A Proposed Algorithm for Multivariate Artificial Neural Network

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ABSTRACT

As some physiological presumptions of Brain Learning techniques led to develop Artificial Neural Network (ANN) to compete with the Brain's Natural learning phenomenon. Various Networks and Algorithms have been proposed to enhance the machine learning process and to achieve some thing new. In this paper we have proposed a moderate Algorithm for Multivariate Artificial Neural Network.

Key Words – Neural Networks, Algorithm.

1. INTRODUCTION

For last few decades the studies over brain learning system are being conducted and huge possibilities are being explored to design a competent Artificial Neural Network resembling the brain efficiencies. Also many algorithms in this direction have been proposed by various authors to meet the goal. Here we propose a moderate Algorithm for multivariate artificial neural network.

Let x_i is a neuron with weight w_i so its strength is $w_i\ x_i$, and let we have m_i neurons of type x_i. Then the combined probabilistic strength of type x_i will be

$$\frac{(w_i x_i)^{m_i}}{m_i!}$$

Now let a neural network has n – units with m – external input lines with unified activation function f ($\sum_{i=1}^{n} m_i$). The system output Y for the weight vector w = ($w_1,\ldots,w_n$) may be taken as ($0 \le w_i \le 1$), (Because in case of indefinite large numbers the probabilistic models are best suited for infinity).

$$Y = \sum_{m_1,m_2,\ldots m_{n1}=0}^{\infty} f\left(\sum_{i=1}^{n} m_i\right)\prod_{i=1}^{n} \frac{(w_i x_i)^{m_i}}{m_i!} = \sum_{m=0}^{\infty} f(m) \frac{\left(\sum_{i=1}^{n} w_i x_i\right)^m}{m!} \quad \ldots (1)$$

By using the identity [7]

$$\sum_{m_1,\ldots,m_n=0}^{\infty} f\left(\sum_{i=1}^{n} m_i\right) \prod_{i=1}^{n} \frac{(x_i)^{m_i}}{m_i!} = \sum_{m=0}^{\infty} f(m) \frac{\left(\sum_{i=1}^{n} x_i\right)^m}{m!}$$

Provided the series involved are absolutely convergent.

Now as a group of neurons are similar in structure, the f(m) in (1) may be taken as a modular parameter k^m then

$$Y = \sum_{m=0}^{\infty} \frac{\left(k\sum_{i=1}^{n} w_i x_i\right)^m}{m!}$$

Or

$$Y = e^{kWX} \quad \text{where } WX = \sum_{i=1}^{n} w_i x_i$$

$$\equiv \lambda e^{WX} \quad , \quad (\text{Say})$$

Or

$$Y \ \alpha \ e^{WX}$$

Where λ is a learning constant of the system such that $0 \le \lambda \le 1$.

Thus we see that the system output is directly proportional to exponentially weighted sum of inputs with the constraints of learning capacity.

2. CONCLUSION

Further we are working on modification and application of such algorithms and the outcomes may come soon.

3. REFERENCES

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