INDEX

Practical No: 01

Implement the Following:

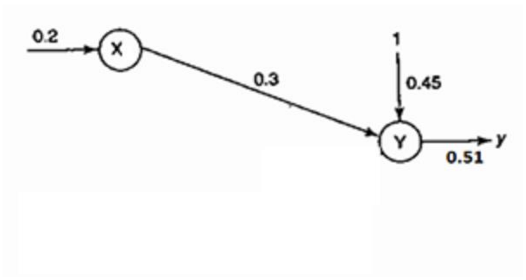
Theory:

Neural networks are artificial systems that were inspired by biological neural networks. These systems learn to perform tasks by being exposed to various datasets and examples without any task-specific rules. Neural networks are based on computational models for threshold logic. Threshold logic is a combination of algorithms and mathematics. Neural networks are based either on the study of the brain or on the application of neural networks to artificial intelligence. The work has led to improvements in finite automata theory. Components of a typical neural network involve neurons, connections which are known as synapses, weights, biases, propagation function, and a learning rule.

A.Design a simple linear neural network model.

Calculate the output of neural net where input X = 0.2, w = 0.3 and bias b 0.45.

Given neural net:



*Yin = wx + b = 0.3*0.2 + 0.45 = 0.51.*

if (yin < 0), then output=y=0

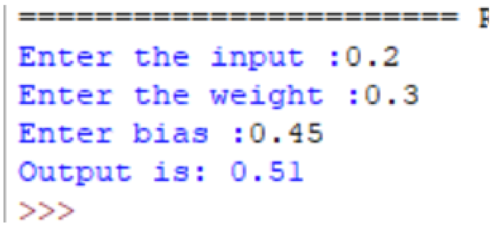
else if (yin >1) then output=y=1

else output=y=yin

Code:

```
inputs = float(input("Enter the input :"))
weights = float(input("Enter the weight :"))
bias = float(input("Enter bias :"))
yin = bias + (inputs * weights)
if yin < 0:
  out = 0
elif yin > 1:
  out= 1
else:
out = yin
print("Output is :",out)
```

Output:



```
======================== R
Enter the input :0.2
Enter the weight :0.3
Enter bias :0.45
Output is: 0.51
>>>
```

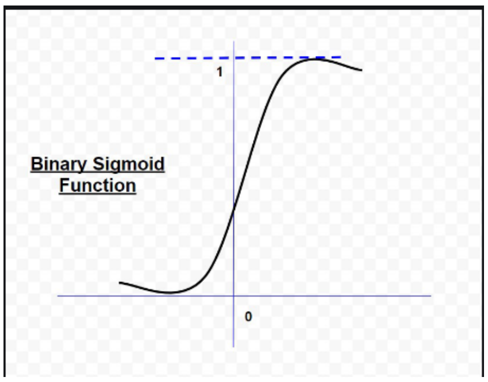
B.Calculate the output of neural net. using both binary and bipolar sigmoidal function.

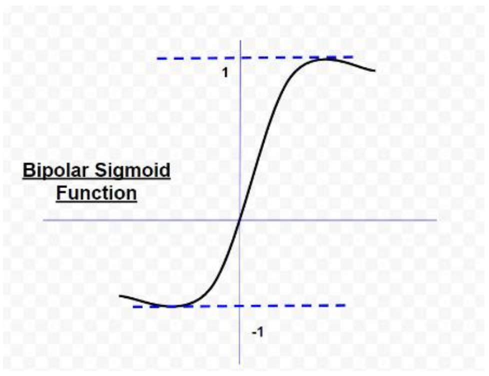
Theory:

- Binary Sigmoid function is by far the most commonly used activation function in neural networks. The need for a sigmoid function stems from the fact that many learning algorithms require the activation function to be differentiable and hence continuous.

A binary sigmoid function is of the form: $y_{out} = f(x) = \frac{1}{1+e^{-kx}}$

where k = steepness or slope parameter, By varying the value of k, a sigmoid function with different slopes can be obtained. It has a range of (0,1). The slope of origin is k/4. As the value of k becomes very large, the sigmoid function becomes a threshold function.





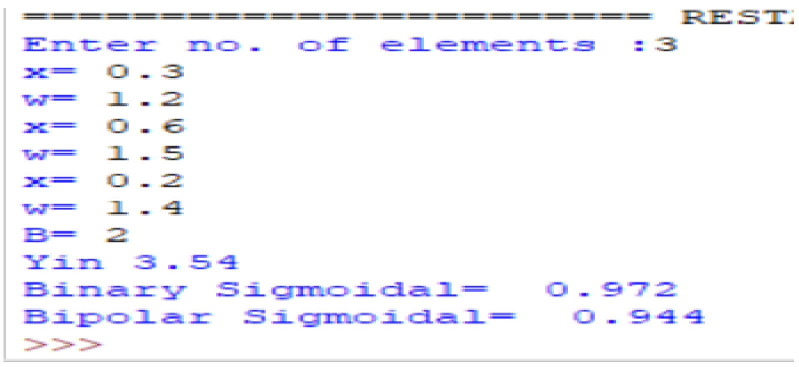
- A **bipolar sigmoid function** is of the form : $y_{out} = f(x) = \frac{1-e^{-kx}}{1+e^{-kx}}$

The range of values of sigmoid functions can be varied depending on the application. However, the range of (-1,+1) is most commonly adopted.

Code:

```
import math

n = int(input("Enter no. of elements :"))

yin = 0

for i in range(0,n):

  x=float(input("x= "))
  w=float(input("w= "))
  yin = yin + (x*w)
b = float(input("B= "))
yin = yin + b

print("Yin",yin)
binary_sigmoidal = (1/(1+(math.e**(-yin))))
print("Binary Sigmoidal= ",round(binary_sigmoidal,3))

bipolar_sigmoidal = (2/(1+(math.e**(-yin)))) - 1
print("Bipolar Sigmoidal= ",round(bipolar_sigmoidal,3))
```

Output:



```
========================== RESTA
Enter no. of elements :3
x= 0.3
w= 1.2
x= 0.6
w= 1.5
x= 0.2
w= 1.4
B= 2
Yin 3.54
Binary Sigmoidal=  0.972
Bipolar Sigmoidal=  0.944
>>>
```

Practical No: 02

Theory:

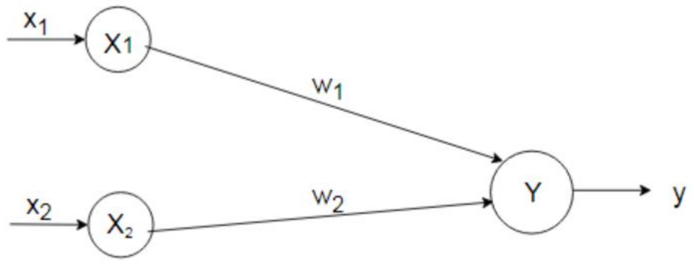
The McCulloch-Pitts neural model, which was the earliest ANN model, has only two types of inputs — Excitatory and Inhibitory. The excitatory inputs have weights of positive magnitude and the inhibitory weights have weights of negative magnitude. The inputs of the McCulloch-Pitts neuron could be either 0 or 1. It has a threshold function as an activation function. So, the output signal yout is 1 if the input ysum is greater than or equal to a given threshold value, else 0.

Implement the Following:

A:Generate AND/NOT function using McCulloch-Pitts neural network.

Theory:

In McCulloch-Pitts Neuron only analysis is performed. It is a logic gate that implements conjunction. Whenever both the inputs are high then only output will be high (1) otherwise low (0). Hence, assume weights be w1 = w2 =1 .The network architecture is



ANDNOT Function:

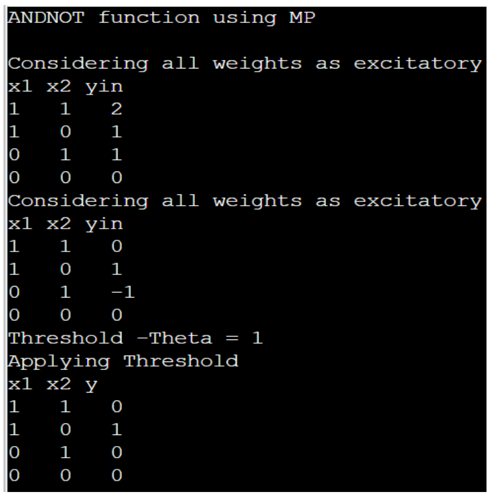
Truth Table:

X1	X2	Y
1	1	0
1	0	1
0	1	0
0	0	0

Code:

```
import numpy as np

print("ANDNOT function using MP\n")

x1inputs = [1,1,0,0]

x2inputs = [1,0,1,0]

print("Considering all weights as excitatory");

w1 = [1,1,1,1]

w2 = [1,1,1,1]

yin = []

print("x1","x2","yin")

for i in range(0,4):
  yin.append(x1inputs[i]*w1[i] + x2inputs[i]*w2[i])
  print(x1inputs[i]," ",x2inputs[i]," ", yin[i])
print("Considering all weights as excitatory");
w1 = [1,1,1,1]
w2 = [-1,-1,-1,-1]
yin = []
print("x1","x2","yin")
for i in range(0,4):
  yin.append(x1inputs[i]*w1[i] + x2inputs[i]*w2[i])
  print(x1inputs[i]," ",x2inputs[i]," ", yin[i])
theta = 2*1-1
print("Threshold -Theta =",theta)
print("Applying Threshold ")
y = []
for i in range(0,4):
  if(yin[i]>=theta):
    value = 1
    y.append(value)
  else:
    value = 0
    y.append(value)
print("x1","x2","y")
for i in range(0,4):
  print(x1inputs[i]," ",x2inputs[i]," ",y[i])
```

Output:



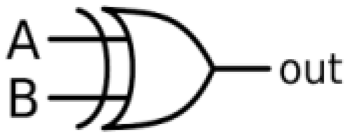
```
ANDNOT function using MP

Considering all weights as excitatory
x1 x2 yin
1   1   2
1   0   1
0   1   1
0   0   0
Considering all weights as excitatory
x1 x2 yin
1   1   0
1   0   1
0   1   -1
0   0   0
Threshold -Theta = 1
Applying Threshold
x1 x2 y
1   1   0
1   0   1
0   1   0
0   0   0
```

B:Generate XOR function using McCulloch-Pitts neural net.

Theory:

The truth table for XOR function is computed as,

X_1	X_2	Y
0	0	0
0	1	1
1	0	1
1	1	0

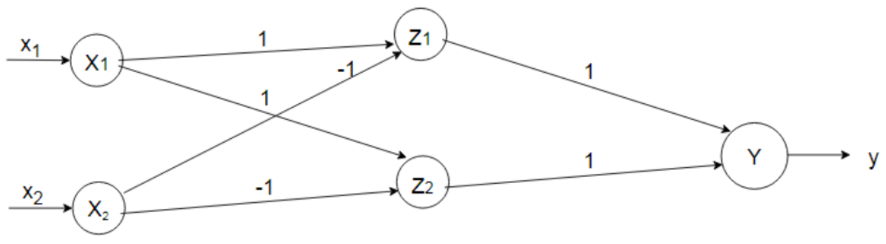


In this case, the output is "ON" only for odd number of 1's. For the rest it is "OFF". XOR function cannot be represented by simple and single logic function, it is represented as

$$y = x_1\overline{x_2} + \overline{x_1}x_2$$
$$y = z_1 + z_2$$

where $z_1 = x_1 . \overline{x_2}$ is the first functio,

and $z_2 = \overline{x_1} . x_2$is the second function. $\Rightarrow y = z_1 + z_2$ is the third function

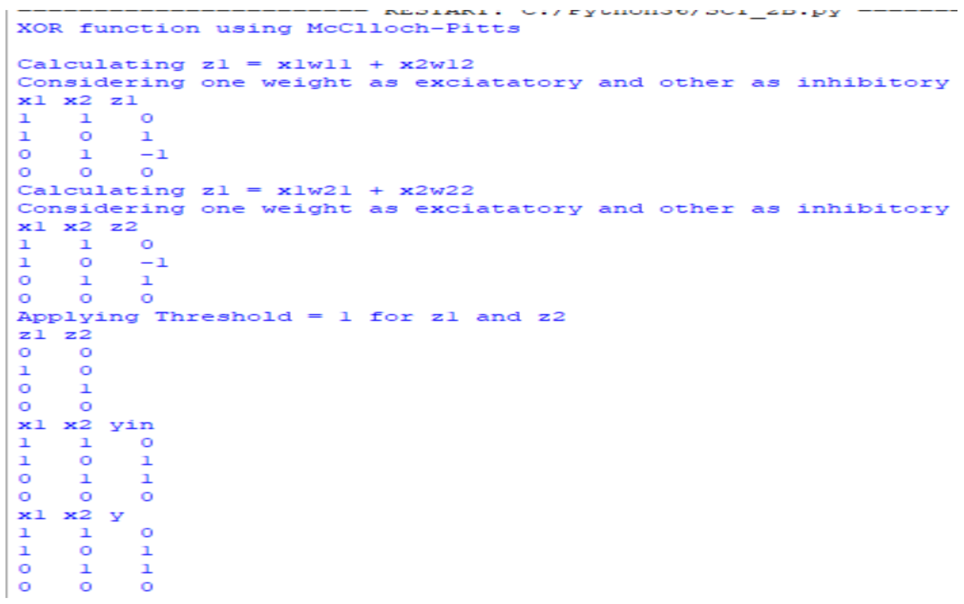


Code:

```
print("XOR function using McClloch-Pitts\n")
x1inputs = [1,1,0,0]
x2inputs = [1,0,1,0]
print("Calculating z1 = x1w11 + x2w12")
print("Considering one weight as exciatatory and other as inhibitory ")
w11 = [1,1,1,1]
w21 = [-1,-1,-1,-1]
print("x1","x2","z1")
z1 = []
for i in range(0,4):
  z1.append(x1inputs[i]*w11[i] + x2inputs[i]*w21[i])
  print(x1inputs[i]," ",x2inputs[i]," ",z1[i])
print("Calculating z1 = x1w21 + x2w22")
print("Considering one weight as exciatatory and other as inhibitory ")
w21 = [-1,-1,-1,-1]
w22 = [1,1,1,1]
```

```
print("x1","x2","z2")
z2 = []
for i in range(0,4):
  z2.append(x1inputs[i]*w21[i] + x2inputs[i]*w22[i])
  print(x1inputs[i]," ",x2inputs[i]," ",z2[i])
print("Applying Threshold = 1 for z1 and z2")
for i in range(0,4):
  if(z1[i]>=1):
    z1[i] = 1
  else:
    z1[i] = 0
  if(z2[i]>=1):
    z2[i]=1
  else:
    z2[i]=0



print("z1","z2")
for i in range(0,4):
  print(z1[i]," ",z2[i]," ")
print("x1" , "x2" , "yin")
yin = []
v1 = 1
v2 = 1
for i in range(0,4):
  yin.append(z1[i]*v1 + z2[i]*v2)
  print(x1inputs[i]," ",x2inputs[i]," ",yin[i])
y=[]
for i in range(0,4):
  if(yin[i]>=1):
    y.append(1)
  else:
    y.append(0)
print("x1","x2","y")
for i in range(0,4):
  print(x1inputs[i]," ",x2inputs[i]," ",y[i])
```

Output:



```
======================= RESTART: C:/Python36/SC1_2B.py =======
XOR function using McClloch-Pitts

Calculating z1 = x1w11 + x2w12
Considering one weight as exciatatory and other as inhibitory
x1 x2 z1
1   1   0
1   0   1
0   1   -1
0   0   0
Calculating z1 = x1w21 + x2w22
Considering one weight as exciatatory and other as inhibitory
x1 x2 z2
1   1   0
1   0   -1
0   1   1
0   0   0
Applying Threshold = 1 for z1 and z2
z1 z2
0   0
1   0
0   1
0   0
x1 x2 yin
1   1   0
1   0   1
0   1   1
0   0   0
x1 x2 y
1   1   0
1   0   1
0   1   1
0   0   0
```

<u>Practical No: 03</u>

Implement the Following:

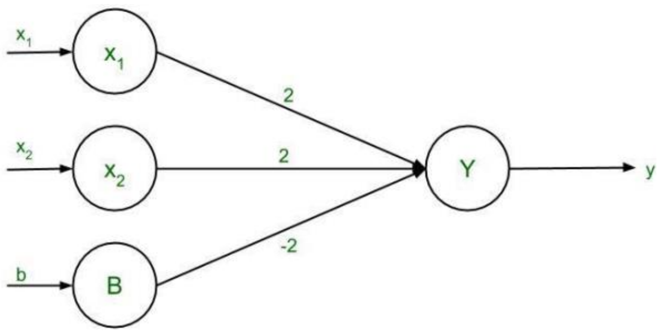
A: Write a program to implement Hebb's rule.

Theory:

Hebb's rule is a postulate proposed by Donald Hebb in 1949. It is a learning rule that describes how neuronal activities influence the connection between neurons, i.e., synaptic plasticity. It provides an algorithm to update the weight of neuronal connections within the neural networks. Hebb's rule provides a simplistic physiology-based model to mimic the activity-dependent features of synaptic plasticity and has been widely used in the area of artificial neural network.

Hebbian Learning Rule Algorithm :

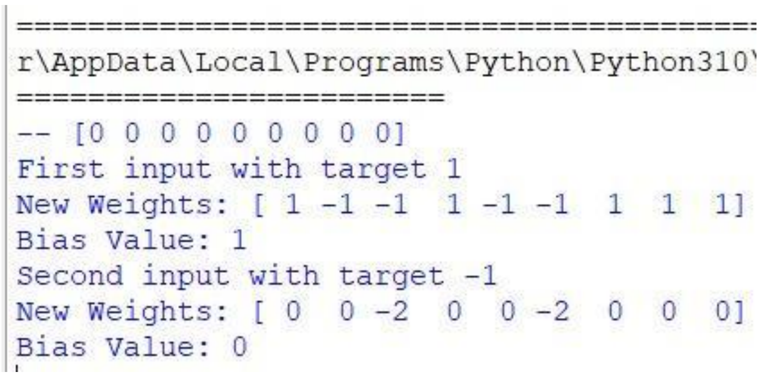
1. Set all weights to zero, wi = 0 for i=1 to n, and bias to zero.
2. For each input vector, S(input vector) : t(target output pair), repeat steps 3-5.
3. Set activations for input units with the input vector Xi = Si for i = 1 to n.
4. Set the corresponding output value to the output neuron, i.e. y = t.
5. Update weight and bias by applying Hebb rule for all i = 1 to n:



<u>Code:</u>

```
import numpy as np


x1 = np.array([1,-1,-1,1,-1,-1,1,1,1,1])

x2 = np.array([1,-1,1,1,-1,1,1,1,1,1])

y = np.array([1,-1])

b = 0


wtold = np.zeros((9,)).astype(int)

wtnew = np.zeros((9,)).astype(int)

print("--",wtold)
print("First input with target 1")
for i in range(0,9):
    wtnew[i] = wtold[i] + x1[i]*y[0]

wtold = wtnew
b = b + y[0]
print("New Weights:",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 Weights:",wtnew)
print("Bias Value:",b)
```

Output:



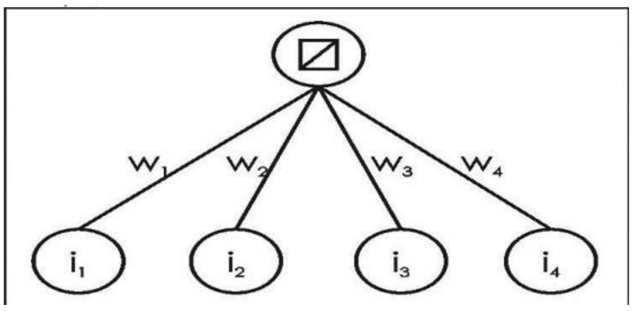
```
=============================================
r\AppData\Local\Programs\Python\Python310
========================
-- [0 0 0 0 0 0 0 0 0]
First input with target 1
New Weights: [ 1 -1 -1  1 -1 -1  1  1  1]
Bias Value: 1
Second input with target -1
New Weights: [ 0  0 -2  0  0 -2  0  0  0]
Bias Value: 0
```

B:Write a program to implement delta rule.

Theory:

The Delta rule in machine learning and neural network environments is a specific type of backpropagation that helps to refine connectionist ML/AI networks, making connections between inputs and outputs with layers of artificial neurons.

The Delta rule is also known as the Delta learning rule. Backpropagation has to do with recalculating input weights for artificial neurons using a gradient method. Delta learning does this using the difference between a target activation and an actual obtained activation. Using a linear activation function, network connections are adjusted. Another way to explain the Delta rule is that it uses an error function to perform gradient descent learning.

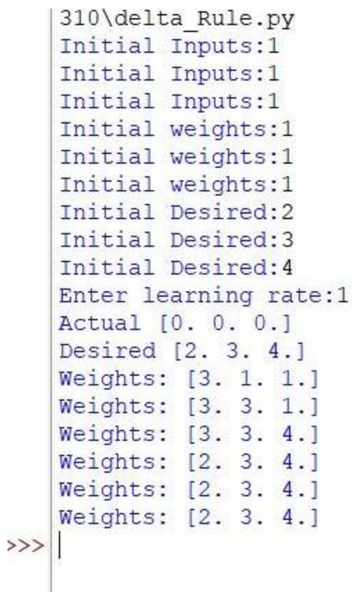


Code:

```
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("Initial Desired:"))


a = float(input("Enter learning rate:"))
```

```
print("Actual",actual)
print("Desired",desired)




while True:
    if np.array_equal(desired,actual):
        break
    else:
        for i in range(0,3):
            weights[i] = weights[i] + a *(desired[i] - actual[i])
            actual = x*weights
            print("Weights:",weights)
```

Output:



```
310\delta_Rule.py
Initial Inputs:1
Initial Inputs:1
Initial Inputs:1
Initial weights:1
Initial weights:1
Initial weights:1
Initial Desired:2
Initial Desired:3
Initial Desired:4
Enter learning rate:1
Actual [0. 0. 0.]
Desired [2. 3. 4.]
Weights: [3. 1. 1.]
Weights: [3. 3. 1.]
Weights: [3. 3. 4.]
Weights: [2. 3. 4.]
Weights: [2. 3. 4.]
Weights: [2. 3. 4.]
>>>
```

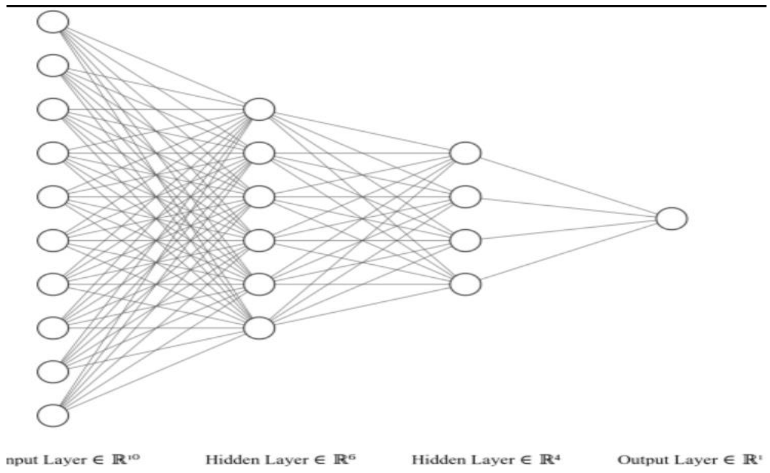
Practical No: 04

Implement the Following:

A:Write a program for BackPropagation Algorithm.

Theory:

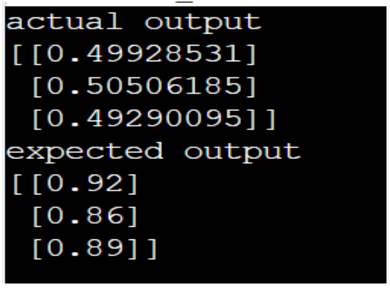
Backpropagation is the essence of neural network training. It is the method of fine-tuning the weights of a neural network based on the error rate obtained in the previous epoch (i.e., iteration). Proper tuning of the weights allows you to reduce error rates and make the model reliable by increasing its generalization. Backpropagation in neural network is a short form for "backward propagation of errors." It is a standard method of training artificial neural networks. This method helps calculate the gradient of a loss function with respect to all the weights in the network.



Code:

```
import numpy as np

X=np.array(([2,9],[1,5],[3,6]),dtype=float)

Y=np.array(([92],[86],[89]),dtype=float)

#scale units

X=X/np.amax(X,axis=0)

Y=Y/100;

class NN(object):

    def __init__(self):

        self.inputsize=2

        self.outputsize=1

        self.hiddensize=3

        self.W1=np.random.randn(self.inputsize,self.hiddensize)

        self.W2=np.random.randn(self.hiddensize,self.outputsize)

    def forward(self,X):

        self.z=np.dot(X,self.W1)

        self.z2=self.sigmoidal(self.z)
        self.z3=np.dot(self.z2,self.W2)
        op=self.sigmoidal(self.z3)
        return op;
    def sigmoidal(self,s):
        return 1/(1+np.exp(-s))
obj=NN()
op=obj.forward(X)
print("actual output\n"+str(op))
print("expected output\n"+str(Y))
```

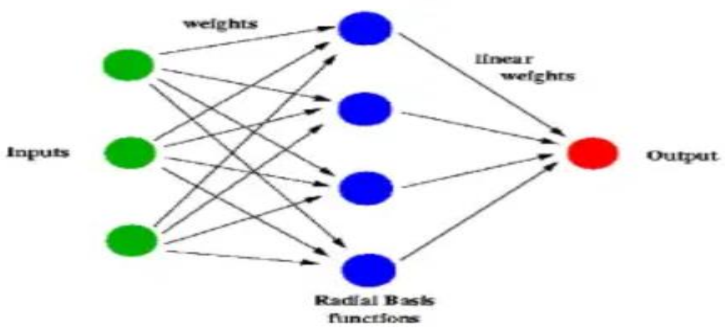
Output:



```
actual output
[[0.49928531]
 [0.50506185]
 [0.49290095]]
expected output
[[0.92]
 [0.86]
 [0.89]]
```

B: Write a program for Error BackPropagation Algorithm.

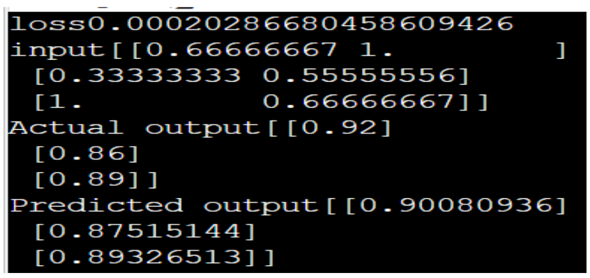
Theory: Error backpropagation. For hidden units, we must propagate the error back from the output nodes (hence the name of the algorithm). Again using the chain rule, we can expand the error of a hidden unit in terms of its posterior nodes:



Code:

```
import numpy as np
X=np.array(([2,9],[1,5],[3,6]),dtype=float)
Y=np.array(([92],[86],[89]),dtype=float)
X=X/np.amax(X,axis=0)Y=Y/100;
class NN(object):
    def __init__(self):
        self.inputsize=2
        self.outputsize=1
        self.hiddensize=3
        self.W1=np.random.randn(self.inputsize,self.hiddensize)
        self.W2=np.random.randn(self.hiddensize,self.outputsize)
    def forward(self,X):
        self.z=np.dot(X,self.W1)
        self.z2=self.sigmoidal(self.z)
        self.z3=np.dot(self.z2,self.W2)
        op=self.sigmoidal(self.z3)
        return op;
    def sigmoidal(self,s):return 1/(1+np.exp(-s))
    def sigmoidalprime(self,s): return s* (1-s)
   def backward(self,X,Y,o):
        self.o_error=Y-o
        self.o_delta=self.o_error * self.sigmoidalprime(o)
        self.z2_error=self.o_delta.dot(self.W2.T)
        self.z2_delta=self.z2_error * self.sigmoidalprime(self.z2)
        self.W1 = self.W1 + X.T.dot(self.z2_delta)
        self.W2= self.W2+ self.z2.T.dot(self.o_delta)
    def train(self,X,Y):
        o=self.forward(X)
        self.backward(X,Y,o)obj=NN()
for i in range(2000):
    print("input"+str(X))
    print("Actual output"+str(Y))
    print("Predicted output"+str(obj.forward(X)))
    print("loss"+str(np.mean(np.square(Y-obj.forward(X)))))
    obj.train(X,Y)
```

<u>**Output:**</u>



```
loss0.00020286680458609426
input[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual output[[0.92]
 [0.86]
 [0.89]]
Predicted output[[0.90080936]
 [0.87515144]
 [0.89326513]]
```

Practical No: 05

Implement the Following:

A:Write a program for Hopfield Network .

Theory:

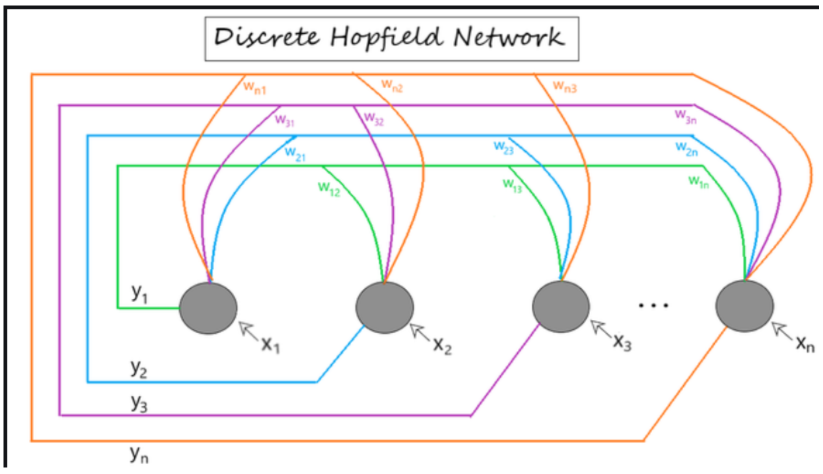
• A Hopfield network is a single-layered and recurrent network in which the neurons are entirely connected, i.e., each neuron is associated with other neurons. If there are two neurons i and j, then there is a connectivity weight wij lies between them which is symmetric wij = wji

• A Hopfield network is at first prepared to store various patterns or memories. Afterward, it is ready to recognize any of the learned patterns by uncovering partial or even some corrupted data about that pattern, i.e., it eventually settles down and restores the closest pattern. Thus, similar to the human brain, the Hopfield model has stability in pattern recognition.

• There are two different approaches to update the nodes:

1] Synchronously: In this approach, the update of all the nodes taking place simultaneously at each time.

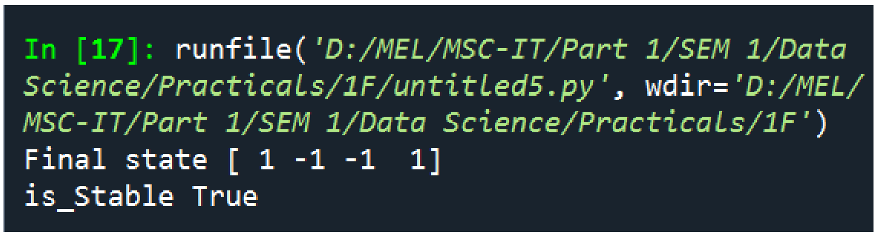
2] Asynchronously: In this approach, at each point of time, update one node chosen randomly or according to some rule. Asynchronous updating is more biologically realistic.



Code:

```
import numpy as np


def compute_next_state(state,weight):
    next_state = np.where(weight @ state>= 0, +1, -1)
    return next_state


def compute_final_state(initial_state,weight,max_iter=1000):
    previous_state = initial_state
    next_state =compute_next_state(previous_state,weight)
    is_stable = np.all(previous_state == next_state)
    n_iter = 0

    while(not is_stable) and (n_iter <= max_iter):
        previous_state = next_state;
        next_state = compute_next_state(previous_state,weight)
        is_stable = np.all(previous_state==next_state)
        n_iter +=1
    return previous_state, is_stable,n_iter
initial_state = np.array([+1,-1,-1,-1])
weight = np.array([
        [0, -1, -1, +1],
        [-1, 0, +1, -1],
        [-1,+1,  0, -1],
        [+1,-1, -1,  0]])

final_state, is_stable, n_iter = compute_final_state(initial_state,weight)
print("Final state",final_state)
print("is_Stable",is_stable)
```

Output:



```
In [17]: runfile('D:/MEL/MSC-IT/Part 1/SEM 1/Data
Science/Practicals/1F/untitled5.py', wdir='D:/MEL/
MSC-IT/Part 1/SEM 1/Data Science/Practicals/1F')
Final state [ 1 -1 -1  1]
is_Stable True
```

Practical No: 06

Implement the Following:

A:Write a program for Linear Separation .

Theory:

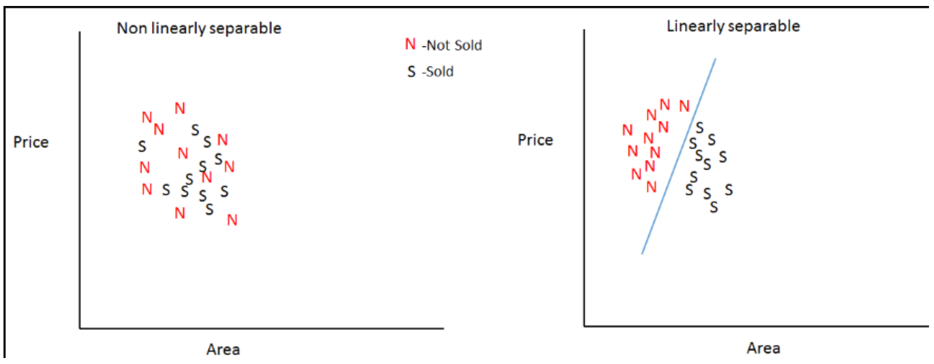
Linear separability is the concept wherein the separation of input space into regions is based on whether the network response is positive or negative.

A decision line is drawn to separate positive and negative responses. The decision line may also be called as the decision-making Line or decision-support Line or linear-separable line. The necessity of the linear separability concept was felt to clarify classify the patterns based upon their output responses.

Generally, the net input calculated to the output unit is given as -

$$y_{in} = b + \sum_{i=1}^{n}(x_i w_i)$$

⇒ The linear separability of the network is based on the decision-boundary line. If there exist weight for which the training input vectors having a positive (correct) response, or lie on one side of the decision boundary and all the other vectors having negative, -1, response lies on the other side of the decision boundary then we can conclude the problem is "Linearly Separable".

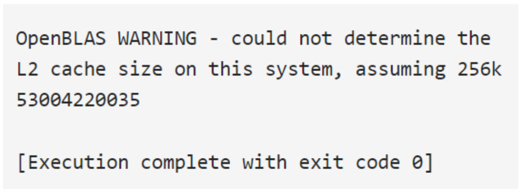


Code:

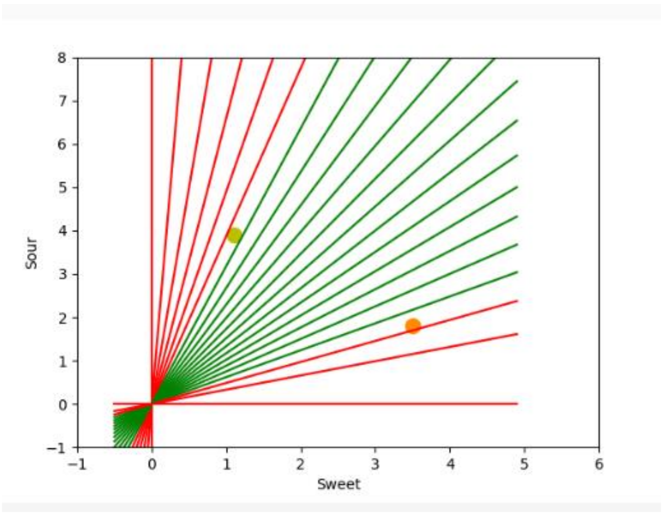
```
import numpy as np

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("Sweet")
ax.set_ylabel("Sour")
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()
print('53004220036')
```

Output:



```
OpenBLAS WARNING - could not determine the
L2 cache size on this system, assuming 256k
53004220035

[Execution complete with exit code 0]
```



Practical No: 07

Implement the Following:

A:Membership and Identity Operators | in, not in .

Theory:

Python offers two membership operators to check or validate the membership of a value. It tests for membership in a sequence, such as strings, lists, or tuples.

in operator: The 'in' operator is used to check if a character/ substring/ element exists in a sequence or not. Evaluate to True if it finds the specified element in a sequence otherwise False.

*'not in' operato*r- Evaluates to true if it does not finds a variable in the specified sequence and false otherwise.

Identity operators

Identity operators are used to compare the objects if both the objects are actually of the same data type and share the same memory location.

There are different identity operators such as

'is' operator – Evaluates to True if the variables on either side of the operator point to the same object and false otherwise.

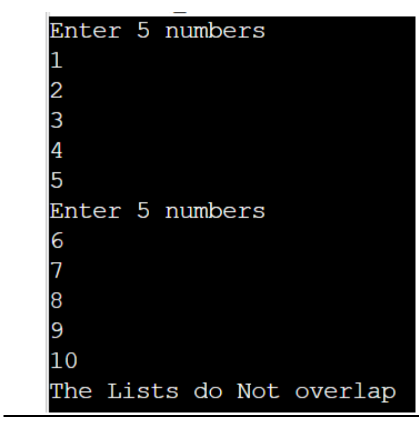
'is not' operator: Evaluates True if both variables are not the same object.

Code:

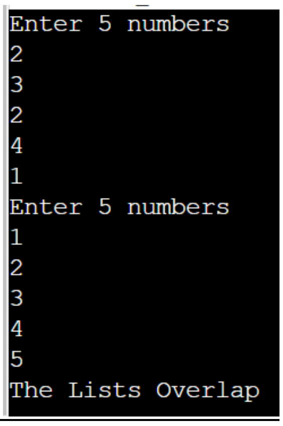
1- In Operator

```
list1=[]
print("Enter 5 numbers")
for i in range(0,5):
    v=int(input())
    list1.append(v)
list2=[]
print("Enter 5 numbers")
for i in range(0,5):
    v=int(input())
    list2.append(v)
flag=0
for i in list1:
    if i in list2:
        flag=1
if(flag==1):
   print("The Lists Overlap")
else:
    print("The Lists do Not overlap")
```

Output:



```
Enter 5 numbers
1
2
3
4
5
Enter 5 numbers
6
7
8
9
10
The Lists do Not overlap
```



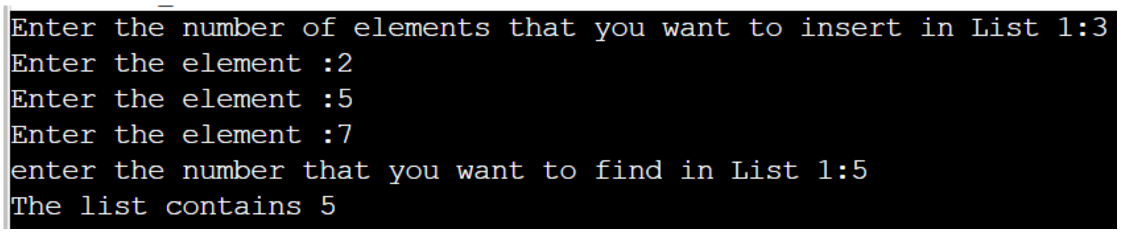
```
Enter 5 numbers
2
3
2
4
1
Enter 5 numbers
1
2
3
4
5
The Lists Overlap
```

2- not In Operator

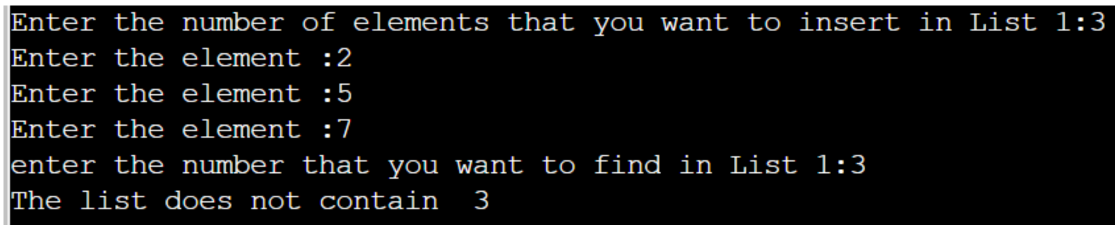
Code:

```
list1=[]
c=int(input("Enter the number of elements that you want to insert in List 1:"))
for i  in range(0,c):
   ele = int(input("Enter the element :"))
   list1.append(ele)
a = int(input("enter the number that you want to find in List 1:"))
if a not in list1:
    print( "The list does not contain ", a )
else:
    print( "The list contains", a )
```

Output:



```
Enter the number of elements that you want to insert in List 1:3
Enter the element :2
Enter the element :5
Enter the element :7
enter the number that you want to find in List 1:5
The list contains 5
```



```
Enter the number of elements that you want to insert in List 1:3
Enter the element :2
Enter the element :5
Enter the element :7
enter the number that you want to find in List 1:3
The list does not contain  3
```

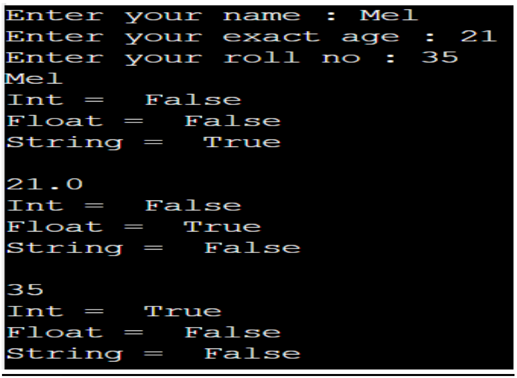
B:Membership and Identity Operators | is, is not.

Code:

1: Implement Membership and Identity Operators is.

```
details =[]
name=input("Enter your name : ")
details.append(name)
age=float(input("Enter your exact age : "))
details.append(age)
roll_no=int(input("Enter your roll no : "))
details.append(roll_no)

for i in details:
    print(i)
    print("Int = ",type(i) is int)
    print("Float = ",type(i) is float)
    print("String = ",type(i) is str)
    print()
```

Output:



```
Enter your name : Mel
Enter your exact age : 21
Enter your roll no : 35
Mel
Int =  False
Float =  False
String =  True

21.0
Int =  False
Float =  True
String =  False

35
Int =  True
Float =  False
String =  False
```

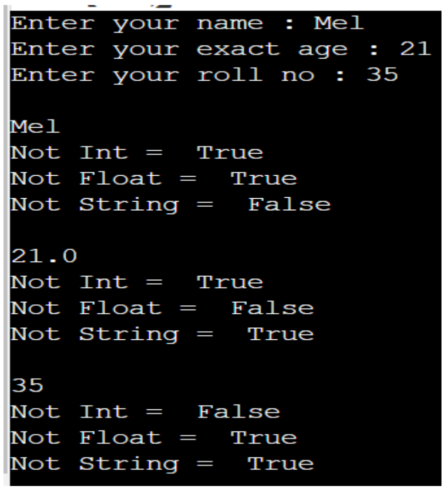
2: Implement Membership and Identity Operators is not.

Code:

```
details =[]
name=input("Enter your name : ")
details.append(name)
age=float(input("Enter your exact age : "))
details.append(age)
roll_no=int(input("Enter your roll no : "))
details.append(roll_no)
```

```
print()
for i in details:
    print(i)
    print("Not Int = ",type(i) is not int)
    print("Not Float = ",type(i) is not float)
    print("Not String = ",type(i) is not str)
    print()
```

Output:



```
Enter your name : Mel
Enter your exact age : 21
Enter your roll no : 35

Mel
Not Int =  True
Not Float =  True
Not String =  False

21.0
Not Int =  True
Not Float =  False
Not String =  True

35
Not Int =  False
Not Float =  True
Not String =  True
```

Practical No: 08

Implement the Following:

A: Find ratios using Fuzzy logic.

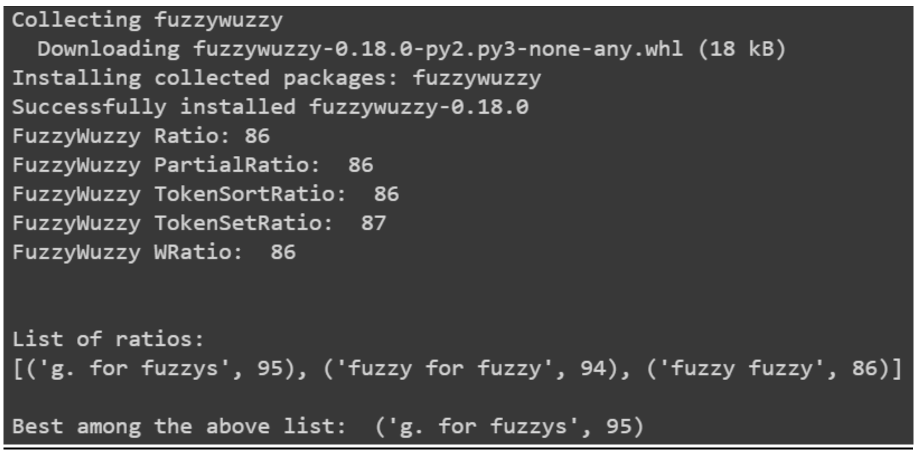
Theory:

FuzzyWuzzy is a library of Python which is used for string matching. Fuzzy string matching is the process of finding strings that match a given pattern. Basically it uses Levenshtein Distance to calculate the differences between sequences.FuzzyWuzzy has been developed and open-sourced by SeatGeek.The FuzzyWuzzy library is built on top of difflib library, python-Levenshtein is used for speed. So it is one of the best way for string matching in python.

Code:

```
!pip install fuzzywuzzy

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 ("FuzzyWuzzy PartialRatio: ", fuzz.partial_ratio(s1, s2))

print ("FuzzyWuzzy TokenSortRatio: ", fuzz.token_sort_ratio(s1, s2))

print ("FuzzyWuzzy TokenSetRatio: ", fuzz.token_set_ratio(s1, s2))

print ("FuzzyWuzzy WRatio: ", 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))
```

Output:



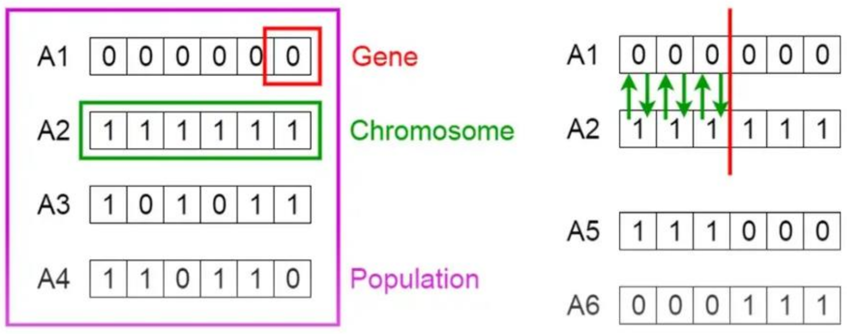
```
Collecting fuzzywuzzy
  Downloading fuzzywuzzy-0.18.0-py2.py3-none-any.whl (18 kB)
Installing collected packages: fuzzywuzzy
Successfully installed fuzzywuzzy-0.18.0
FuzzyWuzzy Ratio: 86
FuzzyWuzzy PartialRatio:  86
FuzzyWuzzy TokenSortRatio:  86
FuzzyWuzzy TokenSetRatio:  87
FuzzyWuzzy WRatio:  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 No: 9

Theory:

The genetic algorithm is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals from the current population to be parents and uses them to produce the children for the next generation.

Over successive generations, the population "evolves" toward an optimal solution. You can apply the genetic algorithm to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, nondifferentiable, stochastic, or highly nonlinear.



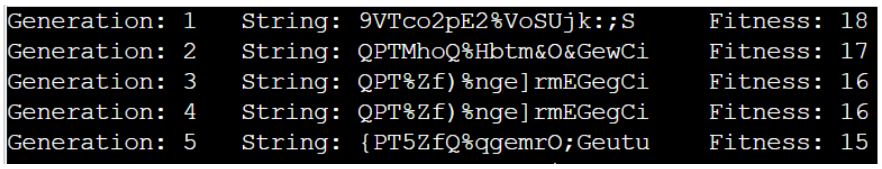
Implement the Following:

A: Implementation of a Simple Genetic Algorithm.

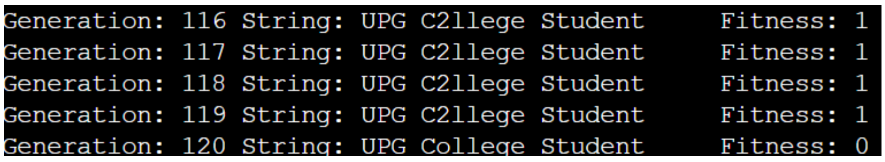
Code:

```
import random

# Number of individuals in each generation

POPULATION_SIZE = 100

# Valid genes

GENES = '''abcdefghijklmnopqrstuvwxyzABCDEFGHIJKLMNOP

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

# Target string to be generated

TARGET = "UPG College Student "

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: 9VTco2pE2%VoSUjk:;S     Fitness: 18
Generation: 2   String: QPTMhoQ%Hbtm&O&GewCi    Fitness: 17
Generation: 3   String: QPT%Zf)%nge]rmEGegCi    Fitness: 16
Generation: 4   String: QPT%Zf)%nge]rmEGegCi    Fitness: 16
Generation: 5   String: {PT5ZfQ%qgemrO;Geutu    Fitness: 15
```



```
Generation: 116 String: UPG C2llege Student      Fitness: 1
Generation: 117 String: UPG C2llege Student      Fitness: 1
Generation: 118 String: UPG C2llege Student      Fitness: 1
Generation: 119 String: UPG C2llege Student      Fitness: 1
Generation: 120 String: UPG College Student      Fitness: 0
```