

Forward propagation.

- 1) unactivated input for hidden layer.

$$z^{(1)} = W^{(1)} A^{(0)} + b^{(1)} \rightarrow \text{①}$$

$7 \times 49 \quad 7 \times 4 \times 49 \quad 7 \times 1$

- 2) $A^{(0)} = X^{T} \quad 4 \times 49$ Transpose of training set

- 3) $A^{(1)} = \text{Relu}(z^{(1)}) = g(z^{(1)}) \rightarrow \text{②}$ feed to activation function.

- 4) $z^{(2)} = W^{(2)} A^{(1)} + b^{(2)} \rightarrow \text{③}$ unactivated input for output layer.
- $1 \times 49 \quad 1 \times 7 \quad 7 \times 49 \quad 1 \times 1$

- 5) $A^{(2)} = z^{(2)} \rightarrow$ use Linear Activation, to output layer, because desired output is price unit.

$$\rightarrow \text{loss function} = \sum_{i=1}^m (y_i - \hat{y})^2 / m = \text{MSE} \quad m = 49$$

(L)

Backward propagation. (by using chain Rule)

- 1) $dA_2 = \partial L / \partial z_2 \rightarrow 2(y_i - \hat{y}) / m$

- 2) $dz_2 = dA_2$

- 3) $dW_2 = \partial L / \partial z_2 \cdot \partial z_2 / \partial W_2$
- $$dW_2 = dA_2 \left(\frac{\partial (W^{(1)} A^{(1)} + b)}{\partial W_2} \right) = dA_2 \cdot A^{(1)T}$$

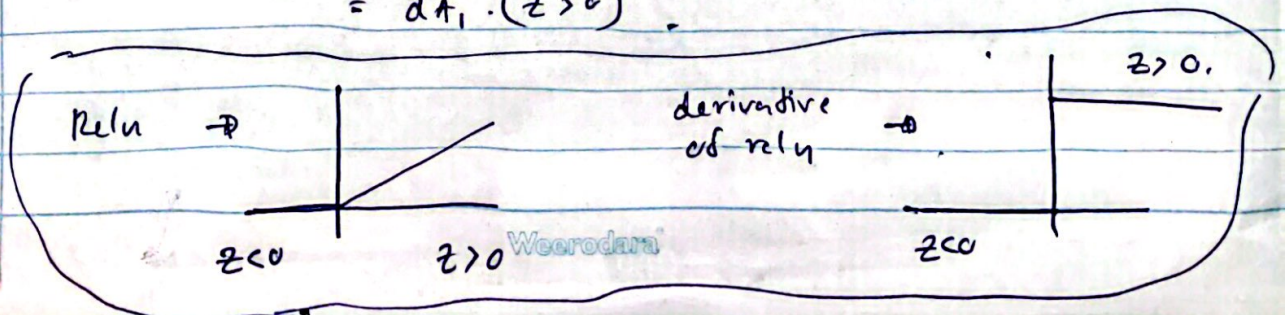
- 4) $db_2 = \partial L / \partial z_2 \cdot \partial z_2 / \partial b_2$ $\partial z_2 / \partial b_2 = 1$

$$db_2 = \partial L / \partial z_2 = \sum dz_2$$

b_2 shared across all examples : Total effect is the sum of effects.

- 5) $dA_1 = \partial L / \partial A_1 = \partial L / \partial z_2 \cdot \partial z_2 / \partial A_1 = dz_2 \cdot W^{(2)T}$

- 6) $dz_1 = \partial L / \partial z_1 = \partial L / \partial A_1 \cdot \partial A_1 / \partial z_1 = dA_1 \cdot (z > 0)$



$$1) dw_1 \Rightarrow \frac{\partial L}{\partial z_1} \cdot \frac{dz_1}{dw_1} = dz_1 \cdot x^T$$

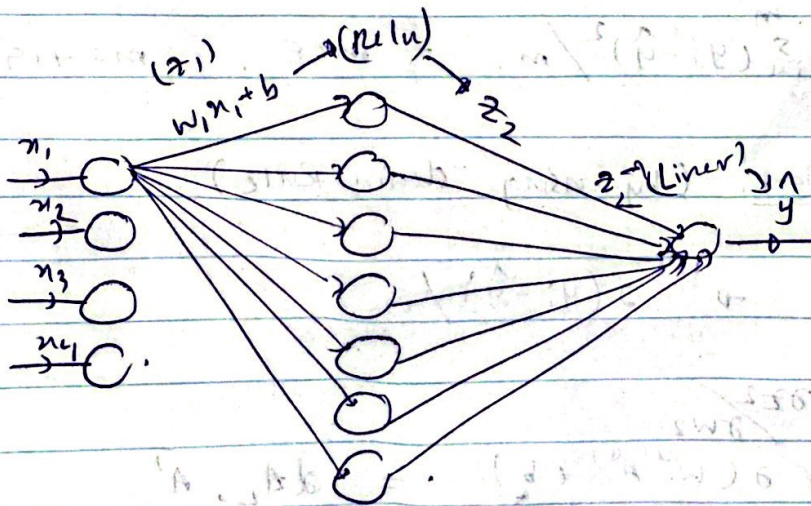
$$2) db_1 \Rightarrow \frac{\partial L}{\partial b_1} = \frac{\partial L}{\partial z_1} \cdot \frac{\partial z_1}{\partial b_1} = \sum dz_1$$

weights update in a way in backpropagation

$$W_{new} = W_{old} - \alpha \frac{\partial L}{\partial W_{old}}$$

α = Learning Rate.

Architecture of the neural network



$$\text{loss} = (y - \hat{y})^2$$