In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import datasets
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from sklearn.metrics import confusion_matrix
from sklearn.impute import SimpleImputer
from sklearn import tree
from sklearn.decomposition import PCA
from sklearn import metrics
import graphviz
```

Problem1

In [2]:
```
datap1=datasets.load_iris()
```

In [3]:
```
type(datap1)
```

Out[3]:
```
sklearn.utils.Bunch
```

In [4]:
```
datap1.feature_names
```

Out[4]:
```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

In [5]:
```
pdDatap1=pd.DataFrame(np.c_[datap1.data,datap1.target],columns=datap1.feature_
names+['class'])
```

In [6]:
```
pdDatap1.head()
```

Out[6]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	class
0	5.1	3.5	1.4	0.2	0.0
1	4.9	3.0	1.4	0.2	0.0
2	4.7	3.2	1.3	0.2	0.0
3	4.6	3.1	1.5	0.2	0.0
4	5.0	3.6	1.4	0.2	0.0

In [7]:
```
pdDatap1.isna().values.any()
```

Out[7]:
```
False
```

In [8]:
```
pdDatap1.iloc[:,-1].value_counts()
```

Out[8]:
```
2.0    50
1.0    50
0.0    50
Name: class, dtype: int64
```

In [9]:
```
xTrainp1,xTestp1,yTrainp1,yTestp1=train_test_split(pdDatap1.iloc[:,:-1],pdData
p1.iloc[:,-1],test_size=0.3)
for i in range(1,6):
    print("For Depth {0} below are the values \n".format(i))
    dtp1=DecisionTreeClassifier(min_samples_split=5,min_samples_leaf=2,max_dep
th=i)
    dtp1.fit(xTrainp1, yTrainp1)
    predictp1=dtp1.predict(xTestp1)
    print(confusion_matrix(yTestp1,predictp1))
    print(classification_report(y_true=yTestp1,y_pred=predictp1,target_names=d
atap1.target_names))
    print('############################################################# \n')
#     print('Micro precision is {0}'.format(precision_score(y_true=yTest,y_pre
d=predict,average='micro')))
#     print('Macro precision is {0}'.format(precision_score(y_true=yTest,y_pre
d=predict,average='macro')))
#     print('Weighted precision is {0}'.format(precision_score(y_true=yTest,y_
pred=predict,average='weighted')))
#     print('############################################################
 \n')
#     print('Micro Recall is {0}'.format(recall_score(y_true=yTest,y_pred=pred
ict,average='micro')))
#     print('Macro Recall is {0}'.format(recall_score(y_true=yTest,y_pred=pred
ict,average='macro')))
#     print('Weighted Recal is {0}'.format(recall_score(y_true=yTest,y_pred=pr
edict,average='weighted')))
#     print('############################################################
 \n')
#     print('Micro f1Score is {0}'.format(f1_score(y_true=yTest,y_pred=predic
t,average='micro')))
#     print('Macro f1Score is {0}'.format(f1_score(y_true=yTest,y_pred=predic
t,average='macro')))
#     print('Weighted f1Score is {0}'.format(f1_score(y_true=yTest,y_pred=pred
ict,average='weighted')))
```

```
For Depth 1 below are the values

[[15  0  0]
 [ 0 13  0]
 [ 0 17  0]]
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        15
  versicolor       0.43      1.00      0.60        13
   virginica       0.00      0.00      0.00        17

    accuracy                           0.62        45
   macro avg       0.48      0.67      0.53        45
weighted avg       0.46      0.62      0.51        45

#############################################################

For Depth 2 below are the values

[[15  0  0]
 [ 0 12  1]
 [ 0  3 14]]
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        15
  versicolor       0.80      0.92      0.86        13
   virginica       0.93      0.82      0.87        17

    accuracy                           0.91        45
   macro avg       0.91      0.92      0.91        45
weighted avg       0.92      0.91      0.91        45

#############################################################

For Depth 3 below are the values

[[15  0  0]
 [ 0 12  1]
 [ 0  0 17]]
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        15
  versicolor       1.00      0.92      0.96        13
   virginica       0.94      1.00      0.97        17

    accuracy                           0.98        45
   macro avg       0.98      0.97      0.98        45
weighted avg       0.98      0.98      0.98        45

#############################################################

For Depth 4 below are the values

[[15  0  0]
 [ 0 12  1]
 [ 0  0 17]]
              precision    recall  f1-score   support
```

```
        setosa       1.00      1.00      1.00        15
    versicolor       1.00      0.92      0.96        13
     virginica       0.94      1.00      0.97        17

      accuracy                           0.98        45
     macro avg       0.98      0.97      0.98        45
  weighted avg       0.98      0.98      0.98        45

#############################################################

For Depth 5 below are the values

[[15  0  0]
 [ 0 12  1]
 [ 0  0 17]]
              precision    recall  f1-score   support

        setosa       1.00      1.00      1.00        15
    versicolor       1.00      0.92      0.96        13
     virginica       0.94      1.00      0.97        17

      accuracy                           0.98        45
     macro avg       0.98      0.97      0.98        45
  weighted avg       0.98      0.98      0.98        45

#############################################################


C:\Users\venka\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:
1437: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

The recall and precision vallues increase as the height of the tree increases as there is more IG at each level so the maximum Precision and recall are observed at height 2 to 5.
The ***f1-score*** increases if the bot the perecision and recall are high this can be obsereved from the height 2-5.
Micro calculates the metrics taking the True Positive,True Negative,False Positive ,False negative into consideration.
Macro calclates the metrics without taking the class imbalance into consideration.
Weighted calcluates the metrics taking into consieration of weighted imbalances.

Problem2

In [2]:
```
breastCancerDatap2=pd.read_csv("https://archive.ics.uci.edu/ml/machine-learnin
g-databases/breast-cancer-wisconsin/breast-cancer-wisconsin.data",header=None,
                              names=['Samplenumber','ClumpThickness','Uniformit
yCellSize','UniformCellShape','MarginAdhesion','SingleCellSize','BareNuclei',
'BlandChromatin','NormalNucl','Mitoses','Class'],na_values=['?'])
```

In [3]:
```
breastCancerDatap2.isna().values.any()
```

Out[3]:
```
True
```

In [4]:
```
breastCancerDatap2.isnull().values.any()
```

Out[4]:
```
True
```

In [5]:
```
print(breastCancerDatap2.dtypes)
```

```
Samplenumber           int64
ClumpThickness         int64
UniformityCellSize     int64
UniformCellShape       int64
MarginAdhesion         int64
SingleCellSize         int64
BareNuclei           float64
BlandChromatin         int64
NormalNucl             int64
Mitoses                int64
Class                  int64
dtype: object
```

In [6]:
```
breastCancerDatap2['BareNuclei'].value_counts()
```

Out[6]:
```
1.0     402
10.0    132
5.0      30
2.0      30
3.0      28
8.0      21
4.0      19
9.0       9
7.0       8
6.0       4
Name: BareNuclei, dtype: int64
```

In [7]:
```
breastCancerDatap2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 699 entries, 0 to 698
Data columns (total 11 columns):
Samplenumber          699 non-null int64
ClumpThickness        699 non-null int64
UniformityCellSize    699 non-null int64
UniformCellShape      699 non-null int64
MarginAdhesion        699 non-null int64
SingleCellSize        699 non-null int64
BareNuclei            683 non-null float64
BlandChromatin        699 non-null int64
NormalNucl            699 non-null int64
Mitoses               699 non-null int64
Class                 699 non-null int64
dtypes: float64(1), int64(10)
memory usage: 60.2 KB
```

In [8]:
```
imputep2=SimpleImputer(strategy='mean')
breastCancerDatap2['BareNuclei']=imputep2.fit_transform(breastCancerDatap2[['B
areNuclei']])
```

In [9]:
```
xTrainPr2,xTestpr2,yTrainpr2,yTestpr2=train_test_split(breastCancerDatap2.iloc
[:,:-1],breastCancerDatap2.iloc[:,-1],test_size=0.3,)
```

In [10]:
```
print(xTrainPr2.shape)
print(xTestpr2.shape)
print(yTrainpr2.shape)
print(yTestpr2.shape)
```

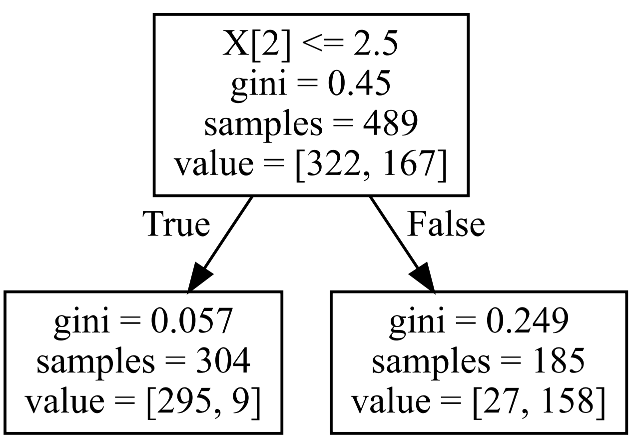
```
(489, 10)
(210, 10)
(489,)
(210,)
```

In [11]:
```
dtPr2=DecisionTreeClassifier(min_samples_leaf=2,min_samples_split=5,max_depth=
1)
dtPr2.fit(xTrainPr2,yTrainpr2)
predictPr2=dtPr2.predict(xTestpr2)
print(classification_report(y_true=yTestpr2,y_pred=predictPr2))
print(confusion_matrix(y_true=yTestpr2,y_pred=predictPr2))
```

```
              precision    recall  f1-score   support

           2       0.98      0.90      0.93       136
           4       0.84      0.96      0.89        74

    accuracy                           0.92       210
   macro avg       0.91      0.93      0.91       210
weighted avg       0.93      0.92      0.92       210

[[122  14]
 [  3  71]]
```

In [12]:
```
graphviz.Source(tree.export_graphviz(dtPr2))
```

Out[12]:

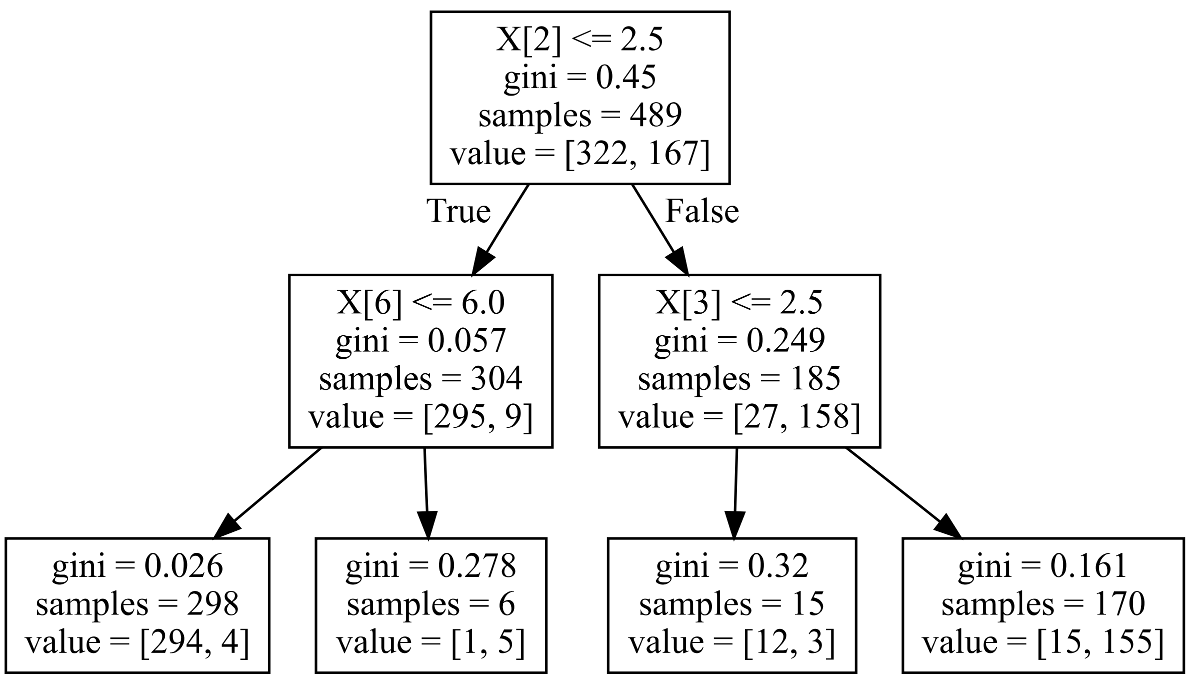


In [13]:
```
dtPr2v2=DecisionTreeClassifier(min_samples_leaf=2,min_samples_split=5,max_dept
h=2)
dtPr2v2.fit(xTrainPr2,yTrainpr2)
predictPr2v2=dtPr2v2.predict(xTestpr2)
print(classification_report(y_true=yTestpr2,y_pred=predictPr2v2))
print(confusion_matrix(y_true=yTestpr2,y_pred=predictPr2v2))
```

```
              precision    recall  f1-score   support

           2       0.97      0.94      0.96       136
           4       0.90      0.95      0.92        74

    accuracy                           0.94       210
   macro avg       0.93      0.94      0.94       210
weighted avg       0.94      0.94      0.94       210

[[128   8]
 [  4  70]]
```

In [14]:
```
graphviz.Source(tree.export_graphviz(dtPr2v2))
```

Out[14]:



Problem 3

In [2]:
```
dataPr3=pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-database
s/breast-cancer-wisconsin/wdbc.data',names=['id', 'diagnosis','radiusMean','te
xtureMean','perimeterMean','areaMean','smoothnessMean','compactnessMean', 'con
cavityMean','oncavePointsMean', 'symmetryMean', 'fractalDimensionMean','radius
Se', 'textureSe', 'perimeterSe', 'areaSe', 'smoothnessSe','compactnessSe', 'co
ncavitySe', 'concave pointsSe', 'symmetrySe','fractalDimensionSe', 'radiusWors
t', 'textureWorst','perimeterWorst', 'areaWorst', 'smoothnessWorst','compactne
ssWorst', 'concavityWorst', 'concavePointsWorst','symmetryWorst', 'fractalDime
nsionWorst'])
```

In [3]:
```
dataPr3.head()
```

Out[3]:

	id	diagnosis	radiusMean	textureMean	perimeterMean	areaMean	smoothnessMean
0	842302	M	17.99	10.38	122.80	1001.0	0.11840
1	842517	M	20.57	17.77	132.90	1326.0	0.08474
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960
3	84348301	M	11.42	20.38	77.58	386.1	0.14250
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030

5 rows × 32 columns

In [4]:
```
dataPr3.iloc[:,-1].shape
```

Out[4]: (569,)

In [5]:
```
dataPr3[["diagnosis"]].shape
```

Out[5]: (569, 1)

In [6]:
```
pca=PCA(n_components=1)
```

In [7]:
```
prinicpalComponents=pca.fit_transform(dataPr3.iloc[:,2:])
print(pca.explained_variance_ratio_)
print(prinicpalComponents.shape)
print(prinicpalComponents[:,0].shape)
```

```
[0.98204467]
(569, 1)
(569,)
```

In [8]:
```
xTrainPr3,xTestPr3,yTrainPr3,yTestPr3=train_test_split(prinicpalComponents,dat
aPr3[["diagnosis"]],test_size=0.3)
```

In [9]:
```
dtPr3=DecisionTreeClassifier(max_depth=1, min_samples_split=5, min_samples_lea
f=2)
dtPr3.fit(xTrainPr3,yTrainPr3)
predict=dtPr3.predict(xTestPr3)
print(classification_report(y_pred=predict,y_true=yTestPr3))
```

```
              precision    recall  f1-score   support

           B       0.90      0.97      0.94       114
           M       0.94      0.79      0.86        57

    accuracy                           0.91       171
   macro avg       0.92      0.88      0.90       171
weighted avg       0.91      0.91      0.91       171
```

In [10]:
```
print(confusion_matrix(y_pred=predict,y_true=yTestPr3))
```

```
[[111   3]
 [ 12  45]]
```

In [11]:
```
pca2=PCA(n_components=1)
prinicpalComponentsv2=pca.fit_transform(dataPr3.iloc[:,2:])
```

In [12]:
```
xTrainPr3v2,xTestPr3v2,yTrainPr3v2,yTestPr3v2=train_test_split(prinicpalCompon
entsv2,dataPr3[["diagnosis"]],test_size=0.3)
```

In [13]:
```
dtPr3v2=DecisionTreeClassifier(max_depth=1, min_samples_split=5, min_samples_l
eaf=2)
dtPr3v2.fit(xTrainPr3v2,yTrainPr3v2)
predictv2=dtPr3v2.predict(xTestPr3v2)
print(classification_report(y_pred=predict,y_true=yTestPr3v2))
```

```
              precision    recall  f1-score   support

           B       0.64      0.71      0.67       112
           M       0.31      0.25      0.28        59

    accuracy                           0.55       171
   macro avg       0.48      0.48      0.48       171
weighted avg       0.53      0.55      0.54       171
```

In [14]:
```
print(confusion_matrix(y_pred=predictv2,y_true=yTestPr3v2))
```

```
[[109   3]
 [ 12  47]]
```

Problem4

In [2]:
```
feature1p4=np.random.normal(5,2,500)
feature2p4=np.random.normal(-5,2,500)
print(feature1p4.shape)
print(feature2p4.shape)
class1p4=np.repeat(0,500)
class2p4=np.repeat(1,500)
data1p4=pd.DataFrame({'feature':feature1p4,'classLabel':class1p4})
data2p4=pd.DataFrame({'feature':feature2p4,'classLabel':class2p4})
```

```
(500,)
(500,)
```

In [3]:
```
data1p4.head()
```

Out[3]:

	feature	classLabel
0	6.000080	0
1	0.550831	0
2	3.645289	0
3	6.771784	0
4	5.445052	0

In [4]:
```
data2p4.head()
```

Out[4]:

	feature	classLabel
0	-8.339510	1
1	-4.475830	1
2	-1.711105	1
3	-5.510317	1
4	-5.583594	1

In [5]:
```
finalDatap4=pd.concat([data1p4,data2p4])
finalDatap4.head()
```

```
   feature  classLabel
0  6.000080           0
1  0.550831           0
2  3.645289           0
3  6.771784           0
4  5.445052           0
(1000, 2)
```

In [6]:
```
xTrainP4,xTestP4,yTrainP4,yTestP4=train_test_split(finalDatap4[['feature']],finalDatap4['classLabel'],test_size=0.3)
```

In [7]:
```
dtp4 = DecisionTreeClassifier(max_depth=2)
dtp4.fit(xTrainP4, yTrainP4)
predictp4=dtp4.predict(xTestP4)
```

In [14]:
```
fprp4,tprp4,thresholdsp4=metrics.roc_curve(y_score=predictp4,y_true=yTestP4)
```

In [15]:
```
print("THRESHOLD is {0}".format(thresholdsp4))
```

```
THRESHOLD is [2 1 0]
```

Recitation

Chapter 2

Exercise 2)
1) Count of C0 is 10
count of C1 is 10
Gini=1-(10/20)^2 -(10/20)^2
=0.5

Exercise 2)
2) As ID are unique probability of each id is 1/20
As there are only two possibilities of classes for the each ID Gini index of each id is 0
so total GInin Index=20*(1/20)*0=0

Exercise 2)
3)
Female count=10
Male count=10
Gini=1-(10/20)^2 -(10/20)^2
=0.5

Exercise 2)
4)
Family car Type Probability= 4/20=0.2
Sports car Type Probability= 8/20=0.4
Luxury car Type Probability= 8/20=0.4

P(Family|C1) =0.75 P(Family|C0) =0.25

gini=1-(0.75)^2-(0.25)^2
=1-0.5625-0.0625
=0.375

P(Sports|C1) =0 P(Sports|C0) =1
gini=1-(0)^2-(1)^2
=0

P(Luxury|C1) =0.125 P(Luxury|C0) =0.875

gini=1-(0.125)^2-(0.875)^2
=1-0.015625-0.765625
=0.21875

Gini Index= (0.2*0.375)+(0.4*0)+(0.4*0.21875) =0.1625

Exercise 2)
5)
Small Shirt size: 5/20=0.25
Medium Shirt size: 7/20=0.35
Large Shirt size: 4/20=0.2
Extra Large size: 4/20=0.2

P(Small|C1) =2/5=0.4 P(Small|C0) =3/5=0.6
Gini=1-(0.4)^2-(0.6)^2
=0.48
P(Medium|C1) =4/7=0.5714 P(Medium|C0) =3/7=0.428
Gini=1-(0.5714)^2-(0.428)^2
=0.49
P(Large|C1) =2/4=0.5 P(Large|C0) =2/4=0.5

Gini=1-(0.5)^2-(0.5)^2
=0.5
P(ExtraLarge|C1) =2/4=0.5 P(ExtraLarge|C0) =2/4=0.5

Gini=1-(0.5)^2-(0.5)^2
=0.5
Gini Index=(0.25*0.48)+(0.35*0.49)+(0.2*0.5)+(0.2*0.5)
=0.4915

Exercise 2)
6)
Lower ther gini index better it is from above ***carType*** has lower Gini i.e. ***Gini of carType=0.1625***

Exercise 2)
7)
It is just a primary key needed for RDBMS to store data it holds no rela meaning.

Exercise 6)
1)
Gini inex= 1-(3/10)^2-(7/10)^2
= 0.42
Miscalssification Error=1-(7/10)
=0.3

Exercise 6)
2)
ginic1=1-1-(3/3)^2-(0/3)^2
=0
ginic2=1-(4/7)^2-(3/7)^2
=0.489

Exercise 6)
3)
misClassficationC1=1-Max((3/3),(0/3)) =0 misClassficationC2=1-Max((4/7),(3/7)) =1-(4/7) =0.428

In [ ]: