```
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
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
        /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")
        d = pd.read csv("salary.csv")
```

In [4]: df

Out[4]:

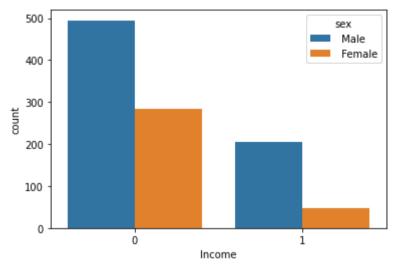
: 	Unnamed: 0	age	Workclass	fnlwgt	education	education- num	marital- status	occupation	relationship	race	sex	capital- gain	capital- loss	hours- per- week	nat cou
0	0	39	State-gov	77516	Bachelors	13	Never- married	Adm- clerical	Not-in-family	White	Male	2174	0	40	Uni St
1	1	50	Self-emp- not-inc	83311	Bachelors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

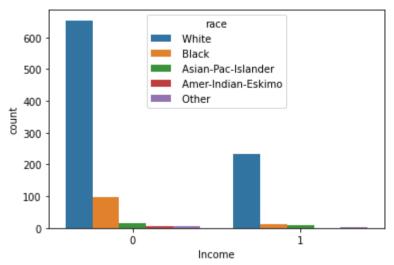
```
In [5]: df.drop(["Unnamed: 0"], axis=1,inplace = True)
In [6]: df["Income"].value_counts()
Out[6]: 0
             778
             254
        Name: Income, dtype: int64
        sns.countplot(x='Income',data=df, palette='hls')
In [7]:
        plt.show()
           800
            700
           600
           500
         400
            300
           200
           100
```

Income

```
In [8]: plt.figure()
    sns.countplot(data=df,x="Income",hue="sex")
    plt.show()
```



```
In [9]: plt.figure()
sns.countplot(data=df,x="Income",hue="race")
plt.show()
```



#To Check Missing Value:-

```
In [10]: df.isnull().sum()
Out[10]: age
                            0
         Workclass
                            0
         fnlwgt
         education
                            0
         education-num
         marital-status
                            0
         occupation
                            0
         relationship
                            0
                            0
         race
         sex
         capital-gain
                            0
         capital-loss
                            0
         hours-per-week
                            0
         native-country
                            0
         Income
         dtype: int64
```

## Data Type:

```
In [37]: df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 1032 entries, 0 to 1031
         Data columns (total 15 columns):
                              Non-Null Count Dtype
              Column
              _____
                              1032 non-null
              Workclass
                                             int64
                              1032 non-null
              education
                                             int64
              marital-status 1032 non-null
                                             int64
              occupation
                              1032 non-null
                                              int64
              relationship
                              1032 non-null
                                             int64
                              1032 non-null
                                             int64
              race
                             1032 non-null
                                             int64
              sex
              native-country 1032 non-null
                                              int64
                              1032 non-null
                                              int64
              age
              fnlwgt
          9
                             1032 non-null
                                             int64
          10 education-num 1032 non-null
                                              int64
          11 capital-gain
                             1032 non-null
                                             int64
          12 capital-loss
                             1032 non-null
                                             int64
          13 hours-per-week 1032 non-null
                                              int64
          14 Income
                              1032 non-null
                                             int64
         dtypes: int64(15)
         memory usage: 121.1 KB
In [12]: df num = df.select dtypes(["float64","int64"])
```

In [13]: df\_num

Out[13]:

	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 [15]: df\_cat

## Out[15]:

	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 Black	Male	United-States	
4	Private	Bachelors	Married-civ-spouse	Prof-specialty	Wife		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

```
In [16]: le = LabelEncoder()
```

```
In [17]: for col in df_cat:
    le = LabelEncoder()
    df_cat[col] = le.fit_transform(df_cat[col])
```

/usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:3: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy)

This is separate from the ipykernel package so we can avoid doing imports until

In [18]: df\_cat

Out[18]:

	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 [20]: df

Out[20]:

	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 [22]: X.head()

Out[22]:

	Workclass	education	marital- status	occupation	relationship	race	sex	native- country	age	fnlwgt	education- num	capital- gain	capital- loss	hours-per- week
0	5	9	4	0	1	4	1	28	39	77516	13	2174	0	40
1	4	9	2	3	0	4	1	28	50	83311	13	0	0	13
2	2	11	0	5	1	4	1	28	38	215646	9	0	0	40
3	2	1	2	5	0	2	1	28	53	234721	7	0	0	40
4	2	9	2	9	5	2	0	4	28	338409	13	0	0	40

```
In [23]: y.head()
Out[23]: 0
         Name: Income, dtype: int64
In [24]: X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=1)
         #Logistic Regression :-
In [49]: log = LogisticRegression(max_iter=120)
In [50]: log.fit(X_train,y_train)
Out[50]: LogisticRegression(C=1.0, class weight=None, dual=False, fit intercept=True,
                            intercept_scaling=1, l1_ratio=None, max_iter=120,
                            multi_class='auto', n_jobs=None, penalty='12',
                            random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                            warm_start=False)
```

```
In [51]: log.score(X test,y test)
Out[51]: 0.8
In [52]: v pred = log.predict(X test)
     print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(log.score(X test, y test)))
     Accuracy of logistic regression classifier on test set: 0.80
In [53]: v pred = log.predict(X test)
In [54]: |y_pred
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0,
         1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0,
         0, 01)
```

## **Evaluation Matrics:**

```
In [55]: accuracy_score(y_test,y_pred)
Out[55]: 0.8
```

```
In [56]: precision_score(y_test,y_pred)
Out[56]: 0.6785714285714286
In [57]: recall score(y test,y pred)
Out[57]: 0.2638888888888888
In [58]: f1_score(y_test,y_pred)
Out[58]: 0.38
In [59]: print(classification_report(y_test,y_pred))
                                    recall f1-score
                        precision
                                                        support
                             0.81
                                      0.96
                                                 0.88
                                                            238
                    0
                                                 0.38
                    1
                             0.68
                                      0.26
                                                            72
                                                 0.80
                                                            310
             accuracy
                            0.75
                                      0.61
                                                 0.63
                                                            310
            macro avg
         weighted avg
                                                 0.76
                            0.78
                                      0.80
                                                            310
 In [ ]:
```