Neural Networks

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Overview

- Objectives
- What a neural network is
- Types of neural networks
- How Neural Networks Work
- Coding a Neural Network
- Results
- Conclusion

Objectives

- Explore the different types of neural network models
- Explore the uses of different types of neural network models
- Explore how a neural network works from a high level
- Explore how to use a neural network to classify handwritten digits from 0-9
- Code a neural network to classify handwritten digits from 0-9

What is Neural Network Is

- Complex computational model
- Interconnected layers
- Each neuron has a bias
- Each connection has a weight

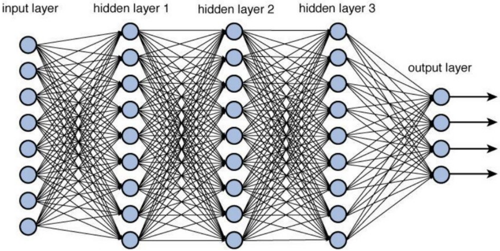


Figure: Representation of a neural network

Types of Neural Network

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

Types of Neural Network

Perceptron

- Simplest component of a neural network
- Inputs between 0 and 1
- $\mathbf{y} = \sigma(\mathbf{W} \cdot \mathbf{x} + b)$
- Where **y** is the output, **W** is a vector of the weights, **x** is a vector of the inputs, b is the bias and σ is the activation function.

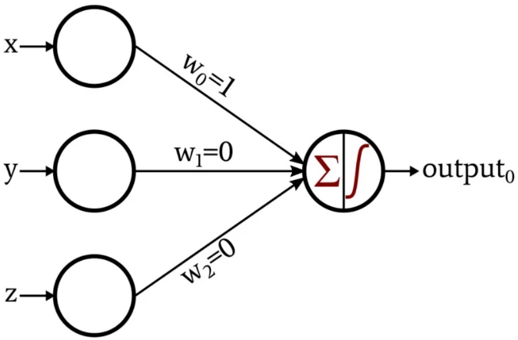


Figure: Perceptron

Types of Neural Network

Feed Forward Neural Network

- Set of interconnected layers
- Linear classification only
- $\mathbf{y}_n = \sigma(\mathbf{W}_n \cdot \mathbf{y}_{n-1} + \mathbf{b}_n)$
- 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.

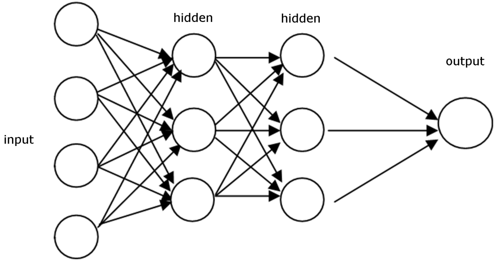


Figure: Feed Forward Neural Network

Types of Neural Network

Multi-layer Perceptron

- Much like a feed forward network
- Data can travel backwards as well as forwards
- Allows for training of the network
- $\mathbf{y}_n = \sigma(\mathbf{W}_n \cdot \mathbf{y}_{n-1} + \mathbf{b}_n)$
- 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.

Types of Neural Network

Convolutional Neural Network

- Often used for image recognition
- Each neuron on the first layer only processes information from a small part of the image

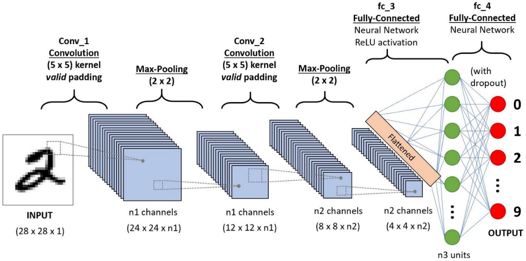


Figure: Convolutional Neural Network

How Neural Networks Work

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

How Neural Networks Work

Structure

- Input Layer
- Output Layer
- Hidden Layers

How Neural Networks Work

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.

How Neural Networks Work

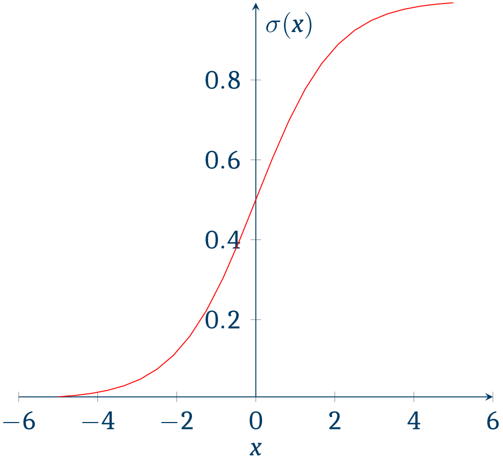
Activation Functions

- Sigmoid
- Tanh
- ReLU
- Leaky ReLU

Activation Functions

Sigmoid

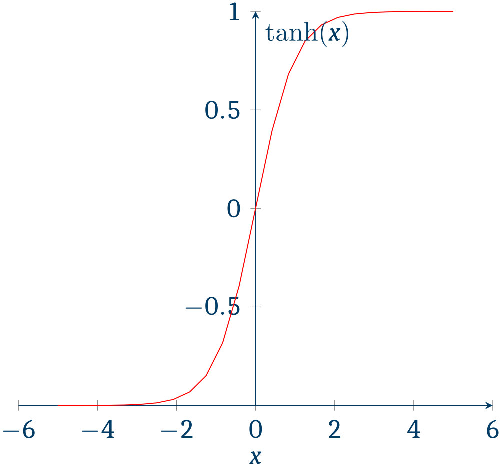
$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{1}$$



Activation Functions

Tanh

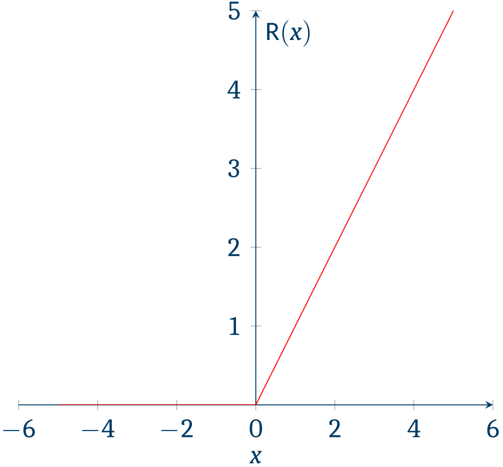
$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$



Activation Functions

ReLU

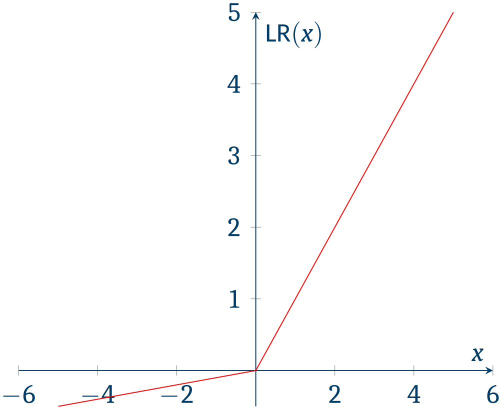
$$\text{ReLU}(x) = \max(0, x) \tag{3}$$



Activation Functions

leaky ReLU

$$\text{Leaky ReLU}(x) = \max(0.1x, x) \qquad (4)$$



How Neural Networks Work

Loss Functions

- Mean Squared Error (MSE)
- Cross Entropy Loss (or Log Loss)

Loss Functions

Mean Squared Error

$$(MSE) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{5}$$

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.

Loss Functions

Cross Entropy Loss

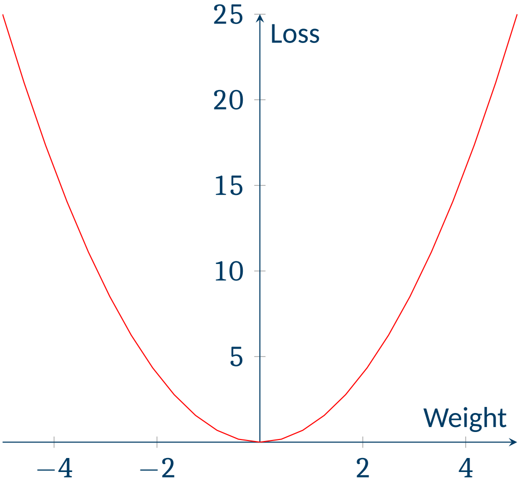
$$(CEL) = -\frac{1}{n}\sum_{i=1}^{n}(y_i \times \log(\hat{y}_i)) \tag{6}$$

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.

How Neural Networks Work

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

Coding a Neural Network

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

Coding a Neural Network

Data

- 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

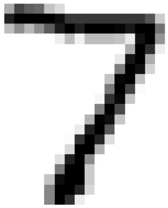


Figure: MNIST Example

Defining the Model

Layers

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

Defining the Model

Loss Function

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

Defining the Model

Activation Function

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

Coding a Neural Network

Training the Model

- Split the data into equal sized batches
- Forward Propagation for the whole epoch
- Backpropagation after each epoch

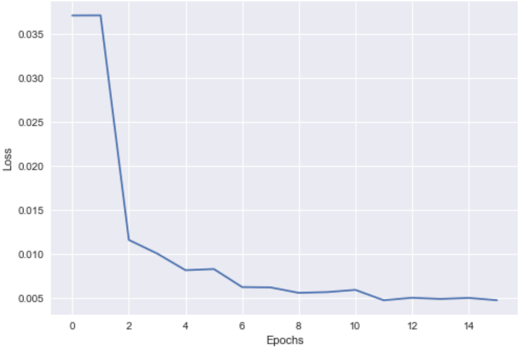


Figure: Loss over epochs

Coding a Neural Network

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

Coding a Neural Network

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