PROBLEM STATEMENTS

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

Importing Libraries that will come handy for the projects

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:
```
columns = ['Age', 'Work Class', 'Final Weight', 'Education', 'Education Number', 'Ma
          'Relationship', 'Race', 'Sex', 'Capital Gain', 'Capital Loss', 'Hours per
data = pd.read_csv("D:\\data set\\adult.data", names = columns)
```

In [3]:
```
data
```

Out[3]:

	Age	Work Class	Final Weight	Education	Education Number	Marital Status	Occupation	Relationship	Race	S
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	M
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	M
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	M
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	M
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Fem
...	...	...	...	...	...	...	...	...	...	
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Fem
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	M

	Age	Work Class	Final Weight	Education	Education Number	Marital Status	Occupation	Relationship	Race	S
32558	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Fem
32559	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	M
32560	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Fem

32561 rows × 15 columns

From the above code we can observe that the data set contains 32561 rows × 15 columns.

Exploratory Data Analysis (EDA)

In [4]:

```
data.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   Work Class      32561 non-null  object
 2   Final Weight    32561 non-null  int64 
 3   Education       32561 non-null  object
 4   Education Number 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  Country         32561 non-null  object
 14  Income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

From the above we can observe that our data do not contain any missing value and our target value "Income" has an Object datatype, so before moving further lets convert it into numerical datatype

In [5]:

```
from sklearn.preprocessing import LabelEncoder

labelEncoder = LabelEncoder()
data['Income'] = labelEncoder.fit_transform(data['Income'])
```

In [6]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
```

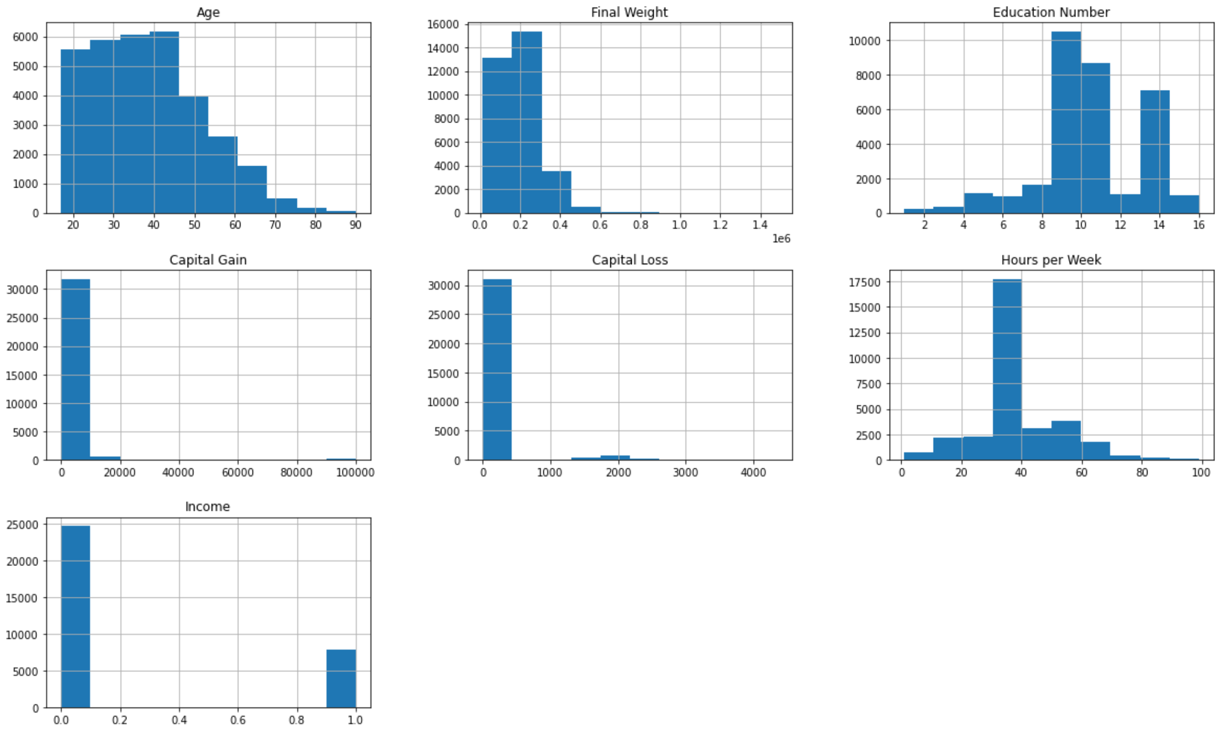
```
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Age               32561 non-null  int64 
 1   Work Class        32561 non-null  object
 2   Final Weight      32561 non-null  int64 
 3   Education         32561 non-null  object
 4   Education Number  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  Country           32561 non-null  object
 14  Income            32561 non-null  int32 
dtypes: int32(1), int64(6), object(8)
memory usage: 3.6+ MB
```

In [7]:

```
data.hist(figsize=(20,12))
```

Out[7]:

```
array([[<AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'Final Weight'}>,
        <AxesSubplot:title={'center':'Education Number'}>],
       [<AxesSubplot:title={'center':'Capital Gain'}>,
        <AxesSubplot:title={'center':'Capital Loss'}>,
        <AxesSubplot:title={'center':'Hours per Week'}>],
       [<AxesSubplot:title={'center':'Income'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



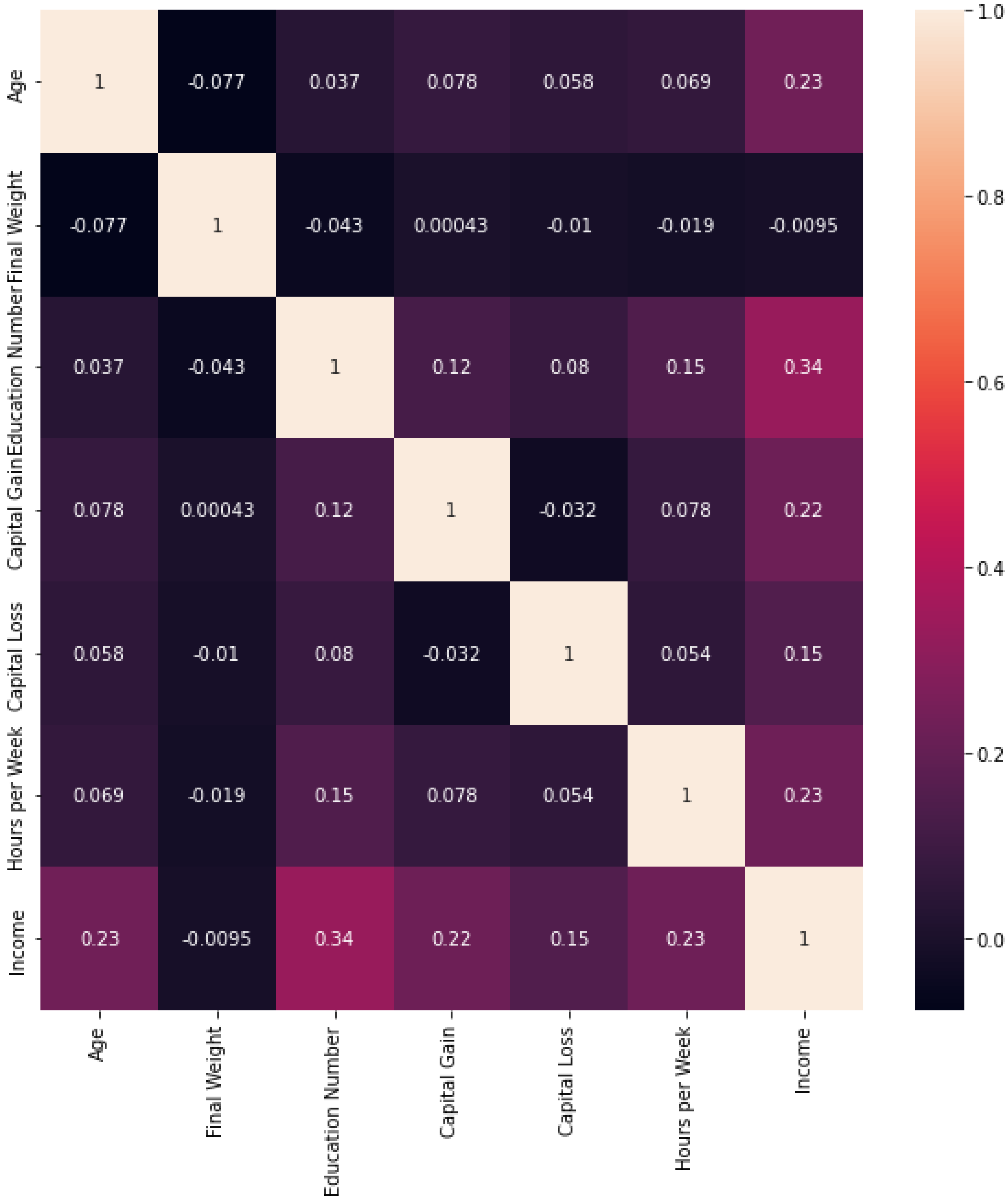
From the above graphs we can conclude

a) Age and Hours per Week column can be group into bins. b) In column Capital Gain,Capital Loss and Final Weight the data is left skewed.

In [8]:

```
plt.figure(figsize=(10,10))
sns.heatmap(data.corr(),annot = True)
```

Out[8]: <AxesSubplot:>



From the above graph we can observe that there is not very high linear correlation with the target column("Income") and final wweight column have zero correlation with the target value. so we can drop it.

AGE

bucketing the age columns into different bins as shown below

a) 0-25: Young

b) 25-50: Adult

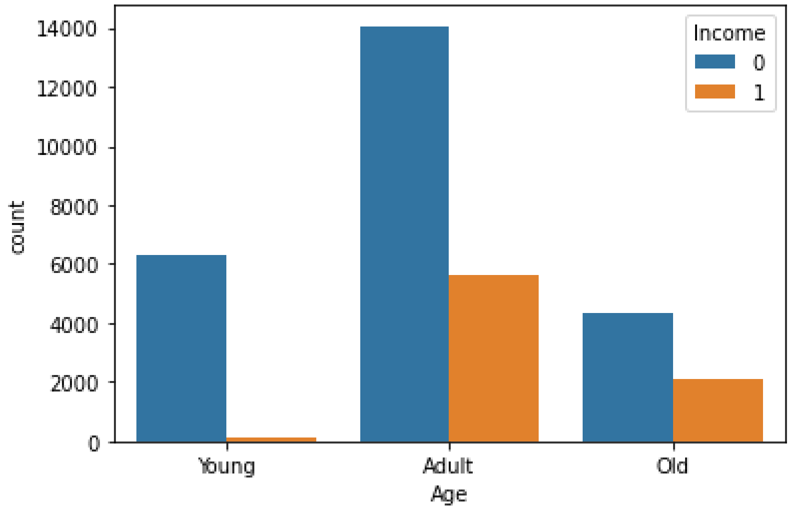
c) 50-100: Old

In [9]:
```
data['Age'] = pd.cut(data['Age'], bins = [0, 25, 50, 100], labels = ['Young', 'Adult
```

In [10]:

```
sns.countplot(x = 'Age', hue = 'Income', data = data)
```

Out[10]: <AxesSubplot:xlabel='Age', ylabel='count'>



From the above graph it can be observed that there is very less young people having Income grated than $50K

Hours per Week

bucketing the age columns into different bins as shown below

a) 0-30: Low Hrs

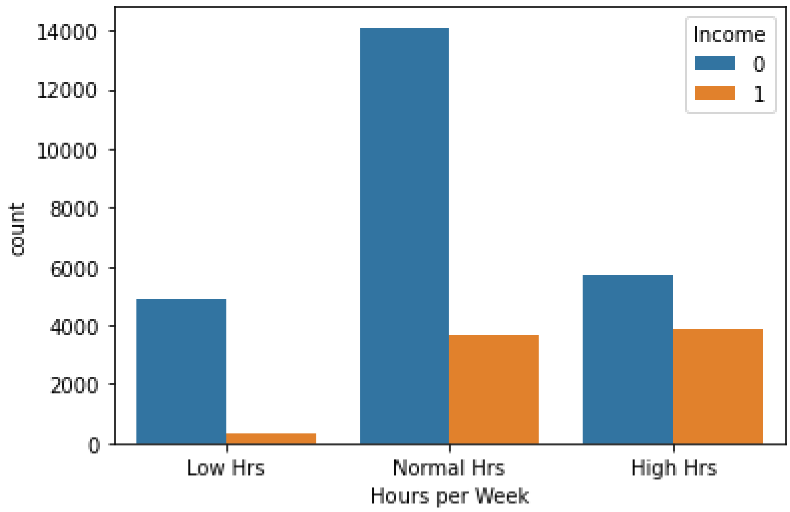
b) 30-40: Normal Hrs

c) 40-100:High Hrs

In [11]:
```
data['Hours per Week'] = pd.cut(data['Hours per Week'], bins = [0, 30, 40, 100], lab
```

In [12]:
```
sns.countplot(x = 'Hours per Week', hue = 'Income', data = data)
```

Out[12]: <AxesSubplot:xlabel='Hours per Week', ylabel='count'>



From the above graph it can be observe that as the working hours increase the no of people receving more than 50k also increase.

Final Weight

As already discussed we can drop the column as it have zero correlation with the target column.

In [13]:
```
data.drop(['Final Weight'], axis = 1, inplace = True)
```

In [14]:
```
data
```

Out[14]:

	Age	Work Class	Education	Education Number	Marital Status	Occupation	Relationship	Race	Sex	Ca
0	Adult	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	
1	Adult	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	Adult	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	
3	Old	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	
4	Adult	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	
...	...	...	...	...	...	...	...	...	...	
32556	Adult	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	
32557	Adult	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	
32558	Old	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	
32559	Young	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	
32560	Old	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	1

32561 rows × 14 columns

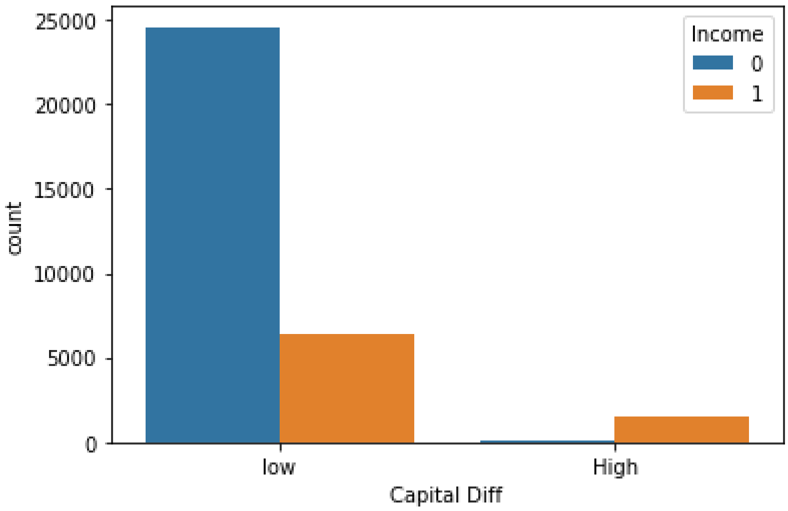
Capital Gain and Capital loss

Using the above two column we can come up with new feature. Capital_diff= Capital Gain-Capital loss

In [15]:
```
data['Capital Diff'] = data['Capital Gain'] - data['Capital Loss']
data.drop(['Capital Gain'], axis = 1, inplace = True)
```

```
data.drop(['Capital Loss'], axis = 1, inplace = True)
data['Capital Diff'] = pd.cut(data['Capital Diff'], bins = [-5000, 5000, 100000], la
sns.countplot(x = 'Capital Diff', hue = 'Income', data = data)
```

Out[15]: <AxesSubplot:xlabel='Capital Diff', ylabel='count'>



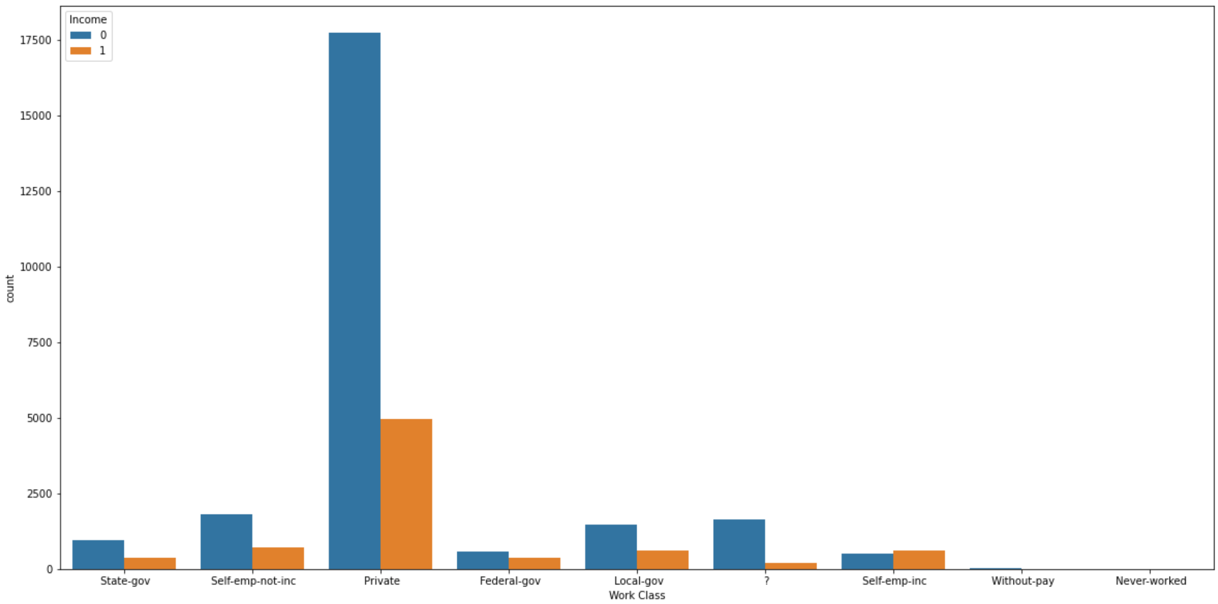
we can observe that for both the category low and high people with hight Income (more than 50k)

Work Class

In [16]:

```
plt.figure(figsize=(20,10))
sns.countplot(x = 'Work Class', hue = 'Income', data = data)
```

Out[16]: <AxesSubplot:xlabel='Work Class', ylabel='count'>



From the above graph it can be observed that "without pay" and "Never-worked" column have very less records so it is safe to remove them. we can also observe a category "?" , it is a error and have very low vaalue so we can remove it too.

In [17]:

```
data = data.drop(data[data['Work Class'] == ' ?'].index)
data = data.drop(data[data['Work Class'] == ' Without-pay'].index)
data = data.drop(data[data['Work Class'] == ' Never-worked'].index)
```

In [18]:
```
data
```

Out[18]:

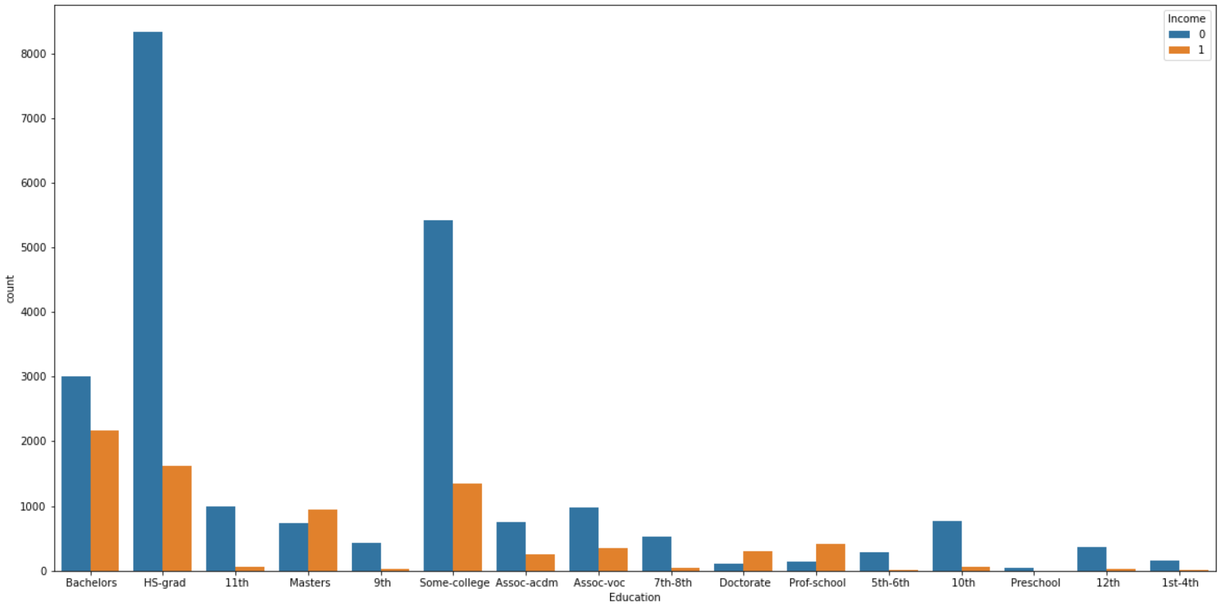
	Age	Work Class	Education	Education Number	Marital Status	Occupation	Relationship	Race	Sex	H
0	Adult	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	N
1	Adult	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	Adult	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	N
3	Old	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	N
4	Adult	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	N
...	...	...	...	...	...	...	...	...	...	
32556	Adult	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	N
32557	Adult	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	N
32558	Old	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	N
32559	Young	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	
32560	Old	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	N

30704 rows × 13 columns

Education and Education Number

In [19]:
```
plt.figure(figsize=(20,10))
sns.countplot(x = 'Education', hue = 'Income', data = data)
```

Out[19]: <AxesSubplot:xlabel='Education', ylabel='count'>



In [20]:
```
data['Education'].value_counts()
```

Out[20]:
```
HS-grad         9959
Some-college    6772
Bachelors       5182
Masters         1675
Assoc-voc       1321
11th            1056
Assoc-acdm      1019
10th             831
7th-8th          572
Prof-school      558
9th              463
Doctorate        398
12th             393
5th-6th          303
1st-4th          156
Preschool         46
Name: Education, dtype: int64
```

Marital Status and Relationship

In [21]:
```
data['Relationship'].value_counts()
```

Out[21]:
```
Husband           12700
Not-in-family      7865
Own-child          4520
Unmarried          3269
Wife               1432
Other-relative      918
Name: Relationship, dtype: int64
```

In [22]:
```
data['Marital Status'].value_counts()
```

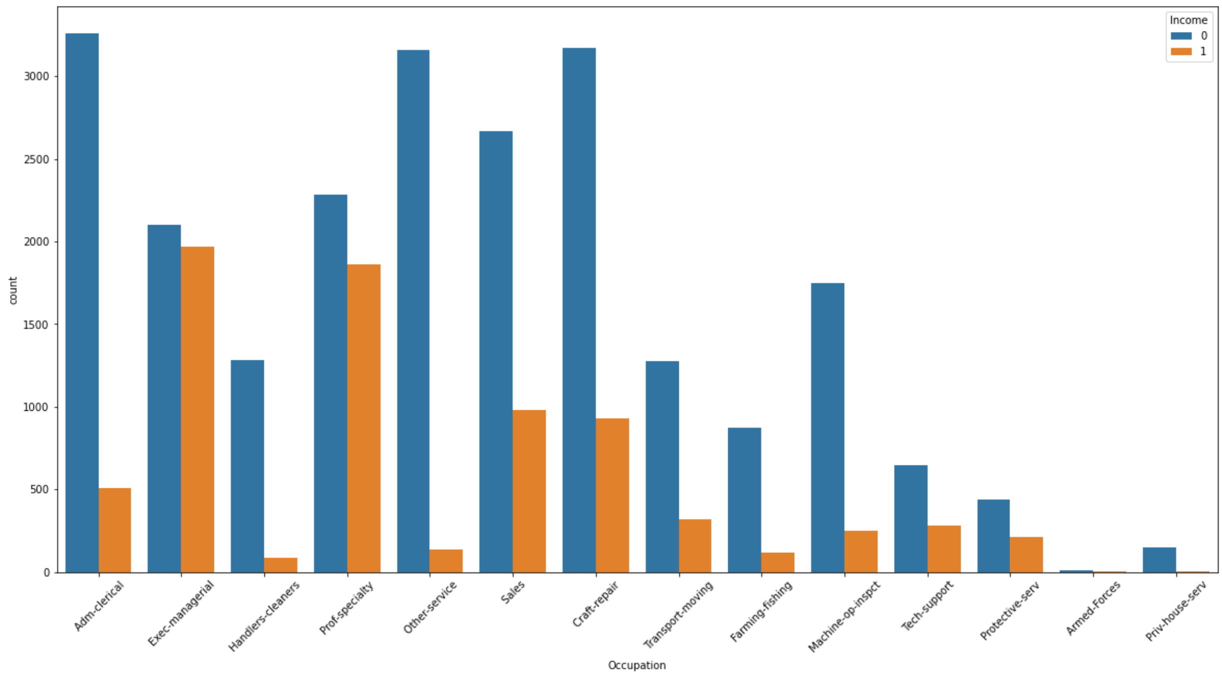
Out[22]:
```
Married-civ-spouse       14331
Never-married             9908
Divorced                  4258
Separated                  959
Widowed                    839
Married-spouse-absent      388
```

```
 Married-AF-spouse          21
Name: Marital Status, dtype: int64
```

Occupation

In [23]:
```
plt.figure(figsize=(20,10))
plt.xticks(rotation = 45)
sns.countplot(x = 'Occupation', hue = 'Income', data = data)
```

Out[23]: <AxesSubplot:xlabel='Occupation', ylabel='count'>

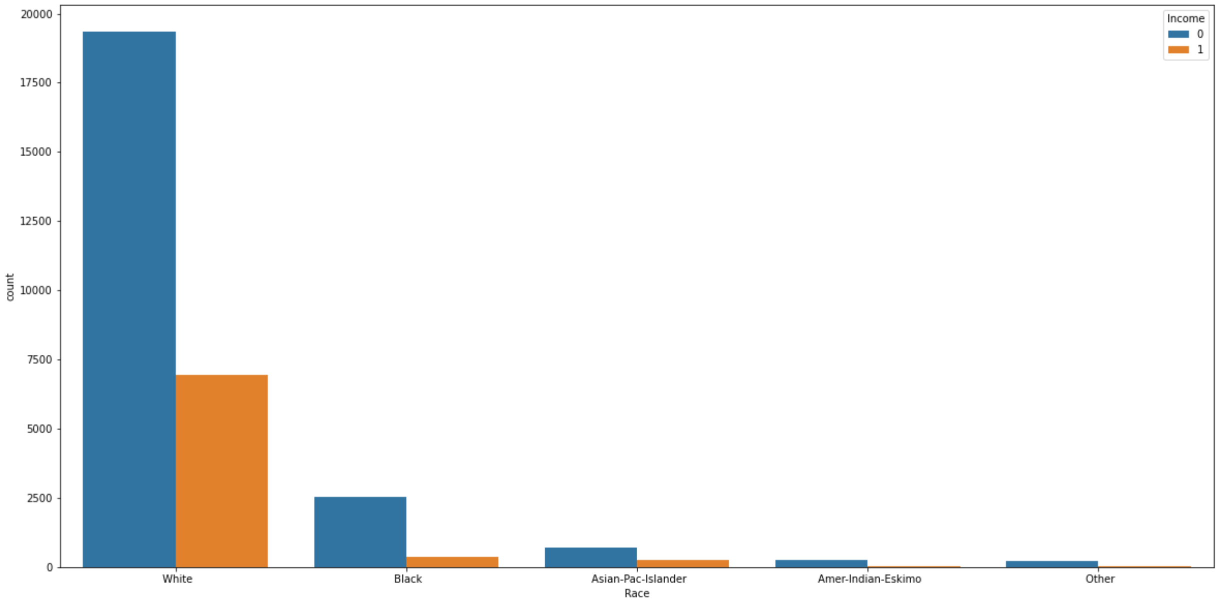


From the above grap it can be observe that there is no missing value and there is all unique catagories so we can keep it as it is

Race

In [24]:
```
plt.figure(figsize=(20,10))
sns.countplot(x = 'Race', hue = 'Income', data = data)
```

Out[24]: <AxesSubplot:xlabel='Race', ylabel='count'>

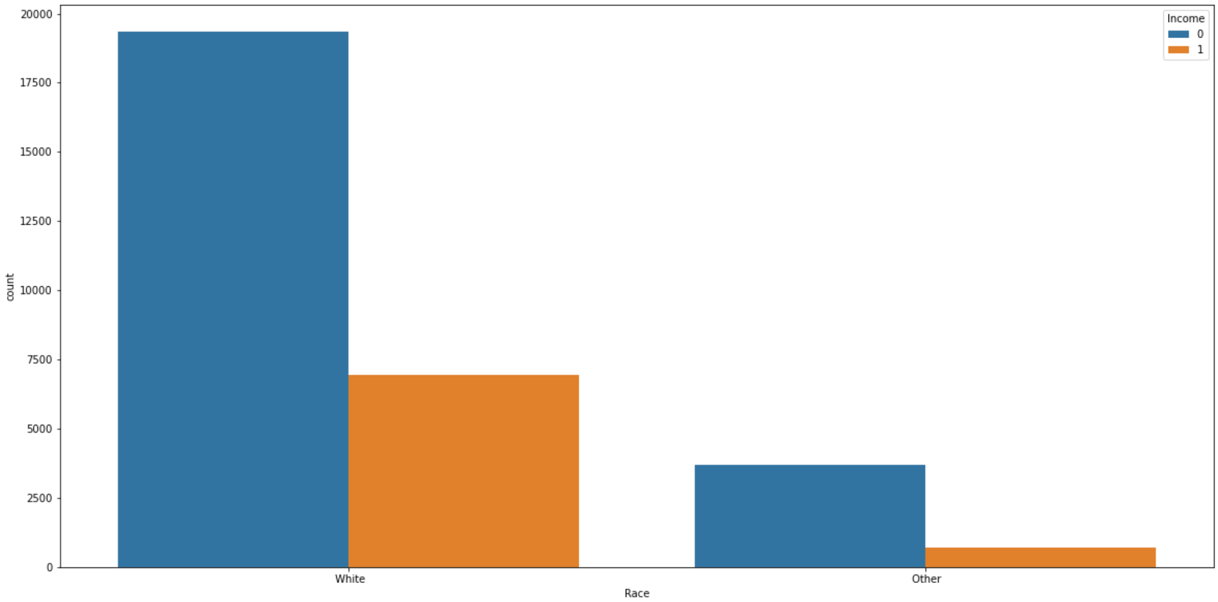


From the above graph it can be observed that the maximum information is about white people so we can combine other categories in one as others.

In [25]:
```
data['Race'].replace([' Black', ' Asian-Pac-Islander', ' Amer-Indian-Eskimo', ' Othe
```

In [26]:
```
plt.figure(figsize=(20,10))
sns.countplot(x = 'Race', hue = 'Income', data = data)
```

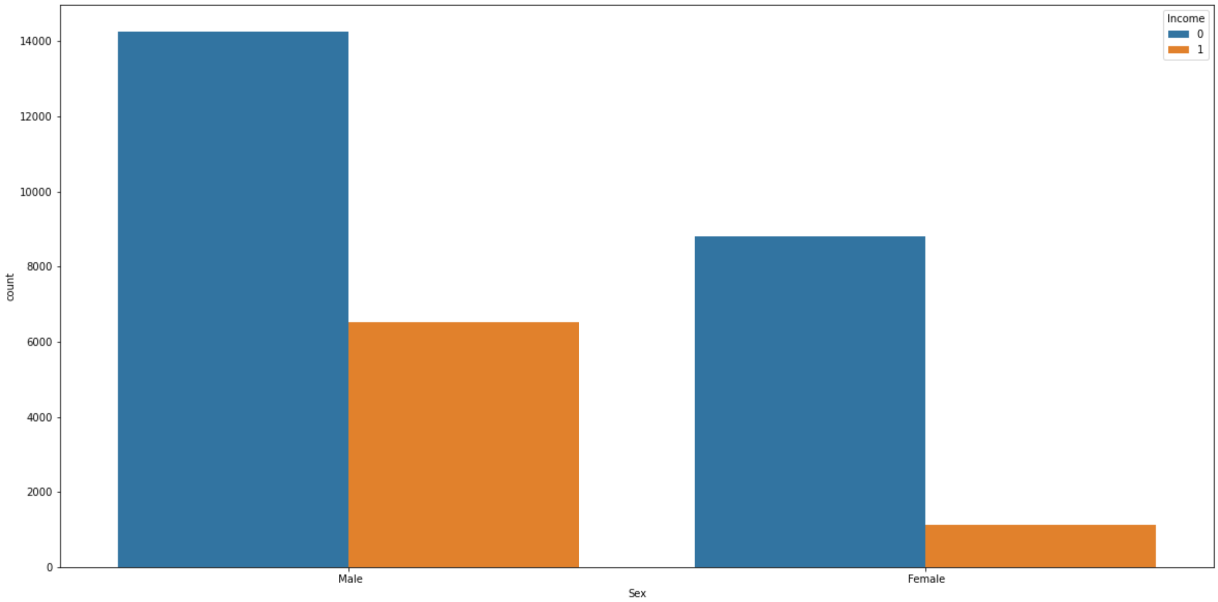
Out[26]:
```
<AxesSubplot:xlabel='Race', ylabel='count'>
```



Sex

In [27]:
```
plt.figure(figsize=(20,10))
sns.countplot(x = 'Sex', hue = 'Income', data = data)
```

Out[27]:
```
<AxesSubplot:xlabel='Sex', ylabel='count'>
```



From the above it can be observe that there are more Male than compare to Female and there are more male reciving salary more than 50k

Country

In [28]:
```
data['Country'].value_counts()
```

Out[28]:
```
United-States                27491
Mexico                         610
?                              556
Philippines                    187
Germany                        128
Puerto-Rico                    109
Canada                         107
India                          100
El-Salvador                    100
Cuba                            92
England                         86
Jamaica                         80
South                           71
China                           68
Italy                           68
Dominican-Republic              67
Vietnam                         64
Guatemala                       63
Japan                           59
Poland                          56
Columbia                        56
Iran                            42
Taiwan                          42
Haiti                           42
Portugal                        34
Nicaragua                       33
Peru                            30
Greece                          29
France                          27
Ecuador                         27
Ireland                         24
Hong                            19
Cambodia                        18
Trinadad&Tobago                 18
Thailand                        17
```

```
Laos                          17
Yugoslavia                    16
Outlying-US(Guam-USVI-etc)    14
Hungary                       13
Honduras                      12
Scotland                      11
Holand-Netherlands             1
Name: Country, dtype: int64
```

From the above it can be observed that there is some category with "?" that can be droped and majorty of people are from "US" so we can create two category as " US and OTHERS"

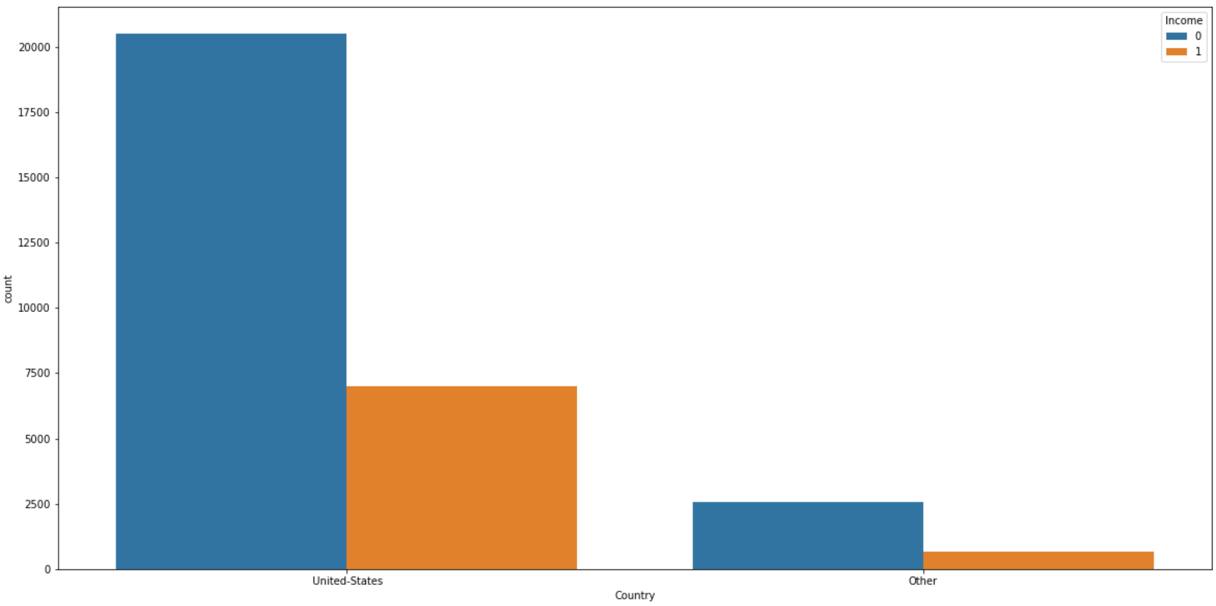
In [33]:

```
dataset = data.drop(data[data['Country'] == ' ?'].index)
countries = np.array(data['Country'].unique())
countries = np.delete(countries, 0)
data['Country'].replace(countries, 'Other', inplace = True)
```

In [34]:

```
plt.figure(figsize=(20,10))
sns.countplot(x = 'Country', hue = 'Income', data = dataset)
```

Out[34]: `<AxesSubplot:xlabel='Country', ylabel='count'>`



Splitting the datasets into features and target value

In [35]:

```
data
```

Out[35]:

	Age	Work Class	Education	Education Number	Marital Status	Occupation	Relationship	Race	Sex	H W
0	Adult	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	Nc
1	Adult	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	Adult	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	Nc

	Age	Work Class	Education	Education Number	Marital Status	Occupation	Relationship	Race	Sex	H
3	Old	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Other	Male	N
4	Adult	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Other	Female	N
...	...	...	...	...	...	...	...	...	...	
32556	Adult	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	N
32557	Adult	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	N
32558	Old	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	N
32559	Young	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	
32560	Old	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	N

30704 rows × 13 columns

In [37]:

```
y = data['Income']
x= data.drop(['Income'], axis = 1)
x = pd.get_dummies(x)
print("Total features: {}".format(x.shape[1]))
```

```
Total features: 64
```

In [38]:

```
x
```

Out[38]:

	Education Number	Age_Young	Age_Adult	Age_Old	Work Class_ Federal-gov	Work Class_ Local-gov	Work Class_ Private	Work Class_ Self-emp-inc	Work Class_ Self-emp-not-inc	Work Class_ State-gov
0	13	0	1	0	0	0	0	0	0	1
1	13	0	1	0	0	0	0	0	1	0
2	9	0	1	0	0	0	1	0	0	0
3	7	0	0	1	0	0	1	0	0	0
4	13	0	1	0	0	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...
32556	12	0	1	0	0	0	1	0	0	0

	Education Number	Age_Young	Age_Adult	Age_Old	Work Class_ Federal-gov	Work Class_ Local-gov	Work Class_ Private	Work Class_ Self-emp-inc	Work Class_ Self-emp-not-inc	Work Class_ State-gov
32557	9	0	1	0	0	0	1	0	0	0
32558	9	0	0	1	0	0	1	0	0	0
32559	9	1	0	0	0	0	1	0	0	0
32560	9	0	0	1	0	0	0	1	0	0

30704 rows × 64 columns

In [39]:

```
y
```

Out[39]:

```
0        0
1        0
2        0
3        0
4        0
        ..
32556    0
32557    1
32558    0
32559    0
32560    1
Name: Income, Length: 30704, dtype: int32
```

In [41]:

```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.30, random_s
```

Machine learning

Importing libraries

In [42]:

```
from sklearn.metrics import f1_score, accuracy_score
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
```

In [43]:

```
classifiers = [GaussianNB(),
               SVC(kernel = 'rbf', probability = True),
               DecisionTreeClassifier(random_state = 0),
               RandomForestClassifier(n_estimators = 100, random_state = 0),
               GradientBoostingClassifier(random_state = 0)]
classifier_names = ["Gaussian Naive Bayes",
                    "Support Vector Classifier",
                    "Decision Tree Classifier",
                    "Random Forest Classifier",
                    "Gradient Boosting Classifier"]
accuracies = []
```

In [45]:
```
for i in range(len(classifiers)):
    classifier = classifiers[i]
    classifier.fit(x_train, y_train)
    y_pred = classifier.predict(x_test)
    print("{}:".format(classifier_names[i]))
    print("F1 score: {:.2f}".format(f1_score(y_test, y_pred)))
    accuracy = accuracy_score(y_test, y_pred)*100
    accuracies.append(accuracy)
```

```
Gaussian Naive Bayes:
F1 score: 0.61
Support Vector Classifier:
F1 score: 0.63
Decision Tree Classifier:
F1 score: 0.61
Random Forest Classifier:
F1 score: 0.65
Gradient Boosting Classifier:
F1 score: 0.66
```

From the above result it can be observe that "Gradient Boosting Classifier: F1 score: 0.66" is performing best

In [ ]: