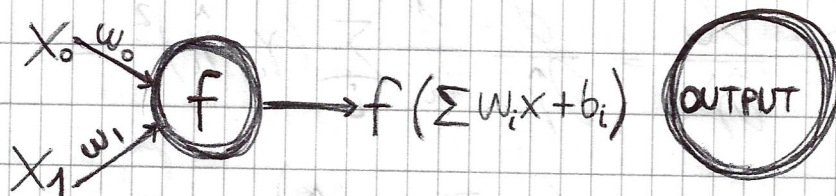


Neural Networks

NEURAL NETWORKS

SINGLE NEURON ONE LAYER

FORWARD
PROPAGATION



Linear + activation
 $wx + b$ $f \rightarrow \sigma$

IN PRACTICE
we have
INPUT + OUTPUT
Layers

$$\hat{y} = \text{OUTPUT} = \sigma(\sum w_i x_i + b_i)$$

$$= \frac{1}{1 + e^{-\sum w_i x_i + b}}$$

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

Qual è l'errore?

Loss \leftrightarrow Cost function

CALCULATE THE ERROR

... usiamo la mean-squared error

$$C = (y - \hat{y})^2$$

Come cambia la Cost function rispetto alle variazioni di w e b ?

BACKWARD
PROPAGATION

$$\frac{\partial C}{\partial w_i} = \frac{\partial C}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \cdot} \cdot \frac{\partial \cdot}{\partial w_i}$$

argomento
della f

$$\textcircled{A} \quad \frac{\partial C}{\partial \hat{y}} = \frac{\partial}{\partial \hat{y}} \frac{1}{n} \sum_i (y_i - \hat{y}_i)^2 =$$

$$= \frac{2}{n} \sum_i (y_i - \hat{y}_i)$$

$$\textcircled{B} \quad \frac{\partial \sigma(\cdot)}{\partial \cdot} = \frac{e^{-x}}{(1+e^{-x})^2} = \frac{(1+e^{-x}) - 1}{1+e^{-x}} \cdot \frac{1}{1+e^{-x}} =$$

$$= (1 - \sigma(x)) \cdot \sigma(x)$$

$$\textcircled{C} \quad \frac{\partial \cdot}{\partial w_i} = \frac{\partial (\sum w x + b)}{\partial w_i} = x_i$$

What about Bias?

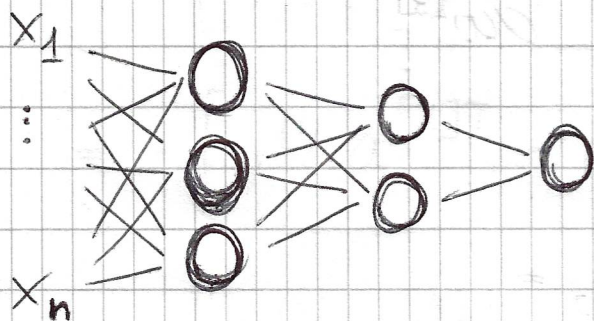
$$\frac{\partial C}{\partial b} = \downarrow$$

$$\Rightarrow \boxed{\frac{\partial C}{\partial w_i} = \frac{2}{n} \times \sum (y - \hat{y}) \times \sigma(\cdot) \times x_i \times (1 - \sigma(\cdot)) \times x_i}$$

$$\frac{2}{n} \times \sum (y - \hat{y}) \times \sigma(\cdot) \times (1 - \sigma(\cdot))$$

\Rightarrow Adjustment \rightarrow Weights = weight + adjustment
Bias = Bias + adjustment

+ Hidden Layers = Deep Learning



FORWARD
PROPAGATION

$$z^{[1]} = w^{[1]}x + b^{[1]}$$

$$a^{[1]} = \sigma(z^{[1]})$$

$$z^{[2]} = w^{[2]}a^{[1]} + b^{[2]}$$

$$a^{[2]} = \sigma(z^{[2]})$$

$$z^{[3]} = w^{[3]}a^{[2]} + b^{[3]}$$

$$a^{[3]} = \sigma(z^{[3]})$$

Define the loss function ~~for the logistic~~

$$L_{\text{TOR}} = \frac{1}{n} \sum \mathcal{L}^{(i)} \rightarrow \text{if we have multiple (batch) samples}$$

$$\mathcal{L}^{(i)} = -[y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log (1 - \hat{y}^{(i)})]$$

LOGISTIC LOSS

$$\frac{\partial L}{\partial w^{[3]}} \rightarrow \frac{\partial L}{\partial w^{[2]}} \rightarrow \frac{\partial L}{\partial w^{[1]}}$$

Backward...

$$\frac{\partial L}{\partial w^{[3]}} = \frac{\partial L}{\partial ?} \cdot \frac{\partial ?}{\partial w^{[3]}} =$$

$$= \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial w^{[3]}}$$

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial w^{[1]}} = \frac{\partial L}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial a^{[1]}} \cdot \frac{\partial a^{[1]}}{\partial z^{[1]}} \cdot \frac{\partial z^{[1]}}{\partial w^{[1]}}$$

$$\begin{aligned} \frac{\partial L}{\partial w^{[3]}} &= - \left[\gamma^{(i)} \frac{\partial}{\partial w^{[3]}} \left(\log \sigma(w^{[3]} a^{[2]} + b^{[3]}) \right) + \right. \\ &\quad \left. + (1 - \gamma^{(i)}) \frac{\partial}{\partial w^{[3]}} \left(\log (1 - \sigma(w^{[3]} a^{[2]} + b^{[3]})) \right) \right] \\ &= - \left[\gamma^{(i)} \frac{1}{\sigma(w^{[3]} a^{[2]} + b^{[3]})} \cdot a^{[2]} \cdot (1 - \sigma(w^{[3]} a^{[2]} + b^{[3]})) \cdot a^{[2]T} + \right. \\ &\quad \left. + (1 - \gamma^{(i)}) \frac{1}{1 - \sigma(w^{[3]} a^{[2]} + b^{[3]})} \cdot (-1) \cdot \sigma(w^{[3]} a^{[2]} + b^{[3]}) \cdot a^{[2]T} \right] \end{aligned}$$

$$= - \left[\gamma^{(i)} (1 - a^{[3]}) a^{[2]T} - (1 - \gamma^{(i)}) a^{[3]} \cdot a^{[2]T} \right]$$

$$= - \left[\gamma^{(i)} a^{[2]T} - a^{[3]} a^{[2]T} \right]$$

$$= - \left[\gamma^{(i)} - a^{[3]} \right] a^{[2]T}$$

$$\rightarrow \frac{\partial L}{\partial w^{[3]}} = - \frac{1}{n} \sum_{i=1}^n (\gamma^{(i)} - a^{[3]}) a^{[2]T}$$

$$\frac{\partial L}{\partial w^{[2]}} = \underbrace{\left(\frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \right)}_{(a^{[3]} - \gamma)} \underbrace{\left(\frac{\partial z^{[3]}}{\partial a^{[2]}} \right)}_{w^{[3]T}} \underbrace{\left(\frac{\partial a^{[2]}}{\partial z^{[2]}} \right)}_{\text{Sigmoid } a^{[2]}(1-a^{[2]})} \underbrace{\left(\frac{\partial z^{[2]}}{\partial w^{[2]}} \right)}_{a^{[1]T}}$$

$$\begin{aligned} \frac{\partial L}{\partial w^{[2]}} &= (a^{[3]} - \gamma) \cdot w^{[3]T} \times a^{[2]} (1 - a^{[2]}) a^{[1]T} \\ &= w^{[3]T} \times a^{[2]} (1 - a^{[2]}) \cdot (a^{[3]} - \gamma) \cdot a^{[1]T} \end{aligned}$$

$$\frac{\partial L}{\partial w^{[2]}} = \frac{1}{n} \sum_i \frac{\partial L}{\partial w^{[2]}}$$