Code to import CSV file

In [1]:
```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving salary.csv to salary.csv
```

Importing Basic Libraries :

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import LabelEncoder
import warnings
warnings.filterwarnings(action="ignore")
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecat
ed. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

In [3]:
```
df = pd.read_csv("salary.csv")
#a = pd.read_csv("salary.csv")
```

In [4]:
```
df
```

Out[4]:

	Unnamed: 0	age	Workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	nat cou
0	0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	Uni Sta
1	1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	Uni Sta
2	2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	Uni Sta
3	3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	Uni Sta
4	4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	C
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1027	1114	34	Private	290763	HS-grad	9	Divorced	Handlers-cleaners	Own-child	White	Female	0	0	40	Uni Sta
1028	1116	36	Private	51100	Some-college	10	Married-civ-spouse	Craft-repair	Husband	White	Male	0	0	40	Uni Sta
1029	1117	41	Private	227644	HS-grad	9	Married-civ-spouse	Transport-moving	Husband	White	Male	0	0	50	Uni Sta
1030	1118	58	Local-gov	205267	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	White	Female	0	0	40	Uni Sta
1031	1119	53	Private	288020	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	Asian-Pac-Islander	Male	0	0	40	Ja

1032 rows × 16 columns

Unwanted Column Removing :

In [5]:
```
df.drop(["Unnamed: 0"], axis=1,inplace = True)
```

Missing value :

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
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
```

Data Type :

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1032 entries, 0 to 1031
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             1032 non-null   int64
 1   Workclass       1032 non-null   object
 2   fnlwgt          1032 non-null   int64
 3   education       1032 non-null   object
 4   education-num   1032 non-null   int64
 5   marital-status  1032 non-null   object
 6   occupation      1032 non-null   object
 7   relationship    1032 non-null   object
 8   race            1032 non-null   object
 9   sex             1032 non-null   object
 10  capital-gain    1032 non-null   int64
 11  capital-loss    1032 non-null   int64
 12  hours-per-week  1032 non-null   int64
 13  native-country  1032 non-null   object
 14  Income          1032 non-null   int64
dtypes: int64(7), object(8)
memory usage: 121.1+ KB
```

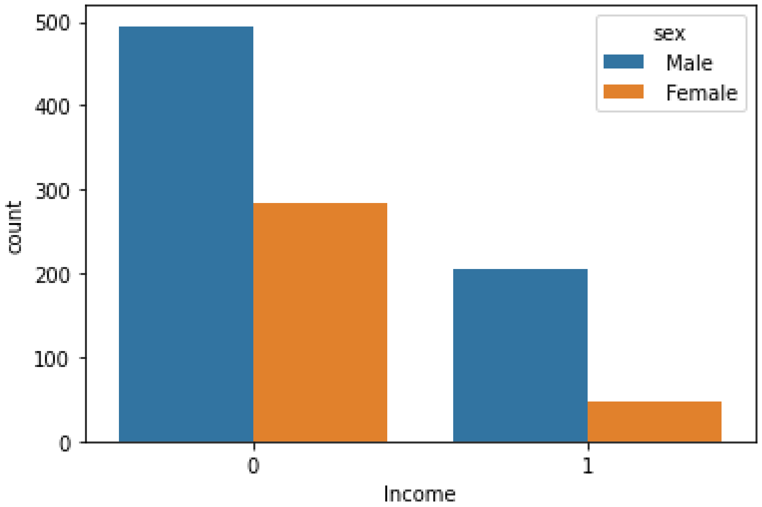
Seprating Categorical & Numaric Column :

In [8]:
```
cat_col = ["sex","occupation","marital-status","relationship","Workclass","education","race","native-country"]
```

In [9]:
```
cat_col
```

Out[9]:
```
['sex',
 'occupation',
 'marital-status',
 'relationship',
 'Workclass',
 'education',
 'race',
 'native-country']
```

In [10]:
```
for col in cat_col:
  plt.figure()
  sns.countplot(data=df,x="Income", hue=col)
  plt.show()
  print("-------------------------------------------")
```



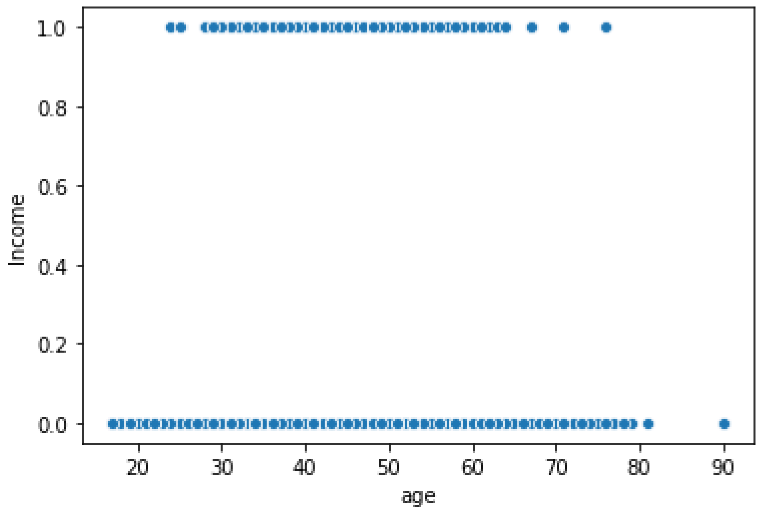

```
------------------------------------------
```

In [11]:
```
num_col = ["age","fnlwgt","education-num","capital-gain","capital-loss","hours-per-week"]
```

In [12]:
```
num_col
```

Out[12]:
```
['age',
 'fnlwgt',
 'education-num',
 'capital-gain',
 'capital-loss',
 'hours-per-week']
```

In [14]:
```
for col in num_col:
  plt.figure()
  sns.scatterplot(data=df, x=col, y="Income")
  plt.show()
  print("-------------------------------------------")
```




```
-------------------------------------------
```

In [15]:
```
df_num = df.select_dtypes(["float64","int64"])
```

In [16]:
```
df_num
```

Out[16]:

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	Income
0	39	77516	13	2174	0	40	0
1	50	83311	13	0	0	13	0
2	38	215646	9	0	0	40	0
3	53	234721	7	0	0	40	0
4	28	338409	13	0	0	40	0
...	...	...	...	...	...	...	...
1027	34	290763	9	0	0	40	0
1028	36	51100	10	0	0	40	0
1029	41	227644	9	0	0	50	0
1030	58	205267	13	0	0	40	1
1031	53	288020	13	0	0	40	0

1032 rows × 7 columns

In [17]:
```
df_cat = df.select_dtypes(object)
```

In [18]:
```
df_cat
```

Out[18]:

	Workclass	education	marital-status	occupation	relationship	race	sex	native-country
0	State-gov	Bachelors	Never-married	Adm-clerical	Not-in-family	White	Male	United-States
1	Self-emp-not-inc	Bachelors	Married-civ-spouse	Exec-managerial	Husband	White	Male	United-States
2	Private	HS-grad	Divorced	Handlers-cleaners	Not-in-family	White	Male	United-States
3	Private	11th	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	United-States
4	Private	Bachelors	Married-civ-spouse	Prof-specialty	Wife	Black	Female	Cuba
...	...	...	...	...	...	...	...	...
1027	Private	HS-grad	Divorced	Handlers-cleaners	Own-child	White	Female	United-States
1028	Private	Some-college	Married-civ-spouse	Craft-repair	Husband	White	Male	United-States
1029	Private	HS-grad	Married-civ-spouse	Transport-moving	Husband	White	Male	United-States
1030	Local-gov	Bachelors	Married-civ-spouse	Prof-specialty	Wife	White	Female	United-States
1031	Private	Bachelors	Married-civ-spouse	Prof-specialty	Husband	Asian-Pac-Islander	Male	Japan

1032 rows × 8 columns

Baseline Model :

In [19]:
```
le = LabelEncoder()
```

In [21]:
```
for col in df_cat:
  le = LabelEncoder()
  df_cat[col] = le.fit_transform(df_cat[col])
```

In [22]:
```
df_cat
```

Out[22]:

	Workclass	education	marital-status	occupation	relationship	race	sex	native-country
0	5	9	4	0	1	4	1	28
1	4	9	2	3	0	4	1	28
2	2	11	0	5	1	4	1	28
3	2	1	2	5	0	2	1	28
4	2	9	2	9	5	2	0	4
...	...	...	...	...	...	...	...	...
1027	2	11	0	5	3	4	0	28
1028	2	15	2	2	0	4	1	28
1029	2	11	2	13	0	4	1	28
1030	1	9	2	9	5	4	0	28
1031	2	9	2	9	0	1	1	18

1032 rows × 8 columns

In [23]:
```
df = pd.concat([df_cat,df_num],axis=1)
```

In [24]:
```
df
```

Out[24]:

	Workclass	education	marital-status	occupation	relationship	race	sex	native-country	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	Income
0	5	9	4	0	1	4	1	28	39	77516	13	2174	0	40	0
1	4	9	2	3	0	4	1	28	50	83311	13	0	0	13	0
2	2	11	0	5	1	4	1	28	38	215646	9	0	0	40	0
3	2	1	2	5	0	2	1	28	53	234721	7	0	0	40	0
4	2	9	2	9	5	2	0	4	28	338409	13	0	0	40	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1027	2	11	0	5	3	4	0	28	34	290763	9	0	0	40	0
1028	2	15	2	2	0	4	1	28	36	51100	10	0	0	40	0
1029	2	11	2	13	0	4	1	28	41	227644	9	0	0	50	0
1030	1	9	2	9	5	4	0	28	58	205267	13	0	0	40	1
1031	2	9	2	9	0	1	1	18	53	288020	13	0	0	40	0

1032 rows × 15 columns

In [26]:
```
def train_model(X_train,X_test):
  log = LogisticRegression()
  log.fit(X_train,y_train)
  y_pred = log.predict(X_test)
  print(classification_report(y_test,y_pred))
```

In [27]:
```
X = df.iloc[:,:-1]
y = df.iloc[:,-1]
```

In [28]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=1)
```

In [29]:
```
train_model(X_train,X_test)
```

```
              precision    recall  f1-score   support

           0       0.81      0.96      0.88       238
           1       0.68      0.26      0.38        72

    accuracy                           0.80       310
   macro avg       0.75      0.61      0.63       310
weighted avg       0.78      0.80      0.76       310
```

Chi2 and Anova Test :

chi2 :

In [31]:
```
#chi2
from sklearn.feature_selection import chi2
# ANOVA
from sklearn.feature_selection import f_regression
# common function for both
from sklearn.feature_selection import SelectKBest
```

In [32]:
```
chi2 = SelectKBest(score_func=chi2,k=10)
```

In [33]:
```
X_train_chi = chi2.fit_transform(X_train,y_train)
```

In [34]:
```
X_test_chi = chi2.transform(X_test)
```

In [35]:
```
train_model(X_train_chi,X_test_chi)
```

```
              precision    recall  f1-score   support

           0       0.80      0.96      0.87       238
           1       0.62      0.22      0.33        72

    accuracy                           0.79       310
   macro avg       0.71      0.59      0.60       310
weighted avg       0.76      0.79      0.75       310
```

In [36]:
```
chi2.scores_
```

Out[36]:
```
array([1.60667219e+00, 6.46272080e-01, 2.85524856e+01, 2.69228910e-01,
       4.28508247e+01, 6.51262333e-01, 3.88273433e+00, 5.29629278e-02,
       1.43215169e+02, 2.08905154e+04, 4.51886417e+01, 7.86853758e+05,
       1.98133155e+04, 1.23675492e+02])
```

In [37]:
```
df.columns
```

Out[37]:
```
Index(['Workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'sex', 'native-country', 'age', 'fnlwgt',
       'education-num', 'capital-gain', 'capital-loss', 'hours-per-week',
       'Income'],
      dtype='object')
```

In [38]:
```
chi2.get_support()
```

Out[38]:
```
array([ True, False,  True, False,  True, False,  True, False,  True,
        True,  True,  True,  True,  True])
```

Anova :

In [39]:
```
anova = SelectKBest(score_func=f_regression,k=4)
```

In [40]:
```
X_train_f = anova.fit_transform(X_train,y_train)
X_test_f = anova.transform(X_test)
```

In [41]:
```
train_model(X_train_f,X_test_f)
```

```
              precision    recall  f1-score   support

           0       0.83      0.95      0.89       238
           1       0.69      0.35      0.46        72

    accuracy                           0.81       310
   macro avg       0.76      0.65      0.67       310
weighted avg       0.80      0.81      0.79       310
```

In [42]:
```
anova.scores_
```

Out[42]:
```
array([ 3.855057  ,  0.51247514, 34.01671063,  0.10304801, 24.01569722,
        3.22653221, 12.36335806,  0.08849767, 35.87430298,  0.34703723,
       87.75938546, 86.66744615, 11.18286257, 40.91992553])
```

In [44]:
```
df.columns
```

Out[44]:
```
Index(['Workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'sex', 'native-country', 'age', 'fnlwgt',
       'education-num', 'capital-gain', 'capital-loss', 'hours-per-week',
       'Income'],
      dtype='object')
```

In [45]:
```
anova.get_support()
```

Out[45]:
```
array([False, False, False, False, False, False, False, False,  True,
       False,  True,  True, False,  True])
```

Wrapper Method (Forward Selection) :

In [46]:
```
features = df.columns.tolist()[:-1]
```

In [47]:
```
features
```

Out[47]:
```
['Workclass',
 'education',
 'marital-status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native-country',
 'age',
 'fnlwgt',
 'education-num',
 'capital-gain',
 'capital-loss',
 'hours-per-week']
```

In [48]:
```
cols = []
```

In [50]:
```
for col in features:
  cols.append(col)
  X = df[cols]
  y = df["Income"]
  X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=1)
  log = LogisticRegression()
  log.fit(X_train,y_train)
  y_pred = log.predict(X_test)
  print(col,"----> precision: ",precision_score(y_test,y_pred),"recall: ",recall_score(y_test,y_pred))
```

```
Workclass ----> precision:  0.0 recall:  0.0
education ----> precision:  0.0 recall:  0.0
marital-status ----> precision:  0.0 recall:  0.0
occupation ----> precision:  0.0 recall:  0.0
relationship ----> precision:  0.0 recall:  0.0
race ----> precision:  0.0 recall:  0.0
sex ----> precision:  0.0 recall:  0.0
native-country ----> precision:  0.0 recall:  0.0
age ----> precision:  0.2 recall:  0.041666666666666664
fnlwgt ----> precision:  0.0 recall:  0.0
education-num ----> precision:  0.0 recall:  0.0
capital-gain ----> precision:  0.5666666666666667 recall:  0.2361111111111111
capital-loss ----> precision:  0.6666666666666666 recall:  0.25
hours-per-week ----> precision:  0.6785714285714286 recall:  0.2638888888888889
```

Principal Component Analysis :

In [51]:
```
from sklearn.decomposition import PCA
```

In [52]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=1)
```

In [53]:
```
pca = PCA(n_components=5,random_state=1)
```

In [54]:
```
X_train_pca = pca.fit_transform(X_train)
```

In [55]:
```
X_test_pca = pca.transform(X_test)
```

In [56]:
```
train_model(X_train_pca,X_test_pca)
```

```
              precision    recall  f1-score   support

           0       0.85      0.89      0.87       238
           1       0.57      0.46      0.51        72

    accuracy                           0.79       310
   macro avg       0.71      0.68      0.69       310
weighted avg       0.78      0.79      0.79       310
```

In [57]:
```
components = pca.components_
```

In [59]:
```
components[0]
```

Out[59]:
```
array([ 3.40042108e-07, -1.33962105e-06,  6.89948962e-07, -2.67201320e-07,
        9.49268155e-07, -7.71548627e-07, -6.75004521e-08, -2.64531132e-06,
       -7.24832430e-06,  9.99999750e-01, -1.41921124e-06,  7.07377252e-04,
       -1.95570803e-05, -8.45583433e-06])
```

In [60]:
```
df.columns
```

Out[60]:
```
Index(['Workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'sex', 'native-country', 'age', 'fnlwgt',
       'education-num', 'capital-gain', 'capital-loss', 'hours-per-week',
       'Income'],
      dtype='object')
```

In [61]:
```
components[1]
```

Out[61]:
```
array([-4.10236592e-06,  3.49832297e-05, -4.88315133e-05, -4.36540333e-05,
       -7.08592082e-05,  2.66548473e-05,  4.54902444e-06,  5.74320323e-05,
        3.85812993e-04, -7.07522637e-04,  1.56328738e-04,  9.99953258e-01,
       -9.60468184e-03,  7.37797432e-04])
```

In [ ]: