

Building a Neural Network using only Maths

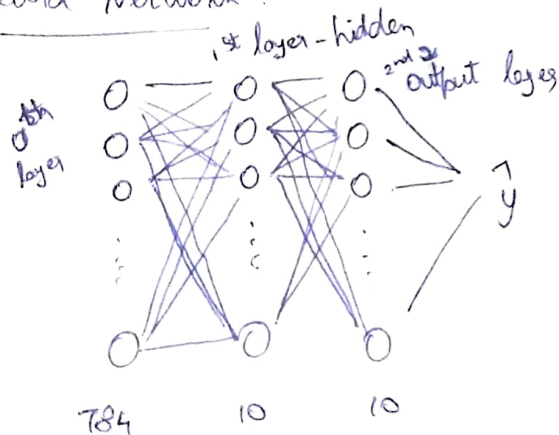
MNIST Dataset:

- we are going to be using 28×28 Pixels
- m training images

$$\boxed{784} \times 28$$

$$X = \begin{bmatrix} - & x^{(1)} & - \\ - & x^{(2)} & - \\ & \vdots & \\ - & x^{(m)} & - \end{bmatrix}^T \Rightarrow \begin{bmatrix} | & | & \dots & | \\ x^{(1)} & x^{(2)} & \dots & x^{(m)} \\ | & | & \dots & | \end{bmatrix}$$

Neural Network:



2 layers

$w \rightarrow$ weight

$b \rightarrow$ bias

$A \rightarrow$ Matrix

$z^{[1]}$ unactivated first layer

$z^{[2]}$ " second "

Forward Propagation:

$$A^{[0]} = X \quad (784 \times m)$$

$$z^{[1]} = w^{[1]} \cdot A^{[0]} + b^{[1]}$$

$$A^{[1]} = g(z^{[1]}) \Rightarrow \text{ReLU}(z^{[1]})$$

$$z^{[2]} = w^{[2]} \cdot A^{[1]} + b^{[2]}$$

$$A^{[2]} = \text{softmax}(z^{[2]})$$

output \Rightarrow Softmax \Rightarrow Probabilities

$$\Rightarrow \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

softmax fn. $\Rightarrow \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$

Back Propagation:

For optimizing the weights.

$$dZ^{[2]} = A^{[2]} - Y$$

$$dW^{[2]} = \frac{1}{m} dZ^{[2]} \cdot A^{[1]T}$$

$$db^{[2]} = \frac{1}{m} \sum dZ^{[2]}$$

$$dZ^{[1]} = W^{[2]T} \cdot dZ^{[2]} * g'(Z^{[1]})$$

$$dW^{[1]} = \frac{1}{m} \sum dZ^{[1]} \cdot X^T$$

$$db^{[1]} = \frac{1}{m} \sum dZ^{[1]}$$

updating:

$$W^{[1]} = W^{[1]} - \alpha dW^{[1]}$$

$$W^{[2]} = W^{[2]} - \alpha dW^{[2]}$$

$$b^{[1]} = b^{[1]} - \alpha db^{[1]}$$

$$b^{[2]} = b^{[2]} - \alpha db^{[2]}$$

$dZ^{[2]} \rightarrow$ error of the
2nd layer

(how much the output layer
is off from the actual)

\rightarrow one-hot-encode

$g' \rightarrow$ derivative of the
activation function

$\alpha \rightarrow$ learning rate