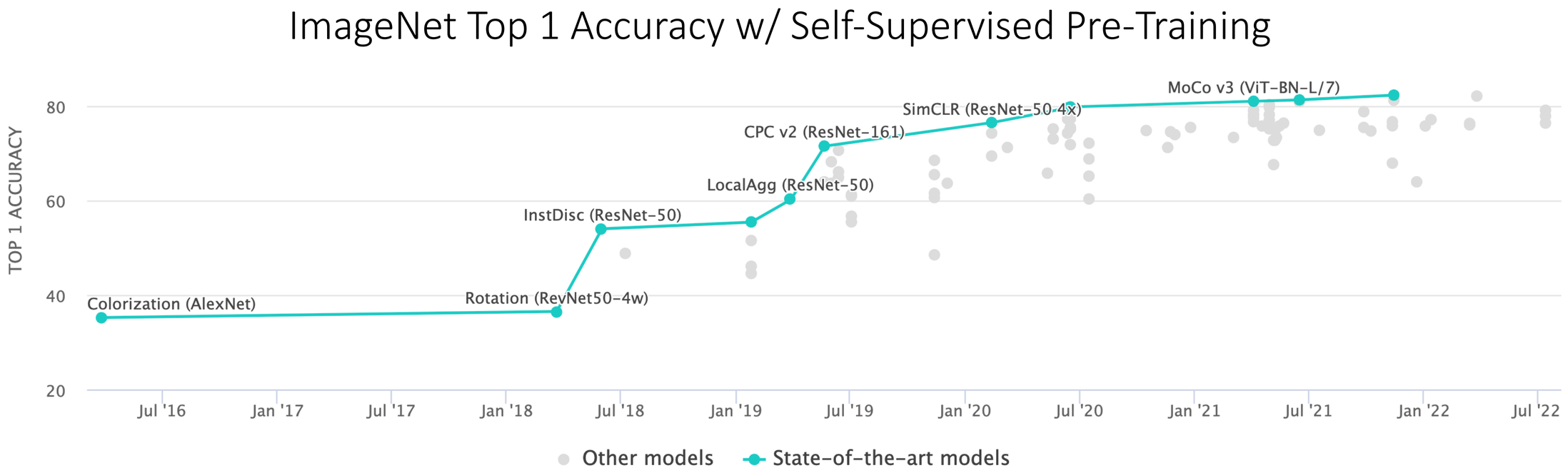
Solutions to requiring a large batch size

1. **Store representations from previous batches** (“momentum contrast”)
   He, Fan, Wu, Xie, Girshick. MoCo. CVPR 2020
   - Good results with mini batch size of 256

2. Predict representation of same image under different augmentation (“BYOL”)
   Grill*, Strub*, Altché*, Tallec* Richemond*, et al. BYOL. NeurIPS 2020
   - No negatives required!
   - More resilient to batch size



Performance of contrastive learning



Contrastive methods are **near state-of-the-art** in self-supervised pre-training for visual data.

Plot source: paperswithcode.com

Contrastive learning beyond augmentations

We don’t have good engineered augmentations for many applications!

1. ***Learn*** the augmentations in adversarial manner (but perturbations bounded to ℓ_1 sphere)

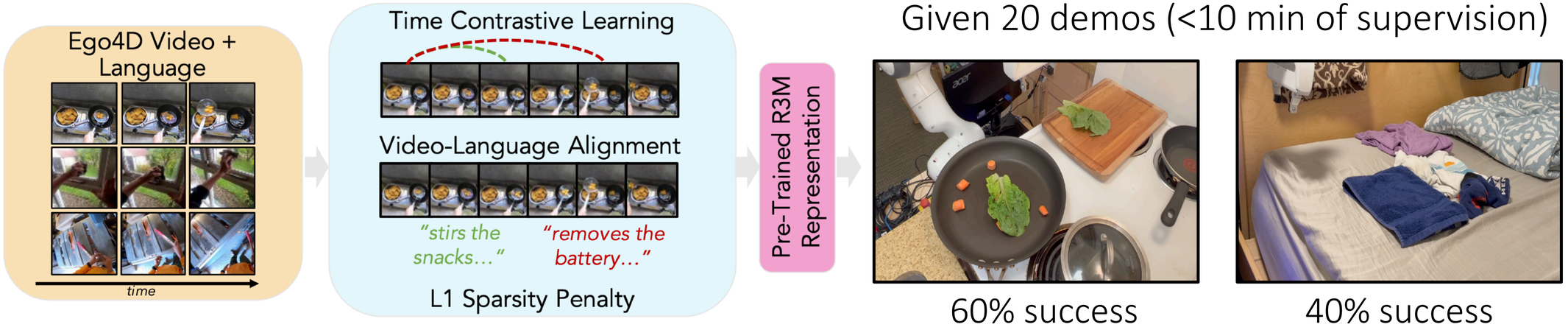
   Tamkin, Wu, Goodman. Viewmaker Networks. ICLR 2021

   —> competitive with SimCLR on image data

   —> good results on speech & sensor data

2. ***Time-contrastive learning*** on ***videos*** effective for robotics pre-training

   Nair, Rajeswaran, Kumar, Finn, Gupta. R3M. CoRL 2022.



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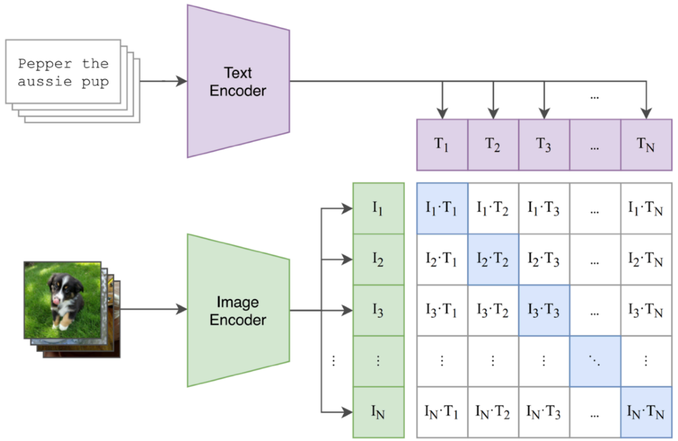
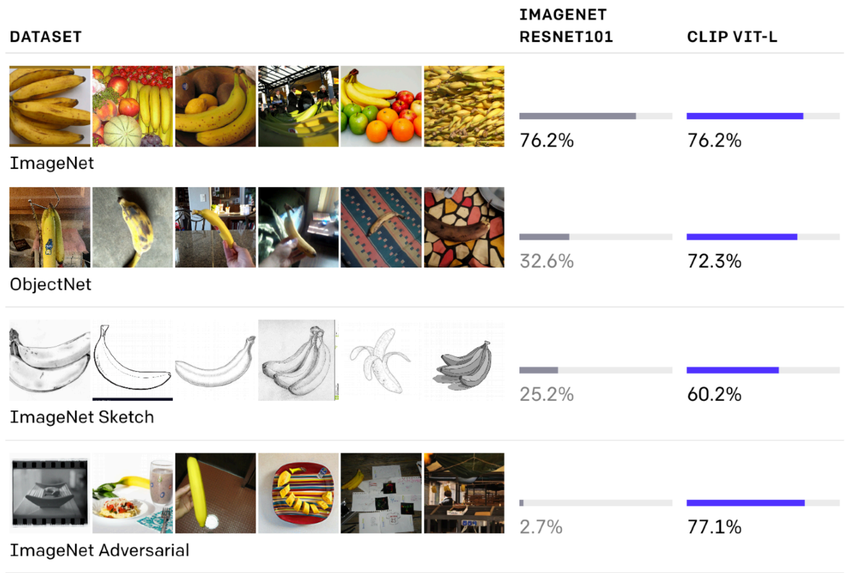
3. **Image-text** contrastive pre-training produces robust zero-shot models
   Radford*, Kim*, et al. CLIP. 2021.





Summary of Contrastive Learning

Pros:

+ General, effective framework
+ No generative modeling required
+ Can incorporate domain knowledge through augmentations

Challenges:

- *Negatives* can be hard to select
- Often requires *large batch size*
- Most successful with augmentations

Contrastive Learning as Meta-Learning

Meta-learning algorithm

1. Given unlabeled dataset $\{x_i\}$.
2. Create image class y_i from each datapoint via data augmentation $\mathscr{D}_i := \{\tilde{x}_i, \tilde{x}_i', \dots\}$
3. Run your favorite meta-learning algorithm.

Differences:

- SimCLR samples **one task** per minibatch; meta-learning usually samples **multiple**
- SimCLR compares **all pairs** of samples; meta-learning compares query examples only to support examples & not to other query examples.

Contrastive Learning as Meta-Learning

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Contrastive vs. meta-learning representations, transfer from ImageNet

	Flowers102	DTD	VOC2007	Aircraft	Food101	SUN397	CIFAR-10	CIFAR-100
SimCLR	92.4	72.7	66.0	83.7	86.3	57.4	94.8	79.1
ProtoNet	92.7	71.5	64.7	83.9	86.2	56.4	96.0	79.1
R2-D2	**94.5**	**73.8**	**69.9**	**86.2**	**86.9**	**59.7**	**96.7**	**82.8**

Representations transfer similarly well.

Ni, Shu, Souri, Goldblum, Goldstein. ICLR 2022

Plan for Today

Recap

- Problem formulation
- Contrastive learning

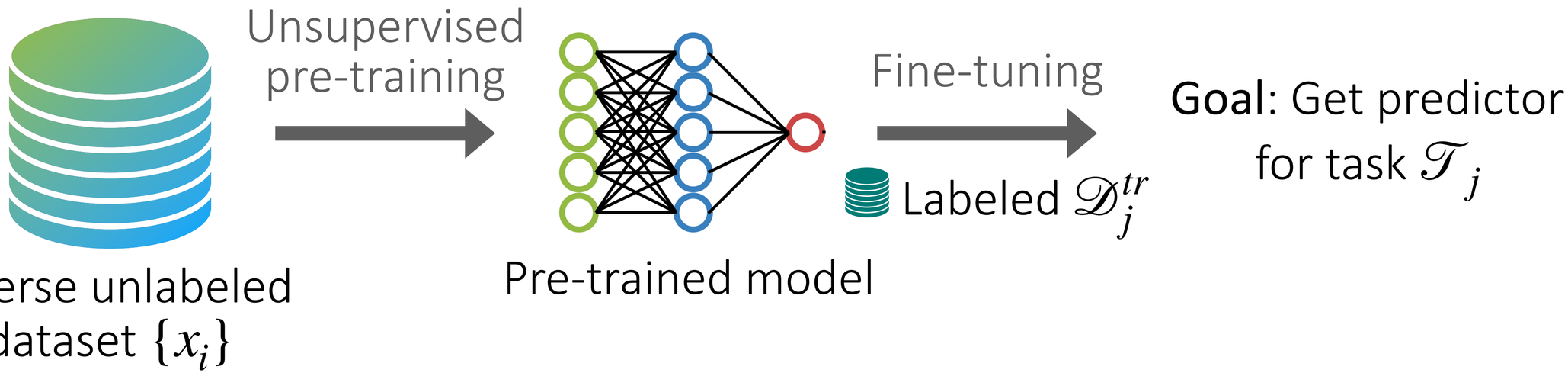
Reconstruction-based unsupervised pre-training

- Why reconstruction?
- Autoencoders
- *Masked* autoencoders: BERT, MAE
- Autoregressive models: GPT, Flamingo

Goals for by the end of lecture:

- Familiarize you with widely-used methods for unsupervised pre-training
- Introduce methods for efficient fine-tuning of pre-trained models
- Prepare you for HW3

Unsupervised Pre-Training Set-Up



Key Idea of Contrastive Learning

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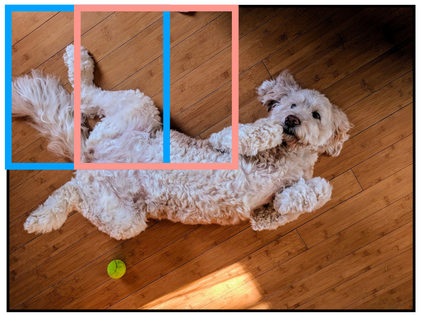
Examples with the same class label

(Requires labels, related to Siamese nets, ProtoNets)

Augmented versions of the example

(flip & crop)

Nearby image patches



Nearby video frames

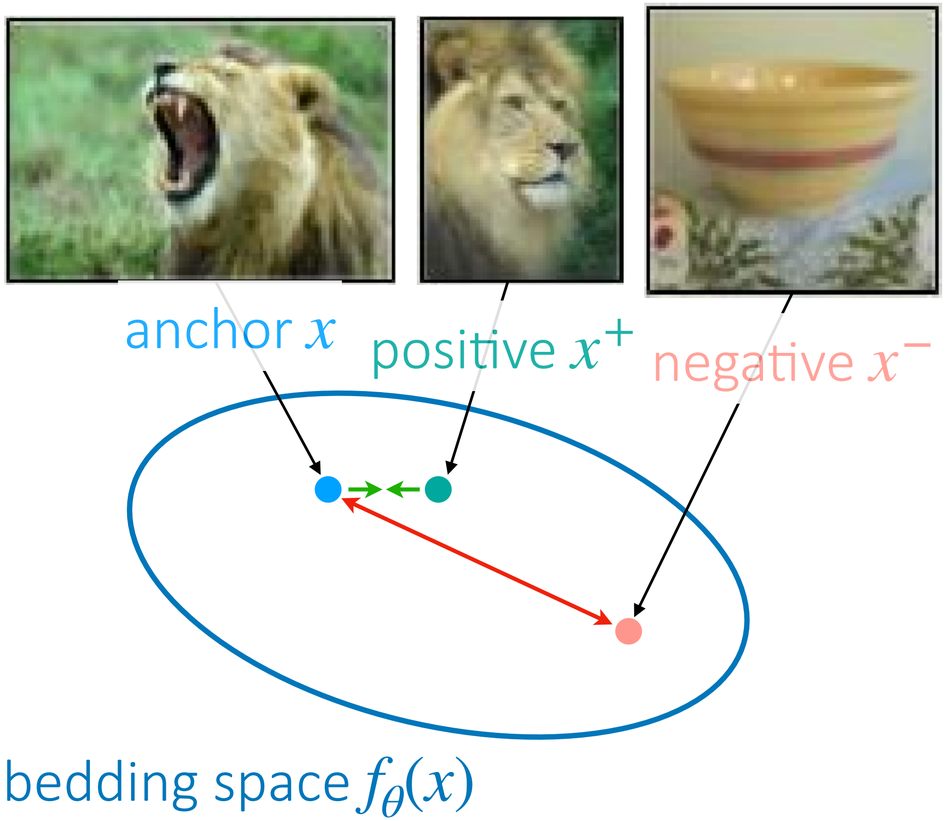
Dog credit to Maggie & Luke

van den Oord, Li, Vinyals. CPC. 2018; Chen, Kornblith, Norouzi, Hinton. SimCLR. ICML 2020

Contrastive Learning Implementation

Similar examples should have **similar representations**

Need to both **compare** & *contrast*!



V1. Triplet loss:

$$\min_\theta \sum_{(x,x^+,x^-)} \max\left(0,\ \|f_\theta(x) - f_\theta(x^+)\|^2 - \|f_\theta(x) - f_\theta(x^-)\|^2 + \epsilon\right)$$

Schroff, Kalenichenko, Philbin. CVPR 2015

Contrastive Learning Implementation

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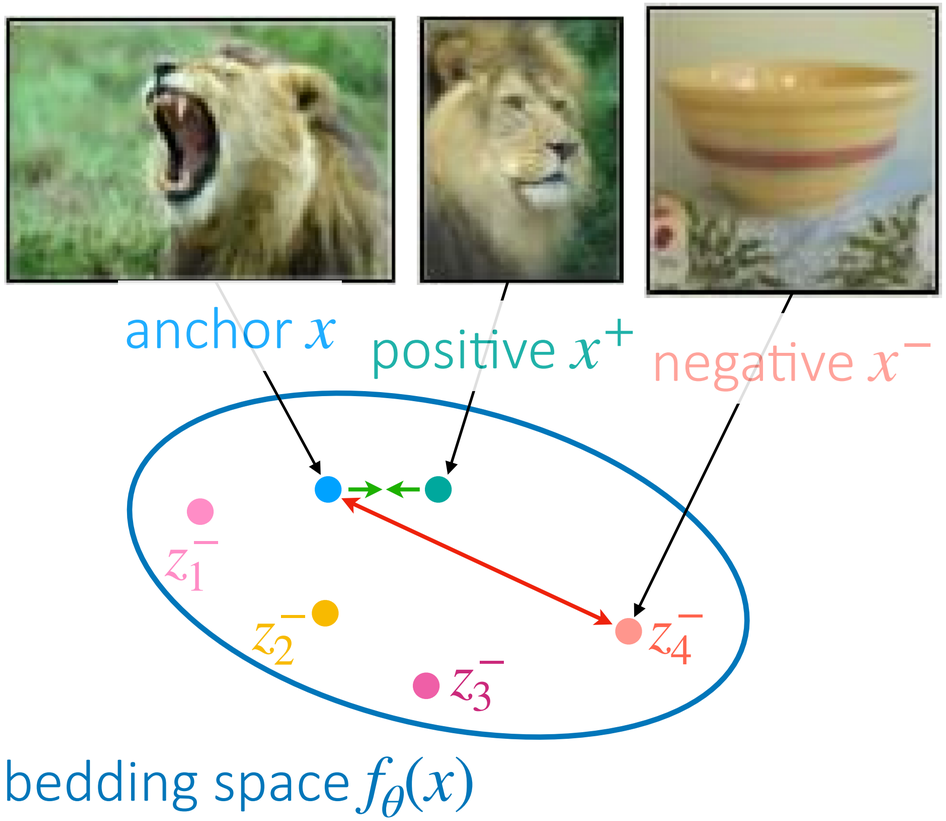

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V2. From binary to N-way classification (aka **simCLR***):

$$\mathscr{L}_{\text{N-way}}(\theta) = -\sum_z \log \frac{\exp(-d(z, z^+))}{\sum_i \exp(-d(z, z_i^-))}$$

*also known as the **NT-Xent** loss, when $d(\cdot, \cdot)$ is **scaled cosine similarity**

Sohn. N-Pair Loss Objective. NIPS 2016; Chen, Kornblith, Norouzi, Hinton. SimCLR. ICML 2020

Contrastive Learning Implementation

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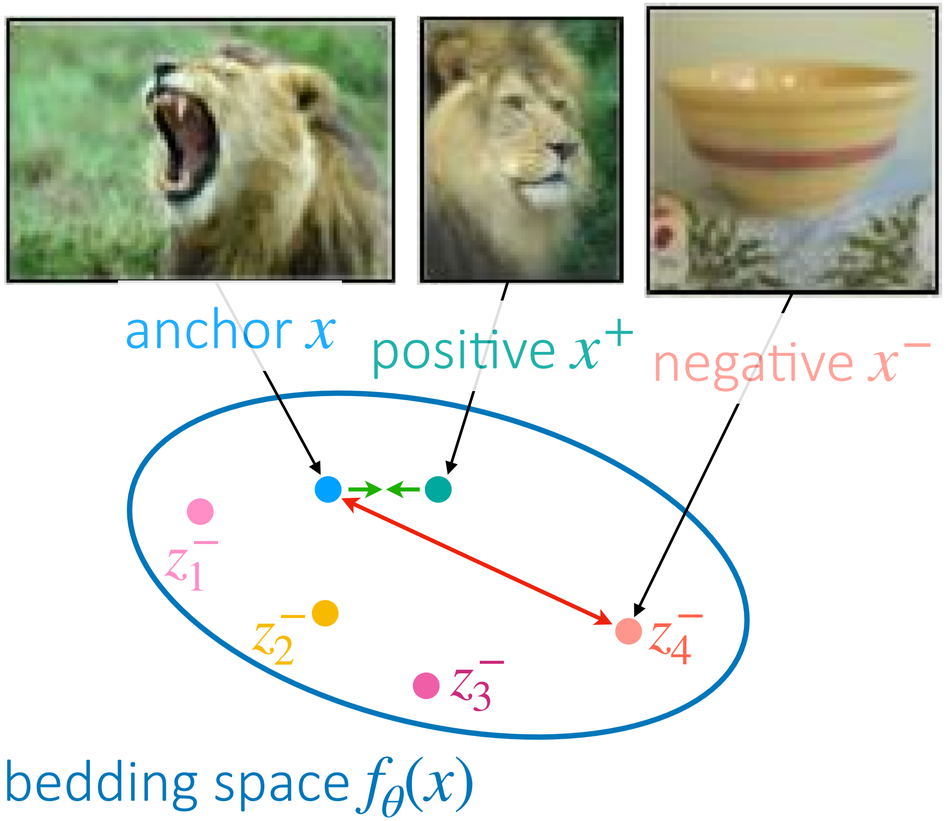

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V2. From binary to N-way classification (aka **simCLR***):

$$\mathcal{L}_{\text{N-way}}(\theta) = -\sum_z \log \frac{\exp(-d(z, z^+))}{\exp(-d(z, z^+)) + \sum_i \exp(-d(z, z_i^-))}$$

Positive score in denominator → loss read as "*classification loss when discriminating positive pair from negatives*"

*also known as the **NT-Xent** loss, when $d(\cdot, \cdot)$ is **scaled cosine similarity**

Sohn. N-Pair Loss Objective. NIPS 2016; Chen, Kornblith, Norouzi, Hinton. SimCLR. ICML 2020

Plan for Today

Recap

- Problem formulation
- Contrastive learning

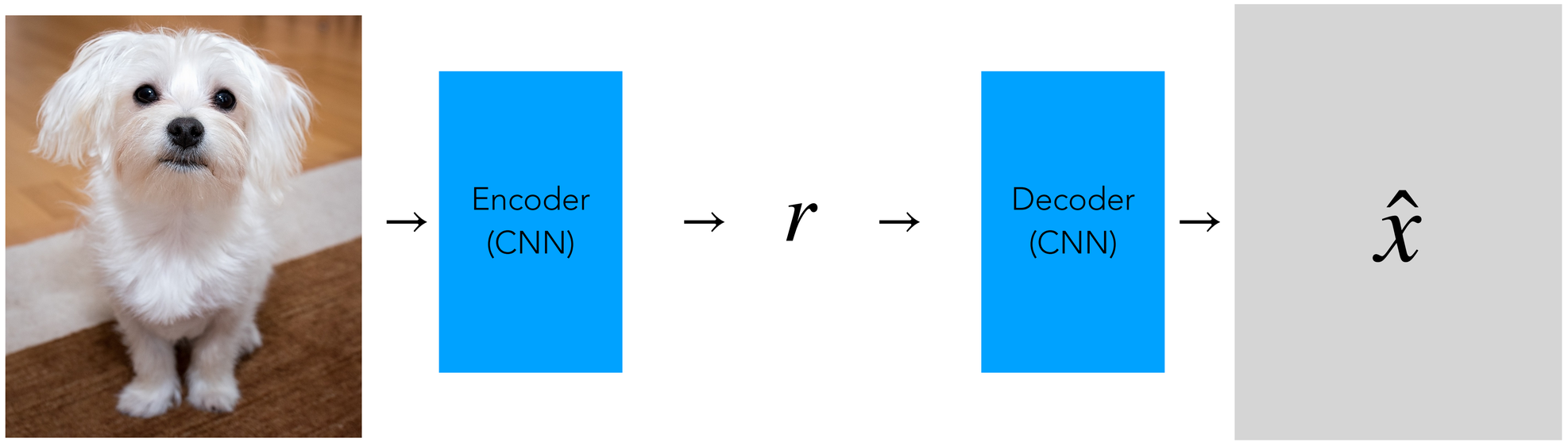
Reconstruction-based unsupervised pre-training

- **Why reconstruction?**
- Autoencoders
- *Masked* autoencoders: BERT, MAE
- Autoregressive models: GPT, Flamingo
- Emergent behaviors in large models

Why reconstruction?

Simple intuition: a good representation of an input should be sufficient to **reconstruct** it

Bonus: *no need to worry about pesky things like* ***sampling negatives*** *or* ***large batch sizes!***



Input image, sentence, audio signal, etc.

Reconstruction of input image

If the encoder is producing a "good" representation, a reasonably-sized decoder should be able to produce **reconstruction** $\hat{x}$ very close to **input** x from **representation** r

Autoencoders: a first attempt

Simple intuition: a good representation lets us **reconstruct** the input

x

Input image, sentence, audio signal, etc.

→ Encoder (CNN) → r → Decoder (CNN) →

$\hat{x}$

Reconstruction of input image

$$\mathcal{L} = d(x, \hat{x})$$

Loss function is reconstruction error, e.g. L2 distance:

$$d(x, \hat{x}) = \|x - \hat{x}\|^2$$

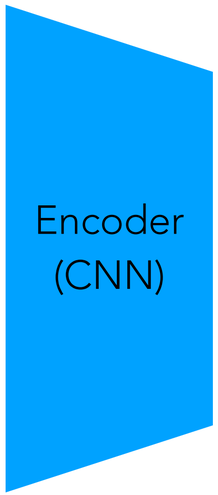
What can go wrong here?

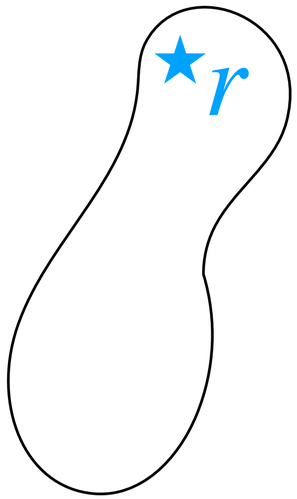
Is the **identity function** a good encoder/decoder?

Autoencoders: adding a bottleneck

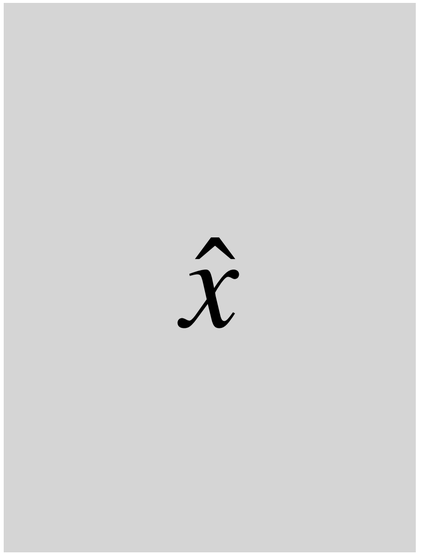
x

Input image, sentence, audio signal, etc.





Compact, latent representation of input image



Reconstruction of input image

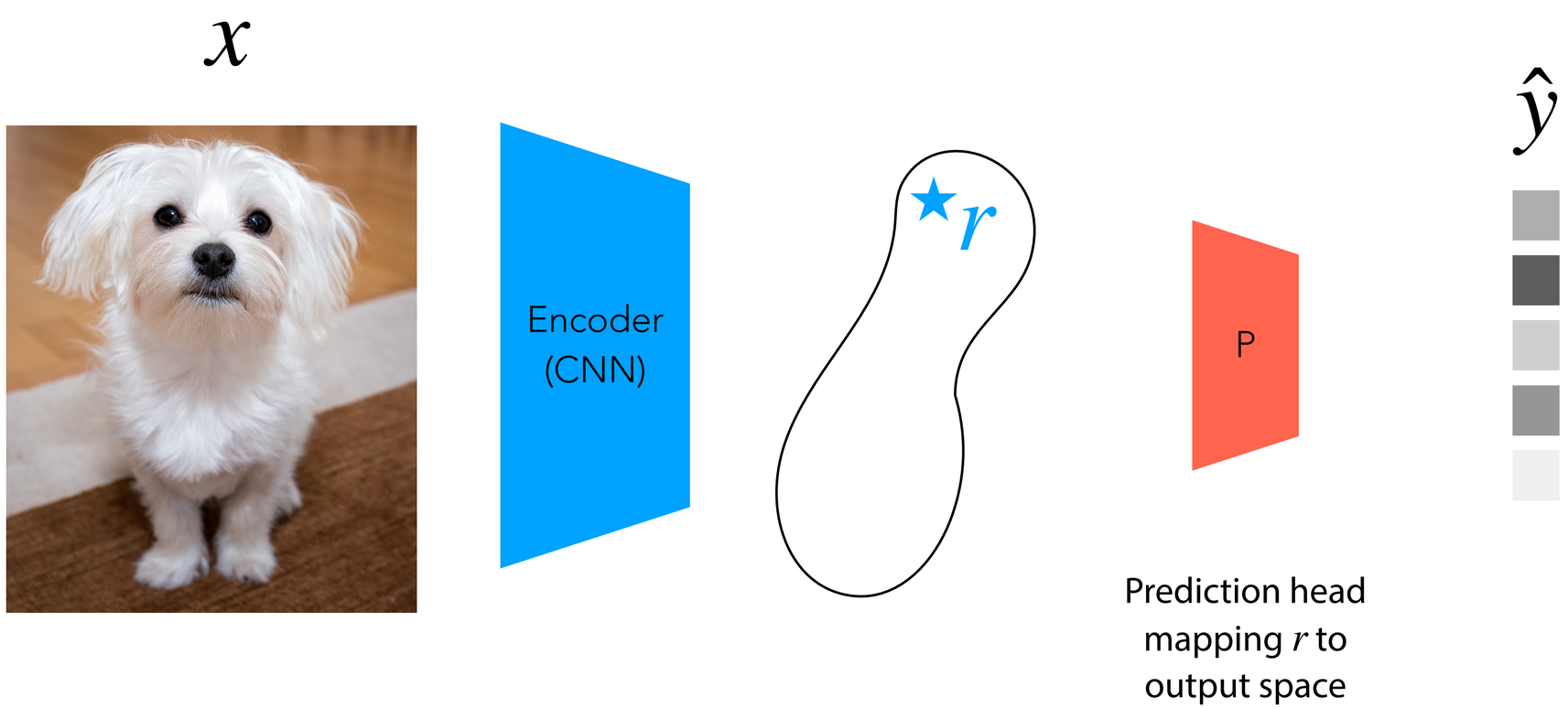
$$\mathcal{L} = d(x, \hat{x})$$

Loss function is reconstruction error, e.g. L2 distance:

$$d(x, \hat{x}) = \|x - \hat{x}\|^2$$

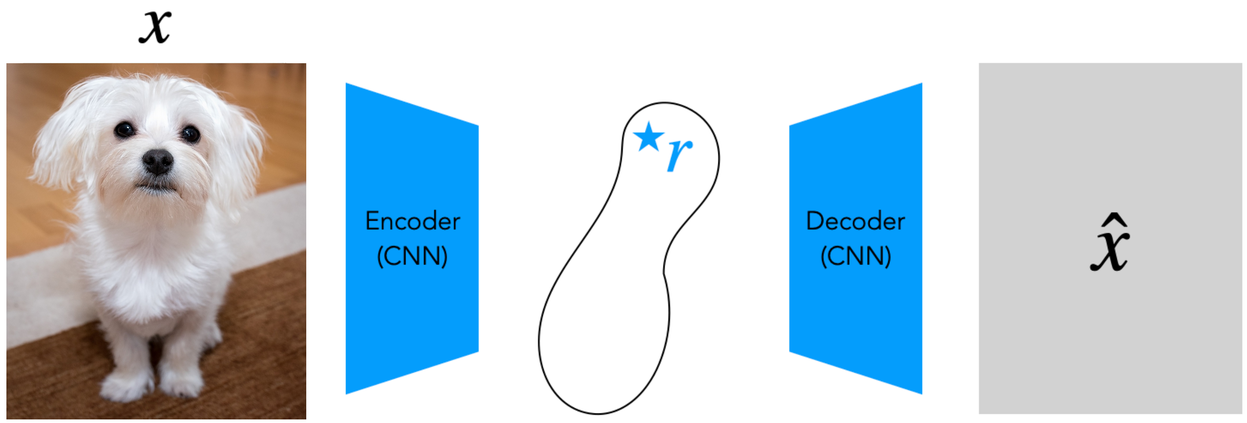
Key idea: latent representation is **bottlenecked**, e.g., **lower-dimensional** than the input → *Hope:* latent dimensions are forced to represent **high-level** concepts that **generalize** to other tasks

Autoencoders: few-shot learning



Few-shot learning recipe: freeze encoder, fine-tune prediction head using our few-shot data
(e.g., a linear layer)

Autoencoders



Pros:

- Simple, general
- Just need to pick $d(x, \hat{x})$
- No need to select positive/negative pairs

Cons:

- Need to design a bottlenecking mechanism
- Relatively poor few-shot performance

Why?

r is just **memorizing** details of x needed to minimize pixel-level reconstruction loss → r is more like a **hash** of x than a **conceptual summary**

How do we encourage the encoder to extract high-level features?

One strategy is **other types of bottlenecks**:

- **information** bottlenecks (adding noise)
- **sparsity** bottlenecks (zero most dimensions)
- **capacity** bottlenecks (weak decoder)

In practice, *we'll stop worrying about designing bottlenecks and just make the task a little* ***harder***

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- Autoregressive models: GPT, Flamingo

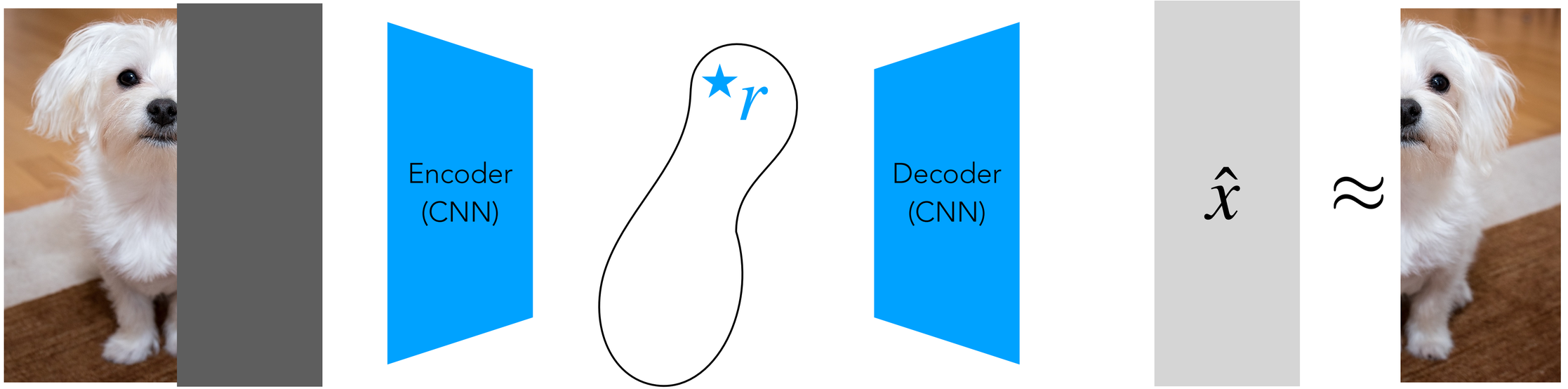
Beyond the bottleneck: ***masked*** **autoencoders**

Ultimately, **regular** autoencoders are trying to predict x from… x (through z)

We bottleneck z to avoid **totally degenerate** solutions, but what if the task is just "too easy", admitting unhelpful solutions?

Masked autoencoders use a **more difficult** learning task to encourage the encoder to extract more meaningful features

x



Masked input image

Latent representation

Reconstruction of **masked portion** (or **entire**) input image

Beyond the bottleneck: ***masked* autoencoders**

General recipe for ***pre-training*** *masked autoencoder* f_θ*:*

1. Choose **distance function** $d(\cdot, \cdot) \rightarrow \mathbb{R}$
2. For **train batch** examples x_i :

These pieces are our design choices/control knobs

A. Sample $\tilde{x}_i,\ y_i \sim$ `mask(` x_i `)`

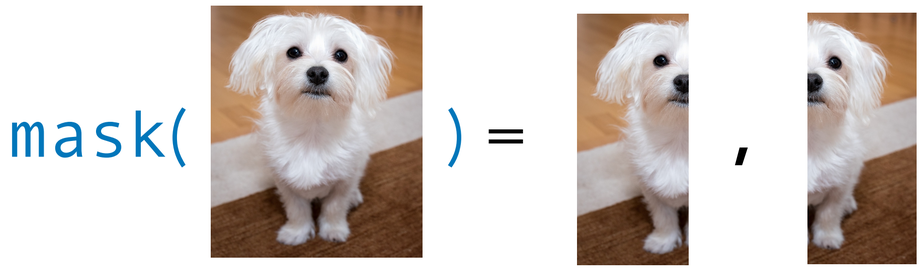
B. Make prediction $\hat{y}_i = f_\theta(\tilde{x}_i)$

C. Compute loss $\mathcal{L}_i = d(y_i, \hat{y}_i)$

$\tilde{x}_i$, y_i are typically two ***disjoint*** *sub-regions of x_i*

in some cases, the target y_i may be all of x_i

x_i $\quad$ $\tilde{x}_i$ $\quad$ y_i



f_θ **:** CNN or **Transformer** (stay tuned)

$d(y, \hat{y}) = \|y - \hat{y}\|^2$

x_i

`mask(` *Joe Biden is the US president* `)` =

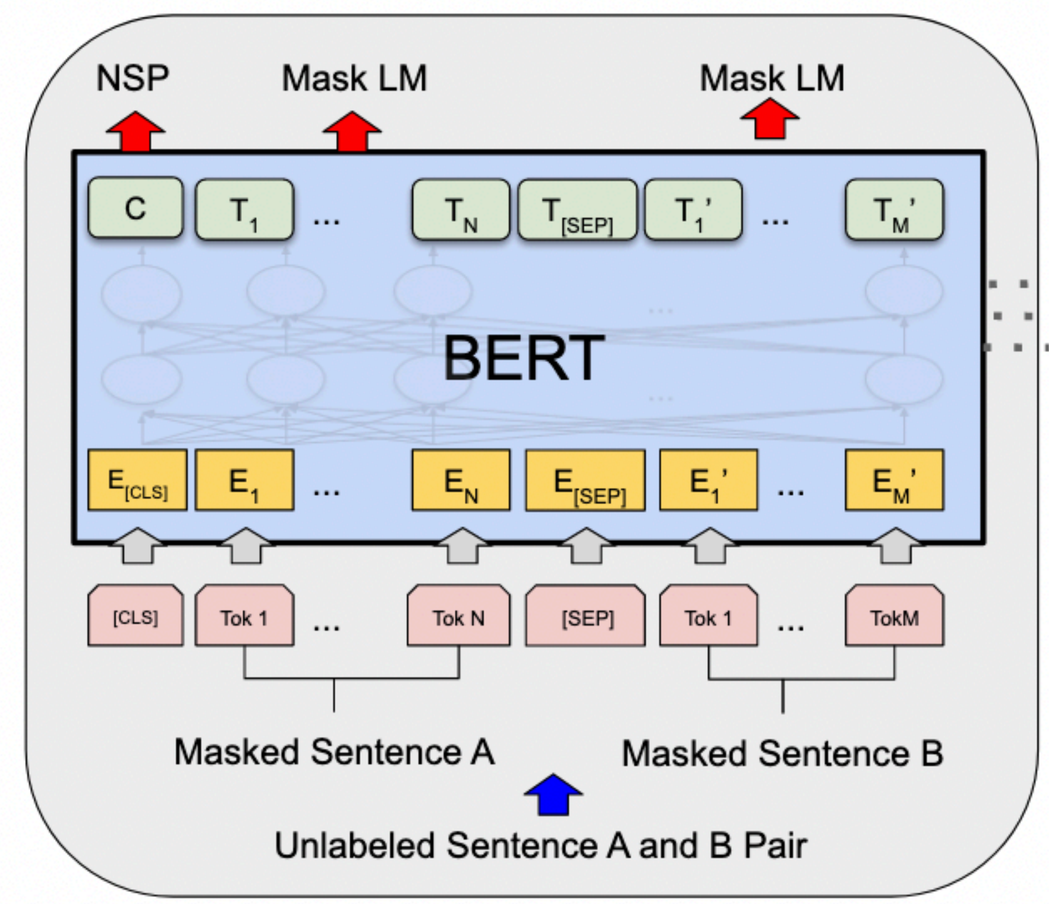
$\tilde{x}_i$ $\quad$ y_i

Joe <mask> is the US <mask>, { Biden; president }

f_θ **: Transformer (**e.g., **BERT**; stay tuned**)**

$d(y, \hat{y}) = \mathrm{KL}\left(y \| \hat{y}\right)$

Masked autoencoders for language: **BERT** (Devlin et al, 2017)



Case study: **BERT** as a masked autoencoder

x : [CLS] Joe Biden is the US president. [SEP] He was inaugurated on January...

t : 0 1 2 3 4 5 6 7 8 9 10 11 12

$\tilde{x}$: [CLS] Joe <mask> is the US <mask>. [SEP] He <mask> inaugurated on January...

BERT

$y_2 =$ **Biden**

$y_6 =$ **president**

$y_9 =$ **was**

Target word *for each masked index*

$p_\theta^2(\cdot \mid \tilde{x})$ $p_\theta^6(\cdot \mid \tilde{x})$ $p_\theta^9(\cdot \mid \tilde{x})$

Probability distribution *over possible words at each masked index j*

$$d(y, \hat{y}) = \sum_j \mathrm{KL}(y_j \,\|\, \hat{y}_j) = -\log p_\theta^2(\textbf{Biden} \mid \tilde{x}) - \log p_\theta^6(\textbf{president} \mid \tilde{x}) - \log p_\theta^9(\textbf{was} \mid \tilde{x})$$

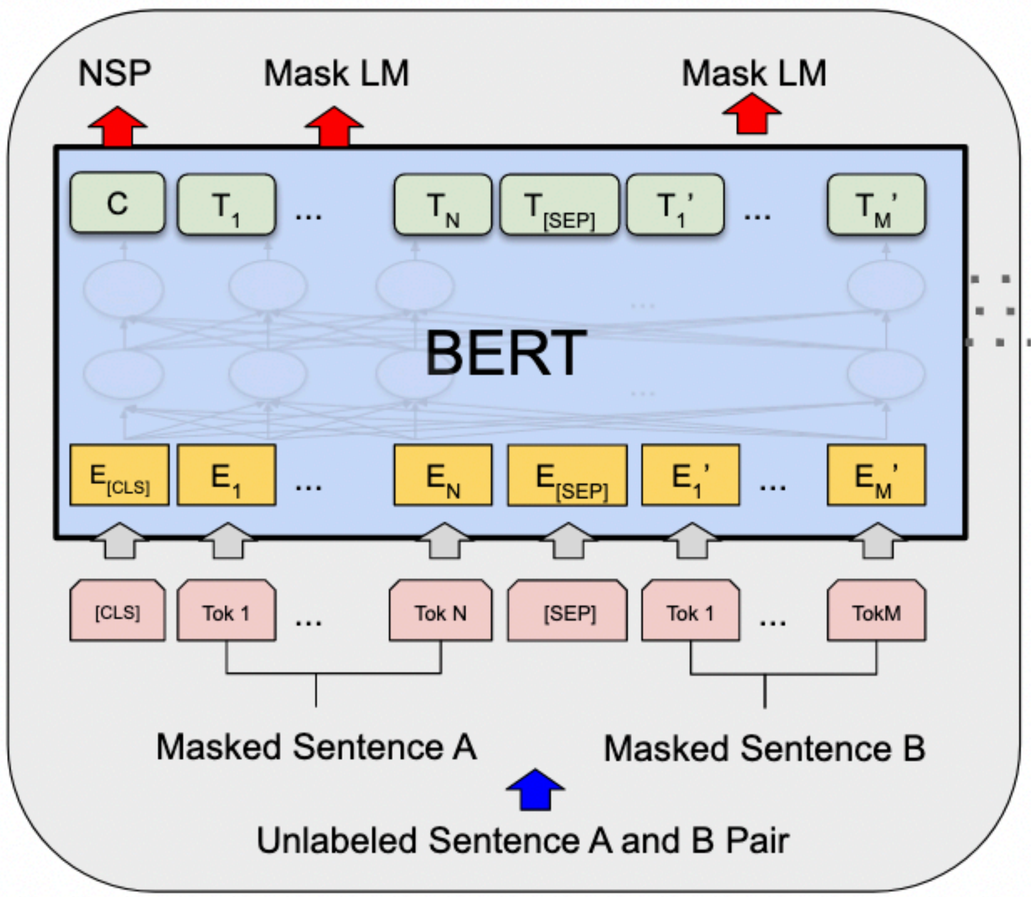
Details of BERT masking:

1. Choose **random 15%*** of input timesteps
2. Of these, **80%** are replaced with <mask> token
3. Replace **other 20%** with a **random** token

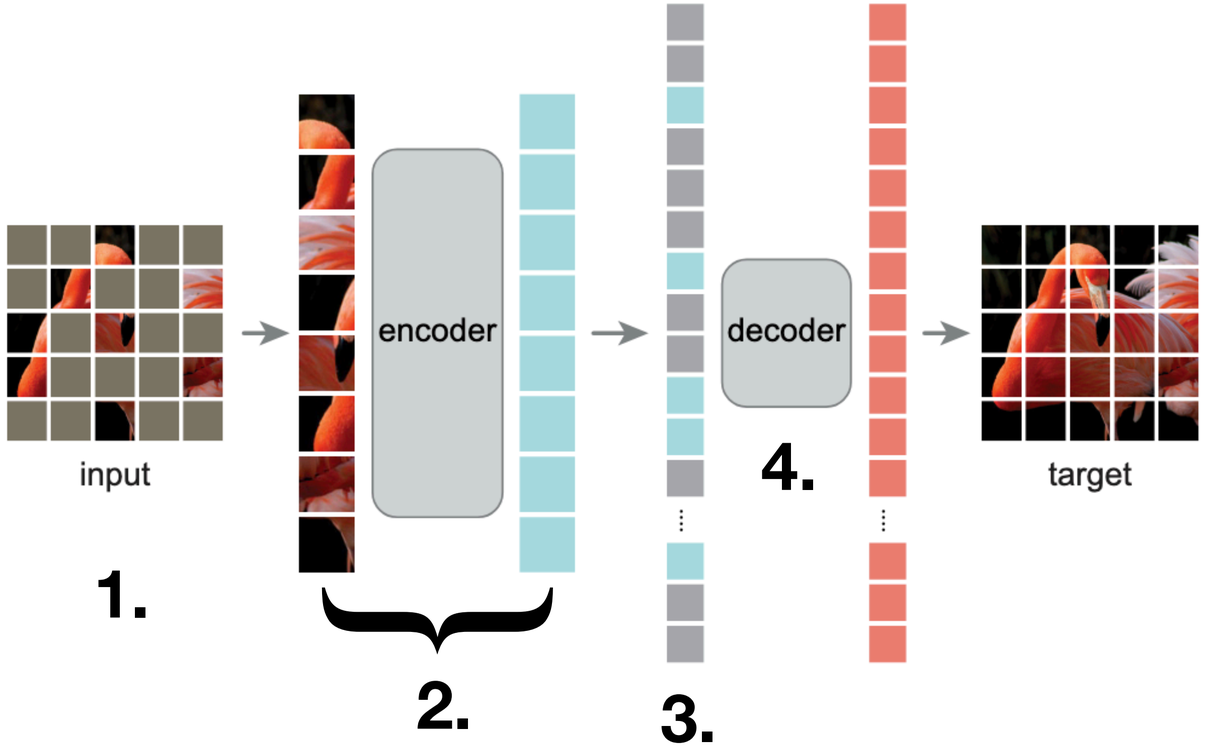
*It's possible we can do better than just picking **random** timesteps:

- Mask **longer** spans of text
- Selecting for **information-dense** spans

Masked autoencoders for language:
BERT (Devlin et al, 2017)



For **images**:
MAE (He et al, 2021)



Instead of words, we have a sequence of ***image patches***

1. Mask **~75%** of image patches
2. Compute representations of **only** unmasked patches
3. Insert **placeholder** patches at masked locations
4. Decode back into original image

Fine-tune on top of the output of ***step 2***

More recently: Masked AEs give state-of-the-art **few-shot image classification** performance

*The unsupervised masked autoencoding recipe works better than pre-training **with labels** on the **same data!***

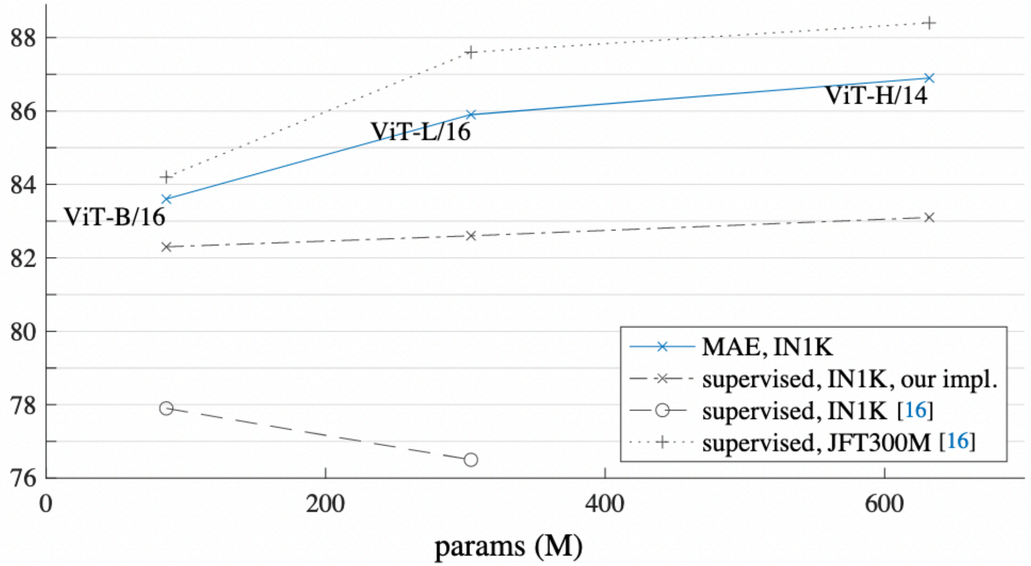


Figure 8. **MAE pre-training *vs*. supervised pre-training**, evaluated by fine-tuning in ImageNet-1K (224 size). We compare with the original ViT results [16] trained in IN1K or JFT300M.

*When **fine-tuning** (not just **linear probing** on frozen pre-trained model), better than **contrastive learning**!*

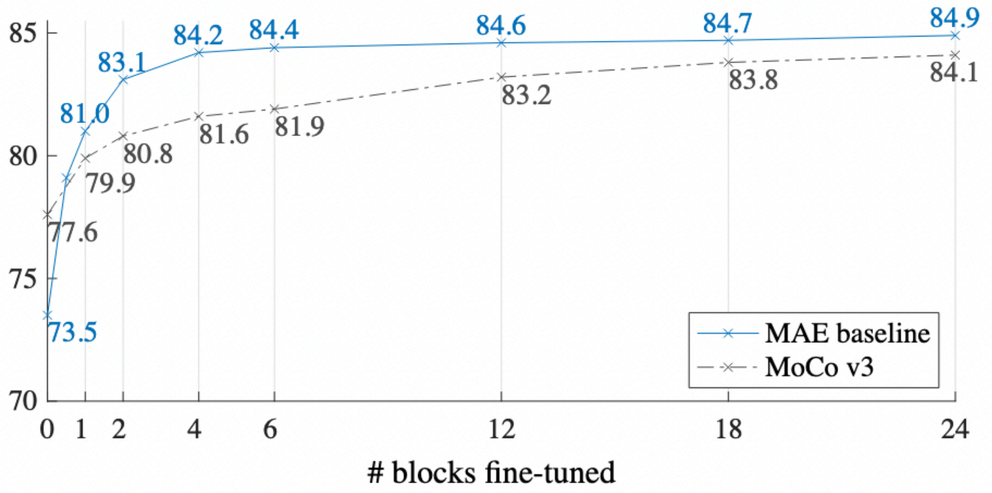


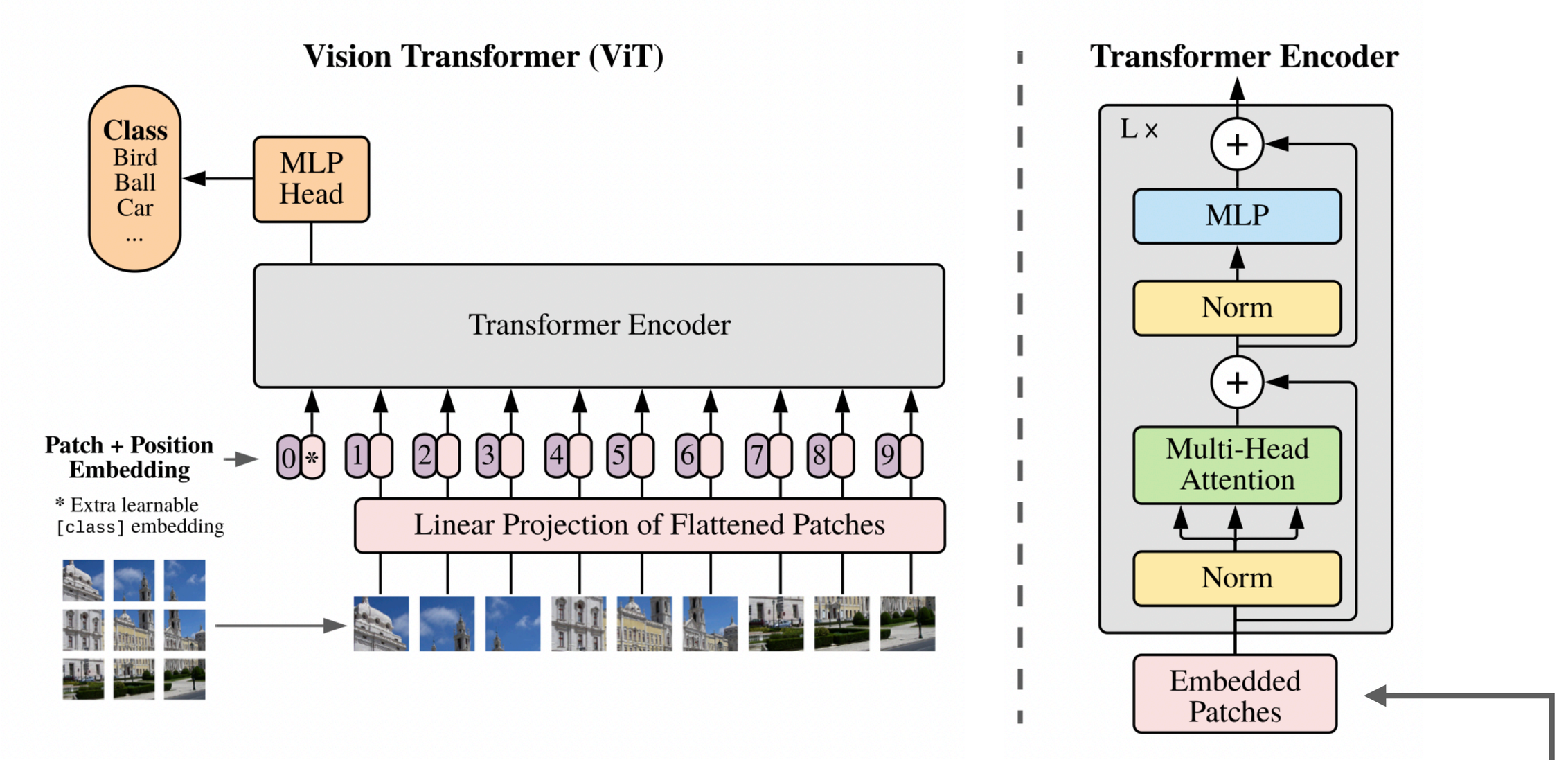
Figure 9. **Partial fine-tuning** results of ViT-L w.r.t. the number of fine-tuned Transformer blocks under the default settings from Table 1. Tuning 0 blocks is linear probing; 24 is full fine-tuning. Our MAE representations are less linearly separable, but are consistently better than MoCo v3 if one or more blocks are tuned.

He et al, 2021

A (very quick) overview of Transformers

Image by Ray Shrewsberry from Pixabay

A (very quick) overview of Transformers



The **~only difference** between Transformers for vision/language/RL/molecules/etc. is what we do for this initial **embedding step**

ViT; Dosovitskiy, Beyer, Kolesnikov, et al. (2021)

Transformers in a bit more detail

length-T input sequence

input tokens $I \in |\text{vocab}|^T$

input embeddings $E \in \mathbb{R}^{T \times d}$

Joe **587**

Biden **27504**

is **243**

the **75**

US **5478**

President **3938**

tokenize → *embed lookup* →

e_1 e_2 e_3 e_4 e_5 e_6

+ positional embeddings

Three separate linear projections of inputs X:

"queries" *"keys"* *"values"*

$$X_Q = XW_Q, \quad X_K = XW_K, \quad X_V = XW_V$$

inputs to block $X \in \mathbb{R}^{T \times d}$

self-attention output *self-attention matrix* *value matrix*

$$A = \text{sm}\left(X_Q X_K^\top\right) X_V \in \mathbb{R}^{T \times d}$$

outputs of block $O \in \mathbb{R}^{T \times d}$

x_1 x_2 x_3 x_4 x_5 x_6

norm $\mu(x_t) = 0$ $\sigma(x_t) = 1$ →

$\frac{e^{x_3^Q \cdot x_2^K}}{\sum_t^T e^{x_3^Q \cdot x_t^K}}$

self-attention & norm →

+ residual connection

a_1 a_2 a_3 a_4 a_5 a_6

MLP →

+ residual connection

o_1 o_2 o_3 o_4 o_5 o_6

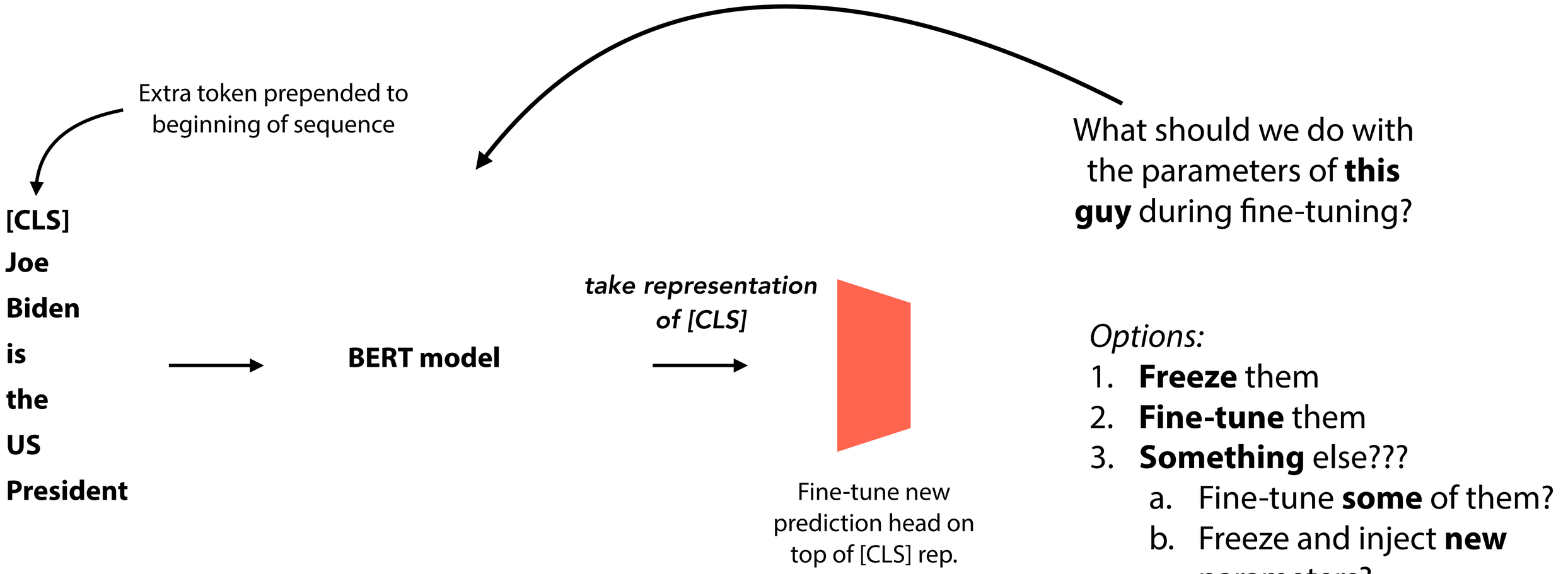
project to vocab. size dimensions →

$p_\theta^t(\cdot) \in \mathbb{R}^{|\text{vocab}|}$

$p_\theta^1(\cdot)$ $p_\theta^2(\cdot)$ $p_\theta^3(\cdot)$ $p_\theta^4(\cdot)$ $p_\theta^5(\cdot)$ $p_\theta^6(\cdot)$

One **transformer block;** repeat typically **6-96** times

So… how do we ~~pre-train~~ fine-tune Transformers?



Options:

1. **Freeze** them
2. **Fine-tune** them
3. **Something** else???
    a. Fine-tune **some** of them?
    b. Freeze and inject **new** parameters?

LoRA: Low-rank adaptation of language models (Hu et al., 2021)

What if we just want to fine-tune our model… "a little bit"?

What does "a little bit" even mean? <discuss>

1. *Preserve the **knowledge** in the **pre-trained model** (to avoid overfitting)*
2. *Avoid needing to store a **new version** of **every single** parameter in the model (to save space)*

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Associative *[key-value]* memory view of linear transform **(Kohonen, 1972)**

Consider the **linear transform**, the building block of NNs & Transformers

$$W = \sum_r v_r u_r^\top$$ *For rank-r matrix, we have this decomposition (with orthogonal u_r by SVD)*

Therefore, $$Wx = \left(\sum_r v_r u_r^\top \right) x = \sum_r v_r \left(u_r^\top x \right) \rightarrow$$ Wx produces a sum over the **'memories'** v_r weighted by the **relevance** $u_r^\top x$ (each u_r is a **'key'**)

*"A little bit" means **only add a few memories** → only make a **low-rank** change to W*

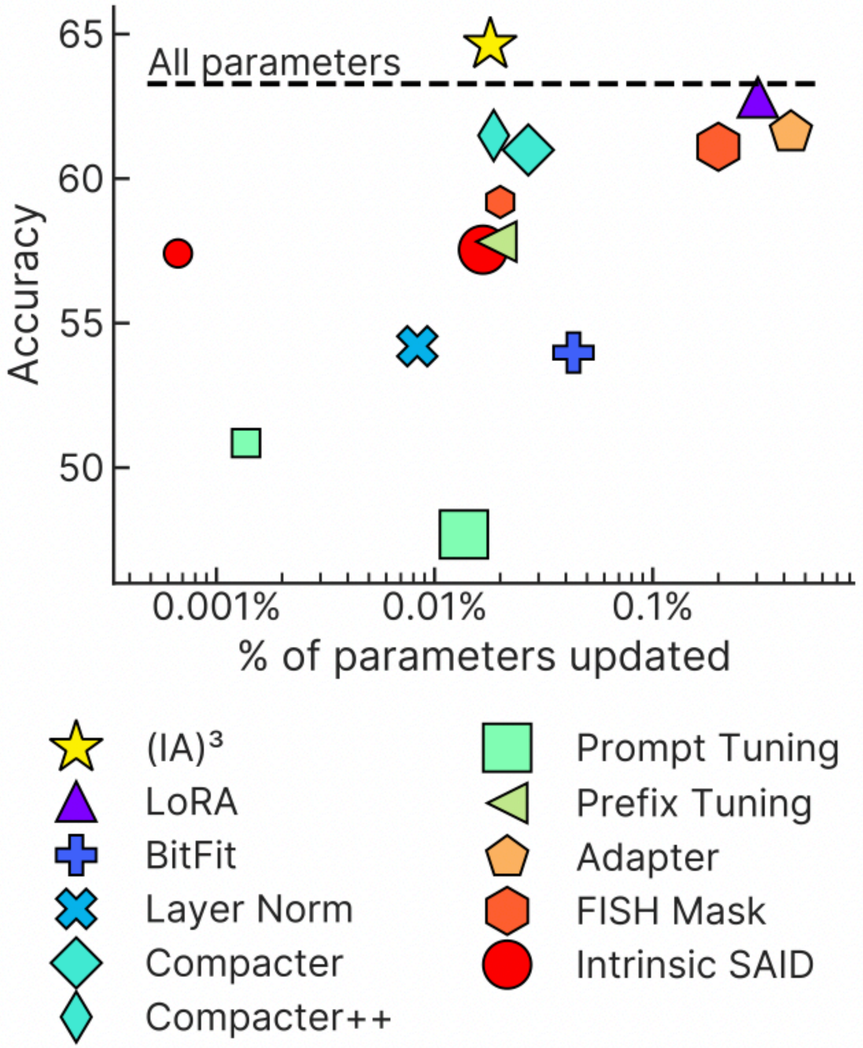
LoRA: $$W_{ft} = W_0 + AB^\top, \quad A, B \in \mathbb{R}^{d \times p}$$

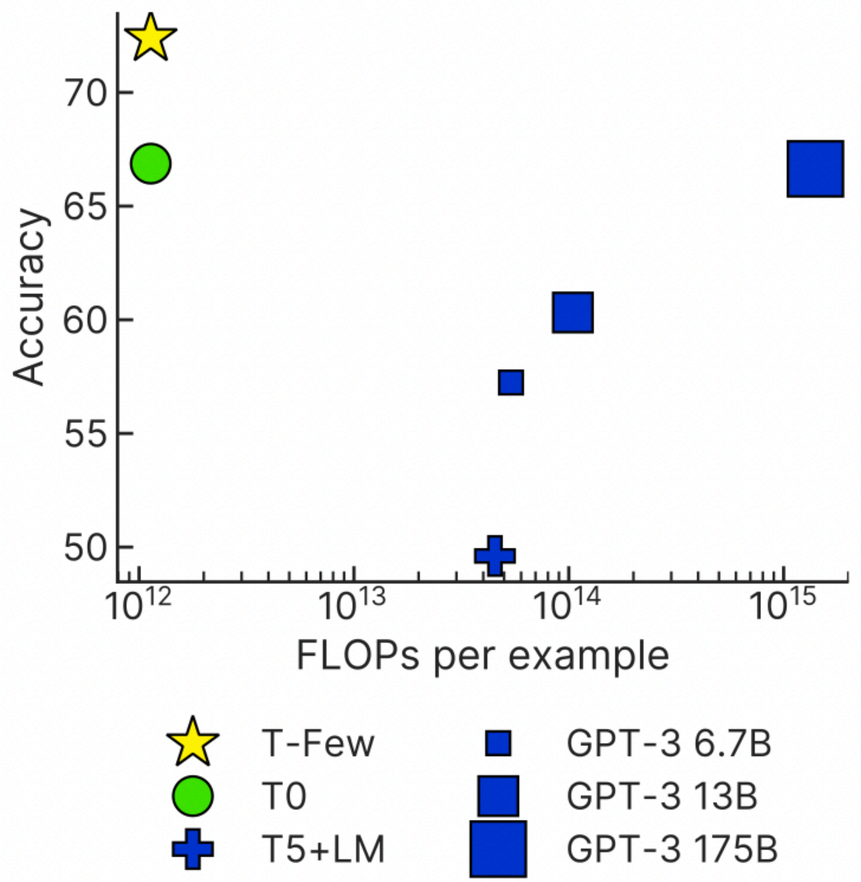
pre-trained weights **(frozen)**

new **low-rank residual (fine-tuned)**

$AB^\top$ should be **zero-initialized (how?)**

(Many) other approaches to "lightweight" fine-tuning





*When "few-shot" means **~20-70,** lightweight fine-tuning (**T-Few**) can outperform in-context learning in **much** larger models!*

T-Few; Lu, Tam, Muqeeth, et al. (2022)

You will compare fine-tuning and in-context learning in HW3!

Plan for Today

Recap

- Problem formulation
- Contrastive learning

Reconstruction-based unsupervised pre-training

- Why reconstruction?
- Autoencoders
- *Masked* autoencoders: BERT, MAE
- **Autoregressive models**: GPT, Flamingo

Striving for simplicity: **autoregressive models**

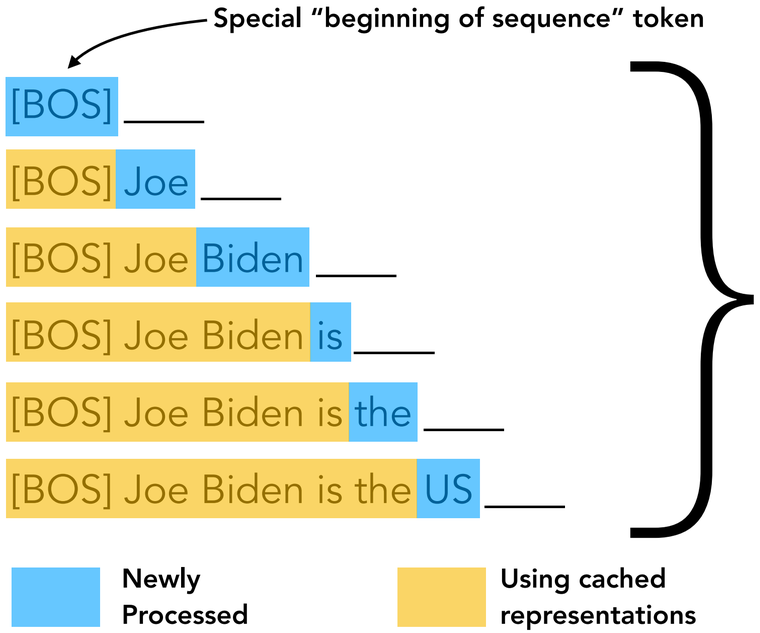
(recall from the black-box meta-learning lecture!)

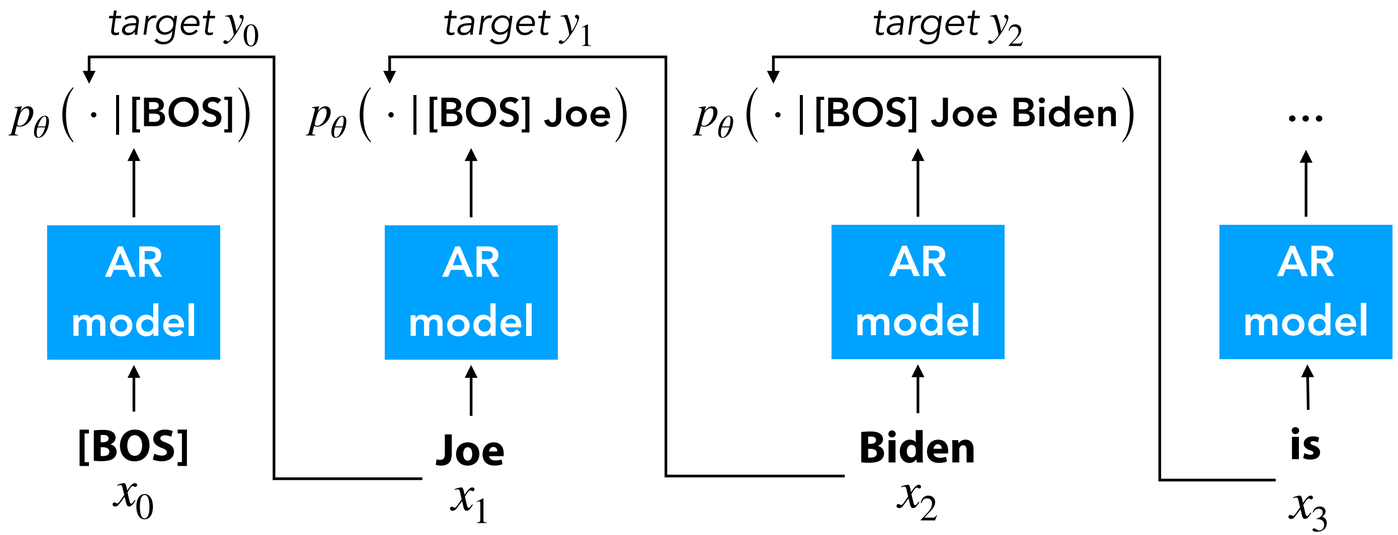
*What are some **downsides** of masked autoencoders?*

1. Need to pick `mask`
2. Only using ~15% of the example for training
3. Difficult to sample from

Instead of masking a **random subset,** what if we just *predict the next word/pixel/token?* → No need to pick a masking strategy; **mask every token!**

Simply learn $p_\theta(x_t \mid x_{<t})$, probability of the **next token** given the **previous tokens**





Autoregressive Transformers let us compute each $p_\theta(x_t \mid x_{<t})$ efficiently: we can **re-use** representations from the previous step

Autoregressive Transformers are *everywhere* these days

...for vision too!
...and RL/decision-making!
...and vision + language!

Improving Language Understanding by Generative Pre-Training

Language Models are Unsupervised Multitask Learners

Language Models are Few-Shot Learners

Megatron-LM: Training Multi-Billion Parameter Language Models Using Model Parallelism

OPT: Open Pre-trained Transformer Language Models

Generative Pretraining from Pixels

Mark Chen [1] Alec Radford [1] Rewon Child [1] Jeff Wu [1] Heewoo Jun [1] Prafulla Dhariwal [1] David Luan [1]

Decision Transformer: Reinforcement Learning via Sequence Modeling

WebGPT: Browser-assisted question-answering with human feedback

Announcing GPT-NeoX-20B

Announcing GPT-NeoX-20B, a 20 billion parameter model trained in collaboration with CoreWeave.

February 2, 2022 · Connor Leahy

As of February 9, 2022, GPT-NeoX-20B checkpoints are available for download from The Eye unde Apache 2.0. More in-depth information on GPT-NeoX-20B can be found in the associated technical report on arXiv.

Looking for a demo? Try GPT-NeoX-20B via CoreWeave and Anlatan's inference service, GooseAI!

DeepMind

28-04-2022

Flamingo: a Visual Language Model for Few-Shot Learning

Jean-Baptiste Alayrac[*,‡], Jeff Donahue[*], Pauline Luc[*], Antoine Miech[*], Iain Barr[†], Yana Hasson[†], Karel Lenc[†], Arthur Mensch[†], Katie Millican[†], Malcolm Reynolds[†], Roman Ring[†], Eliza Rutherford[†], Serkan Cabi, Tengda Han, Zhitao Gong, Sina Samangooei, Marianne Monteiro, Jacob Menick, Sebastian Borgeaud, Andrew Brock, Aida Nematzadeh, Sahand Sharifzadeh, Mikolaj Binkowski, Ricardo Barreira, Oriol Vinyals, Andrew Zisserman, Karen Simonyan[*,‡]

[*]Equal contributions, ordered alphabetically, [†]Equal contributions, ordered alphabetically, [‡]Equal senior contributions

Case study: **Flamingo**

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*Equal contributions, ordered alphabetically, †Equal contributions, ordered alphabetically, ‡Equal senior contributions

How would you build a multimodal autoregressive model? From scratch? (NO)

[so far] Fine-tuning to **specialize:**

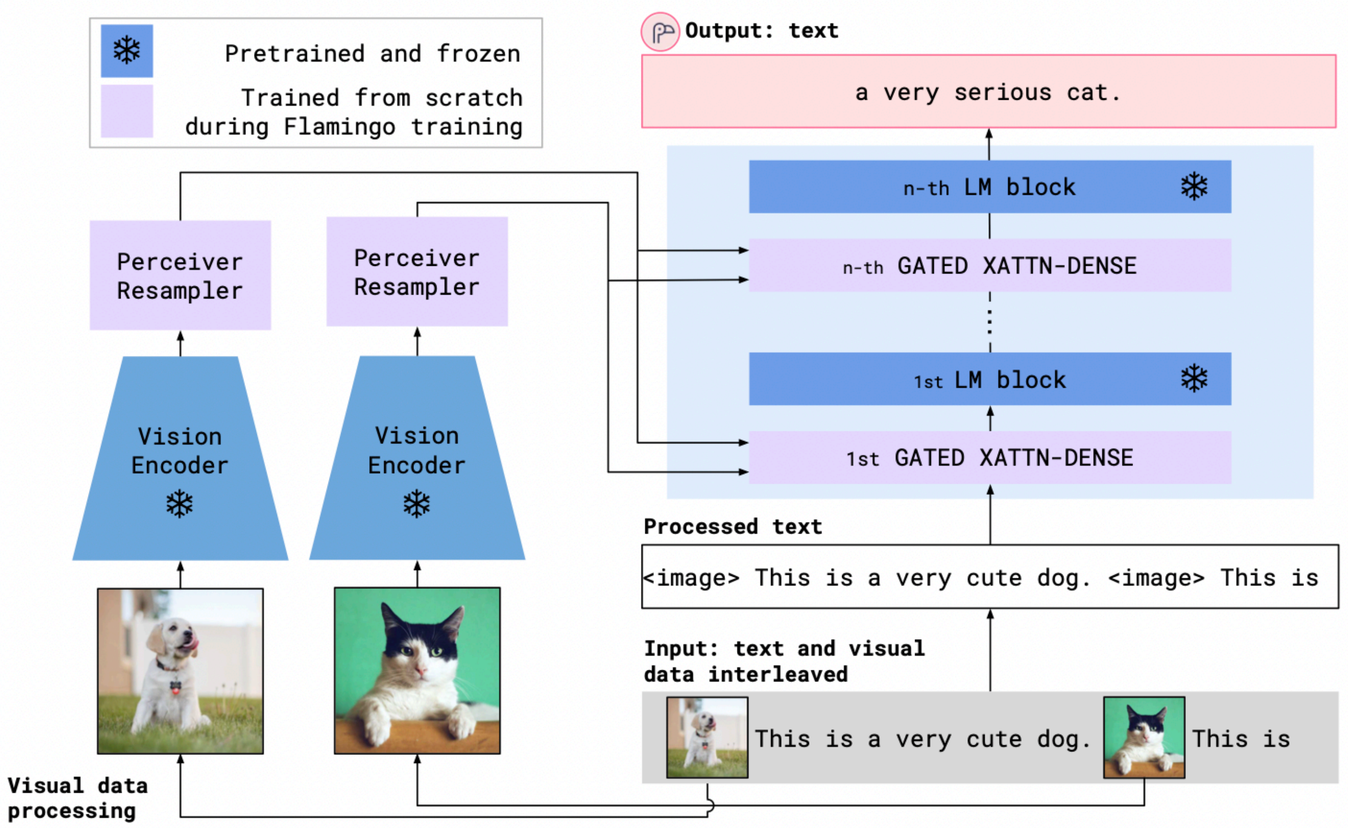
General-purpose LM + Few-shot data = Task-specific LM

Flamingo

Fine-tuning to **combine models:**

General-purpose LM + General-purpose Vision Model + Multimodal data

= General-purpose Vision-Language Model



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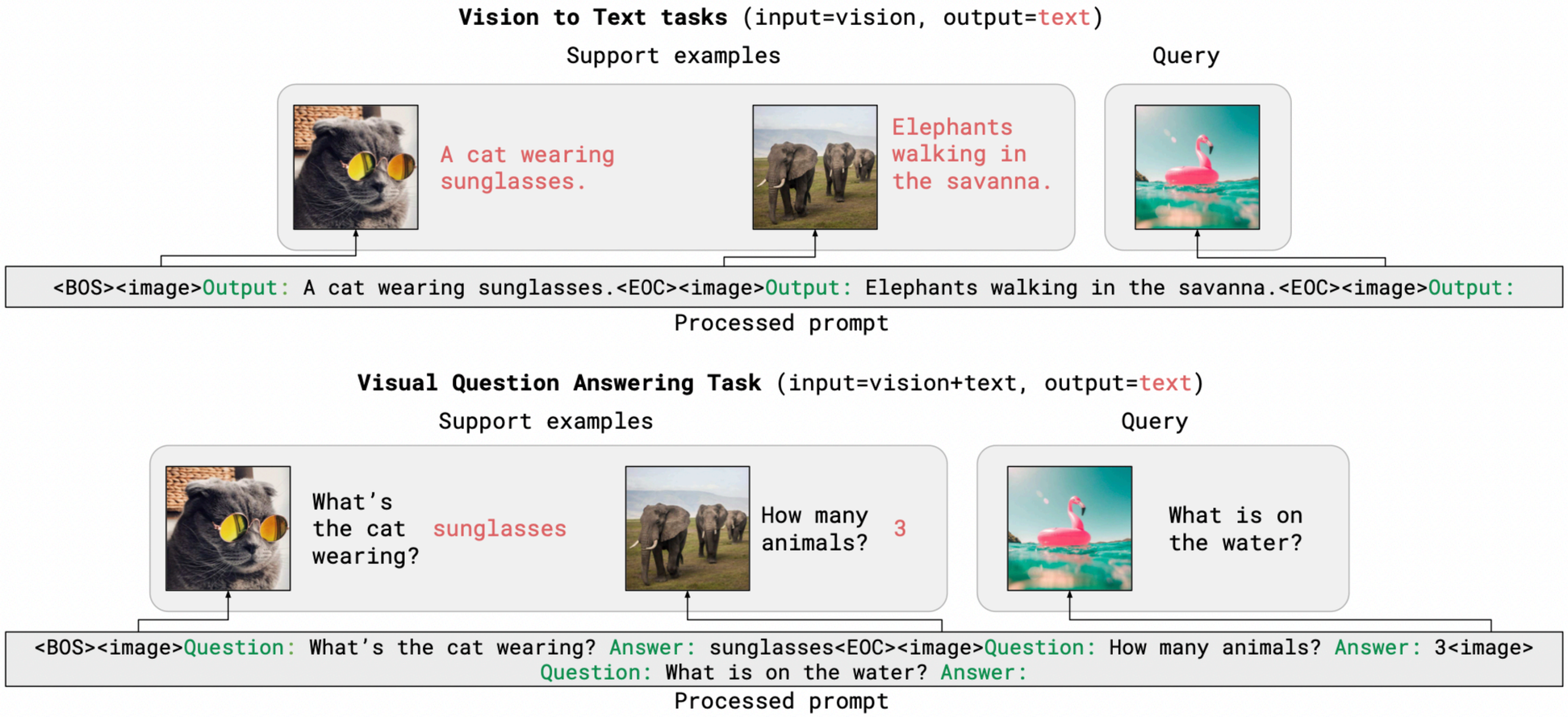

*In-context few-shot learning on sequences that freely mix **text** and **images!** Enables few-shot captioning, visual question-answering, etc.*

Case study: **Flamingo**

DeepMind

28-04-2022

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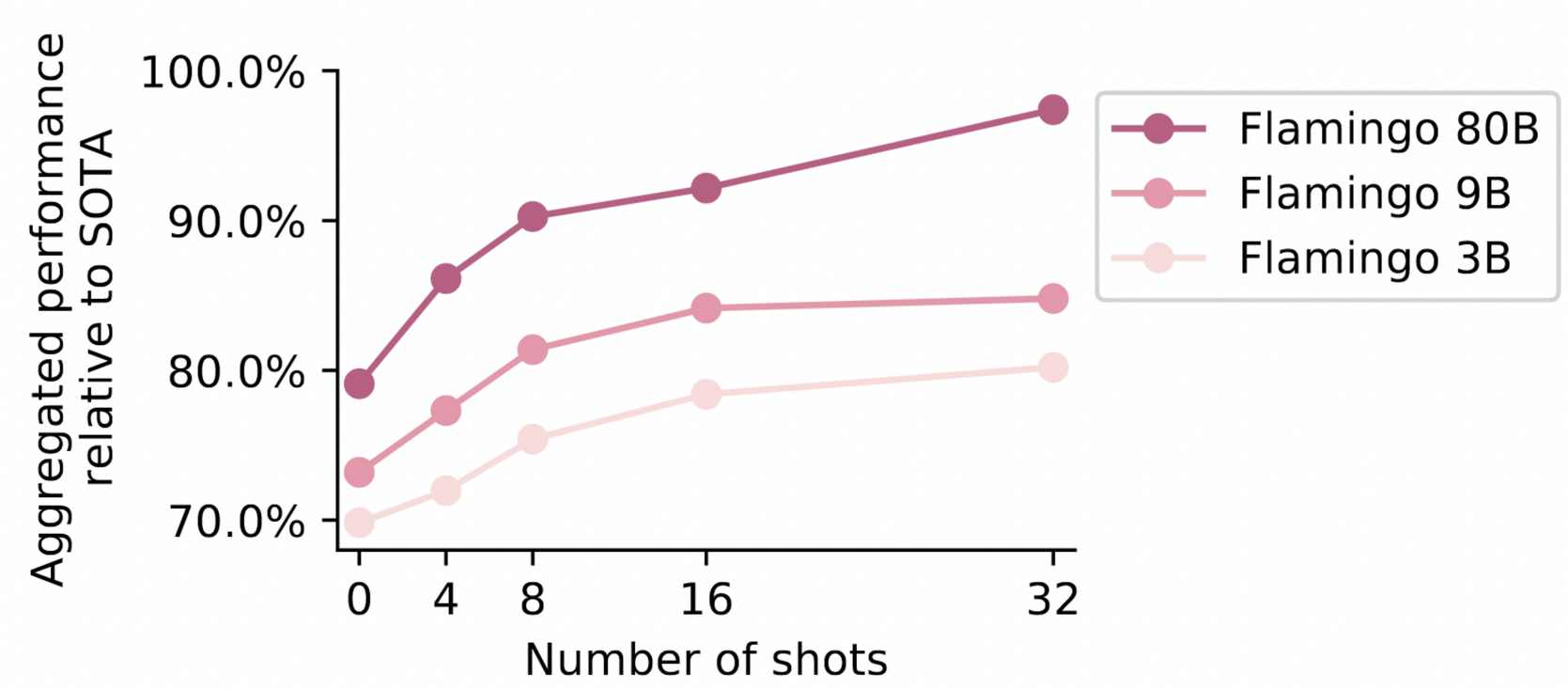

Few-shot Flamingo ≈ **Non-Few-shot state of the art!**

Are AR models really **different** from masked autoencoders?

General recipe for training masked autoencoder f_θ:

1. Choose **distance function** $d(\cdot, \cdot) \to \mathbb{R}$
2. For **train batch** examples x_i :
   - **A.** Sample $\tilde{x}_i,\ y_i \sim \texttt{mask}(x_i)$
   - **B.** Make prediction $\hat{y}_i = f_\theta(\tilde{x}_i)$
   - **C.** Compute loss $= d(y_i, \hat{y}_i)$

AR models are just masked AEs with a special choice of `mask`

Masked autoencoder:

$\tilde{x}$:	y :
Joe	
<mask>	Biden
is	
the	
<mask>	US
President	

AR model:

$\tilde{x}$:	y :
Joe	
Biden	
is	
the	
US	
____	President

Summary of today

1. *Intuition for autoencoders (AEs): "A good **representation** lets us **reconstruct** the input"*
2. ***Masked** AEs learn to restore a **partially-deleted** input & help avoid degeneracies in unmasked AEs*
3. ***State of the art** in pre-training for few-shot learning in **language & vision***
4. ***Autoregressive** models (e.g., GPT-3) are **special case** of masked AEs; give a generative model for free at some cost to fine-tuning performance*

Contrastive Learning vs AEs vs Masked AEs

Contrastive learning:

+ *Learns very high-quality representations*
+ *Don't need as large a model*
- *Need to select negatives carefully**
- *Generally needs larger batch size**
- *Cross-example dependencies can make implementation more difficult*

** new methods are addressing these downsides but are more difficult to interpret/analyze*

(Bottlenecked) Autoencoders:

+ *Simple to implement*
+ *No need to select pos/neg pairs; just* $d(x, \hat{x})$
- *Generally need a larger model*
- *Need to design a bottleneck*
- *(Comparatively) poor few-shot performance*
- *Not generally used in practice*

Masked autoencoders:

+ ***Few-shot** performance as good or better than contrastive*
+ ***AR special case** gives generative model for free*
- ***Raw representations** (without fine-tuning) still can be lower quality than contrastive*