In [450…

```
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sb
import graphviz as graphviz
from sklearn.metrics import confusion_matrix
from graphviz import Digraph
from sklearn.preprocessing import OrdinalEncoder
from sklearn.model_selection import train_test_split
from sklearn import datasets # import standard datasets
from sklearn import tree     # decision tree classifier
from sklearn import naive_bayes # naive bayes classifier
from sklearn import svm        # svm classifier
from sklearn import ensemble   # ensemble classifiers
from sklearn import metrics    # performance evaluation metrics
from sklearn import model_selection
from sklearn import preprocessing
from sklearn.metrics import classification_report
from sklearn.preprocessing import MinMaxScaler
from sklearn import datasets # import standard datasets
from sklearn import neighbors  # knn classifier
#from sklearn.model_selection import train_test_split
#from sklearn.model_selection import cross_val_score
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import StratifiedKFold
%matplotlib inline
```

Part A

Question 1: Group Info

Group Name: Plum

Group Member: Eric Grant

Question 2: Decision Trees

(a)

Original:

1 - (100/210)^2 - (50/210)^2 - (60/210)^2 = 0.63

Split 1:

N(1,1) = 1 - (56/68)^2 - (12/68)^2 - 0 = 0.29

N(1,2) = 1 - (44/142)^2 - (38/142)^2 - (60/142)^2 = 0.65

Total Gain = 0.63 - (0.29 + 0.65) / 2 = 0.16

Split 2:

N(2,1) = 1 - (62/80)^2 - (18/80)^2 - 0 = 0.35

N(2,2) = 1 - (28/63)^2 - (11/63)^2 - (24/63)^2 = 0.63

N(2,3) = 1 - (10/67)^2 - (21/67)^2 - (36/67)^2 = 0.59

Total Gain = 0.63 - (0.35 + 0.63 + 0.59) / 3 = 0.11

(b)

Split 1 has the most gain and is the preffered node.

(c)

All logs are base 2

Original:

-(100/210)log(100/210) - (50/210)log(50/210) - (60/210)log(60/210) = 1.52

Split 1:

N(1,1) = -(56/68)log(56/68) - (12/68)log(12/68) - 0 = 0.67

N(1,2) = -(44/142)log(44/142) - (38/142)log(38/142) - (60/142)log(60/142) = 1.56

Total Gain = 1.52 - (0.67 + 1.56) / 2 = 0.41

Split 2:

N(2,1) = -(62/80)log(62/80) - (18/80)log(18/80) - 0 = 0.77

N(2,2) = -(28/63)log(28/63) - (11/63)log(11/63) - (24/63)log(24/63) = 1.49

N(2,3) = -(10/67)log(10/67) - (21/67)log(21/67) - (36/67)log(36/67) = 1.42

Total Gain = 1.52 - (0.77 + 1.49 + 1.42) / 3 = 0.29

(d)

Split 1 has the most gain and is the preffered node.

Question 3: Naıve Bayes Classification

(a)

In [451…

```
fruits = pd.read_csv('./fruit.txt', delimiter = ",", header=None)
fruits.columns = ["Type", "Weight", "Height", "Width"]
fruits = fruits[fruits['Type'] != 3]
apples = fruits[fruits['Type'] == 1]
oranges = fruits[fruits['Type'] == 2]
totalApple = fruits[fruits['Type'] == 1].size
totalOrange = fruits[fruits['Type'] == 2].size
totalFruit = fruits.size
totalTypes = 2
```

```
totalWeights = 2
totalHeights = 3
totalWidths = 3
alpha = 1

data = [
    ["P(apple)",totalApple/totalFruit],
    ["P(orange)",totalOrange/totalFruit]
    ]

table01 = pd.DataFrame(data, columns=['Prior','Prob.'])
display(table01)
print()

data = [
    ["P(Wt = 0 | apple)", (apples[ apples['Weight'] == 0 ].size + alpha) / (tota
    ["P(wt = 1 | apple)", (apples[ apples['Weight'] == 1 ].size + alpha) / (tota
    ["P(wt = 0 | orange)", (oranges[ oranges['Weight'] == 0 ].size + alpha) / (t
    ["P(wt = 1 | orange)", (oranges[ oranges['Weight'] == 1 ].size + alpha) / (t
    ]

table02 = pd.DataFrame(data, columns=['Cond.','Prob.'])
display(table02)
print()

data = [
    ["P(Ht = 0 | apple)", (apples[ apples['Height'] == 0 ].size + alpha) / (tota
    ["P(Ht = 1 | apple)", (apples[ apples['Height'] == 1 ].size + alpha) / (tota
    ["P(Ht = 2 | apple)", (apples[ apples['Height'] == 2 ].size + alpha) / (tota
    ["P(Ht = 0 | orange)", (oranges[ oranges['Height'] == 0 ].size + alpha) / (t
    ["P(Ht = 1 | orange)", (oranges[ oranges['Height'] == 1 ].size + alpha) / (t
    ["P(Ht = 2 | orange)", (oranges[ oranges['Height'] == 2 ].size + alpha) / (t
    ]

table03 = pd.DataFrame(data, columns=['Cond.','Prob.'])
display(table03)
print()

data = [
    ["P(Wid = 0 | apple)", (apples[ apples['Width'] == 0 ].size + alpha) / (tota
    ["P(Wid = 1 | apple)", (apples[ apples['Width'] == 1 ].size + alpha) / (tota
    ["P(Wid = 2 | apple)", (apples[ apples['Width'] == 2 ].size + alpha) / (tota
    ["P(Wid = 0 | orange)", (oranges[ oranges['Width'] == 0 ].size + alpha) / (t
    ["P(Wid = 1 | orange)", (oranges[ oranges['Width'] == 1 ].size + alpha) / (t
    ["P(Wid = 2 | orange)", (oranges[ oranges['Width'] == 2 ].size + alpha) / (t
    ]

table04 = pd.DataFrame(data, columns=['Cond.','Prob.'])
display(table04)
print()
```

	Prior	Prob.
0	P(apple)	0.5
1	P(orange)	0.5

	Cond.	Prob.
0	P(Wt = 0 | apple)	0.884615

	Cond.	Prob.
1	P(wt = 1 | apple)	0.115385
2	P(wt = 0 | orange)	0.628205
3	P(wt = 1 | orange)	0.371795

	Cond.	Prob.
0	P(Ht = 0 | apple)	0.316456
1	P(Ht = 1 | apple)	0.670886
2	P(Ht = 2 | apple)	0.012658
3	P(Ht = 0 | orange)	0.569620
4	P(Ht = 1 | orange)	0.265823
5	P(Ht = 2 | orange)	0.164557

	Cond.	Prob.
0	P(Wid = 0 | apple)	0.569620
1	P(Wid = 1 | apple)	0.367089
2	P(Wid = 2 | apple)	0.063291
3	P(Wid = 0 | orange)	0.215190
4	P(Wid = 1 | orange)	0.367089
5	P(Wid = 2 | orange)	0.417722

(b)

Sample 1:

apple = 0.5 *0.115385* 0.670886 *0.569620 = 0.02204719368*
orange = 0.5 0.371795 *0.265823* 0.215190 = 0.0106337927
Predicted = apple

Sample 2:

apple = 0.5 *0.884615* 0.316456 *0.367089 = 0.05138176384*
orange = 0.5 0.628205 *0.569620* 0.367089 = 0.06567922103
Predicted = orange

Sample 3:

apple = 0.5 *0.884615* 0.316456 *0.367089 = 0.05138176384*
orange = 0.5 0.628205 *0.569620* 0.367089 = 0.06567922103
Predicted = orange

Sample 4:

apple = 0.5 *0.115385* 0.316456 *0.569620 = 0.01039963082*

orange = 0.5 0.371795 *0.569620* 0.215190 = 0.02278667007

Predicted = orange

(c)

Sample 1: TP

Sample 2: FN

Sample 3: TN

Sample 4: TN

Part B

Question 4

In [452…

```
data = [
    [1, 0.98],
    [0, 0.92],
    [1, 0.85],
    [0, 0.77],
    [0, 0.71],
    [1, 0.64],
    [1, 0.50],
    [1, 0.39],
    [0, 0.34],
    [0, 0.31]
    ]

newData = []
for d1 in data:
    TP = 0
    FP = 0
    TN = 0
    FN = 0
    for d2 in data:
        if d2[1] >= d1[1] and d2[0] == 1:
            TP += 1
        elif d2[1] >= d1[1] and d2[0] == 0:
            FP += 1
        elif d2[1] < d1[1] and d2[0] == 1:
            FN += 1
        elif d2[1] < d1[1] and d2[0] == 0:
            TN += 1
    newData.append([d1[1], TP/(TP+FN), FP/(FP+TN), (TP+TN)/(TP+FP+FN+TN)])

matrix = pd.DataFrame(newData, columns=['Thres.','TPR','FPR','Acc.'])
display(matrix)
```

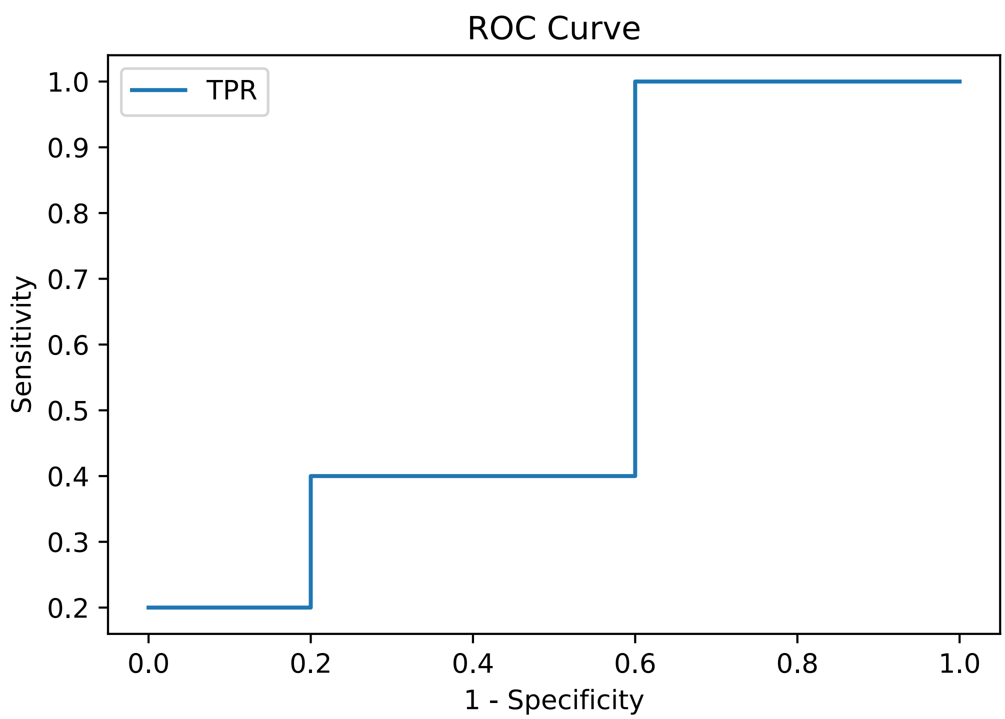
	Thres.	TPR	FPR	Acc.
0	0.98	0.2	0.0	0.6

	Thres.	TPR	FPR	Acc.
1	0.92	0.2	0.2	0.5
2	0.85	0.4	0.2	0.6
3	0.77	0.4	0.4	0.5
4	0.71	0.4	0.6	0.4
5	0.64	0.6	0.6	0.5
6	0.50	0.8	0.6	0.6
7	0.39	1.0	0.6	0.7
8	0.34	1.0	0.8	0.6
9	0.31	1.0	1.0	0.5

Question 5

In [453…

```
roc = matrix.plot(x="FPR", y="TPR", title="ROC Curve")
roc.set(xlabel="1 - Specificity", ylabel="Sensitivity")
plt.show()
```



Question 6: Spam Trees

(a)

In [454…

```
colList = ["day of week","time of day","size.kb","box","local","digits","name","
colListNoSpam = ["day of week","time of day","size.kb","box","local","digits","r
spam = pd.read_csv("./spam.csv", usecols=colList)
```

(b)

In [455…

```
error = round(len(spam[spam["spam"] == "yes"]) / len(spam),4)*100
print("i.\tPercent Emails Spam:", error, "%")
print("ii.\tCosntant classifier should always predict not spam.")
print("iii.\tError Rate:", error,"%")
```

```
i.      Percent Emails Spam: 32.7 %
ii.     Cosntant classifier should always predict not spam.
iii.    Error Rate: 32.7 %
```

(c)

In [456…

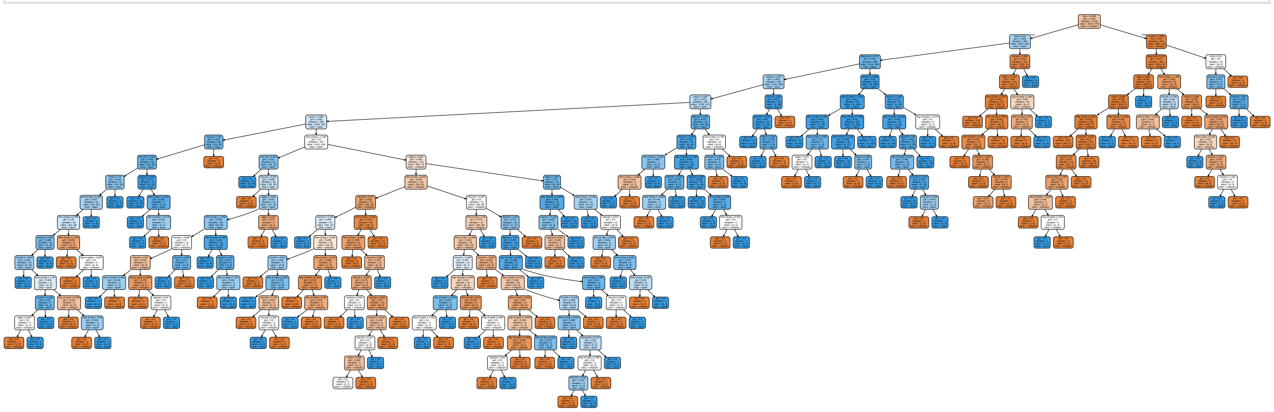
```
spamNum = spam.copy()
enc = OrdinalEncoder()
enc.fit(spam)
spamNum[colList] = enc.transform(spam)

xtrain, xtest, ytrain, ytest = train_test_split(spamNum[colListNoSpam], spamNum[

scaler = preprocessing.StandardScaler().fit(xtrain)
Xtrain_transformed = scaler.transform(xtrain)
Xtest_transformed = scaler.transform(xtest)
```

(d)

In [457…

```
dt = tree.DecisionTreeClassifier()
dtf = dt.fit(Xtrain_transformed, ytrain)
dot_data = tree.export_graphviz(dt, out_file=None, feature_names=colListNoSpam,
graph = graphviz.Source(dot_data)
graph
```

Out[457…



(e)

By deafult GINI index is used for selection.

(f)

In [458…

```
ypred_test = dtf.predict(Xtest_transformed)
print("Accuracy:", round(metrics.accuracy_score(ytest, ypred_test),2))
```

```
matrix = confusion_matrix(ytest, ypred_test)
total=sum(sum(matrix))
sensitivity = matrix[0,0]/(matrix[0,0]+matrix[0,1])
specificity = matrix[1,1]/(matrix[1,0]+matrix[1,1])
print("Sensitivity:", round(sensitivity,2))
print("Specificity:", round(specificity,2))

fpr, tpr, thresholds = metrics.roc_curve(ytest, ypred_test)
print("AUC:", round(metrics.auc(fpr, tpr), 2))
```

```
Accuracy: 0.91
Sensitivity: 0.95
Specificity: 0.82
AUC: 0.88
```

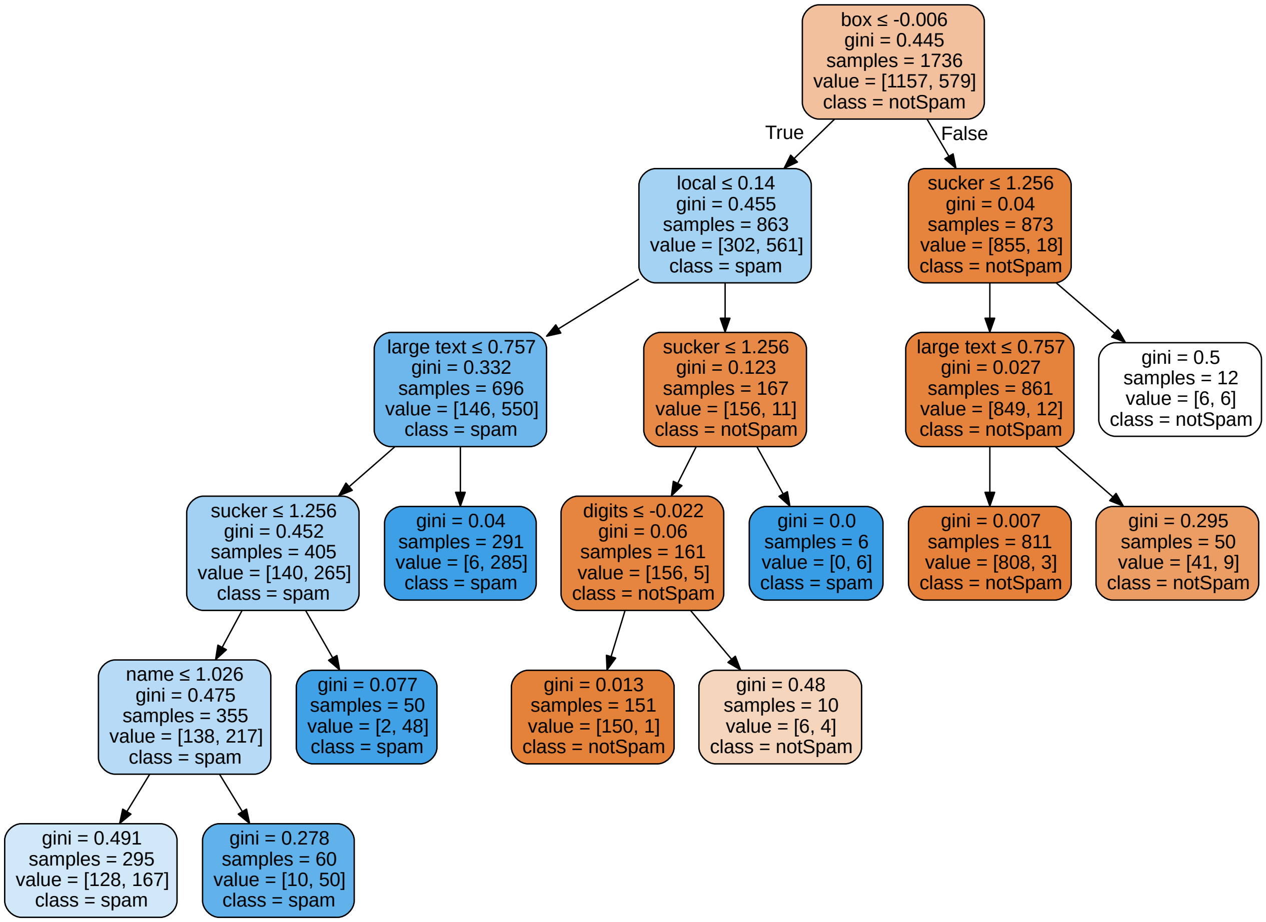
(g)

In [459…

```
dt = tree.DecisionTreeClassifier(max_leaf_nodes = 10, min_samples_leaf = 5, max_
dtf = dt.fit(Xtrain_transformed, ytrain)
dot_data = tree.export_graphviz(dt, out_file=None, feature_names=colListNoSpam,
graph = graphviz.Source(dot_data)

ypred_test = dtf.predict(Xtest_transformed)
print("Accuracy:", round(metrics.accuracy_score(ytest, ypred_test),2))

matrix = confusion_matrix(ytest, ypred_test)
total=sum(sum(matrix))
sensitivity = matrix[0,0]/(matrix[0,0]+matrix[0,1])
specificity = matrix[1,1]/(matrix[1,0]+matrix[1,1])
print("Sensitivity:", round(sensitivity,2))
print("Specificity:", round(specificity,2))

fpr, tpr, thresholds = metrics.roc_curve(ytest, ypred_test)
print("AUC:", round(metrics.auc(fpr, tpr), 2))

graph
```

```
Accuracy: 0.89
Sensitivity: 0.87
Specificity: 0.93
AUC: 0.9
```

Out[459…



Question 7: Spam Spam Spam

(a) + (b)

In [460…

```
xData = spamNum[colListNoSpam].to_numpy()
yData = spamNum["spam"].to_numpy()

finalDataAcc = []
finalDataSen = []
finalDataSpe = []
finalDataAuc = []

skf = StratifiedKFold(n_splits=10, shuffle=True, random_state=3)
for trainIndex, testIndex in skf.split(xData, yData):
    #clear arrays
    acc = []
    sen = []
    spe = []
    auc = []

    #set up data
    x_train, x_test = xData[trainIndex], xData[testIndex]
    y_train, y_test = yData[trainIndex], yData[testIndex]
    scaler = preprocessing.MinMaxScaler().fit(x_train)
    x_train_transformed = scaler.transform(x_train)
    x_test_transformed = scaler.transform(x_test)

    #knn 3 - 15
    for n in [3,7,11,15]:
```

```
        knn = neighbors.KNeighborsClassifier(n_neighbors=n)
        knn.fit(x_train_transformed, y_train)
        y_pred_test = knn.predict(x_test_transformed)
        matrix = confusion_matrix(y_test, y_pred_test)
        total=sum(sum(matrix))
        sensitivity = matrix[0,0]/(matrix[0,0]+matrix[0,1])
        specificity = matrix[1,1]/(matrix[1,0]+matrix[1,1])
        fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_test)
        acc.append(round(metrics.accuracy_score(y_test, y_pred_test),2))
        sen.append(round(sensitivity,2))
        spe.append(round(specificity,2))
        auc.append(round(metrics.auc(fpr, tpr), 2))

    #decision tree full
    dt = tree.DecisionTreeClassifier()
    dtf = dt.fit(x_train_transformed, y_train)
    y_pred_test = dtf.predict(x_test_transformed)
    matrix = confusion_matrix(y_test, y_pred_test)
    total=sum(sum(matrix))
    sensitivity = matrix[0,0]/(matrix[0,0]+matrix[0,1])
    specificity = matrix[1,1]/(matrix[1,0]+matrix[1,1])
    fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_test)
    acc.append(round(metrics.accuracy_score(y_test, y_pred_test),2))
    sen.append(round(sensitivity,2))
    spe.append(round(specificity,2))
    auc.append(round(metrics.auc(fpr, tpr), 2))

    #decision tree prunned
    dt = tree.DecisionTreeClassifier(max_leaf_nodes = 10, min_samples_leaf = 5,
    dtf = dt.fit(x_train_transformed, y_train)
    y_pred_test = dtf.predict(x_test_transformed)
    matrix = confusion_matrix(y_test, y_pred_test)
    total=sum(sum(matrix))
    sensitivity = matrix[0,0]/(matrix[0,0]+matrix[0,1])
    specificity = matrix[1,1]/(matrix[1,0]+matrix[1,1])
    fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_test)
    acc.append(round(metrics.accuracy_score(y_test, y_pred_test),2))
    sen.append(round(sensitivity,2))
    spe.append(round(specificity,2))
    auc.append(round(metrics.auc(fpr, tpr), 2))

    #Naive Bayes
    gnb = naive_bayes.GaussianNB()
    y_pred_test = gnb.fit(x_train_transformed, y_train).predict(x_test_transform
    matrix = confusion_matrix(y_test, y_pred_test)
    total=sum(sum(matrix))
    sensitivity = matrix[0,0]/(matrix[0,0]+matrix[0,1])
    specificity = matrix[1,1]/(matrix[1,0]+matrix[1,1])
    fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_test)
    acc.append(round(metrics.accuracy_score(y_test, y_pred_test),2))
    sen.append(round(sensitivity,2))
    spe.append(round(specificity,2))
    auc.append(round(metrics.auc(fpr, tpr), 2))

    #append final data
    finalDataAcc.append(acc)
    finalDataSen.append(sen)
    finalDataSpe.append(spe)
    finalDataAuc.append(auc)

dfAcc = pd.DataFrame(data=finalDataAcc, index=["F_1", "F_2", "F_3", "F_4", "F_5'
```

```
dfSen = pd.DataFrame(data=finalDataSen, index=["F_1", "F_2", "F_3", "F_4", "F_5'
dfSpe = pd.DataFrame(data=finalDataSpe, index=["F_1", "F_2", "F_3", "F_4", "F_5'
dfAuc = pd.DataFrame(data=finalDataAuc, index=["F_1", "F_2", "F_3", "F_4", "F_5'

dfAcc.loc['mean'] = dfAcc.mean()
dfSen.loc['mean'] = dfSen.mean()
dfSpe.loc['mean'] = dfSpe.mean()
dfAuc.loc['mean'] = dfAuc.mean()

print("Accuracy:")
display(dfAcc)

print("\nSensitivity:")
display(dfSen)

print("\nSpecificity:")
display(dfSpe)

print("\nAuc:")
display(dfAuc)
```

```
Accuracy:
```

	kNN_3	kNN_7	kNN_11	kNN_15	TreeF	TreeP	NB
F_1	0.900	0.910	0.910	0.910	0.900	0.890	0.890
F_2	0.900	0.910	0.910	0.900	0.920	0.890	0.890
F_3	0.880	0.900	0.900	0.910	0.880	0.880	0.880
F_4	0.920	0.930	0.940	0.940	0.940	0.910	0.920
F_5	0.920	0.890	0.900	0.890	0.880	0.900	0.880
F_6	0.890	0.890	0.880	0.890	0.890	0.880	0.880
F_7	0.920	0.910	0.920	0.930	0.930	0.870	0.880
F_8	0.920	0.930	0.920	0.920	0.940	0.900	0.870
F_9	0.930	0.920	0.920	0.910	0.940	0.890	0.900
F_10	0.930	0.920	0.930	0.940	0.900	0.920	0.890
mean	0.911	0.911	0.913	0.914	0.912	0.893	0.888

```
Sensitivity:
```

	kNN_3	kNN_7	kNN_11	kNN_15	TreeF	TreeP	NB
F_1	0.940	0.940	0.940	0.940	0.930	0.860	0.960
F_2	0.920	0.950	0.950	0.940	0.940	0.850	0.960
F_3	0.880	0.900	0.900	0.900	0.940	0.830	0.940
F_4	0.970	0.950	0.960	0.960	0.970	0.900	0.980
F_5	0.960	0.930	0.950	0.940	0.920	0.880	0.960
F_6	0.890	0.890	0.890	0.890	0.900	0.840	0.950
F_7	0.950	0.940	0.950	0.960	0.940	0.820	0.940
F_8	0.970	0.950	0.950	0.960	0.980	0.880	0.960
F_9	0.960	0.950	0.940	0.940	0.970	0.880	0.970

	kNN_3	kNN_7	kNN_11	kNN_15	TreeF	TreeP	NB
F_10	0.980	0.980	0.980	0.990	0.980	0.910	0.970
mean	0.942	0.938	0.941	0.942	0.947	0.865	0.959

```
Specificity:
```

	kNN_3	kNN_7	kNN_11	kNN_15	TreeF	TreeP	NB
F_1	0.83	0.860	0.850	0.860	0.850	0.960	0.760
F_2	0.86	0.850	0.850	0.820	0.870	0.970	0.750
F_3	0.87	0.890	0.900	0.920	0.770	0.970	0.770
F_4	0.83	0.890	0.900	0.900	0.860	0.930	0.790
F_5	0.85	0.820	0.800	0.800	0.800	0.960	0.720
F_6	0.90	0.900	0.870	0.890	0.890	0.970	0.730
F_7	0.86	0.860	0.860	0.860	0.920	0.990	0.750
F_8	0.82	0.870	0.860	0.850	0.870	0.940	0.680
F_9	0.86	0.850	0.870	0.860	0.890	0.920	0.760
F_10	0.82	0.790	0.820	0.830	0.750	0.940	0.730
mean	0.85	0.858	0.858	0.859	0.847	0.955	0.744

```
Auc:
```

	kNN_3	kNN_7	kNN_11	kNN_15	TreeF	TreeP	NB
F_1	0.880	0.900	0.890	0.90	0.890	0.910	0.860
F_2	0.890	0.900	0.900	0.88	0.910	0.910	0.850
F_3	0.880	0.900	0.900	0.91	0.860	0.900	0.860
F_4	0.900	0.920	0.930	0.93	0.920	0.920	0.880
F_5	0.900	0.870	0.870	0.87	0.860	0.920	0.840
F_6	0.900	0.900	0.880	0.89	0.890	0.910	0.840
F_7	0.910	0.900	0.900	0.91	0.930	0.900	0.840
F_8	0.890	0.910	0.910	0.90	0.930	0.910	0.820
F_9	0.910	0.900	0.910	0.90	0.930	0.900	0.870
F_10	0.900	0.880	0.900	0.91	0.860	0.930	0.850
mean	0.896	0.898	0.899	0.90	0.898	0.911	0.851