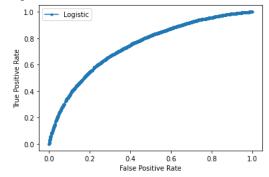
```
from google.colab import files
uploaded = files.upload()
     Choose Files No file chosen
                                       Upload widget is only available when the cell has been executed in the current browser session. Please rerun
     this cell to enable.
     Saving readv.outcome1.csv to readv.outcome1.csv
import pandas as pd
import io
outcome1 = pd.read_csv(io.BytesIO(uploaded['ready.outcome1.csv']))
            v000
                  v007
                        v012 v013 v025
                                           v106 v190 \
     0
             NG7
                  2018
                          40
                                 6
                                       1
                          37
                                                    5
     1
             NG7
                  2018
                                        1
     2
             NG7
                  2018
                          27
                                 3
                                                    5
     3
             NG7
                  2018
                          27
                                 3
                                        1
                                                    5
                                              3
     4
             NG7
                  2018
                          24
                                        1
                                              3
                                                    5
     120648
            ZW7
                  2015
     120649
             ZW7
                  2015
                          32
     120650
            ZW7
                  2015
                                 2
                          24
                                        0
                                                    2
                                              2
     120651
             ZW7
                  2015
                          40
                                 6
                                        0
                                                    3
     120652 ZW7
                  2015
                                                                          v501b ... \
                                             v501
                                                       v501a
                                                                  Never married ...
     0
                             living with partner Unmarried
     1
                                          married
                                                     Married
                                                                        Married ...
     2
                                          married
                                                     Married
                                                                        Married ...
                                                                        Married ...
     3
                                          married
                                                     Married
     4
             no longer living together/separated Unmarried Formerly married ...
                                                                           . . .
                                                                        Married ...
     120648
                                          married
                                                     Married
     120649
                                          married
                                                     Married
                                                                        Married
                                                                                 . . .
     120650
                                          married
                                                     Married
                                                                        Married
                                                                                . . .
     120651
                                          married
                                                                        Married ...
                                                     Married
     120652
                                          married
                                                     Married
                                                                        Married
             v000_GH6 v000_KE6 v000_ML7
                                            v000_NG7
                                                     v000_ZA7
                                                                v000_ZM7
                                                                           v000_ZW7
     0
                    0
                              0
                                         0
                                                   1
                                                             0
                                                                        0
                                                                                  0
     1
                    0
                              0
                                         0
                                                   1
                                                              0
                                                                        0
                                                                                  0
     2
                    0
                              0
                                         0
                                                   1
                                                              0
                                                                        0
                                                                                  0
     3
                    0
                              0
                                         0
                                                   1
                                                             0
                                                                        0
                                                                                  0
     4
                    0
                              0
                                         0
                                                   1
                                                              0
                                                                        0
                                                                                  0
     120648
                    0
                              0
                                         0
                                                   0
                                                                        0
                                                                                  1
     120649
                    0
                              0
                                         a
                                                   0
                                                             0
                                                                        a
                                                                                  1
     120650
                    0
                              0
                                         0
                                                   0
                                                                        0
                                                                                  1
     120651
                    0
                              0
                                         0
                                                   0
                                                                        0
                                                                                  1
     120652
                    0
                              0
                                         0
                                                   0
                                                                        0
                                     v501b_Married v501b_Never married
             v501b_Formerly married
     0
                                   0
                                                  0
                                                                        1
     1
                                   0
                                                  1
                                                                        0
     2
                                   0
                                                                        0
     3
                                   0
                                                  1
                                                                        0
     4
                                   1
                                                  0
                                                                        0
     120648
                                   0
                                                                        0
                                                  1
     120649
                                   0
                                                                        0
                                                  1
     120650
                                   0
                                                  1
                                                                        0
     120651
                                                                        0
     120652
     [120653 rows x 33 columns]
from sklearn.model_selection import train_test_split
outcome1_train, outcome1_test = train_test_split(
outcome1, test_size=0.20, stratify=outcome1[['v000', 'child_loss']])
x_train = outcome1_train[['v000_A07', 'v000_EG6', 'v000_ET7', 'v000_GA6', 'v000_GH6', 'v000_KE6', 'v000_ML7', 'v000_NG7', 'v000_ZA7',
                           'v000_ZM7', 'v000_ZW7', 'v013', 'v025', 'v106', 'v190', 'v501b_Formerly married', 'v501b_Married',
                           'v501b_Never married', 'first.sex', 'v228', 'smoke']]
y_train = outcome1_train['lost_child']
y2_train = outcome1_train['child_loss']
x_test = outcome1_test[['v000_A07', 'v000_EG6', 'v000_ET7', 'v000_GA6', 'v000_GH6', 'v000_KE6', 'v000_ML7', 'v000_NG7', 'v000_ZA7',
```

```
'v000_ZM7', 'v000_ZW7', 'v013', 'v025', 'v106', 'v190', 'v501b_Formerly married', 'v501b_Married',
                          'v501b_Never married', 'first.sex', 'v228', 'smoke']]
y_test = outcome1_test['lost_child']
y2_test = outcome1_test['child_loss']
print(outcome1_train.shape, outcome1_test.shape)
print(x_train.shape, x_test.shape)
     (96522, 33) (24131, 33)
     (96522, 21) (24131, 21)
# roc curve and auc
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot
# fit a model
model = LogisticRegression(solver='lbfgs')
model.fit(x_train, y2_train)
# predict probabilities
lr_probs = model.predict_proba(x_test)
# keep probabilities for the positive outcome only
lr_probs = lr_probs[:, 1]
# calculate scores
lr_auc = roc_auc_score(y2_test, lr_probs)
# summarize scores
print('Logistic: ROC AUC=%.3f' % (lr_auc))
# calculate roc curves
lr_fpr, lr_tpr, _ = roc_curve(y2_test, lr_probs)
# plot the roc curve for the model
pyplot.plot(lr_fpr, lr_tpr, marker='.', label='Logistic')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
     Logistic: ROC AUC=0.743
```



```
from sklearn.neighbors import KNeighborsClassifier
knn_train_accuracy = []
knn_test_accuracy = []
knn_test2_accuracy = []
neighbors_settings = range(1, 20)

for n_neighbors in neighbors_settings:
    clf = KNeighborsClassifier(n_neighbors = n_neighbors)
    clf2 = KNeighborsClassifier(n_neighbors = n_neighbors)
    clf2:fit(x_train, y_train)
    clf2.fit(x_train, y2_train)

knn_train_accuracy.append(clf.score(x_train, y_train))
knn_test_accuracy.append(clf.score(x_test, y_test))
```

```
knn_train2_accuracy.append(clf.score(x_train, y2_train))
knn_test2_accuracy.append(clf.score(x_test, y2_test))
```

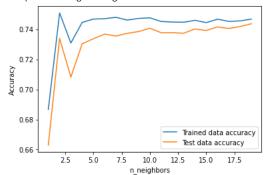
```
%matplotlib inline
import matplotlib.pyplot as plt

plt.plot(neighbors_settings, knn_train_accuracy, label= "Trained data accuracy")
plt.plot(neighbors_settings, knn_test_accuracy, label= "Test data accuracy")
plt.ylabel("Accuracy")
plt.xlabel("n_neighbors")
plt.legend()
```

## cmatplotlib.legend.Legend at 0x7f22f6aaab10> 0.76 0.74 0.70 0.68 | Tained data accuracy | Test data accu

```
plt.plot(neighbors_settings, knn_train2_accuracy, label= "Trained data accuracy")
plt.plot(neighbors_settings, knn_test2_accuracy, label= "Test data accuracy")
plt.ylabel("Accuracy")
plt.xlabel("n_neighbors")
plt.legend()
```

## <matplotlib.legend.Legend at 0x7f22f69dced0>



```
print (knn_train_accuracy)
print (knn_train2_accuracy)
```

 $[0.6977580240774124, 0.7478087897059738, 0.7461614968608193, 0.7546776900602972, 0.7550092206957999, 0.7577857897681357, 0.7591844346366 \\ [0.686672468452788, 0.75077184476078, 0.7307764033070181, 0.7444831230185864, 0.7466795134787924, 0.746938521787779, 0.747860591367771, \\ [0.686672468452788, 0.75077184476078, 0.7307764033070181, 0.7444831230185864, 0.7466795134787924, 0.746938521787779, 0.747860591367771, \\ [0.686672468452788, 0.75077184476078, 0.7307764033070181, 0.7444831230185864, 0.7466795134787924, 0.746938521787779, 0.747860591367771, \\ [0.686672468452788, 0.75077184476078, 0.7307764033070181, 0.7444831230185864, 0.7466795134787924, 0.746938521787779, 0.747860591367771, \\ [0.686672468452788, 0.75077184476078, 0.7307764033070181, 0.7444831230185864, 0.7466795134787924, 0.746938521787779, 0.747860591367771, \\ [0.686672468452788, 0.75077184476078, 0.7307764033070181, 0.7444831230185864, 0.7466795134787924, 0.746938521787779, 0.747860591367771, \\ [0.686672468452788, 0.75077184476078, 0.740764033070181, 0.7444831230185864, 0.7466795134787924, 0.746938521787779, 0.747860591367771, \\ [0.686672468452788, 0.75077184476078, 0.746978518, 0.746978518, 0.7469785134, 0.746978784, 0.7469785134, 0.746978784, 0.7469785134, 0.746978784, 0.746978784, 0.746978784, 0.746978784, 0.7469784, 0.7469784, 0.7469784, 0.7469784, 0.7469784, 0.7469784, 0.74697$ 

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict

model = MultinomialNB()
model.fit(x_train, y_train)
labels = model.predict(x_test)
nb_train_accuracy = []
nb_test_accuracy = []
nb_train_accuracy.append(model.score(x_train, y_train))
```

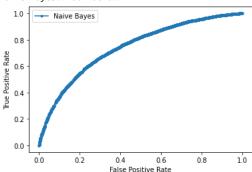
nb\_test\_accuracy.append(model.score(x\_test, y\_test))

print(nb\_train\_accuracy, nb\_test\_accuracy)

```
model 2 = MultinomialNB()
model_2.fit(x_train, y2_train)
labels_2 = model_2.predict(x_test)
nb2_train_accuracy = []
nb2_test_accuracy = []
nb2 train accuracy.append(model 2.score(x train, y2 train))
nb2_test_accuracy.append(model_2.score(x_test, y2_test))
print(nb2_train_accuracy, nb2_test_accuracy)
cv_train = cross_val_score(model, x_train, y_train, cv = 10, scoring = "accuracy")
cv_test = cross_val_score(model, x_test, y_test, cv = 10, scoring = "accuracy")
cv_train2 = cross_val_score(model_2, x_train, y2_train, cv = 10, scoring = "accuracy")
cv_test2 = cross_val_score(model_2, x_test, y2_test, cv = 10, scoring = "accuracy")
print("Percent accuracy within each fold (First): \n")
print(cv_train, "\n", cv_test)
print("\nMean & SD accuracy: \n")
print(cv_train.mean(), cv_test.mean())
print(cv_train.std(), cv_test.std())
print("\nPercent accuracy within each fold (Second): \n")
print(cv_train2, "\n", cv_test2)
print("\nMean & SD accuracy: \n")
print(cv_train2.mean(), cv_test2.mean())
print(cv_train2.std(), cv_test2.std())
cv_labels = cross_val_predict(model, x_test, y_test, cv=10)
cv_labels2 = cross_val_predict(model_2, x_test, y2_test, cv=10)
accuracy = pd.DataFrame()
accuracy2 = pd.DataFrame()
accuracy = accuracy.append([["Naive Baye's", (cv_train.mean()), (cv_test.mean())]])
accuracy2 = accuracy2.append([["Naive Baye's", (cv_train2.mean()), (cv_test2.mean())]])
     [0.7540975114481673] [0.7543823297832664]
     [0.7703425125878038] [0.7687621731382869]
    Percent accuracy within each fold (First):
     [0.75240858 0.75479126 0.75310816 0.75300456 0.75663075 0.75290095
      0.75476585 0.75435143 0.75486946 0.7538334 ]
     [0.75144988 0.75093245 0.75631993 0.75300456 0.75549109 0.75714878
     0.75549109 0.75259014 0.75300456 0.7538334 ]
    Mean & SD accuracy:
    0.7540664401177554 0.7539265872409563
    0.0012051280451909068 0.0019899742075337387
    Percent accuracy within each fold (Second):
    [0.76898374 0.77105563 0.76543722 0.77186075 0.77289681 0.77092831
     0.77134273 0.76864898 0.77020307 0.77175715]
     [0.76677713 0.76336511 0.7708247 0.76916701 0.77786987 0.76543722
     0.77414007 0.76253626 0.76460837 0.76875259]
    Mean & SD accuracy:
     0.7703114376360753 0.7683478335212023
    0.0020363900774159243 0.004633716958841678
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import make_pipeline
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot
# fit a model
model_2 = MultinomialNB()
model_2.fit(x_train, y2_train)
# predict probabilities
nb_probs = model_2.predict_proba(x_test)
# keep probabilities for the positive outcome only
nb_probs = nb_probs[:, 1]
# calculate scores
```

```
nb_auc = roc_auc_score(y2_test, nb_probs)
# summarize scores
print('Naive Bayes: ROC AUC=%.3f' % (nb_auc))
# calculate roc curves
nb_fpr, nb_tpr, _ = roc_curve(y2_test, nb_probs)
# plot the roc curve for the model
pyplot.plot(lr_fpr, lr_tpr, marker='.', label='Naive Bayes')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
```

## Naive Bayes: ROC AUC=0.729



from sklearn.tree import DecisionTreeClassifier

```
tree = DecisionTreeClassifier(random_state=0)
tree.fit(x_train, y_train)
labels_tree = tree.predict(x_test)
tree_2 = DecisionTreeClassifier(random_state=0)
tree_2.fit(x_train, y2_train)
labels_tree2 = tree_2.predict(x_test)
print("Accuracy on training set: \{:.3f\}".format(tree.score(x\_train, y\_train)))
print("Accuracy on test set: {:.3f}".format(tree.score(x_test, y_test)))
print("Accuracy on training set: {:.3f}".format(tree_2.score(x_train, y2_train)))
print("Accuracy on test set: {:.3f}".format(tree_2.score(x_test, y2_test)))
cv_train = cross_val_score(tree, x_train, y_train, cv = 10, scoring = "accuracy")
cv_test = cross_val_score(tree, x_test, y_test, cv = 10, scoring = "accuracy")
cv_train2 = cross_val_score(tree_2, x_train, y2_train, cv = 10, scoring = "accuracy")
cv_test2 = cross_val_score(tree_2, x_test, y2_test, cv = 10, scoring = "accuracy")
print("Percent accuracy within each fold (First): \n")
print(cv_train, "\n", cv_test)
print("\nMean & SD accuracy: \n")
print(cv_train.mean(), cv_test.mean())
print(cv_train.std(), cv_test.std())
print("\nPercent accuracy within each fold (Second): \n")
print(cv_train2, "\n", cv_test2)
print("\nMean & SD accuracy: \n")
print(cv_train2.mean(), cv_test2.mean())
print(cv_train2.std(), cv_test2.std())
cv_labels = cross_val_predict(tree, x_test, y_test, cv=10)
cv_labels2 = cross_val_predict(tree_2, x_test, y2_test, cv=10)
accuracy = accuracy.append([["Decision Tree (Entropy)", (cv_train.mean()), (cv_test.mean())]])
accuracy2 = accuracy2.append([["Decision Tree (Entropy)", (cv_train2.mean()), (cv_test2.mean())]])
    Accuracy on training set: 0.786
    Accuracy on test set: 0.754
    Accuracy on training set: 0.806
    Accuracy on test set: 0.773
    Percent accuracy within each fold (First):
```

```
[0.75044028 0.75427328 0.75321177 0.75145048 0.75393701 0.7538334
      0.75393701 0.75082884 0.75238293 0.75435143]
      [0.73363712 0.73518442 0.71653543 0.72689598 0.72813925 0.74264401
      0.72440945 0.7273104 0.73062578 0.7273104 ]
     Mean & SD accuracy:
     0.7528646424206326\ 0.7292692234928795
     0.0014073972366819359 0.0065965379951465125
     Percent accuracy within each fold (Second):
     [0.77250596 0.77240236 0.77154994 0.7708247 0.7745545 0.77393286
      0.77496892 0.77310402 0.76978864 0.771860751
      [0.75476388 0.74595939 0.74015748 0.75341898 0.75093245 0.76004973
      0.74513054 0.74513054 0.75134687 0.74678823]
     Mean & SD accuracy:
     0.7725492653510293 0.7493678092052474
     0.0015552839454131431 0.005522756117813724
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import roc_curve
from sklearn.metrics import roc auc score
from matplotlib import pyplot
from sklearn.tree import DecisionTreeClassifier
# fit a model
model_2 = DecisionTreeClassifier(random_state=0)
model_2.fit(x_train, y2_train)
# predict probabilities
dtc_probs = model_2.predict_proba(x_test)
# keep probabilities for the positive outcome only
dtc_probs = dtc_probs[:, 1]
# calculate scores
dtc_auc = roc_auc_score(y2_test, dtc_probs)
# summarize scores
print('Decision Tree: ROC AUC=%.3f' % (dtc_auc))
# calculate roc curves
dtc_fpr, dtc_tpr, _ = roc_curve(y2_test, dtc_probs)
# plot the roc curve for the model
pyplot.plot(dtc_fpr, dtc_tpr, marker='.', label='Decision Tree')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
     Decision Tree: ROC AUC=0.758
        1.0

    Decision Tree

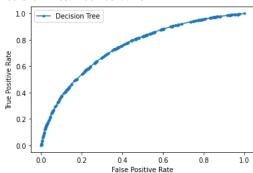
        0.8
      Frue Positive Rate
        0.6
        0.4
        0.2
        0.0
            0.0
                                                     1.0
                    0.2
                            0.4
                                    0.6
                                             0.8
                           False Positive Rate
from sklearn.tree import DecisionTreeClassifier
clf_gini = DecisionTreeClassifier(criterion = "gini", random_state = 100, max_depth = 10, min_samples_leaf=1)
clf_gini.fit(x_train, y_train)
labels_gini = clf_gini.predict(x_test)
clf_gini2 = DecisionTreeClassifier(criterion = "gini", random_state = 100, max_depth = 10, min_samples_leaf=1)
clf_gini2.fit(x_train, y2_train)
labels_gini2 = clf_gini2.predict(x_test)
```

print("Accuracy on training set: {:.3f}".format(clf\_gini.score(x\_train, y\_train)))

```
print("Accuracy on test set: {:.3f}".format(clf_gini.score(x_test, y_test)))
print("Accuracy on training set (Child loss): {:.3f}".format(clf_gini2.score(x_train, y2_train)))
print("Accuracy on test set (Child loss): {:.3f}".format(clf_gini2.score(x_test, y2_test)))
cv_train = cross_val_score(clf_gini, x_train, y_train, cv = 10, scoring = "accuracy")
cv_test = cross_val_score(clf_gini, x_test, y_test, cv = 10, scoring = "accuracy")
cv_train2 = cross_val_score(clf_gini2, x_train, y2_train, cv = 10, scoring = "accuracy")
cv_test2 = cross_val_score(clf_gini2, x_test, y2_test, cv = 10, scoring = "accuracy")
print("Percent accuracy within each fold (First): \n")
print(cv_train, "\n", cv_test)
print("\nMean & SD accuracy: \n")
print(cv_train.mean(), cv_test.mean())
print(cv_train.std(), cv_test.std())
print("\nPercent accuracy within each fold (Second): \n")
print(cv_train2, "\n", cv_test2)
print("\nMean & SD accuracy: \n")
print(cv_train2.mean(), cv_test2.mean())
print(cv_train2.std(), cv_test2.std())
cv_labels = cross_val_predict(clf_gini, x_test, y_test, cv=10)
cv_labels2 = cross_val_predict(clf_gini2, x_test, y2_test, cv=10)
accuracy = accuracy.append([["Decision Tree (Gini)", (cv_train.mean()), (cv_test.mean())]])
accuracy2 = accuracy2.append([["Decision Tree (Gini)", (cv_train2.mean()), (cv_test2.mean())]])
     Accuracy on training set: 0.761
     Accuracy on test set: 0.755
     Accuracy on training set (Child loss): 0.778
     Accuracy on test set (Child loss): 0.770
     Percent accuracy within each fold (First):
     [0.75282296 0.75675956 0.75663075 0.75393701 0.75466225 0.75714878
      0.75476585 0.75393701 0.7555947 0.7576668 ]
      [0.76056338 0.74968918 0.74305843 0.75549109 0.75051803 0.75010361
      0.74222959 0.74720265 0.74554496 0.74554496]
     Mean & SD accuracy:
     0.755392565452619 0.7489945891678292
     0.0015318416924185215 0.005367389578657666
     Percent accuracy within each fold (Second):
     [0.77126282 0.77302393 0.76968504 0.77134273 0.77393286 0.77776627
      0.77092831 0.76875259 0.76989225 0.77331123]
      [0.77050539 0.76750932 0.7443017 0.77952756 0.76668048 0.76460837
      0.75631993 0.76295068 0.76502279 0.75673436]
     Mean & SD accuracy:
     0.7719898022508265 0.7634160586247305
     0.0024944699016082104 0.008954490148631243
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot
from sklearn.tree import DecisionTreeClassifier
# fit a model
model_2 = DecisionTreeClassifier(criterion = "gini", random_state = 100, max_depth = 10, min_samples_leaf=1)
model_2.fit(x_train, y2_train)
# predict probabilities
dtc_probs = model_2.predict_proba(x_test)
# keep probabilities for the positive outcome only
dtc_probs = dtc_probs[:, 1]
# calculate scores
dtc_auc = roc_auc_score(y2_test, dtc_probs)
# summarize scores
print('Decision Tree: ROC AUC=%.3f' % (dtc_auc))
# calculate roc curves
dtc_fpr, dtc_tpr, _ = roc_curve(y2_test, dtc_probs)
# plot the roc curve for the model
pyplot.plot(dtc_fpr, dtc_tpr, marker='.', label='Decision Tree')
# axis labels
```

```
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
```

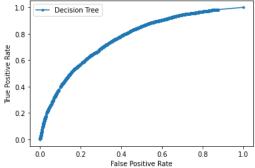
Decision Tree: ROC AUC=0.745



from sklearn.ensemble import RandomForestClassifier

```
forest = RandomForestClassifier(n_estimators=100, random_state=0)
forest.fit(x_train, y_train)
labels_rf = forest.predict(x_test)
forest_2 = RandomForestClassifier(n_estimators=100, random_state=0)
forest_2.fit(x_train, y2_train)
labels_rf2 = forest.predict(x_test)
print("Accuracy on training set: {:.3f}".format(forest.score(x_train, y_train)))
print("Accuracy on test set: {:.3f}".format(forest.score(x_test, y_test)))
print("Accuracy on training set (Child loss): {:.3f}".format(forest_2.score(x_train, y2_train)))
print("Accuracy on test set (Child loss): {:.3f}".format(forest_2.score(x_test, y2_test)))
cv_train = cross_val_score(forest, x_train, y_train, cv = 10, scoring = "accuracy")
cv_test = cross_val_score(forest, x_test, y_test, cv = 10, scoring = "accuracy")
cv_train2 = cross_val_score(forest_2, x_train, y2_train, cv = 10, scoring = "accuracy")
cv_test2 = cross_val_score(forest_2, x_test, y2_test, cv = 10, scoring = "accuracy")
print("Percent accuracy within each fold (First): \n")
print(cv_train, "\n", cv_test)
print("\nMean & SD accuracy: \n")
print(cv_train.mean(), cv_test.mean())
print(cv_train.std(), cv_test.std())
print("\nPercent accuracy within each fold (Second): \n")
print(cv_train2, "\n", cv_test2)
print("\nMean & SD accuracy: \n")
print(cv_train2.mean(), cv_test2.mean())
print(cv_train2.std(), cv_test2.std())
cv_labels = cross_val_predict(forest, x_test, y_test, cv=10)
cv_labels2 = cross_val_predict(forest_2, x_test, y2_test, cv=10)
accuracy = accuracy.append([["Random Forest", (cv_train.mean()), (cv_test.mean())]])
accuracy2 = accuracy2.append([["Random Forest", (cv_train2.mean()), (cv_test2.mean())]])
    Accuracy on training set: 0.786
    Accuracy on test set: 0.755
     Accuracy on training set (Child loss): 0.806
    Accuracy on test set (Child loss): 0.773
    Percent accuracy within each fold (First):
     [0.7518906  0.75675956  0.75486946  0.75290095  0.75497306  0.75486946
     0.75663075 0.75300456 0.75642354 0.75414422]
     [0.74316487 0.73684211 0.73186904 0.7310402 0.73559884 0.75341898
     0.73435557 0.73352673 0.73642768 0.73352673]
    Mean & SD accuracy:
    0.7546466157256468 0.7369770756373153
    0.001592367488739728 0.006347166156062973
```

```
Percent accuracy within each fold (Second):
     [0.77074485 0.77426707 0.77041028 0.77020307 0.77673021 0.77755906
      0.77818069 0.77507252 0.77527973 0.77175715]
      [0.75724938 0.74761707 0.75051803 0.76212184 0.75217571 0.76419395
      0.74968918 0.75176129 0.75176129 0.74968918]
     Mean & SD accuracy:
     0.7740204619569686 0.7536776937679808
     0.002887619475658153 0.005317746940072504
from sklearn.feature extraction.text import TfidfVectorizer
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot
from \ sklearn. ensemble \ import \ Random Forest Classifier
# fit a model
model_2 = RandomForestClassifier(n_estimators=100, random_state=0)
model_2.fit(x_train, y2_train)
# predict probabilities
dtc_probs = model_2.predict_proba(x_test)
# keep probabilities for the positive outcome only
dtc_probs = dtc_probs[:, 1]
# calculate scores
dtc_auc = roc_auc_score(y2_test, dtc_probs)
# summarize scores
print('Random Forest: ROC AUC=%.3f' % (dtc_auc))
# calculate roc curves
dtc_fpr, dtc_tpr, _ = roc_curve(y2_test, dtc_probs)
# plot the roc curve for the model
pyplot.plot(dtc_fpr, dtc_tpr, marker='.', label='Random Forest')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
     Decision Tree: ROC AUC=0.766
             Decision Tree
        0.8
```



from sklearn.ensemble import GradientBoostingClassifier

```
gbrt = GradientBoostingClassifier(random_state=0, max_depth = 10)
gbrt.fit(x_train, y_train)
labels_gbrt = gbrt.predict(x_test)

gbrt_2 = GradientBoostingClassifier(random_state=0, max_depth = 10)
gbrt_2.fit(x_train, y2_train)
labels_gbrt2 = gbrt_2.predict(x_test)

print("Accuracy on training set: {:.3f}".format(gbrt.score(x_train, y_train)))
print("Accuracy on test set: {:.3f}".format(gbrt.score(x_test, y_test)))

print("Accuracy on training set (Child loss): {:.3f}".format(gbrt_2.score(x_train, y2_train)))
print("Accuracy on test set (Child loss): {:.3f}".format(gbrt_2.score(x_test, y2_test)))

cv_train = cross_val_score(gbrt, x_train, y_train, cv = 10, scoring = "accuracy")
cv_test = cross_val_score(gbrt, x_test, y_test, cv = 10, scoring = "accuracy")
```

```
cv_trainz = cross_vai_score(gort_z, x_train, yz_train, cv = i0, scoring = accuracy )
cv_test2 = cross_val_score(gbrt_2, x_test, y2_test, cv = 10, scoring = "accuracy")
print("Percent accuracy within each fold (First): \n")
print(cv_train, "\n", cv_test)
print("\nMean & SD accuracy: \n")
print(cv_train.mean(), cv_test.mean())
print(cv_train.std(), cv_test.std())
print("\nPercent accuracy within each fold (Second): \n")
print(cv_train2, "\n", cv_test2)
print("\nMean & SD accuracy: \n")
print(cv_train2.mean(), cv_test2.mean())
print(cv_train2.std(), cv_test2.std())
cv_labels = cross_val_predict(gbrt, x_test, y_test, cv=10)
cv_labels2 = cross_val_predict(gbrt_2, x_test, y2_test, cv=10)
accuracy = accuracy.append([["Gradient Boost", (cv_train.mean()), (cv_test.mean())]])
accuracy2 = accuracy2.append([["Gradient Boost", (cv_train2.mean()), (cv_test2.mean())]])
 Accuracy on training set: 0.782
     Accuracy on test set: 0.758
     Accuracy on training set (Child loss): 0.798
     Accuracy on test set (Child loss): 0.774
     Percent accuracy within each fold (First):
     [0.75479126 0.75945302 0.75880646 0.75528388 0.75714878 0.7595317
      0.7595317 0.75549109 0.75787402 0.75797762]
      [0.73943662\ 0.74222959\ 0.73228346\ 0.73518442\ 0.73849979\ 0.74844592
      0.73062578 0.74098632 0.73974306 0.73477 ]
     Mean & SD accuracy:
     0.7575889531260217 0.7382204957886565
     0.0017456579478918016 0.0049619438942587885
     Percent accuracy within each fold (Second):
     [0.77374909\ 0.77654615\ 0.77289681\ 0.7727932\ 0.77911314\ 0.78201409
      0.77704103 0.77445089 0.77486531 0.77807708]
      [0.76636288 0.76626606 0.75466225 0.76336511 0.75507667 0.76792375
      0.75507667 0.75839204 0.76170742 0.75466225]
     Mean & SD accuracy:
     0.776154679908361 0.7603495083761633
     0.0028281639056204184 0.0051342023407811325
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot
from sklearn.ensemble import GradientBoostingClassifier
# fit a model
model_2 = GradientBoostingClassifier(random_state=0, max_depth = 10)
model_2.fit(x_train, y2_train)
# predict probabilities
dtc_probs = model_2.predict_proba(x_test)
# keep probabilities for the positive outcome only
dtc_probs = dtc_probs[:, 1]
# calculate scores
dtc_auc = roc_auc_score(y2_test, dtc_probs)
# summarize scores
print('Decision Tree: ROC AUC=%.3f' % (dtc_auc))
# calculate roc curves
dtc_fpr, dtc_tpr, _ = roc_curve(y2_test, dtc_probs)
# plot the roc curve for the model
pyplot.plot(dtc_fpr, dtc_tpr, marker='.', label='Gradient Boosting')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
```

```
Decision Tree: ROC AUC=0.769
       1.0

    Decision Tree

       0.8
       0.6
     Positive
       0.4
       0.2
       0.0
                                            0.8
                                                    1.0
                    0.2
                            0.4
                                    0.6
           0.0
from sklearn.svm import SVC
svc = SVC()
svc.fit(x_train, y_train)
labels_svc = svc.predict(x_test)
svc_2 = SVC()
svc_2.fit(x_train, y2_train)
labels_svc2 = svc_2.predict(x_test)
print("Accuracy on training set: {:.3f}".format(svc.score(x_train, y_train)))
print("Accuracy on test set: {:.3f}".format(svc.score(x_test, y_test)))
print("Accuracy on training set (Child loss): {:.3f}".format(svc_2.score(x_train, y2_train)))
print("Accuracy on test set (Child loss): {:.3f}".format(svc_2.score(x_test, y2_test)))
cv_train = cross_val_score(svc, x_train, y_train, cv = 10, scoring = "accuracy")
cv_test = cross_val_score(svc, x_test, y_test, cv = 10, scoring = "accuracy")
cv_train2 = cross_val_score(svc_2, x_train, y2_train, cv = 10, scoring = "accuracy")
cv_test2 = cross_val_score(svc_2, x_test, y2_test, cv = 10, scoring = "accuracy")
print("Percent accuracy within each fold (First): \n")
print(cv_train, "\n", cv_test)
print("\nMean & SD accuracy: \n")
print(cv_train.mean(), cv_test.mean())
print(cv_train.std(), cv_test.std())
print("\nPercent accuracy within each fold (Second): \n")
print(cv_train2, "\n", cv_test2)
print("\nMean & SD accuracy: \n")
print(cv_train2.mean(), cv_test2.mean())
print(cv_train2.std(), cv_test2.std())
cv_labels = cross_val_predict(svc, x_test, y_test, cv=10)
cv_labels2 = cross_val_predict(svc_2, x_test, y2_test, cv=10)
accuracy = accuracy.append([["SVM", (cv_train.mean()), (cv_test.mean())]])
accuracy2 = accuracy2.append([["SVM", (cv_train2.mean()), (cv_test2.mean())]])
     Accuracy on training set: 0.755
    Accuracy on test set: 0.755
    Accuracy on training set (Child loss): 0.769
    Accuracy on test set (Child loss): 0.768
                                               Traceback (most recent call last)
    NameError
     <ipython-input-4-f4c30bb4500c> in <module>
          15 print("Accuracy on test set (Child loss): {:.3f}".format(svc_2.score(x_test, y2_test)))
          16
     ---> 17 cv_train = cross_val_score(svc, x_train, y_train, cv = 10, scoring = "accuracy")
          18 cv_test = cross_val_score(svc, x_test, y_test, cv = 10, scoring = "accuracy")
    NameError: name 'cross_val_score' is not defined
      SEARCH STACK OVERFLOW
cv_train = cross_val_score(svc, x_train, y_train, cv = 10, scoring = "accuracy")
cv_test = cross_val_score(svc, x_test, y_test, cv = 10, scoring = "accuracy")
cv_train2 = cross_val_score(svc_2, x_train, y2_train, cv = 10, scoring = "accuracy")
cv_test2 = cross_val_score(svc_2, x_test, y2_test, cv = 10, scoring = "accuracy")
```

```
print("Percent accuracy within each fold (First): \n")
print(cv_train, "\n", cv_test)
print("\nMean & SD accuracy: \n")
print(cv_train.mean(), cv_test.mean())
print(cv_train.std(), cv_test.std())
print("\nPercent accuracy within each fold (Second): \n")
print(cv_train2, "\n", cv_test2)
print("\nMean & SD accuracy: \n")
print(cv_train2.mean(), cv_test2.mean())
print(cv_train2.std(), cv_test2.std())
cv_labels = cross_val_predict(svc, x_test, y_test, cv=10)
cv_labels2 = cross_val_predict(svc_2, x_test, y2_test, cv=10)
accuracy = accuracy.append([["SVM", (cv_train.mean()), (cv_test.mean())]])
accuracy2 = accuracy2.append([["SVM", (cv_train2.mean()), (cv_test2.mean())]])
     Percent accuracy within each fold (First):
     [0.75427328 0.75530923 0.75435143 0.75528388 0.75528388 0.75590551
      0.75600912 0.75507667 0.75777041 0.75497306]
      [0.75144988 0.75217571 0.75217571 0.75259014 0.75176129 0.75341898
      0.75300456 0.75134687 0.75259014 0.75217571]
     Mean & SD accuracy:
     0.7554236470937297 0.752268899715055
     0.0009450310292319527 0.0006224884138372644
     Percent accuracy within each fold (Second):
     [0.7677406  0.76680825  0.76844177  0.76719851  0.77206797  0.76792375
      0.76906341 0.76875259 0.76947783 0.76989225]
      [0.76594863 0.75839204 0.77248239 0.7670949 0.77041028 0.76626606
      0.76999586 0.76336511 0.76295068 0.76585164]
     Mean & SD accuracy:
     0.768736691371271 0.7662757584486957
     0.0014461655059533117 0.003899930540227518
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot
from sklearn.svm import SVC
# fit a model
model_2 = SVC()
model_2.fit(x_train, y2_train)
# predict probabilities
dtc_probs = model_2.predict_proba(x_test)
# keep probabilities for the positive outcome only
dtc probs = dtc probs[:, 1]
# calculate scores
dtc_auc = roc_auc_score(y2_test, dtc_probs)
# summarize scores
print('Decision Tree: ROC AUC=%.3f' % (dtc_auc))
# calculate roc curves
dtc_fpr, dtc_tpr, _ = roc_curve(y2_test, dtc_probs)
# plot the roc curve for the model
pyplot.plot(dtc_fpr, dtc_tpr, marker='.', label='Decision Tree')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
```

```
Traceback (most recent call last)
    AttributeError
     <ipython-input-12-695de4de1df7> in <module>
           9 model_2.fit(x_train, y2_train)
          10 # predict probabilities
     ---> 11 dtc probs = model 2.predict proba(x test)
          12 # keep probabilities for the positive outcome only
          13 dtc_probs = dtc_probs[:, 1]
                                     - 💲 1 frames -
     /usr/local/lib/python3.8/dist-packages/sklearn/svm/_base.py in _check_proba(self)
                def _check_proba(self):
         798
                    if not self.probability:
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
clf = KNeighborsClassifier(n_neighbors = 8)
clf2 = KNeighborsClassifier(n_neighbors = 2)
clf.fit(x_train, y_train)
clf2.fit(x_train, y2_train)
print("Accuracy on training set: {:.3f}".format(clf.score(x_train, y_train)))
print("Accuracy on test set: {:.3f}".format(clf.score(x_test, y_test)))
print("Accuracy on training set (Child loss): {:.3f}".format(clf2.score(x_train, y2_train)))
print("Accuracy on test set (Child loss): {:.3f}".format(clf2.score(x_test, y2_test)))
cv_train = cross_val_score(clf, x_train, y_train, cv = 10, scoring = "accuracy")
cv_test = cross_val_score(clf, x_test, y_test, cv = 10, scoring = "accuracy")
cv_train2 = cross_val_score(clf2, x_train, y2_train, cv = 10, scoring = "accuracy")
cv_test2 = cross_val_score(clf2, x_test, y2_test, cv = 10, scoring = "accuracy")
print("Percent accuracy within each fold (First): \n")
print(cv_train, "\n", cv_test)
print("\nMean & SD accuracy: \n")
print(cv_train.mean(), cv_test.mean())
print(cv_train.std(), cv_test.std())
print("\nPercent accuracy within each fold (Second): \n")
print(cv_train2, "\n", cv_test2)
print("\nMean & SD accuracy: \n")
print(cv_train2.mean(), cv_test2.mean())
print(cv_train2.std(), cv_test2.std())
cv_labels = cross_val_predict(clf, x_test, y_test, cv=10)
cv_labels2 = cross_val_predict(clf2, x_test, y2_test, cv=10)
accuracy = accuracy.append([["KNN", (cv_train.mean()), (cv_test.mean())]])
accuracy2 = accuracy2.append([["KNN", (cv_train2.mean()), (cv_test2.mean())]])
```

```
Accuracy on training set: 0.759
Accuracy on test set: 0.748
Accuracy on training set (Child loss): 0.775
Accuracy on test set (Child loss): 0.758
Percent accuracy within each fold (First):
[0.74484616\ 0.73572982\ 0.73767095\ 0.74181517\ 0.74316204\ 0.74823871
 0.74005387 0.74564857 0.74254041 0.74088272]
 [0.74606462 0.7405719 0.74140075 0.74264401 0.75217571 0.74388728
 0.74761707 0.74595939 0.7405719 0.74264401]
Mean & SD accuracy:
0.7420588419396318 0.7443536649555311
0.0035364894759353153 0.003474572792013889
Percent accuracy within each fold (Second):
[0.7518906  0.74743603  0.7555947  0.7537298  0.75580191  0.75435143
 0.75145048 0.7594281 0.75528388 0.75300456]
 [0.74606462 0.75051803 0.7480315 0.74595939 0.75051803 0.75134687
 0.75922089 0.74098632 0.74388728 0.74720265]
Mean & SD accuracy:
0.7537971474654559 0.748373557205842
0.0030284279033088975 0.004722795807931974
                                            Traceback (most recent call last)
<ipython-input-8-d594213c5a2b> in <module>
     36 cv_labels2 = cross_val_predict(clf2, x_test, y2_test, cv=10)
---> 38 accuracy = accuracy.append([["KNN", (cv_train.mean()), (cv_test.mean())]])
39 accuracy2 = accuracy2.append([["KNN", (cv_train2.mean()), (cv_test2.mean())]])
NameError: name 'accuracy' is not defined
```

• >