Predicting IBM Employee Attrition Python Jupyter Notebook

Part 4 - Build a Decision Tree Model

Import numpy and pandas.

In [1]:
```
import numpy as np
import pandas as pd
```

Import data visualization libraries and set %matplotlib inline.

In [2]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Import churn modeling pickle file into a Pandas dataframe called churn_model2.

In [3]:
```
churn_model2 = pd.read_pickle('../data/churn_modeling_data.pickle')
```

Define X and y to split data into training and test data sets, and construct decision tree model.

In [4]:
```
X = churn_model2.drop(['Churn'], axis=1)
y = churn_model2['Churn']
```

Tune decision tree model to avoid overfitting.

In [5]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.cross_validation import cross_val_score
```

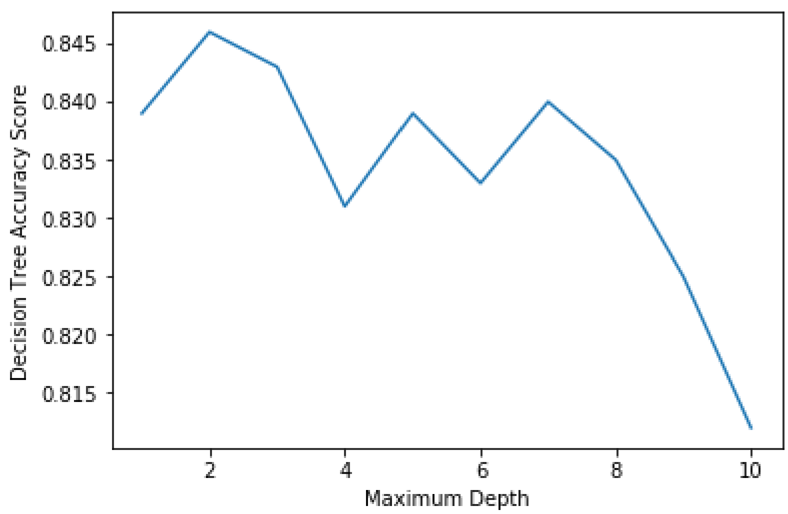
```
C:\Users\kyrma\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\cros
s_validation.py:41: DeprecationWarning: This module was deprecated in version
0.18 in favor of the model_selection module into which all the refactored class
es and functions are moved. Also note that the interface of the new CV iterator
s are different from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [6]:
```
max_depth_range1 = range(1, 11)

acc_scores3 = []

for depth in max_depth_range1:
    treereg = DecisionTreeClassifier(max_depth=depth, random_state=123)
    scores3 = cross_val_score(treereg, X, y, cv=14, scoring='accuracy')
    acc_scores3.append(scores3.mean().round(3))

print(acc_scores3)
```

```
[0.839, 0.846, 0.843, 0.831, 0.839, 0.833, 0.84, 0.835, 0.825, 0.812]
```

In [7]:
```
plt.plot(max_depth_range1, acc_scores3)
plt.xlabel('Maximum Depth')
plt.ylabel('Decision Tree Accuracy Score')
```

Out[7]:
```
Text(0,0.5,'Decision Tree Accuracy Score')
```



- The maximum depth of the decision tree should be 2 since the tree has the maximum accuracy score of 0.846.

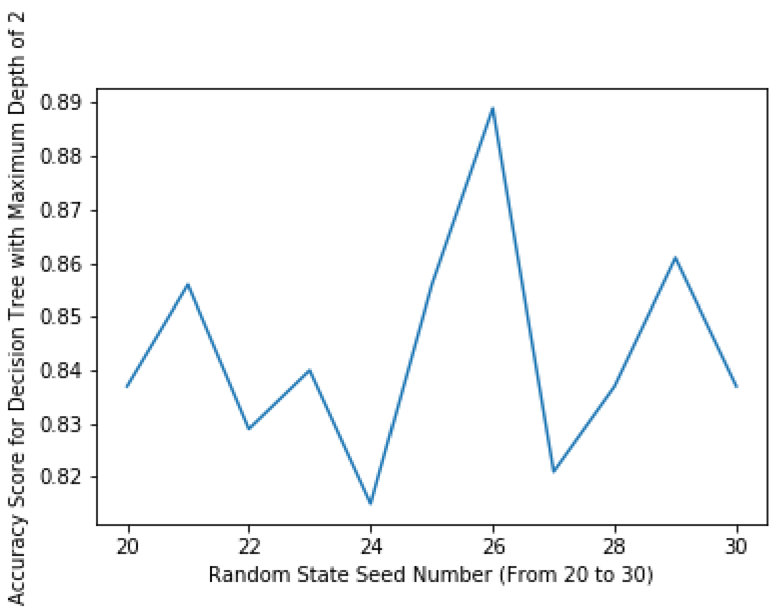
Decide which random state seed number will produce the highest accuracy score for a decision tree with a maximum depth of 2.

In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn import metrics
```

In [9]:
```
seed_range2 = range(20, 31)

acc_scores4 = []

for seed in seed_range2:
    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=seed)
    treereg = DecisionTreeClassifier(max_depth=2, random_state=123)
    treereg.fit(X_train, y_train)
    y_pred = treereg.predict(X_test)
    acc_scores4.append(metrics.accuracy_score(y_test, y_pred).round(3))
```

In [10]:
```
plt.plot(seed_range2, acc_scores4)
plt.xlabel('Random State Seed Number (From 20 to 30)')
plt.ylabel('Accuracy Score for Decision Tree with Maximum Depth of 2')
```

Out[10]:
```
Text(0,0.5,'Accuracy Score for Decision Tree with Maximum Depth of 2')
```



- 26 is the random state seed number that will produce the highest accuracy score for the decision tree with a maximum depth of 2.

Split churn / attrition modeling data into training and test sets.

In [11]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=26)
```

In [12]:
```
print(churn_model2.shape)
print(X_train.shape)
print(X_test.shape)
```

```
(1470, 11)
(1102, 10)
(368, 10)
```

Fit a decision tree with maximum depth of 2 on training data set.

In [13]:
```
treereg = DecisionTreeClassifier(max_depth=2, random_state=123)
treereg.fit(X_train, y_train)
```

Out[13]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', 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=123,
            splitter='best')
```

Make predictions on test data set and calculate accuracy.

In [14]:
```
y_pred = treereg.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred).round(3))
```

```
0.889
```

Compute null accuracy manually.

In [15]:
```
print(1 - y_test.mean())
```

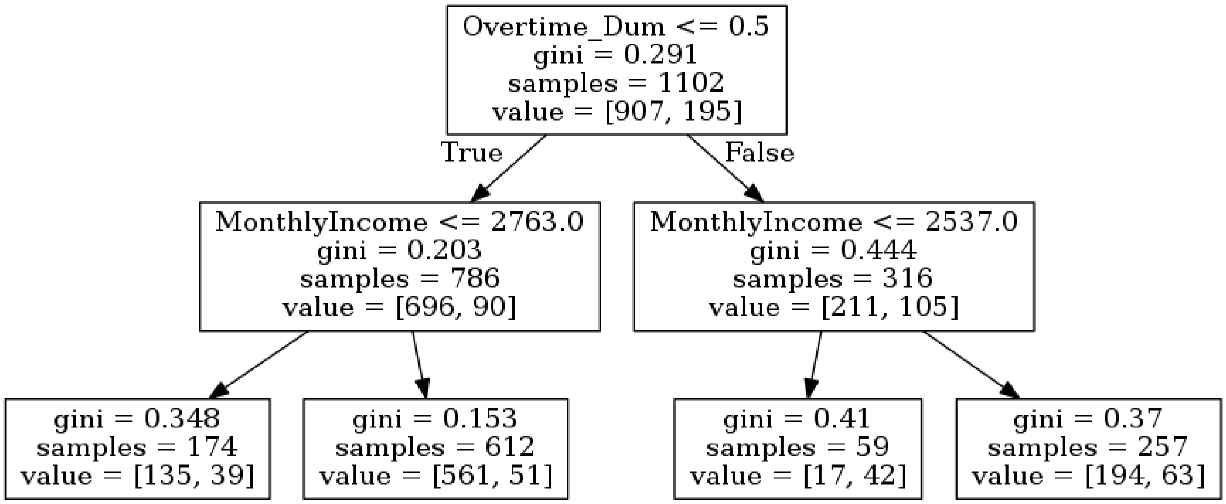
```
0.8858695652173914
```

Create GraphViz file of decision tree and display it in the notebook.

In [16]:
```
from sklearn.tree import export_graphviz
from IPython.display import Image
from IPython.display import display
```

In [17]:
```
feature_cols = ['Age', 'DistanceFromHome', 'EnvironmentSatisfaction', 'JobInvolve
                'Sales_Rep', 'Single', 'BusTravLevel', 'Overtime_Dum']
export_graphviz(treereg, out_file='Churn_Decision_Tree.dot', feature_names=featur
```

In [18]:
```
display(Image('Churn_Decision_Tree.png'))
```



List out decision tree predictor features and their respective importances.

In [19]:
```
pd.DataFrame({'feature':feature_cols, 'importance':treereg.feature_importances_})
```

Out[19]:

	feature	importance
4	MonthlyIncome	0.551401
9	Overtime_Dum	0.448599
0	Age	0.000000
1	DistanceFromHome	0.000000
2	EnvironmentSatisfaction	0.000000
3	JobInvolvement	0.000000
5	StockOptionLevel	0.000000
6	Sales_Rep	0.000000
7	Single	0.000000
8	BusTravLevel	0.000000

Print confusion matrix to calculate accuracy and error rates plus precision and recall.

In [20]:
```
print(metrics.confusion_matrix(y_test, y_pred))
```

```
[[320   6]
 [ 35   7]]
```

Calculate accuracy rate.

In [21]:
```
float(320 + 7) / float(320 + 6 + 35 + 7)
```

Out[21]: 0.8885869565217391

Calculate misclassification / error rate.

In [22]:
```
float(35 + 6) / float(320 + 6 + 35 + 7)
```

Out[22]: 0.11141304347826086

Calculate precision to measure how confident the decision tree model is for capturing the positives.

In [23]:
```
float(7) / float(6 + 7)
```

Out[23]: 0.5384615384615384

Calculate recall / sensitivity to measure how well the decision tree model is capturing the positives.

In [24]:
```
float(7) / float(35 + 7)
```

Out[24]: 0.16666666666666666

Calculate specificity to measure how well the decision tree model is capturing the negatives.

In [25]:
```
float(320) / float(320 + 6)
```

Out[25]: 0.9815950920245399

List out false positives in test data set.

In [26]:
```
X_test[y_test < y_pred]
```

Out[26]:

	Age	DistanceFromHome	EnvironmentSatisfaction	JobInvolvement	MonthlyIncome	StockOpti
1402	31	2	3	0	1129	
1028	41	5	1	3	2127	
925	42	7	1	3	2372	
889	27	14	0	2	2235	
1087	34	7	1	2	2308	
632	42	2	1	2	2515	

List out false negatives in test data set.

In [27]:
```
X_test[y_test > y_pred]
```

Out[27]:

	Age	DistanceFromHome	EnvironmentSatisfaction	JobInvolvement	MonthlyIncome	StockOpti
1223	47	9	2	0	12936	
469	32	11	3	3	4707	
264	28	2	0	2	3485	
182	41	20	1	2	3140	
1438	23	9	3	2	1790	
849	43	9	0	0	5346	
50	48	1	0	1	5381	
1167	35	15	0	0	5440	
568	55	2	3	2	19859	
1379	27	22	0	1	2863	
562	33	1	3	2	2686	
1112	38	2	2	2	4855	
363	33	5	3	2	2851	
414	24	1	0	2	3202	
525	24	3	0	2	4577	
111	34	7	0	0	6074	
689	20	4	0	2	2973	
667	41	2	1	0	2778	
1365	29	24	2	3	1091	
980	31	2	2	1	2785	
1036	31	2	1	2	3722	
69	36	9	3	1	3388	
777	21	10	2	1	1416	
1162	35	10	3	1	10306	
761	36	15	0	2	4834	
1085	31	3	3	2	4084	
1395	31	26	0	2	5617	
1452	50	1	1	2	6728	
928	44	15	0	2	7978	
102	20	6	3	1	2926	
1031	46	9	0	2	10096	
693	36	3	2	1	10325	
662	20	2	2	1	2044	
656	32	25	0	2	2795	

	Age	DistanceFromHome	EnvironmentSatisfaction	JobInvolvement	MonthlyIncome	StockOpti
939	32	7	3	2	4883	