Credit-Score-Classification-Project

April 3, 2024

1.Importing Data

A dataset is loaded from a CSV file for initial inspection. The process includes exploring basic properties such as the dataset's shape, the first and last few rows, and the data types of its columns. To enhance data handling, specific columns undergo data type transformation, notably to the 'category' type for more accurate categorization.

[871]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from collections import Counter
from sklearn.model_selection import train_test_split
from collections import OrderedDict
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, accuracy_score, recall_score,␣
 ↪precision_score, f1_score, classification_report
from tabulate import tabulate

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

Reading the Data from File

[872]:
```
#Load the dataset from the CSV fil
data = 'train.csv'

#Read the dataset into a pandas DataFrame
dataset = pd.read_csv(data)
```

Find shape of the dataset

[873]:
```
dataset.shape
```

[873]:
```
(100000, 28)
```

Display top 10 rows of the dataset

[874]:
```
dataset.head(10)
```

[874]:
```
       ID Customer_ID     Month           Name   Age          SSN  \
0  0x1602   CUS_0xd40   January  Aaron Maashoh    23  821-00-0265
1  0x1603   CUS_0xd40  February  Aaron Maashoh    23  821-00-0265
2  0x1604   CUS_0xd40     March  Aaron Maashoh  -500  821-00-0265
3  0x1605   CUS_0xd40     April  Aaron Maashoh    23  821-00-0265
4  0x1606   CUS_0xd40       May  Aaron Maashoh    23  821-00-0265
5  0x1607   CUS_0xd40      June  Aaron Maashoh    23  821-00-0265
6  0x1608   CUS_0xd40      July  Aaron Maashoh    23  821-00-0265
7  0x1609   CUS_0xd40    August            NaN    23    #F%$D@*&8
8  0x160e  CUS_0x21b1   January  Rick Rothackerj   28_  004-07-5839
9  0x160f  CUS_0x21b1  February  Rick Rothackerj    28  004-07-5839

  Occupation Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  …  \
0  Scientist      19114.12            1824.843333                  3  …
1  Scientist      19114.12                    NaN                  3  …
2  Scientist      19114.12                    NaN                  3  …
3  Scientist      19114.12                    NaN                  3  …
4  Scientist      19114.12            1824.843333                  3  …
5  Scientist      19114.12                    NaN                  3  …
6  Scientist      19114.12            1824.843333                  3  …
7  Scientist      19114.12            1824.843333                  3  …
8    _______      34847.84            3037.986667                  2  …
9    Teacher      34847.84            3037.986667                  2  …

   Credit_Mix  Outstanding_Debt Credit_Utilization_Ratio  \
0           _            809.98                26.822620
1        Good            809.98                31.944960
2        Good            809.98                28.609352
3        Good            809.98                31.377862
4        Good            809.98                24.797347
5        Good            809.98                27.262259
6        Good            809.98                22.537593
7        Good            809.98                23.933795
8        Good            605.03                24.464031
9        Good            605.03                38.550848

      Credit_History_Age  Payment_of_Min_Amount Total_EMI_per_month  \
0  22 Years and 1 Months                    No           49.574949
1                    NaN                    No           49.574949
2  22 Years and 3 Months                    No           49.574949
3  22 Years and 4 Months                    No           49.574949
4  22 Years and 5 Months                    No           49.574949
5  22 Years and 6 Months                    No           49.574949
6  22 Years and 7 Months                    No           49.574949
7                    NaN                    No           49.574949
```

```
8  26 Years and 7 Months                    No          18.816215
9  26 Years and 8 Months                    No          18.816215

  Amount_invested_monthly                 Payment_Behaviour  \
0       80.41529543900253   High_spent_Small_value_payments
1      118.28022162236736    Low_spent_Large_value_payments
2         81.699521264648   Low_spent_Medium_value_payments
3       199.4580743910713    Low_spent_Small_value_payments
4      41.420153086217326  High_spent_Medium_value_payments
5      62.430172331195294                            !@9#%8
6       178.3440674122349    Low_spent_Small_value_payments
7      24.785216509052056  High_spent_Medium_value_payments
8        104.291825168246    Low_spent_Small_value_payments
9       40.39123782853101   High_spent_Large_value_payments

      Monthly_Balance Credit_Score
0  312.49408867943663         Good
1  284.62916249607184         Good
2   331.2098628537912         Good
3  223.45130972736786         Good
4  341.48923103222177         Good
5   340.4792117872438         Good
6   244.5653167062043         Good
7  358.12416760938714     Standard
8  470.69062692529184     Standard
9   484.5912142650067         Good

[10 rows x 28 columns]
```

Check last 10 rows of the dataset

[875]:
```
dataset.tail(10)
```

[875]:
```
             ID Customer_ID     Month           Name  Age          SSN  \
99990  0x25fe0  CUS_0x8600      July  Sarah McBridec   28  031-35-0942
99991  0x25fe1  CUS_0x8600    August  Sarah McBridec   29  031-35-0942
99992  0x25fe6  CUS_0x942c   January           Nicks   24  078-73-5990
99993  0x25fe7  CUS_0x942c  February           Nicks   25  078-73-5990
99994  0x25fe8  CUS_0x942c     March           Nicks   25  078-73-5990
99995  0x25fe9  CUS_0x942c     April           Nicks   25  078-73-5990
99996  0x25fea  CUS_0x942c       May           Nicks   25  078-73-5990
99997  0x25feb  CUS_0x942c      June           Nicks   25  078-73-5990
99998  0x25fec  CUS_0x942c      July           Nicks   25  078-73-5990
99999  0x25fed  CUS_0x942c    August           Nicks   25  078-73-5990

      Occupation Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  …  \
99990  Architect      20002.88            1929.906667                 10  …
99991  Architect      20002.88            1929.906667                 10  …
```

```
99992   Mechanic      39628.99           3359.415833                4  …
99993   Mechanic     39628.99_           3359.415833                4  …
99994   Mechanic      39628.99           3359.415833                4  …
99995   Mechanic      39628.99           3359.415833                4  …
99996   Mechanic      39628.99           3359.415833                4  …
99997   Mechanic      39628.99           3359.415833                4  …
99998   Mechanic      39628.99           3359.415833                4  …
99999   Mechanic     39628.99_           3359.415833                4  …

       Credit_Mix  Outstanding_Debt Credit_Utilization_Ratio  \
99990         Bad            3571.7                25.123535
99991         Bad            3571.7                37.140784
99992           _            502.38                32.991333
99993        Good            502.38                29.135447
99994           _            502.38                39.323569
99995           _            502.38                34.663572
99996           _            502.38                40.565631
99997        Good            502.38                41.255522
99998        Good            502.38                33.638208
99999        Good            502.38                34.192463

           Credit_History_Age  Payment_of_Min_Amount Total_EMI_per_month  \
99990                     NaN                    Yes           60.964772
99991    6 Years and 3 Months                    Yes           60.964772
99992   31 Years and 3 Months                     No           35.104023
99993   31 Years and 4 Months                     No        58638.000000
99994   31 Years and 5 Months                     No           35.104023
99995   31 Years and 6 Months                     No           35.104023
99996   31 Years and 7 Months                     No           35.104023
99997   31 Years and 8 Months                     No           35.104023
99998   31 Years and 9 Months                     No           35.104023
99999  31 Years and 10 Months                     No           35.104023

      Amount_invested_monthly                 Payment_Behaviour  \
99990       173.2755025599617   Low_spent_Large_value_payments
99991       34.66290609052614  High_spent_Large_value_payments
99992       401.1964806036356   Low_spent_Small_value_payments
99993       180.7330951944497  Low_spent_Medium_value_payments
99994      140.58140274528395 High_spent_Medium_value_payments
99995       60.97133255718485  High_spent_Large_value_payments
99996       54.18595028760385 High_spent_Medium_value_payments
99997       24.02847744864441  High_spent_Large_value_payments
99998      251.67258219721603   Low_spent_Large_value_payments
99999       167.1638651610451                           !@9#%8

      Monthly_Balance Credit_Score
99990      228.750392     Standard
```

```
99991      337.362988    Standard
99992       189.64108        Poor
99993      400.104466    Standard
99994      410.256158        Poor
99995      479.866228        Poor
99996       496.65161        Poor
99997      516.809083        Poor
99998      319.164979    Standard
99999      393.673696        Poor

[10 rows x 28 columns]
```

Get an overview of the dataset

[876]:
```
dataset.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
```

Here, the columns - Month, Occupation, Type_of_Loan, Credit_Mix, Payment_of_Min_Amount, Payment_Behaviour, Credit_Score are categorical. Hence, we modify the datatypes of these columns to category.

[877]:
```python
#Changing the datatype of the above mentioned columns to category

dataset.Month = dataset.Month.astype('category')
dataset.Occupation = dataset.Occupation.astype('category')
dataset.Type_of_Loan = dataset.Type_of_Loan.astype('category')
dataset.Credit_Mix = dataset.Credit_Mix.astype('category')
dataset.Payment_of_Min_Amount = dataset.Payment_of_Min_Amount.astype('category')
dataset.Payment_Behaviour = dataset.Payment_Behaviour.astype('category')
dataset.Credit_Score = dataset.Credit_Score.astype('category')
```

[878]:
```python
#Looking at the modified datatypes of the data

dataset.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  category
 3   Name                      90015 non-null   object
 4   Age                       100000 non-null  object
 5   SSN                       100000 non-null  object
 6   Occupation                100000 non-null  category
 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   category
 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  category
 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  category
 23  Total_EMI_per_month       100000 non-null  float64
 24  Amount_invested_monthly   95521 non-null   object
 25  Payment_Behaviour         100000 non-null  category
 26  Monthly_Balance           98800 non-null   object
 27  Credit_Score              100000 non-null  category
dtypes: category(7), float64(4), int64(4), object(13)
memory usage: 17.0+ MB
```

Check Null values in the dataset

[879]:
```
dataset.isnull().sum()
```

[879]:
```
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
```

Check duplicates in the dataset

[880]:
```
dataset.duplicated().sum()
```

[880]:
```
0
```

[881]:
```
for col in df.columns:
    print(f'{col} : {pd.api.types.infer_dtype(dataset[col])}')
```

```
ID : string
Customer_ID : string
Month : categorical
Name : string
Age : string
SSN : string
Occupation : categorical
Annual_Income : string
Monthly_Inhand_Salary : floating
Num_Bank_Accounts : integer
Num_Credit_Card : integer
Interest_Rate : integer
Num_of_Loan : string
Type_of_Loan : categorical
Delay_from_due_date : integer
Num_of_Delayed_Payment : string
Changed_Credit_Limit : string
Num_Credit_Inquiries : floating
Credit_Mix : categorical
Outstanding_Debt : string
Credit_Utilization_Ratio : floating
Credit_History_Age : string
Payment_of_Min_Amount : categorical
Total_EMI_per_month : floating
Amount_invested_monthly : string
Payment_Behaviour : categorical
Monthly_Balance : mixed
Credit_Score : categorical
```

Monthly__Balance has mixed types!

2.Data Cleaning

In the data cleaning phase, the focus is to addressing null values and potential outliers in the dataset. Columns that feature underscores or mixed types are cleaned or modified to ensure consistency. Additionally, any columns with significant missing values or those deemed unnecessary for the model's purpose are dropped to streamline the dataset.

[882]:
```
dataset.dtypes
```

[882]:
```
ID                              object
Customer_ID                     object
Month                         category
Name                            object
Age                             object
SSN                             object
```

```
Occupation                  category
Annual_Income                 object
Monthly_Inhand_Salary        float64
Num_Bank_Accounts              int64
Num_Credit_Card                int64
Interest_Rate                  int64
Num_of_Loan                   object
Type_of_Loan                category
Delay_from_due_date            int64
Num_of_Delayed_Payment        object
Changed_Credit_Limit          object
Num_Credit_Inquiries         float64
Credit_Mix                  category
Outstanding_Debt              object
Credit_Utilization_Ratio     float64
Credit_History_Age            object
Payment_of_Min_Amount       category
Total_EMI_per_month          float64
Amount_invested_monthly       object
Payment_Behaviour           category
Monthly_Balance               object
Credit_Score                category
dtype: object
```

[883]:

```
#A function to remove the '_' in the data

def removeUnderscore(value):
    first_index = 0
    last_index = len(value) - 1
    while first_index <= last_index:
        if value[first_index] == '_':
            first_index += 1
        if value[last_index] == '_':
            last_index -= 1
        if '_' not in value[first_index : last_index + 1]:
            if value[first_index : last_index + 1] == '':
                return 0
            else:
                return value[first_index : last_index + 1]


def modifyData(columns):
    for each_column in columns:
        data = [str(value) for value in list(dataset[each_column])]
        new_data = []
        for value in data:
            if value == 'nan':
```

```
                new_data.append(float('nan'))
            else:
                new_data.append(float(removeUnderscore(value)))

        dataset[each_column] = new_data

modifyData(['Age', 'Annual_Income', 'Num_of_Loan', 'Num_of_Delayed_Payment',␣
 ↪'Outstanding_Debt', 'Changed_Credit_Limit',
           'Amount_invested_monthly', 'Monthly_Balance'])
```

[884]:
```
#Looking at the datatypes of the data
dataset.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  category
 3   Name                      90015 non-null   object
 4   Age                       100000 non-null  float64
 5   SSN                       100000 non-null  object
 6   Occupation                100000 non-null  category
 7   Annual_Income             100000 non-null  float64
 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  float64
 13  Type_of_Loan              88592 non-null   category
 14  Delay_from_due_date       100000 non-null  int64
 15  Num_of_Delayed_Payment    92998 non-null   float64
 16  Changed_Credit_Limit      100000 non-null  float64
 17  Num_Credit_Inquiries      98035 non-null   float64
 18  Credit_Mix                100000 non-null  category
 19  Outstanding_Debt          100000 non-null  float64
 20  Credit_Utilization_Ratio  100000 non-null  float64
 21  Credit_History_Age        90970 non-null   object
 22  Payment_of_Min_Amount     100000 non-null  category
 23  Total_EMI_per_month       100000 non-null  float64
 24  Amount_invested_monthly   95521 non-null   float64
 25  Payment_Behaviour         100000 non-null  category
 26  Monthly_Balance           98800 non-null   float64
 27  Credit_Score              100000 non-null  category
dtypes: category(7), float64(12), int64(4), object(5)
memory usage: 17.0+ MB
```

[885]:
```
#Missing data by columns in the dataset
dataset.isnull().sum().sort_values(ascending = False)
```

[885]:
```
Monthly_Inhand_Salary       15002
Type_of_Loan                11408
Name                         9985
Credit_History_Age           9030
Num_of_Delayed_Payment       7002
Amount_invested_monthly      4479
Num_Credit_Inquiries         1965
Monthly_Balance              1200
ID                              0
Changed_Credit_Limit            0
Payment_Behaviour               0
Total_EMI_per_month             0
Payment_of_Min_Amount           0
Credit_Utilization_Ratio        0
Outstanding_Debt                0
Credit_Mix                      0
Delay_from_due_date             0
Customer_ID                     0
Num_of_Loan                     0
Interest_Rate                   0
Num_Credit_Card                 0
Num_Bank_Accounts               0
Annual_Income                   0
Occupation                      0
SSN                             0
Age                             0
Month                           0
Credit_Score                    0
dtype: int64
```

Get overall statistics of the dataset

[886]:
```
dataset.describe()
```

[886]:
```
                 Age  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
count  100000.000000   1.000000e+05           84998.000000      100000.000000
mean      110.649700   1.764157e+05            4194.170850          17.091280
std       686.244717   1.429618e+06            3183.686167         117.404834
min      -500.000000   7.005930e+03             303.645417          -1.000000
25%        24.000000   1.945750e+04            1625.568229           3.000000
50%        33.000000   3.757861e+04            3093.745000           6.000000
75%        42.000000   7.279092e+04            5957.448333           7.000000
max      8698.000000   2.419806e+07           15204.633333        1798.000000

       Num_Credit_Card  Interest_Rate    Num_of_Loan  Delay_from_due_date  \
```

```
count     100000.00000  100000.000000  100000.000000         100000.000000
mean          22.47443      72.466040       3.009960             21.068780
std          129.05741     466.422621      62.647879             14.860104
min            0.00000       1.000000    -100.000000             -5.000000
25%            4.00000       8.000000       1.000000             10.000000
50%            5.00000      13.000000       3.000000             18.000000
75%            7.00000      20.000000       5.000000             28.000000
max         1499.00000    5797.000000    1496.000000             67.000000

       Num_of_Delayed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries  \
count            92998.000000         100000.000000          98035.000000
mean                30.923342             10.171791             27.754251
std                226.031892              6.880628            193.177339
min                 -3.000000             -6.490000              0.000000
25%                  9.000000              4.970000              3.000000
50%                 14.000000              9.250000              6.000000
75%                 18.000000             14.660000              9.000000
max               4397.000000             36.970000           2597.000000

       Outstanding_Debt  Credit_Utilization_Ratio  Total_EMI_per_month  \
count     100000.000000             100000.000000        100000.000000
mean        1426.220376                 32.285173          1403.118217
std         1155.129026                  5.116875          8306.041270
min            0.230000                 20.000000             0.000000
25%          566.072500                 28.052567            30.306660
50%         1166.155000                 32.305784            69.249473
75%         1945.962500                 36.496663           161.224249
max         4998.070000                 50.000000         82331.000000

       Amount_invested_monthly  Monthly_Balance
count             95521.000000     9.880000e+04
mean                637.412998    -3.036437e+22
std                2043.319327     3.181295e+24
min                   0.000000    -3.333333e+26
25%                  74.534002     2.700922e+02
50%                 135.925682     3.367192e+02
75%                 265.731733     4.702202e+02
max               10000.000000     1.602041e+03
```

From the above summary statistics, we can see that there are outliers present in the data. We will take care of these in the next sections.

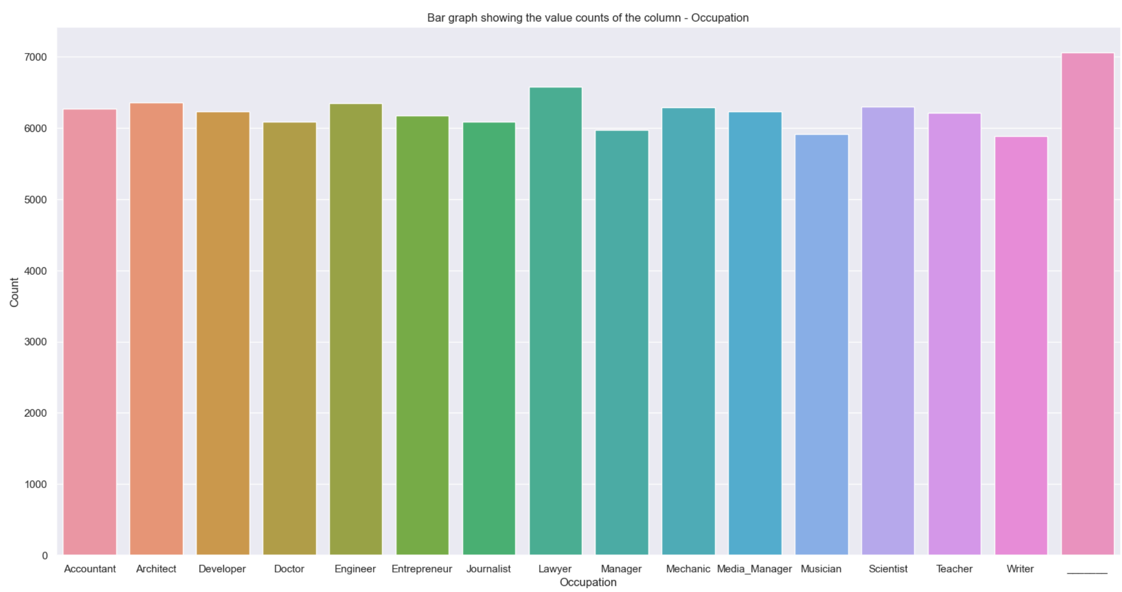
3.Data Analysis

In the analysis phase, We look at how data is spread out in different columns like jobs, credit mix, and loan types. We count the values and use charts to make this easier to understand. We also study how credit scores vary across different groups to spot patterns and trends.

[887]:
```python
#Value counts of the column - Occupation
occupation_count = dataset['Occupation'].value_counts(dropna = False)
occupation_count
```

[887]:
```
_______          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: Occupation, dtype: int64
```

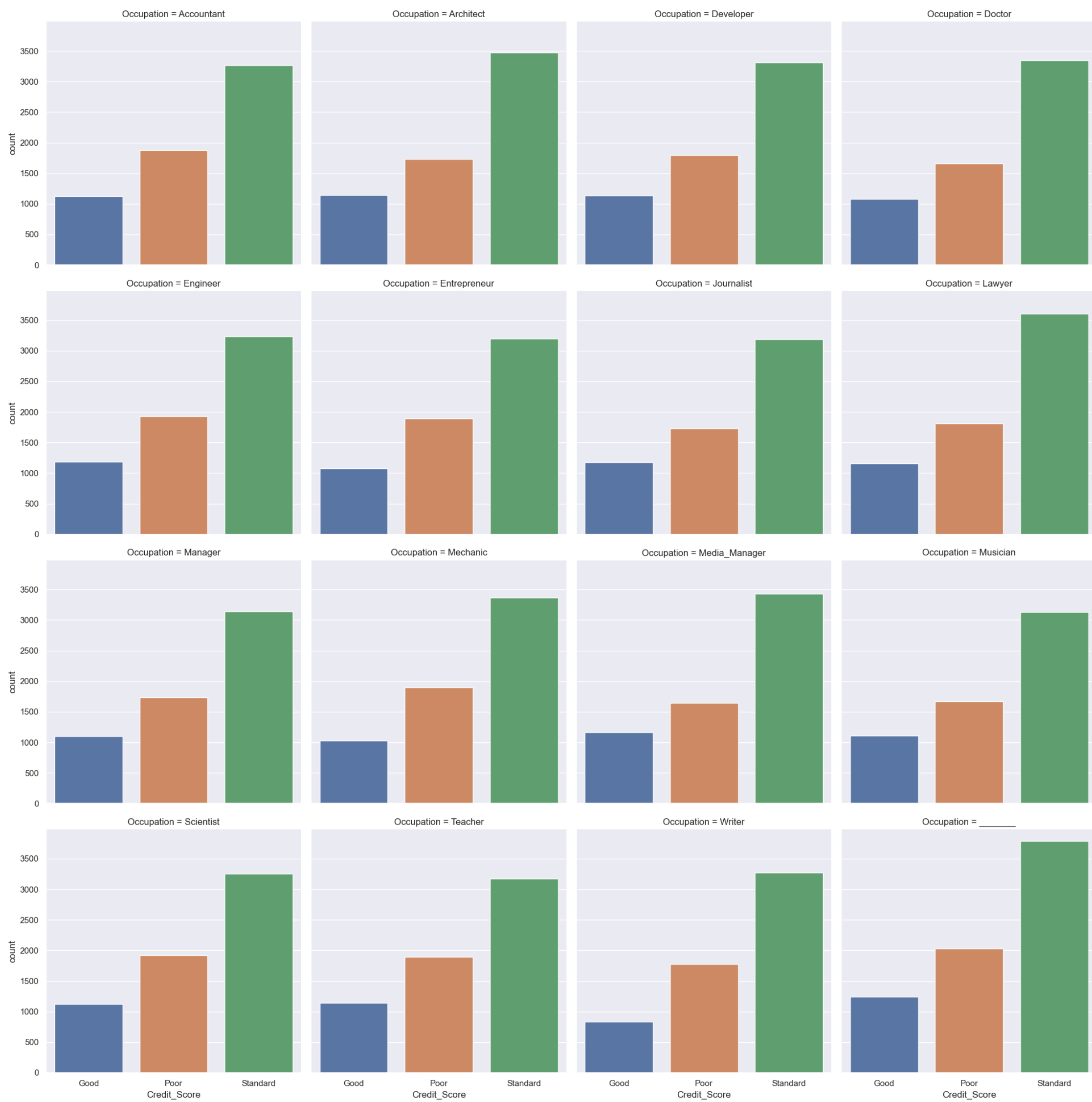
[888]:
```python
#Bar graph showing the value counts of the column - Occupation
sns.set(rc={'figure.figsize': (20, 10)})
sns.barplot(x=occupation_count.index, y=occupation_count.values)
plt.title('Bar graph showing the value counts of the column - Occupation')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Occupation', fontsize=12)
plt.show()
```



From the above graph, we can see that most of the jobs are ‘unnamed’.

[891]:
```
#Distribution of Credit_Score for each Occupation

sns.catplot(x='Credit_Score', col='Occupation', data=dataset, kind='count',␣
    ↪col_wrap=4)
```

[891]: `<seaborn.axisgrid.FacetGrid at 0x26e2066e770>`



From the above graphs, we can see that most of the people have a Credit Score in the Standard range for all the Occupations.

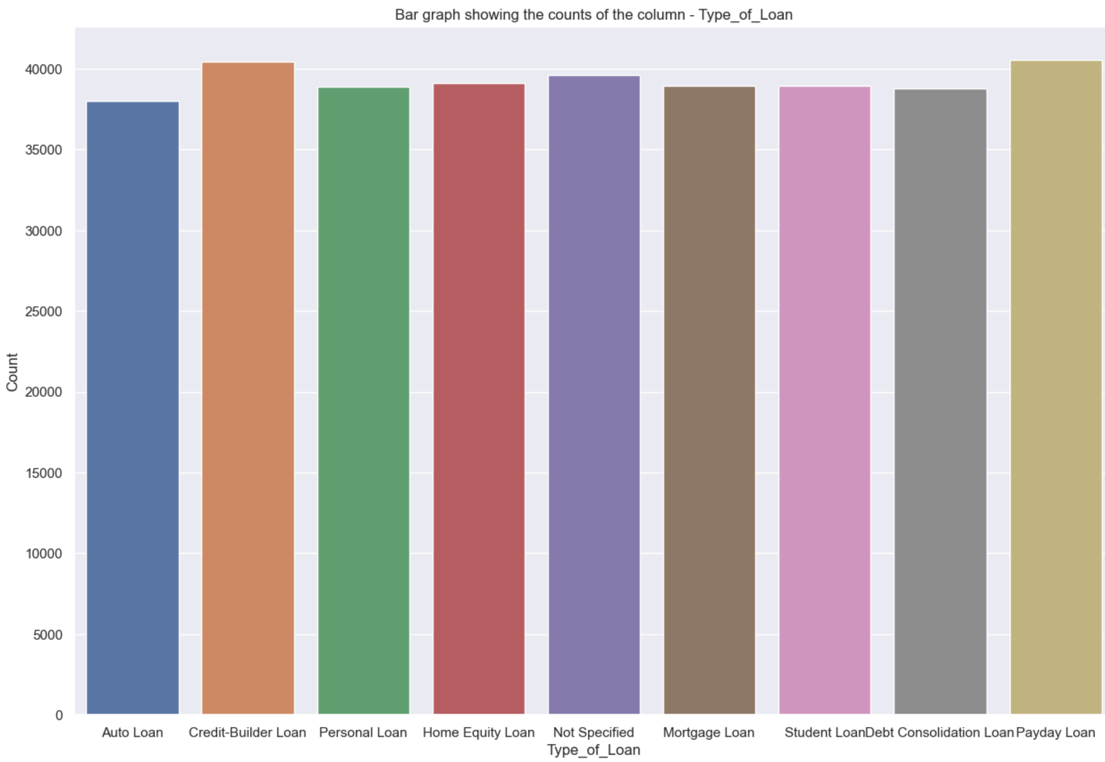
[892]:
```python
#Categorical variable - Type of Loan
#Fetching the not null data of the column - Type of Data

index_values = ~dataset['Type_of_Loan'].isnull().values
loan_type_data = list(dataset['Type_of_Loan'][index_values])
```

[893]:
```python
#Create a dictionary to store the counts of all the various loan types

loan_type_dict = dict()
for value in loan_type_data:
    values = value.split(',')
    for each_value in values:
        loan_type = each_value.strip(' ')
        if 'and' in loan_type:
            loan_type = loan_type[4 : ]
        if loan_type in loan_type_dict:
            loan_type_dict[loan_type] += 1
        else:
            loan_type_dict[loan_type] = 1

loan_type_dict
```

[893]:
```
{'Auto Loan': 37992,
 'Credit-Builder Loan': 40440,
 'Personal Loan': 38888,
 'Home Equity Loan': 39104,
 'Not Specified': 39616,
 'Mortgage Loan': 38936,
 'Student Loan': 38968,
 'Debt Consolidation Loan': 38776,
 'Payday Loan': 40568}
```

[895]:
```python
#Bar graph showing the counts of the column - Type_of_Loan

sns.set(rc = {'figure.figsize': (15, 10)})
sns.barplot(x=list(loan_type_dict.keys()), y=list(loan_type_dict.values()))
plt.title('Bar graph showing the counts of the column - Type_of_Loan')
plt.ylabel('Count', fontsize = 12)
plt.xlabel('Type_of_Loan', fontsize = 12)
```

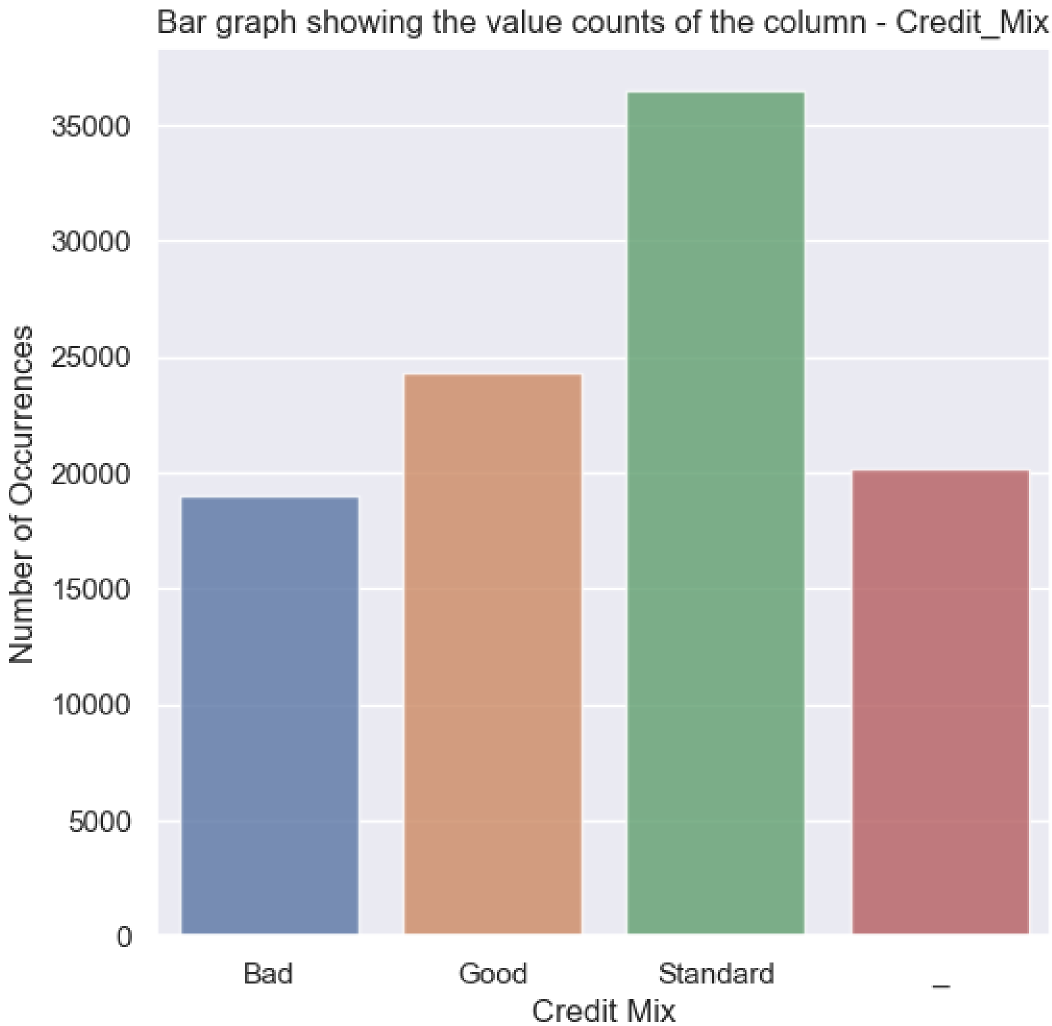
[895]:
```
Text(0.5, 0, 'Type_of_Loan')
```



[896]:
```
#Categorical variable - Credit_MIx
#Value counts of the column - Credit_Mix

credit_mix_count = dataset['Credit_Mix'].value_counts(dropna = False)
credit_mix_count
```

[896]:
```
Standard    36479
Good        24337
_           20195
Bad         18989
Name: Credit_Mix, dtype: int64
```

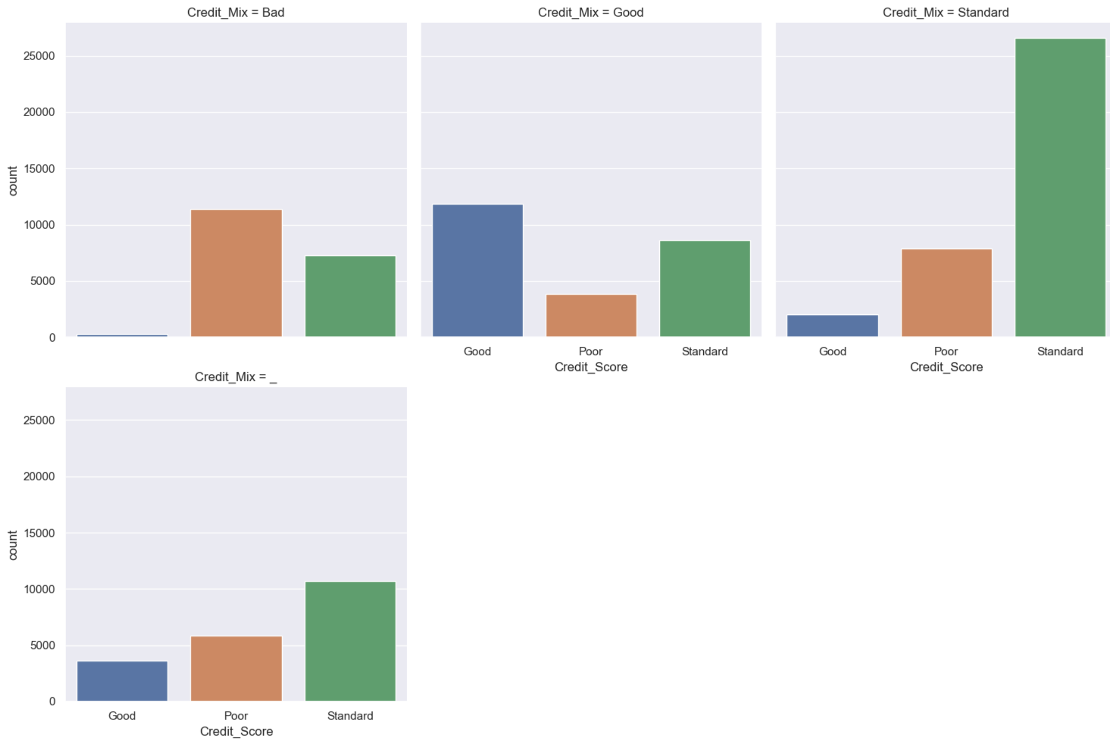
[682]:
```
#Bar graph showing the value counts of the column - Credit_Mix

sns.set(rc = {'figure.figsize': (6, 6)})
sns.barplot(x=credit_mix_count.index, y=credit_mix_count.values, alpha = 0.8)
plt.title('Bar graph showing the value counts of the column - Credit_Mix')
plt.ylabel('Number of Occurrences', fontsize = 12)
plt.xlabel('Credit Mix', fontsize = 12)
plt.show()
```



From the above graph, we can see that most of the customers have a 'Standard' credit mix.

[897]:
```
#Distribution of Credit_Score for each Credit_Mix

sns.catplot(x='Credit_Score', col = 'Credit_Mix', data = dataset, kind =␣
↪'count', col_wrap = 3)
```

[897]: <seaborn.axisgrid.FacetGrid at 0x26dfed35c90>

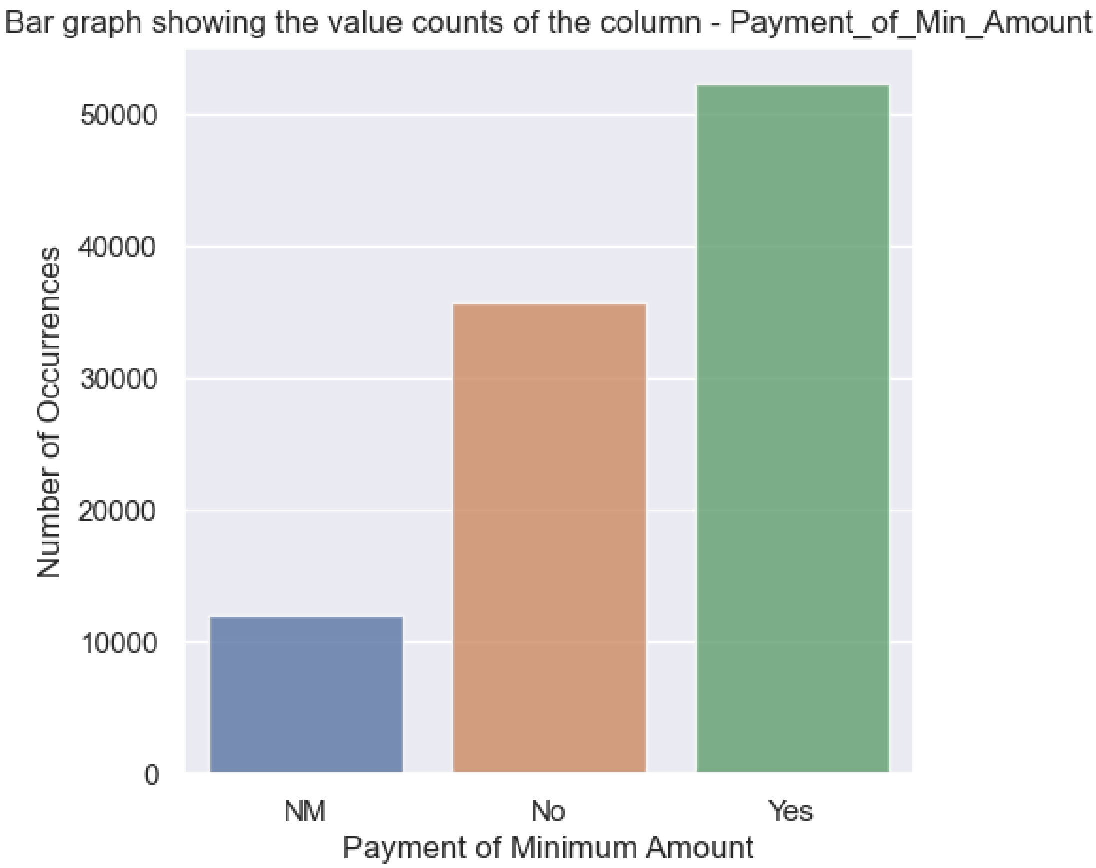


From the above graphs, we can see that the columns - Credit_Mix and Credit_Score are almost similar.

[898]:
```
#Categorical variable - Payment_of_Min_Amount
#Value counts of the column - Payment_of_Min_Amount

min_amount_count = dataset['Payment_of_Min_Amount'].value_counts(dropna = False)
min_amount_count
```

[898]:
```
Yes     52326
No      35667
NM      12007
Name: Payment_of_Min_Amount, dtype: int64
```

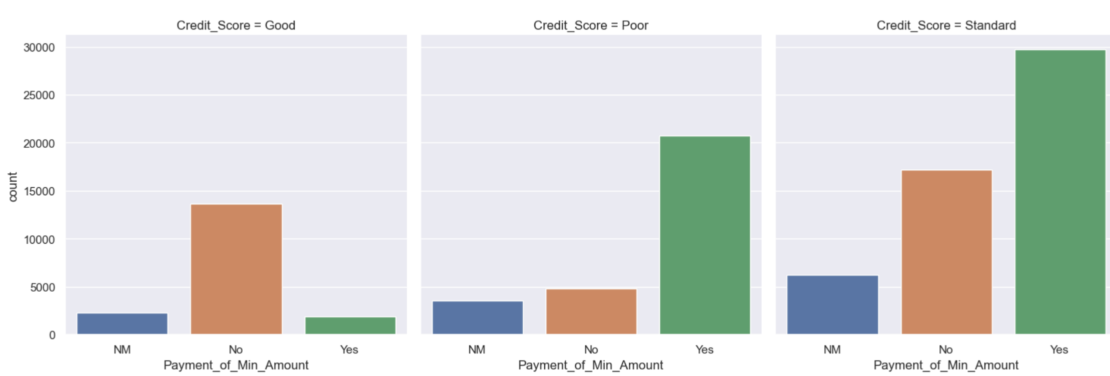
[685]:
```
#Bar graph showing the value counts of the column - Payment_of_Min_Amount

sns.set(rc = {'figure.figsize': (5, 5)})
sns.barplot(x=min_amount_count.index, y=min_amount_count.values, alpha = 0.8)
plt.title('Bar graph showing the value counts of the column -␣
↪Payment_of_Min_Amount')
plt.ylabel('Number of Occurrences', fontsize = 12)
plt.xlabel('Payment of Minimum Amount', fontsize = 12)
plt.show()
```



From the above graph, we can see that most of the customer's paid a minimum amount for their loans.

[899]:
```
#Distribution of Payment_of_Min_Amount for each Credit Score

sns.catplot(x='Payment_of_Min_Amount', col = 'Credit_Score', data = dataset,␣
    ↪kind = 'count', col_wrap = 3)
```

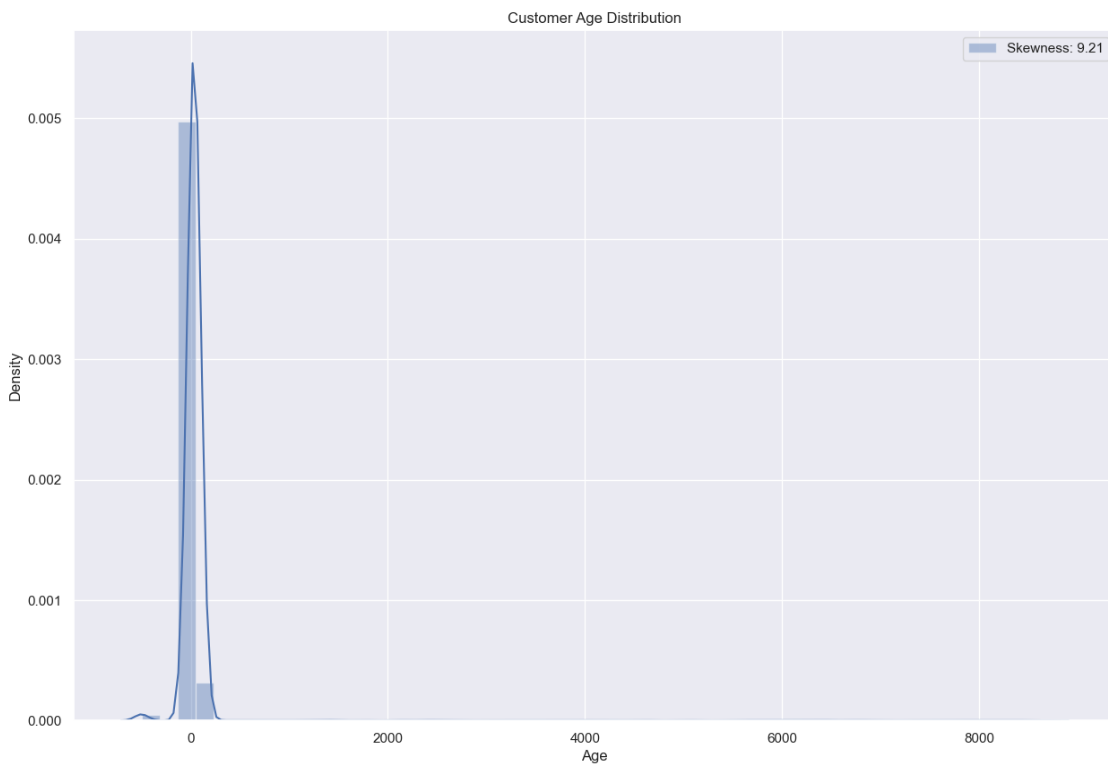
[899]: <seaborn.axisgrid.FacetGrid at 0x26dff2cac50>



From the above graphs, we can see that the most of the customers with a good credit score didn't pay the minimum amount for the loan. Similarly, customers with a poor credit score paid the minimum amount for the loan.

[901]:
```
#Numerical variable - Age
# Understanding the distribution of the column - Age

sns.distplot(dataset['Age'], label = 'Skewness: %.2f'%(dataset['Age'].skew()))
plt.legend(loc = 'best')
plt.title('Customer Age Distribution')
```

[901]: Text(0.5, 1.0, 'Customer Age Distribution')

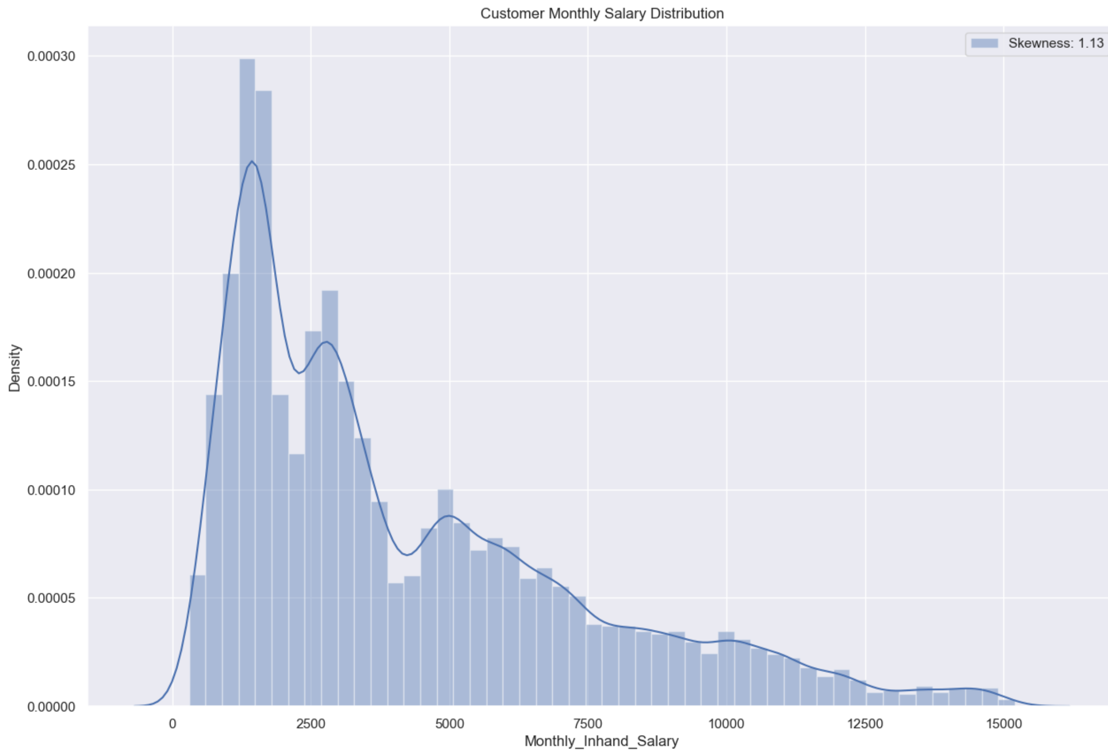


From the above graph, we can see that the above graph has a high degree of skewness.

[902]:
```
#Numerical variable - Monthly_Inhand_Salary
#Understanding the distribution of the column - Monthly_Inhand_Salary

sns.distplot(dataset['Monthly_Inhand_Salary'], label = 'Skewness: %.
↪2f'%(dataset['Monthly_Inhand_Salary'].skew()))
plt.legend(loc = 'best')
```

```
plt.title('Customer Monthly Salary Distribution')
```

[902]: Text(0.5, 1.0, 'Customer Monthly Salary Distribution')

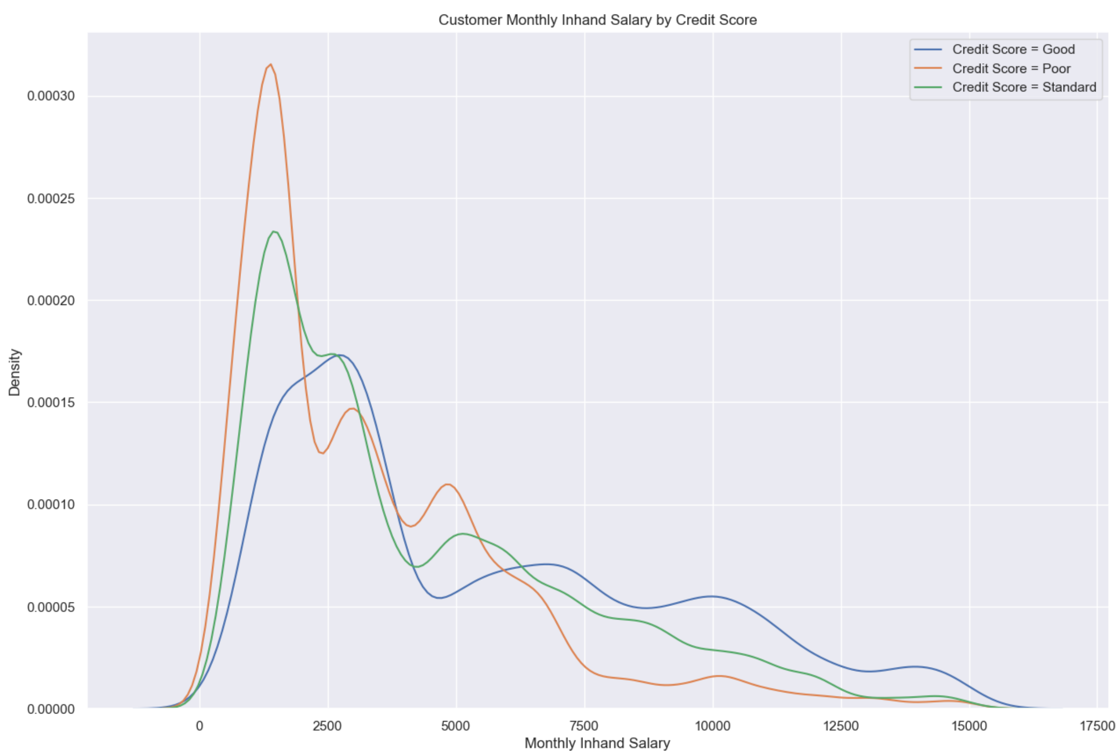


From the above graph, we can see that the distribution is right skewed and has a slight degree of skewness.

[903]:
```
#Monthly Inhand Salary distribution by Credit Score

grid = sns.FacetGrid(dataset, col = 'Credit_Score')
grid.map(sns.distplot, 'Monthly_Inhand_Salary')
plt.show()
```

```
[904]: # Merging the above graphs into one

sns.kdeplot(dataset['Monthly_Inhand_Salary'][dataset['Credit_Score'] ==␣
 ↪'Good'], label = 'Credit Score = Good')
sns.kdeplot(dataset['Monthly_Inhand_Salary'][dataset['Credit_Score'] ==␣
 ↪'Poor'], label = 'Credit Score = Poor')
sns.kdeplot(dataset['Monthly_Inhand_Salary'][dataset['Credit_Score'] ==␣
 ↪'Standard'], label = 'Credit Score = Standard')
plt.xlabel('Monthly Inhand Salary')
plt.legend()
plt.title('Customer Monthly Inhand Salary by Credit Score')
```

```
[904]: Text(0.5, 1.0, 'Customer Monthly Inhand Salary by Credit Score')
```

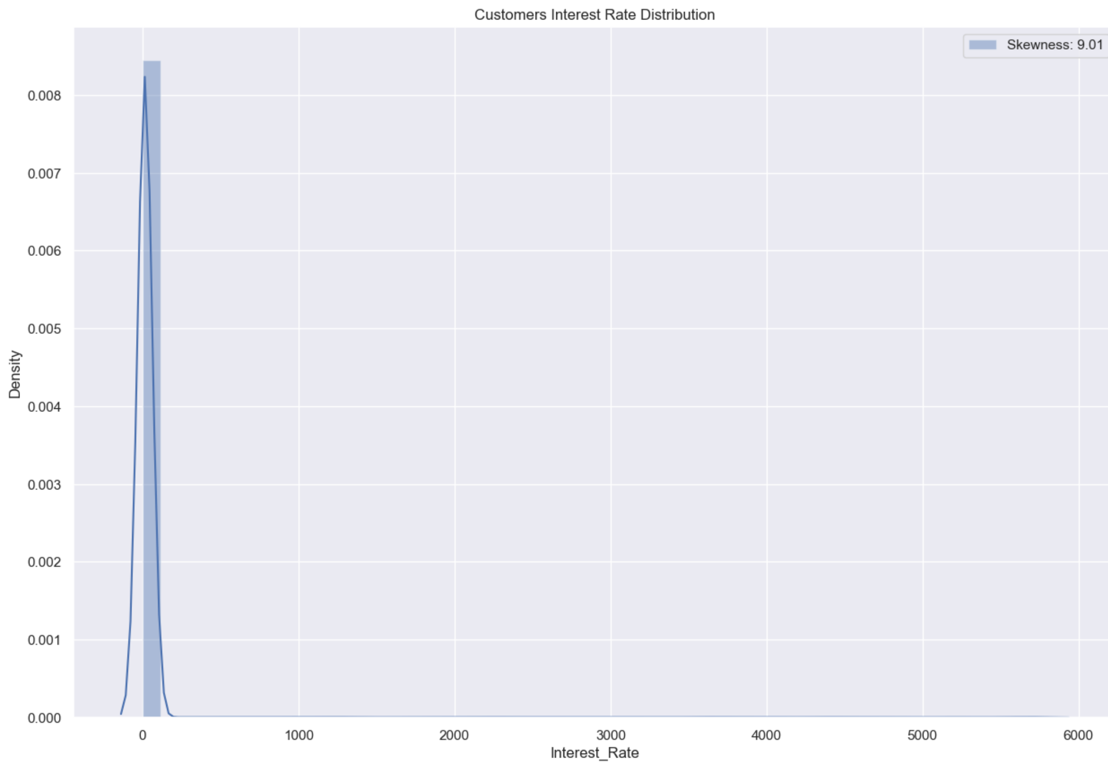


From the above graph, we can see that most of the customer's who have a Poor credit score have a low monthly inhand salary than compared to the customer's who have a Standard and a Good credit score.

```
[905]: #Numerical variable - Interest_Rate
#Understanding the distribution of the column - Interest_Rate
```

```
sns.distplot(dataset['Interest_Rate'], label = 'Skewness: %.
 ↪2f'%(dataset['Interest_Rate'].skew()))
plt.legend(loc = 'best')
plt.title('Customers Interest Rate Distribution')
```

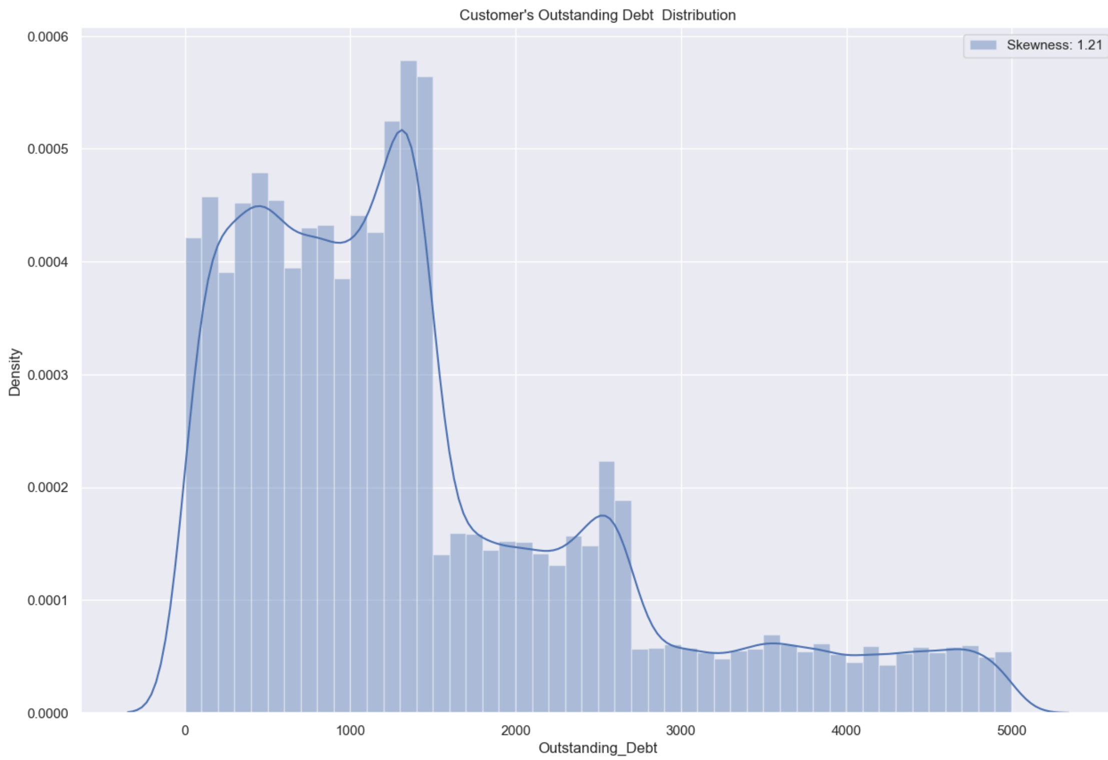
[905]: Text(0.5, 1.0, 'Customers Interest Rate Distribution')



From the above graph, we can see that the above graph has a high degree of skewness.

[906]:
```
#Numerical variable - Outstanding_Debt
#Understanding the distribution of the column - Outstanding_Debt

sns.distplot(dataset['Outstanding_Debt'], label = 'Skewness: %.
 ↪2f'%(dataset['Outstanding_Debt'].skew()))
plt.legend(loc = 'best')
plt.title("Customer's Outstanding Debt  Distribution")
```

[906]: Text(0.5, 1.0, "Customer's Outstanding Debt Distribution")



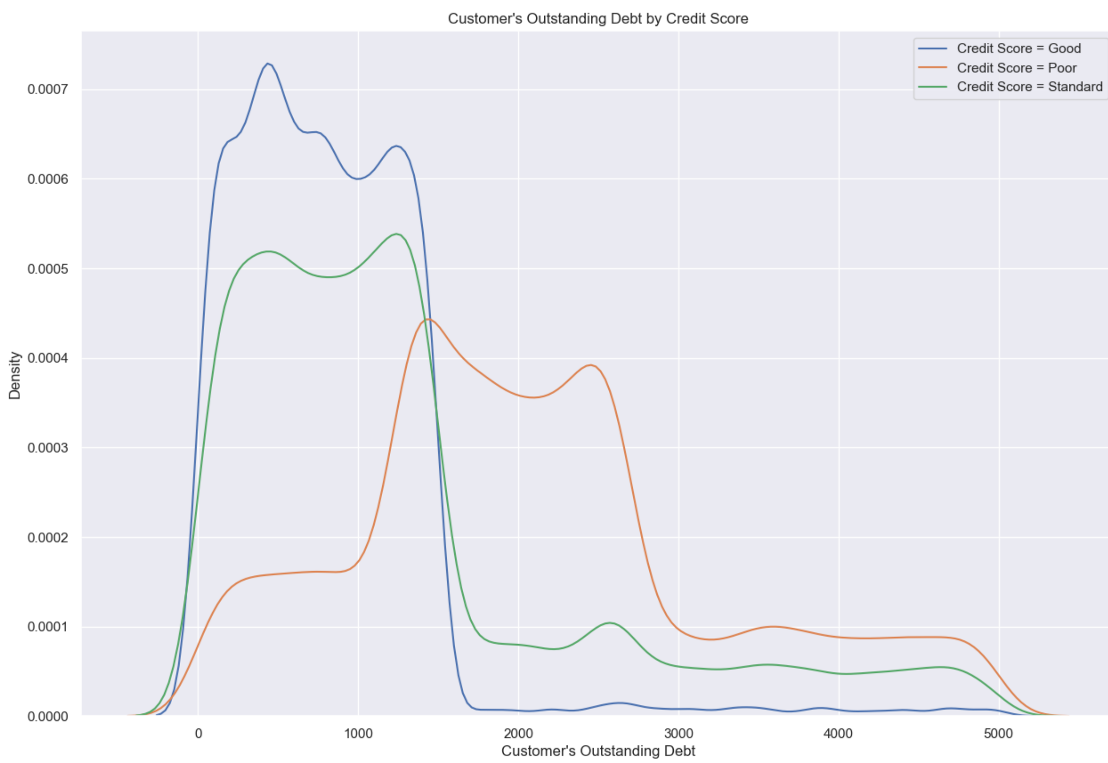
[907]:
```
#Outstanding Debt distribution by Credit Score

grid = sns.FacetGrid(dataset, col = 'Credit_Score')
grid.map(sns.distplot, 'Outstanding_Debt')
```

[907]: <seaborn.axisgrid.FacetGrid at 0x26d05dbd5a0>

[908]:
```
#Merging the above graphs into one
```

```
sns.kdeplot(dataset['Outstanding_Debt'][dataset['Credit_Score'] == 'Good'],␣
 ↪label = 'Credit Score = Good')
sns.kdeplot(dataset['Outstanding_Debt'][dataset['Credit_Score'] == 'Poor'],␣
 ↪label = 'Credit Score = Poor')
sns.kdeplot(dataset['Outstanding_Debt'][dataset['Credit_Score'] == 'Standard'],␣
 ↪label = 'Credit Score = Standard')
plt.xlabel("Customer's Outstanding Debt")
plt.legend()
plt.title("Customer's Outstanding Debt by Credit Score")
```

[908]: Text(0.5, 1.0, "Customer's Outstanding Debt by Credit Score")



From the above graph, we can see that customer's who have a Good credit score have very low outstanding debt than compared to the customer's who have Standard and Poor credit score.

Data preprocessing

[909]:
```
#Detect and remove outliers in numerical variables

def detect_outliers(df, n, features_list):
    outlier_indices = []
    for feature in features_list:
        Q1 = np.percentile(df[feature], 25)
```

```
        Q3 = np.percentile(df[feature], 75)
        IQR = Q3 - Q1
        outlier_step = 1.5 * IQR
        outlier_list_col = df[(df[feature] < Q1 - outlier_step) | (df[feature]␣
 ↪> Q3 + outlier_step)].index
        outlier_indices.extend(outlier_list_col)
    outlier_indices = Counter(outlier_indices)
    multiple_outliers = list(key for key, value in outlier_indices.items() if␣
 ↪value > n)
    return multiple_outliers

# List of numerical columns
numerical_columns = list(dataset.select_dtypes('number').columns)
print('Numerical columns: {}'.format(numerical_columns))

# Detect and drop outliers
outliers_to_drop = detect_outliers(dataset, 2, numerical_columns)
print("We will drop these {} indices: ".format(len(outliers_to_drop)),␣
 ↪outliers_to_drop)
```

```
Numerical columns: ['Age', 'Annual_Income', 'Monthly_Inhand_Salary',
'Num_Bank_Accounts', 'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan',
'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Limit',
'Num_Credit_Inquiries', 'Outstanding_Debt', 'Credit_Utilization_Ratio',
'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance']
We will drop these 484 indices:  [1293, 2902, 3189, 3690, 7036, 7882, 8558,
8660, 9736, 9879, 10840, 12673, 13036, 13486, 15026, 17379, 17827, 18004, 18349,
20250, 20537, 20538, 22612, 24240, 24736, 25123, 25603, 25878, 25923, 27836,
27875, 28278, 30249, 31288, 31399, 31985, 33553, 34160, 34565, 34582, 35270,
35783, 36015, 36053, 36855, 36985, 37534, 39169, 39393, 41557, 41749, 43050,
44633, 44634, 45410, 46737, 47961, 48455, 48536, 48794, 50233, 51828, 53352,
54009, 54030, 56161, 56166, 58772, 59049, 60088, 60659, 61146, 61938, 62054,
63816, 64165, 65928, 68449, 68810, 69041, 73756, 76155, 77767, 78865, 78900,
81038, 81041, 82992, 83102, 84577, 85316, 86615, 88487, 91181, 91920, 92783,
92874, 95054, 95268, 95782, 96236, 96522, 97348, 98139, 99124, 420, 2355, 2358,
3015, 3688, 3829, 4650, 7693, 8690, 8743, 8798, 9180, 9382, 10026, 12492, 13262,
17382, 19586, 24739, 26600, 26604, 28350, 29884, 30437, 30451, 30637, 32218,
32223, 34437, 34560, 35411, 35413, 35475, 35478, 36201, 37374, 37529, 37941,
41727, 42637, 42953, 42957, 44404, 46864, 47178, 49382, 52396, 53280, 53353,
54480, 56256, 56582, 56583, 60820, 62954, 66458, 72982, 73772, 74433, 74435,
75734, 75822, 77135, 78918, 79379, 80650, 81963, 82995, 87826, 88481, 89194,
90032, 92877, 94963, 94964, 94967, 2137, 2174, 2806, 5216, 8557, 13913, 14825,
15831, 23303, 27838, 29593, 31290, 39769, 39771, 40196, 45395, 46491, 55560,
59048, 60638, 70729, 70731, 70734, 84293, 84430, 86457, 90236, 90770, 97427,
97796, 3178, 3759, 4769, 6154, 8740, 9321, 9737, 10956, 13054, 14417, 19301,
21666, 22161, 25935, 26337, 27554, 29131, 29307, 29694, 30227, 32053, 32080,
32184, 33339, 34748, 36285, 37470, 37522, 38147, 38199, 38363, 39170, 39247,
```

```
39727, 42485, 43508, 44390, 45768, 48486, 51107, 53051, 53553, 54025, 56425,
60172, 60865, 60910, 63003, 67208, 69486, 70019, 73486, 73991, 76156, 76443,
84853, 86555, 89685, 95206, 95424, 96051, 98083, 345, 2299, 2609, 3689, 3756,
7032, 10470, 12668, 12670, 13458, 17880, 22121, 27556, 28775, 29149, 29309,
30230, 30253, 44419, 48454, 51106, 51163, 56429, 57287, 60093, 63529, 64167,
66830, 68926, 69369, 75083, 76435, 77220, 77918, 79035, 81711, 92878, 97297,
2614, 2755, 3693, 4471, 4649, 4652, 6226, 6534, 9322, 10815, 12702, 13482,
14831, 15481, 17956, 18191, 28768, 29594, 30760, 31682, 35104, 36852, 37375,
38104, 38720, 38727, 39172, 39174, 40530, 41723, 50711, 54947, 58172, 59202,
63380, 64697, 68057, 72546, 76438, 76446, 80953, 84291, 84951, 85313, 86552,
89607, 92876, 95518, 96587, 97798, 98143, 98627, 98927, 99403, 99853, 584, 585,
586, 587, 588, 589, 590, 591, 8554, 12696, 12697, 12698, 12699, 12700, 12701,
12703, 15177, 20681, 26832, 27557, 29596, 30248, 30768, 31687, 35105, 35914,
35918, 36280, 36281, 36282, 36283, 36284, 36286, 36287, 37087, 40534, 41559,
42970, 42971, 42972, 42973, 42975, 43448, 43449, 43450, 43451, 43452, 43453,
43454, 43455, 46736, 46738, 46739, 46740, 46741, 46742, 47177, 47183, 54031,
56426, 57255, 59928, 59929, 59930, 59931, 59932, 59933, 59934, 59935, 65934,
66461, 67209, 68061, 70252, 70253, 70254, 70255, 71368, 71370, 71372, 71375,
72085, 72903, 78482, 78912, 78913, 78914, 78915, 78916, 78917, 78919, 79910,
81375, 86554, 86925, 86927, 96842, 96846, 99168, 99169, 99170, 99171, 99173,
99174, 99175, 1478, 2898, 2899, 13053, 28661, 39168, 95517, 96584, 96585, 96586,
96589, 96590, 96591]
```

Now let's look at the data present in the rows.

[910]:
```
dataset.iloc[outliers_to_drop, :]
```

[910]:
```
            ID Customer_ID     Month          Name     Age          SSN  \
1293    0x1d93   CUS_0xb9ea      June  Aileen Wangy  2744.0  202-04-9323
2902    0x2700   CUS_0x67ff      July       Barlyni  7992.0  017-88-1687
3189    0x28af   CUS_0x3fa8      June        Kumarp   471.0  283-56-6375
3690    0x2ba0   CUS_0x29b2     March     Martinnet  1170.0  626-80-0791
7036    0x3f3a   CUS_0x3949       May        Scotto  6520.0  908-89-0498
…          …          …        …           …       …         …
96585  0x24bef   CUS_0xbe4d  February  Breidthardtb    27.0  676-67-1298
96586  0x24bf0   CUS_0xbe4d     March  Breidthardtb    27.0  676-67-1298
96589  0x24bf3   CUS_0xbe4d      June           NaN    27.0  676-67-1298
96590  0x24bf4   CUS_0xbe4d      July  Breidthardtb    27.0  676-67-1298
96591  0x24bf5   CUS_0xbe4d    August  Breidthardtb    27.0  676-67-1298

          Occupation  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
1293          Writer       9133.045                    NaN                  6
2902         Manager      82700.320            6625.693333                  8
3189          Writer     177243.920           14526.326667                  4
3690   Media_Manager      59930.040            5207.170000                  7
7036        Musician      63353.680            5356.473333                  9
…                …             …                    …                …
96585   Entrepreneur      71738.160            5820.180000                  7
```

```
96586   Entrepreneur     71738.160             NaN                  7
96589   Entrepreneur     71738.160     5820.180000                  7
96590   Entrepreneur     71738.160     5820.180000                  7
96591   Entrepreneur     71738.160     5820.180000                  7

       …  Credit_Mix  Outstanding_Debt  Credit_Utilization_Ratio  \
1293   …         Bad           3035.88                 36.669441
2902   …         Bad           4659.60                 39.950138
3189   …        Good            488.95                 37.041853
3690   …         Bad           4474.29                 32.303684
7036   …         Bad           4362.52                 31.463332
…    …           …                 …                         …
96585  …         Bad           4320.49                 28.977497
96586  …         Bad           4320.49                 24.809802
96589  …         Bad           4320.49                 29.395568
96590  …           _           4320.49                 26.766928
96591  …           _           4320.49                 35.354489

          Credit_History_Age  Payment_of_Min_Amount  Total_EMI_per_month  \
1293    9 Years and 4 Months                    Yes         77767.000000
2902   12 Years and 1 Months                    Yes           392.114333
3189   28 Years and 9 Months                     NM           284.804197
3690   1 Years and 11 Months                    Yes           156.596164
7036    1 Years and 2 Months                     NM           390.451288
…                        …                    …                  …
96585   5 Years and 4 Months                    Yes           446.366715
96586   5 Years and 5 Months                    Yes           446.366715
96589   5 Years and 8 Months                    Yes           446.366715
96590   5 Years and 9 Months                    Yes           446.366715
96591  5 Years and 10 Months                    Yes           446.366715

       Amount_invested_monthly                 Payment_Behaviour  \
1293                 48.454512                            !@9#%8
2902              10000.000000  High_spent_Medium_value_payments
3189                485.387942                            !@9#%8
3690                165.383895  High_spent_Medium_value_payments
7036                233.035327    Low_spent_Large_value_payments
…                       …                               …
96585               118.788667  High_spent_Medium_value_payments
96586               287.084007   Low_spent_Medium_value_payments
96589               545.426595    Low_spent_Small_value_payments
96590               168.901072  High_spent_Medium_value_payments
96591               285.547536    Low_spent_Large_value_payments

      Monthly_Balance  Credit_Score
1293       269.053164          Good
2902       372.265534          Poor
```

```
3189        942.440528      Standard
3690        448.736941      Standard
7036        182.160718      Standard
…                …           …
96585       266.862618      Standard
96586       128.567278          Poor
96589              NaN          Poor
96590       216.750214          Poor
96591       120.103749      Standard

[484 rows x 28 columns]
```

We will drop these rows from the dataset.

[911]:
```python
#Drop outliers and reset index

print("Before: {} rows".format(len(dataset)))
dataset = dataset.drop(outliers_to_drop, axis = 0).reset_index(drop = True)
print("After: {} rows".format(len(dataset)))
```

```
Before: 100000 rows
After: 99516 rows
```

[912]:
```python
#Lets look at the new dataset

dataset
```

[912]:
```
            ID Customer_ID     Month           Name    Age          SSN  \
0       0x1602   CUS_0xd40   January  Aaron Maashoh   23.0  821-00-0265
1       0x1603   CUS_0xd40  February  Aaron Maashoh   23.0  821-00-0265
2       0x1604   CUS_0xd40     March  Aaron Maashoh -500.0  821-00-0265
3       0x1605   CUS_0xd40     April  Aaron Maashoh   23.0  821-00-0265
4       0x1606   CUS_0xd40       May  Aaron Maashoh   23.0  821-00-0265
…          …         …        …              …      …          …
99511  0x25fe9  CUS_0x942c     April          Nicks   25.0  078-73-5990
99512  0x25fea  CUS_0x942c       May          Nicks   25.0  078-73-5990
99513  0x25feb  CUS_0x942c      June          Nicks   25.0  078-73-5990
99514  0x25fec  CUS_0x942c      July          Nicks   25.0  078-73-5990
99515  0x25fed  CUS_0x942c    August          Nicks   25.0  078-73-5990

      Occupation  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0      Scientist       19114.12            1824.843333                  3
1      Scientist       19114.12                    NaN                  3
2      Scientist       19114.12                    NaN                  3
3      Scientist       19114.12                    NaN                  3
4      Scientist       19114.12            1824.843333                  3
…          …             …                      …                 …
99511   Mechanic       39628.99            3359.415833                  4
```

```
99512   Mechanic       39628.99            3359.415833                  4
99513   Mechanic       39628.99            3359.415833                  4
99514   Mechanic       39628.99            3359.415833                  4
99515   Mechanic       39628.99            3359.415833                  4

       …  Credit_Mix  Outstanding_Debt  Credit_Utilization_Ratio  \
0      …           _            809.98                 26.822620
1      …        Good            809.98                 31.944960
2      …        Good            809.98                 28.609352
3      …        Good            809.98                 31.377862
4      …        Good            809.98                 24.797347
…    …          …               …                        …
99511  …           _            502.38                 34.663572
99512  …           _            502.38                 40.565631
99513  …        Good            502.38                 41.255522
99514  …        Good            502.38                 33.638208
99515  …        Good            502.38                 34.192463

          Credit_History_Age  Payment_of_Min_Amount  Total_EMI_per_month  \
0       22 Years and 1 Months                     No            49.574949
1                         NaN                     No            49.574949
2       22 Years and 3 Months                     No            49.574949
3       22 Years and 4 Months                     No            49.574949
4       22 Years and 5 Months                     No            49.574949
…                         …                    …                    …
99511   31 Years and 6 Months                     No            35.104023
99512   31 Years and 7 Months                     No            35.104023
99513   31 Years and 8 Months                     No            35.104023
99514   31 Years and 9 Months                     No            35.104023
99515  31 Years and 10 Months                     No            35.104023

       Amount_invested_monthly                 Payment_Behaviour  \
0                    80.415295   High_spent_Small_value_payments
1                   118.280222    Low_spent_Large_value_payments
2                    81.699521   Low_spent_Medium_value_payments
3                   199.458074    Low_spent_Small_value_payments
4                    41.420153  High_spent_Medium_value_payments
…                          …                                …
99511                60.971333   High_spent_Large_value_payments
99512                54.185950  High_spent_Medium_value_payments
99513                24.028477   High_spent_Large_value_payments
99514               251.672582    Low_spent_Large_value_payments
99515               167.163865                            !@9#%8

      Monthly_Balance  Credit_Score
0          312.494089          Good
1          284.629162          Good
```

```
2          331.209863          Good
3          223.451310          Good
4          341.489231          Good
…               …            …
99511      479.866228          Poor
99512      496.651610          Poor
99513      516.809083          Poor
99514      319.164979      Standard
99515      393.673696          Poor

[99516 rows x 28 columns]
```

Drop and fill missing values Here, we will drop the columns - ID, Customer_ID, Name, SSN, Credit_Mix, Num_of_Loan, Credit_Utilization_Ratio, Credit_History_Age, Payment_Behavior, Annual_Income, Monthly_Balance, Num_Bank_Accounts, Num_Credit_Card from the datasets.

[913]:
```
#Dropping the columns from the dataset

dataset.drop(['ID', 'Customer_ID', 'Name', 'SSN', 'Credit_Mix', 'Num_of_Loan',
             'Credit_Utilization_Ratio', 'Credit_History_Age',␣
 ↪'Payment_Behaviour',
             'Annual_Income', 'Monthly_Balance', 'Num_Bank_Accounts',␣
 ↪'Num_Credit_Card'], axis = 1, inplace = True)
dataset
```

[913]:
```
          Month    Age Occupation  Monthly_Inhand_Salary  Interest_Rate  \
0       January   23.0  Scientist            1824.843333              3
1      February   23.0  Scientist                    NaN              3
2         March -500.0  Scientist                    NaN              3
3         April   23.0  Scientist                    NaN              3
4           May   23.0  Scientist            1824.843333              3
…           …    …      …                     …            …
99511     April   25.0   Mechanic            3359.415833              7
99512       May   25.0   Mechanic            3359.415833              7
99513      June   25.0   Mechanic            3359.415833           5729
99514      July   25.0   Mechanic            3359.415833              7
99515    August   25.0   Mechanic            3359.415833              7

                                           Type_of_Loan  Delay_from_due_date  \
0      Auto Loan, Credit-Builder Loan, Personal Loan,…                    3
1      Auto Loan, Credit-Builder Loan, Personal Loan,…                   -1
2      Auto Loan, Credit-Builder Loan, Personal Loan,…                    3
3      Auto Loan, Credit-Builder Loan, Personal Loan,…                    5
4      Auto Loan, Credit-Builder Loan, Personal Loan,…                    6
…                                                  …                  …
99511                         Auto Loan, and Student Loan                   23
```

```
99512                        Auto Loan, and Student Loan                      18
99513                        Auto Loan, and Student Loan                      27
99514                        Auto Loan, and Student Loan                      20
99515                        Auto Loan, and Student Loan                      18

       Num_of_Delayed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries  \
0                         7.0                 11.27                   4.0
1                         NaN                 11.27                   4.0
2                         7.0                  0.00                   4.0
3                         4.0                  6.27                   4.0
4                         NaN                 11.27                   4.0
…                         …                    …                     …
99511                     7.0                 11.50                   3.0
99512                     7.0                 11.50                   3.0
99513                     6.0                 11.50                   3.0
99514                     NaN                 11.50                   3.0
99515                     6.0                 11.50                   3.0

       Outstanding_Debt Payment_of_Min_Amount  Total_EMI_per_month  \
0                809.98                    No            49.574949
1                809.98                    No            49.574949
2                809.98                    No            49.574949
3                809.98                    No            49.574949
4                809.98                    No            49.574949
…                 …                    …                    …
99511            502.38                    No            35.104023
99512            502.38                    No            35.104023
99513            502.38                    No            35.104023
99514            502.38                    No            35.104023
99515            502.38                    No            35.104023

       Amount_invested_monthly Credit_Score
0                    80.415295         Good
1                   118.280222         Good
2                    81.699521         Good
3                   199.458074         Good
4                    41.420153         Good
…                        …           …
99511                60.971333         Poor
99512                54.185950         Poor
99513                24.028477         Poor
99514               251.672582     Standard
99515               167.163865         Poor

[99516 rows x 15 columns]
```

[914]:
```
#Looking at the missing values in the dataset

dataset.isnull().sum().sort_values(ascending = False)
```

[914]:
```
Monthly_Inhand_Salary      14931
Type_of_Loan               11392
Num_of_Delayed_Payment      6972
Amount_invested_monthly     4452
Num_Credit_Inquiries        1949
Month                          0
Age                            0
Occupation                     0
Interest_Rate                  0
Delay_from_due_date            0
Changed_Credit_Limit           0
Outstanding_Debt               0
Payment_of_Min_Amount          0
Total_EMI_per_month            0
Credit_Score                   0
dtype: int64
```

From the above data, we can see that there are missing values in the columns - Monthly_Inhand_Salary, Type_of_Loan, Num_of_Delayed_Payment, Amount_invested_monthly, Num_Credit_Inquiries. Here, we will focus on removing the missing values in the columns - Monthly_Inhand_Salary, Num_of_Delayed_Payment, Amount_invested_monthly, and Num_Credit_Inquiries. However, we will replace the missing values in the column - Type_of_Loan in the Feature Engineering section.

Here, for replacing the missing values in the column - Monthly_Inhand_Salary, we will use the column Credit_Score and find the mean of the salary based on the Credit Score.

[921]:
```
#Handling missing values - Monthly_Inhand_Salary
#Finding the mean value of the column - Monthly_Inhand_Salary in the dataset␣
↪using Credit_Score

salary_good_mean = np.mean(dataset[dataset['Credit_Score'] ==␣
↪'Good']['Monthly_Inhand_Salary'])
salary_poor_mean = np.mean(dataset[dataset['Credit_Score'] ==␣
↪'Poor']['Monthly_Inhand_Salary'])
salary_standard_mean = np.mean(dataset[dataset['Credit_Score'] ==␣
↪'Standard']['Monthly_Inhand_Salary'])

(salary_good_mean, salary_poor_mean, salary_standard_mean)
```

[921]:
```
(5379.965723477946, 3371.847702514712, 4238.79360473507)
```

[922]:
```
#Finding the indices of the rows where Monthly_Inhand_Salary is null
index_values = dataset['Monthly_Inhand_Salary'].isnull()
```

[923]:
```python
#Replacing the missing values in the column Monthly_Inhand_Salary using the
↪decision logic
for index in range(len(dataset)):
    if index_values[index]:
        if dataset['Credit_Score'][index] == 'Good':
            dataset.loc[index, 'Monthly_Inhand_Salary'] = salary_good_mean
        elif dataset['Credit_Score'][index] == 'Poor':
            dataset.loc[index, 'Monthly_Inhand_Salary'] = salary_poor_mean
        else:
            dataset.loc[index, 'Monthly_Inhand_Salary'] = salary_standard_mean
```

[924]:
```python
#Checking if there are any missing values of Monthly_Inhand_Salary in the
↪dataset

dataset['Monthly_Inhand_Salary'].isnull().sum()
```

[924]: 0

Here, we will use the median to replace the missing values in the column - Num_of_Delayed_Payment.

[925]:
```python
#Handling missing values - Num_of_Delayed_Payment
#Finding the median value of the column - Num_of_Delayed_Payment in the dataset

payment_index = list(~dataset['Num_of_Delayed_Payment'].isnull())
median_payment = np.median(dataset['Num_of_Delayed_Payment'].loc[payment_index])
median_payment
```

[925]: 14.0

[926]:
```python
#Replacing the missing values of the column - Num_of_Delayed_Payment in the
↪dataset
dataset['Num_of_Delayed_Payment'].fillna(median_payment, inplace = True)
```

[927]:
```python
#Checking if there are any missing values of Num_of_Delayed_Payment in the
↪dataset
dataset['Num_of_Delayed_Payment'].isnull().sum()
```

[927]: 0

Here, we will use the median to replace the missing values in the column - Amount_invested_monthly.

[928]:
```python
#Handling missing values - Amount_invested_monthly
#Finding the median value of the column - Amount_invested_monthly in the dataset

amount_index = list(~dataset['Amount_invested_monthly'].isnull())
median_amount = np.median(dataset['Amount_invested_monthly'].loc[amount_index])
```

```
median_amount
```

[928]: 135.91926936353195

[929]:
```
#Replacing the missing values of the column - Amount_invested_monthly in the
↪dataset

dataset['Amount_invested_monthly'].fillna(median_amount, inplace = True)
```

[930]:
```
#Checking if there are any missing values of Amount_invested_monthly in the
↪dataset

dataset['Amount_invested_monthly'].isnull().sum()
```

[930]: 0

Here, we will use the median to replace the missing values in the column - Num_Credit_Inquiries.

[931]:
```
#Handling missing values - Num_Credit_Inquiries
#Finding the median value of the column - Num_Credit_Inquiries in the dataset

inquiries_index = list(~dataset['Num_Credit_Inquiries'].isnull())
median_inquiries = np.median(dataset['Num_Credit_Inquiries'].
↪loc[inquiries_index])
median_inquiries
```

[931]: 6.0

[932]:
```
#Replacing the missing values of the column - Num_Credit_Inquiries in the
↪dataset

dataset['Num_Credit_Inquiries'].fillna(median_inquiries, inplace = True)
```

[933]:
```
#Checking if there are any missing values of Num_Credit_Inquiries in the dataset

dataset['Num_Credit_Inquiries'].isnull().sum()
```

[933]: 0

[934]:
```
#Looking if the dataset has any more missing values apart from Type_of_Loan

dataset.isnull().sum().sort_values(ascending = False)
```

[934]:
```
Type_of_Loan              11392
Month                         0
Age                           0
Occupation                    0
Monthly_Inhand_Salary         0
```

```
Interest_Rate                0
Delay_from_due_date          0
Num_of_Delayed_Payment       0
Changed_Credit_Limit         0
Num_Credit_Inquiries         0
Outstanding_Debt             0
Payment_of_Min_Amount        0
Total_EMI_per_month          0
Amount_invested_monthly      0
Credit_Score                 0
dtype: int64
```

4.Data Engineering

Here, we will create 8 different columns using the loan_type_dict dictionary. Here, we will not consider the value Not Specified for the loan type.

In Data engineering, new features are added to the dataset. This includes changing 'Month', 'Occupation', and 'Payment_of_Min_Amount' into a format that can easily work. The 'Type_of_Loan' is split into several simpler columns, each indicating a specific type of loan. Also, to make the model learn better, some of the numbers in the dataset are adjusted using log transformations to make their distribution more even.

[935]:
```
loan_type_dict
```

[935]:
```
{'Auto Loan': 37992,
 'Credit-Builder Loan': 40440,
 'Personal Loan': 38888,
 'Home Equity Loan': 39104,
 'Not Specified': 39616,
 'Mortgage Loan': 38936,
 'Student Loan': 38968,
 'Debt Consolidation Loan': 38776,
 'Payday Loan': 40568}
```

[936]:
```
#Individual columns for Type_of_Loan
#Creating 8 different lists for each loan type

auto_loan = [0] * (len(dataset))
credit_builder_loan = [0] * (len(dataset))
personal_loan = [0] * (len(dataset))
home_equity_loan = [0] * (len(dataset))
mortgage_loan = [0] * (len(dataset))
student_loan = [0] * (len(dataset))
debt_consolidation_loan = [0] * (len(dataset))
payday_loan = [0] * (len(dataset))
```

[937]:
```
# Using 0's and 1's if a customer has a particular loan
```

```python
for index in range(len(loan_type_data)):
    ### For Auto Loan
    if 'Auto' in loan_type_data[index]:
        auto_loan[index] = 1

    ### For Credit Builder Loan
    if 'Credit-Builder' in loan_type_data[index]:
        credit_builder_loan[index] = 1

    ### For Personal Loan
    if 'Personal' in loan_type_data[index]:
        personal_loan[index] = 1

    ### For Home Equity Loan
    if 'Home' in loan_type_data[index]:
        home_equity_loan[index] = 1

    ### For Mortgage Loan
    if 'Mortgage' in loan_type_data[index]:
        mortgage_loan[index] = 1

    ### For Student Loan
    if 'Student' in loan_type_data[index]:
        student_loan[index] = 1

    ### For Debt Consolidation loan
    if 'Debt' in loan_type_data[index]:
        debt_consolidation_loan[index] = 1

    ### For Payday loan
    if 'Payday' in loan_type_data[index]:
        payday_loan[index] = 1
```

[938]:

```python
#Adding the new columns to the dataset

dataset['Auto_Loan'] = auto_loan
dataset['Credit_Builder_Loan'] = credit_builder_loan
dataset['Personal_Loan'] = personal_loan
dataset['Home_Enquity_Loan'] = home_equity_loan
dataset['Mortgage_Loan'] = mortgage_loan
dataset['Student_Loan'] = student_loan
dataset['Debt_Consolidation_Loan'] = debt_consolidation_loan
dataset['Payday_Loan'] = payday_loan
```

[939]:

```python
#Removing the column - Type_of_loan

dataset.drop(['Type_of_Loan'], axis = 1, inplace = True)
```

[940]:
```
#Looking at the modified dataset

dataset
```

[940]:
```
           Month    Age Occupation  Monthly_Inhand_Salary  Interest_Rate  \
0        January   23.0  Scientist            1824.843333              3
1       February   23.0  Scientist            5379.965723              3
2          March -500.0  Scientist            5379.965723              3
3          April   23.0  Scientist            5379.965723              3
4            May   23.0  Scientist            1824.843333              3
…            …     …         …                    …             …
99511      April   25.0   Mechanic            3359.415833              7
99512        May   25.0   Mechanic            3359.415833              7
99513       June   25.0   Mechanic            3359.415833           5729
99514       July   25.0   Mechanic            3359.415833              7
99515     August   25.0   Mechanic            3359.415833              7

       Delay_from_due_date  Num_of_Delayed_Payment  Changed_Credit_Limit  \
0                        3                     7.0                 11.27
1                       -1                    14.0                 11.27
2                        3                     7.0                  0.00
3                        5                     4.0                  6.27
4                        6                    14.0                 11.27
…                      …                     …                   …
99511                   23                     7.0                 11.50
99512                   18                     7.0                 11.50
99513                   27                     6.0                 11.50
99514                   20                    14.0                 11.50
99515                   18                     6.0                 11.50

       Num_Credit_Inquiries  Outstanding_Debt  … Amount_invested_monthly  \
0                       4.0            809.98  …               80.415295
1                       4.0            809.98  …              118.280222
2                       4.0            809.98  …               81.699521
3                       4.0            809.98  …              199.458074
4                       4.0            809.98  …               41.420153
…                      …               …   …                  …
99511                   3.0            502.38  …               60.971333
99512                   3.0            502.38  …               54.185950
99513                   3.0            502.38  …               24.028477
99514                   3.0            502.38  …              251.672582
99515                   3.0            502.38  …              167.163865

       Credit_Score  Auto_Loan Credit_Builder_Loan  Personal_Loan  \
0              Good          1                   1              1
1              Good          1                   1              1
2              Good          1                   1              1
```

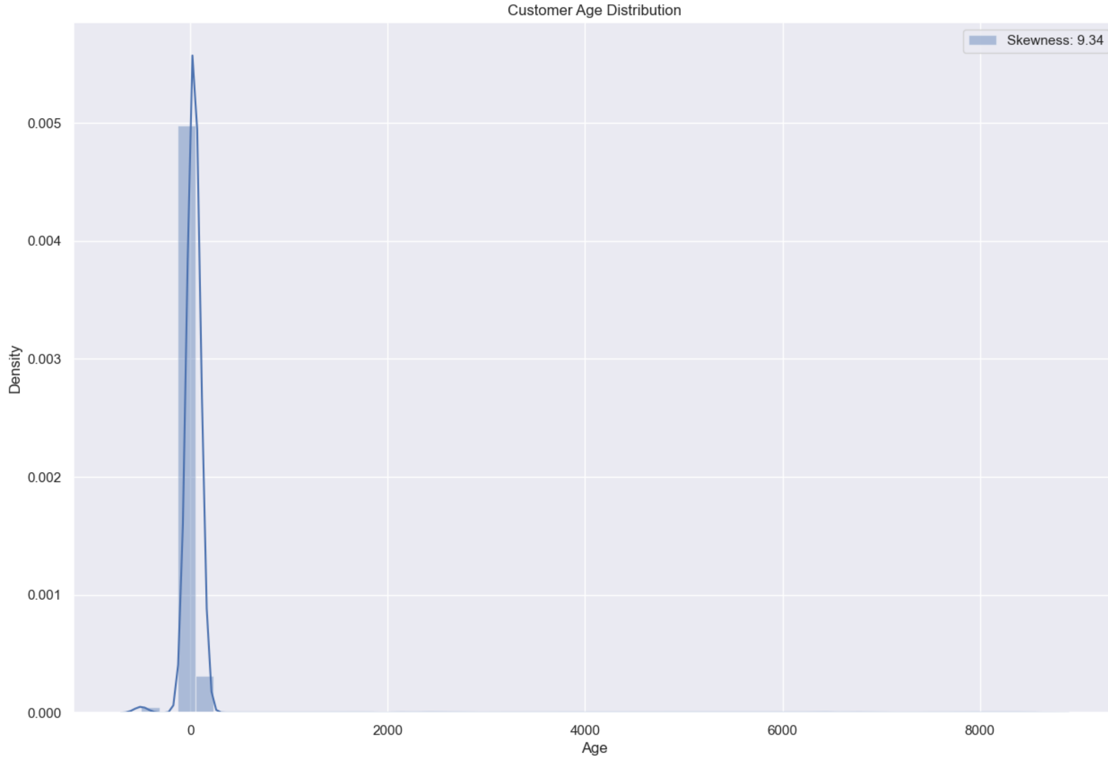
```
3              Good         1                    1              1
4              Good         1                    1              1
…                 …         …                    …              …
99511          Poor         0                    0              0
99512          Poor         0                    0              0
99513          Poor         0                    0              0
99514      Standard         0                    0              0
99515          Poor         0                    0              0

       Home_Enquity_Loan  Mortgage_Loan  Student_Loan  \
0                      1              0             0
1                      1              0             0
2                      1              0             0
3                      1              0             0
4                      1              0             0
…                      …              …             …
99511                  0              0             0
99512                  0              0             0
99513                  0              0             0
99514                  0              0             0
99515                  0              0             0

       Debt_Consolidation_Loan  Payday_Loan
0                            0            0
1                            0            0
2                            0            0
3                            0            0
4                            0            0
…                            …            …
99511                        0            0
99512                        0            0
99513                        0            0
99514                        0            0
99515                        0            0

[99516 rows x 22 columns]
```

[941]:

```
#Log Transforming the column - Age
#Understanding the distribution of the column - Age

sns.distplot(dataset['Age'], label = 'Skewness: %.2f'%(dataset['Age'].skew()))
plt.legend(loc = 'best')
plt.title('Customer Age Distribution')
```

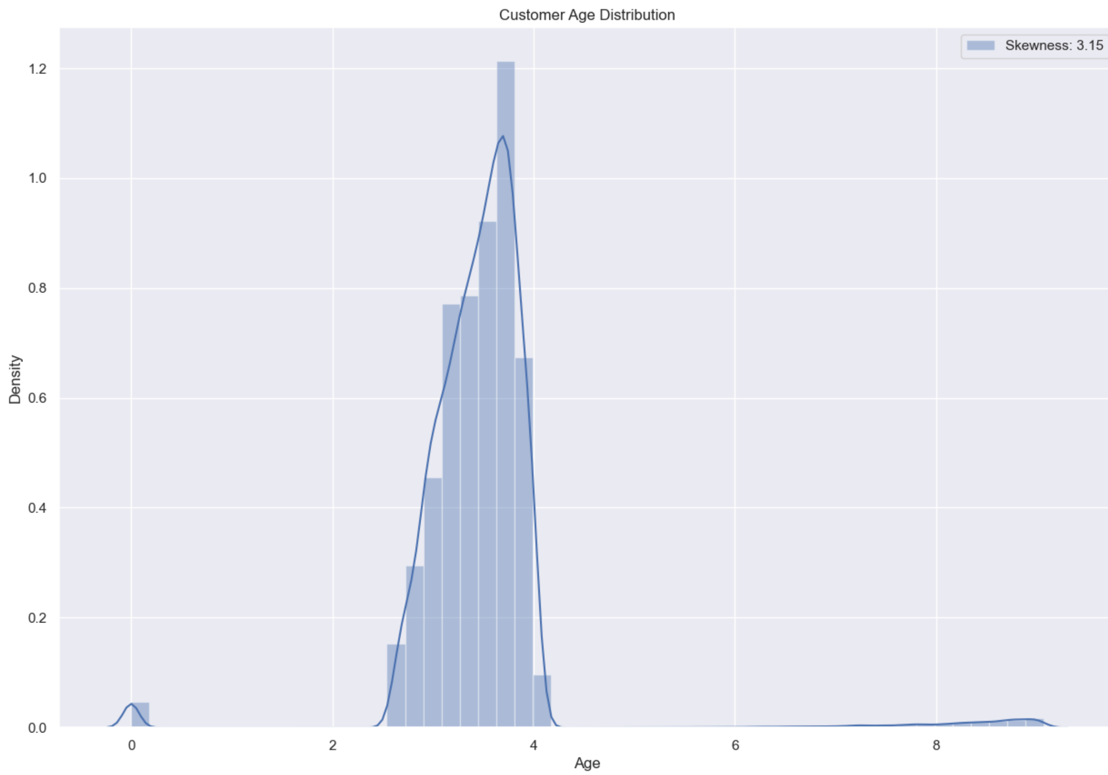
[941]:

```
Text(0.5, 1.0, 'Customer Age Distribution')
```



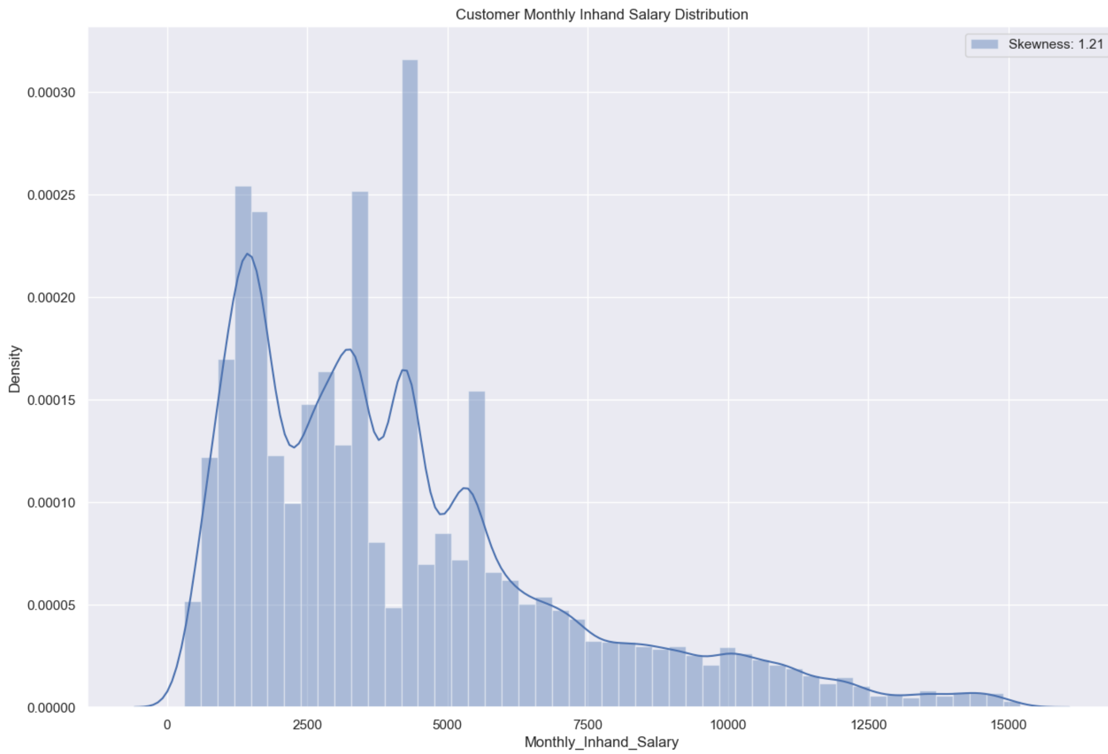
[942]:
```
#Understanding the distribution of the data log(Age)

modified_age = [np.log(age) if age > 0 else 0 for age in dataset['Age']]
dataset['Age'] = modified_age

sns.distplot(dataset['Age'], label = 'Skewness: %.2f'%(dataset['Age'].skew()))
plt.legend(loc = 'best')
plt.title('Customer Age Distribution')
```

[942]: Text(0.5, 1.0, 'Customer Age Distribution')



[943]:
```
#Log Transforming the column - Monthly_Inhand_Salary
#Understanding the distribution of the column - Monthly_Inhand_Salary

sns.distplot(dataset['Monthly_Inhand_Salary'], label = 'Skewness: %.
 ↪2f'%(dataset['Monthly_Inhand_Salary'].skew()))
plt.legend(loc = 'best')
plt.title('Customer Monthly Inhand Salary Distribution')
```

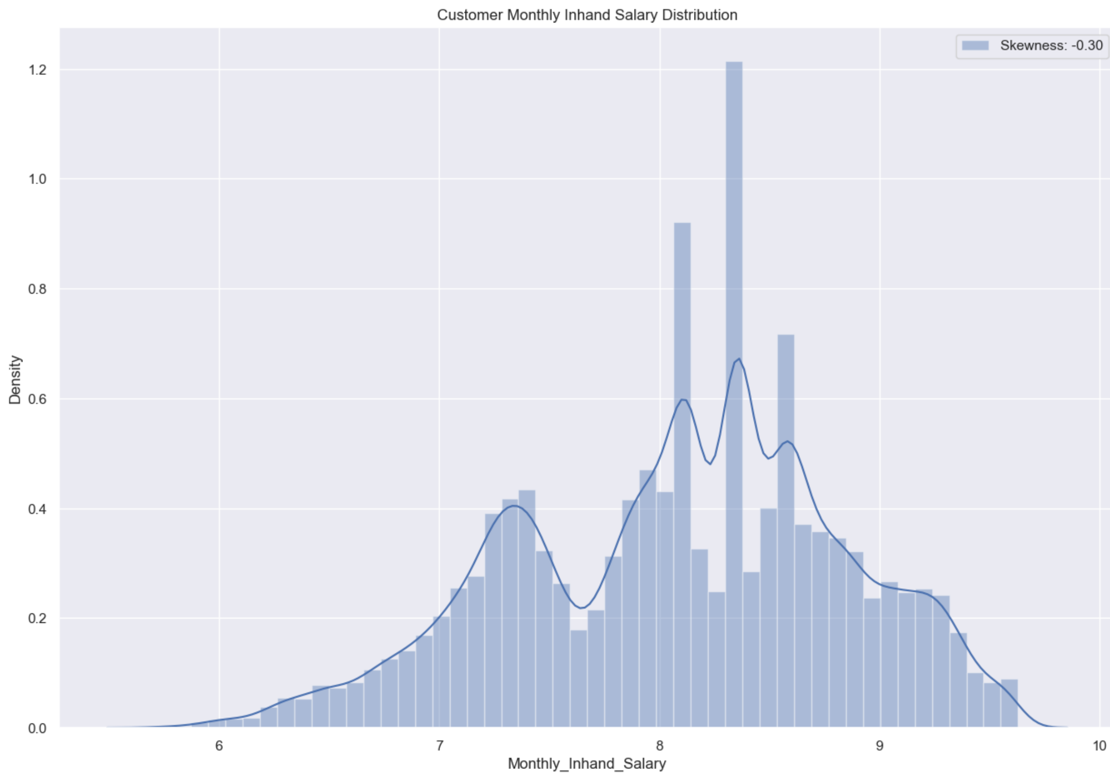
[943]: Text(0.5, 1.0, 'Customer Monthly Inhand Salary Distribution')



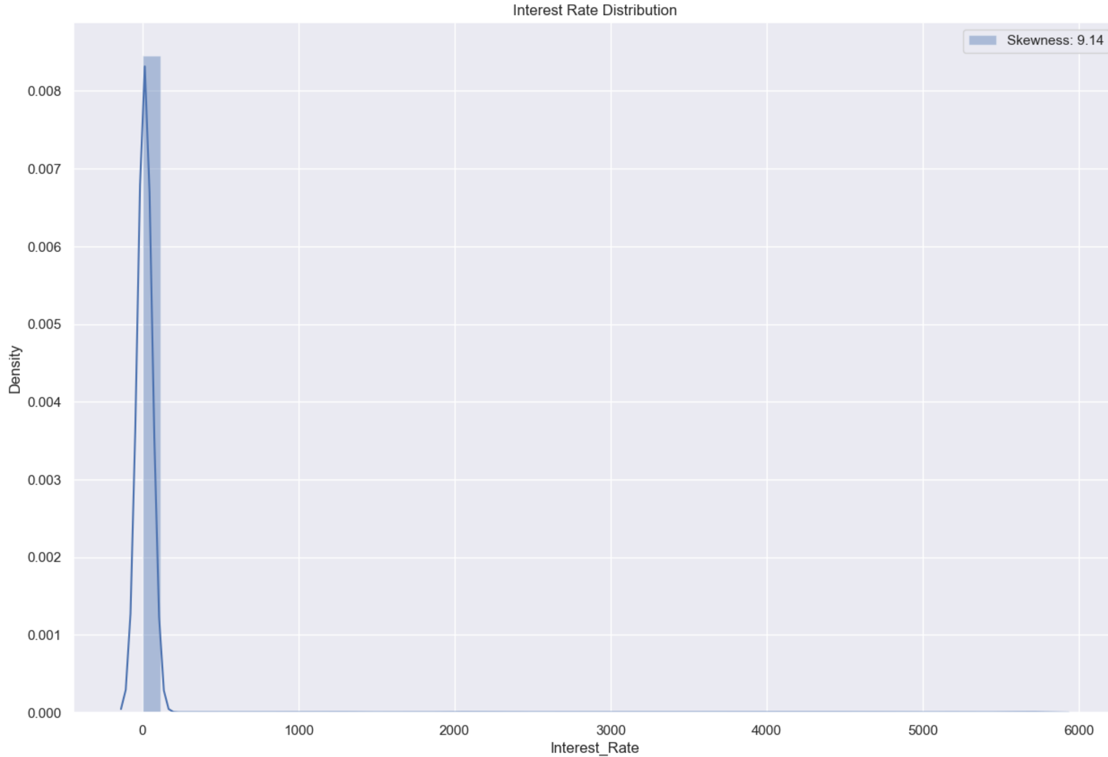
[944]:

```
#Understanding the distribution of the data log(Monthly_Inhand_Salary)

modified_salary = [np.log(salary) if salary > 0 else 0 for salary in␣
↪dataset['Monthly_Salary']]
dataset['Monthly_Inhand_Salary'] = modified_salary

sns.distplot(dataset['Monthly_Inhand_Salary'], label = 'Skewness: %.
↪2f'%(dataset['Monthly_Inhand_Salary'].skew()))
plt.legend(loc = 'best')
plt.title('Customer Monthly Inhand Salary Distribution')
```

[944]: Text(0.5, 1.0, 'Customer Monthly Inhand Salary Distribution')

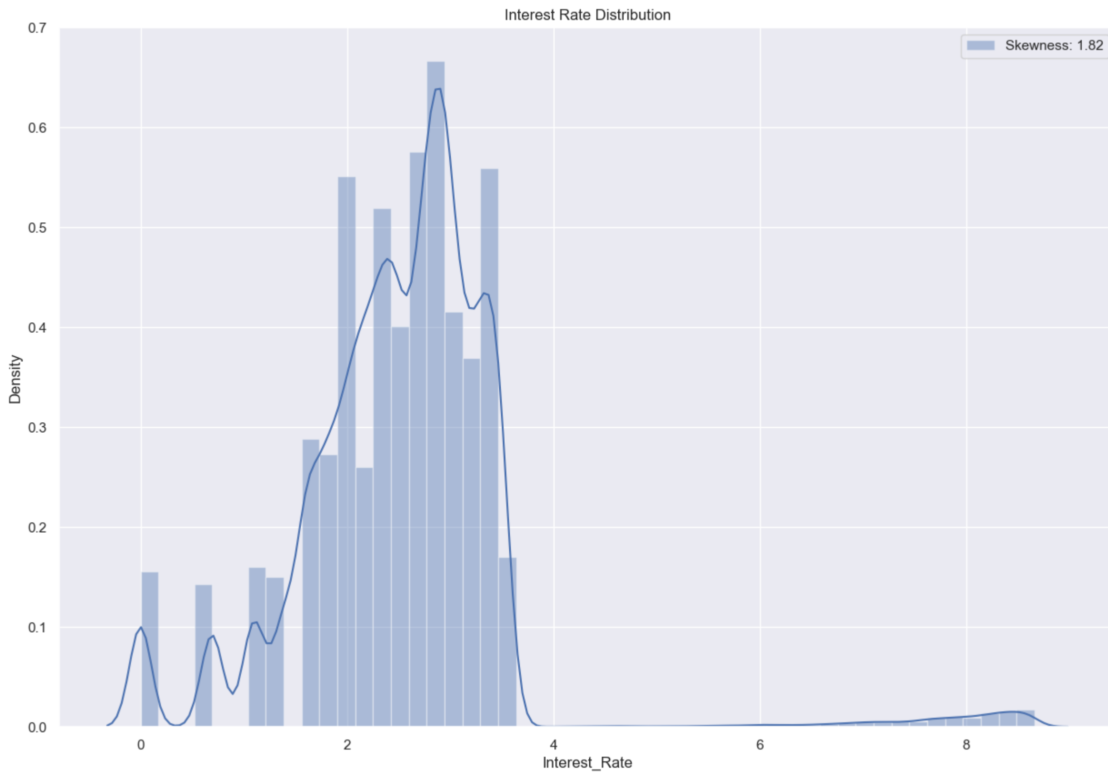



```
[945]: #Log Transforming the column - Interest_Rate
       #Understanding the distribution of the column - Interest_Rate

       sns.distplot(dataset['Interest_Rate'], label = 'Skewness: %.
        ↪2f'%(dataset['Interest_Rate'].skew()))
       plt.legend(loc = 'best')
       plt.title('Interest Rate Distribution')

[945]: Text(0.5, 1.0, 'Interest Rate Distribution')
```



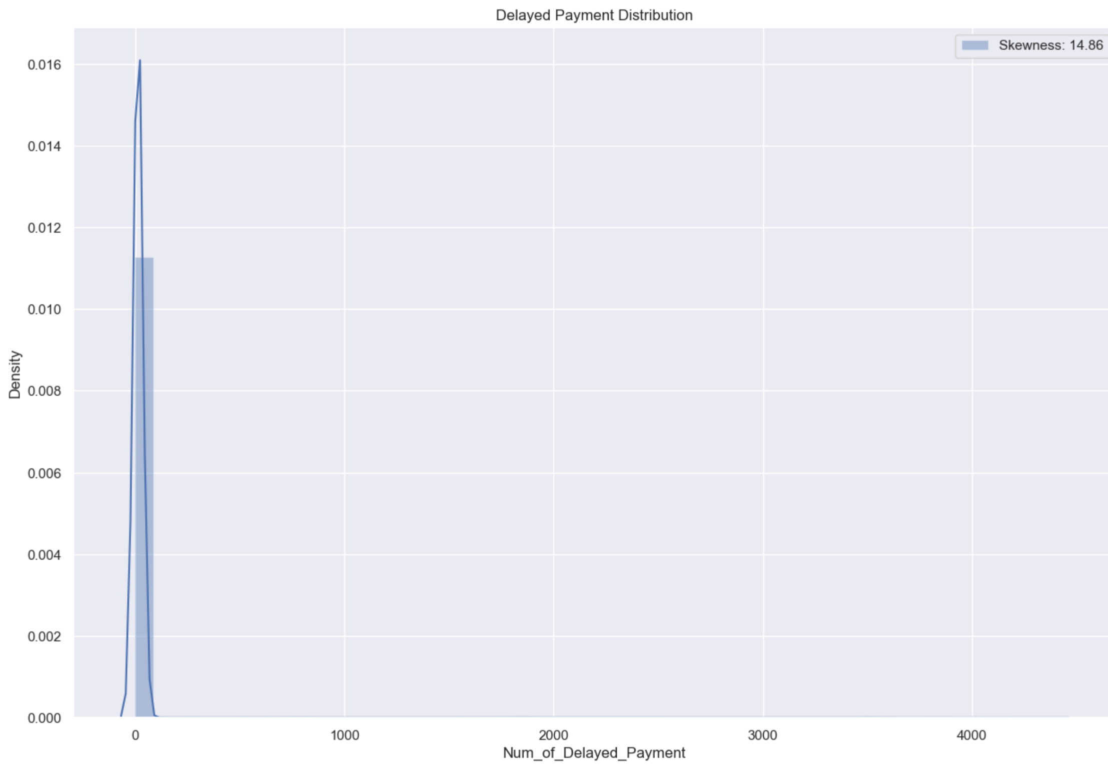
[946]:
```
#Understanding the distribution of the data log(Interest_Rate)

modified_interest = [np.log(interest) if interest > 0 else 0 for interest in␣
↪dataset['Interest_Rate']]
dataset['Interest_Rate'] = modified_interest

sns.distplot(dataset['Interest_Rate'], label = 'Skewness: %.
↪2f'%(dataset['Interest_Rate'].skew()))
plt.legend(loc = 'best')
plt.title('Interest Rate Distribution')
```

[946]:
```
Text(0.5, 1.0, 'Interest Rate Distribution')
```



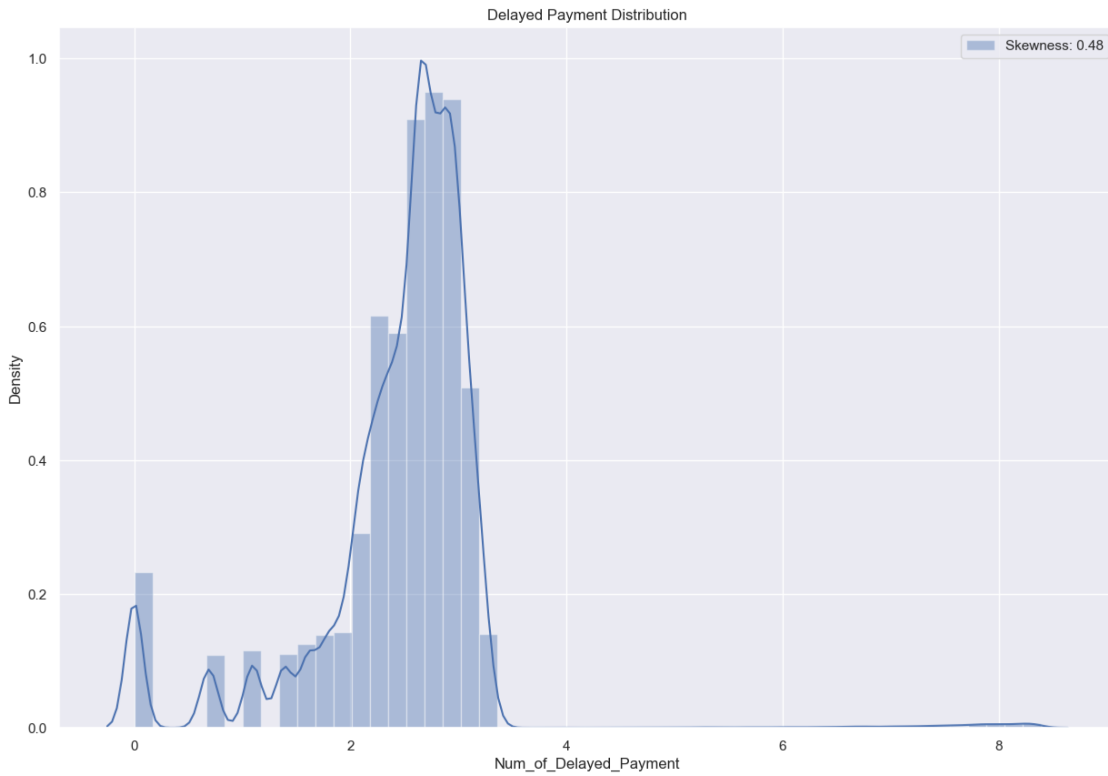
[947]:
```python
#Log Transforming the column - Num_of_Delayed_Payment
#Understanding the distribution of the column - Num_of_Delayed_Payment

sns.distplot(dataset['Num_of_Delayed_Payment'], label = 'Skewness: %.
↪2f'%(dataset['Num_of_Delayed_Payment'].skew()))
plt.legend(loc = 'best')
plt.title('Delayed Payment Distribution')
```

[947]: Text(0.5, 1.0, 'Delayed Payment Distribution')



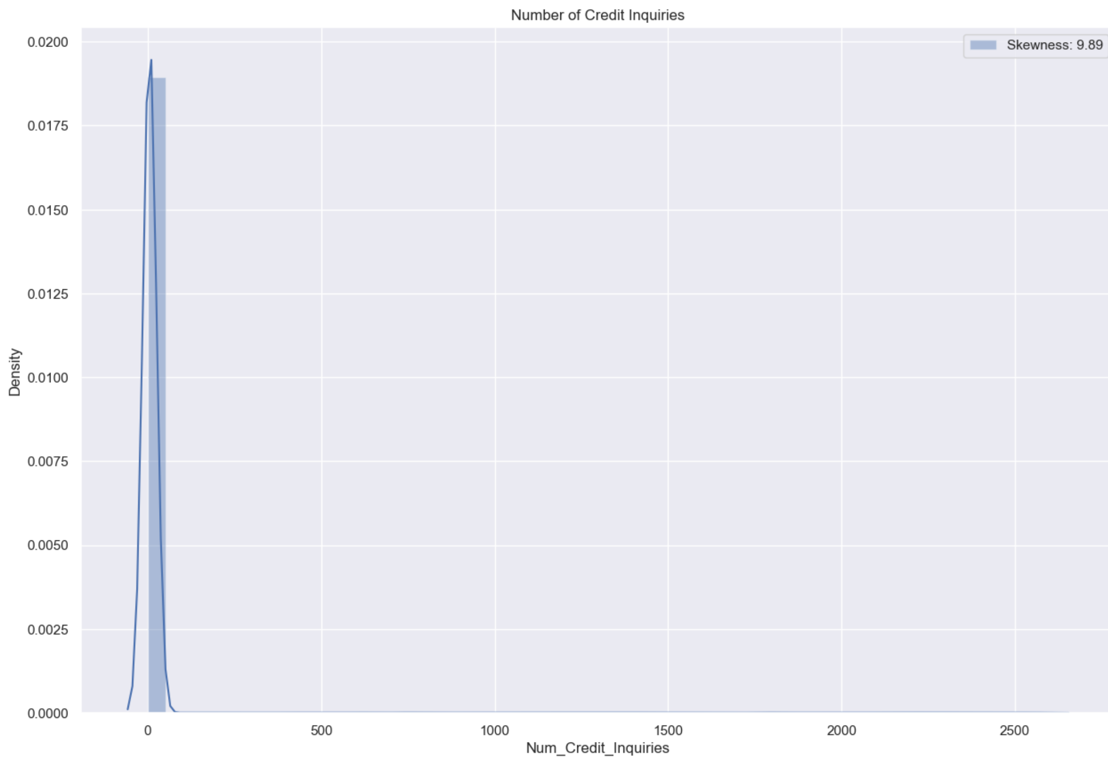
[948]:
```
#Understanding the distribution of the data log(Num_of_Delayed_Payment)

modified_payment = [np.log(payment) if payment > 0 else 0 for payment in␣
↪dataset['Num_of_Delayed_Payment']]
dataset['Num_of_Delayed_Payment'] = modified_payment

sns.distplot(dataset['Num_of_Delayed_Payment'], label = 'Skewness: %.
↪2f'%(dataset['Num_of_Delayed_Payment'].skew()))
plt.legend(loc = 'best')
plt.title('Delayed Payment Distribution')
```

[948]:
```
Text(0.5, 1.0, 'Delayed Payment Distribution')
```



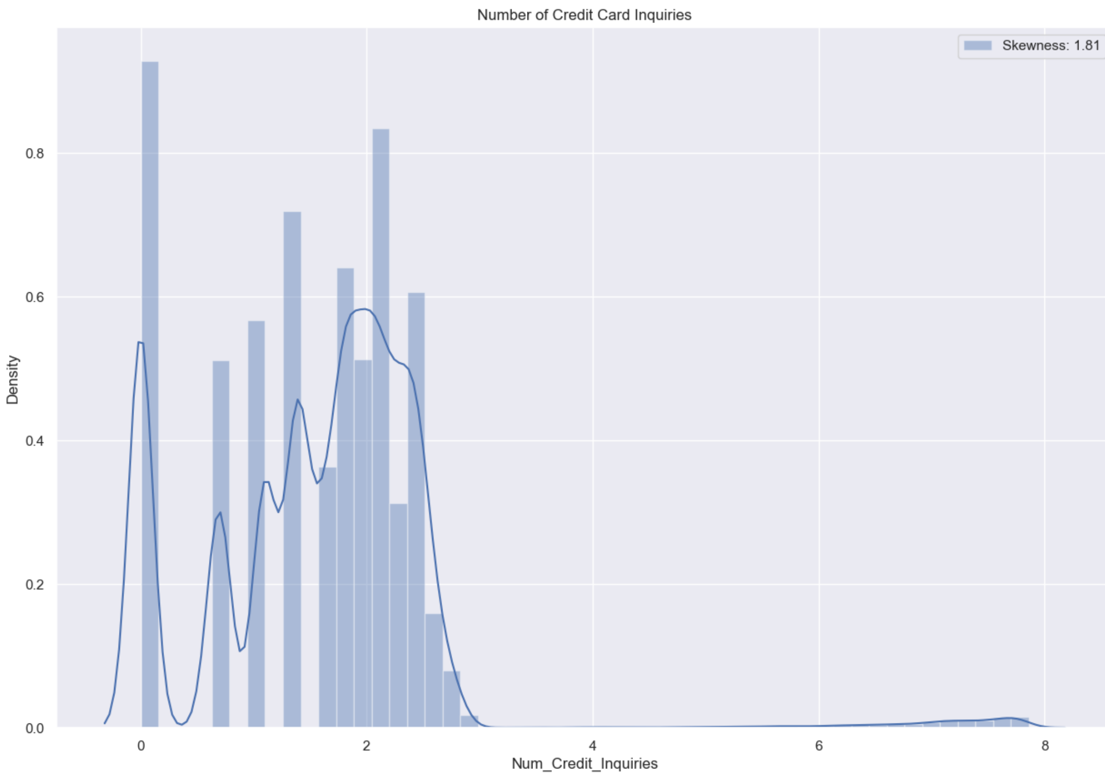
[949]:
```
#Log Transforming the column - Num_Credit_Inquiries
#Understanding the distribution of the column - Num_Credit_Inquiries

sns.distplot(dataset['Num_Credit_Inquiries'], label = 'Skewness: %.
 ↪2f'%(dataset['Num_Credit_Inquiries'].skew()))
plt.legend(loc = 'best')
plt.title('Number of Credit Inquiries')
```

[949]:
```
Text(0.5, 1.0, 'Number of Credit Inquiries')
```



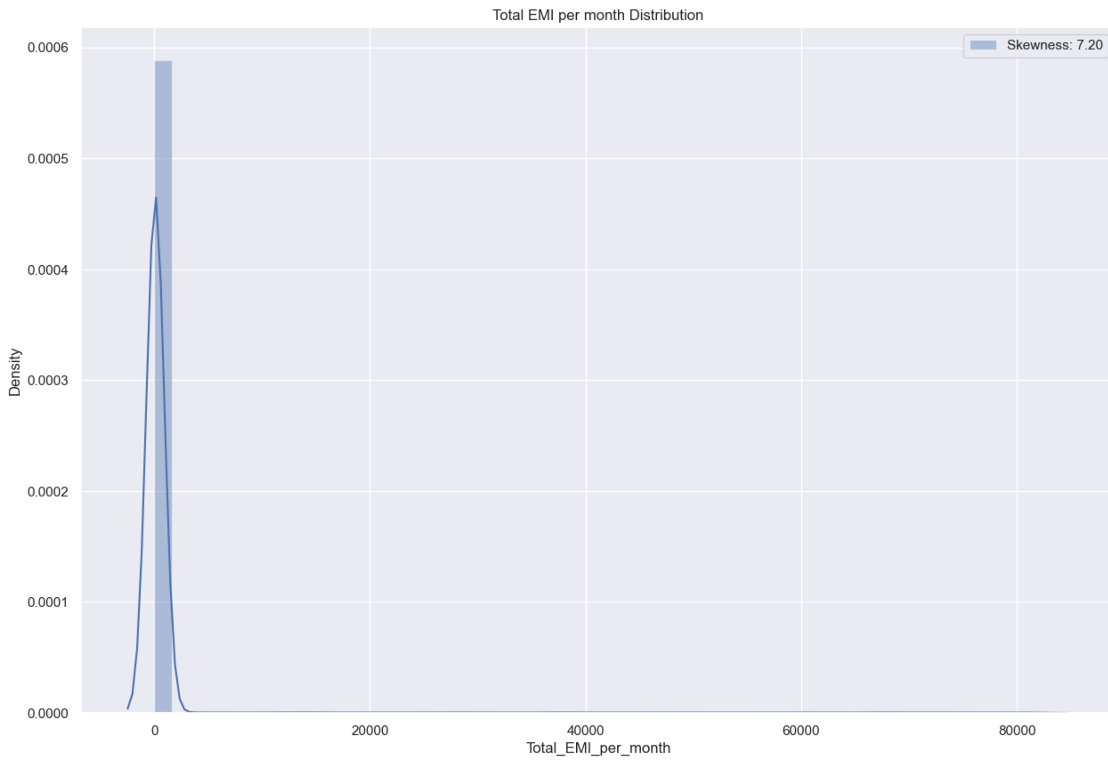
[950]:
```
#Understanding the distribution of the data log(Num_Credit_Inquiries)

modified_inquiries = [np.log(inquiries) if inquiries > 0 else 0 for inquiries␣
↪in dataset['Num_Credit_Inquiries']]
dataset['Num_Credit_Inquiries'] = modified_inquiries

sns.distplot(dataset['Num_Credit_Inquiries'], label = 'Skewness: %.
↪2f'%(dataset['Num_Credit_Inquiries'].skew()))
plt.legend(loc = 'best')
plt.title('Number of Credit Card Inquiries')
```

[950]:
```
Text(0.5, 1.0, 'Number of Credit Card Inquiries')
```



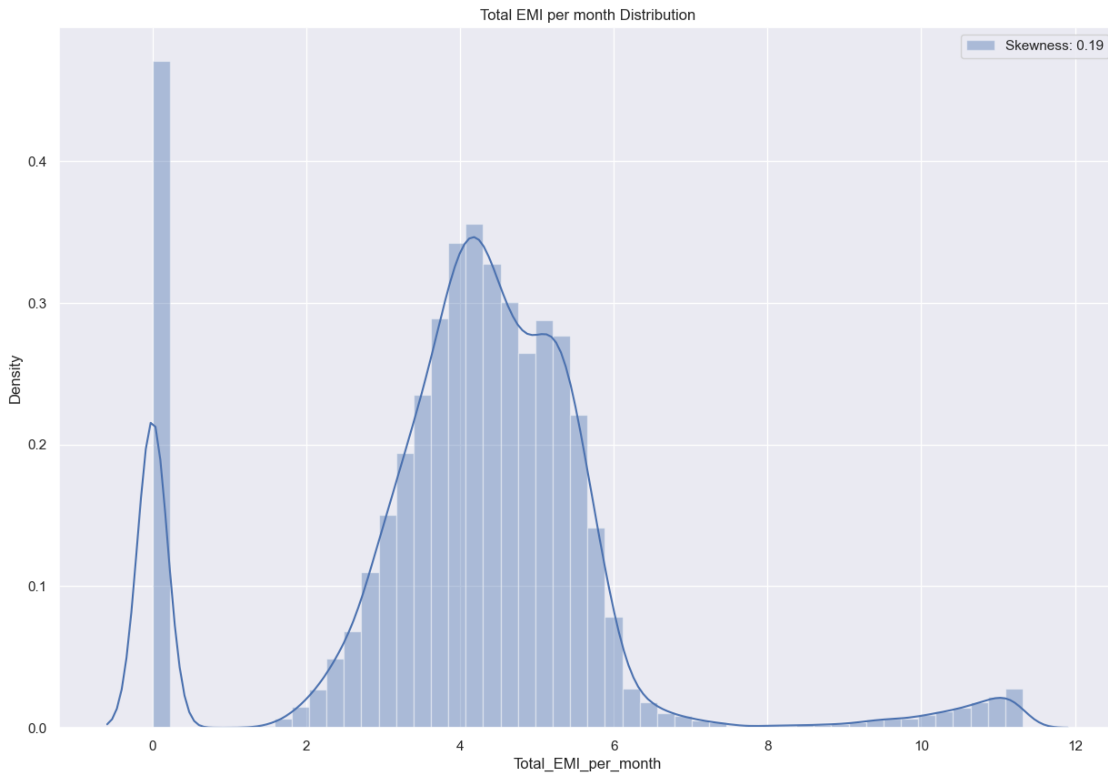
[951]:
```
#Log Transforming the column - Total_EMI_per_month
#Understanding the distribution of the column - Total_EMI_per_month

sns.distplot(dataset['Total_EMI_per_month'], label = 'Skewness: %.
 ↪2f'%(dataset['Total_EMI_per_month'].skew()))
plt.legend(loc = 'best')
plt.title('Total EMI per month Distribution')
```

[951]:
```
Text(0.5, 1.0, 'Total EMI per month Distribution')
```



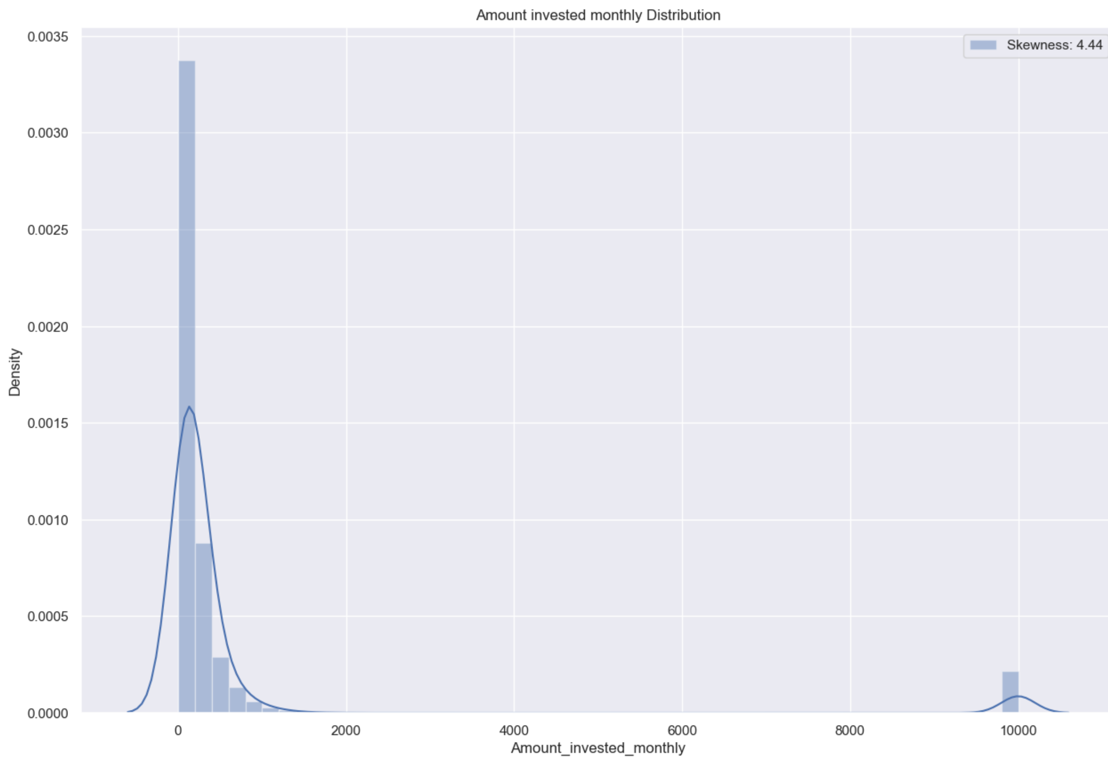
[952]:
```
#Understanding the distribution of the data log(Total_EMI_per_month)

modified_emi = [np.log(emi) if emi > 0 else 0 for emi in␣
↪dataset['Total_EMI_per_month']]
dataset['Total_EMI_per_month'] = modified_emi

sns.distplot(dataset['Total_EMI_per_month'], label = 'Skewness: %.
↪2f'%(dataset['Total_EMI_per_month'].skew()))
plt.legend(loc = 'best')
plt.title('Total EMI per month Distribution')
```

[952]: Text(0.5, 1.0, 'Total EMI per month Distribution')



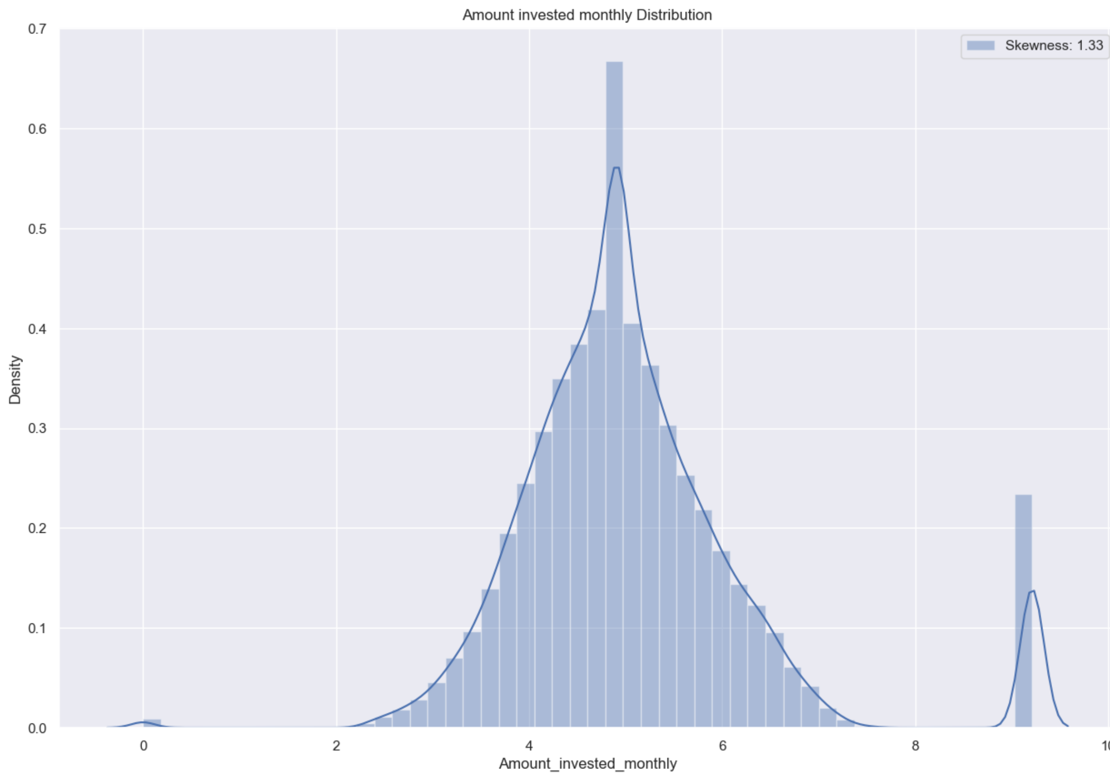
[953]:
```
#Log Transforming the column - Amount_invested_monthly
#Understanding the distribution of the column - Amount_invested_monthly

sns.distplot(dataset['Amount_invested_monthly'], label = 'Skewness: %.
 ↪2f'%(dataset['Amount_invested_monthly'].skew()))
plt.legend(loc = 'best')
plt.title('Amount invested monthly Distribution')
```

[953]:
```
Text(0.5, 1.0, 'Amount invested monthly Distribution')
```



[954]:
```
#Understanding the distribution of the data log(Amount_invested_monthly)

modified_amount = [np.log(amount) if amount > 0 else 0 for amount in␣
↪dataset['Amount_invested_monthly']]
dataset['Amount_invested_monthly'] = modified_amount

sns.distplot(dataset['Amount_invested_monthly'], label = 'Skewness: %.
↪2f'%(dataset['Amount_invested_monthly'].skew()))
plt.legend(loc = 'best')
plt.title('Amount invested monthly Distribution')
```

[954]:
```
Text(0.5, 1.0, 'Amount invested monthly Distribution')
```



Feature Encoding

Feature encoding is the process of turning categorical data in a dataset into numerical data. It is essential that we perform feature encoding because most machine learning models can only interpret numerical data and not data in text form.

[955]:
```
#Encoding the columns - Month, Occupation, Payment_of_Min_Amount of the dataset

encoded_dataset = pd.get_dummies(data = dataset,
                                  columns = ['Month', 'Occupation',␣
 ↪'Payment_of_Min_Amount'])
encoded_dataset
```

[955]:
```
             Age  Monthly_Inhand_Salary  Interest_Rate  Delay_from_due_date  \
0       3.135494               7.509249       1.098612                    3
1       3.135494               8.590437       1.098612                   -1
2       0.000000               8.590437       1.098612                    3
3       3.135494               8.590437       1.098612                    5
4       3.135494               7.509249       1.098612                    6
…          …                      …             …                     …
99511   3.218876               8.119522       1.945910                   23
99512   3.218876               8.119522       1.945910                   18
99513   3.218876               8.119522       8.653296                   27
```

```
99514  3.218876               8.119522      1.945910                   20
99515  3.218876               8.119522      1.945910                   18

       Num_of_Delayed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries  \
0                    1.945910                 11.27              1.386294
1                    2.639057                 11.27              1.386294
2                    1.945910                  0.00              1.386294
3                    1.386294                  6.27              1.386294
4                    2.639057                 11.27              1.386294
…                         …                    …                    …
99511                1.945910                 11.50              1.098612
99512                1.945910                 11.50              1.098612
99513                1.791759                 11.50              1.098612
99514                2.639057                 11.50              1.098612
99515                1.791759                 11.50              1.098612

       Outstanding_Debt  Total_EMI_per_month  Amount_invested_monthly  …  \
0                809.98             3.903486                 4.387204  …
1                809.98             3.903486                 4.773057  …
2                809.98             3.903486                 4.403048  …
3                809.98             3.903486                 5.295604  …
4                809.98             3.903486                 3.723768  …
…                   …                  …                       …   …
99511            502.38             3.558316                 4.110404  …
99512            502.38             3.558316                 3.992422  …
99513            502.38             3.558316                 3.179240  …
99514            502.38             3.558316                 5.528129  …
99515            502.38             3.558316                 5.118975  …

      Occupation_Mechanic  Occupation_Media_Manager  Occupation_Musician  \
0                       0                         0                    0
1                       0                         0                    0
2                       0                         0                    0
3                       0                         0                    0
4                       0                         0                    0
…                     …                       …                    …
99511                   1                         0                    0
99512                   1                         0                    0
99513                   1                         0                    0
99514                   1                         0                    0
99515                   1                         0                    0

       Occupation_Scientist  Occupation_Teacher  Occupation_Writer  \
0                         1                   0                  0
1                         1                   0                  0
2                         1                   0                  0
3                         1                   0                  0
```

```
4                         1                   0                   0
…                      …                 …                …
99511                     0                   0                   0
99512                     0                   0                   0
99513                     0                   0                   0
99514                     0                   0                   0
99515                     0                   0                   0

       Occupation________  Payment_of_Min_Amount_NM  Payment_of_Min_Amount_No  \
0                       0                         0                         1
1                       0                         0                         1
2                       0                         0                         1
3                       0                         0                         1
4                       0                         0                         1
…                    …                       …                       …
99511                   0                         0                         1
99512                   0                         0                         1
99513                   0                         0                         1
99514                   0                         0                         1
99515                   0                         0                         1

       Payment_of_Min_Amount_Yes
0                              0
1                              0
2                              0
3                              0
4                              0
…                           …
99511                          0
99512                          0
99513                          0
99514                          0
99515                          0

[99516 rows x 46 columns]
```

[956]:

```python
#Encoding the Credit Score (Target) column

credit_score_data = encoded_dataset['Credit_Score']
target = []

for each_credit_score in credit_score_data:
    if each_credit_score == 'Good':
        target.append(2)
    elif each_credit_score == 'Standard':
        target.append(1)
    else:
```

```
        target.append(0)

#Removing the Credit Score column

encoded_dataset.drop(['Credit_Score'], axis = 1, inplace = True)

#Adding the Target column

encoded_dataset['Target'] = target
```

[957]:
```
#Looking at the dataset

encoded_dataset
```

[957]:
```
            Age  Monthly_Inhand_Salary  Interest_Rate  Delay_from_due_date  \
0      3.135494               7.509249       1.098612                    3
1      3.135494               8.590437       1.098612                   -1
2      0.000000               8.590437       1.098612                    3
3      3.135494               8.590437       1.098612                    5
4      3.135494               7.509249       1.098612                    6
…          …                    …              …                   …
99511  3.218876               8.119522       1.945910                   23
99512  3.218876               8.119522       1.945910                   18
99513  3.218876               8.119522       8.653296                   27
99514  3.218876               8.119522       1.945910                   20
99515  3.218876               8.119522       1.945910                   18

       Num_of_Delayed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries  \
0                    1.945910                 11.27              1.386294
1                    2.639057                 11.27              1.386294
2                    1.945910                  0.00              1.386294
3                    1.386294                  6.27              1.386294
4                    2.639057                 11.27              1.386294
…                         …                     …                 …
99511                1.945910                 11.50              1.098612
99512                1.945910                 11.50              1.098612
99513                1.791759                 11.50              1.098612
99514                2.639057                 11.50              1.098612
99515                1.791759                 11.50              1.098612

       Outstanding_Debt  Total_EMI_per_month  Amount_invested_monthly  …  \
0                809.98             3.903486                 4.387204  …
1                809.98             3.903486                 4.773057  …
2                809.98             3.903486                 4.403048  …
3                809.98             3.903486                 5.295604  …
4                809.98             3.903486                 3.723768  …
…                  …                  …                     …   …
```

```
99511            502.38             3.558316                3.110404  …
99512            502.38             3.558316                3.992422  …
99513            502.38             3.558316                3.179240  …
99514            502.38             3.558316                5.528129  …
99515            502.38             3.558316                5.118975  …

       Occupation_Media_Manager  Occupation_Musician  Occupation_Scientist  \
0                             0                    0                     1
1                             0                    0                     1
2                             0                    0                     1
3                             0                    0                     1
4                             0                    0                     1
…                           …                  …                   …
99511                         0                    0                     0
99512                         0                    0                     0
99513                         0                    0                     0
99514                         0                    0                     0
99515                         0                    0                     0

       Occupation_Teacher  Occupation_Writer  Occupation________  \
0                       0                  0                   0
1                       0                  0                   0
2                       0                  0                   0
3                       0                  0                   0
4                       0                  0                   0
…                     …                …                 …
99511                   0                  0                   0
99512                   0                  0                   0
99513                   0                  0                   0
99514                   0                  0                   0
99515                   0                  0                   0

       Payment_of_Min_Amount_NM  Payment_of_Min_Amount_No  \
0                             0                         1
1                             0                         1
2                             0                         1
3                             0                         1
4                             0                         1
…                           …                       …
99511                         0                         1
99512                         0                         1
99513                         0                         1
99514                         0                         1
99515                         0                         1

       Payment_of_Min_Amount_Yes  Target
0                              0       2
```

```
1                                  0        2
2                                  0        2
3                                  0        2
4                                  0        2
…                              …      …
99511                              0        0
99512                              0        0
99513                              0        0
99514                              0        1
99515                              0        0

[99516 rows x 46 columns]
```

6.Modelling

Credit Score detection is a classfication problem, we will need to use classfication models, to train on the model to make predictions

Splitting the Training Data

Here, we will split the training data into X_train, X_test, Y_train, and Y_test so that they can be fed to the machine learning models that are used in the next section. Then the model with the best performance will be used to predict the result on the given test dataset.

[958]:
```
#Splitting the data to the matrices X and Y using the training set.

X = encoded_dataset.iloc[:, : -1].values
Y = encoded_dataset.iloc[:, -1].values
```

[959]:
```
#Looking at the new training data - X

X
```

[959]:
```
array([[3.13549422, 7.50924942, 1.09861229, …, 0.        , 1.        ,
         0.        ],
        [3.13549422, 8.59043728, 1.09861229, …, 0.        , 1.        ,
         0.        ],
        [0.        , 8.59043728, 1.09861229, …, 0.        , 1.        ,
         0.        ],
        …,
        [3.21887582, 8.11952238, 8.65329627, …, 0.        , 1.        ,
         0.        ],
        [3.21887582, 8.11952238, 1.94591015, …, 0.        , 1.        ,
         0.        ],
        [3.21887582, 8.11952238, 1.94591015, …, 0.        , 1.        ,
         0.        ]])
```

[960]:
```
#Looking at the new test data - Y
```

```
Y
```

[960]:
```
array([2, 2, 2, …, 0, 1, 0], dtype=int64)
```

[961]:
```
#Dividing the dataset into train and test in the ratio of 70 : 30

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.3,␣
 ↪random_state = 27, shuffle = True)
```

[962]:
```
X_train
```

[962]:
```
array([[3.21887582, 8.60159316, 1.94591015, …, 0.        , 1.        ,
        0.        ],
       [3.36729583, 8.35203398, 2.77258872, …, 0.        , 0.        ,
        1.        ],
       [3.25809654, 8.87083469, 2.19722458, …, 0.        , 1.        ,
        0.        ],
       …,
       [3.40119738, 8.75506823, 3.04452244, …, 0.        , 0.        ,
        1.        ],
       [3.66356165, 8.68014588, 2.48490665, …, 0.        , 0.        ,
        1.        ],
       [3.29583687, 7.85236359, 1.60943791, …, 0.        , 1.        ,
        0.        ]])
```

[963]:
```
X_test
```

[963]:
```
array([[3.40119738, 7.79738713, 2.7080502 , …, 0.        , 0.        ,
        1.        ],
       [2.77258872, 7.29339459, 3.4339872 , …, 0.        , 0.        ,
        1.        ],
       [3.36729583, 8.75700138, 1.09861229, …, 0.        , 1.        ,
        0.        ],
       …,
       [3.55534806, 8.74839724, 2.39789527, …, 0.        , 1.        ,
        0.        ],
       [3.73766962, 8.66749103, 1.60943791, …, 0.        , 0.        ,
        1.        ],
       [3.87120101, 9.02235883, 1.94591015, …, 0.        , 1.        ,
        0.        ]])
```

[964]:
```
Y_train
```

[964]:
```
array([2, 1, 2, …, 1, 1, 2], dtype=int64)
```

[965]:
```
Y_test
```

[965]:
```
array([1, 1, 1, …, 2, 1, 2], dtype=int64)
```

Fit Model

[966]:
```
#Dictionary to store model and its accuracy

model_accuracy = OrderedDict()
```

[967]:
```
#Dictionary to store model and its precision

model_precision = OrderedDict()
```

[968]:
```
#Dictionary to store model and its recall

model_recall = OrderedDict()
```

Applying Logistic Regression

[969]:
```
#Training the Logistic Regression model on the dataset

logistic_classifier = LogisticRegression(random_state = 27)
logistic_classifier.fit(X_train, Y_train)
```

[969]:
```
LogisticRegression(random_state=27)
```

[970]:
```
#Predicting the Test set results

Y_pred = logistic_classifier.predict(X_test)
print(np.concatenate((Y_pred.reshape(len(Y_pred), 1), Y_test.
 ↪reshape(len(Y_test), 1)), 1))
```

```
[[1 1]
 [1 1]
 [2 1]
 …
 [2 2]
 [1 1]
 [1 2]]
```

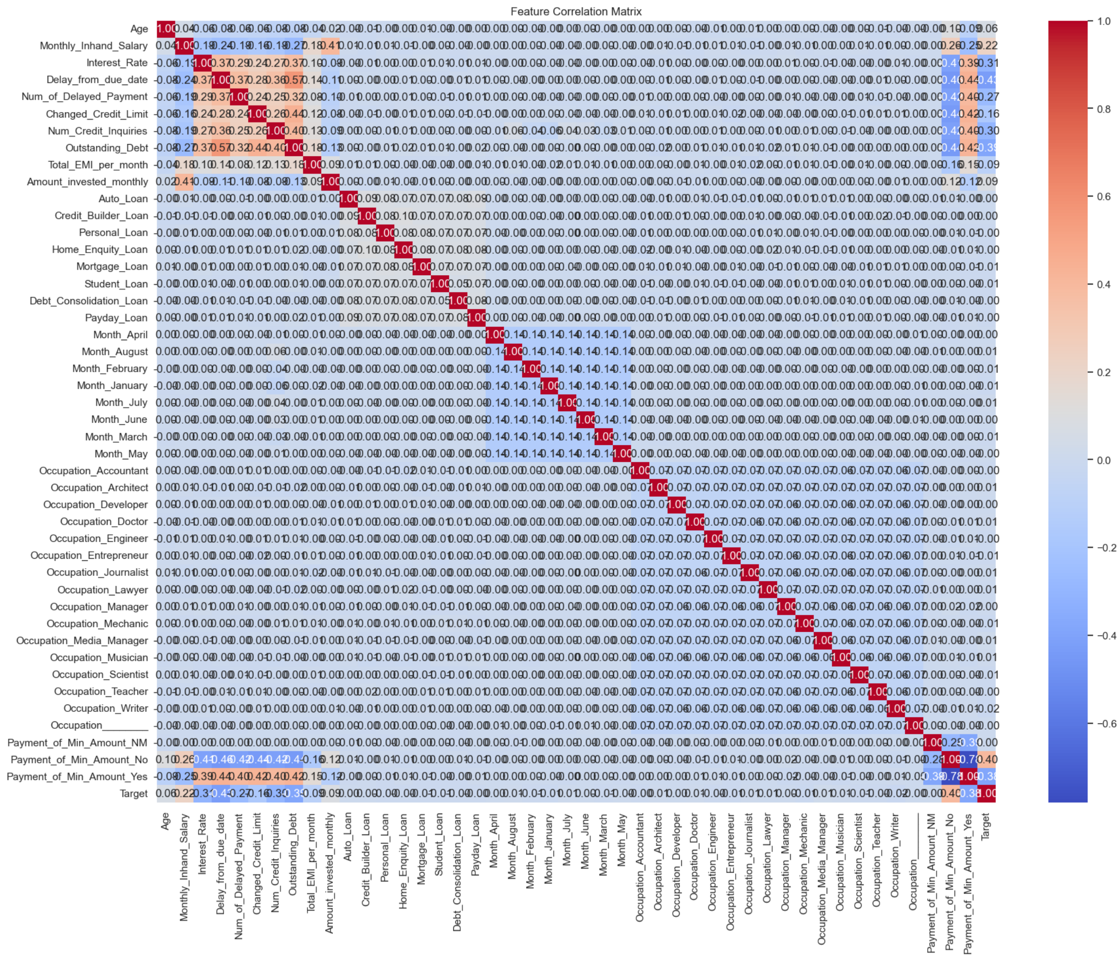
[971]:
```
#Making the confusion matrix

cm = confusion_matrix(Y_test, Y_pred)
print(cm)

### Printing the accuracy, precision, and recall of the model

logistic_accuracy = round(100 * accuracy_score(Y_test, Y_pred), 2)
model_accuracy['Logistic Regression'] = logistic_accuracy

logistic_precision = round(100 * precision_score(Y_test, Y_pred, average =␣
 ↪'weighted'), 2)
```

```
model_precision['Logistic Regression'] = logistic_precision

logistic_recall = round(100 * recall_score(Y_test, Y_pred, average =␣
 ↪'weighted'), 2)
model_recall['Logistic Regression'] = logistic_recall

print('The accuracy of this model is {} %.'.format(logistic_accuracy))
print('The precision of this model is {} %.'.format(logistic_precision))
print('The recall of this model is {} %.'.format(logistic_recall))
```

```
[[ 3365  5107   192]
 [ 1833 13065   986]
 [   76  4002  1229]]
The accuracy of this model is 59.15 %.
The precision of this model is 58.94 %.
The recall of this model is 59.15 %.
```

[972]:

```
# Generate the correlation matrix
correlation_matrix = encoded_dataset.corr()

# Visualize the correlation matrix using a heatmap
plt.figure(figsize=(20, 15))  # You can adjust the figure size as needed
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Feature Correlation Matrix')
plt.show()
```



Model evaluation

[973]:
```
model_accuracy
```

[973]:
```
OrderedDict([('Logistic Regression', 59.15)])
```

[974]:
```
model_precision
```

[974]:
```
OrderedDict([('Logistic Regression', 58.94)])
```

[975]:
```
model_recall
```

[975]:
```
OrderedDict([('Logistic Regression', 59.15)])
```

[976]:
```
table = []
table.append(['S.No.', 'Classification Model', 'Model Accuracy', 'Model␣
↪Precision', 'Model Recall'])
count = 1
```

```python
for model in model_accuracy:
    row = [count, model, model_accuracy[model], model_precision[model],␣
↪model_recall[model]]
    table.append(row)
    count += 1

print(tabulate(table, headers = 'firstrow', tablefmt = 'fancy_grid'))
```

```
   S.No.   Classification Model       Model Accuracy     Model Precision
Model Recall


       1   Logistic Regression                 59.15               58.94
59.15
```

[977]:
```python
# Generating detailed classification report
print("Classification Report:")
print(classification_report(Y_test, Y_pred, target_names=['Good', 'Poor',␣
↪'Standard']))

print('Model Performance Metrics:')
print(f'Accuracy: {logistic_accuracy}%')
print(f'Precision: {logistic_precision}%')
print(f'Recall: {logistic_recall}%')
```

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

        Good       0.64      0.39      0.48      8664
        Poor       0.59      0.82      0.69     15884
    Standard       0.51      0.23      0.32      5307

    accuracy                           0.59     29855
   macro avg       0.58      0.48      0.50     29855
weighted avg       0.59      0.59      0.56     29855

Model Performance Metrics:
Accuracy: 59.15%
Precision: 58.94%
Recall: 59.15%
```

7. Conclusion

Based on the evaluation of the Logistic Regression model for credit score detection, several conclusions can be drawn:

1. **Accuracy Assessment:** The Logistic Regression model achieved an accuracy of approximately 59.15%. This indicates that the model's predictions were correct for nearly 59.15% of the instances in the test dataset.

2. **Precision Analysis:** The precision score, which measures the proportion of true positive predictions among all positive predictions made by the model, was around 58.94%. This suggests that when the model predicted a certain credit score category, it was accurate nearly 58.94% of the time.

3. **Recall Evaluation:** The recall score, representing the ability of the model to correctly identify true positives from all actual positives, was approximately 59.15%. This implies that the model successfully captured about 59.15% of the instances belonging to each credit score category.

4. **Classification Report Insights:** Upon examining the detailed classification report, it's evident that the model performed relatively well in distinguishing between "Poor" credit scores, achieving a recall of 0.82. However, it struggled more with "Good" and "Standard" credit scores, with lower recall scores of 0.39 and 0.23, respectively.

5. **Model Performance Metrics Recap:** In summary, the Logistic Regression model demonstrated moderate performance in predicting credit scores. While it provided better accuracy and precision compared to random guessing, there is room for improvement, especially in correctly identifying instances of "Good" and "Standard" credit scores.

6. **Further Considerations:** To enhance model performance, additional feature engineering, model tuning, or exploring alternative algorithms could be beneficial. Additionally, domain expertise and further data analysis may reveal insights to refine the model and better capture the complexities of credit scoring.

[ ]:
```

```