Predicit if the income of the individual is greater than 50k or not.

In [1]:

```
# Importing necessary modules/libraries....
import numpy as np
import pandas as pd
# Importing matplotlib library for data visualisation...
import matplotlib.pyplot as plt
# Importing seaborn for heatmap and correlation
import seaborn as sns
%matplotlib inline
# Libraries for building models on our dataset....
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.model_selection import train_test_split
```

In [2]:

```
# Importing/ Loading the dataset as dataframe in some variable and renaming its columns
income_df = pd.read_excel(r'C:\Users\DELL\Desktop\Machine Learning\Assignment.xlsx', names=
                                            'maritalStatus', 'occupation', 'relationship', '
                                            'sex', 'capitalGain', 'capitalLoss', 'hours-per-
                                            'nativeCountry', 'salary'])
```

In [3]:

```
# Exploring dataset
print("Shape is: ",income_df.shape)
print()
print(income_df.info())
print()
# printing the column names of the dataset
print(income_df.columns)
print()
income_df.head(10)
```

```
Shape is:  (48842, 15)

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
age                  48842 non-null int64
workclass            48842 non-null object
fnlwgt               48842 non-null int64
education            48842 non-null object
education-num        48842 non-null int64
maritalStatus        48842 non-null object
occupation           48842 non-null object
relationship         48842 non-null object
race                 48842 non-null object
sex                  48842 non-null object
capitalGain          48842 non-null int64
capitalLoss          48842 non-null int64
hours-per-week       48842 non-null int64
nativeCountry        48842 non-null object
salary               48842 non-null object
dtypes: int64(6), object(9)
memory usage: 5.6+ MB
None

Index(['age', 'workclass', 'fnlwgt', 'education', 'education-num',
       'maritalStatus', 'occupation', 'relationship', 'race', 'sex',
       'capitalGain', 'capitalLoss', 'hours-per-week', 'nativeCountry',
       'salary'],
      dtype='object')
```

Out[3]:

	age	workclass	fnlwgt	education	education-num	maritalStatus	occupation	relationship	race
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black

	age	workclass	fnlwgt	education	education-num	maritalStatus	occupation	relationship	race
5	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White
6	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-family	Black
7	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White
9	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White

In [4]:

```
# Getting the general overview about dataset
income_df.describe()
```

Out[4]:

	age	fnlwgt	education-num	capitalGain	capitalLoss	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

Cleaning the dataset

In [5]:

```
print("Before cleaning the dataset: \n",income_df['salary'].value_counts())
# Replacing the 50K. with 50K
income_df['salary'] = income_df.salary.apply(lambda x: x.replace('<=50K.', '<=50K'))
income_df['salary'] = income_df.salary.apply(lambda x: x.replace('>50K.', '>50K'))
print()
print("After cleaning the dataset: \n",income_df['salary'].value_counts())
```

```
Before cleaning the dataset:
  <=50K     24720
 <=50K.    12435
 >50K       7841
 >50K.      3846
Name: salary, dtype: int64

After cleaning the dataset:
  <=50K    37155
 >50K     11687
Name: salary, dtype: int64
```

In [6]:

```
print("Before cleaning the dataset: \n",income_df['maritalStatus'].value_counts())
income_df['maritalStatus']=income_df.maritalStatus.apply(lambda x:x.replace('Married-civ-sp
income_df['maritalStatus']=income_df.maritalStatus.apply(lambda x:x.replace('Married-AF-spo
income_df['maritalStatus']=income_df.maritalStatus.apply(lambda x:x.replace('Married-spouse
income_df['maritalStatus']=income_df.maritalStatus.apply(lambda x:x.replace('Separated','Di
print()
print("After cleaning the dataset: \n",income_df['maritalStatus'].value_counts())
```

```
Before cleaning the dataset:
  Married-civ-spouse       22379
 Never-married            16117
 Divorced                  6633
 Separated                 1530
 Widowed                   1518
 Married-spouse-absent      628
 Married-AF-spouse           37
Name: maritalStatus, dtype: int64

After cleaning the dataset:
  Married          23044
 Never-married    16117
 Divorced          8163
 Widowed           1518
Name: maritalStatus, dtype: int64
```

In [7]:

```
hs_grad = ['HS-grad','11th','10th','9th','12th']
elementary = ['1st-4th','5th-6th','7th-8th']
print("Before cleaning the dataset: \n",income_df['maritalStatus'].value_counts())
income_df['education']=income_df.education.apply(lambda x:x.replace('HS-grad','HSGrad'))
income_df['education']=income_df.education.apply(lambda x:x.replace('11th','HSGrad'))
income_df['education']=income_df.education.apply(lambda x:x.replace('10th','HSGrad'))
income_df['education']=income_df.education.apply(lambda x:x.replace('9th','HSGrad'))
income_df['education']=income_df.education.apply(lambda x:x.replace('12th','HSGrad'))
income_df['education']=income_df.education.apply(lambda x:x.replace('1st-4th','elementary_s
income_df['education']=income_df.education.apply(lambda x:x.replace('5th-6th','elementary_s
income_df['education']=income_df.education.apply(lambda x:x.replace('7th-8th','elementary_s
print()
print("After cleaning the dataset: \n",income_df['maritalStatus'].value_counts())
```

```
Before cleaning the dataset:
  Married          23044
 Never-married    16117
 Divorced          8163
 Widowed           1518
Name: maritalStatus, dtype: int64

After cleaning the dataset:
  Married          23044
 Never-married    16117
 Divorced          8163
 Widowed           1518
Name: maritalStatus, dtype: int64
```

In [8]:

```
print("Before replacing the '?' values\n")
income_df.head(20)
```

```
Before replacing the '?' values
```

Out[8]:

	age	workclass	fnlwgt	education	education-num	maritalStatus	occupation	relationsh
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-fam
1	50	Self-emp-not-inc	83311	Bachelors	13	Married	Exec-managerial	Husba
2	38	Private	215646	HSGrad	9	Divorced	Handlers-cleaners	Not-in-fam
3	53	Private	234721	HSGrad	7	Married	Handlers-cleaners	Husba
4	28	Private	338409	Bachelors	13	Married	Prof-specialty	W
5	37	Private	284582	Masters	14	Married	Exec-managerial	W
6	49	Private	160187	HSGrad	5	Married	Other-service	Not-in-fam
7	52	Self-emp-not-inc	209642	HSGrad	9	Married	Exec-managerial	Husba
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-fam
9	42	Private	159449	Bachelors	13	Married	Exec-managerial	Husba
10	37	Private	280464	Some-college	10	Married	Exec-managerial	Husba
11	30	State-gov	141297	Bachelors	13	Married	Prof-specialty	Husba
12	23	Private	122272	Bachelors	13	Never-married	Adm-clerical	Own-ch
13	32	Private	205019	Assoc-acdm	12	Never-married	Sales	Not-in-fam
14	40	Private	121772	Assoc-voc	11	Married	Craft-repair	Husba
15	34	Private	245487	elementary_school	4	Married	Transport-moving	Husba
16	25	Self-emp-not-inc	176756	HSGrad	9	Never-married	Farming-fishing	Own-ch
17	32	Private	186824	HSGrad	9	Never-married	Machine-op-inspct	Unmarri
18	38	Private	28887	HSGrad	7	Married	Sales	Husba
19	43	Self-emp-not-inc	292175	Masters	14	Divorced	Exec-managerial	Unmarri

In [9]:

```
# Replacing ? with null values
income_df['nativeCountry']=income_df.nativeCountry.apply(lambda x:x.replace('?',''))
income_df['occupation']=income_df.occupation.apply(lambda x:x.replace('?',''))
income_df['workclass']=income_df.workclass.apply(lambda x:x.replace('?',''))
print("After replacement\n")
income_df.head(20)
```

```
After replacement
```

Out[9]:

	age	workclass	fnlwgt	education	education-num	maritalStatus	occupation	relationsh
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-fam
1	50	Self-emp-not-inc	83311	Bachelors	13	Married	Exec-managerial	Husba
2	38	Private	215646	HSGrad	9	Divorced	Handlers-cleaners	Not-in-fam
3	53	Private	234721	HSGrad	7	Married	Handlers-cleaners	Husba
4	28	Private	338409	Bachelors	13	Married	Prof-specialty	W
5	37	Private	284582	Masters	14	Married	Exec-managerial	W
6	49	Private	160187	HSGrad	5	Married	Other-service	Not-in-fam
7	52	Self-emp-not-inc	209642	HSGrad	9	Married	Exec-managerial	Husba
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-fam
9	42	Private	159449	Bachelors	13	Married	Exec-managerial	Husba
10	37	Private	280464	Some-college	10	Married	Exec-managerial	Husba
11	30	State-gov	141297	Bachelors	13	Married	Prof-specialty	Husba
12	23	Private	122272	Bachelors	13	Never-married	Adm-clerical	Own-ch
13	32	Private	205019	Assoc-acdm	12	Never-married	Sales	Not-in-fam
14	40	Private	121772	Assoc-voc	11	Married	Craft-repair	Husba
15	34	Private	245487	elementary_school	4	Married	Transport-moving	Husba
16	25	Self-emp-not-inc	176756	HSGrad	9	Never-married	Farming-fishing	Own-ch

	age	workclass	fnlwgt	education	education-num	maritalStatus	occupation	relationsh
17	32	Private	186824	HSGrad	9	Never-married	Machine-op-inspct	Unmarri
18	38	Private	28887	HSGrad	7	Married	Sales	Husba
19	43	Self-emp-not-inc	292175	Masters	14	Divorced	Exec-managerial	Unmarri

In [10]:

```
# Identifying the categorical and numerical parameters
numeric_parameters = income_df.dtypes[income_df.dtypes != "object"]
categorical_parameters = income_df.dtypes[income_df.dtypes == "object"]
print("Categorical variables are:\n"+str(categorical_parameters))
print("\n\nNumeric variables are:\n"+str(numeric_parameters))
```

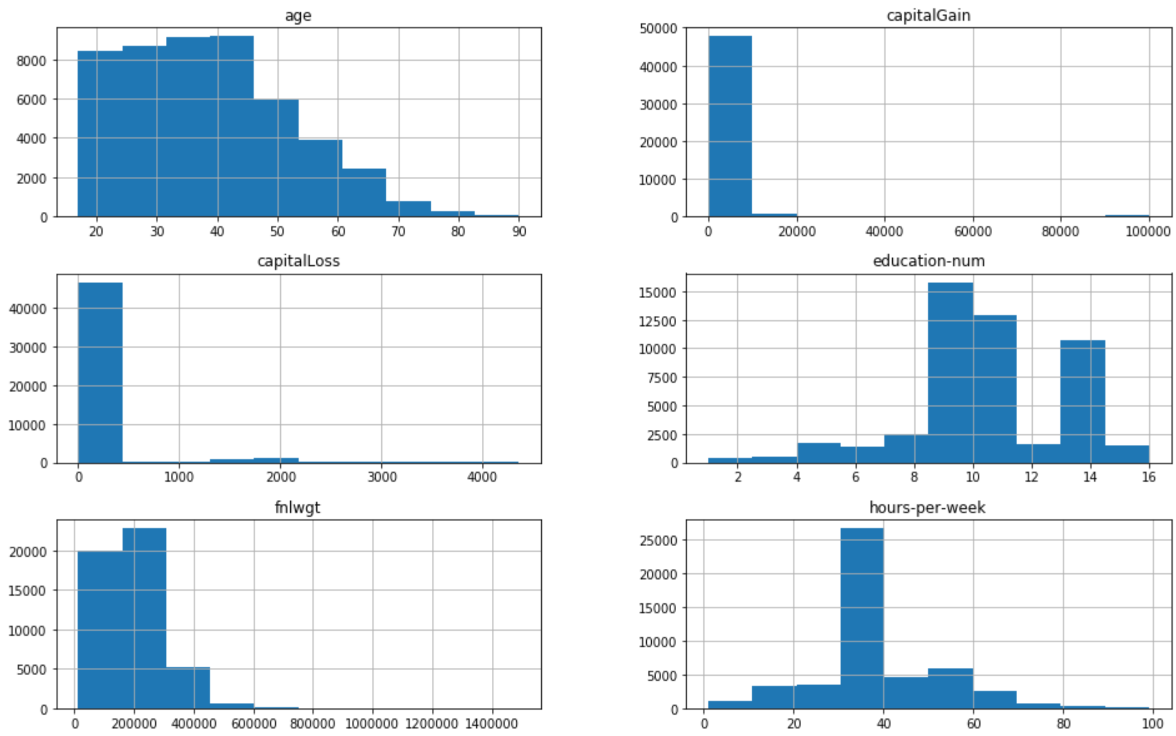
```
Categorical variables are:
workclass        object
education        object
maritalStatus    object
occupation       object
relationship     object
race             object
sex              object
nativeCountry    object
salary           object
dtype: object


Numeric variables are:
age               int64
fnlwgt            int64
education-num     int64
capitalGain       int64
capitalLoss       int64
hours-per-week    int64
dtype: object
```

In [11]:

```
# Plotting histogram of the numerical parameters to identify the outliers
income_df[numeric_parameters.index].hist(figsize=(16,10))
```

Out[11]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000017F9E5CD358
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000017F9FF474A8
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000017F9FF6C710
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000017F9FF95940
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000017F9FFC0BA8
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000017F9FFE7E10
>]],
      dtype=object)
```



In [12]:

```
# Removing outliers from column 'age'
print("Number of observation before removing:",income_df.shape)
age = income_df[income_df['age'] == 90].index
income_df.drop(labels = age,axis = 0,inplace =True)
print("Number of observation after removing:",income_df.shape)
```

```
Number of observation before removing: (48842, 15)
Number of observation after removing: (48787, 15)
```

In [14]:

```
print("Number of observation before removing:",income_df.shape)
fnlwgt = income_df[income_df['fnlwgt'] > 750000].index
income_df.drop(labels = fnlwgt,axis = 0,inplace =True)
print("Number of observation after removing:",income_df.shape)
```

```
Number of observation before removing: (48721, 15)
Number of observation after removing: (48721, 15)
```

In [15]:

```
# Removing the outliers from capitalGain column
print("Number of observation before removing:",income_df.shape)
gain = income_df[income_df['capitalGain'] == 99999].index
income_df.drop(labels = gain,axis = 0,inplace =True)
print("Number of observation after removing:",income_df.shape)
```

```
Number of observation before removing: (48721, 15)
Number of observation after removing: (48477, 15)
```

In [16]:

```
# Dropping column education as education-num has high correlation with education
income_df.drop(['education'], axis=1, inplace=True)
income_df.head(10)
```

Out[16]:

	age	workclass	fnlwgt	education-num	maritalStatus	occupation	relationship	race	sex
0	39	State-gov	77516	13	Never-married	Adm-clerical	Not-in-family	White	Male
1	50	Self-emp-not-inc	83311	13	Married	Exec-managerial	Husband	White	Male
2	38	Private	215646	9	Divorced	Handlers-cleaners	Not-in-family	White	Male
3	53	Private	234721	7	Married	Handlers-cleaners	Husband	Black	Male
4	28	Private	338409	13	Married	Prof-specialty	Wife	Black	Female
5	37	Private	284582	14	Married	Exec-managerial	Wife	White	Female
6	49	Private	160187	5	Married	Other-service	Not-in-family	Black	Female
7	52	Self-emp-not-inc	209642	9	Married	Exec-managerial	Husband	White	Male
8	31	Private	45781	14	Never-married	Prof-specialty	Not-in-family	White	Female
9	42	Private	159449	13	Married	Exec-managerial	Husband	White	Male

In [18]:

```
# Converting categorical variables to numerical ones
dummies = pd.get_dummies(income_df.drop(['salary', 'age', 'capitalGain', 'capitalLoss',
                                        'hours-per-week'], axis=1))
```

In [19]:

```
# printing shape and top rows of the dataset
print("Shape of dummies: ",dummies.shape)
dummies.head(15)
```

```
Shape of dummies:  (48477, 85)
```

Out[19]:

	fnlwgt	education-num	workclass_	workclass_Federal-gov	workclass_Local-gov	workclass_Never-worked	workclass_Private	workclass_Self-em in
0	77516	13	0	0	0	0	0	
1	83311	13	0	0	0	0	0	
2	215646	9	0	0	0	0	1	
3	234721	7	0	0	0	0	1	
4	338409	13	0	0	0	0	1	
5	284582	14	0	0	0	0	1	
6	160187	5	0	0	0	0	1	
7	209642	9	0	0	0	0	0	
8	45781	14	0	0	0	0	1	
9	159449	13	0	0	0	0	1	
10	280464	10	0	0	0	0	1	
11	141297	13	0	0	0	0	0	
12	122272	13	0	0	0	0	1	
13	205019	12	0	0	0	0	1	
14	121772	11	0	0	0	0	1	

15 rows × 85 columns

In [20]:

```
# Concatention of existing columns with newly created ones
merged = pd.concat([income_df, dummies], axis=1)
```

In [21]:

```
print("Shape of dataset now is: ",merged.shape)
merged.head(5)
```

```
Shape of dataset now is:  (48477, 99)
```

Out[21]:

	age	workclass	fnlwgt	education-num	maritalStatus	occupation	relationship	race	sex
0	39	State-gov	77516	13	Never-married	Adm-clerical	Not-in-family	White	Male
1	50	Self-emp-not-inc	83311	13	Married	Exec-managerial	Husband	White	Male
2	38	Private	215646	9	Divorced	Handlers-cleaners	Not-in-family	White	Male
3	53	Private	234721	7	Married	Handlers-cleaners	Husband	Black	Male
4	28	Private	338409	13	Married	Prof-specialty	Wife	Black	Female

5 rows × 99 columns

In [56]:

```
# Printing final columns of the dataset
merged.columns[:100]
```

Out[56]:

```
Index(['age', 'workclass', 'fnlwgt', 'education-num', 'maritalStatus',
       'occupation', 'relationship', 'race', 'sex', 'capitalGain',
       'capitalLoss', 'hours-per-week', 'nativeCountry', 'salary', 'fnlwgt',
       'education-num', 'workclass_ ', 'workclass_ Federal-gov',
       'workclass_ Local-gov', 'workclass_ Never-worked', 'workclass_ Privat
e',
       'workclass_ Self-emp-inc', 'workclass_ Self-emp-not-inc',
       'workclass_ State-gov', 'workclass_ Without-pay',
       'maritalStatus_ Divorced', 'maritalStatus_ Married',
       'maritalStatus_ Never-married', 'maritalStatus_ Widowed',
       'occupation_ ', 'occupation_ Adm-clerical', 'occupation_ Armed-Force
s',
       'occupation_ Craft-repair', 'occupation_ Exec-managerial',
       'occupation_ Farming-fishing', 'occupation_ Handlers-cleaners',
       'occupation_ Machine-op-inspct', 'occupation_ Other-service',
       'occupation_ Priv-house-serv', 'occupation_ Prof-specialty',
       'occupation_ Protective-serv', 'occupation_ Sales',
       'occupation_ Tech-support', 'occupation_ Transport-moving',
       'relationship_ Husband', 'relationship_ Not-in-family',
       'relationship_ Other-relative', 'relationship_ Own-child',
       'relationship_ Unmarried', 'relationship_ Wife',
       'race_ Amer-Indian-Eskimo', 'race_ Asian-Pac-Islander', 'race_ Blac
k',
       'race_ Other', 'race_ White', 'sex_ Female', 'sex_ Male',
       'nativeCountry_ ', 'nativeCountry_ Cambodia', 'nativeCountry_ Canad
a',
       'nativeCountry_ China', 'nativeCountry_ Columbia',
       'nativeCountry_ Cuba', 'nativeCountry_ Dominican-Republic',
       'nativeCountry_ Ecuador', 'nativeCountry_ El-Salvador',
       'nativeCountry_ England', 'nativeCountry_ France',
       'nativeCountry_ Germany', 'nativeCountry_ Greece',
       'nativeCountry_ Guatemala', 'nativeCountry_ Haiti',
       'nativeCountry_ Holand-Netherlands', 'nativeCountry_ Honduras',
       'nativeCountry_ Hong', 'nativeCountry_ Hungary', 'nativeCountry_ Indi
a',
       'nativeCountry_ Iran', 'nativeCountry_ Ireland', 'nativeCountry_ Ital
y',
       'nativeCountry_ Jamaica', 'nativeCountry_ Japan', 'nativeCountry_ Lao
s',
       'nativeCountry_ Mexico', 'nativeCountry_ Nicaragua',
       'nativeCountry_ Outlying-US(Guam-USVI-etc)', 'nativeCountry_ Peru',
       'nativeCountry_ Philippines', 'nativeCountry_ Poland',
       'nativeCountry_ Portugal', 'nativeCountry_ Puerto-Rico',
       'nativeCountry_ Scotland', 'nativeCountry_ South',
       'nativeCountry_ Taiwan', 'nativeCountry_ Thailand',
       'nativeCountry_ Trinadad&Tobago', 'nativeCountry_ United-States',
       'nativeCountry_ Vietnam', 'nativeCountry_ Yugoslavia'],
      dtype='object')
```

In [22]:

```
# dropping the categorical columns
final_df = merged.drop(['workclass', 'maritalStatus', 'occupation', 'relationship',
                        'race', 'sex', 'nativeCountry'], axis=1)
print("Printing shape of the dataset: ",final_df.shape)
final_df.head(10)
```

```
Printing shape of the dataset:  (48477, 92)
```

Out[22]:

	age	fnlwgt	education-num	capitalGain	capitalLoss	hours-per-week	salary	fnlwgt	education-num	workc
0	39	77516	13	2174	0	40	<=50K	77516	13	
1	50	83311	13	0	0	13	<=50K	83311	13	
2	38	215646	9	0	0	40	<=50K	215646	9	
3	53	234721	7	0	0	40	<=50K	234721	7	
4	28	338409	13	0	0	40	<=50K	338409	13	
5	37	284582	14	0	0	40	<=50K	284582	14	
6	49	160187	5	0	0	16	<=50K	160187	5	
7	52	209642	9	0	0	45	>50K	209642	9	
8	31	45781	14	14084	0	50	>50K	45781	14	
9	42	159449	13	5178	0	40	>50K	159449	13	

10 rows × 92 columns

In [23]:

```
# Splitting into training and testing data
X_train, X_test, y_train, y_test = train_test_split(final_df.drop('salary', axis=1), final_
                                                    test_size=0.33, random_state=1)
```

In [24]:

```
# printing the size of the train and test variables
print("X_train size: ",X_train.shape)
print("X_test size: ",X_test.shape)
```

```
X_train size:  (32479, 91)
X_test size:  (15998, 91)
```

Applying Logistic Regression

In [25]:

```
lr=LogisticRegression()
lr.fit(X_train, y_train)
predictions = lr.predict(X_test)
print(metrics.classification_report(y_test, predictions))
print("Accuracy for Logistic Regression model is: ",metrics.accuracy_score(y_test, predicti
```

```
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:4
33: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)

              precision    recall  f1-score   support

       <=50K       0.80      0.97      0.88     12220
        >50K       0.71      0.24      0.36      3778

   micro avg       0.80      0.80      0.80     15998
   macro avg       0.76      0.60      0.62     15998
weighted avg       0.78      0.80      0.76     15998

Accuracy for Logistic Regression model is:  0.7974121765220653
```

Applying KNN

In [26]:

```
knn=KNeighborsClassifier()
knn.fit(X_train, y_train)
predictions = knn.predict(X_test)
print(metrics.classification_report(y_test, predictions))
print("Accuracy for KNN model is: ",metrics.accuracy_score(y_test, predictions))
```

```
              precision    recall  f1-score   support

       <=50K       0.81      0.92      0.86     12220
        >50K       0.54      0.31      0.39      3778

   micro avg       0.78      0.78      0.78     15998
   macro avg       0.68      0.61      0.63     15998
weighted avg       0.75      0.78      0.75     15998

Accuracy for KNN model is:  0.7752844105513189
```

Applying Decision Tree Classifier

In [27]:

```
dt=DecisionTreeClassifier()
dt.fit(X_train, y_train)
predictions = dt.predict(X_test)
print(metrics.classification_report(y_test, predictions))
print("Accuracy for Decision Tree Classifier model is: ",metrics.accuracy_score(y_test, pre
```

```
              precision    recall  f1-score   support

       <=50K       0.88      0.88      0.88     12220
        >50K       0.62      0.62      0.62      3778

   micro avg       0.82      0.82      0.82     15998
   macro avg       0.75      0.75      0.75     15998
weighted avg       0.82      0.82      0.82     15998

Accuracy for Decision Tree Classifier model is:  0.8199774971871484
```

Applying Random Forest Classifier

In [28]:

```
rf = RandomForestClassifier(n_estimators=100)
rf.fit(X_train, y_train)
predictions = rf.predict(X_test)
print(metrics.classification_report(y_test, predictions))
print("Accuracy for Random Forest Classifier model is: ",metrics.accuracy_score(y_test, pre
```

```
              precision    recall  f1-score   support

       <=50K       0.89      0.93      0.91     12220
        >50K       0.74      0.61      0.67      3778

   micro avg       0.86      0.86      0.86     15998
   macro avg       0.81      0.77      0.79     15998
weighted avg       0.85      0.86      0.85     15998

Accuracy for Random Forest Classifier model is:  0.8574196774596825
```

Applying GaussianNB

In [29]:

```
nb=GaussianNB()
nb.fit(X_train, y_train)
predictions = nb.predict(X_test)
print(metrics.classification_report(y_test, predictions))
print("Accuracy for Naive Bayes model is: ",metrics.accuracy_score(y_test, predictions))
```

```
              precision    recall  f1-score   support

       <=50K       0.81      0.95      0.87     12220
        >50K       0.63      0.29      0.40      3778

   micro avg       0.79      0.79      0.79     15998
   macro avg       0.72      0.62      0.64     15998
weighted avg       0.77      0.79      0.76     15998

Accuracy for Naive Bayes model is:  0.7924115514439305
```

Applying Gradient Boosting Classifier

In [30]:

```
gbm = GradientBoostingClassifier()
gbm.fit(X_train, y_train)
predictions = gbm.predict(X_test)
print(metrics.classification_report(y_test, predictions))
print("Accuracy for Gradient Boosting model is: ",metrics.accuracy_score(y_test, predictior
```

```
              precision    recall  f1-score   support

       <=50K       0.89      0.95      0.92     12220
        >50K       0.80      0.61      0.69      3778

   micro avg       0.87      0.87      0.87     15998
   macro avg       0.84      0.78      0.80     15998
weighted avg       0.87      0.87      0.86     15998

Accuracy for Gradient Boosting model is:  0.870796349543693
```

In [ ]:

```

```