Load Dataset, basic info about the dataset

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

In [ ]:
```
# Load data
df = pd.read_csv('/content/Credit_score.csv')
```

In [ ]:
```
# Data overview
print(df.head())
print(df.info())
```

```
       ID Customer_ID     Month           Name   Age          SSN Occupation  \
0  0x1602   CUS_0xd40   January  Aaron Maashoh    23  821-00-0265  Scientist
1  0x1603   CUS_0xd40  February  Aaron Maashoh    23  821-00-0265  Scientist
2  0x1604   CUS_0xd40     March  Aaron Maashoh  -500  821-00-0265  Scientist
3  0x1605   CUS_0xd40     April  Aaron Maashoh    23  821-00-0265  Scientist
4  0x1606   CUS_0xd40       May  Aaron Maashoh    23  821-00-0265  Scientist

  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  ...  \
0      19114.12            1824.843333                  3  ...
1      19114.12                    NaN                  3  ...
2      19114.12                    NaN                  3  ...
3      19114.12                    NaN                  3  ...
4      19114.12            1824.843333                  3  ...

   Num_Credit_Inquiries  Credit_Mix Outstanding_Debt Credit_Utilization_Ratio  \
0                   4.0           _           809.98                26.822620
1                   4.0        Good           809.98                31.944960
2                   4.0        Good           809.98                28.609352
3                   4.0        Good           809.98                31.377862
4                   4.0        Good           809.98                24.797347

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

   Amount_invested_monthly                Payment_Behaviour Monthly_Balance
0              80.41529544   High_spent_Small_value_payments     312.4940887
1              118.2802216    Low_spent_Large_value_payments     284.6291625
2              81.69952126   Low_spent_Medium_value_payments     331.2098629
3              199.4580744    Low_spent_Small_value_payments     223.4513097
4              41.42015309  High_spent_Medium_value_payments      341.489231

[5 rows x 27 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11513 entries, 0 to 11512
Data columns (total 27 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   ID                        11513 non-null  object
 1   Customer_ID               11513 non-null  object
 2   Month                     11513 non-null  object
 3   Name                      10367 non-null  object
 4   Age                       11513 non-null  object
 5   SSN                       11513 non-null  object
 6   Occupation                11513 non-null  object
 7   Annual_Income             11513 non-null  object
 8   Monthly_Inhand_Salary     9797 non-null   float64
 9   Num_Bank_Accounts         11513 non-null  int64
 10  Num_Credit_Card           11513 non-null  int64
 11  Interest_Rate             11513 non-null  int64
 12  Num_of_Loan               11513 non-null  object
 13  Type_of_Loan              10145 non-null  object
 14  Delay_from_due_date       11513 non-null  int64
 15  Num_of_Delayed_Payment    10699 non-null  object
 16  Changed_Credit_Limit      11513 non-null  object
 17  Num_Credit_Inquiries      11275 non-null  float64
 18  Credit_Mix                11513 non-null  object
 19  Outstanding_Debt          11513 non-null  object
 20  Credit_Utilization_Ratio  11513 non-null  float64
 21  Credit_History_Age        10439 non-null  object
 22  Payment_of_Min_Amount     11513 non-null  object
```

```
 23  Total_EMI_per_month       11513 non-null  float64
 24  Amount_invested_monthly   11012 non-null  object
 25  Payment_Behaviour         11513 non-null  object
 26  Monthly_Balance           11366 non-null  object
dtypes: float64(4), int64(4), object(19)
memory usage: 2.4+ MB
None
```

In [ ]:
```
print(df.describe())
```

```
       Monthly_Inhand_Salary  Num_Bank_Accounts  Num_Credit_Card  \
count            9797.000000        11513.000000     11513.000000
mean             4293.962454           17.505342        24.784331
std              3187.283356          121.349593       139.373202
min               355.208333            0.000000         0.000000
25%              1677.030833            3.000000         4.000000
50%              3247.849167            6.000000         5.000000
75%              6088.586667            8.000000         7.000000
max             14836.736670         1789.000000      1486.000000

       Interest_Rate  Delay_from_due_date  Num_Credit_Inquiries  \
count   11513.000000         11513.000000          11275.000000
mean       73.804569            21.187267             24.978625
std       470.399485            14.637448            179.234223
min         1.000000            -5.000000              0.000000
25%         7.000000            10.000000              3.000000
50%        14.000000            18.000000              5.000000
75%        20.000000            28.000000              9.000000
max      5747.000000            67.000000           2592.000000

       Credit_Utilization_Ratio  Total_EMI_per_month
count              11513.000000         11513.000000
mean                  32.259859          1392.741679
std                    5.151945          8195.654041
min                   20.172942             0.000000
25%                   27.922281            28.452848
50%                   32.273284            67.413314
75%                   36.502389           168.351364
max                   50.000000         82204.000000
```

Data Cleaning, Identify and address any missing values, mismatch data types, inconsistencies

In [ ]:
```
# Data cleaning
print(df.isnull().sum())
```

```
ID                            0
Customer_ID                   0
Month                         0
Name                       1146
Age                           0
SSN                           0
Occupation                    0
Annual_Income                 0
Monthly_Inhand_Salary      1716
Num_Bank_Accounts             0
Num_Credit_Card               0
Interest_Rate                 0
Num_of_Loan                   0
Type_of_Loan               1368
Delay_from_due_date           0
Num_of_Delayed_Payment      814
Changed_Credit_Limit          0
Num_Credit_Inquiries        238
Credit_Mix                    0
Outstanding_Debt              0
Credit_Utilization_Ratio      0
Credit_History_Age         1074
Payment_of_Min_Amount         0
Total_EMI_per_month           0
Amount_invested_monthly     501
Payment_Behaviour             0
Monthly_Balance             147
dtype: int64
```

In [ ]:
```
# Fill missing 'Name' values within each 'Customer_ID' group
def fill_missing_names(group):
    mode_value = group.mode().iloc[0] if not group.mode().empty else 'Unknown'
    return group.fillna(mode_value)

df['Name'] = df.groupby('Customer_ID')['Name'].transform(fill_missing_names)
```

Clean Age Column

In [ ]:
```
# Step 1: Clean the Age column
df['Age'] = df['Age'].replace('_', '', regex=True).replace('-', '', regex=True).ast
df['Age'] = pd.to_numeric(df['Age'], errors='coerce')

# Step 2: Define a function to replace invalid values with the mode
def fill_inconsistent_with_mode(group):
    mode_age = group.mode()[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_age if pd.isna(x) or x < 0 or x>90 else x)

# Step 3: Apply the function to each group
df['Age'] = df.groupby('Customer_ID')['Age'].transform(fill_inconsistent_with_mode)
```

In [ ]:
```
# Step 1:Clean the SSN Column F%$D@*&8
df['SSN']=df['SSN'].replace('#F%$D@*&8',np.nan)

# Step 2: Define a function to replace null values with the mode
def fill_SSN(group):
    mode_value = group.mode().iloc[0] if not group.mode().empty else 'Unknown'
    return group.fillna(mode_value)
# Step 3: Apply the function to each group
df['SSN'] = df.groupby('Customer_ID')['SSN'].transform(fill_SSN)
```

In [ ]:
```
# Step 1:Clean the Occupation column with '--------'
df['Occupation']=df['Occupation'].replace('_______',np.nan)

# Step 2: Define a function to replace null values with the mode
def fill_Occupation(group):
    mode_data = group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.fillna(mode_data)

# Step 3: Apply the function to each group
df['Occupation'] = df.groupby('Customer_ID')['Occupation'].transform(fill_Occupatic
```

In [ ]:
```
#Annual_Income
# Step 1: Remove underscores from the 'Annual Salary' column
df['Annual_Income'] = df['Annual_Income'].replace('_', '', regex=True).astype(str)

# Step 2: Convert the column to numeric, forcing errors to NaN
df['Annual_Income'] = pd.to_numeric(df['Annual_Income'], errors='coerce')

# Step 3: Define a function to fill inconsistent values with the mode of the group
def fill_with_mode(group):
    mode_value = group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_value if pd.isna(x) or x>180000 else x)

# Step 4: Apply the function to each group
df['Annual_Income'] = df.groupby('Customer_ID')['Annual_Income'].transform(fill_wit
```

In [ ]:
```
# Fill missing 'Monthly_Inhand_Salary' values within each 'Customer_ID' group

def fill_monthly_salary(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.fillna(mode_value)

df['Monthly_Inhand_Salary'] = df.groupby('Customer_ID')['Monthly_Inhand_Salary'].tr
```

In [ ]:
```
# Clean Num_Bank_Accounts column

def fill_Num_Bank_acct(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_value if pd.isna(x) or x>11 else x)

df['Num_Bank_Accounts'] =df.groupby('Customer_ID')['Num_Bank_Accounts'].transform(f
```

In [ ]:
```
# Clean Num_Credit_Card column
def fill_Num_Credit_Card(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_value if pd.isna(x) or x>11 else x)

df['Num_Credit_Card']=df.groupby('Customer_ID')['Num_Credit_Card'].transform(fill_N
```

In [ ]:
```
#Clean Interest_Rate Column

def Fill_Interest_Rate(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_value if pd.isna(x) or x>34 else x)


df['Interest_Rate'] = df.groupby('Customer_ID')['Interest_Rate'].transform(Fill_Int
```

Clean Num_of_Loan column

In [ ]:
```
#Clean Column Num_of_Loan
print(df['Num_of_Loan'].unique())
```

```
['4' '1' '3' '967' '-100' '0' '0_' '2' '3_' '2_' '7' '5' '5_' '6' '8' '8_'
 '9' '9_' '4_' '7_' '1_' '1464' '6_' '622' '352' '472' '1017' '945' '146'
 '563' '341' '444' '720' '1485' '49' '737' '1106' '466' '728' '313' '843'
 '597_' '617' '119' '663' '640' '92_' '1019' '501' '1302' '39' '716' '848'
 '931' '1214' '186' '424' '1001' '1110' '1152' '457' '1433' '1187' '52'
 '1480' '1047' '1035' '1347_' '33']
```

In [ ]:
```
# Remove non-numeric characters and replace them with empty strings
df['Num_of_Loan'] = df['Num_of_Loan'].replace('_','', regex=True).astype(str)

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

# Optionally, fill NaN values with a default value, e.g., 0
df['Num_of_Loan'] = df['Num_of_Loan'].fillna(0).astype(int)
```

In [ ]:
```
def Fill_Num_of_Loan(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_value if pd.isna(x) or x< 0 or x>9 else x)

df['Num_of_Loan']=df.groupby('Customer_ID')['Num_of_Loan'].transform(Fill_Num_of_Lo
```

Clean Type_of_Loan Column

In [ ]:
```
# Fill missing 'Type_of_Loan' values within each 'Customer_ID' group
def fill_Type_of_Loan(group):
    mode_value = group.mode().iloc[0] if not group.mode().empty else 'Unknown'
    return group.fillna(mode_value)

df['Type_of_Loan'] = df.groupby('Customer_ID')['Type_of_Loan'].transform(fill_missi
```

In [ ]:
```
df['Type_of_Loan'].iloc[712:740]
```

Out[ ]:

	Type_of_Loan
712	Unknown
713	Unknown
714	Unknown
715	Unknown
716	Unknown
717	Unknown
718	Unknown
719	Unknown
720	Unknown
721	Unknown
722	Unknown
723	Unknown
724	Unknown
725	Unknown
726	Unknown
727	Unknown
728	Unknown
729	Unknown
730	Unknown
731	Unknown
732	Unknown
733	Unknown
734	Unknown
735	Unknown
736	Student Loan
737	Student Loan
738	Student Loan
739	Student Loan

dtype: object

In [ ]:

```
# Step 1: Remove unwanted characters (e.g., underscores)
df['Num_of_Delayed_Payment'] = df['Num_of_Delayed_Payment'].replace('_', '', regex=

# Step 2: Convert the column to numeric, coercing errors to NaN
df['Num_of_Delayed_Payment'] = pd.to_numeric(df['Num_of_Delayed_Payment'], errors='

# Step 3: Define the function to fill missing or invalid values
def fill_Num_of_Delayed_Payment(group):
    mode_value = group.mode().iloc[0] if not group.mode().empty else np.nan
```

```
    return group.apply(lambda x: mode_value if pd.isna(x) or x > 28 else x)

# Step 4: Apply the transformation
df['Num_of_Delayed_Payment'] = df.groupby('Customer_ID')['Num_of_Delayed_Payment'].

# Step 5: Handle any remaining NaN values (if there are any left after transformati
# You can fill NaNs with 0, or another strategy (e.g., the mode of the entire colum
df['Num_of_Delayed_Payment'] = df['Num_of_Delayed_Payment'].fillna(0)

# Step 6: Convert the column to integer
df['Num_of_Delayed_Payment'] = df['Num_of_Delayed_Payment'].astype(int)
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11513 entries, 0 to 11512
Data columns (total 27 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   ID                        11513 non-null  object 
 1   Customer_ID               11513 non-null  object 
 2   Month                     11513 non-null  object 
 3   Name                      11513 non-null  object 
 4   Age                       11513 non-null  int64  
 5   SSN                       11513 non-null  object 
 6   Occupation                11513 non-null  object 
 7   Annual_Income             11513 non-null  float64
 8   Monthly_Inhand_Salary     11513 non-null  float64
 9   Num_Bank_Accounts         11513 non-null  int64  
 10  Num_Credit_Card           11513 non-null  int64  
 11  Interest_Rate             11513 non-null  int64  
 12  Num_of_Loan               11513 non-null  int64  
 13  Type_of_Loan              11513 non-null  object 
 14  Delay_from_due_date       11513 non-null  int64  
 15  Num_of_Delayed_Payment    11513 non-null  int64  
 16  Changed_Credit_Limit      11513 non-null  object 
 17  Num_Credit_Inquiries      11275 non-null  float64
 18  Credit_Mix                11513 non-null  object 
 19  Outstanding_Debt          11513 non-null  object 
 20  Credit_Utilization_Ratio  11513 non-null  float64
 21  Credit_History_Age        10439 non-null  object 
 22  Payment_of_Min_Amount     11513 non-null  object 
 23  Total_EMI_per_month       11513 non-null  float64
 24  Amount_invested_monthly   11012 non-null  object 
 25  Payment_Behaviour         11513 non-null  object 
 26  Monthly_Balance           11366 non-null  object 
dtypes: float64(5), int64(7), object(15)
memory usage: 2.4+ MB
```

In [ ]:
```
#Changed_Credit_Limit
df['Changed_Credit_Limit']=df['Changed_Credit_Limit'].replace('_','',regex=True).as
df['Changed_Credit_Limit']=pd.to_numeric(df['Changed_Credit_Limit'],errors='coerce'

def fill_changed_credit_limit(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.fillna(mode_value)

df['Changed_Credit_Limit']=df.groupby('Customer_ID')['Changed_Credit_Limit'].transf
```

In [ ]:
```
#Num_Credit_Inquiries
def fill_Num_Credit_Inquiries(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_value if pd.isna(x) or x> 17 else x)
```

```
df['Num_Credit_Inquiries']=df.groupby('Customer_ID')['Num_Credit_Inquiries'].transf
```

In [ ]:
```
#Credit_Mix
df['Credit_Mix']=df['Credit_Mix'].replace('_','',regex=True)

# Define a function to fill empty strings with the mode value
def fill_credit_mix(group):
    mode_value = group.mode().iloc[0] if not group.mode().empty else ''
    return group.replace('', mode_value)

# Apply the function to each group
df['Credit_Mix'] = df.groupby('Customer_ID')['Credit_Mix'].transform(fill_credit_mi
```

In [ ]:
```
df['Credit_Mix'].head(30)
```

Out[ ]:

	Credit_Mix
0	Good
1	Good
2	Good
3	Good
4	Good
5	Good
6	Good
7	Good
8	Good
9	Good
10	Good
11	Good
12	Good
13	Good
14	Good
15	Good
16	Good
17	Good
18	Good
19	Good
20	Good
21	Good
22	Good
23	Good
24	Good
25	Good
26	Good
27	Good
28	Good
29	Good

dtype: object

Outstanding_Debt

In [ ]:

```
df['Outstanding_Debt']=df['Outstanding_Debt'].replace('_','',regex=True)
df['Outstanding_Debt']=pd.to_numeric(df['Outstanding_Debt'],errors='coerce')
```

```
def fill_Outstanding_Debt(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_value if x>5000 or pd.isna(x) else x)

df['Outstanding_Debt'] =df.groupby('Customer_ID')['Outstanding_Debt'].transform(fil
```

In [ ]:
```
df['Outstanding_Debt'].iloc[360:375]
```

Out[ ]:

	Outstanding_Debt
360	3422.49
361	3422.49
362	3422.49
363	3422.49
364	3422.49
365	3422.49
366	3422.49
367	3422.49
368	2797.17
369	2797.17
370	2797.17
371	2797.17
372	2797.17
373	2797.17
374	2797.17

dtype: float64

In [ ]:
```
#!@9#%8 Payment_Behaviour

df['Payment_Behaviour']=df['Payment_Behaviour'].replace('!@9#%8','',regex=True).ast

def fill_Payment_Behaviour(group):
    mode_value=group.mode().iloc[0] if not group.mode().empty else ''
    return group.replace('',mode_value)

df['Payment_Behaviour']=df.groupby('Customer_ID')['Payment_Behaviour'].transform(fi
```

Credit History Age

In [ ]:
```
import re

def convert_to_months(age_str):
    if pd.isna(age_str):
        return np.nan
    # Use a regular expression to extract numbers before "Years" and "Months"
    match = re.match(r"(\d+)\s*Years?\s*and\s*(\d+)\s*Months?", age_str)
    if match:
```

```
        years, months = int(match.group(1)), int(match.group(2))
        return years * 12 + months
    return np.nan  # Return NaN if the string is not in the expected format

# Apply the function to the Credit_History_Age column
df['Credit_History_Age_Months'] = df['Credit_History_Age'].apply(convert_to_months)

# Define a function to increment missing values within a group
def fill_na_with_increment(group):
   # Fill NA in the first row if present
    if pd.isna(group.iloc[0]):
        # Find the first non-NA value
        first_non_na = group.dropna().iloc[0] if not group.dropna().empty else np.r
        # Fill the first NA with the first non-NA value minus 1
        group.iloc[0] = first_non_na - 1
    # Iterate over the group and add 1 to the previous value where NA is found
    for i in range(1, len(group)):
        if pd.isna(group.iloc[i]):
            group.iloc[i] = group.iloc[i-1] + 1
    return group

# Apply the function to each group
df['Credit_History_Age_Months'] = df.groupby('Customer_ID')['Credit_History_Age_Mor

# Step 1: Convert the total months into years and months
df['Years'] = df['Credit_History_Age_Months'] // 12
df['Months'] = df['Credit_History_Age_Months'] % 12

# Step 2: Combine years and months into the desired format
df['Credit_History_Age'] = df['Years'].astype(int).astype(str) + ' Years and ' + df

# Drop the intermediate columns if not needed
df.drop(columns=['Years', 'Months'], inplace=True)
# Drop the helper column
df.drop(columns=['Credit_History_Age_Months'], inplace=True)
```

Payment_of_Min_Amount

In [ ]:
```
df['Payment_of_Min_Amount'].unique()
```

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

In [ ]:
```
# Fill missing 'Payment_of_Min_Amount' values within each 'Customer_ID' group
def fill_Payment_of_Min_Amount(group):
    mode_value = group.mode().iloc[0] if not group.mode().empty else 'Unknown'
    return group.fillna(mode_value)

df['Payment_of_Min_Amount'] = df.groupby('Customer_ID')['Payment_of_Min_Amount'].tr

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

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

Total_EMI_per_month

In [ ]:
```
df['Total_EMI_per_month'].dtype
```

Out[ ]:
```
dtype('float64')
```

In [ ]:
```
df['Total_EMI_per_month'].isna().sum()
```

Out[ ]:
```
0
```

In [ ]:
```
# Fill missing 'Payment_of_Min_Amount' values within each 'Customer_ID' group
# Function to fill mode for integer and null values
def fill_Total_EMI_per_month(group):
    mode_value = group.mode().iloc[0] if not group.mode().empty else np.nan
    return group.apply(lambda x: mode_value if pd.isna(x) or x>1780 else x)

df['Total_EMI_per_month'] = df.groupby('Customer_ID')['Total_EMI_per_month'].transf
```

In [ ]:
```
df['Total_EMI_per_month'].iloc[4022:4037]
```

Out[ ]:

	Total_EMI_per_month
4022	674.761560
4023	674.761560
4024	182.739733
4025	479.261240
4026	479.261240
4027	479.261240
4028	479.261240
4029	479.261240
4030	479.261240
4031	479.261240
4032	78.145085
4033	78.145085
4034	78.145085
4035	78.145085
4036	78.145085

dtype: float64

In [ ]:
```
df['Amount_invested_monthly'].dtype
```

Out[ ]:
```
dtype('O')
```

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

Out[ ]:
```
501
```

In [ ]:
```
#Amount_invested_monthly

# Replace this pattern __10000__ with nan

df['Amount_invested_monthly'] = df['Amount_invested_monthly'].replace('__10000__','
df['Amount_invested_monthly'] = pd.to_numeric(df['Amount_invested_monthly'],errors=

df['Amount_invested_monthly']=df.groupby('Customer_ID')['Amount_invested_monthly'].
```

In [ ]:
```
df['Amount_invested_monthly'].dtype
```

Out[ ]:
```
dtype('float64')
```

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

Out[ ]:
```
0
```

In [ ]:
```
df['Amount_invested_monthly'].iloc[15:68]
```

Out[ ]:

	Amount_invested_monthly
15	218.904344
16	168.413703
17	232.860384
18	199.450565
19	825.216270
20	430.947528
21	257.808099
22	263.174163
23	199.450565
24	81.228859
25	124.881820
26	83.406509
27	272.334037
28	199.450565
29	84.952848
30	71.283675
31	125.617250
32	276.725394
33	74.443641
34	173.138651
35	96.785485
36	62.723278
37	37.643638
38	181.011983
39	181.330901
40	98.674410
41	172.939214
42	150.059734
43	618.202391
44	177.951836
45	235.790325
46	348.509399
47	42.635590
48	378.171253
49	698.873271
50	188.064321

	Amount_invested_monthly
51	337.434956
52	263.378909
53	86.566388
54	930.391898
55	870.522382
56	162.441009
57	38.436983
58	199.720765
59	220.552192
60	199.450565
61	199.450565
62	55.459781
63	29.326364
64	215.193516
65	212.235602
66	470.385796
67	225.082050

dtype: float64

In [ ]:
```
df['Monthly_Balance'].dtype
```

Out[ ]:
```
dtype('O')
```

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

Out[ ]:
```
147
```

In [ ]:
```
df['Monthly_Balance']=pd.to_numeric(df['Monthly_Balance'],errors='coerce')
df['Monthly_Balance']=df.groupby('Customer_ID')['Monthly_Balance'].fillna(df['Montl
```

In [ ]:
```
df['Monthly_Balance'].dtype
```

Out[ ]:
```
dtype('float64')
```

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

Out[ ]:
```
0
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11513 entries, 0 to 11512
Data columns (total 27 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   ID                        11513 non-null  object 
 1   Customer_ID               11513 non-null  object 
 2   Month                     11513 non-null  object 
 3   Name                      11513 non-null  object 
 4   Age                       11513 non-null  int64  
 5   SSN                       11513 non-null  object 
 6   Occupation                11513 non-null  object 
 7   Annual_Income             11513 non-null  float64
 8   Monthly_Inhand_Salary     11513 non-null  float64
 9   Num_Bank_Accounts         11513 non-null  int64  
 10  Num_Credit_Card           11513 non-null  int64  
 11  Interest_Rate             11513 non-null  int64  
 12  Num_of_Loan               11513 non-null  int64  
 13  Type_of_Loan              11513 non-null  object 
 14  Delay_from_due_date       11513 non-null  int64  
 15  Num_of_Delayed_Payment    11513 non-null  int64  
 16  Changed_Credit_Limit      11513 non-null  float64
 17  Num_Credit_Inquiries      11513 non-null  float64
 18  Credit_Mix                11513 non-null  object 
 19  Outstanding_Debt          11513 non-null  float64
 20  Credit_Utilization_Ratio  11513 non-null  float64
 21  Credit_History_Age        11513 non-null  object 
 22  Payment_of_Min_Amount     11513 non-null  object 
 23  Total_EMI_per_month       11513 non-null  float64
 24  Amount_invested_monthly   11513 non-null  float64
 25  Payment_Behaviour         11513 non-null  object 
 26  Monthly_Balance           11513 non-null  float64
dtypes: float64(9), int64(7), object(11)
memory usage: 2.4+ MB
```

In [ ]:
```
df.isna().sum()
```

Out[ ]:

	0
ID	0
Customer_ID	0
Month	0
Name	0
Age	0
SSN	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

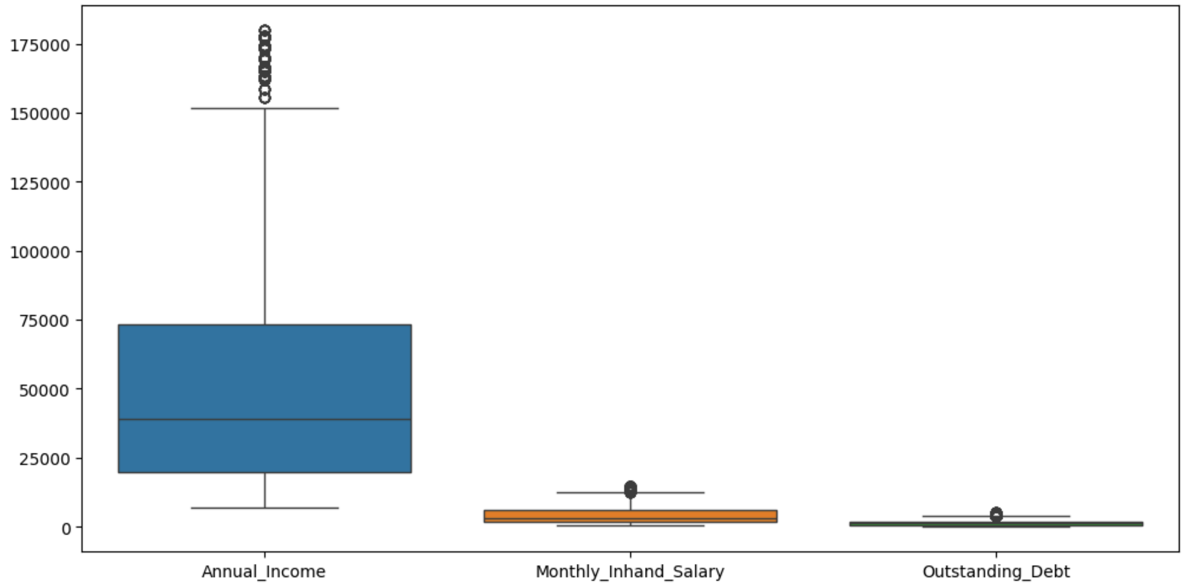
dtype: int64

Handle Outliers and appropriate Visualizations

In [ ]:

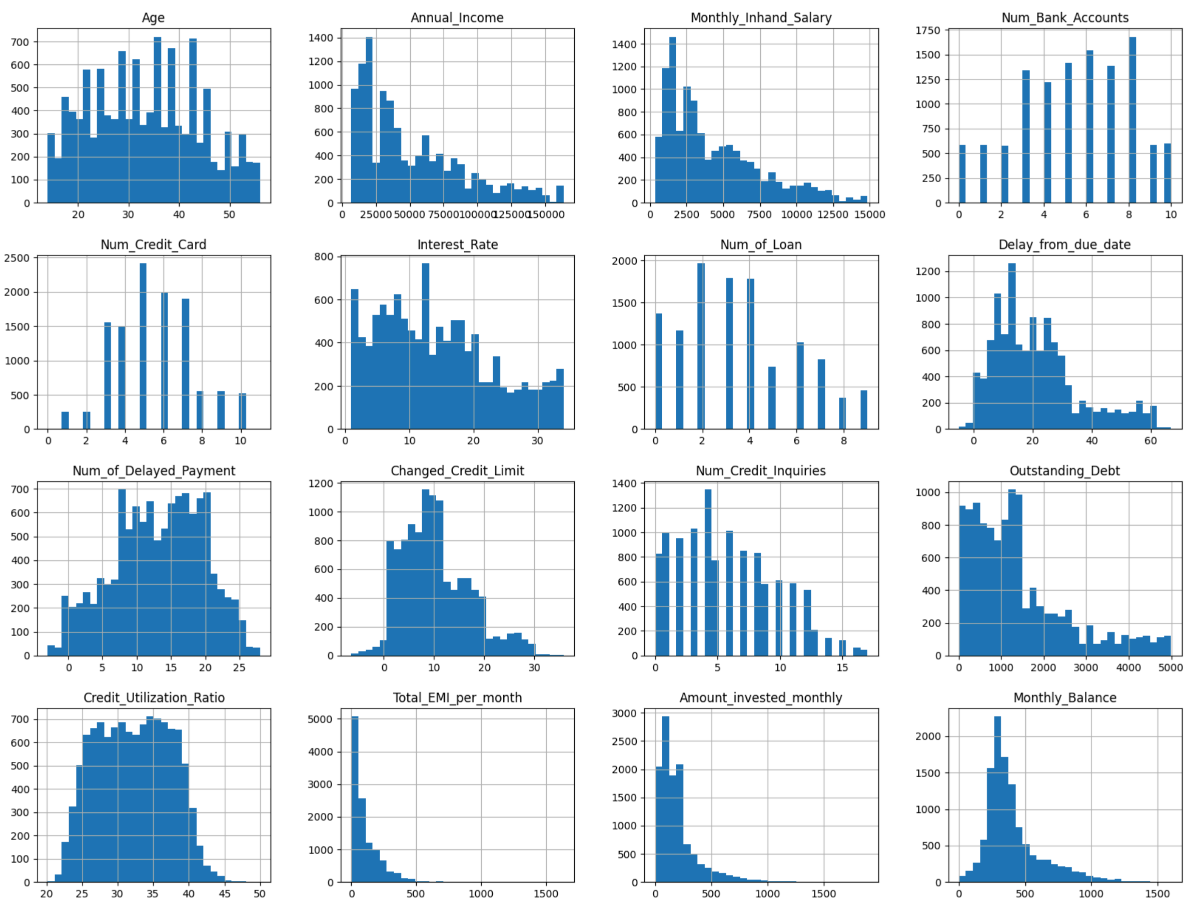
```
# Visualize potential outliers using box plots
plt.figure(figsize=(12, 6))
sns.boxplot(data=df[['Annual_Income', 'Monthly_Inhand_Salary', 'Outstanding_Debt']]
plt.show()
```

```
# Handling outliers can involve capping, flooring, or removing them
# Example: Capping outliers at the 99th percentile
cap = df['Annual_Income'].quantile(0.99)
df.loc[df['Annual_Income'] > cap, 'Annual_Income'] = cap
```



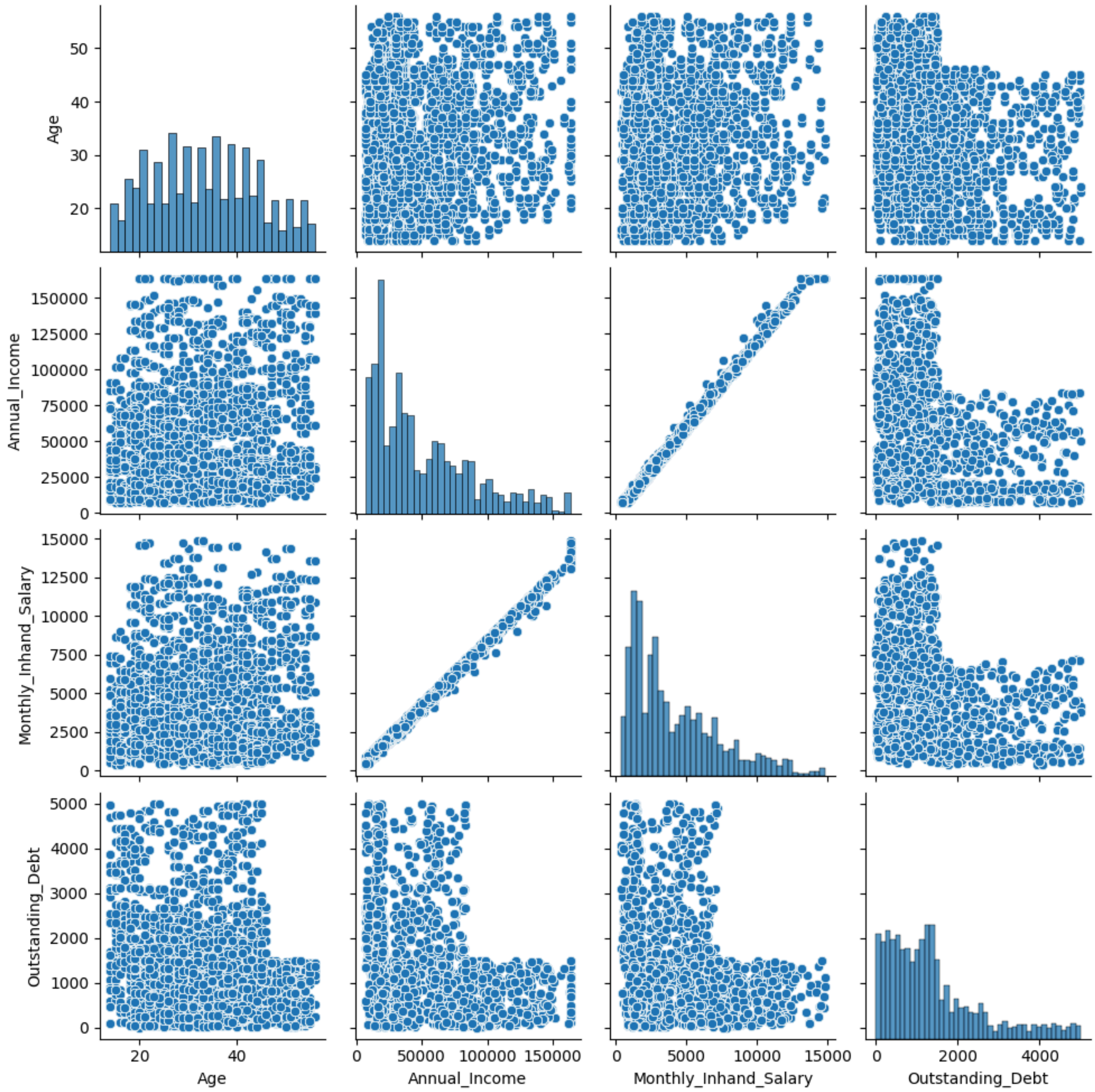
In [ ]:

```
# Histograms for continuous variables
df.hist(bins=30, figsize=(20, 15))
plt.show()
```

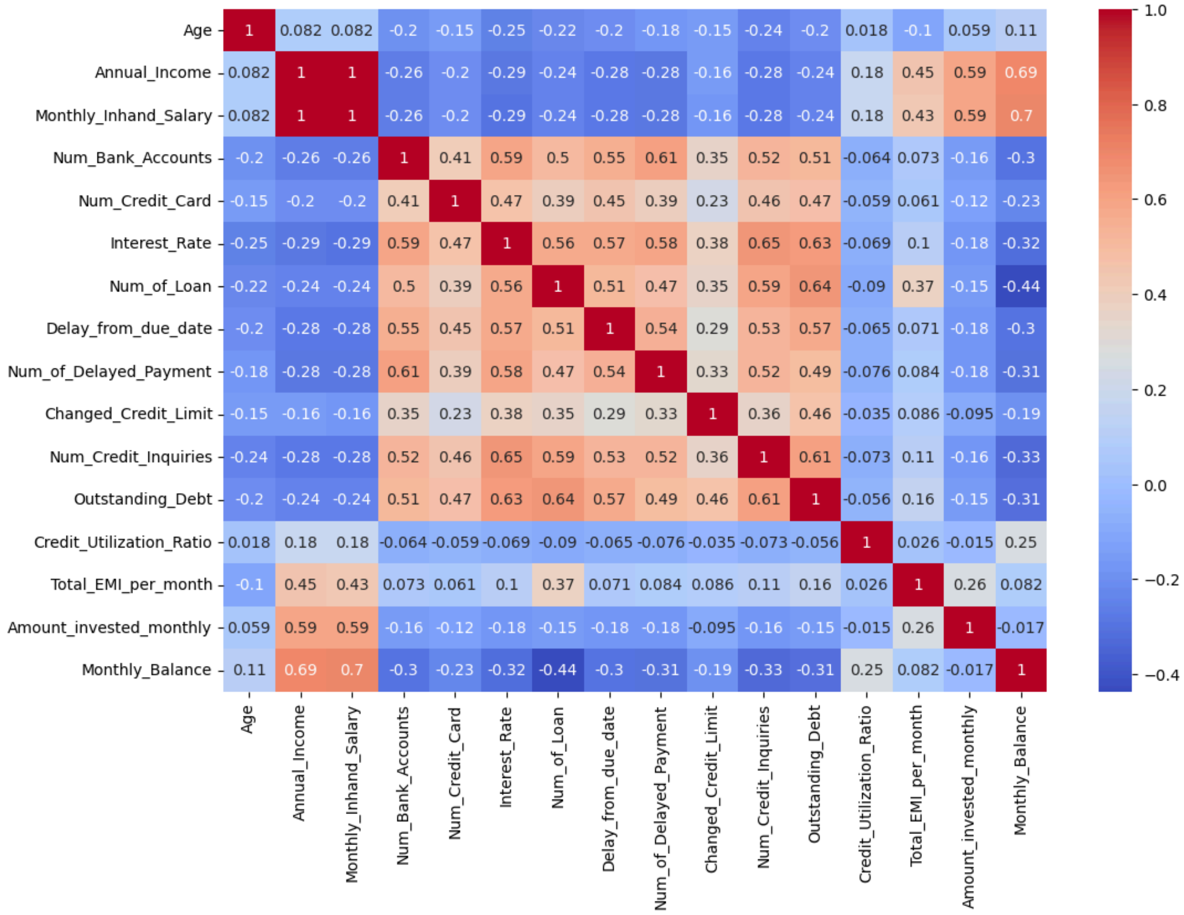


In [ ]:

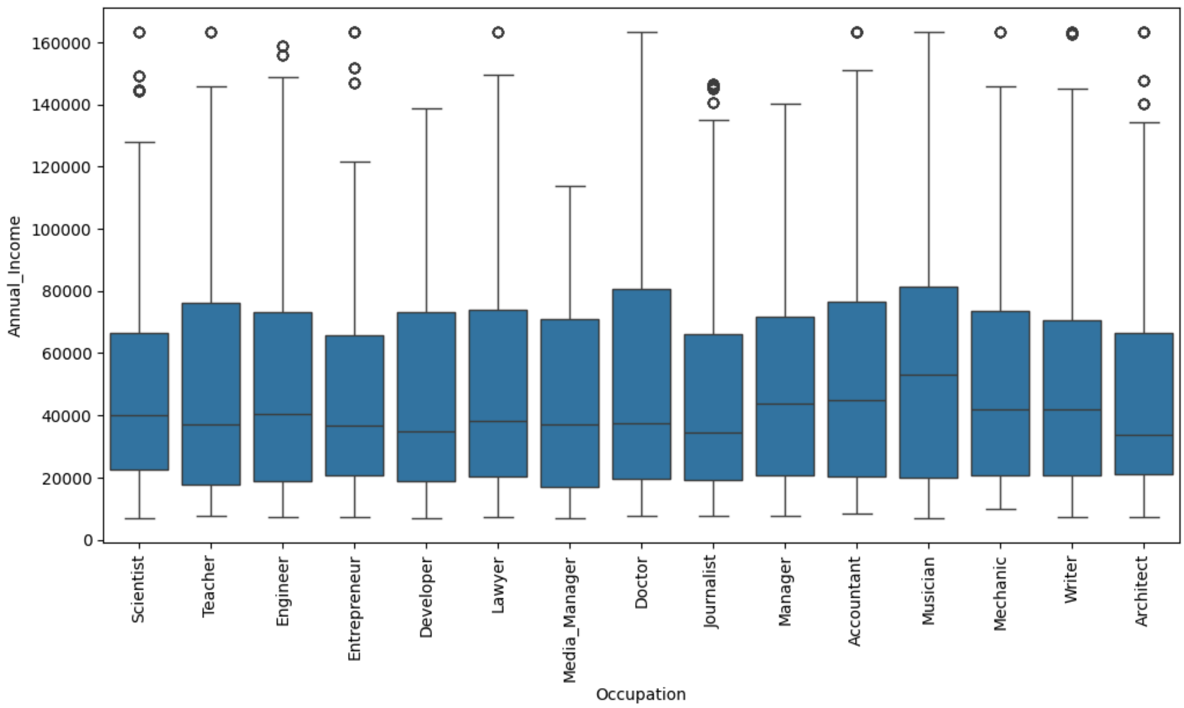
```
# Scatter plots to explore relationships between variables
sns.pairplot(df[['Age', 'Annual_Income', 'Monthly_Inhand_Salary', 'Outstanding_Debt
plt.show()
```



In [ ]:
```
# Correlation matrix and heatmap
# Select the columns of interest
selected_columns = df[['Age','Annual_Income','Monthly_Inhand_Salary','Num_Bank_Acco
corr_matrix =  selected_columns.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.show()
```

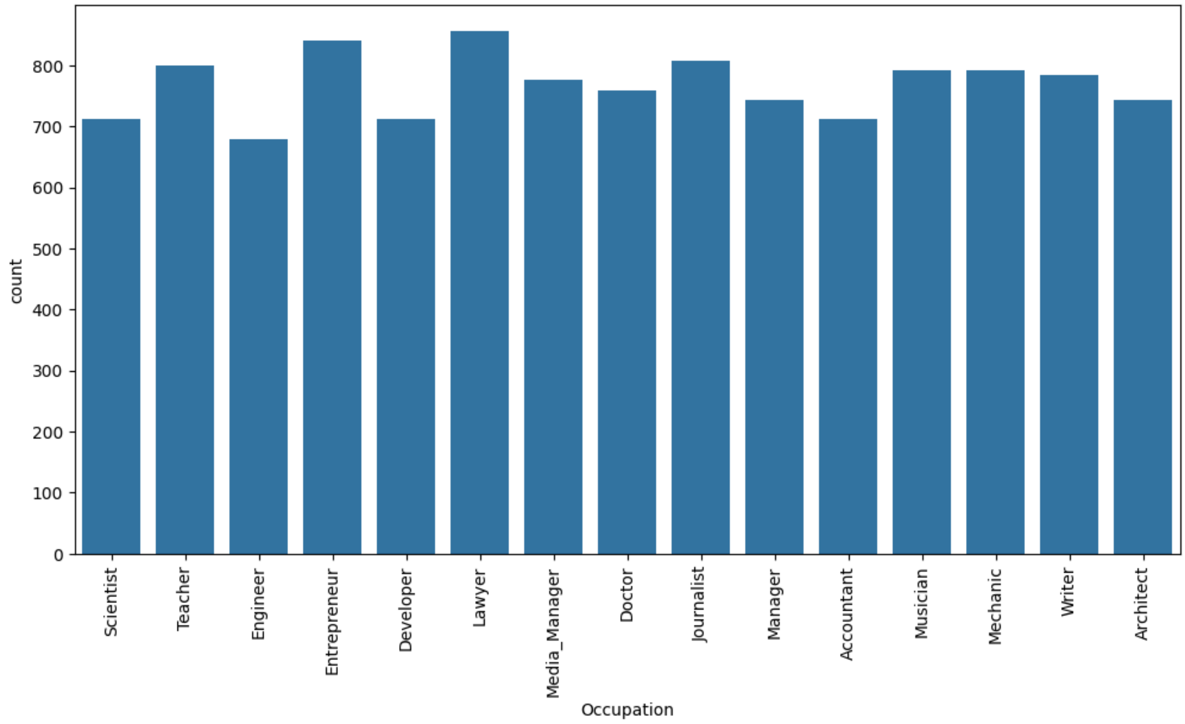


In [ ]:
```
# Box plots for categorical variables against continuous variables
plt.figure(figsize=(12, 6))
sns.boxplot(x='Occupation', y='Annual_Income', data=df)
plt.xticks(rotation=90)
plt.show()
```

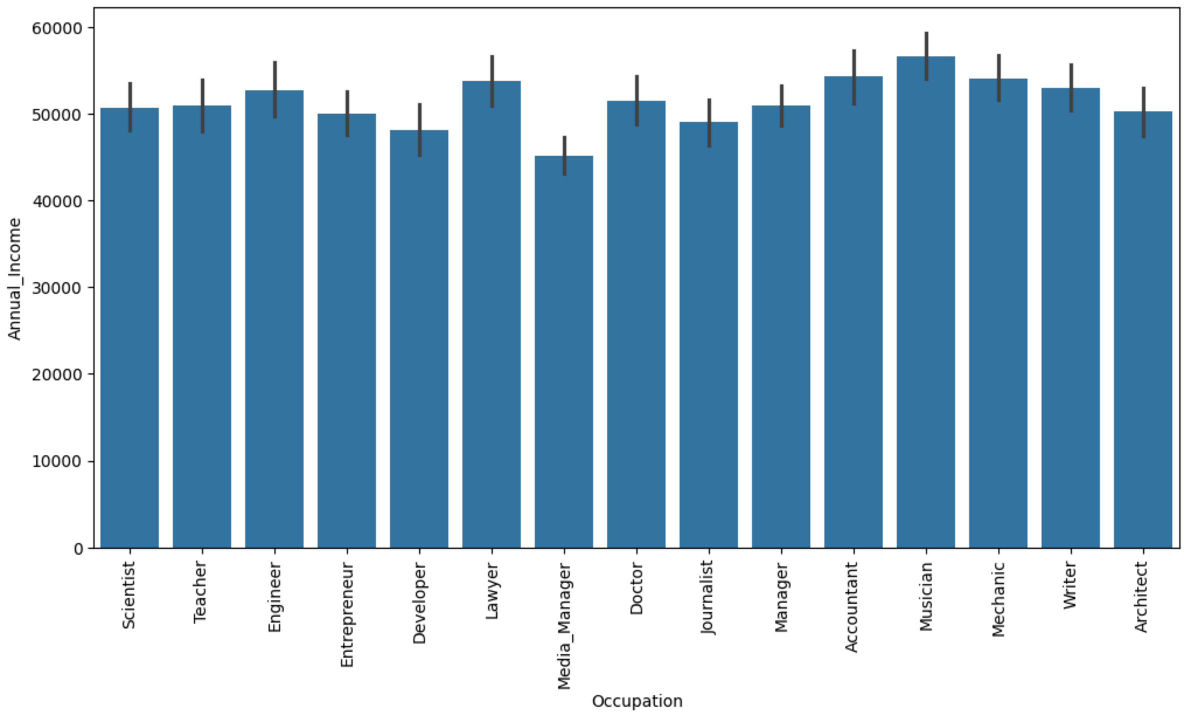


Identify Relationships and Patterns

In [ ]:
```
# Count plots for categorical variables
plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='Occupation')
plt.xticks(rotation=90)
plt.show()
```



In [ ]:
```
# Bar plots to show mean values of a variable grouped by another variable
plt.figure(figsize=(12, 6))
sns.barplot(x='Occupation', y='Annual_Income', data=df)
plt.xticks(rotation=90)
plt.show()
```



Feature Engineering - Creating new features that can be leveraged for the

calculation of credit scores

In [ ]:
```
# Feature engineering (example: creating a new feature for debt-to-income ratio)
df['Debt_to_Income_Ratio'] = df['Outstanding_Debt'] / df['Annual_Income']
```

1. Payment History

Late Payments Count: Count the number of times payments were delayed

In [ ]:
```
df['Late_Payments_Count'] = df['Num_of_Delayed_Payment'].apply(lambda x: int(x) if
```

In [ ]:
```
df['Late_Payment_Indicator'] = df['Late_Payments_Count'].apply(lambda x: 1 if x > 0
```

1. Credit Inquiries

In [ ]:
```
df['Total_Credit_Inquiries'] = df.groupby('Customer_ID')['Num_Credit_Inquiries'].tr
df[['Customer_ID','Total_Credit_Inquiries']].head(20)
```

Out[ ]:

	Customer_ID	Total_Credit_Inquiries
0	CUS_0xd40	32.0
1	CUS_0xd40	32.0
2	CUS_0xd40	32.0
3	CUS_0xd40	32.0
4	CUS_0xd40	32.0
5	CUS_0xd40	32.0
6	CUS_0xd40	32.0
7	CUS_0xd40	32.0
8	CUS_0x21b1	16.0
9	CUS_0x21b1	16.0
10	CUS_0x21b1	16.0
11	CUS_0x21b1	16.0
12	CUS_0x21b1	16.0
13	CUS_0x21b1	16.0
14	CUS_0x21b1	16.0
15	CUS_0x21b1	16.0
16	CUS_0x2dbc	24.0
17	CUS_0x2dbc	24.0
18	CUS_0x2dbc	24.0
19	CUS_0x2dbc	24.0

1. Credit History Length

In [ ]:
```
# Compute the length of the credit history.

import re

def convert_to_months(age_str):
    if pd.isna(age_str):
        return np.nan
    # Use a regular expression to extract numbers before "Years" and "Months"
    match = re.match(r"(\d+)\s*Years?\s*and\s*(\d+)\s*Months?", age_str)
    if match:
        years, months = int(match.group(1)), int(match.group(2))
        return years * 12 + months
    return np.nan  # Return NaN if the string is not in the expected format

# Apply the function to the Credit_History_Age column
df['Credit_History_Age_Months'] = df['Credit_History_Age'].apply(convert_to_months)
```

In [ ]:
```
#Calculate Credit History Length: Use the Credit_History_Months to compute the leng
df['Credit_History_Length'] = df['Credit_History_Age_Months'].max() - df['Credit_Hi
df['Credit_History_Length'].dtype
```

Out[ ]:
```
dtype('int64')
```

1. Payment Trends

Calculate Payment Behavior Trends: Determine if there’s a pattern in Payment_Behaviour

In [ ]:
```
df['Credit_Mix'].iloc[165:185]
```

Out[ ]:

	Credit_Mix
165	Standard
166	Standard
167	Standard
168	Bad
169	Bad
170	Bad
171	Bad
172	Bad
173	Bad
174	Bad
175	Bad
176	Good
177	Good
178	Good
179	Good
180	Good
181	Good
182	Good
183	Good
184	Standard

dtype: object

In [ ]:
```
df['Payment_trends'] = df['Credit_Mix'].apply(lambda x: 1 if x in ['Good','Standarc
```

In [ ]:
```
df['Payment_trends'].iloc[165:185]
```

Out[ ]:

	Payment_trends
165	1
166	1
167	1
168	0
169	0
170	0
171	0
172	0
173	0
174	0
175	0
176	1
177	1
178	1
179	1
180	1
181	1
182	1
183	1
184	1

dtype: int64

1. Normalization/Scaling : Normalize or scale features to ensure that all features contribute equally to the analysis

In [ ]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df[['Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts', 'Num_Credit_Carc
    'Interest_Rate', 'Num_of_Loan', 'Changed_Credit_Limit', 'Num_Credit_Inquiries',
    'Outstanding_Debt', 'Credit_Utilization_Ratio',
    'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance']] = scaler.
    df[['Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts', 'Num_Credit_
        'Interest_Rate', 'Num_of_Loan', 'Changed_Credit_Limit', 'Num_Credit_Inquiri
        'Outstanding_Debt', 'Credit_Utilization_Ratio',
        'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance']]
)
```

In [ ]:

```
df.columns
```

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

Hypothetical Credit Score Calculation:

1. Hypothetical Credit Score Calculation:

In [ ]:
```python
# Selecting relevant features for the hypothetical credit score calculation
features = [
    'Num_of_Delayed_Payment',
    'Late_Payments_Count',
    'Credit_Utilization_Ratio',
    'Credit_History_Length',
    'Payment_trends',
    'Total_EMI_per_month',
    'Outstanding_Debt'
]

# Subsetting the data
df_selected = df[features]
df_selected.head()
```

Out[ ]:

	Num_of_Delayed_Payment	Late_Payments_Count	Credit_Utilization_Ratio	Credit_History_Length
0	7	7	-1.055422	139
1	4	4	-0.061125	138
2	7	7	-0.708599	137
3	4	4	-0.171204	136
4	4	4	-1.448547	135

In [ ]:
```python
df_selected.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11513 entries, 0 to 11512
Data columns (total 7 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Num_of_Delayed_Payment    11513 non-null  int64  
 1   Late_Payments_Count       11513 non-null  int64  
 2   Credit_Utilization_Ratio  11513 non-null  float64
 3   Credit_History_Length     11513 non-null  int64  
 4   Payment_trends            11513 non-null  int64  
 5   Total_EMI_per_month       11513 non-null  float64
 6   Outstanding_Debt          11513 non-null  float64
dtypes: float64(3), int64(4)
memory usage: 629.7 KB
```

1. Assign weights to each feature

In [ ]:

```python
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler


# Normalize the selected features to a range of 0 to 1
scaler = MinMaxScaler()
df_normalized = pd.DataFrame(scaler.fit_transform(df_selected), columns=features)

# Add Customer_ID to the normalized dataframe for later aggregation
df_normalized['Customer_ID'] = df['Customer_ID']


# Assign weights to each feature
weights = {
    'Num_of_Delayed_Payment': 0.3,
    'Outstanding_Debt': 0.1,
    'Credit_Utilization_Ratio': 0.2,
    'Credit_History_Length': 0.1,
    'Payment_trends': 0.3
}

# Calculate the weighted sum for the credit score
df_normalized['Credit_Score'] = (
    df_normalized['Num_of_Delayed_Payment'] * weights['Num_of_Delayed_Payment'] +
    df_normalized['Outstanding_Debt'] * weights['Outstanding_Debt'] +
    df_normalized['Credit_Utilization_Ratio'] * weights['Credit_Utilization_Ratio']
    df_normalized['Credit_History_Length'] * weights['Credit_History_Length'] +
    df_normalized['Payment_trends'] * weights['Payment_trends']
)


df_normalized['Credit_Score'] = 300 + df_normalized['Credit_Score'] * 550

# Aggregate the credit scores by Customer_ID (if needed)
customer_credit_scores = df_normalized.groupby('Customer_ID')['Credit_Score'].mean(

# Sort customers by credit score
customer_credit_scores = customer_credit_scores.sort_values(by='Credit_Score', asce

customer_credit_scores.head(30)
```

Out[ ]:

	Customer_ID	Credit_Score
981	CUS_0x92ef	706.934379
1424	CUS_0xed3	706.394991
377	CUS_0x437c	701.382163
666	CUS_0x6895	700.993796
160	CUS_0x28ec	696.796772
1109	CUS_0xa2f7	695.450993
516	CUS_0x55e4	690.963890
141	CUS_0x271e	690.445341
818	CUS_0x7c21	690.119654
986	CUS_0x93bb	688.509052
369	CUS_0x42ac	688.305881
929	CUS_0x8bae	687.842016
520	CUS_0x564a	687.551129
775	CUS_0x7620	687.441152
844	CUS_0x7fe3	685.062766
88	CUS_0x1e9b	684.858889
1279	CUS_0xb6ad	684.001637
1062	CUS_0x9d7	683.812669
562	CUS_0x5bb9	682.862358
111	CUS_0x232b	682.733720
1436	CUS_0xfdd	681.564923
370	CUS_0x42fb	681.390473
595	CUS_0x6015	680.811403
423	CUS_0x4948	680.800939
589	CUS_0x5f36	680.697945
106	CUS_0x2242	680.495056
771	CUS_0x7590	679.415305
892	CUS_0x87ba	679.136144
535	CUS_0x5793	678.975485
846	CUS_0x804	678.395316

1. Assign Credit Score Labels

In [ ]:

```
# Define bins for categorizing credit scores
bins = [300, 579, 669, 739, 799, 850]
labels = ['Poor', 'Fair', 'Good', 'Very Good', 'Excellent']

# Assign labels based on the credit score
```

```
df_normalized['Credit_Rating'] = pd.cut(df_normalized['Credit_Score'], bins=bins, l
df_normalized.head(20)
```

Out[ ]:

	Num_of_Delayed_Payment	Late_Payments_Count	Credit_Utilization_Ratio	Credit_History_Length
0	0.322581	0.250000	0.222941	0.344913
1	0.225806	0.142857	0.394676	0.342432
2	0.322581	0.250000	0.282844	0.339950
3	0.225806	0.142857	0.375663	0.337469
4	0.225806	0.142857	0.155041	0.334988
5	0.225806	0.142857	0.237681	0.332506
6	0.354839	0.285714	0.079279	0.330025
7	0.290323	0.214286	0.126089	0.327543
8	0.225806	0.142857	0.143866	0.210918
9	0.129032	0.035714	0.616149	0.208437
10	0.064516	0.000000	0.437590	0.205955
11	0.193548	0.107143	0.637331	0.203474
12	0.129032	0.035714	0.496360	0.200993
13	0.096774	0.000000	0.442822	0.198511
14	0.225806	0.142857	0.367410	0.196030
15	0.225806	0.142857	0.427830	0.193548
16	0.354839	0.285714	0.283092	0.473945
17	0.290323	0.214286	0.721815	0.471464
18	0.322581	0.250000	0.212789	0.468983
19	0.258065	0.178571	0.648026	0.466501

1. Analyze and Visualize the Results

In [ ]:

```
# Display summary statistics of the credit scores
print(df_normalized['Credit_Score'].describe())
```

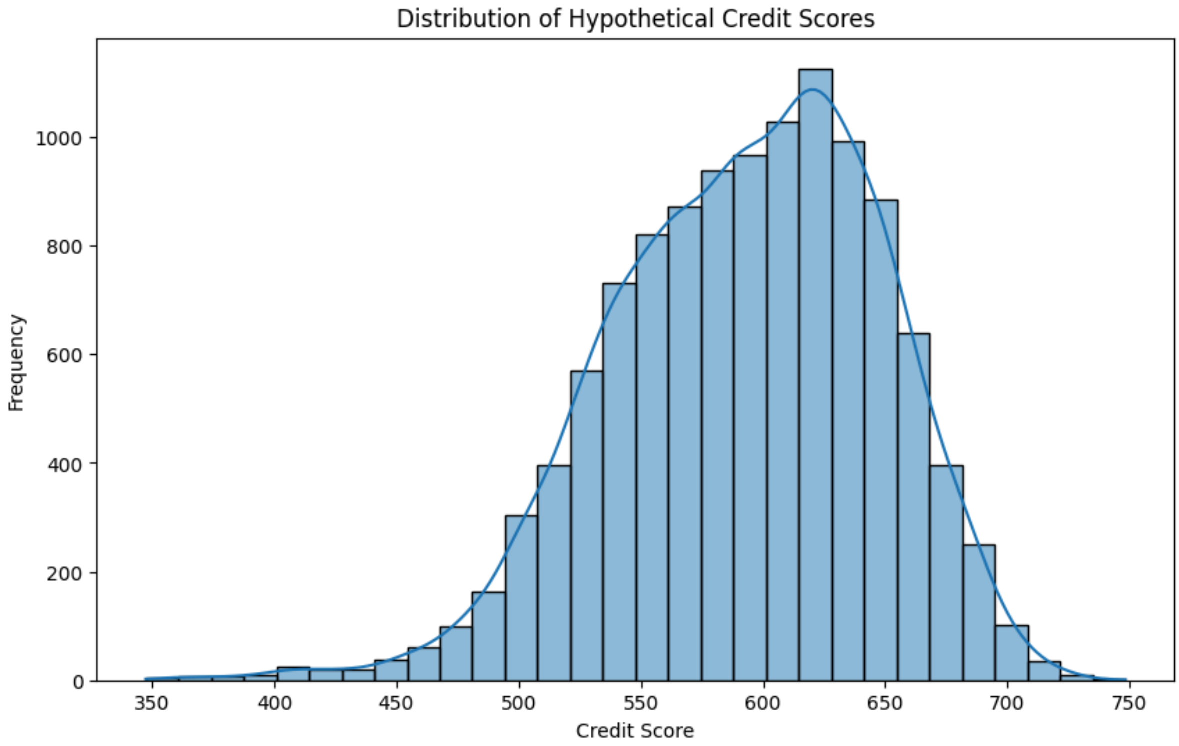
```
count    11513.000000
mean       592.787108
std         54.858675
min        347.489730
25%        554.703011
50%        597.202021
75%        633.437477
max        748.277889
Name: Credit_Score, dtype: float64
```

Plot the distribution of credit scores

In [ ]:

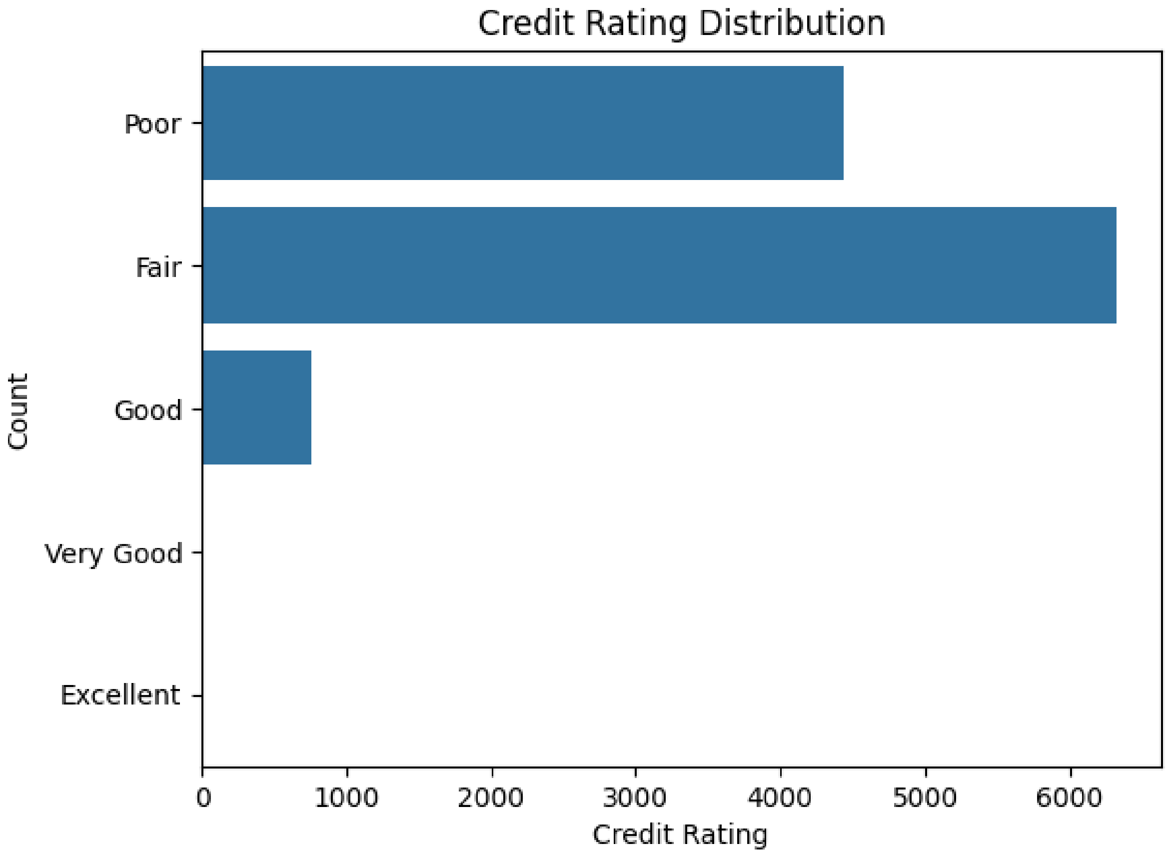
```
plt.figure(figsize=(10, 6))
sns.histplot(df_normalized['Credit_Score'], bins=30, kde=True)
```

```
plt.title('Distribution of Hypothetical Credit Scores')
plt.xlabel('Credit Score')
plt.ylabel('Frequency')
plt.show()
```



Count of each credit rating

In [ ]:
```
sns.countplot(df_normalized['Credit_Rating'])
plt.title('Credit Rating Distribution')
plt.xlabel('Credit Rating')
plt.ylabel('Count')
plt.show()
```



Insights and Recommendations

 # Key insights

1. Distribution of Annual Income is right-skewed.
2. There is a positive correlation between Annual Income and Monthly Inhand Salary.
3. High number of delayed payments are associated with higher interest rates.
4. Occupation seems to have a significant impact on Annual Income.

5. Delayed Payments and Late Payments: Customers with a higher number of delayed payments and late payments generally have lower credit scores. For example, a customer with Num_of_Delayed_Payment and Late_Payments_Count both being high tends to have a lower credit score.

6. Credit Utilization Ratio: The credit utilization ratio seems to play a significant role in determining the credit score. Higher credit utilization ratios are often associated with lower credit scores.

7. Credit History Length: Customers with longer credit histories tend to have better credit scores. For instance, a customer with a credit history length closer to 0.5 (normalized value) generally has a higher score.

8. Outstanding Debt: The amount of outstanding debt also impacts the credit score. Customers with lower outstanding debt tend to have higher credit scores, which indicates better financial management.

9. Annual Income Outliers: There are several outliers above the upper whisker. These represent individuals with significantly higher annual incomes compared to the rest of the population.
10. The compact distribution of Outstanding_Debt suggests that debt levels are more consistent across individuals, possibly indicating that debt is managed similarly by most people in this dataset.

Recommendations:

1. Improve Payment Timeliness:

Customers should focus on making timely payments to reduce the number of delayed payments and late payments. This can significantly improve their credit scores.

1. Manage Credit Utilization: Customers should aim to keep their credit utilization ratio low. A utilization ratio below 30% is generally recommended to maintain a good credit score.

2. Extend Credit History: Customers with shorter credit histories should focus on maintaining open and active accounts over time. The length of credit history is a key factor in improving credit scores.

3. Reduce Outstanding Debt: Customers should work on reducing their outstanding debt. Lower debt levels not only improve credit scores but also reflect better financial stability.

4. Personalized Financial Advice: Offering personalized financial advice based on individual credit score components could help customers understand the specific areas they need to work on to improve their credit ratings.

5. Monitor Payment Behavior: Regular monitoring and analysis of payment behavior trends can help identify customers at risk of falling into lower credit score categories, enabling early interventions.

By focusing on these recommendations, customers can work towards improving their credit scores, leading to better credit ratings and access to more favorable financial opportunities.