

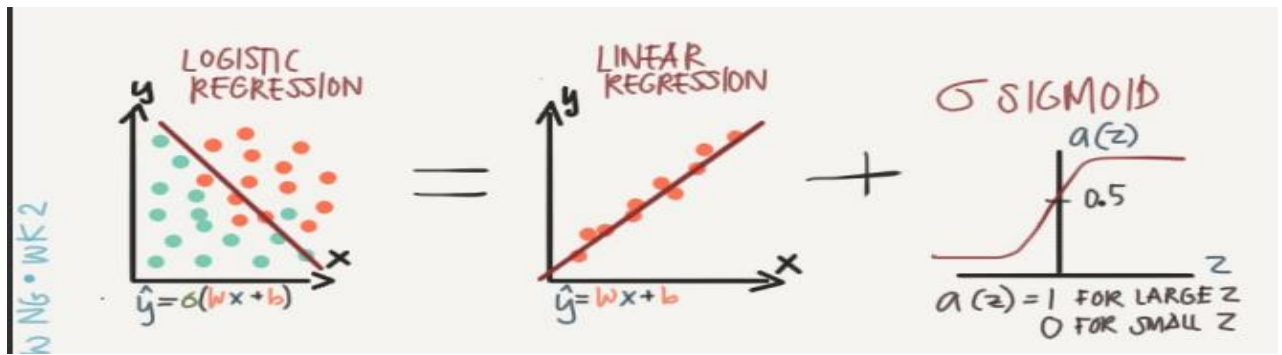
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DAY 5:

WEEK 2 NEURAL NETWORKS AND DEEP LEARNING:

Logistic Regression is given by

$$\rightarrow \hat{y} = \sigma(w^T x + b), \text{ where } \sigma(z) = \frac{1}{1+e^{-z}}$$



Loss Error Function is  $L(\hat{y}, y)$

It computes error on a single training example.

Loss (error) function:  $L(\hat{y}, y) = \frac{1}{2} (\hat{y} - y)^2$

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

The diagram also shows a graph of the loss function, which is a parabola opening upwards, indicating that the loss is minimized when the predicted value  $\hat{y}$  is equal to the target value  $y$ .

If  $y=1$ , then  $\text{Loss} = -\log \hat{y} \Rightarrow \hat{y}$  should be large

If  $y=0$ , then  $\text{Loss} = -(\log(1-\hat{y})) \Rightarrow \log(1-\hat{y})$  should be large.  $\Rightarrow \hat{y}$  should be small.

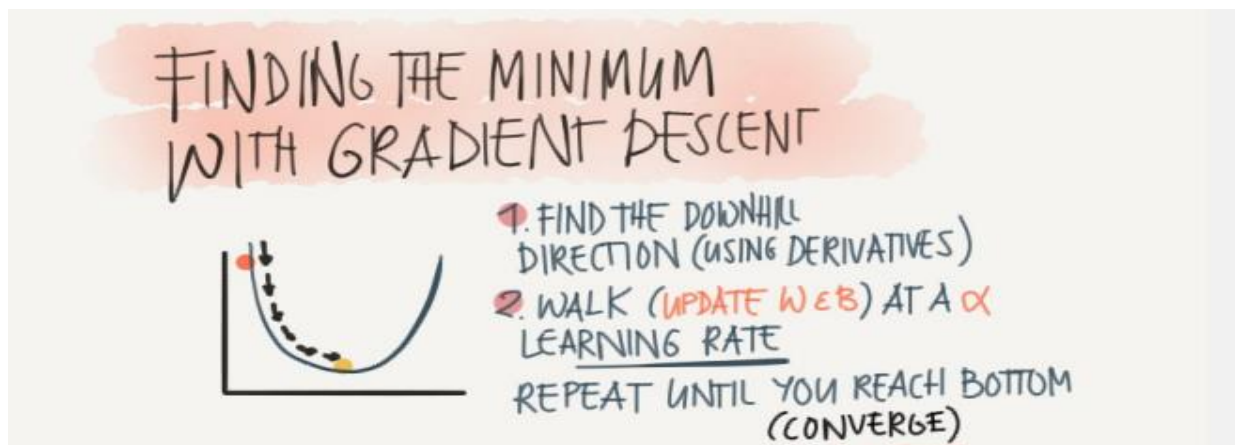
COST FUNCTION:

It computes error on the entire training set.

It is the average of the loss functions on the entire training set.

Cost function:  $J(w,b) = \frac{1}{m} \sum_{i=1}^m \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = -\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log \hat{y}^{(i)} + (1-y^{(i)}) \log (1-\hat{y}^{(i)})]$

## GRADIENT DESCENT:

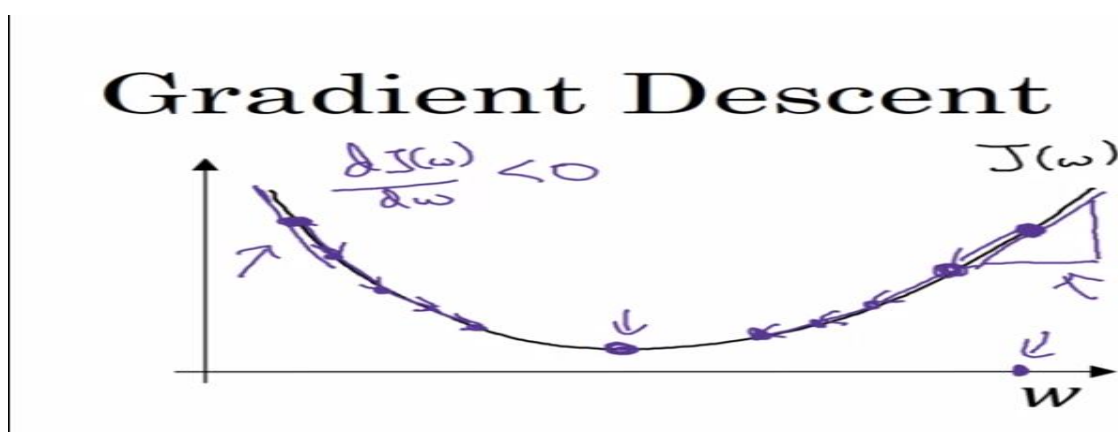


$$W := w - \alpha \frac{dJ(w)}{dw}$$

$\alpha$  = Learning Rate

$J(w) > 0$  then  $W$  is large and the value decreases.

$J(w) < 0$  then  $W$  is small and the value decreases.

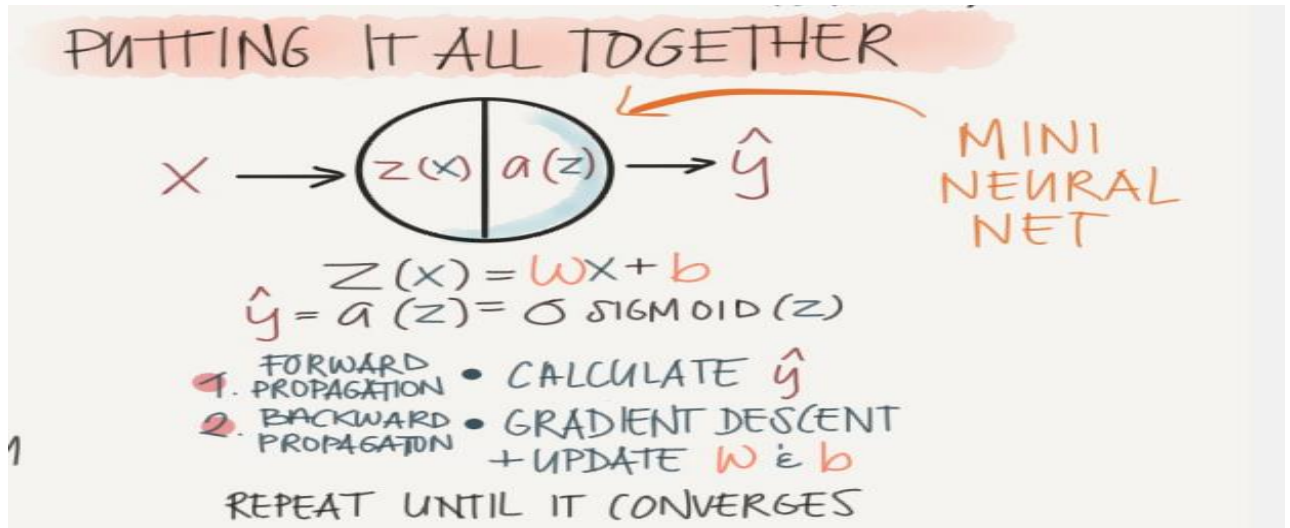


$$w = w - \alpha \frac{dJ(w,b)}{dw}$$

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

A convex function has one local optima.

## FORWARD AND BACKWARD PROPAGATION:



One step of backward propagation on a computational graph yields derivative of final output variable.

## Logistic regression derivatives

