

Introduction to Machine Learning (Neural Networks)

Schedule

- I. Introduction
- II. Logistic regression (review)
- III. Neural network
- VI. Convolutional NN
- V. Other

Related Terms

Deep Learning

Neural Networks

Artificial Intelligence

Data Science

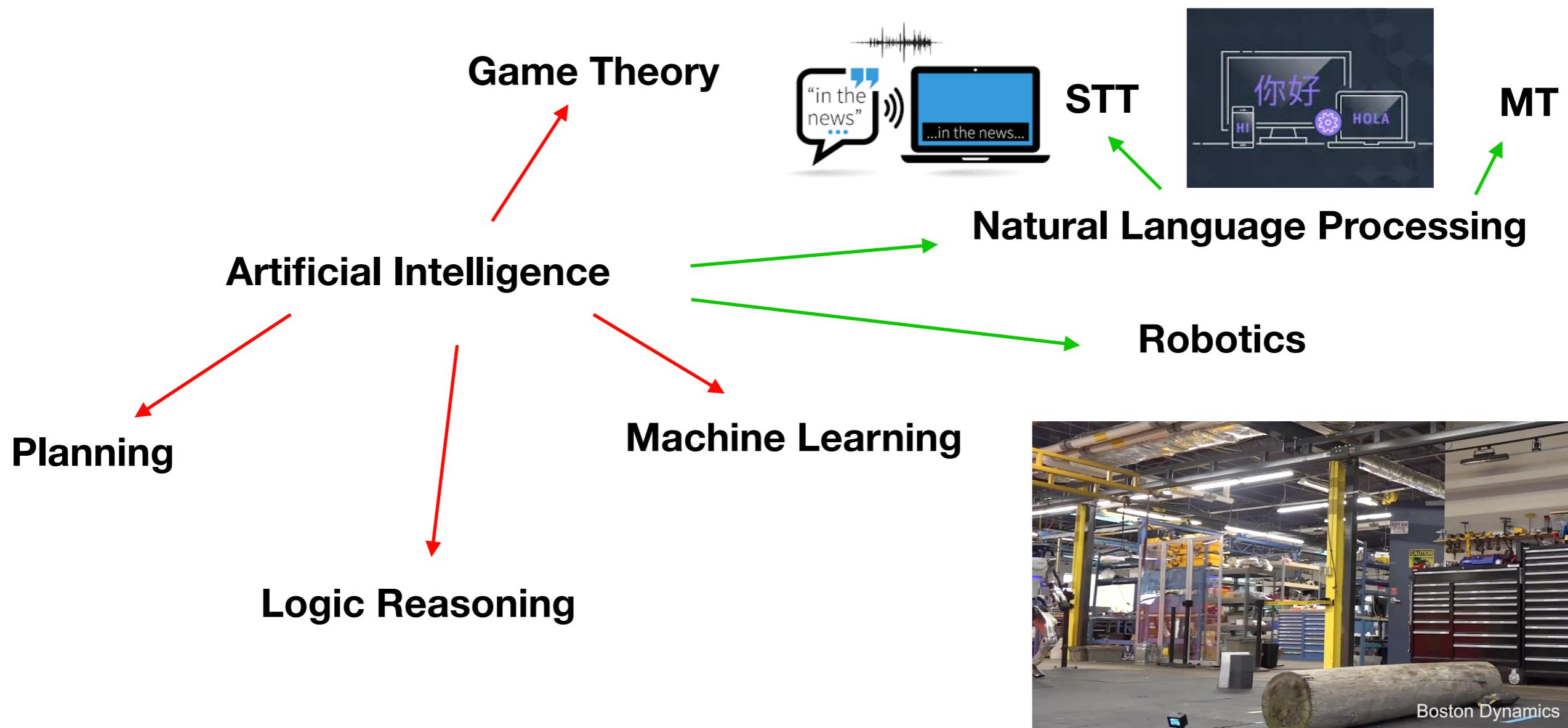
Machine Learning

Data Mining

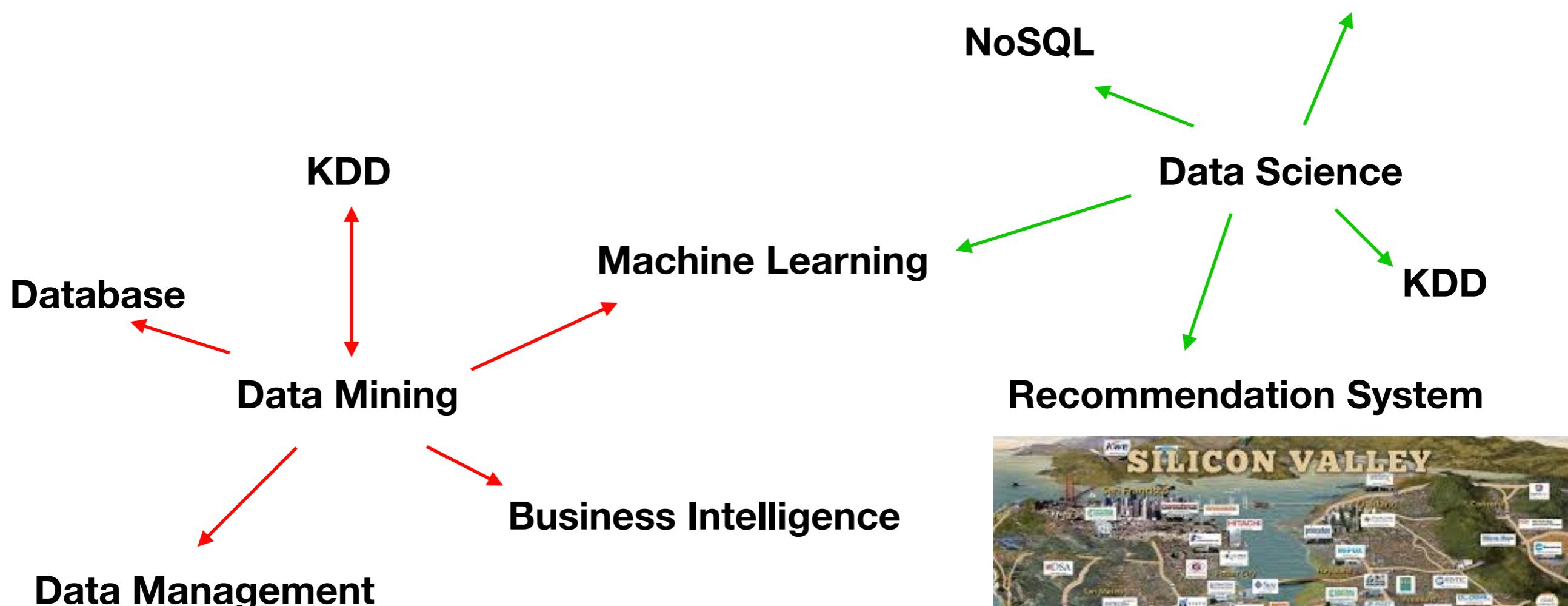
Pattern Recognition

Statistical Modeling

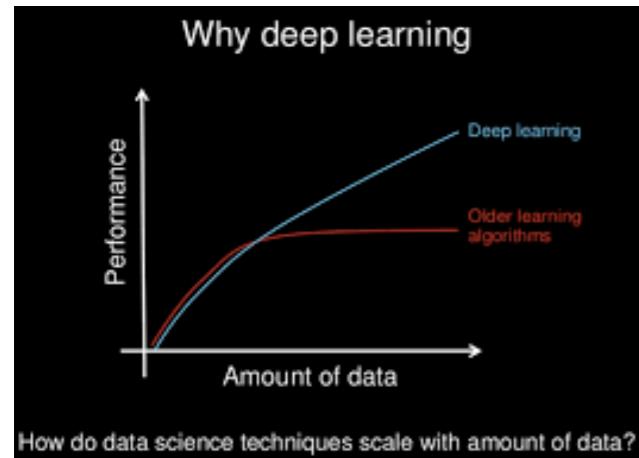
Related Terms



Related Terms



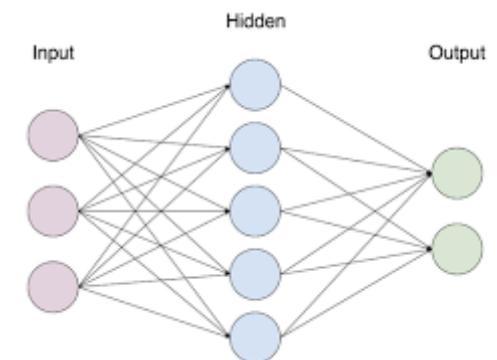
Related Terms



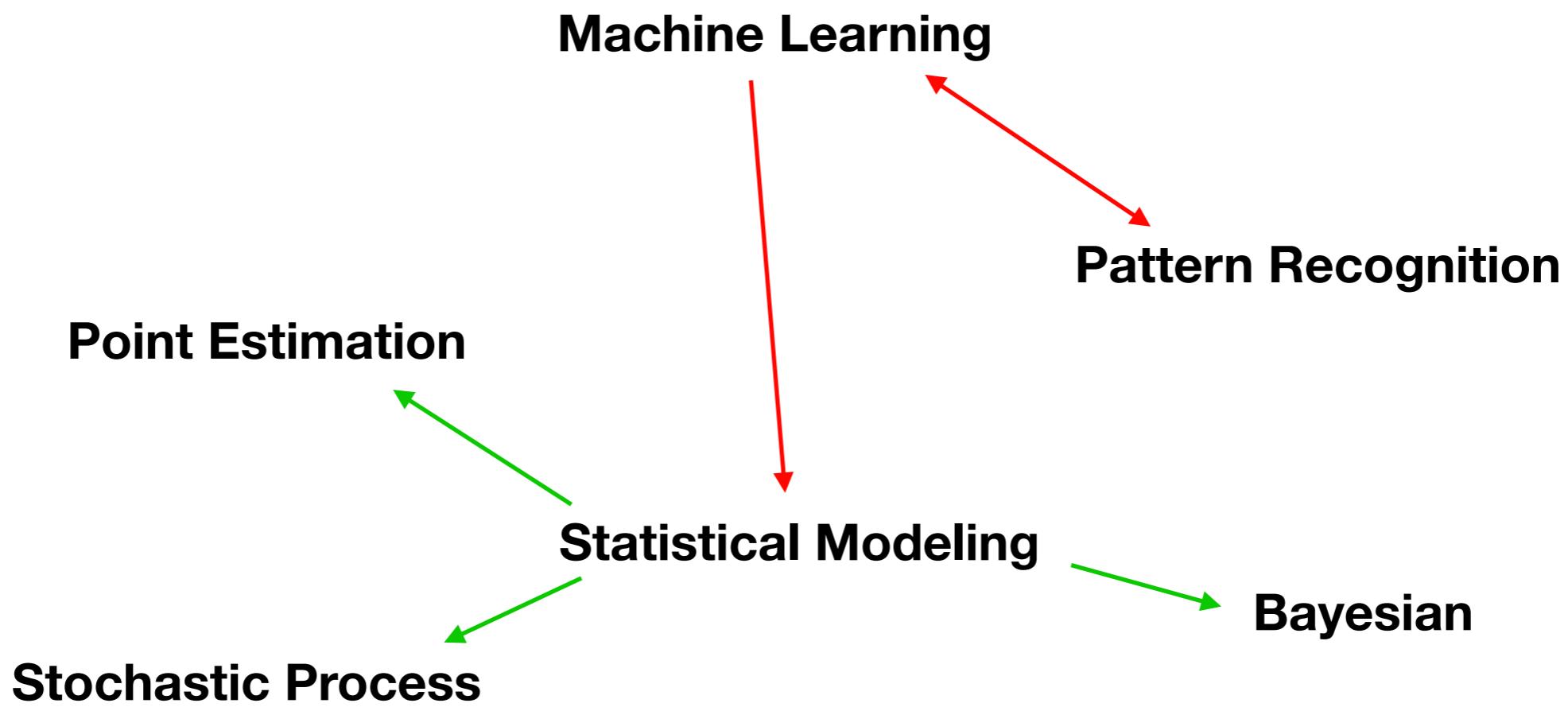
Deep Learning

Neural Networks

Machine Learning



Related Terms



Related Terms

Deep Learning

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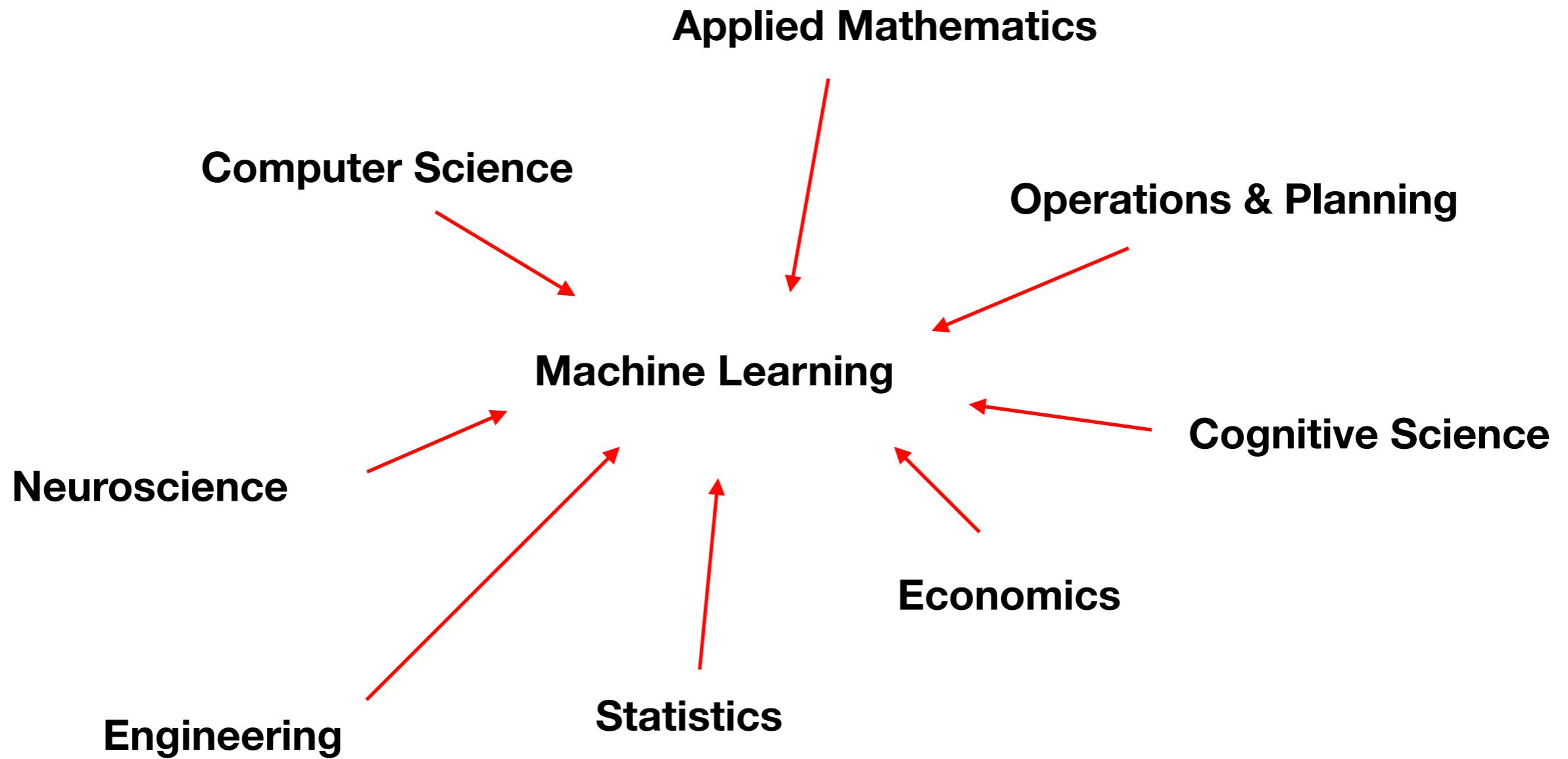
Machine Learning

Data Mining

Pattern Recognition

Statistical Modeling

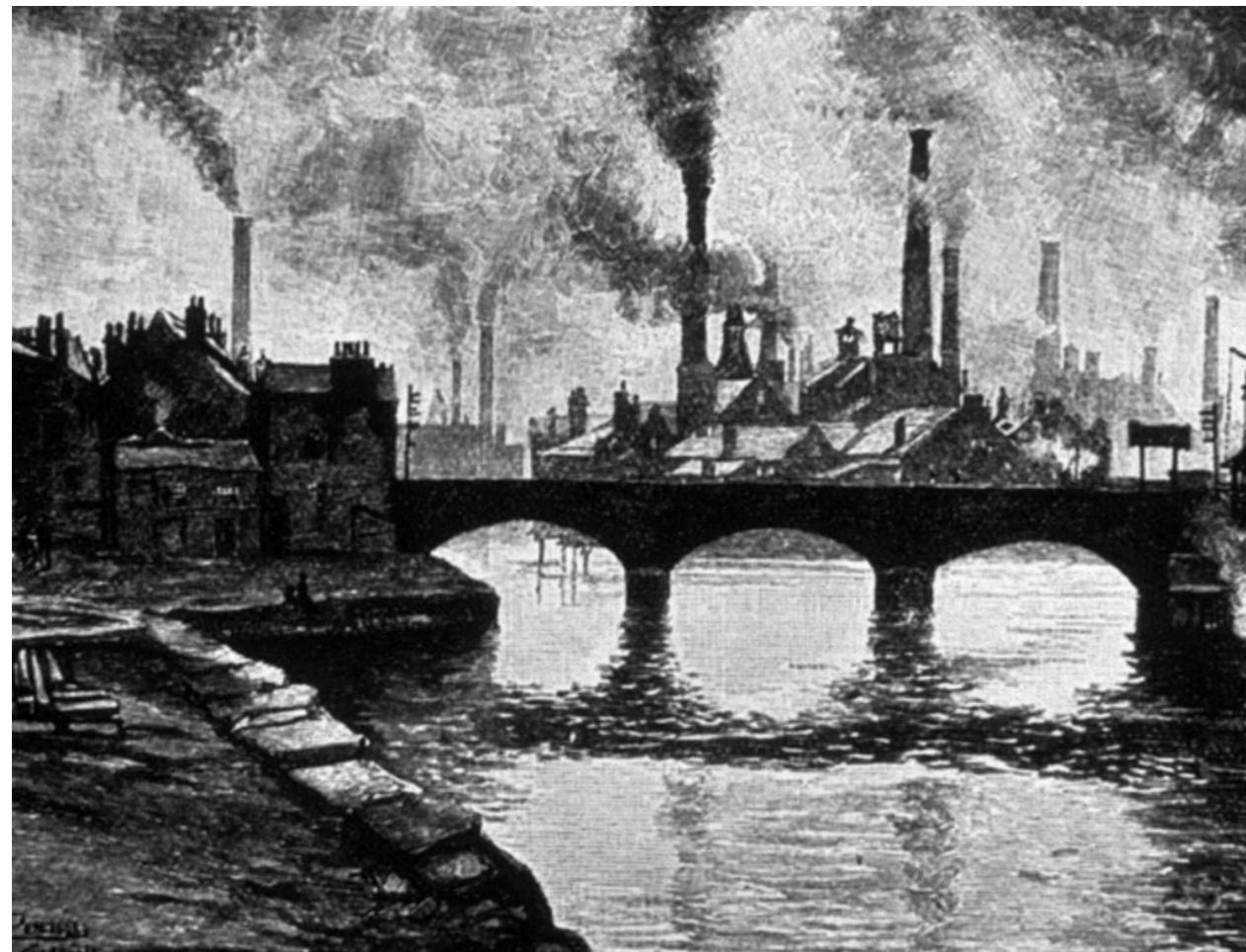
RELATED Fields



Information Revolution Era

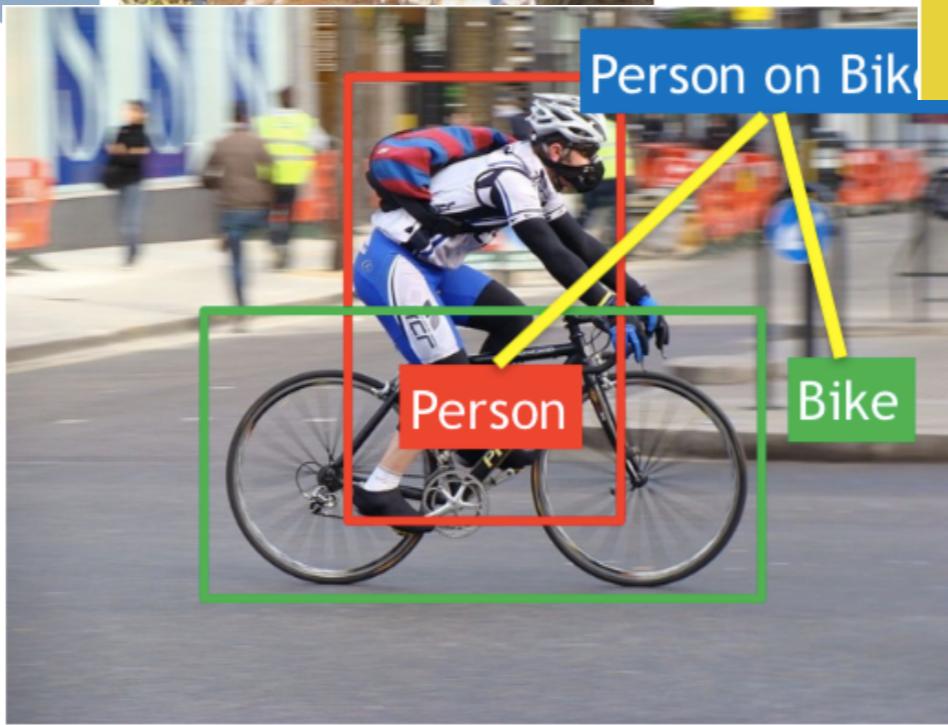
We have abundant of data:

- People: the web, blog, social network, government
- Science: biomedical data, climate data, scientific literature
- Business: e-commerce, e-trading, advertising, personalisation.



We need tools for
understanding, and decision-
making from the data.

Application: Computer Vision



Wall

Desk

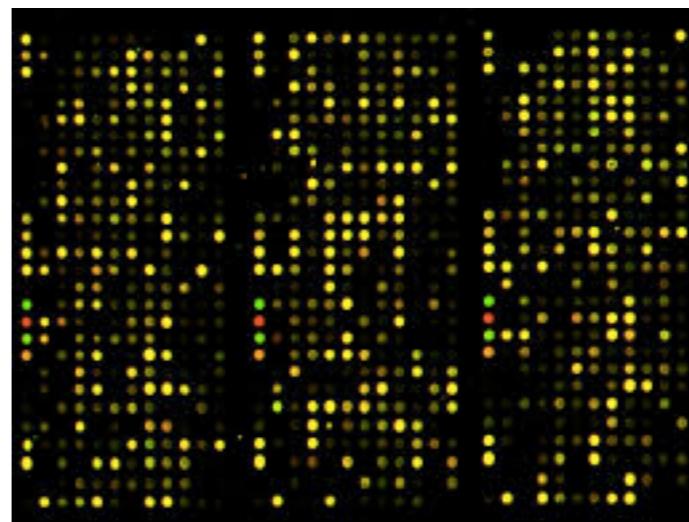
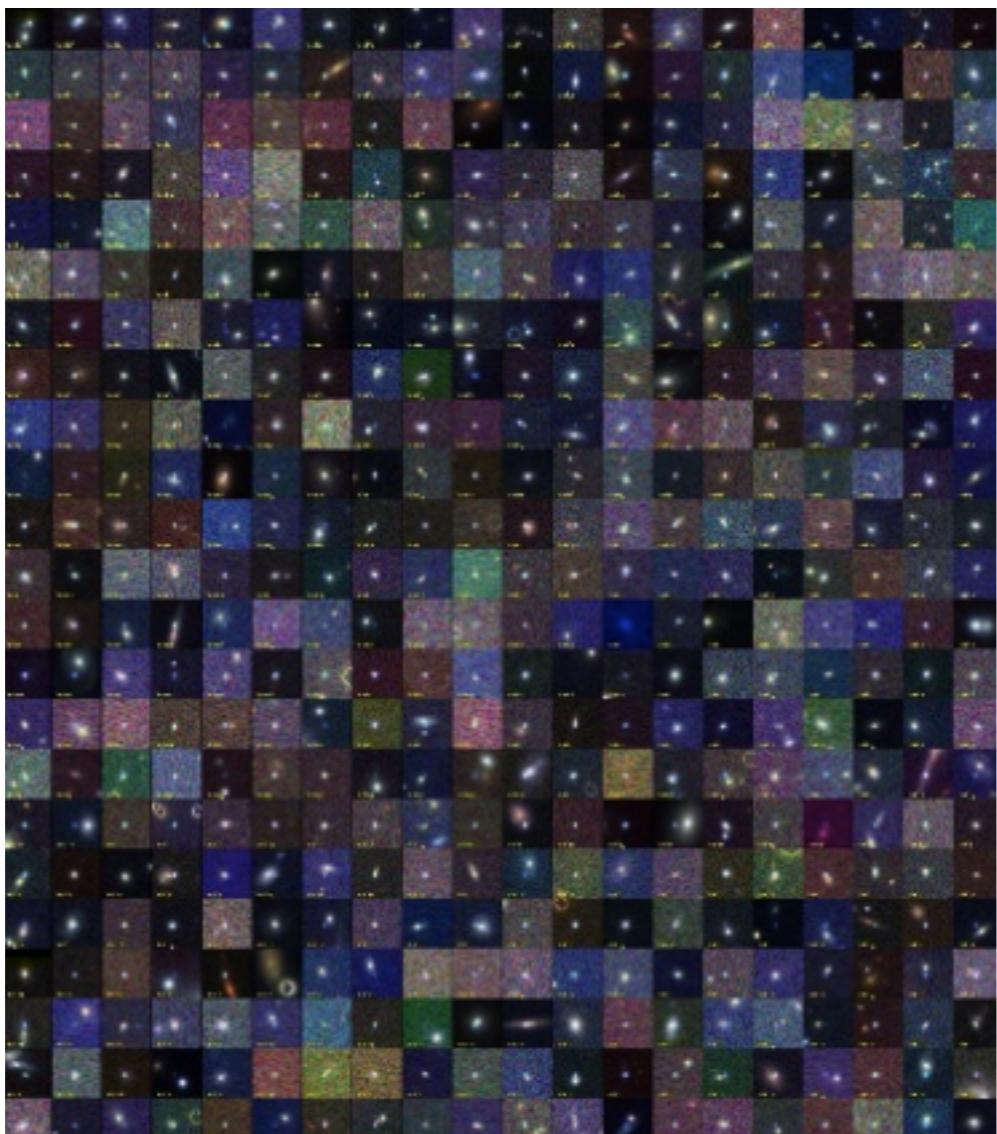
Laptop

Glass

Wire

- **Detection(face/object)**
- **Recognition**
- **Captioning**
- **Segmentation**
- ...

Application: biomedical & astronomy



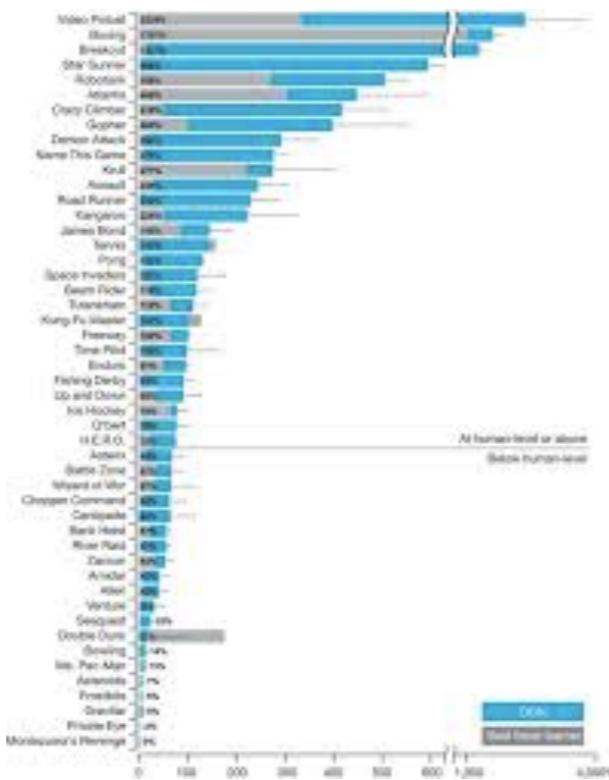
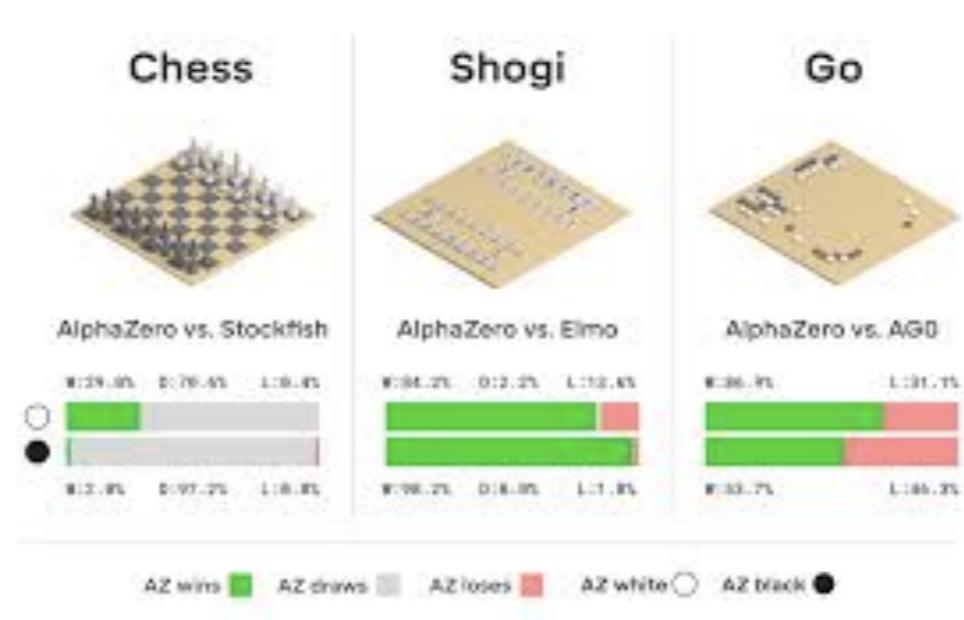
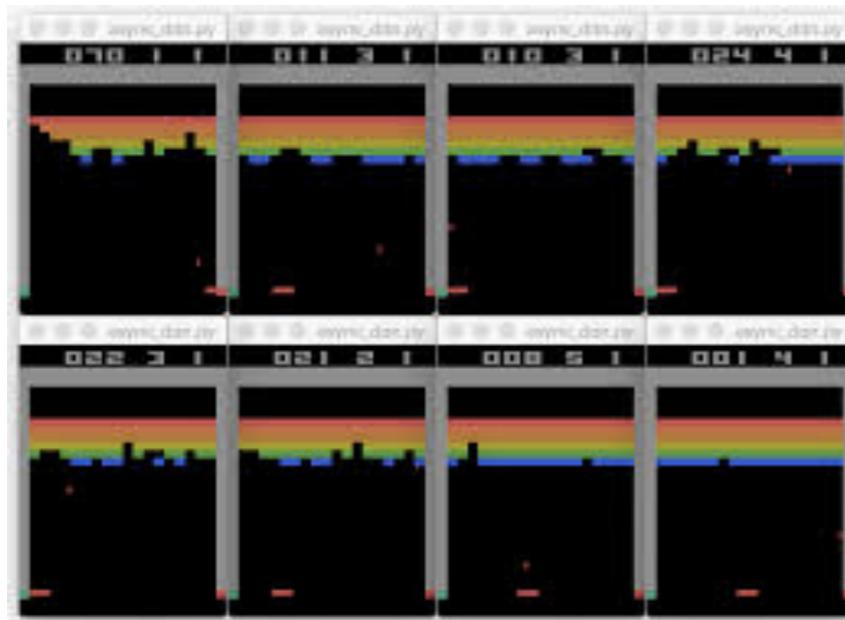
- Microarray(compressed sensing)
- astronomy

Application: Recommendation System

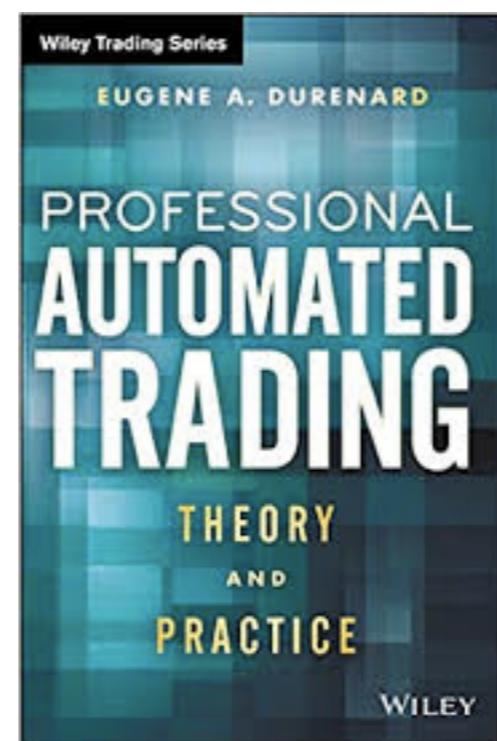


- **Recommendation system is everywhere.**
- **It is one of the backbone of Internet.**

Application: Games



Application: Automated Trading



Types of Learning

- The machine is given a series of **input**:

$$x_1, x_2, x_3, \dots$$

- **Supervised learning**: the machine is also given a corresponding **output** y_1, y_2, y_3, \dots . The task is to learn the correct output given the input.
- **Unsupervised learning**: the machine is asked to build a **model** for prediction, decision making, etc.
- **Reinforcement learning**: the machine can perform an **action** a_1, a_2, a_3, \dots based on the input to update the world, the world can give back some **rewards** r_1, r_2, r_3, \dots . The task here is usually to maximize the rewards.

Typical Problems

There are many applications of machine learning, but we often see application can be modeled around a few problems. Here are some:

- Classification
- Regression
- Clustering
- Dimensionality Reduction

Classification

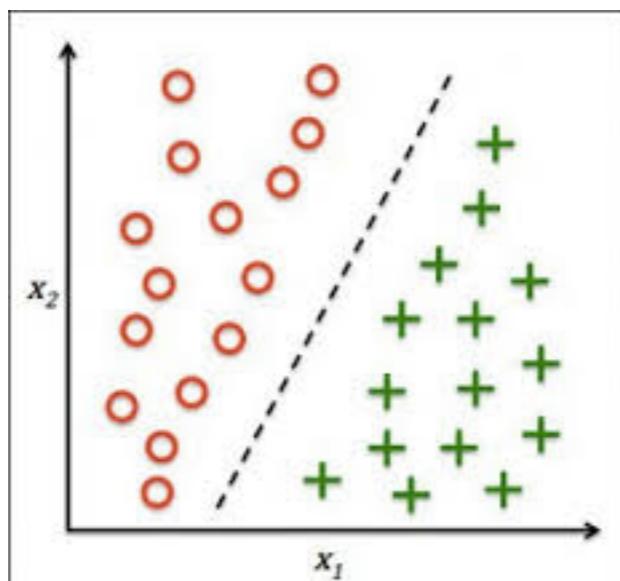
- The data is represented in some vector space.
- Let's say we have **input** data.

$$x = (x_1, x_2, x_3, \dots)$$

- For each of the input data, it's represented by a vector. We call it **features**.
- For each of the input data, we know their discrete **class labels**.

$$y = (y_1, y_2, y_3, \dots)$$

- The goal is to give the correct label for some given new data.



Example:

- Healthy or ill?
- Spam or normal email?
- Is it an apple, a pear, or an orange?

Classification Example: Iris Data

- 4 features, 3 classes, and 150 instances.
- The features are the sepal length, sepal width, petal length, and petal width in cm.
- The classes are three iris species: setosa, versicolor, and virginica.
- The data is collected by Anderson (1935) and used by Fisher (1936) with linear discriminant function.

```
5.1,3.5,1.4,0.2,Iris-setosa  
4.9,3.0,1.4,0.2,Iris-setosa  
4.7,3.2,1.3,0.2,Iris-setosa
```

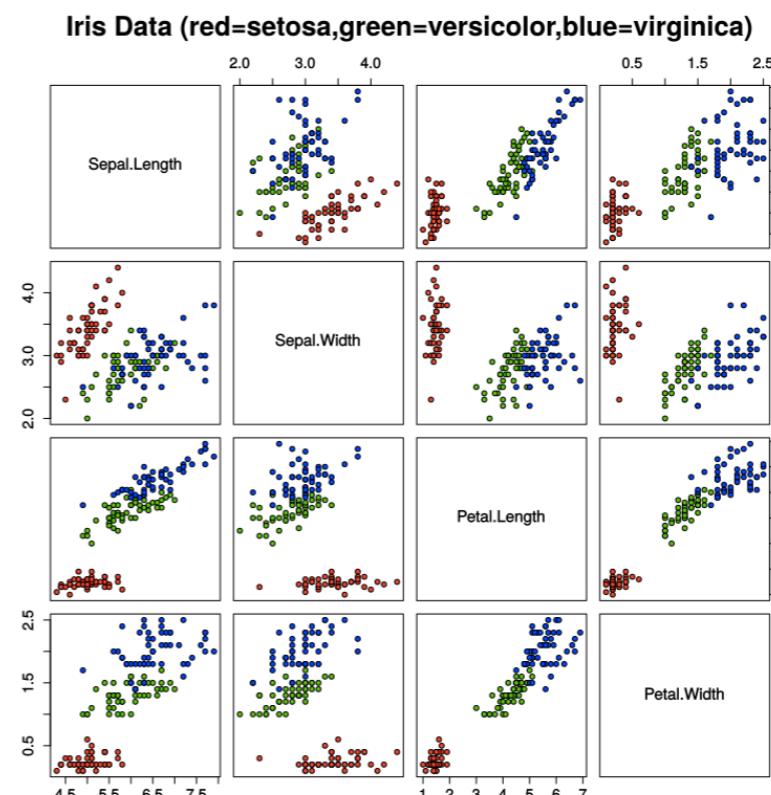
...

```
7.0,3.2,4.7,1.4,Iris-versicolor  
6.4,3.2,4.5,1.5,Iris-versicolor  
6.9,3.1,4.9,1.5,Iris-versicolor
```

...

```
6.3,3.3,6.0,2.5,Iris-virginica  
5.8,2.7,5.1,1.9,Iris-virginica  
7.1,3.0,5.9,2.1,Iris-virginica
```

...



Regression

- The data is represented in some vector space.
- Let's say we have **input** data.

$$x = (x_1, x_2, x_3, \dots)$$

- For each of the input data, it's represented by a vector. We call it **features**.
- For each of the input data, we know their corresponding **value**.

$$y = (y_1, y_2, y_3, \dots)$$

- The goal is to give the appropriate **value** for some given new data.



Example:

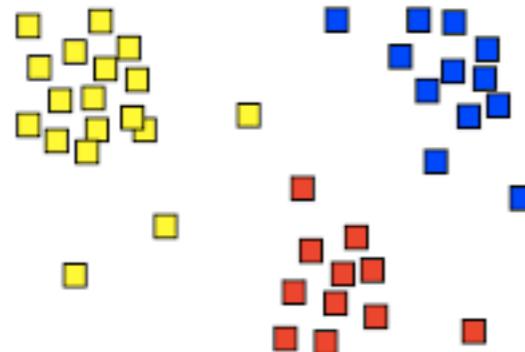
- Stock price prediction?
- Quality control?

Clustering

- The data is represented in some vector space.
- Let's say we have **input** data.

$$x = (x_1, x_2, x_3, \dots)$$

- For each of the input data, it's represented by a vector. We call it **features**.
- We want to group the data into clusters so that **data points in the same cluster are similar to each other than data points belonging to different clusters**.



Example:

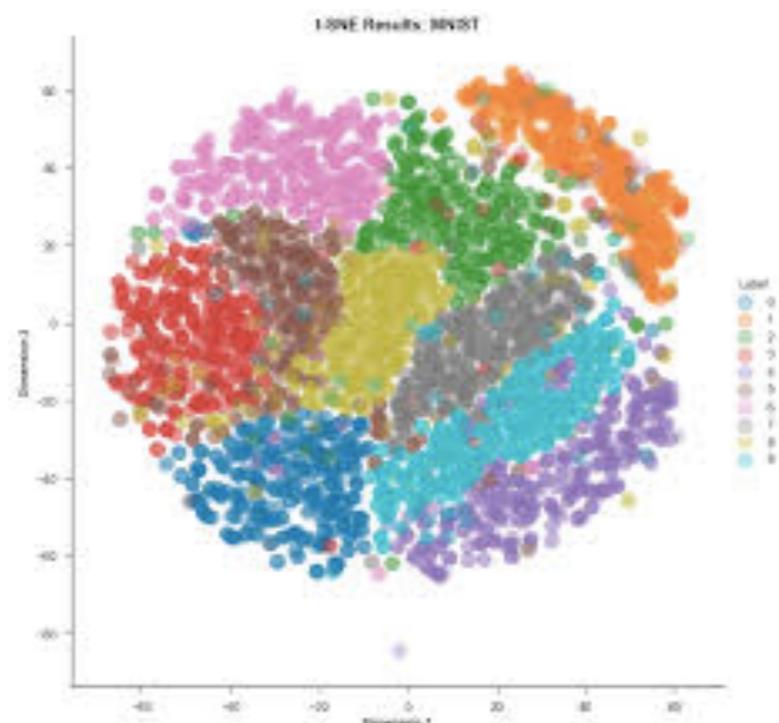
- Stories into topics.
- Movies into categories.
- Genes by similar function.

Dimensionality Reduction

- The data is represented in some vector space.
- Let's say we have **input** data.

$$x = (x_1, x_2, x_3, \dots)$$

- For each of the input data, it's represented by a vector. We call it **features**.
- We want to **discover and model the intrinsic dimension of the data and/or to project the high dimensional data into lower dimension while preserve the relevant information**.



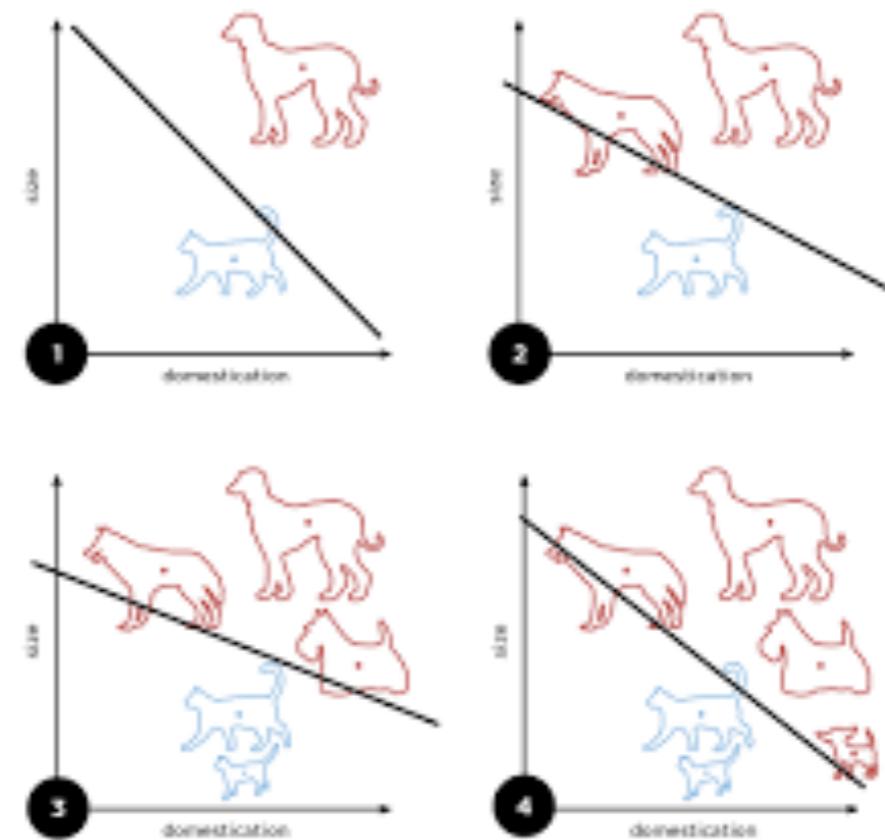
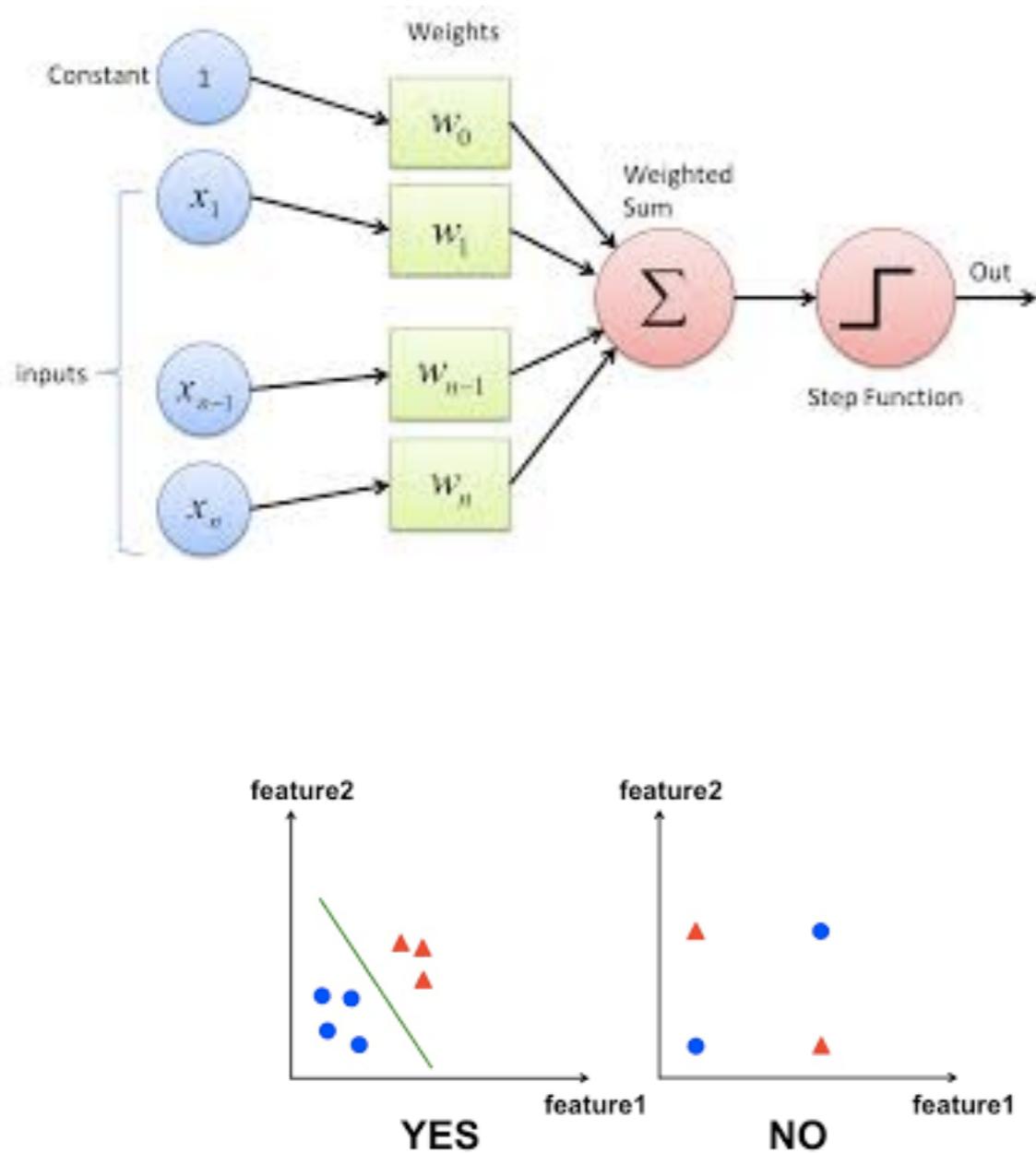
Example:

- t-sne/umap for visualization.

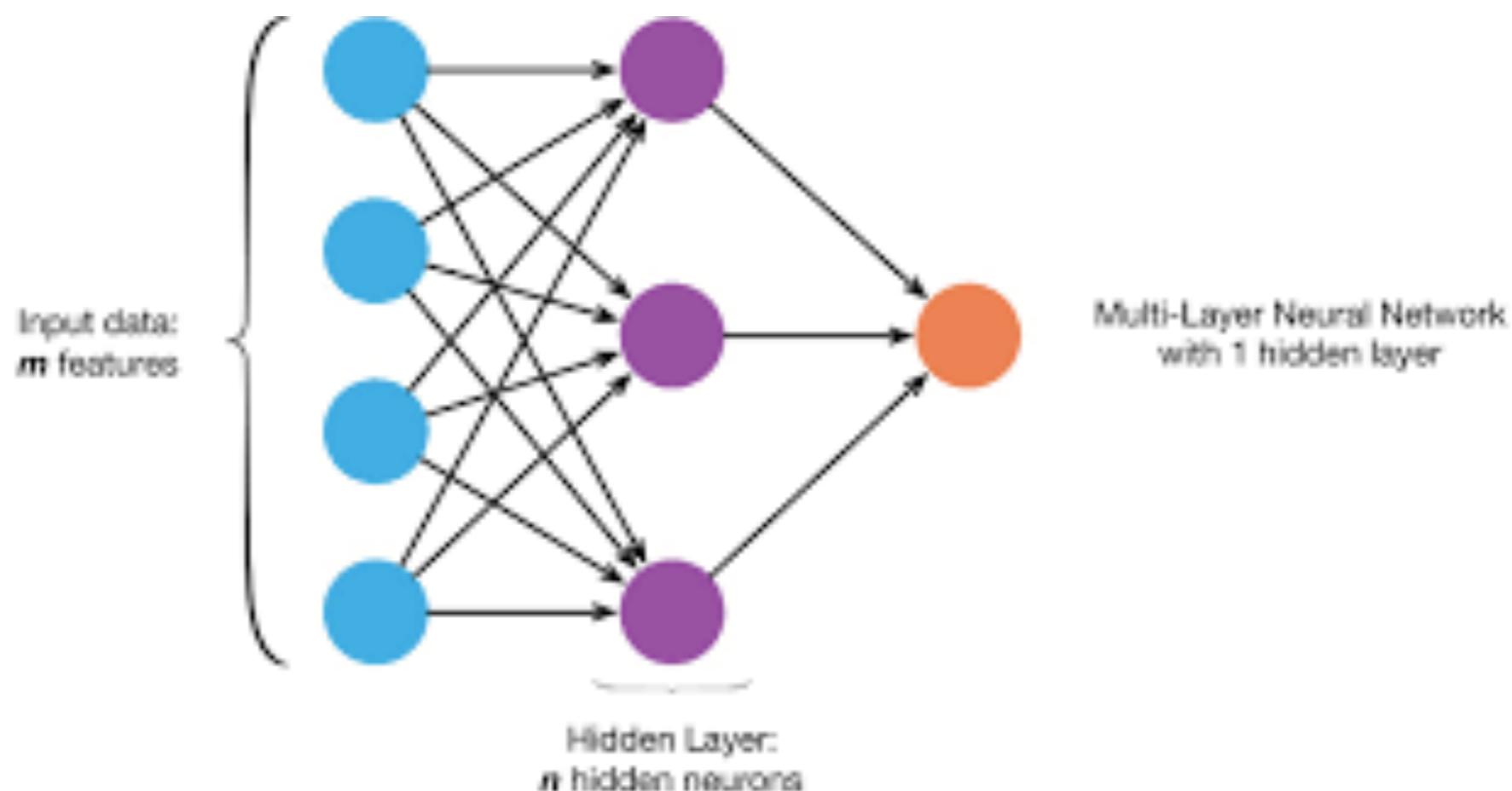
Artificial Neural Network

- Perceptron
- Multiple Layer Perceptron (MLP)
- Stacked Boltzmann Machine
- Back-propagation
- Convolutional Neural Network
- Information Bottleneck and Autoencoder
- Recurrent Neural Network
- Go Deeper!
- ...

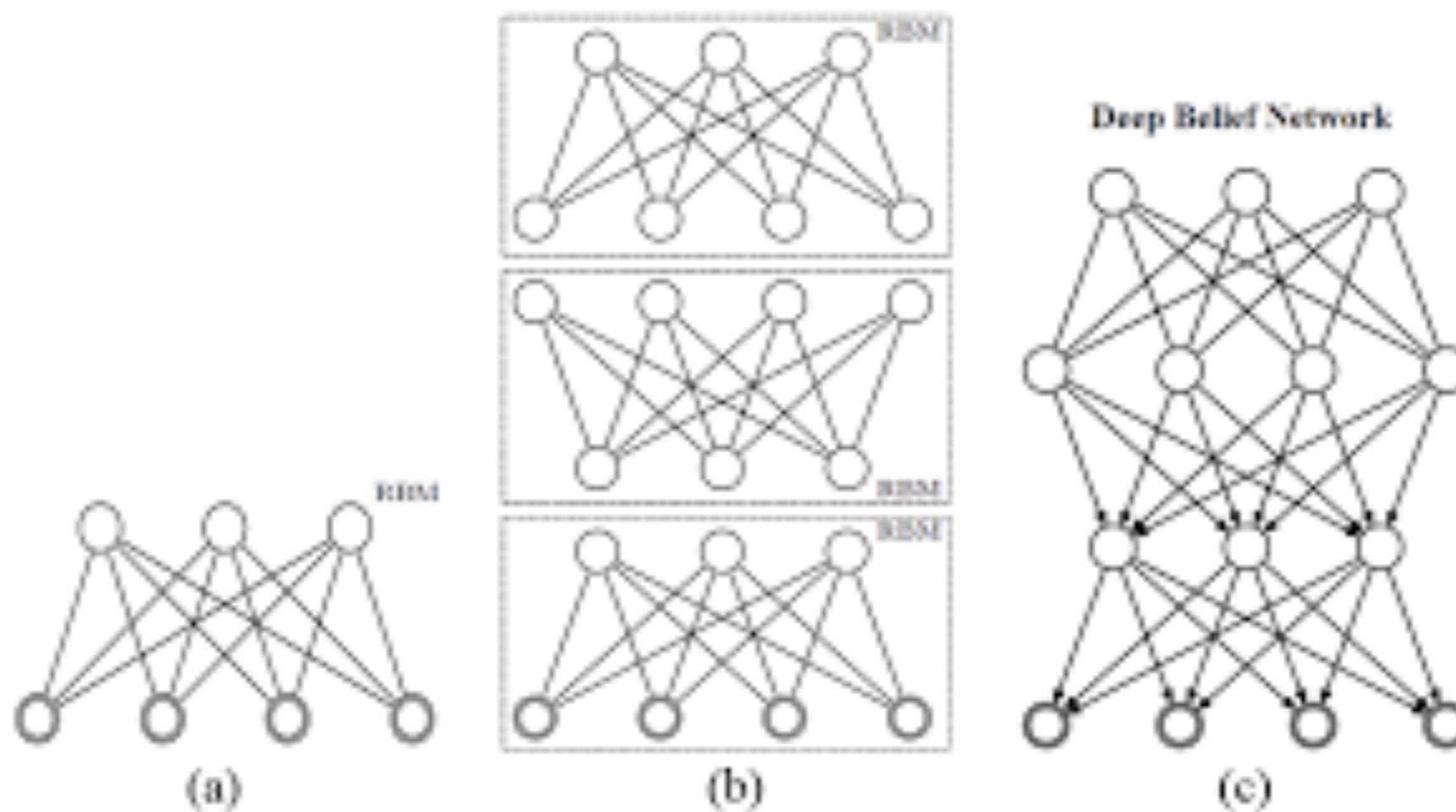
Perceptron



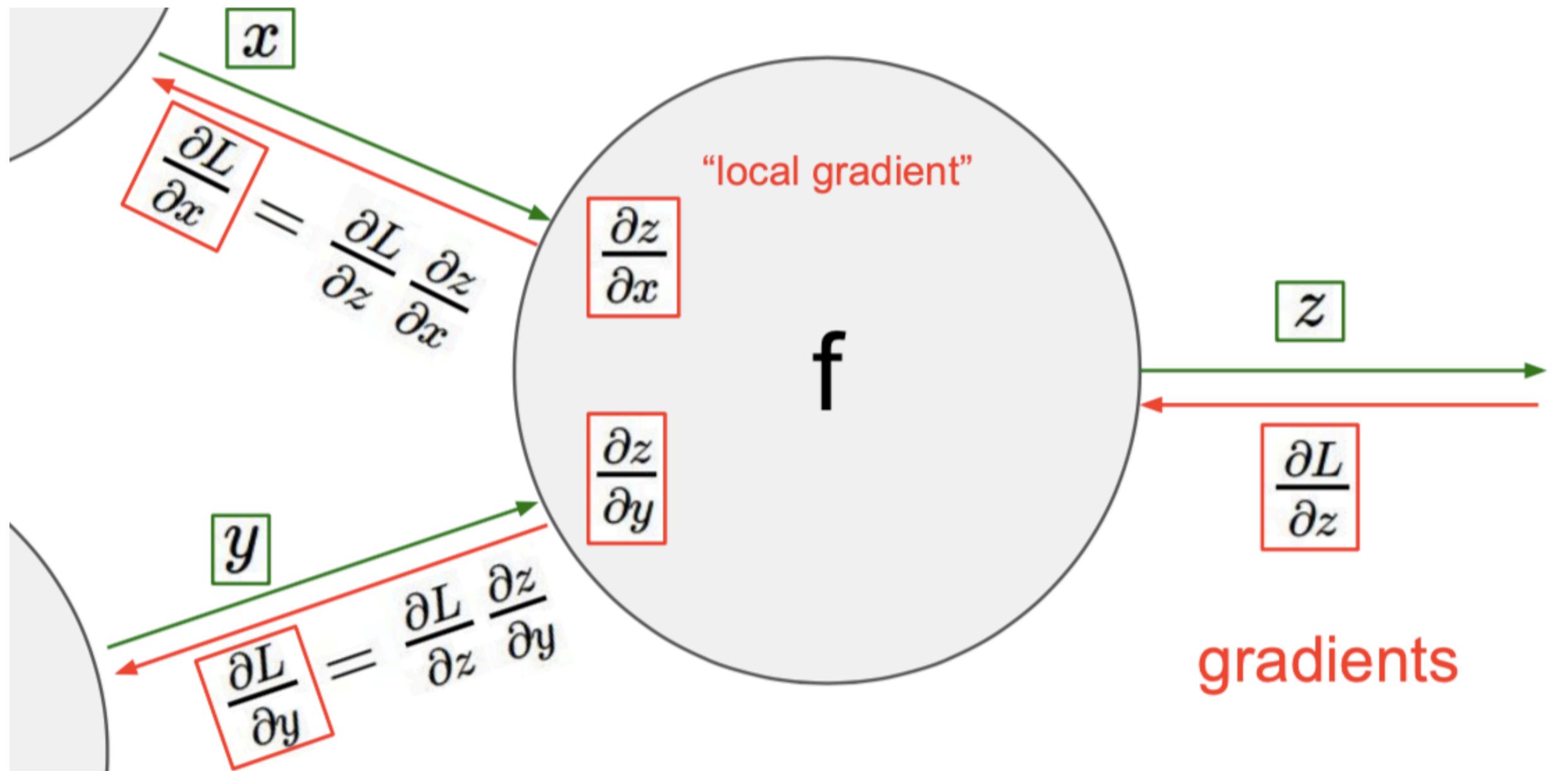
Multiple Layer Perceptron



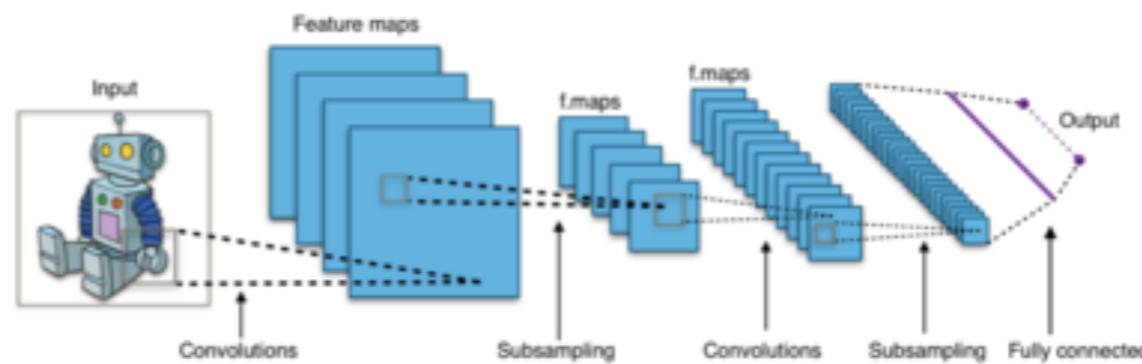
Stacked Restricted Boltzmann Machine



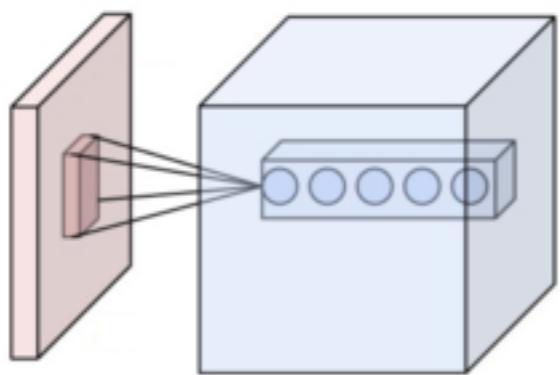
Back-propagation



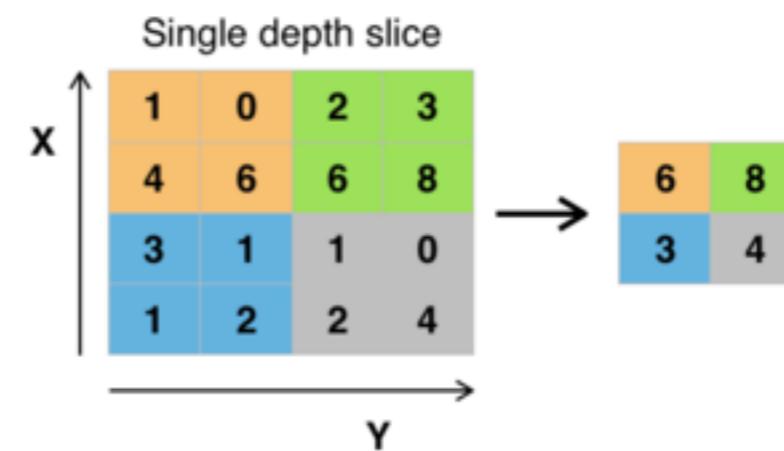
Convolutional Neural Network



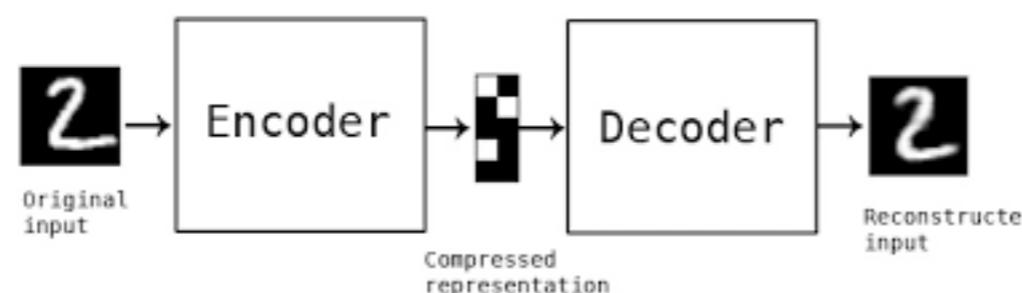
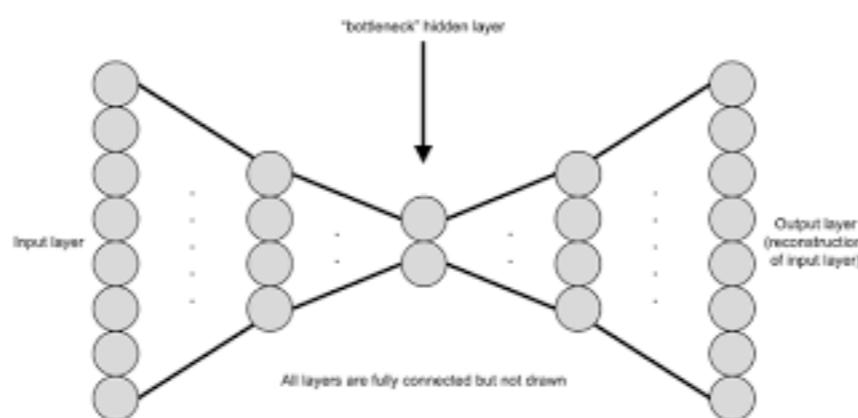
Convolutional Operator



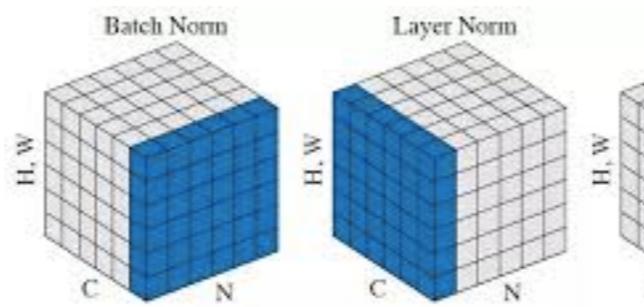
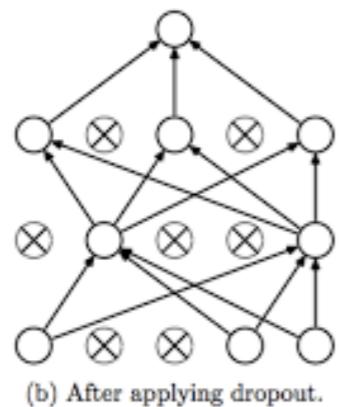
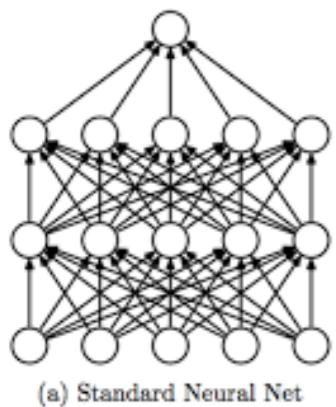
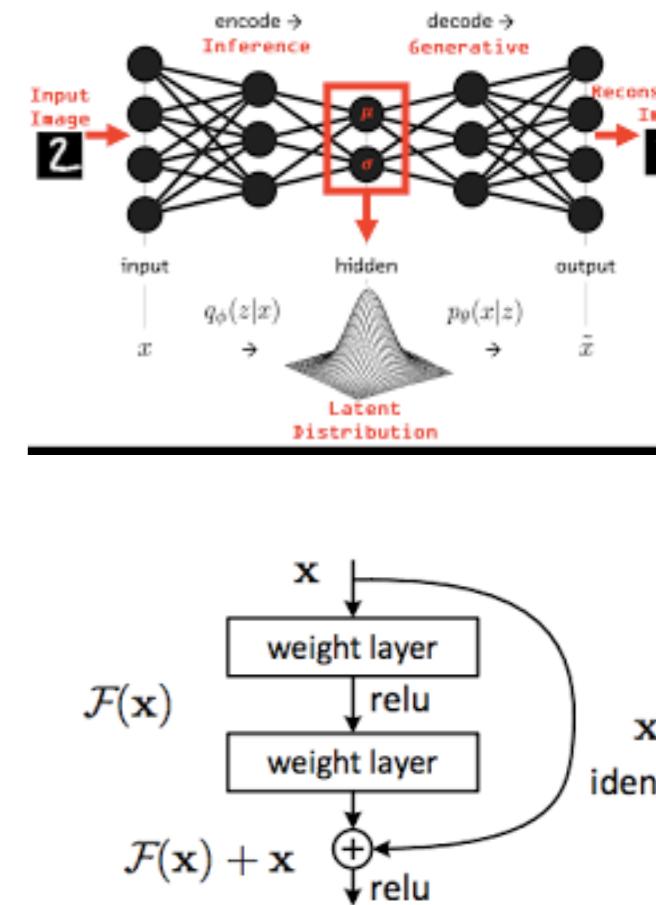
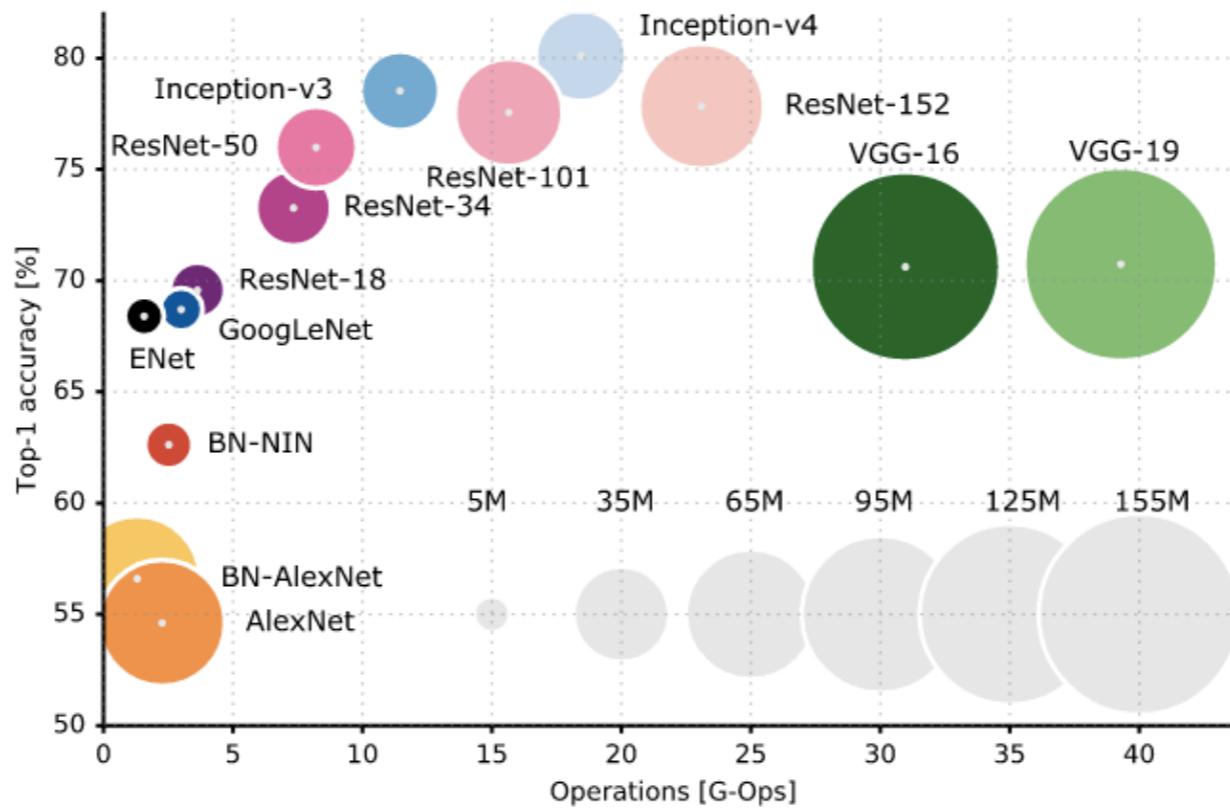
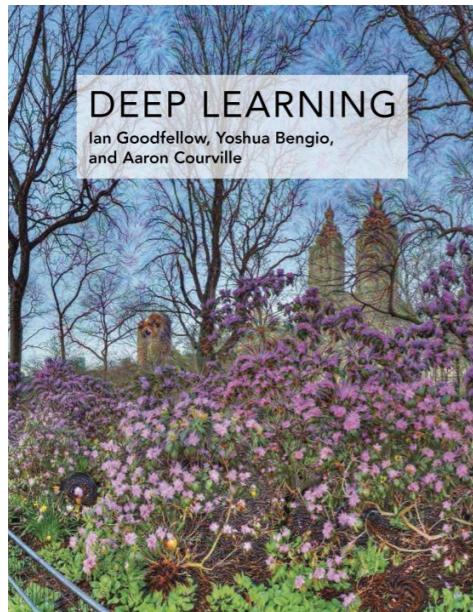
Pooling



Information Bottleneck & Autoencoder



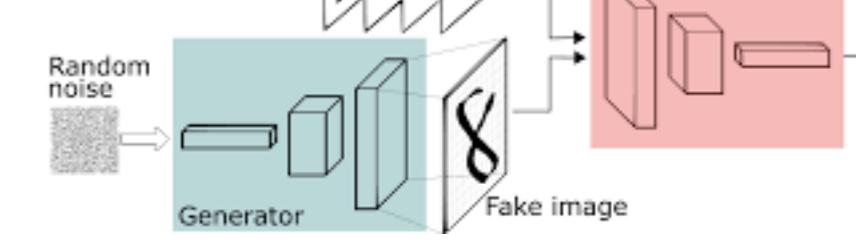
Deep Networks



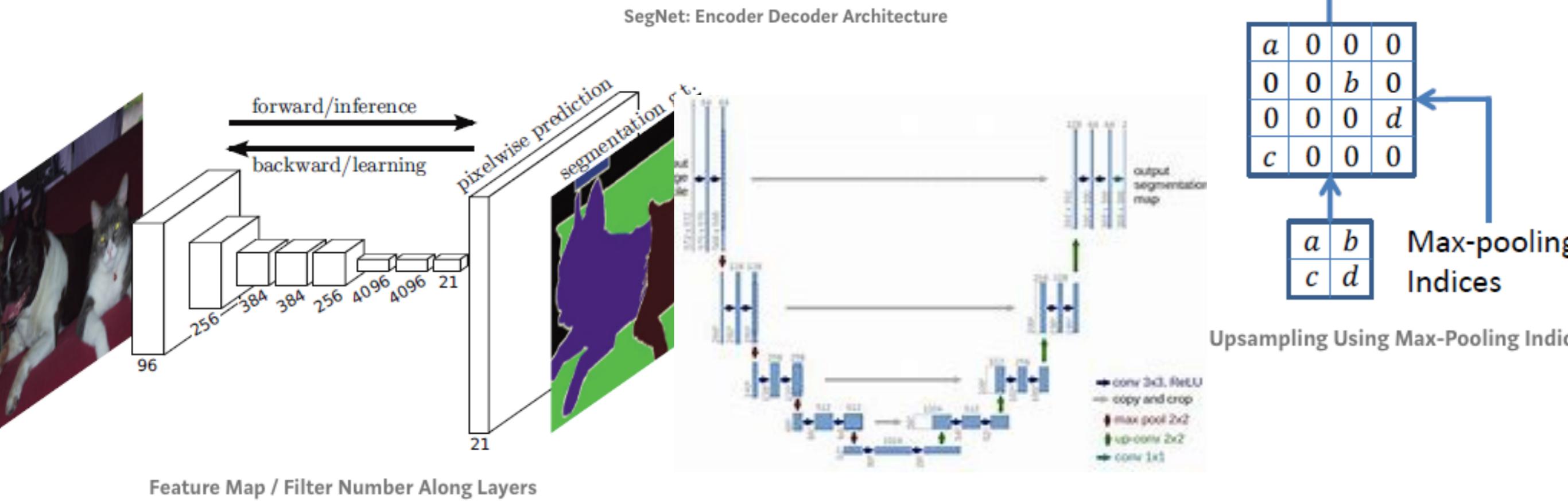
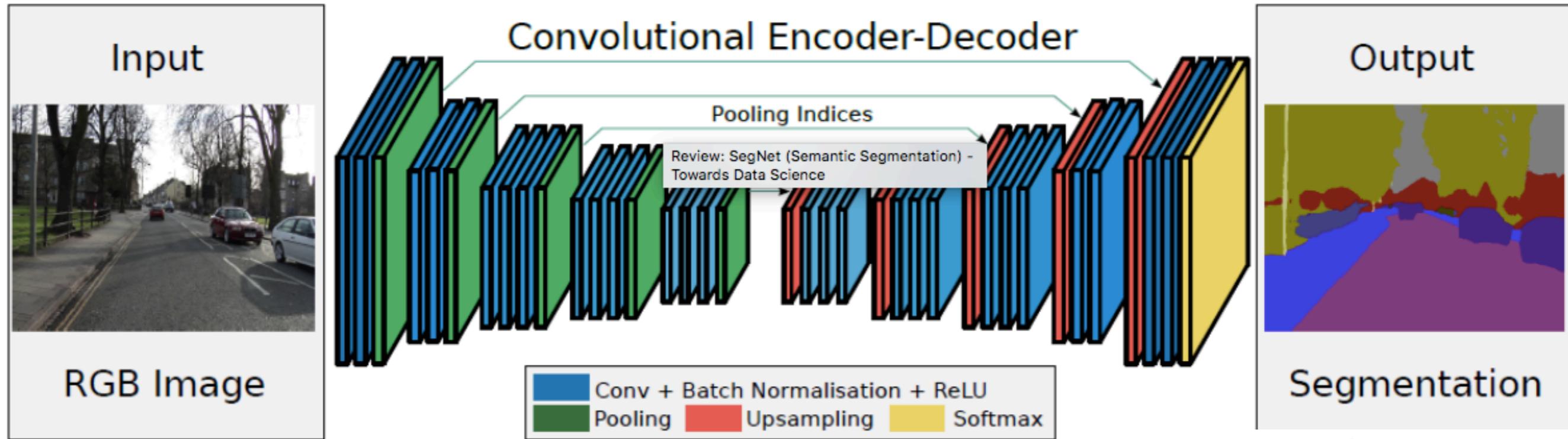
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$6 \times 6 \times 32 \quad \begin{matrix} \text{ } & \text{ } \\ \text{ } & \text{ } \end{matrix} \quad = \quad 6 \times 6 \times n_c$

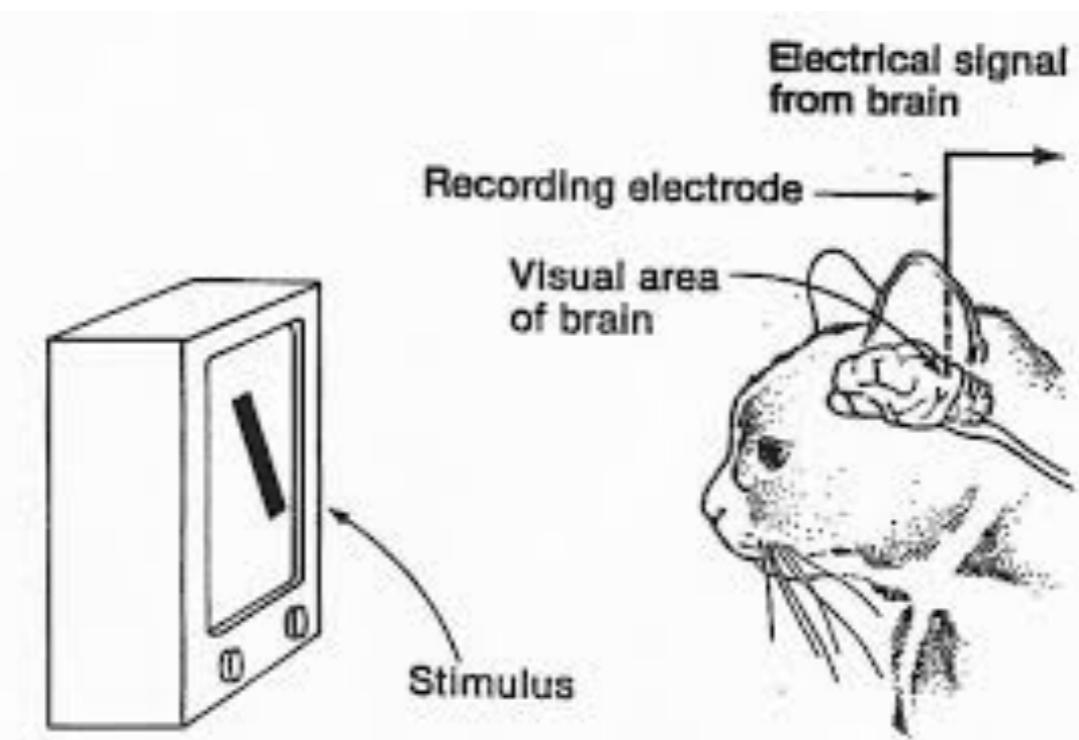
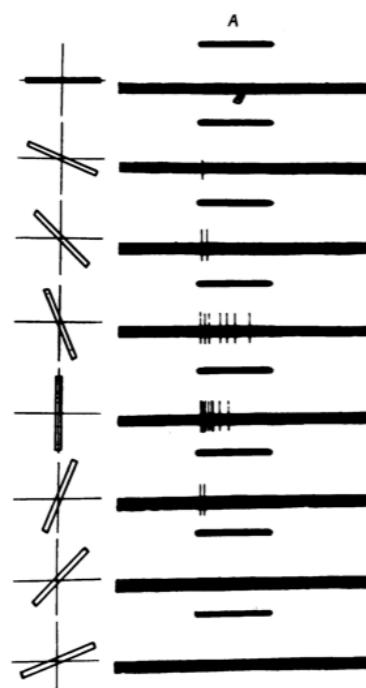
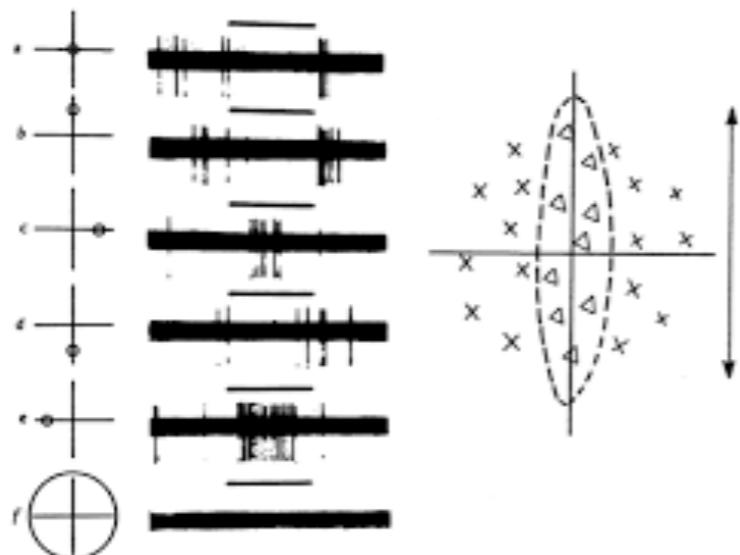


Segmentation



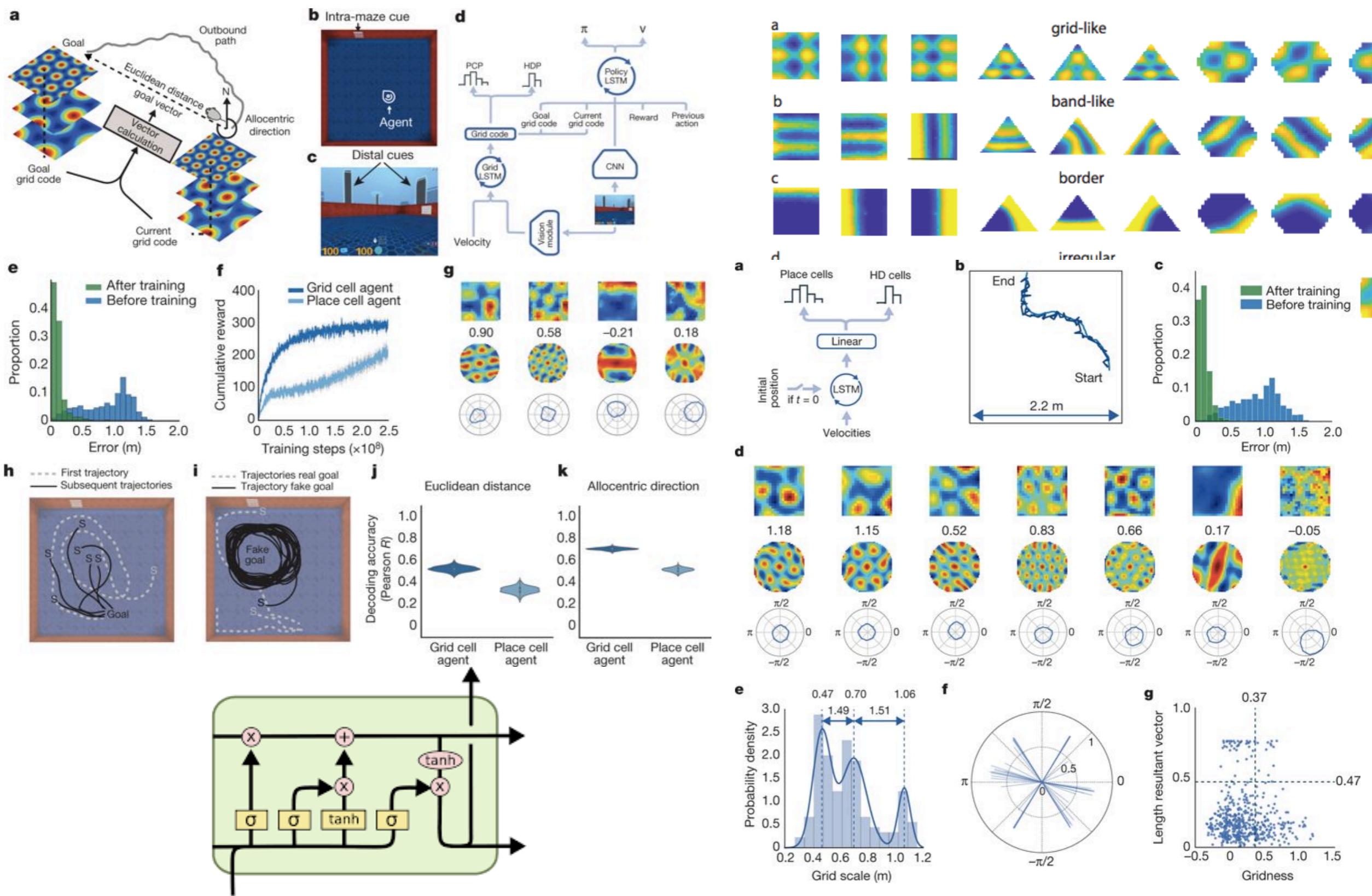
Some
neuroscience
flavor

Vision System and Convolutional Neural Network



- Hubel, Wiesel, and Sperry
- Nobel Prize 1982

Grid Cell and LSTM



Summary

- Machine learning concept and boundary.
- Applications of machine learning.
- 3 Types of machine learning.
- Commonly seen machine learning problem.
- Artificial neural networks/deep learning.
- Examples of joint work on neuroscience and ANN.

Review (probability)

- Random Variable/Expectation/Variance
- Conjugate prior/Exponential family/sufficient statistic

- Bayesian
$$f_X(x \mid \boldsymbol{\theta}) = h(x) \exp\left(\boldsymbol{\eta}(\boldsymbol{\theta}) \cdot \mathbf{T}(x) - A(\boldsymbol{\theta})\right)$$
- Bias-variance decomposition

$$\mathbb{E}\left[\left(y - \hat{f}(x)\right)^2\right] = \left(\text{Bias}[\hat{f}(x)]\right)^2 + \text{Var}[\hat{f}(x)] + \sigma^2$$

where

$$\text{Bias}[\hat{f}(x)] = \mathbb{E}[\hat{f}(x)] - f(x)$$

and

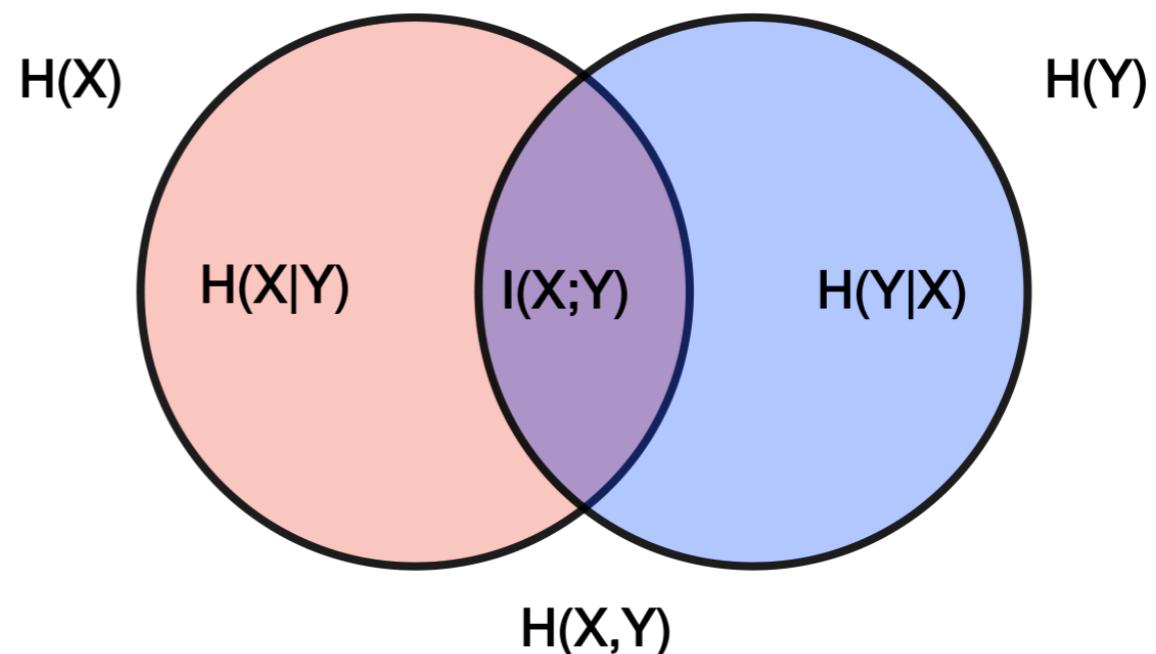
$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

$$\text{Var}[\hat{f}(x)] = \mathbb{E}[\hat{f}(x)^2] - \mathbb{E}[\hat{f}(x)]^2$$

Review (information theory)

- Entropy
- Cross entropy
- Mutual information

$$S = - \sum_i P_i \log P_i$$



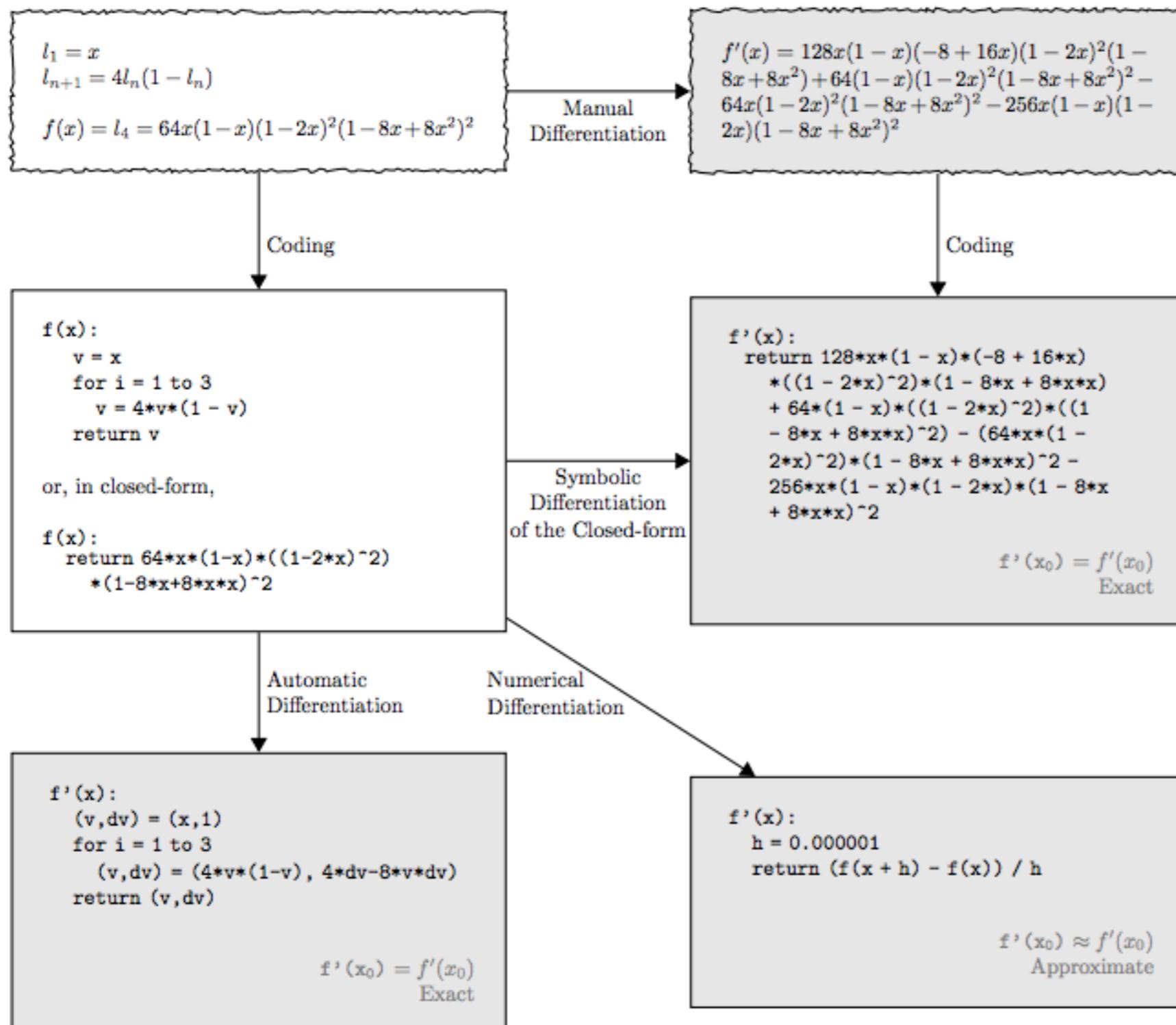
Reading

- C. Bishop, Pattern recognition and machine learning(PRML), chapter 5 Neural networks.

homework assignment

- PRML, 5.1, 5.4
- In a machine learning competition on a binary classification problem, you are allowed to submit your answer and the competition will give you a number in $[0,1]$ back indicating the correct rate. How many submissions you need in order to crack out all the labels? Say there are 1024 samples.

Computation of derivatives



- Manually working out derivatives and coding them;
- numerical differentiation;
- symbolic differentiation;
- automatic differentiation/algorithmic differentiation.

