



Neural Network Overview

미래연구소 12기 3주차

0. Week 2에서 배운 내용



Logistic Regression(로지스틱 회귀) - Binary Cross Entropy

Gradient Descent(경사하강법)

Backward Propagation(오차역전파)

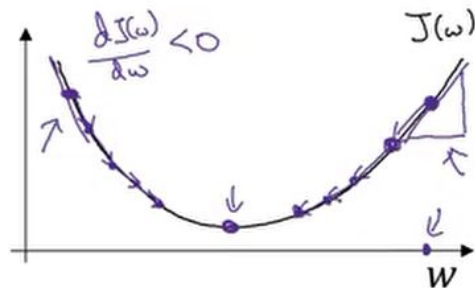
Vectorization(벡터화)

Binary Cross Entropy

$$BCE = -\frac{1}{N} \sum_{i=0}^N y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)$$

Gradient Descent

Gradient Descent



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

learning rate

$\frac{dJ(w)}{dw} = ?$

$J(w, b)$

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

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

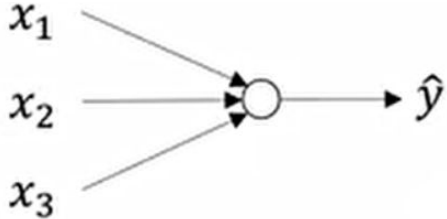
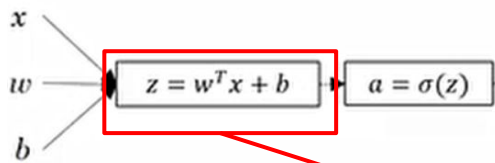
$\frac{\partial J(w, b)}{\partial w}$

$\frac{\partial J(w, b)}{\partial b}$

$\frac{\partial}{\partial}$ "partial derivative"

J

한 번의 parameter update

		계산 과정
모델		<p>($x = (x_1, x_2, x_3)$, y)가 m개 주어진다. = (X, Y)</p> <ol style="list-style-type: none"> 1) w_1, w_2, w_3, b initialize 2) $\text{np.dot}(w.T, X) + b \Rightarrow Z$ $\text{sigmoid}(Z) \Rightarrow A = Y^{\wedge}$ 3) compute $J(w, b)$ 4) backpropagation $\Rightarrow dw, db$ 5) $w = w - \alpha dw, b = b - \alpha db$
computation graph		
	$\text{np.dot}(w.T, X) + b = \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \begin{bmatrix} x_1^{(1)} & x_1^{(2)} \\ x_2^{(1)} & x_2^{(2)} \\ x_3^{(1)} & x_3^{(2)} \end{bmatrix} + b$	

실제 행렬 계산

<새로운 표현법>

w 앞의 숫자: unit index = 현재 layer index

w 뒤의 숫자: feature index = 이전 layer index

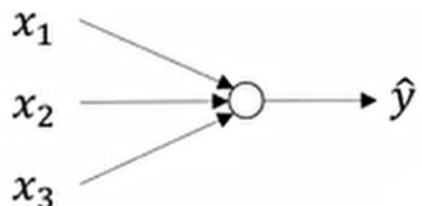

$$\begin{aligned} & np.dot(w.T, X) + b = \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \begin{bmatrix} x_1^{(1)} & x_1^{(2)} \\ x_2^{(1)} & x_2^{(2)} \\ x_3^{(1)} & x_3^{(2)} \end{bmatrix} + b \\ & np.dot(w.T, X) + b = \begin{bmatrix} -w.T - \end{bmatrix} \begin{bmatrix} x_1^{(1)} & x_1^{(2)} \\ x_2^{(1)} & x_2^{(2)} \\ x_3^{(1)} & x_3^{(2)} \end{bmatrix} + b \\ & np.dot(w.T, X) + b = \begin{bmatrix} w_{1\ 1} & w_{1\ 2} & w_{1\ 3} \end{bmatrix} \begin{bmatrix} x_1^{(1)} & x_1^{(2)} \\ x_2^{(1)} & x_2^{(2)} \\ x_3^{(1)} & x_3^{(2)} \end{bmatrix} + b \end{aligned}$$



image2vector

$\begin{pmatrix} 255 \\ 231 \\ \dots \\ 94 \\ 142 \end{pmatrix}$

/255

$x_0^{(i)}$

/255

$x_1^{(i)}$

...

...

/255

$x_{12286}^{(i)}$

/255

$x_{12287}^{(i)}$

w_0

w_1

w_{12286}

w_{12287}

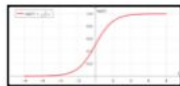
$w^T x^{(i)} + b$

σ

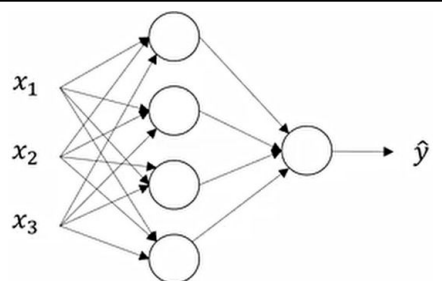
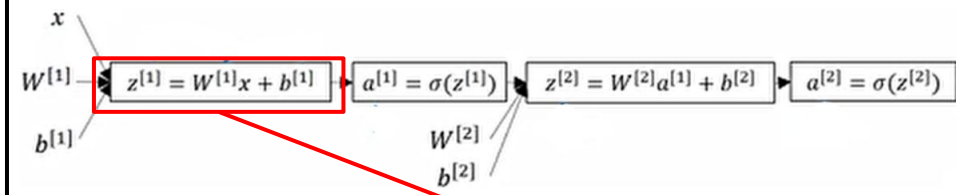
0.73

$0.73 > 0.5$

"it's a cat"

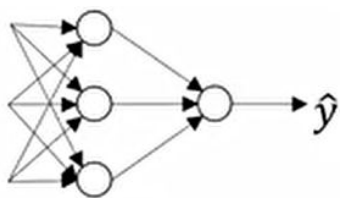


1. Week 3에서 배울 내용

모델		<p>week 2 모델 연산에서</p> <p>forward propagation backward propagation</p> <p>부분만 2배로 증가</p>
computation graph		
	$np.dot(W^{[1]}, X) + b = \begin{bmatrix} w_{1\ 1} & w_{1\ 2} & w_{1\ 3} \\ w_{2\ 1} & w_{2\ 2} & w_{2\ 3} \\ w_{3\ 1} & w_{3\ 2} & w_{3\ 3} \\ w_{4\ 1} & w_{4\ 2} & w_{4\ 3} \end{bmatrix} \begin{bmatrix} x_1^{(1)} & x_1^{(2)} \\ x_2^{(1)} & x_2^{(2)} \\ x_3^{(1)} & x_3^{(2)} \end{bmatrix} + b$	

1. Week 3에서 배울 내용

x_1
 x_2
 x_3



$$np.dot(W^{(1)}, X) + b = \begin{bmatrix} -w_1 & T- \\ -w_2 & T- \\ -w_3 & T- \\ -w_4 & T- \end{bmatrix} \begin{bmatrix} x_1^{(1)} & x_1^{(2)} \\ x_2^{(1)} & x_2^{(2)} \\ x_3^{(1)} & x_3^{(2)} \end{bmatrix} + b$$

$$np.dot(W^{(1)}, X) + b = \begin{bmatrix} w_{1\ 1} & w_{1\ 2} & w_{1\ 3} \\ w_{2\ 1} & w_{2\ 2} & w_{2\ 3} \\ w_{3\ 1} & w_{3\ 2} & w_{3\ 3} \\ w_{4\ 1} & w_{4\ 2} & w_{4\ 3} \end{bmatrix} \begin{bmatrix} x_1^{(1)} & x_1^{(2)} \\ x_2^{(1)} & x_2^{(2)} \\ x_3^{(1)} & x_3^{(2)} \end{bmatrix} + b$$

2. Week 3에서 주로 다뤄질 내용



- 1) hidden layer의 등장: lec 2
- 2) hidden unit(node)가 여러 개인 상황: lec 3 ~ lec 5
- 3) activation function: lec 6 ~ 8
- 4) hidden layer가 있을 때의 5가지 step 진행: lec 9 ~ lec 10
- 5) initialization (unit이 여러 개인 상황): lec 11