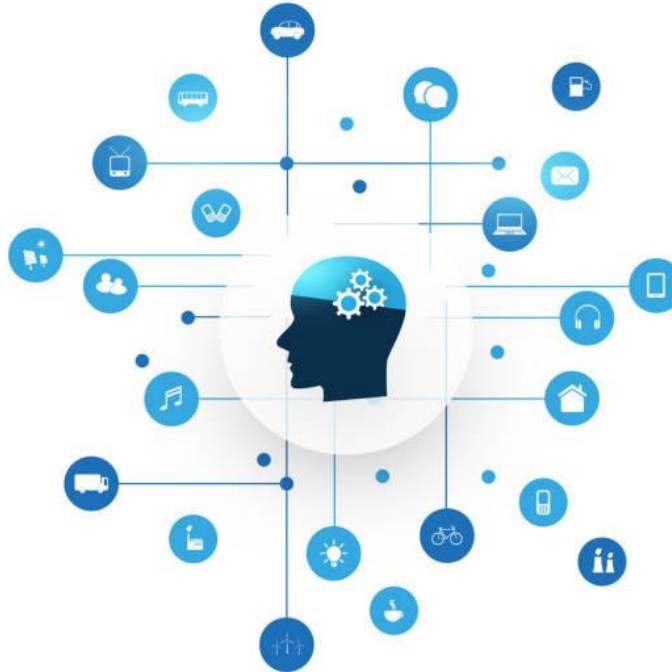


# Introduction to Machine Learning for Beginners



# Some Applications



# Why Now?

→ Availability of huge amount of data

# Why Now?

- Availability of huge amount of data
- Powerful machines that can handle computations quickly

# Why Now?

- Availability of huge amount of data
- Powerful machines that can handle computations quickly
- Advancement of technology and knowledge among people

# Learning from Data

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

# Supervised Learning

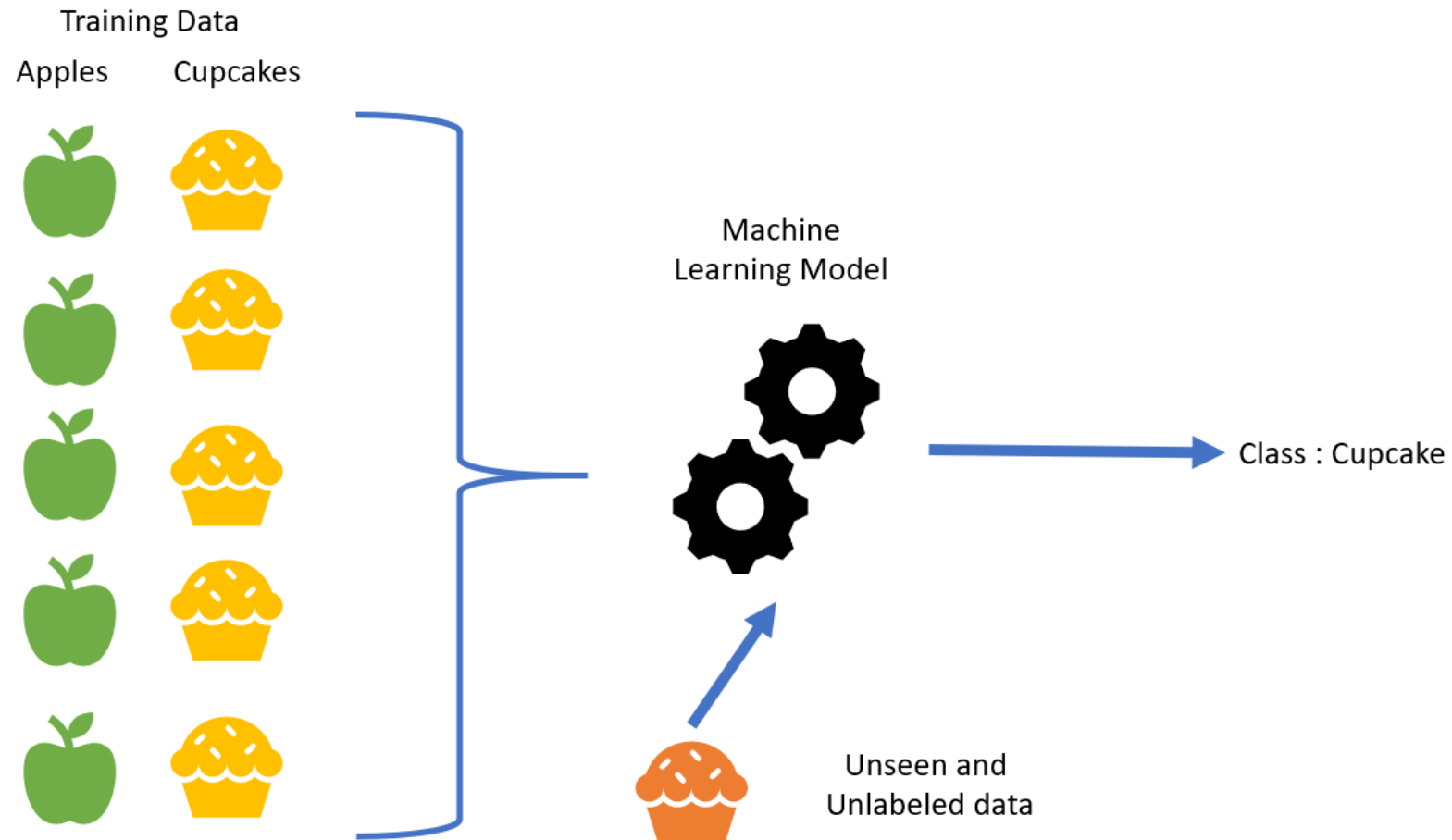


“Dog”



“Cat”

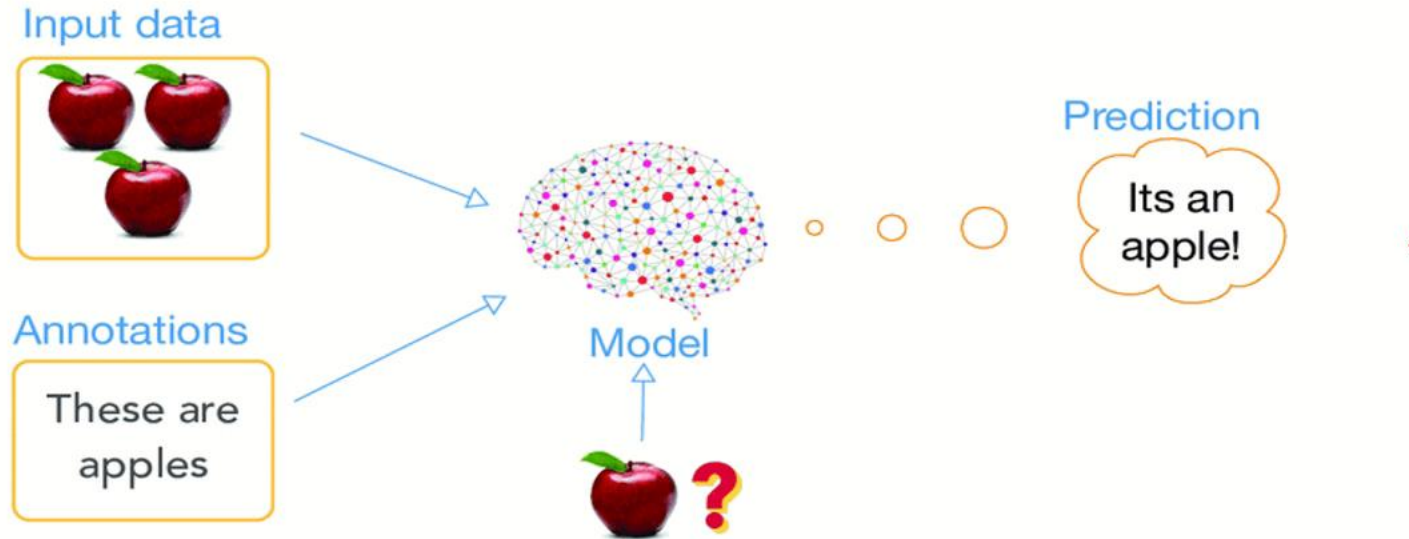
# Supervised Learning



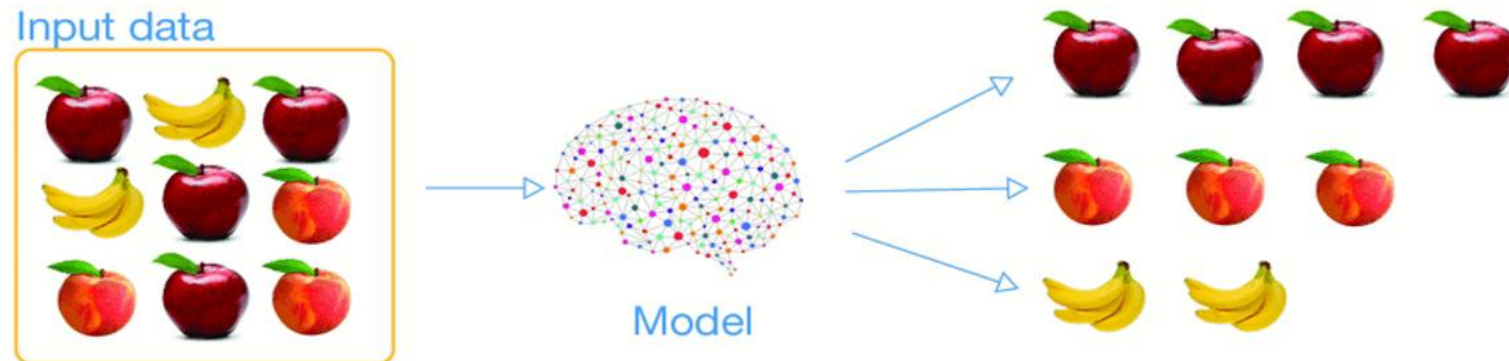


# Unsupervised Learning

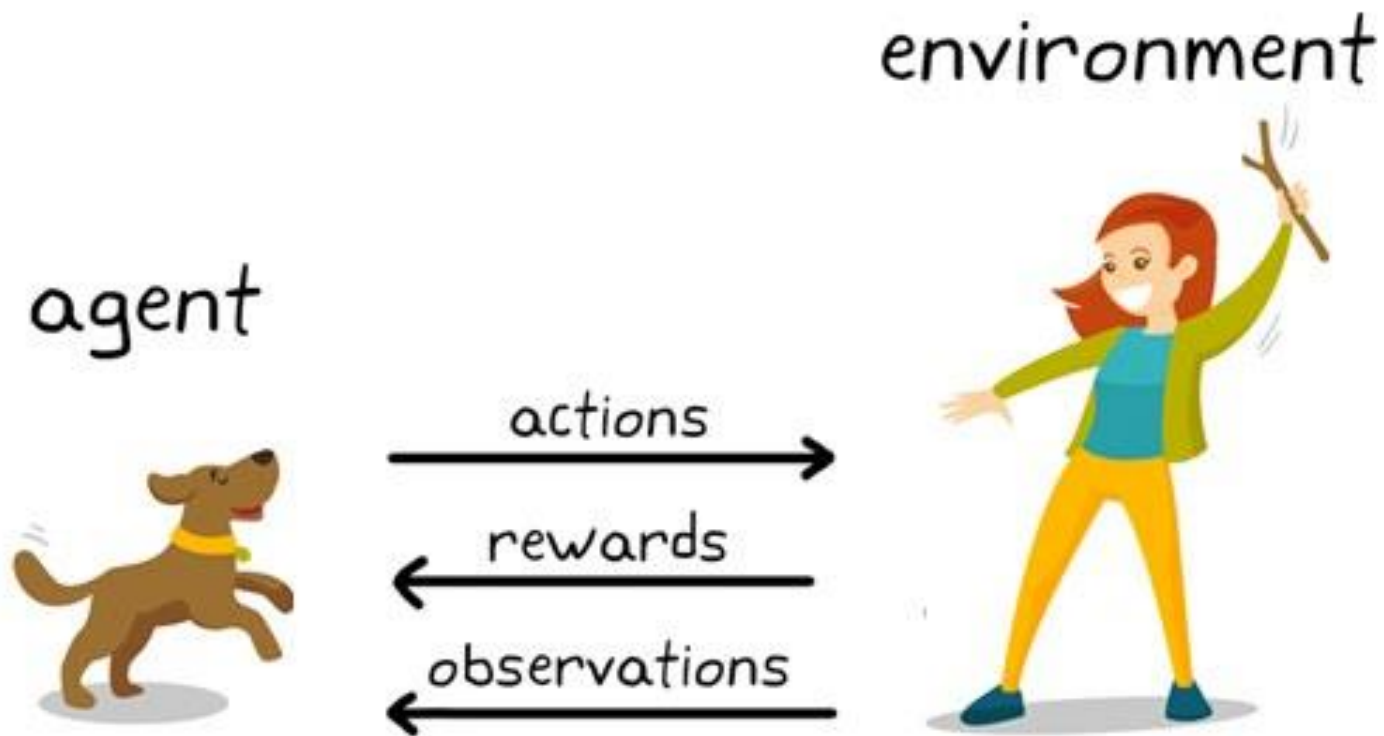
supervised learning



unsupervised learning



# Reinforcement Learning



# Features

# Regression

# Classification

# Clustering

# Data Encoding and Preprocessing

→ Images

# Data Encoding and Preprocessing

→ Images

→ Videos



# Data Encoding and Preprocessing

- Images
- Videos
- Audio

# Data Encoding and Preprocessing

- Images
- Videos
- Audio
- Text
- One Hot encoding

# Data Encoding and Preprocessing

- Images
- Videos
- Audio
- Text
- One Hot encoding
- Data standardization

# Model

→ Model is a **function** in the **feature space**

# Model

- Model is a function in the feature space
- Dimensions
- Parameters
- Hyperparameters

# Error/Cost and Optimization

Result of training: values of parameters.

| $x_1$ | $x_2$ | $y$ |
|-------|-------|-----|
| 2     | 10    | -1  |
| 3     | -4    | 1   |
| -3    | 100   | -1  |
| 10    | 20    | 1   |

$$\hat{y}_i = f(x_{1i}, x_{2i}) = \underline{a}x_{1i} + \underline{b}x_{2i} + \underline{c}$$

$$\hat{y}_i - y_i = 0$$

$$\hat{y}_i = f(x_{1i}, x_{2i})$$

$$\hat{y}_i = y_i$$

$y_{\text{Pred}}$ ,

$$\hat{y}_i, y_i$$

# Error/Cost and Optimization

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2.$$

# Linear Regression

| $x_i$ | $y_i$ |
|-------|-------|
| 2     | 5     |
| -3    | -2    |
| 7     | 5.9   |

$$\hat{y}_i = \underline{a}x_i + \underline{b}$$

$$\underline{ax_i + b} = \underline{y_i}$$

$$\begin{bmatrix} x_i & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = y_i$$



# Linear Regression

$$ax_i + b = y_i$$

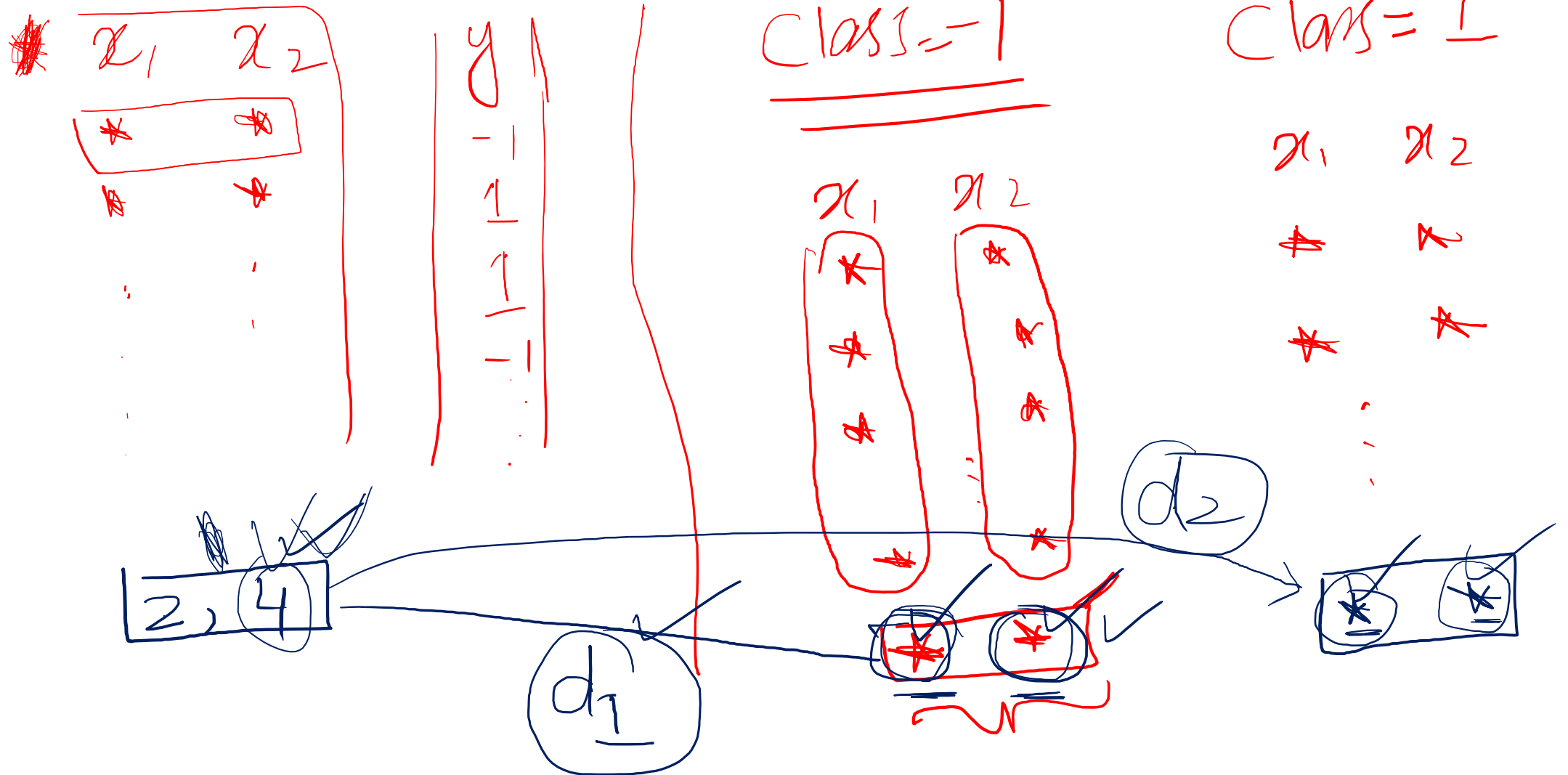
$$\begin{bmatrix} x_i & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = y_i$$

$$\begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ x_3 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix}$$

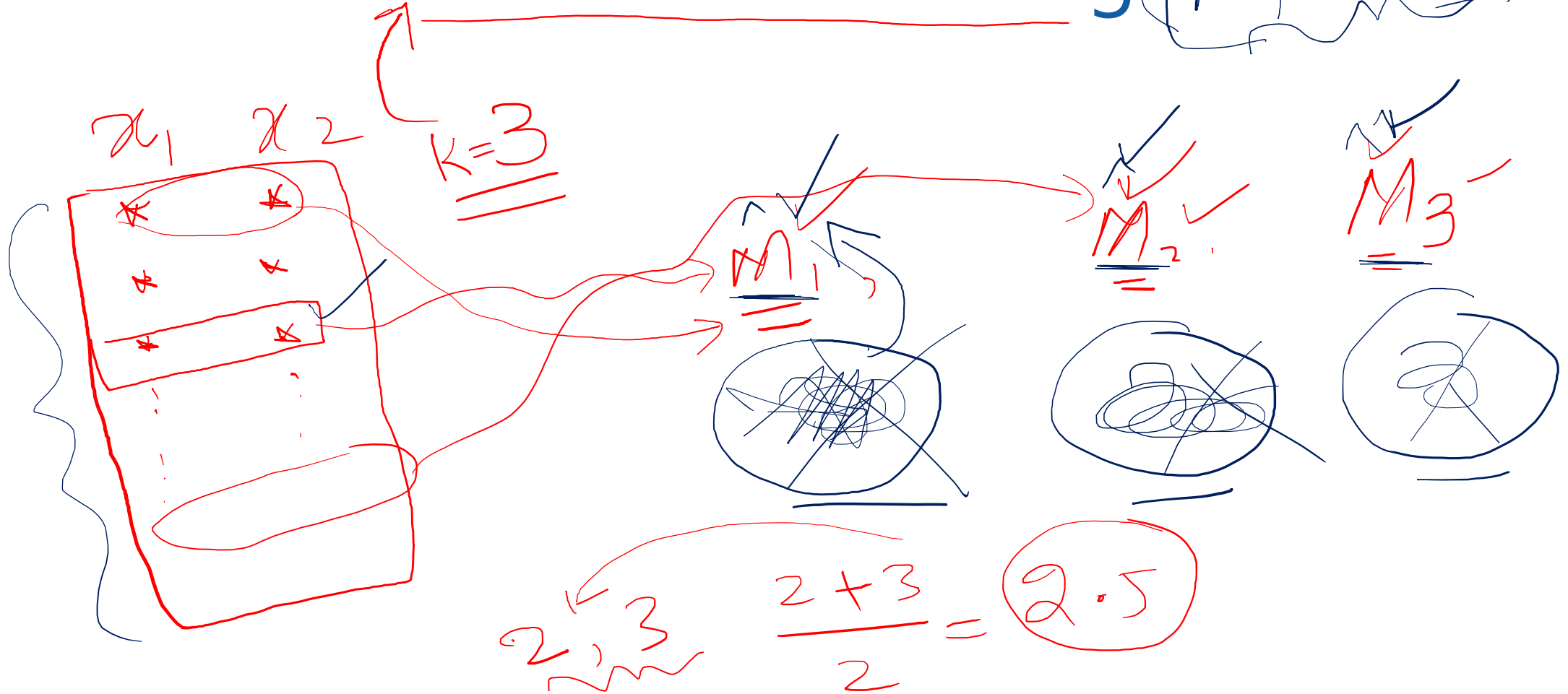
$$\begin{matrix} X & a & = & y \\ n \times 2 & 2 \times 1 & & n \times 1 \end{matrix}$$

$$X \cdot a = y$$

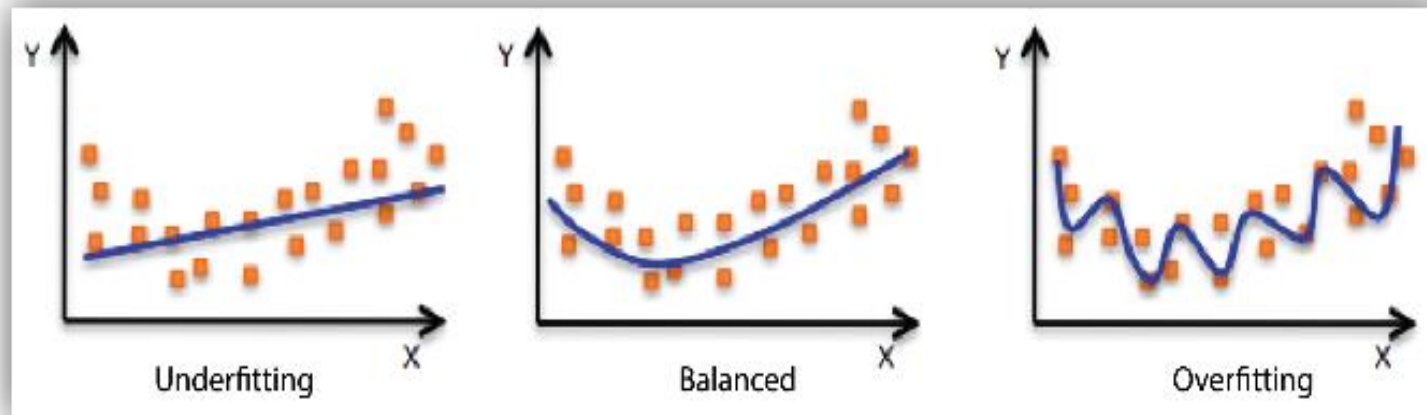
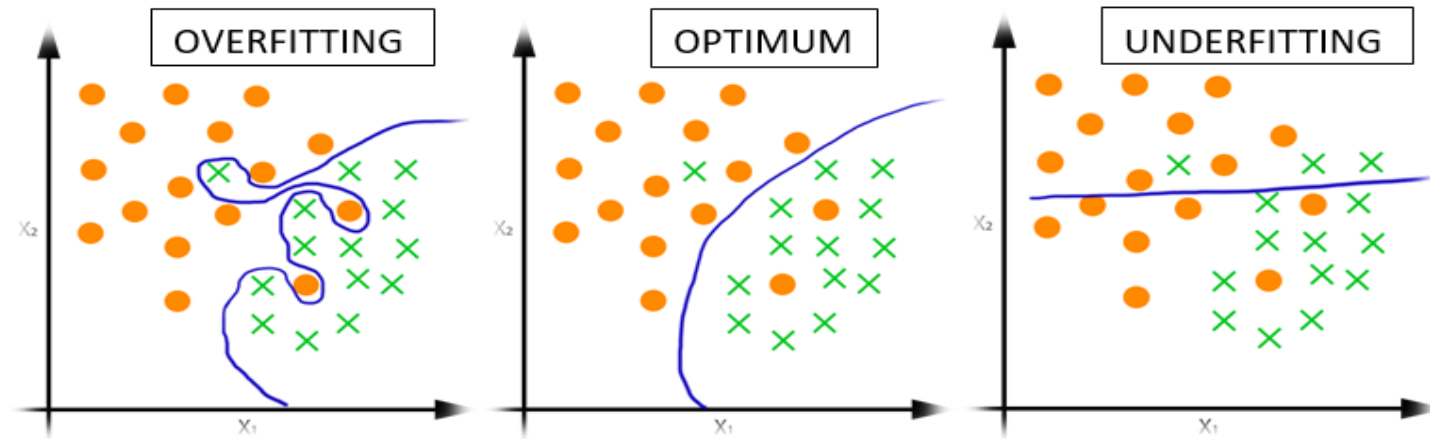
# Minimum-to-mean distance Classifier



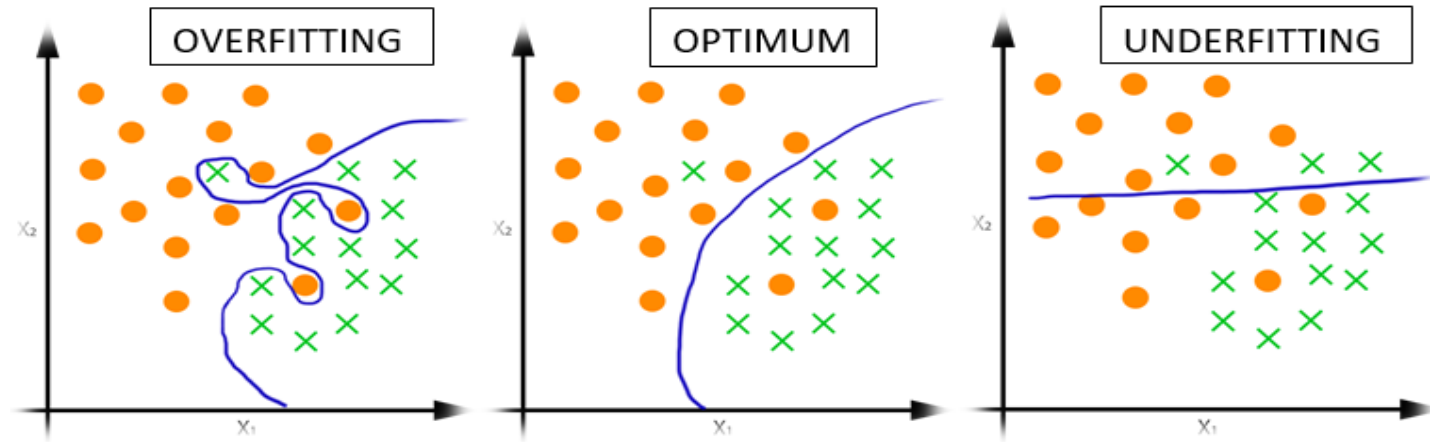
# K-means Clustering (NP-hard)



# Overfitting

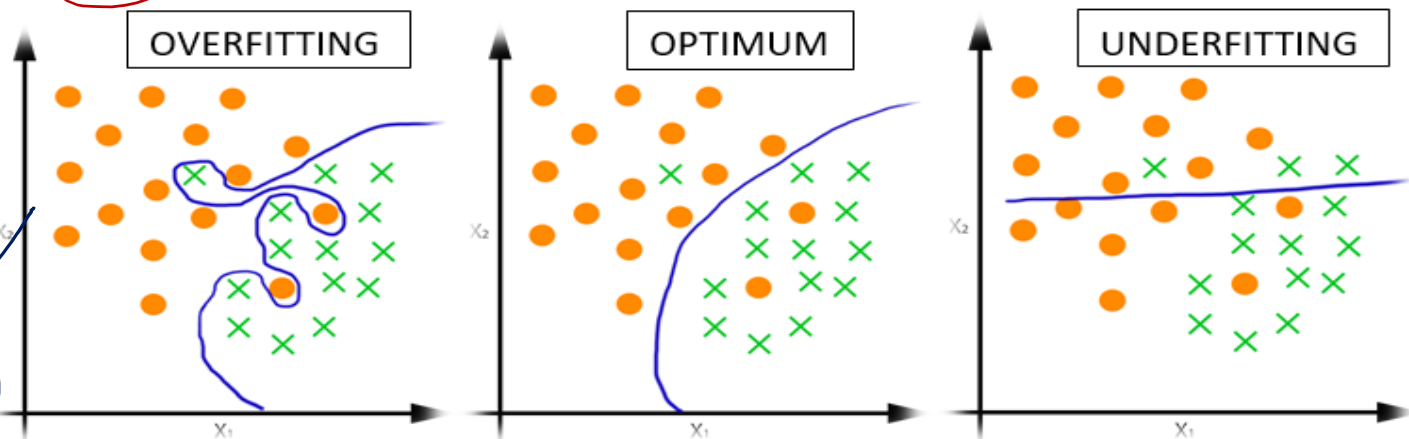


# Generalization and Validation Set

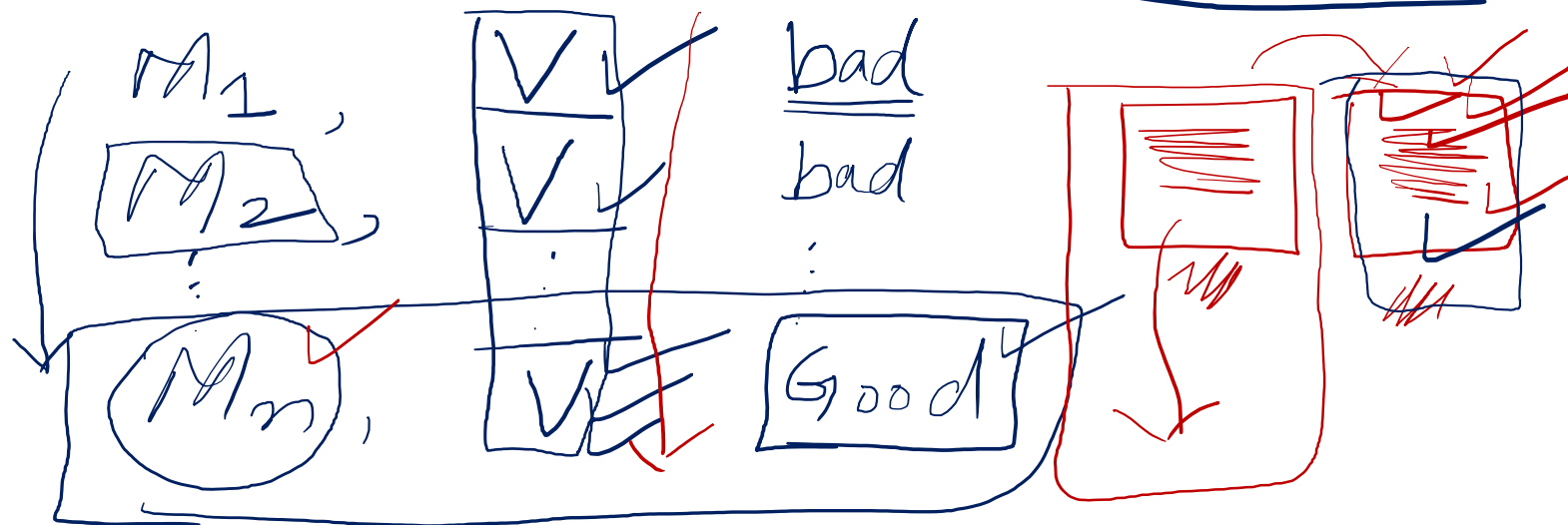
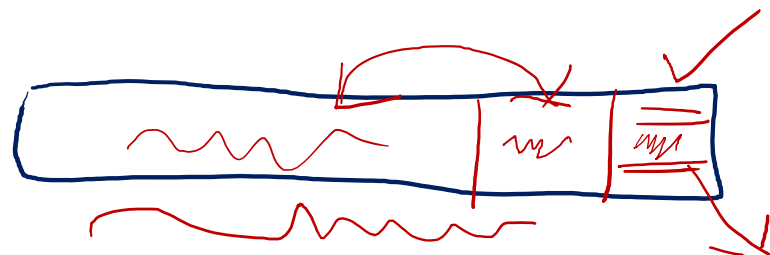


# Data Snooping and the Test set

$A_1$  ✓  
 $A_2$  ✓  
...  
 $A_n$

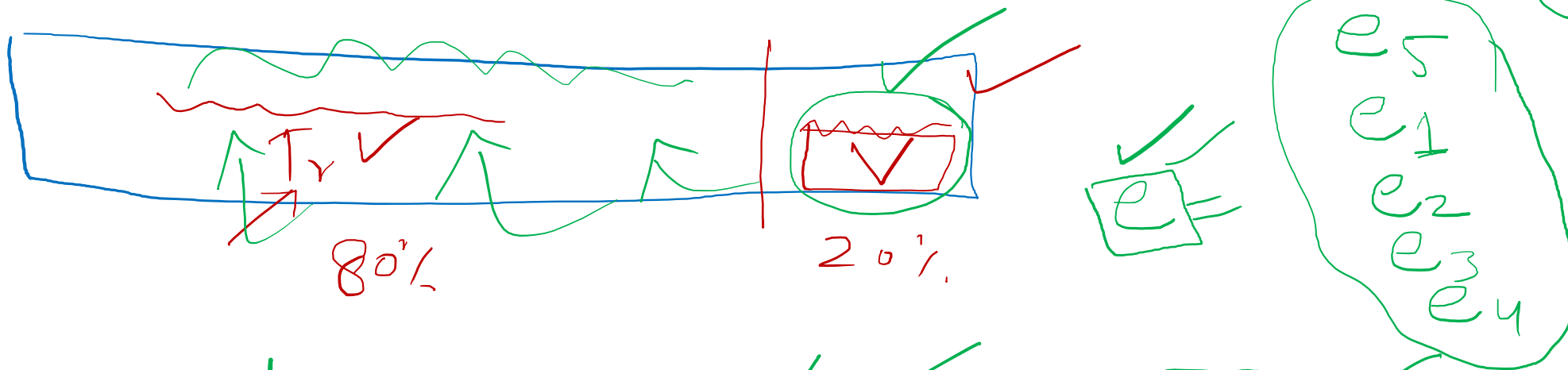
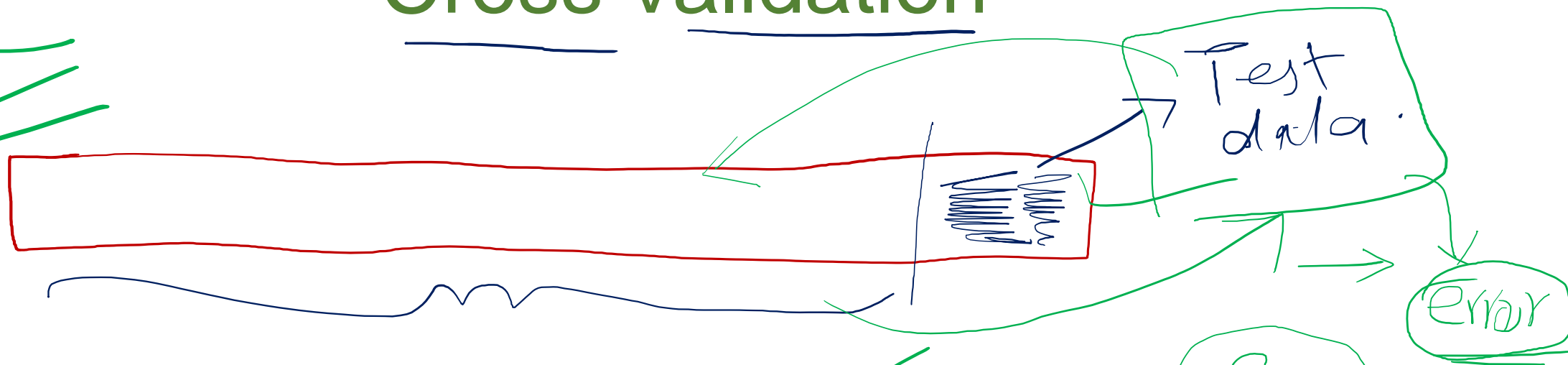


If you torture the data long enough, it will confess.



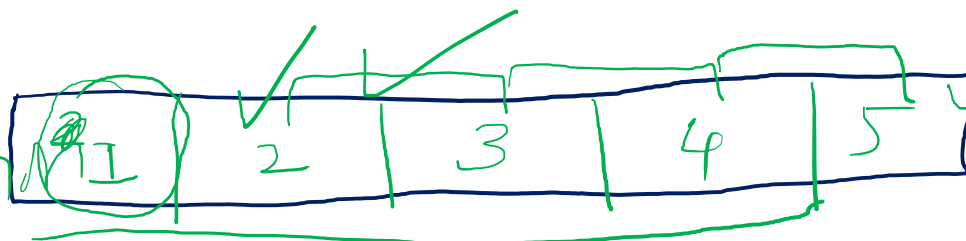
BE

# Cross Validation



K-fold

cross validation



# Performance measures

Accuracy ✓

Error

$$\frac{(MSE)}{(\hat{y} - y)^2}$$

$$\underline{\underline{Acc}} = \frac{\text{# of true predictions}}{\text{# of samples}}$$

$$\frac{80}{100} = 80\%$$





# Performance measures

Confusion Matrix

|       |       |       |       |
|-------|-------|-------|-------|
|       | $C_1$ | $C_2$ | $C_3$ |
| $C_1$ | a     | b     | c     |
| $C_2$ | d     | e     | f     |
| $C_3$ | g     | h     | k     |

$$\text{Recall} = \frac{a}{a+b}$$

Precision

$$\frac{TP}{TP+FP}$$

$$\frac{a}{a+c}$$

|       |       |       |
|-------|-------|-------|
|       | $P_1$ | $P_2$ |
| $C_1$ | a     | b     |
| $C_2$ | c     | d     |

# Probability Distributions and Curse of Dimensionality


$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

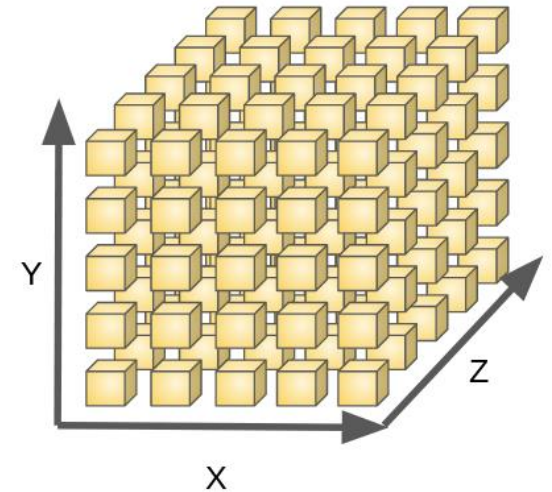
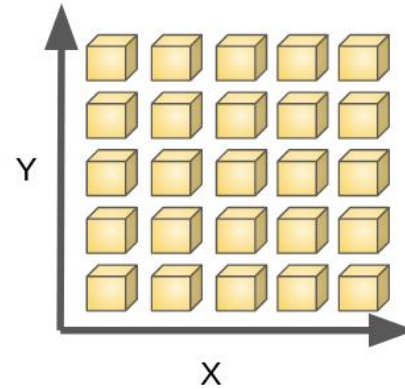
Probability of A occurring given evidence B has already occurred

Probability of B occurring given evidence A has already occurred

Probability of A occurring

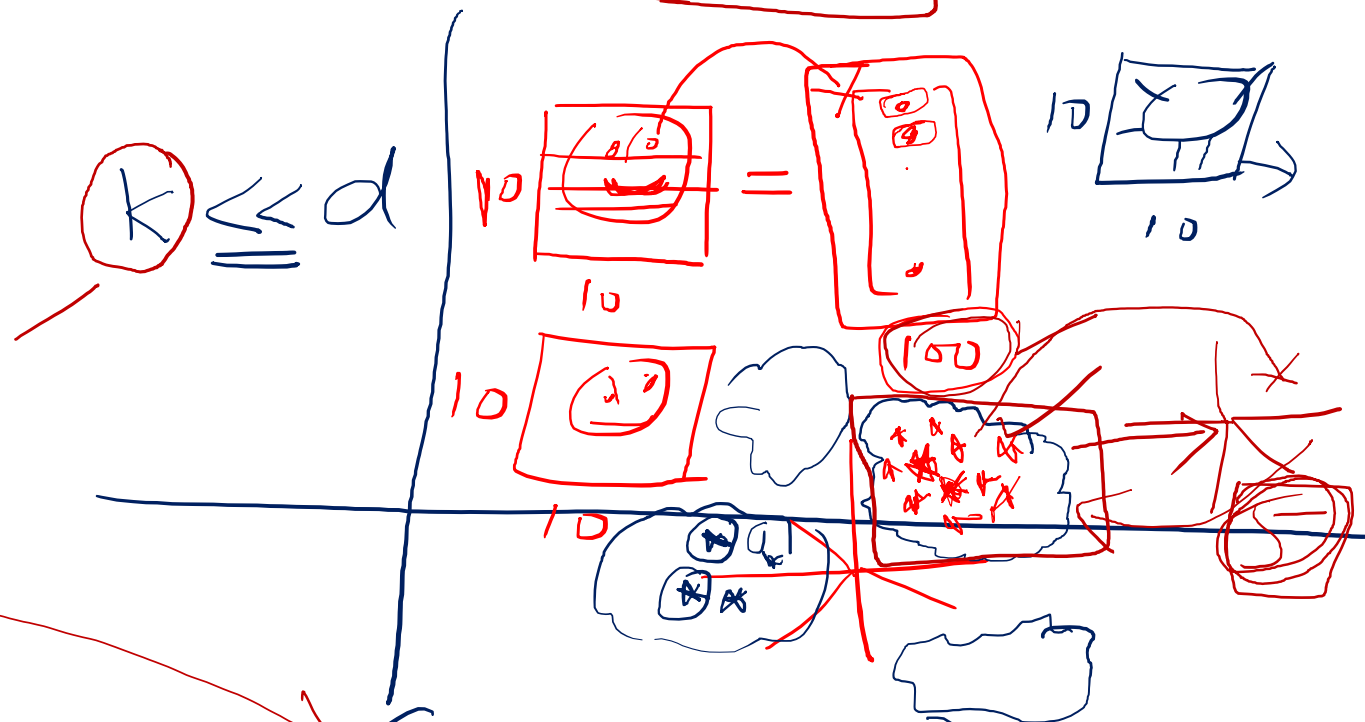
Probability of B occurring





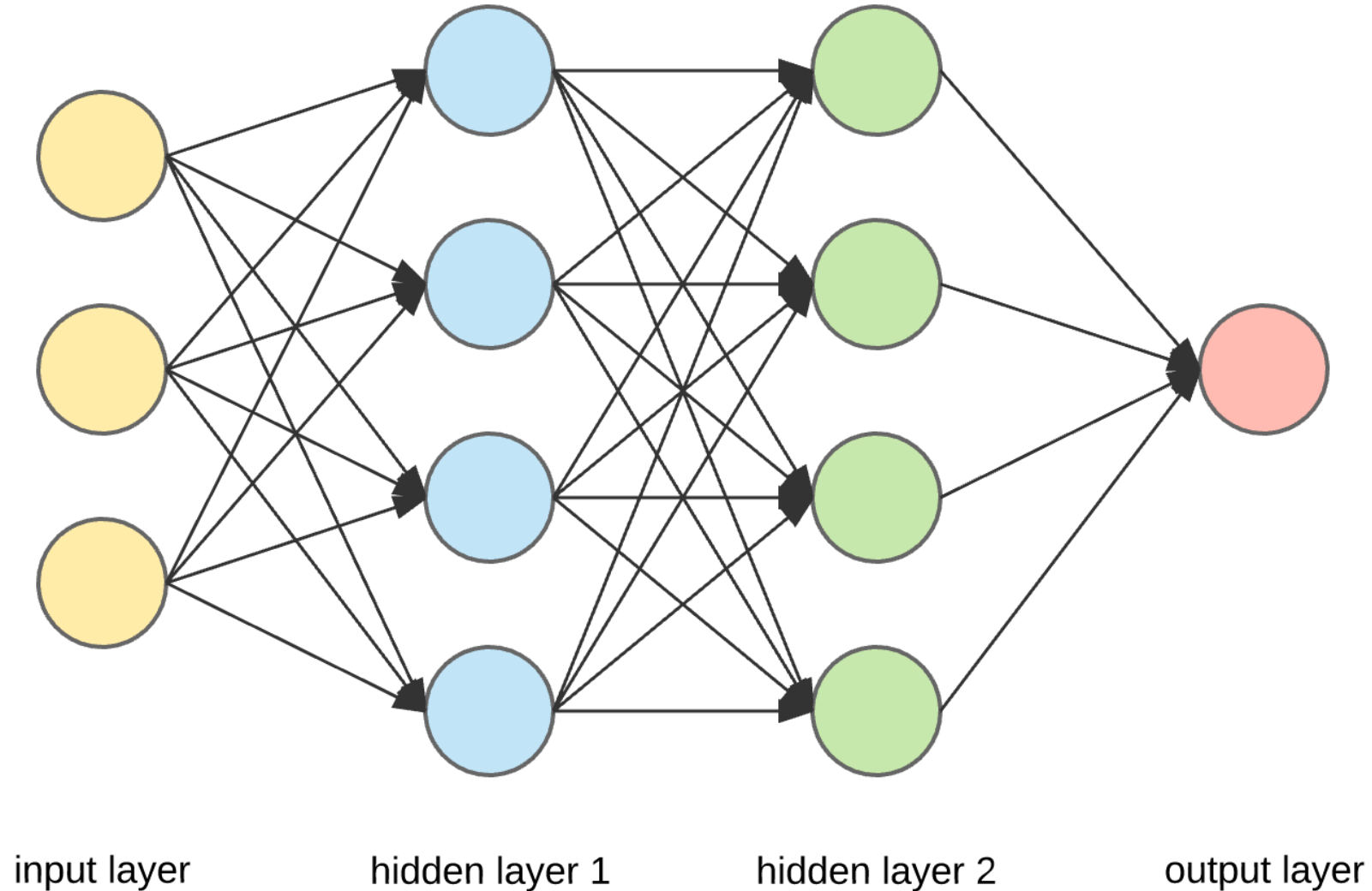
# Dimensionality Reduction PCA

$$X_{N \times d} \rightsquigarrow X_2_{N \times k}, \quad k \ll d$$

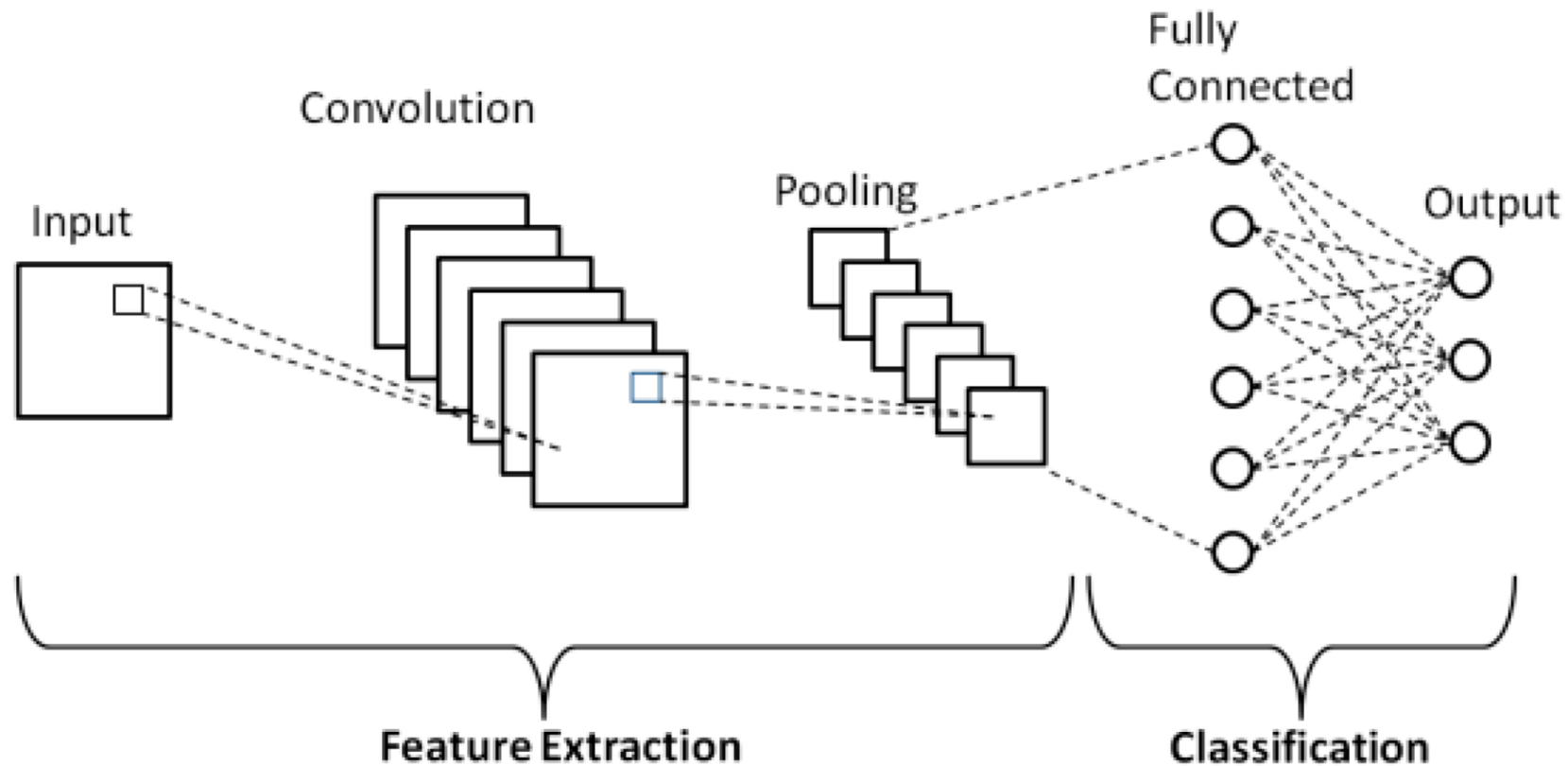


$$(X_{N \times d}, y_{N \times 1}) \xrightarrow{\text{FLD}} (X_2_{N \times k}, y_{N \times 1})$$

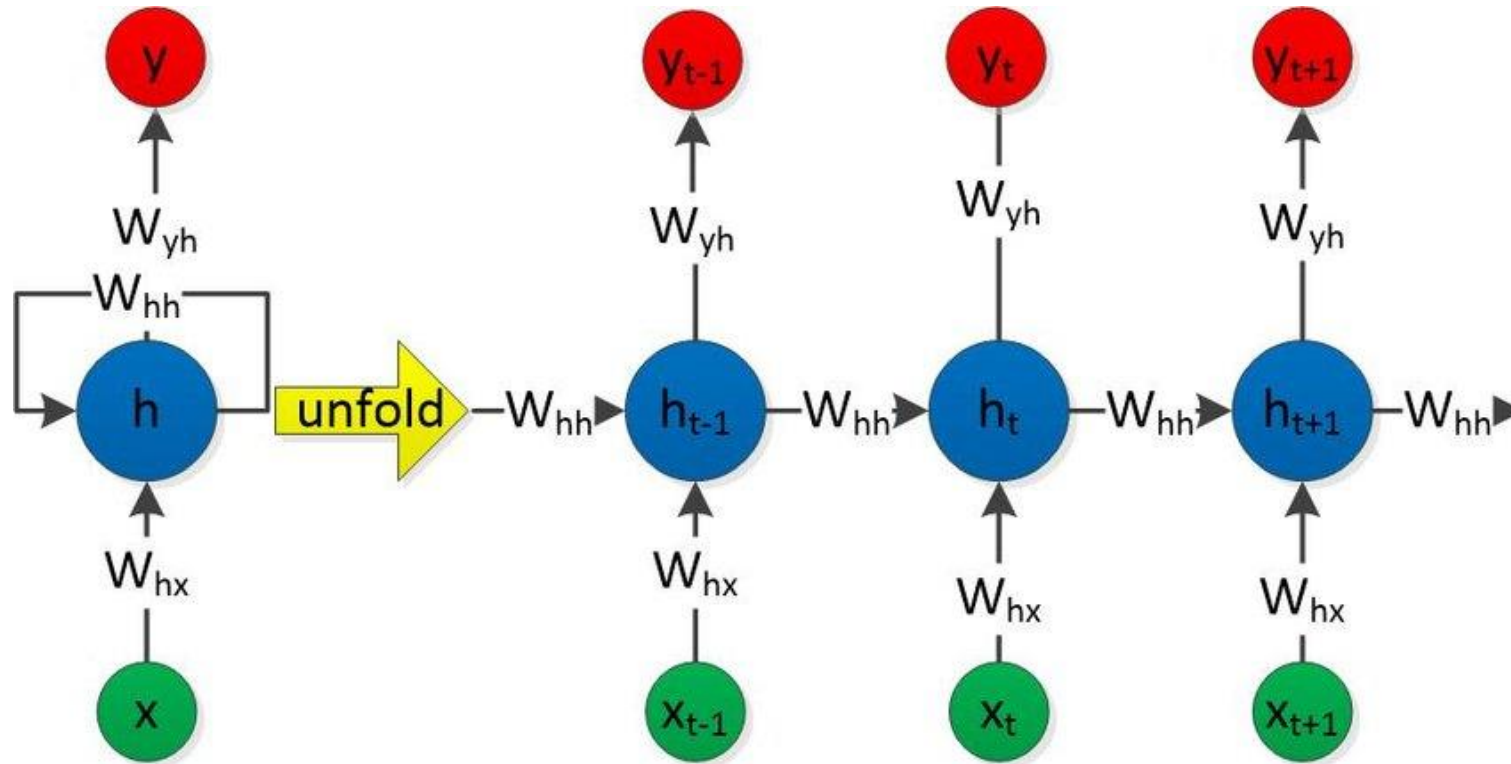
# Deep Learning: ANNs



# Deep Learning: CNNs



# Deep Learning: RNNs



# Mathematical wrap-up

$$f(x) = ax + b$$

~~$$f_w(x_i, y_i)$$~~

$$w = \begin{bmatrix} a \\ b \end{bmatrix}$$

The diagram shows the loss function 
$$\frac{1}{n} \sum_{i=1}^n L(f_w(x_i), y_i) + \lambda \gamma(w)$$
 enclosed in a green rounded rectangle. A blue rounded rectangle is nested inside, containing the first two terms. Annotations include green checkmarks above the summation, the loss function  $L$ , and the model output  $f_w(x_i)$ . A green box highlights  $f_w(x_i)$ , with an arrow pointing to the  ~~$f_w(x_i, y_i)$~~  term above. Another arrow points from the  $f_w(x_i)$  box to the  $w$  in the regularization term  $\gamma(w)$ . The regularization term  $\gamma(w)$  is also annotated with green checkmarks.

# Mathematical wrap-up

→  $f$ ,  $L$ , Preprocessing, regularizer  
quantity 1:

$$V_{\text{ex}} = \sum_{i=1}^N (x_i - m_k)^2$$



# Mathematical wrap-up

$$\sum_{l=1}^{N_k} (x_l^0 - m_k)$$

$$V_k = \sum_{x \in C_k} (x - m_k)^2$$

$$\sum_{l=1}^K V_l^0$$

# Mathematical wrap-up

$$f_w(x_i) = \underline{w_1} x_{i1}^2 + \underline{w_2} x_{i2}^2 + \underline{w_3} x_{i1} x_{i2} + w_4 x_{i1} + w_5 x_{i2} + w_6$$

$$\begin{bmatrix} x_{i1}^2 & x_{i2}^2 & x_{i1} x_{i2} & x_{i1} & x_{i2} & 1 \end{bmatrix}$$

$$g_w(x_i) = w_1 x_{i1} + w_2 x_{i2} + w_3$$

$$\begin{bmatrix} x_{i1} & x_{i2} & 1 \end{bmatrix}$$

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$$

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \end{bmatrix}$$

# Mathematical wrap-up

$\rightarrow P(y=1|x) = \alpha$

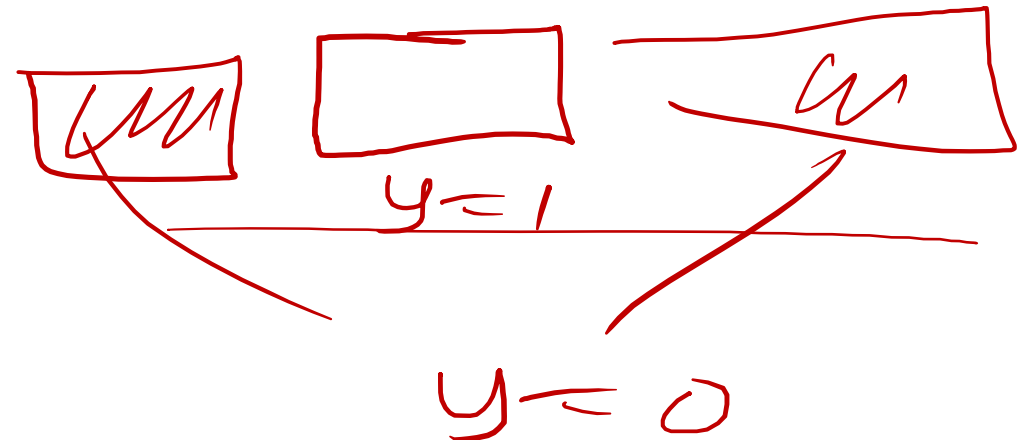
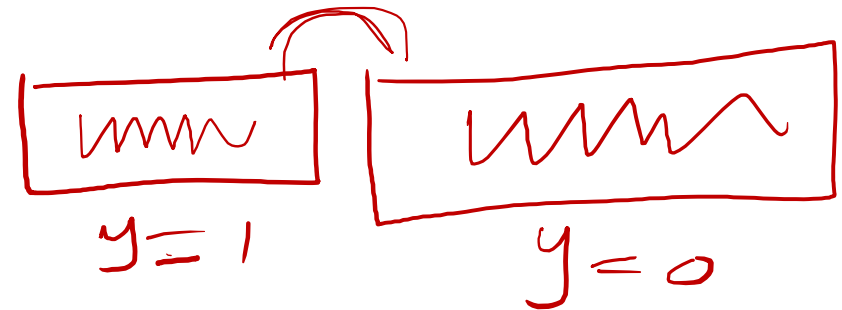
$\rightarrow P(y=0|x) = 1 - \alpha$

$P(y_2=1|x) = \alpha_2$

$P(y_3=1|x) = \alpha_3$

11

$\alpha_t$



# Mathematical wrap-up

LOM:

~~$W^T$~~

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix}$$

$$g_k = W_k^T x_i + w_{k0}$$

$$x_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ x_{id} \end{bmatrix}$$

$$\sum_{i=1}^N \left( W_k^T x_i + w_{k0} - g_k \right)^2 + \lambda W_k^T W$$

# Mathematical wrap-up

Logistic regression

~~prob~~  $f_w(\underline{x_i}) = \boxed{P_i} = p(y=1 | x_i)$

$P_i = \frac{1}{1 + e^{-w^T x_i + w_0}}$   $\rightarrow$  Gross entropy

# Mathematical wrap-up

$$\begin{aligned} \underbrace{P(y_i=1|x_i)}_{\text{circled}} &= \underline{p_i} \\ \underbrace{P(y_i=0|x_i)}_{\text{bracketed}} &= \underline{1-p_i} \end{aligned}$$

$$p_i = \frac{1}{1 + e^{\underbrace{-w^T x_i + w_0}_{\text{circled}}}}$$

# Mathematical wrap-up

