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# NEURAL NETWORK

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***Abstract*- This research paper gives a short description of what an artificial neural network is and its biological motivation .A clear description of the various ANN models and its network topologies has been given. It also focuses on the different learning paradigms. This paper also focuses on the applications of ANN.**

## I. INTRODUCTION

In machine learning and related fields, **artificial neural networks** (**ANNs**) are basically computational models ,inspired by the biological nervous system (in particular the brain), and are used to estimate or the approximate functions that can depend on a large number of inputs applied . Artificial neural networks are generally presented as systems of interconnected nerve cells or neurons("as they are called") which can compute values from inputs, and are capable of learning,which is possible only due to their adaptive nature.

Information that flows through the network affects the structure of the ANN because a neural network changes - or learns, in a sense - based on that input and output.

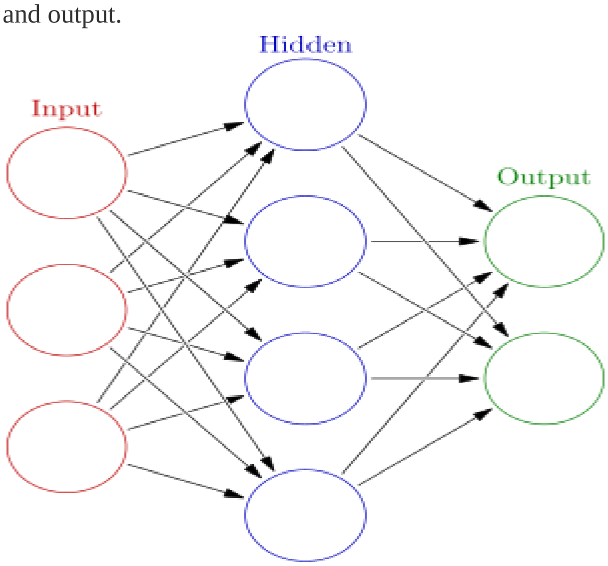



FIG:Basic structure of an ANN

### *1.1.BIOLOGICAL MOTIVATION*

The human brain is a great information processor, even though it functions quite slower than an ordinary computer. Many researchers in *the field of* artificial intelligence look to the organization of the brain as a model for building intelligent machines.*If we think* of a sort of the analogy between the complex webs of interconnected neurons in a brain and the densely interconnected units making up an artificial neural network, where each unit,which is just like a biological neuron,is capable of taking in a number of inputs and also producing an output.

The complexity of real neurons is highly abstracted when modelling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (i.e the strength of the respective signals), and then is computed by a mathematical function which determines the activation of the neuron. Another function computes the output of the artificial neuron (sometimes in dependance of a certainthreshold). ANNs combine artificial neurons in order to process information.

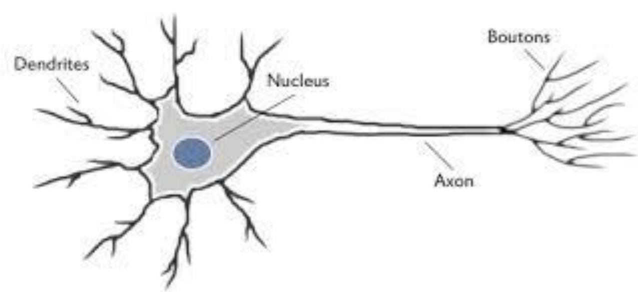



FIG:Biological neuron

A biological neuron has a cell body, a branching Input structure (the dendrIte) and a branching output structure (the axon).

• Axons connect to dendrites via synapses.

• Electro-chemical signals are propagated from the dendritic input, through the cell body, and down the axon to other neurons.

## II. NETWORK TOPOLOGY

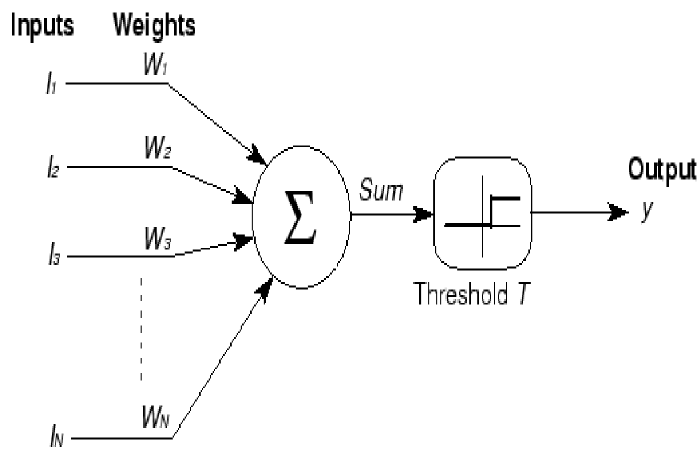
Accordingly to its topology an ANN can be classified as a feedforward or feedback (also called recurrent) ANN.
Given a feedforward ANN, by properly numbering the units we can
define a weight matrix W which is lower-triangular and has a zero diagonal (the unit
does not feedback into itself). A feedforward ANN arranged in layers, where the units
are connected only to the units situated in the next consecutive layer, is called a strictly
feedforward ANN.
In a feedback network feedback loops are allowed to exist. A
feedforward ANN implements a static mapping from its input space to its output space
while a feedback ANN is, in general, a nonlinear dynamical system and therefore the
stability of the network is one of the main concerns.
ANNs can also be classified as synchronized or asynchronized according to the
timing of the application of the activation rule.
In synchronized ANNs, we can imaginethe equivalent of a central clock that is used by all units in the network such that all ofthem, simultaneously, sample their inputs, calculate their net input and their activation and output values, i.e. a synchronous update is used. Such an update can be seen as adiscrete difference equation that approximates an underlying continuous differentialequation. In asynchronizedANNs, at each point in time, there is an maximum of only one unit being updated. Normally, whenever the updating is allowed, a unit is selectedat random to be updated and the activation values of the other units are kept constant.In some models of feedback ANNs such a procedure helps, but does not guarantee, thestability of the network and is generally used when asynchronous update can result instability problems.

## III. MODELS OF ANN

There are different models of the ANN.They have been discussed as follows:

### *3.1.MCCULLOCH PITTS(MCP)*

In 1943 Warren S. McCulloch, a neuroscientist, and Walter Pitts, a logician, published "A logical calculus of the ideas immanent in nervous activity" in the Bulletin of Mathematical Biophysics . In this model McCulloch and Pitts tried to understand how the brain could produce highly complex patterns by using many basic cells that are connected together. These basic brain cells are called neurons, and McCulloch and Pitts gave a highly simplified model of a neuron in their paper. The McCulloch and Pitts model of a neuron has made an important contribution to the development of artificial neural networks which model key features of biological neurons.




The McCulloch-Pitts neural model is also known as linear threshold gate. It is a neuron of a set of inputs $I_1, I_2, I_3, ..., I_m$ and one output $y$. The linear threshold gate simply classifies the set of inputs into two different classes. Thus the output $y$ is binary. Such a function can be described mathematically using these equations:

$$Sum = \sum_{i=1}^{N} I_i W_i, \qquad (2.1)$$

$$y = f(Sum). \qquad (2.2)$$

$W_1, W_2, W_3, ..., W_m$ are weight values normalized in the range of either $(0,1)$ or $(-1,1)$ and associated with each input line, is the weighted sum, and $T$ is a threshold constant. The function $f$ is a linear step function at threshold $T$.

*3.2.FEEDFORWRD NETWORK*

A feedforward neural network is a biologically inspired classification algorithm. It consist of a possibly large number of simple neuron-like processing *units*, organized in *layers*. Every unit in a layer is connected with all the units in the previous layer. These connections are not all equal, each connection may have a different strength or *weight*. The weights on these connections encode the knowledge of a network. Often the units in a neural network are also called *nodes*.
Data enters at the inputs and passes through the network, layer by layer, until it arrives at the outputs. During normal operation, that is when it acts as a classifier, there is no feedback between layers. This is why they are called *feedforward* neural networks.

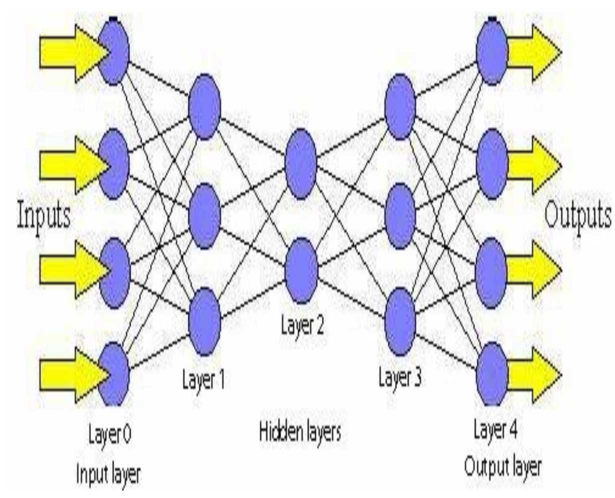



FIG:Feedforward network

*3.3.FEEDBACK NETWORK*
A **recurrent neural network** (RNN) is any network whose neurons send feedback signals to each other. This concept includes a huge number of possibilities. A number of reviews already exist of some types of RNNs.Typically, these reviews consider RNNs that are artificial neural networks (aRNN) useful in technological applications. To complement these contributions, the present summary focuses on biological recurrent neural networks (bRNN) that are found in the brain. Since feedback is ubiquitous in the brain, this task, in full generality, could include most of the brain's dynamics. The current review divides bRNNS into those in which feedback signals occur in neurons within a single processing layer, which occurs in networks for such diverse functional roles as storing spatial patterns in short-term memory, winner-take-all decision making, contrast enhancement and normalization, hill climbing, oscillations of multiple types (synchronous, traveling waves, chaotic), storing temporal sequences of events in working memory, and serial learning of lists; and those in which feedback signals occur between multiple processing layers, such as occurs when bottom-up adaptive filters activate learned recognition categories and top-down learned expectations focus attention on expected patterns of critical features and thereby modulate both types of learning.

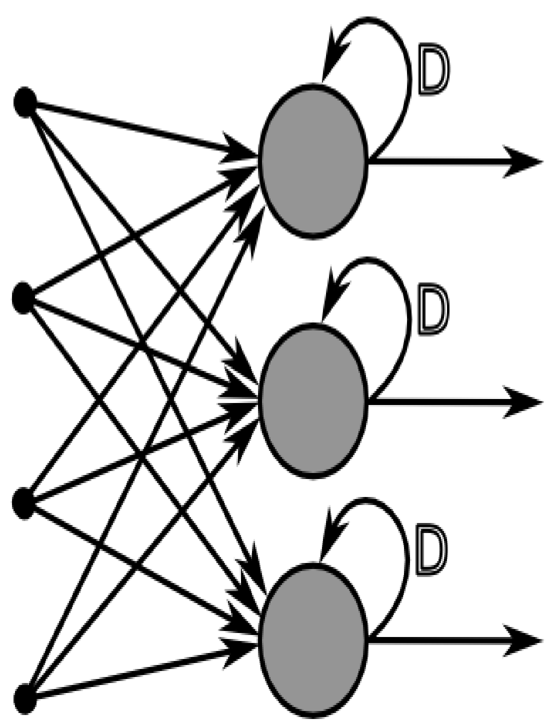



FIG:Feedback Network

## IV. LEARNING

There are three major learning paradigms, each corresponding to a particular abstract learning task.

### *4.1.SUPERVISED LEARNING*

In supervised learning, we are given a set of example pairs $(x, y), x \in X, y \in Y$ and the aim is to find a function *f* in the allowed class of functions that matches the examples. In other words, we wish to *infer* how the mapping implied by the data and the cost function is related to the mismatch between our mapping and the data.

### *4.2.UNSUPERVISED LEARNING*

In unsupervised learning we are given some data *x*, and a cost function which is to be minimized which can be any function of *x* and the network's output, *f*. The cost function is determined by the task formulation. Most applications fall within the domain of estimation problems such as statistical modeling, compression, filtering, blind source separation and clustering.

### *4.3.REINFORCEMENT LEARNING*

In reinforcement learning, data *x* is usually not given, but generated by an agent's interactions with the environment. At each point in time *t*, the agent performs an action $y_t$ and the environment generates an observation $x_t$ and an instantaneous cost $c_t$, according to some (usually unknown) dynamics.

## V. APPLICATIONS

There are numerous applications of ANN.They have been discussed as follows:

- **Science**

  Pattern Recognition,Recipes and Chemical Formulation Optimization,Chemical Compound Identification,Physical System Modeling,Ecosystem Evaluation,Polymer Identification,Recognizing Genes,Botanical Classification,Signal Processing: Neural Filtering,Biological Systems Analysis,Ground Level Ozone Prognosis,Odor Analysis and Identification
- **Educational**

  Teaching Neural Networks,Neural Network Research,College Application Screening,Predict Student Performance

- **Energy**

  Electrical Load Forecasting,Energy Demand Forecasting,Short and Long-Term Load Estimation,Predicting Gas/Coal,Index Prices,Power Control Systems,Hydro Dam Monitoring

- **Others including:**

  Sports Betting,Making Horse and Dog Racing Picks,Quantitative Weather Forecasting,Games Development,Optimization Problems, Routing,Agricultural Production Estimates,Financial,Dtata mining,sales and marketing,Operational analysis,Medical,Industrial,Pattern Classification,Clustering/Categorization,Function approximation, Prediction/Forecasting,Optimization,Content-addressable Memory, Control

## VI. CONCLUSION

We have seen that artificial neural networks based on simple models for neurons and their connections can be very successful .

In general, neural networks provide good solutions to problems with the following features:

- The problem makes use of `noisy' data
- Fast processing may be required. We may not need the most perfect solution to the problem. We might just want a reasonably good one quickly.
- There are no simple rules for solving the problem - all we have are a set of sample solutions. The network can `trained' on these so that it produces good responses to similar new cases.

Neural networks are suitable for predicting time series mainly because of learning only from examples, without any need to add additional information that can bring more confusion than prediction effect. Neural networks are able to generalize and are resistant to noise. On the other hand, it is generally not possible to determine exactly what a neural network learned and it is also hard to estimate possible prediction error.

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