

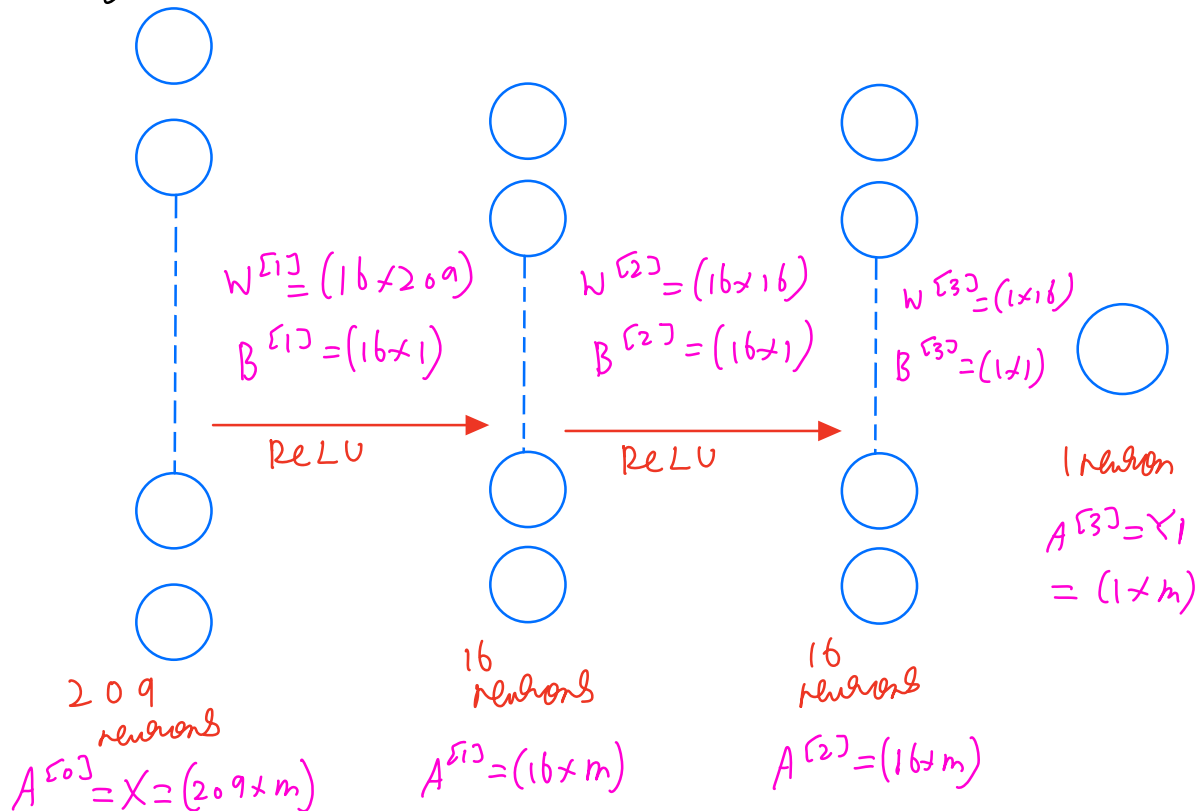
Initial data:

1.) $X = (m \times 209)$

2.) $Y = (m \times 1)$

→ Take transpose of X , $X^T = (209 \times m)$ and Y , $Y^T = (1 \times m)$

Design:



Forward Propagation:

1.) $Z^{[1]} = (W^{[1]} @ A^{[0]}) + B^{[1]}$

2.) $A^{[1]} = \text{ReLU}(Z^{[1]})$

3.) $Z^{[2]} = (W^{[2]} @ A^{[1]}) + B^{[2]}$

4.) $A^{[2]} = \text{ReLU}(Z^{[2]})$

5.) $Z^{[3]} = (W^{[3]} @ A^{[2]}) + B^{[3]}$

6.) $A^{[3]} = Y^T = Z^{[3]}$

Backward Propagation:

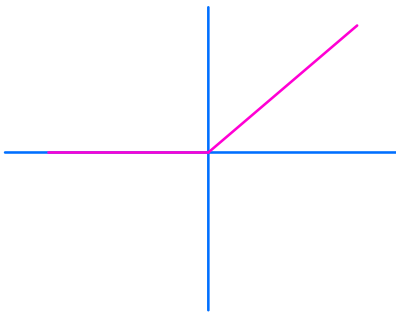
- 1.) $error = Y - \hat{Y}$ ($1 \times m$)
- 2.) $dW^{[l]} = \left(\frac{1}{n}\right) * (error^{[l]} @ A^{[l-1]})$
 \uparrow ($1 \times m$) \downarrow ($m \times m$)
- 3.) $dB^{[l]} = \left(\frac{1}{n}\right) * \sum error$
- 4.) $error^{[l-1]} = (W^{[l]} \cdot T @ error^{[l]}) * g'(z^{[l-1]})$
 \downarrow (1×16) \uparrow ($1 \times m$)
- 5.) repeat from step 2

Update Parameters:

- 1.) $W^{[l]} = W^{[l]} - \alpha dW^{[l]}$
- 2.) $B^{[l]} = B^{[l]} - \alpha dB^{[l]}$

Activation Function:

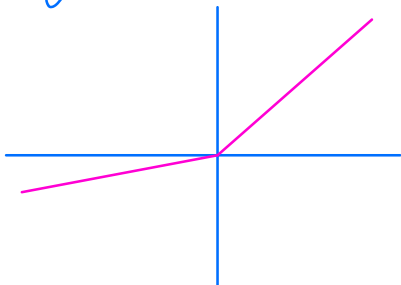
- 1.) ReLU: (Rectified Linear Unit)



$$f(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$$

$$f'(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ 1 & \text{for } x > 0 \end{cases}$$

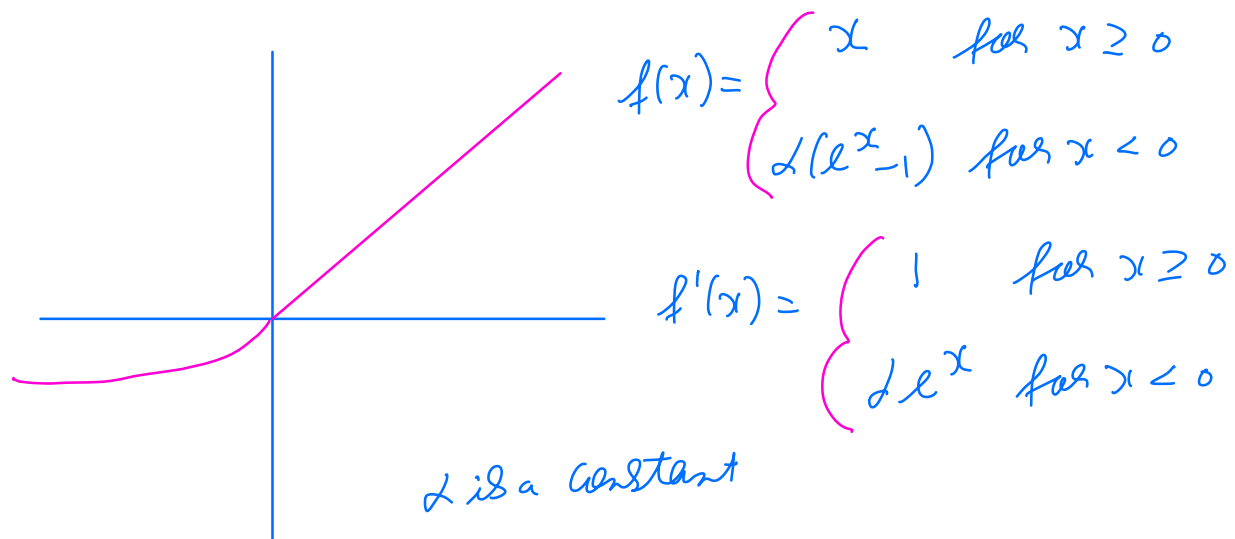
- 2.) leaky ReLU:



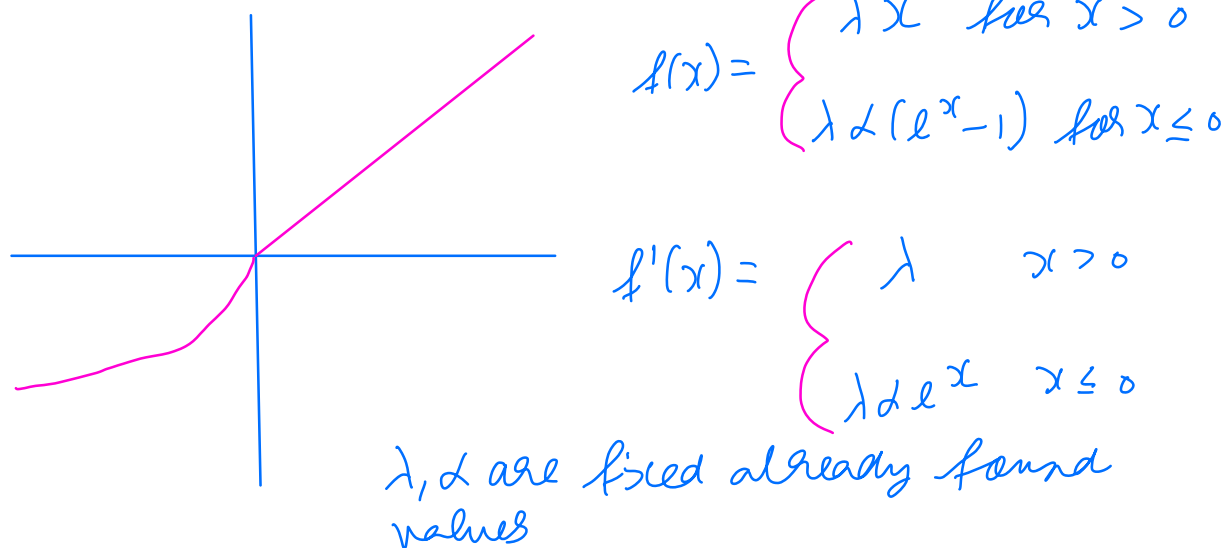
$$f(x) = \begin{cases} 0.01x & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$$

$$f'(x) = \begin{cases} 0.01 & \text{for } x \leq 0 \\ 1 & \text{for } x > 0 \end{cases}$$

3.) ELU: (Exponential Linear Unit)



4.) SELU: (Scaled Exponential Linear Unit)



→) All game around the same accuracy but SELU and ELU were computationally expensive.

Data Preprocessing Tried:

- 1.) Tried removing outliers but messed up the model
- 2.) Rather than one hot encoding 3 categorical features each one was labelled. But drastically reduced the accuracy.

Initial weights and Biases:

- 1.) For biases 3 things tried

i) initially all zero

ii) all set to 0.01

iii) all from random normal distributions

2nd one worked best

- 2.) For weights 3 things tried

i) Random values from normal distributions

ii) Glorot Initialization $\rightarrow \text{mean} = 0$

$$\sigma^2 = \frac{1}{f_{\text{an in}} + f_{\text{an out}}} = \frac{1}{2}$$

$f_{\text{an in}} = \text{i/p neurons}$

$f_{\text{an out}} = \text{out neurons}$

iii) He Initialization $\rightarrow \text{mean} = 0$

$$\sigma^2 = \frac{1}{f_{\text{an in}}}$$

3rd one worked best