creditrisk

October 9, 2024

[58]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

[59]:
```
df = pd.read_csv("/content/Credit_score.csv")
df.head()
```

[59]:
```
       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  …  \
0      19114.12            1824.843333                  3  …
1      19114.12                    NaN                  3  …
2      19114.12                    NaN                  3  …
3      19114.12                    NaN                  3  …
4      19114.12            1824.843333                  3  …

   Num_Credit_Inquiries  Credit_Mix Outstanding_Debt Credit_Utilization_Ratio  \
0                   4.0           _           809.98                26.822620
1                   4.0        Good           809.98                31.944960
2                   4.0        Good           809.98                28.609352
3                   4.0        Good           809.98                31.377862
4                   4.0        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 Monthly_Balance
0             80.41529544   High_spent_Small_value_payments     312.4940887
1             118.2802216    Low_spent_Large_value_payments     284.6291625
2             81.69952126   Low_spent_Medium_value_payments     331.2098629
3             199.4580744    Low_spent_Small_value_payments     223.4513097
4             41.42015309  High_spent_Medium_value_payments      341.489231

[5 rows x 27 columns]
```

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

[60]:
```
Index(['ID', 'Customer_ID', 'Month', 'Name', 'Age', 'SSN', 'Occupation',
       'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
       'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan', 'Type_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',
       'Payment_of_Min_Amount', 'Total_EMI_per_month',
       'Amount_invested_monthly', 'Payment_Behaviour', 'Monthly_Balance'],
      dtype='object')
```

[61]:
```
df.shape
```

[61]:
```
(100000, 27)
```

[62]:
```
#Data type of every column
df.dtypes
```

[62]:
```
ID                           object
Customer_ID                  object
Month                        object
Name                         object
Age                          object
SSN                          object
Occupation                   object
Annual_Income                object
Monthly_Inhand_Salary       float64
Num_Bank_Accounts             int64
Num_Credit_Card               int64
Interest_Rate                 int64
Num_of_Loan                  object
Type_of_Loan                 object
Delay_from_due_date           int64
```

```
Num_of_Delayed_Payment       object
Changed_Credit_Limit         object
Num_Credit_Inquiries        float64
Credit_Mix                   object
Outstanding_Debt             object
Credit_Utilization_Ratio    float64
Credit_History_Age           object
Payment_of_Min_Amount        object
Total_EMI_per_month         float64
Amount_invested_monthly      object
Payment_Behaviour            object
Monthly_Balance              object
dtype: object
```

[63]:

```
cat_columns, num_columns = list() , list()
CAT_THRESHOLD = 20
print("-"*150)
for col in df.columns:
  if df[col].nunique() > CAT_THRESHOLD:
    num_columns.append(col)
    print(col, " : " , df[col].nunique())

  else:
    cat_columns.append(col)
    print(col, " : " , df[col].nunique(),"\n")
    print(df[col].unique(),"\n")

  print("-"*150)
```

```
--------------------------------------------------------------------------------
----------------------------------------------------------------------
ID  :  100000
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Customer_ID  :  12500
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Month  :  8

['January' 'February' 'March' 'April' 'May' 'June' 'July' 'August']

--------------------------------------------------------------------------------
----------------------------------------------------------------------
Name  :  10139
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Age  :  1788
```

```
--------------------------------------------------------------------------------
----------------------------------------------------------------------
SSN  :  12501
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Occupation  :  16

['Scientist' '_______' 'Teacher' 'Engineer' 'Entrepreneur' 'Developer'
 'Lawyer' 'Media_Manager' 'Doctor' 'Journalist' 'Manager' 'Accountant'
 'Musician' 'Mechanic' 'Writer' 'Architect']

--------------------------------------------------------------------------------
----------------------------------------------------------------------
Annual_Income  :  18940
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Monthly_Inhand_Salary  :  13235
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Num_Bank_Accounts  :  943
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Num_Credit_Card  :  1179
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Interest_Rate  :  1750
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Num_of_Loan  :  434
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Type_of_Loan  :  6260
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Delay_from_due_date  :  73
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Num_of_Delayed_Payment  :  749
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Changed_Credit_Limit  :  3635
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Num_Credit_Inquiries  :  1223
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Credit_Mix  :  4
```

```
['_' 'Good' 'Standard' 'Bad']

--------------------------------------------------------------------------------
------------------------------------------------------------------
Outstanding_Debt  :  13178
--------------------------------------------------------------------------------
------------------------------------------------------------------
Credit_Utilization_Ratio  :  99998
--------------------------------------------------------------------------------
------------------------------------------------------------------
Credit_History_Age  :  404
--------------------------------------------------------------------------------
------------------------------------------------------------------
Payment_of_Min_Amount  :  3

['No' 'NM' 'Yes']

--------------------------------------------------------------------------------
------------------------------------------------------------------
Total_EMI_per_month  :  14950
--------------------------------------------------------------------------------
------------------------------------------------------------------
Amount_invested_monthly  :  91049
--------------------------------------------------------------------------------
------------------------------------------------------------------
Payment_Behaviour  :  7

['High_spent_Small_value_payments' 'Low_spent_Large_value_payments'
 'Low_spent_Medium_value_payments' 'Low_spent_Small_value_payments'
 'High_spent_Medium_value_payments' '!@9#%8'
 'High_spent_Large_value_payments']

--------------------------------------------------------------------------------
------------------------------------------------------------------
Monthly_Balance  :  98790
--------------------------------------------------------------------------------
------------------------------------------------------------------
```

[64]:
```
#Info of each dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 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
dtypes: float64(4), int64(4), object(19)
memory usage: 20.6+ MB
```

[65]:
```
df.isnull().sum()[df.isnull().sum() > 0 ]
```

[65]:
```
Name                        9985
Monthly_Inhand_Salary      15002
Type_of_Loan               11408
Num_of_Delayed_Payment      7002
Num_Credit_Inquiries        1965
Credit_History_Age          9030
Amount_invested_monthly     4479
Monthly_Balance             1200
dtype: int64
```

The above collumns tend to have missing values. Hence feature engineering steps needed to impute values

[66]:
```
name_map_df = df[df['Name'].notnull()][['Customer_ID','Name']].
 ↪drop_duplicates().reset_index(drop=True)
df.loc[df['Name'].isnull(),'Name'] = df[df['Name'].isnull()]['Customer_ID'].
 ↪replace(dict(name_map_df.values))
```

Names of customers have been imputed as per the customer id in missing cells

[67]:
```
loan_type_map_df = df[df['Monthly_Inhand_Salary'].
 ↪notnull()][['Customer_ID','Monthly_Inhand_Salary']].drop_duplicates().
 ↪reset_index(drop=True)
df.loc[df['Monthly_Inhand_Salary'].isnull(),'Monthly_Inhand_Salary'] =␣
 ↪df[df['Monthly_Inhand_Salary'].isnull()]['Customer_ID'].
 ↪replace(dict(loan_type_map_df.values))
```

Monthly inhand salary of customers have been imputed as per the customer id in missing cells

[68]:
```
credit_mix_map_df = df[df['Credit_Mix'] != '_' ][['Customer_ID','Credit_Mix']].
 ↪drop_duplicates().reset_index(drop=True)
df.loc[df['Credit_Mix'] == '_','Credit_Mix'] = df[df['Credit_Mix'] ==␣
 ↪'_']['Customer_ID'].replace(dict(credit_mix_map_df.values))
```

Blank values of credit mix replaced with the Credit Mix of the respective customer

[69]:
```
occupation_map_df = df[df['Occupation'] != '_______'␣
 ↪][['Customer_ID','Occupation']].drop_duplicates().reset_index(drop=True)
df.loc[df['Occupation'] == '_______','Occupation'] = df[df['Occupation'] ==␣
 ↪'_______']['Customer_ID'].replace(dict(occupation_map_df.values))
```

Blank values of occupation replaced with the Credit Mix of the respective customer

[70]:
```
df.isnull().sum()[df.isnull().sum() > 0 ]
```

[70]:
```
Type_of_Loan              11408
Num_of_Delayed_Payment     7002
Num_Credit_Inquiries       1965
Credit_History_Age         9030
Amount_invested_monthly    4479
Monthly_Balance            1200
dtype: int64
```

[71]:
```
df['Num_Credit_Inquiries'] = df['Num_Credit_Inquiries'].fillna(method='ffill')
```

Front Fill Technique used to impute Num_Credit_Inquiries keeping it same to the previous entry of the month

[72]:
```
df['Credit_History_Age'] = df['Credit_History_Age'].fillna(value='NA')
```

[73]:
```
df['Type_of_Loan'] = df['Type_of_Loan'].fillna(value='Not Specified')
```

[74]:
```
delayed_payment_map_df = df[df['Num_of_Delayed_Payment'].
 ↪notnull()][['Customer_ID','Num_of_Delayed_Payment']].reset_index(drop=True)
delayed_payment_map_df['Num_of_Delayed_Payment']  =␣
 ↪delayed_payment_map_df['Num_of_Delayed_Payment'].apply(lambda x:int(str(x).
 ↪split('_')[0]))
```

```
delayed_payment_map_df = delayed_payment_map_df.groupby('Customer_ID').
    ↪agg({'Num_of_Delayed_Payment':'median'})
df.loc[df['Num_of_Delayed_Payment'].isnull() ,'Num_of_Delayed_Payment'] =␣
    ↪df[df['Num_of_Delayed_Payment'].isnull()]['Customer_ID'].
    ↪replace(dict(delayed_payment_map_df.reset_index().values))
```

Null Delayed payment value is replaced by median of delayed payment values

[75]:
```
df.isnull().sum()[df.isnull().sum() > 0 ]
```

[75]:
```
Amount_invested_monthly    4479
Monthly_Balance            1200
dtype: int64
```

[76]:
```
df.loc[df['Amount_invested_monthly'] == '__10000__','Amount_invested_monthly']␣
    ↪= np.NAN
df.loc[df['Amount_invested_monthly'] == '0','Amount_invested_monthly'] = 0
```

[77]:
```
df['Amount_invested_monthly'] = df['Amount_invested_monthly'].astype('float')
```

[78]:
```
monthly_invested_map_df = df[df['Amount_invested_monthly'].
    ↪notnull()][['Customer_ID','Amount_invested_monthly']].reset_index(drop=True)
monthly_invested_map_df = monthly_invested_map_df.groupby('Customer_ID').
    ↪agg({'Amount_invested_monthly':'median'})
df.loc[df['Amount_invested_monthly'].isnull() ,'Amount_invested_monthly'] =␣
    ↪df[df['Amount_invested_monthly'].isnull()]['Customer_ID'].
    ↪replace(dict(monthly_invested_map_df.reset_index().values))
```

Null Amount_invested_monthly value is replaced by median of Amount_invested_monthly

[79]:
```
df.isnull().sum()[df.isnull().sum() > 0 ]
```

[79]:
```
Monthly_Balance    1200
dtype: int64
```

[80]:
```
df.loc[df['Monthly_Balance'] == '0','Monthly_Balance'] = 0
df.loc[df['Monthly_Balance'] ==␣
    ↪'__-333333333333333333333333333__','Monthly_Balance'] = np.NAN
```

[81]:
```
df['Monthly_Balance'] = df['Monthly_Balance'].astype('float')
```

[82]:
```
monthly_balance_map_df = df[df['Monthly_Balance'].
    ↪notnull()][['Customer_ID','Monthly_Balance']].reset_index(drop=True)
monthly_balance_map_df = monthly_balance_map_df.groupby('Customer_ID').
    ↪agg({'Monthly_Balance':'median'})
```

```
df.loc[df['Monthly_Balance'].isnull() ,'Monthly_Balance'] =␣
↪df[df['Monthly_Balance'].isnull()]['Customer_ID'].
↪replace(dict(monthly_balance_map_df.reset_index().values))
```

Null Monthly_Balance value is replaced by median of Monthly_Balance

[83]:
```
df['Age'] = df['Age'].apply(lambda x:str(x).replace('_',''))
df['Age'] = df['Age'].apply(lambda x:str(x).replace('-',''))

df['Age'] = df['Age'].astype('int')
```

[84]:
```
df['Annual_Income'] = df['Annual_Income'].apply(lambda x:str(x).replace('_',''))
df['Annual_Income'] = df['Annual_Income'].astype('float')
```

[85]:
```
df['Num_of_Loan'] = df['Num_of_Loan'].apply(lambda x:str(x).replace('_',''))
df['Num_of_Loan'] = df['Num_of_Loan'].astype('int')
```

[86]:
```
df['Num_of_Delayed_Payment'] = df['Num_of_Delayed_Payment'].apply(lambda x:
↪str(x).replace('_',''))
df['Num_of_Delayed_Payment'] = df['Num_of_Delayed_Payment'].astype('float')
```

[87]:
```
df.loc[df['Changed_Credit_Limit'] == '_','Changed_Credit_Limit'] = 0
df['Changed_Credit_Limit'] = df['Changed_Credit_Limit'].astype('float')
```

[88]:
```
df['Outstanding_Debt'] = df['Outstanding_Debt'].apply(lambda x:str(x).
↪replace('_',''))
df['Outstanding_Debt'] = df['Outstanding_Debt'].astype('float')
```

No null values in the dataset

[89]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 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                      100000 non-null  object
 4   Age                       100000 non-null  int64
 5   SSN                       100000 non-null  object
 6   Occupation                100000 non-null  object
 7   Annual_Income             100000 non-null  float64
 8   Monthly_Inhand_Salary     100000 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  int64
 13  Type_of_Loan              100000 non-null  object
 14  Delay_from_due_date       100000 non-null  int64
 15  Num_of_Delayed_Payment    100000 non-null  float64
 16  Changed_Credit_Limit      100000 non-null  float64
 17  Num_Credit_Inquiries      100000 non-null  float64
 18  Credit_Mix                100000 non-null  object
 19  Outstanding_Debt          100000 non-null  float64
 20  Credit_Utilization_Ratio  100000 non-null  float64
 21  Credit_History_Age        100000 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   100000 non-null  float64
 25  Payment_Behaviour         100000 non-null  object
 26  Monthly_Balance           100000 non-null  float64
dtypes: float64(10), int64(6), object(11)
memory usage: 20.6+ MB
```

[90]:
```
df.isnull().sum()[df.isnull().sum() > 0 ]
```

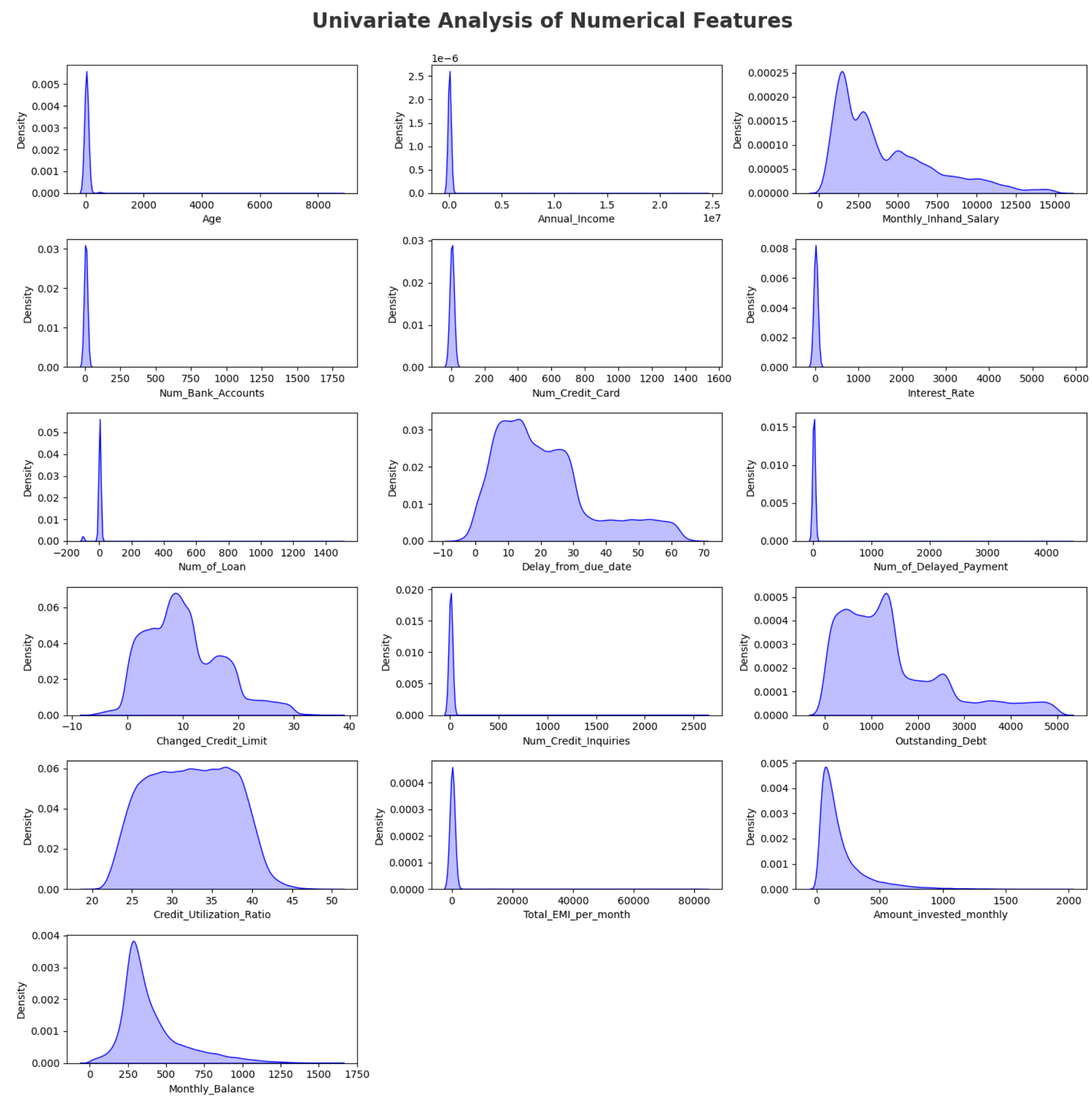
[90]:
```
Series([], dtype: int64)
```

[91]:
```
cat_columns, num_columns = list() , list()

for col in df.columns:
  if df[col].dtype == 'O':
    cat_columns.append(col)
  else:
    num_columns.append(col)

print(cat_columns)
print(num_columns)
```

```
['ID', 'Customer_ID', 'Month', 'Name', 'SSN', 'Occupation', 'Type_of_Loan',
'Credit_Mix', 'Credit_History_Age', 'Payment_of_Min_Amount',
'Payment_Behaviour']
['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']
```

[92]:
```
plt.figure(figsize=(15,15))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20,␣
 ↪fontweight='bold', alpha=0.8, y=1.)
```

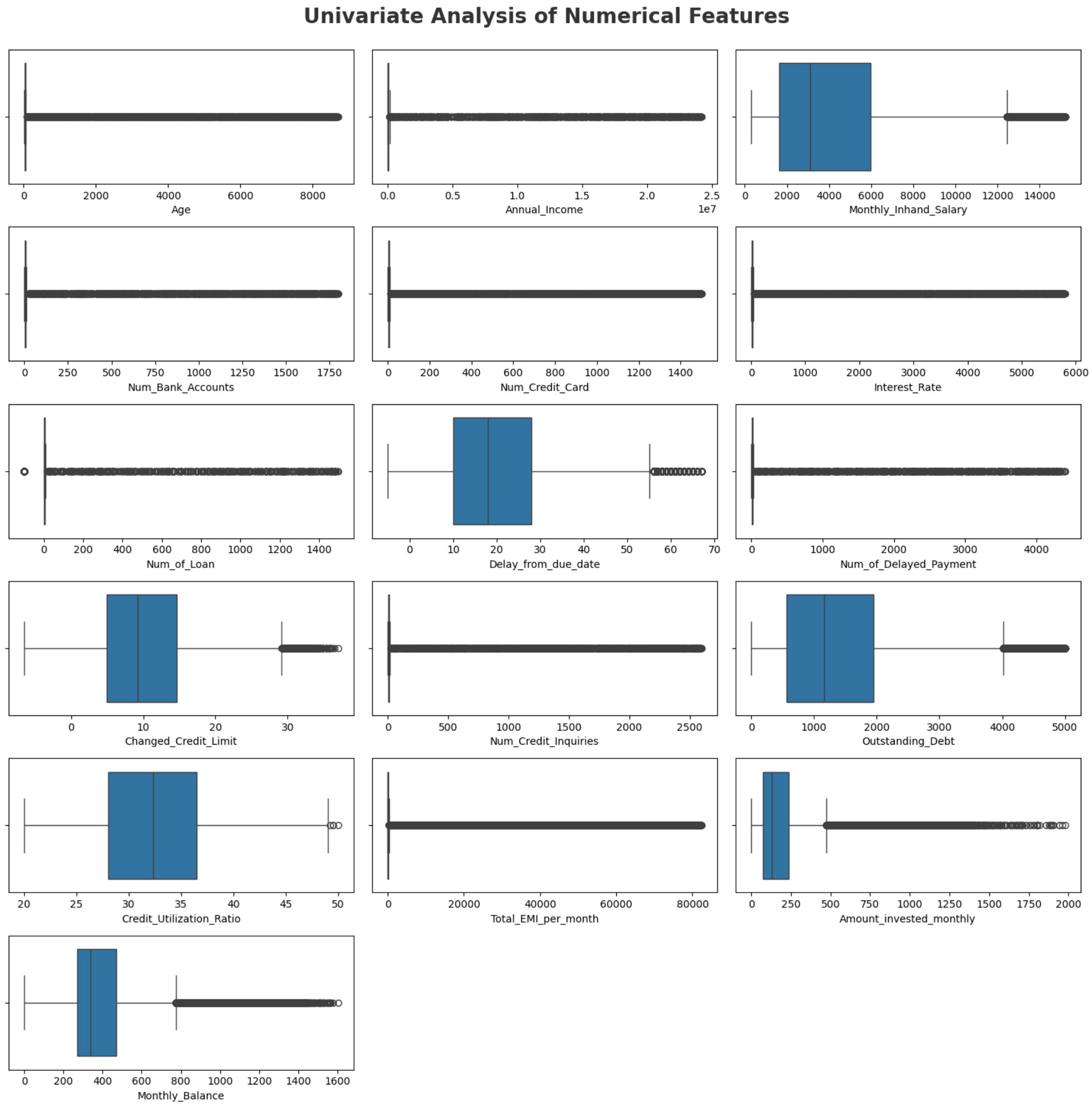
```
for i in range(0, len(num_columns)):
    plt.subplot(6, 3, i+1)
    sns.kdeplot(x=df[num_columns[i]],shade=True, color='b')
    plt.xlabel(num_columns[i])
    plt.tight_layout()
```



Above is the distribution of all numerical attributes

[93]:
```
plt.figure(figsize=(15, 15))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20,␣
 ↪fontweight='bold', alpha=0.8, y=1.)

for i in range(0, len(num_columns)):
```

```
    plt.subplot(6, 3, i+1)
    sns.boxplot(x=df[num_columns[i]])
    plt.xlabel(num_columns[i])
    plt.tight_layout()
```



Above is the distribution of all numerical attributes where it can be seen collumns having alot of outliers

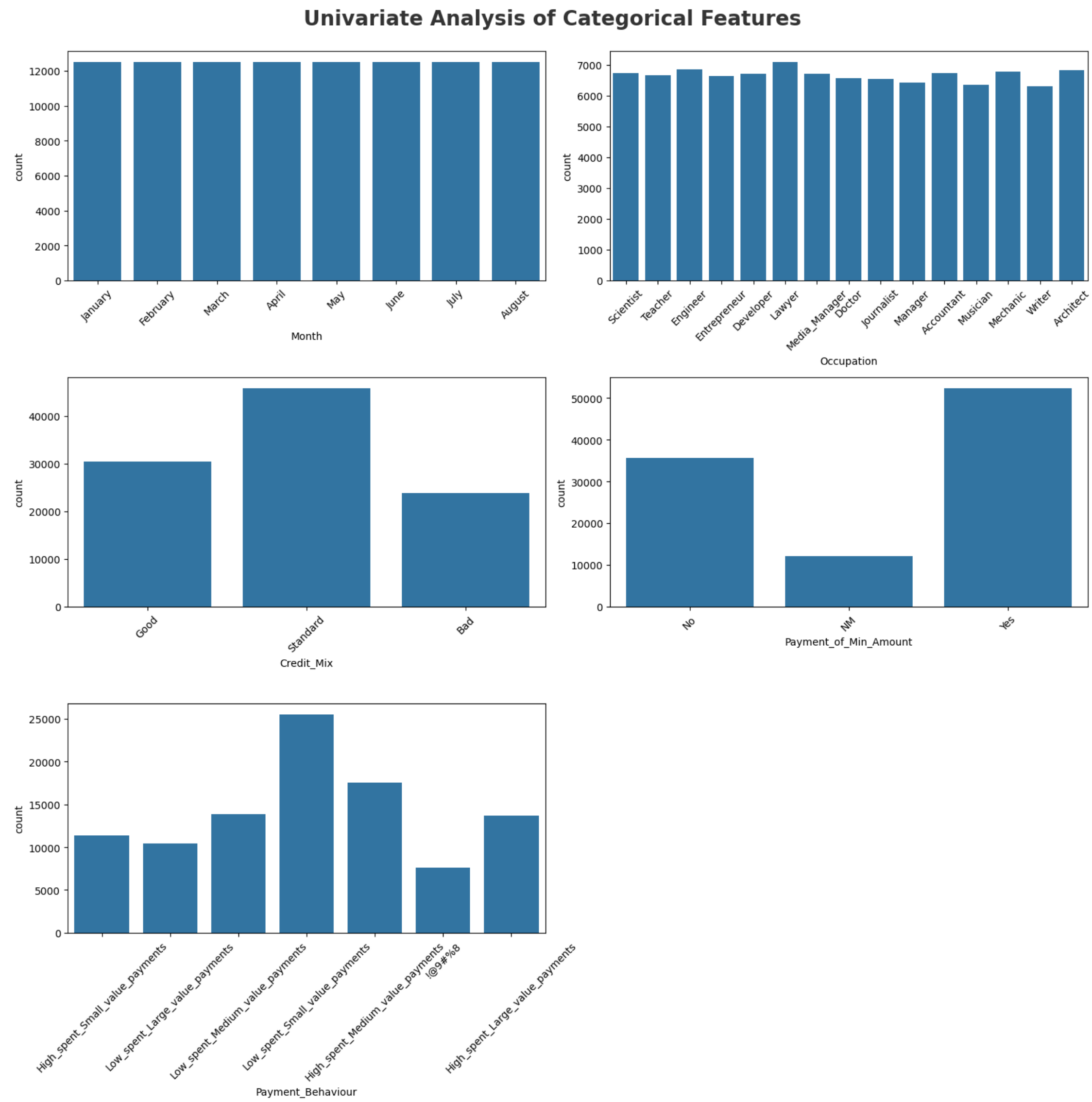
[94]:
```
cat_columns = list()
CAT_THRESHOLD = 20

for col in df.columns:
  if df[col].nunique() < CAT_THRESHOLD:
```

```
    cat_columns.append(col)
```

[95]:
```
cat_columns
```

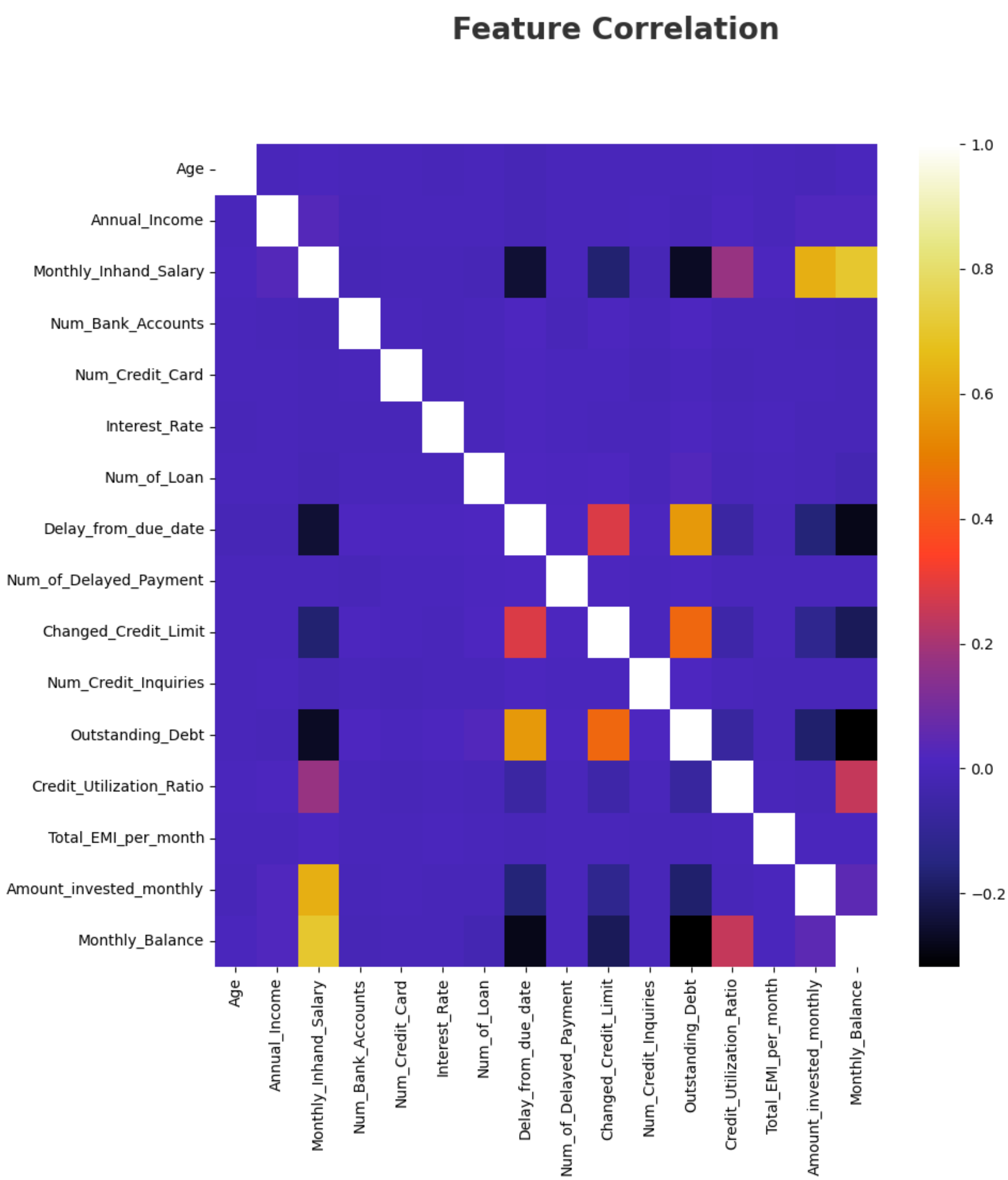
[95]:
```
['Month',
 'Occupation',
 'Credit_Mix',
 'Payment_of_Min_Amount',
 'Payment_Behaviour']
```

[96]:
```
plt.figure(figsize=(15, 15))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20,␣
 ↪fontweight='bold', alpha=0.8, y=1.)
for i in range(0, len(cat_columns)):
    plt.subplot(3, 2, i+1)
    sns.countplot(x=df[cat_columns[i]])
    plt.xlabel(cat_columns[i])
    plt.xticks(rotation=45)
    plt.tight_layout()
```



1. Low spent medium value payments look to be the majority of the payment behaviour.
2. Majority of the customers pay the minimum amount.
3. Majority of the customers have a standard credit rating.

[97]:
```
plt.figure(figsize = (10,10))
plt.suptitle('Feature Correlation', fontsize=20, fontweight='bold', alpha=0.8, y=1.)
sns.heatmap(df[num_columns].corr(), cmap="CMRmap")
plt.show()
```



[98]:
```
df.head()
```

[98]:
```
       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  …  \
0       19114.12            1824.843333                  3  …
1       19114.12            1824.843333                  3  …
2       19114.12            1824.843333                  3  …
3       19114.12            1824.843333                  3  …
4       19114.12            1824.843333                  3  …

   Num_Credit_Inquiries  Credit_Mix  Outstanding_Debt  \
0                   4.0        Good            809.98
1                   4.0        Good            809.98
2                   4.0        Good            809.98
3                   4.0        Good            809.98
4                   4.0        Good            809.98

  Credit_Utilization_Ratio     Credit_History_Age  Payment_of_Min_Amount  \
0                26.822620  22 Years and 1 Months                     No
1                31.944960                     NA                     No
2                28.609352  22 Years and 3 Months                     No
3                31.377862  22 Years and 4 Months                     No
4                24.797347  22 Years and 5 Months                     No

   Total_EMI_per_month  Amount_invested_monthly  \
0            49.574949                80.415295
1            49.574949               118.280222
2            49.574949                81.699521
3            49.574949               199.458074
4            49.574949                41.420153

                  Payment_Behaviour  Monthly_Balance
0   High_spent_Small_value_payments       312.494089
1    Low_spent_Large_value_payments       284.629163
2   Low_spent_Medium_value_payments       331.209863
3    Low_spent_Small_value_payments       223.451310
4  High_spent_Medium_value_payments       341.489231

[5 rows x 27 columns]
```

[99]:
```
df.columns
```

[99]:
```
Index(['ID', 'Customer_ID', 'Month', 'Name', 'Age', 'SSN', 'Occupation',
       'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
       'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan', 'Type_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',
       'Payment_of_Min_Amount', 'Total_EMI_per_month',
```

```
       'Amount_invested_monthly', 'Payment_Behaviour', 'Monthly_Balance'],
      dtype='object')
```

On aggregating the columns

[100]:
```python
agg_df = df.groupby('Customer_ID').agg({
    "Annual_Income": "max",
    "Monthly_Inhand_Salary": "max",
    "Num_Bank_Accounts": "max",
    "Num_Credit_Card": "max",
    "Interest_Rate": "max",
    "Num_of_Loan" : "max",
    "Delay_from_due_date": "max",
    "Num_of_Delayed_Payment": "max",
    "Changed_Credit_Limit": "max",
    "Num_Credit_Inquiries": "max",
    "Outstanding_Debt": "max",
    "Credit_Utilization_Ratio": "max",
    "Total_EMI_per_month": "median",
    "Amount_invested_monthly":"median",
    'Monthly_Balance':'median'}).reset_index()
```

[101]:
```python
agg_df.head()
```

[101]:
```
  Customer_ID  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0  CUS_0x1000       30625.94            2706.161667                  6
1  CUS_0x1009       52312.68            4250.390000                  6
2  CUS_0x100b      113781.39            9549.782500                  1
3  CUS_0x1011       58918.47            5208.872500                  3
4  CUS_0x1013       98620.98            7962.415000                  3

   Num_Credit_Card  Interest_Rate  Num_of_Loan  Delay_from_due_date  \
0                5             27            2                   67
1                5             17         1094                   10
2                4              1            0                   19
3                3             17            3                   29
4                3              6            3                   16

   Num_of_Delayed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries  \
0                    28.0                  2.63                  11.0
1                  1749.0                  9.73                   4.0
2                     9.0                 11.34                2271.0
3                    17.0                 14.42                1965.0
4                     9.0                  4.33                   3.0

   Outstanding_Debt  Credit_Utilization_Ratio  Total_EMI_per_month  \
0           1562.91                 40.082272            42.941090
```

```
1          202.68                 40.286997           108.366467
2         1030.20                 43.829630             0.000000
3          473.14                 29.198639           123.434939
4         1233.51                 41.920614           228.018084

   Amount_invested_monthly  Monthly_Balance
0               145.467484       340.080534
1               152.968494       417.869641
2               520.541236       824.355725
3               383.350845       263.677975
4               320.088813       513.134603
```

EMI to Debt Ration - Tells % of how much a customers pays monthly to clear his outstanding debt.

[102]:
```
agg_df['EMI_To_Debt_Ratio'] = agg_df['Total_EMI_per_month']/
 ↪agg_df['Outstanding_Debt']
```

Invetsment to Debt Ration - Tells % of how much a customers invests monthly compared to his outstanding debt.

[115]:
```
agg_df["Investment_To_Debt_Ratio"] = agg_df['Amount_invested_monthly']/
 ↪agg_df['Outstanding_Debt']
```

Savings Ratio - Monthly Balance to Monthly Inhand Salary ratio tells us the amount a person saves

[116]:
```
agg_df['Savings_Ratio'] = agg_df['Monthly_Balance']/
 ↪agg_df['Monthly_Inhand_Salary']
```

[117]:
```
agg_df['Credit_Utilization_Ratio'] = agg_df['Credit_Utilization_Ratio']/100
```

Calculating the scores:

Methodology:

1. Considering sources of debt that is Num_of_Loan and Num_Credit_Card a person holds would be part of calculating ones credit score.
2. Any delayed payment would lead to an increase in credit risk
3. Debt to Investment ratio outlines the amount of debt a user can afford
4. Credit utilisation ratio outlines the ratio a customer makes to use his credit

Thus all above factors outline the score of a customer.

Higher the score riskier would be allowing credit to the customer

[118]:
```
agg_df["Score"] = (agg_df['Num_of_Loan']+␣
 ↪agg_df['Num_Credit_Card'])*agg_df['Num_of_Delayed_Payment']*␣
 ↪agg_df["Investment_To_Debt_Ratio"] *␣
 ↪agg_df['Num_Credit_Inquiries']*agg_df['Credit_Utilization_Ratio']
```

[119]:
```
agg_df
```

[119]:
```
      Customer_ID  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0      CUS_0x1000      30625.940            2706.161667                  6
1      CUS_0x1009      52312.680            4250.390000                  6
2      CUS_0x100b     113781.390            9549.782500                  1
3      CUS_0x1011      58918.470            5208.872500                  3
4      CUS_0x1013      98620.980            7962.415000                  3
…             …            …                    …                  …
12495   CUS_0xff3      17032.785            1176.398750                  0
12496   CUS_0xff4      25546.260            2415.855000                  8
12497   CUS_0xff6     117639.920            9727.326667                  5
12498   CUS_0xffc      60877.170            5218.097500                  6
12499   CUS_0xffd      41398.440            3749.870000                  8

       Num_Credit_Card  Interest_Rate  Num_of_Loan  Delay_from_due_date  \
0                    5             27            2                   67
1                    5             17         1094                   10
2                    4              1            0                   19
3                    3             17            3                   29
4                    3              6            3                   16
…                  …            …          …                  …
12495             1168           3808            3                   14
12496                7             14            5                   16
12497                6              1            2                    1
12498                8             27            8                   46
12499                7             13            6                   25

       Num_of_Delayed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries  \
0                        28.0                  2.63                  11.0
1                      1749.0                  9.73                   4.0
2                         9.0                 11.34                2271.0
3                        17.0                 14.42                1965.0
4                         9.0                  4.33                   3.0
…                         …                   …                   …
12495                    11.0                 13.86                   5.0
12496                    14.0                 10.83                   5.0
12497                     7.0                 16.40                   4.0
12498                    19.0                 12.82                  13.0
12499                    12.0                 12.07                1801.0

       Outstanding_Debt  Credit_Utilization_Ratio  Total_EMI_per_month  \
0               1562.91                  0.004008            42.941090
1                202.68                  0.004029           108.366467
2               1030.20                  0.004383             0.000000
3                473.14                  0.002920           123.434939
4               1233.51                  0.004192           228.018084
```

```
…                …                    …                    …
12495          1229.08             0.003843            33.299764
12496           758.44             0.003933           101.328637
12497           338.30             0.004250           126.638453
12498          1300.13             0.003829           272.809169
12499          1701.88             0.003992           182.976650

       Amount_invested_monthly  Monthly_Balance  EMI_To_Debt_Ratio  \
0                   145.467484       340.080534           0.027475
1                   152.968494       417.869641           0.534668
2                   520.541236       824.355725           0.000000
3                   383.350845       263.677975           0.260885
4                   320.088813       513.134603           0.184853
…                      …               …                 …
12495                82.828925       280.587085           0.027093
12496               110.758490       303.249291           0.133601
12497               527.019623       734.676144           0.374338
12498               152.923588       339.864267           0.209832
12499               163.946311       301.930977           0.107514

       Investment_To_Debt_Ratio  Savings_Ratio         Score
0                      0.093075       0.125669      0.804328
1                      0.754729       0.098313  23377.791493
2                      0.505282       0.086322    181.059382
3                      0.810227       0.050621    474.167845
4                      0.259494       0.064445      0.176226
…                         …             …            …
12495                  0.067391       0.238514     16.679538
12496                  0.146035       0.125525      0.482500
12497                  1.557847       0.075527      1.483109
12498                  0.117622       0.065132      1.779868
12499                  0.096332       0.080518    108.035172

[12500 rows x 20 columns]
```

Outlines the credit score for each customer.

[120]:
```python
agg_df[['Customer_ID','Score']]
```

[120]:
```
      Customer_ID         Score
0      CUS_0x1000      0.804328
1      CUS_0x1009  23377.791493
2      CUS_0x100b    181.059382
3      CUS_0x1011    474.167845
4      CUS_0x1013      0.176226
…           …             …
12495   CUS_0xff3     16.679538
```

```
12496   CUS_0xff4      0.482500
12497   CUS_0xff6      1.483109
12498   CUS_0xffc      1.779868
12499   CUS_0xffd    108.035172

[12500 rows x 2 columns]
```

[ ]: