

A SIMPLE ARTIFICIAL NEURAL NETWORK
DEVELOPMENT SYSTEM
FOR
STUDY AND RESEARCH

by

David Southworth

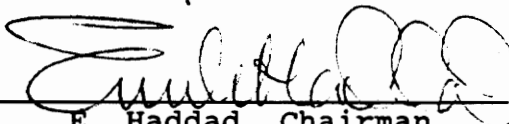
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Approved:


E. Haddad, Chairman


C. Egyhazy


R. Schneider

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Committee Chairman: Emile Haddad
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(ABSTRACT)

This research paper proposes the design and implementation of an Artificial Neural Network (ANN) development system which will provide the foundation and a tool for study and research in ANN architectures and algorithms. A system was developed which allows for the implementation of networks and for the modification of common and interesting network parameters and algorithms. This establishes a versatile and effective model from which to proceed with ANN study.

The system design is an initial prototype providing a generic and dynamic interface which allows the versatility to implement simple networks on a Personal Computer and modify their parameters, architectures, and algorithms. It also allows the monitoring of the internal conditions of the network, providing a basis for detailed data collection and research.

Several different neural nets were implemented and trained on the system. Various feedforward networks using the

Delta Rule and the backpropagation learning algorithms were trained in the supervised mode to solve problems in pattern recognition. Modifications to these networks were then used to compare training and operational characteristics between the different architectures. A classic one layer Hopfield net using a recurrent feedback, associative memory architecture was also implemented and trained in the unsupervised mode. An unsupervised Hebbian learning algorithm was also implemented and tested on the system.

Several enhancements are proposed which will increase the versatility of the system and aid in the further study of Artificial Neural Network implementations and characteristics.

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SECTION 1

INTRODUCTION

Artificial Neural Networks (ANNs) have been inspired by their biological counterparts, the real neural networks of the human brain. The mysteries of how the brain actually operates is little understood although its general operation, in a gross sense, has been studied thoroughly. Rough models of the brain and its functions form the pattern and the basis for Artificial Neural Networks.

In recent years, there has emerged a new interest in the use of Artificial Neural Networks as an innovative computational approach to problems that are considered very difficult, if not intractable, to solve on conventional von Neumann machines.

These applications include pattern matching and recognition, decision making in a fuzzy environment, and adaptive control.

The human brain solves these kind of problems in an elegant, although still unclear, fashion. Humans see an incomplete image, perhaps partially obscured by shadows or other objects, and can identify it almost immediately. No one of the billions of neurons in the brain is especially important, yet together they form a marvelous processor that outperforms machines in most recognition tasks.

One might argue that it is impossible to build an

artificial neural network if real ones are not well understood. Even so, ANNs are being built and simulated on conventional digital computers. The first tentative steps for implementing them in hardware is also taking place. These are not exact models of real neural systems but they do generalize the concepts of actual "wetware". We do not fully understand how actual neural networks operate but still we can grasp many of the concepts well enough to simulate in software.

There is a great necessity for further research in artificial, as well as biological, neural networks. We must know much more about learning algorithms, interconnection philosophies, layering requirements, size requirements, and how best to implement all of those into hardware and/or software. All these issues need to be addressed along with the biological, chemical and behavioral study of actual networks if the artificial and real world are to ever approach convergence.

The purpose of this Artificial Neural Network Development System project is to construct a structural implementation which will provide a vehicle for the further study and research of Neural Network architectures. The development system provides a foundation for the student to create networks of different sizes and architectures, with variable parameters and computational algorithms, and see them in operation. It includes the capability to vary several of the

parameters of ANN implementations which are of interest in current research. These include such things as the interconnection of the nodes within the network, the implementation of multi-layer networks, fully or partially connected networks, and recurrent (feedback) networks. Also included are neural body activation algorithms, learning algorithms of the network, and the number and size of layers within the network. A complete implementation, where these parameters are selectable and modifiable by the user, will provide a versatile and effective tool and a foundation for further study and research in ANN architectures and capabilities. This project is meant as a first step in the development of such a simulation system.

The intended users of this system are students studying the functions and use of neural networks. Such users may be studying, for example, the effects of various parameters on neural nets, exploring the use of different learning algorithms, different activation functions or connection architectures. The development system was created to support such capabilities.

The user interface for this system was partially completed in satisfaction of course requirements for Human Computer Interaction [CS 5714] finished in Fall 1989) [1]. Since that time, several enhancements, changes and additions have been made to the implemented system.

SECTION 2

ARTIFICIAL NEURAL NETWORK BACKGROUND

Figure 1 is a sketch of two simple neural cells with one interconnection (synapse). There could be many more such interconnections.

The neural body is the main computational element of both the biological neural network and its artificial counterpart. It receives electrical inputs from one, hundreds, or thousands of other neural bodies via its dendrites. The electrical pulses traveling along the dendrites may be excitatory or inhibitory. The neuron essentially averages its inputs over a short period of time. If the end result exceeds a certain threshold, the neuron "fires", sending an electrical signal out along its axons. Each axon is, in turn, connected through synapses to the dendrites of other neurons and the pattern continues. This simplistic description of actual neuron operations and interconnections is what most artificial networks are patterned after.

Memory is "distributed" throughout the neural network and is manifested in a multitude of neurons, their connections and weights, and their averaging functions which determine their time to fire. A single neuron, or even many neurons, with their multiple connections do not constitute the complete memory of a system. In fact, after an ANN has been trained,

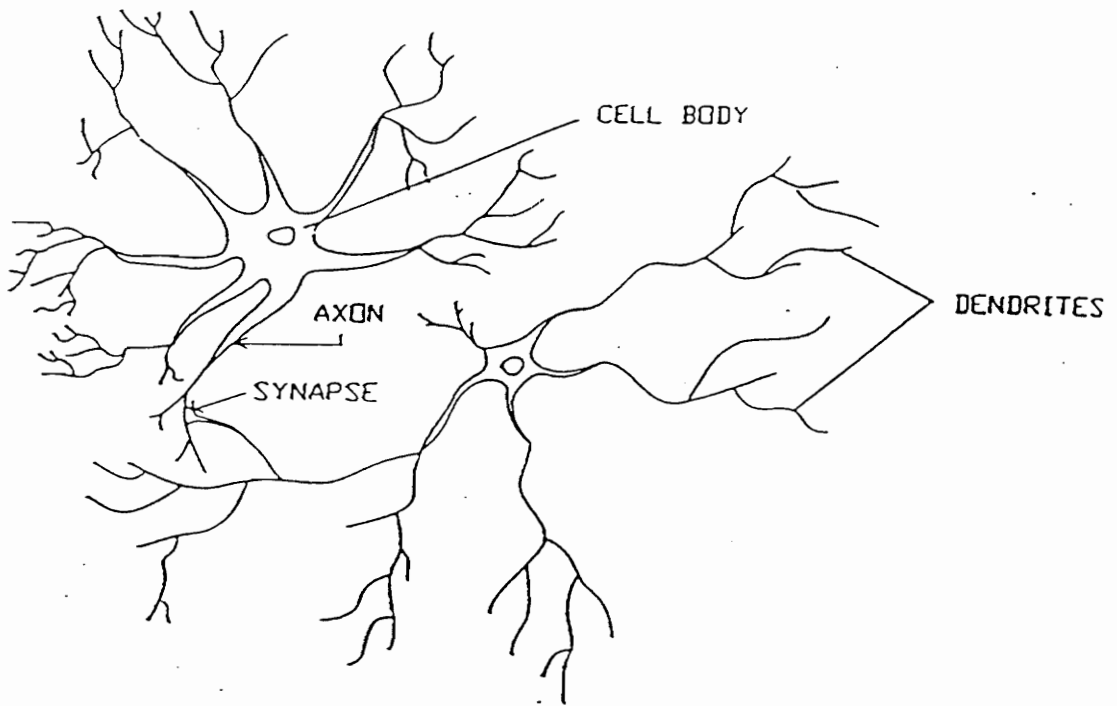


Figure 1. Biological Neurons

many neurons and their connections may be removed with little or no effect on the outcome of the computations of the network. The memory of the system is truly distributed across, and throughout the network.

The artificial neuron, Figure 2, first envisioned and developed by Rosenblatt [2] was patterned after the functions of the biological neuron. Essentially, a set of inputs is applied with each input representing either the output of another neuron or a stimulus from the outside world. Each input is multiplied by a corresponding "weight". The weighted inputs are then summed, producing an output called SUM for purposes of this paper (the general term in the literature for SUM is NET). The set of weights associated with each neuron and corresponding to each input is a vector W. This weight vector is multiplied and summed with the vector of all the inputs, X, to the neuron. This forms the relationship:

$$[X] [W] = \text{SUM}$$

The thresholding function (F) of the neuron, commonly called the neuron activation function, is then applied to SUM, which produces the output, or firing of the neuron, called OUT.

In the Artificial Neural Network, the neuron is represented by the summation process coupled with the activation function. The dendrites are simulated by the

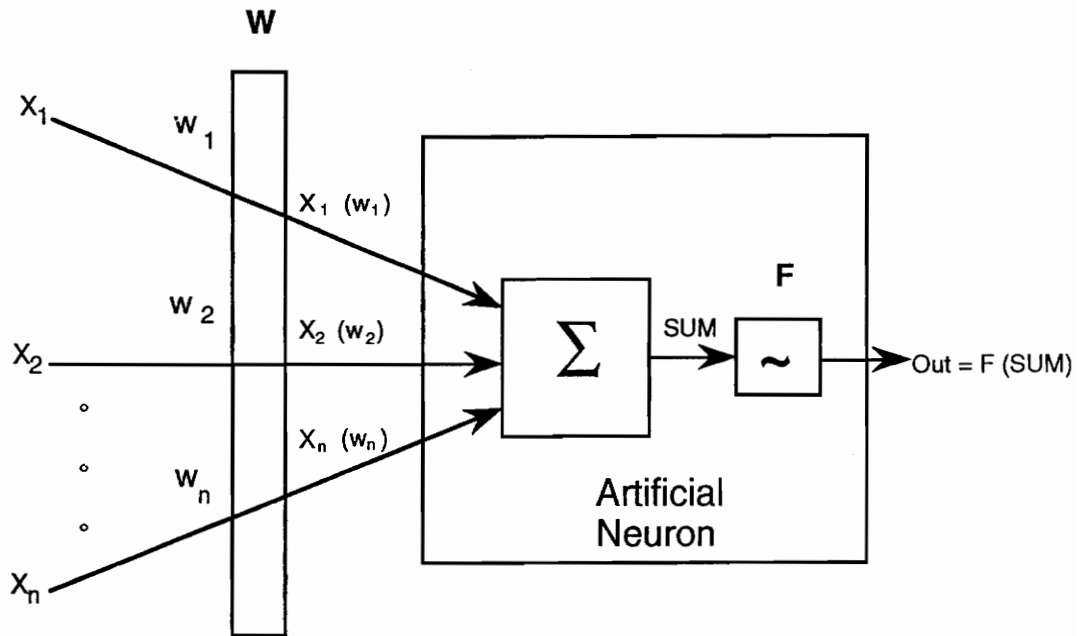


Figure 2. Artificial Neuron

inputs and weight vector to the neural body, while the axons are represented by the output lines of the neuron which become inputs to the weight vector of the next neural layer. The synapse connections are represented by the connectivity between the layers which may be fully or partially connected. In a fully connected network all neurons of one layer are connected to every neuron in the following layer. In a partially connected network, some of these connections will be missing. The connectivity and how it affects the computational power of certain networks is one of the objects of current research in the field.

The activation function (F) of the neuron may be a simple linear or non-linear function, or a more complex non-linear function. Multi-layer networks using a linear activation function, such as

$$\text{OUT} = C * \text{SUM}$$

where C is some constant, have been shown to have no more representational power than a single layer network with the same function [3]. Networks today universally use non-linear activation functions such as a simple threshold function (Figure 3a) where

OUT = 1 if SUM \geq Threshold

OUT = 0 if SUM < Threshold

or other, more complex non-linear functions which permit more general and stable network activities.

Often, activation functions in current research follow the sigmoid model expressed as

$$\text{OUT} = 1 / (1 + e^{-\text{sum}}) \quad (\text{Equation 1})$$

This form (Figure 3b) allows the network to handle a wide range of signals where the output is "squashed" to produce low gain for large inputs and a higher gain for smaller inputs. In Figure 3b, the neuron produces a continuous, compressed output (OUT) within the range of zero and one. Some algorithms requiring discrete, binary outputs may further apply a separate thresholding function to OUT. If OUT then exceeds this threshold level, the neuron fires and applies a signal to its axons or output lines. If below the threshold, the output is zero.

Figure 3c shows a modified Sigmoid function. This simple enhancement to the Sigmoid Function, as described by Stornetta and Huberman [4], allows for output values in the range of -0.5 to +0.5 which often reduces training time of the network since

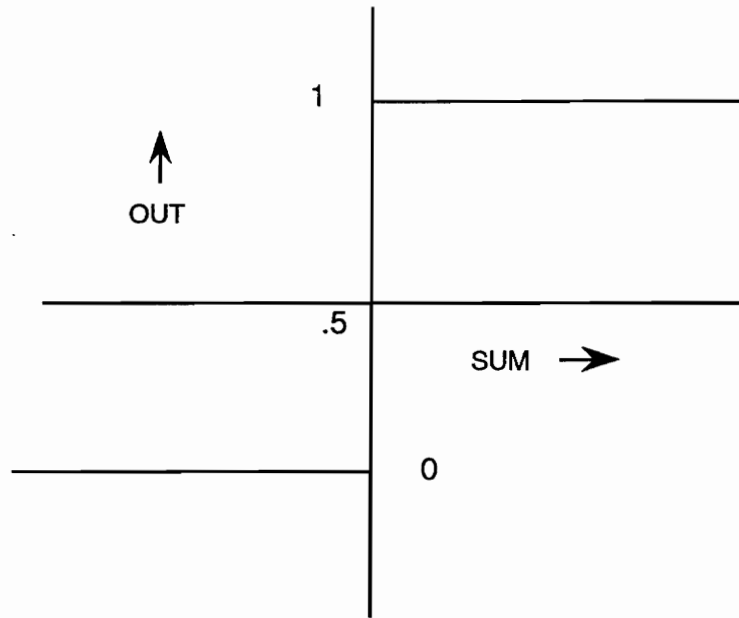


Figure 3a. Simple Threshold Activation Function

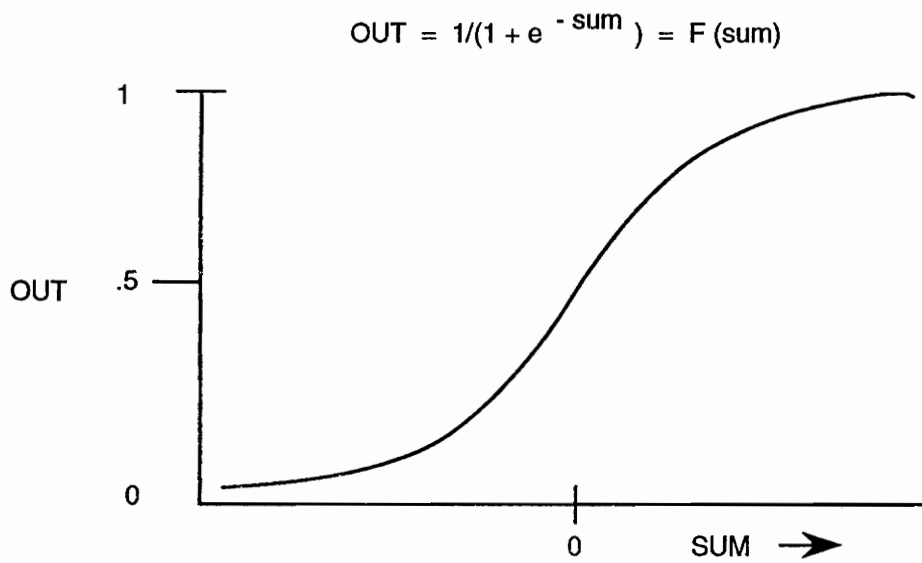


Figure 3b. Sigmoid Activation Function

$$\text{OUT} = -.5 + 1/(1 + e^{-\text{sum}}) = F(\text{sum})$$

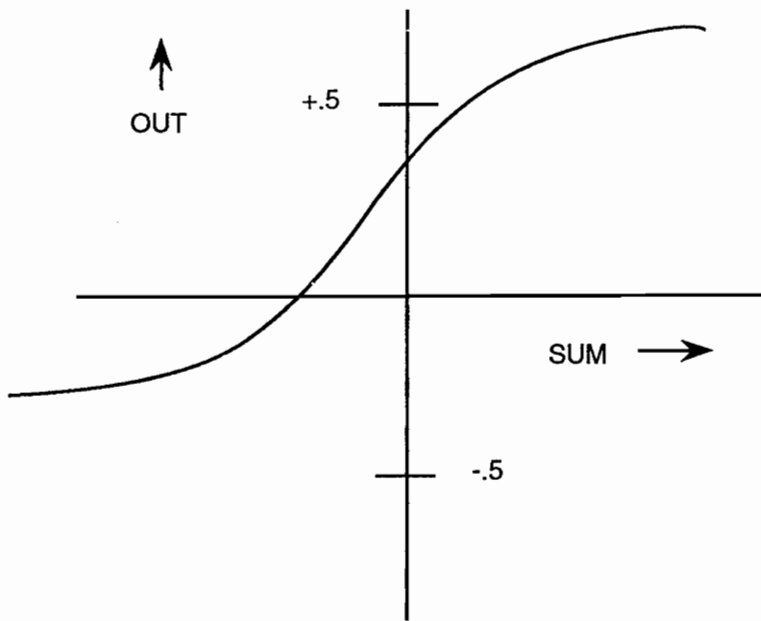


Figure 3c. Modified Sigmoid Activation Function

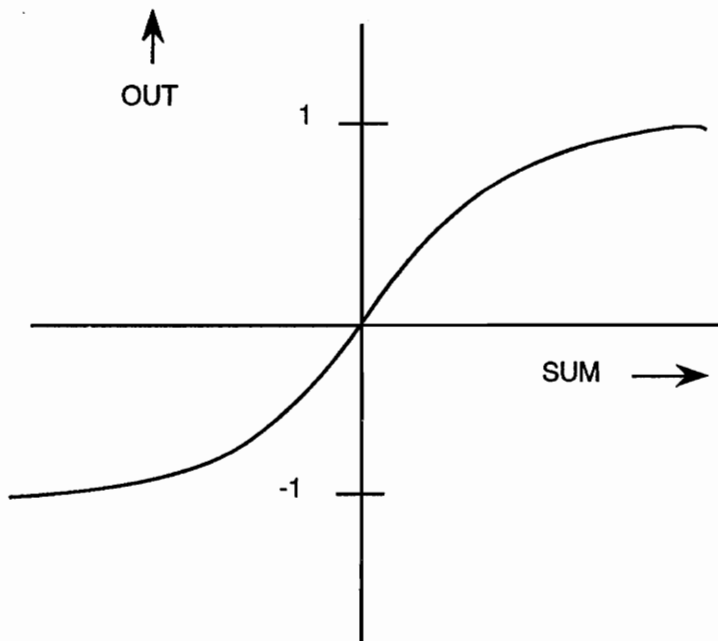


Figure 3d. Hyperbolic Tangent Activation Function

the majority of the values of OUT take on values other than values close to zero. Input range also is changed from 0/1 to $-.5/+5$ which allows all weights in the first hidden layer to be trained. One common learning algorithm, backpropagation, produces training where weight changes are proportional to the output values of the input neurons. Thus, inputs of 0 allow no training of the weights through which those input values are connected. In several training algorithms, especially backpropagation, this modified activation function allows the weight to be multiplied by input values which are not close to zero. This tends to speed up training time.

Figure 3d shows another common activation function, the hyperbolic tangent function. It has the same general shape as the sigmoid. As with the Modified Sigmoid Function, this function also generates zero output when $SUM = 0$. However, in this case output values range from -1.0 to $+1.0$. OUT again generates either positive or negative numbers which allows for inhibitory signals, as well as excitatory ones.

A multi-layer, fully connected network is shown in Figure 4. A layer is considered to be a set of neural bodies and their associated input weight vectors (weight vectors are normally associated with the layer with which they affect the input). Thus Figure 4 possesses two layers. The input layer, commonly referred to in the literature as layer 0, in effect does no computation. It merely serves as a distribution

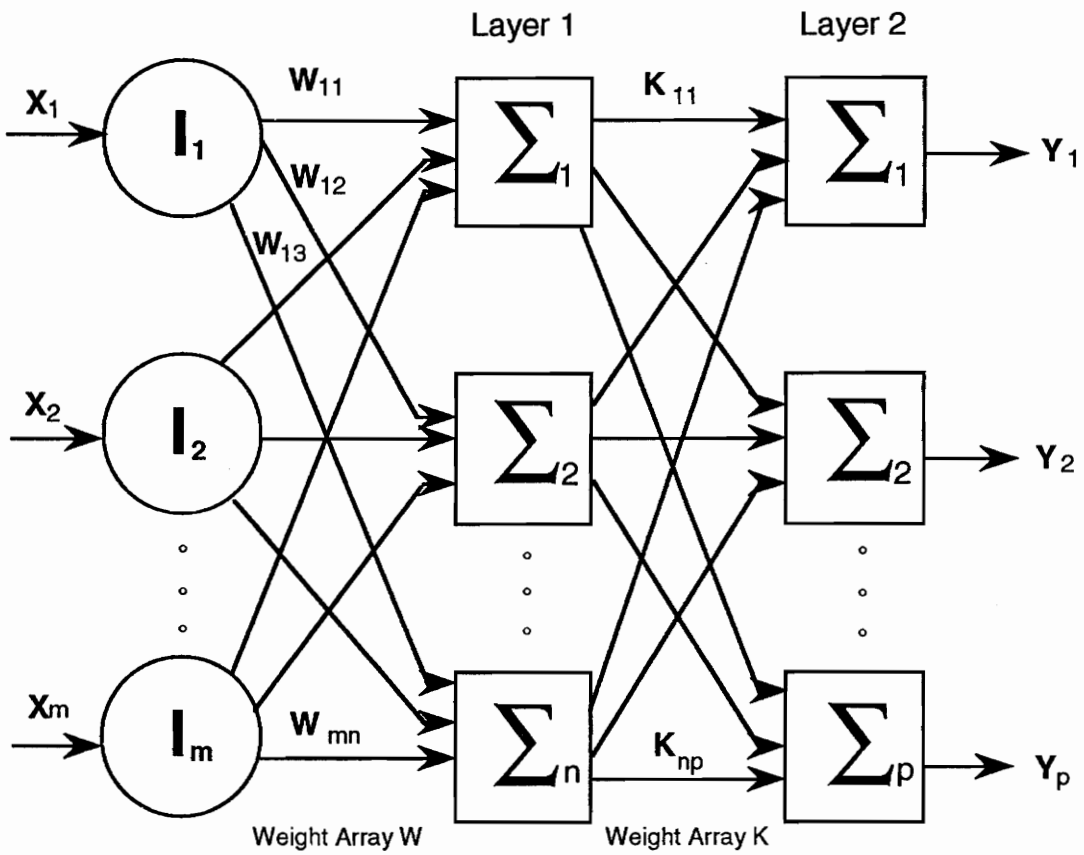


Figure 4. Two Layer Neural Network Model

center for the first set of inputs and weights and is, therefore, not considered a true layer. Layer 0 does not possess an associated weight vector. The first set of weights is associated with layer 1. The output layer usually performs a computation through its associated weight vector and, therefore, functions as a layer. In Figure 4 the output layer is also layer 2. Layer 1 is often referred to as a "hidden" layer, since its input and output, and therefore its computational contribution to the network cannot be "seen" by the user.

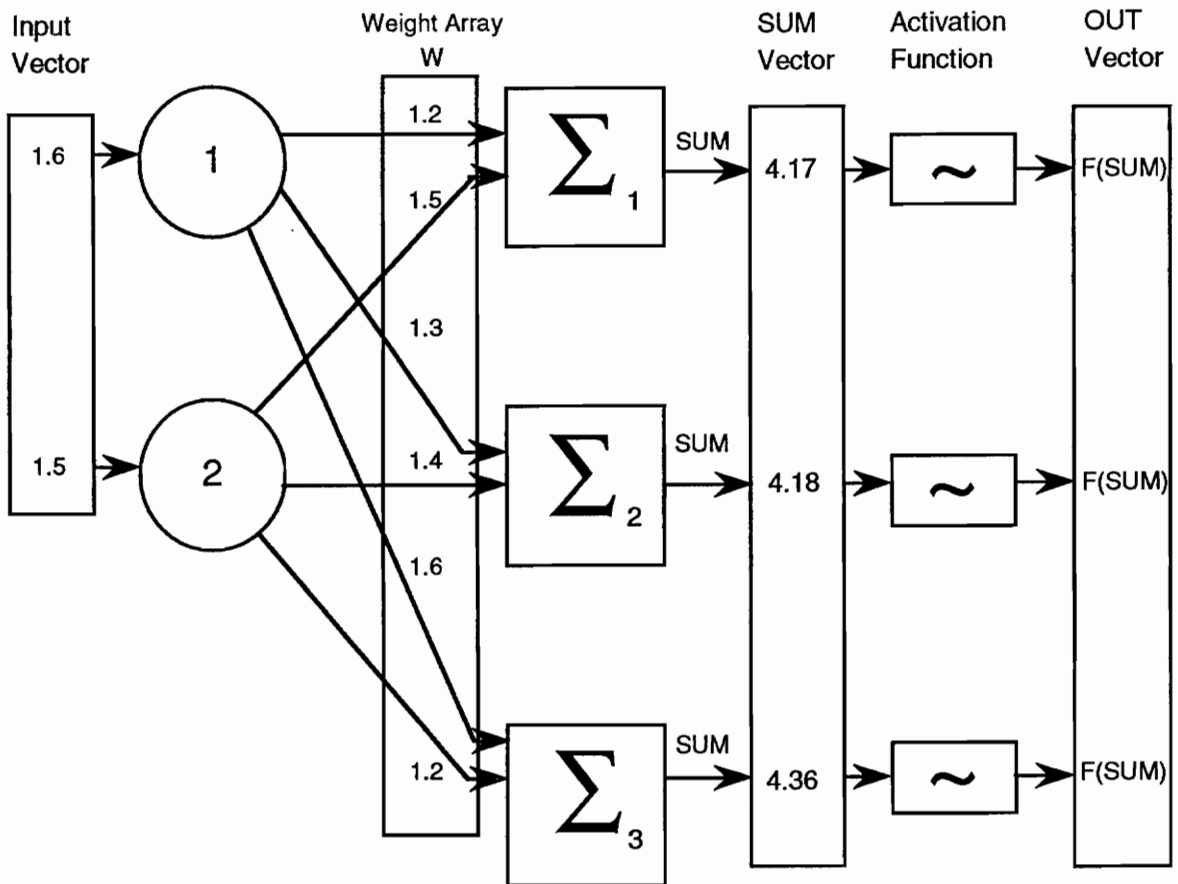
The set of inputs to the network in Figure 4 has each of its elements connected to each neuron in the next layer through an individual weight, shown as W_{mn} . This fully connected network has a feedforward architecture since the output of one layer feeds forward only, as input to the next layer. Feedback, or recurrent, networks are also possible where the outputs of a layer may feed back, through an associated weight vector, to itself or to earlier layers. These feedback architectures may also be fully connected or connected to a lesser extent, as with feedforward connections.

Variations of these types of architectures are limited only by the researcher's imagination and the computational power of the machine on which the network is implemented. Often, in the machine representation, the weight vectors are

considered to be elements of a matrix (W) with m rows and n columns where m is the number of inputs and n is the number of neurons. Thus $W_{2,1}$ would represent the weight connecting the second input to the first neuron in the layer. Lack of a connection between an input and a neuron would be signified by a 0 in the respective component of the matrix. Calculating the set of neuron outputs (SUM) for a layer is then a simple matrix multiplication with $SUM = NW$ where N is a vector of inputs to the layer, W is the weight matrix, and SUM is the output vector. This calculation is illustrated in Figure 5. The activation function is then applied to SUM of each neuron resulting in OUT . This resulting output vector serves as the input vector to the next layer. In this manner, networks of any number of layers may be built.

Of all the capabilities of artificial neural networks, probably the most interesting is their apparent ability to learn. Many training algorithms have been developed but this remains an area of intense research.

Training algorithms are generally categorized as supervised training or unsupervised training. In supervised training, each set of inputs is paired with a set of correct outputs. A training set is presented, over and over, to the network until the network produces the correct outputs a satisfactory percentage of the time. The algorithm itself



$$\begin{bmatrix} 1.6 & 1.5 \end{bmatrix} \times \begin{bmatrix} 1.2 & 1.3 & 1.6 \\ 1.5 & 1.4 & 1.2 \end{bmatrix} = \begin{bmatrix} 4.17 & 4.18 & 4.36 \end{bmatrix}$$

Figure 5. Network Computation

feeds back the difference between the correct output and the actual output and modifies the weight values of each layer according to a predetermined procedure. Through this process, the outputs of the net gradually converge to an acceptable level. When the network produces the correct output for all inputs, it is said to have "converged" or to have reached convergence. Figure 6 shows the general, supervised learning procedure and how the results of the training are fed back through the network.

In unsupervised learning, the same general method is applied except there is no output for comparison. Again, the weights are changed according to a set algorithmic procedure until similar inputs produce outputs that are consistent. The training algorithm thus extracts statistical properties of the training set and groups the input vectors into classes. The final output patterns produced by the network must then be transformed into a comprehensible and usable form. This generally is not a difficult task but is a step not required in a supervised training scenario.

Feedforward, backpropagation networks are examples of supervised training while self-organizing networks are examples of unsupervised training. Hopfield nets (Figure 7) are single layer, recurrent networks that are often used in associative memory (content addressable) memory applications. The weights in a Hopfield net are first initialized via a very

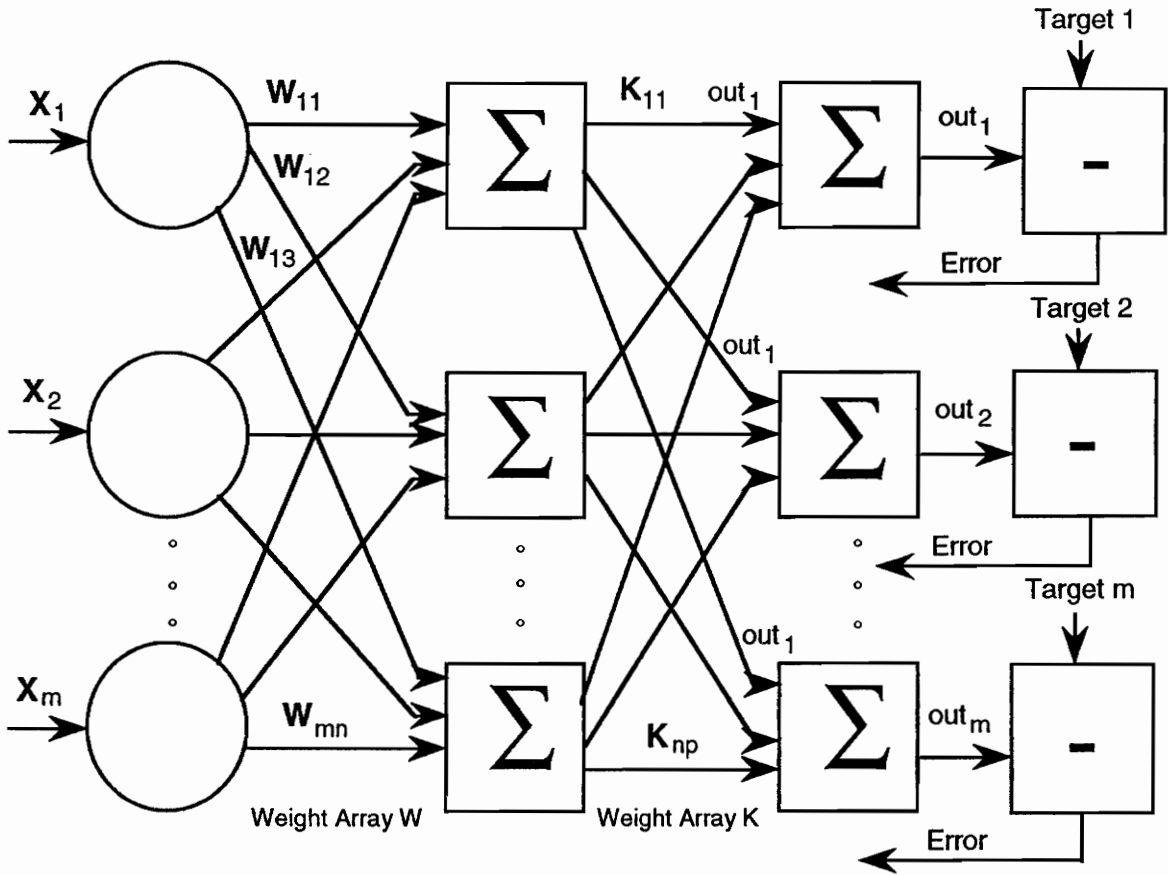


Figure 6. Network Learning

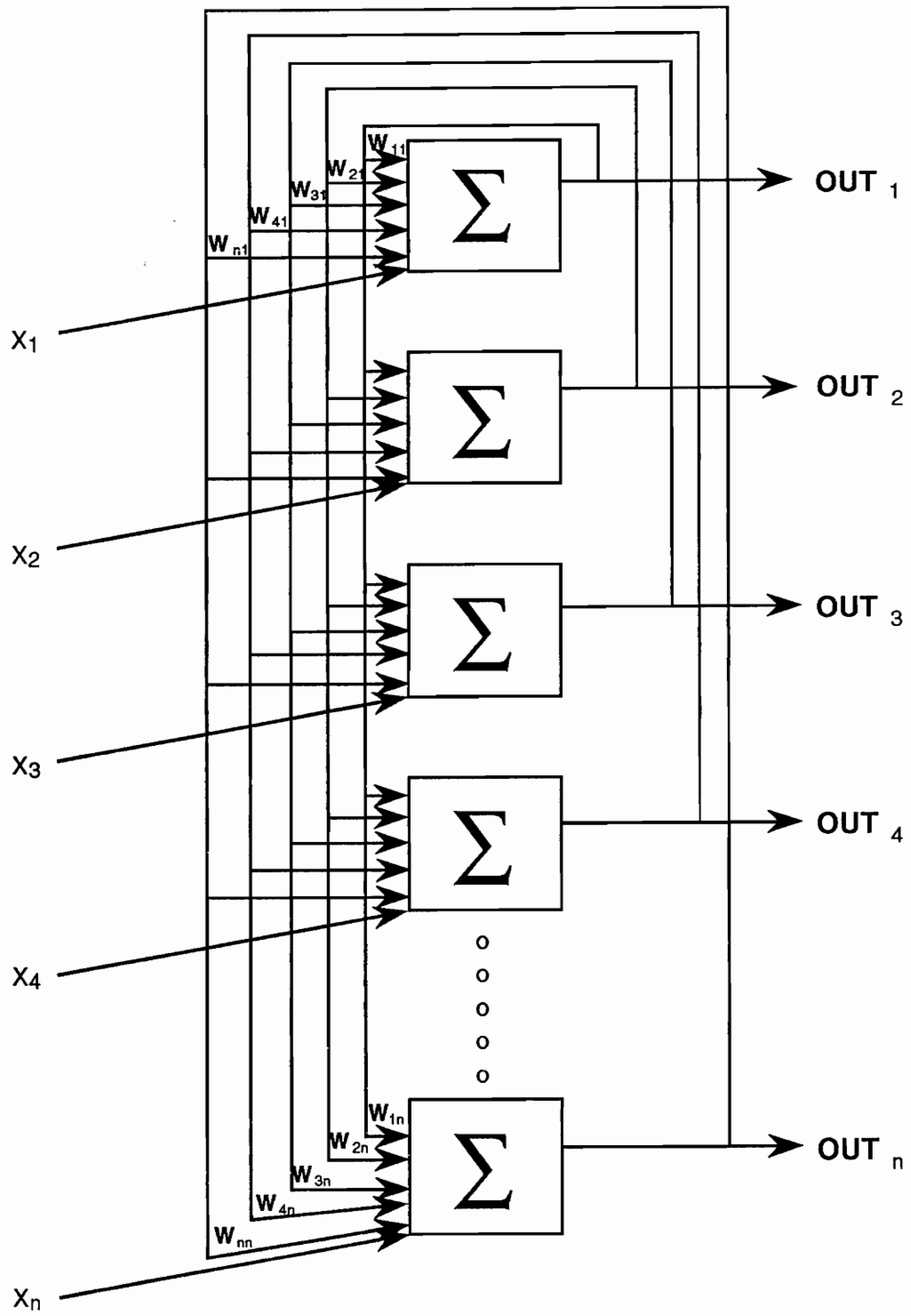


Figure 7. Hopfield Network

specific algorithm using exemplar, or example, patterns from all classes to be recognized by the network. The weights are not changed after this initialization. As such, the Hopfield net cannot be said to be trained in the normal sense. However, since this type of network is widespread in the study of ANNs it has been implemented on this development system.

The supervised training network in the form of a feedforward, backpropagation net and the recurrent, unsupervised Hopfield net will be discussed thoroughly throughout this report. Both have been implemented on the subject development system. Further implementations of self-organizing networks using the Hebbian learning algorithm will be briefly discussed. Other supervised and unsupervised nets using different training algorithms will also be discussed in the context of how they might be implemented on the prototype development system.

SECTION 3

DEVELOPMENT SYSTEM DESCRIPTION

This Artificial Neural Network Development System was designed and implemented on a personal computer. It is a system for use in research and investigation of the capabilities and functions of Artificial Neural Networks (ANN) and was designed as a tool to aid in that study. A modifiable ANN development system was evolved in which several of the common parameters in ANN implementations may be manipulated by the user without the necessity of a full software development. The ANN Development System consists of the network algorithms and computational functions, and the user interface. The interface to the system supports the selection of the variable parameters, provides a display of the parameters selected, and causes the selections to be invoked within the ANN computational software. The interface also provides for the normal input of data into the selected ANN implementation, displays that input, and displays the output of the final computation that the ANN performs on that input data. Additionally, it visually displays dynamic data as the Artificial Neural Network performs its computations.

Since the system implementation is meant to be a research and study tool, it not only supports the basic input and output common to any ANN, but it also implements the

capability to vary the system's internal, normally hidden representations and keep the user informed of the choices he/she has made. These design criteria required an in-depth task analysis/use model of which ANN parameters should be variable, what the student needs to know about those variations, and how they should be displayed. Once the selections have been made by the user, the system allows data to be inputted to the ANN, computations to be made, and final net output to be displayed.

The interface for a conventional ANN--one which is meant to run a single application with a single architecture--must only support input and display the output in some format applicable to that specific application. It need only implement a single algorithm for training and output calculation. One such application was the Hopfield Net implemented by Springsteen in his Masters project [5]. The ANN development system for the present project requires a much more generic and dynamic interface which will allow the user not only to modify the parameters of the network, but also the algorithms themselves. This gives the user an adaptable, multi-purpose capability for the study of networks. The system developed for this project, therefore, has the potential for creating an unlimited number of vastly different networks, with different capacities and computational capabilities, running in different problem domains.

Since this system is intended for the study of multi-layered Artificial Neural Networks, the user will also be interested in the internal conditions of the network as it is performing its computations. He will want to be able to monitor the changing conditions of the "internals" of the network. The development system therefore also allows this monitoring of the hidden layers to take place.

Finally, the system also supports the normal input and output for the network. Its versatility will allow a wide range of input and output formats and the networks created can support a wide range of application domains.

The background section of this paper described some typical ANN configurations and how they operate. It presented the various functioning sections of an ANN and how they interrelate. These functional sections are what the user deals with when studying the effects of various factors on the networks. The user variables of an ANN include the following:

1. Number of Layers.
2. Size (number of neurons and associated weights) of each layer.
3. Connectivity (number of connections) of each layer to the next layer.
4. Direction of connectivity (forward, backward).
5. Neuron Activation Functions.
6. Learning Algorithms.

7. Various factors used to moderate, smooth, or vary the amount of training or speed of training. Momentum, training rate coefficient, saturation level, and tolerance will be discussed later in this report.

The user may have occasion to modify any one or all of the above variables in carrying out his studies of ANNs. The development system allows the user to vary these factors expeditiously in a logical fashion, as well as display the selections and parameters he has chosen.

Researchers are interested in how particular parameters vary and change during the learning cycle of an ANN. These parameters include the initial weight settings, the final weight settings, and the dynamics of how changes in weights for a particular layer occurred. They are also interested in firing rates of neurons within the net. The system allows this data to be collected and printed out at the end of a session. In addition, graphic display of data in real time during the training and operation cycle of the net has been implemented. This allows the user to visually see the net in action.

SYSTEM ARCHITECTURE

This ANN simulation system was developed to enable students to quickly implement artificial neural networks of interest, to vary network topologies and architectures, and to modify or develop new algorithms of interest in their study of the general area of Artificial Neural Networks. It has been implemented in Turbo Pascal 4.0, running on a 12 MHz AT class machine with 1 Mb of main memory and VGA graphics capability. Transportability to other machines with CGA, EGA, or mono capability or with different system features was not a design goal. The system was designed with extensibility and ease of adding new network features in mind.

As system development progressed, it became evident that several broad categories of nets existed that were characteristically implemented in incompatible ways. This necessitated analogous categories of delineation within the system to allow for ease of implementation of these nets. Figure 8 shows the division of these categories.

Nets are first divided into the definition of either supervised or unsupervised training modes. Recurrent and feedforward nets are then specified within these categories. Within these areas, networks are usually similar in their implementation, only the specifics of basic algorithms being subject to change. The overall architecture and basic

functional methodology remains similar, if not identical, across the ANNs within one of these specific categorizations. For example, a feedforward net using the backpropagation learning algorithm is basically the same net as a feedforward net using a Delta learning rule. Both use a supervised training sequence of application of the input, computation of the output, a comparing of the output to the required output, and an adjusting of the weights within the net in order to reduce the error. This sequence of events is iterated until the net output produces acceptable results. Within the two networks the specifics of the learning algorithm change, possibly even the activation function, the network topology, or the computation of the input to layers within the network, but the basic overall network paradigm remains consistent.

From the development system's standpoint, the biggest difference between supervised and unsupervised networks is the sequence of events and whether or not target vectors should be read from the input file. Specifying the networks produced on the development system in this manner enforces the sequence of events and permits a single format for the input file no matter what type of network is specified. This removes a major source for error in the development of a new network. Also, when viewed this way, networks are more easily modified and new algorithms are more easily implemented. The system

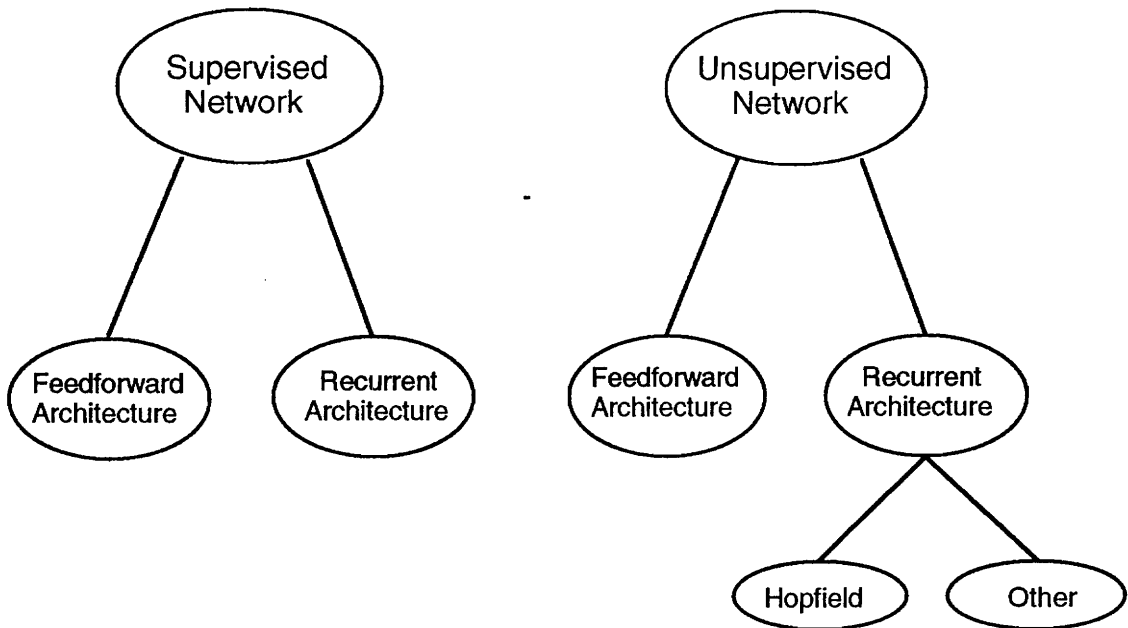


Figure 8. Network Implementation Categories

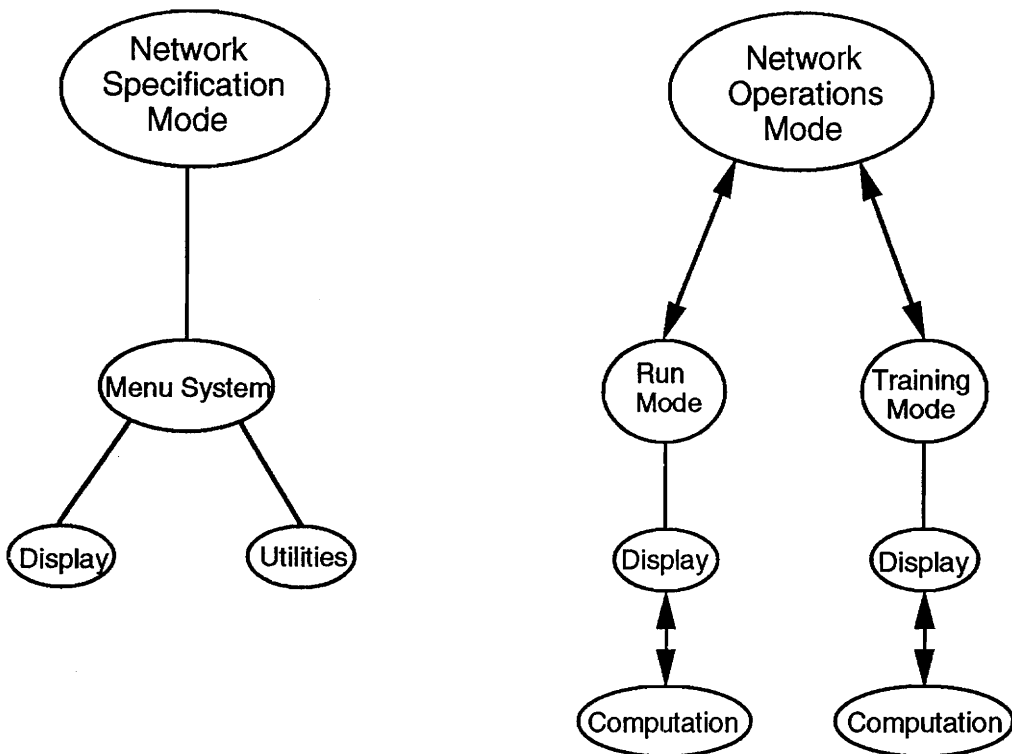


Figure 9. Development System Modes

becomes modifiable and extensible from the operator's point of view.

The system is comprised of four main functional sub-areas (Menu system, Display, Computation, and the I/O Utilities) specified in eight separate units. The source code for these units is fully reproduced in Appendices B through J. The units are:

1. unit nnglobal - global declarations
2. unit menus - menu system
3. unit weights - part of the menu system for weight setting and display
4. unit grafstuf - graphical display system
5. unit ioutil - input/output utilities
6. unit math - network computations and learning algorithms
7. unit ops_stuf - provides interface between the menu system (specification mode) and the display system (operations mode)
8. unit mathutil - initialization routines and other utilities

There are also two main modes of operations -- the Network Specification Mode and the Network Operations Mode (See Figure 9).

MENU SYSTEM

The Menu System is the primary user interface for creating a network and modifying its parameters. The Menu system is functionally rigid in the sequence displayed to the operator. This allows for a strict ordering of the sequence of events that take place and ensures that previous, required selections are made before dependent selections are made. The overall menu architecture and functionality is displayed in Figure 10.

The menu system itself is comprised of seven functional areas, and their associated menus. As shown in Figure 10, these are designated as the Main, Layer Data, Net Architecture, Connectivity, Weights, Activation Function, and Learning Algorithm menus. In many cases, sub-menus within these functional areas are available for individual parameter selection. Individual functional area menu and sub-menu displays are represented in Figures 12 through 24.

Figure 11 depicts the generic menu layout chosen for the development system. When the system is first turned on, the Main System Menu, Figure 12, is displayed and a default ANN is created. The operator is now in the Network Specification Mode of operation. A previously created network may now be loaded from disk or a network may be created manually through the use of the menu system. If a network is loaded from disk,

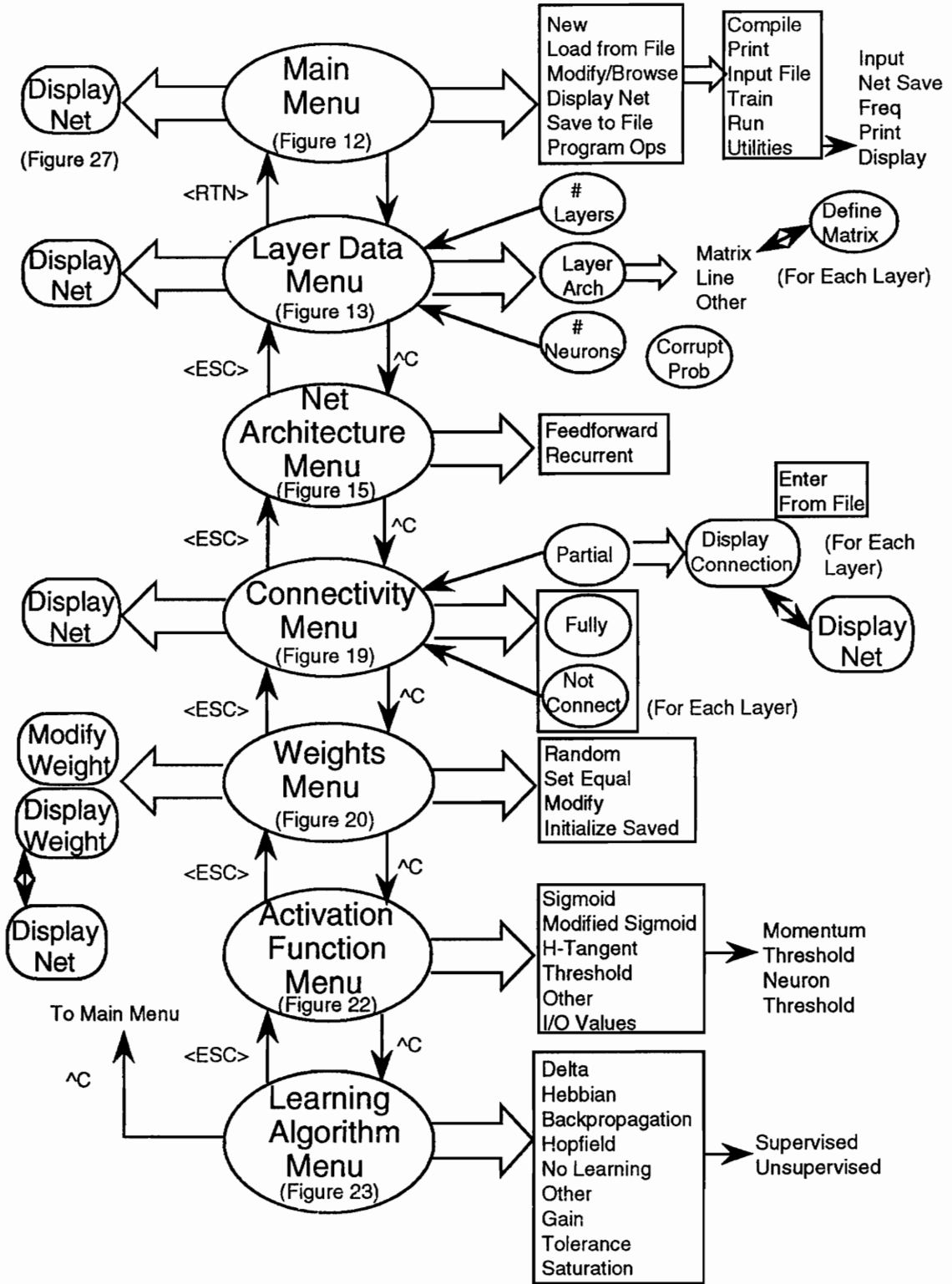


Figure 10. Menu System Interface Architecture

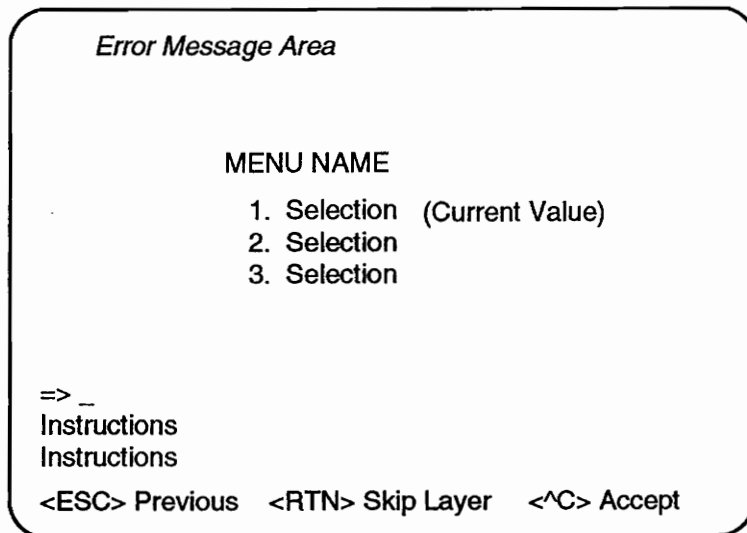


Figure 11. Menu Template

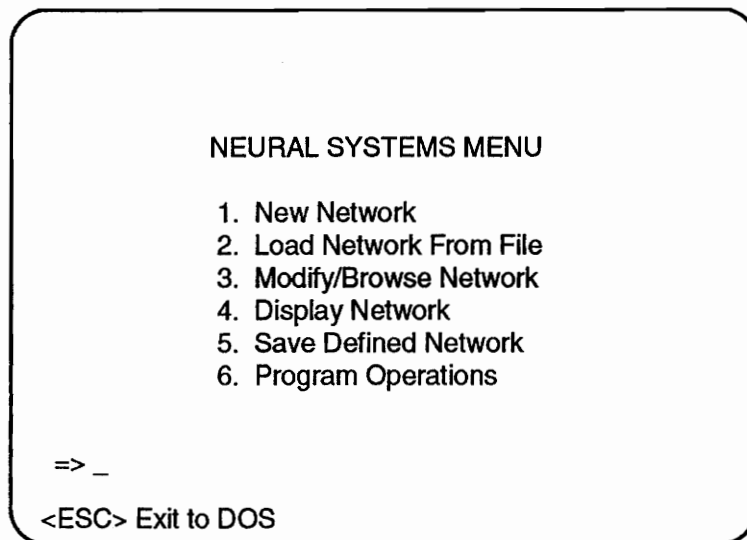


Figure 12. Main Menu

modifications may still be made via the sequence of menus. Networks may also be saved to disk from the Main System Menu (See Appendix A). The menu system allows the operator to create a network from established paradigms in a building block fashion and allows for the modification of specific parameters within the network, as discussed previously. Creation of new algorithms or modifications of existing ones for use within the net must be done via actual modification/addition to the Pascal code of the system. The code for these areas has intentionally been developed to be readily modifiable in order to accomplish this requirement. Only a certain specified number of easily identified and collocated procedures are required to be modified in order to add new algorithms. The system, as presented, does not include the capability to compile new code internally from within the system.

Once a major function (Layer Data, Net Architecture, Connectivity, Weights, Activation Function, Learning Algorithm) has been selected and completed, it is accepted via a ^C command. This leads to the next menu in the chain for further selections. An <ESC> from any of these menus returns to the previous menu although it maintains any changes made to the menu just vacated. A ^C command at the final menu (Learning Algorithm) unwinds the chain and returns the user to the Main menu. Sub-menus offer selections to be made within

the main function but may be accepted by <ESC>, <RTN>, etc. depending on the individual menu. This selection is specified in all cases on the command line (line #24) of the individual menus.

As shown in Figure 10, at several steps along the way, a Display Net option is available to the operator to allow display of the network content. Figure 27, page 53, shows an example of the display that is available. This gives the operator a graphical representation of all entries. He can also browse through the menu system for a textual representation of the same data.

The overall layer specification is made from the Layer Data menu (See Figure 13). Here the number of layers is selected, the number of neurons per layer (currently a maximum of 80 due to computer memory limitations) and the layer architecture are specified. As shown in Figure 10, selection of a choice in the Layer Data menu leads to a sub-menu for that selection (See Figures 14, 15, and 17).

The layer architecture is specified as either a line or matrix. This is strictly for display purposes since the internal representation is simply a one dimensional array of neurons. If a matrix architecture is selected the Define Matrix menu, Figure 16, is displayed after acceptance of the layer data specification.

The convention for layer numbering in this development

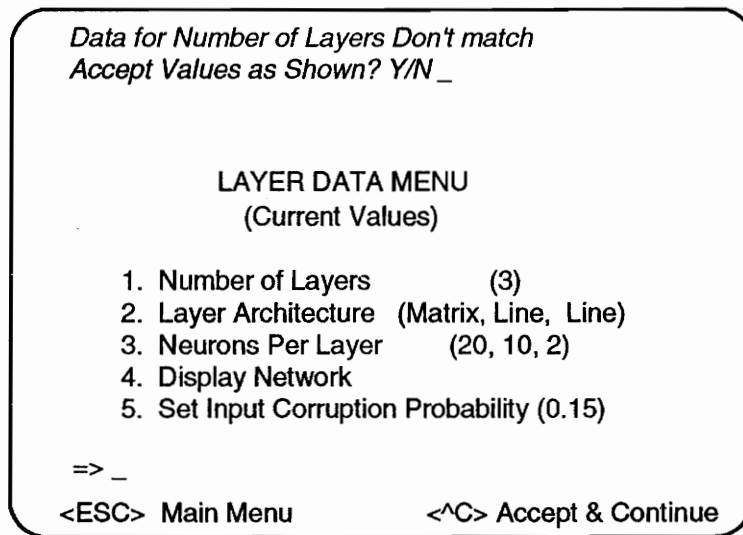


Figure 13. Layer Data Menu

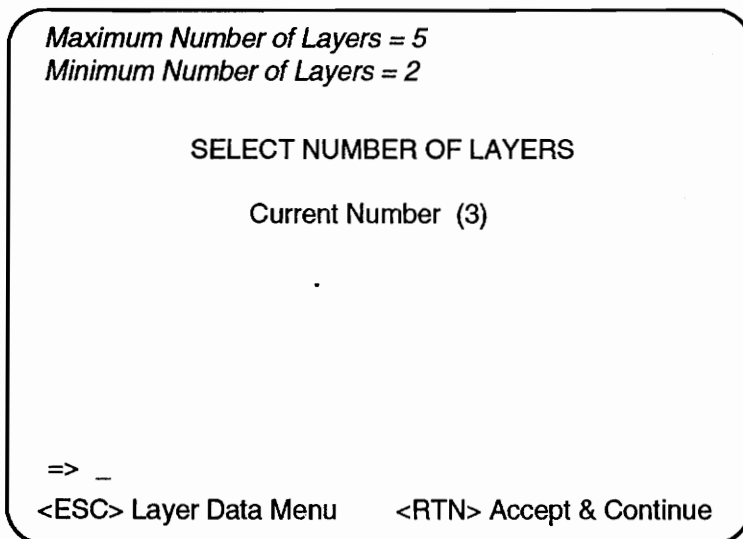


Figure 14. Number of Layers Selection

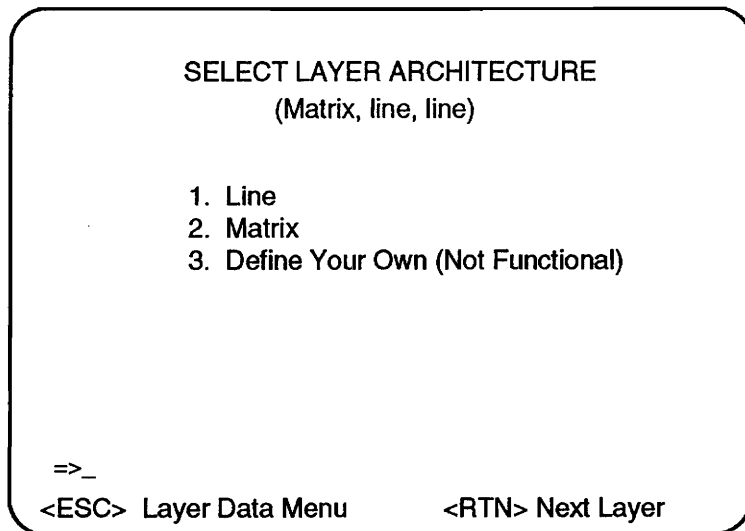


Figure 15. Layer Architecture Selection Menu

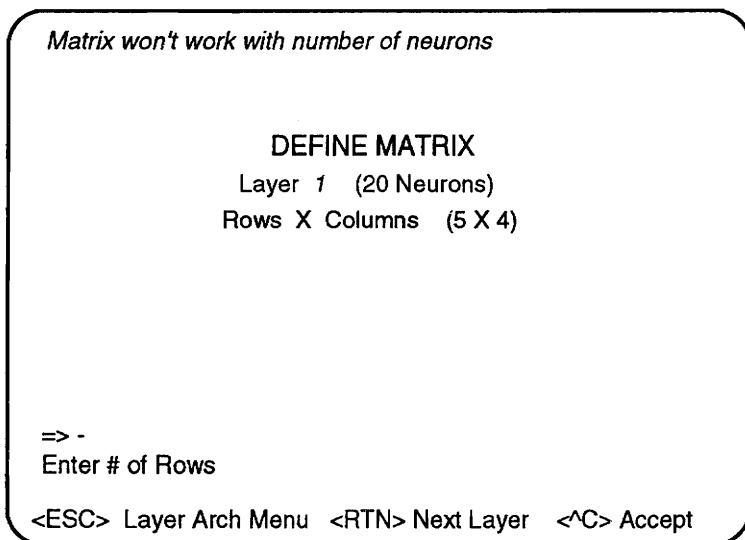


Figure 16. Define Matrix Menu

system is for the input layer to be layer 1 (not as discussed in the background section, where it was noted that, in the literature, the input layer is normally layer 0). This convention was chosen to maintain consistency throughout the source code of the development system. All array and matrix indices specified throughout the source code also begin with 1 rather than 0. Thus all computations within a network specified on the development system will commence with layer 2. A single-layer network will actually be specified as having two layers. Layer 1 is always the input layer and provides no computational value, as was discussed previously in relation to layer zero. Layer one merely distributes the input to layer two, the first computational layer in the network.

The corruption probability selection from the Layer Data menu allows for the specification of a percentage of neurons in the input layer to be randomly selected for changing the binary value of their outputs. This simulates noise within the system and a less than perfect input in a random fashion and is often used in the study of how well certain networks generalize and produce correct results with partial input.

Following the Layer Data Selection Menu is the Network Architecture Menu (Figure 18). Feedforward and recurrent options are available for selection. Fully recurrent networks have not been implemented in this version of the system. If

SELECT NUMBER OF NEURONS PER LAYER
Current Selections (35, 80, 8)
Layer Number 1

=> _

<ESC> Layer Data Menu <RTN> Accept & Continue

Figure 17. Neurons Per Layer Selection Menu

SELECT NET ARCHITECTURE
(Feedforward)

1. Feedforward Only
2. Recurrent

=> _

<ESC> Layer Data Menu <^C> Accept & Continue

Figure 18. Network Architecture Selection Menu

a recurrent network is specified, the output of the output layer is fed back as input to the input layer. A fully recurrent network would allow the selection of various options to feed back output from any layer to any previous layer, as well as to itself. These various options were not implemented due to memory limitations and remain as future system enhancements to be developed for higher capacity machines. Each optional set of layer connections requires an 80 X 80 matrix of weight values, and, possibly, a separate 80 X 80 matrix for saved_weight values, depending on the training algorithm.

The Connectivity Menu (Figure 19) allows for the selection of fully connected or partially connected layers. Full connectivity is the default condition. Each layer may be sequenced through and specified as fully or partially connected. When a layer has been specified as partially connected, the operator may remove or replace individual connections as well as remove a random number of connections. He may also restore full connectivity. Figure 19a displays the menu for modifying the connections of a layer. This menu is invoked if the operator has defined one or more layers as partially connected. This same functionality is also available in the display mode while the network is in the run mode.

Each layer has a full matrix of weights available through

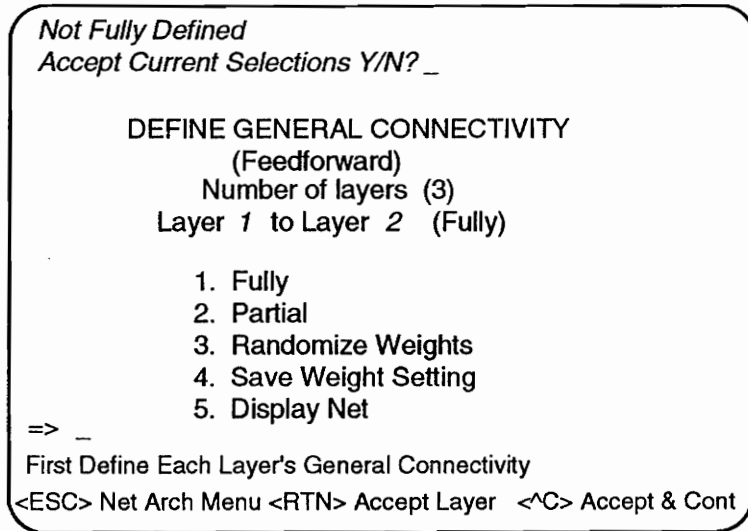


Figure 19. Define Connectivity Menu

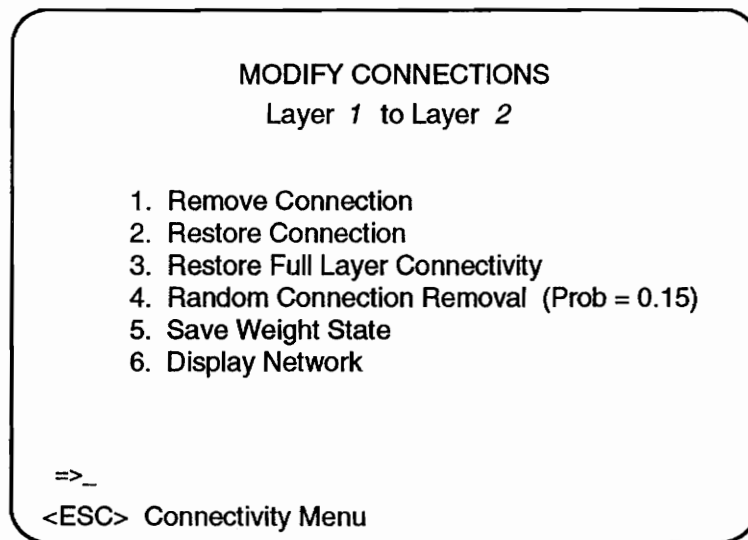


Figure 19a. Modify Connections Menu

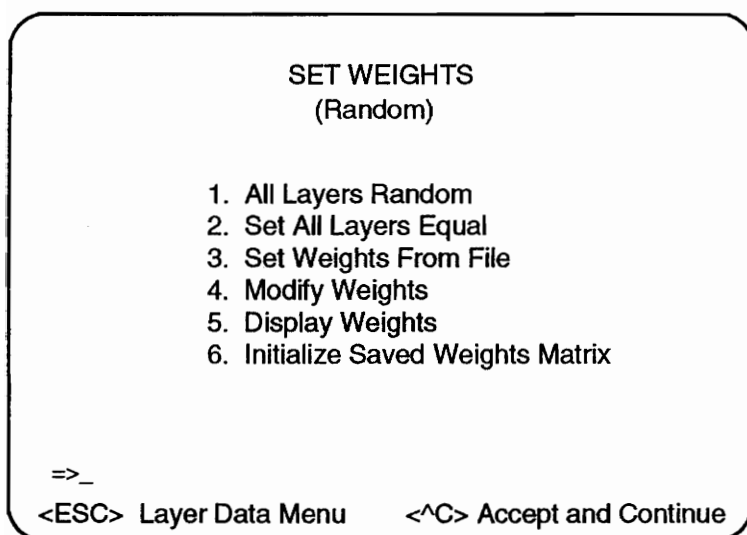


Figure 20. Set Weights Menu

WEIGHTS
Layer 1 to Layer 2 (Fully)

Layer 2 Neurons

		1	2	3	4	
Layer 1 Neurons	1	1.3	.6	-1.1	.4	(More)
	2	1.2	0	0	-1.5	
	3	1.4	-.4	1.2	2.5	
	4	1.1	1.3	0	.8	
	5	.2	-1.2	.3	0	

<ESC> Set Weights Menu <SPACE> More Layer

Figure 21. Display Weights

which it connects to the previous layer. The weight matrices are implemented as dynamic variables, with pointers specified in the layer description (See Appendix B). Weight values may be displayed and/or modified via the menu selections (Figures 20 and 21). Separate dynamic weight matrices are implemented for saving weight values from previous iterations during training. These saved weight values are used in several training algorithms and are available for operator use if needed for his specific requirements.

The current system uses the saved weight values in the backpropagation training algorithm. If they don't already exist, the operator may select an option to initialize a set for each network layer. This action creates the new dynamic variables and initializes their values to zero. This is often appropriate when training is restarted. Randomizing the weight matrices is also available. This is often done at the start of training to ensure that training will take place. It has been shown [3, 4] that training often cannot be accomplished if the initial set of weights are equal.

Various neuron activation functions are available for use, or the operator may specify and code his own. The interface specification must be adhered to for self coding. The activation functions implemented in the current system are depicted in Figure 3a, 3c, and 3d and are specified in Appendix H. Selections are made from the Activation Function

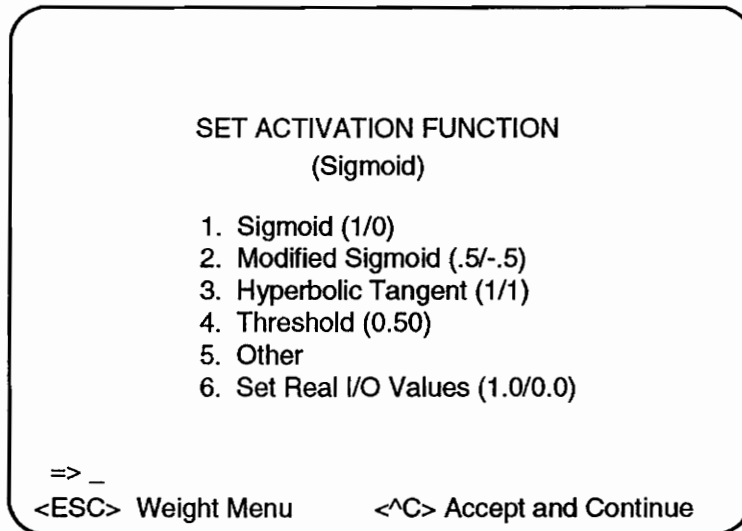


Figure 22. Activation Function Menu

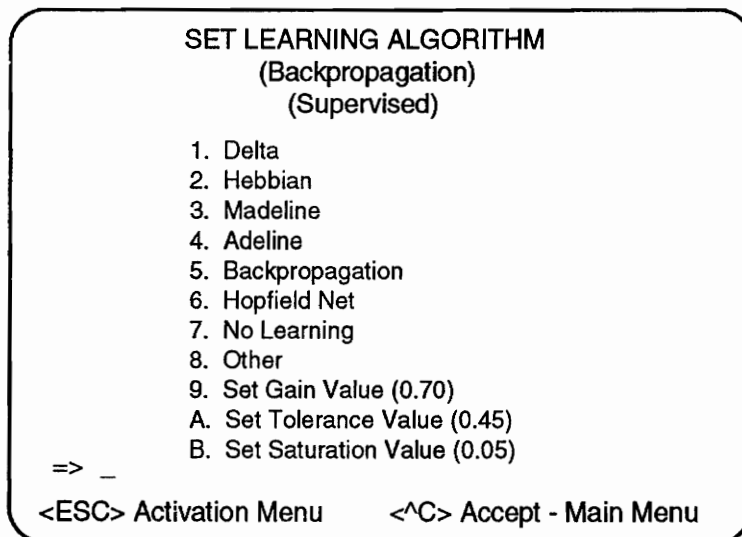


Figure 23. Learning Algorithm Selection Menu

Menu, Figure 22. Default floating point input/output values to represent the binary value of the neuron are specified for each activation function (Sigmoid (1.0/0.0), Modified Sigmoid (0.5/-0.5), Threshold (1.0/0.0), Hyperbolic Tangent (1.0/-1.0)), but may be modified to fit the operator's desires and specific algorithm requirements in the Activation Function menu. When a particular activation function is selected, the operator is then cued to choose values for specific parameters required by the function (threshold values, momentum, etc.). Momentum is a parameter often used in the backpropagation algorithm for smoothing (See the discussion on backpropagation).

The final menu selection (Figure 23) is for the specific learning algorithm. Various implemented options are available and are specified in Appendix H. A no-learning option may be selected, but is not specifically required for simple operation of the net with no training. The operator may specify and code his own algorithm ensuring that he respects the interface specified in Appendix H. In this case the "other" selection would be appropriate for use and the new code for the learning algorithm would be placed in the "other" selector in the case statement for procedure Learning_Rule in the Math unit (See Appendix H). If the operator produces code for his own learning algorithm, he must specify whether it is a supervised or non-supervised algorithm as this will effect

the sequence of events occurring within the network.

Hopfield nets are a special class of networks, as previously discussed, and have been coded into this system since they are often studied. Selection of Hopfield in this menu sets up a specific chain of events unique to the Hopfield network. This sequence of events is discussed under the Hopfield implementation section of this report.

With this same menu (Figure 23), the operator may also specify certain factors used in the training algorithms selected. Current choices available include gain, saturation, and tolerance. These equate to factor1, 2, and 3 respectively in the net_description data type (See Appendix B). These factors may be specified as the operator sees fit for user defined algorithms.

Acceptance of this final menu selection returns the operator to the Main Menu (Figures 10 and 12). The network is now fully specified. From the Main Menu the operator may return through any of the operations discussed previously, change any of the selections, or browse through the specification to ensure correct selections. Finally, the operator may select Network Operations which then puts him into the Network Operations Menu (Figure 24) and the Network Operations Mode (Figure 9). From this menu the operator may select the functions of the Operations Mode, including selection of an input file, printing of the network save_state

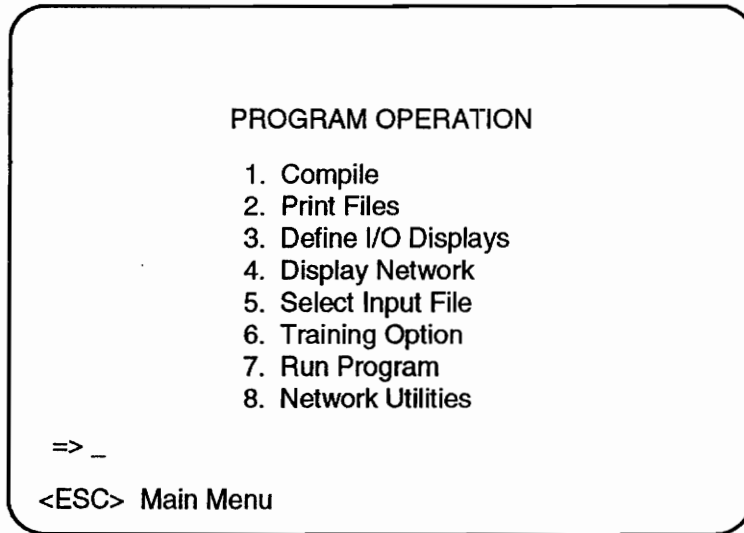


Figure 24. Program Operation Menu

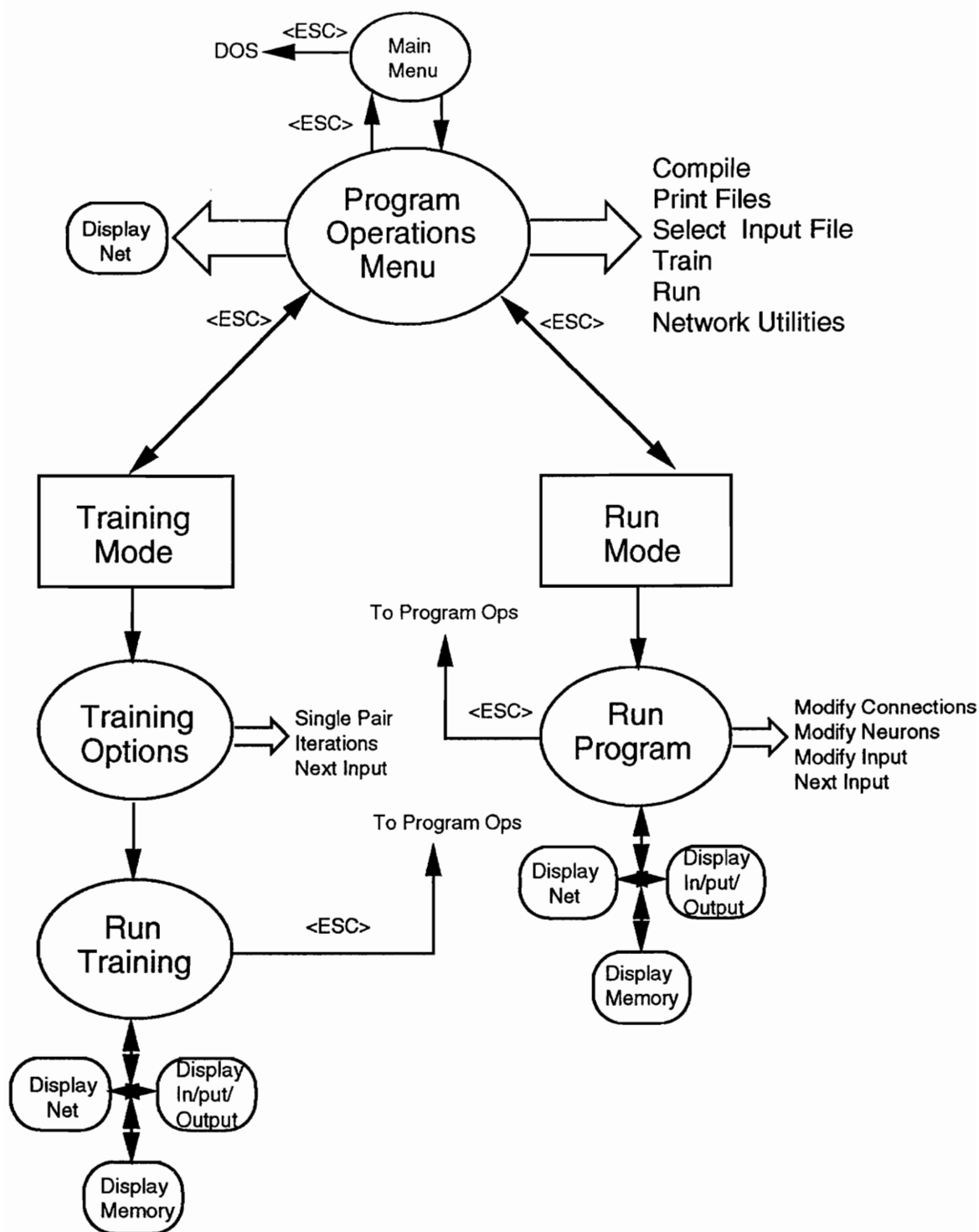


Figure 25. Operations Mode Control Flow

files, or Network Utilities. The compilation function is not currently available, as stated earlier.

Also available for selection are the Training mode and Run mode. Either one of these selections puts the operator into the display system and readies the system to run or train the specified network. If Run or Train Mode is selected before an input file is specified, an error message is generated and the system is returned to Operation Menu to select the file. Operational flow of control is depicted in Figure 25.

The network and neuron architectures of the Artificial Neural Network development system are embodied in two main data structures -- `net_description_type` and `layer_type`. The source code specification may be found in Appendix B. These two structures are records and have the following construction:

`net_description_type` (specifies network architecture)

```

net_name      : DOS file name
net_architecture : feedforward or recurrent
num_layers   : number of layers in the network
activation    : activation algorithm (threshold, sigmoid,
              mod_sigmoid, user defined, etc.)
threshold    : threshold value (used in most training
              algorithms)
learning     : type of learning algorithm to be used
              (Delta, Backpropagation, user-defined,
              etc.)
Factor       : Training rate coefficient (ie. n in Delta
              Rule - see below)
Factor1      : User_defined factor

```


Factor2 : User_defined factor
 Factor3 : User_defined factor
 momentum : Factor used in Backpropagation Algorithm
 for smoothing
 random_weights : boolean for initial weight settings
 of random rather than hand set or
 loaded from a file.
 save_state : Boolean to save network state
 periodically
 iterate : How often to save the network state
 one_value : Real value used internally by the net to
 represent a binary 1 (usually 1.0 or
 0.5). Default values depending on
 activation function or may be specified
 by the user.
 zero_value : Real value used internally by the net to
 represent a binary 0 (0.0, -0.5, -1.0).
 See one_value.

layer_type (Specifies individual layer data - layers is
 an array variable [1..num_layers] of
 layer_type. Each layer - up to five - has a
 layer_type associated with it)

connection_kind : fully or partially connected to
 next layer
 neurons : number of neurons in the layer
 neural_set : array of record of values for each
 neuron in the layer. The record
 contains arrays for the binary value
 (1/0), the real value used in net
 computations, and a threshold value
 for use in algorithms that make use
 of individual neuron thresholds. Also
 included is a rate value which shows
 how often the neuron has fired.
 architecture : line or matrix. Used for display
 purposes.
 arch_row_length : used for matrix architecture
 arch_col_length : used for matrix architecture
 weights : a pointer to the weights matrix
 representing each neuron's weight
 connection to each of the previous layer's
 neurons.
 saved_weights : a pointer to a weights matrix
 similar to weights. Used in some
 training algorithms to remember the
 previous set of weights before a

training iteration. May be used for other user defined purposes.

delta_vector : Array of real numbers to hold the Delta values. Used in several training algorithms.

connections : a pointer to a connection matrix to represent if a connection is present between a neuron in layer n to a neuron in layer n + 1;

out_layer : boolean value representing the last layer in the net - the output layer.

These two data structures, taken together, completely represent the state of the network. Specific data from these two structures are saved to disk files periodically during network operation and training if requested through the Network Utilities Menu, Figure 26. See Appendix A for a description of how the network is saved.

NETWORK UTILITIES

The Network Utilities menu, Figure 26, is selectable from the Program Operations menu and makes certain specific functions available to the operator. Currently implemented are selection of an input file (identical to the function available on the Program Operations Menu described earlier), Network Save, the frequency of state saves, a print option, and the Display Net option which is identical to that implemented throughout the system as described above.

The Net Save function is a toggle switch (boolean

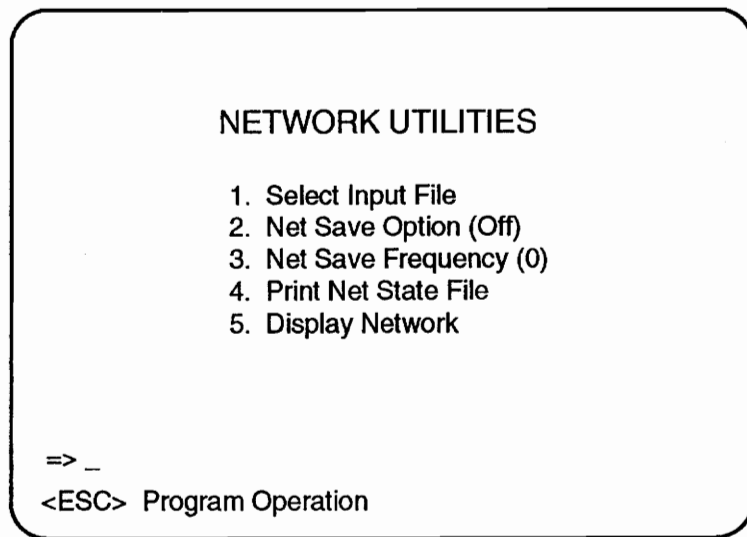


Figure 26. Network Utilities Menu

variable in Net_Description) which tells the system if the operator wants to save the state of the network periodically to a file. This is most often used during training in order to have a record of how the network progresses toward convergence during the training cycle. It is most useful during continuous, automatic training. The frequency selection allows the operator to specify the frequency of the saves. This is a simple counter that saves the state of the network after the proper number of iterations have been made. This "snapshot" of the network is appended to the file. See Appendix A for a description of the network save state option. The data saved is basically the data in the net_description and layers data structures of the implemented network (see Appendix B). The data saved could then be used as the input for another program developed especially to analyze this data. The print function allows the operator to print out the history of net saves that he has maintained during network training. Appendix J provides an example of the printout of the saved network data.

DISPLAY

The Display system is the primary user interface during network operation, computation and training. As discussed before under the Menu System, included also in the display

system is the graphical representation of the network architecture and parameters selected up to the point of display (Figure 27).

The display interface uses the Turbo Pascal graphics capability to display the network input and corresponding output. The display is divided into two sections and shows the input and output layers of the network, in either a line or matrix architecture as specified in the network parameters. An example display is shown in Figure 28.

Figure 28 depicts a network with a 6 X 4 neuron matrix architecture as the input layer and an 8 neuron line architecture as the output layer. A colored square represents a neuron with a binary output of 1 while a white or empty square represents a neuron with a binary output of 0.

When a network has been specified as requiring supervised learning and as having a line architecture as the output, two output displays are presented, as shown in Figure 28. The line on the left represents the actual output of the network while the one on the right is the target output as specified in the training set. This allows the operator to visually compare the two in order to see how the network is performing. This dual display of output is available in both the training and run mode of the network.

The mode line at the top of the display labels the input and the output and the mode of operation -- either the Run

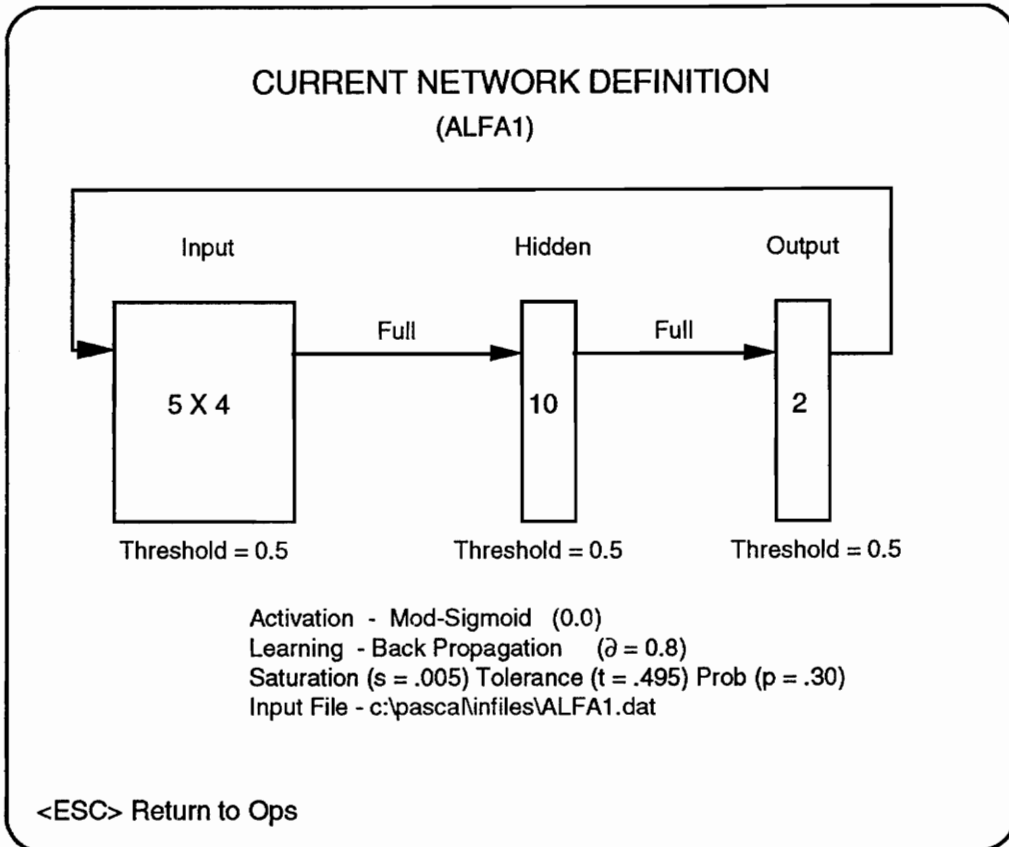
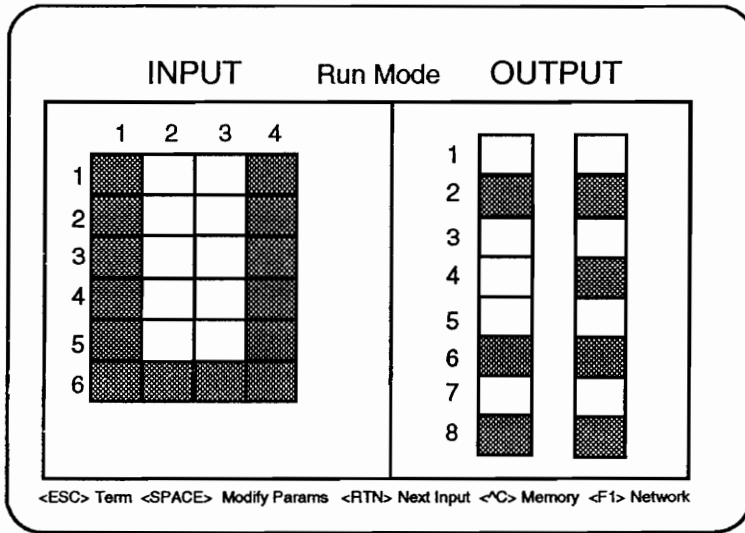


Figure 27. Display Network Screen



Modify Params Command Line

<ESC> Display <F1> Mod Input <F2> Mod Neurons <F3> Mod Connections <F4> Corrupt

Figure 28. Network Operations Display

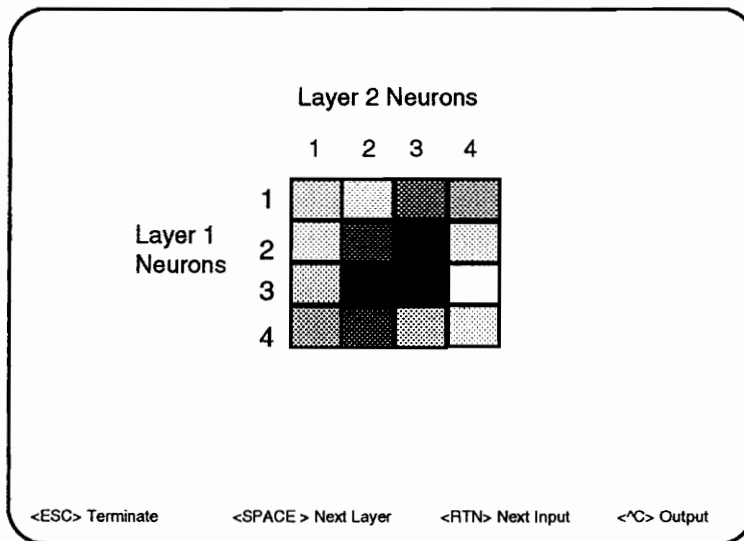


Figure 29. Memory Display

mode or the Training Mode. The Command Selection line at the bottom of the display allows for selection of the various functions available while in the Program Operations Mode. From here, if in the Run mode, selecting Next Input will cause the following events to occur -- the next input will be read, the system will calculate the output as specified by the network computational algorithm, and the screen will be updated to display the current input and associated, computed, output. The current computational algorithm is implemented as specified in Appendix H and displayed in Figure 5, since this is the algorithm universally used throughout the literature. Modifications to this could easily be incorporated into the system.

In the Training Mode, if in a supervised training system, the same sequence will occur except the appropriate training algorithm will be executed prior to the display update. The operator can thus see how the network output changes and converges toward a solution, during a training session. If using an unsupervised training network, the network will either operate as above if output comparisons are made or it may completely train the net for the specific set of inputs all at once, as is the case with the Hopfield net. It depends on the algorithm specified by the operator.

The Memory selection on the Command Line (Figure 28) changes the display from Input/Output to a representation of

the network memory, a display of a layer's associated weight matrix. An example of this display is shown in Figure 29. The weights are shown as a matrix and are color coded according to their specific value. If space allows, the weight value itself is also displayed in the center of the square. Each layer is selectable for display. The operator may also run the next input from this display if so desired. If in the Training Mode he can then see how the weights are changed by the training algorithm for that specific input at that specific stage of the training cycle.

The Modify Parameters option on the command line (Figure 28) displays a new command line which will allow the operator to modify the input either through a manual means or through a corruption process which randomly corrupts the input as discussed earlier. The operator may also remove individual neurons from the net or disable specific connections between layers to see how a previously trained network is affected if these connections or neurons are eliminated. These disablings may also be used to monitor their affect while network training is taking place.

Also available, although not shown on the command line, is a multiple iteration capability which will operate the net for a specific, selectable number of iterations. This function is most useful during training where hundreds or even thousands of training iterations may be required to fully

train the network. This function is selectable through the <SHIFT> T command. The operator is then cued to choose the number of iterations. Once initiated the network automatically runs through the number of cycles selected before the operator regains manual control.

Available also in the display mode is the capability to display the network architecture as described before and shown in Figure 27.

COMPUTATION

The network computation functions are implemented internally within the system and are not visible to the user except through their effects on the display system. All the network calculation and training algorithms are located within the Math Unit, as specified in Appendix H, and are thus localized for easy access and modification. To summarize the computational sequence, a set of inputs is applied to each neuron, each representing either the input from the outside world (the input layer) or the output from other neurons (a hidden layer). Each input is multiplied by a corresponding weight, all the weighted inputs to a single neuron are summed and then sent through an activation function to determine the output of the neuron. The output of each neuron (OUT), as well as the input from layer 0, is represented by a real value

(layers[x].neural_set.real_value[i]) and a binary value (layers[x].neural_set.binary_value[i]). These data structures are specified in the Layer_type data structure as shown in Appendix B. The floating point values are normally used for network algorithmic computations while the binary values, representing an ON/OFF or FIRE/NOFIRE state, are used for display to the operator via the display mode. The output vector of a layer, which includes the outputs of each neuron in the layer, is then applied to form another weighted input to each neuron in the next layer (See Figures 2, 4, and 5).

Appendix H is the source listing for the algorithmic implementations (Math Unit). The above computation is implemented in the Calculate_Output procedure. This procedure calls Calculate_Activation which, in turn, applies the appropriate activation algorithm. Several popular, non-linear functions are implemented in the current version of the system, including the Threshold, Sigmoid, and Modified Sigmoid. Provision for the Hyperbolic Tangent function has been made but has not yet been implemented.

Provision for a user defined activation function has also been made and could be implemented in code for the user defined case in calculate_activation or through a called procedure defined by the user. The user must be careful to meticulously follow the interface definition of the calculate_activation procedure. The activation function is

specified through the Activation Function Menu (Figure 22), as discussed previously, and is embodied in the activation field of the net_description record (Appendix B).

Most training algorithms are implemented through calls by the Learning_rule procedure (Appendix H). As with the activation function, the training algorithm to be applied to the network is specified through the Menu system and is embodied in the learning field of the net_description record (Appendix B). Three learning algorithms, Backpropagation, Delta, and Hebbian, have been implemented in the current version of the system. Additionally, a Hopfield net has been implemented although this may not be considered a true training algorithm since the weights are completely specified prior to network operation. Again, provision for a user defined algorithm has been made and is implementable through the "other" definition in the learning type.

In all cases, the call to the learning_rule procedure is controlled from within the Display Mode during network operations. If in the Training Mode, the learning algorithm will be called as required by the network specification (feedforward, recurrent, supervised, unsupervised). If in the Run Mode, the network simply computes its output from the applied input with no learning algorithm is exercised.

The Math Unit also contains all the matrix operations required to calculate appropriate network requirements. These

include matrix multiplies, vector multiplication and addition, the inner product, matrix and vector transposition, and vector/matrix multiplication.

SECTION 4

IMPLEMENTATIONS ON THE DEVELOPMENT SYSTEM

Several different architectures and paradigms have been implemented on this prototype system in order to demonstrate its ability to support different neural net models. The networks implemented include the following:

1. A single layer, two input, single output network trained with the Delta rule learning algorithm to recognize binary functions (and, or, nand, nor, etc.) (Figure 30).
2. A two layer, two input, single output network, trained with the backpropagation learning algorithm to recognize the exclusive-or and exclusive-nor binary functions (Figure 34).
3. A multiple layer network consisting of 35 input nodes, 80 hidden layer nodes, and 8 output nodes, trained with the backpropagation learning paradigm to recognize the letters of the alphabet and the integers and produce the proper ASCII code for the character (Figure 35).
4. A four layer network consisting of 35 input nodes, 80 and 20 hidden layer nodes, and 8 output nodes to see if training would be different from that which took

place in number 3 above.

5. A single layer Hopfield net trained in the unsupervised mode, via the traditional Hopfield algorithm, to recognize several letters of the alphabet and recall them under various conditions of corrupted (noisy) input (Figure 38).

Although not specifically implemented, other network algorithms for both supervised and unsupervised modes are discussed as to their proposed implementation on the prototype system.

The following discussion elaborates on the various network implementations on the prototype system.

DELTA RULE

The single layer network was first described by McCulloch and Pitts in 1943 [6] and extensively studied by Rosenblatt in 1962 [2]. The basic model is as shown in Figures 2, 4 and 5 as described before. It uses a fully connected, feedforward architecture, with a hard limiting, non-linear threshold function as shown in Figure 3a. This model forms the basis for all neural system architectures today and was often called

the perceptron model. The basic model multiplies the value of each input by an associated weight and sums to a total. If the resulting total is greater than a predetermined threshold, the model outputs a binary one, or if less, outputs a binary zero.

The simple perceptron learning procedure, first described by Rosenblatt and then generalized further to include continuous (vice binary) inputs and outputs, is called the Delta rule algorithm and is applied as follows:

1. Initialize the weights and threshold to some small, random value.
2. Present the input to the net. Each input vector to the input layer of the network has an associated target (correct) output vector for comparison. The two vectors, input and target output are collectively called the training pair.
3. Calculate the actual output of the net as depicted in Figure 5.
4. Compare the actual output vector to the target in the training pair and modify the weights according to the following algorithm:
 - a. $\delta = T_j - A_j$
 - b. $\Delta_i = g \delta x_i$

$$c. \quad w_i = w_i + \Delta_i$$

where:

T_j = target output for j th neuron
 A_j = actual output for j th neuron
 g = gain factor, $0 \leq g \leq 1$ (Controls average size of weight change)
 x_i = i th input value
 Δ_i = factor added to weight $_i$
 w_i = weight associated with i th input

If the actual output matches the target output then $\Delta_i = 0$ and no adjustment is made to the weight setting for that input.

5. Repeat the process until the network is trained satisfactorily.

This network and associated learning algorithm was the first to be made operational on the development system as a demonstration of the representational capability of the prototype. The initial network developed is as shown in Figure 30. Using the Delta rule as described and as specified in Appendix H, procedure `delta_calculation`, the network was trained to recognize 14 of the 16 binary functions for two inputs as follows:

	<u>Input</u>				<u>Required Output</u>				<u>Function</u>
	<u>A</u>	<u>B</u>	<u>C</u>	<u>D</u>	<u>A</u>	<u>B</u>	<u>C</u>	<u>D</u>	
1.	1	1/1	0/0	1/0	0	1/0/0/0			And
2.		"				1/1/1/0			Or
3.		"				0/0/0/1			Nor
4.		"				0/0/1/1			Not A
5.		"				0/1/0/1			Not B
6.		"				0/1/1/1			Nand
7.		"				1/0/1/1			B or not A
8.		"				1/1/0/1			A or not B
9.		"				0/0/1/0			B and not A
10.		"				0/1/0/0			A and not B
11.		"				1/1/0/0			A ignore B
12.		"				1/0/1/0			B ignore A
13.		"				0/0/0/0			Null
14.		"				1/1/1/1			All
15.		"				0/1/1/0			Exclusive-or
16.		"				1/0/0/1			Exclusive-nor

The final two functions, the exclusive-or and exclusive-nor, were shown by Minsky and Papert [7] to be linearly inseparable and therefore, not representable (or trainable) on a single layer network (See Figures 30 and 31). This limitation was quickly substantiated by the simple network under study.

The Exclusive-or function, as depicted in Figure 31, shows that all possible combinations of inputs and outputs are comprised of four points on a plane, A_1 , B_1 , A_0 , and B_0 , where the x coordinate value is one input and the y coordinate value is the other input. Using the single layer network in Figure

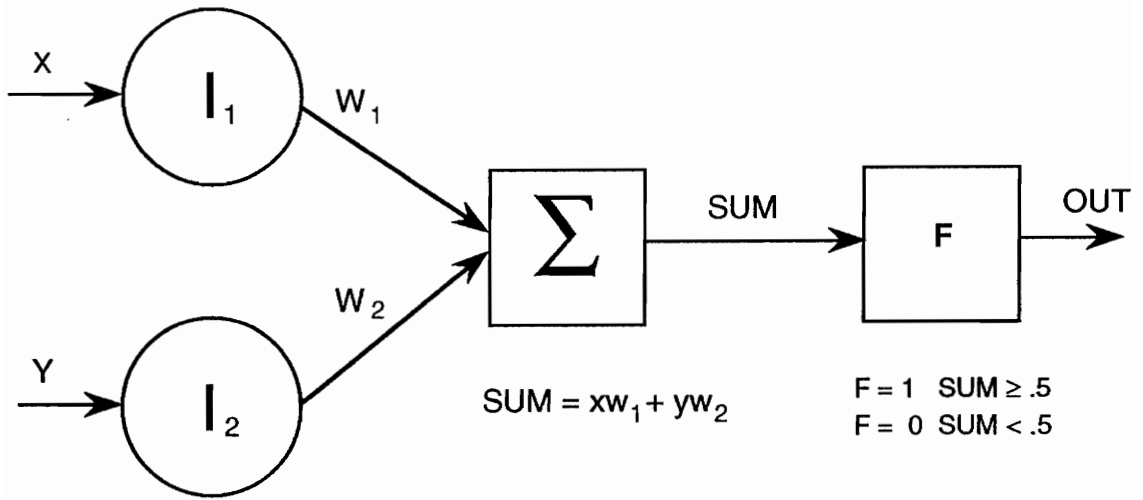
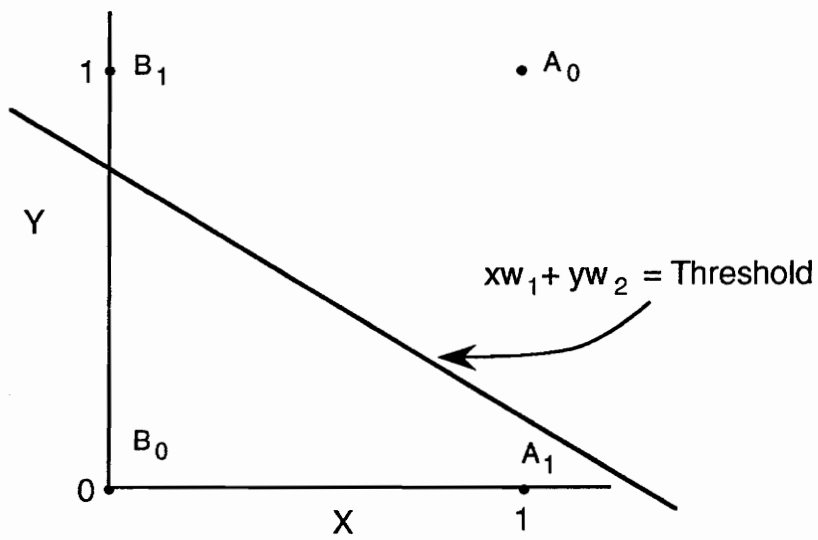


Figure 30. Single Layer Binary Function Network



	x Value	y Value	Required Output
A ₁	1	0	1
B ₁	0	1	1
A ₀	1	1	0
B ₀	0	0	0

Figure 31. Exclusive-or Function

30, where $SUM = xw_1 + yw_2$, it can be seen that no combination of values for the two weights, w_1 and w_2 , will produce the relationship required by the table of Figure 31. The threshold line in the figure is where the equation $F(SUM)$ must divide the plane. All values to the right of this line will yield a one whereas all value to the left will yield a zero. Changing the values of w_1 and w_2 , as well as the threshold value, will change the slope and position of this line. However, no matter what values are used, the line cannot be positioned so that both A_1 and B_1 will fall to the right while A_0 and B_0 fall to the left, as required by the truth table, to satisfy the requirements of the exclusive-or (XOR) function. This is also the case with the exclusive-nor (XNOR) function. Conversely, a plot of the other 14 binary functions will reveal that they are linearly separable through manipulation of the weight and threshold values and are thus able to be represented, and trained, on a single layer network.

The XOR and XNOR class of functions is said to be linearly inseparable and is a major limitation of the single layer network. This limitation can be overcome through the use of multi-layer networks, and it was, in fact, known early on that multiple layer networks could learn any function that they could represent [2, 3], including the XOR function. However, until the backpropagation algorithm was developed, it

remained a mystery how to systematically train these networks.

BACKPROPAGATION

The development of the backpropagation learning algorithm, with its ability to train multi-layer networks, brought about a resurgence of interest in Artificial Neural Networks. Rumelhart, Hinton, and Williams first presented the method in 1986 [8], although several others had discussed it earlier in 1974 and 1982 [3].

The basic architecture used in the backpropagation network implementation on the development system was described earlier and is as shown in Figures 2 , 3b, and 5. A fully connected, feedforward network was specified. The previously discussed method of neuron activation level calculations using SUM and a Sigmoid activation function for each neuron was developed and implemented.

During training, training pairs are presented to the network, one at a time. The input is applied to the first layer and neuron outputs are calculated, as in Figure 5, for each layer. The final calculation is for the output layer. The output of each neuron in the output layer is then compared to the target output. If there is a difference between the two, the network is trained and the weights are adjusted for each layer. The next input is then presented to the net, the

output is calculated, the output again is compared to the new target vector, and the network is trained again. This continues until the net is satisfactorily trained to calculate the proper output for each input. Training may then be stopped and the network will continue to recognize the now familiar input patterns. No further training is necessary. This paradigm is illustrated in Figure 6.

The backpropagation algorithm, as coded in the development system, operates as the name implies (refer to Figures 32 and 33) [3, 9] moving backward through the network beginning with the computed output and the associated weights that produced that output. The weight values are first adjusted for the output layer. (Since the target value is known, this adjustment is made using a modification to the Delta rule already discussed). The output from a neuron in the output layer is first subtracted from its associated target value, producing an error signal. This error is multiplied by the derivative of the Sigmoid function for the output neuron (q) value, yielding a δ value (the derivative for the Sigmoid function is simply $(OUT_q)(1 - OUT_q)$). This simplicity, along with the compression attributes discussed before, is the reason the Sigmoid Function is often used as the network activation function of choice). The δ value, calculated as follows, is computed for each neuron in the

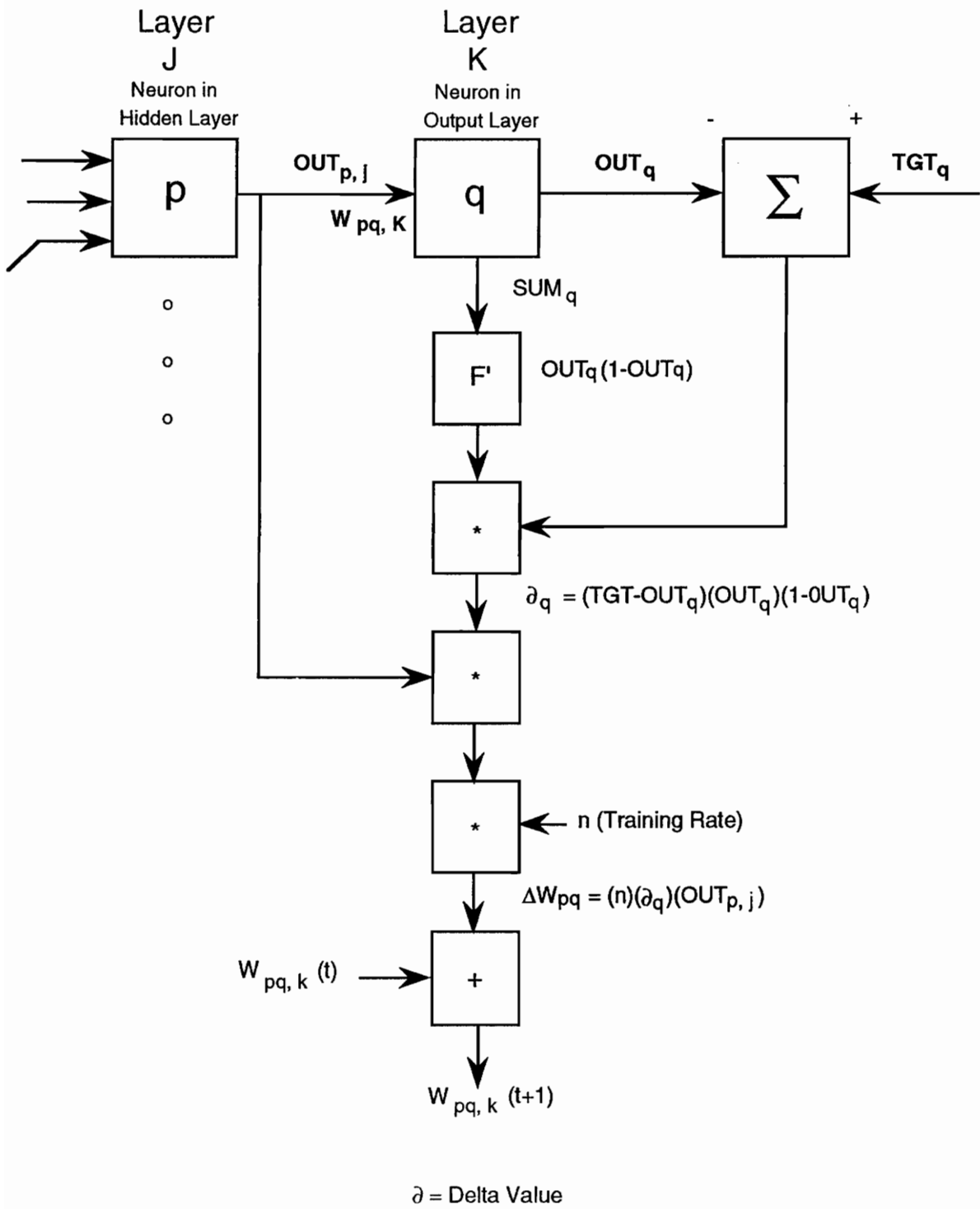


Figure 32. Backpropagation (Output Layer)

output layer:

$$\delta_q = \text{OUT}_q(1 - \text{OUT}_q)(\text{Target} - \text{OUT}_q) \quad (\text{Equation 2})$$

δ_q is then multiplied by OUT_p from the neuron in the previous layer for the weight to be modified. This product is multiplied by a training rate coefficient n (0.01 to 1.0) and the result added to the weight. The calculation, is

$$\Delta W_{pq, k} = n * \delta_{q, k} * \text{OUT}_{p, j} \quad (\text{Equation 3})$$

$$W_{pq, k}(t+1) = W_{pq, k}(t) + \Delta W_{pq, k} \quad (\text{Equation 4})$$

Where:

$W_{pq, k}(t)$ = the value of the weight from neuron p in the previous hidden layer to neuron q in the output layer k at the time before adjustment.

$W_{pq, k}(t + 1)$ = value of the weight at the time after adjustment.

$\text{OUT}_{p, j}$ = the value of OUT for neuron p in the hidden layer j

(Note that p and q relate to specific neurons while j and k refer to a layer.)

After the weights have been adjusted for the output layer as described above, all weights must then be adjusted for each hidden layer. δ s must be generated for each neuron in the

hidden layers without the help of a target vector, since none exists for the hidden layers.

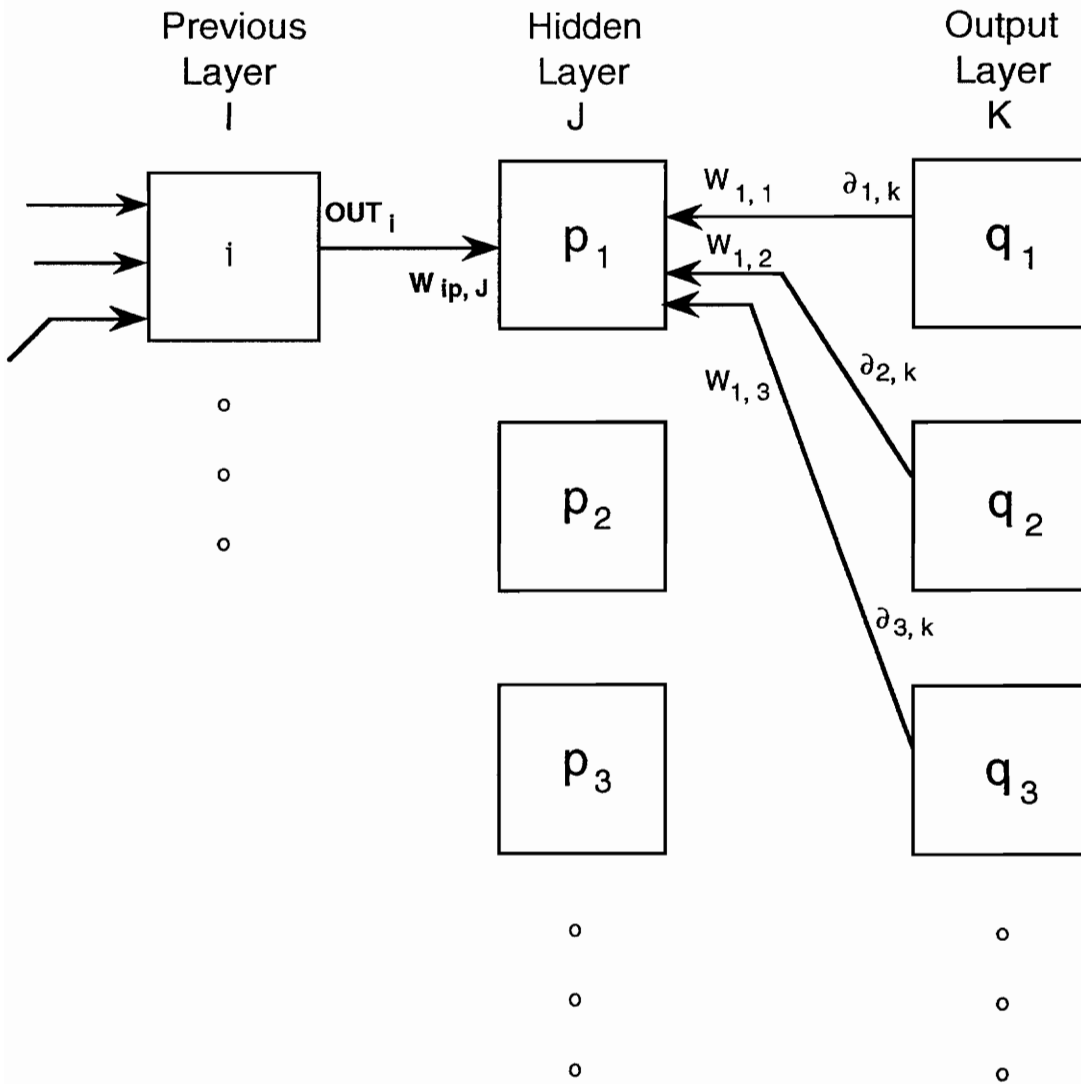
The Backpropagation learning algorithm trains each hidden layer by propagating the error determined by the target vector back through the network, determining a δ value for each neuron in each hidden layer and adjusting all weights involved. Equations 3 and 4 above are then used again to determine all new corresponding weight values.

Values for δ in the hidden layers are generated using Equation 5 as follows:

$$\delta_{pj} = \text{OUT}_{pj}(1 - \text{OUT}_{pj}) (\sum_{q,k} \delta_{q,k} W_{pq,k}) \quad (\text{Equation 5})$$

This process is shown in Figure 33. Using this δ value calculated for each neuron in the hidden layer, Equations 3 and 4 can then be used to calculate the new weight values for that hidden layer. These new δ values are then used to propagate back through the weight values before adjustment in a similar manner to find new δ values for the next, previous hidden layer. This process is continued until the weights have been adjusted for all layers in the network.

There is no limitation to the number of layers that the backpropagation algorithm can effectively handle. Training time obviously increases with the number of layers as well as



$$\partial_{p_j} = OUT_{p_j}(1-OUT_{p_j}) \left(\sum_q \partial_{q,k} W_{p,q} \right)$$

$$\Delta w_{ip} = (n)(\partial_{p_j})(OUT_i)$$

∂ = Delta value

Figure 33. Backpropagation (Hidden Layer)

with the number of neurons in each layer.

The saved_weight data structure (See Appendix B - global declarations) was provided for the backpropagation algorithm as a means to have both the previous weights, $W(t)$ (saved_weights) and the adjusted weights, $W(t + 1)$ (weights data structure) available for the computation.

The saved_weights data structure also proved beneficial for the computation of a momentum term, which in some cases improves training time and enhances the stability of the process by smoothing out the calculations [5, 9]. The momentum process adds a term to the weight adjustment that is proportional to the amount of the previous weight change. Equation 3 is then modified to

$$\Delta W_{pq,k}(t) = n * \delta_{q,k} * OUT_{p,j} + \alpha [W_{pq,k}(t-1)] \quad (\text{Equation 6})$$

where α is the momentum coefficient (0.0 - 1.0)

If a coefficient of 0 is used, then momentum is not a factor; if 1 is used, then the full weight change of the previous iteration is used in the calculation. Values from .7 to .9 are common when momentum is used.

The above process was used to train the net shown in Figure 34 to recognize the exclusive-or and exclusive-nor functions. Through several training sessions it became clear

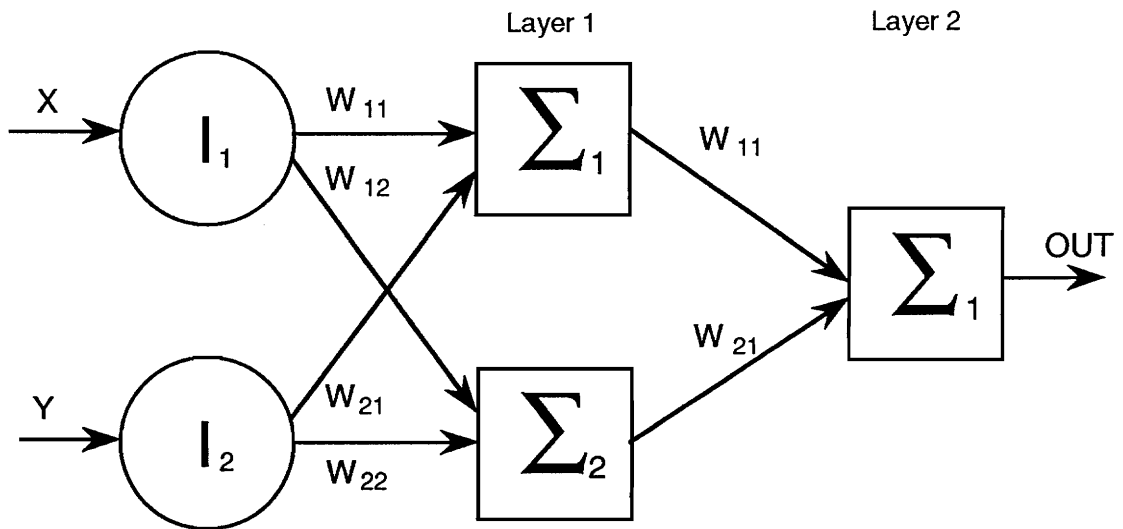


Figure 34. Two Layer Binary Function Network

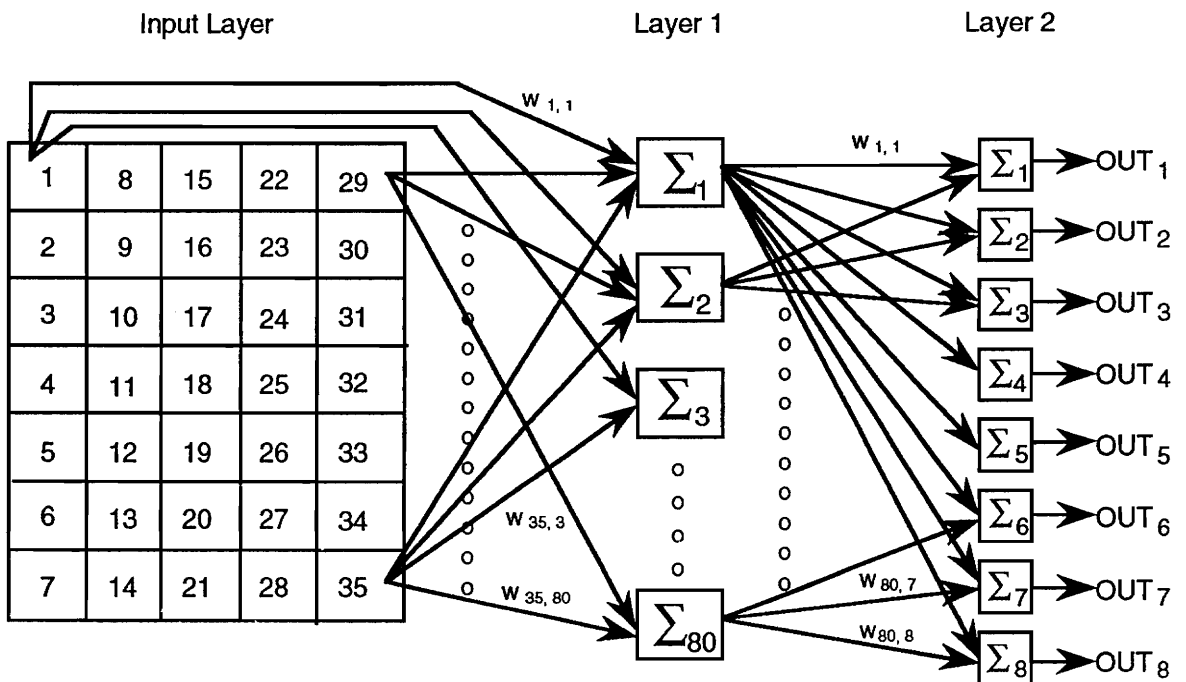


Figure 35. ASCII Code Two Layer Network

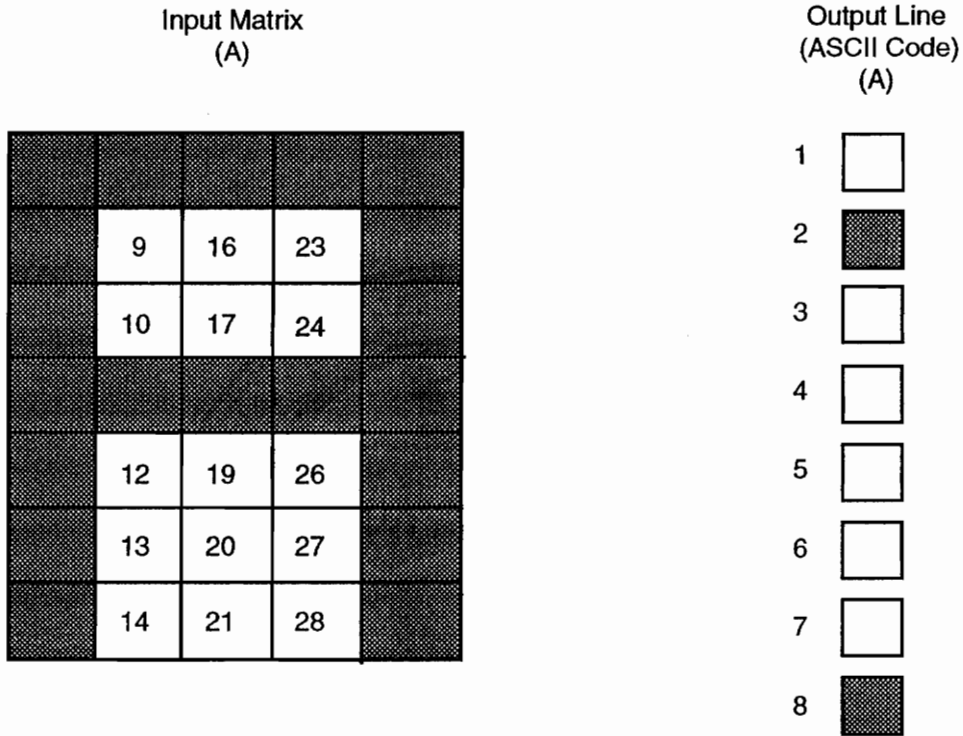
that the network would not always train as expected. The network would often oscillate back and forth and never settle on the correct weight values. In these cases, the only alternative was to reset the weights to low random values, initialize the saved weights to zero, and start the training sessions again.

This phenomenon of instability reflects some of the problems encountered with the use of the backpropagation algorithm. Rumelhart, Hinton, and Williams [8] have proven that if the solution to a problem can be represented by a network, then the backpropagation algorithm will converge to a solution. This proof however assumes infinitesimally small weight adjustment steps. This is impractical in real networks and often leads to problems of network paralysis and local minima. As the network trains, weights can be adjusted to very large values which tend to force neurons to operate at very large values of OUT. The derivative of the squashing function in this region is correspondingly extremely small (See Figures 3b and 3c) which tends to bring training to a standstill since training is proportional to this derivative. One method for overcoming this paralysis is discussed in the next section and is implemented through a saturation function which helps to bring these neurons out of saturation. Other methods for handling this paralysis include the use of smaller step sizes which is accomplished through a reduced gain factor

(n). This however tends to increase training time. There is very little theory or practical guidance to show how to select step size for the training of networks. If too small, training time will be slow; if too large, training may reach paralysis or oscillate resulting in continuous temporal instability. This results in the network "unlearning" previously learned training sets.

There are several algorithms discussed in the literature which adaptively reduce step size automatically as training progresses. These algorithms could easily be integrated with those presented on the current prototype development system.

Next, a larger, more complex network was specified to recognize the alphabet characters and integers. This network (See Figure 35) consisted of an input matrix of 35 neurons arranged in a 5 X 7 grid, a hidden layer of 80 neurons, and an output layer of 8 neurons to represent the ASCII code of the characters presented to the net. Figure 36 displays a representative input and output for this network. A neural output of a binary one is represented, in Figure 36, by a colored square while an output of a binary zero is represented by a blank square. Thus, each character can be represented in the input matrix by a unique sequence of ones and zeros from the input file. Each training pair (character and ASCII representation) is specified by two lines in the input file, as shown in Figure 36.



Input File

```
11111111001000100100010010001111111
01000001
```

Figure 36. ASCII Network Input/Output Representation

The network was fully connected, utilized a modified sigmoid activation function and the backpropagation learning algorithm. Utilization of the modified sigmoid activation function required the input layer of the network to be set to +.5 to represent a binary 1 (ON condition) and a -.5 to represent a binary 0 (OFF condition). This is accomplished in the software of the development system in order to maintain consistency of data input from the input file. Thus, the data input file uses the standard 1/0 for all network input no matter what algorithm is being used. The development system converts the input to the proper floating point value for use of the functions and algorithms specified through the menu system for that particular network. One_value and zero_value in net_description is set to these required values when the activation function is selected in the Menu system (See Appendix B). The neural floating point value is then set to these required values upon reading the input from the file. The neuron binary value remains as one or zero for display purposes. This is accomplished through the set_input_layer procedure in the ioutil unit, Appendix G.

The complete alphabet, in a form similar to that shown in Figure 36, plus all ten integers, was presented to the network. The network was satisfactorily trained to recognize all 36 characters. Some of the training data collected is presented in Figure 37.

During network training, large numbers of neuron outputs summed through the weight matrix for input to a single neuron in the next layer, tend to yield large values of SUM. This, when using a sigmoidal activation function, tends to drive the output of the next layer toward a saturated (maximum) value. Also, because the backpropagation training algorithm uses δ values which are based on the first derivative of the sigmoidal function, weight correction values tend toward zero at these saturated values. Network paralysis often results from these factors.

A method discussed by Wasserman [3] helps to solve paralysis problems without greatly affecting training already accomplished. Saturated neurons are identified through their OUT values. If the magnitude of a signal approaches the limiting value (called saturation in the development system), rather than training all weights in the normal fashion, weights feeding that neuron are operated on by a squashing function similar to the sigmoidal activation function. The saturation value is set in the Menu system (Figure 23) and is a value close to zero. This equates to a first derivative value of OUT close to the extremes of the function (see Figure 3c). The range of the function is set to +5/-5 and is implemented as follows:

$$w_{mn} = -5 + 10/[1 + \exp^{(-w_{mn}/5)}] \quad (\text{Equation 7})$$

This function greatly reduces the magnitude of excessively large weights while not affecting small weights as much. It also preserves symmetry between the weights feeding the neuron, thereby maintaining relative differences between the weights. Weights associated with neurons that are not saturated are trained normally. The use of this procedure to draw neurons out of saturation greatly reduced training time in the backpropagation implementation of the alphabet recognition net.

While training the alphabet recognition network, it was noticed that output values would often oscillate back and forth between the correct level and an incorrect response. The results of such oscillations can be seen in some high numbers of training trials shown in Figure 37. As one letter became trained, another previously trained to a correct response would yield incorrect output. Due to the distributed nature of the memory of the network being resident within the weight matrix as a whole, as a letter would continue training, even though it had a correct response, the weight changes would tend to correct in the wrong direction for other letters, thus pulling them out of convergence (the correctly trained state).

Backpropagation Algorithm Results

26 Letter Alphabet
Gain Factor (n) = .7

<u>Network Specification</u>	<u>Training Trials</u>	<u>Number of Letters Trained</u>
Saturation = 0 Tolerance = 0	500	6
	2800	17
	5000	12
	6000	15
	7000	17
	8000	18
	9000	17
Saturation = .001 Tolerance = 0	500	20
	600	21
	700	24
	800	22
	900	22
Saturation = .001 Tolerance = .45	500	25
	600	26
	700	26
	800	26

Figure 37. ASCII Code Network Results

With use of the Delta Rule in perceptron training, unlike with backpropagation, if the actual output matches the target output, then $\Delta_i = 0$ and no adjustment is made to the weight setting for that input. It was hypothesized that if the backpropagation algorithm could be made to act more like the Delta rule in this regard, where no training takes place once the response converges, then this correction in the wrong direction might be minimized, if not eliminated altogether.

An optional tolerance value was therefore created and integrated into the backpropagation algorithm. Thus, if the output of the net is within the specified tolerance for the difference between the target value and the output value (TGT - OUT), no training will take place for that particular neuron. If the difference is out of tolerance (there is a large variance between the output of a neuron and what it should be) then training will take place in the normal fashion. The algorithm was easily introduced as

```

If abs (tgt - out) >= tolerance factor
  then train
  else neuron  $\delta$  value := 0

```

Setting the δ value to 0 for the output neuron in question ensured that the associated weights feeding that neuron would not be adjusted as the backpropagation algorithm

progressed back through the layers.

Figure 37 shows some of the training data collected on network training with and without a saturation factor and a tolerance factor. The figure shows the number of letters trained (recognized correctly by the network) after specific numbers of trials had been completed. A trial consisted of one complete cycle of the presentation of a letter to the net, calculation of the network output, and training of the weights via the backpropagation algorithm. The alphabet was repeatedly sequenced through, one letter at a time. Thus, the network had seen each letter one time after 26 trials, twice after 52 trials, etc.

As shown in Figure 37, introducing the saturation and tolerance functions into the backpropagation algorithm not only greatly reduced training time but in fact was the only way the net could be fully trained without an inordinate number of training iterations. This was a good example of how the development system can be used to quickly implement enhancements that the student may wish to try in order to study or improve the capabilities of network functions.

One further network was implemented on the system to observe its effect on training time and network operation capabilities. This was a four layer network, with the same parameters as in the previous network, except that it had an additional hidden layer of 20 neurons between the 80 neuron

layer and the output layer. Again, the network was trained on the ASCII character set described previously. The number of training cycles required to fully train the network did not change significantly (it took about 700) but the total training time did increase because of the additional layer involved in the training algorithm. The time taken to complete successive training cycles visibly decreased as training progressed due to the positive effect of the saturation and tolerance factors on the necessity for training on each cycle.

Although not fully investigated, it appears that this complex network is more robust than the three layer network (connections and neurons could be removed from this network without as deleterious an affect as such a removal had on the three layer network). This initial impression needs further study.

Use of the development system is an excellent and convenient vehicle for studying the effects of various parametric changes on the learning and performance of Neural Networks. Such use makes it an easy matter to modify and study, under controlled conditions, various factors such as gain (training rate), momentum, tolerance, saturation, removal of connections, activation algorithms, etc. Hidden layers can be added to the network, as was done above, or the number of neurons in the hidden layers can be varied to see how this

would affect training time and the robustness of the network after training. Through the use of this system the student can now spend his time studying the effects of these parameters in a straight forward and simple fashion.

Another possible scenario for the backpropagation network would be to compare the use of the Sigmoid Function with that of the Modified Sigmoid Function to see if the premise for the development of the Modified Sigmoid, that of reduced training time, is true. This is easily accomplished on the development system by training a single basic network using the two different activation functions, all else remaining equal. Nothing more than a few keystrokes would be required of the system operator to make such a comparison.

HOPFIELD NET

A Hopfield net has also been implemented on the development system in order to demonstrate the system's versatility. Hopfield rekindled much of the interest shown in neural networks in the early 1980's through his extensive work with what is now known as the Hopfield Net [3, 10, 11, 12]. This network can be used as an associative memory or a content addressable memory. Its simplest implementation is a single layer, containing N nodes, using a simple threshold non-linear activation function (Figures 7, 3a), with binary inputs of 1

and -1. Items to be recognized, or recalled, are represented as N-bit binary numbers and are stored in the network in a distributed manner across the system of weight values.

The network developed on the prototype system is shown in Figure 38. It is obvious from the figure that the Hopfield net is radically different from the backpropagation network described earlier (See Figure 35). It consists of only a single layer and it is recurrent, that is, computed outputs are fed back as new inputs. The implementation of the Hopfield net on the development system actually calls for two layers, as is shown in Figure 38. Layer one, the input layer, is merely for input and distribution of those values to the next layer through the weight values. It performs no calculations. Layer two is the output layer. All outputs are routed back to the input layer as input for the next iteration. In the classic Hopfield Net, the output is fed back through weight values as shown in Figure 7. The architecture used for the development system implementation of the Hopfield Net (Figure 38) is, however, functionally equivalent to that depicted in Figure 7. Classic Hopfield network operation methodology is enforced in this prototype system.

The network is different from other common networks in that it uses neither a supervised training algorithm nor an unsupervised training algorithm. The weights are set prior to

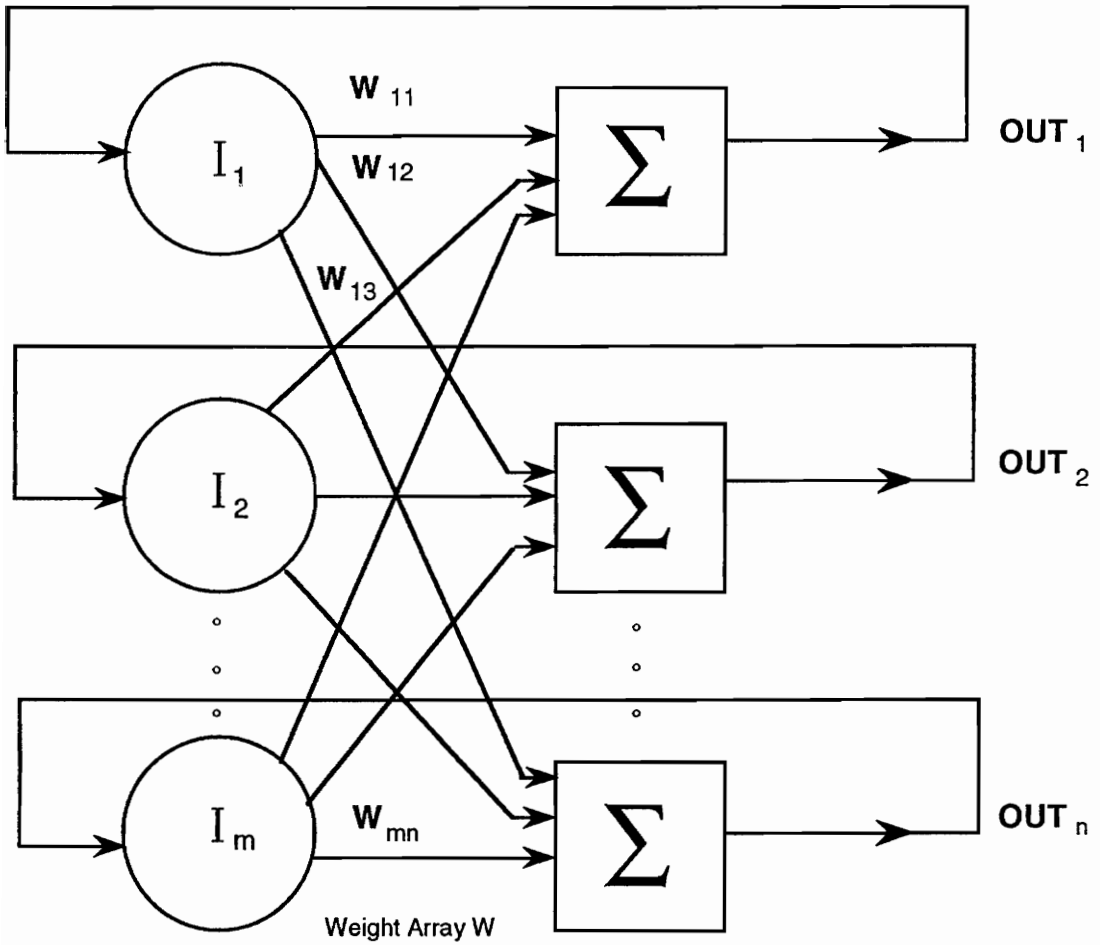


Figure 38. Hopfield Network Implementation

network operations using an algorithm that isolates unique characteristics of examples (called exemplars) of each class of input patterns to be recognized by the network. To set the weights, each exemplar is presented to the network, one after the other, and the following algorithm is applied:

$$\begin{aligned}
 W_{ij} &= \sum_{s=1}^m x_{i,s} * x_{j,s} && \text{for } i \neq j && \text{(Equation 8)} \\
 &= 0 && \text{for } i = j
 \end{aligned}$$

Where:

W_{ij} is the weight connection of the i th neuron to the j th neuron
 m is the number of items to be stored in the network
 s is a particular item presented
 $x_{i,s}$ is the i th binary digit of item s
 $x_{j,s}$ is the j th binary digit of the same item s

When the weights are set in this fashion, they form a symmetric matrix of values with zeros on the main diagonal. In other words, $W_{ij} = W_{ji}$ for $i \neq j$ and $W_{ii} = 0$ for all i . Recurrent networks have been shown to be stable if they meet this criterion [3, 9], although it is not a necessary condition.

The output of a neuron is calculated as described earlier for the backpropagation network. A weighted sum of the inputs of the layer is taken, producing a SUM value which is then

applied to an activation function -- in this case a simple threshold -- which produces the OUT value of the neuron. If the OUT value is greater than the threshold, output is 1, otherwise output is -1. The threshold value is normally set to 0 under these conditions.

The network computation equations are as follows and are similar to those described earlier for the feedforward networks:

$$\text{SUM}_j(t+1) = \sum w_{ij} * \text{OUT}_i(t) \quad (\text{Equation 9})$$

$$\begin{aligned} \text{OUT}_j(t+1) &= 1 \text{ if } \text{SUM}_j(t+1) \geq T && (\text{Equation 10}) \\ &= -1 \text{ if } \text{SUM}_j(t+1) < T \end{aligned}$$

Where:

T is the threshold value
t is time
t+1 is the next iteration after t

Since the network is recurrent, the output of each iteration becomes the input for the next iteration, which is the reason for the use of OUT at time t in Equation 9.

Once the network has been trained, a portion of an input data set can be withheld from the network and the full corresponding output data set will be returned. This is what is meant by associative memory. As with humans, where partial data such as a picture somewhat obscured by shadows produces

a complete memory of that picture, so too the Hopfield net will produce a complete memory of the exemplar when a partially corrupted input is applied.

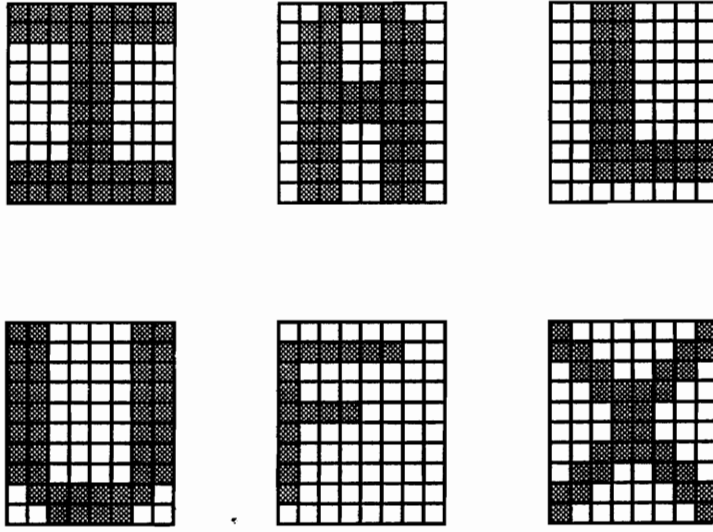
Hopfield network operations are classically performed in the following order. This methodology was enforced in the prototype system for the Hopfield net implementation. First the weights are initialized as specified in Equation 8 operating on the complete set of exemplars included in the input file. The network, by virtue of it being specified as a recurrent, unsupervised, Hopfield net is trained by iterating through each exemplar one time and setting the weights as per Equation 8. The weight matrix is said to be trained for the submitted set of exemplars and will not be altered during further work with that specific set. The Hopfield net is coded on the development system to train in this special fashion when the Training mode is entered. The flow of control within the system is described in the next section (See Figure 40).

A trained Hopfield Net is then initialized by first specifying an input file (one exemplar per input file) and entering the Run Mode. This input pattern exemplar is applied as input to the net. This initialization may either be the complete exemplar or a corrupt version of that exemplar. If an exemplar is not corrupted, the output of the net will always reproduce the original exemplar pattern. An exemplar

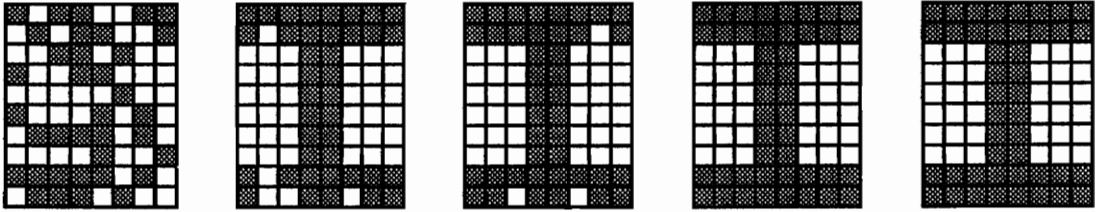
input may be corrupted by randomly reversing each bit (neuron output value) read from the input file with a specified probability. This corruption is applied through a selection option available in the Run Mode, Figures 28 and 42, and is accomplished in the `corrupt_input` procedure located in the math unit, Appendix H. `Corrupt_input` is called from the `modify_parameters` procedure in the `grafstuf` unit, Figure 42 and Appendix E. The corruption probability is set in the menu system as described earlier (Figure 13).

The net is then iterated (that is, output is computed, output is compared to the input, and then the input is set to the computed output) until the output shows no difference between itself and the input, at which time the net is said to have converged.

The network developed on the prototype system is shown in Figure 38 as described earlier. It included 80 neurons in its layer arranged in a matrix architecture of 10 rows by 8 columns (10 x 8). Thus, layer one and two are identical matrices, layer one being the input and distribution layer, layer two being the output and computational layer. Figure 39 depicts the 6 input patterns presented to the network to be trained. As described below, these patterns were hand crafted in order to produce good results on the network. Corrupted exemplars were then presented and were successfully recalled by the network when the corruption probability was at .20 or



Exemplars

Input
(.25 Corruption Probability)

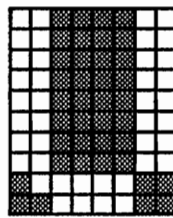
1

2

3

4

Exemplar Iteration



One Common Spurious State

Figure 39. Hopfield Exemplars

below. As the probability increased, the successful recall deteriorated rapidly. A common spurious state for the letter I with corruption probabilities of greater than .25 is also depicted in Figure 39. This essentially reproduced and confirmed the results reported by Springsteen [5].

The Hopfield net has two major limitations when used in this fashion. First, the number of patterns that can be stored and recovered are limited. If too many patterns are stored, the net may converge to novel patterns not seen before. Such convergences are spurious states and will produce a "no match" output. Hopfield showed that this will occur rarely if the number of classes to be identified is kept below $.15N$, where N is the number of nodes in the net. For the prototype system with a maximum of 80 nodes in a layer, this equates to a limitation of 12 classes for identification. A second limitation is that the exemplar patterns will be unstable if they share many bits in common with other patterns. Springsteen [5] includes an excellent discussion of Hamming distance between exemplars to minimize the commonality between bits. The exemplars used in the example presented here were hand crafted to increase this Hamming distance. This greatly increased the effectiveness of the net. Data collected on exemplars with small Hamming distances confirmed that instability is indeed a problem with Hopfield nets.

HEBBIAN LEARNING

Hebbian learning is an unsupervised training method [3]. It involves local interaction between two neurons and requires no teacher and no global feedback system, as does backpropagation. In essence, the Hebbian Learning theory states that a connection between two neurons is strengthened (the weight factor w is increased) whenever those two neurons fire. This concept is expressed in the formula

$$w_{ij}(t + 1) = w_{ij}(t) + \text{OUT}_i \text{OUT}_j \quad (\text{Equation 11})$$

Where:

$\text{OUT}_i = F(\text{SUM}_i)$ = output level of the source neuron
 $\text{OUT}_j = F(\text{SUM}_j)$ = output level of the destination neuron
 t = training iteration

With this algorithm, the synapse strength may be thought to increase according to the excitation levels of the two neurons that it connects. When the activation function F is of a sigmoid form, this learning algorithm is called Signal Hebbian Learning.

This learning algorithm was implemented on the development system using the modified sigmoid activation function. The `Signal_Hebb` procedure in the math unit,

Appendix H, is called in the normal fashion through the Learning_Rule procedure, Figure 40. Since this is an unsupervised training algorithm however, when next_input is called, the setting of the output buffer for the target vector is skipped, as shown in Figure 41.

A network of 36 neurons in the input layer, arranged in a 6 x 6 matrix, 55 neurons in the hidden layer, and a line output layer of 5 neurons was established to demonstrate Hebbian learning on the development system. A series of 5 input sets, dividing the input matrix into five distinct patterns, was presented to the net. It was hoped that the training sessions would result in distinct outputs, thus essentially self-organizing the input into identifiable outputs. This result, however, was only partially achieved with two of the patterns yielding unique results, the other three resulting in no output at all.

The implementation of the Hebbian learning algorithm will require further analysis for its successful use, including the implemented algorithm itself as well as the network architecture used in the study. Once again, although unsuccessful, the development system provides an excellent vehicle for the further modification and analysis of this particular area of study. Further work in the area will provide insight into the Hebbian learning algorithm and the architecture used to implement it.

SECTION 5

DEVELOPMENT SYSTEM DATA FLOW

Figure 40 depicts the main data flow paths in the Training Mode and the Run Mode during network operations. As discussed in the previous sections, the system first determines if it is in the training mode or the run mode. This is accomplished in the Run_Network_Menu procedure in the Menu system which provides the Operations Menu, Figure 24. The global boolean variable "Train" is set to TRUE when the Training mode is selected and set to FALSE when the Run mode is selected.

As can be seen from Figure 40, the network functions in the operations mode are normally controlled from Display_Net_Output procedure specified in the grafstuf unit, Appendix E. The system calls appropriate procedures as determined by whether the network is characterized as a supervised or unsupervised net and then whether it is a recurrent or feedforward type architecture. These procedures for the operation of the network are all specified in the math unit, Appendix H. If it is an unsupervised, recurrent network, the further characterization of whether or not it is a Hopfield net is necessary in order to determine the sequence and procedures for reading input files and setting the input layer to the proper values. This proper sequencing of events

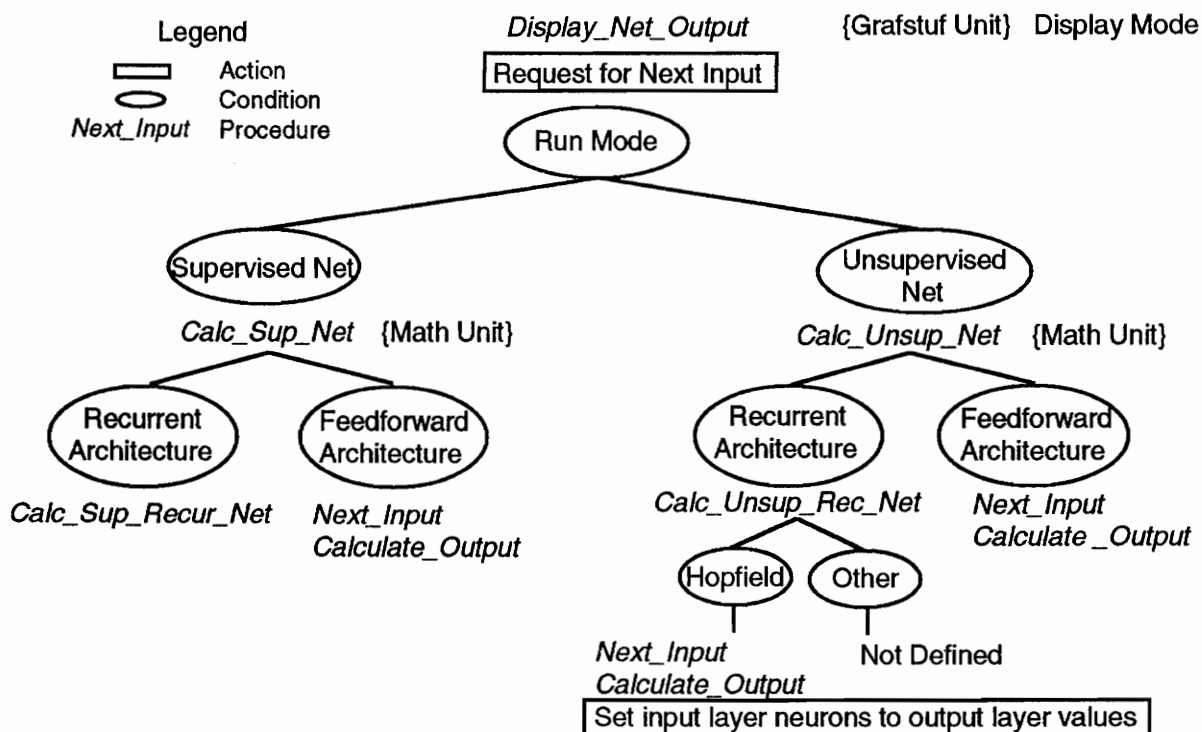
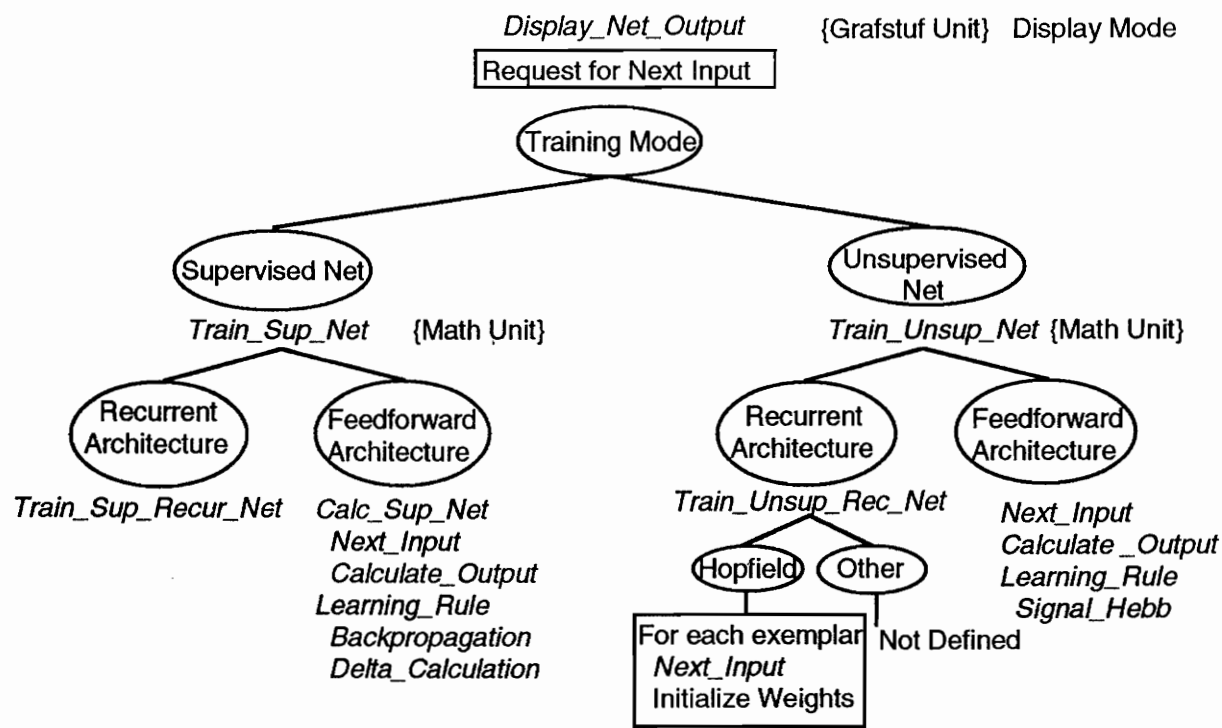


Figure 40. Display Mode Data Flow

is important primarily for the input file read operations, whether it is read at all, whether the target vector is read or skipped, etc. as explained previously and shown in the implementation categories depicted in Figure 8. This allows the system to require only one format for input files, thus enforcing consistency and easing extensibility requirements. If in the training mode, the final course of action is to call the `Learning_Rule` procedure, also located in the math unit, which in turn calls the proper learning algorithm as specified in the `Net_Description` variable (See Appendix B).

Figure 41 depicts the data flow through two important procedures for carrying out network operations. The first is `calculate_output`, specified in the math unit, Appendix H. This procedure establishes the basic algorithm for calculating the output of the network and is the same for all networks no matter what their characterization. The second is the `next_input` procedure, specified in the `ioutil` unit, Appendix G. This procedure also helps to maintain the proper sequencing of events by determining whether a target vector should be read from the input file or skipped. Aside from that determination, it also sets the input and output buffers to the values read from the input file, and then calls `set_input_layer` which sets the input layer neuron binary and real values to the proper equivalent numbers.

Figure 42 displays the procedure nesting and calling

Calculate_Output {Math Unit}

- For each layer
- *weight_matrix_multiply*
Multiply input vector by weight matrix of layer
 - For each neuron in the layer
Calculate_Activation
 - Set neuron output to the activation level to be input for next layer

Next_Input {ioutil unit}

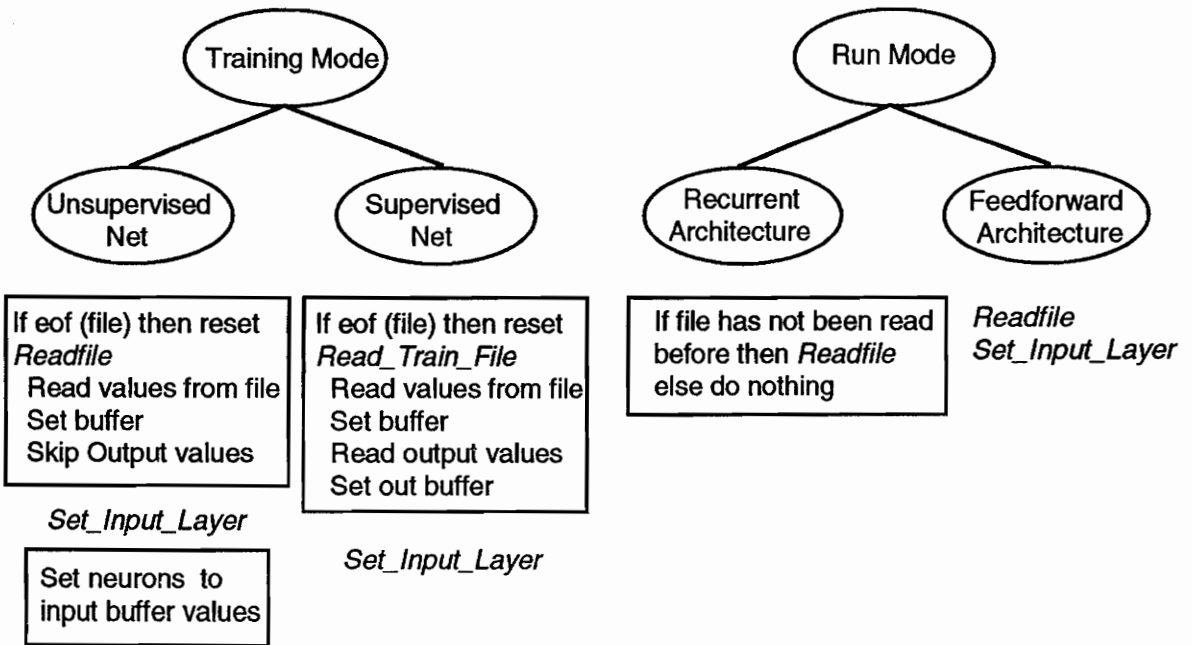


Figure 41. Calculate_Output and Next_Input Procedures

sequence schema specified in the `display_net_output` and the `display_memory` procedures (Display Mode). The Display Mode is entered from the `run_network_menu` (Program Operations Menu) through either the `display_memory` or `display_net_output` procedure when the Run Program or Training Option is selected (Figure 24). Similar capabilities exist whether the system is displaying a memory (weight) map or the network input and calculated output.

While in the display mode, the operator may toggle between the memory display and the input/output display. If toggled, the occurrences within the system are as follows: if in the `display_net_output` procedure, the procedure is exited, thus returning to the `run_program` procedure in the `ops_stuf` unit. A flag is set and the `display_memory` procedure is entered from the `run_program` procedure. The same sequence of events occurs while in the `display_memory` procedure (See Appendix E). The `ops_stuf` unit includes the procedures which supply the interface between the Menu system and the Display system.

When first entered, the options available to the operator in the `display_net_output` are Display Memory, Next Input, Save State, Modify Parameters, and Display Network (See Figure 28). As discussed previously, the Save State option is available through the <SHIFT> S command or automatically through the selection of periodic saves (Figure 26). The <SHIFT> S

command is not displayed on the command line in the Display Mode. For various selections made, Figure 42 shows the sequence of procedure calls initiated by that selection for the Run Mode. A similar sequence also occurs in the Training Mode.

<i>Run_Program</i>	(Set Train Flag to False)	{Ops_Stuf Unit}
	(Called from the Program Operations Menu)	
<i>Display_Memory</i>		{grafstuf unit}
<i>Train_Sup_Net</i>		{math unit} initiated by next input selection
<i>Calc_Sup_Net</i>		" "
<i>Train_Unsup_Net</i>		" "
<i>Calc_Unsup_Net</i>		" "
<i>Save_State</i>		{ioutil unit}
	(Save the state of the network to file)	
<i>Display_Net_Output</i>		{grafstuf unit}
<i>Train_Sup_Net</i>		{math unit} initiated by next input selection
<i>Calc_Sup_Net</i>		" "
<i>Train_Unsup_Net</i>		" "
<i>Calc_Unsup_Net</i>		" "
<i>Save_State</i>		{ioutil unit}
<i>Modify_Parameters</i>		{grafstuf unit}
<i>Modify_Input</i>		
	(Manually set input of each neuron in input layer)	
<i>Modify_Neurons</i>		{grafstuf unit}
	(Delete/Restore Neurons in each layer)	
<i>Get_Removal_Probability</i>		
<i>Remove_Random_Neurons</i>		
<i>Display_Network</i>		
<i>Net_Display</i>		
<i>Draw_Layer_Box</i>		
<i>Draw_FFArrows</i>		
<i>Modify_Connections</i>		{grafstuf unit}
	(Delete/Restore individual connections)	
<i>Get_Removal_Probability</i>		
<i>Remove_Random_Connections</i>		
<i>Display_Network</i>		
<i>Corrupt_Input</i>		{math unit}
	(Randomly reverse input values)	
<i>Calculate_Output</i>		{math unit}
<i>Display_Network</i>		{grafstuf unit}
<i>Net_Display</i>		
<i>Draw_Layer_Box</i>		
<i>Draw_FFArrows</i>		

Figure 42. Operations Run Mode Procedure Map

SECTION 6

PROPOSED IMPROVEMENTS

As stated in the introduction, the development system is a prototype. As such, it is meant to be an initial version that supports the concept of a general system that will allow the creation and study of diverse network architectures and paradigms. The described networks created on the system support this stipulation. The development system should be exercised additionally with several other network types and training algorithms such as Bidirectional Associative Memories (BAMs), Counterpropagation nets, Outstar and Instar, and Self-Organizing nets to get a better idea of the system's generality, extensibility, and I/O compatibility with different network paradigms.

As network implementation and study of different network operations progressed, several improvements to the current development system were envisioned to be helpful to future users.

First among these would be the capability to display the output of the hidden layers. This would greatly enhance the user's view and understanding of the network's operation. Current capabilities only allow for the display of the input layer and the output layer. It would be of benefit to be able to see the outcome of the network computations for each hidden layer in a similar manner to how weight values are displayable

for all layers. This is especially true when developing new training algorithms -- to be able to see if the computation and therefore, the implementation is correct. With multi-layer networks it becomes especially tedious to determine correct performance without this capability. Suggested methodology for this enhancement would be similar to the implementation for the memory display, allowing the operator to cycle through the layers displaying layer n to the left in Figure 28 and layer $n + 1$ to the right. The methodology for displaying hidden layers on the screen will need to be thoroughly analyzed, as in the case of the 80 neuron layer line architecture that will not comfortably fit on the display screen. Perhaps splitting it into 4, 20 neuron lines for display would be the best approach. Whatever the method of display, it should be made as clear as possible without adding unnecessary confusion for the user. A display of the actual numerical output of these hidden layers would also be helpful.

Additionally, the current system procedure for removal of a connection between two neurons is to set the weight value for that connection to zero. This, in effect, disconnects that neuron from participation in the computation of the output for the neuron in the next layer. A more reasonable method for implementation is through the use of connection matrices as specified in the `layer_type` definition (Appendix B). The definition of connections, through a dynamic variable

connection matrix associated with each layer (similar to the weight matrix associated with each layer), 1 specifying a connection, 0 specifying no connection, would be a cleaner, more extensible way of defining connectivity. For each computation of a neuron's output through the associated weight to a neuron in the next layer, a check would be made of the connection matrix. If connected (matrix value 1) the computation would be made; if not connected, that computation would be skipped. Such a positive approach would be especially useful when studying the effects of partial connectivity on training of the network. With the present system, the study of the effects of connectivity is a cumbersome task, not satisfactorily solved, since the system cannot distinguish between a weight value of zero meaning no connection and a transient zero value resulting from the state of training. A drawback with this proposed implementation on the current system, of course, is its affect on available memory, and therefore maximum network size.

A second enhancement would allow for the display of individual neuron firing rates in a fashion similar to the display of the weight (memory) matrices. This desirable capability would allow for visual presentation of active and less active neurons in the network. The display could be color-coded to visually depict activity rates. (See the discussion below concerning the memory display and the

Suggestions for Further Research for a discussion concerning neuron firing rate data).

A third proposed improvement to the system would be the inclusion of full recurrency in the modeling capabilities of the program. As discussed previously, the only recurrency allowed in the present system is from the output layer back to the input layer. There are many experimental networks under current study that make use of recurrency between the hidden layers as well as within a single layer back to itself. This would require a full design review to determine how best to implement such a capability. However, with the current system's isolation of network categories, as discussed in the system architecture section and as depicted in Figures 8 and 40, this should be a task of only modest difficulty.

A weakness in the current system's design and its effect on extensibility, concern the use of different activation functions and their impact on the implementation of learning algorithms and network computation. For instance, in the case of the backpropagation algorithm, as shown in Figure 32 and 33 and in Equations 2 and 5, the computations depend on the derivative of a Sigmoid function. One of the benefits of the Sigmoid function, as described earlier, was the simplicity of the derivative (Equation 2). This derivative value (the slope of the sigmoid curve at the computed OUT value) is dependent on the value of OUT which, in turn, varies depending on

whether the activation function is a Sigmoid or a Modified Sigmoid. These computation problems are currently handled within the backpropagation algorithm (Appendix H). The addition of new activation functions will therefore also require a modification of the learning algorithms which they affect. In fact, the simple threshold activation function cannot be used with the current implementation of the backpropagation algorithm since the derivative formula does not hold for that function. This hampers the ease with which new functions and algorithms may be incorporated into the system. The system design should be reviewed to see if extensibility in this area can be improved.

The display of weight matrices (memory) associated with each network computation layer can also be improved. The original desired functionality was to color-code weight values to allow the user to observe patterns and concentrations as well as the relative strength of the weight values. While pretty, the display implemented (grafstuf unit [Appendix E]; procedure `display_weights`) does not always clearly convey to the user these relative weight values. The human interface aspects of these color displays should be reviewed as well as the range of weight value differentiation in order to provide the most meaningful information to the user. Methods for display of actual weight values should also be investigated since the current procedure (displaying them if there is room,

not displaying them if the weight boundary squares are too small) is less than satisfactory.

A final suggested improvement to the system is to develop the capability to compile and link new code into the system through the menu system. This optional selection has been made available in the Program Operations Menu (Figure 24), although it is not currently functional. The desired functionality of this capability is to allow the user to design and write new source code from within the development system, save it to a pre-specified file of skeleton source code, and compile it online as a unit. The scope of this functionality would be limited to a few specific areas such as activation functions and learning algorithms. These would be compiled as separate units and then linked to the rest of the system. The basis for this has been established through the (generally) complete separation of the menu system from the operations mode of the development system. These two functional areas are interfaced only through the two procedures in the `op_stuf` unit (Appendix I). The separation of activation functions and learning algorithms through case statement calls (Appendix H) also supports this desired functionality. Developing this capability would require an extensive redesign of the system. Nevertheless, its implementation would give the user a simple and straight forward method to experiment with different algorithms.

SECTION 7

SUGGESTIONS FOR FURTHER RESEARCH

The use of this Development System, among other things, allows the student to easily see the affect of different conditions on various networks. Some additional areas of study were suggested in the discussion of the backpropagation algorithm and in the proposed improvements section. Additionally, some other uses that have not been exercised in the described system implementations are the following:

1. A modification of current algorithms to include the collection and display of neuron firing rate data. This variable is included in the individual neuron specification (Appendix B) but has not been included in network algorithm implementations.
2. Use of individual neuron thresholds in training algorithms and network computations. The current networks use a global threshold to determine the binary output of a neuron. The effect of individual thresholds is a topic of current research in the area. This variable is also included in the individual neuron specification and is available for implementation in network algorithms.

3. Modification of existing learning algorithms, or implementation of new learning algorithms, to include the training of the neuron threshold. Varying the threshold in some consistent manner could speed training time significantly. This could be done for the global threshold or individual neuron thresholds and is another topic of ongoing research in ANNs.
4. Investigation of the relative effects of other desaturation algorithms on network training. As discussed in Wasserman [3], there has been no effort to optimize the desaturation function used in the current system. Other functions may prove to be superior to the one implemented in the present Development System. In order to provide this capability to offer different desaturation functions, a further design review should be made to decide how best to incorporate it.

SECTION 8

SUMMARY

A prototype Artificial Neural Network Development System has been proposed, designed, and implemented on an AT class Personal Computer. This system is meant to be an aid to students studying the use and operations of various ANNs that are of interest. The proposed system permits the simple modification of common parameters of neural networks as well as the implementation of novel architectures and algorithms. The system design, operation, and data flow are all described and documented. Specific implementations of the Delta Rule and backpropagation learning algorithms, an unsupervised Hebbian learning algorithm, and Hopfield nets are also described. Improvements to the system are suggested as well as proposed research topics that may be realized using the system as presented.

The system has been shown to provide a viable approach to the study of neural networks without requiring a full system development for each network or variable of interest.

The complete source code for the system and algorithms is presented in Appendices B through J to this report.

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APPENDIX A
Development System Specifications

DEVELOPMENT SYSTEM SPECIFICATIONS and INFORMATION

- . Maximum Number of Layers (max_layers) 5
- . Maximum Number of Neurons per Layer (max_bodies) 80
- . Input limited to binary values (1, 0)
- . No continuous value inputs
- . Output values for each neuron are available through the neuron's floating point value -
`layers[x].neural_set.real_value[y].`
- . Input values in the data file must equal 1 or 0. These values are then converted to a real value (1.0/-1.0, 1.0/0.0, .5/-.5 etc.). Default values for these real numbers are included and depend on the type of training and activation function. The conversion values are assigned to `net_description.one_value` and `net_description.zero_value` in the `net_description_data` variable. They may also be specified by the operator through the menu system. All network computations use the floating point values. Integer (binary) values are used only for input and output displays.
- . A matrix architecture for the input layer and the output layer still uses a line as internal representation and computations for the neurons of that layer. Thus a 5 X 5 matrix designated by the operator is represented internally by the system as a line of 25 neurons. The matrix architecture specified by the user is for display purposes only. Thus a number, letter, or other graphic may be displayed as the input or the output of the network. Input data is read directly from the input file and placed in the line representation of the layer. Order for display of the matrix is by column, thus column 1 is read first from the line, then column 2, etc. In the example above, input 1 through 5 would represent the first column in the matrix, 6 through 10 the second column, etc.
- . The system, when reading the input file, expects every other line to be either a line of data for supervised training or an empty line. Thus, if the data has no input line for a supervised training pair (as would be the case in an unsupervised training mode), the data **must** still include a blank line (RTN) after each data line.

- . The computation of output for all networks is the same. Input data is read and placed in the binary values (`layers[x].neural_set.binary_value[y]`) for each neuron in the layer. Real value equivalents, as specified by the operator or defaulted by the program are placed in `layers[x].neural_set.real_value[y]`. Computation for each layer in the network is accomplished by summing the layer weights multiplied by the output value of each neuron in the previous layer [x]. This value is then sent through the activation function which determines the value of `layers[x+1].neural_set.real_value[j]` for all j (neurons) in layer x+1. Thresholding functions for each activation function then determine the value of `layers[x+1].neural_set.binary_value[j]`. This process is shown in Figure 5. The process continues for each layer until the output layer is reached. Output is displayed in binary format (on, off) according to `layers[out_layer].neural_set.binary_value[j]` for all j (neurons) in the output layer. As with input data, output data is displayed column by column for matrix architectures.
- . A specified network and all its data can be saved manually by the operator. When saved, it is automatically saved to four DOS files. The File Name is specified by the operator and file name extensions (.1, .2, .3, and .4) are automatically added to the filename. Filename.1 is of type `net_description` and holds all net description data. Filename.2 is of type `layer_type` and holds all the layer data. Filename.3 is of type `connection_matrix` and holds the neuron connection data for each layer. Currently, the connection matrix is not used in the development system. Therefore, Filename.3 is saved as an empty file. Connections that have been removed are specified as weights equal to zero in the weight matrix. Filename.4 is of type `weight_matrix` and holds all the weights for each layer in the net.
- . When the operator specifies periodic saves of the network state, each save is appended to file `netstate.3` and `netstate.4`. `Netstate.1` and `netstate.4` are overwritten since this data does not change as the network operates. Once `netstate` files are opened they are not closed until done so manually by the operator or the network is exited to DOS. The operator must therefore be careful to close the files if a new network is specified without exiting and states of the old network are desired to be saved.
- . In order to print the `netstate` file the operator is required to manually select this option through the menu

system. The system reads the values of each data file (netstate.1 through netstate.4) and creates a network conforming to those values. Thus, in order to print the previously saved network states, the current network in the system is destroyed to allow the creation of the new one for printing. The operator is alerted to this fact and can choose either to continue, or skip the printing until he saves the current network.

- . Saving the network and saving the state of network, although similar in function, are two distinct operations. Saving the state periodically saves the values of the network to four distinct files called netstate.1 through netstate.4. It is used to later analyze the operation of the network, normally after the completion of a training session. Saving the network saves the same data but only once, and then to a DOS file specified by the operator (filename.1 through filename.4). This function is used to save a network in order to recall it later so the operator need not re-specify and train the network each time. Basically, the final state of the network is saved when the operator selects this option.

APPENDIX B

Development System Main Program
and
Global Declarations

Appendix B through Appendix J constitute the
complete development system program listing

Program Neural_System;

Uses Crt, Graph, nnglobal, grafstuf, menus, mathutil;

```
begin      {Neural_System}
  origmode := lastmode;
  TextColor (yellow);
  Initialize_graphics;{set the graphics mode-grafstuf unit}
  Initialize_stuff;      {Mathutil unit}
  Initialize_layers;     {Mathutil unit}
  RestoreCrtMode; {Reset to textmode-toggle back and forth}
  System_Menu;      {Menus unit}
  closegraph;
  textmode (origmode);
  textbackground (black);
  TextColor (yellow);
end.      {Neural_System}
```

{-----}

```
unit nnglobal;
```

```
interface
```

```
Const
```

```
learning_kind : packed array [0..7] of string[16] =
    ('Delta', 'Hebbian', 'Madaline',
     'Adaline', 'Back Propagation',
     'Hopfield', 'No Learning', 'Other');
training_kind : packed array[0..2] of string[12] =
    ('Supervised', 'Unsupervised', 'None');
activation_kind : packed array [0..4] of string[16] =
    ('Sigmoid', 'Modified Sigmoid',
     'HypTangent', 'Threshold', 'Other');
rows           = 80;    {Max Rows in a matrix}
columns        = 80;    {Max Columns in a matrix}
linesize      = 80;    {Max neurons in a line}
max_layers     = 5;     {Max number of layers in network}
stringsize     = 20;
max_bodies     = 80;    {Max neurons in a layer}
```

```
Type
```

```
activation_type = (Sigmoid, Mod_Sigmoid, HypTangent,
                  Threshold, you_define);
learning_type   = (delta, hebb, madaline, adaline, backp,
                  Hopfield, none, other);
training_type   = (supervised, unsupervised, zip);
layer_arch_type = (Lines, Matrices);
connection_type = (Fully, Partial, Not_Connected);
layerange       = 1..max_layers;
linerange       = 0..linesize;
linetype        = packed array [linerange] of char;
BinaryType      = -1..1;
DeltaVectorType = packed array[1..max_bodies] of real;
BodyValueType   = record
    Binary_value : packed array
        [1..max_bodies] of BinaryType;
    Real_value   : packed array
        [1..max_bodies] of real;
    threshold    : packed array
        [1..max_bodies] of real;
    rate         : integer;
end;
net_arch_type   = (feedforward, recurrent);
```

```

net_description_type = record
    net_name      : string [80];{MS Dos}
    net_arch      : net_arch_type;
    num_layers    : layerange;
    activation     : activation_type;
    threshold     : real;    {Activation}
                    {threshold value}
    learning      : learning_type;
    training      : training_type;
    factor        : real;    {various}
                    {factors for}
                    {Learn Algorithms}
    factor1       : real;
    factor2       : real;
    factor3       : real;
    momentum      : real;    {Momentum}
    random_weights : boolean;
    set_weights   : boolean;
    save_state    : boolean;{State}
                    {saved periodically?}
    iterate       : integer; {Save}
                    {how often?}
    one_value     : real;    {I/O}
                    {value representation}
    zero_value    : real;
end;

strng           = packed array [1..stringsize] of char;
row             = 1..rows;
column         = 0..columns;
connection_matrix = record
    value : packed array [1..max_bodies,
                        1..max_bodies] of '0'..'1';
                    {Connected or not}
    col_length : integer;
    row_length : integer;
end;

weight_matrix = record
    value : packed array [1..max_bodies,
                        1..max_bodies] of real;
    col_length : integer;
    row_length : integer;
end;

connection_ptr = ^connection_matrix;
weight_ptr     = ^weight_matrix;

```

```

layer_type      = record
    FFConnection_kind : Connection_type;
                    {Full or Partial}
    Neurons          : integer; {Number per}
                    {layer}
    Neural_Set       : BodyValueType;
    Arch             : layer_Arch_type; {Layer}
                    {Architecture}
    Arch_row_length  : integer; {Matrix}
                    {Row length}
    arch_col_length  : integer; {Matrix}
                    {Col length}
    weights          : weight_ptr; {Points}
                    {to weight vector}
    saved_weights    : weight_ptr; {weights}
                    {from time t-1}
    delta_vector     : DeltaVectorType;
    connections      : connection_ptr; {Ptr}
                    {to connection matrix}
    out_layer        : boolean; {last layer}
end;
IntegerBufferType = packed array [1..max_bodies] of
    BinaryType;
RealBufferType    = packed array [1..max_bodies] of real;

```

Var

```

M           : weight_matrix; {For general matrix calcs}
arch_set    : layerange;
neuron_set  : layerange;
ColNo       : linerange;
ColsOnLine  : linerange;
EndOfLine   : boolean;
layers      : packed array [layerange] of layer_type;
                    {Layer Data}

lin         : linetype;
net_name    : string [12]; {filename for saving to disk}
net_description : net_description_type; {Network}
                    {specification}

NextChar    : char;
num_layers  : layerange; {Layers in the net}
train       : boolean; {for reading files in training}
                    {mode}

s           : string [80];
InFileName  : string [80];
IOCode      : integer;
graphdriver : integer; {Following for Graphics Use}
graphmode   : integer;
errorcode   : integer;

```

```
MaxX, MaxY      : integer;
origmode        : word;
in_buffer       : IntegerBufferType;      {Buffer for input}
out_buffer      : IntegerBufferType;      {Buffer for output}
r_out_buffer    : RealBufferType;         {Buffer for reals}
infile          : text;                   {Input file}
savefile1       : file of net_description_type; {Save Network}
savefile2       : file of layer_type;      {Save Network}
savefile3       : file of connection_matrix; {Save Network}
savefile4       : file of weight_matrix;   {Save Network}
```

implementation

end.

APPENDIX C

Development System Menu Listing
(Unit Menus)

Appendix B through Appendix J constitute the
complete development system program listing

```

{-----}

{This Unit (menus) provides the dialogue menus for the}
{system}

{-----}

Unit Menus;

interface

uses graph, crt, grafstuf, printer, ops_stuf, nnglobal,
      mathutil, ioutil, weights;

Procedure System_Menu;

implementation

{-----}

Procedure Number_of_Neurons;

var
  ch      : char;
  i, j, int : integer;

begin   {Number_of_Neurons}
  repeat
    clrscr;
    gotoxy (20, 8);
    writeln ('SELECT NUMBER OF NEURONS FOR EACH LAYER');
    gotoxy (20, 10);
    write ('Current Selections (');
    write (Layers [1].neurons);
    for i := 2 to num_layers do
      write (' ', Layers [i].neurons); {write number for
                                      each layer}
    write (')');
    gotoxy (10, 24);
    writeln ('                               <RTN> Skip Layer');
    gotoxy (1, 21);
    write ('=> ');
    i := 1;
    while i <= num_layers do {Number of layers selected or
                              default value}
      begin
        gotoxy (20, 11);
        clreol;
        write (' ');

```

```

reverse;
writeln ('Layer Number ', i);    {reverse video}
normvid;
gotoxy (4, 21);    {place cursor after =>}
clreol;
getline;
if (ColsOnLine > 0) and (Nextchar in ['0'..'9'])
  then
    begin
      process_number (int);
      if int > max_bodies
        then
          begin
            gotoxy (10, 2);
            reverse;
            write ('Exceeds Max Neuron Limit (',
                  max_bodies, ')');
            normvid;
            gotoxy (1, 21);
            clreol;    {Erase =>}
            gotoxy (1, 23);
            write ('<RTN> to continue');
            readln;
            i := i - 1;    {Set to repeat layer}
            gotoxy (1, 23);
            clreol;    {Erase <RTN>..}
            gotoxy (10, 2);    {Clear error message}
            clreol;
            gotoxy (1, 21);
            write ('=> ');
          end
        else
          begin
            layers[i].neurons := int;
            gotoxy (20, 10);
            clreol;
            write ('Current Selections (');
            write (Layers [1].neurons);
            for j := 2 to num_layers do
              write (' ', Layers [j].neurons);
              {write each layer}
            write (')');
          end;
        end;
      i := i + 1;
    end;
neuron_set := num_layers;    {Need to initialize}
gotoxy (20, 11);
clreol;    {clear layer number status}

```



```

gotoxy (10, 24);
writeln ('<ESC> Layer Data Menu                                <RTN> Modify
                                                Numbers');

gotoxy (1, 21);
clreol;
write ('=> ');
ch := readkey;
until ch = chr (27) {ESC to exit to system menu}
end;      {Number_of_Neurons}

{-----}

{Number_of_Layers establishes the menu for specifying the}
{Number_of_layers}

Procedure Number_of_Layers;

var
  ch : char;
  i  : integer;

begin      {Number_of_Layers}
  repeat
    clrscr;
    gotoxy (20, 8);
    writeln ('SELECT NUMBER OF LAYERS');
    gotoxy (20, 10);
    writeln ('      Current Number ('
                                net_description.num_layers, ')');
    gotoxy (10, 24);
    write ('                                                <RTN> Accept and
                                                Continue');

    gotoxy (1, 21);
    write ('=> ');
    ch := readkey;
    while not (ch in ['1'.. '9', chr (13)]) do
      repeat_input (ch);
    case ch of
      '1'      : begin
                  gotoxy (10, 2);
                  reverse;
                  write ('Minimum Number of Layers = 2');
                  normvid;
                  gotoxy (1, 23);
                  write ('<RTN> to Continue');
                  readln;
                  gotoxy (1, 23);
                  clreol;      {Clear <RTN>..}
                end;
    end;
  until ch = chr (27);
end;

```

```

        end;
    '2'..'9' : begin
        if ord (ch) - 48 > max_layers
        then
            begin
                gotoxy (10, 2);
                reverse;
                writeln ('Layers Exceed Maximum (' ,
                    max_layers, ')');
                normvid;
                gotoxy (1, 23);
                write ('<RTN> to Continue');
                readln;
                gotoxy (1, 23);
                clreol;
            end
            else num_layers := ord (ch) - 48;
                {Convert to integer}
        end;
    end; {case}
    for i := 1 to (num_layers - 1) do
        layers[i].out_layer := false; {Set layers to not the
            last one}
        layers[num_layers].out_layer := true; {set last layer
            to true}
        net_description.num_layers := num_layers;
    until ch = chr (13); {RTN to exit to layer menu}
end; {Number_of_Layers}

{-----}

Procedure Get_Training_Mode;

var
    i : integer;
    ch : char;

begin {Get_Training_Mode}
    repeat
        clrscr;
        gotoxy (20, 8);
        writeln ('SELECT TRAINING MODE');
        gotoxy (20, 9);
        for i := 1 to (10 - (length (training_kind
            [ord(net_description.training)]
                Div 2)) do
            write (' '); {center the name}
            write ((' '); {write the kind of training}

```

```

write (training_kind [ord(net_description.training)],
      ')');
gotoxy (1, 21);
write ('=> ');
gotoxy (20, 11);
write ('1. Supervised');
gotoxy (20, 12);
write ('2. Unsupervised');
gotoxy (20, 13);
write ('3. None');
gotoxy (10, 24);
writeln ('<ESC> Learning                                <^C>
                                                Accept');

gotoxy (1, 21);
clreol;
write ('=> ');
repeat
  ch := readkey;
until ch in ['1'..'3', #27, #3];
case ch of
  '1' : net_description.training := supervised;
  '2' : net_description.training := unsupervised;
  '3' : net_description.training := zip;
end;
until ch in [#27, #3] {ESC or ^C to exit to learning
menu}
end;      {Get_Training_Mode}

{-----}

Procedure Learning (var flag : char);
var
  ch      : char;
  i, y    : integer;
  gain    : real;
  result  : integer;

begin  {Learning}
repeat
  clrscr;
  gotoxy (20, 6);
  write ('SET LEARNING ALGORITHM');
  gotoxy (20, 7);
  for i := 1 to (10 - (length (learning_kind
                        [ord(net_description.learning)])
                  Div 2)) do
    write (' ');      {center the name}
  write ((' ');      {write the kind of learning}

```

```

write (learning_kind [ord(net_description.learning)],
      '));
gotoxy (20, 8);
for i := 1 to (10 - (length (training_kind
                        [ord(net_description.training)]
                        Div 2)) do
    write (' ');    {center the name}
write ('(');      {write the kind of training}
write (training_kind [ord(net_description.training)],
      '));
y := 10;
for i := 1 to 8 do
    begin
        gotoxy (20, y);
        write (i, '. ', learning_kind [i-1]);
        y := y + 1;
    end;
i := i + 1;
gotoxy (20, y);
write (i, '. Set Gain Value ('
      net_description.factor:4:2, '));
i := i + 1;
y := y + 1;
gotoxy (20, y);
write ('A. Set Tolerance Value ('
      net_description.factor1:4:3, '));
i := i + 1;
y := y + 1;
gotoxy (20, y);
write ('B', '. Set Saturation Value ('
      net_description.factor2:4:4, '));
gotoxy (10, 24);
writeln ('<ESC> Activation Menu          <^C> Accept - Go
      to Main Menu');
gotoxy (1, 22);
write ('=> ');
ch := readkey;
while not (ch in ['1'..'9', 'A', 'a', 'B', 'b', #27,
                  #03]) do
    repeat_input (ch);
case ch of
    '1'      : begin
                Net_description.learning := delta;
                Net_description.training := supervised;
            end;
    '2'      : begin
                Net_description.learning := hebb;
                Net_description.training := unsupervised;
            end;

```

```

'3'      : begin
           Net_description.learning := Madaline;
           Net_description.training := supervised;
           end;
'4'      : begin
           Net_description.learning := adaline;
           Net_description.training := supervised;
           end;
'5'      : begin
           Net_description.learning := backp;
           Net_description.training := supervised;
           end;
'6'      : begin
           Net_description.learning := Hopfield;
           Net_description.training := unsupervised;
           end;
'7'      : begin
           Net_description.learning := none;
           Net_description.training := zip;
           end;
'8'      : begin
           net_description.learning := other;
           get_training_mode;
           end;
'9'..'b' : begin
           clrscr;
           gotoxy (20, 8);
           case ch of
             '9' : begin
                   write ('Enter Gain Value [n]
                               ');
                   write (('(',
                           net_description.
                               factor:4:2, ')');
                   end;
             'A', 'a' : begin
                   write ('Enter Tolerance Value
                               [t] ');
                   write (('(',
                           net_description.
                               factor1:4:3, ')');
                   end;
             'B', 'b' : begin
                   write ('Enter Saturation Value
                               [s] ');
                   write (('(',
                           net_description.
                               factor2:4:4, ')');
                   end;
           end;

```

```

end; {case}
repeat
  gotoxy (1, 21);
  write ('=> ');
  {$I-};
  readln (gain);{Fix for rtn or esc!!!!}
  result := ioreult;
  {$I+}
  {Check for real number}
  if result <> 0      {not A real number}
  then
    begin
      gotoxy (1, 1);
      reverse;
      write ('Illegal real number');
      normvid;
      gotoxy (4, 23);
      write ('<RTN> to Continue');
      readln;
      readln;
      gotoxy (1, 23);
      clreol;
    end
  else
    case ch of
      '9' : net_description.factor :=
            gain; {gain on delta}
      'A', 'a' : net_description.factor1 :=
                gain; {Tolerance}
      'B', 'b' : net_description.factor2 :=
                gain; {Saturation}
    end; {case}
  until result = 0;
end;
#3      : begin
        flag := #6;{Set flag to jump to main menu}
        exit;
        end;
end; {case}
until ch = chr (27);
end; {Learning}

{-----}

```

```

Procedure Activation_Function (var flag : char);

var
  ch      : char;
  activate : real;
  momentum : real;
  I, a, j : integer;
  result  : integer;

begin {Activation_Function}
  activate := net_description.threshold; {Default if
                                         threshold chosen}
  momentum := net_description.momentum;
  repeat
    clrscr;
    gotoxy (20, 8);
    write ('SET ACTIVATION FUNCTION');
    gotoxy (20, 9);
    case net_description.activation of
      Sigmoid      : write ('(Sigmoid [ $\alpha$  = ',
                           net_description.momentum:4:2, '])');
      Mod_Sigmoid : write ('(Modified Sigmoid [ $\alpha$  = ',
                           net_description.momentum
                               :4:2, '])');
      HypTangent  : write (' (Hyperbolic Tangent)');
      Threshold   : write ('(Simple Threshold [' ,
                           activate:4:2, '])');
    end; {case}
    gotoxy (20, 11);
    write ('1. Sigmoid (1/0)');
    gotoxy (20, 12);
    write ('2. Modified Sigmoid (.5/-0.5)');
    gotoxy (20, 13);
    write ('3. H-Tangent (1/-1)');
    gotoxy (20, 14);
    write ('4. Simple Threshold (' ,
        net_description.threshold:5:4, '));
    gotoxy (20, 15);
    write ('5. Other');
    gotoxy (20, 16);
    write ('6. Set Real I/O Values (' ,
        net_description.one_value:2:1, '/',
        net_description.zero_value:2:1, '));
    gotoxy (10, 24);
    writeln ('<ESC> Weight Menu      <^C> Accept and
            Continue');

    gotoxy (1, 21);
    write ('=> ');
    ch := readkey;
  until ch = '^C';
end;

```



```

write ('=> ');
{$I-};
readln (momentum);{Fix for rtn or esc!!}
result := ioresult;
{$I+}
{Check for real number}
if result = 0      {A real number}
  then net_description.threshold :=
                                     momentum
  else
    begin
      gotoxy (1, 1);
      reverse;
      write ('Illegal real number');
      normvid;
      gotoxy (4, 23);
      write ('<RTN> to Continue');
      readln;
      readln;
      gotoxy (1, 23);
      clreol;
      momentum :=
                  net_description.threshold;
    end;
until result = 0;
repeat
  clrscr;  {get neuron threshold value}
  gotoxy (20, 8);
  write ('Enter Individual Neuron
                                     Threshold Value (');
  write (layers[2].neural_set.
                                     threshold[1]:5:4, ')');
  gotoxy (1, 21);
  write ('=> ');
  {$I-};
  readln (momentum);{Fix for rtn or esc!!}
  result := ioresult;
  {$I+}
  {Check for real number}
  if result <> 0      {A real number}
    then
      begin
        gotoxy (1, 1);
        reverse;
        write ('Illegal real number');
        normvid;
        gotoxy (4, 23);
        write ('<RTN> to Continue');
        readln;

```

```

        readln;
        gotoxy (1, 23);
        clreol;
        momentum :=
            layers[2].neural_set.threshold[1];
    end;
until result = 0;
for a := 2 to net_description.num_layers
    do
        for j := 1 to layers[a].neurons do
            layers[a].neural_set.threshold[j] :=
                momentum;
if ch = '1' {Sigmoid activation}
then
begin
    net_description.one_value := 1.0;
    net_description.zero_value := 0.0;
end
else {mod_sigmoid activation}
begin
    net_description.one_value := 0.5;
    net_description.zero_value := -0.5;
end;
end;
'3' : begin {HypTangent}
    net_description.activation := HypTangent;
    net_description.one_value := 1.0;
    net_description.zero_value := -1.0;
end;
'4' : begin {Simple Threshold}
    repeat
        clrscr;
        gotoxy (20, 8);
        write ('Enter Threshold Value ', '(');
        write (net_description.Threshold:4:2,
            ');');
        gotoxy (1, 21);
        write ('=> ');
        {$I-};
        readln (Activate);{Fix for rtn or esc!}
        result := ioreult;
        {$I+}
        {Check for real number}
        if result = 0 {A real number}
        then
            begin
                net_description.threshold :=
                    activate;

```

```

        net_description.activation :=
                                threshold;
    end
else
    begin
        gotoxy (1, 1);
        reverse;
        write ('Illegal real number');
        normvid;
        gotoxy (4, 23);
        write ('<RTN> to Continue');
        write (#7);
        readln;
        readln;
        gotoxy (1, 23);
        clreol;
        net_description.activation :=
                                threshold;
        activate :=
            net_description.threshold;
    end;
until result = 0;
net_description.one_value := 1.0;
net_description.zero_value := 0.0;
end;
'5' : begin      {You Define}
    net_description.activation := you_define;
    net_description.one_value := 1.0;
                                {Modify for setting}
    net_description.zero_value := 0.0;
end;
'6' : begin
    repeat
        clrscr;      {get one_value}
        gotoxy (20, 8);
        with net_description do
            begin
                write ('Enter Real Value for 1 (');
                write (One_value:2:1, ')');
            end;
        gotoxy (1, 21);
        write ('=> ');
        {$I-};
        read (momentum);{Fix for rtn or esc!!!!}
        result := ioreult;
        {$I+}
        {Check for real number}
    end repeat;
end;

```

```

if result = 0      {A real number}
  then net_description.one_value :=
                                     momentum
else
  begin
    gotoxy (1, 1);
    reverse;
    write ('Illegal real number');
    normvid;
    gotoxy (4, 23);
    write ('<RTN> to Continue');
    readln;
    readln;
    gotoxy (1, 23);
    clreol;
    momentum :=
                net_description.momentum;
  end;
until result = 0;
repeat
  clrscr;   {get zero_value}
  gotoxy (20, 8);
  with net_description do
    begin
      write ('Enter Real Value for 0 (');
      write (zero_value:2:1, ')');
    end;
  gotoxy (1, 21);
  write ('=> ');
  {$I-};
  read (momentum);{Fix for rtn or esc!!!!}
  result := ioread;
  {$I+}
  {Check for real number}
  if result = 0      {A real number}
    then net_description.zero_value :=
                                                momentum
  else
    begin
      gotoxy (1, 1);
      reverse;
      write ('Illegal real number');
      normvid;
      gotoxy (4, 23);
      write ('<RTN> to Continue');
      readln;
      readln;
      gotoxy (1, 23);
      clreol;
    end;
  end;

```

```

                                momentum :=
                                    net_description.threshold;
                                end;
                                until result = 0;
                                end;
                                #3      : Learning (flag);    {<^C>}
end;    {case}
if flag = #6      {Unwind out of menus to Main}
then exit;
until ch = chr (27);    {<ESC>}
end;    {Activation_Function}

{-----}

Procedure Set_Weights (var flag : char);

var
    ch : char;
    i : integer;
    update : boolean;    {flag for modifying weights}

begin    {Set_Weights}
    repeat
        update := false;
        clrscr;
        gotoxy (20, 8);
        write ('SET WEIGHTS');
        gotoxy (20, 9);
        if net_description.random_weights
            then write (('Random'))
            else write (('Set Weights'));    {File or console????}
        gotoxy (20, 11);
        write ('1. All Layers Random');
        gotoxy (20, 12);
        write ('2. Set All Weights Equal');
        gotoxy (20, 13);
        write ('3. Set Weights from File');
        gotoxy (20, 14);
        write ('4. Modify Weights');
        gotoxy (20, 15);
        write ('5. Display Weights');
        gotoxy (20, 16);
        write ('6. Display Saved_Weights');
        gotoxy (20, 17);
        write ('7. Initialize Saved Weights Matrix');
        gotoxy (10, 24);
        writeln ('<ESC> Connectivity Menu          <^C> Accept
                                                         and Continue');
        gotoxy (1, 21);
    end repeat;
end;

```

```

write ('=> ');
ch := readkey;
while not (ch in ['1', '2', '3', '4', '5', '6', '7',
                 #27, #3]) do
  repeat_input (ch);
case ch of
  '1'      : begin
              if net_description.random_weights
              then
                begin
                  gotoxy (10, 1);
                  reverse;
                  write ('Random Weights Already
                          Set!');

                  gotoxy (10, 2);
                  write ('Set Again? Y/N');
                  normvid;
                  ch := readkey;
                  if ch in ['N', 'n']
                  then
                    begin {Don't do anything}
                    end
                  else
                    begin
                      net_description.random_weights
                          := true;
                      net_description.set_weights :=
                          false;
                      Set_Random_Weights;
                    end;
                  end
              else
                begin
                  net_description.random_weights :=
                      true;
                  net_description.set_weights := false;
                  Set_Random_Weights;
                end;
              end;
  '2'      : begin
              net_description.random_weights := false;
              net_description.set_weights := true;
              Set_Equal_Weights;
            end;
  '3'      : begin
              net_description.random_weights := false;
              net_description.set_weights := true;
            end;

```

```

'4' : begin
      ch := 'y';
      if layers[2].saved_weights <> nil
      then
        begin
          clrscr;
          gotoxy (1, 1);
          reverse;
          write ('WARNING - Saved_Weights should
                be deleted');
          write (' - Y/N?');
          normvid;
          repeat
            ch := readkey;
          until ch in ['Y', 'y', 'N', 'n'];
          if ch in ['y', 'Y']
            then for i := 2 to
                  net_description.num_layers do
                  begin
                    dispose
                      (layers[i].saved_weights);
                    layers[i].saved_weights := nil;
                  end;
          end;
          if ch in ['Y', 'y']
            then
              begin
                net_description.set_weights :=
                  true;
                update := true;
                Display_Weights (1, update, true);
                {weights unit}
                gotoxy (1, 22);
                clreol;
                write ('Do You wish to initialize
                      saved_weights??');
                write (' - Y/N');
                ch := readkey;
                if ch in ['Y', 'y']
                  then init_saved_weights;
                     {Mathutil unit}
                update := false;
              end;
          end;
'5' : Display_Weights (1, update, true);
'6' : Display_Weights (1, false, false); {No
      update/pass saved weights}
'7' : init_saved_weights; {Mathutil unit}
#3  : Activation_Function (flag); {Math unit}

```

```

    end;    {case}
    if flag = #6    {Unwind out of menus to Main}
        then exit;
    until ch = chr (27);
end;    {Set_Weights}

{-----}

Procedure Display_and_Enter_Partials;

begin {Display_and_Enter_Partials}
    clrscr;
    gotoxy (20, 3);
    write ('Connectivity For Layers Shown');
    gotoxy (20, 10);
    writeln ('This is a stubb for Recurrent Network
                Connectivity Definition');
    write ('Press any key to continue');
    repeat
        until keypressed;
end;    {Display_and_Enter_Partials}

{-----}

Procedure Define_Partial_Connectivity_Menu (var ch : char);

var
    i : integer;

begin    {Define_Partial_Connectivity_Menu}
    repeat
        i := 1;
        repeat    {Feedforward direction}
            clrscr;
            gotoxy (15, 8);
            writeln ('DEFINE CONNECTIVITY FOR EACH PARTIALLY
                CONNECTED LAYER');

            gotoxy (15, 14);
            write ('1.  Modify Connections');
            gotoxy (15, 15);
            write ('2.  Display Network');
            gotoxy (1, 24);
            write ('<ESC> General Connectivity Menu           <RTN>
                Skip Layer');

            write ('           <^C> Accept');
            gotoxy (1, 21);
            write ('=> ');
            while (layers[i].FFconnection_kind <> partial) and (i <
                num_layers) do

```



```

i := i + 1; {Find next partially connected layer}
if layers[i].FFconnection_kind = partial
then
  begin
    gotoxy (20, 9);
    write ('Layer ');
    reverse;
    write (i:2);
    normvid;
    write (' to Layer ');
    reverse;
    write (i + 1:2);
    normvid;
    clreol;
    write (' (Partial)');
    gotoxy (4, 21);
    ch := readkey;
    while not (ch in ['1', '2', #3, #13, #27]) do
      repeat_input (ch);
    case ch of
      '1' : Modify_Connections (ch, i, 'Connectivity
                                Menu');
      '2' : Display_Network (5);
      #3 : begin {Provisions only}
            exit;
          end;
      #13 : begin {<RTN> Skip this layer}
            i := i + 1;
          end;
      #27 : exit; {<ESC> exit to connectivity menu}
    end; {case}
  end;
until i = num_layers;
if Net_Description.net_arch = recurrent
then
  repeat
    i := 1; {Stubb!!!!!!!!!!!!}
    clrscr;
    gotoxy (20, 8);
    writeln ('DEFINE CONNECTIVITY FOR EACH PARTIAL
                                CONNECTION');

    i := num_layers;
    gotoxy (20,10);
    write ('1. Display and Enter Connections for the
                                Layer');

    gotoxy (8, 24);
    writeln ('<ESC> General Connectivity Menu <RTN>
                                Skip Layer <^C> Accept');

    gotoxy (1, 21);

```

```

write ('=> ');
while (layers[i].FFconnection_kind <> partial)
    and (i < num_layers - 1) do
i := i - 1;
if layers[i].FFconnection_kind = partial
then
begin
gotoxy (20, 9);
write ('Layer ');
reverse;
write (i:2);
normvid;
write (' to Layer ');
reverse;
write (i + 1:2);
normvid;
clreol;
write (' (Partial)');
gotoxy (20, 11);
{Display the connectivity Matrix}
gotoxy (4, 21);
{Go through the recurrent layers}
gotoxy (4, 21);
ch := readkey;
while not (ch in ['1', chr (03), chr (13), chr
(27)]) do
repeat_input (ch);
case ch of
'1' : Display_and_Enter_Partial;
#3 : begin {Provisions only}
end;
#13 : begin {Skip this layer}
end;
#27 : exit; {exit to connectivity menu}
end; {case}
end;
until i = 1;
until ch = chr (27) {ESC to exit to connectivity menu}
end; {Define_Partial_Connectivity_Menu}

{-----}

```

```

Procedure Net_Connectivity_Menu (var flag : char);

var
  ch : char;

{-----}

Procedure Set_R_Arch (var ch : char);

var
  i, result : integer;

begin
  {Set_R_Arch}
  gotoxy (1, 21);
  clreol;
  write ('=> ');
  ch := readkey;
  while not (ch in ['1'.. '4', chr (27), chr (03), chr
(13)]) do
    repeat_input (ch);
  case ch of
    '1' : begin
      Layers[i].FFconnection_kind := fully;
      end; {Define structures}
    '2' : Layers[i].FFconnection_kind := Partial;
    '3' : Layers[i].FFconnection_kind := Not_Connected;
    '4' : Display_Network (4);
    #13 : begin {<RTN> Skip to next layer connection}
      end;
    #27 : begin
      end;
  end; {case}
  if (ch in [#27, #3, '3'])
    then exit; {ESC Net Connectivity => Set_Weights}
end; {Set_R_Arch}

{-----}

Procedure Set_FF_Arch (var ch : char);

var
  i, j : integer;
  Part : boolean; {Is this a partial connection?}

begin
  {Set_FF_Arch}
  Part := false;
  for i := 1 to (num_layers - 1) do
    begin
      gotoxy (20, 12);

```

```

write ('Layer ');
reverse;
write (i:2);
normvid;
write (' to Layer ');
reverse;
write (i + 1:2);
normvid;
write (' ');
clreol;
if layers[i].FFconnection_kind = fully
    then write ('(Fully)')
    else write ('(Partial)');
gotoxy (1, 21);
clreol;
write ('=> ');
ch := readkey;
while not (ch in ['1', '2', '3', '4', #27, #3, #13])
do
    repeat_input (ch);
case ch of
    '1' : if (layers[i].FFconnection_kind = partial) and
        (layers[i + 1].saved_weights = nil)
        then
            begin
                gotoxy (1, 1);
                reverse;
                write ('No saved_weights.. Cannot
                    restore! <RTN>');
                repeat
                until keypressed;
                normvid;
                gotoxy (1, 1);
                clreol;
            end
        else if (layers[i].FFconnection_kind =
            partial)
        then
            begin
                gotoxy (1, 1);
                reverse;
                write ('WARNING.. All weights in
                    this layer will be');
                writeln (' restored!!');
                write (' <RTN> to Continue <ESC>
                    to Quit');
                repeat
                ch := readkey;
                until ch in [#13, #27];
            end
        end
end

```

```

normvid;
if ch = #13
then
begin
begin
Layers[i].FFconnection_kind :=
Fully;
layers[i + 1].weights^ :=
layers[i + 1].saved_weights^;
end;
gotoxy (1, 1);
clreol;
gotoxy (1, 2);
clreol;
ch := '1';
end;
'2' : Layers[i].FFconnection_kind := Partial;
'3' : begin {Randomize Weight Settings}
gotoxy (1, 1);
reverse;
writeln ('WARNING! This will destroy all
weight settings');
write ('<RTN> to Continue <ESC> to
Quit');
repeat
ch := readkey
until ch in [#13, #27];
normvid;
if ch = #13 {RTN}
then
begin
begin
gotoxy (1, 5);
write ('Working...');
set_random_weights; {unit weights}
net_description.random_weights :=
true;
net_description.set_weights := false;
end;
gotoxy (1, 1);
clreol;
gotoxy (1, 2);
clreol;
gotoxy (1, 5);
clreol;
ch := '3';
end;
'4' : begin {Save weight settings}
for j := 2 to num_layers do
begin
if layers[j].saved_weights = nil

```

```

        then new (layers[j].saved_weights);
        layers[j].saved_weights^ :=
            layers[j].weights^;
    end;
    gotoxy (1, 1);
    reverse;
    write ('Saved_Weights set to Weight values.
        <RTN>');

    normvid;
    repeat
    until keypressed;
    gotoxy (1, 1);
    clreol;
end;
'5' : Display_Network (4);
#3  : begin
    For j := 1 to num_layers do
        if layers[j].FFConnection_kind = partial
            then Part := true;
        if Part
            then
                begin
                    Define_Partial_connectivity_menu
                        (ch);

                    if ch = #27
                        then
                            begin
                                ch := #126;
                                exit;
                            end;
                        end
                    else exit;
                end;
            {Else return to Connection menu passing
                ^C}
        #13 : begin
            {<RTN> Skip to next layer
                connection}
        end;
    end;
end; {case}
if (ch in [#27, #3, '4'])
    then exit; {ESC Net Connectivity => Set_Weights}
end;
end; {Set_FF_Arch}

{-----}

begin {Net_Connectivity_Menu}
    repeat
        clrscr;
        gotoxy (20, 8);

```

```

writeln ('DEFINE GENERAL CONNECTIVITY');
gotoxy (20, 9);
case Net_Description.net_arch of
  feedforward : writeln ('      (Feedforward)');
  recurrent   : writeln ('      (Recurrent)');
end; {case}
gotoxy (20, 10);
write ('Number of Layers           (' , num_layers, ')');
gotoxy (20, 14);
writeln ('1. Fully');
gotoxy (20, 15);
write ('2. Partial');
gotoxy (20, 16);
if net_description.net_arch = recurrent
then
  begin
    write ('3. Not Connected');
    gotoxy (20, 17);
    write ('4. Randomize Weights ');
    gotoxy (20, 18);
    write ('5. Save Weight Settings');
    gotoxy (20, 19);
    write ('6. Display Network');
    gotoxy (20, 19);
  end
else
  begin
    write ('3. Randomize Weights');
    gotoxy (20, 17);
    write ('4. Save Weight Settings');
    gotoxy (20, 18);
    write ('5. Display Network'); {All layers
                           connected in feedforward}
  end;
gotoxy (8, 24);
write ('<ESC> Net Arch Menu   <RTN> Accept Layer   <^C>
      Accept and Continue');
if net_description.net_arch = feedforward
then Set_FF_Arch (ch) {Pass ch to escape to net
                     architecture from set..}

else Set_R_Arch (ch);
if ch = chr (03)
then Set_Weights (flag);
if flag = #6 {Unwind out of menus to Main}
then exit;
until ch = chr (27); {ESC Exit to Net_Architecture}
end; {Net_Connectivity_Menu}

{-----}

```

```

Procedure Net_Architecture (var flag : char);

var
  ch : char;

begin  {Net_Architecture}
  repeat
    clrscr;
    gotoxy (20, 8);
    writeln ('SELECT NET ARCHITECTURE');
    gotoxy (20, 9);
    case Net_Description.net_arch of
      feedforward : writeln ('    (Feedforward)');
      recurrent    : writeln ('    (Recurrent)');
    end;  {case}
    gotoxy (20, 12);
    writeln ('1. Feedforward Only');
    gotoxy (20, 13);
    write  ('2. Recurrent');
    gotoxy (10, 24);
    writeln ('<ESC> Input Layer Data          <^C> Accept and
                                                    Continue');

    gotoxy (1, 21);
    write ('=> ');
    ch := readkey;
    while not (ch in ['1', '2', chr (27), chr (03)]) do
      repeat_input (ch);
    case ch of
      '1' : Net_Description.net_arch := feedforward;
      '2' : Net_Description.net_arch := recurrent;
      #3  : net_connectivity_menu (flag);
    end;  {case}
    if flag = #6      {Unwind out of menus to Main}
      then exit;
    until ch = chr (27);  {ESC Exit to System_Menu}
  end;      {Net_Architecture}

  {-----}

Procedure Define_Matrix (var ch : char);

var
  i, j, k, int, a : integer;
  matrix_ok       : boolean;

begin  {Define_Matrix}
  repeat
    for i := 1 to num_layers do
      if layers[i].arch = matrices {do only if matrix}

```



```

begin
  gotoxy (10, 2);
  reverse;
  if int > max_bodies
  then
    write ('Exceeds Max
           Neuron Limit (',
           max_bodies, ')')
    else write ('0 Rows
               Illegal!');
  normvid;
  gotoxy (1, 21);
  clreol; {Erase =>}
  gotoxy (1, 22);
  clreol; {Erase cue message}
  write ('<RTN> to
         continue');
  readln;
  gotoxy (1, 22);
  clreol; {Erase <RTN>..}
  gotoxy (10, 2); {Clear
                  error message}
  clreol;
  gotoxy (1, 21);
  write ('=> ');
end
else
begin
  j := int;
  gotoxy (1, 22);
  clreol; {Remove cue}
  if (layers[i].neurons mod
      j) <> 0
  then
  begin
    gotoxy (10, 1);
    reverse;
    write ('Matrix Not
           Symetrical!');
    normvid;
    gotoxy (20, 11);
    write ('Rows X Cols
           (', j, ' X ?');
    gotoxy (1, 21);
    write ('<RTN> to
           Continue');
    readln;
    gotoxy (10, 1);
    clreol;
  end
end

```

```

end
else
begin
matrix_ok := true;
k :=
layers[i].
neurons div j;
gotoxy (20, 11);
write ('Rows X Cols
(', j, ' X ', k);
layers[i].
arch_row_length := j;
layers[i].
arch_col_length := k;
end;
end;
end
else
begin
gotoxy (10, 2);
reverse;
write ('Illegal Entry');
normvid;
gotoxy (1, 21);
clreol; {Erase =>}
gotoxy (1, 22);
clreol; {Erase cue message}
write ('<RTN> to continue');
readln;
gotoxy (1, 22);
clreol; {Erase <RTN>..}
gotoxy (10, 2); {Clear error
message}

clreol;
gotoxy (1, 21);
write ('=> ');
end;
end;
'2' : Display_Network (3);
#27 : Exit;
#3 : begin
matrix_OK := true;
for a := 1 to
net_description.num_layers do
if layers[a].arch_row_length
*layers[a].arch_col_length
<> layers[a].neurons {Not
symetrical}
then matrix_OK := false;

```

```

        if not matrix_OK
        then
            begin
                gotoxy (10, 2);
                reverse;
                write ('At least one matrix
                        not symmetrical!');
                normvid;
                gotoxy (1, 21);
                clreol;           {Erase =>}
                gotoxy (1, 22);
                clreol;           {Erase cue
                                    message}
                write ('<RTN> to continue');
                readln;
                gotoxy (1, 22);
                clreol;           {Erase <RTN>..}
                gotoxy (10, 2);   {Clear error
                                    message}
                clreol;
                gotoxy (1, 21);
                write ('=> ');
            end
        else exit;
    end;
end; {case}
until matrix_ok;
until ch = chr (27); {ESC Exit to System_Menu}
end; {Define_Matrix}

{-----}

Procedure Layer_Architecture;

var
    ch    : char;
    i, j  : integer;

begin {Layer_Architecture}
    repeat
        clrscr;
        gotoxy (20, 8);
        writeln ('SELECT LAYER ARCHITECTURE FOR EACH LAYER');
        gotoxy (20, 9);
        clreol;
        case Layers [1].Arch of
            lines      : write (' (Line');
            matrices   : write (' (Matrix');
        {write architecture code
          for each layer}
    end;
end;

```

```

end; {case}
for j := 2 to num_layers do
  case Layers [j].Arch of
    lines      : write ('', Line');
    matrices   : write ('', Matrix');
  end; {case}
write ('');
gotoxy (20, 13);
writeln ('1. Line');
gotoxy (20, 14);
writeln ('2. Matrix');
gotoxy (20, 15);
writeln ('3. Define Your Own (Not Functional)');
gotoxy (10, 24);
writeln ('<ESC> Layer Data Menu          <RTN> Next
                                     Layer');

gotoxy (1, 21);
write ('=> ');
for i := 1 to num_layers do {Number of layers selected
                             or default value}
  begin
    gotoxy (20, 11);
    clreol;
    write ('          ');
    reverse;
    writeln ('Layer Number ', i); {reverse video}
    normvid;
    gotoxy (4, 21);
    ch := readkey;
    while not (ch in ['1', '2', '3', chr (13), chr
                      (27)]) do
      repeat_input (ch);
    case ch of
      '1' : layers[i].arch := lines;
      '2' : layers[i].arch := matrices;
      '3' : begin {Provisions only}
              end;
      #13 : begin {Skip this layer}
              end;
      #27 : exit; {exit to layer_menu}
    end; {case}
    gotoxy (20, 9); {Clear default values to reprint}
    clreol;
    case Layers [1].Arch of {write architecture code
                              for each layer}
      lines      : write ('          (Line');
      matrices   : write ('          (Matrix');
    end; {case}
  for j := 2 to num_layers do

```

```

        case Layers [j].Arch of
            lines      : write ('', Line');
            matrices : write ('', Matrix');
        end; {case}
    write ('')';
end;
arch_set := num_layers;
until ch = chr (27); {ESC to exit to system menu}
end; {Layer_Architecture}

{-----}

Procedure Get_Corruption_Prob;

var
    prob  : real;
    result : integer;

begin {Get_Corruption_Prob}
    repeat
        clrscr; {get momentum value}
        gotoxy (20, 8);
        write ('Enter Corruption Probability [p] (');
        write (net_description.factor3:4:2, ')');
        gotoxy (1, 21);
        write ('=> ');
        {$I-};
        readln (prob); {Fix for rtn or esc!!!!}
        result := ioreult;
        {$I+};
        {Check for real number and correct probability}
        if (result = 0) and ((Prob <= 1) and (Prob >= 0)) {A
                                                    real number}
        then net_description.factor3 := prob
        else
            begin
                gotoxy (1, 1);
                reverse;
                write ('Illegal real number or probability');
                normvid;
                gotoxy (4, 23);
                write ('<RTN> to Continue');
                repeat
                    until keypressed;
                gotoxy (1, 23);
                clreol;
                prob := net_description.factor3;
            end;
    until result = 0;
end;

```

```

end;      {Get_Corruption_Prob}

{-----}

{Layer_Menu establishes the Neural Network Menu on the}
  {screen}

Procedure Layer_Menu (var flag : char);

var
  ch : char;
  i : integer;
  mat : boolean;  {Matrix architecture for this layer?}

begin      {Layer_Menu}
  repeat
    clrscr;
    gotoxy (20, 8);
    writeln ('  LAYER DATA MENU');
    gotoxy (20, 9);
    writeln ('  (Current Values)');
    gotoxy (10, 12);
    writeln ('1.  Number of Layers                (',
                                                    num_layers, ')');
    gotoxy (10, 13);
    write ('2.  Layer Architecture                ');
    case Layers [1].Arch of      {write architecture code
                                for each layer}
      lines      : write ('(Line)');
      matrices   : write ('(Matrix)');
    end;  {case}
    for i := 2 to num_layers do
      case Layers [i].Arch of
        lines      : write (' , Line');
        matrices   : write (' , Matrix');
      end;  {case}
    write (' ');
    gotoxy (10, 14);
    write ('3.  Number of Neurons Per Layer      (',
                                                    Layers[1].Neurons);
    for i := 2 to Num_Layers do
      write (' , ', Layers [i].Neurons);
    write (' ');
    gotoxy (10, 15);
    write ('4.  Display Network');
    gotoxy (10, 16);
    write ('5.  Set Input Corruption Probability  (',
                                                    net_description.factor3:4:2, ')');
  end repeat;
end;

```



```

neuron_set := num_layers;
for i := 1 to num_layers do
  with layers[i] do
    if arch = matrices
      then mat := true
    else
      begin
        arch_row_length :=
          neurons;
        arch_col_length := 1;
      end;
    if mat
      then Define_Matrix (ch);
    if ch = #27
      then ch := #6 {Don't exit}
      else Net_Architecture (flag) {^C
        accepts}
      end
    end
  end
else
  begin
    arch_set := num_layers; {set flags}
    neuron_set := num_layers;
    for i := 1 to num_layers do
      with layers[i] do
        if arch = matrices
          then mat := true
        else
          begin
            arch_row_length := neurons;
            arch_col_length := 1;
          end;
        if mat
          then Define_Matrix (ch);
        if ch = #27
          then ch := #6 {Don't exit}
          else Net_Architecture (flag) {^C
            continues}
          end;
        end;
      end;
    end; {case}
    if Flag = #6 {Unwind out of menus to Main}
      then exit;
    until ch = chr (27); {ESC Exit to System_Menu}
  end; {Layer_Menu}

{-----}

```

```

Procedure Define_Displays;

begin   {Define_Displays}
end;    {Define_Displays}

{-----}

Procedure Network_Uilities;

var
  ch : char;
  i  : integer;
  mat : boolean;   {Matrix architecture for this layer?}

begin   {Layer_Menu}
  repeat
    clrscr;
    gotoxy (20, 8);
    writeln ('   NETWORK UTILITIES MENU');
    gotoxy (20, 12);
    write ('1.  Select Input File');
    gotoxy (20, 13);
    write ('2.  Net Save Option (');
    if net_description.save_state
      then write ('ON)')   {Save option on or off}
      else write ('OFF)');
    gotoxy (20, 14);
    write ('3.  Net Save Frequency (',
          net_description.iterate, ')');
    gotoxy (20, 15);
    write ('4.  Print Net State Files');
    gotoxy (20, 16);
    write ('5.  Display Network');
    gotoxy (10, 24);
    writeln ('<ESC>  Program Operations');
    gotoxy (1, 21);
    write ('=> ');
    ch := readkey;
    while not (ch in ['1'..'5', #27]) do
      repeat_input (ch);
    case ch of
      '1' : Get_Input_File;           {Ioutil unit}
      '2' : Save_Net_Option;         {Ioutil Unit}
      '3' : Save_Freq_Option;        {Ioutil unit}
      '4' : Print_Files;             {Ioutil Unit}
      '5' : Display_Network (10);    {Grafstuf unit}
    end; {case}
  until ch = #27; {ESC exit to Program Operations}
end; {Network_Uilities}

```

```

{-----}
{Run_Network establishes the high level Program Operations}
  {Menu}

Procedure Run_Network_Menu;

var
  ch   : char;
  flag : char;   {Set to return to main from final menu}

begin  {Run_Network}
  repeat
    flag := #0;
    clrscr;
    gotoxy (20, 8);
    writeln (' PROGRAM OPERATIONS');
    gotoxy (20, 10);
    writeln ('1.  Compile');
    gotoxy (20, 11);
    writeln ('2.  Print Files');
    gotoxy (20, 12);
    writeln ('3.  Define I/O Displays');
    gotoxy (20, 13);
    writeln ('4.  Display Network');
    gotoxy (20, 14);
    writeln ('5.  Select Input File');
    gotoxy (20, 15);
    writeln ('6.  Training Option');
    gotoxy (20, 16);
    writeln ('7.  Run Program');
    gotoxy (20, 17);
    write ('8.  Network Utilities');
    gotoxy (10, 24);
    writeln ('<ESC>  Exit to Main Menu');
    gotoxy (1, 21);
    write ('=> ');
    ch := readkey;
    while not (ch in ['1'..'8', #27]) do
      repeat_input (ch);
    case ch of
      '1' : begin
              Compile;
            end;
      '2' : Print_Files;
      '3' : Define_Displays;
      '4' : Display_Network (7); {grafstuf unit}
      '5' : Get_Input_File;     {ioutil unit}
    end;
  end;
end;

```

```

    '6' : begin
        train := true;
        Training (Flag);    {Ops_Stuf Unit}
    end;
    '7' : begin
        train := false;
        Run_Program (Flag); {Ops_Suf unit}
    end;
    '8' : Network_Uilities;
end; {case}
until ch = chr (27);    {ESC Exit to Main Menu}
end;    {Run_Network}

```

```

{-----}

```

```

{System_Menu establishes the top level System Menu }

```

```

Procedure System_Menu;

```

```

var

```

```

    ch    : char;
    flag  : char;    {Set to return to main from final menu}
    S     : string;

```

```

begin    {System_Menu}

```

```

    repeat

```

```

        flag := #0;
        clrscr;
        gotoxy (20, 8);
        writeln (' NEURAL SYSTEM MENU');
        gotoxy (20, 10);
        writeln ('1.  New Network');
        gotoxy (20, 11);
        writeln ('2.  Load Network File From Disk');
        gotoxy (20, 12);
        writeln ('3.  Modify/Browse Network');
        gotoxy (20, 13);
        writeln ('4.  Display Network');
        gotoxy (20, 14);
        writeln ('5.  Save Defined Network');
        gotoxy (20, 15);
        writeln ('6.  Program Operations');
        gotoxy (10, 24);
        writeln ('<ESC>  Exit to DOS');
        gotoxy (1, 21);
        write ('=> ');
        ch := readkey;
        while not (ch in ['1', '2', '3', '4', '5', '6', chr
                          (27)]) do

```

```

repeat_input (ch);
case ch of
'1' : begin
      Get_Network_Name (S); {Mathutil unit}
      Net_description.net_name := S;
      Layer_Menu (flag);
    end;
'2' : Load_File;           {ioutil unit}
'3' : Layer_Menu (flag);
'4' : Display_Network (1);
'5' : Save_Network;       {ioutil unit}
'6' : Run_Network_Menu;
#27 : begin
      gotoxy (1, 21);
      reverse;
      write ('Do you really want to exit?');
      normvid;
      write (' Y/N ');
      ch := readkey;
      if ch in ['Y', 'y']
      then
        begin
          ch := #27; {Exit to Dos}
          clrscr;
        end;
      end;
    end; {case}
until ch = chr (27); {ESC Exit to Operating System}
normvid;
textcolor (yellow);
end; {Neural_Menu}

{-----}

end.

```

APPENDIX D

Development System Weight Menu Unit Listing
(Unit Weights)

Appendix B through Appendix J constitute the
complete development system program listing

```

{-----}

{Unit weights manipulates the weight data and structures}
{via the menu system}

{-----}

unit weights;

interface

uses graph, crt, grafstuf, mathutil, nnglobal, ioutil;

Procedure Display_Weights (menu : integer; update, normal :
boolean);
Procedure Set_Random_Weights;
Procedure Set_Equal_Weights;

implementation    {weights}

{-----}

Procedure Set_Weight_Display (i, menu : integer; normal :
                             boolean);

const
  prev : packed array [1..2] of string[13] =
    ('Set Weights', 'Equal Weights');

begin  {Set_Weight_Display}
  clrscr;
  gotoxy (30, 1);
  if normal
    then write ('WEIGHTS')
    else write ('SAVED_WEIGHTS');
  gotoxy (1, 50);
  write ('<ESC> ', Prev[menu], ' <SPACE> Rest of Layer
                                     <RTN> Next Layer');

  write (' <F1> Display Net');
  gotoxy (15, 3);
  write ('Layer ');
  reverse;
  write (i - 1:2);
  normvid;
  write (' to Layer ');
  reverse;
  write (i:2);
  normvid;
  clreol;

```

```

if Layers[i - 1].FFconnection_kind = partial
  then write (' (Partially Connected)')
  else write (' (Fully Connected)');
                                     {Center the Display!!!!}
gotoxy (25, 6);
write ('Layer ', i, ' Neurons (' , layers[i].neurons,
                                     ')');
gotoxy (1, 12);           {Fix for number of neurons}
write ('Layer ', i - 1);
gotoxy (1, 13);
write ('Neurons');
gotoxy (1, 15);
write ('(' , layers[i - 1].neurons, ')');
gotoxy (16, 8);
end;      {Set_Weight_Display}

```

```

-----}
Procedure Show_Weight_Sets (var ch : char; i, menu :
  integer; update, normal : boolean; w_ptr :
  weight_ptr);

```

```

var
  j, k, x, y      : integer;
  count1, count2  : integer;  {Tracks row/col blocks}
  count_r, count_c : integer;  {Keeps track of rows and
                                columns}

```

```

{-----}

```

```

Function Get_Real_Number (lin : linetype; y : integer):
real;

```

```

var
  num, num1, j : real;
  int          : integer;
  x            : integer;
  neg          : boolean;

```

```

begin  {Get_real_number}
  neg := false;  {check for negative number}
  x := 0;
  int := 0;
  while x < y do  {y = length of string read in}
    begin
      x := x + 1;
      if lin[x] = '-'
        then
          begin

```



```

        neg := true;
        x := x + 1;
    end;
while lin[x] in ['0'..'9'] do
    begin
        int := int * 10 + (ord (lin[x]) - ord ('0'));
        x := x + 1;
    end;
if lin[x] = '.'
then
    begin
        x := x + 1;
        num := int * 1.0;    {convert to real}
        if lin[x] in ['0'..'9']
        then
            begin
                j := 1.0;
                num1 := 0.0;
                while (lin[x] in ['0'..'9']) and (x <= y)
                    do
                        begin
                            j := j * 0.1;    {set next decimal
                                                place}
                            int := ord (lin[x]) - ord ('0');
                            num1 := num1 + (int * j);
                            x := x + 1;
                        end;
                        num := num + num1;
                    end;
            end
        else
            num := int * 1.0;    {convert to real if no decimal}
        end;
    if neg
    then num := 0.0 - num;
    Get_Real_Number := num;    {return real number}
end;    {Get_real_number}

```

```
{-----}
```

```
Procedure Modify_Weights (c, r : integer);
```

```
var
    s                : string [12];
    x, y, lgth, j    : integer;
    count_c, count_r : integer;
    lgth1            : integer;    {length of previous entry}
    W                : weight_ptr;
```

```

begin {Modify_Weights}
  count_c := c;
  count_r := r;
  gotoxy (1, 48);
  new (w); {get new weight ptr}
  w^:= layers[i].weights^;
  reverse;
  write ('ENTER NEW WEIGHTS - <ESC> to cancel  <^C> to
                                             Update');

  x := 14;
  y := 10;
  lgth1 := 0;
  repeat
    s := ''; {empty string}
    reverse;
    gotoxy (x, y);
    write (w^.value[c, r]:4:1);
    repeat
      ch := readkey;
    until ch in [#3, #13, #27, #0, '-', '.', '0'..'9']; {^C,
RTN, ESC, Arrow, ., int}

  case ch of
    #0 : begin
      ch := readkey;
      case ch of
        #80 : begin {down arrow}
          normvid;
          gotoxy (x, y);
          write (w^.value[c, r]:4:1);
          if (r = count_r + 34) or (r =
                                             w^.row_length)
            then
              begin
                y := 10;
                r := count_r;
              end
            else
              begin
                y := y + 1;
                r := r + 1;
              end;
          gotoxy (x, y);
          reverse;
          write (w^.value[c, r]:4:1);
          lgth1 := 0;
        end;
        #77 : begin {right arrow}
          normvid;
          gotoxy (x, y);

```

```

write (w^.value[c, r]:4:1);
if (c = count_c + 9) or (c =
                                w^.col_length)
then
  begin
    x := 14;
    c := count_c;
  end
else
  begin
    x := x + 5;
    c := c + 1;
  end;
gotoxy (x, y);
reverse;
write (w^.value[c, r]:4:1);
lgth1 := 0;
end;
#72 : begin {up arrow}
      normvid;
      gotoxy (x, y);
      write (w^.value[c, r]:4:1);
      if r > count_r
      then
        begin
          y := y - 1;
          r := r - 1;
        end;
      gotoxy (x, y);
      reverse;
      write (w^.value[c, r]:4:1);
      lgth1 := 0;
    end;
#75 : begin {left arrow}
      normvid;
      gotoxy (x, y);
      write (w^.value[c, r]:4:1);
      if c > count_c
      then
        begin
          x := x - 5;
          c := c - 1;
        end;
      gotoxy (x, y);
      reverse;
      write (w^.value[c, r]:4:1);
      lgth1 := 0;
    end;
end; {case}

```

```

end;
#13 : begin      {RTN}
  normvid;
  gotoxy (x, y);
  write (w^.value[c, r]:4:1);
  x := 14;
  c := count_c;
  if (r < (count_r + 34)) and (r <
                                w^.row_length)
  then
    begin
      r := r + 1;
      y := y + 1;
    end;
  gotoxy (x, y);
  reverse;
  write (w^.value[c, r]:4:1);
  lgth1 := 0;
end;
'.' , '-' , '0'..'9' : begin
  s := '';
  if ch = '.'
  then
    begin
      s := '0.'; {Add leading 0
                  for real number}
      lgth := 2;
    end
  else
    begin
      s := ch;
      lgth := 1;
    end;
  gotoxy (x, y);
  write (ch);
  x := x + 1;
  repeat
    repeat
      ch := readkey;
    until ch in [#13, #27, '.',
                 '0'..'9']; {RTN, ESC..}
    if not (ch in [#13, #27])
      {<RTN>, <ESC>}
    then
      begin
        s := s+ch;
        lgth := lgth + 1;
        gotoxy (x, y);
        write (ch);

```

```

        x := x + 1;
    end;
until ch in [#13, #27];
if ch = #13 {RTN}
then
begin
    x := x - length (s);
    gotoxy (x, y);
    for j := x to (x + lgth + 1)
    do
        begin
            gotoxy (j, y);
            write (' ');
        end;
    gotoxy (x, y);
    write (s);
    lgth1 := lgth;
    for j := 1 to length (s) do
        lin[j] := s[j]; {transfer
                        to buffer}
    w^.value [c, r] :=
        get_real_number (lin,
                        length (s));
    end;
end;
#3 : begin
    layers[i].weights^ := w^; {^C accepts new weights}
    net_description.random_weights := false; {set to updated
    {Search for weights set to 0. If found set
    to partially}
    {connected. To be Implemented}
end;
end; {case}
until ch in [#27, #3]; {ESC, ^C}
dispose (w);
normvid;
gotoxy (1, 48);
clreol;
end; {Modify_Weights}

{-----}

begin {Show_Weight_Sets}
count1 := 0;
count2 := 0;
count_r := 0;
count_c := 0;
while count1 < layers[i].weights^.col_length do

```

```

begin
  while count2 < layers[i].weights^.row_length do
    begin
      j := count_c;
      Set_Weight_Display (i, menu, normal);
      while (j < count_c + 10) and (j <
          w_ptr^.col_length) do
        begin
          j := j + 1;
          if j > 9
            then write (j, ' ')
            else write (j, ' ');
          end;
          y := 9; {Seed for next loop}
          k := count_r;
          while (k < count_r + 35) and (k <
              w_ptr^.row_length) do
            begin
              k := k + 1;
              x := 11;
              y := y + 1;
              gotoxy (x, y);
              write (k);
              x := 14;
              gotoxy (x, y);
              j := count_c;
              while (j < count_c + 10) and (j <
                  w_ptr^.col_length) do
                begin
                  j := j + 1;
                  write (w_ptr^.value[j, k]:4:1, ' ');
                end;
            end; {while k...}
          count2 := count2 + 35;
          if (count2 < w_ptr^.row_length) or
            (count1 + 10 < w_ptr^.col_length)
            then
              begin
                gotoxy (72, 25);
                write ('(More)');
              end;
          if update
            then modify_weights (count_c + 1, count_r + 1);
          count_r := count_r + 35;
          ch := readkey;
          while not (ch in [#32, #13, #27, #0]) do {SPACE,
              RTN, ESC, F1}
            repeat_input (ch);
        end;
      end;
    end;
  end;
end;

```

```

case ch of
  #0 : begin
    ch := readkey;
    if ch = #59 {F1}
    then
      begin
        Display_Network (6);
        textmode (lo(lastmode) +
                  font8x8); {Restore}
        {reduced size display}
      end
    else write (#7);
    end;
  #13 : exit; {<RTN> Go to next layer display}
  #32 : begin {<SPACE> Finish the weight display}
    end;
  #27 : exit; {<ESC> to previous menu}
end; {case}
end; {while count2}
count2 := 0;
count1 := count1 + 10;
count_c := count_c + 10;
count_r := 0;
end; {while count1}
end; {Show_Weight_Sets}

```

```
{-----}
```

```

Procedure Display_Weights (menu : integer; update, normal :
                          boolean);

```

```

var
  i      : integer;
  ch     : char;
  origmode : word;
  w_ptr  : weight_ptr;

```

```

begin {Display_Weights}
  origmode := lastmode;
  textmode (lo(lastmode) + font8x8); {Reduce size for
                                     display of more data}
  normvid;
  new (w_ptr);
  repeat
    for i := 2 to Num_layers do
      begin
        if normal {Display layer weights}
        then w_ptr^ := layers[i].weights^
        else w_ptr^ := layers[i].saved_weights^;

```

```

Show_Weight_Sets (ch, i, menu, update, normal,
                  w_ptr);
if ch = #27      {<ESC>}
  then
    begin
      textmode (origmode);
      directvideo := false;
      normvid;
      dispose (w_ptr);   {Destroy temporary pointer}
      exit;
    end;
  end;
until ch = #27;      {<ESC>}
dispose (w_ptr);    {Destroy temporary pointer}
textmode (origmode);
directvideo := false;
normvid;
end; {Display_Weights}

```

```
{-----}
```

```
Procedure Set_Random_Weights;
```

```
var
```

```

  i, j, k : integer;
  r, r1, c : real;
  ch : char;

```

```

begin {Set_Random_Weights}
  randomize; {Initialize random number generator to reals}
  for i := 2 to net_description.num_layers do
    begin
      for j := 1 to max_bodies do
        for k := 1 to max_bodies do
          begin
            r := (random (5) + random);
            c := random;
            if c < 0.20
              then r := 0.0 - r; {negate}
            layers[i].weights^.value[k, j] := r;
          end;
        layers[i-1].FFConnection_kind := fully;
      end;
    end;
  end; {Set_Random_Weights}

```

```
{-----}
```



```

Procedure Set_Equal_Weights;

var
  i, j, k      : integer;
  weight       : real;
  ch           : char;
  result       : integer;

begin {Set_Equal_Weights}
  repeat
    for i := 2 to num_layers do {Number of layers selected
                                or default value}
      begin
        clrscr;
        gotoxy (20, 8);
        writeln ('SET EQUAL WEIGHT FOR INDIVIDUAL LAYERS');
        gotoxy (10, 24);
        write ('<ESC> Set Weights Menu           <RTN> Next Layer');

        gotoxy (30, 10);
        clreol;
        reverse;
        write ('Layer Number ', i); {reverse video}
        normvid;
        gotoxy (20, 14);
        write ('1. Set Weights');
        gotoxy (20, 15);
        write ('2. Display Weights');
        gotoxy (1, 21);
        write ('=> ');
        ch := readkey;
        while not (ch in ['1', '2', #13, #27]) do
          repeat_input (ch);
        case ch of
          '1' : repeat
            gotoxy (1, 22);
            write ('Enter Weight Value');
            gotoxy (4, 21);
            clreol;
            {$I-};
            readln (weight); {Fix for rtn or esc!!!!}
            result := ioreult;
            {$I+}
            {Check for real number}
            if result = 0 {A real number}
            then
              begin
                for j := 1 to max_bodies do
                  for k := 1 to max_bodies do

```

```

        layers[i].weights^.value[k, j]
                               := weight;
if weight = 0
  then layers[i].FFConnection_kind
                               := Not_Connected
  else layers[i].FFConnection_kind
                               := fully;
end
else
begin
  gotoxy (1, 1);
  reverse;
  write ('Illegal real number');
  normvid;
  gotoxy (1, 22);
  clreol;
  write ('<RTN> to Continue');
  write (#7);
  readln;
  gotoxy (1, 1);
  clreol;
end;
      until (result = 0);
      '2' : Display_Weights (2, false, true);
      #13 : begin      {Skip this layer}
            end;
      #27 : exit;      {exit to layer_menu}
end; {case}
end;
  until ch = chr (27); {ESC to exit to system menu}
end;      {Set_Equal_Weights}

{-----}
end.      {weights unit}

```

APPENDIX E

Development System Display Unit Listing
(Unit Grafstuf)

Appendix B through Appendix J constitute the
complete development system program listing

```
unit grafstuf;
```

```
interface
```

```
uses graph, crt, nnglobal, math, ioutil, mathutil;
```

```
Procedure Display_Network (i : integer);
```

```
Procedure Net_Display (i : integer);
```

```
Procedure Display_Net_Output (var ch : char; var semaphore : integer);
```

```
Procedure Display_Memory (var ch : char; var semaphore : integer);
```

```
Procedure Initialize_Graphics;
```

```
Procedure Modify_Connections (var ch : char; layer : integer; str : string);
```

```
implementation
```

```
{-----}
```

```
Function Minimum (x, y : integer): integer;
```

```
begin {Minimum}
```

```
  if x <= y
```

```
    then Minimum := x
```

```
    else Minimum := y;
```

```
end; {Minimum}
```

```
{-----}
```

```
Procedure LITTFont; external; {$L Litt.obj}
```

```
Procedure VGADriver; external; {$L egavga.obj}
```

```
{-----}
```

```
Procedure Initialize_Graphics; {Also in Unit Mathutil}
```

```
begin {Initialize_Graphics}
```

```
  origmode := lastmode;
```

```
  clrscr;
```

```
  directvideo := false;
```

```
  if RegisterBGIFont (@LITTFont) < 0 then
```

```
    begin
```

```
      reverse;
```

```
      write ('Error In Registering font: ');
```

```
      normvid;
```

```
      write (graphErrorMsg (GraphResult));
```

```
      gotoxy (1, 21);
```

```
      write ('<RTN> to Continue');
```

```

    readln;
    clrscr;
    exit; {Make flag to leave graphics also}
end;
if RegisterBGIDriver (@VGADriver) < 0 then
begin
    reverse;
    write ('Error In Registering driver: ');
    normvid;
    write (graphErrorMsg (GraphResult));
    gotoxy (1, 21);
    write ('<RTN> to Continue');
    readln;
    clrscr;
    exit; {Make flag to leave graphics also}
end;
graphdriver := detect;
initgraph (graphdriver, graphmode, '');
errorcode := graphresult;
if errorcode <> grok then
begin
    Reverse;
    writeln ('Error In Initializing graphics');
    normvid;
    write ('Errorcode = ', errorcode);
    gotoxy (1, 21);
    write ('<RTN> to Continue');
    readln;
    clrscr;
    exit; {Make flag to leave graphics also}
end;
TextColor (Yellow);
SetColor (Yellow);
MaxX := GetMaxX;    {Get Screen Resolution Values}
MaxY := GetMaxY;
end;    {Initialize_Graphics}

{-----}

Procedure FullPort;

begin {FullPort}
    SetViewPort (0, 0, MaxX, MaxY, ClipOn);
end;    {FullPort}

{-----}

```

```
{Writes title of the display seen at the top of the
display}
```

```
Procedure Write_Header (Header : string; i : integer);
```

```
begin {Write_Header}
  FullPort;
  SetTextStyle (SmallFont, HorizDir, 6);
  SetTextJustify (CenterText, TopText);
  OutTextXY (MaxX div 2, i, Header);
end; {Write_Header}
```

```
{-----}
```

```
{Writes the command line at the bottom of the display}
```

```
Procedure Write_Command_Line (S : string; i : integer);
```

```
const
```

```
  Previous_Menu : packed array [0..12] of string [21] = ('',
    'Main Menu', 'Layer Data', 'Define Matrix',
    'Connectivity Matrix', 'Partial
    Connectivity', 'Display Weights',
    'Operations', 'Memory', 'Output', 'Network
    Utilities', 'Modify Neurons', 'Modify
    Connections');
```

```
var
```

```
  msg : string;
```

```
begin {Write_Command_Line}
  SetTextStyle (SmallFont, HorizDir, 5);
  SetTextStyle (DefaultFont, HorizDir, 1);
  SetTextJustify (LeftText, BottomText);
  OutTextXY (0, MaxY - 10, S+Previous_Menu[i]);
end; {Write_Command_Line}
```

```
{-----}
```

```
{Displays the graphic representation of the network
specified by the user}
```

```
Procedure Net_Display (i : integer);
```

```
type
```

```
  {'w' & 'x' start coords, 'y' & 'z' finish coords for
  arrows}
```

```
  coord_type = packed array [1..max_layers, 'w'..'z'] of
  integer;
```



```

        line (arrow_coords^[j, 'y'] + width + 20,
              arrow_coords^[j, 'x'] - (8 * TextHeight ('M')),
              arrow_coords^[1, 'w'] - width1 - 20,
              arrow_coords^[j, 'x'] - (8 * TextHeight ('M')));
        line (arrow_coords^[1, 'w'] - width1 - 20,
              arrow_coords^[j, 'x'] - (8 * TextHeight ('M')),
              arrow_coords^[1, 'w'] - width1 - 20,
              arrow_coords^[1, 'x'] + 10);
        line (arrow_coords^[1, 'w'] - width1 - 20,
              arrow_coords^[1, 'x'] + 10,
              arrow_coords^[1, 'w'] - width1,
              arrow_coords^[1, 'x'] + 10);
        line (arrow_coords^[1, 'w'] - width1,
              arrow_coords^[1, 'x'] + 10,
              arrow_coords^[1, 'w'] - width1 - 6,
              arrow_coords^[1, 'x'] + 6);
        line (arrow_coords^[1, 'w'] - width1,
              arrow_coords^[1, 'x'] + 10,
              arrow_coords^[1, 'w'] - width1 - 6,
              arrow_coords^[1, 'x'] + 16);
    end;
end;    {Draw_FF_Arrows}

{-----}

{Draws the layer representations of each layer in the
network}

Procedure Draw_Layer_Box (x, y : integer);

begin    {Draw_Layer_Box}
    SetFillStyle (SolidFill, LightBlue);
    Bar (x, y, x + width, y + height);
    SetColor (lightBlue);
    Rectangle (x, y, x + width, y + height);
    SetColor (White);
end;    {Draw_Layer_Box}

{-----}

begin    {Net_Display}
    FullPort;
    ClearDevice;
    New (Arrow_Coords);
    Write_Header ('CURRENT NETWORK DEFINITION', 45);
    SetColor (white);
    SetTextStyle (SmallFont, HorizDir, 5);
    OutTextXY (MaxX Div 2, 70,
               ('+net_description.net_name+'));

```



```

SetColor (yellow);
Write_Command_Line ('<ESC> ', i);
SetTextJustify (CenterText, CenterText);
GetViewSettings (ViewInfo);
with ViewInfo do
  begin
    center_width := (X2 Div Num_Layers) Div 2;
    height := (Y2 Div 3) - 10;
  end;
y := height + 10;
x := 0;
for j := 1 to Num_layers do
  begin
    if layers[j].arch = matrices
      then width := center_width           {Matrix Width}
      else width := center_width Div 2;    {Line width}
    Border := x;
    x := x + center_width - (width div 2);
    Draw_Layer_Box (x, y);
    if j = 1
      then msg := 'Input'           {Write layer type over box}
      else if layers[j].out_layer
          then msg := 'Output'
          else msg := 'Hidden';
    OutTextXY (x + (width Div 2), y - TextHeight ('H') -
                                                       4, Msg);
    if layers[j].arch = matrices      {Write layer size
                                       inside box}
      then
        begin
          str (layers[j].arch_row_length, s1);
          str (layers[j].arch_col_length, s2);
          msg := concat (s1, ' Rows');
          OutTextXY ((Border + center_width), (y + (height
                                                       Div 2) -15), Msg);
          OutTextXY ((Border + center_width), (y + (height
                                                       Div 2)), 'X');
          Msg := concat(s2, ' Cols');
          OutTextXY ((Border + center_width), (y + (height
                                                       Div 2) +15), Msg);
        end
      else
        begin
          str (layers[j].neurons, s1);
          msg := s1;
          OutTextXY ((Border + center_width), (y + (height
                                                       Div 2)), Msg);
        end;
    str (j, s1);           {Write Layer # under box}
  end;
end;

```

```

msg := concat (('(', s1, ')'));
OutTextXY (x + (width Div 2), y + Height + TextHeight
           ('H') + 4, msg);
str (layers[j].neural_set.threshold[1]:2:2, s1);
msg := concat ('(th = ', s1, ')');
if j > 1      {Write layer thrshld under box}
  then OutTextXY (x + (width Div 2), y + Height +
                2*(TextHeight ('H') + 4), msg);
arrow_coords^[j, 'w'] := x + width;
arrow_coords^[j, 'x'] := y + 4*TextHeight ('M');
if j > 1
  then
    begin      {Finish Arrow Coords for previous layer}
      arrow_coords^[j-1, 'y'] := x;
      arrow_coords^[j-1, 'z'] := y + 4*TextHeight
                                ('M');
    end;
  x := x + (width div 2) + center_width;
end;
str (net_description.threshold:2:2, s1);
Msg := concat ('Activation - ', Activation_kind[ord
           (net_description.activation)], ' (thrshld
           = ', s1, ')');
OutTextXY (MaxX Div 2, ((2 * Height) + 70), msg);
if (net_description.learning = delta) or
    (net_description.learning = backp)
  then
    begin
      str (net_description.factor:4:2, s1);
      str (net_description.momentum:2:2, s2);
      msg := concat ('Learning - ', Learning_kind[ord
           (net_description.learning)]+' (n =
           '+s1+')', ' (α = ', s2, ')');
    end
  else msg := concat ('Learning - ', Learning_kind[ord
           (net_description.learning)]);
OutTextXY (MaxX Div 2, ((2 * Height) + 90), msg);
str (net_description.factor1:4:3, s1);
str (net_description.factor2:4:4, s2);
str (net_description.factor3:4:4, s3);
msg := concat ('(t = ', s1, ')', ' (s = ', s2, ')',
              ' (p = ', s3, ')');
OutTextXY (MaxX Div 2, ((2 * Height) + 110), msg);
if length (infilename) > 0
  then
    begin
      msg := ('Input File : '+infilename);
      OutTextXY (MaxX Div 2, ((2 * Height) + 130), msg);
    end;
end;

```

```

for j := 1 to (num_layers - 1) do    {Draw Arrows}
begin
  if layers[j].FFConnection_kind = fully
    then Msg := '(Full)'
  else if layers[j].FFConnection_kind = Partial
    then Msg := '(Partial)';
  Draw_FF_Arrows (j);
  OutTextXY (arrow_coords^ [j, 'w'] + ((arrow_coords^[j,
    'y'] - arrow_coords^[j, 'w']) Div 2),
    (arrow_coords^[j, 'x'] - TextHeight ('M') -
    4), Msg);
  end;
repeat
  ch := readkey;
until Ch = #27;
dispose (arrow_coords);
end;      {Net_Display}

{-----}

{Sets graphmode (graphics) and calls net_display}

Procedure Display_Network (i : integer);

begin    {Display_Network}
  SetGraphMode (graphmode);  {Return to graphics mode}
  Net_Display (i);
  RestoreCrtMode;  {back to text}
end;      {Display_Network}

{-----}

{Draws the square neuron representation and the memory
square representation for the I/O display}

Procedure Draw_Memory_Box (x, y, width, height : integer;
  Color, Bord : word);

var
  center_width   : integer;
  center_height  : integer;
  j              : integer;
  Border         : integer;
  ViewInfo       : ViewPortType;

begin    {Draw_Memory_Box}
  SetFillStyle (SolidFill, color);
  Bar (x, y, x + width, y + height);
  SetColor (Bord);

```

```

    Rectangle (x, y, x + width, y + height);
    SetColor (yellow);
end;      {Draw_Memory_Box}

```

```
{-----}
```

```
{Provides the shell menu for removal and restoration of
individual neurons within each layer.}
```

```
Procedure Modify_Neurons (var ch : char);
```

```
var
```

```

    layer, int, i, j : integer;
    saved              : boolean;
    prob              : real;

```

```
begin      { Modify_Neurons}
```

```
    layer := 2;
```

```
    prob := 0.0;
```

```
    RestoreCrtMode;
```

```
    repeat
```

```
        clrscr;
```

```
        gotoxy (20, 8);
```

```
        write ('Modify Neurons');
```

```
        gotoxy (22, 9);
```

```
        write ('(Layer ', layer, ')');
```

```
        gotoxy (20, 11);
```

```
        write ('1. Remove Neuron');
```

```
        gotoxy (20, 12);
```

```
        write ('2. Restore Neuron');
```

```
        gotoxy (20, 13);
```

```
        write ('3. Restore Trained Configuration');
```

```
        gotoxy (20, 14);
```

```
        write ('4. Random Neuron Removal (Prob = ', prob:2:2,
                                                    ')');
```

```
        gotoxy (20, 15);
```

```
        write ('5. Save Weight State');
```

```
        gotoxy (20, 16);
```

```
        write ('6. Display Network');
```

```
        gotoxy (1, 24);
```

```
        write ('<ESC> Run Network
```

```
                <RTN> for
                next layer');
```

```
        gotoxy (1, 21);
```

```
        clreol;
```

```
        write ('=> ');
```

```
        repeat
```

```
            ch := readkey;
```

```
        until ch in ['1'..'6', #27, #13];      {nums, <ESC>, <RTN>}
```

```

case ch of
  '1' : begin
      {remove neuron}
      {alert if no saved_weights}
      repeat
        clrscr;
        gotoxy (1, 20);
        write ('Select Neuron for Deletion (Layer ',
              layer, ')');

        gotoxy (1, 21);
        write ('=> ');
        gotoxy (1, 24);
        write ('Enter Number or <RTN> for No
              Entry');

        gotoxy (4, 21); {place cursor after =>}
        clreol;
        getline; {mathutil unit}
        if (ColsOnLine > 0) and (Nextchar in
              ['0'..'9'])
          then
            begin
              process_number (int); {mathutil unit}
              if int > layers[layer].neurons
                then
                  begin
                    gotoxy (10, 2);
                    reverse;
                    write ('Exceeds Layer Neurons
                          (', layers[layer].neurons, ')');
                    normvid;
                    gotoxy (1, 21);
                    clreol; {Erase =>}
                    gotoxy (1, 24);
                    clreol;
                    gotoxy (1, 23);
                    write ('<RTN> to continue');
                    repeat
                      ch := readkey
                      until ch = #13;
                      gotoxy (1, 23);
                      clreol; {Erase <RTN>..}
                      gotoxy (10, 2); {Clear error
                                      message}

                      clreol;
                      gotoxy (1, 21);
                      write ('=> ');
                    end
                  else
                    begin
                      if layer <

```

```

net_description.num_layers
then
  for i := 1 to layers[layer +
    1].neurons do
    layers[layer + 1].weights^.
      value[i, int] := 0.0;
    {all connections := 0}
  for i := 1 to layers[layer -
    1].neurons do
    layers[layer].weights^.
      value[int, i] := 0.0;
    {all input := 0}
  end;
end;
gotoxy (1, 24);
clrscr;
write ('<^C> To Accept          <RTN> to
      Select Another Neuron');
ch := readkey;
until ch = #3;          {<^C> to exit}
clrscr;
end;
'2' : begin
      {restore Neuron}
  if ((layer = net_description.num_layers) and
      (layers[layer].saved_weights = nil)) or
      ((layer < net_description.num_layers) and
      ((layers[layer].saved_weights = nil) or
      (layers[layer + 1].saved_weights = nil)))
  then
  begin
    clrscr;
    gotoxy (1, 1);
    reverse;
    write ('No saved state exists! <RTN> to
          Continue');

    repeat
      ch := readkey;
    until ch = #13;
  end
  else
  repeat
    clrscr;
    gotoxy (1, 20);
    write ('Select Neuron for Resoration
          (Layer ', layer, ')');
    gotoxy (1, 24);
    write ('Enter Number or <RTN> for No
          Entry');
    gotoxy (1, 21);

```

```

write ('=> ');
clreol;
getline;                                {mathutil unit}
if (ColsOnLine > 0) and (Nextchar in
                               ['0'..'9'])
then
  begin
    process_number (int);               {mathutil
                                         unit}
    if int > layers[layer].neurons
    then
      begin
        gotoxy (10, 2);
        reverse;
        write ('Exceeds Layer
                Neurons (' , layers[layer].
                        neurons, ')');
        normvid;
        gotoxy (1, 21);
        clreol;                          {Erase =>}
        gotoxy (1, 24);
        clreol;
        gotoxy (1, 23);
        write ('<RTN> to continue');
        repeat
          ch := readkey;
        until ch = #13;
        gotoxy (1, 23);
        clreol;                          {Erase <RTN>..}
        gotoxy (10, 2);                  {Clear
                                         error message}
        clreol;
        gotoxy (1, 21);
        write ('=> ');
      end
    else
      begin
        if layer <
          net_description.num_layers
        then
          for i := 1 to
            layers[layer + 1].
              neurons do
            layers[layer + 1].
              weights^.value[i, int]
              := layers[layer + 1].
                saved_weights^.
                  value[i, int];
          for i := 1 to layers

```

```

[layer - 1].neurons do
layers[layer].weights^
value[int, i] :=
layers[layer].
saved_weights^
value[int, i];
end;
end;
gotoxy (1, 24);
clrscr;
write ('<^C> To Accept RTN> to
Select Another Neuron');
ch := readkey;
until ch = #3; {<^C> to exit}
clrscr;
end;
'3' : begin {restore trained configuration}
saved := true;
for i := 2 to net_description.num_layers do
if layers[i].saved_weights <> nil
then layers[i].weights^ :=
layers[i].saved_weights^
else saved := false; {single layer with
no S_W poss?}
if not saved
then
begin
clrscr;
gotoxy (1, 1);
reverse;
write ('At least one saved state
doesn''t exist!');
normvid;
gotoxy (1, 2);
write ('Others May Have Been Saved.
<RTN> to Continue');
repeat
ch := readkey;
until ch = #13;
end
else
begin
gotoxy (1, 1);
reverse;
write ('Weights Restored! <RTN>');
repeat
ch := readkey;
until ch = #13;
normvid;

```



```

        ch := '>'
    end;
end;
'4' : begin
    {random neuron removal}
    get_removal_probability (prob); {math unit}
    remove_random_neurons (prob, layer); {math
                                           unit}

    gotoxy (1, 1);
    reverse;
    write ('Neurons Removed! <RTN>');
    repeat
        ch := readkey;
    until ch = #13;
    normvid;
    ch := '<';
end;
'5' : begin
    {save weight state}
    clrscr;
    gotoxy (1, 1);
    reverse;
    write ('Previous saved state will be destroyed
           - Continue? Y/N');
    repeat
        ch := readkey
    until ch in ['Y', 'y', 'n', 'N'];
    normvid;
    if ch in ['Y', 'y']
    then
        begin
            for i := 2 to net_description.num_layers
            do
                begin
                    if layers[i].saved_weights = nil
                    then new(layers[i].saved_weights);
                    layers[i].saved_weights^ :=
                        layers[i].weights^;
                end;
            end;
            clrscr;
            gotoxy (1, 1);
            reverse;
            write ('Weights Saved! <RTN>');
            repeat
                ch := readkey;
            until ch = #13;
            normvid;
        end
    else
        begin
            clrscr;

```

```

        gotoxy (1, 1);
        reverse;
        write ('Weights Not Saved! <RTN>');
        repeat
            ch := readkey;
            until ch = #13;
            normvid;
        end;
    end;
    '6' : Display_Network (11); {display network}
    #13 : begin {<RTN>}
        if layer = net_description.num_layers
            then layer := 2
            else layer := layer + 1;
        end;
    end; {case}
until ch in [#27]; {<ESC>}
SetGraphMode (graphmode);
end; { Modify_Neurons}

{-----}

{Include file for Procedure Modify_Connections. File too}
{large for Pascal editor. Provides menu for modifications}
{to connections, removal, restoration, etc.}

{$I connect.pas}

{-----}

{Main procedure for displaying the network computations,
input, output, memory state, etc.}

Procedure Display_Net_Output (var ch : char; var semaphore :
                             integer);

var
    comline          : string;
    viewport         : ViewPortType;
    ViewPort1, ViewPort2 : ViewPortType;
    ColSpace, RowSpace : integer;
    ColSpace1, RowSpace1 : integer;
    x, y, x3, y3     : integer; {Square and Number
                                coordinates}
    i, j, k, z, it   : integer; {Counters}
    R, C, A          : integer; {For finding minimum
                                number}
    outlayer         : integer;
    s                : string[8];

```

```

hue                : byte;
converge           : boolean;

{-----}

{Enables the manual modification of input values to the
network. Also allows for the random corruption of the input
values}

Procedure Modify_Input (viewport : ViewPortType; var ch :
                        char);

var
  x, y      : integer;
  x4, y4    : integer;
  k, j      : integer;

begin  {Modify_Input}
  ClearViewPort;
  comline := '<ESC> Run Mode  <^C> Accept/Calculate  <RTN>
                        Change  <';
  comline := comline+#27#24#25#26+'> Next Neuron';
  with viewport do
    OutTextXY (20, (y2-y1) Div 2, comline);
  with ViewPort1 do
    SetViewPort (x1, y1, x2, y2, true);
    SetTextStyle (SmallFont, HorizDir, 4);
    SetTextJustify (CenterText, CenterText);
  repeat
    with viewport1 do
      begin
        if layers[1].arch = lines
          then
            begin
              x := x1 + ((x2-x1) Div 2);
              if layers[1].neurons > 2
                then y := TextHeight ('8') + RowSpace Div 2
                else if layers[1].neurons = 1
                  then y := (y2-y1) Div 2
                  else y := (y2-y1) Div 2 - (RowSpace Div
                                                2);
              SetColor (Yellow);
              OutTextXY (x, y, 'X');
              i := 1;
              repeat
                repeat
                  ch := readkey;
                until ch in [#27, #13, #3, #0];
                case ch of

```

```

#0 : begin
  ch := readkey;
  case ch of
    #80 : begin    {Down Arrow}
      if layers[1].neural_set.binary_value[i] = 1
        then SetColor (blue)
        else SetColor (LightGray);
      OutTextXY (X, Y, 'X'); {Erase 'X'}
      SetColor (Yellow);
      if i < layers[1].neurons
        then
          begin
            y := y + RowSpace;    {next square}
            i := i + 1;
            OutTextXY (x, y, 'X');
          end
        else {Was last neuron in line layer}
          begin
            i := 1;
            y := y -
              (layers[1].neurons-1)*RowSpace;
              {reset to first}
            OutTextXY (x, y, 'X');
          end;
        end;
    #72 : begin    {Up Arrow}
      if layers[1].neural_set.binary_value[i] = 1
        then SetColor (blue)
        else SetColor (LightGray);
      OutTextXY (X, Y, 'X');    {Erase 'X'}
      SetColor (Yellow);
      if i > 1 {Not first neuron}
        then
          begin
            y := y - RowSpace;    {next square}
            i := i - 1;
            OutTextXY (x, y, 'X');
          end
        else {Was first neuron in line layer}
          begin
            i := Layers[1].neurons;
            y := y +
              (layers[1].neurons-1)*RowSpace;
              {reset to last}
            OutTextXY (x, y, 'X');
          end;
        end;
      end;
    end; {case}
  end;
end;

```

```

#13 : begin    {<RTN>}
      if layers[1].neural_set.binary_value[i] = 1
      then    {Was blue and set}
      begin
        hue := lightgray;
        layers[1].neural_set.binary_value[i] := 0;
      end
      else    {Was lightgray and not set}
      begin
        hue := blue;
        layers[1].neural_set.binary_value[i] := 1;
      end;
      x3 := x - (ColSpace Div 2);
      y3 := y - (RowSpace Div 2);
      Draw_Memory_Box (x3, y3, ColSpace, RowSpace,
                      hue, white);

      SetColor (Yellow);
      OutTextXY (x, y, 'X'); {Replace 'X'}
    end;
#3  : begin    {Return to Modify_Parameters}
      if layers[1].neural_set.binary_value[i] = 1
      then SetColor (Blue)
      else SetColor (LightGray);
      OutTextXY (x, y, 'X'); {Erase 'X'}
      SetColor (yellow);
      case net_description.training of
        supervised : calculate_output; {math unit}
        unsupervised : if net_description.learning <>
                        Hopfield then calculate_output;
        zip          : calculate_output {math unit}
      end; {case}
    end
  end; {case}
until ch in [#27, #3]; {ESC to exit, ^C to compute}
end
else    {Layer Architecture = matrices}
  begin
    x := x1 + ((x2-x1) Div 2);
    if layers[1].arch_col_length Mod 2 = 0 {Even # of
                                           Cols}
    then x := x - ((layers[1].arch_col_length Div
                    2)*ColSpace) + ColSpace Div 2
    else x := x - ((layers[1].arch_col_length Div
                    2)*ColSpace);
    y := y1 + ((y2-y1) Div 2);           {Center of viewport}
    if layers[1].arch_row_length Mod 2 = 0 {Even # of
                                           Rows}
    then y := y - ((layers[1].arch_row_length Div
                    2)*RowSpace) + RowSpace Div 2
  end
end

```

```

else y := y - ((layers[1].arch_row_length Div
                2)*RowSpace);
y4 := y;      {Save y value for future use}
x4 := x;      {Save x for future use}
SetColor (Yellow);
OutTextXY (x, y, 'X');
i := 1;       {i counts neurons in layer}
j := 1;       {j counts columns in matrix architecture}
k := 1;       {k counts rows in matrix architecture}
repeat
  repeat
    ch := readkey;
  until ch in [#27, #13, #3, #0];
  case ch of
    #0 : begin
      ch := readkey;
      case ch of
        #80 : begin          {down arrow}
          if layers[1].neural_set.
              binary_value[i] = 1
          then SetColor (blue)
          else SetColor (LightGray);
          OutTextXY (X, Y, 'X'); {Erase
                                  the 'X'}
          SetColor (Yellow);
          if k < layers[1].arch_row_length
          then
            begin
              y := y + RowSpace; {Next
                                  square}
              i := i + 1;
              k := k + 1;
              OutTextXY (x, y, 'X');
            end
          else {Last neuron in row}
            begin
              k := 1;
              i := i - (layers[1].
                arch_row_length-1);
              y := y4;
              OutTextXY (x, y, 'X');
            end;
          end;
        #72 : begin          {Up Arrow}
          if layers[1].neural_set.
              binary_value[i] = 1
          then SetColor (blue)
          else SetColor (LightGray);
          OutTextXY (x, y, 'X'); {Erase 'X'}
        end;
      end;
    end;
  end;
end;

```

```

SetColor (Yellow);
if k > 1
  then
    begin
      i := i - 1;
      k := k - 1;
      y := y - RowSpace;
      OutTextXY (x, y, 'X');
    end
  else {First neuron in column}
    begin
      i := i + (layers[1].
                arch_row_length-1);
      k := layers[1].
            arch_row_length;
      y := y + (RowSpace *
                (layers[1].arch_row_length-1));
      OutTextXY (x, y, 'X');
    end
end;
#75 : begin {Left Arrow}
      if layers[1].neural_set.
          binary_value[i] = 1
      then SetColor (blue)
      else SetColor (LightGray);
      OutTextXY (x, y, 'X'); {Erase
                              the 'X'}
      SetColor (Yellow);
      if j > 1
        then
          begin
            j := j - 1;
            i := i - layers[1].
                  arch_row_length;
            x := x - ColSpace;
            OutTextXY (x, y, 'X');
          end
        else {First column in matrix}
          begin
            j := layers[1].
                  arch_col_length;
            i := i+((layers[1].
                    arch_col_length-1)*
                  layers[1].arch_row_length);
            x := x + (ColSpace *
                    (layers[1].
                    arch_col_length-1));
            OutTextXY (x, y, 'X');
          end
        end
end

```

```

        end;
#77 : begin {Right Arrow}
    if layers[1].neural_set.binary_value[i] = 1
    then SetColor (blue)
    else SetColor (LightGray);
    OutTextXY (x, y, 'X'); {Erase the 'X'}
    SetColor (Yellow);
    if j < layers[1].arch_col_length
    then
        begin
            j := j + 1;
            i := i + layers[1].arch_row_length;
            x := x + ColSpace;
            OutTextXY (x, y, 'X');
        end
    else {Last column in matrix}
        begin
            j := 1;
            i := i - ((layers[1].arch_col_length
                - 1) * layers[1].
                    arch_row_length);
            x := x4;
            OutTextXY (x, y, 'X');
        end;
    end;
end; {case}
end;
#13 : begin {<RTN>}
    if layers[1].neural_set.binary_value[i] = 1
    then {Was blue and set}
        begin
            hue := lightgray;
            layers[1].neural_set.binary_value[i] := 0;
            layers[1].neural_set.real_value[i] :=
                net_description.zero_value;
        end
    else {Was lightgray and not set}
        begin
            hue := blue;
            layers[1].neural_set.binary_value[i] := 1;
            layers[1].neural_set.real_value[i] :=
                net_description.one_value;
        end;
    end;
    x3 := x - (ColSpace Div 2);
    y3 := y - (RowSpace Div 2);
    Draw_Memory_Box (x3, y3, ColSpace, RowSpace,
        hue, white);
    SetColor (Yellow);
    OutTextXY (x, y, 'X'); {Replace 'X'}

```



```

end;
#3 : begin      {Return to Modify_Parameters and
                calculate net}
    if layers[1].neural_set.binary_value[i] = 1
    then SetColor (Blue)
    else SetColor (LightGray);
    OutTextXY (x, y, 'X');    {Erase 'X'}
    SetColor (yellow);
    case net_description.training of
        supervised      : calculate_output; {math unit}
        unsupervised    : if net_description.learning
                           <> Hopfield
                           then calculate_output;
        zip              : calculate_output {math unit}
    end;    {case}
    end;
end; {case}
until ch in [#27, #3];
end;
end;
until ch in [#27, #3];
end;    {Modify_Input}

```

```
{-----}
```

{Main procedure used to call procedures for changing neurons, connections, varying input, etc.}

Procedure Modify_Parameters;

var

```

ch : char;
viewport : ViewPortType;

```

begin {Modify_Parameters}

repeat

```

    SetTextStyle (DefaultFont, HorizDir, 1);
    SetTextJustify (LeftText, BottomText);
    SetViewPort (0, MaxY-TextHeight ('M')-11, MaxX, MaxY,
                true);
    ClearViewPort;

```

```

    comline := '<ESC> Accept <F1> Mod Input <F2> Mod
                Neurons'; ;
    comline := comline+'<F3> Mod Connections <F4> Corrupt';

```

```

    GetViewSettings (Viewport);

```

with viewport do

```

    OutTextXY (20, (y2-y1) Div 2, comline);

```

repeat

```

    ch := readkey;

```

```

until ch in [#0, #27];
case ch of
  #0 : begin
    ch := readkey;
    case ch of
      #59 : Modify_Input (viewport, ch);      {F1}
      #60 : Modify_Neurons (ch);              {F2}
      #61 : begin                              {F3}
        RestoreCrtMode;
        Modify_Connections (ch, 1, 'Run
                               Network');
        SetGraphMode (graphmode);
      end;
      #62 : begin                              {F4}
        Corrupt_input (net_description.
                       factor3); {Math unit}
        case net_description.training of
          supervised : calculate_output;
                       {math unit}
          unsupervised : if
            net_description.learning <>
              Hopfield
            then calculate_output;
                  {math unit}
          zip : calculate_output;
              {math unit}
        end; {case}
      end;
    end; {case}
  end;
end; {case}
until ch in [#27, #62, #3]; {<ESC>, <F4>, <^C>}
end; {Modify_Parameters}

{-----}

begin {Display_Net_Output}
  repeat
    FullPort;
    SetColor (yellow);
    ClearDevice;
    Write_Header ('INPUT OUTPUT',
                  5);

    SetColor (white);
    if train
      then write_header ('Training Mode', 4)
      else write_header ('Run Mode', 4);
    SetColor (yellow);

```

```

Comline := '<ESC> Quit <SPACE> Mod Params <RTN> Next
           Input';
Comline := concat (ComLine, ' <F1> Network <^C>
                   Memory');
Write_Command_Line (ComLine, 0);
SetViewPort (0, 20+(TextHeight('M')), MaxX,
             MaxY-20-(TextHeight('M')), ClipOn);
GetViewSettings (viewport);
SetColor (LightGray);
SetTextStyle (SmallFont, HorizDir, 5);
with ViewPort do
begin
    {Draw Border around screen}
    line (0, 0, 0, y2-28);
    line (0, 0, x2, 0);
    line ((x2-x1) Div 2, 0, (x2-x1) Div 2, y2-28);
    line (0, y2-28, x2, y2-28);
    line (x2, y2-28, x2, 0);
    SetViewPort (x1+1, y1+1, (x2-x1) Div 2 - 1, y2-1,
                true);

    GetViewSettings (ViewPort1);
    SetViewPort ((x2-x1) Div 2 + 1, y1+1, x2 - 1, y2-1,
                true);

    GetViewSettings (ViewPort2);
end;
SetTextStyle (SmallFont, HorizDir, 4);
SetTextJustify (CenterText, CenterText);
with layers[1] do
    {Draw Input}
begin
    if arch = lines then
        {Line Layer Architecture}
        begin
            with viewport1 do
                begin
                    SetViewPort (x1, y1, x2, y2, true);
                    RowSpace :=
                    ((y2-TextHeight('8'))-(y1+TextHeight('8')))
                    Div layers[1].neurons;
                    if (neurons = 1) or (neurons = 2)
                        then RowSpace := RowSpace Div 3;
                                {Reduce size for one}
                    ColSpace := RowSpace; {Will display a
                                square}
                    x := x1 + ((x2-x1) Div 2);
                    x := x - (ColSpace Div 2); {first square
                                x coordinate}
                    if neurons > 2
                        then y := TextHeight('8') {First
                                square y coordinate}
                    else
                        if neurons = 1

```

```

        then y := ((y2 - y1) Div 2) - RowSpace
                                     Div 2
        else y := ((y2 - y1) Div 2) -
                 RowSpace;
    end;
x3 := x - 3*TextWidth('15'); {Number position}
y3 := y + (RowSpace Div 2);
SetColor (white);
for i := 1 to neurons do    {Write neuron numbers
                             vertically}
    begin
        str (i, s);
        OutTextXY (x3, y3, s);
        y3 := y3 + RowSpace;
    end;
x3 := x; {Reset to first square coordinates}
y3 := y;
for i := 1 to neurons do
    begin
        case neural_set.binary_value [i] of
            1 : hue := Blue;
            0 : hue := lightgray;
        end; {case}
        Draw_Memory_Box (x3, y3, ColSpace, RowSpace,
                         hue, white);
        y3 := y3 + RowSpace;
    end;
end
else if arch = matrices then    {Matrix Layer
                                 Architecture}
    begin
        with viewport1 do
            begin
                SetViewPort (x1, y1, x2, y2, true);
                R :=
                ((y2-5*TextHeight('8'))-(y1+5*TextHeight('8')))
                Div layers[1].arch_row_length;
                C :=
                ((x2-5*TextWidth('25'))-(x1+5*TextWidth('25')))
                Div layers[1].arch_col_length;
                RowSpace := Minimum (R, C); {Find smallest
                                           dimension}
                ColSpace := RowSpace; {Will display a
                                        square}
                x := x1 + ((x2-x1) Div 2); {Center of
                                             viewport}
                if layers[1].arch_col_length Mod 2 = 0
                    {Even # of Cols}
                then x := x - ((layers[1].arch_col_length

```

```

                Div 2)*ColSpace)
    else x := x - ((layers[1].arch_col_length
                Div 2)*ColSpace)
                - ColSpace Div 2;
    y := y1 + ((y2-y1) Div 2);    {Center of
                                viewport}
    if layers[1].arch_row_length Mod 2 = 0
        {Even # of Cols}
    then y := y - ((layers[1].arch_row_length
                Div 2)*RowSpace)
    else y := y - ((layers[1].arch_row_length
                Div 2)*RowSpace)
                - RowSpace Div 2;
    end;
    x3 := x - 3*TextWidth('25'); {Row Number
                                position}
    y3 := y + (RowSpace Div 2);
    SetColor (white);
    for i := 1 to layers[1].arch_row_length do
        {Vertical row numbers}
    begin
        str (i, s);
        OutTextXY (x3, y3, s);
        y3 := y3 + RowSpace;
    end;
    x3 := x + (ColSpace Div 2);
    y3 := y - (RowSpace Div 2);
    for i := 1 to layers[1].arch_col_length do
        {Horiz Col numbers}
    begin
        str (i, s);
        OutTextXY (x3, y3, s);
        x3 := x3 + ColSpace;
    end;
    x3 := x; {Reset to first square coordinates}
    y3 := y;
    i := 1;
    for j := 1 to layers[1].arch_col_length do
    begin
        for k := 1 to layers[1].arch_row_length do
        begin
            case neural_set.binary_value [i] of
                1 : hue := Blue;
                0 : hue := lightgray;
            end; {case}
            Draw_Memory_Box (x3, y3, ColSpace,
                            RowSpace, hue, white);
            y3 := y3 + RowSpace;
            i := i + 1;
        end;
    end;
end;

```

```

        end;
        y3 := y;           {Reset to top row}
        x3 := x3 + ColSpace {Move over one column}
    end;
end;
end;
outlayer := net_description.num_layers;
with layers[outlayer] do {Draw Output}
begin
    if arch = lines then {Line Layer Architecture}
    begin
        with viewport2 do
        begin
            if net_description.training = supervised
            then A := 3 {divide out viewport for
                        display of tgt}
            else A := 2; {vector also}
            SetViewPort (x1, y1, x2, y2, true);
            RowSpace1 :=
            ((y2-TextHeight('8'))-(y1+TextHeight('8')))
            Div layers[outlayer].neurons;
            if (neurons = 1) or (neurons = 2)
            then RowSpace1 := RowSpace1 Div 4;
                        {Reduce square size}
            ColSpace1 := RowSpace1; {Will display a
                                    square}
            x := (x2-x1) Div A; {set center of output
                                line}
            x := x - (ColSpace1 Div 2); {first square
                                        x coordinate}
            if neurons > 2
            then y := TextHeight('8') {First
                                        square y coordinate}
            else
            if neurons = 1
            then y := ((y2 - y1) Div 2) -
                    RowSpace1 Div 2
            else y := ((y2 - y1) Div 2) -
                    RowSpace1;
            end;
            x3 := x - 3*TextWidth('15'); {Number position}
            y3 := y + (RowSpace1 Div 2);
            SetColor (white);
            for i := 1 to neurons do {Write neuron numbers
                                    vertically}
            begin
                str (i, s);
                OutTextXY (x3, y3, s);
                y3 := y3 + RowSpace1;
            end;
        end;
    end;
end;

```

```

end;
x3 := x; {Reset to first square coordinates}
y3 := y;
for i := 1 to neurons do
begin
  case neural_set.binary_value [i] of
    1 : hue := Blue;
    0 : hue := lightgray;
  end; {case}
  Draw_Memory_Box (x3, y3, ColSpace1,
                  RowSpace1, hue, white);
  SetTextJustify (LeftText, CenterText);
  str (neural_set.real_value[i]:3:4, s);
  SetColor (black); {write weight values in
                    memory box}
  OutTextXY (x3 + 3, y3 + RowSpace Div 2 -
            TextHeight ('8'), s);
  if A = 3
  then
  begin
    str (r_out_buffer[i]:3:4, s);
    OutTextXY (x3 + 3, y3 +(RowSpace Div
                          2) + TextHeight ('8'), s);
  end;
  SetColor (yellow);
  SetTextJustify (CenterText, BottomText);
  y3 := y3 + RowSpace1;
end; {for i := 1 to neurons}
if A = 3 then
begin
  x3 := 2 * x;
  x3 := x3 + (ColSpace1 div 2); {reset to
                                first sqr coordinates}
  y3 := y;
  for i := 1 to neurons do
  begin
    if r_out_buffer[i] =
      net_description.one_value
    then hue := Blue
    else hue := lightgray;
    Draw_Memory_Box (x3, y3, ColSpace1,
                    RowSpace1, hue, white);
    SetTextJustify (LeftText, CenterText);
    y3 := y3 + RowSpace1;
  end; {for i := 1 to neurons}
end; {if A = 3}
end
end

```

```

else if arch = matrices then      {Matrix Layer
                                   Architecture}
begin
  with viewport2 do
    begin
      SetViewPort (x1, y1, x2, y2, true);
      R := ((y2-5*TextHeight('8'))
            -(y1+5*TextHeight('8')))
            Div layers[outlayer].arch_row_length;
      C := ((x2-5*TextWidth('25'))
            -(x1+5*TextWidth('25')))
            Div layers[outlayer].arch_col_length;
      RowSpace1 := Minimum (R, C); {Find smallest
                                   dimension}
      ColSpace1 := RowSpace1; {Will display a
                                square}
      x := (x2-x1) Div 2;          {Center of viewport}
      if layers[outlayer].arch_col_length Mod 2 =
          0 {Even # of Cols}
      then x := x - ((layers[outlayer].
                     arch_col_length Div 2)*ColSpace1)
      else x := x - ((layers[outlayer].
                     arch_col_length Div 2)*ColSpace1) -
                    ColSpace1 Div 2;
      y := y1 + ((y2-y1) Div 2);  {Center of
                                   viewport}
      if layers[outlayer].arch_row_length Mod 2 =
          0 {Even # of Cols}
      then y := y - ((layers[outlayer].
                     arch_row_length Div 2)*RowSpace1)
      else y := y - ((layers[outlayer].
                     arch_row_length Div 2)*RowSpace1) -
                    RowSpace1 Div 2;
    end;
    x3 := x - 3*TextWidth('25'); {Row Number
                                   position}
    y3 := y + (RowSpace1 Div 2);
    SetColor (white);
    for i := 1 to layers[outlayer].arch_row_length
      do {Vert row #}
      begin
        str (i, s);
        OutTextXY (x3, y3, s);
        y3 := y3 + RowSpace1;
      end;
    x3 := x + (ColSpace1 Div 2);
    y3 := y - (RowSpace1 Div 2);

```



```

for i := 1 to layers[outlayer].arch_col_length
    do {Horiz Col #}
    begin
        str (i, s);
        OutTextXY (x3, y3, s);
        x3 := x3 + ColSpace1;
    end;
x3 := x;    {Reset to first square coordinates}
y3 := y;
i := 1;
for j := 1 to layers[outlayer].arch_col_length
    do
    begin
        for k := 1 to layers[outlayer].
            arch_row_length do
            begin
                case neural_set.binary_value [i] of
                    1 : hue := Blue;
                    0 : hue := lightgray;
                end;    {case}
                Draw_Memory_Box (x3, y3, ColSpace1,
                    RowSpace1, hue, white);
                SetTextJustify (leftText, CenterText);
                str (neural_set.real_value[i]:3:4, s);
                SetColor (black);    {write weight values
                    in memory box}
                OutTextXY (x3 + 3, y3 + RowSpace Div 2,
                    s);
                str (r_out_buffer[i]:3:4, s);
                OutTextXY (x3 + 3, y3 +(RowSpace Div 2)
                    + 2 * TextHeight ('8'), s);
                SetColor (yellow);
                SetTextJustify (CenterText, BottomText);
                y3 := y3 + RowSpace1;
                i := i + 1;
            end;
            y3 := y;    {Rest to top row}
            x3 := x3 + ColSpace1    {Move over one column}
        end;
    end;
end;
repeat
    ch := readkey;
until (ch in [#27, #3, #13, #32, #0, 'T', 'S']);

```

```

case ch of
  #0 : begin
    ch := readkey;
    if ch = #59 {F1}
      then semaphore := 3;          {Display_Network}
    end;
  #13 : begin                      {<RTN>}
    case net_description.training of
      supervised : begin
        if train
          then train_sup_net
                {math unit}
          else calc_sup_net;
                {math unit}
        end;
      unsupervised : begin
        if train
          then train_unsup_net (ch)
                {math unit}
          else calc_unsup_net;
                {math unit}
        end;
      zip : begin
        next_input;
        calculate_output;
                {math unit}
      end;
    end; {case}
  end;
  'T' : begin                      {continual training}
    z := 0;
    gotoxy (44, 23);
    write ('Enter number of iterations ');
    readln (it);
    gotoxy (44, 23);
    textcolor (black);
    write (' ');
    textcolor (yellow);
    gotoxy (44, 22);
    write (it);
    repeat
      case net_description.training of
        supervised : begin
          if train
            then train_sup_net
                  {math unit}
            else calc_sup_net;
                  {math unit}
          end;
        end;
      end;
    end;
  end;
end;

```

```

        unsupervised : begin
            if train
                then train_unsup_net
                    (ch) {math unit}
                else calc_unsup_net;
                    {math unit}
            end;
        zip
            : begin
                next_input;
                calculate_output;
                    {math unit}
            end;
        end; {case}
        gotoxy (44, 23);
        z := z + 1;
        write ('Z = ', z);
        if net_description.iterate > 0 {Don't
            divide by 0}
            then if z mod net_description.iterate = 0
                then save_state (z); {ioutil unit}
            until z = it;
        end;
        'S' : Save_State (0); {ioutil unit}
        #32 : Modify_Parameters; {<SPACE>}
        #3 : semaphore := 1; {Switch to Display_Memory
            <ESC>}
        end; {case}
        until (ch in [#27, #59, #3]); {<ESC>, <F1>, or <^C>}
    end; {Display_Net_Output}

{-----}

{Provides the memory display while in the display mode}

Procedure Display_Memory (var ch : char; var semaphore :
    integer);

var
    ComLine, s : string;
    viewport1, viewport2 : ViewPortType;
    i, j, k, x, y : integer;
    x3, y3 : integer;
    rows, cols, hue : integer;
    RowSpace, ColSpace : integer;
    check : real;

begin {Display_Memory}
    FullPort;
    SetColor (yellow);

```

```

ClearDevice;
Write_Header ('RELATIVE WEIGHT VALUES', 5);
Comline := '<ESC> Quit    <Space> Next Layer    <RTN> Next
           Input';
Comline := concat (ComLine, '    <F1> Network    <^C>
           Output');
Write_Command_Line (ComLine, 0);
SetViewPort (0, 20+(TextHeight('M')), MaxX,
             MaxY-20-(TextHeight('M')), ClipOn);
GetViewSettings (viewport1);
j := 2;    {Layer 2}
repeat    {Display Layer Headers and Labels}
  SetTextStyle (SmallFont, HorizDir, 4);
  with viewport1 do
    begin
      ClearViewPort;
      SetViewPort (x1, y1, x2, y2, true);
      RowSpace := ((y2-5*TextHeight('8'))-
                  (y1+5*TextHeight('8')))
                  Div layers[j-1].neurons;
      ColSpace := (x2-(x1+TextWidth('Layer 5 25  ')))
                  Div layers[j].neurons;
      x := TextWidth ('Layer 5 25  ');
      x := x + ((x2-x) Div 2);    {Center of viewport}
      x := x - ((layers[j].neurons Div 2)*ColSpace);
                                     {x is top left}
      if layers[j].neurons Mod 2 <> 0    {Odd # of Cols
        then x := x - (ColSpace Div 2); {first square }
      y := y1 + ((y2-y1) Div 2);    {Center of viewport}
      y := y - ((layers[j-1].neurons Div 2)*RowSpace);
                                     {y is top left}
      if layers[j-1].neurons Mod 2 <> 0 {Odd # of Rows
        then y := y - (RowSpace Div 2);    coordinate of}
                                     {first square}
      SetColor (white);
      SetTextJustify (LeftText, CenterText);
      str (j-1, S);
      OutTextXY (0, (y2-y1) Div 2, 'Layer '+S);
      OutTextXY (0, ((y2-y1) Div 2) + TextHeight ('L') +
                  4, 'Neurons');
      x3 := x - TextWidth(' 2'); {Row Number position}
      y3 := y + (RowSpace Div 2);
      SetTextJustify (CenterText, CenterText);
      for i := 1 to layers[j-1].neurons do {Vertical row
                                           numbers}
        begin
          str (i, s);
          OutTextXY (x3, y3, s);
        end
    end
  end
end

```

```

        y3 := y3 + RowSpace;
    end;
    str (j, s);
    SetTextJustify (LeftText, BottomText);
    OutTextXY ((x+(x2-x)) Div 2, y-(4*TextHeight('8')),
        'Layer '+s+ ' Neurons');
    x3 := x + (ColSpace Div 2);
    y3 := y - (TextHeight ('8'));
    SetTextJustify (CenterText, BottomText);
    for i := 1 to layers[j].neurons do{Horiz Colnumbers}
        begin
            str (i, s);
            OutTextXY (x3, y3, s);
            x3 := x3 + ColSpace;
        end;
    end;
repeat{Show memory weights in color within the viewport}
    x3 := x;          {Reset to first square coordinates}
    y3 := y;
    for rows := 1 to layers[j-1].neurons do
        begin          {Draw square for each entry in weight
                        matrix for layer j}
            for cols := 1 to layers[j].neurons do
                begin
                    check := layers[j].weights^.value[cols, rows];
                    if check = 0          {Revise the colors!!!!}
                        then hue := Black
                    else if (check <= -6.0)
                        then hue := Darkgray
                    else if (check > -6.0) and (check <= -5.0)
                        then hue := Blue
                    else if (check > -5.0) and (check <= -4.0)
                        then hue := Brown
                    else if (check > -4.0) and (check <= -3.0)
                        then hue := red
                    else if (check > -3.0) and (check <= -2.0)
                        then hue := Green
                    else if (check > -2.0) and (check <= -1.0)
                        then hue := Magenta
                    else if (check > -1.0) and (check <= -0.0)
                        then hue := Lightblue
                    else if (check > 0.0) and (check <= 1.0)
                        then hue := Cyan
                    else if (check > 1.0) and (check <= 2.0)
                        then hue := Lightgray
                    else if (check > 2.0) and (check <= 3.0)
                        then hue := Lightcyan
                    else if (check > 3.0) and (check <= 4.0)
                        then hue := Lightred
                end
            end
        end
    end
end

```

```

else if (check > 4.0) and (check <= 5.0)
  then hue := Lightmagenta
else if (check > 5.0) and (check <= 6.0)
  then hue := Lightgreen
else if (check > 6.0) and (check <= 7.0)
  then hue := Yellow
else if (check > 7.0)
  then hue := White;
Draw_Memory_Box (x3, y3, ColSpace, RowSpace,
                 hue, white);
SetTextJustify (CenterText, CenterText);
str (layers[j].weights^.value[cols, rows]:2:2,
     s);
SetColor (black); {write weight values in
                  memory box}
if layers[j-1].neurons < 25 then
  OutTextXY (x3 + (ColSpace Div 2), y3 +
            RowSpace Div 2, s);
SetColor (yellow);
SetTextJustify (CenterText, BottomText);
x3 := x3 + ColSpace; {Move square over
                    one column}
end;
x3 := x; {Reset to Original}
y3 := y3 + RowSpace; {Increment by one row}
end;
repeat
  ch := readkey;
until (ch in [#27, #3, #13, #32, #0]);
case ch of
  #0 : begin
    ch := readkey;
    if ch = #59 {F1}
      then semaphore := 4; {Switch to
                          Display_Network}
    end;
  #13 : begin {<RTN>} {fix for recurrent networks!!!}
    case net_description.training of
      supervised : begin
        if train
          then train_sup_net
            {math unit}
          else calc_sup_net;
            {math unit}
        end;
      end;
    end;
  end;
end;

```

```

        unsupervised : begin
            if train
                then train_unsup_net
                     (ch) {math unit}
                else calc_unsup_net;
                     {math unit}
            end;
        zip          : begin
            next_input;
            calculate_output;
                     {math unit}
            end;
        end; {case}
    end;
#32 : begin          {<SPACE>}
    if j = net_description.num_layers
        then j := 2 {reset to first iteration}
        else j := j + 1; {increment layer}
    end;
'S' : Save_State (0);
#3  : semaphore := 2; {Switch to
                        Display_Net_Output}
end; {case}
until (ch in [#27, #3, #32, #59]); {<^C>, <ESC>,
                                     <SPACE>, or <F1>}
until (ch in [#27, #3, #59]); {<^C>, <ESC>, or <F1>}
end; {Display_Memory}

end. {GrafStuff Unit}

```

APPENDIX F

Development System Display Unit Listing
(Connection Modification Include File)

Appendix B through Appendix J constitute the
complete development system program listing


```

{-----}

{This is an include file to the grafstuf unit.  Allows}
{modification of connectivity between the layers of the}
{network.  This procedures can be accessed through both the}
{menu system and the display system for modifications to}
{the connectivity definitions.                                }

{-----}

{Allows for removal/restoration of individual connections}
{or for the random removal of connections}

Procedure Modify_Connections (var ch : char; layer :
                               integer; str :string);

var
  int, i, j, n : integer;
  GResult      : integer;  {Store results of GraphResults}
  saved, modify : boolean;
  prob         : real;
  connections   : packed array[1..max_bodies] of boolean;
                               {connected?}
  disconnected   : boolean;

begin  {Modify_Connections}
  prob := 0.0;
  int := 0;
  repeat
    clrscr;
    gotoxy (20, 8);
    write ('Modify Connections');
    gotoxy (22, 9);
    write ('(Layer ');
    reverse;
    write(' ', layer, ' ');
    normvid;
    write (' to Layer ');
    reverse;
    write (' ', layer + 1, ' ');
    normvid;
    write (')');
    gotoxy (20, 11);
    write ('1.  Remove Connection');
    gotoxy (20, 12);
    write ('2.  Restore Connection');
    gotoxy (20, 13);
    write ('3.  Restore Full Layer Connectivity');
    gotoxy (20, 14);
  until ch = 'q';
end;

```

```

write ('4. Random Connection Removal (Prob = ',
                                             prob:2:2, ')');
gotoxy (20, 15);
write ('5. Save Weight State');
gotoxy (20, 16);
write ('6. Display Network');
gotoxy (1, 24);
write ('<ESC> ', str, '                                <RTN> for
                                                         next layer');

gotoxy (1, 21);
clreol;
write ('=> ');
repeat
  ch := readkey;
until ch in ['1'..'6', #27, #13];    {nums, <ESC>, <RTN>}
case ch of
  '1' : begin
        {remove connection}
        if layers[layer + 1].saved_weights = nil
        then
          begin
            clrscr;
            gotoxy (1, 1);
            reverse;
            write ('Saved state doesn''t exist!');
            write (' Will not be able to
                                                         restore!');
            normvid;
            gotoxy (1, 3);
            write ('<RTN> to Continue <ESC> to
                                                         Quit');
            repeat
              ch := readkey;
            until ch in [#13, #27];
          end;
        if (ch = #13) or (layers[layer +
                                                         1].saved_weights <> nil)
        then
          begin
            ch := '1';
            modify := false;
            i := 0;
            clrscr;
            gotoxy (1, 15);
            write ('Select Connection for Deletion
                                                         (Layer ', layer);
            writeln (' to Layer ', layer + 1, ')');
          end;
        end;

```

```

repeat
  repeat
    gotoxy (1, 21);
    clreol;
    write ('=> ');
    gotoxy (1, 24);
    clreol;
    write ('Enter Numbers for Layer ', layer, ' or
          <RTN> ');

    writeln ('for No Entry');
    write ('(Neurons in layer = ',
          layers[layer].neurons, ')');
    gotoxy (4, 21);    {place cursor after =>}
    getline;          {mathutil unit}
    if (ColsOnLine > 0) and (Nextchar in ['0'..'9'])
      then
        begin
          process_number (int);    {mathutil unit}
          if int > layers[layer].neurons
            then
              begin
                gotoxy (10, 2);
                reverse;
                write ('Exceeds Layer Neurons (',
                      layers[layer].neurons, ')');
                normvid;
                gotoxy (1, 21);
                clreol;    {Erase =>}
                gotoxy (1, 24);
                clreol;
                gotoxy (1, 23);
                write ('<RTN> to continue');
                repeat
                  ch := readkey
                until ch = #13;
                gotoxy (1, 23);
                clreol;    {Erase <RTN>..}
                gotoxy (10, 2); {Clear error message}
                clreol;
                gotoxy (1, 21);
                write ('=> ');
              end
            else
              if ch = #13{<RTN>- 2nd layer designation}
                then
                  begin
                    j := int;
                    connections[j] := false;
                    modify := true;
                  end
                end
          end
        end
      end
    end
  end
end

```

```

end
else {1st layer neuron designation}
begin
  i := int;
  if layer =
    net_description.num_layers
  then layer := 1
  else layer := layer + 1;
  for j := 1 to
    layers[layer].neurons do
    if layers[layer].weights^.
      value[j, i] = 0.0
    then connections[j] := false
    else connections[j] := true;
  end;
end;
gotoxy (1, 24);
clreol;
write ('<^C> To Accept & Continue
                                             <ESC> to Exit');
write ('          <RTN> to Accept Neuron');
gotoxy (1, 25);
clreol;
ch := readkey;
until ch in [#3, #13, #27];      {<^C> to exit}
until ch in [#3, #27];        {<^C> or <ESC> to exit}
if ch = #3  {^C to accept/ESC exit with no change}
then
  if (i > 0) and modify
  then
    begin
      for n := 1 to layers[layer].neurons do
        if connections[n] = false
        then
          layers[layer].weights^.value[n, i] := 0.0;
          layers[layer -
            1].FFConnection_kind := partial;
        end;
      clrscr;
      if layer >= net_description.num_layers
      then layer := 1;
    end;
  end;
'2' : begin          {restore connection}
  disconnected := false;
  if (layer < net_description.num_layers) and
    (layers[layer + 1].saved_weights = nil)
  then
    begin

```

```

clrscr;
gotoxy (1, 1);
reverse;
write ('No saved state exists! <RTN> to
                                     Continue');

repeat
  ch := readkey;
until ch = #13;
normvid;
end
else
begin
  modify := false;
  i := 0;
  clrscr;
  gotoxy (1, 15);
  write ('Select Connection to Restore
                                     (Layer ', layer);
  write (' to Layer ', layer + 1, ')');
  gotoxy (1, 5);
  reverse;
  write ('Neurons in layer ', layer);
  write (' with Disconnections');
  normvid;
  gotoxy (3, 7);
  for j := 1 to layers[layer].neurons do
    begin
      for n := 1 to layers[layer +
                                     1].neurons do
        if layers[layer +
                    1].weights^.value[n, j] = 0.0
          then disconnected := true;
        if disconnected then write (j:3);
          {write disconnected neuron}
        disconnected := false;
      end;
    end;
  repeat
    gotoxy (1, 21);
    clreol;
    write ('=> ');
    gotoxy (1, 24);
    clreol;
    write ('Enter Numbers for Layer ', layer);
    write (' or <RTN> for No Entry');
    gotoxy (4, 21); {place cursor after =>}
    getline;      {mathutil unit}
    if (ColsOnLine > 0) and (Nextchar in
                              ['0'..'9'])
      then

```

```

begin
  process_number (int); {mathutil unit}
  if int > layers[layer].neurons
  then
    begin
      gotoxy (10, 2);
      reverse;
      write ('Exceeds Layer Neurons
              (', layers[layer].neurons, ')');
      normvid;
      gotoxy (1, 21);
      clreol;          {Erase =>}
      gotoxy (1, 24);
      clreol;
      gotoxy (1, 23);
      write ('<RTN> to continue');
      repeat
        ch := readkey
      until ch = #13;
      gotoxy (1, 23);
      clreol;          {Erase <RTN>..}
      gotoxy (10, 2);  {Clear}
                        {error message}

      clreol;
      gotoxy (1, 21);
      write ('=> ');
    end
  else
    if ch = #13 {layer + 1}
    then
      begin
        j := int;
        connections[j] := true;
        modify := true;
      end
    else {layer}
      begin
        i := int;
        if layer =
          net_description.num_layers
        then layer := 1
        else layer := layer + 1;
        for j := 1 to
          layers[layer].neurons do
          if
            layers[layer].weights^.value
              [j, i] = 0.0
          then
            connections[j] := false

```

```

else
    connections[j] := true;
gotoxy (1, 9);
reverse;
write ('Neurons in
        layer ', layer);
write (' with
        Disconnections from');
write (' Layer ',
        layer - 1);
normvid;
write (' (Neuron ', i, ')');
gotoxy (3, 11);
for j := 1 to
    layers[layer].neurons do
if layers[layer].weights^
    value[j, i] = 0.0
    then write (j:3);
        {disconnected}
end;
end;
gotoxy (1, 24);
clreol;
write ('<^C> To Accept & Continue
        <ESC> to Exit');
write ('    <RTN> to Accept Neuron');
ch := readkey;
until ch in [#3, #27];{<^C> or <ESC> to exit}
if ch <> #27    {ESC exit with no change}
then
    if (i > 0) and modify
    then
        for n := 1 to
            layers[layer].neurons do
                if (connections[n] = true) and
                    (layers[layer].weights^.value[n, i] = 0.0)
                then
                    layers[layer].weights^.value[n, i] :=
                    layers[layer].saved_weights^.value[n, i];
clrscr;
gotoxy (1, 1);
reverse;
if modify
    then write ('Selected Connections
                Restored!  <RTN>')
    else write ('No Connections
                Restored!  <RTN>');
repeat
until keypressed;

```

```

normvid;
if layer >= net_description.num_layers
  then layer := 1;
for n := 2 to net_description.num_layers do
  begin
    disconnected := false;
    for j := 1 to layers[n].neurons do
      for i := 1 to layers[n - 1].neurons do
        if
          layers[n].weights^.value[i, j] = 0.0
        then disconnected := true;
      if disconnected
        then layers[n -
          1].FFConnection_kind := partial
        else layers[n -
          1].FFConnection_kind := fully;
    end;
  end;
end;
'3' : begin {restore full connectivity for the layer}
  saved := true;
  if layers[layer + 1].saved_weights <> nil
    then layers[layer+1].weights^ :=
      layers[layer+1].saved_weights^
    else saved := false; {single layer with no}
      {S_W poss?}
  if not saved
    then
      begin
        clrscr;
        gotoxy (1, 1);
        reverse;
        write ('Saved state doesn''t exist!');
        normvid;
        gotoxy (1, 2);
        write ('Connectivity Not Restored.
          <RTN> to Continue');
        repeat
          ch := readkey;
        until ch = #13;
      end
    else
      begin
        gotoxy (1, 1);
        reverse;
        write ('Connections Restored! <RTN>');
        repeat
          ch := readkey;
        until ch = #13;
      end
    end
  end
end

```



```

        normvid;
        ch := '>';
    end;
    for n := 2 to net_description.num_layers do
    begin
        disconnected := false;
        for j := 1 to layers[n].neurons do
            for i := 1 to layers[n - 1].neurons do
                if layers[n].weights^.value[i, j] =
                    0.0
                then disconnected := true;
            if disconnected
            then layers[n - 1].FFConnection_kind :=
                partial
            else layers[n - 1].FFConnection_kind :=
                fully;
            end;
        end;
    end;
'4' : begin
        {random connection removal}
        get_removal_probability (prob);    {math unit}
        remove_random_connections (prob, layer);
        {math unit}

        gotoxy (1, 1);
        reverse;
        write ('Connections Removed! <RTN>');
        repeat
            ch := readkey;
        until ch = #13;
        normvid;
        ch := '<';
    end;
'5' : begin
        {save weight state}
        clrscr;
        gotoxy (1, 1);
        reverse;
        write ('Previous saved state will be destroyed
            - Continue? Y/N');
        repeat
            ch := readkey
        until ch in ['Y', 'y', 'n', 'N'];
        normvid;
        if ch in ['Y', 'y']
        then
            begin
                for i := 2 to net_description.num_layers
                do
                    begin
                        if layers[i].saved_weights = nil
                        then new

```

```

                                (layers[i].saved_weights);
layers[i].saved_weights^ :=
                                layers[i].weights^;
    end;
    clrscr;
    gotoxy (1, 1);
    reverse;
    write ('Weights Saved! <RTN>');
    repeat
        ch := readkey;
    until ch = #13;
    normvid;
end
else
begin
    clrscr;
    gotoxy (1, 1);
    reverse;
    write ('Weights Not Saved! <RTN>');
    repeat
        ch := readkey;
    until ch = #13;
    normvid;
end;
end;
'6' : Display_Network (12); {display network}
#13 : begin                    {<RTN>}
    if str = 'Run Network' {From Display Mode}
    then if layer >= (net_description.num_layers
                    - 1)
        then layer := 1
        else layer := layer + 1;
    end;
end;
end;                            {case}
until ch in [#27]; {<ESC>}
end;    {Modify_Connections}

{-----}

```

APPENDIX G

Development System Input/Output Utility
Unit Listing
(Unit ioutil)

Appendix B through Appendix J constitute the
complete development system program listing

```

{-----}
{Unit ioutil provides file read/write routines and the}
{input of the next data input line and its proper}
{formatting for the algorithm in use}

```

```

{-----}

```

```

Unit ioutil;

```

Interface

```

uses nnglobal, mathutil, crt, printer;

```

```

Procedure Reverse;
Procedure Normvid;
Procedure Get_Input_File;
Procedure Save_Network;
Procedure Load_File;
Procedure Compile;
Procedure Print_Files;
Procedure Save_State (z : integer);
Procedure Save_Net_Option;
Procedure Save_Freq_Option;
Procedure readfile;
Procedure ReadTrainFile;
Procedure Next_Input;

```

Implementation

```

{-----}

```

```

Procedure Reverse;

```

```

begin
  textbackground (white);
  textcolor (black);
end;

```

```

{-----}

```

```

Procedure NormVid;

```

```

begin
  normvideo;
  textcolor (yellow);
end;

```

```

{-----}

```

```

Procedure Get_File_Name (var Name : string; var ch : char);

var
  File_OK : boolean;
  f       : integer;
  s       : string[80];

begin  {Get_File_Name}
  clrscr;
  repeat
    File_Ok := false;
    gotoxy (1, 20);
    write ('Enter File Name');
    gotoxy (1, 21);
    write ('"*" Indicates c:\pascal\infiles\');
    gotoxy (1, 22);
    write ('=> ');
    Readln (name);
    if name[1] = '*'
    then
      begin
        delete (name, 1, 1);
        s := 'c:\pascal\infiles\' + name;
        name := s;
      end;
    reverse;
    gotoxy (1, 23);
    write (name);
    gotoxy (1, 24);
    write ('File Name OK?  Y/N  <ESC>');
    normvid;
    repeat
      ch := readkey;
      gotoxy (27, 24);
    until ch in ['Y', 'y', 'N', 'n', #27];
    clrscr;
    if ch in ['Y', 'y']
    then File_OK := true;
  until File_OK or (ch = #27);
end;  {Get_File_Name}

{-----}

```

```
Procedure Get_Input_File;
```

```
var
```

```
  name : string;
  ch    : Char;
  f     : integer;
```

```
begin {Get_Input_File}
```

```
  ch := '6'; {Set to some value other than <ESC>}
```

```
  Get_File_Name (name, ch);
```

```
  if ch = #27
```

```
    then exit; {<ESC> set from get_file_name}
```

```
  if (infilename <> 'NONE SELECTED') and (length
                                           (InFileName) > 0)
```

```
    then
```

```
      begin
```

```
        close (infile); {close old file if open}
```

```
        infilename := 'NONE SELECTED';
```

```
      end;
```

```
  {$I-}
```

```
    assign (infile, name);
```

```
    reset (infile);
```

```
  {$I+}
```

```
  f := ioresult;
```

```
  if f <> 0 {not a valid name}
```

```
    then
```

```
      begin
```

```
        gotoxy (1, 1);
```

```
        reverse;
```

```
        write ('File Not Found! Hit any key to continue');
```

```
        normvid;
```

```
        repeat
```

```
          until keypressed;
```

```
      end
```

```
    else InFileName := name;
```

```
end; {Get_Input_File}
```

```
{-----}
```

```
Procedure Save_Network;
```

```
var
```

```
  name : string;
```

```
  ch   : char;
```

```
  i, f : integer;
```

```
  w, ws : weight_ptr;
```

```

begin      {Save_Network}
  repeat
    ch := '6'; {set to some value other than <ESC>}}
    Get_File_Name (name, ch);
    if ch = #27
      then exit;    {<ESC> set from get_file_name}
    {$I-}
      assign (savefile1, Name+'.1');
      reset (savefile1);
    {$I+}
    f := ioreult;
    if f = 0    {file already exists}
      then
        repeat
          gotoxy (1, 1);
          reverse;
          write ('File Exists!  Overwrite?  Y/N');
          normvid;
          read (ch);
          until ch in ['Y', 'y', 'N', 'n'];
        until ch in ['Y', 'y'];
    assign (savefile1, name+'.1');
    assign (savefile2, name+'.2');
    assign (savefile3, name+'.3');
    assign (savefile4, name+'.4');
    rewrite (savefile1);
    rewrite (savefile2);
    rewrite (savefile3);
    rewrite (savefile4);
    write (savefile1, net_description);
    close (savefile1);
    for i := 2 to net_description.num_layers do
      begin
        write (savefile4, layers[i].weights^);
        write (savefile4, layers[i].saved_weights^);
      end;
    close (savefile4);
    for i := 1 to net_description.num_layers do
      begin
        w := layers[i].weights; {Temporary pointer to weights}
        layers[i].weights := nil; {to be saved set to nil}
        ws := layers[i].saved_weights; {Temporary pointer}
        layers[i].saved_weights := nil; {saved set to nil}
        write (savefile2, layers[i]);{Save layer data to file}
        layers[i].weights := w; {reset to weights}
        layers[i].saved_weights := ws;{reset to saved weights}
      { write (savefile3, layers[i].connections^); }
      end;
  end;

```

```

close (savefile2);
close (savefile3);
end;    {Save_Network}

```

```
{-----}
```

```
Procedure Load_File;
```

```

var
  name      : string;
  ch        : char;
  i, f      : integer;

```

```
begin
```

```
  repeat
```

```
    ch := '6';    {set ch to something other than <ESC>}
    Get_File_Name (name, ch);
```

```
    if ch = #27
```

```
      then exit;    {<ESC> set from get_file_name}
```

```
    {$I-}
```

```
      assign (savefile1, name+'.1');
```

```
      reset (savefile1);
```

```
    {$I+}
```

```
    f := ioreult;
```

```
    if f <> 0    {file does not exists}
```

```
      then
```

```
        begin
```

```
          gotoxy (1, 1);
```

```
          reverse;
```

```
          write ('File Not Found!  Press <RTN> to
```

```
                continue');
```

```
          normvid;
```

```
          readln;
```

```
        end;
```

```
  until f = 0;
```

```
  assign (savefile1, name+'.1');
```

```
  assign (savefile2, name+'.2');
```

```
  assign (savefile3, name+'.3');
```

```
  assign (savefile4, name+'.4');
```

```
  reset (savefile1);
```

```
  reset (savefile2);
```

```
  reset (savefile3);
```

```
  reset (savefile4);
```

```
  for i := 1 to net_description.num_layers do {Initialize}
                                          {pointers to nil}
```

```
    begin
```

```
      if layers[i].weights <> nil
```

```
        then
```

```
          begin
```



```

        dispose (layers[i].weights);
        layers[i].weights := nil;
    end;
    if layers[i].saved_weights <> nil
    then
        begin
            dispose (layers[i].saved_weights);
            layers[i].saved_weights := nil;
        end;
    if layers[i].connections <> nil
    then
        begin
            dispose (layers[i].connections);
            layers[i].connections := nil;
        end;
    end;
    read (savefile1, net_description);
    net_description.save_state := false; {For File integrity}
                                        {always load false}
    net_description.iterate := 0; {0 when save_state is false}
    num_layers := net_description.num_layers;
    close (savefile1);
    for i := 1 to net_description.num_layers do
        begin
            read (savefile2, layers[i]);
            {read (savefile3, layers[i].connections^);} {Not}
                                                    {defined yet}
        end;
    close (savefile2);
    close (savefile3);
    Initialize_Weights;
    for i := 2 to net_description.num_layers do
        begin
            read (savefile4, layers[i].weights^);
            if layers[i].saved_weights = nil
            then new (layers[i].saved_weights);
            read (savefile4, layers[i].saved_weights^);
        end;
    close (savefile4);
end;    {Load_File}

{-----}

Procedure Compile;

begin    {Compile}
    {Not defined yet}
end;    {Compile}

```

```

{-----}

Procedure Print_Files;

var
  i, f, x, y, z : integer;
  count         : integer;
  ch            : char;

begin {Print_Files}
  clrscr;
  gotoxy (1, 1);
  reverse;
  write ('WARNING! Printing will destroy the current
         Network! Proceed? Y/N');
  normvid;
  repeat
    ch := readkey;
  until ch in ['Y', 'y', 'N', 'n'];
  if ch in ['N', 'n']
    then exit;
  if net_description.save_state = false
    then
      begin
        assign (savefile1, 'c:\pascal\infiles\netstate.1');
        assign (savefile2, 'c:\pascal\infiles\netstate.2');
        assign (savefile3, 'c:\pascal\infiles\netstate.3');
        assign (savefile4, 'c:\pascal\infiles\netstate.4');
      end;
  reset (savefile1);
  reset (savefile2);
  reset (savefile3);
  reset (savefile4);
  for i := 1 to max_layers do {Initialize pointers to nil}
    begin
      if layers[i].weights <> nil
        then
          begin
            dispose (layers[i].weights);
            layers[i].weights := nil;
          end;
      if layers[i].saved_weights <> nil
        then
          begin
            dispose (layers[i].saved_weights);
            layers[i].saved_weights := nil;
          end;
    end;
end;

```

```

    if layers[i].connections <> nil
    then
        begin
            dispose (layers[i].connections);
            layers[i].connections := nil;
        end;
    end;
read (savefile1, net_description); {net description data}
num_layers := net_description.num_layers;
close (savefile1);
for i := 1 to net_description.num_layers do
    begin
        read (savefile2, layers[i]); {layer data}
        {read (savefile3, layers[i].connections^);} {Not}
                                                {defined yet}
    end;
writeln (lst, 'NET DESCRIPTION');
writeln (lst);
with net_description do
    begin
        writeln (lst, net_name);
        writeln (lst, 'Net Architecture ', ord (net_arch));
        writeln (lst, num_layers, ' layers');
        writeln (lst, 'Activation Type ', ord (activation));
        writeln (lst, 'Threshold ', threshold:4:2);
        writeln (lst, 'Learning Type ', ord (learning));
        writeln (lst, 'Factor - ', factor:4:3, ' Factor1 - ',
            factor1:4:3, ' Factor2 - ', factor2:4:3, '
            Factor3 - ', factor3:4:3);
        writeln (lst, 'Momentum ', momentum:4:2);
        writeln (lst, 'Input values ', one_value:3:1, ' / ',
            zero_value:3:1);
        writeln (lst);
    end;
for i := 1 to num_layers do
    begin
        writeln (lst, 'LAYER ', i);
        writeln (lst, ' Connection type ', ord
            (layers[i].FFconnection_kind));
        writeln (lst, ' Number of Neurons ',
            layers[i].neurons);
        writeln (lst, ' Layer threshold ',
            layers[i].neural_set.threshold[1]:4:2);
    end;
writeln (lst);
count := 1;
x := net_description.iterate;
reset (savefile2); {prime pump for repeat loop - set to}
                    {first record}

```

```

repeat
  for i := 1 to net_description.num_layers do
    begin
      read (savefile2, layers[i]);    {layer data}
      {read (savefile3, layers[i].connections^);} {Not}
                                          {defined yet}
    end;
    initialize_weights; {layers data had weight ptr = nil}
    writeln (lst, 'ITERATION NUMBER ', count * x);
    writeln (lst, 'Order is - Binary value, Real value,
                                          Threshold, Rate');
    writeln (lst);
    for i := 1 to num_layers do
      begin
        writeln (lst, 'LAYER ', i);
        writeln (lst);
        for y := 1 to layers[i].neurons do
          begin
            write (lst, ' ');
            write (lst, y, '. ',
                  layers[i].neural_set.binary_value[y], ' ');
            write (lst,
                  layers[i].neural_set.real_value[y]:4:4, ' ');
            write (lst,
                  layers[i].neural_set.threshold[y]:4:2, ' ');
            writeln (lst, layers[i].neural_set.rate);
          end;
        if i > 1    {layer 2 and above for weights}
        then
          begin
            read (savefile4, layers[i].weights^);
            writeln (lst);
            writeln (lst, 'Weight values for layer ', i);
            writeln (lst);
            for y := 1 to layers[i].weights^.row_length do
              begin
                write (lst, y, '. ');
                for z := 1 to
                  layers[i].weights^.col_length do
                  write (lst, layers[i].weights^.value[z,
                    y]:4:2, ' ');
                writeln (lst);
              end;
            writeln (lst);
          end;
        end;
      end;
    count := count + 1;
  until eof (savefile2);
  close (savefile2);

```

```

close (savefile3);
close (savefile4);
net_description.save_state := false;
net_description.iterate := 0;
end; {Print_Files}

{-----}

Procedure Save_State (z : integer);

var
  w, ws : weight_ptr;
  ch     : char;
  i     : integer;

begin {Save_State}
  if (net_description.save_state = true) and (z = 0)
    {manually selected for save}
  then
    begin
      gotoxy (1, 1);
      write ('Do you want to purge previous Savefiles?
              Y/N/<ESC>');

      repeat
        ch := readkey;
      until ch in ['Y', 'y', 'N', 'n', #27];
      if ch in ['Y', 'y']
        then
          begin
            rewrite (savefile1);
            rewrite (savefile2);
            rewrite (savefile3);
            rewrite (savefile4);
          end
        else if ch = #27
          then exit; {if 'N' then continue with no}
                   {rewrite}
        end
    else if net_description.save_state = false
    then
      begin
        assign (savefile1, 'c:\pascal\infiles\netstate.1');
        assign (savefile2, 'c:\pascal\infiles\netstate.2');
        assign (savefile3, 'c:\pascal\infiles\netstate.3');
        assign (savefile4, 'c:\pascal\infiles\netstate.4');
        rewrite (savefile1);
        rewrite (savefile2);
        rewrite (savefile3);
        rewrite (savefile4);
      end
    end
end;

```

```

        net_description.save_state := true;
    end; {if save_state true than don't rewrite - just}
        {continue}
if (net_description.iterate = z) or (z = 0)
    then write (savefile1, net_description); {Only save}
        {once}
for i := 2 to net_description.num_layers do
    write (savefile4, layers[i].weights^);
for i := 1 to net_description.num_layers do
    begin
        w := layers[i].weights; {Temporary pointer to weights}
        layers[i].weights := nil; {to be saved set to nil}
        ws := layers[i].saved_weights; {Temporary pointer}
        layers[i].saved_weights := nil; {saved set to nil}
        write (savefile2, layers[i]);{Save layer data to file}
        layers[i].weights := w; {reset to weights}
        layers[i].saved_weights := ws;{reset to saved weights}
    {
        write (savefile3, layers[i].connections^); }
    end;
end; {Save_State}

{-----}

```

```

Procedure Save_net_Option;

```

```

    var
        ch   : char;
        f    : integer;

begin {Save_Net_Option}
    clrscr;
    if net_description.save_state = true
    then
        begin
            gotoxy (1, 1);
            reverse;
            write ('Overwrite Existing NetState File?
                    Y/<ESC>');

            gotoxy (1, 2);
            normvid;
            write ('                OR                ');
            gotoxy (1, 3);
            reverse;
            write ('Toggle Net Save Option to OFF? (Close files)
                    -T-');

            normvid;
            repeat
                ch := readkey;
            until ch in ['Y', 'y', 'T', 't', #27];

```

```

if ch in ['T', 't']
  then
    begin
      net_description.iterate := 0;
      net_description.save_state := false;
      close (savefile1);
      close (savefile2);
      close (savefile3);
      close (savefile4);
      exit;
    end
  else if ch = #27
    then exit;
  end
else {net_description.save_state = false}
  begin
    assign (savefile1, 'c:\pascal\infiles\netstate.1');
    assign (savefile2, 'c:\pascal\infiles\netstate.2');
    assign (savefile3, 'c:\pascal\infiles\netstate.3');
    assign (savefile4, 'c:\pascal\infiles\netstate.4');
    if net_description.iterate = 0
      then net_description.iterate := 1;
    end;
    rewrite (savefile1);
    rewrite (savefile2);
    rewrite (savefile3);
    rewrite (savefile4);
    net_description.save_state := true;
  end; {Save_Net_Option}

```

```
{-----}
```

```
Procedure Save_Freq_Option;
```

```
var
```

```
  n, f : integer;
```

```
begin {Save_Freq_Option}
```

```
  repeat
```

```
    clrscr;
```

```
    gotoxy (1, 20);
```

```
    writeln ('Enter Number of Iterations Between Saves (0 -
                                                    1000)');
```

```
    write ('Enter 0 for no saves');
```

```
    gotoxy (1, 22);
```

```
    write ('=> ');
```

```
    {$I-}
```

```
    readln (n);
```

```
    {$I+}
```

```

    f := ioresult;
until (f = 0) and (n >= 0) and (n <= 1000);
if (n > 0) and (net_description.save_state = false)
then
    begin
        gotoxy (1, 1);
        reverse;
        write ('Ensure Save State it toggled to "ON" - <RTN>
                to continue');

        normvid;
        readln;
    end;
net_description.iterate := n;
if n = 0
then net_description.save_state := false;
end;    {Save_Freq_Option}

{-----}

Procedure Set_Input_Layer;

var
    i : integer;

begin    {Set_Input_Layer}
    with layers[1] do
        begin
            for i := 1 to neurons do
                begin
                    neural_set.binary_value[i] := In_Buffer[i];
                    if neural_set.binary_value[i] = 1
                    then neural_set.real_value[i] :=
                                net_description.one_value
                    else neural_set.real_value[i] :=
                                net_description.zero_value;
                end;
            end;    {with layers[1]}
        end;    {Set_Input_Layer}

{-----}

Procedure ReadTrainFile;

var
    i, x : integer;

begin    {ReadTrainFile}
    if eof (infile)
    then reset (infile);    {If at the end then start over}

```



```

for i := 1 to layers[1].neurons do
  begin
    read (infile, x);
    In_Buffer [i] := x;
  end;
readln (infile); {Advance to next line - training values}
for i := 1 to layers [net_description.num_layers].neurons
  do
    begin
      read (infile, x);
      Out_Buffer [i] := x;
      if x = 1
        then r_out_buffer[i] := net_description.one_value
        else r_out_buffer[i] := net_description.zero_value;
      end;
      readln (infile); {Advance to next input line}
    end; {ReadTrainFile}

{-----}

Procedure ReadFile;

var
  i, x : integer;

begin {readfile}
  if eof (infile)
    then reset (infile); {If at the end then start over}
  for i := 1 to layers[1].neurons do
    begin
      read (infile, x);
      In_Buffer [i] := x;
    end;
    readln (infile); {Advance to next line}
    readln (infile); {Skip training vector pair}
  end; {readfile}

{-----}

Procedure Next_Input;{Sets buffers to training set values}
  {if not a training scenario - out_buffer values}
  {will be ignored}

var
  i : integer;

begin {Next_Input}
  if Train {Training Mode}
    then
      case net_description.training of

```

```

    unsupervised : ReadFile;
    supervised   : ReadTrainFile;
    zip          : ReadFile;
end {case}
else {Run Mode}
if net_description.learning = hopfield
then
begin
    if not eof (infile) {Do not read input except}
    then readfile      {on first iteration with}
                        {Hopfield Net}
    else exit;         {Do not set input layer}
end
else ReadFile; {Run mode and not Hopfield - Sup or}
                        {Unsup training}
Set_Input_Layer; {What about recurrent nets????}
end; {Next_Input}

{-----}

end. {ioutil}

```

APPENDIX H

Development System Math Unit Listing
(Unit Math)

Appendix B through Appendix J constitute the
complete development system program listing

```

{-----}

{This unit (Math) includes all the matrix and vector}
{algebra routines, neuron activation, and learning}
{algorithms.}

{-----}

unit math;

interface

uses nnglobal, crt, ioutil;

Procedure Calculate_Output;
Procedure Learning_Rule;
Procedure Corrupt_input (prob : real);
Procedure Remove_Random_Neurons (prob : real; layer :
integer);
Procedure Remove_Random_Connections (prob : real; layer :
integer);
Procedure Get_Re moval_Probability (var prob : real);
Procedure Train_Sup_Net;
Procedure Train_Unsup_Net (var ch : char);
Procedure Calc_Sup_Net;
Procedure Calc_Unsup_Net;

Implementation

{-----}

Procedure Error_Routine;

begin {Error_Routine}
  begin
    writeln ('Error occurred'); {Needs more functionality}
    readln;
  end;
end; {Error_Routine}

{-----}

Procedure Delta_Calculation (n : real);

var
  delta      : real;
  correction : real;
  i, k, j    : integer;
  x, y      : integer;

```

```

begin {Delta_Calculation}                                {Make work for
multiple layers!!!!}
  with layers[net_description.num_layers] do {output layer}
  begin
    for i := 1 to neurons do
      begin
        delta := r_out_buffer[i] -
                neural_set.real_value[i];
        for j := 1 to layers[1].neurons do
          begin
            Correction := n * delta *
                layers[1].neural_set.real_value[j];
            weights^.value[i, j] := weights^.value[i, j] +
                correction;
          end;
        end;
      end;
    end;
  end; {Delta_Calculation}

```

```

{-----}

```

```

Procedure Corrupt_input (prob : real);
var
  i, x : integer;
begin {Corrupt_input}
  randomize;
  with layers[1] do
    begin
      if net_description.learning = Hopfield
      then
        begin
          reset (infile);
          for i := 1 to neurons do
            begin
              read (infile, x);
              neural_set.binary_value[i] := x;
            end;
          readln (infile);
        end;
      for i := 1 to neurons do
        begin
          x := neural_set.binary_value[i];
          if random < prob {reverse values}
          then
            if x = 1
            then x := 0
            else x := 1;
          end;
        end;
      end;
    end;
  end;

```

```

neural_set.binary_value[i] := x; {set value to
                                   input file value}
if x = 1
  then neural_set.real_value[i] :=
        net_description.one_value
  else neural_set.real_value[i] :=
        net_description.zero_value;
if net_description.learning = hopfield
  then
  begin {Force output to input values for
        initialization}
    layers[2].neural_set.binary_value[i] :=
        neural_set.binary_value[i];
    layers[2].neural_set.real_value[i] :=
        neural_set.real_value[i];
  end;
end;
end; {with layers..}
end; {Corrupt_input}

{-----}

Procedure Remove_Random_Neurons (prob : real; layer :
                                   integer);

var
  i, j : integer;

begin {Remove_Random_Neurons}
  randomize;
  for j := 1 to layers[layer].neurons do
  begin
    if random < prob {remove neuron}
    then
      begin
        if layer < net_description.num_layers
        then
          for i := 1 to layers[layer + 1].neurons do
            layers[layer + 1].weights^.value[i, j] :=
              0.0;
          for i := 1 to layers[layer - 1].neurons do
            layers[layer].weights^.value[j, i] := 0.0;
          end;
        end;
      end;
    end;
  end; {Remove_Random_Neurons}

{-----}

```

```

Procedure Remove_Random_Connections (prob : real; layer :
                                     integer);

var
  i, j      : integer;
  connected : boolean;

begin {Remove_Random_Connections}
  connected := true;
  if layers[layer + 1].saved_weights <> nil {restore
                                             weights if possible}
  then layers[layer + 1].weights^:= layers[layer +
                                             1].saved_weights^;
  randomize;
  for j := 1 to layers[layer].neurons do
    for i := 1 to layers[layer + 1].neurons do
      if random < prob {remove connection}
      then
        begin
          layers[layer + 1].weights^.value[i, j] := 0.0;
          connected := false;
        end;
      if not connected {For network display}
      then layers[layer].FFConnection_kind := partial
      else layers[layer].FFConnection_kind := fully;
    end; {Remove_Random_Connections}

  {-----}

Procedure Get_Removal_Probability (var prob : real);

var
  result : integer;

begin {Get_Removal_Probability}
  repeat
    clrscr;
    gotoxy (20, 8);
    write ('Enter Neuron Removal Probability (', prob:2:2,
          ')');

    gotoxy (1, 21);
    write ('=> ');
    {$I-};
    readln (prob); {Fix for rtn or esc!!!!}
    result := ioread;
    {$I+}
    {Check for real number and correct probability}
  until result < 0 or result > 1;
end;

```

```

if (result <> 0) or ((Prob > 1) or (Prob < 0)) {Not
                                     correct value}
  then
    begin
      gotoxy (1, 1);
      reverse;
      write ('Illegal real number or probability');
      normvid;
      gotoxy (4, 23);
      write ('<RTN> to Continue');
      repeat
        until keypressed;
      gotoxy (1, 23);
      clreol;
    end;
  until result = 0;
end;    {Get_Removal_Probability}

{-----}

Procedure Back_Propagation (n : real);

var
  delta, delta1, delta2, delta3 : real;
  correction, m_correction      : real;
  i, x, y, j, k                 : integer;
  {M                             : weight_matrix;}
  vector                        : DeltaVectorType;
  origmode                      : word;

{-----}

{Matrix_Transpose changes rows of matrix to columns of the}
{output matrix      }

Procedure Weight_Matrix_Transpose (k : layerange);

var
  c    : integer;
  r    : integer;

begin  {Weight_Matrix_Transpose}
  for r := 1 to layers[k].saved_weights^.row_length do
    {Transpose rows}
    for c := 1 to layers[k].saved_weights^.col_length do
      {to columns}
      M.value [r, c] := layers[k].saved_weights^.value
                                     [c, r];
  M.col_length := layers[k].saved_weights^.row_length;

```



```

    M.row_length := layers[k].saved_weights^.col_length;
end;    {Weight_Matrix_Transpose}

{-----}

Function Delta_Dot_Product (Vec : DeltaVectorType; c, layer
                           : integer) : real;

var
    hold : real;
    j    : integer;

begin {Delta_Dot_Product}
    hold := 0.0;
    for j := 1 to layers[layer].neurons do
        hold := hold + (vec[j] * M.value[c, j]);
    Delta_Dot_Product := hold;
end;    {Delta_Dot_Product}

{-----}

Procedure Matrix_Vector_Multiply (vec : DeltaVectorType;
    var vector : DeltaVectorType; layer : layerrange);
var
    c : integer;

begin {Weight_Matrix_Multiply}
    for c := 1 to layers[layer-1].neurons do
        vector[c] := Delta_Dot_Product (vec, c, layer);
    end;    {Weight_Matrix_Multiply}

{-----}

begin {Back_Propogation}
    with layers[net_description.num_layers] do {output Layer}
        begin
            M := saved_weights^; {M = weights at time T-1};
            saved_weights^ := weights^; {set saved_weights to
                                         time T}

            for i := 1 to neurons do
                if abs (r_out_buffer[i] - neural_set.real_value[i])
                    >= net_description.factor1 {Train only if out of
                                                tolerance}
                then
                    begin
                        delta3 := r_out_buffer[i] -
                            neural_set.real_value[i];    {tgt-out}

```

```

if net_description.activation = mod_sigmoid
  then delta1 := 0.5 +
        neural_set.real_value[i] {out}
  else delta1 := neural_set.real_value[i];
delta2 := 1 - delta1; {1 - out}
delta := delta1 * delta2 * delta3; {out(1 -
                                out)(tgt - out)}
layers[net_description.num_layers].
  delta_vector[i] := delta;
for j := 1 to layers[net_description.
  num_layers - 1].neurons do
begin
  if weights^.value[i, j] = 0.0 {not
                                connected}
  then
    begin {do nothing}
    end
  else
    if (delta1 * delta2) >=
      net_description.factor2
    then {neuron not saturated}
    begin
      m_correction :=
        net_description.momentum *
        (weights^.value[i, j]
          - M.value[i, j]);
{- momentum correction =  $\alpha$  (weight (t) - weight (t-1))-}
      Correction := (n * delta *
        layers[net_description.
num_layers-1].neural_set.real_value[j]) + m_correction;
      weights^.value[i, j] :=
        weights^.value[i, j] + correction;
    end
    else weights^.value[i, j] := (-5 +
      10/(1 + exp (-weights^.value[i,
        j]/5)));
    {Out approaching saturation - desaturate the neuron}
    end;
  end
  else
    layers[net_description.num_layers].
      delta_vector[i] := 0.0;
end; {with}
for k := (net_description.num_layers) downto 3 do
begin
  Weight_Matrix_Transpose (k);
  matrix_vector_multiply (layers[k].delta_vector,
    vector, k);
  M := layers[k-1].saved_weights^{weights at time t-1}

```

```

layers[k-1].saved_weights^ := layers[k-1].weights^;
                                {weights at t}
for i := 1 to layers[k-1].neurons do
begin
  if net_description.activation = mod_sigmoid
  then delta1 := 0.5 + layers[k-1].neural_set.
                                real_value[i]
  else delta1 := layers[k-1].neural_set.
                                real_value[i]; {out}
  delta2 := 1 - delta1;      {1- out}
  delta := delta1 * delta2 * vector[i];
                                {(out)(1-out)(Σδw)}
  layers[k-1].delta_vector[i] := delta;
  for j := 1 to layers[k-2].neurons do
  begin
    if layers[k-1].weights^.value[i, j] = 0.0
                                {not connected}
    then
      begin {do nothing}
      end
    else
      if (delta1 * delta2) >=
                                net_description.factor2
      then
        begin
          m_correction :=
            net_description.momentum *
            (layers[k-1].weights^.value[i,
              j] - M.value[i, j]);
          correction := (n * delta *
            layers[k-2].neural_set.
            real_value[j]) + m_correction;
          layers[k-1].weights^.value[i, j] :=
            layers[k-1].weights^.
            value[i, j] + correction;
        end
      else layers[k-1].weights^.value[i, j] :=
            (-5 + 10/(1 + exp (-layers[k-1].
            weights^.value[i, j]/5)));
    {Out approaching saturation - desaturate the neuron}
  end;
end;
end;
end;      {Back_Propogation}

{-----}

```

```
Procedure Signal_Hebb;
```

```
var
```

```
  i, j, k      : integer;
  delta1, delta2 : real;
  saturation   : real;
```

```
begin {signal_hebb}
```

```
  for i := 2 to net_description.num_layers do
```

```
    begin
```

```
      for j := 1 to layers[i].neurons do
```

```
        begin
```

```
          if net_description.activation = mod_sigmoid
```

```
            then delta1 := 0.5 +
```

```
              layers[i].neural_set.real_value[j]
```

```
            else delta1 := layers[i].neural_set.
```

```
              real_value[j]; {out}
```

```
          delta2 := 1 - delta1; {1- out}
```

```
          Saturation := (delta1 * delta2);
```

```
          if saturation < net_description.factor2
```

```
            {de-saturate neuron}
```

```
          then
```

```
            for k := 1 to layers[i-1].neurons do
```

```
              layers[i].weights^.value[j, k] := (-5 +
```

```
                10/(1 + exp (-layers[i].weights^.
                  value[j, k]/5)))
```

```
            else for k := 1 to layers[i-1].neurons do
```

```
              begin
```

```
                if ((layers[i].neural_set.real_value[j] >=
                    net_description.threshold) and
```

```
                    (layers[i-1].neural_set.real_value[k] >=
                    net_description.threshold))
```

```
                then
```

```
                  begin
```

```
                    if (layers[i].neural_set.real_value[j]
                        < 0) and (layers[i-1].neural_set.
```

```
                        real_value[k] < 0)
```

```
                    then
```

```
                      layers[i].weights^.value[j, k] :=
```

```
                        layers[i].weights^.value[j, k] -
```

```
                        (layers[i].neural_set.
```

```
                          real_value[j] * layers[i-1].
```

```
                          neural_set.real_value[k])
```

```
                    else
```

```
                      layers[i].weights^.value[j, k] :=
```

```
                        layers[i].weights^.value[j, k] +
```

```
                        (layers[i].neural_set.
```

```
                          real_value[j] * layers[i-1].
```

```
                          neural_set.real_value[k]);
```

```
                  end
```

```
                end
```

```
              end
```

```
            end
```

```
          end
```

```
        end
```

```
      end
```

```
    end
```

```
end {signal_hebb};
```

```

                end
            else
                layers[i].weights^.value[j, k] :=
                    layers[i].weights^.value[j, k] -
                    (layers[i].neural_set.real_value[j] *
                    layers[i-1].neural_set.real_value[k])
            end;
        end;
    end;
end;    {signal_hebb}

{-----}

Procedure user_defined;

begin    {other}
end;    {other}

{-----}

Procedure Madline;

begin    {Madline}
end;    {Madline}

{-----}

Procedure Adline;

begin    {Adline}
end;    {Adline}

{-----}

Procedure Learning_Rule;

begin {Learning_Rule}
    case net_description.learning of
        delta: Delta_Calculation (net_description.factor);
                {gain factor param}
        backp: Back_Propropagation (net_description.factor);
        Hebb : Signal_Hebb;
        Other: User_defined;
        madaline : madline;
        adaline : adline;
    end; {case}
end; {Learning_Rule}

{-----}

```

```
Procedure Calculate_Output;
```

```
type
```

```
  SumType = record
    value : packed array [1..max_bodies] of real;
    length : integer;
  end;
```

```
var
```

```
  layer, i, n, y : integer;
  vector, sum, out : SumType;
  origmode : word;
```

```
{-----}
```

```
Function Weight_Dot_Product (Vector : SumType; c, i :
integer) : real;
```

```
var
```

```
  hold : real;
  j : integer;
```

```
begin {Weight_Dot_Product}
```

```
  hold := 0.0;
```

```
  for j := 1 to vector.length do
```

```
    begin
```

```
      hold := hold + (vector.value[j] *
                      layers[i].weights^.value[c, j]);
```

```
    end;
```

```
  Weight_Dot_Product := hold;
```

```
end; {Weight_Dot_Product}
```

```
{-----}
```

```
Procedure Weight_Matrix_Multiply (vector : SumType; layer :
layerange; var sum : SumType);
```

```
var
```

```
  c : integer;
```

```
begin {Weight_Matrix_Multiply}
```

```
  for c := 1 to layers[layer].neurons do
```

```
    sum.value[c] := Weight_Dot_Product (vector, c, layer);
```

```
    sum.length := layers[layer].neurons;
```

```
end; {Weight_Matrix_Multiply}
```

```
{-----}
```

```

Procedure Calculate_Activation (sum : SumType; layer :
                               layerange; var out : SumType);

var
  i : integer;

begin    {Calculate_Activation}
  case net_description.activation of
    Threshold : begin
      for i := 1 to sum.length do
        begin
          if sum.value[i] >
              net_description.threshold
          then
            begin {fires if above threshold}
              out.value[i] :=
                net_description.one_value;
              layers[layer].neural_set.
                binary_value[i] := 1;
              layers[layer].neural_set.
                real_value[i] :=
                net_description.one_value;
            end
          else
            begin
              out.value[i] :=
                net_description.zero_value;
              layers[layer].neural_set.
                binary_value[i] := 0;
              layers[layer].neural_set.
                real_value[i] :=
                net_description.zero_value;
            end;
          end;
        end;
      end;
    Sigmoid : begin
      for i := 1 to sum.length do
        begin
          out.value[i] := (1/(1 + exp
              (-sum.value[i])));
          if out.value[i] >=
              net_description.threshold
          then
            layers[layer].neural_set.
              binary_value[i] := 1
          else
            layers[layer].neural_set.
              binary_value[i] := 0;
            layers[layer].neural_set.

```

```

                                real_value[i] := out.value[i];
                                end;
                                end;
Mod_Sigmoid : begin
    for i := 1 to sum.length do
    begin
        out.value[i] := -0.5 + (1/(1 + exp
                                (-sum.value[i])));
        if out.value[i] >=
                                net_description.threshold
        then
            layers[layer].neural_set.
                binary_value[i] := 1
        else
            layers[layer].neural_set.
                binary_value[i] := 0;
        layers[layer].neural_set.
            real_value[i] := out.value[i];
        end;
    end;
    end;
HypTangent : begin
    end;
end; {case}
out.length := sum.length;
end; {Calculate_Activation}

{-----}

begin {Calculate_Output}
    with layers[1] do
        begin
            for i := 1 to neurons do
                vector.value[i] := neural_set.real_value[i];
                {vector.value[neurons + 1] := 1; {bias input}
            vector.length := neurons;
            end; {with layers[1]}
            for layer := 2 to net_description.num_layers do
                begin
                    Weight_Matrix_Multiply (vector, layer, sum);
                    Calculate_Activation (sum, layer, out);
                    vector := out; {Out becomes input for next layer
                                    calculations}
                end;
            end;
        end; {Calculate_Output}

{-----}

```



```

Procedure Calc_Sup_Recur_Net;

begin {Calc_Recur_Net}
end; {Calc_Recur_Net}

{-----}

Procedure Calc_Sup_Net;

begin {Calc_Sup_Net}
  if net_description.net_arch = feedforward
  then
    begin
      next_input;          {ioutil unit}
      calculate_output;    {math unit}
    end
  else calc_sup_recur_net;
end; {Calc_Sup_Net}

{-----}

Procedure Calc_Unsup_Recur_Net;

var
  converge : boolean;
  i         : integer;

begin {Calc_Unsup_Recur_Net}
  if net_description.learning = Hopfield
  then
    begin
      next_input;      {ioutil}
      Converge := true;
      Calculate_Output; {math Unit}
      for i := 1 to
        layers[net_description.num_layers].neurons do
      begin
        if layers[net_description.num_layers].
          neural_set.binary_value[i]
          <> layers[1].neural_set.binary_value[i]
          then converge := false;
        layers[1].neural_set.real_value[i] :=
          layers[net_description.num_layers].
            neural_set.real_value[i];
        layers[1].neural_set.binary_value[i] :=
          layers[net_description.num_layers].
            neural_set.binary_value[i];
      end; {for i := 1 to ...}
    end
  end;

```



```

        if i <> j
            then layers[2].weights^.value[i,
                j] := layers[2].weights^.
                    value[i, j] + (layers[1].
                        neural_set.real_value[i] *
                            layers[1].neural_set.
                                real_value[j]);
                write ('*');
            end;
        close (infile);
        infilename := 'NONE SELECTED';
        gotoxy (1, 2);
        write ('Hopfield Net Initialized');
        repeat
            until keypressed;
        gotoxy (1, 1);
        clreol;
        gotoxy (1, 2);
        clreol;
        ch := #27;    {<ESC> out of net output}
    end;
    other      : begin    {Provisions for user definition}
                end;
end;          {case}
end;          {Train_Unsup_Recur_Net}

{-----}

Procedure Train_Sup_Recur_Net;

begin    { Train_Sup_Recur_Net}
    case net_description.learning of
        other : begin
                end;
    end;    {case}
end;      { Train_Sup_Recur_Net}

{-----}

Procedure Train_Unsup_Net (var ch : char);

var
    i, j, num, x : integer;

begin    {Train_Unsup_Net}
    if net_description.net_arch = feedforward
    then
        begin
            Calc_Unsup_Net;

```

```
        Learning_Rule;      {Math unit}
    end
    else train_unsup_recur_net (ch);
end;      {Train_Unsup_Net}

{-----}

Procedure Train_Sup_Net;

begin    {Train_Sup_Net}
    if net_description.net_arch = feedforward
    then
        begin
            Calc_Sup_Net;
            Learning_Rule;      {Math unit}
        end
    else train_sup_recur_net;
end;      {Train_Sup_Net}

{-----}

end.    {Math Unit}
```

APPENDIX I

Development System Network Operations Unit Listing
(Unit Ops_Stuf)

Appendix B through Appendix J constitute the
complete development system program listing

```

{-----}
{Unit Op_stuff provides the transition entry point from the}
{menu system to the display (graphics) mode via either the}
{Training Mode or the Run Mode.}
{-----}

Unit Ops_Stuf;

Interface

uses crt, graph, nnglobal, grafstuf, mathutil;

    Procedure Training (var Flag : Char);
    Procedure Run_Program (var Flag : Char);

Implementation

{-----}

{Entry to display via training}

Procedure Training (var Flag : Char);

var
    ch          : char;
    semaphore   : integer;
    i           : integer;
    f           : integer;
    check       : boolean;

begin {Training}
    {$I-}
    check := eof (infile);           {check for open file}
    {$I+}
    f := ioresult;
    if f <> 0
        then
            begin
                clrscr;
                gotoxy (1, 1);
                reverse;
                write ('Input File Not Open!! - Hit any key to
                        continue');

                normvid;
                repeat
                until keypressed;
                exit; {return to program operations menu}
            end
        end;
end;

```

```

    end;
SetGraphMode (graphmode);
ch := '1';                                     {Initialize}
if net_description.learning = backp
  then Init_Saved_Weights;                     {mathutil unit}
semaphore := 2;
repeat
  case semaphore of
    1 : Display_Memory (ch, Semaphore);        {In grafstuf}
    2 : Display_Net_Output (ch, Semaphore);    {In grafstuf}
    3 : begin
        Net_Display (9);                       {In grafstuf}
        semaphore := 2;   {Came from Display_Net_Output}
      end;
    4 : begin
        Net_Display (8);                       {In grafstuf}
        semaphore := 1;   {Came from Display_Memory}
      end;
  end; {case}
until ch = #27;                                {<ESC> for Terminate}
RestoreCrtMode;
end;      {Training}

```

```

{-----}

```

```

{Entry to display via run mode}

```

```

Procedure Run_Program (var Flag : Char);

```

```

var

```

```

  ch          : char;
  Semaphore   : integer;
  f, i, x     : integer;
  check       : boolean;

```

```

begin {Run_Program}

```

```

  {$I-}
  check := eof (infile);           {check for open file}
  {$I+}

```

```

  f := ioresult;

```

```

  if f <> 0

```

```

    then

```

```

      begin

```

```

        clrscr;

```

```

        gotoxy (1, 1);

```

```

        reverse;

```

```

        write ('Input File Not Open!! - Hit any key to
               continue');

```

```

        normvid;

```

```

        repeat
        until keypressed;
        exit;      {return to program operations menu}
    end;
if net_description.learning = hopfield
    then reset (infile); {reset for hopfield special case}
SetGraphMode (graphmode);
ch := '1';      {Initialize}
semaphore := 2;
repeat
    case semaphore of
        1 : Display_Memory (ch, Semaphore);      {In grafstuf}
        2 : Display_Net_Output (ch, Semaphore); {In grafstuf}
        3 : begin
            Net_Display (9);      {In grafstuf}
            semaphore := 2; {Came from Display_Net_Output}
        end;
        4 : begin
            Net_Display (8);      {In grafstuf}
            semaphore := 1;      {Came from Display_Memory}
        end;
    end; {case}
until ch = #27;      {<ESC> for Terminate}
RestoreCrtMode;
end;      {Run_Program}

{-----}

end.      {Ops_Stuf}

```


APPENDIX J

Development System Math Utility Unit Listing
(Unit MathUtil)

Appendix B through Appendix J constitute the
complete development system program listing

```

{-----}
{Unit mathutil provides various initialization routines and}
{various other utilities}
{-----}

Unit MathUtil;

Interface

uses
  nnglobal, crt, graph;

Procedure Initialize_Weights;
Procedure Init_Saved_Weights;
Procedure Initialize_stuff;
Procedure Initialize_Layers;
Procedure Repeat_Input (var ch : char);
Procedure GetChar;
Procedure GetLine;
Procedure Process_Number (var int: integer);
Procedure Get_Network_Name (var S : string);
Function HeapFunc (size : word) : integer;

Implementation

{-----}

{F+}
Function HeapFunc (size : word) : integer;

begin
  gotoxy (1, 12);
  write ('Error in heap allocation of ', size, ' Hit any key
                                               to continue');

  HeapFunc := 1;
  repeat
  until keypressed;
end;
{$F-}

{-----}

```

```

Procedure Initialize_Weights;

var
  i, j, k : integer;

begin {Initialize_Weights}
  heapError := @heapfunc;
  for i := 2 to net_description.num_layers do
    begin
      if layers[i].weights = nil
        then new (layers [i].weights);
      if layers[i].weights = nil
        then exit;    {Heap overflow}
      for j := 1 to max_bodies do
        for k := 1 to max_bodies do
          layers[i].weights^.value[j, k] := 0.0;
        layers[i].weights^.col_length := layers[i].neurons;
          {Reset}
        layers[i].weights^.row_length := layers[i-1].neurons;
      end;
      if max_layers > net_description.num_layers
        then for i := max_layers downto
              (net_description.num_layers + 1) do
          begin
            if layers[i].weights <> nil
              then
                begin
                  dispose (layers[i].weights);
                  layers[i].weights := nil;
                end;
            if layers[i].saved_weights <> nil
              then
                begin
                  dispose (layers[i].saved_weights);
                  layers[i].saved_weights := nil;
                end;
          end;
          net_description.set_weights := true;
          net_description.random_weights := false;
        end; {Initialize_Weights}

    {-----}
  
```

```

Procedure Init_Saved_Weights;

var
  i, j, k : integer;

begin
  {Init_Saved_Weights}
  heapError := @heapfunc;
  for i := 2 to net_description.num_layers do
    begin
      if layers[i].saved_weights = nil
        then new (layers[i].saved_weights);
      if layers[i].saved_weights = nil
        then exit;      {Heap overflow}
      for j := 1 to max_bodies do
        for k := 1 to max_bodies do
          layers[i].saved_weights^.value[j, k] := 0.0;
        layers[i].saved_weights^ := layers[i].weights^;
      end;
      if max_layers > net_description.num_layers
        then for i := max_layers downto
              (net_description.num_layers + 1) do
          begin
            if layers[i].saved_weights <> nil
              then
                begin
                  dispose (layers[i].saved_weights);
                  layers[i].saved_weights := nil;
                end;
          end;
    end;
  {Init_Saved_Weights}

  {-----}

Procedure Initialize_Layers;

var
  i, j : integer;

begin
  {Initialize_Layers}
  num_layers := 3;      {Default value}
  arch_set := num_layers;
  neuron_set := num_layers;
  for i := 1 to max_layers do
    begin
      layers[i].Arch := lines;
      layers[i].neurons := 5;
      layers[i].FFconnection_kind := fully;  {Connection to}
                                              {next layer}
      layers[i].out_layer := false;
    end;
  end;

```

```

layers[i].arch_row_length := 1;
layers[i].arch_col_length := 1;
layers[i].weights := nil;
layers[i].saved_weights := nil;
layers[i].connections := nil;
for j := 1 to max_bodies do
begin
  layers[i].neural_set.binary_value[j] := 0;
                                {neurons set to binary 0}
  layers[i].neural_set.threshold[j] := 0.0; {Neuron}
                                {threshold}
  layers[i].neural_set.rate := 0;
end;
end;
Net_Description.num_layers := num_layers; {Set default}
                                {values}

Net_Description.net_name := 'Name?';
Net_Description.Learning := backp;
Net_Description.Training := supervised;
Net_Description.factor := 0.7;      {Gain factor}
Net_Description.factor1 := 0.0;    {Tolerance}
Net_Description.factor2 := 0.0;    {Saturation}
Net_Description.factor3 := 0.0;    {Corruption Probability}
Net_Description.Activation := Sigmoid;
Net_Description.threshold := 0.5;
Net_Description.momentum := 0.7;
Net_Description.net_arch := feedforward;
Net_Description.random_weights := false;
Net_Description.set_weights := false;
Net_Description.iterate := 0;
Net_Description.save_state := false;
Net_Description.one_value := 1.0;
Net_Description.zero_value := 0.0;
layers[num_layers].out_layer := true; {Set final layer}
                                {to true}
end; {Initialize_Layers}

{-----}

Procedure Reverse;

begin
  textbackground (white);
  textcolor (black);
end;

{-----}

```

```
Procedure Repeat_Input (var ch : char);
```

```
begin
  write (#7); {Ring bell - illegal entry}
  gotoxy (4, 21);
  clreol; {Clear from cursor to end of line}
  ch := readkey;
end;
```

```
{-----}
```

```
Procedure Initialize_stuff;
```

```
begin {Initialize_stuff}
  Infilename := 'NONE SELECTED';
end; {Initialize_stuff}
```

```
{-----}
```

```
Procedure FullPort;
```

```
begin {FullPort}
  SetViewport (0, 0, MaxX, MaxY, ClipOn);
end; {FullPort}
```

```
{-----}
```

```
Procedure GetChar;
```

```
begin {GetChar}
  if ColNo > ColsOnLine
  then EndOfLine := true
  else
    begin
      NextChar := Lin [ColNo];
      ColNo := ColNo + 1;
    end;
end; {GetChar}
```

```
{-----}
```

```
Procedure GetLine;
```

```
var
  i : integer;
```

```
begin {GetLine}
  i := 1;
  ColNo := 1;
```

```

ColsOnLine := 0;
readln (S);    {Read input from console.  Place in S}
if length (s) <> 0 then    {if no input will not return}
                        {value}
begin
  while i <= length (S) do
    begin
      ColsOnLine := ColsOnLine + 1;
      Lin [ColsOnLine] := S[i];    {Transfer S to buffer}
      i := i + 1;
    end;
  NextChar := ' ';    {Prime the pump if valid line}
  EndOfLine := false;
  while (nextchar = ' ') and (not EndofLine) do
    GetChar;    {Skip initial blanks - make nextchar}
                {1st valid int}
  end;
end;    {GetLine}

{-----}

{Process_Number reads characters from the input buffer and}
{converts them to integers.}

Procedure Process_Number (var int : integer);

begin    {Process_Number}
  int := ord (nextchar) - ord ('0');
  getchar;
  while ((nextchar in ['0'..'9']) and (not EndofLine)) do
    begin
      int := int * 10 + (ord (nextchar) - ord ('0'));
      getchar;
    end;
end;    {Process_Number}

{-----}

Procedure Get_Network_Name (var S : string);

begin    {Get_Network_Name;} {Put some more checks in this!!}
  S := '';
  clrscr;
  gotoxy (20, 15);
  write ('Enter Network MsDos File or Path Name');
  gotoxy (37-(length (net_description.net_name) Div 2), 17);
  write (('(', net_description.net_name, ')');
  gotoxy (5, 24);
  write ('<RTN> Accept');

```

```
gotoxy (1, 21);
write ('=> ');
Getline;
while (not EndofLine) do
  begin
    if nextchar in ['a'..'z']
      then nextchar := chr (ord (nextchar) - 32);
      S := concat (S, NextChar);
      getchar;
    end;
    if length (S) = 0
      then S := net_description.net_name;
end;    {Get_Network_Name;}

{-----}
end.
```


APPENDIX K

Network Saved State Data Printout

NET DESCRIPTION

ALFA1

Net Architecture 0

3 layers

Activation Type 1

Threshold 0.00

Learning Type 4

Factor - 0.700 Factor1 - 0.495 Factor2 - 0.001,

Factor3 - 0.000

Momentum 0.70

Input values 0.5 / -0.5

LAYER 1

Connection type 0

Number of Neurons 35

Layer threshold 0.50

LAYER 2

Connection type 0

Number of Neurons 80

Layer threshold 0.00

LAYER 3

Connection type 0

Number of Neurons 8

Layer threshold 0.00

ITERATION NUMBER 0

Order is - Binary value, Real value, Threshold, Rate

LAYER 1

1. 1 0.5000 0.50 0
 2. 1 0.5000 0.50 0
 3. 1 0.5000 0.50 0
 4. 1 0.5000 0.50 0
 5. 1 0.5000 0.50 0
 6. 1 0.5000 0.50 0
 7. 1 0.5000 0.50 0
 8. 1 0.5000 0.50 0
 9. 0 -0.5000 0.50 0
 10. 0 -0.5000 0.50 0
 11. 1 0.5000 0.50 0
 12. 0 -0.5000 0.50 0
 13. 0 -0.5000 0.50 0
 14. 0 -0.5000 0.50 0
 15. 1 0.5000 0.50 0
 16. 0 -0.5000 0.50 0
 17. 0 -0.5000 0.50 0
 18. 1 0.5000 0.50 0
 19. 0 -0.5000 0.50 0
 20. 0 -0.5000 0.50 0
 21. 0 -0.5000 0.50 0
 22. 1 0.5000 0.50 0
 23. 0 -0.5000 0.50 0
 24. 0 -0.5000 0.50 0
 25. 1 0.5000 0.50 0
 26. 0 -0.5000 0.50 0
 27. 0 -0.5000 0.50 0
 28. 0 -0.5000 0.50 0

29. 1 0.5000 0.50 0
30. 1 0.5000 0.50 0
31. 1 0.5000 0.50 0
32. 1 0.5000 0.50 0
33. 1 0.5000 0.50 0
34. 1 0.5000 0.50 0
35. 1 0.5000 0.50 0

LAYER 2

1. 0 -0.2733 0.00 0
2. 0 -0.2979 0.00 0
3. 1 0.2790 0.00 0
4. 1 0.4607 0.00 0
5. 0 -0.0970 0.00 0
6. 0 -0.4094 0.00 0
7. 0 -0.2226 0.00 0
8. 1 0.3160 0.00 0
9. 0 -0.4954 0.00 0
10. 0 -0.3544 0.00 0
11. 0 -0.0316 0.00 0
12. 1 0.4040 0.00 0
13. 1 0.2550 0.00 0
14. 0 -0.1614 0.00 0
15. 0 -0.4256 0.00 0
16. 0 -0.3173 0.00 0
17. 1 0.4000 0.00 0
18. 1 0.4446 0.00 0
19. 1 0.2395 0.00 0
20. 0 -0.4045 0.00 0
21. 1 0.1182 0.00 0
22. 1 0.1346 0.00 0
23. 1 0.3773 0.00 0
24. 0 -0.0204 0.00 0
25. 1 0.3873 0.00 0
26. 0 -0.0687 0.00 0
27. 1 0.0609 0.00 0
28. 1 0.4437 0.00 0
29. 0 -0.1460 0.00 0
30. 0 -0.4898 0.00 0
31. 1 0.2339 0.00 0
32. 1 0.0963 0.00 0
33. 0 -0.2328 0.00 0
34. 0 -0.4957 0.00 0
35. 0 -0.1171 0.00 0
36. 0 -0.1508 0.00 0
37. 0 -0.4916 0.00 0
38. 0 -0.3655 0.00 0
39. 0 -0.4689 0.00 0
40. 0 -0.4610 0.00 0
41. 1 0.3558 0.00 0
42. 1 0.1155 0.00 0
43. 0 -0.4356 0.00 0
44. 0 -0.4300 0.00 0
45. 1 0.3077 0.00 0
46. 0 -0.3825 0.00 0
47. 1 0.2515 0.00 0
48. 0 -0.2148 0.00 0
49. 0 -0.4249 0.00 0

50. 1 0.2047 0.00 0
 51. 1 0.0111 0.00 0
 52. 1 0.4039 0.00 0
 53. 0 -0.3801 0.00 0
 54. 0 -0.2510 0.00 0
 55. 0 -0.0914 0.00 0
 56. 1 0.1600 0.00 0
 57. 1 0.4629 0.00 0
 58. 0 -0.1925 0.00 0
 59. 0 -0.2996 0.00 0
 60. 1 0.2822 0.00 0
 61. 1 0.0084 0.00 0
 62. 1 0.3217 0.00 0
 63. 0 -0.0481 0.00 0
 64. 1 0.4272 0.00 0
 65. 0 -0.0371 0.00 0
 66. 1 0.3771 0.00 0
 67. 0 -0.4101 0.00 0
 68. 0 -0.1211 0.00 0
 69. 0 -0.3587 0.00 0
 70. 1 0.3286 0.00 0
 71. 1 0.1769 0.00 0
 72. 0 -0.4924 0.00 0
 73. 1 0.2806 0.00 0
 74. 1 0.4852 0.00 0
 75. 0 -0.2162 0.00 0
 76. 0 -0.2830 0.00 0
 77. 0 -0.2927 0.00 0
 78. 0 -0.2851 0.00 0
 79. 0 -0.4625 0.00 0
 80. 0 -0.0879 0.00 0

Weight values for layer 2

1. -1.01 -1.30 -0.17 1.34 0.29 -1.29 -0.14 -0.86 -1.29 -1.74 0.91 -0.86 0.13 -0.50 -1.68 -0.33 0.32 0.06 0.42
 -0.42 -0.04 0.05 0.53 -0.37 0.84 -0.85 -1.49 0.07 0.20 -1.83 1.24 -0.91 0.71 -1.07 -0.62 -0.06 -0.11 -0.72 -0.03
 -0.02 0.26 -1.43 -0.31 -0.80 -0.47 -1.72 -1.54 -0.60 -0.20 -0.72 0.58 0.63 -0.62 -0.08 -0.53 -1.99 -0.71 -0.89
 -1.19 0.58 -1.63 2.71 0.44 0.08 0.48 1.35 -0.01 -1.02 -1.05 -0.02 0.56 -0.75 -0.87 -0.13 -1.04 -1.72 0.76 -1.45
 2.04 -1.43
 2. -0.42 -0.77 0.27 1.37 -1.04 -1.17 0.58 -0.84 -1.24 0.64 0.41 0.52 -0.27 -1.21 -0.27 -0.48 0.98 0.89 1.37 1.00
 0.68 0.57 0.53 0.10 0.93 -0.65 0.07 1.74 0.02 -0.47 -0.33 -0.58 0.84 -1.23 -0.64 0.14 -1.17 -1.31 -1.13 -0.06
 0.73 -0.06 -0.66 0.68 -0.22 -1.34 0.97 -1.71 -0.82 0.36 -0.18 1.04 -0.27 0.63 -0.13 -1.41 0.72 -0.64 -0.41 -0.22
 -0.40 0.20 -0.32 0.18 -0.08 1.22 -0.98 -0.75 -0.39 -0.59 -0.83 -0.31 -0.67 -0.82 -1.41 -0.97 0.14 -0.81 -0.95 -0.96
 3. 0.39 0.49 -0.38 0.25 0.72 0.56 0.51 0.73 -0.92 0.01 0.59 -0.76 0.85 0.21 -0.09 -1.04 0.80 0.42 0.07 -0.75
 0.14 0.33 0.06 0.58 0.57 -0.78 0.02 1.96 -0.10 -1.47 -0.92 -0.44 -0.45 -0.12 0.20 -0.06 -0.59 -0.27 -0.27 -0.31
 1.61 -0.75 -0.75 1.74 -0.05 -0.51 -0.46 -1.05 -1.00 -0.02 0.91 -0.56 -0.33 -0.32 -0.34 -2.05 0.25 0.93 -1.25 1.81
 -1.38 0.54 -0.08 0.01 -0.70 0.04 -0.52 1.24 -0.57 -0.25 0.43 -0.56 -0.57 0.40 -0.56 0.12 1.71 -0.97 1.57 1.01
 4. -1.71 -0.25 -0.33 0.76 -0.79 0.96 -0.18 -1.16 -1.22 -0.69 0.29 0.27 0.31 -0.55 -0.52 -0.73 0.67 0.16 1.59
 -0.01 0.81 1.31 0.24 0.24 -0.21 -0.37 1.37 0.32 -0.42 0.14 0.33 0.75 -0.22 -0.58 0.15 1.06 -1.22 -1.07 -0.80
 0.09 1.26 0.12 1.40 -1.02 0.05 -1.45 -0.24 0.47 -0.15 0.44 -0.12 -0.39 -0.15 0.12 -0.63 -2.01 0.98 0.25 -1.73
 -0.18 -0.45 -1.26 -0.82 0.05 -0.45 0.91 -0.34 -0.96 0.15 -1.11 1.02 -0.54 -0.24 -0.97 -0.19 -0.98 0.62 -1.06 1.38
 0.97
 5. -0.79 -1.32 -1.69 0.56 0.63 -0.53 0.13 1.21 -1.10 -1.08 0.19 0.96 0.38 0.65 -1.71 0.92 -0.46 0.32 -0.52 0.56
 0.28 0.01 0.21 -0.17 1.05 -0.44 -0.14 1.31 -0.23 -0.91 0.20 0.37 -0.52 -1.29 -0.23 -0.29 0.71 -1.23 -0.63 0.44
 0.93 -0.35 -1.68 -0.15 -0.90 -1.22 -0.46 -0.44 -0.61 0.18 0.19 0.18 0.77 0.17 -0.13 -1.69 0.07 0.10 -0.62 -1.16
 -0.30 -0.23 -0.93 0.29 -0.20 1.19 -0.19 1.83 0.28 -0.98 1.93 -1.55 1.73 1.65 -1.28 -0.76 0.37 -1.63 -2.96 -1.54
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 0.20 0.84 0.21 0.36 1.23 -0.69 -1.59 1.31 0.67 -0.97 -0.60 1.18 -1.02 0.20 0.14 0.02 -0.40 -1.11 -0.72 -1.46
 0.52 -0.28 -0.62 -1.32 -0.90 0.98 -0.55 1.16 -0.71 0.57 -1.20 0.08 -0.24 -0.42 -0.74 1.36 0.18 0.07 -1.17 -0.36

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 7. -1.49 -0.35 -1.12 0.11 0.33 -2.00 0.15 -0.51 -0.36 -0.02 -0.05 0.58 -0.32 -0.65 0.02 -0.82 0.79 0.39 0.60 0.30
 0.63 0.31 0.46 0.27 0.23 -0.47 -0.32 0.95 0.54 -0.52 -0.67 -0.36 -1.80 -0.34 0.56 0.31 -0.13 -1.06 -1.04 0.18
 1.84 0.01 0.76 -1.91 -1.03 0.00 0.63 0.19 -0.41 0.39 -0.23 -0.02 -0.53 0.15 0.13 1.42 0.89 0.04 -0.72 -1.35
 -0.91 0.35 1.07 0.38 0.58 0.34 0.15 -0.86 -1.00 -0.31 0.72 0.21 0.93 -0.03 -0.35 -0.83 1.93 -0.70 0.73 -0.70
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 -0.56 -0.57 -1.01 -0.99 -0.78 -0.22 0.01 0.84 -0.41 0.01 -1.25 1.12 -0.35 -0.24 0.92 -0.80 -0.76 0.12 -1.26 0.44
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 14. -0.85 0.02 -1.70 0.38 0.72 -0.22 0.60 -0.78 1.24 0.70 0.59 0.04 -0.14 -0.83 -1.91 0.13 -0.64 0.54 -1.07 0.22
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 15. 0.32 -1.55 -0.18 0.05 0.39 -0.25 0.39 0.16 -1.36 -1.59 0.58 0.75 0.88 -1.21 -1.60 -0.32 0.83 0.15 0.79 -0.41
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 16. -1.24 -0.67 -0.96 1.90 0.51 -0.20 0.04 -1.08 -0.57 -1.40 0.68 0.19 1.05 0.30 -1.76 0.69 0.37 -0.67 0.60 0.81
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 17. -1.72 0.89 -0.44 0.60 -0.14 -0.55 0.88 -0.68 1.43 -1.51 0.99 -0.46 0.48 0.29 -1.23 -0.25 -0.10 -0.92 -0.59
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 18. -1.40 -0.10 1.38 1.47 0.15 -0.49 0.44 -0.38 -1.11 -1.61 -0.26 1.03 0.16 0.57 -1.12 -0.68 0.31 0.82 -0.89
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 19. -0.15 0.36 -1.61 -0.04 0.13 -0.11 1.66 -1.08 0.76 -1.11 0.49 -0.34 -0.18 0.01 -1.13 0.78 0.88 0.63 0.51 1.02
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 1.28 -0.53 -1.17 0.98 1.00 -0.86 -0.23 -0.98 0.01 0.51 -0.92 -0.08 -1.04 1.24 0.85 -0.01 0.66 0.44 -0.58 -0.65
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 20. -0.32 0.13 -0.42 1.50 0.42 -0.50 0.17 1.04 0.18 -0.67 0.98 0.75 0.75 -0.46 -0.93 -0.94 0.13 0.42 -1.63 0.09

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 21. -0.59 -1.43 -1.54 -0.81 0.31 -2.38 0.19 -1.09 -0.36 -0.84 1.32 0.00 0.86 -0.50 -1.24 -0.85 -0.70 0.16 0.79
 -0.29 -0.29 1.45 0.41 -0.26 0.14 -1.28 -0.61 1.70 -0.54 0.36 -1.45 -0.63 -0.62 -0.63 -0.25 -0.22 -0.78 -1.59 -0.65
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 22. -0.48 -0.09 0.38 -0.25 0.38 -1.20 0.44 -0.63 -0.74 -1.40 0.60 0.70 0.72 -0.11 -1.96 -1.17 0.53 -0.02 0.30
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 23. 0.62 0.17 -1.63 -1.30 -0.37 -1.68 0.94 -0.63 -0.78 -0.77 0.58 0.40 0.84 0.54 -1.51 -0.38 0.58 0.42 1.40 1.05
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 24. -0.92 -0.01 -0.72 1.81 0.37 1.44 0.19 -0.54 0.11 -0.04 0.90 0.12 -1.11 -1.06 0.49 -0.81 0.85 0.73 0.09 0.45
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 28. -1.15 -0.80 -0.44 0.92 0.06 -0.87 0.84 -0.63 -0.65 -0.80 0.23 0.47 1.17 -0.34 0.07 0.26 -0.45 0.50 1.53 0.15
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 29. 0.46 -0.05 -1.38 0.95 0.23 0.76 -0.21 -0.84 0.34 -0.73 0.02 0.35 -0.67 -0.22 0.84 0.42 0.25 0.02 0.25 0.32
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 0.66 0.31 0.29 0.41 0.22 0.93 -0.02 -0.34 0.72 -0.31 -0.41 -0.11 -0.66 0.80 -1.17 -0.08 0.40 -1.21 -0.14 -0.77
 -0.86 -0.13 -0.91 -1.39 0.20 -0.45 -1.19 1.13 0.96 -1.00 0.31 -1.34 0.54 0.71 0.61 -0.49 0.22 0.20 0.65 0.14
 -1.21 1.64 2.11 -1.08 0.61 -0.58 0.42 0.31 -0.31 0.50 -0.33 -0.70 -0.59 -0.31 -0.64 -1.11 -0.52 1.40 -1.02 -1.06
 -0.88
 33. -0.60 -0.57 -0.29 0.87 1.11 -1.71 0.74 -0.83 0.33 -1.21 0.84 1.23 1.18 0.02 -0.11 -0.42 -0.24 0.22 0.23
 -0.73 0.92 0.09 0.80 0.33 0.72 -1.36 -0.11 0.94 -0.61 -0.39 -0.30 -0.41 -0.85 -0.62 0.94 0.02 -0.63 0.56 -1.02
 1.63 0.20 0.60 -0.59 0.78 0.42 0.01 0.77 -0.52 -0.46 1.25 -0.42 0.73 -0.66 0.59 -0.69 -0.67 0.02 0.40 -1.57 1.49

-0.74 1.00 -0.28 0.07 1.19 -0.37 0.21 0.07 0.70 0.02 1.14 -0.50 -0.78 0.59 -0.70 1.07 0.32 -0.89 0.60 -0.29
 34. -1.75 0.10 -1.73 1.35 -0.34 -1.55 1.15 -0.27 0.43 0.13 -0.46 1.00 0.26 -0.86 -1.64 -0.34 0.71 0.30 0.24 0.57
 0.11 0.54 1.17 0.92 -0.21 -1.28 -0.69 -0.94 -0.41 -0.28 -0.97 0.40 0.08 -0.57 0.12 -0.51 -0.42 1.54 -0.29 0.61
 -0.45 0.53 -0.61 -0.66 -1.12 1.68 -1.02 -0.21 1.21 0.67 -0.79 -0.30 0.74 0.51 -0.60 -0.94 0.59 0.38 -0.92 -1.58
 0.32 0.86 -1.04 0.85 -0.08 0.69 0.22 -0.83 0.34 1.53 0.01 -0.94 -1.04 0.66 0.39 -1.03 -2.48 -1.47 0.60 0.74
 35. -0.90 1.38 0.72 0.66 0.24 -0.34 -0.61 -0.64 -0.98 -1.12 0.81 0.83 0.35 -0.66 -1.55 -0.38 0.08 0.27 -1.07
 -0.44 0.25 0.92 0.10 0.32 1.32 -1.71 0.35 0.90 -0.02 -0.09 -0.72 -0.15 -0.70 -0.41 0.68 0.18 0.00 -0.08 -0.83
 -0.74 1.14 -0.57 -0.26 -0.92 -0.04 -0.98 -0.29 -0.77 0.99 -0.08 -1.06 0.25 -0.53 0.80 0.28 0.97 0.14 0.34 -0.18
 -0.94 -0.88 -2.07 -1.11 0.83 0.27 0.50 -0.22 -2.05 0.57 -0.36 0.64 -1.57 0.03 -0.02 -1.82 -0.27 0.21 0.73 -1.13
 -0.38

LAYER 3

1. 0 -0.3485 0.00 0
 2. 1 0.2570 0.00 0
 3. 0 -0.2273 0.00 0
 4. 0 -0.3218 0.00 0
 5. 0 -0.1159 0.00 0
 6. 0 -0.2202 0.00 0
 7. 0 -0.2353 0.00 0
 8. 1 0.1861 0.00 0

Weight values for layer 3

1. 0.97 0.02 0.06 0.45 0.27 0.19 0.17 0.43
 2. -0.67 -0.07 0.22 -0.31 0.67 -0.31 -0.28 0.07
 3. 0.15 -0.01 -0.26 0.08 0.10 -0.89 -0.21 0.09
 4. 1.26 0.21 0.58 0.35 -0.33 0.20 0.18 0.13
 5. -1.24 -0.09 -0.20 0.34 -0.18 -0.07 0.08 -0.11
 6. 0.69 0.13 0.07 0.79 0.19 0.00 0.66 -0.20
 7. 1.55 -0.63 0.86 0.33 -0.45 -0.72 -0.17 0.11
 8. -0.06 0.12 -0.15 -0.93 0.12 0.01 0.08 -0.10
 9. -0.10 0.14 0.26 0.73 -0.21 0.31 -0.24 0.63
 10. 0.39 -0.05 0.12 0.24 -0.04 -0.57 0.45 -0.03
 11. -0.74 -0.39 0.37 -0.29 0.90 -0.00 0.46 -0.16
 12. 0.28 0.33 0.03 -0.28 0.65 -0.12 -0.09 0.21
 13. 0.41 -0.20 -0.28 -0.22 0.01 0.26 -0.48 0.41
 14. 0.61 0.23 -0.58 -0.36 -0.08 -0.16 0.06 0.10
 15. -0.01 -0.01 0.07 0.05 -0.00 0.17 1.06 -0.71
 16. 0.30 -0.35 0.23 0.28 -0.14 0.17 -0.07 0.12
 17. 0.43 0.03 0.07 0.32 -0.13 -0.20 -0.05 -0.01
 18. 0.28 0.15 -0.15 0.49 0.20 0.35 -0.28 0.47
 19. 0.41 0.29 0.27 0.41 -0.46 0.13 0.17 0.43
 20. 0.23 0.16 -0.38 -0.50 0.15 -0.31 0.51 0.37
 21. 0.94 0.16 0.25 0.02 0.25 0.25 -0.09 0.18
 22. 0.53 0.13 -0.04 0.23 0.03 0.03 0.18 0.26
 23. -1.04 0.40 -0.61 -0.18 0.10 -0.07 0.01 0.21
 24. 0.58 -0.22 0.08 -0.04 -0.16 -0.04 -0.16 0.29
 25. 1.42 -0.27 0.48 -0.23 0.01 -0.05 0.30 0.02
 26. 0.40 -0.06 0.18 0.32 -0.31 -0.37 0.19 -0.63
 27. 0.03 0.10 -0.12 -0.30 -0.15 0.08 0.87 0.32
 28. -0.04 0.29 0.17 0.31 -0.33 0.82 -0.20 0.94
 29. 0.43 -0.08 -0.04 0.08 -0.27 -0.68 -0.25 0.05
 30. 0.43 -0.06 -0.04 0.20 -0.01 -0.06 -0.05 0.38
 31. -0.09 0.32 -0.16 -0.09 -0.11 -0.05 -0.77 0.17
 32. 0.81 0.33 0.29 0.15 0.21 -0.17 -0.43 -0.39
 33. 0.54 -0.07 0.11 0.33 0.56 0.18 -0.20 0.07
 34. 0.86 0.01 0.37 -0.32 0.32 0.41 -0.52 -0.17
 35. 0.52 0.09 0.50 0.09 0.13 0.21 -0.10 0.08

36. -0.47 0.24 -0.27 -0.62 0.37 -0.17 0.13 -0.19
37. -0.09 -0.00 -0.30 0.12 0.64 -0.27 0.10 0.26
38. 0.04 0.01 0.07 0.12 -0.06 0.53 0.28 -0.29
39. 0.98 0.02 0.12 -0.36 0.18 0.13 -0.54 0.02
40. -1.03 0.22 -0.33 0.21 0.05 0.28 -1.10 0.16
41. 0.60 0.26 0.38 0.16 -0.38 -0.44 0.61 0.87
42. -1.20 0.34 -0.06 -0.46 0.45 0.44 -0.35 0.25
43. -0.36 0.07 -0.03 -0.61 -0.10 0.14 0.36 0.17
44. 0.08 0.23 -0.03 0.29 -0.67 0.50 -0.07 1.05
45. -1.52 0.43 -0.62 1.03 -0.60 -0.63 0.01 0.19
46. 0.36 -0.00 0.47 0.09 0.16 -0.26 0.35 -0.71
47. 0.76 -0.11 0.32 0.05 0.06 0.32 0.26 -0.03
48. 0.36 -0.03 0.44 0.45 0.24 0.56 -0.53 -0.27
49. 0.38 0.21 0.13 0.28 0.27 -0.27 0.32 0.65
50. 0.96 -0.18 0.40 -0.45 0.16 -0.56 -0.05 0.13
51. -0.29 -0.10 0.15 0.13 0.11 -0.19 -0.37 0.18
52. 0.47 0.10 -0.10 0.24 -0.03 0.57 0.00 -0.02
53. 0.95 -0.24 0.29 -0.28 -0.15 0.71 0.77 -0.37
54. 0.99 0.17 0.03 0.19 0.11 0.19 0.66 0.84
55. 0.86 -0.09 -0.08 0.49 0.28 -0.92 0.07 -0.11
56. 0.56 -0.29 0.50 0.13 0.61 -1.23 -0.06 -0.19
57. -0.19 0.13 0.04 -0.05 -0.19 -0.41 0.03 -0.65
58. -0.72 0.06 -0.63 0.23 0.12 -0.19 0.01 -0.21
59. 0.93 0.07 0.01 0.44 -0.42 -0.28 -0.11 -0.36
60. -0.25 0.04 0.49 0.76 0.05 -0.00 -0.62 0.11
61. 0.77 -0.22 0.25 -0.25 -0.52 0.26 0.00 -0.03
62. 0.33 0.27 -0.23 0.46 -0.17 0.25 -0.82 0.15
63. -0.54 0.50 -0.14 0.01 -0.45 -0.21 0.49 -0.47
64. -0.48 -0.22 0.61 -0.06 0.62 -0.06 -0.26 0.18
65. 0.77 -0.34 0.30 -0.08 0.83 -0.56 0.02 0.60
66. 0.22 0.11 0.20 -0.02 -0.01 -0.21 0.06 0.27
67. -1.28 0.11 0.07 0.28 -0.34 0.36 -0.05 -0.23
68. 0.88 -0.27 0.36 -0.03 -0.82 0.46 -0.18 -0.13
69. 1.56 -0.61 0.81 0.13 0.19 0.17 0.11 0.34
70. 0.01 0.19 -0.43 -0.70 0.26 -0.05 -0.24 0.17
71. 0.19 -0.15 0.21 -0.20 -0.17 -0.28 0.15 0.72
72. 0.78 -0.03 0.61 -0.09 0.04 0.47 -0.34 -0.32
73. 0.25 0.53 -0.29 -0.42 -0.08 0.22 -0.33 -0.01
74. -0.34 0.47 -0.04 -0.20 0.33 -0.10 0.23 -0.19
75. 0.72 -0.03 -0.40 0.56 0.34 -0.35 0.21 0.60
76. 0.61 -0.05 0.51 -0.27 -0.01 0.20 0.04 0.55
77. 0.02 0.71 0.15 -0.01 0.67 0.71 -0.54 -0.20
78. -0.46 0.34 0.15 -0.05 0.36 -0.42 0.08 -0.18

Vita

David Southworth was born on June 17, 1946 in Los Angeles, California. He served for twenty-one years in the United States Navy as a Naval Flight Officer and also held several positions in weapon and computer systems acquisition and in computer technology research and development. He is currently working for RBC, Inc., a defense contracting firm, as a Program Manager providing support to the Navy in the acquisition of various weapon systems. Mr. Southworth holds a Bachelor of Arts in Psychology from Northwestern University and a Master of Science in Systems Management from the University of Southern California.

A handwritten signature in black ink, appearing to read 'David Southworth', with a long horizontal flourish extending to the right.