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Introduction to Artificial Neural Networks-IV

Paper : -PCSC-504

Section-A

1.

(I) Synaptic Weights provides the .... method for the design of neural network.
Ans: Traditional

(II) Elements of nn is:
Ans: Adder

(III) In hebb's learning , if two neurons on either side of synapse are activated simultaneously, then the strength of the synapse is...............
Ans : Increased

(IV) Benefits of NN is:
Ans: Fault Tolerance

(I) Write down output calculation formula in single layer perceptron.

Ans:

$$v = \sum_{i=1}^{m} w_i x_i + b_j$$

W= synaptic weight

X= inputs

b_j= bias

(ii) Write any two application of Neural Network.

Ans: Explain any two application in detail.

for example Traffic control, Betting on horse race, Music Diagnosis

(iii) What is Artificial intelligence?

Ans: Artificial intelligence is a branch of computer science which is concerned with the study and creation of computer system that exhibit some form of intelligence.

Section-B

2. Explain the benifits of ANN.

Ans: **Benefits of ANN**

It is apparent that a neural network derives its computing power through, first, its massively parallel distributed structure and, second, its ability to learn and therefore generalize. *Generalization* refers to the neural network producing reasonable outputs for inputs not encountered during training (learning). These two information processing capabilities make it possible for neural networks to solve complex (large-scale) problems that are currently intractable. In practice, however, neural networks cannot pro- vide the solution by working individually. Rather, they need to be integrated into a consistent system engineering approach. Specifically, a complex problem of interest is *decomposed* into a number of relatively simple tasks, and neural networks are assigned a subset of the tasks that *match* their inherent capabilities. It is important to recognize, however, that we have a long way to go (if ever) before we can build a computer architecture that mimics a human brain.

The use of neural networks offers the following useful properties and capabilities:

1- *Nonlinearity.* An artificial neuron can be linear or nonlinear. A neural net- work, made up of an interconnection of nonlinear neurons, is itself nonlinear. Moreover, the non1inearity is of a special kind in the sense that it is *distributed* throughout the network. Nonlinearity is a highly important property, particularly if the under1ying physical mechanism responsible for generation of the input signal (e.g., speech signal) is inherently nonlinear.

2. *input-Output Mapping.* A popular paradigm of learning called *learning with a teacher or supervised learning* involves modification of the synaptic weights of a neural network by applying a set of labelled *training samples* or *task examples.* Each example consists of a unique *input signal* and a corresponding *desired response.* The network is presented with an example picked at random from the set, and the synaptic weights (free parameters) of the network are modified to minimize the difference between the desired response and the actual response of the network produced by the input signal in accordance with an appropriate statistical criterion. The training of the network is repeated for many examples in the set until the network reaches a steady state where there are no further significant changes in the synaptic weights. The previously applied training examples may be reapplied during the training session but in a different order.

'rhus the network learns from the examples by constructing an *input-output mapping* for the problem at hand. Such an approach brings to mind the study of *nonparametric statistical inference,* which is a branch of statistics dealing with model-free estimation, or, from a biological viewpoint, *tabula rasa* learning (Geman et. al., 1992); the term "nonparametric" is used here to signify the fact that no prior assumptions are made on a statistical mode] for the input data. Consider, for example, a *pattern classification* task, where the requirement is to assign an input signal representing a physical object or event to one of several prespecified categories (classes). In a non parametric approach to this problem, the requirement is to "estimate" arbitrary decision boundaries in the input signal space for the pattern, classification task using a set of examples, and to do so *without* invoking a probabilistic distribution model. A similar point of view is implicit in the supervised learning paradigm, which suggests a close analogy between the input-output mapping performed by a neural network and nonparametric statistical inference.

3. *Adaptively*. Neural networks have a built-in capability to *adapt* their synapticweights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily *retrained* to deal with minor changes in the operating environmental conditions. Moreover, when it is operating in a *non stationary* environment (i.e., one where statistics change with time), a neural net- work can be designed to change its synaptic weights in real time. The natural architecture of a neural network for pattern classification, signal processing, and control applications, coupled with the adaptive capability of the network, make it a useful tool in adaptive pattern classification, adaptive signal processing, and adaptive control. As a general rule, it may be. said that the more adaptive we make a system, all the time ensuring that the system remains stable, the more robust its performance will likely be when the system is required to operate in a non stationary environment. It should be emphasized, however, that adaptivety does not always lead to robustness; indeed, it may do the very opposite. For example, an adaptive

4. *Evidential Response*. In the context of pattern classification, a neural network system with short time constants may change rapidly and therefore tend to respond to spurious disturbances, causing a drastic degradation in system performance. To realize the full benefits of adaptivity, the principal time constants of the system should be long enough for the system to ignore spurious disturbances and yet short enough to respond to meaningful changes in the environment; the problem described here is referred to as the *stability-plasticity dilemma* (Grossberg, 11)88b) can be designed to provide information not only about which particular pattern to *select*, but also about the *confidence* in the decision made. This latter information may be used to reject ambiguous patterns, should they arise, and thereby improve the classification performance of the network.

5. *Contextual Information*. Knowledge is represented by the very structure and
activation state of a neural network. Every neuron in the network is potentially affected by the global activity of all other

neurons in the network. Consequently, con- textual information is dealt with naturally by a neural network.

you should write the following points in details

6 Fault Tolerance

7 VLSI Implement ability

3. Explain the properties of neural network as directed graph.

Ans: you should explain the rule related to flow of signals in various parts of the graph with diagram and also write the following properties.

A neural network is a directed graph consisting of nodes with interconnecting synaptic and activation links, and is characterized by four properties:

1. *Each neuron is represented by a set of linear synaptic links, an externally applied bias, and a p03'Sibly nonlinear activation link. The bias is represented by a synaptic link connected w an input fixed at +1.*
2. *The synaptic links of a neuron weight their respective input signals.*
3. *The weighted sum uf the input signals defines the induct::d local field of the neuron in question.*
4. *The activation link squashes the induced local field of the neuron w produce an output.*

4. Explain Hebbian learing.

Ans: HEBBIAN LEARNING

Hebb's postulate of learning is the oldest and most famous of all learning rules; it is named in honor of the neuropsychologist Hebb (1949). Quoting from Hebb's book. *The Organization of Behavior* (l949,p.l12):

> When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic changes take place in l11e or both cells such that A's efficiency as one of the cells firing B, is increased.

Hebb proposed this change as a basis of associative learning (at the cellular level), which would result in an enduring modification in the activity pattern of a spatially distributed "assembly of nerve cells."

This state ment is made in a neurobio1ogical context. We may expand and .rephrase it as a two-part rule (Stem, 1973; Changeux and Danchin, 1976);

1. *lf two neurons on either side of a synapse (connection) are activated simultaneously (i.e., synchronously),then the strength of that synapse is selectively increased.*

2. *If two neurons on either side of a synapse are activated asynchronously, then that synapse* is *selectively weakened or eliminated.*

You should explain the hebbian learning with any problem.

5. Briefly explain single layer perceptron.

In the formative years of neural networks (1943–1958), several researchers stand out for their pioneering contributions:

- McCulloch and Pitts (1943) for introducing the idea of neural networks as computing machines.
- Hebb (1949) for postulating the first rule for self-organized learning.
- Rosenblatt (1958) for proposing the perceptron as the first model for learning with a teacher (i.e., supervised learning).

The perceptron is the simplest form of a neural network used for the classification of patterns said to be *linearly separable* (i.e., patterns that lie on opposite sides of a hyperplane). Basically, it consists of a single neuron with adjustable synaptic weights and bias. The algorithm used to adjust the free parameters of this neural network first appeared in a learning procedure developed by Rosenblatt (1958, 1962) for his perceptron brain model.[1] Indeed, Rosenblatt proved that if the patterns (vectors) used to train the perceptron are drawn from two linearly separable classes, then the perceptron algorithm converges and positions the decision surface in the form of a hyperplane between the two classes. The proof of convergence of the algorithm is known as the *perceptron convergence theorem*. The perceptron built around a *single neuron* is limited to performing pattern classification with only two classes (hypotheses). By expanding the output (computation) layer of the perceptron to include more than one neuron, we may correspondingly form classification with more than two classes. However, the classes have to be linearly separable for the perceptron to work properly. The important point is that insofar as the basic theory of the perceptron as a pattern classifier is concerned, we need consider only the case of a single neuron. The extension of the theory to the case of more than one neuron is trivial.

The single neuron also forms the basis of an *adaptive filter*, a functional block that is basic to the ever-expanding subject of *signal processing*. The development of adaptive filtering owes much to the classic paper of Widrow and Hoff (1960) for pioneering the so-called *least-mean-square (LMS) algorithm*, also known as the *delta rule*. The LMS algorithm is simple to implement yet highly effective in application. Indeed, it is the workhorse of *linear* adaptive filtering, linear in the sense that the neuron operates in its linear mode. Adaptive filters have been successfully applied in such diverse fields as antennas, communication systems, control systems, radar, sonar, seismology, and biomedical engineering (Widrow and Stearns, 1985; Haykin, 1996).

In the signal-flow graph model of Fig. 1 , the synaptic weights of the perceptron are denoted by $w_1, w_2, \ldots, w_m$. Correspondingly, the inputs applied to the perceptron

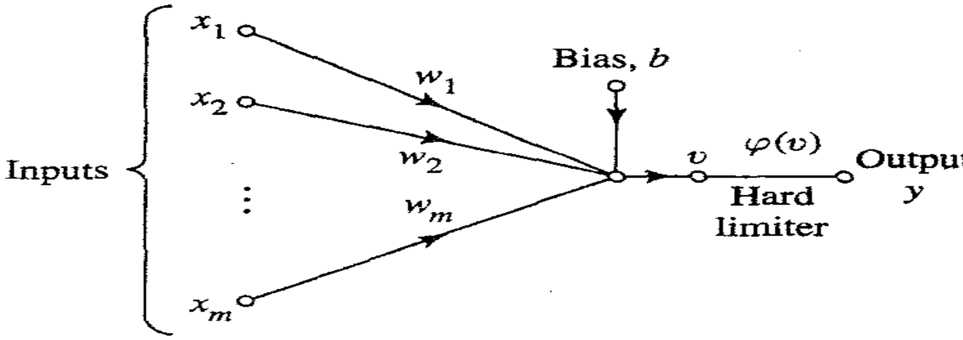

FIGURE 1 Signal-flow graph of the perceptron.

are denoted by $x_1, x_2, \ldots, x_m$. The externally applied bias is denoted by b. From the model we find that the hard limiter input or induced local field of the neuron is

$$v = \sum_{i=1}^{m} w_i x_i + b$$

The goal of the perceptron is to correctly classify the set of externally applied stimuli $x_1, x_2, \ldots, x_m$ into one of two classes, $\mathscr{C}_1$ or $\mathscr{C}_2$. The decision rule for the classification is to assign the point represented by the inputs $x_1, x_2, \ldots, x_m$ to class $\mathscr{C}_1$ if the perceptron output y is $+1$ and to class $\mathscr{C}_2$ if it is -1.

6. Explain the types of Activation function.

Ans:

You should write follwing activation function with graph.

1. Identity Function

2. Binary step function

3. Bipolar step function

4. Sigmoidal Functions

7. Explain the Neural Network Architecture.

Ans:

Architecture OF A NEURON

A *neuron* is an information-processing unit that is fundamental to the operation of a neural network. The *model* of a neuron, which forms the basis for deigning (artificial) neural networks. Here we identify three basic • elements of the neuronal model:

1. A set of *synapse* or *connecting links,*
2. An *adder*.
3. An *activation function*

You should explain this elements.

8. Explain reinforcement learning.

Ans:

You should explain reinforcement learning with diagram.