19CST302 - Neural Networks & Deep Learning

Feed Forward Neural Network

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Definition

A feedforward neural network is one of the simplest types of artificial neural networks devised. In this network, the information moves in only one direction—forward—from the input nodes, through the hidden nodes (if any), and to the output nodes. There are no cycles or loops in the network. Feedforward neural networks were the first type of artificial neural network invented and are simpler than their counterparts like recurrent neural networks and convolutional neural networks.

Overview

Feed forward neural networks are artificial neural networks in which nodes do not form loops. This type of neural network is also known as a multi-layer neural network as all information is only passed forward. During data flow, input nodes receive data, which travel through hidden layers, and exit output nodes.

Structure
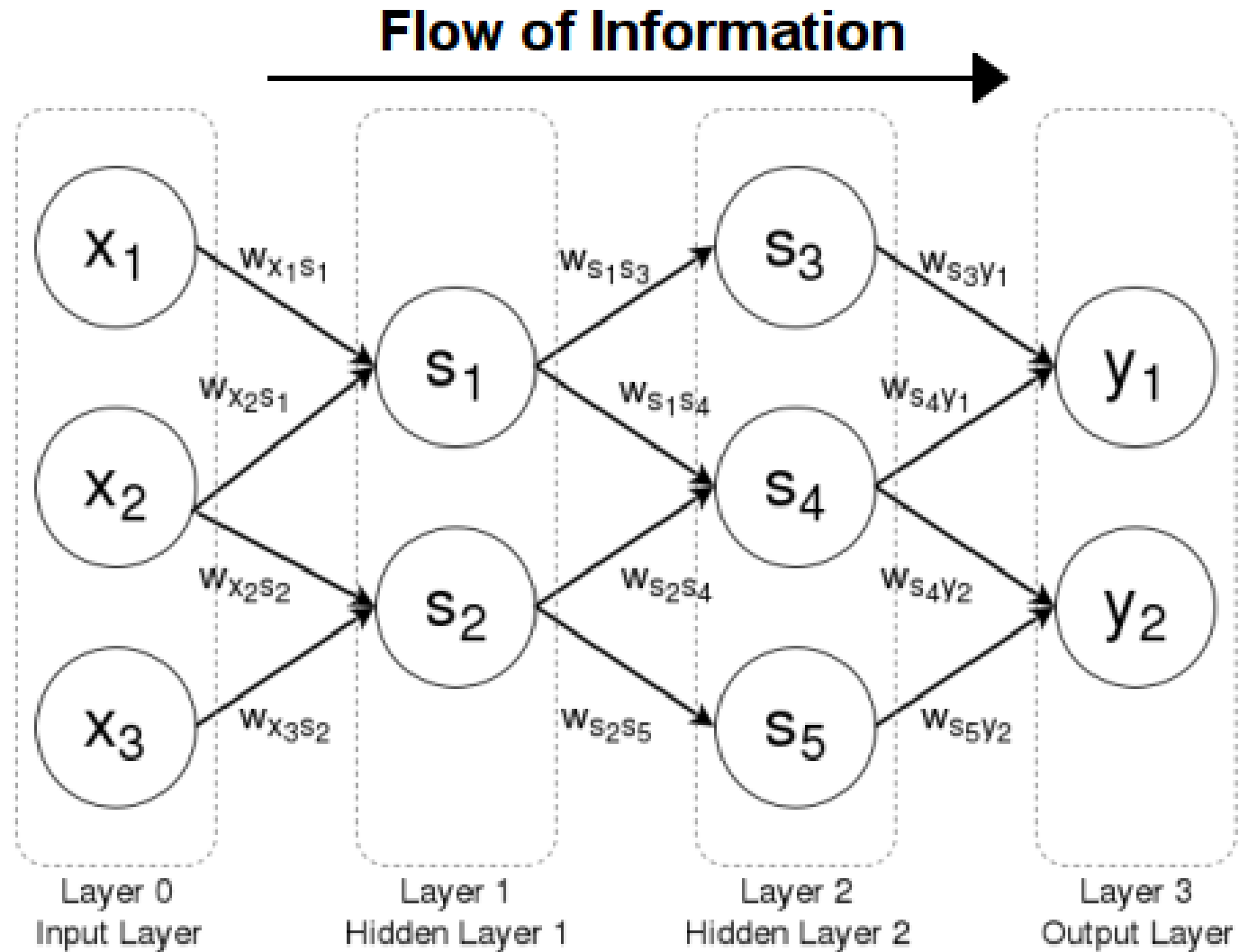
Forward propagation

Forward propagation is a fundamental process in feed-forward neural networks (FFNNs) that involves passing input data through the network's layers to produce output predictions. This process is crucial for making predictions and performing tasks such as classification, regression, or pattern recognition. It refers to the sequential flow of information through the network's layers from the input layer to the output layer. Each layer consists of multiple neurons, and connections between neurons are weighted. The goal of forward propagation is to compute the activation levels of neurons in each layer, ultimately producing the network's output prediction.

Training FFNNs using supervised learning

The primary objective of training FFNNs using supervised learning is to adjust the network's parameters to minimize the discrepancy between predicted outputs and actual outputs. This is achieved by iteratively updating the weights and biases of the network based on the computed loss, using optimization algorithms such as gradient descent. Understanding the training process is crucial for effectively training neural network models to perform various tasks and achieve high performance in real-world applications.

- **Training Data**

     Training data serves as the foundation for teaching the neural network to generalize patterns and relationships present in the data. It comprises input features along with corresponding target outputs. The quality, quantity, and diversity of training data directly influence the model's ability to learn and generalize.

- **Labels**

     Labels, also known as ground truth or target outputs, provide supervision to the learning process. They define the correct output corresponding to each input instance in the training data. Labels guide the training process by indicating the desired prediction for each input example.

- **Loss Function**

     The loss function quantifies the discrepancy between the predicted outputs generated by the model and the actual outputs provided in the training data. The choice of loss function directly impacts the model's learning behavior and the type of tasks it is optimized for. Different loss functions are suited for different types of tasks, such as regression, classification, or sequence generation.

Gradient Descent

Gradient descent is a fundamental optimization algorithm used in training feed-forward neural networks (FFNNs) to minimize the loss function and improve model performance. The primary objective of gradient descent in FFNNs is to adjust the network's parameters (weights and biases) iteratively to minimize the loss function.

By updating the parameters in the direction of the negative gradient of the loss function, gradient descent aims to find the optimal set of parameters that lead to the lowest possible loss, thus improving the model's predictive accuracy.

Conclusion

Feed Forward Neural Networks serve as a fundamental building block in the field of artificial intelligence and machine learning. Their sequential flow of information, coupled with non-linear activation functions, enables them to model complex relationships within data and make accurate predictions. Understanding the structure, training process, and applications of FFNNs is essential for leveraging their capabilities in solving real-world problems and driving innovation in various domains.