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Neural Networks Pattern Classification for Certainty in Measurement of Position and Momentum with Heisenberg Uncertainty Principle

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Abstract – Heisenberg uncertainly principle can be discussed by using the pattern classification technique of Artificial Neutral Networks with Back propagation learning rue. In this process a suitable arrangement can be constructed that contains the control of two experiments, one of which is designed to measure the position and other one is designed to measure the momentum of a sub-atomic particle (the electron). The Control system will determine either the position of momentum of electron, which less uncertain for any wavelength of light at any instant and start measuring the less uncertain quantity with the corresponding experiment.

Keywords: Artificial Neutral Network, Pattern Classification, Heisenberg uncertainty Principle.

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INTRODUCTION

Can a machine take some decision and set the environment or some experiment situation according to this decision? The answer of this question is in affirmative that a lump of silicon and metal can take the decision and behave according to this decision as we human can do. Human performs all decision processing task with biological neutral network structure (Muller and Reinhardt, 1991) We can simulate this structure in a serial fashion that provides the parallelism that exists in the brain, and we call this structure as artificial neutral network (ANN). ANN consists of numerous simple processing elements. (PE) (McCulloch and Pitts, 1943), which can be globally programmed for computation. We can train the ANN for some specific application and it also learns from examples. Once the network has been trained, it is capable of performing the task with the accuracy as the human can do (Simpson, 1990). The field of ANN came into prominence mainly because of our ability to deal with natural performance in terms of process and constitutes activation dynamics and of Neutral Network is governed by neuronal dynamics that constitutes activation dynamics and synaptic dynamics (Kosko, 1991). When we train the network then this training process encode the pattern synaptic weights (Hebb, 949). In the pattern recognition task (Kanal, 1987) we given an input to the network and we can analyze that this input will find a meaningful categorization or classification. Network can be trained with the appropriate classification corresponding to input-output pattern, with any learning law (Hassoun, 1995). These learning laws may be either unsupervised learning laws (Zurada, 1992) or supervised learning laws (Rumelhart, et. al., 1986)

Various classification problems can be accomplished by the use of ANN which consists of layers of processing units, each one of which feeds the input to the next layer in a feedforward manner (Sontag, 1992) through set of connection weights. In the presence of pattern classification the connection weights are required to produce the appropriate classification for the various input patterns those are not be given in the training set. For such an updating of weights in super-history mode, it becomes necessary to know the desired output for each unit in the hidden and input layers so that the error the difference between the desired and actual outputs from each units may be used to guide the updation in weights. We may use the propagation learning rule (Werbos, 1974, Hush and Horne, 1993) in which differentiable non-linear output function for each unit in the hidden and output layers and propagated the error from output layer to the hidden layers for updating the weights. As we know that the Heisenberg uncertainty principle is the natural phenomenon that can arrive at from the point of view of wave particle duality. We might want to observe a sub-atomic particle and measure its position and momentum of the particle. For observing the particle, we must shine light of certain wavelength on it. If the wavelength of observing light is longer then there will be a great uncertainty in measuring of particle's position and if it shorter then there will be a great uncertainty in measuring the momentum of the particle i.e, the momentum and position of the particle cannot be simultaneously measured with certainty for any wavelength of observing light. It can also be shown that if any one of either position or momentum is likely to be certain with some measure then the other one become the uncertain with the same measure.

In this present paper, we are using the pattern classification technique with artificial neutral networks to train a system, which is capable to identify for which wavelength of observing light the position or momentum will likely to be measured. The suitable system for this purpose can be constructed that contains the control of two experiments A and B, where experiment A measures the position and experiment B measures the momentum of a sub-atomic particle, The system will decide whether the position or momentum is less uncertain for a certain wavelength of observing light sat any instant and starts measuring the less uncertain quantity with the corresponding experiment. Hence to accomplish this task we can start with back propagation supervisory learning algorithm of artificial neutral networks for training the network for proper classification of measurement in position and measurement in momentum for any wavelength of observing light to decide the control mechanism of the experiments. The technique can also be used to determine the prediction for measuring the position and momentum of the particle for a different wavelength of the observing light for which the network has not been trained.

HEISENBERG'S UNCERTAINTY PRINCIPLE WITH PATTERN CLASSIFICATION:

Heisenberg proposed a very interesting that is direct consequence of dual nature of particle (Heisenberg, 1972). According to classical mechanics a moving particle has a definite momentum and occupies a definite position in space and it is possible to determine both position and momentum at any instant. In quantum mechanics a particle is described by a wave packet, which moves with group velocity. Quantum theory comes out into play when we associate the wavelength with the momentum of the corresponding particle. If the wave packet does not have a well defined wavelength, the particle does not have a well defined momenturn, This means that there is not only an uncertainty in its momentum, caused by the spread in spread wavelength. The two uncertainties are interrelated, because the spread in wavelength (i.e, the uncertainty position). If we want to localize the particle more precisely, that is, if we want to confine in wave packet to a smaller region, this will result in an increase in the spread in wavelength and thus in an increase in the uncertainty in the momentum of the particle. According to Bohr's probability interpretation (Bordm, et. al., 1926), the particle may be found any where within the wave packet. For a large wave packet with many crests the spreadness in velocity is very small so that the particle velocity can be accurately determined, but the position of position of particle become very uncertain. On the other hand for a small wave packet, the position of the particle can be more or less fixed but the velocity spreads of such a packet is very large so that it becomes uncertain. Hence it is impossible to measure simultaneously both the position and momentum of a particle with certainty at any instant. The precise mathematical form of this relation between the uncertainty in position and momentum of a particle is given by Heisenberg as:

$$\Delta p \,.\, \Delta x \geq \frac{h}{4\pi} \qquad \ldots(1)$$

This equation indicates that the particle cannot possess a definite position as well as momentum at any instant and measurement process introduces the indeterminacy of the order Δp Δx. This indeterminacy is inherent in nature of a moving particle. Thus it can be understood by the Heisenberg uncertainty principle that in the sub atomic world both the momentum and position of a particle cannot be measure simultaneously with accuracy; but then will have to remain completely ignorant about the other one.

Now in the process of measuring either the momentum or position, which is less uncertain for the observing light, we can consider a system, which consists of a light source with n adjustable slit apparatus as shown in Fig.1, in which the width of slit can be increased or decreased and the observing photon beam of a certain wavelength λ comes out from the slit that strikes the electron. We can observe the electron with the help of a microscope of high resolution. Each photon of light has the momentum

$$\frac{h}{\lambda}$$

When these photons bounce off the electron, the original momentum will be changed. The exact amount of the change in momentum Δp cannot be predicted but it will be of the same order as the photon momentum.

i.e.

$$\Delta p \approx \frac{h}{\lambda} \qquad \ldots(2)$$

Because light has dual nature, wave nature as well s particle nature, we are not able to determine the exact location of electron in the substance regardless of high resolution instruments.

An estimate of minimum uncertainty in measurement of position of electron may be of one photon wavelength.

$$\Delta x \geq \lambda \qquad \ldots(3)$$

Hence the shorter the wavelength, the smaller the uncertainty in position. If we use light of short wavelength to increase the certainty in measurement of electron in the substance, there will be a corresponding decrease in the certainty in measurement of momentum of electron because the higher momentum of striking photon will perturb the motion of electron to a great extent. Light of longer wavelength will cause more certainty in measurement of electron with less certainty in measurement of position.

The system also consists of two experiment A and B, where experiment A measures the position and experiment B measures the momentum of electron. The two experiments A ad B are controlled by the intelligent network in such a way that experiment A will work only when the position of electron is likely to be measured with less uncertainty than the momentum and experiment B will work ony when the experiment works, then other site idle, i.e, these two experiments cannot work simultaneously for a certain wavelength of striking photon.

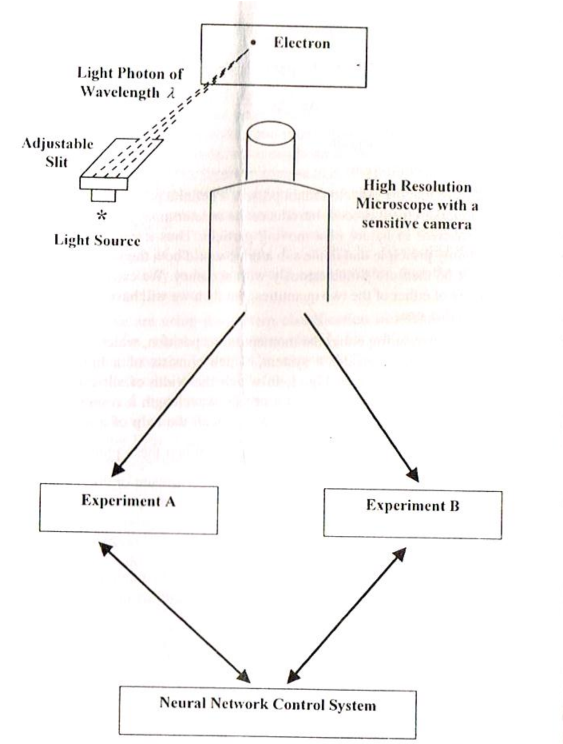

Fig. 1. Neural network control mechanism for measurement in position and momentum.

Thus for different wavelength of light photon, we can collect the input output patterns in which the different wavelength of observing light can be considered as the input patterns and corresponding the less uncertainty observation either in position or momentum can be considered as output pattern. Thus, the network can classify the input pattern the form of wavelength $(\lambda_1, \lambda_2, \ldots \lambda_i \ldots \lambda_j \ldots \lambda_n)$ into two classes, Class A and Class B. If the network produces an output I for any input pattern for which the light has shorter wavelength $(\lambda_1, \lambda_2, \ldots \lambda_i)$, then it belongs to class A and network will start experiment A. If the network produces an output 0 for any input pattern for which the slit has large width, say $(\lambda_i, \lambda_{j+1} \ldots \Lambda_n)$ then it belongs to class B and network will start experiment B.

To accomplish the task of pattern classification, we consider a multiple layer feed forward Artificial neutral networks (Sontag, 1992) as in Fig.2 with the non-linear differentiable function in all processing units of output and all hidden layers. The number of processing units in the input layer corresponds to the dimensionality of the input pattern vectors, which are linear. The number of output processing units corresponds to the number of distinct classes in the pattern classification. The problem that we are considering, containing only the two pattern classes one for position and other for momentum, can be classified with linear separability using only one processing output unit. The number of hidden layers decide the shape of convex and in the problem that we are discussing here involves only the linear separable classes so there is no necessity of any hidden layer but for the better and efficient classification, we may consider the one hidden layer with two processing units.

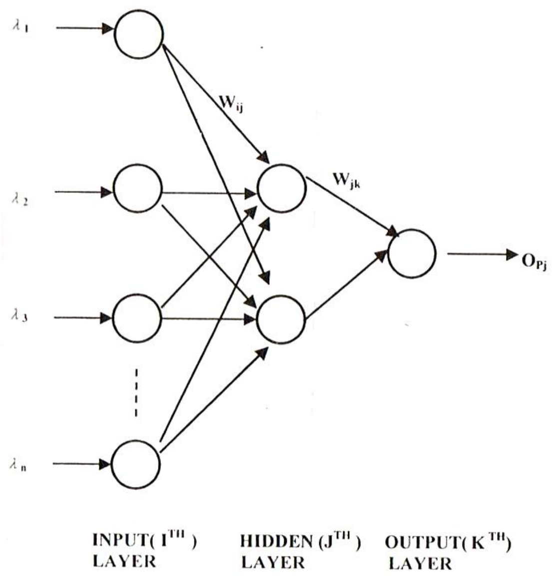

Fig. 2. Artificial neural netowrk structure.

Now we can use the method of back propagation leaving rule (Werbos, 1974) so that a network can be trained to capture the mapping implicit in the set of input output pattern collected during an experiment and simultaneously expected to model the unknown system or function from which the prediction can be made for the new or untrained set of date (Bordm, et. al., 1926).

Let us consider the input pattern (λ_j, λ_2,…. λ_i) from the set of input patterns for which the experiment A should work. This pattern can be trained to the system by defining the error as squared difference between the desired output and actual output as:

$$E_p = \frac{1}{2}\sum_j (t_{pj} - O_{pj})^2 \qquad \ldots(4)$$

Here the target output should be I.

i.e.

$$E_A = \frac{1}{2}\sum_j (1 - O_{Aj})^2 \qquad \ldots(5)$$

where, EA = Error function for experiment A.

QAj = Actual output for experiment A at node j

Thus, we are here providing training in the network for learning the patter for experiment A, hence O_{Aj} should be near to 1 for providing the correct classification and it can be achieved by reducing the error (E_A) with modification in weights of processing units of hidden and output layers as (Werbos, 1974).

$$w_{ij}(t+1)^h = w_{ij}(t) + \eta \dot{f}(net_{Aj})(1 - O_{Aj})O_{Ai} \qquad \ldots.6$$

$$w_{ij}(t+1)^o = w_{ij}(t) + \eta \dot{f}(net_{Aj}) \sum_k \delta_{Ak} w_{jK} \qquad \ldots(7)$$

If the input pattern is (λ_j λ_j…. λ_n) then the experiment B should work. This pattern can also be trained by the system by defining the error for which the target output should be 0;

$$E_B = \frac{1}{2}\sum_j (0 - O_{Bj})^2 \qquad \ldots(8)$$

where E_B = Error function for experiment B

Q_Bj = Actual output for experiment B at node j.

Thus, we are here providing training to the network for leaving the pattern experiment B, hence O_{nj} should be near to O for producing the correct classification and it can be achieved by reducing the error (E_B) with modification in weights of processing units of hidden and output layers as;

ALORITHM :

(1) Initialize the weights and threshold in the network for (w_1, w_2….. w_1…. w_j….. w_n) and (θ_1, θ_2….. θ_i…. θ_j….. θ_n) from the small random numbers.

(2) Present the input pattern in the form of different wavelength of observing light to the network as;

(λ_1, λ_2….. λ_i…. λ_j….. λ_n)

Select the desire output for the observed input pattern as;

For input pattern (λ_1, λ_2….. λ_i), the desired output is 1.

Fr input pattern (λ_j, λ_{j+1}….. λ_n), the desired output is 0.

(3) Do until the error is minimized up to a certain limit. Begin Compute the output function as :

$$O_{Pj} = f(w_{ij} O_{Pi}) \qquad \ldots..9$$

adjust the weight in output and hidden units as :

$$\Delta_p{}^{o} w_{ij} = \eta \dot{f}(net_{pj})(t_{pj} - o_{pj})o_{pi}$$
$$\Delta_p{}^{h} w_{ij} = \eta \dot{f}(net_{pj}) \sum_k \delta_{pk} w_{jk} \qquad \text{......10}$$

End

(4) If the output is classified in class A then the system will start the experiment A otherwise experiment B.

There is no situation that the two uncertainties are the same so there is no question of miss classification]

From the above discussion it can be understood that the network can be trained to decide which experiment should operate at any instant.

We can also use this arrangement for predicting the uncertainty in measurement of either position or momentum at any instant for any unknown input pattern in the form of light with different wavelengths, which has not been used during the training to the network. To meet this goal we can consider an unknown pattern λ_{j+k} and the network produced an interpolated version of the output class corresponding to the input learning pattern close to the given test input pattern. Thus, the network has been trained to capture the mapping implicit in the set of input output pattern and simultaneously expected to model the unknown function from which the prediction can be made about the new or untrained set of data. Hence the trained network will predict can be made about the new or untrained set of date. Hence the trained to be measured with certainty for the new unknown input pattern. Thus, if the network produces the interpolated version of output 1, then the position is less uncertain with respect to momentum. So the experiment A for measuring the position will conduct while setting other idle. And if the network produces the interpolated version of output O, then the position is less uncertain will respect to momentum. So the experiment B for measuring the momentum will conduct.

CONCLUSION:

Any sub – atomic particle such as an electron in a substance be observed without changing its momentum. To look at an electron, we must shine light of certain wavelength on it and the light photon strikes to the electron, cause the change in momentum of electron. Because of dual nature of particle there will be some indeterminacy in measurement of position and momentum of electron. To find out whether the position or light, we are using the neural network pattern classification technique with Back Propagation learning rule. In this process a suitable arrangement can be constructed that contains the control of two experiments, one of which can be used to determine the position and other one can be used to determine the momentum of electron. The Neutral Network control system will decide whether position or momentum of electron is likely to be certain for any wavelength of striking light photon and starts measuring the less quantity with the corresponding experiment.

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