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Homework 4

CSCE 421 500

November 30, 2022

Question: Predicting one's hireability based on their job interview

(1) (1.5 point) Decision tree: Use a decision tree to estimate each interviewee's hirability score based on their physiological and vocal measures. Use 3-fold cross-validation, according to which you will randomly assign each sample (i.e., participant) to one fold. Please collect the estimated hirability score on the test data from each fold. After all, folds are done, please report the average absolute error across all folds. Experiment with 3-4 values of the tree depth and report the results.
Note: All folds will not have the same number of samples.

Code

General Libraries

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
import warnings
warnings.filterwarnings('ignore')
```

Data

```
#Read the data from 'data.csv' and dropna
dataset= pd.read_csv('data.csv')
dataset = dataset.dropna()
dataset
```

	PID	SCL	SCRamp	SCRfreq	HRmean	ACCmean	Energy	ZCR	VoiceProb	Hirability
0	P1	0.827077	0.094424	2.898792	73.276206	66.491987	0.005447	0.120261	0.403078	4
1	P2	5.183890	0.244549	5.219806	102.502828	65.031908	0.005782	0.074726	0.457309	5
3	P4	0.211715	0.008790	2.299042	80.258785	65.260810	0.006127	0.091186	0.437544	3
4	P5	0.082192	0.011505	1.299459	71.348170	66.607203	0.005081	0.076909	0.374498	4
5	P6	0.517391	0.029026	3.098709	67.658486	64.071636	0.004374	0.076218	0.423185	4
6	P7	4.811771	0.149931	6.972349	95.436294	65.195180	0.004903	0.052587	0.423719	5
7	P8	0.196216	0.035307	0.799667	52.604792	65.468119	0.003720	0.074693	0.456545	4
8	P9	0.342106	0.010594	1.099542	83.181398	63.967582	0.005858	0.114835	0.424477	4
9	P10	0.408798	0.042047	1.999167	62.833577	65.411525	0.006067	0.095510	0.548340	5
10	P11	1.388692	0.072733	5.097876	67.133943	66.474274	0.007599	0.097902	0.399308	5
11	P12	6.382972	0.136715	12.540704	85.995250	64.769594	0.004456	0.085148	0.389516	3
12	P13	0.027574	0.005786	0.181749	66.809818	64.340107	0.009299	0.107363	0.395502	5

Data Preprocessing

```
#split the dataframe
x = dataset.values[:, 2:9]
y = dataset.values[:, 9]
y=y.astype('int')

#split the data
xtrain, xtest, ytrain, ytest =train_test_split(x, y, test_size = 0.3, random_state = 100)
```

Decision Tree (Scores and MAE)

```
#libraries
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import accuracy_score
from sklearn import tree

#decision tree classifier- 3 fold cross validation
depth = []
for i in range(1,4):
    clf = tree.DecisionTreeClassifier(criterion = "entropy", random_state = 42, max_depth = i)
    print(clf)
    # Perform 3-fold cross validation
    scores = cross_val_score(estimator=clf, X=x, y=y, cv=3, n_jobs=5)
    depth.append((scores.mean()))
print("Scores: ", depth)

clf.fit(xtrain, ytrain)
y_pred = clf.predict(xtest)

#decision tree regressor
dtr = DecisionTreeRegressor(random_state=42, max_depth=1)
dtr.fit(xtrain, ytrain)
y_pred = dtr.predict(xtest)
mae = mean_absolute_error(ytest, y_pred)
print("Mean Absolute Error: {:.3f}".format(mae))
```

Output

```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=1,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=42, splitter='best')
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=2,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=42, splitter='best')
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=42, splitter='best')
Scores:  [0.20000000000000004, 0.3, 0.3]
Mean Absolute Error: 0.917
```

Reflections

For this part I utilized the decision tree classifier and regressor to train the data and get the scores when the max depth of the trees are different.

(2) (1 point) Decision tree visualization: Provide a plot of the root, nodes, and decision boundaries of the best decision tree. Briefly discuss the resulting model.

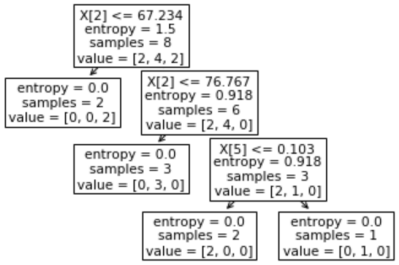
Code

Plot (clf)

```
tree.plot_tree(clf)
```

Output

```
[Text(111.60000000000001, 190.26, 'X[2] <= 67.234\nentropy = 1.5\nsamples = 8\nvalue = [2, 4, 2]'),
 Text(55.800000000000004, 135.9, 'entropy = 0.0\nsamples = 2\nvalue = [0, 0, 2]'),
 Text(167.4, 135.9, 'X[2] <= 76.767\nentropy = 0.918\nsamples = 6\nvalue = [2, 4, 0]'),
 Text(111.60000000000001, 81.53999999999999, 'entropy = 0.0\nsamples = 3\nvalue = [0, 3, 0]'),
 Text(223.20000000000002, 81.53999999999999, 'X[5] <= 0.103\nentropy = 0.918\nsamples = 3\nvalue = [2, 1, 0]'),
 Text(167.4, 27.180000000000007, 'entropy = 0.0\nsamples = 2\nvalue = [2, 0, 0]'),
 Text(279.0, 27.180000000000007, 'entropy = 0.0\nsamples = 1\nvalue = [0, 1, 0]')]
```



Reflections

The tree has a few important components which include the leaf node, root node and branches. In this we let the leaf nodes, which is the criteria be "entropy" and the sample sizes vary. We can also see that the branches are connected from the right hand side to get to the target values.

(3) (1.5 points) Random forest: Repeat the same task as in question (2) using a random forest. Experiment with 3-4 different values of the number of trees. Compare and contrast the performance of the decision tree with the random forest.

Code

Data Preprocessing

```
#Data preprocessing
x = dataset.values[:, 2:9]
y = dataset.values[:, 9]
y=y.astype('int')

#split the data
x_train, x_test, y_train, y_test =train_test_split(x, y, test_size = 0.3, random_state = 42)
```

Random Forest Classifier/ Regressor (MAE)

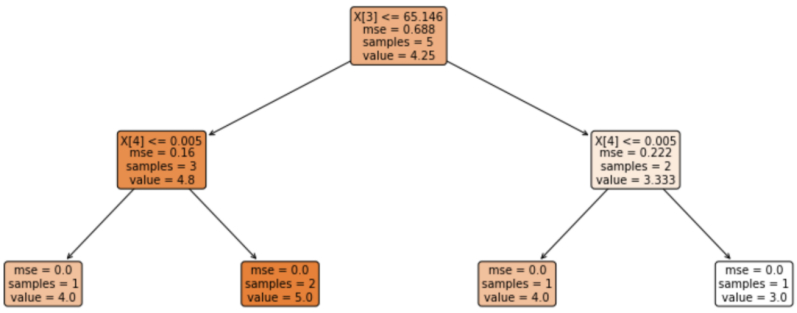
```
#Random forest classifier
trees = [5, 10, 15]
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
from sklearn.metrics import mean_absolute_error

for i in trees:
    rfc = RandomForestClassifier(n_estimators=i, max_depth=3,random_state=42)
    print(rfc)
    rfc.fit(x_train, y_train)
    y_pred = rfc.predict(x_test)
    #print(accuracy_score(y_test, y_pred))

first_tree = rfr.estimators_[0]
plt.figure(figsize=(15,6))
tree.plot_tree(first_tree,fontsize=10,filled=True, rounded=True)

second_tree = rfr.estimators_[1]
plt.figure(figsize=(15,6))
tree.plot_tree(second_tree,fontsize=10,filled=True, rounded=True)

third_tree = rfr.estimators_[2]
plt.figure(figsize=(15,6))
tree.plot_tree(third_tree,fontsize=10,filled=True, rounded=True)

#Random forest regressor
for i in trees:
    rfr = RandomForestRegressor(n_estimators= i, max_depth=3, random_state=42)

    rfr.fit(x_train, y_train)
    y_pred = rfr.predict(x_test)
    print(i, "Trees")
    print('Mean Absolute Error:', mean_absolute_error(y_test, y_pred))
```

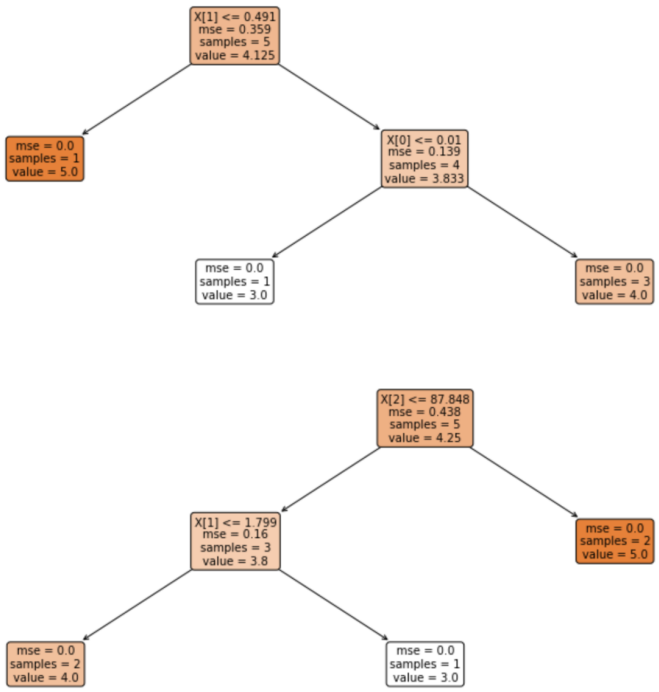
Output

MAE for different number of trees

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=3, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=5,
                       n_jobs=None, oob_score=False, random_state=42, verbose=0,
                       warm_start=False)
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=3, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10,
                       n_jobs=None, oob_score=False, random_state=42, verbose=0,
                       warm_start=False)
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=3, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=15,
                       n_jobs=None, oob_score=False, random_state=42, verbose=0,
                       warm_start=False)
5 Trees
Mean Absolute Error: 1.1
10 Trees
Mean Absolute Error: 1.0250000000000001
15 Trees
Mean Absolute Error: 1.0666666666666669
```

Graphs for the trees





Reflections

Compare and contrast the performance of the decision tree with the random forest.

From the results of the random forest, we know that using the random forest algorithm is unbiased. Because there is more than one tree, and each tree is trained on random training data sets, the overall chance of bias is low compared to decision trees, and we can see this based on the plots.
Within the different tree sizes for random forest above, the average accuracies were similar, so I plotted all the trees.