Machine Learning and Artificial Intelligence

Lab 09 – Semi and Self Supervised Learning

24/05/2022

Learning types

- We have seen the typical learning paradigm in ML, which is that of learning based on labeled, ground truth examples a.k.a **supervised learning.**

- We have also seen how, relying on the notion of distance or density, ML algorithms can understand patterns in the data without needing any labels a.k.a **unsupervised learning.**

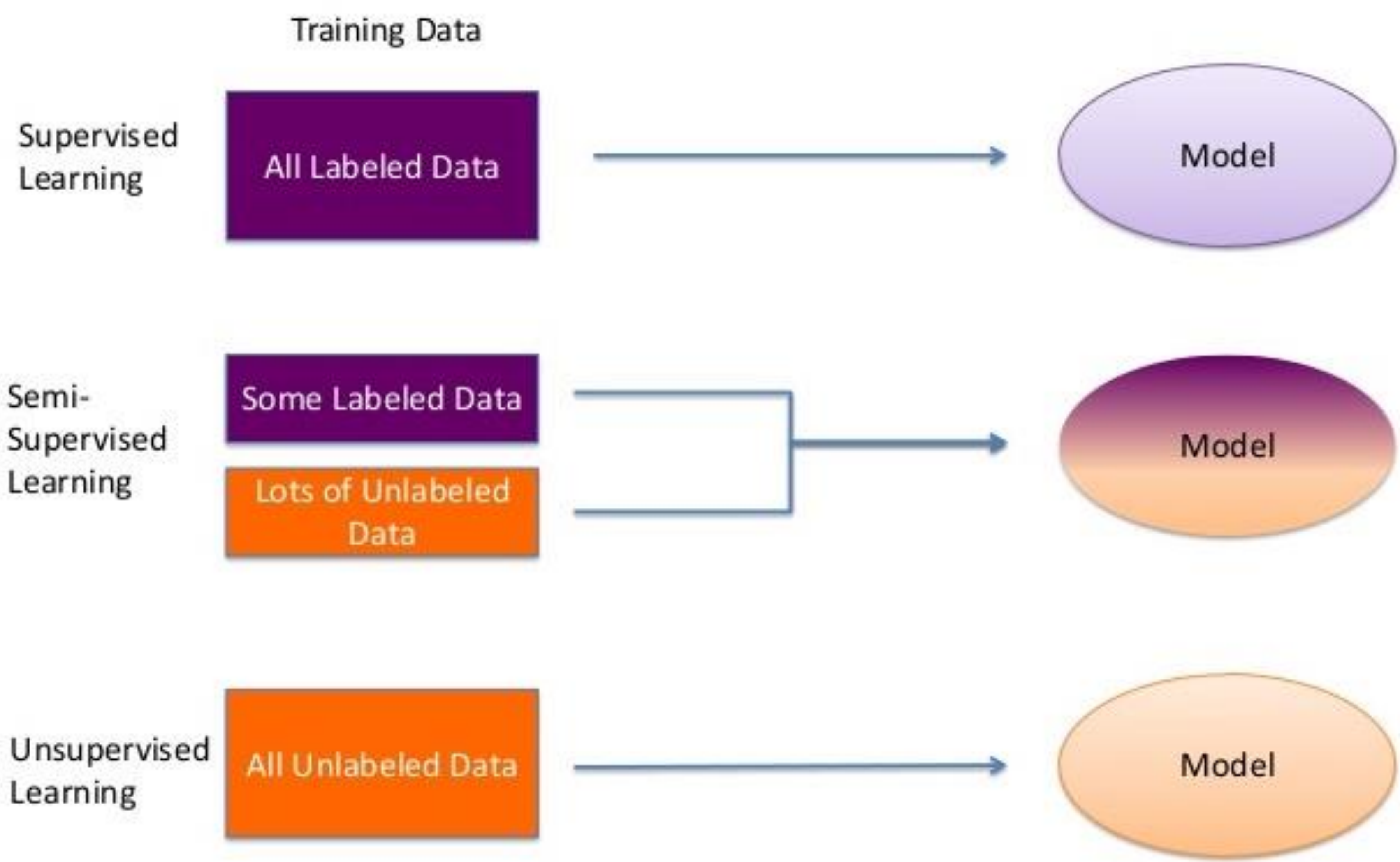
- Humans though can be considered to lie a silver lining between these two cases. We do not require millions of labeled data and multiple iterations for training. But we need a few guiding points and then we can create supervision for ourselves i.e., we can train ourselves and understand underlying patterns.

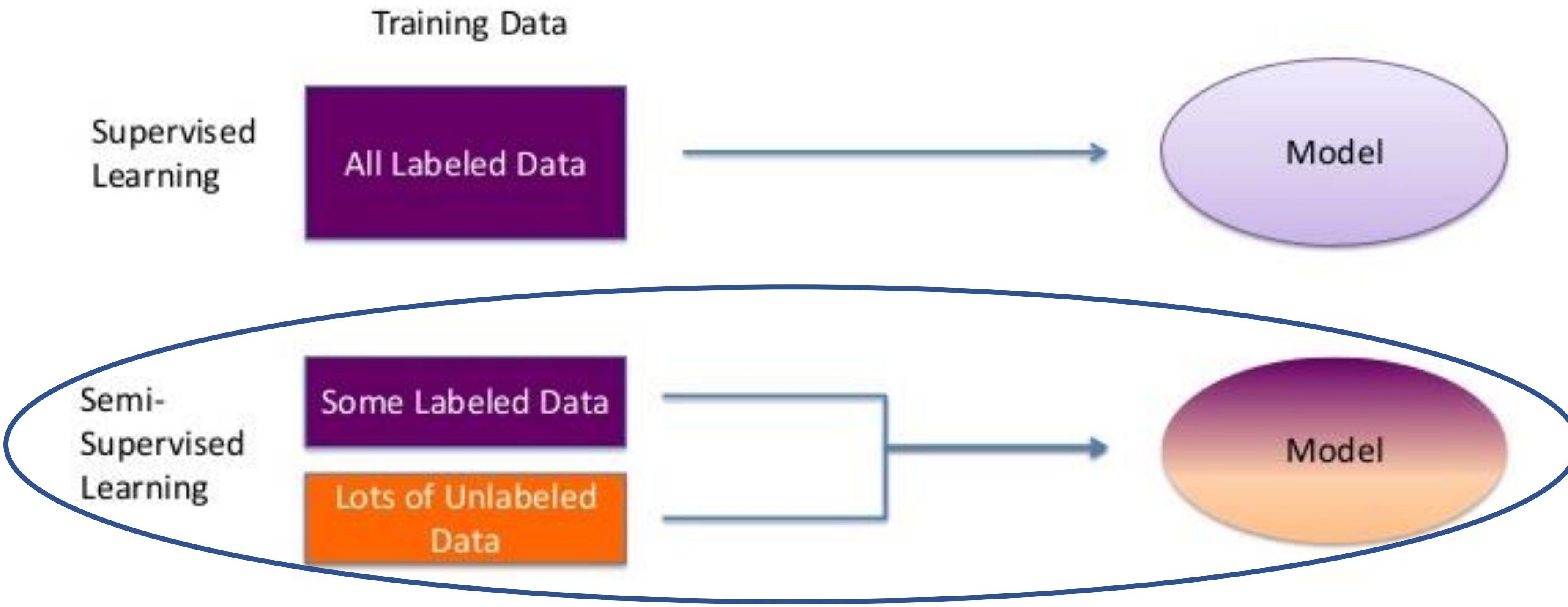
Learning types

- Two viewpoints:
  1. Instead of relying on labeled data, **create your own labels from unlabeled data and transform the problem into a supervised learning problem.** The idea here is that we wish to learn some kind of general features from the data, knowing that these are not going to be enough to perform extremely well on a task. Nevertheless, after **fine-tuning*** these features, we can get great performance with little cost.

  2. In practice, we'll often have a few labeled examples and then several unlabeled examples. This means we can try to first solve the problem in a supervised manner, based on the few data that we do have and then use what was learned in order to continuously train the model. This paradigm is called **semi-supervised learning**. Differently from case 1, semi-supervised learning is applied directly to the desired task and therefore does not require what is known as a pretext tasks, i.e., a task which creates the general representation of the data

* Fine-tuning refers to the process of specializing some general features learned previously in order to become more representative of the current task. It is a very powerful and important concept stemming from the macro-area of transfer learning, and we will explore it in the following labs.


Training Data
Supervised Learning
All Labeled Data
Model
Semi-Supervised Learning
Some Labeled Data
Lots of Unlabeled Data
Model
Unsupervised Learning
All Unlabeled Data
Model



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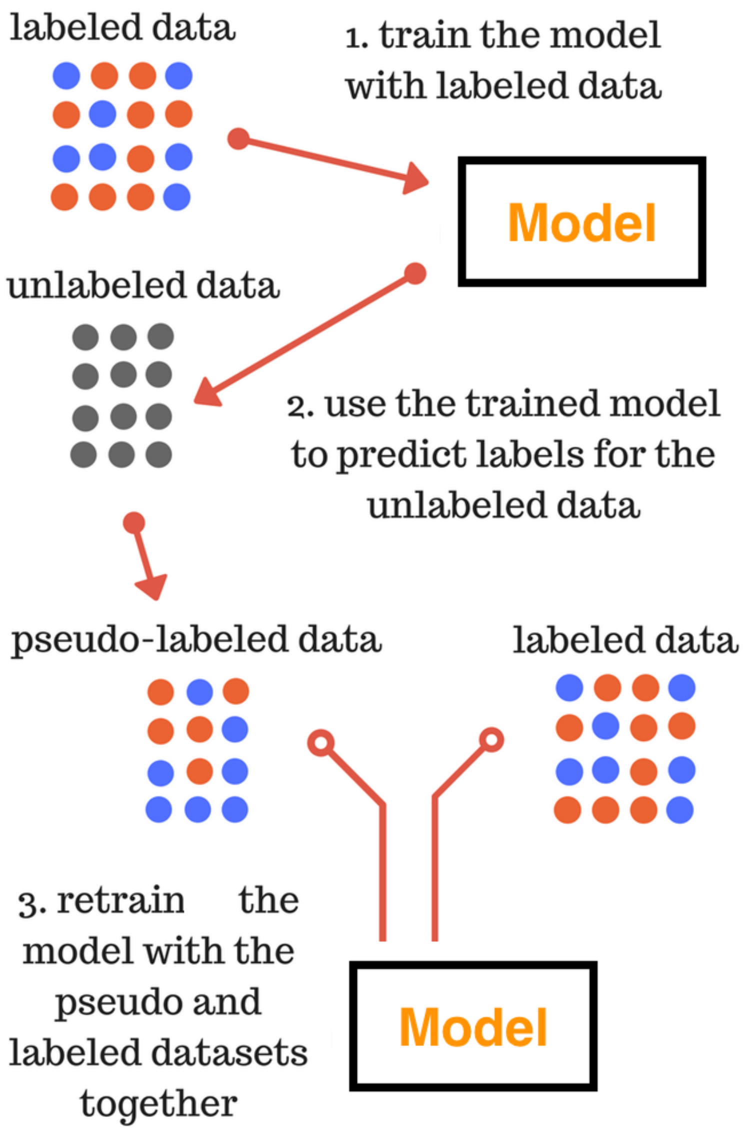
Model

Advantages of SSL

1. Allows us to take advantage of unlabelled data, which is abundant and cheap (e.g. crawlers).

2. It improves the model robustness by introducing more examples and therefore possibly providing a more precise decision boundary.

Pseudo labeling



Practical problem: MNIST

We want to recognize and classify images of handwritten digits:
https://en.wikipedia.org/wiki/MNIST_database

The MNIST dataset is fully labeled but let's simulate a more "realistic" scenario where we have managed to label only 1000 digits, meaning 100 labels per class. In this case, we could use SSL and Pseudo Labeling to harness the full power of the dataset.

Sklearn Links

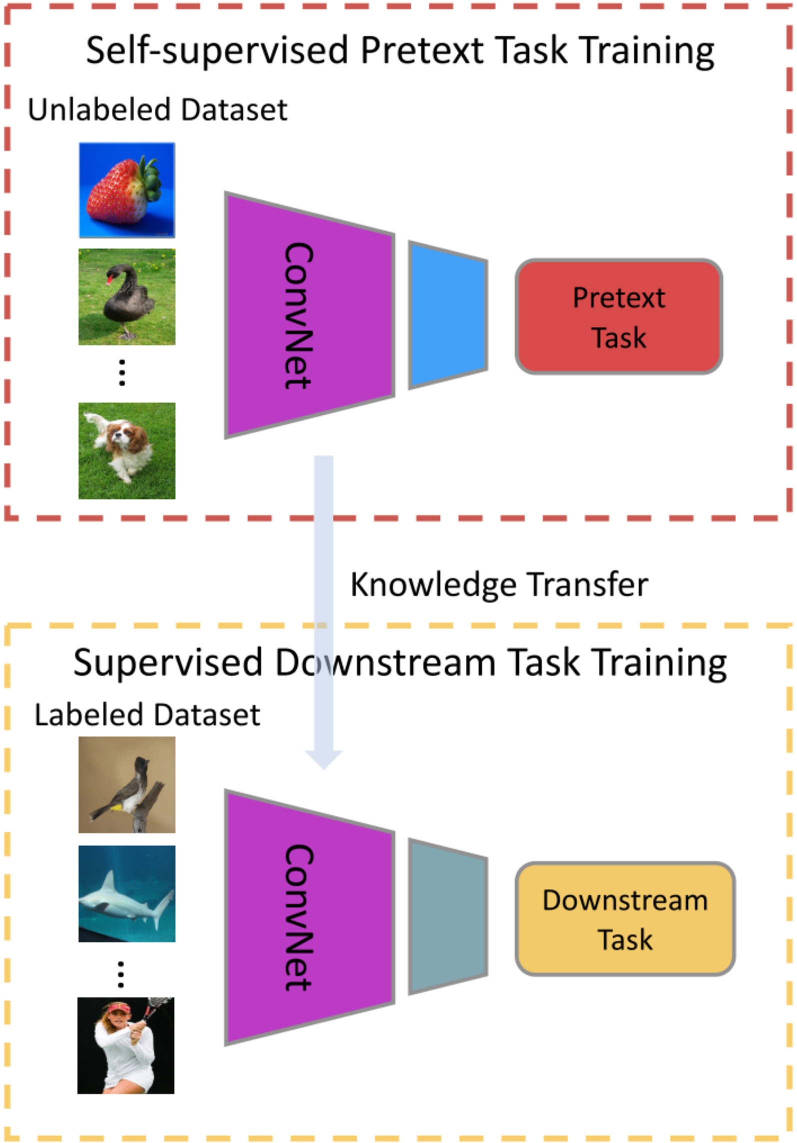
- https://scikit-learn.org/stable/modules/generated/sklearn.multiclass.OneVsRestClassifier.html

- https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html#sklearn.svm.SVC

- https://scikit-learn.org/stable/modules/classes.html#classification-metrics

Exercise

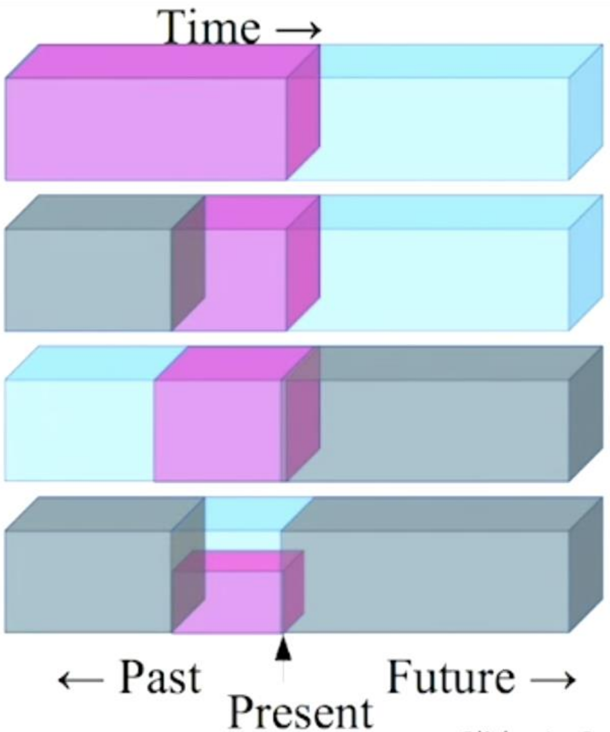
- Closely related to Deep Learning, but let's take another, more detailed look at **self-supervised learning.**



- A bit outside of the practical scope of this course, but it's useful to know that this kind of learning paradigm exists, since it can often be applied in the real world on big-data scenarios

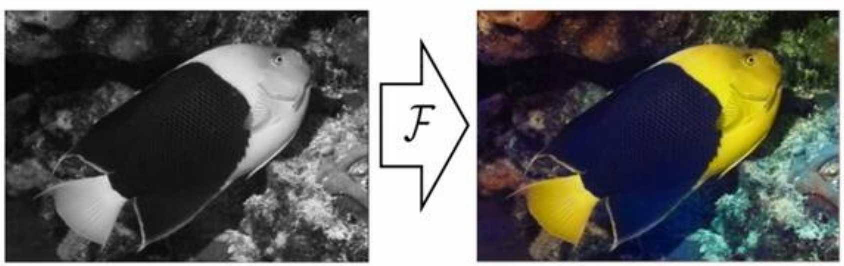
Sequential pretext tasks

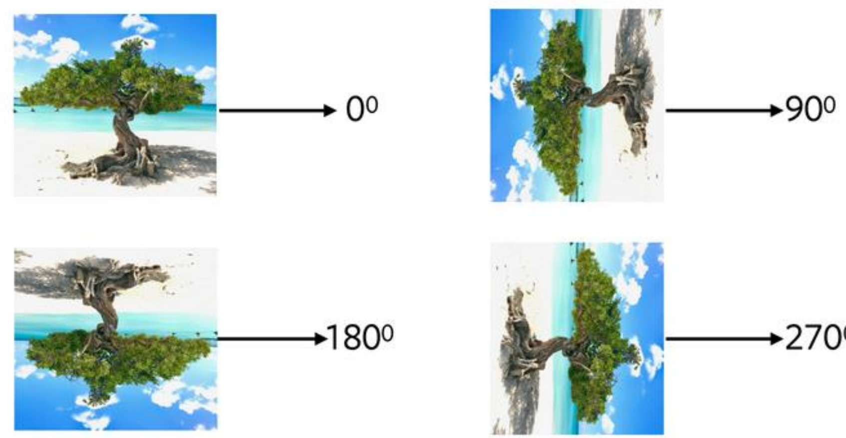
- Predict any part of the input from any other part.
- Predict the future from the past.
- Predict the future from the recent past.
- Predict the past from the present.
- Predict the top from the bottom.
- Predict the occluded from the visible
- Pretend there is a part of the input you don't know and predict that.



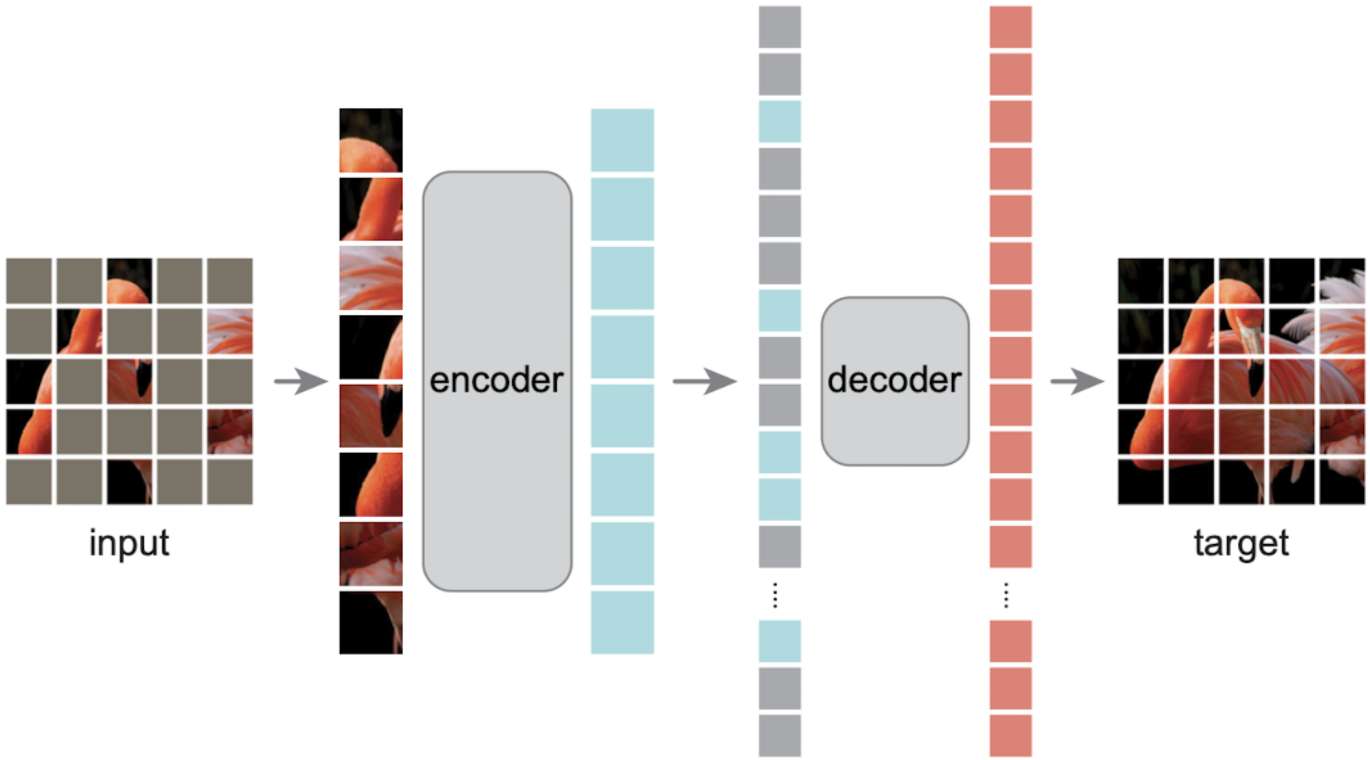
Slide: LeCun

Vision pretext tasks

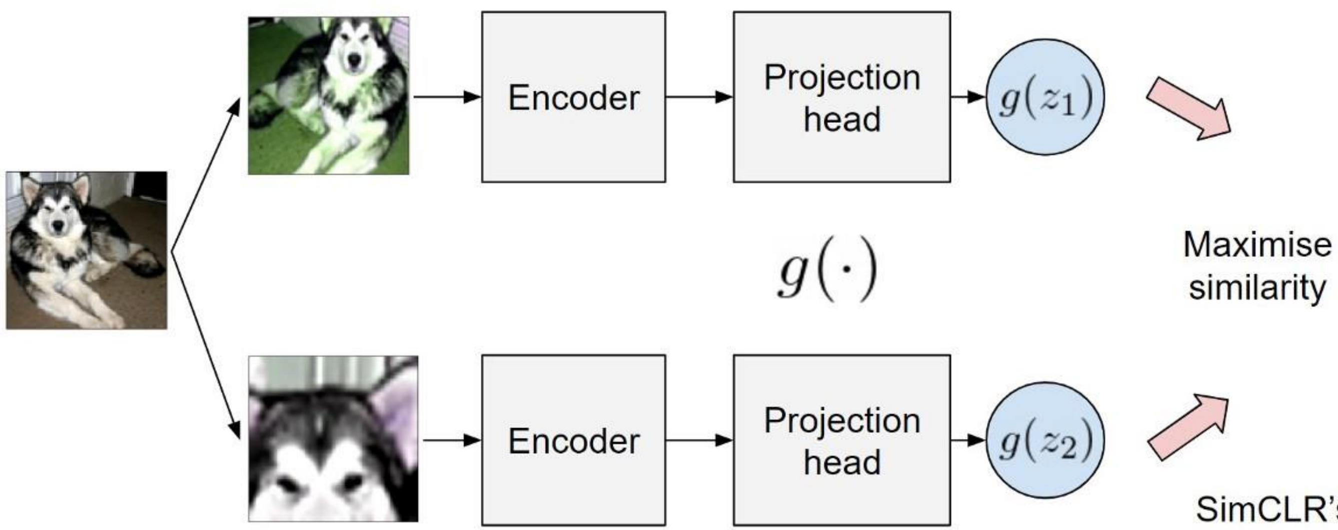




Pretext tasks – recent trends



Pretext tasks – recent trends



SimCLR's architecture (Chen et al., 2020)