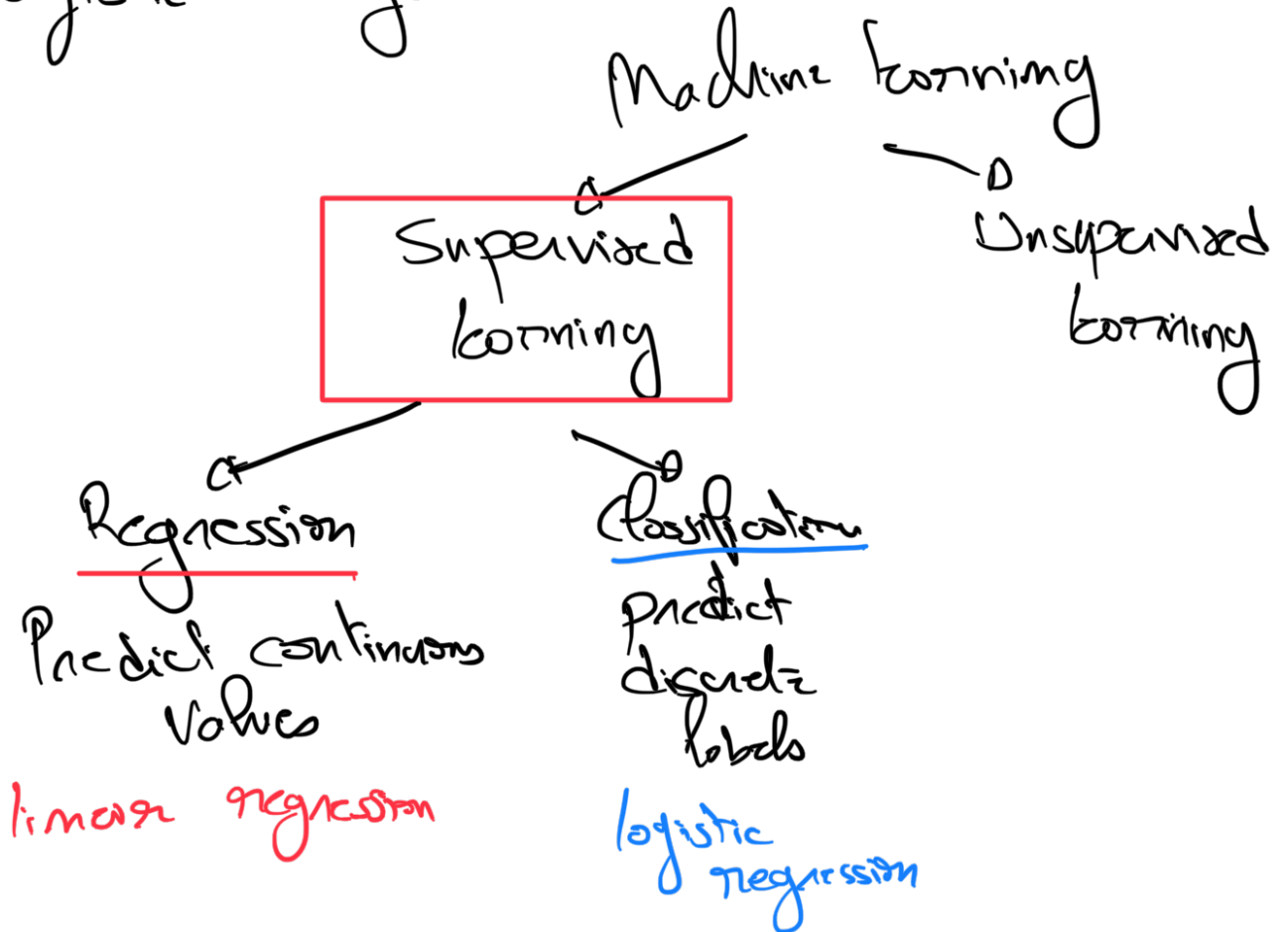
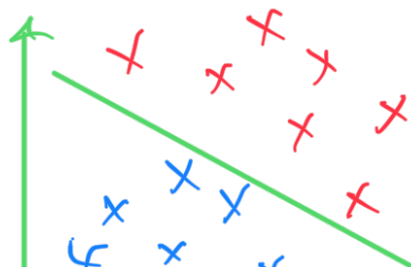


logistic Regression:



Binary logistic regression

$$y \in \{0, 1\}$$





problem \rightarrow

$$\hat{y} = x\theta$$

$y \in \{0, 1\}$

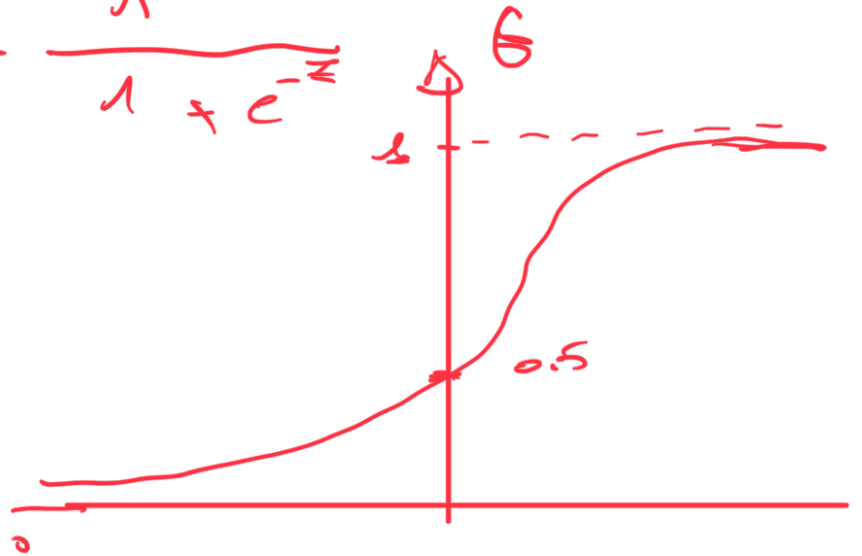
$$\hat{y} = P(y=1|x)$$

$$\hat{y} = \sigma(\underbrace{x\theta}_z)$$

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

$$\lim_{z \rightarrow -\infty} \sigma(z) = 0$$

$$\lim_{z \rightarrow +\infty} \sigma(z) = 1$$



Assume a Threshold

Predict $\hat{y} = 1$ if $\sigma(z) \geq 0.5$

Predict $\hat{y} = 0$ if $\sigma(z) < 0.5$

finding good σ

↓
loss function

⇒ define a new loss function

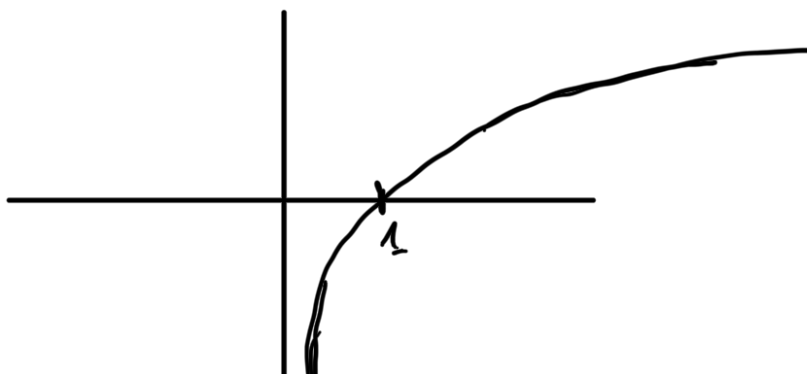
Binary cross entropy loss

$$J(\sigma) = \frac{1}{N} \sum_{i=1}^N y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$

$y_i \in \{0, 1\}$

$$\underline{\underline{\text{cost}(y, \hat{y})}} = - y \log(\hat{y}) - \underline{(1 - y) \log(1 - \hat{y})}$$

$$\text{cost}(y, \hat{y}) = \begin{cases} -\log(\hat{y}) & \text{if } \underline{y=1} \\ -\log(1 - \hat{y}) & \text{if } \underline{y=0} \end{cases}$$



$$\lim_{x \rightarrow 0} \log(x) = -\infty$$

$$\lim_{x \rightarrow +\infty} \log(x) = +\infty$$

$$\log(1) = 0$$

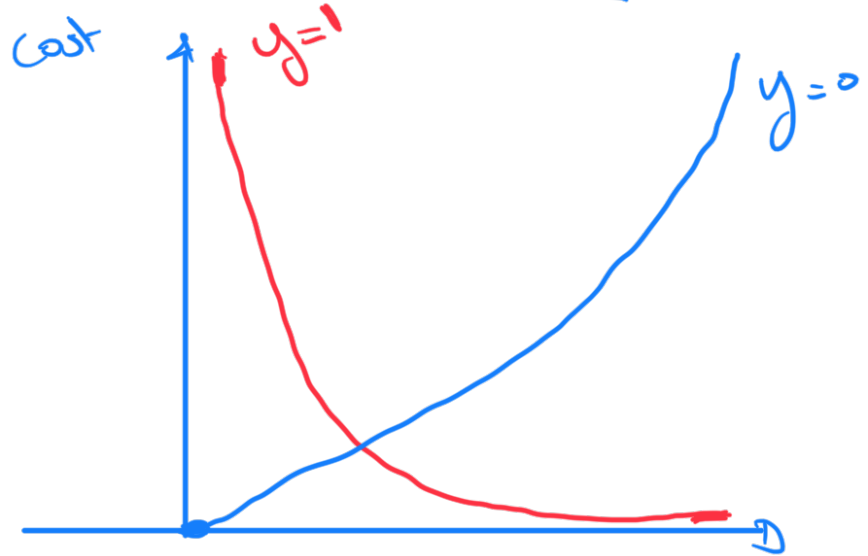
cost

$$\begin{cases} -\log(\hat{y}) \\ -\log(1-\hat{y}) \end{cases}$$

$$\hat{y} = \sigma(x\theta)$$

if $y=1$
if $y=0$

$$\begin{cases} -\log(\sigma(x\theta)) & \text{if } y=1 \\ -\log(1-\sigma(x\theta)) & \text{if } y=0 \end{cases}$$



$$\hat{y} = \sigma(x\theta)$$

if $y=1$ and $\hat{y} = \sigma(x\theta) \rightarrow 0$

$$-\log(\hat{y}) \rightarrow +\infty$$

$$\hat{y} = \sigma(x\theta) \rightarrow 1$$

if $y=0$ and $\hat{y} = \sigma(x\theta) \rightarrow 0$

$$\log(1-\hat{y}) = 0$$

$$\text{if } y=0 \text{ and } \hat{y} = \sigma(x\theta) \rightarrow 1$$

How to find the optimal θ

$$J(\theta)$$

$$\hat{y} = f(x_0)$$

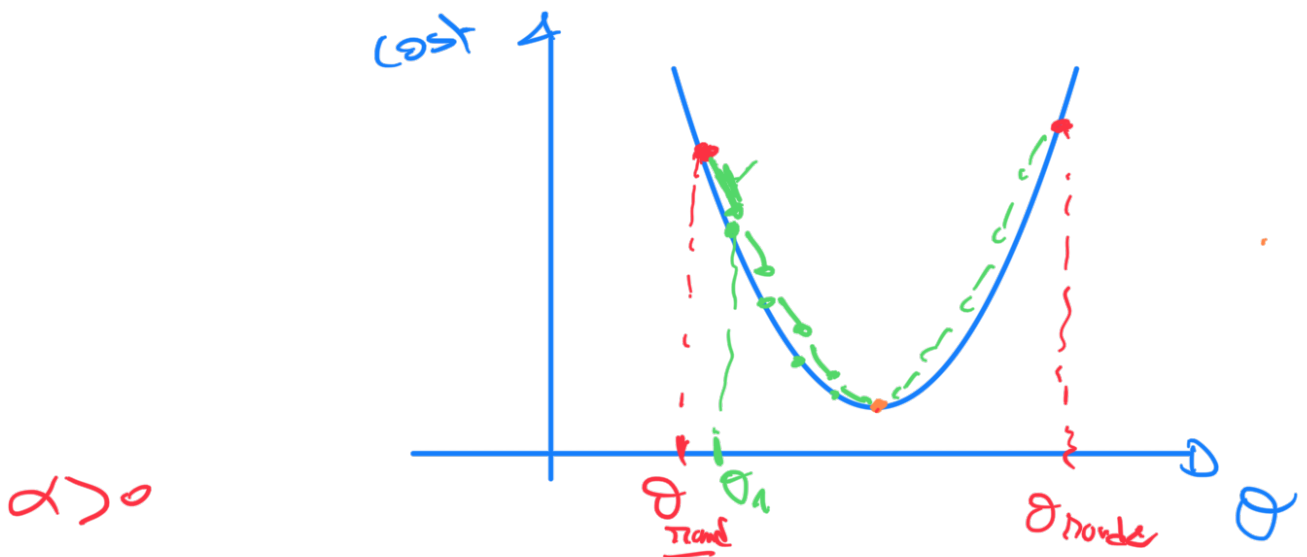
$$\frac{\partial J(\theta)}{\partial \theta} = 0$$

Gradient Descent:

Initialize θ
 Repeat until convergence
 $\theta_j \leftarrow \theta_j - \alpha \left(\frac{\partial J}{\partial \theta_j} \right)$

learning rate

$j = 0 \dots N$



$$\theta_{j+1} \leftarrow \theta_{j_{\min}} - \alpha \left(\frac{\partial J}{\partial \theta_{j_{\min}}} \right)$$

θ_j is a vector

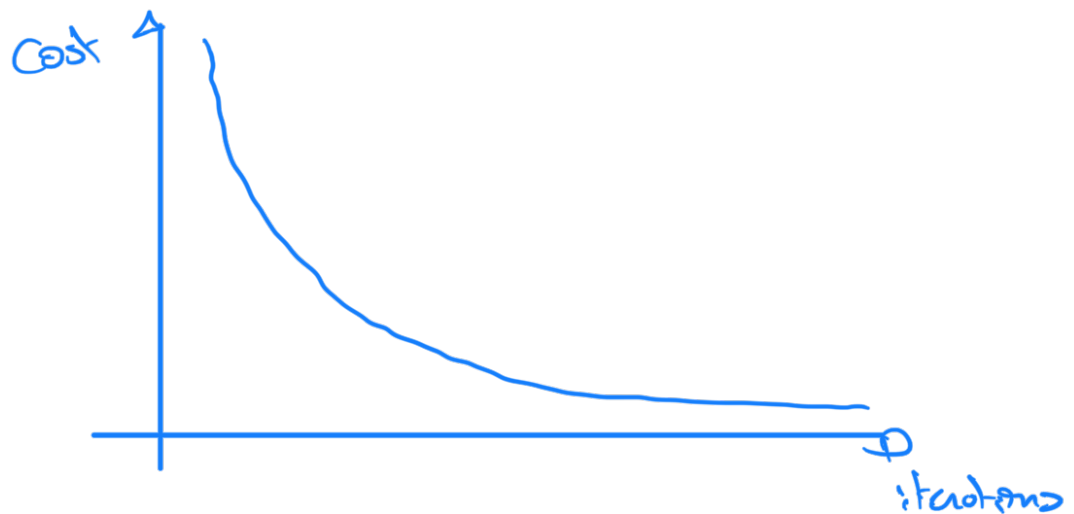
J decreasing
 $J' < 0$

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial J}{\partial \theta_j}$$

J increasing
 $J' > 0$

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial J}{\partial \theta_j}$$

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial J}{\partial \theta_j}$$



* mini batch (stochastic) GD

* learning rate

