

# Deep Learning Standalone – for Chemistry

<https://bit.ly/2ZxelbL>

Github 저장소 링크

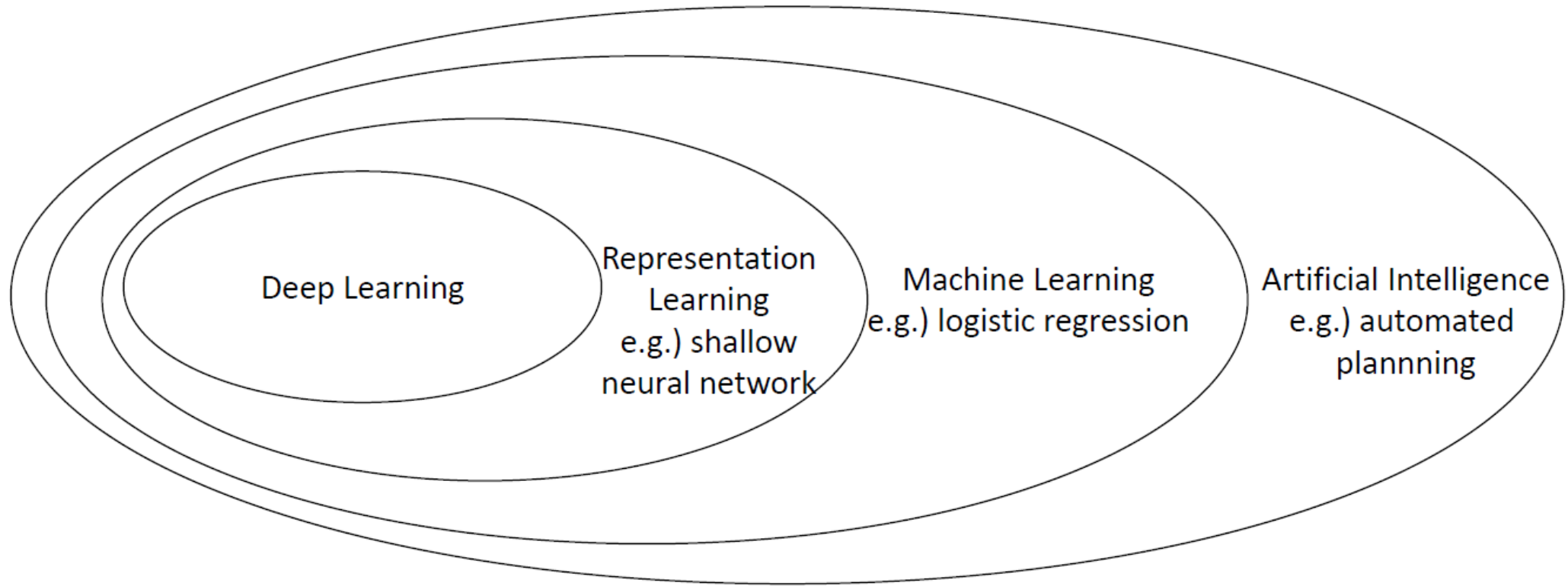
1. ML Basic
2. Pytorch Basic
3. MLP with Fingerprint Representation
4. CNN with SMILES Representation
5. GNN with Graph Representation
6. Experiment Management and Hyperparameter  
Tuning with Tensorboard
7. Practical Tips

# What is Machine Learning?

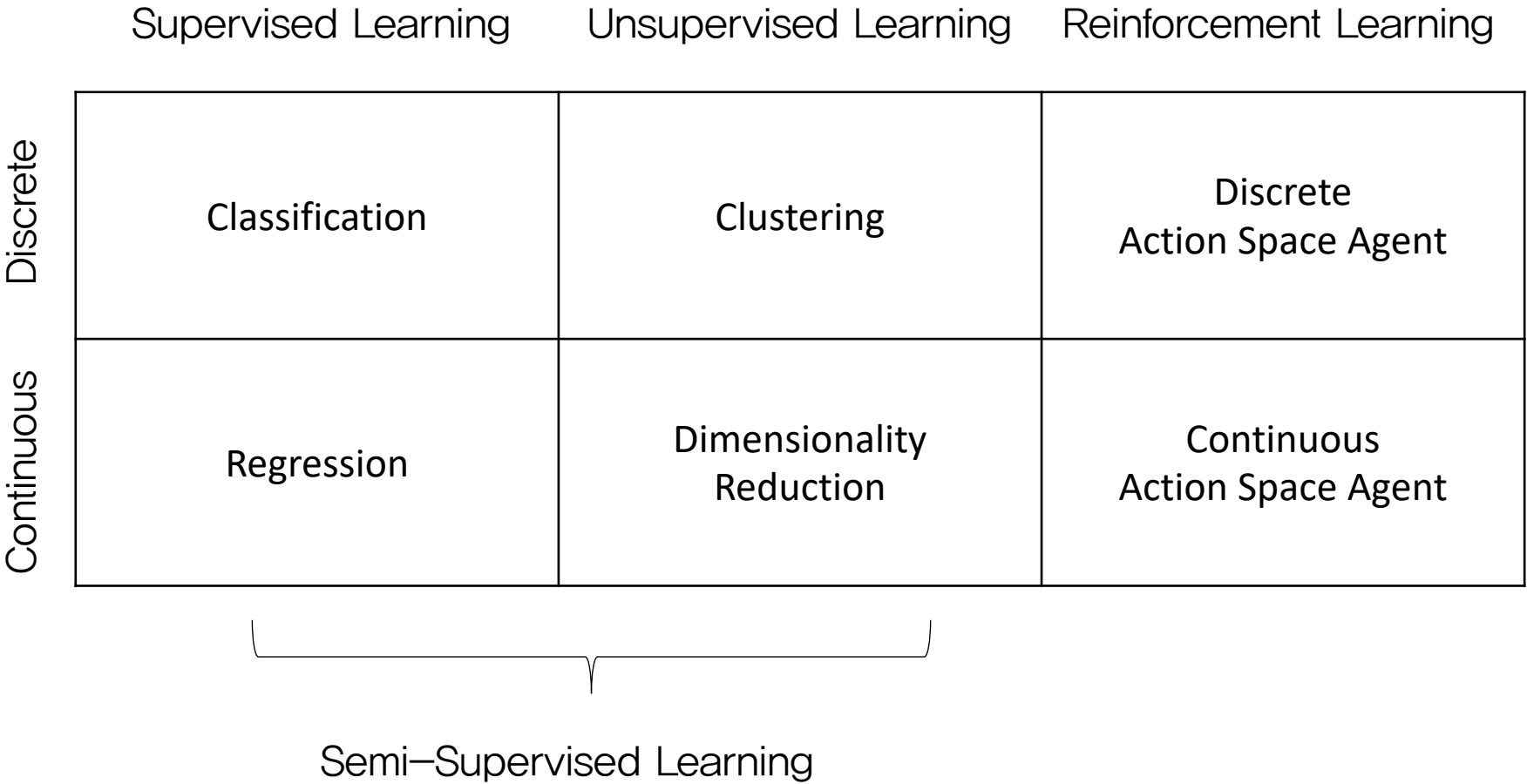
“A Field of study that gives computer the ability to learn without being explicitly programmed”

— Arthur Samuel, 1959

# Deep Learning, Machine Learning, Artificial Intelligence



# Categories of ML Problems



# Categories of ML Problems

	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Discrete	Classification	Clustering	Discrete Action Space Agent
Continuous	Regression	Dimensionality Reduction	Continuous Action Space Agent

Semi-Supervised Learning

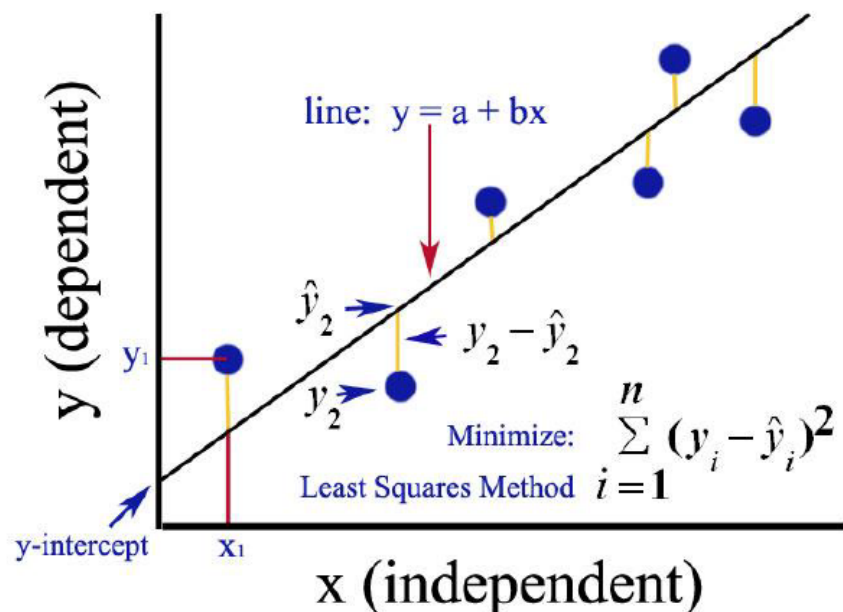
# Regression Problem



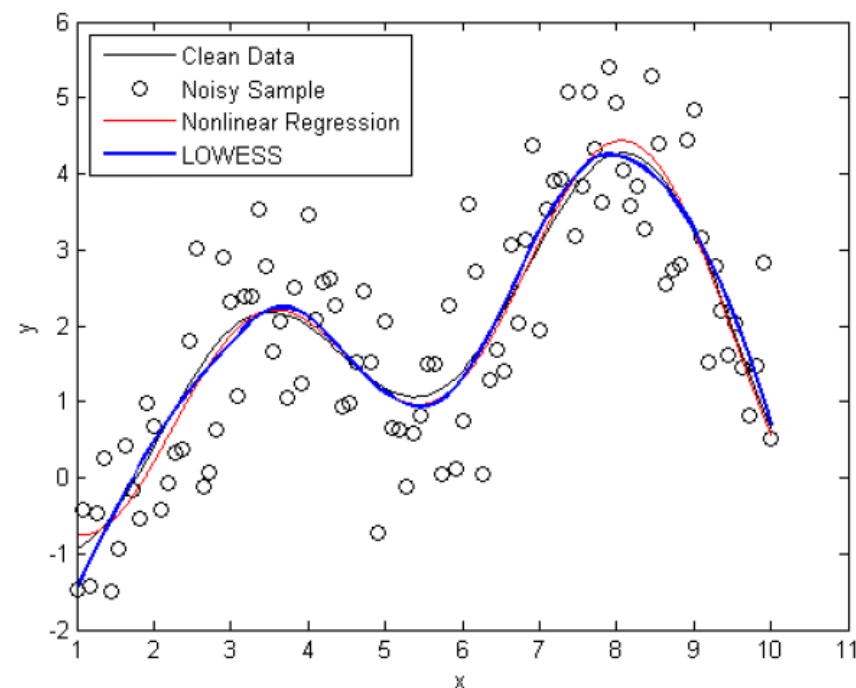
Price Prediction Based on Gi-Young Style Chart Analysis

# Regression Problem

Fit the prediction function  $f(x)$  to the training data,  
to predict continuous real value



Linear regression



Nonlinear regression

# Categories of ML Problems

	Supervised Learning	Unsupervised Learning	Reinforcement Learning
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Semi-Supervised Learning



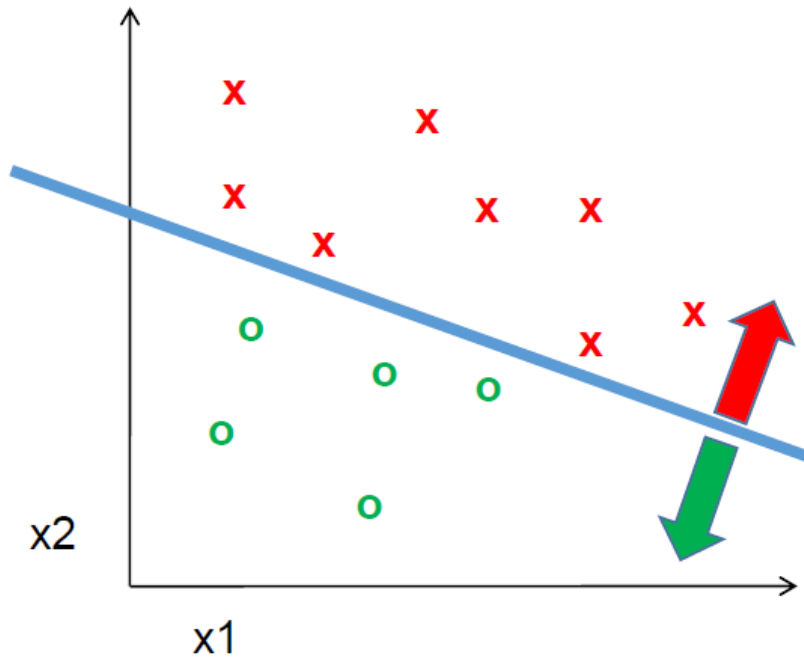
# Classification Problem



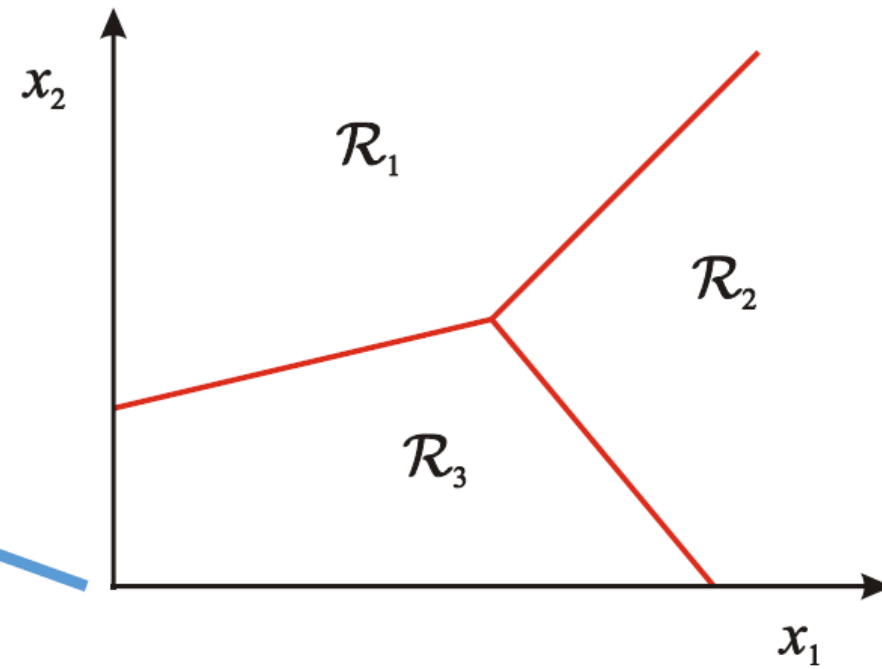
Chihuahua or Muffin?

# Classification Problem

Identifying which of a set of categories a new instance belongs

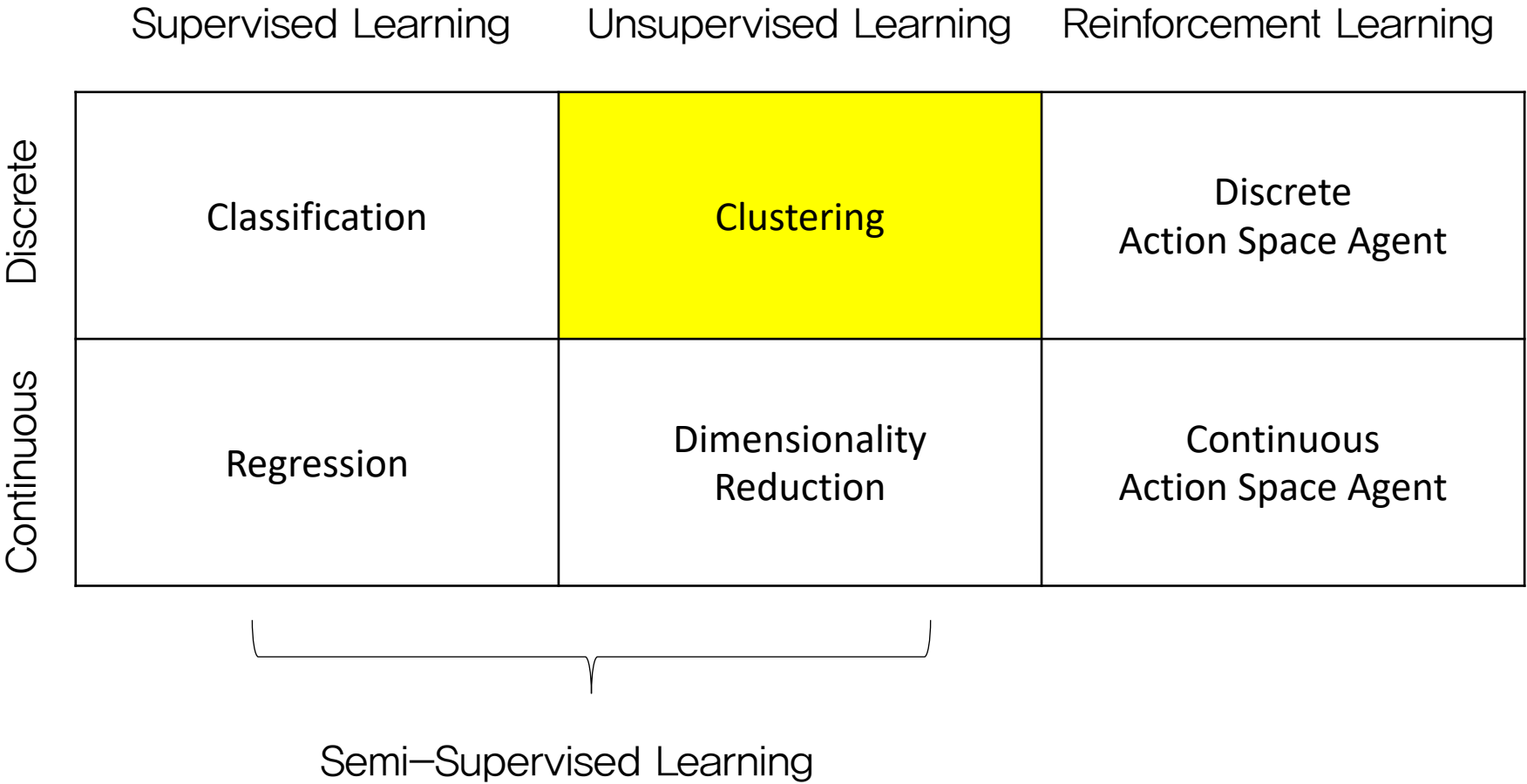


Binary Classification

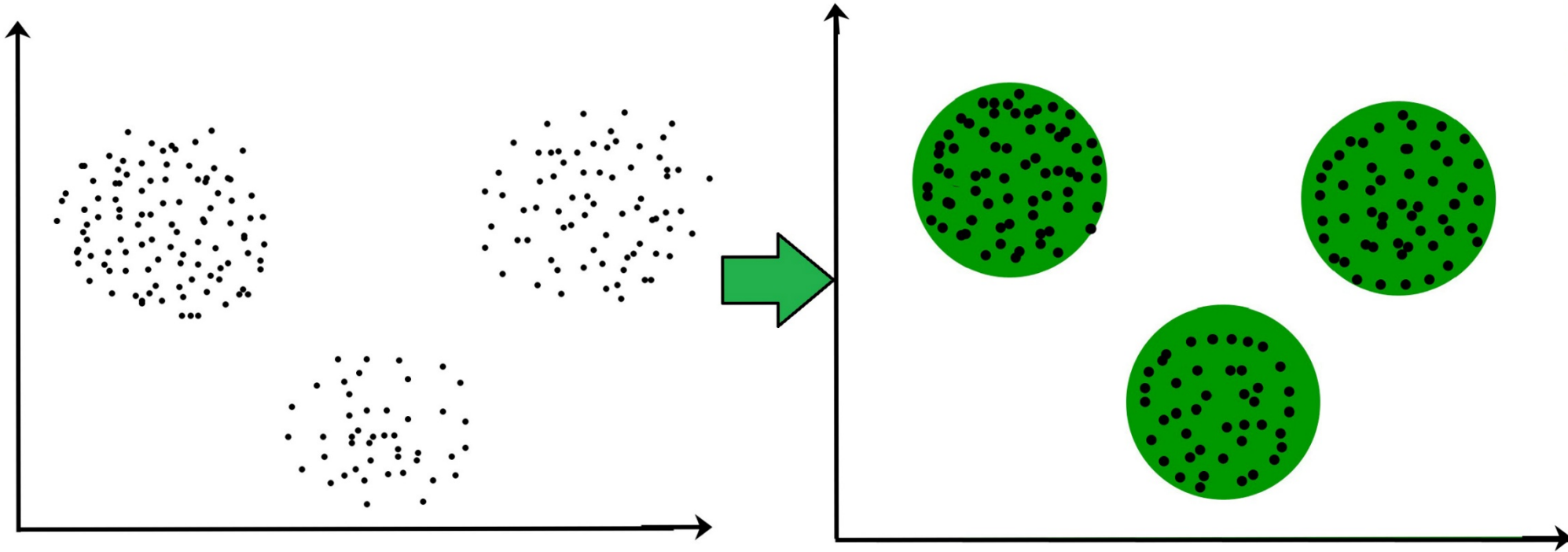


Multi-class Classification

# Categories of ML Problems



# Clustering Problem

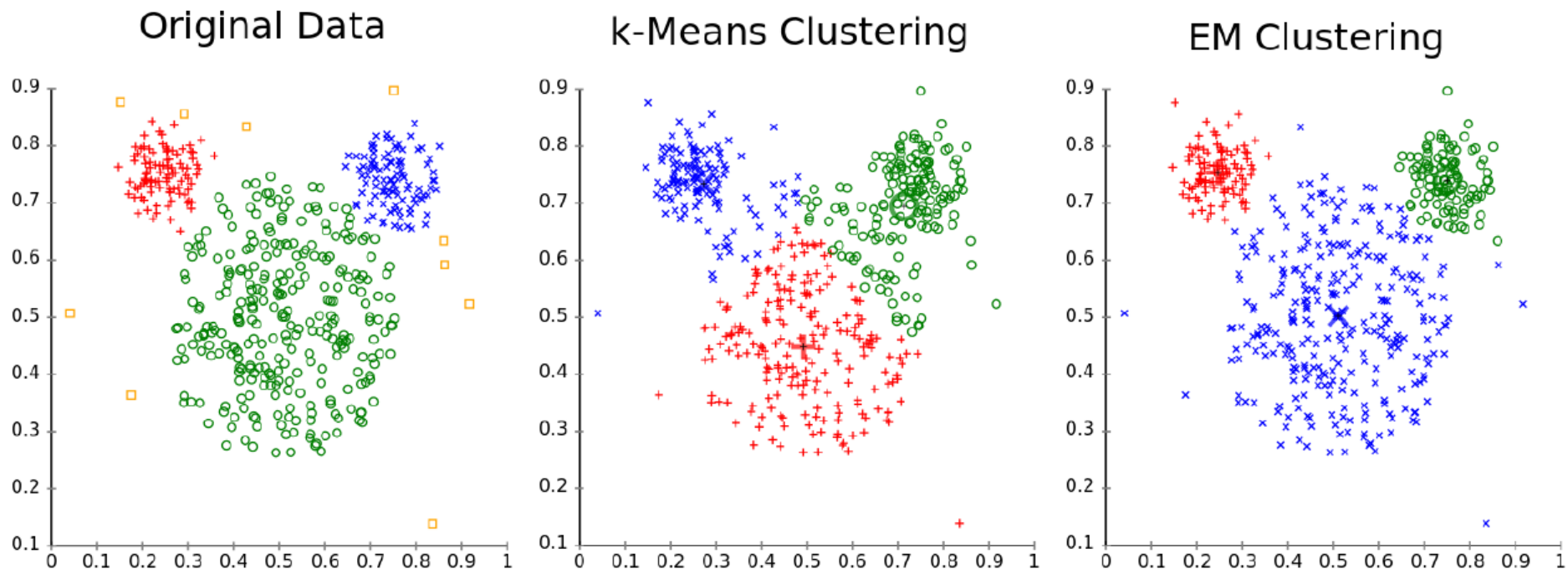


Grouping similar samples into K groups

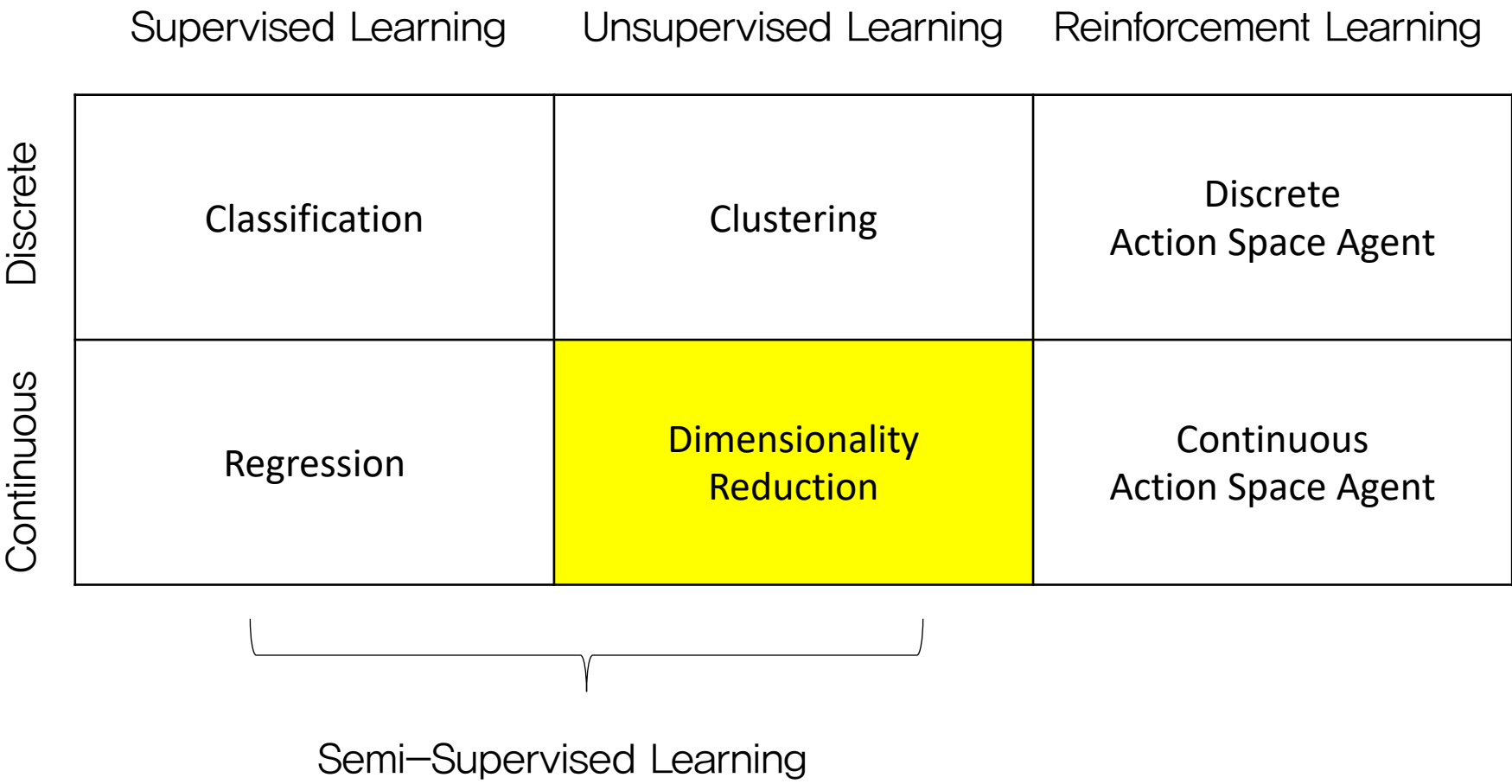
# Clustering Problem

Automatic grouping of instances, such that the instances that belong to the same clusters are more similar to each other than to those in the other groups

Different cluster analysis results on "mouse" data set:

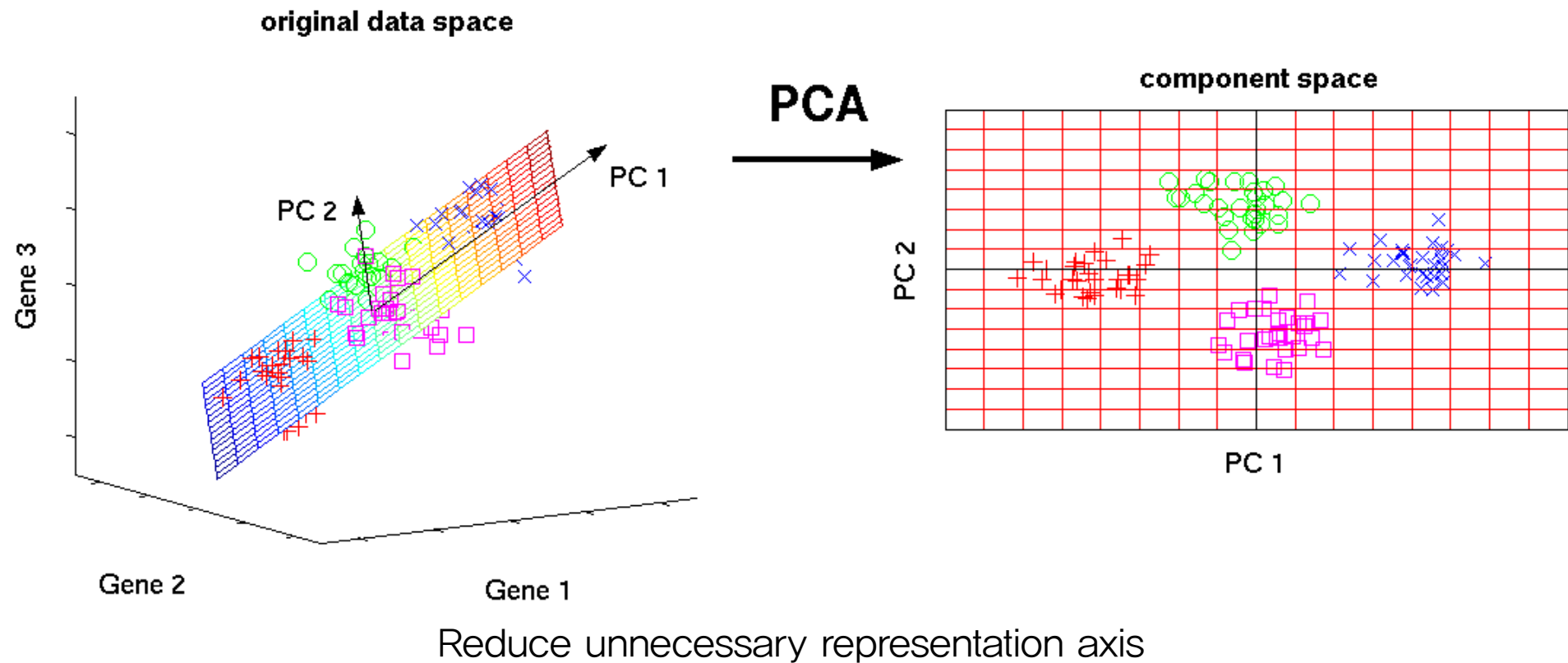


# Categories of ML Problems

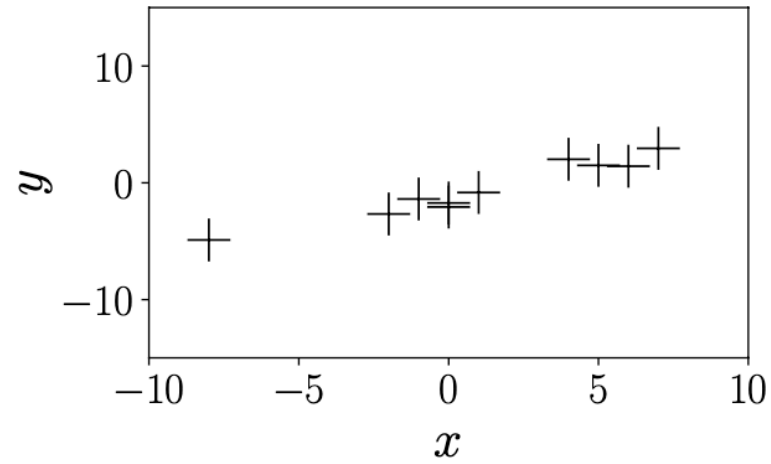


# Dimensionality Reduction Problem

Reduce the dimension of input data, to avoid the effect of the curse of dimensionality

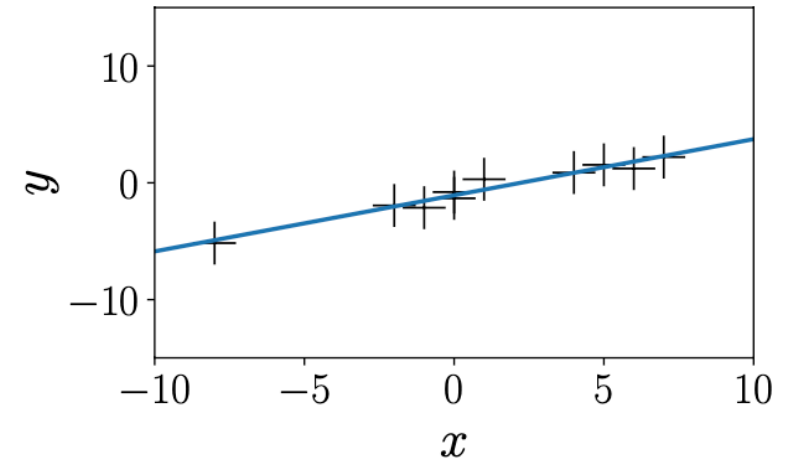
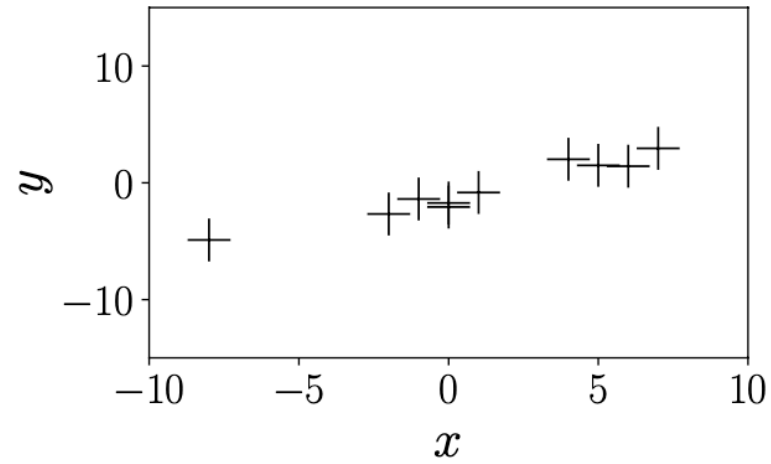
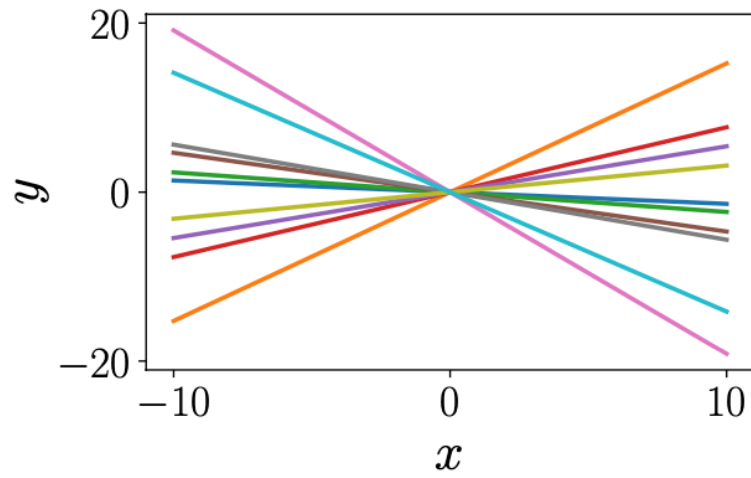


# Basic of ML – Linear Regression





# Basic of ML – Linear Regression



# Basic of ML – Linear Regression

**Hypothesis**

Model

**Cost**

Loss

**Optimization**

# Basic of ML – Linear Regression

## Hypothesis

Model

$$H(x) = Wx + b$$

## Cost

Loss

## Optimization

# Basic of ML – Linear Regression

## Hypothesis

Model

$$H(x) = Wx + b$$

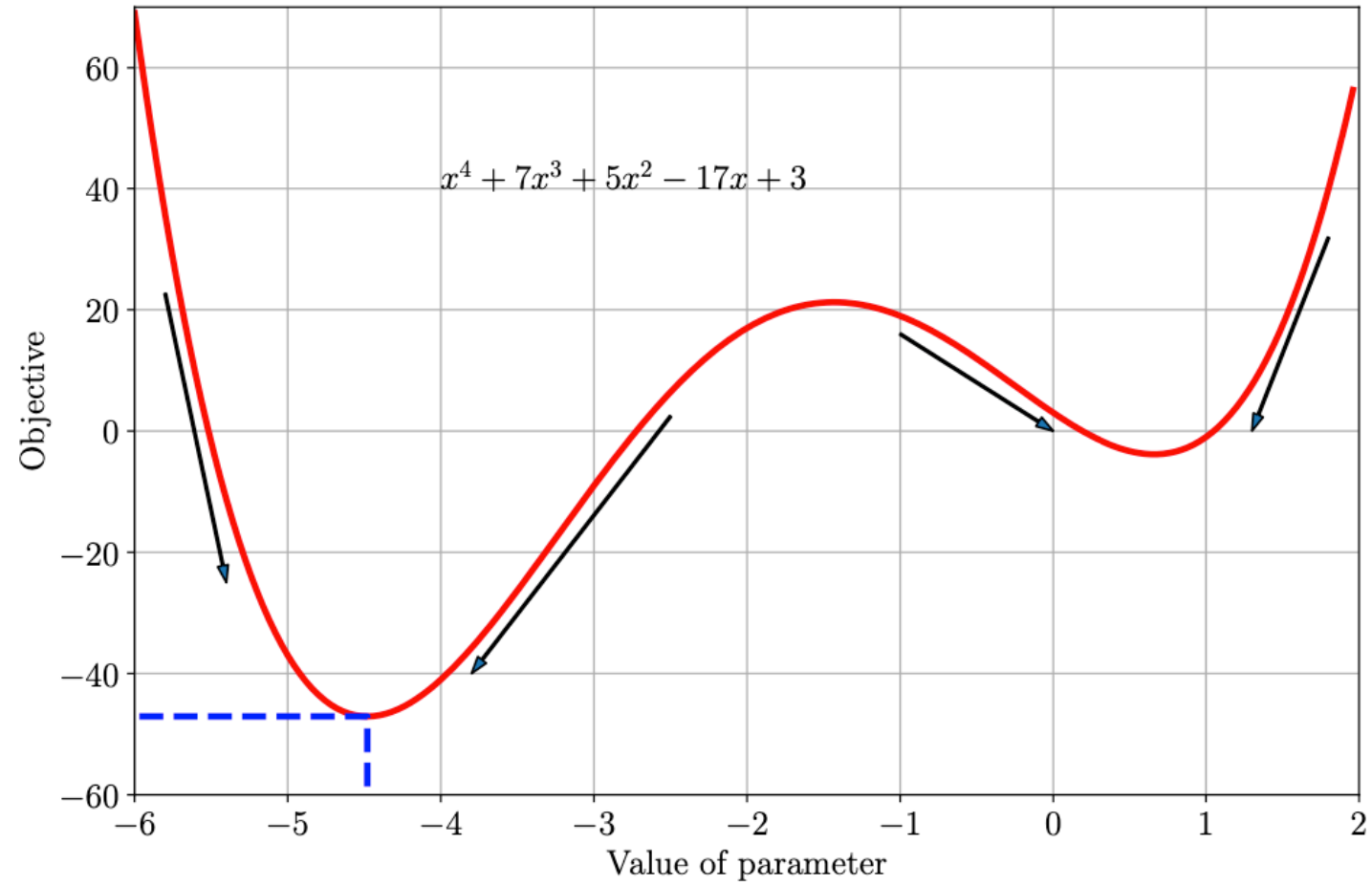
## Cost

Loss

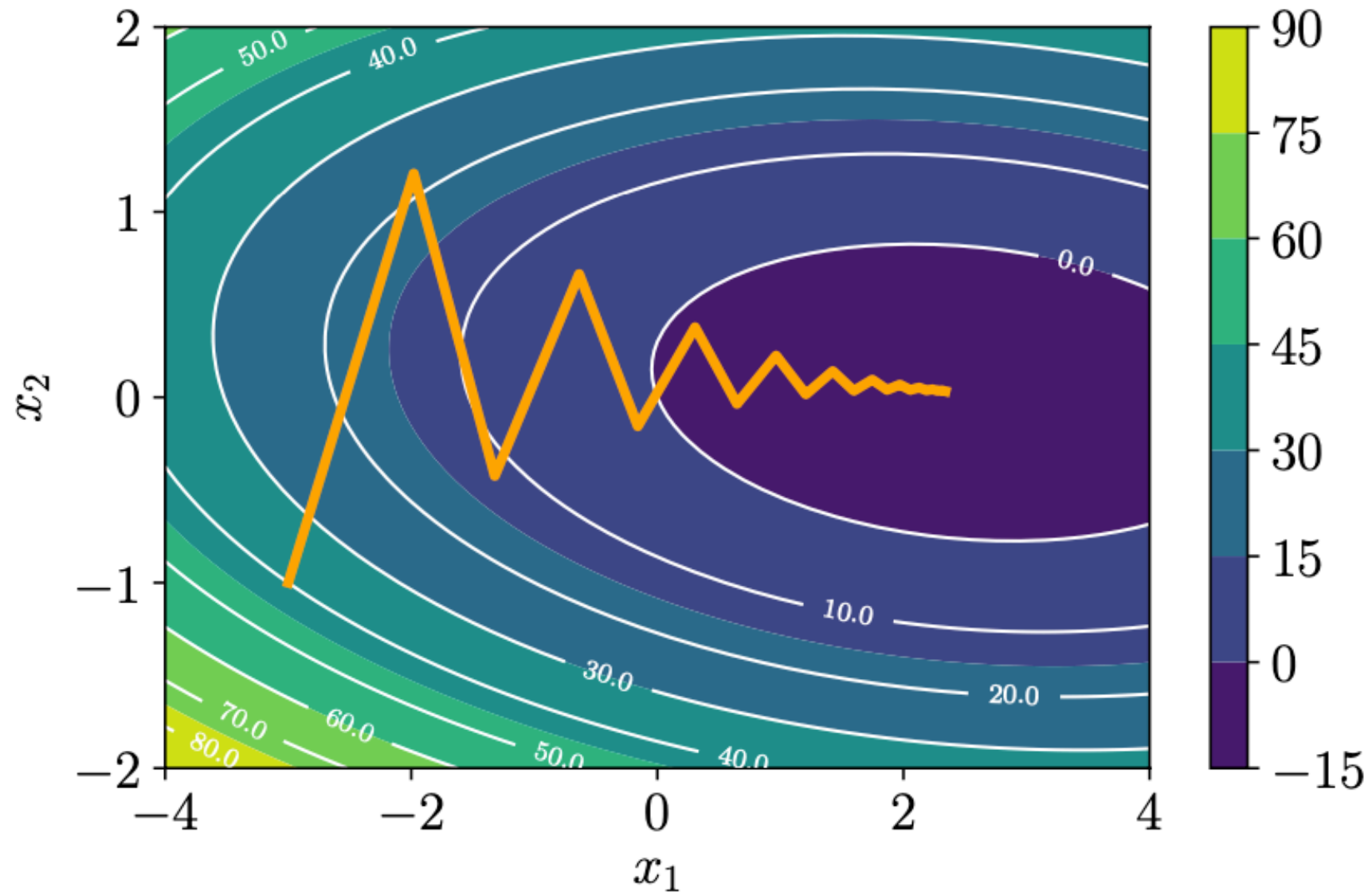
$$cost(W, b) = \frac{1}{m} \sum_{i=1}^m (H(x^{(i)}) - y^{(i)})^2$$

## Optimization

# Gradient Descent – 1D input



# Gradient Descent – 2D input



# Basic of ML – Linear Regression

## Hypothesis

Model

$$H(x) = Wx + b$$

## Cost

Loss

$$cost(W, b) = \frac{1}{m} \sum_{i=1}^m (H(x^{(i)}) - y^{(i)})^2$$

## Optimization

$$W := W - \alpha \frac{\partial}{\partial W} cost(W)$$

# Stochastic Gradient Descent

Calculate gradient for small chunk (mini-batch) of whole training dataset, rather than the whole training dataset (batch).

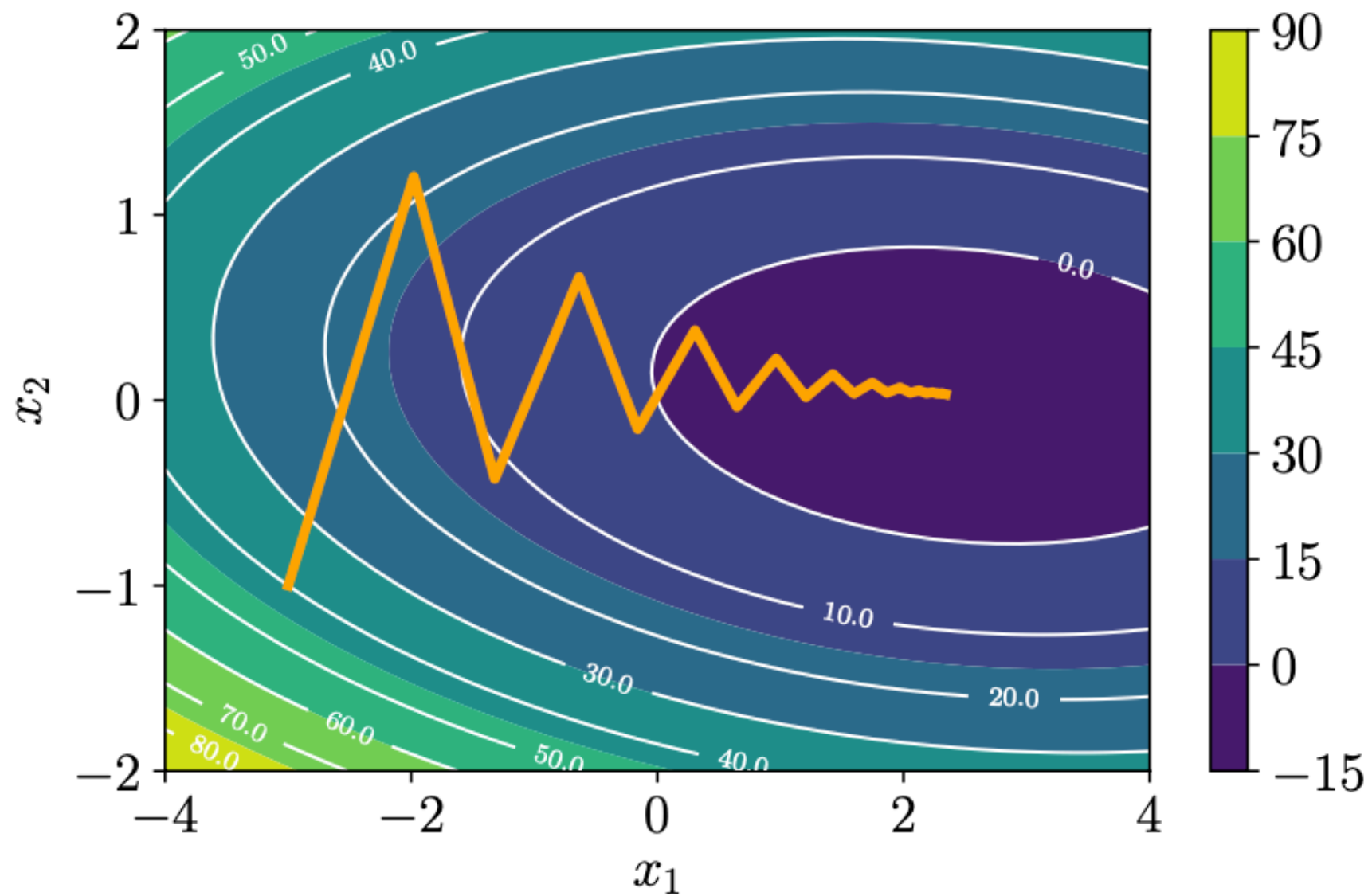
Stochastic since the gradient is not deterministic, but stochastic depending on the mini-batch

Faster than batch gradient descent, while converging similar.

Can avoid local minima by stochasticity.



# Stochastic Gradient Descent



# Basic of ML – Linear Regression

## Hypothesis

Model

$$H(X) = XW$$

## Cost

Loss

## Optimization

$$\begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \\ x_{41} & x_{42} & x_{43} \\ x_{51} & x_{52} & x_{53} \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = \begin{pmatrix} x_{11}w_1 + x_{12}w_2 + x_{13}w_3 \\ x_{21}w_1 + x_{22}w_2 + x_{23}w_3 \\ x_{31}w_1 + x_{32}w_2 + x_{33}w_3 \\ x_{41}w_1 + x_{42}w_2 + x_{43}w_3 \\ x_{51}w_1 + x_{52}w_2 + x_{53}w_3 \end{pmatrix}$$

# Basic of ML – Linear Regression

## Hypothesis

Model

$$H(X) = XW$$

$$\begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \\ x_{41} & x_{42} & x_{43} \\ x_{51} & x_{52} & x_{53} \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = \begin{pmatrix} x_{11}w_1 + x_{12}w_2 + x_{13}w_3 \\ x_{21}w_1 + x_{22}w_2 + x_{23}w_3 \\ x_{31}w_1 + x_{32}w_2 + x_{33}w_3 \\ x_{41}w_1 + x_{42}w_2 + x_{43}w_3 \\ x_{51}w_1 + x_{52}w_2 + x_{53}w_3 \end{pmatrix}$$

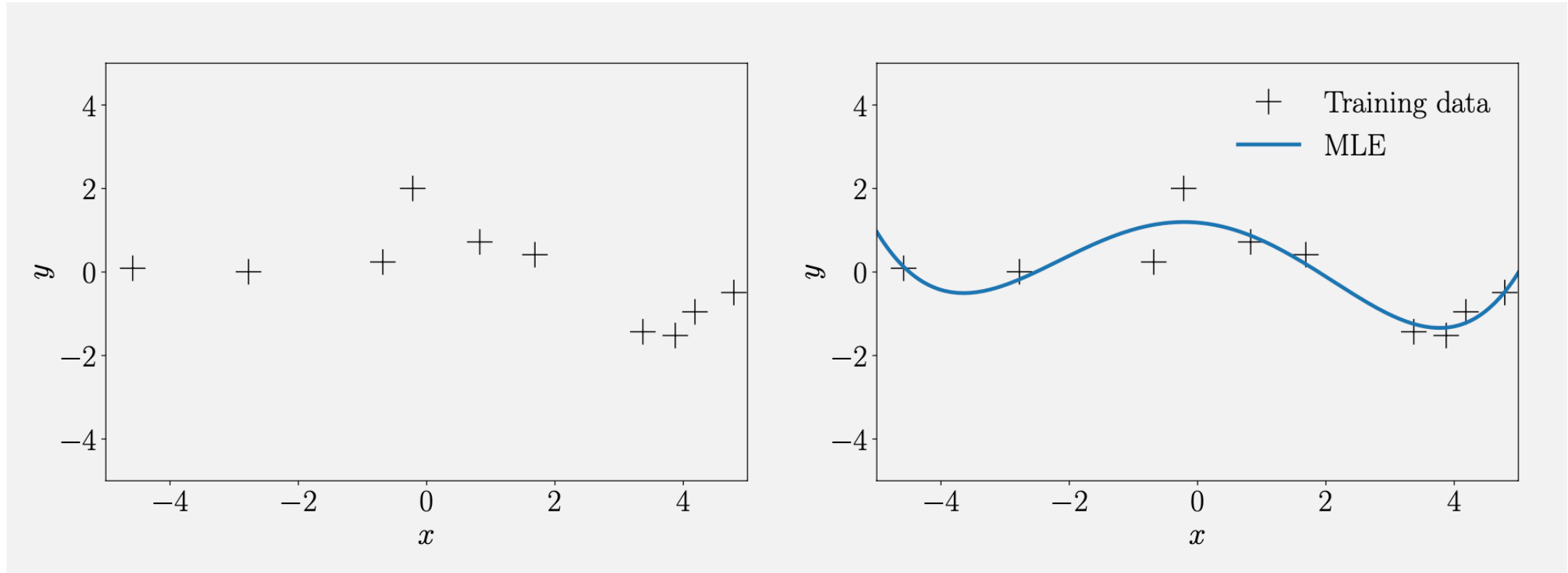
## Cost

Loss

$$cost(W, b) = \frac{1}{m} \sum_{i=1}^m (H(x_1^{(i)}, x_2^{(i)}, \dots, x_n^{(i)}) - y^{(i)})^2$$

## Optimization

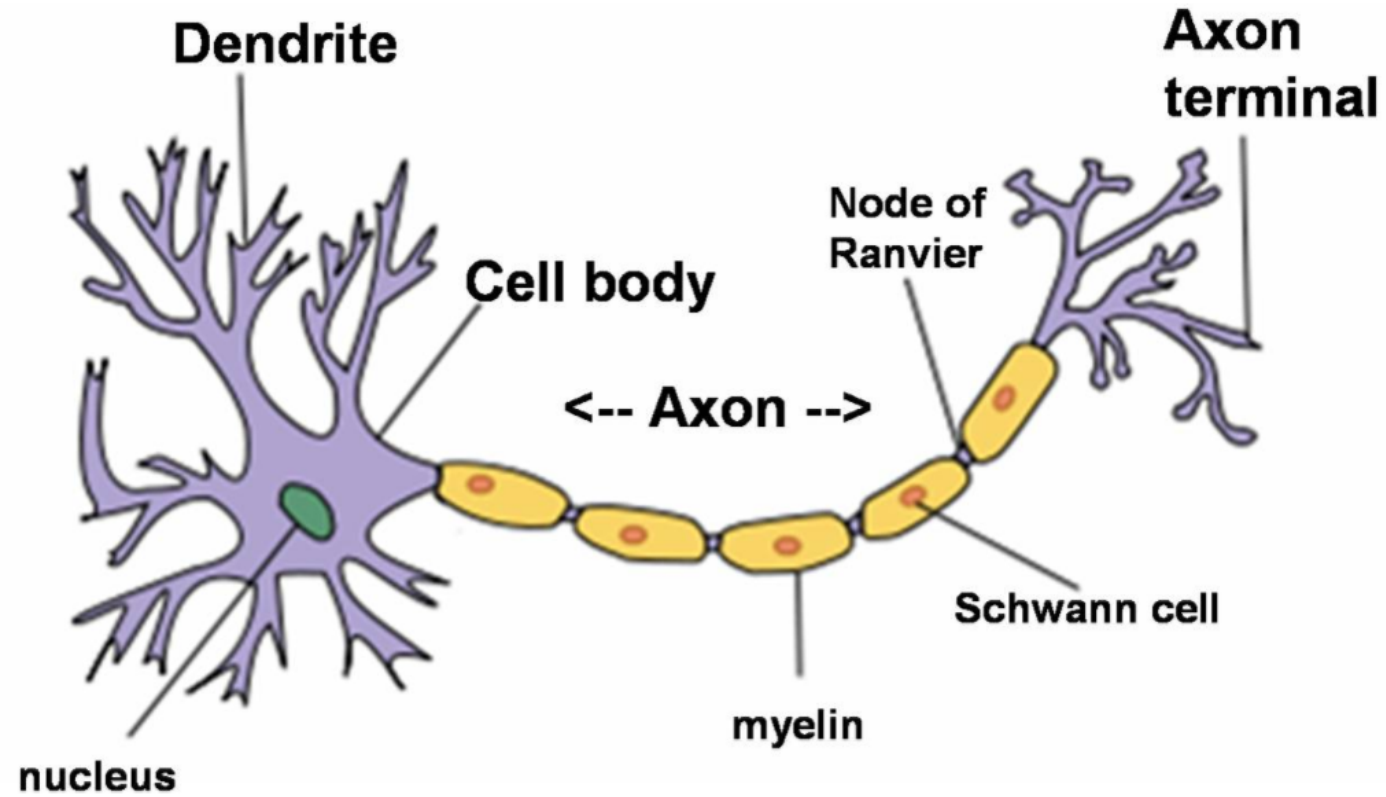
# Basic of ML – Linear Regression



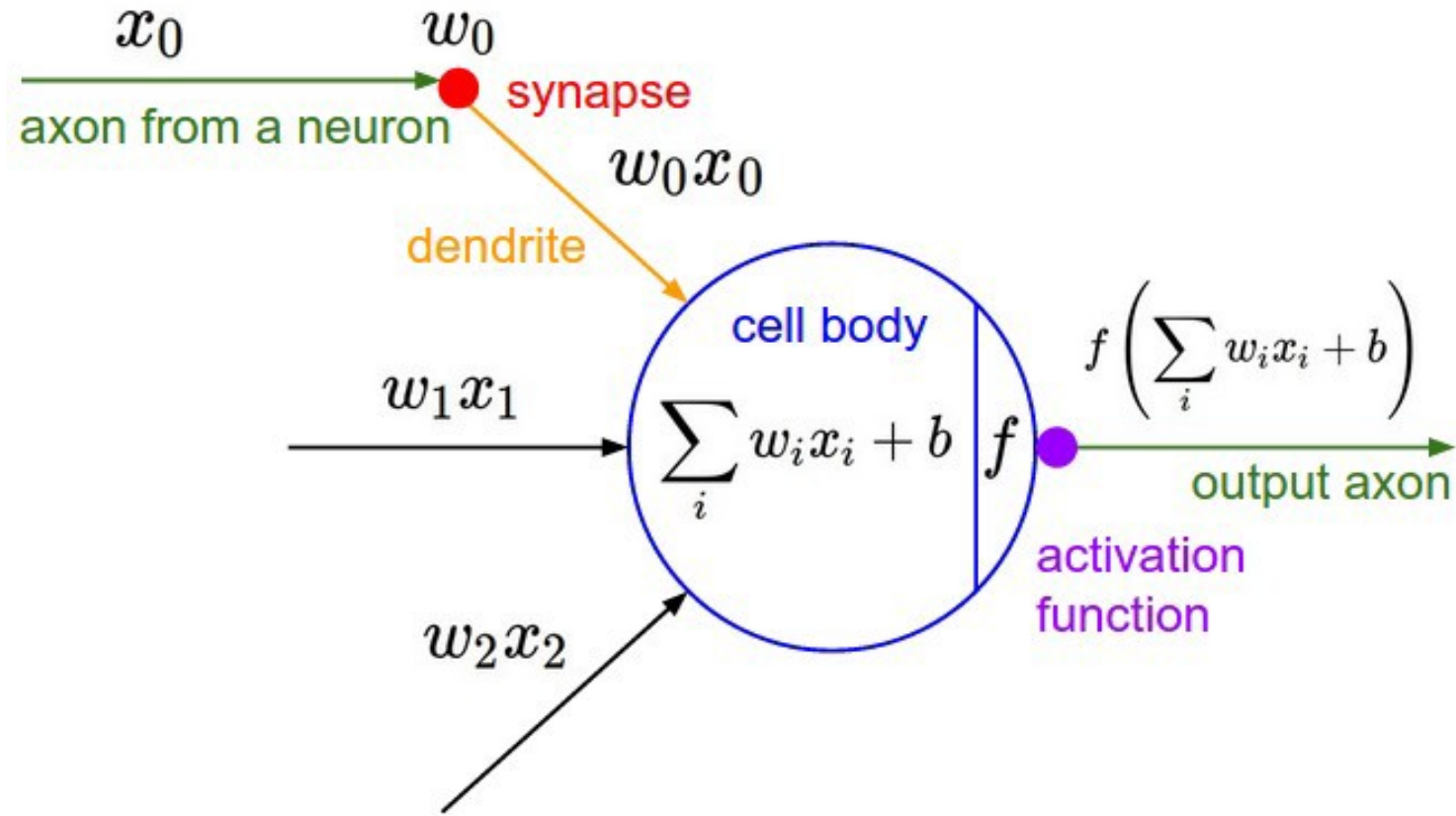
# Limitation of ML – MNIST/Cat or Dog?



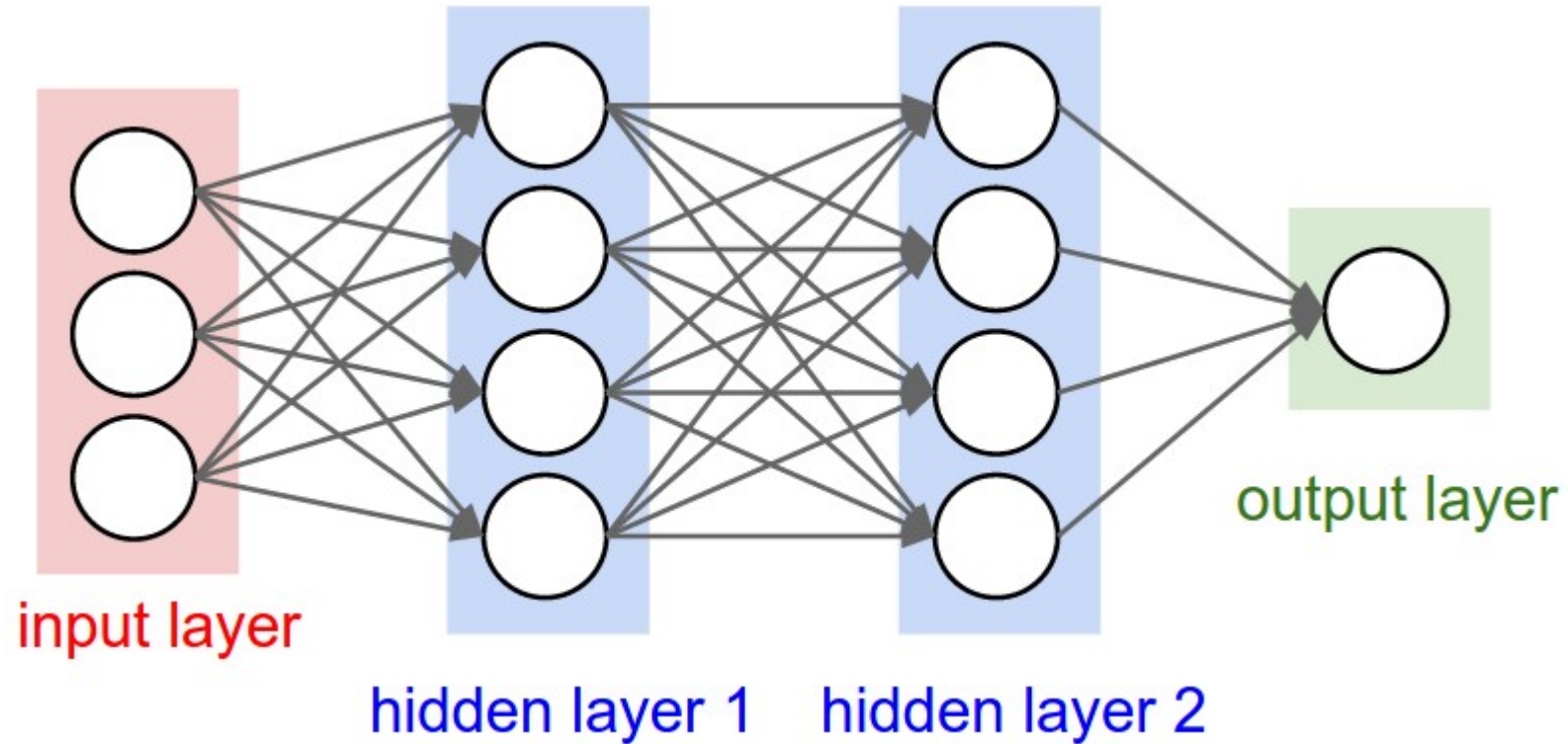
# Structure of Neuron



# Modeling Neuron (1957)

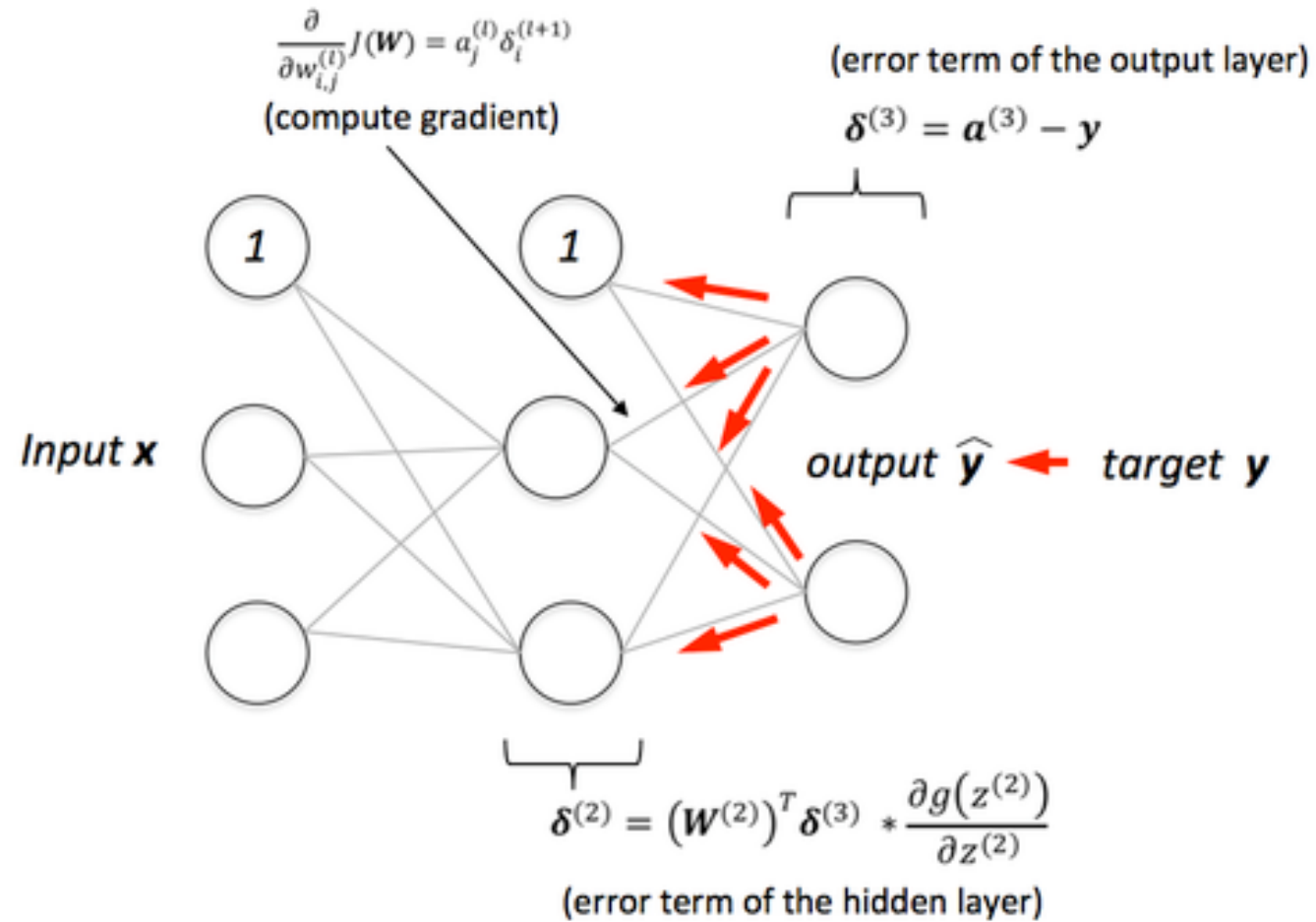


# Multilayer Perceptron (1969)





# Backpropagation (1986)



# Backpropagation

# Backpropagation

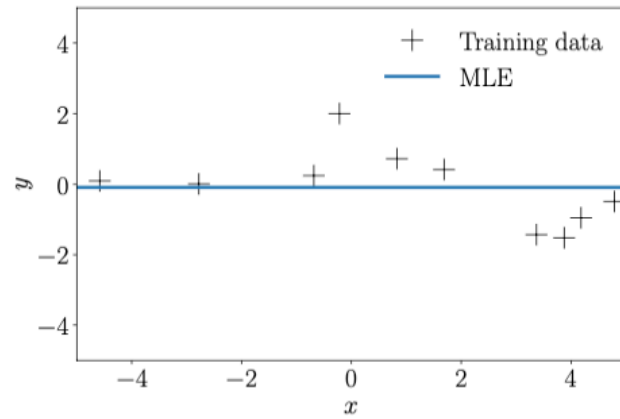
# Universal Approximation Theorem

A feed-forward network with single hidden layer is sufficient to represent any function, but the required hidden unit might be infinitely large and may fail to learn.

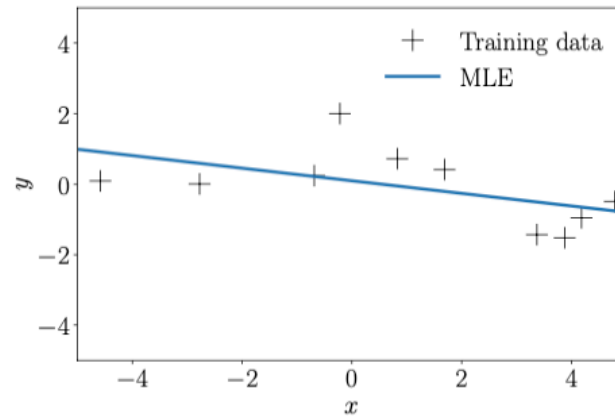
Using deeper model can reduce the number of required units for representing desired function.



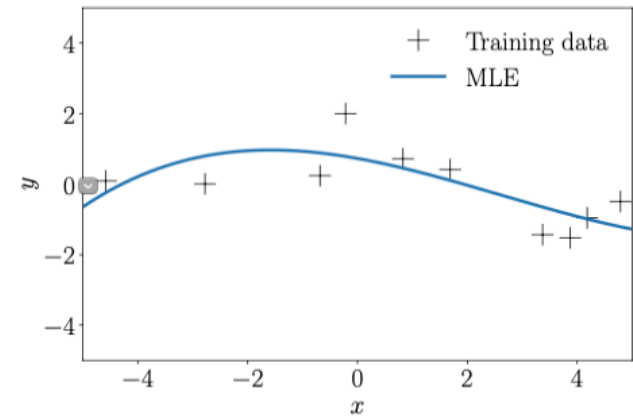
# Overfitting – Linear Regression



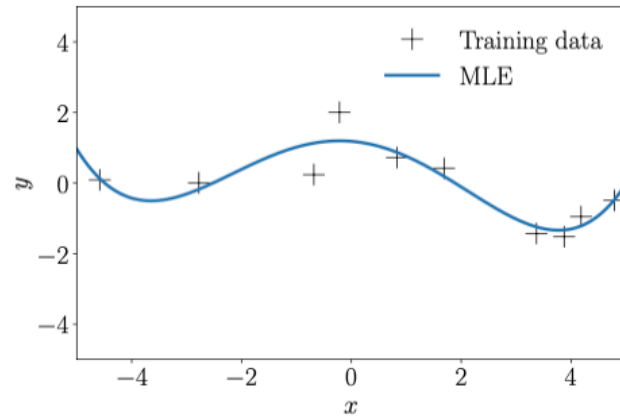
(a)  $M = 0$



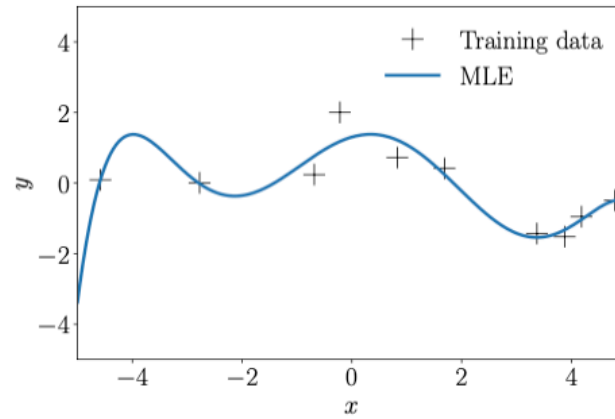
(b)  $M = 1$



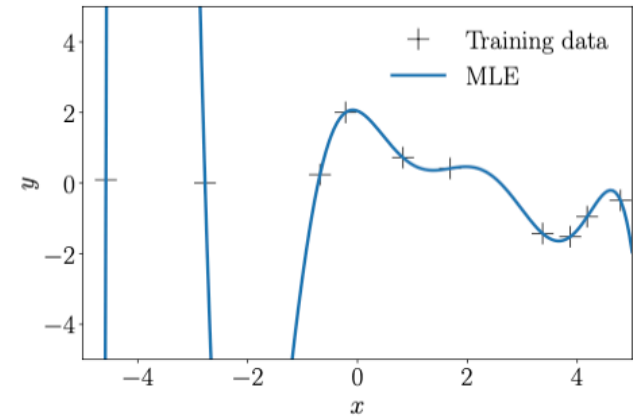
(c)  $M = 3$



(d)  $M = 4$

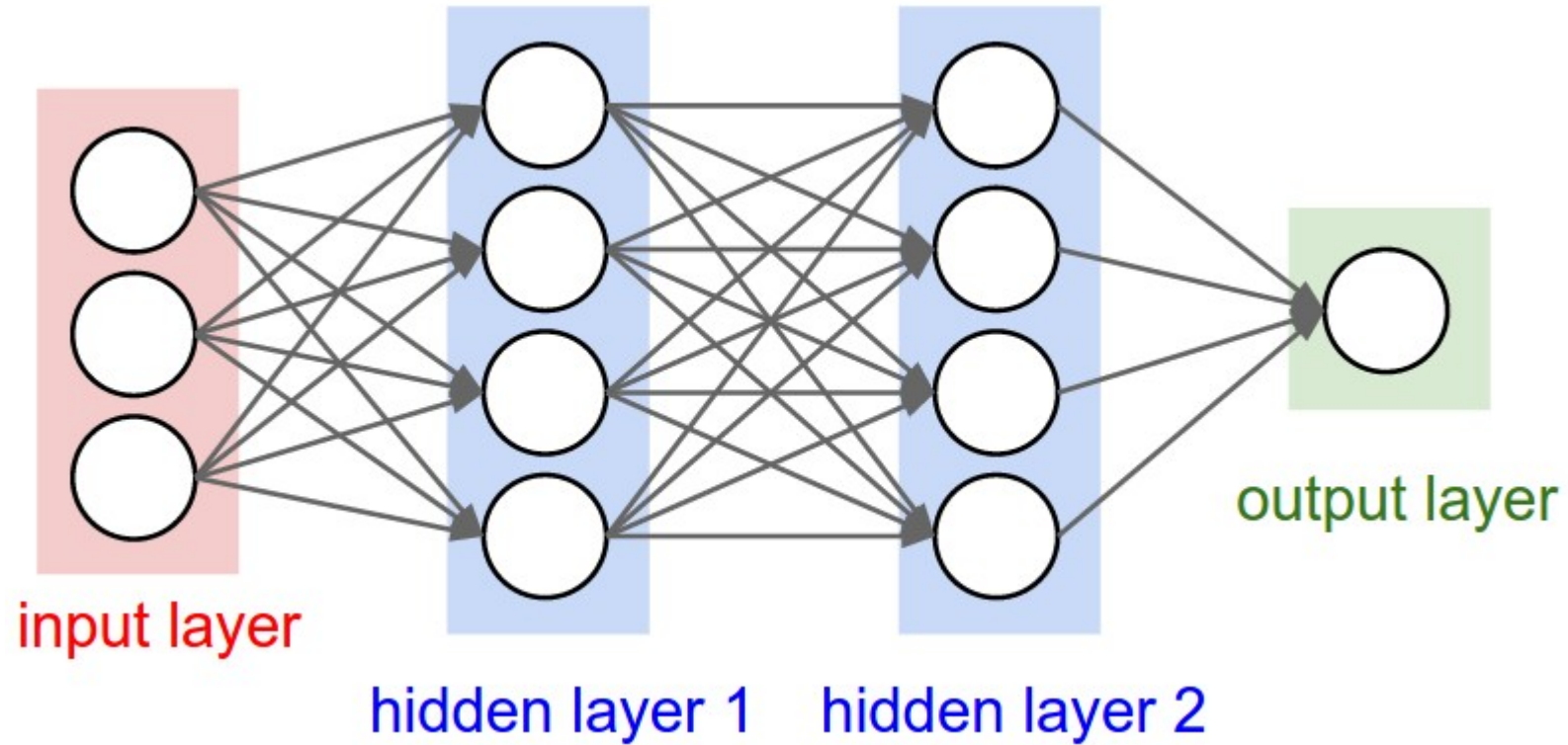


(e)  $M = 6$

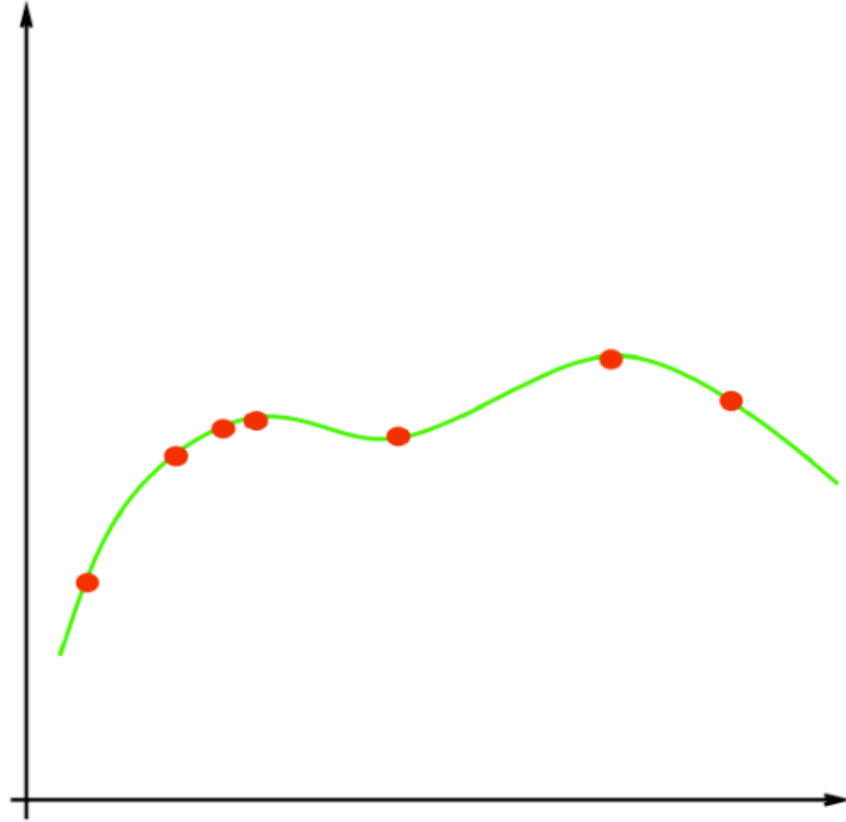


(f)  $M = 9$

# Overfitting – MLP

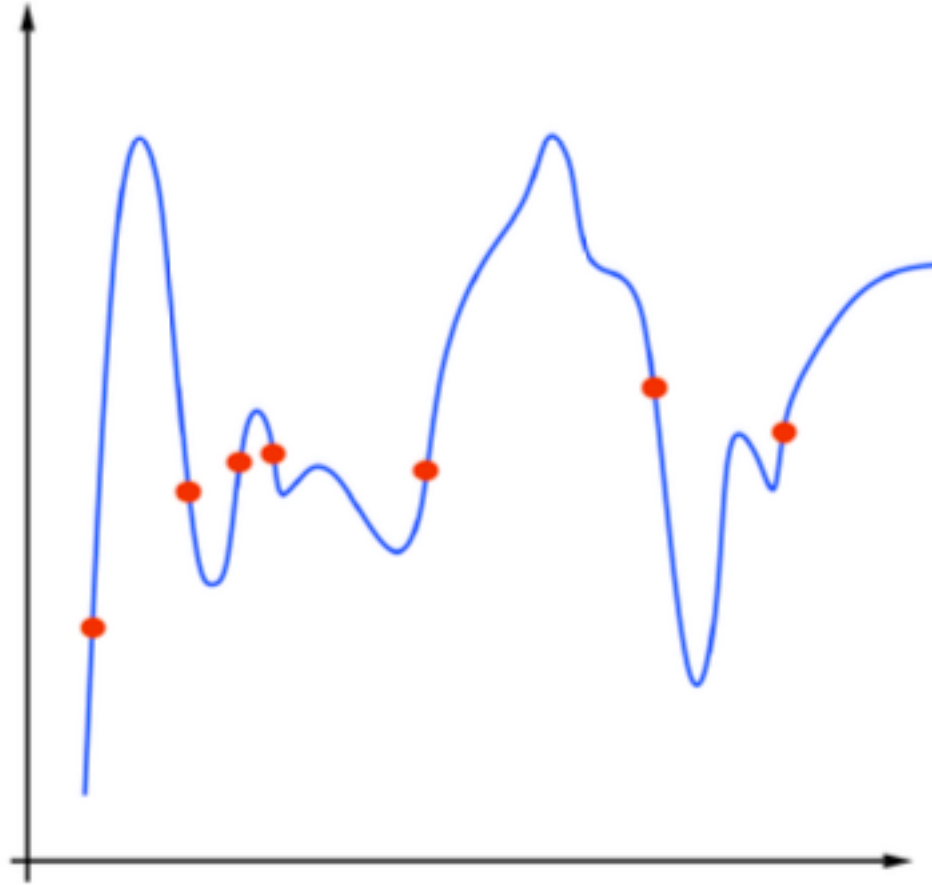


# Overfitting – True Distribution



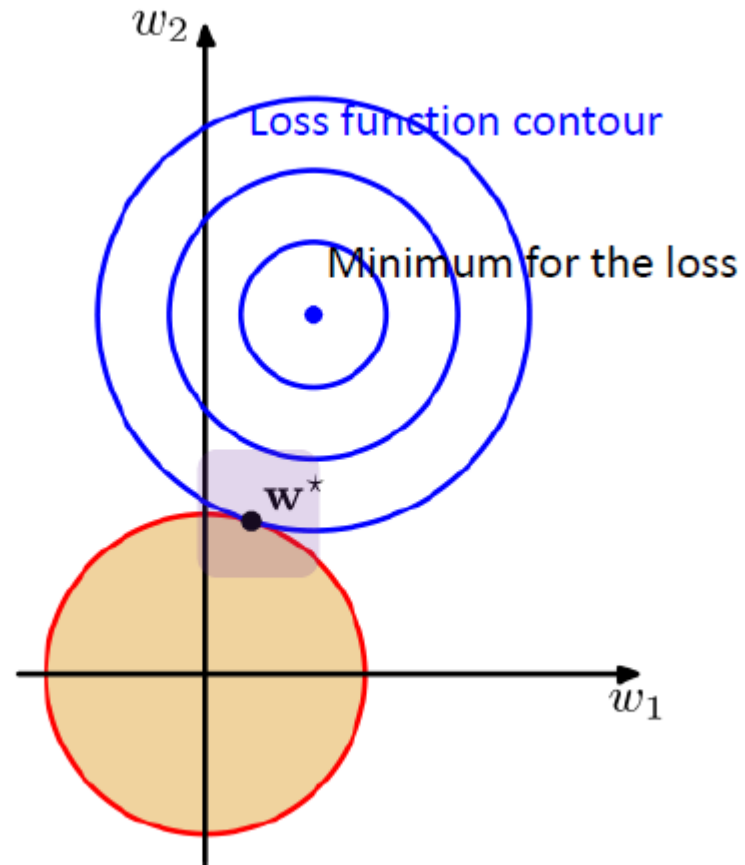


## Overfitting – True Distribution



# Training, Validation, and Test Set

# L2 Regularization



# Hyperparameter Tuning