

Neural Networks

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What a Neural Network Is

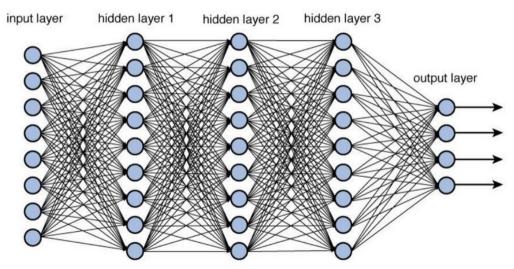


Figure: Representation of a neural network



Types of Neural Network

- Perceptron
- Feed Forward Neural Network
- Multi-layer Perceptron



Types of Neural Network

Perceptron

$$\mathbf{y} = \sigma(\mathbf{W} \cdot \mathbf{x} + b)$$
 (1)

Where \mathbf{y} is the output, \mathbf{W} is a vector of the weights, \mathbf{x} is a vector of the inputs, \mathbf{b} is the bias and σ is the activation function.

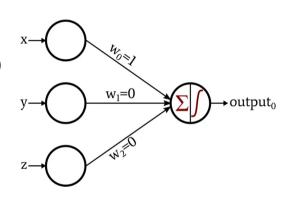


Figure: Perceptron



Types of Neural Network

Feed Forward Neural Network

$$\mathbf{y}_n = \sigma(\mathbf{W}_n \cdot \mathbf{y}_{n-1} + \mathbf{b}_n)$$
 (2)

Where \mathbf{y}_n is the output vector of the nth layer, \mathbf{W}_n is the weight matrix of the nth layer, \mathbf{y}_{n-1} is the output vector of the previous layer, \mathbf{b}_n is the bias vector of the nth layer, and σ is the activation function.

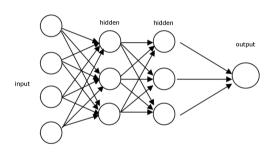


Figure: Feed Forward Neural Network

$$\mathbf{y}_n = \sigma(\mathbf{W}_n \cdot \mathbf{y}_{n-1} + \mathbf{b}_n) \tag{3}$$

Where \mathbf{y}_n is the output vector of the nth layer, \mathbf{W}_n is the weight matrix of the nth layer, \mathbf{y}_{n-1} is the output vector of the previous layer, \mathbf{b}_n is the bias vector of the nth layer, and σ is the activation function.



- Collection of interconnected neurons
- Each neuron has a bias
- Each connection has a weight



Structure

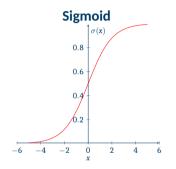
- Input Layer
- Output Layer
- Hidden Layers

Forward Propagation

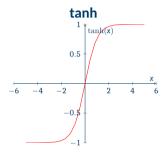
- Inputs are passed through the network to get a prediction
- $\mathbf{y}_n = \sigma(\mathbf{W}_n \cdot \mathbf{y}_{n-1} + \mathbf{b}_n)$
- Where \mathbf{y}_n is the output vector of the nth layer, \mathbf{W}_n is the weight matrix of the nth layer, \mathbf{y}_{n-1} is the output vector of the previous layer, \mathbf{b}_n is the bias vector of the nth layer, and σ is the activation function.



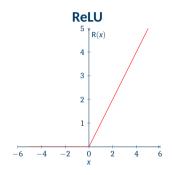
Activation Functions



$$\sigma(\mathbf{x}) = \frac{1}{1 + \mathbf{e}^{-\mathbf{x}}}$$



$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$



$$ReLU(x) = max(0, x)$$



Loss Functions

$$(MSE) = \frac{1}{n} \sum_{i=1}^{n} (\hat{\gamma}_i - \gamma_i)^2$$

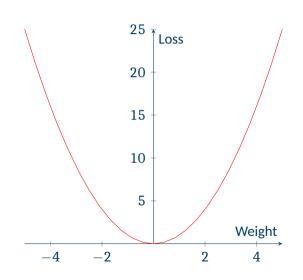
$$(CEL) = -\frac{1}{n} \sum_{i=1}^{n} (\gamma_i \times \log(\hat{\gamma}_i))$$

Where n is the number if sample, y_i is the desired output of the network and \hat{y}_i is the actual output of the network.



Backpropagation

- Data moves backwards through the network
- · Weights and biases adjusted
- Loss must be calculated
- Weights and biases can be changed proportionally to the gradient
- Process is repeated





How Neural Networks Work Training

- Forward Propagation
- Backpropagation
- Repeat



- Data
- Defining the Model
- Training the Model
- Testing the Model



- Data is very important
- MNIST dataset
- Dataset must be split into 'test' and 'train' subsets
- 50000 images in the 'train' subset
- 10000 images in the 'test' subset



Figure: MNIST Example



- 784 input neurons
- 350 hidden neurons
- 10 output neurons

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2$$
 (4)

Defining the Model

Activation Function

$$\sigma(\mathbf{x}) = \frac{1}{1 + e^{-\mathbf{x}}}$$

(5)

$$2\sigma'(x) = x(1-x) \tag{6}$$



Training the Model

• Split the data into equal sized batches

 Forward Propagation for the whole epoch

• Backpropagation after each epoch

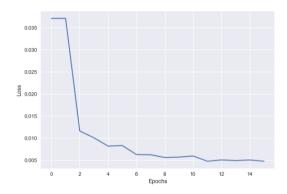


Figure: Loss over epochs



Testing the Model

- Test the model on unseen data
- Run the test dataset through the model
- Calculate accuracy by keeping track of how many correct predictions were made
- 95.32% accuracy



Testing the Model

• Input labels: 8, 5, 8, 9, 1, 9, 7, 2, 8

• predictions: 5, 5, 8, 9, 1, 9, 7, 2, 8

88% accuracy

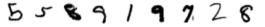


Figure: Inputs for example predictions



Conclusion

- Complex models used for many different tasks
- Easier and quicker to use a library
- I have gained knowledge of neural networks