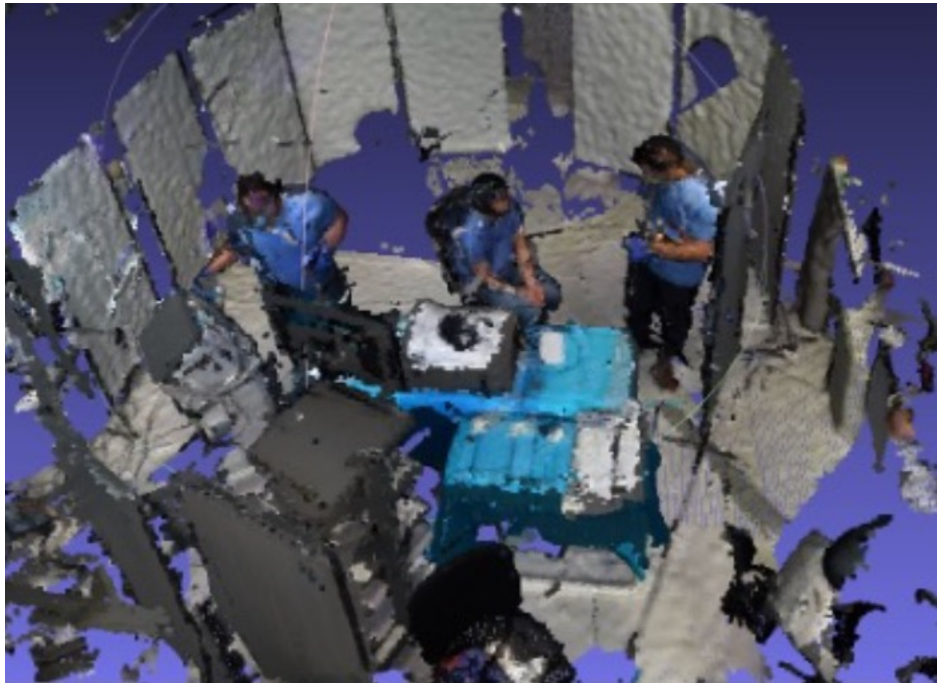
Machine Learning Review

Tuesday 8h00 – 8h45

Géraldine Conti, Matthew Vowels, Bern Winter School on Machine Learning 2023, Muerren

Who am I?

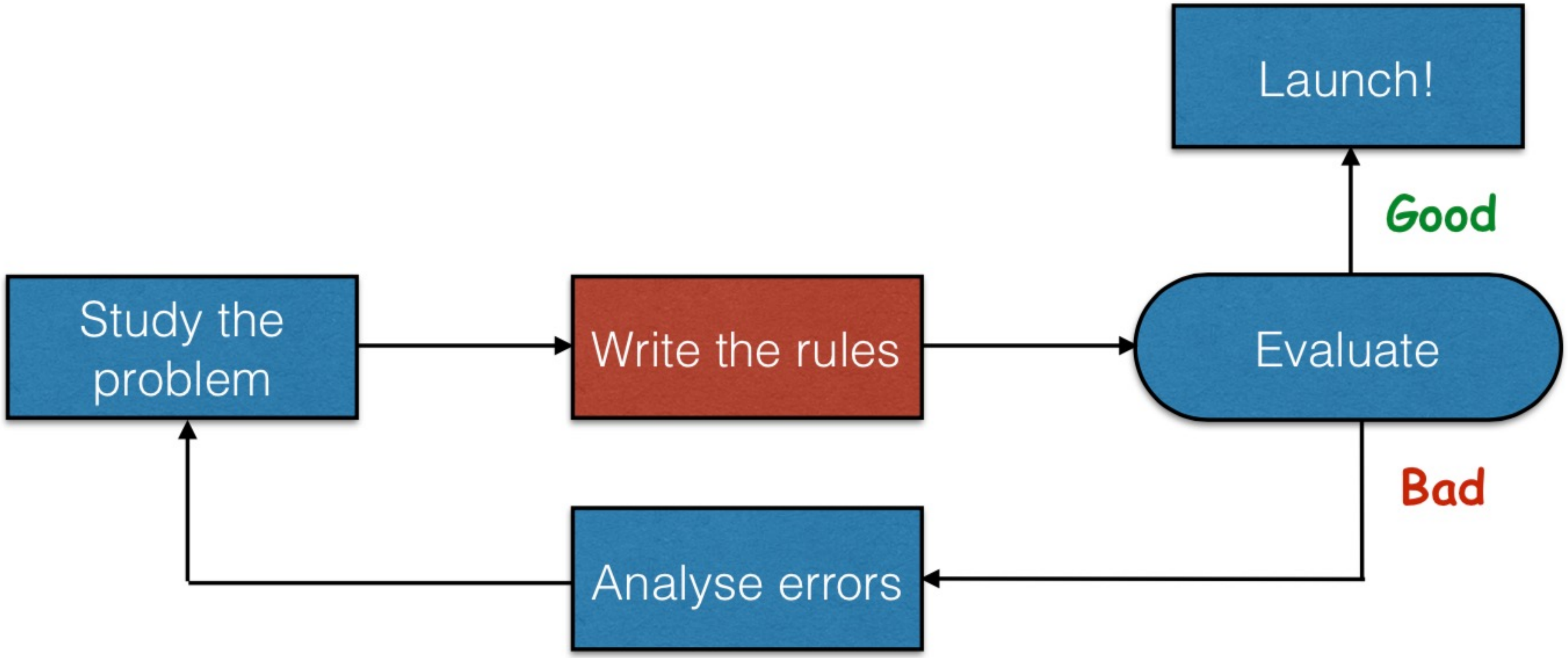
- Engineering PhD @ CVSSP, Surrey UK
- Appl. Math / Statistics for Human Sciences PhD UNIL, Switzerland
- Post-doc Sheffield
- Senior Researcher @ The Sense
- Junior Lecturer @ UNIL
- Affiliate member of AI @ Surrey and machine learning CVSSP, University of Surrey
- Research interests:
    - Causal Inference
    - Causal Discovery
    - Semiparametrics
    - Deep Latent Variable Modeling
    - Computer Vision
    - Multimodal Fusion
    - Algorithmic Finance



Useful Resources

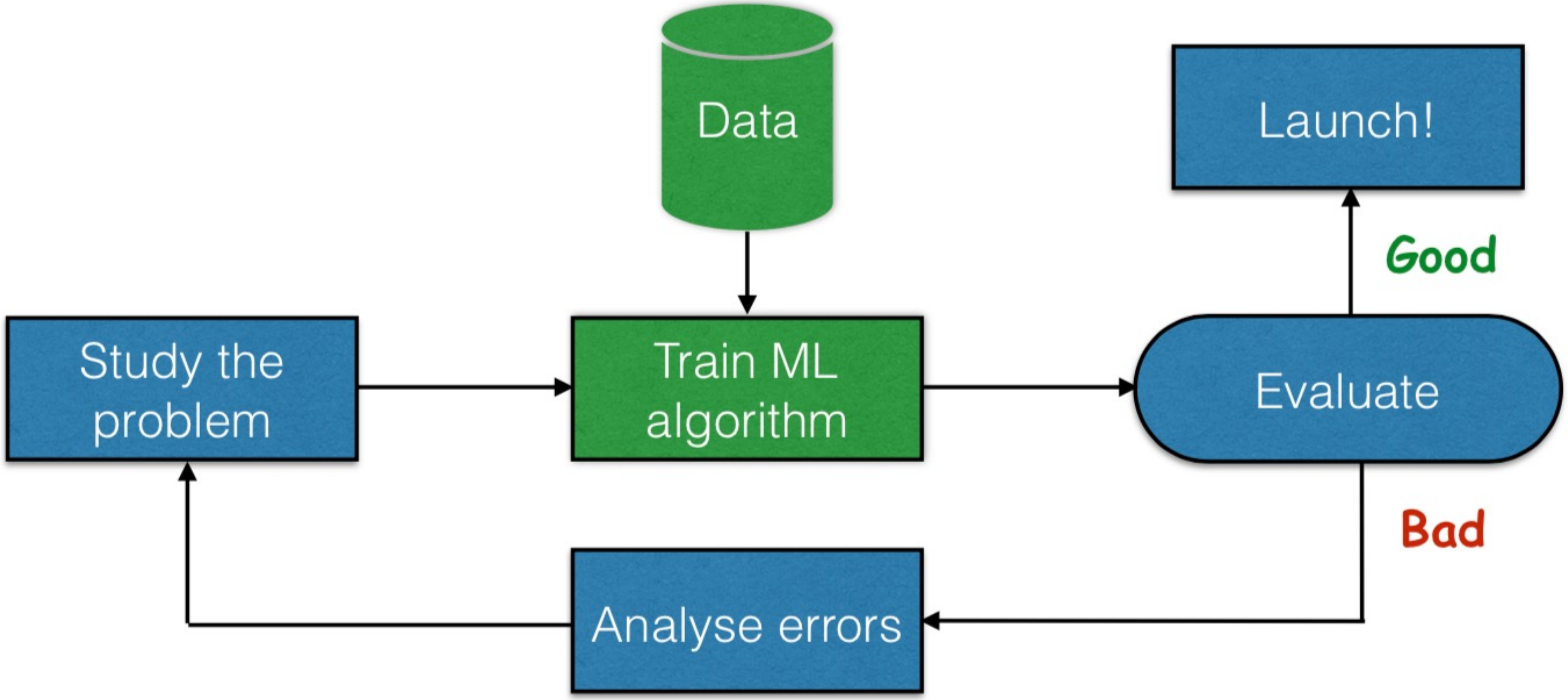
- **Deep Learning book (Goodfellow, Bengio, Courville)**
- **Lightning AI course with Sebastian Raschka**
  https://lightning.ai/pages/courses/deep-learning-fundamentals/
- **Machine Learning @ Stanford (Prof Andrew Ng)**
  https://www.coursera.org/specializations/deep-learning

Traditional approach (Software 1.0)



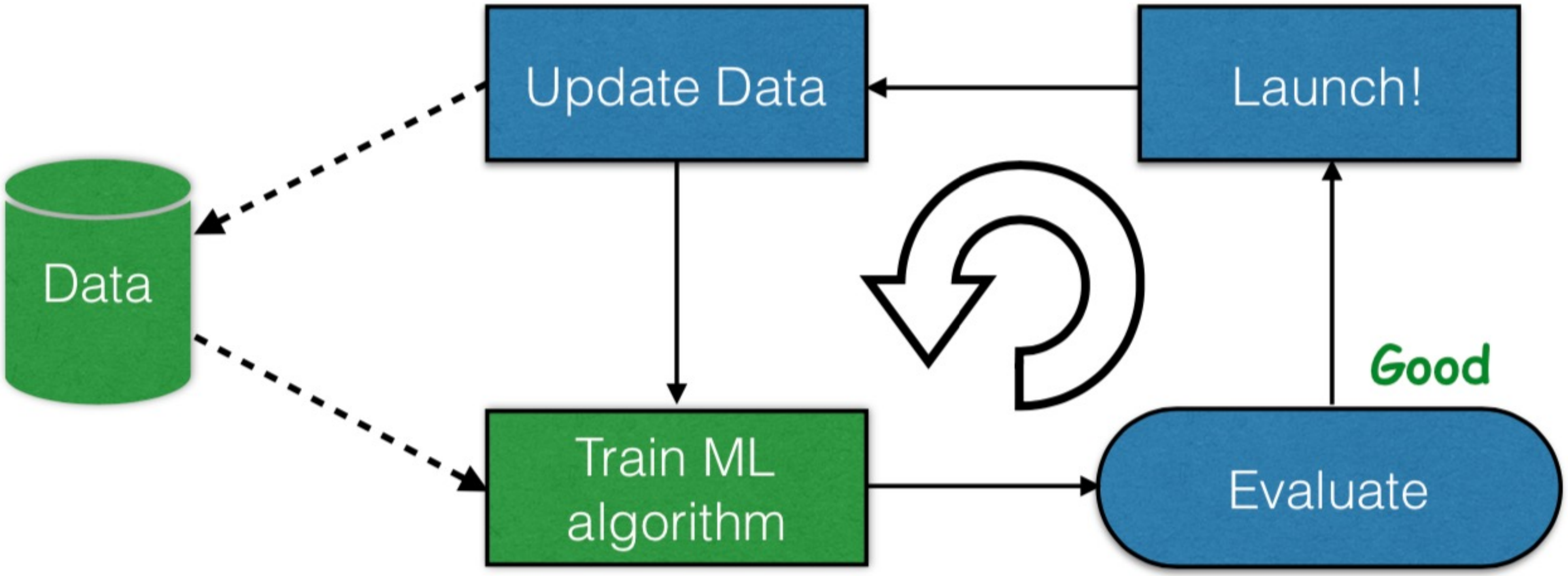
List of all the knowledge and formal rules

Machine Learning approach (Software 2.0)



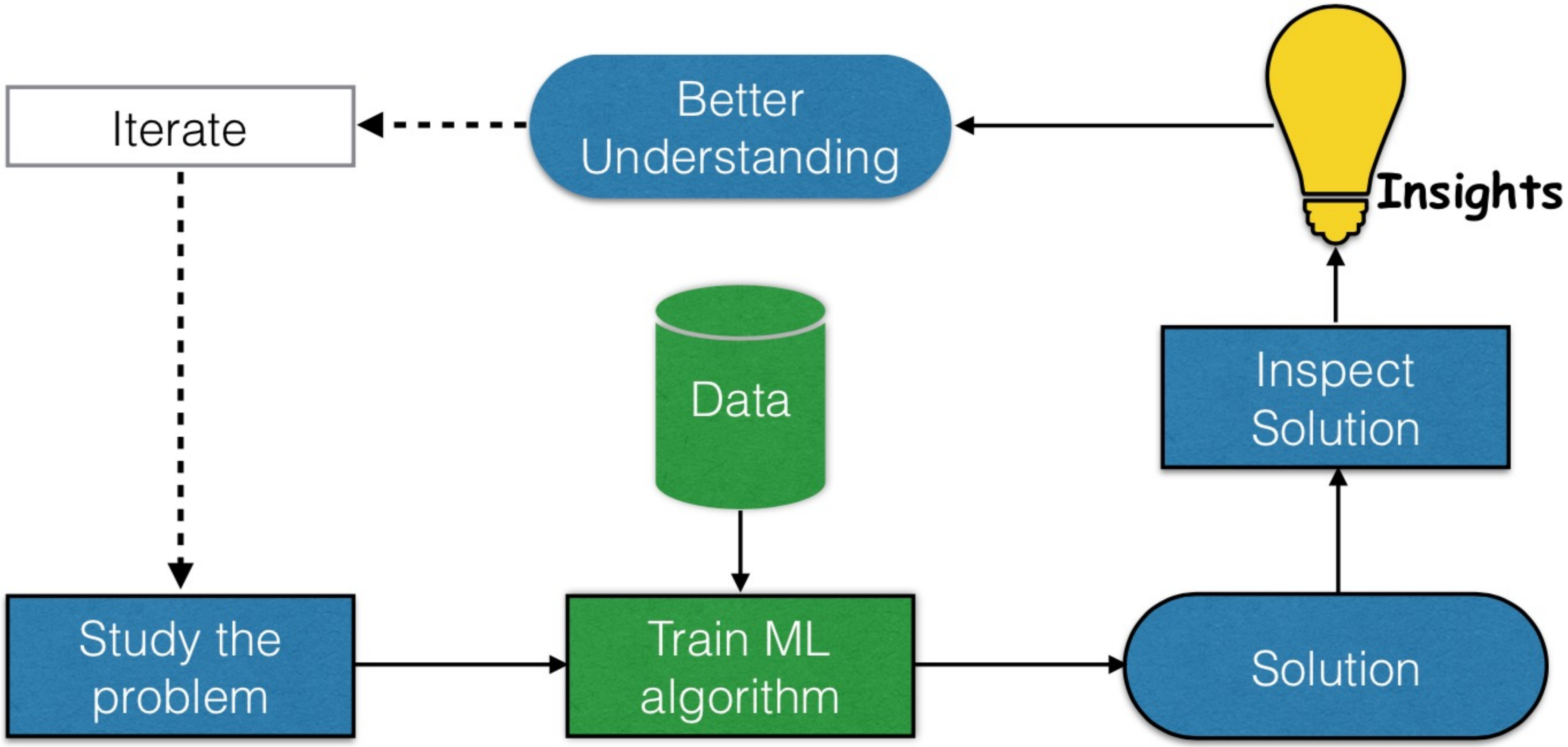
Learning from examples

Machine Learning approach (Software 2.0)



Adapting to change

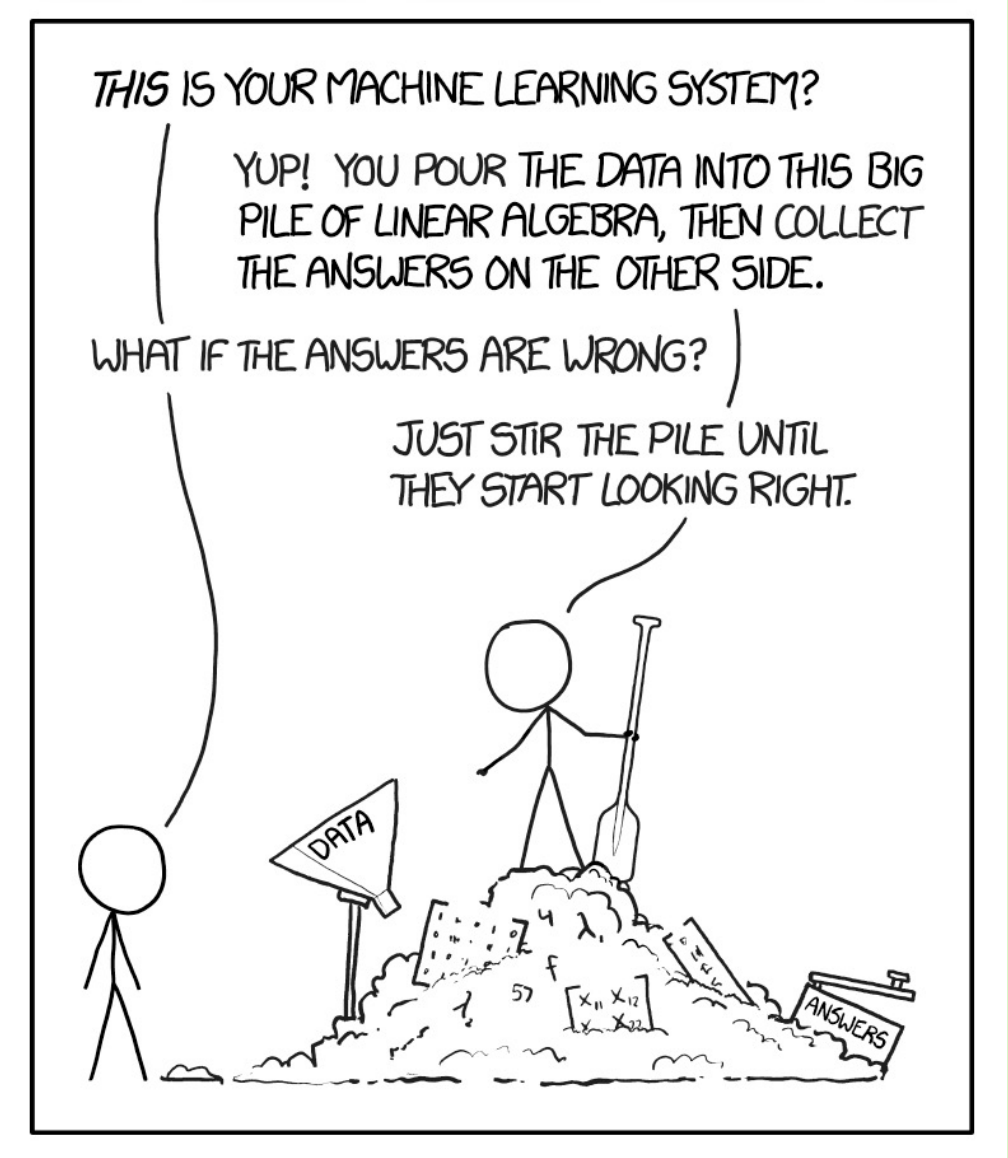
Machine Learning approach (Software 2.0)



Help Humans learn

What is Machine Learning ?

"Can machines do what we (as thinking entities) can do?"
(Turing)

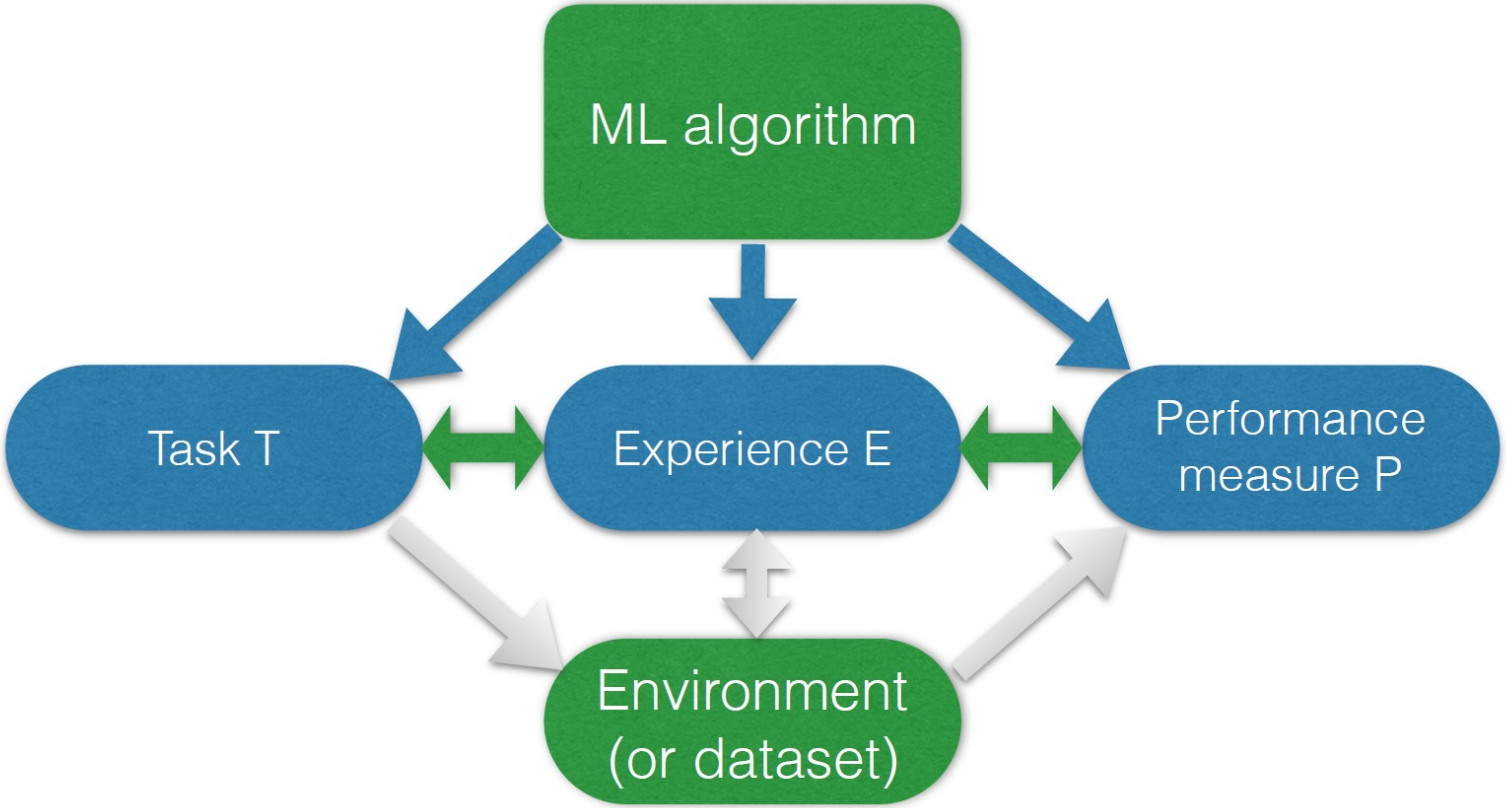


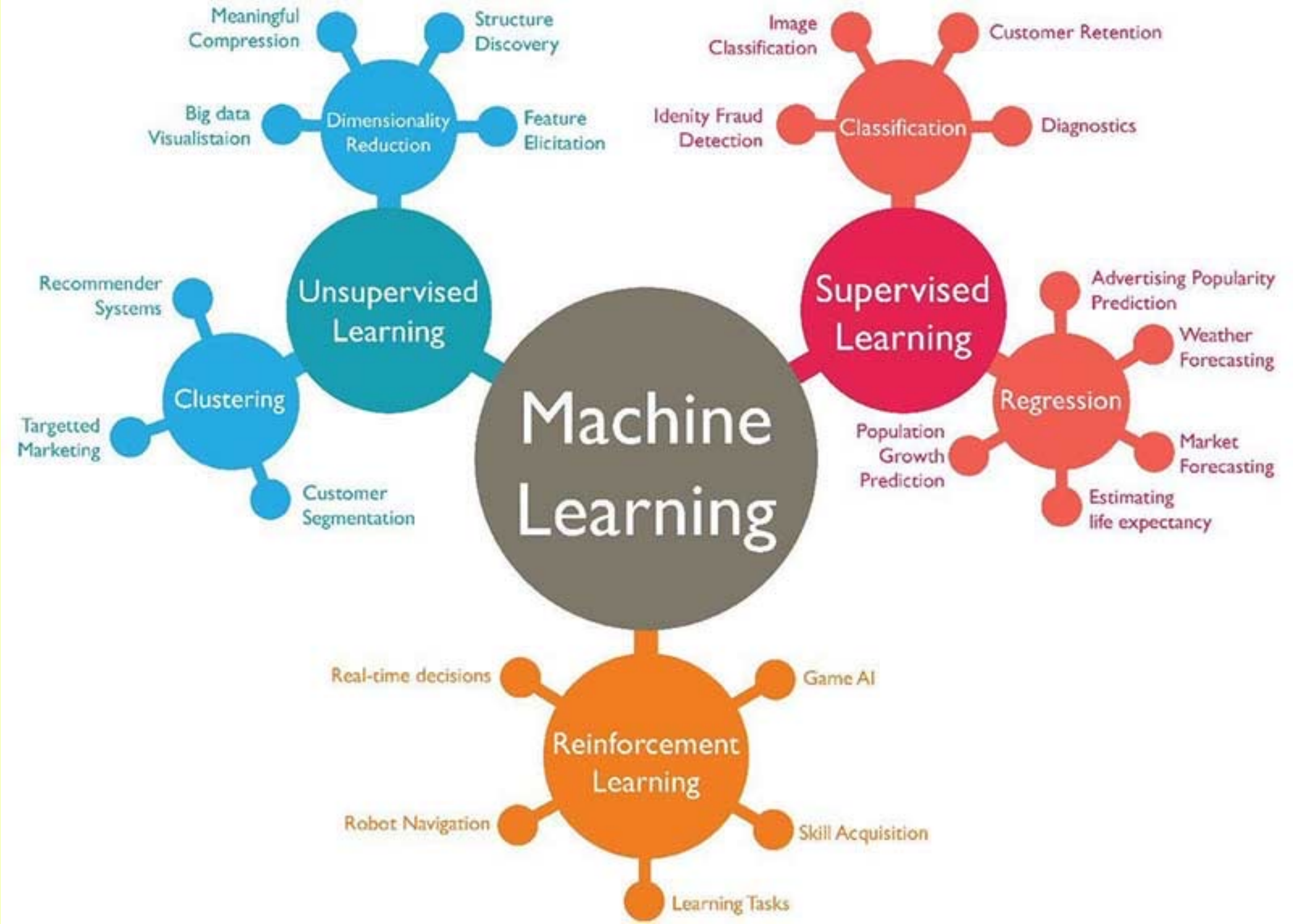
Definition… in words

« A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.»

Tom M. Mitchell (1997)

Definition… schematically





Experience E

What data to use to solve the task

Learning Pillars : How much information is given to the ML algorithm

Learning Pillars

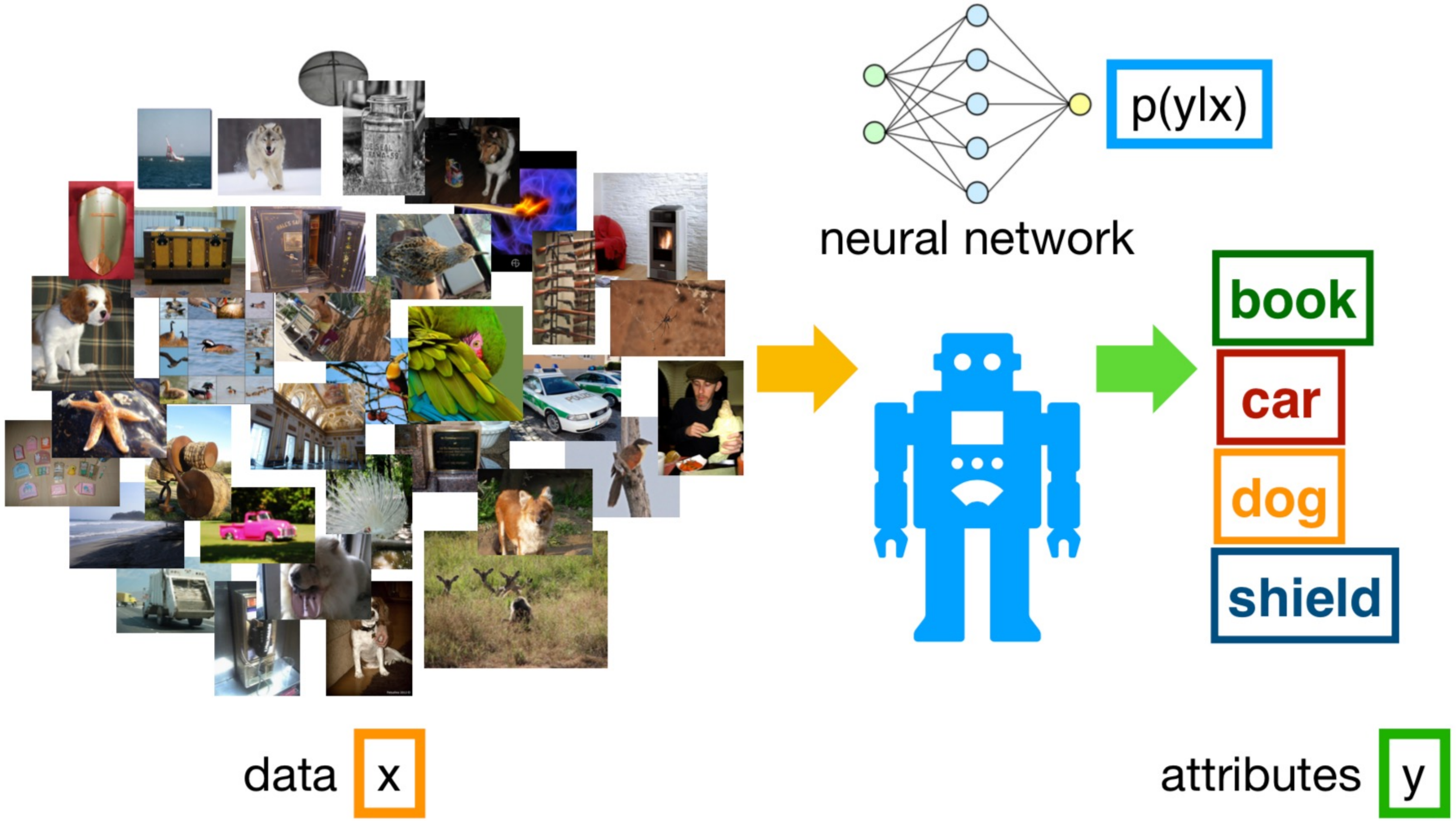
Supervised Learning

Unsupervised Learning

Reinforcement Learning

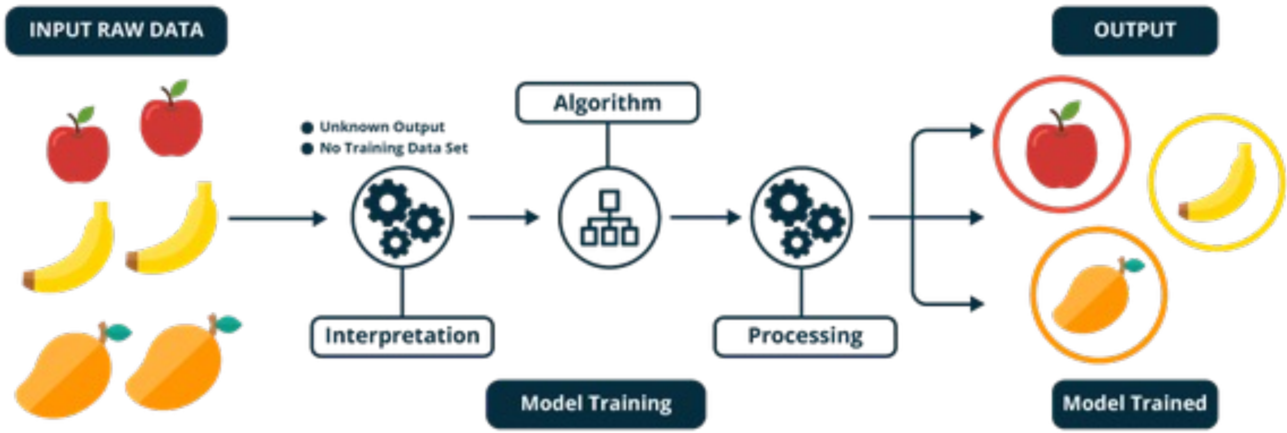
Supervised Learning

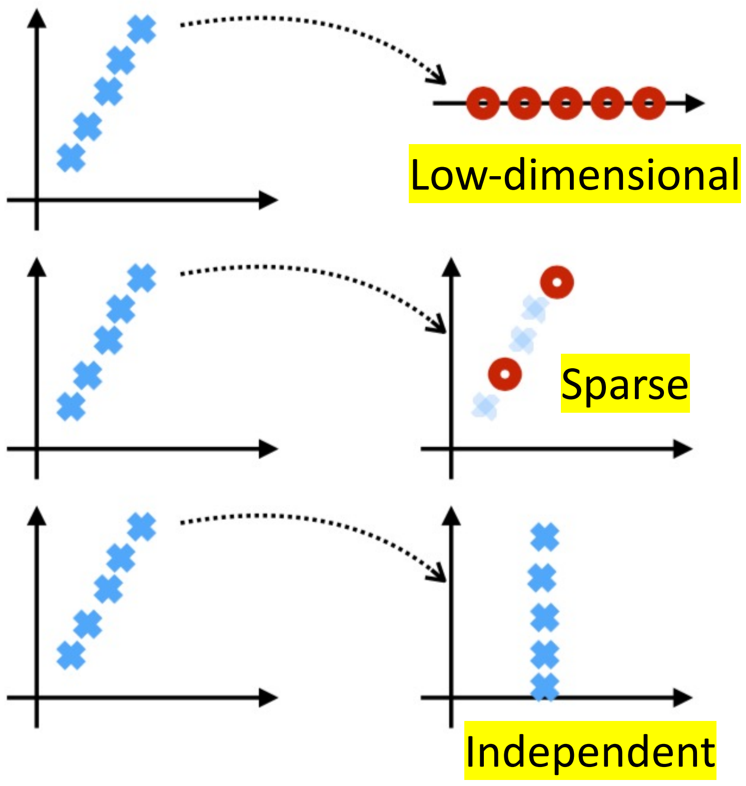
- Prediction of an output **y** given an input **x**



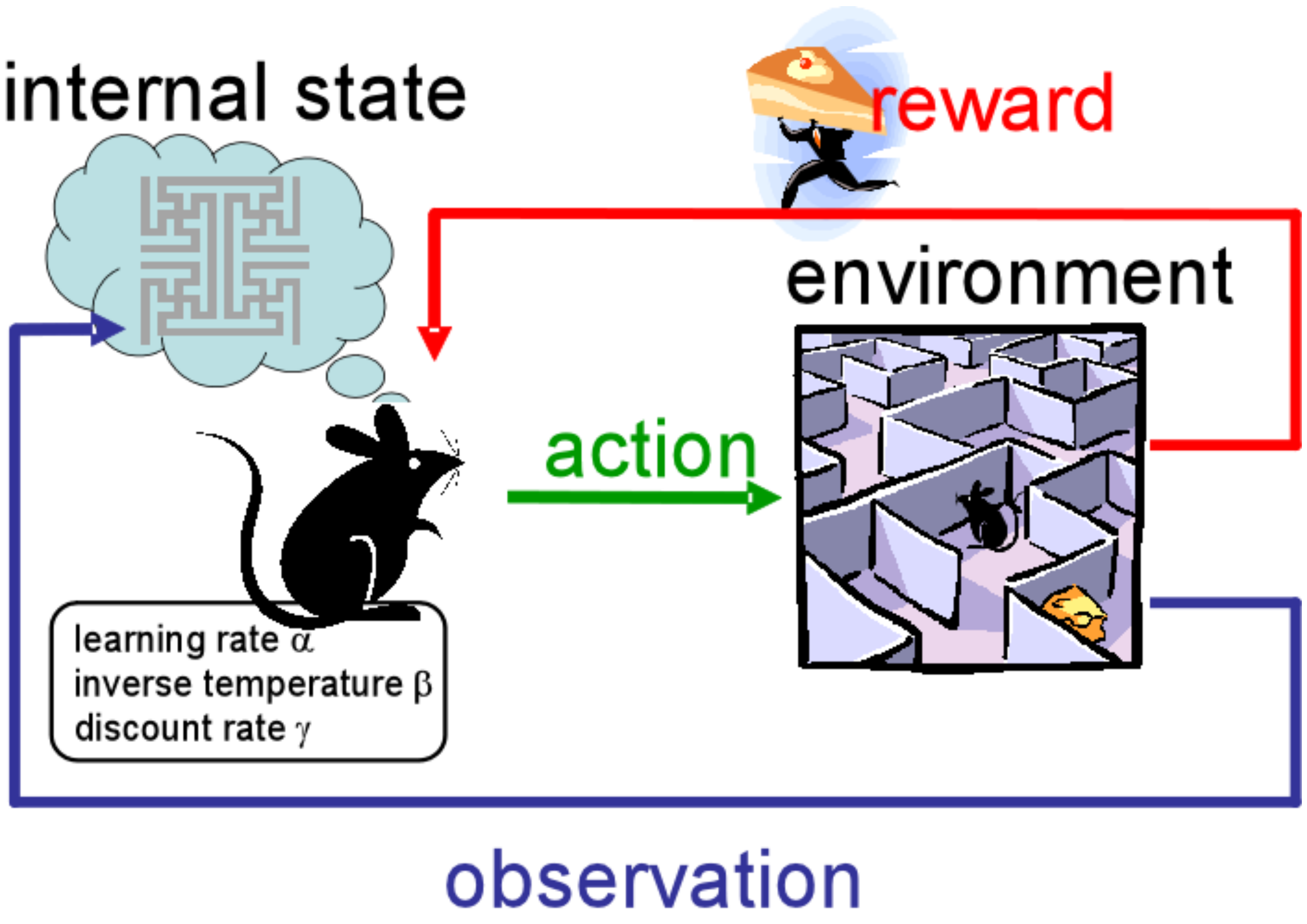
Unsupervised Learning

- Find a *suitable data representation*
  - Preserving all task-relevant information
  - Simpler than the original data and easier to use





Reinforcement Learning



Data assumption

- IID (independent and identically distributed)

1) Come from the *same distribution*

$$p_{x^{(i)}}(x) = p_{x^{(j)}}(x)$$

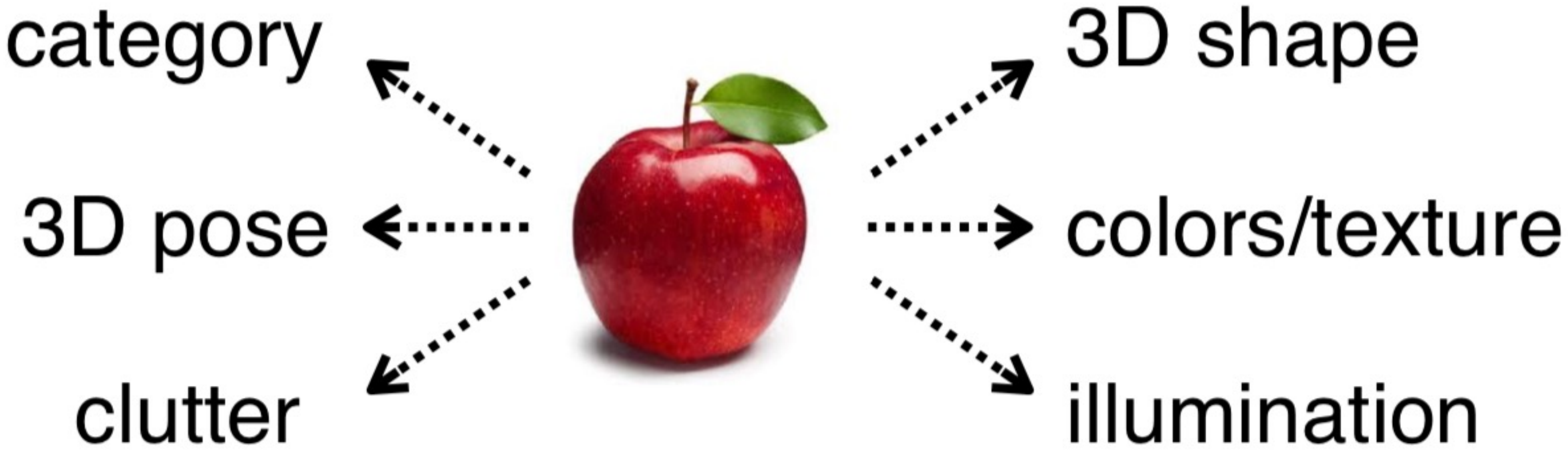
2) Are *independent*

$$p\left(x^{(1)}, \ldots, x^{(m)}\right) = \prod_{i=1}^{m} p\left(x^{(i)}\right)$$

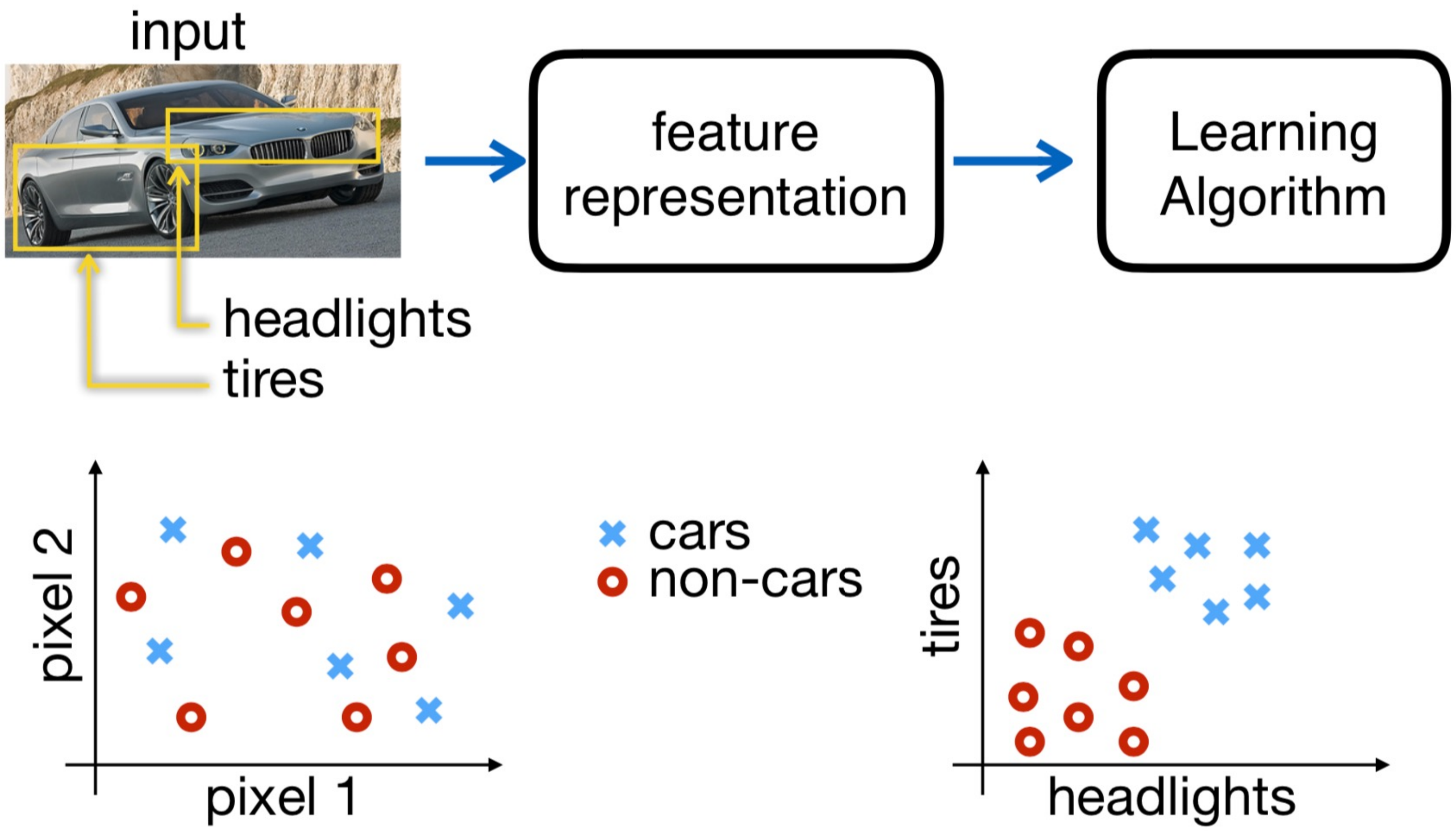
Features

- Data often encoded into more focused relevant information (features or internal representation) to simplify the decision

$$\underset{\text{data}}{x} \rightarrow \underset{\text{feature}}{\phi(x)}$$

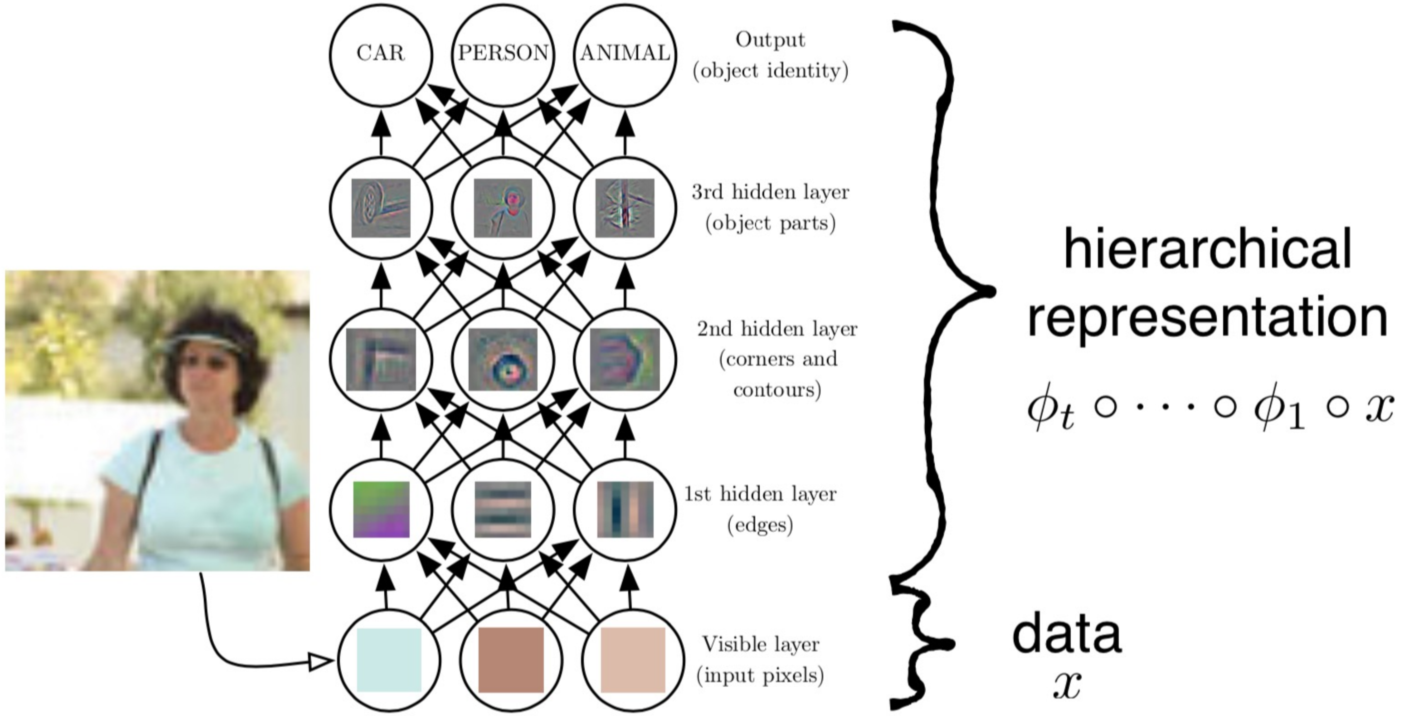


Features Example :Image classification



Deep Learning

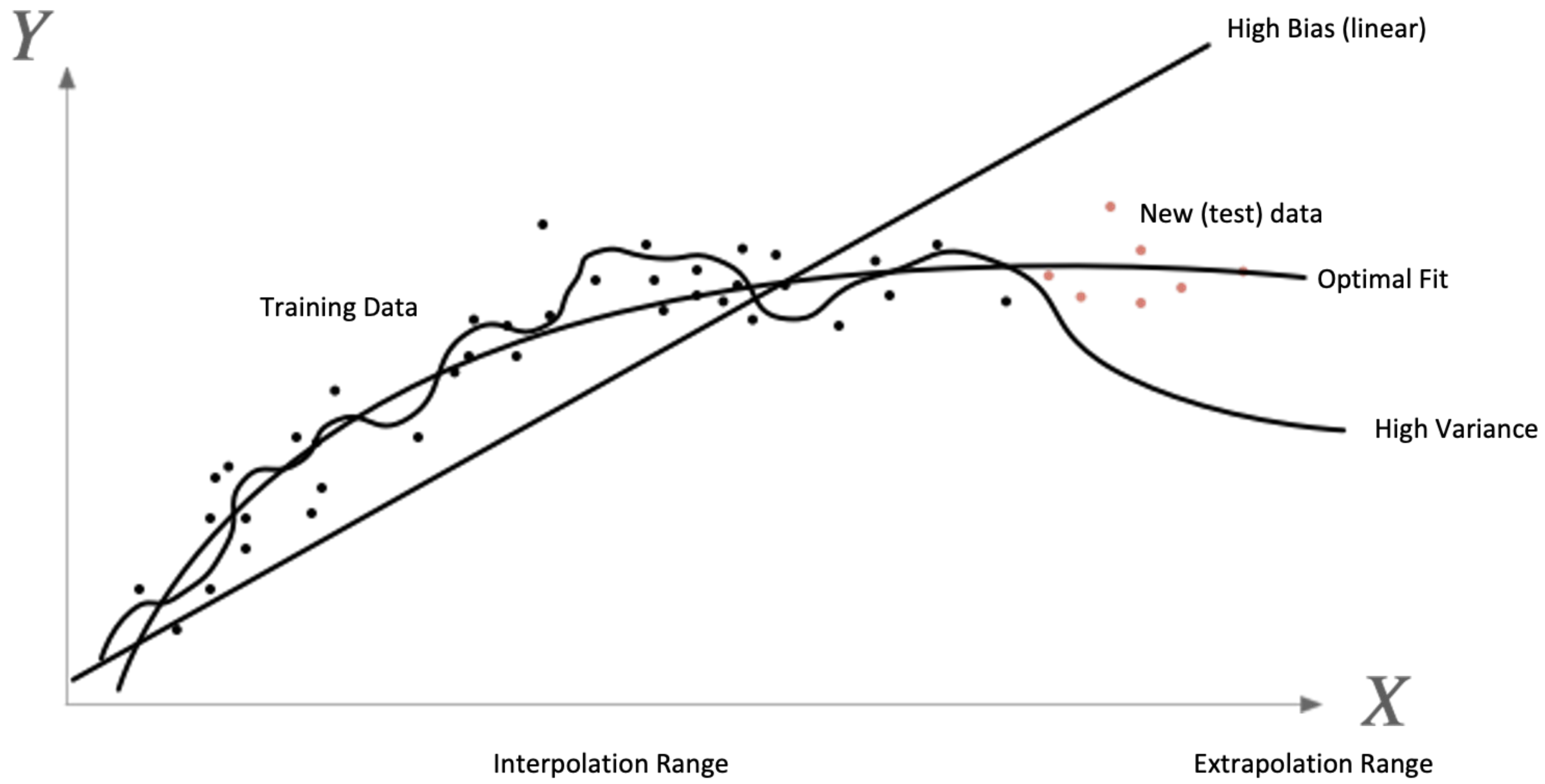
« Build a machine that can learn from experience and understand the world as a hierarchy of concepts »



Training/Validation/Test sets

- Separate the data into 2(3) sets
  - Training set for training
  - Development / Validation set to find the best parameters
  - (Test set to estimate the performance)
- Separation depends on size of the dataset
- Make sure no algorithmic decisions are being made using data which are also being used to test the algorithm

Training/Validation/Test sets



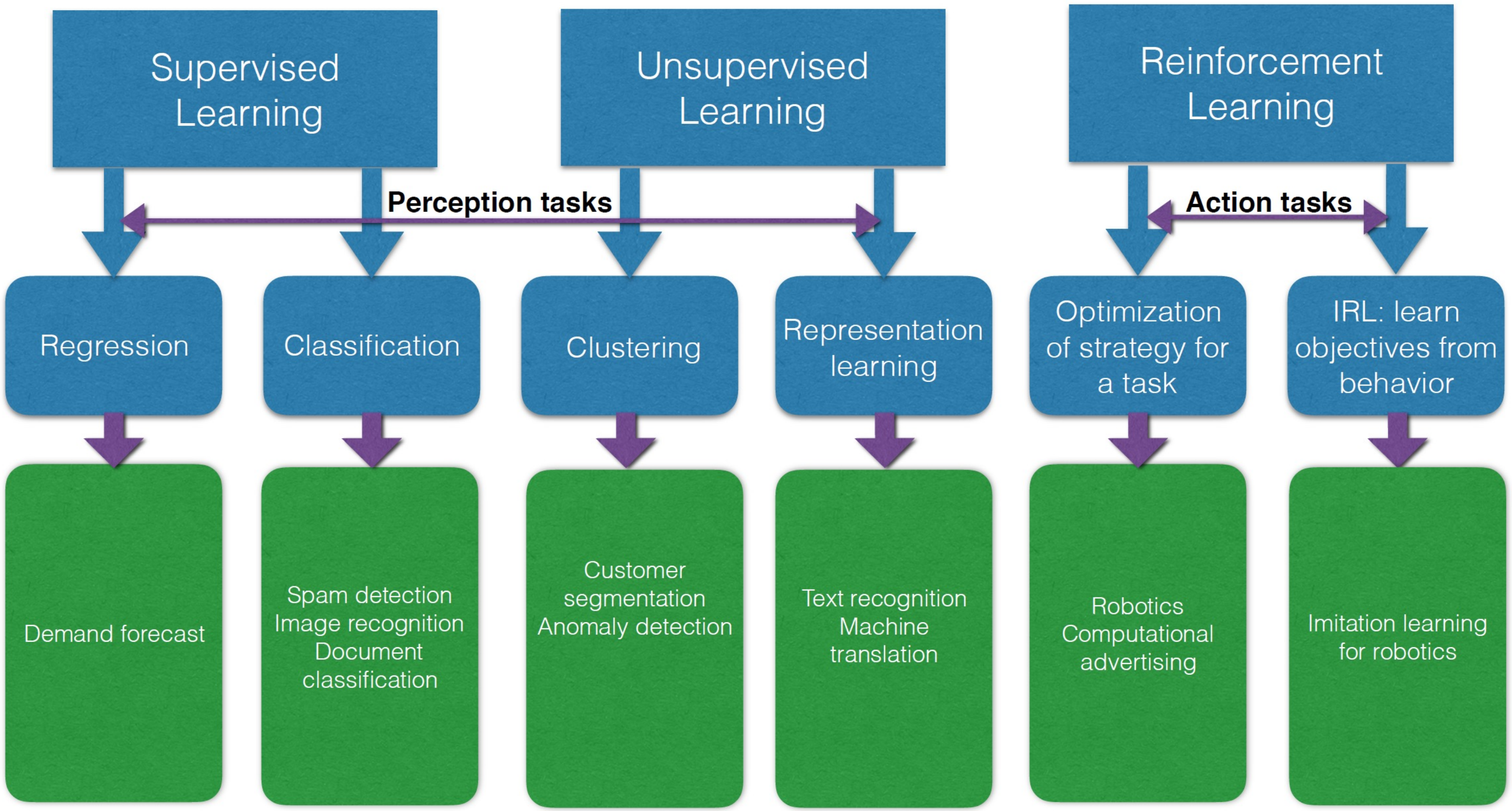
Training/Validation/Test sets

- See/consider also
  - K-fold cross-validation
  - Leave-one-out cross-validation (k=n)
  - Nested cross-validation

Task T

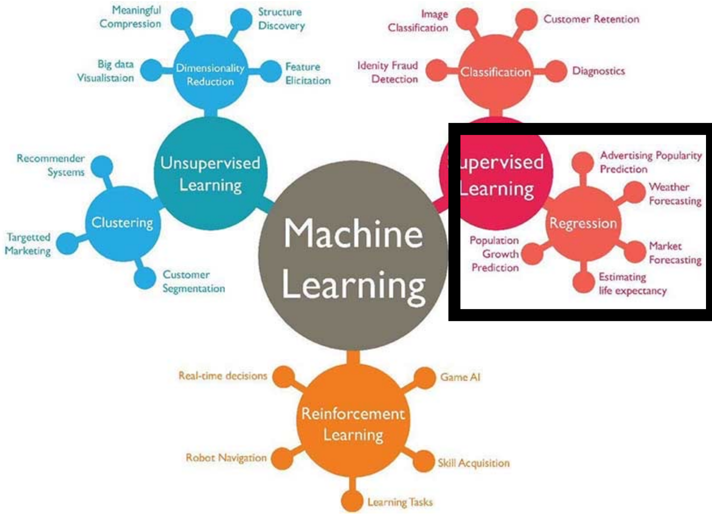
Find the function f that satisfies f(x) = y using the *training set*

Problem Types



Regression

Predict results within *a continuous output*

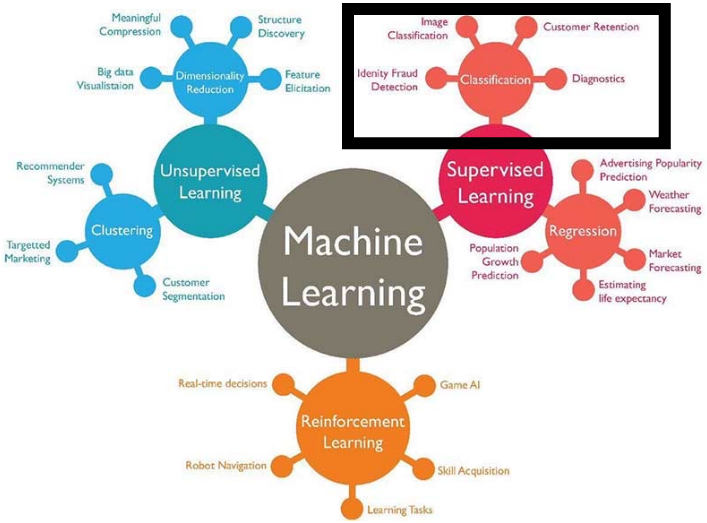


$82000

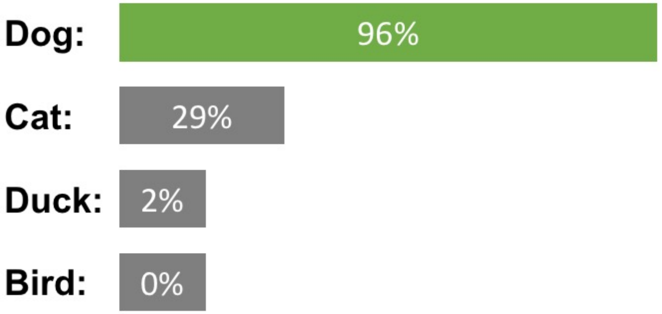
$55500

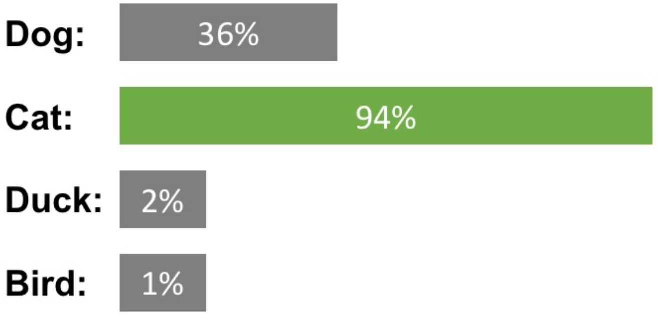
???

Classification

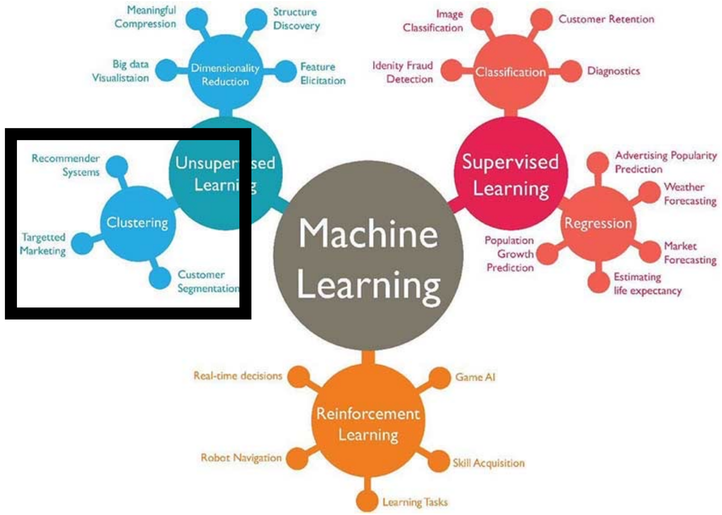


- categorize new inputs as belonging to one of a set of categories → Predict results within *a discrete output (categories)*

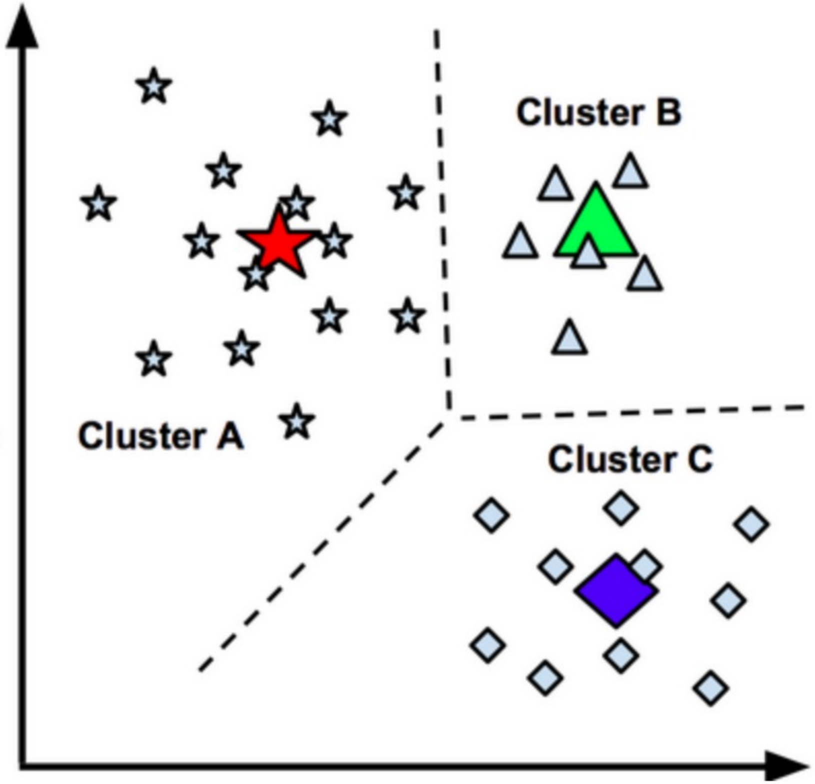




Clustering

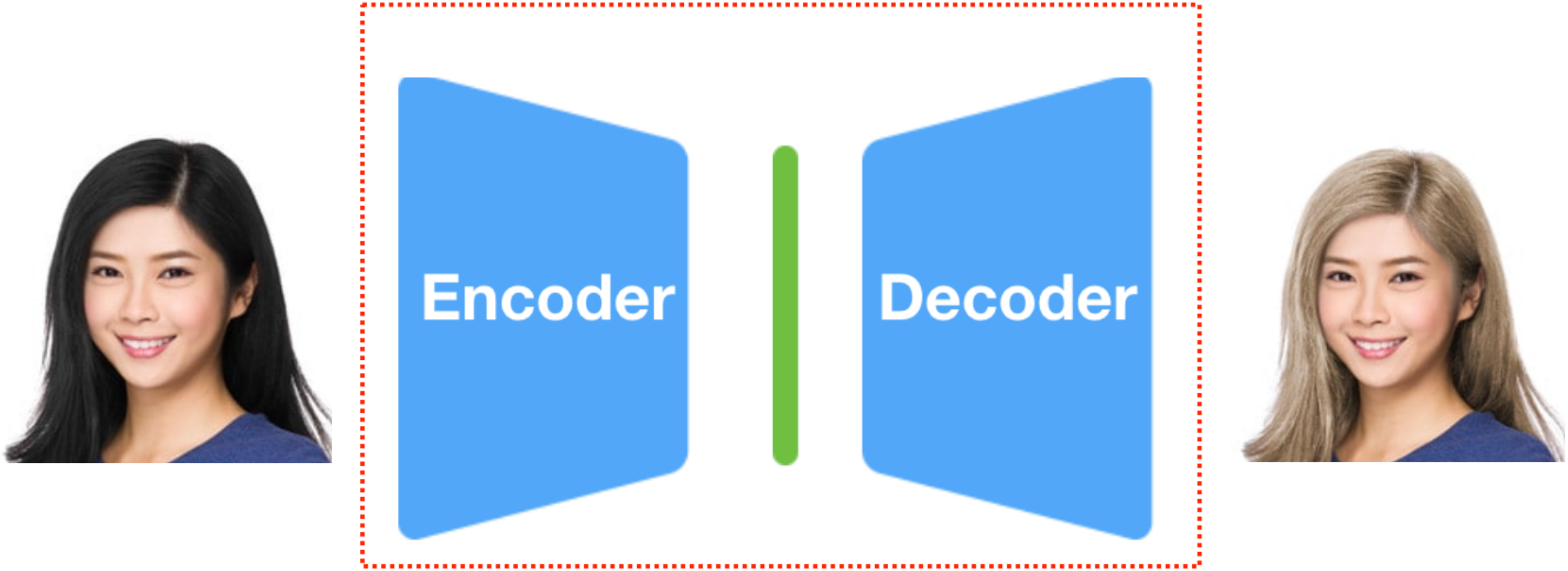


- create a set of categories, for which individual data instances have a set of common or similar characteristics.



Data Generation

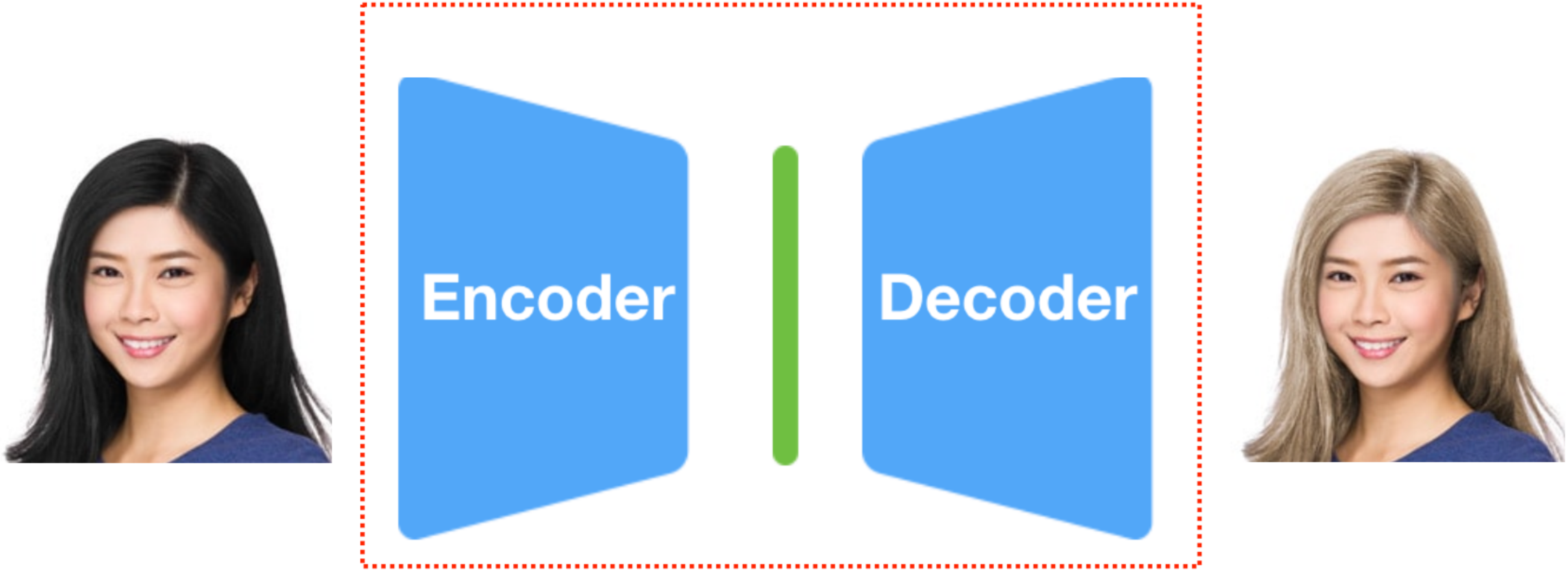
- generate appropriately novel data



Autoencoder

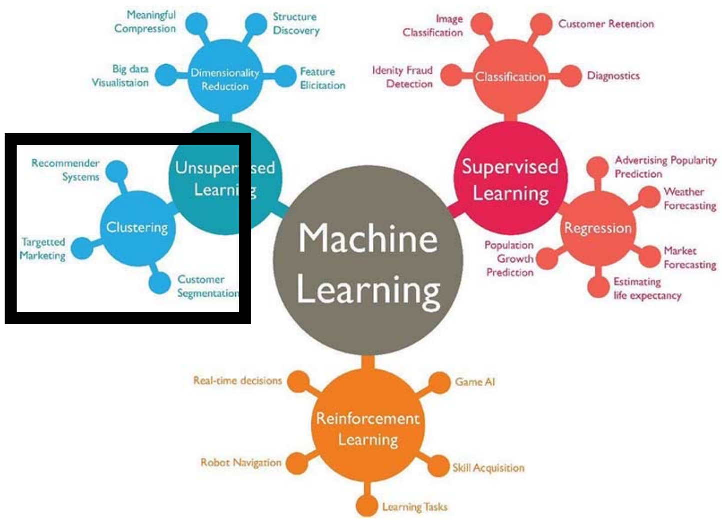
Data Generation

- generate appropriately novel data

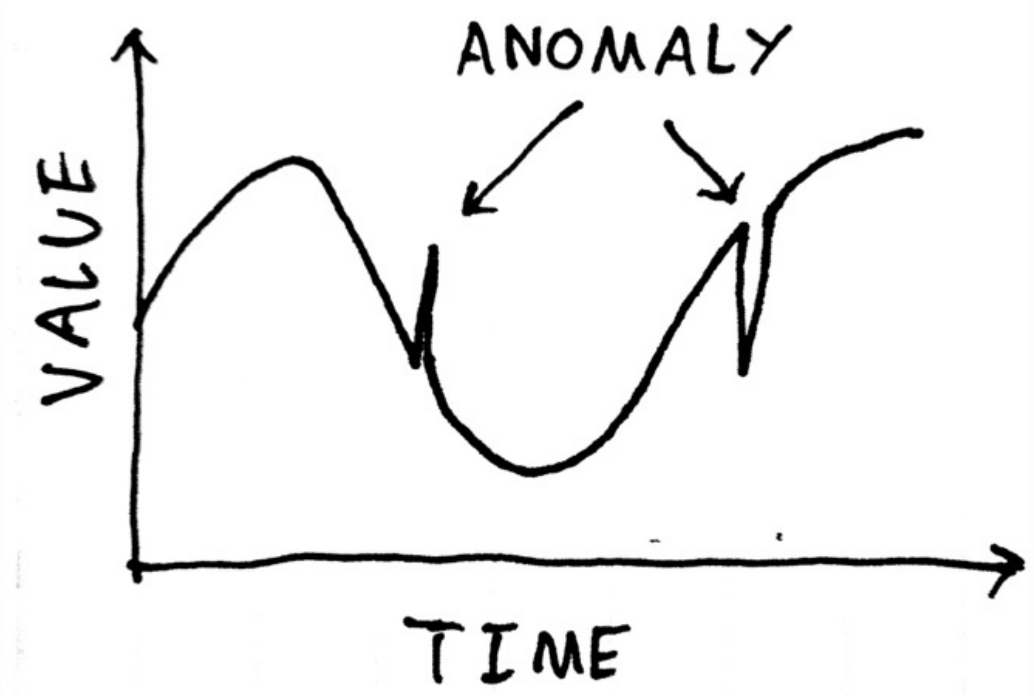


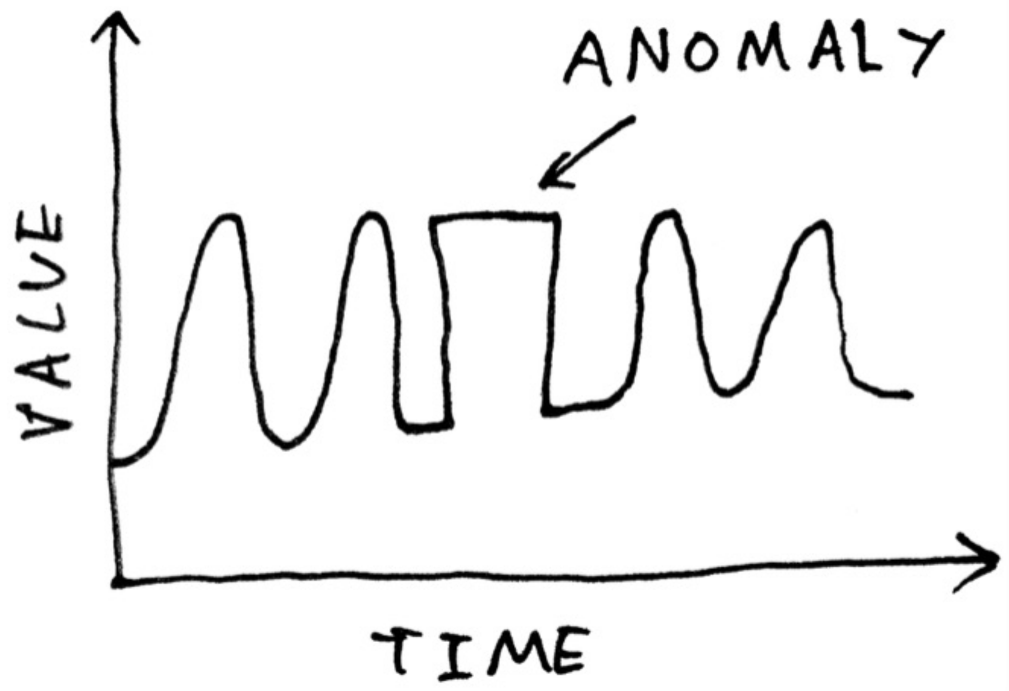
Autoencoder

Anomaly Detection



- determine whether specific inputs are out of the ordinary.





Representation Learning

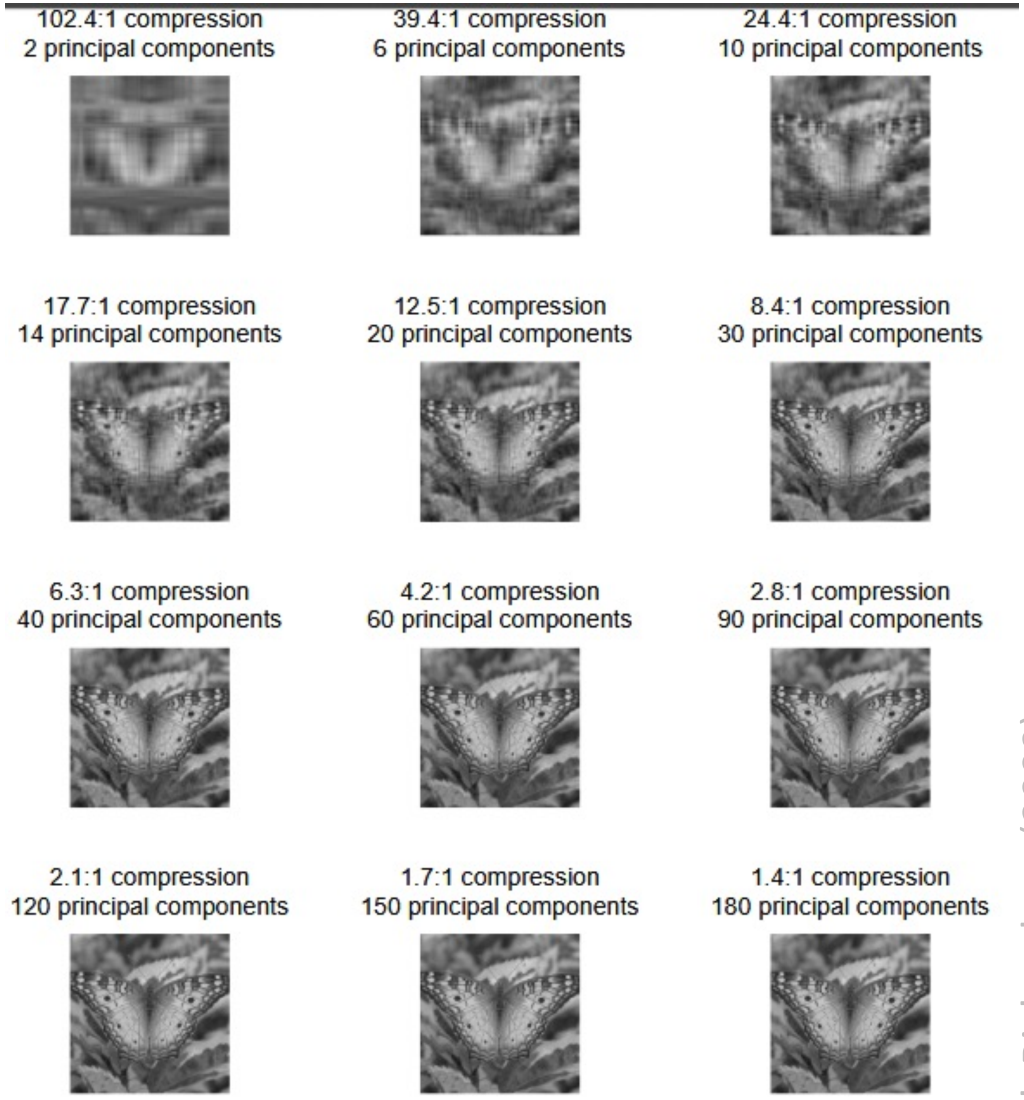
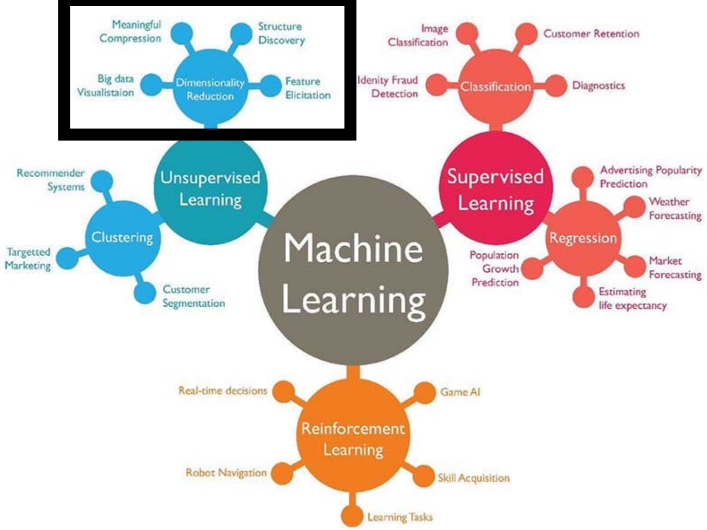


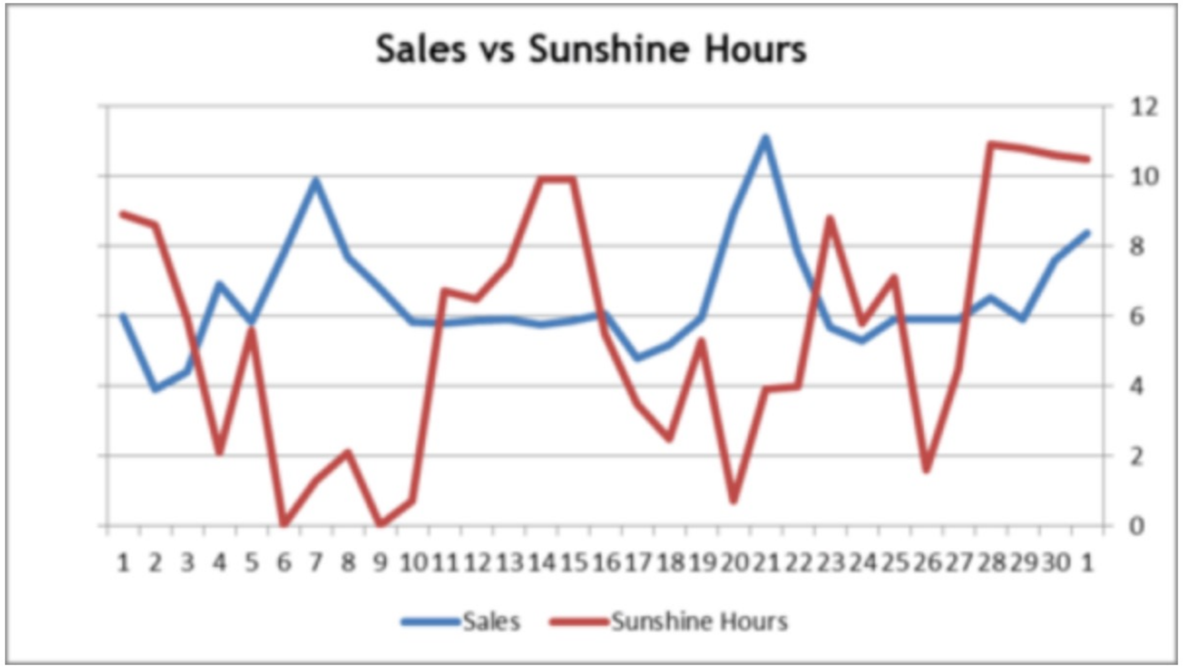
Figure 10: The visual effect of retaining principal components

Mark Richardson (2009)



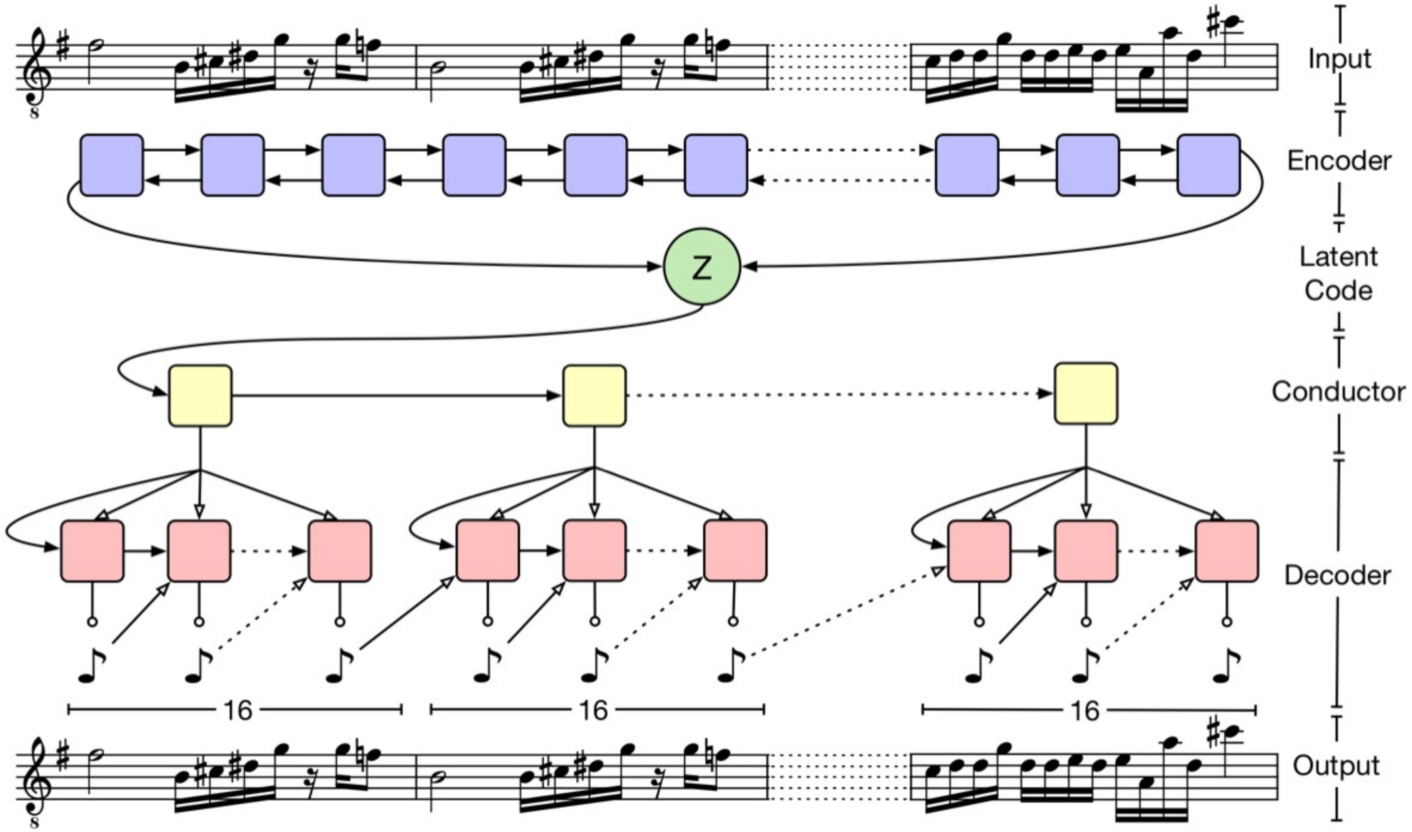
Continuous Estimation

- estimate the next numeric value in a sequence (*prediction* for time series data)



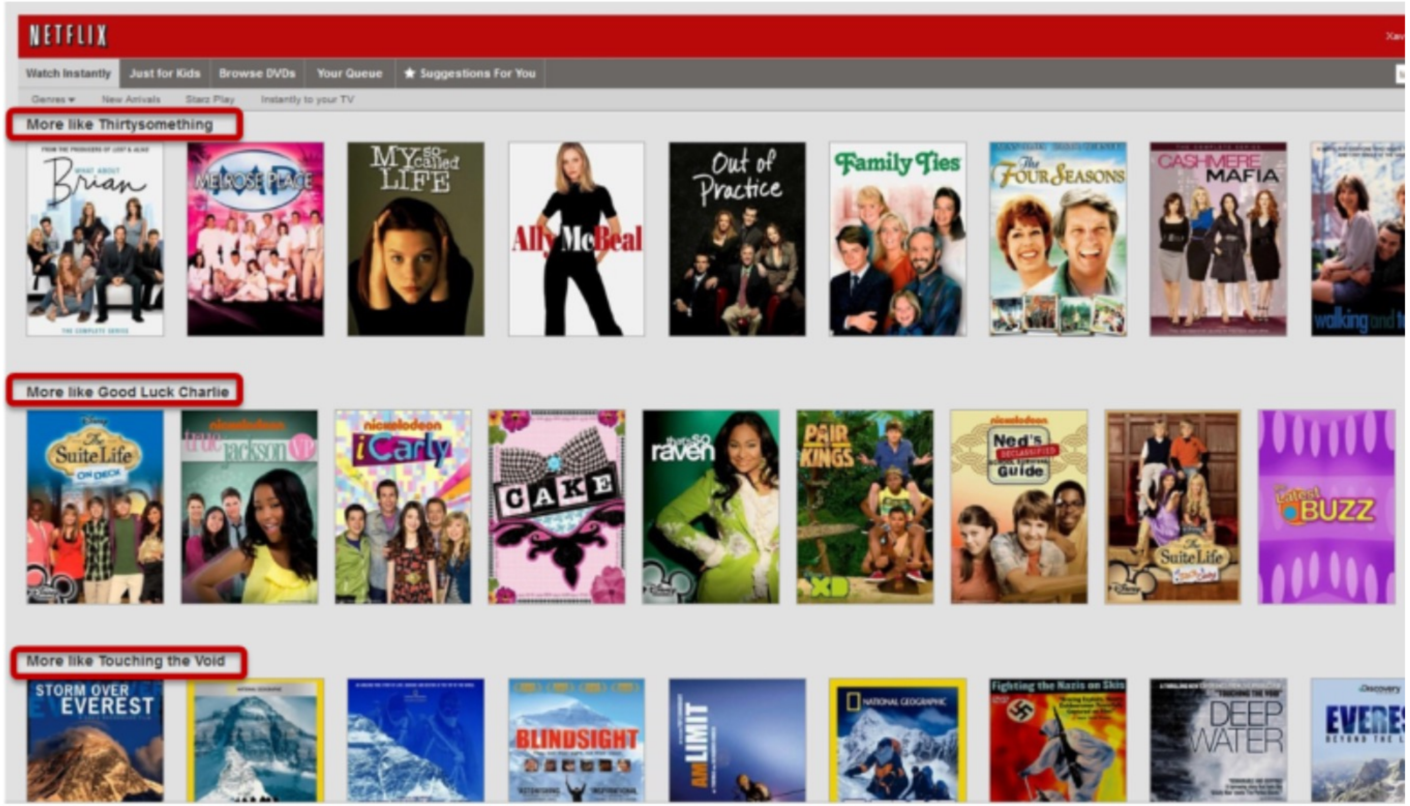
Data Generation

- generate appropriately novel data



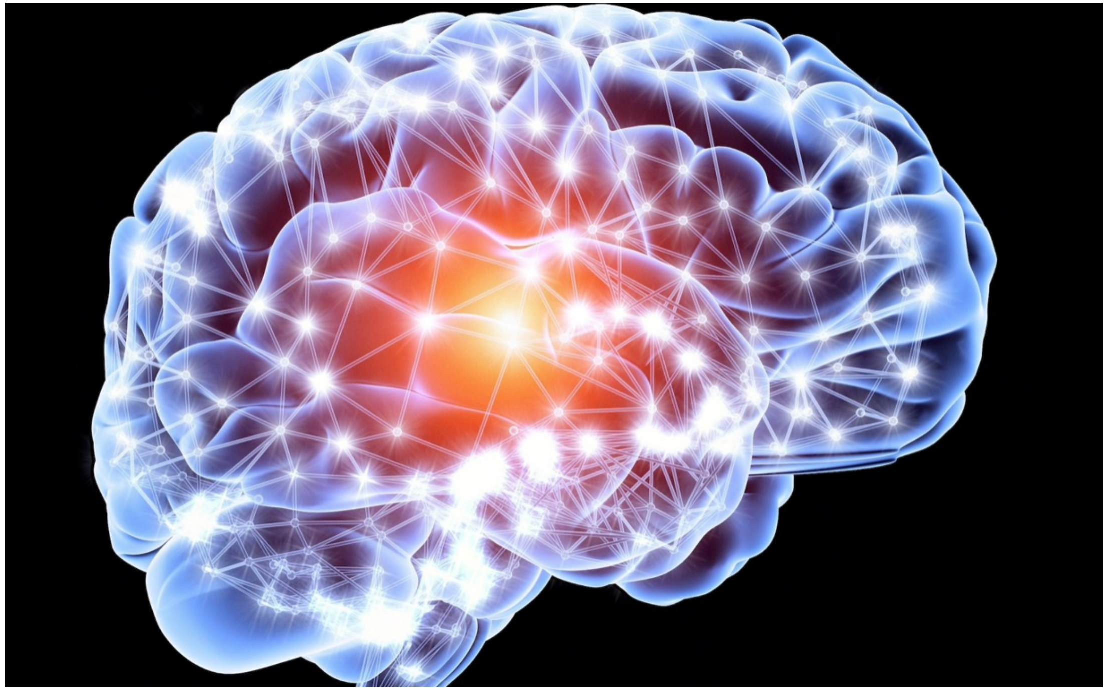
Ranking

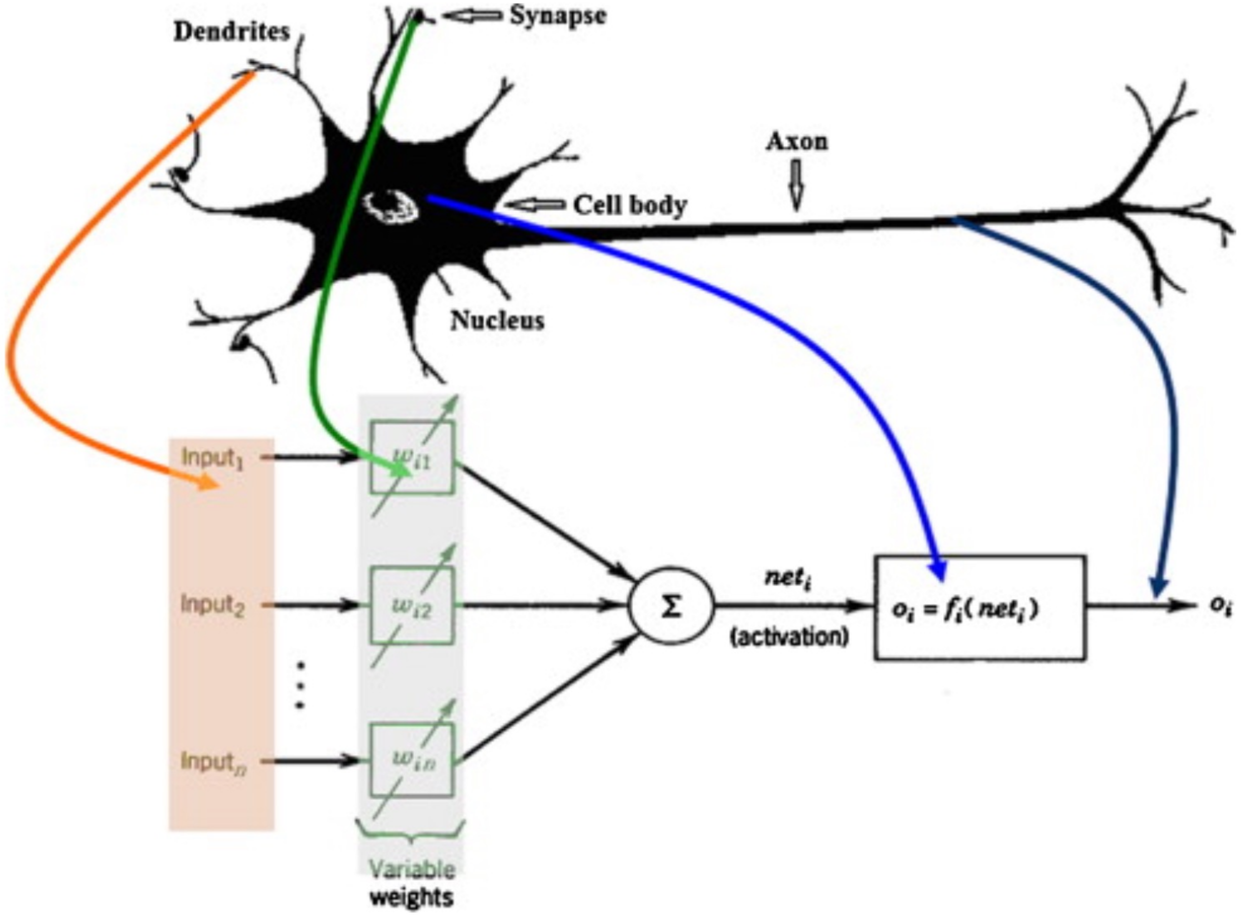
- Used in information retrieval problems
- Used in recommendation systems



Neural Network (NN)

- Learning algorithm inspired by *how the brain works*





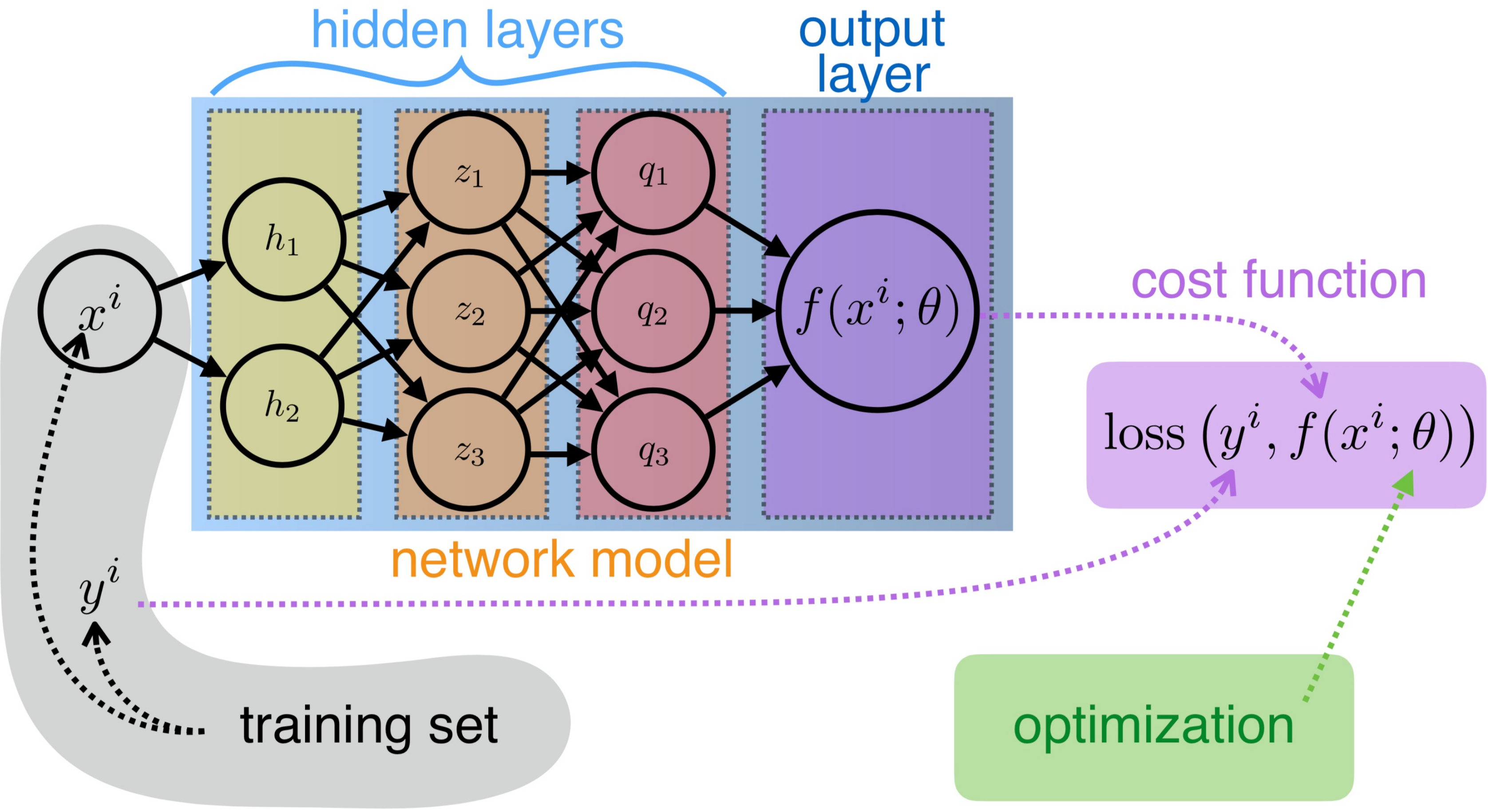
Deploying a Neural Network

Given a task (in terms of **I/O mappings**), we need :

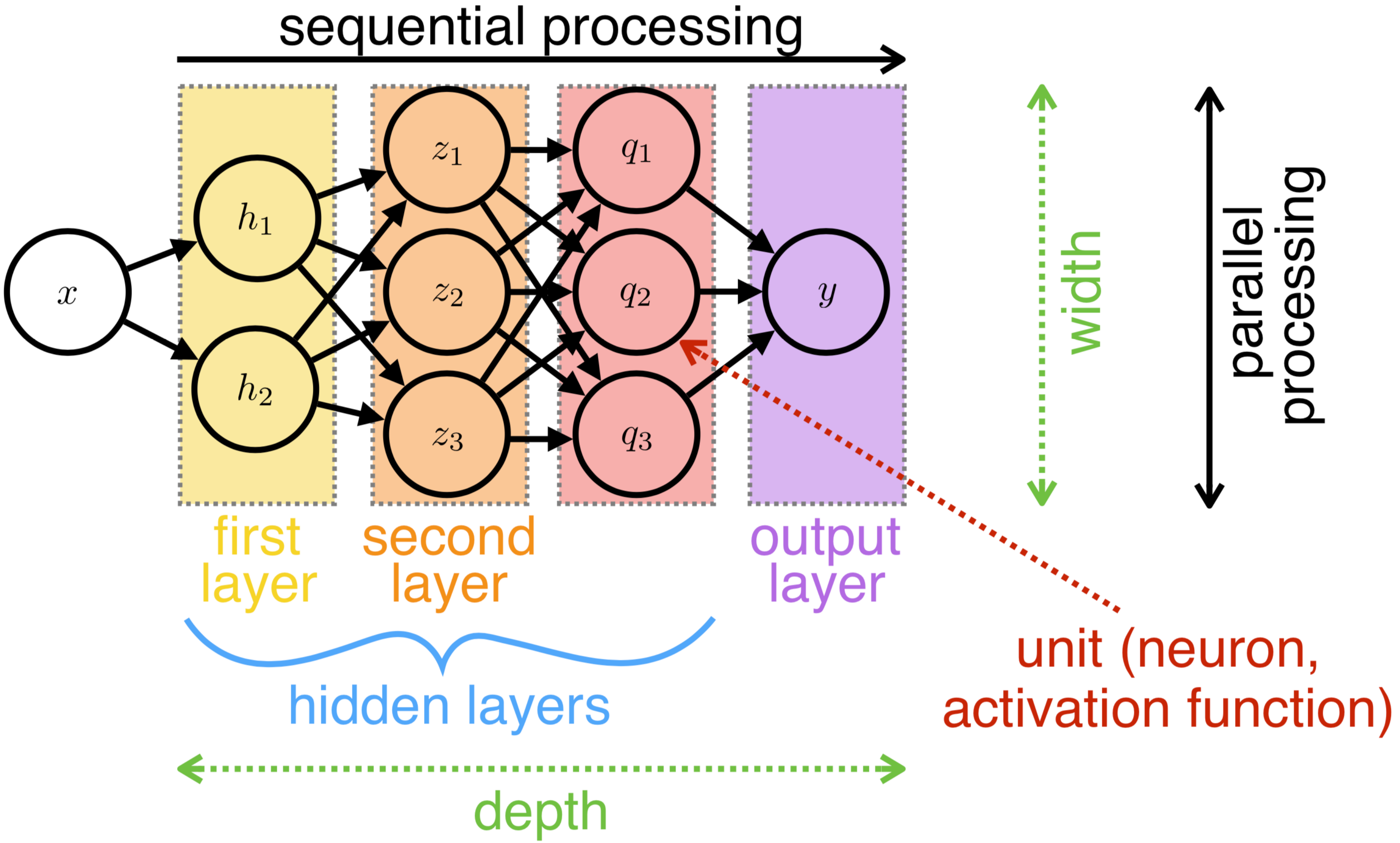
1) **Network model**

2) **Cost function (/objective/loss function)**

3) **Optimization**

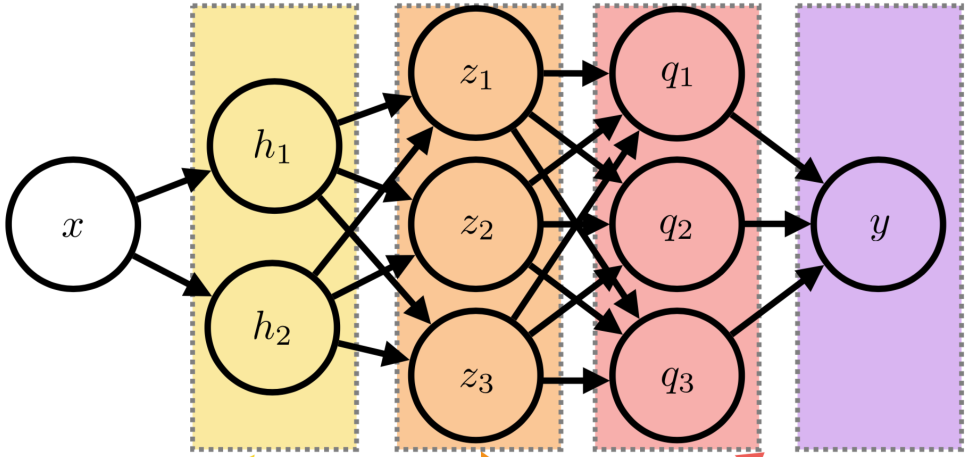


Network model



Activation functions

Different types of activation functions for the hidden layers and the output layer



$$y = f_4(q_1, q_2, q_3)$$

$$\boxed{y = f_4(f_{3,1}(f_{2,1}(f_{1,1}(x), f_{1,2}(x)), \dots), \dots)}$$

Hierarchical representation

$$h_1 = f_{1,1}(x)$$
$$h_2 = f_{1,2}(x)$$

$$z_1 = f_{2,1}(h_1, h_2)$$
$$z_2 = f_{2,2}(h_1, h_2)$$
$$z_3 = f_{2,3}(h_1, h_2)$$

$$q_1 = f_{3,1}(z_1, z_2, z_3)$$
$$q_2 = f_{3,2}(z_1, z_2, z_3)$$
$$q_3 = f_{3,3}(z_1, z_2, z_3)$$

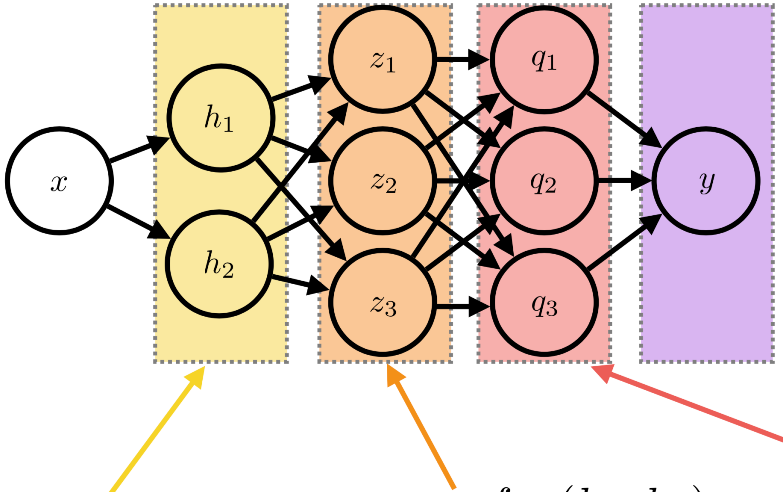
Fully connected

$$\boxed{f_{2,2}(h_1, h_2) = w_1 h_1 + w_2 h_2 + b_{2,2}}$$

Weights w and bias b parameters to optimize

Activation functions

Different types of activation functions for the hidden layers and the output layer



$$y = f_4(q_1, q_2, q_3)$$

$$h_1 = f_{1,1}(x)$$
$$h_2 = f_{1,2}(x)$$

$$z_1 = f_{2,1}(h_1, h_2)$$
$$z_2 = f_{2,2}(h_1, h_2)$$
$$z_3 = f_{2,3}(h_1, h_2)$$

$$q_1 = f_{3,1}(z_1, z_2, z_3)$$
$$q_2 = f_{3,2}(z_1, z_2, z_3)$$
$$q_3 = f_{3,3}(z_1, z_2, z_3)$$

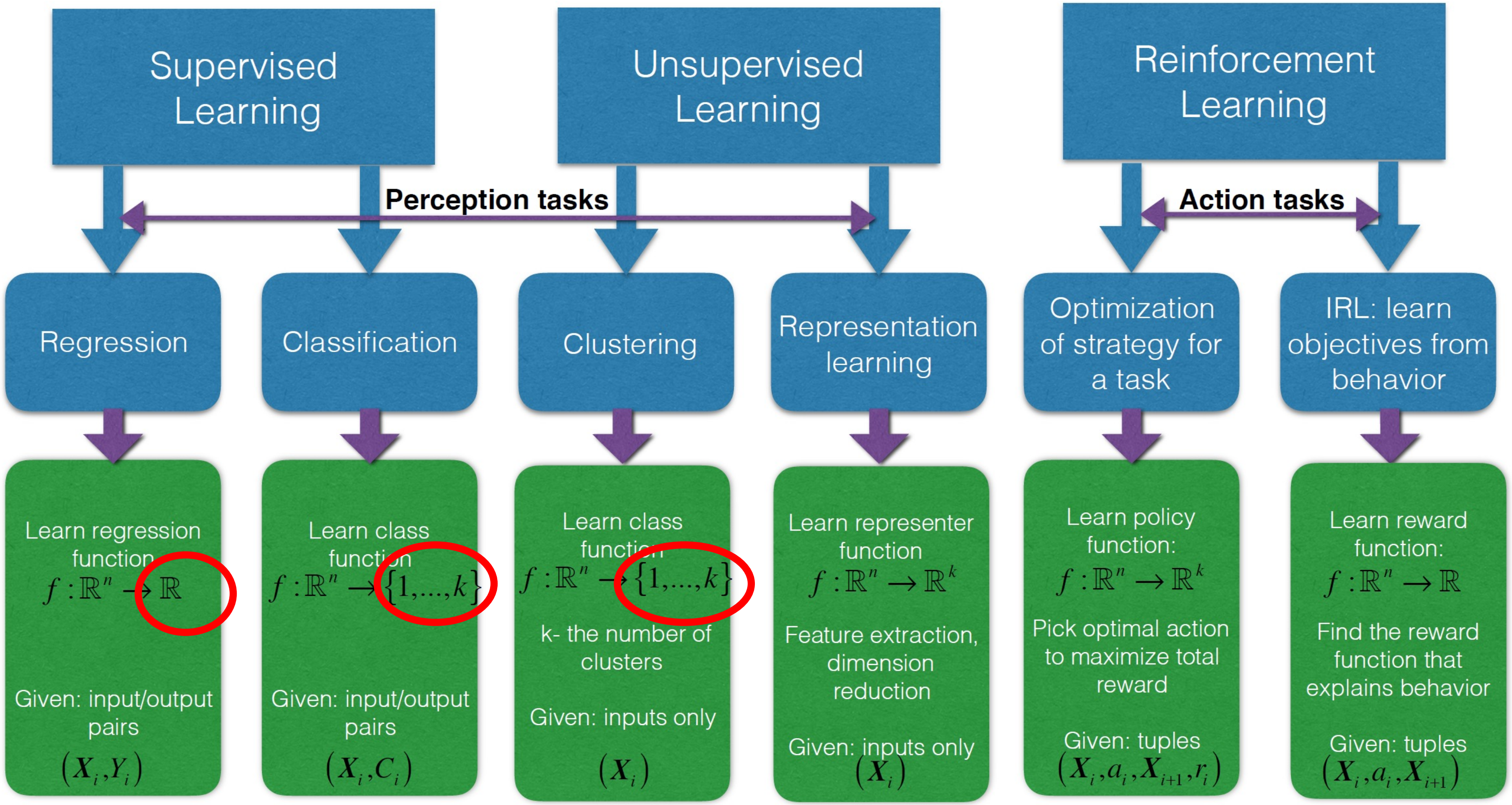
(3,1) **(3,2)** **(2,1)**

$$Z = W_z H$$

Fully connected

$$\boxed{f_{2,2}(h_1, h_2) = w_1 h_1 + w_2 h_2 + b_{2,2}}$$

Neural Network Outputs

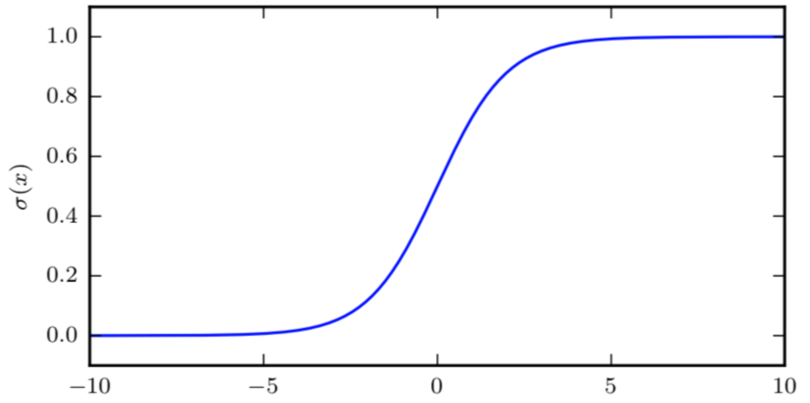


Output layer : activation functions

1) Classification : probability vector

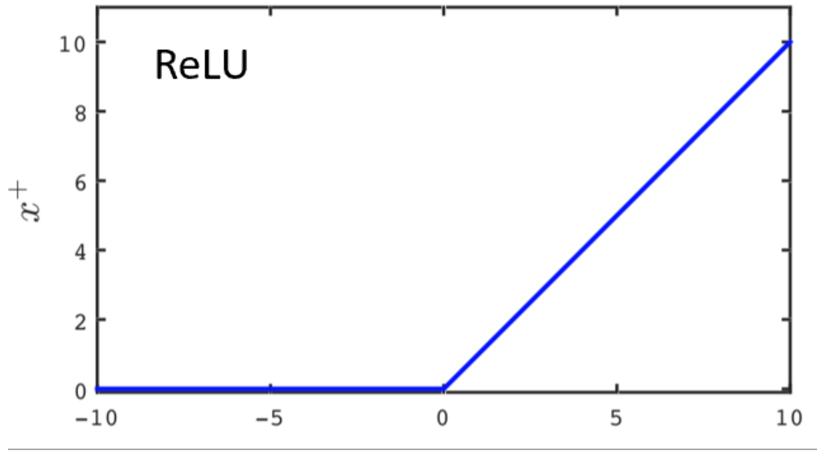
- Sigmoid (binary class)
- Softmax (multiple class)

$$Z = \sigma(W_z H)$$



2) Regression : mean estimate

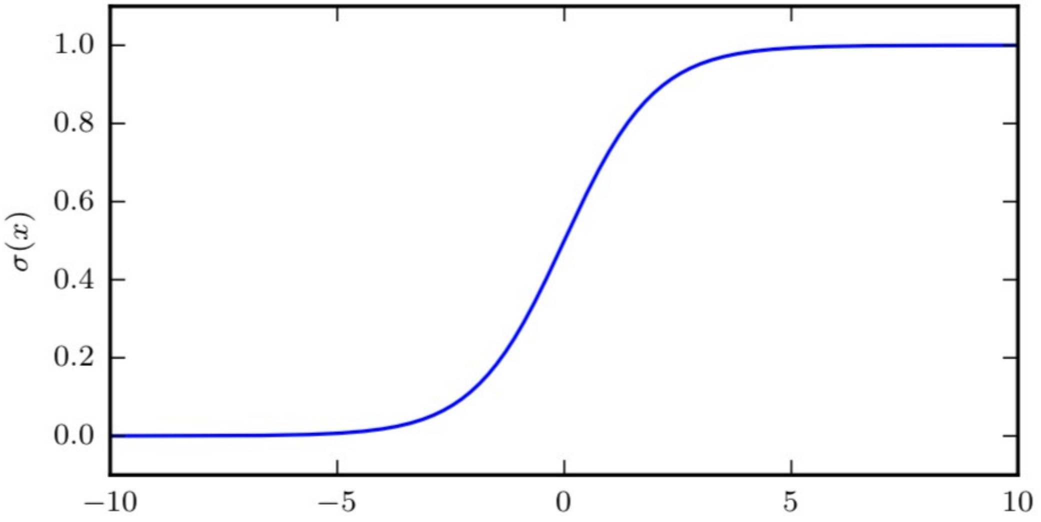
- ReLU
- Softplus
- Smoothed max
- Generalization of ReLU (leaky ReLU,…)



Sigmoid and softmax

Sigmoid (*two-class* classifier) :

$$\boxed{\sigma(x) = \frac{1}{1+e^{-x}}}$$



Softmax (*multi-class* classifier) :

$$\boxed{\mathrm{softmax}(z)_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}}$$

ReLU, softplus and smoothed max

Softplus (smooth approx. of ReLU) :

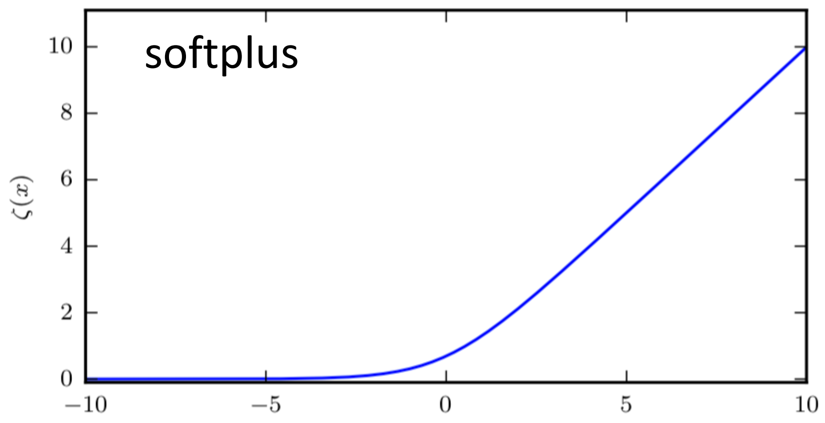
$$\zeta(x) = \log(1 + \exp(x))$$

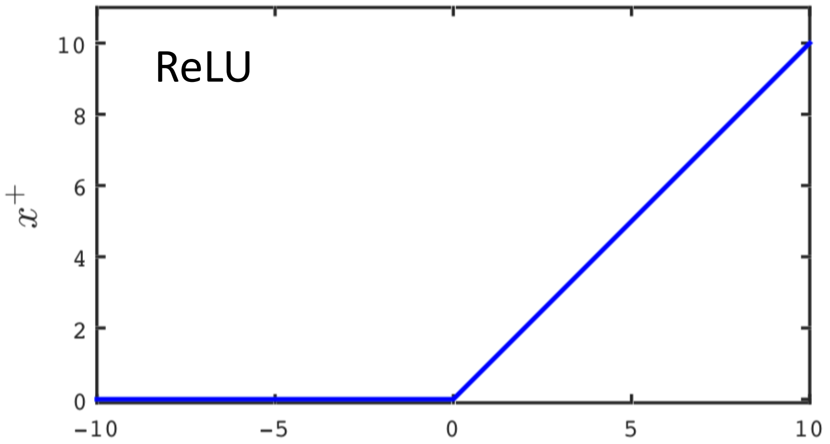
Smoothed max (*extension* of softplus) :

$$\zeta(x) = \log \sum_j \exp(x_i)$$

ReLU (Rectified Linear Unit) :

$$x^+ = \max(0, x)$$





Let's start playing !

Tutorial 1: 9h-10h00

Introduction to Pytorch