

$$\bar{y} = f(w^T x + b)$$

loss error function

$$h(\bar{y}, y) = -y \log \bar{y} + (1-y) \log(1-\bar{y})$$

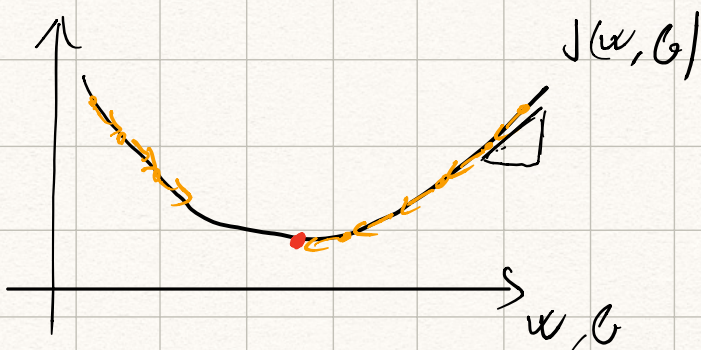
Cost function

$$J(w, b) = \frac{1}{m} \sum_{i=1}^m h(\bar{y}_i, y_i) = -\frac{1}{m} \sum_{i=1}^m [y_i \log \bar{y}_i + (1-y_i) \log(1-\bar{y}_i)]$$

↳ A predikcia mennyire jól közelíti a ground truth értéket

↳ keressük azt a  $(w, b)$ -t ami minimalizálja  $J(w, b)$ -t

Gradient descent



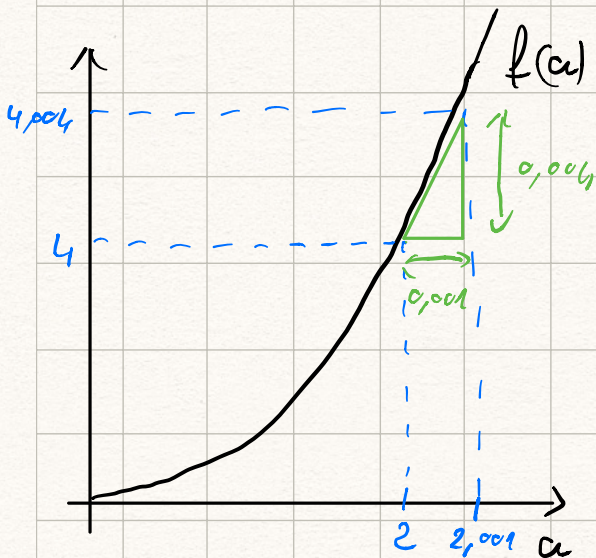
Repeat {

$$w := w - \eta \frac{\partial J(w, b)}{\partial w}$$

$$b := b - \eta \frac{\partial J(w, b)}{\partial b}$$

}

Intuition about derivatives (slope of  $f(a)$ )



1)  $a = 2, f(a) = 4$

$$\frac{d}{da} f(a) = 4$$

2)  $a = 5, f(a) = 25$

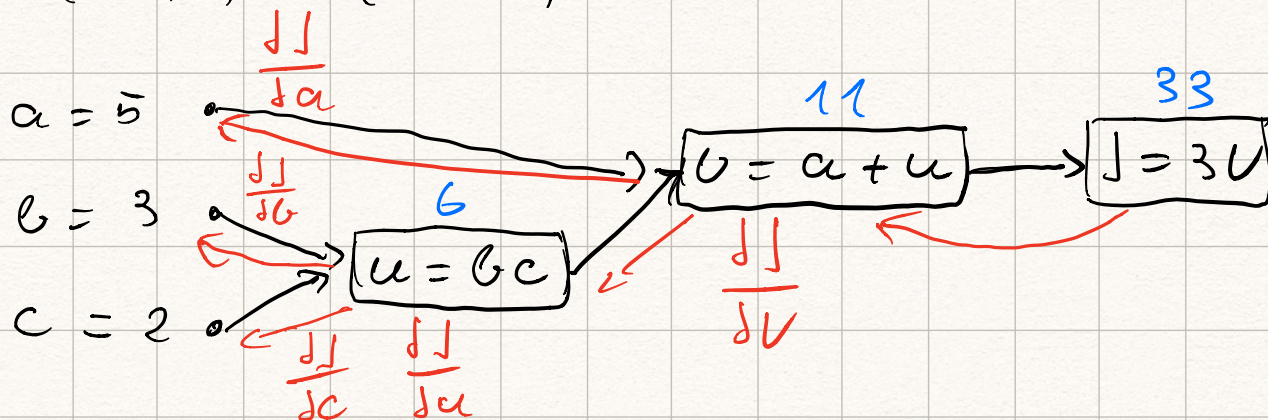
$$\frac{d}{da} f(a) = 10$$

$$\frac{d}{da} f(a) = \frac{d}{da} a^2 = 2a$$

# Computation graph

→ forward path  
← backward path

$$J(a, b, c) = 3(a + bc)$$



$$J = 3v$$

$$v = 11 \rightarrow J = 33$$

$$v' = 11, 001 \rightarrow J' = 33, 003$$

$$\Rightarrow \frac{dJ}{dv} = 3$$

$$a = 5 \rightarrow 5, 001$$

$$v = 11 \rightarrow 11, 001$$

$$J = 33 \rightarrow 33, 003$$

$$\Rightarrow \frac{dJ}{da} = \frac{dJ}{dv} \frac{dv}{da} = 3 \cdot 1 = 3$$

chain-rule

$$u = 6 \rightarrow 6, 001$$

$$v = 11 \rightarrow 11, 001$$

$$J = 33 \rightarrow 33, 003$$

$$\Rightarrow \frac{dJ}{du} = \frac{dJ}{dv} \frac{dv}{du} = 3 \cdot 1 = 3$$

$$b = 3 \rightarrow 3, 001$$

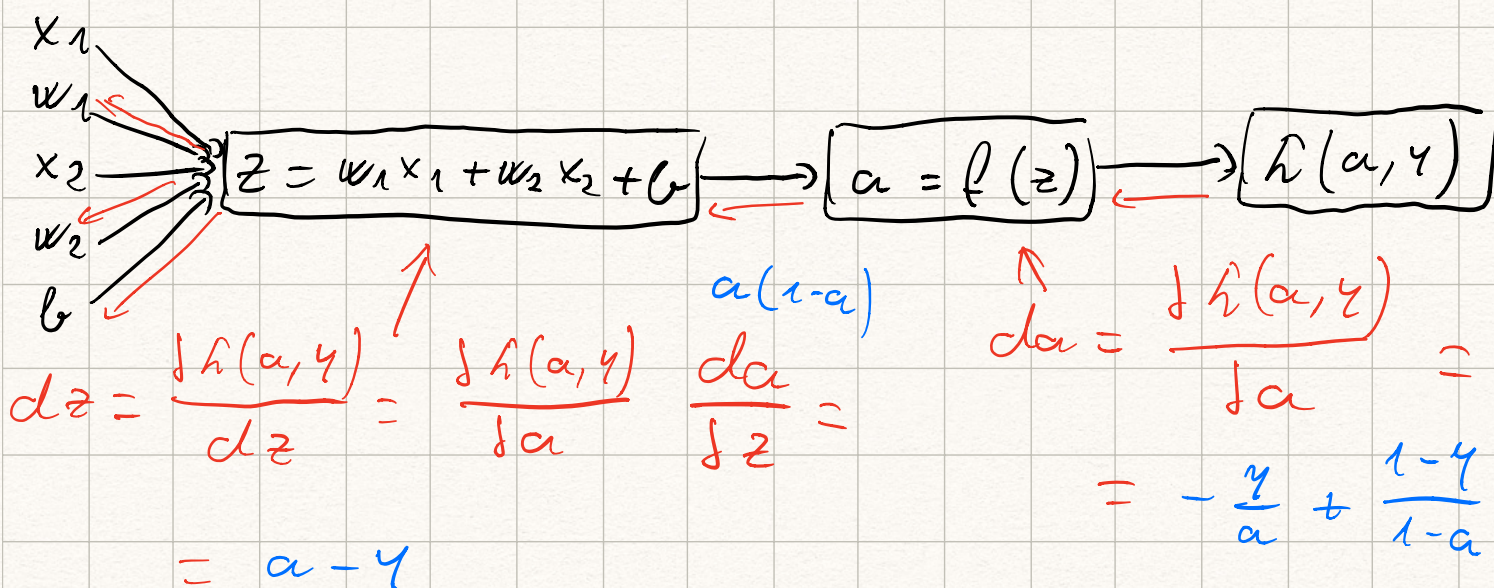
$$c = 2$$

$$u = bc = 6 \rightarrow 6, 002$$

$$\Rightarrow \frac{dJ}{db} = \frac{dJ}{du} \frac{du}{db} = 3 \cdot 2 = 6$$

$$\frac{dJ}{dc} = \frac{dJ}{du} \frac{du}{dc} = 3 \cdot 3 = 9$$

# logistic regression derivatives



$$\left. \begin{aligned} \frac{\partial \hat{h}}{\partial w_1} &= dw_1 = x_1 dz \\ dw_2 &= x_2 dz \\ db &= dz \end{aligned} \right\} \Rightarrow$$

$$\begin{aligned} w_1 &:= w_1 - \eta dz \\ w_2 &:= w_2 - \eta dz \\ b &:= b - \eta db \end{aligned}$$

## Vectorization for speed

$z = 0$   
for  $i$  in range( $m$ ):  
 $z += w[i] * x[i]$   
 $z += b$

$$\Rightarrow z = \underbrace{np.\text{dot}(w, x)}_{w^T x} + b$$