

## Exp 6 - (Implement Gradient Descent and Back propagation in DNN)

AIM:- Implementing gradient descent & Back propagation in deep NN.

Pseudocode:- 1) Initialize network parameters (weight & bias) randomly.

2) For each epoch:

a. For each training sample  $(x, y)$ :

i) Forward pass

→ Compute activation layer by layer until output is obtained

ii) Compute loss

→ Calculate error b/w predicted output & true label.

iii) Backward pass

→ Compute gradient of loss w.r.t output layer parameters.

→ propagate error backward through hidden layers using chain rule.

→ Compute gradient of loss w.r.t each weight & bias

iv) Update parameters.

$$\theta = \theta - \eta \cdot \left( \frac{\partial \text{loss}}{\partial \theta} \right)$$

value of  $\eta$  = learning rate.

v) Repeat until convergence or stopping condition is that (max epochs or minimal loss).

### Justification:

- Gradient Descent :- It provides an efficient optimization in high dimensional NN.
- Back propagation :- Uses chain rule of calculus to compute partial derivative of the loss function w.r.t all network parameters.
- Allows efficient computation of gradients across multiple layers instead of computing derivatives independently.

Result: By succeeding epoch, loss is being reduced

Q ✓

## Observations

Epoch 0, loss = 1.076

Epoch 1000, loss = 0.6932

Epoch 2000, loss = 0.6931

Epoch 3000, loss = 0.6931

Epoch 4000, loss = 0.6931

Epoch 5000, loss = 0.6931

Epoch 6000, loss = 0.6931

Epoch 7000, loss = 0.6931

Epoch 8000, loss = 0.6931

Epoch 9000, loss = 0.693

## Final Prediction

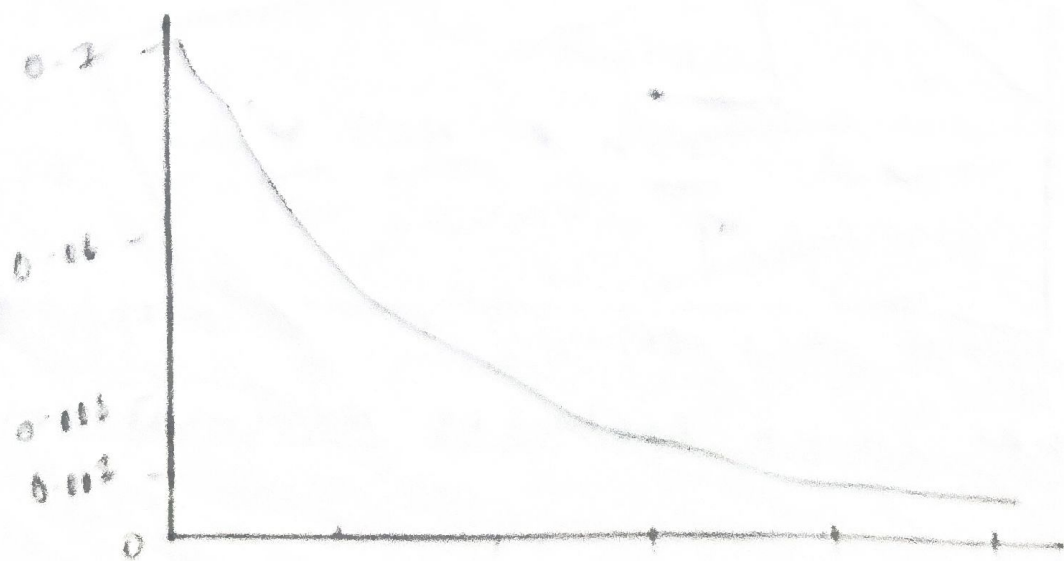
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## Final prediction



Epochs vs Loss