

Loss Estimation  
 $\text{Loss} = L(\underline{y}, \underline{\hat{y}}) = L(\underline{y} - (\underline{W}^T \cdot \underline{x} + \underline{b}))$

objective = 0 Loss or Min Loss

① MSE - Mean Squared Error -  $\sum_{i=1}^m \frac{(y_i - \hat{y}_i)^2}{m} \Rightarrow$  Continuous for linear output

② BCE - Binary cross entropy -  $\sum_{i=0}^m [-y_i \log(\hat{y}_i) - (1 - y_i) \log(1 - \hat{y}_i)]$  - for Sigmoid Activation

③ Categorical cross entropy (CCE)  $\Rightarrow \sum_{i=0}^m \max(0, 1 - y_i \hat{y}_i)$  - with Softmax Activation

Loss =  $L(\underline{y} - \underline{W}^T \cdot \underline{x}) - ①$  min Loss wrt  $\underline{W}$

Actual  $\rightarrow$  unknown - Random

Back propagation

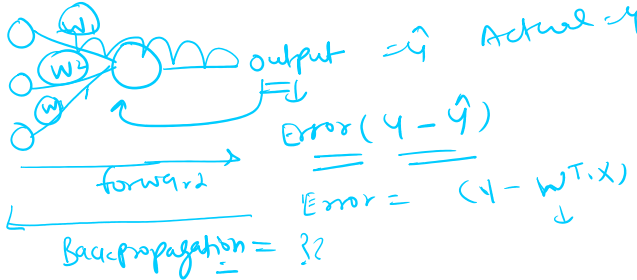
We go backwards - Why??

Min Loss

Loss =  $L(\underline{y} - (\underline{W}^T \cdot \underline{x} + \underline{b}))$  - What is unknown here??

What's the objective here??

W=0??



Neural Networks -  
 1) Architecture  
 2) Steps  
 3) Weights  
 4) Hidden layers  
 5) Explain via graphs  
 6) Refer to NNI deck

Questions -  
 1) Why weights are required  
 a. Theory  
 b. Technically

Steps to be explained in NNI