

ps8

March 11, 2019

1. Decision trees

```
In [2]: import pandas as pd
        biden = pd.read_csv("biden.txt")
        biden.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1807 entries, 0 to 1806
Data columns (total 6 columns):
biden      1807 non-null int64
female     1807 non-null int64
age        1807 non-null int64
educ       1807 non-null int64
dem        1807 non-null int64
rep        1807 non-null int64
dtypes: int64(6)
memory usage: 84.8 KB
```

(a)

```
In [4]: from sklearn.model_selection import train_test_split
        from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier
        import numpy as np
        X = biden[["female", "age", "educ", "dem", "rep"]].values
        y = biden["biden"].values
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state=42)
        biden_tree = DecisionTreeRegressor(max_depth=3, min_samples_leaf=5)
        biden_tree.fit(X_train, y_train)
```

```
Out[4]: DecisionTreeRegressor(criterion='mse', max_depth=3, max_features=None,
                               max_leaf_nodes=None, min_impurity_decrease=0.0,
                               min_impurity_split=None, min_samples_leaf=5,
                               min_samples_split=2, min_weight_fraction_leaf=0.0,
                               presort=False, random_state=None, splitter='best')
```

```
In [57]: from sklearn.tree import export_graphviz
          import graphviz
```

```

import pydotplus
biden_tree_viz = export_graphviz(
    biden_tree,
    out_file=None,
    feature_names=["female", "age", "educ", "dem", "rep"],
    class_names=biden.biden,
    rounded=True,
    filled=True,
)

pydot_graph = pydotplus.graph_from_dot_data(biden_tree_viz)
pydot_graph.set_size('8,8!')
pydot_graph.write_png('resized_tree.png')

```

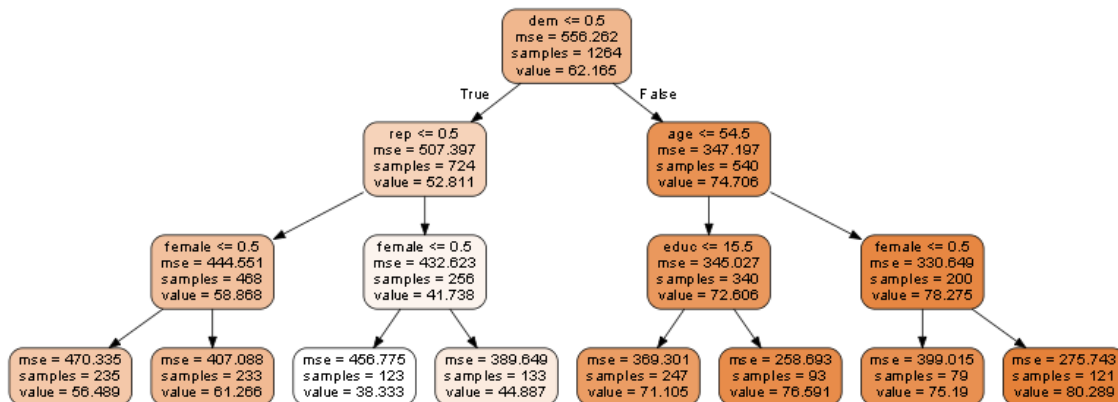
Out [57]: True

```

In [58]: from IPython.display import Image
         Image(filename='resized_tree.png')

```

Out [58]:



```

In [12]: from sklearn.metrics import mean_squared_error
         y_pred = biden_tree.predict(X_test)
         MSE1 = mean_squared_error(y_test, y_pred)
         print('test MSE=', MSE1)

```

test MSE= 396.1937146321307

The binary decision tree splits the predictors into eight leaves. The mse on test set is around 396.19. The first predictor is dem, which indicates affiliation with Democrats. The left branch of the first node contains people who are not affiliated with Democratic Party and the right who are affiliated with Democratic Party. The second predictor of the left branch is rep, which indicates whether the respondent is affiliated with Republicans. The following predictors have the similar mode. The mses in the final eight leaves are mainly between 35 and 85.

(b)

```
In [15]: from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
param_dist1 = {'max_depth': [3, 10],
               'min_samples_split': sp_randint(2, 20),
               'min_samples_leaf': sp_randint(2, 20)}
random_search = RandomizedSearchCV(DecisionTreeRegressor(), param_distributions=param_dist1,
                                   n_iter=100, n_jobs=-1, cv=5, random_state=25, scoring='neg_mean_squared_error')
rs_fit1 = random_search.fit(X_train, y_train)
print(rs_fit1.best_params_)
print('MSE = ', abs(rs_fit1.best_score_))#best_score_ can be negative

{'max_depth': 3, 'min_samples_leaf': 2, 'min_samples_split': 9}
MSE = 404.7488359884144
```

(c)

```
In [17]: from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
param_dist2 = {"n_estimators": [10, 200],
               "max_depth": [3, 10],
               "min_samples_split": sp_randint(2, 20),
               "min_samples_leaf": sp_randint(2, 20),
               "max_features": sp_randint(1, 5)}
random_search2 = RandomizedSearchCV(RandomForestRegressor(), param_distributions=param_dist2,
                                     n_iter=100, n_jobs=-1, cv=5, random_state=25, scoring='neg_mean_squared_error')
rs_fit2 = random_search2.fit(X_train, y_train)
print(rs_fit2.best_params_)
print('MSE = ', abs(rs_fit2.best_score_))#best_score_ can be negative

{'max_depth': 3, 'max_features': 3, 'min_samples_leaf': 17, 'min_samples_split': 12, 'n_estimators': 100}
MSE = 397.89422745189773
```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection_search.py:841: DeprecationWarning: DeprecationWarning)

2. Classifier “horse” race

```
In [21]: auto=pd.read_csv("Auto.csv", na_values='?')
auto.head()
```

```
Out[21]:
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	\
0	18.0	8	307.0	130.0	3504	12.0	70	
1	15.0	8	350.0	165.0	3693	11.5	70	
2	18.0	8	318.0	150.0	3436	11.0	70	
3	16.0	8	304.0	150.0	3433	12.0	70	
4	17.0	8	302.0	140.0	3449	10.5	70	

	origin		name
0	1	chevrolet	chevelle malibu
1	1	buick	skylark 320
2	1	plymouth	satellite
3	1	amc	rebel sst
4	1	ford	torino

```
In [25]: auto['mpg_high'] = (auto['mpg']>=auto['mpg'].median()).astype('int')
auto.dropna(inplace=True)
auto["orgn1"]=np.where(auto["origin"]==1,1,0)
auto["orgn2"]=np.where(auto["origin"]==2,1,0)
auto["constant"]=1
auto.head()
```

```
Out [25]:
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	\
0	18.0	8	307.0	130.0	3504	12.0	70	
1	15.0	8	350.0	165.0	3693	11.5	70	
2	18.0	8	318.0	150.0	3436	11.0	70	
3	16.0	8	304.0	150.0	3433	12.0	70	
4	17.0	8	302.0	140.0	3449	10.5	70	

	origin		name	mpg_high	orgn1	orgn2	constant
0	1	chevrolet	chevelle malibu	0	1	0	1
1	1	buick	skylark 320	0	1	0	1
2	1	plymouth	satellite	0	1	0	1
3	1	amc	rebel sst	0	1	0	1
4	1	ford	torino	0	1	0	1

(a)

```
In [29]: from sklearn.linear_model import LogisticRegression
yvals = auto["mpg_high"].values
Xvars=auto[["constant","cylinders","displacement","horsepower",
            "weight","acceleration","year","orgn1","orgn2"]].values
logit = LogisticRegression().fit(Xvars,yvals)
logit.coef_
```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarning
FutureWarning)

```
Out [29]: array([[ -0.07294486,  -0.09530101,  -0.00121801,  -0.07133085,  -0.00331596,
                   -0.19412659,   0.26596842,  -0.34333934,   0.27100873]])
```

```
In [31]: from sklearn.model_selection import KFold
from sklearn.metrics import classification_report
kf_log = KFold(n_splits=4, shuffle=True, random_state=25)
kf_log.get_n_splits(Xvars)
MSE_vec_kf = np.zeros(4)
```

```

ytest_vec = np.zeros(auto.shape[0])
ypred_vec = np.zeros(auto.shape[0])
k_ind = int(0)

for train_index, test_index in kf_log.split(Xvars):
    X_train, X_test = Xvars[train_index], Xvars[test_index]
    y_train, y_test = yvals[train_index], yvals[test_index]
    Logit = LogisticRegression()
    Logit.fit(X_train, y_train)
    y_pred = Logit.predict(X_test)
    ytest_vec[test_index] = y_test
    ypred_vec[test_index] = y_pred
    MSE_vec_kf[k_ind] = (y_test != y_pred).mean()
    print('MSE for test set', k_ind, ' is', MSE_vec_kf[k_ind])
    k_ind += 1

MSE_kf = MSE_vec_kf.mean()
print('Test estimate MSE k-fold = {}'.format(MSE_kf))
print(classification_report(ytest_vec, ypred_vec))

```

```

MSE for test set 0 is 0.14285714285714285
MSE for test set 1 is 0.09183673469387756
MSE for test set 2 is 0.07142857142857142
MSE for test set 3 is 0.08163265306122448
Test estimate MSE k-fold = 0.09693877551020408.

```

	precision	recall	f1-score	support
0.0	0.92	0.89	0.90	196
1.0	0.89	0.92	0.90	196
micro avg	0.90	0.90	0.90	392
macro avg	0.90	0.90	0.90	392
weighted avg	0.90	0.90	0.90	392

```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarning
FutureWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarning
FutureWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarning
FutureWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarning
FutureWarning)

```

Therefore, the error rate for mpg_high=0 is $1 - 0.92 = 0.08$. The error rate for mpg_high=1 is $1 - 0.89 = 0.11$.

(b)

```
In [36]: param_dist3 = {"n_estimators": [10, 200],
                        "max_depth": [3, 8],
                        "min_samples_split": sp_randint(2, 20),
                        "min_samples_leaf": sp_randint(2, 20),
                        "max_features": sp_randint(1, 8)}
random_search3 = RandomizedSearchCV(RandomForestRegressor(), param_distributions=param_dist3,
                                    n_iter=100, n_jobs=-1, cv=4, random_state=25, scoring='neg_mean_squared_error')
rs_fit3 = random_search3.fit(Xvars, yvals)
print(rs_fit3.best_params_)
print('MSE = ', abs(rs_fit3.best_score_))

{'max_depth': 8, 'max_features': 3, 'min_samples_leaf': 15, 'min_samples_split': 2, 'n_estimators': 10}
MSE = 0.09062757253378131
```

(c)

```
In [39]: from scipy.stats import uniform as sp_uniform
         from sklearn.svm import SVC
param_dist4 = {"C": sp_uniform(loc=0.2, scale=4.0),
               "gamma": ["scale", "auto"],
               "shrinking": [True, False]}
random_search4 = RandomizedSearchCV(SVC(kernel='rbf'), param_distributions=param_dist4,
                                    n_iter=100, n_jobs=-1, cv=4, random_state=25, scoring='neg_mean_squared_error')
rs_fit4 = random_search4.fit(Xvars, yvals)
print(rs_fit4.best_params_)
print('MSE = ', abs(rs_fit4.best_score_))

{'C': 1.1775180640974197, 'gamma': 'scale', 'shrinking': False}
MSE = 0.11734693877551021
```

(d)

Comparing the mse of each model, I think the random forest model is the best predictor of mpg high since its mse is around 0.090, which is the smallest.

In []: