| Practical No | Details | Date | Sign |
|---|---|---|---|
| **1** | Implement the following: | | |
| **a** | Design a simple linear neural network model. | | |
| **b** | Calculate the output of neural net using both binary and bipolar sigmoidal function. | | |
| **2** | Implement the following: | | |
| **a** | Generate AND/NOT function using McCulloch-Pitts neural net. | | |
| **b** | Generate XOR function using McCulloch-Pitts neural net. | | |
| **3** | Implement the Following | | |
| **a** | Write a program to implement Hebb's rule. | | |
| **b** | Write a program to implement of delta rule. | | |
| **4** | Implement the Following | | |
| **a** | Write a program for Back Propagation Algorithm | | |
| **b** | Write a program for error Backpropagation algorithm. | | |
| **5.** | Implement the Following | | |
| **a** | Write a program for Hopfield Network. | | |
| **b** | Write a program for Radial Basis function | | |
| **6.** | Implement the Following | | |
| **a** | Kohonen Self organizing map | | |
| **b** | Adaptive resonance theory | | |
| **7.** | Implement the Following | | |
| **a** | Write a program for Linear separation. | | |
| **b** | Write a program for Hopfield network model for associative memory | | |
| **8.** | Implement the Following | | |
| **a** | Membership and Identity Operators \| in, not in, | | |
| **b.** | Membership and Identity Operators is, is not | | |
| **9.** | Implement the Following | | |
| **a** | Find ratios using fuzzy logic | | |
| **b** | Solve Tipping problem using fuzzy logic | | |
| **10.** | Implement the Following | | |
| **a** | Implementation of Simple genetic algorithm | | |
| **b** | Create two classes: City and Fitness using Genetic algorithm | | |

## Practical 1a

**Aim: Design a simple linear neural network model.**

```
x=float(input("Enter value of x:"))
w=float(input("Enter value of weight w:"))
b=float(input("Enter value of bias b:"))

net = int(w*x+b)
if(net<0):    out=0
elif((net>=0)&(net<=1))
:
   out =net
else:
   out=1
print("net=",net)
print("output=",out)
```

Output:

```
=== RESTART: C:/Users/prath/AppData/
Enter value of x:2
Enter value of weight w:3
Enter value of bias b:4.5
net= 10
output= 1
```

1b: Calculate the output of neural net using both binary and bipolar sigmoidal function.

For the network shown in the figure 1, calculate the net input to output neuron.

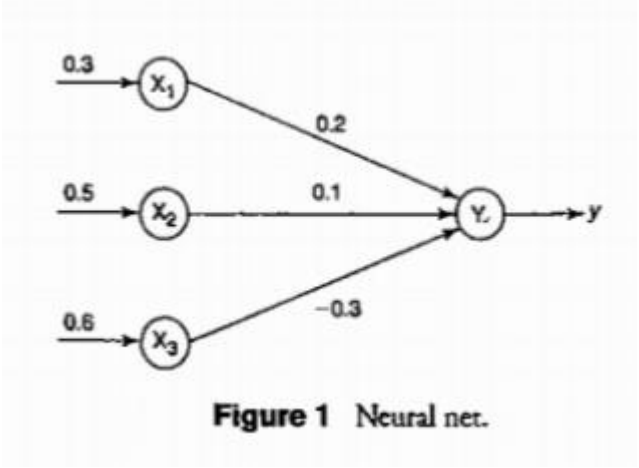



**Figure 1** Neural net.

**Solution** :The given neural net consist of three input neurons and one output neuron. The inputs and weight are

[x1, x2, x3] = [0.3, 0.5, 0.6]

[w1, w2, w3] = [0.2, 0.1, -0.3]

The net input can be calculated as

Yin = x1w1+x2w2+x3w3

= 0.3*0.2+0.5*0.1+0.6*(-0.3)

= -0.07

**Code :**

```
# number of elements as input
n = int(input("Enter number of elements : "))

# In[2]: print("Enter the inputs") inputs = []
# creating an empty list for inputs

# iterating till the range
for i in range(0, n):
        ele = float(input())
        inputs.append(ele) # adding the
element

print(inputs)
```

```
# In[3]: print("Enter the weights")
# creating an empty list for
weights weights = []

# iterating till the range
for i in range(0, n):
        ele = float(input())
        weights.append(ele) # adding the
element

print(weights)

# In[4]:
print("The net input can be calculated as   Yin = x1w1 + x2w2 + x3w3")

# In[5]: Yin = []
for i in range(0,
n):
        Yin.append(inputs[i]*weights[i]) print(round(sum(Yin),3))
```

**Output :**

```
Enter number of elements : 3
Enter the inputs
0.3
0.5
0.6
[0.3, 0.5, 0.6]
Enter the weights
0.2
0.1
-0.3
[0.2, 0.1, -0.3]
The net input can be calculated as   Yin = x1w1 + x2w2 + x3w3
-0.07
```

**1. Problem statement :**

1. Calculate the net input for the network shown in Figure 2 with bias included in the network.

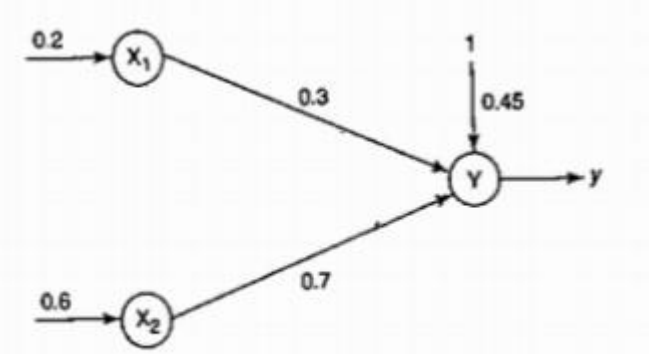



**Figure 2** Simple neural net.

**Solution:** The given net consists of two input neurons, a bias and an output neuron. The inputs are

$[x_1, X_2] = [0.2, 0.6]$ and the weights are $[w_1, w_2] = [0.3, 0.7]$. Since the bias is included $b = 0.45$ and bias input $x_o$ is equal to 1, the net input is calculated as

$$Yin = b + x_1W_1 + X_2W_2$$
$$= 0.45 + 0.2 \text{ X } 0.3 + 0.6 \text{ X } 0.7$$
$$= 0.45 + 0.06 + 0.42 = 0.93$$

Therefore $y_m = 0.93$ is the net input.

**Code :**

```
n = int(input("Enter number of elements : "))

print("Enter the inputs:")
inputs = [] # creating an empty list for inputs
for i in range(0, n):
        ele = float(input())
        inputs.append(ele) # adding the
element  print(inputs)

print("Enter the weights:")
weights = []  for i in
range(0, n):
        ele = float(input())
        weights.append(ele) # adding the
element  print(weights)

b=float(input("Enter bias value:")) print("The net input can be
calculated as   Yin = b + x1w1 + x2w2:")

Yin = [] for i in
range(0, n):
        Yin.append(inputs[i]*weights[i]) print(round((sum(Yin)+b),3))
```

Output:

```
Enter number of elements : 2
Enter the inputs:
0.2
0.6
[0.2, 0.6]
Enter the weights:
0.3
0.7
[0.3, 0.7]
Enter bias value:0.45
The net input can be calculated as   Yin = b + x1w1 + x2w2:
0.93
```

## Practical 2a:

**Aim: Implement AND/NOT function using McCulloch-Pits neuron (use binary data representation).**

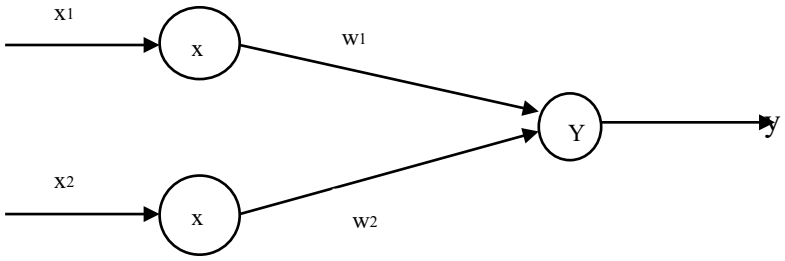
**Solution:**

In the case of AND/NOT function, the response is true if the first input is true and the second input is false. For all the other variations, the response is false. The truth table for ANDNOT function is given in Table below.

**Truth Table:**

| $x_1$ | $x_2$ | y |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 1 | 0 |
| 1 | 0 | 1 |
| 1 | 1 | 0 |

The given function gives an output only when $x_1 = 1$ and $x_2 = 0$. The weights have to be decided only after the analysis. The net can be represent as shown in figure below:




Neural net (weights fixed after analysis).

Case 1: Assume that both weights $w_1$ and $w_2$. are excitatory, i.e.,

$$w_1 = w_2 = 1$$

Then for the four inputs calculate the net input using

$$y_{ij} = x_1 w_1 + x_2 w_2$$

For inputs

(1, 1), $y_{ij} = 1 \times 1 + 1 \times 1 = 2$
(1, 0), $y_{ij} = 1 \times 1 + 0 \times 1 = 1$

(0, 1), $y_{ij} = 0 \times 1 + 1 \times 1 = 1$

(0, 0), $y_{ij} = 0 \times 1 + 0 \times 1 = 0$

From the calculated net inputs, it is not possible to fire the neuron form input (1, 0) only. Hence, J-. weights are not suitable.

Assume one weight as excitatory and the other as inhibitory, i.e.,

$$w_1 = 1, w_2 = -1$$

Now calculate the net input. For the inputs

(1,1), $y_{in} = 1 \times 1 + 1 \times -1 = 0$

(1,0), $y_{in} = 1 \times 1 + 0 \times -1 = 1$

(0,1), $y_{in} = 0 \times 1 + 1 \times -1 = -1$

(0, 0), $y_{in} = 0 \times 1 + 0 \times -1 = 0$

From the calculated net inputs, now it is possible to fire the neuron for input (1, 0) only by fixing a threshold of 1, i.e., $\theta \geq 1$ for Y unit. Thus,

$$w_1 = 1, w_2 = -1; \theta \geq 1$$

Note: The value is calculated using the following: $\theta$

$\geq nw - p$

$\theta \geq 2 \times 1 - 1$

$\theta \geq 1$

Thus, the output of neuron Y can be written as

$$y = f(y_{in}) = \{$$

0 if $y_{in} \geq 1$

1 if $y_{in} < 1$

Code:

```
# enter the no of inputs num_ip = int(input("Enter
the number of inputs : "))

#Set the weights with value
1 w1 = 1 w2 = 1

print("For the ", num_ip , " inputs calculate the net input using yin = x1w1 + x2w2 ")

x1 = [] x2 = [] for j in
range(0, num_ip):     ele1 =
int(input("x1 = "))     ele2
= int(input("x2 = "))
x1.append(ele1)
```

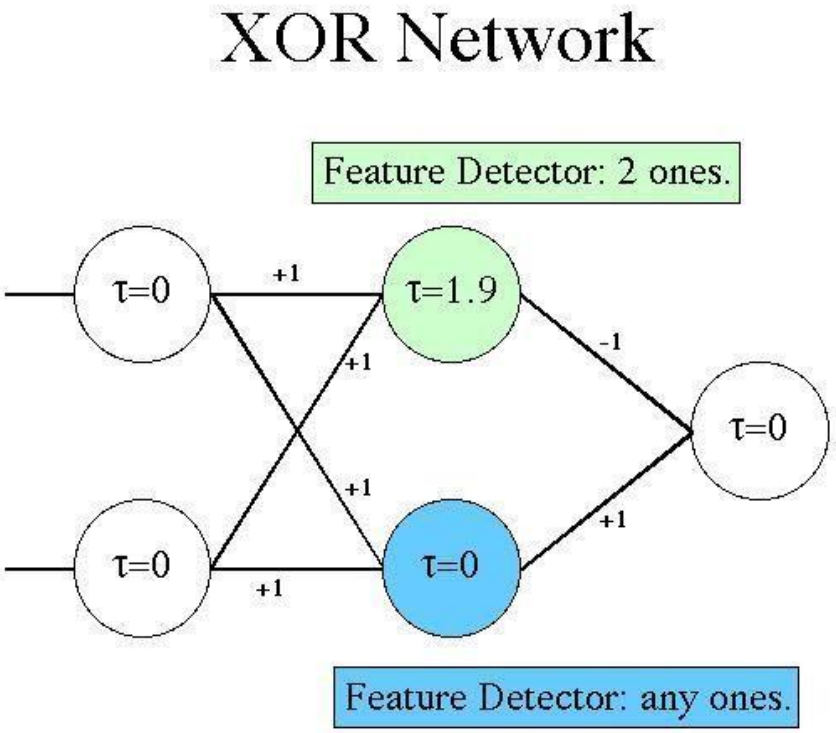
```
x2.append(ele2) print("x1
= ",x1) print("x2 = ",x2)
n = x1 * w1 m
= x2 * w2

Yin = [] for i in range(0,
num_ip):
        Yin.append(n[i] + m[i])
print("Yin = ",Yin)

#Assume one weight as excitatory and the other as inhibitory, i.e.,

Yin = [] for i in range(0,
num_ip):
        Yin.append(n[i] - m[i])
print("After assuming one weight as excitatory and the other as inhibitory Yin = ",Yin)

#From the calculated net inputs, now it is possible to fire the neuron for input (1, 0) #only
by fixing a threshold of 1, i.e., θ ≥ 1 for Y unit.
#Thus, w1 = 1, w2 = -1; θ ≥ 1

Y=[]

for i in range(0, num_ip):
   if(Yin[i]>=1):
        ele=  1
        Y.append(ele)
if(Yin[i]<1):
        ele=  0
        Y.append(ele) print("Y
= ",Y)
```

Output:

```
Enter the number of inputs : 4
For the  4  inputs calculate the net input using yin = x1w1 + x2w2

x1 = 0

x2 = 0

x1 = 0

x2 = 1

x1 = 1

x2 = 0

x1 = 1

x2 = 1
x1 =  [0, 0, 1, 1]
x2 =  [0, 1, 0, 1]
Yin =  [0, 1, 1, 2]
 After assuming one weight as excitatory and the other as inhibitory Yin =  [0, 1, -1, 0]
Y =  [0, 1, 0, 0]

In [14]:
```

**Practical 2b:**

**Aim: Generate XOR function using McCulloch-Pitts neural net**




The XOR (exclusive or) function is defined by the following truth table:

| **Input1** | **Input2** | **XOR Output** |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 1 |
| 1 | 1 | 0 |

#Getting weights and threshold value

import numpy as np print('Enter

weights') w11=int(input('Weight

w11=')) w12=int(input('weight

w12=')) w21=int(input('Weight

w21=')) w22=int(input('weight

```
w22=')) v1=int(input('weight v1='))
v2=int(input('weight v2='))
print('Enter Threshold Value')
theta=int(input('theta='))
x1=np.array([0, 0, 1, 1])
x2=np.array([0, 1, 0, 1])
z=np.array([0, 1, 1, 0]) con=1
y1=np.zeros((4,)) y2=np.zeros((4,))
y=np.zeros((4,)) while con==1:
zin1=np.zeros((4,))
zin2=np.zeros((4,))
zin1=x1*w11+x2*w21
zin2=x1*w21+x2*w22

   print("z1",zin1)
print("z2",zin2)     for i in
range(0,4):         if
zin1[i]>=theta:
y1[i]=1         else:
y1[i]=0                 if
zin2[i]>=theta:
            y2[i]=1
else:             y2[i]=0
yin=np.array([])
yin=y1*v1+y2*v2
for i in range(0,4):
if yin[i]>=theta:
            y[i]=1
else:
            y[i]=0
```

```
   print("yin",yin)
print('Output of Net')
y=y.astype(int)
print("y",y)
print("z",z)

   if np.array_equal(y,z):
      con=0
else:
      print("Net is not learning enter another set of weights and Threshold value")
w11=input("Weight w11=")       w12=input("weight w12=")
w21=input("Weight w21=")       w22=input("weight w22=")
v1=input("weight v1=")       v2=input("weight v2=")       theta=input("theta=")

print("McCulloch-Pitts Net for XOR
function") print("Weights of Neuron Z1")
print(w11) print(w21) print("weights of
Neuron Z2") print(w12)
print(w22) print("weights of
Neuron Y") print(v1)
print(v2) print("Threshold
value") print(theta)
```

```
Enter weights
Weight w11=1
weight w12=-1
Weight w21=-1
weight w22=1
weight v1=1
weight v2=1
Enter Threshold Value
theta=1
z1 [ 0 -1  1  0]
z2 [ 0  1 -1  0]
yin [0. 1. 1. 0.]
Output of Net
y [0 1 1 0]
z [0 1 1 0]
McCulloch-Pitts Net for XOR function
Weights of Neuron Z1
1
-1
weights of Neuron Z2
-1
1
weights of Neuron Y
1
1
Threshold value
1
```

## Practical 3a.

**Aim: Write a program to implement Hebb's rule.**

The Hebbian Learning Rule is a learning rule that specifies how much the weight of the connection between two units should be increased or decreased in proportion to the product of their activation. The rule builds on Hebbs's 1949 learning rule which states that the connections between two neurons might be strengthened if the neurons fire simultaneously. The Hebbian Rule works well as long as all the input patterns are orthogonal or uncorrelated. The requirement of orthogonality places serious limitations on the Hebbian Learning Rule. A more powerful learning rule is the delta rule, which utilizes the discrepancy between the desired and actual output of each output unit to change the weights feeding into it.

**Hebb's rule with an analogy. Psychology and neuroscience**

**The Hebb's principle or Hebb's rule**

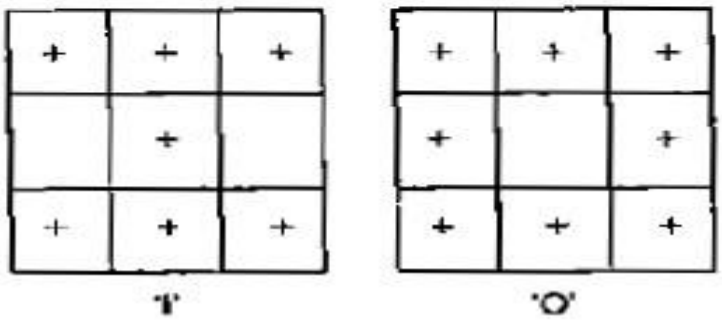
Hebb says that "when the axon of a cell A is close enough to excite a B cell and takes part on its activation in a repetitive and persistent way, some type of growth process or metabolic change takes place in one or both cells, so that increases the efficiency of cell A in the activation of B ".

***'neurons that fire together wire together'***

It is customary to be summarized as "neurons that fire together wire together".That is, the simultaneous activation of nearby neurons leads to an increase in the strength of synaptic connection between them.

It is important to note that the neurons must be previously connected, sufficiently close to one another, so that the synapse can be reinforced. Hebb's principle can be described as a method of determining how to alter the weights between model neurons. The weight between two neurons increases if the two neurons activate simultaneously, and reduces if they activate separately. Nodes that tend to be either both positive or both negative at the same time have strong positive weights, while those that tend to be opposite have strong negative weights.

**Using the Hebb rule, find the weights required to perform the following classifications of the given input patterns shown in Figure 16. The pattern is shown as 3 × 3 matrix form in the squares. The "+" symbols represent the value "1" and empty squares indicate "−1." Consider "I" belongs to the members of class (so has target value 1) and "O" does not belong to the members of class (so has target value −1).**




```
import numpy as np
#first pattern
x1=np.array([1,1,1,-1,1,-1,1,1,1])
#second pattern
x2=np.array([1,1,1,1,-1,1,1,1,1])
#initialize bais value b=0
#define target
y=np.array([1,-1])

wtold=np.zeros((9,))
wtnew=np.zeros((9,))

wtnew=wtnew.astype(int)
wtold=wtold.astype(int)

bais=0 print("First input with
target =1") for i in range(0,9):
   wtold[i]=wtold[i]+x1[i]*y[0]
wtnew=wtold b=b+y[0]
print("new wt =",
wtnew)
print("Bias value",b)
```

```
print("Second input with target =-1") for
i in range(0,9):
wtnew[i]=wtold[i]+x2[i]*y[1]
b=b+y[1] print("new wt
=", wtnew)
print("Bias value",b)
```

Output:

```
First input with target =1
new wt = [ 1  1  1 -1  1 -1  1  1  1]
Bias value 1
Second input with target =-1
new wt = [ 0  0  0 -2  2 -2  0  0  0]
Bias value 0
```

**Practical 3b:**

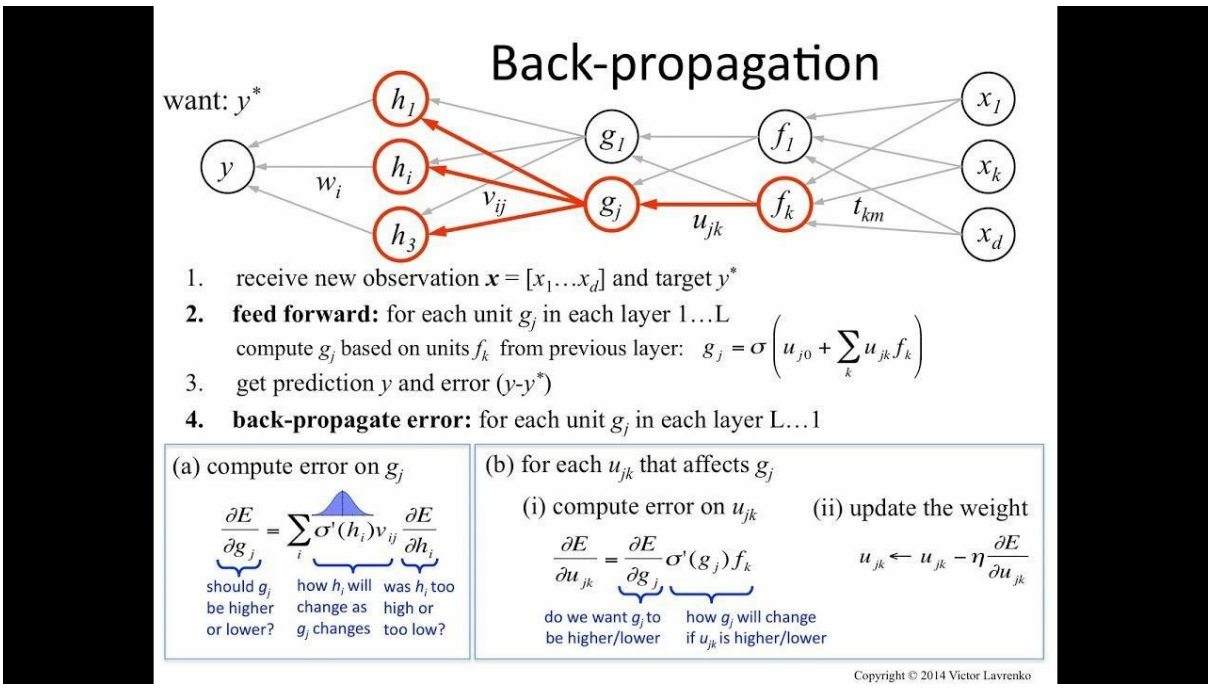
**Aim: Write a program to implement of delta rule.**

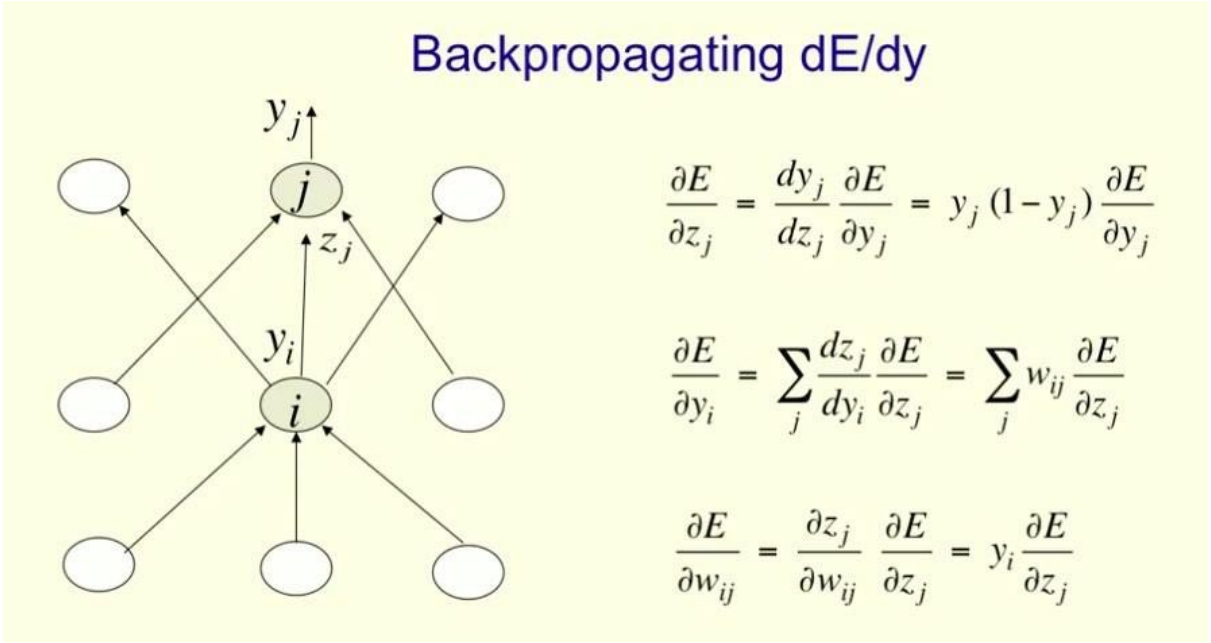
```
#supervised learning import
numpy as np import time
np.set_printoptions(precision=2
) x=np.zeros((3,))
weights=np.zeros((3,))
desired=np.zeros((3,))
actual=np.zeros((3,))


for i in range(0,3):
   x[i]=float(input("Initial inputs:")) for i in
range(0,3):
weights[i]=float(input("Initial weights:"))
for i in range(0,3):
   desired[i]=float(input("Desired output:")) a=float(input("Enter
learning rate:"))
actual=x*weights
print("actual",actual)
print("desired",desired)

while True:     if
np.array_equal(desired,actual):
      break   #no change    else:       for i in range(0,3):
weights[i]=weights[i]+a*(desired[i]-actual[i])
actual=x*weights                print("weights",weights)
print("actual",actual)              print("desired",desired)
print("*"*30)  print("Final  output")  print("Corrected
weights",weights)
print("actual",actual) print("desired",desired)
```

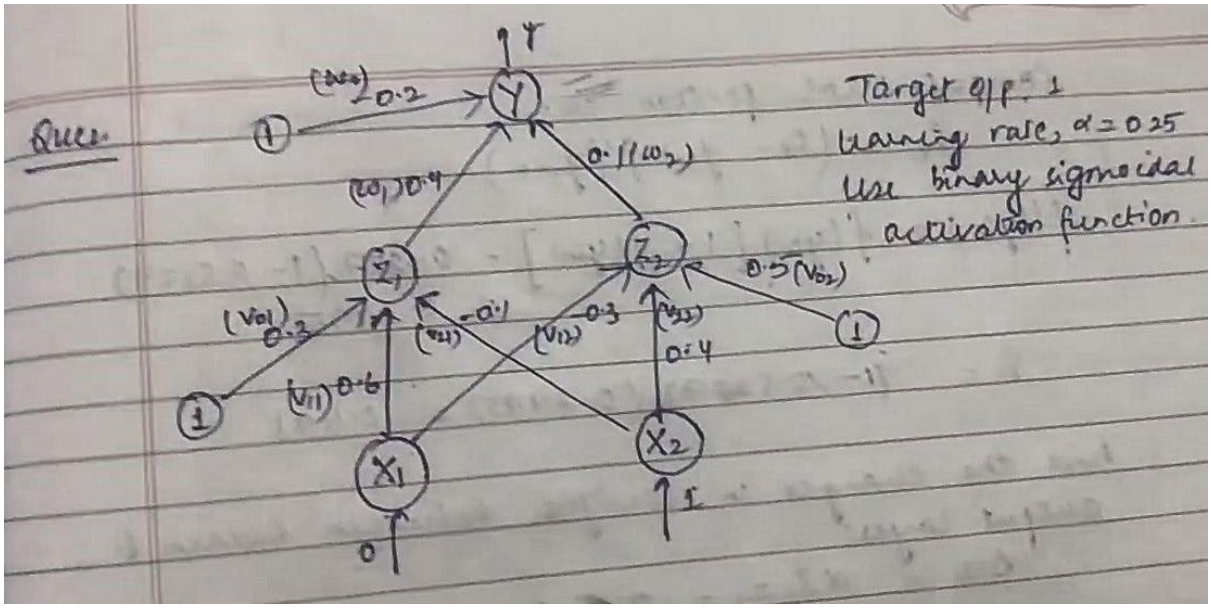
```
Initial inputs:1
Initial inputs:1
Initial inputs:1
Initial weights:1
Initial weights:1
Initial weights:1
Desired output:2
Desired output:3
Desired output:4
Enter learning rate:1
actual [1. 1. 1.]
desired [2. 3. 4.]
weights [2. 3. 4.]
actual [2. 3. 4.]
desired [2. 3. 4.]
******************************
Final output
corrected weights [2. 3. 4.]
actual [2. 3. 4.]
desired [2. 3. 4.]
```

**Practical 4a:**

**Aim: Write a program for Back Propagation Algorithm**






```
import numpy as np import decimal
import math
np.set_printoptions(precision=2)
v1=np.array([0.6, 0.3]) v2=np.array([-
0.1, 0.4]) w=np.array([-0.2,0.4,0.1])
b1=0.3 b2=0.5 x1=0 x2=1 alpha=0.25
print("calculate net input to z1 layer")
zin1=round(b1+
x1*v1[0]+x2*v2[0],4)
print("z1=",round(zin1,3))

print("calculate net input to z2 layer")
zin2=round(b2+ x1*v1[1]+x2*v2[1],4)
print("z2=",round(zin2,4)) print("Apply activation
function to calculate output") z1=1/(1+math.exp(-
zin1)) z1=round(z1,4) z2=1/(1+math.exp(-zin2))
z2=round(z2,4) print("z1=",z1) print("z2=",z2)

print("calculate net input to output layer")
yin=w[0]+z1*w[1]+z2*w[2]
```

```
print("yin=",yin)

print("calculate net output")
y=1/(1+math.exp(-yin))
print("y=",y)

fyin=y *(1- y) dk=(1-
y)*fyin print("dk",dk)

dw1= alpha * dk * z1 dw2=
alpha * dk * z2 dw0= alpha
* dk

print("compute error portion in delta")

din1=dk* w[1]
din2=dk* w[2]
print("din1=",din1)
print("din2=",din2)
print("error in delta")
fzin1= z1 *(1-z1)
print("fzin1",fzin1)
d1=din1* fzin1 fzin2=
z2 *(1-z2)
print("fzin2",fzin2)
d2=din2* fzin2

print("d1=",d1) print("d2=",d2)
```

```
print("Changes in weights between input and hidden
layer") dv11=alpha * d1 * x1 print("dv11=",dv11)
dv21=alpha * d1 * x2 print("dv21=",dv21) dv01=alpha *
d1  print("dv01=",dv01) dv12=alpha * d2 * x1
print("dv12=",dv12) dv22=alpha * d2 * x2
print("dv22=",dv22) dv02=alpha * d2  print("dv02=",dv02)

print("Final weights of
network") v1[0]=v1[0]+dv11
v1[1]=v1[1]+dv12
print("v=",v1)

v2[0]=v2[0]+dv21
v2[1]=v2[1]+dv22
print("v2",v2)

w[1]=w[1]+dw1
w[2]=w[2]+dw2
b1=b1+dv01
b2=b2+dv02
w[0]=w[0]+dw0

print("w=",w) print("bias
b1=",b1, " b2=",b2)
```

```
z1= 0.2
calculate net input to z2 layer
z2= 0.9
Apply activation function to calculate output
z1= 0.5498
z2= 0.7109
calculate net input to output layer
yin= 0.09101
calculate net output
y= 0.5227368084248941
dk 0.11906907074145694
compute error portion in delta
din1= 0.04762762829658278
din2= 0.011906907074145694
error in delta
fzin1 0.24751996
fzin2 0.20552119000000002
d1= 0.011788788650865037
d2= 0.0024471217110978417
Changes in weights between input and hidden layer
dv11= 0.0
dv21= 0.0029471971627162592
dv01= 0.0029471971627162592
dv12= 0.0
dv22= 0.0006117804277744604
dv02= 0.0006117804277744604
Final weights of network
v= [0.6 0.3]
v2 [-0.1  0.4]
w= [-0.17  0.42  0.12]
bias b1= 0.30294719716271623  b2= 0.5006117804277744
```

**Practical 4b**

**Aim: Write a Program For Error Back Propagation Algorithm (Ebpa) Learning**

```
import math a0=-1 t=-1 w10=float(input("Enter
weight first network")) b10=float(input("Enter
base first network:")) w20=float(input("Enter
weight second network:")) b20=float(input("Enter
base second network:"))
c=float(input("Enter learning coefficient:"))
n1=float(w10*c+b10)
a1=math.tanh(n1)
n2=float(w20*a1+b20)
a2=math.tanh(float(n2))
e=t-a2 s2=-2*(1-
a2*a2)*e
s1=(1-a1*a1)*w20*s2

w21=w20-(c*s2*a1) w11=w10-(c*s1*a0) b21=b20-
(c*s2) b11=b10-(c*s1) print("The updated weight of
first n/w w11=",w11) print("The uploaded weight of
second n/w w21= ",w21) print("The updated base of
first n/w b10=",b10)
print("The updated base of second n/w b20= ",b20)
```

```
Enter weight first network:12
Enter base first network:35
Enter weight second network:23
Enter base second network:45
Enter learning coefficient:11
The updated weight of first n/w w11= 12.0
The uploaded weight of second n/w w21=  23.0
The updated base of first n/w b10= 35.0
The updated base of second n/w b20=  45.0
```

**Practical 5a:**

**Aim: Write a program for Hopfield Network**.

## Algorithm

*Step 0.* Initialize activations of all units.
Initialize $\Delta t$ to a small value.

*Step 1.* While the stopping condition is false, do Steps 2–6.

*Step 2.* Perform Steps 3–5 $n^2$ times ($n$ is the number of cities).

*Step 3.* Choose a unit at random.

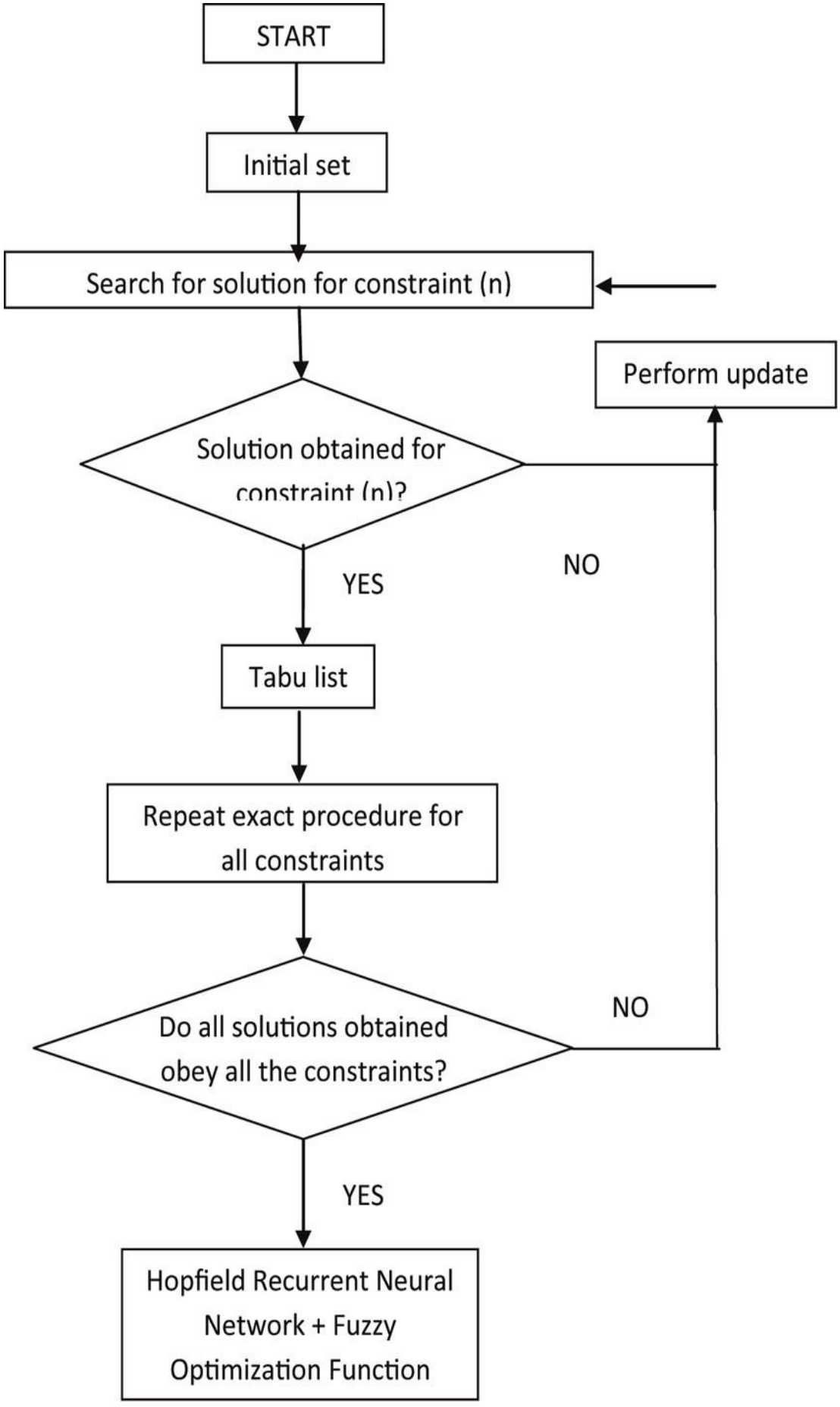
*Step 4.* Change activity on selected unit:

$$u_{x,i}(\text{new}) = u_{x,i}(\text{old}) + \Delta t[-u_{x,i}(\text{old}) - A\sum_{j\neq i} v_{x,j} - B\sum_{y\neq x} v_{y,i} + C\{N - \sum_{x}\sum_{j} v_{x,j}\} - D\sum_{y\neq x} d_{x,y}(v_{y,i+1} + v_{y,i-1})].$$

*Step 5.* Apply output function:

$$v_{x,i} = 0.5[1 + \tanh(\alpha u_{x,i})].$$

*Step 6.* Check stopping condition.


START
Initial set
Search for solution for constraint (n)
Perform update
Solution obtained for constraint (n)?
NO
YES
Tabu list
Repeat exact procedure for all constraints
Do all solutions obtained obey all the constraints?
NO
YES
Hopfield Recurrent Neural Network + Fuzzy Optimization Function

Code:

```
class Neuron:    def
__init__(self, j):
      # Constructor to initialize weights based on the provided array
self.activation = 0
      self.weightv = [j[i] for i in range(4)]

   def act(self, m, x):
      # Activation function to calculate the weighted sum
a = sum(x[i] * self.weightv[i] for i in range(m))       return
a

class Network:    def
__init__(self, a, b, c, d):
      # Constructor to create a network with four neurons
self.nrn = [Neuron(a), Neuron(b), Neuron(c), Neuron(d)]
self.output = [0, 0, 0, 0]

   def threshld(self, k):
# Threshold function
if k >= 0:          return 1
else:
         return 0

   def activation(self, patrn):
      # Activation function for the entire network
for i in range(4):
         print(f"\nnrn[{i}].weightv is {self.nrn[i].weightv}")
self.nrn[i].activation = self.nrn[i].act(4, patrn)
print(f"Activation is {self.nrn[i].activation}")          self.output[i]
= self.threshld(self.nrn[i].activation)          print(f"Output value
is {self.output[i]}\n")

def main():
   patrn1 = [1, 0, 1, 0]
wt1 = [0, -3, 3, -3]    wt2
= [-3, 0, -3, 3]    wt3 =
[3, -3, 0, -3]    wt4 = [-3,
3, -3, 0]

   print("THIS PROGRAM IS FOR A HOPFIELD NETWORK WITH A SINGLE LAYER OF")
print("4 FULLY INTERCONNECTED NEURONS. THE NETWORK SHOULD RECALL THE")
print("PATTERNS 1010 AND 0101 CORRECTLY.\n")

   # Create the network by calling its constructor.
   # The constructor calls the neuron constructor as many times as the number of
# neurons in the network.
   h1 = Network(wt1, wt2, wt3, wt4)
```

```
    # Present a pattern to the network and get the activations of the neurons
h1.activation(patrn1)

    # Check if the pattern given is correctly recalled and give a message
for i in range(4):        if h1.output[i] == patrn1[i]:
        print(f"\nPattern = {patrn1[i]}, Output = {h1.output[i]}, Component matches")
else:
        print(f"\nPattern = {patrn1[i]}, Output = {h1.output[i]}, Discrepancy occurred")

    print("\n\n")

    patrn2 = [0, 1, 0, 1]
    h1.activation(patrn2)

    for i in range(4):        if
h1.output[i] == patrn2[i]:
        print(f"\nPattern = {patrn2[i]}, Output = {h1.output[i]}, Component matches")
else:
        print(f"\nPattern = {patrn2[i]}, Output = {h1.output[i]}, Discrepancy occurred")

if __name__ == "__main__":
    main()
```

Output:

```
Python 3.10.7 (tags/v3.10.7:6cc6b13, Sep  5 2022, 14:08:36) [MSC v.1933 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.

================== RESTART: C:\Users\prath\bomb\Hopefield.py ==================
THIS PROGRAM IS FOR A HOPFIELD NETWORK WITH A SINGLE LAYER OF
4 FULLY INTERCONNECTED NEURONS. THE NETWORK SHOULD RECALL THE
PATTERNS 1010 AND 0101 CORRECTLY.


nrn[0].weightv is [0, -3, 3, -3]
Activation is 3
Output value is 1


nrn[1].weightv is [-3, 0, -3, 3]
Activation is -6
Output value is 0


nrn[2].weightv is [3, -3, 0, -3]
Activation is 3
Output value is 1


nrn[3].weightv is [-3, 3, -3, 0]
Activation is -6
Output value is 0


Pattern = 1, Output = 1, Component matches

Pattern = 0, Output = 0, Component matches

Pattern = 1, Output = 1, Component matches

Pattern = 0, Output = 0, Component matches
```

```
nrn[0].weightv is [0, -3, 3, -3]
Activation is -6
Output value is 0


nrn[1].weightv is [-3, 0, -3, 3]
Activation is 3
Output value is 1


nrn[2].weightv is [3, -3, 0, -3]
Activation is -6
Output value is 0


nrn[3].weightv is [-3, 3, -3, 0]
Activation is 3
Output value is 1


Pattern = 0, Output = 0, Component matches

Pattern = 1, Output = 1, Component matches

Pattern = 0, Output = 0, Component matches

Pattern = 1, Output = 1, Component matches
```

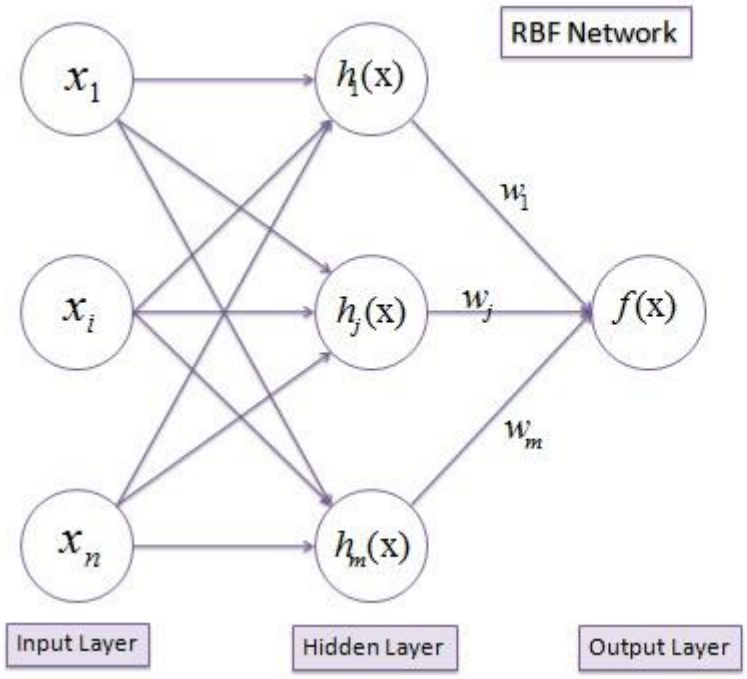
**Practical 5b:**

**Aim:Write a program for Radial Basis function**

**Radial Basis Function Networks (RBF)**

RBF networks have three layers: input layer, hidden layer and output layer. One neuron in the input layer corresponds to each predictor variable. With respects to categorical variables, *n*-1 neurons are used where *n* is the number of categories. Hidden layer has a variable number of neurons. Each neuron

consists of a radial basis function centered on a point with the same dimensions as the predictor variables. The output layer has a weighted sum of outputs from the hidden layer to form the network outputs.




$$f(x) = \sum_{j=1}^{m} w_j h_j(x)$$

$$h(x) = \exp\left(-\frac{(x-c)^2}{r^2}\right)$$

**Algorithm**

$h(x)$ is the Gaussian activation function with the parameters $r$ (the radius or standard deviation) and $c$ (the center or average taken from the input space) defined separately at each RBF unit. The learning process is based on adjusting the parameters of the network to reproduce a set of input-output patterns. There are three types of parameters; the weight $w$ between the hidden nodes and the output nodes, the center $c$ of each neuron of the hidden layer and the unit width $r$.

**Unit Center (*c*)**

, Any clustering algorithm can be used to determine the RBF unit centers (e.g., K-means clustering). A set of clusters each with *r*-dimensional centers is determined by the number of input variables or nodes of the input layer. The cluster centers become the centers of the RBF units. The number of clusters, *H* is

a design parameter and determines the number of nodes in the hidden layer. The K-means clustering algorithm proceeds as follows:

1. Initialize the center of each cluster to a different randomly selected training pattern.
2. Assign each training pattern to the nearest cluster. This can be accomplished by calculating the Euclidean distances between the training patterns and the cluster centers.
3. When all training patterns are assigned, calculate the average position for each cluster center. They then become new cluster centers.
4. Repeat steps 2 and 3, until the cluster centers do not change during the subsequent iterations.

**Unit width (*r*)**

When the RBF centers have been established, the width of each RBF unit can be calculated using the Knearest neighbors algorithm. A number K is chosen, and for each center, the K nearest centers is found. The root-mean squared distance between the current cluster center and its K nearest neighbors is calculated, and this is the value chosen for the unit width (*r*). So, if the current cluster center is $c_j$, the *r* value is:

$$r_j = \sqrt{\frac{\sum_{i=1}^{k} (c_j - c_i)^2}{k}}$$

A typical value for K is 2, in which case s is set to be the average distance from the two nearest neighboring cluster centers.

**Weights (*w*)**

Using the linear mapping, **w** vector is calculated using the output vector (**y**) and the design matrix **H**.

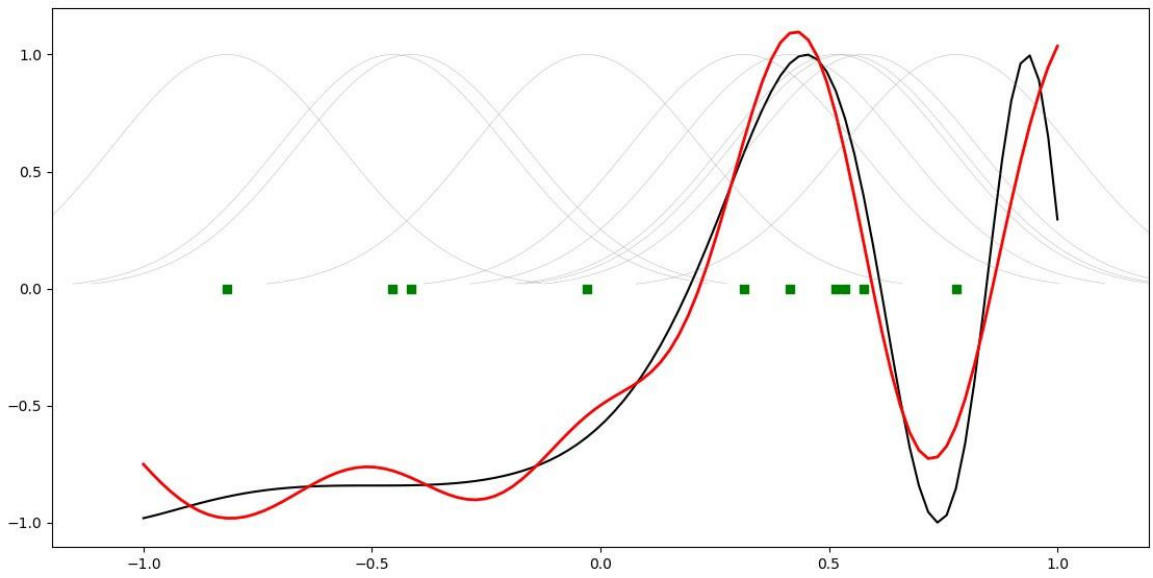
$$y = wH$$
$$w = (H'H)\, H'y$$

The basis functions are (unnormalized) gaussians, the output layer is linear and the weights are learned by a simple pseudo-inverse.

```
from scipy import * from
scipy.linalg import norm, pinv from
matplotlib import pyplot as plt

class RBF:

    def __init__(self, indim, numCenters, outdim):
        self.indim =indim        self.outdim =outdim        self.numCenters
=numCenters        self.centers =[random.uniform(-1, 1, indim) for i in
range(numCenters)]        self.beta =8        self.W
=random.random((self.numCenters, self.outdim))

    def _basisfunc(self, c, d):        assert
len(d) ==self.indim        return exp(-
self.beta *norm(c-d)**2)

    def _calcAct(self, X):
        # calculate activations of RBFs
        G =zeros((X.shape[0], self.numCenters),
float)        for ci, c in enumerate(self.centers):
for xi, x in enumerate(X):                G[xi,ci]
=self._basisfunc(c, x)        return G

    def train(self, X, Y):
        """ X: matrix of dimensions n x indim
y: column vector of dimension n x 1 """        #
choose random center vectors from training set
rnd_idx
=random.permutation(X.shape[0])[:self.numC
```

```
enters]        self.centers =[X[i,:] for i in
rnd_idx]

        print("center", self.centers)
        # calculate activations of RBFs
G =self._calcAct(X)         print (G)

        # calculate output weights (pseudoinverse)
self.W =dot(pinv(G), Y)

    def test(self, X):
        """ X: matrix of dimensions n x indim """

        G =self._calcAct(X)
Y =dot(G, self.W)
return Y



if __name__ =='__main__':
    # ----- 1D Example ------------------------------------------------
n =100

    x =mgrid[-1:1:complex(0,n)].reshape(n,
1)     # set y and add random noise      y
=sin(3*(x+0.5)**3-1)
    # y += random.normal(0, 0.1, y.shape)

    # rbf regression
    rbf =RBF(1, 10,
1)     rbf.train(x, y)
z =rbf.test(x)
```

```
    # plot original data
plt.figure(figsize=(12, 8))
plt.plot(x, y, 'k-')

    # plot learned model
plt.plot(x, z, 'r-', linewidth=2)

    # plot rbfs     plt.plot(rbf.centers,
zeros(rbf.numCenters), 'gs')

    for c in rbf.centers:        # RF prediction lines        cx
=arange(c-0.7, c+0.7, 0.01)        cy
=[rbf._basisfunc(array([cx_]), array([c])) for cx_ in cx]
plt.plot(cx, cy, '-', color='gray', linewidth=0.2)

    plt.xlim(-1.2, 1.2)
plt.show()
```



**Practical 6a:**

**Aim: Self-Organizing Maps**

The SOM algorithm is used to compress the information to produce a similarity graph while preserving the topologic relationship of the input data space.

The basic SOM model construction algorithm can be interpreted as follows:

1) Create and initialize a matrix (weight vector) randomly to hold the neurons. If the matrix can be initialized with order and roughly compiles with the input density function, the map will converge quickly

2) Read the input data space. For each observation (instance), use the optimum fit approach, which is based on the Euclidean distance

c = $aaaaaa_{ii}$ min || x – $mm_{ii}$ ||

to find the neuron which best matches this observation. Let x denote the training vector from the observation and $mmii$ denote a single neuron in the matrix. Update that neuron to resemble that observation using the following equation:

$mmii\ (tt + 1) = mmii\ (tt) + h(tt)[xx(tt) - mmii\ (tt)]$ (4) $mmii(tt)$:

the weight vector before the neuron is updated.

$(tt + 1)$: the weight vector after the neuron is updated.

$(tt)$: the training vector from the observation.

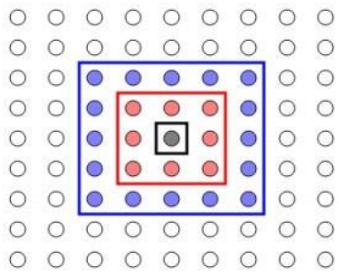
$h(tt)$: the neighborhood function (a smoothing kernel defined over the lattice points), defined though the following equation:

$h(tt) = \{\ \alpha\alpha(tt), ii \in NNNN\ 0, ii \in NNNN$ (5)

: the neighborhood set, which decreases with time.

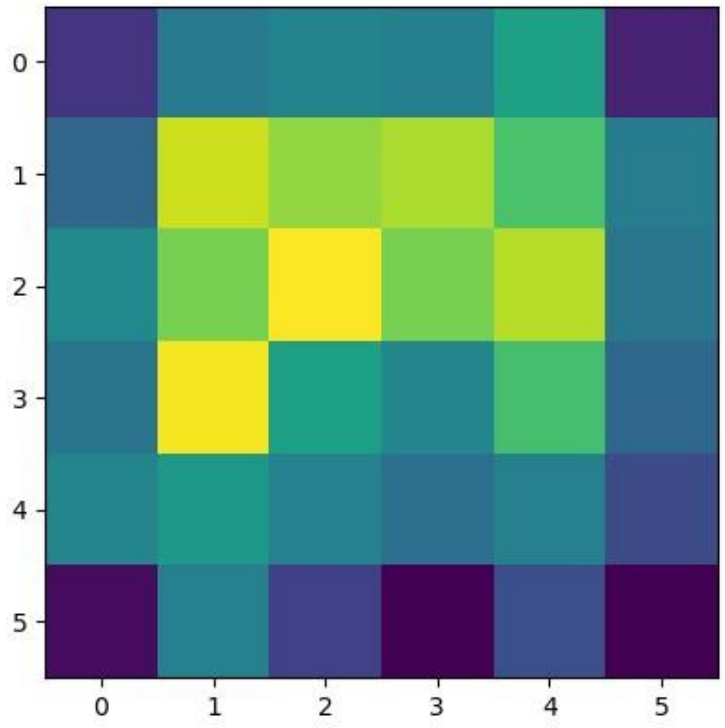
$(tt)$: the learning-rate factor which can be linear, exponential or inversely proportional.

It is a monotonically decreasing function of time (t)



In general, SOMs might be useful for visualizing high-dimensional data in terms of its similarity structure. Especially large SOMs (i.e. with large number of Kohonen units) are known to perform mappings that preserve the topology of the original data, i.e. neighboring data points in input space will also be represented in adjacent locations on the SOM.

```
from minisom import MiniSom
import matplotlib.pyplot as plt
data = [[ 0.80, 0.55, 0.22, 0.03],
[ 0.82, 0.50, 0.23, 0.03],
[ 0.80, 0.54, 0.22, 0.03],
[ 0.80, 0.53, 0.26, 0.03],
[ 0.79, 0.56, 0.22, 0.03],
[ 0.75, 0.60, 0.25, 0.03], [ 0.77, 0.59, 0.22, 0.03]] som = MiniSom(6, 6, 4,
sigma=0.3, learning_rate=0.5) # initialization of 6x6 SOM
som.train_random(data, 100) # trains the SOM with 100 iterations
plt.imshow(som.distance_map()) plt.show()
```



## Practical No.6 (b)

**Aim:** Implementation of Adaptive resonance theory.

```
from future import print_function from future import division
import numpy as np
 class ART:
    ''' ART class
    Usage example:
    ----------
    # Create a ART network with input of size 5 and 20 internal
    units
    >>>network = ART(5,10,0.5)
    '''
definit(self, n=5, m=10, rho=.5):
        '''
        Create network with specified shape
        Paramet
        ers:
        --------
           n
 : int    Size of
 input   m : int
           Maximum number of internal
        units rho : float
           Vigilance parameter
        '''
        # Comparison layer
           self.F1 = np.ones(n)       #
  Recognition layer self.F2 =
  np.ones(m)     # Feedforward
  weights          self.Wf =
```

```
np.random.random((m,n))       #
Feedback weights        self.Wb =
np.random.random((n,m))
      #Vigilance
self.rho = rho
      # Number of active
units in F2 self.active = 0 def
learn(self, X):
      ''' Learn X '''
      # Compute F2 output and sort them (I)
self.F2[...] = np.dot(self.Wf, X)
      I =
      np.argsort(self.F2[:self.active].ravel())[::-1]
      for i in I:
        # Check if nearest memory is above the
vigilance level d = (self.Wb[:,i]*X).sum()/X.sum() if d >=
self.rho: # Learn data self.Wb[:,i] *= X self.Wf[i,:] =
self.Wb[:,i]/(0.5+self.Wb[:,i].sum())                return
self.Wb[:,i], i
      # No match found, increase the number of active
      units
# and make the newly active unit to learn data          if
self.active < self.F2.size:
i = self.activeself.Wb[:,i] *= X
self.Wf[i,:] = self.Wb[:,i]/(0.5+self.Wb[:,i].sum())
self.active += 1 return self.Wb[:,i], i return
      None,None
  ----------------------------------------------------
  _n      ___=  '_m       '
#
if
```

```
  np.random.seed(1)
    # Example 1 : very simple data
    #
    ------------------------------------------------
    network = ART( 5, 10, rho=0.5)
data = [" O ",              " O O",
"       O",
         " O O",
"       O",
         " O O",
"       O",
         " OO O",
         " OO ",
         " OO O",
         " OO ",
         "OOO ",
         "OO ",
"O       ",
         "OO ",
         "OOO ",
         "OOOO ",
         "OOOOO",
"O       ",
" O      ",
         " O ",
"       O ",
"       O",
         " O O",
         " OO O",
         " OO ",
```

```
            "OOO ",
            "OO ",
            "OOOO ",
            "OOOOO"]
    X = np.zeros(len(data[0]))      for i
  in range(len(data)):      for j in
  range(len(data[i])):      X[j] =
  (data[i][j] == 'O')          Z, k =
  network.learn(X)
  print("|%s|"%data[i],"-> class", k)
     # Example 2 : Learning letters
     #
  ----------------------------------------------
  def letter_to_array(letter):       ''' Convert a letter to a
  numpy array ''' shape = len(letter), len(letter[0])
            Z = np.zeros(shape, dtype=int)    forrow in
  range(Z.shape[0]):       for column in
  range(Z.shape[1]):       if
  letter[row][column] == '#':
Z[row][column] = 1          return Z     def
  print_letter(Z):
        ''' Print an array as if it was a letter'''
for row in range(Z.shape[0]):              for
  col in
               range(Z.sh
               ape[1]): if
               Z[row,col]:
              print( '#', end="" )
  else:    print( ' ', end="" )
            print( )
```

```
 A = letter_to_array( [' #### ',
'#                  #',
'#                  #',
                  '######',
'#                  #',
'#                  #',
'#                 #'] )
 B = letter_to_array( ['##### ',
'#                  #',
'#                  #',
                  '##### ',
'#                  #',
'#                  #',
                  '##### '] )
 C = letter_to_array( [' #### ',
'#                  #',
'#                   ',
'#                   ',
'#                   ',
'#                  #',
                  ' #### '] )
 D = letter_to_array( ['##### ',
'#                  #',
'#                  #',
'#                  #',
'#                  #',
'#                  #',
                  '##### '] )
 E = letter_to_array( ['######', '#          ',
'#                   ',
```

```
                '#### ',
'#                  ',
'#                  ',
                '######'] )
 F = letter_to_array( ['######', '#          ',
'#                  ',
                '#### ',
'#                  ',
'#                  ',
'#                 '] )

samples = [A,B,C,D,E,F]          network
 = ART( 6*7, 10, rho=0.15 )
for i in range(len(samples)):              Z, k =
 network.learn(samples[i].ravel())
 print("%c"%(ord('A')+i),"-> class",k)
 print_letter(Z.reshape(7,6))
```

**Output**

```
|    O | -> class 0
 | O O| -> class 1
|     O| -> class 1
 | O O| -> class 2
|     O| -> class 1
 | O O| -> class 3
|     O| -> class 1
 | OO O| -> class 4
 | OO | -> class 5
 | OO O| -> class 6
 | OO | -> class 6
 |OOO | -> class 6
```

|OO | -> class 7

|O | -> class 8

|OO | -> class 9

|OOO | -> class 6

|OOOO | -> class None
|OOOOO| -> class None

|O | ->

class 8 | O

| ->

class 5

| O | -> class 6

| O | -> class 0

| O| -> class 1

| O O| -> class 3

| OO O| -> class None

| OO | -> class None
|OOO | -> class None

|OO | -> class 9

|OOOO | -> class None

|OOOOO| -> class None

A -> class 0

####

# #

# #

######

# #

# #

# #

B -> class 0

####

# #

# #

```
 #####
#     #
#     #
 #
 C -> class 0
 ####
#     #
 #
 #
 #
#     #

 D -> class 0
 ####
#     #
 #
 #
 #
#     #

 E -> class 0
 ####
 #
 #
 #
 #
 #
 F -> class 0
 ####
 #
 #
 #
```

#

#

**Example 2 : Testing ART by creating array dataset** import numpy as np # compute sigmoid nonlinearity def sigmoid(x): output = 1/(1+np.exp(-x)) return output

# convert output of sigmoid function to its derivative def sigmoid_output_to_derivative(output):

return output*(1-output) #

input dataset

X = np.array([ [0,1],

[0,1],

[1,0],

[1,0] ])

# output dataset y

= np.array([[0,0,1,1]]).T

# seed random numbers to make calculation # deterministic (just a good practice) np.random.seed(1)

# initialize weights randomly with mean 0 synapse_0 = 2*np.random.random((2,1)) 1 for iter in range(10000): # forward propagation layer_0 = X

layer_1 = sigmoid(np.dot(layer_0,synapse_0))

# how much did we miss?

layer_1_error = layer_1 - y

# multiply how much we missed by the # slope of the sigmoid at the values in l1 layer_1_delta =

layer_1_error * sigmoid_output_to_derivative(layer_1)

synapse_0_derivative = np.dot(layer_0.T,layer_1_delta)

```
    # update weights
    synapse_0 -=
synapse_0_derivative print ("Output
After Training:") print (layer_1)
```

**Output**

```
Output After Training:
[[0.00505119]
[0.00505119]
[0.99494905]
[0.99494905]]
```

----------X

**Example 3: By providing data**

```
pattern import math import sys
N = 4 # Number of components in an input vector.
M = 3 # Max number of clusters to be formed.
VIGILANCE = 0.4
PATTERNS = 7
TRAINING_PATTERNS = 4 # Use this many for training, the rest are for tests.
PATTERN_ARRAY = [[1, 1, 0, 0],
                 [0, 0, 0, 1],
                 [1, 0, 0, 0],
                 [0, 0, 1, 1],
                 [0, 1, 0, 0],
                 [0, 0, 1, 0],
                 [1, 0, 1, 0]]
class ART1_Example1:
def init(self, inputSize, numClusters, vigilance,
numPatterns, numTraining, patternArray):
        self.mInputSize = inputSize
  self.mNumClusters = numClusters
  self.mVigilance = vigilance
  self.mNumPatterns = numPatterns
```

```
  self.mNumTraining = numTraining
  self.mPatterns = patternArray self.bw = [] #
  Bottom-up weights. self.tw = [] # Top-down
  weights.
        self.f1a = [] # Input layer.
  self.f1b = [] # Interface layer.
self.f2 = []return          def
  initialize_arrays(self):          # Initialize
  bottom-up weight matrix.
  sys.stdout.write("Weights initialized to:")
  for i in range(self.mNumClusters):
  self.bw.append([0.0] * self.mInputSize)
  for j in range(self.mInputSize):
              self.bw[i][j] = 1.0 / (1.0 +
  self.mInputSize)
  sys.stdout.write(str(self.bw[i][j]) + ", ")
  sys.stdout.write("\n")
sys.stdout.write("\n")                # Initialize top-
  down weight matrix. for i in
  range(self.mNumClusters):
  self.tw.append([0.0] * self.mInputSize)
  for j in range(self.mInputSize):
              self.tw[i][j] = 1.0
              sys.stdout.write(str(self.tw[i][j]) + ",
")                    sys.stdout.write("\n")
  sys.stdout.write("\n") self.f1a = [0.0] *
  self.mInputSize self.f1b = [0.0] *
  self.mInputSize self.f2 = [0.0] *
  self.mNumClusters return def
  get_vector_sum(self, nodeArray): total = 0
```

```
  length = len(nodeArray) for i in
  range(length):
            total += nodeArray[i]
  return total     def
  get_maximum(self, nodeArray):
  maximum = 0;
  foundNewMaximum = False;
  length = len(nodeArray)
  done = False  while not done:
foundNewMaximum = False                    for i in
  range(length): if i != maximum: if
  nodeArray[i] >
  nodeArray[maximum]: maximum = i
  foundNewMaximum = True
  if foundNewMaximum == False:
              done = True          return maximum         def
  test_for_reset(self, activationSum, inputSum, f2Max):
doReset = False                    if(float(activationSum) /
  float(inputSum) >= self.mVigilance):          doReset =
  False # Candidate is accepted.          else:     self.f2[f2Max]
  = -1.0 # Inhibit.        doReset = True # Candidate is
  rejected. return doReset       def update_weights(self,
  activationSum, f2Max):
        # Update bw(f2Max) for i
  in range(self.mInputSize):
     self.bw[f2Max][i] = (2.0 * float(self.f1b[i])) / (1.0 + float(activationSum))
for i in range(self.mNumClusters):              for j in range(self.mInputSize):
              sys.stdout.write(str(self.bw[i][j]) + ",
  ")       sys.stdout.write("\n")
  sys.stdout.write("\n")          # Update
```

```
tw(f2Max)     for i in
range(self.mInputSize):
            self.tw[f2Max][i] = self.f1b[i]
for i in range(self.mNumClusters):
for j in range(self.mInputSize):
                sys.stdout.write(str(self.tw[i][j]) + ",
")       sys.stdout.write("\n")
sys.stdout.write("\n")            return   def
ART1(self):   inputSum = 0 activationSum
= 0     f2Max = 0       reset =
True sys.stdout.write("Begin
       ART1:\n")
for k in range(self.mNumPatterns):
            sys.stdout.write("Vector: " + str(k) + "\n\n")
            # Initialize f2 layer activations to
0.0 for i in range(self.mNumClusters):
self.f2[i] = 0.0
            # Input pattern() to f1
layer. for i in
range(self.mInputSize):
                self.f1a[i] =
self.mPatterns[k][i] # Compute sum
of input pattern.
            inputSum = self.get_vector_sum(self.f1a)
sys.stdout.write("InputSum (si) = " + str(inputSum) + "\n\n") #
Compute activations for each node in the f1 layer.
            # Send input signal from f1a to the fF1b layer.
for i in range(self.mInputSize):
                self.f1b[i] = self.f1a[i]
            # Compute net input for each node in
the f2 layer. for i in
```

```
range(self.mNumClusters): for j in
range(self.mInputSize):
                self.f2[i] += self.bw[i][j] *
float(self.f1a[j])
sys.stdout.write(str(self.f2[i]) + ", ")
sys.stdout.write("\n")
        sys.stdout.write("\n") reset = True
        while reset == True:
            # Determine the largest value of the f2 nodes.
f2Max = self.get_maximum(self.f2)
            # Recompute the f1a to f1b activations (perform
            AND function)
for i in range(self.mInputSize):
         sys.stdout.write(str(self.f1b[i]) + " * " + str(self.tw[f2Max][i]) + " = " + str(self.f1b[i] *
self.tw[f2Max][i]) + "\n")
                self.f1b[i] = self.f1a[i] *
                              math.floor(self.tw[f2Max][i]) #
                              Compute sum of input pattern.
                              activationSum =
self.get_vector_sum(self.f1b)
            sys.stdout.write("ActivationSum (x(i)) = " + str(activationSum) +
"\n\n") reset = self.test_for_reset(activationSum, inputSum, f2Max)         # Only
use number of TRAINING_PATTERNS for training, the rest are tests.
          if k < self.mNumTraining:
             self.update_weights(activationSum, f2Max)
          sys.stdout.write("Vector #" + str(k) + " belongs to
          cluster #" + str(f2Max) + "\n\n")
return def print_results(self):
       sys.stdout.write("Final weight
values:\n")                for i in
range(self.mNumClusters):   for j in range(self.mInputSize):
            sys.stdout.write(str(self.bw[i][j]) + ", ")
```

```
sys.stdout.write("\n")
        sys.stdout.write("\n")
for i in range(self.mNumClusters):
for j in range(self.mInputSize):
                sys.stdout.write(str(self.tw[i][j]) + ",
")       sys.stdout.write("\n")
sys.stdout.write("\n")           return if_        ___
      __name == '        main    ':
   art1 = ART1_Example1(N, M, VIGILANCE,
PATTERNS, TRAINING_PATTERNS,
PATTERN_ARRAY)
   art1.initialize_arrays()
art1.ART1()
art1.print_results()
```

**Output**

```
Python 3.7.4 (tags/v3.7.4:e09359112e, Jul 8 2019, 19:29:22) [MSC v.1916 32 bit (Intel)] on
win32 Type "help", "copyright", "credits" or "license()" for more information. >>>
== RESTART: E:/SPDT/MSCSem1/Soft
Computing/MSC/MSC/Practical6/Pract6B_3.py ==
Weights initialized to:0.2, 0.2, 0.2, 0.2,
0.2, 0.2, 0.2, 0.2, 0.2,
0.2, 0.2, 0.2, 1.0,
1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0,
Begin ART1:
Vector: 0
InputSum (si) = 2
0.2, 0.4, 0.4, 0.4, 0.2,
0.4, 0.4, 0.4,
0.2, 0.4, 0.4, 0.4,
1 * 1.0 = 1.0
1 * 1.0 = 1.0
0 * 1.0 = 0.0
0 * 1.0 = 0.0
ActivationSum (x(i)) = 2
0.6666666666666666, 0.6666666666666666, 0.0, 0.0,
0.2, 0.2, 0.2, 0.2,
```

0.2, 0.2, 0.2, 0.2,
1, 1, 0, 0,
1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0,
Vector #0 belongs to cluster #0
Vector: 1
InputSum (si) = 1
0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.2,
0.0, 0.0, 0.0, 0.2,
0 * 1.0 = 0.0
0 * 1.0 = 0.0
0 * 1.0 = 0.0
1 * 1.0 = 1.0
ActivationSum (x(i)) = 1
0.6666666666666666, 0.6666666666666666, 0.0, 0.0,
0.0, 0.0, 0.0, 1.0,
0.2, 0.2, 0.2, 0.2,
1, 1, 0, 0,
0, 0, 0, 1,
1.0, 1.0, 1.0, 1.0,
Vector #1 belongs to cluster #1
Vector: 2
InputSum (si) = 1
0.6666666666666666, 0.6666666666666666,
0.6666666666666666, 0.6666666666666666,
0.0, 0.0, 0.0, 0.0,
0.2, 0.2, 0.2, 0.2,
1 * 1 = 1
0 * 1 = 0
0 * 0 = 0
0 * 0 = 0
ActivationSum (x(i)) = 1
1.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 1.0,
0.2, 0.2, 0.2, 0.2,
1, 0, 0, 0,
0, 0, 0, 1,
1.0, 1.0, 1.0, 1.0,
Vector #2 belongs to cluster #0
Vector: 3
InputSum (si) = 2
0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 1.0,
0.0, 0.0, 0.2, 0.4,
0 * 0 = 0

0 * 0 = 0
1 * 0 = 0
1 * 1 = 1
ActivationSum (x(i)) = 1
1.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 1.0,
0.2, 0.2, 0.2, 0.2,
1, 0, 0, 0,
0, 0, 0, 1,
1.0, 1.0, 1.0, 1.0,
Vector #3 belongs to cluster #1
Vector: 4

InputSum (si) = 1
0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0,
0.0, 0.2, 0.2, 0.2,
0 * 1.0 = 0.0
1 * 1.0 = 1.0
0 * 1.0
= 0.0 0
* 1.0 =
0.0
ActivationSum (x(i)) = 1
Vector #4 belongs to cluster #2
Vector: 5
InputSum (si) = 1
0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0,
0.0, 0.0, 0.2, 0.2,
0 * 1.0 = 0.0
0 * 1.0 = 0.0
1 * 1.0 = 1.0
0 * 1.0 = 0.0
ActivationSum (x(i)) = 1
Vector #5 belongs to cluster #2
Vector: 6
InputSum (si) = 2
1.0, 1.0, 1.0, 1.0, 0.0,
0.0, 0.0, 0.0,
0.2, 0.2, 0.4, 0.4,
1 * 1 = 1
0 * 0 = 0
1 * 0 = 0
0 * 0 = 0
ActivationSum (x(i)) = 1

Vector #6 belongs to cluster
#0 Final weight values:
1.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 1.0,
0.2, 0.2, 0.2, 0.2,
1, 0, 0, 0,
0, 0, 0, 1,
1.0, 1.0, 1.0, 1.0,

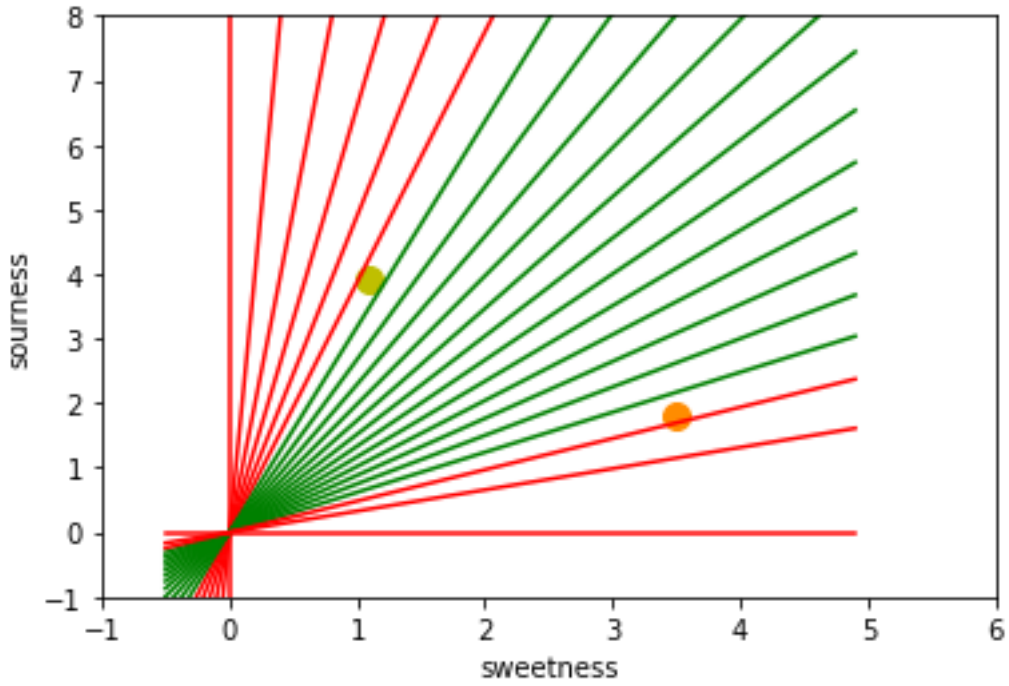
**Practical 7a:**

**Aim: Line Separation**

You could imagine that you have two attributes describing am eddible object like a fruit for example: "sweetness" and "sourness"
We could describe this by points in a two-dimensional space. The x axis for the sweetness and the y axis for the sourness. Imagine now that we have two fruits as points in this space, i.e. an orange at position (3.5, 1.8) and a lemon at (1.1, 3.9).
We could define dividing lines to define the points which are more lemon-like and which are more orange-like. The following program calculates and renders a bunch of lines. The red ones are completely unusable for this purpose, because they are not separating the classes. Yet, it is obvious that even the green ones are not all useful.

```
import numpy as np import
matplotlib.pyplot as plt def
create_distance_function(a, b, c):
   """ 0 = ax + by + c """
def distance(x, y):
      """ returns tuple (d, pos)
d is the distance
         If pos == -1 point is below the line,
         0 on the line and +1 if above the line
      """        nom = a * x + b * y + c        if
nom == 0:            pos = 0        elif (nom<0 and
b<0) or (nom>0 and b>0):            pos = -1
else:
         pos = 1        return (np.absolute(nom) / np.sqrt( a **
2 + b ** 2), pos)     return distance

points = [ (3.5, 1.8), (1.1, 3.9) ] fig, ax
= plt.subplots()
ax.set_xlabel("sweetness")
ax.set_ylabel("sourness")
ax.set_xlim([-1, 6]) ax.set_ylim([-1,
8]) X = np.arange(-0.5, 5, 0.1) colors =
["r", ""] # for the samples size = 10 for
(index, (x, y)) in enumerate(points):
if index== 0:
      ax.plot(x, y, "o", color="darkorange", markersize=size)
else:
      ax.plot(x, y, "oy", markersize=size)
      step = 0.05 for x in
np.arange(0, 1+step, step):
slope = np.tan(np.arccos(x))
```

```
    dist4line1 = create_distance_function(slope, -1, 0)
    #print("x: ", x, "slope: ", slope)
    Y = slope * X

    results = []     for point in points:
results.append(dist4line1(*point))
    #print(slope, results)     if
(results[0][1] != results[1][1]):
        ax.plot(X, Y, "g-")
else:
        ax.plot(X, Y, "r-")

plt.show()
```



**Practical 7b:**

**Aim: Hopfield Network model of associative memory**

The Hopfield model (226), consists of a network of N neurons, labeled by a lower index i, with $1 \leq i \leq N$. Similar to some earlier models (335; 304; 549), neurons in the Hopfield model have only two states. A neuron i is 'ON' if its state variable takes the value $S_i=+1$ and 'OFF' (silent) if $S_i=-1$. The dynamics evolves in discrete time with time steps $\Delta t$. There is no refractoriness and the duration of a time step is typically not specified. If we take $\Delta t=1$ms, we can interpret $S_i(t)=+1$ as an action potential of neuron i at time t. If we take $\Delta t=500$ms, $S_i(t)=+1$ should rather be interpreted as an episode of high firing rate.

Neurons interact with each other with weights $w_{ij}$. The input potential of neuron i, influenced by the activity of other neurons is

$$h_i(t)=\sum_j w_{ij} S_j(t). \qquad (17.2)$$

The input potential at time t influences the probabilistic update of the state variable $S_i$ in the next time step:

$$\text{Prob}\{S_i(t+\Delta t)=+1 \mid h_i(t)\}=g(h_i(t))=g(\sum_j w_{ij} S_j(t)) \qquad (17.3)$$

where g is a monotonically increasing gain function with values between zero and one. A common choice is $g(h)=0.5[1+\tanh(\beta h)]$ with a parameter $\beta$. For $\beta \to \infty$, we have $g(h)=1$ for $h>0$ and zero otherwise. The dynamics are therefore deterministic and summarized by the update rule

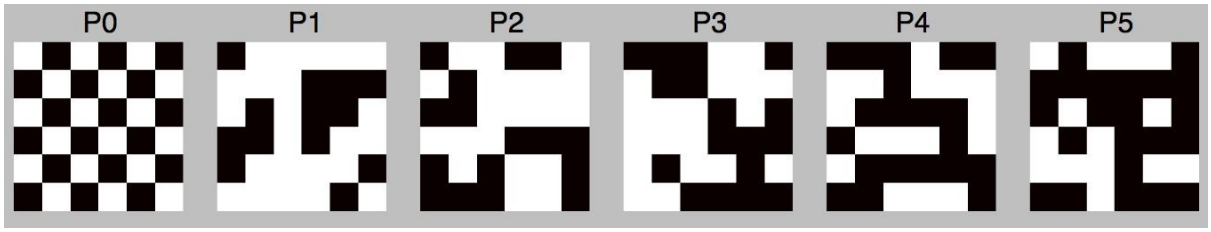
$$S_i(t+\Delta t)=\text{sgn}[h(t)] \qquad (17.4)$$

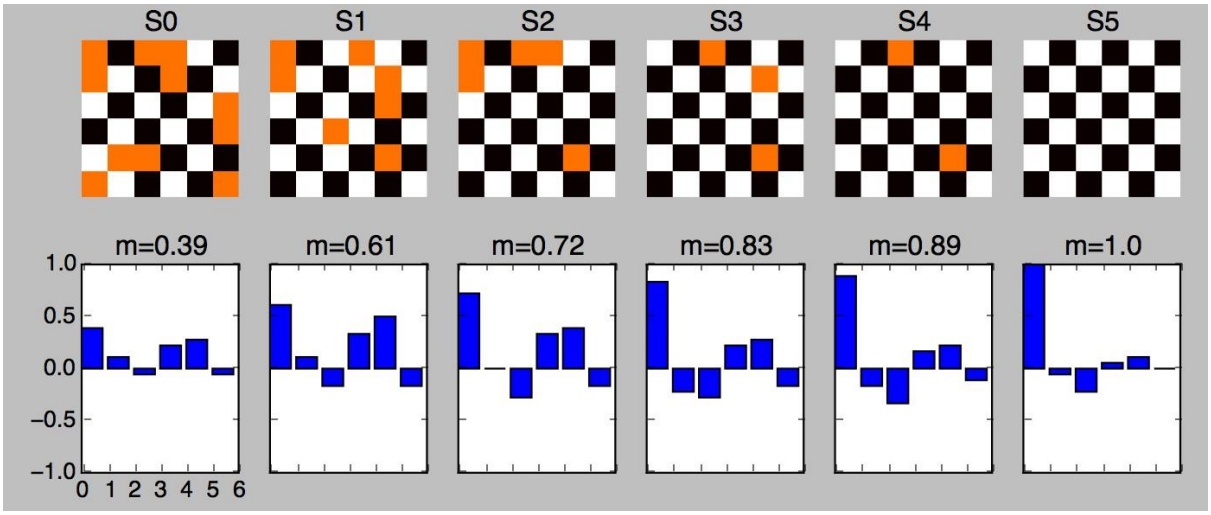
For finite $\beta$ the dynamics are stochastic. In the following we assume that in each time step all neurons are updated synchronously (parallel dynamics), but an update scheme where only one neuron is updated per time step is also possible.

**Source code:**

```
%matplotlib inline
from neurodynex.hopfield_network import network, pattern_tools, plot_tools

pattern_size = 5

# create an instance of the class HopfieldNetwork
hopfield_net = network.HopfieldNetwork(nr_neurons= pattern_size**2)
# instantiate a pattern factory
factory = pattern_tools.PatternFactory(pattern_size, pattern_size)
```

```
# create a checkerboard pattern and add it to the pattern list
checkerboard = factory.create_checkerboard() pattern_list
= [checkerboard]

# add random patterns to the list
pattern_list.extend(factory.create_random_pattern_list(nr_patterns=3, on_probability=0.5))
plot_tools.plot_pattern_list(pattern_list)
# how similar are the random patterns and the checkerboard? Check the overlaps
overlap_matrix = pattern_tools.compute_overlap_matrix(pattern_list)
plot_tools.plot_overlap_matrix(overlap_matrix)

# let the hopfield network "learn" the patterns. Note: they are not stored #
explicitly but only network weights are updated !
hopfield_net.store_patterns(pattern_list)

# create a noisy version of a pattern and use that to initialize the network noisy_init_state
= pattern_tools.flip_n(checkerboard, nr_of_flips=4)
hopfield_net.set_state_from_pattern(noisy_init_state)

# from this initial state, let the network dynamics evolve.
states = hopfield_net.run_with_monitoring(nr_steps=4)

# each network state is a vector. reshape it to the same shape used to create the patterns.
states_as_patterns = factory.reshape_patterns(states)
# plot the states of the network
plot_tools.plot_state_sequence_and_overlap(states_as_patterns, pattern_list, reference_idx=0,
suptitle="Network dynamics")
```




S0
S1
S2
S3
S4
S5
m=0.39
m=0.61
m=0.72
m=0.83
m=0.89
m=1.0
1.0
0.5
0.0
−0.5
−1.0
0 1 2 3 4 5 6

**Practical 8a:**

**Aim: Membership and Identity operators in, not in.**

**Python Code**

```
# Python program to
illustrate # Finding
common member in
list # using 'in' operator
list1=[1,2,3,4,5]
list2=[6,7,8,9] for item in
list1: if item in list2:
        print("overlapping")      else:
 print("not overlapping")
```

**Output** not
overlapping

**Python Code**

```
# Python program to illustrate
# Finding common member
in list # without using 'in'
operator

# Define a function() that takes two lists def
overlapping(list1,list2):

 c=0
d=0 for i
in list1:
         c+=1 for i in list2:
 d+=1 for i in range(0,c):
for j in range(0,d):
if(list1[i]==list2[j]):
                            re
turn 1 return 0
list1=[1,2,3,4,5]
list2=[6,7,8,9]
if(overlapping(list1,list2
)): print("overlapping")
       else: print("not
overlapping")
```

**Output**
not
overlappi
ng

**Python Code:** # Python
program to illustrate
# not 'in' operator x = 24 y =
20 list = [10, 20, 30,

40, 50 ]; if ( x not in

list ):

print ("x is NOT present in given
list") else: print ("x is present in
given list") if ( y in list
): print ("y is present in given list")
else: print ("y is NOT present in
given list")

**Output** x is NOT
present in given list y is
present in given list

## Practical 8b: Membership and Identity Operators is, is not

**Python Code**

```
# Python program to illustrate
the use # of 'is' identity
operator x = 5 if (type(x) is
int):
        print ("true") else:
           print ("false")
```

**Output**

true

**Python Code**

```
# Python program to
illustrate the # use of 'is
not' identity operator x
= 5.2 if (type(x) is not
int):
        print ("true") else:
           print ("false")
```

**Output**

true

**Practical 9a:**

Find the ratios using fuzzy logic

pip install fuzzywuzzy

# Python code showing all the ratios together,

# make sure you have installed fuzzywuzzy module

```
from fuzzywuzzy import fuzz
from fuzzywuzzy import process

s1 = "I love fuzzysforfuzzys" s2 = "I am loving fuzzysforfuzzys"
print ("FuzzyWuzzy Ratio:", fuzz.ratio(s1, s2))  print
("FuzzyWuzzyPartialRatio: ", fuzz.partial_ratio(s1, s2))  print
("FuzzyWuzzyTokenSortRatio: ", fuzz.token_sort_ratio(s1, s2))
print ("FuzzyWuzzyTokenSetRatio: ", fuzz.token_set_ratio(s1, s2))
print ("FuzzyWuzzyWRatio: ", fuzz.WRatio(s1, s2),'\n\n')

# for process library,  query = 'fuzzys for fuzzys' choices = ['fuzzy for
fuzzy', 'fuzzy fuzzy', 'g. for fuzzys']  print ("List of ratios: ") print
(process.extract(query, choices), '\n') print ("Best among the above list:
",process.extractOne(query, choices))
```

```
FuzzyWuzzy Ratio: 86
FuzzyWuzzyPartialRatio:  86
FuzzyWuzzyTokenSortRatio:  86
FuzzyWuzzyTokenSetRatio:  87
FuzzyWuzzyWRatio:  86


List of ratios:
[('g. for fuzzys', 95), ('fuzzy for fuzzy', 94), ('fuzzy fuzzy', 86)]

Best among the above list:  ('g. for fuzzys', 95)
```

**Practical 9b:**

**Aim: Solve Tipping Problem using fuzzy logic**

Fuzzy Control Systems: The Tipping Problem
==========

The 'tipping problem' is commonly used to illustrate the power of fuzzy logic principles to generate complex behavior from a compact, intuitive set of expert rules.

If you're new to the world of fuzzy control systems, you might want to check out the `Fuzzy Control Primer <../userguide/fuzzy_control_primer.html>`_ before reading through this worked example.

The Tipping Problem
---

Let's create a fuzzy control system which models how you might choose to tip at a restaurant. When tipping, you consider the service and food quality, rated between 0 and 10. You use this to leave a tip of between 0 and 25%.

We would formulate this problem as:

* Antecednets (Inputs)
  - `service`
* Universe (ie, crisp value range): How good was the service of the wait staff, on a scale of 0 to 10?
* Fuzzy set (ie, fuzzy value range): poor, acceptable, amazing
  - `food quality`
* Universe: How tasty was the food, on a scale of 0 to 10?
* Fuzzy set: bad, decent, great
* Consequents (Outputs)
  - `tip`
* Universe: How much should we tip, on a scale of 0% to 25%
* Fuzzy set: low, medium, high
* Rules
- IF the *service* was good *or* the *food quality* was good, THEN the tip will be high.
- IF the *service* was average, THEN the tip will be medium.
- IF the *service* was poor *and* the *food quality* was poor THEN the tip will be low.
* Usage
  - If I tell this controller that I rated:
* the service as 9.8, and
* the quality as 6.5, - it would recommend I leave:

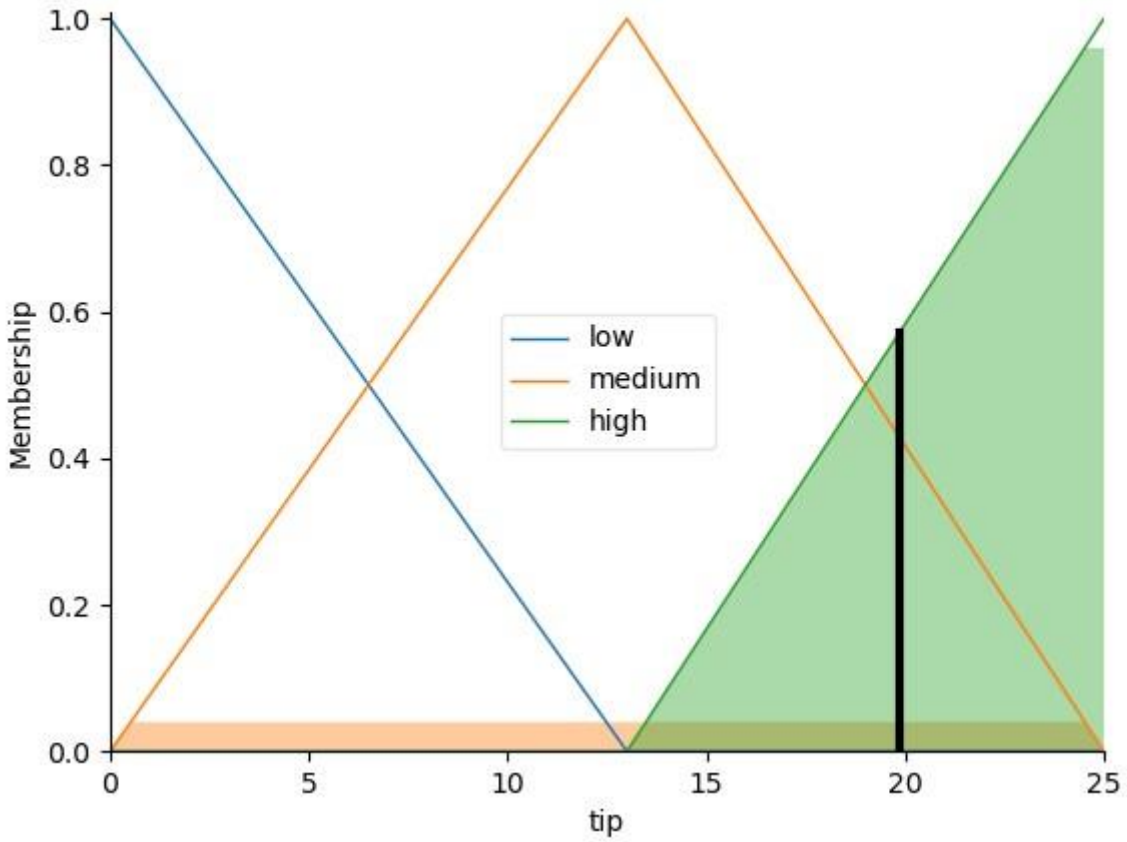
* a 20.2% tip.

Creating the Tipping Controller Using the skfuzzy control API
---

We can use the `skfuzzy` control system API to model this. First, let's define fuzzy variables **Code:**

```
import numpy as np import
skfuzzy as fuzz
from skfuzzy import control as ctrl

quality = ctrl.Antecedent(np.arange(0, 11, 1), 'quality')
service = ctrl.Antecedent(np.arange(0, 11, 1), 'service') tip
= ctrl.Consequent(np.arange(0, 26, 1), 'tip')

quality.automf(3)
service.automf(3)

tip['low'] = fuzz.trimf(tip.universe, [0, 0, 13]) tip['medium']
= fuzz.trimf(tip.universe, [0, 13, 25])
tip['high'] = fuzz.trimf(tip.universe, [13, 25, 25])

quality['average'].view()

service.view()
tip.view()


rule1 = ctrl.Rule(quality['poor'] | service['poor'], tip['low'])
rule2 = ctrl.Rule(service['average'], tip['medium']) rule3 =
ctrl.Rule(service['good'] | quality['good'], tip['high'])

rule1.view()

tipping_ctrl = ctrl.ControlSystem([rule1, rule2, rule3])


tipping = ctrl.ControlSystemSimulation(tipping_ctrl)

# Pass inputs to the ControlSystem using Antecedent labels with Pythonic API
tipping.input['quality'] = 6.5
tipping.input['service'] = 9.8

# Crunch the numbers
tipping.compute()
```

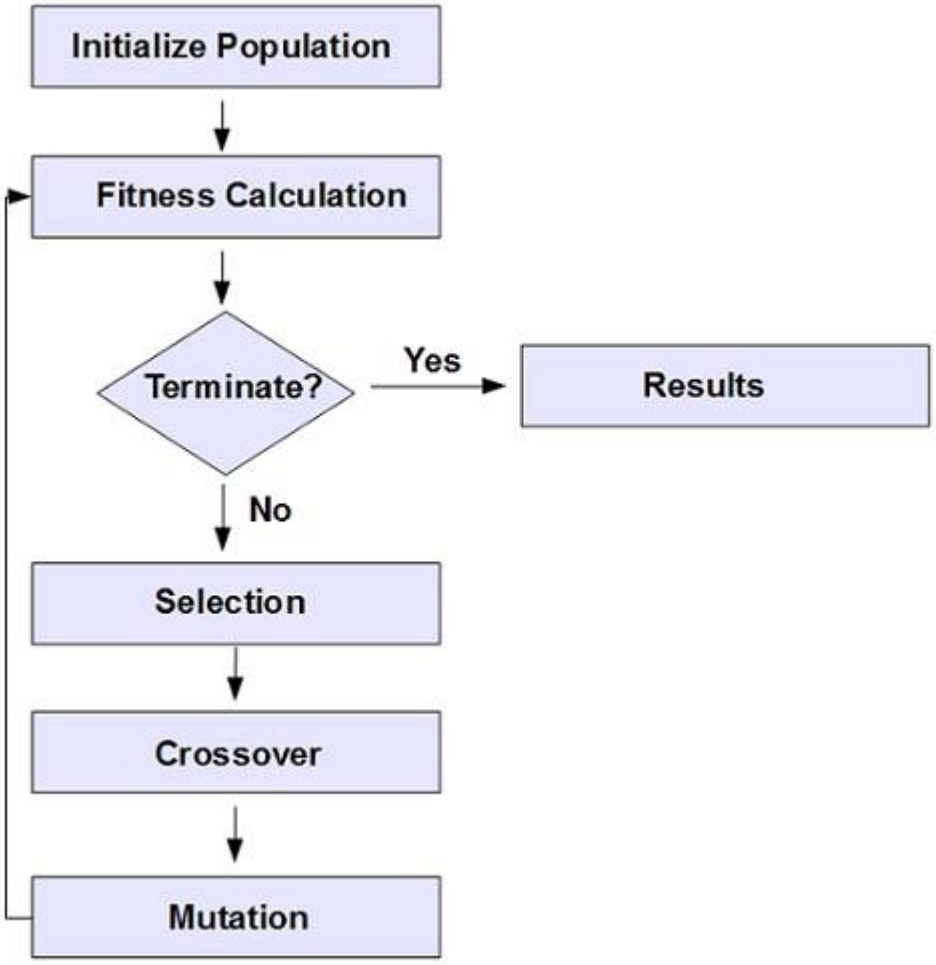
print tipping.output['tip'] tip.view(sim=tipping)

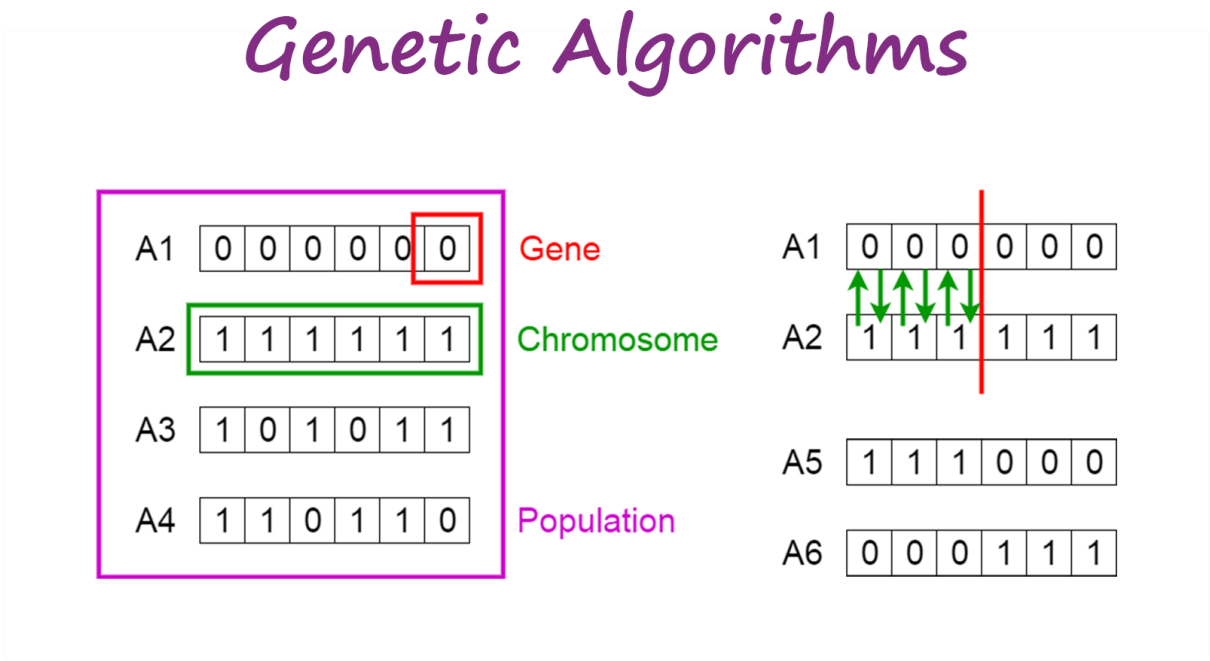



The resulting suggested tip is ** 19.8476**

**Practical 10:**

**Aim: Implementation of simple genetic algorithm**






```
import random

# Number of individuals in each generation
POPULATION_SIZE =100

# Valid genes
GENES ='''abcdefghijklmnopqrstuvwxyzABCDEFGHIJKLMNOP QRSTUVWXYZ
1234567890, .-;:_!"#%&/()=?@${[]}'''

# Target string to be generated
TARGET ="Mithilesh Chauhan"

class Individual(object):
    '''
    Class representing individual in population
    '''
    def __init__(self, chromosome):
self.chromosome =chromosome
self.fitness =self.cal_fitness()

    @classmethod     def
mutated_genes(self):
        '''
        create random genes for mutation
        '''
```

```
        global GENES
        gene =random.choice(GENES)
        return gene

    @classmethod     def
create_gnome(self):
        '''
        create chromosome or string of genes
        '''
        global TARGET          gnome_len =len(TARGET)
return[self.mutated_genes() for _ in range(gnome_len)]

    def mate(self, par2):
        '''
        Perform mating and produce new offspring
        '''

        # chromosome for offspring          child_chromosome =[]
for gp1, gp2 in zip(self.chromosome, par2.chromosome):

            # random probability
            prob =random.random()

            # if prob is less than 0.45, insert gene
            # from parent 1
if prob< 0.45:
                child_chromosome.append(gp1)

            # if prob is between 0.45 and 0.90, insert
            # gene from parent 2
elif prob< 0.90:
                child_chromosome.append(gp2)

            # otherwise insert random gene(mutate),
            # for maintaining diversity
else:
                child_chromosome.append(self.mutated_genes())

        # create new Individual(offspring) using
# generated chromosome for offspring
        return Individual(child_chromosome)

    def cal_fitness(self):
        '''
        Calculate fittness score, it is the number of
characters in string which differ from target          string.
        '''
```

```
        global TARGET
fitness =0
        for gs, gt in zip(self.chromosome, TARGET):
            if gs !=gt: fitness+=1
        return fitness

# Driver code  def
main():
    global POPULATION_SIZE

    #current generation
    generation =1

    found =False
    population =[]

    # create initial population      for _ in
range(POPULATION_SIZE):
gnome =Individual.create_gnome()
                population.append(Individual(gnome))

    while not found:

        # sort the population in increasing order of fitness score
        population =sorted(population, key =lambda x:x.fitness)

        # if the individual having lowest fitness score ie.
        # 0 then we know that we have reached to the target
        # and break the loop          if
population[0].fitness <=0:
            found =True
            break

        # Otherwise generate new offsprings for new generation
new_generation =[]

        # Perform Elitism, that mean 10% of fittest population
        # goes to the next generation          s
=int((10*POPULATION_SIZE)/100)
        new_generation.extend(population[:s])

        # From 50% of fittest population,
Individuals          # will mate to produce
offspring          s
=int((90*POPULATION_SIZE)/100)          for _
in range(s):
```

```
            parent1 =random.choice(population[:50])
parent2 =random.choice(population[:50])
child =parent1.mate(parent2)
            new_generation.append(child)

        population =new_generation

        print("Generation: {}\tString: {}\tFitness:
{}".format(generation,"".join(population[0].chromosome),population[0].fitness))
generation +=1


    print("Generation: {}\tString: {}\tFitness: {}".format(generation,
"".join(population[0].chromosome),
population[0].fitness))

if __name__ =='__main__':
main()
```

Output:

```
Generation: 1    String: tO{"-?=jH[k8=B4]Oe@}    Fitness: 18
Generation: 2    String: tO{"-?=jH[k8=B4]Oe@}    Fitness: 18
Generation: 3    String: .#lRWf9k_Ifslw #O$k_    Fitness: 17
Generation: 4    String: .-1Rq?9mHqk3Wo]3rek_    Fitness: 16
Generation: 5    String: .-1Rq?9mHqk3Wo]3rek_    Fitness: 16
Generation: 6    String: A#ldW) #lIkslwcVek)    Fitness: 14
Generation: 7    String: A#ldW) #lIkslwcVek)    Fitness: 14
Generation: 8    String: (, o x _x%Rs=, 6Peek3    Fitness: 13
                         .
                         .
.
Generation: 29    String: I lope Geeks#o, Geeks    Fitness: 3
Generation: 30    String: I loMeGeeksfoBGeeks    Fitness: 2
Generation: 31    String: I love Geeksfo0Geeks    Fitness: 1
Generation: 32    String: I love Geeksfo0Geeks    Fitness: 1
Generation: 33    String: I love Geeksfo0Geeks    Fitness: 1
Generation: 34    String: I love GeeksforGeeks    Fitness: 0
```

**Practical 10b:**

**Aim:Create two classes: City and Fitness using Genetic algorithm**
First create a City class that will allow us to create and handle our cities.

Create Population
https://towardsdatascience.com/evolution-of-a-salesman-a-complete-genetic-algorithmtutorial-for-python-6fe5d2b3ca35

```
import numpy as np, random, operator, pandas as pd, matplotlib.pyplot as plt
from tkinter import Tk, Canvas, Frame, BOTH, Text import math class City:
    def __init__(self, x, y):
        self.x = x
self.y = y

    def distance(self, city):
        xDis = abs(self.x - city.x)         yDis =
abs(self.y - city.y)         distance = np.sqrt((xDis
** 2) + (yDis ** 2))         return distance

    def __repr__(self):
        return "(" + str(self.x) + "," + str(self.y) +
")" class Fitness:     def __init__(self, route):
        self.route = route
self.distance = 0
self.fitness= 0.0

    def     routeDistance(self):
if       self.distance       ==0:
pathDistance = 0             for
i in range(0, len(self.route)):
                fromCity = self.route[i]
toCity = None                if i + 1 <
```

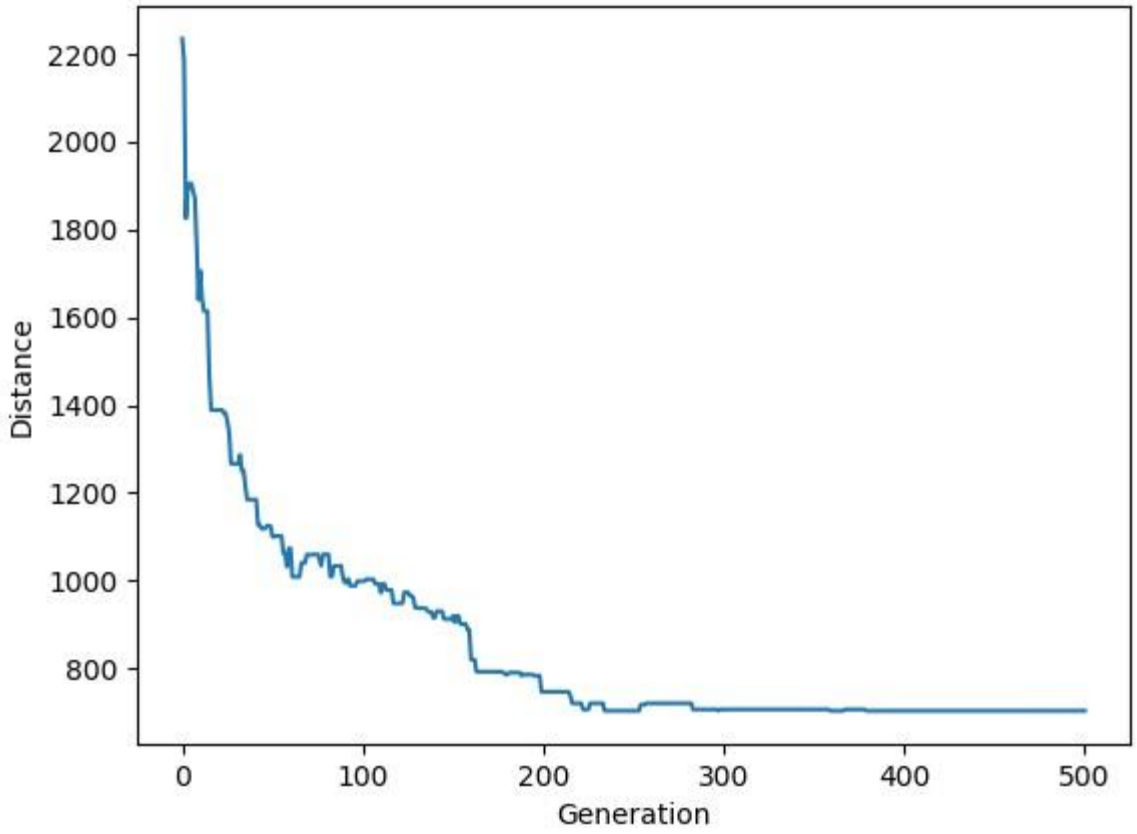
```
len(self.route):                    toCity =
self.route[i + 1]                 else:
                    toCity = self.route[0]
pathDistance += fromCity.distance(toCity)
self.distance = pathDistance          return self.distance


   def routeFitness(self):         if self.fitness == 0:
self.fitness = 1 / float(self.routeDistance())
return self.fitness def createRoute(cityList):
   route = random.sample(cityList,
len(cityList))     return route def
initialPopulation(popSize, cityList):
   population = []     for i in
range(0, popSize):
      population.append(createRoute(cityList))
return population


def rankRoutes(population):
   fitnessResults = {}      for i in
range(0,len(population)):
      fitnessResults[i] = Fitness(population[i]).routeFitness()     return
sorted(fitnessResults.items(), key = operator.itemgetter(1), reverse = True) def
selection(popRanked, eliteSize):

   selectionResults = []     df = pd.DataFrame(np.array(popRanked),
columns=["Index","Fitness"])     df['cum_sum'] = df.Fitness.cumsum()
df['cum_perc'] = 100*df.cum_sum/df.Fitness.sum()


   for i in range(0, eliteSize):
      selectionResults.append(popRanked[i][0])
for i in range(0, len(popRanked) - eliteSize):
```

```
        pick = 100*random.random()
for i in range(0, len(popRanked)):
if pick <= df.iat[i,3]:
                selectionResults.append(popRanked[i][0])
                break     return
selectionResults



def matingPool(population, selectionResults):
    matingpool = []     for i in range(0,
len(selectionResults)):         index =
selectionResults[i]
matingpool.append(population[index])
return matingpool


def breed(parent1, parent2):
    child = []
childP1 = []
childP2 = []


    geneA = int(random.random() * len(parent1))
geneB = int(random.random() * len(parent1))


    startGene = min(geneA, geneB)
endGene = max(geneA, geneB)


    for i in range(startGene, endGene):
childP1.append(parent1[i])


    childP2 = [item for item in parent2 if item not in childP1]
```

```
    child = childP1 + childP2
return child


def breedPopulation(matingpool, eliteSize):
    children = []     length = len(matingpool) - eliteSize
pool = random.sample(matingpool, len(matingpool))

    for i in range(0,eliteSize):
        children.append(matingpool[i])

    for i in range(0, length):         child = breed(pool[i],
pool[len(matingpool)-i-1])
children.append(child)
    return children

def mutate(individual, mutationRate):
for swapped in range(len(individual)):
if(random.random() < mutationRate):
            swapWith = int(random.random() * len(individual))

            city1 = individual[swapped]
city2 = individual[swapWith]

            individual[swapped] = city2
individual[swapWith] = city1      return
individual
```

```
def mutatePopulation(population, mutationRate):
    mutatedPop = []

    for ind in range(0, len(population)):         mutatedInd =
mutate(population[ind], mutationRate)
mutatedPop.append(mutatedInd)     return mutatedPop



def nextGeneration(currentGen, eliteSize, mutationRate):
popRanked = rankRoutes(currentGen)     selectionResults
= selection(popRanked, eliteSize)     matingpool =
matingPool(currentGen, selectionResults)     children =
breedPopulation(matingpool, eliteSize)     nextGeneration
= mutatePopulation(children, mutationRate)     return
nextGeneration

def geneticAlgorithm(population, popSize, eliteSize, mutationRate, generations):
    pop = initialPopulation(popSize, population)
print("Initial distance: " + str(1 / rankRoutes(pop)[0][1]))

    for i in range(0, generations):
        pop = nextGeneration(pop, eliteSize, mutationRate)

    print("Final distance: " + str(1 /
rankRoutes(pop)[0][1]))     bestRouteIndex =
rankRoutes(pop)[0][0]     bestRoute =
pop[bestRouteIndex]     return bestRoute

def geneticAlgorithmPlot(population, popSize, eliteSize, mutationRate, generations):
```

```
    pop = initialPopulation(popSize, population)
progress = []     progress.append(1 /
rankRoutes(pop)[0][1])


    for i in range(0, generations):
        pop = nextGeneration(pop, eliteSize, mutationRate)
progress.append(1 / rankRoutes(pop)[0][1])
plt.plot(progress)     plt.ylabel('Distance')
plt.xlabel('Generation')     plt.show() def main():
cityList = []     for i in range(0,25):
cityList.append(City(x=int(random.random() * 200),
y=int(random.random() * 200)))

    geneticAlgorithmPlot(population=cityList, popSize=100,
eliteSize=20, mutationRate=0.01, generations=500) if __name__ ==
'__main__':
    main()
```


2200
2000
1800
1600
1400
1200
1000
800
Distance
0
100
200
300
400
500
Generation