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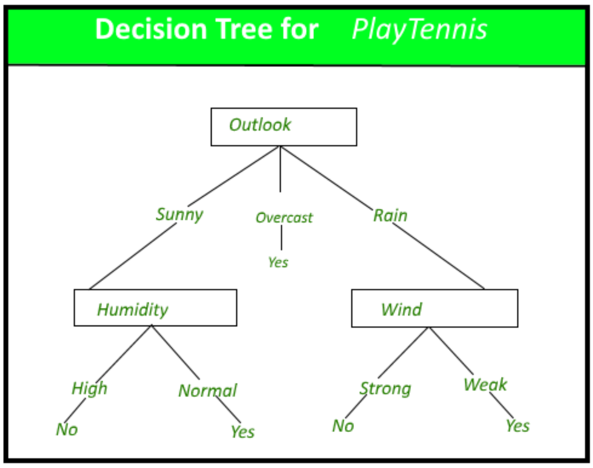
|---|
| Experiment No. 3 |
| Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model |
| Date of Performance: 14/08/23 |
| Date of Submission: 22/08/23 |

**Aim:** Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model.

**Objective:** To perform various feature engineering tasks, apply Decision Tree Algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score. Improve the performance by performing different data engineering and feature engineering tasks.

**Theory:**

Decision Tree is the most powerful and popular tool for classification and prediction. A Decision tree is a flowchart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.




**Dataset:**

Predict whether income exceeds $50K/yr based on census data. Also known as "Adult" dataset.

Attribute Information:

Listing of attributes:

>50K, <=50K.

age: continuous.

workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.

fnlwgt: continuous.

education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.

education-num: continuous.

marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.

occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.

relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.

race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.

sex: Female, Male.

capital-gain: continuous.

capital-loss: continuous.

hours-per-week: continuous.

native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

**Code:**

**Conclusion:**

Most features have low correlations, indicating they offer distinct predictive information, reducing redundancy in the dataset.

Accuracy is 84.58%.

In terms of precision, recall, and F1-Score, Random Forest exhibited a more balanced trade off between precision and recall, whereas Decision Tree tended to prioritize one metric over the other. Additionally, Random Forest's ensemble approach facilitated better generalization, mitigating overfitting risks compared to Decision Trees, which are more sensitive to data variations. However, Decision Trees trained faster individually, while Random Forest required more time due to its multiple tree ensembl

```
# Import libraries
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# To ignore warning messages
import warnings
warnings.filterwarnings('ignore')
```

```
df=pd.read_csv("adult.csv")
df.head(10)
```

| | age | workclass | fnlwgt | education | education.num | marital.status | occupation | relationship | race | sex | capital.gain | capital.loss |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 90 | ? | 77053 | HS-grad | 9 | Widowed | ? | Not-in-family | White | Female | 0 | 4356 |
| **1** | 82 | Private | 132870 | HS-grad | 9 | Widowed | Exec-managerial | Not-in-family | White | Female | 0 | 4356 |
| **2** | 66 | ? | 186061 | Some-college | 10 | Widowed | ? | Unmarried | Black | Female | 0 | 4356 |
| **3** | 54 | Private | 140359 | 7th-8th | 4 | Divorced | Machine-op-inspct | Unmarried | White | Female | 0 | 3900 |
| **4** | 41 | Private | 264663 | Some-college | 10 | Separated | Prof-specialty | Own-child | White | Female | 0 | 3900 |
| **5** | 34 | Private | 216864 | HS-grad | 9 | Divorced | Other-service | Unmarried | White | Female | 0 | 3770 |
| **6** | 38 | Private | 150601 | 10th | 6 | Separated | Adm-clerical | Unmarried | White | Male | 0 | 3770 |
| **7** | 74 | State-gov | 88638 | Doctorate | 16 | Never-married | Prof-specialty | Other-relative | White | Female | 0 | 3683 |
| **8** | 68 | Federal-gov | 422013 | HS-grad | 9 | Divorced | Prof-specialty | Not-in-family | White | Female | 0 | 3683 |
| **9** | 41 | Private | 70037 | Some-college | 10 | Never-married | Craft-repair | Unmarried | White | Male | 0 | 3004 |

```
print ("Rows     : " ,df.shape[0])
print ("Columns  : " ,df.shape[1])
print ("\nFeatures : \n" ,df.columns.tolist())
print ("\nMissing values :  ", df.isnull().sum().values.sum())
print ("\nUnique values :  \n",df.nunique())
```

```
Rows     :  32561
Columns  :  15

Features :
 ['age', 'workclass', 'fnlwgt', 'education', 'education.num', 'marital.status', 'occupation', 'relationship', 'race', 'sex', 'capital.g

Missing values :   0

Unique values :
 age                  73
workclass             9
fnlwgt            21648
education            16
education.num        16
marital.status        7
occupation           15
relationship          6
race                  5
sex                   2
capital.gain        119
capital.loss         92
hours.per.week       94
native.country       42
income                2
dtype: int64
```

**Preprocessing**

```
# encode categorical variables using label Encoder
from sklearn import preprocessing
df_categorical = df.select_dtypes(include=['object'])
df_categorical.head()
```

| | workclass | education | marital.status | occupation | relationship | race | sex | native.country | income |
|---|---|---|---|---|---|---|---|---|---|
| **0** | ? | HS-grad | Widowed | ? | Not-in-family | White | Female | United-States | <=50K |
| **1** | Private | HS-grad | Widowed | Exec-managerial | Not-in-family | White | Female | United-States | <=50K |
| **2** | ? | Some-college | Widowed | ? | Unmarried | Black | Female | United-States | <=50K |
| **3** | Private | 7th-8th | Divorced | Machine-op-inspct | Unmarried | White | Female | United-States | <=50K |
| **4** | Private | Some-college | Separated | Prof-specialty | Own-child | White | Female | United-States | <=50K |

```
# apply label encoder to df_categorical
le = preprocessing.LabelEncoder()
df_categorical = df_categorical.apply(le.fit_transform)
df_categorical.head()
```

| | workclass | education | marital.status | occupation | relationship | race | sex | native.country | income |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 11 | 6 | 0 | 1 | 4 | 0 | 39 | 0 |
| **1** | 4 | 11 | 6 | 4 | 1 | 4 | 0 | 39 | 0 |
| **2** | 0 | 15 | 6 | 0 | 4 | 2 | 0 | 39 | 0 |
| **3** | 4 | 5 | 0 | 7 | 4 | 4 | 0 | 39 | 0 |
| **4** | 4 | 15 | 5 | 10 | 3 | 4 | 0 | 39 | 0 |

```
# Next, Concatenate df_categorical dataframe with original df (dataframe)
# Drop earlier duplicate columns which had categorical values
df = df.drop(df_categorical.columns,axis=1)
df = pd.concat([df,df_categorical],axis=1)
df.head()
```

| | age | fnlwgt | education.num | capital.gain | capital.loss | hours.per.week | workclass | education | marital.status | occupation | relationshi |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 90 | 77053 | 9 | 0 | 4356 | 40 | 0 | 11 | 6 | 0 | 1 |
| **1** | 82 | 132870 | 9 | 0 | 4356 | 18 | 4 | 11 | 6 | 4 | 1 |
| **2** | 66 | 186061 | 10 | 0 | 4356 | 40 | 0 | 15 | 6 | 0 | 4 |
| **3** | 54 | 140359 | 4 | 0 | 3900 | 40 | 4 | 5 | 0 | 7 | 4 |
| **4** | 41 | 264663 | 10 | 0 | 3900 | 40 | 4 | 15 | 5 | 10 | 3 |

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   fnlwgt          32561 non-null  int64
 2   education.num   32561 non-null  int64
 3   capital.gain    32561 non-null  int64
 4   capital.loss    32561 non-null  int64
 5   hours.per.week  32561 non-null  int64
 6   workclass       32561 non-null  int64
 7   education       32561 non-null  int64
 8   marital.status  32561 non-null  int64
 9   occupation      32561 non-null  int64
 10  relationship    32561 non-null  int64
 11  race            32561 non-null  int64
 12  sex             32561 non-null  int64
 13  native.country  32561 non-null  int64
 14  income          32561 non-null  int64
dtypes: int64(15)
memory usage: 3.7 MB
```

```
# convert target variable income to categorical
df['income'] = df['income'].astype('category')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   fnlwgt          32561 non-null  int64
 2   education.num   32561 non-null  int64
 3   capital.gain    32561 non-null  int64
 4   capital.loss    32561 non-null  int64
 5   hours.per.week  32561 non-null  int64
 6   workclass       32561 non-null  int64
 7   education       32561 non-null  int64
 8   marital.status  32561 non-null  int64
 9   occupation      32561 non-null  int64
 10  relationship    32561 non-null  int64
 11  race            32561 non-null  int64
 12  sex             32561 non-null  int64
 13  native.country  32561 non-null  int64
 14  income          32561 non-null  category
dtypes: category(1), int64(14)
memory usage: 3.5 MB
```

***Model Building***

```
from sklearn.model_selection import train_test_split
X = df.drop('income',axis=1)
y = df['income']
```

```
X.head(3)
```

| | age | fnlwgt | education.num | capital.gain | capital.loss | hours.per.week | workclass | education | marital.status | occupation | relationshi |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 90 | 77053 | 9 | 0 | 4356 | 40 | 0 | 11 | 6 | 0 | 1 |
| **1** | 82 | 132870 | 9 | 0 | 4356 | 18 | 4 | 11 | 6 | 4 | 1 |
| **2** | 66 | 186061 | 10 | 0 | 4356 | 40 | 0 | 15 | 6 | 0 | 4 |

```
y.head(3)
```

```
0    0
1    0
2    0
Name: income, dtype: category
Categories (2, int64): [0, 1]
```

```
#train test split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.30,random_state=99)
X_train.head()
```

| | age | fnlwgt | education.num | capital.gain | capital.loss | hours.per.week | workclass | education | marital.status | occupation | relatior |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **5728** | 30 | 117963 | 13 | 0 | 0 | 40 | 4 | 9 | 2 | 1 | |
| **10700** | 18 | 80564 | 9 | 0 | 0 | 60 | 0 | 11 | 4 | 0 | |
| **29425** | 31 | 242984 | 10 | 0 | 0 | 40 | 4 | 15 | 5 | 6 | |
| **2088** | 37 | 588003 | 13 | 15024 | 0 | 40 | 4 | 9 | 2 | 4 | |
| **16292** | 40 | 170730 | 9 | 0 | 0 | 50 | 4 | 11 | 2 | 3 | |

```
from sklearn.tree import DecisionTreeClassifier
dt_default = DecisionTreeClassifier(max_depth=5)
dt_default.fit(X_train,y_train)
```

```
▾       DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5)
```

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
y_pred_default = dt_default.predict(X_test)
print(classification_report(y_test,y_pred_default))
```

```
              precision    recall  f1-score   support

           0       0.86      0.95      0.90      7475
           1       0.76      0.50      0.60      2294

    accuracy                           0.84      9769
   macro avg       0.81      0.72      0.75      9769
weighted avg       0.84      0.84      0.83      9769
```

```
print(confusion_matrix(y_test,y_pred_default))
print(accuracy_score(y_test,y_pred_default))
```

```
[[7111  364]
 [1154 1140]]
0.8446105026102979
```

```
!pip install pydotplus
```

```
Requirement already satisfied: pydotplus in /usr/local/lib/python3.10/dist-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in /usr/local/lib/python3.10/dist-packages (from pydotplus) (3.1.1)
```

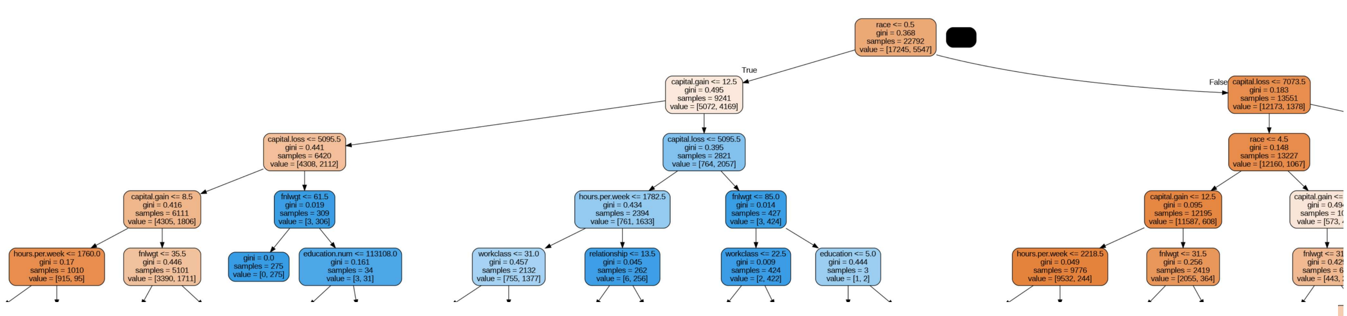
```
from IPython.display import Image
from six import StringIO
from sklearn.tree import export_graphviz
import pydotplus,graphviz

# Putting features
features = list(df.columns[1:])
features
```

```
['fnlwgt',
 'education.num',
 'capital.gain',
 'capital.loss',
 'hours.per.week',
 'workclass',
 'education',
 'marital.status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native.country',
 'income']
```

```
dot_data = StringIO()
export_graphviz(dt_default, out_file=dot_data,
                feature_names=features, filled=True,rounded=True)

graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```




The hyperparameter min_samples_leaf indicates the minimum number of samples required to be at a leaf. So if the values of min_samples_leaf is less, say 5, then the will be constructed even if a leaf has 5, 6 etc. observations (and is likely to overfit). Let's see what will be the optimum value for min_samples_leaf.

```
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
n_folds = 5
parameters = {'min_samples_leaf': range(5, 200, 20)}

dtree = DecisionTreeClassifier(criterion = "gini",random_state = 100)
# fit tree on training data
tree = GridSearchCV(dtree, parameters,cv=n_folds,scoring="accuracy")
tree.fit(X_train, y_train)
```

```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

```
scores = tree.cv_results_
pd.DataFrame(scores).head()
```

| | mean_fit_time | std_fit_time | mean_score_time | std_score_time | param_min_samples_leaf | params | split0_test_score | split1_tes |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.175513 | 0.025540 | 0.006999 | 0.002027 | 5 | {'min_samples_leaf': 5} | 0.828032 | ( |
| 1 | 0.276930 | 0.111199 | 0.009619 | 0.003121 | 25 | {'min_samples_leaf': 25} | 0.843606 | ( |
| 2 | 0.266601 | 0.034173 | 0.012981 | 0.004724 | 45 | {'min_samples_leaf': 45} | 0.850625 | ( |
| 3 | 0.108708 | 0.007625 | 0.010889 | 0.005835 | 65 | {'min_samples_leaf': 65} | 0.850186 | ( |
| 4 | 0.120745 | 0.016959 | 0.011103 | 0.011498 | 85 | {'min_samples_leaf': 85} | 0.849309 | ( |

The hyperparameter min_samples_split is the minimum no. of samples required to split an internal node. Its default value is 2, which means that even if a node is having 2 samples it can be furthur divided into leaf nodes.

```
scores = tree.cv_results_
pd.DataFrame(scores).head()
```

| | mean_fit_time | std_fit_time | mean_score_time | std_score_time | param_min_samples_leaf | params | split0_test_score | split1_tes |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.228439 | 0.065863 | 0.013353 | 0.006299 | 5 | {'min_samples_leaf': 5} | 0.828032 | ( |
| 1 | 0.127333 | 0.016337 | 0.006742 | 0.000326 | 25 | {'min_samples_leaf': 25} | 0.843606 | ( |
| 2 | 0.110355 | 0.018286 | 0.007531 | 0.002102 | 45 | {'min_samples_leaf': 45} | 0.850625 | ( |
| 3 | 0.098082 | 0.006524 | 0.007646 | 0.002988 | 65 | {'min_samples_leaf': 65} | 0.850186 | ( |
| 4 | 0.114428 | 0.034493 | 0.010196 | 0.005237 | 85 | {'min_samples_leaf': 85} | 0.849309 | ( |

### Finding The Optimal Hyperparameters

```
param_grid = {
    'max_depth': range(5, 15, 5),
    'min_samples_leaf': range(50, 150, 50),
    'min_samples_split': range(50, 150, 50),
    'criterion': ["entropy", "gini"]
}
```

```
n_folds = 5
dtree = DecisionTreeClassifier()
grid_search = GridSearchCV(estimator = dtree, param_grid = param_grid,cv = n_folds, verbose = 1)
grid_search.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
▸ DecisionTreeClassifier
```

```
cv_results = pd.DataFrame(grid_search.cv_results_)
cv_results
```

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **3** | 0.042746 | 0.002226 | 0.003615 | 0.000125 | entropy | 5 | 100 |

```
print("best accuracy", grid_search.best_score_)
print(grid_search.best_estimator_)
```

```
best accuracy 0.8530186783184268
DecisionTreeClassifier(max_depth=10, min_samples_leaf=100, min_samples_split=50)
```

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **5** | 0.070040 | 0.004616 | 0.003872 | 0.000332 | entropy | 10 | 50 |

```
clf_gini = DecisionTreeClassifier(criterion = "gini",
                                  random_state = 100,
                                  max_depth=10,
                                  min_samples_leaf=50,
                                  min_samples_split=50)
clf_gini.fit(X_train, y_train)
```

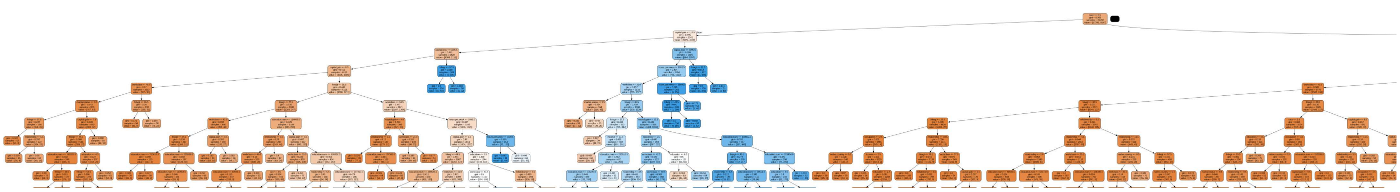
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=10, min_samples_leaf=50, min_samples_split=50,
                       random_state=100)
```

```
clf_gini.score(X_test,y_test)
```

```
0.8520831200737026
```

```
dot_data = StringIO()
export_graphviz(clf_gini, out_file=dot_data,feature_names=features,filled=True,rounded=True)

graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```



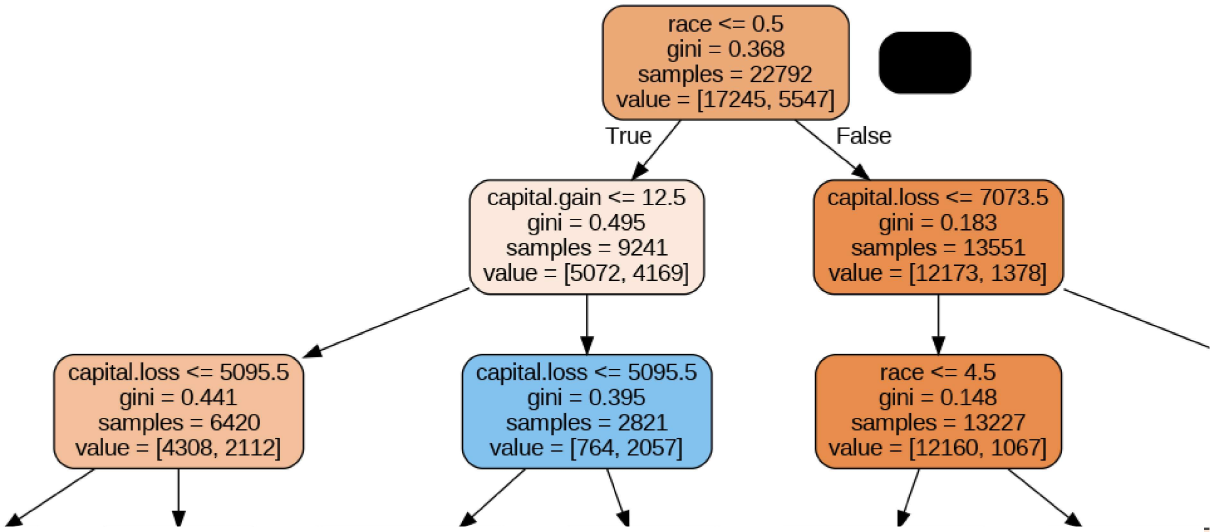
```
# tree with max_depth = 3
clf_gini = DecisionTreeClassifier(criterion = "gini",
                                  random_state = 100,
                                  max_depth=3,
                                  min_samples_leaf=50,
                                  min_samples_split=50)
clf_gini.fit(X_train, y_train)

# score
print(clf_gini.score(X_test,y_test))
```

```
0.8400040945849114
```

```
dot_data = StringIO()
export_graphviz(clf_gini, out_file=dot_data,feature_names=features,filled=True,rounded=True)

graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```




```
from sklearn.metrics import classification_report,confusion_matrix
y_pred = clf_gini.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.95      0.90      7475
           1       0.76      0.47      0.58      2294

    accuracy                           0.84      9769
   macro avg       0.81      0.71      0.74      9769
weighted avg       0.83      0.84      0.83      9769
```

```
print(confusion_matrix(y_test,y_pred))
```

```
[[7136  339]
 [1224 1070]]
```