Deep Learning 1

2025-2026 – Pascal Mettes

Lecture 8

From supervised to unsupervised deep learning

Previous lecture

Lecture	Title
1	Intro and history of deep learning
3	Deep learning optimization I
5	Convolutional deep learning
7	Graph deep learning
9	Multi-modal deep learning
11	What doesn't work in deep learning
13	Q&A

Lecture	Title
2	AutoDiff
4	Deep learning optimization II
6	Attention-based deep learning
8	From supervised to unsupervised deep learning
10	Generative deep learning
12	Non-Euclidean deep learning
14	Deep learning for videos

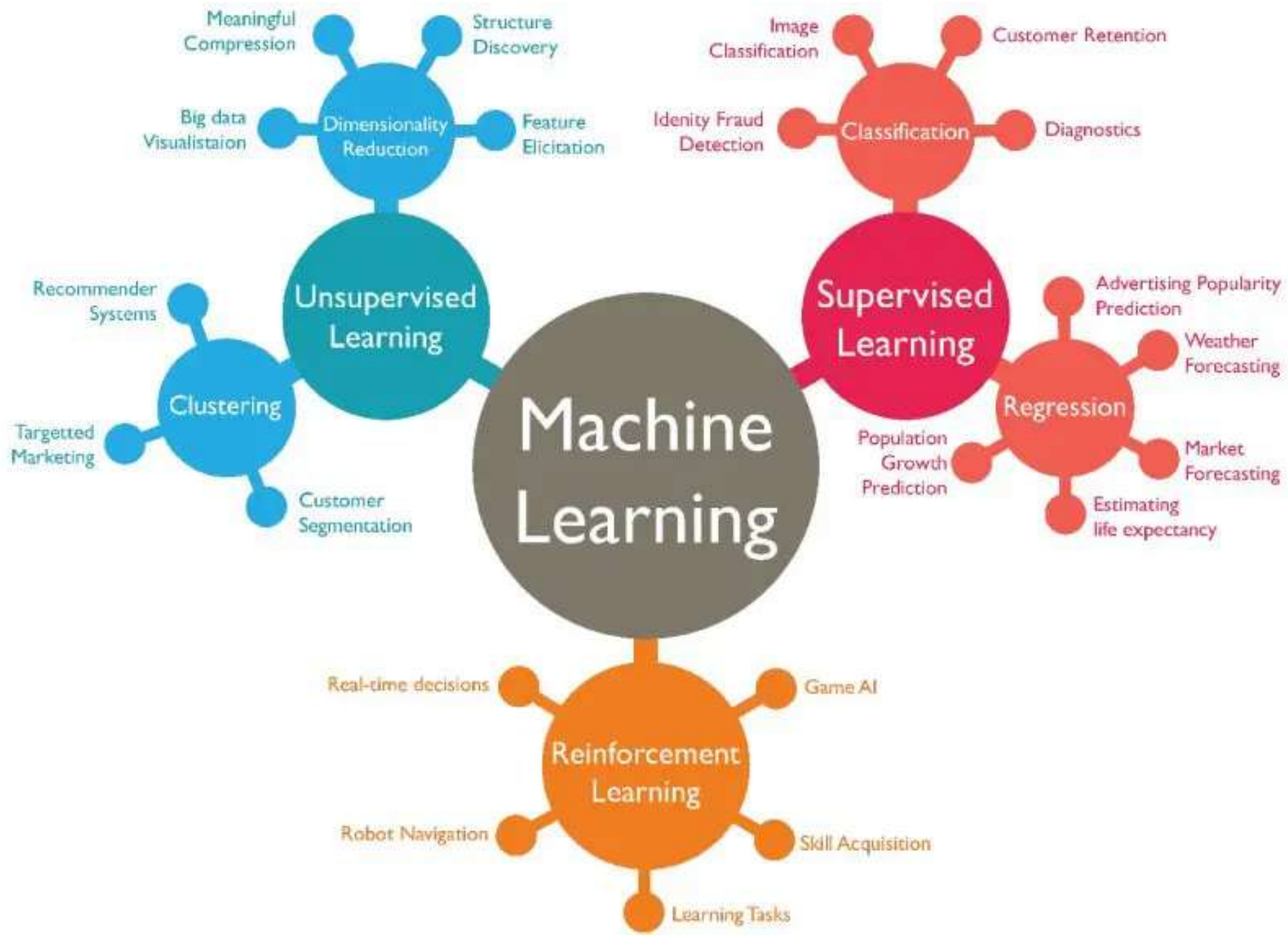
This lecture

Self-supervised learning for vision

Self-supervised learning for language

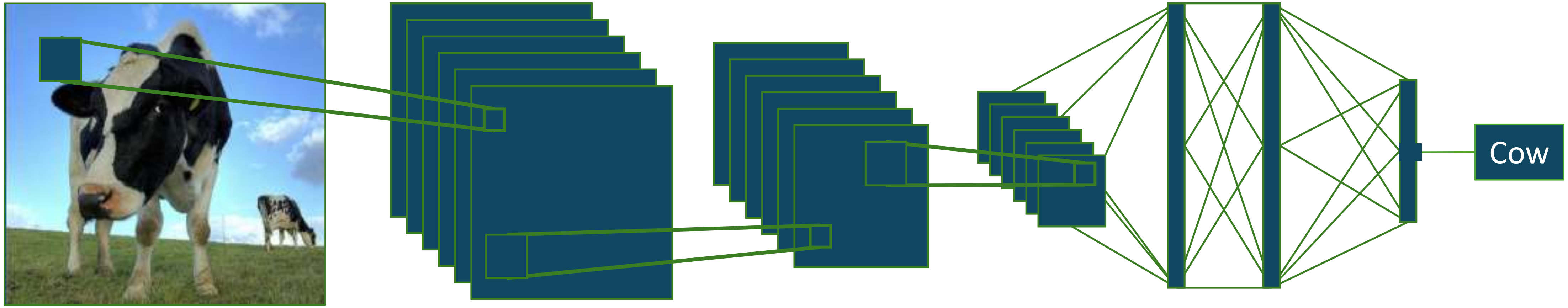
In between supervised and self-supervised learning

Traditional pillars of machine learning



Strength and weakness of supervision in DL

Supervision makes it possible to propagate signals back to train networks.



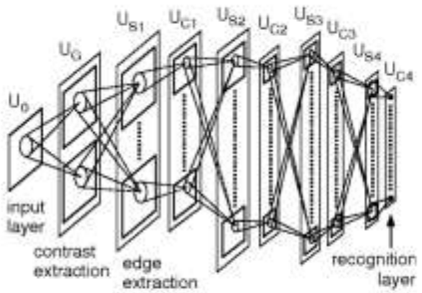
Classification labels no longer the backbone of latest models, why?

Self-supervised learning

Data as fuel for deep learning

Algorithms

Deep neural networks



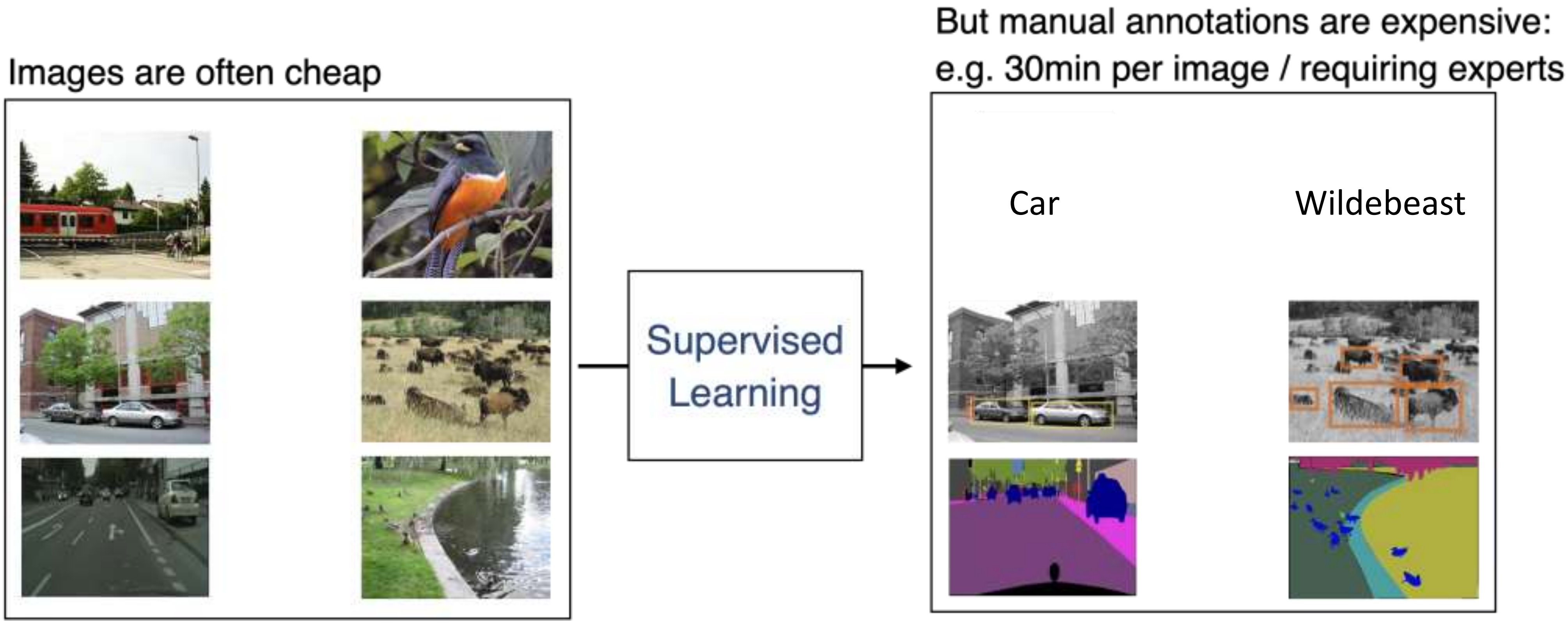
Hardware

GPUs

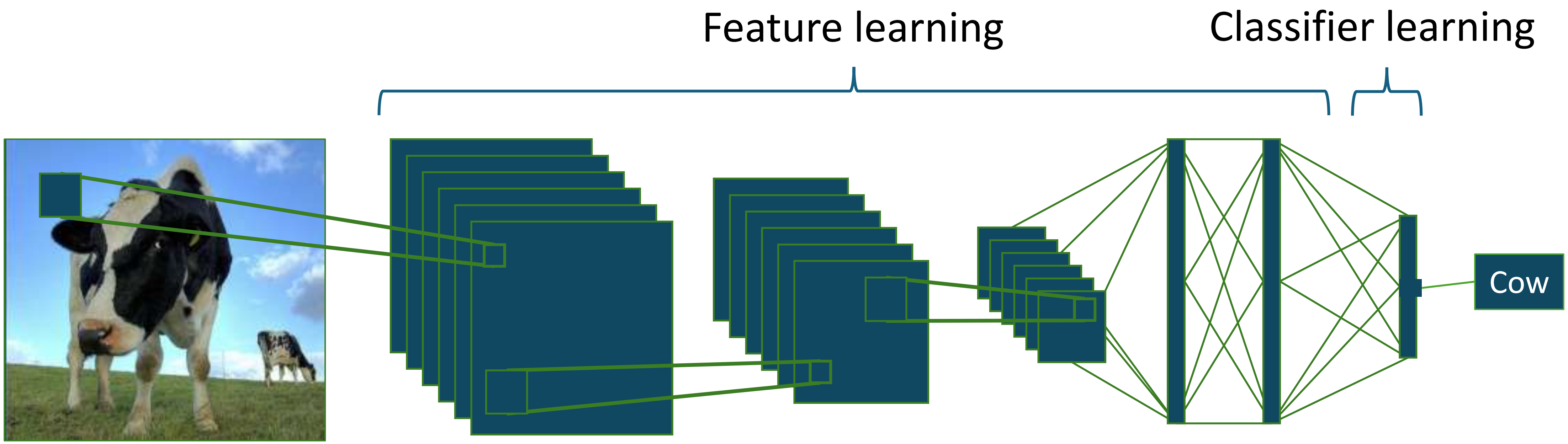
Data

Large scale datasets

The bottleneck of data



The two stages of deep learning

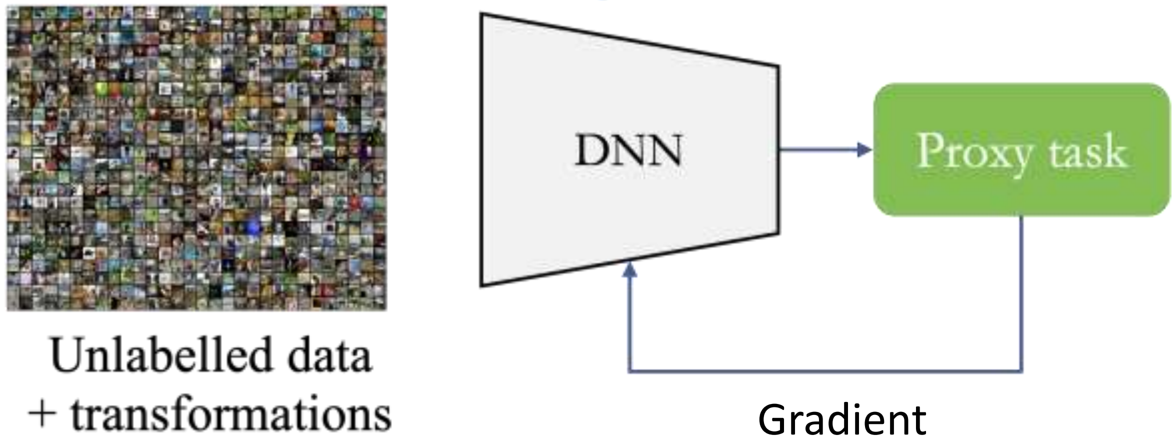


The final layer requires labels, but is that also true for all other layers?

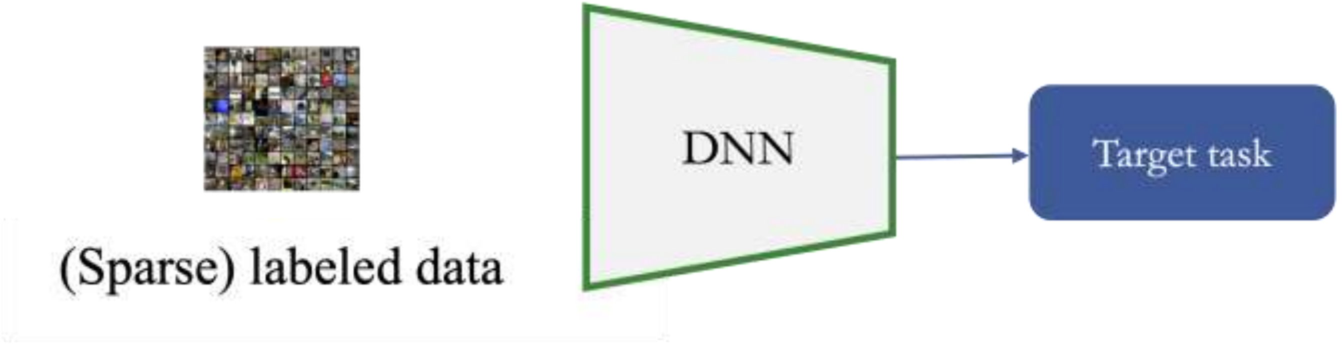
Solving the problem of expensive annotations: self

Main idea of self-supervised learning

Phase 1: Pretraining



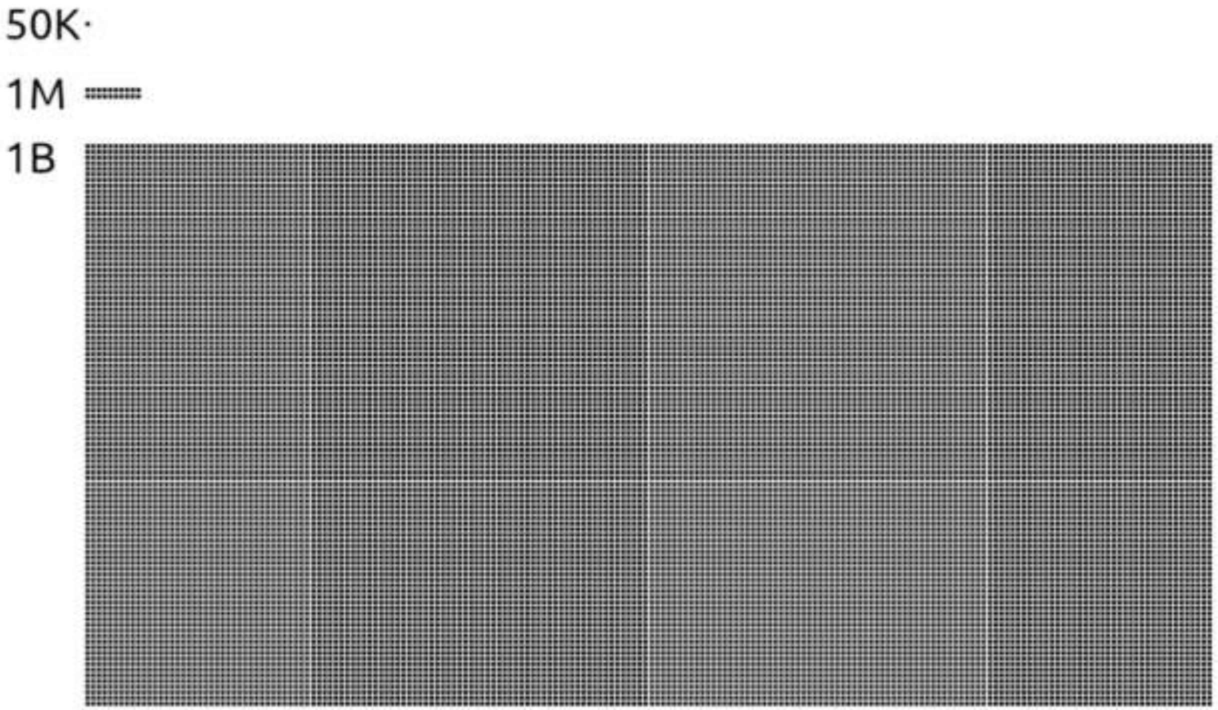
Phase 2: Downstream tasks



Why do we want self-supervised learning?

Reason 1: Scalability

ImageNet
~1 million annotated images



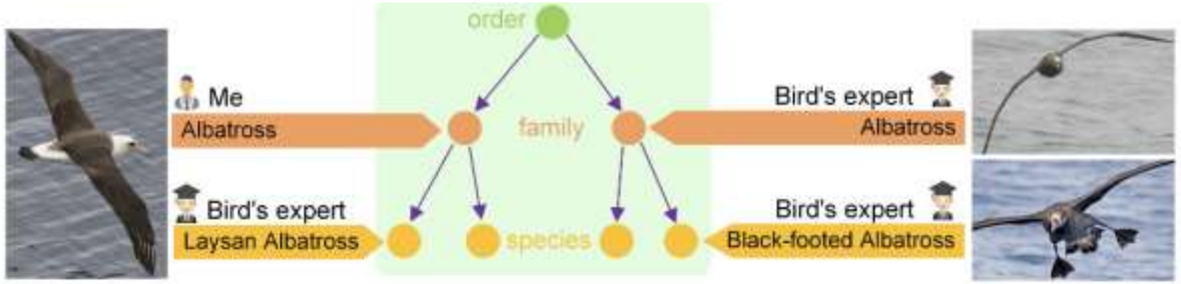
Instagram
~50 billion images floating about

The web is filled with unanontated data.

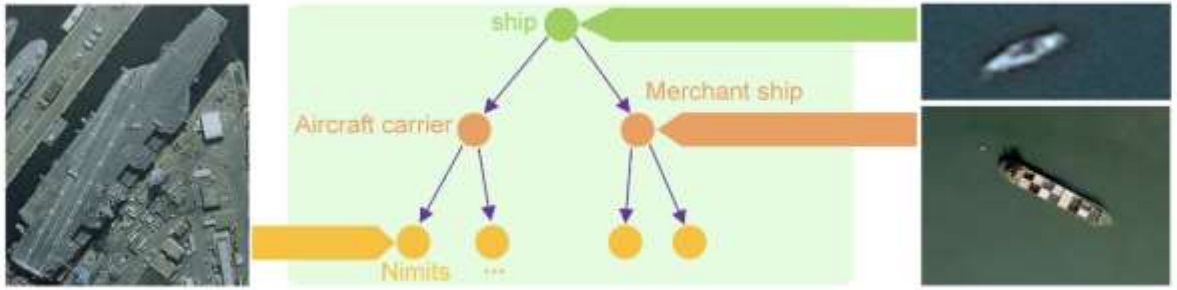
Reason 2: Generalizability

We want models that generalize to many domains and shifts.

Reason 3: Label are not perfect



(a) Differences in domain knowledge and interference from the image occlusion.



(b) Large variations of image resolutions.

Chen et al. 2022

Labels can be ambiguous, biased, or simply wrong.

Reason 4: Humans are self-supervised

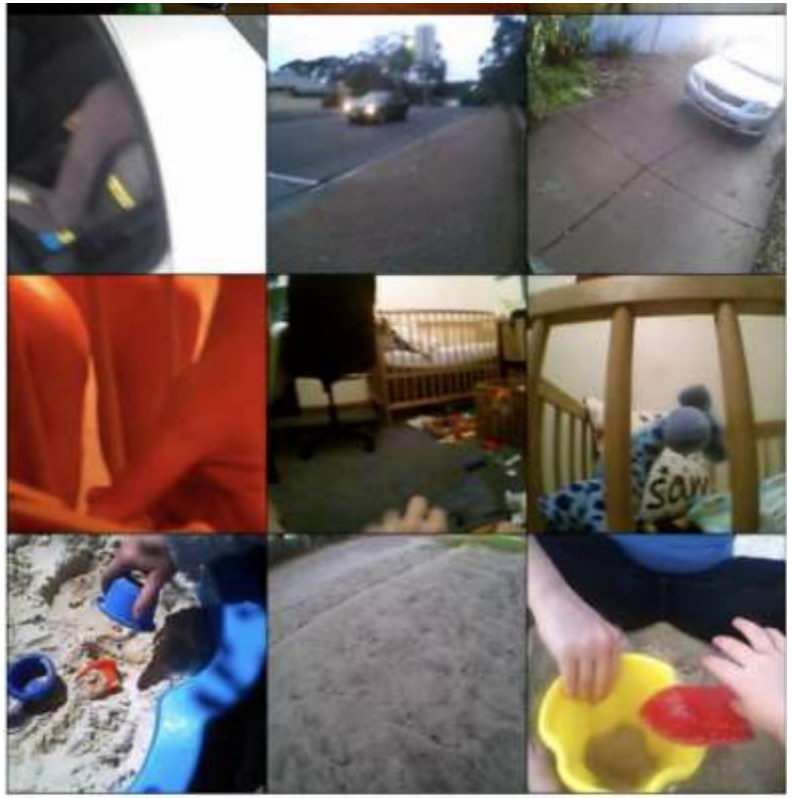
Meta AI Research Publications

RESEARCH

Self-supervised learning: The dark matter of intelligence

March 4, 2021

As babies, we learn how the world works largely by observation. We form generalized predictive models about objects in the world by learning concepts such as object permanence and gravity. Later in life, we observe the world, act on it, observe again, and build hypotheses to explain how our actions change our environment by trial and error.



Still a lot of lessons from human learning that can be transferred.

How do we train deep networks without labels?

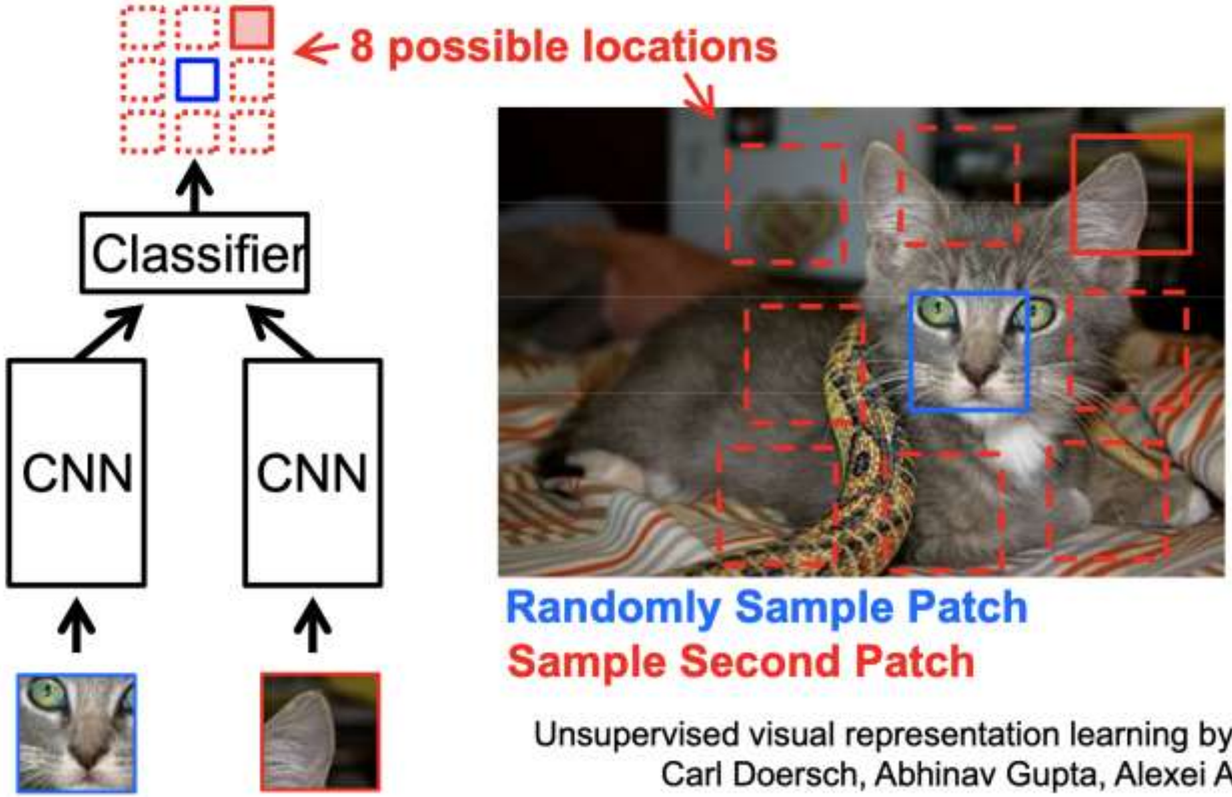
Self-supervied visual learning

The first popular domain for self-supervised learning.

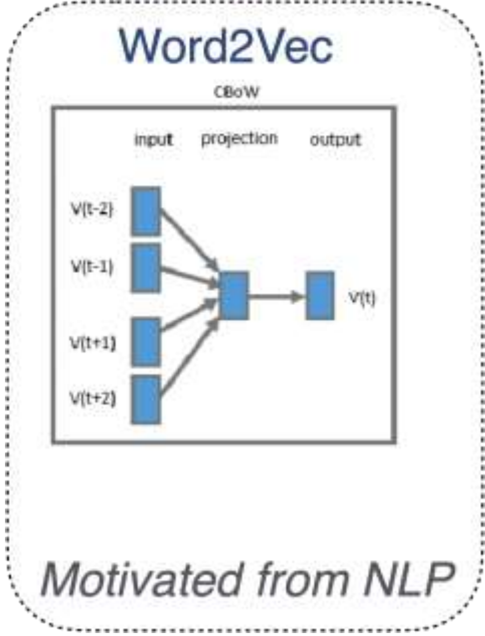
Main idea: exploit the structure of images and videos to learn without labels.

Goal is not to develop new algorithms, but borrow losses from supervised learning and think of your own loss functions.

Early attempt: relative positioning

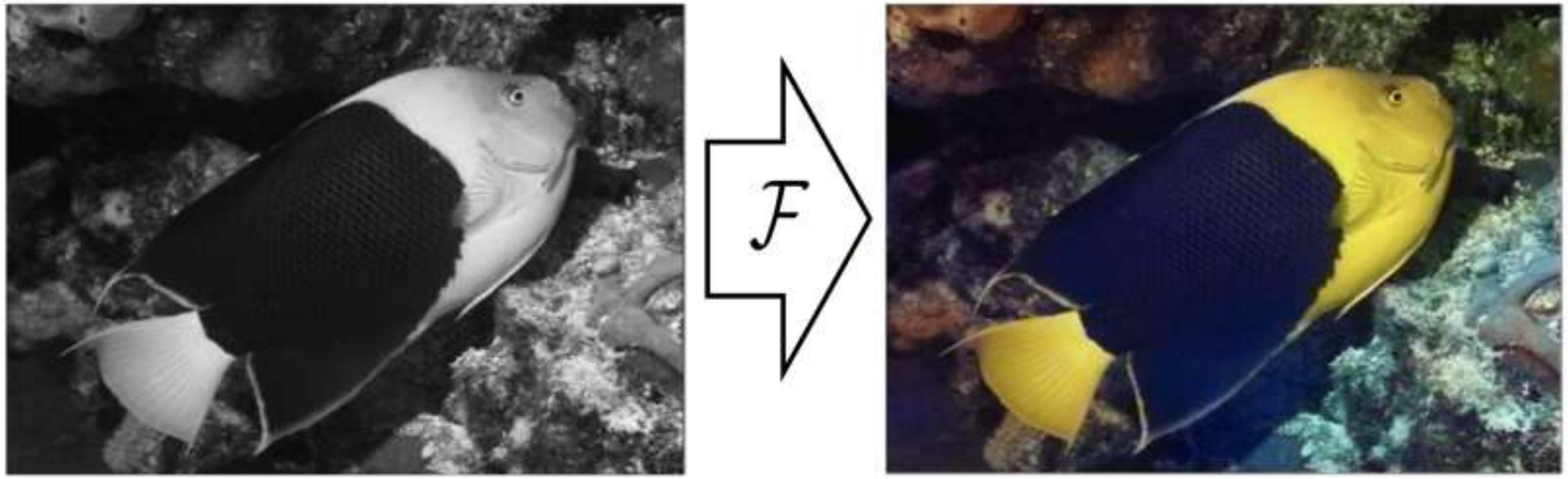


Unsupervised visual representation learning by context prediction,
Carl Doersch, Abhinav Gupta, Alexei A. Efros, ICCV 2015



[Zhang et al. ECCV 2016]

Learning by coloring

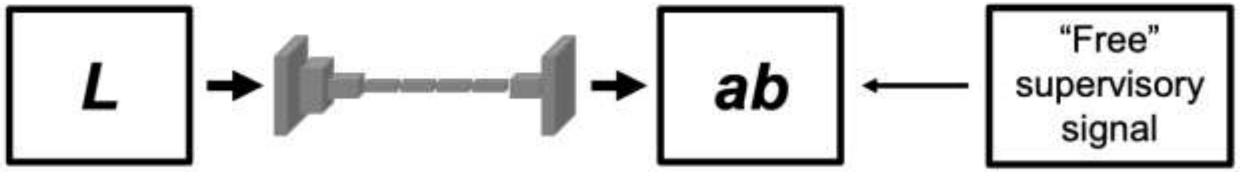


Grayscale image: *L* channel

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

Concatenate (L,ab)

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



Visual results

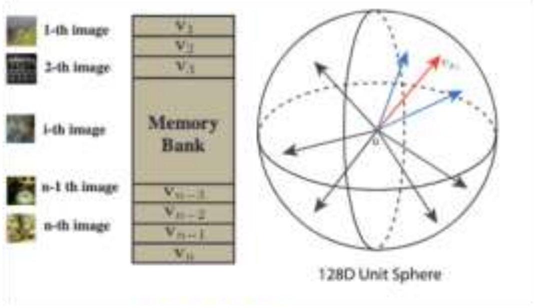
The representations for learning color can be used to initialize a new network.

Learning by rotations

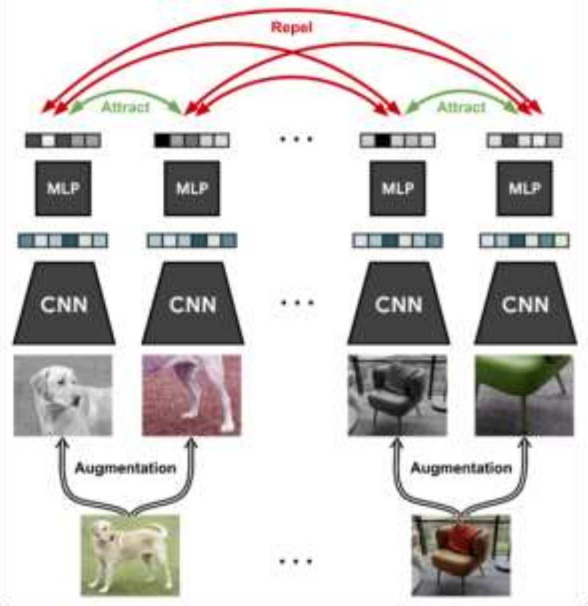
90° rotation | 270° rotation | 180° rotation | 0° rotation | 270° rotation

Assumption: if we know the object, we understand which rotation is most natural.

Modern approach: contrastive self-supervision



NPID



SimCLR

The contrastive loss for positive pairs i,j:

$$\ell_{i,j} = -\log \frac{\exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \ _{[k\neq i]} \exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)},$$

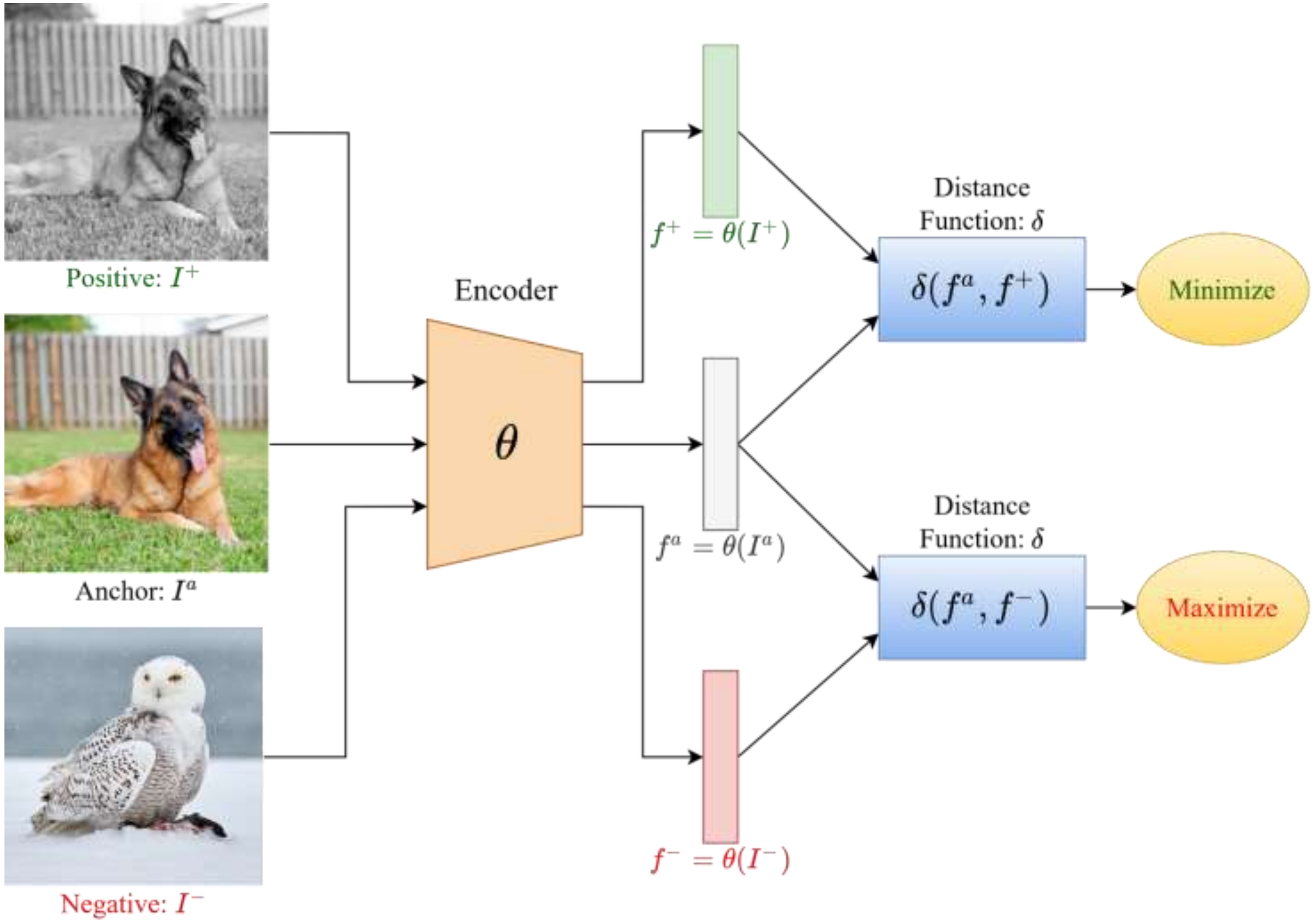
with z_i, z_j embeddings for images *i* and *j* ,

τ a temperature, *sim() is the dot-product*

"non-parametric" softmax

Enforces image uniqueness and augmentation invariance.

How to train with contrastive losses



Self-supervised learning is conservative supervised learning

Contrastive supervised learning:

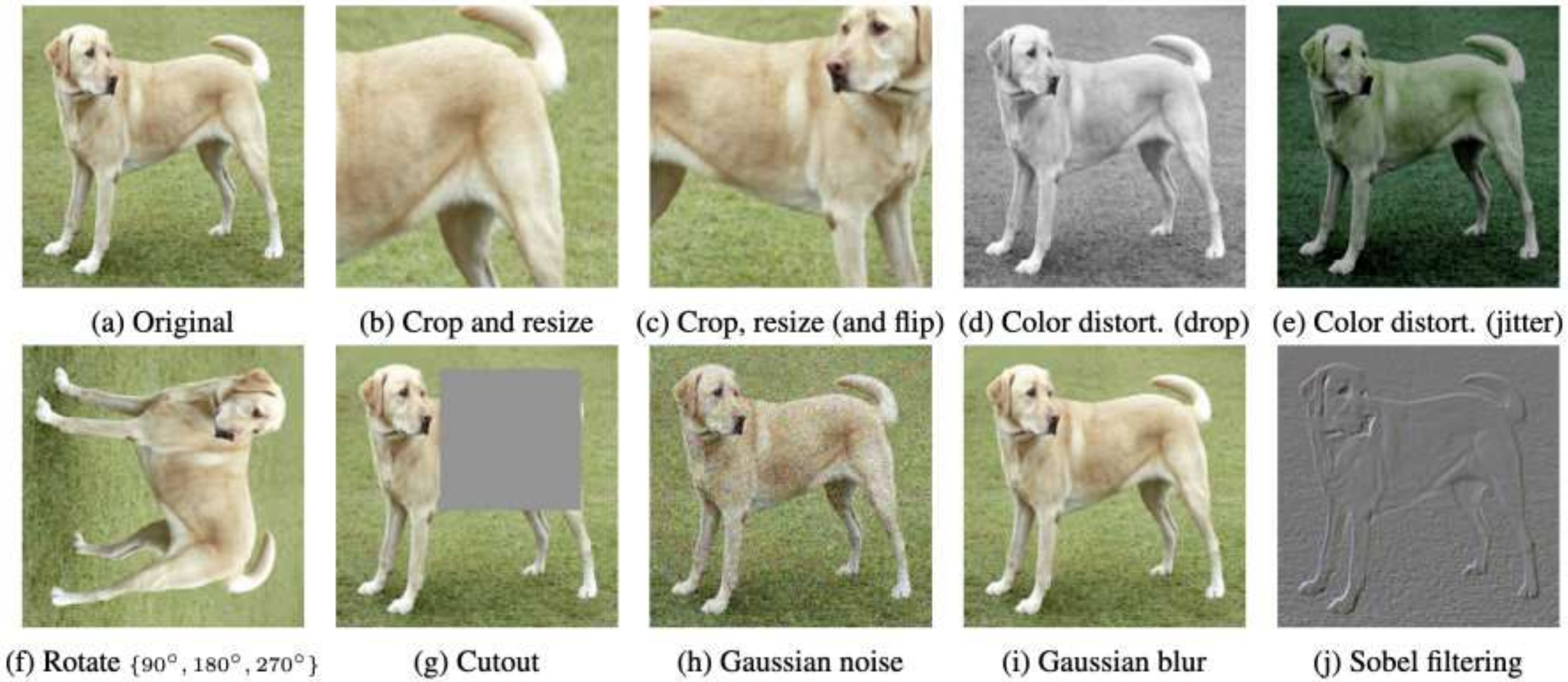
Pull samples of same class together, push others away.

Contrastive self-supervised learning:

Pull augmented versions of same sample together, push others away.

[Chen et al. ICLR 2020]

Self-supervised learning is learning augmentation invariance



We want augmentations of a sample to lead to the same embedding representation.

Self-supervised video learning

Videos have a super strong extra signal to learn from: time.

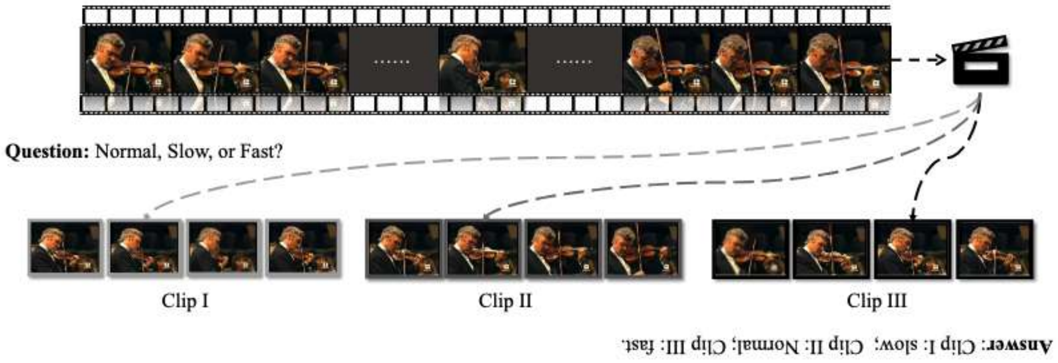
How can time be used for pretext tasks?

Predict temporal order.

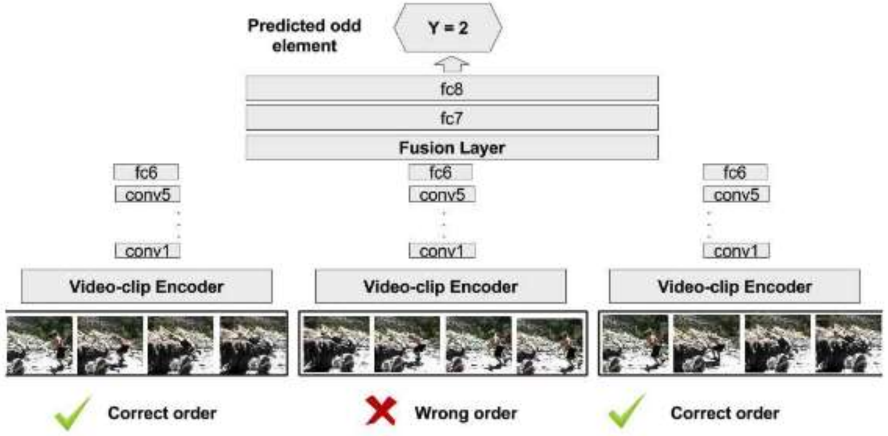
Predict whether video is played in reverse or not.

Predict alignment between video and audio.

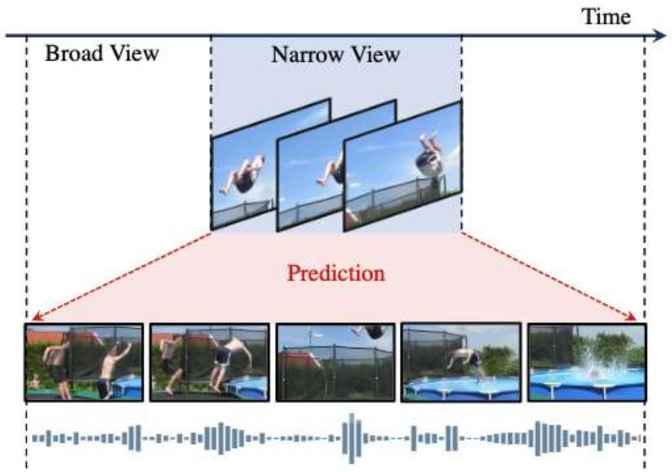
Examples of self-supervised video learning



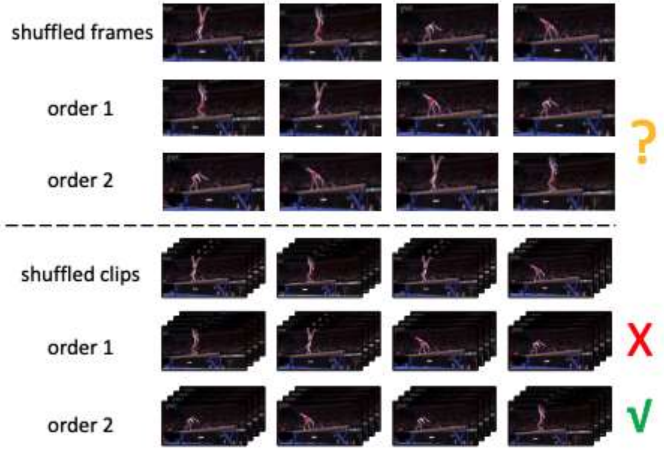
Wang et al. (2020): Predict pace.



Basura et al. (2017): Predict odd-one-out.



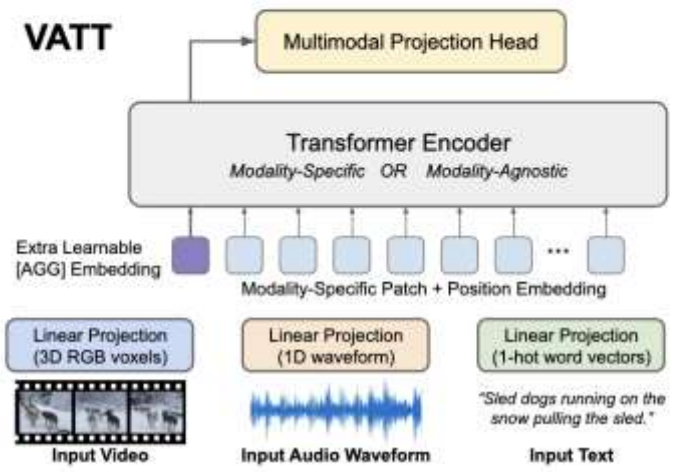
Recasens et al. (2021): Narrow to broad prediction.



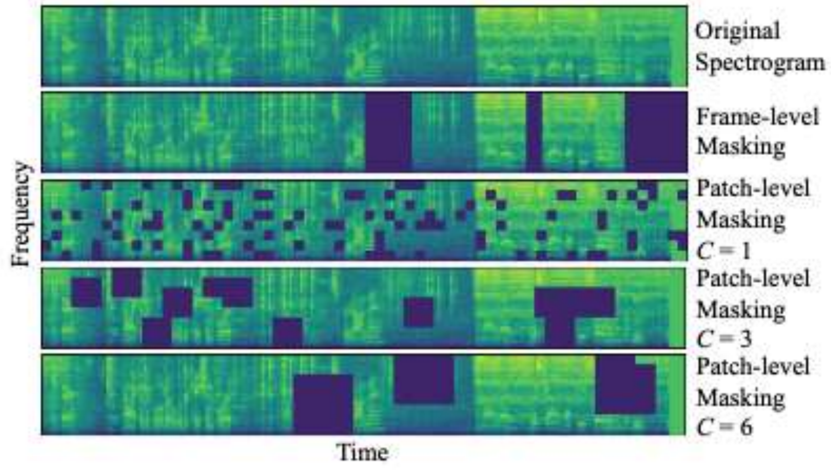
Xu et al. (2019): Predict clip order.

Break

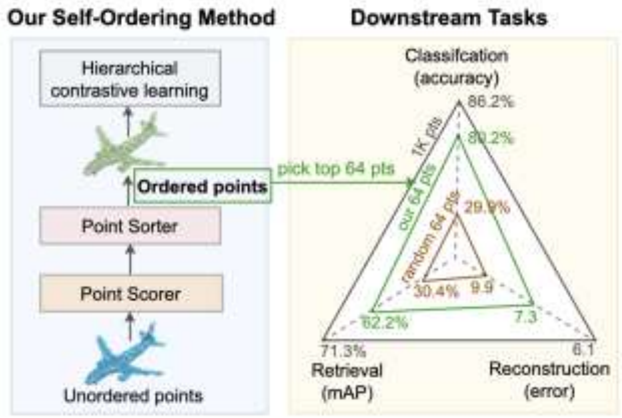
Self-supervised learning on other modalities



[Akbari et al. NeurIPS 2021]



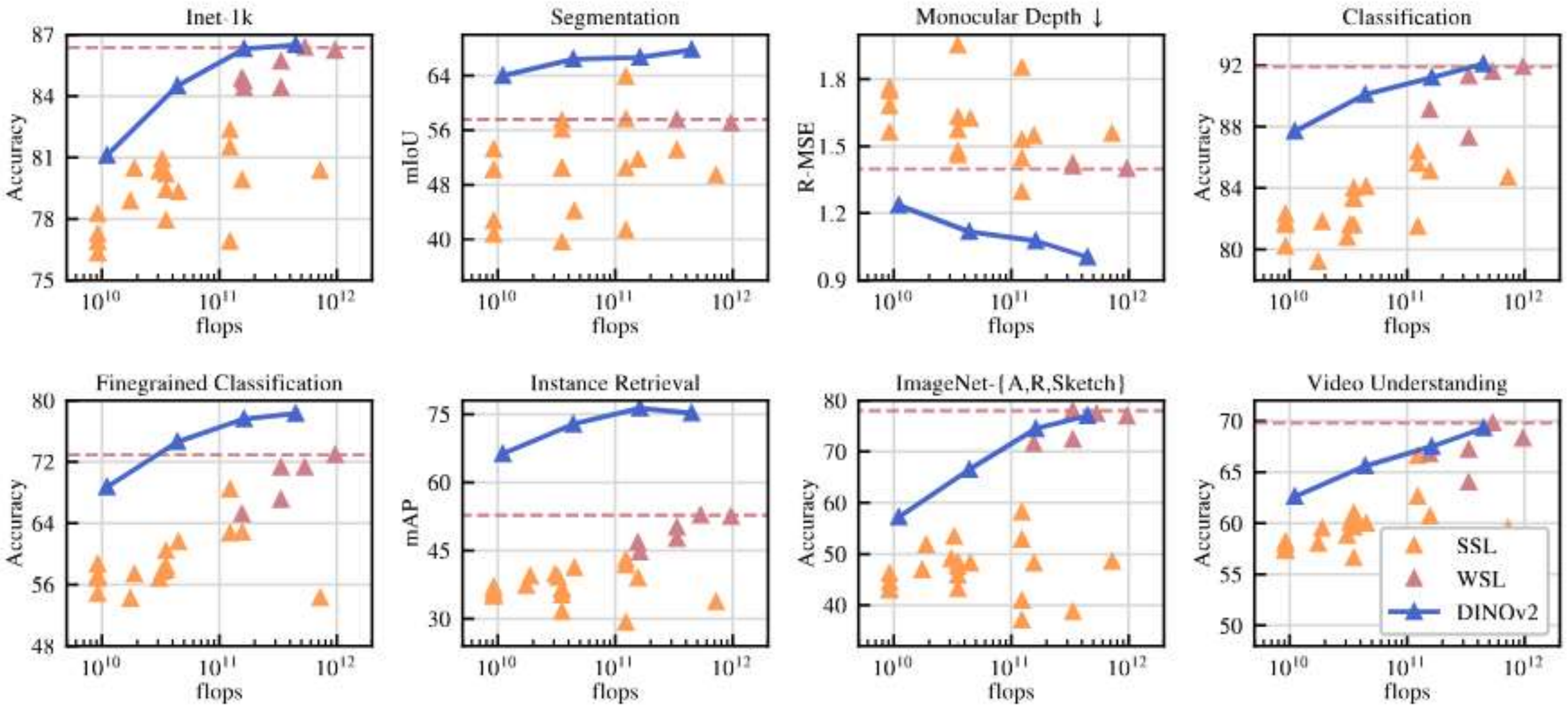
[Gong et al. AAAI 2022]



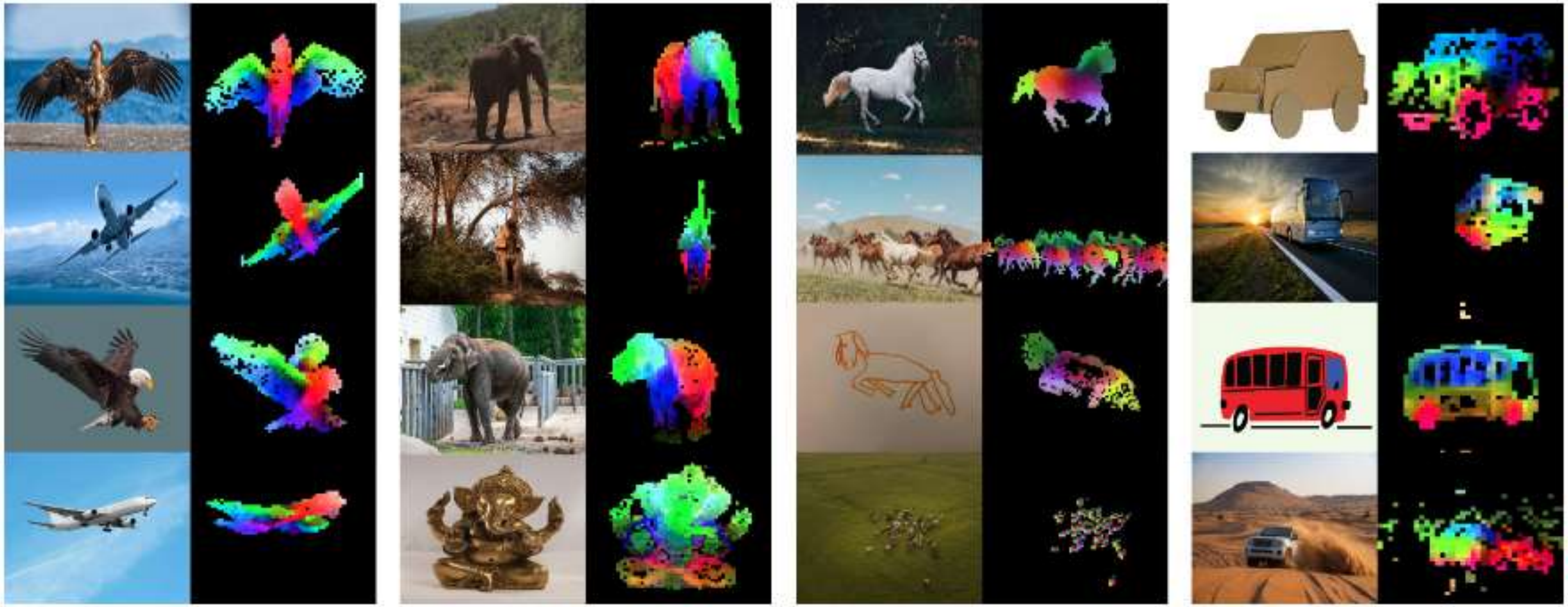
[Yang et al. ICCV 2023]

How good are self-supervised models?
A DINOv2 study

DINOv2 (2024): Contrastive learning + patch-level masking + tricks + 142M dataset.



How good are self-supervised models? A DINOv2 study


(a) (b) (c) (d)

Supervised networks struggle when being deployed in new settings, self-supervised networks thrive in such settings.

Self-supervised learning for language

What if our data is a collection of sentences?

“The quick brown fox jumps over the lazy dog.”

I.e., how can we train Large Language Models on the internet?

Masked Language Modelling

Main idea is simple: remove some tokens and predict them.

Set of classification labels:	All tokens.
Targets:	Tokens that were removed.

Just like self-supervised visual learning, the problem falls back to a standard classification setup, but now with “free labels”.

Masked Language Modelling

Standard setting: Sample 15% of tokens and replace with [MASK].

"The quick brown [MASK] jumps over the [MASK] dog."

Modified MLM: Sample 15% of tokens. Replace 80% with [MASK], 10% with random token, and 10% left unchanged.

"The quick brown [oven] jumps over the [maybe] dog."

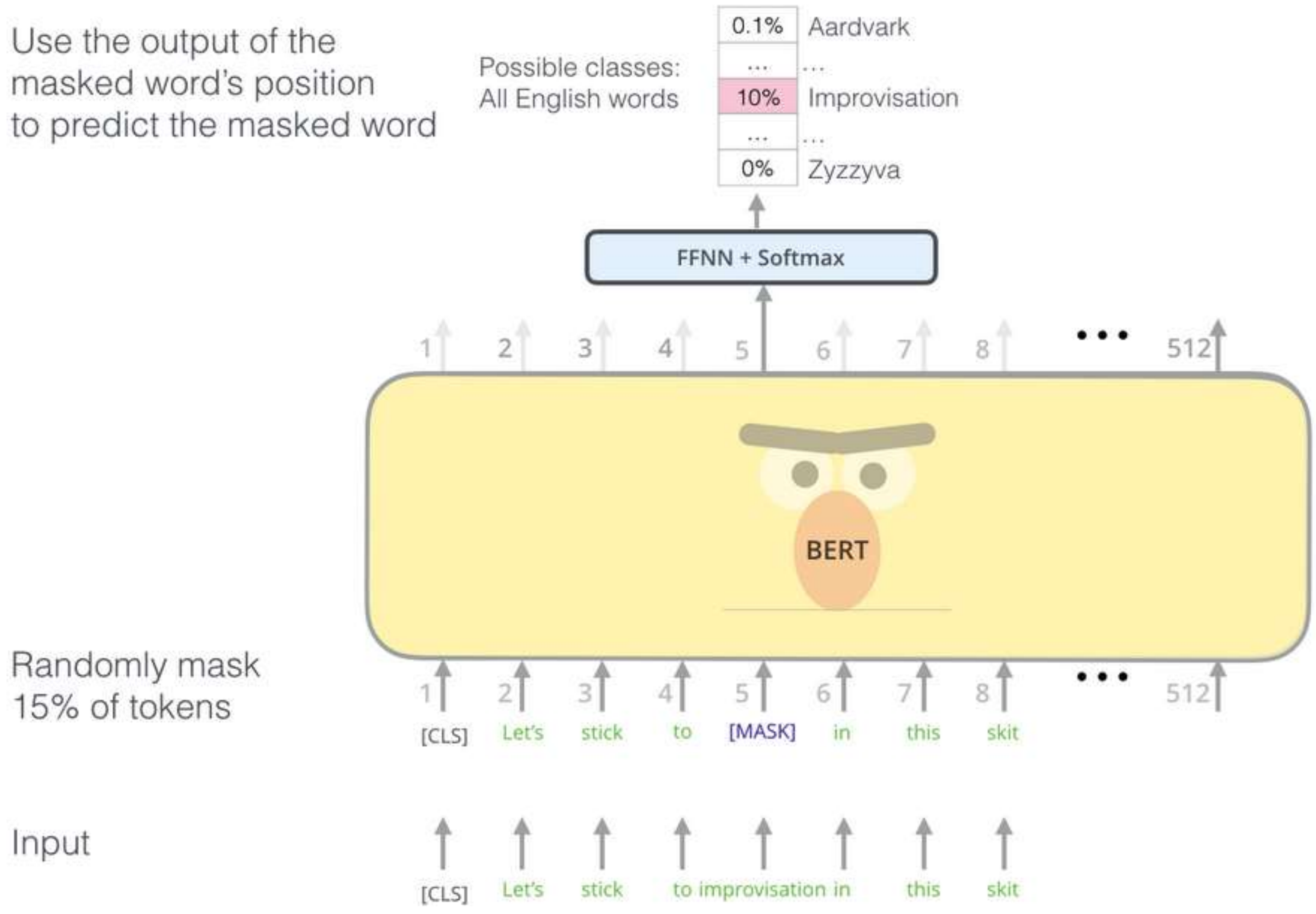
"The quick brown [fox] jumps over the [lazy] dog."

Modified Masked Language Modelling

For 80% of the sampled tokens, we simply need to predict the masked input.

For 10% of the tokens, the model needs to figure out that the word needs to be replaced.

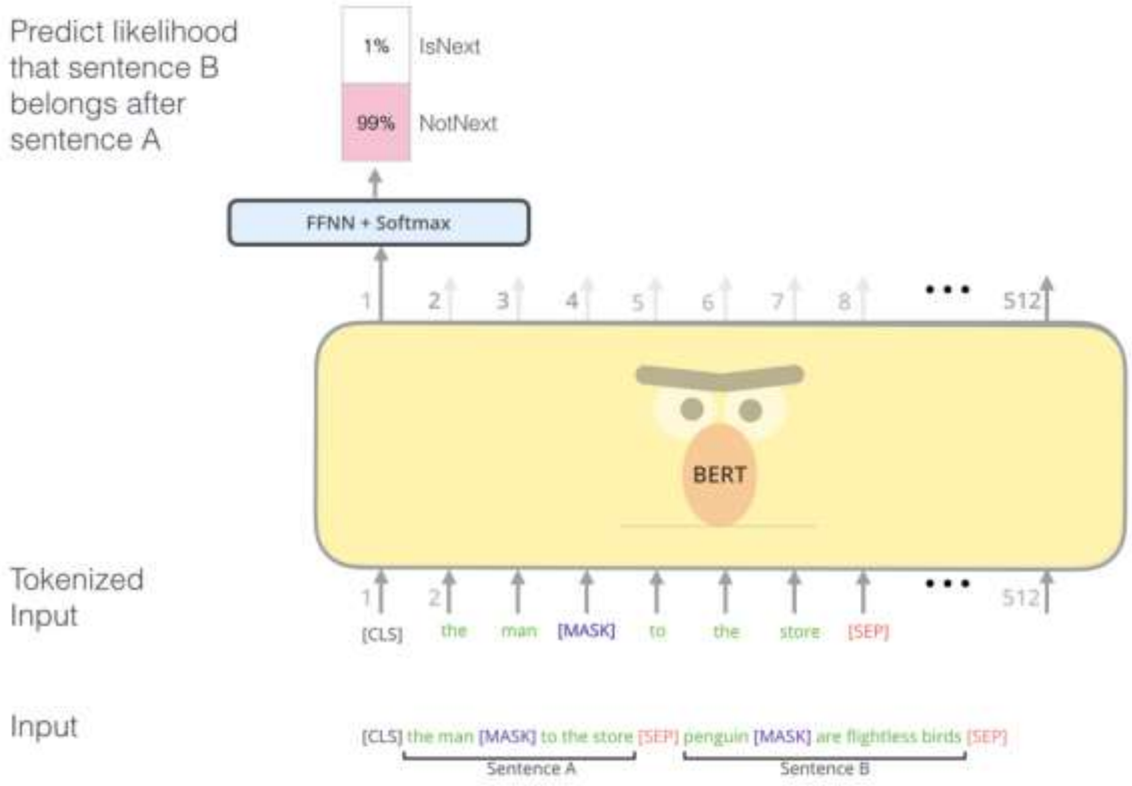
For the remaining 10%, the model needs to figure out to do nothing.



https://jalammar.github.io/illustrated-bert/

Next Sentence Prediction

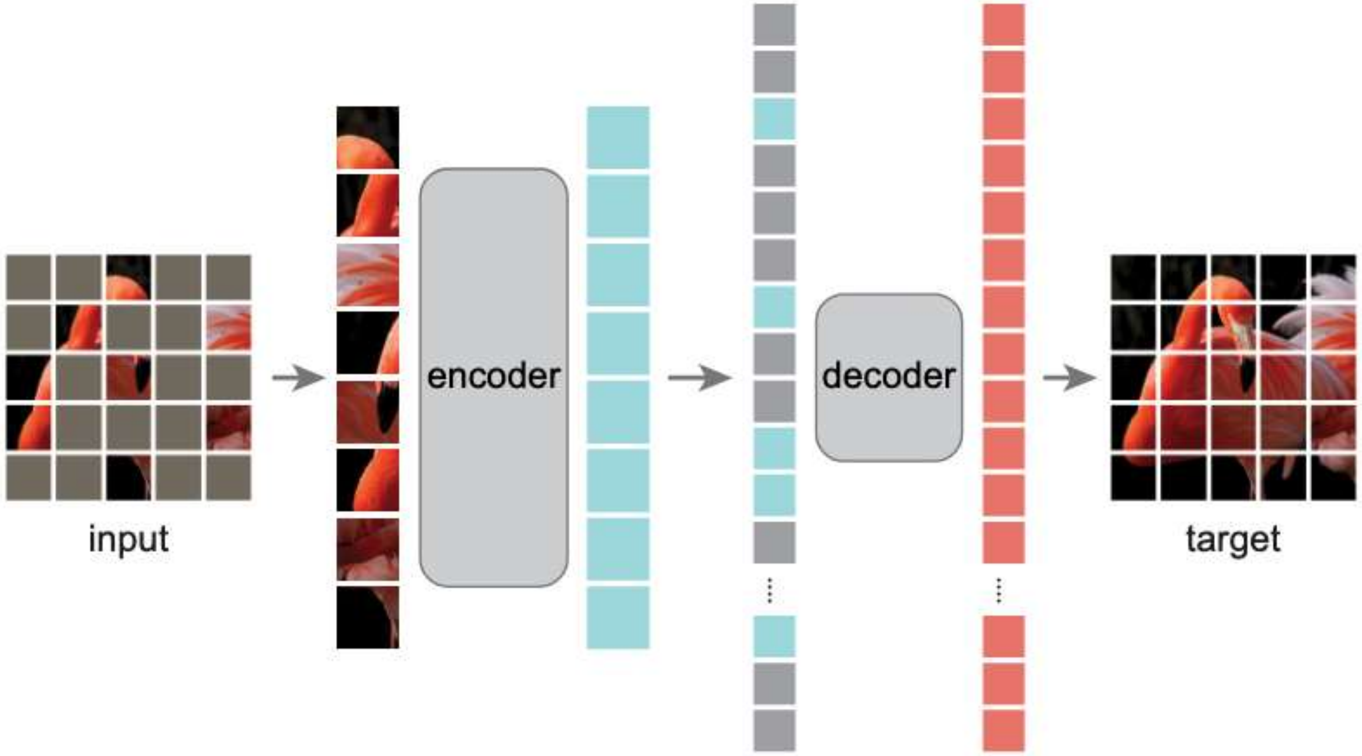
Main idea: Given two sentences, predict whether the first follows the second.



How to automatically generate “labels” for this setting?

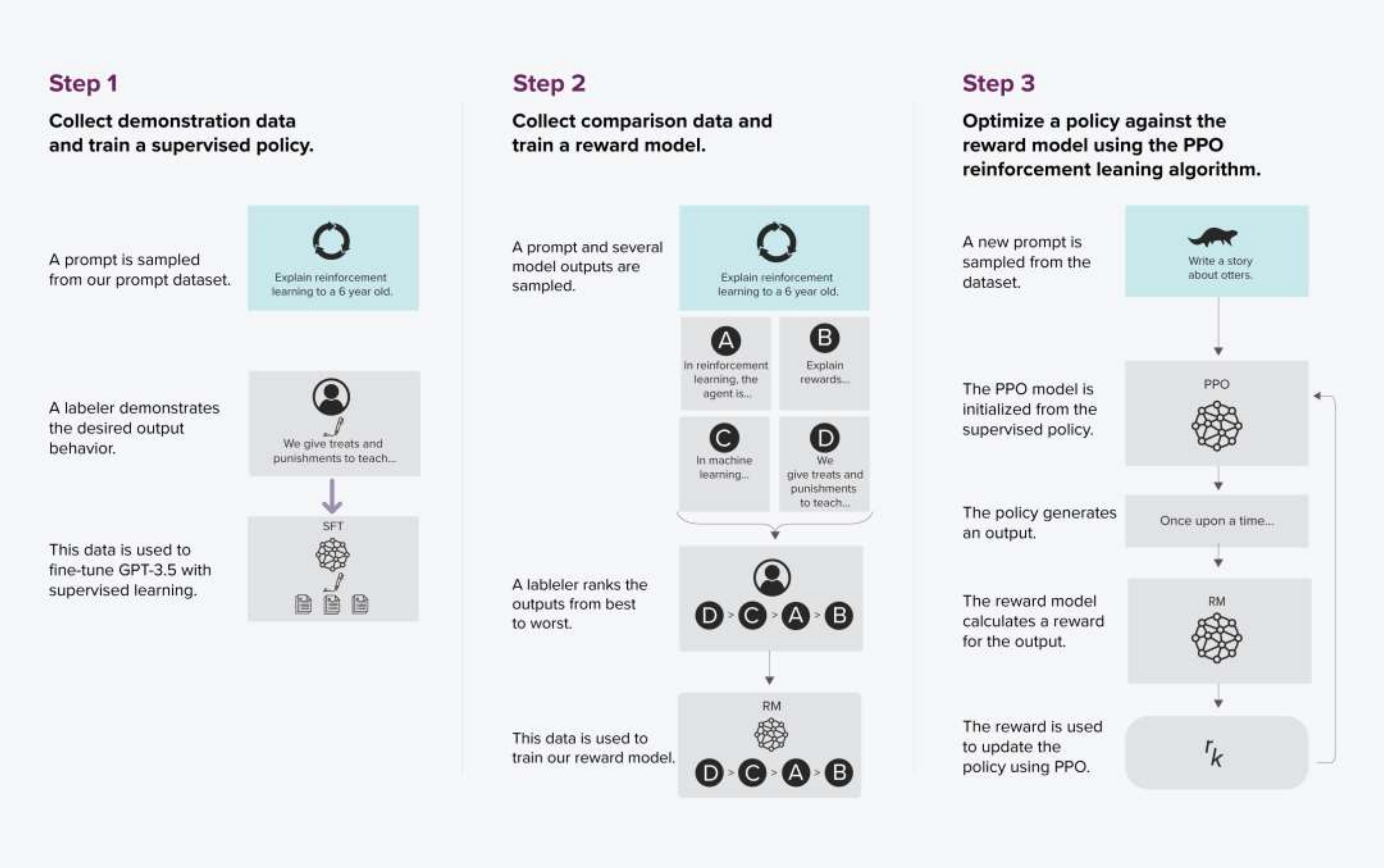
MLM in vision: masked autoencoding

Many ideas from one domain are inspiration for the next domain.



“Masked Autoencoders Are Scalable Vision Learners” He et al. CVPR 2022

Revisiting RLHF



RLHF from a supervision perspective

Self-supervision (GPT) is not enough for Large Language Models (ChatGPT).

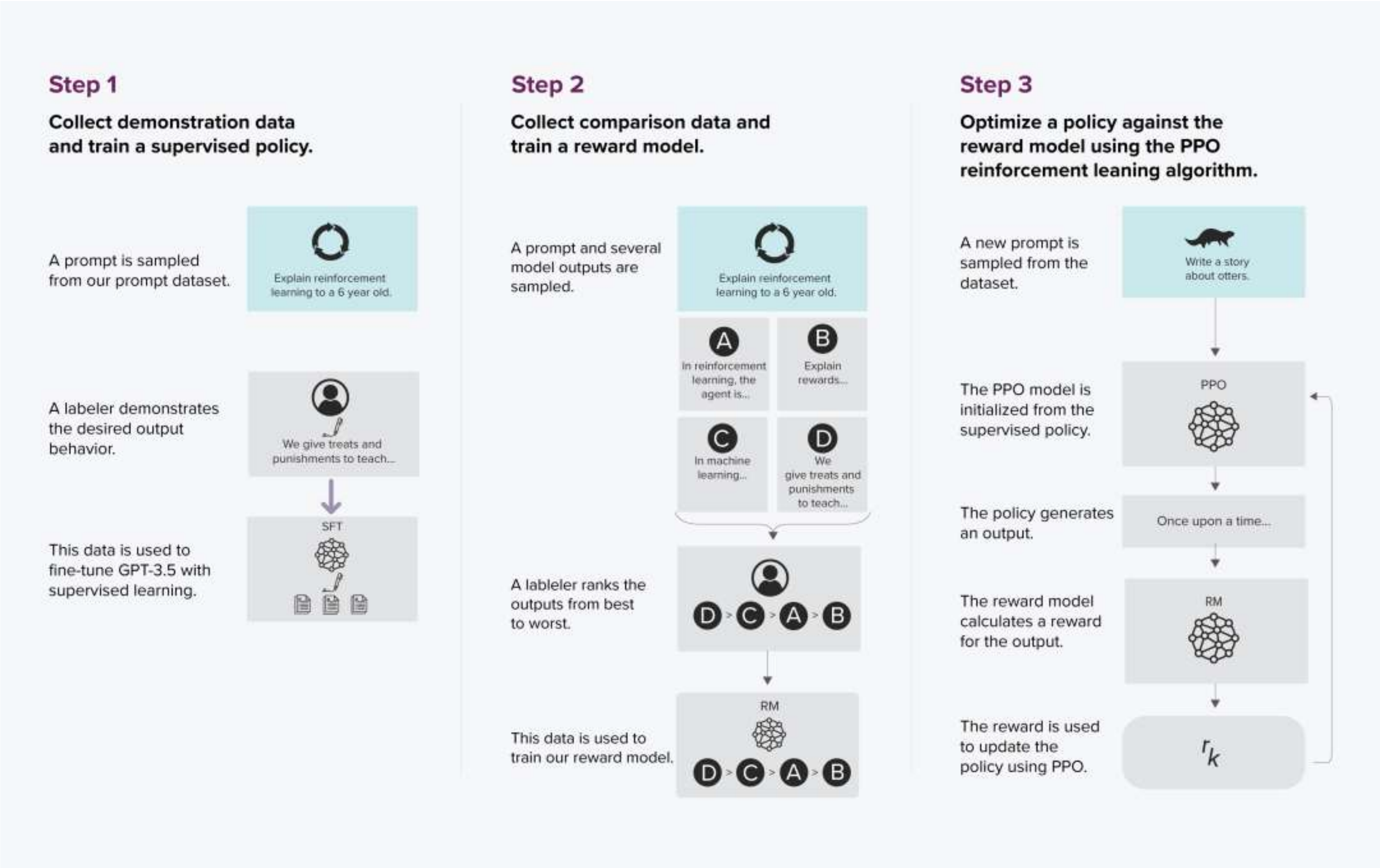
Prompt: Explain why we need water to survive as humans.

(Imaginary) GPT: Explain why humans die when not given any water.

What is going on here?

We lack alignment with the intent of the user input.

This needs human supervision.

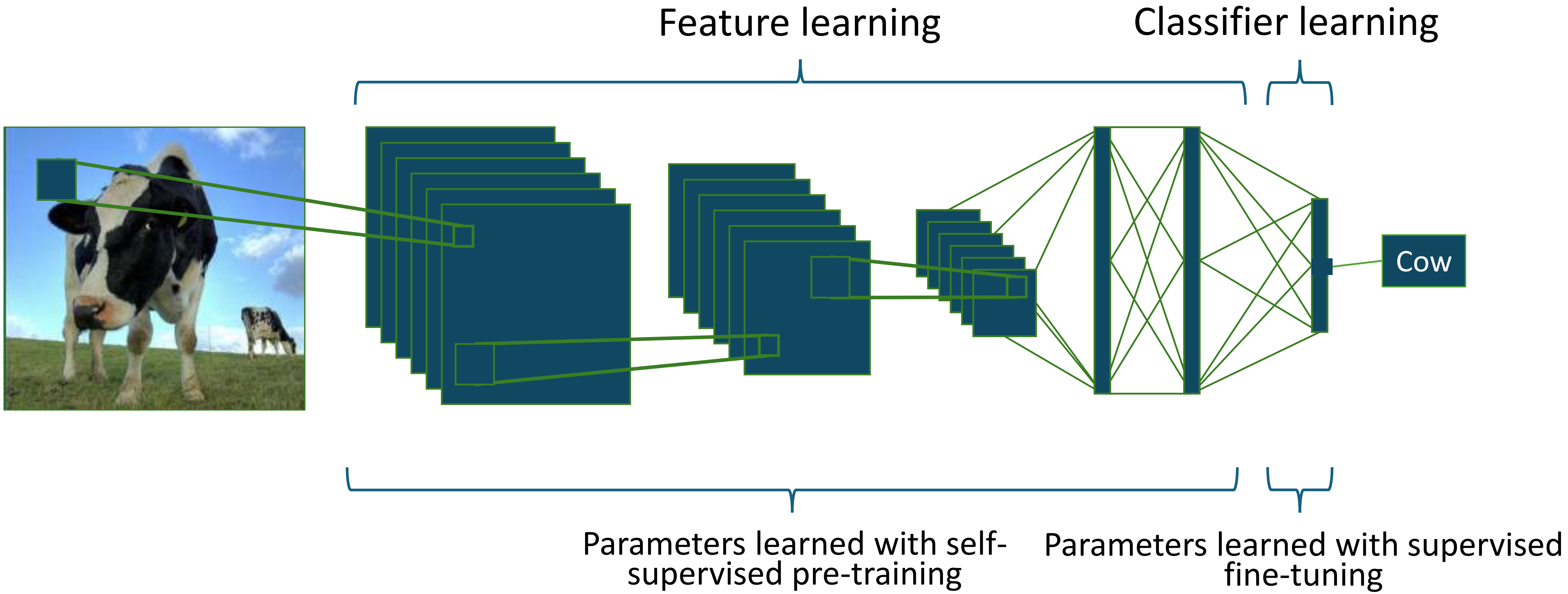

Step 1
Collect demonstration data and train a supervised policy.
A prompt is sampled from our prompt dataset.
Explain reinforcement learning to a 6 year old.
A labeler demonstrates the desired output behavior.
We give treats and punishments to teach...
SFT
This data is used to fine-tune GPT-3.5 with supervised learning.
Step 2
Collect comparison data and train a reward model.
A prompt and several model outputs are sampled.
Explain reinforcement learning to a 6 year old.
A
In reinforcement learning, the agent is...
B
Explain rewards...
C
In machine learning...
D
We give treats and punishments to teach...
A lableler ranks the outputs from best to worst.
D > C > A > B
RM
This data is used to train our reward model.
D > C > A > B
Step 3
Optimize a policy against the reward model using the PPO reinforcement leaning algorithm.
A new prompt is sampled from the dataset.
Write a story about otters.
The PPO model is initialized from the supervised policy.
PPO
The policy generates an output.
Once upon a time...
The reward model calculates a reward for the output.
RM
The reward is used to update the policy using PPO.
r_k

LLM = Transformer + self-supervised pre-training + human aligned tuning

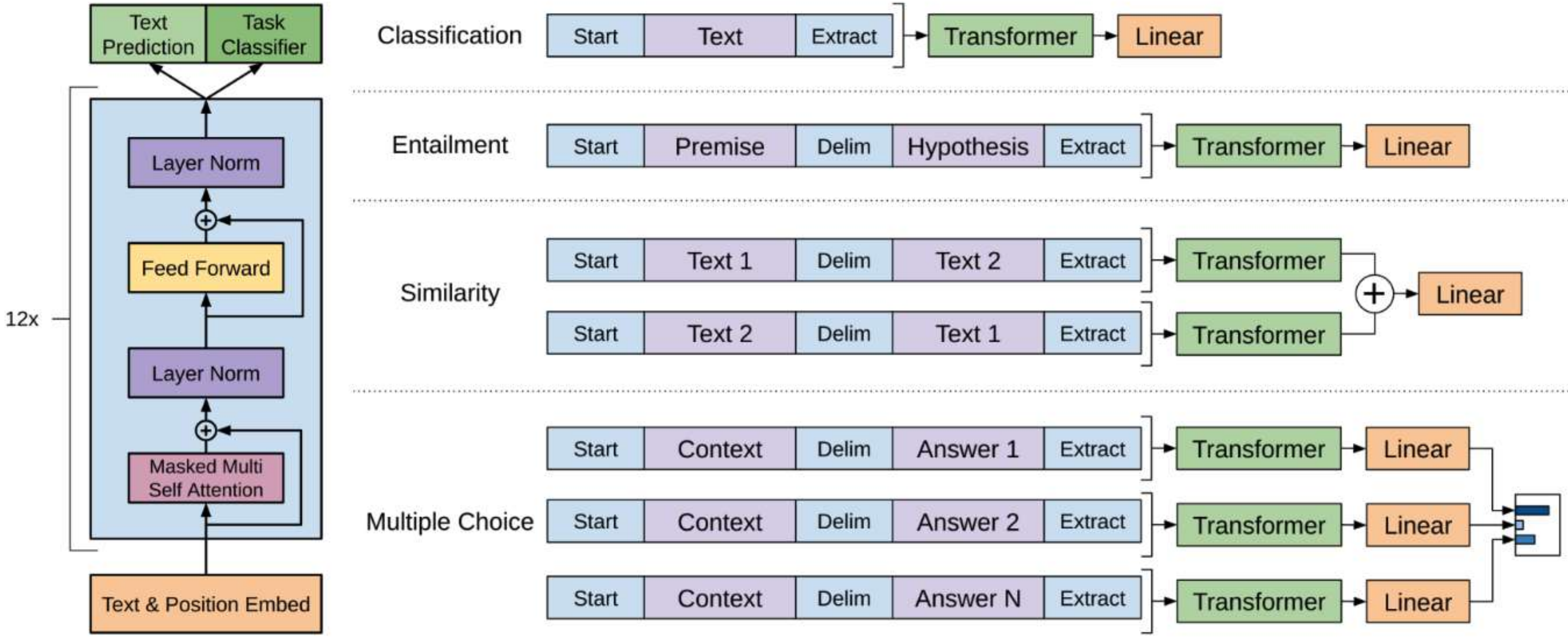
Discussion: why are they so good? And is this all you need for deep learning?

Is there something in between supervised and self-supervised learning?

Classical setup: pre-training and fine-tuning

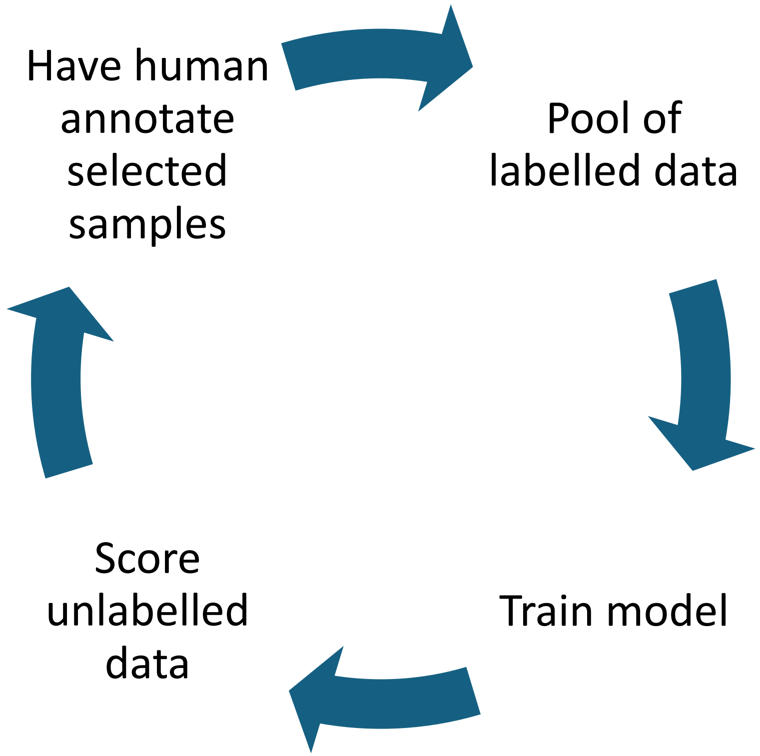


Examples of fine-tuning in language



Active learning

Assume we only have an unlabelled training set. Is it possible to simultaneously label samples and train a model?



Which samples to select?

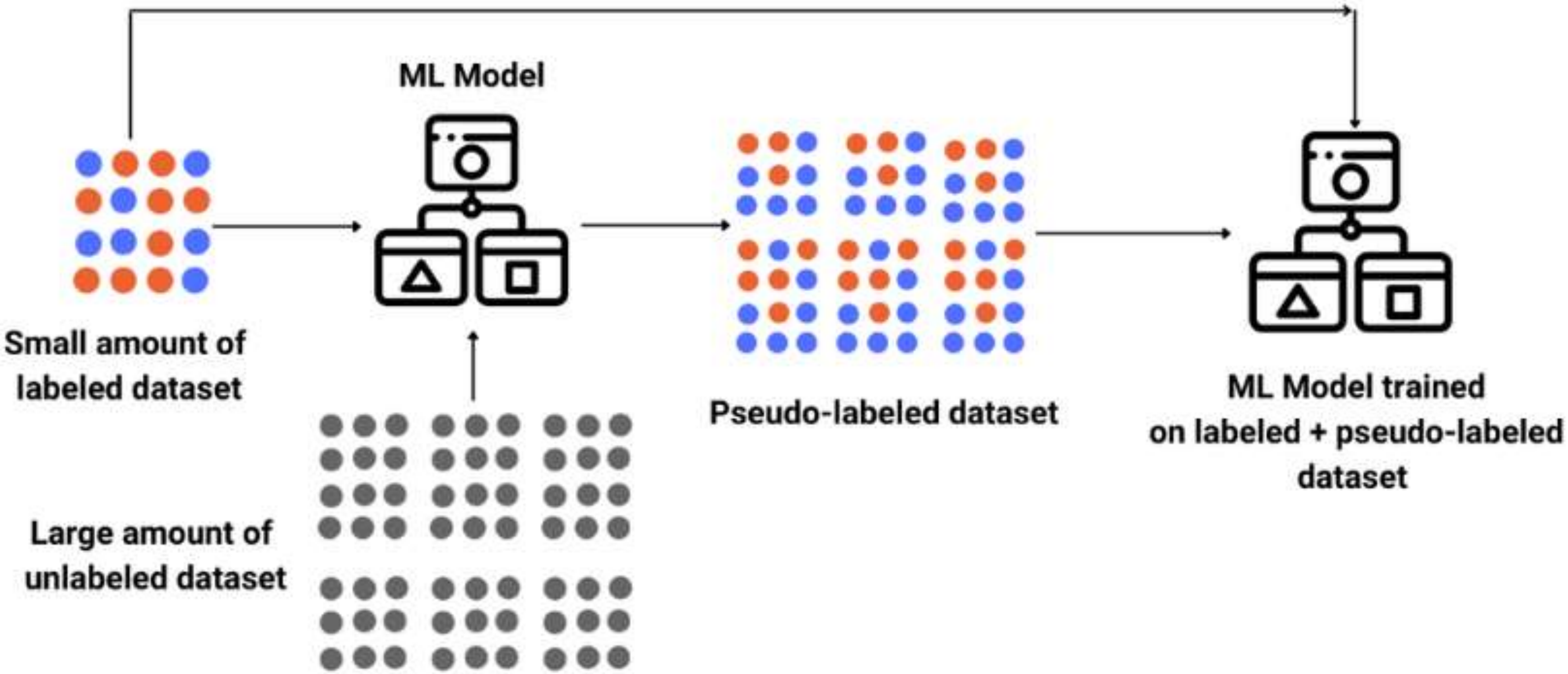
Random: randomly select (ignore scoring).

Most uncertain: closest to the decision bounary, or lowest norm in embedding space (second to last layer), or highest likelihood entropy.

Group-based metrics: Uniformity over classes to avoid biases.

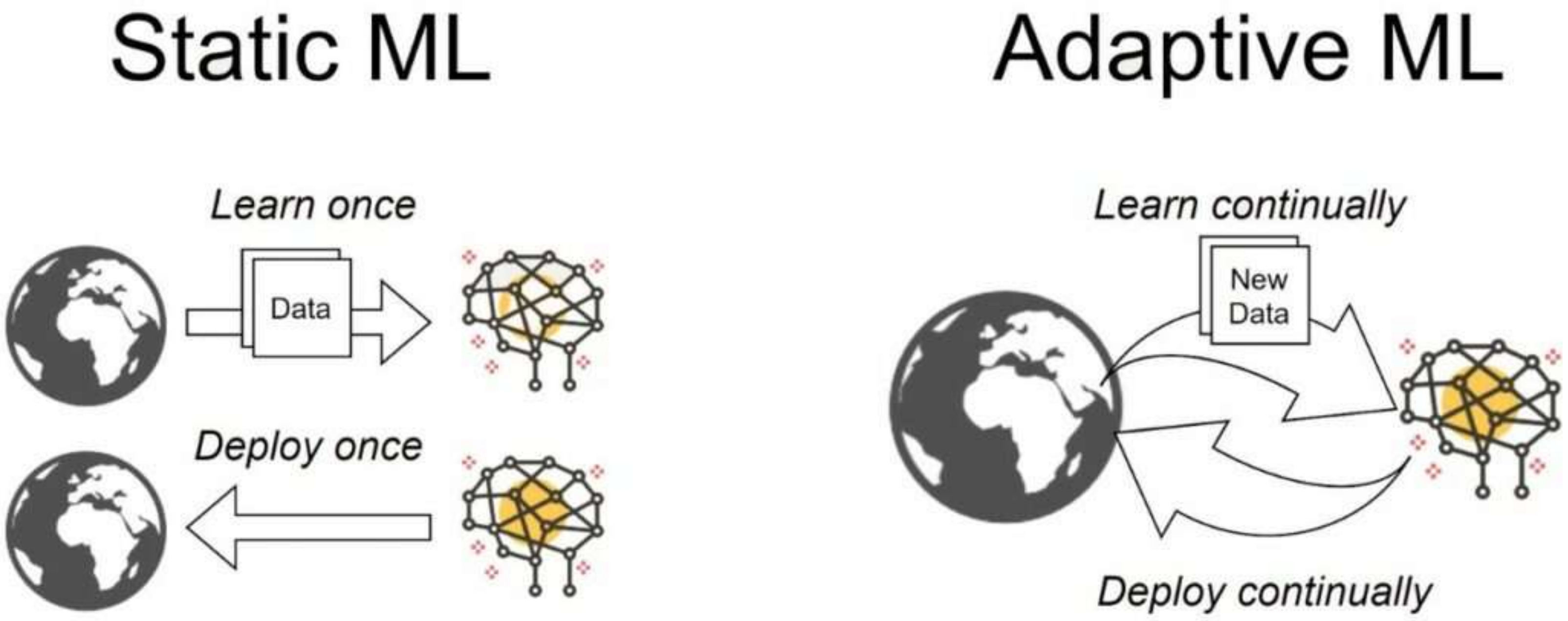
Mix: Combine a mix of X% random and (100-X)% uncertain+group.

Semi-supervised learning



Continual learning

In the real world, there is no such thing as a static dataset.



Shockingly, we can’t just train on new data! Much more in lecture 11.

Is self-supervised learning truly without supervision?

My view on supervised vs self-supervised learning

Supervised learning

Label by sample.

Invariance defined
at global semantic level.

Self-supervised learning

Label by rule.

Invariance defined
at geometric or local semantic level.

Self-supervised learning is conservative supervised learning from pre-defined invariances.

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Learning and reflection

TODO

Thank you