



Vidyavardhini's College of Engineering & Technology

Department of Computer Engineering

Experiment No. 4
Apply Random Forest Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance: 14-08-2023
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Vidyavardhini's College of Engineering & Technology

Department of Computer Engineering

Aim: Apply Random Forest Algorithm on Adult Census Income Dataset and analyze the performance of the model.

Objective: Able to perform various feature engineering tasks, apply Random Forest Algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score.

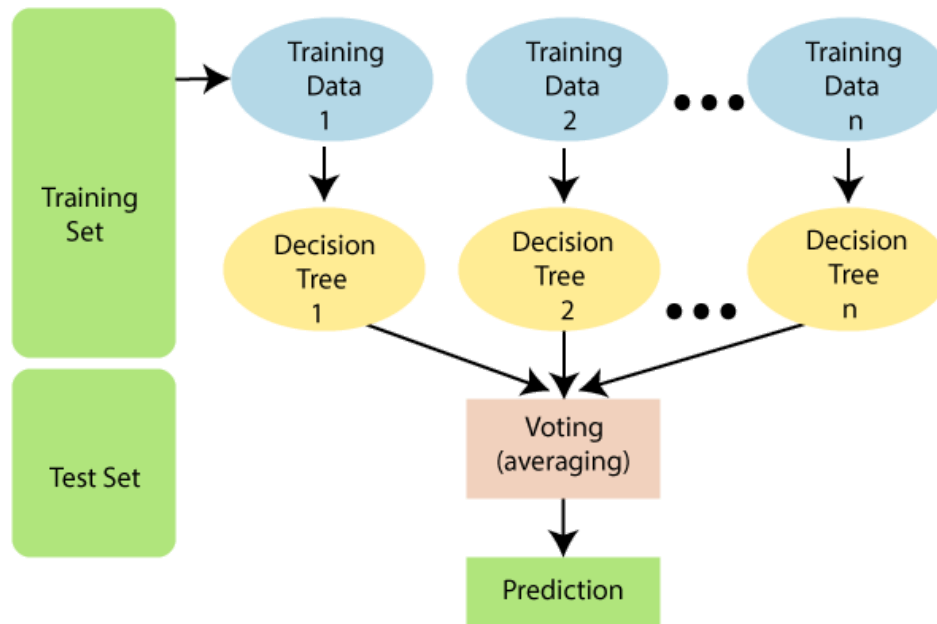
Theory:

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

The below diagram explains the working of the Random Forest algorithm:



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.



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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, Trinidad & Tobago, Peru, Hong, Holand-Netherlands.

```
# Import libraries
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
sns.set(style='white', context='notebook', palette='deep')

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import GridSearchCV, cross_val_score, StratifiedKFold, learning_curve, train_test_split, KFold
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score

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

# Adult dataset path
adult_dataset_path = "adult_dataset.csv"

# Function for loading adult dataset
def load_adult_data(adult_path=adult_dataset_path):
    csv_path = os.path.join(adult_path)
    return pd.read_csv(csv_path)

# Calling load adult function and assigning to a new variable df
df = load_adult_data()
# load top 3 rows values from adult dataset
df.head(3)
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Female
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	Female

```
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.gain', 'capital.loss', 'hours.per.week', 'native.country', 'income']

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
```

```
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   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  income        32561 non-null   object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
df.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	

```
df.head()
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	Fe
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Fe
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Fe
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	Fe
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Fe
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Fe

```
# checking "?" total values present in particular 'workclass' feature
df_check_missing_workclass = (df['workclass']=='?').sum()
df_check_missing_workclass

1836
```

```
# checking "?" total values present in particular 'occupation' feature
df_check_missing_occupation = (df['occupation']=='?').sum()
df_check_missing_occupation

1843
```

```
# checking "?" values, how many are there in the whole dataset
df_missing = (df=='?').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
income            0
dtype: int64

percent_missing = (df=='?').sum() * 100/len(df)
percent_missing

age              0.000000
workclass        5.638647
fnlwgt           0.000000
education         0.000000
education.num     0.000000
marital.status    0.000000
occupation        5.660146
relationship       0.000000
race              0.000000
sex              0.000000
capital.gain      0.000000
capital.loss      0.000000
hours.per.week    0.000000
native.country    1.790486
income            0.000000
dtype: float64

# find total number of rows which doesn't contain any missing value as '?'
df.apply(lambda x: x != '?',axis=1).sum()

age              32561
workclass        30725
fnlwgt           32561
education         32561
education.num     32561
marital.status    32561
occupation        30718
relationship       32561
race              32561
sex              32561
capital.gain      32561
capital.loss      32561
hours.per.week    32561
native.country    31978
income            32561
dtype: int64

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

   age  workclass  fnlwgt  education  education.num  marital.status  occupation  relationship  race
1   82    Private  132870    HS-grad              9         Widowed  Exec-manage...  Not-in-family  White  Fe
3   54    Private  140359    7th-8th              4         Divorced  Machine-op-inspct  Unmarried  White  Fe
4   41    Private  264663  Some-college            10         Separated  Prof-specialty  Own-child  White  Fe
5   34    Private  216864    HS-grad              9         Divorced  Other-service  Unmarried  White  Fe
6   29    Private  150601    10th              6         Separated  Adm-...  Unmarried  White  Fe

# select all categorical variables
df_categorical = df.select_dtypes(include=['object'])

# checking whether any other column contains '?' value
df_categorical.apply(lambda x: x=='?',axis=1).sum()

workclass      0
education       0
marital.status  0
occupation      7
relationship     0
race            0
sex             0
native.country  556
income          0
dtype: int64
```

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

```
df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 1 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  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
df_categorical = df.select_dtypes(include=['object'])
df_categorical.head()
```

	workclass	education	marital.status	occupation	relationship	race	sex	native.country	income
1	Private	HS-grad	Widowed	Exec-managerial	Not-in-family	White	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
5	Private	HS-grad	Married	Other-service	Married	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
1	2	11	6	3	1	4	0	38	0
3	2	5	0	6	4	4	0	38	0
4	2	15	5	9	3	4	0	38	0
5	2	11	0	7	4	4	0	38	0
6	2	0	5	0	4	4	1	38	0

```
# Next, Concatenate df_categorical dataframe with original df (dataframe)

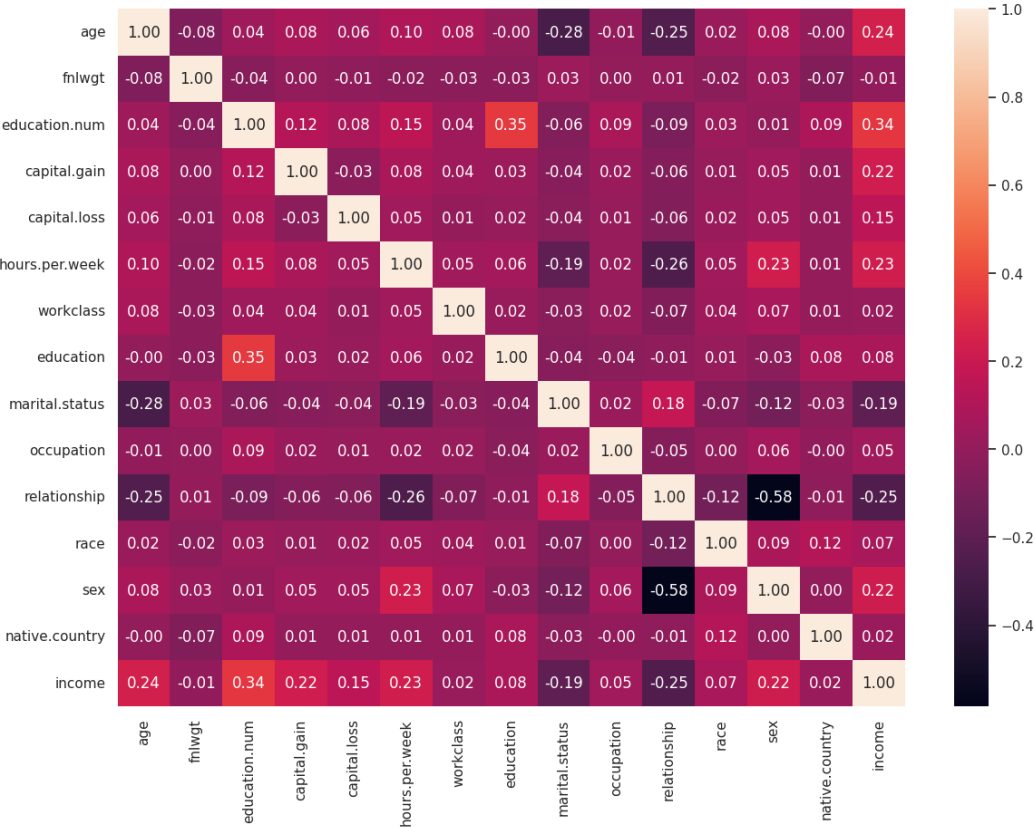
# first, Drop earlier duplicate columns which had categorical values
df = df.drop(df_categorical.columns,axis=1)
df = pd.concat([df,df_categorical],axis=1)
df.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marita
1	82	132870	9	0	4356	18	2	11	
3	54	140359	4	0	3900	40	2	5	
4	41	264663	10	0	3900	40	2	15	
5	34	216864	9	0	3770	45	2	11	
6	38	150601	6	0	3770	40	2	0	


```
# look at column type
df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 1 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  income              30162 non-null  int64
dtypes: int64(15)
memory usage: 3.7 MB
```

```
plt.figure(figsize=(14,10))
sns.heatmap(df.corr(),annot=True,fmt='.2f')
plt.show()
```



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

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 1 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  income                30162 non-null  category
dtypes: category(1), int64(14)
memory usage: 3.5 MB
```

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

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

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

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

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marita
1	82	132870	9	0	4356	18	2	11	
3	54	140359	4	0	3900	40	2	5	
4	41	264663	10	0	3900	40	2	15	

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

```
1    0
3    0
4    0
Name: 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)
```

```
X_train.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	ma
14520	23	200677	6	0	0	40	2	0	
23129	56	179781	9	0	0	40	2	11	
9866	53	246562	3	0	0	40	3	4	
13520	48	101299	12	0	0	45	2	7	
16572	52	139347	9	0	0	40	2	11	

```
test_size = 0.20
seed = 7
num_folds = 10
scoring = 'accuracy'
```

```
# Params for Random Forest
num_trees = 100
max_features = 3
```

```
models = []
```

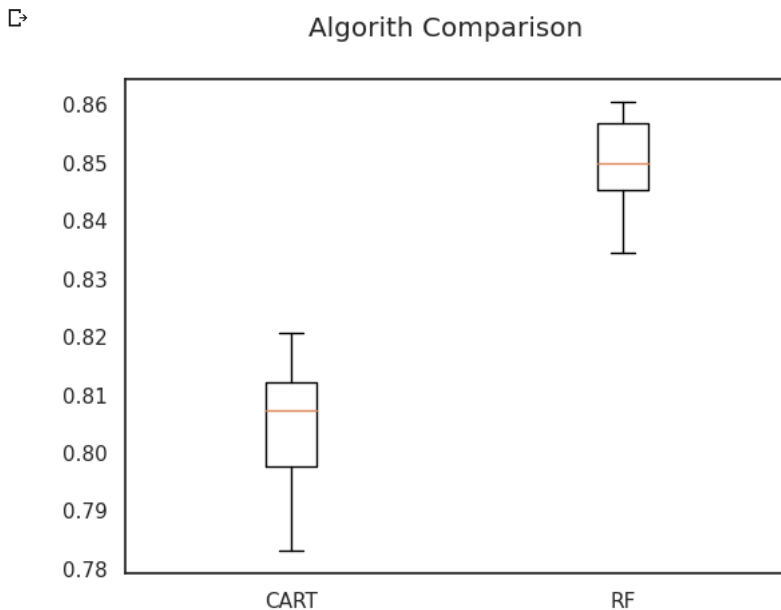
```
models.append(('CART', DecisionTreeClassifier()))
```

```
models.append((CART, DecisionTreeClassifier()))
models.append(('RF', RandomForestClassifier(n_estimators=num_trees, max_features=max_features)))

results = []
names = []
for name, model in models:
    kfold = KFold(n_splits=10, shuffle=True, random_state=seed)
    cv_results = cross_val_score(model, X_train, y_train, cv=kfold, scoring='accuracy')
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)

    CART: 0.804784 (0.010526)
    RF: 0.849742 (0.007561)
```

```
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



```
...
Commented Out to Reduce Script Time - Took 20 Minutes to run.
best_n_estimator = 250
best_max_feature = 5
# Tune Random Forest
n_estimators = np.array([50,100,150,200,250])
max_features = np.array([1,2,3,4,5])
param_grid = dict(n_estimators=n_estimators,max_features=max_features)
model = RandomForestClassifier()
kfold = KFold(n_splits=num_folds, random_state=seed)
grid = GridSearchCV(estimator=model, param_grid=param_grid, scoring=scoring, cv=kfold)
grid_result = grid.fit(X_train, y_train)
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
...

'\nCommented Out to Reduce Script Time - Took 20 Minutes to run.\nbest_n_estimator = 250\nbest_max_fea
ture = 5\n# Tune Random Forest\nn_estimators = np.array([50,100,150,200,250])\nmax_features = np.array
([1,2,3,4,5])\nparam_grid = dict(n_estimators=n_estimators,max_features=max_features)\nmodel = RandomF
orestClassifier()\nkfold = KFold(n_splits=num_folds, random_state=seed)\ngrid = GridSearchCV(estimator
=model, param_grid=param_grid, scoring=scoring, cv=kfold)\ngrid_result = grid.fit(X_train, y_train)\nnp
rint("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))\nmeans = grid_result.c

random_forest = RandomForestClassifier(n_estimators=250,max_features=5)
random_forest.fit(X_train, y_train)
predictions = random_forest.predict(X_test)
print("Accuracy: %s%" % (100*accuracy_score(y_test, predictions)))
print(confusion_matrix(y_test, predictions))
print(classification_report(y_test, predictions))
```

```
Accuracy: 85.4528577111789%
[[5241  431]
 [ 666 1203]]
precision    recall  f1-score   support

      0       0.89       0.92       0.91       5672
      1       0.74       0.64       0.69       1869

 accuracy          0.85          0.85          0.85       7541
 macro avg          0.81          0.78          0.80       7541
 weighted avg          0.85          0.85          0.85       7541
```



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Conclusion:

1. Observations about the data set from the correlation heat map:
 - Education Number vs. Income: There is a moderate positive correlation (around 0.34) between "education.num" (which likely represents the level of education) and "income." This suggests that, on average, individuals with higher education tend to have higher incomes.
 - Age vs. Education Number: There is a mild positive correlation (around 0.04) between "age" and "education.num." This indicates that, on average, older individuals tend to have slightly higher levels of education.
 - Capital Gain vs. Income: There is a positive correlation (around 0.22) between "capital.gain" and "income." This suggests that individuals with higher capital gains are more likely to have higher incomes.
 - Capital Loss vs. Income: There is a positive correlation (around 0.15) between "capital.loss" and "income." This implies that individuals with higher capital losses are more likely to have higher incomes.
 - Age vs. Hours per Week: There is a very weak positive correlation (around 0.10) between "age" and "hours.per.week," indicating that older individuals may work slightly more hours per week.
 - Education Number vs. Hours per Week: There is a very weak positive correlation (around 0.15) between "education.num" and "hours.per.week," suggesting that individuals with higher education levels might work slightly longer hours.
2. Accuracy: The accuracy of the model is approximately 85.45%, which means that the model correctly predicted the income class for around 85.45% of the samples in the test set.
3. The confusion matrix provides insights into the model's performance with respect to different classes. It shows that:
 - True Negative (TN): 5241 instances were correctly classified as "income = 0."
 - False Positive (FP): 431 instances were wrongly classified as "income = 1" when they were actually "income = 0."
 - False Negative (FN): 666 instances were wrongly classified as "income = 0" when they were actually "income = 1."
 - True Positive (TP): 1203 instances were correctly classified as "income = 1."
4. Precision: Precision for "income = 0" is approximately 0.89, which means that out of all instances predicted as "income = 0," around 89% were actually "income = 0." Precision for "income = 1" is approximately 0.74, indicating that out of all instances predicted as "income = 1," around 74% were actually "income = 1."



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5. Recall (Sensitivity): Recall for "income = 0" is approximately 0.92, meaning that out of all instances that are actually "income = 0," the model correctly identified around 92% of them. Recall for "income = 1" is approximately 0.64, indicating that out of all instances that are actually "income = 1," the model captured around 64% of them.
6. F1-Score: The F1-score is the harmonic mean of precision and recall, providing a balanced measure of model performance. The weighted average F1-score is approximately 0.85, indicating a reasonable balance between precision and recall.
7. Comparison:
 - Accuracy: The Random Forest model has slightly higher accuracy compared to the Decision Tree model, indicating that it is better at overall classification.
 - Precision: Both models have higher precision for predicting "income = 0" (higher income group) compared to "income = 1" (lower income group). The Random Forest model has slightly better precision for both classes.
 - Recall: The Random Forest model has higher recall for both classes, indicating that it is better at correctly capturing instances of both "income = 0" and "income = 1." In particular, the Random Forest model has notably improved recall for the "income = 1" class.
 - F1-Score: The F1-scores for both models follow similar trends as precision and recall. The Random Forest model generally performs better in terms of F1-score for both classes.
 - Confusion Matrix: The confusion matrices show that the Random Forest model has fewer false positives and false negatives compared to the Decision Tree model.

The Random Forest algorithm generally outperforms the Decision Tree algorithm in terms of accuracy, precision, recall, and F1-score on the Adult Census Income Dataset.