



# Deep learning

- computational power
- data available
- Algorithms

바탕이 되어서 발전

## Logistic Regression

ex) Find cat

i) initialize  $w, b$

ii) find the optimal  $w, b$

iii) Use  $\hat{y} = \sigma(wx + b)$  to predict

$$\text{Loss} = -[y \log \hat{y} + (1-y) \log(1-\hat{y})]$$

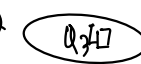
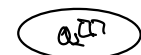
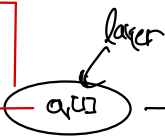
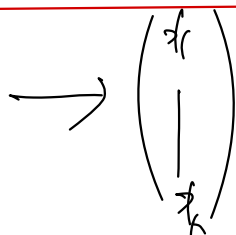
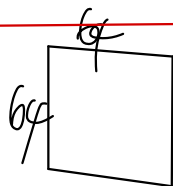
Gradient Descent

$$\begin{aligned} w &= w - \alpha \frac{dw}{d\text{Loss}} \\ b &= b - \alpha \frac{db}{d\text{Loss}} \end{aligned}$$

(Ex) Network = linear + activation

(Ex) Model = architecture + parameters

ex) Find cat / lion / iguana



$$\hat{y}_i = \sigma(a^{[3]}_i) = \sigma(w^{[3]}_i x + b^{[3]}_i)$$

$z^{(3)}$

\* 장점이 data가 충분하면 성능이 차이나 차이가 작을 것이 분명하게 이해한다.  $\rightarrow$  robust 함

$\rightarrow$  data 문제점 존재함. 특징공학 문제점 있음  $\downarrow$  해결책 존재함

(예) unique animal on an image

$$\begin{matrix} \square \\ \vdots \end{matrix} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \end{pmatrix} \begin{matrix} \text{---} \text{ } z_1^{(n)} \\ \text{---} \text{ } z_2^{(n)} \\ \text{---} \text{ } z_3^{(n)} \end{matrix} = \frac{e^{z_1^{(n)}}}{\sum e^{z_k^{(n)}}} \quad \left. \begin{matrix} 3 \text{ class} \\ \text{함수} \end{matrix} \right\}$$

\* softmax를 적용해서 최종 출력은 softmax multi-class regression.

이제 머신러닝 training에 대해서 공부함

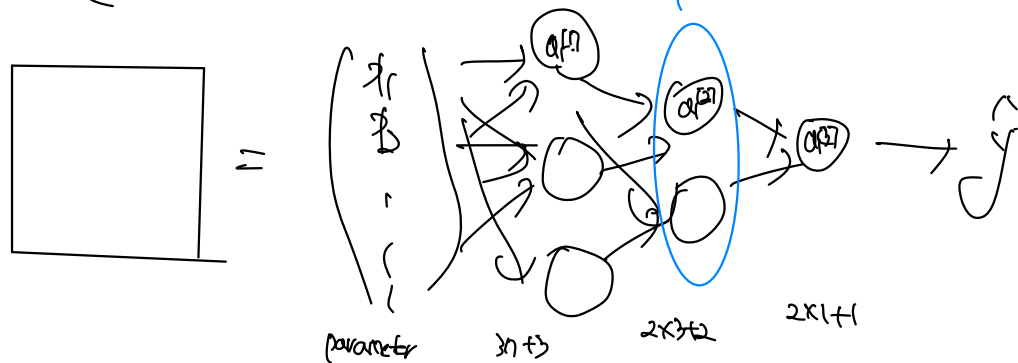
\* Cross-entropy loss

$$J_{CE} = - \sum_{k=1}^3 y_k \log \hat{y}_k$$

end to end learning  
black box model

Neural Networks

hidden layer



## Propagation equations

$$X = \begin{pmatrix} x^{(1)} & x^{(2)} & \dots & x^{(m)} \end{pmatrix} \quad \text{m examples ..}$$

id of example

Solve by Broadcasting  
 $(3,1) \rightarrow (3,m)$

$$y^{(1)} = \begin{pmatrix} y^{(1)} & y^{(2)} & \dots \end{pmatrix}$$

$$z^{(1)} = w^{(1)} x + b^{(1)}$$

$(3,1) = (3,n)(n,1) + (3,1)$

$\xrightarrow{\text{mth ex.}}$

$$(3,m) = (3,n)(n,m) + \underline{(3,1)}$$

\* 이런 Architecture 사용할 때는 정형화 작업이 필요함.

Optimizing  $w^{(1)}, w^{(2)}, w^{(3)}, b^{(1)}, b^{(2)}, b^{(3)}$

define loss/cost function

← batch 평균 사용함

$$J(\hat{y}, y) = \frac{1}{m} \sum_{i=1}^m J^{(i)}$$

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

## Backward Propagation

해상도는 720,  $\forall l=1,2,3$

$$\begin{aligned} w^{(1)} &= w^{(1)} - \alpha \frac{\partial J}{\partial w^{(1)}} \\ b^{(1)} &= b^{(1)} - \alpha \frac{\partial J}{\partial b^{(1)}} \end{aligned}$$

$$\frac{dy}{dx} \xrightarrow{\text{chain rule}} \frac{dy}{dz}$$

$$\frac{dy}{dx} = \frac{dy}{dz} \cdot \frac{dz}{dx} \cdot \frac{dx}{dz}$$

$$\frac{dy}{dx} = \left( \frac{dy}{dz} \right) \cdot \frac{dz}{dx} \cdot \frac{dx}{dz} \cdot \frac{dz}{dx} \cdot \frac{dx}{dz}$$