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Data Driven Modeling Using Reinforcement Learning in Autonomous Agents

By

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ABSTRACT

This research has aspired to build a system which is capable of solving problems by means of its past experience, especially an autonomous agent that can learn from trial and error sequences. To achieve this, connectionist neural network architectures are combined with the reinforcement learning methods. And the credit assignment problem in multi layer perceptron (MLP) architectures is altered. In classical credit assignment problems, actual output of the system and the previously known data in which the system tries to approximate are compared and the discrepancy between them is attempted to be minimized. However, temporal difference credit assignment depends on the temporary successive outputs. By this new method, it is more feasible to find the relation between each event rather than their consequences.

Also in this thesis k-means algorithm is modified. Moreover MLP architectures is written in C++ environment, like Backpropagation, Radial Basis Function Networks, Radial Basis Function Link Net, Self-organized neural network, k-means algorithm. And with their combination for the Reinforcement learning, temporal difference learning, and Q-learning architectures were realized, all these algorithms are simulated, and these simulations are created in C++ environment.

As a result, reinforcement learning methods used have two main disadvantages during the process of creating autonomous agent. Firstly its training time is too long, and too many input parameters are needed to train the system. Hence it is seen that hardware implementation is not feasible yet. Further research is considered necessary.

ÖZ

Hazırlanan bu tez bazı yapay zeka öğrenme metodlarını makina mühendisliği bakış açısından incelemektedir. Bilgisayar teknolojisindeki gelişmeler pek çok disiplinde olduğu gibi makina mühendisliğinde de problem çözme metodlarını geriye döndürülemez bir şekilde değiştirmiştir.

Hazırlanan bu tezin amacı geçmiş deneyimlerine dayanarak öğrenebilen bir sistem geliştirmektir, özelde ise, deneme yanılma ile öğrenen otonom bir ajan geliştirmektir. Bu amacı gerçekleştirmek için bağlantısal yapay sinir ağları takviyeli öğrenme metodları ile birleştirilmiştir. Ve sistemin o anki çıktısı ile yakınsamaya çalıştığı değer arasındaki farkı en küçüklemeye çalışan klasik kredi atama metodu yerine, geçici başarılı hamleler arasındaki farkı en küçüklemeye çalışan geçici farklar metodu kullanılmıştır. Bu yeni metodun avantajı olaylarla yalnız sonuç arasındaki ilşkiyi değil aynı zamanda olayların birbiriyle olan ilşkilerini de yakalamaya çalışmasıdır.

Ayrıca bu tez çalışması sırasında K-means algoritmasında değişiklikler yapılmış, çeşitli çok tabakalı algılayıcı algoritmaları C++ ortamında gerçeklenmiştir. Bu algoritmalar Backpropagation, Radial Basis Function Network, Radial Basis Function Link Net, Self-organized neural network, k-means algoritmalarıdır. Bu algoritmalar takviyeli öğrenme metodlarından geçici farklar metodu ve Q-learning algoritmaları ile birlikte C++ ortamında gerçeklenmiştir.

Sonuç olarak, uygulanan takviyeli öğrenme metodlarının gerçek problemlere uygulanmasına engel olan iki yönü olduğu görülmüştür bunlar; programların öğrenme sürelerinin çok uzun ve yapay sinir ağlarını eğitebilmek için gerekli olan girdi sayısının çok fazla olmasıdır. İleride yapılacak çalışmalarda bunların iyileştirilmesi gerekmektedir.

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CHAPTER 1

INTRODUCTION

Throughout the history, humans have always been fascinated by intelligence. It is this very trait that separates homo sapiens from other living beings. Philosophers, thinkers, scientists all attempted to understand and make a definition of such an intangible yet such a conspicuous quality as intelligence. Understanding the secrets of the human brain will always be an interesting research area for scientists.

Artificial Intelligence research areas comprise many mathematical methods and biologically inspired architectural methods as well. This research mostly built on the Neural Networks (NNs) methods. The author prefers to use NNs, because they have strong approximation capabilities, yet suffers from generalization difficulties. And it is proven to be a robust function approximator.

Connectionist NNs are inspired from biological structures, but it is only inspiration that should be kept in mind. To understand what is placed behind this inspiration, biological neurons will be briefly discussed. Biological neurons are comprised of three parts; Axon, dendrite, and soma. In this structure, dendrites are used to supply the input data, and then the system responds through the axon after the input is processed at soma. As it is the case with the biological neurons, an algorithm can be developed by Object Oriented programming methods. C++ computer language has been used to create Simulated Artificial Neural Networks (SANNs).

Developing simulated artificial neural networks in C++ IDE brings us great flexibility. Once a node is described as a class, then it can be reused for another time. Also C++ programming language is much faster than the other editors like MATLAB.

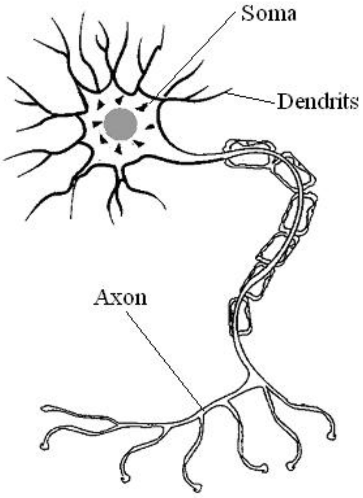


Figure 1.1 A biological neuron

The connectionist NNs first developed in the simplest form by Widrow and Hoff [1] which consist of two layers, input layer and output node but only the output node has an activation function, which is a linear function and it can only solve linearly separable problems. This simple architecture named ADALINE NN.

After ADALINE NN, new architectures are developed like Multi Layer Perceptrons (MLP). In MLPs some new activation functions are utilized like sigmoid or Gaussian activation functions.

Indeed AI methods can be subsumed into three main categories, they are supervised, unsupervised and reinforcement algorithms. MLPs are the most popular and widely used supervised algorithms. Supervised algorithms need input-output pairs. With these pairs, through the error propagation, network approximates a function. Apart from supervised algorithms in unsupervised algorithm there is no error to back propagate and there is no target to reach, instead, this type of algorithms only works on input pairs and tries to arrange inputs according to pre-specified rules. These rules can be some declaration such as minimize the cluster centers or distance between inputs and cluster centers. Reinforcement learning (RL) attempts to learn from its past experience and it is expected that after each trial it is going to respond more rationally. In this research all these AI methods are used.

Self-Organized NNs are used as an unsupervised learning method, which is developed by Teuvo Kohonen [2]. And Radial basis NNs and Backpropagation NNs are used as MLP. Q-Learning and Temporal Difference reinforcement learning are implemented as reinforcement algorithms.

1.1 Motivation

AI methods are not a panacea, indeed these methods were developed to create intelligent systems, and however their mathematical power, robustness and their ease of implementation make them widely used tools both in engineering and operational sciences, also Neural Network models are used for simulating and understanding the nature of the biological neurons.

If the parameters can be tuned appropriately, the system can be easily identified to be built and predictions can be made over its future behavior.

We are inspired from the nature and during this research an autonomous agent is intended to be built, that can learn from its environment and respond to new conditions rationally. In nature, there are relatively simple animals that can carry out many complex daily tasks, and we want to create a system which resembles these relatively simple yet skillful biological animals. But it remains only as an inspiration at the moment and the rest is simulations, mathematical modeling and crude experimentation.

CHAPTER 2

MULTI LAYER PERCEPTRONS

MLP algorithms will be described in the following sections. MLPs fundamental points will be introduced at back propagation section. Then Radial Basis Function NN and Radial Basis Function Link Net structures will be discussed.

2.1 Back propagation

Having developed ADALINE linear separator, there are still some questions, like, is there a computational method that this structure can be used in multiple layers? If we can find a way prompt the middle layer nodes to respond in an appropriate way to approximate the associated output? This procedure is named credit assignment problem.

Back propagation (BP) algorithm was the answer to these questions. This algorithm and architecture was the first developed MLP architecture, it can contain more than one output and more than one middle layer.

BP algorithm is needed because so far only the linear separator was used and from the classification point of view, they can only separate the clusters that can be divided by a line. However in real life problems there are too many complex situations exist that we have to use more intricate lines. MLP structure and algorithm gives us that opportunity.

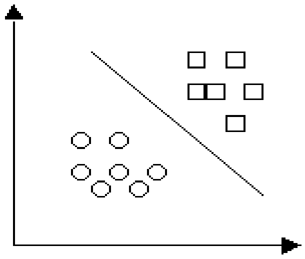


Figure 2.1 Linearly separable two clusters

To train a MLP, Gradient Descent method can be used. This method provides us a tool to direct the middle layer nodes to follow the appropriate direction to minimize the distance between the target value and the actual output.

To train the network, input values and target values are used in which represented by “x” and “t” symbols respectively.

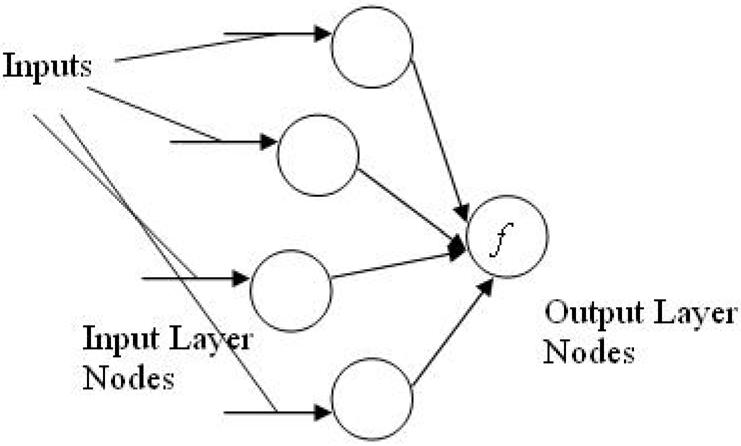


Figure 2.2 Architectural structures of ADALINE NNs.

In BP algorithm every middle and output layer uses an activation function. Mostly sigmoid activation functions are used, hence the output of the network will be between 0 and 1. Also Gaussian distribution can be used as an activation function because of the formation of the function this structure is named as Radial Basis NN.

In MLP every input layer node is connected to the every middle layer node and every middle layer node is cooperated to the every output layer node. Process begins when the input data is presented to the input layer. Consequently, these data is multiplied by the corresponding link value which is called weight. This multiplication is used to weight the input values. After the multiplication is done, summation of this value is presented to the activation function and this process goes on to the end of the output layer. After this procedure output value compared with the expected output value and the distance between them are taken as an error to back propagate. Hence, it is called back propagation.

$$E = \sum_{j=1}^{J} (t_j - z_j)^2 \qquad (1)$$

“E” represents the total error term and “z” is the actual output for the input “j”.

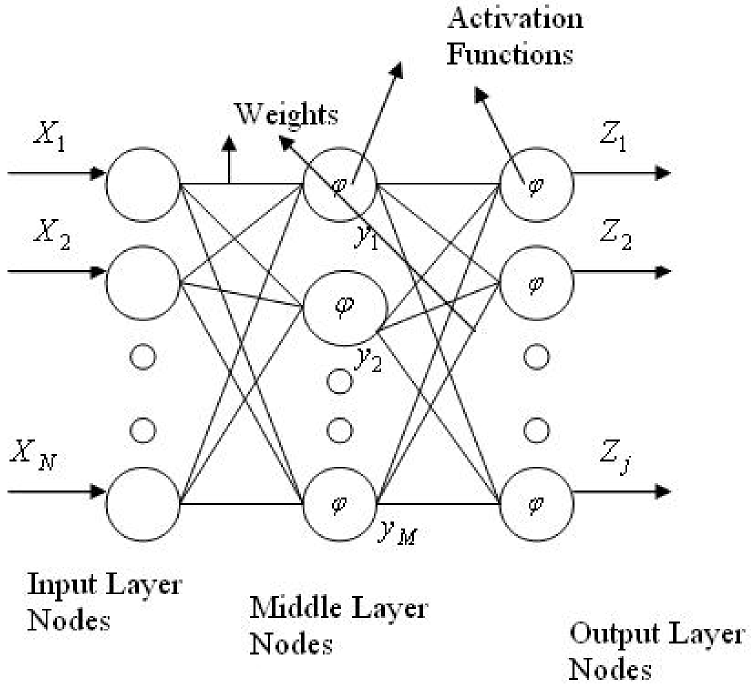


Figure 2.3 Structures of MLPs.

The BP scheme is in the following form:

The derivative of the error with respect to the weight connecting i to j is;

$$\frac{\partial E}{\partial W_{ij}} = \delta_j y_i \tag{2}$$

To change weights from unit i to unit j by;

$$\Delta W_{ij} = -\eta \delta_j y_i \tag{3}$$

Where;
η is the learning rate ($\eta > 0$)
δ_j is the error for unit j
y_i is the input from unit i

Every middle layer node employs an activation function. BP process, a sigmoid function is used because sigmoid function can easily be calculated and differentiable form.

$$y = f(a) = \frac{1}{1+e^{-a}} \tag{4}$$

And its derivative is;

$$f'(a) = f(a)(1 - f(a)) \tag{5}$$

Every input value is calculated in weighted form;

$$y(x) = w^T f(x) \tag{6}$$

It is crucial to compute the error term for both output units and the middle units. For output unit

$$\delta_k = (y_k - y_{\text{target}}). \tag{7}$$

For hidden unit

$$\delta_j = y_j(1 - y_j)\sum_k W_{ij}\delta_k. \tag{8}$$

Gradient descent algorithm physically means that, magnitude of error and the direction is calculated so as to minimize the error, new weight values are driven in the opposite direction. The learning rate determines the amount of update in the specified direction.

2.2 Radial Basis Function NNs

Radial basis function NN (RBFNN) was first developed in 1964 as potential function [3, 4], but first used for non-linear regression in [5]. RBFNNs were brought to widespread attention by Broomhead & Lowe [6] and Moody & Darken [7].

RBFNNs are widely used because they can be trained in a fast and robustly manner. Also it has strong scientific base. RBFNNs have the same structure with MLP. Every input layer node is connected to the every middle layer node and every middle layer node is connected to the every output node.

RBFNNs use Gaussian distribution function as an activation function;

$$\varphi(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-m)^2}{2\sigma^2}} \tag{9}$$

Where x is the input, m is mean and σ expression is the standard variance. Gaussian function given in (9) gives the maximum value when the center of the distribution and the input value are the same. If the input datum is very close to the cluster center, Gaussian function produces an output which is very close to unity. On the other hand if the datum is far from the center, the output value will be close to zero. This decrease from 1 to zero is proportional to datum point distance from the center. Its distribution can be seen at figure 2.4. As output nodes are the summation nodes.

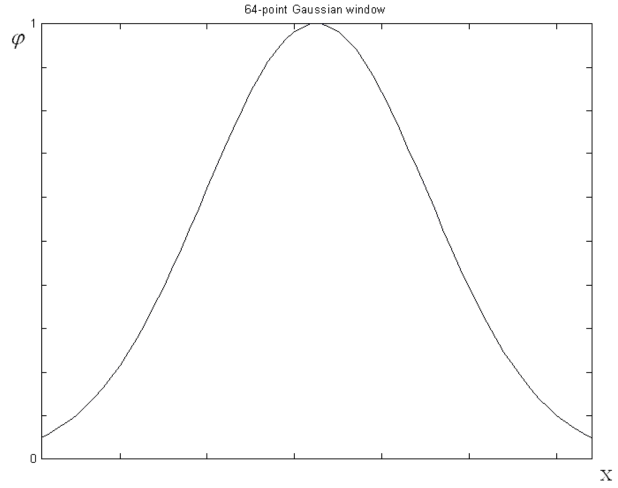


Figure 2.4 Gaussian function

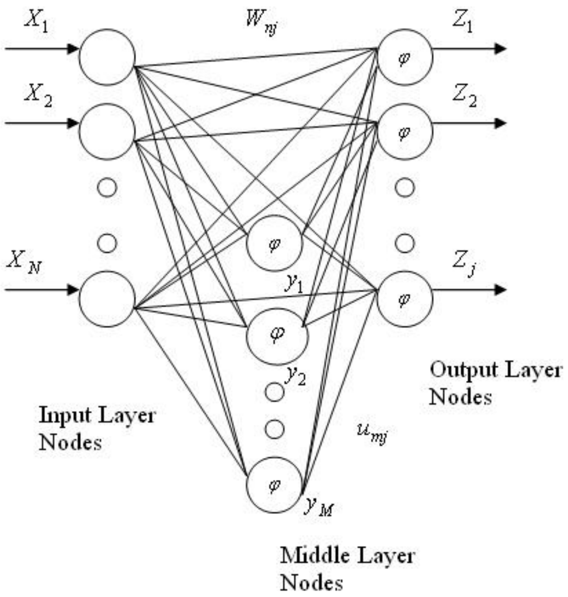


Figure 2.5 Structure of RBFLN.

Some slight modification can be done on this architecture. Every input layer node can be combined to the every output layer node like bias nodes. With these architectural changes better approximation performance can be obtained and this structure is named as Radial Basis Function Link Net (RBFLN) [8] and it is stated that it gives better performance than RBFNN. Because with the RBFLN algorithm additional links that combine the input nodes to the output nodes also gives us a chance to cover the linear portion of the feature space. Its structure can be seen at the figure 2.5.

RBFNN is needed because even the old structures are capable of drawing some complex separator line, the clusters can not be separated appropriately. In these situations the density distribution around the unknown datum can be used to separate these clusters. There is a method to find the density which is named Parzen's method of density estimation

2.3 Parzen's Method of Density Estimation

Parzen [9], suggested an excellent method for estimating the uni-variate probability density function from random sample. As the sample size increases this method converges to the true density function. Parzen's probability density function (PDF) estimator uses a weight function, W (d), which is called a kernel, has its largest at d=0 and which decreases rapidly as the absolute value of d increases. One of these weight functions is centered at each training sample point, with the value of each sample's function at a given abscissa x being determined by the distance d between x and that sample point. His PDF estimator is a scaled sum of that function for all sample cases.

Parzen's method mathematically stated as in the following form. A sample of size n from a single population is collected. And an estimated density function is obtained like Gaussian.

$$g(x) = \frac{1}{n\sigma} \sum_{i=1}^{n} W(\frac{x - x_i}{\sigma}) \tag{10}$$

The scaling parameter sigma defines the width of the bell curve that surrounds each sample point. Calculating the appropriate sigma value has profound effect on the solution, if it is too small because individual training cases to exert too much influence, losing the benefit of aggregate information. Values of sigma that are too large cause so much blurring that the details of the density are lost, often distorting the density estimate badly.

We have considerable freedom in choosing the weight function. There are surprisingly few restrictions on its properties. [9] And [10] state them explicitly. There are some simple definitions to develop a new weight function.

-The weight function must be bounded.

$$\sup_{d}|W(d)|<\infty$$

-The weight function must rapidly go to zero as its argument increases in absolute value. This restriction, which is the most likely violated by careless experimenters, is expressed in two conditions.

$$\int_{-\infty}^{+\infty}|W(x)|\,dx<\infty$$

$$\lim_{x\to\infty}|xW(x)|=0$$

-The weight function must be properly normalized if the estimate is going to be a density function, rather than just a constant multiple of a density function.

$$\int_{-\infty}^{+\infty}W(x)dx=1$$

-In order to achieve correct asymptotic behavior, the window must become narrower as the sample size increases. If we express sigma as a function of n, the sample size, two conditions must be true.

$$\lim_{n\to\infty}\sigma_n=0$$

$$\lim_{n\to\infty}n\sigma_n=\infty$$

2.4 Training Methods

Both RBFNN and RBFLN can be trained with the same procedure except for the additional links. And again the gradient descent training algorithm is used. According to this algorithm centers, sigma terms and all weights are updated following the given procedure.

Error term is found by;

$$E=\sum_{q=1}^{Q}\left\{\sum_{j=1}^{J}(t_j-z_j)^2\right\}$$

Where;

J =1.....J (J is the number of output nodes)

m=1....M (M is the number of middle layer nodes)

q =1....Q (Q is the number of inputs)

t = Target

C= Center of a cluster

S = σ (sigma)

$$W(t+1) = W(t) - \eta(\partial E / \partial W)$$

$$C(t+1) = C(t) - \eta(\partial E / \partial C)$$

$$S(t+1) = S(t) - \eta(\partial E / \partial S)$$

Output value is given as in the following formulation;

$$z_j = [1/M] \left\{ \sum_{m=1}^{M} W_{mj} \varphi_m \right\}$$

For this section calculations are given for the RBFLN shown in figure 2.5 however it can easily be implemented to the RBFNN case.

The RBFNN has an input layer of N nodes, a hidden layer of M nodes and an output layer of J nodes. Calculation begins when the input vectors x are presented to the input layer. The outputs from the m-th hidden layer neurode and the j-th output layer neurode, respectively, for the q-th input exemplar vector are

$$y_m^{(q)} = \exp\left[-\left\| x^q - v^m \right\|^2 / (2\sigma_m^2) \right] \qquad (11)$$

$$z_j^{(q)} = (1/M) \left[\sum_{m=1}^{M} u_{mj} y_m^{(q)} + b_j \right]. \qquad (12)$$

“v” stands for the cluster center and the “σ” stands for the spread parameter.

Where m=1…M and j=1 …J. The weights u_{mj} are on the connection lines from the hidden layer to the output layer. “b” term represents the bias term, if it is employed.

Given a sample of Q input exemplar feature vectors and a set of Q associated output target vectors

$$\left\{x^{(q)} : q = 1,......Q\right\} \qquad \text{and} \qquad \left\{t^{(q)} : q = 1,......Q\right\}$$

The training of an RBFNN consists of the following two stages: i) initialization of the centers, spread parameters and weights; and ii)weight and parameter adjustment to minimize the output total sum squared error E (TSSE) defined as the sum of the partial sum-squared errors (PSSEs) in

$$E = \sum_{q=1}^{Q}\left\{E^{(q)}\right\} = \sum_{q=1}^{Q}\left\{\sum_{j=1}^{J}(t_j^{(q)} - z_j^{(q)})^2\right\} \tag{13}$$

The RBFLN output components differ from equation for RBFNNs and are given by

$$z_j^{(q)} = \left[1/(M+N)\right]\left\{\sum_{m=1}^{M} u_{mj} y_m^{(q)} + \sum_{n=1}^{N} w_{nj} x_n^{(q)}\right\} \tag{14}$$

Training on the weights is extremely quick via steepest descent per iteration

$$u_{mj} \leftarrow u_{mj} - \eta_1(\partial E/\partial U_{mj}) = u_{mj} + (\eta_1/(M+N))\sum_{q=1}^{Q}(t_j^{(q)} - z_j^{(q)})y_m^{(q)} \tag{15}$$

$$w_{nj} \leftarrow w_{nj} - \eta_2(\partial E/\partial w_{nj}) = w_{nj} + (\eta_2/(M+N))\sum_{q=1}^{Q}(t_j^{(q)} - z_j^{(q)})x_n^{(q)} \tag{16}$$

Each center (v) and spread parameter (σ) can also be updated with steepest descent via

$$v_n \leftarrow v_n - \eta_3(\partial E/\partial v_n) = v_n^{(m)} + \left[\eta_3/\sigma_m^2\right]\sum_{q=1}^{Q}\left\{\sum_{j=1}^{J}(t_j^{(q)} - z_j^{(q)})u_{mj}\right\}y_m^{(q)}(x_n^{(q)} - v_n^{(m)}) \tag{17}$$

$$\sigma_m^2 \leftarrow \sigma_m^2 - \eta_4(\partial E/\partial \sigma_m^2) = \sigma_m^2 + \left[\eta_4/\sigma_m^4\right]\sum_{q=1}^{Q}\left\{\sum_{j=1}^{J}(t_j^{(q)} - z_j^{(q)})u_{mj}\right\}\left[y_m^{(q)}\left\|x_n^{(q)} - v_n^{(m)}\right\|^2\right] \tag{18}$$

2.5 Responsive Perturbation Training

Responsive perturbation training (RPT) is a newly proposed [11] algorithm in the traning arena. It uses the general philosophy of combining genetic algorithms (GA) and simulated annealing (SA). Nonetheless, in RPT, both the GA and the SA are changed in such a way that neither is the original optimization method other than the slight semblance in the guidelines. For example, when a population is created, individuals are not converted to binary strings, since no crossing occurs. Instead of selecting the best performing individuals, only the best is kept.

Perturbation replaces the crossing. A new family of individuals are created by perturbing the best solution. This guarantees that all the offsprings are the variations of the best parent. The pertubation is a gaussian noise, whose variance is monotonically decreasing or simply given by a function, added to the selected individual.

RPA is a simple and robust algorithm. Its simplicity saves on CPU time. Weight and sigma update equations are given by

$$S(i,j) = S(i,j) + (\text{percent error}) * R,$$

$$w(i,j) = w(i,j) + (\text{percent error}) * R,$$

Where i=1...K, j=1...number of individuals, and

R = k * r. Here k is a suitable coefficient, less than unity, and r is Gaussian noise with zero mean.

Thus RPA is an error-driven process. With the carefully arranged coefficient, weight and spread parameters are perturbed less and less in amplitude by use of the error term. This eliminates the occasional need for hill-climbing. Unless the error reaches a certain level, the perturbation amplitude never drops and the algorithm keeps searching within a specified search radius. At the outset, error is high and a rough search starts, and a neighborhood of solution is sought to converge to. Once the neighborhood is roughly spotted, the search closes in on the optimal vectors. Usually, towards the final stages of the search, noise variance is reduced, and the coupled effect of error and the reduced noise variance help smoothen the computed vectors.

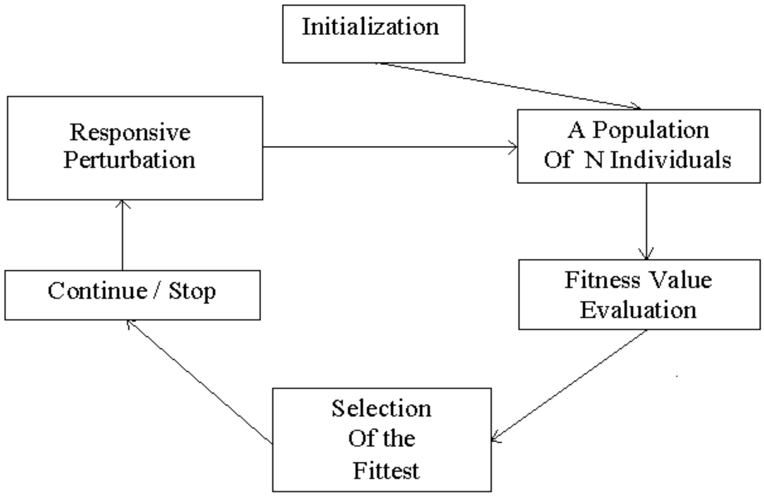


Figure 2.6 Responsive Perturbation Algorithm [11].

2.6 How Does It Work?

Apart from the BP in RBFNN, every middle layer represents a cluster which has a center in Gaussian distribution and they are represented by the mean (m) and cluster diameter which is given by sigma (σ). If we can represent the feature space with an optimum number of clusters and appropriate sigma and mean, function can be more easily approximated. And if the feature space can be sufficiently covered, systems response will be improved.

However many nodes can be used at middle layer which means that more clusters are used and it gives more accurate solutions, on the other hand operator should avoid from over-fitting because it will not be a healthy solution.

And with the RBFLN algorithm additional links that combine the input nodes to the output nodes also gives us a chance to cover the linear portion of the feature space.

It can easily be seen that the RBFNN needs cluster centers and we will see that these centers can be initialized more accurately than a random process. A unsupervised algorithm and a supervised algorithm are utilized to compliment them.

2.7 Clustering Algorithms

In a real world problem most of the time data must be arranged to make them useful in applications where number of data is too many to calculate, most of the time plenty of data is available, so their number must be decreased. Even in these conditions a new datum must be classified correctly especially in pattern recognition application.

However as in the RBFNN, cluster centers must be known. With clustering algorithms cluster centers can be found appropriately to cover the feature space.

To visualize the clustering methods, following application will be introduced. For the following data some vehicles are shown as a point in the figure 2.7 according to their weight and speed.

As in the table 2.1, if a vehicle's correct cluster is not known, at first sight it is hard to recognize from the list of data. However if the data is drawn to a table it is more easy to obtain the relation between these data.

Normalized data are used for this application to obtain more healthy solutions and it is a good practice to use normalized data. In this application there are six clusters sports vehicles, medium market cars, trucks, race cars, semi-expensive and sports vehicles.

Instead of drawing a figure, an algorithm can be written to do this. In literature there are some algorithms. In the following section these algorithms will be examined. The author prefers k-means and SONN application to represent the supervised and unsupervised algorithms respectively.

Table 2.1 Vehicle speed and weight information

				Normalized	
	Speed	Weight		Speed	Weight
1	220	1300	Sports Vehicles	0.5571	0.3182
2	230	1400		0.5952	0.3446
3	260	1500		0.7095	0.3711
4	140	800	Medium Market Cars	0.2524	0.1860
5	155	950		0.3095	0.2256
6	130	600		0.2143	0.1331
7	100	3000	Trucks	0.1000	0.7678
8	105	2500		0.1190	0.6355
9	110	3500		0.1381	0.9000
10	290	475	Race Cars	0.8238	0.1000
11	275	510		0.7667	0.1093
12	310	490		0.9000	0.1040
13	180	1050	Semi-expensive	0.4048	0.2521
14	200	1100	Sports Vehicles	0.4810	0.2653
15	205	1000		0.5000	0.2388

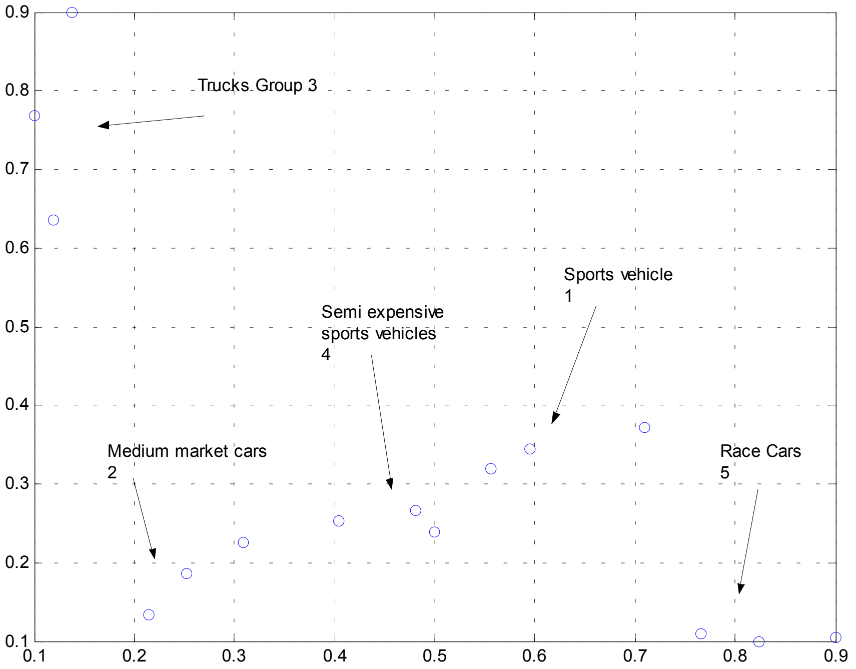


Figure 2.7 Graphical representations of vehicles

2.7.1 Self-Organizing Neural Networks

Self-organizing neural network (SONN) is first developed by Teuvo Kohonen (1982). SONN is an algorithm that can be used to cluster data. Indeed MLP type neural networks can also be used for clustering. However MLP type algorithms are known as a supervised algorithm, it means that network is trained with some known data and then the network response is used for clustering unknown data.

For SONN, there is no error to back propagate or desired output for the system instead system decides its response according to the results that find with its algorithm.

Its structure consists of two layers input layer and kohonen layer, as it is shown at the figure 2.8.

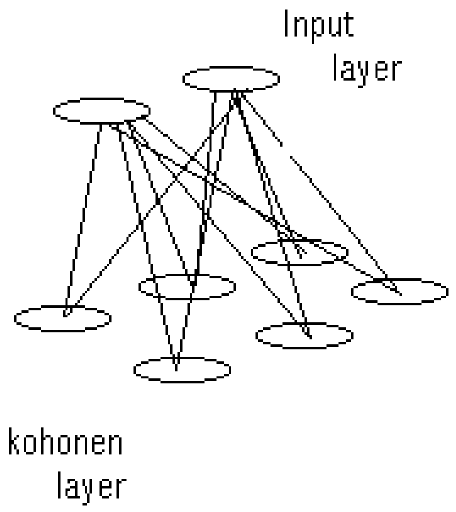


Figure 2.8 Structure of SONN

Input layer is used to present the data. Kohonen layer nodes and their positions represent the topological position of clusters and its link values can be assumed as their center position.

Computation begins when the input data presented to the input layer. And every input datum is compared with every kohonen layer node and their Euclidian distance is calculated. After this calculation a winner node is found for each input datum as follows.

$$Dist_{x,y}(t) = \sqrt{\sum_{k=0} (n_{0,k}(t) - w_{0,k\rightarrow 1,(x,y)}(t))^2}$$

Where $n_{0,k}(t)$: the k^{th} node in the input layer at the time "t". $w_{0,k\rightarrow 1,(x,y)}(t)$ represents the link value which is combined to the k^{th} node in the input layer from node at kohonen layer which is placed at (x,y).

Algorithm of SONN is inspired from biology. In human brain there is a layer which is called cerebral cortex. At cerebral cortex biological process depends on lateral interaction like SONN. As in the figure 2.9 after calculation of the winning node, winning node and its neighbors are updated. Nodes that are placed outside of this boundary do not participate in learning.

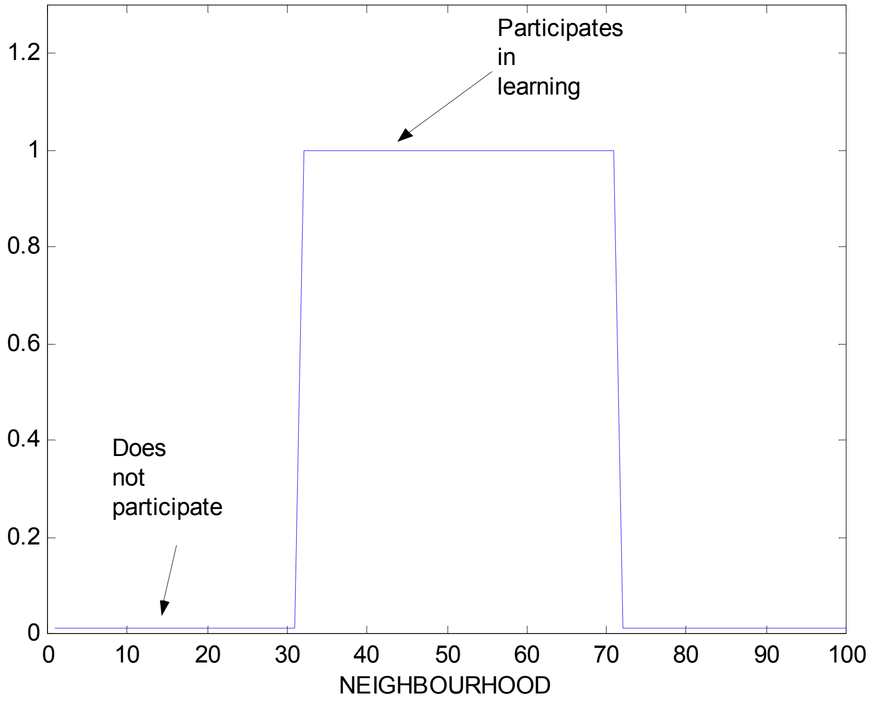


Figure 2.9 Step functions that used to determine the nodes within the neighborhood

$$N_{i,j}(t) = \begin{cases} 1 & \text{if} \quad Win_{row}(t) - H(t) \le i \le Win_{row}(t) + H(t) \\ & \text{and} \\ 0 & \text{othervise} \qquad Win_{col}(t) - H(t) \le i \le Win_{col}(t) + H(t) \end{cases}$$

“N” term shows whether this node participates in learning or not. “H” represents the width of the neighborhood of the winning node and it is decreased as the time is increased. Learning rate parameter (Lr) should be decreased appropriately. Neighborhood (H) and learning rate parameter should be minimum for the last 10% of the iteration.

Weight values are updated according to the following procedure.

$$\Delta_{i,k\to 1,(i,j)}(t+1) = N_{win_{row}(t+1)win_{col}(t+1)} Lr(t)(n_{0,i}(t+1) - w_{0,k\to 1,(i,j)}(t))$$

$$W_{0,k\to 1,(i,j)}(t+1) = W_{0,k\to i,j}(t) + \Delta_{0,k\to 1,(i,k)}(t+1)$$

2.7.2 K-Means Algorithm

K-means algorithm is a widely used clustering algorithm. Its strength comes from its simple mathematical fundamentals, hence it can be easily implement able. However k-means algorithm has supervised type and heuristic nature. So it must be applied for many k terms.

Term “k” comes from the initialized number of clusters hence before running the program, we know, how many clusters we are going to have. This procedure tries to divide the feature space into number of “k” slices, according to the Euclidian distance equation. Performance index for the ith cluster;

$$F_i = \sum_{j=1}^{Ni} \left\| x_j \cdot Z_i \right\|^2$$

This algorithm is iterative k based on minimization of a performance index F.
K: Number of clusters specified by user.
F: Sum of squared distance of all points in a cluster to the cluster center.

$$F_i = \sum_{j=1}^{Ni} F_i$$

We have ınput data $\{X_1, X_2, ...X_N\}$

1) Choose initial cluster centers $\{Z_1^1, Z_2^1, ...Z_K^1\}$

2) Each individual input datum $\{X_i\}_{i=1}^{N}$ classified into the one of the k number of clusters according to the distance between initial cluster centers and itself. And than the input datum is assigned to the cluster, which has minimum distance.

$$X \in Cluster\ Z_i^{(j)} \quad \text{M, if} \quad \left\| x - Z_m^j \right\|^2 \le \left\| x - Z_p^j \right\|^2 \quad \forall \quad P \ne m \quad \text{P, m=1, 2...K}$$

3) Update all cluster centers for i=1, 2 …K. Distance of all patterns to the new cluster centers should be minimized.

4) If the centers are not changed for some number of iteration, iteration can be stopped, otherwise go to step 2.

The k-means algorithm finds locally optimal solutions with respect to the clustering error. It is a fast iterative algorithm that has been used in many clustering applications. It is a point-based clustering method that starts with the cluster centers initially placed at arbitrary positions and proceeds by moving the cluster centers at each step in order to minimize the clustering error. The main disadvantage of the method lies in its sensitivity to initial positions of the cluster centers. Therefore, in order to obtain near optimal solutions using the k-means algorithm several runs must be done differing in the initial positions of the cluster centers.

-1- It implies that the data clusters are ball-shaped because it performs clustering based on the Euclidean distance.

-2-Also there is the dead-unit problem. That is, if some units are initialized far away from the input data set in comparison with other units, they then immediately become dead without learning chance any more in the whole learning process.

-3-It needs to pre-determine the cluster number. When k equals to optimum number of k, the k-means algorithm can correctly find out the clustering centers. Otherwise, it will lead to an incorrect clustering result, where some of centers do not locate at the centers of the corresponding clusters. Instead, they are either at some boundary points among different clusters or at points biased from some cluster centers.

2.7.3 K-means as a NLP problem

Clustering problem is solved from a NLP standpoint. Rather than applying the standard procedure, helpful constraints are added to have more control over the segmentation process. For example, the first constraint may help eliminate outlier clusters if certain clusters fail to contain enough samples. The second constraint, however, is only indirectly controllable by use of h, the minimum prescribed number of samples that a cluster ought to possess, and determines the maximum allowable allotment of samples to any cluster during the running of the code.

Terminology

k_i : Clusters, $i = 1..K$,

K : The total number of clusters,

h : The minimum number of data points required in a cluster to constitute a cluster.

N : The total number of data,

D : Data space, a dim x N matrix.

d_i : Vector of dimension dim, i = 1 .. N,

P_i : The number of data points in i^{th} cluster, i = 1 ..K,

c_i : i^{th} cluster center of dimension dim, i = 1 .. K.

$$\bigcup_{i=1}^{K} k_i = D \tag{19}$$

$$k_i \cap k_j = \varnothing, \qquad i \neq j \tag{20}$$

-2- States that no fuzzy membership exists between the clusters and the clustering is, in fact, a hard clustering.

$$h \subseteq \mathrm{P}_i \subset \mathrm{D} \tag{21}$$

$$\mathrm{N} \geq K \geq 2 \tag{22}$$

The Problem Statement;

Minimize Cost Function

$$\mathrm{J} = \sum_{i=1}^{K} \left(\sum_{j=1}^{N} \left\| \mathrm{ci} - \mathrm{dj} \right\|^2 \right), \quad dj \in ki \tag{23}$$

s.t.

i) $P_i \geq h$, where i = 1... K, (24)

and

$$\textbf{ii)}\, P_i \le \left[(N - \sum_{r=1}^{i-1} \mathrm{P_r}) - (K-i)h \right],$$

$$\text{Where i = 1... K.} \tag{25}$$

The constraint (24) enforces the lower limit in that the number of data within any cluster may not be less than the prespecified h, and (25), given the data space, determines the upper limit.

It should be noted that

$$\sum_{i=1}^{K} P_i = N \tag{26}$$

And the membership to any cluster is derived as follows

$$\begin{aligned} &d_j \in k_i \ \text{ if } \|c_i - d_j\|^2 \le \|\mathrm{c_k - d_j}\|^2, \quad \mathrm{i \ne k} \\ &\text{else} \\ &d_j \in k_k, \quad \mathrm{i, k = 1..K, \ j = 1..N} \end{aligned} \tag{27}$$

2.8 Combining Techniques

Learning techniques are often divided into supervised, unsupervised and reinforcement learning (RL). Supervised learning requires the explicit provision of input-output pairs. And the task is constructing a mapping from one to the other. Unsupervised learning has no concept of target data, and performs processing on the input data. In contrast, RL uses a scalar reward signal to evaluate input-output pairs and hence discover, through trial and error, the optimal outputs for each input. In this sense, RL can be thought of as intermediary to supervised and unsupervised learning since some form of supervision is present, albeit in the weaker guise of the reward signal. This method of learning is most suited to problems where an optimal input-output mapping is unavailable a priori, but where a method for evaluating any given input-output pair is available instead.

Often these three learning paradigms can be combined. For example, supervised learning may be used to achieve forms of unsupervised learning as in the autoassociative MLP of [12]. Conversely, unsupervised learning can be used to support supervised learning as, for example, in radial basis networks [13] and also the SOM-MLP hybrid model of [14]. Alternatively, supervised learning can be embeded within an RL framework. Examples are common, the Q-AHC algorithm of [15] (Based on the adaptive heuristic critic (AHC) and actor-critic models of [16], [17], the backgammon learning application of [18,19], the QCON arhitecture of [20], and the lift scheduler of Crites and [21], all of which make use of the MLP and the backpropagation training algorithm. Similarly, unsupervised learning may also be used to provide representation and generalization within RL as in the self-organizing map (SOM) based approaches of [22, 23].

In this research, radial basis function NN is used as a main function approximator. In the process, it is crucial to cover the feature space. It is known that, to cover the feature space radial basis cluster centers must be chosen appropriately. If the centers can not be obtain appropriately computation time takes to long and most probably the results will not be healthy.

To obtain the cluster centers the author prefers to use K-Means and SONN. Additionally slight modifications are made on K-Means algorithm and also its performance is compared.

2.8.1 SONN & RBFNN

When the SONNs are used, number of clusters that will be obtained at the end of the process is not known or given initially. This is very useful for the process that the system is searching through the unknown region. Sometimes our data base is very huge and it needs to be diminished that can be used in process. Otherwise it needs huge time to be processed.

It is much better when the cluster represented by a center and the cluster's diameter instead of great number of data point. This flexibility can be implemented through the nature of RBFNN.

This algorithm will be discussed deeply at the simulations and experiments section. However its simple architecture will be given in this section.

2.8.2 K-Means & RBFNN

In this combining techniques section, aim is to find the right cluster centers appropriately and in the previous section unsupervised algorithm is used however in this algorithm a supervised algorithm was used.

Both conventional K-means algorithm and the author modified K-means algorithm need to be given initial number of cluster centers. Hence k-means algorithm has a draw back. So, if the number of clusters can not be given appropriately, most probably the solutions will be incorrect. Also this algorithm will be discussed in depth at simulation and experiments' section.

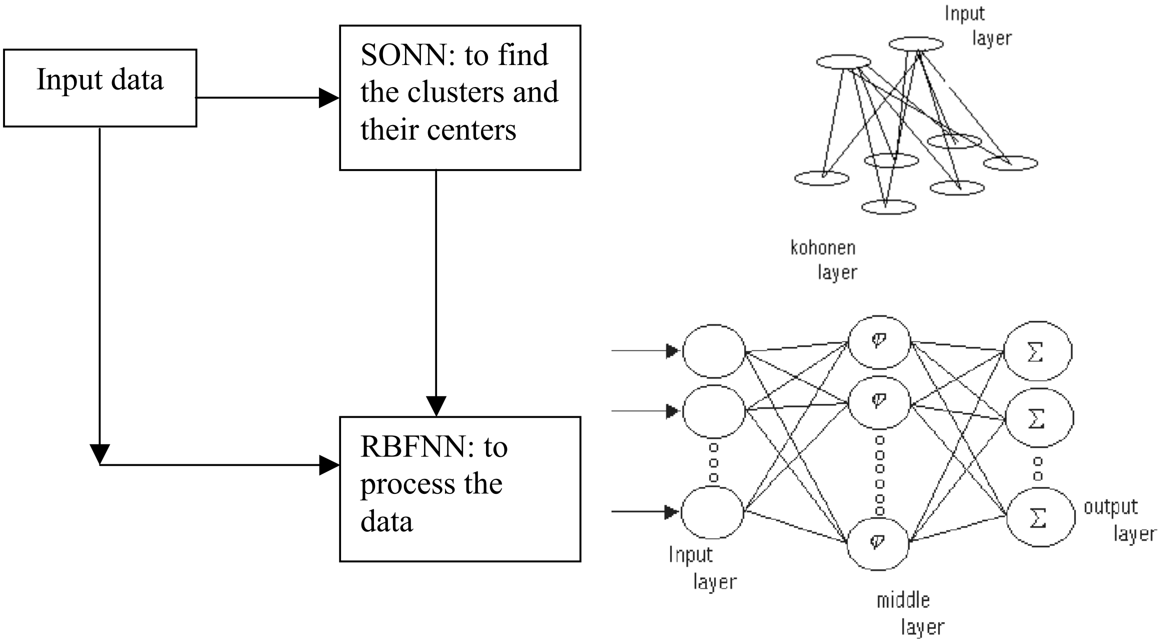


Figure 2.10 Combined structures of SONN&RBFNN

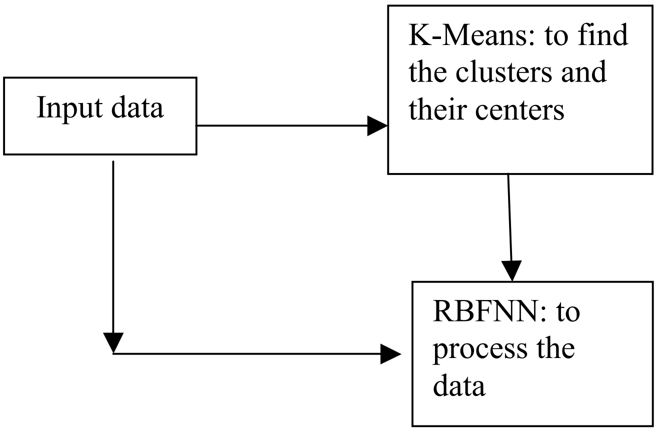

Input data
K-Means: to find the clusters and their centers
RBFNN: to process the data

Figure 2.11 Combined structures of K-Means & RBFNN

CHAPTER 3

REINFORCEMENT LEARNING

Reinforcement learning dates back to the early days of cybernetics and work in statistics, psychology, neuroscience, and computer science. In the last five to ten years, it has attracted increasing interest in the machine learning and artificial intelligence communities. Its promise is beguiling a way of programming agents by reward and punishment without needing to specify how the task is to be achieved. But there are formidable computational obstacles to fulfilling the promise [24].

Reinforcement learning is the problem faced by an agent who must learn behavior through trial-and-error interactions with a dynamic environment. The work described here has a strong family resemblance to widely mentioned work in psychology, but differs considerably in the details and in the use of the word reinforcement." It is appropriately thought of as a class of problems, rather than as a set of techniques.

There are two main strategies that are used in reinforcement problems. First is to search the space to find the optimal solution, which is used in genetic algorithms and some other novel search techniques. And the other is statistical and dynamic programming methods. The author prefers to use these statistical methods. There is no formally justified method.

In the following sections, some fundamental reinforcement lexicon will be briefly discussed and then other crucial points will be given. For instance, should the agent explore the environment? Or should it trust its previous knowledge? If the answer: yes the agent should explore the environment and then there is another question. How often should the agent explore. At this point trade off between exploration and exploitation will be discussed.

To realize how a reinforcement learning agent behave or decide. TD (λ) and Q-Learning algorithms is going to be presented.

3.1 Reinforcement-Learning Model

In the standard reinforcement-learning model, an agent is connected to its environment via perception and action, as depicted in Figure 3.1 [24] On each step of interaction the agent Receives an input, i, and some indication of the current state, s, of the environment; the agent then chooses an action, a, to generate as output. The action changes the state of the environment, and the value of this state transition is communicated to the agent through a scalar reinforcement signal, r. The agent's behavior, B, should choose actions that tend to increase the long-run sum of values of the reinforcement signal. It can learn to do this over time by systematic trial and error, guided by a wide variety of algorithms that are the subject of later subsections of this thesis.

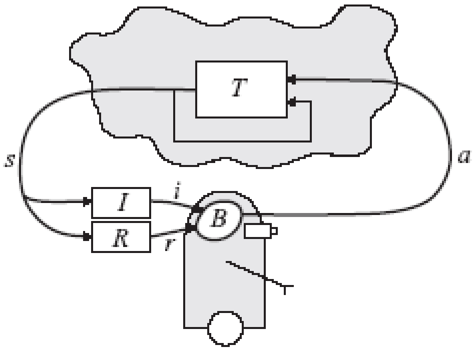


Figure 3.1 Reinforcement agent and its interrreaction with environment

The model consists of

A discrete set of environment states, S;

A discrete set of agent actions, A; and

A set of scalar reinforcement signals; generally between {0, 1}, or the real numbers.

The figure 3.1 also includes an input function I, this parameter settle on how the agent views the environment state; we will assume that it is the identity function. An intuitive way to understand the relation between the agent and its environment is with the following example dialogue [24].

Environment: You are in state 65. You have 4 possible actions.

Agent: I'll take action 2.

Environment: You received a reinforcement of 7 units. You are now in state 15. You have 2 possible actions.

Agent: I'll take action 1.

Environment: You received a reinforcement of -4 units. You are now in state 65. You have 4 possible actions.

Agent: I'll take action 2.

Environment: You received a reinforcement of 5 units. You are now in state 44. You have 5 possible actions.

...

...

The agent's job is to find a policy π, mapping states to actions, that maximizes some long-run measure of reinforcement. We expect, in general, that the environment will be non-deterministic; that is, that taking the same action in the same state on two different occasions may result in different next states and/or different reinforcement values. This happens in our example above: from state 65, applying action 2 produces differing reinforcements and differing states on two occasions. However, we assume the environment is stationary; that is, that the probabilities of making state transitions or receiving specific reinforcement signals do not change over time.

Reinforcement learning differs from widely studied supervised learning algorithm. In reinforcement learning there is no input/output pairs. Supervised algorithms are trained to give the known solution for the known input, however in reinforcement learning algorithm the agent tries to learn the optimum through the trial and error sequences. It is the most important difference.

Reinforcement learning agent should be able to gather the appropriate data and exploration and exploitation dilemma should be solved.

Some aspects of reinforcement learning are closely related to search and planning issues in artificial intelligence. AI search algorithms generate a satisfactory trajectory through a graph of states. Planning operates in a similar manner, but typically within a construct with more complexity than a graph, in which states are represented by compositions of logical expressions instead of atomic symbols. These AI algorithms are less general than the reinforcement-learning methods, in that they require a predefined model of state transitions, and with a few exceptions assume determinism. On the other hand, reinforcement learning, at least in the kind of discrete cases for which theory has been developed, assumes that the entire state space can be enumerated and stored in memory an assumption to which conventional search algorithms are not tied.

3.2 Models of Optimal Behavior

To start the optimal behavior or learning algorithms, there is a question that needs to be answered. What will be the optimality and how should the agent take into account its future. And how should the agent decide about its actual action. In literature there are three main methods to find the optimality.

The *finite-horizon model* is the easiest to think about; at a given moment in time, the agent should optimize its expected reward for the next h steps:

$$E\left(\sum_{t=0}^{h} r_t\right) \tag{28}$$

there is no need to worry about what will happen after this sequence. In this and subsequent expressions, r_t represents the scalar reward received t steps through the future. This model can be used in two ways. In the first, the agent will have a non-stationary policy; that is, one that can change over time. On its first step it will take what is termed an h-step optimal action. This is defined to be the best action available given that it has h steps remaining in which to act and gain reinforcement. On the next step it will take a (h-1)-step optimal action, and so on, until it finally takes a 1-step optimal action and terminates. In the second, the agent does receding-horizon control, in which it always takes the h-step optimal action. The agent always take action according to the same policy, but the value of h limits how far ahead it looks in choosing its actions. The finite-horizon model is not always suitable. In many cases we may not know the precise length of the agent's life in real applications.

The infinite-horizon discounted model takes the long-run reward of the agent into account, but rewards that are received in the future are geometrically discounted according to discount factor, (where $0 \le \gamma < 1$):

$$E\left(\sum_{t=0}^{\infty} \gamma^t r_t\right) \tag{29}$$

We can explain in several ways. It can be seen as an interest rate, a probability of living another step, or as a mathematical trick to bind the infinite sum. The model is conceptually similar to receding-horizon control, but the discounted model is more mathematically tractable than the finite-horizon model. This is a main reason for the wide attention this model has received.

Another optimality criterion is the average-reward model, in which the agent is supposed to take actions that optimize its long-run average reward:

$$\lim_{h\to\infty} E\left(\frac{1}{h}\sum_{t=0}^{h} r_t\right) \tag{30}$$

This method is called as a gain optimal policy; it can be seen as the limiting case of the infinite-horizon discounted model as the discount factor approaches 1 [26]. Problem with this criterion is that there is no way to discriminate between two policies, one of which gains a large amount of reward in the initial phases and the other of which does not. Reward gained on any initial prefix of the agent's life is surpassed by the long-run average performance. It is possible to generalize this model so that it takes into account both the long run average and the amount of initial reward than can be gained. In the generalized, bias optimal model, a policy is preferred if it maximizes the long-run average and ties are broken by the initial extra reward. Figure 3.2 [24] contrasts these models of optimality by providing an environment in which changing the model of optimality changes the optimal policy. In this example, circles represent the states of the environment and arrows are state transitions. There is only a single action choice from every state except the start state, which is in the upper left and marked with an incoming arrow. All rewards are zero except where marked. Under a finite-horizon model with h = 5, the three actions yield rewards of +6.0, +0.0, and +0.0, so the first action should be chosen; under an infinite-horizon discounted model with = 0.9, the three choices yield +16.2, +59.0, and +58.5 so the second action should be chosen; and under the average reward model, the third action should be chosen since it leads to an average reward of +11. If we change h to 1000 and to 0.2, then the second action is optimal for the finite-horizon model and the first for the infinite-horizon discounted model; however, the average reward model will always prefer the best long-term average. Since the choice of optimality model and parameters matters so much, it is important to choose it carefully in any application.

The finite-horizon model is appropriate when the agent's lifetime is known; one important aspect of this model is that as the length of the remaining lifetime decreases, the agent's policy may change. A system with a hard deadline would be appropriately modeled this way. The relative usefulness of infinite-horizon discounted and bias-optimal models is still under debate. Bias-optimality has the advantage of not requiring a discount parameter; however, algorithms for finding bias-optimal policies are not yet as well-understood as those for finding optimal infinite-horizon discounted policies.

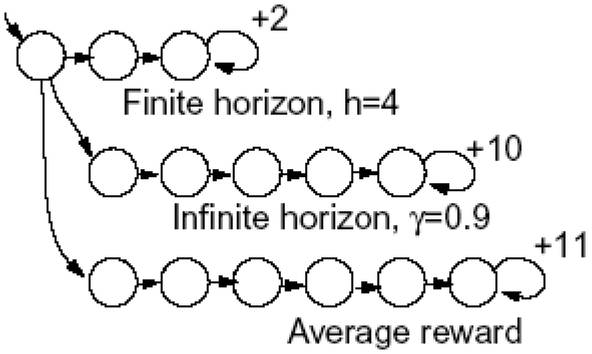


Figure 3.2 Comparing Models of Optimality. All unlabeled arrows produce a reward of zero.

3.3 Exploitation versus Exploration

Main difference between reinforcement learning and supervised learning is that a reinforcement-learner must explicitly explore its environment. In order to underline the problems of exploration, we treat a very simple case in this section. The fundamental issues and approaches described here will, in many cases, and can be used to understand the more complex issues in the following chapters.

The simplest possible reinforcement-learning problem is known as the k-armed bandit problem, which has been the subject of a great deal of study in the statistics and applied mathematics literature [26]. The agent is in a room with a collection of k gambling machines (each called a “one-armed bandit" in colloquial English). The agent is permitted a fixed number of pulls, h. Any arm may be pulled on each turn. The machines do not require a deposit to play; the only cost is in wasting a pull playing a suboptimal machine. When arm i is pulled, machine i pays off 1 or 0, according to some underlying probability parameter p_i, where payoffs are independent events and the $p_i s$ are unknown. What should the agent's strategy be?

This problem illustrates the fundamental tradeoff between exploitation and exploration. The agent might believe that a particular arm has a fairly high payoff probability; should it choose that arm all the time, or should it choose another one that it has less information about, but seems to be worse? Answers to these questions depend on how long the agent is expected to play the game; the longer the game lasts, the worse the consequences of prematurely converging on a sub-optimal arm, and the more the agent should explore.

There is a wide variety of solutions to this problem. We will consider a representative selection of them, but for a deeper discussion and a number of important theoretical results, see the book by [26]. We use the term “action" to indicate the agent's choice of arm to pull. This eases the transition into delayed reinforcement models.

3.4 Dynamic-Programming Approach

If the agent is going to be performing for a total of h steps, it can use basic Bayesian analysis to solve for an optimal strategy [26]. This requires an assumed prior joint distribution for the parameters $\{p_i\}$, the most natural of which is that each p_i is independently uniformly distributed between 0 and 1. We compute a mapping from belief states to actions. Here, a belief state can be represented as a tabulation of action choices and payoffs: $\{n_1, w_1, n_2, w_2, ...n_k, w_k\}$ denotes a state of play in which each arm i has been pulled n_i times with w_i payoffs. We write $V^*(n_1, w_1, n_2, w_2, ...n_k, w_k)$ as the expected payoff remaining, given that a total of h pulls are available, and we use the remaining pulls optimally.

If $\sum_i n_i = h$, then there are no remaining pulls, and. This is the basis of a recursive definition. If we know the w_i value for all belief states with t pulls remaining, we can compute the V^* value of any belief state with t + 1 pulls remaining:

$V^*(n_1, w_1, n_2, w_2, ...n_k, w_k) = \max_i E$ (Future payoff if agent takes action i, then acts optimally for remaining pulls)

Where p_i is the posterior subjective probability of action i paying off given n_i, w_i and our prior probability. For the uniform priors, which result in a beta distribution,

$$p_i = (w_i + 1) = (n_i + 2).$$

The expense of filling in the table of V^* values in this way for all attainable belief states is linear in the number of belief states times actions, and thus exponential in the horizon.

3.5 Delayed Reward

In reinforcement learning most of the case, the agent's actions determine not only its immediate reward, but also the next state of the environment. These environments can be thought of as networks of bandit problems, but the agent must take into account the next state as well as the immediate reward when it decides which action to take. In the long run the agent also determines the future rewards. The agent will have to be able to learn from delayed reinforcement: it may take a long sequence of actions, receiving unimportant reinforcement, and then finally arrive at a state with high reinforcement. The agent must be able to learn which of its actions are desirable based on reward that can take place arbitrarily far in the future.

3.6 Markov Decision Processes

For the delayed reinforcement modeling, Markov decision processes (MDPs) can be used to describe. An MDP consists of

-a set of states S,

-a set of actions A,

-a reward function $R : S \times A \rightarrow R$, and

-a state transition function $T : S \times A \rightarrow \prod(S)$, where a member of $\prod(S)$ is a probability distribution over the set S (i.e. it maps states to probabilities). We write $T(s,a,s')$ for the probability of making a transition from state s to state s' using action a. The state transition function probabilistically specifies the next state of the environment as a function of its current state and the agent's action. The reward function specifies expected instantaneous reward as a function of the current state and action. The model is Markov if the state transitions are independent of any previous environment states or agent actions.

There are many good references to MDP models [27, 28, 29, and 30].

3.7 Finding a Policy Given a Model

Before searching algorithms for learning to move in MDP environments, we will explore techniques for determining the optimal policy given a correct model. These dynamic programming techniques will serve as the foundation and inspiration for the learning algorithms to follow. We restrict our attention mainly to finding optimal policies for the infinite-horizon discounted model, but most of these algorithms can be assumed similar for the finite horizon and average-case models as well. We rely on the result that, for the infinite-horizon discounted model, there exists an optimal deterministic stationary policy [27].

We will speak of the optimal value of a state-it is the expected infinite discounted sum of reward that the agent will gain if it starts in that state and executes the optimal policy. Using π as a complete decision policy, it is written

$$V^*(s) = \max_{\pi} E\left(\sum_{t=0}^{\infty} \gamma^t r_t \right) \tag{31}$$

The optimal value function is unique and can be defined as the solution to the simultaneous equations

$$V^*(s) = \max_{a} E\left(R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') V^*(s') \right), \forall s \in S \tag{32}$$

Which assert that the value of a state s is the expected instantaneous reward plus the expected discounted value of the next state, using the best available action. Given the optimal value function, we can specify the optimal policy as

$$\pi^*(s) = \arg\max_{a} \left(R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') V^*(s') \right) \tag{33}$$

3.8 Learning an Optimal Policy

In the previous section we reviewed methods for obtaining an optimal policy for an MDP assuming that we already had a model. The model consists of knowledge of the state transition probability function $T(s,a,s')$ and the reinforcement function R(s,a). Reinforcement learning is primarily concerned with how to obtain the optimal policy when such a model is not known in advance. The agent must interact with its environment directly to obtain information which, by means of an appropriate algorithm, can be processed to produce an optimal policy.

At this point, there are two ways to proceed.

-Model-free: Learn a controller without learning a model.

- Model-based: Learn a model, and use it to derive a controller.

Which approach is better? This is a matter of some debate in the reinforcement-learning community. A number of algorithms have been proposed on both sides. This question also appears in other fields, such as adaptive control, where the dichotomy is between direct and indirect adaptive control.

The biggest problem facing a reinforcement-learning agent is temporal credit assignment. How do we know whether the action just taken is a good one, when it might have far reaching effects? One strategy is to wait until the “end" and reward the actions taken if the result was good and punish them if the result was bad. In ongoing tasks, it is difficult to know what the “end" is, and this might require a great deal of memory. Instead, we will use insights from value iteration to adjust the estimated value of a state based on the immediate reward and the estimated value of the next state. This class of algorithms is known as temporal difference methods [31]. We will consider two different temporal-difference learning strategies for the discounted infinite-horizon model.

3.9 TEMPORAL DIFFERENCE LEARNING

So far, some neural network and classification methods are discussed. These methods can be assumed as prediction methods. For instance, classification methods predict the cluster of the unknown data. Also conventional neural network methods predict the output for unknown input according to the known input output pairs. These methods assign credits by means of the difference between actual output and the predicted output. Temporal Difference Learning methods assign credits by means of the temporally successive predictions. Although such temporal difference methods have been used in samuel’s checker player, Holland’s bucket brigade and in the Adaptive Heuristic Critic. The author prefers to use TD methods because it requires less memory and less computational time than conventional methods and it gives better results for real world problems. In literature there are some real world applications show that TD methods deserve to be investigated and used in real engineering and robotics problems. Especially [17] applied the TD method to Backgammon and obtains the world master level backgammon player computer software.

This research purpose is to create an autonomous agent that is capable to learn from its past experience. After having built this kind a system, there is no need to know the output that should be instead it is enough to gather sensory inputs from the environment and let the agent learn its optimal behavior. Fro instance, agent should predict whether this formation will led to win or end up with loss or from the cloud formation it can be capable to predict whether it is going to be rain or not. For particular economic condition whether the stock market will rise [32].

Apart from conventional learning algorithm credit assignment is made by means of the difference between temporary successive predictions, whether there is a change between the predictions over time. For example, suppose a weatherman attempts to predict on each day of the week whether it will rain on the following Saturday. The conventional approach is to compare each prediction to the actual outcome whether or not it does rain on Saturday. A TD approach, on the other hand, is to compare each day's prediction with that made on the following day. If a 50% chance of rain is predicted on Monday, and a 75% chance on Tuesday, then a TD method increases predictions for days similar to Monday, whereas a conventional method might either increase or decrease them depending on Saturday's actual outcome.

TD methods have two kinds of advantages over conventional prediction learning methods. First, they are more incremental and therefore easier to compute. For example, the TD method for predicting Saturday's weather can update each day's prediction on the following day, whereas the conventional method must wait until Saturday, and then make the changes for all days of the week. The conventional method would have to do more computing at one time than the TD method and would require more storage during the week. The second advantage of TD methods is that they tend to make more efficient use of their experience: they converge faster and produce better predictions. We argue that the predictions of TD methods are both more accurate and easier to compute than those of conventional methods.

The earliest and best-known use of a TD method was in [33] celebrated checker-playing program. For each pair of successive game positions, the program used the difference between the evaluations assigned to the two positions to modify the earlier one's evaluation. Similar methods have been used in [34] bucket brigade, in Adaptive Heuristic Critic [16, 17], and in learning systems studied by [35, 36, 37]. TD methods have also been proposed as models of classical conditioning [38, 39, 40, 41, and 42].

Although TD prediction method is applied successfully, TD method can not be understood theoretically, most probably because it is being used in complex problems. In these systems TD employed as a better evaluation function predictor.

The TD method explanation is focused on numerical prediction processes rather than on rule-based or symbolic prediction. The approach taken here is much like that used in connectionism and in Samuel's original work our predictions are based on numerical features combined using adjustable parameters or "weights."

This research uses TD methods with conventional methods in some simple application to compare their performance. TD methods presented here can be directly extended to multilayer networks.

3.9.1 TEMPORAL DIFFERENCE AND SUPERVISED METHODS IN PREDICTION POBLEMS

Supervised learning techniques are known as the most important and widely used learning paradigms. Supervised learning methods try to approximate the relation between input and output pairs. After learning takes place, when the input presented, the system responds it according to this relation. This paradigm has been used in pattern classification, concept acquisition, learning from examples, system identification, and associative memory. For example, in pattern classification and concept acquisition, the first item is an instance of some pattern or concept, and the second item is the name of that concept. In system identification, the learner must reproduce the input-output behavior of some unknown system. Here, the first item of each pair is an input and the second is the corresponding output.

Supervised learning methods can be applied any type of learning algorithms. If the pair wise tabulation of the used data can be obtained, the supervised algorithm can be trained. For whether forecasting one can gather data for Monday prediction as input and Saturday actual output as the target value to predict the Saturday’s whether in the same way Tuesday and Wednesday’s data can be trained according to the actual output of the Saturday. It is easy to understand and analyze. It is called supervised prediction method and it is widely used. However it is not preferable and this type of prediction method is not appropriate for this kind of problem.

3.9.2 SINGLE STEP AND MULTI-STEP PREDICTION

In TD methods there are two types of prediction methods; one of them is the single step prediction and the other one is called the multi-step prediction problem. In single step prediction correctness of the prediction will be given at each step. In multi-step prediction the correctness of the prediction is not revealed until more then one step takes place, however partial information is revealed at each step. For example, the weather prediction problem mentioned above is a multi-step prediction problem because inconclusive evidence relevant to the correctness of Monday's prediction becomes available in the form of new observations on Tuesday, Wednesday, Thursday and Friday. On the other hand, if each day's weather were to be predicted on the basis of the previous day's observations that is, on Monday predict Tuesday's weather, on Tuesday predict Wednesday's weather, etc. one would have a single-step prediction problem, assuming no further observations were made between the time of each day's prediction and its confirmation or denial on the following day.

In single step application it is not possible to distinguish the difference from supervised algorithm. Hence the advantage of the TD learning paradigm can be obtained in multi step prediction problem. For example, predictions about next year's economic performance are not confirmed or disconfirmed all at once, but rather bit by bit as the economic situation is observed through the year. The likely outcome of elections is updated with each new poll, and the likely outcome of a chess game is updated with each move.

In real world many single step prediction can be thought as multi step prediction. For pattern recognition problem mostly supervised algorithms are used with known correctly classified pair of data. However when human sees something, he or she has a concept about the object that is seen and after each perception this concept is updated with the information that gives us a capability to update.

3.9.3 Computational issues

In this section some practical issues is going to be discussed with the theoretical issues. During this section TD family of learning will be discussed on the basis of supervised learning procedure. Mostly on Widrow-Hoff learning rule as it was discussed. And then other different TD learning procedures will be introduced.

We consider multi-step prediction problems in which experience comes in observation-outcome sequences of the form $x_1, x_2, x_3, ...x_m, z$ where each x_t is a vector of observations available at time *t* in the sequence, and *z* is the outcome of the sequence. Many such sequences will normally be experienced. The components of each x_t are assumed to be real-valued measurements or features, and *z is* assumed to be a real-valued scalar. For each observation outcome sequence, the learner produces a corresponding sequence of predictions $P_1, P_2, P_3, ...P_m,$ each of which is an estimate of *z*. In general, each P_t can be a function of all preceding observation vectors up through time *t,* but, for simplicity, here we assume that it is a function only of x_t. The predictions are also based on a vector of modifiable parameters or weights, w. P_t 's functional dependence on x_t and w will sometimes be denoted explicitly by writing it as $P(x_t, w)$.

Learning can be described as the update procedure of the w. In TD learning weights are updated after a sequence completed and a terminal state is reached. Not after each observation.

$$w = w + \sum_{t=1}^{m} \Delta w_t \tag{34}$$

This procedure can be cast into more or less incremental phases. One can update the weights after each observation or all the sequences completed.

Supervised learning algorithm considers the input and output as pairs $(x_1, z), (x_2, z), ... (x_m, z)$. The increment in weights depends on the difference between P_t and z, as the time progresses. The supervised learning formulation can be given as in the following form.

$$\Delta w_t = \alpha(z - P_t)\nabla_w P_t, \tag{35}$$

α term stand for the learning parameter and effect the learning. $\nabla_w P_t$ term stands for the partial derivative of the term P_t with respect to each component of w.

For example, consider the special case in which P_t is a linear function of x_t and w, that is, in which $P_t = w^T x_t = \sum_i w(i) x_t(i)$, where w(i) and $x_t(i)$ are the i'th components of w and x_t, respectively. In this case we have $\nabla_w P_t = x_t$, and the formulation reduces to the well known Widrow-Hoff rule [1]:

$$\Delta w_t = \alpha(z - w^T x_t) x_t, \tag{36}$$

This linear learning method is also known as the "delta rule," the ADALINE, and the LMS filter. It is widely used in connectionism, pattern recognition, signal processing, and adaptive control. The basic idea is that the difference $z - w^T x_t$ represents the scalar error between the prediction, $w^T x_t$, and what it should have been, *z.* This is multiplied by the observation vector x_t to determine the weight changes because x_t indicates how changing each weight will affect the error. For example, if the error is positive and $x_t(i)$ is positive, then $w_i(t)$ will be increased, increasing $w^T x_t$ and reducing the error. The Widrow-Hoff rule is simple, effective, and robust.

Having being given formulation is for the one layer problems generalization has already been made in Backpropagation procedure. In this case P_t is solved in multilayer structure as a nonlinear case. However, only difference is the way to solve the partial differential of the gradient $\nabla_w P_t$.

In these equations there is a disadvantage, Δw_t depends on the final outcome z. It means that all the formation until the final sate must be stored and the sequential process is not allowed.

However in TD methods this process can be changed into incremental procedure by the change; if $z - P_t$ assumed as the sum of all predictions.

$$z - P_t = \sum_{k=t}^{m} (P_{k+1} - P_k) \tag{37}$$

Hence the fallowing formulation can be obtained;

$$w = w + \sum_{t=1}^{m} \alpha (z - P_t) \nabla_w P_t = w + \sum_{t=1}^{m} \alpha \sum_{k=t}^{m} (P_{k+1} - P_k) \nabla_w P_t \tag{38}$$

$$= w + \sum_{t=1}^{m} \alpha \sum_{k=t}^{k} (P_{k+1} - P_k) \nabla_w P_t$$

$$= w + \sum_{t=1}^{m} \alpha (P_{t+1} - P_t) \sum_{k=1}^{t} \nabla_w P_k$$

At the end converting to the equation (34);

$$\Delta w_t = \alpha (P_{t+1} - P_t) \sum_{k=1}^{t} \nabla_w P_k \tag{39}$$

Unlike (38), this equation can be computed incrementally, because each Δw_t depends only on a pair of successive predictions and on the sum of all past values for $\nabla_w P_t$. This saves substantially on memory, because it is no longer necessary to individually remember all past values of $\nabla_w P_t$. Equation (39) also makes much milder demands on the computational speed of the device that implements it; although it requires slightly more arithmetic operations overall (the additional ones are those needed to accumulate $\sum_{k=1}^{t} \nabla_w P_k$), they can be distributed over time more evenly. Whereas (39) computes one increment to *w* on each time step, (38) must wait until a sequence is completed and then compute all of the increments due to that sequence. If *M* is the maximum possible length of a sequence, then under many circumstances (39) will require only 1/Mth of the memory and speed required by (38).

Equation (39) is called TD (1) procedure. This type of learning algorithms are called $TD(\lambda)$ procedure and this will be investigated in the following section.

3.9.4 $TD(\lambda)$ Learning procedures

Influence of TD learning procedure comes from its sensitivity of to the changes between successive predictions. However supervised algorithms are sensitive to the changes between the predictions and the final outcome. When there is a change occurs between P_t and P_{t+1} then it effects the changes on weights Δw_t. These changes predict the difference between the all input data or the some portions of the previous inputs. When the equation (39) is applied to a prediction problem, all the predictions are affected equally. However for some reasons when latest predictions make more alternation on the system, this will give more correct solution. It can be obtained by the following formulations. In which alterations to the predictions of observation vectors occurring *k* steps in the past are weighted according to λ^k for $0 \le \lambda \le 1$:

$$\Delta w_t = \alpha(P_{t+1} - P_t)\sum_{k=1}^{t} \lambda^{t-k} \nabla_w P_k \qquad (40)$$

For λ =1 equation (40) will be equal to the equation (39). And this procedure is called as the TD (λ) algorithms. Hence the equation (39) called as TD (1).

Change of past predictions can be weighted in ways other than the exponential form given above, and this may be appropriate for particular applications. However, an important advantage to the exponential form is that it can be computed incrementally. Given that e_t is the value of the sum in (40) for *t,* we can incrementally compute e_t + 1, using only current information.

$$e_{t+1} = \sum_{K=1}^{t+1} \lambda^{t+1-k} \nabla_w P_k$$

$$= \nabla_w P_{t+1} + \sum_{K=1}^{t} \lambda^{t+1-k} \nabla_w P_k$$

$$= \nabla_w P_{t+1} + \lambda e_t$$

When the term λ is chosen less then 1, the learning procedure weight changes differ from any supervised learning. And this difference reaches its maximum point when the term λ is chosen as 0. If the term λ equals to the 0, it means that weight changes affected by the most recent changes.

$$\Delta w_t = \alpha(P_{t+1} - P_t)\nabla_w P_t$$

With these calculations, supervised learning algorithm is obtained with a little difference. The term z, which is final outcome, is replaced by the term P_{t+1}. This shows that supervised learning mechanism is the same when the λ term is chosen as 0.

3.9.5 $TD(\lambda)$ Learning procedures outperforms supervised scheme?

In literature there are some examples that show TD learning scheme outperforms supervised algorithms. However there is an intuitive denial, because in supervised learning the final outcome is known and the predictions are updated according to this actual information. On the other hand TD learning procedure tries to minimize the temporal difference. With this scheme one can converge more rapidly and accurately in dynamic world problems, which is ubiquitous. Almost any real system is a dynamical system, including the weather, national economies, and chess games. In this section, we develop two illustrative examples: a game-playing example to help develop intuitions, and a random-walk example as a simple demonstration with experimental results.

3.9.6 A Game Playing Example

Game playing consists of sequences of positions. Some of them is lead our game to win while others lead to loss. This can be backgammon or one of the card games. For example there is a state that we know that with 90% probability it leads to loss but with only 10% probability leads to win. However after a novel game formation this “bad” game condition is played and it leads us to win. How one can assign the credits to these game positions. This situation is showed at the figure 3.3.

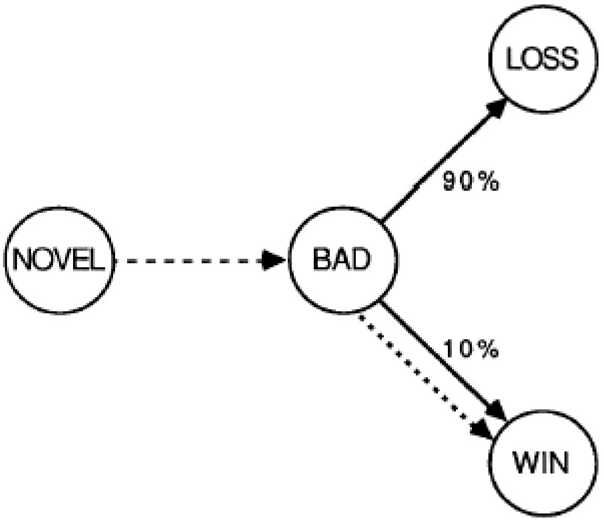


Figure 3.3 A novel game position that can reach win or loss.

Classical supervised learning procedure assigns the credits according to the final outcome however this will affect the novel position as well. However TD methods assign credits according to the temporal difference between successive predictions. Indeed there is a disadvantage that in this example, we have ignored the possibility that the bad state's previously learned evaluation is in error. Such errors will inevitably exist and will affect the efficiency of TD methods in ways that cannot easily be evaluated in an example of this sort. The example does not prove TD methods will be better on balance, but it does demonstrate that a subsequent prediction can easily be a better performance standard than the actual outcome.

This game-playing example can also be used to show how TD methods can fail. Suppose the bad state is usually followed by defeats except when it is preceded by the novel state, in which case it always leads to a victory. In this odd case, TD methods could not perform better and might perform worse than supervised-learning methods. Although there are several techniques for eliminating or minimizing this sort of problem, it remains a greater difficulty for TD methods than it does for supervised-learning methods. TD methods try to take advantage of the information provided by the temporal sequence of states, whereas supervised-learning methods ignore it. It is possible for this information to be misleading, but more often it should be helpful.

3.9.7 A Random Walk Example

So far TD methods discussed in a relatively complex way, however to make clear the definition and to pave the way to theoretical results the notion of the TD learning must be understood. In the following section there is an example which can be also used to identify the nature of the Markov decision process. In the following example which is called Bounded Random Walks.

In the bounded random walks, agent can choose an action to move right or left. Game is terminated when the agent reaches to the one of the terminal state. This play ground is shown in the figure 3.4.

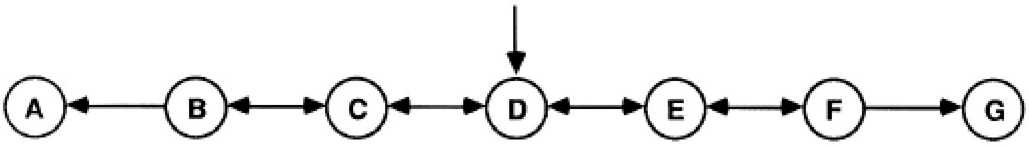


Figure 3.4 Random walk example.

Terminal states are the right most or the left most states in which "G" or "A" respectively. Every game starts from the state "D". If either edge state *(A or G)* is entered, the walk terminates. A typical walk might be DCDEFG. Suppose we wish to estimate the probabilities of a walk ending in the rightmost state, *G,* given that it is in each of the other states.

When the linear supervised learning scheme is used, and the final outcome given when the system reaches to the state A z=0, if reaches to the state G z=1. The learning methods estimated the expected value of *z;* for this choice of *z,* its expected value is equal to the probability of a right-side termination. For each non-terminal state *i,* there was a corresponding observation vector x_i; if the walk was in state *i* at time *t* then $x_t = x_i$. Thus, if the walk DCDEFG occurred, then the learning procedure would be given the sequence XD, XC, XD, XE, X F, 1. The vectors $\{x_i\}$ were the unit basis vectors of length 5, that is, four of their components were 0 and the fifth was 1 (e.g., XD =(0,0,1,0,0)T), with the one appearing at a different component for each state. Thus, if the state the walk was in at time *t* has its 1 at the ith component of its observation vector, then the prediction $P_t = w^T x_t$ was simply the value of the ith component of *w.* We use this particularly simple case to make this example as clear as possible. The theorems we prove later for a more general class of dynamical systems require only that the set of observation vectors $\{x_i\}$ be linearly independent.

3.9.8 Theoretical Approach to the TD Learning

So far, TD learning procedure has been discussed in a more heuristic way. However to understand the way it works and how it works, some theoretical notions need to be developed also to make further development more scientific approach is needed. In the following section this theoretical approach will be developed. The theory developed here relate to the linear TD (0) procedure and a class of tasks characterized by the random walk example discussed in the previous section. Two major results are presented: 1) an asymptotic convergence theorem for linear TD (0) when presented with new data sequences; and 2) a theorem that linear TD (0) converges under repeated presentations to the optimal estimates. Finally, how TD methods can be viewed as gradient-descent procedures.

3.9.10 TD (0) Learning

Through this section process is assumed as a Markov decision process, in which next state depends only on the current state. The states are defined as in the following form, T stands for the terminal states and N stands for the non-terminal states. The term P_{ij} stands for the probability of transition from state i to state j. In which the agent stands at state i, $(i \in N, j \in N \cup T)$. The "absorbing" property means that indefinite cycles among the non-terminal states are not possible; all sequences except for a set of zero probability eventually terminate. Given an initial state q_1, an absorbing Markov process provides a way of generating a state sequence $q_1, q_2, q_{3,......} q_{m+1}$, where $q_{m+1} \in T$. the initial state is chosen probabilistically from among the non-terminal states will be assumed, each with probability μ_i. As in the random walk example, the learning algorithms direct knowledge of the state sequence will not be given, but only of a related observation-outcome sequence $x_1, x_2, x_{3,.....} x_m, z$. Each numerical observation vector x_t is chosen dependent only on the corresponding non-terminal state q_t, and the scalar outcome z is chosen dependent only on the terminal state q_{m+1}. In what follows, we assume that there is a specific observation vector x_i

corresponding to each non-terminal state *i* such that if $q_t = i$, then $x_t = x_i$. For each non-terminal state *j,* we assume outcomes *z* are selected from an arbitrary probability distribution with expected value Z_j.

To go forward for this section, it needs to be proved that this learning scheme converges asymptotically. This problem can be cast into map the input states x_is into the final outcome z. That is, we want the predictions $P(x_i, w)$ to equal $E\{z \mid i\}, \forall i \in N$. Let us call these the *ideal predictions.* Given complete knowledge of the Markov process, they can be computed as follows:

$$E\{z \mid i\} = \sum_{j \in T} p_{ij}\bar{z}_j + \sum_{j \in N} p_{ij} \sum_{k \in T} p_{jk}\bar{z}_k + \sum_{j \in N} p_{ij} \sum_{k \in N} p_{jk} \sum_{l \in T} p_{kl}\bar{z}_l + \ldots\ldots \tag{41}$$

For any matrix *M,* let $[M]_{ij}$ denote its ij'th component, and, for any vector *v,* let $[v]_i$ denote its i'th component. Let *Q* denote the matrix with entries $[Q]_{ij} = p_{ij}$ for $ij \in N$, and let *h* denote the vector with components $[h]_i = \sum_{j \in T} p_{ij}\bar{z}_j$ for $i \in N$. Then we can write the above equation as

$$E\{z \mid i\} = \left[\sum_{k=0}^{\infty} Q^k h\right]_i = \left[I - Q^{-1} h\right]_i \tag{42}$$

Q^k is the probabilities of going from one non-terminal state to another in *k* Steps; for an absorbing Markov process, these probabilities must all converge to 0 as $k \to \infty$.

For any absorbing Markov chain, for any distribution of starting probabilities μ_i, for any outcome distributions with finite expected values $\bar{z}_j$, and for any linearly independent set of observation vectors $\{x_i \mid i \in N\}$, there exists an $\varepsilon > 0$ such that, for all positive a < e$\alpha < \varepsilon$ and for any initial weight vector, the predictions of linear TD (0) (with weight updates after each sequence) converge in expected value to the ideal predictions . That is, if w_n denotes the weight vector after n sequences have been experienced, then

$$\lim_{n\to\infty} E\left\{x_i^T w_n\right\} = E\{z \mid i\} = \left[\left(I - Q^{-1}h\right)\right]_i, \forall i \in N$$

PROOF: Linear TD (0) updates w_n after each sequence as follows, where m denotes the number of observation vectors in the sequence:

$$w_{n+1} = w_n + \sum_{t=1}^{m} \alpha(P_{t+1} - P_t)\nabla_w P_t$$

$$w_{n+1} = w_n + \sum_{t=1}^{m-1} \alpha(P_{t+1} - P_t)\nabla_w P_t + \alpha(z - P_m)\nabla_w P_m$$

$$w_{n+1} = w_n + \sum_{t=1}^{m-1} \alpha(w_n^T x_{q_{t+1}} - w_n^T x_{q_t})x_{q_t} + \alpha(z - w_n^T x_{q_m})x_{q_m}$$

Where x_{q_t} is the observation vector corresponding to the state q_t entered at time *t* within the sequence. This equation allows us to separate the system into transition from initial state to the next state.

$$w_{n+1} = w_n + \sum_{i\in N}\sum_{j\in N} n_{ij}\alpha(w_n^T x_j - w_n^T x_i)x_i + n_{ij}\alpha(z - w_n^T x_i)x_i$$

Where n_{ij} denotes the number of times the transition $i \to j$ occurs in the

Sequence. (For $j \in T$, all but one of the n_{ij} is 0.)

In this process random number generator is used hence the actions that is taken by agent are independent o each other. Expected value of each state can be calculated as in the following form.

$$E\{w_{n+1} \mid w_n\} = w_n + \sum_{i\in N}\sum_{j\in T} d_i P_{ij}\alpha(w_n^T x_j - w_n^T x_i)x_i + \sum_{i\in N}\sum_{j\in T} d_i P_{ij}\alpha(\bar{z}_j - w_n^T x_i)x_i$$

Where d_i is the expected number of times the Markov chain is in state i in one sequence, so that $d_i p_{ij}$ is the expected value of n_{ij}.

$$d^T = \mu^T (I - Q)^{-1}$$

Where $[d]_i = d_i$ and $[\mu]_i = \mu_i$, $i \in N$. Each d_i is strictly positive, because any state for which $d_i = 0$ has no probability of being visited and can be discarded. Let $\overline{w}_n$

denote the expected value of w_n. Then, since the dependence of $E\{w_{n+1} \mid w_n\}$ on w_n is linear, we can write

$$\overline{w}_{n+1} = \overline{w}_n + \sum_{i\in N}\sum_{j\in N} d_i p_{ij}\alpha(w_n^T x_j - w_n^T x_i)x_i + \sum_{i\in N}\sum_{j\in T} d_i p_{ij}\alpha(\overline{z}_j - \overline{w}_n^T x_i)x_i$$

an iterative update formula in w_n that depends only on initial conditions. Now we rearrange terms and convert to matrix and vector notation, letting D denote the diagonal matrix with diagonal entries $[D]_{ii} = d_i$ and X denote the matrix with columns x_i.

$$\overline{w}_{n+1} = \overline{w}_n + \alpha \sum_{i\in N} d_i x_i \Big(\sum_{j\in N} p_{ij}\overline{z}_j + \sum_{j\in N} p_{ij}\overline{w}_n^T - \overline{w}_n^T x_i \sum_{j\in N\cup T} p_{ij} \Big)$$

$$\overline{w}_{n+1} = \overline{w}_n + \alpha \sum_{i\in N} d_i x_i \Big([h] + \sum_{j\in N} p_{ij}\overline{w}_n^T x_j - \overline{w}_n^T x_i \Big)$$

$$= \overline{w}_n + \alpha XD(h + QX^T\overline{w}_n - X^T\overline{w}_n)$$

$$X^T\overline{w}_{n+1} = X^T\overline{w}_n + \alpha X^T XD(h + QX^T\overline{w}_n - X^T\overline{w}_n)$$

$$= \alpha XDh + (I - QX^T XD(I-Q)X^T\overline{w}_n$$

$$\sum_{k=0}^{n-1} (I - \alpha X^T XD(I-Q))^k \alpha X^T XDh + (I - \alpha X^T XD(I-Q))^n X^T w_0$$

when the following equation is assumed $\lim_{n\to\infty}(I - \alpha X^T XD(I-Q))^n = 0$ and the following theorem is true, if $\lim_{n\to\infty} A^n = 0$, then I-A has an inverse, and $(I-A)^{-1} = \sum_{i=0}^{\infty} A^i$. Equations converge to

$$\lim_{n\to\infty} X^T\overline{w}_n = (I - (I - \alpha X^T XD(I-Q)))^{-1}\alpha X^T XDh$$

$$= (I-Q)^{-1}D^{-1}(X^T X)^{-1}\alpha^{-1}\alpha X^T XDh$$

$$= (I - Q)^{-1} h$$

$$\lim_{n \to \infty} E\left\{x_i^T w_n\right\} = \left[(I - Q)^{-1} h\right]_i, \forall_i \in N$$

This is the desired result. Note that D^{-1} must exist because *D is* diagonal with all positive diagonal entries, and $(X^T X)^{-1}$must exist.

It thus remains to show that $\lim_{n \to \infty} (I - \alpha X^T XD(I - Q))^n = 0$. We do this by first showing that *D (I-Q)* is positive definite, and then that $X^T XD(I - Q)$ has a full set of eigen values all of whose real parts are positive. This will enable us to show that *a* can be chosen such that all eigen values of $I - \alpha X^T XD(I - Q)$ are less than 1 in modulus, which assures us that its powers converge.

3.9.11 Gradient Descent in TD Learning

Gradient descent learning method is widely used in MLP. This method guaranties to converge if the learning rate chosen small enough and the number of iteration is suffice to converge. Gradient descent method is also called as hill climbing method. Which is tries to minimize the overall error j (w). In this method gradient of the overall error is calculated and the system's weights tuned through the opposite direction. This can be formalized as follows.

$$\Delta w_t = -\alpha \overline{\nabla}_w j(w_t)$$

Where the term α represents the learning rate and gives us the step size for the hill climbing.

For the multi step prediction problem, system tries to approximate the term $p_t = p(x_t, w)$to the term $E\{z \mid x_t\}$ and the error can be calculated by the difference between target value and the prediction's Euclidian distance.

$$j(w) = E_X\left\{(E\{z \mid x\} - p(x, w))^2\right\}$$

where Ex{ } denotes the expectation operator over observation vectors x. *J(w)* measures the error for a weight vector averaged over all observation vectors, but at each time step one usually obtains additional information about only a single observation vector. The usual next step, therefore, is to define a per-observation error measure Q(w,x) with the property that $E_x\{Q(w,x)\} = j(w)$. For a multi-step prediction problem,

$$Q(w,x) = (E\{z \mid x\} - p(x,w))^2$$

To determine the each step's increment gradient of the each error is computed as following $\nabla_w Q(w,x_t)$, and if the following equation is assumed correct $E_x\{\nabla_w Q(w,x)\} = \nabla_w j(w)$. Weight update rule becomes as follows;

$$\Delta w_t = -\alpha \nabla_w Q(w,x_t)$$

$$= 2\alpha(E\{z \mid x_t\} - p(x_t,w))\nabla_w p(x_t,w)$$

In this prediction problem $E\{z \mid x_t\}$ is not known or predicted initially. One can use supervised learning methods to predict the expected value. In this case $E\{z \mid x_t\}$ is matched to the actual outcome z. On the other hand if the TD method is used $E\{z \mid x_t\}$ is matched to the next state prediction $p(x_{t+1},w)$. In the last case the TD (0) prediction method is obtained, in which every prediction approximate to the subsequent prediction.

3.10 Q-Learning

Q-learning was first developed by Watkins [44, 45]. Q-learning is relatively simple and easy to implement. Because of these specifications, it is widely used. If $Q^*(s,a)$ is the discounted expected value of the taking action a in state s. Note that $V^*(s)$ is the value of s assuming the best action is taken initially, and so $V^*(s) = \max_a Q^*(s,a)$. $Q^*(s,a)$ can hence be written recursively as

$$Q^*(s,a) = R(s,a) + \gamma \sum T(s,a,s') \max_{a''} Q^*(s',a')$$

Note also that, since $V^*(s) = \max_a Q^*(s,a)$, we have $\pi(s) = \arg\max_a Q^*(s,a)$ as an optimal policy.

Q-learning procedure can be cast into iterative form. At each step agent takes the action which has maximum Q value. These values are stored in tabular form. And if each state visited infinitely, while the term α is decayed appropriately. Q values approximate the optimal value with probability 1 [44, 46, and 47].

After the Q values approximate to the optimal values, greedy action selection method can be used. In literature, there is no formally justified method for the exploration & exploitation dilemma.

3.11 Problem Description

The problem is to build a system which can interact with its environment, and learns from its past experience in dynamically changing conditions. To achieve this task, system must be capable of learn in trial and error sequence. However how can the system know that its action is reasonable or optimal in that condition? To test whether the chosen action leads to win or lose, a utility must be assigned to tell the system it is improving itself or it has to try something else. In the figure 3.1 a solution to this problem is proposed by [46]. This system can be improved by adding extra networks.

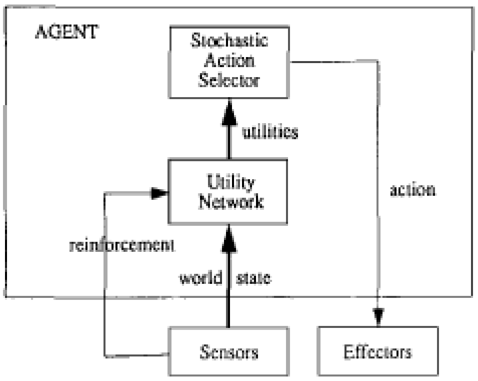


Figure 3.1 Framework for connectionist Q-learning.

In the figure 3.1 connectionist Q-learning is given as an example. And in the following its algorithm is given as a pseudo code.

```
1. x ← current state; for each action $i, U_i \leftarrow util(x,i)$
2. a ← select(U,T);
3. Perform action a; (y;r) ← new state and reinforcement;
```

4. $u' \leftarrow r + \gamma \max\{util(y,k) \mid k \in actions\}$

5. Adjust utility network by backpropagating error ΔU

through it with input x, where $\Delta U_i = \begin{cases} u' - U & \text{If i=a} \\ 0 & \text{otherwise} \end{cases}$

6. Go to 1.

Generally speaking, the utility of an action *a* in response to a state *x* is equal to the immediate payoff *r* plus the best utility that can be obtained from the next state *y,* discounted by γ Therefore, the desired *util* function must satisfy

$$u' \leftarrow r + \gamma \max\{util(y,k) \mid k \in actions\}$$

CHAPTER 4

EXPERIMENTS

So far supervised, unsupervised and reinforcement learning algorithms are discussed. During the preparation of this thesis many applications are made. In this chapter, these experiments and their results will be discussed.

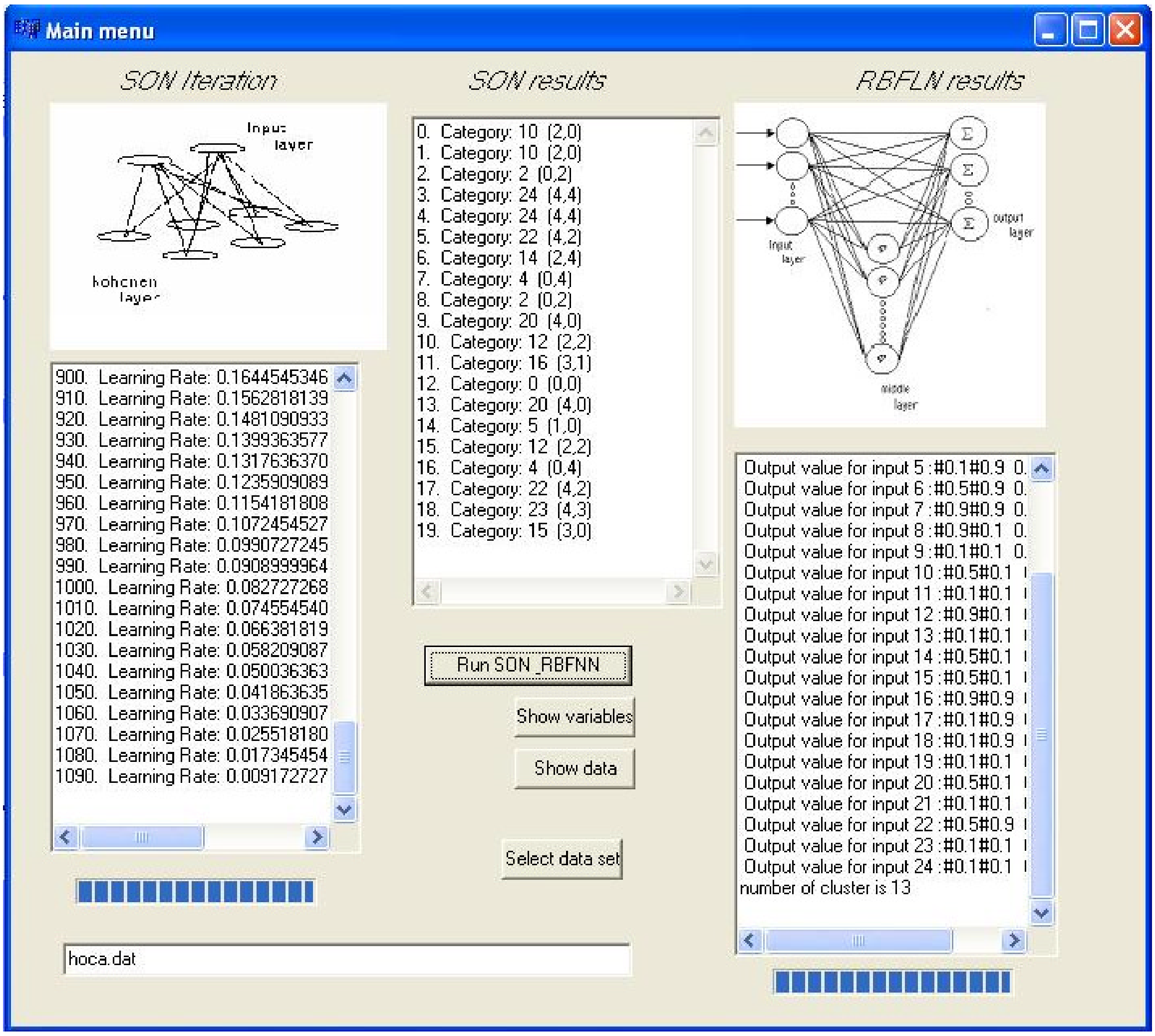
Neural network applications are all written in C++ ID environment. Their interface samples are given at appendix A.

4.1 Simulation for Combined Techniques

Two combinations were simulated. First SON and RBFLN with gradient descent training, and secondly K-means and RBFNN with RP training. The simulation data are obtained from [24] and in appendix B. For RPT, case 1, R is 0.15 and R is reduced by an amount of 0.01 every 10% of the running of the code. For case 2, again R is taken 0.15, and reduced by 25% after the first half of the training, and in the last tenth of the running, it is reduced by 90%. RP training was run for 5000 epochs for both cases, and the rate of acceptance based on the fitness is about half for the first case and one third for the latter.

In this study, two novel ideas have been presented. K-means clustering is formulated as a NLP, and by specific constraints, outlier clustering was eliminated. Once a minimum number of samples to be contained in a cluster was specified, no such cluster is allowed below that certain limit.

And finally, a new heuristic training is proffered. Training of a RBF neural network has been carried out by two distinct ways. In the first, a self organizing map is used to cluster a given data set and then the cluster centers are used to train RBFLN parameters via gradient descent. In the second, K-means clustering is used to partition the set. Then the centers were fed to the RBFNN. Spread constants and the weights were trained by use of responsive perturbation training.



```
900.  Learning Rate: 0.1644545346
910.  Learning Rate: 0.1562818139
920.  Learning Rate: 0.1481090933
930.  Learning Rate: 0.1399363577
940.  Learning Rate: 0.1317636370
950.  Learning Rate: 0.1235909089
960.  Learning Rate: 0.1154181808
970.  Learning Rate: 0.1072454527
980.  Learning Rate: 0.0990727245
990.  Learning Rate: 0.0908999964
1000.  Learning Rate: 0.082727268
1010.  Learning Rate: 0.074554540
1020.  Learning Rate: 0.066381819
1030.  Learning Rate: 0.058209087
1040.  Learning Rate: 0.050036363
1050.  Learning Rate: 0.041863635
1060.  Learning Rate: 0.033690907
1070.  Learning Rate: 0.025518180
1080.  Learning Rate: 0.017345454
1090.  Learning Rate: 0.009172727
```

```
hoca.dat
```

```
0.  Category: 10  (2,0)
1.  Category: 10  (2,0)
2.  Category: 2  (0,2)
3.  Category: 24  (4,4)
4.  Category: 24  (4,4)
5.  Category: 22  (4,2)
6.  Category: 14  (2,4)
7.  Category: 4  (0,4)
8.  Category: 2  (0,2)
9.  Category: 20  (4,0)
10.  Category: 12  (2,2)
11.  Category: 16  (3,1)
12.  Category: 0  (0,0)
13.  Category: 20  (4,0)
14.  Category: 5  (1,0)
15.  Category: 12  (2,2)
16.  Category: 4  (0,4)
17.  Category: 22  (4,2)
18.  Category: 23  (4,3)
19.  Category: 15  (3,0)
```

```
Output value for input 5 :#0.1#0.9  0.
Output value for input 6 :#0.5#0.9  0.
Output value for input 7 :#0.9#0.9  0.
Output value for input 8 :#0.9#0.1  0.
Output value for input 9 :#0.1#0.1  0.
Output value for input 10 :#0.5#0.1
Output value for input 11 :#0.1#0.1
Output value for input 12 :#0.9#0.1
Output value for input 13 :#0.1#0.1
Output value for input 14 :#0.5#0.1
Output value for input 15 :#0.5#0.1
Output value for input 16 :#0.9#0.9
Output value for input 17 :#0.1#0.9
Output value for input 18 :#0.1#0.9
Output value for input 19 :#0.1#0.1
Output value for input 20 :#0.5#0.1
Output value for input 21 :#0.1#0.1
Output value for input 22 :#0.5#0.9
Output value for input 23 :#0.1#0.1
Output value for input 24 :#0.1#0.1
number of cluster is 13
```

Figure 4.1 Windows interface for the combined NNs.

The results in the simulations have shown that this method is already promising. Yet further analysis on how to pick the error coefficient, and a more elaborate error function to lower the perturbation amplitude will enhance the overall network training

Table 4.1 Experiment results

Original test data	RBF with SON 11 clusters	RBF with SON 13 clusters	RBF with SON Every datum is a center	Responsive Perturbation Testing, 10 individuals(1)	Responsive Perturbation Testing, 10 individuals. (2)
66	67.0	67.3	67.8	66.5230	69.0616
66	59.8	59.7	61.8	60.7654	64.1022
81	59.8	55.0	65.5	62.0122	70.0467
53	45.5	44.6	44.8	49.6030	65.5347
79	78.8	79.9	86.8	84.3361	85.3412
Error	23.29	28.0	19.69	13.26	11.65

4.2 TEST BASE FOR TD and Q-LEARNING

The TD and Q-learning methods are tested in simulations. In these simulations a square shape room is drawn. And an agent is placed to an initial position, and then the agent is asked to go to the predefined target position. This configuration can be assumed as a car backing problem. After some trial and error sequences, the agent reaches the target directly, both in Q-learning and TD prediction. However there is a difference between the rooms that the agent initially roamed. There is an obstacle in Q-learning simulation, but there is no obstacle for the TD learning.

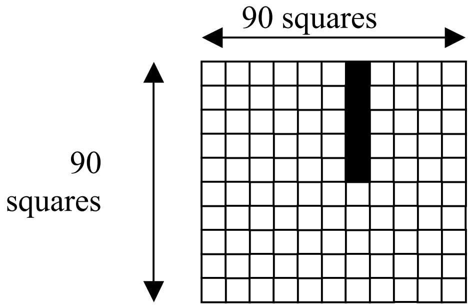


Figure 4.2 Room for Q-learning

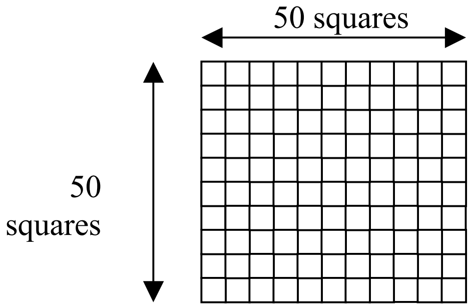


Figure 4.3 Room for TD learning

During the Q-learning application, 50×50 square room was used. The initial starting position was x=15, y=15.The target position to which the agent tries to reach is placed at x=70, y=30. Simulation results can be seen as screen shots in figure 4.4 and 4.5.

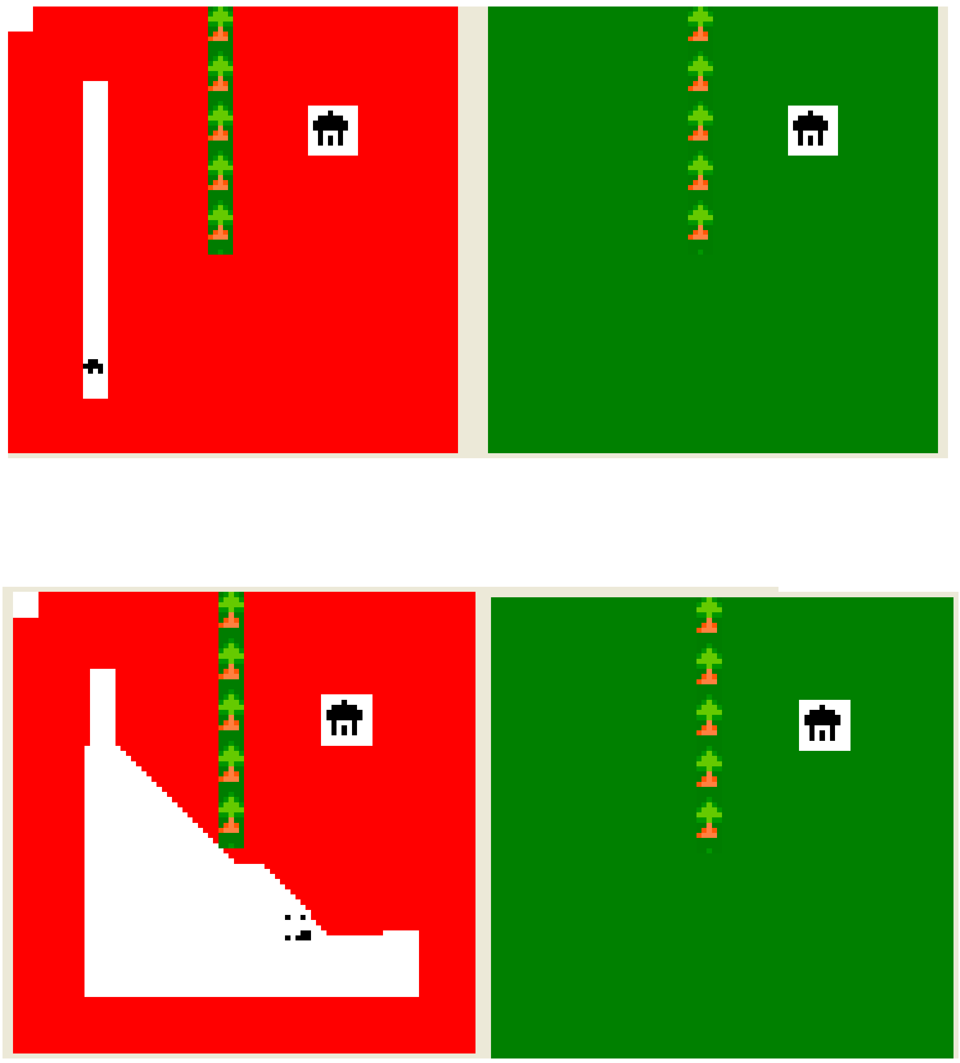


Figure 4.4 Windows application results for Q-learning

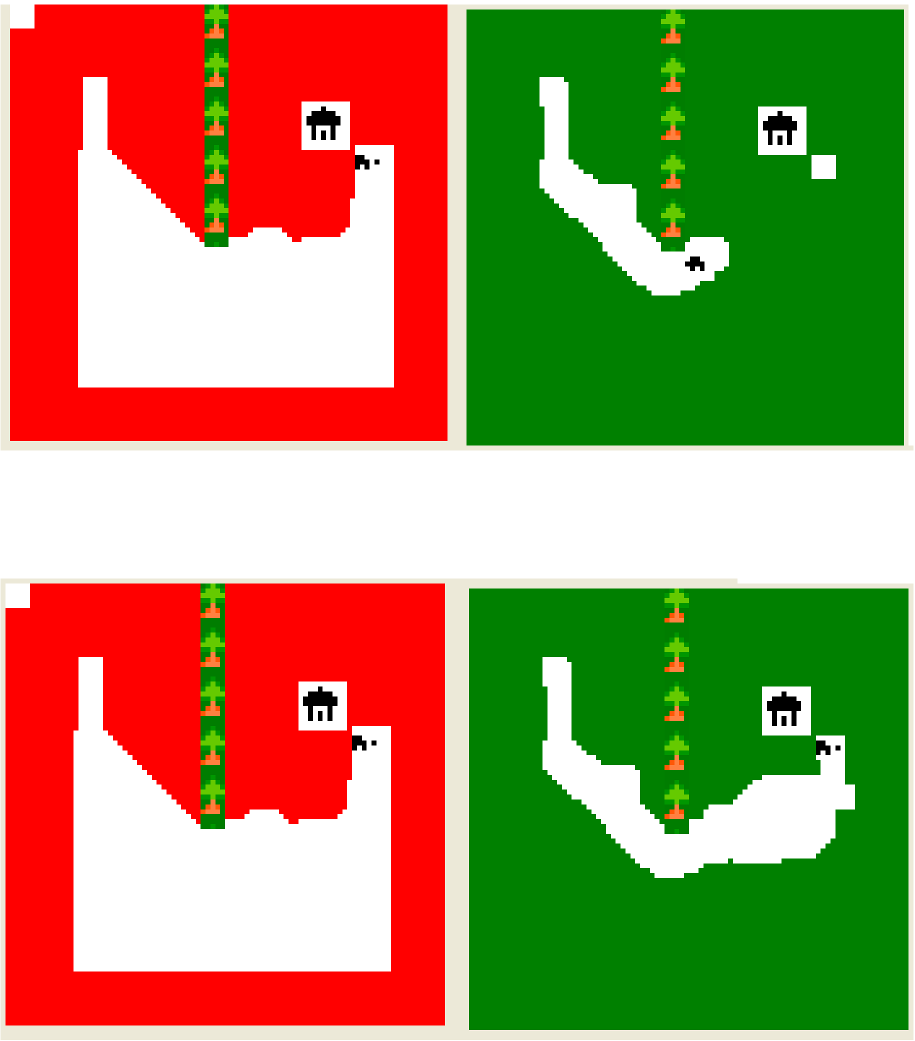


Figure 4.5 After learning took place, agent directly found the target

In these figures red squares and the green squares stand for the same room, however learning takes place at red square and after learning, at the green square agent is initialized to the starting point, and then reaches the target in a much better way. One can ask why the agent is not asked to follow the shortest path instead of trial and error sequence. The reason is that, if there happens to be an obstacle on the shortest path agent may not escape from the obstacle.

On the other hand the test base for the TD learning is little different from the Q-learning room. In TD learning there is no obstacle. Agent is initialized at starting point x=20, y=20, and the target is positioned at x=40, y=40.

During the Backpropagation-TD learning training one of the most important problems is to represent the dynamic environment. At the first experiment direct state position of the agent is presented to the network, it means that the network has two inputs and one output. These two inputs are directly given ‘x’ and ‘y’ coordinates of the agent. And the one output stands for the success probability of the agent’s action, which is taken from here and leads to win or lose. However these two inputs did not suffice to represent the dynamic environment. And the agent could not reach to the target.

In the second experiment, the room, in which the agent roams, is divided into four subsections. Therefore the network has six inputs and one output. Again the agent could not reach the target. However, as in the figure 4.6 the four sub areas can easily be seen. In that figure the brighter the color, the higher the success probability. That means the agent tries to follow the bright colors.

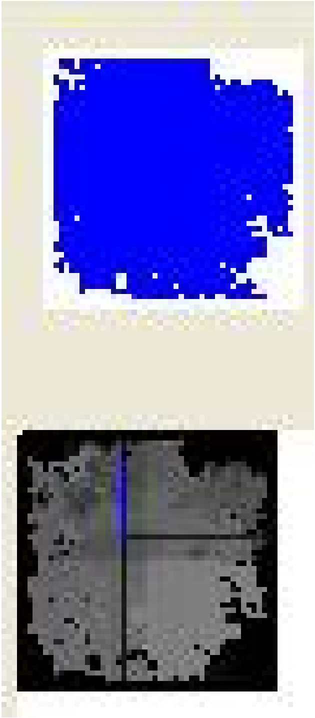


Figure 4.6 TD learning results: Room is divided into four regions.

The upper part of the figure 4.6, 4.7 and 4.8, which are blue colored, shows the explored region by the agent.

Previous simulation shows that, if the number of input is enough to represent the environment, agent can learn from trial and error sequence. So this time the number of input is increased to 102. Where, 50 inputs for the x axis and 50 inputs for the y axis to represent the position of the agent. Lastly two inputs for the exact position of the agent. At this time agent could learn and reach the target as in the figure 4.7.

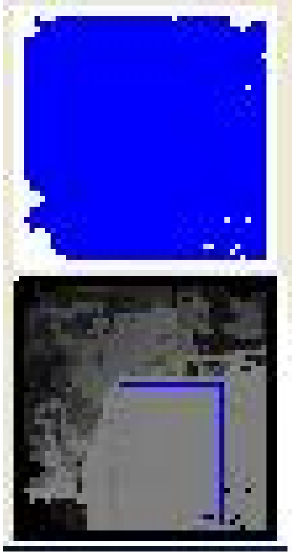


Figure 4.7 After learning took place, agent is able to go directly.

If the learning parameters can be tuned appropriately, learning can take place much faster.

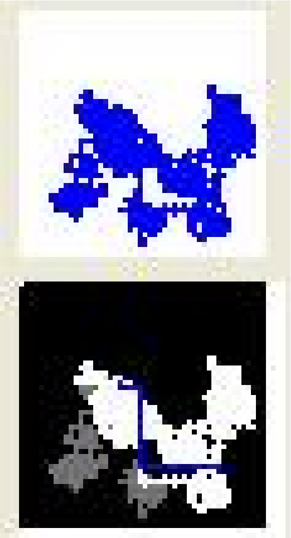


Figure 4.8 If the learning parameters are changed appropriately, learning can take place much faster.

CHAPTER 5

CONCLUSIONS

Through this research, various AI methods are investigated. And their formal definitions and fundamentals are given with their applications as well. Aim of this research was to develop a system which interacts with its environment. And during this interaction with the environment the system will be capable of gathering information about its environment and response to the dynamic changes in a reasonable way.

In this thesis learning methods are divided into three main groups, these are supervised algorithms, unsupervised algorithms and reinforcement learning in which the genetic algorithms are included. MLP algorithms are utilized as supervised algorithms. In the subsequent sections Backpropagation NNs, RBFNNs, and RBFLNs are discussed. Their fundamentals are given and then their performance and robustness are compared with each other. SONNs and K-means algorithms are discussed as unsupervised methods. And, K-means algorithm is modified by author and it is shown that this new modified K-means outperform the classic k-means algorithm.

Reinforcement learning is the most important subject of this thesis, since reinforcement learning gives us an ability to teach the agent or system by its past experience. Also the supervised and unsupervised methods are utilized to improve the reinforcement learning. Finally, supervised methods are used as complementary methods for reinforcement learning. In literature there are some other applications that used unsupervised learning scheme with reinforcement learning.

Temporal difference method has studied intensively in the reinforcement learning chapter, which was the method discussed in depth. Also the Q-learning method is discussed and simulated. When the performance of these two reinforcement methods are compared, for the simple one obstacle case Q-learning seams faster than TD learning. However because of the memory usage of the Q-learning, generalization capability is lower than the TD learning procedure. On the other hand training time of the TD learning is too long because of the trial and error scheme. The navigation application which is presented in this thesis takes between two and four hours according to the initial position of the target and the agent. Also in literature TD-Backgammon training time is given as several months.

In the future, training time must be decreased. In literature there is no way formally presented to heal this training time problem for all cases. Also there is another difficulty to implement the TD learning method to complex real world problems. Connectionists TD structure needs many inputs to represent the environment and the dynamic system. These problems are yet to be tackled as future work.

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APPENDIX A

CODE INTERFACE SAMPLES

These codes are developed from [50]. There are thousands of rows codes, hence It is not possible to show all the codes.

```
class Base_Link   // Base Neural-Network Link class
    {
    private:


        static int ticket;


    protected:
        int id;                    // ID number for link
        double *value;             // Value(s) for Link
        Base_Node *in_node;        // Node instance link is comming from
        Base_Node *out_node;       // Node instance link is going to
        int value_size;


    public:
        Base_Link( int size=1 );       // Constructor
         ~Base_Link( void );           // Destructor for Base Links
         virtual void Save( ofstream &outfile );
         virtual void Load( ifstream &infile );
         inline virtual double Get_Value( int id=WEIGHT );
         inline virtual void Set_Value( double new_val, int id=WEIGHT);
        inline virtual void Set_In_Node( Base_Node *node, int id );
        inline virtual void Set_Out_Node( Base_Node *node, int id );
        inline virtual Base_Node *In_Node( void );
        inline virtual Base_Node *Out_Node( void );
        inline virtual char *Get_Name( void );
        inline virtual void Update_Weight( double new_val );
        inline int Get_ID( void );
        inline virtual double In_Value( int mode=NODE_VALUE );
        inline virtual double Out_Value( int mode=NODE_VALUE );
        inline virtual double In_Error( int mode=NODE_ERROR );
        inline virtual double Out_Error( int mode=NODE_ERROR );
        inline virtual double Weighted_In_Value( int mode=NODE_VALUE );
        inline virtual double Weighted_Out_Value( int mode=NODE_VALUE );
        inline virtual double Weighted_In_Error( int mode=NODE_VALUE );
         inline virtual double Weighted_Out_Error( int mode=NODE_VALUE );
         inline virtual int Get_Set_Size( void );
        inline virtual void Epoch( int mode=0 );
    };
//--------------------------------------------------------------------------
class LList                              // Linked-List Support Class
    {
    private:

        struct NODE
            {
            NODE *next, *prev;
            Base_Link *element;
            };

        NODE *head,*tail,*curr;
        int count;

    public:
        LList( void );
        ~LList( void );
         int Add_To_Tail( Base_Link *element );
        int Add_Node( Base_Link *element );
         int Del_Node( void );
         int Del( Base_Link *element );
         int Find( Base_Link *element );
        inline void Clear( void );
        inline int Count( void );
        inline void Reset_To_Head( void );
        inline void Reset_To_Tail( void );
        inline Base_Link *Curr( void );
        inline void Next( void );
        inline void Prev( void );
    };
//-----------------------------------------------------------------------
class Base_Node           // Base Neural-Network Node
    {
    private:
        static int ticket;

    protected:
        int id;           // Identification Number
        double *value;     // Value(s) stored by this node
        int value_size;    // Number of Values stored by this node
        double *error;     // Error value(s) stored by this node
        int error_size;    // Number of Error values stored by this node

        LList in_links;    // List for input links
        LList out_links;   // List for output links

    public:
        Base_Node( int v_size=1, int e_size=1 );    // Constructor
        ~Base_Node( void  );                        // Destructor
        LList *In_Links( void );
        LList *Out_Links( void );
        virtual void Run( int mode=0 );
        virtual void Learn( int mode=0 );
        virtual void Epoch( int code=0 );
        virtual void Load( ifstream &infile );
        virtual void Save( ofstream &outfile);
        inline virtual double Get_Value( int id=NODE_VALUE );
        inline virtual void Set_Value( double new_val, int id=NODE_VALUE );
        inline virtual double Get_Error( int id=NODE_ERROR );
        inline virtual void Set_Error( double new_val, int id=NODE_ERROR );
        inline int Get_ID( void );
        inline virtual char *Get_Name( void );
        void Create_Link_To( Base_Node &to_node, Base_Link *link );
        virtual void Print( ofstream &out );
        void Set_Centers (Base_Node *from_node);
        double Compute_Distance();
        double Compute_Sigma (Base_Node *Onode);
        virtual double Transfer_Function();
        double Compute_Min_Distance(Base_Node *Onode,int dump);
        double Update_Sigma(double Lr,double output_error,double weight,
        double node_value,double distance,double prev_sigma);
        void Update_Center(double error,double lr);
        virtual void Learn2(int mode, int dump, int additive, int inputs,double Lr);

        friend void Connect( Base_Node &from_node, Base_Node &to_node,
                    Base_Link *link );
        friend void Connect( Base_Node &from_node, Base_Node &to_node,
                    Base_Link &link );
        friend void Connect( Base_Node *from_node, Base_Node *to_node,
                    Base_Link *link );
        friend int Disconnect( Base_Node *from_node, Base_Node *to_node);

        friend double Random( double lower_bound, double upper_bound );
    };
//---------------------------------------------------------------------
class Feed_Forward_Node : public Base_Node  // This derived class provides
        {                         // a generic feed-forward
                                 // neural-network node which
                                 // can be used by the ADALINEs
                                 // and Backprop networks.

       protected:
            virtual double Transfer_Function( double value );

         public:
            Feed_Forward_Node( int v_size=1, int e_size=1 );  // Constructor
            virtual void Run( int mode=0 );
             virtual char *Get_Name( void );
          };
//------------------------------------------------------------------------
class RB_Node : public Feed_Forward_Node
    {
    protected:

           double *Center;
//         virtual double Transfer_Function(double value/*Base_Node *Onode*/);
    public:
        RB_Node( int v_size=1, int e_size=0 );   // Default of 1 value set member
      (NODE_VALUE)
        virtual char *Get_Name( void );
        void Set_Centers (Base_Node *from_node/*,Base_Node *to_node*/);
        double Compute_Sigma (/*Base_Node *Main_Node,*/Base_Node *Onode);
        double Update_Sigma(double Lr,double output_error,double weight,
        double node_value,double distance,double prev_sigma);
        virtual void Save(ofstream &outfile);
        virtual void Load(ifstream &infile);



        void Creat_Center(int num)
        {
        Center=new double[num];
        for (int i=0;i<num;i++)
        Center[i]=0.0;
        }
        void Set_Center(double new_val,int id) { Center[id]=new_val;}
```

```
            double Get_Center(int id) {return Center[id];}
     };
//-----------------------------------------------------------------------
class RB_Link : public Base_Link
     {
     public:
            RB_Link( int size=1 );   // default of 2 link value set members (WEIGHT,
          DELTA)
            virtual void Save( ofstream &outfile );
            virtual void Load( ifstream &infile );
          /*  virtual char *Get_Name( void );
            virtual void Update_Weight( double new_val );*/
     };
//-----------------------------------------------------------------------
class RB_Output_Node : public RB_Node
     {
     public:
            RB_Output_Node( double lr, double mt, int v_size=3, int e_size=1 );
  //   default   of   3   value   set   members   (NODE_VALUE,   LEARNING_RATE,
          MOMENTUM)
  // default of 1 error set member (NODE_ERROR)
            virtual void Save(ofstream &outfile);
            virtual void Load(ifstream &infile);
     protected:
            virtual double Compute_Error( int mode=0 );
            virtual void Learn( int mode=0);
            virtual void Learn2( int mode=0,int dump=0, int additive=0,int inputs=0,double
          Lr=0);

            virtual char *Get_Name( void );
            virtual void Run (int mode=0);
     };
//-----------------------------------------------------------------------
class RB_Middle_Node : public RB_Node
```

```
   {
   public:
       RB_Middle_Node(int v_size=10, int e_size=1 );
// default of 3 value set members
     (NODE_VALUE,LEARNING_RATE,MOMENTUM)
// default of 1 error set member (NODE_ERROR)
        // additionaly 5 centers
        //and 1 sigma
        //1 distance
       virtual char *Get_Name( void );
       void Set_Sigma(double new_val) {Sigma=new_val;}
       double Get_Sigma() {return Sigma;}
       double Compute_Distance(/*Base_Node *Node*/);
       virtual double Transfer_Function(/*Base_Node *Onode*/);
 //    double Compute_Min_Distance(Base_Node *Onode,int dump);

       virtual void Save(ofstream &outfile);
       virtual void Load(ifstream &infile);
   protected:
       virtual double Compute_Error( int mode=0 );
       double Sigma;
     //  virtual void Run(Base_Node *Node);
   };
//------------------------------------------------------------------------

class RB_Additive_Node : public RB_Node
   {
   public:
       RB_Additive_Node (double lr, double mt, int v_size=10, int e_size=1);
        // default of 3 value set members
     (NODE_VALUE,+LEARNING_RATE,+MOMENTUM)
        // default of 1 error set member (NODE_ERROR)
        // additionaly 5 centers
        //and 1 sigma
```

```
         //1 distance
         virtual char *Get_Name( void );
         void Set_Sigma(double new_val) {Sigma=new_val;}
         double Get_Sigma() {return Sigma;}
         double Compute_Distance(/*Base_Node *Node*/);
         virtual double Transfer_Function(/*Base_Node *Onode*/);
  //     double Compute_Min_Distance(Base_Node *Onode,int dump);

         virtual void Save(ofstream &outfile);
         virtual void Load(ifstream &infile);
    protected:
         virtual double Compute_Error( int mode=0 );
         double Sigma;
       //  virtual void Run(Base_Node *Node);
    };
//----------------------------------------------------------------------
```

APPENDIX B

TEST DATA

No:	Cutting Speed	Feed	Time	Fx	Fz	Flank Wear
1	200	0.05	10	150	110	38
2	200	0.05	20	180	120	48
3	300	0.05	60	200	120	114
4	200	0.1	10	220	190	38
5	200	0.1	20	230	150	58
6	200	0.1	60	270	190	59
7	250	0.1	10	200	150	51
8	300	0.1	20	230	190	89
9	300	0.05	40	180	120	81
10	200	0.05	80	180	140	79
11	250	0.05	50	220	200	89
12	200	0.05	60	250	120	74
13	300	0.05	20	130	80	58
14	200	0.05	100	220	90	84
15	250	0.05	20	150	120	53
16	250	0.05	60	220	120	99
17	300	0.1	10	210	140	56
18	200	0.1	40	260	190	71
19	200	0.1	30	250	210	66
20	200	0.05	70	210	110	76
21	250	0.05	40	220	130	79
22	200	0.05	30	150	10	53
23	250	0.1	20	230	170	81
24	200	0.05	40	200	120	66
25	200	0.05	50	210	120	66
Max	300	0.1	100	270	210	114
Min	200	0.05	10	130	10	38