# Credit EDA & Credit Score Calculation

**Problem statement:** To conduct a thorough exploratory data analysis (EDA) and deep analysis of a comprehensive dataset containing basic customer details and extensive credit-related information. The aim is to create new, informative features, calculate a hypothetical credit score, and uncover meaningful patterns, anomalies, and insights within the data.

```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
import seaborn as sns
```

#### Downloading the data

```
!gdown 1pljm6_3nxcFS9UMIFm124HBsjNZP6ACA

Downloading...
From: https://drive.google.com/uc?id=1pljm6_3nxcFS9UMIFm124HBsjNZP6ACA
To: /content/Credit_score.csv
   0% 0.00/27.4M [00:00<?, ?B/s]  69% 18.9M/27.4M [00:00<00:00,
188MB/s] 100% 27.4M/27.4M [00:00<00:00, 199MB/s]
```

#### Reading the data

```
df= pd.read_csv('Credit_score.csv')
df

            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

...        ...         ...       ...            ...   ...          ...

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  ...  \
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  ...
...          ...           ...                    ...                .
..  ...
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  ...

       Num_Credit_Inquiries  Credit_Mix Outstanding_Debt  \
0                       4.0           _           809.98
1                       4.0        Good           809.98
2                       4.0        Good           809.98
3                       4.0        Good           809.98
4                       4.0        Good           809.98
...                     ...         ...              ...
99995                   3.0           _           502.38
99996                   3.0           _           502.38
99997                   3.0        Good           502.38
99998                   3.0        Good           502.38
99999                   3.0        Good           502.38

      Credit_Utilization_Ratio      Credit_History_Age
Payment_of_Min_Amount  \
0                    26.822620   22 Years and 1 Months
No
1                    31.944960                     NaN
```

```
No
2                    28.609352   22 Years and 3 Months
No
3                    31.377862   22 Years and 4 Months
No
4                    24.797347   22 Years and 5 Months
No
...                        ...                     ...
...
99995                34.663572   31 Years and 6 Months
No
99996                40.565631   31 Years and 7 Months
No
99997                41.255522   31 Years and 8 Months
No
99998                33.638208   31 Years and 9 Months
No
99999                34.192463  31 Years and 10 Months
No

      Total_EMI_per_month  Amount_invested_monthly  \
0               49.574949              80.41529544
1               49.574949              118.2802216
2               49.574949              81.69952126
3               49.574949              199.4580744
4               49.574949              41.42015309
...                   ...                      ...
99995           35.104023              60.97133256
99996           35.104023              54.18595029
99997           35.104023              24.02847745
99998           35.104023              251.6725822
99999           35.104023              167.1638652

                      Payment_Behaviour Monthly_Balance
0       High_spent_Small_value_payments     312.4940887
1        Low_spent_Large_value_payments     284.6291625
2       Low_spent_Medium_value_payments     331.2098629
3        Low_spent_Small_value_payments     223.4513097
4      High_spent_Medium_value_payments      341.489231
...                                 ...             ...
99995   High_spent_Large_value_payments      479.866228
99996  High_spent_Medium_value_payments       496.65161
99997   High_spent_Large_value_payments      516.809083
99998    Low_spent_Large_value_payments      319.164979
99999                            !@9#%8      393.673696

[100000 rows x 27 columns]
```

**Shape of the data**

```
df.shape
```

```
(100000, 27)
```

```
df.info()
```

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

## OBSERVATIONS

- There are missing values present in dataset.
- Dataset has both numerical and string values.
- Datatypes are not correctly assigned

```
df.describe().T
```

```
                             count          mean           std
min  \
```

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

                                  25%          50%          75%
max
Monthly_Inhand_Salary     1625.568229  3093.745000  5957.448333
15204.63333
Num_Bank_Accounts            3.000000     6.000000     7.000000
1798.00000
Num_Credit_Card              4.000000     5.000000     7.000000
1499.00000
Interest_Rate                8.000000    13.000000    20.000000
5797.00000
Delay_from_due_date         10.000000    18.000000    28.000000
67.00000
Num_Credit_Inquiries         3.000000     6.000000     9.000000
2597.00000
Credit_Utilization_Ratio    28.052567    32.305784    36.496663
50.00000
Total_EMI_per_month         30.306660    69.249473   161.224249
82331.00000

df.describe(exclude=np.number).T

                          count  unique
top  \
ID                       100000  100000
0x1602
Customer_ID              100000   12500
CUS_0xd40
Month                    100000       8
January
Name                      90015   10139
Langep
Age                      100000    1788
38
```

```
SSN                        100000   12501                         #F%
$D@*&8
Occupation                 100000      16
_______
Annual_Income              100000   18940
36585.12
Num_of_Loan                100000     434
3
Type_of_Loan                88592    6260                     Not
Specified
Num_of_Delayed_Payment      92998     749
19
Changed_Credit_Limit       100000    3635
_
Credit_Mix                 100000       4
Standard
Outstanding_Debt           100000   13178
1360.45
Credit_History_Age          90970     404            15 Years and 11
Months
Payment_of_Min_Amount      100000       3
Yes
Amount_invested_monthly     95521   91049
__10000__
Payment_Behaviour          100000       7
Low_spent_Small_value_payments
Monthly_Balance             98800   98790  __-
333333333333333333333333333__

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

## OBSERVATIONS:-

- Customer_ID has 12500 unique values. It means we have data of 12500 customers.
- Month has only 8 unique values. Better to analyse further which months are present.
- Age has 1788 unique values. This looks strange as general age range is from 0-100.
- SSN has 12501 unique values, whereas Customer_ID only has only 12500 unique values. There is a possibility that incorrect SSN value is entered for one of the customer as same person can't have multiple SSN.
- We can see the there the most occuring SSN looks like a garabge value
- The dataset needs data cleaning as we can see the there are underscores present in few of the columns

# MISSING VALUES, DATA INCOSISTENCY, DATA MISMATCH & OUTLIER TREATMENT

```
df.isna().sum()/len(df)*100
```

```
ID                           0.000
Customer_ID                  0.000
Month                        0.000
Name                         9.985
Age                          0.000
SSN                          0.000
Occupation                   0.000
Annual_Income                0.000
Monthly_Inhand_Salary       15.002
Num_Bank_Accounts            0.000
Num_Credit_Card              0.000
Interest_Rate                0.000
Num_of_Loan                  0.000
Type_of_Loan                11.408
Delay_from_due_date          0.000
Num_of_Delayed_Payment       7.002
Changed_Credit_Limit         0.000
Num_Credit_Inquiries         1.965
Credit_Mix                   0.000
Outstanding_Debt             0.000
Credit_Utilization_Ratio     0.000
Credit_History_Age           9.030
Payment_of_Min_Amount        0.000
Total_EMI_per_month          0.000
Amount_invested_monthly      4.479
Payment_Behaviour            0.000
Monthly_Balance              1.200
dtype: float64
```

## Column : Name

```
df.sort_values(by=['Customer_ID', 'Month'], inplace=True)
df['Name'] = df.groupby('Customer_ID')
['Name'].fillna(method='ffill').fillna(method='bfill')
```

#### Summary

- There are 9985 null values.
- Cleaning Step - Assign same Name value to each Customer_ID

## Column : Age

```
df['Age'].value_counts().sort_values(ascending=True).head(10)
```

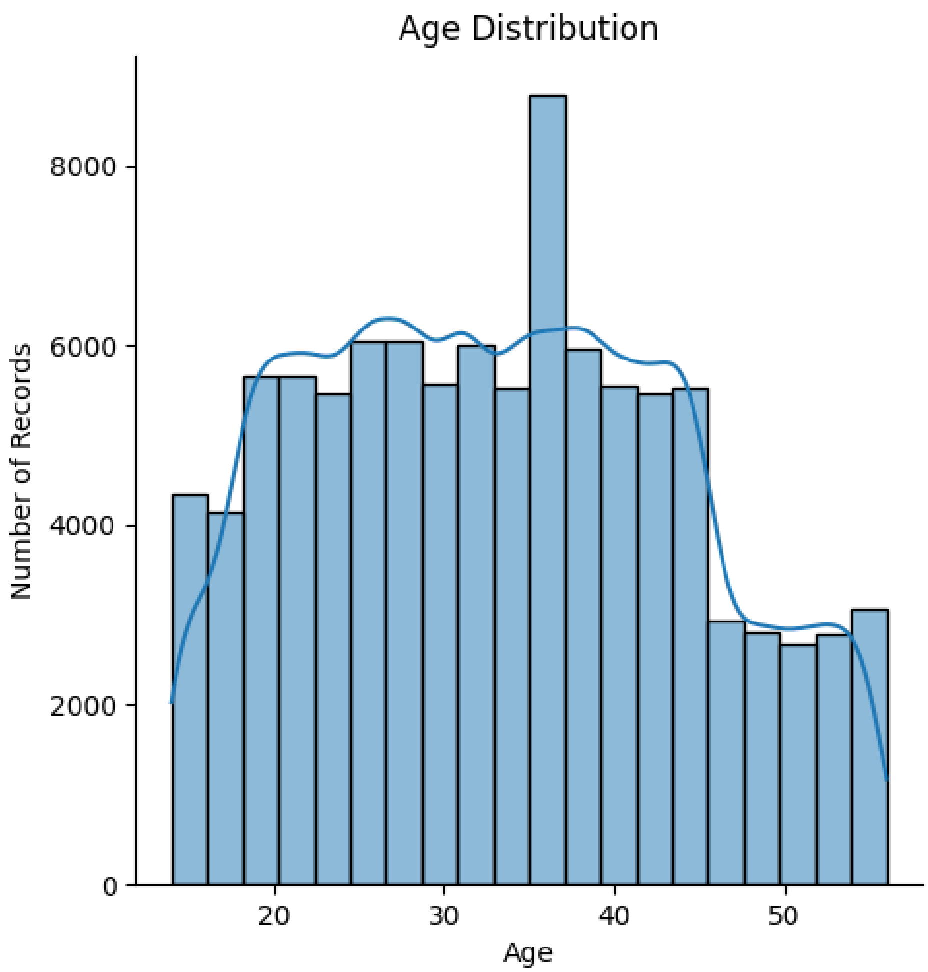
```
919     1
6032    1
8698    1
6520    1
2395    1
5583    1
2182    1
1420    1
6697    1
2108    1
Name: Age, dtype: int64
```

```
df['Age'] = df['Age'].str.replace('_', '')
df['Age'] = df['Age'].str.replace('-', '')
df['Age'] = df['Age'].astype(int)
df['Age'] = df['Age'].where((df['Age'] >= 0) & (df['Age'] <= 120),
pd.NA)
df['Age'] = df.groupby('Customer_ID')['Age'].transform(lambda x:
x.fillna(x.mode().iloc[0]))

df['Age'] = df.groupby('Customer_ID')['Age'].transform(lambda x:
x.replace(x.max(),x.mode().iloc[0]))

df['Age'] = df.groupby('Customer_ID')['Age'].transform(lambda x:
x.replace(x.min(),x.mode().iloc[0]))

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

df['Age'].nunique()
```

```
43
```

```
sns.displot(data=df, x=df['Age'], kde=True, bins=20)
plt.xlabel('Age')
plt.ylabel('Number of Records')
plt.title('Age Distribution')
```

```
plt.xticks(rotation=0)
plt.show()
```




**Summary**

- There are 1788 unique values of Age and it is stored as an object.
- Having 1788 distinct values of Age mean that there is a lot of dirty data.
- After cleaning up Age value, 43 distinct Age remains.

## Column : SSN

```
df['SSN'].value_counts().sort_values(ascending=True).head(10)
```

```
604-62-6133    4
642-73-7670    4
856-06-6147    4
331-28-1921    4
286-44-9634    4
753-72-2651    4
838-33-4811    4
```

```
629-97-8199    5
070-10-9637    5
589-66-2211    5
Name: SSN, dtype: int64

df['SSN'] = df['SSN'].str.replace('_', '')

def replace_irregular_ssn(group):
  actual_ssn = group.loc[group['SSN'] != '#F%$D@*&8', 'SSN'].iloc[0]
  group_ssn = group.loc[group['SSN'] == '#F%$D@*&8', 'SSN'] =
actual_ssn
  return group
df=
df.groupby('Customer_ID').apply(replace_irregular_ssn).reset_index(dro
p=True)

df['SSN'].value_counts()

913-74-1218    8
523-90-6933    8
236-25-0124    8
331-24-3360    8
311-38-7874    8
              ..
360-58-3081    8
341-94-5301    8
702-76-0398    8
282-99-1365    8
832-88-8320    8
Name: SSN, Length: 12500, dtype: int64

df[df['SSN']=='#F%$D@*&8']

Empty DataFrame
Columns: [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]
Index: []

[0 rows x 27 columns]
```

**Summary**

- There are 12501 unique SSN values in the dataset.
- 5572 entries has random/garbage value as SSN value

## Column : Occupation

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

_______          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

#Using dataframe df: customer IDs with 2 kinds of occupation
df['Occupation'].str.get_dummies().sum(axis=1).value_counts()[2:]

Series([], dtype: int64)

def replace_underscore_occupation(group):
    mode_occupation = group['Occupation'].mode().iloc[0]
    if mode_occupation != '_______':
        group['Occupation'] = group['Occupation'].replace('_______',
mode_occupation)
    else:
        non_underscore_modes = group['Occupation'][group['Occupation']
!= '_______'].mode()
        if not non_underscore_modes.empty:
            non_underscore_mode = non_underscore_modes.iloc[0]
            group['Occupation'] =
group['Occupation'].replace('_______', non_underscore_mode)

    return group
df=
df.groupby('Customer_ID').apply(replace_underscore_occupation).reset_i
ndex(drop=True)

df['Occupation'].value_counts()

Lawyer           7096
Engineer         6864
Architect        6824
Mechanic         6776
```

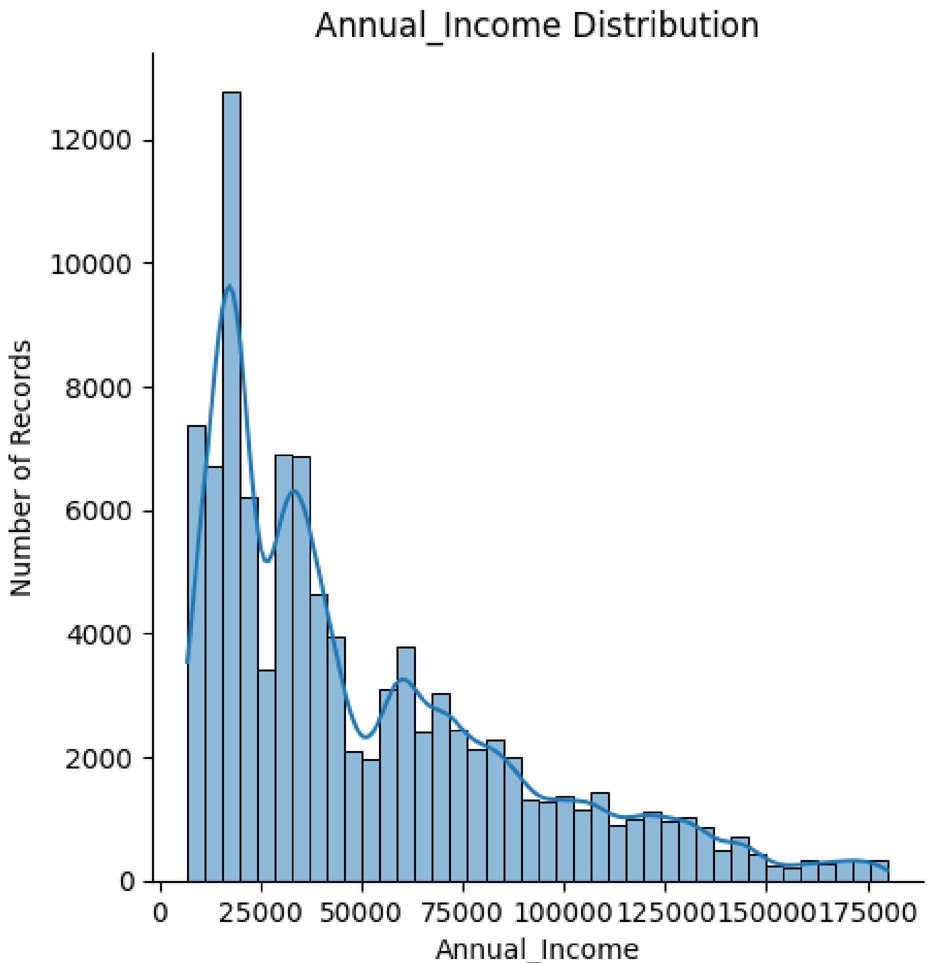
```
Accountant       6744
Scientist        6744
Media_Manager    6720
Developer        6720
Teacher          6672
Entrepreneur     6648
Doctor           6568
Journalist       6536
Manager          6432
Musician         6352
Writer           6304
Name: Occupation, dtype: int64
```

**Summary**

- There are 16 unique Occupation values.
- 7062 records are marked with garbage value.

# Column: Annual_Income

```
df['Annual_Income'] = df['Annual_Income'].str.replace('_', '')
df['Annual_Income'] = df['Annual_Income'].astype(float)

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

0

df['Annual_Income'] = df.groupby('Customer_ID')
['Annual_Income'].transform(lambda x: x.mode().iloc[0])

print(df['Annual_Income'].min(),df['Annual_Income'].max())

7005.93 179987.28

sns.displot(data=df, x=df['Annual_Income'], kde=True, bins=40)
plt.xlabel('Annual_Income')
plt.ylabel('Number of Records')
plt.title('Annual_Income Distribution')
plt.xticks(rotation=0)
plt.show()
```



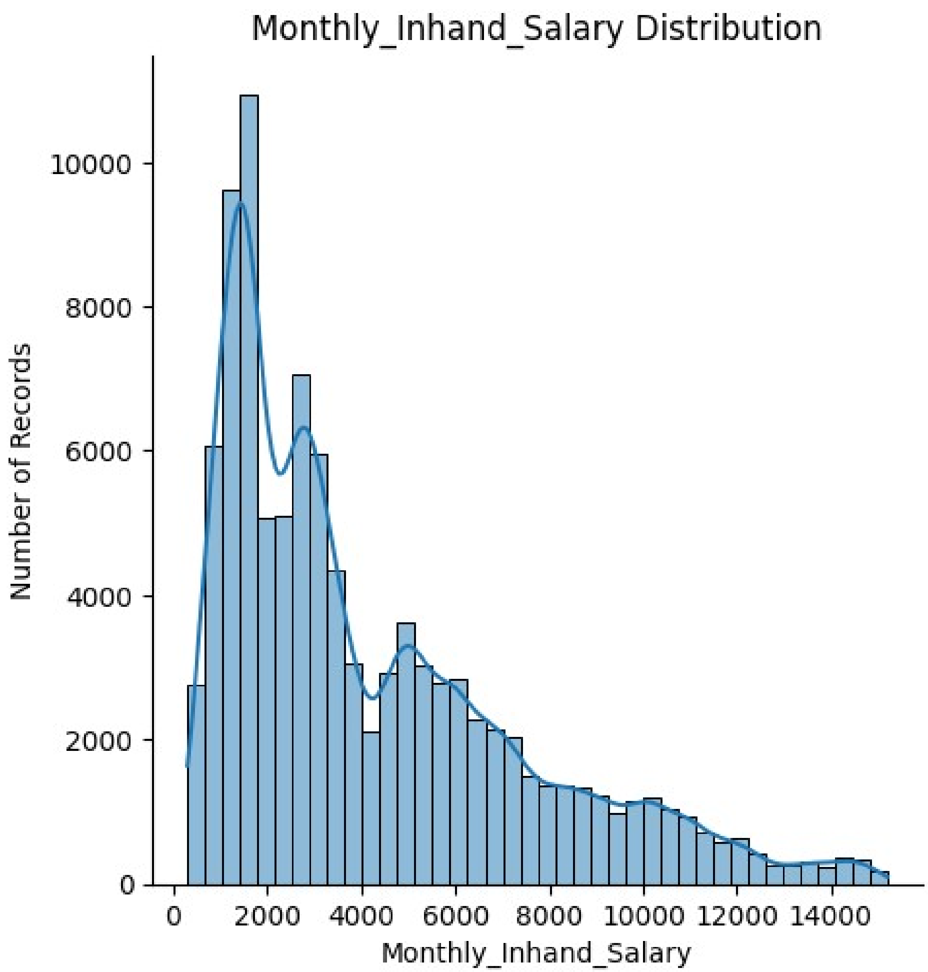

**Summary**

- Annual Income has no null values.
- Most customers have a low Annual income.
- Distribution is right skewed.

# Column : Monthly_Inhand_salary

```
nan_count_by_customer = df.groupby('Customer_ID')
['Monthly_Inhand_Salary'].apply(lambda x: x.isna().sum())
nan_count_by_customer.value_counts()

1    4862
0    3401
2    2904
3    1048
4     240
5      42
6       3
Name: Monthly_Inhand_Salary, dtype: int64
```

```
df.sort_values(by=['Customer_ID', 'Month'], inplace=True)
df['Monthly_Inhand_Salary'] = df.groupby('Customer_ID')
['Monthly_Inhand_Salary'].fillna(method='ffill').fillna(method='bfill'
)

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

0

sns.displot(data=df, x=df['Monthly_Inhand_Salary'], kde=True, bins=40)
plt.xlabel('Monthly_Inhand_Salary')
plt.ylabel('Number of Records')
plt.title('Monthly_Inhand_Salary Distribution')
plt.xticks(rotation=0)
plt.show()
```




**Summary**

- There are null values present.
- No outliers were present for Monthly Income Salary.

- Most customers have a low monthly income. Distribution is right skewed.

## Column: Num_Bank_Accounts

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

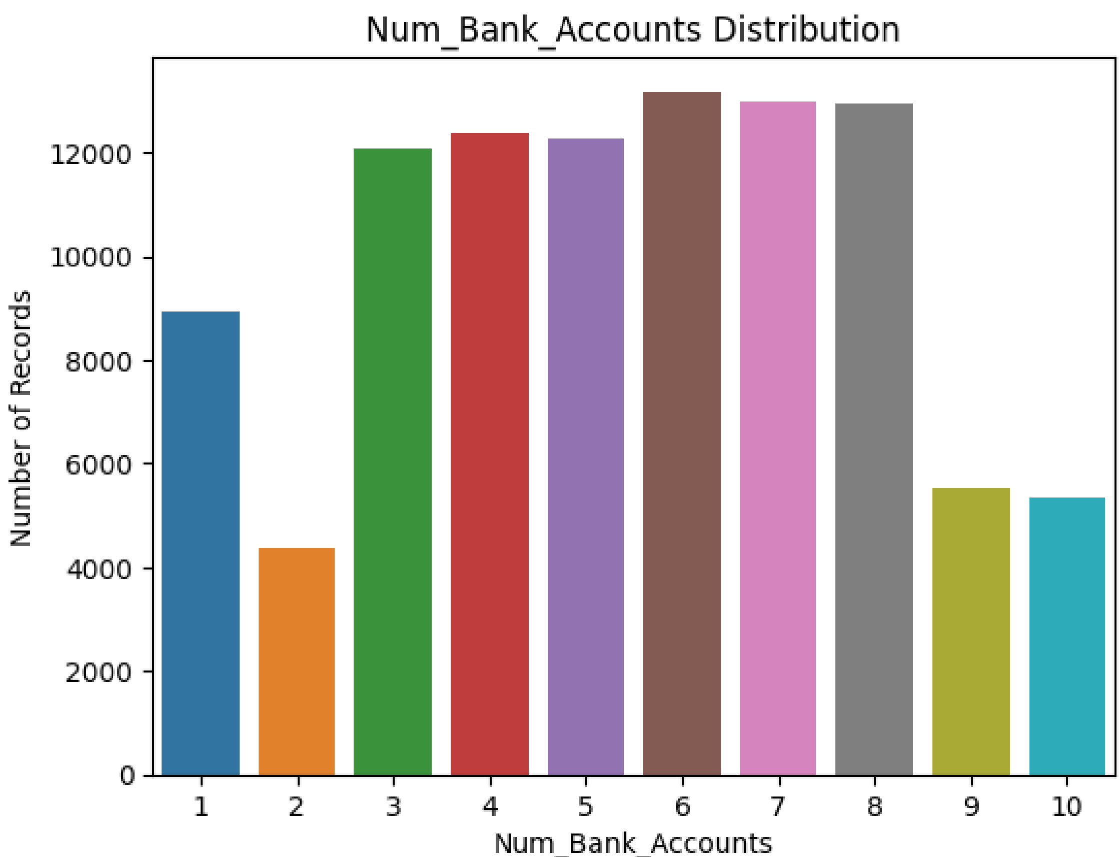
```
6       13001
7       12823
8       12765
4       12186
5       12118
        ...
795         1
1252        1
935         1
1350        1
796         1
Name: Num_Bank_Accounts, Length: 943, dtype: int64
```

```
grouped_modes = df.groupby('Customer_ID')
['Num_Bank_Accounts'].apply(lambda x: x.mode().iloc[0])
df['Num_Bank_Accounts'] =
df['Num_Bank_Accounts'].mask(df['Num_Bank_Accounts'] !=
df['Customer_ID'].map(grouped_modes),
df['Customer_ID'].map(grouped_modes))
df['Num_Bank_Accounts'] = df['Num_Bank_Accounts'].apply(lambda x: 1 if
x <= 0 else x)
```

```
df['Num_Bank_Accounts'].value_counts().sort_values()
```

```
2      4352
10     5328
9      5512
1      8952
3     12096
5     12272
4     12392
8     12936
7     12976
6     13184
Name: Num_Bank_Accounts, dtype: int64
```

```
sns.countplot(data=df, x=df['Num_Bank_Accounts'])
plt.xlabel('Num_Bank_Accounts')
plt.ylabel('Number of Records')
plt.title('Num_Bank_Accounts Distribution')
plt.xticks(rotation=0)
plt.show()
```




Summary

- There are some outliers,negative values in Num Bank Accounts
- After cleaning, there are 11 possible value of this field
- Num Bank Accounts ranging from 0 to 10.
- Majority of customers has no. of bank accounts between 3 to 8.
- For the customers having credit card and their respective Num_bank_accounts were 0 are alloted atleast 1.

# Column : Num_Credit_Card

```
df['Num_Credit_Card'].value_counts().sort_values(ascending=True)

1108        1
592         1
1198        1
1376        1
475         1
        ...
3       13277
4       14030
6       16559
7       16615
```

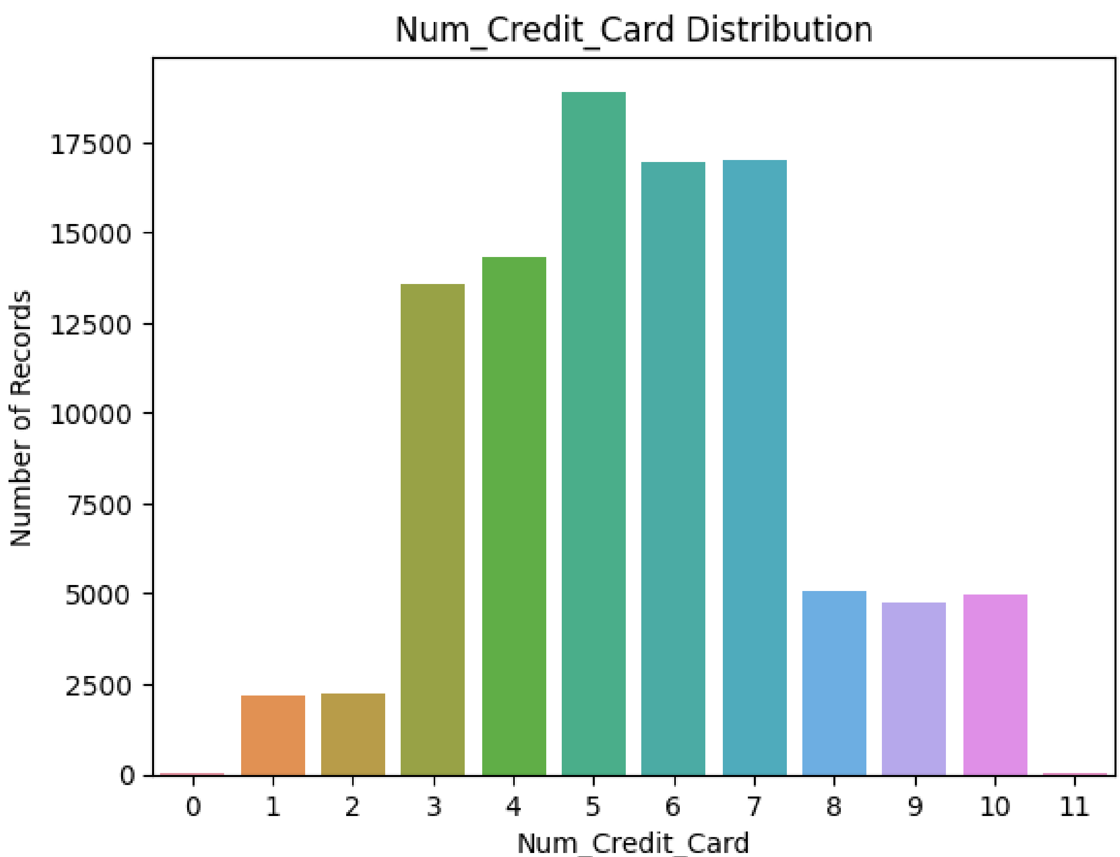
```
5        18459
Name: Num_Credit_Card, Length: 1179, dtype: int64
```

```
grouped_modes = df.groupby('Customer_ID')
['Num_Credit_Card'].apply(lambda x: x.mode().iloc[0])
df['Num_Credit_Card'] = df.apply(lambda row:
grouped_modes[row['Customer_ID']] if row['Num_Credit_Card'] !=
grouped_modes[row['Customer_ID']] else row['Num_Credit_Card'], axis=1)
```

```
df['Num_Credit_Card'].value_counts().sort_values(ascending=True)
```

```
0        16
11       40
1      2184
2      2208
9      4736
10     4960
8      5096
3     13576
4     14336
6     16960
7     16984
5     18904
Name: Num_Credit_Card, dtype: int64
```

```
sns.countplot(data=df, x=df['Num_Credit_Card'])
plt.xlabel('Num_Credit_Card')
plt.ylabel('Number of Records')
plt.title('Num_Credit_Card Distribution')
plt.xticks(rotation=0)
plt.show()
```




**Summary**

- There are outliers present in the field as there are 1179 unique values of number of credit card.
- After removing outliers, number of credit cards range from 0 to 11 with most of the customers having credit cards in the range of 3 to 7 with peak at 5.

# Column : Interest_Rate

```
df['Interest_Rate'].value_counts().sort_values(ascending=True)
```

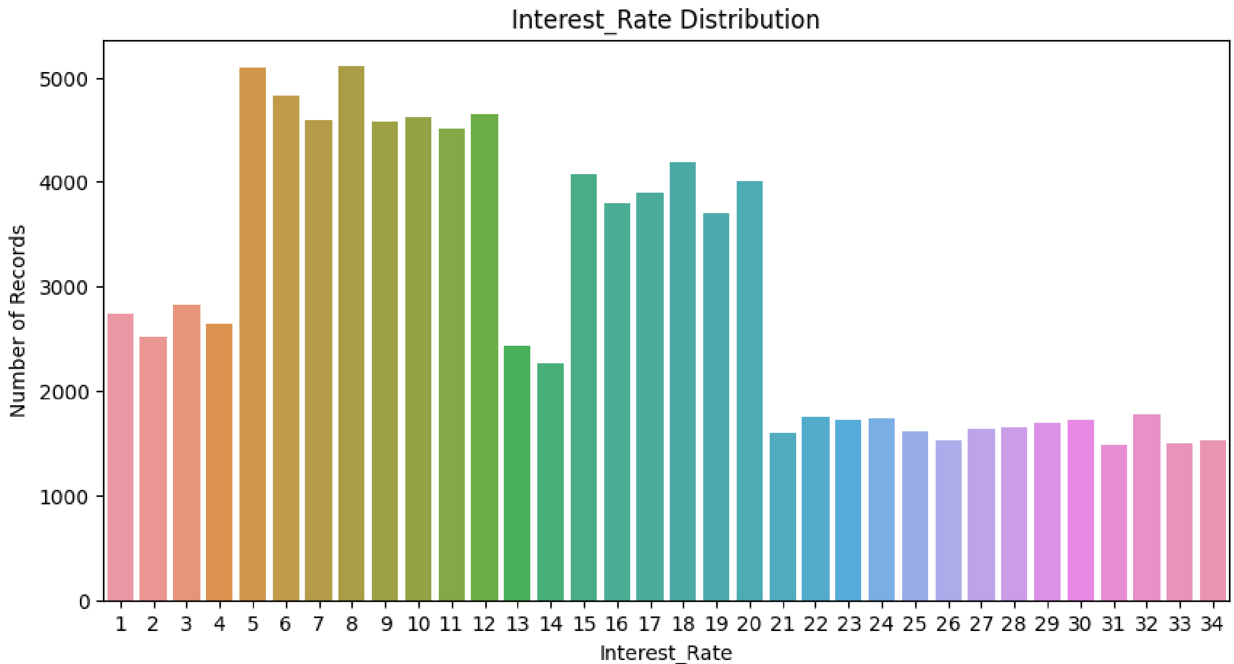
```
5397       1
3193       1
5279       1
524        1
464        1
        ...
10      4540
12      4540
6       4721
5       4979
8       5012
Name: Interest_Rate, Length: 1750, dtype: int64
```

```python
grouped_modes = df.groupby('Customer_ID')
['Interest_Rate'].apply(lambda x: x.mode().iloc[0])
df['Interest_Rate'] = df.apply(lambda row:
grouped_modes[row['Customer_ID']] if row['Interest_Rate'] !=
grouped_modes[row['Customer_ID']] else row['Interest_Rate'], axis=1)

df['Interest_Rate'].value_counts().sort_values(ascending=True)
```

```
31    1488
33    1496
34    1528
26    1528
21    1592
25    1608
27    1640
28    1648
29    1696
23    1720
30    1728
24    1736
22    1752
32    1776
14    2272
13    2432
2     2520
4     2640
1     2744
3     2824
19    3704
16    3800
17    3888
20    4008
15    4072
18    4192
11    4512
9     4576
7     4584
10    4616
12    4648
6     4832
5     5096
8     5104
Name: Interest_Rate, dtype: int64
```

```python
plt.figure(figsize=(10,5))
sns.countplot(data=df, x=df['Interest_Rate'])
plt.xlabel('Interest_Rate')
plt.ylabel('Number of Records')
plt.title('Interest_Rate Distribution')
```

```
plt.xticks(rotation=0)
plt.show()
```




**Summary**

- There were outliers present, after cleaning them up, interest rate ranges from 1% to 34%.

# Column : Num_of_Loan

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

```
array(['2', '1094', '4', '4_', '0', '0_', '3', '8', '-100', '8_', '1',
       '1_', '9', '7', '1222', '6', '5', '119', '3_', '6_', '2_',
'9_',
       '143_', '7_', '5_', '1150', '351', '52', '95', '614', '504',
       '1241', '1496', '17', '966', '330', '290', '193', '520', '50',
       '1265', '352', '571', '190', '995', '55', '433', '590', '661',
       '313', '1027_', '92_', '1017', '904', '1132_', '1008', '49',
'737',
       '546', '1096', '1461', '548', '939', '243', '1014', '924',
'526',
       '1447', '1228', '1129', '968', '285', '1484', '716', '1236',
'801',
       '809', '137', '208', '875', '1187', '621', '350', '911',
'1023',
       '855', '802', '967', '1296', '640', '1131_', '639', '1365',
'254',
       '1040', '141', '349', '659', '1480', '1259', '889', '70',
```

```
'344',
        '898', '41', '1412', '1353', '720', '1154', '295', '238',
'100',
        '54', '237', '868', '1214', '873', '33', '895', '1482', '1384',
        '182', '1289', '439', '563', '31', '597', '649', '1053',
'1036',
        '1457', '814', '484', '1359', '252', '282', '945', '65', '781',
        '905', '545', '684', '1400', '1035', '84', '372', '143', '733',
        '103', '58', '251', '27_', '848', '652', '1416', '999', '1451',
        '996', '527', '773', '302', '18', '392', '1294', '910', '628',
        '430', '404', '728', '799', '745', '1217', '515', '147',
'1135',
        '449', '1474', '697', '1297', '1307', '123', '1106', '1463',
        '1219_', '1433', '191', '501', '464', '654', '1320_', '438',
'510',
        '860', '891', '132', '638', '138', '926', '753', '267', '606',
        '983', '1406', '1345', '841', '816', '663', '1439', '323',
'1137',
        '1103', '56', '164', '437', '89', '201', '23', '1391', '1181',
        '348', '686', '1015', '341', '1348', '1329', '1182', '148',
'529',
        '527_', '231', '1196', '1464', '562', '1152', '622', '955',
'1470',
        '336', '447', '897', '1257', '752', '1225', '679', '288',
'943',
        '1459_', '1210', '29', '1227', '1372', '1085', '235_', '1048',
        '291', '1319', '1039', '227_', '834', '1001', '153', '629',
'1019',
        '1369', '1393', '778', '742', '613', '1318', '936', '316',
'1444',
        '1151', '931', '1204', '172', '635', '311', '1209', '831',
'1030',
        '229', '1054', '444', '832', '394', '1127', '1091', '1002',
'462',
        '1387', '1363', '1088', '1279', '1419', '843', '1112', '87',
'917',
        '833', '280', '581', '859', '952', '596', '1216', '378_',
'1313',
        '1430', '1185_', '174', '275', '497', '284', '630_', '198',
'1495',
        '1311_', '1441', '274', '540', '601', '935', '216', '719',
'332',
        '1160', '32', '192', '1354', '1312', '1225_', '838', '242',
'329',
        '1110', '1340', '958', '701', '1047', '387', '820', '579',
'1202',
        '186', '636', '1371', '961', '126', '940', '157', '1382',
'101',
        '1320', '241', '1424', '863', '1300', '1302', '1159', '819',
```

```
'507',
       '696', '217', '538', '463', '1478', '321', '196', '466', '633',
       '289', '146', '785_', '359', '1465', '867', '662', '574',
'1298',
       '1077', '494', '1171_', '1485', '455', '136', '39', '300',
'1271',
       '1347_', '424', '1131', '131_', '699', '365', '19', '415',
'869',
       '227', '657', '1046', '1178', '777', '359_', '292', '228',
'492',
       '420', '1274', '416', '927', '78', '215', '457', '1006',
'1189',
       '83', '795', '881', '405', '757', '978', '319', '597_',
'1129_',
       '1074', '1070', '696_', '991', '653', '617', '656', '418',
'472'],
      dtype=object)
```

```
df['Num_of_Loan'] = df['Num_of_Loan'].str.replace('_', '')
df['Num_of_Loan'] = df['Num_of_Loan'].str.replace('-', '')
df['Num_of_Loan'] = df['Num_of_Loan'].astype(int)

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

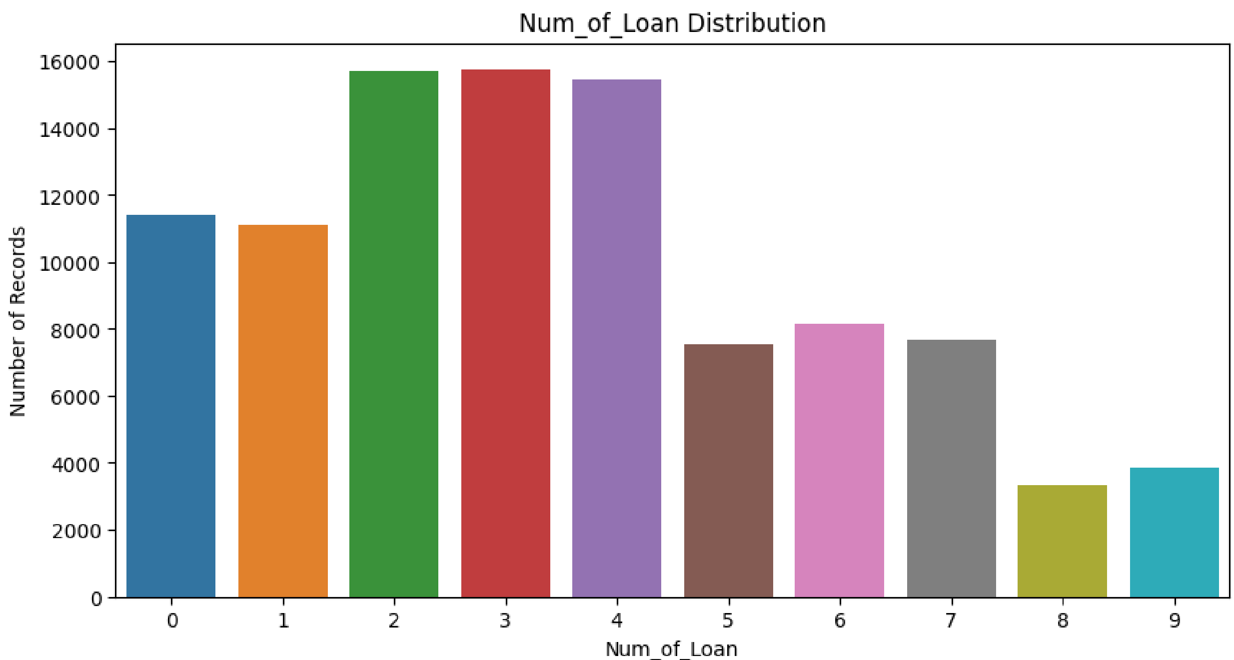
```
3      15104
2      15032
4      14743
0      10930
1      10606
       ...
860        1
510        1
438        1
571        1
472        1
Name: Num_of_Loan, Length: 413, dtype: int64
```

```
grouped_modes = df.groupby('Customer_ID')['Num_of_Loan'].apply(lambda
x: x.mode().iloc[0])
df['Num_of_Loan'] = df.apply(lambda row:
grouped_modes[row['Customer_ID']] if row['Num_of_Loan'] !=
grouped_modes[row['Customer_ID']] else row['Num_of_Loan'], axis=1)

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

```
3    15752
2    15712
4    15456
0    11408
1    11128
6     8144
```

```
7     7680
5     7528
9     3856
8     3336
Name: Num_of_Loan, dtype: int64
```

```
plt.figure(figsize=(10,5))
sns.countplot(data=df, x=df['Num_of_Loan'])
plt.xlabel('Num_of_Loan')
plt.ylabel('Number of Records')
plt.title('Num_of_Loan Distribution')
plt.xticks(rotation=0)
plt.show()
```




# Column : Type_of_Loan

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

```
array(['Credit-Builder Loan, and Home Equity Loan',
       'Not Specified, Home Equity Loan, Credit-Builder Loan, and
Payday Loan',
       nan, ...,
       'Not Specified, Student Loan, Student Loan, Credit-Builder
Loan, and Auto Loan',
       'Credit-Builder Loan, Payday Loan, Not Specified, Student Loan,
Student Loan, Home Equity Loan, Home Equity Loan, and Home Equity
Loan',
       'Auto Loan, Payday Loan, Payday Loan, Mortgage Loan, Payday
```

```
Loan, and Home Equity Loan'],
      dtype=object)
```

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

```
11408
```

```
filtered_df = df[pd.isna(df['Type_of_Loan'])]
filtered_df[['Customer_ID','Num_of_Loan','Num_Credit_Card','Type_of_Lo
an']]
```

```
      Customer_ID  Num_of_Loan  Num_Credit_Card Type_of_Loan
16     CUS_0x100b            0                4          NaN
17     CUS_0x100b            0                4          NaN
18     CUS_0x100b            0                4          NaN
19     CUS_0x100b            0                4          NaN
20     CUS_0x100b            0                4          NaN
...           ...          ...              ...          ...
99947   CUS_0xfe5            0                4          NaN
99948   CUS_0xfe5            0                4          NaN
99949   CUS_0xfe5            0                4          NaN
99950   CUS_0xfe5            0                4          NaN
99951   CUS_0xfe5            0                4          NaN

[11408 rows x 4 columns]
```

```
df.loc[(df['Num_of_Loan'] == 0) & (df['Num_Credit_Card'] > 0),
'Type_of_Loan'] = df['Type_of_Loan'].fillna('Not Specified')
```

```
df.loc[(df['Num_of_Loan'] == 0) & (df['Num_Credit_Card'] == 0) &
(df['Total_EMI_per_month'] == 0), 'Type_of_Loan'] = 'Not Specified'
```

```
loan_types = df['Type_of_Loan'].str.replace('and',
',').str.get_dummies(', ')
```

```
# Concatenate the new columns with the original DataFrame
df  = pd.concat([df, loan_types], axis=1)
```

## Used One hot coding to convert these columns

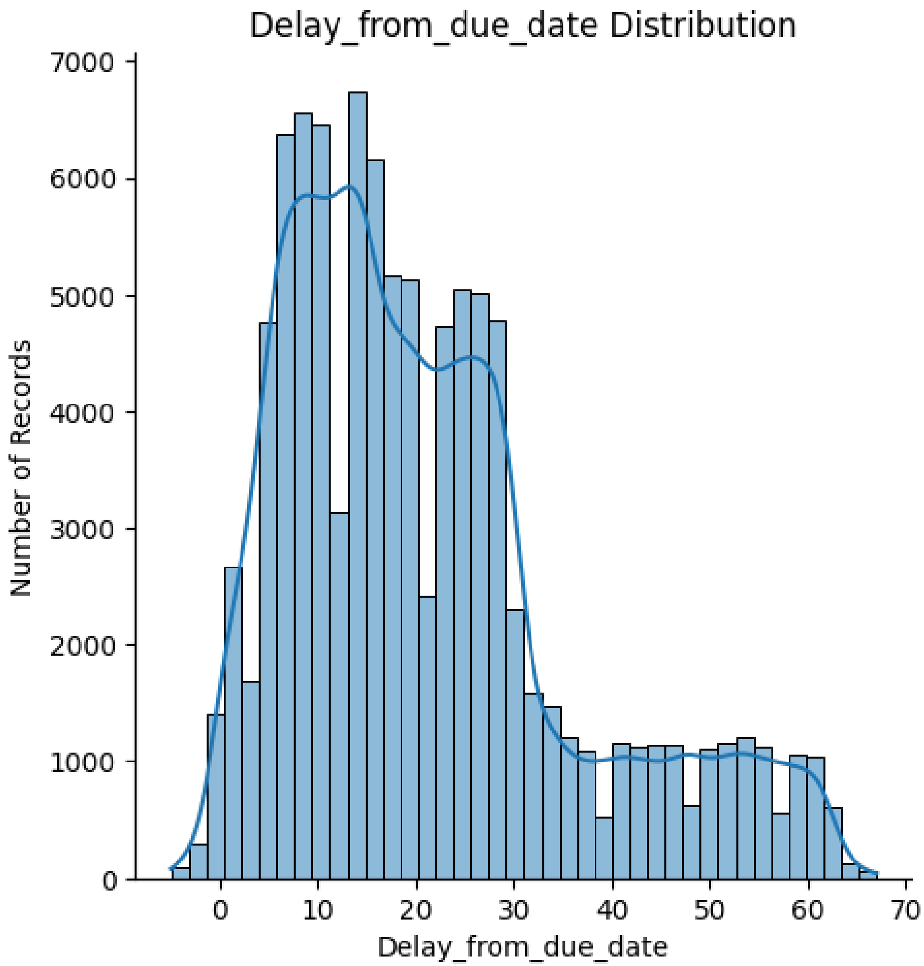
#### We have 9 types of Loans

- auto loan
- credit-builder loan
- debt consolidation loan
- home equity loan
- mortgage loan
- not specified
- payday loan
- personal loan -student loan

```
col_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','Auto Loan',
       'Credit-Builder Loan', 'Debt Consolidation Loan', 'Home Equity
Loan',
       'Mortgage Loan', 'Not Specified', 'Payday Loan', 'Personal
Loan',
       'Student 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=df[col_order]

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

0
```

## Column : Delay_from_due_date

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

array([64, 57, 62, 67, 10,  5,  8,  3, 14, 19,  9, 27, 29, 12, 16,  6,
24,
        0, -4, -5,  1, 15, 23, 28, 18, 13, 11, 25, 50, 47, 48, 46,  7,
2,
       -3,  4, 30, 21, 17, 20, 22, 35, 40, 26, 31, 58, 59, 63, 37, 42,
43,
       38, 55, 41, 36, 52, 54, 53, 49, -2, 44, 39, 61, 34, 33, -1, 45,
51,
       60, 66, 56, 32, 65])

df['Delay_from_due_date'].dtypes

dtype('int64')

plt.figure(figsize=(10,5))
sns.displot(data=df, x=df['Delay_from_due_date'], kde= True, bins =40)
plt.xlabel('Delay_from_due_date')
plt.ylabel('Number of Records')
plt.title('Delay_from_due_date Distribution')
plt.xticks(rotation=0)
plt.show()

<Figure size 1000x500 with 0 Axes>
```




**Delay from due date ranges from -5 to 67 as the values can be before the due date and after the due date.**

# Column : Num_of_Delayed_Payment

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

7002

df['Num_of_Delayed_Payment'].unique()

array(['25', '26', '23', '28', '18', '16', '1749', '19', '7', '8',
'9',
       '15', '13', nan, '12', '17_', '10', '20', '22', '1', '5', '2',
       '11', '17', '15_', '14', '3', '4', '6', '21', '8_', '11_', '0',
       '2230', '24', '18_', '-2', '19_', '1636', '20_', '-1', '16_',
       '921', '9_', '1766', '21_', '12_', '6_', '1_', '25_', '0_', '-
3',
       '1572', '5_', '14_', '3_', '3162', '27', '1034', '4211', '4_',
       '2712', '1832', '22_', '3251', '7_', '867', '13_', '4106',
'3951',
```

```
        '2216', '24_', '10_', '2_', '1640', '2142_', '754', '974',
'1180',
        '1359', '320', '2250', '3621', '2438', '531', '3738', '2566',
        '719', '4326', '223', '1833', '3881', '23_', '439', '1614',
'3495',
        '960', '4075', '3119', '4302', '121', '2081', '3894', '3484',
        '2594', '4126', '3944', '2553', '1820', '819', '27_', '3629',
        '2080', '1480', '2801', '359', '94', '473', '2072', '2604',
'306',
        '1633', '4262', '2488', '2008', '2955', '1647', '1691', '468',
        '1150', '3491', '4178', '1215', '3793', '3623', '2672', '2508',
        '1867', '4340', '1862', '1282', '1422', '441', '1204', '519',
        '2938', '371', '594', '663_', '46', '3458', '2658', '4134',
'2907',
        '2047', '4011', '2991', '4319', '674', '4216', '2671', '-2_',
        '2323', '271', '2184', '2628', '2381', '3191', '2376', '2260',
        '4005', '426', '399', '337', '3069', '3156', '4231', '1750',
'372',
        '2378', '876', '2279', '3545', '1222', '3764', '1663', '3200',
        '1890', '2728', '4069', '559', '1598', '3316', '2753', '1687',
        '281', '84', '4047', '1354', '4135', '2533', '2018', '708',
'1509',
        '4360', '3726', '1825', '1864', '3112', '1329', '-3_', '733',
        '1765', '775', '3684', '3212', '3478', '2400', '4278', '3636',
        '871', '3946', '3900', '2534', '49', '26_', '197', '1295_',
'1841',
        '1478', '4172', '2638', '3972', '1211', '905', '1699', '2324',
        '1325', '1706', '2056', '2903', '2569', '4293', '2621', '2924',
        '1792', '1338', '3107', '430', '714', '2015', '2879', '1673',
        '4024', '415', '2569_', '-1_', '1900', '1852', '2945', '4249',
        '195', '2280', '132', '384', '3148', '642', '3539', '3905',
'3171',
        '3050', '1911', '804', '2493', '85', '1463', '3208', '3031',
        '2560', '1795', '1664', '3739', '1481', '3861_', '1172',
'1014',
        '1106', '4219', '3751', '3051', '1989', '2149', '1323_', '739',
        '47', '1735', '2255', '1263', '1718', '2566_', '4002', '4295',
        '1402', '1086', '3329', '2873', '4113', '3037', '848_', '813',
        '2413', '2521', '2142', '926', '3707', '210', '2348', '3216',
        '1450', '2021', '2766', '3340', '3447', '1328', '2913', '615',
        '4241', '3313', '1994', '2420', '532', '538', '1411', '2511',
        '3529', '4169', '107', '1191', '2823', '283', '3580', '2354',
        '3765', '1332', '1530', '3926', '3706', '3099', '3790', '1850',
        '2131', '2697', '2239', '162', '2590', '904', '1370', '847',
        '3103', '3661', '1216', '544', '1985', '4185', '3502', '3533',
        '106', '3368', '1301', '853', '3840_', '4191', '523', '3318',
        '2128', '1015', '4022', '4280', '585', '2578', '3819', '972',
        '602', '2060', '2278', '264', '3845', '1502', '221', '3688',
        '1154', '1473', '666', '3920_', '2237_', '1243', '1976',
```

```
'1192',
        '450', '1552', '1278', '3097_', '851', '3040', '2127', '1685',
        '4096', '4042', '1511', '1523', '3815', '3855', '4161', '133',
        '3750', '252', '2397', '217', '88', '2529', '309', '273',
'2286',
        '1079', '2694', '166', '3632', '1443', '1199', '4107', '2875',
        '834', '808', '2429', '3457', '2219_', '577', '3721', '3011',
        '2729', '2492', '4282', '182', '3858', '1743', '2615', '3092',
        '2950', '3536', '3355', '1823', '238', '2943', '4077', '4095',
        '3865', '1861', '3708', '183_', '1184', '846', '709', '4239',
        '2926', '1087_', '2707', '4159', '1371', '3142', '2882', '787',
        '3392', '2793', '3568', '845', '1975', '1073', '3919', '3909',
        '2334', '640', '1541', '2759', '4023', '2751', '1471', '1256',
        '2657', '2274', '1096', '3009', '1164', '3155', '2148', '2737',
        '86', '3522', '4281', '2523', '3489', '3177', '3154', '3415',
        '1606', '1967', '3864', '3300', '1392', '1869', '1177', '3407',
        '887', '145', '4144', '4384', '969', '3499', '2854', '1538',
        '3559', '3402', '2666', '1004', '2705', '2314', '2138', '3754',
        '583', '98', '2044', '1697', '2959', '3722', '933', '4051',
'2655',
        '1849', '2689', '3222', '2552', '2794_', '2006', '829', '1063',
        '28_', '2162', '3105', '1045', '1859', '4397', '1337', '3060',
        '3467', '683', '2677', '938', '2956', '1389', '1653', '351',
'693',
        '3243', '1941', '2165', '2070', '4270', '2141', '4019', '3260',
        '2461', '3404', '2007', '2616', '482', '3268', '398', '1571',
        '3488', '2617', '2810', '2311', '700', '2756', '1181', '2896',
        '4128', '3083', '3078', '416', '2503', '1473_', '2506', '742',
        '3229', '3253', '4053', '1553', '1236', '2591', '1732', '707',
        '4164', '411', '4292', '3115', '749', '2185', '1946', '3584',
        '1953', '3978', '541', '3827', '809', '142', '2276', '2317',
        '3749', '2587', '2636', '3416', '3370', '3766', '2278_',
'4311',
        '1489', '130', '294', '827', '3796', '1801', '1218', '4059',
        '2768', '4266', '1579', '1952', '2457', '3179', '290', '2589',
        '1608', '2196', '2820', '2418', '3245', '2076', '2573', '1133',
        '2812', '2498', '1668', '2777', '3870', '186', '2860', '2609',
        '3955', '2300', '2570', '508', '793', '1954', '211', '80',
'1775',
        '676', '1049', '2384', '1891', '102', '4344', '1061', '1879',
        '3574', '662', '529', '3043', '2834', '3104', '1060', '929',
        '2297', '659', '2262', '3878', '4324', '3336', '4388', '2450',
        '3511', '3763', '4251', '192', '3960', '4043', '1996', '1178',
        '2660', '3776', '3660', '1874', '1534', '3175', '2645', '4139',
        '996', '2351', '2352', '2001', '3880', '1018', '758_', '4337',
        '3869', '823', '2544', '2585', '497', '3274', '3456', '2385',
        '196', '923', '2431', '3010', '2243', '1884', '778', '175',
'2167',
        '2222', '1531', '72', '265', '2954', '800', '3847', '779',
```

```
'4037',
       '3391', '4298', '2919', '3492', '52', '1498', '328', '1536',
       '2204', '1087'], dtype=object)
```

```
df['Num_of_Delayed_Payment'] =
df['Num_of_Delayed_Payment'].str.replace('_', '')
df['Num_of_Delayed_Payment'] =
df['Num_of_Delayed_Payment'].str.replace('-', '')
df['Num_of_Delayed_Payment'] =
df['Num_of_Delayed_Payment'].astype(float)
```

```
df['Num_of_Delayed_Payment'].value_counts().sort_values(ascending=True
)
```

```
1668.0       1
2658.0       1
3458.0       1
439.0        1
531.0        1
          ...
15.0      5237
10.0      5309
16.0      5312
17.0      5412
19.0      5481
Name: Num_of_Delayed_Payment, Length: 708, dtype: int64
```

```
df1 = df[pd.isna(df['Num_of_Delayed_Payment'])]
df1[['Customer_ID','Num_of_Loan','Num_Credit_Card','Num_of_Delayed_Pay
ment']]
```

```
      Customer_ID  Num_of_Loan  Num_Credit_Card
Num_of_Delayed_Payment
26      CUS_0x1011            3                3
NaN
31      CUS_0x1011            3                3
NaN
33      CUS_0x1013            3                3
NaN
55      CUS_0x1018            8                7
NaN
66      CUS_0x102d            1                3
NaN
...            ...          ...              ...                       ..
.
99935    CUS_0xfe3            4                5
NaN
99937    CUS_0xfe4            7                3
NaN
99942    CUS_0xfe4            7                3
```

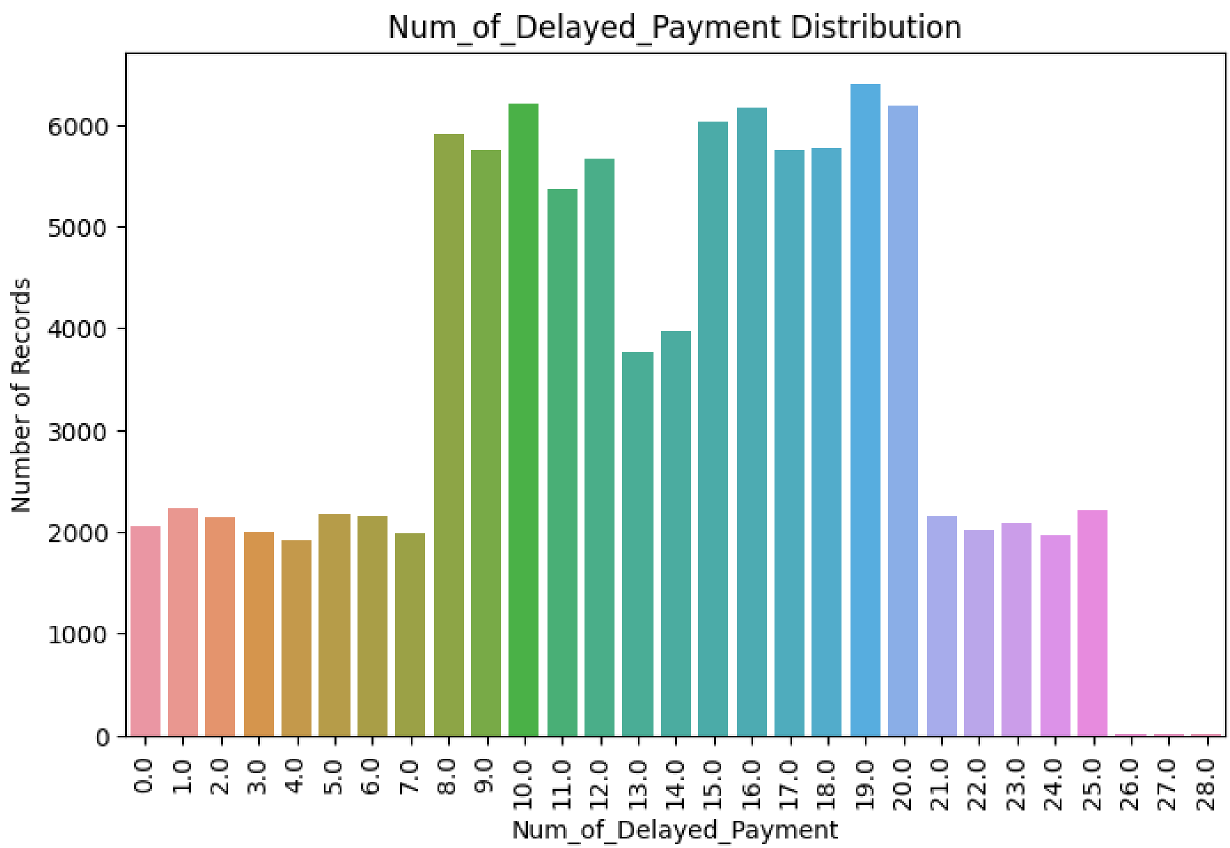
```
NaN
99980   CUS_0xff6            2                 6
NaN
99999   CUS_0xffd            6                 7
NaN

[7002 rows x 4 columns]
```

```
grouped_modes = df.groupby('Customer_ID')
['Num_of_Delayed_Payment'].apply(lambda x: x.mode().iloc[0])
df['Num_of_Delayed_Payment'] = df.apply(lambda row:
grouped_modes[row['Customer_ID']] if row['Num_of_Delayed_Payment'] !=
grouped_modes[row['Customer_ID']] else row['Num_of_Delayed_Payment'],
axis=1)

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

```
19.0    6392
10.0    6200
20.0    6184
16.0    6160
15.0    6032
8.0     5904
18.0    5760
17.0    5752
9.0     5744
12.0    5664
11.0    5368
14.0    3976
13.0    3752
1.0     2232
25.0    2208
5.0     2176
6.0     2160
21.0    2152
2.0     2136
23.0    2088
0.0     2056
22.0    2024
3.0     2000
7.0     1976
24.0    1968
4.0     1912
27.0       8
28.0       8
26.0       8
Name: Num_of_Delayed_Payment, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.countplot(data=df, x=df['Num_of_Delayed_Payment'])
```

```
plt.xlabel('Num_of_Delayed_Payment')
plt.ylabel('Number of Records')
plt.title('Num_of_Delayed_Payment Distribution')
plt.xticks(rotation=90)
plt.show()
```




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

```
0
```

# Column : Changed_Credit_Limit

```
df['Changed_Credit_Limit'].dtypes
```

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

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

```
_           2091
8.22         135
11.5         127
11.32        126
7.35         121
```

```
          ...
-2.02       1
35.84       1
-4.88       1
-3.49       1
33.61       1
Name: Changed_Credit_Limit, Length: 3635, dtype: int64
```

```
df['Changed_Credit_Limit'] =
df['Changed_Credit_Limit'].str.replace('_', '')
df['Changed_Credit_Limit'] =
df['Changed_Credit_Limit'].str.replace('-', '')
df['Changed_Credit_Limit'] = df['Changed_Credit_Limit'].replace('',
'0')
df['Changed_Credit_Limit'] = df['Changed_Credit_Limit'].astype(float)
```

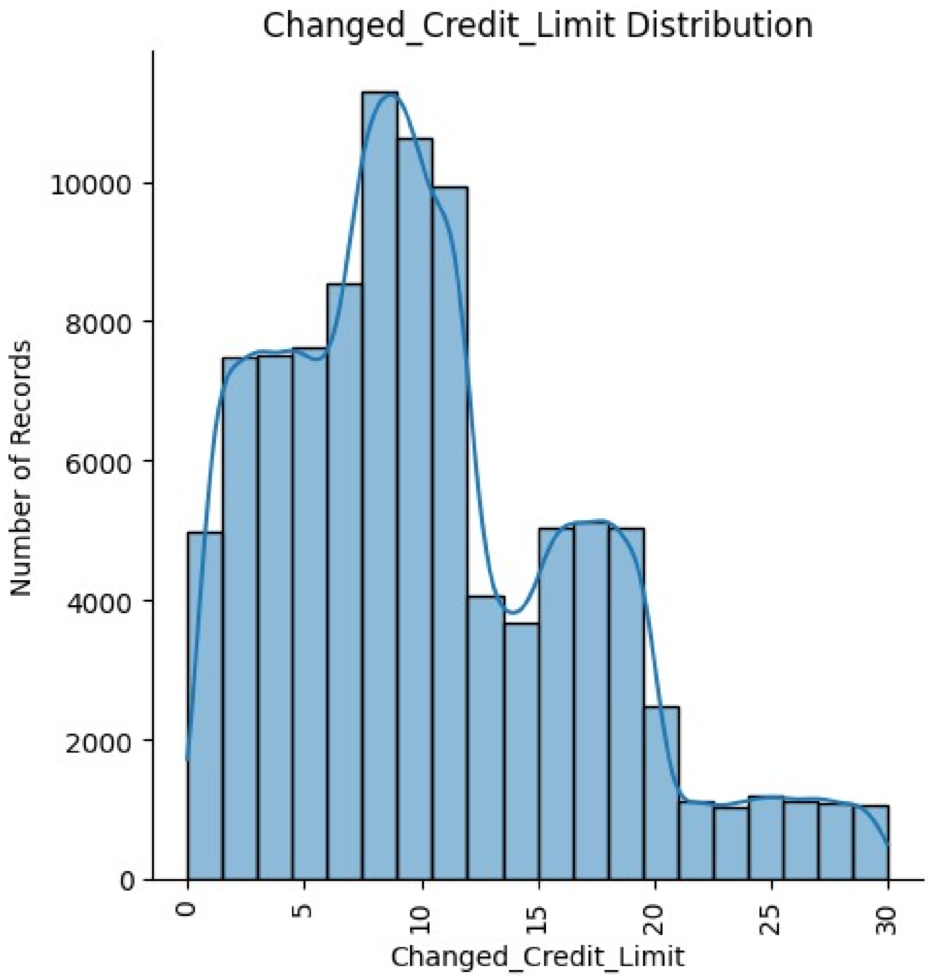
```
grouped_modes = df.groupby('Customer_ID')
['Changed_Credit_Limit'].apply(lambda x: x.mode().iloc[0])
df['Changed_Credit_Limit'] = df.apply(lambda row:
grouped_modes[row['Customer_ID']] if row['Changed_Credit_Limit'] !=
grouped_modes[row['Customer_ID']] else row['Changed_Credit_Limit'],
axis=1)
```

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

```
8.22     152
11.50    152
11.32    144
7.69     136
7.35     136
        ...
21.87      8
29.90      8
26.06      8
29.14      8
23.16      8
Name: Changed_Credit_Limit, Length: 2521, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.displot(data=df, x=df['Changed_Credit_Limit'], kde=True, bins=20)
plt.xlabel('Changed_Credit_Limit')
plt.ylabel('Number of Records')
plt.title('Changed_Credit_Limit Distribution')
plt.xticks(rotation=90)
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```




## Column : Num_Credit_inquiries

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

```
1965
```

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

```
4.0       11271
3.0        8890
6.0        8111
7.0        8058
2.0        8028
          ...
253.0         1
2352.0        1
2261.0        1
519.0         1
1801.0        1
Name: Num_Credit_Inquiries, Length: 1223, dtype: int64
```

```
df2 = df[pd.isna(df['Num_Credit_Inquiries'])]
df2[['Customer_ID','Num_of_Loan','Num_Credit_Card','Num_Credit_Inquiri
es']]
```

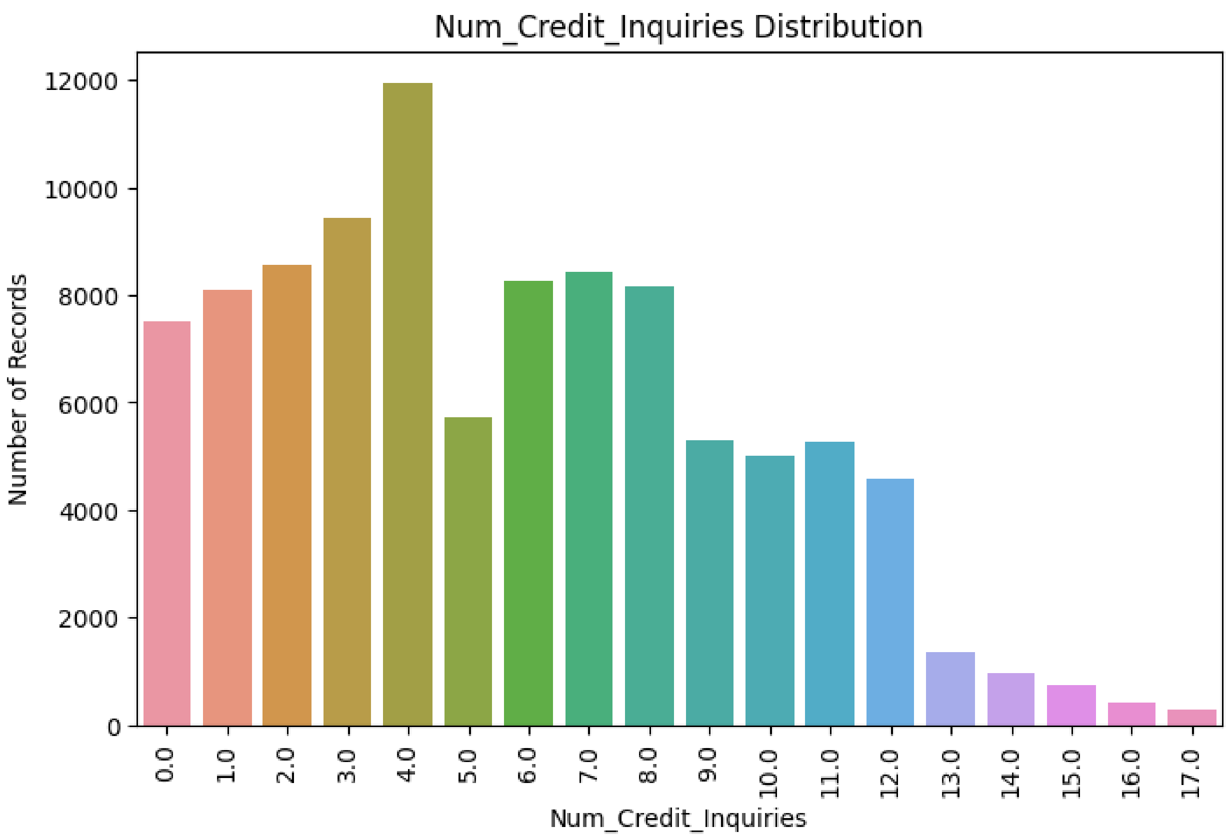
```
      Customer_ID  Num_of_Loan  Num_Credit_Card  Num_Credit_Inquiries
55     CUS_0x1018            8                7                   NaN
118    CUS_0x1041            9                8                   NaN
161    CUS_0x1051            1                5                   NaN
190    CUS_0x105b            0                4                   NaN
235    CUS_0x107c            6               10                   NaN
...           ...          ...              ...                   ...
99847   CUS_0xfb4            4                6                   NaN
99968   CUS_0xff4            5                7                   NaN
99970   CUS_0xff4            5                7                   NaN
99979   CUS_0xff6            2                6                   NaN
99994   CUS_0xffd            6                7                   NaN

[1965 rows x 4 columns]
```

```
grouped_modes = df.groupby('Customer_ID')
['Num_Credit_Inquiries'].apply(lambda x: x.mode().iloc[0])
df['Num_Credit_Inquiries'] = df.apply(lambda row:
grouped_modes[row['Customer_ID']] if row['Num_Credit_Inquiries'] !=
grouped_modes[row['Customer_ID']] else row['Num_Credit_Inquiries'],
axis=1)

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

```
4.0     11936
3.0      9416
2.0      8568
7.0      8416
6.0      8264
8.0      8152
1.0      8104
0.0      7504
5.0      5728
9.0      5304
11.0     5280
10.0     5016
12.0     4592
13.0     1344
14.0      960
15.0      728
16.0      416
17.0      272
Name: Num_Credit_Inquiries, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.countplot(data=df, x=df['Num_Credit_Inquiries'])
```

```
plt.xlabel('Num_Credit_Inquiries')
plt.ylabel('Number of Records')
plt.title('Num_Credit_Inquiries Distribution')
plt.xticks(rotation=90)
plt.show()
```




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

```
0
```

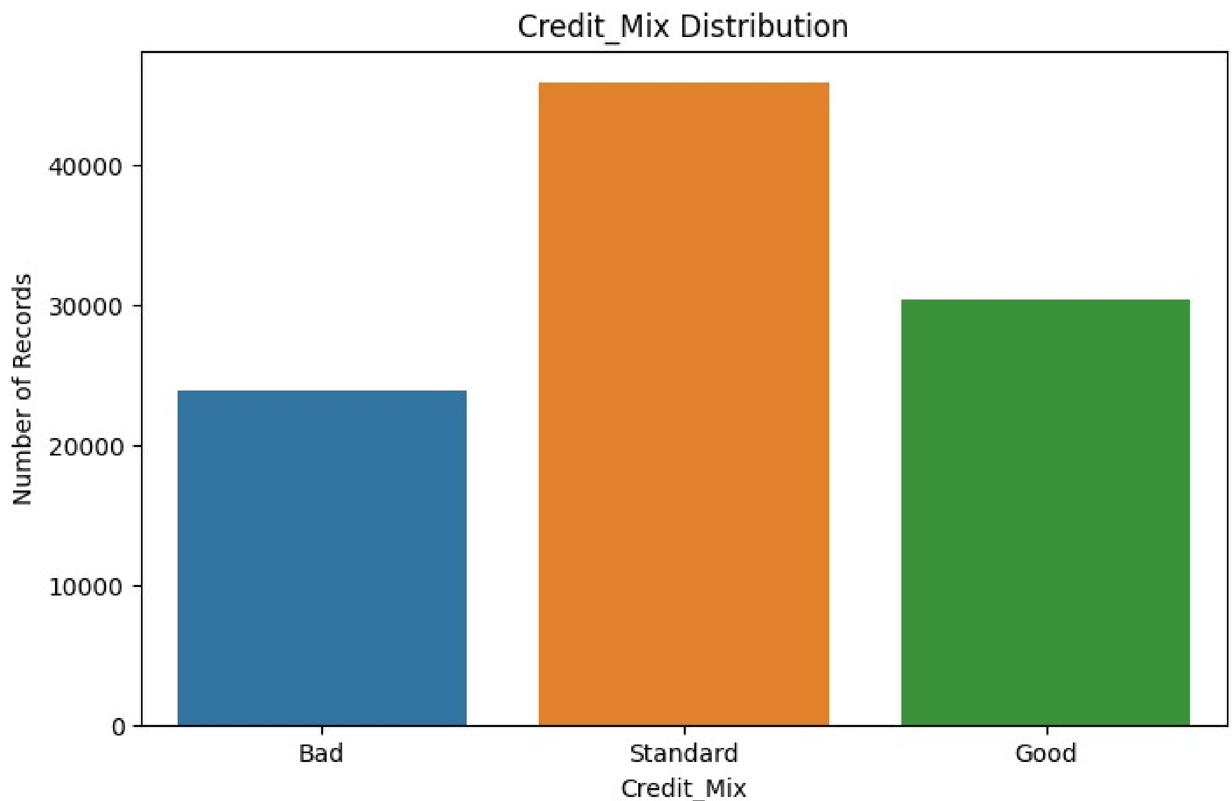
## Column : Credit_mix

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

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

```
df['Credit_Mix'] = df['Credit_Mix'].replace('_', np.nan)
```

```
df.sort_values(by=['Customer_ID', 'Month'], inplace=True)
df['Credit_Mix'] = df.groupby('Customer_ID')
['Credit_Mix'].fillna(method='ffill').fillna(method='bfill')

df['Credit_Mix'].value_counts()

Standard    45848
Good        30384
Bad         23768
Name: Credit_Mix, dtype: int64

plt.figure(figsize=(8,5))
sns.countplot(data=df, x=df['Credit_Mix'])
plt.xlabel('Credit_Mix')
plt.ylabel('Number of Records')
plt.title('Credit_Mix Distribution')
plt.xticks(rotation=0)
plt.show()
```




**Summary**

- There are 3 types of Credit Mix - Standard, Good, Bad
- About 20k records of Credit Mix is marked as a garbage value (_).

## Column : Outstanding Debt

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

```
1360.45     24
460.46      23
1151.7      23
1109.03     23
100.3       16
            ..
3530.13_     1
1181.44_     1
4078.71_     1
2362.56_     1
1799.87_     1
Name: Outstanding_Debt, Length: 13178, dtype: int64
```

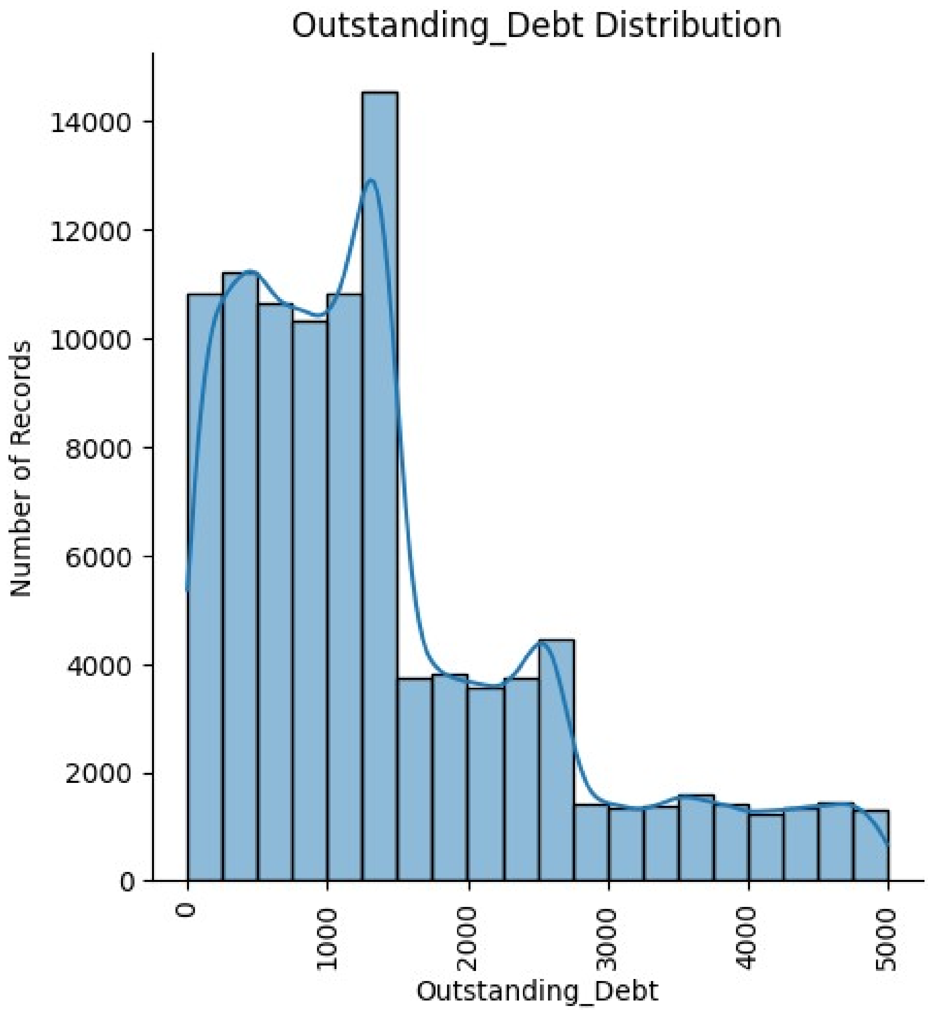
```
df[['Customer_ID', 'Outstanding_Debt']]
```

```
      Customer_ID Outstanding_Debt
0       CUS_0x1000          1562.91
1       CUS_0x1000          1562.91
2       CUS_0x1000          1562.91
3       CUS_0x1000          1562.91
4       CUS_0x1000          1562.91
...            ...              ...
99995    CUS_0xffd          1701.88
99996    CUS_0xffd          1701.88
99997    CUS_0xffd          1701.88
99998    CUS_0xffd          1701.88
99999    CUS_0xffd          1701.88

[100000 rows x 2 columns]
```

```
df['Outstanding_Debt'] = df['Outstanding_Debt'].str.replace('_', '')
df['Outstanding_Debt'] = df['Outstanding_Debt'].astype(float)
```

```
plt.figure(figsize=(8,5))
sns.displot(data=df, x=df['Outstanding_Debt'], kde=True, bins=20)
plt.xlabel('Outstanding_Debt')
plt.ylabel('Number of Records')
plt.title('Outstanding_Debt Distribution')
plt.xticks(rotation=90)
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```

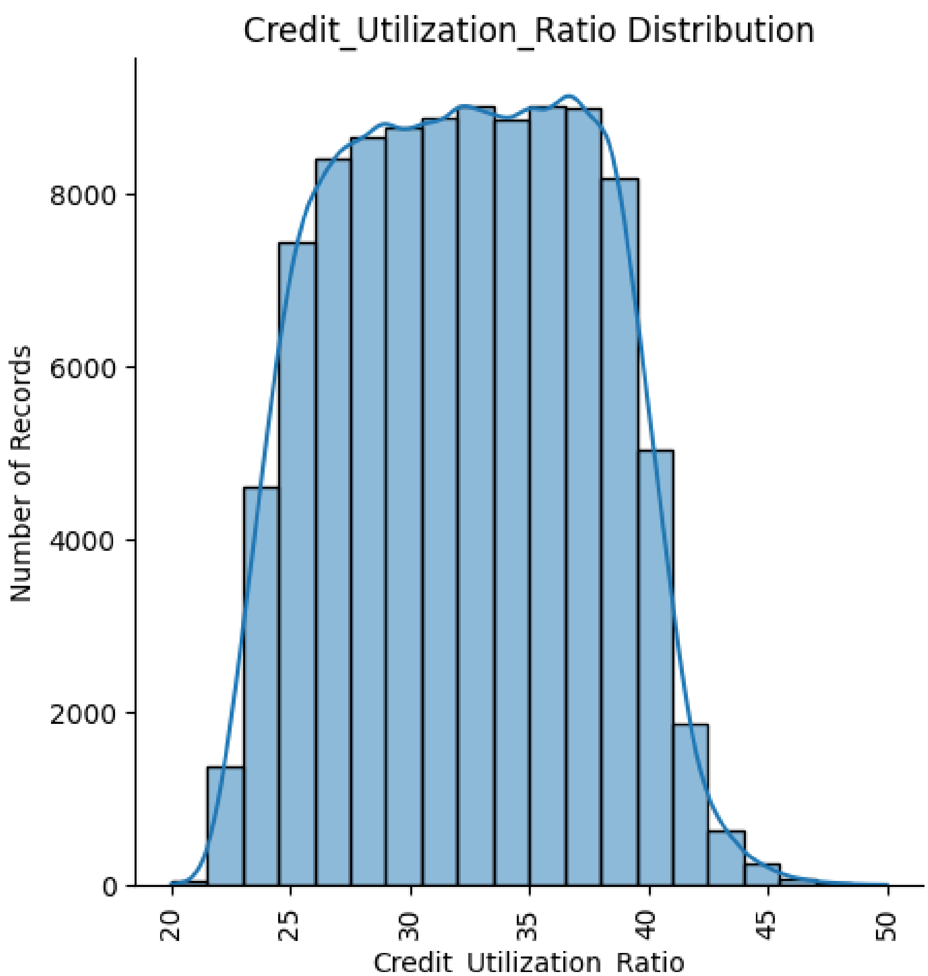



## Column : Credit Utilization Ratio

```
df['Credit_Utilization_Ratio']
=df['Credit_Utilization_Ratio'].round(2)

df['Credit_Utilization_Ratio']

0        32.84
1        30.08
2        29.44
3        26.61
4        38.15
         ...
99995    29.51
99996    33.92
99997    36.97
99998    25.18
99999    26.17
Name: Credit_Utilization_Ratio, Length: 100000, dtype: float64
```

```
plt.figure(figsize=(8,5))
sns.displot(data=df, x=df['Credit_Utilization_Ratio'], kde=True,
bins=20)
plt.xlabel('Credit_Utilization_Ratio')
plt.ylabel('Number of Records')
plt.title('Credit_Utilization_Ratio Distribution')
plt.xticks(rotation=90)
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```




## Column : Credit_history_Age

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

```
9030
```

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

```
15 Years and 11 Months    446
19 Years and 4 Months     445
19 Years and 5 Months     444
17 Years and 11 Months    443
19 Years and 3 Months     441
                         ...
0 Years and 3 Months       20
0 Years and 2 Months       15
33 Years and 7 Months      14
33 Years and 8 Months      12
0 Years and 1 Months        2
Name: Credit_History_Age, Length: 404, dtype: int64
```

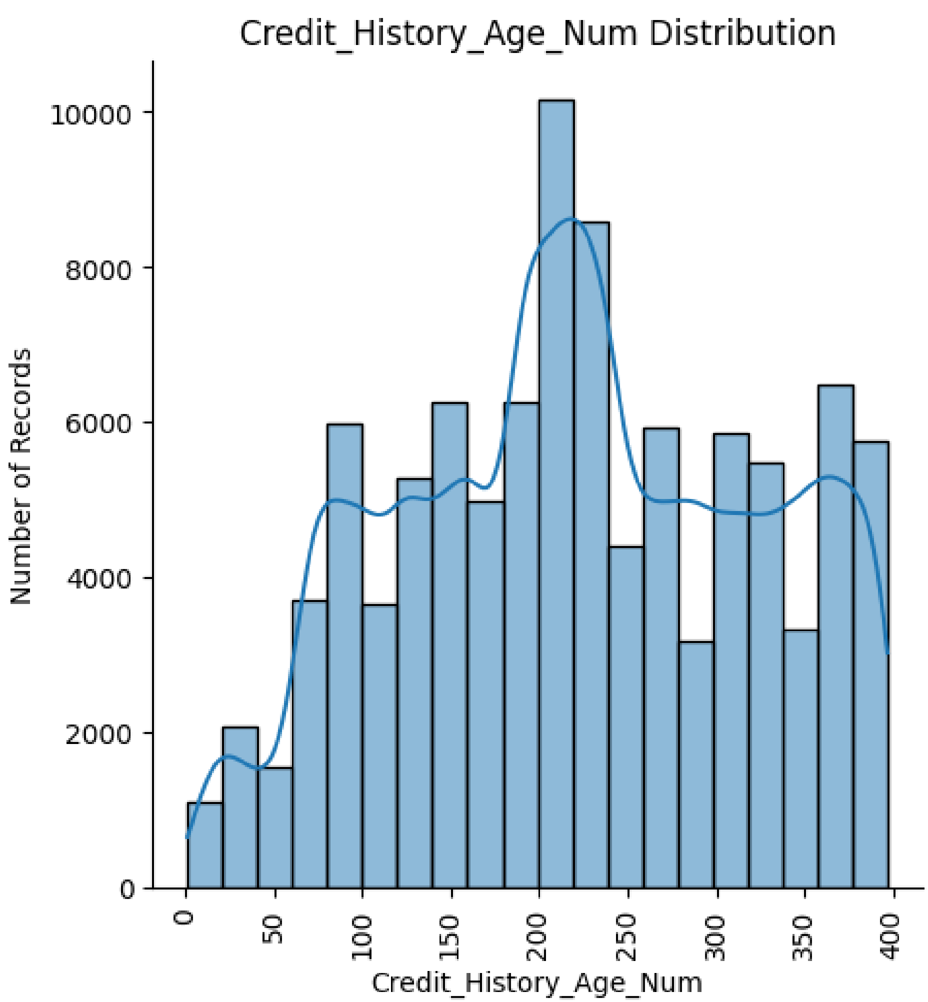
```
grouped_modes = df.groupby('Customer_ID')
['Credit_History_Age'].apply(lambda x: x.mode().iloc[0])
df['Credit_History_Age'] = df.apply(lambda row:
grouped_modes[row['Customer_ID']] if row['Credit_History_Age'] !=
grouped_modes[row['Customer_ID']] else row['Credit_History_Age'],
axis=1)

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

```
0
```

```
df1 = pd.DataFrame(df['Credit_History_Age'])

def convert_to_months(age_str):
    parts = age_str.split()
    years = int(parts[0])
    months = int(parts[3])
    total_months = years * 12 + months
    return total_months

df['Credit_History_Age_Num'] = df['Credit_History_Age'].apply(lambda
x: convert_to_months(x))

df[['Credit_History_Age','Credit_History_Age_Num']]
```

```
          Credit_History_Age  Credit_History_Age_Num
0      10 Years and 2 Months                     122
1      10 Years and 2 Months                     122
2      10 Years and 2 Months                     122
3      10 Years and 2 Months                     122
4      10 Years and 2 Months                     122
...                      ...                     ...
99995  18 Years and 2 Months                     218
99996  18 Years and 2 Months                     218
99997  18 Years and 2 Months                     218
99998  18 Years and 2 Months                     218
99999  18 Years and 2 Months                     218
```

```
[100000 rows x 2 columns]

print(df['Credit_History_Age_Num'].min(),
df['Credit_History_Age_Num'].max())

1 397

plt.figure(figsize=(8,5))
sns.displot(data=df, x=df['Credit_History_Age_Num'], kde=True,
bins=20)
plt.xlabel('Credit_History_Age_Num')
plt.ylabel('Number of Records')
plt.title('Credit_History_Age_Num Distribution')
plt.xticks(rotation=90)
plt.show()

<Figure size 800x500 with 0 Axes>
```



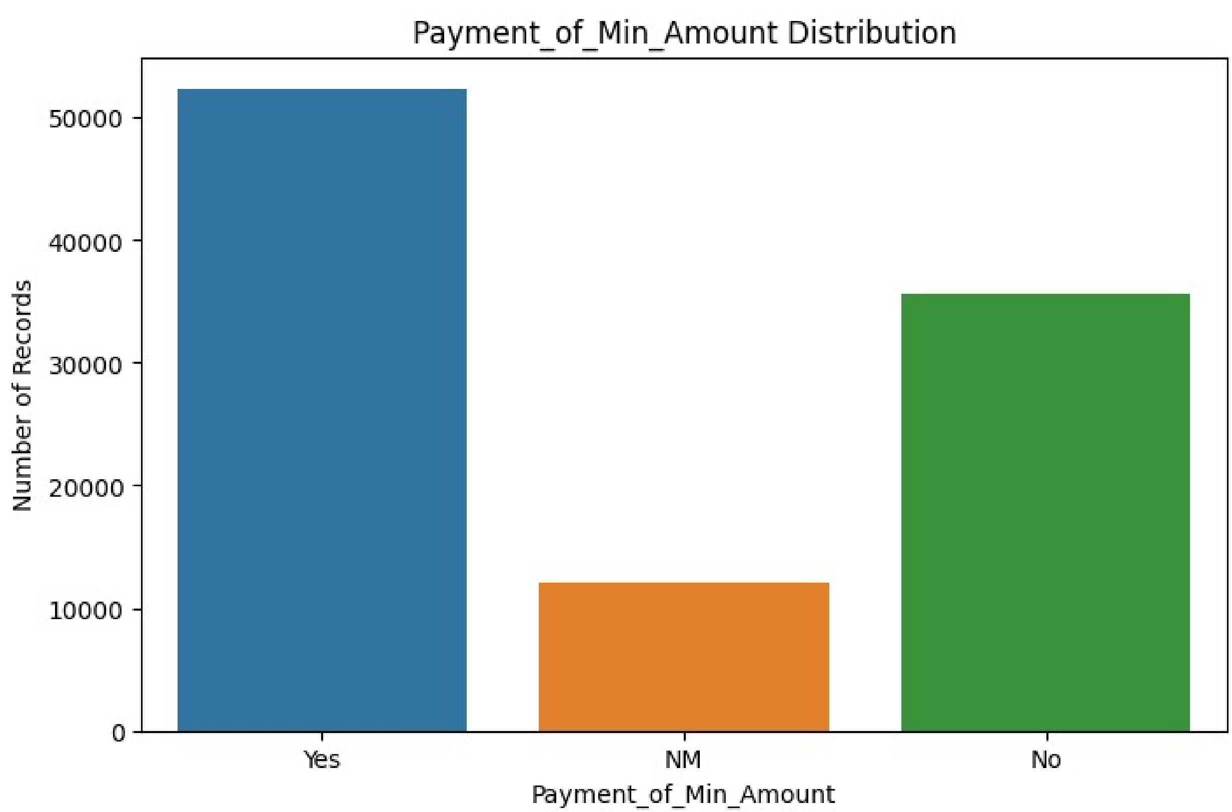
**We have converted credit history age into months as previous format was object datatype plus they were not in analytic form.**

# Column : Payment_of_min_Amount

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

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

```
plt.figure(figsize=(8,5))
sns.countplot(data=df, x=df['Payment_of_Min_Amount'])
plt.xlabel('Payment_of_Min_Amount')
plt.ylabel('Number of Records')
plt.title('Payment_of_Min_Amount Distribution')
plt.xticks(rotation=0)
plt.show()
```




# Column : Total_EMI_per_month

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

```
0.000000        10613
42.941090           8
72.798279           8
119.461755          8
263.655491          8
                ...
39156.000000        1
26128.000000        1
75532.000000        1
78386.000000        1
22380.000000        1
Name: Total_EMI_per_month, Length: 14950, dtype: int64
```

```
grouped_modes = df.groupby('Customer_ID')
['Total_EMI_per_month'].apply(lambda x: x.mode().iloc[0])
df['Total_EMI_per_month'] = df.apply(lambda row:
grouped_modes[row['Customer_ID']] if row['Total_EMI_per_month'] !=
grouped_modes[row['Customer_ID']] else row['Total_EMI_per_month'],
axis=1)
```

```
print(df['Total_EMI_per_month'].min(),df['Total_EMI_per_month'].max())
```

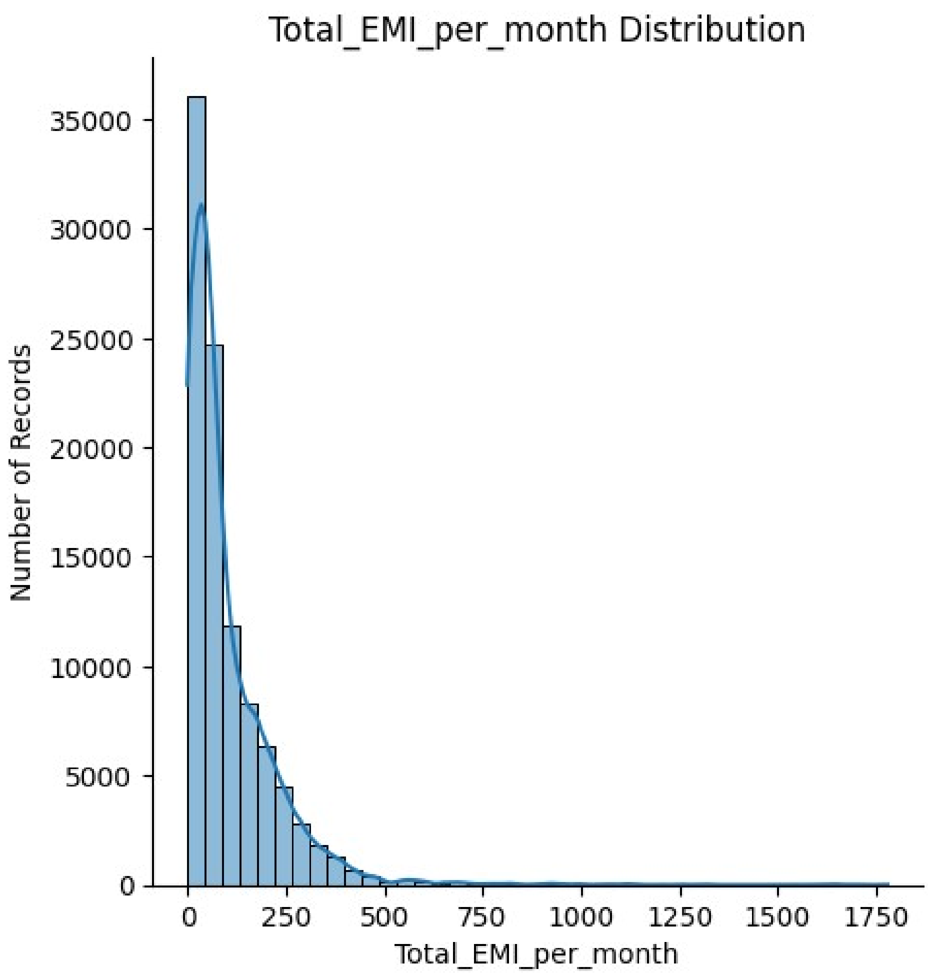
```
0.0 1779.103254
```

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

```
0.000000      11072
42.941090         8
107.489365        8
78.047064         8
230.815449        8
              ...
341.841495        8
400.386423        8
85.356930         8
61.845295         8
182.976650        8
Name: Total_EMI_per_month, Length: 11117, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.displot(data=df, x=df['Total_EMI_per_month'], kde=True, bins=40)
plt.xlabel('Total_EMI_per_month')
plt.ylabel('Number of Records')
plt.title('Total_EMI_per_month Distribution')
plt.xticks(rotation=0)
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```




## Column : Amount_invested_monthly

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

```
4479
```

```
df['Amount_invested_monthly'].dtypes
```

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

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

```
__10000__      4305
0               169
87.90990881       1
459.5317247       1
752.475627        1
               ...
105.7266479       1
138.9942681       1
289.9612607       1
```

```
76.53803865       1
104.6294735       1
Name: Amount_invested_monthly, Length: 91049, dtype: int64
```

```
df['Amount_invested_monthly'] =
pd.to_numeric(df['Amount_invested_monthly'], errors='coerce')
df['Amount_invested_monthly'] =
df['Amount_invested_monthly'].replace(0, np.nan)
df['Amount_invested_monthly']
```

```
0         87.909909
1         77.314276
2        176.132567
3        244.750283
4        266.597160
            ...
99995    195.529273
99996    257.989693
99997     47.007379
99998    336.130231
99999    104.629474
Name: Amount_invested_monthly, Length: 100000, dtype: float64
```

```
df[df['Amount_invested_monthly']==0]
```

```
Empty DataFrame
Columns: [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, Auto Loan,
Credit-Builder Loan, Debt Consolidation Loan, Home Equity Loan,
Mortgage Loan, Not Specified, Payday Loan, Personal Loan, Student
Loan, Delay_from_due_date, Num_of_Delayed_Payment,
Changed_Credit_Limit, Num_Credit_Inquiries, Credit_Mix,
Outstanding_Debt, Credit_Utilization_Ratio, Credit_History_Age,
Payment_of_Min_Amount, Total_EMI_per_month, Amount_invested_monthly,
Payment_Behaviour, Monthly_Balance, Credit_History_Age_Num]
Index: []

[0 rows x 37 columns]
```

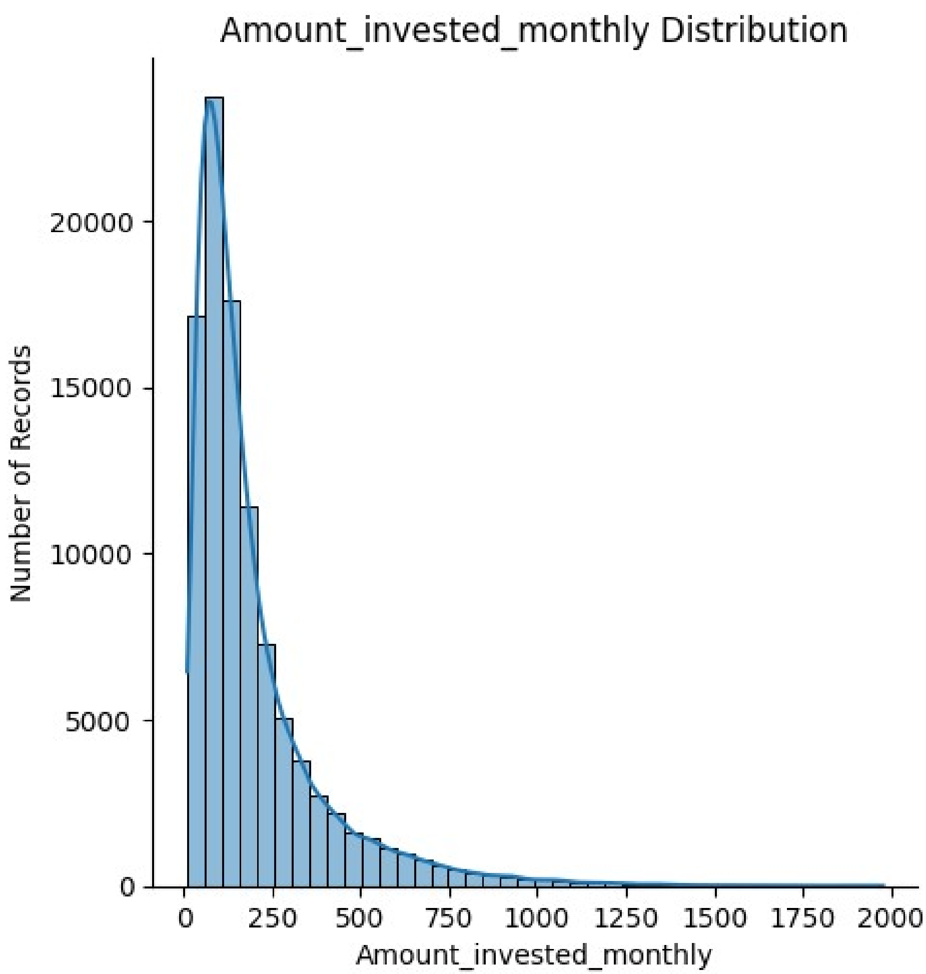
```
df['Amount_invested_monthly'].isna().sum()
```

```
8953
```

```
mean_per_customer = df.groupby('Customer_ID')
['Amount_invested_monthly'].mean()
mask = df['Amount_invested_monthly'].isna()
df.loc[mask, 'Amount_invested_monthly'] = df.loc[mask,
'Customer_ID'].map(mean_per_customer)
```

```
plt.figure(figsize=(8,5))
sns.displot(data=df, x=df['Amount_invested_monthly'], kde=True,
bins=40)
plt.xlabel('Amount_invested_monthly')
plt.ylabel('Number of Records')
plt.title('Amount_invested_monthly Distribution')
plt.xticks(rotation=0)
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```




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

```
0
```

```
df['Amount_invested_monthly']= df['Amount_invested_monthly'].round(2)
```

## Column : Payment_Behaviour

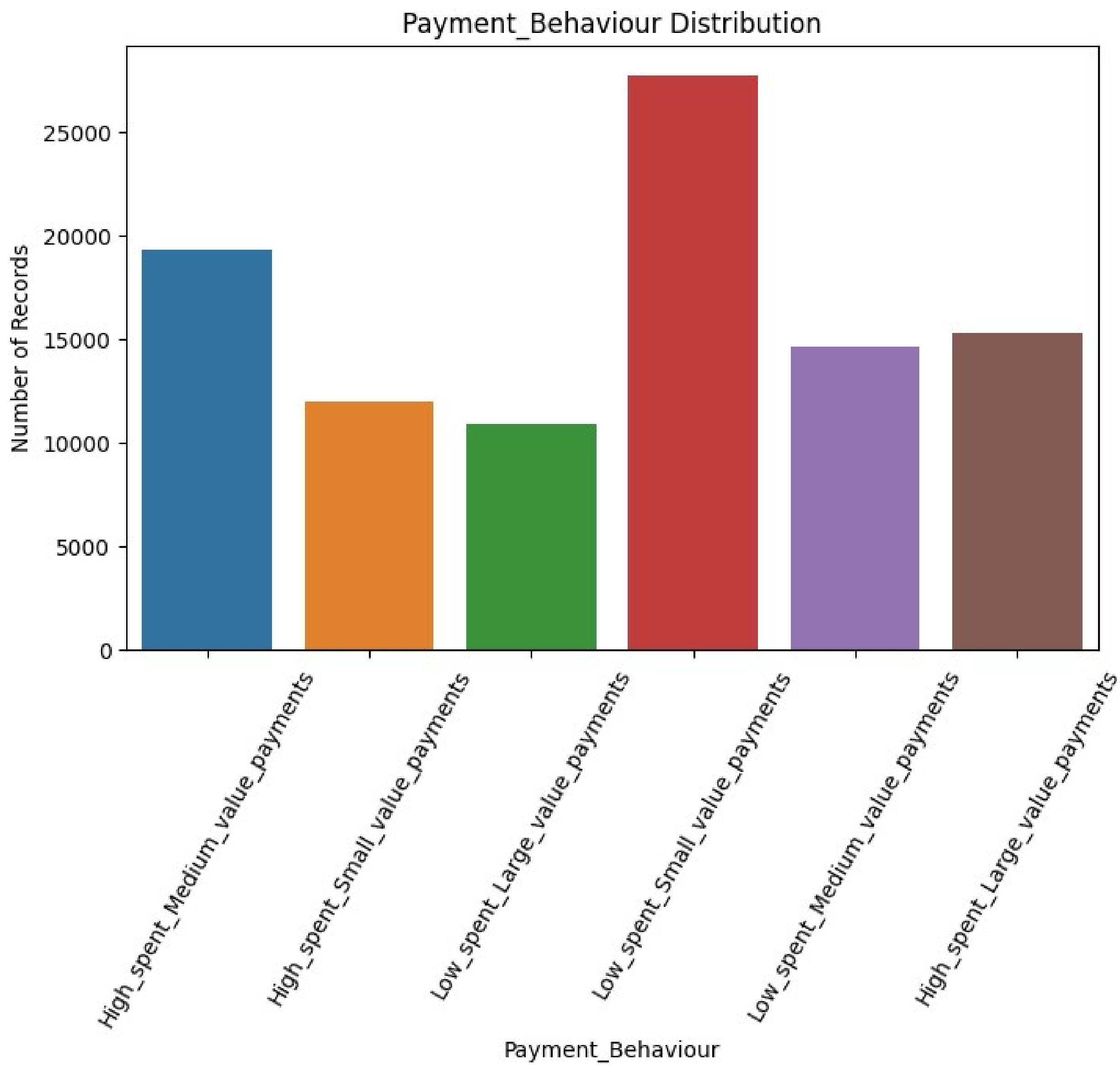
```
df['Payment_Behaviour'].value_counts()
```

```
Low_spent_Small_value_payments      25513
High_spent_Medium_value_payments    17540
Low_spent_Medium_value_payments     13861
High_spent_Large_value_payments     13721
High_spent_Small_value_payments     11340
Low_spent_Large_value_payments      10425
!@9#%8                               7600
Name: Payment_Behaviour, dtype: int64
```

```
df['Payment_Behaviour'] = df['Payment_Behaviour'].replace('!@9#%8',
np.nan)
df['Payment_Behaviour'] = df.groupby('Customer_ID')
['Payment_Behaviour'].transform(lambda x: x.fillna(x.mode().iloc[0]))
print(df['Payment_Behaviour'].value_counts())
```

```
Low_spent_Small_value_payments      27767
High_spent_Medium_value_payments    19366
High_spent_Large_value_payments     15348
Low_spent_Medium_value_payments     14621
High_spent_Small_value_payments     11980
Low_spent_Large_value_payments      10918
Name: Payment_Behaviour, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.countplot(data=df, x=df['Payment_Behaviour'])
plt.xlabel('Payment_Behaviour')
plt.ylabel('Number of Records')
plt.title('Payment_Behaviour Distribution')
plt.xticks(rotation=60)
plt.show()
```




## Column : Monthly_Balance

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

1200

df['Monthly_Balance'].dtypes

dtype('O')

df['Monthly_Balance'].value_counts()

__-333333333333333333333333333__    9
350.0148691                         2
695.0571561                         2
```

```
419.7651674                         1
615.6677195                         1
                                   ..
259.3760946                         1
343.7619864                         1
288.6680278                         1
468.4784226                         1
337.380877                          1
Name: Monthly_Balance, Length: 98790, dtype: int64
```

```
df['Monthly_Balance'].nunique()
```

```
98790
```

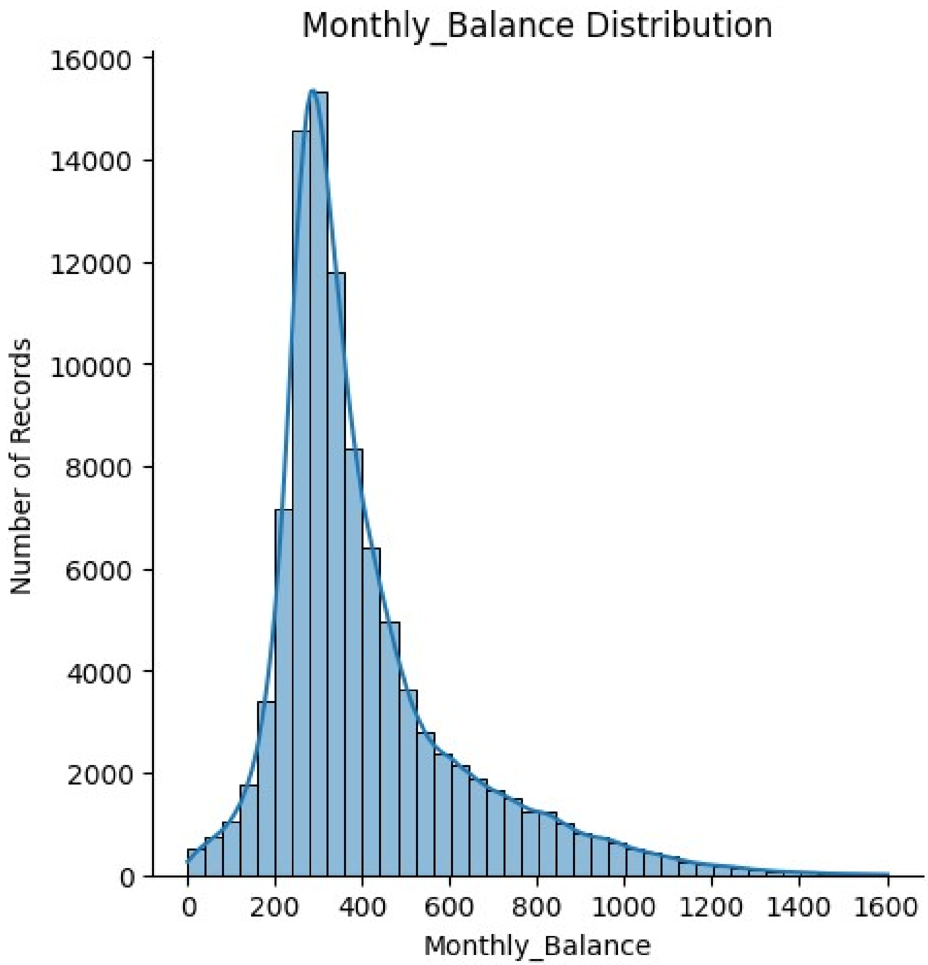
```
df['Monthly_Balance'] = df['Monthly_Balance'].replace('__-
333333333333333333333333333__', np.nan)
df['Monthly_Balance'] = pd.to_numeric(df['Monthly_Balance'],
errors='coerce')
df['Monthly_Balance'] = df.groupby('Customer_ID')
['Monthly_Balance'].transform(lambda x: x.fillna(x.mean()))
```

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

```
261.565962    5
464.392372    4
238.332338    4
215.181452    4
164.119697    4
             ..
319.503931    1
345.075800    1
338.115057    1
344.112554    1
337.380877    1
Name: Monthly_Balance, Length: 99757, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.displot(data=df, x=df['Monthly_Balance'], kde=True, bins=40)
plt.xlabel('Monthly_Balance')
plt.ylabel('Number of Records')
plt.title('Monthly_Balance Distribution')
plt.xticks(rotation=0)
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```

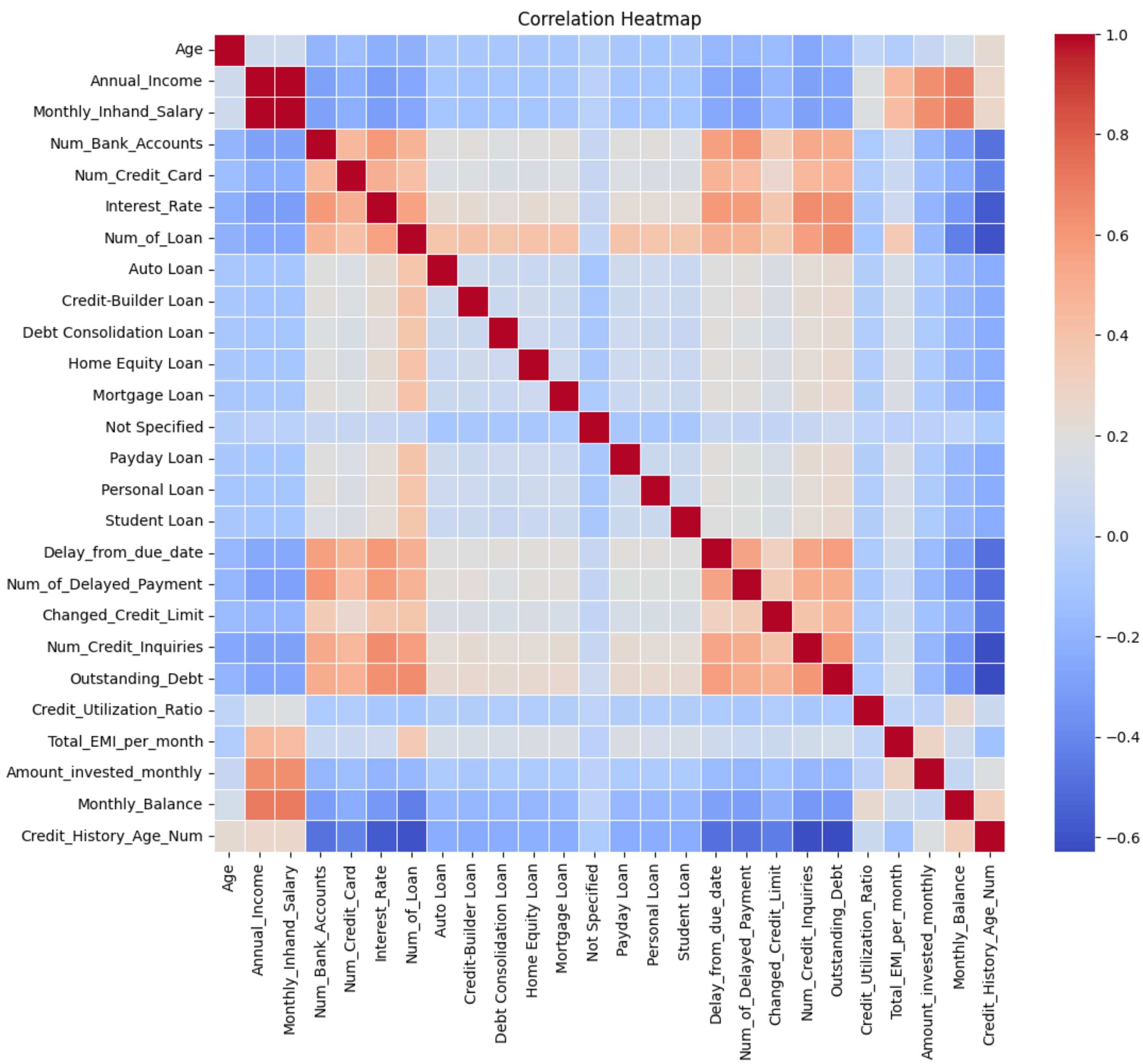



```
df['Monthly_Balance'].isna().sum()
```

```
0
```

## HEATMAP For checking correlation

```
plt.figure(figsize=(12, 10))
sns.heatmap(df.corr(), cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```




## Summary

- Strong Psoitive Correlation can seen among features like annual_income, Monthly_inhand_salary, Monthly Balance and amount invested Monthly.
- Positive Correlation can be found among features like Num_Credit_inquiries, outstanding debt, Num_of_delayed_payment, Num_Bank_Account.
- Strong negative correlation can be found among Credit_history_age, outstanding debt, Num_of _loan, interest rate.

```
columns_to_drop = ['Credit_History_Age', 'Type_of_Loan']
df.drop(columns=columns_to_drop, inplace=True)

df.describe().T
```

```
                              count          mean           std
min  \
Age                        100000.0     33.274590     10.764414
14.000000
Annual_Income              100000.0  50505.123449  38299.422093
7005.930000
Monthly_Inhand_Salary      100000.0   4198.262107   3187.363227
303.645417
Num_Bank_Accounts          100000.0      5.411840      2.508237
1.000000
Num_Credit_Card            100000.0      5.532720      2.067504
0.000000
Interest_Rate              100000.0     14.532080      8.741330
1.000000
Num_of_Loan                100000.0      3.532880      2.446356
0.000000
Auto Loan                  100000.0      0.305600      0.460663
0.000000
Credit-Builder Loan        100000.0      0.317280      0.465420
0.000000
Debt Consolidation Loan    100000.0      0.310400      0.462660
0.000000
Home Equity Loan           100000.0      0.314000      0.464119
0.000000
Mortgage Loan              100000.0      0.313600      0.463958
0.000000
Not Specified              100000.0      0.430880      0.495202
0.000000
Payday Loan                100000.0      0.319440      0.466262
0.000000
Personal Loan              100000.0      0.311040      0.462921
0.000000
Student Loan               100000.0      0.310400      0.462660
0.000000
Delay_from_due_date        100000.0     21.068780     14.860104     -
5.000000
Num_of_Delayed_Payment     100000.0     13.266640      6.194986
0.000000
Changed_Credit_Limit       100000.0     10.392847      6.511672
0.000000
Num_Credit_Inquiries       100000.0      5.677760      3.827248
0.000000
Outstanding_Debt           100000.0   1426.220376   1155.129026
0.230000
Credit_Utilization_Ratio   100000.0     32.285183      5.116880
20.000000
Total_EMI_per_month        100000.0    105.543371    125.810030
0.000000
Amount_invested_monthly    100000.0    195.838897    195.041856
10.010000
```

```
Monthly_Balance            100000.0    403.120320    214.014558
0.007760
Credit_History_Age_Num     100000.0    220.156240     99.580975
1.000000

                                    25%           50%           75%  \
Age                           24.000000     33.000000     42.000000
Annual_Income              19342.972500  36999.705000  71683.470000
Monthly_Inhand_Salary       1626.594167   3096.066250   5957.715000
Num_Bank_Accounts              3.000000      5.000000      7.000000
Num_Credit_Card                4.000000      5.000000      7.000000
Interest_Rate                  7.000000     13.000000     20.000000
Num_of_Loan                    2.000000      3.000000      5.000000
Auto Loan                      0.000000      0.000000      1.000000
Credit-Builder Loan            0.000000      0.000000      1.000000
Debt Consolidation Loan        0.000000      0.000000      1.000000
Home Equity Loan               0.000000      0.000000      1.000000
Mortgage Loan                  0.000000      0.000000      1.000000
Not Specified                  0.000000      0.000000      1.000000
Payday Loan                    0.000000      0.000000      1.000000
Personal Loan                  0.000000      0.000000      1.000000
Student Loan                   0.000000      0.000000      1.000000
Delay_from_due_date           10.000000     18.000000     28.000000
Num_of_Delayed_Payment         9.000000     14.000000     18.000000
Changed_Credit_Limit           5.500000      9.340000     14.670000
Num_Credit_Inquiries           3.000000      5.000000      8.000000
Outstanding_Debt             566.072500   1166.155000   1945.962500
Credit_Utilization_Ratio      28.050000     32.310000     36.500000
Total_EMI_per_month           29.049047     66.033915    145.582332
Amount_invested_monthly       74.640000    131.210000    239.480000
Monthly_Balance              270.189030    337.114461    471.570652
Credit_History_Age_Num       142.000000    216.000000    299.000000

                                    max
Age                           56.000000
Annual_Income             179987.280000
Monthly_Inhand_Salary      15204.633330
Num_Bank_Accounts             10.000000
Num_Credit_Card               11.000000
Interest_Rate                 34.000000
Num_of_Loan                    9.000000
Auto Loan                      1.000000
Credit-Builder Loan            1.000000
Debt Consolidation Loan        1.000000
Home Equity Loan               1.000000
Mortgage Loan                  1.000000
Not Specified                  1.000000
Payday Loan                    1.000000
Personal Loan                  1.000000
Student Loan                   1.000000
```

```
Delay_from_due_date           67.000000
Num_of_Delayed_Payment        28.000000
Changed_Credit_Limit          29.980000
Num_Credit_Inquiries          17.000000
Outstanding_Debt            4998.070000
Credit_Utilization_Ratio      50.000000
Total_EMI_per_month         1779.103254
Amount_invested_monthly     1977.330000
Monthly_Balance             1602.040519
Credit_History_Age_Num       397.000000
```

```
df.describe(include='object').T
```

| | count | unique | top | freq |
|---|---|---|---|---|
| ID | 100000 | 100000 | 0x1628d | 1 |
| Customer_ID | 100000 | 12500 | CUS_0x1000 | 8 |
| Month | 100000 | 8 | April | 12500 |
| Name | 100000 | 10139 | Jessicad | 48 |
| SSN | 100000 | 12500 | 913-74-1218 | 8 |
| Occupation | 100000 | 15 | Lawyer | 7096 |
| Credit_Mix | 100000 | 3 | Standard | 45848 |
| Payment_of_Min_Amount | 100000 | 3 | Yes | 52326 |
| Payment_Behaviour | 100000 | 6 | Low_spent_Small_value_payments | 27767 |

## LABEL ENCODING FEATURES

```
df["Payment_of_Min_Amount"] =
df["Payment_of_Min_Amount"].replace({"Yes": 1, "No": 0, "NM": 0})

df["Credit_Mix"] = df["Credit_Mix"].replace({"Standard": 1, "Good": 2,
"Bad": 0})

df["Payment_Behaviour"] = df["Payment_Behaviour"].replace({
      "Low_spent_Small_value_payments": 1,
      "High_spent_Medium_value_payments": 2,
      "Low_spent_Medium_value_payments": 3,
      "High_spent_Large_value_payments": 4,
      "High_spent_Small_value_payments": 5,
      "Low_spent_Large_value_payments": 6
  })
```

1. Low_spent_Small_value_payments: 1
2. High_spent_Small_value_payments: 2
3. Low_spent_Medium_value_payments: 3
4. High_spent_Medium_value_payments: 4
5. Low_spent_Large_value_payments: 5
6. High_spent_Large_value_payments: 6

This numeric representation captures the hierarchy where higher numbers represent higher spent value or larger payments.

## FEATURE ENGINEERING

```
df['Monthly_Debt_to_Income_Ratio'] = df['Outstanding_Debt'] /
df['Monthly_Inhand_Salary']

df['Monthly_Debt_Repayment_Capacity'] = df['Monthly_Inhand_Salary'] -
df['Total_EMI_per_month']

df["Payment_History_Score"] = (
      -1 * df["Delay_from_due_date"]
      -1 * df["Num_of_Delayed_Payment"]
      + 1 * df["Payment_of_Min_Amount"]
  )
```

# CREDIT SCORE CALCULATION

Selected features for credit score calulcation with their weights:

1. Payment history score
- Weight: 0.30
- Strongest predictor of future credit behavior.
1. Credit History Age in Months
- Weight: 0.20
- Longer credit history indicates responsible credit usage.Weighted moderately to reflect its significance.
1. Monthly Debt-to-Income Ratio (MDTIR)
- Weight: 0.15
- Lower ratio indicates better ability to manage debt.Weighted lower due to potential fluctuations in income.
1. Credit Utilization Ratio
- Weight: 0.10
- Lower ratio suggests responsible credit card usage.Weighted lower as it's a snapshot of current utilization.
1. Monthly Debt Repayment Capacity
- Weight: 0.05
- Reflects ability to manage existing debt.

1. Outstanding Debt
- Weight: 0.05
- Higher debt increases risk of default.
1. Num_Credit_Inquiries
- Weight: 0.05
- Fewer inquiries suggest lower credit-seeking behavior.
1. Payment Behaviour
- Weight: 0.05
- Insights into spending patterns and payment tendencies.
1. Credit Mix
- Weight: 0.05
- Taking different types of credit

```
def calculate_credit_score(data):

  # Group by Customer ID, handling month-level data and calculating
scores
  grouped_data = data.groupby("Customer_ID").agg(
      Payment_History_Score=("Payment_History_Score", "mean"),
      Credit_History_Age_Num=("Credit_History_Age_Num", "max"),  # Use
maximum history age
      Monthly_Debt_to_Income_Ratio=("Monthly_Debt_to_Income_Ratio",
"mean"),
      Credit_Utilization_Ratio=("Credit_Utilization_Ratio", "mean"),

Monthly_Debt_Repayment_Capacity=("Monthly_Debt_Repayment_Capacity",'me
an'),
      Outstanding_Debt=("Outstanding_Debt", "mean"),
      Num_Credit_Inquiries=("Num_Credit_Inquiries", "sum"),
      Payment_Behaviour=("Payment_Behaviour","mean"),# Use average
payment behaviour encoding
      Credit_Mix=("Credit_Mix","mean")
  )

    # Standardize values for numerical features
  grouped_data = (grouped_data - grouped_data.mean()) /
grouped_data.std()

  # Calculate weighted scores
  grouped_data["credit_score"] = (
      0.30 * grouped_data["Payment_History_Score"]
      + 0.20 * grouped_data["Credit_History_Age_Num"]
      + 0.15 * (1-grouped_data["Monthly_Debt_to_Income_Ratio"])
#Inverse relation as lower the value better the financials
      + 0.10 * (1-grouped_data["Credit_Utilization_Ratio"]) #inverse
relation
      + 0.05 * grouped_data["Monthly_Debt_Repayment_Capacity"]
      + 0.05 * grouped_data["Outstanding_Debt"]
      + 0.05 * (1-grouped_data["Num_Credit_Inquiries"]) #Inverse
```

```
relation
      + 0.05 * grouped_data["Payment_Behaviour"]
      + 0.05 * grouped_data["Credit_Mix"]
  )

  # Normalize scores to a range of 0 to 100
  grouped_data["credit_score"] = (grouped_data["credit_score"] -
grouped_data["credit_score"].min()) /
(grouped_data["credit_score"].max() -
grouped_data["credit_score"].min()) * 100
  # Map scores to the original FICO scale (300 to 850)
  min_range, max_range = 300, 850
  grouped_data["credit_score"] = (grouped_data["credit_score"] *
(max_range - min_range) / 100) + min_range

  return grouped_data.reset_index()


# Calculate scores for all customers
credit_scores_df = calculate_credit_score(df)
credit_scores_df[["Customer_ID","credit_score"]]
```

```
      Customer_ID  credit_score
0      CUS_0x1000    495.215414
1      CUS_0x1009    765.188490
2      CUS_0x100b    725.966507
3      CUS_0x1011    678.701861
4      CUS_0x1013    731.596559
...           ...           ...
12495   CUS_0xff3    682.252337
12496   CUS_0xff4    687.775950
12497   CUS_0xff6    799.658279
12498   CUS_0xffc    561.434848
12499   CUS_0xffd    676.226487

[12500 rows x 2 columns]
```

```
max_value=credit_scores_df['credit_score'].max()
credit_scores_df[credit_scores_df['credit_score'] == max_value]
```

```
     Customer_ID  Payment_History_Score  Credit_History_Age_Num  \
5701  CUS_0x65bf                1.45596                1.745692

      Monthly_Debt_to_Income_Ratio  Credit_Utilization_Ratio  \
5701                     -0.617335                  -0.53696

      Monthly_Debt_Repayment_Capacity  Outstanding_Debt
Num_Credit_Inquiries  \
5701                         2.484007         -0.796567                -
1.222183
```

```
      Payment_Behaviour  Credit_Mix  credit_score
5701           1.033527     1.27412         850.0
```

```python
min_value=credit_scores_df['credit_score'].min()
credit_scores_df[credit_scores_df['credit_score'] == min_value]
```

```
     Customer_ID  Payment_History_Score  Credit_History_Age_Num  \
8310  CUS_0x8c6f              -1.830869               -1.507828

      Monthly_Debt_to_Income_Ratio  Credit_Utilization_Ratio  \
8310                      10.03639                 -0.798419

      Monthly_Debt_Repayment_Capacity  Outstanding_Debt
Num_Credit_Inquiries  \
8310                         -1.22304          1.971018
2.696945

      Payment_Behaviour  Credit_Mix  credit_score
8310          -1.124135   -1.454655         300.0
```

## Insights

1. We have record of 12500 unique customers
2. In the dataset, we have data for each customer over the course of 8 months(from January to August)
3. We have following types of loans

- auto loan
- credit-builder loan
- debt consolidation loan
- home equity loan
- mortgage loan
- not specified
- payday loan
- personal loan
- student loan

1. Most customers have a low Annual income and Distribution is right skewed.
2. Most customers have a low monthly income. Distribution is right skewed.
3. Majority of customers has no. of bank accounts between 3 to 8.
4. Number of credit cards range from 0 to 11 with most of the customers having credit cards in the range of 3 to 7 with peak at 5.
5. Interest rate ranges from 1% to 34%.
6. Very few customers invest greater than 2k amount per month.
7. Customers typically take anywhere from 2 to 4 loans, with the maximum number being 9.
8. Typically, most customers belong to the Low_spent_small_value_payments and High_spent_medium-value_payments.
9. Minimum Credit history is 1 month with highest as 397.

For credit score calculation we have used following features with their respective weights

- Selected features for credit score calulcation with their weights:

1. Payment histroy score: (Weight: 0.30)
2. Credit History Age in Months (Weight: 0.20)
3. Monthly Debt-to-Income Ratio (MDTIR) (Weight: 0.15)
4. Credit Utilization Ratio (Weight: 0.10)
5. Monthly Debt Repayment Capacity (Weight: 0.05)
6. Outstanding Debt (Weight: 0.05)
7. Num_Credit_Inquiries (Weight: 0.05)
8. Payment Behaviour (Weight: 0.05)
9. Credit_mix (Weight: 0.05)

# Recommendations

- Engage with domain experts, such as credit analysts and financial professionals, to gain insights into the nuances of creditworthiness. Their expertise can guide the selection of features, model design, and interpretation of results, ultimately improving the reliability of the credit score.

- Algorithms like random forests, gradient boosting, or neural networks may reveal hidden patterns and correlations within the data that traditional scoring models might overlook.

- Consider expanding the set of features used for credit score calculation. This could involve incorporating alternative data sources such as social media behavior, rental payment history, or utility bill payments. Experimenting with new features can provide a more comprehensive and accurate representation of an individual's financial responsibility and creditworthiness.

- The current credit score model uses a basic set of factors to calculate scores. To enhance reliability, we can delve into adjusting the importance of each factor through various weighting schemes. For example, we might assign more weight to factors that have a stronger impact on creditworthiness, such as payment history and credit utilization. This way, the model can better reflect the nuances of individual financial behavior.