

Lecture 6- I

Softmax classification: Multinomial classification

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Logistic regression

→ Base:

$$H_L(x) = \underline{w}x$$

$\begin{matrix} 1 & 0 \\ 2 & 0 \\ 1 & 0 \end{matrix}$

Binary output \rightarrow

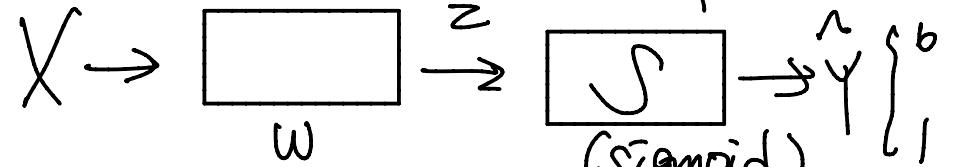
$Z = H_L(x)$, $\therefore g(z) = \begin{cases} 0 \\ 1 \end{cases}$

Logistic function.

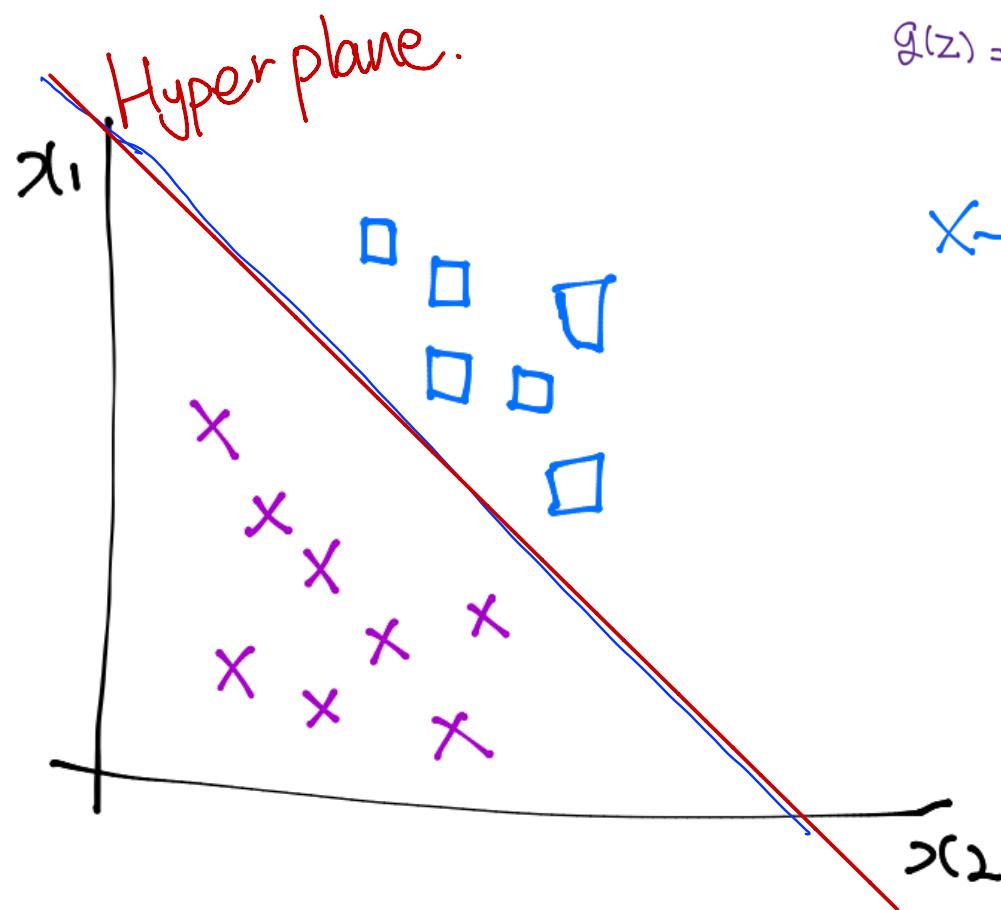
$$g(z) = \frac{1}{1 + e^{-z}}$$

Sigmoid
Logistic.

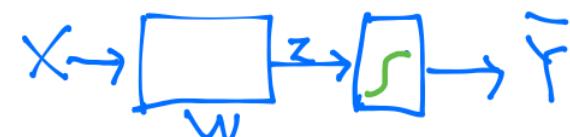
$$H_R(x) = g(H_L(x))$$



Logistic regression



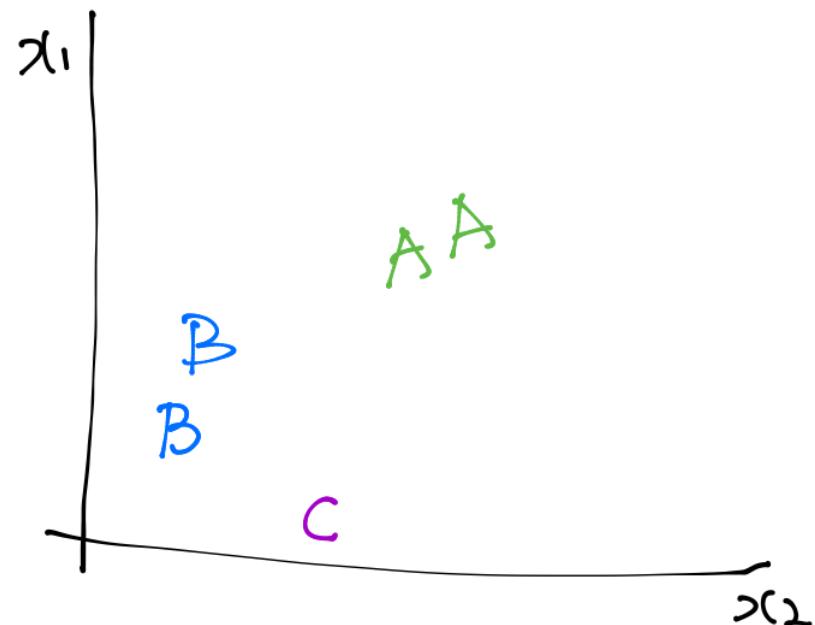
$$g(z) = \frac{1}{1+e^{-z}} \quad H_R(x) = g(H_L(x))$$



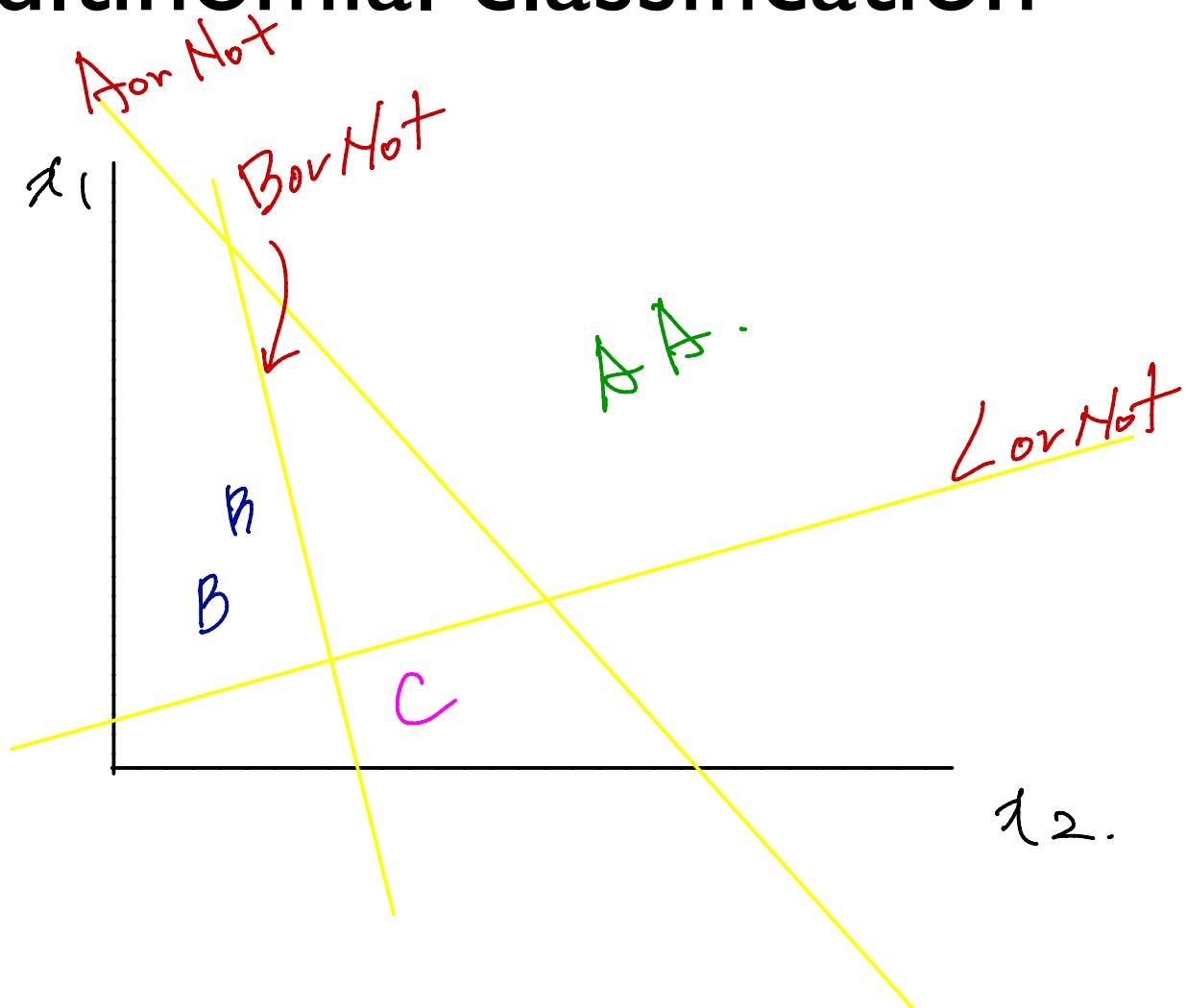
Multinomial classification

(여러가지 class)

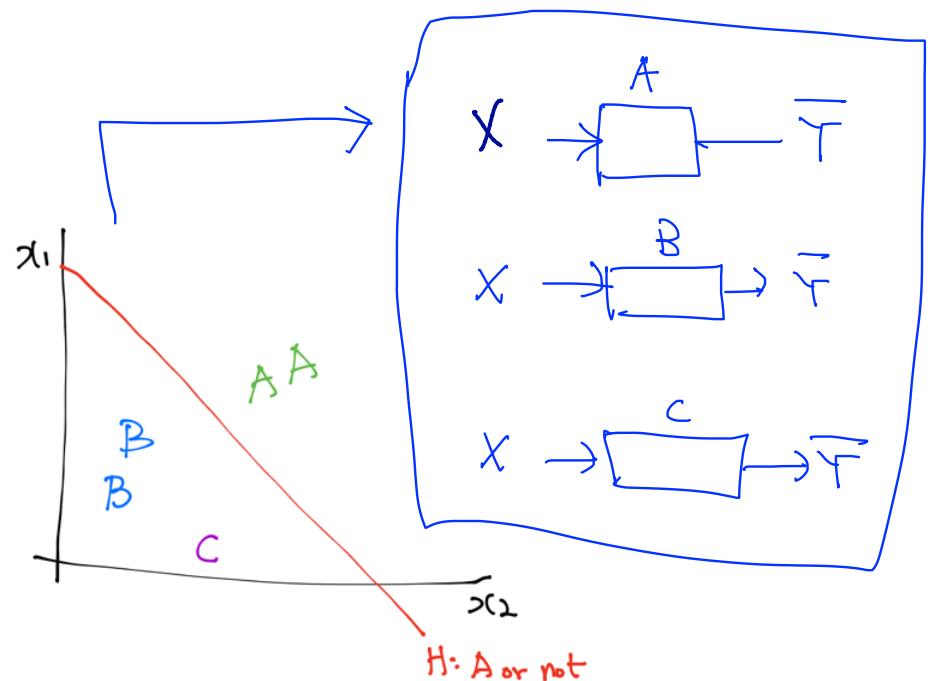
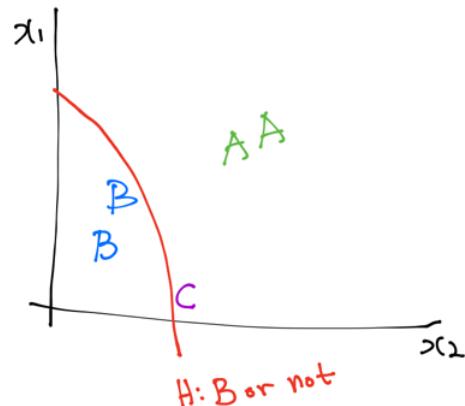
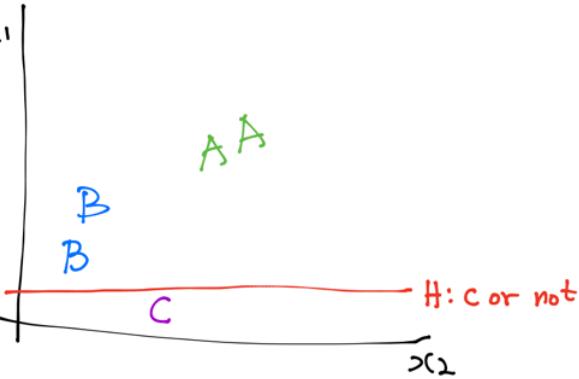
x1 (hours)	x2 (attendance)	y (grade)
10	5	A
9	5	A
3	2	B
2	4	B
11	1	C



Multinomial classification



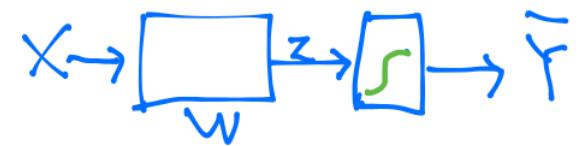
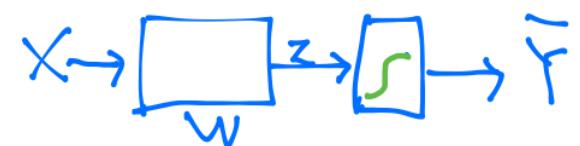
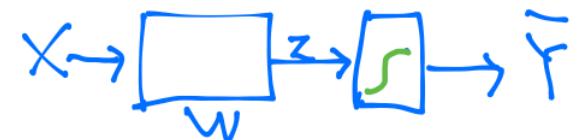
Multinomial classification



Multinomial classification

$$\begin{aligned}
 w & \quad [w_1 \ w_2 \ w_3] \begin{bmatrix} x \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} = H(x) \\
 & [w_1 \ w_2 \ w_3] \begin{bmatrix} x \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} = [w_1x_1 + w_2x_2 + w_3x_3] \\
 & [w_1 \ w_2 \ w_3] \begin{bmatrix} x \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} = [w_1x_1 + w_2x_2 + w_3x_3]
 \end{aligned}$$

w는 각 클래스에 대한 가중치를 갖는다.



Multinomial classification

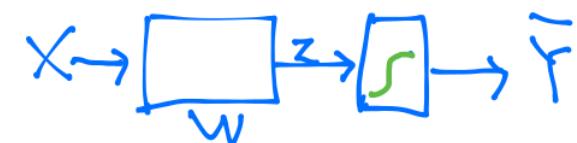
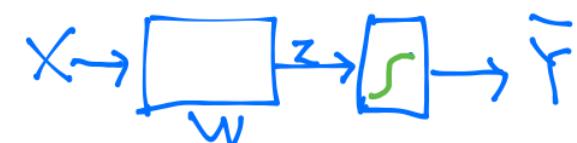
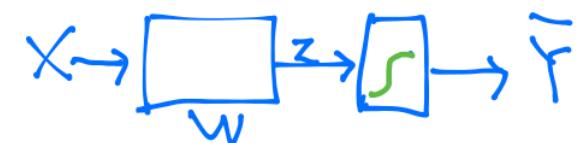
$$\begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = [w_1x_1 + w_2x_2 + w_3x_3]$$

↓

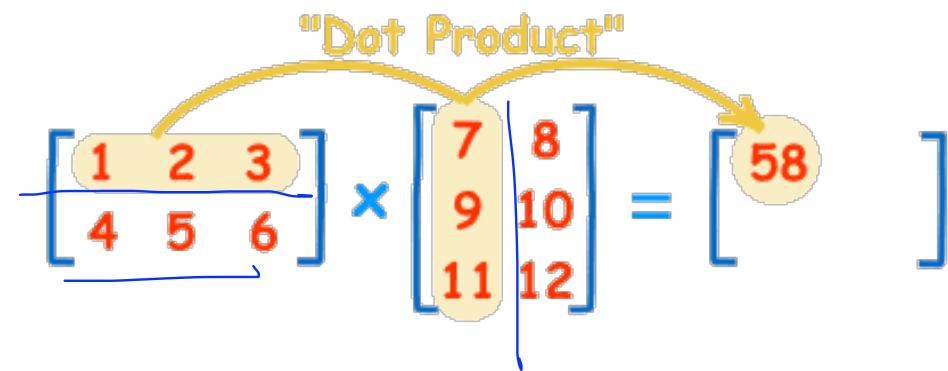
↳

$$\begin{bmatrix} w_{A1} & w_{A2} & w_{A3} \\ w_{B1} & w_{B2} & w_{B3} \\ w_{C1} & w_{C2} & w_{C3} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} =$$

Mat Mult



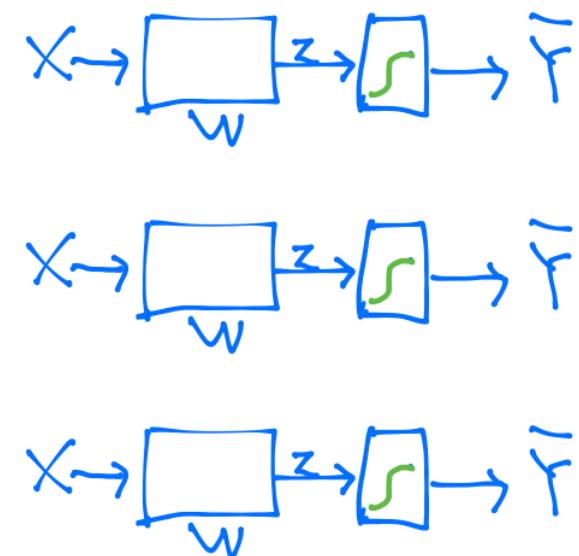
Matrix multiplication



<https://www.mathsisfun.com/algebra/matrix-multiplying.html>

Multinomial classification

$$\begin{bmatrix} w_{A1} & w_{A2} & w_{A3} \\ w_{B1} & w_{B2} & w_{B3} \\ w_{C1} & w_{C2} & w_{C3} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} w_{A1}x_1 + w_{A2}x_2 + w_{A3}x_3 \\ w_{B1}x_1 + w_{B2}x_2 + w_{B3}x_3 \\ w_{C1}x_1 + w_{C2}x_2 + w_{C3}x_3 \end{bmatrix}$$



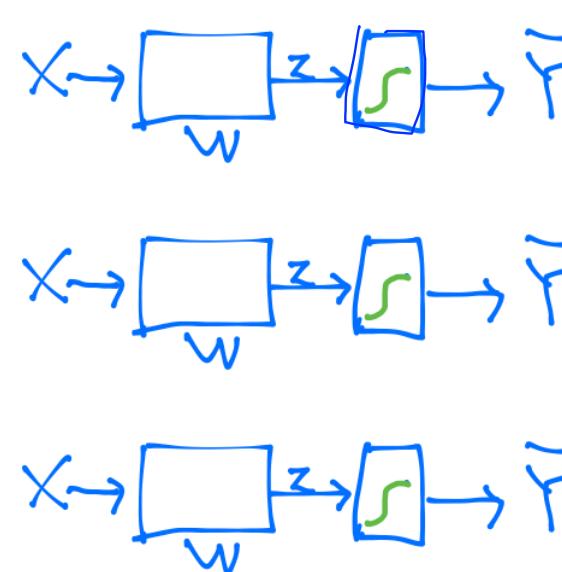
Multinomial classification

$$\begin{bmatrix} w_{A1} & w_{A2} & w_{A3} \\ w_{B1} & w_{B2} & w_{B3} \\ w_{C1} & w_{C2} & w_{C3} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} w_{A1}x_1 + w_{A2}x_2 + w_{A3}x_3 \\ w_{B1}x_1 + w_{B2}x_2 + w_{B3}x_3 \\ w_{C1}x_1 + w_{C2}x_2 + w_{C3}x_3 \end{bmatrix} = \begin{bmatrix} \bar{y}_A \\ \bar{y}_B \\ \bar{y}_C \end{bmatrix}$$

$\checkmark H_A(x)$ $x \rightarrow [W] \rightarrow z \rightarrow [S] \rightarrow \bar{Y}$
 $\checkmark H_B(x)$ $x \rightarrow [W] \rightarrow z \rightarrow [S] \rightarrow \bar{Y}$
 $\checkmark H_C(x)$ $x \rightarrow [W] \rightarrow z \rightarrow [S] \rightarrow \bar{Y}$

Using matrix multiplication
 Matrix X
 → Feature vector

Where is sigmoid?

$$\begin{bmatrix} w_{A1} & w_{A2} & w_{A3} \\ w_{B1} & w_{B2} & w_{B3} \\ w_{C1} & w_{C2} & w_{C3} \end{bmatrix}
 \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}
 =
 \begin{bmatrix} w_{A1}x_1 + w_{A2}x_2 + w_{A3}x_3 \\ w_{B1}x_1 + w_{B2}x_2 + w_{B3}x_3 \\ w_{C1}x_1 + w_{C2}x_2 + w_{C3}x_3 \end{bmatrix}
 =
 \begin{bmatrix} \bar{y}_A \\ \bar{y}_B \\ \bar{y}_C \end{bmatrix}$$


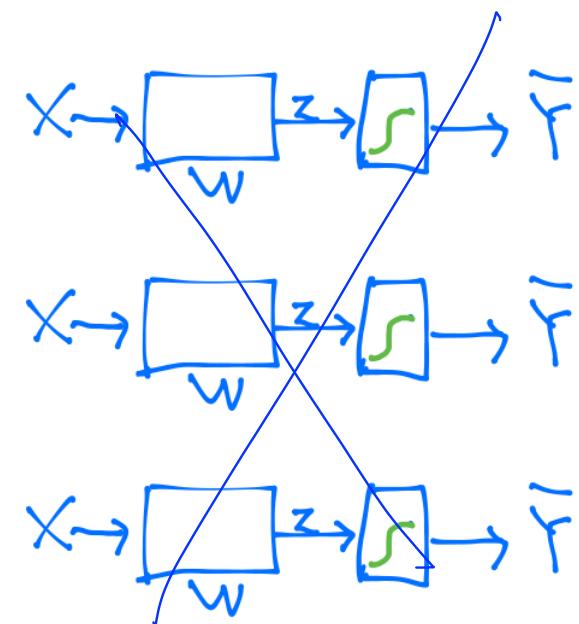
Lecture 6-2

Softmax classification: softmax and cost function

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Where is sigmoid?

$$\begin{bmatrix} w_{A1} & w_{A2} & w_{A3} \\ w_{B1} & w_{B2} & w_{B3} \\ w_{C1} & w_{C2} & w_{C3} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} w_{A1}x_1 + w_{A2}x_2 + w_{A3}x_3 \\ w_{B1}x_1 + w_{B2}x_2 + w_{B3}x_3 \\ w_{C1}x_1 + w_{C2}x_2 + w_{C3}x_3 \end{bmatrix} = \begin{bmatrix} \bar{y}_A \\ \bar{y}_B \\ \bar{y}_C \end{bmatrix}$$



Where is sigmoid?

$$\begin{bmatrix} w_{A1} & w_{A2} & w_{A3} \\ w_{B1} & w_{B2} & w_{B3} \\ w_{C1} & w_{C2} & w_{C3} \end{bmatrix}
 \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}
 = \begin{bmatrix} w_{A1}x_1 + w_{A2}x_2 + w_{A3}x_3 \\ w_{B1}x_1 + w_{B2}x_2 + w_{B3}x_3 \\ w_{C1}x_1 + w_{C2}x_2 + w_{C3}x_3 \end{bmatrix}
 = \begin{bmatrix} \bar{y}_A \\ \bar{y}_B \\ \bar{y}_C \end{bmatrix}$$

↓
 $\overbrace{\hspace{10em}}^{0 \sim 1}$



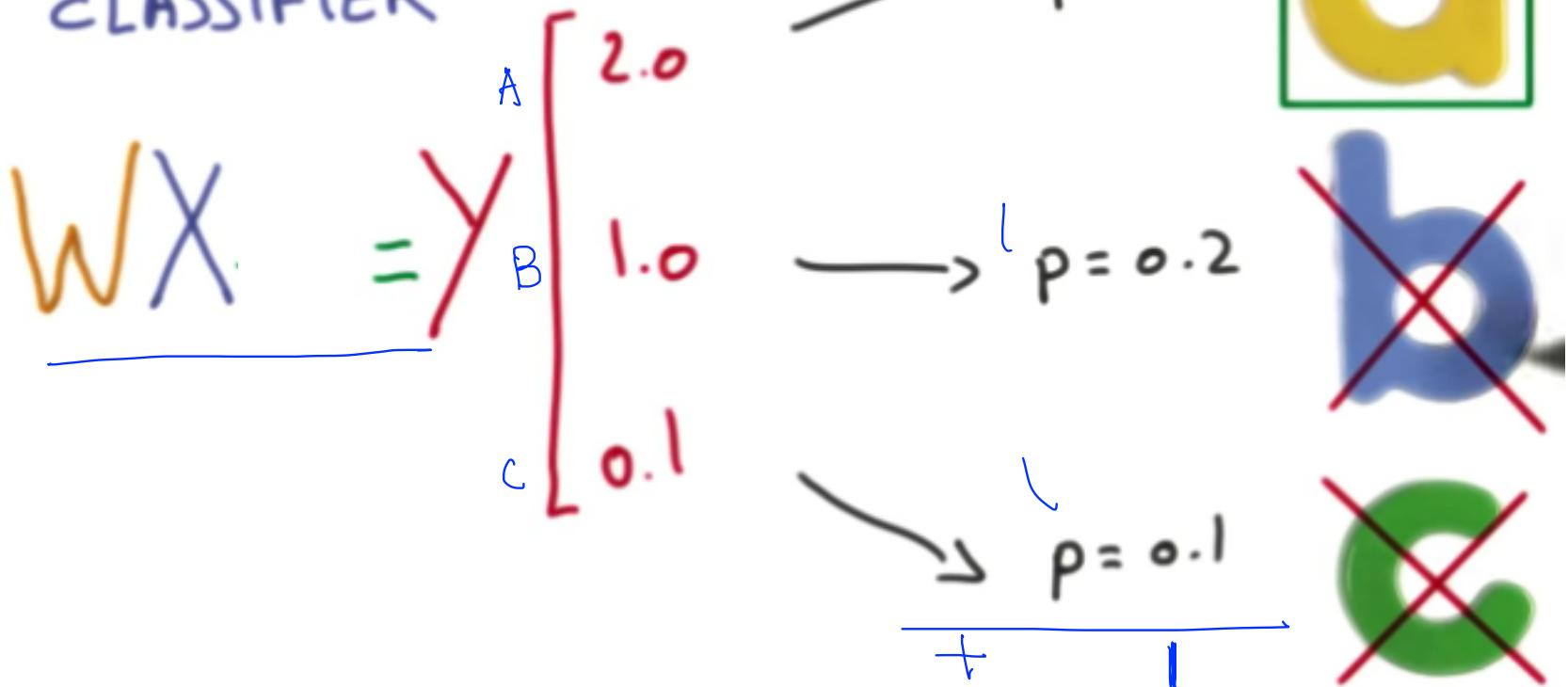


Exponential decay

Sigmoid?

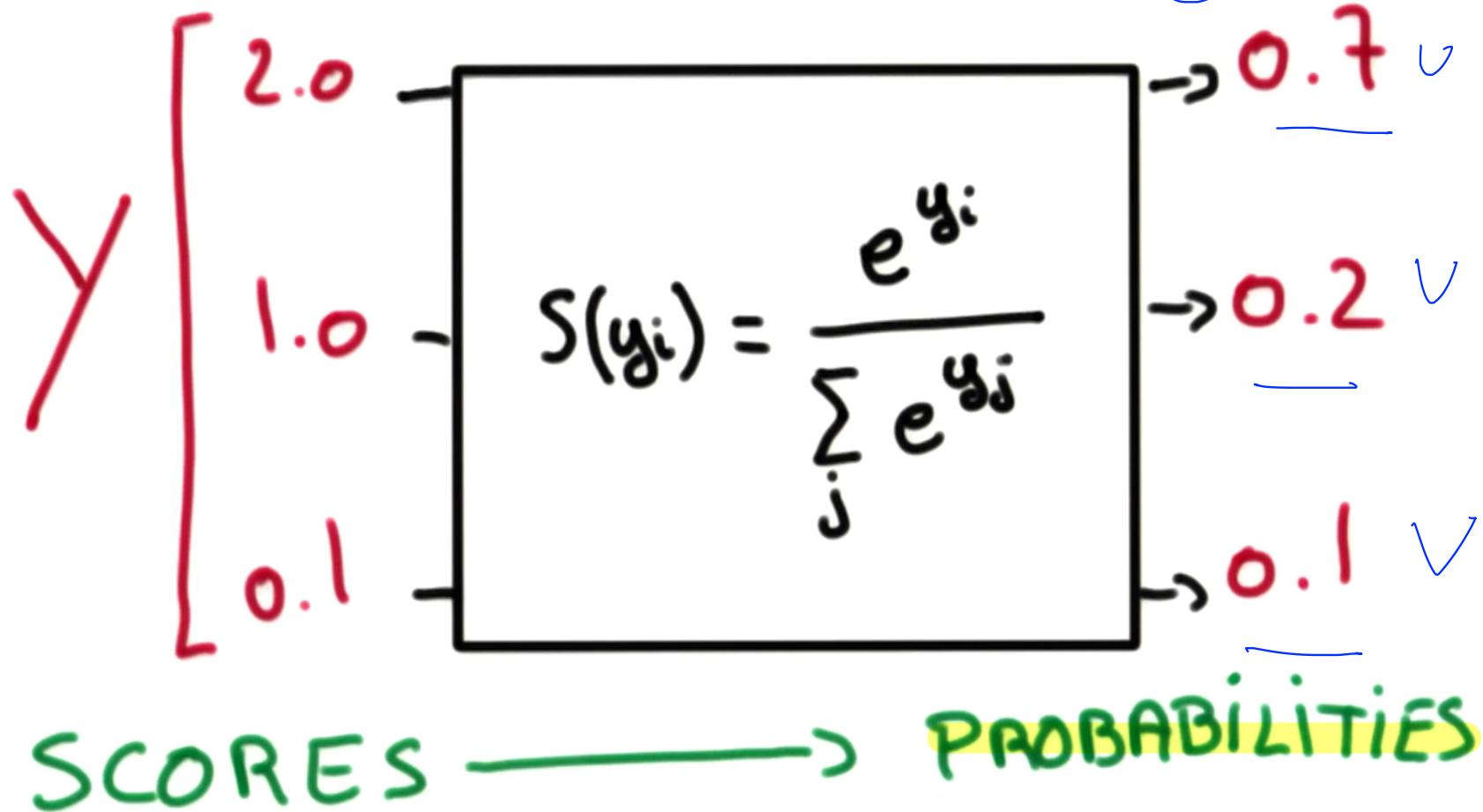
$$0 \sim 1$$

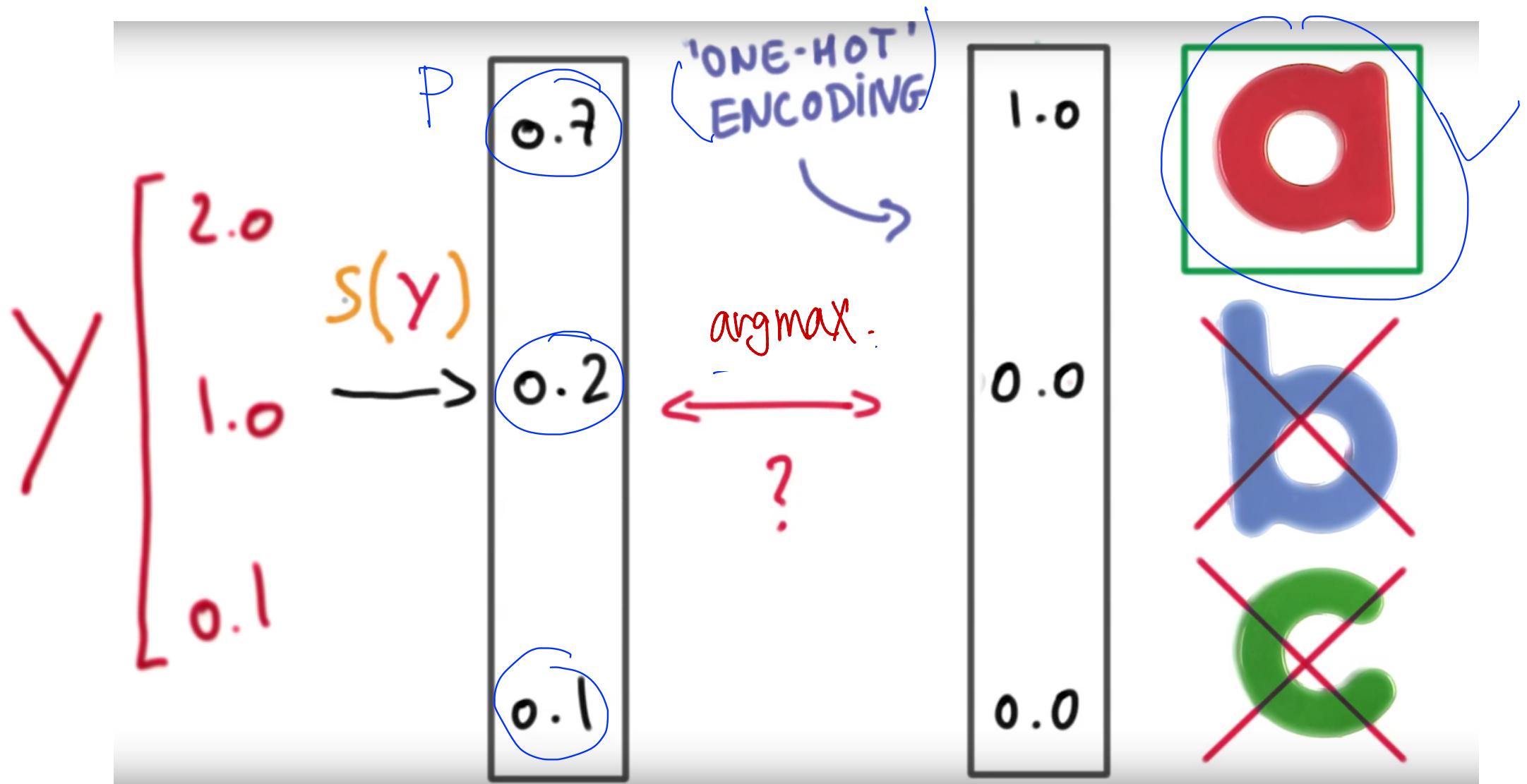
LOGISTIC
CLASSIFIER



SOFTMAX

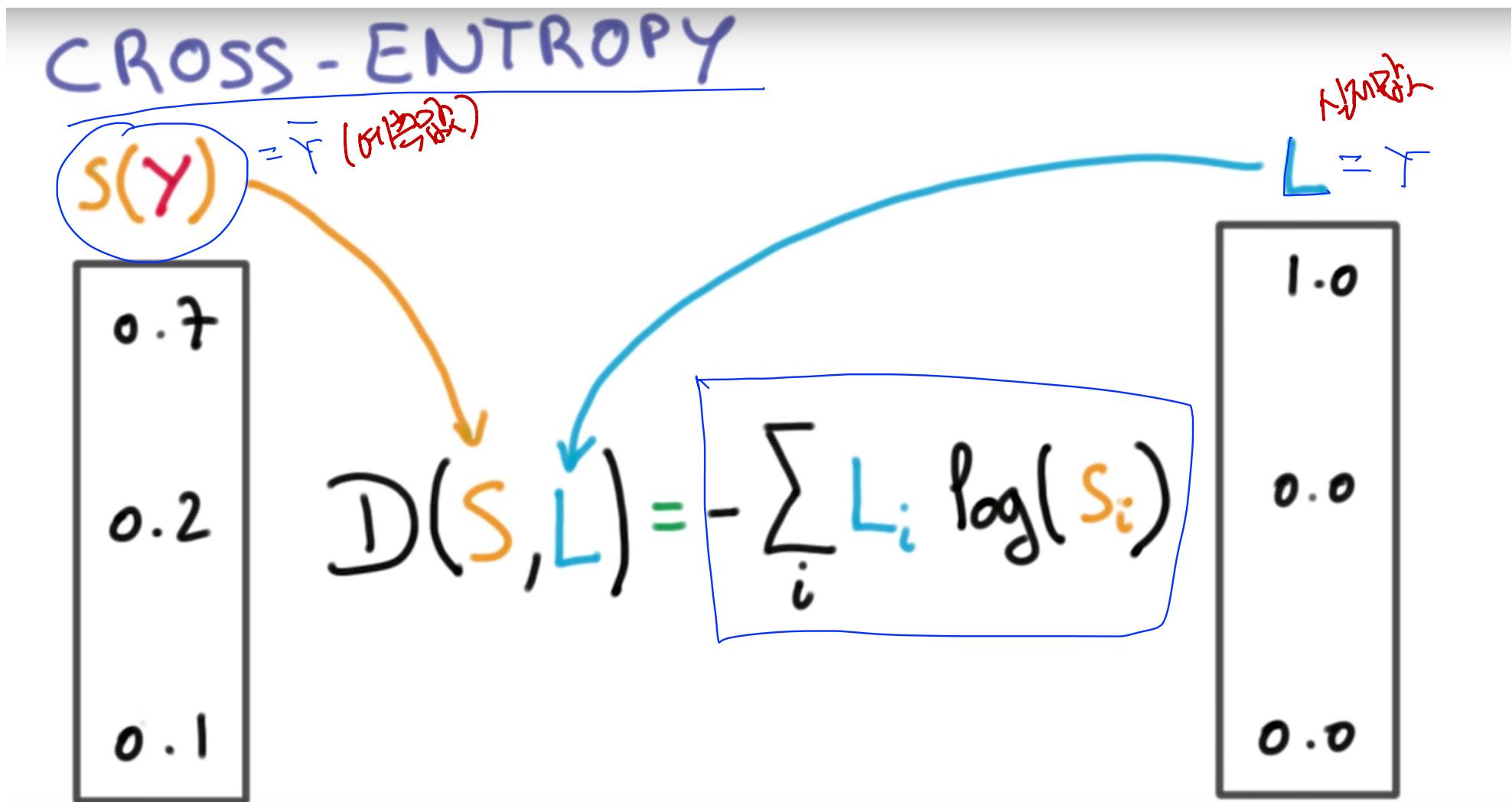
- ① $\cup \sim 1$
- ② $\Sigma = 1$





<https://www.udacity.com/course/viewer#/c-ud730/l-6370362152/m-6379811817>

Cost function



Cross-entropy cost function

$$-\sum_i L_i \log(s_i) = -\sum_i L_i \log(\bar{y}_i) = \sum_i (L_i) * (-\log(\bar{y}_i))$$

$$Y = L = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = B$$

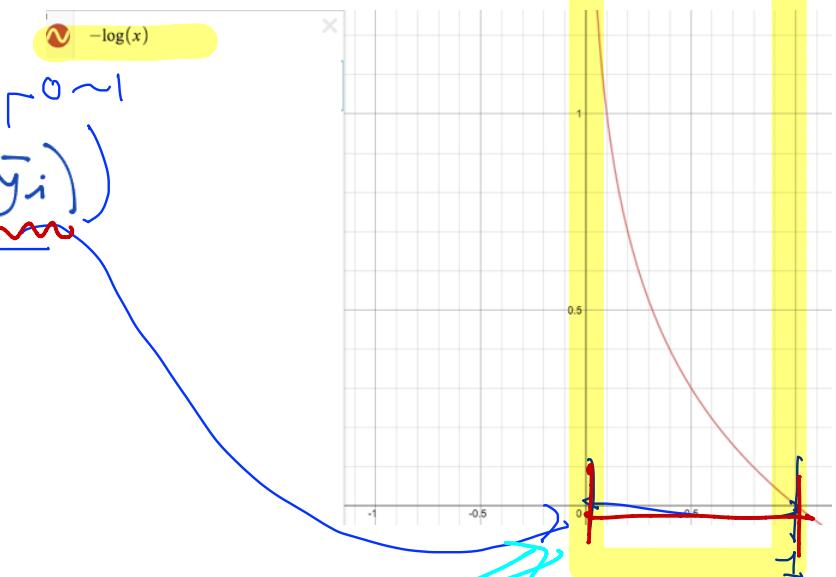
$$\hat{Y} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = B \text{(ok)} \quad \begin{matrix} \text{cost} \\ \text{vs.} \\ \text{label} \end{matrix}$$

$$\hat{Y} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = A(x) \quad \begin{matrix} \text{cost} \\ \uparrow \end{matrix}$$

$$\begin{bmatrix} 0 \\ 1 \end{bmatrix} \otimes -\log \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \otimes \begin{bmatrix} \infty \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \xrightarrow{\text{Sum}} 0$$

*optimal
approximate
normal (label)*

$$\begin{bmatrix} 0 \\ 1 \end{bmatrix} \otimes -\log \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \otimes \begin{bmatrix} 0 \\ \infty \end{bmatrix} = \begin{bmatrix} 0 \\ \infty \end{bmatrix} \xrightarrow{\text{Sum}} \infty$$



Cross-entropy cost function

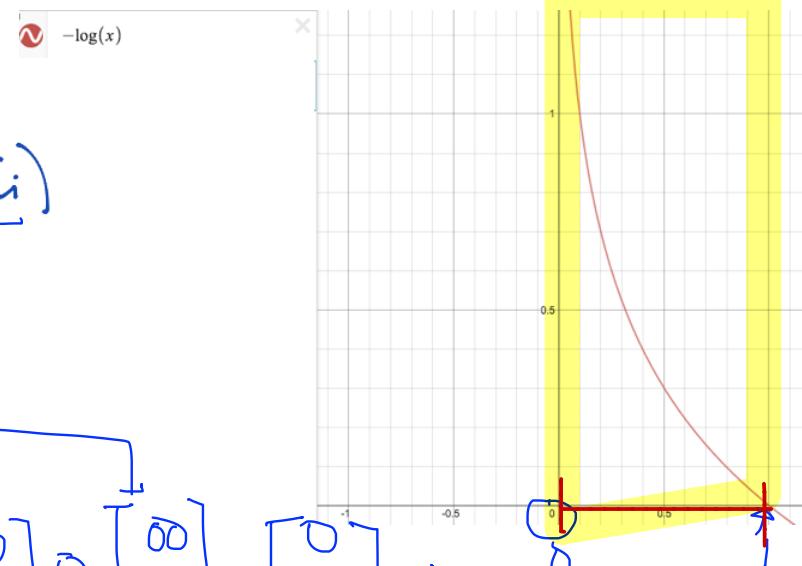
$$-\sum_i L_i \log(s_i)$$

$$-\sum_i L_i \log(\bar{y}_i) = \sum_i L_i * -\log(\bar{y}_i)$$

$$\underline{Y} = \underline{L} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \underline{\underline{B}}$$

$$\underline{Y} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \text{ B (OK)} \rightarrow \begin{bmatrix} 0 \\ 1 \end{bmatrix} \odot \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \odot \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow 0$$

$$\underline{Y} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \text{A (X)}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \odot \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \odot \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \infty$$



Cross-entropy cost function

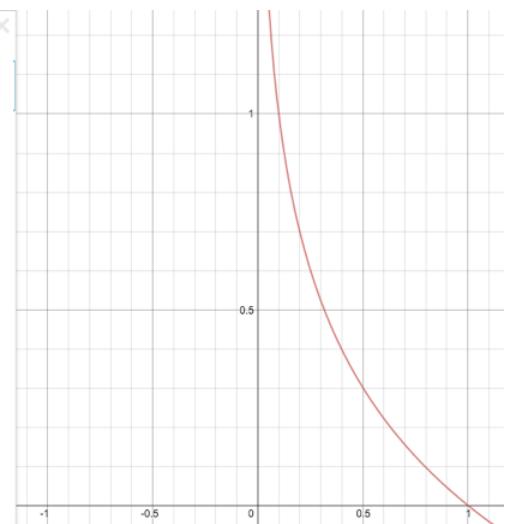
$$-\sum_i L_i \log(s_i)$$

$$-\sum_i L_i \log(\bar{y}_i) = \underline{\sum_i L_i * -\log(\bar{y}_i)}$$

$$L = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = A$$

$$\cancel{Y = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 0} \quad \text{element mul}$$

$$\tilde{Y} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = B \quad \text{, } \quad \begin{bmatrix} 1 \\ 0 \end{bmatrix} \odot \begin{bmatrix} 0 \\ \infty \end{bmatrix} = \underbrace{\begin{bmatrix} 0 \\ 0 \end{bmatrix}}_{\text{wavy}} \Rightarrow 0$$



Logistic cost VS cross entropy

$C(H(x), y) = y \log(H(x)) - (1 - y) \log(1 - H(x))$

$D(S, L) = -\sum_i L_i \log(S_i)$

Element mult

$L_i = \frac{w_1 + b}{H(x)}$

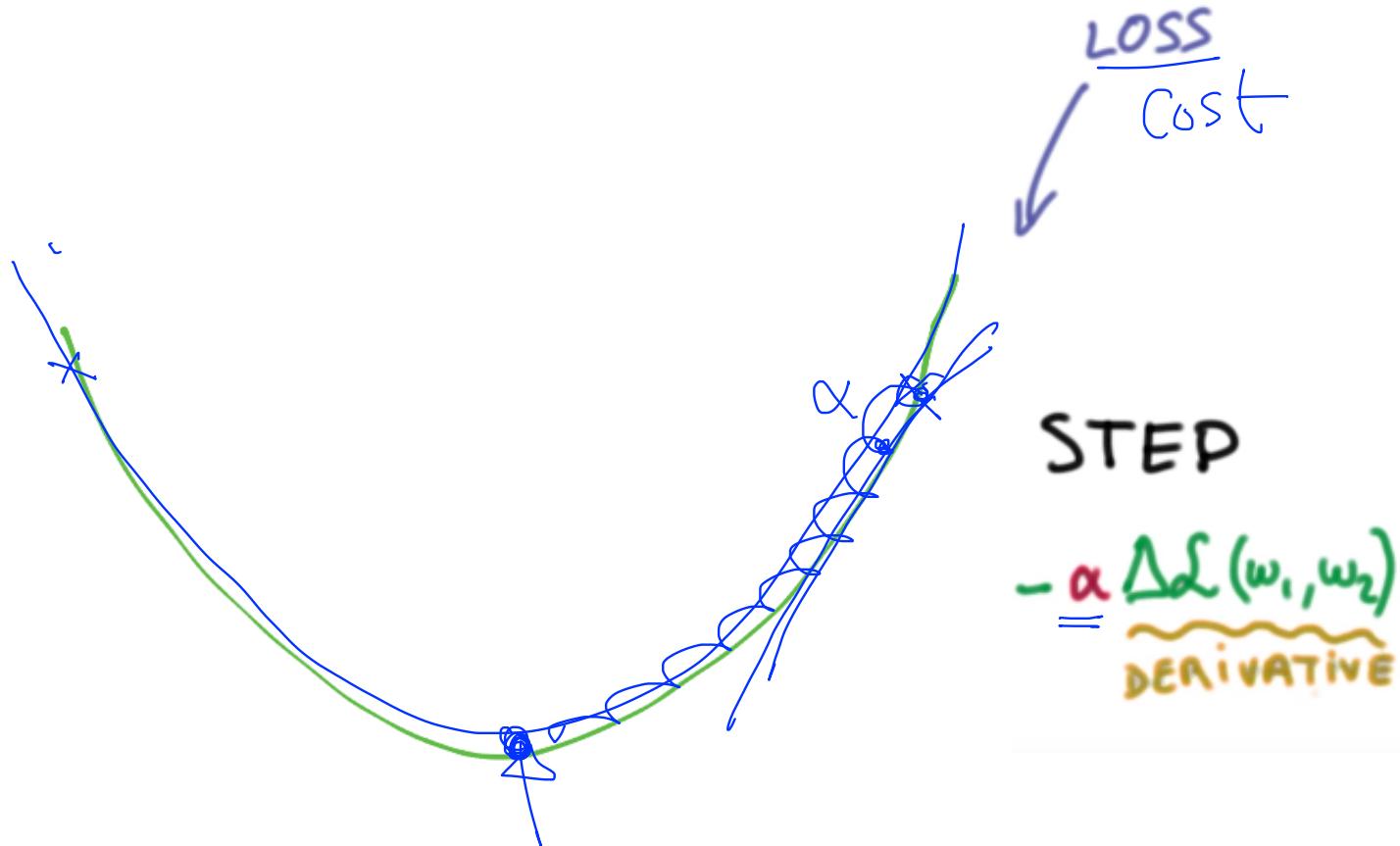
$\{L_i^0\} \rightarrow L_1 \times \log(M_1(x_1)) + L_2 \times \log(M_2(x_2))$

Logistic Cost

Cost function

$$L = \frac{1}{N} \sum_i D(s(wx_i + b), L_i)$$

Gradient descent



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Applications & Tips

