BLOG REPORT

OF

Census Income Project

MADE BY:

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INTRODUCTION

Census money income is defined as income received on a regular basis (exclusive of certain money receipts such as capital gains) before payments for personal income taxes, social security, union dues, Medicare deductions, etc. Therefore, money income does not reflect the fact that some families receive part of their income in the form of noncash benefits, such as food stamps, health benefits, subsidized housing, and goods produced and consumed on the farm.

The Census Bureau reports income from several major household surveys and programs. Each differs from the others in some way, such as the length and detail of its questionnaire, the number of households included (sample size), and the methodology used.

Description of final weight

The weights on the Current Population Survey (CPS) files are controlled to independent estimates of the civilian non-institutional population of the US. These are prepared monthly for us by Population Division here at the Census Bureau. We use 3 sets of controls. These are:

1. A single cell estimate of the population 16+ for each state.
2. Controls for Hispanic Origin by age and sex.
3. Controls by Race, age and sex.

We use all three sets of controls in our weighting program and "rake" through them 6 times so that by the end we come back to all the controls we used. The term estimate refers to population totals derived from CPS by creating "weighted tallies" of any specified socio-economic characteristics of the population. People with similar demographic characteristics should have similar weights. There is one important caveat to remember about this statement. That is that since the CPS sample is actually a collection of 51 state samples, each with its own probability of selection, the statement only applies within state.

Business case

This data was extracted from the 1994 Census bureau database by Ronny Kohavi and Barry Becker (Data Mining and Visualization, Silicon Graphics). A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1) && (HRSWK>0)).

TASK

The prediction task is to determine whether a person makes over $50K a year.

Objective:

The techniques in the machine learning is to improve the accuracy of detection on various imbalanced datasets. A machine learning system works by:

1. INPUT DATA
2. EXTRACT FILES
3. TRAIN ALGORITHM
4. CREATE A MODEL

All this steps are involved along with the algorithm on the partial training datasets and then it is tested on the test datasets, finally it is then examined by some random splits .The data in the datasets are handled by certain rules.

About Dataset

The dataset is about the census income dataset. The prediction task is to determine whether a person makes over $50K a year.

DATA ANALYSIS

Importing Required Library-

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
from sklearn.model_selection import cross_val_score

import warnings
warnings.filterwarnings('ignore')
```

Extracting dataset

```
data = pd.read_csv('https://raw.githubusercontent.com/dsrscientist/dataset1/master/census_income.csv')
```

```
data
```

	Age	Workclass	Fnlwgt	Education	Education_num	Marital_status	Occupation	Relationship	Race	Sex	Capital_gain	Capital_loss	Hours_per_v
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	40
...	...	...	...	...	...	...	...	...	...	...	...	...	...
32555	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38
32556	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40
32557	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40
32558	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20
32559	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40

32560 rows × 15 columns

Census Income Project-

In this dataset we have 14 independent variable and 1 dependent variable.

Dependent Variable or Target Variable

Income
<=50K
<=50K
<=50K
<=50K
<=50K
...
<=50K
>50K
<=50K
<=50K
>50K

This is my dependent variable which shows if the person has more then 50k income or less then 50k income.

CHECKING FOR NULL VALUES:

```
: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32560 entries, 0 to 32559
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Age             32560 non-null  int64 
 1   Workclass       32560 non-null  object
 2   Fnlwgt          32560 non-null  int64 
 3   Education       32560 non-null  object
 4   Education_num   32560 non-null  int64 
 5   Marital_status  32560 non-null  object
 6   Occupation      32560 non-null  object
 7   Relationship    32560 non-null  object
 8   Race            32560 non-null  object
 9   Sex             32560 non-null  object
 10  Capital_gain    32560 non-null  int64 
 11  Capital_loss    32560 non-null  int64 
 12  Hours_per_week  32560 non-null  int64 
 13  Native_country  32560 non-null  object
 14  Income          32560 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
: data.shape
```

```
: (32560, 15)
```

```
: data.isna().sum()
```

```
: Age               0
  Workclass         0
  Fnlwgt            0
  Education         0
  Education_num     0
  Marital_status    0
  Occupation        0
  Relationship      0
  Race              0
  Sex               0
  Capital_gain      0
  Capital_loss      0
  Hours_per_week    0
  Native_country    0
  Income            0
  dtype: int64
```

There is no null values in the dataset.

There are 6 integer & 9 object Data type. Also there is no null value in the given dataset.

DATA ANALYSIS

Now we have to analyze our object columns

```
: {column:len(data[column].unique()) for column in data.select_dtypes('object').columns}
```

```
: {'Education': 16,
   'Income': 2,
   'Marital_status': 7,
   'Native_country': 42,
   'Occupation': 15,
   'Race': 5,
   'Relationship': 6,
   'Sex': 2,
   'Workclass': 9}
```

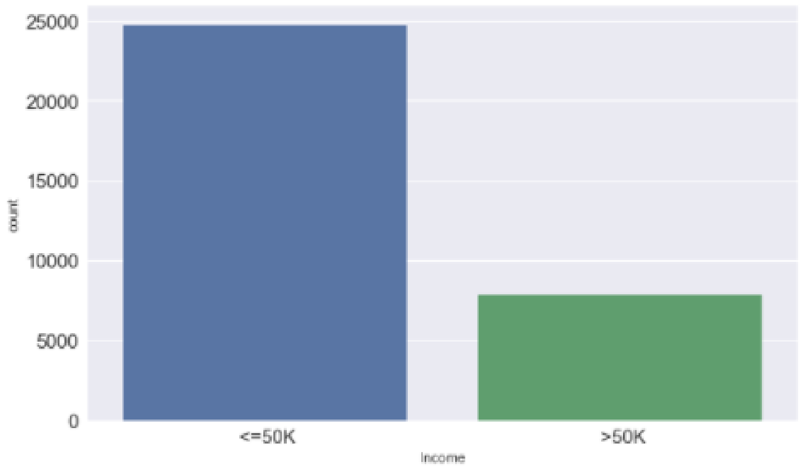
This code is showing how many unique values we have in each column this will really help me to perform EDA.

Exploratory Data Analysis

Univariate Analysis

Univariate analysis is perhaps the simplest form of statistical analysis. Like other forms of statistics, it can be inferential or descriptive.

```
: plt.figure(figsize = (10,6),facecolor='white')
  sns.countplot(x='Income', data = data)
  plt.tick_params(labelsize=15)
  plt.show()


  data['Income'].value_counts()
```

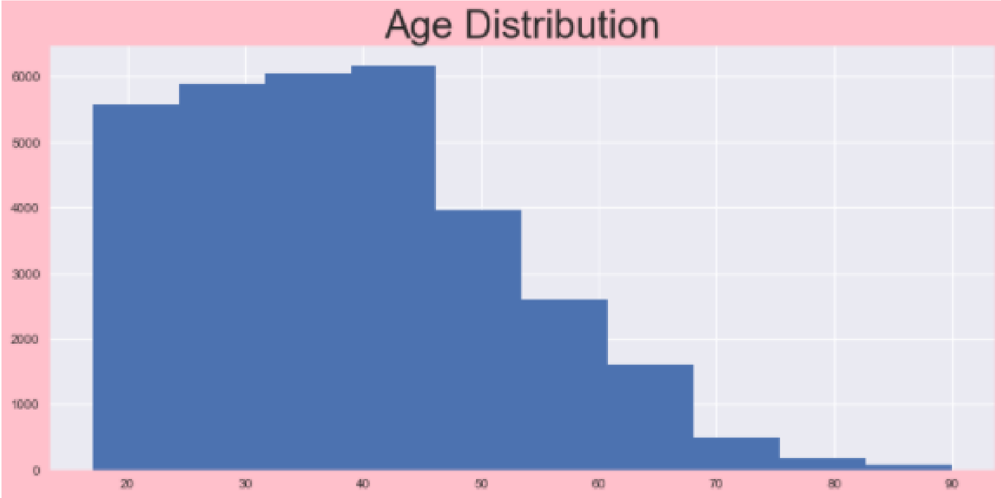



```
:  <=50K    24719
   >50K      7841
  Name: Income, dtype: int64
```

Observation:

The highest number of population are earning less than 50k

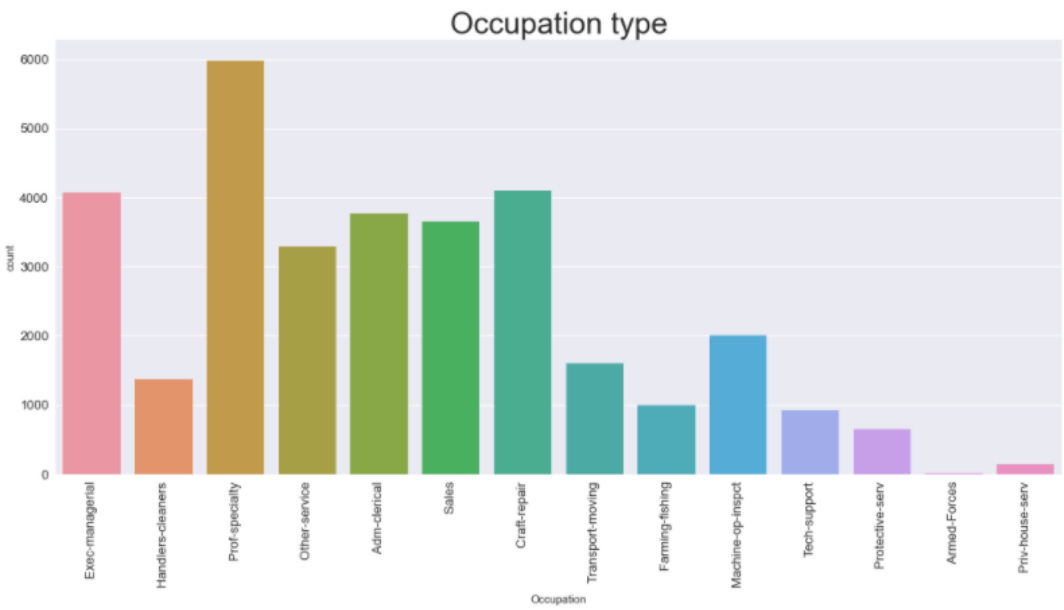
```
plt.figure(figsize = (13,6),facecolor='pink')
plt.hist(data['Age'])
plt.title("Age Distribution", fontsize = 30)

plt.show()
```



People between age group 20-40 are highest working population.

Maximum people who are working are in Age group of 20-40 years.

```
plt.figure(figsize = (18,8))
ax=sns.countplot(x="Occupation", data=data)
ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
plt.tick_params(labelsize=13)
plt.title("Occupation type", fontsize = 30)
plt.show()
```

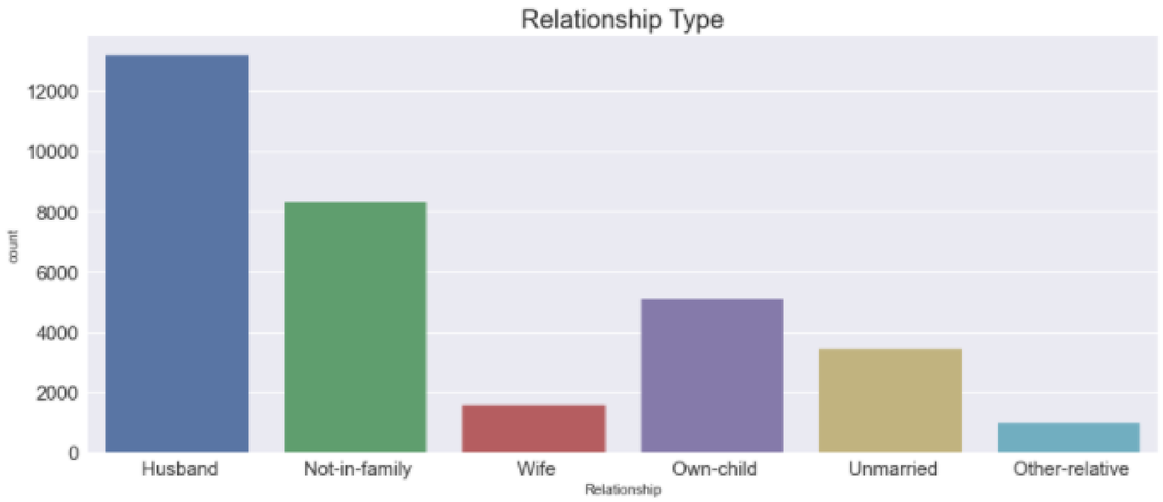


Highest number of population are in PROF-SPECIALITY occupation.

Armed Forces have least number of population among all the occupations.

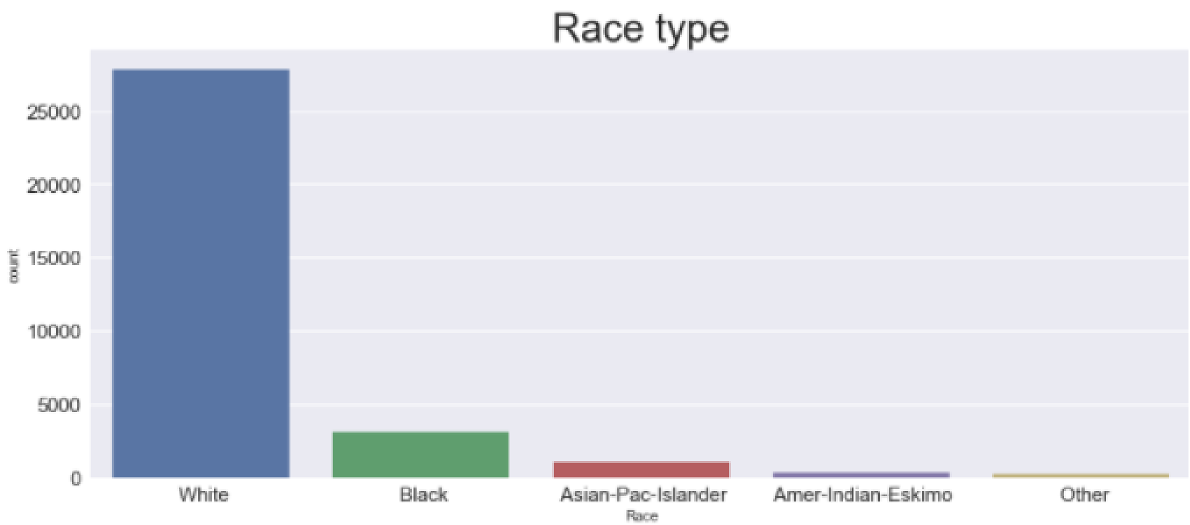
Maximum numbers of people are in PRO-SPECIALITY occupation.

```
plt.figure(figsize = (15,6))
sns.countplot(x="Relationship", data=data)
plt.title("Relationship Type", fontsize = 20)
plt.tick_params(labelsize=15)
plt.show()
```



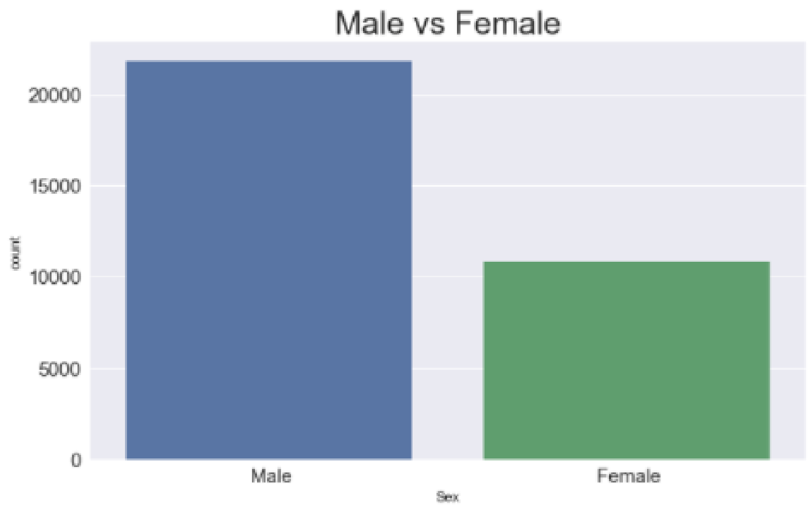
Husband have highest percentage in working profile.

```
plt.figure(figsize = (15,6))
sns.countplot(x="Race", data=data)
plt.title("Race type", fontsize = 30)
plt.tick_params(labelsize=15)
plt.show()
```



Population of White race is highest.

```
plt.figure(figsize = (10,6))
sns.countplot(x="Sex", data=data)
plt.title("Male vs Female", fontsize = 25)
plt.tick_params(labelsize=15)
plt.show()
```

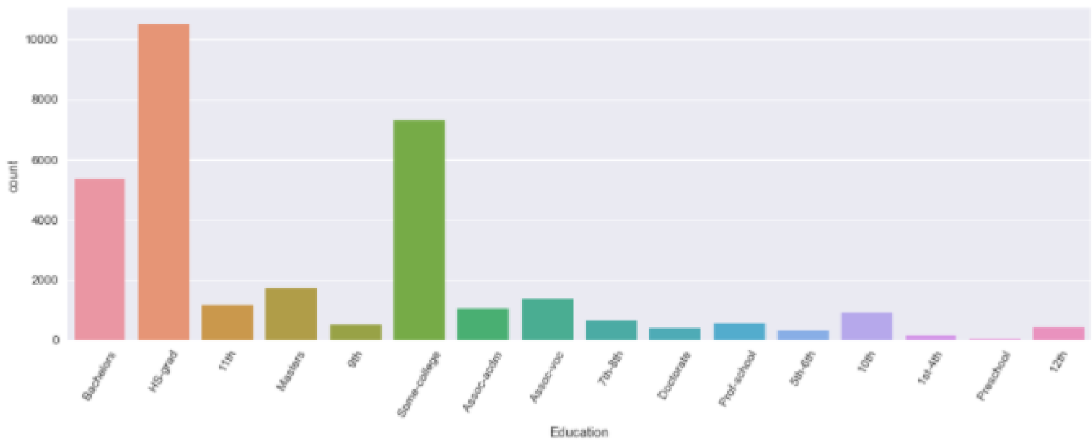


No. of count for male is higher than female.

NUMBER OF MALES ARE HIGHER THAN FEMALES.

```
plt.figure(figsize = [15,5])
sns.countplot(x='Education',data=data)
plt.xticks(rotation=60)

data['Education'].value_counts()
```

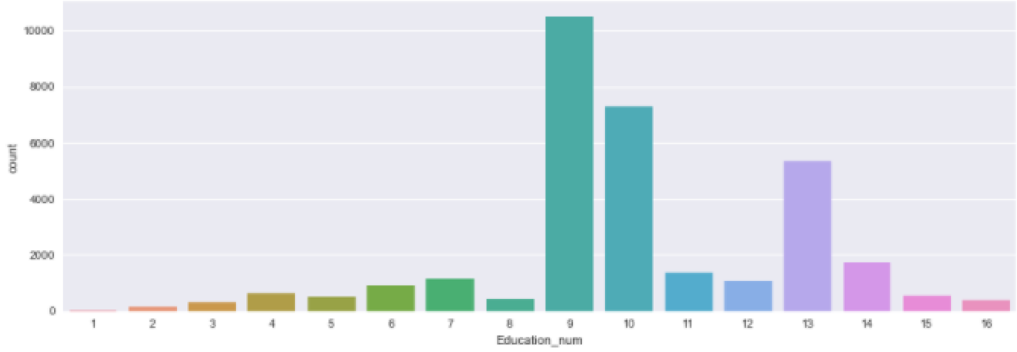
```
HS-grad         10501
Some-college     7291
Bachelors        5354
Masters          1723
Assoc-voc        1382
11th             1175
Assoc-acdm       1067
10th              933
7th-8th           646
Prof-school       576
9th               514
12th              433
Doctorate         413
5th-6th           333
1st-4th           168
Preschool          51
Name: Education, dtype: int64
```



Max people have been HS-GRAD.

```
plt.figure(figsize = [15,5])

sns.countplot(x='Education_num',data=data)
plt.xticks()

data['Education_num'].value_counts()
```

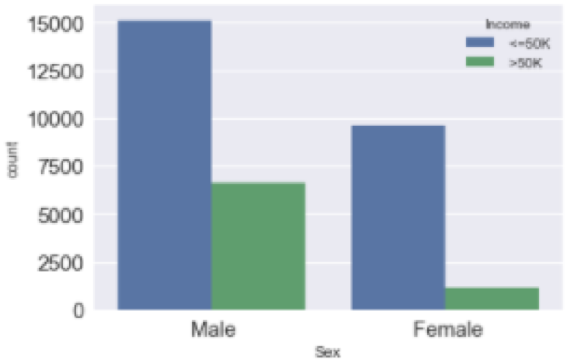
```
9     10501
10     7291
13     5354
14     1723
11     1382
7      1175
12     1067
6       933
4       646
15      576
5       514
8       433
16      413
3       333
2       168
1        51
Name: Education_num, dtype: int64
```



Bivariate Analysis-

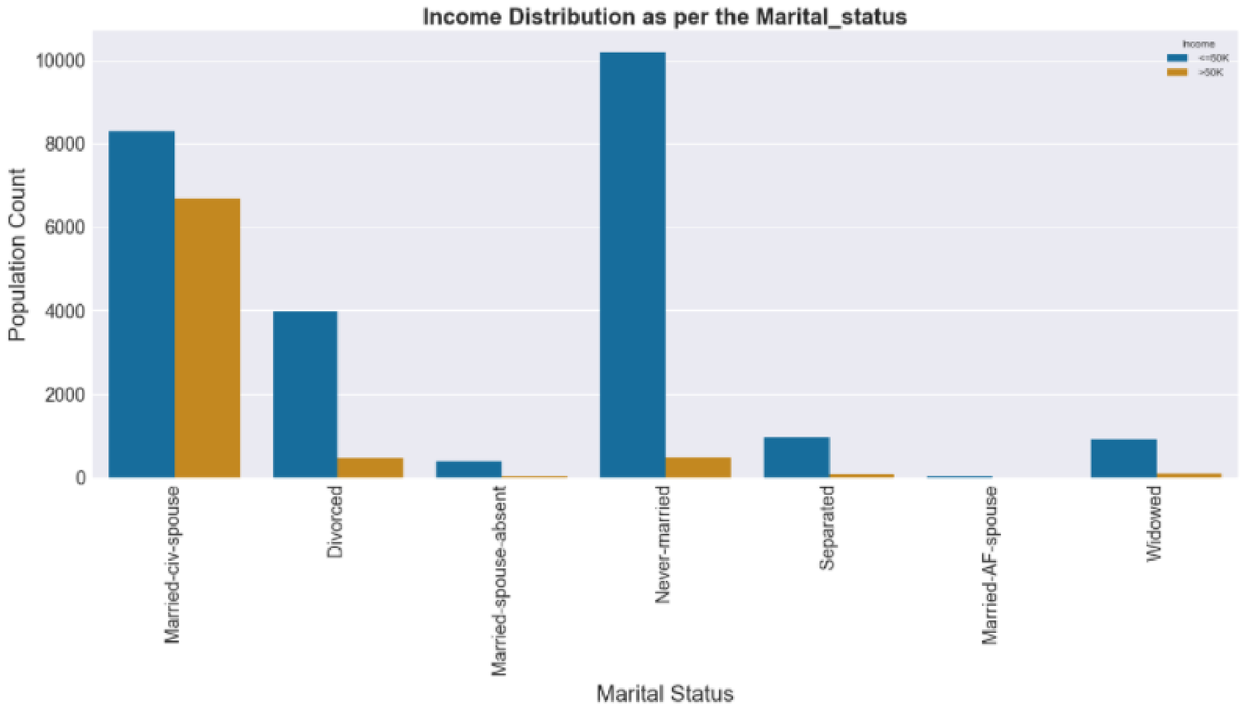
Bivariate analysis is one of the simplest forms of quantitative (statistical) analysis. It involves the analysis of two variables (often denoted as X, Y), for the purpose of determining the empirical relationship between them.

```
sns.countplot(data['Sex'],hue=data['Income'])
plt.tick_params(labelsize=15)
```



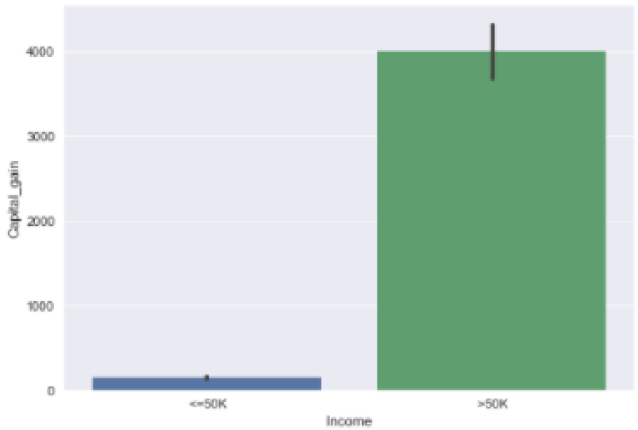
Percentage of Males are earning over ">50K" are higher than female.

```python
plt.style.use('seaborn')
plt.figure(figsize=(20, 8))
sns.countplot(data['Marital_status'],hue=data['Income'], palette='colorblind')
plt.title('Income Distribution as per the Marital_status', fontdict={'fontsize': 22, 'fontweight': 'bold'})
plt.xlabel('Marital Status', fontdict={'fontsize': 22})
plt.ylabel('Population Count', fontdict={'fontsize': 22})
plt.xticks(rotation=90)
plt.tick_params(labelsize=18)
plt.show()
```




```python
sns.barplot(x = 'Income', y = 'Capital_gain', data = data)
```

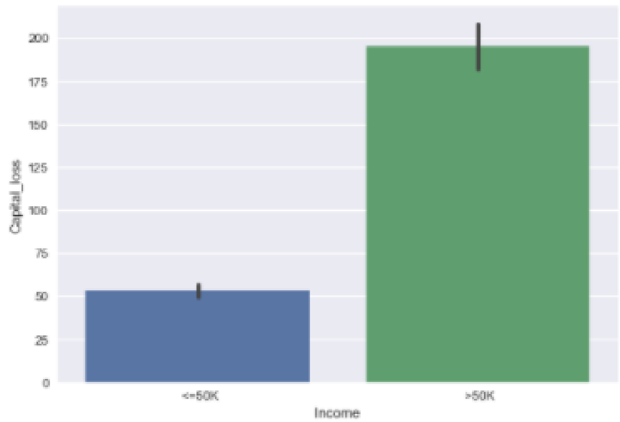
```
<AxesSubplot:xlabel='Income', ylabel='Capital_gain'>
```



people earning more than 50k are leading to more capital gain.

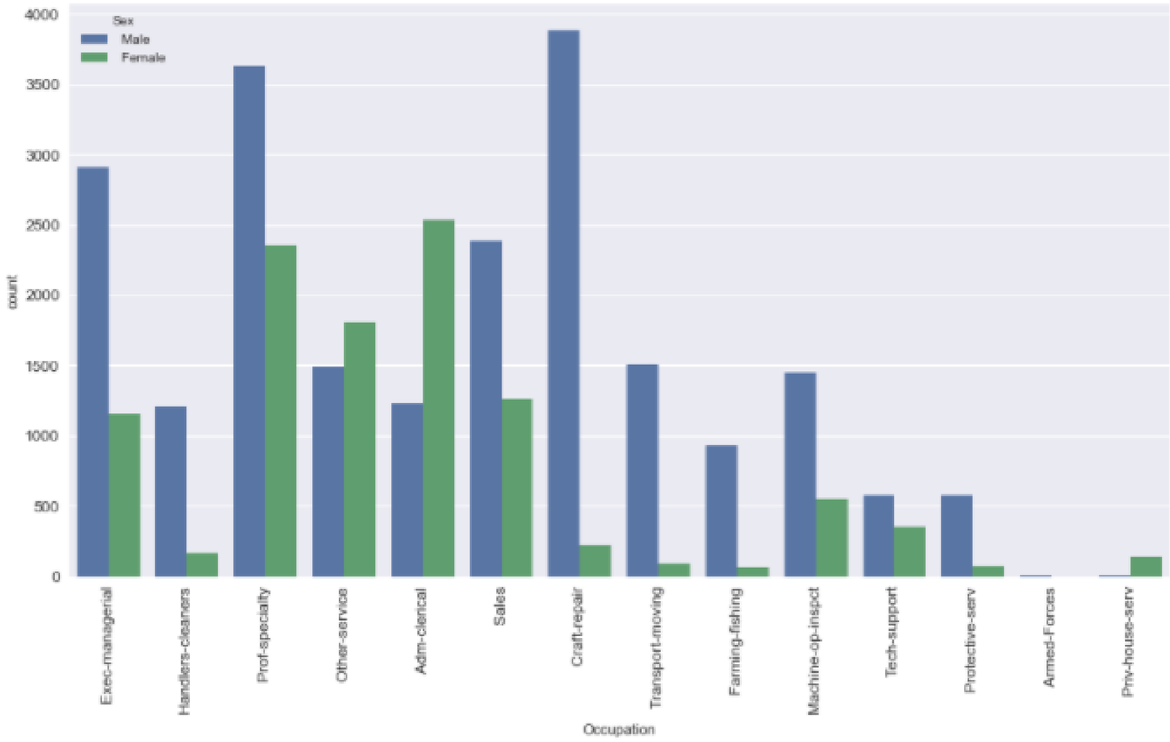
```python
sns.barplot(x = 'Income', y = 'Capital_loss', data = data)
```

```
<AxesSubplot:xlabel='Income', ylabel='Capital_loss'>
```



people earning more than 50k are leading to more capital loss.

```
plt.figure(figsize=(15,8))
ax = sns.countplot(data['Occupation'], hue=data['Sex'])
ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
plt.tick_params(labelsize=12)
plt.show()
```



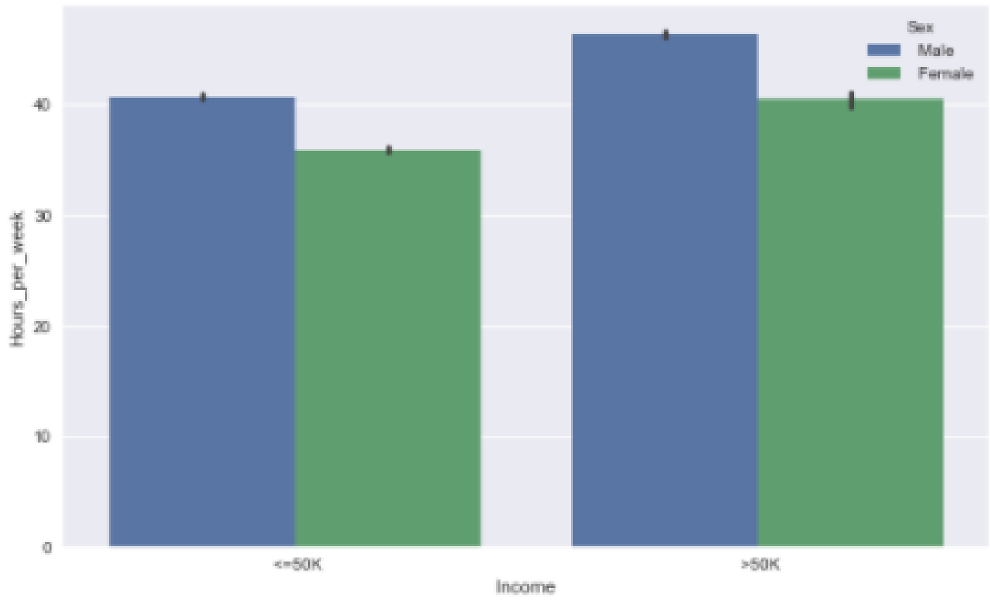
In most of the occupation number of males compared to females are high.

Multivariate Analysis

Multivariate analysis is based on the statistical principle of multivariate statistics, which involves observation and analysis of more than one statistical outcome variable at a time.

[117]:
```
plt.figure(figsize = (10,6))
sns.barplot(x=data['Income'],y=data['Hours_per_week'],hue=data['Sex'])
```

t[117]:
```
<AxesSubplot:xlabel='Income', ylabel='Hours_per_week'>
```

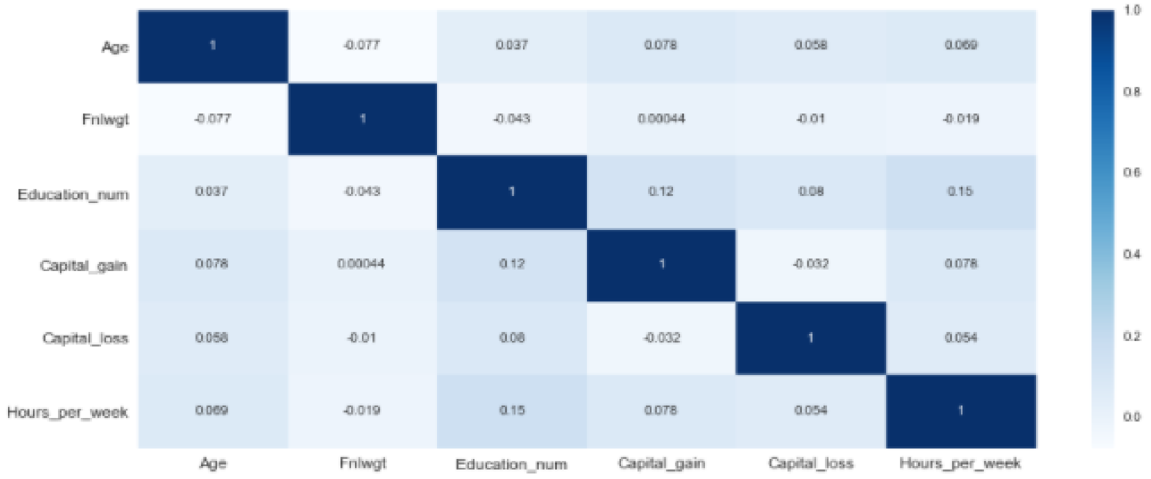


working hours of male and female are higher who are earning more than 50k.

Correlation

To calculate the **correlation** between two variables in **Python,** we can use the Numpy corrcoef () function.

```
plt.figure(figsize=(15,6))
sns.heatmap(data.corr(),annot=True,cmap='Blues')
plt.tick_params(labelsize=12)

plt.show()
```




```
data.corr()
```

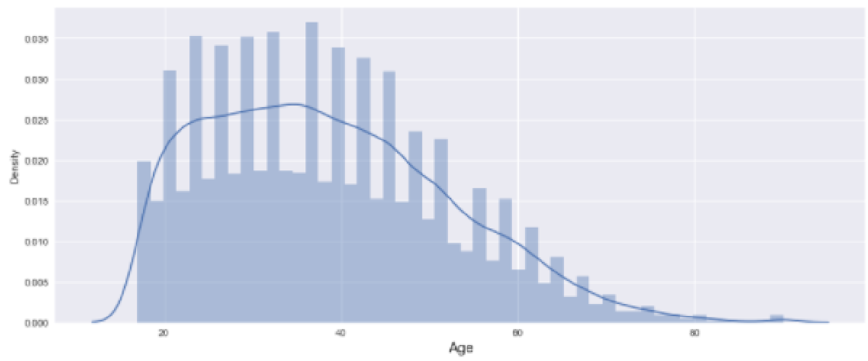
	Age	Fnlwgt	Education_num	Capital_gain	Capital_loss	Hours_per_week
Age	1.000000	-0.076646	0.036527	0.077674	0.057775	0.068756
Fnlwgt	-0.076646	1.000000	-0.043159	0.000437	-0.010259	-0.018770
Education_num	0.036527	-0.043159	1.000000	0.122627	0.079932	0.148127
Capital_gain	0.077674	0.000437	0.122627	1.000000	-0.031614	0.078409
Capital_loss	0.057775	-0.010259	0.079932	-0.031614	1.000000	0.054256
Hours_per_week	0.068756	-0.018770	0.148127	0.078409	0.054256	1.000000

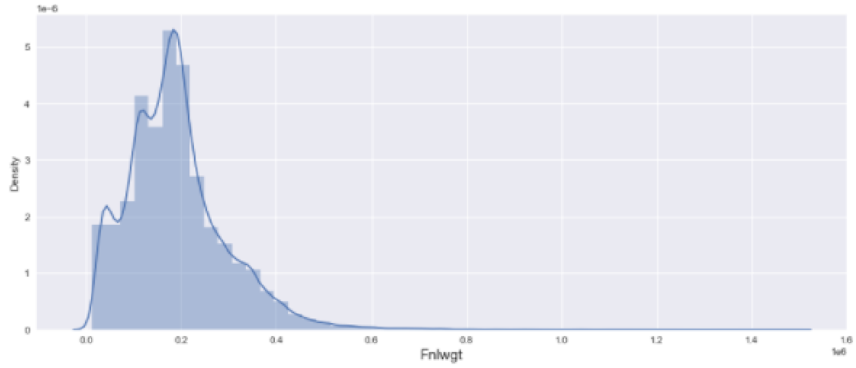
Correlation is seemed to be good like education having good +ve correlation and relationship and sex having -ve correlation and rest of the columns are also having correlation but at low level.

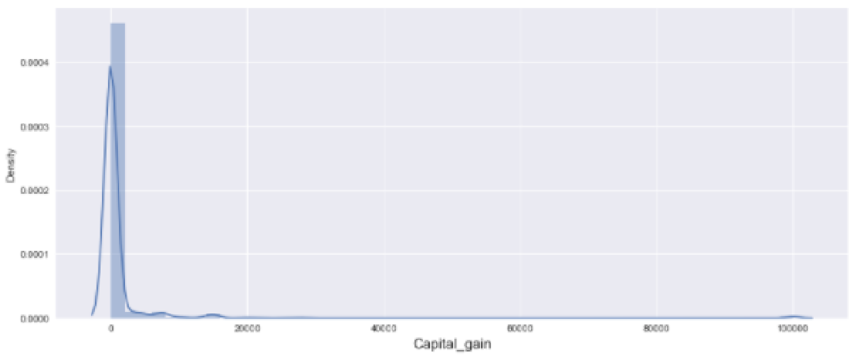
Checking Outliers [If Any Remove Them]-

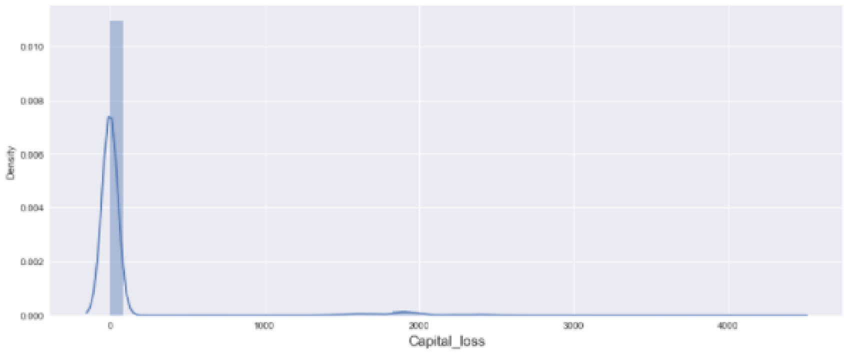
Removing Outliers

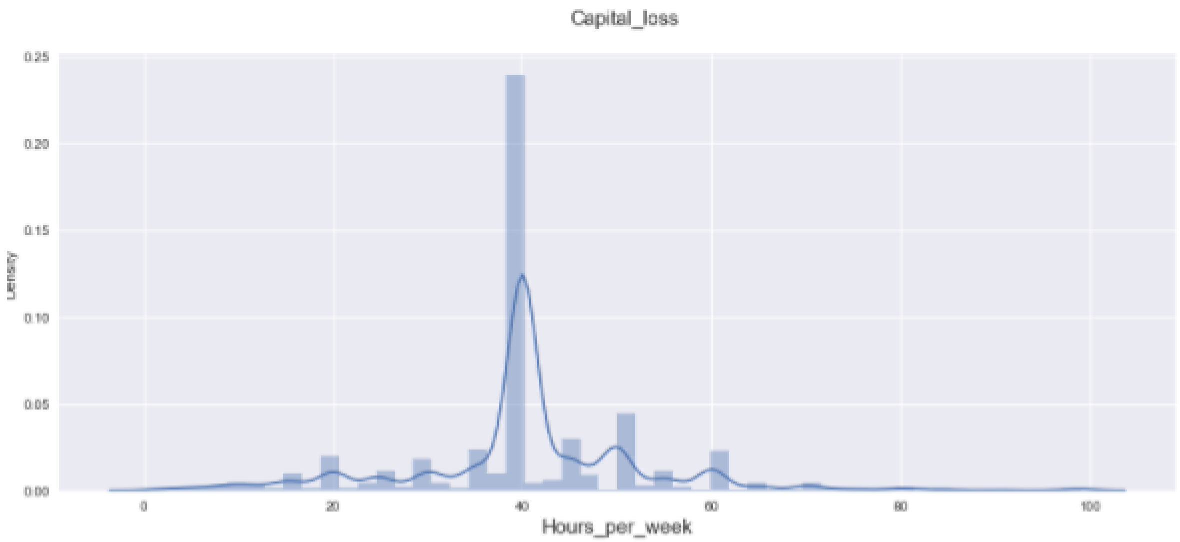
```
for i in data.columns:

    if data[i].dtype!='object':
        plt.figure(figsize=[15,6])
        sns.distplot(data[i])
        plt.xlabel(i,fontsize=15)
    plt.show()
```











There are many ways to remove outliers like Z-Score, IQR-Method

IQR Method

```
Q1 = data[features].quantile(0.25)
Q3 = data[features].quantile(0.75)
IQR = Q3-Q1

data_new1 = data[~((data[features] < (Q1-1.5*IQR)) | (data[features]> (Q3 + 1.5*Q3))).any(axis = 1)]
```

```
print('Shape - Before and After:\n')
print('Shape Before'.ljust(20),":",data.shape)
print('Shape After'.ljust(20),":",data_new1.shape)
print('Percentage Loss'.ljust(20),":",((data.shape[0]-data_new1.shape[0])/data.shape[0])*100)
```

```
Shape - Before and After:

Shape Before         : (32560, 14)
Shape After          : (24491, 14)
Percentage Loss      : 24.78194103194103
```

z-score Method

```
from scipy.stats import zscore

z=np.abs(zscore(data[features]))
threshold = 3
data_new2 = data[(z<3).all(axis=1)]
```

```
print('Shape - Before and After:\n')
print('Shape Before'.ljust(20),":",data.shape)
print('Shape After'.ljust(20),":",data_new2.shape)
print('Percentage Loss'.ljust(20),":",((data.shape[0]-data_new2.shape[0])/data.shape[0])*100)
```

```
Shape - Before and After:

Shape Before         : (32560, 14)
Shape After          : (31461, 14)
Percentage Loss      : 3.3753071253071254
```

After applying z-score method percentage loss is less.

```
data_new = data_new2.copy()
```

Checking Skewness[if any remove it]-

Skewness is the degree of distortion from a normal distribution for machine learning model.

```
: data.skew()

: Age                0.558738
  Fnlwgt             1.446972
  Capital_gain      11.953690
  Capital_loss       4.594549
  Hours_per_week     0.227636
  dtype: float64

: data_new.skew()

: Age               0.475267
  Fnlwgt            0.632635
  Capital_gain      5.087653
  Capital_loss      4.544726
  Hours_per_week   -0.345858
  dtype: float64
```

The value for skewness is 0.5 to -0.5 if we have a value greater then 0.5 or less then -0.5 it means our data is skewed and we can only reduce skewness of continuous columns as we can see our data also have some skewness.

Removing Skewness-

```
from sklearn.preprocessing import PowerTransformer

scaler = PowerTransformer(method='yeo-johnson')

data_new['Capital_gain'] = scaler.fit_transform(data_new['Capital_gain'].values.reshape(-1,1))
data_new['Fnlwgt'] = scaler.fit_transform(data_new['Fnlwgt'].values.reshape(-1,1))
data_new['Capital_loss'] = scaler.fit_transform(data_new['Capital_loss'].values.reshape(-1,1))
```

Removing skewness with the help of power transformer i am using method=’yeo-johnson’ because it will also deal with the -vs skewed data.

```
data_new.skew()

Age               0.475267
Fnlwgt           -0.034708
Capital_gain      3.176483
Capital_loss      4.277175
Hours_per_week   -0.345858
dtype: float64

data_new.dtypes

Age                int64
Workclass         object
Fnlwgt           float64
Education         object
Marital_status    object
Occupation        object
Relationship      object
Race              object
Sex               object
Capital_gain     float64
Capital_loss     float64
Hours_per_week     int64
Native_country    object
Income            object
dtype: object
```

Implementing LabelEncoder

In **Python Label Encoding,** we need to replace the categorical value using a numerical value ranging between zero and the total number of classes minus one. For instance, if the value of the categorical variable has six different classes, we will use 0, 1, 2, 3, 4, and 5.

```
l1 = ['Marital_status','Sex','Race','Workclass','Education','Occupation','Relationship']
```

```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

for i in l1:
    if data_new[i].dtypes=='object':
        data_new[i]= le.fit_transform(data_new[i].values.reshape(-1,1))
data_new.head()
```

	Age	Workclass	Fnlwgt	Education	Marital_status	Occupation	Relationship	Race	Sex	Capital_gain	Capital_loss	Hours_per_week	Native_country
0	50	5	-1.116536	9	2	3	0	4	1	-0.288606	-0.22226	13	United-States
1	38	3	0.423719	11	0	5	1	4	1	-0.288606	-0.22226	40	United-States
2	53	3	0.603774	1	2	5	0	2	1	-0.288606	-0.22226	40	United-States
3	28	3	1.483944	9	2	9	5	2	0	-0.288606	-0.22226	40	Cuba
4	37	3	1.045276	12	2	3	5	4	0	-0.288606	-0.22226	40	United-States

```
l2=pd.get_dummies(data_new['Native_country'])
```

```
data_new=pd.concat([data_new.drop('Native_country',axis=1),l2],axis=1)
```

```
data_new.head()
```

	Age	Workclass	Fnlwgt	Education	Marital_status	Occupation	Relationship	Race	Sex	Capital_gain	...	Portugal	Puerto-Rico	Scotland	South	Taiwan	T
0	50	5	-1.116536	9	2	3	0	4	1	-0.288606	...	0	0	0	0	0	0
1	38	3	0.423719	11	0	5	1	4	1	-0.288606	...	0	0	0	0	0	0
2	53	3	0.603774	1	2	5	0	2	1	-0.288606	...	0	0	0	0	0	0
3	28	3	1.483944	9	2	9	5	2	0	-0.288606	...	0	0	0	0	0	0
4	37	3	1.045276	12	2	3	5	4	0	-0.288606	...	0	0	0	0	0	0

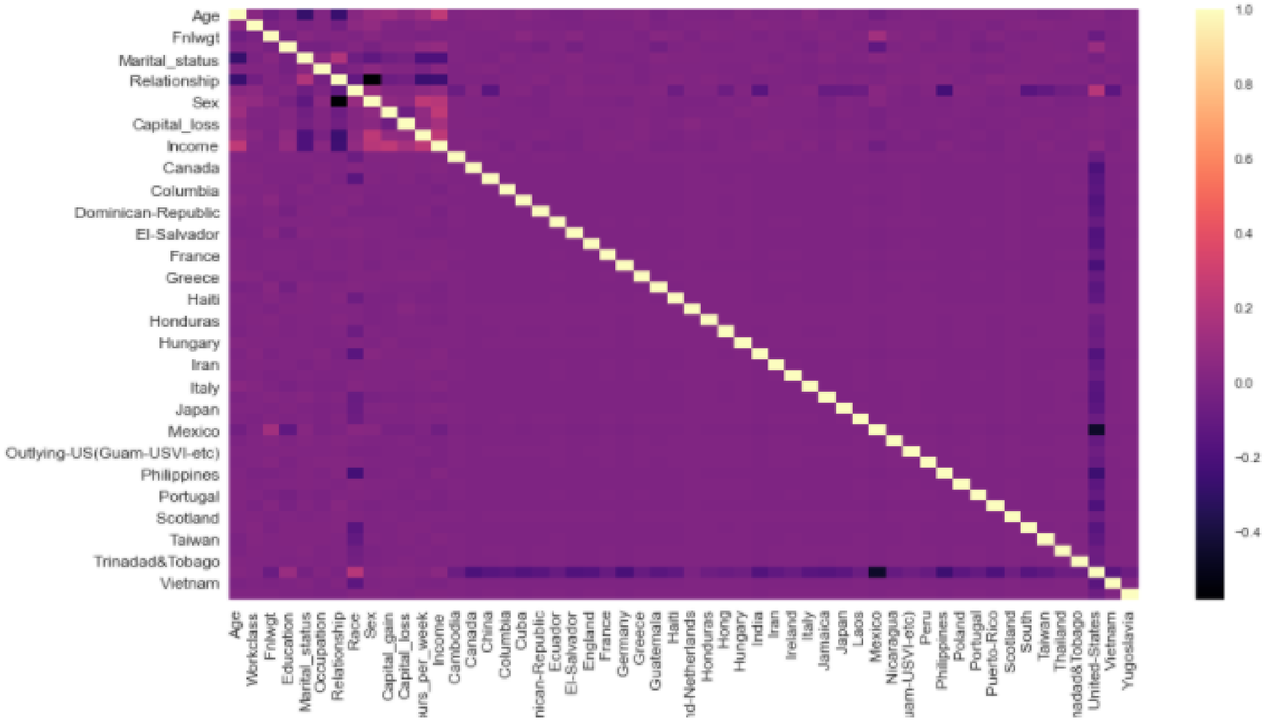
5 rows × 54 columns

LABELING

```
data_new['Income'] = le.fit_transform(data_new['Income'].values.reshape(-1,1))
data_new['Income'].value_counts()
```

```
0    24049
1     7412
Name: Income, dtype: int64
```

```
plt.figure(figsize=(15,8))
sns.heatmap(data_new.corr(),annot=False,cmap='magma')
plt.tick_params(labelsize=12)
plt.show()
```



SPLITTING LABELS AND FEATURES

```
X = data_new.drop(columns = 'Income')
Y = data_new['Income']
```

BALANCING

```
from imblearn.over_sampling import SMOTE

sm=SMOTE()
X_over,Y_over = sm.fit_resample(X,Y)
```

```
round(Y_over.value_counts(normalize=True)*100,2).astype('str')+'%'
```

```
0    50.0%
1    50.0%
Name: Income, dtype: object
```

SCALING

Feature scaling is a very important step in machine learning in datasets we usually have some extremely high values and some min values so feature scaling is used to convert them between 0–1 range so our model can easily interpret values but if we are using tree base model we don't need to scale our values this is one of the advantages of tree base models.

```
from sklearn.preprocessing import StandardScaler
Scaler = StandardScaler()

X_scaled = Scaler.fit_transform(X_over)
```

```
from sklearn.linear_model import LogisticRegression

maxAccuracy = 0
maxAcc = 0

for i in range(200):
    x_train,x_test,y_train,y_test = train_test_split(X_scaled,Y_over,test_size = 0.20,random_state = i)
    LR = LogisticRegression()
    LR.fit(x_train,y_train)
    pred = LR.predict(x_test)
    acc = accuracy_score(y_test,pred)
    if acc>maxAccuracy:
        maxAccuracy = acc
        maxAcc = i

print('Maximum accuracy is ',maxAccuracy, ' with Random State ',maxAcc)
```

```
Maximum accuracy is  0.7615384615384615  with Random State  196
```

Here I am using StandardScaler to scale values.

Splitting Data into train and test-

Splitting Data- TESTING & TRAINING

```
x_train,x_test,y_train,y_test = train_test_split(X_scaled,Y_over,test_size = 0.20,random_state = maxAcc)
```

I am using train test split to split my data into train and test and i am using 30% of data for testing and rest of all data for training.

Model Building-

Importing library for machine learning model building

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

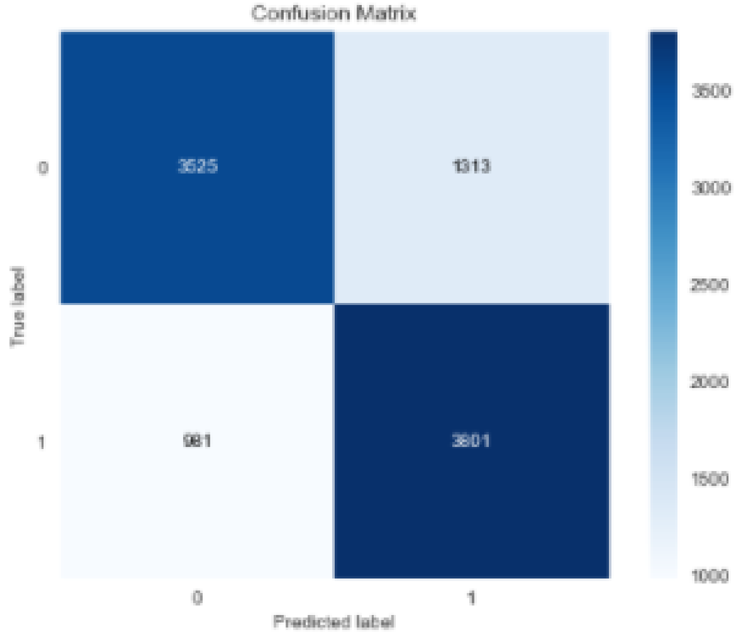
1. LOGISTIC REGRESSION

Logistic regression models a relationship between predictor variables and a categorical response variable.

```
Log_Reg = LogisticRegression()
Log_Reg.fit(x_train,y_train)
y_pred_log = Log_Reg.predict(x_test)

print("Accuracy Score:",accuracy_score(y_test,y_pred_log))
A1 = accuracy_score(y_test,y_pred_log)

print("Cross Validation Score: ", cross_val_score(Log_Reg,X_scaled,Y_over,cv=5))
print('Avg_Cross_Validation Score: ',cross_val_score(Log_Reg,X_scaled,Y_over,cv=5).mean())
CV1 = cross_val_score(Log_Reg,X_scaled,Y_over,cv=5).mean()
```

```
Accuracy Score: 0.7615384615384615
Cross Validation Score:  [0.72027027 0.73659044 0.75696466 0.75537998 0.76983054]
Avg_Cross_Validation Score:  0.7478071769339053
```

```
import scikitplot as skplt
skplt.metrics.plot_confusion_matrix(y_test,y_pred_log)
plt.show()
print(classification_report(y_test,y_pred_log))
```




```
              precision    recall  f1-score   support

           0       0.78      0.73      0.75      4838
           1       0.74      0.79      0.77      4782

    accuracy                           0.76      9620
   macro avg       0.76      0.76      0.76      9620
weighted avg       0.76      0.76      0.76      9620
```

2. RANDOM FOREST CLASSIFIER

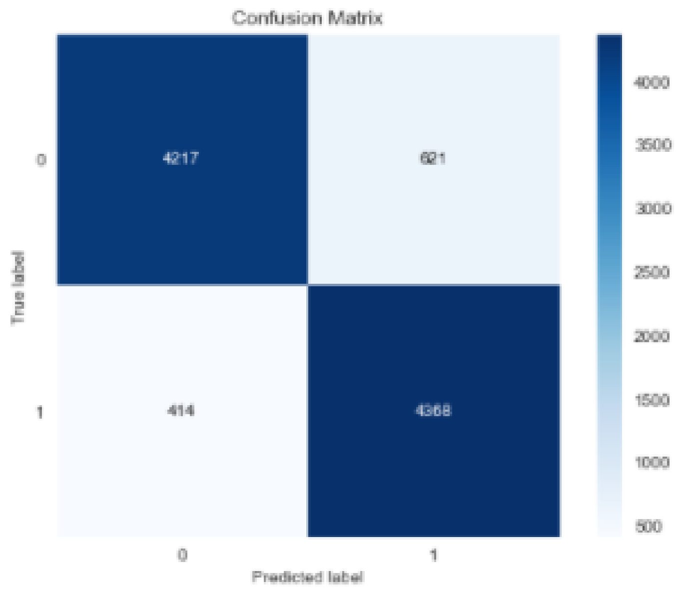
Random Forest is a flexible, easy to use machine learning algorithm that produces great results most of the time with minimum time spent on hyper-parameter tuning.

```
Rand2 = RandomForestClassifier()
Rand2.fit(x_train,y_train)
y_pred_rand2 = Rand2.predict(x_test)

A2 = accuracy_score(y_test,y_pred_rand2)

CV2 = cross_val_score(Rand2,X_scaled,Y_over,cv=5).mean()
```

```
print("Accuracy Score:",A2)
print("Cross Validation Score: ", cross_val_score(Rand2,X_scaled,Y_over,cv=5))
print('Avg_Cross_Validation Score: ',CV2)
```

```
Accuracy Score: 0.8924116424116424
Cross Validation Score:  [0.84844075 0.86975052 0.90654886 0.91017777 0.90622726]
Avg_Cross_Validation Score:  0.8883329641027947
```

```
skplt.metrics.plot_confusion_matrix(y_test,y_pred_rand2)
plt.show()
print(classification_report(y_test,y_pred_rand2))
```



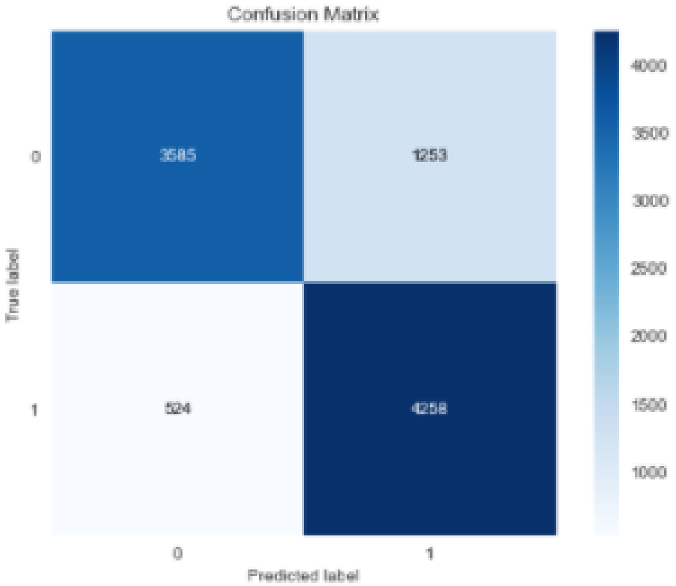

```
              precision    recall  f1-score   support

           0       0.91      0.87      0.89      4838
           1       0.88      0.91      0.89      4782

    accuracy                           0.89      9620
   macro avg       0.89      0.89      0.89      9620
weighted avg       0.89      0.89      0.89      9620
```

3. SVC

```
from sklearn.svm import SVC
sv=SVC()
sv.fit(x_train,y_train)
y_pred_sv = sv.predict(x_test)
A6 = accuracy_score(y_test,y_pred_sv)
print("Accuracy Score:",A6)
print("Cross Validation Score: ", cross_val_score(sv,X_scaled,Y_over,cv=5))
CV6 = cross_val_score(sv,X_scaled,Y_over,cv=5).mean()
print('Avg_Cross_Validation Score: ',CV6)
```

```
Accuracy Score: 0.8152806652806652
Cross Validation Score:  [0.77182952 0.7981289  0.83160083 0.83075164 0.82971203]
Avg_Cross_Validation Score:  0.8124045834441924
```

```
skplt.metrics.plot_confusion_matrix(y_test,y_pred_sv)
plt.show()
print(classification_report(y_test,y_pred_sv))
```




```
              precision    recall  f1-score   support

           0       0.87      0.74      0.80      4838
           1       0.77      0.89      0.83      4782

    accuracy                           0.82      9620
   macro avg       0.82      0.82      0.81      9620
weighted avg       0.82      0.82      0.81      9620
```

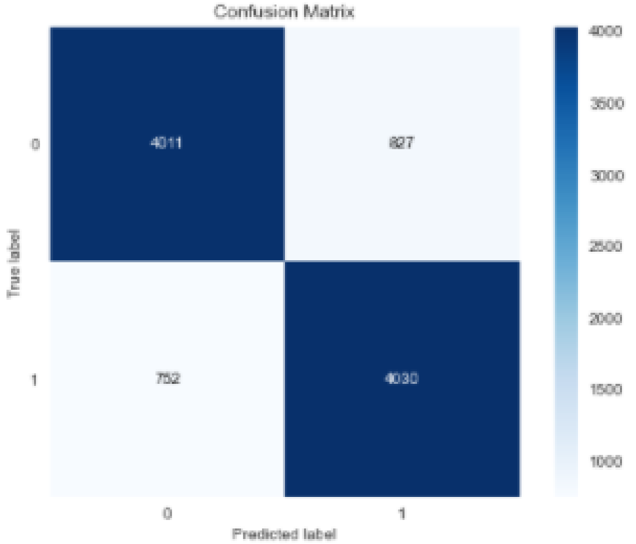
4. Decision Tree Classifier

Decision tree is a type of supervised learning algorithm that can be used for both regression and **classification** problems. The algorithm uses training data to create rules that can be represented by a tree structure.

```
dt = DecisionTreeClassifier()
dt.fit(x_train,y_train)
y_pred_dt = dt.predict(x_test)
A3 = accuracy_score(y_test,y_pred_dt)
print("Accuracy Score:",A3)
print("Cross Validation Score: ", cross_val_score(dt,X_scaled,Y_over,cv=5))
CV3 = cross_val_score(dt,X_scaled,Y_over,cv=5).mean()
print('Avg_Cross_Validation Score: ',CV3)
```

```
Accuracy Score: 0.8358627858627858
Cross Validation Score:  [0.80384615 0.82359667 0.84615385 0.85809336 0.85195966]
Avg_Cross_Validation Score:  0.8380605108695347
```

```
skplt.metrics.plot_confusion_matrix(y_test,y_pred_dt)
plt.show()
print(classification_report(y_test,y_pred_dt))
```




```
              precision    recall  f1-score   support

           0       0.84      0.83      0.84      4838
           1       0.83      0.84      0.84      4782

    accuracy                           0.84      9620
   macro avg       0.84      0.84      0.84      9620
weighted avg       0.84      0.84      0.84      9620
```

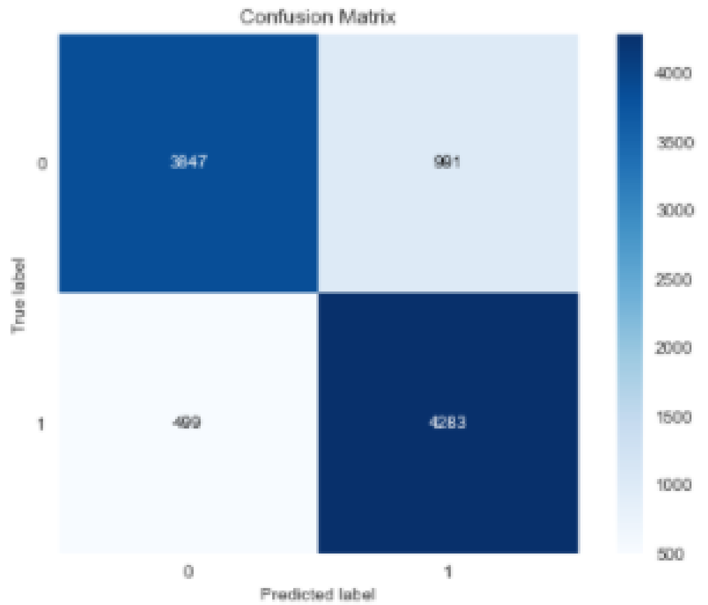
5. KNeighbors Classifier

The **k-neighbors** is commonly used and easy to apply classification method which implements the k neighbors queries to classify data. It is an instant-based and non-parametric learning method.

```
knn=KNeighborsClassifier()
knn.fit(x_train,y_train)
y_pred_knn = knn.predict(x_test)
A4 = accuracy_score(y_test,y_pred_knn)
print("Acicuracy Score:",A4)
print("Cross Validation Score: ", cross_val_score(knn,X_scaled,Y_over,cv=5))
CV4 = cross_val_score(knn,X_scaled,Y_over,cv=5).mean()
print('Avg_Cross_Validation Score: ',CV4)
```

```
Acicuracy Score: 0.8451143451143451
Cross Validation Score:  [0.8002079  0.82525988 0.85686071 0.8609003  0.86838549]
Avg_Cross_Validation Score:  0.8423228541743979
```

```
skplt.metrics.plot_confusion_matrix(y_test,y_pred_knn)
plt.show()
print(classification_report(y_test,y_pred_knn))
```




```
              precision    recall  f1-score   support

           0       0.89      0.80      0.84      4838
           1       0.81      0.90      0.85      4782

    accuracy                           0.85      9620
   macro avg       0.85      0.85      0.84      9620
weighted avg       0.85      0.85      0.84      9620
```

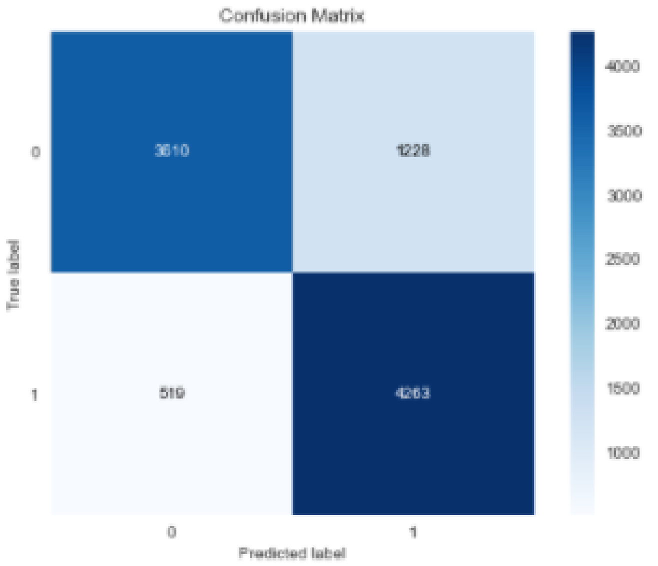
6. ADABOOST CLASSIFIER

AdaBoost classifier **builds a strong** classifier **by combining multiple poorly performing** classifiers so that you will get **high accuracy strong** classifier.

```
from sklearn.ensemble import AdaBoostClassifier
adb= AdaBoostClassifier(n_estimators=10)
adb.fit(x_train,y_train)
y_pred_adb = adb.predict(x_test)
A5 = accuracy_score(y_test,y_pred_adb)
print("Accuracy Score:",A5)
print("Cross Validation Score: ", cross_val_score(adb,X_scaled,Y_over,cv=5))
CV5 = cross_val_score(adb,X_scaled,Y_over,cv=5).mean()
print('Avg_Cross_Validation Score: ',CV5)
```

```
Accuracy Score: 0.8183991683991684
Cross Validation Score:  [0.79844075 0.81070686 0.82234927 0.81983574 0.82160308]
Avg_Cross_Validation Score:  0.8145871401001872
```

```
skplt.metrics.plot_confusion_matrix(y_test,y_pred_adb)
plt.show()
print(classification_report(y_test,y_pred_adb))
```



	precision	recall	f1-score	support
0	0.87	0.75	0.81	4838
1	0.78	0.89	0.83	4782

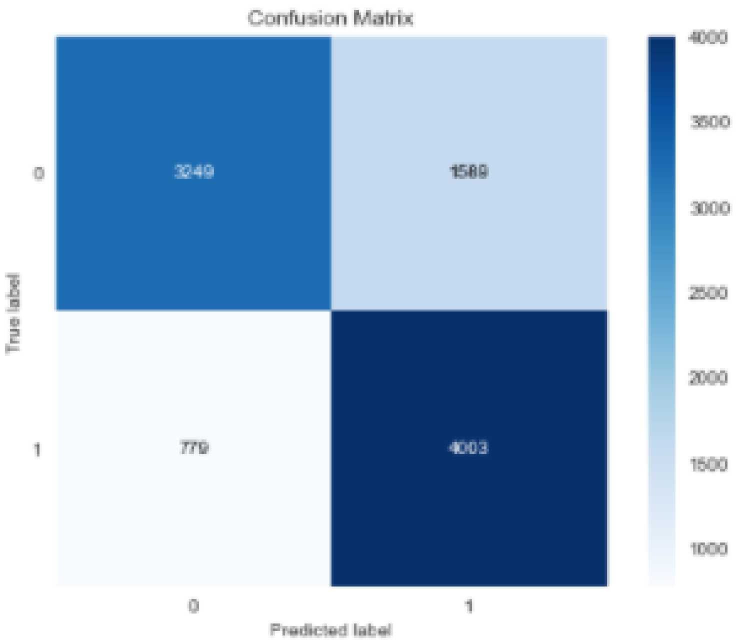
7. BernoulliNB

BernoulliNB implements the naive Bayes training and **classification** algorithms for data that is distributed according to multivariate Bernoulli distributions; i.e., there may be multiple features but each one is assumed to be a binary-valued (Bernoulli, boolean) variable.

```
from sklearn.naive_bayes import BernoulliNB
nb=BernoulliNB()
nb.fit(x_train,y_train)
y_pred_nb = nb.predict(x_test)
A7 = accuracy_score(y_test,y_pred_nb)
print("Accuracy Score:",A7)
print("Cross Validation Score: ", cross_val_score(nb,X_scaled,Y_over,cv=5))
CV7 = cross_val_score(nb,X_scaled,Y_over,cv=5).mean()
print('Avg_Cross_Validation Score: ',CV7)
```

```
Accuracy Score: 0.7538461538461538
Cross Validation Score:  [0.72900208 0.74594595 0.74615385 0.74935024 0.74872648]
Avg_Cross_Validation Score:  0.7438357188507931
```

```
skplt.metrics.plot_confusion_matrix(y_test,y_pred_nb)
plt.show()
print(classification_report(y_test,y_pred_nb))
```




```
              precision    recall  f1-score   support

           0       0.81      0.67      0.73      4838
           1       0.72      0.84      0.77      4782

    accuracy                           0.75      9620
   macro avg       0.76      0.75      0.75      9620
weighted avg       0.76      0.75      0.75      9620
```

CHECKING OVERALL SCORE:

```
Overall_Score = pd.DataFrame({'Model':['Logistic Regression','Random Forest Classifier','Decision Tree',
                                       'KNeighbors Classifier','AdaBoost Classifier','SVC','BernoulliNB Classifier'],
                              'Accuracy_Score':[A1,A2,A3,A4,A5,A6,A7],
                              'Cross_Validation_Score':[CV1,CV2,CV3,CV4,CV5,CV6,CV7]})
Overall_Score['Difference'] = Overall_Score['Accuracy_Score'] - Overall_Score['Cross_Validation_Score']
```

```
Overall_Score
```

	Model	Accuracy_Score	Cross_Validation_Score	Difference
0	Logistic Regression	0.761538	0.747807	0.013731
1	Random Forest Classifier	0.892412	0.888333	0.004079
2	Decision Tree	0.835863	0.838061	-0.002198
3	KNeighbors Classifier	0.845114	0.842323	0.002791
4	AdaBoost Classifier	0.818399	0.814587	0.003812
5	SVC	0.815281	0.812405	0.002876
6	BernoulliNB Classifier	0.753846	0.743836	0.010010

```
Overall_Score['Difference'].min()
```

```
-0.002197725006748863
```

```
Overall_Score[Overall_Score['Difference']==-0.002197725006748863]
```

	Model	Accuracy_Score	Cross_Validation_Score	Difference
2	Decision Tree	0.835863	0.838061	-0.002198

Model Performance Result

From every model I trained Decision Tree is giving me good accuracy and performance metrics.

Hyperparameter Tuning

We will Do Hyperparameter tuning of my model to get some better result.

```
from sklearn.model_selection import GridSearchCV
param_grid={'max_features':['auto','sqrt'],'min_samples_leaf':range(10),'splitter':['best','rand'],
           'min_weight_fraction_leaf':[0.0,0.1],'min_samples_split':range(8),'criterion':['gini']}
gridsearch=GridSearchCV(estimator=dt,param_grid=param_grid,cv=5)
gridsearch.fit(x_train,y_train)
```

```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini'],
                         'max_features': ['auto', 'sqrt'],
                         'min_samples_leaf': range(0, 10),
                         'min_samples_split': range(0, 8),
                         'min_weight_fraction_leaf': [0.0, 0.1],
                         'splitter': ['best', 'rand']})
```

```
print(gridsearch.best_score_, gridsearch.best_params_)
```

```
0.8288632255737518 {'criterion': 'gini', 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_lea
f': 0.0, 'splitter': 'best'}
```

```
DT = DecisionTreeClassifier(criterion = 'gini', max_features = 'sqrt', min_samples_leaf = 1, min_samples_split= 2,
                            min_weight_fraction_leaf= 0.0, splitter = 'best')
DT.fit(x_train,y_train)
y_pred = DT.predict(x_test)
```

Saving The Model

```
import joblib
joblib.dump(DT,'Census_Project.obj')
```

```
['Census_Project.obj']
```

Saving the model for future use by using joblib it will save my model in obj format

Performance Metrics

```
print("Accuracy Score:",accuracy_score(y_test,y_pred))
print("Cross Validation Score: ", cross_val_score(DT,X_scaled,Y_over,cv=5))
print('Avg_Cross_Validation Score: ',cross_val_score(DT,X_scaled,Y_over,cv=5).mean())
```

```
Accuracy Score: 0.8453222453222453
Cross Validation Score:  [0.79449064 0.82744283 0.85654886 0.85320719 0.85871712]
Avg_Cross_Validation Score:  0.8343182574162926
```

```
print('\nConfusion Matrix')
skplt.metrics.plot_confusion_matrix(y_test,y_pred)
plt.show()
```

```
Confusion Matrix
```

Conclusion-

In this blog we have learned how to make an end to end machine learning project. Our model is now ready with 83.5% Accuracy

For the detailed coding please go through the below direct link which relates to the coding part of our model:

GOTO: https://github.com/shubhamshuklaa/INTERSHIP-17-FLIP-ROBO-/blob/main/census.ipynb

THANKYOU