Decision tree for income.csv

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
import pandas as pd
from matplotlib import style
from matplotlib import pyplot as plt
#import graphviz as gr
%matplotlib inline
style.use("fivethirtyeight")
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
pd.set_option("display.max_columns", 60)
pd.set_option('display.max_rows', 50)
pd.set_option('display.width', 1000)
```

```
import pandas as pd
import numpy as np
income=pd.read_csv("/content/drive/MyDrive/DataMining/Files/income.csv")
income.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   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64
 3   education       32561 non-null  object
 4   education_num   32561 non-null  int64
 5   marital_status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital_gain    32561 non-null  int64
 11  capital_loss    32561 non-null  int64
 12  hours_per_week  32561 non-null  int64
 13  native_country  32561 non-null  object
 14  high_income     32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
income.describe()
```

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.437456
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.347429
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

```
# checking " ?" values, how many are there in the whole dataset
df_missing = (income ==' ?').sum()
df_missing
```

```
age                 0
workclass        1836
fnlwgt              0
education           0
education_num       0
marital_status      0
occupation       1843
relationship        0
race                0
sex                 0
capital_gain        0
capital_loss        0
hours_per_week      0
native_country    583
high_income         0
dtype: int64
```

Detect missing values and label them as NaN

```
# Find which categorical attributes contain any missing value label
for col in income:
    ser = pd.Series(income[col])   # convert attribute/column to series
    if ser.isin([' ?']).any():
        print(col, income[col].dtype)
```

```
workclass object
occupation object
native_country object
```

```
# Find frequency counts for all categorical attributes/coulumns
for col in income:
    if income[col].dtype == 'object':
        print(income[col].value_counts())
```

```
 Other-relative      981
Name: relationship, dtype: int64
 White                27816
 Black                 3124
 Asian-Pac-Islander    1039
 Amer-Indian-Eskimo     311
 Other                  271
Name: race, dtype: int64
 Male      21790
 Female    10771
Name: sex, dtype: int64
 United-States                 29170
 Mexico                          643
 ?                               583
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Guatemala                        64
 Japan                            62
 Poland                           60
 Columbia                         59
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 France                           29
 Greece                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Cambodia                         19
 Trinadad&Tobago                  19
 Laos                             18
 Thailand                         18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Honduras                         13
 Hungary                          13
 Scotland                         12
 Holand-Netherlands                1
Name: native_country, dtype: int64
 <=50K    24720
 >50K      7841
Name: high_income, dtype: int64
```

```
# dropping the rows having missing values in workclass
income = income[income['workclass'] !=' ?']
income.head()
```

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_country	high_income
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

```
# dropping the "?"s from occupation and native.country
income = income[income['occupation'] !=' ?']
income = income[income['native_country'] !=' ?']
income
```

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	race	sex	capital_ga
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	
...	...	...	...	...	...	...	...	...	...	...	
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	

```
# check the dataset whether cleaned or not?
income.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             30162 non-null  int64
 1   workclass       30162 non-null  object
 2   fnlwgt          30162 non-null  int64
 3   education       30162 non-null  object
 4   education_num   30162 non-null  int64
 5   marital_status  30162 non-null  object
 6   occupation      30162 non-null  object
 7   relationship    30162 non-null  object
 8   race            30162 non-null  object
 9   sex             30162 non-null  object
 10  capital_gain    30162 non-null  int64
 11  capital_loss    30162 non-null  int64
 12  hours_per_week  30162 non-null  int64
 13  native_country  30162 non-null  object
 14  high_income     30162 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
from sklearn import preprocessing

# encode categorical variables using label Encoder

# select all categorical variables
info_categorical = income.select_dtypes(include=['object'])
info_categorical.head()
```

	workclass	education	marital_status	occupation	relationship	race	sex	native_country	high_income
0	State-gov	Bachelors	Never-married	Adm-clerical	Not-in-family	White	Male	United-States	<=50K
1	Self-emp-not-inc	Bachelors	Married-civ-spouse	Exec-managerial	Husband	White	Male	United-States	<=50K
2	Private	HS-grad	Divorced	Handlers-cleaners	Not-in-family	White	Male	United-States	<=50K
3	Private	11th	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	United-States	<=50K
4	Private	Bachelors	Married-civ-spouse	Prof-specialty	Wife	Black	Female	Cuba	<=50K

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

	workclass	education	marital_status	occupation	relationship	race	sex	native_country	high_income
0	5	9	4	0	1	4	1	38	0
1	4	9	2	3	0	4	1	38	0
2	2	11	0	5	1	4	1	38	0
3	2	1	2	5	0	2	1	38	0
4	2	9	2	9	5	2	0	4	0

```
# Next, Concatenate info_categorical dataframe with original info (dataframe)

# first, Drop earlier duplicate columns which had categorical values
income = income.drop(info_categorical.columns,axis=1)
income = pd.concat([income,info_categorical],axis=1)
income.head()
```

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week	workclass	education	marital_status	occupation	relationship	race	sex	native_country	high_income
0	39	77516	13	2174	0	40	5	9	4	0	1	4	1	38	0
1	50	83311	13	0	0	13	4	9	2	3	0	4	1	38	0

```
# recheck at column type
income.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             30162 non-null  int64
 1   fnlwgt          30162 non-null  int64
 2   education_num   30162 non-null  int64
 3   capital_gain    30162 non-null  int64
 4   capital_loss    30162 non-null  int64
 5   hours_per_week  30162 non-null  int64
 6   workclass       30162 non-null  int64
 7   education       30162 non-null  int64
 8   marital_status  30162 non-null  int64
 9   occupation      30162 non-null  int64
 10  relationship    30162 non-null  int64
 11  race            30162 non-null  int64
 12  sex             30162 non-null  int64
 13  native_country  30162 non-null  int64
 14  high_income     30162 non-null  int64
dtypes: int64(15)
memory usage: 3.7 MB
```

#Since here we have high_income as target/predicted variable we can see it's showing integer though we need to figure out labelled as <=50$K\ and$ >50K and >50K as categorical.
Let's convert target class/variable int32 to categorical(labelled as <=50$Kand$>50Kand>50K)

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

```
# check income info again whether everything is in right format or not
income.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             30162 non-null  int64
 1   fnlwgt          30162 non-null  int64
 2   education_num   30162 non-null  int64
 3   capital_gain    30162 non-null  int64
 4   capital_loss    30162 non-null  int64
 5   hours_per_week  30162 non-null  int64
 6   workclass       30162 non-null  int64
 7   education       30162 non-null  int64
 8   marital_status  30162 non-null  int64
 9   occupation      30162 non-null  int64
 10  relationship    30162 non-null  int64
 11  race            30162 non-null  int64
 12  sex             30162 non-null  int64
 13  native_country  30162 non-null  int64
 14  high_income     30162 non-null  category
dtypes: category(1), int64(14)
memory usage: 3.5 MB
```

Model Building and Evaluation Let's first build a decision tree with default hyperparameters. Then we'll use cross-validation to tune them.

```
# Importing train_test_split
from sklearn.model_selection import train_test_split
```

```
# Putting independent variables/features to X
X = income.drop('high_income',axis=1)

# Putting response/dependent variable/feature to y
y = income['high_income']
```

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

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week	workclass	education	marital_status	occupation	relationship	race	sex	native_country
0	39	77516	13	2174	0	40	5	9	4	0	1	4	1	38
1	50	83311	13	0	0	13	4	9	2	3	0	4	1	38
2	38	215646	9	0	0	40	2	11	0	5	1	4	1	38

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

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

```
# Splitting the data into train and test
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	occupa
24363	28	31493	13	0	0	40	2	9	4	
15648	26	93806	10	0	0	55	4	15	2	
4445	57	52267	14	0	0	50	1	12	2	
23991	62	345780	11	0	0	40	2	8	0	
26857	47	102628	14	15024	0	55	2	12	2	

```
# Importing decision tree classifier from sklearn library
from sklearn.tree import DecisionTreeClassifier
```

```
# Fitting the decision tree with default hyperparameters, apart from
# max_depth which is 5 so that we can plot and read the tree.
dt_default = DecisionTreeClassifier(max_depth=5)
dt_default.fit(X_train,y_train)
```

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

```
# Let's check the evaluation metrics of our default model

# Importing classification report and confusion matrix from sklearn metrics
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score

# making predictions
y_pred_default = dt_default.predict(X_test)

# Printing classifier report after prediction
print(classification_report(y_test,y_pred_default))
```

```
              precision    recall  f1-score   support

           0       0.85      0.95      0.90      6813
           1       0.77      0.50      0.60      2236

    accuracy                           0.84      9049
   macro avg       0.81      0.72      0.75      9049
weighted avg       0.83      0.84      0.83      9049
```

```
# Printing confusion matrix and accuracy
print(confusion_matrix(y_test,y_pred_default))
print(accuracy_score(y_test,y_pred_default))
```

```
[[6488  325]
 [1126 1110]]
0.8396507901425572
```

```
# We need the graphviz library to plot a tree

!pip install pydotplus
```

```
Requirement already satisfied: pydotplus in /usr/local/lib/python3.7/dist-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from pydotplus) (3.0.7)
```

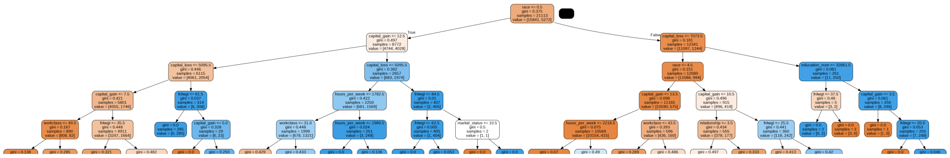
```
import six
import sys
sys.modules['sklearn.externals.six'] = six
```

```
# Importing required packages for visualization
from IPython.display import Image
from sklearn.externals.six import StringIO
from sklearn.tree import export_graphviz
import pydotplus,graphviz
```

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

```
['fnlwgt',
 'education_num',
 'capital_gain',
 'capital_loss',
 'hours_per_week',
 'workclass',
 'education',
 'marital_status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native_country',
 'high_income']
```

```
# plotting tree with max_depth=3
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 default tree is quite complex, and we need to simplify it by tuning the hyperparameters

Tuning max_depth Let's first try to find the optimum values for max_depth and understand how the value of max_depth affects the decision tree.

Here, we are creating a dataframe with max_depth in range 1 to 80 and checking the accuracy score corresponding to each max_depth.

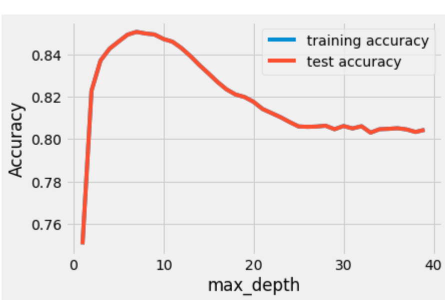
```
# GridSearchCV to find optimal max_depth
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV


# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'max_depth': range(1, 40)}

# instantiate the model
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(cv=5, estimator=DecisionTreeClassifier(random_state=100),
             param_grid={'max_depth': range(1, 40)}, scoring='accuracy')
```

```
# scores of GridSearch CV
scores = tree.cv_results_
pd.DataFrame(scores).head()
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	params	split0_test_score	split1_test_score	split2_test_score	split3_test_score	split4_test_s
0	0.022291	0.005857	0.004515	0.000219	1	{'max_depth': 1}	0.750178	0.750178	0.750414	0.750355	0.75
1	0.026054	0.001628	0.004160	0.000377	2	{'max_depth': 2}	0.826427	0.817192	0.821217	0.822596	0.82
2	0.041837	0.008621	0.004279	0.000325	3	{'max_depth': 3}	0.839924	0.830452	0.836609	0.837518	0.84
3	0.062124	0.005504	0.005938	0.002386	4	{'max_depth': 4}	0.846555	0.834478	0.839451	0.845097	0.84
4	0.055936	0.005666	0.005506	0.001988	5	{'max_depth': 5}	0.849396	0.836609	0.843476	0.850782	0.84

```
#plotting accuracies with max_depth
plt.figure()
plt.plot(scores["param_max_depth"],
         scores["mean_test_score"],
         label="training accuracy")
plt.plot(scores["param_max_depth"],
         scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("max_depth")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Tuning min_samples_leaf 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.

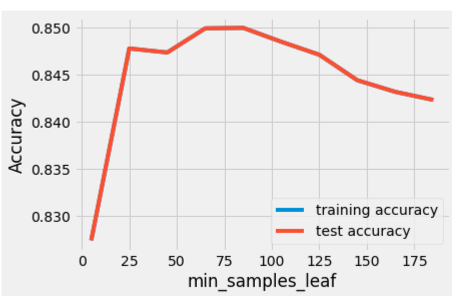
```
# GridSearchCV to find optimal max_depth
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV


# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'min_samples_leaf': range(5, 200, 20)}

# instantiate the model
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(cv=5, estimator=DecisionTreeClassifier(random_state=100),
             param_grid={'min_samples_leaf': range(5, 200, 20)},
             scoring='accuracy')
```

```
# scores of GridSearch CV
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_sco
0	0.089672	0.004405	0.004493	0.000632	5	{'min_samples_leaf': 5}	0.8290
1	0.073691	0.001183	0.003743	0.000609	25	{'min_samples_leaf': 25}	0.8486
2	0.066327	0.001994	0.003234	0.000024	45	{'min_samples_leaf': 45}	0.8491
3	0.060660	0.001002	0.003232	0.000121	65	{'min_samples_leaf': 65}	0.8555
4	0.059629	0.001857	0.003197	0.000042	85	{'min_samples_leaf': 85}	0.8546

```
# plotting accuracies with min_samples_leaf
plt.figure()
plt.plot(scores["param_min_samples_leaf"],
         scores["mean_test_score"],
         label="training accuracy")
plt.plot(scores["param_min_samples_leaf"],
         scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("min_samples_leaf")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Tuning min_samples_split 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.

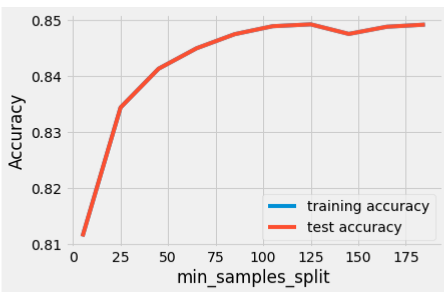
```
# GridSearchCV to find optimal min_samples_split
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV


# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'min_samples_split': range(5, 200, 20)}

# instantiate the model
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(cv=5, estimator=DecisionTreeClassifier(random_state=100),
             param_grid={'min_samples_split': range(5, 200, 20)},
             scoring='accuracy')
```

```
# scores of GridSearch CV
scores = tree.cv_results_
pd.DataFrame(scores).head()
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_min_samples_split	params	split0_test_sc
0	0.096140	0.003453	0.004243	0.000135	5	{'min_samples_split': 5}	0.806
1	0.088092	0.002334	0.003784	0.000280	25	{'min_samples_split': 25}	0.834
2	0.086523	0.002936	0.003431	0.000112	45	{'min_samples_split': 45}	0.841
3	0.082860	0.000492	0.003394	0.000083	65	{'min_samples_split': 65}	0.842
4	0.097482	0.036274	0.004222	0.001800	85	{'min_samples_split': 85}	0.848

```
# plotting accuracies with min_samples_leaf
plt.figure()
plt.plot(scores["param_min_samples_split"],
         scores["mean_test_score"],
         label="training accuracy")
plt.plot(scores["param_min_samples_split"],
         scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("min_samples_split")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



We can now use GridSearchCV to find multiple optimal hyperparameters together. Note that this time, we'll also specify the criterion (gini/entropy or IG)

```
# Create the parameter grid
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

# Instantiate the grid search model
dtree = DecisionTreeClassifier()
grid_search = GridSearchCV(estimator = dtree, param_grid = param_grid,
                          cv = n_folds, verbose = 1)

# Fit the grid search to the data
grid_search.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['entropy', 'gini'],
                         'max_depth': range(5, 15, 5),
                         'min_samples_leaf': range(50, 150, 50),
                         'min_samples_split': range(50, 150, 50)},
             verbose=1)
```

```
# cv results
cv_results = pd.DataFrame(grid_search.cv_results_)
cv_results
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_criterion	param_max_depth	param_min_samples_leaf
0	0.042292	0.001283	0.003049	0.000066	entropy	5	50
1	0.043239	0.001953	0.003011	0.000044	entropy	5	50
2	0.042038	0.002517	0.002985	0.000074	entropy	5	100
3	0.042339	0.002139	0.003290	0.000614	entropy	5	100
4	0.067556	0.002531	0.003396	0.000387	entropy	10	50
5	0.066829	0.000707	0.003197	0.000065	entropy	10	50
6	0.063523	0.002769	0.003198	0.000071	entropy	10	100
7	0.062740	0.001845	0.003229	0.000152	entropy	10	100
8	0.034466	0.000326	0.003046	0.000099	gini	5	50
9	0.034639	0.000309	0.003082	0.000147	gini	5	50
10	0.035791	0.002843	0.003005	0.000059	gini	5	100
11	0.034138	0.000318	0.003000	0.000052	gini	5	100
12	0.058143	0.003523	0.003124	0.000020	gini	10	50
13	0.056400	0.000521	0.003137	0.000043	gini	10	50
14	0.054670	0.002606	0.003490	0.000632	gini	10	100

```
# printing the optimal accuracy score and hyperparameters
print("best accuracy", grid_search.best_score_)
print(grid_search.best_estimator_)
```

```
best accuracy 0.8477714525573508
DecisionTreeClassifier(max_depth=10, min_samples_leaf=100, min_samples_split=50)
```

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

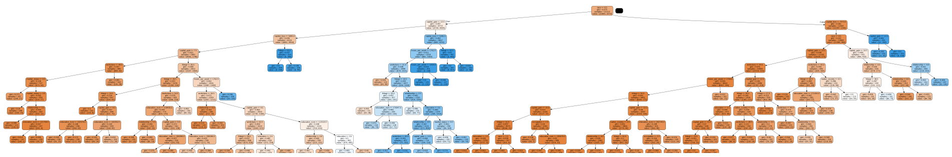
```
DecisionTreeClassifier(max_depth=10, min_samples_leaf=100, min_samples_split=50,
                       random_state=100)
```

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

```
0.8453972814675654
```

```
# plotting the tree
dot_data = StringIO()
export_graphviz(clf_gini, out_file=dot_data,feature_names=features,filled=True,rounded=True)
```

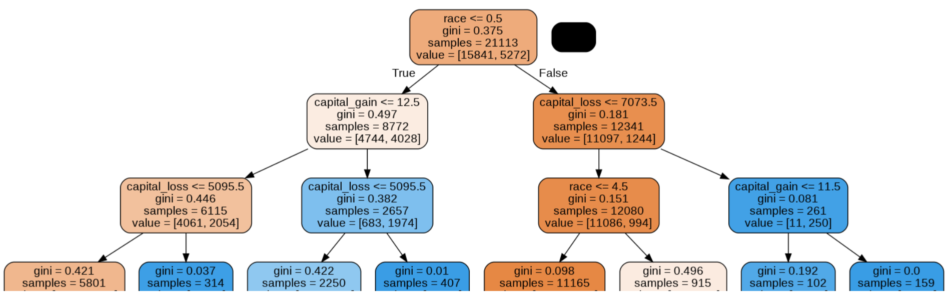
```
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```



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

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

```
0.8331307326776439
```

```
# plotting tree with max_depth=3
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())
```




```
# classification metrics
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       0.84      0.95      0.90      6813
           1       0.77      0.46      0.58      2236

    accuracy                           0.83      9049
   macro avg       0.81      0.71      0.74      9049
weighted avg       0.83      0.83      0.82      9049
```

```
# confusion matrix
print(confusion_matrix(y_test,y_pred))
```

```
[[6502  311]
 [1199 1037]]
```

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