Experiment No. 4
Apply Random Forest Algorithm on Adult Census Income Dataset and analyze the performance of the model
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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.

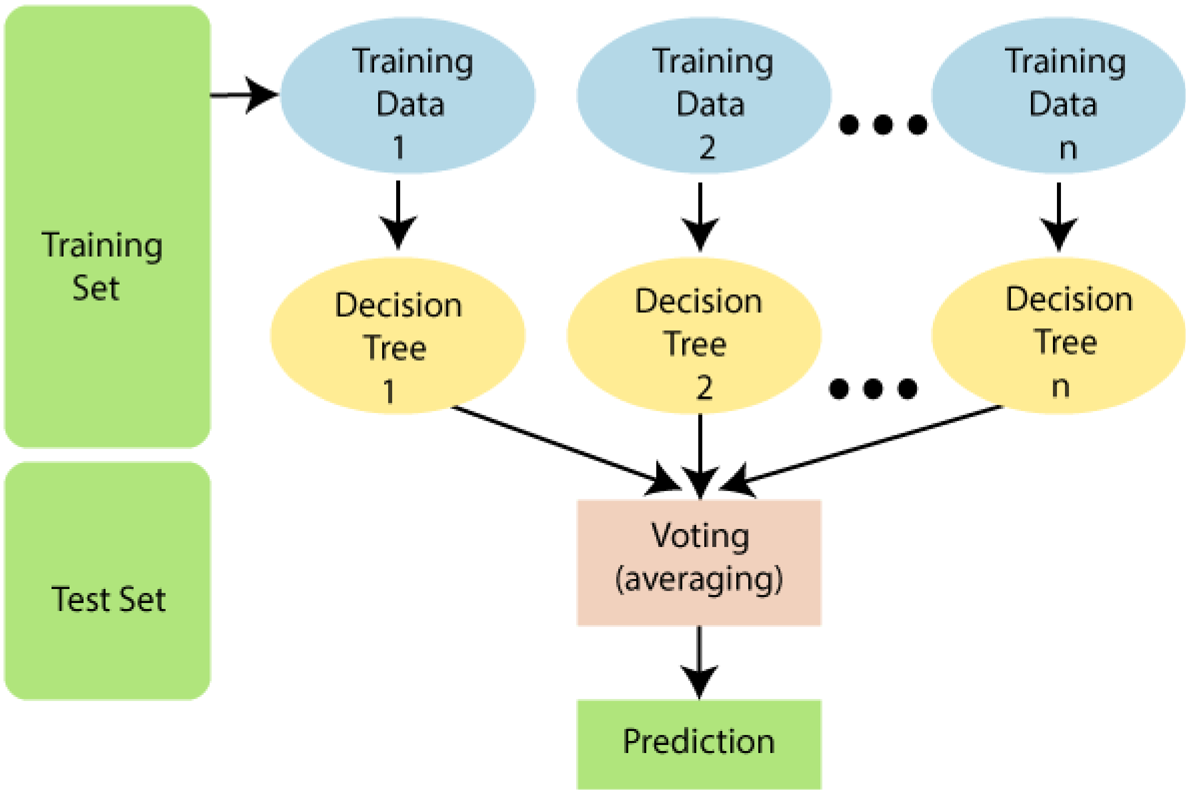
Theory:

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.

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, Marriedspouse-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, OutlyingUS(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:

These variables don't have many significant linear relationships with one another; instead, their correlations are typically weaker. Age shows a marginally favourable link with the quantity of schooling and weekly hours worked. There is a little positive association between education levels and capital gains. Additionally, there is a somewhat negative association between capital losses and profits.

Accuracy: 85.44% of the time, the model accurately predicts income levels in the majority of cases.

True positives (8015), false positives (628), and false negatives (1047) are shown in the confusion matrix. Actual negatives (1819) forecasts.

Precision: 0.74 for income number one and 0.08 for income number zero.

Recall: 0.93 is the recall for income 0 and 0.63 is the recall for income 1.

Fl-score: A measure of overall model efficacy, the Fl-score is the mean of precision and recall. There are 0 for 0.91 and 1 for 0.68 in it.

Generally speaking, Random Forest produces superior outcomes to Decision Trees. Multiple Decision Tree forecasts are combined in the Random Forest model, which can increase generalisation and accuracy.

```
# 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 = "/content/adult.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	educational-num	marital-status	occupation	relationship	race	gender	capital-gain
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0

```
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 :  48842
Columns :  15

Features :
 ['age', 'workclass', 'fnlwgt', 'education', 'educational-num', 'marital-status', 'occupation', 'relationship', 'race', 'gender', '

Missing values :  0

Unique values :
 age                  74
workclass             9
fnlwgt            28523
education            16
educational-num      16
marital-status        7
occupation           15
relationship          6
race                  5
gender                2
capital-gain        123
capital-loss         99
hours-per-week       96
native-country       42
income                2
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   age              48842 non-null  int64
 1   workclass        48842 non-null  object
 2   fnlwgt           48842 non-null  int64
 3   education        48842 non-null  object
```

```
 4   educational-num  48842 non-null  int64
 5   marital-status   48842 non-null  object
 6   occupation       48842 non-null  object
 7   relationship     48842 non-null  object
 8   race             48842 non-null  object
 9   gender           48842 non-null  object
 10  capital-gain     48842 non-null  int64
 11  capital-loss     48842 non-null  int64
 12  hours-per-week   48842 non-null  int64
 13  native-country   48842 non-null  object
 14  income           48842 non-null  object
dtypes: int64(6), object(9)
memory usage: 5.6+ MB
```

```
df.describe()
```

	age	fnlwgt	educational-num	capital-gain	capital-loss	hours-per-week
count	48842.000000	4.884200e+04	48842.000000	48842.000000	48842.000000	48842.000000
mean	38.643585	1.896641e+05	10.078089	1079.067626	87.502314	40.422382
std	13.710510	1.056040e+05	2.570973	7452.019058	403.004552	12.391444
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.175505e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.781445e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.376420e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.490400e+06	16.000000	99999.000000	4356.000000	99.000000

```
df.head()
```

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gender	capital-gain
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	0

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

```
2799
```

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

```
2809
```

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

```
age                  0
workclass         2799
fnlwgt               0
education            0
educational-num      0
marital-status       0
occupation        2809
relationship         0
race                 0
gender               0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country     857
income               0
dtype: int64
```

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

```
age               0.000000
workclass         5.730724
fnlwgt            0.000000
education         0.000000
educational-num   0.000000
marital-status    0.000000
occupation        5.751198
relationship      0.000000
race              0.000000
gender            0.000000
capital-gain      0.000000
capital-loss      0.000000
hours-per-week    0.000000
native-country    1.754637
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               48842
workclass         46043
fnlwgt            48842
education         48842
educational-num   48842
marital-status    48842
occupation        46033
relationship      48842
race              48842
gender            48842
capital-gain      48842
capital-loss      48842
hours-per-week    48842
native-country    47985
income            48842
dtype: int64
```

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

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gender	capital-gain
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688
5	34	Private	198693	10th	6	Never-married	Other-service	Not-in-family	White	Male	0

```
# 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        10
relationship       0
race               0
gender             0
native-country   811
income             0
dtype: int64
```

```
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	gender	native-country	income

```
# 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	gender	native-country	income
0	2	1	4	6	3	2	1	39	0
1	2	11	2	4	0	4	1	39	0
2	1	7	2	10	0	4	1	39	1
3	2	15	2	6	0	2	1	39	1
5	2	0	4	7	1	4	1	39	0

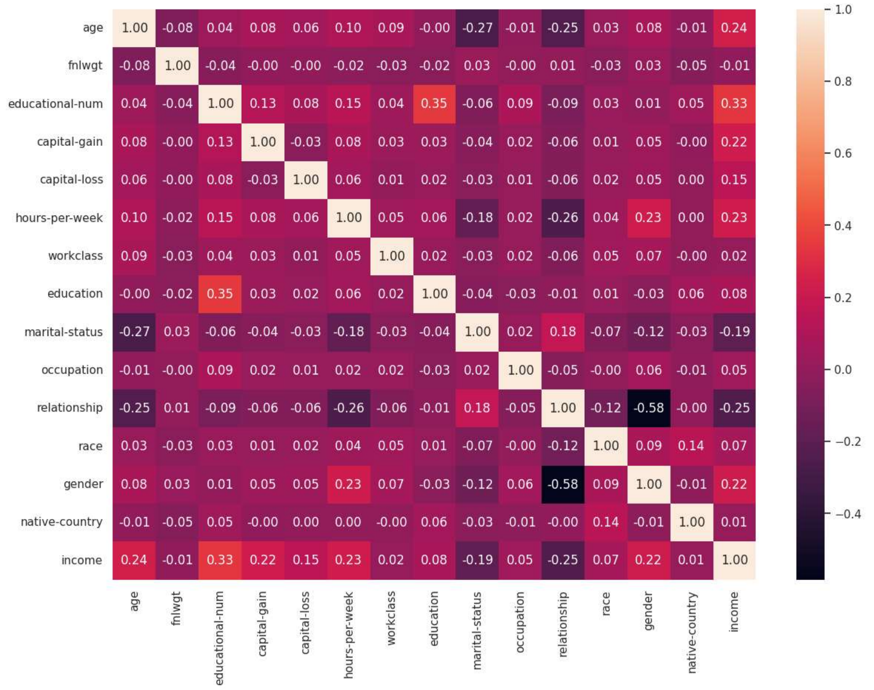
```
# Next, Concatenate df_categorical dataframe with original df (dataframe)
# first, Drop earlier duplicate columns which had categorical values
df = df.drop(df_categorical.columns,axis=1)
df = pd.concat([df,df_categorical],axis=1)
df.head()
```

	age	fnlwgt	educational-num	capital-gain	capital-loss	hours-per-week	workclass	education	marital-status	occupation	relati
0	25	226802	7	0	0	40	2	1	4	6	
1	38	89814	9	0	0	50	2	11	2	4	
2	28	336951	12	0	0	40	1	7	2	10	
3	44	160323	10	7688	0	40	2	15	2	6	
5	34	198693	6	0	0	30	2	0	4	7	

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 46033 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   age              46033 non-null  int64
 1   fnlwgt           46033 non-null  int64
 2   educational-num  46033 non-null  int64
 3   capital-gain     46033 non-null  int64
 4   capital-loss     46033 non-null  int64
 5   hours-per-week   46033 non-null  int64
 6   workclass        46033 non-null  int64
 7   education        46033 non-null  int64
 8   marital-status   46033 non-null  int64
 9   occupation       46033 non-null  int64
 10  relationship     46033 non-null  int64
 11  race             46033 non-null  int64
 12  gender           46033 non-null  int64
 13  native-country   46033 non-null  int64
 14  income           46033 non-null  int64
dtypes: int64(15)
memory usage: 5.6 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: 46033 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype   
---  ------           --------------  -----   
 0   age              46033 non-null  int64   
 1   fnlwgt           46033 non-null  int64   
 2   educational-num  46033 non-null  int64   
 3   capital-gain     46033 non-null  int64   
 4   capital-loss     46033 non-null  int64   
 5   hours-per-week   46033 non-null  int64   
 6   workclass        46033 non-null  int64   
 7   education        46033 non-null  int64   
 8   marital-status   46033 non-null  int64   
 9   occupation       46033 non-null  int64   
 10  relationship     46033 non-null  int64   
 11  race             46033 non-null  int64   
 12  gender           46033 non-null  int64   
 13  native-country   46033 non-null  int64   
 14  income           46033 non-null  category
dtypes: category(1), int64(14)
memory usage: 5.3 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	educational-num	capital-gain	capital-loss	hours-per-week	workclass	education	marit sta
0	25	226802	7	0	0	40	2	1	
1	38	89814	9	0	0	50	2	11	

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

```
0    0
1    0
2    1
```

```
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	educational-num	capital-gain	capital-loss	hours-per-week	workclass	education	m
13554	58	196502	10	0	0	60	2	15	
46282	27	297457	9	0	0	40	2	11	
25679	27	30244	9	0	0	80	4	11	
8775	42	165309	9	0	0	50	2	11	

```
test_size = 0.20
seed = 7
num_folds = 10
scoring = 'accuracy'
# Params for Random Forest
num_trees = 100
max_features = 3
```

```
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: 85.44617256060475%
[[8015  628]
 [1047 1819]]
              precision    recall  f1-score   support

           0       0.88      0.93      0.91      8643
           1       0.74      0.63      0.68      2866

    accuracy                           0.85     11509
   macro avg       0.81      0.78      0.80     11509
weighted avg       0.85      0.85      0.85     11509
```