

**S.E.A.COLLEGE OF ENGINEERING & TECHNOLOGY,**  
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**Department of Computer Science and Engineering &  
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**BE - VII SEMESTER**

**ARTIFICIAL INTELLIGENCE AND  
MACHINE LEARNING LABORATORY  
18CSL76**

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# 1. Implement A\* Search Algorithm.

## Program :

```
class Node():
    """A node class for A* Pathfinding"""

    def __init__(self, parent=None, position=None):
        self.parent = parent
        self.position = position

        self.g = 0
        self.h = 0
        self.f = 0

    def __eq__(self, other):
        return self.position == other.position

# Simulate popping from a priority queue. The node with least f value is popped from queue

def pop_queue(que):
    # Get the current node
    current_node = que[0]
    current_index = 0
    for index, item in enumerate(que):
        if item.f < current_node.f:
            current_node = item
            current_index = index

    # Pop current off open list, add to closed list
    return que.pop(current_index)

def astar(maze, start, end):
    """Returns a list of tuples as a path from the given start to the given end in the given maze"""

    # Create start and end node
    start_node = Node(None, start)
    start_node.g = start_node.h = start_node.f = 0
    end_node = Node(None, end)
    end_node.g = end_node.h = end_node.f = 0

    # Initialize both open and closed list
    open_list = []
    closed_list = []

    # Add the start node
    open_list.append(start_node)

    # Loop until you find the end
    while len(open_list) > 0:

        current_node = pop_queue(open_list)
        closed_list.append(current_node)

        # Found the goal
        if current_node == end_node:
            path = []
            current = current_node
            while current is not None:
                path.append(current.position)
                current = current.parent
            return path[::-1] # Return reversed path
```

```

# Generate children
children = []
for new_position in [(0, -1), (0, 1), (-1, 0), (1, 0), (-1, -1), (-1, 1), (1, -1), (1, 1)]: # Adjacent squares

    # Get node position
    node_position = (current_node.position[0] + new_position[0], current_node.position[1] + new_position[1])

    # Make sure within range
    if node_position[0] > (len(maze) - 1) or node_position[0] < 0 or node_position[1] > (len(maze[len(maze)-1]) - 1) or node_position[1] < 0:
        continue

    # Make sure walkable terrain
    if maze[node_position[0]][node_position[1]] != 0:
        continue

    # Create new node
    new_node = Node(current_node, node_position)

    # Append
    children.append(new_node)

# Loop through children
for child in children:

    # if Child is on the closed list, skip it
    child_in_closed = False
    for closed_child in closed_list:
        if child == closed_child:
            child_in_closed = True
            break
    if child_in_closed:
        continue

    # Create the f, g, and h values
    child.g = current_node.g + 1

    dx = abs(child.position[0] - end_node.position[0])
    dy = abs(child.position[1] - end_node.position[1])
    D = 1 # distance to next horizontal/vertical node
    D2 = 1 # distance to next diagonal node

    child.h = D * (dx + dy) + (D2 - 2 * D) * min(dx, dy)
    #child.h = ((child.position[0] - end_node.position[0]) ** 2) + ((child.position[1] - end_node.position[1]) ** 2)
    child.f = child.g + child.h

    # Child is already in the open list
    discard_child = False
    for open_node in open_list:
        if child == open_node:
            if child.g < open_node.g:
                open_node.g = child.g
                open_node.f = open_node.g + open_node.h
                open_node.parent = current_node
            discard_child = True
            break

```

```

        # Add the child to the open list
        if discard_child == False:
            open_list.append(child)

def main():

    maze = [[0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
            [0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
            [0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
            [0, 0, 0, 0, 1, 0, 1, 0, 0, 0],
            [0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
            [0, 0, 0, 0, 0, 0, 1, 0, 0, 0],
            [0, 0, 0, 0, 1, 0, 1, 0, 0, 0],
            [0, 0, 0, 0, 1, 0, 1, 0, 0, 0],
            [0, 0, 0, 0, 1, 0, 1, 0, 0, 0],
            [0, 0, 0, 0, 1, 0, 1, 0, 0, 0],
            [0, 0, 0, 0, 0, 0, 0, 0, 0.2, 0]]

    start = (0, 0)
    end = (0, 9)

    path = astar(maze, start, end)
    print(path)

if __name__ == '__main__':
    main()

```

**Output :**

```
[(0, 0), (1, 1), (2, 2), (3, 3), (4, 3), (5, 4), (4, 5), (4, 6), (3, 7), (2, 7), (1, 8), (0, 9)]
```

```

a = (1,2)
b = (1,2)
if a==b:
    print("Same")

```

**Output :**

Same

## 2. Implement AO\* Search Algorithm.

### Program :

```
class Node:
    def __init__(self, index, cost, visited=False, is_solved=False, and_map=False, or_map=False):
        self.index=index
        self.cost=cost
        self.visited=visited
        self.is_solved=is_solved
        self.and_map= and_map
        self.or_map = or_map
        self.children=()

    def __str__(self):
        return f'{self.index}: {self.cost}'

    def set_children(self, ch):
        self.children=ch

adj=[]
n_nodes = 21
#heuristic costs
cost=[None,0,40,2,4,1,2,3,50,60,70,80,4,5,8,9,6,7,90,90,90,90]
and_edges={}
for i in range(n_nodes+1):
    n=Node(i, cost[i])
    adj.append(n)

adj[1].set_children((adj[2],adj[3],adj[4]))
adj[2].set_children((adj[5],adj[6],adj[7]))
adj[3].set_children((adj[8],adj[9]))
adj[4].set_children((adj[10],adj[11]))
adj[5].set_children((adj[12],adj[13])); adj[6].set_children((adj[14],adj[15]))
adj[7].set_children((adj[16],adj[17])); adj[8].set_children((adj[18],))
adj[9].set_children((adj[19],)); adj[10].set_children((adj[20],)); adj[11].set_children((adj[21],))

and_edges[adj[1]] = (adj[3],adj[4])
adj[3].and_map = adj[4].and_map = True

and_edges[adj[2]] = (adj[5],adj[6], adj[7])
adj[5].and_map = adj[6].and_map = adj[7].and_map=True

for a in adj:
    if len(a.children)==0: a.is_solved=True
    if a.and_map==False: a.or_map=True
    #print(f'{a.index} and {a.and_map} or {a.or_map}')
```

```

def get_key(and_edges, c):
    for idx, ae in and_edges.items():
        if c in ae: return idx, ae

def explore_head(head):
    print(f'Head: {head.index}, Cost: {head.cost}')
    head.visited=True; temp_cost = MAX; temp_map={}
    for c in head.children:
        if temp_map.get(c,False): continue;

        if c.and_map: # if the child is in the and edge
            temp_solved=True
            #calculate the cost and check if there are more nodes in the and edge
            idx,ae = get_key(and_edges,c)
            cc=0
            for aek in ae:
                cc+=aek.cost+EDGE
                temp_map[aek]=True
                temp_solved=temp_solved and aek.is_solved
            temp_cost = min(temp_cost,cc)

            if temp_solved:
                head.is_solved=True

        else: # else if child is in the or edge
            temp_cost = min(temp_cost,c.cost+EDGE)
            temp_map[c]=True
            if c.is_solved: head.is_solved=True
    #head is explored now update the best value of head i.e. temp_cost
    if temp_cost < MAX:
        head.cost=temp_cost
        print(f'Updated head cost {head.cost}')

def find_best_move(head):
    #find the best move
    isAnd=False
    bestCost=MAX;bestMove=None; bestAndIndex=-1
    temp_map1={}
    for c in head.children:
        if temp_map1.get(c,False):continue

        if c.or_map:
            if bestCost>c.cost+EDGE:
                bestCost = c.cost+EDGE
                bestMove=c; isAnd=False
                temp_map1[c]=True
            print(f'or edge {c.index}, {bestCost}')
        else:
            cc=0
            idx,ae = get_key(and_edges,c)
            for aek in ae:
                cc+=aek.cost+EDGE
                temp_map1[aek]=True
            print(f'and-pair {idx.index}-{c.index}')

        print(f'bestCost {bestCost} cc {cc}')
        if bestCost>cc and cc!=0:
            bestCost = cc; bestAndIndex = idx; bestMove = c
            isAnd=True

```

```

    print(f'\nmoving forward, finding the best move,i>>{c.index}')
    if isAnd:
        print(f'and edge, cost: {bestCost}')
    else:
        print(f'or edge, cost: {bestCost}')

if isAnd:
    for ae in and_edges[bestAndIndex]:
        print(f'isAnd: {isAnd} and, aoStarUtil {ae.index}')
        aostarUtil(ae)
else:
    print(f'isAnd: {isAnd} or, aoStarUtil {bestMove.index}')
    aostarUtil(bestMove)

def check_update(head):
    temp_cost=MAX; temp_map={}
    for c in head.children:
        if temp_map.get(c,False):continue
        if c.or_map:
            if c.is_solved: head.is_solved=True
            temp_cost= min(temp_cost, c.cost+EDGE)
            temp_map[c]=True
        elif c.and_map:
            f=True;cc=0
            idx,ae = get_key(and_edges,c)
            for aek in ae:
                f = f and aek.is_solved
                cc+=aek.cost+EDGE
                temp_map[aek]=True

            temp_cost = min(temp_cost,cc)
            print(f'temp_cost=min({temp_cost},{cc})')

            if f:
                head.is_solved=True
                break

    if temp_cost<=MAX:
        head.cost = temp_cost

    print(f'Updated Cost of node {head.index} {head.cost}')

def aostarUtil(head):
    if head.visited ==False:
        explore_head(head)
    else:
        find_best_move(head)
        #check if any of the options were solved
        #if there are multiple solved nodes , select the best out of them
        #also update the current cost i.e. head cost while backtracking to the root
        check_update(head)

def aostar(head):
    iter = 0
    while head.is_solved==False and iter <MAX:
        print(f'\n **Iteration {iter}')
        aostarUtil(head)
        iter+=1
    for a in adj:
        print(a.index,': ',a.cost, end=" ")

```



```
MAX=1000
EDGE=5 #g cost of edge
aostar(adj[1])
```

## Output :

```
**Iteration 0
Head: 1, Cost: 0
Updated head cost 16

**Iteration 1
or edge 2, 45

moving forward, finding the best move,i>>2
or edge, cost: 45
and-pair 1-3
and-pair 1-3
bestCost 45 cc 16

moving forward, finding the best move,i>>3
and edge, cost: 16
isAnd: True and, aoStarUtil 3
Head: 3, Cost: 2
Updated head cost 55
isAnd: True and, aoStarUtil 4
Head: 4, Cost: 4
Updated head cost 75
temp_cost=min(45,140)
Updated Cost of node 1 45

**Iteration 2
or edge 2, 45

moving forward, finding the best move,i>>2
or edge, cost: 45
and-pair 1-3
and-pair 1-3
bestCost 45 cc 140

moving forward, finding the best move,i>>3
or edge, cost: 45
isAnd: False or, aoStarUtil 2
Head: 2, Cost: 40
Updated head cost 21
temp_cost=min(26,140)
Updated Cost of node 1 26

**Iteration 3
or edge 2, 26

moving forward, finding the best move,i>>2
or edge, cost: 26
and-pair 1-3
and-pair 1-3
bestCost 26 cc 140

moving forward, finding the best move,i>>3
or edge, cost: 26
isAnd: False or, aoStarUtil 2
and-pair 2-5
and-pair 2-5
and-pair 2-5
bestCost 1000 cc 21
```

```

moving forward, finding the best move,i>>5
and edge, cost: 21
isAnd: True and, aoStarUtil 5
Head: 5, Cost: 1
Updated head cost 9
isAnd: True and, aoStarUtil 6
Head: 6, Cost: 2
Updated head cost 13
isAnd: True and, aoStarUtil 7
Head: 7, Cost: 3
Updated head cost 11
temp_cost=min(48,48)
Updated Cost of node 2 48
temp_cost=min(53,140)
Updated Cost of node 1 53
0 : None 1 : 53 2 : 48 3 : 55 4 : 75 5 : 9 6 : 13 7 : 11 8 : 50 9 : 60 10 : 70 11 : 80 12 : 4 13 : 5 14 : 8 15 :
9 16 : 6 17 : 7 18 : 90 19 : 90 20 : 90 21 : 90

```

3. For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all Hypotheses consistent with the training examples.

### Program:

```
import csv
a = []
print("\n The Given Training Data Set \n")
with open('data1.csv', 'r') as csvFile:
    reader = csv.reader(csvFile)
    for row in reader:
        a.append(row)
        print(row)
num_attributes = len(a[0])-1 # we don't want last col which is target concet ( yes/no)
print("\n The initial value of hypothesis: ")
S = ['0'] * num_attributes
G = ['?'] * num_attributes
print("\n The most specific hypothesis S0 : [0,0,0,0,0,0]\n")
print("\n The most general hypothesis G0 : [?,?,?,?,?,?]\n")
for j in range(0,num_attributes):
    S[j] = a[0][j];
# Comparing with Remaining Training Examples of Given Data Set
print("\n Candidate Elimination algorithm Hypotheses Version Space Computation\n")
temp=[]
for i in range(0,len(a)):
    if a[i][num_attributes]=='1':
        for j in range(0,num_attributes):
            if a[i][j]!=S[j]:
                S[j]='?'
        for j in range(0,num_attributes):
            for k in range(0,len(temp)):
                if temp[k][j] != '?' and temp[k][j] != S[j]:
                    del temp[k] #remove it if it's not matching with the specific hypothesis
        print(" For Training Example No :{0} the hypothesis is S{0} ".format(i+1),S)
        if (len(temp)==0):
            print(" For Training Example No :{0} the hypothesis is G{0} ".format(i+1),G)
        else:
            print(" For Training Example No :{0} the hypothesis is G{0}".format(i+1),temp)
    if a[i][num_attributes]=='0':
        for j in range(0,num_attributes):
            if S[j] != a[i][j] and S[j]!='?': #if not matching with the specific Hypothesis
                G[j]=S[j]
            temp.append(G) # this is the version space to store all Hypotheses
            G = ['?'] * num_attributes
        print(" For Training Example No :{0} the hypothesis is S{0} ".format(i+1),S)
        print(" For Training Example No :{0} the hypothesis is G{0}".format(i+1),temp)
```

### Dataset to be considered is as follows:-

sunny	warm	normal	strong	warm	same	1
sunny	warm	high	strong	warm	same	1
rainy	cold	high	strong	warm	change	0
sunny	warm	high	strong	cool	change	1

### The output is as follows:-

The Given Training Data Set

```
['sunny', 'warm', 'normal', 'strong', 'warm', 'same', '1']  
['sunny', 'warm', 'high', 'strong', 'warm', 'same', '1']  
['rainy', 'cold', 'high', 'strong', 'warm', 'change', '0']  
['sunny', 'warm', 'high', 'strong', 'cool', 'change', '1']
```

The initial value of hypothesis:

The most specific hypothesis  $S_0$  : [0,0,0,0,0,0]

The most general hypothesis  $G_0$  : [?, ?, ?, ?, ?, ?]

Candidate Elimination algorithm   Hypotheses Version Space Computation

```
For Training Example No :1 the hypothesis is S1  ['sunny', 'warm', 'normal', 'strong',  
'warm', 'same']  
For Training Example No :1 the hypothesis is G1  ['?', '?', '?', '?', '?', '?']  
For Training Example No :2 the hypothesis is S2  ['sunny', 'warm', '?', 'strong',  
'warm', 'same']  
For Training Example No :2 the hypothesis is G2  ['?', '?', '?', '?', '?', '?']  
For Training Example No :3 the hypothesis is S3  ['sunny', 'warm', '?', 'strong',  
'warm', 'same']  
For Training Example No :3 the hypothesis is G3  [['sunny', '?', '?', '?', '?', '?'],  
['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'same']]  
For Training Example No :4 the hypothesis is S4  ['sunny', 'warm', '?', 'strong', '?',  
'?']  
For Training Example No :4 the hypothesis is G4  [['sunny', '?', '?', '?', '?', '?'],  
['?', 'warm', '?', '?', '?', '?']]
```

**4. Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.**

**Program:**

```
import pandas as pd
from pandas import DataFrame
df_tennis= DataFrame.from_csv('data3.csv')
print(df_tennis)
def entropy(probs):
    import math
    return sum([-prob*math.log(prob,2) for prob in probs])

def entropy_of_list(a_list):
    from collections import Counter
    cnt=Counter(x for x in a_list)
    print("NO AND YES CLASSES: ",a_list.name,cnt)
    num_instances=len(a_list)*1.0
    probs=[x/num_instances for x in cnt.values()]
    return entropy(probs)
total_entropy=entropy_of_list(df_tennis['Target'])
print("ENTROPY OF GIVEN PLAYTENNIS DATA SET : ",total_entropy)

def information_gain(df,split_attribute_name,target_attribute_name,trace=0):
    print("INFORMATION GAIN CALCULATION OF ",split_attribute_name)
    df_split=df.groupby(split_attribute_name)
    for name,group in df_split:
        print(name)
        print(group)
    nobs=len(df.index)*1.0
    df_agg_ent=df_split.agg({target_attribute_name: [entropy_of_list, lambda x: len(x)/nobs]})[target_attribute_name]
    df_agg_ent.columns=['Entropy','PropObservations']
    new_entropy=sum(df_agg_ent['Entropy']*df_agg_ent['PropObservations'])
    old_entropy=entropy_of_list(df[target_attribute_name])
    return (old_entropy-new_entropy)

print("INFO-GAIN FOR OUTLOOK IS : "+str(information_gain(df_tennis,'Outlook','Target'))+"\n")
print("INFO-GAIN FOR HUMIDITY IS : "+str(information_gain(df_tennis,'Humidity','Target'))+"\n")
print("INFO-GAIN FOR WIND IS : "+str(information_gain(df_tennis,'Wind','Target'))+"\n")
print("INFO-GAIN FOR TEMPERATURE IS : "+str(information_gain(df_tennis,'Temperature','Target'))+"\n")
```

**The dataset to be considered is as follows :-**

Outlook	Temperat	Humidity	Wind	Target
sunny	hot	high	weak	no
sunny	hot	high	strong	no
overcast	hot	high	weak	yes
rain	mild	high	weak	yes
rain	cool	normal	weak	yes
rain	cool	normal	strong	no
overcast	cool	normal	strong	yes
sunny	mild	high	weak	no
sunny	cool	normal	weak	yes
rain	mild	normal	weak	yes
sunny	mild	normal	strong	yes
overcast	mild	high	strong	yes
overcast	hot	normal	weak	yes
rain	mild	high	strong	no

**The output is:**

```

      Temperature Humidity   Wind Target
Outlook
sunny      hot      high    weak    no
sunny      hot      high  strong    no
overcast   hot      high    weak    yes
rain       mild     high    weak    yes
rain       cool     normal  weak    yes
rain       cool     normal  strong   no
overcast   cool     normal  strong   yes
sunny      mild     high    weak    no
sunny      cool     normal  weak    yes
rain       mild     normal  weak    yes
sunny      mild     normal  strong   yes
overcast   mild     high    strong   yes
overcast   hot      normal  weak    yes
rain       mild     high    strong   no
NO AND YES CLASSES: Target Counter({'yes': 9, 'no': 5})
ENTROPY OF GIVEN PLAYTENNIS DATA SET : 0.9402859586706309
```



INFORMATION GAIN CALCULATION OF Outlook  
overcast

	Temperature	Humidity	Wind	Target
Outlook				
overcast	hot	high	weak	yes
overcast	cool	normal	strong	yes
overcast	mild	high	strong	yes
overcast	hot	normal	weak	yes
rain				

	Temperature	Humidity	Wind	Target
Outlook				
rain	mild	high	weak	yes
rain	cool	normal	weak	yes
rain	cool	normal	strong	no
rain	mild	normal	weak	yes
rain	mild	high	strong	no
sunny				

	Temperature	Humidity	Wind	Target
Outlook				
sunny	hot	high	weak	no
sunny	hot	high	strong	no
sunny	mild	high	weak	no
sunny	cool	normal	weak	yes
sunny	mild	normal	strong	yes

NO AND YES CLASSES: Target Counter({'yes': 4})

NO AND YES CLASSES: Target Counter({'yes': 3, 'no': 2})

NO AND YES CLASSES: Target Counter({'no': 3, 'yes': 2})

NO AND YES CLASSES: Target Counter({'yes': 9, 'no': 5})

INFO-GAIN FOR OUTLOOK IS : 0.2467498197744391

INFORMATION GAIN CALCULATION OF Humidity  
high

	Temperature	Humidity	Wind	Target
Outlook				
sunny	hot	high	weak	no
sunny	hot	high	strong	no
overcast	hot	high	weak	yes
rain	mild	high	weak	yes
high				

	Temperature	Humidity	Wind	Target
Outlook				
sunny	mild	high	weak	no
overcast	mild	high	strong	yes
rain	mild	high	strong	no
normal				

	Temperature	Humidity	Wind	Target
Outlook				
rain	cool	normal	weak	yes
rain	cool	normal	strong	no
overcast	cool	normal	strong	yes
sunny	cool	normal	weak	yes
rain	mild	normal	weak	yes
sunny	mild	normal	strong	yes
overcast	hot	normal	weak	yes

NO AND YES CLASSES: Target Counter({'yes': 2, 'no': 2})

NO AND YES CLASSES: Target Counter({'no': 2, 'yes': 1})

NO AND YES CLASSES: Target Counter({'yes': 6, 'no': 1})

NO AND YES CLASSES: Target Counter({'yes': 9, 'no': 5})

INFO-GAIN FOR HUMIDITY IS : 0.1619576049392195

# INFORMATION GAIN CALCULATION OF Wind

	Temperature	Humidity	Wind	Target
Outlook				
sunny	hot	high	strong	no
rain	cool	normal	strong	no
overcast	cool	normal	strong	yes
sunny	mild	normal	strong	yes
overcast	mild	high	strong	yes
rain	mild	high	strong	no
weak				

	Temperature	Humidity	Wind	Target
Outlook				
sunny	hot	high	weak	no
overcast	hot	high	weak	yes
rain	mild	high	weak	yes
rain	cool	normal	weak	yes
sunny	mild	high	weak	no
sunny	cool	normal	weak	yes
rain	mild	normal	weak	yes
overcast	hot	normal	weak	yes

NO AND YES CLASSES: Target Counter({'yes': 3, 'no': 3})

NO AND YES CLASSES: Target Counter({'yes': 6, 'no': 2})

NO AND YES CLASSES: Target Counter({'yes': 9, 'no': 5})

INFO-GAIN FOR WIND IS : 0.04812703040826927

## INFORMATION GAIN CALCULATION OF Temperature

	Temperature	Humidity	Wind	Target
Outlook				
sunny	hot	high	weak	no
sunny	hot	high	strong	no
overcast	hot	high	weak	yes
cool				

	Temperature	Humidity	Wind	Target
Outlook				
rain	cool	normal	weak	yes
rain	cool	normal	strong	no
overcast	cool	normal	strong	yes
sunny	cool	normal	weak	yes
hot				

	Temperature	Humidity	Wind	Target
Outlook				
overcast	hot	normal	weak	yes
mild				

	Temperature	Humidity	Wind	Target
Outlook				
rain	mild	high	weak	yes
sunny	mild	high	weak	no
rain	mild	normal	weak	yes
sunny	mild	normal	strong	yes
overcast	mild	high	strong	yes
rain	mild	high	strong	no

NO AND YES CLASSES: Target Counter({'no': 2, 'yes': 1})

NO AND YES CLASSES: Target Counter({'yes': 3, 'no': 1})

NO AND YES CLASSES: Target Counter({'yes': 1})

NO AND YES CLASSES: Target Counter({'yes': 4, 'no': 2})

NO AND YES CLASSES: Target Counter({'yes': 9, 'no': 5})

INFO-GAIN FOR TEMPERATURE IS : 0.11815917264727838



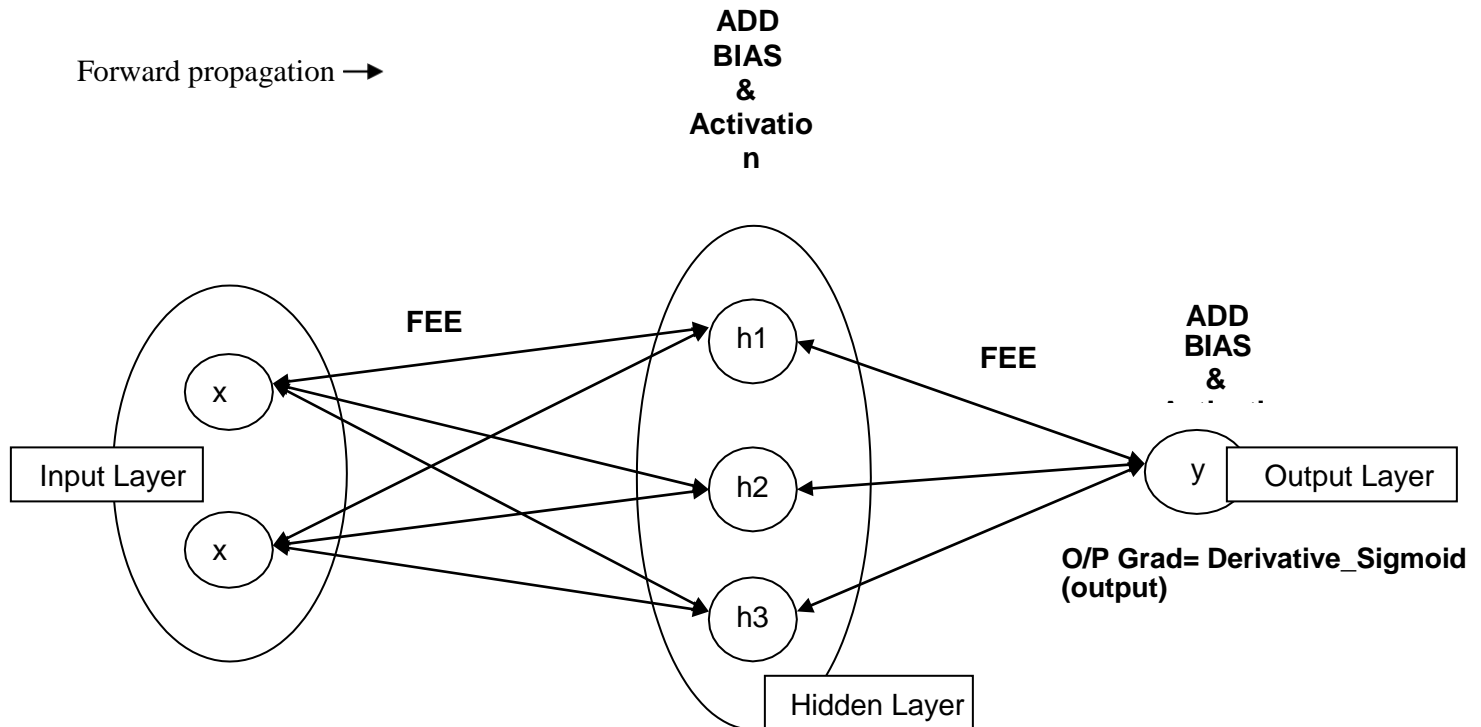
## 5. Build an Artificial Neural Network by implementing the Back propagation algorithm and test the same using appropriate data sets.

### Program:

```
1 import numpy as np
2 X = np.array([[2, 9], [1, 5], [3, 6]], dtype=float)
3 y = np.array([[92], [86], [89]], dtype=float)
4 X = X/np.amax(X,axis=0) # maximum of X array longitudinally
5 y = y/100
6 #Sigmoid Function
7 def sigmoid (x):
8     return 1/(1 + np.exp(-x))
9 #Derivative of Sigmoid Function
10 def derivatives_sigmoid(x):
11     return x * (1 - x)
12 #Variable initialization
13 epoch=1
14 #Setting training iterations
15 lr=0.1 #Setting learning rate
16 inputlayer_neurons = 2 #number of features in data set
17 hiddenlayer_neurons = 3 #number of hidden layers neurons
18 output_neurons = 1 #number of neurons at output layer
19 #weight and bias initialization
20 wh=np.random.uniform(size=(inputlayer_neurons,hiddenlayer_neurons))
21 bh=np.random.uniform(size=(1,hiddenlayer_neurons))
22 wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons))
23 bout=np.random.uniform(size=(1,output_neurons))
24 #draws a random range of numbers uniformly of dim x*y
25 for i in range(epoch):
26     #Forward Propagation
27     hinp1=np.dot(X,wh)
28     hinp=hinp1 + bh
29     hlayer_act = sigmoid(hinp)
30     outinp1=np.dot(hlayer_act,wout)
31     outinp= outinp1+ bout
32     output = sigmoid(outinp)
33     #Backpropagation
34     EO = y-output
35     outgrad = derivatives_sigmoid(output)
36     d_output = EO* outgrad
37     EH = np.dot(d_output,wout.T)
38     #wout.T is used to calculate the transpose of wout
39     hiddengrad = derivatives_sigmoid(hlayer_act)
40     #how much hidden layer wts contributed to error
41     d_hiddenlayer = EH * hiddengrad
42     #Update weights and bias for next iteration
43     wout += np.dot(hlayer_act.T,d_output) *lr
44     # dotproduct of nextlayererror and currentlayerop
45     bout += np.sum(d_output, axis=0) *lr
46     wh += X.T.dot(d_hiddenlayer) *lr
47     bh += np.sum(d_hiddenlayer, axis=0) *lr
48 print("Input: \n" + str(X))
49 print("Actual Output: \n" + str(y))
50 print("Predicted Output: \n" ,output)
51 print("Final Error In Predicted Output: \n" ,str(y-output))
```

## For this we consider:

Forward propagation →



Hidden \_Error = Delta\_ O/P\*Transpose(Weight  
O/P)      Hidden\_Grad=      Derivative\_Sigmoid  
(Hidden\_layer\_ACT)      Delta\_Hidden=  
Hidden\_Error\* Hidden\_Grad

← Backward Propagation

## The output is as follows:

```
Input:
[[0.66666667 1.
  [0.33333333 0.55555556]
  [1.          0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
[[0.88169538]
 [0.8710618 ]
 [0.88065579]]
Final Error In Predicted Output:
[[ 0.03830462]
 [-0.0110618 ]
 [ 0.00934421]]
```

6. Write a program to implement the naïve Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.

The dataset to be considered is as follows :-

Outlook	Temperat	Humidity	Wind	Target
sunny	hot	high	weak	no
sunny	hot	high	strong	no
overcast	hot	high	weak	yes
rain	mild	high	weak	yes
rain	cool	normal	weak	yes
rain	cool	normal	strong	no
overcast	cool	normal	strong	yes
sunny	mild	high	weak	no
sunny	cool	normal	weak	yes
rain	mild	normal	weak	yes
sunny	mild	normal	strong	yes
overcast	mild	high	strong	yes
overcast	hot	normal	weak	yes
rain	mild	high	strong	no

**Program:**

```
1 import numpy as np
2 import csv
3 def read_data(filename):
4     with open(filename,'r') as csvfile:
5         datareader = csv.reader(csvfile)
6         metadata = next(datareader)
7         traindata=[]
8         for row in datareader:
9             traindata.append(row)
10        print(traindata,"\n")
11        print("Metadata is:\n ",metadata)
12    return (metadata, traindata)
13
14 def splitDataset(dataset, splitRatio):
15     trainSize = int(len(dataset) * splitRatio)
16     trainSet = []
17     testset = list(dataset)
18     i=0
19     while len(trainSet) < trainSize:
20         trainSet.append(testset.pop(i))
21    return [trainSet, testset]
```

```

22 def classify(train,test):
23     train_rows = train.shape[0] #total training rows
24     test_rows=test.shape[0] #total testing rows
25     train_col = train.shape[1]
26     test_col = test.shape[1]
27     print("training data size=",train_rows)
28     print("test data size=",test.shape[0])
29     countYes,countNo,probYes,probNo=0,0,0,0
30     print("target    count    probability")
31     for x in range(train_rows):
32         if train[x,train_col-1] == 'yes':
33             countYes +=1
34         if train[x,train_col-1] == 'no':
35             countNo +=1
36     probYes=countYes/train_rows
37     probNo= countNo / train_rows
38     print('Yes',"\\t",countYes,"\\t",probYes)
39     print('No',"\\t",countNo,"\\t",probNo)
40     prob0 =np.zeros((test_col-1))
41     prob1 =np.zeros((test_col-1))
42     accuracy=0
43     for t in range(test_rows):
44         for k in range (test.shape[1]-1): #test.shape[1] refers to columns
45             count1,count0=0,0
46             for j in range (train_rows):
47                 if test[t,k] == train[j,k] and train[j,train_col-1]=='no':
48                     count0+=1
49                 if test[t,k]==train[j,k] and train[j,train_col-1]=='yes':
50                     count1+=1
51             prob0[k]=count0/countNo
52             prob1[k]=count1/countYes
53     probno=probNo
54     probyes=probYes
55     for i in range(test_col-1):
56         probno=probno*prob0[i]
57         probyes=probyes*prob1[i]
58         if probno>probyes:
59             predict='no'
60         else:
61             predict='yes'
62         if predict == test[t,test_col-1]:
63             accuracy+=1
64     final_accuracy=(accuracy/test_rows)*100
65     print("accuracy",final_accuracy,"%")
66     return
67 metadata,traindata= read_data("data3.csv")
68 splitRatio=0.8
69 trainingset, testset=splitDataset(traindata, splitRatio)
70 training=np.array(trainingset)
71 testing=np.array(testset)
72 print("Training :\\n",training,"\\nTesting: \\n",testing)
73 classify(training,testing)

```

## The output is as follows:

```
[[ 'sunny', ' hot', ' high', 'weak', 'no'], [ 'sunny', ' hot', ' high', 'strong', 'no'],  
[ 'overcast', ' hot', ' high', 'weak', 'yes'], [ 'rain', 'mild', ' high', 'weak', 'yes'],  
[ 'rain', 'cool', 'normal', 'weak', 'yes'], [ 'rain', 'cool', 'normal', 'strong', 'no'],  
[ 'overcast', 'cool', 'normal', 'strong', 'yes'], [ 'sunny', 'mild', 'high', 'weak',  
'no'], [ 'sunny', 'cool', 'normal', 'weak', 'yes'], [ 'rain', 'mild', 'normal', 'weak',  
'yes'], [ 'sunny', 'mild', 'normal', 'strong', 'yes'], [ 'overcast', 'mild', 'high',  
'strong', 'yes'], [ 'overcast', 'hot', 'normal', 'weak', 'yes'], [ 'rain', 'mild', 'high',  
'strong', 'no']]
```

Metadata is:

```
['Outlook', 'Temperature', 'Humidity', 'Wind', 'Target']
```

Training :

```
[[ 'sunny' ' hot' ' high' 'weak' 'no']  
[ 'sunny' ' hot' ' high' 'strong' 'no']  
[ 'overcast' ' hot' ' high' 'weak' 'yes']  
[ 'rain' 'mild' ' high' 'weak' 'yes']  
[ 'rain' 'cool' 'normal' 'weak' 'yes']  
[ 'rain' 'cool' 'normal' 'strong' 'no']  
[ 'overcast' 'cool' 'normal' 'strong' 'yes']  
[ 'sunny' 'mild' 'high' 'weak' 'no']  
[ 'sunny' 'cool' 'normal' 'weak' 'yes']  
[ 'rain' 'mild' 'normal' 'weak' 'yes']  
[ 'sunny' 'mild' 'normal' 'strong' 'yes']]
```

Testing:

```
[[ 'overcast' 'mild' 'high' 'strong' 'yes']  
[ 'overcast' 'hot' 'normal' 'weak' 'yes']  
[ 'rain' 'mild' 'high' 'strong' 'no']]
```

training data size= 11

test data size= 3

target	count	probability
Yes	7	0.6363636363636364
No	4	0.36363636363636365
accuracy	66.66666666666666 %	









7. Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using  $k$ -Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Java/Python ML library classes/API in the program.

**Program:**

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 import pandas as pd
4 from sklearn.cluster import KMeans
5 from sklearn.mixture import GaussianMixture
6 df1 = pd.read_csv("data8.csv")
7 print(df1)
8 f1 = df1['Distance_Feature'].values
9 f2 = df1['Speeding_Feature'].values
10 X = np.matrix(list(zip(f1,f2)))
11 plt.plot(1)
12 plt.subplot(511)
13 plt.xlim([0, 100])
14 plt.ylim([0, 50])
15 plt.title('Dataset')
16 plt.ylabel('speeding_feature')
17 plt.xlabel('distance_feature')
18 plt.scatter(f1,f2)
19 colors = ['b', 'g', 'r']
20 markers = ['o', 'v', 's']
21 # create new plot and data for K- means algorithm
22 plt.plot(2)
23 ax=plt.subplot(513)
24 kmeans_model = KMeans(n_clusters=3).fit(X)
25 for i, l in enumerate(kmeans_model.labels_):
26     plt.plot(f1[i], f2[i], color=colors[l],marker=markers[l])
27 plt.xlim([0, 100])
28 plt.ylim([0, 50])
29 plt.title('K- Means')
30 plt.ylabel('speeding_feature')
31 plt.xlabel('distance_feature')
```

```

32 # create new plot and data for gaussian mixture i.e. EM Algorithm
33 plt.plot(3)
34 plt.subplot(515)
35 gmm=GaussianMixture(n_components=3).fit(X)
36 labels= gmm.predict(X)
37 for i, l in enumerate(labels):
38     plt.plot(f1[i], f2[i], color=colors[l], marker=markers[l])
39 plt.xlim([0, 100])
40 plt.ylim([0, 50])
41 plt.title('Gaussian Mixture')
42 plt.ylabel('speeding_feature')
43 plt.xlabel('distance_feature')
44 plt.show()

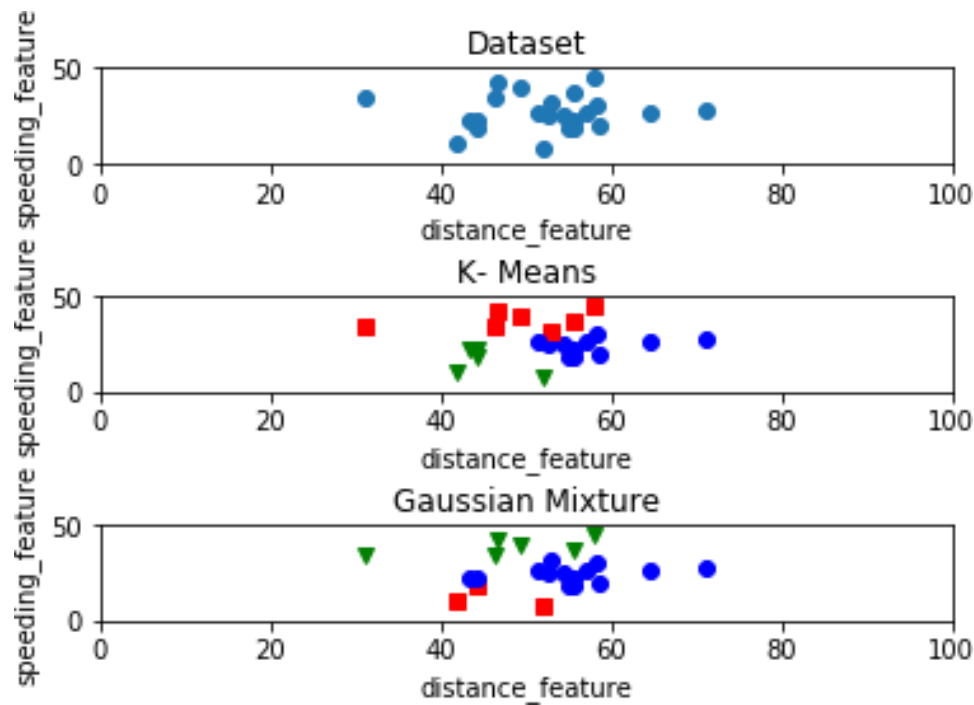
```

**The dataset to be considered is:**

1	Driver_ID	Distance_Feature	Speeding_Feature
2	3423311935	71.24	28
3	3423313212	52.53	25
4	3423313724	64.54	27
5	3423311373	55.69	22
6	3423310999	54.58	25
7	3423313857	41.91	10
8	3423312432	58.64	20
9	3423311434	52.02	8
10	3423311328	31.25	34
11	3423312488	44.31	19
12	3423311254	49.35	40
13	3423312943	58.07	45
14	3423312536	44.22	22
15	3423311542	55.73	19
16	3423312176	46.63	43
17	3423314176	52.97	32
18	3423314202	46.25	35
19	3423311346	51.55	27
20	3423310666	57.05	26
21	3423313527	58.45	30
22	3423312182	43.42	23
23	3423313590	55.68	37
24	3423312268	55.15	18

## The output is as follows:

	Driver_ID	Distance_Feature	Speeding_Feature	Unnamed: 3
0	3423311935	71.24	28	NaN
1	3423313212	52.53	25	NaN
2	3423313724	64.54	27	NaN
3	3423311373	55.69	22	NaN
4	3423310999	54.58	25	NaN
5	3423313857	41.91	10	NaN
6	3423312432	58.64	20	NaN
7	3423311434	52.02	8	NaN
8	3423311328	31.25	34	NaN
9	3423312488	44.31	19	NaN
10	3423311254	49.35	40	NaN
11	3423312943	58.07	45	NaN
12	3423312536	44.22	22	NaN
13	3423311542	55.73	19	NaN
14	3423312176	46.63	43	NaN
15	3423314176	52.97	32	NaN
16	3423314202	46.25	35	NaN
17	3423311346	51.55	27	NaN
18	3423310666	57.05	26	NaN
19	3423313527	58.45	30	NaN
20	3423312182	43.42	23	NaN
21	3423313590	55.68	37	NaN
22	3423312268	55.15	18	NaN



8. Write a program to implement *k*-Nearest Neighbor algorithm to classify the iris data set. Print both correct and wrong predictions. Java/Python ML library classes can be used for this problem.

**Program:**

```
1 from sklearn import datasets
2 iris=datasets.load_iris()
3 iris_data=iris.data
4 iris_labels=iris.target
5 from sklearn.model_selection import train_test_split
6 x_train,x_test,y_train,y_test=train_test_split(iris_data,iris_labels,test_size=0.30)
7
8 from sklearn.neighbors import KNeighborsClassifier
9 classifier=KNeighborsClassifier(n_neighbors=5)
10 classifier.fit(x_train,y_train)
11 y_pred=classifier.predict(x_test)
12
13 from sklearn.metrics import classification_report,confusion_matrix
14 print('Confusion matrix is as follows')
15 print(confusion_matrix(y_test,y_pred))
16 print('Accuracy Metrics')
17 print(classification_report(y_test,y_pred))
```

**The data set to be considered is:**

Iris Flower dataset from SKLearn is imported .

**The output is as follows:**

```
Confusion matrix is as follows
```

```
[[16  0  0]
 [ 0 19  3]
 [ 0  1  6]]
```

```
Accuracy Metrics
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	16
1	0.95	0.86	0.90	22
2	0.67	0.86	0.75	7
micro avg	0.91	0.91	0.91	45
macro avg	0.87	0.91	0.88	45
weighted avg	0.92	0.91	0.91	45

## 9. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

### Program:

```
1 import matplotlib.pyplot as plt
2 import pandas as pd
3 import numpy as np
4 def kernel(point, xmat, k):
5     m,n=np1.shape(xmat) #size of matrix m
6     weights=np1.mat(np1.eye(m)) #np.eye returns mat with 1 in the diagonal
7     for j in range(m):
8         diff=point-xmat[j]
9         weights[j,j]=np1.exp(diff*diff.T/(-2.0*k**2))
10    return weights
11 def localWeight(point,xmat,yamat,k):
12     wei=kernel(point,xmat,k)
13     W=(xmat.T*(wei*xmat)).I*(xmat.T*(wei*yamat.T))
14    return W
15 def localWeightRegression(xmat,yamat,k):
16     row,col=np1.shape(xmat) #return 244 rows and 2 columns
17     ypred=np1.zeros(row)
18     for i in range(row):
19         ypred[i]=xmat[i]*localWeight(xmat[i],xmat,yamat,k)
20    return ypred
21 data=pd.read_csv('data10.csv')
22 bill=np1.array(data.total_bill)
23 tip=np1.array(data.tip)
24 mbill=np1.mat(bill)
25 mtip=np1.mat(tip)
26 mbillMatCol=np1.shape(mbill)[1] # 1 for vertical i.e columns
27 onesArray=np1.mat(np1.ones(mbillMatCol))
28 #hstack concate horizontal lists it takes one value from the fist and one from the second
29 xmat=np1.hstack((onesArray.T,mbill.T))
30 ypred=localWeightRegression(xmat,mtip,2)
31 SortIndex=xmat[:,1].argsort(0)
32 #argsort take the index of each and sort them according to the orginal value
33 xsort=xmat[SortIndex][:,0]
34 fig= plt.figure()
35 ax=fig.add_subplot(1,1,1)
36 ax.scatter(bill,tip,color='blue')
37 ax.plot(xsort[:,1],ypred[SortIndex],color='red',linewidth=1)
38 plt.xlabel('Total bill')
39 plt.ylabel('tip')
40 plt.show();
```

## **The dataset considered is:**

The overall dataset consists of over 200 hypothesis values. Out of this First 24 are given below:

1	total_bill	tip
2	16.99	1.01
3	10.34	1.66
4	21.01	3.5
5	23.68	3.31
6	24.59	3.61
7	25.29	4.71
8	8.77	2
9	26.88	3.12
10	15.04	1.96
11	14.78	3.23
12	10.27	1.71
13	35.26	5
14	15.42	1.57
15	18.43	3
16	14.83	3.02
17	21.58	3.92
18	10.33	1.67
19	16.29	3.71
20	16.97	3.5
21	20.65	3.35
22	17.92	4.08
23	20.29	2.75
24	15.77	2.23
25	39.42	7.58

## **The output is:**

