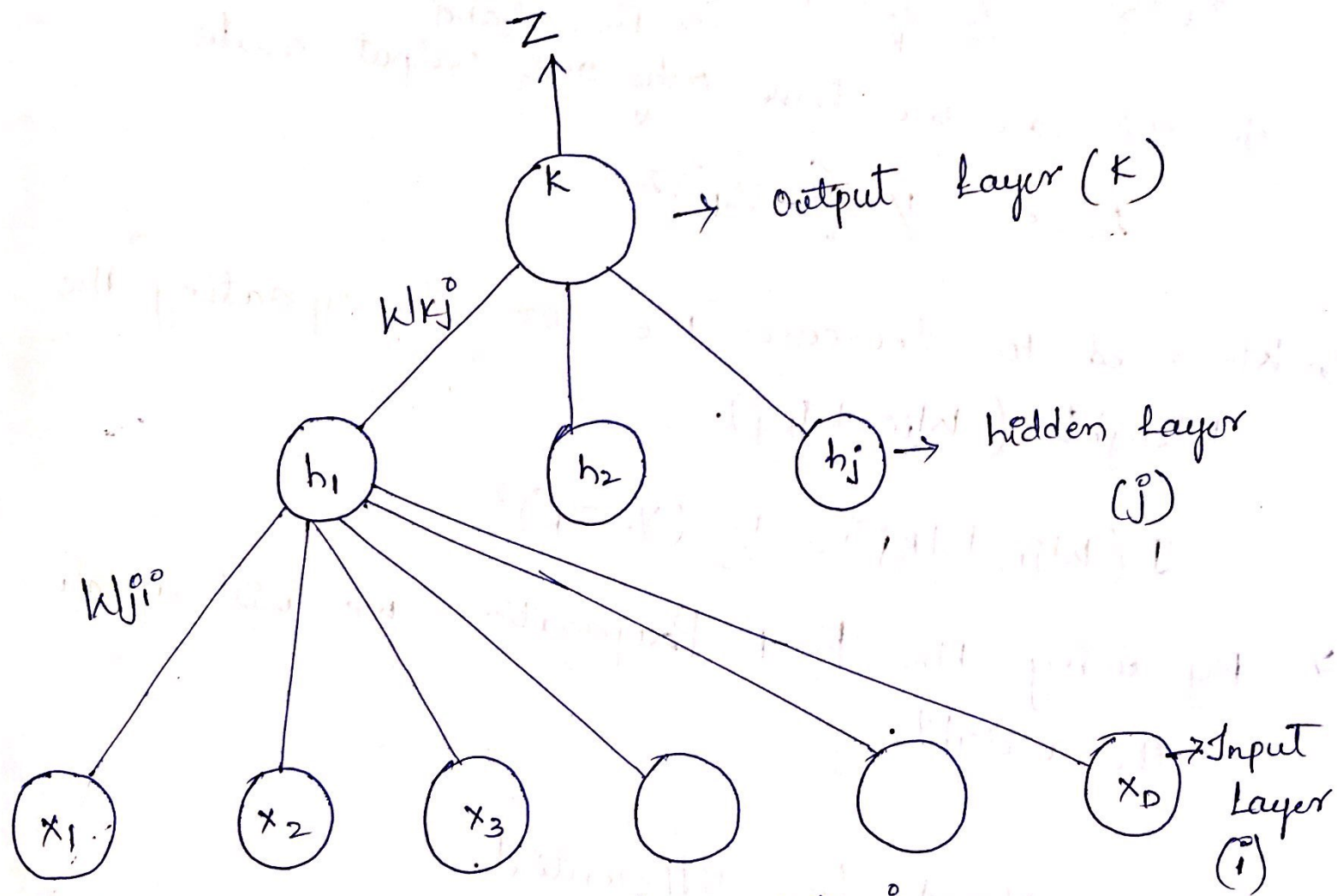


① 3-Layers Neural Network for Regression :-



$W_{ji}^o \rightarrow$ weights from the layer i to j

$W_{Kj}^o \rightarrow$ weights from the layer j to K

$$h_j = F(\text{net}_j)$$

$\rightarrow F \rightarrow$ is the Activation Function that is used in the hidden layer

$$\text{net}_j = \sum_i W_{ji}^o \cdot x_i^o$$

$$K = \text{net}_K$$

$\rightarrow Z \rightarrow$ output i.e. predicted output

$$\text{net}_K = \sum_j W_{Kj}^o \cdot h_j$$

→ The Loss function in this case is SSE (Sum of Squared Errors) ③

$$\text{Loss} = \frac{1}{2} \sum_k (\underbrace{y_k}_{\text{True Label}} - \underbrace{z_k}_{\text{predicted Label}})^2$$

In this case we have only one output node

$$\text{Loss} = \frac{1}{2} (Y - Z_k)^2$$

→ We need to decrease the loss by updating the weights (W_{ji} , W_{kj}).

$$J(W_{ji}, W_{kj}) = \frac{1}{2} (Y - Z_k)^2$$

→ By using the Back Propagation we will update the weights.

∂ → stands for differential.

$$\frac{\partial J}{\partial W_{kj}} = \frac{\partial}{\partial W_{kj}} \left(\frac{1}{2} (Y - Z_k)^2 \right)$$

$$= \frac{1}{2} \frac{\partial}{\partial W_{kj}} (Y - Z_k)^2$$

$$= \frac{1}{2} (Y - Z_k) \cdot \frac{\partial}{\partial W_{kj}} (Y - Z_k)$$

$$= (Y - Z_k) \cdot \frac{\partial}{\partial W_{kj}} (Y - Z_k)$$

$$= -(Y - Z_k) \cdot \frac{\partial}{\partial W_{kj}} (Z_k)$$

$$= Z_k = \text{net}_k$$

$$= -(Y - Z_k) \cdot \frac{\partial}{\partial W_{kj}} (\text{net}_k)$$

$$= -(Y - Z_k) \cdot \frac{\partial}{\partial W_{kj}} \left(\sum_j W_{kj} \cdot h_j \right)$$

$$= -(Y - Z_k) \cdot h_j$$

By using the Gradient Descent Update Rule:-

$$W_{kj}^{\text{new}} = W_{kj}^{\text{old}} - \lambda \left(\frac{\partial J}{\partial W_{kj}} \right)$$

$\lambda \rightarrow$ Learning rate

$$W_{kj}^{\text{new}} = W_{kj}^{\text{old}} - \lambda \left(-(Y - Z_k) \cdot h_j \right)$$

$$W_{kj}^{\text{new}} = W_{kj}^{\text{old}} + \lambda (Y - Z_k) \cdot h_j$$

$$\frac{\partial J}{\partial w_{ji}^o} = \frac{1}{2} \frac{\partial (y - z_k)^2}{\partial w_{ji}^o}$$

$$= \left(\frac{1}{2}\right) (2) (y - z_k) \cdot \frac{\partial}{\partial w_{ji}^o} (y - z_k)$$

$$= (y - z_k) \cdot \frac{\partial}{\partial w_{ji}^o} (y - z_k)$$

$$= -(y - z_k) \cdot \frac{\partial}{\partial w_{ji}^o} (z_k)$$

$$= -(y - z_k) \cdot \frac{\partial}{\partial w_{ji}^o} (\text{net}_k)$$

$$= -(y - z_k) \cdot \frac{\partial}{\partial w_{ji}^o} \left(\sum_k w_{kj}^o \cdot h_j^o \right)$$

$$= -(y - z_k) \cdot w_{kj}^o \cdot \frac{\partial}{\partial w_{ji}^o} (h_j^o)$$

$$= -(y - z_k) \cdot w_{kj}^o \cdot \frac{\partial}{\partial w_{ji}^o} F(\text{net}_j^o)$$

$$\boxed{\frac{\partial F(g(x))}{\partial x} = \frac{\partial F(g(x))}{\partial g(x)} \cdot \frac{\partial g(x)}{\partial x}}$$

(5)

$$= -(Y - Z_k) \cdot W_{kj} \cdot \frac{\partial f(\text{net}_j)}{\partial \text{net}_j} \cdot \frac{\partial \text{net}_j}{\partial W_{ji}}$$

$$= -(Y - Z_k) \cdot W_{kj} \cdot F'(\text{net}_j) \cdot \frac{\partial (\sum_i W_{ji} \cdot X_i)}{\partial W_{ji}}$$

$$= -(Y - Z_k) \cdot W_{kj} \cdot F'(\text{net}_j) \cdot \frac{\partial}{\partial W_{ji}} \left(\sum_i W_{ji} \cdot X_i \right)$$

$$= -(Y - Z_k) \cdot W_{kj} \cdot F'(\text{net}_j) \cdot X_i$$

$F'()$ \rightarrow differential of the activation function used in the hidden layer.

$$W_{ji}^{\text{New}} = W_{ji}^{\text{old}} + \lambda \left(\frac{\partial J}{\partial W_{ji}} \right)$$

$$W_{ji}^{\text{New}} = W_{ji}^{\text{old}} + \lambda (Y - Z_k) \cdot W_{kj} \cdot F'(\text{net}_j) \cdot X_i$$