

## Bharatiya Vidya Bhavan's Sardar Patel Institute of Technology

Bhavan's Campus, Munshi Nagar, Andheri (West), Mumbai-400058-India (Autonomous College Affiliated to University of Mumbai)

BE-ETRX UID:2019110039 Sub-Minor ML

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Exp 2B

**Aim:** To build and predict the model using logistic regression on the given Credit score dataset.

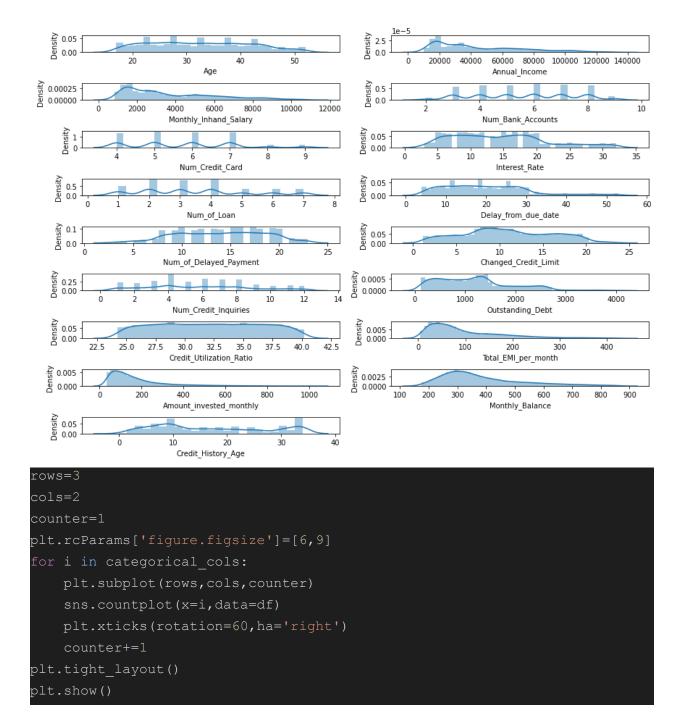
## Code:

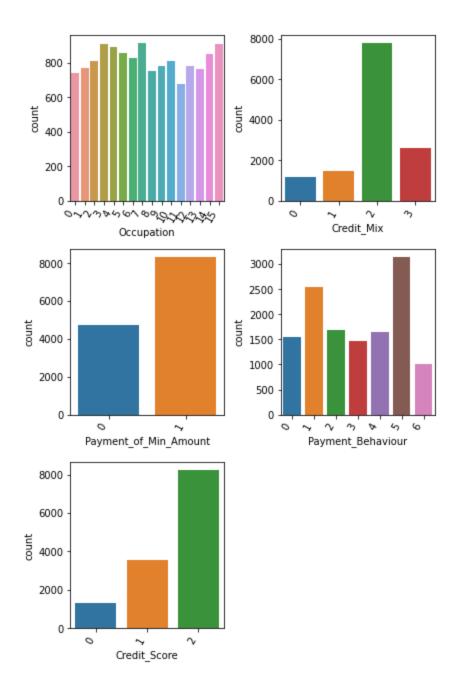
```
import warnings
import pandas as pd
from pandas.api.types import is numeric dtype
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder as le
from sklearn.model selection import train test split
from sklearn.preprocessing import RobustScaler as rbScaler
from sklearn.linear model import LogisticRegression as lgrClassifier
from sklearn import metrics
from statsmodels.stats.outliers influence import variance inflation factor
warnings.filterwarnings('ignore')
%matplotlib inline
from google.colab import drive
drive.mount('/content/drive')
df = pd.read csv('/content/drive/MyDrive/data/train.csv',
low memory=False)
Df.shape
```

```
null_count = df.isnull().sum().sort_values(ascending=False)
null_count
```

Monthly_Inhand_Salary	15002
Type_of_Loan	11408
Name	9985
Credit_History_Age	9030
Num_of_Delayed_Payment	7002
Amount_invested_monthly	4479
Num_Credit_Inquiries	1965
Monthly_Balance	1200
ID	0
Changed_Credit_Limit	0
Payment_Behaviour	0
Total_EMI_per_month	0
Payment_of_Min_Amount	0
Credit_Utilization_Ratio	0
Outstanding_Debt	0
Credit Mix	0
Delay_from_due_date	0
Customer_ID	0
Num_of_Loan	0
Interest_Rate	0
Num_Credit_Card	0
Num_Bank_Accounts	0
Annual Income	0
Occupation	0
SSN	0
Age	0
Month	0
Credit_Score	0
dtype: int64	

```
[ ] num_cols = ['Age', 'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
            'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan',
            'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Limit',
            'Num_Credit_Inquiries', 'Outstanding_Debt', 'Credit_Utilization_Ratio',
           'Total_EMI_per_month', 'Amount_invested_monthly',
           'Monthly_Balance', 'Credit_History_Age']
    categorical_cols = ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount',
            'Payment_Behaviour', 'Credit_Score']
irrelavent_coulumns = ['ID', 'Customer_ID', 'Month', 'Name', 'SSN']
    df.drop(columns=irrelavent_coulumns, inplace=True, axis=1)
[ ] df = df.applymap(
        lambda x: x if x is np.NaN or not \
            isinstance(x, str) else str(x).strip('_')).replace(
                ['', 'nan', '!@9#%8', '#F%$D@*&8'], np.NaN
            )
def take years(x):
    if x is not None:
        return str(x).strip()[0:2]
df.Credit History Age=df.Credit History Age.apply(take years)
df['Credit History Age'] = df['Credit History Age'].replace({'na': np.NaN})
df.Age = df.Age.astype(int)
df.Annual_Income = df.Annual_Income.astype(float)
df.Num of Loan = df.Num of Loan.astype(int)
df.Num of Delayed Payment = df.Num of Delayed Payment.astype(float)
df.Changed_Credit_Limit = df.Changed_Credit_Limit.astype(float)
df.Outstanding Debt = df.Outstanding Debt.astype(float)
df.Amount invested monthly = df.Amount invested monthly.astype(float)
df.Monthly_Balance = df.Monthly_Balance.astype(float)
rows=10
cols=2
counter=1
plt.rcParams['figure.figsize']=[12, 9]
for i in num cols:
    plt.subplot(rows, cols, counter)
    sns.distplot(df[i])
    counter+=1
plt.tight layout()
plt.show()
```





```
df['Payment_of_Min_Amount'] = df['Payment_of_Min_Amount'].replace({'NM': 'No'})

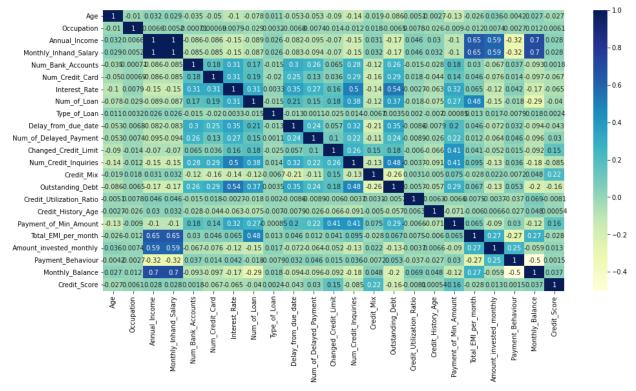
plt.rcParams['figure.figsize'] = [3,3]
sns.countplot(x='Payment_of_Min_Amount', data=df)
plt.xticks(rotation=60, ha='right')
plt.tight_layout()
plt.show()
```

```
def remove_outlier(df):
    low = .05
    high = .95
    quant_df = df.quantile([low, high])
    print(quant_df)
    for name in list(df.columns):
        if is_numeric_dtype(df[name]):
            df = df[(df[name] > quant_df.loc[low, name]) & (df[name] < quant_df.loc[high, name])]
    return df

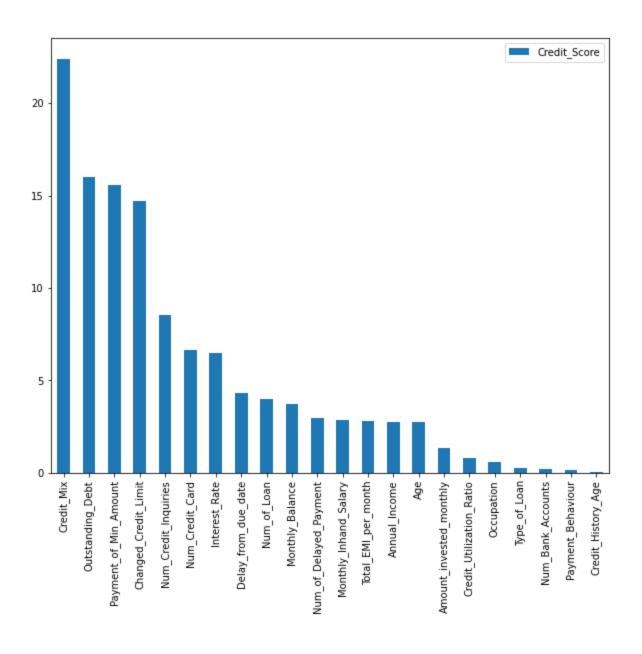
df = remove_outlier(df)</pre>
```

```
Age Annual Income Monthly Inhand Salary Num Bank Accounts \
0.05 16.0
                 9743.51
                                    836.125833
                                                              1.0
0.95 53.0
               134533.32
                                   10828.226500
                                                             10.0
     Num Credit Card Interest Rate Num of Loan Delay from due date \
0.05
                 3.0
                               2.0
                                            0.0
                                                                 3.0
                10.0
0.95
                               33.0
                                            8.0
                                                                54.0
     Num of Delayed Payment Changed Credit Limit Num Credit Inquiries \
0.05
                        2.0
                                            1.16
                                                                   0.0
0.95
                       24.0
                                            23.60
                                                                  13.0
     Outstanding Debt Credit Utilization Ratio Total EMI per month \
          118.5465
0.05
                                      24.230834
0.95
            4073.7605
                                     40.220207
                                                         437.012753
     Amount invested monthly Monthly Balance
0.05
                   31.893067
                                  174.599433
0.95
                                  862.590861
                 1149.405785
df.interpolate(method='linear', inplace=True)
```

```
Occupation le = le()
Type of Loan le = le()
Credit Mix le = le()
Credit History Age le = le()
Payment of Min Amount le = le()
Payment Behaviour le = le()
Credit Score le = le()
df['Occupation'] = Occupation le.fit transform(df['Occupation'])
df['Type of Loan'] = Type of Loan le.fit transform(df['Type of Loan'])
df['Credit Mix'] = Credit Mix le.fit transform(df['Credit Mix'])
df['Credit History Age'] =
Credit History Age le.fit transform(df['Credit History Age'])
df['Payment of Min Amount'] =
Payment of Min Amount le.fit transform(df['Payment of Min Amount'])
df['Payment Behaviour'] =
Payment Behaviour le.fit transform(df['Payment Behaviour'])
df['Credit Score'] = Credit Score le.fit transform(df['Credit Score'])
plt.figure(figsize = (16,8))
sns.heatmap(df.corr() , annot = True, cmap = "YlGnBu")
```

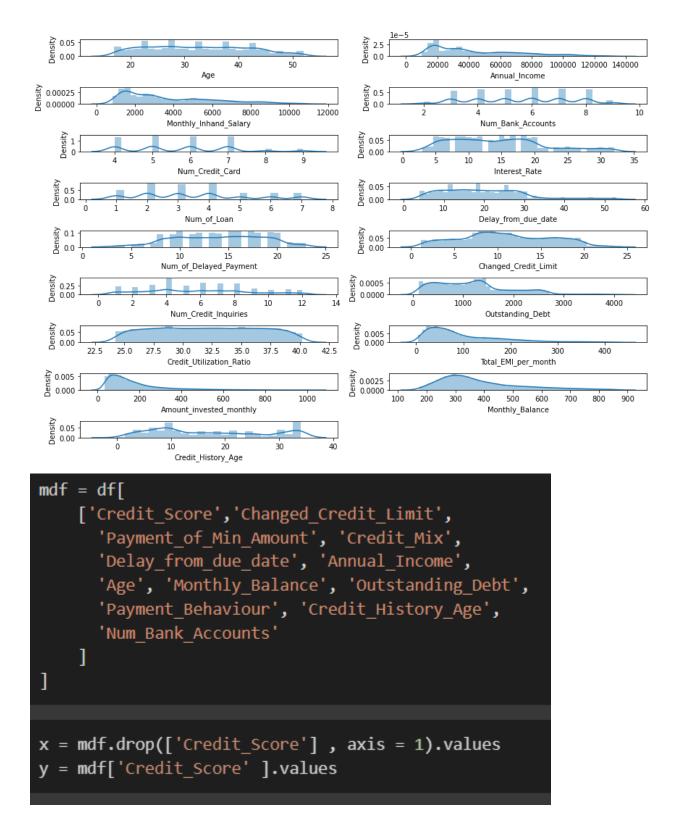


```
pd.DataFrame(abs(df.corr()['Credit_Score'].drop('Credit_Score')*100).sort_
values(
    ascending=False)).plot.bar(figsize = (10,8))
```

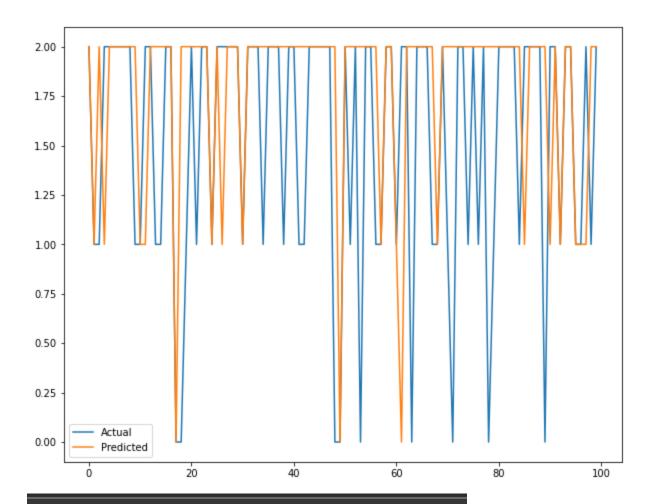


```
round(abs(df.corr()['Credit Score']*100).sort_values(ascending=False), 2)
 Credit Score
                            100.00
 Credit Mix
                            22.41
 Outstanding Debt
                            16.01
 Payment of Min Amount
                            15.55
 Changed Credit Limit
                            14.70
 Num Credit Inquiries
                            8.52
 Num Credit Card
                             6.66
                            6.48
 Interest Rate
                             4.30
 Delay from due date
                             3.98
 Num of Loan
 Monthly Balance
                             3.74
 Num of Delayed Payment
                            2.97
 Monthly Inhand Salary
                             2.84
 Total EMI per month
                             2.80
 Annual Income
                             2.77
 Age
                             2.75
 Amount invested monthly
                            1.34
 Credit Utilization Ratio
                             0.81
 Occupation
                             0.61
 Type of Loan
                             0.24
 Num Bank Accounts
                             0.18
 Payment Behaviour
                             0.15
 Credit History Age
 Name: Credit_Score, dtype: float64
numeric cols = df.select dtypes(exclude = "object").columns
vif df = df[numeric cols]
vif data = pd.DataFrame()
vif data["feature"] = vif df.columns
vif data["VIF"] = [variance inflation factor(vif df.values ,i) for i in
range(len(vif df.columns))]
vif data.head(17)
percent missing = df.isnull().sum() * 100 / len(df)
missing value df = pd.DataFrame({'column name': df.columns,
                                  'percent missing': percent missing})
missing value df.sort values('percent missing', ascending=False,
inplace=True)
missing value df
numeric cols = df.select dtypes(exclude = "object").columns
vif df = df[numeric cols]
```

```
vif_data = pd.DataFrame()
vif_data["feature"] = vif_df.columns
vif_data["VIF"] = [variance_inflation_factor(vif_df.values ,i) for i in
range(len(vif_df.columns))]
vif_data.head(17)
rows=10
cols=2
counter=1
plt.rcParams['figure.figsize']=[12, 9]
for i in num_cols:
    plt.subplot(rows, cols, counter)
    sns.distplot(df[i])
    counter+=1
plt.tight_layout()
plt.show()
```



```
x_train , x_test , y_train , y_test = train_test_split(x,y , test_size= 0.2 , random_state=50)
print([x_train.shape, y_train.shape, x_test.shape, y_test.shape])
ro_scaler = rbScaler()
x_train = ro_scaler.fit_transform(x_train)
x_test = ro_scaler.fit_transform(x_test)
[x_train.shape, x_test.shape]
lgr = lgrClassifier(C = 100)
lgr.fit(x_train , y_train)
lgr_score = lgr.score(x_train , y_train)
lgr_score_t = lgr.score(x_test , y_test)
y_pred1 = lgr.predict(x_test)
dd = pd.DataFrame({"Y_test" : y_test , "y_pred1": y_pred1})
plt.figure(figsize=(10,8))
plt.plot(dd[:100])
plt.legend(["Actual" , "Predicted"])
print(f"Train Score: {lgr_score}")
print(f"Test Score: {lgr_score_t}")
```



print(f"Train Score: {lgr\_score}")
print(f"Test Score: {lgr\_score\_t}")

Train Score: 0.6983261597321856 Test Score: 0.6866870696250956

## Conclusion:

- Logistic regression is an example of supervised learning. It is used to calculate or
  predict the probability of a binary (yes/no) event occurring. An example of logistic
  regression could be applying machine learning to determine if a person is likely
  to be infected with COVID-19 or not. Since we have two possible outcomes to
  this question yes they are infected, or no they are not infected this is called
  binary classification.
- In linear regression, the outcome is continuous and can be any possible value. However in the case of logistic regression, the predicted outcome is discrete and restricted to a limited number of values.
- Logistic regression is a classification algorithm used to find the probability of event success and event failure. It is used when the dependent variable is binary(0/1, True/False, Yes/No) in nature. It supports categorizing data into discrete classes by studying the relationship from a given set of labeled data. It learns a linear relationship from the given dataset and then introduces a non-linearity in the form of the Sigmoid function.
- We successfully carried out the experiment.