CSCI316 Group Assignment 1 (Group 7) - Jan 2024

January 29, 2024

1 CSCI316 - Group Assignment 1 (Group 7)

1.1 Group Members:

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1.2 Objective

The objective of this task is to develop an end-to-end data mining project by using the Python machine learning library Scikit-Learn

1.3 Task

Given a person's credit-related information, build a machine learning model that can classify the credit score.

1.4 Algorithm used:

1. **Naïve Bayes**
2. **Artificial Neural Networks (ANN)**
3. **k-Nearest Neighbors (kNN)**
4. **Random Forest**

1.5 User Defined Features

1. **Outstanding_Debt/Monthly_Balance** - it represents a debt ratio on monthly balance.
2. **Late_Payment_Frequency** - This shows how many days later this customer is than the mean overdue date
3. **Additional_Interest_For_Month** - This represents the additional interest amount for month, by multiplying outstanding debt and interest rate

1.6 Table of contents

3. Data Exploration
4. Data Pre-processing
5. Implementing the different models
6. Model Evaluation

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2 1. Summary

The goal of the Credit Score Classification project was to provide a reliable and precise method for credit score classification.

In order to obtain understanding of the dataset, the project started with an exploratory data analysis (EDA) phase. After the EDA, missing value management, duplication removal, and fixing any flaws or inconsistencies in the dataset were all part of the data cleaning process. To prepare the data for modeling, further data transformation techniques were used, such as feature scaling and categorical variable encoding.

The goal of the model creation and assessment phase was to create at least classification models that could correctly predict the categories of credit scores. Four algorithms, including **random forests, naïve bayes, KNN, and ANN** were tested and their performance assessed. To address the issue of class imbalance, techniques such as resampling the minority classes was employed. Metrics like accuracy, precision, recall, and F1-score were evaluated as part of the model evaluation process to gauge the model's performance and make sure it could accurately identify credit ratings.

---

3 2. Importing Related Libraries

[ ]:
```
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import StratifiedShuffleSplit, GridSearchCV
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪accuracy_score, roc_auc_score

# Libraries related to models and classifiers will imported in the respective␣
 ↪parts
```

4 3. Data Exploration

4.1 Getting basic understanding of the data set

[ ]:
```
preview_dataframe = pd.read_csv('train.csv')
```

[ ]:
```
preview_dataframe.head()
```

[ ]:
```
       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]
```

[ ]:
```
print(f"Train data size: {preview_dataframe.shape}")
```

```
Train data size: (100000, 28)
```

[ ]:
```
preview_dataframe.columns
```

[ ]:
```
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',
       'Credit_Score'],
      dtype='object')
```

[ ]:
```
preview_dataframe.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
```

[ ]:
```
preview_dataframe.describe().T
```

[ ]:
```
                             count         mean          std         min  \
Monthly_Inhand_Salary      84998.0  4194.170850  3183.686167  303.645417
Num_Bank_Accounts         100000.0    17.091280   117.404834   -1.000000
Num_Credit_Card           100000.0    22.474430   129.057410    0.000000
Interest_Rate             100000.0    72.466040   466.422621    1.000000
Delay_from_due_date       100000.0    21.068780    14.860104   -5.000000
Num_Credit_Inquiries       98035.0    27.754251   193.177339    0.000000
Credit_Utilization_Ratio  100000.0    32.285173     5.116875   20.000000
Total_EMI_per_month       100000.0  1403.118217  8306.041270    0.000000

                                  25%          50%          75%           max
Monthly_Inhand_Salary     1625.568229  3093.745000  5957.448333  15204.633333
Num_Bank_Accounts            3.000000     6.000000     7.000000   1798.000000
Num_Credit_Card              4.000000     5.000000     7.000000   1499.000000
Interest_Rate                8.000000    13.000000    20.000000   5797.000000
Delay_from_due_date         10.000000    18.000000    28.000000     67.000000
Num_Credit_Inquiries         3.000000     6.000000     9.000000   2597.000000
Credit_Utilization_Ratio    28.052567    32.305784    36.496663     50.000000
Total_EMI_per_month         30.306660    69.249473   161.224249  82331.000000
```

[ ]:
```
preview_dataframe.describe(exclude = np.number).T
```

[ ]:
```
                          count  unique                          top  \
ID                       100000  100000                      0x25fb6
Customer_ID              100000   12500                   CUS_0x942c
Month                    100000       8                      January
Name                      90015   10139                       Langep
Age                      100000    1788                           38
SSN                      100000   12501                  #F%$D@*&8
Occupation               100000      16                      _______
Annual_Income            100000   18940                     20867.67
Num_of_Loan              100000     434                            3
Type_of_Loan              88592    6260                Not Specified
Num_of_Delayed_Payment    92998     749                           19
Changed_Credit_Limit     100000    4384                            _
Credit_Mix               100000       4                     Standard
Outstanding_Debt         100000   13178                      1360.45
Credit_History_Age        90970     404      15 Years and 11 Months
Payment_of_Min_Amount    100000       3                          Yes
Amount_invested_monthly   95521   91049                    __10000__
Payment_Behaviour        100000       7  Low_spent_Small_value_payments
```

```
Monthly_Balance            98800   98792  __-333333333333333333333333333__
Credit_Score              100000       3                          Standard

                            freq
ID                             1
Customer_ID                    8
Month                      12500
Name                          44
Age                         2833
SSN                         5572
Occupation                  7062
Annual_Income                 16
Num_of_Loan                14386
Type_of_Loan                1408
Num_of_Delayed_Payment      5327
Changed_Credit_Limit        2091
Credit_Mix                 36479
Outstanding_Debt              24
Credit_History_Age           446
Payment_of_Min_Amount      52326
Amount_invested_monthly     4305
Payment_Behaviour          25513
Monthly_Balance                9
Credit_Score               53174
```

[ ]:
```
preview_dataframe.isnull().sum()
```

[ ]:
```
ID                              0
Customer_ID                     0
Month                           0
Name                         9985
Age                             0
SSN                             0
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Type_of_Loan                11408
Delay_from_due_date             0
Num_of_Delayed_Payment       7002
Changed_Credit_Limit            0
Num_Credit_Inquiries         1965
Credit_Mix                      0
Outstanding_Debt                0
```

```
Credit_Utilization_Ratio        0
Credit_History_Age           9030
Payment_of_Min_Amount           0
Total_EMI_per_month             0
Amount_invested_monthly      4479
Payment_Behaviour               0
Monthly_Balance              1200
Credit_Score                    0
dtype: int64
```

4.2 Findings

1. There are missing values
2. Train dataset has both numerical and string values
3. There are odd valus (#F%$D@*&8, _______, !@9#%8, etc)
4. ***Customer_ID*** has ***12500*** unique values. It means we have data of 12500 customers.
5. ***Month*** has only ***8*** unique values.
6. ***Age*** has ***1788*** unique values. This looks strange as general age range is from ***0-100***.
7. ***SSN*** has ***12501*** unique values, whereas ***Customer_ID*** only has only ***12500*** unique values. There is a possibility that incorrect SSN value is entered for one of the customer as same person can't have multiple SSN.

4.3 Getting into deeper details of each attributes - Categorical

[ ]:
```
# function for displaying column details
def get_column_detail(df, column):
  print("**"*20)
  print()
  print(f"Details of column [{column}]")

  #column data type
  print(f"\nData Type: {df[column].dtype}")

  #check null values
  null_numbers = df[column].isnull().sum()

  if null_numbers == 0:
    print("\nThere is no null value")
  elif null_numbers > 0 :
    print(f"\nThere are {null_numbers} null values")

  #displaying info about unique values
  print(f"\nNumber of Unique Values: {df[column].nunique()}")
```

```
    #displaying distribution of Column
    print("\nDistribution of column: \n")
    print(df[column].value_counts(dropna = False))
    print()
    print("**"*20)
```

[ ]:
```
# function for displaying distribution of 2 columns
def cross_plot(df, column1, column2, rotation = 0):
    print("**"*20)
    print(f"distribution plot of {column1} and {column2}")

    pd.crosstab(df[column1], df[column2]).plot(kind = 'bar', stacked = True)

    plt.xlabel(f'{column1}')
    plt.ylabel('Number of Records')
    plt.title(f'{column1} & {column2} Distribution')
    plt.xticks(rotation=rotation)
```

[ ]:
```
def displot_plot(df, column, rotation=0, bins=20):
    print("**"*20)
    print(f'\n{column} Distribution')

    sns.displot(data=df, x=column, kde=True, bins=bins)

    plt.xlabel(f'{column}')
    plt.ylabel('Number of Records')
    plt.title(f'{column} Distribution')
    plt.xticks(rotation=rotation)

    plt.show()
```

[ ]:
```
Target_att = 'Credit_Score'
```

4.3.1 01. Credit_Score

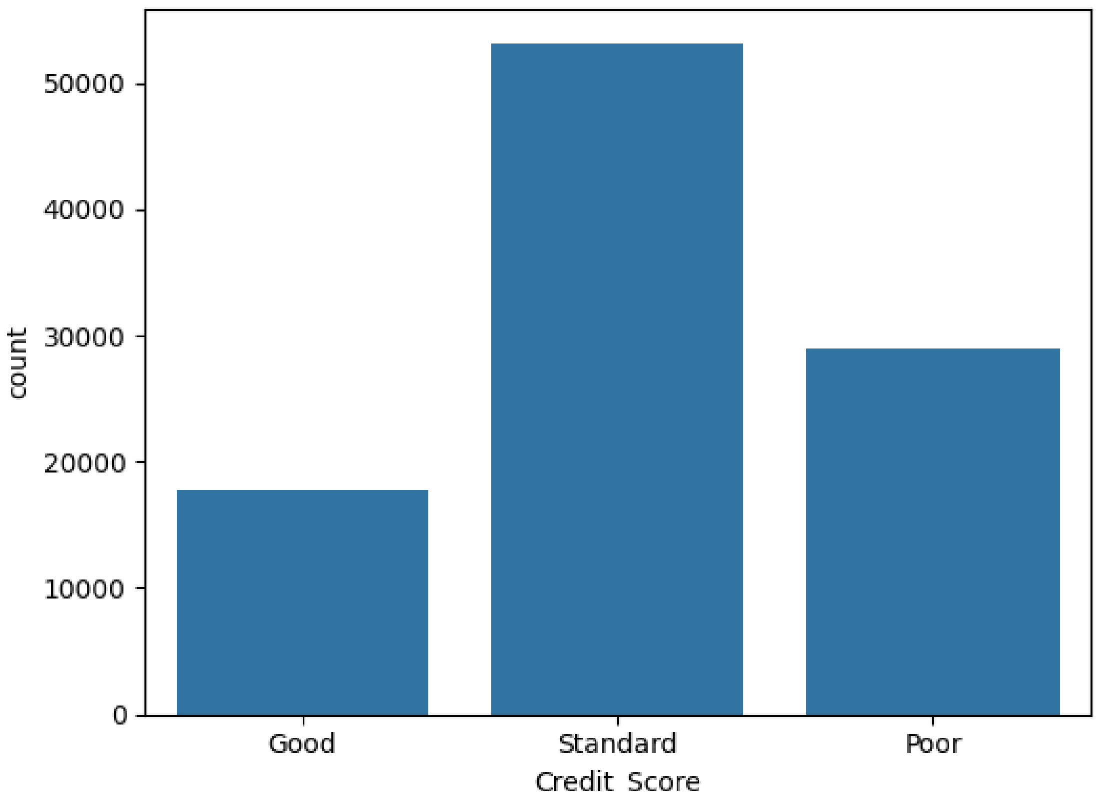
Findings: * class value is imbalanced

[ ]:
```
get_column_detail(preview_dataframe, 'Credit_Score')
```

```
****************************************

Details of column [Credit_Score]

Data Type: object

There is no null value
```

```
Number of Unique Values: 3

Distribution of column:

Credit_Score
Standard    53174
Poor        28998
Good        17828
Name: count, dtype: int64

****************************************
```

[ ]:
```python
sns.countplot(preview_dataframe, x = 'Credit_Score')
plt.show()
```



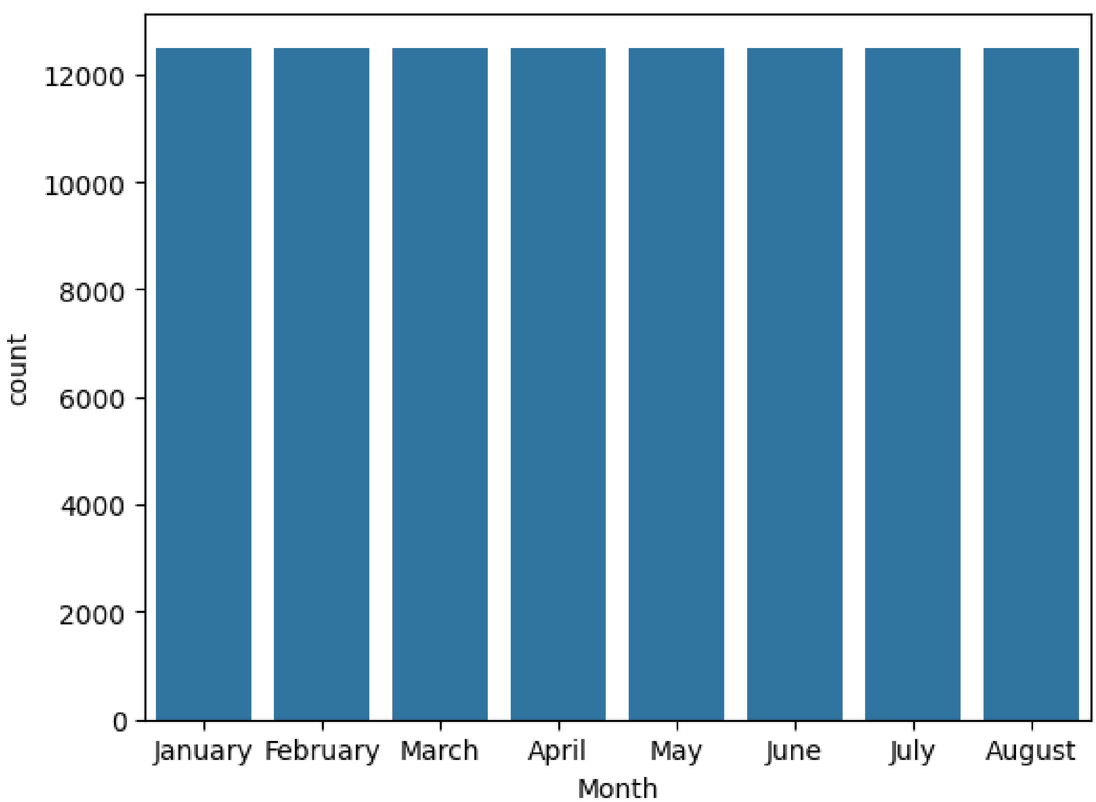
4.3.2 02. Month

[ ]:
```python
get_column_detail(preview_dataframe, 'Month')
```

```
****************************************

Details of column [Month]
```

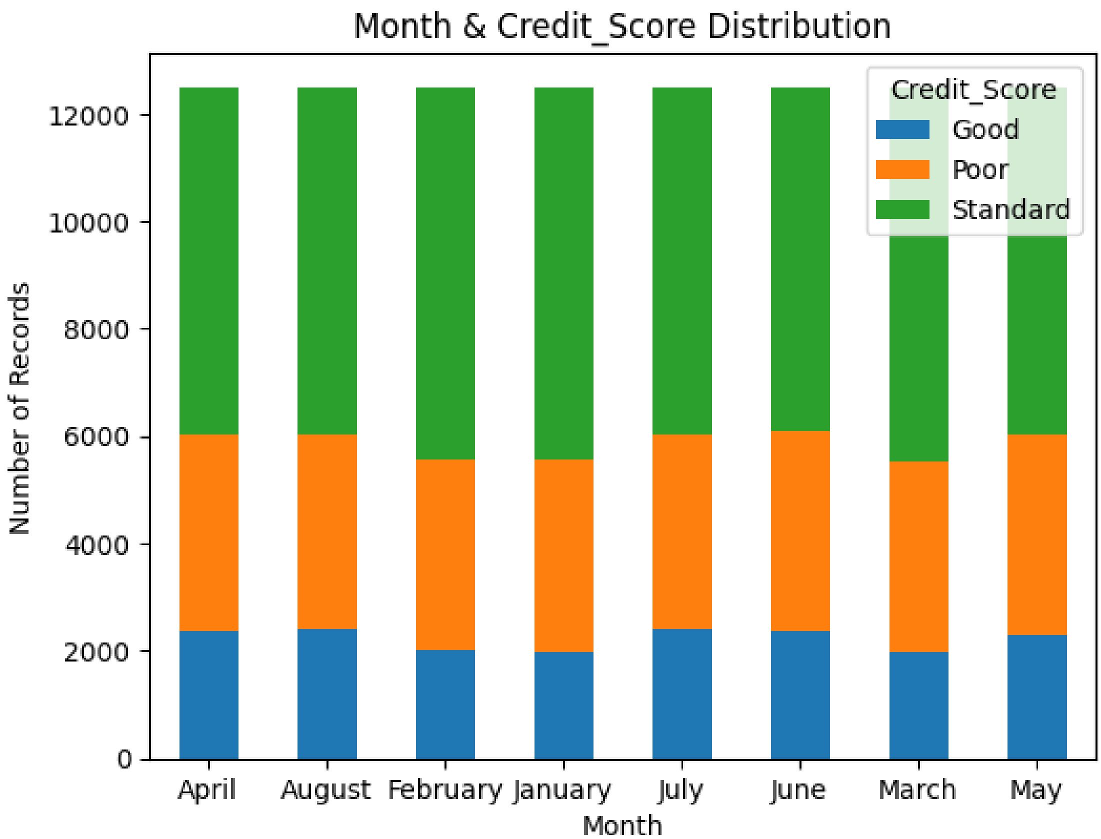
```
Data Type: object

There is no null value

Number of Unique Values: 8

Distribution of column:

Month
January      12500
February     12500
March        12500
April        12500
May          12500
June         12500
July         12500
August       12500
Name: count, dtype: int64

****************************************
```

[ ]:
```
sns.countplot(preview_dataframe, x = 'Month')
plt.show()
```



[ ]:
```
cross_plot(preview_dataframe, 'Month', Target_att)
```

```
****************************************
distribution plot of Month and Credit_Score
```



4.3.3 03. Occupation

Findings: * value '_______' needs to be replaced

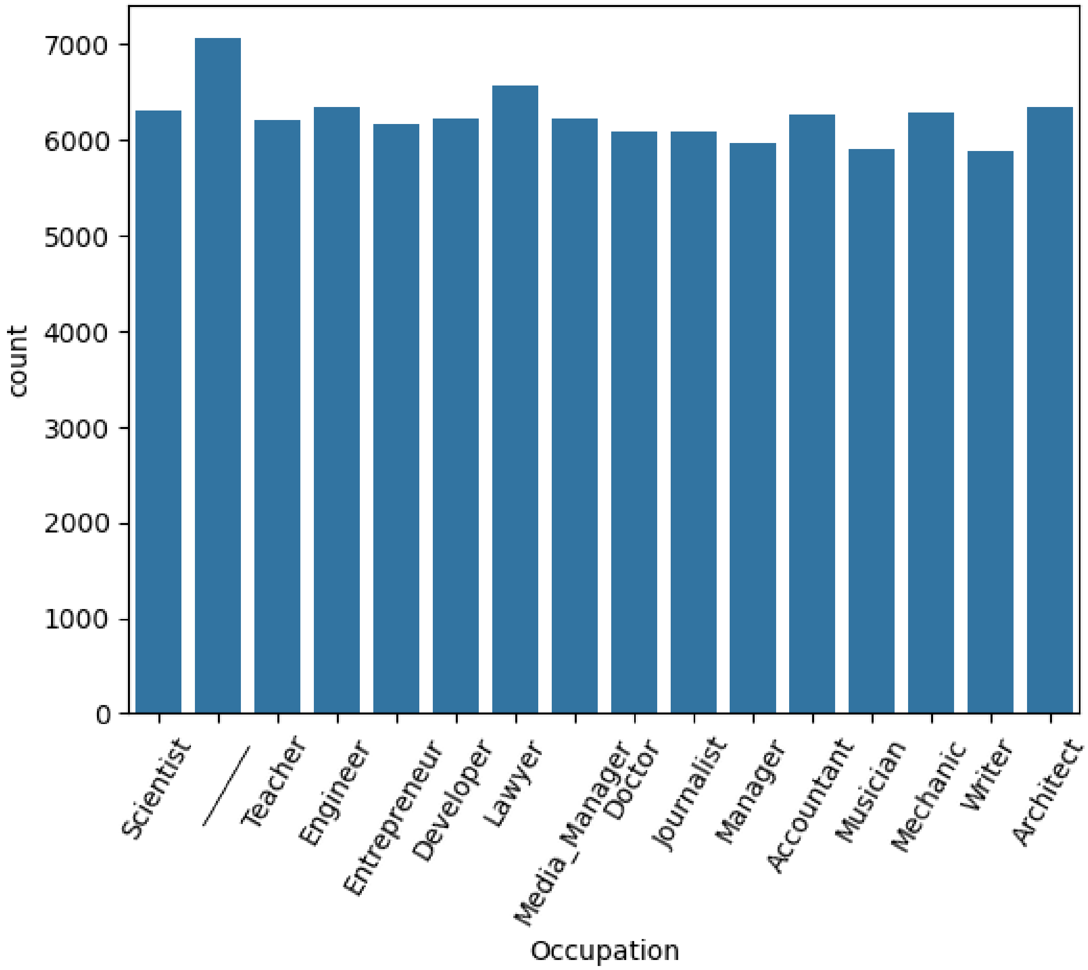
[ ]:
```
get_column_detail(preview_dataframe, 'Occupation')
```

```
****************************************

Details of column [Occupation]

Data Type: object

There is no null value
```

```
Number of Unique Values: 16

Distribution of column:

Occupation
_______          7062
Lawyer           6575
Architect        6355
Engineer         6350
Scientist        6299
Mechanic         6291
Accountant       6271
Developer        6235
Media_Manager    6232
Teacher          6215
Entrepreneur     6174
Doctor           6087
Journalist       6085
Manager          5973
Musician         5911
Writer           5885
Name: count, dtype: int64

****************************************
```

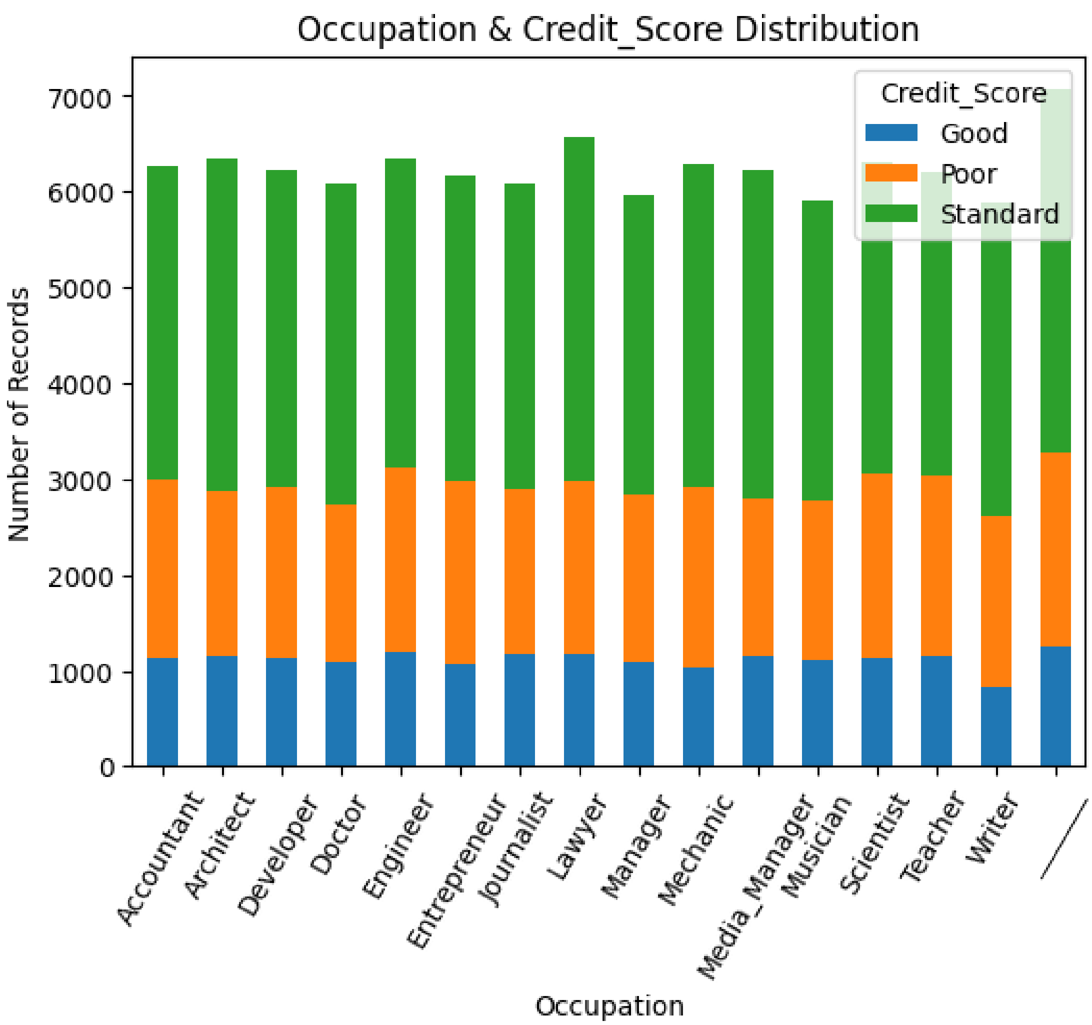
[ ]:

```
sns.countplot(preview_dataframe, x = 'Occupation')
plt.xticks(rotation = 60)
plt.show()
```




```
[ ]: cross_plot(preview_dataframe, 'Occupation', Target_att, rotation = 60)
```

```
****************************************
distribution plot of Occupation and Credit_Score
```



4.3.4 04. Type of Loan

Findings: * null values

[ ]:
```
get_column_detail(preview_dataframe, 'Type_of_Loan')
```

```
****************************************

Details of column [Type_of_Loan]

Data Type: object

There are 11408 null values

Number of Unique Values: 6260
```

```
Distribution of column:

Type_of_Loan
NaN
11408
Not Specified
1408
Credit-Builder Loan
1280
Personal Loan
1272
Debt Consolidation Loan
1264
                                                                  …
Debt Consolidation Loan, Auto Loan, Personal Loan, Debt Consolidation Loan,
Student Loan, and Credit-Builder Loan                                8
Student Loan, Auto Loan, Student Loan, Credit-Builder Loan, Home Equity Loan,
Debt Consolidation Loan, and Debt Consolidation Loan        8
Debt Consolidation Loan, Personal Loan, Mortgage Loan, Personal Loan, Not
Specified, Mortgage Loan, and Home Equity Loan                  8
Student Loan, Home Equity Loan, Student Loan, Personal Loan, Not Specified, Auto
Loan, Auto Loan, and Debt Consolidation Loan             8
Payday Loan, Student Loan, Credit-Builder Loan, Mortgage Loan, and Auto Loan
8
Name: count, Length: 6261, dtype: int64

****************************************
```

4.3.5 05. Credit Mix

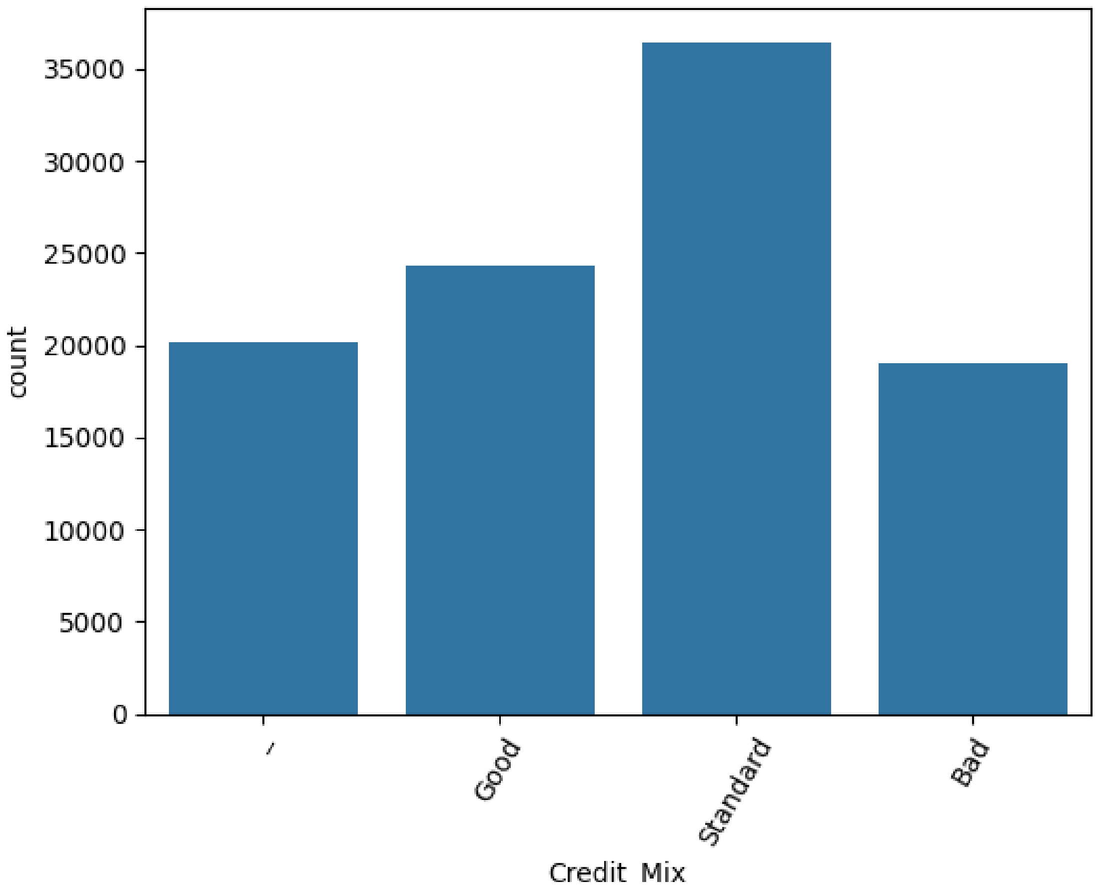
Findings: * it seems higly correlated to "Credit score" * "-" needs to be replaced

[ ]:
```
get_column_detail(preview_dataframe, 'Credit_Mix')
```

```
****************************************

Details of column [Credit_Mix]

Data Type: object

There is no null value

Number of Unique Values: 4

Distribution of column:

Credit_Mix
Standard    36479
```

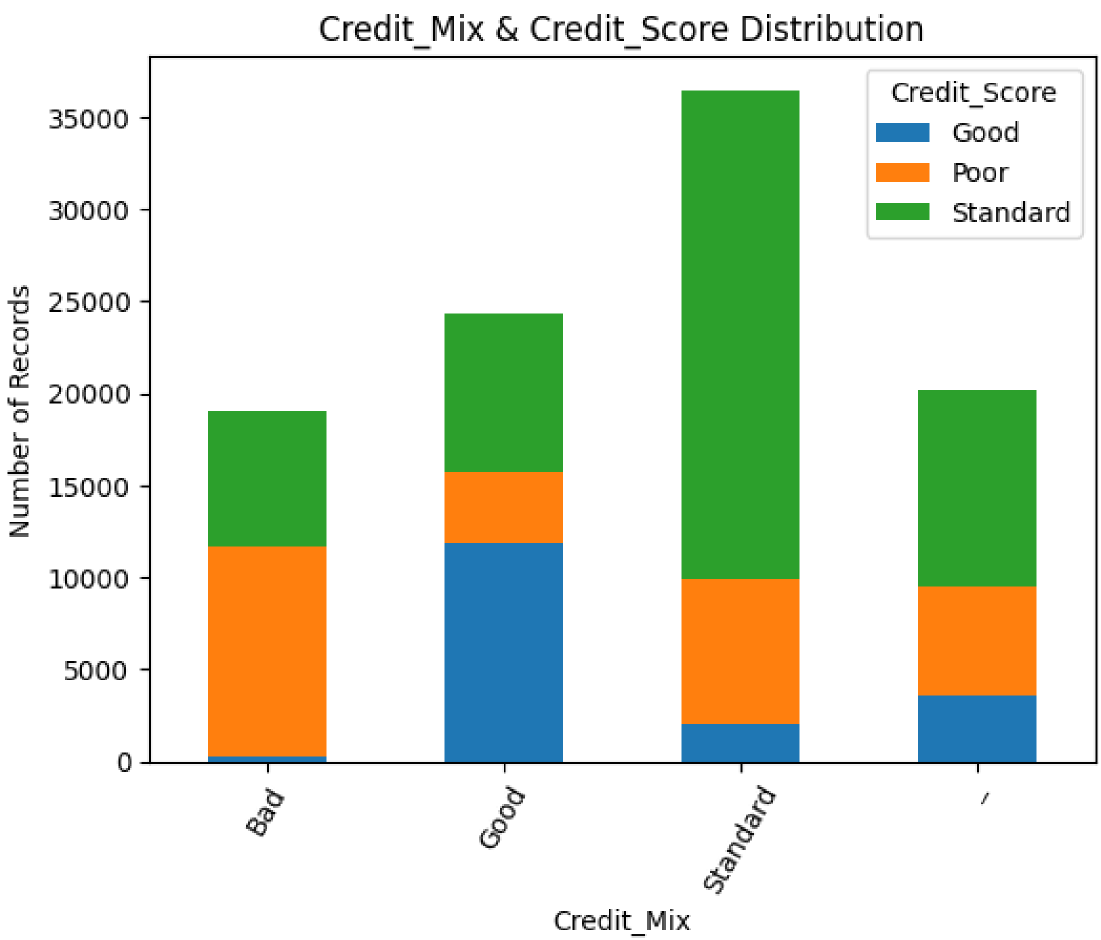
```
Good        24337
_           20195
Bad         18989
Name: count, dtype: int64

****************************************
```

[ ]:
```
sns.countplot(preview_dataframe, x = 'Credit_Mix')
plt.xticks(rotation = 60)
plt.show()
```



[ ]:
```
cross_plot(preview_dataframe, 'Credit_Mix', Target_att, rotation = 60)
```

```
****************************************
distribution plot of Credit_Mix and Credit_Score
```



4.3.6 06. Payment of Min amount

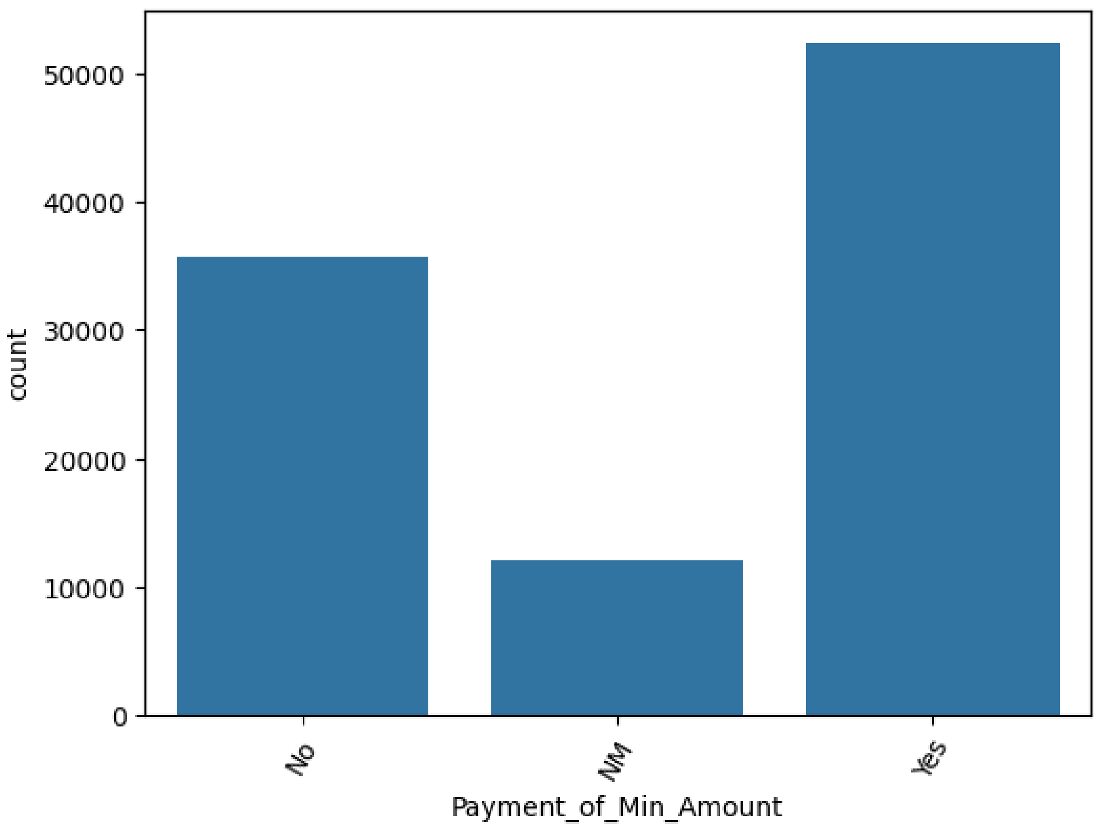
Findings: * it seems higly correlated to "Credit score"

[ ]:
```
get_column_detail(preview_dataframe, 'Payment_of_Min_Amount')
```

```
****************************************

Details of column [Payment_of_Min_Amount]

Data Type: object

There is no null value

Number of Unique Values: 3

Distribution of column:
```

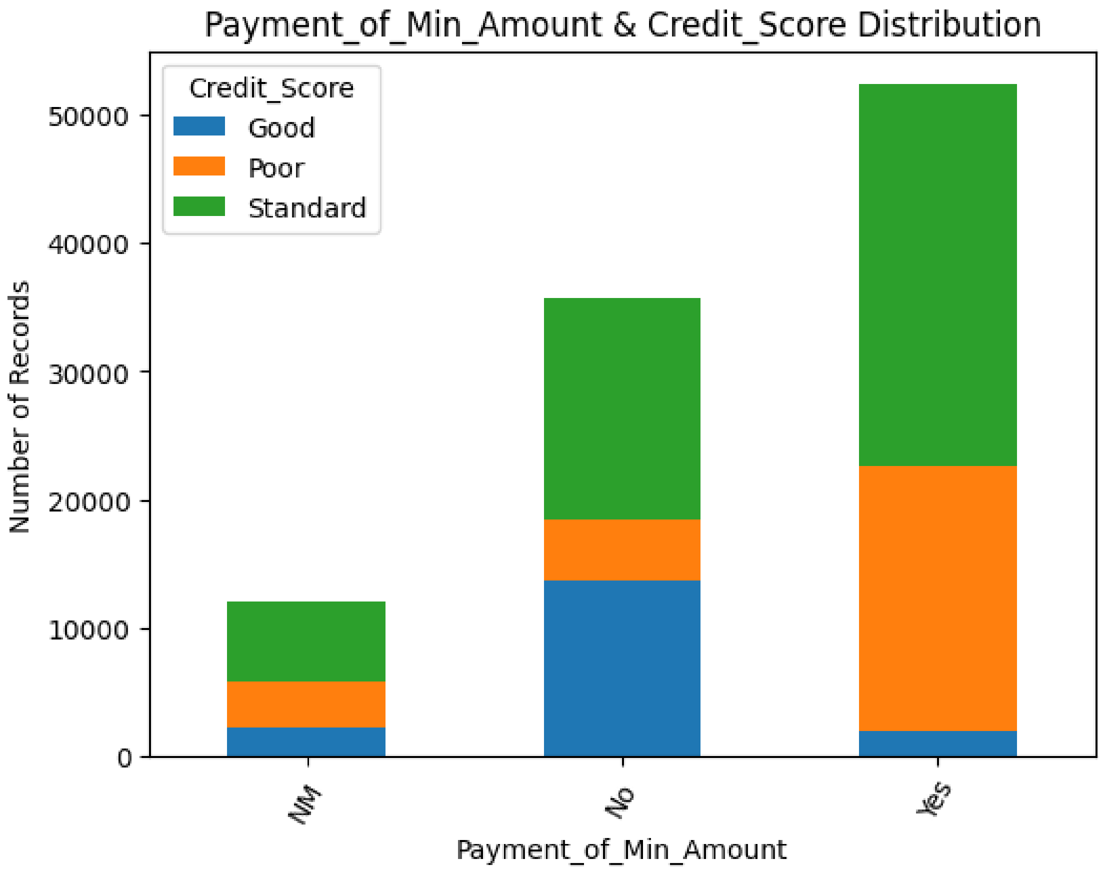
```
Payment_of_Min_Amount
Yes    52326
No     35667
NM     12007
Name: count, dtype: int64

****************************************
```

[ ]:
```
sns.countplot(preview_dataframe, x = 'Payment_of_Min_Amount')
plt.xticks(rotation = 60)
plt.show()
```



[ ]:
```
cross_plot(preview_dataframe, 'Payment_of_Min_Amount', Target_att, rotation =
↪60)
```

```
****************************************
distribution plot of Payment_of_Min_Amount and Credit_Score
```



4.3.7 07. Payment Behaviour

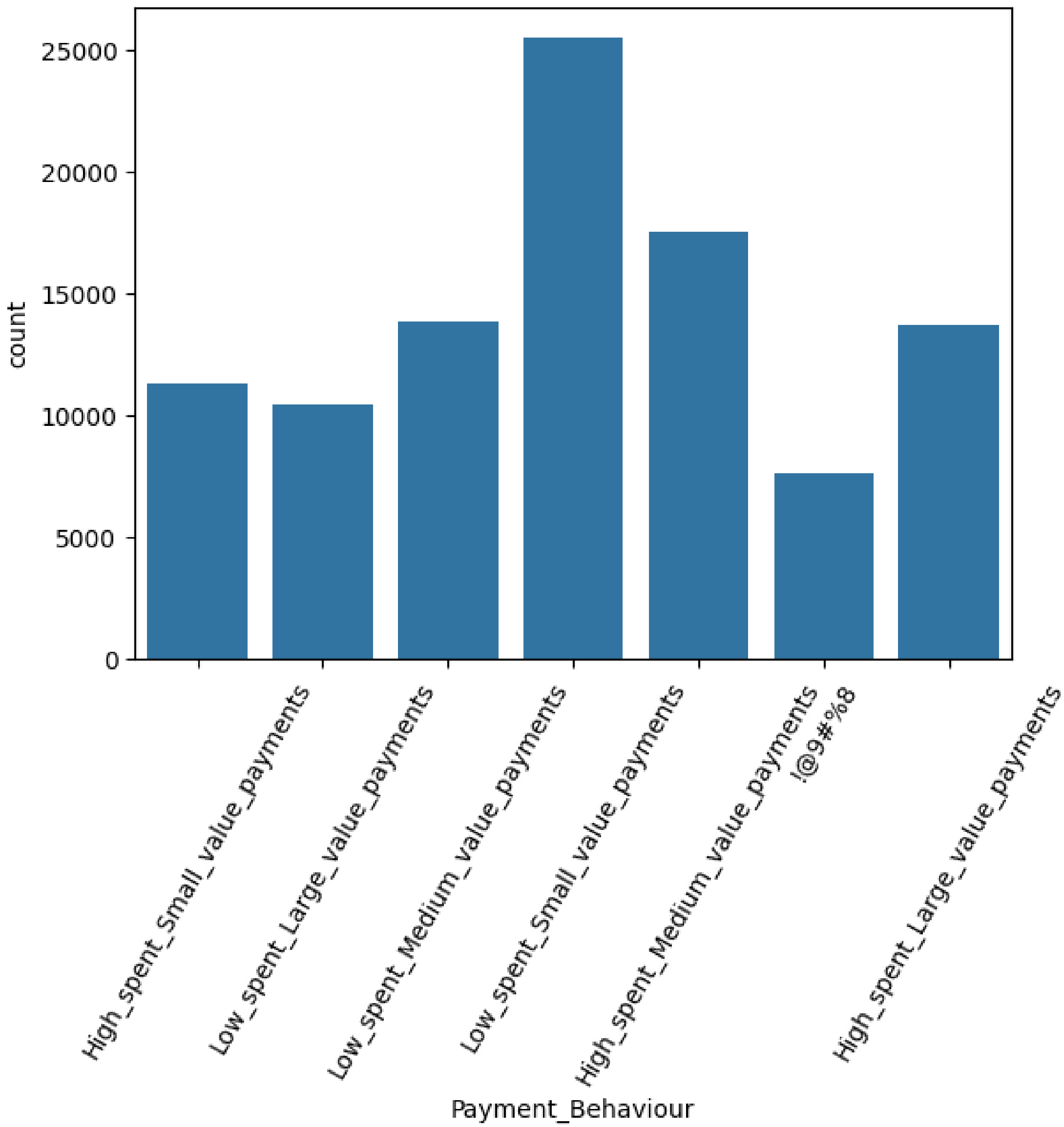
Findings: * strange value: !@9#%8

[ ]:
```
get_column_detail(preview_dataframe, 'Payment_Behaviour')
```

```
****************************************

Details of column [Payment_Behaviour]

Data Type: object

There is no null value

Number of Unique Values: 7

Distribution of column:

Payment_Behaviour
Low_spent_Small_value_payments      25513
```

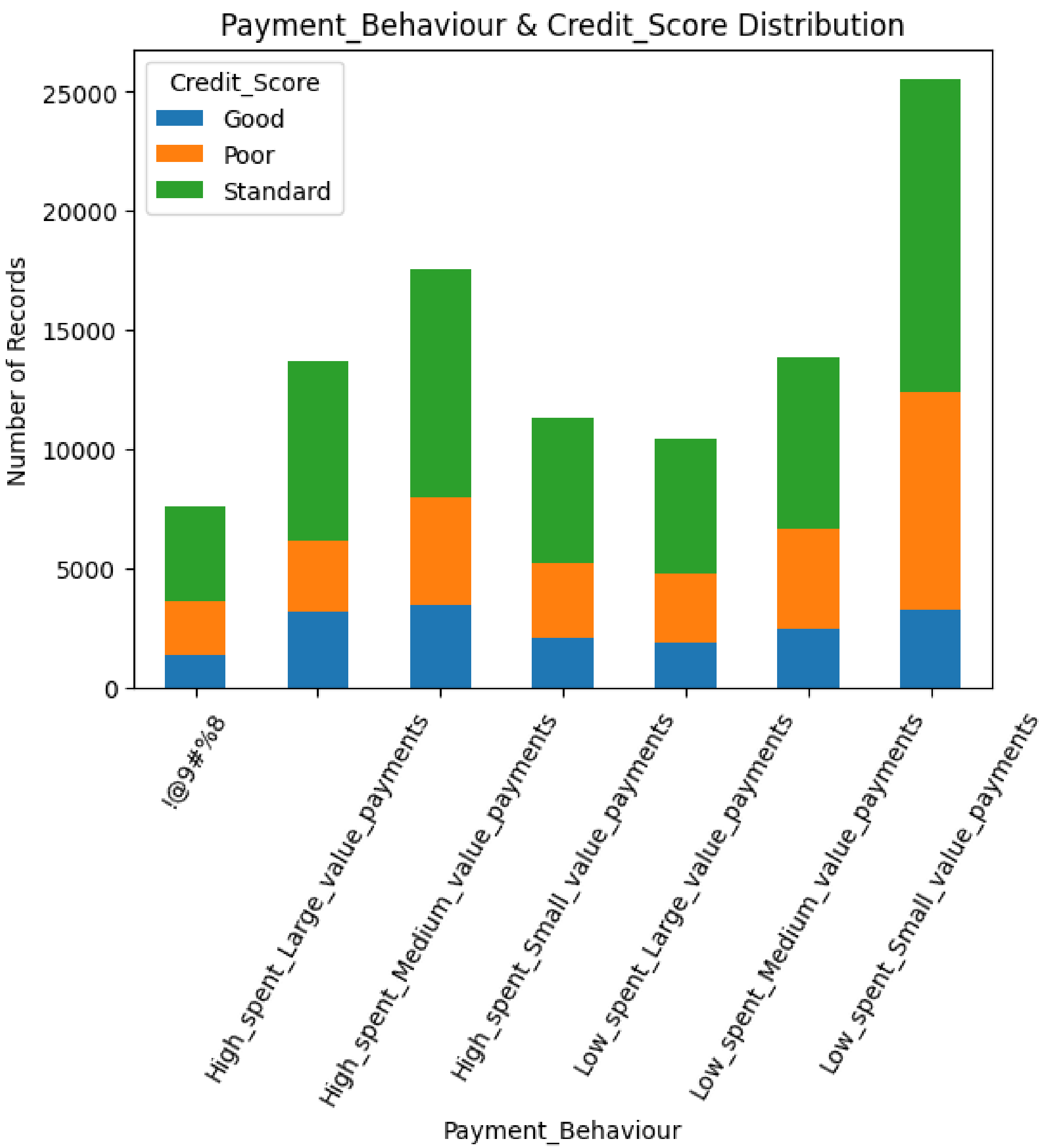
```
High_spent_Medium_value_payments    17540
Low_spent_Medium_value_payments     13861
High_spent_Large_value_payments     13721
High_spent_Small_value_payments     11340
Low_spent_Large_value_payments      10425
!@9#%8                               7600
Name: count, dtype: int64

****************************************
```

[ ]:
```
sns.countplot(preview_dataframe, x = 'Payment_Behaviour')
plt.xticks(rotation = 60)
plt.show()
```



[ ]:
```
cross_plot(preview_dataframe, 'Payment_Behaviour', Target_att, rotation = 60)
```

```
****************************************
distribution plot of Payment_Behaviour and Credit_Score
```



4.4 Getting into deeper details of each attributes - Numerical

4.4.1 01. Age

Findings: * age above 100 or below 0 should be replaced

[ ]:
```
get_column_detail(preview_dataframe, 'Age')
```

```
***************************************

Details of column [Age]

Data Type: object

There is no null value

Number of Unique Values: 1788

Distribution of column:

Age
38      2833
28      2829
31      2806
26      2792
32      2749
        …
325        1
6611       1
3779       1
5751       1
3966       1
Name: count, Length: 1788, dtype: int64

***************************************
```

4.4.2 02. Annual Income

[ ]:
```
get_column_detail(preview_dataframe, 'Annual_Income')
```

```
***************************************

Details of column [Annual_Income]

Data Type: object

There is no null value

Number of Unique Values: 18940
```

```
Distribution of column:

Annual_Income
20867.67      16
17273.83      16
36585.12      16
9141.63       15
33029.66      15
              ..
3874136.0      1
42588.14_      1
32291.88_      1
28730.26_      1
17770.795_     1
Name: count, Length: 18940, dtype: int64

****************************************
```

4.4.3 03. Monthly_Inhand_Salary

Findings: * null values

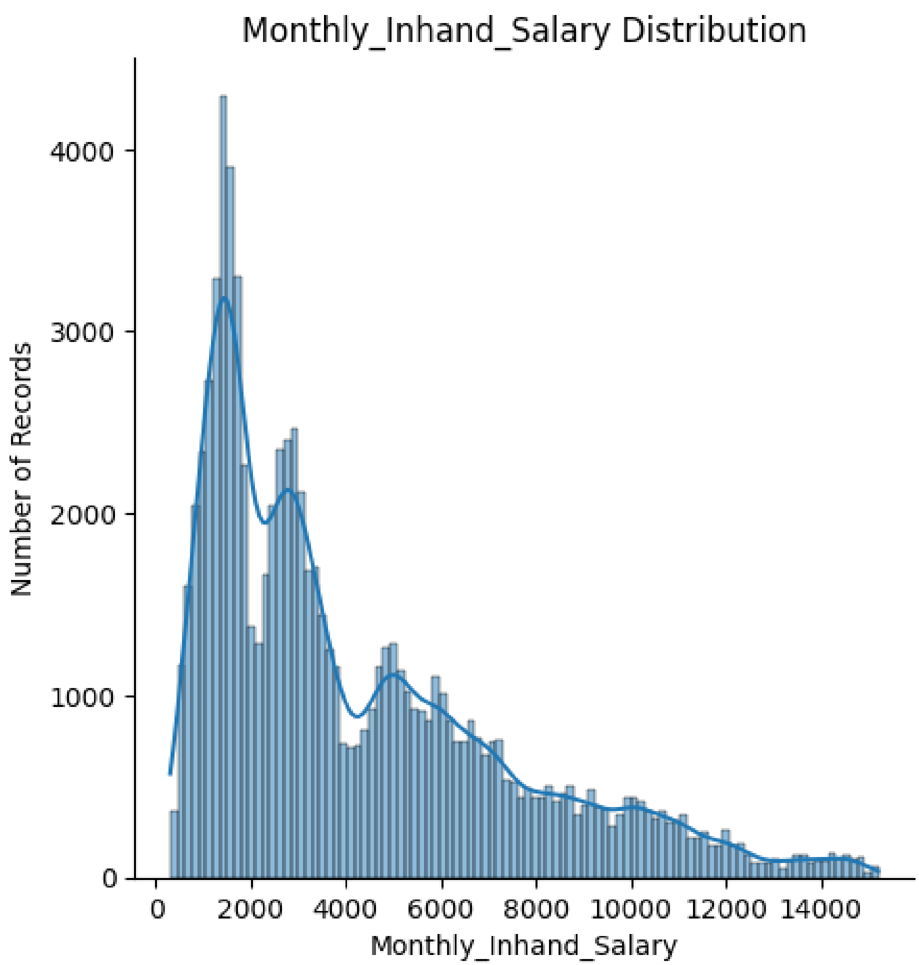
```
[ ]: get_column_detail(preview_dataframe, 'Monthly_Inhand_Salary')
```

```
****************************************

Details of column [Monthly_Inhand_Salary]

Data Type: float64

There are 15002 null values

Number of Unique Values: 13235

Distribution of column:

Monthly_Inhand_Salary
NaN              15002
6769.130000         15
2295.058333         15
6082.187500         15
6358.956667         15
                …
1698.145919          1
1515.410833          1
1465.444744          1
1879.396612          1
```

```
2760.869167        1
Name: count, Length: 13236, dtype: int64

****************************************
```

```
[ ]: displot_plot(preview_dataframe, 'Monthly_Inhand_Salary', bins=100)
```

```
****************************************

Monthly_Inhand_Salary Distribution
```



4.4.4 04. Num Bank Accounts

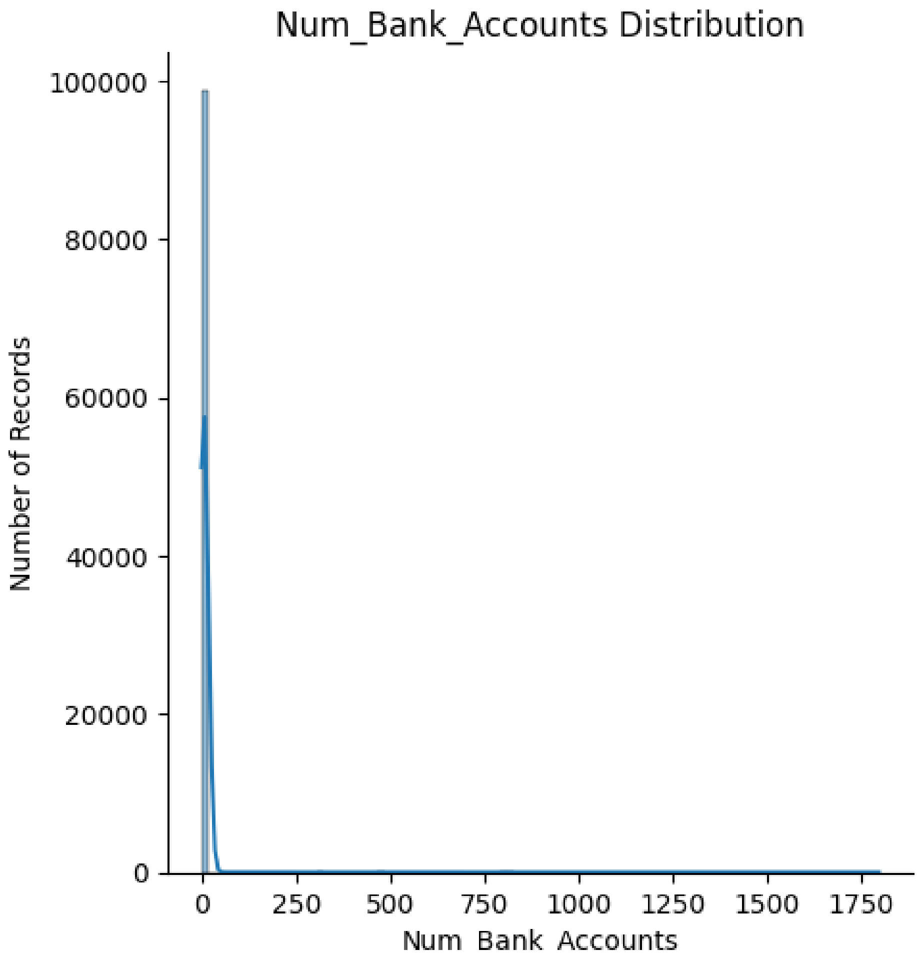
Findings: * outliers should be replaced

```
[ ]: get_column_detail(preview_dataframe, 'Num_Bank_Accounts')
```

```
****************************************

Details of column [Num_Bank_Accounts]

Data Type: int64

There is no null value

Number of Unique Values: 943

Distribution of column:

Num_Bank_Accounts
6       13001
7       12823
8       12765
4       12186
5       12118
        …
665         1
1388        1
1429        1
1588        1
1777        1
Name: count, Length: 943, dtype: int64

****************************************
```

[ ]:
```
displot_plot(preview_dataframe, 'Num_Bank_Accounts', bins=100)
```

```
****************************************

Num_Bank_Accounts Distribution
```



4.4.5 05. Num_Credit_Card

Findings: * outliers should be replaced

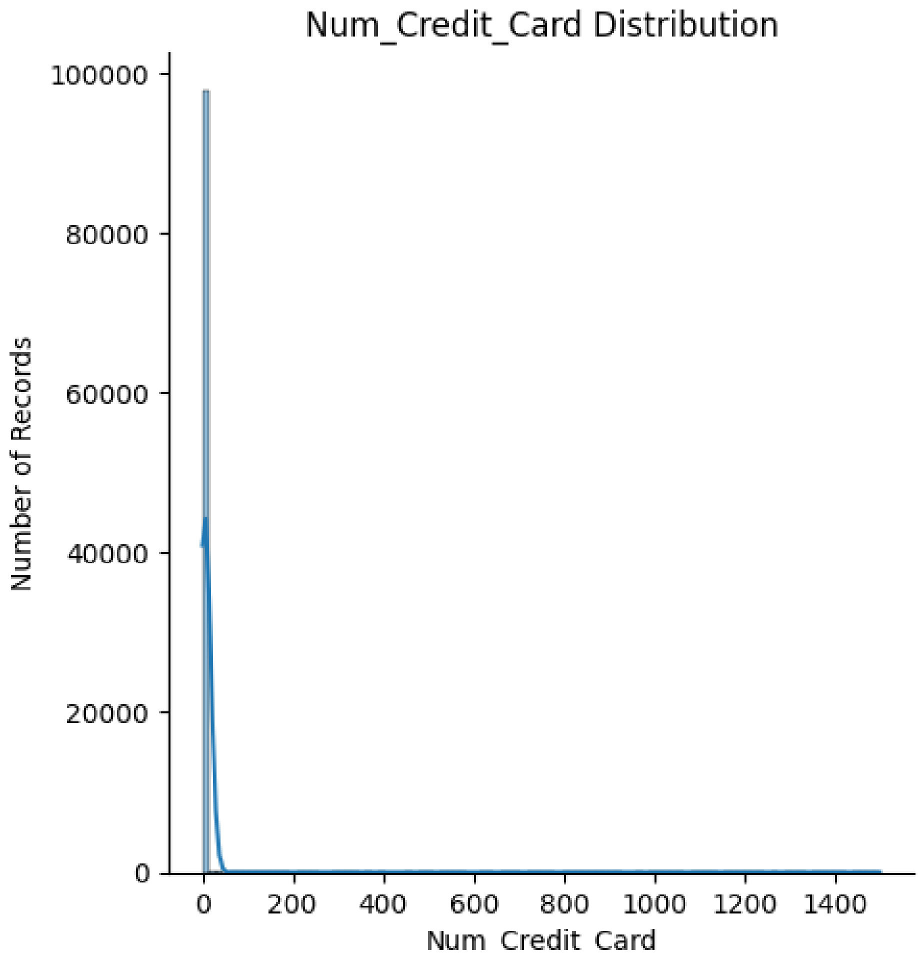
[ ]:
```
get_column_detail(preview_dataframe, 'Num_Credit_Card')
```

```
****************************************

Details of column [Num_Credit_Card]

Data Type: int64

There is no null value

Number of Unique Values: 1179

Distribution of column:
```

```
Num_Credit_Card
5      18459
7      16615
6      16559
4      14030
3      13277
       …
551        1
426        1
784        1
673        1
599        1
Name: count, Length: 1179, dtype: int64

****************************************
```

[ ]:
```
displot_plot(preview_dataframe, 'Num_Credit_Card', bins=100)
```

```
****************************************

Num_Credit_Card Distribution
```



4.4.6 06. Interest_Rate

Findings: * outliers should be replaced

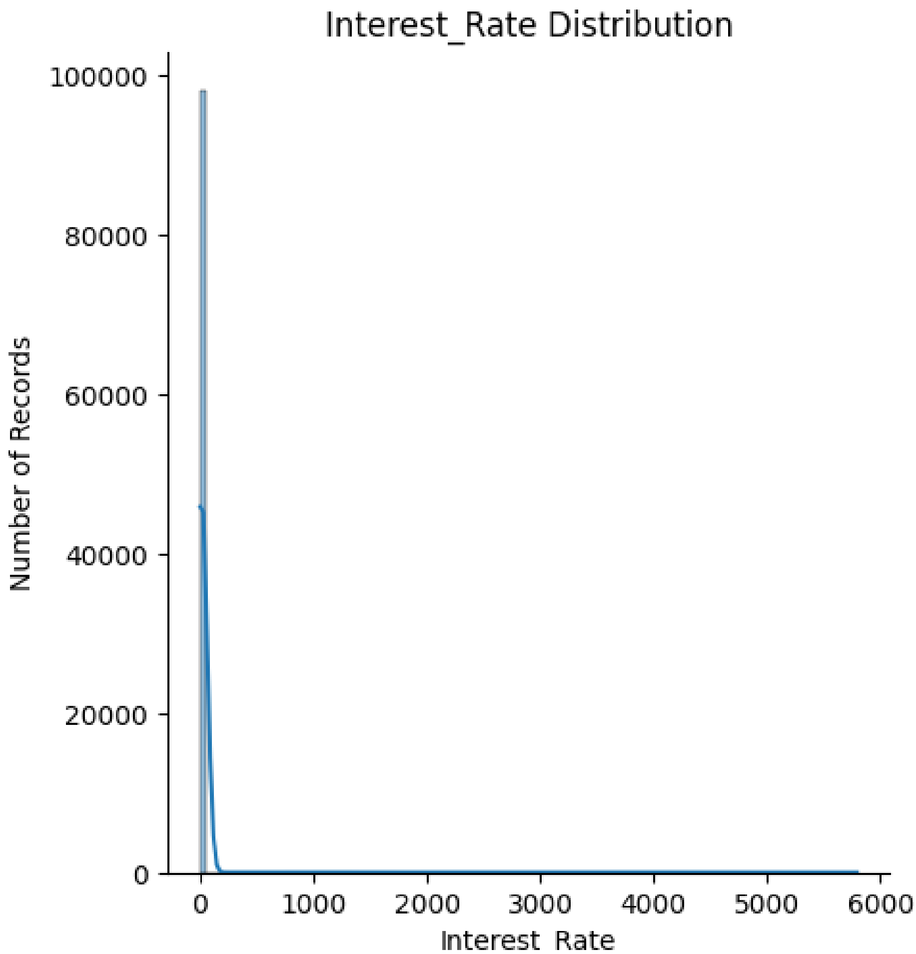
```
[ ]: get_column_detail(preview_dataframe, 'Interest_Rate')
```

```
****************************************

Details of column [Interest_Rate]

Data Type: int64

There is no null value

Number of Unique Values: 1750

Distribution of column:
```

```
Interest_Rate
8       5012
5       4979
6       4721
10      4540
12      4540
        …
3782       1
3849       1
2206       1
4828       1
1683       1
Name: count, Length: 1750, dtype: int64

****************************************
```

[ ]:
```
displot_plot(preview_dataframe, 'Interest_Rate', bins=100)
```

```
****************************************

Interest_Rate Distribution
```



4.4.7 07. Delay_from_due_date

Findings: * outliers should be replaced

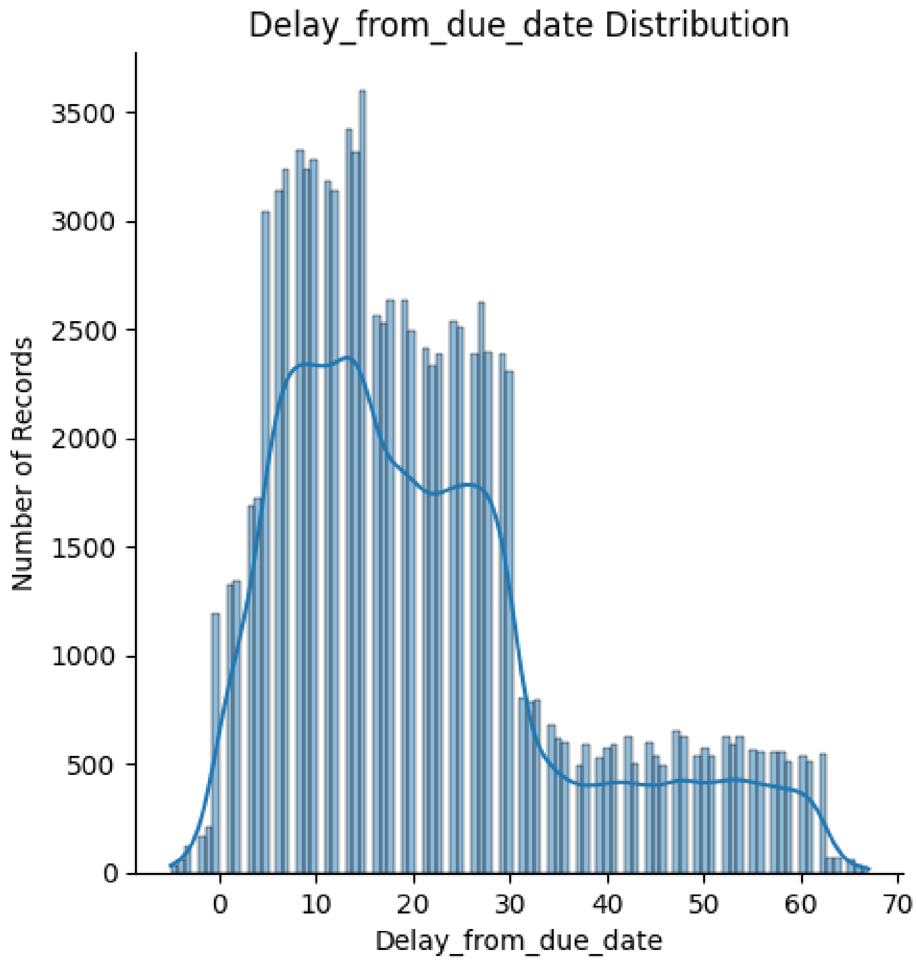
[ ]:
```
get_column_detail(preview_dataframe, 'Delay_from_due_date')
```

```
****************************************

Details of column [Delay_from_due_date]

Data Type: int64

There is no null value

Number of Unique Values: 73

Distribution of column:
```

```
Delay_from_due_date
 15    3596
 13    3424
 8     3324
 14    3313
 10    3281
       …
-4       62
 65      56
-5       33
 66      32
 67      22
Name: count, Length: 73, dtype: int64

****************************************
```

[ ]:
```
displot_plot(preview_dataframe, 'Delay_from_due_date', bins=100)
```

```
****************************************

Delay_from_due_date Distribution
```



4.4.8 08. Num_Credit_Inquiries

Findings: * outlier should be replaced * null values

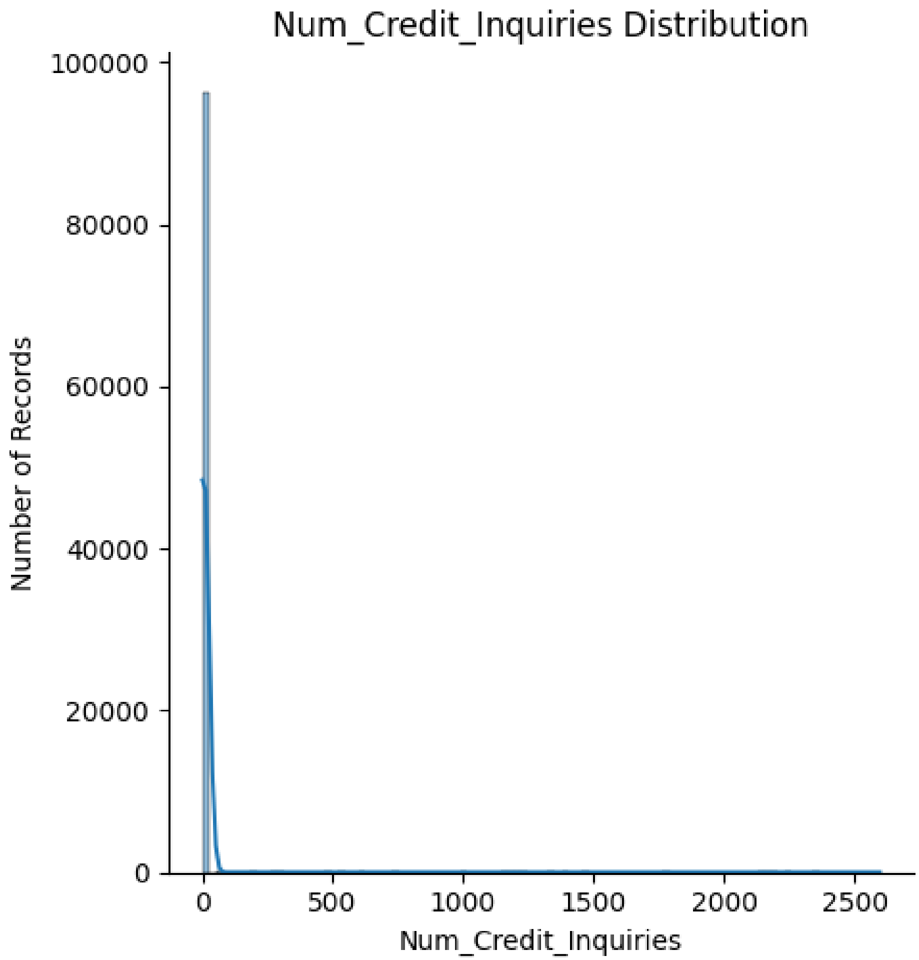
[ ]:
```
get_column_detail(preview_dataframe, 'Num_Credit_Inquiries')
```

```
****************************************

Details of column [Num_Credit_Inquiries]

Data Type: float64

There are 1965 null values

Number of Unique Values: 1223

Distribution of column:
```

```
Num_Credit_Inquiries
4.0       11271
3.0        8890
6.0        8111
7.0        8058
2.0        8028
          …
719.0         1
2239.0        1
2001.0        1
1953.0        1
2473.0        1
Name: count, Length: 1224, dtype: int64

****************************************
```

[ ]:
```
displot_plot(preview_dataframe, 'Num_Credit_Inquiries', bins=100)
```

```
****************************************

Num_Credit_Inquiries Distribution
```



4.4.9 09. Credit__Utilization__Ratio

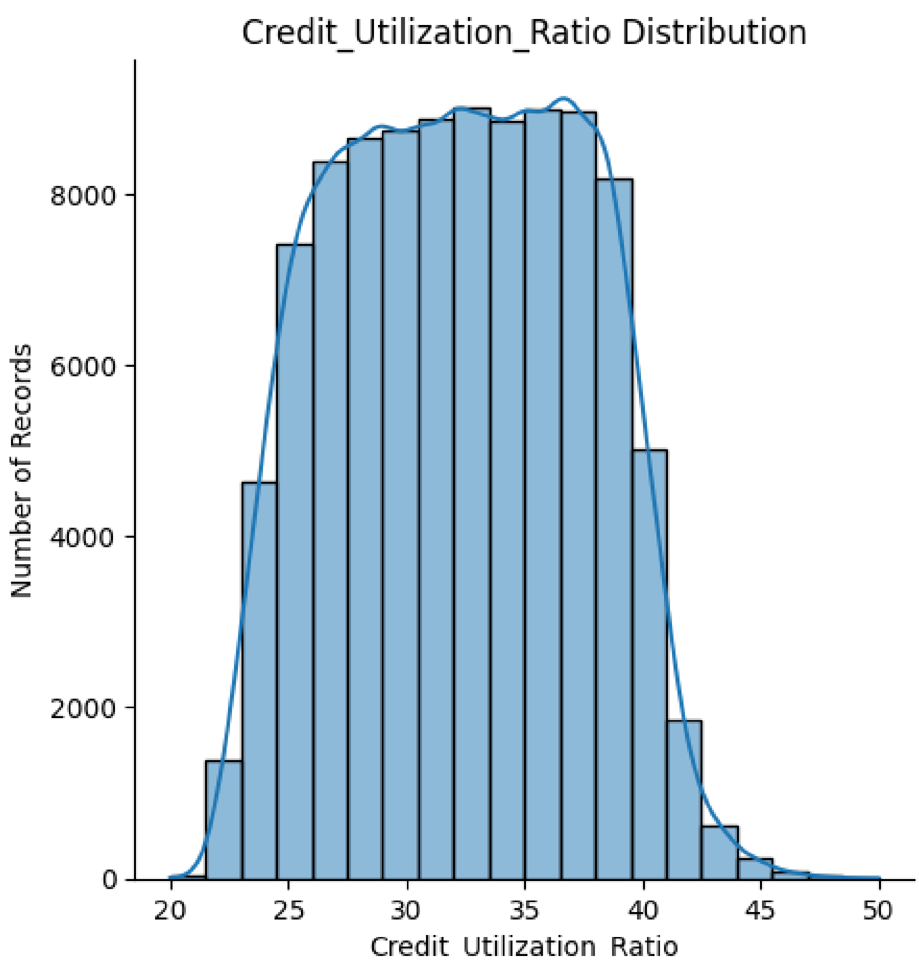
[ ]:
```
get_column_detail(preview_dataframe, 'Credit_Utilization_Ratio')
```

```
****************************************

Details of column [Credit_Utilization_Ratio]

Data Type: float64

There is no null value

Number of Unique Values: 100000

Distribution of column:

Credit_Utilization_Ratio
```

```
27.289440    1
33.494867    1
31.738359    1
30.625298    1
23.140640    1
            ..
31.377862    1
24.797347    1
27.262259    1
22.537593    1
23.933795    1
Name: count, Length: 100000, dtype: int64

****************************************
```

[ ]:
```
displot_plot(preview_dataframe, 'Credit_Utilization_Ratio')
```

```
****************************************

Credit_Utilization_Ratio Distribution
```



4.4.10 10. Total_EMI_per_month

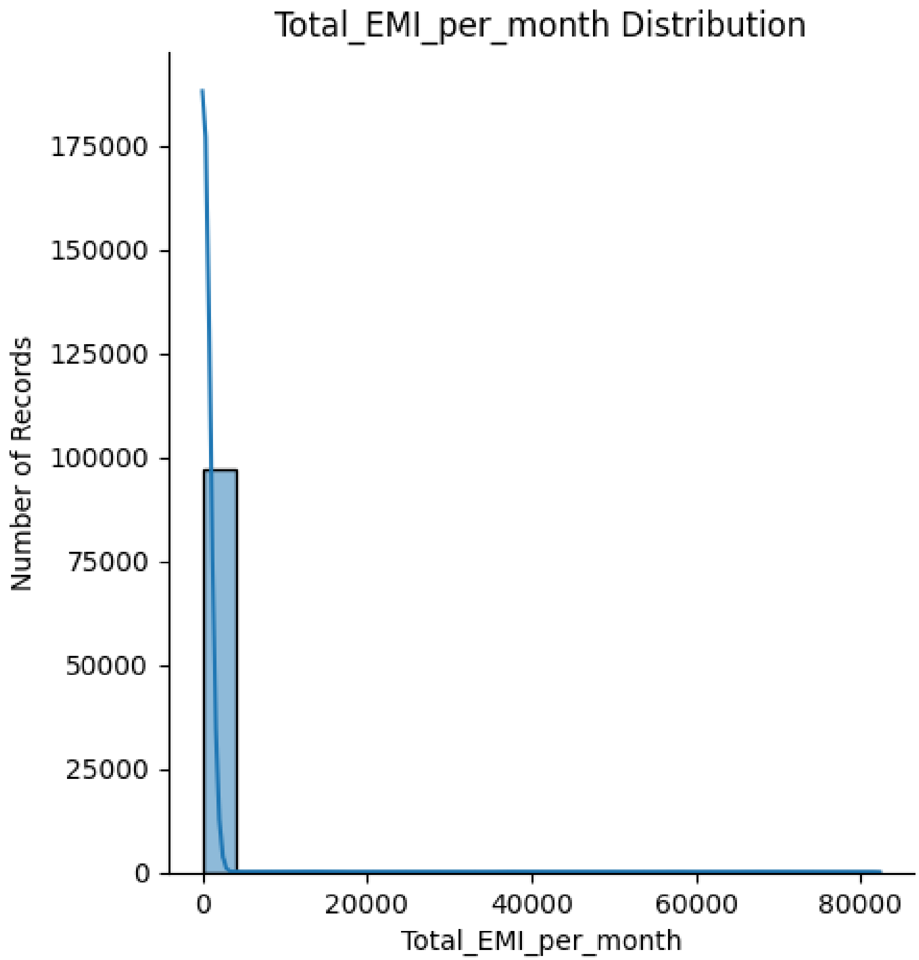
Findings: * outliers should be replaced

[ ]:
```
get_column_detail(preview_dataframe, 'Total_EMI_per_month')
```

```
****************************************

Details of column [Total_EMI_per_month]

Data Type: float64

There is no null value

Number of Unique Values: 14950

Distribution of column:

Total_EMI_per_month
0.000000        10613
54.037058           8
30.230996           8
54.079318           8
45.341401           8
                 …
61445.000000        1
73821.000000        1
55113.000000        1
61723.000000        1
31660.000000        1
Name: count, Length: 14950, dtype: int64

****************************************
```

[ ]:
```
displot_plot(preview_dataframe, 'Total_EMI_per_month', rotation=0)
```

```
****************************************

Total_EMI_per_month Distribution
```



4.5 Finding after going through each attributes in depth

1. Need to replace outliers
2. Need to replace strange values
3. Need to replace null values
4. Payment of Min amount and credit mix seems to be higly correlated to target
5. Target Columns is Imbalanced

5 4. Data Pre-processing

5.1 Read data from csv file

[ ]:
```
# Replace some error values to NaN when reading the csv
data = pd.read_csv("train.csv", na_values=['nan', '_', '_______', '#F%$D@*&8',␣
↪'!@9#%8', '__10000__'])

data.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                       94428 non-null   object 
 6   Occupation                92938 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      97909 non-null   float64
 17  Num_Credit_Inquiries      98035 non-null   float64
 18  Credit_Mix                79805 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   91216 non-null   float64
 25  Payment_Behaviour         92400 non-null   object 
 26  Monthly_Balance           98800 non-null   object 
 27  Credit_Score              100000 non-null  object 
dtypes: float64(6), int64(4), object(18)
memory usage: 21.4+ MB
```

5.2 Pre-processing

[ ]:
```python
# Function for reducing the outliers
def outlier_handling(df, median, target):
    id = df['Customer_ID']
    tar = df[target]
    if (abs(median[id] - tar) > 1):
        return median[id].astype(np.int64)
    else:
        return tar
```

```
[ ]: # Copy the data into a new DataFrame to not corrupt the original data
df = data.copy()

# Drop the columns which are not required
df.drop(['Name'], axis=1, inplace=True)
df.drop(['SSN'], axis=1, inplace=True)
```

5.2.1 Change the data type of the columns

```
[ ]: # Remove the error values from the data
df["Age"] = df["Age"].str.replace("_","")
df["Annual_Income"] = df["Annual_Income"].str.replace("_","")
df["Num_of_Loan"] = df["Num_of_Loan"].str.replace("_","")
df["Num_of_Delayed_Payment"] = df["Num_of_Delayed_Payment"].str.replace("_","")
```

```
[ ]: # Convert the data type of the columns to numeric
to_numeric_columns = ['Age', 'Annual_Income', 'Num_of_Loan',␣
 ↪'Num_of_Delayed_Payment', 'Num_Credit_Inquiries', 'Changed_Credit_Limit',␣
 ↪'Amount_invested_monthly', 'Outstanding_Debt', 'Monthly_Balance']
df[to_numeric_columns] = df[to_numeric_columns].apply(pd.to_numeric,␣
 ↪errors='coerce')
df['Month'] = pd.to_datetime(df['Month'], format="%B").dt.month.astype(np.int64)
```

5.2.2 Fill the missing values

```
[ ]: # Fill the missing values with the mean, mode and first value matches to␣
 ↪Customer_ID
fillna_with_mean = ['Monthly_Inhand_Salary', 'Num_Credit_Inquiries',␣
 ↪'Changed_Credit_Limit', 'Outstanding_Debt', 'Amount_invested_monthly',␣
 ↪'Monthly_Balance']
fillna_with_mode = ['Occupation', 'Payment_of_Min_Amount',␣
 ↪'Num_of_Delayed_Payment', 'Credit_Mix']
fillna_with_first = ['Age', 'Type_of_Loan']
df[fillna_with_mean] = df[fillna_with_mean].fillna(df.
 ↪groupby('Customer_ID')[fillna_with_mean].transform('mean'))
df[fillna_with_mode] = df[fillna_with_mode].fillna(df.
 ↪groupby('Customer_ID')[fillna_with_mode].transform(lambda x: x.mode().
 ↪iloc[0]))
df[fillna_with_first] = df[fillna_with_first].fillna(df.
 ↪groupby('Customer_ID')[fillna_with_first].transform('first'))
df['Type_of_Loan'].fillna("Not Specified", inplace=True)
df['Age'] = df['Age'].astype(np.int64)
```

5.2.3 Reduce the outliers

```
[ ]: # Reduce outliers from the data, and replace them with the median
outlier_columns = ['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', 'Num_Credit_Inquiries',␣
 ↪'Outstanding_Debt',\
                    'Total_EMI_per_month', 'Amount_invested_monthly',␣
 ↪'Monthly_Balance']
medians = {}
for i in range(len(outlier_columns)):
    median = df.groupby('Customer_ID')[outlier_columns[i]].median()
    df[outlier_columns[i]] = df.apply(lambda row: outlier_handling(row, median,␣
 ↪outlier_columns[i]), axis=1)

print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 26 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   ID                        100000 non-null  object
 1   Customer_ID               100000 non-null  object
 2   Month                     100000 non-null  int64
 3   Age                       100000 non-null  int64
 4   Occupation                100000 non-null  object
 5   Annual_Income             100000 non-null  float64
 6   Monthly_Inhand_Salary     100000 non-null  float64
 7   Num_Bank_Accounts         100000 non-null  int64
 8   Num_Credit_Card           100000 non-null  int64
 9   Interest_Rate             100000 non-null  int64
 10  Num_of_Loan               100000 non-null  int64
 11  Type_of_Loan              100000 non-null  object
 12  Delay_from_due_date       100000 non-null  int64
 13  Num_of_Delayed_Payment    100000 non-null  int64
 14  Changed_Credit_Limit      100000 non-null  float64
 15  Num_Credit_Inquiries      100000 non-null  float64
 16  Credit_Mix                100000 non-null  object
 17  Outstanding_Debt          100000 non-null  float64
 18  Credit_Utilization_Ratio  100000 non-null  float64
 19  Credit_History_Age        90970 non-null   object
 20  Payment_of_Min_Amount     100000 non-null  object
 21  Total_EMI_per_month       100000 non-null  float64
 22  Amount_invested_monthly   100000 non-null  float64
 23  Payment_Behaviour         92400 non-null   object
```

```
 24  Monthly_Balance           100000 non-null  float64
 25  Credit_Score              100000 non-null  object
dtypes: float64(9), int64(8), object(9)
memory usage: 19.8+ MB
None
```

5.2.4 Label encoding on categorical columns

[ ]:

```python
# Getting unique values for non-numerical columns
nonNumCols = df.select_dtypes(include=['object']).columns

for col in nonNumCols:
    print(col)
    print(df[col].unique())
```

```
ID
['0x1602' '0x1603' '0x1604' … '0x25feb' '0x25fec' '0x25fed']
Customer_ID
['CUS_0xd40' 'CUS_0x21b1' 'CUS_0x2dbc' … 'CUS_0xaf61' 'CUS_0x8600'
 'CUS_0x942c']
Occupation
['Scientist' 'Teacher' 'Engineer' 'Entrepreneur' 'Developer' 'Lawyer'
 'Media_Manager' 'Doctor' 'Journalist' 'Manager' 'Accountant' 'Musician'
 'Mechanic' 'Writer' 'Architect']
Type_of_Loan
['Auto Loan, Credit-Builder Loan, Personal Loan, and Home Equity Loan'
 'Credit-Builder Loan' 'Auto Loan, Auto Loan, and Not Specified' …
 'Home Equity Loan, Auto Loan, Auto Loan, and Auto Loan'
 'Payday Loan, Student Loan, Mortgage Loan, and Not Specified'
 'Personal Loan, Auto Loan, Mortgage Loan, Student Loan, and Student Loan']
Credit_Mix
['Good' 'Standard' 'Bad']
Credit_History_Age
['22 Years and 1 Months' nan '22 Years and 3 Months'
 '22 Years and 4 Months' '22 Years and 5 Months' '22 Years and 6 Months'
 '22 Years and 7 Months' '26 Years and 7 Months' '26 Years and 8 Months'
 '26 Years and 9 Months' '26 Years and 10 Months' '26 Years and 11 Months'
 '27 Years and 0 Months' '27 Years and 1 Months' '27 Years and 2 Months'
 '17 Years and 9 Months' '17 Years and 10 Months' '17 Years and 11 Months'
 '18 Years and 1 Months' '18 Years and 2 Months' '18 Years and 3 Months'
 '18 Years and 4 Months' '17 Years and 3 Months' '17 Years and 4 Months'
 '17 Years and 5 Months' '17 Years and 6 Months' '17 Years and 7 Months'
 '17 Years and 8 Months' '30 Years and 8 Months' '30 Years and 9 Months'
 '30 Years and 10 Months' '30 Years and 11 Months' '31 Years and 0 Months'
 '31 Years and 1 Months' '31 Years and 2 Months' '31 Years and 3 Months'
 '32 Years and 0 Months' '32 Years and 2 Months' '32 Years and 3 Months'
 '32 Years and 5 Months' '32 Years and 6 Months' '30 Years and 7 Months'
 '14 Years and 8 Months' '14 Years and 9 Months' '14 Years and 10 Months'
```

```
'14 Years and 11 Months' '15 Years and 0 Months' '15 Years and 1 Months'
'15 Years and 2 Months' '21 Years and 4 Months' '21 Years and 5 Months'
'21 Years and 6 Months' '21 Years and 7 Months' '21 Years and 8 Months'
'21 Years and 9 Months' '21 Years and 10 Months' '21 Years and 11 Months'
'26 Years and 6 Months' '19 Years and 2 Months' '19 Years and 3 Months'
'19 Years and 4 Months' '19 Years and 5 Months' '19 Years and 6 Months'
'19 Years and 7 Months' '19 Years and 8 Months' '25 Years and 5 Months'
'25 Years and 6 Months' '25 Years and 7 Months' '25 Years and 8 Months'
'25 Years and 9 Months' '25 Years and 10 Months' '25 Years and 11 Months'
'26 Years and 0 Months' '27 Years and 3 Months' '27 Years and 4 Months'
'27 Years and 5 Months' '8 Years and 11 Months' '9 Years and 0 Months'
'9 Years and 1 Months' '9 Years and 2 Months' '9 Years and 3 Months'
'9 Years and 4 Months' '9 Years and 6 Months' '18 Years and 5 Months'
'18 Years and 6 Months' '18 Years and 8 Months' '18 Years and 9 Months'
'16 Years and 10 Months' '16 Years and 11 Months' '17 Years and 0 Months'
'17 Years and 1 Months' '17 Years and 2 Months' '29 Years and 2 Months'
'29 Years and 3 Months' '29 Years and 4 Months' '29 Years and 6 Months'
'29 Years and 8 Months' '29 Years and 9 Months' '6 Years and 5 Months'
'6 Years and 6 Months' '6 Years and 7 Months' '6 Years and 8 Months'
'6 Years and 9 Months' '6 Years and 10 Months' '6 Years and 11 Months'
'7 Years and 0 Months' '27 Years and 6 Months' '27 Years and 7 Months'
'27 Years and 8 Months' '27 Years and 9 Months' '18 Years and 7 Months'
'19 Years and 9 Months' '19 Years and 10 Months' '10 Years and 1 Months'
'10 Years and 2 Months' '10 Years and 3 Months' '10 Years and 4 Months'
'10 Years and 5 Months' '10 Years and 6 Months' '10 Years and 7 Months'
'10 Years and 8 Months' '32 Years and 9 Months' '32 Years and 10 Months'
'32 Years and 11 Months' '33 Years and 0 Months' '33 Years and 1 Months'
'33 Years and 4 Months' '12 Years and 3 Months' '12 Years and 4 Months'
'12 Years and 5 Months' '12 Years and 6 Months' '12 Years and 7 Months'
'12 Years and 8 Months' '12 Years and 10 Months' '12 Years and 9 Months'
'13 Years and 8 Months' '13 Years and 11 Months' '14 Years and 0 Months'
'14 Years and 1 Months' '14 Years and 2 Months' '14 Years and 3 Months'
'30 Years and 3 Months' '30 Years and 4 Months' '30 Years and 5 Months'
'30 Years and 6 Months' '8 Years and 9 Months' '8 Years and 10 Months'
'18 Years and 10 Months' '18 Years and 11 Months' '19 Years and 0 Months'
'19 Years and 1 Months' '8 Years and 8 Months' '13 Years and 1 Months'
'13 Years and 2 Months' '13 Years and 3 Months' '13 Years and 5 Months'
'13 Years and 6 Months' '13 Years and 7 Months' '22 Years and 0 Months'
'26 Years and 1 Months' '26 Years and 2 Months' '13 Years and 4 Months'
'13 Years and 9 Months' '27 Years and 11 Months' '28 Years and 0 Months'
'28 Years and 1 Months' '28 Years and 2 Months' '28 Years and 3 Months'
'28 Years and 4 Months' '28 Years and 5 Months' '28 Years and 6 Months'
'7 Years and 10 Months' '7 Years and 11 Months' '8 Years and 0 Months'
'8 Years and 1 Months' '8 Years and 2 Months' '8 Years and 3 Months'
'8 Years and 4 Months' '8 Years and 5 Months' '24 Years and 3 Months'
'24 Years and 4 Months' '24 Years and 5 Months' '24 Years and 6 Months'
'24 Years and 7 Months' '24 Years and 8 Months' '24 Years and 9 Months'
'1 Years and 2 Months' '1 Years and 3 Months' '1 Years and 4 Months'
```

```
'1 Years and 5 Months' '1 Years and 6 Months' '1 Years and 7 Months'
'1 Years and 8 Months' '10 Years and 11 Months' '11 Years and 0 Months'
'11 Years and 1 Months' '11 Years and 2 Months' '11 Years and 3 Months'
'11 Years and 4 Months' '11 Years and 5 Months' '11 Years and 6 Months'
'19 Years and 11 Months' '20 Years and 0 Months' '20 Years and 1 Months'
'10 Years and 9 Months' '10 Years and 10 Months' '14 Years and 4 Months'
'14 Years and 5 Months' '14 Years and 6 Months' '20 Years and 8 Months'
'20 Years and 9 Months' '20 Years and 10 Months' '20 Years and 11 Months'
'21 Years and 0 Months' '21 Years and 1 Months' '21 Years and 2 Months'
'21 Years and 3 Months' '0 Years and 4 Months' '0 Years and 5 Months'
'0 Years and 6 Months' '0 Years and 8 Months' '0 Years and 9 Months'
'0 Years and 10 Months' '31 Years and 7 Months' '31 Years and 8 Months'
'31 Years and 9 Months' '31 Years and 10 Months' '31 Years and 11 Months'
'32 Years and 1 Months' '12 Years and 11 Months' '13 Years and 0 Months'
'27 Years and 10 Months' '11 Years and 7 Months' '11 Years and 8 Months'
'11 Years and 9 Months' '11 Years and 10 Months' '24 Years and 10 Months'
'24 Years and 11 Months' '25 Years and 0 Months' '25 Years and 1 Months'
'25 Years and 2 Months' '25 Years and 3 Months' '18 Years and 0 Months'
'31 Years and 4 Months' '31 Years and 5 Months' '31 Years and 6 Months'
'5 Years and 2 Months' '5 Years and 3 Months' '5 Years and 4 Months'
'5 Years and 5 Months' '5 Years and 6 Months' '5 Years and 7 Months'
'5 Years and 8 Months' '5 Years and 9 Months' '2 Years and 11 Months'
'3 Years and 0 Months' '3 Years and 1 Months' '3 Years and 2 Months'
'3 Years and 3 Months' '3 Years and 4 Months' '3 Years and 5 Months'
'3 Years and 6 Months' '16 Years and 4 Months' '16 Years and 5 Months'
'16 Years and 6 Months' '16 Years and 7 Months' '16 Years and 8 Months'
'16 Years and 9 Months' '22 Years and 11 Months' '23 Years and 0 Months'
'23 Years and 2 Months' '23 Years and 3 Months' '23 Years and 4 Months'
'23 Years and 5 Months' '23 Years and 6 Months' '8 Years and 6 Months'
'8 Years and 7 Months' '4 Years and 5 Months' '4 Years and 6 Months'
'4 Years and 7 Months' '4 Years and 8 Months' '4 Years and 9 Months'
'4 Years and 10 Months' '4 Years and 11 Months' '5 Years and 0 Months'
'32 Years and 8 Months' '33 Years and 2 Months' '33 Years and 3 Months'
'12 Years and 2 Months' '32 Years and 4 Months' '29 Years and 11 Months'
'30 Years and 0 Months' '30 Years and 2 Months' '26 Years and 3 Months'
'26 Years and 4 Months' '26 Years and 5 Months' '7 Years and 6 Months'
'7 Years and 7 Months' '7 Years and 8 Months' '7 Years and 9 Months'
'28 Years and 7 Months' '28 Years and 8 Months' '28 Years and 9 Months'
'28 Years and 10 Months' '29 Years and 5 Months' '29 Years and 7 Months'
'20 Years and 2 Months' '20 Years and 3 Months' '20 Years and 4 Months'
'20 Years and 5 Months' '20 Years and 6 Months' '20 Years and 7 Months'
'28 Years and 11 Months' '29 Years and 0 Months' '13 Years and 10 Months'
'1 Years and 9 Months' '1 Years and 10 Months' '1 Years and 11 Months'
'33 Years and 5 Months' '33 Years and 6 Months' '33 Years and 7 Months'
'33 Years and 8 Months' '29 Years and 1 Months' '5 Years and 1 Months'
'5 Years and 10 Months' '5 Years and 11 Months' '6 Years and 0 Months'
'6 Years and 1 Months' '6 Years and 2 Months' '6 Years and 3 Months'
'22 Years and 9 Months' '22 Years and 10 Months' '23 Years and 1 Months'
```

```
 '22 Years and 2 Months' '15 Years and 4 Months' '15 Years and 5 Months'
 '15 Years and 6 Months' '15 Years and 7 Months' '15 Years and 8 Months'
 '15 Years and 9 Months' '15 Years and 10 Months' '15 Years and 11 Months'
 '2 Years and 3 Months' '2 Years and 4 Months' '2 Years and 5 Months'
 '2 Years and 6 Months' '2 Years and 7 Months' '2 Years and 8 Months'
 '2 Years and 9 Months' '2 Years and 10 Months' '2 Years and 0 Months'
 '16 Years and 2 Months' '16 Years and 3 Months' '22 Years and 8 Months'
 '9 Years and 5 Months' '9 Years and 7 Months' '9 Years and 8 Months'
 '9 Years and 9 Months' '11 Years and 11 Months' '12 Years and 0 Months'
 '12 Years and 1 Months' '24 Years and 2 Months' '16 Years and 0 Months'
 '16 Years and 1 Months' '14 Years and 7 Months' '25 Years and 4 Months'
 '15 Years and 3 Months' '7 Years and 1 Months' '7 Years and 2 Months'
 '7 Years and 3 Months' '7 Years and 4 Months' '7 Years and 5 Months'
 '23 Years and 7 Months' '23 Years and 8 Months' '23 Years and 9 Months'
 '30 Years and 1 Months' '29 Years and 10 Months' '9 Years and 10 Months'
 '9 Years and 11 Months' '10 Years and 0 Months' '2 Years and 2 Months'
 '23 Years and 10 Months' '23 Years and 11 Months' '24 Years and 0 Months'
 '24 Years and 1 Months' '6 Years and 4 Months' '0 Years and 1 Months'
 '0 Years and 2 Months' '0 Years and 3 Months' '0 Years and 7 Months'
 '3 Years and 8 Months' '32 Years and 7 Months' '3 Years and 7 Months'
 '3 Years and 9 Months' '3 Years and 10 Months' '0 Years and 11 Months'
 '1 Years and 0 Months' '1 Years and 1 Months' '4 Years and 4 Months'
 '3 Years and 11 Months' '4 Years and 0 Months' '4 Years and 1 Months'
 '4 Years and 2 Months' '4 Years and 3 Months' '2 Years and 1 Months']
Payment_of_Min_Amount
['No' 'NM' 'Yes']
Payment_Behaviour
['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' nan 'High_spent_Large_value_payments']
Credit_Score
['Good' 'Standard' 'Poor']
```

[ ]:

```
categorical_cols = df[['Occupation','Payment_of_Min_Amount','Payment_Behaviour']]

# Initialize a LabelEncoder for each categorical/nominal column
# Month,
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le

# Converting ordinal data ['Credit_Mix','Credit_Score']
customScoreMapping = {'Good': 2, 'Standard': 1, 'Poor': 0}
df['Credit_Score'] = df['Credit_Score'].map(customScoreMapping)
```

```python
customMixMapping = {'Good': 2, 'Standard': 1, 'Bad': 0}
df['Credit_Mix'] = df['Credit_Mix'].map(customMixMapping)

# Converting Credit History Age into months
# Extract years and months using regular expressions
df['Years'] = df['Credit_History_Age'].str.extract('(\d+) Years', expand=False).
 ↪astype(float)
df['Months'] = df['Credit_History_Age'].str.extract('(\d+) Months',␣
 ↪expand=False).astype(float)

# Calculate the total duration in months
df['Credit_History_Age'] = df['Years'] * 12 + df['Months']
df['Credit_History_Age'] = df.groupby('Customer_ID')['Credit_History_Age'].
 ↪transform(lambda x: x.interpolate(method='index', limit_direction='both') if␣
 ↪x.count() > 1 else x)

df.drop(['ID','Customer_ID','Type_of_Loan'], axis=1, inplace=True)
df.drop(['Years','Months'], axis=1 ,inplace=True)

df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 23 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   Month                     100000 non-null  int64
 1   Age                       100000 non-null  int64
 2   Occupation                100000 non-null  int64
 3   Annual_Income             100000 non-null  float64
 4   Monthly_Inhand_Salary     100000 non-null  float64
 5   Num_Bank_Accounts         100000 non-null  int64
 6   Num_Credit_Card           100000 non-null  int64
 7   Interest_Rate             100000 non-null  int64
 8   Num_of_Loan               100000 non-null  int64
 9   Delay_from_due_date       100000 non-null  int64
 10  Num_of_Delayed_Payment    100000 non-null  int64
 11  Changed_Credit_Limit      100000 non-null  float64
 12  Num_Credit_Inquiries      100000 non-null  float64
 13  Credit_Mix                100000 non-null  int64
 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  int64
 18  Total_EMI_per_month       100000 non-null  float64
```

```
 19  Amount_invested_monthly   100000 non-null  float64
 20  Payment_Behaviour         100000 non-null  int64
 21  Monthly_Balance           100000 non-null  float64
 22  Credit_Score              100000 non-null  int64
dtypes: float64(10), int64(13)
memory usage: 17.5 MB
```

[ ]:

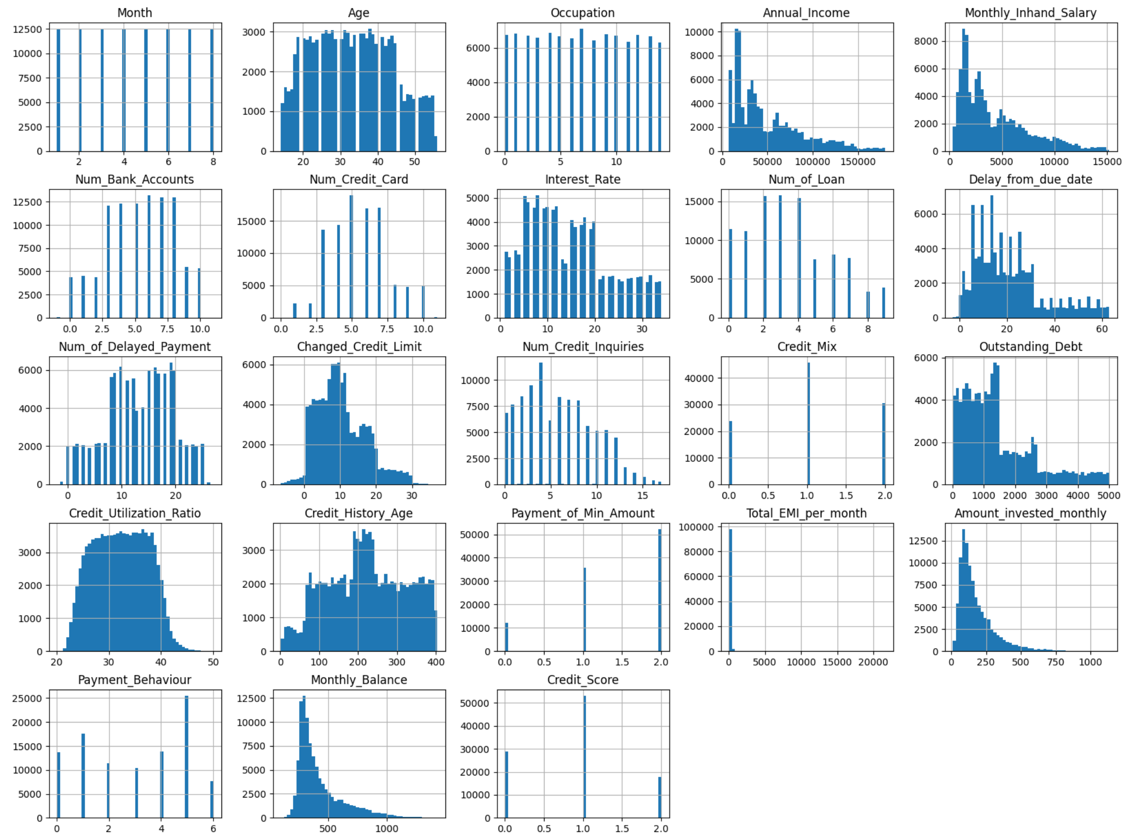
```
   Month  Age  Occupation  Annual_Income  Monthly_Inhand_Salary  \
0      1   23          12       19114.12            1824.843333
1      2   23          12       19114.12            1824.843333
2      3   23          12       19114.12            1824.843333
3      4   23          12       19114.12            1824.843333
4      5   23          12       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

   Delay_from_due_date  …  Credit_Mix  Outstanding_Debt  \
0                    3  …           2            809.98
1                    3  …           2            809.98
2                    3  …           2            809.98
3                    3  …           2            809.98
4                    3  …           2            809.98

   Credit_Utilization_Ratio  Credit_History_Age  Payment_of_Min_Amount  \
0                 26.822620               265.0                      1
1                 31.944960               266.0                      1
2                 28.609352               267.0                      1
3                 31.377862               268.0                      1
4                 24.797347               269.0                      1

   Total_EMI_per_month  Amount_invested_monthly  Payment_Behaviour  \
0            49.574949                80.415295                  2
1            49.574949                81.000000                  3
2            49.574949                81.699521                  4
3            49.574949                81.000000                  5
4            49.574949                81.000000                  1

   Monthly_Balance  Credit_Score
0            321.0             2
1            321.0             2
2            321.0             2
3            321.0             2
```

```
4            321.0            2

[5 rows x 23 columns]
```

5.2.5 Diagrams after preprocessing (to check if all issues are resolved)

```
[ ]: df.hist(bins=50, figsize=(20,15))
```

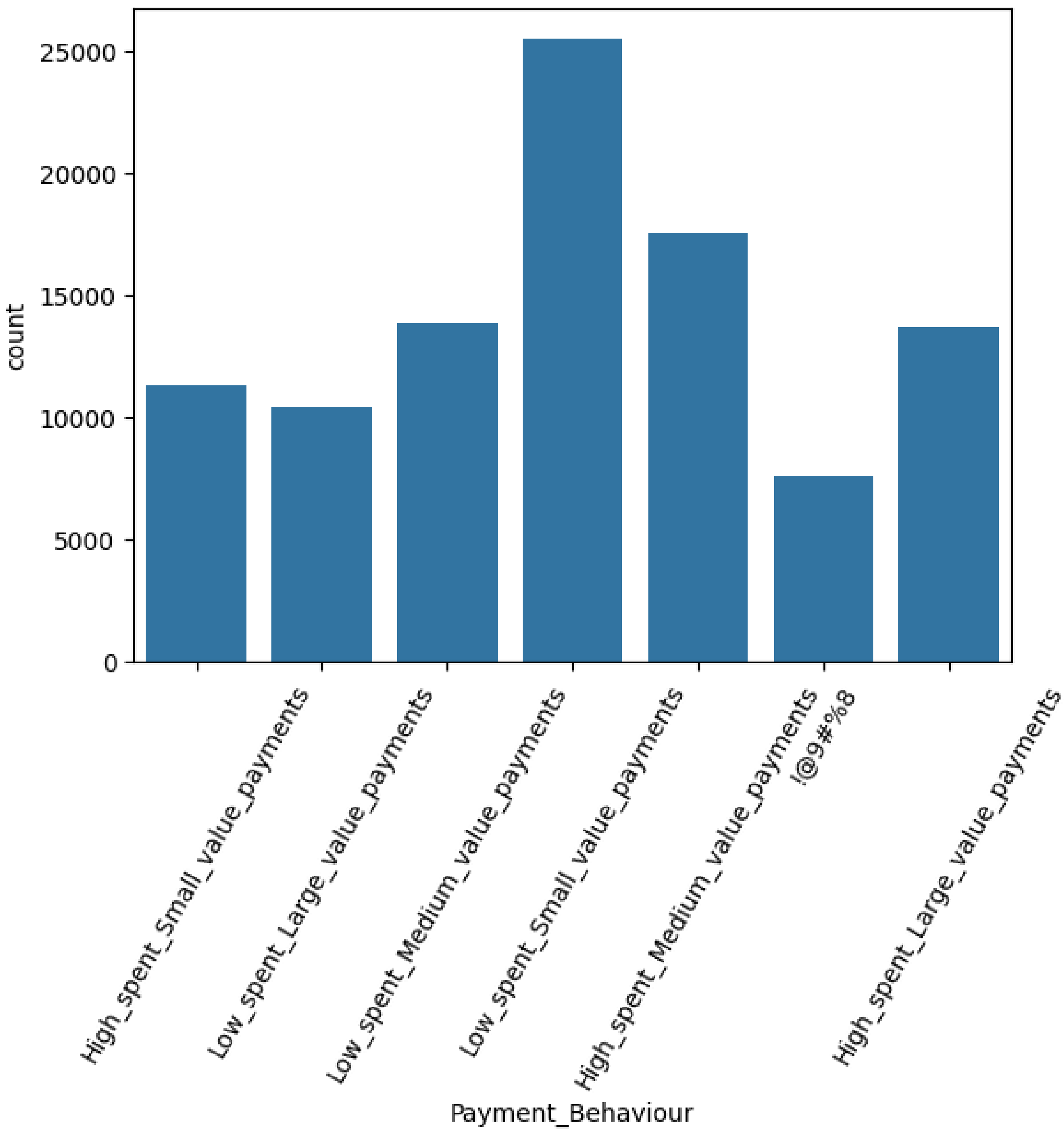
```
[ ]: array([[<Axes: title={'center': 'Month'}>,
            <Axes: title={'center': 'Age'}>,
            <Axes: title={'center': 'Occupation'}>,
            <Axes: title={'center': 'Annual_Income'}>,
            <Axes: title={'center': 'Monthly_Inhand_Salary'}>],
           [<Axes: title={'center': 'Num_Bank_Accounts'}>,
            <Axes: title={'center': 'Num_Credit_Card'}>,
            <Axes: title={'center': 'Interest_Rate'}>,
            <Axes: title={'center': 'Num_of_Loan'}>,
            <Axes: title={'center': 'Delay_from_due_date'}>],
           [<Axes: title={'center': 'Num_of_Delayed_Payment'}>,
            <Axes: title={'center': 'Changed_Credit_Limit'}>,
            <Axes: title={'center': 'Num_Credit_Inquiries'}>,
            <Axes: title={'center': 'Credit_Mix'}>,
            <Axes: title={'center': 'Outstanding_Debt'}>],
           [<Axes: title={'center': 'Credit_Utilization_Ratio'}>,
            <Axes: title={'center': 'Credit_History_Age'}>,
            <Axes: title={'center': 'Payment_of_Min_Amount'}>,
            <Axes: title={'center': 'Total_EMI_per_month'}>,
            <Axes: title={'center': 'Amount_invested_monthly'}>],
           [<Axes: title={'center': 'Payment_Behaviour'}>,
            <Axes: title={'center': 'Monthly_Balance'}>,
            <Axes: title={'center': 'Credit_Score'}>, <Axes: >, <Axes: >]],
          dtype=object)
```



Removing strange values

Before

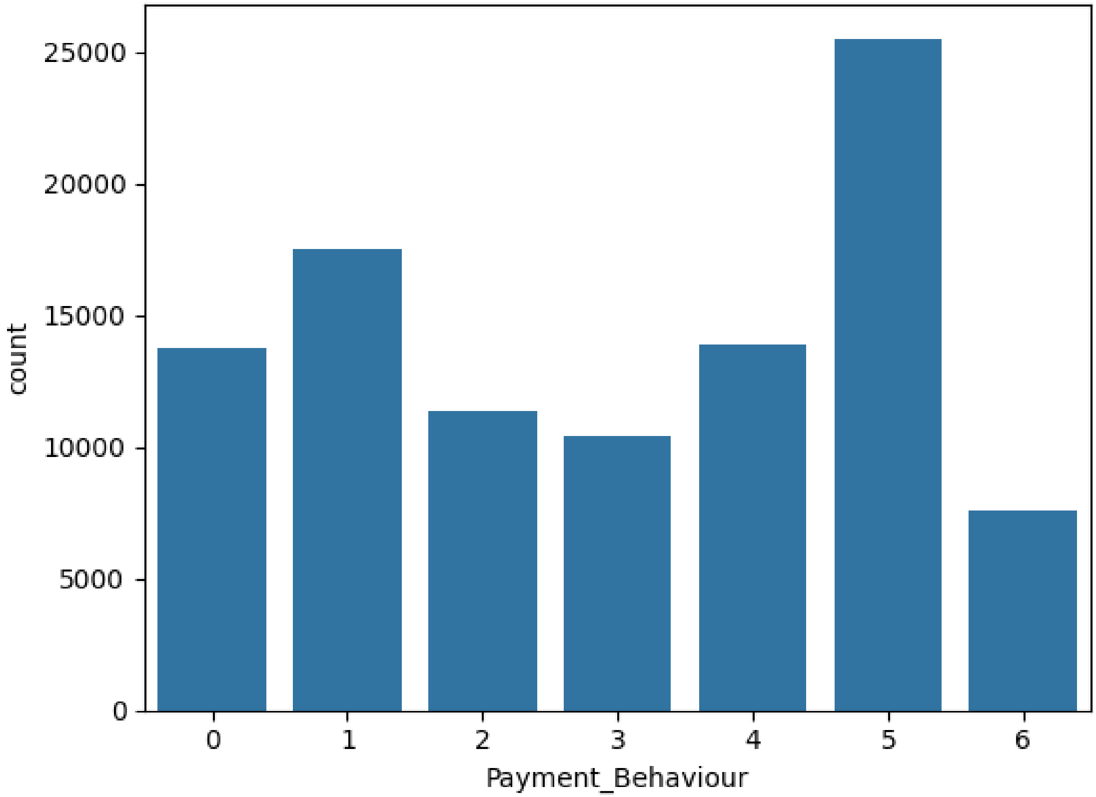
[ ]:
```
sns.countplot(preview_dataframe, x = 'Payment_Behaviour')
plt.xticks(rotation = 60)
plt.show()
```



After

[ ]:
```
sns.countplot(df, x = 'Payment_Behaviour')
```

[ ]: <Axes: xlabel='Payment_Behaviour', ylabel='count'>

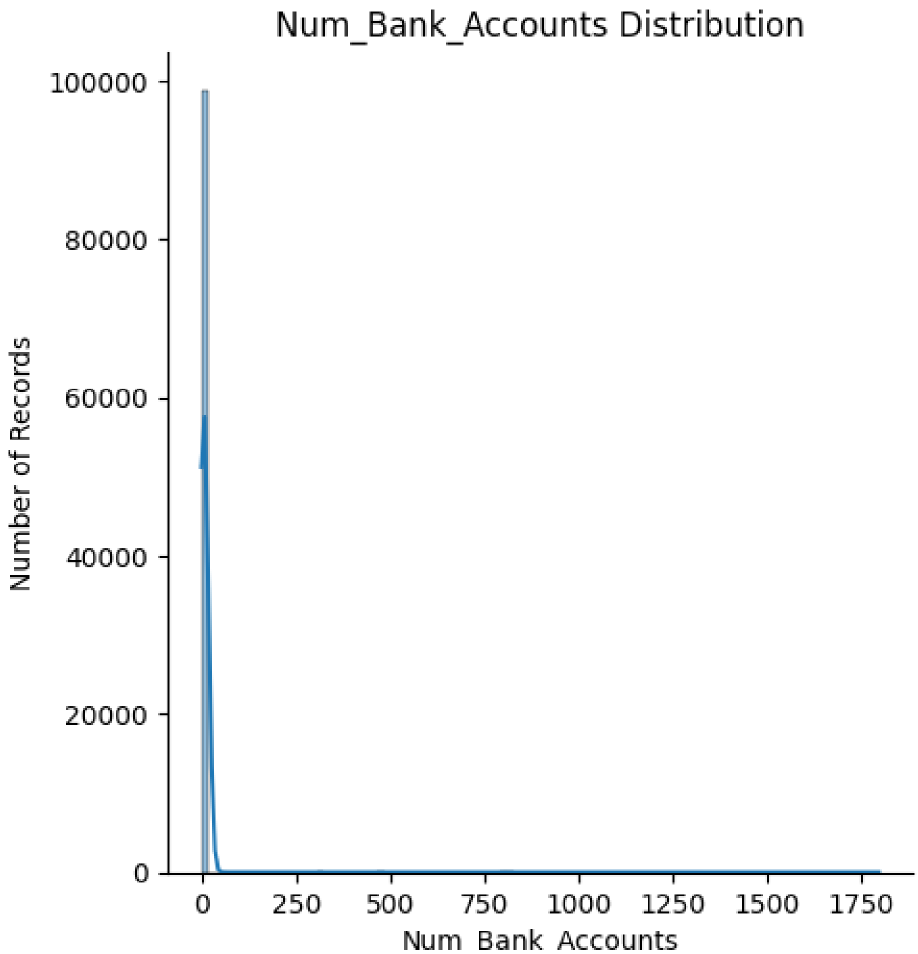


handling outliers - 1

Before

```
[ ]: displot_plot(preview_dataframe, 'Num_Bank_Accounts', bins=100)
```

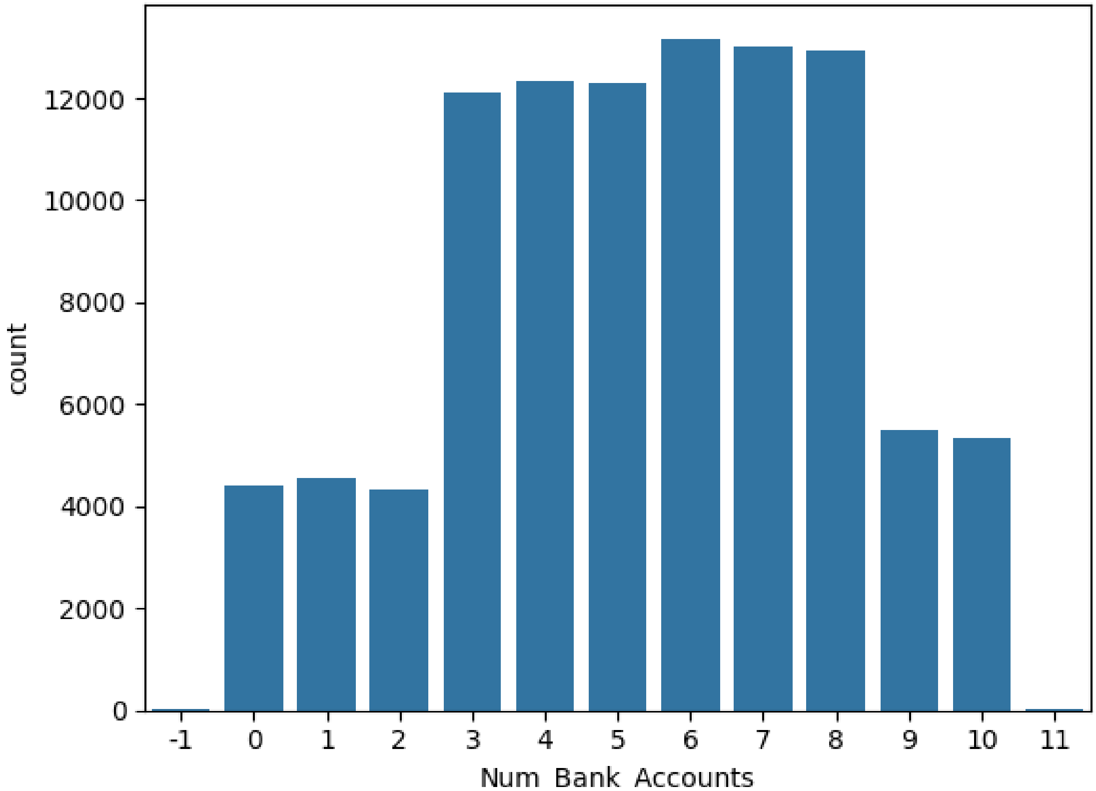
```
****************************************

Num_Bank_Accounts Distribution
```



After

```
[ ]: sns.countplot(df, x = 'Num_Bank_Accounts')
```

```
[ ]: <Axes: xlabel='Num_Bank_Accounts', ylabel='count'>
```

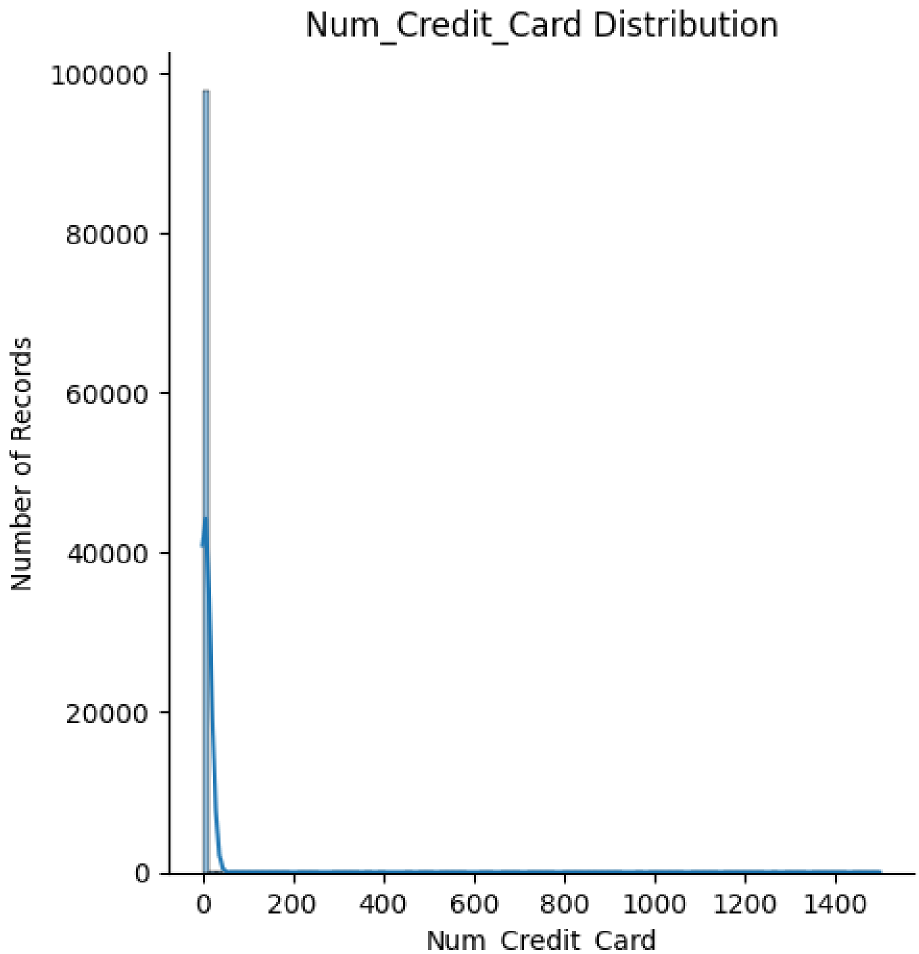


handling outliers - 2

Before

[ ]:
```
displot_plot(preview_dataframe, 'Num_Credit_Card', bins=100)
```

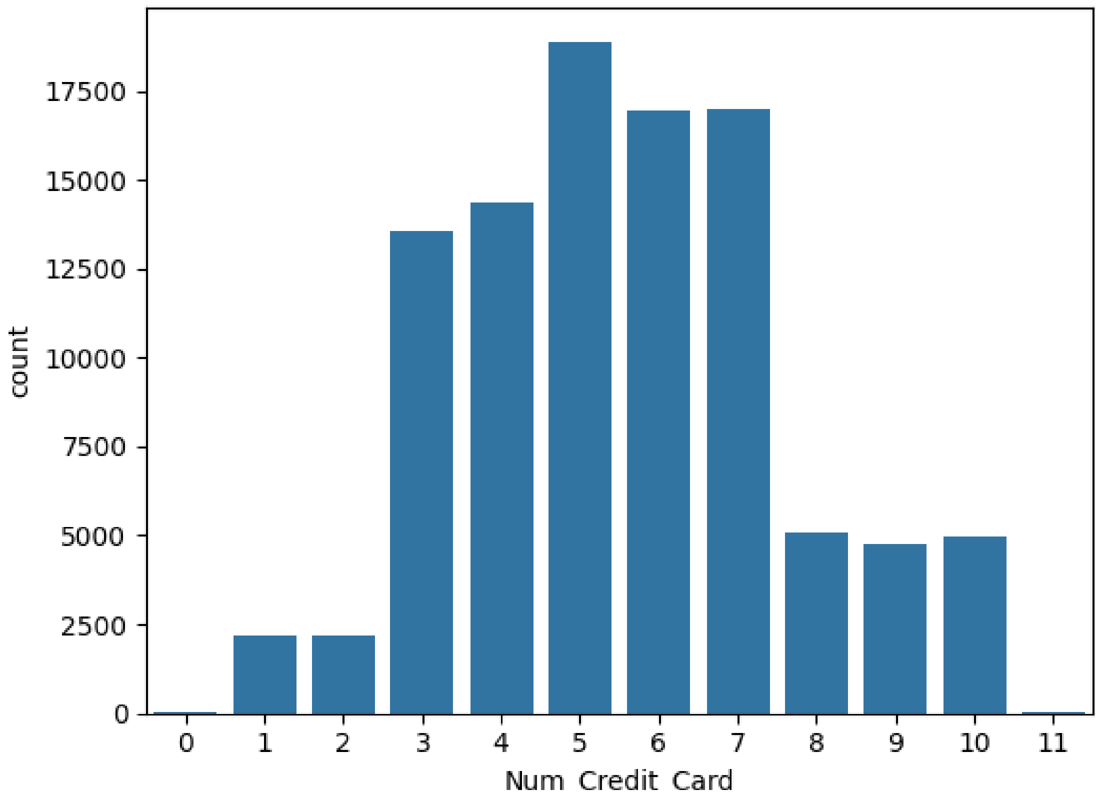
```
****************************************

Num_Credit_Card Distribution
```



After

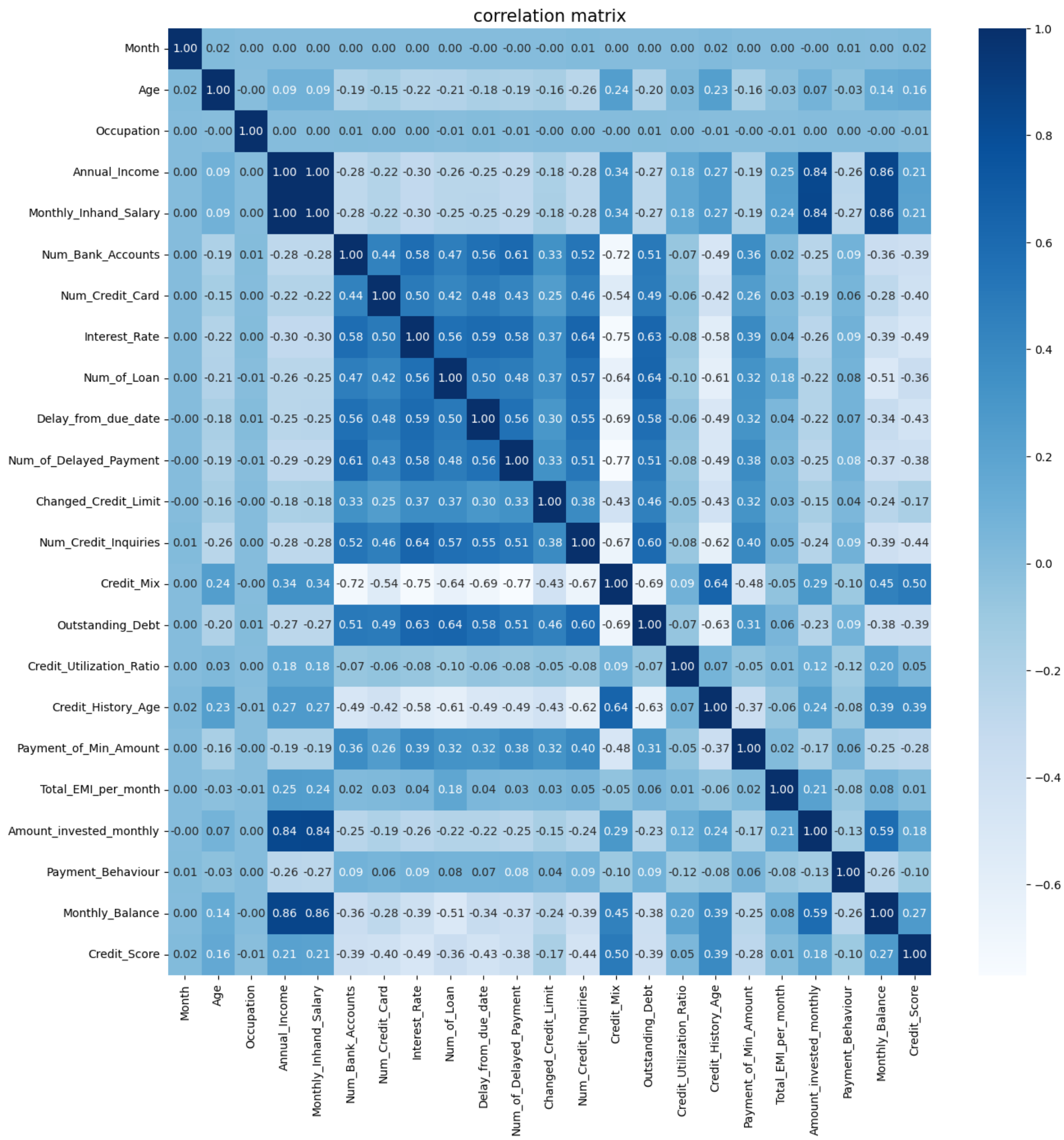
```
[ ]: sns.countplot(df, x = 'Num_Credit_Card')
```

```
[ ]: <Axes: xlabel='Num_Credit_Card', ylabel='count'>
```



5.2.6 Visualize the data correlation

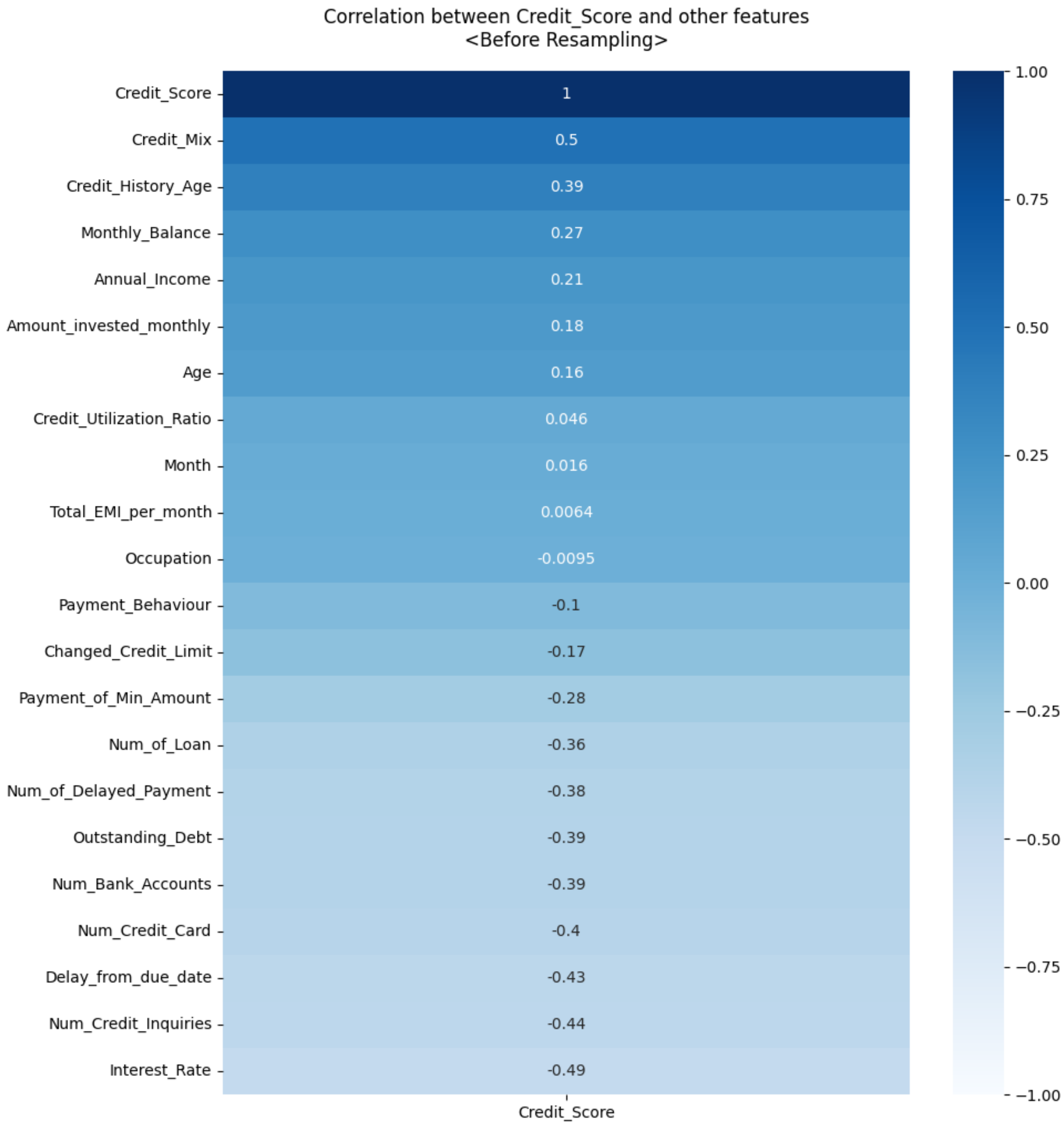
[ ]:
```
df_corr=df.select_dtypes(include=["float64","int64"]).corr()

plt.figure(figsize=(15,15))
plt.title("correlation matrix",fontsize=15)
sns.heatmap(df_corr, annot=True, cmap="Blues", fmt=".2f")
plt.show()
```



[ ]:
```
# Drop the unnecessary columns (has same correlation with other columns)
df.drop('Monthly_Inhand_Salary', axis=1, inplace=True)
```

[ ]:
```
plt.figure(figsize=(10,12))
heatmap = sns.heatmap(df.corr()[['Credit_Score']].
  ↪sort_values(by='Credit_Score', ascending=False), vmin=-1, vmax=1,␣
  ↪annot=True, cmap='Blues')
heatmap.set_title('Correlation between Credit_Score and other features\n<Before␣
  ↪Resampling>', fontdict={'fontsize':12}, pad=16)
```

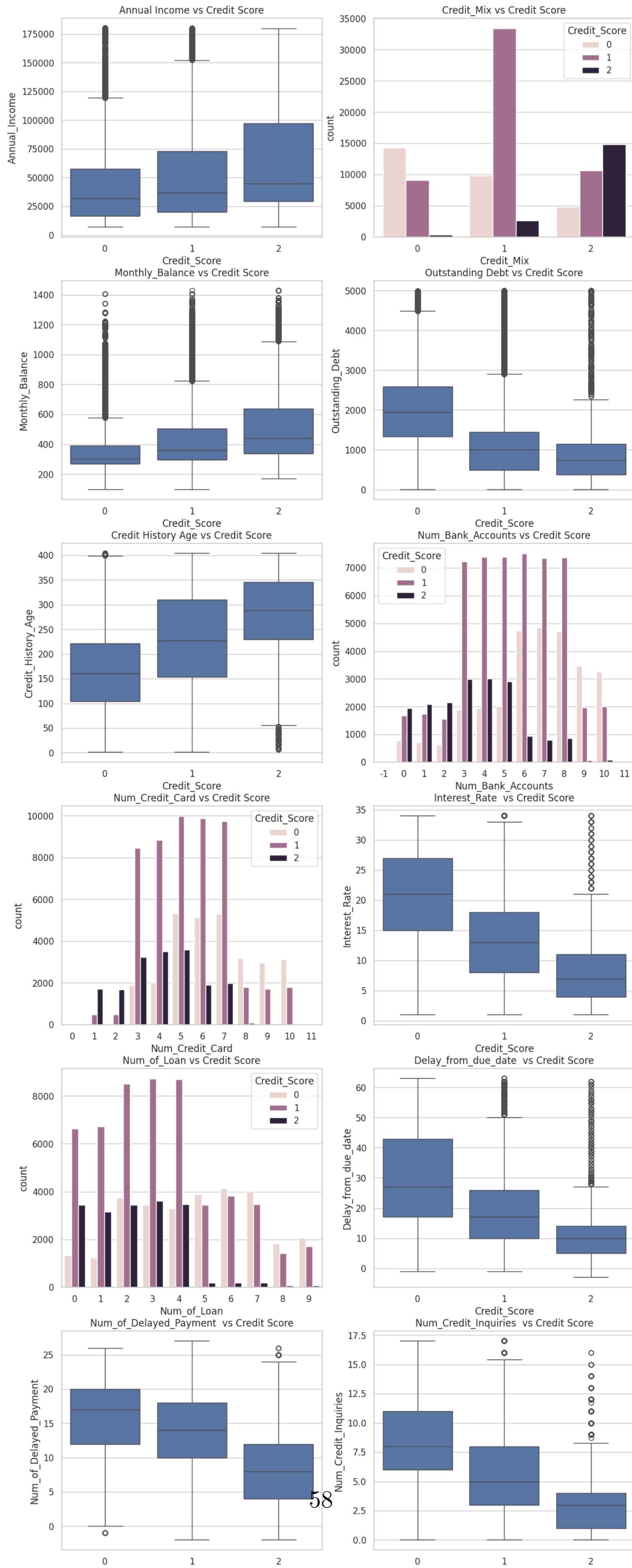
[ ]: Text(0.5, 1.0, 'Correlation between Credit_Score and other features\n<Before Resampling>')



[ ]:
```
# Create subplots for each feature
# Set the style of the plots
sns.set(style="whitegrid")
# Create subplots for each feature
fig, axes = plt.subplots(nrows=6, ncols=2, figsize=(13, 35))

# Here we use the unencoded dataframe for clarity purposes
# Categorical/Discrete data against credit score
```

```
sns.countplot(hue='Credit_Score', x='Num_Bank_Accounts', data=df, ax=axes[2, 1])
axes[2, 1].set_title("Num_Bank_Accounts vs Credit Score")

sns.countplot(hue='Credit_Score', x='Num_Credit_Card', data=df, ax=axes[3, 0])
axes[3, 0].set_title("Num_Credit_Card vs Credit Score")

sns.countplot(hue='Credit_Score', x='Num_of_Loan', data=df, ax=axes[4, 0])
axes[4, 0].set_title("Num_of_Loan vs Credit Score")

sns.countplot(hue='Credit_Score', x='Credit_Mix', data=df, ax=axes[0, 1])
axes[0, 1].set_title("Credit_Mix vs Credit Score")


# Continuous data agaisnt credt score
sns.boxplot(x='Credit_Score', y='Annual_Income', data=df, ax=axes[0, 0])
axes[0, 0].set_title("Annual Income vs Credit Score")

sns.boxplot(x='Credit_Score', y='Monthly_Balance', data=df, ax=axes[1, 0])
axes[1, 0].set_title("Monthly_Balance vs Credit Score")

sns.boxplot(x='Credit_Score', y='Outstanding_Debt', data=df, ax=axes[1, 1])
axes[1, 1].set_title("Outstanding Debt vs Credit Score")

sns.boxplot(x='Credit_Score', y='Credit_History_Age', data=df, ax=axes[2, 0])
axes[2, 0].set_title("Credit History Age vs Credit Score")

sns.boxplot(x='Credit_Score', y='Interest_Rate', data=df, ax=axes[3, 1])
axes[3, 1].set_title("Interest_Rate  vs Credit Score")

sns.boxplot(x='Credit_Score', y='Delay_from_due_date', data=df, ax=axes[4, 1])
axes[4, 1].set_title("Delay_from_due_date  vs Credit Score")

sns.boxplot(x='Credit_Score', y='Num_of_Delayed_Payment', data=df, ax=axes[5,␣
 ↪0])
axes[5, 0].set_title("Num_of_Delayed_Payment  vs Credit Score")

sns.boxplot(x='Credit_Score', y='Num_Credit_Inquiries', data=df, ax=axes[5, 1])
axes[5, 1].set_title("Num_Credit_Inquiries  vs Credit Score")
```

[ ]: Text(0.5, 1.0, 'Num_Credit_Inquiries vs Credit Score')


Annual Income vs Credit Score
Annual_Income
Credit_Score
Credit_Mix vs Credit Score
count
Credit_Mix
Credit_Score
0
1
2
Monthly_Balance vs Credit Score
Monthly_Balance
Credit_Score
Outstanding Debt vs Credit Score
Outstanding_Debt
Credit_Score
Credit History Age vs Credit Score
Credit_History_Age
Credit_Score
Num_Bank_Accounts vs Credit Score
count
Num_Bank_Accounts
Num_Credit_Card vs Credit Score
count
Num_Credit_Card
Interest_Rate vs Credit Score
Interest_Rate
Credit_Score
Num_of_Loan vs Credit Score
count
Num_of_Loan
Delay_from_due_date vs Credit Score
Delay_from_due_date
Credit_Score
Num_of_Delayed_Payment vs Credit Score
Num_of_Delayed_Payment
Credit_Score
Num_Credit_Inquiries vs Credit Score
Num_Credit_Inquiries
Credit_Score

5.3 Data Oversampling

```
[ ]: from sklearn.preprocessing import StandardScaler
     from sklearn.utils import resample

     # Create and copy the data into DataFrame X, y
     X = df.drop('Credit_Score', axis=1)
     y = df['Credit_Score']

     # Create a new DataFrame for resampling
     X_resampled = X.copy()
     y_resampled = y.copy()

     print("Before Resampling:  y=0:", X[y==0].shape[0], ", y=1:", X[y==1].shape[0],␣
      ↪", y=2:", X[y==2].shape[0])

     # The data is biased to y=1. To solve the data imbalance, oversample the data.
     X_sample, y_sample = resample(X[y==2], y[y==2], replace=True, n_samples=X[y==1].
      ↪shape[0])
     X_resampled = np.vstack((X_resampled[(y_resampled==0) | (y_resampled==1)],␣
      ↪X_sample))
     y_resampled = np.hstack((y_resampled[(y_resampled==0) | (y_resampled==1)],␣
      ↪y_sample))

     X_sample, y_sample = resample(X[y==0], y[y==0], replace=True, n_samples=X[y==1].
      ↪shape[0])
     X_resampled = np.vstack((X_resampled[(y_resampled==1) | (y_resampled==2)],␣
      ↪X_sample))
     y_resampled = np.hstack((y_resampled[(y_resampled==1) | (y_resampled==2)],␣
      ↪y_sample))

     X_resampled = pd.DataFrame(X_resampled, columns=X.columns)
     y_resampled = pd.Series(y_resampled)

     # Check each class has a same size
     print("After Resampling:   y=0:", X_resampled[y_resampled==0].shape[0], ", y=1:
      ↪", X_resampled[y_resampled==1].shape[0], ", y=2:",␣
      ↪X_resampled[y_resampled==2].shape[0])
```

```
Before Resampling:  y=0: 28998 , y=1: 53174 , y=2: 17828
After Resampling:   y=0: 53174 , y=1: 53174 , y=2: 53174
```

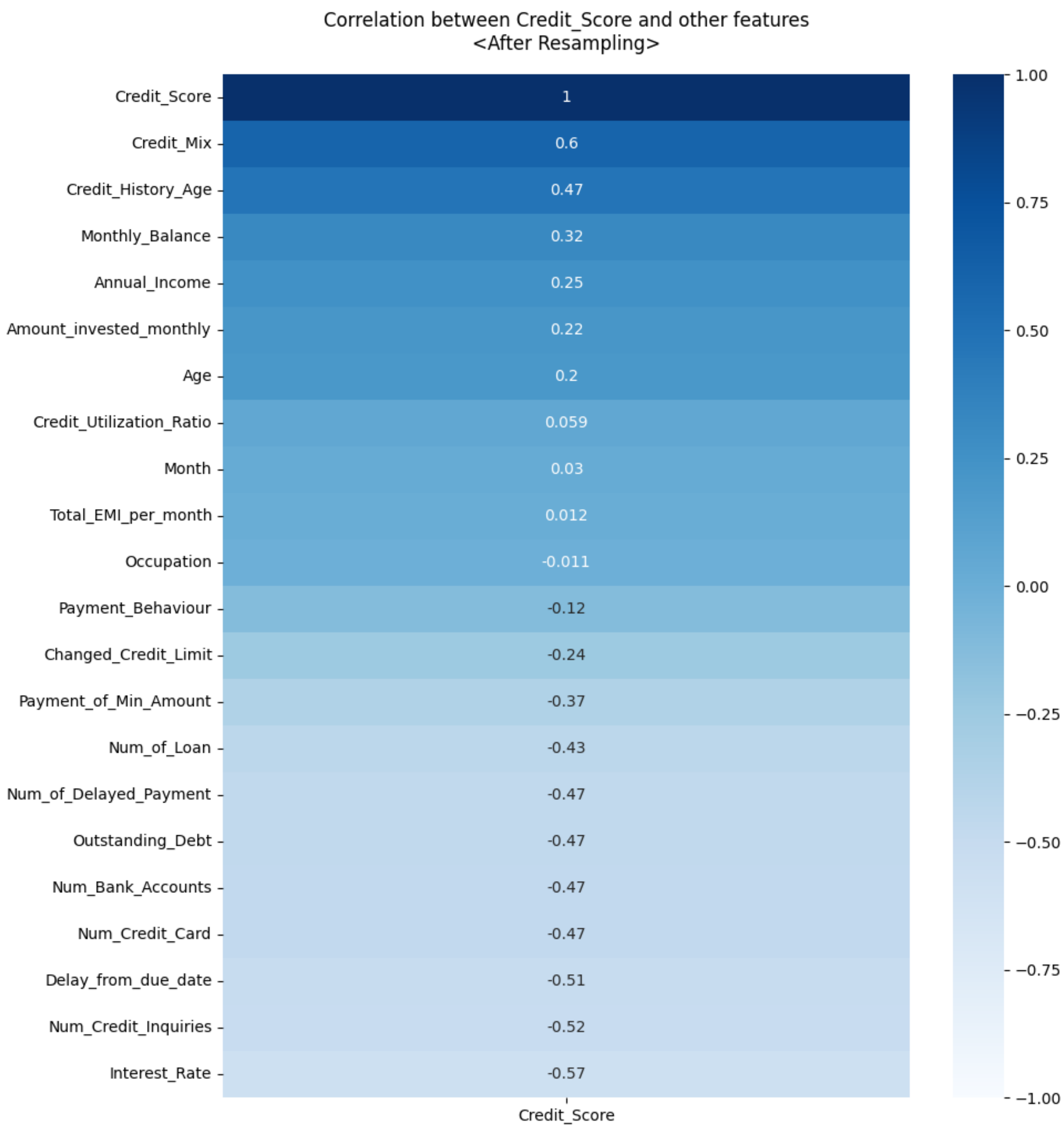
So, we handled

1. Replace outliers

2. Replace strange values
3. Replace null values
4. Target Columns is now balanced

[ ]:
```
# Check the correlation after oversampling
df_temp = pd.DataFrame(np.vstack((X_resampled.T, y_resampled)).T, columns=df.
 ↪columns)

plt.figure(figsize=(10,12))
heatmap = sns.heatmap(df_temp.corr()[['Credit_Score']].
 ↪sort_values(by='Credit_Score', ascending=False), vmin=-1, vmax=1,␣
 ↪annot=True, cmap='Blues')
heatmap.set_title('Correlation between Credit_Score and other features\n<After␣
 ↪Resampling>', fontdict={'fontsize':12}, pad=16)
```

[ ]:
```
Text(0.5, 1.0, 'Correlation between Credit_Score and other features\n<After
Resampling>')
```



5.4 User-Defined Transformer

We defined 3 features

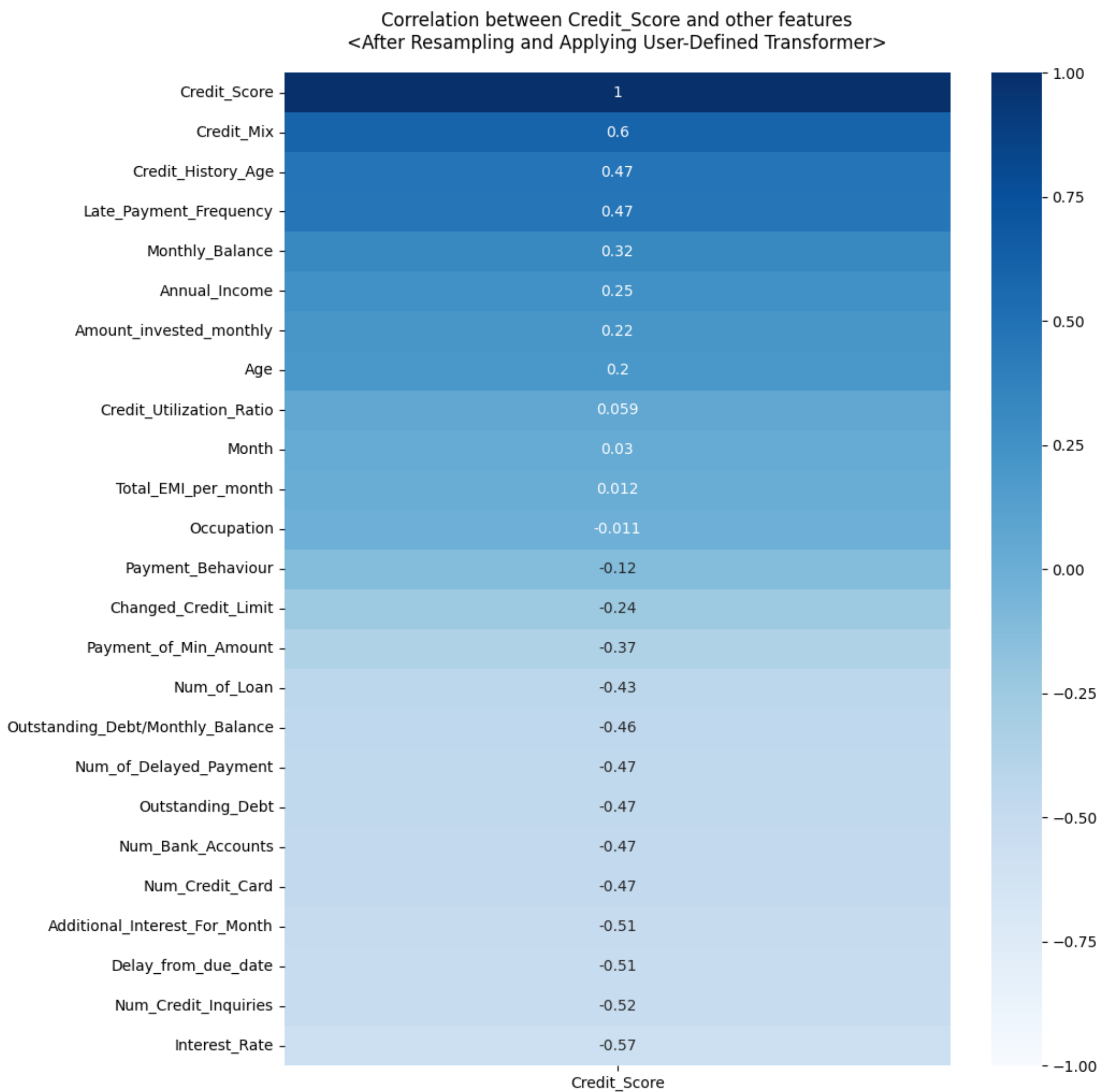
1. **Outstanding_Debt/Monthly_Balance** - This represents a debt ratio on monthly balance.
2. **Late_Payment_Frequency** - This shows how many days later this customer is than the mean overdue date
3. **Additional_Interest_For_Month** - This represents the additional interest amount for month, by multiplying outstanding debt and interest rate

[ ]:
```python
from sklearn.base import BaseEstimator, TransformerMixin

# Define class for User-Defined Transformer
class UserDefinedTransformer(BaseEstimator, TransformerMixin):
    # Initialize
    def __init__(self, include=True):
        pass

    # Define a fit function
    def fit(self, X, y=None):
        return self

    # Define a transform function
    def transform(self, X, y=None):
        # Find the columns
        outstanding = np.where(X.columns == 'Outstanding_Debt')[0][0]
        balance = np.where(X.columns == 'Monthly_Balance')[0][0]
        num_of_delayed_payment = np.where(X.columns ==␣
↪'Num_of_Delayed_Payment')[0][0]
        interest_rate = np.where(X.columns == 'Interest_Rate')[0][0]

        # Copy the column to prevent corruption
        transformed_df = X.copy()

        # Create three new columns
        transformed_df['Outstanding_Debt/Monthly_Balance'] = X.iloc[:
↪,outstanding]/X.iloc[:,balance]
        transformed_df['Late_Payment_Frequency'] = X.iloc[:
↪,num_of_delayed_payment].mean() - X.iloc[:,num_of_delayed_payment]
        transformed_df['Additional_Interest_For_Month'] = X.iloc[:
↪,interest_rate] * X.iloc[:,outstanding]

        return transformed_df
```

[ ]:
```python
transformer = UserDefinedTransformer(include=True)

# Apply the transformer
X_transformed = transformer.transform(X_resampled)

transformed_columns = np.append(X_resampled.columns, ['Outstanding_Debt/
↪Monthly_Balance', 'Late_Payment_Frequency', 'Additional_Interest_For_Month',␣
↪'Credit_Score'])
df_temp = pd.DataFrame(np.vstack((X_transformed.T, y_resampled)).T,␣
↪columns=transformed_columns)

# Show the correlation after applying the transformer
plt.figure(figsize=(10,12))
```

```
heatmap = sns.heatmap(df_temp.corr()[['Credit_Score']].
↪sort_values(by='Credit_Score', ascending=False), vmin=-1, vmax=1,␣
↪annot=True, cmap='Blues')
heatmap.set_title('Correlation between Credit_Score and other features\n<After␣
↪Resampling and Applying User-Defined Transformer>', fontdict={'fontsize':
↪12}, pad=16)
```

[ ]:
```
Text(0.5, 1.0, 'Correlation between Credit_Score and other features\n<After
Resampling and Applying User-Defined Transformer>')
```



5.5 Split the data using Stratified Split

```
[ ]: split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)

# Create three different train/test set for further testings

# Split the data into train and test sets <Before Resampling>
for train_index, test_index in split.split(X, y):
    X_train, y_train = X.iloc[train_index], y.iloc[train_index]
    X_test, y_test = X.iloc[test_index], y.iloc[test_index]

# Split the data into train and test sets <After Resampling>
for train_index, test_index in split.split(X_resampled, y_resampled):
    X_train_resampled, y_train_resampled = X_resampled.iloc[train_index],␣
 ↪y_resampled.iloc[train_index]
    X_test_resampled, y_test_resampled = X_resampled.iloc[test_index],␣
 ↪y_resampled.iloc[test_index]

# Split the data into train and test sets <After Applying User Defined␣
 ↪Transformer>
for train_index, test_index in split.split(X_transformed, y_resampled):
    X_train_transformed, y_train_transformed = X_transformed.iloc[train_index],␣
 ↪y_resampled.iloc[train_index]
    X_test_transformed, y_test_transformed = X_transformed.iloc[test_index],␣
 ↪y_resampled.iloc[test_index]

# Normalize the data. To avoid data leakage, fit the scaler after splitting the␣
 ↪data
scaler = StandardScaler()
X_train_resampled_SC = scaler.fit_transform(X_train_resampled)
X_test_resampled_SC = scaler.transform(X_test_resampled)
X_train_transformed_SC = scaler.fit_transform(X_train_transformed)
X_test_transformed_SC = scaler.transform(X_test_transformed)

print("Before Resampling:  X_train:", X_train.shape, ", y_train:", y_train.
 ↪shape, ", X_test:", X_test.shape, ", y_test:", y_test.shape)
print("After Resampling:   X_train:", X_train_resampled.shape, ", y_train:",␣
 ↪y_train_resampled.shape, ", X_test:", X_test_resampled.shape, ", y_test:",␣
 ↪y_test_resampled.shape)
print("After Transformer:  X_train:", X_train_transformed.shape, ", y_train:",␣
 ↪y_train_transformed.shape, ", X_test:", X_test_transformed.shape, ", y_test:
 ↪", y_test_transformed.shape)
```

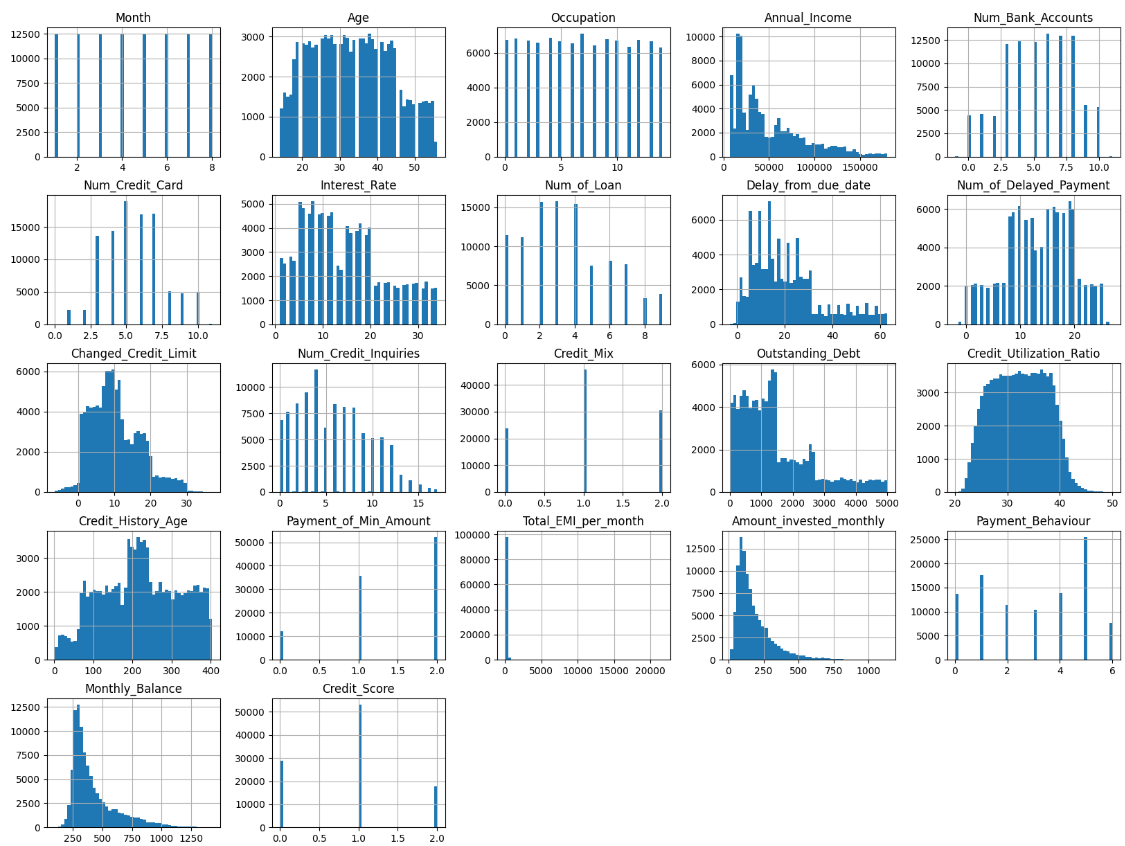
```
Before Resampling:  X_train: (80000, 21) , y_train: (80000,) , X_test: (20000,
21) , y_test: (20000,)
After Resampling:   X_train: (127617, 21) , y_train: (127617,) , X_test: (31905,
21) , y_test: (31905,)
```

```
After Transformer:  X_train: (127617, 24) , y_train: (127617,) , X_test: (31905,
24) , y_test: (31905,)
```

5.5.1 Diagrams after resampling

[ ]:
```
# Histogram before oversampling
df.hist(bins=50, figsize=(20,15))
```

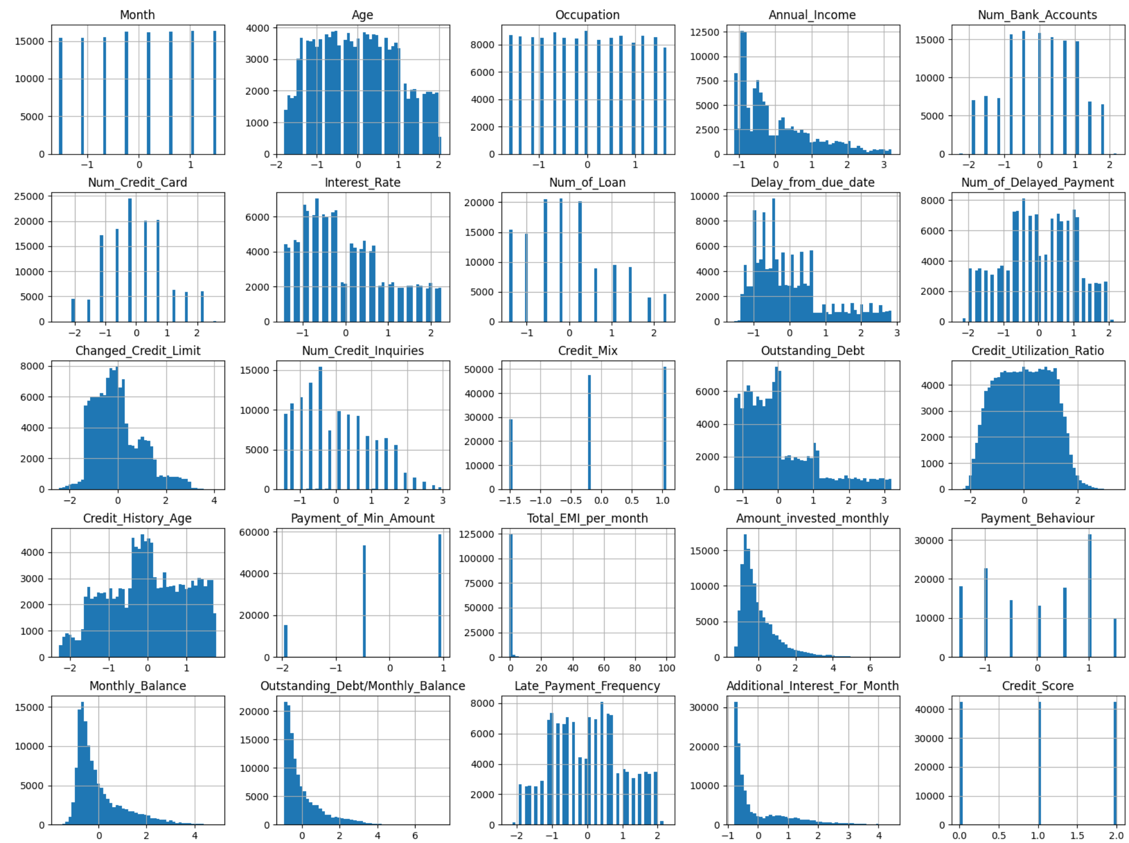
[ ]:
```
array([[<Axes: title={'center': 'Month'}>,
        <Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'Occupation'}>,
        <Axes: title={'center': 'Annual_Income'}>,
        <Axes: title={'center': 'Num_Bank_Accounts'}>],
       [<Axes: title={'center': 'Num_Credit_Card'}>,
        <Axes: title={'center': 'Interest_Rate'}>,
        <Axes: title={'center': 'Num_of_Loan'}>,
        <Axes: title={'center': 'Delay_from_due_date'}>,
        <Axes: title={'center': 'Num_of_Delayed_Payment'}>],
       [<Axes: title={'center': 'Changed_Credit_Limit'}>,
        <Axes: title={'center': 'Num_Credit_Inquiries'}>,
        <Axes: title={'center': 'Credit_Mix'}>,
        <Axes: title={'center': 'Outstanding_Debt'}>,
        <Axes: title={'center': 'Credit_Utilization_Ratio'}>],
       [<Axes: title={'center': 'Credit_History_Age'}>,
        <Axes: title={'center': 'Payment_of_Min_Amount'}>,
        <Axes: title={'center': 'Total_EMI_per_month'}>,
        <Axes: title={'center': 'Amount_invested_monthly'}>,
        <Axes: title={'center': 'Payment_Behaviour'}>],
       [<Axes: title={'center': 'Monthly_Balance'}>,
        <Axes: title={'center': 'Credit_Score'}>, <Axes: >, <Axes: >,
        <Axes: >]], dtype=object)
```



[ ]:
```python
# After oversampling and transforming <training set>
all_columns = np.append(X_resampled.columns, ['Outstanding_Debt/Monthly_Balance', 'Late_Payment_Frequency', 'Additional_Interest_For_Month', 'Credit_Score'])
df_temp = pd.DataFrame(np.vstack((X_train_transformed_SC.T, y_train_transformed)).T, columns=all_columns)
pd.DataFrame(df_temp).hist(bins=50, figsize=(20,15))
```

[ ]:
```
array([[<Axes: title={'center': 'Month'}>,
        <Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'Occupation'}>,
        <Axes: title={'center': 'Annual_Income'}>,
        <Axes: title={'center': 'Num_Bank_Accounts'}>],
       [<Axes: title={'center': 'Num_Credit_Card'}>,
        <Axes: title={'center': 'Interest_Rate'}>,
        <Axes: title={'center': 'Num_of_Loan'}>,
        <Axes: title={'center': 'Delay_from_due_date'}>,
        <Axes: title={'center': 'Num_of_Delayed_Payment'}>],
       [<Axes: title={'center': 'Changed_Credit_Limit'}>,
        <Axes: title={'center': 'Num_Credit_Inquiries'}>,
```

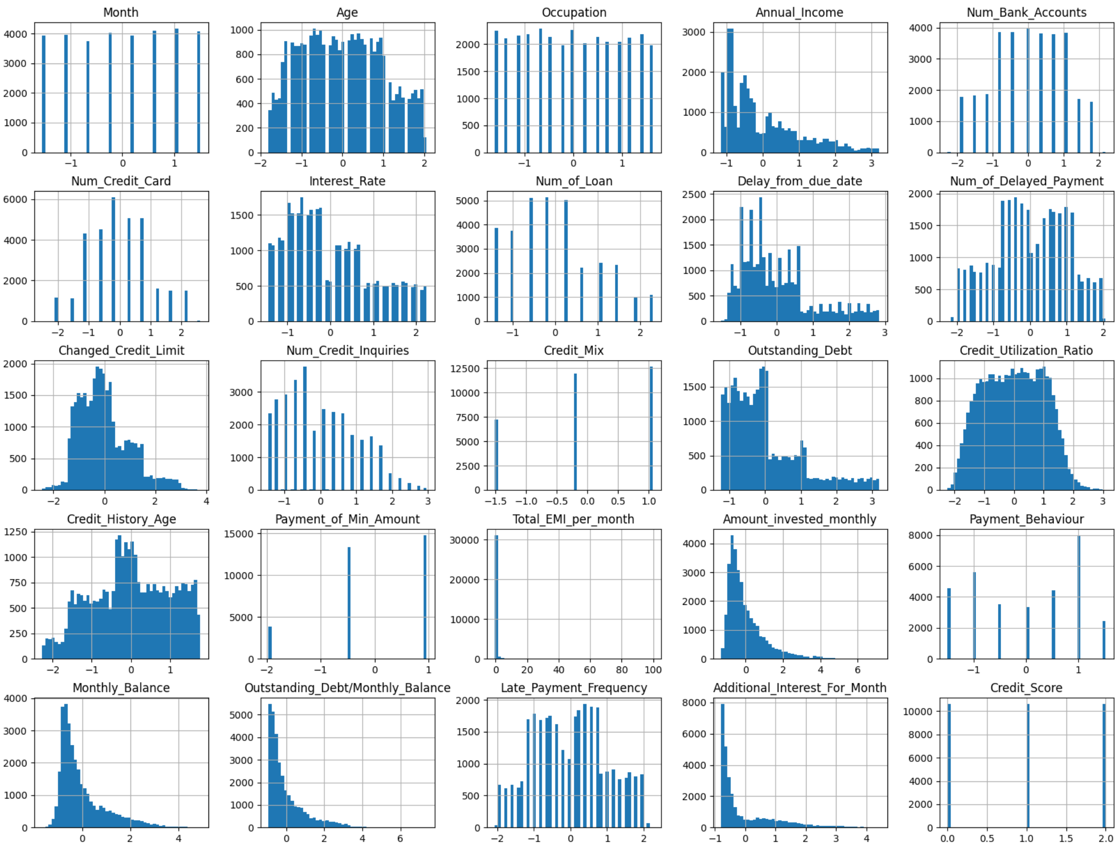
```
 <Axes: title={'center': 'Credit_Mix'}>,
 <Axes: title={'center': 'Outstanding_Debt'}>,
 <Axes: title={'center': 'Credit_Utilization_Ratio'}>],
[<Axes: title={'center': 'Credit_History_Age'}>,
 <Axes: title={'center': 'Payment_of_Min_Amount'}>,
 <Axes: title={'center': 'Total_EMI_per_month'}>,
 <Axes: title={'center': 'Amount_invested_monthly'}>,
 <Axes: title={'center': 'Payment_Behaviour'}>],
[<Axes: title={'center': 'Monthly_Balance'}>,
 <Axes: title={'center': 'Outstanding_Debt/Monthly_Balance'}>,
 <Axes: title={'center': 'Late_Payment_Frequency'}>,
 <Axes: title={'center': 'Additional_Interest_For_Month'}>,
 <Axes: title={'center': 'Credit_Score'}>]], dtype=object)
```



[ ]:
```python
# After oversampling and transforming <test set>
all_columns = np.append(X_resampled.columns, ['Outstanding_Debt/
    ↪Monthly_Balance', 'Late_Payment_Frequency', 'Additional_Interest_For_Month',␣
    ↪'Credit_Score'])
df_temp = pd.DataFrame(np.vstack((X_test_transformed_SC.T, y_test_transformed)).
    ↪T, columns=all_columns)
```

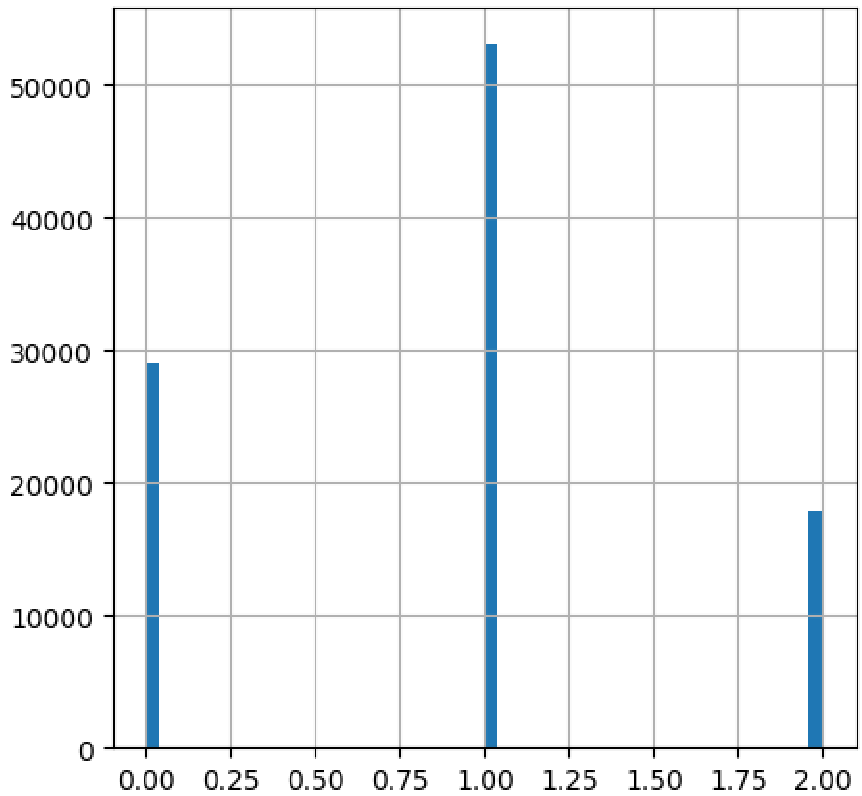
```
pd.DataFrame(df_temp).hist(bins=50, figsize=(20,15))
```

```
[ ]: array([[<Axes: title={'center': 'Month'}>,
            <Axes: title={'center': 'Age'}>,
            <Axes: title={'center': 'Occupation'}>,
            <Axes: title={'center': 'Annual_Income'}>,
            <Axes: title={'center': 'Num_Bank_Accounts'}>],
           [<Axes: title={'center': 'Num_Credit_Card'}>,
            <Axes: title={'center': 'Interest_Rate'}>,
            <Axes: title={'center': 'Num_of_Loan'}>,
            <Axes: title={'center': 'Delay_from_due_date'}>,
            <Axes: title={'center': 'Num_of_Delayed_Payment'}>],
           [<Axes: title={'center': 'Changed_Credit_Limit'}>,
            <Axes: title={'center': 'Num_Credit_Inquiries'}>,
            <Axes: title={'center': 'Credit_Mix'}>,
            <Axes: title={'center': 'Outstanding_Debt'}>,
            <Axes: title={'center': 'Credit_Utilization_Ratio'}>],
           [<Axes: title={'center': 'Credit_History_Age'}>,
            <Axes: title={'center': 'Payment_of_Min_Amount'}>,
            <Axes: title={'center': 'Total_EMI_per_month'}>,
            <Axes: title={'center': 'Amount_invested_monthly'}>,
            <Axes: title={'center': 'Payment_Behaviour'}>],
           [<Axes: title={'center': 'Monthly_Balance'}>,
            <Axes: title={'center': 'Outstanding_Debt/Monthly_Balance'}>,
            <Axes: title={'center': 'Late_Payment_Frequency'}>,
            <Axes: title={'center': 'Additional_Interest_For_Month'}>,
            <Axes: title={'center': 'Credit_Score'}>]], dtype=object)
```



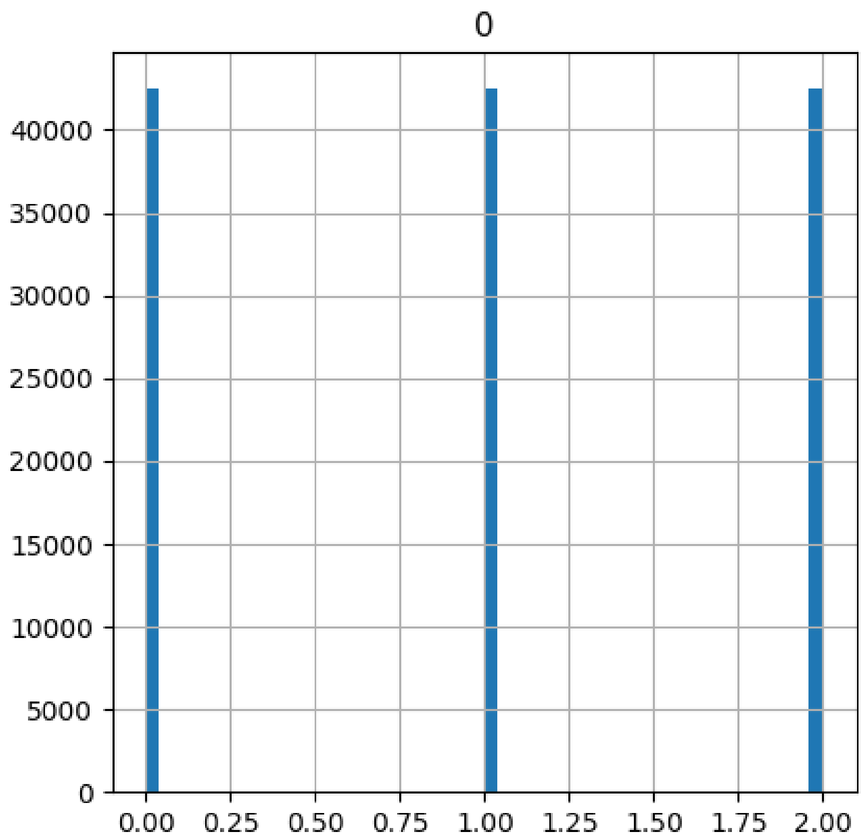
[ ]:
```
# Credit_Score before oversampling
df["Credit_Score"].hist(bins = 50, figsize=(5,5))
```

[ ]: <Axes: >



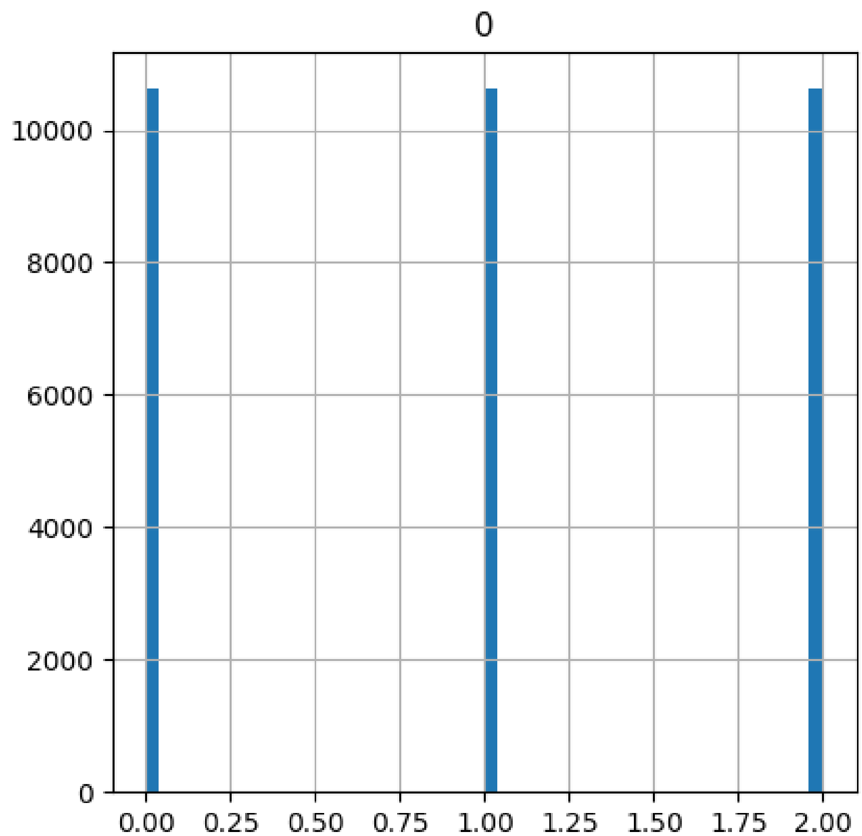
[ ]:
```
# Credit_Score after oversampling <training set>
pd.DataFrame(y_train_resampled).hist(bins=50, figsize=(5,5))
```

[ ]:
```
array([[<Axes: title={'center': '0'}>]], dtype=object)
```



[ ]:
```
# Credit_Score after oversampling <test set>
pd.DataFrame(y_test_resampled).hist(bins=50, figsize=(5,5))
```

[ ]:
```
array([[<Axes: title={'center': '0'}>]], dtype=object)
```



6 5. Implementing the different models

6.1 Declare the helper functions

[ ]:
```
def model_summary(model_name, y_true, y_pred, y_prob):
    accuracy = accuracy_score(y_true, y_pred)
    roc_auc = roc_auc_score(y_true, y_prob, multi_class='ovr')
    report = classification_report(y_true, y_pred, target_names=['Good',␣
↪'Standard', 'Poor'], output_dict=True)

    summary = pd.DataFrame({
        'Model': [model_name],
        'Accuracy': [accuracy],
        'ROC-AUC Score': [roc_auc],
        'Precision (Good)': [report['Good']['precision']],
        'Recall (Good)': [report['Good']['recall']],
        'F1-score (Good)': [report['Good']['f1-score']],
        'Precision (Standard)': [report['Standard']['precision']],
        'Recall (Standard)': [report['Standard']['recall']],
```

```
        'F1-score (Standard)': [report['Standard']['f1-score']],
        'Precision (Poor)': [report['Poor']['precision']],
        'Recall (Poor)': [report['Poor']['recall']],
        'F1-score (Poor)': [report['Poor']['f1-score']],
    })

    return summary
```

[ ]:
```
def confusion_matrix_plot(model_name, confusion_matrix):
    # Display the confusion matrix as a heatmap
    plt.figure(figsize=(5, 3))
    sns.heatmap(confusion_matrix, annot=True, fmt="d", cmap="Blues",\
                xticklabels=['Poor', 'Standard', 'Good'], yticklabels=['Poor',␣
↪'Standard', 'Good'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(model_name)
    plt.show()
```

6.2 Bayesian Classifier

[ ]:
```
df
```

[ ]:
```
       Month  Age  Occupation  Annual_Income  Num_Bank_Accounts  \
0          1   23          12       19114.12                  3
1          2   23          12       19114.12                  3
2          3   23          12       19114.12                  3
3          4   23          12       19114.12                  3
4          5   23          12       19114.12                  3
…          …   …            …              …                  …
99995      4   25           9       39628.99                  4
99996      5   25           9       39628.99                  4
99997      6   25           9       39628.99                  4
99998      7   25           9       39628.99                  4
99999      8   25           9       39628.99                  4

       Num_Credit_Card  Interest_Rate  Num_of_Loan  Delay_from_due_date  \
0                    4              3            4                    3
1                    4              3            4                    3
2                    4              3            4                    3
3                    4              3            4                    3
4                    4              3            4                    3
…                    …              …            …                    …
99995                6              7            2                   21
99996                6              7            2                   21
99997                6              7            2                   21
```

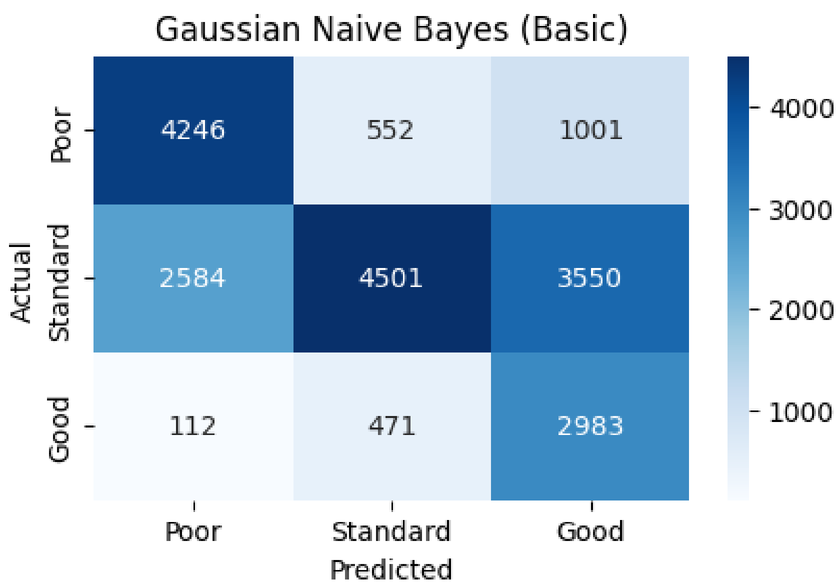
```
99998                   6               7           2                    21
99999                   6               7           2                    21

       Num_of_Delayed_Payment  …  Credit_Mix  Outstanding_Debt  \
0                           5  …           2            809.98
1                           4  …           2            809.98
2                           5  …           2            809.98
3                           4  …           2            809.98
4                           4  …           2            809.98
…                         …  …         …               …
99995                       7  …           2            502.38
99996                       7  …           2            502.38
99997                       6  …           2            502.38
99998                       6  …           2            502.38
99999                       6  …           2            502.38

       Credit_Utilization_Ratio  Credit_History_Age  Payment_of_Min_Amount  \
0                     26.822620               265.0                      1
1                     31.944960               266.0                      1
2                     28.609352               267.0                      1
3                     31.377862               268.0                      1
4                     24.797347               269.0                      1
…                           …                 …                    …
99995                 34.663572               378.0                      1
99996                 40.565631               379.0                      1
99997                 41.255522               380.0                      1
99998                 33.638208               381.0                      1
99999                 34.192463               382.0                      1

       Total_EMI_per_month  Amount_invested_monthly  Payment_Behaviour  \
0                49.574949                80.415295                  2
1                49.574949                81.000000                  3
2                49.574949                81.699521                  4
3                49.574949                81.000000                  5
4                49.574949                81.000000                  1
…                      …                      …                …
99995            35.104023               153.000000                  0
99996            35.104023               153.000000                  1
99997            35.104023               153.000000                  0
99998            35.104023               153.000000                  3
99999            35.104023               153.000000                  6

       Monthly_Balance  Credit_Score
0                321.0             2
1                321.0             2
2                321.0             2
3                321.0             2
```

```
4                321.0            2
…                …           …
99995            405.0            0
99996            405.0            0
99997            405.0            0
99998            405.0            1
99999            405.0            0

[100000 rows x 22 columns]
```

6.2.1 Gaussian Naïve Bayes with basic data

[ ]:
```
# Gaussian Naive Bayes
from sklearn.naive_bayes import GaussianNB
NBclassifier = GaussianNB()
NBclassifier.fit(X_train, y_train)

gnb_pred_basic = NBclassifier.predict(X_test)
gnb_pred_basic_prob = NBclassifier.predict_proba(X_test)

# Summary of the predictions made by the classifier
print(classification_report(y_test, gnb_pred_basic))
confusion_matrix_plot('Gaussian Naive Bayes (Basic)', confusion_matrix(y_test,␣
↪gnb_pred_basic))
# Accuracy score

print('Accuracy:', accuracy_score(y_test, gnb_pred_basic))
```

```
             precision    recall  f1-score   support

           0       0.61      0.73      0.67      5799
           1       0.81      0.42      0.56     10635
           2       0.40      0.84      0.54      3566

    accuracy                           0.59     20000
   macro avg       0.61      0.66      0.59     20000
weighted avg       0.68      0.59      0.59     20000
```

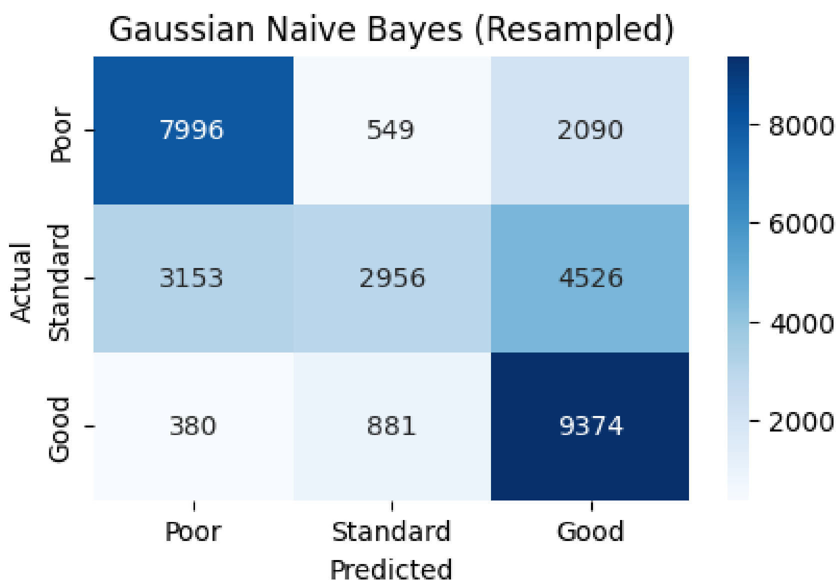



```
Accuracy: 0.5865
```

6.2.2 Gaussian Naïve Bayes with resampled data

```
[ ]: NBclassifier.fit(X_train_resampled, y_train_resampled)
     gnb_pred_resampled = NBclassifier.predict(X_test_resampled)
     gnb_pred_resampled_prob = NBclassifier.predict_proba(X_test_resampled)

     # Summary of the predictions made by the classifier
     print(classification_report(y_test_resampled, gnb_pred_resampled))
     confusion_matrix_plot('Gaussian Naive Bayes (Resampled)',␣
      ↪confusion_matrix(y_test_resampled, gnb_pred_resampled))
     # Accuracy score
     print('Accuracy:', accuracy_score(y_test_resampled, gnb_pred_resampled))
```

```
              precision    recall  f1-score   support

           0       0.69      0.75      0.72     10635
           1       0.67      0.28      0.39     10635
           2       0.59      0.88      0.70     10635

    accuracy                           0.64     31905
   macro avg       0.65      0.64      0.61     31905
weighted avg       0.65      0.64      0.61     31905
```

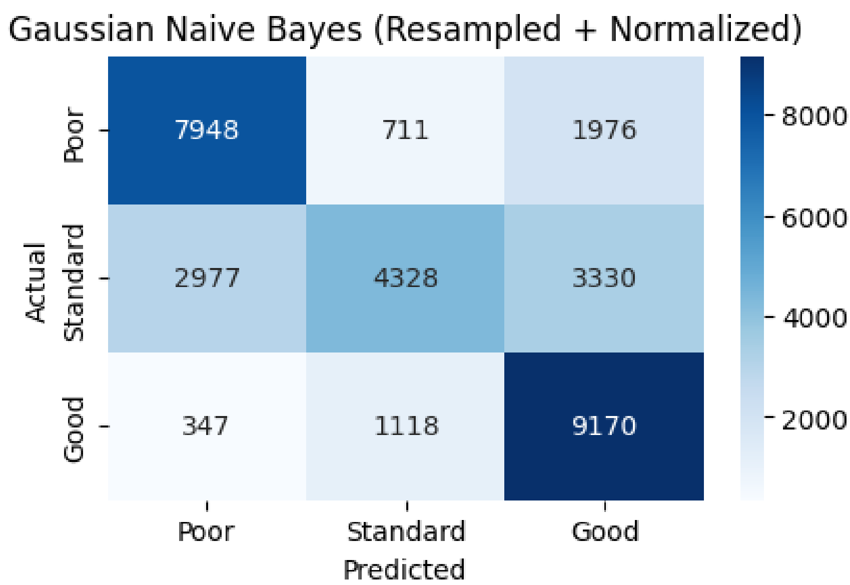



```
Accuracy: 0.6370788277699421
```

6.2.3 Gaussian Naïve Bayes with resampled, normalized data

[ ]:
```python
NBclassifier.fit(X_train_resampled_SC, y_train_resampled)
gnb_pred_resampled_SC = NBclassifier.predict(X_test_resampled_SC)
gnb_pred_resampled_SC_prob = NBclassifier.predict_proba(X_test_resampled_SC)

# Summary of the predictions made by the classifier
print(classification_report(y_test_resampled, gnb_pred_resampled_SC))
confusion_matrix_plot('Gaussian Naive Bayes (Resampled + Normalized)',␣
 ↪confusion_matrix(y_test_resampled, gnb_pred_resampled_SC))
# Accuracy score
print('Accuracy:', accuracy_score(y_test_resampled, gnb_pred_resampled_SC))
```

```
              precision    recall  f1-score   support

           0       0.71      0.75      0.73     10635
           1       0.70      0.41      0.52     10635
           2       0.63      0.86      0.73     10635

    accuracy                           0.67     31905
   macro avg       0.68      0.67      0.66     31905
weighted avg       0.68      0.67      0.66     31905
```



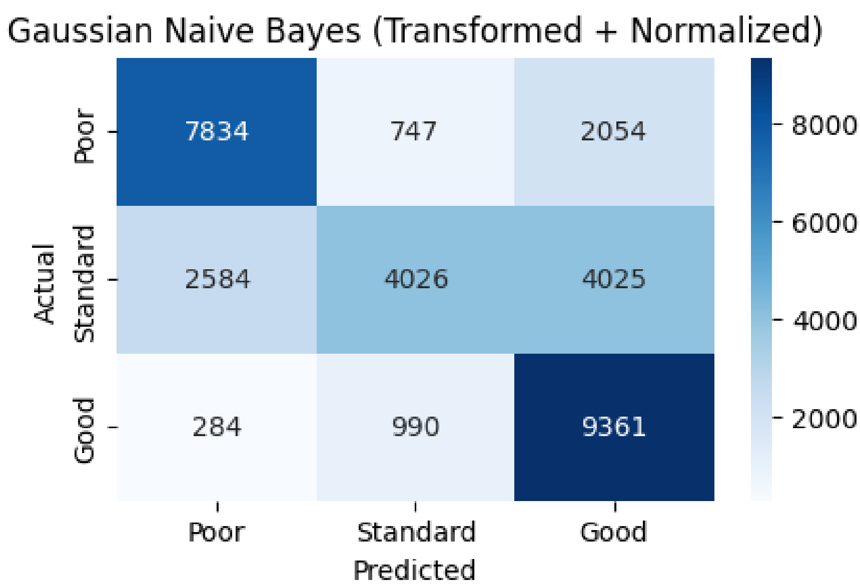

```
Accuracy: 0.6721830434101238
```

6.2.4 Hyper-parameter tuning the Naïve Bayes Classifier with Transformed Data

```
[ ]: # Define the Gaussian Naive Bayes model
gnb = GaussianNB()

# Define the hyperparameter grid for var_smoothing
params = {'var_smoothing': np.logspace(0,-9, num=100)}

# Use GridSearchCV to find the best var_smoothing parameter
grid_search = GridSearchCV(estimator = gnb, param_grid=params, cv=5, n_jobs=-1,␣
 ↪scoring='accuracy')
grid_search.fit(X_train_transformed_SC, y_train_transformed)

# Get the best var_smoothing parameter
print(grid_search.best_params_)

#predicting
gnb_pred_transformed = grid_search.predict(X_test_transformed_SC)
gnb_pred_transformed_prob = grid_search.predict_proba(X_test_transformed_SC)

# Summary of the predictions made by the classifier
print(classification_report(y_test_transformed, gnb_pred_transformed))
confusion_matrix_plot('Gaussian Naive Bayes (Transformed + Normalized)',␣
 ↪confusion_matrix(y_test_transformed, gnb_pred_transformed))
# Evaluate the model
```

```
accuracy = accuracy_score(y_test_transformed, gnb_pred_transformed)
print("Accuracy:", accuracy)
```

```
{'var_smoothing': 0.0003511191734215131}
              precision    recall  f1-score   support

           0       0.73      0.74      0.73     10635
           1       0.70      0.38      0.49     10635
           2       0.61      0.88      0.72     10635

    accuracy                           0.67     31905
   macro avg       0.68      0.67      0.65     31905
weighted avg       0.68      0.67      0.65     31905
```




```
Accuracy: 0.6651308572324087
```

6.2.5 Comparison of the results

[ ]:
```
gnb_basic_summary = model_summary('Gaussian Naive Bayes (Basic)', y_test,␣
↪gnb_pred_basic, gnb_pred_basic_prob)
gnb_resampled_summary = model_summary('Gaussian Naive Bayes (Resampled)',␣
↪y_test_resampled, gnb_pred_resampled, gnb_pred_resampled_prob)
gnb_resampled_SC_summary = model_summary('Gaussian Naive Bayes (Resampled +␣
↪Normalized)', y_test_resampled, gnb_pred_resampled_SC,␣
↪gnb_pred_resampled_SC_prob)
```

```
gnb_transformed_SC_summary = model_summary('Gaussian Naive Bayes (Transformed +␣
↪Normalized)', y_test_transformed, gnb_pred_transformed,␣
↪gnb_pred_transformed_prob)

gnb_summary = pd.concat([gnb_basic_summary, gnb_resampled_summary,␣
↪gnb_resampled_SC_summary, gnb_transformed_SC_summary])
gnb_summary
```

[ ]:

```
                                        Model  Accuracy  ROC-AUC Score  \
0                  Gaussian Naive Bayes (Basic)  0.586500       0.767024
0              Gaussian Naive Bayes (Resampled)  0.637079       0.784156
0   Gaussian Naive Bayes (Resampled + Normalized)  0.672183       0.794185
0  Gaussian Naive Bayes (Transformed + Normalized)  0.665131       0.790039

   Precision (Good)  Recall (Good)  F1-score (Good)  Precision (Standard)  \
0          0.611639       0.732195         0.666510              0.814808
0          0.693555       0.751857         0.721530              0.673963
0          0.705110       0.747344         0.725613              0.702940
0          0.732013       0.736624         0.734311              0.698594

   Recall (Standard)  F1-score (Standard)  Precision (Poor)  Recall (Poor)  \
0           0.423225             0.557089          0.395938       0.836511
0           0.277950             0.393582          0.586241       0.881429
0           0.406958             0.515484          0.633462       0.862247
0           0.378561             0.491035          0.606282       0.880207

   F1-score (Poor)
0         0.537477
0         0.704150
0         0.730357
0         0.718006
```

6.3 Artificial Neural Networks (ANN)

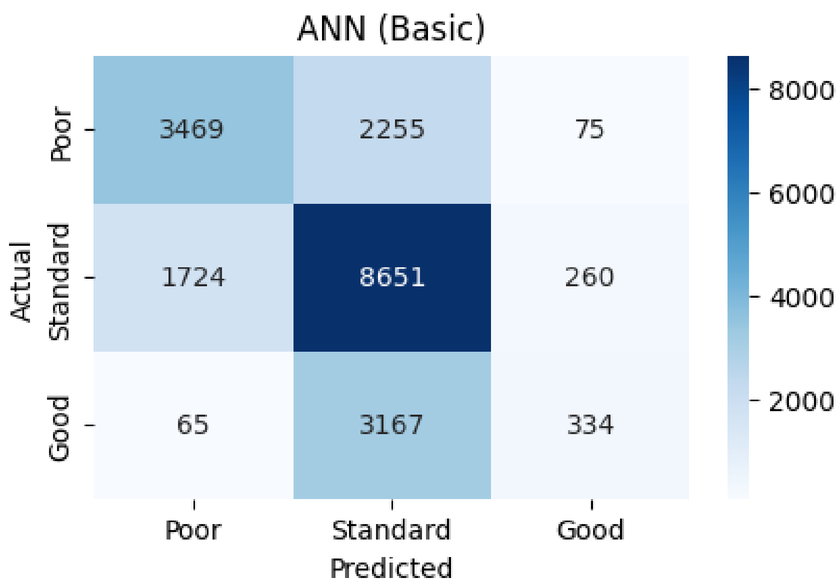
6.3.1 ANN with basic data

[ ]:

```
from sklearn.neural_network import MLPClassifier

# Define the MLPClassifier with some basic parameters
mlp = MLPClassifier(hidden_layer_sizes=(256,128,128,64), max_iter=500,␣
↪activation='relu',\
                    solver='adam', random_state=57, early_stopping=True,␣
↪verbose=False,\
                    validation_fraction=0.1)

# Fit the basic training set
mlp.fit(X_train, y_train)
```

```
# Accuracy
ann_pred_basic = mlp.predict(X_test)
ann_pred_basic_prob = mlp.predict_proba(X_test)
print(classification_report(y_test, ann_pred_basic, zero_division=0))
confusion_matrix_plot('ANN (Basic)', confusion_matrix(y_test, ann_pred_basic))
accuracy = mlp.score(X_test, y_test)
print("Accuracy:", accuracy)
```

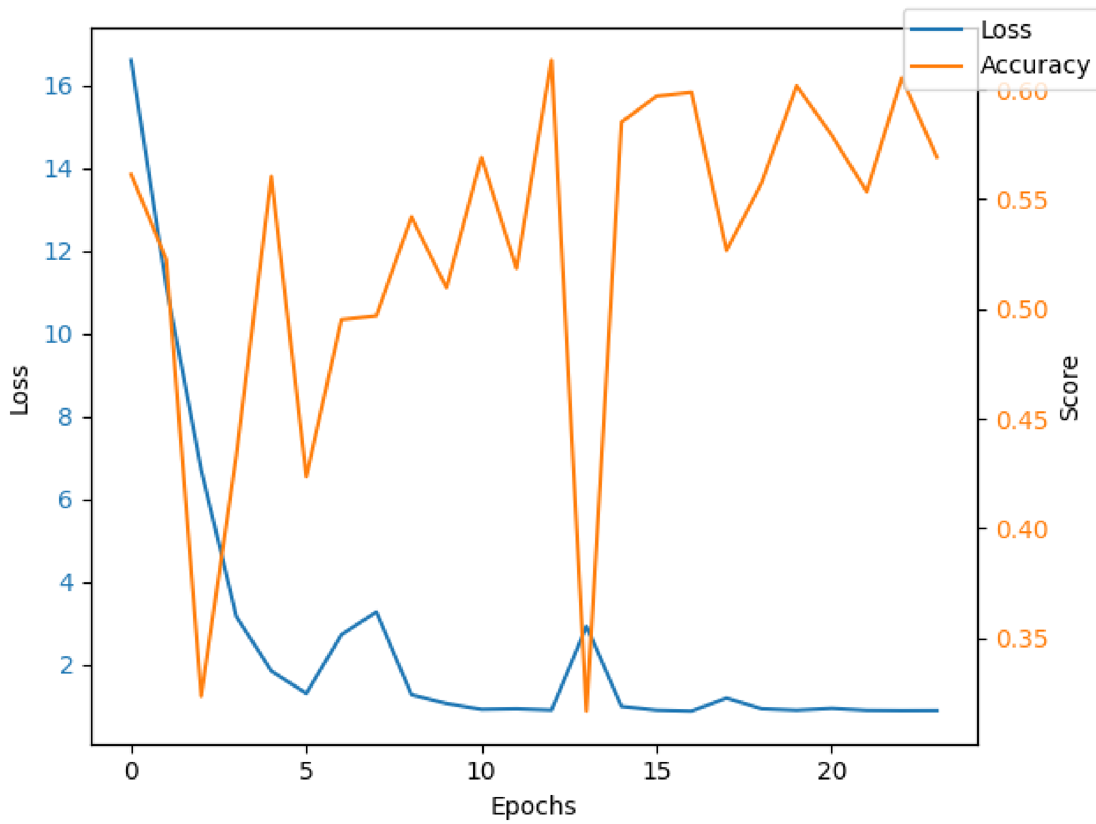
```
              precision    recall  f1-score   support

           0       0.66      0.60      0.63      5799
           1       0.61      0.81      0.70     10635
           2       0.50      0.09      0.16      3566

    accuracy                           0.62     20000
   macro avg       0.59      0.50      0.50     20000
weighted avg       0.61      0.62      0.58     20000
```




```
Accuracy: 0.6227
```

[ ]:
```
# Show loss and accuracy graph
def show_loss_graph(model):
    fig, ax1 = plt.subplots()

    color = 'tab:blue'
```

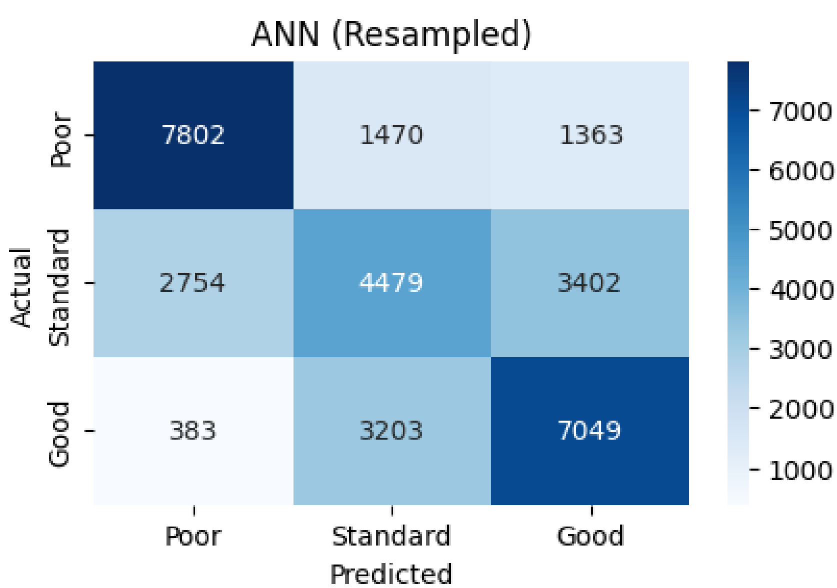
```
    ax1.set_xlabel('Epochs')
    ax1.set_ylabel('Loss')
    ax1.plot(model.loss_curve_, color=color)
    ax1.tick_params(axis='y', labelcolor=color)

    color = 'tab:orange'
    ax2 = ax1.twinx()
    ax2.set_ylabel('Score')
    ax2.plot(model.validation_scores_, color=color)
    ax2.tick_params(axis='y', labelcolor=color)
    fig.tight_layout()
    fig.legend(['Loss', 'Accuracy'], loc='upper right')
    fig.show()

show_loss_graph(mlp)
```



6.3.2 ANN with resampled data

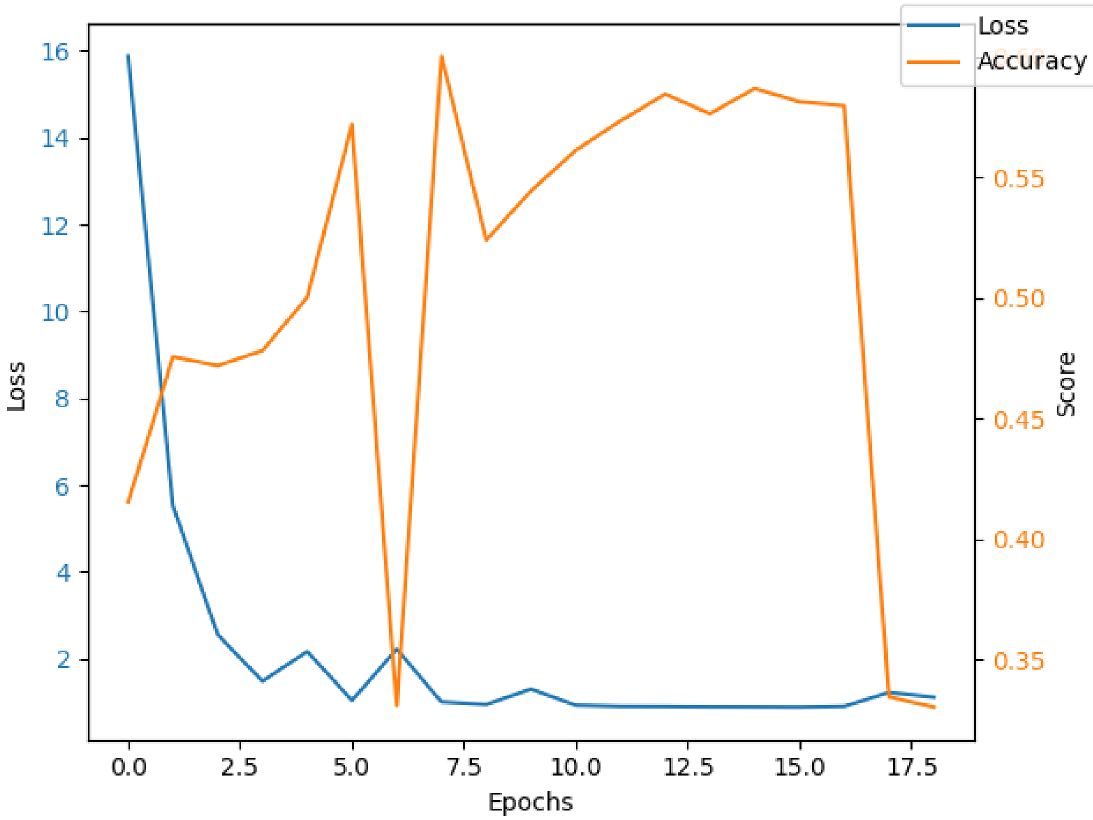
[ ]:
```
# Fit the resampled data
mlp.fit(X_train_resampled, y_train_resampled)

# Accuracy
ann_pred_resampled = mlp.predict(X_test_resampled)
ann_pred_resampled_prob = mlp.predict_proba(X_test_resampled)
print(classification_report(y_test_resampled, ann_pred_resampled,␣
 ↪zero_division=0))
confusion_matrix_plot('ANN (Resampled)', confusion_matrix(y_test_resampled,␣
 ↪ann_pred_resampled))
accuracy = mlp.score(X_test_resampled, y_test_resampled)
print("Accuracy:", accuracy)
```

```
              precision    recall  f1-score   support

           0       0.71      0.73      0.72     10635
           1       0.49      0.42      0.45     10635
           2       0.60      0.66      0.63     10635

    accuracy                           0.61     31905
   macro avg       0.60      0.61      0.60     31905
weighted avg       0.60      0.61      0.60     31905
```




```
Accuracy: 0.6058611502899232
```

[ ]:
```
show_loss_graph(mlp)
```



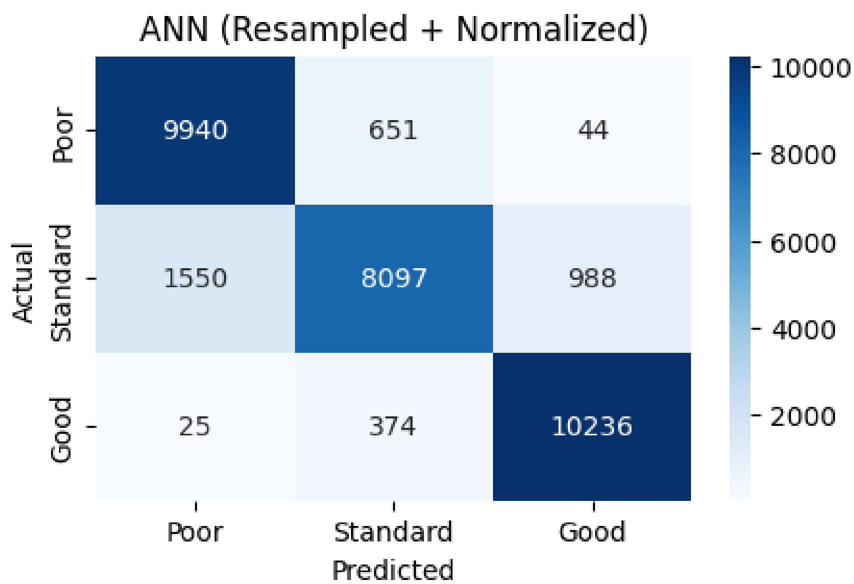
Faces **Exploding gradient problem**.

This can happen when the data is not in the same range. When some of the data has extrimely higher values then the others, the loss function may did not work properly. To solve this, we need to normalize the data.

6.3.3 ANN with resampled, normalized data

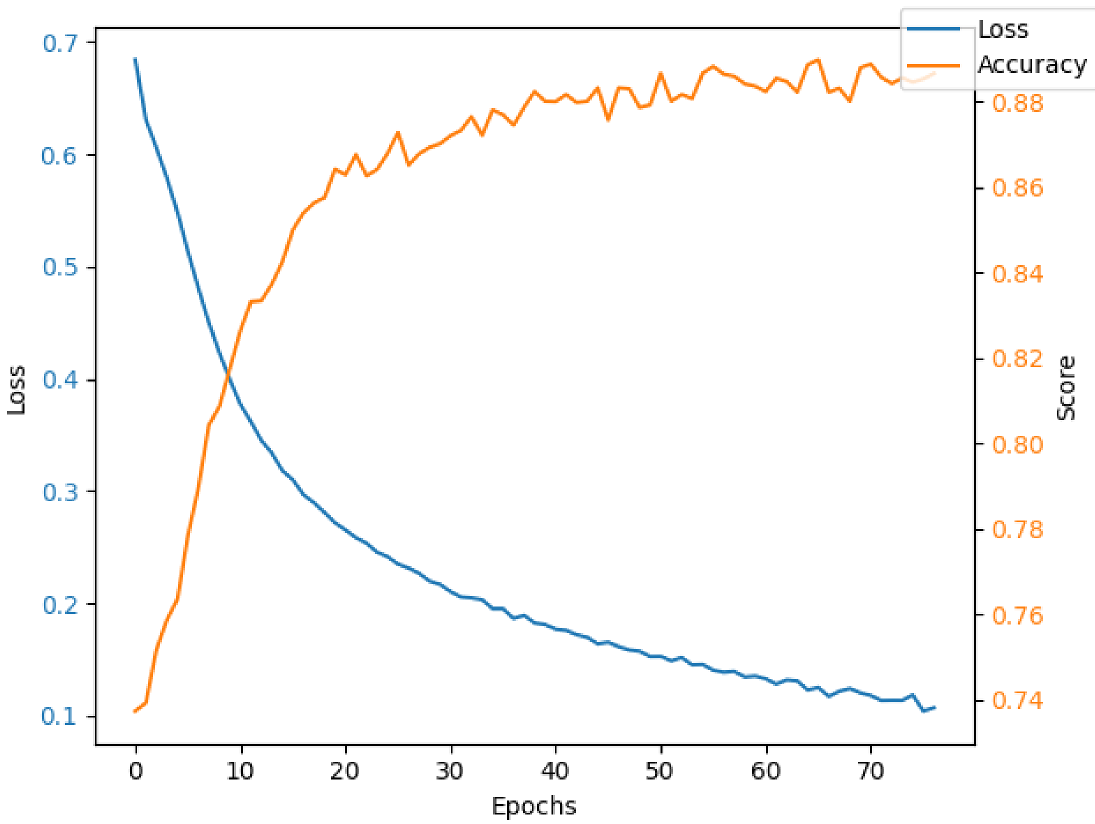
[ ]:
```
# Fit the resampled, normalized data
mlp.fit(X_train_resampled_SC, y_train_resampled)
# Accuracy
ann_pred_resampled_SC = mlp.predict(X_test_resampled_SC)
ann_pred_resampled_SC_prob = mlp.predict_proba(X_test_resampled_SC)
print(classification_report(y_test_resampled, ann_pred_resampled_SC,␣
↪zero_division=0))
confusion_matrix_plot('ANN (Resampled + Normalized)',␣
↪confusion_matrix(y_test_resampled, ann_pred_resampled_SC))
accuracy = mlp.score(X_test_resampled_SC, y_test_resampled)
print("Accuracy:", accuracy)
```

```
              precision    recall  f1-score   support

           0       0.86      0.93      0.90     10635
           1       0.89      0.76      0.82     10635
           2       0.91      0.96      0.93     10635

    accuracy                           0.89     31905
   macro avg       0.89      0.89      0.88     31905
weighted avg       0.89      0.89      0.88     31905
```




```
Accuracy: 0.886162043566839
```

[ ]:
```
show_loss_graph(mlp)
```



6.3.4 Hyper-parameter tuning the ANN with Transformed Data

[ ]:
```
# Check the current parameters
mlp.get_params()
```

[ ]:
```
{'activation': 'relu',
 'alpha': 0.0001,
 'batch_size': 'auto',
 'beta_1': 0.9,
 'beta_2': 0.999,
 'early_stopping': True,
 'epsilon': 1e-08,
 'hidden_layer_sizes': (256, 128, 128, 64),
 'learning_rate': 'constant',
 'learning_rate_init': 0.001,
 'max_fun': 15000,
 'max_iter': 500,
 'momentum': 0.9,
 'n_iter_no_change': 10,
 'nesterovs_momentum': True,
```

```
 'power_t': 0.5,
 'random_state': 57,
 'shuffle': True,
 'solver': 'adam',
 'tol': 0.0001,
 'validation_fraction': 0.1,
 'verbose': False,
 'warm_start': False}
```

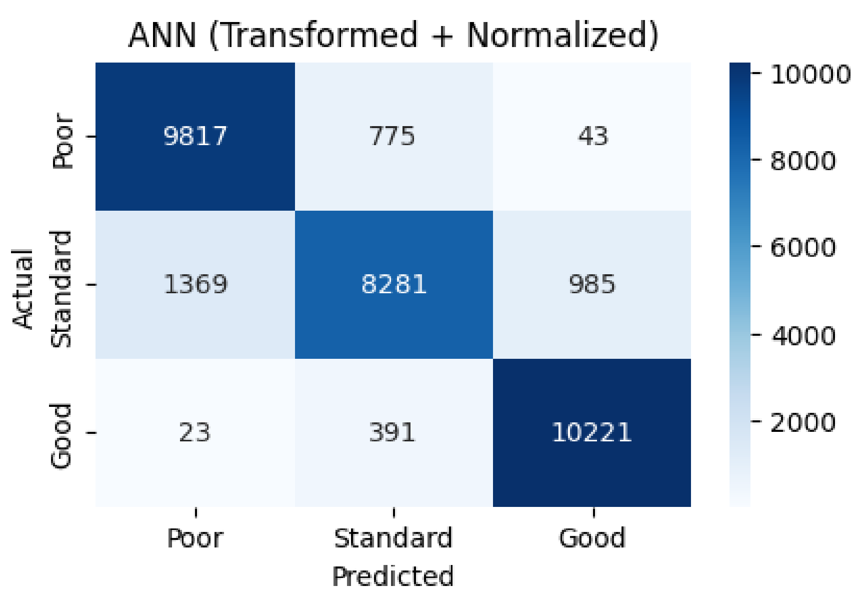
[ ]:
```
# Add some parameters to perform Grid Search
param_distribs = {
    "warm_start": [True],
    "hidden_layer_sizes": [(256,128,128,64), (128, 128, 64, 64), (256, 128, 64,␣
 ↪32), (128, 64, 32), (256, 256, 128, 64)],
    "activation": ["relu", "tanh"],
    "learning_rate_init": [1e-2, 1e-3]
}

# Initialize the GridSearchCV with 3 folds
rnd_search_cv = GridSearchCV(mlp, param_distribs, cv=3, verbose=2)

# Fit transformed set
rnd_search_cv.fit(X_train_transformed_SC, y_train_transformed)

# Accuracy
ann_pred_transformed = rnd_search_cv.best_estimator_.
 ↪predict(X_test_transformed_SC)
ann_pred_transformed_prob = rnd_search_cv.best_estimator_.
 ↪predict_proba(X_test_transformed_SC)
print(classification_report(y_test_transformed, ann_pred_transformed,␣
 ↪zero_division=0))
confusion_matrix_plot('ANN (Transformed + Normalized)',␣
 ↪confusion_matrix(y_test_transformed, ann_pred_transformed))
accuracy = rnd_search_cv.score(X_test_transformed_SC, y_test_transformed)
print("Accuracy:", accuracy)

# Check the best estimator and its parameters
print(rnd_search_cv.best_estimator_)
print(rnd_search_cv.best_params_)
```

```
Fitting 3 folds for each of 20 candidates, totalling 60 fits
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.01, warm_start=True; total time= 1.3min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.01, warm_start=True; total time= 2.3min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.01, warm_start=True; total time= 2.9min
```

```
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.4min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.2min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.7min
[CV] END activation=relu, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.01, warm_start=True; total time= 2.2min
[CV] END activation=relu, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.01, warm_start=True; total time= 1.6min
[CV] END activation=relu, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.01, warm_start=True; total time= 1.2min
[CV] END activation=relu, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.4min
[CV] END activation=relu, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.4min
[CV] END activation=relu, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.6min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time= 1.6min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time= 2.5min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time= 2.4min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time= 1.5min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time= 1.4min
[CV] END activation=relu, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time= 2.4min
[CV] END activation=relu, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time=  52.1s
[CV] END activation=relu, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time= 1.1min
[CV] END activation=relu, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time=  35.0s
[CV] END activation=relu, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time=  56.4s
[CV] END activation=relu, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time=  23.5s
[CV] END activation=relu, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time=  41.0s
[CV] END activation=relu, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.01, warm_start=True; total time= 6.6min
[CV] END activation=relu, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.01, warm_start=True; total time= 3.3min
[CV] END activation=relu, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.01, warm_start=True; total time= 5.3min
```

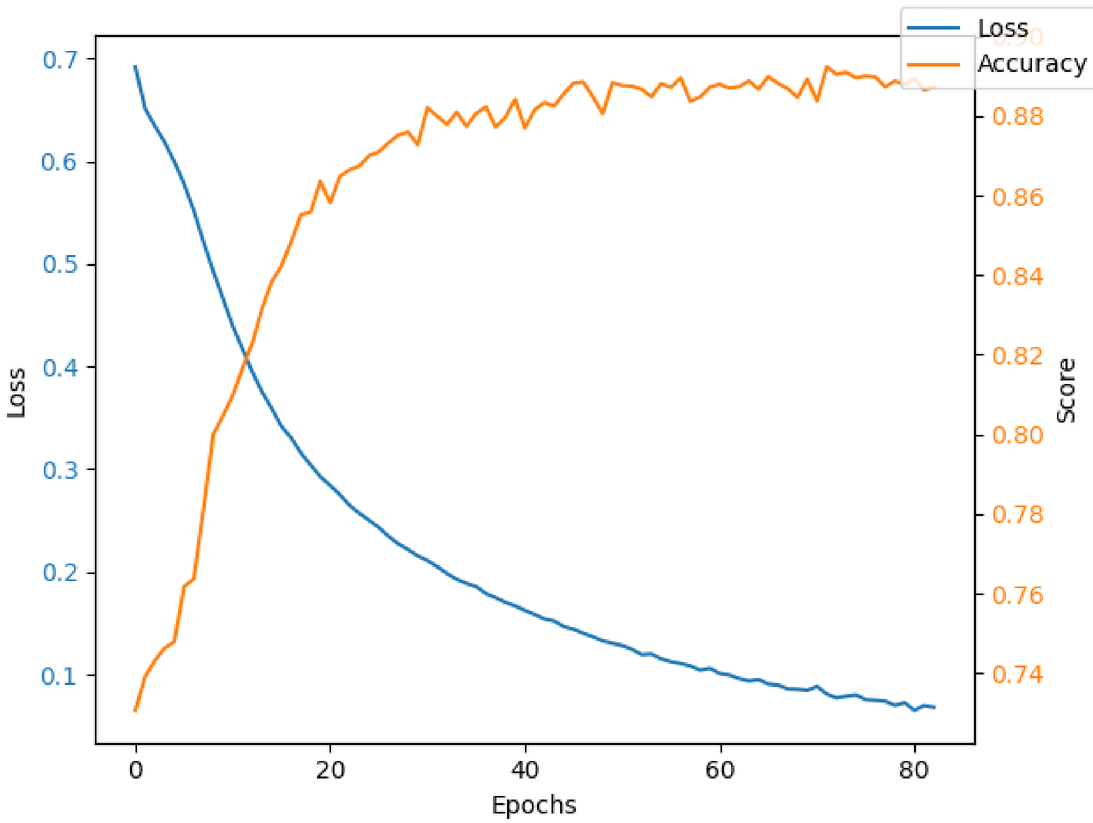
```
[CV] END activation=relu, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.3min
[CV] END activation=relu, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.7min
[CV] END activation=relu, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.2min
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.01, warm_start=True; total time=  40.8s
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.01, warm_start=True; total time=  27.2s
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.01, warm_start=True; total time=  41.8s
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.7min
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.3min
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.4min
[CV] END activation=tanh, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.01, warm_start=True; total time=  28.3s
[CV] END activation=tanh, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.01, warm_start=True; total time=  37.5s
[CV] END activation=tanh, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.01, warm_start=True; total time=  43.9s
[CV] END activation=tanh, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.001, warm_start=True; total time=  59.4s
[CV] END activation=tanh, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.1min
[CV] END activation=tanh, hidden_layer_sizes=(128, 128, 64, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.0min
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time=  25.6s
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time=  36.0s
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time=  26.0s
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time= 1.4min
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time= 1.5min
[CV] END activation=tanh, hidden_layer_sizes=(256, 128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time= 1.7min
[CV] END activation=tanh, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time=  28.6s
[CV] END activation=tanh, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time=  20.4s
[CV] END activation=tanh, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.01, warm_start=True; total time=  17.3s
```

```
[CV] END activation=tanh, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time=  53.3s
[CV] END activation=tanh, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time=  39.5s
[CV] END activation=tanh, hidden_layer_sizes=(128, 64, 32),
learning_rate_init=0.001, warm_start=True; total time=  46.5s
[CV] END activation=tanh, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.01, warm_start=True; total time=  41.5s
[CV] END activation=tanh, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.01, warm_start=True; total time=  36.0s
[CV] END activation=tanh, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.01, warm_start=True; total time=  24.0s
[CV] END activation=tanh, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.9min
[CV] END activation=tanh, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.3min
[CV] END activation=tanh, hidden_layer_sizes=(256, 256, 128, 64),
learning_rate_init=0.001, warm_start=True; total time= 1.5min
              precision    recall  f1-score   support

           0       0.88      0.92      0.90     10635
           1       0.88      0.78      0.82     10635
           2       0.91      0.96      0.93     10635

    accuracy                           0.89     31905
   macro avg       0.89      0.89      0.89     31905
weighted avg       0.89      0.89      0.89     31905
```



```
Accuracy: 0.8876038238520608
MLPClassifier(activation='tanh', early_stopping=True,
              hidden_layer_sizes=(256, 128, 128, 64), max_iter=500,
              random_state=57, warm_start=True)
{'activation': 'tanh', 'hidden_layer_sizes': (256, 128, 128, 64),
'learning_rate_init': 0.001, 'warm_start': True}
```

[ ]:
```python
# Show loss graph
show_loss_graph(rnd_search_cv.best_estimator_)
```



6.3.5 Comparison of the results

[ ]:
```python
ann_basic_summary = model_summary('ANN (Basic)', y_test, ann_pred_basic,␣
 ↪ann_pred_basic_prob)
ann_resampled_summary = model_summary('ANN (Resampled)', y_test_resampled,␣
 ↪ann_pred_resampled, ann_pred_resampled_prob)
ann_resampled_SC_summary = model_summary('ANN (Resampled + Normalized)',␣
 ↪y_test_resampled, ann_pred_resampled_SC, ann_pred_resampled_SC_prob)
```

```
ann_transformed_SC_summary = model_summary('ANN (Transformed + Normalized)',␣
↪y_test_transformed, ann_pred_transformed, ann_pred_transformed_prob)

ann_summary = pd.concat([ann_basic_summary, ann_resampled_summary,␣
↪ann_resampled_SC_summary, ann_transformed_SC_summary])
ann_summary
```

[ ]:

```
                          Model  Accuracy  ROC-AUC Score  Precision (Good)  \
0                   ANN (Basic)  0.622700       0.773137          0.659757
0               ANN (Resampled)  0.605861       0.745290          0.713228
0    ANN (Resampled + Normalized)  0.886162       0.948996          0.863222
0  ANN (Transformed + Normalized)  0.887604       0.952555          0.875814

   Recall (Good)  F1-score (Good)  Precision (Standard)  Recall (Standard)  \
0       0.598207         0.627476              0.614723           0.813446
0       0.733615         0.723278              0.489401           0.421157
0       0.934650         0.897517              0.887634           0.761354
0       0.923084         0.898828              0.876575           0.778655

   F1-score (Standard)  Precision (Poor)  Recall (Poor)  F1-score (Poor)
0             0.700259          0.499253       0.093662         0.157733
0             0.452721          0.596665       0.662811         0.628001
0             0.819659          0.908413       0.962482         0.934666
0             0.824719          0.908614       0.961072         0.934107
```

Normalization is a significant factor in ANN. It can improve the accuracy of the model.

The ROC-AUC score of the model with normalizad data is above 0.94, which is higher than the model without normalization. This means that the model with normalized data is more accurate(less random) than the model without normalization.

6.4 k-Nearest Neighbors (kNN)

6.4.1 Default kNN with basic data

Odd number will be selected for value "k" to avoid ties in classification.

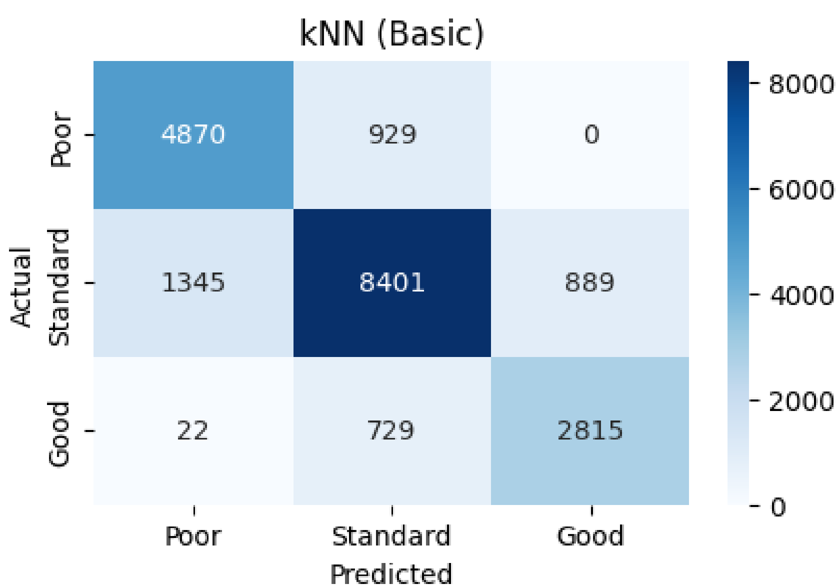
https://www.ibm.com/topics/knn#:~:text=The%20choice%20of%20k%20will,optimal%20k%20for%20your%20da

[ ]:

```
from sklearn.neighbors import KNeighborsClassifier

# Create and train a classification model
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)

# Make predictions on the testing set
knn_pred_basic = knn_model.predict(X_test)
knn_pred_basic_prob = knn_model.predict_proba(X_test)
```

```python
# Evaluate the model
accuracy = accuracy_score(y_test, knn_pred_basic)
print(f"Accuracy: {accuracy}")

classification_report_result = classification_report(y_test, knn_pred_basic)
print("Classification Report:\n",
      classification_report_result)
confusion_matrix_plot('kNN (Basic)', confusion_matrix(y_test, knn_pred_basic))
```

```
Accuracy: 0.8043
Classification Report:
               precision    recall  f1-score   support

           0       0.78      0.84      0.81      5799
           1       0.84      0.79      0.81     10635
           2       0.76      0.79      0.77      3566

    accuracy                           0.80     20000
   macro avg       0.79      0.81      0.80     20000
weighted avg       0.81      0.80      0.80     20000
```



6.4.2 Evaluation with Cross-Validation

[ ]:
```
from sklearn.model_selection import cross_val_score, KFold

# Choose k-fold cross-validation method
kfold = KFold(n_splits=5, shuffle=True, random_state=42)
# Perform cross-validation
scores = cross_val_score(knn_model, X_train,
                         y_train, scoring='accuracy', cv=kfold)

# Evaluate results
print("Cross-Validation Scores:", scores)
print("Mean Accuracy:", scores.mean())
```

```
Cross-Validation Scores: [0.7739375 0.7796875 0.7825    0.776875  0.781    ]
Mean Accuracy: 0.7788
```

6.4.3 kNN Model with Resampling and Normalization

[ ]:
```
from sklearn.preprocessing import MinMaxScaler

# Normalize the features using MinMaxScaler
minMaxscaler = MinMaxScaler()

X_train_minMaxNormalized = minMaxscaler.fit_transform(X_train_resampled)
X_test_minMaxNormalized = minMaxscaler.fit_transform(X_test_resampled)
```

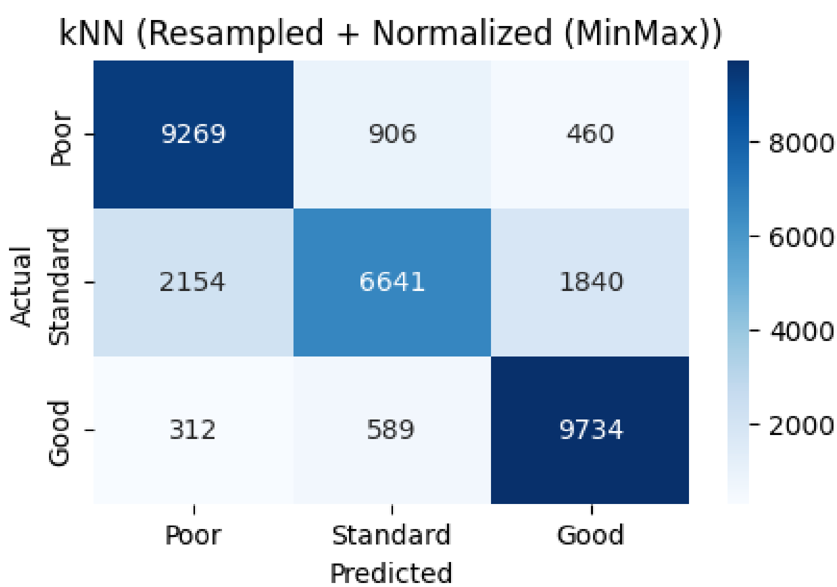
kNN Model with different Normalization Method

kNN with resampled, min-max scaled data

[ ]:
```
# Create and train a classification model using MinMaxScaler
minMax_knn_model = KNeighborsClassifier(n_neighbors=5)
minMax_knn_model.fit(X_train_minMaxNormalized, y_train_resampled)

# Make predictions on the testing set
knn_pred_resampled_MM = minMax_knn_model.predict(X_test_minMaxNormalized)
knn_pred_resampled_MM_prob = minMax_knn_model.
 ↪predict_proba(X_test_minMaxNormalized)

# Evaluate the model
accuracy = accuracy_score(y_test_resampled, knn_pred_resampled_MM)
print(f"Accuracy: {accuracy}")

classification_report_result = classification_report(y_test_resampled,␣
 ↪knn_pred_resampled_MM)
print("Classification Report:\n",
      classification_report_result)
```

```
confusion_matrix_plot('kNN (Resampled + Normalized (MinMax))',
 ↪confusion_matrix(y_test_resampled, knn_pred_resampled_MM))
```

```
Accuracy: 0.8037611659614481
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.87      0.83     10635
           1       0.82      0.62      0.71     10635
           2       0.81      0.92      0.86     10635

    accuracy                           0.80     31905
   macro avg       0.80      0.80      0.80     31905
weighted avg       0.80      0.80      0.80     31905
```



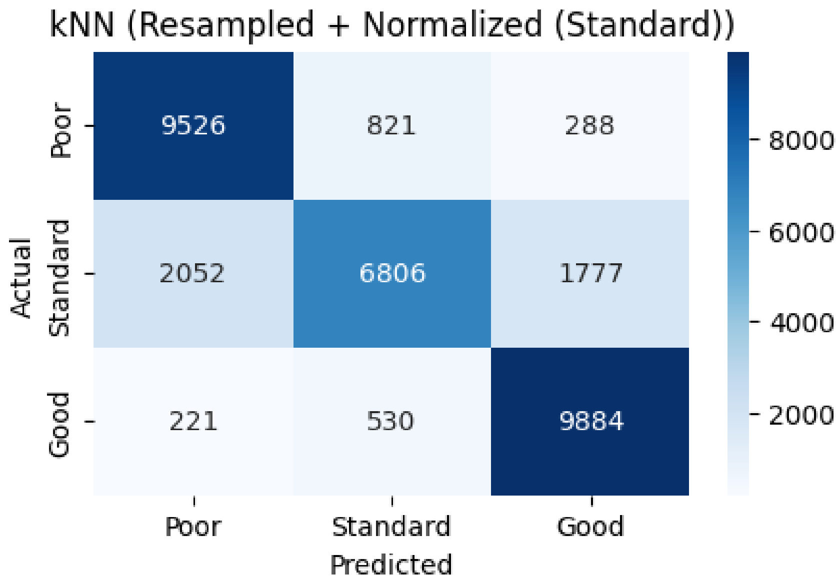
[ ]:
```
# Using model whose data that was normalized using MinMaxScale

# Choose k-fold cross-validation method
kfold = KFold(n_splits=5, shuffle=True, random_state=42)
# Perform cross-validation
scores = cross_val_score(minMax_knn_model, X_train_minMaxNormalized,
                         y_train_resampled, scoring='accuracy', cv=kfold)

# Evaluate results
print("Cross-Validation Scores:", scores)
print("Mean Accuracy:", scores.mean())
```

```
Cross-Validation Scores: [0.78443818 0.78455571 0.78721153 0.78678055
 0.78431219]
Mean Accuracy: 0.7854596325362372
```

kNN with resampled, normalized data

```
[ ]: # Create and train a classification model using StandardScaler
std_knn_model = KNeighborsClassifier(n_neighbors=5)
std_knn_model.fit(X_train_resampled_SC, y_train_resampled)

# Make predictions on the testing set
knn_pred_resampled_SC = std_knn_model.predict(X_test_resampled_SC)
knn_pred_resampled_SC_prob = std_knn_model.predict_proba(X_test_resampled_SC)

# Evaluate the model
accuracy = accuracy_score(y_test_resampled, knn_pred_resampled_SC)
print(f"Accuracy: {accuracy}")

classification_report_result = classification_report(y_test_resampled,␣
 ↪knn_pred_resampled_SC)
print("Classification Report:\n",
      classification_report_result)
confusion_matrix_plot('kNN (Resampled + Normalized (Standard))',␣
 ↪confusion_matrix(y_test_resampled, knn_pred_resampled_SC))
```

```
Accuracy: 0.8216893903776837
Classification Report:
               precision    recall  f1-score   support

           0       0.81      0.90      0.85     10635
           1       0.83      0.64      0.72     10635
           2       0.83      0.93      0.88     10635

    accuracy                           0.82     31905
   macro avg       0.82      0.82      0.82     31905
weighted avg       0.82      0.82      0.82     31905
```



[ ]:
```python
# Using model whose data that was normalized using StandardScaler

# Choose k-fold cross-validation method
kfold = KFold(n_splits=5, shuffle=True, random_state=42)
# Perform cross-validation
scores = cross_val_score(std_knn_model, X_train_resampled_SC,
                         y_train_resampled, scoring='accuracy', cv=kfold)

# Evaluate results
print("Cross-Validation Scores:", scores)
print("Mean Accuracy:", scores.mean())
```

```
Cross-Validation Scores: [0.80704435 0.80684846 0.80413744 0.80825138
0.80515613]
Mean Accuracy: 0.8062875532436878
```

6.4.4 Hyper-parameter tuning the kNN with transformed data

[ ]:
```python
# Using GridSearch for model with Min-Max Normalized to check for the best␣
↪parameters
param_grid = {
    'n_neighbors': [1, 5, 10, 15, 20],
    'weights': ['uniform', 'distance'],
    'p': [1, 2]
}

X_train_transformed_MM = minMaxscaler.fit_transform(X_train_transformed)
```

```
X_test_transformed_MM = minMaxscaler.fit_transform(X_test_transformed)

grid_search = GridSearchCV(
    minMax_knn_model, param_grid=param_grid, scoring='accuracy', cv=5)
grid_search.fit(X_train_transformed_MM, y_train_transformed)

print("Best Hyperparameters:", grid_search.best_params_)
print("Best Accuracy on Validation Set:", grid_search.best_score_)

# Evaluate on the test set
best_model = grid_search.best_estimator_
test_accuracy = best_model.score(X_test_transformed_MM, y_test_transformed)
print("Accuracy on Test Set:", test_accuracy)
```

```
Best Hyperparameters: {'n_neighbors': 1, 'p': 1, 'weights': 'uniform'}
Best Accuracy on Validation Set: 0.902489493836887
Accuracy on Test Set: 0.9107663375646451
```

[ ]:
```
# Using GridSearch for model with Standard Normalized to check for the best␣
↪parameters
param_grid = {
    'n_neighbors': [1, 5, 10, 15, 20],
    'weights': ['uniform', 'distance'],
    'p': [1, 2]
}

grid_search = GridSearchCV(
    std_knn_model, param_grid=param_grid, scoring='accuracy', cv=5)
grid_search.fit(X_train_transformed_SC, y_train_transformed)

print("Best Hyperparameters:", grid_search.best_params_)
print("Best Accuracy on Validation Set:", grid_search.best_score_)

# Evaluate on the test set
best_model = grid_search.best_estimator_
test_accuracy = best_model.score(X_test_transformed_SC, y_test_transformed)
print("Accuracy on Test Set:", test_accuracy)
```

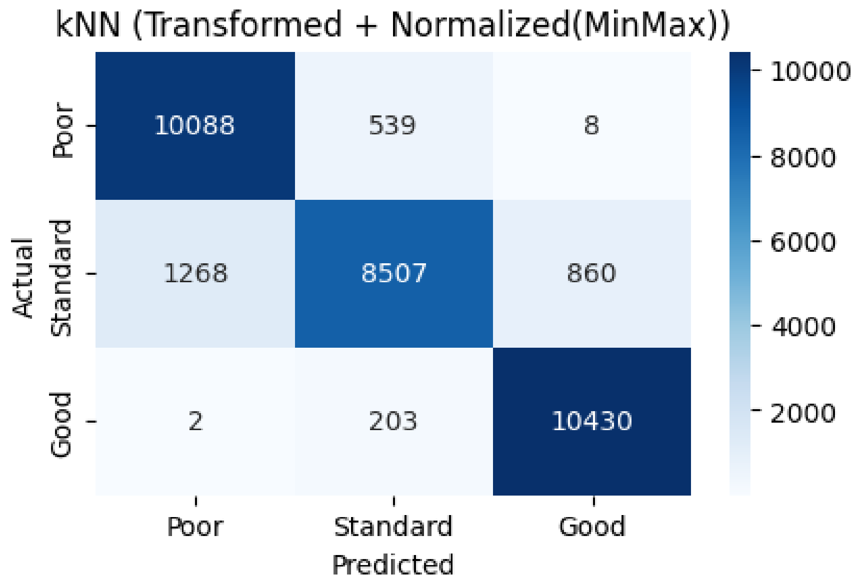
```
Best Hyperparameters: {'n_neighbors': 1, 'p': 1, 'weights': 'uniform'}
Best Accuracy on Validation Set: 0.9024738220050399
Accuracy on Test Set: 0.9104529070678578
```

6.4.5 Recompiling the kNN Model with the best hyper-parameters

[ ]:
```
# Create and train a classification model using MinMaxScaler
minMax_knn_model = KNeighborsClassifier(n_neighbors=1, p=1, weights='uniform')
# knn_model.fit(X_train_normalized, y_train)
```

```
minMax_knn_model.fit(X_train_minMaxNormalized, y_train_transformed)

# Make predictions on the testing set
# predictions = knn_model.predict(X_test_normalized)
knn_pred_transformed_MM = minMax_knn_model.predict(X_test_minMaxNormalized)
knn_pred_transformed_MM_prob = minMax_knn_model.
 ↪predict_proba(X_test_minMaxNormalized)

# Evaluate the model
accuracy = accuracy_score(y_test_transformed, knn_pred_transformed_MM)
print(f"Accuracy: {accuracy}")

classification_report_result = classification_report(y_test_transformed,␣
 ↪knn_pred_transformed_MM)
print("Classification Report:\n",
      classification_report_result)
confusion_matrix_plot('kNN (Transformed + Normalized(MinMax))',␣
 ↪confusion_matrix(y_test_transformed, knn_pred_transformed_MM))
```

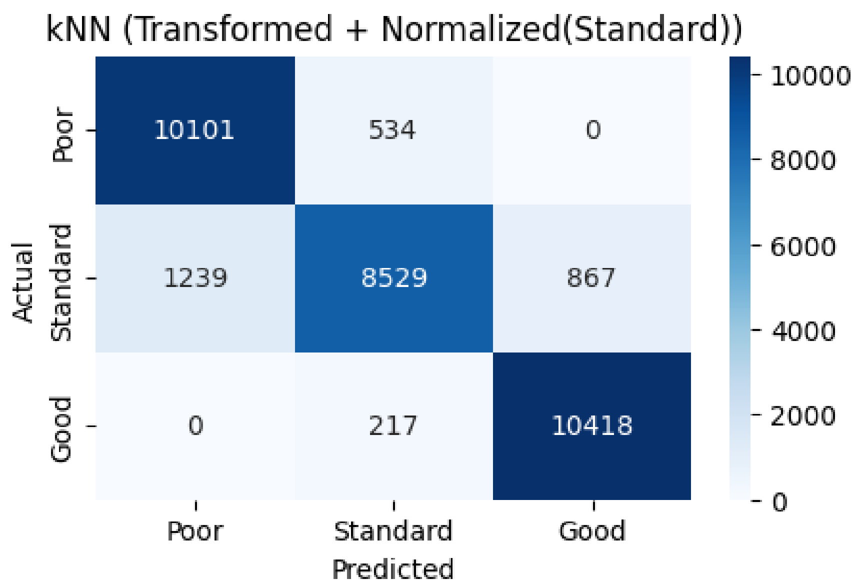
```
Accuracy: 0.9097320169252469
Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.95      0.92     10635
           1       0.92      0.80      0.86     10635
           2       0.92      0.98      0.95     10635

    accuracy                           0.91     31905
   macro avg       0.91      0.91      0.91     31905
weighted avg       0.91      0.91      0.91     31905
```



[ ]:
```
# Create and train a classification model using Standard_Scaler
std_knn_model = KNeighborsClassifier(n_neighbors=1, p=1, weights='uniform')
# knn_model.fit(X_train_normalized, y_train)
std_knn_model.fit(X_train_transformed_SC, y_train_transformed)

# Make predictions on the testing set
# predictions = knn_model.predict(X_test_normalized)
knn_pred_transformed_SC = std_knn_model.predict(X_test_transformed_SC)
knn_pred_transformed_SC_prob = std_knn_model.
 ↪predict_proba(X_test_transformed_SC)

# Evaluate the model
accuracy = accuracy_score(y_test_transformed, knn_pred_transformed_SC)
print(f"Accuracy: {accuracy}")

classification_report_result = classification_report(y_test_transformed,␣
 ↪knn_pred_transformed_SC)
print("Classification Report:\n",
      classification_report_result)
confusion_matrix_plot('kNN (Transformed + Normalized(Standard))',␣
 ↪confusion_matrix(y_test_transformed, knn_pred_transformed_SC))
```

```
Accuracy: 0.9104529070678578
Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.95      0.92     10635
```

```
           1       0.92      0.80      0.86     10635
           2       0.92      0.98      0.95     10635

    accuracy                           0.91     31905
   macro avg       0.91      0.91      0.91     31905
weighted avg       0.91      0.91      0.91     31905
```



6.4.6 Comparison of the results

```
[ ]: knn_basic_summary = model_summary('kNN (Basic)', y_test, knn_pred_basic,␣
      ↪knn_pred_basic_prob)
     knn_resampled_MM_summary = model_summary('kNN (Resampled +␣
      ↪Normalized(MinMax))', y_test_resampled, knn_pred_resampled_MM,␣
      ↪knn_pred_resampled_MM_prob)
     knn_resampled_SC_summary = model_summary('kNN (Resampled +␣
      ↪Normalized(Standard))', y_test_resampled, knn_pred_resampled_SC,␣
      ↪knn_pred_resampled_SC_prob)
     knn_transformed_MM_summary = model_summary('kNN (Transformed +␣
      ↪Normalized(MinMax))', y_test_transformed, knn_pred_transformed_MM,␣
      ↪knn_pred_transformed_MM_prob)
     knn_transformed_SC_summary = model_summary('kNN (Transformed +␣
      ↪Normalized(Standard))', y_test_transformed, knn_pred_transformed_SC,␣
      ↪knn_pred_transformed_SC_prob)
```

```
knn_summary = pd.concat([knn_basic_summary, knn_resampled_MM_summary,␣
↪knn_resampled_SC_summary, knn_transformed_MM_summary,␣
↪knn_transformed_SC_summary])
knn_summary
```

[ ]:
```
                                      Model  Accuracy  ROC-AUC Score  \
0                               kNN (Basic)  0.804300       0.921987
0      kNN (Resampled + Normalized(MinMax))  0.803761       0.920635
0    kNN (Resampled + Normalized(Standard))  0.821689       0.929057
0    kNN (Transformed + Normalized(MinMax))  0.909732       0.932299
0  kNN (Transformed + Normalized(Standard))  0.910453       0.932840

   Precision (Good)  Recall (Good)  F1-score (Good)  Precision (Standard)  \
0          0.780824       0.839800         0.809239              0.835172
0          0.789859       0.871556         0.828699              0.816249
0          0.807357       0.895722         0.849247              0.834375
0          0.888185       0.948566         0.917383              0.919775
0          0.890741       0.949788         0.919317              0.919073

   Recall (Standard)  F1-score (Standard)  Precision (Poor)  Recall (Poor)  \
0           0.789939             0.811926          0.759989       0.789400
0           0.624448             0.707581          0.808875       0.915280
0           0.639962             0.724351          0.827182       0.929384
0           0.799906             0.855663          0.923172       0.980724
0           0.801975             0.856540          0.923172       0.979596

   F1-score (Poor)
0         0.774415
0         0.858794
0         0.875310
0         0.951078
0         0.950547
```

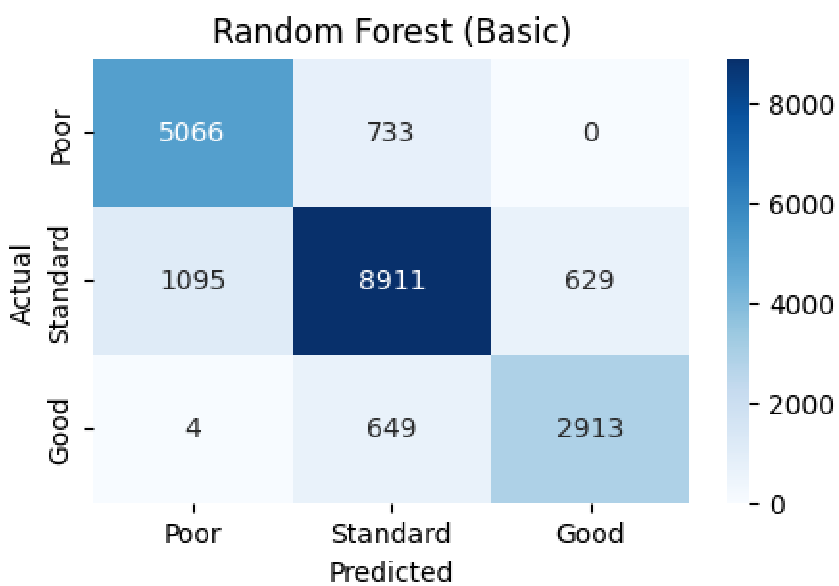
6.5 Random Forest

6.5.1 Random Forest with basic data

[ ]:
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(
    class_weight= 'balanced',
    n_estimators= 100,
    random_state= 42
)

rfc.fit(X_train, y_train)
```

```
rfc_pred_basic = rfc.predict(X_test)
rfc_pred_basic_prob = rfc.predict_proba(X_test)

# Printing of classification report and confusion matrix
print("Test")
print(classification_report(y_test, rfc_pred_basic))
confusion_matrix_plot('Random Forest (Basic)', confusion_matrix(y_test,␣
 ↪rfc_pred_basic))
```

```
Test
              precision    recall  f1-score   support

           0       0.82      0.87      0.85      5799
           1       0.87      0.84      0.85     10635
           2       0.82      0.82      0.82      3566

    accuracy                           0.84     20000
   macro avg       0.84      0.84      0.84     20000
weighted avg       0.85      0.84      0.84     20000
```

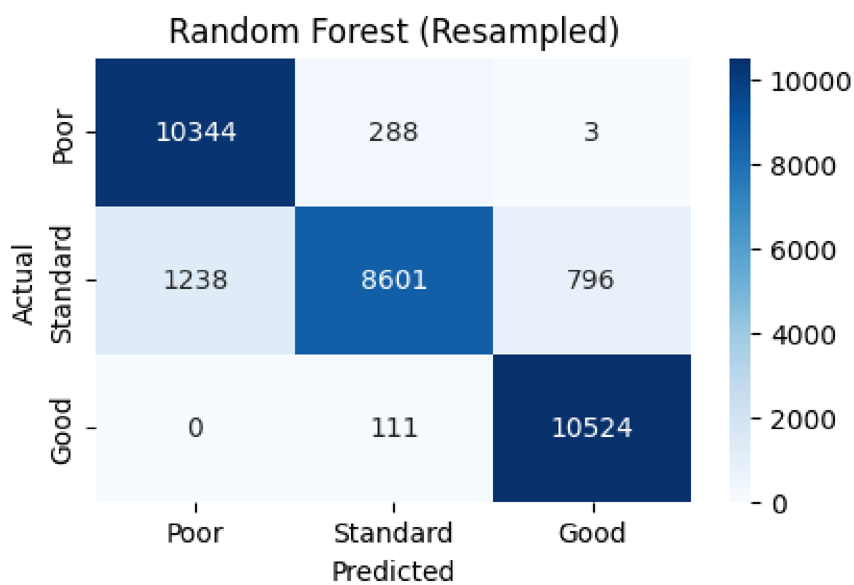


6.5.2 Random Forest with resampled data

[ ]:
```
rfc.fit(X_train_resampled, y_train_resampled)

rfc_pred_resampled = rfc.predict(X_test_resampled)
rfc_pred_resampled_prob = rfc.predict_proba(X_test_resampled)
```

```
# Printing of classification report and confusion matrix
print("Test")
print(classification_report(y_test_resampled, rfc_pred_resampled))
confusion_matrix_plot('Random Forest (Resampled)',␣
 ↪confusion_matrix(y_test_resampled, rfc_pred_resampled))
```

```
Test
              precision    recall  f1-score   support

           0       0.89      0.97      0.93     10635
           1       0.96      0.81      0.88     10635
           2       0.93      0.99      0.96     10635

    accuracy                           0.92     31905
   macro avg       0.93      0.92      0.92     31905
weighted avg       0.93      0.92      0.92     31905
```

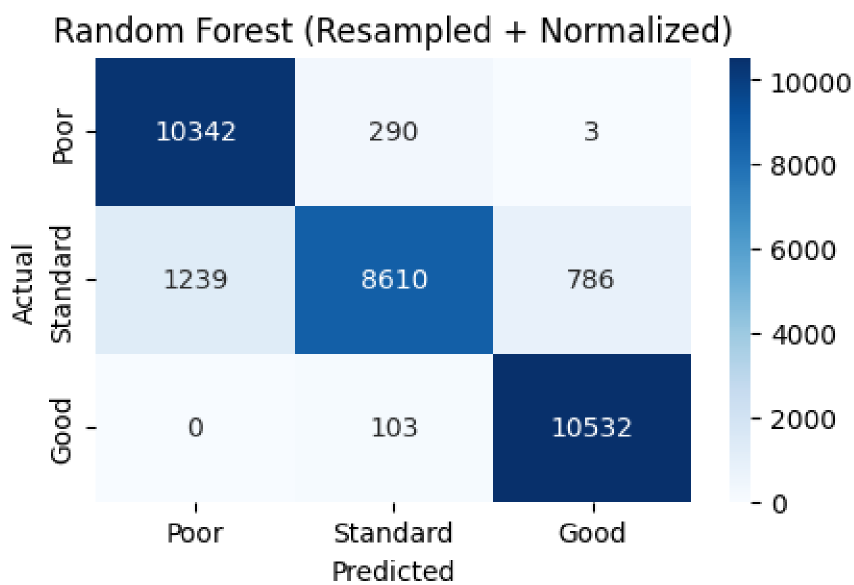


6.5.3 Random Forest with resampled, normalized data

[ ]:
```
rfc.fit(X_train_resampled_SC, y_train_resampled)

rfc_pred_resampled_SC = rfc.predict(X_test_resampled_SC)
rfc_pred_resampled_SC_prob = rfc.predict_proba(X_test_resampled_SC)

# Printing of classification report and confusion matrix
```

```
print("Test")
print(classification_report(y_test_resampled, rfc_pred_resampled_SC))
confusion_matrix_plot('Random Forest (Resampled + Normalized)',␣
 ↪confusion_matrix(y_test_resampled, rfc_pred_resampled_SC))
```

```
Test
              precision    recall  f1-score   support

           0       0.89      0.97      0.93     10635
           1       0.96      0.81      0.88     10635
           2       0.93      0.99      0.96     10635

    accuracy                           0.92     31905
   macro avg       0.93      0.92      0.92     31905
weighted avg       0.93      0.92      0.92     31905
```



6.5.4 Hyper-parameter tuning the Random Forest Model with Transformed Data

[ ]:
```
rfc.get_params()
```

[ ]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'class_weight': 'balanced',
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'sqrt',
```

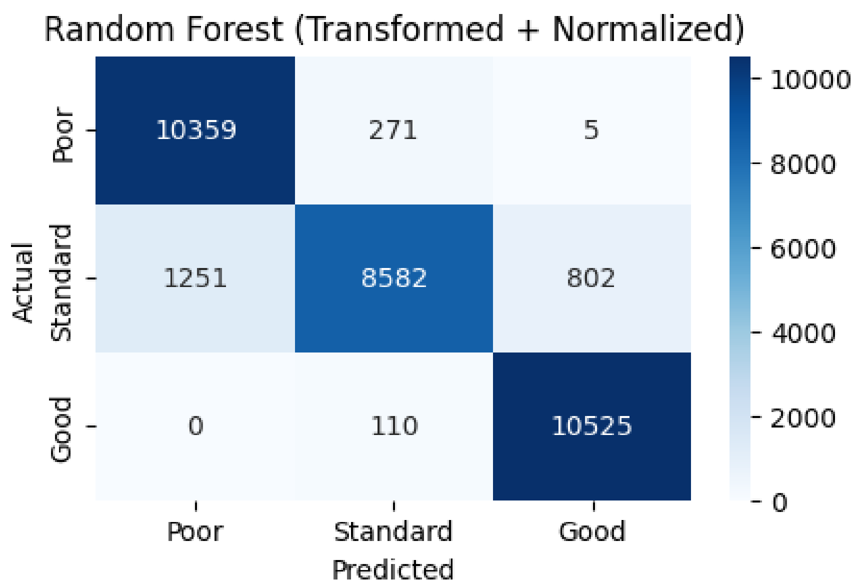
```
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'monotonic_cst': None,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

[ ]:
```
model = RandomForestClassifier(
    class_weight= 'balanced',
    n_estimators= 100,
    random_state= 42
)

params = {
    'class_weight': ['balanced'],
    'n_estimators': [75, 100],
    'criterion'   : ["gini", "entropy"],
    'max_features': ['sqrt', None],
    'min_samples_split': [2, 5, 10],
    'max_depth' : [10, 20, None]
}

gridSearch = GridSearchCV(
    estimator = model,
    param_grid = params,
    error_score='raise',
    n_jobs = -1,
    refit=True,
    cv=5,
)

gridSearch.fit(X_train_transformed_SC, y_train_transformed)

bestParams = gridSearch.best_params_
```

[ ]:
```
finalModel = RandomForestClassifier(**bestParams)

finalModel.fit(X_train_transformed_SC, y_train_transformed)

rfc_pred_transformed = finalModel.predict(X_test_transformed_SC)
```

```python
rfc_pred_transformed_prob = finalModel.predict_proba(X_test_transformed_SC)

# Printing of classification report and confusion matrix
print("Test with tuned Hyperparameters")
print()
print("Parameters: ")
print(finalModel.get_params())
print()
print("Classification report: ")
print(classification_report(y_test_transformed, rfc_pred_transformed))
confusion_matrix_plot('Random Forest (Transformed + Normalized)',␣
 ↪confusion_matrix(y_test_transformed, rfc_pred_transformed))
```

```
Test with tuned Hyperparameters

Parameters:
{'bootstrap': True, 'ccp_alpha': 0.0, 'class_weight': 'balanced', 'criterion':
'gini', 'max_depth': None, 'max_features': 'sqrt', 'max_leaf_nodes': None,
'max_samples': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1,
'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'monotonic_cst': None,
'n_estimators': 100, 'n_jobs': None, 'oob_score': False, 'random_state': None,
'verbose': 0, 'warm_start': False}

Classification report:
              precision    recall  f1-score   support

           0       0.89      0.97      0.93     10635
           1       0.96      0.81      0.88     10635
           2       0.93      0.99      0.96     10635

    accuracy                           0.92     31905
   macro avg       0.93      0.92      0.92     31905
weighted avg       0.93      0.92      0.92     31905
```



6.5.5 Comparison of the results

[ ]:
```
rfc_basic_summary = model_summary('Random Forest (Basic)', y_test,␣
 ↪rfc_pred_basic, rfc_pred_basic_prob)
rfc_resampled_summary = model_summary('Random Forest (Resampled)',␣
 ↪y_test_resampled, rfc_pred_resampled, rfc_pred_resampled_prob)
rfc_resampled_SC_summary = model_summary('Random Forest (Resampled +␣
 ↪Normalized)', y_test_resampled, rfc_pred_resampled_SC,␣
 ↪rfc_pred_resampled_SC_prob)
rfc_transformed_SC_summary = model_summary('Random Forest (Transformed +␣
 ↪Normalized)', y_test_transformed, rfc_pred_transformed,␣
 ↪rfc_pred_transformed_prob)

rfc_summary = pd.concat([rfc_basic_summary, rfc_resampled_summary,␣
 ↪rfc_resampled_SC_summary, rfc_transformed_SC_summary])
rfc_summary
```

[ ]:
```
                                    Model  Accuracy  ROC-AUC Score  \
0                   Random Forest (Basic)  0.844500       0.944504
0               Random Forest (Resampled)  0.923648       0.984035
0    Random Forest (Resampled + Normalized)  0.924118       0.984170
0  Random Forest (Transformed + Normalized)  0.923554       0.983616

   Precision (Good)  Recall (Good)  F1-score (Good)  Precision (Standard)  \
0          0.821736       0.873599         0.846874              0.865734
0          0.893110       0.972638         0.931179              0.955667
```

```
0          0.893014       0.972449         0.931041              0.956348
0          0.892248       0.974048         0.931355              0.957492

   Recall (Standard)  F1-score (Standard)  Precision (Poor)  Recall (Poor)  \
0           0.837894             0.851586          0.822417       0.816882
0           0.808745             0.876089          0.929436       0.989563
0           0.809591             0.876871          0.930307       0.990315
0           0.806958             0.875804          0.928786       0.989657

   F1-score (Poor)
0         0.819640
0         0.958557
0         0.959373
0         0.958256
```

7 6. Model Evaluation

[ ]:
```
# Show the summary of all models
overall_summary = pd.concat([gnb_summary, ann_summary, knn_summary,␣
↪rfc_summary])
overall_summary
```

[ ]:
```
                                            Model  Accuracy  ROC-AUC Score  \
0                     Gaussian Naive Bayes (Basic)  0.586500       0.767024
0                 Gaussian Naive Bayes (Resampled)  0.637079       0.784156
0    Gaussian Naive Bayes (Resampled + Normalized)  0.672183       0.794185
0  Gaussian Naive Bayes (Transformed + Normalized)  0.665131       0.790039
0                                      ANN (Basic)  0.622700       0.773137
0                                  ANN (Resampled)  0.605861       0.745290
0                     ANN (Resampled + Normalized)  0.886162       0.948996
0                   ANN (Transformed + Normalized)  0.887604       0.952555
0                                      kNN (Basic)  0.804300       0.921987
0             kNN (Resampled + Normalized(MinMax))  0.803761       0.920635
0           kNN (Resampled + Normalized(Standard))  0.821689       0.929057
0           kNN (Transformed + Normalized(MinMax))  0.909732       0.932299
0         kNN (Transformed + Normalized(Standard))  0.910453       0.932840
0                            Random Forest (Basic)  0.844500       0.944504
0                        Random Forest (Resampled)  0.923648       0.984035
0           Random Forest (Resampled + Normalized)  0.924118       0.984170
0         Random Forest (Transformed + Normalized)  0.923554       0.983616

   Precision (Good)  Recall (Good)  F1-score (Good)  Precision (Standard)  \
0          0.611639       0.732195         0.666510              0.814808
0          0.693555       0.751857         0.721530              0.673963
0          0.705110       0.747344         0.725613              0.702940
0          0.732013       0.736624         0.734311              0.698594
```

0	0.659757	0.598207	0.627476	0.614723
0	0.713228	0.733615	0.723278	0.489401
0	0.863222	0.934650	0.897517	0.887634
0	0.875814	0.923084	0.898828	0.876575
0	0.780824	0.839800	0.809239	0.835172
0	0.789859	0.871556	0.828699	0.816249
0	0.807357	0.895722	0.849247	0.834375
0	0.888185	0.948566	0.917383	0.919775
0	0.890741	0.949788	0.919317	0.919073
0	0.821736	0.873599	0.846874	0.865734
0	0.893110	0.972638	0.931179	0.955667
0	0.893014	0.972449	0.931041	0.956348
0	0.892248	0.974048	0.931355	0.957492

	Recall (Standard)	F1-score (Standard)	Precision (Poor)	Recall (Poor) \
0	0.423225	0.557089	0.395938	0.836511
0	0.277950	0.393582	0.586241	0.881429
0	0.406958	0.515484	0.633462	0.862247
0	0.378561	0.491035	0.606282	0.880207
0	0.813446	0.700259	0.499253	0.093662
0	0.421157	0.452721	0.596665	0.662811
0	0.761354	0.819659	0.908413	0.962482
0	0.778655	0.824719	0.908614	0.961072
0	0.789939	0.811926	0.759989	0.789400
0	0.624448	0.707581	0.808875	0.915280
0	0.639962	0.724351	0.827182	0.929384
0	0.799906	0.855663	0.923172	0.980724
0	0.801975	0.856540	0.923172	0.979596
0	0.837894	0.851586	0.822417	0.816882
0	0.808745	0.876089	0.929436	0.989563
0	0.809591	0.876871	0.930307	0.990315
0	0.806958	0.875804	0.928786	0.989657

	F1-score (Poor)
0	0.537477
0	0.704150
0	0.730357
0	0.718006
0	0.157733
0	0.628001
0	0.934666
0	0.934107
0	0.774415
0	0.858794
0	0.875310
0	0.951078
0	0.950547

```
0         0.819640
0         0.958557
0         0.959373
0         0.958256
```

[ ]:
```python
# Show the summary, sort by Accuracy
overall_summary.sort_values(by=['Accuracy'])
```

[ ]:
```
                                          Model  Accuracy  ROC-AUC Score  \
0                  Gaussian Naive Bayes (Basic)  0.586500       0.767024
0                               ANN (Resampled)  0.605861       0.745290
0                                   ANN (Basic)  0.622700       0.773137
0              Gaussian Naive Bayes (Resampled)  0.637079       0.784156
0 Gaussian Naive Bayes (Transformed + Normalized)  0.665131       0.790039
0   Gaussian Naive Bayes (Resampled + Normalized)  0.672183       0.794185
0          kNN (Resampled + Normalized(MinMax))  0.803761       0.920635
0                                   kNN (Basic)  0.804300       0.921987
0        kNN (Resampled + Normalized(Standard))  0.821689       0.929057
0                         Random Forest (Basic)  0.844500       0.944504
0                  ANN (Resampled + Normalized)  0.886162       0.948996
0                ANN (Transformed + Normalized)  0.887604       0.952555
0        kNN (Transformed + Normalized(MinMax))  0.909732       0.932299
0      kNN (Transformed + Normalized(Standard))  0.910453       0.932840
0      Random Forest (Transformed + Normalized)  0.923554       0.983616
0                     Random Forest (Resampled)  0.923648       0.984035
0        Random Forest (Resampled + Normalized)  0.924118       0.984170

   Precision (Good)  Recall (Good)  F1-score (Good)  Precision (Standard)  \
0          0.611639       0.732195         0.666510              0.814808
0          0.713228       0.733615         0.723278              0.489401
0          0.659757       0.598207         0.627476              0.614723
0          0.693555       0.751857         0.721530              0.673963
0          0.732013       0.736624         0.734311              0.698594
0          0.705110       0.747344         0.725613              0.702940
0          0.789859       0.871556         0.828699              0.816249
0          0.780824       0.839800         0.809239              0.835172
0          0.807357       0.895722         0.849247              0.834375
0          0.821736       0.873599         0.846874              0.865734
0          0.863222       0.934650         0.897517              0.887634
0          0.875814       0.923084         0.898828              0.876575
0          0.888185       0.948566         0.917383              0.919775
0          0.890741       0.949788         0.919317              0.919073
0          0.892248       0.974048         0.931355              0.957492
0          0.893110       0.972638         0.931179              0.955667
0          0.893014       0.972449         0.931041              0.956348

   Recall (Standard)  F1-score (Standard)  Precision (Poor)  Recall (Poor)  \
```

```
0           0.423225          0.557089         0.395938        0.836511
0           0.421157          0.452721         0.596665        0.662811
0           0.813446          0.700259         0.499253        0.093662
0           0.277950          0.393582         0.586241        0.881429
0           0.378561          0.491035         0.606282        0.880207
0           0.406958          0.515484         0.633462        0.862247
0           0.624448          0.707581         0.808875        0.915280
0           0.789939          0.811926         0.759989        0.789400
0           0.639962          0.724351         0.827182        0.929384
0           0.837894          0.851586         0.822417        0.816882
0           0.761354          0.819659         0.908413        0.962482
0           0.778655          0.824719         0.908614        0.961072
0           0.799906          0.855663         0.923172        0.980724
0           0.801975          0.856540         0.923172        0.979596
0           0.806958          0.875804         0.928786        0.989657
0           0.808745          0.876089         0.929436        0.989563
0           0.809591          0.876871         0.930307        0.990315

   F1-score (Poor)
0         0.537477
0         0.628001
0         0.157733
0         0.704150
0         0.718006
0         0.730357
0         0.858794
0         0.774415
0         0.875310
0         0.819640
0         0.934666
0         0.934107
0         0.951078
0         0.950547
0         0.958256
0         0.958557
0         0.959373
```

[ ]:

```
# Show the best accuracy models of each implementations
gnb_highest_accuracy = gnb_summary[gnb_summary['Accuracy'] ==␣
 ↪gnb_summary['Accuracy'].max()]
ann_highest_accuracy = ann_summary[ann_summary['Accuracy'] ==␣
 ↪ann_summary['Accuracy'].max()]
knn_highest_accuracy = knn_summary[knn_summary['Accuracy'] ==␣
 ↪knn_summary['Accuracy'].max()]
rfc_highest_accuracy = rfc_summary[rfc_summary['Accuracy'] ==␣
 ↪rfc_summary['Accuracy'].max()]
```

```
best_model_summary = pd.concat([gnb_highest_accuracy, ann_highest_accuracy,␣
↪knn_highest_accuracy, rfc_highest_accuracy])
best_model_summary.sort_values(by=['Accuracy'])
```

```
[ ]:                                           Model  Accuracy  ROC-AUC Score  \
0  Gaussian Naive Bayes (Resampled + Normalized)  0.672183       0.794185
0               ANN (Transformed + Normalized)  0.887604       0.952555
0     kNN (Transformed + Normalized(Standard))  0.910453       0.932840
0       Random Forest (Resampled + Normalized)  0.924118       0.984170

   Precision (Good)  Recall (Good)  F1-score (Good)  Precision (Standard)  \
0          0.705110       0.747344         0.725613              0.702940
0          0.875814       0.923084         0.898828              0.876575
0          0.890741       0.949788         0.919317              0.919073
0          0.893014       0.972449         0.931041              0.956348

   Recall (Standard)  F1-score (Standard)  Precision (Poor)  Recall (Poor)  \
0           0.406958             0.515484          0.633462       0.862247
0           0.778655             0.824719          0.908614       0.961072
0           0.801975             0.856540          0.923172       0.979596
0           0.809591             0.876871          0.930307       0.990315

   F1-score (Poor)
0         0.730357
0         0.934107
0         0.950547
0         0.959373
```

7.1 Conclusion

We can find that the accuracy of all four models increases as resampling, fine tuning, and data become normalized.

Among them, the model that showed the greatest performance improvement was the ANN model, which recorded an accuracy of 88.8% based on ANN (Transformed + Normalized) from an accuracy of about 60.6% based on the original data, showing a significant increase of approximately 28.2%p.

The model that showed the highest accuracy among the four models was the Random forest model, which showed 92.4% accuracy.