CSCI316 Group Assignment 2 (Group 7) - Jan 2024

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CSCI316 - Group Assignment 2 (Group 7)

Group Members:

- Wootaek Lim (7898848)
- Chew Wei Hong (7911130)
- Minseo Yun (8225746)
- Yam Shi Xuan Jonathan (8380053)

Objective

> The objective of this task is to develop an end-to-end data mining project by using the Apache MLlib library.

Task

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

Algorithm used:

1. **Logistic Regression**
2. **Artificial Neural Networks (ANN) - Multilayer Perceptron (MLP)**
3. **Decision Tree**
4. **Random Forest**

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1 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 **Logistic Regression, ANN, Decision Tree, and Random Forest** 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.

---

2 2. Importing Related Libraries

[1]:
```
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from functools import reduce
import pyspark
from pyspark import SparkConf, SparkContext
from pyspark.sql import SparkSession, functions as F
from pyspark.sql.window import Window
from pyspark.ml.feature import StringIndexer, StandardScaler, VectorAssembler
from pyspark.ml import Pipeline
from pyspark.ml.classification import LogisticRegression,␣
↪MultilayerPerceptronClassifier, DecisionTreeClassifier,␣
↪RandomForestClassifier
from pyspark.ml.evaluation import MulticlassClassificationEvaluator,␣
↪BinaryClassificationEvaluator
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
from pyspark.mllib.evaluation import MulticlassMetrics
```

[2]:
```
# Set up the spark environment
conf = SparkConf().setAppName("CSCI316")
conf = (conf.setMaster('local[*]')
        .set('spark.executor.memory', '32G')
        .set('spark.driver.memory', '32G')
        .set('spark.driver.maxResultSize', '32G'))
sc = SparkContext(conf=conf)
```

```
sc.setLogLevel("OFF")
spark = SparkSession(sc)
```

```
24/02/18 16:13:13 WARN Utils: Set SPARK_LOCAL_IP if you need to bind to another
address
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use
setLogLevel(newLevel).
24/02/18 16:13:14 WARN NativeCodeLoader: Unable to load native-hadoop library
for your platform… using builtin-java classes where applicable
24/02/18 16:13:14 WARN Utils: Service 'SparkUI' could not bind on port 4040.
Attempting port 4041.
24/02/18 16:13:14 WARN Utils: Service 'SparkUI' could not bind on port 4041.
Attempting port 4042.
24/02/18 16:13:14 WARN Utils: Service 'SparkUI' could not bind on port 4042.
Attempting port 4043.
24/02/18 16:13:14 WARN Utils: Service 'SparkUI' could not bind on port 4043.
Attempting port 4044.
24/02/18 16:13:14 WARN Utils: Service 'SparkUI' could not bind on port 4044.
Attempting port 4045.
24/02/18 16:13:14 WARN Utils: Service 'SparkUI' could not bind on port 4045.
Attempting port 4046.
```

3 3. Data Exploration

3.1 Getting basic understanding of the data set

[3]:
```
preview_dataframe = pd.read_csv('train.csv')
```

[4]:
```
preview_dataframe.head()
```

[4]:
```
       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]
```

[5]:
```python
print(f"Train data size: {preview_dataframe.shape}")
```

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

[6]:
```python
preview_dataframe.columns
```

[6]:
```
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')
```

[7]:
```python
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
```

[8]:

```
preview_dataframe.describe().T
```

[8]:

```
                             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
```

[9]:
```
preview_dataframe.describe(exclude = np.number).T
```

[9]:
```
                          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
```

[10]:
```python
preview_dataframe.isnull().sum()
```

[10]:
```
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
```

3.2 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.

3.3 Getting into deeper details of each attributes - Categorical

[11]:
```
# 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)
```

[12]:
```
# 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)
```

[13]:
```
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()
```

[14]:

```
Target_att = 'Credit_Score'
```

3.3.1 01. Credit_Score

Findings: * class value is imbalanced

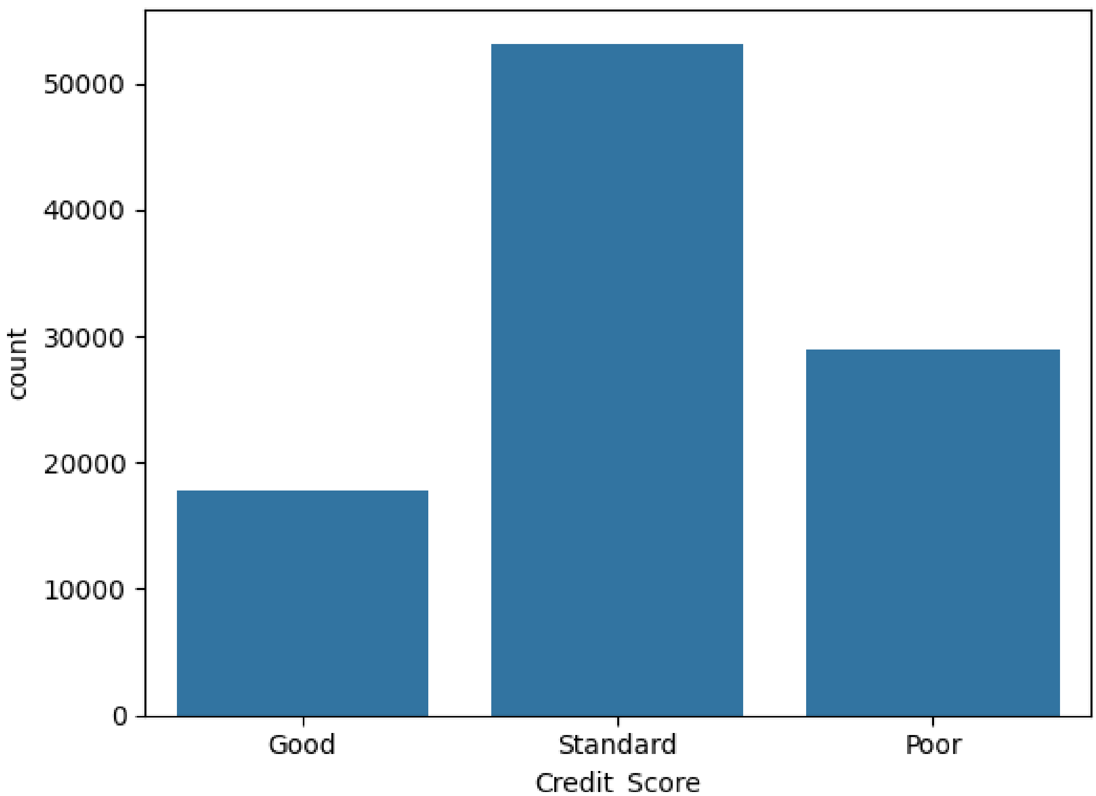
[15]:

```
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

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

[16]:

```
sns.countplot(preview_dataframe, x = 'Credit_Score')
plt.show()
```



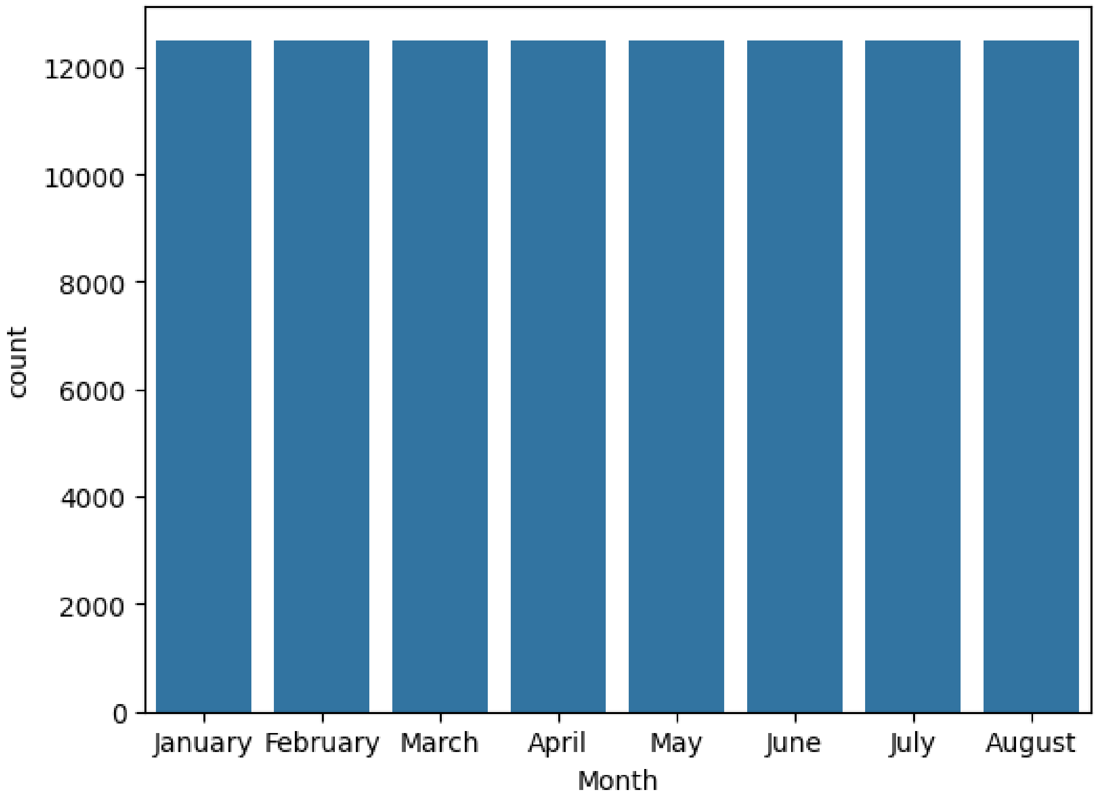
3.3.2 02. Month

[17]:
```
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
```

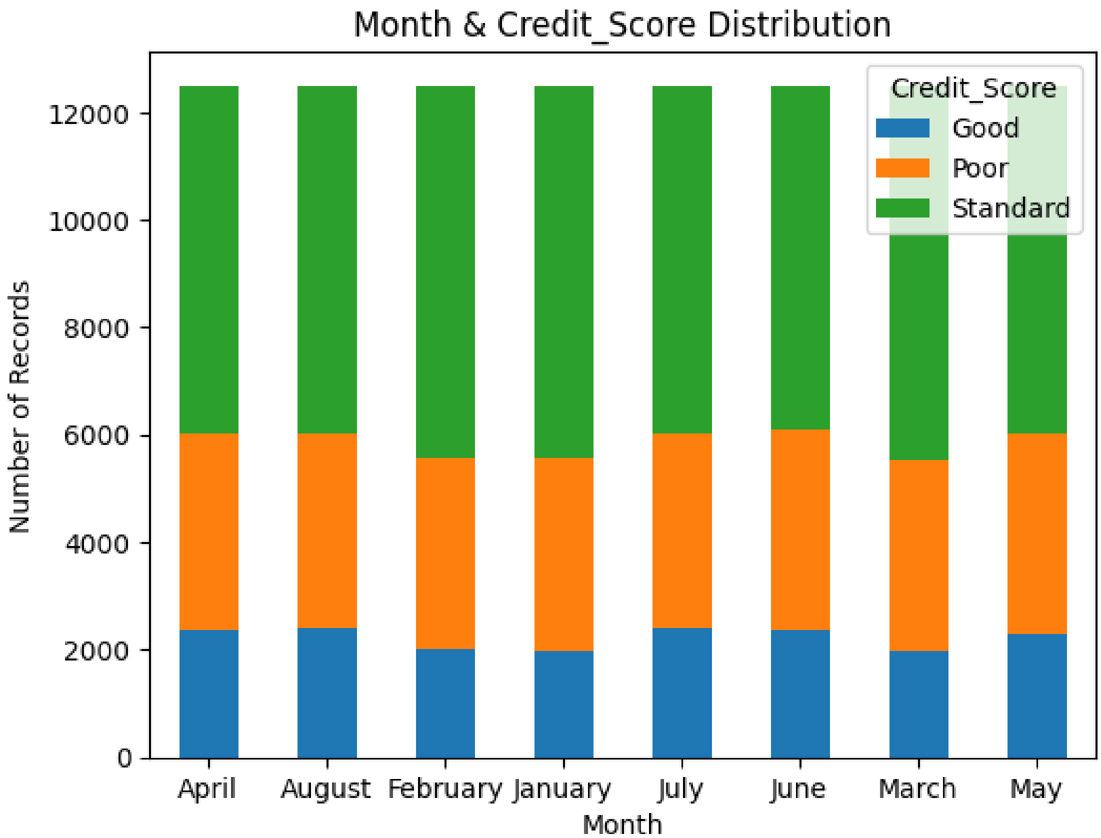
```
May         12500
June        12500
July        12500
August      12500
Name: count, dtype: int64

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

[18]:
```python
sns.countplot(preview_dataframe, x = 'Month')
plt.show()
```



[19]:
```python
cross_plot(preview_dataframe, 'Month', Target_att)
```

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



3.3.3 03. Occupation

Findings: * value '_______' needs to be replaced

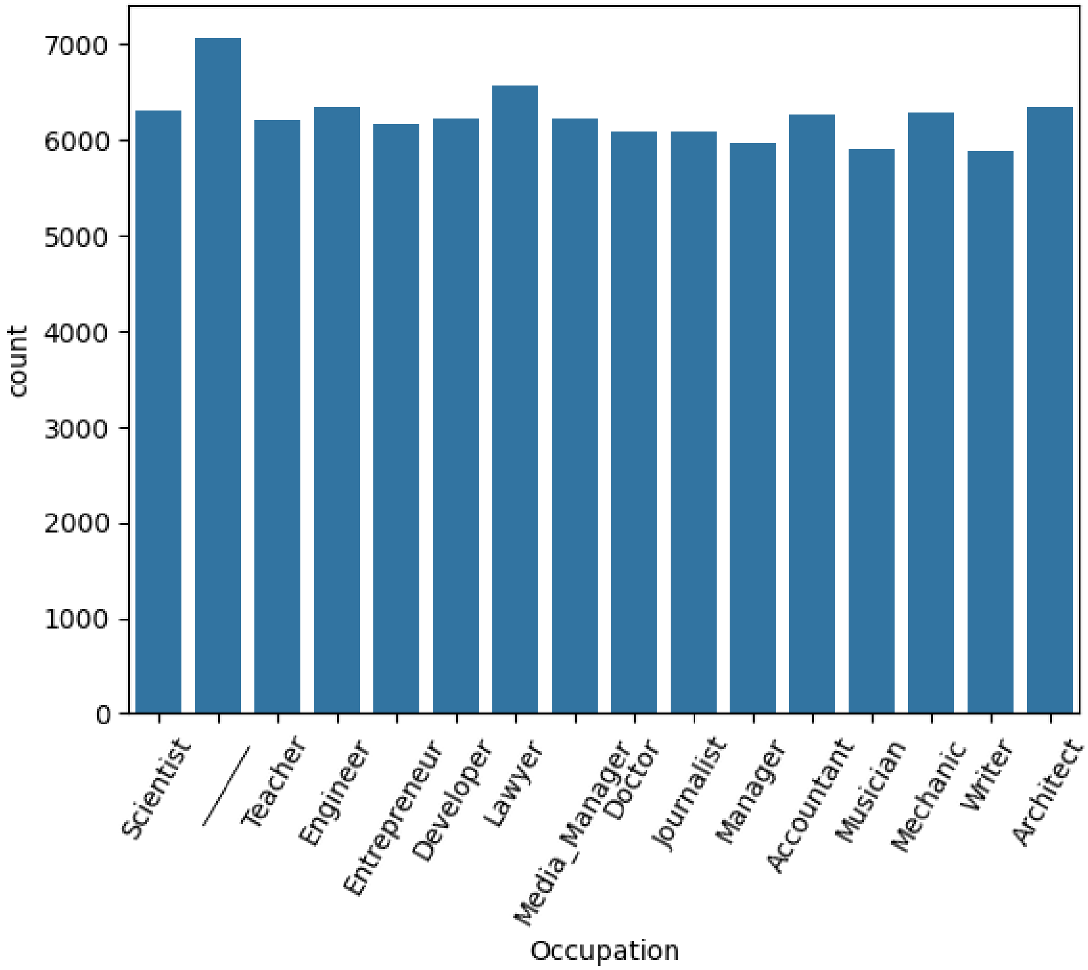
[20]:
```
get_column_detail(preview_dataframe, 'Occupation')
```

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

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

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

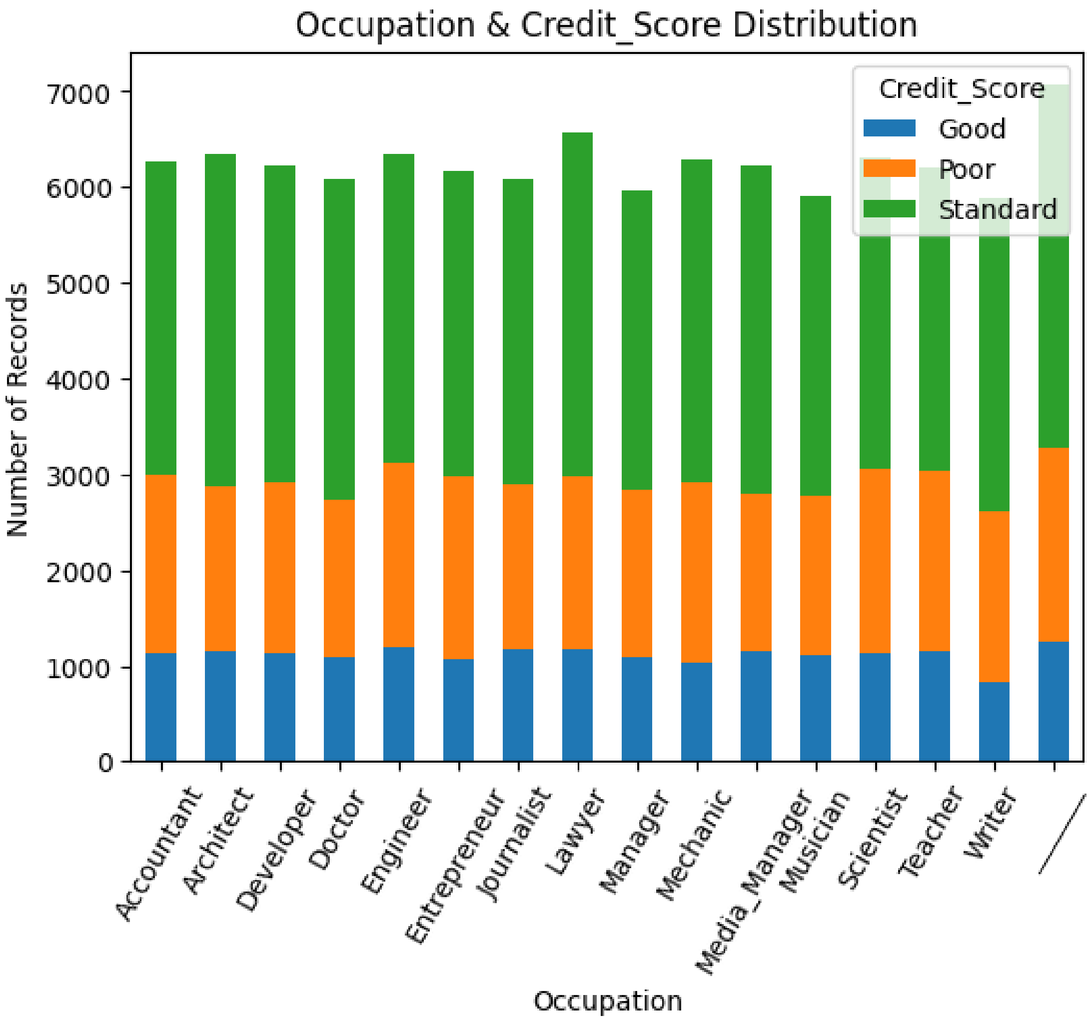
[21]:

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



[22]:
```
cross_plot(preview_dataframe, 'Occupation', Target_att, rotation = 60)
```

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



3.3.4 04. Type of Loan

Findings: * null values

[23]:
```
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

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

3.3.5 05. Credit Mix

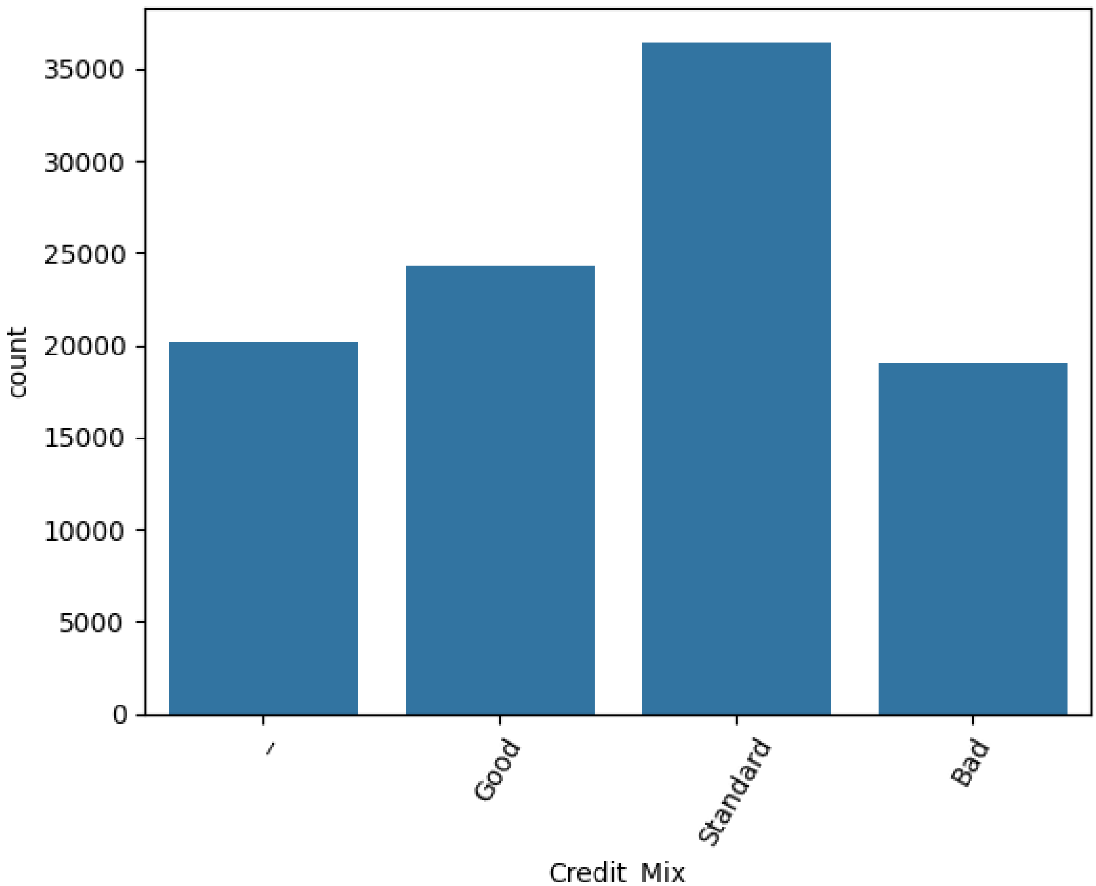
Findings: * it seems higly correlated to "Credit score" * "-" needs to be replaced

[24]:
```
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
```

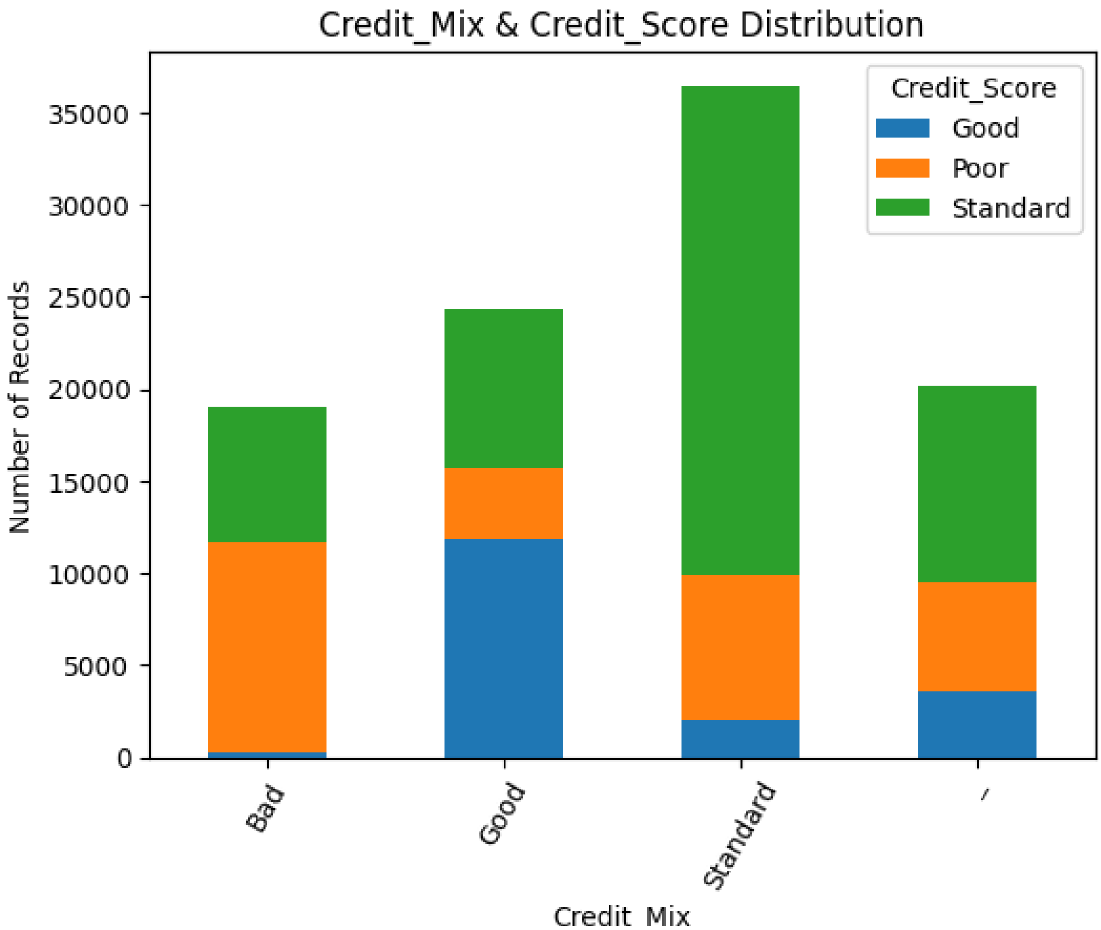
```
Good        24337
_           20195
Bad         18989
Name: count, dtype: int64

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

[25]:
```
sns.countplot(preview_dataframe, x = 'Credit_Mix')
plt.xticks(rotation = 60)
plt.show()
```



[26]:
```
cross_plot(preview_dataframe, 'Credit_Mix', Target_att, rotation = 60)
```

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



3.3.6 06. Payment of Min amount

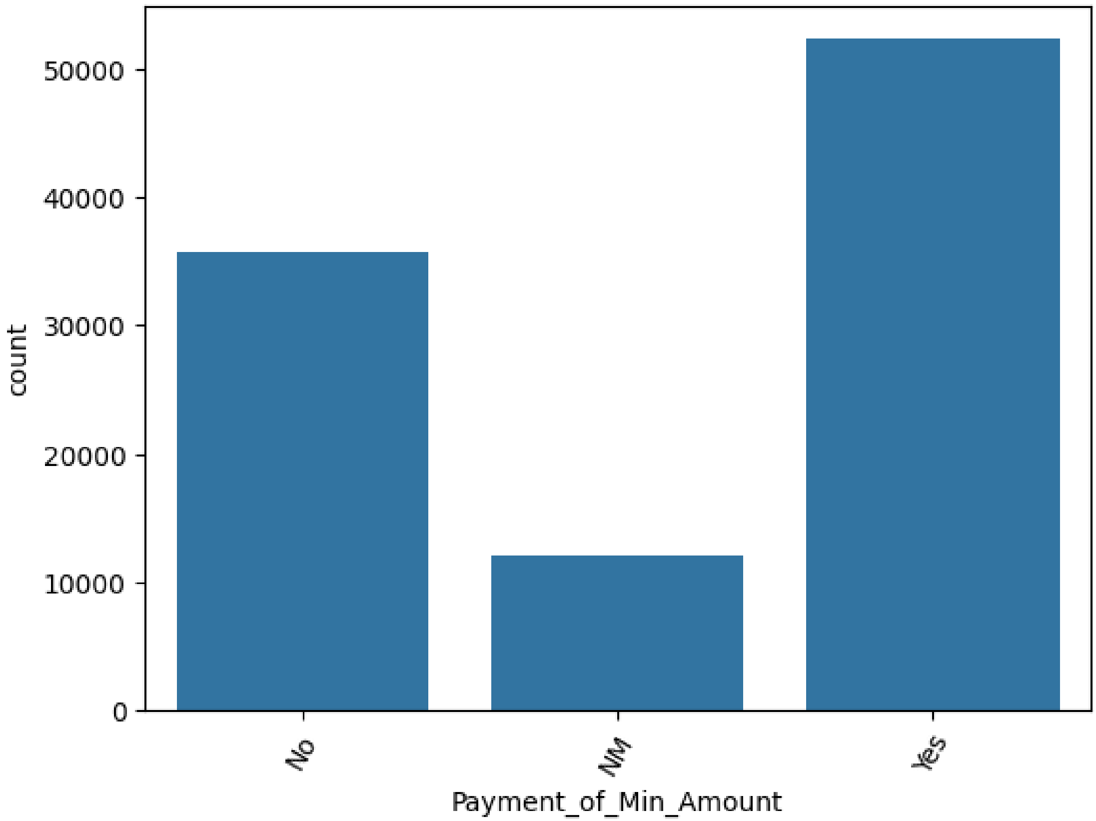
Findings: * it seems higly correlated to "Credit score"

[27]:
```
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:
```

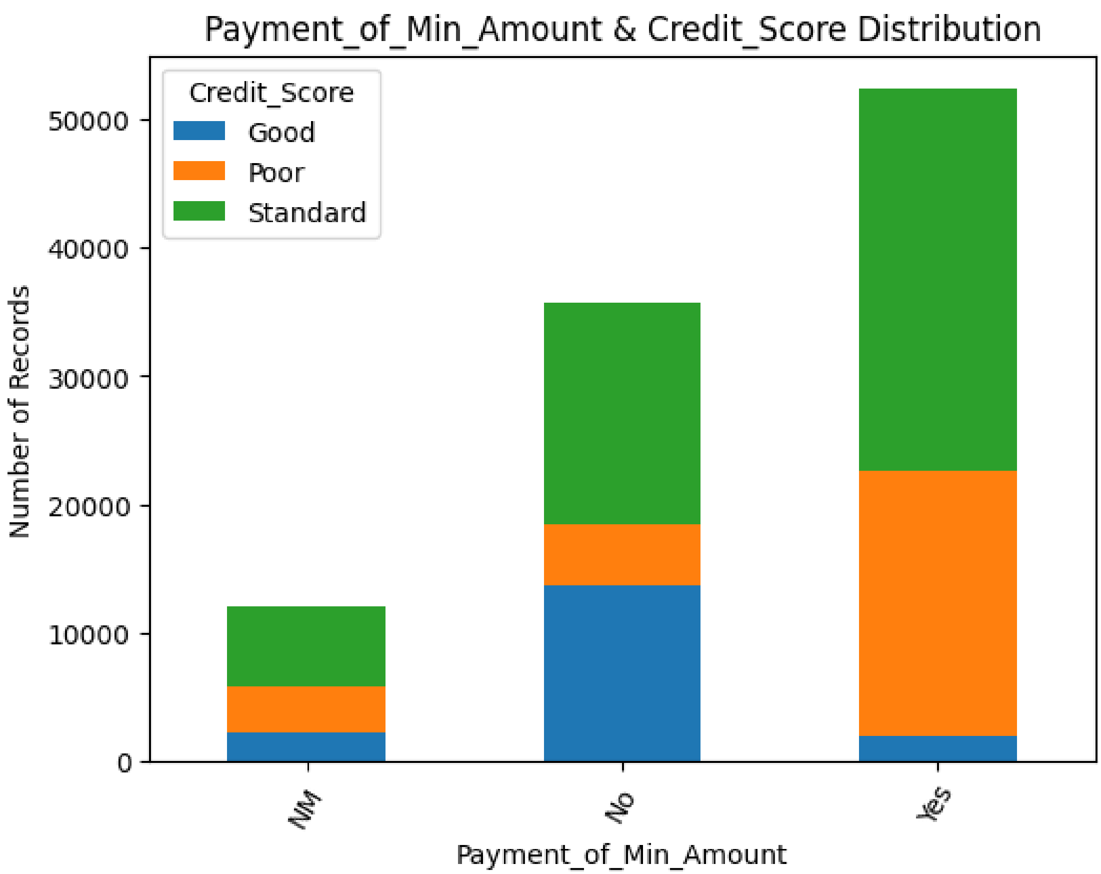
```
Payment_of_Min_Amount
Yes    52326
No     35667
NM     12007
Name: count, dtype: int64

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

[28]:
```
sns.countplot(preview_dataframe, x = 'Payment_of_Min_Amount')
plt.xticks(rotation = 60)
plt.show()
```



[29]:
```
cross_plot(preview_dataframe, 'Payment_of_Min_Amount', Target_att, rotation =␣
↪60)
```

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



3.3.7 07. Payment Behaviour

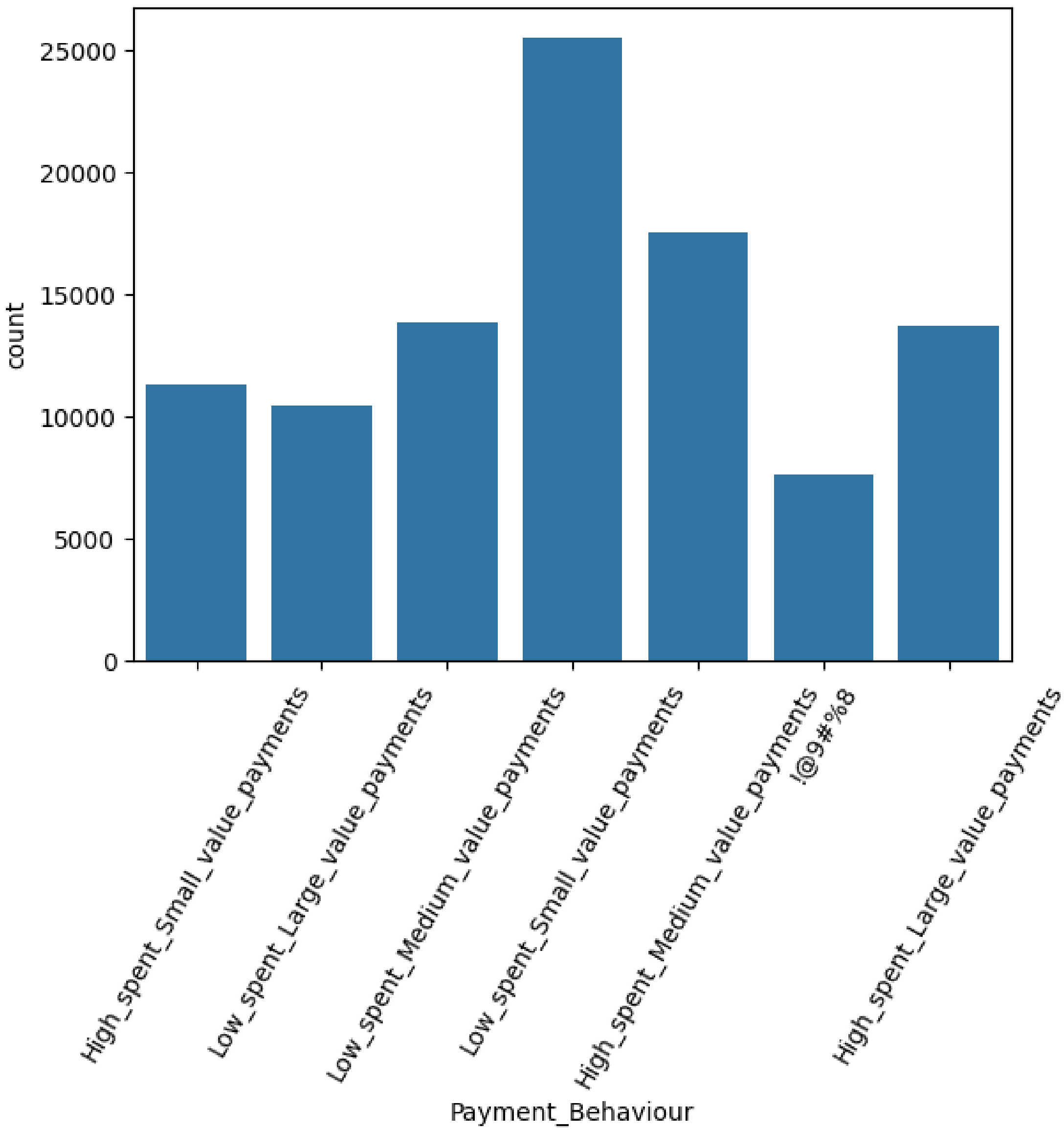
Findings: * strange value: !@9#%8

[30]:
```
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
```

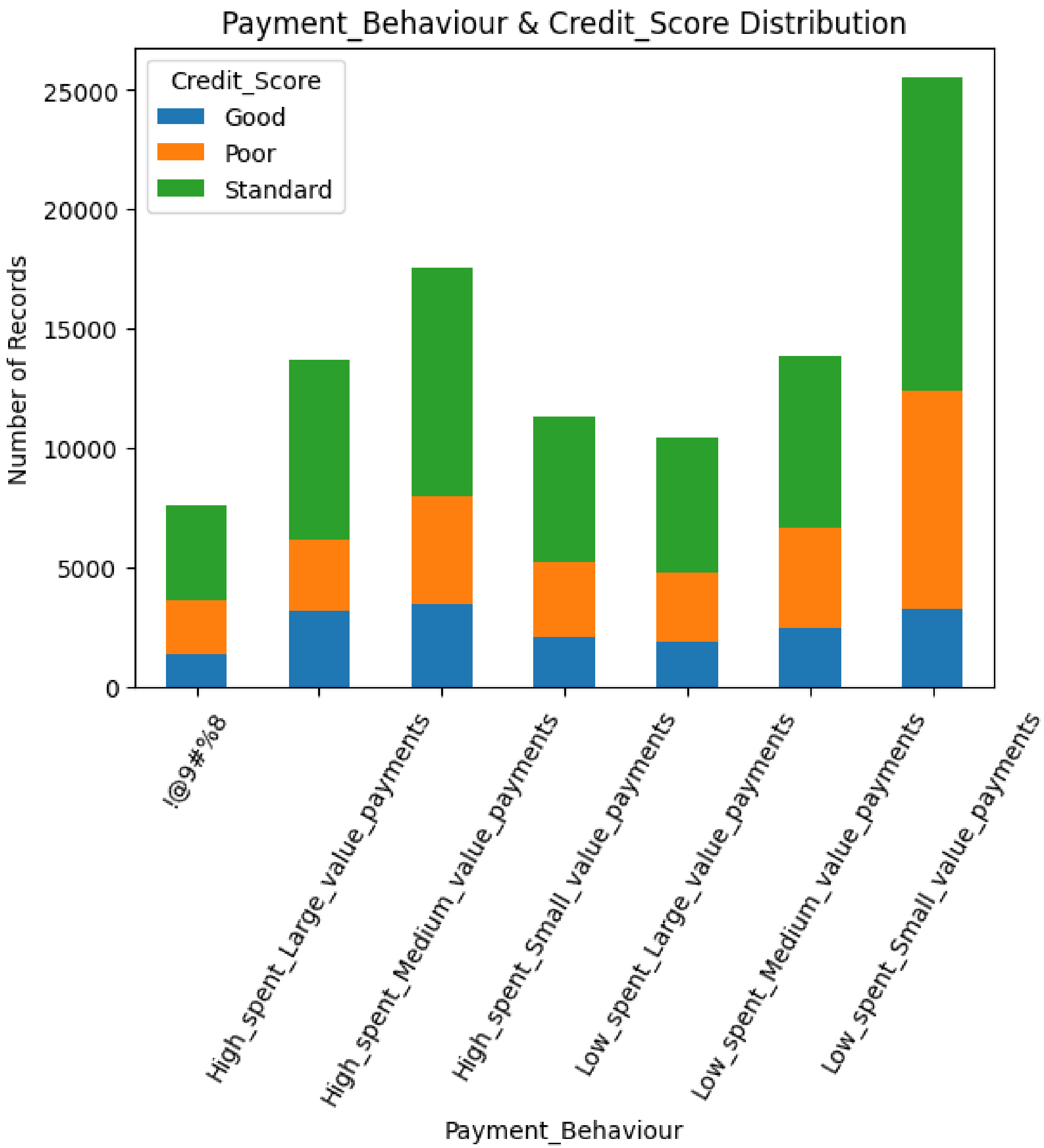
```
High_spent_Medium_value_payments    17540
Low_spent_Medium_value_payments     13861
High_spent_Large_value_payments     13721
High_spent_Small_value_payments     11340
Low_spent_Large_value_payments      10425
!@9#%8                               7600
Name: count, dtype: int64

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

[31]:
```python
sns.countplot(preview_dataframe, x = 'Payment_Behaviour')
plt.xticks(rotation = 60)
plt.show()
```



[32]:
```
cross_plot(preview_dataframe, 'Payment_Behaviour', Target_att, rotation = 60)
```

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



3.4 Getting into deeper details of each attributes - Numerical

3.4.1 01. Age

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

[33]:
```
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

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

3.4.2 02. Annual Income

[34]:
```
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

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

3.4.3 03. Monthly_Inhand_Salary

Findings: * null values

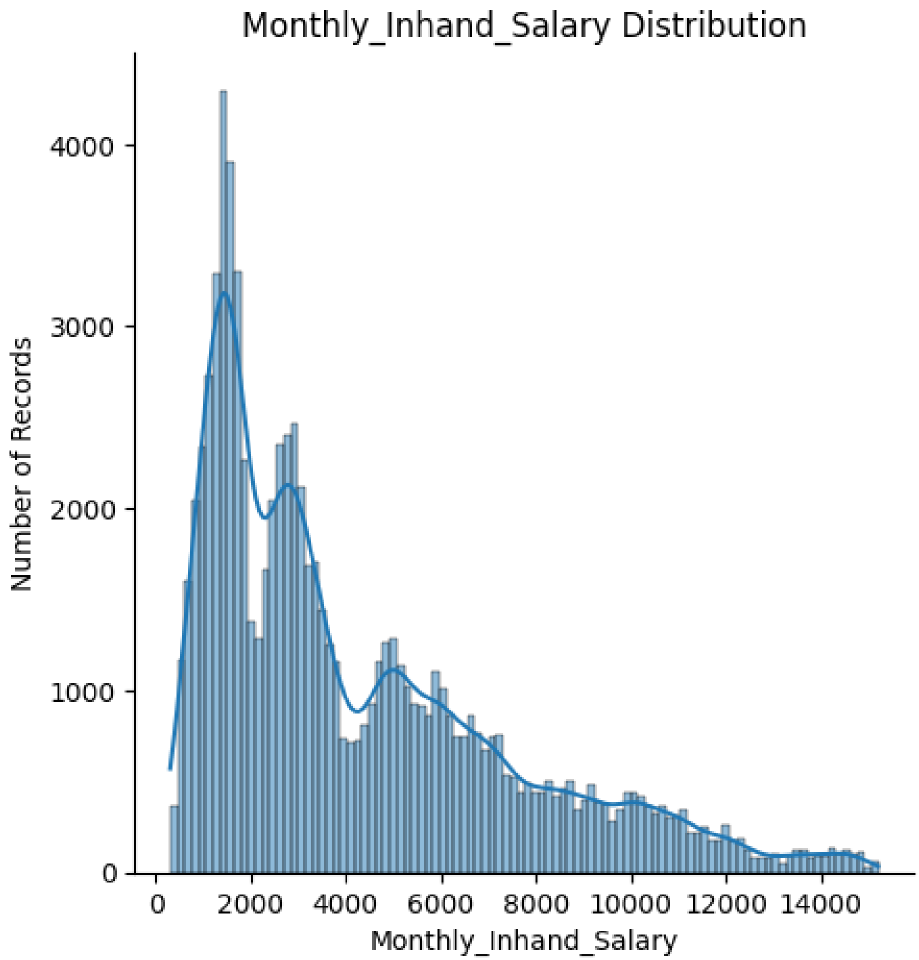
[35]:
```
get_column_detail(preview_dataframe, 'Monthly_Inhand_Salary')
```

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

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

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

[36]:
```
displot_plot(preview_dataframe, 'Monthly_Inhand_Salary', bins=100)
```

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

Monthly_Inhand_Salary Distribution
```



3.4.4 04. Num Bank Accounts

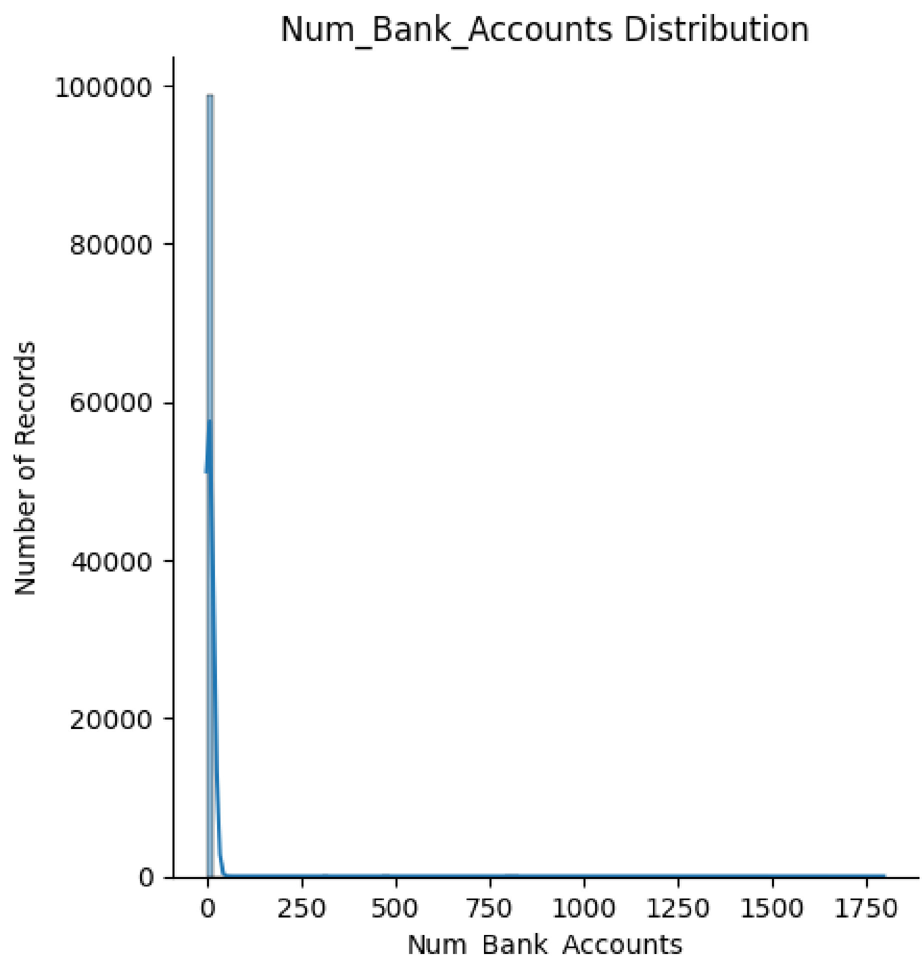
Findings: * outliers should be replaced

[37]:
```
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

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

[38]:
```
displot_plot(preview_dataframe, 'Num_Bank_Accounts', bins=100)
```

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

Num_Bank_Accounts Distribution
```



3.4.5 05. Num_Credit_Card

Findings: * outliers should be replaced

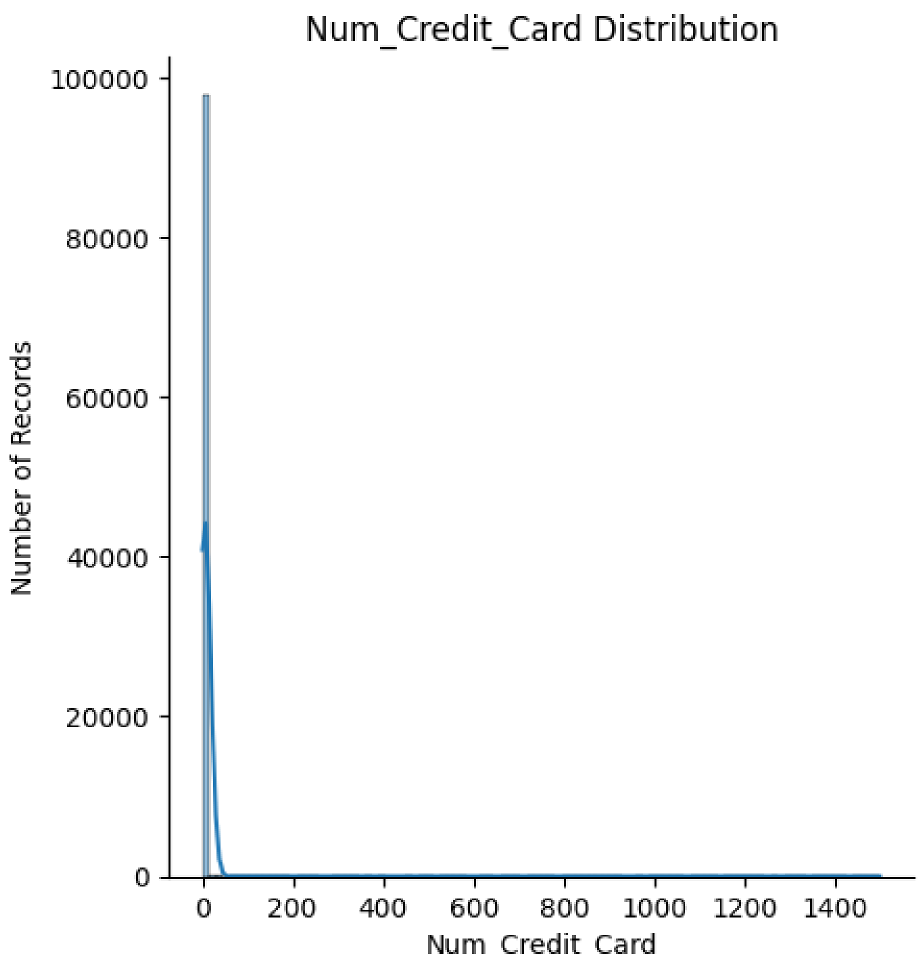
[39]:
```
get_column_detail(preview_dataframe, 'Num_Credit_Card')
```

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

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

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

[40]:
```
displot_plot(preview_dataframe, 'Num_Credit_Card', bins=100)
```

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

Num_Credit_Card Distribution
```



3.4.6 06. Interest_Rate

Findings: * outliers should be replaced

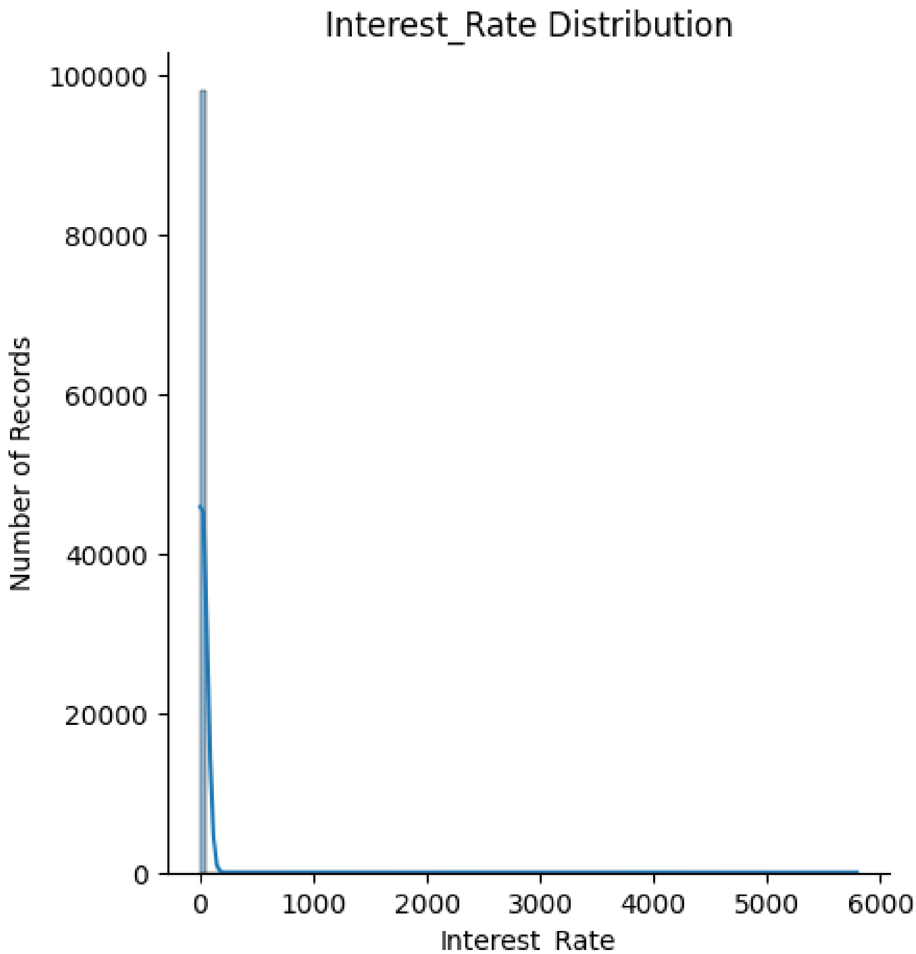
[41]:
```
get_column_detail(preview_dataframe, 'Interest_Rate')
```

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

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

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

[42]:
```python
displot_plot(preview_dataframe, 'Interest_Rate', bins=100)
```

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

Interest_Rate Distribution
```



3.4.7 07. Delay_from_due_date

Findings: * outliers should be replaced

[43]:
```
get_column_detail(preview_dataframe, 'Delay_from_due_date')
```

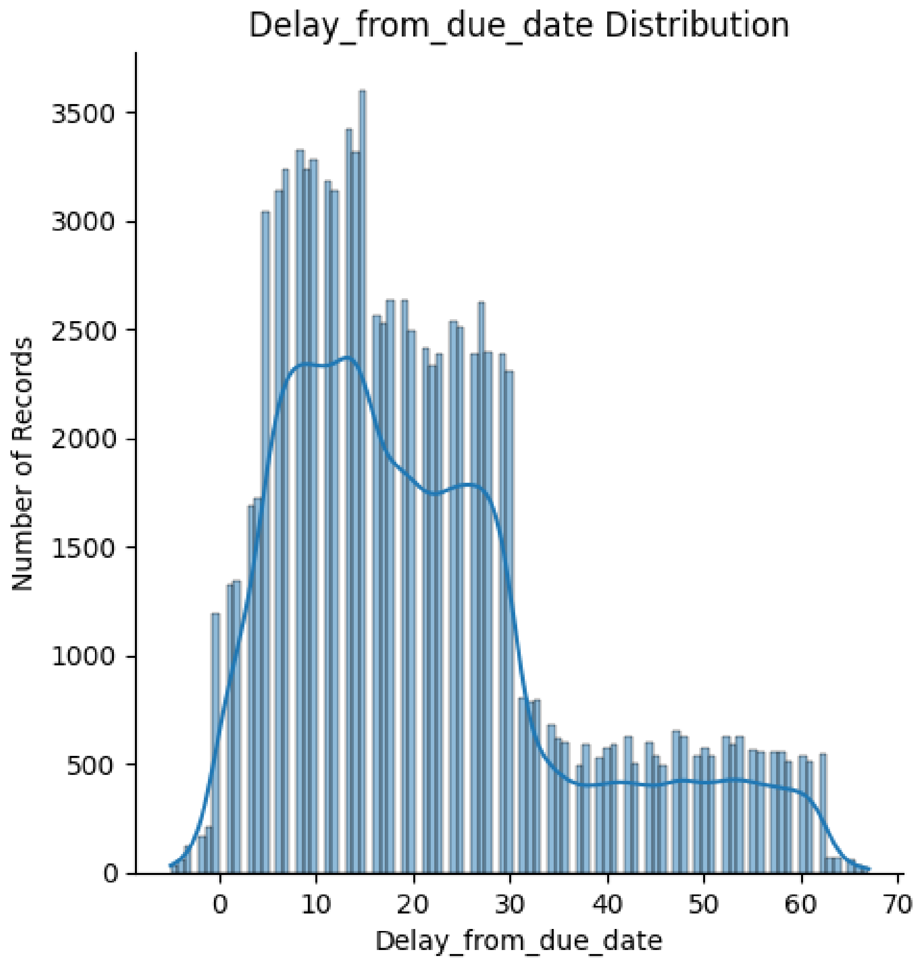
```
****************************************

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

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

[44]:

```
displot_plot(preview_dataframe, 'Delay_from_due_date', bins=100)
```

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

Delay_from_due_date Distribution
```



3.4.8 08. Num_Credit_Inquiries

Findings: * outlier should be replaced * null values

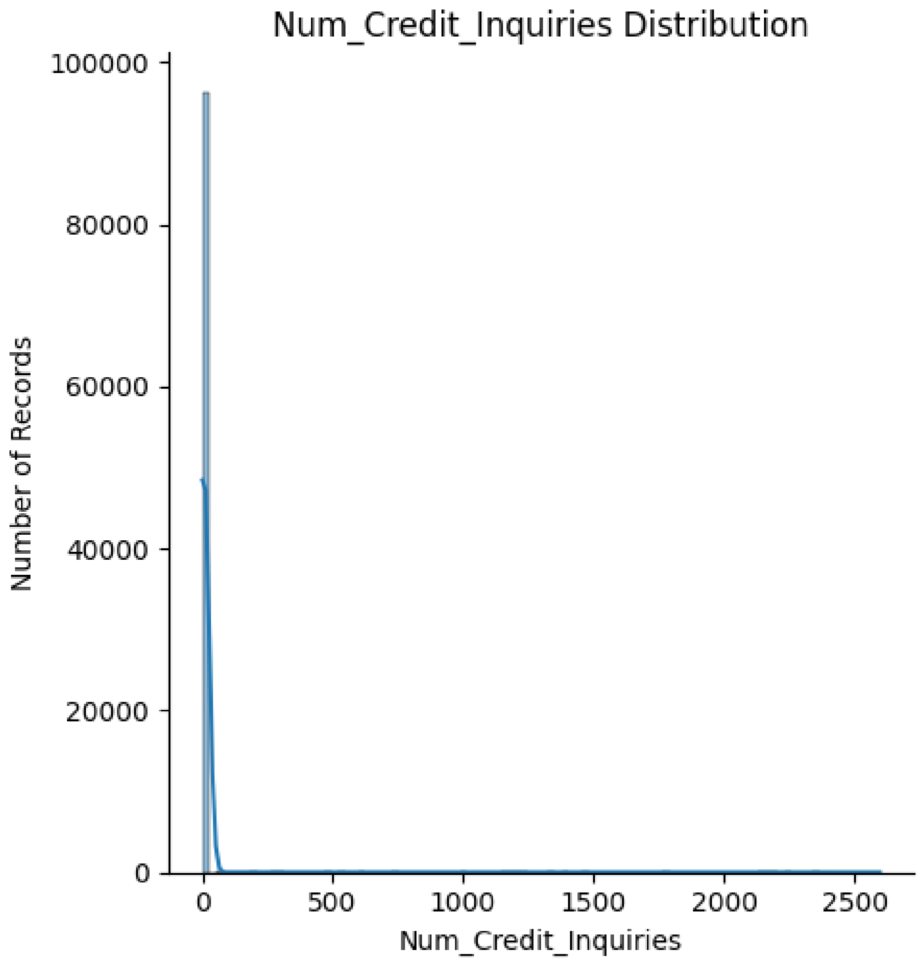
[45]:
```
get_column_detail(preview_dataframe, 'Num_Credit_Inquiries')
```

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

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

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

[46]:
```python
displot_plot(preview_dataframe, 'Num_Credit_Inquiries', bins=100)
```

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

Num_Credit_Inquiries Distribution
```



3.4.9 09. Credit_Utilization_Ratio

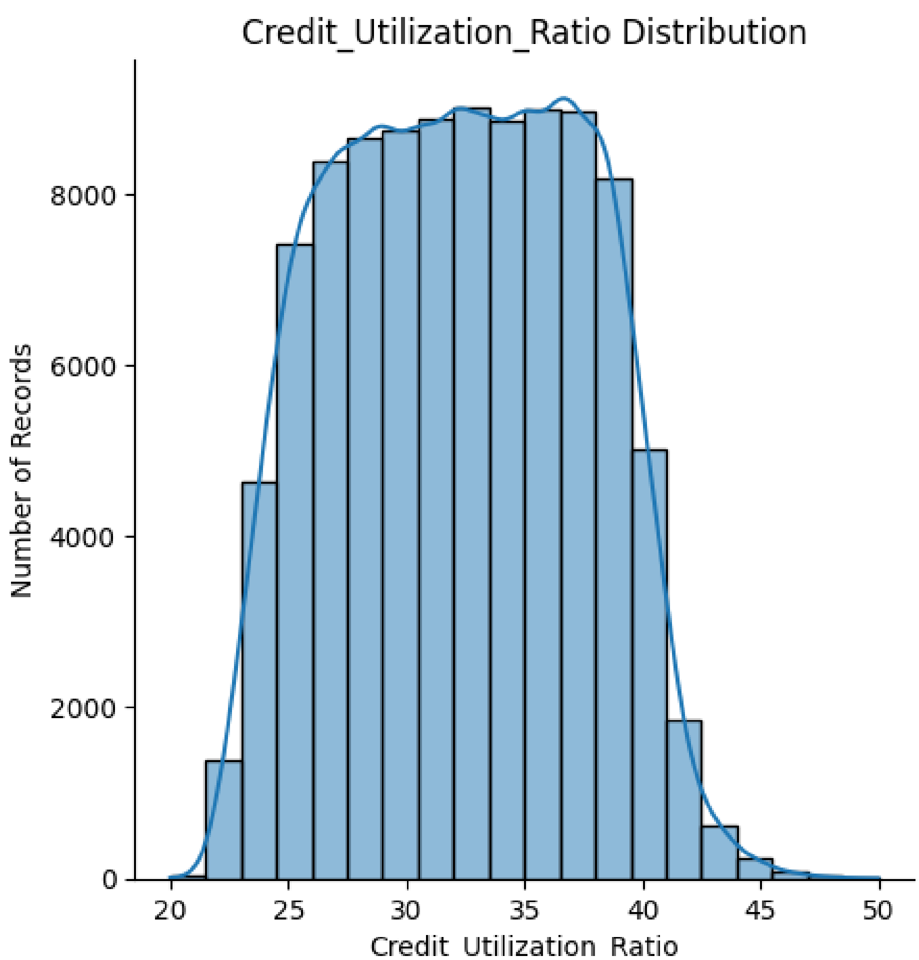
[47]:
```
get_column_detail(preview_dataframe, 'Credit_Utilization_Ratio')
```

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

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

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

[48]:
```
displot_plot(preview_dataframe, 'Credit_Utilization_Ratio')
```

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

Credit_Utilization_Ratio Distribution
```



3.4.10 10. Total_EMI_per_month

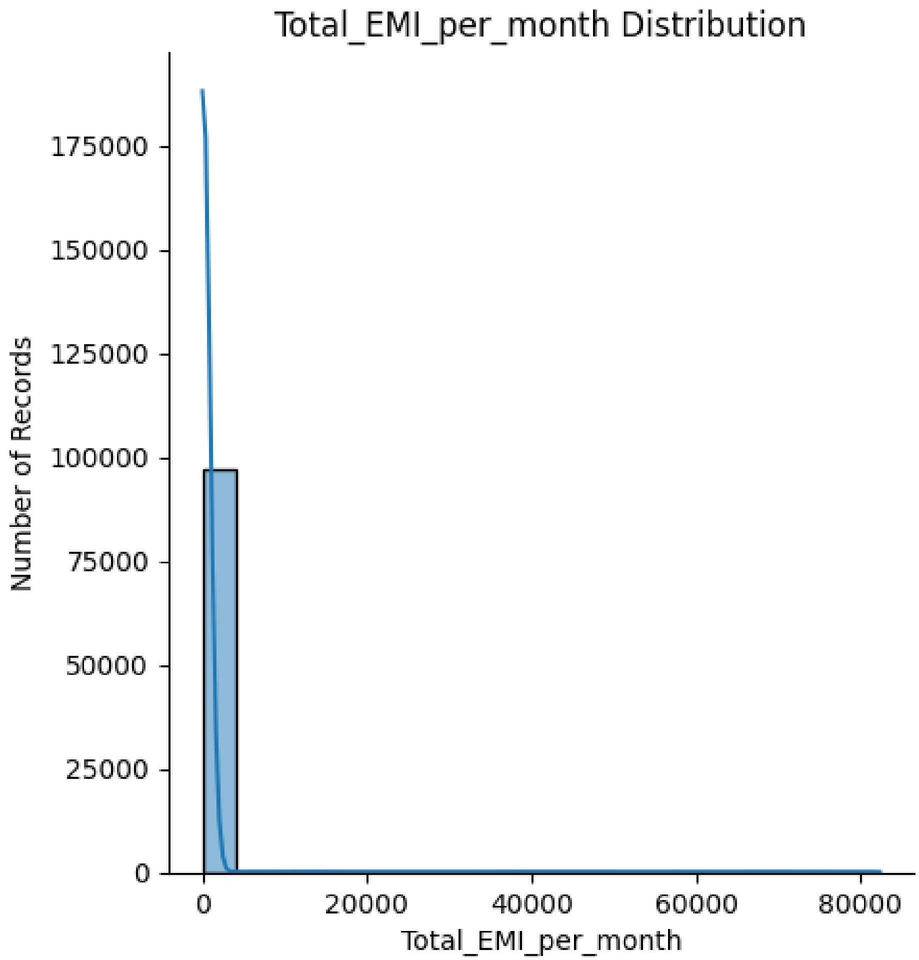
Findings: * outliers should be replaced

[49]:
```
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

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

[50]:
```
displot_plot(preview_dataframe, 'Total_EMI_per_month', rotation=0)
```

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

Total_EMI_per_month Distribution
```



3.5 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

4 4. Data Pre-processing

4.1 Read data from csv file into a spark dataframe

[51]:
```
# Read the data into a spark dataframe
data = spark.read.csv("train.csv", header=True, inferSchema=True)

data.printSchema()
```

```
root
 |-- ID: string (nullable = true)
 |-- Customer_ID: string (nullable = true)
 |-- Month: string (nullable = true)
 |-- Name: string (nullable = true)
 |-- Age: string (nullable = true)
 |-- SSN: string (nullable = true)
 |-- Occupation: string (nullable = true)
 |-- Annual_Income: string (nullable = true)
 |-- Monthly_Inhand_Salary: double (nullable = true)
 |-- Num_Bank_Accounts: integer (nullable = true)
 |-- Num_Credit_Card: integer (nullable = true)
 |-- Interest_Rate: integer (nullable = true)
 |-- Num_of_Loan: string (nullable = true)
 |-- Type_of_Loan: string (nullable = true)
 |-- Delay_from_due_date: integer (nullable = true)
 |-- Num_of_Delayed_Payment: string (nullable = true)
 |-- Changed_Credit_Limit: string (nullable = true)
 |-- Num_Credit_Inquiries: double (nullable = true)
 |-- Credit_Mix: string (nullable = true)
 |-- Outstanding_Debt: string (nullable = true)
 |-- Credit_Utilization_Ratio: double (nullable = true)
 |-- Credit_History_Age: string (nullable = true)
 |-- Payment_of_Min_Amount: string (nullable = true)
 |-- Total_EMI_per_month: double (nullable = true)
 |-- Amount_invested_monthly: string (nullable = true)
 |-- Payment_Behaviour: string (nullable = true)
 |-- Monthly_Balance: string (nullable = true)
 |-- Credit_Score: string (nullable = true)
```

[52]:
```
data.show(5)
```

```
+------+-----------+--------+------------+----+-----------+----------+---------
----+---------------------+-----------------+---------------+-------------+-----
------+--------------------+-------------------+----------------------+---------
-----------+--------------------+----------+----------------+------------------
-----+--------------------+---------------------+-------------------+-----------
------------+--------------------+------------------+------------+
|    ID|Customer_ID|   Month|        Name| Age|        SSN|Occupation|Annual_In
come|Monthly_Inhand_Salary|Num_Bank_Accounts|Num_Credit_Card|Interest_Rate|Num_o
f_Loan|        Type_of_Loan|Delay_from_due_date|Num_of_Delayed_Payment|Changed_C
redit_Limit|Num_Credit_Inquiries|Credit_Mix|Outstanding_Debt|Credit_Utilization_
Ratio|  Credit_History_Age|Payment_of_Min_Amount|Total_EMI_per_month|Amount_inve
sted_monthly|   Payment_Behaviour|   Monthly_Balance|Credit_Score|
+------+-----------+--------+------------+----+-----------+----------+---------
----+---------------------+-----------------+---------------+-------------+-----
------+--------------------+-------------------+----------------------+---------
```

```
-----------+-------------------+----------+---------------+------------------
-----+-------------------+--------------------+------------------+----------
------------+-------------------+-----------------+------------+
|0x1602|  CUS_0xd40| January|Aaron Maashoh|  23|821-00-0265| Scientist|
19114.12|   1824.8433333333328|               3|              4|           3|
4|Auto Loan, Credit…|                 3|                     7|
11.27|                 4.0|         _|          809.98|
26.822619623699016|22 Years and 1 Mo…|                   No|
49.57494921489417|
80.41529543900253|High_spent_Small_…|312.49408867943663|       Good|
|0x1603|  CUS_0xd40|February|Aaron Maashoh|  23|821-00-0265| Scientist|
19114.12|                NULL|               3|              4|           3|
4|Auto Loan, Credit…|                -1|                  NULL|
11.27|                 4.0|      Good|          809.98|      31.94496005538421|
NA|                   No|  49.57494921489417|
118.28022162236736|Low_spent_Large_v…|284.62916249607184|       Good|
|0x1604|  CUS_0xd40|   March|Aaron Maashoh|-500|821-00-0265| Scientist|
19114.12|                NULL|               3|              4|           3|
4|Auto Loan, Credit…|                 3|                     7|
_|                 4.0|      Good|          809.98|      28.60935202206993|22
Years and 3 Mo…|                  No|  49.57494921489417|
81.699521264648|Low_spent_Medium_…| 331.2098628537912|       Good|
|0x1605|  CUS_0xd40|   April|Aaron Maashoh|  23|821-00-0265| Scientist|
19114.12|                NULL|               3|              4|           3|
4|Auto Loan, Credit…|                 5|                     4|
6.27|                 4.0|      Good|          809.98|
31.377861869582354|22 Years and 4 Mo…|                   No|
49.57494921489417|
199.4580743910713|Low_spent_Small_v…|223.45130972736786|       Good|
|0x1606|  CUS_0xd40|     May|Aaron Maashoh|  23|821-00-0265| Scientist|
19114.12|   1824.8433333333328|               3|              4|           3|
4|Auto Loan, Credit…|                 6|                  NULL|
11.27|                 4.0|      Good|          809.98|
24.797346908844986|22 Years and 5 Mo…|                   No|
49.57494921489417|
41.420153086217326|High_spent_Medium…|341.48923103222177|       Good|
+------+----------+--------+-------------+----+-----------+---------+---------
----+-------------------+----------------+--------------+------------+-----
------+-------------------+-----------------+--------------------+---------
-----------+-------------------+----------+---------------+------------------
-----+-------------------+--------------------+------------------+----------
------------+-------------------+-----------------+------------+
only showing top 5 rows
```

4.2 Pre-processing

[53]:
```
# 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
```

[54]:
```
# Copy the data into a new DataFrame to not corrupt the original data
df = data.drop("Name", "SSN")
```

4.2.1 Change the data type of the columns

[55]:
```
# In the ['Age', 'Annual Income'] column, if the value has underbar, replace␣
↪the underbar with empty space
columns = ['Age', 'Annual_Income', 'Num_of_Loan', 'Num_of_Delayed_Payment']
for column in columns:
    df = df.withColumn(column, F.regexp_replace(column, "_", ""))
```

[56]:
```
# If there is a value ['nan', '_', '_______', '#F%$D@*&8', '!@9#%8',␣
↪'__10000__'] in the whole data, replace it with null
for column in df.columns:
    df = df.withColumn(column, F.when(F.col(column).isin(['nan', '_',␣
↪'_______', '#F%$D@*&8', '!@9#%8', '__10000__']), None).otherwise(F.
↪col(column)))
```

[57]:
```
# 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']
for column in to_numeric_columns:
    # Can be int or float
    df = df.withColumn(column, df[column].cast("numeric"))
```

4.2.2 Fill the missing values

[58]:
```
# 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']
mean_window = Window.partitionBy('Customer_ID')
```

```
fillna_with_mode = ['Occupation', 'Payment_of_Min_Amount',␣
↪'Num_of_Delayed_Payment', 'Credit_Mix']
mode_window = Window.partitionBy('Customer_ID')
fillna_with_first = ['Age', 'Type_of_Loan']

for column in fillna_with_mean:
    df = df.withColumn(column, F.when(F.col(column).isNull(), F.avg(column).
↪over(mean_window)).otherwise(F.col(column)))

for column in fillna_with_mode:
    mode_val = df.groupBy('Customer_ID', column).count().orderBy(F.
↪desc('count')).select(column).limit(1).collect()[0][0]
    df = df.withColumn(column, F.when(F.col(column).isNull(), mode_val).
↪otherwise(F.col(column)))

for column in fillna_with_first:
    first_window = Window.partitionBy('Customer_ID').orderBy(column)
    df = df.withColumn(column, F.when(F.col(column).isNull(), F.first(column).
↪over(first_window)).otherwise(F.col(column)))

df = df.fillna('Not Specified', subset=['Type_of_Loan', 'Payment_Behaviour'])
df = df.withColumn('Age', df['Age'].cast("int"))
```

[59]:
```
# Check null counts
df.select([F.count(F.when(F.col(c).isNull(), c)).alias(c) for c in df.columns]).
↪show()

# Show column counts and data types
df.select([F.count(F.col(c)).alias(c) for c in df.columns]).show()
df.printSchema()
```

```
+---+-----------+-----+---+----------+-------------+--------------------+------
-----------+---------------+-------------+-----------+------------+-------------
------+---------------------+--------------------+-------------------+--------
--+----------------+-------------------------+------------------+---------------
-----+-------------------+-----------------------+-----------------+------------
---+------------+
| ID|Customer_ID|Month|Age|Occupation|Annual_Income|Monthly_Inhand_Salary|Num_Ba
nk_Accounts|Num_Credit_Card|Interest_Rate|Num_of_Loan|Type_of_Loan|Delay_from_du
e_date|Num_of_Delayed_Payment|Changed_Credit_Limit|Num_Credit_Inquiries|Credit_M
ix|Outstanding_Debt|Credit_Utilization_Ratio|Credit_History_Age|Payment_of_Min_A
mount|Total_EMI_per_month|Amount_invested_monthly|Payment_Behaviour|Monthly_Bala
nce|Credit_Score|
+---+-----------+-----+---+----------+-------------+--------------------+------
-----------+---------------+-------------+-----------+------------+-------------
```

```
------+----------------------+--------------------+--------------------+--------
--+----------------+------------------------+------------------+----------------
-----+-------------------+-----------------------+-----------------+------------
---+------------+
|  0|          0|    0|  0|         0|            0|                    0|
0|              0|            0|          0|           0|                  0|
0|                   0|                   0|         0|               0|
0|                 0|                    0|                  0|
0|                0|              0|           0|
+---+-----------+-----+---+----------+-------------+---------------------+------
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[Stage 21:====================================>                     (5 + 3) / 8]

+------+-----------+------+------+----------+-------------+---------------------
+-----------------+---------------+-------------+-----------+------------+------
-------------+----------------------+--------------------+--------------------+-
---------+----------------+------------------------+------------------+---------
------------+-------------------+-----------------------+-----------------+-----
----------+------------+
|    ID|Customer_ID| Month|   Age|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|C
redit_Mix|Outstanding_Debt|Credit_Utilization_Ratio|Credit_History_Age|Payment_o
f_Min_Amount|Total_EMI_per_month|Amount_invested_monthly|Payment_Behaviour|Month
ly_Balance|Credit_Score|
+------+-----------+------+------+----------+-------------+---------------------
+-----------------+---------------+-------------+-----------+------------+------
-------------+----------------------+--------------------+--------------------+-
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------------+-------------------+-----------------------+-----------------+-----
----------+------------+
|100000|     100000|100000|100000|    100000|       100000|
100000|           100000|         100000|       100000|     100000|      100000|
100000|                100000|              100000|              100000|
100000|          100000|                  100000|            100000|
100000|             100000|                 100000|           100000|
100000|      100000|
+------+-----------+------+------+----------+-------------+---------------------
+-----------------+---------------+-------------+-----------+------------+------
-------------+----------------------+--------------------+--------------------+-
---------+----------------+------------------------+------------------+---------
------------+-------------------+-----------------------+-----------------+-----
----------+------------+
```

```
root
 |-- ID: string (nullable = true)
 |-- Customer_ID: string (nullable = true)
 |-- Month: string (nullable = true)
 |-- Age: integer (nullable = true)
 |-- Occupation: string (nullable = true)
 |-- Annual_Income: decimal(10,0) (nullable = true)
 |-- Monthly_Inhand_Salary: double (nullable = true)
 |-- Num_Bank_Accounts: integer (nullable = true)
 |-- Num_Credit_Card: integer (nullable = true)
 |-- Interest_Rate: integer (nullable = true)
 |-- Num_of_Loan: decimal(10,0) (nullable = true)
 |-- Type_of_Loan: string (nullable = false)
 |-- Delay_from_due_date: integer (nullable = true)
 |-- Num_of_Delayed_Payment: decimal(10,0) (nullable = true)
 |-- Changed_Credit_Limit: decimal(14,4) (nullable = true)
 |-- Num_Credit_Inquiries: decimal(14,4) (nullable = true)
 |-- Credit_Mix: string (nullable = true)
 |-- Outstanding_Debt: decimal(14,4) (nullable = true)
 |-- Credit_Utilization_Ratio: double (nullable = true)
 |-- Credit_History_Age: string (nullable = true)
 |-- Payment_of_Min_Amount: string (nullable = true)
 |-- Total_EMI_per_month: double (nullable = true)
 |-- Amount_invested_monthly: decimal(14,4) (nullable = true)
 |-- Payment_Behaviour: string (nullable = false)
 |-- Monthly_Balance: decimal(14,4) (nullable = true)
 |-- Credit_Score: string (nullable = true)
```

4.2.3 Reduce the outliers

[60]:
```
# Reduce outliers from the data, and replace them with the median
outlier_columns_int = ['Age', 'Num_Bank_Accounts', 'Num_Credit_Card',␣
 ↪'Interest_Rate',\
                       'Num_of_Loan', 'Delay_from_due_date',␣
 ↪'Num_of_Delayed_Payment']
outlier_columns_float = ['Annual_Income', 'Num_Credit_Inquiries',␣
 ↪'Outstanding_Debt',\
                     'Total_EMI_per_month', 'Amount_invested_monthly',␣
 ↪'Monthly_Balance']

# Convert spark dataframe to pandas dataframe
df = df.toPandas()

for i in range(len(outlier_columns_int)):
```

```python
    df[outlier_columns_int[i]] = df[outlier_columns_int[i]].astype(np.int64)  # Convert 'decimal.Decimal' to 'float'
    median = df.groupby('Customer_ID')[outlier_columns_int[i]].median()
    df[outlier_columns_int[i]] = df.apply(lambda row: outlier_handling(row, median, outlier_columns_int[i]), axis=1)

for i in range(len(outlier_columns_float)):
    df[outlier_columns_float[i]] = df[outlier_columns_float[i]].astype(np.float64)  # Convert 'decimal.Decimal' to 'float'
    median = df.groupby('Customer_ID')[outlier_columns_float[i]].median()
    df[outlier_columns_float[i]] = df.apply(lambda row: outlier_handling(row, median, outlier_columns_float[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  object
 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  object
 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        100000 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         100000 non-null  object
 24  Monthly_Balance           100000 non-null  float64
 25  Credit_Score              100000 non-null  object
```

```
dtypes: float64(8), int64(7), object(11)
memory usage: 19.8+ MB
None
```

4.2.4 Change the categorical data to numerical data

```
[61]: df['Month'] = pd.to_datetime(df['Month'], format="%B").dt.month.astype(np.int64)

# 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)

# Converting ordinal data ['Credit_Mix','Credit_Score']
customScoreMapping = {'Good': 2.0, 'Standard': 1.0, 'Poor': 0.0}
df['Credit_Score_index'] = df['Credit_Score'].map(customScoreMapping)

customMixMapping = {'Good': 2.0, 'Standard': 1.0, 'Bad': 0.0}
df['Credit_Mix_index'] = df['Credit_Mix'].map(customMixMapping)

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

# Convert it back to spark dataframe
df = spark.createDataFrame(df)

# Convert the categorical columns to numerical columns
# Occupation, Credit_Mix, Payment_of_Min_Amount, Payment_Behaviour, Credit_Score
indexers = [StringIndexer(inputCol=column, outputCol=column+"_index") for␣
↪column in ['Occupation', 'Payment_of_Min_Amount', 'Payment_Behaviour']]
pipeline = Pipeline(stages=indexers)
df = pipeline.fit(df).transform(df)
df.printSchema()

# Convert it back to pandas dataframe
df = df.toPandas()

df.drop(['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount',␣
↪'Payment_Behaviour', 'Credit_Score'], axis=1, inplace=True)
```

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

```
root
 |-- Month: long (nullable = true)
 |-- Age: long (nullable = true)
 |-- Occupation: string (nullable = true)
 |-- Annual_Income: double (nullable = true)
 |-- Monthly_Inhand_Salary: double (nullable = true)
 |-- Num_Bank_Accounts: long (nullable = true)
 |-- Num_Credit_Card: long (nullable = true)
 |-- Interest_Rate: long (nullable = true)
 |-- Num_of_Loan: long (nullable = true)
 |-- Delay_from_due_date: long (nullable = true)
 |-- Num_of_Delayed_Payment: long (nullable = true)
 |-- Changed_Credit_Limit: decimal(38,18) (nullable = true)
 |-- Num_Credit_Inquiries: double (nullable = true)
 |-- Credit_Mix: string (nullable = true)
 |-- Outstanding_Debt: double (nullable = true)
 |-- Credit_Utilization_Ratio: double (nullable = true)
 |-- Credit_History_Age: double (nullable = true)
 |-- Payment_of_Min_Amount: string (nullable = true)
 |-- Total_EMI_per_month: double (nullable = true)
 |-- Amount_invested_monthly: double (nullable = true)
 |-- Payment_Behaviour: string (nullable = true)
 |-- Monthly_Balance: double (nullable = true)
 |-- Credit_Score: string (nullable = true)
 |-- Credit_Score_index: double (nullable = true)
 |-- Credit_Mix_index: double (nullable = true)
 |-- Occupation_index: double (nullable = false)
 |-- Payment_of_Min_Amount_index: double (nullable = false)
 |-- Payment_Behaviour_index: double (nullable = false)

<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   Annual_Income             100000 non-null  float64
 3   Monthly_Inhand_Salary     100000 non-null  float64
 4   Num_Bank_Accounts         100000 non-null  int64
 5   Num_Credit_Card           100000 non-null  int64
 6   Interest_Rate             100000 non-null  int64
```

```
 7   Num_of_Loan                 100000 non-null  int64
 8   Delay_from_due_date         100000 non-null  int64
 9   Num_of_Delayed_Payment      100000 non-null  int64
 10  Changed_Credit_Limit        100000 non-null  object
 11  Num_Credit_Inquiries        100000 non-null  float64
 12  Outstanding_Debt            100000 non-null  float64
 13  Credit_Utilization_Ratio    100000 non-null  float64
 14  Credit_History_Age          100000 non-null  float64
 15  Total_EMI_per_month         100000 non-null  float64
 16  Amount_invested_monthly     100000 non-null  float64
 17  Monthly_Balance             100000 non-null  float64
 18  Credit_Score_index          100000 non-null  float64
 19  Credit_Mix_index            100000 non-null  float64
 20  Occupation_index            100000 non-null  float64
 21  Payment_of_Min_Amount_index 100000 non-null  float64
 22  Payment_Behaviour_index     100000 non-null  float64
dtypes: float64(14), int64(8), object(1)
memory usage: 17.5+ MB
```

[61]:

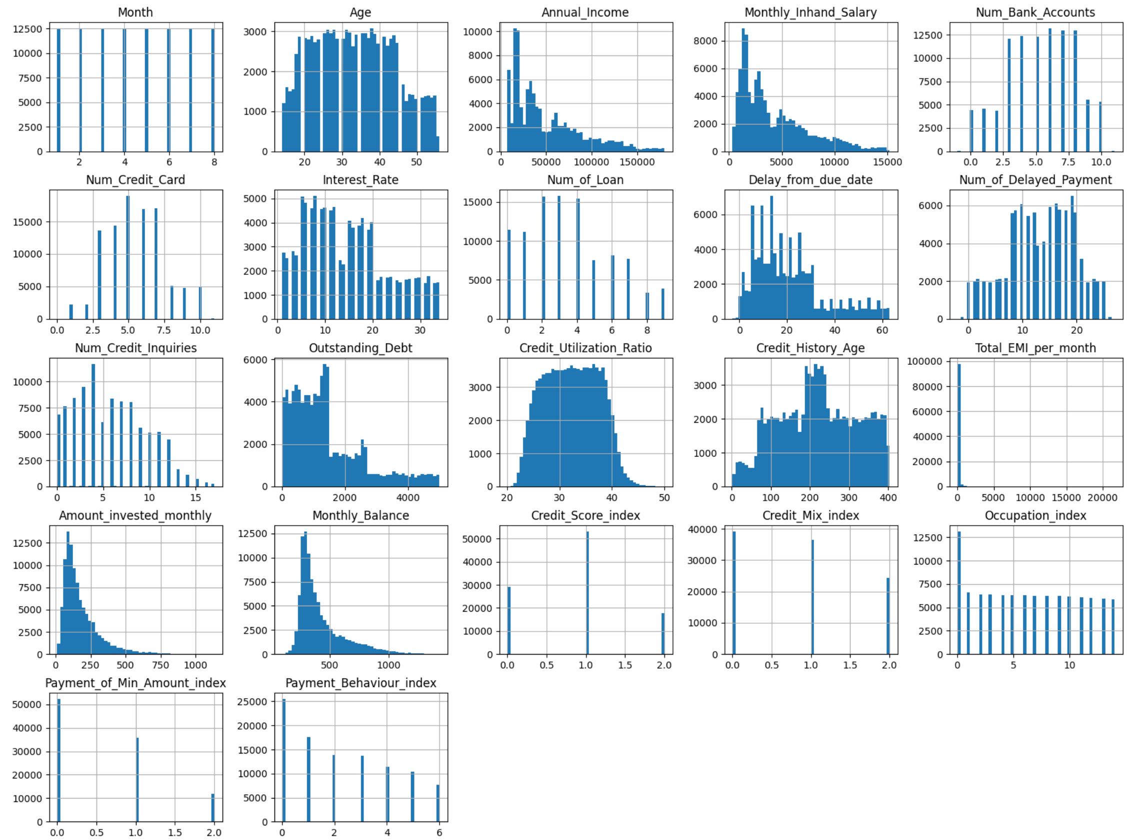
```
   Month  Age  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0      1   18       113781.0              9549.7825                  1
1      2   18       113781.0              9549.7825                  1
2      3   18       113781.0              9549.7825                  1
3      4   18       113781.0              9549.7825                  1
4      5   19       113781.0              9549.7825                  1

   Num_Credit_Card  Interest_Rate  Num_of_Loan  Delay_from_due_date  \
0                4              1            0                   14
1                4              1            0                   14
2                4              1            0                   14
3                4              1            0                   14
4                4              1            0                   14

   Num_of_Delayed_Payment  … Credit_Utilization_Ratio  Credit_History_Age  \
0                       7  …                37.998760               183.0
1                       7  …                35.947655               184.0
2                       7  …                43.829630               185.0
3                       7  …                31.016086               186.0
4                       7  …                32.035662               187.0

   Total_EMI_per_month  Amount_invested_monthly  Monthly_Balance  \
0                  0.0                 505.0000            824.0
1                  0.0                 505.0000            824.0
2                  0.0                 505.3333            824.0
3                  0.0                 505.3333            824.0
4                  0.0                 505.0000            824.0
```

```
   Credit_Score_index  Credit_Mix_index  Occupation_index  \
0                 0.0               2.0               8.0
1                 0.0               0.0               8.0
2                 0.0               2.0               8.0
3                 1.0               2.0               8.0
4                 0.0               2.0               8.0

   Payment_of_Min_Amount_index  Payment_Behaviour_index
0                          1.0                      2.0
1                          1.0                      5.0
2                          1.0                      3.0
3                          1.0                      3.0
4                          1.0                      0.0

[5 rows x 23 columns]
```

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

[62]:
```
df.hist(bins=50, figsize=(20,15))
```

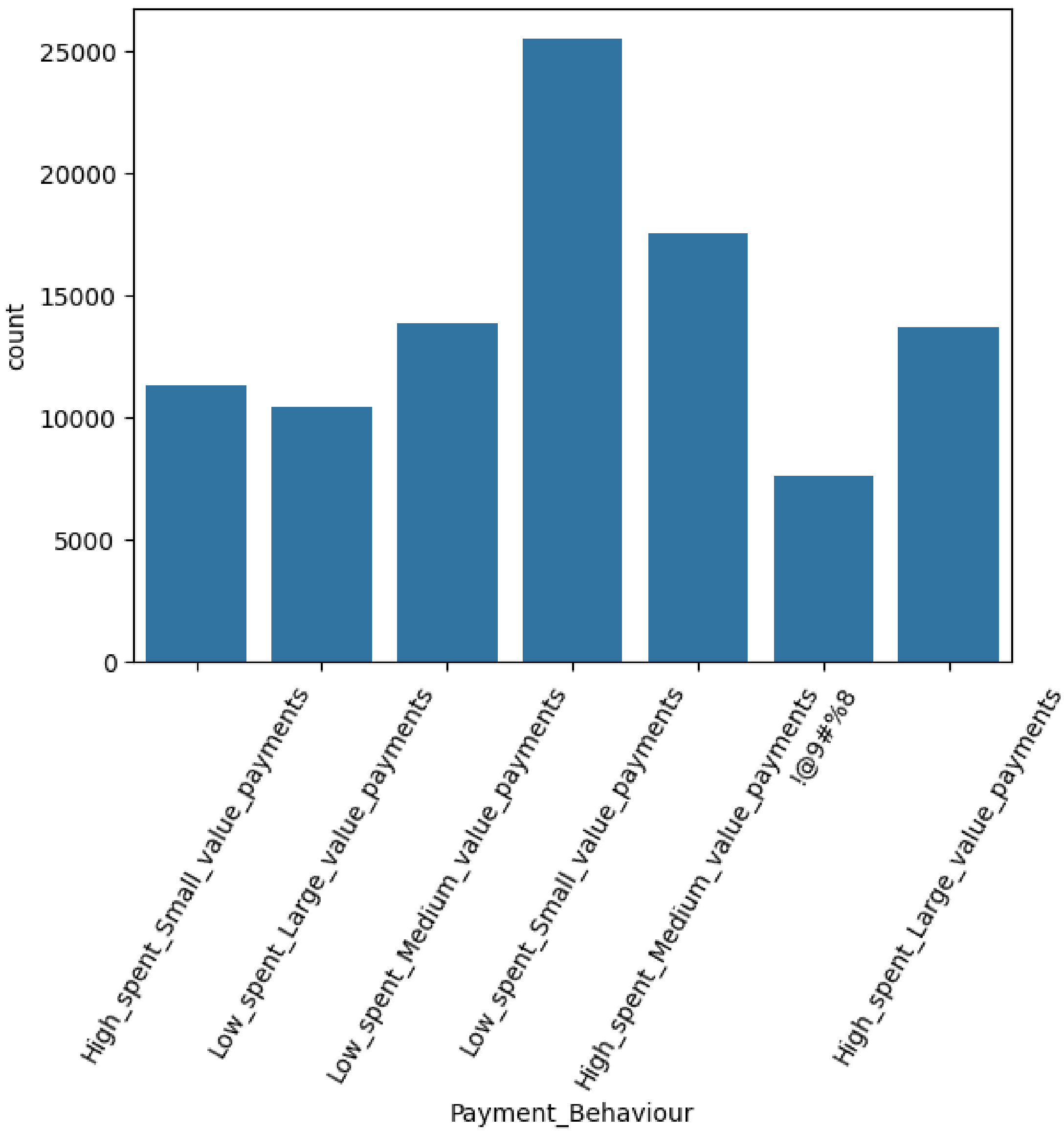
[62]:
```
array([[<Axes: title={'center': 'Month'}>,
        <Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'Annual_Income'}>,
        <Axes: title={'center': 'Monthly_Inhand_Salary'}>,
        <Axes: title={'center': 'Num_Bank_Accounts'}>],
       [<Axes: title={'center': 'Num_Credit_Card'}>,
        <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': 'Num_Credit_Inquiries'}>,
        <Axes: title={'center': 'Outstanding_Debt'}>,
        <Axes: title={'center': 'Credit_Utilization_Ratio'}>,
        <Axes: title={'center': 'Credit_History_Age'}>,
        <Axes: title={'center': 'Total_EMI_per_month'}>],
       [<Axes: title={'center': 'Amount_invested_monthly'}>,
        <Axes: title={'center': 'Monthly_Balance'}>,
        <Axes: title={'center': 'Credit_Score_index'}>,
        <Axes: title={'center': 'Credit_Mix_index'}>,
        <Axes: title={'center': 'Occupation_index'}>],
       [<Axes: title={'center': 'Payment_of_Min_Amount_index'}>,
        <Axes: title={'center': 'Payment_Behaviour_index'}>, <Axes: >,
        <Axes: >, <Axes: >]], dtype=object)
```



Removing strange values

Before

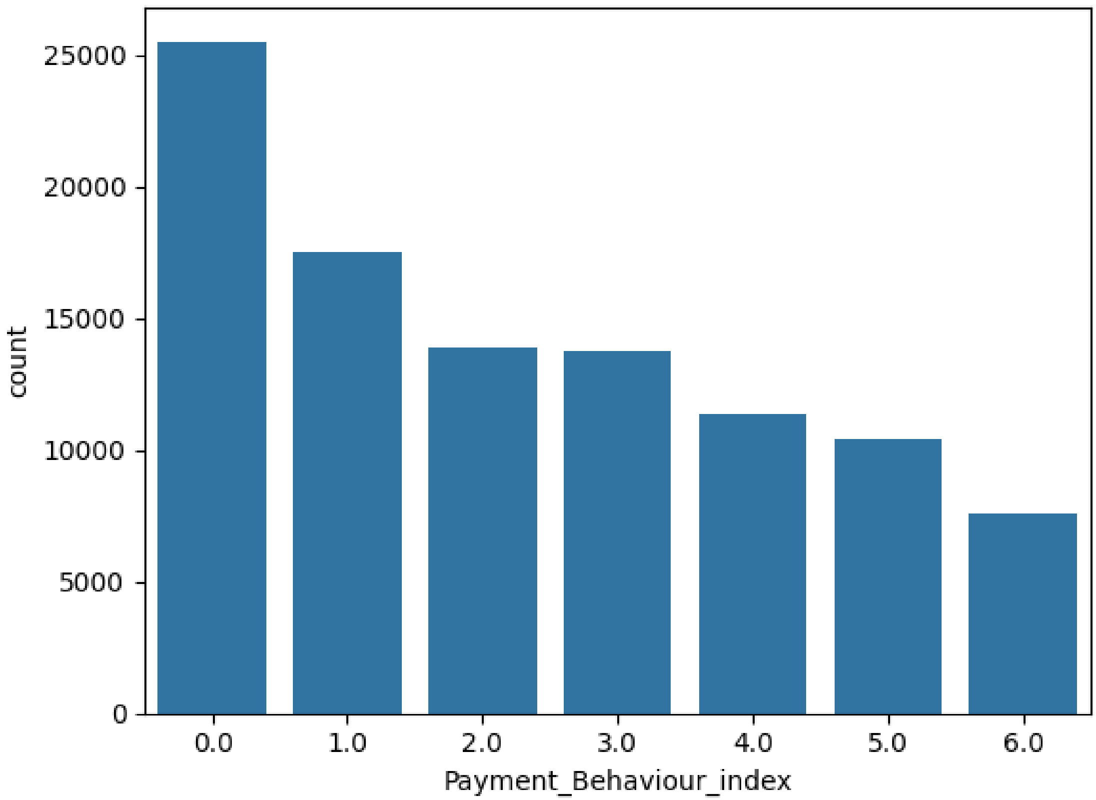
[63]:
```python
sns.countplot(preview_dataframe, x = 'Payment_Behaviour')
plt.xticks(rotation = 60)
plt.show()
```



After

[64]:
```
sns.countplot(df, x = 'Payment_Behaviour_index')
```

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

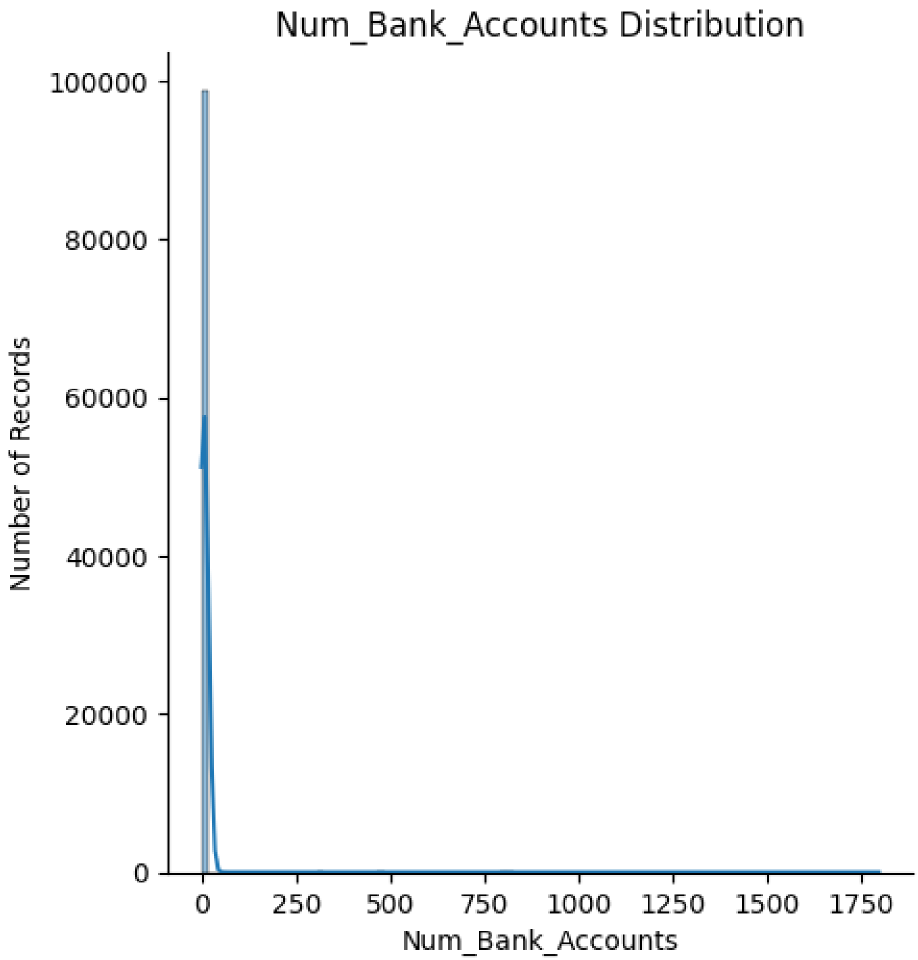


handling outliers - 1

Before

[65]:
```
displot_plot(preview_dataframe, 'Num_Bank_Accounts', bins=100)
```

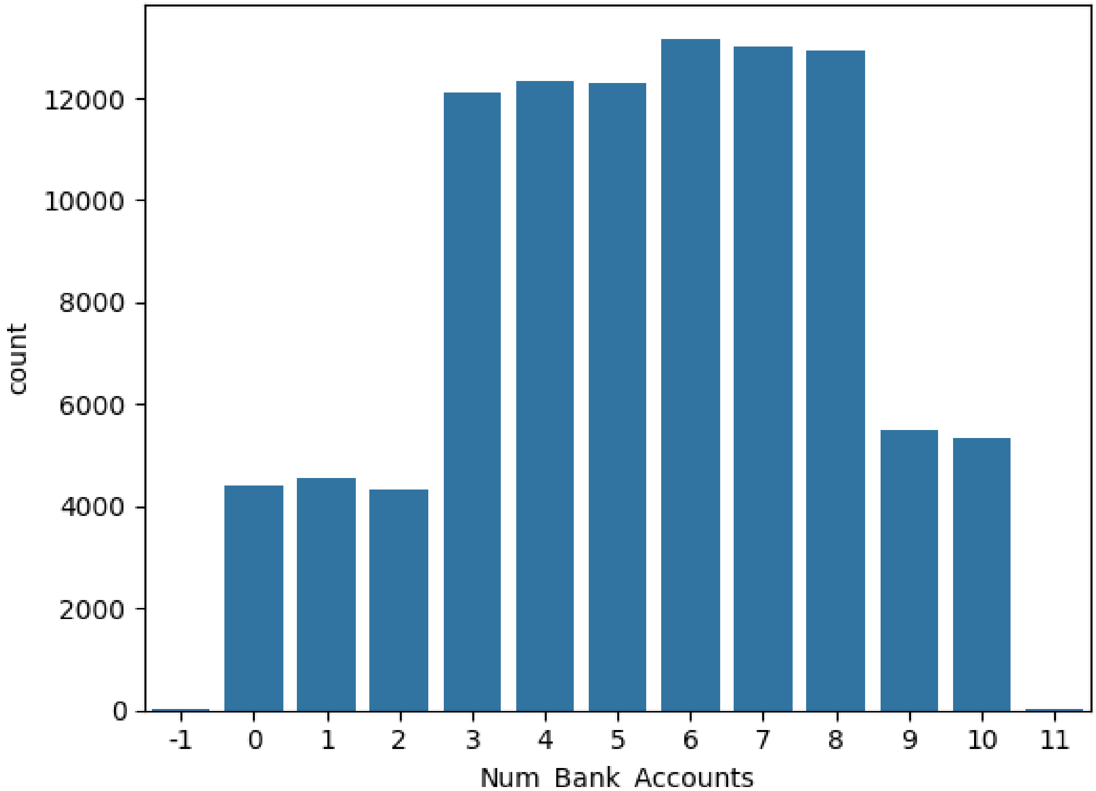
```
****************************************

Num_Bank_Accounts Distribution
```



After

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

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

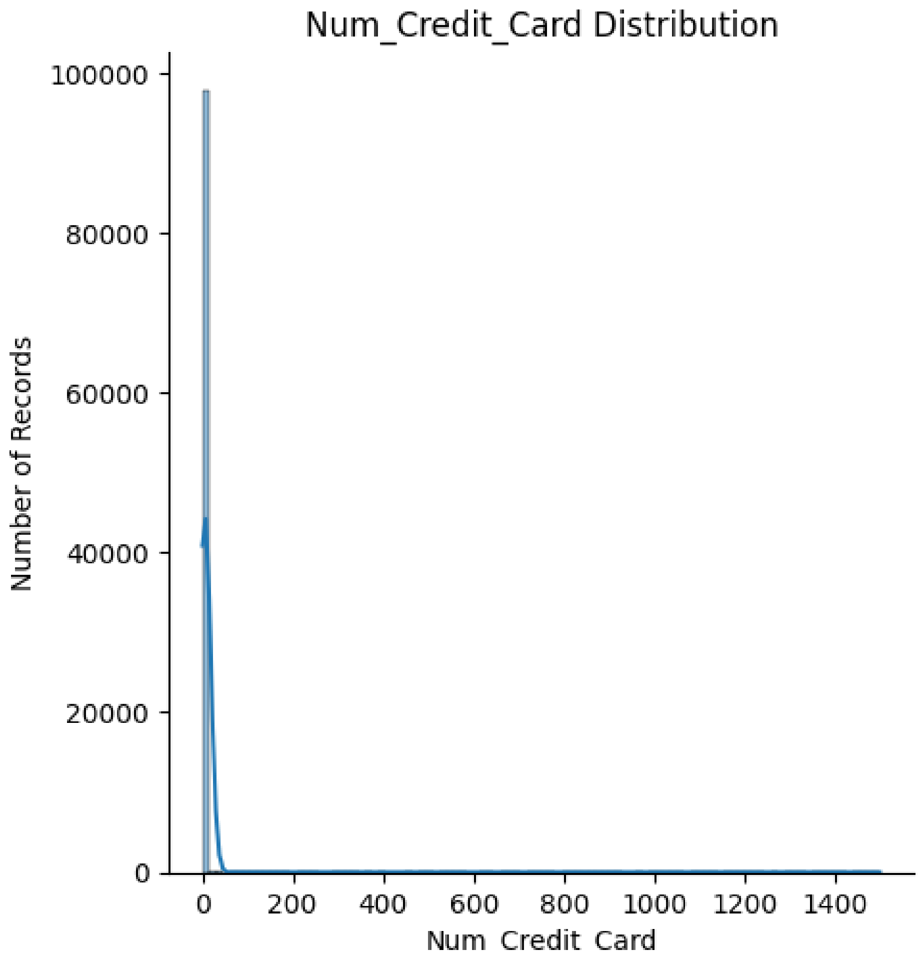


handling outliers - 2

Before

[67]:
```
displot_plot(preview_dataframe, 'Num_Credit_Card', bins=100)
```

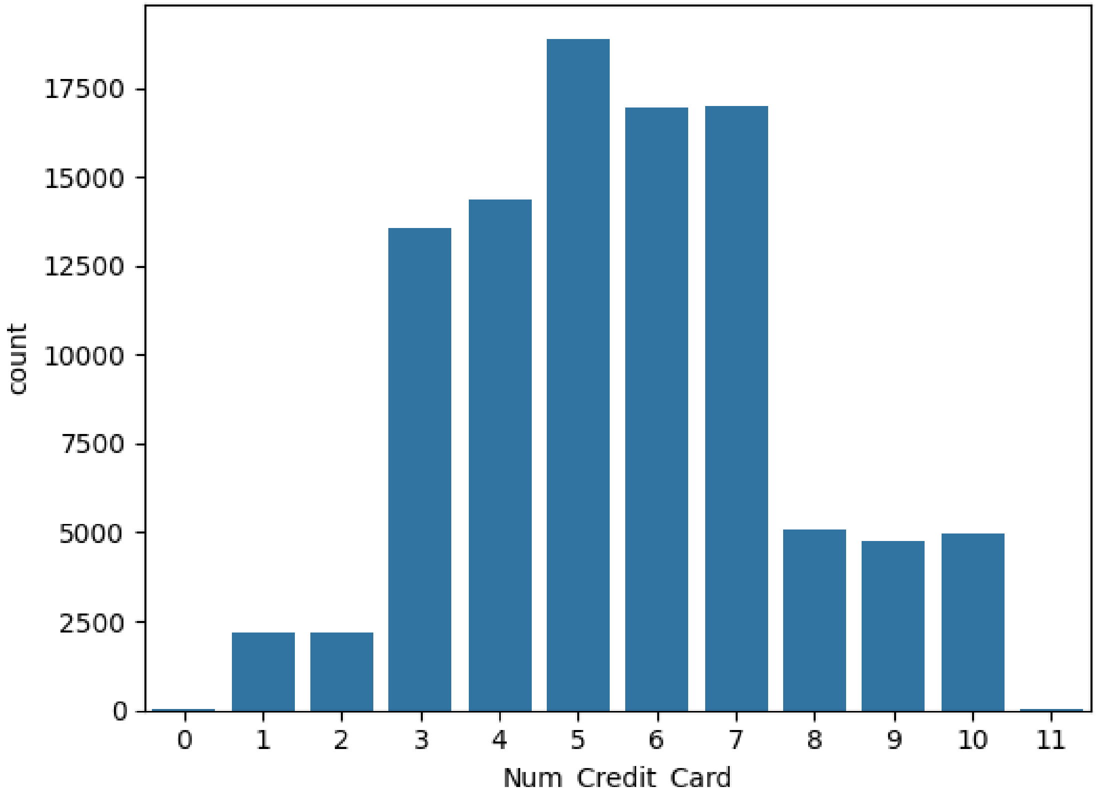
```
****************************************

Num_Credit_Card Distribution
```



After

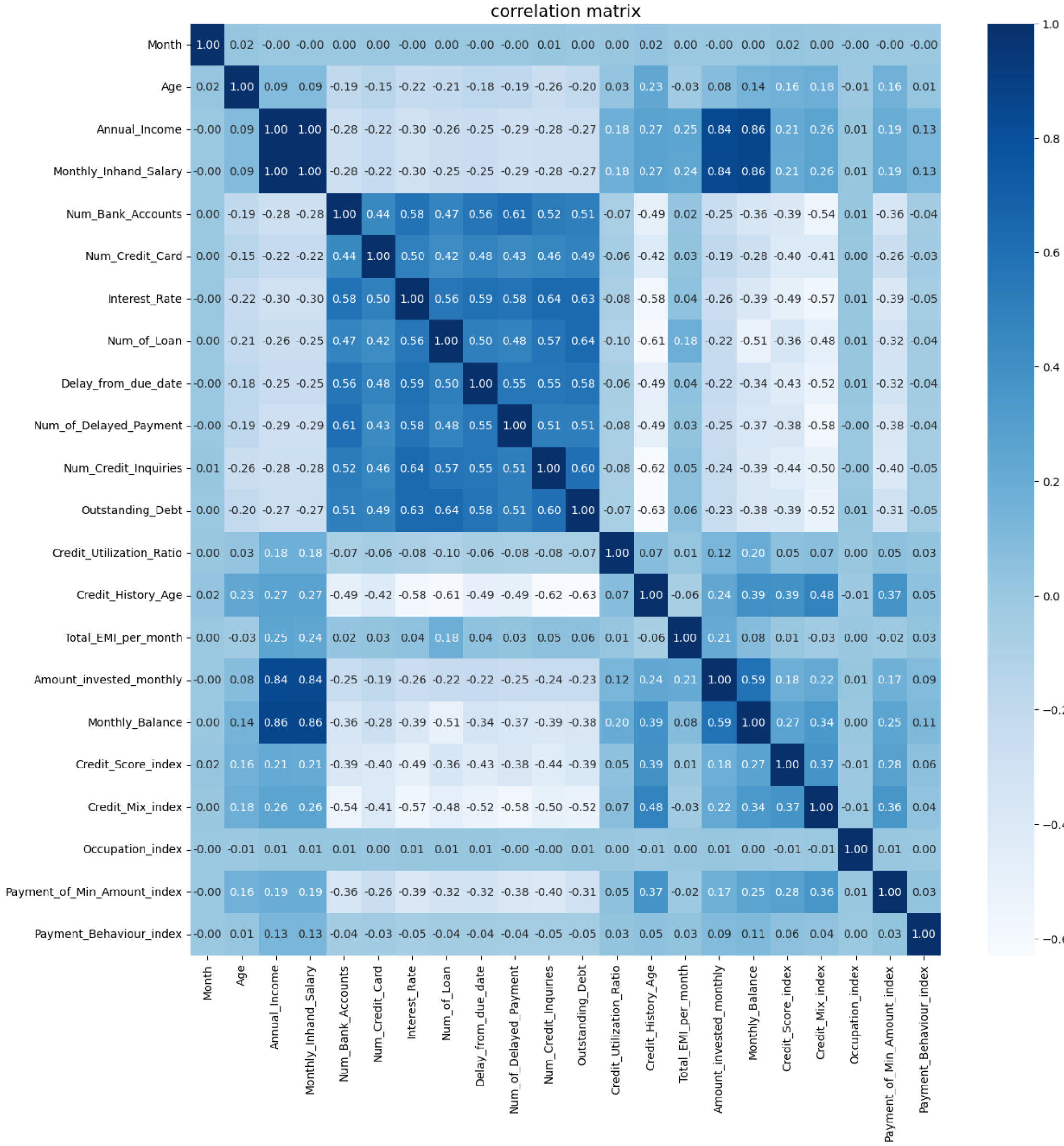
[68]:
```
sns.countplot(df, x = 'Num_Credit_Card')
```

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



4.2.6 Visualize the data correlation

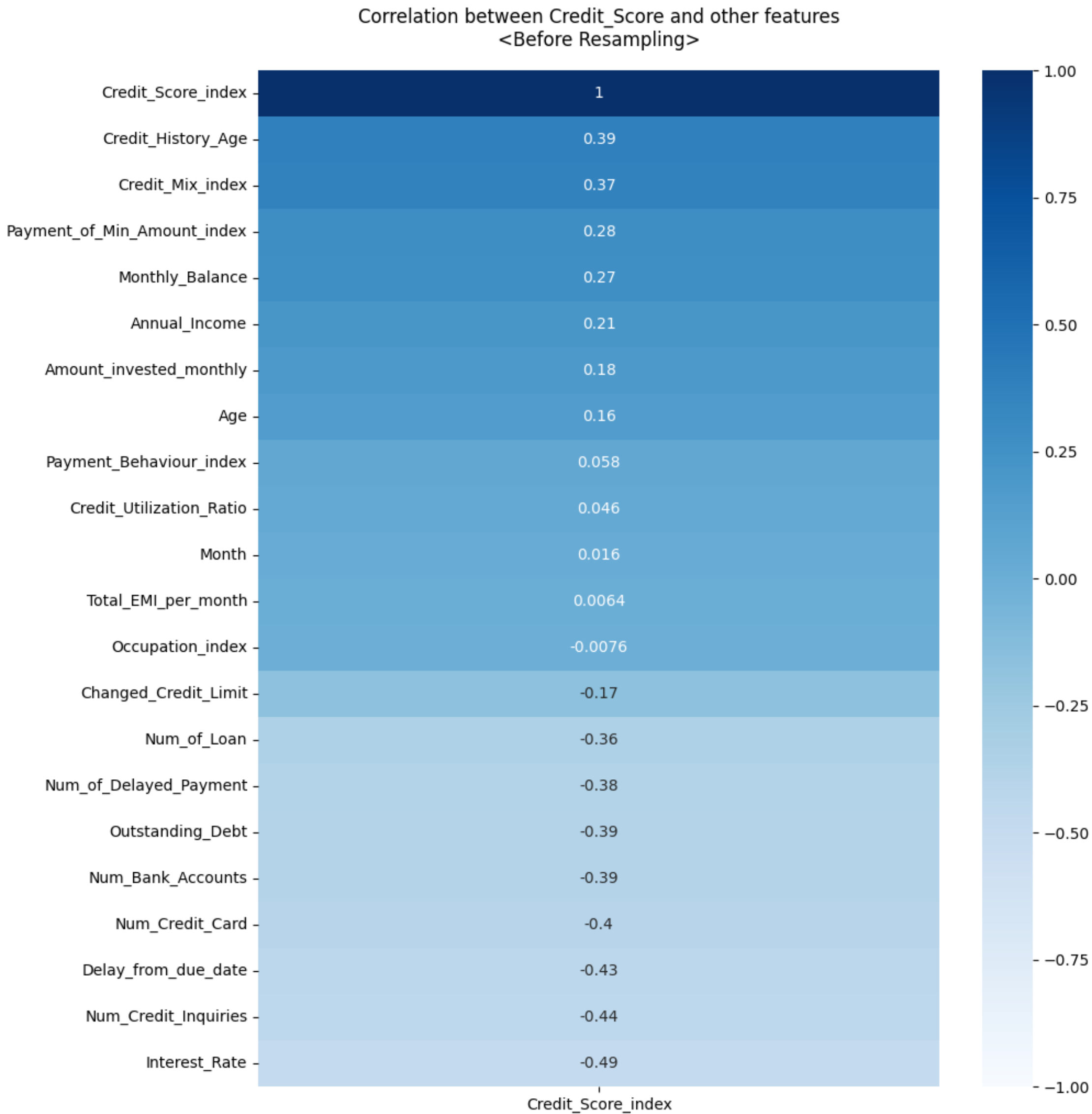
[69]:
```
df_corr=df.select_dtypes(include=["float64","int64"]).corr()

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



[70]:
```
# Drop the unnecessary columns (has same correlation with other columns)
df.drop('Monthly_Inhand_Salary', axis=1, inplace=True)
```

[71]:
```
plt.figure(figsize=(10,12))
heatmap = sns.heatmap(df.corr()[['Credit_Score_index']].
  ↪sort_values(by='Credit_Score_index', 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)
```

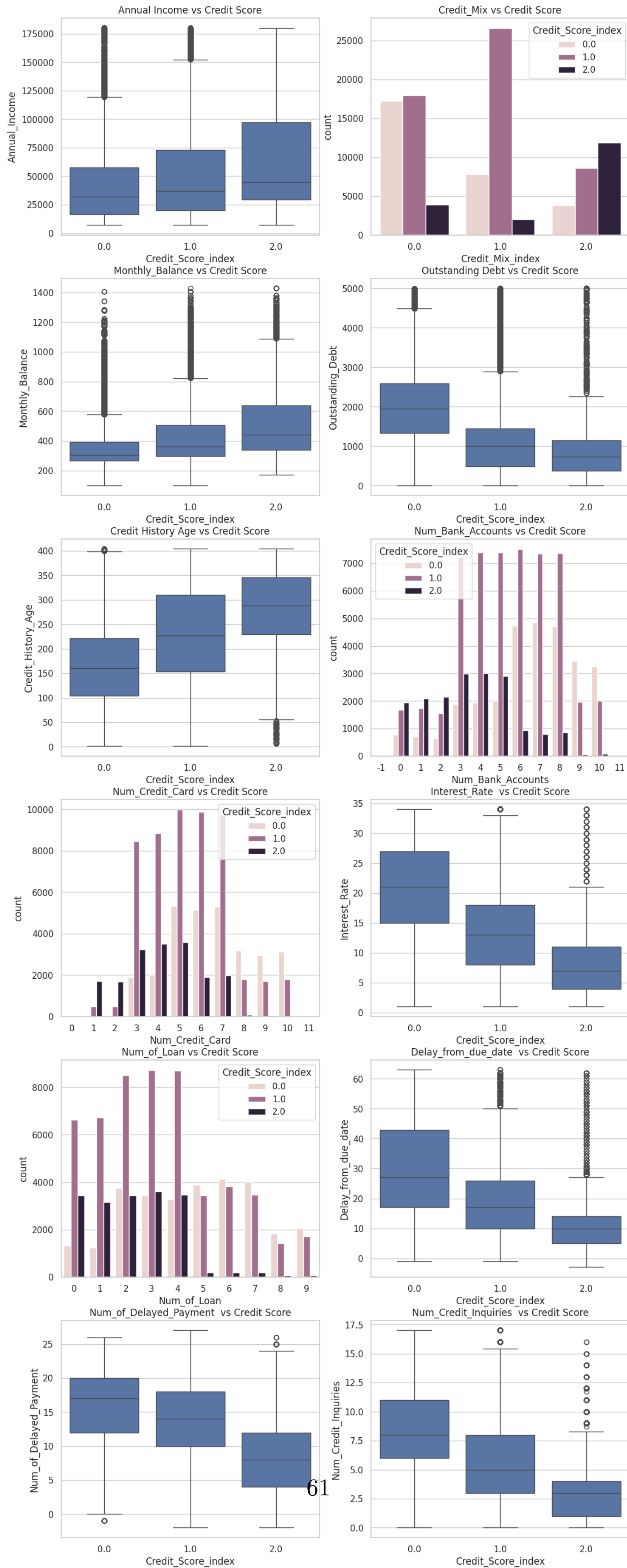
[71]: Text(0.5, 1.0, 'Correlation between Credit_Score and other features\n<Before Resampling>')



[72]:
```python
# 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_index', 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_index', 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_index', 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_index', x='Credit_Mix_index', 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_index', y='Annual_Income', data=df, ax=axes[0, 0])
axes[0, 0].set_title("Annual Income vs Credit Score")

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

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

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

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

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


Annual Income vs Credit Score
Annual_Income
Credit_Score_index
Credit_Mix vs Credit Score
count
Credit_Mix_index
Credit_Score_index
0.0
1.0
2.0
Monthly_Balance vs Credit Score
Monthly_Balance
Credit_Score_index
Outstanding Debt vs Credit Score
Outstanding_Debt
Credit_Score_index
Credit History Age vs Credit Score
Credit_History_Age
Credit_Score_index
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_index
Num_of_Loan vs Credit Score
count
Num_of_Loan
Delay_from_due_date vs Credit Score
Delay_from_due_date
Credit_Score_index
Num_of_Delayed_Payment vs Credit Score
Num_of_Delayed_Payment
Credit_Score_index
Num_Credit_Inquiries vs Credit Score
Num_Credit_Inquiries
Credit_Score_index

4.3 Convert the data back to spark dataframe

[73]:
```
# Convert it back to spark dataframe
df = spark.createDataFrame(df)
df.printSchema()
```

```
root
 |-- Month: long (nullable = true)
 |-- Age: long (nullable = true)
 |-- Annual_Income: double (nullable = true)
 |-- Num_Bank_Accounts: long (nullable = true)
 |-- Num_Credit_Card: long (nullable = true)
 |-- Interest_Rate: long (nullable = true)
 |-- Num_of_Loan: long (nullable = true)
 |-- Delay_from_due_date: long (nullable = true)
 |-- Num_of_Delayed_Payment: long (nullable = true)
 |-- Changed_Credit_Limit: decimal(38,18) (nullable = true)
 |-- Num_Credit_Inquiries: double (nullable = true)
 |-- Outstanding_Debt: double (nullable = true)
 |-- Credit_Utilization_Ratio: double (nullable = true)
 |-- Credit_History_Age: double (nullable = true)
 |-- Total_EMI_per_month: double (nullable = true)
 |-- Amount_invested_monthly: double (nullable = true)
 |-- Monthly_Balance: double (nullable = true)
 |-- Credit_Score_index: double (nullable = true)
 |-- Credit_Mix_index: double (nullable = true)
 |-- Occupation_index: double (nullable = true)
 |-- Payment_of_Min_Amount_index: double (nullable = true)
 |-- Payment_Behaviour_index: double (nullable = true)
```

4.4 Combine all the features into a single vector

[74]:
```
# Create a list of input columns excluding the categorical columns
input_cols = [col for col in df.columns if col not in
              ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount',␣
 ↪'Payment_Behaviour', 'Credit_Score', 'Credit_Score_index']]

# Create a VectorAssembler to combine the selected input columns into a single␣
 ↪"features" column
assembler = VectorAssembler(inputCols=input_cols, outputCol="features")
# Transform the train and test DataFrames to include the "features" column
df = assembler.transform(df)
print(df.count())
```

```python
df.show(5)
inputLength = len(assembler.getInputCols())
print(inputLength)
```

```
100000
+-----+---+-------------+-----------------+---------------+-------------+-------
----+-------------------+----------------------+--------------------+-----------
---------+----------------+------------------------+------------------+---------
----------+-----------------------+---------------+-----------------+----------
------+----------------+----------------------------+----------------------+----
-----------------+
|Month|Age|Annual_Income|Num_Bank_Accounts|Num_Credit_Card|Interest_Rate|Num_of_
Loan|Delay_from_due_date|Num_of_Delayed_Payment|Changed_Credit_Limit|Num_Credit_
Inquiries|Outstanding_Debt|Credit_Utilization_Ratio|Credit_History_Age|Total_EMI
_per_month|Amount_invested_monthly|Monthly_Balance|Credit_Score_index|Credit_Mix
_index|Occupation_index|Payment_of_Min_Amount_index|Payment_Behaviour_index|
features|
+-----+---+-------------+-----------------+---------------+-------------+-------
----+-------------------+----------------------+--------------------+-----------
---------+----------------+------------------------+------------------+---------
----------+-----------------------+---------------+-----------------+----------
------+----------------+----------------------------+----------------------+----
-----------------+
|    1| 18|     113781.0|                1|              4|            1|
0|                 14|                     7|11.00000000000000...|
1.0|          1030.0|       37.99875980252553|             183.0|
0.0|                    505.0|          824.0|               0.0|              2.0|
8.0|                        1.0|                   2.0|[1.0,18.0,113781...|
|    2| 18|     113781.0|                1|              4|            1|
0|                 14|                     7|11.00000000000000...|
1.0|          1030.0|       35.94765528296622|             184.0|
0.0|                    505.0|          824.0|               0.0|              0.0|
8.0|                        1.0|                   5.0|[2.0,18.0,113781...|
|    3| 18|     113781.0|                1|              4|            1|
0|                 14|                     7|11.00000000000000...|
1.0|          1030.0|      43.829630018622844|             185.0|
0.0|                 505.3333|          824.0|               0.0|              2.0|
8.0|                        1.0|                   3.0|[3.0,18.0,113781...|
|    4| 18|     113781.0|                1|              4|            1|
0|                 14|                     7|10.57140000000000...|
1.0|          1030.0|      31.016086286438927|             186.0|
0.0|                 505.3333|          824.0|               1.0|              2.0|
8.0|                        1.0|                   3.0|[4.0,18.0,113781...|
|    5| 19|     113781.0|                1|              4|            1|
0|                 14|                     7|11.00000000000000...|
1.0|          1030.0|       32.03566222451002|             187.0|
0.0|                    505.0|          824.0|               0.0|              2.0|
```

```
8.0|                         1.0|                    0.0|[5.0,19.0,113781…|
+-----+---+-------------+-----------------+---------------+-------------+-------
----+-------------------+----------------------+--------------------+-----------
---------+----------------+------------------------+------------------+---------
----------+-----------------------+---------------+------------------+----------
------+----------------+---------------------------+----------------------+----
----------------+
only showing top 5 rows

21
```

4.5 Data Oversampling with Spark

[75]:
```python
# Split the DataFrame into minority and majority classes
class_0 = df.filter("Credit_Score_index = 0.0")
class_1 = df.filter("Credit_Score_index = 1.0")
class_2 = df.filter("Credit_Score_index = 2.0")

class_0_ratio = class_1.count() / class_0.count()
class_2_ratio = class_1.count() / class_2.count()

print(class_0.count(), class_1.count(), class_2.count())

# Oversample each minority class
oversampled_class_0 = class_0.sample(True, class_0_ratio, seed=42)
oversampled_class_2 = class_2.sample(True, class_2_ratio, seed=42)

# Combine oversampled minority classes with majority class
df_resampled = class_1.union(oversampled_class_0)
df_resampled = df_resampled.union(oversampled_class_2)

# Show the oversampled DataFrame
df_resampled.show(5)
df_resampled.groupBy('Credit_Score_index').count().show()
```

```
28998 53174 17828
+-----+---+-------------+-----------------+---------------+-------------+-------
----+-------------------+----------------------+--------------------+-----------
---------+----------------+------------------------+------------------+---------
----------+-----------------------+---------------+------------------+----------
------+----------------+---------------------------+----------------------+----
----------------+
|Month|Age|Annual_Income|Num_Bank_Accounts|Num_Credit_Card|Interest_Rate|Num_of_
Loan|Delay_from_due_date|Num_of_Delayed_Payment|Changed_Credit_Limit|Num_Credit_
Inquiries|Outstanding_Debt|Credit_Utilization_Ratio|Credit_History_Age|Total_EMI
_per_month|Amount_invested_monthly|Monthly_Balance|Credit_Score_index|Credit_Mix
_index|Occupation_index|Payment_of_Min_Amount_index|Payment_Behaviour_index|
features|
```

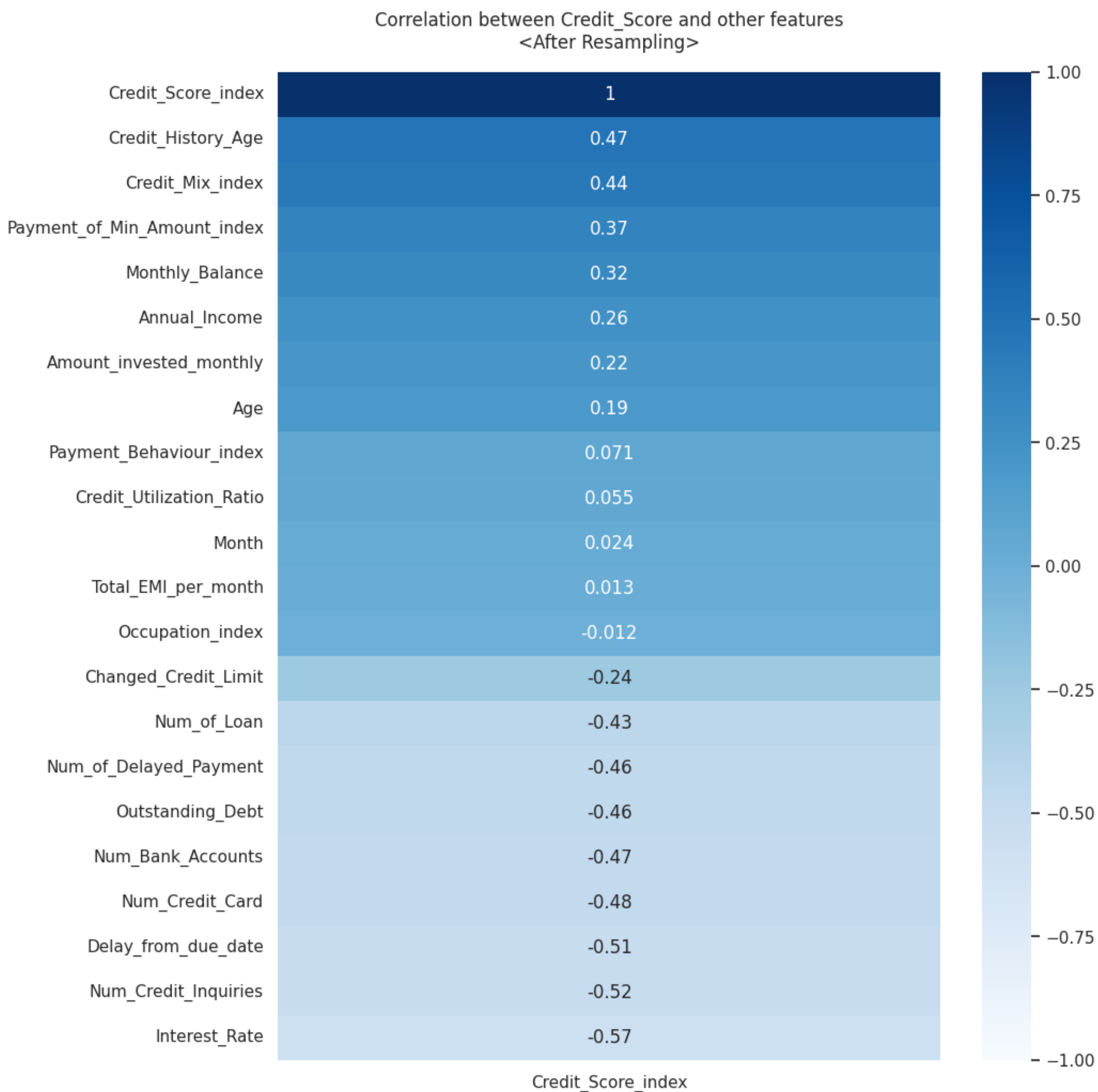
```
+-----+---+-------------+------------------+----------------+-------------+-------
----+--------------------+-----------------------+---------------------+-----------
---------+----------------+-------------------------+------------------+---------
----------+-----------------------+----------------+------------------+----------
------+----------------+----------------------------+-----------------------+----
----------------+
|    4| 18|     113781.0|                 1|               4|            1|
0|                 14|                     7|10.57140000000000…|
1.0|          1030.0|      31.016086286438927|             186.0|
0.0|                505.3333|           824.0|               1.0|              2.0|
8.0|                      1.0|                       3.0|[4.0,18.0,113781…|
|    7| 19|     113781.0|                 1|               4|            1|
0|                 14|                     7|11.00000000000000…|
1.0|          1030.0|       29.17479515251761|             189.0|
0.0|                   505.0|           824.0|               1.0|              2.0|
8.0|                      2.0|                       3.0|[7.0,19.0,113781…|
|    8| 19|     113781.0|                 1|               4|            1|
0|                 14|                     8|8.000000000000000000|
1.0|          1030.0|      28.592942540839356|             190.0|
0.0|                   505.0|           824.0|               1.0|              2.0|
8.0|                      1.0|                       4.0|[8.0,19.0,113781…|
|    1| 40|      60411.0|                 4|               7|           17|
4|                 23|                     9|8.000000000000000000|
9.0|          1853.0|      26.605192490068692|             188.0|
149.9263873826631|                   184.0|           478.0|               1.0|
1.0|            1.0|                         0.0|
0.0|[1.0,40.0,60411.0…|
|    2| 40|      60411.0|                 4|               7|           17|
4|                 23|                     9|8.428600000000000000|
9.0|          1853.0|      25.625530295771803|             189.0|
149.9263873826631|                   184.0|           478.0|               1.0|
1.0|            1.0|                         0.0|
1.0|[2.0,40.0,60411.0…|
+-----+---+-------------+------------------+----------------+-------------+-------
----+--------------------+-----------------------+---------------------+-----------
---------+----------------+-------------------------+------------------+---------
----------+-----------------------+----------------+------------------+----------
------+----------------+----------------------------+-----------------------+----
----------------+
only showing top 5 rows

+------------------+-----+
|Credit_Score_index|count|
+------------------+-----+
|               1.0|53174|
|               0.0|53192|
|               2.0|53456|
+------------------+-----+
```

So, we handled

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

[76]:
```
# Check the correlation after oversampling
df_temp = df_resampled.toPandas().drop('features', axis=1)

plt.figure(figsize=(10,12))
heatmap = sns.heatmap(df_temp.corr()[['Credit_Score_index']].
 ↪sort_values(by='Credit_Score_index', 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)
```

[76]:
```
Text(0.5, 1.0, 'Correlation between Credit_Score and other features\n<After
Resampling>')
```



4.6 Split the data using Stratified Split

[77]:
```
def stratified_train_test_split(df, stratify_col_name, train_fraction):
    # Separate the data into classes
    classes = df.select(stratify_col_name).distinct().collect()

    # Split each class into train and test using randomSplit
    train_data = []
    test_data = []

    for class_label in classes:
        class_df = df.filter(df[stratify_col_name] ==␣
↪class_label[stratify_col_name])
```

```
        splits = class_df.randomSplit([train_fraction, 1.0 - train_fraction],␣
↪seed=42)

        train_data.append(splits[0])
        test_data.append(splits[1])

    # Union all the train and test sets
    train = reduce(lambda x, y: x.union(y), train_data)
    test = reduce(lambda x, y: x.union(y), test_data)

    train = train.orderBy(F.rand())
    test = test.orderBy(F.rand())

    return train, test
```

[78]:
```
# Copy only the 'features' and 'Credit_Score_index' columns to a new DataFrame
new_df = df.select("features", "Credit_Score_index")
train, test = stratified_train_test_split(new_df, "Credit_Score_index", 0.8)
```

[79]:
```
# Copy only the 'features' and 'Credit_Score_index' columns to a new DataFrame
new_df_resampled = df_resampled.select("features", "Credit_Score_index")
train_resampled, test_resampled = stratified_train_test_split(new_df_resampled,␣
↪"Credit_Score_index", 0.8)
```

4.7 Normalized the data

[80]:
```
# Use standard scaler to scale the features
scaler = StandardScaler(inputCol='features', outputCol='features_scaled',␣
↪withStd=True, withMean=True)
```

[81]:
```
# Normalize the data using StandardScaler
train = scaler.fit(train).transform(train)
test = scaler.fit(test).transform(test)
```

[82]:
```
# Normalize the data using StandardScaler
train_resampled = scaler.fit(train_resampled).transform(train_resampled)
test_resampled = scaler.fit(test_resampled).transform(test_resampled)
```

[83]:
```
print("Before Resampling:  Train:", train.count(), ", Test:", test.count())
print("After Resampling:   Train:", train_resampled.count(), ", Test:",␣
↪test_resampled.count())
```

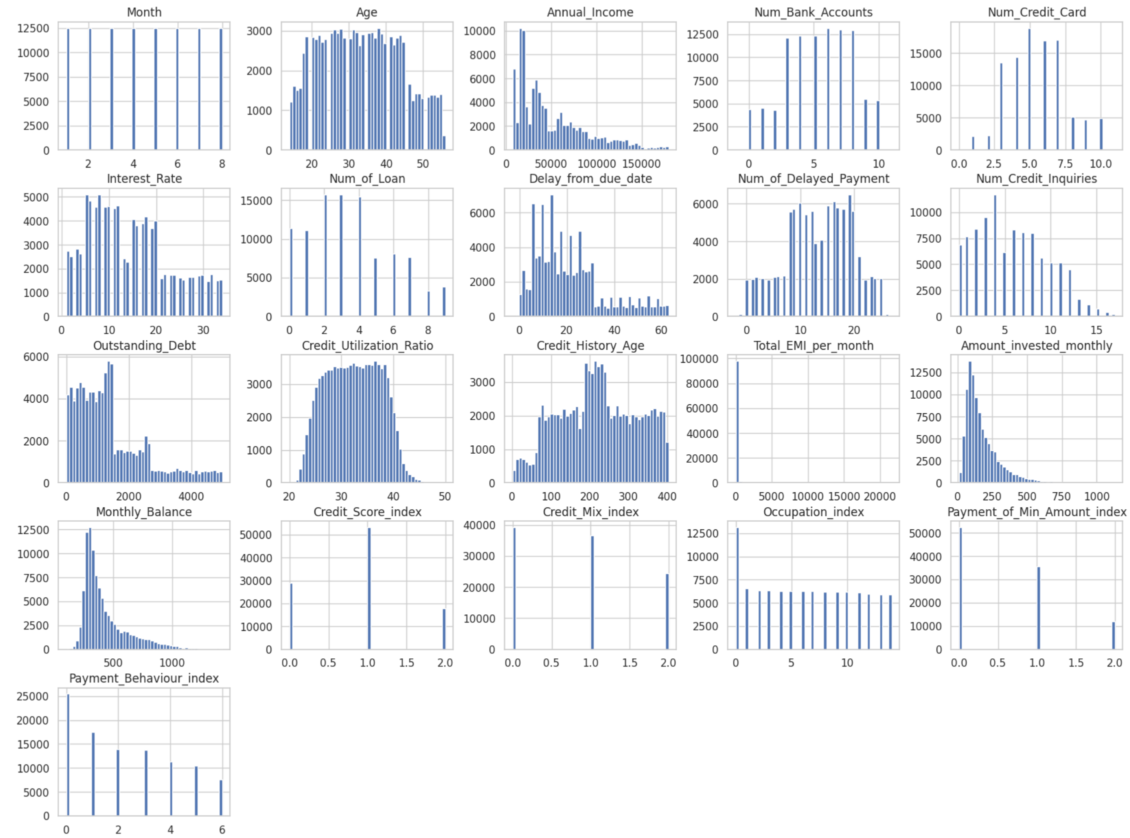
```
Before Resampling:  Train: 80134 , Test: 19866
```

```
After Resampling:   Train: 128041 , Test: 31781
```

4.8 Diagrams after resampling

[84]:
```python
# Histogram before oversampling
df_toPandas = df.toPandas()
df_toPandas.hist(bins=50, figsize=(20,15))
```

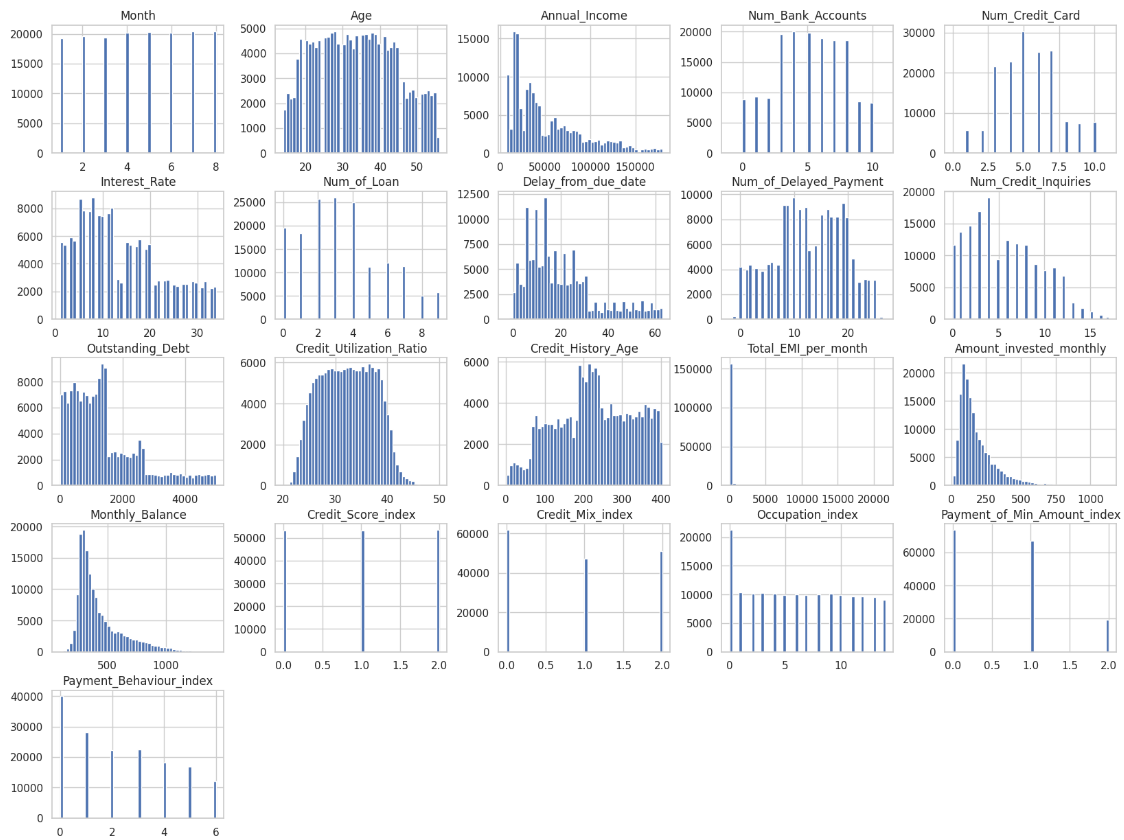
[84]:
```
array([[<Axes: title={'center': 'Month'}>,
        <Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'Annual_Income'}>,
        <Axes: title={'center': 'Num_Bank_Accounts'}>,
        <Axes: title={'center': 'Num_Credit_Card'}>],
       [<Axes: title={'center': 'Interest_Rate'}>,
        <Axes: title={'center': 'Num_of_Loan'}>,
        <Axes: title={'center': 'Delay_from_due_date'}>,
        <Axes: title={'center': 'Num_of_Delayed_Payment'}>,
        <Axes: title={'center': 'Num_Credit_Inquiries'}>],
       [<Axes: title={'center': 'Outstanding_Debt'}>,
        <Axes: title={'center': 'Credit_Utilization_Ratio'}>,
        <Axes: title={'center': 'Credit_History_Age'}>,
        <Axes: title={'center': 'Total_EMI_per_month'}>,
        <Axes: title={'center': 'Amount_invested_monthly'}>],
       [<Axes: title={'center': 'Monthly_Balance'}>,
        <Axes: title={'center': 'Credit_Score_index'}>,
        <Axes: title={'center': 'Credit_Mix_index'}>,
        <Axes: title={'center': 'Occupation_index'}>,
        <Axes: title={'center': 'Payment_of_Min_Amount_index'}>],
       [<Axes: title={'center': 'Payment_Behaviour_index'}>, <Axes: >,
        <Axes: >, <Axes: >, <Axes: >]], dtype=object)
```



[85]:
```
# Histogram after oversampling
df_toPandas_resampled = df_resampled.toPandas()
df_toPandas_resampled.hist(bins=50, figsize=(20,15))
```

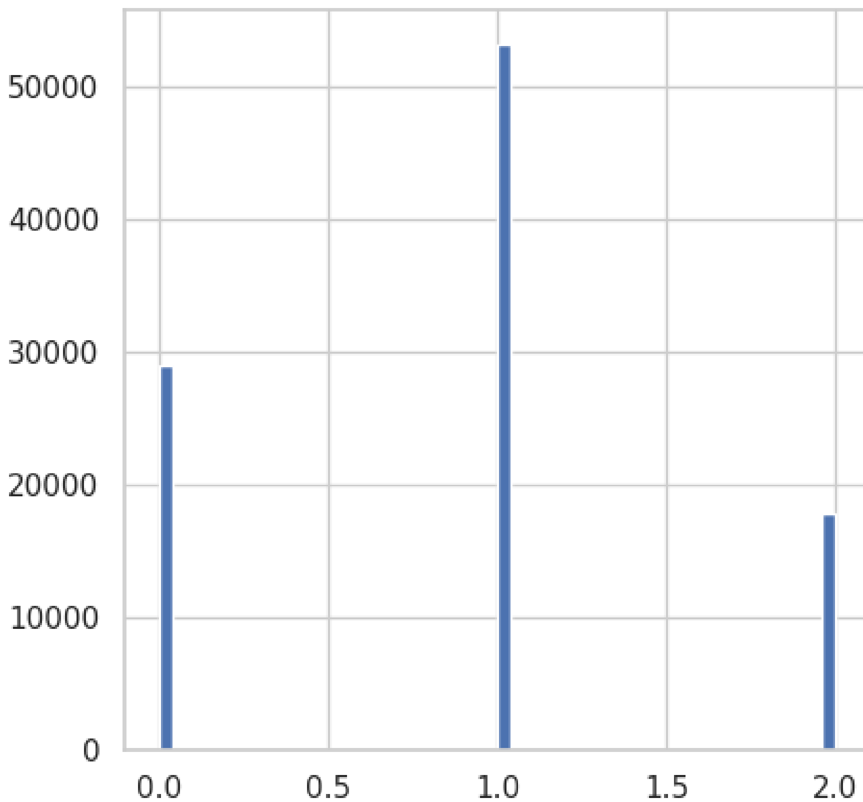
[85]:
```
array([[<Axes: title={'center': 'Month'}>,
        <Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'Annual_Income'}>,
        <Axes: title={'center': 'Num_Bank_Accounts'}>,
        <Axes: title={'center': 'Num_Credit_Card'}>],
       [<Axes: title={'center': 'Interest_Rate'}>,
        <Axes: title={'center': 'Num_of_Loan'}>,
        <Axes: title={'center': 'Delay_from_due_date'}>,
        <Axes: title={'center': 'Num_of_Delayed_Payment'}>,
        <Axes: title={'center': 'Num_Credit_Inquiries'}>],
       [<Axes: title={'center': 'Outstanding_Debt'}>,
        <Axes: title={'center': 'Credit_Utilization_Ratio'}>,
        <Axes: title={'center': 'Credit_History_Age'}>,
        <Axes: title={'center': 'Total_EMI_per_month'}>,
        <Axes: title={'center': 'Amount_invested_monthly'}>],
```

```
[<Axes: title={'center': 'Monthly_Balance'}>,
 <Axes: title={'center': 'Credit_Score_index'}>,
 <Axes: title={'center': 'Credit_Mix_index'}>,
 <Axes: title={'center': 'Occupation_index'}>,
 <Axes: title={'center': 'Payment_of_Min_Amount_index'}>],
[<Axes: title={'center': 'Payment_Behaviour_index'}>, <Axes: >,
 <Axes: >, <Axes: >, <Axes: >]], dtype=object)
```



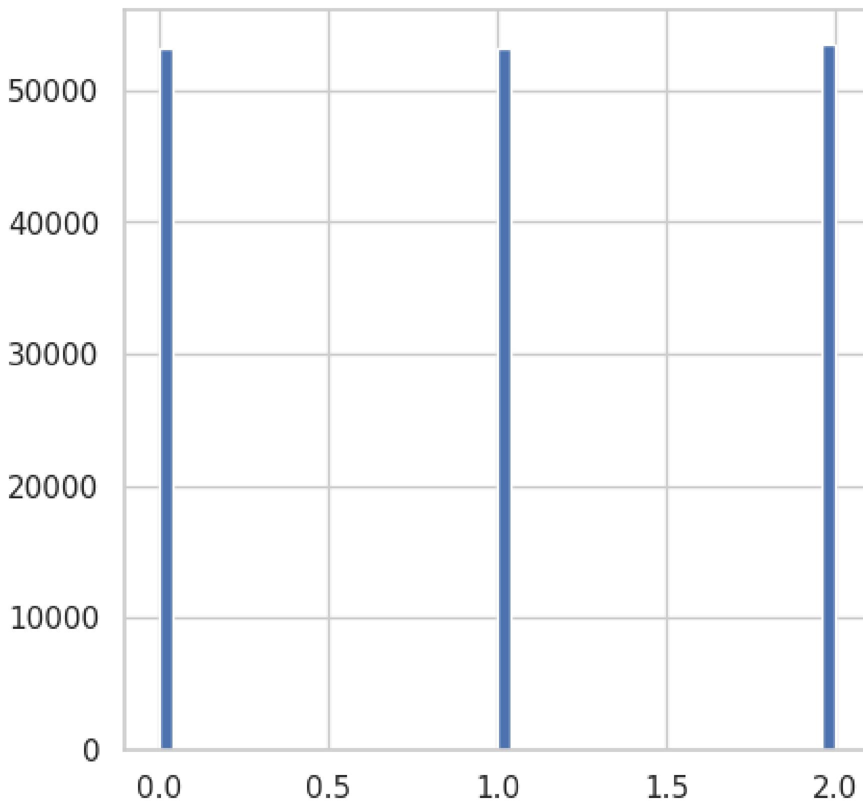
[86]:
```python
# Credit_Score before oversampling
df_toPandas["Credit_Score_index"].hist(bins = 50, figsize=(5,5))
```

[86]: `<Axes: >`



[87]:
```
# Credit_Score after oversampling <training set>
df_toPandas_resampled["Credit_Score_index"].hist(bins = 50, figsize=(5,5))
```

[87]: <Axes: >



5 5. Implementing the different models

5.1 Declare the helper functions

[88]:
```
# Function to print all the metrics based on each model's predictions
def model_summary(model_name, predictions):
    accuracy_eval = MulticlassClassificationEvaluator(labelCol =␣
 ↪'Credit_Score_index', metricName = 'accuracy')
    precision_eval = MulticlassClassificationEvaluator(labelCol =␣
 ↪'Credit_Score_index', metricName = 'precisionByLabel')
    recall_eval = MulticlassClassificationEvaluator(labelCol =␣
 ↪'Credit_Score_index', metricName = 'recallByLabel')
    f1_eval = MulticlassClassificationEvaluator(labelCol =␣
 ↪'Credit_Score_index', metricName = 'f1')
    evaluator = BinaryClassificationEvaluator(labelCol = 'Credit_Score_index',␣
 ↪rawPredictionCol = 'prediction', metricName = 'areaUnderROC')

    accuracy = accuracy_eval.evaluate(predictions)
    precision = precision_eval.evaluate(predictions)
    recall = recall_eval.evaluate(predictions)
```

```
    f1 = f1_eval.evaluate(predictions)
    roc_auc = evaluator.evaluate(predictions)

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

    return summary
```

[89]:
```
# Display the confusion matrix as a heatmap
def confusion_matrix_plot(model_name, confusion_matrix):
    plt.figure(figsize=(5, 3))
    sns.heatmap(confusion_matrix, annot=True, fmt=".0f", cmap="Blues",\
                xticklabels=['Poor', 'Standard', 'Good'], yticklabels=['Poor',␣
↪'Standard', 'Good'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(model_name)
    plt.show()
```

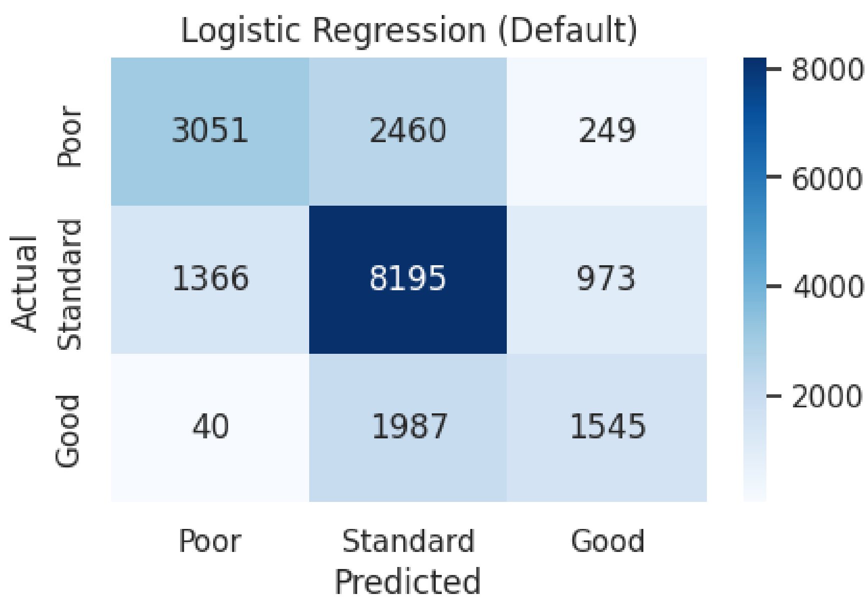
[90]:
```
# Define the Multi-class Clssification Evaluator
evaluator = MulticlassClassificationEvaluator(labelCol="Credit_Score_index",␣
↪predictionCol="prediction", metricName="accuracy")
```

5.2 Logistic Regression

5.2.1 Before tuning, original data

[91]:
```
lr_default = LogisticRegression(featuresCol="features",␣
↪labelCol="Credit_Score_index")
lr_pipeline_default = Pipeline(stages = [lr_default])
LRmodel_default = lr_pipeline_default.fit(train)

lr_result_default = LRmodel_default.transform(test)

# evaluator = MulticlassClassificationEvaluator(labelCol="Credit_Score_index",␣
↪predictionCol="prediction")
lr_accuracy_default = evaluator.evaluate(lr_result_default)

# Convert DataFrame to RDD for MulticlassMetrics
lr_predictionAndLabels_default = lr_result_default.select("prediction",␣
↪"Credit_Score_index").rdd
```

```
# Initialize MulticlassMetrics
lr_metrics_default = MulticlassMetrics(lr_predictionAndLabels_default)

# Create a confusion matrix
lr_confusion_matrix_default = lr_metrics_default.confusionMatrix()

# Display the confusion matrix
confusion_matrix_plot("Logistic Regression (Default)",␣
↪lr_confusion_matrix_default.toArray())
```



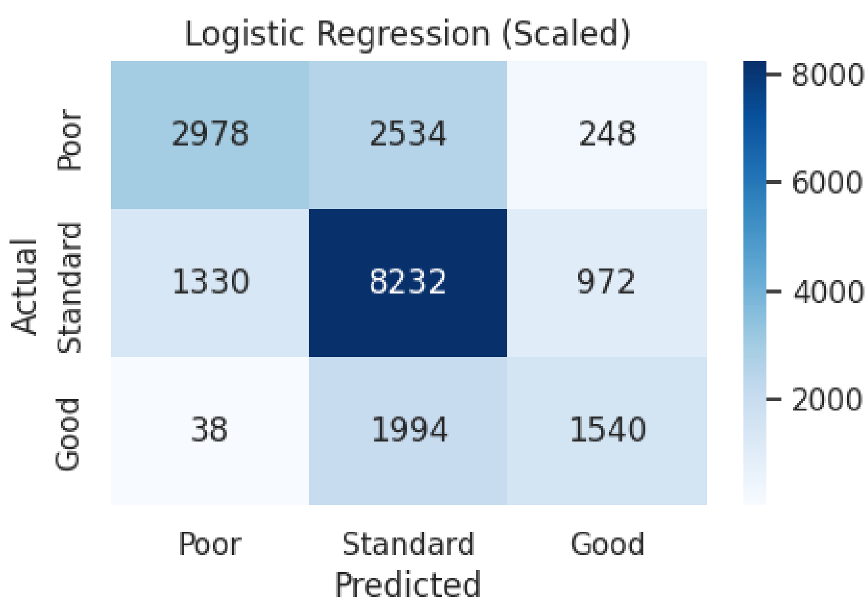
[92]:
```
print(f"Logistic Regression Accuracy (Before tuning, original data) :␣
↪{lr_accuracy_default * 100:.5f}% ")
```

```
Logistic Regression Accuracy (Before tuning, original data) : 64.38639%
```

5.2.2 Before tuning, scaled data

[93]:
```
lr_default_scaled = LogisticRegression(featuresCol="features_scaled",␣
↪labelCol="Credit_Score_index")
lr_pipeline_default_scaled = Pipeline(stages = [lr_default_scaled])
LRmodel_default_scaled = lr_pipeline_default_scaled.fit(train)

lr_result_default_scaled = LRmodel_default_scaled.transform(test)
```

```
# evaluator = MulticlassClassificationEvaluator(labelCol="Credit_Score_index",␣
↪predictionCol="prediction")
lr_accuracy_scaled = evaluator.evaluate(lr_result_default_scaled)

# Convert DataFrame to RDD for MulticlassMetrics
lr_predictionAndLabels_scaled = lr_result_default_scaled.select("prediction",␣
↪"Credit_Score_index").rdd

# Initialize MulticlassMetrics
lr_metrics_scaled = MulticlassMetrics(lr_predictionAndLabels_scaled)

# Create a confusion matrix
lr_confusion_matrix_scaled = lr_metrics_scaled.confusionMatrix()

# Display the confusion matrix
confusion_matrix_plot("Logistic Regression (Scaled)",␣
↪lr_confusion_matrix_scaled.toArray())
```

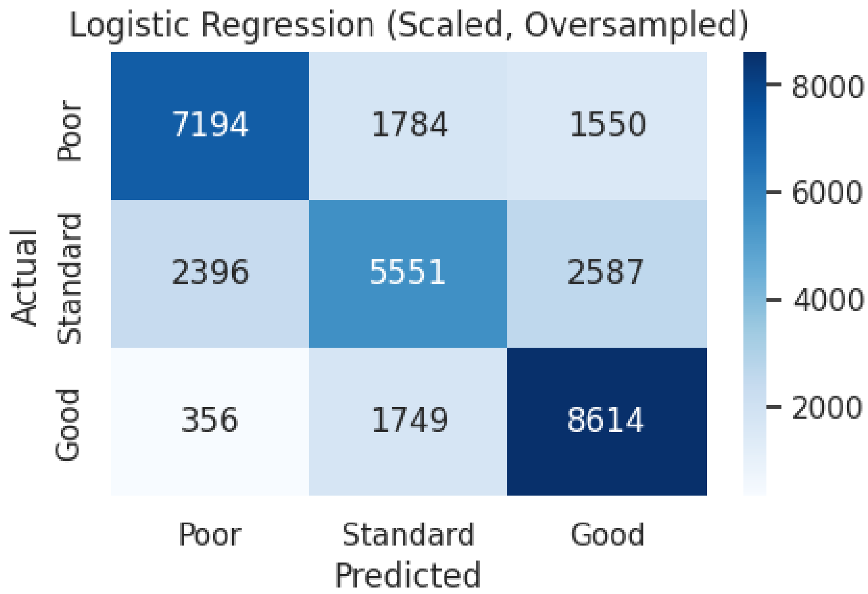


[94]:
```
print(f"Logistic Regression Accuracy (Before tuning, scaled data) :␣
↪{lr_accuracy_scaled * 100:.5f}% ")
```

```
Logistic Regression Accuracy (Before tuning, scaled data) : 64.18001%
```

5.2.3 Before tuning, scaled data & oversampledData

[95]:
```
lr_pipeline_default_scaled_over = Pipeline(stages = [lr_default_scaled])
LRmodel_default_scaled_over = lr_pipeline_default_scaled_over.
 ↪fit(train_resampled)

lr_result_default_scaled_over = LRmodel_default_scaled_over.
 ↪transform(test_resampled)

# evaluator = MulticlassClassificationEvaluator(labelCol="Credit_Score_index",␣
 ↪predictionCol="prediction")
lr_accuracy_scaled_over = evaluator.evaluate(lr_result_default_scaled_over)

# Convert DataFrame to RDD for MulticlassMetrics
lr_predictionAndLabels_default_scaled_over = lr_result_default_scaled_over.
 ↪select("prediction", "Credit_Score_index").rdd

# Initialize MulticlassMetrics
lr_metrics_default_scaled_over =␣
 ↪MulticlassMetrics(lr_predictionAndLabels_default_scaled_over)

# Create a confusion matrix
lr_confusion_matrix_default_scaled_over = lr_metrics_default_scaled_over.
 ↪confusionMatrix()

# Display the confusion matrix
confusion_matrix_plot("Logistic Regression (Scaled, Oversampled)",␣
 ↪lr_confusion_matrix_default_scaled_over.toArray())
```



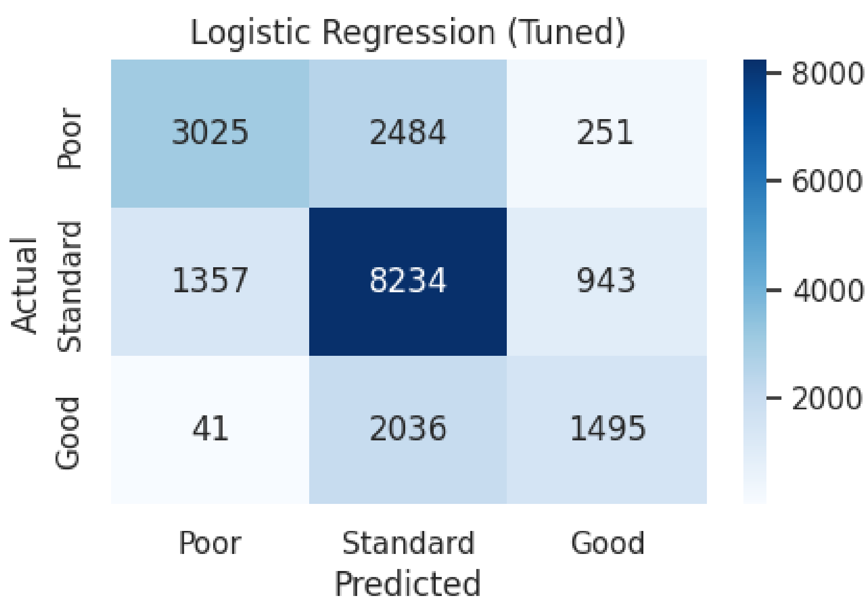
[96]:
```
print(f"Logistic Regression Accuracy (Before tuning, scaled data &
↪oversampledData) : {lr_accuracy_scaled_over * 100:.5f}% ")
```

```
Logistic Regression Accuracy (Before tuning, scaled data & oversampledData) :
67.20682%
```

5.2.4 After Tuning, Original Data

[97]:
```
# Define a pipeline with Logistic Regression model
lr_pipeline = Pipeline(stages=[lr_default])

# Define grid of parameters to search
lr_paramGrid = (ParamGridBuilder()
             .addGrid(lr_default.maxIter, [50, 100, 200])  # Search for the
↪best value of maxIter
             .addGrid(lr_default.regParam, [0.01, 0.1, 1.0])  # Search for the
↪best value of regParam
             .build())

# Define CrossValidator with 5 folds
lr_crossval = CrossValidator(estimator=lr_pipeline,
                          estimatorParamMaps=lr_paramGrid,
                          evaluator=evaluator,
                          numFolds=5)

# Fit CrossValidator to training data
lr_cvModel = lr_crossval.fit(train)
```

```
# Use the best model found by CrossValidator to make predictions on the test␣
↪data
lr_result_tuned = lr_cvModel.transform(test)

# Convert DataFrame to RDD for MulticlassMetrics
lr_predictionAndLabels_cv = lr_result_tuned.select("prediction",␣
↪"Credit_Score_index").rdd

# Initialize MulticlassMetrics
lr_metrics_cv = MulticlassMetrics(lr_predictionAndLabels_cv)

# Create a confusion matrix
lr_confusion_matrix_cv = lr_metrics_cv.confusionMatrix()

# Display the confusion matrix
confusion_matrix_plot("Logistic Regression (Tuned)", lr_confusion_matrix_cv.
↪toArray())
```

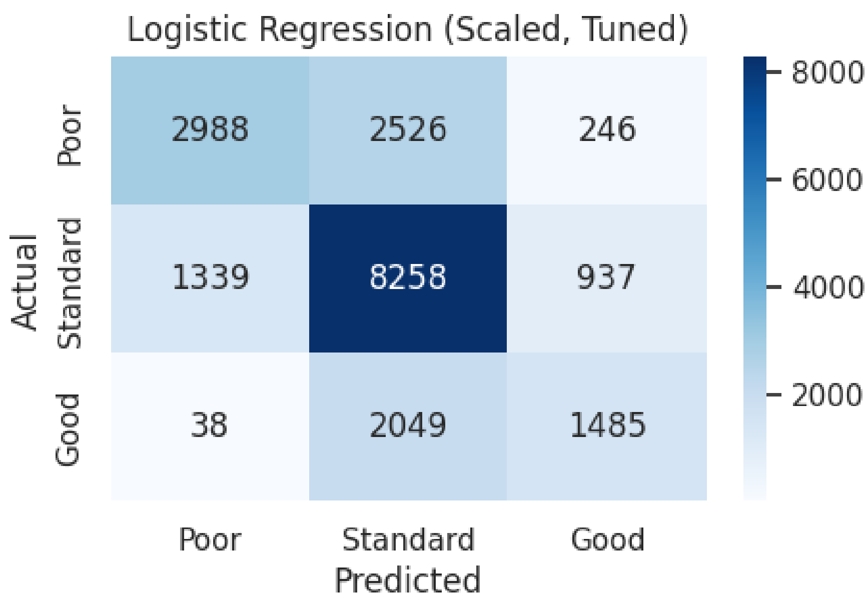


[98]:
```
# Evaluate the performance of the best model
lr_accuracy_tuned = evaluator.evaluate(lr_result_tuned)

print(f"Logistic Regression Accuracy (After tuning, original data) :␣
↪{lr_accuracy_tuned * 100:.5f}% ")
```

```
Logistic Regression Accuracy (After tuning, original data) : 64.20014%
```

5.2.5 After Tuning, scaled Data

```
[99]: # Define a pipeline with Logistic Regression model
lr_pipeline_scaled = Pipeline(stages=[lr_default_scaled])

# Define grid of parameters to search
lr_paramGrid = (ParamGridBuilder()
             .addGrid(lr_default_scaled.maxIter, [50, 100, 200])  # Search for␣
 ↪the best value of maxIter
             .addGrid(lr_default_scaled.regParam, [0.01, 0.1, 1.0])  # Search␣
 ↪for the best value of regParam
             .build())

# Define CrossValidator with 5 folds
lr_crossval_scaled = CrossValidator(estimator=lr_pipeline_scaled,
                          estimatorParamMaps=lr_paramGrid,
                          evaluator=evaluator,
                          numFolds=5)

# Fit CrossValidator to training data
lr_cvModel_scaled = lr_crossval_scaled.fit(train)

# Use the best model found by CrossValidator to make predictions on the test␣
 ↪data
lr_result_tuned_scaled = lr_cvModel_scaled.transform(test)

# Convert DataFrame to RDD for MulticlassMetrics
lr_predictionAndLabels_cv_scaled = lr_result_tuned_scaled.select("prediction",␣
 ↪"Credit_Score_index").rdd

# Initialize MulticlassMetrics
lr_metrics_cv_scaled = MulticlassMetrics(lr_predictionAndLabels_cv_scaled)

# Create a confusion matrix
lr_confusion_matrix_cv_scaled = lr_metrics_cv_scaled.confusionMatrix()

# Display the confusion matrix
confusion_matrix_plot("Logistic Regression (Scaled, Tuned)",␣
 ↪lr_confusion_matrix_cv_scaled.toArray())
```



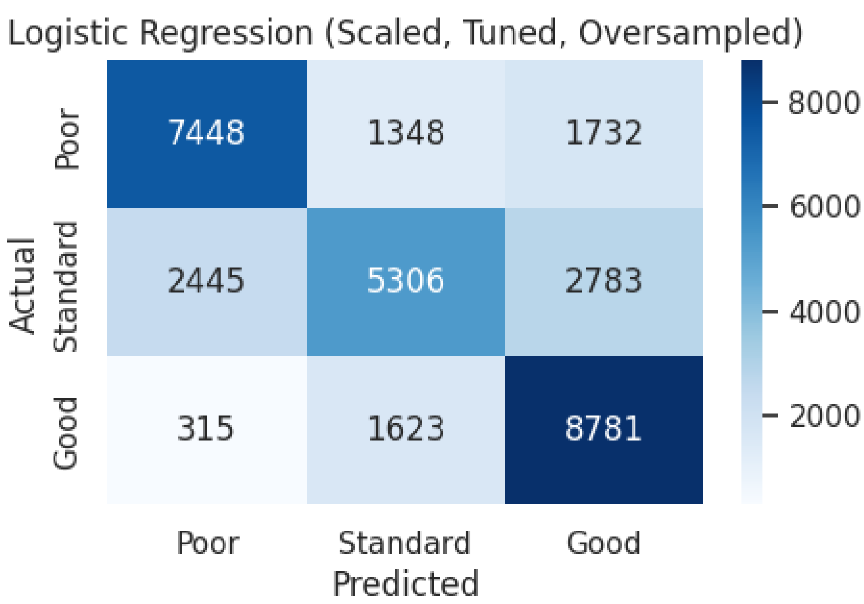

```
[100]: # Evaluate the performance of the best model
lr_accuracy_tuned_scaled = evaluator.evaluate(lr_result_tuned_scaled)

print(f"Logistic Regression Accuracy (After tuning, scaled data) :␣
↪{lr_accuracy_tuned_scaled * 100:.5f}% ")
```

```
Logistic Regression Accuracy (After tuning, scaled data) : 64.08437%
```

5.2.6 After Tuning, scaled & oversampled Data

```
[101]: # Define a pipeline with Logistic Regression model
lr_pipeline_scaled = Pipeline(stages=[lr_default_scaled])

# Define grid of parameters to search
lr_paramGrid = (ParamGridBuilder()
             .addGrid(lr_default_scaled.maxIter, [50, 100, 200])  # Search for␣
↪the best value of maxIter
             .addGrid(lr_default_scaled.regParam, [0.01, 0.1, 1.0])  # Search␣
↪for the best value of regParam
             .build())

# Define CrossValidator with 5 folds
lr_crossval = CrossValidator(estimator=lr_pipeline_scaled,
                            estimatorParamMaps=lr_paramGrid,
                            evaluator=evaluator,
                            numFolds=5)
```

```
# Fit CrossValidator to training data
lr_cvModel_scaled_over = lr_crossval.fit(train_resampled)

# Use the best model found by CrossValidator to make predictions on the test␣
↪data
lr_result_tuned_scaled_over = lr_cvModel_scaled_over.transform(test_resampled)

# Convert DataFrame to RDD for MulticlassMetrics
lr_predictionAndLabels_cv_scaled_over = lr_result_tuned_scaled_over.
↪select("prediction", "Credit_Score_index").rdd

# Initialize MulticlassMetrics
lr_metrics_cv_scaled_over =␣
↪MulticlassMetrics(lr_predictionAndLabels_cv_scaled_over)

# Create a confusion matrix
lr_confusion_matrix_cv_scaled_over = lr_metrics_cv_scaled_over.confusionMatrix()

# Display the confusion matrix
confusion_matrix_plot("Logistic Regression (Scaled, Tuned, Oversampled)",␣
↪lr_confusion_matrix_cv_scaled_over.toArray())
```



[102]:
```
# Evaluate the performance of the best model
lr_accuracy_tuned_scaled_over = evaluator.evaluate(lr_result_tuned_scaled_over)
```

```
print(f"Logistic Regression Accuracy (After tuning, scaled & oversampled data) :
↪ {lr_accuracy_tuned_scaled_over * 100:.5f}% ")
```

```
[Stage 14401:==================================================>   (233 + 19) / 252]

Logistic Regression Accuracy (After tuning, scaled & oversampled data) :
67.76061%
```

5.2.7 Comparison of the results

[103]:
```
lr_basic_summary = model_summary('Logistic Regression (Basic)',␣
↪lr_result_default)
lr_scaled_summary = model_summary('Logistic Regression (Normalized)',␣
↪lr_result_default_scaled)
lr_resampled_summary = model_summary('Logistic Regression (Resampled)',␣
↪lr_result_default_scaled_over)
lr_tuned_summary = model_summary('Logistic Regression (Tuned)', lr_result_tuned)
lr_tuned_scaled_summary = model_summary('Logistic Regression (Tuned +␣
↪Normalized)', lr_result_tuned_scaled)
lr_tuned_scaled_over_summary = model_summary('Logistic Regression (Tuned +␣
↪Normalized + Resampled)', lr_result_tuned_scaled_over)

lr_summary = pd.concat([lr_basic_summary, lr_scaled_summary,␣
↪lr_resampled_summary, lr_tuned_summary, lr_tuned_scaled_summary,␣
↪lr_tuned_scaled_over_summary])
lr_summary
```

[103]:
```
                                          Model  Accuracy  ROC-AUC Score  \
0                  Logistic Regression (Basic)  0.643864       0.737523
0             Logistic Regression (Normalized)  0.641800       0.733582
0              Logistic Regression (Resampled)  0.672068       0.796285
0                  Logistic Regression (Tuned)  0.642001       0.734438
0       Logistic Regression (Tuned + Normalized)  0.640844       0.732612
0  Logistic Regression (Tuned + Normalized + Resa…  0.677606       0.796808

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.684541          0.529687            0.635806
0             0.685228          0.517014            0.633117
0             0.723306          0.683321            0.667946
0             0.683925          0.525174            0.633096
0             0.684536          0.518750            0.631498
0             0.729624          0.707447            0.671606
```

5.3 Artificial Neural Networks (ANN)

[104]:
```
inputLength = len(assembler.getInputCols())
print(inputLength)
```

21

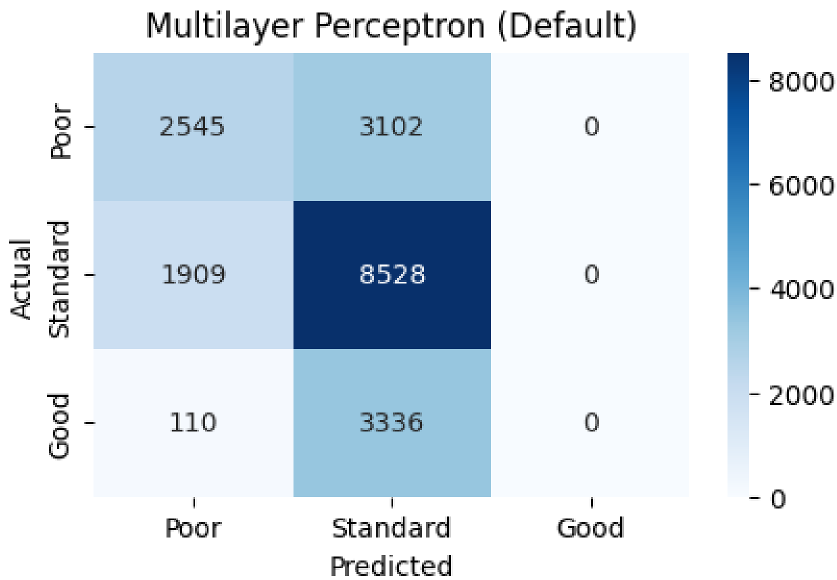
[105]:
```
# Defining the layers for the neural network
mlp_default = MultilayerPerceptronClassifier(featuresCol="features",
                                             labelCol="Credit_Score_index",
                                             maxIter=100,
                                             layers=[inputLength, 64, 32, 3],
                                             blockSize=128, seed=42)

mlp_scaled = MultilayerPerceptronClassifier(featuresCol="features_scaled",
                                            labelCol="Credit_Score_index",
                                            maxIter=100,
                                            layers=[inputLength, 64, 32, 3],
                                            blockSize=128, seed=42)
```

5.3.1 Before tuning, original data

[106]:
```
# Fit the pipeline with the updated train DataFrame
mlp_pipeline_default = Pipeline(stages=[mlp_default])
mlp_model_default = mlp_pipeline_default.fit(train)

# Transform the test DataFrame using the fitted pipeline
mlp_results_default = mlp_model_default.transform(test)

mlp_accuracy_default = evaluator.evaluate(mlp_results_default)

mlp_predictionAndLabels_default = mlp_results_default.select("prediction",␣
 ↪"Credit_Score_index").rdd
mlp_metrics_default = MulticlassMetrics(mlp_predictionAndLabels_default)
mlp_confusion_matrix_default = mlp_metrics_default.confusionMatrix()

print("Accuracy :", mlp_accuracy_default)
print(model_summary('Multilayer Perceptron (Default)', mlp_results_default))
confusion_matrix_plot('Multilayer Perceptron (Default)',␣
 ↪mlp_confusion_matrix_default.toArray())
```

```
Accuracy : 0.566973886328725


                             Model  Accuracy  ROC-AUC Score  \
0  Multilayer Perceptron (Default)  0.566974       0.652626
```

```
   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.557625          0.450682            0.502944
```

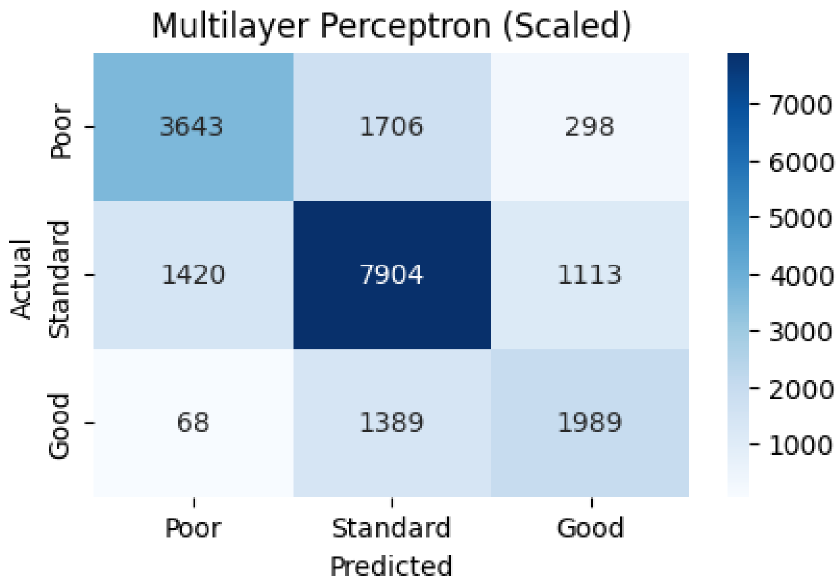


5.3.2 Before tuning, scaled data

[107]:
```python
# Fit the pipeline with the updated train DataFrame
mlp_pipeline_scaled = Pipeline(stages=[mlp_scaled])
mlp_model_scaled = mlp_pipeline_scaled.fit(train)

# Transform the test DataFrame using the fitted pipeline
mlp_results_scaled = mlp_model_scaled.transform(test)

mlp_accuracy_scaled = evaluator.evaluate(mlp_results_scaled)

mlp_predictionAndLabels_scaled = mlp_results_scaled.select("prediction",␣
 ↪"Credit_Score_index").rdd
mlp_metrics_scaled = MulticlassMetrics(mlp_predictionAndLabels_scaled)
mlp_confusion_matrix_scaled = mlp_metrics_scaled.confusionMatrix()

print("Accuracy (Scaled) :", mlp_accuracy_scaled)
print(model_summary('Multilayer Perceptron (Scaled)', mlp_results_scaled))
confusion_matrix_plot('Multilayer Perceptron (Scaled)',␣
 ↪mlp_confusion_matrix_scaled.toArray())
```

```
Accuracy (Scaled) : 0.6930875576036867
```

```
                         Model  Accuracy  ROC-AUC Score  \
0  Multilayer Perceptron (Scaled)  0.693088       0.785059

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.709998          0.645121            0.692092
```



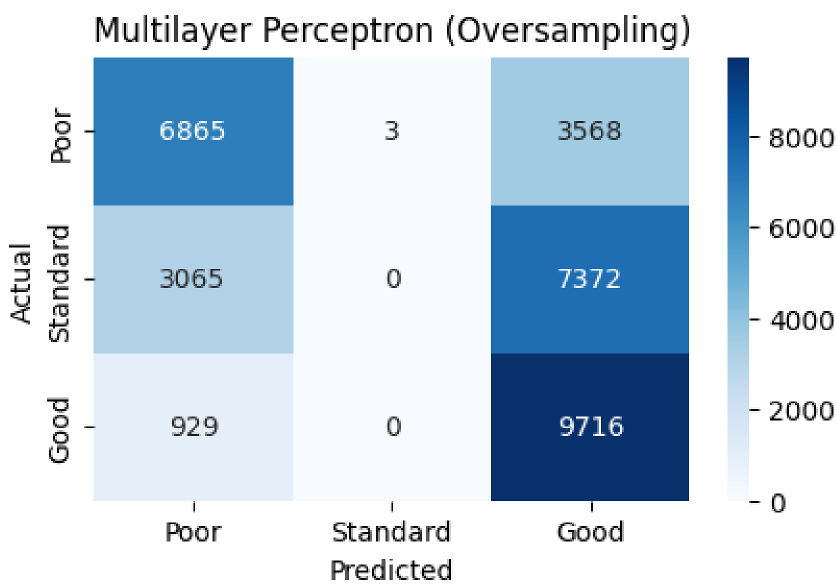
5.3.3 Before tuning, over-sampled data

[108]:

```
# Fit the pipeline with the updated train DataFrame
mlp_pipeline_oversample = Pipeline(stages=[mlp_default])
mlp_model_oversample = mlp_pipeline_oversample.fit(train_resampled)

# Transform the test DataFrame using the fitted pipeline
mlp_results_oversample = mlp_model_oversample.transform(test_resampled)

mlp_accuracy_oversample = evaluator.evaluate(mlp_results_oversample)

mlp_predictionAndLabels_oversample = mlp_results_oversample.
 ↪select("prediction", "Credit_Score_index").rdd
mlp_metrics_oversample = MulticlassMetrics(mlp_predictionAndLabels_oversample)
mlp_confusion_matrix_oversample = mlp_metrics_oversample.confusionMatrix()

print("Accuracy (Oversampling) :", mlp_accuracy_oversample)
print(model_summary('Multilayer Perceptron (Oversampling)',␣
 ↪mlp_results_oversample))
```

```
confusion_matrix_plot('Multilayer Perceptron (Oversampling)',␣
↪mlp_confusion_matrix_oversample.toArray())
```

```
Accuracy (Oversampling) : 0.52608033504664
                                  Model  Accuracy  ROC-AUC Score  \
0  Multilayer Perceptron (Oversampling)   0.52608       0.734301

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.632194          0.657819             0.42316
```



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.

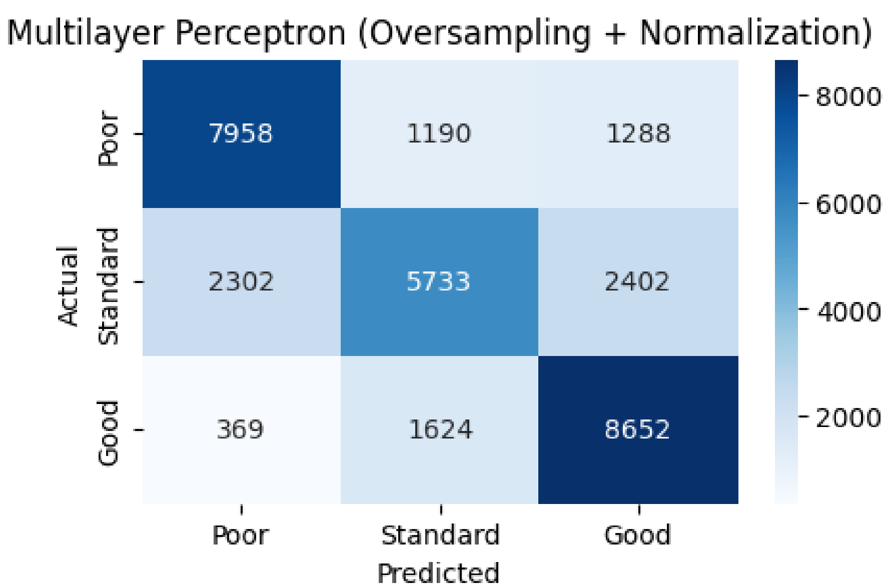
5.3.4 Before tuning, scaled & over-sampled data

[109]:
```
# Fit the pipeline with the updated train DataFrame
mlp_pipeline_normalized = Pipeline(stages=[mlp_scaled])
mlp_model_normalized = mlp_pipeline_normalized.fit(train_resampled)

# Transform the test DataFrame using the fitted pipeline
mlp_results_normalized = mlp_model_normalized.transform(test_resampled)
```

```
mlp_accuracy_normalized = evaluator.evaluate(mlp_results_normalized)

mlp_predictionAndLabels_normalized = mlp_results_normalized.
 ↪select("prediction", "Credit_Score_index").rdd
mlp_metrics_normalized = MulticlassMetrics(mlp_predictionAndLabels_normalized)
mlp_confusion_matrix_normalized = mlp_metrics_normalized.confusionMatrix()

print("Accuracy (After scaling + Oversampling) :", mlp_accuracy_normalized)
print(model_summary('Multilayer Perceptron (Oversampling + Normalization)',␣
 ↪mlp_results_normalized))
confusion_matrix_plot('Multilayer Perceptron (Oversampling + Normalization)',␣
 ↪mlp_confusion_matrix_normalized.toArray())
```

```
Accuracy (After scaling + Oversampling) : 0.7088965035852529
```

```
                                                Model  Accuracy  ROC-AUC Score  \
0  Multilayer Perceptron (Oversampling + Normaliz…  0.708897       0.826288

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.748706          0.762553            0.704427
```



5.3.5 Hyper-parameter tuning the ANN with scaled & over-sampled data

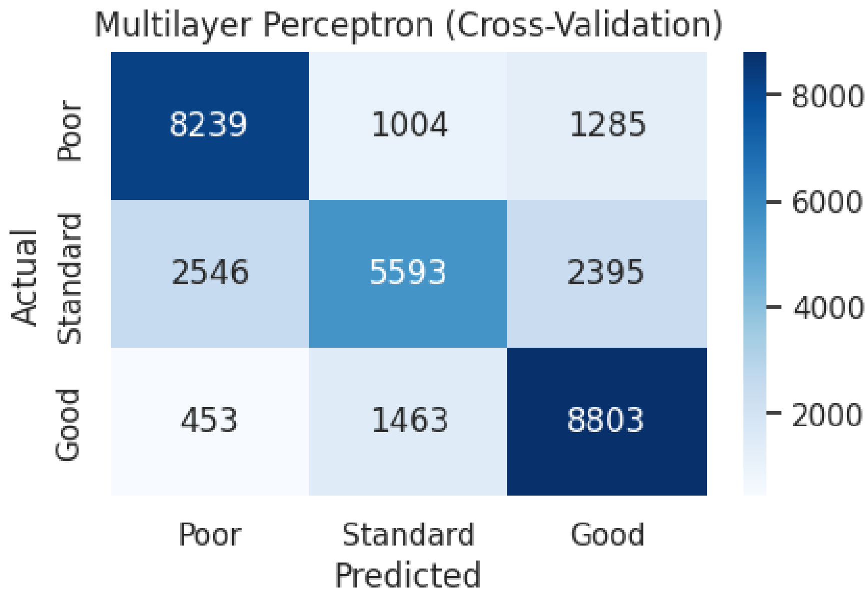
[110]:
```
# Check the current parameters
mlp_model_oversample.stages[0].extractParamMap()
```

[110]:
```
{Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='blockSize',
doc='block size for stacking input data in matrices. Data is stacked within
partitions. If block size is more than remaining data in a partition then it is
adjusted to the size of this data.'): 128,
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='featuresCol',
doc='features column name.'): 'features',
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='labelCol',
doc='label column name.'): 'Credit_Score_index',
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='maxIter',
doc='max number of iterations (>= 0).'): 100,
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7',
name='predictionCol', doc='prediction column name.'): 'prediction',
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7',
name='probabilityCol', doc='Column name for predicted class conditional
probabilities. Note: Not all models output well-calibrated probability
estimates! These probabilities should be treated as confidences, not precise
probabilities.'): 'probability',
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7',
name='rawPredictionCol', doc='raw prediction (a.k.a. confidence) column name.'):
'rawPrediction',
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='seed',
doc='random seed.'): 42,
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='solver',
doc='The solver algorithm for optimization. Supported options: l-bfgs, gd.'):
'l-bfgs',
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='stepSize',
doc='Step size to be used for each iteration of optimization (>= 0).'): 0.03,
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='tol',
doc='the convergence tolerance for iterative algorithms (>= 0).'): 1e-06,
 Param(parent='MultilayerPerceptronClassifier_e53b4d0a25c7', name='layers',
doc='Sizes of layers from input layer to output layer E.g., Array(780, 100, 10)
means 780 inputs, one hidden layer with 100 neurons and output layer of 10
neurons.'): [21,
  64,
  32,
  3]}
```

[111]:
```
mlp_paramGrid = ParamGridBuilder() \
    .addGrid(mlp_scaled.layers, [(inputLength, 64, 32, 3),
                                 (inputLength, 128, 64, 32, 3),
                                 (inputLength, 256, 128, 128, 64, 3)])\
    .addGrid(mlp_scaled.solver, ['l-bfgs', 'gd'])\
```

```
    .addGrid(mlp_scaled.blockSize, [64, 128])\
    .addGrid(mlp_scaled.stepSize, [0.03, 0.1, 0.3])\
    .build()

mlp_crossVal = CrossValidator(estimator=mlp_pipeline_normalized,
                          estimatorParamMaps=mlp_paramGrid,
                          ␣
  ↪evaluator=MulticlassClassificationEvaluator(labelCol='Credit_Score_index'),
                          numFolds=2)

mlp_cvModel = mlp_crossVal.fit(train_resampled)

mlp_result_cv = mlp_cvModel.transform(test_resampled)
mlp_bestModel = mlp_cvModel.bestModel
# Show the best model
mlp_bestModel.stages[0].extractParamMap()
mlp_accuracy_cv = evaluator.evaluate(mlp_result_cv)

mlp_predictionAndLabels_cv = mlp_result_cv.select("prediction",␣
  ↪"Credit_Score_index").rdd
mlp_metrics_cv = MulticlassMetrics(mlp_predictionAndLabels_cv)
mlp_confusion_matrix_cv = mlp_metrics_cv.confusionMatrix()

print("Accuracy (After Hyperparameter Tuning) :", mlp_accuracy_cv)
print(model_summary('Multilayer Perceptron (Cross-Validation)', mlp_result_cv))
confusion_matrix_plot('Multilayer Perceptron (Cross-Validation)',␣
  ↪mlp_confusion_matrix_cv.toArray())
```

```
Accuracy (After Hyperparameter Tuning) : 0.712217991881942
[Stage 40015:==============================================>    (232 + 20) / 252]
                                      Model  Accuracy  ROC-AUC Score  \
0  Multilayer Perceptron (Cross-Validation)  0.712218       0.825597

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.733138           0.78258            0.706118
```



[112]:
```python
# Show the best model
mlp_bestModel.stages[0].extractParamMap()
```

[112]:
```
{Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='blockSize',
doc='block size for stacking input data in matrices. Data is stacked within
partitions. If block size is more than remaining data in a partition then it is
adjusted to the size of this data.'): 64,
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='featuresCol',
doc='features column name.'): 'features_scaled',
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='labelCol',
doc='label column name.'): 'Credit_Score_index',
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='maxIter',
doc='max number of iterations (>= 0).'): 100,
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3',
name='predictionCol', doc='prediction column name.'): 'prediction',
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3',
name='probabilityCol', doc='Column name for predicted class conditional
probabilities. Note: Not all models output well-calibrated probability
estimates! These probabilities should be treated as confidences, not precise
probabilities.'): 'probability',
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3',
name='rawPredictionCol', doc='raw prediction (a.k.a. confidence) column name.'):
'rawPrediction',
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='seed',
doc='random seed.'): 42,
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='solver',
doc='The solver algorithm for optimization. Supported options: l-bfgs, gd.'):
```

```
'l-bfgs',
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='stepSize',
doc='Step size to be used for each iteration of optimization (>= 0).'): 0.03,
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='tol',
doc='the convergence tolerance for iterative algorithms (>= 0).'): 1e-06,
 Param(parent='MultilayerPerceptronClassifier_e9878a37f6d3', name='layers',
doc='Sizes of layers from input layer to output layer E.g., Array(780, 100, 10)
means 780 inputs, one hidden layer with 100 neurons and output layer of 10
neurons.'): [21,
  64,
  32,
  3]}
```

5.3.6 Comparison of the results

[113]:

```
ann_basic_summary = model_summary('ANN (Basic)', mlp_results_default)
ann_scaled_summary = model_summary('ANN (Normalized)', mlp_results_scaled)
ann_resampled_summary = model_summary('ANN (Resampled)', mlp_results_oversample)
ann_normalized_summary = model_summary('ANN (Normalized + Resampled)',␣
 ↪mlp_results_normalized)
ann_tuned_summary = model_summary('ANN (Tuned + Normalized + Resampled)',␣
 ↪mlp_result_cv)

ann_summary = pd.concat([ann_basic_summary, ann_scaled_summary,␣
 ↪ann_resampled_summary, ann_normalized_summary, ann_tuned_summary])
ann_summary
```

[113]:

```
                                 Model  Accuracy  ROC-AUC Score  \
0                          ANN (Basic)  0.566974       0.652626
0                     ANN (Normalized)  0.693088       0.785059
0                      ANN (Resampled)  0.526080       0.734301
0         ANN (Normalized + Resampled)  0.708897       0.826288
0  ANN (Tuned + Normalized + Resampled)  0.712218       0.825597

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.557625          0.450682            0.502944
0             0.709998          0.645121            0.692092
0             0.632194          0.657819            0.423160
0             0.748706          0.762553            0.704427
0             0.733138          0.782580            0.706118
```

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 0.82, 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.

From the findings from **Assignment 1**, the best activation function was ***'relu'*** and ***'tanh'***, and the best solver was ***'adam'***. But the Spark MLlib support only ***'sigmoid'*** for activation function, ***'l-bfgs'*** and ***'sgd'*** as solver, which showed poor performance in scikit-learn. This can be considered as a reason why the model accuracy is not as high as the model in Assignment 1.

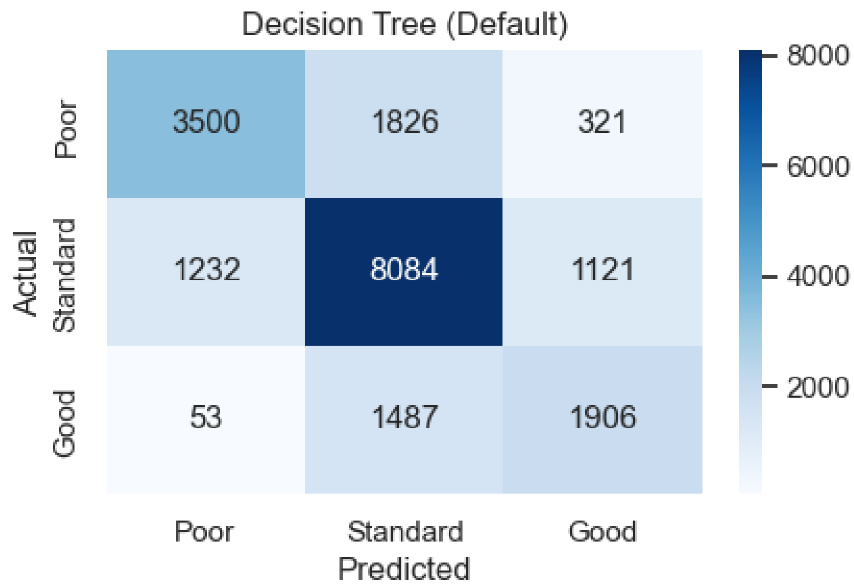
5.4 Decision Tree

5.4.1 Default Decision Tree Model

[114]:
```
# Default DT Model
dt_default = DecisionTreeClassifier(labelCol = 'Credit_Score_index',␣
 ↪featuresCol = 'features')
dt_pipeline_default = Pipeline(stages=[dt_default])
dt_model_default = dt_pipeline_default.fit(train)

# select example rows to display.
dt_results_default = dt_model_default.transform(test)
dt_results_default.show(5)

dt_predictionAndLabels_default = dt_results_default.select("prediction",␣
 ↪"Credit_Score_index").rdd
dt_metrics_default = MulticlassMetrics(dt_predictionAndLabels_default)
dt_confusion_matrix_default = dt_metrics_default.confusionMatrix()

print(model_summary('Decision Tree (Default)', dt_results_default))
confusion_matrix_plot('Decision Tree (Default)', dt_confusion_matrix_default.
 ↪toArray())
```

```
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|            features|Credit_Score_index|     features_scaled|
rawPrediction|         probability|prediction|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|[1.0,32.0,28806.0…|
1.0|[-1.5186985063700…|[3243.0,25786.0,4…|[0.09715689505377…|       1.0|
|[8.0,44.0,37464.0…|
1.0|[1.53591975094968…|[9280.0,2909.0,37.0]|[0.75903811549157…|       0.0|
|[5.0,29.0,20790.0…|
0.0|[0.22679764066981…|[3243.0,25786.0,4…|[0.09715689505377…|       1.0|
|[1.0,55.0,176015…|
1.0|[-1.5186985063700…|[702.0,1949.0,144…|[0.17155425219941…|       1.0|
|[5.0,40.0,31357.0…|
1.0|[0.22679764066981…|[1005.0,3644.0,50…|[0.10364030112405…|       2.0|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
only showing top 5 rows
```

```
                  Model  Accuracy  ROC-AUC Score  Precision (Overall)  \
0  Decision Tree (Default)  0.690732       0.779277             0.731452

   Recall (Overall)  F1-score (Overall)
0          0.619798            0.688749
```

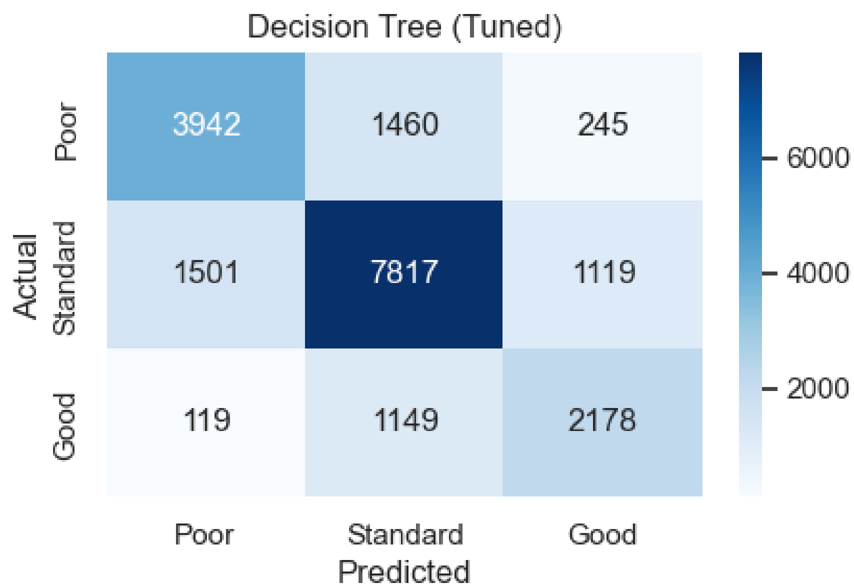


[115]:

```
# Parameter grids
dt_paramGrid = (ParamGridBuilder()
             .addGrid(dt_default.impurity, ['gini', 'entropy'])
             .addGrid(dt_default.maxDepth, [5, 10, 15])
             .addGrid(dt_default.maxBins, [2,4]) # Going over "4" bins will␣
 ↪slightly increase the accuracy but it is not worth the computational power
             .build())

dt_crossval = CrossValidator(estimator=dt_pipeline_default,
                          estimatorParamMaps=dt_paramGrid,
                          evaluator=evaluator,
                          numFolds=5)

# Train the model using the training set find the best parameters for the model␣
 ↪from the parameter grid
tunedDTModel = dt_crossval.fit(train)
dt_best_model = tunedDTModel.bestModel

# Extract the Decision Tree classifier from the pipeline
best_dt_model = dt_best_model.stages[-1]
```

```
# Display tuned model's performance
dt_tuned_predictions = dt_best_model.transform(test)

dt_predictionAndLabels_default_tuned = dt_tuned_predictions.
 ↪select("prediction", "Credit_Score_index").rdd
dt_metrics_default_tuned =␣
 ↪MulticlassMetrics(dt_predictionAndLabels_default_tuned)
dt_confusion_matrix_default_tuned = dt_metrics_default_tuned.confusionMatrix()

print(f"Tuned predictions for {best_dt_model}:")
print(f"Best DT Impurity: {best_dt_model.getImpurity()}")
print(f"Best DT Min Instances Per Node: {best_dt_model.
 ↪getMinInstancesPerNode()}")
print(f"Best DT Max Bins: {best_dt_model.getMaxBins()}")


print()
print(model_summary('Decision Tree (Default Tuned)', dt_tuned_predictions))
confusion_matrix_plot('Decision Tree (Tuned)',␣
 ↪dt_confusion_matrix_default_tuned.toArray())
```

```
Tuned predictions for DecisionTreeClassificationModel:
uid=DecisionTreeClassifier_399883cff332, depth=15, numNodes=9857, numClasses=3,
numFeatures=21:
Best DT Impurity: gini
Best DT Min Instances Per Node: 1
Best DT Max Bins: 4

                           Model  Accuracy  ROC-AUC Score  \
0  Decision Tree (Default Tuned)   0.71362        0.80738

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.708738           0.69807             0.71383
```



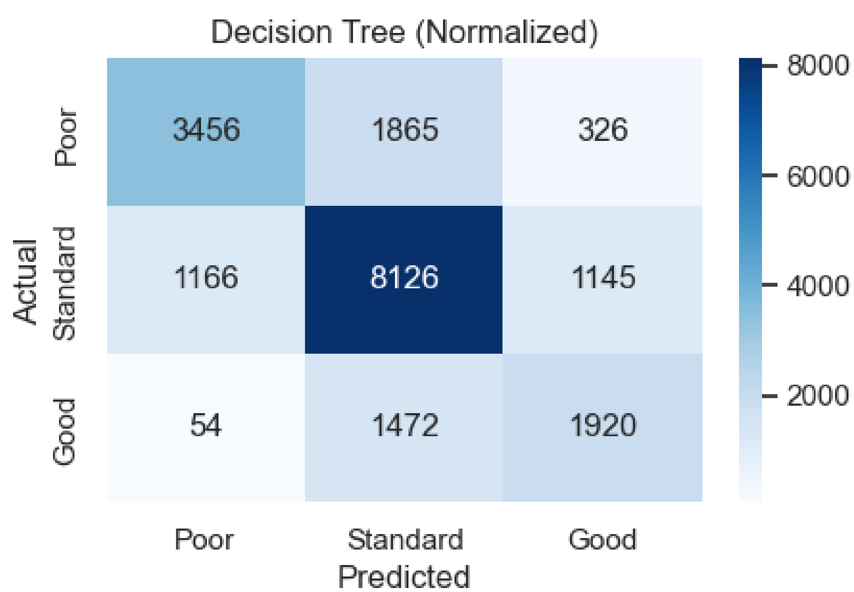
5.4.2 Normalized Decision Tree Model

[116]:
```
# Normalize DT Model
dt_normalize = DecisionTreeClassifier(labelCol = 'Credit_Score_index',␣
↪featuresCol = 'features_scaled')
dt_pipeline_normalize = Pipeline(stages=[dt_normalize])
dt_model_normalize = dt_pipeline_normalize.fit(train)


# select example rows to display.
dt_results_normalize = dt_model_normalize.transform(test)
dt_results_normalize.show(5)

dt_predictionAndLabels_normalize = dt_results_normalize.select("prediction",␣
↪"Credit_Score_index").rdd
dt_metrics_normalize = MulticlassMetrics(dt_predictionAndLabels_normalize)
dt_confusion_matrix_normalize = dt_metrics_normalize.confusionMatrix()

print(model_summary('Decision Tree (Normalized)', dt_results_normalize))
confusion_matrix_plot('Decision Tree (Normalized)',␣
↪dt_confusion_matrix_normalize.toArray())
```

```
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|            features|Credit_Score_index|     features_scaled|
rawPrediction|         probability|prediction|
+--------------------+------------------+--------------------+------------------
```

```
--+--------------------+----------+
|[1.0,32.0,28806.0…|
1.0|[-1.5186985063700…|[3303.0,25870.0,4…|[0.09847942754919…|       1.0|
|[8.0,44.0,37464.0…|
1.0|[1.53591975094968…|[9118.0,2809.0,32.0]|[0.76243833096412…|       0.0|
|[5.0,29.0,20790.0…|
0.0|[0.22679764066981…|[3303.0,25870.0,4…|[0.09847942754919…|       1.0|
|[1.0,55.0,176015…|
1.0|[-1.5186985063700…|[702.0,1954.0,144…|[0.17126128323981…|       1.0|
|[5.0,40.0,31357.0…|
1.0|[0.22679764066981…|[1008.0,3645.0,50…|[0.10390681373054…|       2.0|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
only showing top 5 rows
```

```
                        Model  Accuracy  ROC-AUC Score  Precision (Overall)  \
0  Decision Tree (Normalized)  0.691347       0.778566             0.739093

   Recall (Overall)  F1-score (Overall)
0          0.612006             0.68929
```

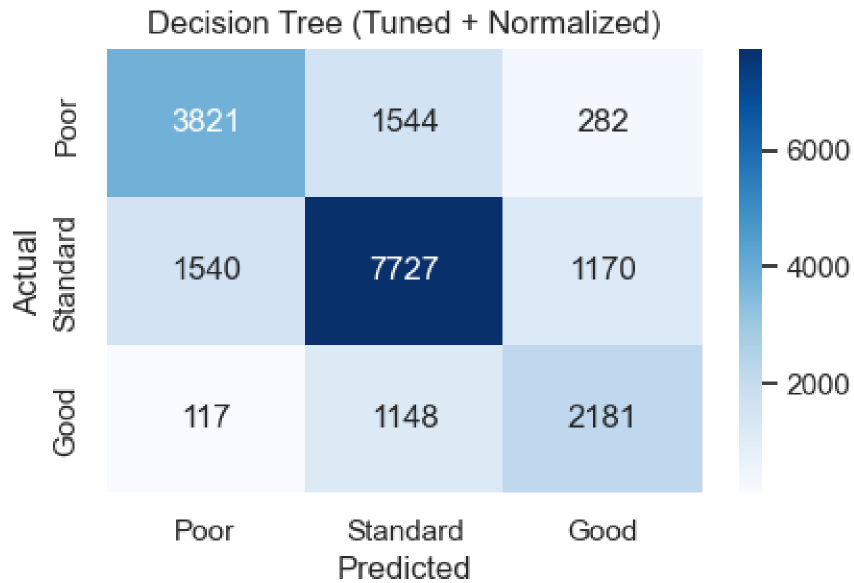


[117]:
```
# Parameter grids
dt_paramGrid = (ParamGridBuilder()
             .addGrid(dt_normalize.impurity, ['gini', 'entropy'])
             .addGrid(dt_normalize.maxDepth, [5, 10, 15])
```

```
            .addGrid(dt_normalize.maxBins, [2,4])
            .build())

crossval = CrossValidator(estimator=dt_pipeline_normalize,
                          estimatorParamMaps=dt_paramGrid,
                          evaluator=evaluator,
                          numFolds=5)


# Train the model using the training set find the best parameters for the model␣
 ↪from the parameter grid
tunedDTModel_normalize = crossval.fit(train)
dt_best_model_norm = tunedDTModel_normalize.bestModel

# Extract the Decision Tree classifier from the pipeline
best_dt_model_norm = dt_best_model_norm.stages[-1]

# Display tuned model's performance
dt_tuned_normalized_predictions = dt_best_model_norm.transform(test)

dt_predictionAndLabels_normalize_tuned = dt_tuned_normalized_predictions.
 ↪select("prediction", "Credit_Score_index").rdd
dt_metrics_normalize_tuned =␣
 ↪MulticlassMetrics(dt_predictionAndLabels_normalize_tuned)
dt_confusion_matrix_normalize_tuned = dt_metrics_normalize_tuned.
 ↪confusionMatrix()

print(f"Tuned predictions for {best_dt_model_norm}:")
print(f"Best DT Impurity: {best_dt_model_norm.getImpurity()}")
print(f"Best DT Min Instances Per Node: {best_dt_model_norm.
 ↪getMinInstancesPerNode()}")
print(f"Best DT Max Bins: {best_dt_model_norm.getMaxBins()}")
print()
print(model_summary('Decision Tree (Normalized + Tuned)',␣
 ↪dt_tuned_normalized_predictions))
confusion_matrix_plot('Decision Tree (Tuned + Normalized)',␣
 ↪dt_confusion_matrix_normalize_tuned.toArray())
```

```
Tuned predictions for DecisionTreeClassificationModel:
uid=DecisionTreeClassifier_3ebfbb25f160, depth=15, numNodes=11483, numClasses=3,
numFeatures=21:
Best DT Impurity: gini
Best DT Min Instances Per Node: 1
Best DT Max Bins: 4
```

```
                              Model  Accuracy  ROC-AUC Score  \
0  Decision Tree (Normalized + Tuned)   0.70297        0.79568

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.697517          0.676642            0.703333
```



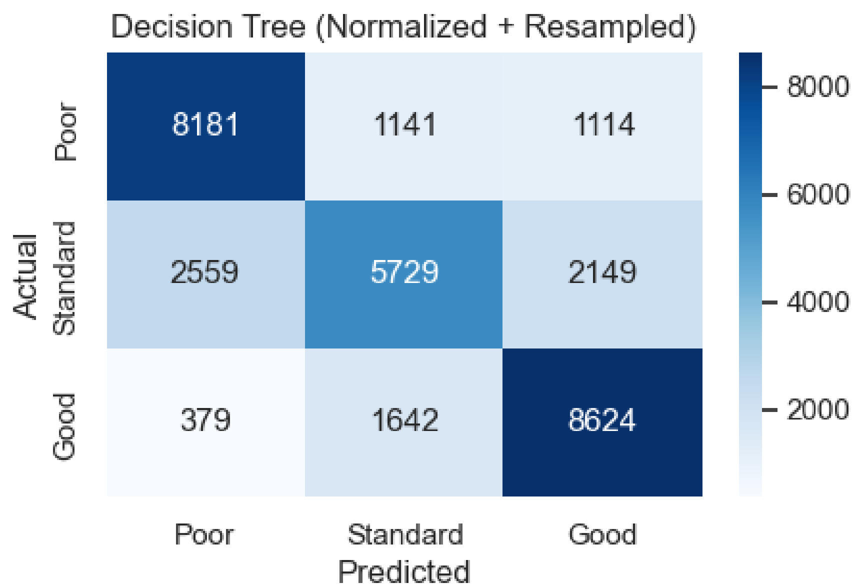
5.4.3 Oversampled Decision Tree Model

[118]:
```
# Oversample DT Model
dt_oversample = DecisionTreeClassifier(labelCol = 'Credit_Score_index',␣
↪featuresCol = 'features_scaled')
dt_pipeline_oversample = Pipeline(stages=[dt_oversample])
dt_model_oversample = dt_pipeline_oversample.fit(train_resampled)


# select example rows to display.
dt_results_oversample = dt_model_oversample.transform(test_resampled)
dt_results_oversample.show(5)

dt_predictionAndLabels_oversample = dt_results_oversample.select("prediction",␣
↪"Credit_Score_index").rdd
dt_metrics_oversample = MulticlassMetrics(dt_predictionAndLabels_oversample)
dt_confusion_matrix_oversample = dt_metrics_oversample.confusionMatrix()
```

```python
print(model_summary('Decision Tree (Normalized + Resampled)',
 ↪dt_results_oversample))
confusion_matrix_plot('Decision Tree (Normalized + Resampled)',
 ↪dt_confusion_matrix_oversample.toArray())
```

```
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|            features|Credit_Score_index|     features_scaled|
rawPrediction|         probability|prediction|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|[4.0,49.0,37188.0…|
2.0|[-0.2266189181776…|[3084.0,6131.0,25…|[0.08850370200309…|       2.0|
|[4.0,34.0,26150.0…|
1.0|[-0.2266189181776…|[3084.0,6131.0,25…|[0.08850370200309…|       2.0|
|[1.0,47.0,22323.0…|
2.0|[-1.5380129164670…|[3084.0,6131.0,25…|[0.08850370200309…|       2.0|
|[5.0,36.0,49216.0…|
1.0|[0.21051241458542…|[6420.0,4905.0,85…|[0.52718016094596…|       0.0|
|[8.0,35.0,72331.0…|
2.0|[1.52190641287477…|[3084.0,6131.0,25…|[0.08850370200309…|       2.0|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
only showing top 5 rows
```

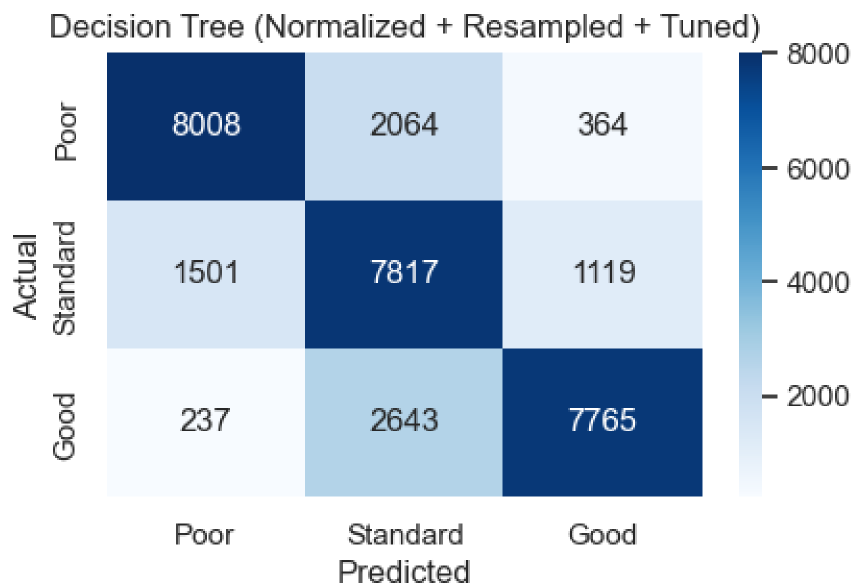
```
                                    Model  Accuracy  ROC-AUC Score  \
0  Decision Tree (Normalized + Resampled)  0.714957       0.831554

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.735768          0.783921            0.710115
```



[119]:
```
# Parameter grids
dt_paramGrid = (ParamGridBuilder()
             .addGrid(dt_oversample.impurity, ['gini', 'entropy'])
             .addGrid(dt_oversample.maxDepth, [5, 10, 15])
             .addGrid(dt_oversample.maxBins, [2,4])
             .build())

dt_crossval = CrossValidator(estimator=dt_pipeline_oversample,
                          estimatorParamMaps=dt_paramGrid,
                          evaluator=evaluator,
                          numFolds=5)

# Train the model using the training set find the best parameters for the model␣
↪from the parameter grid
dt_tunedDTModel = crossval.fit(train_resampled)
dt_best_model_over = tunedDTModel.bestModel

# Extract the Decision Tree classifier from the pipeline
best_dt_model_over = dt_best_model_over.stages[-1]

# Display tuned model's performance
dt_tuned_over_predictions = dt_best_model_over.transform(test_resampled)

dt_predictionAndLabels_oversample_tuned = dt_tuned_over_predictions.
↪select("prediction", "Credit_Score_index").rdd
dt_metrics_oversample_tuned =␣
↪MulticlassMetrics(dt_predictionAndLabels_oversample_tuned)
```

```python
dt_confusion_matrix_oversample_tuned = dt_metrics_oversample_tuned.
 ↪confusionMatrix()

print(f"Tuned predictions for {best_dt_model_over}:")
print(f"Best DT Impurity: {best_dt_model_over.getImpurity()}")
print(f"Best DT Min Instances Per Node: {best_dt_model_over.
 ↪getMinInstancesPerNode()}")
print(f"Best DT Max Bins: {best_dt_model_over.getMaxBins()}")
print()
print(model_summary('Decision Tree (Normalized + Resampled + Tuned)',␣
 ↪dt_tuned_over_predictions))
confusion_matrix_plot('Decision Tree (Normalized + Resampled + Tuned)',␣
 ↪dt_confusion_matrix_oversample_tuned.toArray())
```

```
Tuned predictions for DecisionTreeClassificationModel:
uid=DecisionTreeClassifier_399883cff332, depth=15, numNodes=9857, numClasses=3,
numFeatures=21:
Best DT Impurity: gini
Best DT Min Instances Per Node: 1
Best DT Max Bins: 4

[Stage 48918:======================================>            (191 + 37) / 252]
                                            Model  Accuracy  ROC-AUC Score  \
0  Decision Tree (Normalized + Resampled + Tuned)  0.748461       0.875471

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0              0.82167          0.767344            0.751906
```



5.4.4 Comparison of the results

[120]:
```
dt_basic_summary = model_summary('Decision Tree (Basic)', dt_results_default)
dt_basic_tuned_summary = model_summary('Decision Tree (Tuned)',␣
↪dt_tuned_predictions)
dt_normalized_summary = model_summary('Decision Tree (Normalized)',␣
↪dt_results_normalize)
dt_normalized_tuned_summary = model_summary('Decision Tree (Tuned +␣
↪Normalized)', dt_tuned_normalized_predictions)
dt_resampled_summary = model_summary('Decision Tree (Normalized + Resampled)',␣
↪dt_results_oversample)
dt_resampled_tuned_summary = model_summary('Decision Tree (Tuned + Normalized +␣
↪Resampled)', dt_tuned_over_predictions)

dt_summary = pd.concat([dt_basic_summary, dt_basic_tuned_summary,␣
↪dt_normalized_summary, dt_normalized_tuned_summary, dt_resampled_summary,␣
↪dt_resampled_tuned_summary])
dt_summary
```

[120]:
```
                                 Model  Accuracy  ROC-AUC Score  \
0                Decision Tree (Basic)  0.690732       0.779277
0                Decision Tree (Tuned)  0.713620       0.807380
0           Decision Tree (Normalized)  0.691347       0.778566
0     Decision Tree (Tuned + Normalized)  0.702970       0.795680
```

```
0         Decision Tree (Normalized + Resampled)  0.714957       0.831554
0  Decision Tree (Tuned + Normalized + Resampled)  0.748461       0.875471

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.731452          0.619798            0.688749
0             0.708738          0.698070            0.713830
0             0.739093          0.612006            0.689290
0             0.697517          0.676642            0.703333
0             0.735768          0.783921            0.710115
0             0.821670          0.767344            0.751906
```

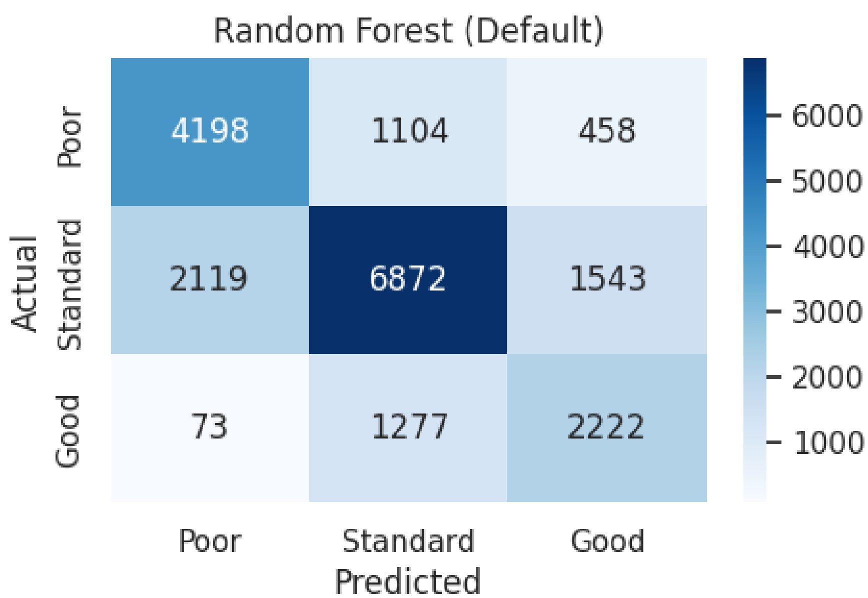
5.5 Random Forest

5.5.1 Before tuning, original data

[121]:
```
rf_original = RandomForestClassifier(labelCol="Credit_Score_index",␣
↪featuresCol="features")

rf_model_original = rf_original.fit(train)

rf_predictions_original = rf_model_original.transform(test)

rf_predictions_original.show(5)

# Select (prediction, true label) and compute test error
rf_accuracy_original = evaluator.evaluate(rf_predictions_original)

rf_predictionAndLabels_original = rf_predictions_original.select("prediction",␣
↪"Credit_Score_index").rdd
rf_metrics_original = MulticlassMetrics(rf_predictionAndLabels_original)
rf_confusion_matrix_original = rf_metrics_original.confusionMatrix()

print("Accuracy (untuned, original data) : ", rf_accuracy_original)

print(rf_model_original)
confusion_matrix_plot('Random Forest (Default)', rf_confusion_matrix_original.
↪toArray())
```

```
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|            features|Credit_Score_index|     features_scaled|
rawPrediction|         probability|prediction|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|[1.0,32.0,28806.0…|
1.0|[-1.5186985063700…|[2.00265155566961…|[0.10013257778348…|       1.0|
```

```
|[8.0,44.0,37464.0…|
1.0|[1.53591975094968…|[14.5397312906727…|[0.72698656453363…|        0.0|
|[5.0,29.0,20790.0…|
0.0|[0.22679764066981…|[2.53269485329153…|[0.12663474266457…|        1.0|
|[1.0,55.0,176015…|
1.0|[-1.5186985063700…|[2.95401759216555…|[0.14770087960827…|        2.0|
|[5.0,40.0,31357.0…|
1.0|[0.22679764066981…|[2.89497095158733…|[0.14474854757936…|        2.0|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
only showing top 5 rows

Accuracy (untuned, original data) :  0.6690828551293667
RandomForestClassificationModel: uid=RandomForestClassifier_650e827bfcf7,
numTrees=20, numClasses=3, numFeatures=21
```

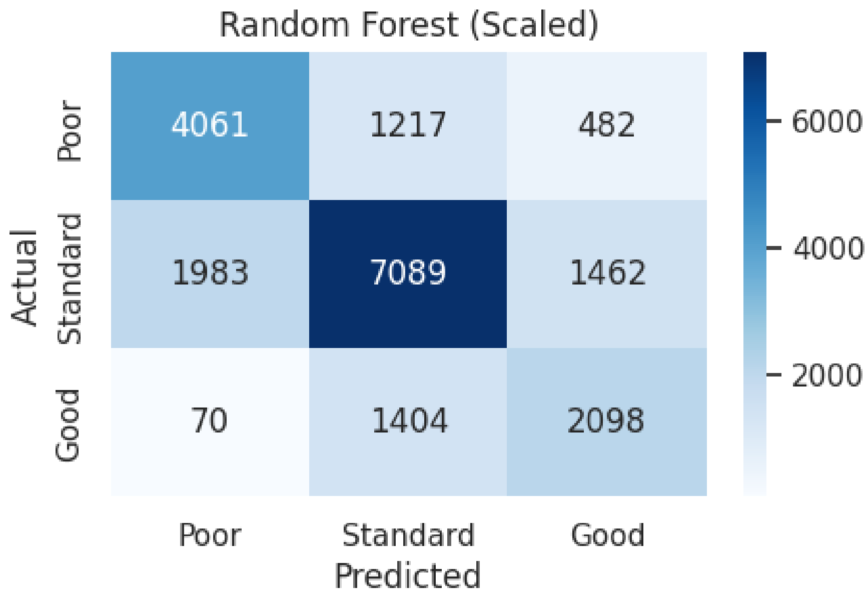


5.5.2 Before tuning, scaled data

[122]:
```
rf_scaled = RandomForestClassifier(labelCol="Credit_Score_index",␣
↪featuresCol="features_scaled")

rf_model_scaled = rf_scaled.fit(train)

rf_predictions_scaled = rf_model_scaled.transform(test)

rf_predictions_scaled.show(5)
```

```
# Select (prediction, true label) and compute test error
rf_accuracy_scaled = evaluator.evaluate(rf_predictions_scaled)
print("Accuracy (untuned, scaled data) : ", rf_accuracy_scaled)

rf_predictionAndLabels_scaled = rf_predictions_scaled.select("prediction",␣
↪"Credit_Score_index").rdd
rf_metrics_scaled = MulticlassMetrics(rf_predictionAndLabels_scaled)
rf_confusion_matrix_scaled = rf_metrics_scaled.confusionMatrix()

print(rf_model_scaled)
confusion_matrix_plot('Random Forest (Scaled)', rf_confusion_matrix_scaled.
↪toArray())
```

```
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|            features|Credit_Score_index|     features_scaled|
rawPrediction|         probability|prediction|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|[1.0,32.0,28806.0…|
1.0|[-1.5186985063700…|[1.87315815888543…|[0.09365790794427…|       1.0|
|[8.0,44.0,37464.0…|
1.0|[1.53591975094968…|[13.9795189790512…|[0.69897594895256…|       0.0|
|[5.0,29.0,20790.0…|
0.0|[0.22679764066981…|[2.58103348359119…|[0.12905167417955…|       1.0|
|[1.0,55.0,176015…|
1.0|[-1.5186985063700…|[3.11353708249468…|[0.15567685412473…|       2.0|
|[5.0,40.0,31357.0…|
1.0|[0.22679764066981…|[3.15482926461685…|[0.15774146323084…|       2.0|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
only showing top 5 rows

Accuracy (untuned, scaled data) :  0.666868015705225
RandomForestClassificationModel: uid=RandomForestClassifier_5562fd1b855b,
numTrees=20, numClasses=3, numFeatures=21
```



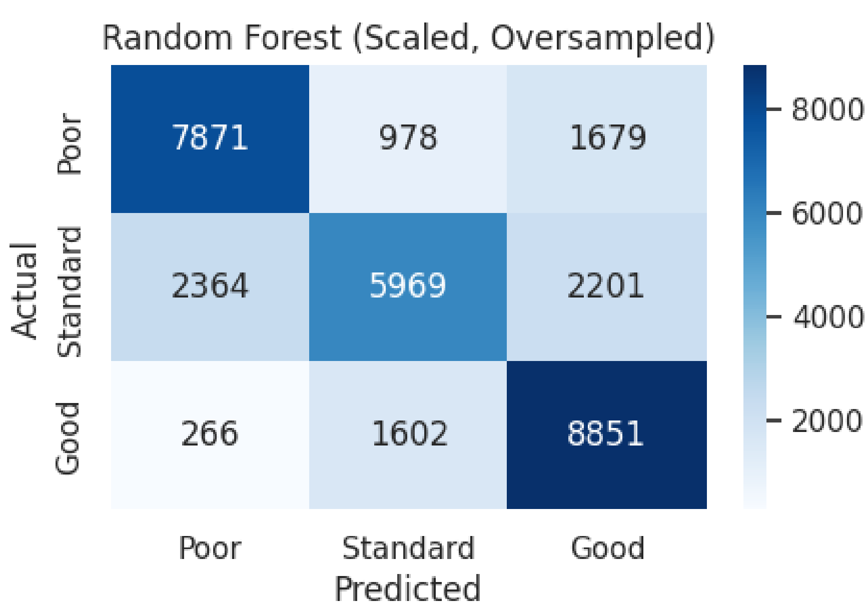
5.5.3 Before tuning, Scaled data & Over-sampled Data

[123]:
```
rf_model_scaled_resample = rf_scaled.fit(train_resampled)

rf_predictions_scaled_resample = rf_model_scaled_resample.
  ↪transform(test_resampled)

rf_predictions_scaled_resample.show(5)

# Select (prediction, true label) and compute test error
rf_accuracy_scaled_resample = evaluator.evaluate(rf_predictions_scaled_resample)
print("Accuracy (untuned, scaled and oversampled) : ", ␣
  ↪rf_accuracy_scaled_resample)

rf_predictionAndLabels_scaled_resample = rf_predictions_scaled_resample.
  ↪select("prediction", "Credit_Score_index").rdd
rf_metrics_scaled_resample =␣
  ↪MulticlassMetrics(rf_predictionAndLabels_scaled_resample)
rf_confusion_matrix_scaled_resample = rf_metrics_scaled_resample.
  ↪confusionMatrix()

print(rf_model_scaled_resample)
confusion_matrix_plot('Random Forest (Scaled, Oversampled)',␣
  ↪rf_confusion_matrix_scaled_resample.toArray())
```

```
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|            features|Credit_Score_index|     features_scaled|
rawPrediction|         probability|prediction|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
|[4.0,49.0,37188.0…|
2.0|[-0.2266189181776…|[2.28720054545465…|[0.11436002727273…|       2.0|
|[4.0,34.0,26150.0…|
1.0|[-0.2266189181776…|[2.41294334551094…|[0.12064716727554…|       2.0|
|[1.0,47.0,22323.0…|
2.0|[-1.5380129164670…|[2.13584680041438…|[0.10679234002071…|       2.0|
|[5.0,36.0,49216.0…|
1.0|[0.21051241458542…|[14.0580955083855…|[0.70290477541927…|       0.0|
|[8.0,35.0,72331.0…|
2.0|[1.52190641287477…|[2.24558317077188…|[0.11227915853859…|       2.0|
+--------------------+------------------+--------------------+------------------
--+--------------------+----------+
only showing top 5 rows
```

```
Accuracy (untuned, scaled and oversampled) :  0.7139800509738523
```

```
RandomForestClassificationModel: uid=RandomForestClassifier_5562fd1b855b,
numTrees=20, numClasses=3, numFeatures=21
```

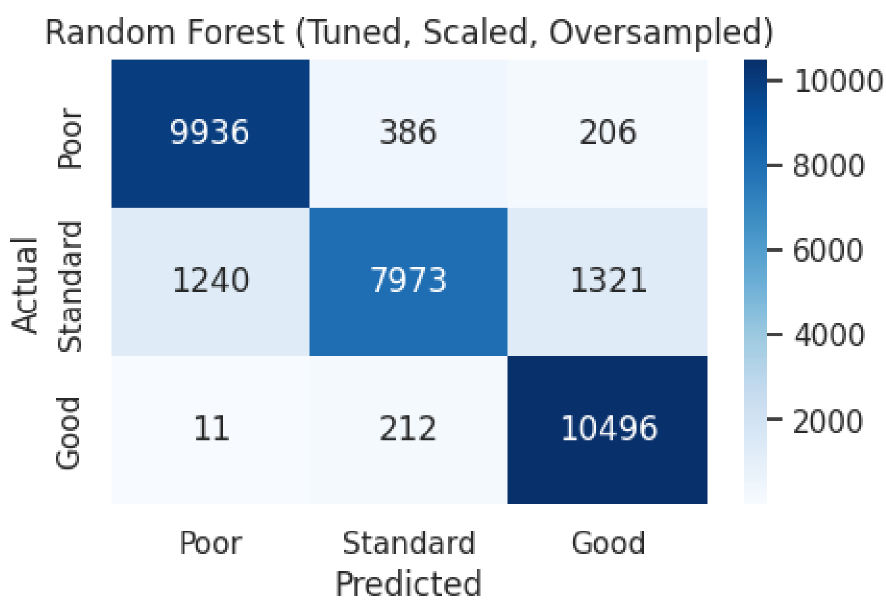


5.5.4 Hyper-parameter tuning the Random Forest Model with scaled & over-sampled data

[124]:
```
# Define the parameter grid to search
rf_paramGrid = (ParamGridBuilder()
             .addGrid(rf_scaled.numTrees, [50, 100])  # Number of trees
             .addGrid(rf_scaled.maxDepth, [5, 10, 20])     # Maximum depth of␣
 ↪each tree
             .build())

# Define the evaluator
evaluator = MulticlassClassificationEvaluator(
    labelCol="Credit_Score_index", predictionCol="prediction",␣
 ↪metricName="accuracy")

# Define CrossValidator
rf_cv_scaled_resample = CrossValidator(estimator=rf_scaled,
                    estimatorParamMaps=rf_paramGrid,
                    evaluator=evaluator,
                    numFolds=5)  # K-fold cross-validation

# Fit the model using CrossValidator
rf_cvModel_scaled_resample = rf_cv_scaled_resample.fit(train_resampled)

# Make predictions on the test data
rf_predictions_cv_scaled_resample = rf_cvModel_scaled_resample.
 ↪transform(test_resampled)

# Evaluate the tuned model
rf_accuracy_cv_scaled_resample = evaluator.
 ↪evaluate(rf_predictions_cv_scaled_resample)
print("Tuned model accuracy (scaled and oversampled):",␣
 ↪rf_accuracy_cv_scaled_resample)

# Convert DataFrame to RDD for MulticlassMetrics
rf_predictionAndLabels_cv_scaled_resample = rf_predictions_cv_scaled_resample.
 ↪select("prediction", "Credit_Score_index").rdd
rf_metrics_cv_scaled_resample =␣
 ↪MulticlassMetrics(rf_predictionAndLabels_cv_scaled_resample)
rf_confusion_matrix_cv_scaled_resample = rf_metrics_cv_scaled_resample.
 ↪confusionMatrix()

# Get the best parameters
rf_bestModel_scaled_resample = rf_cvModel_scaled_resample.bestModel
rf_bestNumTrees_scaled_resample = rf_bestModel_scaled_resample.getNumTrees
rf_bestMaxDepth_scaled_resample = rf_bestModel_scaled_resample.getMaxDepth()
print("Best number of trees:", rf_bestNumTrees_scaled_resample)
```

```
print("Best max depth:", rf_bestMaxDepth_scaled_resample)

confusion_matrix_plot('Random Forest (Tuned, Scaled, Oversampled)',␣
↪rf_confusion_matrix_cv_scaled_resample.toArray())
```

```
Tuned model accuracy (scaled and oversampled): 0.8937730090305529
[Stage 51041:==========================================>              (3 + 1) / 4]
Best number of trees: 100
Best max depth: 20
```



5.5.5 Comparison of the results

[125]:
```
rfc_basic_summary = model_summary('Random Forest (Basic)',␣
↪rf_predictions_original)
rfc_scaled_summary = model_summary('Random Forest (Normalized)',␣
↪rf_predictions_scaled)
rfc_resampled_summary = model_summary('Random Forest (Resampled)',␣
↪rf_predictions_scaled_resample)
rfc_tuned_scaled_over_summary = model_summary('Random Forest (Tuned +␣
↪Normalized + Resampled)', rf_predictions_cv_scaled_resample)
```

```
rfc_summary = pd.concat([rfc_basic_summary, rfc_scaled_summary,
    ↪rfc_resampled_summary, rfc_tuned_scaled_over_summary])
rfc_summary
```

[125]:
```
                                           Model  Accuracy  ROC-AUC Score  \
0                          Random Forest (Basic)  0.669083       0.789323
0                     Random Forest (Normalized)  0.666868       0.781217
0                      Random Forest (Resampled)  0.713980       0.807687
0  Random Forest (Tuned + Normalized + Resampled)  0.893773       0.948878

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.656964          0.728819            0.671179
0             0.664213          0.705035            0.668779
0             0.749548          0.747625            0.709939
0             0.888174          0.943769            0.891125
```

6 6. Model Evaluation

[126]:
```
# Show the summary of all models
overall_summary = pd.concat([lr_summary, ann_summary, dt_summary, rfc_summary])
overall_summary
```

[126]:
```
                                              Model  Accuracy  ROC-AUC Score  \
0                     Logistic Regression (Basic)  0.643864       0.737523
0                Logistic Regression (Normalized)  0.641800       0.733582
0                 Logistic Regression (Resampled)  0.672068       0.796285
0                     Logistic Regression (Tuned)  0.642001       0.734438
0        Logistic Regression (Tuned + Normalized)  0.640844       0.732612
0  Logistic Regression (Tuned + Normalized + Resa…  0.677606       0.796808
0                                     ANN (Basic)  0.566974       0.652626
0                                ANN (Normalized)  0.693088       0.785059
0                                 ANN (Resampled)  0.526080       0.734301
0                   ANN (Normalized + Resampled)  0.708897       0.826288
0           ANN (Tuned + Normalized + Resampled)  0.712218       0.825597
0                             Decision Tree (Basic)  0.690732       0.779277
0                             Decision Tree (Tuned)  0.713620       0.807380
0                        Decision Tree (Normalized)  0.691347       0.778566
0                Decision Tree (Tuned + Normalized)  0.702970       0.795680
0            Decision Tree (Normalized + Resampled)  0.714957       0.831554
0    Decision Tree (Tuned + Normalized + Resampled)  0.748461       0.875471
0                             Random Forest (Basic)  0.669083       0.789323
0                        Random Forest (Normalized)  0.666868       0.781217
0                         Random Forest (Resampled)  0.713980       0.807687
0    Random Forest (Tuned + Normalized + Resampled)  0.893773       0.948878
```

	Precision (Overall)	Recall (Overall)	F1-score (Overall)
0	0.684541	0.529687	0.635806
0	0.685228	0.517014	0.633117
0	0.723306	0.683321	0.667946
0	0.683925	0.525174	0.633096
0	0.684536	0.518750	0.631498
0	0.729624	0.707447	0.671606
0	0.557625	0.450682	0.502944
0	0.709998	0.645121	0.692092
0	0.632194	0.657819	0.423160
0	0.748706	0.762553	0.704427
0	0.733138	0.782580	0.706118
0	0.731452	0.619798	0.688749
0	0.708738	0.698070	0.713830
0	0.739093	0.612006	0.689290
0	0.697517	0.676642	0.703333
0	0.735768	0.783921	0.710115
0	0.821670	0.767344	0.751906
0	0.656964	0.728819	0.671179
0	0.664213	0.705035	0.668779
0	0.749548	0.747625	0.709939
0	0.888174	0.943769	0.891125

[127]:
```python
# Show the summary, sort by Accuracy
overall_summary.sort_values(by=['Accuracy'])
```

[127]:

	Model	Accuracy	ROC-AUC Score	\
0	ANN (Resampled)	0.526080	0.734301	
0	ANN (Basic)	0.566974	0.652626	
0	Logistic Regression (Tuned + Normalized)	0.640844	0.732612	
0	Logistic Regression (Normalized)	0.641800	0.733582	
0	Logistic Regression (Tuned)	0.642001	0.734438	
0	Logistic Regression (Basic)	0.643864	0.737523	
0	Random Forest (Normalized)	0.666868	0.781217	
0	Random Forest (Basic)	0.669083	0.789323	
0	Logistic Regression (Resampled)	0.672068	0.796285	
0	Logistic Regression (Tuned + Normalized + Resa…	0.677606	0.796808	
0	Decision Tree (Basic)	0.690732	0.779277	
0	Decision Tree (Normalized)	0.691347	0.778566	
0	ANN (Normalized)	0.693088	0.785059	
0	Decision Tree (Tuned + Normalized)	0.702970	0.795680	
0	ANN (Normalized + Resampled)	0.708897	0.826288	
0	ANN (Tuned + Normalized + Resampled)	0.712218	0.825597	
0	Decision Tree (Tuned)	0.713620	0.807380	
0	Random Forest (Resampled)	0.713980	0.807687	
0	Decision Tree (Normalized + Resampled)	0.714957	0.831554	

```
0     Decision Tree (Tuned + Normalized + Resampled)  0.748461       0.875471
0     Random Forest (Tuned + Normalized + Resampled)  0.893773       0.948878

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.632194          0.657819            0.423160
0             0.557625          0.450682            0.502944
0             0.684536          0.518750            0.631498
0             0.685228          0.517014            0.633117
0             0.683925          0.525174            0.633096
0             0.684541          0.529687            0.635806
0             0.664213          0.705035            0.668779
0             0.656964          0.728819            0.671179
0             0.723306          0.683321            0.667946
0             0.729624          0.707447            0.671606
0             0.731452          0.619798            0.688749
0             0.739093          0.612006            0.689290
0             0.709998          0.645121            0.692092
0             0.697517          0.676642            0.703333
0             0.748706          0.762553            0.704427
0             0.733138          0.782580            0.706118
0             0.708738          0.698070            0.713830
0             0.749548          0.747625            0.709939
0             0.735768          0.783921            0.710115
0             0.821670          0.767233            0.751906
0             0.888174          0.943769            0.891125
```

[128]:

```
# Show the best accuracy models of each implementations
lr_highest_accuracy = lr_summary[lr_summary['Accuracy'] ==␣
 ↪lr_summary['Accuracy'].max()]
ann_highest_accuracy = ann_summary[ann_summary['Accuracy'] ==␣
 ↪ann_summary['Accuracy'].max()]
dt_highest_accuracy = dt_summary[dt_summary['Accuracy'] ==␣
 ↪dt_summary['Accuracy'].max()]
rfc_highest_accuracy = rfc_summary[rfc_summary['Accuracy'] ==␣
 ↪rfc_summary['Accuracy'].max()]
best_model_summary = pd.concat([lr_highest_accuracy, ann_highest_accuracy,␣
 ↪dt_highest_accuracy, rfc_highest_accuracy])
best_model_summary.sort_values(by=['Accuracy'])
```

[128]:

```
                                             Model  Accuracy  ROC-AUC Score  \
0  Logistic Regression (Tuned + Normalized + Resa…  0.677606       0.796808
0             ANN (Tuned + Normalized + Resampled)  0.712218       0.825597
0     Decision Tree (Tuned + Normalized + Resampled)  0.748461       0.875471
0     Random Forest (Tuned + Normalized + Resampled)  0.893773       0.948878

   Precision (Overall)  Recall (Overall)  F1-score (Overall)
0             0.729624          0.707447            0.671606
```

0	0.733138	0.782580	0.706118
0	0.821670	0.767344	0.751906
0	0.888174	0.943769	0.891125

6.1 Conclusion

We can find that the accuracy of the all four models increased after the data has normalized and oversampled, and hyperparameters were tuned.

Among them, the model that showed the greatest performance improvement was the ANN model, which recorded an accuracy of 71.2% based on ANN (Tuned + Normalized + Resampled) from an accuracy of about 52.6% based on the original data, showing a significant increase of approximately 18.6%p.

The model that showed the highest accuracy among the four models was the Random forest model, which showed 89.4% accuracy.

6.2 Spark MLlib vs Scikit-learn

Spark MLlib is optimal for distributed systems, making it inherently more scalable and suitable for much heavier workloads compared to scikit-learn.

While scikit-learn by default provides much better default parameters and more parameter options. This makes it both easier to create better models and to tune models to a finer degree for better results.