Credit Score Classification

In the taken dataset of the Global finance company, we are tasked with developing an automated system to categorize individuals based on their creditworthiness. Over the years, the company has collected a wealth of credit-related information, and now the management wants to build an intelligent system to segregate people into credit score brackets, reducing manual efforts.

Our task involves leveraging the available credit-related data to train a predictive model that can effectively categorize individuals based on their credit scores. This model will play a crucial role in automating the assessment of creditworthiness, enabling us to make informed decisions efficiently.

To accomplish this, we'll need to preprocess the data, engineer relevant features, and select appropriate algorithms for training the model. Once trained, our model will be capable of classifying new individuals into predefined credit score categories, contributing to our company's goal of enhancing efficiency and accuracy in credit assessment processes.

Load The Data and requisite libraries

```
# run  this cell only if you have errors related to libraries.
!pip uninstall scikit-learn imbalanced-learn
!pip install scikit-learn imbalanced-learn
!pip install category_encoders
!pip install xgboost
!pip install catboost
!pip uninstall scikit-learn
!pip install scikit-learn

# Packages for EDA
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np

# Data Preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PowerTransformer
from sklearn.metrics import mean_squared_error
from imblearn.over_sampling import SMOTE
from sklearn.impute import SimpleImputer
import category_encoders as ce
import re

# Modeling and evaluation
from sklearn.experimental import enable_hist_gradient_boosting
```

```
from sklearn.ensemble import (
    BaggingClassifier,
    ExtraTreesClassifier,
    RandomForestClassifier,
    StackingClassifier,
    HistGradientBoostingClassifier
)
from xgboost import XGBClassifier
from sklearn.metrics import classification_report
import joblib

# Packages options
sns.set(rc={'figure.figsize': [14, 7]}, font_scale=1.2) # Standard
figure size for all
np.seterr(divide='ignore', invalid='ignore', over='ignore') ;

import warnings
warnings.filterwarnings("ignore")
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/experimental/
enable_hist_gradient_boosting.py:16: UserWarning: Since version 1.0,
it is not needed to import enable_hist_gradient_boosting anymore.
HistGradientBoostingClassifier and HistGradientBoostingRegressor are
now stable and can be normally imported from sklearn.ensemble.
  warnings.warn(
```

```
df =
pd.read_csv("../input/credit-score-classification/train.csv",low_memor
y=False)
df.head(5)
```

```
       ID Customer_ID     Month           Name   Age          SSN
Occupation  \
0  0x1602   CUS_0xd40   January  Aaron Maashoh    23  821-00-0265
Scientist
1  0x1603   CUS_0xd40  February  Aaron Maashoh    23  821-00-0265
Scientist
2  0x1604   CUS_0xd40     March  Aaron Maashoh  -500  821-00-0265
Scientist
3  0x1605   CUS_0xd40     April  Aaron Maashoh    23  821-00-0265
Scientist
4  0x1606   CUS_0xd40       May  Aaron Maashoh    23  821-00-0265
Scientist

  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  ...
Credit_Mix  \
0      19114.12            1824.843333                  3  ...
_
1      19114.12                    NaN                  3  ...
Good
```

```
2      19114.12                    NaN                 3  ...
Good
3      19114.12                    NaN                 3  ...
Good
4      19114.12            1824.843333                 3  ...
Good

   Outstanding_Debt Credit_Utilization_Ratio     Credit_History_Age  \
0            809.98                26.822620  22 Years and 1 Months
1            809.98                31.944960                    NaN
2            809.98                28.609352  22 Years and 3 Months
3            809.98                31.377862  22 Years and 4 Months
4            809.98                24.797347  22 Years and 5 Months

   Payment_of_Min_Amount Total_EMI_per_month
Amount_invested_monthly  \
0                     No           49.574949       80.41529543900253

1                     No           49.574949      118.28022162236736

2                     No           49.574949         81.699521264648

3                     No           49.574949       199.4580743910713

4                     No           49.574949      41.420153086217326


                 Payment_Behaviour     Monthly_Balance Credit_Score
0   High_spent_Small_value_payments  312.49408867943663         Good
1    Low_spent_Large_value_payments  284.62916249607184         Good
2   Low_spent_Medium_value_payments   331.2098628537912         Good
3    Low_spent_Small_value_payments  223.45130972736786         Good
4  High_spent_Medium_value_payments  341.48923103222177         Good

[5 rows x 28 columns]
```

Prelimininary Data Univariate Inspection

```
df.shape
```

```
(100000, 28)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 28 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
```

```
 0   ID                        100000 non-null  object
 1   Customer_ID               100000 non-null  object
 2   Month                     100000 non-null  object
 3   Name                      90015 non-null   object
 4   Age                       100000 non-null  object
 5   SSN                       100000 non-null  object
 6   Occupation                100000 non-null  object
 7   Annual_Income             100000 non-null  object
 8   Monthly_Inhand_Salary     84998 non-null   float64
 9   Num_Bank_Accounts         100000 non-null  int64
 10  Num_Credit_Card           100000 non-null  int64
 11  Interest_Rate             100000 non-null  int64
 12  Num_of_Loan               100000 non-null  object
 13  Type_of_Loan              88592 non-null   object
 14  Delay_from_due_date       100000 non-null  int64
 15  Num_of_Delayed_Payment    92998 non-null   object
 16  Changed_Credit_Limit      100000 non-null  object
 17  Num_Credit_Inquiries      98035 non-null   float64
 18  Credit_Mix                100000 non-null  object
 19  Outstanding_Debt          100000 non-null  object
 20  Credit_Utilization_Ratio  100000 non-null  float64
 21  Credit_History_Age        90970 non-null   object
 22  Payment_of_Min_Amount     100000 non-null  object
 23  Total_EMI_per_month       100000 non-null  float64
 24  Amount_invested_monthly   95521 non-null   object
 25  Payment_Behaviour         100000 non-null  object
 26  Monthly_Balance           98800 non-null   object
 27  Credit_Score              100000 non-null  object
dtypes: float64(4), int64(4), object(20)
memory usage: 21.4+ MB
```

Understood that there are a lot of missing values and wrong data types (object) assigned to obviously numerical features like Age, Annual Income

```
df.describe()

       Monthly_Inhand_Salary  Num_Bank_Accounts  Num_Credit_Card  \
count           84998.000000      100000.000000     100000.00000
mean             4194.170850          17.091280         22.47443
std              3183.686167         117.404834        129.05741
min               303.645417          -1.000000          0.00000
25%              1625.568229           3.000000          4.00000
50%              3093.745000           6.000000          5.00000
75%              5957.448333           7.000000          7.00000
max             15204.633333        1798.000000       1499.00000

       Interest_Rate  Delay_from_due_date  Num_Credit_Inquiries  \
count  100000.000000        100000.000000          98035.000000
mean       72.466040            21.068780             27.754251
```

```
std       466.422621          14.860104          193.177339
min         1.000000          -5.000000            0.000000
25%         8.000000          10.000000            3.000000
50%        13.000000          18.000000            6.000000
75%        20.000000          28.000000            9.000000
max      5797.000000          67.000000         2597.000000

       Credit_Utilization_Ratio  Total_EMI_per_month
count             100000.000000        100000.000000
mean                  32.285173          1403.118217
std                    5.116875          8306.041270
min                   20.000000             0.000000
25%                   28.052567            30.306660
50%                   32.305784            69.249473
75%                   36.496663           161.224249
max                   50.000000         82331.000000
```

Understood many data anomalies in the Numerical features like Num_Bank_Accounts has values like -1 Delay_from_due_date has -5. There are also extreme outliers Interest_Rate of 5797%. I have chosen to retain the outliers as in most cases the outlier information is very important in classifying their credit score.

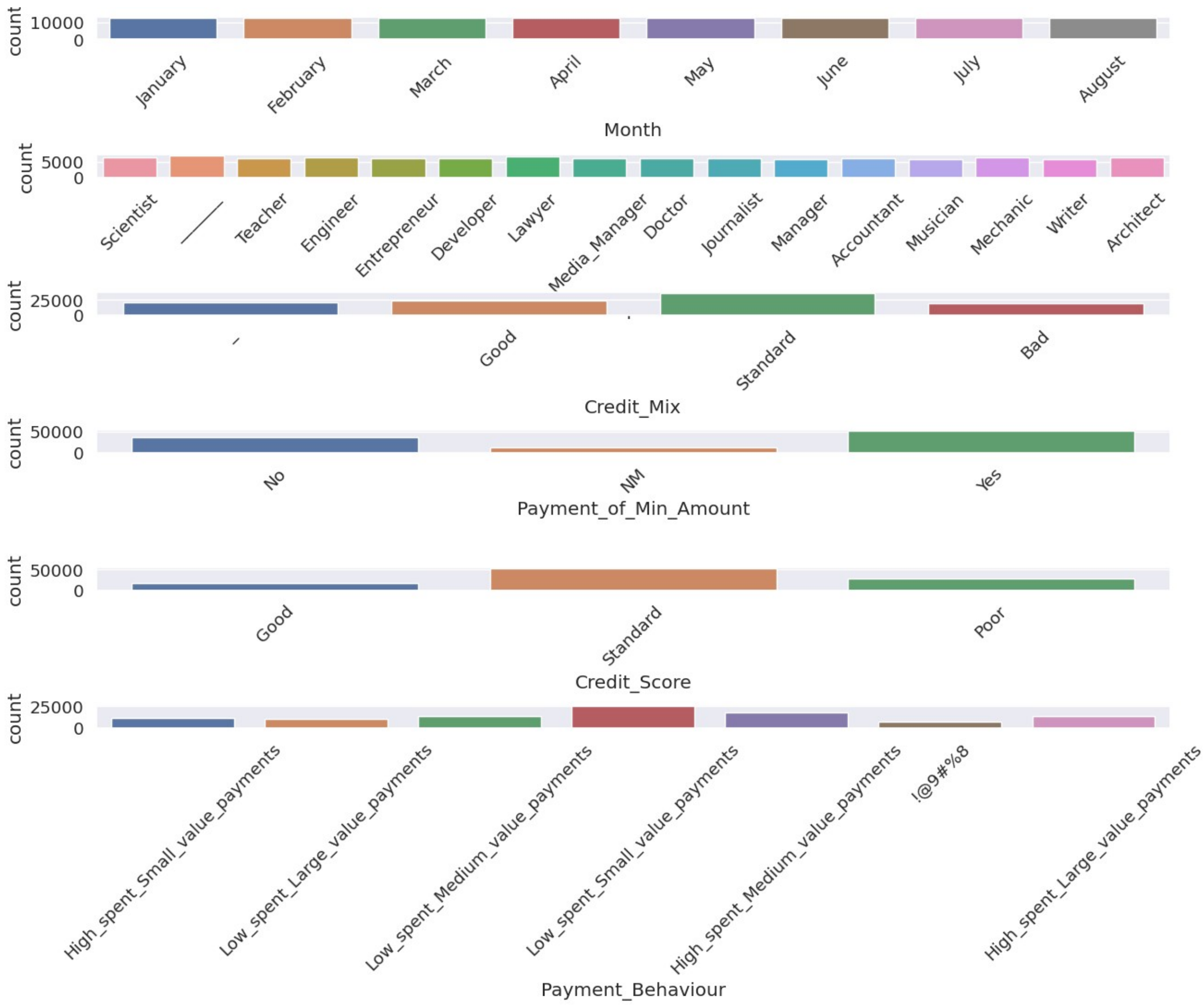
```
df.duplicated().sum()

0
```

There are no duplicates in the data

Analysing Categorical Data

```
fig, axis = plt.subplots(nrows=6, ncols=1, figsize=(15,10))
fig.subplots_adjust(hspace=5)

sns.countplot(x=df["Month"], ax=axis[0])
axis[0].tick_params(axis='x', rotation=45)

sns.countplot(x=df["Occupation"], ax=axis[1])
axis[1].tick_params(axis='x', rotation=45)

sns.countplot(x=df["Credit_Mix"], ax=axis[2])
axis[2].tick_params(axis='x', rotation=45)

sns.countplot(x=df["Payment_of_Min_Amount"], ax=axis[3])
axis[3].tick_params(axis='x', rotation=45)

sns.countplot(x=df["Credit_Score"], ax=axis[4])
axis[4].tick_params(axis='x', rotation=45)

sns.countplot(x=df["Payment_Behaviour"], ax=axis[5])
axis[5].tick_params(axis='x', rotation=45)
```

```
plt.show()
```




```
We can see that there are a few wrong entries like "_" and "!@9#%8"
that should be converted into Null
```

Data Preprocessing

We will have do data preprocessing for the following issues in the dataset

1. The columns ID, Cust_ID, SSN, Name are not useful are the categorization

2. Age, Annual_Income, Num_of_Loan, Num_of_Delayed_Payment, Changed_Credit_Limit, Amount_invested_monthly, Outstanding_Debt,

   Credit_Mix, Monthly_Balance Numerical but show as catogery (need to be fixed)

3.Missing entries:

```
A lot of missing data

Occupation, CreditMix has value "__"
```

1. Wrong entries:

   Num_Bank_Accounts contains negative values

2. Feature Engineering

   Credit_History_Age,Payment_of_Min_Amount,Payment_Behaviour,Credit_Mix,

   Type_of_Loan,Num_Bank_Accounts

```
## The columns ID, SSN, Name are not useful are the categorization

df.drop(["ID","Name","SSN"],axis=1, inplace=True)

df.head()

  Customer_ID     Month   Age Occupation Annual_Income
Monthly_Inhand_Salary  \
0   CUS_0xd40   January    23  Scientist      19114.12
1824.843333
1   CUS_0xd40  February    23  Scientist      19114.12
NaN
2   CUS_0xd40     March  -500  Scientist      19114.12
NaN
3   CUS_0xd40     April    23  Scientist      19114.12
NaN
4   CUS_0xd40       May    23  Scientist      19114.12
1824.843333

   Num_Bank_Accounts  Num_Credit_Card  Interest_Rate Num_of_Loan  ...
\
0                  3                4              3           4  ...

1                  3                4              3           4  ...

2                  3                4              3           4  ...

3                  3                4              3           4  ...

4                  3                4              3           4  ...


  Credit_Mix  Outstanding_Debt Credit_Utilization_Ratio  \
0          _            809.98                26.822620
1       Good            809.98                31.944960
```

```
2       Good              809.98                    28.609352
3       Good              809.98                    31.377862
4       Good              809.98                    24.797347

      Credit_History_Age  Payment_of_Min_Amount Total_EMI_per_month  \
0  22 Years and 1 Months                     No           49.574949
1                    NaN                     No           49.574949
2  22 Years and 3 Months                     No           49.574949
3  22 Years and 4 Months                     No           49.574949
4  22 Years and 5 Months                     No           49.574949

  Amount_invested_monthly                 Payment_Behaviour  \
0       80.41529543900253   High_spent_Small_value_payments
1      118.28022162236736    Low_spent_Large_value_payments
2         81.699521264648   Low_spent_Medium_value_payments
3       199.4580743910713    Low_spent_Small_value_payments
4      41.420153086217326  High_spent_Medium_value_payments

      Monthly_Balance Credit_Score
0  312.49408867943663         Good
1  284.62916249607184         Good
2   331.2098628537912         Good
3  223.45130972736786         Good
4  341.48923103222177         Good

[5 rows x 25 columns]
```

Handling Numerical variables

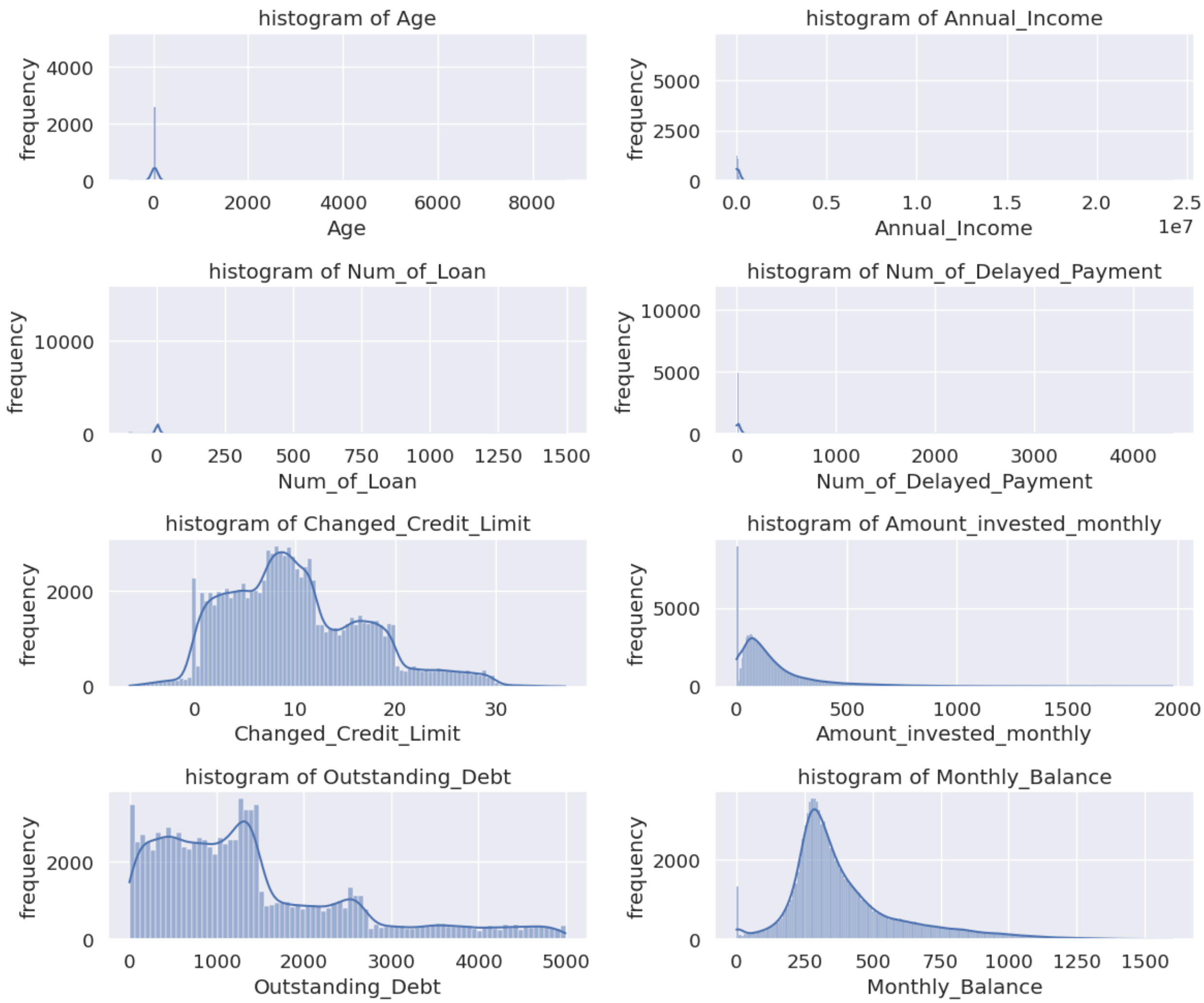
Handling wrong typecasting

```
N_to_fix = ['Age', 'Annual_Income', 'Num_of_Loan', 
'Num_of_Delayed_Payment',
            'Changed_Credit_Limit','Amount_invested_monthly', 
'Outstanding_Debt' , 'Monthly_Balance']

for i in N_to_fix:
    df[i] = pd.to_numeric(df[i], 
errors='coerce').fillna(0).astype(float)
```

This step does the following

1. Conert "object" data types into Numerical
2. The values that are numerical will be converted to numerical and the values that cannot be converted into numerical will be coerced to become Null, on which we will do imputation

```python
fig,axis=plt.subplots(nrows=4,ncols=2,figsize=(12,10))
k=axis.flatten()
for i,p in zip(N_to_fix,k):
    sns.histplot(x=df[i],ax=p,kde=True)
    p.set_title(f"histogram of {i}")
    p.set_xlabel(i)
    p.set_ylabel("frequency")
plt.tight_layout()
plt.show()
```



Type_of_loan

It has multiple types of loans and not all are important so create dummy column for 9 most frequent types of loan

```python
for i in df["Type_of_Loan"].value_counts().head(9).index[1:]:
    df[i] = df["Type_of_Loan"].fillna('').str.contains(i).astype(int)
del df["Type_of_Loan"]
```

```python
## We can see the 9 additional columns having the type of loans
df.head(5)
```

```
  Customer_ID     Month    Age Occupation  Annual_Income  \
0   CUS_0xd40   January   23.0  Scientist       19114.12
1   CUS_0xd40  February   23.0  Scientist       19114.12
2   CUS_0xd40     March -500.0  Scientist       19114.12
3   CUS_0xd40     April   23.0  Scientist       19114.12
4   CUS_0xd40       May   23.0  Scientist       19114.12

   Monthly_Inhand_Salary  Num_Bank_Accounts  Num_Credit_Card
Interest_Rate  \
0            1824.843333                  3                4
3
1                    NaN                  3                4
3
2                    NaN                  3                4
3
3                    NaN                  3                4
3
4            1824.843333                  3                4
3

   Num_of_Loan  ...  Monthly_Balance  Credit_Score  Credit-Builder
Loan  \
0          4.0  ...       312.494089          Good
1
1          4.0  ...       284.629162          Good
1
2          4.0  ...       331.209863          Good
1
3          4.0  ...       223.451310          Good
1
4          4.0  ...       341.489231          Good
1

   Personal Loan Debt Consolidation Loan  Student Loan  Payday Loan  \
0              1                       0             0            0
1              1                       0             0            0
2              1                       0             0            0
3              1                       0             0            0
4              1                       0             0            0

  Mortgage Loan Auto Loan  Home Equity Loan
0             0         1                 1
1             0         1                 1
2             0         1                 1
3             0         1                 1
4             0         1                 1
```

```
[5 rows x 32 columns]
```

Handling wrong entries

```
## The column Num_Bank_Accounts  has some negative values, so we are
converting them to positive by taking their absolute values
df['Num_Bank_Accounts']= df['Num_Bank_Accounts'].abs()

m = {
    "Bad":0,
    "Standard":1,
    "Good":2,
    "_":np.nan
}

df['Credit_Mix'] = df['Credit_Mix'].map(m)

## This is some kind of manual way of doing Ordinal Encoding on
Credit_Mix but also at the same time removing anomoly values like "_"

def parse_years_and_months(arg):
    if isinstance(arg,str):
        age_parts=arg.split("Years and")
        years=int(age_parts[0]) if "Years" in arg else 0
        months_parts=age_parts[1].split("Months")[0] if "Months" in
arg else 0
        months=int(months_parts)
        age=years*12 + months
        return age
    else:
        return 0

df["Credit_History_Age"] =
df["Credit_History_Age"].apply(parse_years_and_months)

## This step converts the Credit_History_Age  feature that has values
in the form of years and months, into completely as months values
```

Handling Missing Data in Numericals

We have so far removed anomoly values and wrong entries in numerical and categorical features and also - typecasted the variables rightly as integers and floats. Now we are to only handle the missing values For the numerical columns the null values are imputed with their closest neighbor in Customer ID ;;; For the Categorical features, they are imputed with the most frequent values

Get all the numerical variables

Convert the Customer_ID column into a sequential numerical

```
df["Customer_ID"].value_counts()

Customer_ID
CUS_0xd40     8
CUS_0x9bf4    8
CUS_0x5ae3    8
CUS_0xbe9a    8
CUS_0x4874    8
             ..
CUS_0x2eb4    8
CUS_0x7863    8
CUS_0x9d89    8
CUS_0xc045    8
CUS_0x942c    8
Name: count, Length: 12500, dtype: int64

df["Customer_ID"] = pd.factorize(df["Customer_ID"])[0] + 1

Numericals = df.select_dtypes(exclude='object').columns[1:]
Numericals

Index(['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', 'Credit_Mix', 'Outstanding_Debt',
       'Credit_Utilization_Ratio', 'Credit_History_Age',
'Total_EMI_per_month',
       'Amount_invested_monthly', 'Monthly_Balance', 'Credit-Builder
Loan',
       'Personal Loan', 'Debt Consolidation Loan', 'Student Loan',
       'Payday Loan', 'Mortgage Loan', 'Auto Loan', 'Home Equity
Loan'],
      dtype='object')

from sklearn.impute import KNNImputer
impute=KNNImputer(n_neighbors=1)

## for col in Numericals:
df[['Customer_ID',col]]=impute.fit_transform(df[['Customer_ID',col]])

##  df[Numericals] = df.groupby('Customer_ID')
[Numericals].transform(lambda x: impute.fit_transform(x))
###df[Numericals] = impute.fit_transform(df[Numericals])

df[Numericals] = df.groupby('Customer_ID')
[Numericals].transform(lambda x:
impute.fit_transform(x.values.reshape(-1, 1)).flatten())
```

```
df[Numericals].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 26 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   Age                       100000 non-null  float64
 1   Annual_Income             100000 non-null  float64
 2   Monthly_Inhand_Salary     100000 non-null  float64
 3   Num_Bank_Accounts         100000 non-null  float64
 4   Num_Credit_Card           100000 non-null  float64
 5   Interest_Rate             100000 non-null  float64
 6   Num_of_Loan               100000 non-null  float64
 7   Delay_from_due_date       100000 non-null  float64
 8   Num_of_Delayed_Payment    100000 non-null  float64
 9   Changed_Credit_Limit      100000 non-null  float64
 10  Num_Credit_Inquiries      100000 non-null  float64
 11  Credit_Mix                100000 non-null  float64
 12  Outstanding_Debt          100000 non-null  float64
 13  Credit_Utilization_Ratio  100000 non-null  float64
 14  Credit_History_Age        100000 non-null  float64
 15  Total_EMI_per_month       100000 non-null  float64
 16  Amount_invested_monthly   100000 non-null  float64
 17  Monthly_Balance           100000 non-null  float64
 18  Credit-Builder Loan       100000 non-null  float64
 19  Personal Loan             100000 non-null  float64
 20  Debt Consolidation Loan   100000 non-null  float64
 21  Student Loan              100000 non-null  float64
 22  Payday Loan               100000 non-null  float64
 23  Mortgage Loan             100000 non-null  float64
 24  Auto Loan                 100000 non-null  float64
 25  Home Equity Loan          100000 non-null  float64
dtypes: float64(26)
memory usage: 19.8 MB
```

As can be seen, all the null values in the Numerical columns are filled

Preprocessing the Categorical Columns

```
df["Payment_Behaviour"].value_counts()
```

```
Payment_Behaviour
Low_spent_Small_value_payments      25513
High_spent_Medium_value_payments    17540
Low_spent_Medium_value_payments     13861
High_spent_Large_value_payments     13721
High_spent_Small_value_payments     11340
```

```
Low_spent_Large_value_payments      10425
!@9#%8                               7600
Name: count, dtype: int64
```

```
df["Payment_Behaviour"]=df["Payment_Behaviour"].replace("!@9#
%8",np.NaN)

## Replaces the anomoly value with null

df["Payment_Behaviour"].value_counts()
```

```
Payment_Behaviour
Low_spent_Small_value_payments      25513
High_spent_Medium_value_payments    17540
Low_spent_Medium_value_payments     13861
High_spent_Large_value_payments     13721
High_spent_Small_value_payments     11340
Low_spent_Large_value_payments      10425
Name: count, dtype: int64
```

```
imputer=SimpleImputer(strategy="most_frequent")
df[["Payment_Behaviour"]]=imputer.fit_transform(df[["Payment_Behaviour
"]])

df["Payment_Behaviour"].count()
```

```
100000
```

```
categorical = df.select_dtypes(include=object)
categorical
```

```
          Month Occupation Payment_of_Min_Amount  \
0       January  Scientist                    No
1      February  Scientist                    No
2         March  Scientist                    No
3         April  Scientist                    No
4           May  Scientist                    No
...         ...        ...                   ...
99995     April   Mechanic                    No
99996       May   Mechanic                    No
99997      June   Mechanic                    No
99998      July   Mechanic                    No
99999    August   Mechanic                    No

                      Payment_Behaviour Credit_Score
0       High_spent_Small_value_payments         Good
1        Low_spent_Large_value_payments         Good
2       Low_spent_Medium_value_payments         Good
3        Low_spent_Small_value_payments         Good
4      High_spent_Medium_value_payments         Good
...                                 ...          ...
```

```
99995   High_spent_Large_value_payments        Poor
99996  High_spent_Medium_value_payments        Poor
99997   High_spent_Large_value_payments        Poor
99998    Low_spent_Large_value_payments    Standard
99999    Low_spent_Small_value_payments        Poor

[100000 rows x 5 columns]
```

```
Occupation=df["Occupation"].value_counts().index[1:]
for i in Occupation:
    df[i]=df["Occupation"].str.contains(i)
del df["Occupation"]

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 46 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   Customer_ID               100000 non-null  int64
 1   Month                     100000 non-null  object
 2   Age                       100000 non-null  float64
 3   Annual_Income             100000 non-null  float64
 4   Monthly_Inhand_Salary     100000 non-null  float64
 5   Num_Bank_Accounts         100000 non-null  float64
 6   Num_Credit_Card           100000 non-null  float64
 7   Interest_Rate             100000 non-null  float64
 8   Num_of_Loan               100000 non-null  float64
 9   Delay_from_due_date       100000 non-null  float64
 10  Num_of_Delayed_Payment    100000 non-null  float64
 11  Changed_Credit_Limit      100000 non-null  float64
 12  Num_Credit_Inquiries      100000 non-null  float64
 13  Credit_Mix                100000 non-null  float64
 14  Outstanding_Debt          100000 non-null  float64
 15  Credit_Utilization_Ratio  100000 non-null  float64
 16  Credit_History_Age        100000 non-null  float64
 17  Payment_of_Min_Amount     100000 non-null  object
 18  Total_EMI_per_month       100000 non-null  float64
 19  Amount_invested_monthly   100000 non-null  float64
 20  Payment_Behaviour         100000 non-null  object
 21  Monthly_Balance           100000 non-null  float64
 22  Credit_Score              100000 non-null  object
 23  Credit-Builder Loan       100000 non-null  float64
 24  Personal Loan             100000 non-null  float64
 25  Debt Consolidation Loan   100000 non-null  float64
 26  Student Loan              100000 non-null  float64
 27  Payday Loan               100000 non-null  float64
 28  Mortgage Loan             100000 non-null  float64
 29  Auto Loan                 100000 non-null  float64
```

```
 30  Home Equity Loan           100000 non-null  float64
 31  Lawyer                     100000 non-null  bool
 32  Architect                  100000 non-null  bool
 33  Engineer                   100000 non-null  bool
 34  Scientist                  100000 non-null  bool
 35  Mechanic                   100000 non-null  bool
 36  Accountant                 100000 non-null  bool
 37  Developer                  100000 non-null  bool
 38  Media_Manager              100000 non-null  bool
 39  Teacher                    100000 non-null  bool
 40  Entrepreneur               100000 non-null  bool
 41  Doctor                     100000 non-null  bool
 42  Journalist                 100000 non-null  bool
 43  Manager                    100000 non-null  bool
 44  Musician                   100000 non-null  bool
 45  Writer                     100000 non-null  bool
dtypes: bool(15), float64(26), int64(1), object(4)
memory usage: 25.1+ MB
```

Now, the categorical variables that require a dummy creation are Payment_Behaviour, Payment_of_Min_Amount, credit_mix

```
df = pd.get_dummies(df.drop(["Credit_Score"],axis=1),drop_first=True)

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 56 columns):
 #   Column                                               Non-Null
Count   Dtype
---  ------
--------------   -----
 0   Customer_ID                                          100000 non-
null  int64
 1   Age                                                  100000 non-
null  float64
 2   Annual_Income                                        100000 non-
null  float64
 3   Monthly_Inhand_Salary                                100000 non-
null  float64
 4   Num_Bank_Accounts                                    100000 non-
null  float64
 5   Num_Credit_Card                                      100000 non-
null  float64
 6   Interest_Rate                                        100000 non-
null  float64
 7   Num_of_Loan                                          100000 non-
null  float64
```

```
 8   Delay_from_due_date                                    100000 non-
null  float64
 9   Num_of_Delayed_Payment                                 100000 non-
null  float64
 10  Changed_Credit_Limit                                   100000 non-
null  float64
 11  Num_Credit_Inquiries                                   100000 non-
null  float64
 12  Credit_Mix                                             100000 non-
null  float64
 13  Outstanding_Debt                                       100000 non-
null  float64
 14  Credit_Utilization_Ratio                               100000 non-
null  float64
 15  Credit_History_Age                                     100000 non-
null  float64
 16  Total_EMI_per_month                                    100000 non-
null  float64
 17  Amount_invested_monthly                                100000 non-
null  float64
 18  Monthly_Balance                                        100000 non-
null  float64
 19  Credit-Builder Loan                                    100000 non-
null  float64
 20  Personal Loan                                          100000 non-
null  float64
 21  Debt Consolidation Loan                                100000 non-
null  float64
 22  Student Loan                                           100000 non-
null  float64
 23  Payday Loan                                            100000 non-
null  float64
 24  Mortgage Loan                                          100000 non-
null  float64
 25  Auto Loan                                              100000 non-
null  float64
 26  Home Equity Loan                                       100000 non-
null  float64
 27  Lawyer                                                 100000 non-
null  bool
 28  Architect                                              100000 non-
null  bool
 29  Engineer                                               100000 non-
null  bool
 30  Scientist                                              100000 non-
null  bool
 31  Mechanic                                               100000 non-
null  bool
 32  Accountant                                             100000 non-
```

```
null  bool
 33  Developer                                              100000 non-
null  bool
 34  Media_Manager                                          100000 non-
null  bool
 35  Teacher                                                100000 non-
null  bool
 36  Entrepreneur                                           100000 non-
null  bool
 37  Doctor                                                 100000 non-
null  bool
 38  Journalist                                             100000 non-
null  bool
 39  Manager                                                100000 non-
null  bool
 40  Musician                                               100000 non-
null  bool
 41  Writer                                                 100000 non-
null  bool
 42  Month_August                                           100000 non-
null  bool
 43  Month_February                                         100000 non-
null  bool
 44  Month_January                                          100000 non-
null  bool
 45  Month_July                                             100000 non-
null  bool
 46  Month_June                                             100000 non-
null  bool
 47  Month_March                                            100000 non-
null  bool
 48  Month_May                                              100000 non-
null  bool
 49  Payment_of_Min_Amount_No                               100000 non-
null  bool
 50  Payment_of_Min_Amount_Yes                              100000 non-
null  bool
 51  Payment_Behaviour_High_spent_Medium_value_payments  100000 non-
null  bool
 52  Payment_Behaviour_High_spent_Small_value_payments   100000 non-
null  bool
 53  Payment_Behaviour_Low_spent_Large_value_payments    100000 non-
null  bool
 54  Payment_Behaviour_Low_spent_Medium_value_payments   100000 non-
null  bool
 55  Payment_Behaviour_Low_spent_Small_value_payments    100000 non-
null  bool
dtypes: bool(29), float64(26), int64(1)
memory usage: 23.4 MB
```

The Dataset is now perfectly cleaned and processed

```
df.drop(["Payment_of_Min_Amount_No"],axis=1, inplace=True)

df_credit_score =
pd.read_csv("../input/credit-score-classification/train.csv",low_memor
y=False)

m={"Poor":0, "Standard":1, "Good":2}
df_credit_score["Credit_Score"]=df_credit_score["Credit_Score"].map(m)

X, y = df , df_credit_score["Credit_Score"]

X.astype(float)
y.astype(float)
### This would ensure the boolean values are also converted to float
for model construction
```

```
0        2.0
1        2.0
2        2.0
3        2.0
4        2.0
        ...
99995    0.0
99996    0.0
99997    0.0
99998    1.0
99999    0.0
Name: Credit_Score, Length: 100000, dtype: float64
```

Since we have 53 columns of float data, it is good practice to bring the values to a Normal(Gaussian) distribution the values before splitting the data. It is done to avoid data skewness

```
## It is usually a good practice to transform the dataset using a
Power Transformer so that all the numerical values will be following a
Gaussian Distribution

scalar= PowerTransformer(method="yeo-johnson", standardize=True)
scalar.fit_transform(X)
```

```
array([[-2.18876414, -0.06515282, -0.25964914, ..., -0.34114941,
        -0.40114129, -0.70360417],
       [-2.18876414, -0.06515282, -0.25964914, ...,  2.93126699,
        -0.40114129, -0.70360417],
       [-2.18876414, -6.13941805, -0.25964914, ..., -0.34114941,
         2.49288722, -0.70360417],
       ...,
       [ 1.55424557, -0.05982162,  0.13583172, ..., -0.34114941,
        -0.40114129, -0.70360417],
```

```
       [ 1.55424557, -0.05982162,  0.13583172, ...,  2.93126699,
        -0.40114129, -0.70360417],
       [ 1.55424557, -0.05982162, -2.59680201, ..., -0.34114941,
        -0.40114129,  1.42125365]])
```

Machine Learning Models

```
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.3,random_state=42)
```

The Models to be choosen

For Better Interpretability - Decision Tree

Feature Types: for datasets that have balanced mix of both categorical and numerical data - Catboost

Handling Non-linear relationships between variables - Xgb SVM

For improving accuracy

Stacking Classifier

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint
from sklearn.metrics import accuracy_score


param_dist = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 5, 10],
    'min_samples_split': randint(2, 11),
    'min_samples_leaf': randint(1, 5),
    'max_features': ['auto', 'sqrt', 'log2']
}
dt = DecisionTreeClassifier(random_state=42)
n_iter = 5

random_search = RandomizedSearchCV(dt, param_distributions=param_dist,
n_iter=n_iter, cv=3, scoring='accuracy', random_state=42)
random_search.fit(X_train, y_train)

best_params = random_search.best_params_
best_dt = DecisionTreeClassifier(**best_params, random_state=42)

best_dt.fit(X_train, y_train)

y_pred_dt = best_dt.predict(X_test)
```

```
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print("Accuracy of DecisionTree:", accuracy_dt)
```

```
Accuracy of DecisionTree: 0.6678
```

```
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score

xgb_model = XGBClassifier(n_estimators=3500, random_state=77)
xgb_model.fit(X_train, y_train)

y_pred_xgb = xgb_model.predict(X_test)

accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
print("Accuracy of xgb:", accuracy_xgb)
```

```
Accuracy of xgb: 0.7995333333333333
```

```
from catboost import CatBoostClassifier, Pool
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform, randint

param_grid = {
    'learning_rate': uniform(0.01, 0.3),
    'depth': randint(4, 10),
    'l2_leaf_reg': uniform(0, 5),
    'iterations': randint(100, 500),
}

catboost = CatBoostClassifier()

random_search = RandomizedSearchCV(catboost,
param_distributions=param_grid, n_iter=10, cv=3, scoring='accuracy',
random_state=42)
random_search.fit(X_train, y_train, verbose=False, plot=False)

# best parameters
best_params = random_search.best_params_
best_catboost = CatBoostClassifier(**best_params)

best_catboost.fit(X_train, y_train, verbose=False)

y_pred_catboost = best_catboost.predict(X_test)


accuracy_catboost = accuracy_score(y_test, y_pred_catboost)
print("Accuracy of CatBoost:", accuracy_catboost)
```

```
Accuracy of CatBoost: 0.7657
```

```
bagging = BaggingClassifier(n_jobs=-1)
extraTrees = ExtraTreesClassifier(max_depth=10, n_jobs=-1)
randomForest = RandomForestClassifier(n_jobs=-1)
histGradientBoosting = HistGradientBoostingClassifier()
XGB = XGBClassifier(n_jobs=-1)

model = StackingClassifier([
    ('bagging', bagging),
    ('extraTress', extraTrees),
    ('randomforest', randomForest),
    ('histGradientBoosting', histGradientBoosting),
    ('XGB', XGB)
], n_jobs=-1)

model.fit(X_train, y_train)
```

```
StackingClassifier(estimators=[('bagging', BaggingClassifier(n_jobs=-
1)),
                               ('extraTress',
                                ExtraTreesClassifier(max_depth=10,
n_jobs=-1)),
                               ('randomforest',
                                RandomForestClassifier(n_jobs=-1)),
                               ('histGradientBoosting',
                                HistGradientBoostingClassifier()),
                               ('XGB',
                                XGBClassifier(base_score=None,
booster=None,
                                              callbacks=None,
                                              colsample_bylevel=None,
                                              colsample_bynode=None...
                                              grow_policy=None,
                                              importance_type=None,

interaction_constraints=None,
                                              learning_rate=None,
max_bin=None,
                                              max_cat_threshold=None,
                                              max_cat_to_onehot=None,
                                              max_delta_step=None,
                                              max_depth=None,
max_leaves=None,
                                              min_child_weight=None,
                                              missing=nan,

monotone_constraints=None,
                                              multi_strategy=None,
                                              n_estimators=None,
n_jobs=-1,
                                              num_parallel_tree=None,
```

```
random_state=None, ...))],
                   n_jobs=-1)

print("Train Score: ",model.score(X_train, y_train))
print("Test Score: ",model.score(X_test, y_test))
y_pred = model.predict(X_test)
accuracy_stacking = accuracy_score(y_pred, y_test)
accuracy_stacking

Train Score:  0.9998428571428571
Test Score:  0.7986333333333333

0.7986333333333333

import plotly.graph_objects as go
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score


accuracy_rf = accuracy_score(y_test, y_pred)
accuracy_xgb = accuracy_score(y_test, y_pred_xgb)

models = ['DecisionTreeClassifier', 'XGBoostClassifier',
"CatBoostClassifier","StackingClassifier" ]
accuracy_values = [accuracy_dt, accuracy_xgb,
accuracy_catboost,accuracy_stacking]
colors = ['turquoise', "palegreen", "lightcoral",'orchid']

fig = go.Figure(data=[go.Bar(x=models, y=accuracy_values,
marker_color=colors)])
fig.update_layout(
    title='Comparison of accuracy between DecisionTreeClassifier,
XGBoostClassifier,CatBoostClassifier and StackingClassifier ',
    xaxis_title='Models',
    yaxis_title='Accuracy'
)
fig.show()
```

The Model with the best accuracy is the "Stacking Classifier" so going ahead with it to make the classification report

Feature Importance for all the models

```
importances = best_dt.feature_importances_

top_indices = importances.argsort()[-5:][::-1]
top_features = X_train.columns[top_indices]
```

```
print("Top 5 features:")
for feature in top_features:
    print(feature)
```

```
Top 5 features:
Interest_Rate
Num_Credit_Inquiries
Credit_Mix
Delay_from_due_date
Outstanding_Debt
```

```
importances = xgb_model.feature_importances_

top_indices = importances.argsort()[-5:][::-1]
top_features = X_train.columns[top_indices]

print("Top 5 features:")
for feature in top_features:
    print(feature)
```

```
Top 5 features:
Credit_Mix
Outstanding_Debt
Month_February
Month_March
Month_January
```

```
importances = best_catboost.feature_importances_

top_indices = importances.argsort()[-5:][::-1]
top_features = X_train.columns[top_indices]

print("Top 5 features:")
for feature in top_features:
    print(feature)
```

```
Top 5 features:
Outstanding_Debt
Credit_Mix
Interest_Rate
Delay_from_due_date
Customer_ID
```

```
print(classification_report(y_pred,y_test))

## Since Stacking Classifier turned out to be the best for testing accuracy, we shall get the classification report for only this model
```

```
              precision    recall  f1-score   support
```

```
           0       0.80      0.79      0.80      8910
           1       0.82      0.81      0.81     16108
           2       0.73      0.78      0.76      4982

    accuracy                           0.80     30000
   macro avg       0.78      0.79      0.79     30000
weighted avg       0.80      0.80      0.80     30000
```