Self-supervised Learning

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Methods Seminar, 29 April 20

Types of Learning

Supervised

Unsupervised

Semi-supervised

Reinforcement

Self-supervised

Types of Learning

- Supervised
- Unsupervised
- Semi-supervised
- Reinforcement
- Self-supervised

Supervised Learning

images

classes

0
1
2
3
4
5
6
7
8
9

Training data

Multiclass Classification →

classes

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Test data

Supervised Learning

Goal: Builds a function that can learn the **mapping between the input and the output**.

Pro: Classes defined, simple to understand

Con: Human-annotated labels, no complex tasks, cannot discover new patterns in dataset, wrong classification ...

→ **the most common case**

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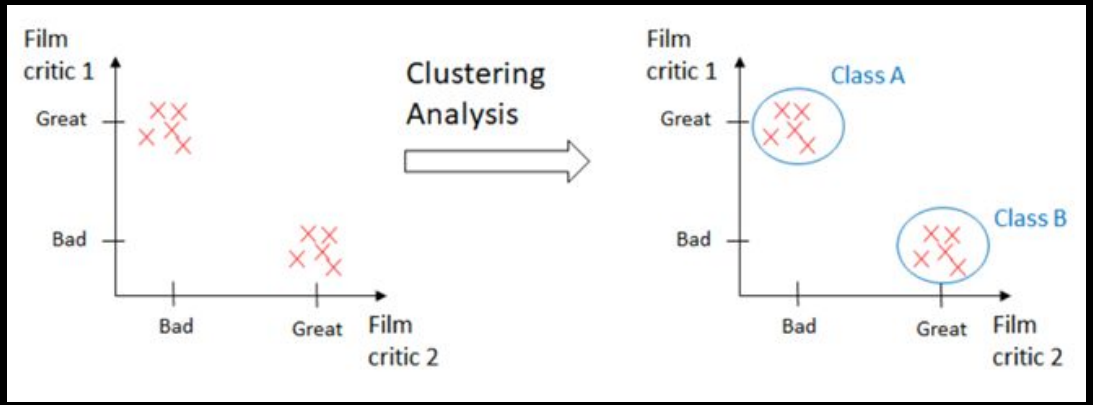
Unsupervised Learning

Goal:	**Detects new patterns** in a dataset with no pre-existing labels and solves the problem of **high-dimensionality.**
Pro:	No human-annotated labels, new patterns
Con:	Interpretation, changing patterns
Methods:	Cluster Analysis, Principal Component Analysis (PCA), Autoencoders, ...

Unsupervised Learning

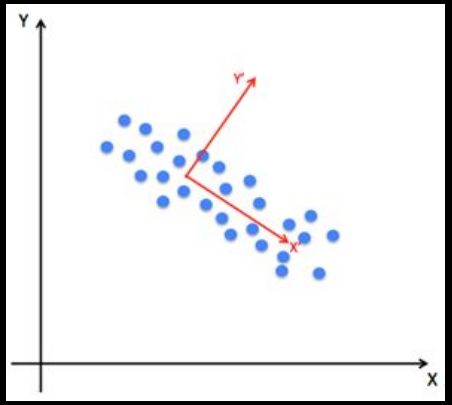
Cluster Analysis



https://towardsdatascience.com/unsupervised-machine-learning-clustering-analysis-d40f2b34ae7e

→ Finding new patterns or grouping

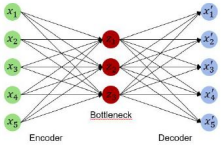
Principal Component Analysis



https://medium.com/machine-learning-bites/machine-learning-unsupervised-learning-principal-component-analysis-8f7ad311027e

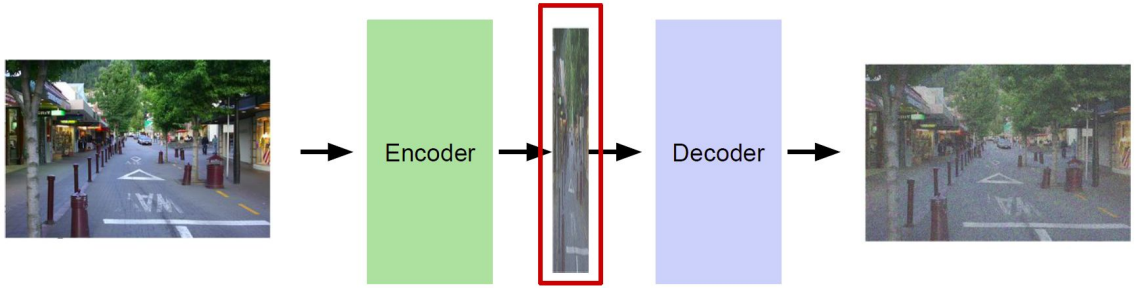
→ Reduce dimensionality

Autoencoders: Example



Shrink the input to lower dimension

Reconstruct the input image



Input

Latent space

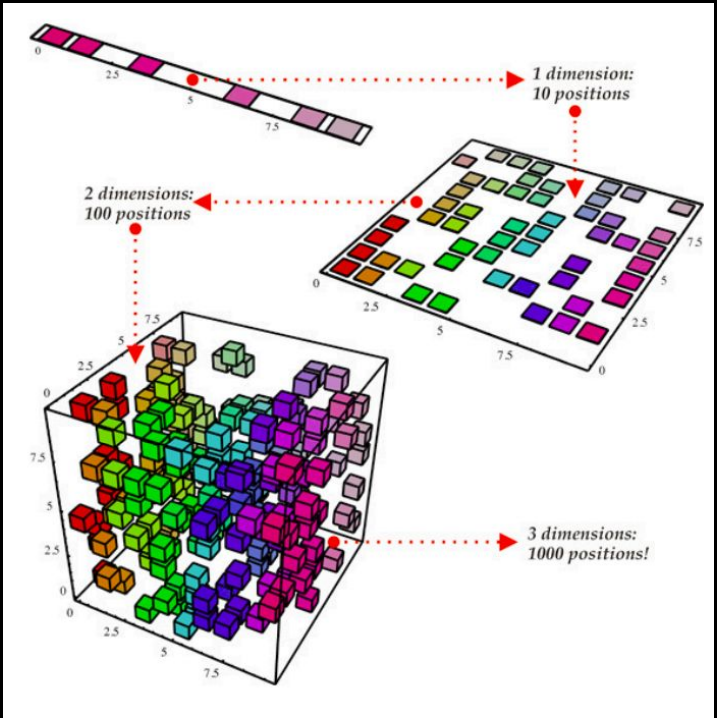
Output

Most relevant features

7

→ Reduce dimensionality

Unsupervised Learning: Dimensionality reduction



http://www.turingfinance.com/artificial-intelligence-and-statistics-principal-component-analysis-and-self-organizing-maps/

Problematic:

- Too many features
- Too many dimensions

→ overfitting

Curse of dimensionality

Solution:

Feature selection, feature extraction, ...

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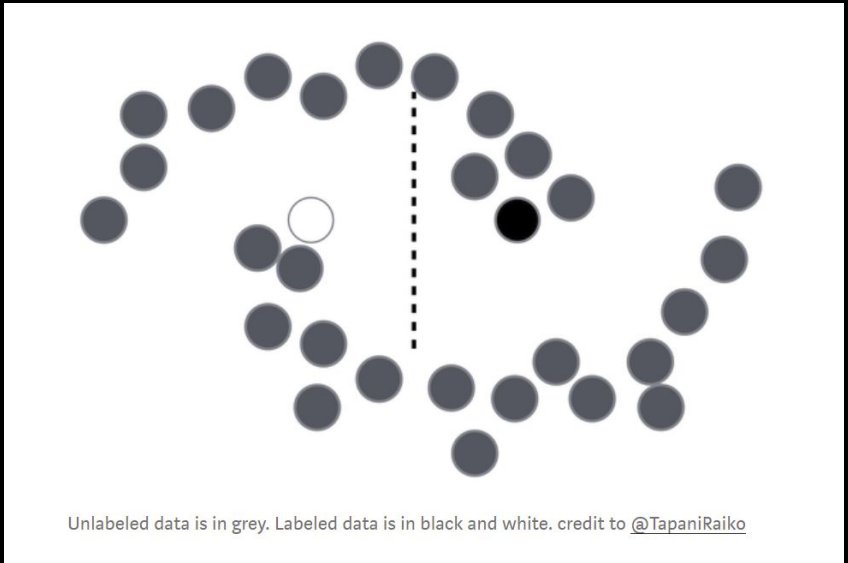
Semi-supervised Learning

Goal: Improves supervised learning by using a **small amount of labeled data** and **a large amount of unlabeled data**.



https://towardsdatascience.com/simple-explanation-of-semi-supervised-learning-and-pseudo-labeling-c2218e8c769b

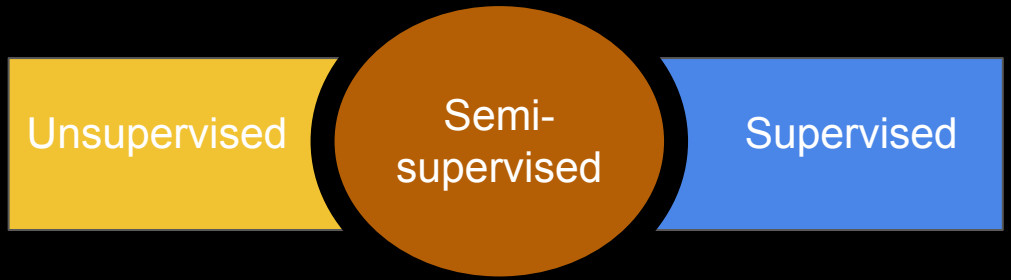
→ Gain valuable information from the unlabeled data

Semi-supervised Learning

Pro: Only few human-annotated labels, can improve model accuracy

Con: Difficult to build model

Methods: Generative models, Low density separation, Graph-based methods, ...



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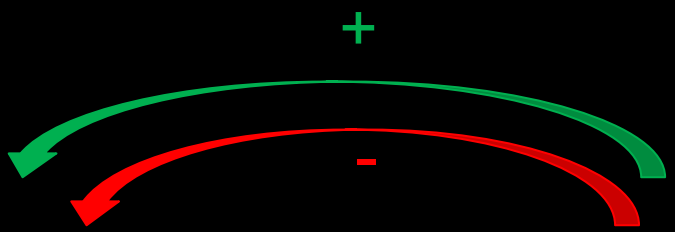
Reinforcement Learning



Actions

Reinforcement Learning

Goal: Find model that maximizes reward

Pro: Maximize performance

Con: Not efficient, expensive

Methods: Markov Decision Processes, Monte Carlo methods, ...

OK for games

NOT for real world

How do humans learn so quickly?

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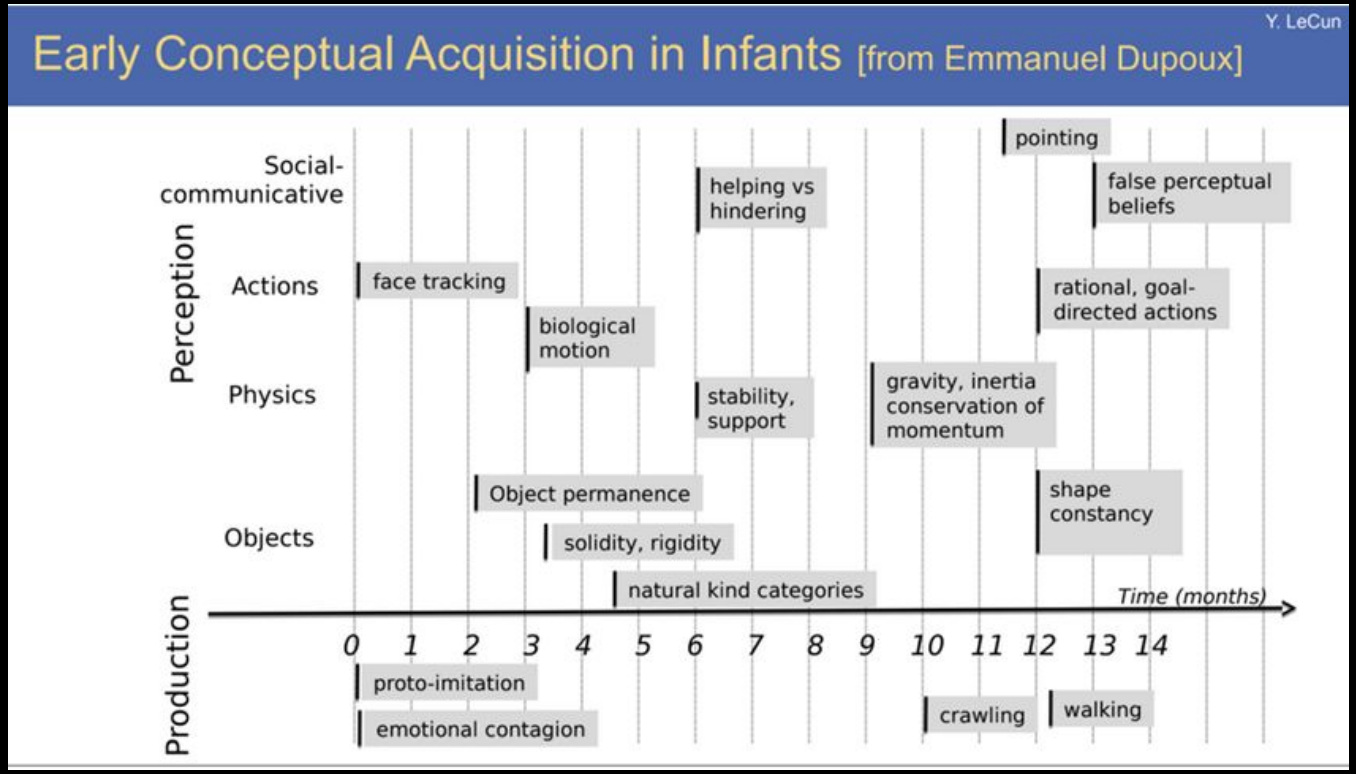
Self-supervised Learning



LeCun, Y

Self-supervised Learning

Pretext tasks

Pre-train the model with prediction tasks

- Automatically created pseudo labels used as training target
- Pretrained weights

Knowledge transfer

Take the parameter of the pretrained model as starting weights in a downstream task

Downstream tasks

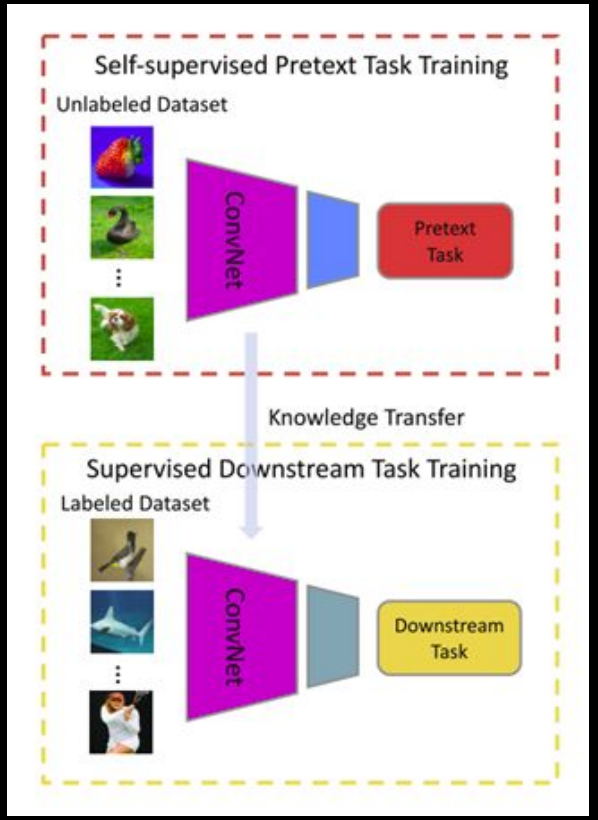
Fine tuning of the model (any supervised problem)

Self-supervised Learning

Goal: **Pre-trains the model** using automatically generated **pseudo-labels from the input data**.

Pro: No labels needed for pretext task, complex tasks

Con: Difficult to find relevant pretext task



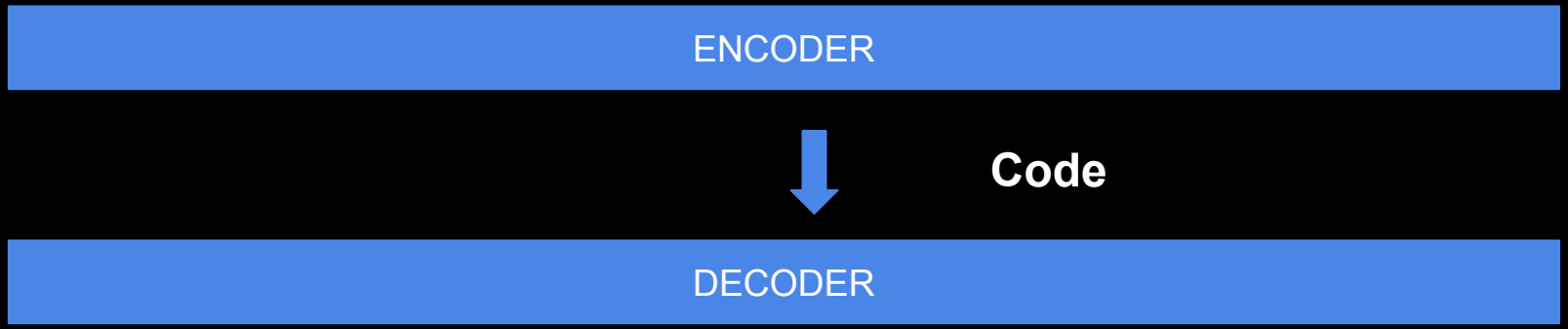
Jing, L et al. 2019

Self-supervised Learning: Pretext tasks

General	Autoencoder ...
Text	Future/masked word prediction ...
Images	Rotation Colorization Inpainting Superresolution Context prediction ...
Videos	Future/masked frame prediction ...
Audio	Restoration ...

Self-supervised Learning: Natural Language Processing (NLP)

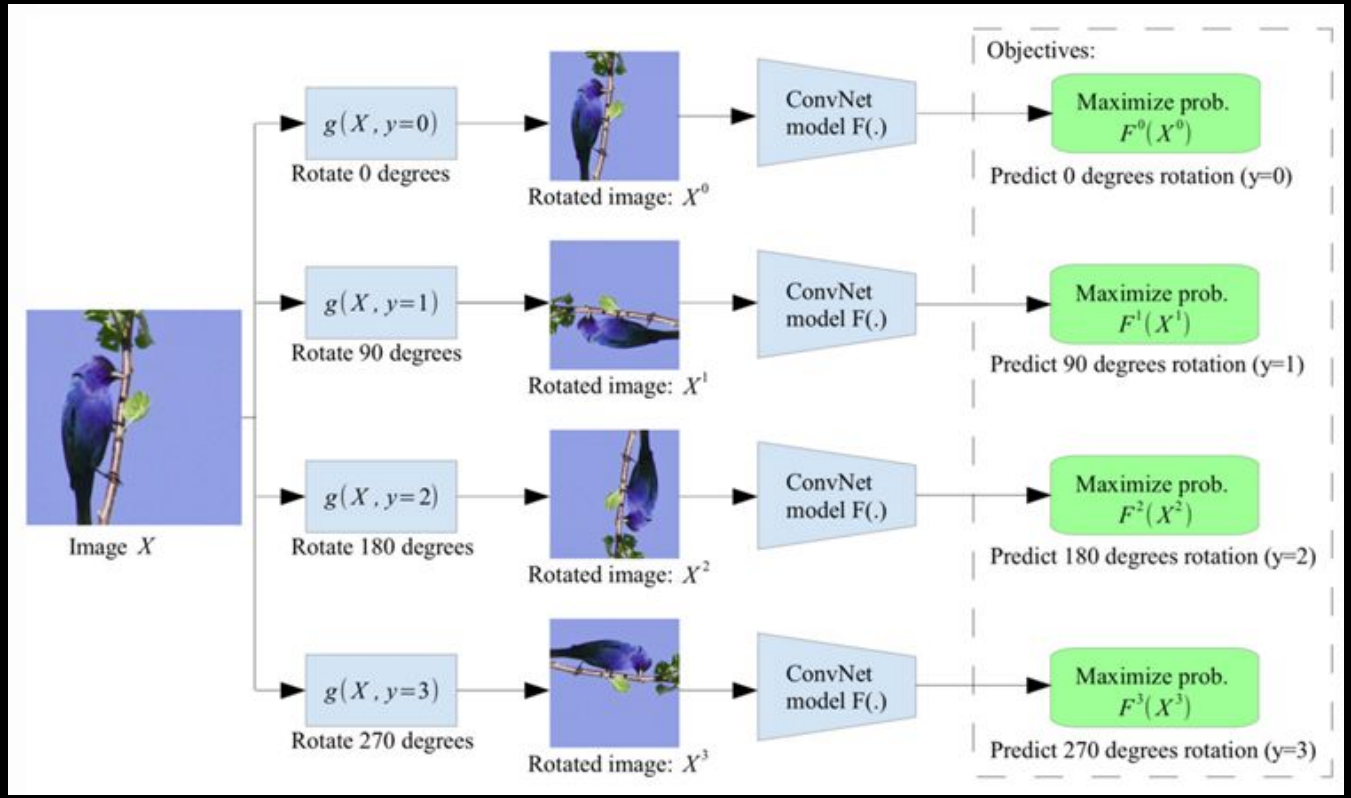
INPUT This is [...] with masked [...] we want to [...].



OUTPUT This is a text with masked words and we want to predict them.

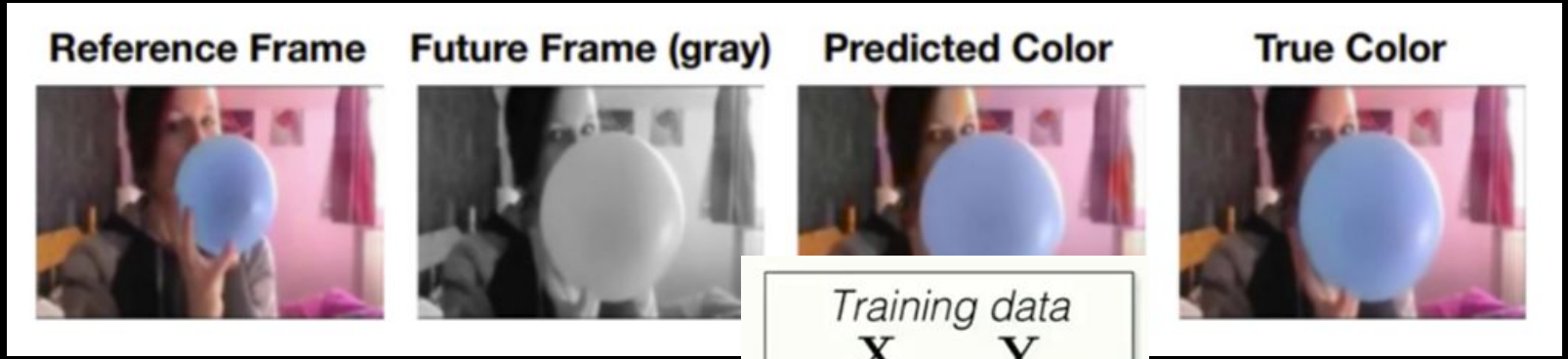
E.g. **BERT** is a technique for NLP pre-training developed by Google.

Self-supervised Learning: Rotation



Gidaris et al. 2018

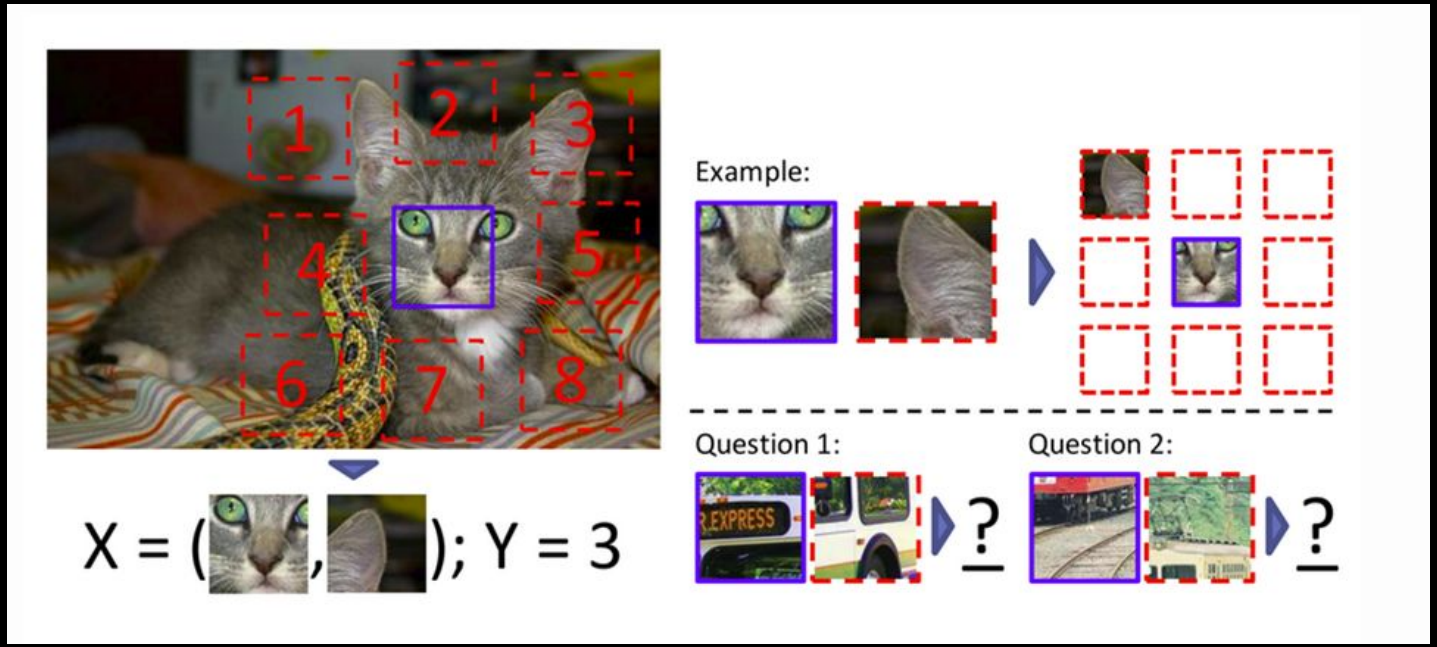
Self-supervised Learning: Colorization



https://www.fast.ai/2020/01/13/self_supervised/

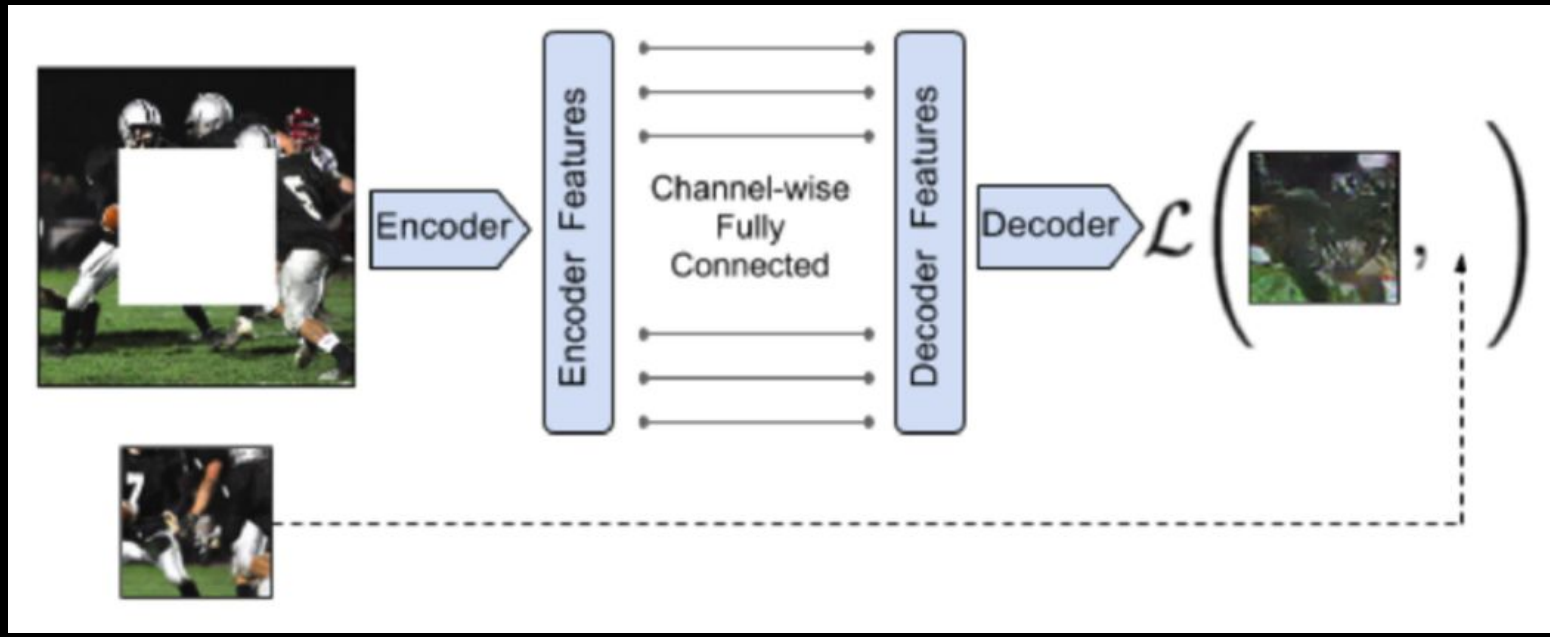
Richard, Z, Dissertation Talk 2018

Self-supervised Learning: Relative position



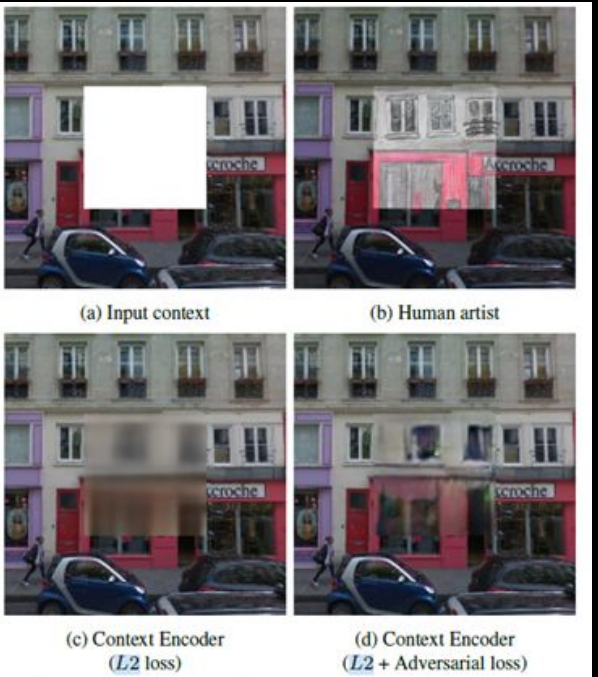
Doersch et al. 2015

Self-supervised Learning: Inpainting



Pathak et al. 2016

Self-supervised Learning: Result of context encoder



(a) Input context (b) Human artist

(c) Context Encoder ($L2$ loss) (d) Context Encoder ($L2$ + Adversarial loss)

Figure 1: Qualitative illustration of the task. Given an image with a missing region (a), a human artist has no trouble inpainting it (b). Automatic inpainting using our *context encoder* trained with $L2$ reconstruction loss is shown in (c), and using both $L2$ and adversarial losses in (d).

Pathak et al. 2016

Self-supervised Learning: Result of context encoder

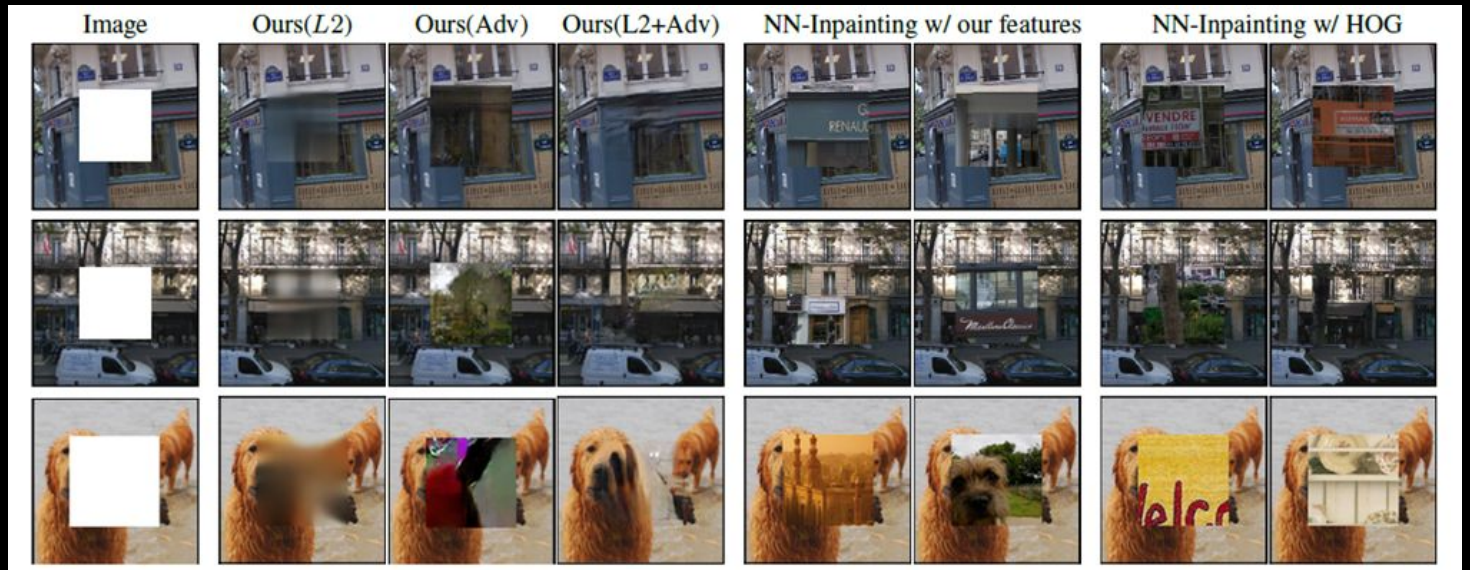


Figure 6: Semantic Inpainting using different methods on *held-out* images. Context Encoder with just L2 are well aligned, but not sharp. Using adversarial loss, results are sharp but not coherent. Joint loss alleviate the weaknesses of each of them. The last two columns are the results if we plug-in the best nearest neighbor (NN) patch in the masked region.

Pathak et al. 2016

Overview

Learning type	**Human-annotated labels?**	**Goal**
Unsupervised	No	Detects new patterns and reduces dimensionality
Supervised	Yes	Mapping between the input and the output
Semi-supervised	Small amount	Improves supervised learning by using small amount of labeled and large amount of unlabeled data
Reinforcement learning	-	Find model that maximizes reward
Self-supervised	Small amount for downstream task	Pre-trains a model using automatically generated pseudo labels from the input data, transfers pre-trained weights to a downstream task.

R Code

Discussion

Where can we apply semi-supervised or self-supervised learning?

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Where can we apply semi-supervised or self-supervised learning?

What pretext task for what purpose?

Useful links for Self-supervised Learning

Overview of existing papers

https://github.com/jason718/awesome-self-supervised-learning

Yann LeCun

https://www.youtube.com/watch?v=SaJL4SLfrcY

Other

https://www.fast.ai/2020/01/13/self_supervised/


(Hinton 2006)
How the brain works: deep learning