□Credit EDA & Credit Score Calculation with Python□

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

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

Exploring the data...□**

```
data = pd.read_csv("Credit_score.csv")

# Set Pandas options to display all columns
pd.set_option('display.max_columns', 50)  # None to display all
columns

data.head()
```


{"type":"dataframe","variable_name":"data"}


```
# Checking the number of rows and columns
print(f"The number of rows: {data.shape[0]} \nThe number of columns:
{data.shape[1]}")
```

```
The number of rows: 100000
The number of columns: 27
```

```
# Check all column names
data.columns
```

```
Index(['ID', 'Customer_ID', 'Month', 'Name', 'Age', 'SSN',
'Occupation',
       'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
       'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan',
'Type_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment',
'Changed_Credit_Limit',
       'Num_Credit_Inquiries', 'Credit_Mix', 'Outstanding_Debt',
       'Credit_Utilization_Ratio', 'Credit_History_Age',
       'Payment_of_Min_Amount', 'Total_EMI_per_month',
       'Amount_invested_monthly', 'Payment_Behaviour',
'Monthly_Balance'],
      dtype='object')
```

□OBSERVATION□

The dataset has **1,00,000 rows** and **27 columns**

Column Name Description:

1. **ID:** Represents a unique identification of an entry.
2. **Customer_ID:** Represents a unique identification of a person.
3. **Month:** Represents the month of the year.
4. **Name:** Represents the name of a person.
5. **Age:** Represents the age of the person.
6. **SSN:** Represents the social security number of a person.
7. **Occupation:** Represents the occupation of the person.
8. **Annual_Income:** Represents the annual income of the person.
9. **Monthly_Inhand_Salary:** Represents the monthly base salary of a person.
10. **Num_Bank_Accounts:** Represents the number of bank accounts a person holds.
11. **Num_Credit_Card:** Represents the number of other credit cards held by a person.
12. **Interest_Rate:** Represents the interest rate on credit card.
13. **Num_of_Loan:** Represents the number of loans taken from the bank.
14. **Type_of_Loan:** Represents the types of loan taken by a person.
15. **Delay_from_due_date:** Represents the average number of days delayed from the payment date.
16. **Num_of_Delayed_Payment:** Represents the average number of payments delayed by a person.
17. **Changed_Credit_Limit:** Represents the percentage change in credit card limit.
18. **Num_Credit_Inquiries:** Represents the number of credit card inquiries.
19. **Credit_Mix:** Represents the classification of the mix of credits
20. **Outstanding_Debt:** Represents the remaining debt to be paid (in USD)
21. **Credit_Utilization_Ratio:** Represents the utilization ratio of credit card.
22. **Credit_History_Age:** Represents the age of credit history of the person.
23. **Payment_of_Min_Amount:** Represents whether only the minimum amount was paid by the person.

24. **Total_EMI_per_month:** Represents the monthly EMI payments (in USD)

25. **Amount_invested_monthly:** Represents the monthly amount invested by the customer (in USD)

26. **Payment_Behaviour:** Represents the payment behavior of the customer (in USD)

27. **Monthly_Balance:** Represents the monthly balance amount of the customer (in USD)

6) Observations on Data

```
# Check the information of the dataset
data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   ID                        100000 non-null  object
 1   Customer_ID               100000 non-null  object
 2   Month                     100000 non-null  object
 3   Name                      90015 non-null   object
 4   Age                       100000 non-null  object
 5   SSN                       100000 non-null  object
 6   Occupation                100000 non-null  object
 7   Annual_Income             100000 non-null  object
 8   Monthly_Inhand_Salary     84998 non-null   float64
 9   Num_Bank_Accounts         100000 non-null  int64
 10  Num_Credit_Card           100000 non-null  int64
 11  Interest_Rate             100000 non-null  int64
 12  Num_of_Loan               100000 non-null  object
 13  Type_of_Loan              88592 non-null   object
 14  Delay_from_due_date       100000 non-null  int64
 15  Num_of_Delayed_Payment    92998 non-null   object
 16  Changed_Credit_Limit      100000 non-null  object
 17  Num_Credit_Inquiries      98035 non-null   float64
 18  Credit_Mix                100000 non-null  object
 19  Outstanding_Debt          100000 non-null  object
 20  Credit_Utilization_Ratio  100000 non-null  float64
 21  Credit_History_Age        90970 non-null   object
 22  Payment_of_Min_Amount     100000 non-null  object
 23  Total_EMI_per_month       100000 non-null  float64
 24  Amount_invested_monthly   95521 non-null   object
 25  Payment_Behaviour         100000 non-null  object
 26  Monthly_Balance           98800 non-null   object
dtypes: float64(4), int64(4), object(19)
memory usage: 20.6+ MB
```

```
# Creating a deep copy
df = data.copy()
```

7) Data preprocessing

7.1) Checking for Duplicates

```
df[df.duplicated()]
```

{"type":"dataframe"}

7.2) Missing value treatmen and Cleaning

```
# How many percentage of data is missing in each column
missing_value = pd.DataFrame({'Missing Value': df.isnull().sum(),
'Percentage': (((df.isnull().sum() / len(df))*100)).round(2)})
missing_value.sort_values(by='Percentage', ascending=False,
inplace=True)
missing_value
```

{"summary":"{\n \"name\": \"missing_value\",\n \"rows\": 27,\n \"fields\": [\n   {\n   \"column\": \"Missing Value\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 4284,\n   \"min\": 0,\n   \"max\": 15002,\n   \"num_unique_values\": 9,\n   \"samples\": [\n   1200,\n   11408,\n   4479\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Percentage\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 4.283605897743103,\n   \"min\": 0.0,\n   \"max\": 15.0,\n   \"num_unique_values\": 9,\n   \"samples\": [\n   1.2,\n   11.41,\n   4.48\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe","variable_name":"missing_value"}

1. ID

```
# Check the datatype
df['ID'].dtype
```

```
dtype('O')
```

```
# Check for nulls
df['ID'].isna().sum()
```

```
0
```

OBSERVATION

- The column is clean

2. Customer_ID

```python
# Check the datatype
df['Customer_ID'].dtype
```

```
dtype('O')
```

```python
# Check for nulls
df['Customer_ID'].isna().sum()
```

```
0
```

OBSERVATION

- The column is clean

3. Month

```python
# Check the datatype
df['Month'].dtype
```

```
dtype('O')
```

```python
# Check for nulls
df['Month'].isna().sum()
```

```
0
```

OBSERVATION

- The column is clean

4. Name

```python
# Dealing with Column Name
# Forward and backward fill
df['Name'] = df.groupby('Customer_ID')['Name'].ffill()
df['Name'] = df.groupby('Customer_ID')['Name'].bfill()
```

OBSERVATION

- The column Name has been delt with forward fill and backward fill after group by Customer_ID

5. Age

```python
# Dealing with Age
df['Age'].dtype
```

```
dtype('O')
```

```python
# Define the pattern to match values like '30_'
pattern = r'\d+_$'
```

```
# Replace values that match the pattern with NaN
df['Age'] = df['Age'].replace(to_replace=pattern, value=np.nan,
regex=True)

# Convert 'Age' column to numeric, coercing errors to NaN
df['Age'] = pd.to_numeric(df['Age'], errors='coerce')

# Replace values which are less than 0 with NaN
df['Age'] = df['Age'].apply(lambda x: np.nan if x < 0 else x)

# Check the number of nulls in column Age
df['Age'].isna().sum()

5825

# Define a function to create a new column to fill the mode values
def fill_mode(series):
    mode_value = series.mode()
    if mode_value is not None:
        return mode_value[0] # chances of bimodal values here we
consider the first value since year of happening is not mentioned.
    else:
        return np.nan

# Apply the function to each group
df['age'] = df.groupby('Customer_ID')['Age'].transform(fill_mode)

df['age'] = df['age'].astype('int64')

df['age'].min(), df['age'].max()

(14, 56)

df['age'].unique()

array([23, 28, 34, 55, 21, 31, 30, 44, 40, 33, 35, 39, 37, 20, 46, 26,
41,
       32, 48, 43, 22, 36, 16, 18, 42, 19, 15, 27, 38, 14, 25, 45, 47,
17,
       53, 24, 54, 29, 49, 51, 50, 52, 56])

# Drop the Original Age column
df.drop(columns=['Age'], inplace=True)
```

OBSERVATION

- In this Age column we have values like 28_ and -500
- Replaced values that match the pattern with NaN
- Replaced values which are less than 0 with NaN
- Created the new column age and filled with mode values for each customer from the old column Age by defining a function.

6. SSN

```
# Dealing with SSN column
df['SSN'].dtype
```

```
dtype('O')
```

```
# Replace special character with NaN
df['SSN'] = df['SSN'].replace("#F%$D@*&8", np.nan)

# Check nulls
df['SSN'].isna().sum()
```

```
5572
```

```
# Forward and backward fill
df['SSN'] = df.groupby('Customer_ID')['SSN'].ffill()
df['SSN'] = df.groupby('Customer_ID')['SSN'].bfill()

# Check
df['SSN'].isna().sum()
```

```
0
```

OBSERVATION

- Replace special character "#F%$D@*&8" with NaN
- Forward and backward fill has been done to replace NaN

7. Occupation

```
# Dealing with occupation
# Check the datatype
df['Occupation'].dtype
```

```
dtype('O')
```

```
# Check unique values
df['Occupation'].unique()
```

```
array(['Scientist', '_______', 'Teacher', 'Engineer', 'Entrepreneur',
       'Developer', 'Lawyer', 'Media_Manager', 'Doctor', 'Journalist',
       'Manager', 'Accountant', 'Musician', 'Mechanic', 'Writer',
       'Architect'], dtype=object)
```

```
# Replace _______ with NaN
df['Occupation'] = df['Occupation'].replace('_______', np.nan)

# Check for nulls
df['Occupation'].isna().sum()
```

```
7062
```

```
# Forward and backward fill
df['Occupation']  = df.groupby('Customer_ID')['Occupation'].ffill()
df['Occupation']  = df.groupby('Customer_ID')['Occupation'].bfill()

# Check for nulls
df['Occupation'].isna().sum()
```

```
0
```

OBSERVATION

- Replace "_______" with NaN
- Forward and backward fill has been done to replace NaN

8. Annual_Income

```
# Dealiing with Annual_Income
# Check the datatype
df['Annual_Income'].dtype
```

```
dtype('O')
```

```
# Define the pattern to match values
pattern = r'_'

# Replace values that match the pattern with NaN
df['Annual_Income'] = df['Annual_Income'].replace(to_replace=pattern,
value=np.nan, regex=True)

# Convert 'Annual_Income' column to numeric, coercing errors to NaN
df['Annual_Income'] = pd.to_numeric(df['Annual_Income'],
errors='coerce')

# To overcome the display problem from "9.067443e+04" to "19114.12"

'''
Adjust Display Settings: Use pd.set_option('display.float_format',
'{:.2f}'.format) to change the display format globally.
'''
# Set display options for floating-point numbers
pd.set_option('display.float_format', '{:.2f}'.format)


# Checking the display
df['Annual_Income'].head(12)
```

```
0    19114.12
1    19114.12
2    19114.12
3    19114.12
4    19114.12
5    19114.12
```

```
6     19114.12
7     19114.12
8     34847.84
9     34847.84
10         NaN
11    34847.84
Name: Annual_Income, dtype: float64
```

```
# Check for nulls
df['Annual_Income'].isna().sum()
```

```
6980
```

```
# Forward and backward fill
df['Annual_Income'] = df.groupby('Customer_ID')
['Annual_Income'].ffill()
df['Annual_Income'] = df.groupby('Customer_ID')
['Annual_Income'].bfill()
```

```
# Check for nulls
df['Annual_Income'].isna().sum()
```

```
0
```

```
# Check the datatype
df['Annual_Income'].dtype
```

```
dtype('float64')
```

OBSERVATION

- Replace values like "34847.84_" with NaN
- Forward and backward fill has been done to replace NaN

9. Monthly_Inhand_Salary

```
# Dealing with Monthly_Inhand_Salary
df['Monthly_Inhand_Salary'].dtype
```

```
dtype('float64')
```

```
# Check for nulls
df['Monthly_Inhand_Salary'].isna().sum()
```

```
15002
```

```
# Display
df['Monthly_Inhand_Salary'].head(8)
```

```
0    1824.84
1        NaN
2        NaN
```

```
3        NaN
4    1824.84
5        NaN
6    1824.84
7    1824.84
Name: Monthly_Inhand_Salary, dtype: float64
```

```
# Forward and backward fill
df['Monthly_Inhand_Salary'] = df.groupby('Customer_ID')
['Monthly_Inhand_Salary'].ffill()
df['Monthly_Inhand_Salary'] = df.groupby('Customer_ID')
['Monthly_Inhand_Salary'].bfill()

# Check for nulls
df['Monthly_Inhand_Salary'].isna().sum()
```

```
0
```

```
# Display check
df['Monthly_Inhand_Salary'].head(8)
```

```
0    1824.84
1    1824.84
2    1824.84
3    1824.84
4    1824.84
5    1824.84
6    1824.84
7    1824.84
Name: Monthly_Inhand_Salary, dtype: float64
```

OBSERVATION

- Forward and backward fill has been done to replace NaN

10. Num_Bank_Accounts

```
# Dealing with Monthly_Inhand_Salary
df['Num_Bank_Accounts'].dtype
```

```
dtype('int64')
```

```
# Check for the number of rows having value -1
len(df[df['Num_Bank_Accounts'] == -1])
```

```
21
```

```
# Replace the value -1 with 0
df['Num_Bank_Accounts'].replace(-1, 0, inplace = True)

# Check for the number of rows having value -1
len(df[df['Num_Bank_Accounts'] == -1])
```

```
0

# Apply the function using transform
df['num_Bank_Accounts'] = df.groupby('Customer_ID')
['Num_Bank_Accounts'].transform(fill_mode)

df['num_Bank_Accounts'].min(), df['num_Bank_Accounts'].max()

(0, 10)

df['num_Bank_Accounts'].unique()

array([ 3,  2,  1,  7,  4,  0,  8,  5,  6,  9, 10])

# Drop the Original Age column
df.drop(columns=['Num_Bank_Accounts'], inplace=True)

df.shape

(100000, 27)
```

OBSERVATION

- Replace the value -1 with 0
- Created the new column num_Bank_Accounts and fill with mode values for each customer from the old column Num_Bank_Accounts by defining a func

11. Num_Credit_Card

```
# Check the datatype
df['Num_Credit_Card'].dtype

dtype('int64')

# Check for nulls
df['Num_Credit_Card'].isna().sum()

0

# Random check
df[df['Customer_ID'] == "CUS_0x22be"][['Name', 'Num_Credit_Card']]
```


```
{"summary":"{\n  \"name\": \"df[df['Customer_ID'] ==
\\\"CUS_0x22be\\\"][['Name', 'Num_Credit_Card']]\",\n  \"rows\": 8,\n
\"fields\": [\n    {\n      \"column\": \"Name\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 1,\n        \"samples\": [\n          \"arbara
Lewish\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Num_Credit_Card\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
```

[\n   0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

```
# Apply the function using transform
df['num_Credit_Card'] = df.groupby('Customer_ID')
['Num_Credit_Card'].transform(fill_mode)

# Drop the Original column
df.drop(columns=['Num_Credit_Card'], inplace=True)

df['num_Credit_Card'].min(), df['num_Credit_Card'].max()

(0, 11)

df['num_Credit_Card'].unique()

array([ 4,  5,  1,  7,  6,  8,  3,  9,  2, 10, 11,  0])

# Random check
df[df['Customer_ID'] == "CUS_0x22be"][['Name', 'num_Credit_Card']]
```

{"summary":"{\n \"name\": \"df[df['Customer_ID'] == \\\"CUS_0x22be\\\"][['Name', 'num_Credit_Card']]\",\n \"rows\": 8,\n \"fields\": [\n   {\n   \"column\": \"Name\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 1,\n   \"samples\": [\n   \"arbara Lewish\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"num_Credit_Card\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0,\n   \"min\": 0,\n   \"max\": 0,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

OBSERVATION

- Created the new column and fill with mode values for each customer from the old column by defining a func

12. Interest_Rate

```
# Check the datatype
df['Interest_Rate'].dtype

dtype('int64')

df['Interest_Rate'].min(), df['Interest_Rate'].max()

(1, 5797)

# Apply the function using transform
df['interest_Rate'] = df.groupby('Customer_ID')
['Interest_Rate'].transform(fill_mode)
```

```
# Drop the Original column
df.drop(columns=['Interest_Rate'], inplace=True)

df['interest_Rate'].min(), df['interest_Rate'].max()

(1, 34)

df['interest_Rate'].unique()

array([ 3,  6,  8,  4,  5, 15,  7, 12, 20,  1, 14, 32, 16, 17, 10, 31,
25,
       18, 19,  9, 24, 13, 33, 11, 21, 29, 28, 30, 23, 34,  2, 27, 26,
22])

df.shape

(100000, 27)
```

OBSERVATION

- Created the new column and fill with mode values for each customer from the old column by defining a func

13. Num_of_Loan

Method 1:

```
# Check the datatype
df['Num_of_Loan'].dtype

dtype('O')

# Define the pattern to match values
pattern = r'-\d+|\d+_$|\d_'

# Replace values that match the pattern with NaN
df['Num_of_Loan'] = df['Num_of_Loan'].replace(to_replace=pattern,
value=np.nan, regex=True)

# Convert 'Annual_Income' column to numeric, coercing errors to NaN
df['Num_of_Loan'] = pd.to_numeric(df['Num_of_Loan'], errors='coerce')

# Define a function to fill NaN values with the mode
def fill_mode(series):
    mode_value = series.mode()
    if not mode_value.empty:
        return mode_value[0]  # Use the first mode if there are
multiple modes
    else:
        return np.nan
```

```python
# Apply the function to fill NaN values with the mode for each
Customer_ID
df['num_of_Loan'] = df.groupby('Customer_ID')
['Num_of_Loan'].transform(fill_mode)

# Change the datatype
df['num_of_Loan'] = df['num_of_Loan'].astype('int')

df['num_of_Loan'].unique()
```

```
array([4, 1, 3, 0, 2, 7, 5, 6, 8, 9])
```

```python
df['num_of_Loan'].value_counts()
```

```
num_of_Loan
3    15752
2    15712
4    15456
0    11408
1    11128
6     8144
7     7680
5     7528
9     3856
8     3336
Name: count, dtype: int64
```

Method 2:

```python
df['Type_of_Loan'].head(40)
```

```
0     Auto Loan, Credit-Builder Loan, Personal Loan,...
1     Auto Loan, Credit-Builder Loan, Personal Loan,...
2     Auto Loan, Credit-Builder Loan, Personal Loan,...
3     Auto Loan, Credit-Builder Loan, Personal Loan,...
4     Auto Loan, Credit-Builder Loan, Personal Loan,...
5     Auto Loan, Credit-Builder Loan, Personal Loan,...
6     Auto Loan, Credit-Builder Loan, Personal Loan,...
7     Auto Loan, Credit-Builder Loan, Personal Loan,...
8                                   Credit-Builder Loan
9                                   Credit-Builder Loan
10                                  Credit-Builder Loan
11                                  Credit-Builder Loan
12                                  Credit-Builder Loan
13                                  Credit-Builder Loan
14                                  Credit-Builder Loan
15                                  Credit-Builder Loan
16                Auto Loan, Auto Loan, and Not Specified
17                Auto Loan, Auto Loan, and Not Specified
18                Auto Loan, Auto Loan, and Not Specified
```

```
19                Auto Loan, Auto Loan, and Not Specified
20                Auto Loan, Auto Loan, and Not Specified
21                Auto Loan, Auto Loan, and Not Specified
22                Auto Loan, Auto Loan, and Not Specified
23                Auto Loan, Auto Loan, and Not Specified
24                                          Not Specified
25                                          Not Specified
26                                          Not Specified
27                                          Not Specified
28                                          Not Specified
29                                          Not Specified
30                                          Not Specified
31                                          Not Specified
32                                                    NaN
33                                                    NaN
34                                                    NaN
35                                                    NaN
36                                                    NaN
37                                                    NaN
38                                                    NaN
39                                                    NaN
Name: Type_of_Loan, dtype: object
```

```
# Check
a = df['Type_of_Loan'][0]
a
```

```
{"type":"string"}
```

```
# Check
len(a.split(","))
```

```
4
```

```
# Check
b = df['Type_of_Loan'][8]
b
```

```
{"type":"string"}
```

```
# Check
len(b.split(","))
```

```
1
```

```
# Check
c = df['Type_of_Loan'][32]
```

```
# Check
type(c)
```

```
float
```

```
# Logic for the function
x = df['Type_of_Loan'][32]
#x = df['Type_of_Loan'][0]

if isinstance(x, float):
  print(0)
else:
  print(len(x.split(",")))
```

```
0
```

```
# Define a function to count the Num_of_Loan from Type_of_Loan column
def len_of_list(elem):
  if isinstance(elem, float):
    return 0
  else:
    return len(elem.split(','))

# Apply the function using transform
df['num_of_Loan_check'] = df['Type_of_Loan'].transform(len_of_list)
```

```
df['num_of_Loan_check'].unique()
```

```
array([4, 1, 3, 0, 2, 7, 5, 6, 8, 9])
```

```
df['num_of_Loan_check'].value_counts()
```

```
num_of_Loan_check
3    15752
2    15712
4    15456
0    11408
1    11128
6     8144
7     7680
5     7528
9     3856
8     3336
Name: count, dtype: int64
```

```
df.shape
```

```
(100000, 29)
```

```
# Drop the Original column
df.drop(columns=['Num_of_Loan','num_of_Loan_check'], inplace=True)
```

```
df.shape
```

```
(100000, 27)
```

```
df.columns
```

```
Index(['ID', 'Customer_ID', 'Month', 'Name', 'SSN', 'Occupation',
       'Annual_Income', 'Monthly_Inhand_Salary', 'Type_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment',
'Changed_Credit_Limit',
       'Num_Credit_Inquiries', 'Credit_Mix', 'Outstanding_Debt',
       'Credit_Utilization_Ratio', 'Credit_History_Age',
       'Payment_of_Min_Amount', 'Total_EMI_per_month',
       'Amount_invested_monthly', 'Payment_Behaviour',
'Monthly_Balance',
       'age', 'num_Bank_Accounts', 'num_Credit_Card', 'interest_Rate',
       'num_of_Loan'],
      dtype='object')
```

OBSERVATION

- Define the pattern to match values
- Replace values that match the pattern with NaN
- Define a function to fill NaN values with the mode

14. Type_of_Loan

```
# Check the datatype
df['Type_of_Loan'].dtype

dtype('O')

# Check for nulls
df['Type_of_Loan'].isna().sum()

11408

value = "No Loan Status"
df['Type_of_Loan'].fillna(value, inplace=True)

# Check for nulls
df['Type_of_Loan'].isna().sum()

0
```

OBSERVATION

- Replaced the null values with "No Loan Status"

15. Delay_from_due_date

Method 1:

```
# Check the datatype
df['Delay_from_due_date'].dtype

dtype('int64')
```

```
df['Delay_from_due_date'].head(8)
```

```
0    3
1   -1
2    3
3    5
4    6
5    8
6    3
7    3
Name: Delay_from_due_date, dtype: int64
```

```
# Replace values which are less than 0 with NaN
df['Delay_from_due_date'] = df['Delay_from_due_date'].apply(lambda x:
np.nan if x < 0 else x)

# Check for nulls
df['Delay_from_due_date'].isna().sum()
```

```
591
```

```
# Define a function to fill NaNs with the mode
def fill_mode_same_column(series):
  # series.mode.iloc[0] --> Since we are consider bimodal or
multimodal
  mode_value = series.mode().iloc[0] if not series.mode().empty else
np.nan
  return series.fillna(mode_value)

# Apply the function using transform
df['Delay_from_due_date'] = df.groupby('Customer_ID')
['Delay_from_due_date'].transform(fill_mode_same_column)

# Chenge the datatype
df['Delay_from_due_date'] = df['Delay_from_due_date'].astype('int')

# Check for nulls
df['Delay_from_due_date'].isna().sum()
```

```
0
```

```
df['Delay_from_due_date'].min(), df['Delay_from_due_date'].max()
```

```
(0, 67)
```

```
df['Delay_from_due_date'].head(8)
```

```
0    3
1    3
2    3
3    5
4    6
```

```
5    8
6    3
7    3
Name: Delay_from_due_date, dtype: int64
```

OBSERVATION

- Replace values which are less than 0 with NaN
- A function is defined to fill NaNs with the mode

16. Num_of_Delayed_Payment

```
df['Num_of_Delayed_Payment'].dtype

dtype('O')

# Define the pattern to match values
pattern = r'-\d+|\d+_$|\d_'

# Replace values that match the pattern with NaN
df['Num_of_Delayed_Payment'] =
df['Num_of_Delayed_Payment'].replace(to_replace=pattern, value=np.nan,
regex=True)

# Convert 'Annual_Income' column to numeric, coercing errors to NaN
df['Num_of_Delayed_Payment'] =
pd.to_numeric(df['Num_of_Delayed_Payment'], errors='coerce')

# Check for datatype
df['Num_of_Delayed_Payment'].dtype

dtype('float64')

# Check for nulls
df['Num_of_Delayed_Payment'].isna().sum()

10368

# Apply the function using transform
df['num_of_Delayed_Payment'] = df.groupby('Customer_ID')
['Num_of_Delayed_Payment'].transform(fill_mode)

# Check for nulls
df['num_of_Delayed_Payment'].isna().sum()

0

# Chenge the datatype
df['num_of_Delayed_Payment'] =
df['num_of_Delayed_Payment'].astype('int')

df['num_of_Delayed_Payment'].min(), df['num_of_Delayed_Payment'].max()
```

```
(0, 28)

df['num_of_Delayed_Payment'].unique()

array([ 4,  6, 15,  7,  2, 14, 11,  0, 20,  8,  9, 10, 12, 19, 21, 16,
17,
        18, 24,  5, 23, 22, 13,  3,  1, 25, 28, 27, 26])

df.drop(columns=['Num_of_Delayed_Payment'], inplace=True)

df.shape

(100000, 27)
```

OBSERVATION

- Cleaned the original coluumn and replaced the wrong elements with NaN.
- Created new column and filled with mode values after groupby.

17. Changed_Credit_Limit

```
df['Changed_Credit_Limit'].dtype

dtype('O')

# Define the pattern to match values
pattern = r'_'

# Replace values that match the pattern with NaN
df['Changed_Credit_Limit'] =
df['Changed_Credit_Limit'].replace(to_replace=pattern, value=np.nan,
regex=True)

# Convert 'Annual_Income' column to numeric, coercing errors to NaN
df['Changed_Credit_Limit'] = pd.to_numeric(df['Changed_Credit_Limit'],
errors='coerce')

# Check for nulls
df['Changed_Credit_Limit'].isna().sum()

2091

# Forward and backward fill
df['Changed_Credit_Limit'] = df.groupby('Customer_ID')
['Changed_Credit_Limit'].ffill()
df['Changed_Credit_Limit'] = df.groupby('Customer_ID')
['Changed_Credit_Limit'].bfill()

# Check for nulls
df['Changed_Credit_Limit'].isna().sum()

0
```

```
df['Changed_Credit_Limit'].min(), df['Changed_Credit_Limit'].max()
```

```
(-6.49, 36.97)
```

OBSERVATION

- Clean and done forward and backward fill for NaN values.

18. Num_Credit_Inquiries

```
df['Num_Credit_Inquiries'].dtype
```

```
dtype('float64')
```

```
df['Num_Credit_Inquiries'].min(), df['Num_Credit_Inquiries'].max()
```

```
(0.0, 2597.0)
```

```
# Apply the function using transform
df['num_Credit_Inquiries'] = df.groupby('Customer_ID')
['Num_Credit_Inquiries'].transform(fill_mode)
```

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

```
# Check for nulls
df['num_Credit_Inquiries'].isna().sum()
```

```
0
```

```
df['num_Credit_Inquiries'].unique()
```

```
array([ 4,  2,  3,  5,  8,  6,  1,  7,  0, 17,  9, 10, 11, 14, 12, 16,
15,
       13])
```

```
df['num_Credit_Inquiries'].min(), df['num_Credit_Inquiries'].max()
```

```
(0, 17)
```

```
df.drop(columns=['Num_Credit_Inquiries'], inplace=True)
```

```
df.shape
```

```
(100000, 27)
```

OBSERVATION

- Created a new column and replace nulls with mode of original column after groupby.

19. Credit_Mix

```
df['Credit_Mix'].dtype
```

```
dtype('O')
```

```python
len(df.loc[df['Credit_Mix'] == '_'])
```

```
20195
```

```python
# Define the pattern to match values
pattern = r'_'

# Replace values that match the pattern with NaN
df['Credit_Mix'] = df['Credit_Mix'].replace(to_replace=pattern,
value=np.nan, regex=True)

# Forward and backward fill
df['Credit_Mix'] = df.groupby('Customer_ID')['Credit_Mix'].ffill()
df['Credit_Mix'] = df.groupby('Customer_ID')['Credit_Mix'].bfill()

df['Credit_Mix'].isna().sum()
```

```
0
```

OBSERVATION

- Cleaned and done forward and backward fill.

20. Outstanding_Debt

```python
# Check the datatype
df['Outstanding_Debt'].dtype
```

```
dtype('O')
```

```python
# Define the pattern to match values
pattern = r'_'

# Replace values that match the pattern with NaN
df['Outstanding_Debt'] =
df['Outstanding_Debt'].replace(to_replace=pattern, value=np.nan,
regex=True)

# Convert 'Annual_Income' column to numeric, coercing errors to NaN
df['Outstanding_Debt'] = pd.to_numeric(df['Outstanding_Debt'],
errors='coerce')

# Check for nulls
df['Outstanding_Debt'].isna().sum()
```

```
1009
```

```python
# Forward and backward fill
df['Outstanding_Debt'] = df.groupby('Customer_ID')
['Outstanding_Debt'].ffill()
df['Outstanding_Debt'] = df.groupby('Customer_ID')
['Outstanding_Debt'].bfill()
```

```
# Check for nulls
df['Outstanding_Debt'].isna().sum()

0

# Check the datatype
df['Outstanding_Debt'].dtype

dtype('float64')
```

OBSERVATION

- Cleaned and done forward and backward fill.

21. Credit_Utilization_Ratio

```
# Check the datatype
df['Credit_Utilization_Ratio'].dtype

dtype('float64')

# Check for nulls
df['Credit_Utilization_Ratio'].isna().sum()

0
```

OBSERVATION

- The column is clean

22. Credit_History_Age

```
# Check the datatype
df['Credit_History_Age'].dtype

dtype('O')

# Check for nulls
df['Credit_History_Age'].isna().sum()

9030

# Created a column by splitting the elements
df['Credit_History_Age_list'] = df['Credit_History_Age'].str.split()

df['Credit_History_Age_list'].head()

0    [22, Years, and, 1, Months]
1                            NaN
2    [22, Years, and, 3, Months]
3    [22, Years, and, 4, Months]
4    [22, Years, and, 5, Months]
Name: Credit_History_Age_list, dtype: object
```

```
type(df['Credit_History_Age_list'][1]) == float
```

```
True
```

```
# Define a function to extract the year
def split_CRA(lst):
  #if type(lst) == float:
  if isinstance(lst, float):
    return 0
  else:
    return int(lst[0])

# Apply the function
df['Credit_History_Age_all'] =
df['Credit_History_Age_list'].apply(split_CRA)

# Apply the function
df['credit_History_Age'] = df.groupby('Customer_ID')
['Credit_History_Age_all'].transform(lambda series: series.max())

df.drop(columns=['Credit_History_Age', 'Credit_History_Age_list',
'Credit_History_Age_all'], inplace=True)

df.shape
```

```
(100000, 27)
```

OBSERVATION

- Created a new column and taken the max value after group by.

23. Payment_of_Min_Amount

```
df['Payment_of_Min_Amount'].dtype
```

```
dtype('O')
```

```
df['Payment_of_Min_Amount'].value_counts()
```

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

```
df['Payment_of_Min_Amount'] =
df['Payment_of_Min_Amount'].replace('NM', 'No')

df['Payment_of_Min_Amount'].value_counts()
```

```
Payment_of_Min_Amount
Yes    52326
```

```
No      47674
Name: count, dtype: int64
```

OBSERVATION

- Replaced 'NM' with 'No'

24. Total_EMI_per_month

```
df['Total_EMI_per_month'].dtype

dtype('float64')

df['Total_EMI_per_month'].isna().sum()

0
```

OBSERVATION

- The column is clean

25. Amount_invested_monthly

```
# Check the datatype
df['Amount_invested_monthly'].dtype

dtype('O')

# Define the pattern to match values
pattern = r'__\d+__$'

# Replace values that match the pattern with NaN
df['Amount_invested_monthly'] =
df['Amount_invested_monthly'].replace(to_replace=pattern,
value=np.nan, regex=True)

# Convert 'Annual_Income' column to numeric, coercing errors to NaN
df['Amount_invested_monthly'] =
pd.to_numeric(df['Amount_invested_monthly'], errors='coerce')

# Check for nulls
df['Amount_invested_monthly'].isna().sum()

8784

# Fill nulls with 0
df['Amount_invested_monthly'] =
df['Amount_invested_monthly'].fillna(0)

# Check for nulls
df['Amount_invested_monthly'].isna().sum()

0
```

```
# Check the datatype
df['Amount_invested_monthly'].dtype
```

```
dtype('float64')
```

OBSERVATION

- Cleaned and filled nulls with 0

26. Payment_Behaviour

```
# Check the datatype
df['Payment_Behaviour'].dtype
```

```
dtype('O')
```

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

# Check for nulls
df['Payment_Behaviour'].isna().sum()
```

```
7600
```

```
# Forward fill and Backward fill
df['Payment_Behaviour'] = df.groupby('Customer_ID')
['Payment_Behaviour'].ffill()
df['Payment_Behaviour'] = df.groupby('Customer_ID')
['Payment_Behaviour'].bfill()

# Check for nulls
df['Payment_Behaviour'].isna().sum()
```

```
0
```

OBSERVATION

- The column is cleane and filled nulls with forward or backward values

27. Monthly_Balance

```
# Check the datatype
df['Monthly_Balance'].dtype
```

```
dtype('O')
```

```
# Convert to numeric
df['Monthly_Balance'] = pd.to_numeric(df['Monthly_Balance'],
errors='coerce')

# Check the datatype
df['Monthly_Balance'].dtype
```

```
dtype('float64')
```

```
# Fill nulls with 0
df['Monthly_Balance'] = df['Monthly_Balance'].fillna(0)

# Check for nulls
df['Monthly_Balance'].isna().sum()
```

```
0
```

```
df.shape
```

```
(100000, 27)
```

OBSERVATION

- Converted to numeric and filled nulls with 0

7.3) Feature Engineering

7.3.1) Creating Cleaned dataframe

```
# Deep copy
df_processed = df.copy()

# Renamed the newly created column to the same original column
rename_dict = {'age':'Age',
               'num_Bank_Accounts':'Num_Bank_Accounts',
               'num_Credit_Card':'Num_Credit_Card',
               'interest_Rate':'Interest_Rate',
               'num_of_Loan':'Num_of_Loan',
               'num_of_Delayed_Payment':'Num_of_Delayed_Payment',
               'num_Credit_Inquiries': 'Num_Credit_Inquiries',
               'credit_History_Age': 'Credit_History_Age'}

df_processed = df_processed.rename(columns = rename_dict)

# Changing the order of column as original columns
new_column_order = [
    'ID', 'Customer_ID', 'Month', 'Name', 'Age', 'SSN', 'Occupation',
'Annual_Income',
    'Monthly_Inhand_Salary', 'Num_Bank_Accounts', 'Num_Credit_Card',
'Interest_Rate',
    'Num_of_Loan', 'Type_of_Loan', 'Delay_from_due_date',
'Num_of_Delayed_Payment',
    'Changed_Credit_Limit', 'Num_Credit_Inquiries', 'Credit_Mix',
'Outstanding_Debt',
    'Credit_Utilization_Ratio', 'Credit_History_Age',
'Payment_of_Min_Amount',
    'Total_EMI_per_month', 'Amount_invested_monthly',
'Payment_Behaviour', 'Monthly_Balance'
```

```
]

df_cleaned = df_processed.reindex(columns=new_column_order)
```

7.3.2) Treating Month

```
# Convert month names to month numbers and replace in the same column
df_cleaned['Month_num'] = pd.to_datetime(df_cleaned['Month'],
format='%B').dt.month
```

7.3.3) *Treating* Credit_Mix

```
df_cleaned['Credit_Mix'].unique()
```

```
array(['Good', 'Standard', 'Bad'], dtype=object)
```

```
# Define a function for assigning numbers for Credit_Mix
def credit_mix(elem):
  if elem == "Good":
    return 2
  elif elem == "Standard":
    return 1
  else:
    return 0

# Apply the function using transform
df_cleaned['Credit_Mix_eq_no'] =
df_cleaned['Credit_Mix'].transform(credit_mix)
```

7.3.4) Treating Payment_of_Min_Amount

```
df_cleaned['Payment_of_Min_Amount'].unique()
```

```
array(['No', 'Yes'], dtype=object)
```

```
# Define a function for assigning numbers for Payment_of_Min_Amount
def Payment_of_Min_Amount(elem):
  if elem == 'Yes':
    return 1
  else:
    return 0

# Apply the function using transform
df_cleaned['Payment_of_Min_Amount_eq_no'] =
df_cleaned['Payment_of_Min_Amount'].transform(Payment_of_Min_Amount)
```

7.3.5) Treating Payment_Behaviour

```
# Define mapping
payment_behaviour_mapping = {
    'High_spent_Small_value_payments': 4,
    'High_spent_Medium_value_payments': 5,
```

```
    'High_spent_Large_value_payments': 6,
    'Low_spent_Small_value_payments': 1,
    'Low_spent_Medium_value_payments': 2,
    'Low_spent_Large_value_payments': 3
}
# Apply mapping
df_cleaned['Payment_Behaviour_Num'] =
df_cleaned['Payment_Behaviour'].map(payment_behaviour_mapping)
```

OBSERVATION

- High_spent_Small_value_payments: Likely to indicate high spending habits with small payments, which might be risky if the behavior is consistent.
- High_spent_Medium_value_payments: Indicates high spending with medium payments, potentially a higher risk.
- High_spent_Large_value_payments: Shows high spending with large payments, which might indicate high financial risk.
- Low_spent_Small_value_payments: Shows low spending with small payments, likely less risky.
- Low_spent_Medium_value_payments: Low spending with medium payments, potentially moderate risk.
- Low_spent_Large_value_payments: Low spending with large payments, might be less risky but could indicate underutilization of credit.

```
# Download the cleaned file
# df_cleaned.to_csv('Credit_score_cleaned', sep=",",index=False)

df_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 31 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   ID                            100000 non-null  object
 1   Customer_ID                   100000 non-null  object
 2   Month                         100000 non-null  object
 3   Name                          100000 non-null  object
 4   Age                           100000 non-null  int64
 5   SSN                           100000 non-null  object
 6   Occupation                    100000 non-null  object
 7   Annual_Income                 100000 non-null  float64
 8   Monthly_Inhand_Salary         100000 non-null  float64
 9   Num_Bank_Accounts             100000 non-null  int64
 10  Num_Credit_Card               100000 non-null  int64
 11  Interest_Rate                 100000 non-null  int64
 12  Num_of_Loan                   100000 non-null  int64
 13  Type_of_Loan                  100000 non-null  object
 14  Delay_from_due_date           100000 non-null  int64
```

```
 15   Num_of_Delayed_Payment        100000 non-null  int64
 16   Changed_Credit_Limit          100000 non-null  float64
 17   Num_Credit_Inquiries          100000 non-null  int64
 18   Credit_Mix                    100000 non-null  object
 19   Outstanding_Debt              100000 non-null  float64
 20   Credit_Utilization_Ratio      100000 non-null  float64
 21   Credit_History_Age            100000 non-null  int64
 22   Payment_of_Min_Amount         100000 non-null  object
 23   Total_EMI_per_month           100000 non-null  float64
 24   Amount_invested_monthly       100000 non-null  float64
 25   Payment_Behaviour             100000 non-null  object
 26   Monthly_Balance               100000 non-null  float64
 27   Month_num                     100000 non-null  int32
 28   Credit_Mix_eq_no              100000 non-null  int64
 29   Payment_of_Min_Amount_eq_no  100000 non-null  int64
 30   Payment_Behaviour_Num         100000 non-null  int64
dtypes: float64(8), int32(1), int64(12), object(10)
memory usage: 23.3+ MB
```

```
# Columns that are in int and float datatype
for i, elem in (enumerate(df_cleaned.columns)):
  if df_cleaned[elem].dtypes != 'object':
    print(f"{i+1}. {elem}: {df_cleaned[elem].nunique(),
df_cleaned[elem].dtypes}")
```

```
5. Age: (43, dtype('int64'))
8. Annual_Income: (13437, dtype('float64'))
9. Monthly_Inhand_Salary: (13235, dtype('float64'))
10. Num_Bank_Accounts: (11, dtype('int64'))
11. Num_Credit_Card: (12, dtype('int64'))
12. Interest_Rate: (34, dtype('int64'))
13. Num_of_Loan: (10, dtype('int64'))
15. Delay_from_due_date: (68, dtype('int64'))
16. Num_of_Delayed_Payment: (29, dtype('int64'))
17. Changed_Credit_Limit: (3634, dtype('float64'))
18. Num_Credit_Inquiries: (18, dtype('int64'))
20. Outstanding_Debt: (12203, dtype('float64'))
21. Credit_Utilization_Ratio: (99998, dtype('float64'))
22. Credit_History_Age: (34, dtype('int64'))
24. Total_EMI_per_month: (14950, dtype('float64'))
25. Amount_invested_monthly: (91048, dtype('float64'))
27. Monthly_Balance: (98790, dtype('float64'))
28. Month_num: (8, dtype('int32'))
29. Credit_Mix_eq_no: (3, dtype('int64'))
30. Payment_of_Min_Amount_eq_no: (2, dtype('int64'))
31. Payment_Behaviour_Num: (6, dtype('int64'))
```

```
# Columns that are in object datatype
for i, elem in (enumerate(df_cleaned.columns)):
  if df_cleaned[elem].dtypes == 'O':
```

```
    print(f"{i+1}. {elem}: {df_cleaned[elem].nunique(),
df_cleaned[elem].dtypes}")
```

```
1. ID: (100000, dtype('O'))
2. Customer_ID: (12500, dtype('O'))
3. Month: (8, dtype('O'))
4. Name: (10139, dtype('O'))
6. SSN: (12500, dtype('O'))
7. Occupation: (15, dtype('O'))
14. Type_of_Loan: (6261, dtype('O'))
19. Credit_Mix: (3, dtype('O'))
23. Payment_of_Min_Amount: (2, dtype('O'))
26. Payment_Behaviour: (6, dtype('O'))
```

7.4) Aggregate Data at Customer Level

```
# Creating a dictionary for aggregation at Customer_ID level
agg_dict = {
    'ID': 'first',
     # Grouped by on Customer_ID so not included
    'Name': 'first',
    'Age': 'first',
    'SSN': 'first',
    'Occupation': 'first',
    'Annual_Income': 'first',
    'Monthly_Inhand_Salary': 'first',
    'Num_Bank_Accounts': 'first',
    'Num_Credit_Card': 'first',
    'Interest_Rate': 'first',
    'Num_of_Loan': 'first',
    'Type_of_Loan': 'first',
    'Delay_from_due_date': 'mean',
    'Num_of_Delayed_Payment': 'first',
    'Changed_Credit_Limit': 'mean',
    'Num_Credit_Inquiries': 'first',
    'Credit_Mix': 'first',
    'Outstanding_Debt': 'first',
    'Credit_Utilization_Ratio': 'mean',
    'Credit_History_Age': 'first',
    'Payment_of_Min_Amount': 'first',
    'Total_EMI_per_month': 'first',
    'Amount_invested_monthly': 'mean',
    # Payment_Behaviour not included
    'Monthly_Balance': 'mean',
    'Credit_Mix_eq_no': 'first',
    'Payment_of_Min_Amount_eq_no': 'first',
    'Payment_Behaviour_Num': 'mean'
}
df_aggregated =
df_cleaned.groupby('Customer_ID').agg(agg_dict).reset_index()
```

```
df_aggregated.head()
```

{"type":"dataframe","variable_name":"df_aggregated"}

```
# Download the cleaned file
#df_aggregated.to_csv('Credit_score_cleaned_aggregated',
sep=",",index=False)

df_aggregated.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12500 entries, 0 to 12499
Data columns (total 28 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Customer_ID                   12500 non-null  object
 1   ID                            12500 non-null  object
 2   Name                          12500 non-null  object
 3   Age                           12500 non-null  int64
 4   SSN                           12500 non-null  object
 5   Occupation                    12500 non-null  object
 6   Annual_Income                 12500 non-null  float64
 7   Monthly_Inhand_Salary         12500 non-null  float64
 8   Num_Bank_Accounts             12500 non-null  int64
 9   Num_Credit_Card               12500 non-null  int64
 10  Interest_Rate                 12500 non-null  int64
 11  Num_of_Loan                   12500 non-null  int64
 12  Type_of_Loan                  12500 non-null  object
 13  Delay_from_due_date           12500 non-null  float64
 14  Num_of_Delayed_Payment        12500 non-null  int64
 15  Changed_Credit_Limit          12500 non-null  float64
 16  Num_Credit_Inquiries          12500 non-null  int64
 17  Credit_Mix                    12500 non-null  object
 18  Outstanding_Debt              12500 non-null  float64
 19  Credit_Utilization_Ratio      12500 non-null  float64
 20  Credit_History_Age            12500 non-null  int64
 21  Payment_of_Min_Amount         12500 non-null  object
 22  Total_EMI_per_month           12500 non-null  float64
 23  Amount_invested_monthly       12500 non-null  float64
 24  Monthly_Balance               12500 non-null  float64
 25  Credit_Mix_eq_no              12500 non-null  int64
 26  Payment_of_Min_Amount_eq_no   12500 non-null  int64
 27  Payment_Behaviour_Num         12500 non-null  float64
dtypes: float64(10), int64(10), object(8)
memory usage: 2.7+ MB
```

```
# Columns that are in int and float datatype
for i, elem in (enumerate(df_aggregated.columns)):
  if df_aggregated[elem].dtypes != 'object':
```

```
    print(f"{i+1}. {elem}: {df_aggregated[elem].nunique(),
df_aggregated[elem].dtypes}")
```

```
4. Age: (43, dtype('int64'))
7. Annual_Income: (12489, dtype('float64'))
8. Monthly_Inhand_Salary: (12489, dtype('float64'))
9. Num_Bank_Accounts: (11, dtype('int64'))
10. Num_Credit_Card: (12, dtype('int64'))
11. Interest_Rate: (34, dtype('int64'))
12. Num_of_Loan: (10, dtype('int64'))
14. Delay_from_due_date: (506, dtype('float64'))
15. Num_of_Delayed_Payment: (29, dtype('int64'))
16. Changed_Credit_Limit: (4796, dtype('float64'))
17. Num_Credit_Inquiries: (18, dtype('int64'))
19. Outstanding_Debt: (12203, dtype('float64'))
20. Credit_Utilization_Ratio: (12500, dtype('float64'))
21. Credit_History_Age: (34, dtype('int64'))
23. Total_EMI_per_month: (11114, dtype('float64'))
24. Amount_invested_monthly: (12500, dtype('float64'))
25. Monthly_Balance: (12500, dtype('float64'))
26. Credit_Mix_eq_no: (3, dtype('int64'))
27. Payment_of_Min_Amount_eq_no: (2, dtype('int64'))
28. Payment_Behaviour_Num: (41, dtype('float64'))
```

```
# Columns that are in object datatype
for i, elem in (enumerate(df_aggregated.columns)):
  if df_aggregated[elem].dtypes == 'O':
    print(f"{i+1}. {elem}: {df_aggregated[elem].nunique(),
df_aggregated[elem].dtypes}")
```

```
1. Customer_ID: (12500, dtype('O'))
2. ID: (12500, dtype('O'))
3. Name: (10139, dtype('O'))
5. SSN: (12500, dtype('O'))
6. Occupation: (15, dtype('O'))
13. Type_of_Loan: (6261, dtype('O'))
18. Credit_Mix: (3, dtype('O'))
22. Payment_of_Min_Amount: (2, dtype('O'))
```

```
# Display the range of attributes
print("Range of attributes:")
print("-" * 20)
df_aggregated.describe(include='all').T
```

```
Range of attributes:
--------------------
```

{"summary":"{\n \"name\": \"df_aggregated\",\n \"rows\": 28,\n
\"fields\": [\n   {\n   \"column\": \"count\",\n
\"properties\": {\n   \"dtype\": \"date\",\n   \"min\":
\"12500\",\n   \"max\": \"12500\",\n

```
\"num_unique_values\": 1,\n        \"samples\": [\n
\"12500\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"unique\",\n      \"properties\": {\n        \"dtype\": \"date\",\n
\"min\": 2,\n        \"max\": 12500,\n        \"num_unique_values\":
6,\n        \"samples\": [\n          12500\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"top\",\n      \"properties\": {\n
\"dtype\": \"category\",\n        \"num_unique_values\": 8,\n
\"samples\": [\n          \"0x1628a\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"freq\",\n      \"properties\": {\n
\"dtype\": \"date\",\n        \"min\": \"1\",\n        \"max\":
\"6524\",\n        \"num_unique_values\": 6,\n        \"samples\": [\n
\"1\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"mean\",\n      \"properties\": {\n        \"dtype\": \"date\",\n
\"min\": 0.52192,\n        \"max\": 191047.36208639998,\n
\"num_unique_values\": 20,\n        \"samples\": [\n          33.282\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"std\",\n      \"properties\": {\
n        \"dtype\": \"date\",\n        \"min\": 0.4995392644809221,\n
\"max\": 1492867.759533881,\n        \"num_unique_values\": 20,\n
\"samples\": [\n          10.766945257073312\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"min\",\n      \"properties\": {\n
\"dtype\": \"date\",\n        \"min\": -1.07,\n        \"max\":
7005.93,\n        \"num_unique_values\": 10,\n        \"samples\": [\n
11.2801204875\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"25%\",\n      \"properties\": {\n        \"dtype\": \"date\",\n
\"min\": 0.0,\n        \"max\": 19491.2,\n
\"num_unique_values\": 19,\n        \"samples\": [\n          24.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"50%\",\n      \"properties\": {\
n        \"dtype\": \"date\",\n        \"min\": 1.0,\n        \"max\":
37667.56,\n        \"num_unique_values\": 17,\n        \"samples\": [\
n          33.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"75%\",\n      \"properties\": {\n        \"dtype\": \"date\",\n
\"min\": 1.0,\n        \"max\": 72957.64499999999,\n
\"num_unique_values\": 19,\n        \"samples\": [\n          42.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"max\",\n      \"properties\": {\
n        \"dtype\": \"date\",\n        \"min\": 1.0,\n        \"max\":
23658189.0,\n        \"num_unique_values\": 20,\n        \"samples\":
[\n          56.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\n}","type":"dataframe"}
```

```python
# Display the statistical summary
print("statistical summary:")
print("-" * 20)
df_aggregated.describe().T
```

```
statistical summary:
--------------------
```

{"summary":"{\n \"name\": \"df_aggregated\",\n \"rows\": 20,\n \"fields\": [\n   {\n   \"column\": \"count\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0.0,\n   \"min\": 12500.0,\n   \"max\": 12500.0,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   12500.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"mean\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 42640.51338752753,\n   \"min\": 0.52192,\n   \"max\": 191047.36208639998,\n   \"num_unique_values\": 20,\n   \"samples\": [\n   33.282\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"std\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 333669.72916625906,\n   \"min\": 0.4995392644809221,\n   \"max\": 1492867.759533881,\n   \"num_unique_values\": 20,\n   \"samples\": [\n   10.766945257073312\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"min\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 1562.9849751398544,\n   \"min\": -1.07,\n   \"max\": 7005.93,\n   \"num_unique_values\": 10,\n   \"samples\": [\n   11.2801204875\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"25%\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 4342.732091695363,\n   \"min\": 0.0,\n   \"max\": 19491.2,\n   \"num_unique_values\": 19,\n   \"samples\": [\n   24.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"50%\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 8395.082894724275,\n   \"min\": 1.0,\n   \"max\": 37667.56,\n   \"num_unique_values\": 17,\n   \"samples\": [\n   33.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"75%\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 16265.750602263657,\n   \"min\": 1.0,\n   \"max\": 72957.64499999999,\n   \"num_unique_values\": 19,\n   \"samples\": [\n   42.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"max\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 5288927.836470696,\n   \"min\": 1.0,\n   \"max\": 23658189.0,\n   \"num_unique_values\": 20,\n   \"samples\": [\n   56.0\n

],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

8) Exploratory data analysis

8.1) Univariate Analysis

```
green_palette = ['#006400', '#008000', '#228B22', '#32CD32',
'#3CB371', '#66CDAA', '#7FFF00', '#00FF7F', '#98FB98', '#ADFF2F']

columns = ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount']

for elem in columns:
  print(f"Column Name: {elem}")
  print(data[elem].value_counts())
  print()
  print(round(((data[elem].value_counts(normalize=True)) * 100),2))
  print("_" * 35)
  print()
```

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

Occupation
_______             7.06
Lawyer              6.58
Architect           6.36
Engineer            6.35
Scientist           6.30
Mechanic            6.29
Accountant          6.27
Developer           6.24
```

```
Media_Manager   6.23
Teacher         6.22
Entrepreneur    6.17
Doctor          6.09
Journalist      6.08
Manager         5.97
Musician        5.91
Writer          5.88
Name: proportion, dtype: float64
___________________________________

Column Name: Credit_Mix
Credit_Mix
Standard    36479
Good        24337
_           20195
Bad         18989
Name: count, dtype: int64

Credit_Mix
Standard   36.48
Good       24.34
_          20.20
Bad        18.99
Name: proportion, dtype: float64
___________________________________

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

Payment_of_Min_Amount
Yes   52.33
No    35.67
NM    12.01
Name: proportion, dtype: float64
___________________________________
```

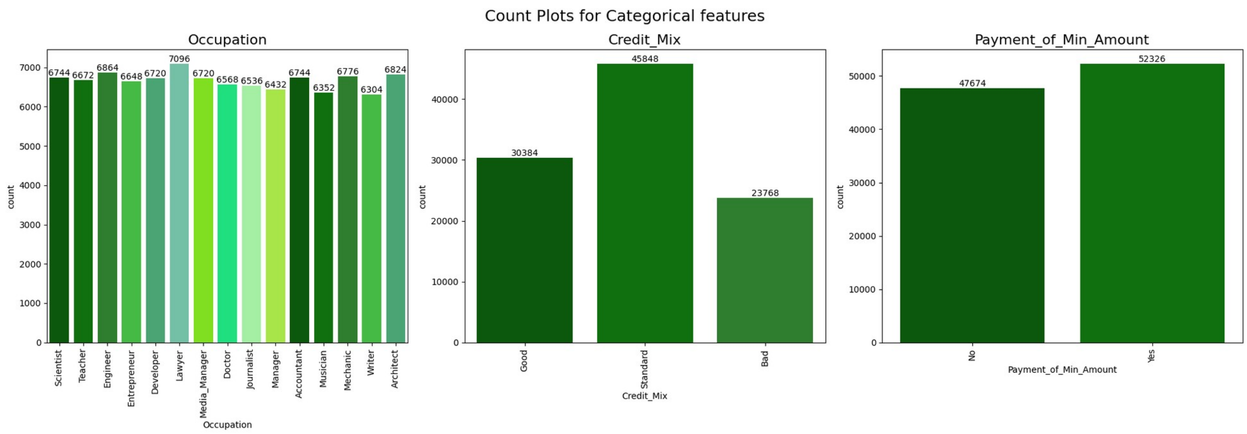
```
# Count Plots for Categorical features
columns = ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount']

plt.figure(figsize=(20,7))
for i, elem in enumerate(columns):
  plt.subplot(1,len(columns),i+1)
  label = sns.countplot(data = df, x = elem, palette = green_palette)
  for i in label.containers:
```

```
    label.bar_label(i)

  plt.xticks(rotation = 90)
  plt.ylabel('count')
  plt.title(elem, fontsize=16)

plt.suptitle("Count Plots for Categorical features", fontsize = 18)
plt.tight_layout()
plt.show()
```



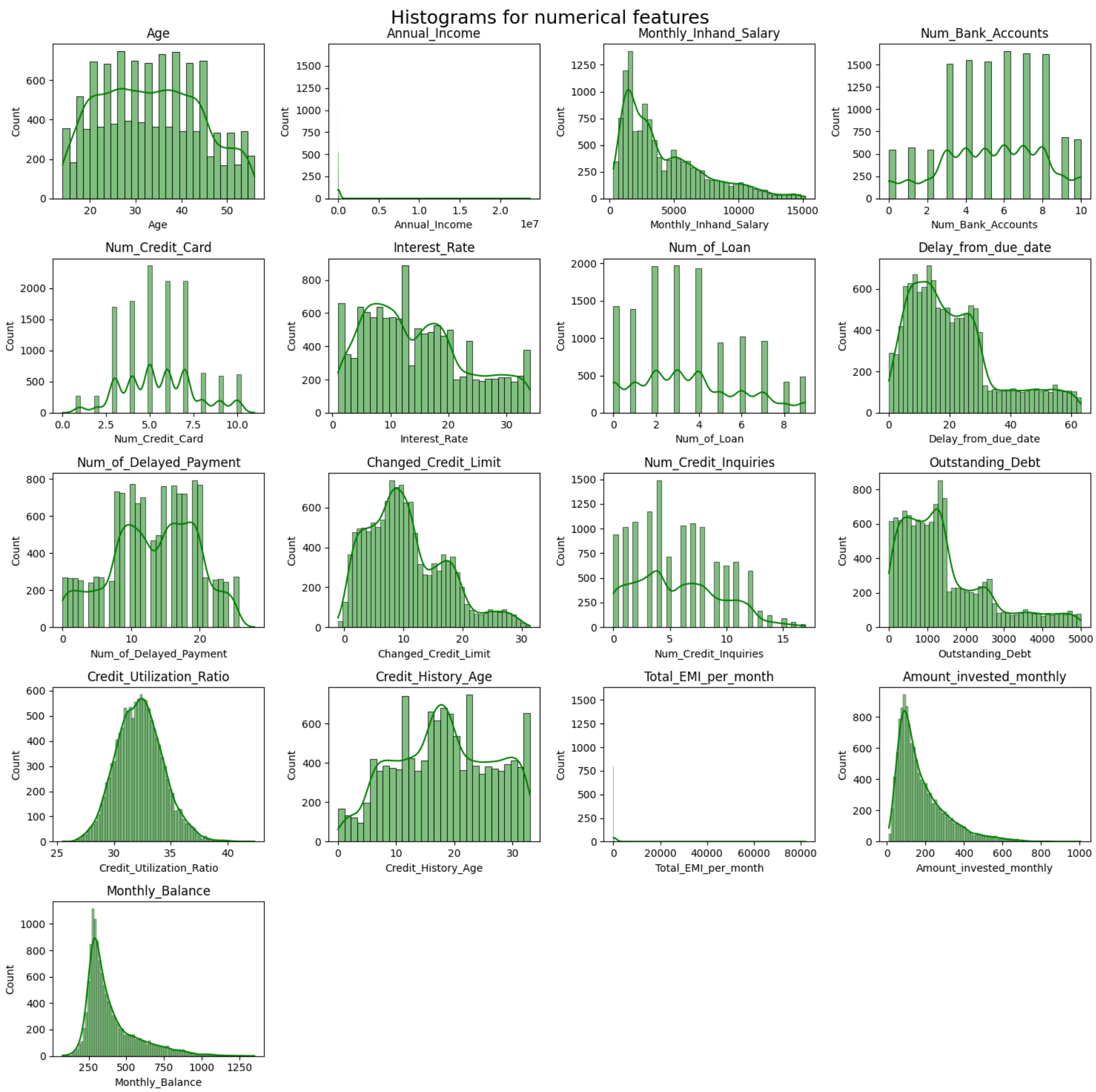
OBSERVATION

- **Occupation**
  - The most common occupations are evenly distributed among high-education or professional roles, such as Lawyer, Architect, Engineer, and Scientist, with a significant proportion of individuals in these roles compared to others.
- **Credit_Mix**
  - The majority of individuals have a "Standard" credit mix, making up 36.48% of the data, while "Good" and "Bad" credit mixes are less prevalent, indicating a generally positive credit mix distribution.
- **Payment_of_Min_Amount**
  - A majority of customers (52.33%) consistently make the minimum payment amount, which suggests a significant portion of the population is managing their payments minimally.

```
# Histograms for numerical columns
num_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', 'Credit_History_Age',
           'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance']
```

```python
plt.figure(figsize=(15,15))
for i, elem in enumerate(num_columns):
  plt.subplot(5,4,i+1)
  sns.histplot(df_aggregated[elem], kde=True, color='green')
  plt.title(elem)

plt.suptitle("Histograms for numerical features", fontsize = 18)
plt.tight_layout()
plt.show()
```



```
# Creating numerical_df
numerical_df = df_aggregated[['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', 'Credit_History_Age',
                              'Total_EMI_per_month',
'Amount_invested_monthly', 'Monthly_Balance']]

# Skewness Coefficient
numerical_df
print("Skewness Coefficient")
print("-" * 20)
print(numerical_df.skew().round(4))
```

```
Skewness Coefficient
--------------------
Age                          0.16
Annual_Income               11.87
Monthly_Inhand_Salary        1.13
Num_Bank_Accounts           -0.19
Num_Credit_Card              0.23
Interest_Rate                0.50
Num_of_Loan                  0.45
Delay_from_due_date          0.99
Num_of_Delayed_Payment      -0.22
Changed_Credit_Limit         0.72
Num_Credit_Inquiries         0.42
Outstanding_Debt             1.21
Credit_Utilization_Ratio     0.28
Credit_History_Age          -0.05
Total_EMI_per_month          7.40
Amount_invested_monthly      1.57
Monthly_Balance              1.61
dtype: float64
```

OBSERVATION

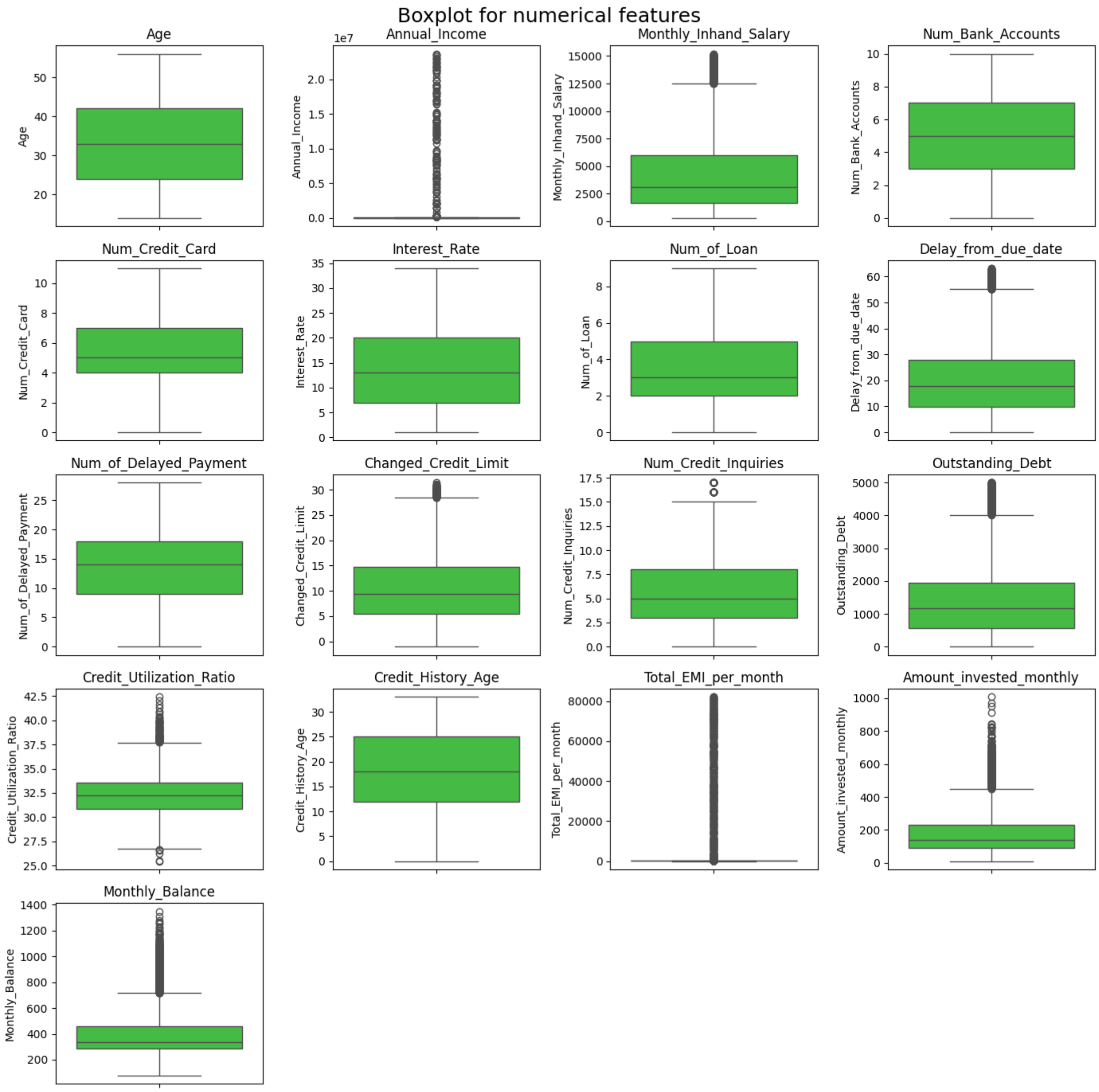
- Annual_Income (11.87): Highly positively skewed, indicating a small number of individuals with very high incomes.
- Credit_Utilization_Ratio (0.28): Mildly positively skewed, with a few high ratios compared to the average.

```
# Box plots for numerical columns
palette = ['#32CD32']

plt.figure(figsize=(14, 14))
```

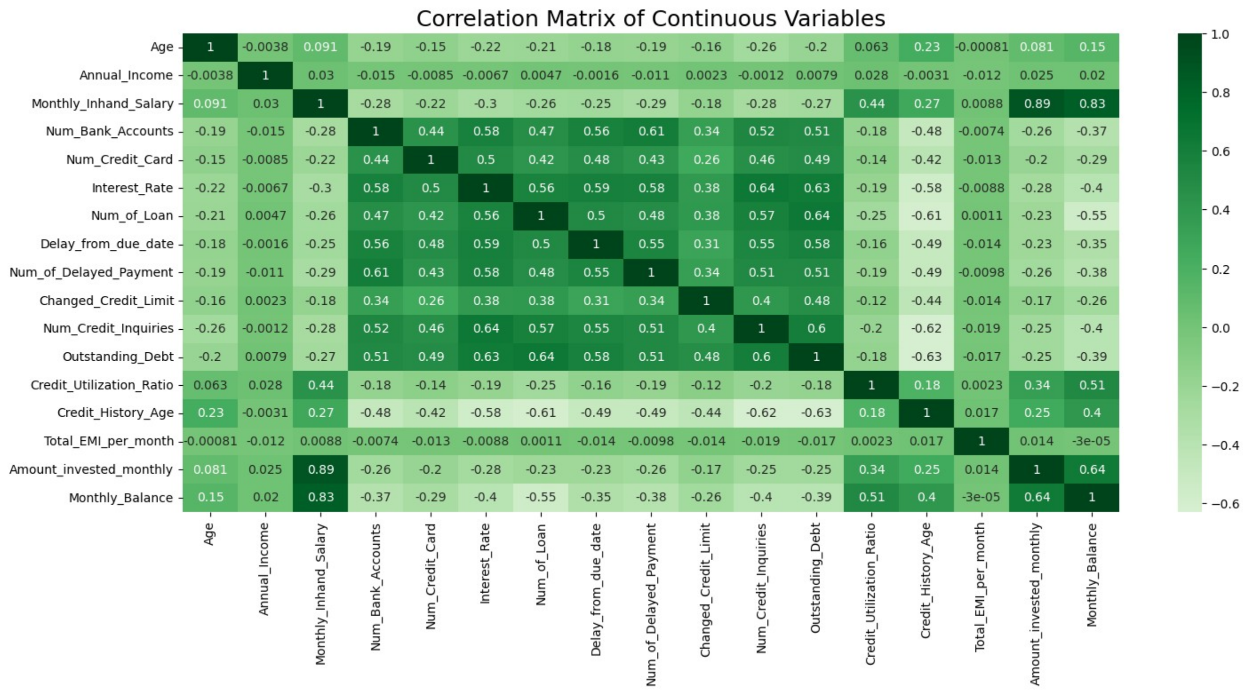
```python
for i, col in enumerate(num_columns):
    plt.subplot(5, 4, i+1)
    sns.boxplot(df_aggregated[col],palette = palette)
    plt.title(col)

plt.suptitle("Boxplot for numerical features", fontsize = 18)
plt.tight_layout()
plt.show()
```



8.2) Bivariate Analysis

```python
# Correlation Matrix of Continuous Variables
plt.figure(figsize=(17, 7))
sns.heatmap(numerical_df.corr(), annot=True, cmap='Greens',center=0)
plt.title('Correlation Matrix of Continuous Variables', fontsize = 18)
plt.show()
```

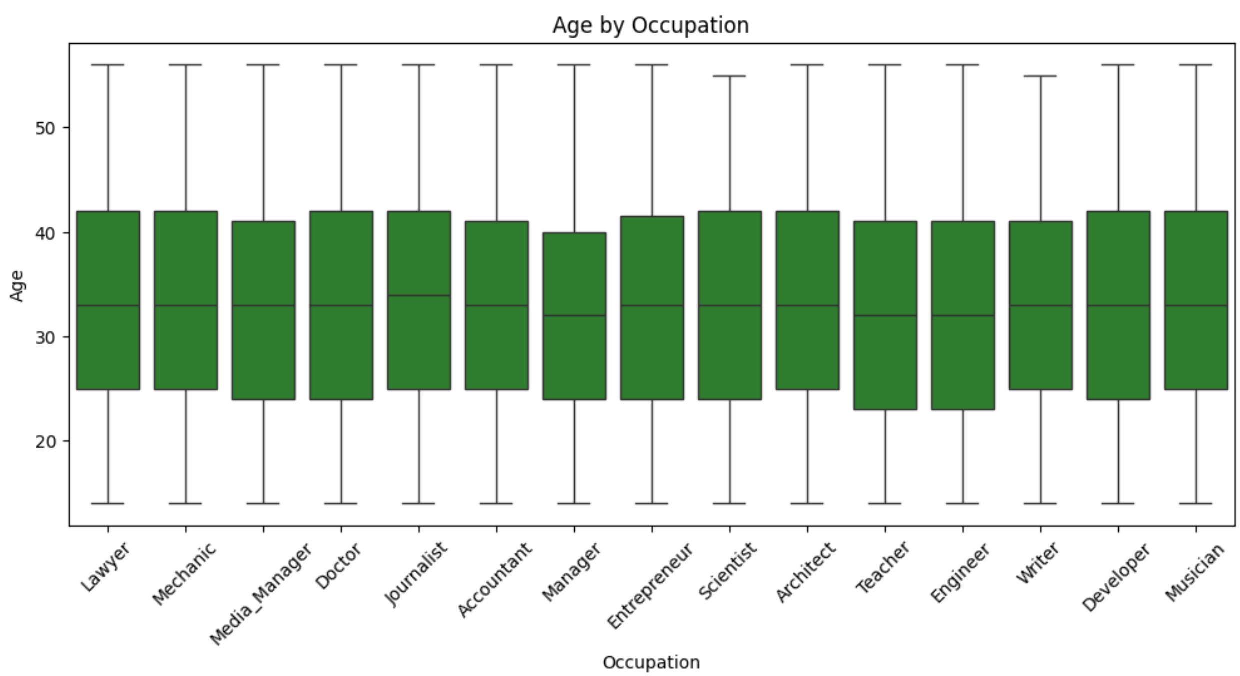


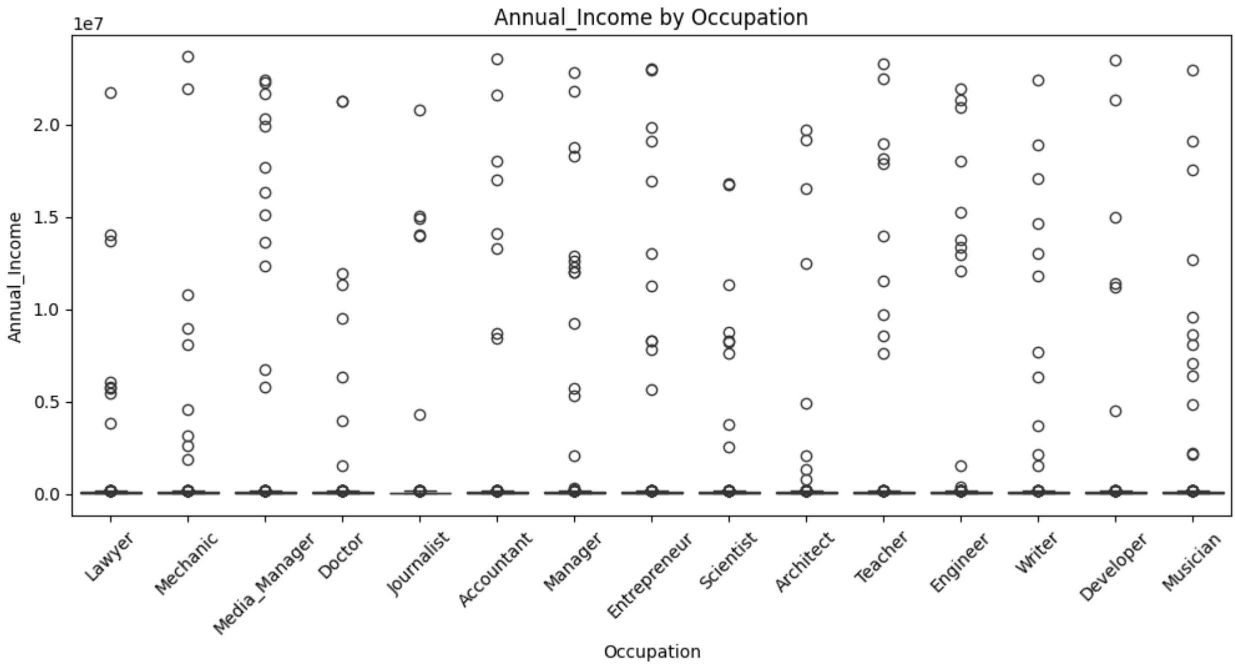
OBSERVATION

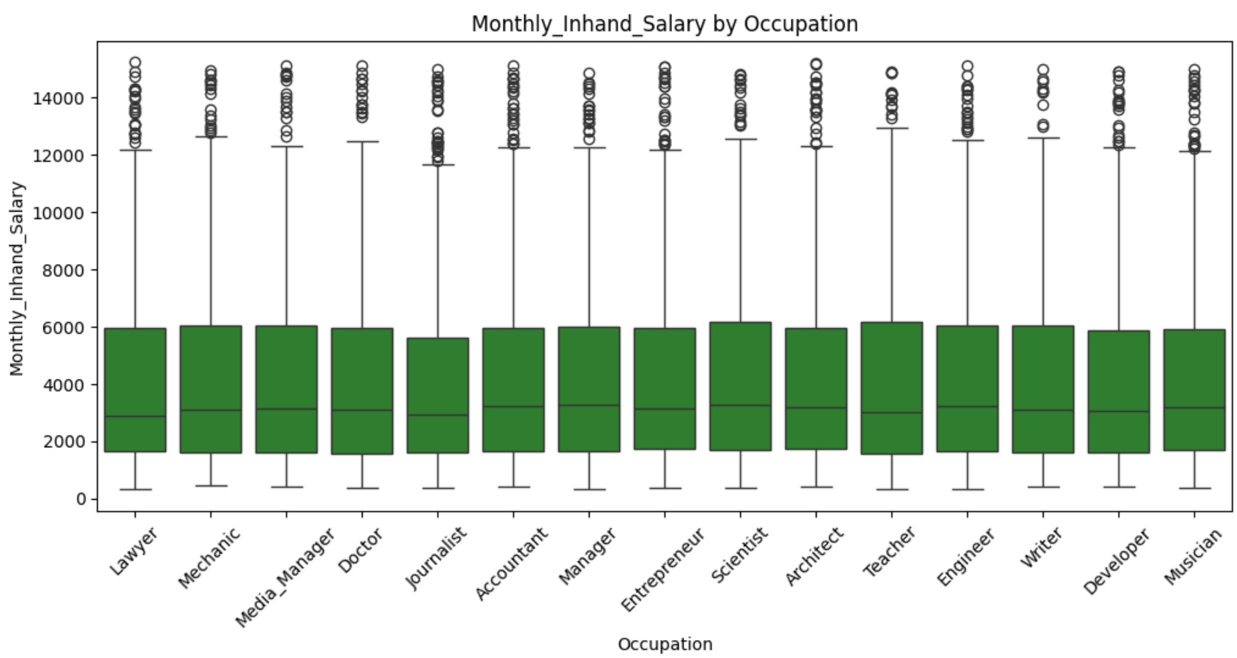
- **High Correlations with Monthly Balance:**
  - Monthly_Inhand_Salary (0.83) and Amount_invested_monthly (0.64) show strong positive correlations with Monthly_Balance. This indicates that individuals with higher monthly salaries and investment amounts tend to have higher monthly balances.
- **Credit Utilization and Outstanding Debt:**
  - Credit_Utilization_Ratio (0.51) and Outstanding_Debt (-0.39) both show positive and negative correlations respectively with Monthly_Balance. High credit utilization and lower outstanding debt are associated with higher and lower monthly balances respectively, which may suggest that higher credit usage contributes to smaller available balances.
- **Negative Correlations with Credit History Age:**
  - Credit_History_Age has a negative correlation with several features, including Num_Bank_Accounts (-0.48) and Num_Credit_Card (-0.42). This suggests that a longer credit history may be associated with fewer accounts and credit cards.
- **Interest Rate and Credit Mix:**

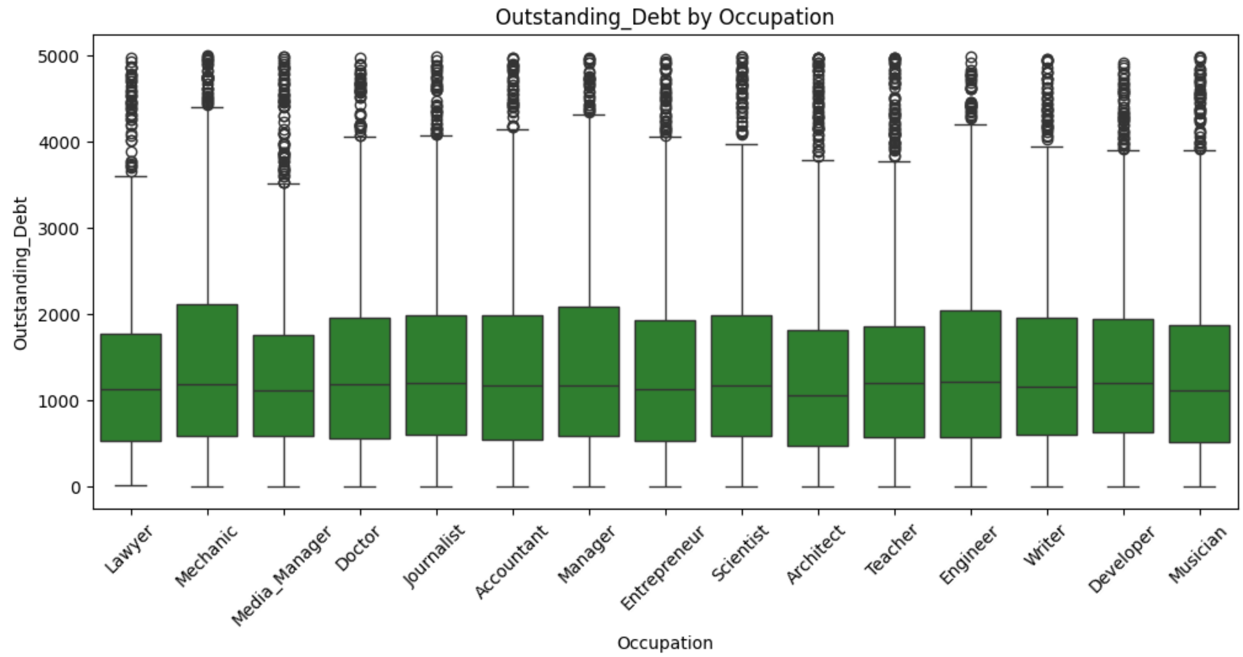
  - Interest_Rate has a strong positive correlation with Num_of_Loan (0.56) and Num_Credit_Inquiries (0.64), indicating that higher interest rates are often associated with a higher number of loans and credit inquiries.
- **Delay from Due Date and Num_of_Delayed_Payment:**
  - Delay_from_due_date (0.55) and Num_of_Delayed_Payment (0.34) are positively correlated, suggesting that greater delays in payments are associated with more instances of delayed payments.
- **Annual Income and Other Features:**
  - Annual_Income has low correlations with other features, suggesting it may not be strongly related to other financial behaviors or attributes in this dataset.

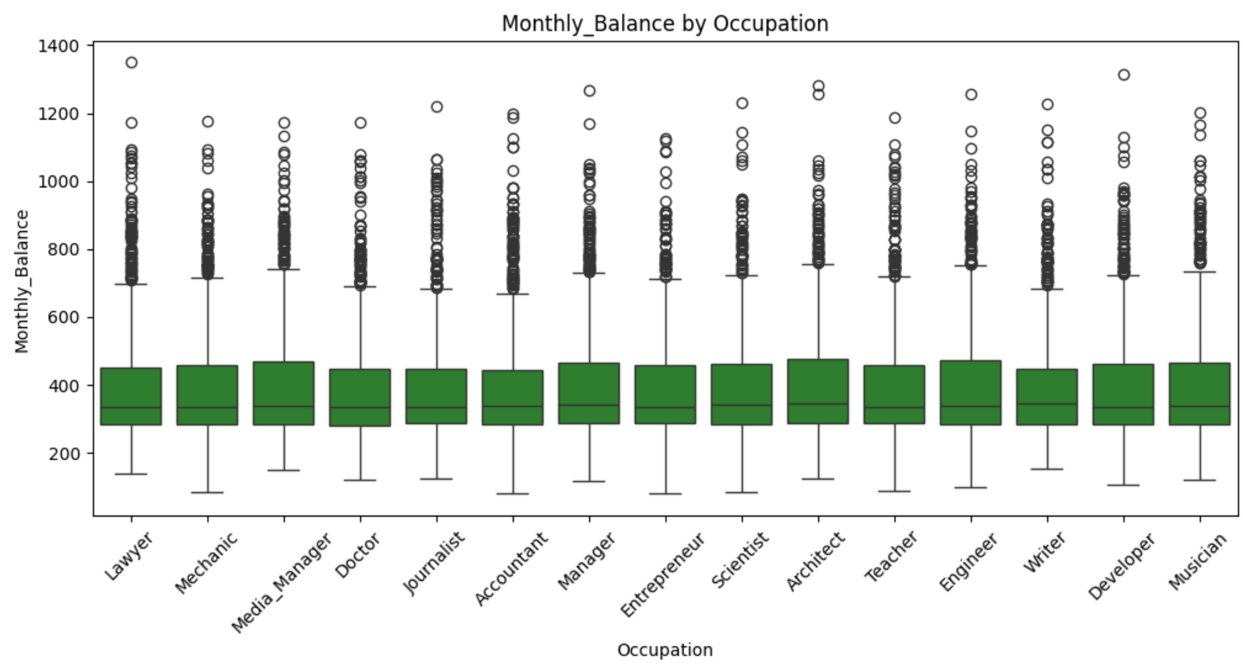
```
# Categorical vs. Numerical
palette = ['#228B22']
for column in ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount']:
    for i, num_column in enumerate(['Age', 'Annual_Income',
'Monthly_Inhand_Salary', 'Outstanding_Debt', 'Monthly_Balance']):
        plt.figure(figsize=(12, 5))
        sns.boxplot(x=df_aggregated[column],
y=df_aggregated[num_column], palette=palette)
        plt.title(f'{num_column} by {column}')
        plt.xticks(rotation=45)
        plt.show()
```

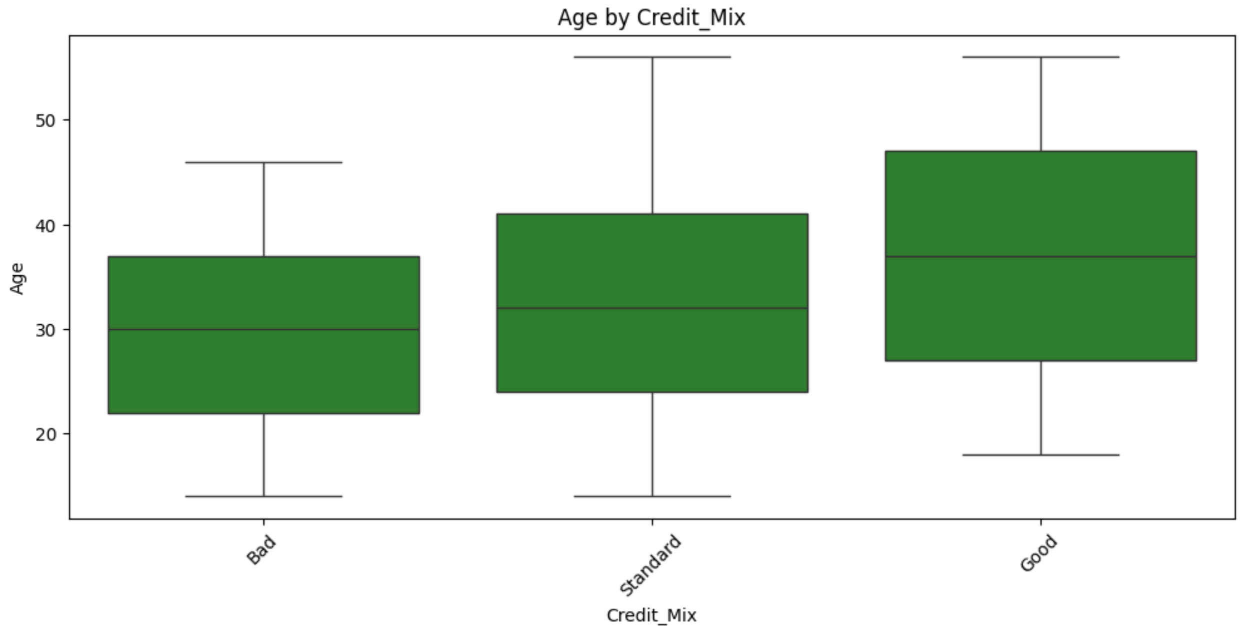


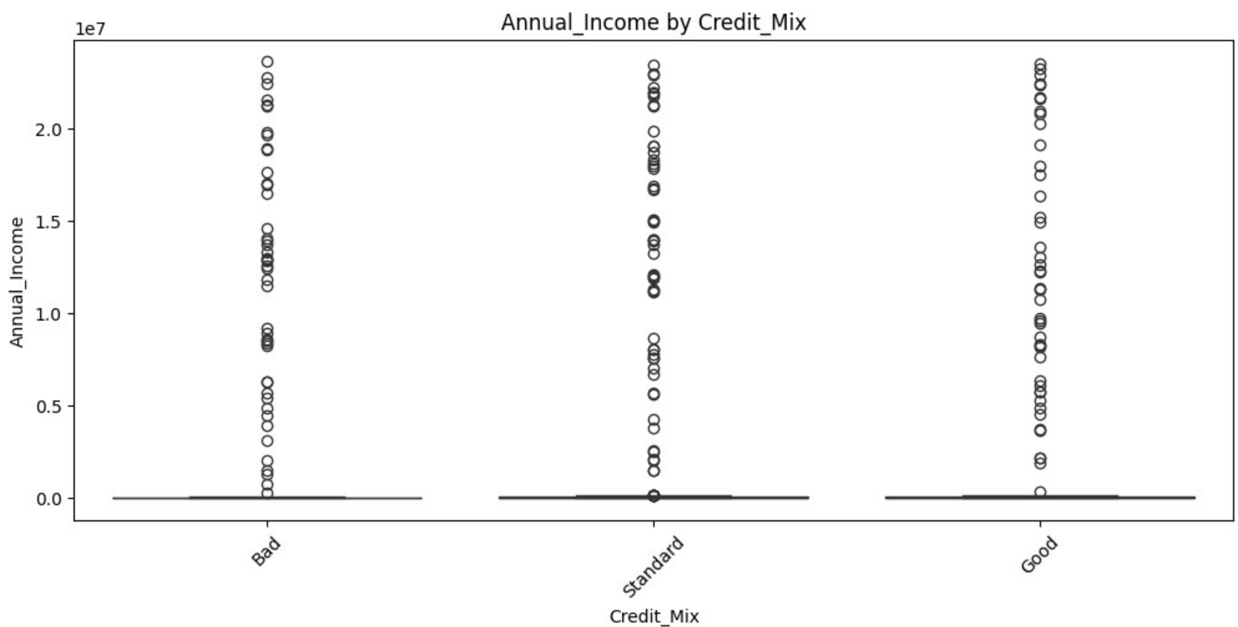

Annual_Income by Occupation
1e7
Annual_Income
2.0
1.5
1.0
0.5
0.0
Lawyer
Mechanic
Media_Manager
Doctor
Journalist
Accountant
Manager
Entrepreneur
Scientist
Architect
Teacher
Engineer
Writer
Developer
Musician
Occupation


Monthly_Inhand_Salary by Occupation
Monthly_Inhand_Salary
14000
12000
10000
8000
6000
4000
2000
0
Lawyer
Mechanic
Media_Manager
Doctor
Journalist
Accountant
Manager
Entrepreneur
Scientist
Architect
Teacher
Engineer
Writer
Developer
Musician
Occupation

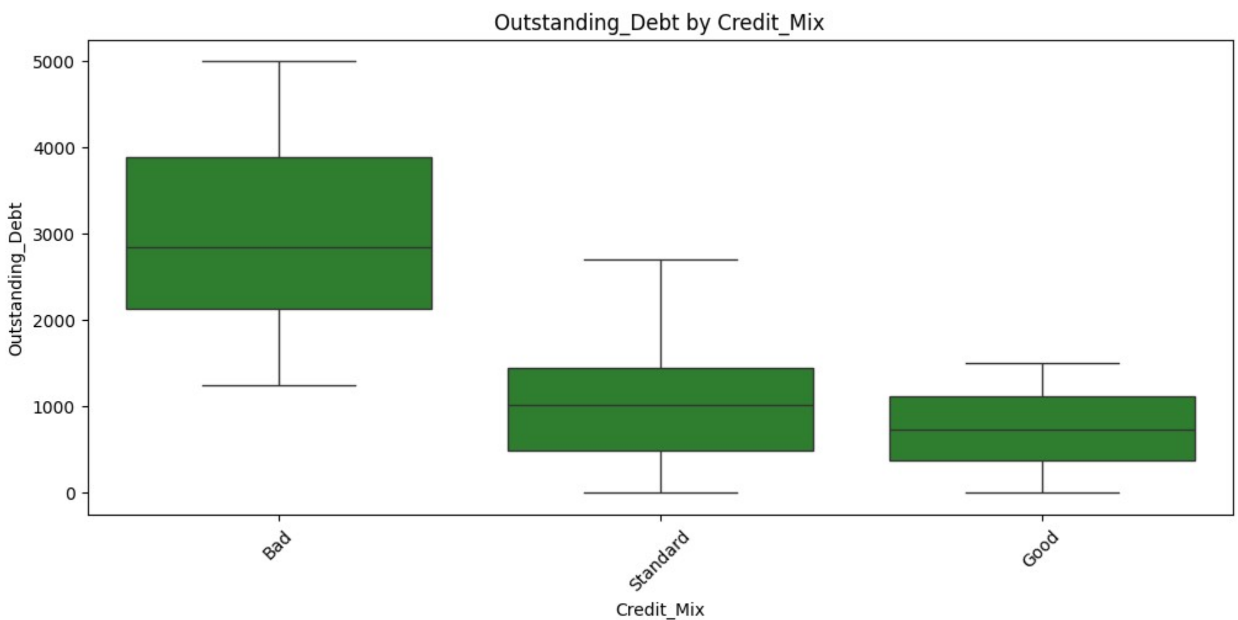

Outstanding_Debt by Occupation
Outstanding_Debt
0
1000
2000
3000
4000
5000
Lawyer
Mechanic
Media_Manager
Doctor
Journalist
Accountant
Manager
Entrepreneur
Scientist
Architect
Teacher
Engineer
Writer
Developer
Musician
Occupation

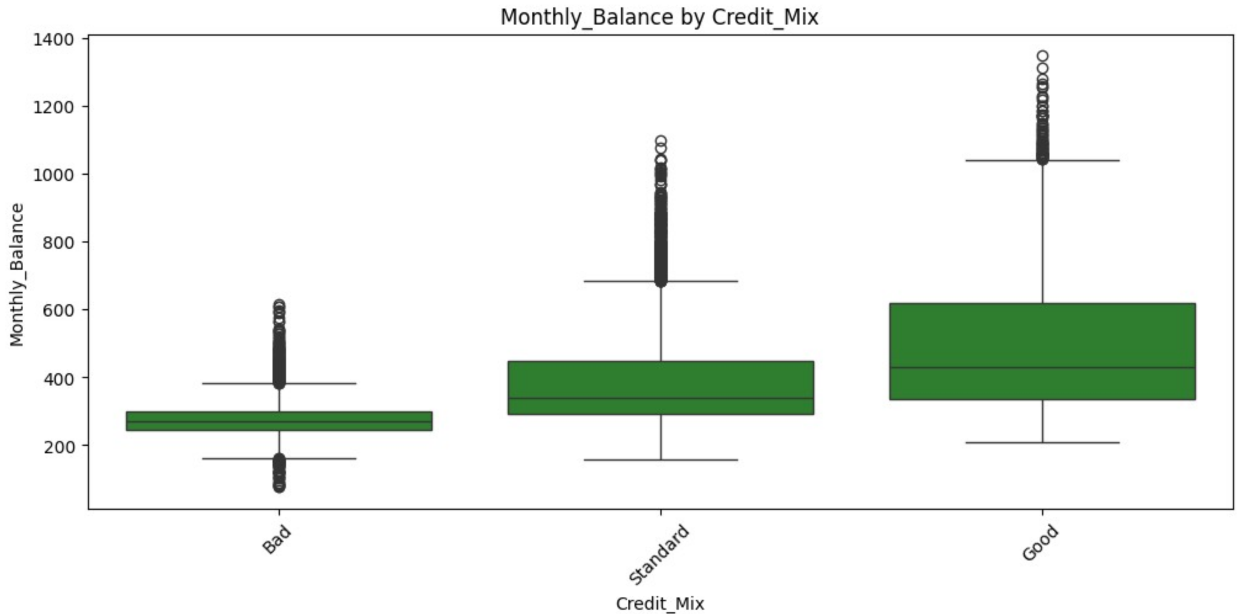

Monthly_Balance by Occupation
Monthly_Balance
200
400
600
800
1000
1200
1400
Lawyer
Mechanic
Media_Manager
Doctor
Journalist
Accountant
Manager
Entrepreneur
Scientist
Architect
Teacher
Engineer
Writer
Developer
Musician
Occupation


Age by Credit_Mix
Age
50
40
30
20
Bad
Standard
Good
Credit_Mix

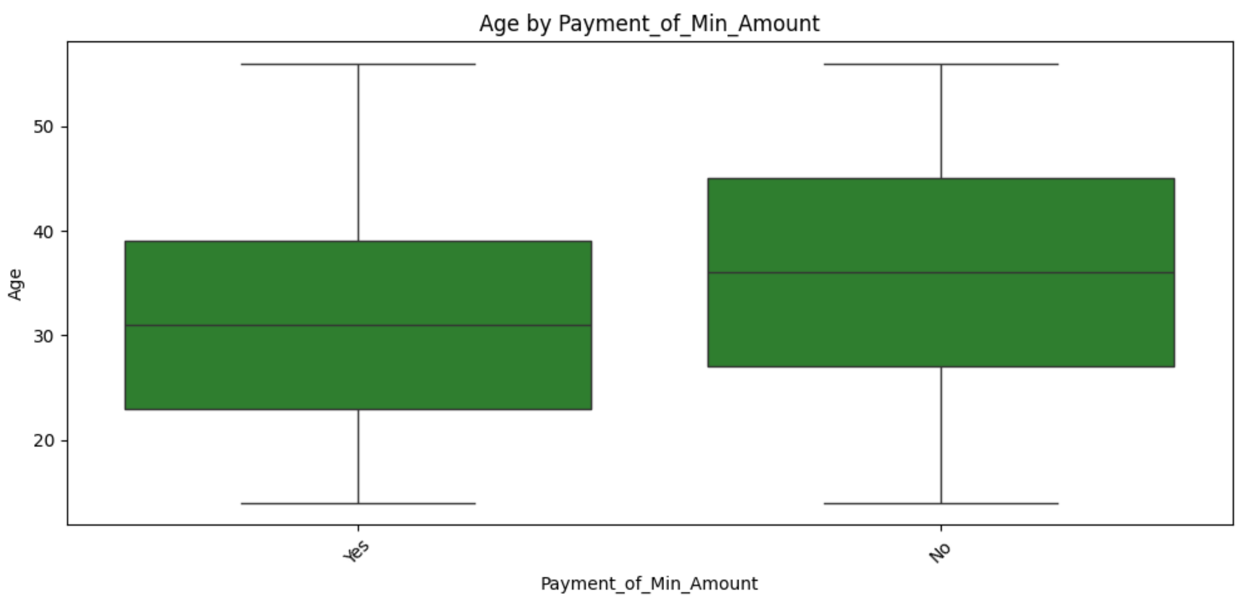

Annual_Income by Credit_Mix
1e7
Annual_Income
2.0
1.5
1.0
0.5
0.0
Bad
Standard
Good
Credit_Mix


Monthly_Inhand_Salary by Credit_Mix
Monthly_Inhand_Salary
14000
12000
10000
8000
6000
4000
2000
0
Bad
Standard
Good
Credit_Mix

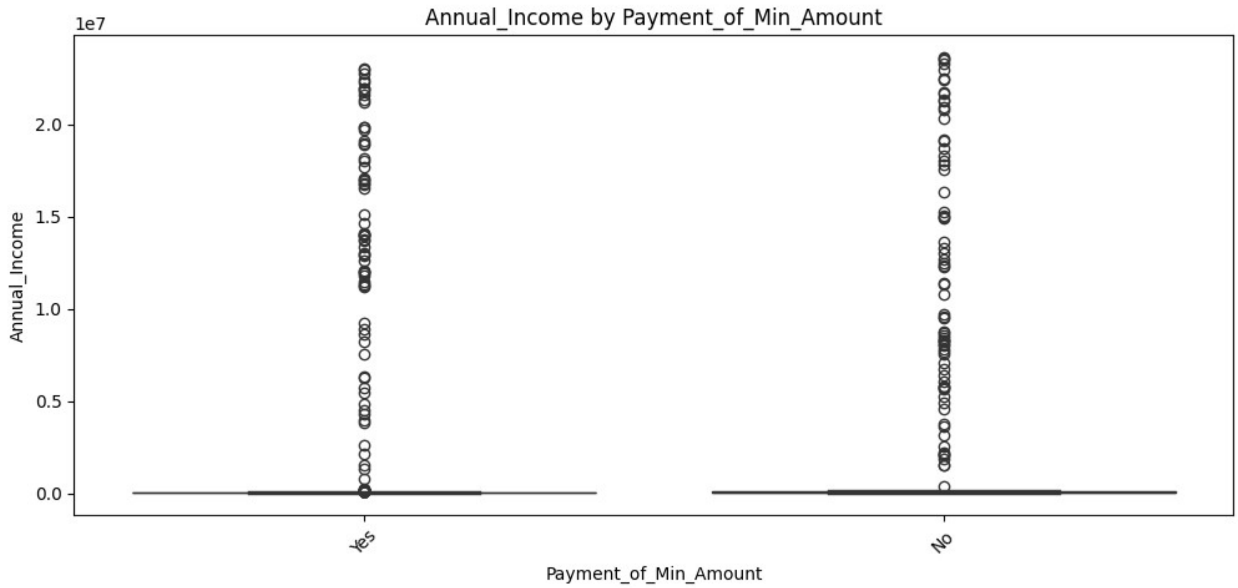

Outstanding_Debt by Credit_Mix
Outstanding_Debt
5000
4000
3000
2000
1000
0
Bad
Standard
Good
Credit_Mix



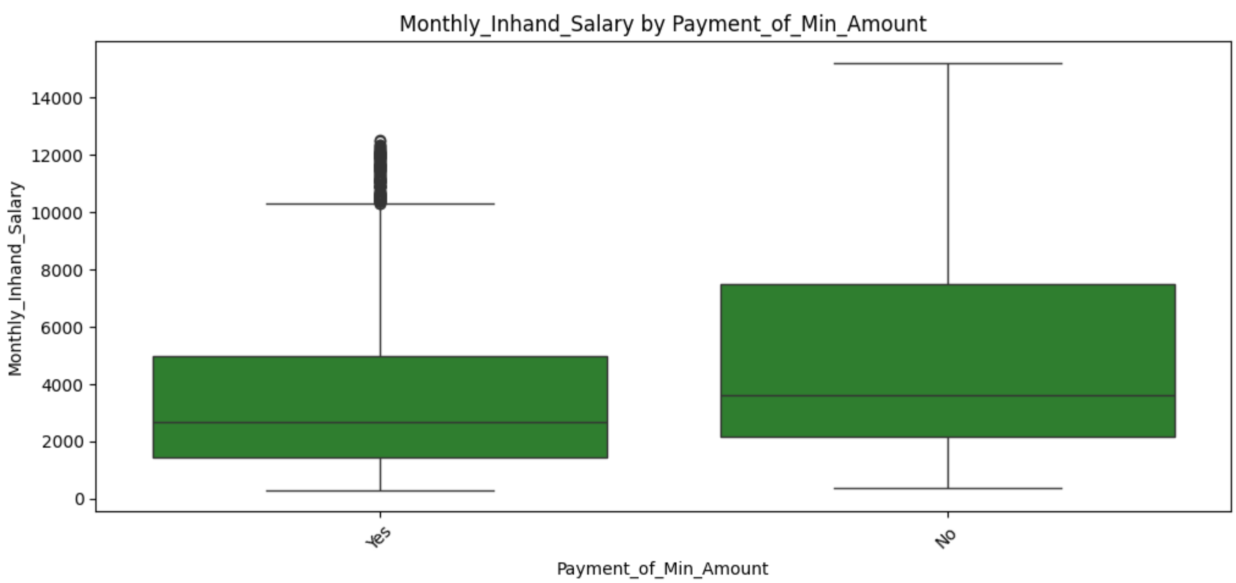
Monthly_Balance by Credit_Mix
1400
1200
1000
800
600
400
200
Monthly_Balance
Bad
Standard
Good
Credit_Mix



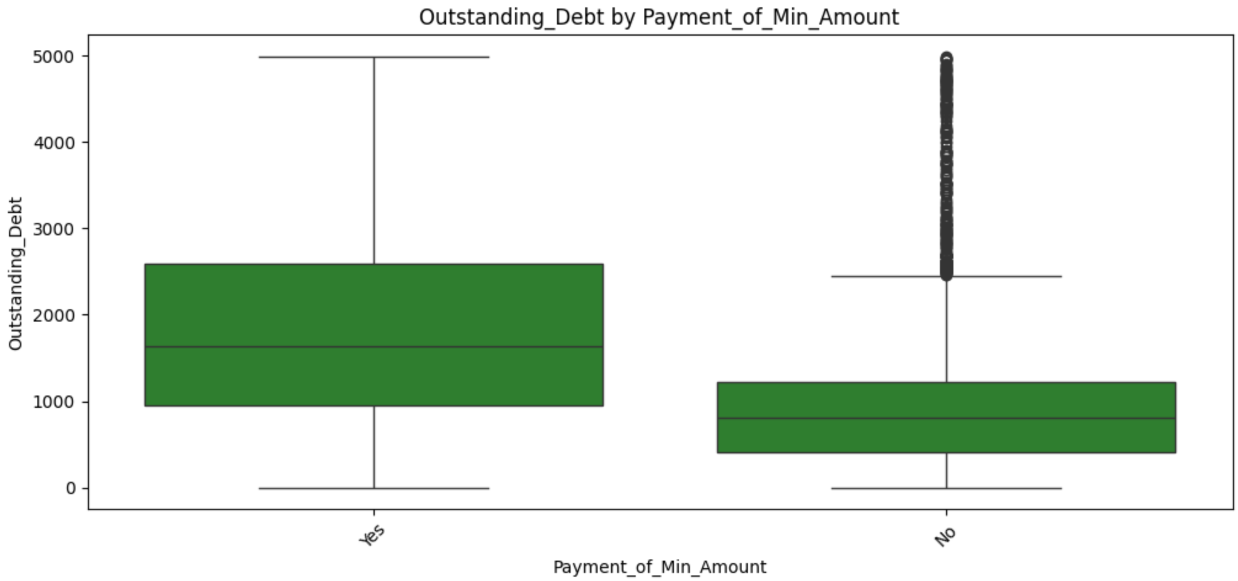
Age by Payment_of_Min_Amount
50
40
30
20
Age
Yes
No
Payment_of_Min_Amount

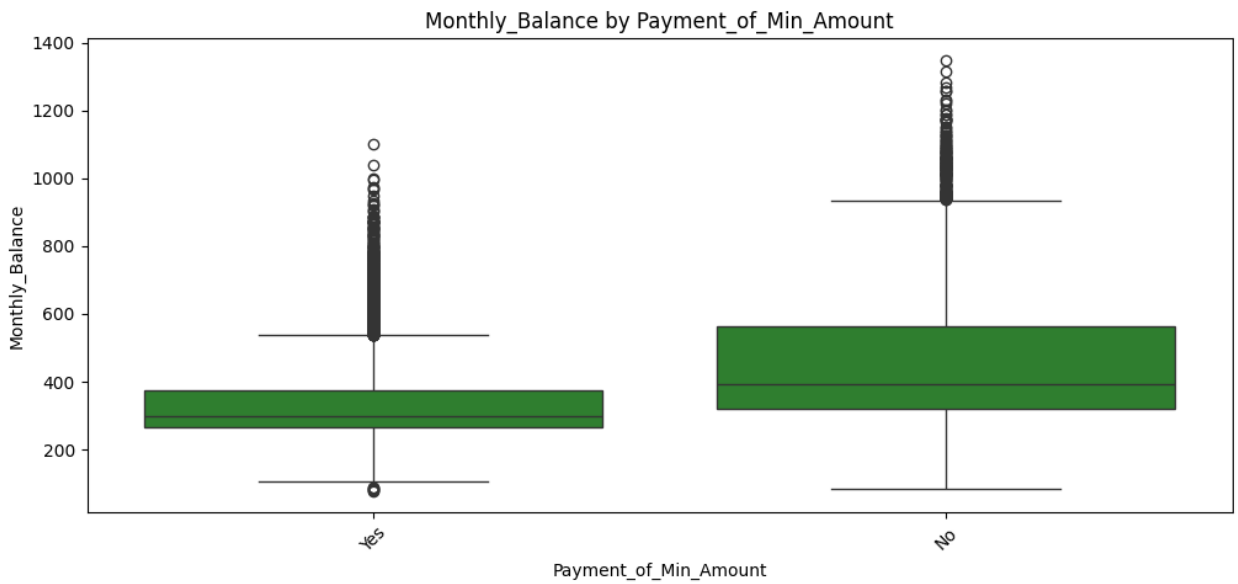


Annual_Income by Payment_of_Min_Amount
1e7
2.0
1.5
1.0
0.5
0.0
Annual_Income
Yes
No
Payment_of_Min_Amount



Monthly_Inhand_Salary by Payment_of_Min_Amount
14000
12000
10000
8000
6000
4000
2000
0
Monthly_Inhand_Salary
Yes
No
Payment_of_Min_Amount






```
# Median values for Credit_Mix
print("Median values for Credit_Mix:")
print("-" * 30)
for elem in (['Age', 'Monthly_Inhand_Salary', 'Outstanding_Debt',
'Monthly_Balance']):
  print(f"Column Name: {elem}")
  print(df_aggregated.groupby('Credit_Mix')[elem].median())
  print()
  print("-" * 50)
```

```
Median values for Credit_Mix:
------------------------------
Column Name: Age
```

```
Credit_Mix
Bad         30.00
Good        37.00
Standard    32.00
Name: Age, dtype: float64

--------------------------------------------------
Column Name: Monthly_Inhand_Salary
Credit_Mix
Bad         1879.71
Good        4509.36
Standard    2927.62
Name: Monthly_Inhand_Salary, dtype: float64

--------------------------------------------------
Column Name: Outstanding_Debt
Credit_Mix
Bad         2849.38
Good         732.22
Standard    1019.44
Name: Outstanding_Debt, dtype: float64

--------------------------------------------------
Column Name: Monthly_Balance
Credit_Mix
Bad         269.91
Good        429.46
Standard    340.38
Name: Monthly_Balance, dtype: float64

--------------------------------------------------
```

OBSERVATION

- **Age:** Individuals classified under "Good" credit mix tend to be older (median age of 37) compared to those with "Bad" credit (median age of 30). This suggests that older individuals may have better credit profiles.
- **Monthly Inhand Salary:** Those with a "Good" credit mix have a significantly higher median monthly inhand salary (4509.36) compared to individuals with "Bad" credit (1879.71). This indicates a positive correlation between higher income and better credit mix.
- **Outstanding Debt:** Individuals with a "Good" credit mix have a lower median outstanding debt (732.22) compared to those with "Bad" credit (2849.38). Lower outstanding debt is associated with better credit profiles.
- **Monthly Balance:** Individuals with a "Good" credit mix have a higher median monthly balance (429.46) than those with a "Bad" credit mix (269.91). This suggests that maintaining a higher monthly balance is linked to a better credit mix.

In summary, individuals with a "Good" credit mix generally have higher incomes, lower outstanding debts, and higher monthly balances, while they are also older compared to those with a "Bad" credit mix.

```
# Median values for Payment_of_Min_Amount
print("Median values for Payment_of_Min_Amount:")
print("-" * 45)
for elem in (['Age', 'Monthly_Inhand_Salary', 'Outstanding_Debt',
'Monthly_Balance']):
  print(f"Column Name: {elem}")
  print(df_aggregated.groupby('Payment_of_Min_Amount')[elem].median())
  print()
  print("-" * 50)
```

```
Median values for Payment_of_Min_Amount:
---------------------------------------------
Column Name: Age
Payment_of_Min_Amount
No     36.00
Yes    31.00
Name: Age, dtype: float64

--------------------------------------------------
Column Name: Monthly_Inhand_Salary
Payment_of_Min_Amount
No     3621.15
Yes    2682.48
Name: Monthly_Inhand_Salary, dtype: float64

--------------------------------------------------
Column Name: Outstanding_Debt
Payment_of_Min_Amount
No      807.00
Yes    1639.90
Name: Outstanding_Debt, dtype: float64

--------------------------------------------------
Column Name: Monthly_Balance
Payment_of_Min_Amount
No     393.49
Yes    298.19
Name: Monthly_Balance, dtype: float64

--------------------------------------------------
```

OBSERVATION

- **Age:** Individuals who do not pay the minimum amount (No) are generally older (median age of 36) compared to those who do pay the minimum amount (Yes) with a median age of 31. This suggests that younger individuals may be more likely to pay the minimum amount.

- **Monthly Inhand Salary:** Individuals who do not pay the minimum amount have a higher median monthly inhand salary (3621.15) compared to those who do pay the minimum amount (2682.48). Higher salaries are associated with a lower likelihood of paying only the minimum amount.
- **Outstanding Debt:** Those who do not pay the minimum amount have a lower median outstanding debt (807.00) compared to those who do pay the minimum amount (1639.90). Higher outstanding debt is linked to the habit of paying only the minimum amount.
- **Monthly Balance:** Individuals who do not pay the minimum amount have a higher median monthly balance (393.49) compared to those who do pay the minimum amount (298.19). A higher monthly balance is associated with the ability to pay more than the minimum amount.

In summary, individuals who do not pay only the minimum amount tend to be older, have higher salaries, lower outstanding debts, and higher monthly balances compared to those who do pay only the minimum amount.

9) Hypothetical Credit Score Calculation

```
# Deep copy
df_cleaned_final = df_cleaned.copy()
df_aggregated_final = df_aggregated.copy()
```

Objective:

To develop a hypothetical credit score calculation methodology inspired by FICO scores using a relevant set of features. The methodology will include calculating scores based on selected features, applying a weighting scheme, and scaling the final scores.

9.1) Calculate credit score

Feature Selection

Based on the correlation matrix and prior analysis, the following features are selected for calculating the hypothetical credit score:

1. Monthly_Inhand_Salary: Strong positive correlation with Monthly Balance.
2. Amount_invested_monthly: Significant positive correlation with Monthly Balance.
3. Credit_Utilization_Ratio: Positive correlation with Monthly Balance, affects creditworthiness.
4. Outstanding_Debt: Shows a negative correlation with Monthly Balance and affects credit risk.
5. Num_Credit_Inquiries: Higher number of inquiries may indicate higher credit risk.
6. Interest_Rate: Affects the cost of borrowing and hence creditworthiness.

7. Num_of_Loan: Reflects the current credit obligations.
8. Delay_from_due_date: Indicates payment behavior and potential risk.
9. Monthly_Balance: Direct measure of financial health.

```
features = {
    'Monthly_Inhand_Salary': 0.15,
    'Amount_invested_monthly': 0.15,
    'Credit_Utilization_Ratio': 0.10,
    'Outstanding_Debt': 0.10,
    'Num_Credit_Inquiries': 0.10,
    'Interest_Rate': 0.10,
    'Num_of_Loan': 0.10,
    'Delay_from_due_date': 0.10,
    'Monthly_Balance': 0.10
}

from sklearn.preprocessing import MinMaxScaler

# Normalize the selected features
scaler = MinMaxScaler()
df_aggregated_final[list(features.keys())] =
scaler.fit_transform(df_aggregated_final[list(features.keys())])

# Calculate credit score
df_aggregated_final['Credit_Score'] = sum(df_aggregated_final[feature]
* weight for feature, weight in features.items())

# Scale to 300-850
df_aggregated_final['Credit_Score'] =
df_aggregated_final['Credit_Score'] * (850 - 300) + 300
```

9.2) Bin scores

```
bins = [300, 499, 649, 749, 850]
labels = ['Poor Credit', 'Fair Credit', 'Good Credit', 'Excellent
Credit']
df_aggregated_final['Credit_Score_Binned'] =
pd.cut(df_aggregated_final['Credit_Score'], bins=bins, labels=labels)
```

9.2.1) Distribution of Credit Scores

```
df_aggregated_final[['Customer_ID','Credit_Score']]
```

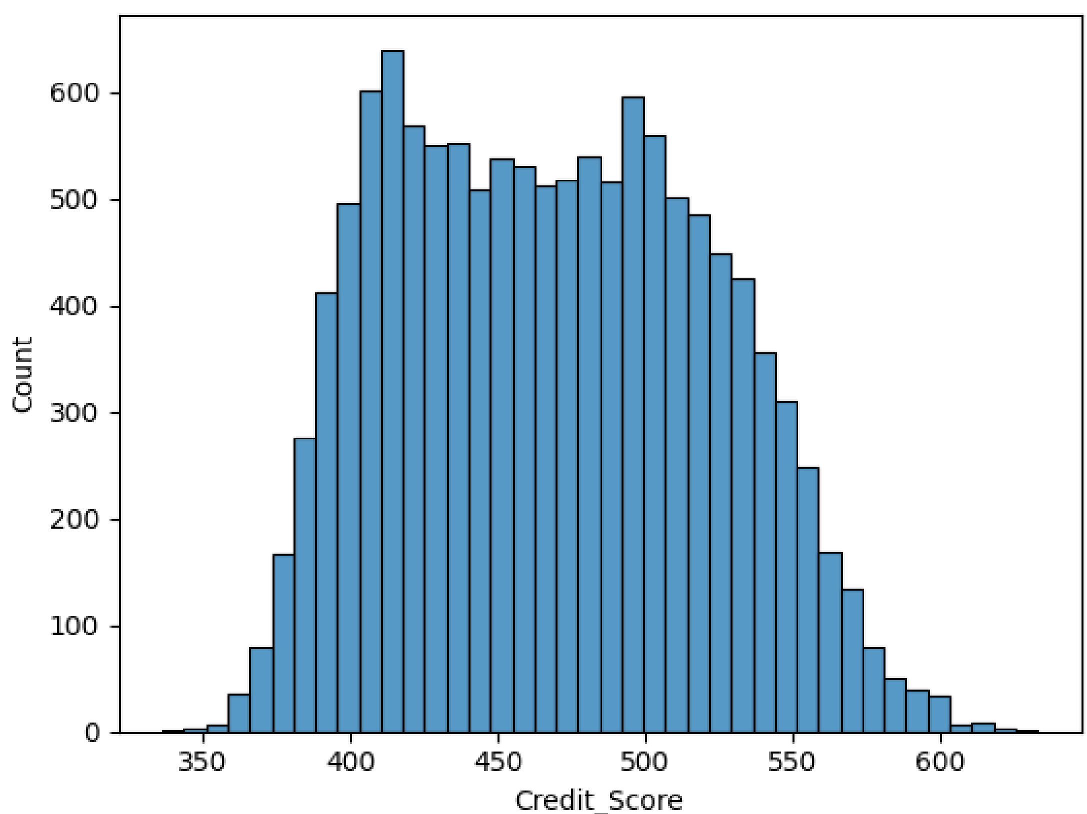

```
{"summary":"{\n  \"name\":
\"df_aggregated_final[['Customer_ID','Credit_Score']]\",\n  \"rows\":
12500,\n  \"fields\": [\n    {\n      \"column\": \"Customer_ID\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 12500,\n        \"samples\": [\n
\"CUS_0x2c08\",\n          \"CUS_0xc1b3\",\n          \"CUS_0x953d\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"Credit_Score\",\n
```

```
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
53.05232089207196,\n        \"min\": 336.00860798882036,\n
\"max\": 632.6697587587246,\n        \"num_unique_values\": 12500,\n
\"samples\": [\n          444.67298263418445,\n
416.4755302036442,\n          413.08997624665443\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe"}
```


```
df_aggregated_final['Credit_Score_Binned'].value_counts()
```

```
Credit_Score_Binned
Poor Credit         8634
Fair Credit         3866
Good Credit            0
Excellent Credit       0
Name: count, dtype: int64
```

```
sns.histplot(df_aggregated_final['Credit_Score'])
plt.show()
```



OBSERVATION

- **Credit Score Distribution:** The majority of customers fall into the "Poor Credit" category, with **8,634 individuals**. This suggests that the weighted credit score calculation, based on the selected features and their weights, tends to assign lower credit scores to most customers.

- **Lack of Higher Credit Scores:** No customers fall into the "Good Credit" or "Excellent Credit" categories. This could indicate that the scoring methodology, weights, or normalization process may not be adequately capturing the variations needed to differentiate between good and excellent credit.

- **Feature Impact:** The selected features and their weights might need reevaluation. For example, the equal weight distribution across features may not reflect their actual impact on creditworthiness. This equal weighting could lead to suboptimal scoring where some features might dominate the score, skewing the results.

- **Further Analysis Required:** The absence of higher credit score categories suggests that further adjustments might be necessary. Consider experimenting with different weighting schemes, revisiting feature selection, or recalibrating the scoring model to ensure a more balanced distribution of credit scores.

In summary, the observed distribution highlights that **most customers are categorized with poor credit, and there is a need to reassess the methodology to better capture and represent varying levels of creditworthiness.**

9.3) Time Frame Analysis for last 3 months

Explore how credit scores and aggregated features vary over different time frames such as the last 3 months. This will help in understanding the temporal aspect of creditworthiness.

9.3.1) Calculate RFM

- **Recency Calculation:**
  - For each customer, calculate the recency based on the last month of payment.
- **Frequency Calculation:**
  - Number of loans taken by each customer.
- **Monetary Calculation:**
  - Sum the Monthly balance amounts for each customer.

```
# Recency calculation
df_cleaned_final['Recency'] = df_cleaned_final.groupby('Customer_ID')
['Month_num'].transform(lambda x: x.max() - x)

# Frequency calculation
df_cleaned_final['Frequency'] =
df_cleaned_final.groupby('Customer_ID')
['Num_of_Loan'].transform('max')

# Monetary calculation
df_cleaned_final['Monetary'] = df_cleaned_final.groupby('Customer_ID')
['Monthly_Balance'].transform('sum')
```

```
# Filter data for the last 3 months
recent_data_final = df_cleaned_final[df_cleaned_final['Month_num'] >=
(df_cleaned_final['Month_num'].max() - 3)]

# Recalculate RFM features
df_recent_rfm_final = recent_data_final.groupby('Customer_ID').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'Monetary': 'mean'
}).reset_index()

# Merge with aggregated data
df_recent_aggregated_final =
df_aggregated_final.merge(df_recent_rfm_final, on='Customer_ID',
how='left')
```

Feature Selection:

- Recency: Recent interactions can indicate more current credit behavior.
- Frequency: Regular usage of credit can reflect on-going creditworthiness.
- Monetary: High balances may indicate better financial management or higher risk.
- Credit Utilization Ratio: High utilization might signal higher risk.
- Outstanding Debt: High debt could indicate higher risk of default.

```
# Define the weights for each feature
weights = {
    'Recency': 0.20,
    'Frequency': 0.15,
    'Monetary': 0.15,
    'Credit_Utilization_Ratio': 0.25,
    'Outstanding_Debt': 0.25
}

from sklearn.preprocessing import MinMaxScaler

# List of features to be scaled
features_to_scale = ['Recency', 'Frequency', 'Monetary',
'Credit_Utilization_Ratio', 'Outstanding_Debt']

scaler = MinMaxScaler()
df_recent_aggregated_final[features_to_scale] =
scaler.fit_transform(df_recent_aggregated_final[features_to_scale])

# Recalculate and bin credit scores
df_recent_aggregated_final['Credit_Score'] =
sum(df_recent_aggregated_final[feature] * weight for feature, weight
in weights.items())
df_recent_aggregated_final['Credit_Score'] =
df_recent_aggregated_final['Credit_Score'] * (850 - 300) + 300
```

```
# Bins
df_recent_aggregated_final['Credit_Score_Binned'] =
pd.cut(df_recent_aggregated_final['Credit_Score'], bins=bins,
labels=labels)
```

9.3.2) Distribution of Credit Scores

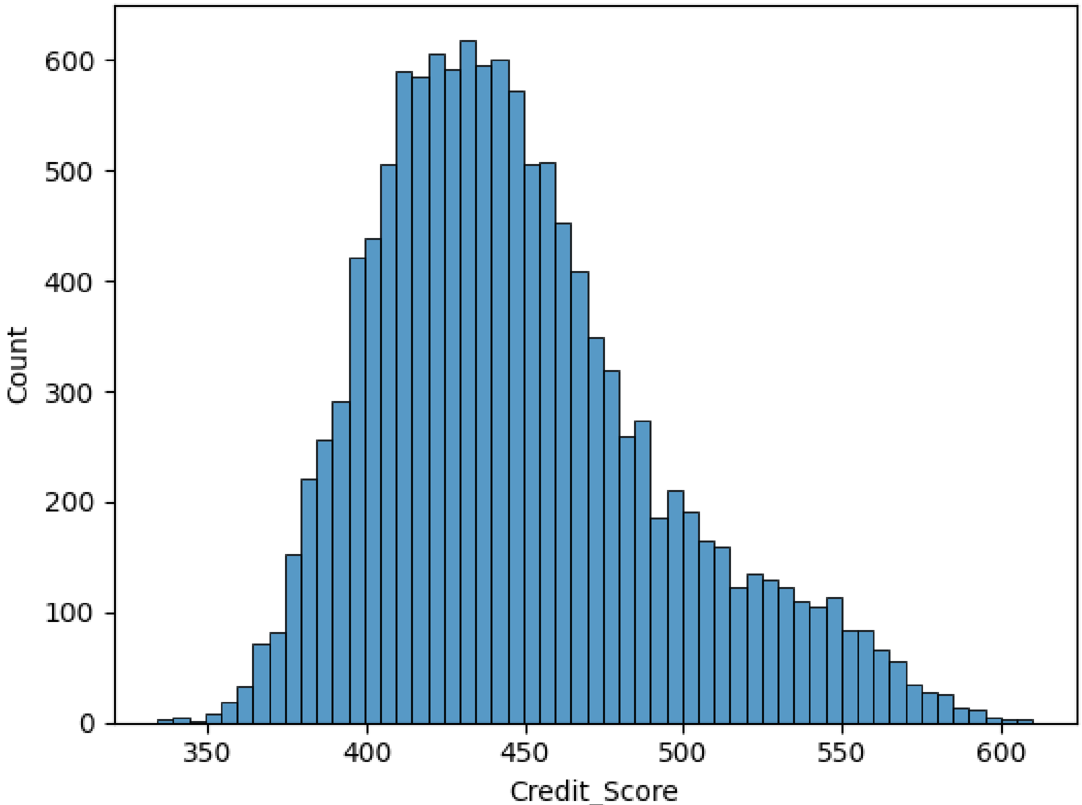
```
df_recent_aggregated_final[['Customer_ID','Credit_Score']]
```


{"summary":"{\n \"name\":
\"df_recent_aggregated_final[['Customer_ID','Credit_Score']]\",\n
\"rows\": 12500,\n \"fields\": [\n   {\n   \"column\":
\"Customer_ID\",\n   \"properties\": {\n   \"dtype\":
\"string\",\n   \"num_unique_values\": 12500,\n
\"samples\": [\n   \"CUS_0x2c08\",\n   \"CUS_0xc1b3\",\n
\"CUS_0x953d\"\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"Credit_Score\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 45.7204761539861,\n   \"min\":
333.90000837138103,\n   \"max\": 610.0096965826749,\n
\"num_unique_values\": 12500,\n   \"samples\": [\n
443.889934190081,\n   399.5448830216132,\n
451.4109155397919\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}


```
# Compare distributions
df_recent_aggregated_final['Credit_Score_Binned'].value_counts()
```

```
Credit_Score_Binned
Poor Credit         10712
Fair Credit          1788
Good Credit             0
Excellent Credit        0
Name: count, dtype: int64
```

```
sns.histplot(df_recent_aggregated_final['Credit_Score'])
plt.show()
```



OBSERVATION

- Based on the results of the time frame analysis, here are the key observations to include:
- **Increased Poor Credit Classification:** The number of customers classified as "Poor Credit" has **increased significantly to 10,712, compared to the earlier analysis**. This suggests that **recent data** might be revealing **more financial distress or challenges among customers, particularly in the last 3 month**s.
- **Decreased Fair Credit Classification:** The count of customers in the **"Fair Credit" category has decreased to 1,788**, which is a significant drop compared to the previous result. This indicates that recent data may be emphasizing lower credit scores, possibly due to recent changes in customer behavior or financial situations.
- **Absence of Higher Credit Scores:** There are still no customers classified under "Good Credit" or "Excellent Credit." This persistent absence in the higher credit score categories indicates that the current scoring methodology or the recent data may not sufficiently differentiate high creditworthiness.
- Impact of Recency, Frequency, and Monetary Factors: The inclusion of recency, frequency, and monetary metrics in the analysis seems to have intensified the classification into lower credit categories. This might suggest that **recent activity**

and monetary behavior have a significant impact on the calculated credit scores.

- **Further Investigation Needed:** The shift in credit score distribution after incorporating recency-based metrics indicates a need for further investigation. It might be necessary to adjust the feature weights, revisit the scaling approach, or consider additional factors to better capture a range of creditworthiness levels.

In summary, the analysis of recent data shows an increased concentration of customers in the "Poor Credit" category and highlights the **need to reassess the scoring methodology to better capture a range of creditworthiness.**

10) Analysis and Insights

- **Credit Mix Impact:** The median values for different credit mix categories (Bad, Good, Standard) indicate that **individuals with "Bad" credit tend to have higher outstanding debt and lower monthly income compared to those with "Good" or "Standard" credit.** This highlights the importance of credit management and debt reduction in improving credit scores.

- **Recency, Frequency, and Monetary (RFM) Analysis:** The recency, frequency, and monetary calculations over the last 3 months reveal that customers with more recent interactions and higher monetary values generally show better credit behaviors. This insight underscores the importance of recent payment behavior in credit scoring.

- **Time Frame Analysis Results:** The **significant increase in the proportion of "Poor Credit" in recent analyses** compared to the overall dataset suggests **that more recent credit behavior is a stronger predictor of creditworthiness. This implies that incorporating recency into credit scoring can enhance its accuracy.**

- **Machine Learning Model Evaluation:** The initial hypothetical credit score calculation and binning show that the majority of customers fall into the "Poor Credit" category, which may indicate the **need for recalibration or additional features** in the scoring model. Machine learning models can help refine the scoring criteria and improve predictive accuracy by identifying key features and interactions that affect credit scores.

These insights can guide adjustments in credit scoring methodologies, feature engineering, and model improvements to better reflect customer creditworthiness and behavior.