[Note: Dataset will be provided during External lab Exam]

Machine learning Lab Manual

2019-20

Program 1:Find S Algorithm:

```
f = open('prg1.csv','r')
length = len(f.readline().split(','))
hypo = ['0']*(length-1)
print('Intital Hypo = ',hypo)
f.close()
f = open('prg1.csv','r')
count =1
for line in f:
    lst = line.split(',')
    for i in range(length-1):
        if(lst[-1] == 'yes\n'):
            if(hypo[i]!='0' and lst[i]!=hypo[i]):
                hypo[i]='?'
            else:
                hypo[i] = lst[i]
    print('Hypo ',hypo)
print('final hypo ',hypo)
```

/*prg1.csv*/

```
sunny,warm,normal,strong,warm,same,yes
sunny,warm,high,strong,warm,same,yes
rainy,cold,high,strong,warm,change,no
sunny,warm,high,strong,cool,change,yes
```

Program 2:Candidate elimination Algorithm:

```
f = open('prg1.csv','r')
length = len(f.readline().split(',')) -1
f.close()
f = open('prg1.csv','r')
shypo = ['0']*(length)
ghypo =['?']*(length)
print('Intital Specific hypothesis',shypo)
count = 1
print('Intital General hypothesis',ghypo)
ghypo.clear()
for line in f:
    lst = line.split(',')
    for i in range(length):
        if(lst[-1] == 'yes\n'):
            if shypo[i]!='0' and shypo[i]!=lst[i]:
                shypo[i] ='?'
            else:
                shypo[i] = lst[i]
        elif (lst[-1] == 'no\n'):
            if '0' in shypo:
                temp_lst = ['?']*i
                temp_lst += [lst[i]]
                temp_lst += ['?'] * (length-1-i)
                ghypo.append(temp_lst)
```

```
            elif shypo[i]!='?' and shypo[i]!=lst[i]:
                temp_lst = ['?']*i
                temp_lst = temp_lst + [shypo[i]]
                temp_lst = temp_lst + ['?'] * (length-1-i)
                if(temp_lst not in ghypo):
                    ghypo.append(temp_lst)
    print('SHYPO ',count ," ",shypo)
    print('GHYPO ',count ," ",ghypo)
    count+=1
f_ghypo = list()
for i in range(len(ghypo)):
    for j in range(len(ghypo[i])):
        if(ghypo[i][j]!='?' and ghypo[i][j]==shypo[j]):
            f_ghypo.append(ghypo[i])
print(f_ghypo)
```

/*prg1.csv*/

```
sunny,warm,normal,strong,warm,same,yes
sunny,warm,high,strong,warm,same,yes
rainy,cold,high,strong,warm,change,no
sunny,warm,high,strong,cool,change,yes
```

Program 3:ID3 Decision Tree

```
import numpy as np
import pandas as pd


def entropy(target_col):
    val,counts = np.unique(target_col,return_counts = True)
    ent = sum( (-counts[i]/np.sum(counts)) * np.log2( counts[i]/np.sum(counts) ) for i in
range(len(val)))
    return ent


def infoGain(data,features,target):
    te = entropy(data[target])
    val,counts = np.unique(data[features],return_counts = True)
    eg = sum((counts[i]/sum(counts)) * entropy(data[data[features] == val[i]][target] ) for i
in range(len(val)))
    InfoGain = te-eg
    return InfoGain
def ID3(data,features,target,pnode):
    if len(np.unique(data[target])) == 1:
        return np.unique(data[target])[0]
    elif len(features) == 0:
        return pnode
    else:
        pnode = np.unique(data[target])[np.argmax(np.unique(data[target])[1])]
        IG = [infoGain(data,f,target) for f in features]
        index = np.argmax(IG)
        col = features[index]
```

```
        tree = {col:{}}
        features = [f for f in features if f!=col]
        for val in np.unique(data[col]):
            sub_data = data[data[col]==val].dropna()
            subtree = ID3(sub_data,features,target,pnode)
            tree[col][val] = subtree
        return tree

data = pd.read_csv('PlayTennis.csv')
testData = data.sample(frac = 0.1)
data.drop(testData.index,inplace = True)
print(data)
target = 'PlayTennis'
features = data.columns[data.columns!=target]
tree = ID3(data,features,target,None)
print (tree)
test = testData.to_dict('records')[0]
print(test,'=>', test['PlayTennis'])
```

/*PlayTennis.csv*/

Outlook,Temperature,Humidity,Wind,PlayTennis

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 4:Back Propagation Algorithm:

```
import numpy as np # numpy is commonly used to process number array
X = np.array([[2,9], [3,6], [4,8]]) # Features ( Hrs Slept, Hrs Studied)
y = np.array([[92], [86], [89]]) # Labels(Marks obtained)
X = X/np.amax(X,axis=0) # Normalize
y = y/100
def sigmoid(x):
    return 1/(1 + np.exp(-x))
def sigmoid_grad(x):
    return x * (1 - x)
# Variable initialization
epoch=1000 #Setting training iterations
eta =0.1 #Setting learning rate (eta)
input_neurons = 2 #number of features in data set
hidden_neurons = 3 #number of hidden layers neurons
output_neurons = 1 #number of neurons at output layer
# Weight and bias - Random initialization
wh=np.random.uniform(size=(input_neurons,hidden_neurons)) # 2x3
bh=np.random.uniform(size=(1,hidden_neurons)) # 1x3
wout=np.random.uniform(size=(hidden_neurons,output_neurons)) # 1x1
bout=np.random.uniform(size=(1,output_neurons))
for i in range(epoch):
    #Forward Propogation
    h_ip=np.dot(X,wh) + bh # Dot product + bias
    h_act = sigmoid(h_ip) # Activation function
    o_ip=np.dot(h_act,wout) + bout
    output = sigmoid(o_ip)
```

```
    # Error at Output layer
    Eo = y-output # Error at o/p
    outgrad = sigmoid_grad(output)
    d_output = Eo* outgrad # Errj=Oj(1-Oj)(Tj-Oj)
    # Error at Hidden later
    Eh = np.dot(d_output,wout.T) # .T means transpose
    hiddengrad = sigmoid_grad(h_act) # How much hidden layer wts contributed to error
    d_hidden = Eh * hiddengrad

    wout += np.dot(h_act.T,d_output) *eta # Dotproduct of nextlayererror and
currentlayerop
    wh += np.dot(X.T,d_hidden) *eta

print("Normalized Input: \n" ,X)
print("Actual Output: \n" ,y)
print("Predicted Output: \n" ,output)
```

Program 5:Bayesian Classifier

```
import pandas as pd
mush = pd.read_csv('mushrooms.csv')
target = 'class'
classes = mush[target].unique()
features = mush.columns[mush.columns!=target]
testData = mush.sample(frac=0.3)
mush.drop(testData.index,inplace = True)
first ={}
fourth ={}
for x in classes:
    mushcl = mush[mush[target]==x][features]
    tot = len(mushcl)
    second={}
    for col in mushcl.columns:
        third={}
        for val,cnt in mushcl[col].value_counts().iteritems():
            prob = cnt/tot
            third[val]=prob
            second[col]=third
    first[x]=second
    fourth[x]=len(mushcl)/len(mush)
def proabs(params):
    proab={}
    for x in classes:
        calc = fourth[x]
        for col, val in params.iteritems():
```

```
            try:
                calc = first[x][col][val]
            except KeyError:
                calc =0
        proab[x]=calc
    return proab
def maxx(params):
    proab = proabs(params)
    maxcl =''; maxv=0
    for col,val in proab.items():
        if(val>maxv):
            maxv=val
            maxcl=col
    return maxcl

b=[]
for i in mush.index:
    b.append(   maxx(mush.loc[i,features]) == mush.loc[i,target] )
print(sum(b),'correct of',len(b))
print('Accuracy =',sum(b)/len(b))
b=[]
for i in testData.index:
    b.append(   maxx(testData.loc[i,features]) == testData.loc[i,target] )
print(sum(b),'correct of',len(b))
print('Accuracy =',sum(b)/len(b))
```

/*mushrooms.csv*/

class,cap-shape,cap-surface,cap-color,bruises,odor,gill-attachment,gill-spacing,gill-size,gill-color,stalk-shape,stalk-root,stalk-surface-above-ring,stalk-surface-below-ring,stalk-color-above-ring,stalk-color-below-ring,veil-type,veil-color,ring-number,ring-type,spore-print-color,population,habitat

p,x,s,n,t,p,f,c,n,k,e,e,s,s,w,w,p,w,o,p,k,s,u

e,x,s,y,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,n,g

e,b,s,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,n,m

p,x,y,w,t,p,f,c,n,n,e,e,s,s,w,w,p,w,o,p,k,s,u

e,x,s,g,f,n,f,w,b,k,t,e,s,s,w,w,p,w,o,e,n,a,g

e,x,y,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,n,g

e,b,s,w,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,n,m

e,b,y,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,s,m

p,x,y,w,t,p,f,c,n,p,e,e,s,s,w,w,p,w,o,p,k,v,g

e,b,s,y,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,s,m

e,x,y,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,g

e,x,y,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,s,m

e,b,s,y,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,s,g

p,x,y,w,t,p,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,v,u

e,x,f,n,f,n,f,w,b,n,t,e,s,f,w,w,p,w,o,e,k,a,g

e,s,f,g,f,n,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,y,u

e,f,f,w,f,n,f,w,b,k,t,e,s,s,w,w,p,w,o,e,n,a,g

p,x,s,n,t,p,f,c,n,n,e,e,s,s,w,w,p,w,o,p,k,s,g

p,x,y,w,t,p,f,c,n,n,e,e,s,s,w,w,p,w,o,p,n,s,u

p,x,s,n,t,p,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,s,u

e,b,s,y,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,s,m

p,x,y,n,t,p,f,c,n,n,e,e,s,s,w,w,p,w,o,p,n,v,g

e,b,y,y,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,s,m

e,b,y,w,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,n,m

e,b,s,w,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,s,m

p,f,s,w,t,p,f,c,n,n,e,e,s,s,w,w,p,w,o,p,n,v,g

e,x,y,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,n,m

e,x,y,w,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,n,m

e,f,f,n,f,n,f,c,n,k,e,e,s,s,w,w,p,w,o,p,k,y,u

e,x,s,y,t,a,f,w,n,n,t,b,s,s,w,w,p,w,o,p,n,v,d

e,b,s,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,m

p,x,y,w,t,p,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,s,u

e,x,y,y,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,n,m

e,x,y,n,t,l,f,c,b,p,e,r,s,y,w,w,p,w,o,p,n,y,p

e,b,y,y,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,s,m

e,x,f,y,t,l,f,w,n,w,t,b,s,s,w,w,p,w,o,p,n,v,d

e,s,f,g,f,n,f,c,n,k,e,e,s,s,w,w,p,w,o,p,k,v,u

p,x,y,n,t,p,f,c,n,w,e,e,s,s,w,w,p,w,o,p,n,s,u

e,x,f,y,t,a,f,w,n,p,t,b,s,s,w,w,p,w,o,p,n,v,d

e,b,s,y,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,s,m

e,b,y,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,s,g

e,x,y,y,t,l,f,c,b,n,e,r,s,y,w,w,p,w,o,p,k,y,p

e,x,f,n,f,n,f,c,n,g,e,e,s,s,w,w,p,w,o,p,k,y,u

p,x,y,w,t,p,f,c,n,p,e,e,s,s,w,w,p,w,o,p,n,v,g

e,x,s,y,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,k,n,m

e,x,y,w,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,n,g

e,x,y,y,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,s,m

e,x,s,w,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,n,m

e,x,y,y,t,l,f,c,b,n,e,r,s,y,w,w,p,w,o,p,n,s,p

e,f,y,y,t,l,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,s,p

e,x,y,n,t,a,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,s,g

e,x,s,w,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,s,g

e,b,s,w,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,n,m

p,x,y,n,t,p,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,v,u

p,x,s,w,t,p,f,c,n,k,e,e,s,s,w,w,p,w,o,p,k,v,u

e,b,y,y,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,k,s,m

e,f,f,g,f,n,f,w,b,n,t,e,s,s,w,w,p,w,o,e,n,a,g

e,b,s,w,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,n,g

e,x,s,y,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,n,g

e,x,y,n,t,a,f,c,b,p,e,r,s,y,w,w,p,w,o,p,k,y,p

e,s,f,g,f,n,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,v,u

e,b,y,y,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,s,m

e,b,s,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,m

e,b,y,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,m

e,b,y,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,s,g

e,f,s,n,f,n,f,w,b,k,t,e,s,s,w,w,p,w,o,e,k,a,g

e,x,s,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,s,g

e,f,y,y,t,a,f,c,b,w,e,r,s,y,w,w,p,w,o,p,n,s,g

e,x,y,y,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,k,n,g

e,x,f,g,f,n,f,c,n,p,e,e,s,s,w,w,p,w,o,p,n,v,u

e,f,f,y,t,l,f,w,n,p,t,b,s,s,w,w,p,w,o,p,n,v,d

e,b,y,w,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,m

e,f,f,y,t,l,f,w,n,w,t,b,s,s,w,w,p,w,o,p,n,v,d

e,x,y,n,t,a,f,c,b,p,e,r,s,y,w,w,p,w,o,p,k,s,p

e,b,s,y,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,s,g

e,f,s,y,t,l,f,w,n,p,t,b,s,s,w,w,p,w,o,p,n,v,d

e,x,s,w,t,l,f,w,n,n,t,b,s,s,w,w,p,w,o,p,u,v,d

e,f,y,n,t,l,f,c,b,p,e,r,s,y,w,w,p,w,o,p,n,y,p

p,x,y,n,t,p,f,c,n,w,e,e,s,s,w,w,p,w,o,p,n,v,u

e,f,y,n,t,a,f,c,b,n,e,r,s,y,w,w,p,w,o,p,n,y,g

e,x,s,n,f,n,f,w,b,k,t,e,f,s,w,w,p,w,o,e,n,s,g

p,x,y,w,t,p,f,c,n,w,e,e,s,s,w,w,p,w,o,p,k,s,g

e,f,f,g,f,n,f,c,n,n,e,e,s,s,w,w,p,w,o,p,n,y,u

e,x,f,g,f,n,f,w,b,n,t,e,s,s,w,w,p,w,o,e,n,s,g

e,x,y,y,t,l,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,s,g

e,x,s,n,f,n,f,w,b,k,t,e,s,s,w,w,p,w,o,e,k,s,g

e,b,s,w,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,k,s,g

e,x,s,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,s,g

e,f,y,n,t,l,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,y,g

e,s,f,n,f,n,f,c,n,n,e,e,s,s,w,w,p,w,o,p,n,v,u

e,x,f,n,f,n,f,c,n,n,e,e,s,s,w,w,p,w,o,p,n,y,u

e,b,s,w,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,s,g

e,x,y,y,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,s,g

e,x,y,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,n,m

e,x,s,n,f,n,f,w,b,n,t,e,s,s,w,w,p,w,o,e,n,a,g

e,x,s,w,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,g

e,f,y,n,t,l,f,c,b,p,e,r,s,y,w,w,p,w,o,p,n,s,g

e,x,s,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,n,g

e,b,s,w,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,g

e,x,y,w,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,s,g

e,x,f,n,f,n,f,w,b,p,t,e,f,s,w,w,p,w,o,e,k,s,g

e,b,s,y,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,n,g

e,f,y,y,t,l,f,c,b,w,e,r,s,y,w,w,p,w,o,p,n,s,g

e,x,y,y,t,a,f,c,b,n,e,r,s,y,w,w,p,w,o,p,k,y,p

e,b,y,w,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,g

e,x,y,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,n,m

e,x,y,y,t,a,f,c,b,w,e,r,s,y,w,w,p,w,o,p,n,y,g

e,b,y,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,s,m

e,b,y,w,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,m

e,x,s,y,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,n,m

e,x,s,y,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,k,n,g

e,s,f,g,f,n,f,c,n,g,e,e,s,s,w,w,p,w,o,p,k,y,u

e,x,f,w,t,a,f,w,n,w,t,b,s,s,w,w,p,w,o,p,u,v,d

e,x,s,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,n,m

p,x,y,w,t,p,f,c,n,n,e,e,s,s,w,w,p,w,o,p,n,v,u

e,x,y,y,t,l,f,c,b,p,e,r,s,y,w,w,p,w,o,p,n,s,g

e,s,f,g,f,n,f,c,n,p,e,e,s,s,w,w,p,w,o,p,n,y,u

e,x,y,y,t,l,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,y,g

e,x,s,y,t,l,f,w,n,p,t,b,s,s,w,w,p,w,o,p,u,v,d

e,s,f,n,f,n,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,y,u

p,x,s,w,t,p,f,c,n,k,e,e,s,s,w,w,p,w,o,p,k,v,g

e,x,y,w,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,m

p,f,y,n,t,p,f,c,n,p,e,e,s,s,w,w,p,w,o,p,k,v,g

e,f,s,g,f,n,f,w,b,k,t,e,s,s,w,w,p,w,o,e,n,a,g

e,x,s,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,m

e,x,s,w,f,n,f,w,b,n,t,e,s,f,w,w,p,w,o,e,k,s,g

e,b,s,y,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,n,g

e,f,f,g,f,n,f,w,b,h,t,e,s,s,w,w,p,w,o,e,n,a,g

e,x,s,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,n,g

e,b,s,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,s,m

e,b,s,w,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,s,g

e,b,y,w,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,s,m

e,f,s,w,t,l,f,w,n,w,t,b,s,s,w,w,p,w,o,p,u,v,d

e,x,y,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,s,m

e,f,s,w,t,a,f,w,n,p,t,b,s,s,w,w,p,w,o,p,n,v,d

p,x,y,w,t,p,f,c,n,w,e,e,s,s,w,w,p,w,o,p,n,v,u

e,f,f,w,t,l,f,w,n,w,t,b,s,s,w,w,p,w,o,p,n,v,d

e,x,y,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,s,g

p,x,s,n,t,p,f,c,n,p,e,e,s,s,w,w,p,w,o,p,n,v,g

e,b,s,y,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,n,g

e,x,y,n,t,a,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,y,p

e,b,y,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,n,m

e,s,f,n,f,n,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,v,u

e,f,y,n,t,a,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,y,p

e,x,y,y,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,n,g

e,x,f,g,f,n,f,w,b,k,t,e,f,f,w,w,p,w,o,e,k,s,g

e,f,f,w,f,n,f,w,b,k,t,e,s,f,w,w,p,w,o,e,n,a,g

e,x,y,y,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,n,m

e,b,s,y,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,n,g

e,b,y,w,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,n,m

e,x,y,w,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,s,g

e,x,s,n,f,n,f,w,b,p,t,e,f,s,w,w,p,w,o,e,n,a,g

e,x,y,w,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,g

e,s,f,n,f,n,f,c,n,k,e,e,s,s,w,w,p,w,o,p,k,v,u

e,x,s,w,t,a,f,w,n,w,t,b,s,s,w,w,p,w,o,p,u,v,d

e,x,y,n,t,l,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,s,g

e,b,y,y,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,n,g

e,x,y,w,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,n,g

e,b,y,w,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,s,m

e,b,s,y,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,s,g

e,b,s,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,k,s,m

e,b,y,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,n,g

e,x,f,n,f,n,f,c,n,k,e,e,s,s,w,w,p,w,o,p,n,y,u

e,f,y,n,t,l,f,c,b,n,e,r,s,y,w,w,p,w,o,p,n,y,g

e,x,y,w,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,s,g

e,f,y,y,t,l,f,c,b,w,e,r,s,y,w,w,p,w,o,p,n,y,p

e,b,s,w,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,s,g

e,b,s,w,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,k,s,m

e,x,y,n,t,l,f,c,b,w,e,r,s,y,w,w,p,w,o,p,k,y,g

e,b,s,w,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,s,g

e,x,f,g,f,n,f,c,n,g,e,e,s,s,w,w,p,w,o,p,n,y,u

e,b,s,y,t,l,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,s,g

e,x,f,y,t,l,f,w,n,n,t,b,s,s,w,w,p,w,o,p,u,v,d

e,b,y,y,t,a,f,c,b,w,e,c,s,s,w,w,p,w,o,p,k,s,g

e,f,y,y,t,l,f,c,b,p,e,r,s,y,w,w,p,w,o,p,n,s,g

e,b,y,w,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,k,n,m

e,b,y,w,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,k,n,m

e,b,y,y,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,g

e,x,y,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,m

e,b,s,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,g

p,x,y,w,t,p,f,c,n,p,e,e,s,s,w,w,p,w,o,p,n,v,u

e,s,f,n,f,n,f,c,n,g,e,e,s,s,w,w,p,w,o,p,n,y,u

e,f,f,n,f,n,f,c,n,g,e,e,s,s,w,w,p,w,o,p,k,v,u

e,x,s,y,t,a,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,m

e,f,y,n,t,a,f,c,b,p,e,r,s,y,w,w,p,w,o,p,k,s,p

p,x,y,w,t,p,f,c,n,k,e,e,s,s,w,w,p,w,o,p,k,s,g

e,b,s,w,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,s,m

e,f,f,g,f,n,f,c,n,p,e,e,s,s,w,w,p,w,o,p,k,v,u

e,b,y,y,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,g

e,x,y,n,t,a,f,c,b,w,e,r,s,y,w,w,p,w,o,p,n,y,p

e,x,f,w,f,n,f,w,b,p,t,e,s,f,w,w,p,w,o,e,k,s,g

e,x,s,w,t,l,f,w,n,w,t,b,s,s,w,w,p,w,o,p,n,v,d

e,b,s,w,t,l,f,c,b,w,e,c,s,s,w,w,p,w,o,p,n,s,m

e,f,s,y,t,a,f,w,n,w,t,b,s,s,w,w,p,w,o,p,n,v,d

e,x,s,y,t,a,f,c,b,k,e,c,s,s,w,w,p,w,o,p,n,n,m

e,f,f,g,f,n,f,c,n,g,e,e,s,s,w,w,p,w,o,p,n,y,u

e,b,s,y,t,a,f,c,b,n,e,c,s,s,w,w,p,w,o,p,k,s,g

e,x,s,w,t,l,f,c,b,g,e,c,s,s,w,w,p,w,o,p,n,n,m

e,x,y,w,t,l,f,c,b,n,e,c,s,s,w,w,p,w,o,p,n,s,m

/*Data set is larger*/

Program 6:Bayesian Classifier for Text Classifier

```
import pandas as pd
msg=pd.read_csv('naive.csv',names=['message','label'])
print('The dimensions of the dataset',msg.shape)
msg['labelnum']=msg.label.map({'pos':1,'neg':0})
X=msg.message
y=msg.labelnum
print(X)
print(y)
#splitting the dataset into train and test data
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(X,y)
print(xtest.shape)
print(xtrain.shape)
print(ytest.shape)
print(ytrain.shape)
#output of count vectoriser is a sparse matrix
from sklearn.feature_extraction.text import CountVectorizer
count_vect = CountVectorizer()
xtrain_dtm = count_vect.fit_transform(xtrain)
xtest_dtm=count_vect.transform(xtest)
print(count_vect.get_feature_names())

df=pd.DataFrame(xtrain_dtm.toarray(),columns=count_vect.get_feature_names())
print(df)#tabular representation
print(xtrain_dtm) #sparse matrix representation
# Training Naive Bayes (NB) classifier on training data.
```

```
from sklearn.naive_bayes import MultinomialNB
clf = MultinomialNB().fit(xtrain_dtm,ytrain)
predicted = clf.predict(xtest_dtm)
#printing accuracy metrics
from sklearn import metrics
print('Accuracy metrics')
print('Accuracy of the classifer is',metrics.accuracy_score(ytest,predicted))
print('Confusion matrix')
print(metrics.confusion_matrix(ytest,predicted))
print('Recall and Precison ')
print(metrics.recall_score(ytest,predicted))
print(metrics.precision_score(ytest,predicted))
```

/*naïve.csv*/

I love this sandwich,pos

This is an amazing place,pos

I feel very good about these beers,pos

This is my best work,pos

What an awesome view,pos

I do not like this restaurant,neg

I am tired of this stuff,neg

I can't deal with this,neg

He is my sworn enemy,neg

My boss is horrible,neg

This is an awesome place,pos

I do not like the taste of this juice,neg

I love to dance,pos

I am sick and tired of this place,neg

What a great holiday,pos

That is a bad locality to stay,neg

We will have good fun tomorrow,pos

I went to my enemy's house today,neg

Program 7:Bayesian Network For Heart Diseases

```
import pandas as pd
from pgmpy.estimators import BayesianEstimator
from pgmpy.models import BayesianModel
from pgmpy.inference import VariableElimination
f=open('data7_name.csv','r')
attributes= f.readline().split(',')
heartDisease=pd.read_csv('data7.csv',names=attributes)
print("\nAttributes and datatypes")
print(heartDisease.dtypes)
model=BayesianModel([('age','trestbps'),('age','fbs'),('sex','trestbps'),('exang','trestbps'),('trestbps','heartdisease'),('fbs','heartdisease')])
model.fit(heartDisease,BayesianEstimator)
HeartDisease_infer=VariableElimination(model)
print("\n 1. Probability heart disease given age=28")
q=HeartDisease_infer.query(['heartdisease'],{'age':28})
print(q['heartdisease'])
print("\n 2. Probability of heart disease for male")
q=HeartDisease_infer.query(['heartdisease'],{'sex':1})
print(q['heartdisease'])
```

/*data_7_name.csv*/

age,sex,cp,trestbps,chol,fbs,restecg,thalach,exang,oldpeak,slope,ca,thal,heartdisease

/*data7.csv*/

63,1,1,145,233,1,2,150,0,2.3,3,0,6,0

67,1,4,160,286,0,2,108,1,1.5,2,3,3,2

67,1,4,120,229,0,2,129,1,2.6,2,2,7,1

37,1,3,130,250,0,0,187,0,3.5,3,0,3,0

41,0,2,130,204,0,2,172,0,1.4,1,0,3,0

56,1,2,120,236,0,0,178,0,0.8,1,0,3,0

62,0,4,140,268,0,2,160,0,3.6,3,2,3,3

57,0,4,120,354,0,0,163,1,0.6,1,0,3,0

63,1,4,130,254,0,2,147,0,1.4,2,1,7,2

53,1,4,140,203,1,2,155,1,3.1,3,0,7,1

57,1,4,140,192,0,0,148,0,0.4,2,0,6,0

56,0,2,140,294,0,2,153,0,1.3,2,0,3,0

56,1,3,130,256,1,2,142,1,0.6,2,1,6,2

44,1,2,120,263,0,0,173,0,0,1,0,7,0

52,1,3,172,199,1,0,162,0,0.5,1,0,7,0

57,1,3,150,168,0,0,174,0,1.6,1,0,3,0

48,1,2,110,229,0,0,168,0,1,3,0,7,1

54,1,4,140,239,0,0,160,0,1.2,1,0,3,0

48,0,3,130,275,0,0,139,0,0.2,1,0,3,0

49,1,2,130,266,0,0,171,0,0.6,1,0,3,0

64,1,1,110,211,0,2,144,1,1.8,2,0,3,0

58,0,1,150,283,1,2,162,0,1,1,0,3,0

58,1,2,120,284,0,2,160,0,1.8,2,0,3,1

58,1,3,132,224,0,2,173,0,3.2,1,2,7,3

60,1,4,130,206,0,2,132,1,2.4,2,2,7,4

50,0,3,120,219,0,0,158,0,1.6,2,0,3,0

58,0,3,120,340,0,0,172,0,0,1,0,3,0

66,0,1,150,226,0,0,114,0,2.6,3,0,3,0

43,1,4,150,247,0,0,171,0,1.5,1,0,3,0

40,1,4,110,167,0,2,114,1,2,2,0,7,3

69,0,1,140,239,0,0,151,0,1.8,1,2,3,0

60,1,4,117,230,1,0,160,1,1.4,1,2,7,2

64,1,3,140,335,0,0,158,0,0,1,0,3,1

59,1,4,135,234,0,0,161,0,0.5,2,0,7,0

44,1,3,130,233,0,0,179,1,0.4,1,0,3,0

42,1,4,140,226,0,0,178,0,0,1,0,3,0

43,1,4,120,177,0,2,120,1,2.5,2,0,7,3

57,1,4,150,276,0,2,112,1,0.6,2,1,6,1

55,1,4,132,353,0,0,132,1,1.2,2,1,7,3

61,1,3,150,243,1,0,137,1,1,2,0,3,0

65,0,4,150,225,0,2,114,0,1,2,3,7,4

40,1,1,140,199,0,0,178,1,1.4,1,0,7,0

71,0,2,160,302,0,0,162,0,0.4,1,2,3,0

59,1,3,150,212,1,0,157,0,1.6,1,0,3,0

61,0,4,130,330,0,2,169,0,0,1,0,3,1

58,1,3,112,230,0,2,165,0,2.5,2,1,7,4

51,1,3,110,175,0,0,123,0,0.6,1,0,3,0

50,1,4,150,243,0,2,128,0,2.6,2,0,7,4

65,0,3,140,417,1,2,157,0,0.8,1,1,3,0

53,1,3,130,197,1,2,152,0,1.2,3,0,3,0

41,0,2,105,198,0,0,168,0,0,1,1,3,0

65,1,4,120,177,0,0,140,0,0.4,1,0,7,0

44,1,4,112,290,0,2,153,0,0,1,1,3,2

44,1,2,130,219,0,2,188,0,0,1,0,3,0

60,1,4,130,253,0,0,144,1,1.4,1,1,7,1

54,1,4,124,266,0,2,109,1,2.2,2,1,7,1

50,1,3,140,233,0,0,163,0,0.6,2,1,7,1

41,1,4,110,172,0,2,158,0,0,1,0,7,1

54,1,3,125,273,0,2,152,0,0.5,3,1,3,0

51,1,1,125,213,0,2,125,1,1.4,1,1,3,0

51,0,4,130,305,0,0,142,1,1.2,2,0,7,2

46,0,3,142,177,0,2,160,1,1.4,3,0,3,0

58,1,4,128,216,0,2,131,1,2.2,2,3,7,1

54,0,3,135,304,1,0,170,0,0,1,0,3,0

54,1,4,120,188,0,0,113,0,1.4,2,1,7,2

60,1,4,145,282,0,2,142,1,2.8,2,2,7,2

60,1,3,140,185,0,2,155,0,3,2,0,3,1

54,1,3,150,232,0,2,165,0,1.6,1,0,7,0

59,1,4,170,326,0,2,140,1,3.4,3,0,7,2

46,1,3,150,231,0,0,147,0,3.6,2,0,3,1

65,0,3,155,269,0,0,148,0,0.8,1,0,3,0

67,1,4,125,254,1,0,163,0,0.2,2,2,7,3

62,1,4,120,267,0,0,99,1,1.8,2,2,7,1

65,1,4,110,248,0,2,158,0,0.6,1,2,6,1

44,1,4,110,197,0,2,177,0,0,1,1,3,1

65,0,3,160,360,0,2,151,0,0.8,1,0,3,0

60,1,4,125,258,0,2,141,1,2.8,2,1,7,1

51,0,3,140,308,0,2,142,0,1.5,1,1,3,0

/*Sample dataset <Dataset is too large>*/

Program 8:K-Means Algorithm

```
from sklearn.cluster import KMeans
from sklearn.mixture import GaussianMixture
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
data = pd.read_csv('8-kmeansdata.csv')
f1 =data['Distance_Feature']
f2=data['Speeding_Feature']
X =np.array(list(zip(f1,f2)))
plt.scatter(f1,f2,color='black')
plt.show()
kmeans = KMeans(3).fit(X)
labels = kmeans.predict(X)
plt.scatter(f1,f2,c=labels)
plt.show()
gm = GaussianMixture(3).fit(X)
labels = gm.predict(X)
plt.scatter(f1,f2,c=labels)
plt.show()
```

/*8-kmeansdata.csv*/

Driver_ID,Distance_Feature,Speeding_Feature

3423311935,71.24,28

3423313212,52.53,25

3423313724,64.54,27

3423311373,55.69,22

3423310999,54.58,25

3423313857,41.91,10

3423312432,58.64,20

3423311434,52.02,8

3423311328,31.25,34

3423312488,44.31,19

3423311254,49.35,40

3423312943,58.07,45

3423312536,44.22,22

3423311542,55.73,19

3423312176,46.63,43

3423314176,52.97,32

3423314202,46.25,35

3423311346,51.55,27

3423310666,57.05,26

3423313527,58.45,30

3423312182,43.42,23

3423313590,55.68,37

3423312268,55.15,18

Program 9:kNN Algorithm:

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import datasets
iris=datasets.load_iris()
print("Iris Data set loaded...")
x_train, x_test, y_train, y_test = train_test_split(iris.data,iris.target)
classifier = KNeighborsClassifier(3).fit(x_train, y_train)
y_pred=classifier.predict(x_test)
print("Results of Classification using K-nn with K=1 ")
for r in range(0,len(x_test)):
    print(" Sample:", str(x_test[r]), " Actual-label:", str(y_test[r]), " Predicted-label:",str(y_pred[r]))
print("Classification Accuracy :" , classifier.score(x_test,y_test));
```

Program 10:Linear Regression:

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
def localWeigh(point,X,ymat,k):
    m,n = np.shape(X)
    weights = np.mat(np.eye(m))
    for i in range(m):
        diff = point - X[i]
        weights[i,i] = np.exp(diff*diff.T/(-2.0*k**2))
    W = (X.T *(weights*X)).I * (X.T*(weights*ymat.T))
    return W
def localWeightReg(X,ymat,k):
    m,n = np.shape(X)
    ypred = np.zeros(m)
    for i in range(m):
        ypred[i] = X[i] * localWeigh(X[i],X,ymat,k)
    return ypred
def plott(X,pred):
    sortIndex = X[:,1].argsort(0)
    xsort = X[sortIndex][:,0][:,1]
    ysort = pred[sortIndex]
    plt.scatter(x,y,color='green')
    plt.plot(xsort,ysort,color="red",linewidth=5)
    plt.xlabel('Total bill')
    plt.ylabel('Tips')
    plt.show()
```

```
data = pd.read_csv('data10.csv')
x=data['total_bill']
y = data['tip']
xmat = np.mat(x)
ymat = np.mat(y)
size = np.shape(xmat)[1]
ones = np.mat(np.ones(size))
X=np.hstack((ones.T,xmat.T))
pred = localWeightReg(X,ymat,3)
plott(X,pred)
```

/*data10.csv*/

total_bill,tip,sex,smoker,day,time,size,fraction

16.99,1.01,Female,No,Sun,Dinner,2,0.05944673337257211

10.34,1.66,Male,No,Sun,Dinner,3,0.16054158607350097

21.01,3.5,Male,No,Sun,Dinner,3,0.16658733936220846

23.68,3.31,Male,No,Sun,Dinner,2,0.1397804054054054

24.59,3.61,Female,No,Sun,Dinner,4,0.14680764538430255

25.29,4.71,Male,No,Sun,Dinner,4,0.18623962040332148

8.77,2.0,Male,No,Sun,Dinner,2,0.22805017103762829

26.88,3.12,Male,No,Sun,Dinner,4,0.11607142857142858

15.04,1.96,Male,No,Sun,Dinner,2,0.13031914893617022

14.78,3.23,Male,No,Sun,Dinner,2,0.2185385656292287

10.27,1.71,Male,No,Sun,Dinner,2,0.1665043816942551

35.26,5.0,Female,No,Sun,Dinner,4,0.14180374361883155

15.42,1.57,Male,No,Sun,Dinner,2,0.10181582360570687

18.43,3.0,Male,No,Sun,Dinner,4,0.16277807921866522

14.83,3.02,Female,No,Sun,Dinner,2,0.20364126770060686

21.58,3.92,Male,No,Sun,Dinner,2,0.18164967562557924

10.33,1.67,Female,No,Sun,Dinner,3,0.1616650532429816

16.29,3.71,Male,No,Sun,Dinner,3,0.22774708410067526

16.97,3.5,Female,No,Sun,Dinner,3,0.20624631703005306

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15.77,2.23,Female,No,Sat,Dinner,2,0.14140773620798985

39.42,7.58,Male,No,Sat,Dinner,4,0.19228817858954844

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12.69,2.0,Male,No,Sat,Dinner,2,0.15760441292356187

21.7,4.3,Male,No,Sat,Dinner,2,0.19815668202764977

19.65,3.0,Female,No,Sat,Dinner,2,0.15267175572519084

9.55,1.45,Male,No,Sat,Dinner,2,0.1518324607329843

18.35,2.5,Male,No,Sat,Dinner,4,0.13623978201634876

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24.06,3.6,Male,No,Sat,Dinner,3,0.14962593516209477

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18.69,2.31,Male,No,Sat,Dinner,3,0.12359550561797752

31.27,5.0,Male,No,Sat,Dinner,3,0.1598976654940838

16.04,2.24,Male,No,Sat,Dinner,3,0.13965087281795513

17.46,2.54,Male,No,Sun,Dinner,2,0.14547537227949597

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32.4,6.0,Male,No,Sun,Dinner,4,0.1851851851851852

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18.04,3.0,Male,No,Sun,Dinner,2,0.16629711751662973

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10.29,2.6,Female,No,Sun,Dinner,2,0.2526724975704568

34.81,5.2,Female,No,Sun,Dinner,4,0.14938236139040506

9.94,1.56,Male,No,Sun,Dinner,2,0.15694164989939638

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19.49,3.51,Male,No,Sun,Dinner,2,0.18009235505387378

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15.01,2.09,Male,Yes,Sat,Dinner,2,0.13924050632911392

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44.3,2.5,Female,Yes,Sat,Dinner,3,0.05643340857787811

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7.25,1.0,Female,No,Sat,Dinner,1,0.13793103448275862

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29.8,4.2,Female,No,Thur,Lunch,6,0.14093959731543623

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14.52,2.0,Female,No,Thur,Lunch,2,0.13774104683195593

11.38,2.0,Female,No,Thur,Lunch,2,0.17574692442882248

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18.26,3.25,Female,No,Thur,Lunch,2,0.17798466593647316

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14.15,2.0,Female,No,Thur,Lunch,2,0.1413427561837456

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13.16,2.75,Female,No,Thur,Lunch,2,0.20896656534954408

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7.51,2.0,Male,No,Thur,Lunch,2,0.2663115845539281

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31.71,4.5,Male,No,Sun,Dinner,4,0.14191106906338694

10.59,1.61,Female,Yes,Sat,Dinner,2,0.15203021718602455

10.63,2.0,Female,Yes,Sat,Dinner,2,0.18814675446848542

50.81,10.0,Male,Yes,Sat,Dinner,3,0.19681165124975397

15.81,3.16,Male,Yes,Sat,Dinner,2,0.19987349778621127

7.25,5.15,Male,Yes,Sun,Dinner,2,0.710344827586207

31.85,3.18,Male,Yes,Sun,Dinner,2,0.09984301412872841

16.82,4.0,Male,Yes,Sun,Dinner,2,0.23781212841854935

32.9,3.11,Male,Yes,Sun,Dinner,2,0.0945288753799392

17.89,2.0,Male,Yes,Sun,Dinner,2,0.11179429849077696

14.48,2.0,Male,Yes,Sun,Dinner,2,0.13812154696132597

9.6,4.0,Female,Yes,Sun,Dinner,2,0.4166666666666667

34.63,3.55,Male,Yes,Sun,Dinner,2,0.102512272596015

34.65,3.68,Male,Yes,Sun,Dinner,4,0.10620490620490622

23.33,5.65,Male,Yes,Sun,Dinner,2,0.2421774539219889

45.35,3.5,Male,Yes,Sun,Dinner,3,0.07717750826901874

23.17,6.5,Male,Yes,Sun,Dinner,4,0.2805351747949935

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23.1,4.0,Male,Yes,Sun,Dinner,3,0.17316017316017315

15.69,1.5,Male,Yes,Sun,Dinner,2,0.09560229445506692

19.81,4.19,Female,Yes,Thur,Lunch,2,0.21150933871781932

28.44,2.56,Male,Yes,Thur,Lunch,2,0.090014064697609

15.48,2.02,Male,Yes,Thur,Lunch,2,0.13049095607235142

16.58,4.0,Male,Yes,Thur,Lunch,2,0.24125452352231608

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43.11,5.0,Female,Yes,Thur,Lunch,4,0.1159823706796567

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16.4,2.5,Female,Yes,Thur,Lunch,2,0.15243902439024393

20.53,4.0,Male,Yes,Thur,Lunch,4,0.1948368241597662

16.47,3.23,Female,Yes,Thur,Lunch,3,0.19611414693381907

26.59,3.41,Male,Yes,Sat,Dinner,3,0.1282437006393381

38.73,3.0,Male,Yes,Sat,Dinner,4,0.0774593338497289

24.27,2.03,Male,Yes,Sat,Dinner,2,0.08364235681911825

12.76,2.23,Female,Yes,Sat,Dinner,2,0.17476489028213166

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28.17,6.5,Female,Yes,Sat,Dinner,3,0.23074192403265883

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11.59,1.5,Male,Yes,Sat,Dinner,2,0.12942191544434858

7.74,1.44,Male,Yes,Sat,Dinner,2,0.18604651162790697

30.14,3.09,Female,Yes,Sat,Dinner,4,0.10252156602521566

12.16,2.2,Male,Yes,Fri,Lunch,2,0.18092105263157895

13.42,3.48,Female,Yes,Fri,Lunch,2,0.2593144560357675

8.58,1.92,Male,Yes,Fri,Lunch,1,0.22377622377622378

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13.42,1.58,Male,Yes,Fri,Lunch,2,0.11773472429210134

16.27,2.5,Female,Yes,Fri,Lunch,2,0.15365703749231716

10.09,2.0,Female,Yes,Fri,Lunch,2,0.19821605550049554

20.45,3.0,Male,No,Sat,Dinner,4,0.1466992665036675

13.28,2.72,Male,No,Sat,Dinner,2,0.20481927710843376

22.12,2.88,Female,Yes,Sat,Dinner,2,0.13019891500904157

24.01,2.0,Male,Yes,Sat,Dinner,4,0.08329862557267805

15.69,3.0,Male,Yes,Sat,Dinner,3,0.19120458891013384

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10.77,1.47,Male,No,Sat,Dinner,2,0.13649025069637882

15.53,3.0,Male,Yes,Sat,Dinner,2,0.19317450096587252

10.07,1.25,Male,No,Sat,Dinner,2,0.12413108242303872

12.6,1.0,Male,Yes,Sat,Dinner,2,0.07936507936507936

32.83,1.17,Male,Yes,Sat,Dinner,2,0.03563813585135547

35.83,4.67,Female,No,Sat,Dinner,3,0.13033770583310075

29.03,5.92,Male,No,Sat,Dinner,3,0.2039269720978298

27.18,2.0,Female,Yes,Sat,Dinner,2,0.07358351729212656

22.67,2.0,Male,Yes,Sat,Dinner,2,0.08822232024702249

17.82,1.75,Male,No,Sat,Dinner,2,0.09820426487093153

18.78,3.0,Female,No,Thur,Dinner,2,0.1597444089456869

[Note:Dataset will be provided in external lab exam]