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

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

```
display(df.head())
```

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Num_
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3	...	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3	...	
2	0x1604	CUS_0xd40	March	Aaron Maashoh	-500	821-00-0265	Scientist	19114.12	NaN	3	...	
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3	...	
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3	...	

5 rows × 27 columns

```
df.shape
```

```
(100000, 27)
```

```
df.info()
```

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

```
df.drop(['ID'],axis=1,inplace=True)
```

```
# Apply split() to extract the number of years from the 'Credit_History_Age' column
df['Credit_History_Age'] = df['Credit_History_Age'].apply(lambda x: int(x.split()[0]) if pd.notnull(x) else 0)
# Calculate the mode of the 'Type_of_Loan' column
```

```
mode_type_of_loan = df['Type_of_Loan'].mode()[0]

# Fill the missing values in the 'Type_of_Loan' column with the mode
df['Type_of_Loan'].fillna(mode_type_of_loan, inplace=True)
```

```
# Convert numerical columns that are currently of type 'object' to numeric, forcing errors to NaN
df['Age'] = pd.to_numeric(df['Age'], errors='coerce')
df['Annual_Income'] = pd.to_numeric(df['Annual_Income'], errors='coerce')
df['Num_of_Loan'] = pd.to_numeric(df['Num_of_Loan'], errors='coerce')
df['Outstanding_Debt'] = pd.to_numeric(df['Outstanding_Debt'], errors='coerce')
df['Amount_invested_monthly'] = pd.to_numeric(df['Amount_invested_monthly'], errors='coerce')
df['Num_of_Delayed_Payment'] = pd.to_numeric(df['Num_of_Delayed_Payment'], errors='coerce')
df['Monthly_Balance'] = pd.to_numeric(df['Monthly_Balance'], errors='coerce')
```

```
# Replace negative values in the selected columns with 0
df[['Num_of_Loan', 'Delay_from_due_date', 'Num_of_Delayed_Payment']] = df[['Num_of_Loan', 'Delay_from_due_date', 'Num_of_Delayed_Paymen
```

Credit Score based on 3m and 6months for each *customer*

```
# Create a mapping of month names to month numbers
month_mapping = {
    'January': 1, 'February': 2, 'March': 3, 'April': 4,
    'May': 5, 'June': 6, 'July': 7, 'August': 8,
    'September': 9, 'October': 10, 'November': 11, 'December': 12
}

# Convert month names to month numbers
df['Month_Number'] = df['Month'].map(month_mapping)

# Define a function to filter and calculate aggregated features
def calculate_aggregated_features(data, start_month, end_month):
    filtered_data = data[
        (data['Month_Number'] >= start_month) &
        (data['Month_Number'] <= end_month)
    ]

    agg_features = filtered_data.groupby('Customer_ID').agg(
        Total_Loan_Amount=('Num_of_Loan', 'sum'),
        Total_Delayed_Payments=('Num_of_Delayed_Payment', 'sum'),
        Total_Outstanding_Debt=('Outstanding_Debt', 'sum'),
        Average_Credit_Utilization=('Credit_Utilization_Ratio', 'mean'),
        Total_EMI=('Total_EMI_per_month', 'sum'),
        Average_Age=('Age', 'mean'),
        Monthly_Inhand_Salary=('Monthly_Inhand_Salary', 'mean')
    ).reset_index()
    return agg_features

# Calculate aggregated features for the last 3 and 6 months
agg_3m = calculate_aggregated_features(df, 1, 3)  # Last 3 months: Feb, Mar, Apr
agg_6m = calculate_aggregated_features(df, 1, 6)  # Last 6 months: Jan, Feb, Mar, Apr

# Hypothetical Credit Score Calculation
def calculate_credit_score(aggregated_df):
    weights = {
        'Total_Loan_Amount': 0.2,
        'Total_Delayed_Payments': -0.2,
        'Total_Outstanding_Debt': -0.2,
        'Average_Credit_Utilization': -0.2,
        'Total_EMI': 0.2,
        'Average_Age': 0.1,
        'Monthly_Inhand_Salary': 0.1
    }

    # Calculate the credit score for each feature based on the defined weights
    for feature, weight in weights.items():
        aggregated_df[f'Credit_Score_{feature}'] = aggregated_df[feature] * weight

    # Sum the individual credit scores to get the total credit score
    aggregated_df['Total_Credit_Score'] = aggregated_df[[f'Credit_Score_{feature}' for feature in weights]].sum(axis=1)

    # Scale the credit score to be between 0 and 1000
    max_score = aggregated_df['Total_Credit_Score'].max()
    min_score = aggregated_df['Total_Credit_Score'].min()
    aggregated_df['Total_Credit_Score'] = ((aggregated_df['Total_Credit_Score'] - min_score) / (max_score - min_score)) * 900

    return aggregated_df

# Calculate credit scores for aggregated data
agg_3m_with_score = calculate_credit_score(agg_3m)
```

```
agg_6m_with_score = calculate_credit_score(agg_6m)

# Merge scores into a single DataFrame for final output
final_output = pd.merge(
    agg_3m_with_score[['Customer_ID', 'Total_Credit_Score']],
    agg_6m_with_score[['Customer_ID', 'Total_Credit_Score']],
    on='Customer_ID',
    suffixes=('_3m', '_6m')
)

final_output.columns = ['Customer_ID', 'Credit_Score_Last_3_Months', 'Credit_Score_Last_6_Months']

print("Final Credit Scores for Each Customer_ID:")
print(final_output)
```

```
Final Credit Scores for Each Customer_ID:
      Customer_ID  Credit_Score_Last_3_Months  Credit_Score_Last_6_Months
0      CUS_0x1000                   57.104171                   76.873108
1      CUS_0x1009                   71.753194                  106.437240
2      CUS_0x100b                   78.643136                   98.185733
3      CUS_0x1011                   78.276402                  104.642421
4      CUS_0x1013                   75.601330                   96.147523
...           ...                         ...                         ...
12495   CUS_0xff3                   58.301028                   81.166023
12496   CUS_0xff4                   67.641912                   93.708738
12497   CUS_0xff6                   89.841464                  114.828256
12498   CUS_0xffc                   69.226254                   91.068894
12499   CUS_0xffd                   59.682442                   78.991650

[12500 rows x 3 columns]
```

```
def get_next_max_value(series, exclude_value):
    # Get value counts
    counts = series.value_counts()

    # Check if the most frequent value is the excluded one
    if counts.idxmax() == exclude_value:
        # Remove the excluded value from the counts
        counts = counts.drop(exclude_value)

    # Return the most frequent value (or next one if excluded)
    return counts.idxmax()

def get_age(series,value):
    # Get value counts
    counts = series.value_counts()
    if counts.idxmax() < value:
        counts = counts.drop(counts.idxmax())
    return counts.idxmax()
```

```
# Aggregating the DataFrame by Customer_ID
df_agg = df.groupby('Customer_ID').agg({
    'Name': lambda x: x.value_counts().idxmax(),      # Take mode of Name
    'Age': lambda x: get_age(x,1),                          # Take maximum Age
    'SSN': lambda x: x.value_counts().idxmax(),       # Take mode of SSN
    'Occupation': lambda x: get_next_max_value(x, '_______'),  # Take mode of Occupation
    'Annual_Income': lambda x: x.value_counts().idxmax(),  # Take mode of Annual Income
    'Monthly_Inhand_Salary': lambda x: x.value_counts().idxmax(),       # Take mean of Monthly Inhand Salary
    'Num_Bank_Accounts': 'max',            # Take max of Num_Bank_Accounts
    'Num_Credit_Card': 'max',              # Take max of Num_Credit_Card
    'Interest_Rate':lambda x: x.value_counts().idxmax(),               # Mean of Interest Rate
    'Num_of_Loan': 'max',                  # Take max of Num_of_Loan
    'Type_of_Loan':lambda x: x.mode()[0] if not x.mode().empty else np.nan,   # Take mode of Type_of_Loan
    'Delay_from_due_date': 'mean',         # Mean of Delay from due date
    'Num_of_Delayed_Payment': 'mean',      # Mean of Num_of_Delayed_Payment
    'Changed_Credit_Limit': 'max',         # Take max of Changed_Credit_Limit
    'Num_Credit_Inquiries': 'mean',        # Mean of Num_Credit_Inquiries
    'Credit_Mix':lambda x: x.value_counts().idxmax(),     # Take mode of Credit Mix
    'Outstanding_Debt': 'mean',            # Mean of Outstanding Debt
    'Credit_Utilization_Ratio': 'mean',    # Mean of Credit Utilization Ratio
    'Credit_History_Age': 'max',           # Take max of Credit History Age
    'Payment_of_Min_Amount': 'first',      # Take first of Payment_of_Min_Amount
    'Total_EMI_per_month': 'mean',         # Mean of Total EMI per month
    'Amount_invested_monthly': 'mean',     # Mean of Amount invested monthly
    'Payment_Behaviour': lambda x: x.value_counts().idxmax(),  # Take mode of Payment_Behaviour
    'Monthly_Balance': 'mean'              # Mean of Monthly Balance
})


# Resetting the index to get Customer_ID as a column
df_agg.reset_index(inplace=True)
```

```
# Show the aggregated DataFrame
df_agg.head()
```

	Customer_ID	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Inter
0	CUS_0x1000	Alistair Barrf	17.0	913-74-1218	Lawyer	30625.94	2706.161667	6	5	
1	CUS_0x1009	Arunah	26.0	063-67-6938	Mechanic	52312.68	4250.390000	6	5	
2	CUS_0x100b	Shirboni	18.0	238-62-0395	Media_Manager	113781.39	9549.782500	1	4	
3	CUS_0x1011	Schneyerh	44.0	793-05-8223	Doctor	58918.47	5208.872500	3	3	
4	CUS_0x1013	Cameront	44.0	930-49-9615	Mechanic	98620.98	7962.415000	3	3	

5 rows × 25 columns

```
df_agg.describe()
```

	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Num_of_Loan	Delay_fro
count	12500.000000	12500.000000	12500.000000	12500.000000	12500.000000	12500.000000	12500.000000	1:
mean	33.282000	50505.123449	4199.448777	96.400720	134.307280	14.532080	29.501360	
std	10.766945	38300.762656	3188.435232	317.256981	336.763023	8.741636	159.361136	
min	14.000000	7005.930000	303.645417	0.000000	1.000000	1.000000	0.000000	
25%	24.000000	19342.972500	1628.239792	4.000000	4.000000	7.000000	2.000000	
50%	33.000000	36999.705000	3095.941666	6.000000	6.000000	13.000000	3.000000	
75%	42.000000	71683.470000	5962.529583	8.000000	9.000000	20.000000	6.000000	
max	56.000000	179987.280000	15204.633330	1798.000000	1499.000000	34.000000	1496.000000	

```
df_agg.isnull().sum()
```

	0
Customer_ID	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

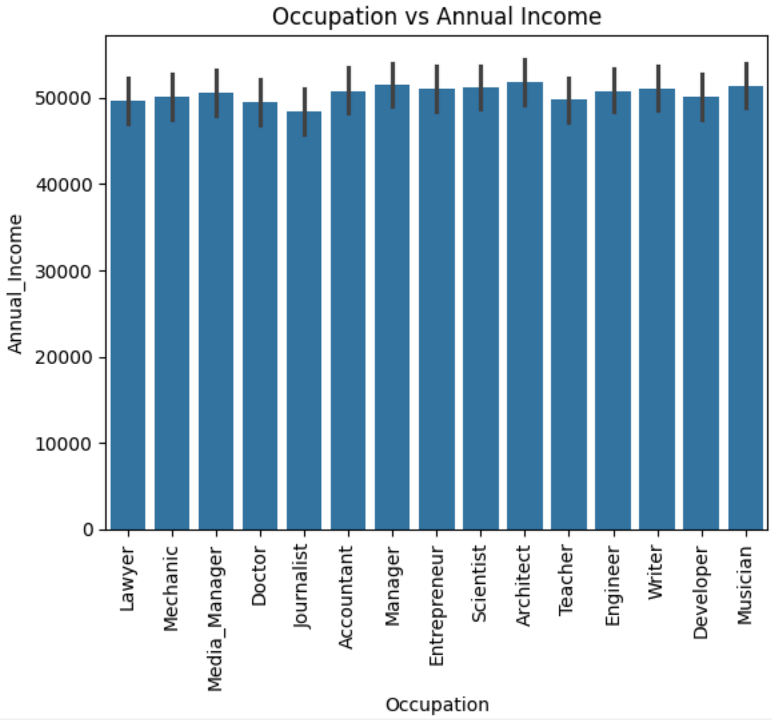
dtype: int64

```
df_agg.columns
```

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

```
df =df_agg.drop_duplicates()
```

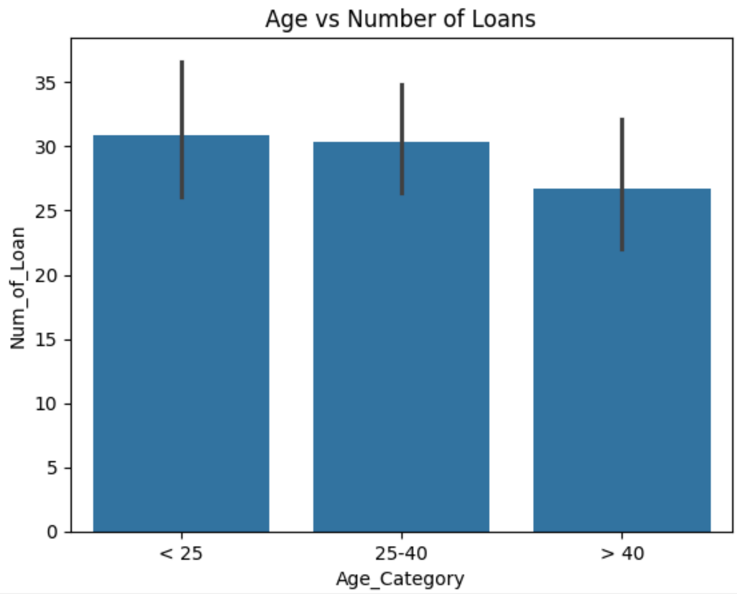
```
# 1. Occupation vs Annual Income
sns.barplot(x='Occupation', y='Annual_Income', data=df_agg)
plt.xticks(rotation=90)
plt.title('Occupation vs Annual Income')
plt.show()
```



Insights : Seems occupation is not influencing Annual Income

```
# Define bins and labels
bins = [-float('inf'), 25, 40, float('inf')]
labels = ['< 25', '25-40', '> 40']

# Create a new column for Age Categories
df_agg['Age_Category'] = pd.cut(df_agg['Age'], bins=bins, labels=labels)
```

```
# 2. Age vs Number of Loans
sns.barplot(x='Age_Category', y='Num_of_Loan', data=df_agg)
plt.title('Age vs Number of Loans')
plt.show()
```

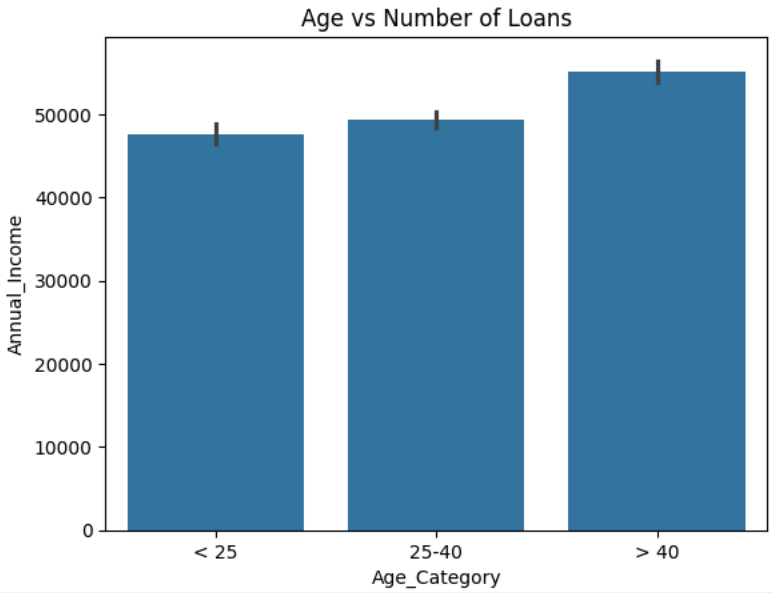


Insights:

1. Customers are age <40 are having more number of loans
2. Age >40 are having less number of loans

```
# 3. Age vs Number of Loans
sns.barplot(x='Age_Category', y='Annual_Income', data=df_agg)
```

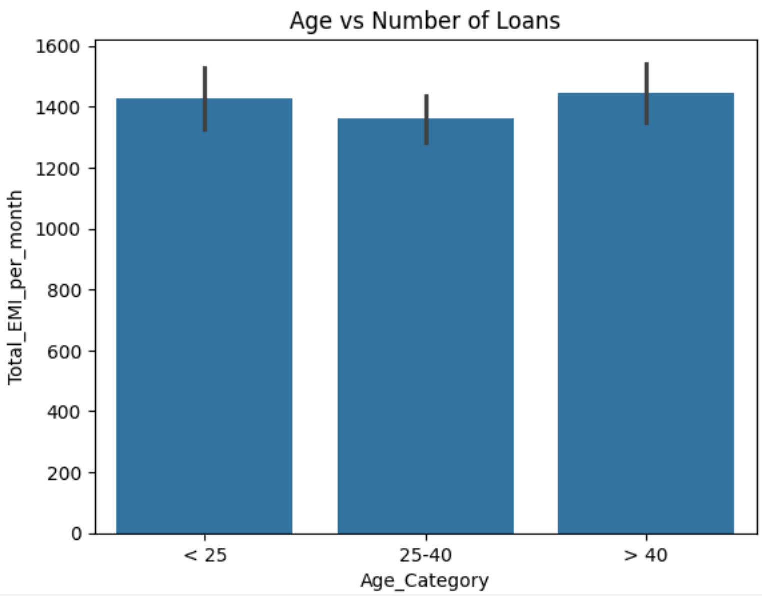
```
plt.title('Age vs Number of Loans')
plt.show()
```



Insights:

- customers age <= 40 their salary is closer
- but customers age > 40 having higher salary and less no of loans

```
# 4. Age vs Number of Loans
sns.barplot(x='Age_Category', y='Total_EMI_per_month', data=df_agg)
plt.title('Age vs Number of Loans')
plt.show()
```



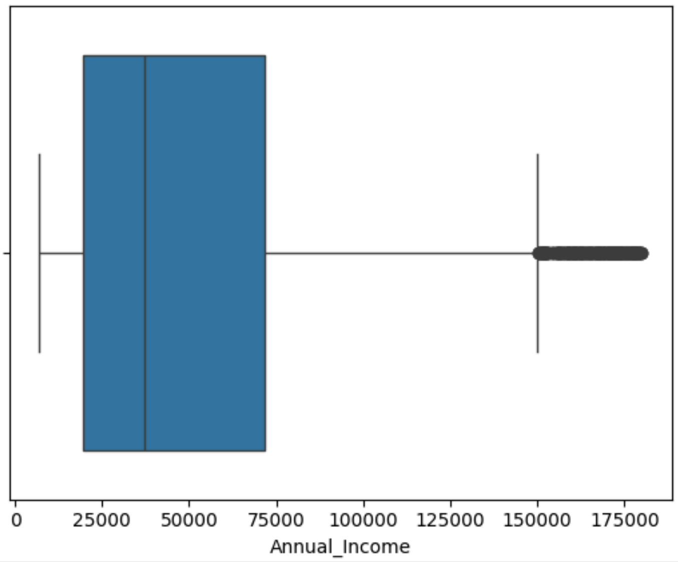
Insights:

- customers age < 25 and >40 are having similar EMI range
- But customers with age >40 are having less number of loans and higher salary

Recommendations :

- Customers with age < 25 having less EMI and less loans we can focus to saction loans
- customers age > 40 are having less EMI can also focus giving short loan
- customers < 25 we can offer long term loans

```
# Box plot for outlier detection
sns.boxplot(x='Annual_Income', data=df)
plt.show()
```




```
df['Debt_to_Income_Ratio'] = df['Outstanding_Debt'] / df['Annual_Income']
```

```
# Flag for bad payment behavior
df['Bad_Payment_Behaviour'] = df['Payment_Behaviour'].apply(lambda x: 1 if 'Delayed' in x else 0)
```

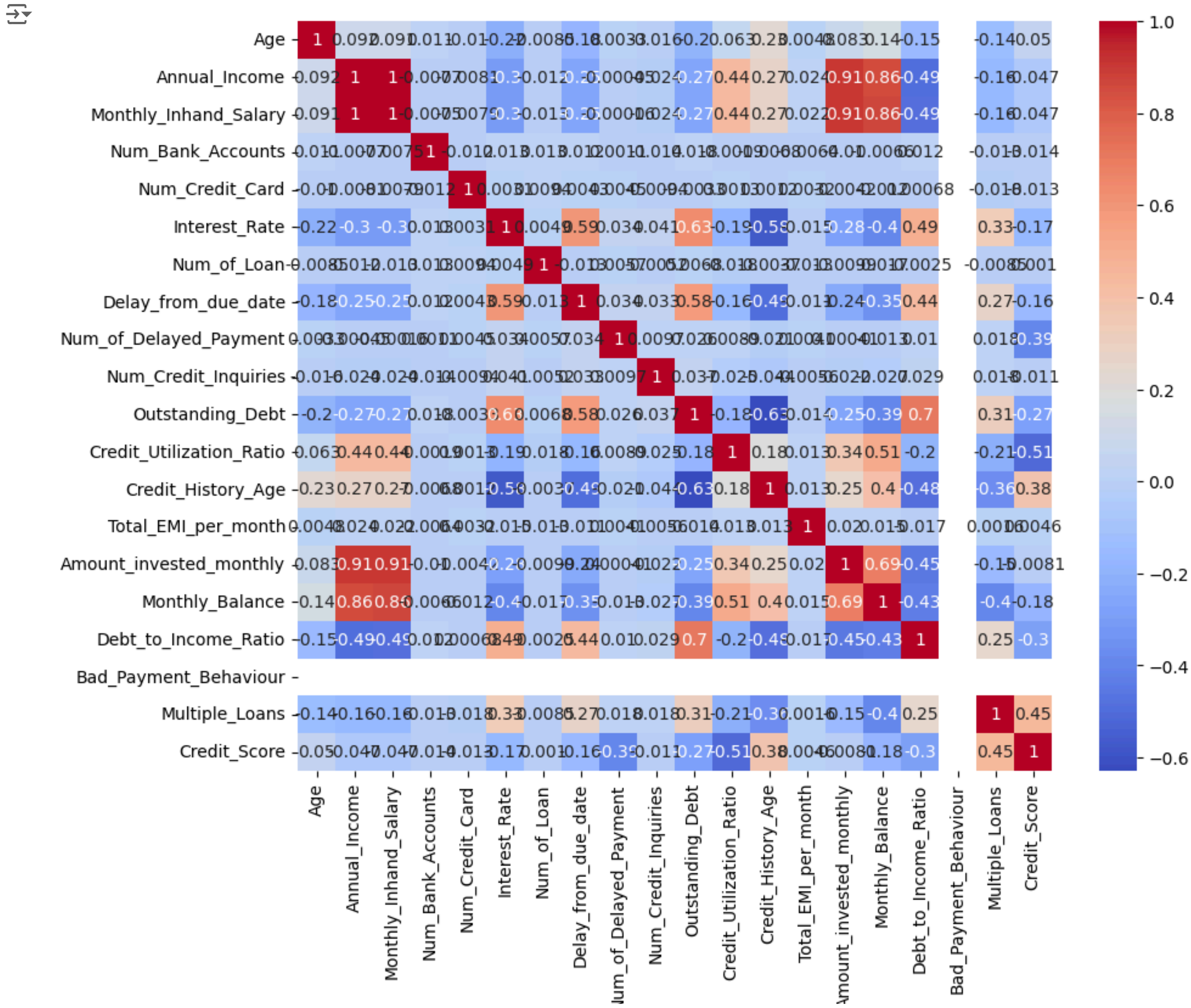
```
# Create flag if person has more than one type of loan
df['Multiple_Loans'] = df['Type_of_Loan'].apply(lambda x: 1 if len(x.split(',')) > 1 else 0)
```

Double-click (or enter) to edit

```
# Normalize the features
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

df[['Credit_Utilization_Ratio', 'Num_of_Delayed_Payment', 'Debt_to_Income_Ratio',
    'Credit_History_Age']] = scaler.fit_transform(df[['Credit_Utilization_Ratio',
    'Num_of_Delayed_Payment', 'Debt_to_Income_Ratio', 'Credit_History_Age']])

# Define weights for each factor
df['Credit_Score'] = (0.35 * (1 - df['Num_of_Delayed_Payment']) +
                      0.30 * (1 - df['Credit_Utilization_Ratio']) +
                      0.15 * df['Credit_History_Age'] +
                      0.15 * (1 - df['Debt_to_Income_Ratio']) +
                      0.10 * df['Multiple_Loans']) * 900

# Display the final score
print(df[['Customer_ID', 'Credit_Score']])
```

```
      Customer_ID  Credit_Score
0      CUS_0x1000    706.278457
1      CUS_0x1009    802.106509
2      CUS_0x100b    628.100067
3      CUS_0x1011    831.155563
4      CUS_0x1013    771.710367
...           ...           ...
12495   CUS_0xff3    744.558451
12496   CUS_0xff4    760.824332
12497   CUS_0xff6    782.334585
12498   CUS_0xffc    706.955371
12499   CUS_0xffd    769.959474

[12500 rows x 2 columns]
```

```
#5. correlation Heatmap
df_numeric = df.select_dtypes(include=['int64', 'float64'])
plt.figure(figsize=(10,8))
sns.heatmap(df_numeric.corr(), annot=True, cmap='coolwarm')
plt.show()
```



To calculate a hypothetical credit score, consider these factors (inspired by FICO scoring):

1. Credit Utilization (30%): Use Credit_Utilization_Ratio.