In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [ ]:
```
data = pd.read_csv("titanic.csv")
data.head()
```

Out[ ]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Em
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	

In [ ]:
```
drop_cols = ["Embarked","Cabin","Name","Ticket","PassengerId"]
data = data.drop(drop_cols,axis=1)
```

In [ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  891 non-null    int64  
 1   Pclass    891 non-null    int64  
 2   Sex       891 non-null    object 
 3   Age       714 non-null    float64
 4   SibSp     891 non-null    int64  
 5   Parch     891 non-null    int64  
 6   Fare      891 non-null    float64
```

```
dtypes: float64(2), int64(4), object(1)
memory usage: 48.9+ KB
```

In [ ]:
```
data = data.fillna(data["Age"].mean())
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  891 non-null    int64  
 1   Pclass    891 non-null    int64  
 2   Sex       891 non-null    object 
 3   Age       891 non-null    float64
 4   SibSp     891 non-null    int64  
 5   Parch     891 non-null    int64  
 6   Fare      891 non-null    float64
dtypes: float64(2), int64(4), object(1)
memory usage: 48.9+ KB
```

In [ ]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data["Sex"] = le.fit_transform(data["Sex"])
```

In [ ]:
```
data.info()
data.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  891 non-null    int64  
 1   Pclass    891 non-null    int64  
 2   Sex       891 non-null    int32  
 3   Age       891 non-null    float64
 4   SibSp     891 non-null    int64  
 5   Parch     891 non-null    int64  
 6   Fare      891 non-null    float64
dtypes: float64(2), int32(1), int64(4)
memory usage: 45.4 KB
```

Out[ ]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	1	22.0	1	0	7.2500
1	1	1	0	38.0	1	0	71.2833
2	1	3	0	26.0	0	0	7.9250
3	1	1	0	35.0	1	0	53.1000
4	0	3	1	35.0	0	0	8.0500

In [ ]:
```
input_cols = ["Pclass","Sex","Age","SibSp","Parch","Fare"]
output_cols = ["Survived"]
```

```
X = data[input_cols]
Y = data[output_cols]
print(X.shape,Y.shape)
```

```
(891, 6) (891, 1)
```

In [ ]:

```
def entropy(cols):
    counts = np.unique(cols,return_counts=True)
    N = float(cols.shape[0])

    ent = 0.0
    for ix in counts[1]:
        p = ix/N
        ent += (-1.0*p*np.log2(p))

    return ent
```

In [ ]:

```
def divided_cols(x_data,fkey,fval):
    x_left = pd.DataFrame([],columns=x_data.columns)
    x_right = pd.DataFrame([],columns=x_data.columns)

    for ix in range(x_data.shape[0]):
        val = x_data[fkey].loc[ix]

        if val>fval:
            x_right = x_right.append(x_data.loc[ix])
        else:
            x_left = x_left.append(x_data.loc[ix])

    return x_left,x_right
```

In [ ]:

```
left,right = divided_cols(data[:10],"Survived",0.5)
print(left)
print(right)
```

```
   Survived  Pclass  Sex        Age  SibSp  Parch     Fare
0       0.0     3.0  1.0  22.000000    1.0    0.0   7.2500
4       0.0     3.0  1.0  35.000000    0.0    0.0   8.0500
5       0.0     3.0  1.0  29.699118    0.0    0.0   8.4583
6       0.0     1.0  1.0  54.000000    0.0    0.0  51.8625
7       0.0     3.0  1.0   2.000000    3.0    1.0  21.0750
   Survived  Pclass  Sex   Age  SibSp  Parch     Fare
1       1.0     1.0  0.0  38.0    1.0    0.0  71.2833
2       1.0     3.0  0.0  26.0    0.0    0.0   7.9250
3       1.0     1.0  0.0  35.0    1.0    0.0  53.1000
8       1.0     3.0  0.0  27.0    0.0    2.0  11.1333
9       1.0     2.0  0.0  14.0    1.0    0.0  30.0708
```

In [ ]:

```
def information_gain(x_data,fkey,fval):
    left,right = divided_cols(x_data,fkey,fval)
    l = float(left.shape[0])/x_data.shape[0]
    r = float(right.shape[0])/x_data.shape[0]

    if l==0 or r==0:
        return -100000
```

```
    i_gain = entropy(x_data.Survived) - (l*entropy(left.Survived)+r*entropy(right.Survi
    return i_gain
```

In [ ]:

```
for ix in X.columns:
    print(ix)
    print(information_gain(data,ix,data[ix].mean()))
```

```
Pclass
0.07579362743608165
Sex
0.2176601066606142
Age
0.0008836151229467681
SibSp
0.009584541813400071
Parch
0.015380754493137694
Fare
0.042140692838995464
```

In [ ]:

```
class DecisionTree:

    def __init__(self,depth=0,max_depth=5):
        self.left = None
        self.right = None
        self.fkey = None
        self.fval = None
        self.depth = depth
        self.max_depth = max_depth
        self.target = None

    def train(self,X_train):
        features = ["Pclass","Sex","Age","SibSp","Parch","Fare"]
        info_gain = []

        for ix in features:
            i_gain = information_gain(X_train,ix,X_train[ix].mean())
            info_gain.append(i_gain)

        self.fkey = features[np.argmax(info_gain)]
        self.fval = X_train[self.fkey].mean()
        print("Making Tree Features is",self.fkey)

        data_left,data_right = divided_cols(X_train,self.fkey,self.fval)
        data_left = data_left.reset_index(drop=True)
        data_right = data_right.reset_index(drop=True)

        if data_left.shape[0]==0 or data_right.shape[0]==0:
            if X_train.Survived.mean() >= 0.5:
                self.target = "Survive"
            else:
                self.target = "Dead"
            return

        if(self.depth>=self.max_depth):
            if X_train.Survived.mean() >= 0.5:
                self.target = "Survive"
```

```
            else:
                self.target = "Dead"
            return

        self.left = DecisionTree(depth=self.depth+1,max_depth=self.max_depth)
        self.left.train(data_left)

        self.right = DecisionTree(depth=self.depth+1,max_depth=self.max_depth)
        self.right.train(data_right)

        if X_train.Survived.mean() >= 0.5:
            self.target = "Survive"
        else:
            self.target = "Dead"
        return

    def predict(self,test):

        if test[self.fkey] > self.fval:
            if self.right==None:
                return self.target
            return self.right.predict(test)
        else:
            if self.left==None:
                return self.target
            return self.left.predict(test)
```

In [ ]:

```
split = int(0.7*data.shape[0])
train_data = data[:split]
test_data = data[split:]
test_data = test_data.reset_index(drop=True)

print(train_data.shape,test_data.shape)
```

```
(623, 7) (268, 7)
```

In [ ]:

```
d = DecisionTree()
d.train(train_data)
```

```
Making Tree Features is Sex
Making Tree Features is Pclass
Making Tree Features is Age
Making Tree Features is SibSp
Making Tree Features is Pclass
Making Tree Features is Age
Making Tree Features is Age
Making Tree Features is SibSp
Making Tree Features is Parch
Making Tree Features is Pclass
Making Tree Features is SibSp
Making Tree Features is Fare
Making Tree Features is Parch
Making Tree Features is Age
Making Tree Features is Pclass
Making Tree Features is Age
Making Tree Features is Age
Making Tree Features is Parch
Making Tree Features is SibSp
```

```
Making Tree Features is Fare
Making Tree Features is Age
Making Tree Features is Age
Making Tree Features is Fare
Making Tree Features is Age
Making Tree Features is Age
Making Tree Features is Fare
Making Tree Features is Age
Making Tree Features is Parch
Making Tree Features is Fare
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Making Tree Features is Parch
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Making Tree Features is Fare
Making Tree Features is Fare
Making Tree Features is SibSp
Making Tree Features is Fare
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Making Tree Features is Pclass
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Making Tree Features is SibSp
Making Tree Features is Age
Making Tree Features is Age
Making Tree Features is Age
Making Tree Features is Parch
Making Tree Features is Age
Making Tree Features is Age
```

In [ ]:

```
pred = []

for ix in range(test_data.shape[0]):
    pred.append(d.predict(test_data.loc[ix]))
```

In [ ]:

```
pred
```

Out[ ]:

```
['Dead',
 'Dead',
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 'Survive',
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'Survive',
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'Dead']
```

In [ ]:
```
le = LabelEncoder()
y_pred = le.fit_transform(pred)
```

In [ ]:
```
y_pred = np.array(y_pred).reshape((-1,1))
y_actual = test_data[output_cols]
print(y_pred.shape,y_actual.shape)
```

```
(268, 1) (268, 1)
```

In [ ]:
```
y_pred = np.array(y_pred).reshape((-1,1))
acc = np.sum(np.array(y_pred)==np.array(y_actual))/y_actual.shape[0]
```

In [ ]:
```
print(acc)
```

```
0.8171641791044776
```

Ensemble Method

In [ ]:
```
X_train = train_data[input_cols]
Y_train = np.array(train_data[output_cols]).reshape((-1,))
X_test = test_data[input_cols]
Y_test = np.array(test_data[output_cols]).reshape((-1,))
```

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [ ]:
```
rf = RandomForestClassifier(n_estimators = 10,criterion='entropy',max_depth=5)
```

In [ ]:

```
rf.fit(X_train,Y_train)
```

Out[ ]:
```
RandomForestClassifier(criterion='entropy', max_depth=5, n_estimators=10)
```

In [ ]:
```
rf.score(X_train,Y_train)
```

Out[ ]:
```
0.8426966292134831
```

In [ ]:
```
rf.score(X_test,Y_test)
```

Out[ ]:
```
0.8171641791044776
```

In [ ]:
```
from sklearn.model_selection import cross_val_score
acc = cross_val_score(RandomForestClassifier(n_estimators=10,max_depth=5,criterion='ent
print(acc)
```

```
0.8170064516129031
```

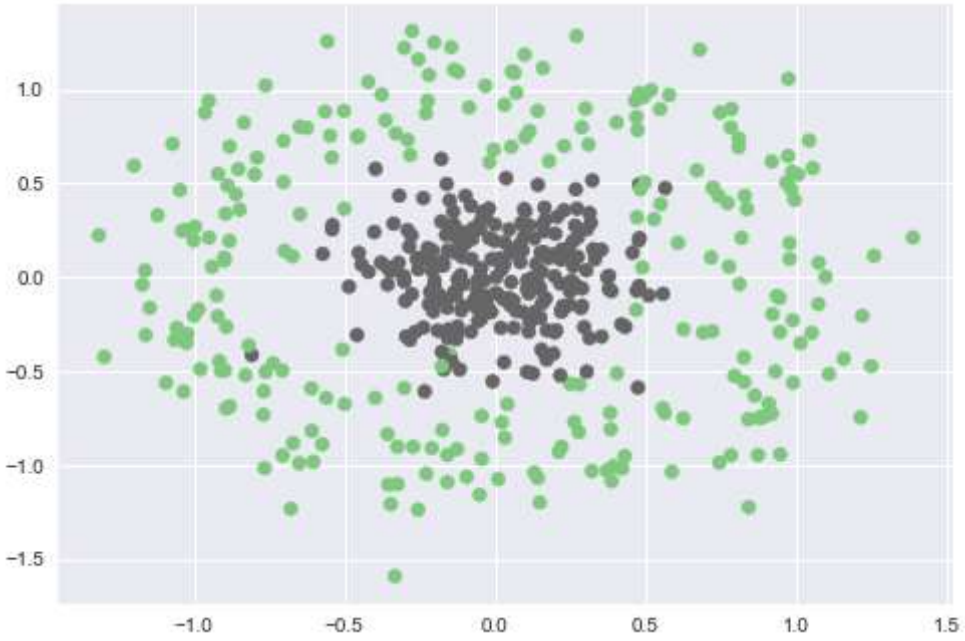
In [ ]:
```

```

In [ ]:
```
from sklearn.datasets import make_circles
import matplotlib.pyplot as plt
import numpy as np
```

In [ ]:
```
X,Y = make_circles(n_samples=500, shuffle=True, noise=0.2, random_state=1, factor=0.2)
```

In [ ]:
```
plt.style.use("seaborn")
plt.scatter(X[:,0],X[:,1],c=Y,cmap=plt.cm.Accent)
plt.show()
```



In [ ]:
```
def softmax(a):
    e_pa = np.exp(a)
    ans = e_pa/np.sum(e_pa,axis=1,keepdims=True) #keepdims to the shape of array same a
    return ans
```

In [ ]:
```
class NeuralNetwork:

    def __init__(self,input_size,layers,output_size):

        np.random.seed(0)

        model = {}

        #Layer 1
        model['W1'] = np.random.randn(input_size,layers[0])
        model['b1'] = np.zeros((1,layers[0]))

        # Layer 2
        model['W2'] = np.random.randn(layers[0],layers[1])
        model['b2'] = np.zeros((1,layers[1]))

        # Layer 3
```

```
        model['W3'] = np.random.randn(layers[1],output_size)
        model['b3'] = np.zeros((1,output_size))

        self.model = model
        self.activation_outputs = None

    def forward(self,x):

        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        b1,b2,b3 = self.model['b1'],self.model['b2'],self.model['b3']

        z1 = np.dot(x,W1)+b1
        a1 = np.tanh(z1)

        z2 = np.dot(a1,W2)+b2
        a2 = np.tanh(z2)

        z3 = np.dot(a2,W3)+b3
        y_ = softmax(z3)

        self.activation_outputs = (a1,a2,y_)
        return y_

    def backward(self,x,y,learning_rate=0.001):

        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        b1,b2,b3 = self.model['b1'],self.model['b2'],self.model['b3']
        a1,a2,y_ = self.activation_outputs
        m = x.shape[0]

        delta3 = y_-y
        dw3 = np.dot(a2.T,delta3)
        db3 = np.sum(delta3,axis=0)

        delta2 = (1-np.square(a2))*np.dot(delta3,W3.T)
        dw2 = np.dot(a1.T,delta2)
        db2 = np.sum(delta2,axis=0)

        delta1 = (1-np.square(a1))*np.dot(delta2,W2.T)
        dw1 = np.dot(x.T,delta1)
        db1 = np.sum(delta1,axis=0)

        #update the Model parameters using gradient descent

        self.model['W1'] -= learning_rate*dw1
        self.model['b1'] -= learning_rate*db1

        self.model['W2'] -= learning_rate*dw2
        self.model['b2'] -= learning_rate*db2

        self.model['W3'] -= learning_rate*dw3
        self.model['b3'] -= learning_rate*db3

    def predict(self,x):
        y_out =self.forward(x)
        return np.argmax(y_out,axis=1)

    def summary(self):
        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        a1,a2,y_ = self.activation_outputs
```

```
        print("W1",W1.shape)
        print("A1",a1.shape)

        print("W2",W2.shape)
        print("A2",a2.shape)

        print("W3",W3.shape)
        print("Y_",y_.shape)
```

In [ ]:
```
def loss(y_oht,p):
    l = -np.mean(y_oht*np.log(p))
    return l

def one_hot(y,depth):

    m = y.shape[0]
    y_oht = np.zeros((m,depth))
    y_oht[np.arange(m),y] = 1

    return y_oht
```

In [ ]:
```
model = NeuralNetwork(input_size=2,layers=[10,5],output_size=2)
```

In [ ]:
```
def train(X,Y,model,epochs,learning_rate,logs=True):
    training_loss = []

    classes=2
    y_hot = one_hot(Y,classes)

    for ix in range(epochs):

        Y_ = model.forward(X)
        l = loss(y_hot,Y_)
        training_loss.append(l)
        model.backward(X,y_hot,learning_rate)

        if(logs):
            print("Epoch %d Loss %.4f"%(ix,l))

    return training_loss
```

In [ ]:
```
losses = train(X,Y,model,500,0.001)
```

```
Epoch 0 Loss 0.3571
Epoch 1 Loss 0.3554
Epoch 2 Loss 0.2593
Epoch 3 Loss 0.2407
Epoch 4 Loss 0.2258
Epoch 5 Loss 0.2132
Epoch 6 Loss 0.2020
Epoch 7 Loss 0.1919
Epoch 8 Loss 0.1827
Epoch 9 Loss 0.1742
```

```
Epoch 10 Loss 0.1664
Epoch 11 Loss 0.1593
Epoch 12 Loss 0.1527
Epoch 13 Loss 0.1467
Epoch 14 Loss 0.1411
Epoch 15 Loss 0.1360
Epoch 16 Loss 0.1313
Epoch 17 Loss 0.1270
Epoch 18 Loss 0.1230
Epoch 19 Loss 0.1193
Epoch 20 Loss 0.1159
Epoch 21 Loss 0.1127
Epoch 22 Loss 0.1098
Epoch 23 Loss 0.1070
Epoch 24 Loss 0.1045
Epoch 25 Loss 0.1021
Epoch 26 Loss 0.0999
Epoch 27 Loss 0.0978
Epoch 28 Loss 0.0958
Epoch 29 Loss 0.0940
Epoch 30 Loss 0.0922
Epoch 31 Loss 0.0906
Epoch 32 Loss 0.0891
Epoch 33 Loss 0.0876
Epoch 34 Loss 0.0862
Epoch 35 Loss 0.0849
Epoch 36 Loss 0.0837
Epoch 37 Loss 0.0825
Epoch 38 Loss 0.0814
Epoch 39 Loss 0.0803
Epoch 40 Loss 0.0793
Epoch 41 Loss 0.0783
Epoch 42 Loss 0.0774
Epoch 43 Loss 0.0765
Epoch 44 Loss 0.0756
Epoch 45 Loss 0.0748
Epoch 46 Loss 0.0740
Epoch 47 Loss 0.0732
Epoch 48 Loss 0.0725
Epoch 49 Loss 0.0718
Epoch 50 Loss 0.0711
Epoch 51 Loss 0.0705
Epoch 52 Loss 0.0699
Epoch 53 Loss 0.0693
Epoch 54 Loss 0.0687
Epoch 55 Loss 0.0681
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Epoch 65 Loss 0.0634
Epoch 66 Loss 0.0630
Epoch 67 Loss 0.0627
Epoch 68 Loss 0.0623
Epoch 69 Loss 0.0619
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Epoch 70 Loss 0.0616
Epoch 71 Loss 0.0612
Epoch 72 Loss 0.0609
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```
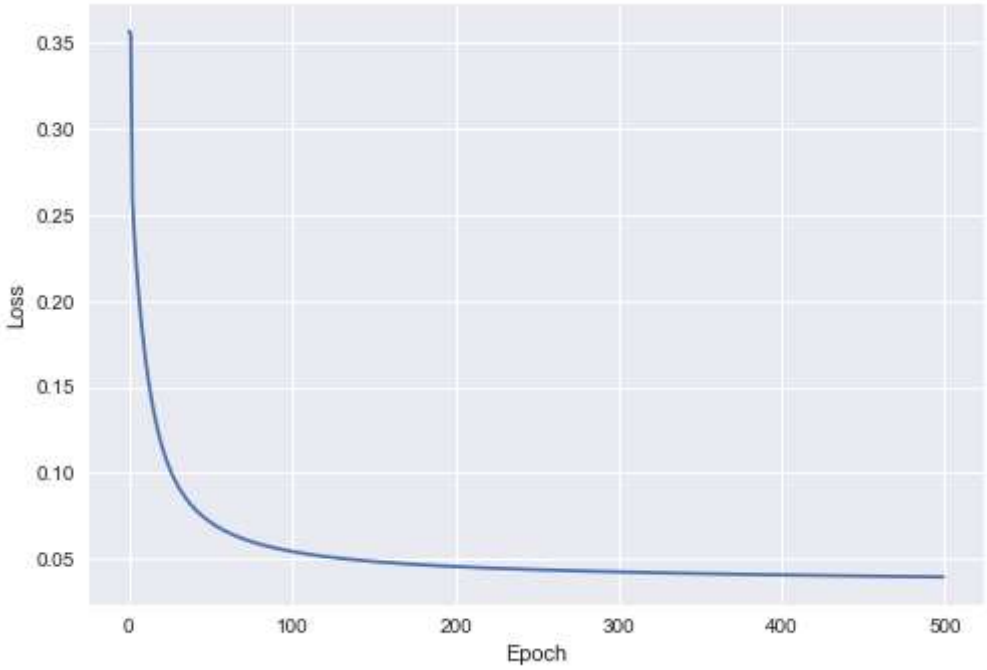

In [ ]:

```
plt.plot(losses)
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.show()
```



In [ ]:

```
outputs = model.predict(X)
print(outputs)
```

```
[1 1 0 0 1 1 1 0 0 0 1 0 1 0 1 0 1 1 0 0 1 1 1 1 0 1 0 1 0 0 0 1 0 1 1 0 0
 0 1 1 1 1 1 0 1 1 1 1 1 0 0 0 0 1 1 0 1 1 0 1 1 0 1 1 1 1 1 1 1 0 1 1 0 0
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```

In [ ]:

```
print(outputs.shape)
```

```
(500,)
```

In [ ]:

```
training_accuracy = np.sum(outputs==Y)/Y.shape[0]
print(training_accuracy)
```

```
0.97
```

In [ ]:

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
```

In [ ]:
```
df = pd.read_csv("mushrooms.csv")
df.head()
print(df.shape)
```

```
(8124, 23)
```

In [ ]:
```
le = LabelEncoder()
ds = df.apply(le.fit_transform)
```

In [ ]:
```
ds.head()
```

Out[ ]:

	type	cap_shape	cap_surface	cap_color	bruises	odor	gill_attachment	gill_spacing	gill_size	gill_c
0	1	5	2	4	1	6	1	0	1	
1	0	5	2	9	1	0	1	0	0	
2	0	0	2	8	1	3	1	0	0	
3	1	5	3	8	1	6	1	0	1	
4	0	5	2	3	0	5	1	1	0	

5 rows × 23 columns

In [ ]:
```
data = ds.values
print(data.shape)
print(type(data))
print(data[:5,:])

data_x = data[:,1:]
data_y = data[:,0]
```

```
(8124, 23)
<class 'numpy.ndarray'>
[[1 5 2 4 1 6 1 0 1 4 0 3 2 2 7 7 0 2 1 4 2 3 5]
 [0 5 2 9 1 0 1 0 0 4 0 2 2 2 7 7 0 2 1 4 3 2 1]
 [0 0 2 8 1 3 1 0 0 5 0 2 2 2 7 7 0 2 1 4 3 2 3]
 [1 5 3 8 1 6 1 0 1 5 0 3 2 2 7 7 0 2 1 4 2 3 5]
 [0 5 2 3 0 5 1 1 0 4 1 3 2 2 7 7 0 2 1 0 3 0 1]]
```

In [ ]:
```
x_train,x_test,y_train,y_test = train_test_split(data_x,data_y,test_size=0.2)
```

In [ ]:
```
print(x_train.shape,y_train.shape)
```

```
print(x_test.shape,y_test.shape)
```

```
(6499, 22) (6499,)
(1625, 22) (1625,)
```

In [ ]:

```
def prior_prob(y_train,label):
    total_examples = y_train.shape[0]
    count_examples = np.sum(y_train==label)

    return (count_examples)/float(total_examples)
```

In [ ]:

```
def cond_prob(x_train,y_train,feature_col,feature_val,label):
    x_filtered = x_train[y_train==label]
    numerator = np.sum(x_filtered[:,feature_col]==feature_val)
    denominator = np.sum(y_train==label)

    return numerator/float(denominator)
```

In [ ]:

```
def predict(x_train,y_train,xtest):
    """xtest is a single testing point, n features """

    classes = np.unique(y_train)
    n_features = x_train.shape[1]
    post_probs = []

    for label in classes:

        likelihood = 1.0

        for f in range(n_features):
            cond = cond_prob(x_train,y_train,f,xtest[f],label)
            likelihood *=cond

        prior = prior_prob(y_train,label)
        post = likelihood*prior
        post_probs.append(post)

    pred = np.argmax(post_probs)
    return pred
```

In [ ]:

```
def score(x_train,y_train,x_test,y_test):
    pred = []

    for i in range(x_test.shape[0]):
        pred_label = predict(x_train,y_train,x_test[i])
        pred.append(pred_label)

    pred = np.array(pred)

    accuracy = np.sum(pred==y_test)/y_test.shape[0]
    return accuracy
```

In [ ]:

```
print(score(x_train,y_train,x_test,y_test))
```

```
0.9993846153846154
```

In [ ]: