Credit EDA & Credit Score Calculation with Python

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.

Imports

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

Data

```
credit_score_data = pd.read_csv(
    "/Users/indraneeldutta/Documents/Scaler/Fintech Domain/Credit
Scoring and EDA/data/Credit Score.csv"
)
```

```
/var/folders/5m/6v9nlkzx2rn5rdpsrw41z6880000gq/T/
ipykernel_59944/2426982786.py:1: DtypeWarning: Columns (26) have mixed
types. Specify dtype option on import or set low_memory=False.
  credit_score_data = pd.read_csv(
```

```
credit_score_data
```

```
             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]
```

EDA

```python
#Display basic information about the dataset
credit_score_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
```

```python
# Display basic statistics
credit_score_data.describe()
```

```
       Monthly_Inhand_Salary  Num_Bank_Accounts  Num_Credit_Card  \
count           84998.000000      100000.000000     100000.00000
mean             4194.170850          17.091280         22.47443
std              3183.686167         117.404834        129.05741
min               303.645417          -1.000000          0.00000
25%              1625.568229           3.000000          4.00000
50%              3093.745000           6.000000          5.00000
75%              5957.448333           7.000000          7.00000
max             15204.633330        1798.000000       1499.00000

       Interest_Rate  Delay_from_due_date  Num_Credit_Inquiries  \
count  100000.000000        100000.000000          98035.000000
mean       72.466040            21.068780             27.754251
std       466.422621            14.860104            193.177339
min         1.000000            -5.000000              0.000000
25%         8.000000            10.000000              3.000000
50%        13.000000            18.000000              6.000000
75%        20.000000            28.000000              9.000000
max      5797.000000            67.000000           2597.000000

       Credit_Utilization_Ratio  Total_EMI_per_month
count             100000.000000        100000.000000
mean                  32.285173          1403.118217
std                    5.116875          8306.041270
min                   20.000000             0.000000
25%                   28.052567            30.306660
50%                   32.305784            69.249473
75%                   36.496663           161.224249
max                   50.000000         82331.000000
```

```python
# Check for missing values
credit_score_data.isnull().sum()
```

```
ID                              0
Customer_ID                     0
Month                           0
Name                         9985
Age                             0
SSN                             0
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Type_of_Loan                11408
Delay_from_due_date             0
Num_of_Delayed_Payment       7002
Changed_Credit_Limit            0
```

```
Num_Credit_Inquiries          1965
Credit_Mix                       0
Outstanding_Debt                 0
Credit_Utilization_Ratio         0
Credit_History_Age            9030
Payment_of_Min_Amount            0
Total_EMI_per_month              0
Amount_invested_monthly       4479
Payment_Behaviour                0
Monthly_Balance               1200
dtype: int64
```

Month

```
credit_score_data["Month"].value_counts()
```

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

Name

```
credit_score_data["Name"].value_counts()
```

```
Name
Langep             44
Stevex             44
Vaughanl           39
Jessicad           39
Raymondr           38
                   ..
Alina Selyukhg      4
Habboushg           4
Mortimerq           4
Ronaldf             4
Timothyl            3
Name: count, Length: 10139, dtype: int64
```

Age

```
credit_score_data["Age"].describe()
```

```
count     100000
unique      1788
```

```
top             38
freq          2833
Name: Age, dtype: object
```

```
credit_score_data["Age"].unique()
```

```
array(['23', '-500', '28_', ..., '4808_', '2263', '1342'],
dtype=object)
```

```
# remove tailing '_'
credit_score_data["Age"] = credit_score_data["Age"].str.replace("_",
"")

# remove '-'
credit_score_data["Age"] = credit_score_data["Age"].str.replace("-",
"")

credit_score_data["Age"] = credit_score_data["Age"].astype(int)

print(f"Min Age: {min(credit_score_data['Age'])}, Max Age:
{max(credit_score_data['Age'])}")
```

```
Min Age: 14, Max Age: 8698
```

```
# replace Age >100 or Age <18 with the median age
median_age = credit_score_data[(credit_score_data['Age'] >= 18) &
(credit_score_data['Age'] <= 100)]['Age'].median()
credit_score_data["Age"] = credit_score_data["Age"].apply(lambda x:
median_age if x < 18 or x > 100 else x)

print(f"Min Age: {min(credit_score_data['Age'])}, Max Age:
{max(credit_score_data['Age'])}")
```

```
Min Age: 18.0, Max Age: 100.0
```

SSN

We do not need the SSN column, so let's just drop it

```
#  drop SSN column
credit_score_data = credit_score_data.drop("SSN", axis=1)

credit_score_data.columns
```

```
Index(['ID', 'Customer_ID', 'Month', 'Name', 'Age', 'Occupation',
       'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
       'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan',
'Type_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment',
'Changed_Credit_Limit',
       'Num_Credit_Inquiries', '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')
```

Occupation

```
credit_score_data["Occupation"].value_counts()
```

```
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
```

```
# replace '_______' with the Occupation based on the Customer ID
occupation_mode = credit_score_data.groupby("Customer_ID")
["Occupation"].agg(
    lambda x: x.mode().iloc[0] if not x.mode().empty else "Unknown"
)
credit_score_data["Occupation"] = credit_score_data.apply(
    lambda row: (
        occupation_mode[row["Customer_ID"]] if row["Occupation"] ==
'_______' else row["Occupation"]
    ),
    axis=1,
)

credit_score_data["Occupation"].value_counts()
```

```
Occupation
Lawyer           7096
Engineer         6864
Architect        6824
Mechanic         6776
Scientist        6744
```

```
Accountant       6744
Developer        6720
Media_Manager    6715
Teacher          6672
Entrepreneur     6648
Doctor           6568
Journalist       6536
Manager          6432
Musician         6352
Writer           6304
_______             5
Name: count, dtype: int64
```

```
credit_score_data[credit_score_data["Occupation"] == "_______"]
```

```
            ID Customer_ID    Month    Name   Age Occupation
Annual_Income  \
93280  0x23892  CUS_0x9e67  January  Marias  24.0    _______
44393.86
93282  0x23894  CUS_0x9e67    March  Marias  24.0    _______
44393.86_
93283  0x23895  CUS_0x9e67    April  Marias  24.0    _______
44393.86
93284  0x23896  CUS_0x9e67      May     NaN  24.0    _______
44393.86
93286  0x23898  CUS_0x9e67     July  Marias  24.0    _______
44393.86

       Monthly_Inhand_Salary  Num_Bank_Accounts  Num_Credit_Card  ...
\
93280            3504.488333                  6                3  ...

93282            3504.488333                  6                3  ...

93283            3504.488333                  6                3  ...

93284            3504.488333                  6                3  ...

93286            3504.488333                  6                3  ...


       Num_Credit_Inquiries Credit_Mix Outstanding_Debt  \
93280                   NaN          _          1270.97
93282                   3.0          _          1270.97
93283                   3.0          _          1270.97
93284                   3.0   Standard          1270.97
93286                   3.0   Standard          1270.97

       Credit_Utilization_Ratio     Credit_History_Age
Payment_of_Min_Amount  \
```

```
93280                     37.328326                       NaN
Yes
93282                     29.115904  20 Years and 5 Months
Yes
93283                     27.476836                       NaN
Yes
93284                     25.366794  20 Years and 7 Months
Yes
93286                     33.895918  20 Years and 9 Months
Yes

       Total_EMI_per_month Amount_invested_monthly  \
93280            63.794335              91.4704338
93282            63.794335             73.10076083
93283            63.794335              218.849479
93284            63.794335             129.9647887
93286            63.794335             430.1717288

                      Payment_Behaviour  Monthly_Balance
93280  High_spent_Medium_value_payments      445.1840641
93282  High_spent_Medium_value_payments       463.553737
93283    Low_spent_Small_value_payments      357.8050189
93284    Low_spent_Large_value_payments      426.6897091
93286    Low_spent_Small_value_payments      146.4827691

[5 rows x 26 columns]
```

Let's Replace '_______' with 'Unknown'

```
credit_score_data["Occupation"] =
credit_score_data["Occupation"].str.replace(
    "_______", "Unknown"
)

credit_score_data["Occupation"].value_counts()

Occupation
Lawyer           7096
Engineer         6864
Architect        6824
Mechanic         6776
Scientist        6744
Accountant       6744
Developer        6720
Media_Manager    6715
Teacher          6672
Entrepreneur     6648
Doctor           6568
Journalist       6536
Manager          6432
```

```
Musician          6352
Writer            6304
Unknown              5
Name: count, dtype: int64
```

Annual Income

```
credit_score_data["Annual_Income"].value_counts()
```

```
Annual_Income
36585.12     16
20867.67     16
17273.83     16
9141.63      15
33029.66     15
             ..
20269.93_     1
15157.25_     1
44955.64_     1
76650.12_     1
4262933       1
Name: count, Length: 18940, dtype: int64
```

Let's replace the tailing '_' with ""

```
credit_score_data["Annual_Income"] =
credit_score_data["Annual_Income"].str.replace(
    "_", ""
)

credit_score_data["Annual_Income"].value_counts()
```

```
Annual_Income
22434.16              16
20867.67              16
40341.16              16
109945.32             16
17273.83              16
                      ..
14187917               1
13363794               1
124900.86000000002     1
56400.18000000001      1
20001329               1
Name: count, Length: 13701, dtype: int64
```

Monthly_Inhand_Salary

```
credit_score_data["Monthly_Inhand_Salary"].value_counts()
```

```
Monthly_Inhand_Salary
6769.130000    15
6358.956667    15
2295.058333    15
6082.187500    15
3080.555000    14
               ..
1087.546445     1
3189.212103     1
5640.117744     1
7727.560450     1
2443.654131     1
Name: count, Length: 13235, dtype: int64
```

Num_Bank_Accounts

```
credit_score_data["Num_Bank_Accounts"].describe()
```

```
count    100000.000000
mean         17.091280
std         117.404834
min          -1.000000
25%           3.000000
50%           6.000000
75%           7.000000
max        1798.000000
Name: Num_Bank_Accounts, dtype: float64
```

```
credit_score_data["Num_Bank_Accounts"].value_counts()
```

```
Num_Bank_Accounts
6       13001
7       12823
8       12765
4       12186
5       12118
        ...
1626        1
1470        1
887         1
211         1
697         1
Name: count, Length: 943, dtype: int64
```

```
credit_score_data[credit_score_data["Num_Bank_Accounts"]>10]
```

```
            ID Customer_ID    Month             Name   Age
Occupation  \
267     0x1791  CUS_0x4004    April          Carlosj  44.0
Writer
288     0x17b2  CUS_0x4080  January        ra Alperx  34.0
```

```
Mechanic
310     0x17d0  CUS_0x42ac     July        Lawrencea  37.0
Musician
339     0x17fd  CUS_0x9bc1    April     Jaisinghanij  42.0
Architect
356     0x1816  CUS_0xaedb      May     Olivia Oranr  19.0
Musician
...        ...         ...      ...              ...   ...
...
99591  0x25d89   CUS_0x544   August  Jon Herskovitzu  29.0
Mechanic
99638  0x25dd0  CUS_0x296f     July  David Millikenh  25.0
Developer
99666  0x25dfc   CUS_0xb09    March           Lianau  31.0
Lawyer
99722  0x25e50  CUS_0x11c7    March   raden Reddallh  53.0
Architect
99916  0x25f72  CUS_0x1619      May      Phil Wahbao  54.0
Media_Manager

      Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
267           58317                    NaN               1414
288        29469.98            2227.831667               1231
310        15566.02            1423.168333                 67
339        20574.47                    NaN                572
356        85554.03            7185.502500               1488
...             ...                    ...                ...
99591      17013.29            1326.774167                813
99638     125271.96           10374.330000               1481
99666     146310.68           12124.556670                474
99722      36817.94            3198.161667                697
99916      20059.98            1523.665000                182

       Num_Credit_Card  ...  Num_Credit_Inquiries Credit_Mix
Outstanding_Debt  \
267                  5  ...                  10.0   Standard
98.97
288                  7  ...                  11.0          _
3421.66
310                  5  ...                   9.0   Standard
1693.95
339                  3  ...                  11.0   Standard
749.95
356                  2  ...                   3.0          _
1095.73
...                ...  ...                   ...        ...
...
99591                1  ...                   3.0          _
1452.79
```

```
99638                7  ...                    7.0       Good
827.56
99666                4  ...                    1.0       Good
928.28
99722                4  ...                    2.0       Good
1019.46
99916                5  ...                    3.0       Good
909.01

       Credit_Utilization_Ratio      Credit_History_Age
Payment_of_Min_Amount  \
267                   29.766107                     NaN
Yes
288                   24.639658                     NaN
Yes
310                   29.706454    8 Years and 4 Months
Yes
339                   36.559538   11 Years and 2 Months
Yes
356                   41.661802  19 Years and 11 Months
No
...                         ...                     ...
...
99591                 28.051684   32 Years and 6 Months
NM
99638                 33.201730   25 Years and 8 Months
NM
99666                 43.274889   22 Years and 3 Months
No
99722                 26.578799   16 Years and 9 Months
No
99916                 29.808796                     NaN
NM

       Total_EMI_per_month Amount_invested_monthly  \
267             149.897199              158.648276
288              69.685459             59.82559612
310              43.070520              80.4844201
339              49.348666             25.16140443
356               0.000000             70.82263262
...                    ...                     ...
99591            13.109663             55.72695329
99638           241.065885             180.5600146
99666            72.250125              121.284825
99722            86.809918             123.9155591
99916            45.076827             49.71299351

                      Payment_Behaviour  Monthly_Balance
267    High_spent_Medium_value_payments      407.9295246
288                              !@9#%8       363.272112
```

```
310                                  !@9#%8      308.7618936
339    High_spent_Medium_value_payments      349.5438459
356     High_spent_Large_value_payments      887.7276174
...                                     ...            ...
99591    Low_spent_Small_value_payments       353.840801
99638                                !@9#%8     855.8071
99666   High_spent_Large_value_payments      1258.920717
99722    Low_spent_Small_value_payments       399.09069
99916   Low_spent_Medium_value_payments       337.57668

[1324 rows x 26 columns]
```

Since there are a lot of outliers, we will use the mode of number of bank accounts to replace the outliers.

```python
# Calculate the mode of Num_Bank_Accounts for each Customer_ID
num_bank_accounts_mode = credit_score_data.groupby("Customer_ID")[
    "Num_Bank_Accounts"
].agg(lambda x: x.mode().iloc[0] if not x.mode().empty else np.nan)

# Replace any value more than the mode with the mode
credit_score_data["Num_Bank_Accounts"] = credit_score_data.apply(
    lambda row: (
        num_bank_accounts_mode[row["Customer_ID"]]
        if row["Num_Bank_Accounts"] >
num_bank_accounts_mode[row["Customer_ID"]]
        else row["Num_Bank_Accounts"]
    ),
    axis=1,
)

credit_score_data["Num_Bank_Accounts"].value_counts()

Num_Bank_Accounts
 6     13189
 7     12976
 8     12922
 4     12401
 5     12266
 3     12095
 9      5494
 10     5321
 1      4547
 0      4396
 2      4361
-1        32
Name: count, dtype: int64
```

We still have number of bank account as -1 for some customers

```python
credit_score_data[credit_score_data["Num_Bank_Accounts"] == -1]
```

```
             ID Customer_ID     Month             Name   Age Occupation  \
30328   0xc7b6  CUS_0x4f2a   January        Margaretf  39.0   Engineer
30329   0xc7b7  CUS_0x4f2a  February        Margaretf  39.0   Engineer
30330   0xc7b8  CUS_0x4f2a     March        Margaretf  39.0   Engineer
30331   0xc7b9  CUS_0x4f2a     April        Margaretf  40.0   Engineer
30332   0xc7ba  CUS_0x4f2a       May        Margaretf  40.0   Engineer
30333   0xc7bb  CUS_0x4f2a      June        Margaretf  40.0   Engineer
30334   0xc7bc  CUS_0x4f2a      July        Margaretf  40.0   Engineer
30335   0xc7bd  CUS_0x4f2a    August        Margaretf  40.0   Engineer
43688  0x115fe  CUS_0xa878   January              NaN  54.0   Engineer
43689  0x115ff  CUS_0xa878  February  Douwe Miedemaz  54.0   Engineer
43690  0x11600  CUS_0xa878     March  Douwe Miedemaz  54.0   Engineer
43691  0x11601  CUS_0xa878     April  Douwe Miedemaz  54.0   Engineer
43692  0x11602  CUS_0xa878       May  Douwe Miedemaz  54.0   Engineer
43693  0x11603  CUS_0xa878      June  Douwe Miedemaz  54.0   Engineer
43694  0x11604  CUS_0xa878      July  Douwe Miedemaz  54.0   Engineer
43695  0x11605  CUS_0xa878    August  Douwe Miedemaz  54.0   Engineer
47208  0x12a9e  CUS_0x43bc   January   Patrick Werrl  36.0     Lawyer
47209  0x12a9f  CUS_0x43bc  February   Patrick Werrl  36.0     Lawyer
47210  0x12aa0  CUS_0x43bc     March   Patrick Werrl  36.0     Lawyer
47211  0x12aa1  CUS_0x43bc     April   Patrick Werrl  36.0     Lawyer
47212  0x12aa2  CUS_0x43bc       May   Patrick Werrl  36.0     Lawyer
47213  0x12aa3  CUS_0x43bc      June              NaN  36.0     Lawyer
47214  0x12aa4  CUS_0x43bc      July   Patrick Werrl  36.0     Lawyer
47215  0x12aa5  CUS_0x43bc    August   Patrick Werrl  36.0     Lawyer
```

```
55632  0x15bfa  CUS_0x5993   January     Stephensonq  34.0  Developer

55633  0x15bfb  CUS_0x5993  February     Stephensonq  40.0  Developer

55634  0x15bfc  CUS_0x5993     March     Stephensonq  40.0  Developer

55635  0x15bfd  CUS_0x5993     April     Stephensonq  40.0  Developer

55636  0x15bfe  CUS_0x5993       May     Stephensonq  40.0  Developer

55637  0x15bff  CUS_0x5993      June             NaN  40.0  Developer

55638  0x15c00  CUS_0x5993      July     Stephensonq  41.0  Developer

55639  0x15c01  CUS_0x5993    August             NaN  41.0  Developer


      Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
30328     128305.76           10434.146670                 -1
30329     128305.76           10434.146670                 -1
30330     128305.76           10434.146670                 -1
30331     128305.76                    NaN                 -1
30332     128305.76           10434.146670                 -1
30333     128305.76           10434.146670                 -1
30334     128305.76           10434.146670                 -1
30335      22136920                    NaN                 -1
43688     117851.07            9870.922500                 -1
43689     117851.07            9870.922500                 -1
43690     117851.07            9870.922500                 -1
43691     117851.07            9870.922500                 -1
43692     117851.07            9870.922500                 -1
43693     117851.07            9870.922500                 -1
43694     117851.07            9870.922500                 -1
43695     117851.07            9870.922500                 -1
47208      22312.07            2013.339167                 -1
47209      22312.07                    NaN                 -1
47210      22312.07            2013.339167                 -1
47211      22312.07            2013.339167                 -1
47212      22312.07            2013.339167                 -1
47213      22312.07            2013.339167                 -1
47214      22312.07            2013.339167                 -1
47215      22312.07            2013.339167                 -1
55632      30352.11            2317.342500                 -1
55633      30352.11            2317.342500                 -1
55634      30352.11                    NaN                 -1
55635      30352.11            2317.342500                 -1
55636      30352.11            2317.342500                 -1
55637      30352.11            2317.342500                 -1
55638      30352.11            2317.342500                 -1
55639      30352.11            2317.342500                 -1
```

```
       Num_Credit_Card  ...  Num_Credit_Inquiries Credit_Mix
Outstanding_Debt  \
30328                    7  ...                   2.0       Good
1151.7
30329                    7  ...                   2.0       Good
1151.7
30330                    6  ...                   6.0       Good
1151.7
30331                    6  ...                   6.0       Good
1151.7_
30332                    6  ...                   6.0       Good
1151.7
30333                    6  ...                   6.0       Good
1151.7
30334                    6  ...                   6.0       Good
1151.7
30335                    6  ...                   6.0          _
1151.7
43688                    7  ...                   1.0          _
607.78
43689                    6  ...                   1.0       Good
607.78
43690                    6  ...                   1.0       Good
607.78
43691                    6  ...                   1.0       Good
607.78
43692                    6  ...                   1.0       Good
607.78
43693                    6  ...                   1.0       Good
607.78
43694                    6  ...                   1.0       Good
607.78
43695                    6  ...                   1.0       Good
607.78
47208                    4  ...                   3.0       Good
51.37
47209                    4  ...                   3.0       Good
51.37
47210                    4  ...                   3.0          _
51.37
47211                    4  ...                   3.0          _
51.37
47212                    3  ...                   3.0          _
51.37
47213                    3  ...                   3.0       Good
51.37
47214                    3  ...                   3.0          _
51.37
```

```
47215                   3  ...                   3.0       Good
51.37
55632                   5  ...                   0.0       Good
644.57
55633                   5  ...                   0.0       Good
644.57
55634                   5  ...                   0.0          _
644.57
55635                   5  ...                   0.0       Good
644.57
55636                 165  ...                   0.0       Good
644.57
55637                   4  ...                   0.0       Good
644.57
55638                   4  ...                   0.0       Good
644.57
55639                   4  ...                   0.0       Good
644.57

       Credit_Utilization_Ratio      Credit_History_Age
Payment_of_Min_Amount  \
30328                 28.555646   22 Years and 3 Months
No
30329                 30.343064   22 Years and 4 Months
No
30330                 40.586736   22 Years and 5 Months
No
30331                 39.369401   22 Years and 6 Months
No
30332                 28.702053   22 Years and 7 Months
No
30333                 34.808390   22 Years and 8 Months
No
30334                 35.206427                     NaN
No
30335                 38.278518  22 Years and 10 Months
No
43688                 31.531889   20 Years and 5 Months
No
43689                 37.286105   20 Years and 6 Months
No
43690                 41.915627   20 Years and 7 Months
No
43691                 41.799942   20 Years and 8 Months
No
43692                 46.244581   20 Years and 9 Months
No
43693                 32.303737  20 Years and 10 Months
No
```

```
43694                    30.709169  20 Years and 11 Months
No
43695                    34.041733   21 Years and 0 Months
No
47208                    22.702101   23 Years and 3 Months
No
47209                    28.443460   23 Years and 4 Months
No
47210                    32.001016   23 Years and 5 Months
No
47211                    29.672067   23 Years and 6 Months
NM
47212                    40.402442   23 Years and 7 Months
No
47213                    34.824443   23 Years and 8 Months
No
47214                    25.649329   23 Years and 9 Months
No
47215                    30.059211  23 Years and 10 Months
No
55632                    37.488977   23 Years and 5 Months
No
55633                    30.230648                     NaN
No
55634                    38.822428   23 Years and 7 Months
No
55635                    36.351893   23 Years and 8 Months
NM
55636                    25.532001   23 Years and 9 Months
NM
55637                    31.813259  23 Years and 10 Months
No
55638                    26.574175  23 Years and 11 Months
No
55639                    32.937399   24 Years and 0 Months
No

       Total_EMI_per_month Amount_invested_monthly  \
30328           196.587321             268.7720818
30329           196.587321             588.7732847
30330           196.587321             230.9223857
30331           196.587321             524.3044178
30332           196.587321             150.0966754
30333           196.587321             1006.698069
30334         42850.000000             172.9920212
30335           196.587321             338.6723032
43688             0.000000             394.2919201
43689             0.000000             668.1444537
43690             0.000000             142.3197888
```

```
43691           0.000000           467.5639226
43692           0.000000                   NaN
43693           0.000000           218.0052232
43694           0.000000            352.801158
43695           0.000000           467.4158246
47208          32.891186           249.7900417
47209          32.891186           145.9530872
47210          32.891186           121.7587399
47211          32.891186           241.0720734
47212          32.891186             __10000__
47213          32.891186           39.79680745
47214          32.891186           148.9327515
47215          32.891186            23.0030935
55632          16.483566            187.641645
55633          16.483566           143.3229725
55634          16.483566           60.68195575
55635          16.483566           54.56979945
55636          16.483566           126.6653453
55637          16.483566           54.82132668
55638          16.483566           64.86083753
55639          16.483566           89.62296249

                      Payment_Behaviour  Monthly_Balance
30328  High_spent_Medium_value_payments      828.0552637
30329    Low_spent_Small_value_payments      548.0540608
30330   High_spent_Large_value_payments      855.9049598
30331    Low_spent_Large_value_payments      592.5229277
30332   High_spent_Large_value_payments      936.7306701
30333   Low_spent_Medium_value_payments      120.1292765
30334   High_spent_Large_value_payments      913.8353243
30335  High_spent_Medium_value_payments      758.1550423
43688  High_spent_Medium_value_payments      842.8003299
43689                            !@9#%8      588.9477963
43690   High_spent_Large_value_payments      1084.772461
43691   High_spent_Small_value_payments      779.5283274
43692   High_spent_Large_value_payments      1037.506338
43693  High_spent_Medium_value_payments      1019.087027
43694  High_spent_Medium_value_payments       884.291092
43695   High_spent_Small_value_payments      779.6764254
47208    Low_spent_Small_value_payments      208.6526886
47209   Low_spent_Medium_value_payments      302.4896431
47210    Low_spent_Small_value_payments      336.6839904
47211    Low_spent_Small_value_payments      217.3706569
47212   High_spent_Small_value_payments      341.0972605
47213  High_spent_Medium_value_payments      378.6459229
47214    Low_spent_Large_value_payments      289.5099788
47215  High_spent_Medium_value_payments      395.4396368
55632    Low_spent_Small_value_payments      317.6090387
55633   High_spent_Small_value_payments      331.9277113
```

```
55634   High_spent_Small_value_payments       414.568728
55635   High_spent_Large_value_payments      400.6808843
55636   Low_spent_Medium_value_payments      368.5853385
55637   High_spent_Large_value_payments      400.4293571
55638                            !@9#%8      400.3898462
55639  High_spent_Medium_value_payments      375.6277213

[32 rows x 26 columns]
```

Let's replace them with 1

```
credit_score_data["Num_Bank_Accounts"] = credit_score_data[
    "Num_Bank_Accounts"
].replace(-1.0, 1.0)

credit_score_data["Num_Bank_Accounts"].value_counts()

Num_Bank_Accounts
6     13189
7     12976
8     12922
4     12401
5     12266
3     12095
9      5494
10     5321
1      4579
0      4396
2      4361
Name: count, dtype: int64

credit_score_data[credit_score_data["Num_Bank_Accounts"] == 0]

            ID Customer_ID     Month             Name   Age Occupation  \
48      0x164a   CUS_0x284a   January           Nadiaq  33.0     Lawyer

49      0x164b   CUS_0x284a  February           Nadiaq  34.0     Lawyer

50      0x164c   CUS_0x284a     March           Nadiaq  34.0     Lawyer

51      0x164d   CUS_0x284a     April           Nadiaq  34.0     Lawyer

52      0x164e   CUS_0x284a       May           Nadiaq  34.0     Lawyer

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

99963  0x25fb9   CUS_0x372c     April  Lucia Mutikanik  34.0     Lawyer

99964  0x25fba   CUS_0x372c       May              NaN  18.0     Lawyer
```

```
99965  0x25fbb  CUS_0x372c      June             NaN  19.0     Lawyer

99966  0x25fbc  CUS_0x372c      July  Lucia Mutikanik  19.0     Lawyer

99967  0x25fbd  CUS_0x372c    August  Lucia Mutikanik  19.0     Lawyer


      Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
48         131313.4           11242.783330                  0
49         131313.4           11242.783330                  0
50         131313.4           10469.207760                  0
51         131313.4           10469.207760                  0
52         131313.4           10469.207760                  0
...             ...                    ...                ...
99963      42903.79                    NaN                  0
99964      42903.79            3468.315833                  0
99965      42903.79            3468.315833                  0
99966      42903.79            3468.315833                  0
99967      42903.79            3468.315833                  0

       Num_Credit_Card  ...  Num_Credit_Inquiries Credit_Mix
Outstanding_Debt  \
48                   1  ...                   2.0       Good
352.16
49                   1  ...                   4.0       Good
352.16
50                   1  ...                   4.0       Good
352.16
51                   1  ...                   4.0       Good
352.16
52                   1  ...                   4.0       Good
352.16
...                ...  ...                   ...        ...
...
99963                4  ...                   1.0       Good
1079.48
99964                4  ...                   1.0       Good
1079.48
99965                4  ...                   1.0       Good
1079.48
99966                4  ...                   1.0       Good
1079.48
99967                4  ...                   1.0       Good
1079.48

       Credit_Utilization_Ratio      Credit_History_Age
Payment_of_Min_Amount  \
48                    32.200509   30 Years and 7 Months
NM
49                    31.983710   30 Years and 8 Months
```

```
No
50                   31.803134   30 Years and 9 Months
NM
51                   42.645785  30 Years and 10 Months
No
52                   40.902517  30 Years and 11 Months
No
...                        ...                     ...
...
99963                30.625298                     NaN
No
99964                23.140640   28 Years and 5 Months
No
99965                35.549456   28 Years and 6 Months
No
99966                35.123480   28 Years and 7 Months
No
99967                35.716618   28 Years and 8 Months
No

       Total_EMI_per_month Amount_invested_monthly  \
48              137.644605             378.1712535
49              137.644605             698.8732707
50              911.220179             188.0643211
51            23834.000000             337.4349563
52            32662.000000             263.3789089
...                    ...                     ...
99963            34.975457             31.19391927
99964            34.975457             450.6460934
99965            34.975457             187.3559686
99966            34.975457             240.8737981
99967            34.975457             115.1849844

                      Payment_Behaviour  Monthly_Balance
48     High_spent_Medium_value_payments      858.4624744
49      High_spent_Small_value_payments      547.7604572
50      High_spent_Large_value_payments      1038.569407
51     High_spent_Medium_value_payments      899.1987716
52      High_spent_Large_value_payments       963.254819
...                                 ...              ...
99963   High_spent_Large_value_payments       520.662207
99964    Low_spent_Small_value_payments       151.210033
99965    Low_spent_Large_value_payments       394.500158
99966   Low_spent_Medium_value_payments       350.982329
99967  High_spent_Medium_value_payments       446.671142

[4396 rows x 26 columns]
```

Let's Handle this anomaly- where some Customer's have 0 Bank Accounts

```python
# Create a mask for customers with 0 bank accounts but at least 1
credit card
mask = (credit_score_data["Num_Bank_Accounts"] == 0) & (
    credit_score_data["Num_Credit_Card"] >= 1
)

# Update Num_Bank_Accounts to 1 for these customers
credit_score_data.loc[mask, "Num_Bank_Accounts"] = 1

credit_score_data[credit_score_data["Num_Bank_Accounts"] == 0]
```

```
Empty DataFrame
Columns: [ID, Customer_ID, Month, Name, Age, Occupation,
Annual_Income, Monthly_Inhand_Salary, Num_Bank_Accounts,
Num_Credit_Card, Interest_Rate, Num_of_Loan, Type_of_Loan,
Delay_from_due_date, Num_of_Delayed_Payment, Changed_Credit_Limit,
Num_Credit_Inquiries, 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 26 columns]
```

Num_Credit_Card

```python
credit_score_data["Num_Credit_Card"].describe()
```

```
count    100000.00000
mean         22.47443
std         129.05741
min           0.00000
25%           4.00000
50%           5.00000
75%           7.00000
max        1499.00000
Name: Num_Credit_Card, dtype: float64
```

```python
credit_score_data["Num_Credit_Card"].value_counts()
```

```
Num_Credit_Card
5       18459
7       16615
6       16559
4       14030
3       13277
        ...
791         1
1118        1
657         1
640         1
```

```
679          1
Name: count, Length: 1179, dtype: int64
```

Similar to Num_Bank_Accounts. We will handle the anomalies the same way for Num_Credit_Card

```python
# Calculate the mode of Num_Bank_Accounts for each Customer_ID
num_bank_accounts_mode = credit_score_data.groupby("Customer_ID")[
    "Num_Credit_Card"
].agg(lambda x: x.mode().iloc[0] if not x.mode().empty else np.nan)

# Replace any value more than the mode with the mode
credit_score_data["Num_Credit_Card"] = credit_score_data.apply(
    lambda row: (
        num_bank_accounts_mode[row["Customer_ID"]]
        if row["Num_Credit_Card"] >
num_bank_accounts_mode[row["Customer_ID"]]
        else row["Num_Credit_Card"]
    ),
    axis=1,
)

credit_score_data["Num_Credit_Card"].value_counts()
```

```
Num_Credit_Card
5     18900
7     16969
6     16949
4     14365
3     13588
8      5073
10     4955
9      4741
2      2224
1      2185
11       30
0        21
Name: count, dtype: int64
```

```python
credit_score_data[credit_score_data["Num_Credit_Card"] == 0]
```

```
           ID Customer_ID     Month           Name   Age
Occupation  \
4712   0x319e  CUS_0x7ce5   January         Singhj  23.0      Writer

4713   0x319f  CUS_0x7ce5  February         Singhj  23.0      Writer

4714   0x31a0  CUS_0x7ce5     March         Singhj  24.0      Writer

4715   0x31a1  CUS_0x7ce5     April         Singhj  24.0      Writer
```

```
4716   0x31a2  CUS_0x7ce5       May          Singhj  24.0      Writer
4717   0x31a3  CUS_0x7ce5      June          Singhj  24.0      Writer
4718   0x31a4  CUS_0x7ce5      July          Singhj  24.0      Writer
4719   0x31a5  CUS_0x7ce5    August          Singhj  24.0      Writer
9278   0x4c5c  CUS_0x73c2      July       Bartuneks  23.0    Mechanic
9279   0x4c5d  CUS_0x73c2    August       Bartuneks  34.0    Mechanic
10588  0x540a  CUS_0xa078       May   Huffstuttert  29.0    Musician
10590  0x540c  CUS_0xa078      July   Huffstuttert  29.0    Musician
10591  0x540d  CUS_0xa078    August   Huffstuttert  29.0    Musician
24976  0xa85a  CUS_0x22be   January             NaN  46.0  Accountant
24977  0xa85b  CUS_0x22be  February  arbara Lewish  46.0  Accountant
24978  0xa85c  CUS_0x22be     March  arbara Lewish  46.0  Accountant
24979  0xa85d  CUS_0x22be     April  arbara Lewish  46.0  Accountant
24980  0xa85e  CUS_0x22be       May  arbara Lewish  46.0  Accountant
24981  0xa85f  CUS_0x22be      June  arbara Lewish  47.0  Accountant
24982  0xa860  CUS_0x22be      July  arbara Lewish  47.0  Accountant
24983  0xa861  CUS_0x22be    August  arbara Lewish  47.0  Accountant

      Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
4712      101912.13            8503.677500                  4
4713      101912.13            8503.677500                  4
4714      101912.13            8503.677500                  4
4715      101912.13            8503.677500                  4
4716      101912.13            8503.677500                  4
4717      101912.13            8503.677500                  4
4718      101912.13            8503.677500                  4
4719      101912.13            8503.677500                  4
9278      116721.18            9552.765000                  1
9279      116721.18            9552.765000                  1
10588      79548.32            6355.026667                  4
10590      79548.32            6355.026667                  4
10591      79548.32            6355.026667                  4
24976       39296.5                    NaN                  4
```

```
24977       39296.5                NaN                  4
24978       39296.5        3261.708333                  4
24979       39296.5        3261.708333                  4
24980       39296.5        3261.708333                  4
24981       39296.5        3261.708333                  4
24982       39296.5                NaN                  4
24983       39296.5        3261.708333                  4

       Num_Credit_Card  ...  Num_Credit_Inquiries Credit_Mix
Outstanding_Debt  \
4712                 0  ...                   2.0       Good
152.6_
4713                 0  ...                   2.0       Good
152.6
4714                 0  ...                   2.0          _
152.6
4715                 0  ...                   NaN          _
152.6
4716                 0  ...                   2.0       Good
152.6
4717                 0  ...                   2.0       Good
152.6
4718                 0  ...                1351.0       Good
152.6
4719                 0  ...                   2.0          _
152.6
9278                 0  ...                   3.0       Good
48.88
9279                 0  ...                   3.0       Good
48.88
10588                0  ...                   NaN       Good
870.51
10590                0  ...                   3.0       Good
870.51
10591                0  ...                   3.0       Good
870.51
24976                0  ...                   NaN          _
187.21
24977                0  ...                   3.0       Good
187.21
24978                0  ...                   3.0       Good
187.21
24979                0  ...                   3.0       Good
187.21_
24980                0  ...                   3.0          _
187.21
24981                0  ...                   3.0       Good
187.21
24982                0  ...                   3.0       Good
```

```
187.21
24983                0  ...                   3.0       Good
187.21

       Credit_Utilization_Ratio      Credit_History_Age 
Payment_of_Min_Amount  \
4712                  29.454223  19 Years and 11 Months 
NM   
4713                  42.143932   20 Years and 0 Months 
No   
4714                  27.336863   20 Years and 1 Months 
No   
4715                  33.506761   20 Years and 2 Months 
No   
4716                  36.707990   20 Years and 3 Months 
No   
4717                  36.928316   20 Years and 4 Months 
No   
4718                  26.630283   20 Years and 5 Months 
NM   
4719                  42.515861   20 Years and 6 Months 
No   
9278                  41.498049   22 Years and 9 Months 
NM   
9279                  33.270882  22 Years and 10 Months 
No   
10588                 25.285875   30 Years and 0 Months 
No   
10590                 30.690501   30 Years and 2 Months 
No   
10591                 35.619724                     NaN 
No   
24976                 27.882810   27 Years and 1 Months 
No   
24977                 23.611041   27 Years and 2 Months 
No   
24978                 39.684426                     NaN 
No   
24979                 39.610210   27 Years and 4 Months 
No   
24980                 35.900354   27 Years and 5 Months 
No   
24981                 27.172053   27 Years and 6 Months 
No   
24982                 36.625408   27 Years and 7 Months 
No   
24983                 35.266602   27 Years and 8 Months 
No
```

```
       Total_EMI_per_month Amount_invested_monthly  \
4712              0.000000             295.8766472
4713              0.000000             349.3415713
4714              0.000000             783.8010626
4715              0.000000             90.13946918
4716              0.000000             346.9351162
4717              0.000000             66.23205273
4718              0.000000             287.4291681
4719              0.000000             411.2736672
9278             82.914222             410.2297823
9279             82.914222             241.9468818
10588           211.214525              228.199661
10590           211.214525             551.2064178
10591           211.214525             570.3824869
24976           124.948667             42.11588844
24977           124.948667             358.9112575
24978           124.948667             75.45833776
24979           124.948667              73.8182497
24980           124.948667             265.7581142
24981           124.948667               __10000__
24982           124.948667             236.0392902
24983           124.948667             165.3201841

                      Payment_Behaviour  Monthly_Balance
4712    Low_spent_Medium_value_payments      834.4911028
4713    Low_spent_Medium_value_payments      781.0261787
4714     Low_spent_Large_value_payments      336.5666874
4715    High_spent_Large_value_payments      1000.228281
4716     Low_spent_Large_value_payments      773.4326338
4717    High_spent_Large_value_payments      1024.135697
4718    Low_spent_Medium_value_payments      842.9385819
4719                             !@9#%8      719.0940828
9278    High_spent_Small_value_payments       722.132496
9279   High_spent_Medium_value_payments      880.4153965
10588  High_spent_Medium_value_payments      446.0884804
10590   Low_spent_Medium_value_payments      153.0817235
10591    Low_spent_Large_value_payments      123.9056545
24976                            !@9#%8      399.1062777
24977    Low_spent_Small_value_payments      132.3109086
24978  High_spent_Medium_value_payments      375.7638284
24979   High_spent_Large_value_payments      367.4039164
24980    Low_spent_Large_value_payments      205.4640519
24981  High_spent_Medium_value_payments      371.8642267
24982    Low_spent_Small_value_payments      255.1828759
24983   High_spent_Small_value_payments       295.901982

[21 rows x 26 columns]

# Create a mask for customers with 0 bank accounts but at least 1
credit card
```

```
mask = (credit_score_data["Num_Credit_Card"] == 0) & (
    credit_score_data["Interest_Rate"] >= 1
)

# Update Num_Bank_Accounts to 1 for these customers
credit_score_data.loc[mask, "Num_Credit_Card"] = 1

credit_score_data["Num_Credit_Card"].value_counts()
```

```
Num_Credit_Card
5     18900
7     16969
6     16949
4     14365
3     13588
8      5073
10     4955
9      4741
2      2224
1      2206
11       30
Name: count, dtype: int64
```

Interest_Rate

```
credit_score_data["Interest_Rate"].value_counts()
```

```
Interest_Rate
8       5012
5       4979
6       4721
12      4540
10      4540
        ...
4995       1
1899       1
2120       1
5762       1
5729       1
Name: count, Length: 1750, dtype: int64
```

We handle the outliers for Interest_Rate Similar to that of Num_Credit_Card and Num_Bank_Accounts

```
# Calculate the mode of Num_Bank_Accounts for each Customer_ID
num_bank_accounts_mode = credit_score_data.groupby("Customer_ID")
["Interest_Rate"].agg(
    lambda x: x.mode().iloc[0] if not x.mode().empty else np.nan
)
```

```python
# Replace any value more than the mode with the mode
credit_score_data["Interest_Rate"] = credit_score_data.apply(
    lambda row: (
        num_bank_accounts_mode[row["Customer_ID"]]
        if row["Interest_Rate"] >
num_bank_accounts_mode[row["Customer_ID"]]
        else row["Interest_Rate"]
    ),
    axis=1,
)

credit_score_data["Interest_Rate"].value_counts()
```

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

Num_of_Loan

```python
credit_score_data["Num_of_Loan"].describe()
```

```
count     100000
unique       434
top            3
freq       14386
Name: Num_of_Loan, dtype: object
```

```python
credit_score_data["Num_of_Loan"].value_counts()
```

```
Num_of_Loan
3        14386
2        14250
4        14016
0        10380
1        10083
         ...
1320_        1
103          1
1444         1
392          1
966          1
Name: count, Length: 434, dtype: int64
```

Let's Clean the data a bit

```python
credit_score_data["Num_of_Loan"] =
credit_score_data["Num_of_Loan"].str.replace("_", "")

credit_score_data["Num_of_Loan"] =
credit_score_data["Num_of_Loan"].str.replace("-", "")

credit_score_data["Num_of_Loan"].value_counts()
```

```
Num_of_Loan
3       15104
2       15032
4       14743
0       10930
1       10606
        ...
321         1
1439        1
663         1
613         1
966         1
Name: count, Length: 413, dtype: int64
```

Let's Handle the outliers

```python
# Ensure Num_of_Loan is numeric
credit_score_data["Num_of_Loan"] = pd.to_numeric(
    credit_score_data["Num_of_Loan"], errors="coerce"
)

# Calculate the mean of Num_of_Loan for each Customer_ID
num_of_loans_mean = credit_score_data.groupby("Customer_ID")
["Num_of_Loan"].mean()

# Replace any value more than the mean with the mean
credit_score_data["Num_of_Loan"] = credit_score_data.apply(
    lambda row: (
        num_of_loans_mean[row["Customer_ID"]]
        if row["Num_of_Loan"] > num_of_loans_mean[row["Customer_ID"]]
        else row["Num_of_Loan"]
    ),
    axis=1,
)

credit_score_data["Num_of_Loan"].value_counts()
```

```
Num_of_Loan
3.000      15104
2.000      15032
4.000      14743
0.000      10930
1.000      10606
           ...
33.625         1
82.250         1
31.500         1
21.500         1
124.250        1
Name: count, Length: 423, dtype: int64
```

Type of loan

```python
# Fill missing values with 'Unknown'
credit_score_data["Type_of_Loan"].fillna("Unknown", inplace=True)

# There are multiple loan types in one cell, split them
credit_score_data["Type_of_Loan"] =
credit_score_data["Type_of_Loan"].apply(
    lambda x: [item.strip() for item in x.split(",")] if "," in x else
[x]
)
```

```
/var/folders/5m/6v9nlkzx2rn5rdpsrw41z6880000gq/T/
ipykernel_59944/595640288.py:2: FutureWarning: A value is trying to be
set on a copy of a DataFrame or Series through chained assignment
```

```
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  credit_score_data["Type_of_Loan"].fillna("Unknown", inplace=True)
```

```
credit_score_data["Type_of_Loan"]
```

```
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...
                               ...
99995                          [Auto Loan, and Student Loan]
99996                          [Auto Loan, and Student Loan]
99997                          [Auto Loan, and Student Loan]
99998                          [Auto Loan, and Student Loan]
99999                          [Auto Loan, and Student Loan]
Name: Type_of_Loan, Length: 100000, dtype: object
```

Delay_from_due_date

```
# Convert the column to integer type, handling any non-numeric values
credit_score_data["Delay_from_due_date"] = pd.to_numeric(
    credit_score_data["Delay_from_due_date"], errors="coerce"
)

# If there are any missing values (although there currently are none),
fill with the median
credit_score_data["Delay_from_due_date"].fillna(
    credit_score_data["Delay_from_due_date"].median(), inplace=True
)
```

```
/var/folders/5m/6v9nlkzx2rn5rdpsrw41z6880000gq/T/
ipykernel_59944/1790097708.py:7: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
```

```
df[col].method(value) instead, to perform the operation inplace on the
original object.


  credit_score_data["Delay_from_due_date"].fillna(
```

Num_of_Delayed_Payment

```
credit_score_data["Num_of_Delayed_Payment"] = credit_score_data[
    "Num_of_Delayed_Payment"
].str.replace("_", "")

# Ensure Num_of_Loan is numeric
credit_score_data["Num_of_Delayed_Payment"] = pd.to_numeric(
    credit_score_data["Num_of_Delayed_Payment"], errors="coerce"
)

# Calculate the mean of Num_of_Loan for each Customer_ID
num_of_delayed_payments_mean =
credit_score_data.groupby("Customer_ID")[
    "Num_of_Delayed_Payment"
].mean()

# Replace any value more than the mean with the mean
credit_score_data["Num_of_Delayed_Payment"] = credit_score_data.apply(
    lambda row: (
        num_of_delayed_payments_mean[row["Customer_ID"]]
        if row["Num_of_Delayed_Payment"]
        > num_of_delayed_payments_mean[row["Customer_ID"]]
        else row["Num_of_Delayed_Payment"]
    ),
    axis=1,
)

credit_score_data[credit_score_data["Num_of_Delayed_Payment"].isna()][
    "Num_of_Delayed_Payment"
]
```

```
1       NaN
4       NaN
30      NaN
32      NaN
33      NaN
         ..
99973   NaN
99974   NaN
99992   NaN
99993   NaN
99998   NaN
Name: Num_of_Delayed_Payment, Length: 7002, dtype: float64
```

```
# Calculate the mean of Num_of_Delayed_Payment for each Customer_ID
num_of_delayed_payments_mean =
credit_score_data.groupby("Customer_ID")[
    "Num_of_Delayed_Payment"
].mean()

# Replace NaN values with the mean
credit_score_data["Num_of_Delayed_Payment"] = credit_score_data.apply(
    lambda row: (
        num_of_delayed_payments_mean[row["Customer_ID"]]
        if pd.isna(row["Num_of_Delayed_Payment"])
        else row["Num_of_Delayed_Payment"]
    ),
    axis=1,
)

credit_score_data["Num_of_Delayed_Payment"]
```

```
0        6.000000
1        5.333333
2        6.000000
3        4.000000
4        5.333333
           ...
99995    6.400000
99996    6.400000
99997    6.000000
99998    6.160000
99999    6.000000
Name: Num_of_Delayed_Payment, Length: 100000, dtype: float64
```

Changed_Credit_Limit

```
credit_score_data["Changed_Credit_Limit"] = credit_score_data[
    "Changed_Credit_Limit"
].replace("_", np.nan)

# Convert the column to numeric, which will turn invalid entries into
NaN
credit_score_data["Changed_Credit_Limit"] = pd.to_numeric(
    credit_score_data["Changed_Credit_Limit"], errors="coerce"
)

# Calculate the mean of 'Changed_Credit_Limit' grouped by
'Customer_ID'
grouped_mean = credit_score_data.groupby("Customer_ID")[
    "Changed_Credit_Limit"
].transform("mean")

# Replace NaN values with the grouped mean
```

```
credit_score_data["Changed_Credit_Limit"].fillna(grouped_mean,
inplace=True)
```

```
/var/folders/5m/6v9nlkzx2rn5rdpsrw41z6880000gq/T/
ipykernel_59944/4050271205.py:16: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  credit_score_data["Changed_Credit_Limit"].fillna(grouped_mean,
inplace=True)
```

```
credit_score_data["Changed_Credit_Limit"].value_counts()
```

```
Changed_Credit_Limit
8.220000     136
11.500000    127
11.320000    126
7.350000     121
10.060000    121
            ...
9.457143       1
24.560000      1
18.472857      1
3.225714       1
17.558571      1
Name: count, Length: 4974, dtype: int64
```

Num_Credit_Inquiries

```
credit_score_data["Num_Credit_Inquiries"] = credit_score_data[
    "Num_Credit_Inquiries"
].replace("_", np.nan)

# Convert the column to numeric, which will turn invalid entries into
NaN
credit_score_data["Num_Credit_Inquiries"] = pd.to_numeric(
    credit_score_data["Num_Credit_Inquiries"], errors="coerce"
)

# Calculate the mean of 'Num_Credit_Inquiries' grouped by
'Customer_ID'
grouped_mean = credit_score_data.groupby("Customer_ID")[
```

```
    "Num_Credit_Inquiries"
].transform("mean")

# Replace NaN values with the grouped mean
credit_score_data["Num_Credit_Inquiries"].fillna(grouped_mean,
inplace=True)
```

```
/var/folders/5m/6v9nlkzx2rn5rdpsrw41z6880000gq/T/
ipykernel_59944/3883386527.py:16: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  credit_score_data["Num_Credit_Inquiries"].fillna(grouped_mean,
inplace=True)
```

```
credit_score_data["Num_Credit_Inquiries"]
```

```
0        4.0
1        4.0
2        4.0
3        4.0
4        4.0
        ...
99995    3.0
99996    3.0
99997    3.0
99998    3.0
99999    3.0
Name: Num_Credit_Inquiries, Length: 100000, dtype: float64
```

Credit_Mix

```
credit_score_data["Credit_Mix"] = credit_score_data[
    "Credit_Mix"
].replace("_", np.nan)

# Calculate the mode of 'Credit_Mix' grouped by 'Customer_ID'
grouped_mode = credit_score_data.groupby("Customer_ID")[
    "Credit_Mix"
].agg(lambda x: x.mode().iloc[0] if not x.mode().empty else np.nan)

# Replace NaN values with the grouped mode
```

```
credit_score_data["Credit_Mix"] = credit_score_data.apply(
    lambda row: (
        grouped_mode[row["Customer_ID"]] if
pd.isnull(row["Credit_Mix"]) else row["Credit_Mix"]
    ),
    axis=1,
)

credit_score_data["Credit_Mix"].value_counts()
```

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

Credit_History_Age

```
def convert_to_years(age_str):
    if pd.isnull(age_str):
        return np.nan
    years, months = 0, 0
    age_str = age_str.lower().replace('years',
'year').replace('months', 'month')
    if 'year' in age_str:
        years = int(age_str.split(' year')[0].strip())
    if 'month' in age_str:
        months = int(age_str.split(' and ')[-1].split(' month')
[0].strip())
    return years + months / 12

credit_score_data['Credit_History_Age'] =
credit_score_data['Credit_History_Age'].apply(convert_to_years)


credit_score_data["Credit_History_Age"]
```

```
0        22.083333
1              NaN
2        22.250000
3        22.333333
4        22.416667
           ...
99995    31.500000
99996    31.583333
99997    31.666667
99998    31.750000
99999    31.833333
Name: Credit_History_Age, Length: 100000, dtype: float64
```

Payment_of_Min_Amount

```
credit_score_data["Payment_of_Min_Amount"].value_counts()
```

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

Amount_invested_monthly

```
credit_score_data["Amount_invested_monthly"]
```

```
0        80.41529544
1        118.2802216
2        81.69952126
3        199.4580744
4        41.42015309
            ...
99995    60.97133256
99996    54.18595029
99997    24.02847745
99998    251.6725822
99999    167.1638652
Name: Amount_invested_monthly, Length: 100000, dtype: object
```

```
credit_score_data["Amount_invested_monthly"] = credit_score_data[
    "Amount_invested_monthly"
].str.replace("__","")

credit_score_data["Amount_invested_monthly"] =
credit_score_data["Amount_invested_monthly"].astype(float)

credit_score_data["Amount_invested_monthly"]
```

```
0         80.415295
1        118.280222
2         81.699521
3        199.458074
4         41.420153
            ...
99995     60.971333
99996     54.185950
99997     24.028477
99998    251.672582
99999    167.163865
Name: Amount_invested_monthly, Length: 100000, dtype: float64
```

Payment_Behaviour

```
credit_score_data["Payment_Behaviour"]
```

```
0          High_spent_Small_value_payments
1           Low_spent_Large_value_payments
2          Low_spent_Medium_value_payments
3           Low_spent_Small_value_payments
4         High_spent_Medium_value_payments
                        ...
99995      High_spent_Large_value_payments
99996     High_spent_Medium_value_payments
99997      High_spent_Large_value_payments
99998       Low_spent_Large_value_payments
99999                               !@9#%8
Name: Payment_Behaviour, Length: 100000, dtype: object
```

```
# Fill 'Payment_Behaviour' with the mode of payment behavior grouped
by 'Customer_ID'
payment_behaviour_mode = credit_score_data.groupby("Customer_ID")
["Payment_Behaviour"].agg(
    lambda x: x.mode().iloc[0] if not x.mode().empty else "Unknown"
)
credit_score_data["Payment_Behaviour"] = credit_score_data.apply(
    lambda row: (
        payment_behaviour_mode[row["Customer_ID"]] if
row["Payment_Behaviour"] != payment_behaviour_mode[row["Customer_ID"]]
else row["Payment_Behaviour"]
    ),
    axis=1,
)
```

Monthly_Balance

```
credit_score_data['Monthly_Balance']
```

```
0         312.4940887
1         284.6291625
2         331.2098629
3         223.4513097
4          341.489231
              ...
99995      479.866228
99996       496.65161
99997      516.809083
99998      319.164979
99999      393.673696
Name: Monthly_Balance, Length: 100000, dtype: object
```

```
credit_score_data["Monthly_Balance"].value_counts()
```

```
Monthly_Balance
__-333333333333333333333333333__    9
350.0148691                         2
```

```
695.0571561                        2
312.4940887                        1
604.3402009                        1
                                  ..
280.6862317                        1
366.289038                         1
151.1882696                        1
306.7502785                        1
393.673696                         1
Name: count, Length: 98790, dtype: int64
```

```
credit_score_data["Monthly_Balance"] =
credit_score_data["Monthly_Balance"].str.replace("__", "")
```

```
credit_score_data["Monthly_Balance"] =
credit_score_data["Monthly_Balance"].str.replace(
    "-", ""
)
```

```
credit_score_data["Monthly_Balance"].value_counts()
```

```
Monthly_Balance
333333333333333333333333333    9
695.0571561                    2
350.0148691                    2
312.4940887                    1
268.5232336                    1
                              ..
315.1430496                    1
348.8652669                    1
329.7982496                    1
218.6369286                    1
214.6149336                    1
Name: count, Length: 97122, dtype: int64
```

```
# Fill 'Monthly_Balance' with the mean of monthly balance grouped by
'Customer_ID'
credit_score_data["Monthly_Balance"] =
pd.to_numeric(credit_score_data["Monthly_Balance"], errors='coerce')
monthly_balance_mean = credit_score_data.groupby("Customer_ID")
["Monthly_Balance"].transform('mean')
credit_score_data["Monthly_Balance"] =
credit_score_data["Monthly_Balance"].fillna(monthly_balance_mean)
```

```
credit_score_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 26 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
```

```
 0   ID                        100000 non-null  object
 1   Customer_ID               100000 non-null  object
 2   Month                     100000 non-null  object
 3   Name                      90015 non-null   object
 4   Age                       100000 non-null  float64
 5   Occupation                100000 non-null  object
 6   Annual_Income             100000 non-null  object
 7   Monthly_Inhand_Salary     84998 non-null   float64
 8   Num_Bank_Accounts         100000 non-null  int64
 9   Num_Credit_Card           100000 non-null  int64
 10  Interest_Rate             100000 non-null  int64
 11  Num_of_Loan               100000 non-null  float64
 12  Type_of_Loan              100000 non-null  object
 13  Delay_from_due_date       100000 non-null  int64
 14  Num_of_Delayed_Payment    100000 non-null  float64
 15  Changed_Credit_Limit      100000 non-null  float64
 16  Num_Credit_Inquiries      100000 non-null  float64
 17  Credit_Mix                100000 non-null  object
 18  Outstanding_Debt          100000 non-null  object
 19  Credit_Utilization_Ratio  100000 non-null  float64
 20  Credit_History_Age        90970 non-null   float64
 21  Payment_of_Min_Amount     100000 non-null  object
 22  Total_EMI_per_month       100000 non-null  float64
 23  Amount_invested_monthly   95521 non-null   float64
 24  Payment_Behaviour         100000 non-null  object
 25  Monthly_Balance           98304 non-null   float64
dtypes: float64(11), int64(4), object(11)
memory usage: 19.8+ MB
```

```
credit_score_data.isna().sum()
```

```
ID                              0
Customer_ID                     0
Month                           0
Name                         9985
Age                             0
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Type_of_Loan                    0
Delay_from_due_date             0
Num_of_Delayed_Payment          0
Changed_Credit_Limit            0
Num_Credit_Inquiries            0
Credit_Mix                      0
Outstanding_Debt                0
```

```
Credit_Utilization_Ratio        0
Credit_History_Age           9030
Payment_of_Min_Amount           0
Total_EMI_per_month             0
Amount_invested_monthly      4479
Payment_Behaviour               0
Monthly_Balance              1696
dtype: int64
```

Handle Missing Values

```python
credit_score_data.isna().sum()
```

```
ID                              0
Customer_ID                     0
Month                           0
Name                         9985
Age                             0
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Type_of_Loan                    0
Delay_from_due_date             0
Num_of_Delayed_Payment          0
Changed_Credit_Limit            0
Num_Credit_Inquiries            0
Credit_Mix                      0
Outstanding_Debt                0
Credit_Utilization_Ratio        0
Credit_History_Age           9030
Payment_of_Min_Amount           0
Total_EMI_per_month             0
Amount_invested_monthly      4479
Payment_Behaviour               0
Monthly_Balance              1696
dtype: int64
```

Name

```python
# Fill 'Name' with the mode of names grouped by 'Customer_ID'
name_mode = credit_score_data.groupby("Customer_ID")["Name"].agg(
```

```
    lambda x: x.mode().iloc[0] if not x.mode().empty else "Unknown"
)
credit_score_data["Name"] = credit_score_data.apply(
    lambda row: (
        name_mode[row["Customer_ID"]] if pd.isnull(row["Name"]) else
row["Name"]
    ),
    axis=1,
)
```

Monthly_Inhand_Salary

```
# Fill 'Monthly_Inhand_Salary' with the median salary grouped by
'Customer_ID'
salary_median = credit_score_data.groupby("Customer_ID")[
    "Monthly_Inhand_Salary"
].median()
credit_score_data["Monthly_Inhand_Salary"] = credit_score_data.apply(
    lambda row: (
        salary_median[row["Customer_ID"]]
        if pd.isnull(row["Monthly_Inhand_Salary"])
        else row["Monthly_Inhand_Salary"]
    ),
    axis=1,
)
```

Credit_History_Age

```
credit_score_data["Credit_History_Age"]

0        22.083333
1              NaN
2        22.250000
3        22.333333
4        22.416667
           ...
99995    31.500000
99996    31.583333
99997    31.666667
99998    31.750000
99999    31.833333
Name: Credit_History_Age, Length: 100000, dtype: float64

# Fill 'Monthly_Inhand_Salary' with the median salary grouped by
'Customer_ID'
credit_history_age_mean = credit_score_data.groupby("Customer_ID")[
    "Credit_History_Age"
].mean()
credit_score_data["Credit_History_Age"] = credit_score_data.apply(
    lambda row: (
```

```
        credit_history_age_mean[row["Customer_ID"]]
        if pd.isnull(row["Credit_History_Age"])
        else row["Credit_History_Age"]
    ),
    axis=1,
)

credit_score_data["Credit_History_Age"].isna().sum()
```

```
np.int64(0)
```

Amount_invested_monthly

```
credit_score_data["Amount_invested_monthly"]
```

```
0         80.415295
1        118.280222
2         81.699521
3        199.458074
4         41.420153
            ...
99995     60.971333
99996     54.185950
99997     24.028477
99998    251.672582
99999    167.163865
Name: Amount_invested_monthly, Length: 100000, dtype: float64
```

```
# Fill 'Monthly_Inhand_Salary' with the median salary grouped by
'Customer_ID'
amount_invested_monthly_mean =
credit_score_data.groupby("Customer_ID")[
    "Amount_invested_monthly"
].mean()
credit_score_data["Amount_invested_monthly"] =
credit_score_data.apply(
    lambda row: (
        amount_invested_monthly_mean[row["Customer_ID"]]
        if pd.isnull(row["Amount_invested_monthly"])
        else row["Amount_invested_monthly"]
    ),
    axis=1,
)

credit_score_data["Amount_invested_monthly"].isna().sum()
```

```
np.int64(0)
```

Monthly_Balance

```
credit_score_data["Monthly_Balance"]
```

```
0        312.494089
1        284.629163
2        331.209863
3        223.451310
4        341.489231
            ...
99995           NaN
99996           NaN
99997           NaN
99998           NaN
99999           NaN
Name: Monthly_Balance, Length: 100000, dtype: float64
```

```
credit_score_data["Monthly_Balance"].fillna(0.0, inplace=True)

# Fill 'Monthly_Inhand_Salary' with the median salary grouped by
'Customer_ID'
monthly_balance_mean = credit_score_data.groupby("Customer_ID")[
    "Monthly_Balance"
].mean()
credit_score_data["Monthly_Balance"] = credit_score_data.apply(
    lambda row: (
        monthly_balance_mean[row["Customer_ID"]]
        if row["Monthly_Balance"] == 0.0
        else row["Monthly_Balance"]
    ),
    axis=1,
)

credit_score_data["Monthly_Balance"].isna().sum()
```

```
np.int64(0)
```

```
credit_score_data
```

```
            ID Customer_ID     Month           Name   Age  
Occupation  \
0       0x1602   CUS_0xd40   January  Aaron Maashoh  23.0   Scientist

1       0x1603   CUS_0xd40  February  Aaron Maashoh  23.0   Scientist

2       0x1604   CUS_0xd40     March  Aaron Maashoh  34.0   Scientist

3       0x1605   CUS_0xd40     April  Aaron Maashoh  23.0   Scientist

4       0x1606   CUS_0xd40       May  Aaron Maashoh  23.0   Scientist
```

```
...        ...        ...        ...            ...   ...        ...

99995  0x25fe9  CUS_0x942c     April          Nicks  25.0   Mechanic

99996  0x25fea  CUS_0x942c       May          Nicks  25.0   Mechanic

99997  0x25feb  CUS_0x942c      June          Nicks  25.0   Mechanic

99998  0x25fec  CUS_0x942c      July          Nicks  25.0   Mechanic

99999  0x25fed  CUS_0x942c    August          Nicks  25.0   Mechanic


      Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0          19114.12            1824.843333                  3
1          19114.12            1824.843333                  3
2          19114.12            1824.843333                  3
3          19114.12            1824.843333                  3
4          19114.12            1824.843333                  3
...             ...                    ...                ...
99995      39628.99            3359.415833                  4
99996      39628.99            3359.415833                  4
99997      39628.99            3359.415833                  4
99998      39628.99            3359.415833                  4
99999      39628.99            3359.415833                  4

       Num_Credit_Card  ...  Num_Credit_Inquiries  Credit_Mix  \
0                    4  ...                   4.0        Good
1                    4  ...                   4.0        Good
2                    4  ...                   4.0        Good
3                    4  ...                   4.0        Good
4                    4  ...                   4.0        Good
...                ...  ...                   ...         ...
99995                6  ...                   3.0        Good
99996                6  ...                   3.0        Good
99997                6  ...                   3.0        Good
99998                6  ...                   3.0        Good
99999                6  ...                   3.0        Good

      Outstanding_Debt  Credit_Utilization_Ratio
Credit_History_Age  \
0               809.98                 26.822620           22.083333

1               809.98                 31.944960           22.361111

2               809.98                 28.609352           22.250000

3               809.98                 31.377862           22.333333

4               809.98                 24.797347           22.416667
```

```
...                  ...                         ...                  ...
99995             502.38                   34.663572            31.500000
99996             502.38                   40.565631            31.583333
99997             502.38                   41.255522            31.666667
99998             502.38                   33.638208            31.750000
99999             502.38                   34.192463            31.833333

       Payment_of_Min_Amount  Total_EMI_per_month
Amount_invested_monthly  \
0                         No            49.574949
80.415295
1                         No            49.574949
118.280222
2                         No            49.574949
81.699521
3                         No            49.574949
199.458074
4                         No            49.574949
41.420153
...                      ...                  ...
...
99995                     No            35.104023
60.971333
99996                     No            35.104023
54.185950
99997                     No            35.104023
24.028477
99998                     No            35.104023
251.672582
99999                     No            35.104023
167.163865

                       Payment_Behaviour  Monthly_Balance
0      High_spent_Medium_value_payments       312.494089
1      High_spent_Medium_value_payments       284.629163
2      High_spent_Medium_value_payments       331.209863
3      High_spent_Medium_value_payments       223.451310
4      High_spent_Medium_value_payments       341.489231
...                                  ...              ...
99995   High_spent_Large_value_payments         0.000000
99996   High_spent_Large_value_payments         0.000000
99997   High_spent_Large_value_payments         0.000000
99998   High_spent_Large_value_payments         0.000000
99999   High_spent_Large_value_payments         0.000000
```

```
[100000 rows x 26 columns]
```

```
credit_score_data.isna().sum()
```

```
ID                          0
Customer_ID                 0
Month                       0
Name                        0
Age                         0
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary       0
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
Type_of_Loan                0
Delay_from_due_date         0
Num_of_Delayed_Payment      0
Changed_Credit_Limit        0
Num_Credit_Inquiries        0
Credit_Mix                  0
Outstanding_Debt            0
Credit_Utilization_Ratio    0
Credit_History_Age          0
Payment_of_Min_Amount       0
Total_EMI_per_month         0
Amount_invested_monthly     0
Payment_Behaviour           0
Monthly_Balance             0
dtype: int64
```

Data Type

```
credit_score_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 26 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   ID                        100000 non-null  object
 1   Customer_ID               100000 non-null  object
 2   Month                     100000 non-null  object
 3   Name                      100000 non-null  object
 4   Age                       100000 non-null  float64
 5   Occupation                100000 non-null  object
```

```
 6   Annual_Income             100000 non-null  object
 7   Monthly_Inhand_Salary     100000 non-null  float64
 8   Num_Bank_Accounts         100000 non-null  int64
 9   Num_Credit_Card           100000 non-null  int64
 10  Interest_Rate             100000 non-null  int64
 11  Num_of_Loan               100000 non-null  float64
 12  Type_of_Loan              100000 non-null  object
 13  Delay_from_due_date       100000 non-null  int64
 14  Num_of_Delayed_Payment    100000 non-null  float64
 15  Changed_Credit_Limit      100000 non-null  float64
 16  Num_Credit_Inquiries      100000 non-null  float64
 17  Credit_Mix                100000 non-null  object
 18  Outstanding_Debt          100000 non-null  object
 19  Credit_Utilization_Ratio  100000 non-null  float64
 20  Credit_History_Age        100000 non-null  float64
 21  Payment_of_Min_Amount     100000 non-null  object
 22  Total_EMI_per_month       100000 non-null  float64
 23  Amount_invested_monthly   100000 non-null  float64
 24  Payment_Behaviour         100000 non-null  object
 25  Monthly_Balance           100000 non-null  float64
dtypes: float64(11), int64(4), object(11)
memory usage: 19.8+ MB
```

```
credit_score_data["Month"] = pd.to_datetime(
    credit_score_data["Month"], format="%B"
).dt.month

credit_score_data["Month"]
```

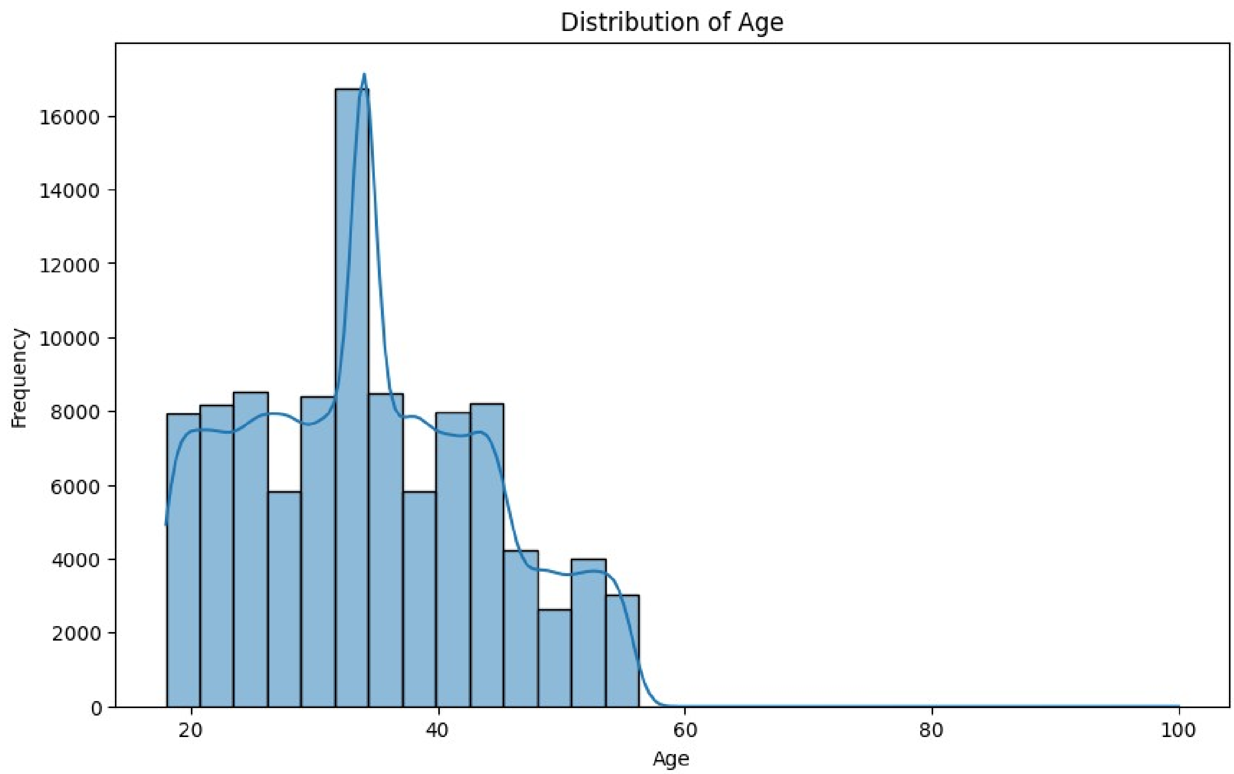
```
0        1
1        2
2        3
3        4
4        5
        ..
99995    4
99996    5
99997    6
99998    7
99999    8
Name: Month, Length: 100000, dtype: int32
```

```
credit_score_data["Annual_Income"] = pd.to_numeric(
    credit_score_data["Annual_Income"], errors="coerce"
)
```

Data Distribution

1. Distribution of Age

```python
# Distribution of Age
plt.figure(figsize=(10, 6))
sns.histplot(credit_score_data["Age"], bins=30, kde=True)
plt.title("Distribution of Age")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```

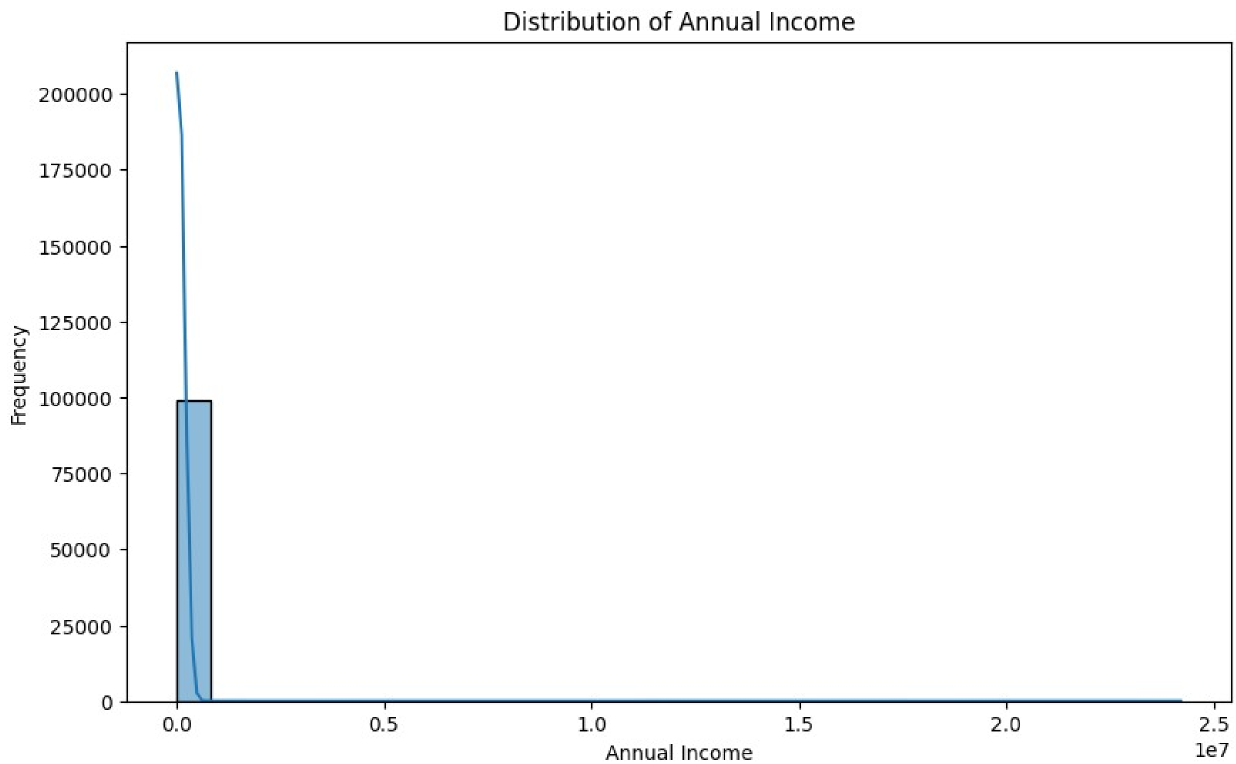


1. Distribution of Annual Income

```python
credit_score_data["Annual_Income"]
```

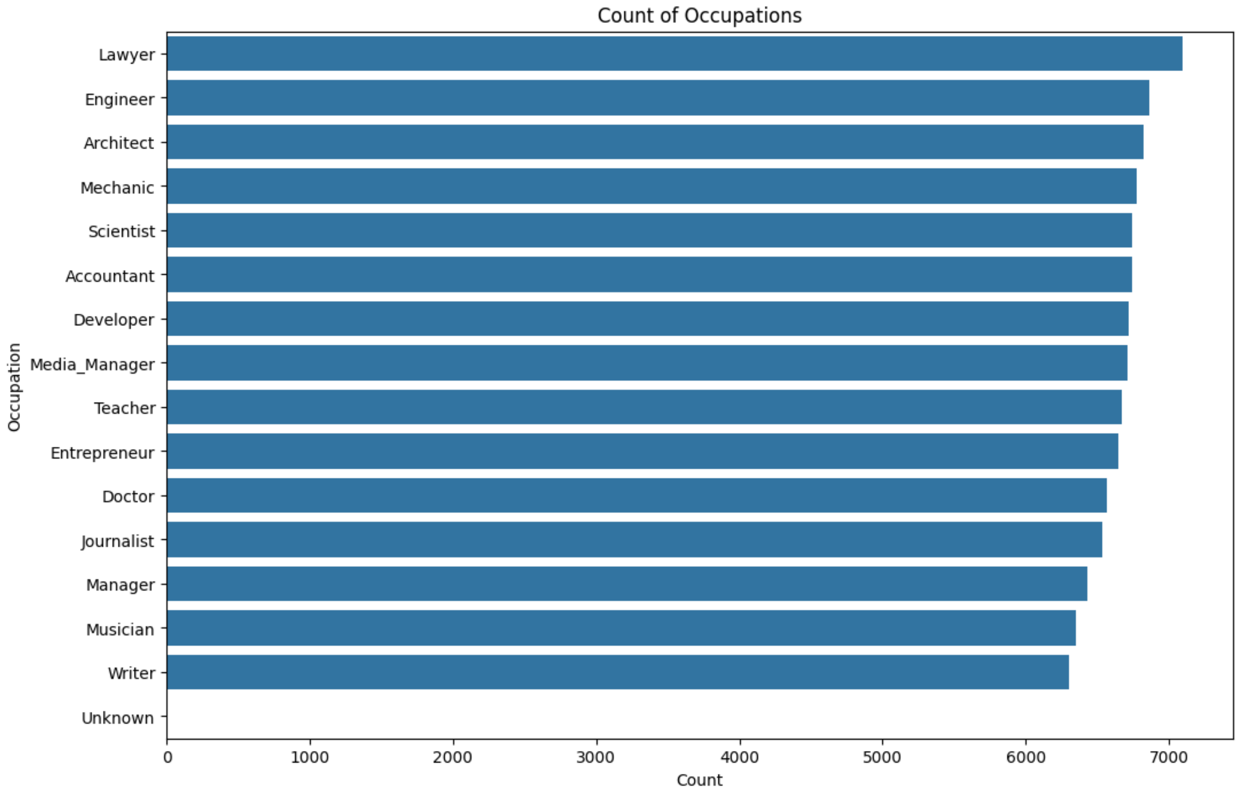
```
0        19114.12
1        19114.12
2        19114.12
3        19114.12
4        19114.12
           ...
99995    39628.99
99996    39628.99
99997    39628.99
99998    39628.99
99999    39628.99
Name: Annual_Income, Length: 100000, dtype: float64
```

```
# Distribution of Annual Income
plt.figure(figsize=(10, 6))
sns.histplot(credit_score_data["Annual_Income"], bins=30, kde=True)
plt.title("Distribution of Annual Income")
plt.xlabel("Annual Income")
plt.ylabel("Frequency")
plt.show()
```



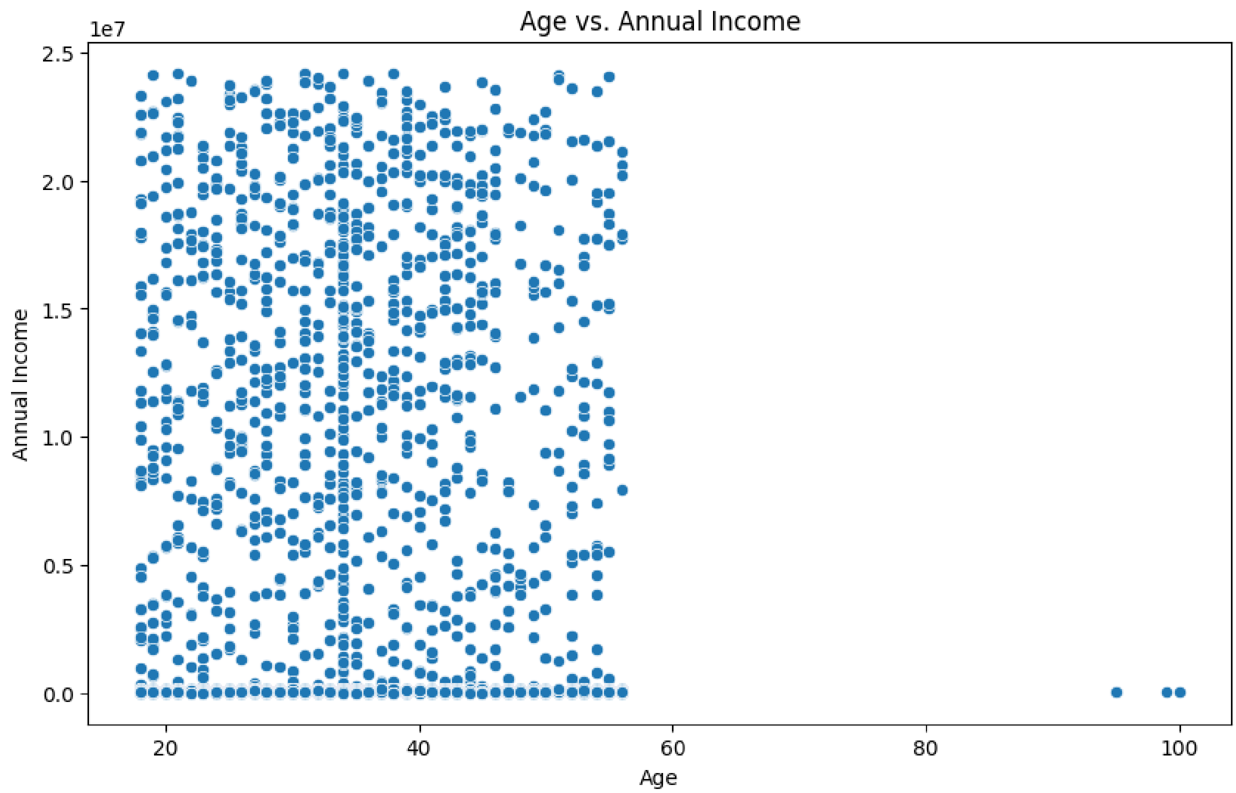
1. Count of Occupations

```
# Count of Occupations
plt.figure(figsize=(12, 8))
sns.countplot(
    y="Occupation",
    data=credit_score_data,
    order=credit_score_data["Occupation"].value_counts().index,
)
plt.title("Count of Occupations")
plt.xlabel("Count")
plt.ylabel("Occupation")
plt.show()
```



1. Scatter Plot of Age vs. Annual Income

```
# Scatter Plot of Age vs. Annual Income
plt.figure(figsize=(10, 6))
sns.scatterplot(x="Age", y="Annual_Income", data=credit_score_data)
plt.title("Age vs. Annual Income")
plt.xlabel("Age")
plt.ylabel("Annual Income")
plt.show()
```



Credit Score Calculation

Let's create a custom FICO-like score, we'll consider the following factors, similar to how FICO scores are generally calculated:

Payment History (35%): This includes factors like the number of delayed payments and whether the customer has paid the minimum amount required.

Amounts Owed (30%): This includes outstanding debt and credit utilization ratio.

Length of Credit History (15%): This includes the age of the credit history.

Credit Mix (10%): This includes the number of loans, credit cards, and the variety of credit types.

New Credit (10%): This includes the number of recent credit inquiries.

Proposed Credit Score Calculation

1. Payment History (35%): A score based on Num_of_Delayed_Payment, Payment_of_Min_Amount, and Payment_Behaviour.
2. Amounts Owed (30%): A score based on Outstanding_Debt and Credit_Utilization_Ratio.
3. Length of Credit History (15%): A score derived from Credit_History_Age.
4. Credit Mix (10%): A score based on Num_of_Loan, Num_Credit_Card, and Credit_Mix.
5. New Credit (10%): A score based on Num_Credit_Inquiries.

```
# Function to calculate custom credit score
def calculate_credit_score(row):
    # Convert Payment_of_Min_Amount to numeric value
    payment_min_value = 1 if row["Payment_of_Min_Amount"] == "Yes"
else 0

    # Convert Payment_Behaviour to numeric value
    payment_behaviour_score = {
        "Low_spent_Large_value_payments": 2,
        "High_spent_Large_value_payments": 1,
        "Low_spent_Small_value_payments": 4,
        "High_spent_Small_value_payments": 3,
        "Low_spent_Medium_value_payments": 5,
        "High_spent_Medium_value_payments": 6,
    }.get(row["Payment_Behaviour"], 0)

    # Payment History (35% of the score)
    payment_history_score = (
        (1 - row["Num_of_Delayed_Payment"] / 100) * 0.35
        + payment_min_value * 0.15
        + payment_behaviour_score * 0.5
    )

    # Amounts Owed (30% of the score)
    amounts_owed_score = (
        1 - row["Outstanding_Debt"] / (row["Annual_Income"] + 1e-9)
    ) * 0.7 + (1 - row["Credit_Utilization_Ratio"] / 100) * 0.3
    amounts_owed_score *= 0.30

    # Length of Credit History (15% of the score)
    credit_history_age_years = int(row["Credit_History_Age"])
    length_of_credit_history_score = (credit_history_age_years / 100)
* 0.15

    # Credit Mix (10% of the score)
    credit_mix_score = 0.1 if row["Credit_Mix"] == "Good" else 0.05
    credit_mix_score += (row["Num_of_Loan"] + row["Num_Credit_Card"])
* 0.01
    credit_mix_score *= 0.10

    # New Credit (10% of the score)
    new_credit_score = (1 - row["Num_Credit_Inquiries"] / 10) * 0.10
```

```python
    # Final credit score
    credit_score = (
        payment_history_score
        + amounts_owed_score
        + length_of_credit_history_score
        + credit_mix_score
        + new_credit_score
    )

    # Scale score to typical credit score range (300-850)
    final_credit_score = 300 + (credit_score * 550)

    return final_credit_score

# Convert relevant columns to numeric, handling any errors
credit_score_data["Num_of_Delayed_Payment"] = pd.to_numeric(
    credit_score_data["Num_of_Delayed_Payment"], errors="coerce"
)
credit_score_data["Outstanding_Debt"] = pd.to_numeric(
    credit_score_data["Outstanding_Debt"], errors="coerce"
)
credit_score_data["Credit_Utilization_Ratio"] = pd.to_numeric(
    credit_score_data["Credit_Utilization_Ratio"], errors="coerce"
)
credit_score_data["Num_of_Loan"] = pd.to_numeric(
    credit_score_data["Num_of_Loan"], errors="coerce"
)
credit_score_data["Num_Credit_Card"] = pd.to_numeric(
    credit_score_data["Num_Credit_Card"], errors="coerce"
)
credit_score_data["Num_Credit_Inquiries"] = pd.to_numeric(
    credit_score_data["Num_Credit_Inquiries"], errors="coerce"
)
credit_score_data["Annual_Income"] = pd.to_numeric(
    credit_score_data["Annual_Income"], errors="coerce"
)

# Apply the function to calculate the custom credit score
credit_score_data["Custom_Credit_Score"] = credit_score_data.apply(
    calculate_credit_score, axis=1
)

# Display the first few rows with the custom credit score
print(credit_score_data[["Customer_ID",
"Custom_Credit_Score"]].head())
```

```
  Customer_ID  Custom_Credit_Score
0   CUS_0xd40          2338.828375
1   CUS_0xd40          2337.576150
```

```
2   CUS_0xd40         2337.943942
3   CUS_0xd40         2340.423530
4   CUS_0xd40         2341.114218

credit_score_data

            ID Customer_ID  Month           Name   Age Occupation  \
0       0x1602   CUS_0xd40      1  Aaron Maashoh  23.0  Scientist
1       0x1603   CUS_0xd40      2  Aaron Maashoh  23.0  Scientist
2       0x1604   CUS_0xd40      3  Aaron Maashoh  34.0  Scientist
3       0x1605   CUS_0xd40      4  Aaron Maashoh  23.0  Scientist
4       0x1606   CUS_0xd40      5  Aaron Maashoh  23.0  Scientist
...        ...         ...    ...            ...   ...        ...
99995  0x25fe9  CUS_0x942c      4          Nicks  25.0   Mechanic
99996  0x25fea  CUS_0x942c      5          Nicks  25.0   Mechanic
99997  0x25feb  CUS_0x942c      6          Nicks  25.0   Mechanic
99998  0x25fec  CUS_0x942c      7          Nicks  25.0   Mechanic
99999  0x25fed  CUS_0x942c      8          Nicks  25.0   Mechanic

       Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0           19114.12            1824.843333                  3
1           19114.12            1824.843333                  3
2           19114.12            1824.843333                  3
3           19114.12            1824.843333                  3
4           19114.12            1824.843333                  3
...              ...                    ...                ...
99995       39628.99            3359.415833                  4
99996       39628.99            3359.415833                  4
99997       39628.99            3359.415833                  4
99998       39628.99            3359.415833                  4
99999       39628.99            3359.415833                  4

       Num_Credit_Card  ...  Credit_Mix  Outstanding_Debt  \
0                    4  ...        Good            809.98
1                    4  ...        Good            809.98
2                    4  ...        Good            809.98
3                    4  ...        Good            809.98
4                    4  ...        Good            809.98
...                ...  ...         ...               ...
99995                6  ...        Good            502.38
99996                6  ...        Good            502.38
99997                6  ...        Good            502.38
99998                6  ...        Good            502.38
99999                6  ...        Good            502.38

      Credit_Utilization_Ratio  Credit_History_Age
Payment_of_Min_Amount  \
0                    26.822620           22.083333
No
1                    31.944960           22.361111
```

```
No
2                     28.609352          22.250000
No
3                     31.377862          22.333333
No
4                     24.797347          22.416667
No
...                         ...                ...
...
99995                 34.663572          31.500000
No
99996                 40.565631          31.583333
No
99997                 41.255522          31.666667
No
99998                 33.638208          31.750000
No
99999                 34.192463          31.833333
No

       Total_EMI_per_month  Amount_invested_monthly  \
0                49.574949                80.415295
1                49.574949               118.280222
2                49.574949                81.699521
3                49.574949               199.458074
4                49.574949                41.420153
...                    ...                      ...
99995            35.104023                60.971333
99996            35.104023                54.185950
99997            35.104023                24.028477
99998            35.104023               251.672582
99999            35.104023               167.163865

                      Payment_Behaviour  Monthly_Balance
Custom_Credit_Score
0      High_spent_Medium_value_payments       312.494089
2338.828375
1      High_spent_Medium_value_payments       284.629163
2337.576150
2      High_spent_Medium_value_payments       331.209863
2337.943942
3      High_spent_Medium_value_payments       223.451310
2340.423530
4      High_spent_Medium_value_payments       341.489231
2341.114218
...                                 ...              ...
...
99995   High_spent_Large_value_payments         0.000000
975.532329
```

```
99996   High_spent_Large_value_payments        0.000000
972.610810
99997   High_spent_Large_value_payments        0.000000
973.039313
99998   High_spent_Large_value_payments        0.000000
976.501884
99999   High_spent_Large_value_payments        0.000000
976.535528

[100000 rows x 27 columns]
```

```
max(credit_score_data['Custom_Credit_Score'])
```

```
2520.5013042192454
```

```
min(credit_score_data["Custom_Credit_Score"])
```

```
-13262.95117522905
```

Let's scale the score to a range of 300 to 850

Let's first normalise each value responsible for the calculation

```
def calculate_credit_score(row):
    # Convert Payment_of_Min_Amount to numeric value
    payment_min_value = 1 if row["Payment_of_Min_Amount"] == "Yes"
else 0

    # Convert Payment_Behaviour to numeric value
    payment_behaviour_score = {
        "Low_spent_Large_value_payments": 2,
        "High_spent_Large_value_payments": 1,
        "Low_spent_Small_value_payments": 4,
        "High_spent_Small_value_payments": 3,
        "Low_spent_Medium_value_payments": 5,
        "High_spent_Medium_value_payments": 6,
    }.get(row["Payment_Behaviour"], 0)

    # Normalize and calculate each component
    # Payment History (35% of the score)
    payment_history_score = (
        1 - np.clip(row["Num_of_Delayed_Payment"] / 100, 0, 1)
    ) * 0.35
    payment_history_score += payment_min_value * 0.15
    payment_history_score += payment_behaviour_score / 6 * 0.5

    # Amounts Owed (30% of the score)
    amounts_owed_score = (
        1 - np.clip(row["Outstanding_Debt"] / (row["Annual_Income"] +
1e-9), 0, 1)
```

```
    ) * 0.7
    amounts_owed_score += (
        1 - np.clip(row["Credit_Utilization_Ratio"] / 100, 0, 1)
    ) * 0.3
    amounts_owed_score *= 0.30

    # Length of Credit History (15% of the score)
    try:
        credit_history_age_years =
int(row["Credit_History_Age"].split()[0])
    except:
        credit_history_age_years = 0
    length_of_credit_history_score = np.clip(credit_history_age_years
/ 25, 0, 1) * 0.15

    # Credit Mix (10% of the score)
    credit_mix_score = 0.1 if row["Credit_Mix"] == "Good" else 0.05
    credit_mix_score += (
        np.clip((row["Num_of_Loan"] + row["Num_Credit_Card"]) / 10, 0,
1) * 0.01
    )
    credit_mix_score *= 0.10

    # New Credit (10% of the score)
    new_credit_score = (1 - np.clip(row["Num_Credit_Inquiries"] / 10,
0, 1)) * 0.10

    # Final credit score
    credit_score = (
        payment_history_score
        + amounts_owed_score
        + length_of_credit_history_score
        + credit_mix_score
        + new_credit_score
    )

    # Rescale the score to the FICO range (300-850)
    final_credit_score = 300 + (credit_score * 550)

    # Ensure the score is within 300 to 850
    return np.clip(final_credit_score, 300, 850)

# Convert relevant columns to numeric, handling any errors
credit_score_data["Num_of_Delayed_Payment"] = pd.to_numeric(
    credit_score_data["Num_of_Delayed_Payment"], errors="coerce"
)
credit_score_data["Outstanding_Debt"] = pd.to_numeric(
    credit_score_data["Outstanding_Debt"], errors="coerce"
)
credit_score_data["Credit_Utilization_Ratio"] = pd.to_numeric(
```

```
    credit_score_data["Credit_Utilization_Ratio"], errors="coerce"
)
credit_score_data["Num_of_Loan"] = pd.to_numeric(
    credit_score_data["Num_of_Loan"], errors="coerce"
)
credit_score_data["Num_Credit_Card"] = pd.to_numeric(
    credit_score_data["Num_Credit_Card"], errors="coerce"
)
credit_score_data["Num_Credit_Inquiries"] = pd.to_numeric(
    credit_score_data["Num_Credit_Inquiries"], errors="coerce"
)
credit_score_data["Annual_Income"] = pd.to_numeric(
    credit_score_data["Annual_Income"], errors="coerce"
)

# Apply the function to calculate the custom credit score
credit_score_data["Custom_Credit_Score"] = credit_score_data.apply(
    calculate_credit_score, axis=1
)

# Display the first few rows with the custom credit score
print(credit_score_data[["Customer_ID",
"Custom_Credit_Score"]].head())
```

```
  Customer_ID  Custom_Credit_Score
0   CUS_0xd40                850.0
1   CUS_0xd40                850.0
2   CUS_0xd40                850.0
3   CUS_0xd40                850.0
4   CUS_0xd40                850.0
```

```
credit_score_data
```

```
            ID Customer_ID  Month           Name   Age Occupation  \
0       0x1602   CUS_0xd40      1  Aaron Maashoh  23.0  Scientist
1       0x1603   CUS_0xd40      2  Aaron Maashoh  23.0  Scientist
2       0x1604   CUS_0xd40      3  Aaron Maashoh  34.0  Scientist
3       0x1605   CUS_0xd40      4  Aaron Maashoh  23.0  Scientist
4       0x1606   CUS_0xd40      5  Aaron Maashoh  23.0  Scientist
...        ...         ...    ...            ...   ...        ...
99995  0x25fe9  CUS_0x942c      4          Nicks  25.0   Mechanic
99996  0x25fea  CUS_0x942c      5          Nicks  25.0   Mechanic
99997  0x25feb  CUS_0x942c      6          Nicks  25.0   Mechanic
99998  0x25fec  CUS_0x942c      7          Nicks  25.0   Mechanic
99999  0x25fed  CUS_0x942c      8          Nicks  25.0   Mechanic

       Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0           19114.12            1824.843333                  3
1           19114.12            1824.843333                  3
2           19114.12            1824.843333                  3
```

```
3           19114.12          1824.843333                  3
4           19114.12          1824.843333                  3
...              ...                  ...                ...
99995       39628.99          3359.415833                  4
99996       39628.99          3359.415833                  4
99997       39628.99          3359.415833                  4
99998       39628.99          3359.415833                  4
99999       39628.99          3359.415833                  4

       Num_Credit_Card  ...  Credit_Mix  Outstanding_Debt  \
0                    4  ...        Good            809.98   
1                    4  ...        Good            809.98   
2                    4  ...        Good            809.98   
3                    4  ...        Good            809.98   
4                    4  ...        Good            809.98   
...                ...  ...         ...               ...   
99995                6  ...        Good            502.38   
99996                6  ...        Good            502.38   
99997                6  ...        Good            502.38   
99998                6  ...        Good            502.38   
99999                6  ...        Good            502.38   

      Credit_Utilization_Ratio  Credit_History_Age 
Payment_of_Min_Amount  \
0                    26.822620           22.083333
No   
1                    31.944960           22.361111
No   
2                    28.609352           22.250000
No   
3                    31.377862           22.333333
No   
4                    24.797347           22.416667
No   
...                        ...                 ...
...   
99995                34.663572           31.500000
No   
99996                40.565631           31.583333
No   
99997                41.255522           31.666667
No   
99998                33.638208           31.750000
No   
99999                34.192463           31.833333
No   

       Total_EMI_per_month  Amount_invested_monthly  \
0                49.574949                80.415295   
1                49.574949               118.280222   
```

```
2                 49.574949                 81.699521
3                 49.574949                199.458074
4                 49.574949                 41.420153
...                     ...                       ...
99995             35.104023                 60.971333
99996             35.104023                 54.185950
99997             35.104023                 24.028477
99998             35.104023                251.672582
99999             35.104023                167.163865

                      Payment_Behaviour  Monthly_Balance
Custom_Credit_Score
0      High_spent_Medium_value_payments       312.494089
850.000000
1      High_spent_Medium_value_payments       284.629163
850.000000
2      High_spent_Medium_value_payments       331.209863
850.000000
3      High_spent_Medium_value_payments       223.451310
850.000000
4      High_spent_Medium_value_payments       341.489231
850.000000
...                                 ...              ...
...
99995   High_spent_Large_value_payments         0.000000
716.830662
99996   High_spent_Large_value_payments         0.000000
713.909143
99997   High_spent_Large_value_payments         0.000000
714.337647
99998   High_spent_Large_value_payments         0.000000
717.800217
99999   High_spent_Large_value_payments         0.000000
717.833861

[100000 rows x 27 columns]
```

```
max(credit_score_data["Custom_Credit_Score"])
```

```
850.0
```

```
min(credit_score_data["Custom_Credit_Score"])
```

```
443.53815606397484
```