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Artificial Neural Networks

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Introduction

The Artificial Neural Network (ANN) is a computational model inspired by the human brain, consisting of a network architecture composed of artificial neurons. It operates similarly to the human brain, simulating its functions. There are two key resemblances between ANN and the human brain: Firstly, knowledge in an ANN is stored in interconnection strengths referred to as synaptic weights and Secondly, ANN acquires knowledge through the process of learning (Lawrence, 1993). The introduction of ANNs has brought about a revolution in the fields of artificial intelligence and machine learning, offering exceptional capabilities in solving complex problems and emulating the functioning of the human brain. The concept of Artificial Neural Networks was initially proposed by Warren McCullough and Walter Pitts in 1943. They are also commonly referred to as Neural Networks (NN), Neural Nets, or Simulated Neural Networks (SNN). The term "Neural" represents the plural form of "Neuron," while "Network" denotes the graph-like structure.

An ANN comprises interconnected artificial neurons, also known as nodes or units, organized into layers. Typically, these layers consist of an input layer, one or more hidden layers, and an output layer. Each neuron within the network receives input signals, performs computations, and generates an output signal, which is then passed on to other neurons within the network (Krenker*et al.*, 2011). The influence of one neuron on another is determined by the strength of connections between them, known as weights. The architecture of the ANN model is given in Fig 1.

Types of ANN

Artificial Neural Networks are classified into different types based on three important criteria: learning rules, activation functions, and interconnections (Krogh, 2008).

Learning rules determine how an ANN adjusts its parameters to enhance its performance. There are two main types of learning rules: parameter learning and structure learning. Parameter learning involves adjusting the connection weights of the network to minimize the error between predicted and target outputs. Examples of parameter learning algorithms include the widely used back propagation algorithm and its variants. Structure learning, on the other hand, focuses on modifying the network's architecture by adding or removing nodes or connections based on specific criteria, allowing the network to adapt during the learning process.

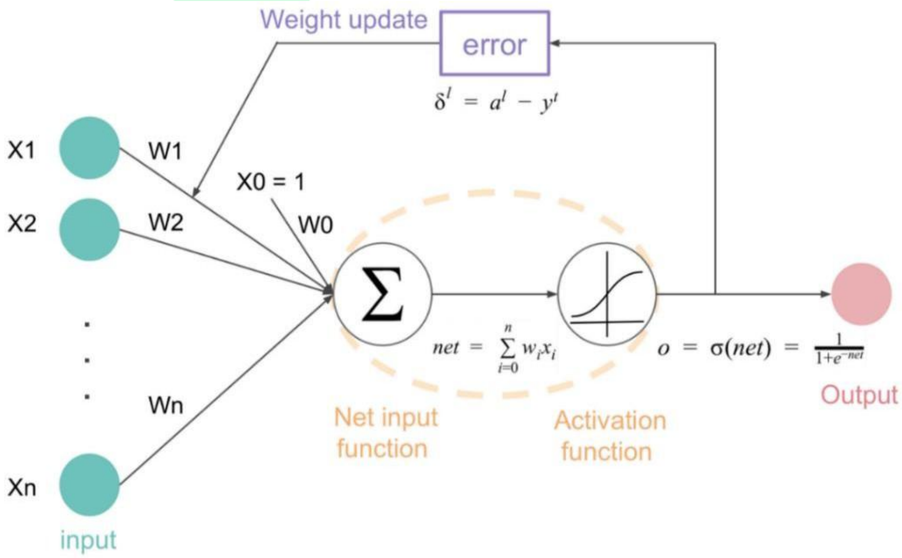

Fig 1 Artificial Neural Model–Perceptron

Activation functions play a crucial role in introducing non-linearity to the output of neurons within an ANN. They enable the network to learn and model complex relationships in the data. Some commonly used activation functions include the sigmoid (logistic) function, which maps the input to a value between 0 and 1, making it suitable for binary classification tasks. The hyperbolic tangent (tanh) function is similar to the sigmoid function but maps the input to a value between -1 and 1. The rectified linear unit (ReLU) sets negative inputs to zero and keeps positive inputs unchanged, and it is widely used in deep learning models. The softmax function is used in the output layer for multi-class classification problems, as it normalizes the output values to represent class probabilities.

Interconnections in ANNs refer to the arrangement and connections between the neurons or units in the network. ANNs typically consist of three main layers: the input layer, the hidden layer(s), and the output layer. The input layer accepts the input data or features provided to the network. The hidden layer(s) exist between the input and output layers, with each neuron in a hidden layer receiving inputs from the previous layer and computing a weighted sum, which is then passed through an activation function. The output layer produces the final output or predictions of the network. The specific interconnections between the layers can vary depending on the architecture of the network (Ripley, 1994). Common configurations include fully connected, where all neurons in one layer are connected to all neurons in the next layer; locally connected, where neurons in one layer are connected to a subset of neurons in the next layer; and convolutional connections, which are used in convolutional neural networks for grid-like data.

Commonly used ANN models

1. Feed forward Neural Network (FNN) is a type of artificial neural network where information flows in a single direction, from input nodes to output nodes. It lacks feedback connections, meaning there are no loops or cycles in the network. FNNs are commonly used for tasks like classification and regression and can be configured as single-layer or multilayer networks.
2. A single-layer feed forward network consists of only one weighted layer, with the input layer fully connected to the output layer. Units in this network often utilize activation functions such as sigmoid to process the inputs.
3. In contrast, a multilayer feed forward network, also known as a multilayer perceptron, contains more than one weighted layer. It includes one or more hidden layers between the input and output layers and typically employs nonlinear activation functions like hyperbolic tangent or logistic functions. This type of network is widely used for tasks like pattern recognition, image processing, and time series analysis.
4. A Feedback ward Neural Network incorporates the back propagation algorithm for adjusting the weights based on the error rate. Back propagation calculates the gradient of the loss function with respect to all the weights in the network, enabling fine-tuning of the weights to reduce errors and improve generalization. Feed backward neural networks are commonly employed for training artificial neural networks.
5. Recurrent Neural Network (RNN) differs from feed forward networks by allowing

feedback loops and the ability to process sequential data. It contains recurrent connections, making it suitable for tasks involving time series data, natural language processing, speech recognition, and machine translation. The hidden layer(s) in RNNs have recurrent connections, enabling memory and context preservation.

6. Convolutional Neural Network (CNN) is specialized for processing grid-like data, such as images and videos. It employs convolutional layers, pooling layers, and fully connected layers. CNNs are highly effective in computer vision tasks like image classification, object detection, and image segmentation.
7. Radial Basis Function Network (RBFN) utilizes radial basis functions as activation functions. Each neuron in an RBFN is assigned a center vector, and the activation is calculated based on the similarity to the center vectors. RBFNs are often used for function approximation, time series prediction, and control systems.

These are just a few examples of ANN models based on different criteria. There are other variations and specialized architectures that can be used depending on the specific problem domain and requirements.

Weights & Bias

Weights are the strength of the connection. Weight indicates the amount of influence a change in the input will have on the output. Input with a low weight value will have no large change on the output and alternatively, a larger weight value will more significantly change the output. Bias represents how far off the predictions are from the irintended value. A low bias makes more assumptions about the form of the output, whereas a high bias value makes fewer assumptions. Weights and bias are both learnable parameters. Initially, weights are randomly applied during the learning process. Later weights are adjusted according to the bias to obtain the desired values for the output. Adjusting the weight will eventually optimize the bias. Some methods for adjusting weights are *Backpropagation* (Distributing the errors backward through the network to be used by neurons) and *Gradient descent* (More efficiently determining optimal weights by using the cost function concept).

Application of ANN

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Artificial Neural Networks (ANNs) have found significant applications in agriculture and research, revolutionizing the way we approach agricultural practices and scientific studies (Luk *et al.*,2001). Here are some notable applications:

- **Crop Yield Prediction**: ANNs can analyze various factors such as weather data, soil conditions, historical yield data, and crop management practices to predict crop yields. This information assists farmers in optimizing their agricultural practices, making informed decisions about planting, irrigation, fertilization, and crop rotation.
- **Pest and Disease Detection:** ANNs can be trained to identify patterns and symptoms associated with pests, diseases, and nutrient deficiencies in crops. By analyzing images or sensor data, ANNs can quickly detect early signs of problems, allowing farmers to take timely preventive measures and minimize crop losses.
- **Plant Disease Diagnosis:** ANNs have been applied to diagnose plant diseases based on visual symptoms and leaf images. By training ANNs on a large dataset of disease-infected plants, they can accurately classify and diagnose various plant diseases, aiding in prompt disease management and reducing the use of chemical treatments.
- **Crop Management and Optimization:** ANNs can optimize irrigation schedules, fertilizer application rates, and other crop management practices. By analyzing real-time data from sensors and weather stations, ANNs can dynamically adjust these factors to maximize crop productivity while minimizing resource usage and environmental impact.
- **Genomics and Plant Breeding:** ANNs are used in genomics research to analyze large-scale genetic datasets and identify genetic markers associated with desired traits. This information can accelerate plant breeding programs by assisting breeders in selecting the best parental lines for crossbreeding and predicting the performance of resulting hybrids.
- **Soil Classification and Mapping:** ANNs can analyze soil properties such as texture, fertility, and organic matter content to classify and map different soil types. This information helps in site-specific soil management, precision agriculture, and optimizing fertilizer and nutrient application based on specific soil characteristics.
- **Climate Change Modelling:** ANNs are utilized in climate change research to model and predict the impact of climate change on agricultural systems. By integrating

climate data, crop models, and ANNs, researchers can simulate future scenarios and assess the vulnerability of different crops to climate change, aiding in adaptation strategies.

Overall, ANNs provide valuable insights and decision support for farmers, researchers, and policymakers in agriculture and research. They enable more efficient resource allocation, improved crop management, and enhanced understanding of complex agricultural systems (Wu and Feng, 2018). As the technology advances, ANNs will continue to play a crucial role in sustainable agriculture and scientific advancements in these fields.

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