# Philadelphia University Faculty of Engineering 

Marking Scheme

Exam Paper<br>BSc CE

Neural Networks and Fuzzy Logic (630514)

Second Exam

First semester
Date: 27/12/2015
Section 1
Weighting $20 \%$ of the module total

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## Marking Scheme Neural Networks and Fuzzy Logic (630514)

The presented exam questions are organized to overcome course material through 4 questions. The all questions are compulsory requested to be answered.

## Marking Assignments

Question 1 This question is attributed with 7 marks if answered properly; the answers are as following:

1) Which of the following equations is the best description of the Perceptron Learning Rule?
a) $\Delta W_{k}=\boldsymbol{\eta} y_{k} X$
b) $\Delta W_{k}=\boldsymbol{\eta}\left(X-W_{k}\right)$
c) $\Delta W_{k}=\eta\left(d_{k}-y_{k}\right) X$
d) $\Delta \boldsymbol{W}_{\boldsymbol{j}}=\boldsymbol{\eta}_{\boldsymbol{j}}\left(\boldsymbol{X}-\boldsymbol{W}_{\boldsymbol{j}}\right)$, where $\boldsymbol{\eta}_{\boldsymbol{j}}<\boldsymbol{\eta}$ and $\boldsymbol{j} \neq \boldsymbol{k}$

Where $\boldsymbol{X}$ is the input vector, $\boldsymbol{\eta}$ is the learning rate, $\boldsymbol{W}_{\boldsymbol{k}}$ is the weight vector, $\boldsymbol{d}_{\boldsymbol{k}}$ is the target output, and $\boldsymbol{y}_{\boldsymbol{k}}$ is the actual output for unit $\boldsymbol{k}$.
2) In the backpropagation algorithm, how is the error function usually defined?
a) $\frac{1}{2} \sum_{j}\left(\right.$ weight $_{j} \times$ input $\left._{j}\right)$ for all inputs $j$
b) $\frac{1}{2} \sum_{j}\left(\text { target }_{j}-\text { output }_{j}\right)^{2}$ for all outputs $j$
c) $\frac{1}{2} \sum_{j}\left(\right.$ target $_{j}-$ output $\left._{j}\right)$ for all outputs $j$
d) None of above
3) A Hopfield network has $\mathbf{1 0}$ neurons. How many adjustable parameters does this network contain?
a) 45
b) 90
c) $\mathbf{1 0 0}$
d) $\mathbf{1 0 2 4}$
4) Give the equation that can be used to convert the unipolar binary data ( $\mathbf{x}$ ) to bipolar binary data ( $\mathbf{y}$ ).
a) $\mathbf{y}=2 \mathrm{x}$
b) $y=-2 x-1$
c) $\mathbf{y}=2 \mathrm{x}+1$
d) $y=2 x-1$
5) If the associated pattern pairs ( $\mathbf{x}, \mathbf{y}$ ) are different and if the model recalls a $\mathbf{y}$ given an $\mathbf{x}$ or vice versa, then it is termed as
a) Auto correlator
b) Auto-associative memory
c) Heteroassociative memory
d) Double associative memory
6) An advantage with gradient descent based methods, such as back propagation, is that they cannot get stuck in local minima.
a) True
b) False
7) The second stage of back propagation training is $\qquad$
a) initialization weights
b) back propagation of errors
c) feed forward
d) updating of weights and bias

Question 2 This question is attributed with 3 marks if answered properly; the answers are as following:


Question 3 This question is attributed with 4 marks if answered properly; the answers are as following:

## Solution <br> Bidirectional associative memory training algorithm:

1) Storage (learning): In the learning step for BAM we need to find weight matrix between, $M$ pairs of patterns (fundamental memories) are stored in the synaptic weights of the network according to the equation:

$$
\mathrm{W}=\sum_{\mathrm{m}=1}^{\mathrm{M}} \mathrm{X}_{\mathrm{m}} \mathrm{Y}_{\mathrm{m}}^{\mathrm{T}}
$$

2) Testing

- We need to confirm that the BAM is able to
- recall $Y_{m}$ when presented $X_{m}$.
- recall $X_{m}$ when presented $Y_{m}$

Using

$$
\mathbf{Y}_{\mathbf{m}}=\operatorname{sign}\left(\mathbf{W}^{\mathbf{T}} \mathbf{X}_{\mathbf{m}}\right), \quad \mathbf{m}=1.2, \ldots, \mathbf{M}
$$

And using

$$
X_{m}=\operatorname{sign}\left(W Y_{m}\right), \quad m=1.2, \ldots, M
$$

3) Retrieval

- Present an unknown vector (probe) $X$ (corrupted or incomplete version of a pattern from set $A$ or $B$ ) to the BAM and retrieve a stored association:

$$
\mathbf{X} \neq \mathbf{X}_{\mathbf{m}}, \quad \mathbf{m}=\mathbf{1}, \mathbf{2}, \ldots, \mathbf{M}
$$

- Initialize the BAM:

$$
\mathbf{X}(\mathbf{0})=\mathbf{X}, \quad \mathbf{p}=\mathbf{0}
$$

- Calculate the BAMM output at iteration p:

$$
\mathbf{Y}(\mathbf{p})=\operatorname{sign}\left[\mathbf{W}^{\mathrm{T}} \mathbf{X}(\mathbf{p})\right]
$$

- Update the input vector $X(p)$ :

$$
\mathbf{X}(p+1)=\operatorname{sign}[\mathbf{W Y}(p)]
$$

- Repeat the iteration until convergence, when input and output remain unchanged.


## Question 4 This question is attributed with 6 marks if answered properly; the answers are as following:

## Solution

a) Step 1: Begin training.

Step 2: For the first vector, (1, 1, 0, 0), do Steps 3-5.
Step 3:

$$
\begin{aligned}
D(1)= & (.2-1)^{2}+(.6-1)^{2} \\
& +(.5-0)^{2}+(.9-0)^{2}=1.86 \\
D(2)= & (.8-1)^{2}+(.4-1)^{2} \\
& +(.7-0)^{2}+(.3-0)^{2}=0.98
\end{aligned}
$$

Step 4: The input vector is closest to output node 2, so

Step 5: The weights on the winning unit are updated:

$$
\begin{aligned}
w_{i 2}(\text { new }) & =w_{i 2}(\text { old })+.6\left[x_{i}-w_{i 2}(\text { old })\right] \\
& =.4 w_{i 2}(\text { old })+.6 x_{i} .
\end{aligned}
$$

This gives the weight matrix
$\left[\begin{array}{ll}.2 & .92 \\ .6 & .76 \\ .5 & .28 \\ .9 & .12\end{array}\right]$.
b) \%Load the data
datal $=[1,1,0,0 ; 0,0,0,1 ; 1,0,0,0 ; 0,0,1,1]^{\prime} ;$
\% Create a Self-Organizing Map
dimensionl $=1$;
dimension2 $=2$;
net = selforgmap ([dimensionl dimension2]);
\% Train the Network
[net, tr] = train (net, datal);
y = net (datal);
\% View the Network
view(net)
\%Plot results using different SOIM plots
figure, plotsomtop (net)
figure, plotsomnc(net)
figure, plotsomnd(net)
figure, plotsomplanes(net)
figure, plotsomhits(net, datal)
figure, plotsompos(net, datal)

