



# ***DLSG – Week 2***

## ***Neural Network Basic***

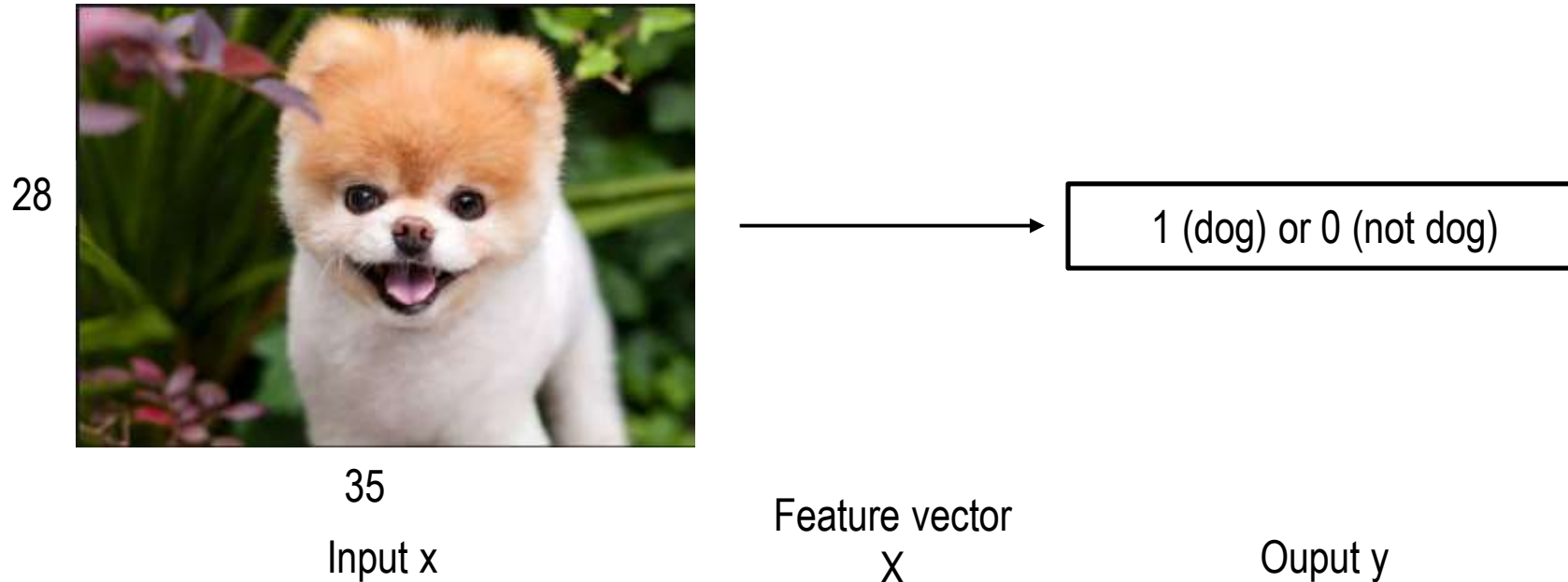
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# Binary Classification

- Pair(x,y) – Single training example
  - Input x: dimensional feature vector
  - Output y: label value 0 or 1



- $n_x = 28 * 35 * 3 = 2940$  dimensions



# Binary Classification

- M pair (x,y) – Multiple training example
  - M = 2



1 (dog) or 0 (not dog)  
1 (cat) or 0 (not cat)

⇒ M train = {(x1,y1), (x2,y2), ..., (xm,ym)}

- Testing set

$$X = \begin{bmatrix} | & | & | & | \\ x^{(1)} & x^{(2)} & \dots & x^{(m)} \\ | & | & | & | \end{bmatrix} \begin{matrix} \uparrow \\ n_x \\ \downarrow \end{matrix}$$

$X \in \mathbb{R}^{n_x \times m}$        $X \cdot \text{shape} = (n_x, m)$



$$Y = [y^{(1)} \ y^{(2)} \ \dots \ y^{(m)}]$$

$Y \in \mathbb{R}^{1 \times m}$   
 $Y \cdot \text{shape} = (1, m)$

Input X

Output Y



# Logistic Regression

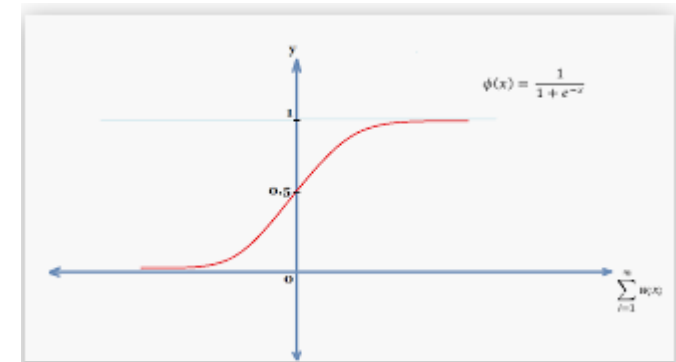
- Input  $x \rightarrow y$  predict  $(\hat{y}) = P(y=1|x)$   
 $x \in R^{n_x}$
- Output  $\hat{y} = w^T x + b$   
Đặt  $w^T x + b = z$

Do  $\hat{y} \in [0,1] \Rightarrow \hat{y}$  tương đương hàm sigmoid  $g(z)$

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

- If  $z \gg 0 \rightarrow g(z) = \frac{1}{1+0} = 1$
- If  $z \ll 0 \rightarrow g(z) = \frac{1}{1+\text{larger number}} = 0$

$\Rightarrow$  Tìm  $w, b$  sao cho  $\hat{y} \sim y$



# Logistic Regress Cost Function

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- Lost function: error for a single training example

$$\begin{aligned}\mathcal{L}(\hat{y}, y) &= \frac{1}{2}(\hat{y} - y)^2 \\ &= -(y \log \hat{y} + (1 - y) \log(1 - \hat{y}))\end{aligned}$$

- Cost function: average of the lost function of m training examples

$$\begin{aligned}J(w, b) &= -\frac{1}{m} \sum_{i=1}^m \mathcal{L}(\hat{y}_i, y_i) \\ &= -\frac{1}{m} \sum_{i=1}^m [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)]\end{aligned}$$



# Gradient Descent

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## Recap:

- Lost function: error for a single training example

$$\mathcal{L}(\hat{y}, y) = \frac{1}{2}(\hat{y} - y)^2$$

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

- Cost function: average of the lost function of m training examples

$$\begin{aligned} J(w, b) &= - \frac{1}{m} \sum_{i=1}^m \mathcal{L}(\hat{y}_i, y_i) \\ &= - \frac{1}{m} \sum_{i=1}^m [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)] \end{aligned}$$



# Gradient Descent

- Gradient descent is do moving point  $(w,b)$  for algorithm converges to minimum value rate

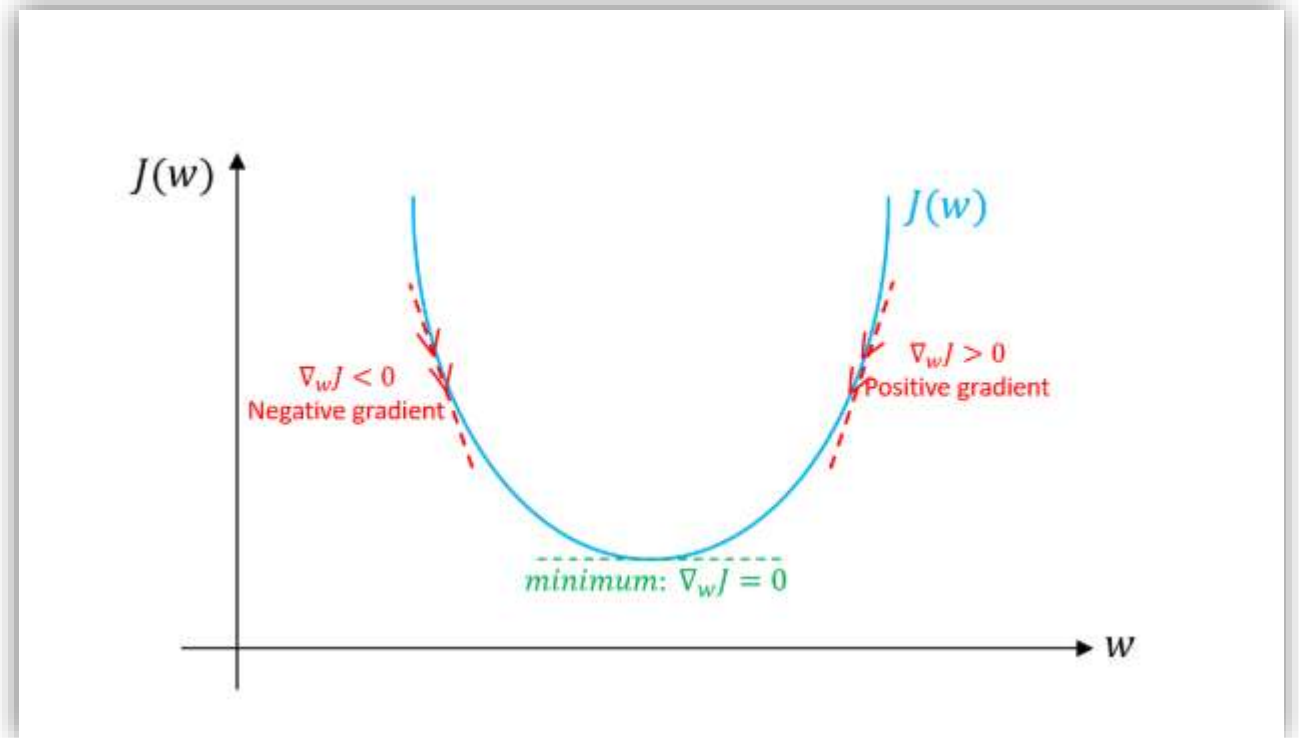
$$dw = \frac{dJ(w,b)}{dw}$$

- Algorithm implement repeat like graph beside:

$$w := w - \alpha \frac{dJ(w,b)}{dw}$$

$$b := b - \alpha \frac{dJ(w,b)}{db}$$

$\alpha$  is learning rate



# Derivative

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- Derivative is the slope of function
- Different point on function → different slope
- Examples:

$$f(a) = a^2$$

- $f(2) = 2^2 = 4$
  - $f(2.001) = 4.0004$
  - $\text{Slope} = \frac{f(2.001) - f(2)}{2.001 - 2} = 4$
  - $f'(2) = 2a = 4$
- => Slope of  $f(a) = 4$  at  $a = 2$

$$f(a) = \ln(a)$$

- $f(2) = \ln(2) = 0.69315$
  - $f(2.001) = 0.69365$
  - $\text{Slope} = \frac{f(2.001) - f(2)}{2.001 - 2} = 0.5$
  - $f'(2) = 1/a = 0.5$
- => Slope of  $f(a) = 0.5$  at  $a = 2$

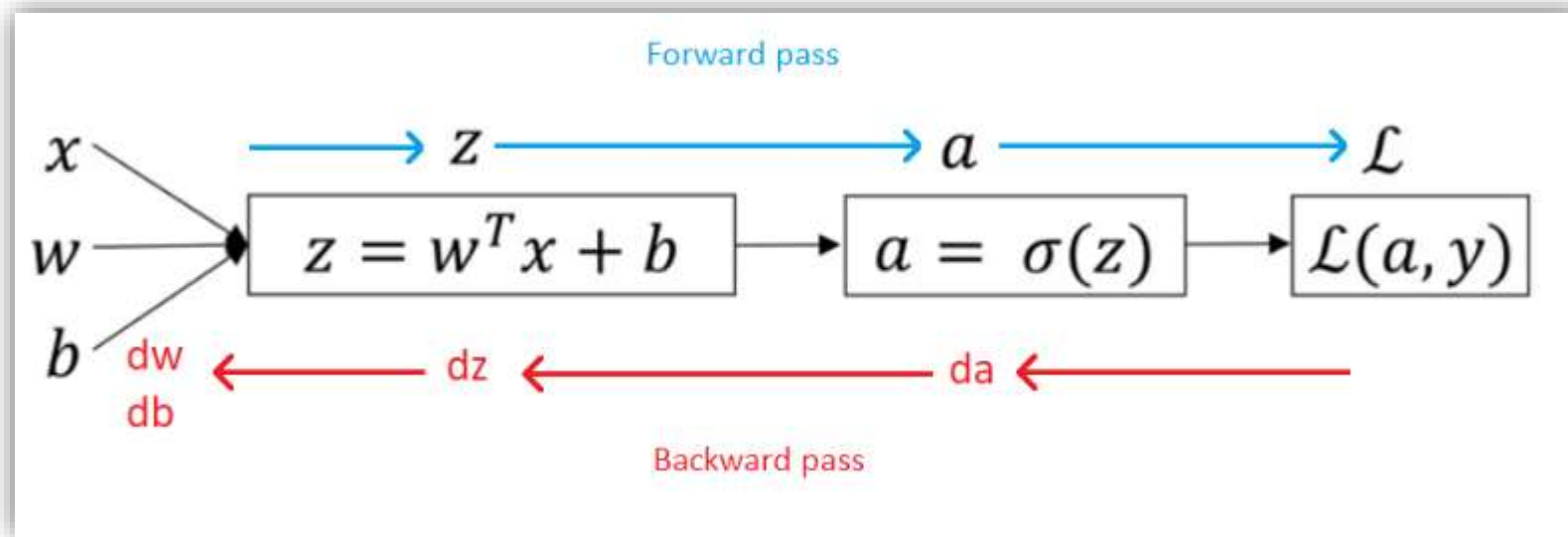
??? What is slope applied in Neural Network and Deep learning





# Derivative with a Computation Graph

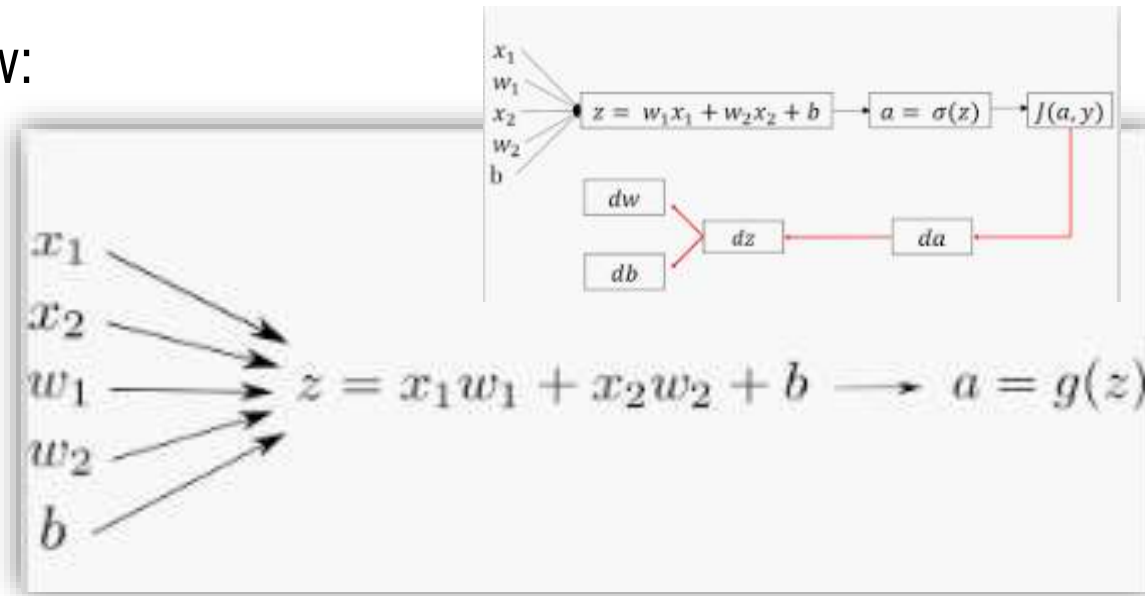
- Computation graph is flow to implement an calculation express
- Base on computation graph, we can analysis follow 2 way:
  - Forward: right to left → calculate derivative
  - Backward: left to right → determine affection of each variable to derivative
- Examples:



# Logistic Regression Gradient Descent

- Logistic Regression recap:
  - $z = w^T x + b$
  - $\hat{y} = a = \text{sigmoid}(z)$
  - $\mathcal{L}(\hat{y}, y) = - (y \log a + (1 - y) \log(1 - a))$

- Forward flow:

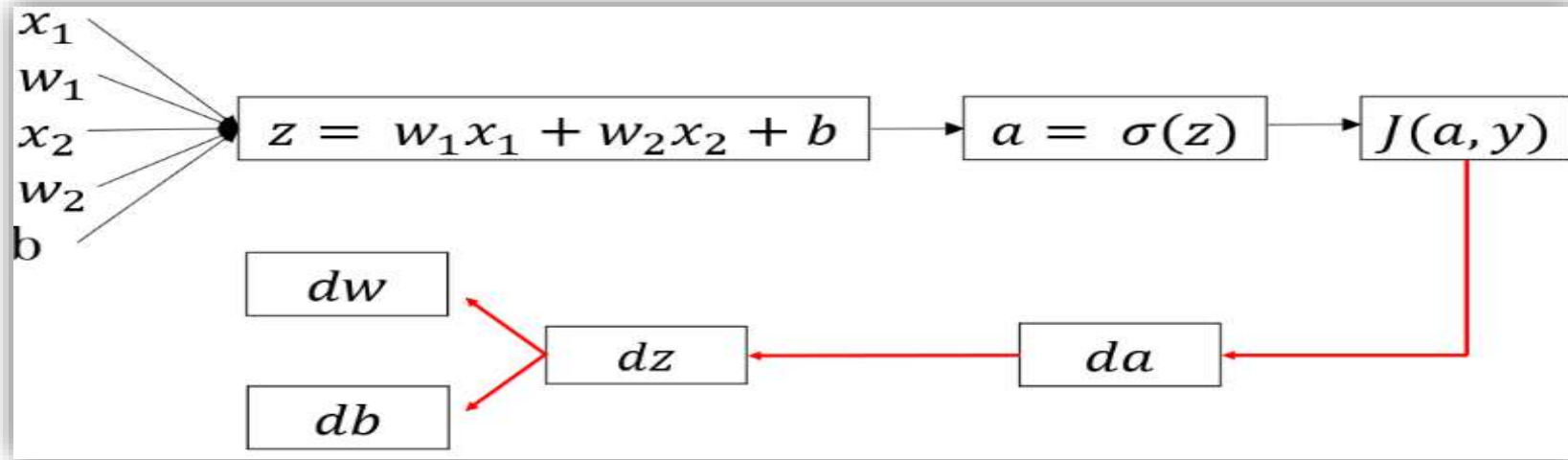


→ ???  $w$ ,  $b$  to minimize  $\mathcal{L}(\hat{y}, y)$



# Logistic Regression Gradient Descent

- Forward flow:



$$da = \frac{d\mathcal{L}(a, y)}{da} = \frac{y}{a} + \frac{1-y}{1-a}$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = dw_1 = x_1 dz$$

$$dz = \frac{d\mathcal{L}(a, y)}{dz} = a - y$$

$$\frac{\partial \mathcal{L}}{\partial w_2} = dw_2 = x_2 dz$$

$$= \frac{df}{da} * \frac{da}{dz} = da * \frac{da}{dz}$$

$$db = dz$$

$$= \frac{-y}{a} + \frac{1-y}{1-a}$$

