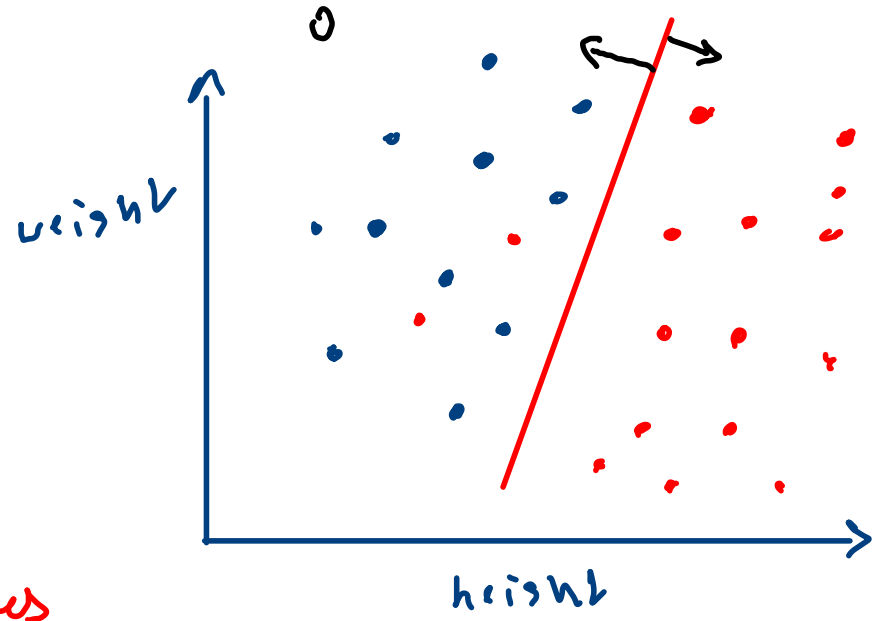


Linear ✓ feature

Logistic Regression \rightarrow Binary
Classification

Assumption \rightarrow linearly separable

Best fit
Line



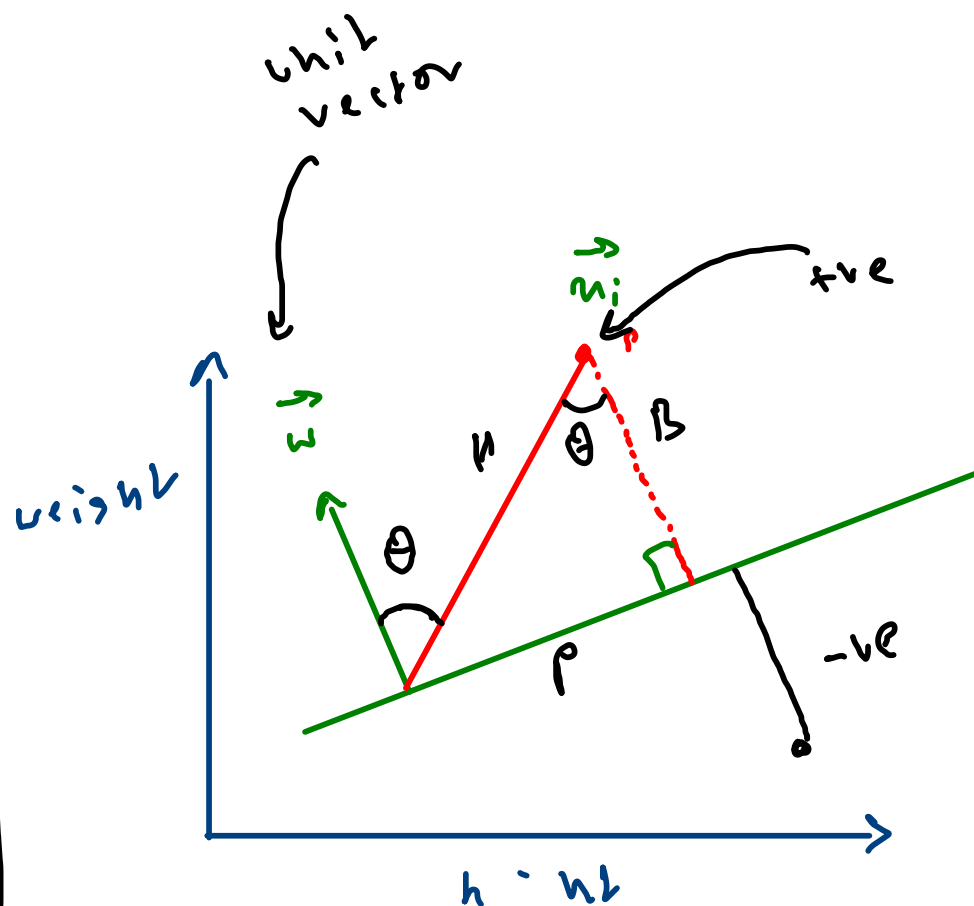
- Best fit Line
- distance
- probability
- Cost function
- Gradient Descent
- Softmax

height	weight	diabetes
•	•	0
•	•	1
•	•	1
		0
		0

$$0 \begin{bmatrix} 0.3 & 0.5 & 0.2 \end{bmatrix}$$

Distance

-ve +ve
0 1



$$\vec{w} \cdot \vec{n} = w n \cos \theta$$

$$= w \checkmark \frac{1}{\checkmark}$$

$$\vec{w} \cdot \vec{n} = \|\vec{w}\| B$$

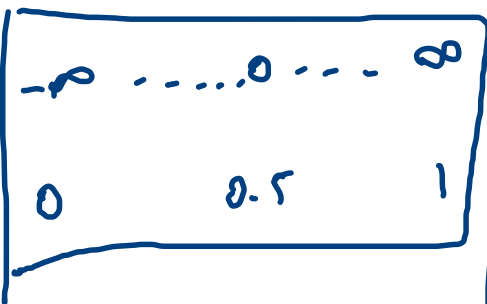
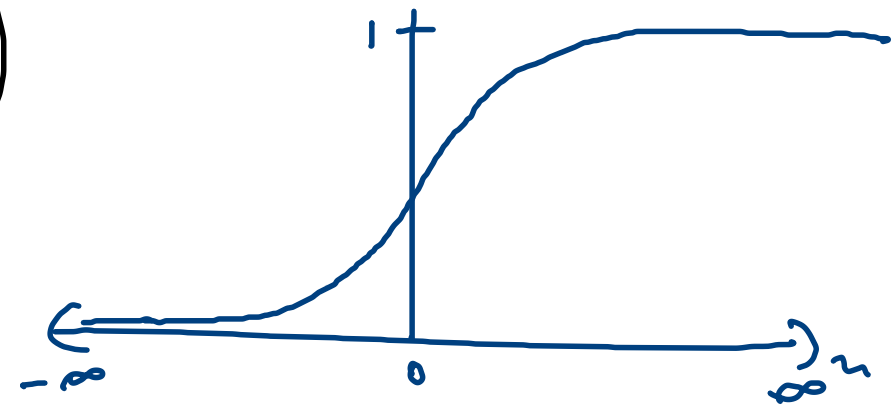
$$B = \frac{\vec{w} \cdot \vec{n}}{\|\vec{w}\|}$$

$$B = \vec{w} \cdot \vec{n}$$

$$B = w n \cos \theta$$

Probability

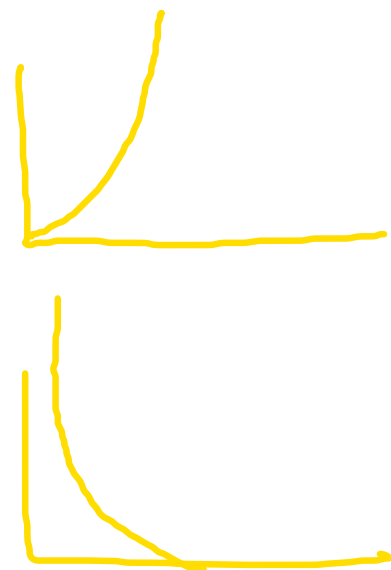
Sigmoid $\sigma(x) = \frac{1}{1 + e^{-x}}$



distance	$\sigma(x)$
∞	1
30	0.7
3	0.6
0	0.5
-3	0.4
-30	0.3
$-\infty$	0

cost function

y_{actual}	$\sigma(w^T x + b)$	cost
0	0	0
0	1	∞
{0, 1}	{0, 1}	
1	0	∞
1	1	0



cost function

$$\begin{cases} -\log[1 - (\sigma(w)) & y = 0 \\ -\log[\sigma(w)] & y = 1 \end{cases}$$

cost function

number of instance

$$= \frac{1}{M} \sum_{i=1}^M - y \left(\log(\sigma(w)) \right) - (1 - y) \left(\log(1 - \sigma(w)) \right)$$

$$\frac{d \text{ cost function}}{d w}$$

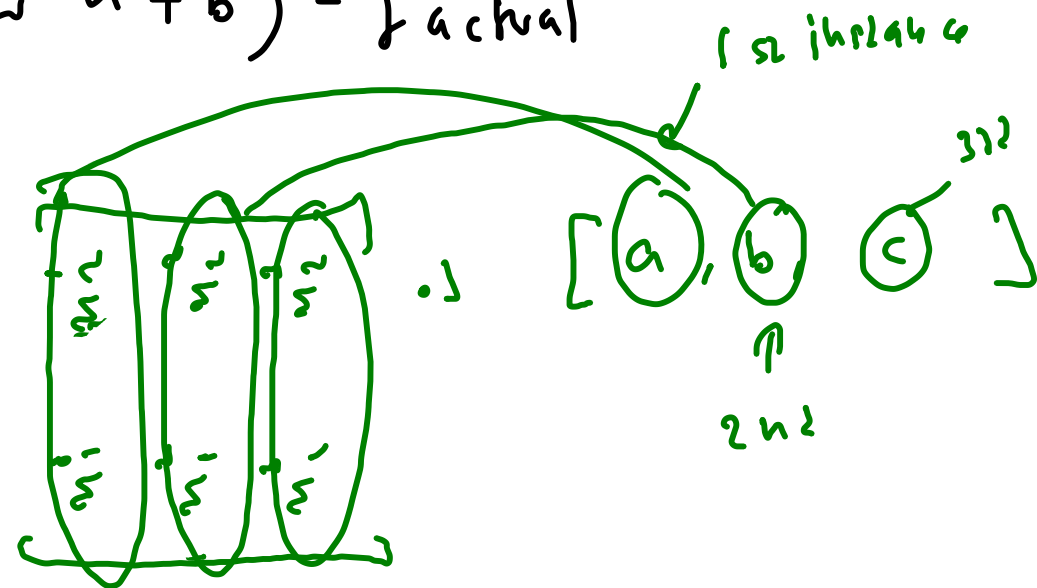
$$\frac{1}{n} \sum \left[\sigma(w^T x + b) - y_{\text{actual}} \right]^2$$

↓
↓
↓
↓
↓

$$\frac{d \text{ cost function}}{d b}$$

$$\frac{1}{n} \sum \sigma(w^T x + b) - y_{\text{actual}}$$

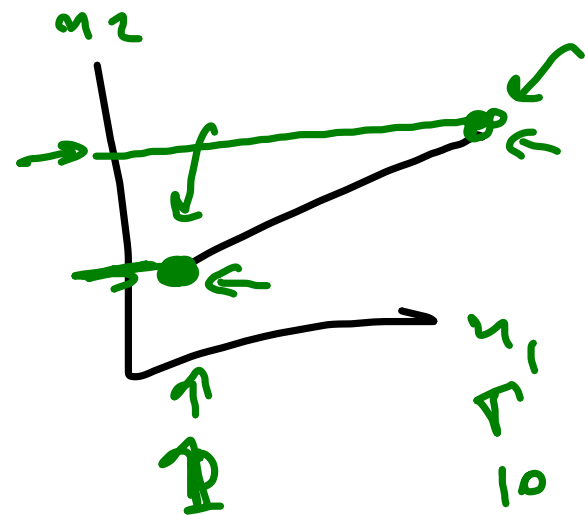
distance = $w^T x + b$
 probability = $\sigma(\text{distance})$



$$\text{distance} = w^T x + b$$

$$0 = \check{m}_1 x_1 + \check{m}_2 x_2 + \check{b}$$

$$\frac{-(m_1 x_1 + b)}{m_2} \leftarrow x_2$$



M
•
W
•

F

• ← Saturday
• ← Sunday

✓
✓
x

←

Linear

+

Logistic

ML

Solve Solution

Titanic
Boston Housing

~~Connectivity~~

Linker2, Twitter
harbor

Softmax

Wish \downarrow Result

One vs rest

overfit

	x_1	x_2	y	y_1	y_2	y_3
1 -	x_{11}	x_{12}	1	1	0	0
2 -	x_{21}	x_{22}	2	0	1	0
3 -	x_{31}	x_{32}	3	0	0	1
4 -	x_{41}	x_{42}	1	1	0	0

underfit

fit

overfit

$$W^1 = [w_1, w_2, w_0]$$

$$W^2 = [w_2, w_1, w_3]$$

$$W^3$$

$$\sigma(\text{under fit}) = \frac{e^{w^1 u}}{e^{w^1 u} + e^{w^2 u} + e^{w^3 u}}$$

$$\sigma(\text{over fit}) = \frac{e^{w^3 u}}{e^{w^1 u} + e^{w^2 u} + e^{w^3 u}}$$

$$\sigma(\text{fit}) = \frac{e^{w^2 u}}{e^{w^1 u} + e^{w^2 u} + e^{w^3 u}}$$

- 1 \rightarrow underfit
- 2 \rightarrow fit
- 3 \rightarrow overfit

Training Softmax

$$\Rightarrow \frac{1}{M} \sum_{i=1}^M - y \left(\log(\sigma(w^T x)) \right) - (1-y) \left(\log(1 - \sigma(w^T x)) \right)$$

$$\Rightarrow \frac{1}{M} \sum_{i=1}^M \sum_{k=1}^K y_k^i \log \left(\underbrace{w_k^T x_i}_{w_k^1 x_i^1 + w_k^2 x_i^2 + \dots + b_k} \right)$$

↑
for all
instances

↑
for all
classes