Default_of_Credit_Card_Clients

Dataset Information This dataset contains information on default payments, demographic factors, credit data, history of payment, and bill statements of credit card clients in Taiwan from April 2005 to September 2005. Content There are 25 variables: ID: ID of each client LIMIT_BAL: Amount of given credit in NT dollars (includes individual and family/supplementary credit SEX: Gender (1=male, 2=female) EDUCATION: (1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown) MARRIAGE: Marital status (1=married, 2=single, 3=others) AGE: Age in years PAY_0: Repayment status in September, 2005 (-1=pay duly, 1=payment delay for one month, 2=payment delay for two months, … 8=payment delay for eight months, 9=payment delay for nine months and above) PAY_2: Repayment status in August, 2005 (scale same as above) PAY_3: Repayment status in July, 2005 (scale same as above) PAY_4: Repayment status in June, 2005 (scale same as above) PAY_5: Repayment status in May, 2005 (scale same as above) PAY_6: Repayment status in April, 2005 (scale same as above) BILL_AMT1: Amount of bill statement in September, 2005 (NT dollar) BILL_AMT2: Amount of bill statement in August, 2005 (NT dollar) BILL_AMT3: Amount of bill statement in July, 2005 (NT dollar) BILL_AMT4: Amount of bill statement in June, 2005 (NT dollar) BILL_AMT5: Amount of bill statement in May, 2005 (NT dollar) BILL_AMT6: Amount of bill statement in April, 2005 (NT dollar) PAY_AMT1: Amount of previous payment in September, 2005 (NT dollar) PAY_AMT2: Amount of previous payment in August, 2005 (NT dollar) PAY_AMT3: Amount of previous payment in July, 2005 (NT dollar) PAY_AMT4: Amount of previous payment in June, 2005 (NT dollar) PAY_AMT5: Amount of previous payment in May, 2005 (NT dollar) PAY_AMT6: Amount of previous payment in April, 2005 (NT dollar) default.payment.next.month: Default payment (1=yes, 0=no) a)How does the probability of default payment vary by categories of different demographic variables? b)Which variables are the strongest predictors of default payment?

In [76]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix
```

In [77]:
```
# read data from the data set UCI Credi Card
df=pd.read_csv('UCI_Credit_Card.csv')
df.head()
```

Out[77]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4
0	1	20000.0	2	2	1	24	2	2	-1	-1	...	0.0
1	2	120000.0	2	2	2	26	-1	2	0	0	...	3272.0
2	3	90000.0	2	2	2	34	0	0	0	0	...	14331.0
3	4	50000.0	2	2	1	37	0	0	0	0	...	28314.0
4	5	50000.0	1	2	1	57	-1	0	-1	0	...	20940.0

5 rows × 25 columns

In [78]:
```
#Ckecking for Nul Values
check_null=df.isnull().sum()*100/df.shape[0]
```

In [79]:
```
#Sorting values

check_null[check_null>0].sort_values(ascending=False)
```

Out[79]:
```
Series([], dtype: float64)
```

In [80]:
```
df.columns                    # Column names
```

Out[80]:
```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
       'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6',
       'default.payment.next.month'],
      dtype='object')
```

In [81]:
```
#Drop Irrelevent columns EDUCATION, MARRIAGE
df.drop(columns=['ID','EDUCATION','MARRIAGE'],inplace=True)
df.head()
```

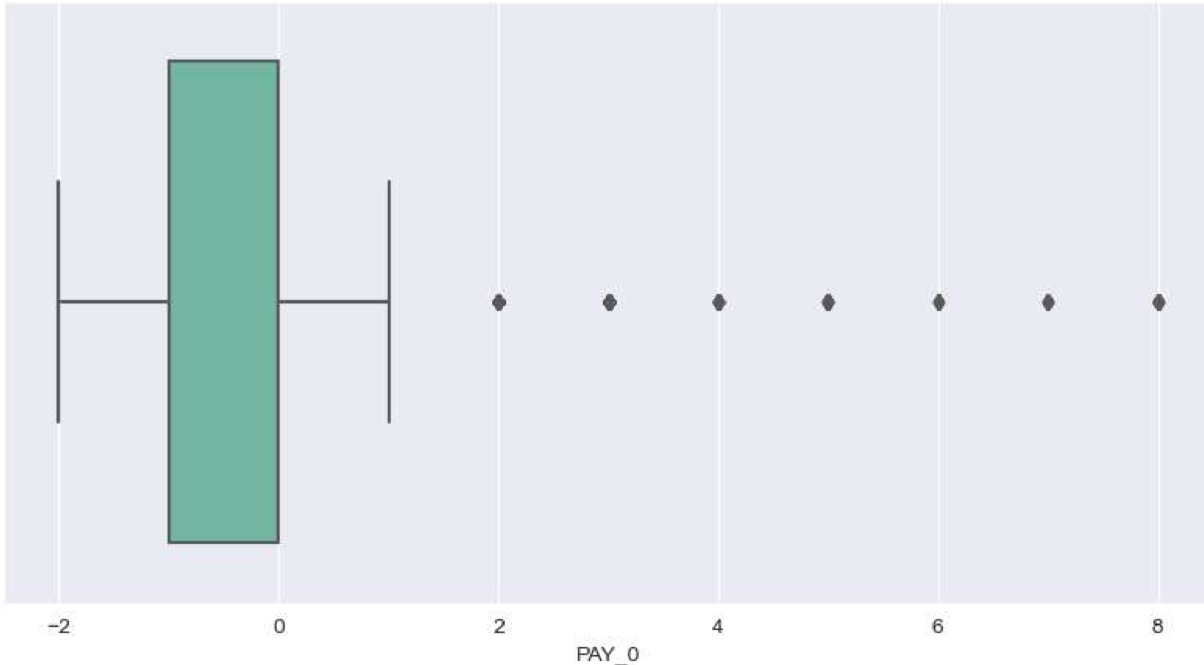
Out[81]:

	LIMIT_BAL	SEX	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	...	BILL_AMT4	BI
0	20000.0	2	24	2	2	-1	-1	-2	-2	3913.0	...	0.0	
1	120000.0	2	26	-1	2	0	0	0	2	2682.0	...	3272.0	
2	90000.0	2	34	0	0	0	0	0	0	29239.0	...	14331.0	
3	50000.0	2	37	0	0	0	0	0	0	46990.0	...	28314.0	
4	50000.0	1	57	-1	0	-1	0	0	0	8617.0	...	20940.0	

5 rows × 22 columns

In [82]:
```
#Draw a box plot to find out the number of outliers for delay repayment column PAY_0
plt.figure(figsize=(10,5))
sns.boxplot(df['PAY_0'])
plt.show()
```

```
C:\Users\KIRAN\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



In [83]:
```
df.head()
```

Out[83]:

	LIMIT_BAL	SEX	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	...	BILL_AMT4	BI
0	20000.0	2	24	2	2	-1	-1	-2	-2	3913.0	...	0.0	
1	120000.0	2	26	-1	2	0	0	0	2	2682.0	...	3272.0	
2	90000.0	2	34	0	0	0	0	0	0	29239.0	...	14331.0	
3	50000.0	2	37	0	0	0	0	0	0	46990.0	...	28314.0	
4	50000.0	1	57	-1	0	-1	0	0	0	8617.0	...	20940.0	

5 rows × 22 columns

In [84]:
```
#Drop columns PAY_2 to PAY_6 as the total no of dues are updated and mentioned in the
df.drop(columns=['PAY_2','PAY_3','PAY_3','PAY_4','PAY_5','PAY_6'],inplace=True)
df.head()
```

Out[84]:

	LIMIT_BAL	SEX	AGE	PAY_0	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BILL_AMT5	BILL_A
0	20000.0	2	24	2	3913.0	3102.0	689.0	0.0	0.0	
1	120000.0	2	26	-1	2682.0	1725.0	2682.0	3272.0	3455.0	3
2	90000.0	2	34	0	29239.0	14027.0	13559.0	14331.0	14948.0	15
3	50000.0	2	37	0	46990.0	48233.0	49291.0	28314.0	28959.0	29
4	50000.0	1	57	-1	8617.0	5670.0	35835.0	20940.0	19146.0	19

In [85]:
```
#Drop columns BILL_AMT_2 to BILL_AMT_6 & PAY_AMT_2 TO PAY_AMT_6 AS BILL_AMT_1 & PAY_AM
df.drop(columns=['BILL_AMT2','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT
df.head()
```

Out[85]:

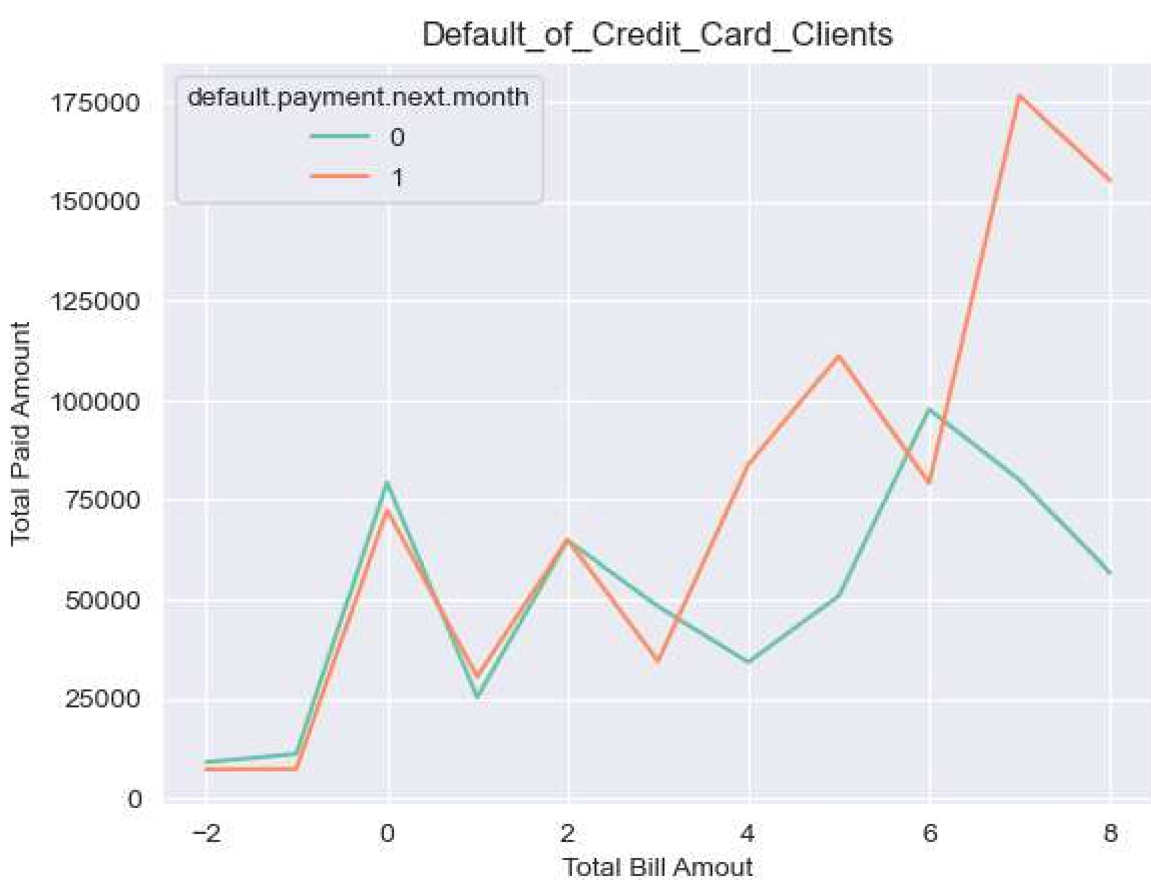
	LIMIT_BAL	SEX	AGE	PAY_0	BILL_AMT1	PAY_AMT1	default.payment.next.month
0	20000.0	2	24	2	3913.0	0.0	1
1	120000.0	2	26	-1	2682.0	0.0	1
2	90000.0	2	34	0	29239.0	1518.0	0
3	50000.0	2	37	0	46990.0	2000.0	0
4	50000.0	1	57	-1	8617.0	2000.0	0

default.payment.next.month: Default payment (1=yes, 0=no)

In [86]:

```
sns.set_style('darkgrid')
sns.set_palette('Set2')
sns.lineplot(x='PAY_0',y='BILL_AMT1',hue='default.payment.next.month',data=df,ci=None)
#default.payment.next.month: Default payment (1=yes, 0=no)

plt.title('Default_of_Credit_Card_Clients')
plt.xlabel('Total Bill Amout')
plt.ylabel('Total Paid Amount')
plt.show()
```



In [87]:

```
df['PAY_0'].unique()
```

Out[87]:

```
array([ 2, -1,  0, -2,  1,  3,  4,  8,  7,  5,  6], dtype=int64)
```

In [ ]:

PAY_0: Repayment status in September, 2005 (-1=pay duly, 1=payment delay for one month, 2=payment delay for two months, ... 8=payment delay for eight months, 9=payment delay for nine months and above)

In [88]:
```
df['PAY_0']
```

Out[88]:
```
0        2
1       -1
2        0
3        0
4       -1
        ..
29995    0
29996   -1
29997    4
29998    1
29999    0
Name: PAY_0, Length: 30000, dtype: int64
```

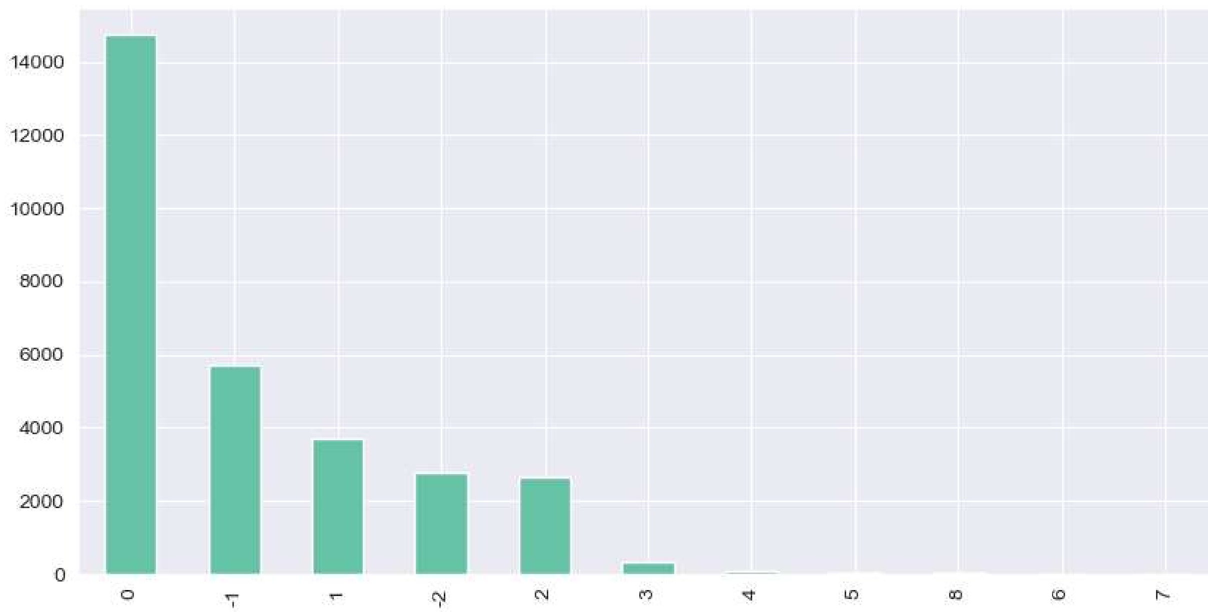
In [89]:
```
# Replacing Values 0 & -2 with -1 which indicates the prompt payment and no dues
df['PAY_0']=df['PAY_0'].replace({'-1':-1})
```

In [90]:
```
df['PAY_0']=df['PAY_0'].replace({'NaN':-1})
```

In [91]:
```
# PLOT BAR CHART TO PROJECT THE COLUMN PAY_0

plt.figure(figsize=(10,5))
df['PAY_0'].value_counts().plot(kind='bar')
```

Out[91]: <AxesSubplot:>



In [92]:
```
df['PAY_0'].unique()
```

Out[92]:
```
array([ 2, -1,  0, -2,  1,  3,  4,  8,  7,  5,  6], dtype=int64)
```

In [70]:
```
df.head()
```

Out[70]:

	LIMIT_BAL	SEX	AGE	PAY_0	BILL_AMT1	BILL_AMT3	PAY_AMT1	default.payment.next.month
0	20000.0	2	24	2	3913.0	689.0	0.0	1
1	120000.0	2	26	-1	2682.0	2682.0	0.0	1
2	90000.0	2	34	0	29239.0	13559.0	1518.0	0
3	50000.0	2	37	0	46990.0	49291.0	2000.0	0
4	50000.0	1	57	-1	8617.0	35835.0	2000.0	0

In [ ]:

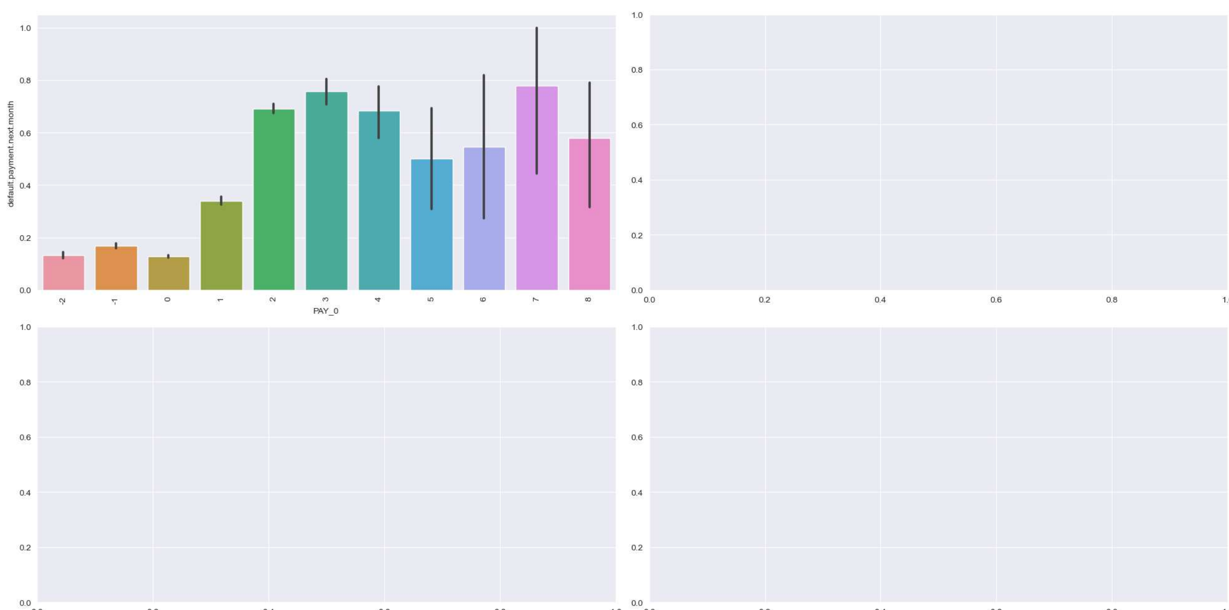
```
# List of catagorial variables to plot

cat_vars=['PAY_0','AGE','BILL_AMT6','PAY_AMT6','SEX']
#Create a figure with subplots
fig,axs=plt.subplots(nrows=2,ncols=2,figsize=(20,10))
axs=axs.flatten()

#Create barplot for each catagorial variable

for i, var in enumerate(cat_vars):
    sns.barplot(x=var,y='default.payment.next.month',data=df,ax=axs[i])
    axs[i].set_xticklabels(axs[i].get_xticklabels(),rotation=90)

    fig.tight_layout()
    plt.show()
```



In [ ]:

In [93]:

```
from sklearn import preprocessing
#Loop over each column in DataFrame where datatype is object
for col in df.select_dtypes(include=['int']).columns:
#Initialize the label coder
    label_encoder=preprocessing.LabelEncoder()

    # Fit the encoder to the unique value in the column
    label_encoder.fit(df[col].unique())
```

```
    #Transform the colum using encoder
    df[col]=label_encoder.transform(df[col])

    #Print the column name and unique encoded values

    print(f"{col}: {df[col].unique()}")
```

```
SEX: [1 0]
AGE: [ 3  5 13 16 36  8  2  7 14 30 20  9 28 18 19  6 26 12 11 33 37  1  4 10
 25 21 22 24 35 23 32 17 42 15 31 27 34 39 29 54 40 52 38  0 46 45 41 49
 51 43 44 50 48 47 55 53]
PAY_0: [ 4  1  2  0  3  5  6 10  9  7  8]
default.payment.next.month: [1 0]
```

In [94]:

```
df.dtypes
```

Out[94]:

```
LIMIT_BAL                     float64
SEX                             int64
AGE                             int64
PAY_0                           int64
BILL_AMT1                     float64
PAY_AMT1                      float64
default.payment.next.month      int64
dtype: object
```

In [ ]:

```

```

In [95]:

```
#CORELATION HEATMAP
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(),fmt='.2g',annot=True)
```

Out[95]: <AxesSubplot:>

In [96]:
```
X=df.drop('default.payment.next.month',axis=1)
y=df['default.payment.next.month']
```

In [97]:
```
#Test Size 20% and Train Size 80%

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=0)
```

LOGISTIC REGRESSOR

In [98]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

#Create a Logostic Regression Model

logreg=LogisticRegression(solver='liblinear',max_iter=10000)

#Define the parameter grid

param_grid={
    'penalty':['l1','l2'],
    'C':[0.01,0.1,1,10]

}

#Perform a gridsearch with cross-validation to find best hyperparameters

grid_search=GridSearchCV(logreg,param_grid,cv=5)
grid_search.fit(X_train,y_train)

# print the best hyperparameters

print(grid_search.best_params_)
```

```
{'C': 10, 'penalty': 'l1'}
```

In [99]:
```
from sklearn.ensemble import RandomForestClassifier
logreg=LogisticRegression(solver='liblinear',max_iter=10000,C=1,penalty='l1')
logreg.fit(X_train,y_train)
```

Out[99]:
```
▾ LogisticRegression
LogisticRegression(C=1, max_iter=10000, penalty='l1', solver='liblinear')
```

In [100…
```
#finding and printing Accuracy Score

y_pred=logreg.predict(X_test)

print('Accuracy Score:',round(accuracy_score(y_test,y_pred)*100,2),'%')
```

```
Accuracy Score: 81.85 %
```

In [101…
```
# Printing All Test Scores
from sklearn.metrics import accuracy_score,f1_score,precision_score,recall_score,jacca
print('F-1 Score',(f1_score(y_test,y_pred,average='micro')))
print('Precision Score:',(precision_score(y_test,y_pred,average='micro')))
```

```
print('Recall Score:',(recall_score(y_test,y_pred,average='micro')))
print('Jaccard Score:',(jaccard_score(y_test,y_pred,average='micro')))
print('Log Loss:',(log_loss(y_test,y_pred)))
```

```
F-1 Score 0.8184999999999999
Precision Score: 0.8185
Recall Score: 0.8185
Jaccard Score: 0.6927634363097757
Log Loss: 6.541923090124763
```

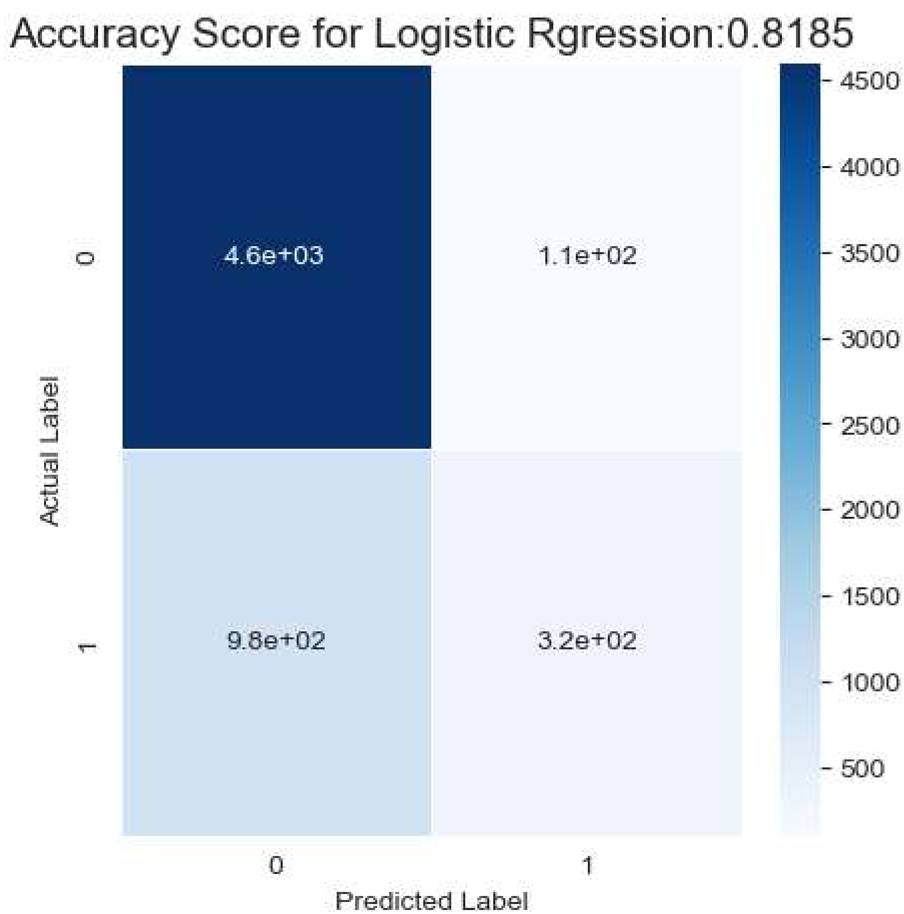
CONFUSION MATRIX IS CORRECT ACCORDING TO THE GIVEN PROBLEM STATEMENT

In [102…

```
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_test,y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5,annot=True,cmap='Blues')
plt.ylabel('Actual Label')
plt.xlabel('Predicted Label')
all_sample_title=('Accuracy Score for Logistic Rgression:{0}'.format(logreg.score(X_te
plt.title(all_sample_title,size=15)
```

Out[102]:

```
Text(0.5, 1.0, 'Accuracy Score for Logistic Rgression:0.8185')
```



In [ ]: