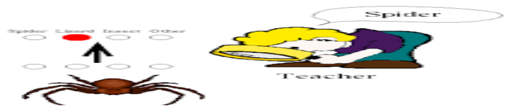


Neural Networks and Fuzzy Logic (630514)

Lecture 14

Associative Neural Networks using Matlab

Example 1: Write a matlab program to find the weight matrix of an auto associative net to store the vector (1 1 -1 -1). Test the response of the network by presenting the same pattern and recognize whether it is a known vector or unknown vector.

The auto associative net has the same inputs and targets. The MATLAB program for the auto associative net is as follows:

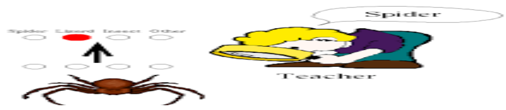
Program

```
%Auotassociative net to store the vector
clc;
clear;
x = [1 1 –1 –1];
w=zeros (4, 4);
w=x'*x;
yin=x*w;
for i=1:4
   if yin(i)>0
      y(i)=1;
   else
      y(i) = –1;
   end
end
disp ('Weight matrix');
disp (w);
if x == y
   disp ('The vector is a Known Vector');
else
   disp ('The vector is a Unknown Vector');
end
```

Output

```
Weight matrix
  1   1 –1  –1
  1    1–1 –1
–1 –1   1    1
–1 –1   1    1
```

The vector is a known vector.



Example 2: **Write an M–file to store the vectors (–1 –1 –1 –1) and (–1 –1 1 1) in an auto associative net. Find the weight matrix. Test the net with (1 1 1 1) as input.**

The MATLAB program for the auto association problem is as follows:

Program

```
clc;
clear;
x=[-1 -1 -1 -1;-1 -1 1 1];
t=[1 1 1 1];
w=zeros (4, 4);
for i=1:2
   w=w + x(i,1:4)'*x(i,1:4);
end
yin = t*w;
for i=1:4
   if yin(i)>0
      y(i)=1;
   else
      y(i)=-1;
   end
end
disp ('The calculated weight matrix');
disp (w);
if x(1,1:4)==y(1:4) | x(2,1:4)==y(1:4)
   disp ('The vector is a Known Vector');
else
   disp ('The vector is a unknown vector');
end
```

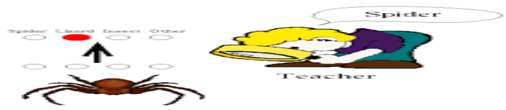
Output

```
The calculated weight matrix
   2   2   0   0
   2   2   0   0
   0   0   2   2
   0   0   2   2
```

The vector is an unknown vector.

Example 3: **Write an M–file to calculate the weights for the following patterns using hetero associative neural net for mapping four input vectors to two output vectors.**

S1	*S2*	*S3*	*S4*	*t1*	*t2*
1	1	0	0	1	0
1	0	1	0	1	0
1	1	1	0	0	1
0	1	1	0	0	1



Solution

```
%Hetero associative NN for mapping input vectors to output vectors
clc;
clear;
x= [1 1 0 0; 1 0 1 0; 1 1 1 0; 0 1 1 0];
t= [1 0; 1 0; 0 1; 0 1];
w=zeros (4, 2);
for i=1:4
   w=w+x (i, 1:4)'*t(i,1:2);
end
disp('Weight matrix');
disp(w);
```

Output

```
 Weight matrix
      2  1
      1  2
      1  2
      0  0
```

Example 4: **Write a MATLAB program to store the vector (1 1 1 0) in bipolar binary form and calculate the weight matrix for Hopfield net.**

```
%The MATLAB program for calculating the weight matrix is as follows
%Discrete Hopfield net
clc;
clear;
x=[1 1 1 0];
w=(2*x'–1)*(2*x–1);
for i=1:4
   w (i, i)=0;
end
disp('Weight matrix');
disp(w);
```

Output

```
 Weight matrix
      0    1    1   -1
      1    0    1   -1
      1    1    0   -1
     -1   -1   -1    0
```

Example 5: **Auto-associative Memories (continuous):**

```
%Auto-associative Memories (continuous)
x1=[-0.3; 0.9; -0.2];
x2=[0.44; -0.7; 0.9];
x3=[0.9; 0.6; 0.8];
Total_M = x1*x1' + x2*x2' + x3*x3';
estimate_x1= Total_M *x1;
estimate_x2= Total_M *x2;
estimate_x3= Total_M *x3;
%Estimates are not perfect because of non-orthogonality of the vectors
```


```
%Euclidean distance between x1 and other key vectors
d11 = norm(x1-estimate_x1);
d21 = norm(x2-estimate_x1);
d31 = norm(x3-estimate_x1);
% As expected the response vector estimate_x1 is closest to x1
%Euclidean distance between x2 and other key vectors
d12 = norm(x1-estimate_x2);
d22 = norm(x2-estimate_x2);
d32 = norm(x3-estimate_x2);
%As expected the response vector estimate_x2 is closest to x2
%Euclidean distance between x3 and other key vectors
d13 = norm(x1-estimate_x3);
d23 = norm(x2-estimate_x3);
d33 = norm(x3-estimate_x3);
%As expected the response vector estimate_x3 is closest to x3
```

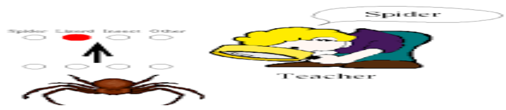
- Matlab code for converting continuous data (**x1** vector) to binary bipolar data.

```
for i=1:length(x1)
   if x1(i)>0
      x1(i) = 1;
   else
     x1(i) = -1;
   end
 end
```

- In Matlab **Hopfield networks** can be implemented as vector matrix manipulations. To make the pattern vectors as easy as possible to read and write we define them as row vectors.
- We prefer to make the calculations within the interval **[−1, 1]** (**bipolar**) as this makes the calculations simpler. It is, however, easier to type in and to visually recognize values in the range **[0, 1]** (**binary**). Therefore, it may be better to use this for input and output. Translate a vector from the binary format into the bipolar.

Example 6:

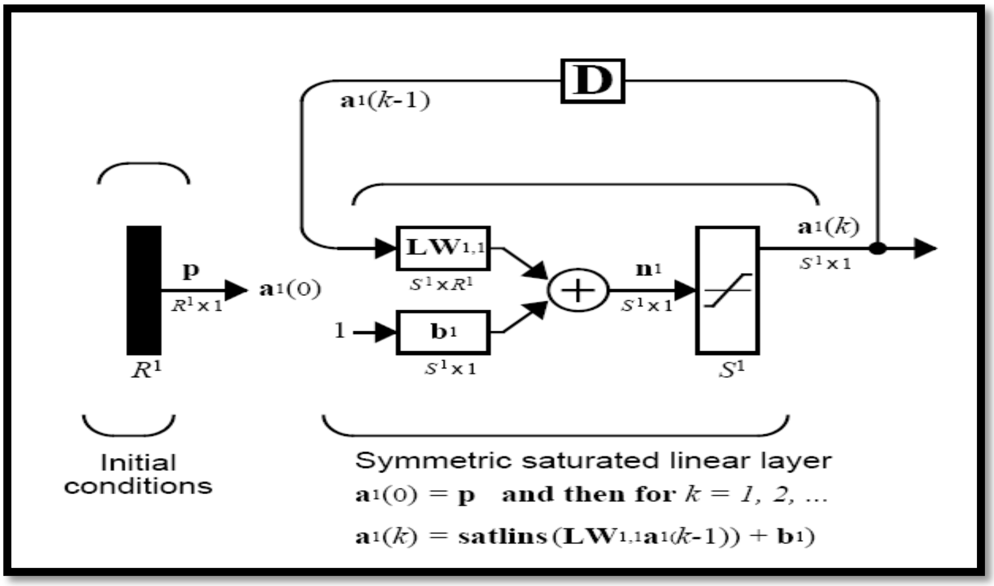
```
%Enter three test patterns.
x1b= [0 0 1 0 1 0 0 1];
x2b= [0 0 0 0 0 1 0 0];
x3b= [0 1 1 0 0 1 0 1];
%Translate a vector from the binary format into the bipolar.
%x1= [-1 -1 1 -1 1 -1 -1 1];
%x2= [-1 -1 -1 -1 -1 1 -1 -1];
%x3=[-1 1 1 -1 -1 1 -1 1];
x1 = 2* x1b -1;
x2 = 2* x2b -1;
x3 = 2* x3b -1;
%Calculate a weight matrix.
w=x1'*x1+x2'*x2+x3'*x3-3*eye (8, 8);
%Check if the network was able to store all three patterns.
```




```
x1test=sign (w*x1');
x2test=sign (w*x2');
x3test=sign (w*x3');
%Convergence and attractors.
%Can the memory recall the stored patterns from distorted inputs
% patterns? Define a few new patters which are distorted versions of
%the original ones:
x1d= [1 0 1 0 1 0 0 1];
x2d= [1 1 0 0 0 1 0 0];
x3d= [1 1 1 0 1 1 0 1];
%x1d has a one bit error, x2d and x3d have two bit errors.
x1d=[1 -1 1 -1 1 -1 -1 1];
x2d=[1 1 -1 -1 -1 1 -1 -1];
x3d=[1 1 1 -1 1 1 -1 1];
```

Hopfield neural networks using Matlab Neural Network Tool Box

- Hopfield neural networks can be simulated by using the Neural Network Tool Box. The architecture is shown below.



- **net = newhop (T)** takes one input argument:
  - **T - R x Q** matrix of **Q** target vectors. (Values must be **+1** or **-1**) and returns a ***new Hopfield recurrent neural network with stable points at the vectors in T***.
  - Hopfield networks consist of a single layer with the **dotprod** weight function, **netsum** net input function, and the **satlins** transfer function.

Example 7:

- Consider the following design example. Suppose that we want to design a network with two stable points in a three-dimensional space **T**.

  T = [-1 -1 1; 1 -1 1]';
- We can execute the design with:

  net = newhop (T);
- To check that the network is stable at these points use them as ***initial layer delay conditions***. If the network is stable we would expect that the outputs

Y will be the same. (Since Hopfield networks have no inputs, the second argument to sim is **Q = 2** when using matrix notation).

```
Ai = T;
[Y, Pf, Af] = sim (net, 2, [ ], Ai);
%Y
```

- To see if the network can correct a corrupted vector, run the following code, which simulates the Hopfield network for five time steps. (Since Hopfield networks have no inputs, the second argument to sim is **{Q TS} = [1 5]** when using cell array notation.)

```
Ai = {[-0.9; -0.8; 0.7]};
[Y, Pf, Af] = sim (net, {1 5}, { },Ai);
%Y{1}
```

- If you run the above code, **Y{1}** will equal **T(:,1)** if the network has managed to convert the corrupted vector **Ai** to the nearest target vector.

Description of sim function

Purpose: simulate a neural network.

Syntax:

```
[Y, Pf, Af, E, perf] = sim (net, P, Pi, Ai, T)
[Y, Pf, Af, E, perf] = sim (net, {Q TS}, Pi, Ai, T)
[Y,Pf,Af,E,perf] = sim(net,Q,Pi,Ai,T)
```

Description sim simulates neural networks.

[Y, Pf, Af, E, perf] = sim (net, P, Pi, Ai, T) takes,

net - Network.
P - Network inputs.
Pi - Initial input delay conditions, default = zeros.
Ai - Initial layer delay conditions, default = zeros.
T - Network targets, default = zeros.

and returns,

Y - Network outputs.
Pf - Final input delay conditions.
Af - Final layer delay conditions.
E - Network errors.
perf- Network performance.

Note that arguments **Pi, Ai, Pf**, and **Af** are optional and need only be used for networks that have input or layer delays.

sim's signal arguments can have two formats: ***cell array or matrix***.