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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.

Exploratory Data Analysis (EDA):

```
# Importing the dataset
import pandas as pd
credit_data_df = pd.read_csv("/content/Credit_score.csv")
credit_data_df.sample(5)
```

```
<ipython-input-3-fa29643ea27d>:3: DtypeWarning: Columns (26) have mix
  credit_data_df = pd.read_csv("/content/Credit_score.csv")
```

	ID	Customer_ID	Month	Name	Age	SSN	Occ
75037	0x1cdab	CUS_0x8bc6	June	Deepa Seetharamann	18	#F%$D@*&8	
68421	0x1a6e7	CUS_0x7c58	June	NaN	29	531-98-6283	
96124	0x2493a	CUS_0xa74e	May	Tim Reidz	30	108-21-3481	
13476	0x64f6	CUS_0x4ff7	May	Chatterjeem	14	366-35-7290	
77902	0x1de74	CUS_0x251e	July	Simon Meadsk	53	744-90-4909	Media_

5 rows × 27 columns

```
# Display the shape of the dataset
dataset_shape = credit_data_df.shape
print(f"Dataset Shape: {dataset_shape}")

# Display column types
print("\nColumn Types:\n")
print(credit_data_df.dtypes)
```

```
Dataset Shape: (100000, 27)

Column Types:

ID                           object
Customer_ID                  object
Month                        object
Name                         object
Age                          object
SSN                          object
Occupation                   object
Annual_Income                object
Monthly_Inhand_Salary       float64
Num_Bank_Accounts             int64
Num_Credit_Card               int64
Interest_Rate                 int64
Num_of_Loan                  object
Type_of_Loan                 object
Delay_from_due_date           int64
Num_of_Delayed_Payment       object
Changed_Credit_Limit         object
Num_Credit_Inquiries        float64
Credit_Mix                   object
Outstanding_Debt             object
Credit_Utilization_Ratio    float64
Credit_History_Age           object
Payment_of_Min_Amount        object
Total_EMI_per_month         float64
Amount_invested_monthly      object
Payment_Behaviour            object
Monthly_Balance              object
dtype: object
```

Insights from the Basic EDA:

Dataset Shape: The dataset contains 100,000 rows and 27 columns, indicating a large number of records with various attributes related to customer credit information.

Column Types: Most of the columns are object types, especially for categorical features such as ID, Customer_ID, Credit_Mix, and Payment_Behaviour. There are some columns with float and int types, particularly for numerical fields like Monthly_Inhand_Salary, Num_Bank_Accounts, Interest_Rate, etc.

```
# Checking for missing values in the dataset
missing_values = credit_data_df.isnull().sum()
missing_values = missing_values[missing_values > 0]  # Only display colu
missing_values
```

	0
Name	9985
Monthly_Inhand_Salary	15002
Type_of_Loan	11408
Num_of_Delayed_Payment	7002
Num_Credit_Inquiries	1965
Credit_History_Age	9030
Amount_invested_monthly	4479
Monthly_Balance	1200

dtype: int64

Insights:

Name: 9,985 missing values. Since names are not likely to provide direct insights into creditworthiness, these missing values can be safely ignored or dropped.

Monthly_Inhand_Salary: 15,002 missing values. This is an important feature for credit score calculation. Imputing missing values using the mean or median salary based on occupation or customer segment.

Type_of_Loan: 11,408 missing values. Understanding the types of loans customers have can influence credit scoring, so we can consider filling in these missing values based on the customer's previous loan types or flagging them as unknown.

Num_of_Delayed_Payments: 7,002 missing values. Delayed payments are crucial for determining credit behavior. Missing values should be filled with a default value like 0, indicating no delays.

Num_Credit_Inquiries: 1,965 missing values. Imputation with the median number of inquiries or a default of 0 could be applied here.

Credit_History_Age: 9,030 missing values. Since credit history is an important predictor of risk, imputing based on available customer data or categorizing missing values separately (as unknown) may work.

Amount_invested_Monthly: 4,479 missing values. This feature is tied to investment behavior and could be imputed based on the customer's income level or dropped if less relevant to the analysis.

Monthly_Balance: 1,200 missing values. Impute with the median or average based on similar customers.

```
# Summary statistics for numerical columns
numerical_summary = credit_data_df.describe()
numerical_summary
```

	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Inte
count	84998.000000	100000.000000	100000.00000	10
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	5

Insights:

Income: The annual income varies widely, and some extreme outliers may skew the data.

Interest_Rate: The standard deviation of the interest rate is extremely high, suggesting errors in the data.

Credit_Utilization_Ratio: This feature is well-distributed, with values between 20 and 50%. This ratio directly impacts the hypothetical credit score calculation.

EMI_per_Month: A high standard deviation (8,306) indicates significant variation in customer loans, which may be due to a few outliers (e.g., very large loans).

```
# Check unique values in categorical columns
categorical_columns = ['Credit_Mix', 'Payment_of_Min_Amount', 'Payment_B
categorical_summary = {col: credit_data_df[col].unique() for col in cate
categorical_summary
```

```
{'Credit_Mix': array(['_', 'Good', 'Standard', 'Bad'],
dtype=object),
 'Payment_of_Min_Amount': array(['No', 'NM', 'Yes'], dtype=object),
 'Payment_Behaviour': array(['High_spent_Small_value_payments',
        'Low_spent_Large_value_payments',
        'Low_spent_Medium_value_payments',
        'Low_spent_Small_value_payments',
        'High_spent_Medium_value_payments', '!@9#%8',
        'High_spent_Large_value_payments'], dtype=object)}
```

Insights:

Credit_Mix: Contains categories: Good, Standard, Bad, and _ (missing values). Credit mix is a strong indicator of risk, so converting _ values to "Unknown" may help in model creation.

Payment_of_Min_Amount: Categories include Yes, No, and NM. NM could be unclear and might need to be redefined as "Not Mentioned" or another logical default based on context.

Payment_Behavior: One entry, !@9#%8, seems to be a data error and should be corrected or replaced. Payment behavior patterns are crucial for identifying credit risks, so categorization needs to be clean.

Handling Missing Data Strategy:

Name: Since names do not influence the analysis, we can drop this column as it is irrelevant.

Monthly_Inhand_Salary: This is an important column. We will impute the missing values with the median salary since it's robust to outliers.

Type_of_Loan: Since it's categorical, we can impute missing values with a placeholder, such as "Unknown".

Num_of_Delayed_Payments: This is important for credit analysis. Missing values can be filled with 0, indicating no delayed payments.

Num_Credit_Inquiries: We can fill missing values with the median number of inquiries, assuming a standard behavior.

Credit_History_Age: Another important factor for credit score. We will impute missing values with "Unknown" as a category.

Amount_Invested_Monthly: This feature can be imputed with the median value, given its financial importance.

Monthly_Balance: Missing values here will also be imputed with the median value to retain numerical continuity.

```
# Drop 'Name' column as it is irrelevant
credit_data_df = credit_data_df.drop(columns=['Name'])

# Impute missing values for 'Monthly_Inhand_Salary' with the median
credit_data_df['Monthly_Inhand_Salary'] = credit_data_df['Monthly_Inhand_

# Impute missing values for 'Type_of_Loan' with 'Unknown'
credit_data_df['Type_of_Loan'] = credit_data_df['Type_of_Loan'].fillna('

# Impute missing values for 'Num_of_Delayed_Payment' with 0
credit_data_df['Num_of_Delayed_Payment'] = credit_data_df['Num_of_Delaye

# Impute missing values for 'Num_Credit_Inquiries' with the median
credit_data_df['Num_Credit_Inquiries'] = credit_data_df['Num_Credit_Inqu

# Impute missing values for 'Credit_History_Age' with 'Unknown'
credit_data_df['Credit_History_Age'] = credit_data_df['Credit_History_Ag
```

```
# Convert 'Amount_invested_monthly' to numeric, coercing invalid values 
credit_data_df['Amount_invested_monthly'] = pd.to_numeric(credit_data_df
# Impute missing values for 'Amount_invested_monthly' with the median
credit_data_df['Amount_invested_monthly'] = credit_data_df['Amount_inves

# Convert 'Amount_invested_monthly' to numeric, coercing invalid values 
credit_data_df['Monthly_Balance'] = pd.to_numeric(credit_data_df['Monthl
# Impute missing values for 'Monthly_Balance' with the median
credit_data_df['Monthly_Balance'] = credit_data_df['Monthly_Balance'].fi

# Verify that missing values have been handled
missing_values_after = credit_data_df.isnull().sum()
missing_values_after
```

	0
ID	0
Customer_ID	0
Month	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

Columns to Check for Outliers:

Monthly_Inhand_Salary

Interest_Rate

Outstanding_Debt

Credit_Utilization_Ratio

Total_EMI_per_month

Amount_invested_monthly

Outlier Detection Method:

Boxplot Visualization: We can use boxplots to visualize outliers.

```python
import matplotlib.pyplot as plt
import seaborn as sns

# List of numerical columns to check for outliers
numeric_cols = ['Monthly_Inhand_Salary', 'Interest_Rate', 'Outstanding_D
                'Credit_Utilization_Ratio', 'Total_EMI_per_month', 'Amou

# Plot boxplots for each numeric column to detect outliers
plt.figure(figsize=(15,10))
for i, col in enumerate(numeric_cols, 1):
    plt.subplot(2, 3, i)
    sns.boxplot(y=credit_data_df[col])
    plt.title(f'Boxplot for {col}')
plt.tight_layout()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py:640: F
  positions = grouped.grouper.result_index.to_numpy(dtype=float)
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/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py:640: F
  positions = grouped.grouper.result_index.to_numpy(dtype=float)
```
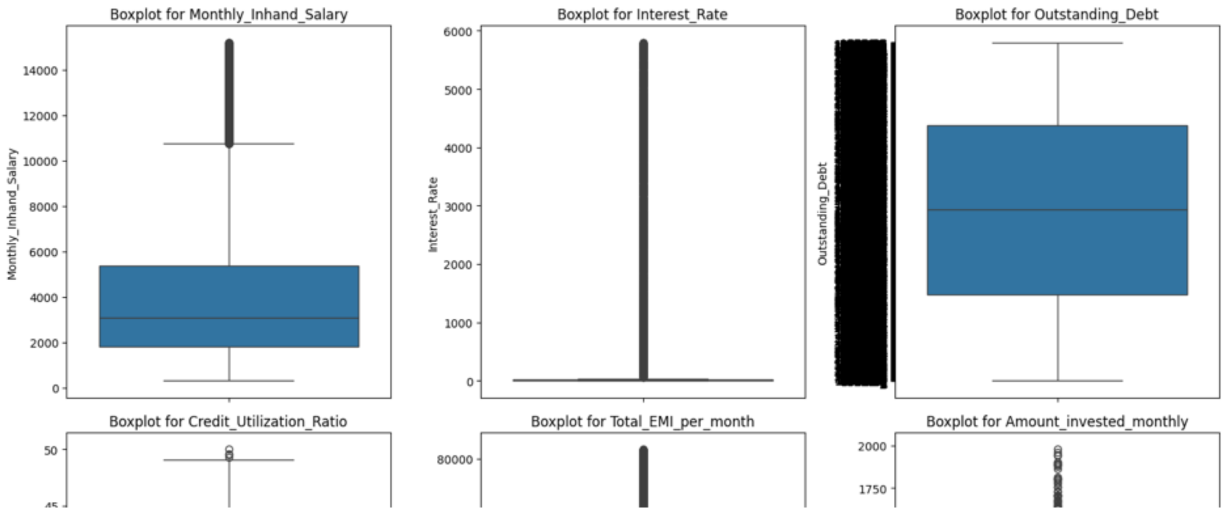



```
# Convert relevant columns to numeric before Z-score calculation
credit_data_df['Monthly_Inhand_Salary'] = pd.to_numeric(credit_data_df['I
credit_data_df['Interest_Rate'] = pd.to_numeric(credit_data_df['Interest_
credit_data_df['Outstanding_Debt'] = pd.to_numeric(credit_data_df['Outsta
credit_data_df['Credit_Utilization_Ratio'] = pd.to_numeric(credit_data_d
credit_data_df['Total_EMI_per_month'] = pd.to_numeric(credit_data_df['To
credit_data_df['Amount_invested_monthly'] = pd.to_numeric(credit_data_df

# Now proceed with Z-score method for outlier detection
from scipy import stats
import numpy as np

# Z-score method to detect outliers
outliers = {}
for col in numeric_cols:
    z_scores = np.abs(stats.zscore(credit_data_df[col].dropna()))
    outliers[col] = np.where(z_scores > 3)

# Display the outliers for each column
outlier_summary = {col: len(outlier_indices[0]) for col, outlier_indices
outlier_summary
```

```
{'Monthly_Inhand_Salary': 1414,
 'Interest_Rate': 1501,
 'Outstanding_Debt': 576,
 'Credit_Utilization_Ratio': 16,
 'Total_EMI_per_month': 2155,
 'Amount_invested_monthly': 2409}
```

Outlier Detection Results: Here's the summary of the number of outliers detected using the Z-score method (Z-score > 3):

Monthly Inhand Salary: 1,414 outliers.

Interest Rate: 1,501 outliers.

Outstanding Debt: 576 outliers.

Credit Utilization Ratio: 16 outliers (relatively few).

Total EMI per month: 2,155 outliers.

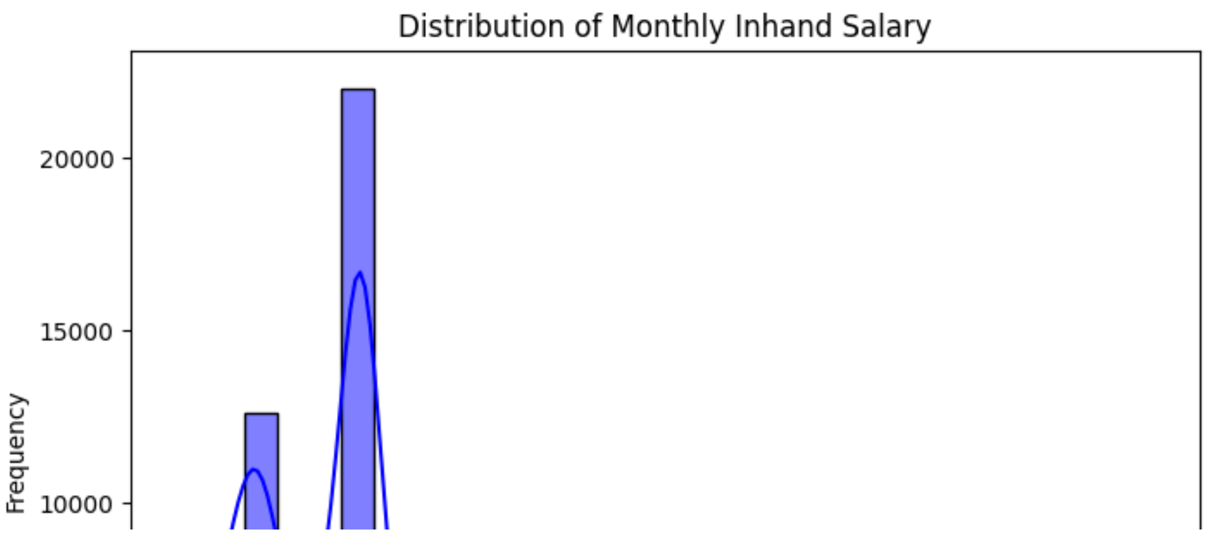
Amount Invested Monthly: 2,409 outliers.

Visual Insights (from Boxplots):

Significant outliers are present in Interest Rate, Total EMI per month, and Amount Invested Monthly. Credit Utilization Ratio has relatively fewer outliers.

Histogram for Monthly Inhand Salary

```
# Histogram for Monthly Inhand Salary
plt.figure(figsize=(8,6))
sns.histplot(credit_data_df['Monthly_Inhand_Salary'], kde=True, bins=30,
plt.title('Distribution of Monthly Inhand Salary')
plt.xlabel('Monthly Inhand Salary')
plt.ylabel('Frequency')
plt.show()
```

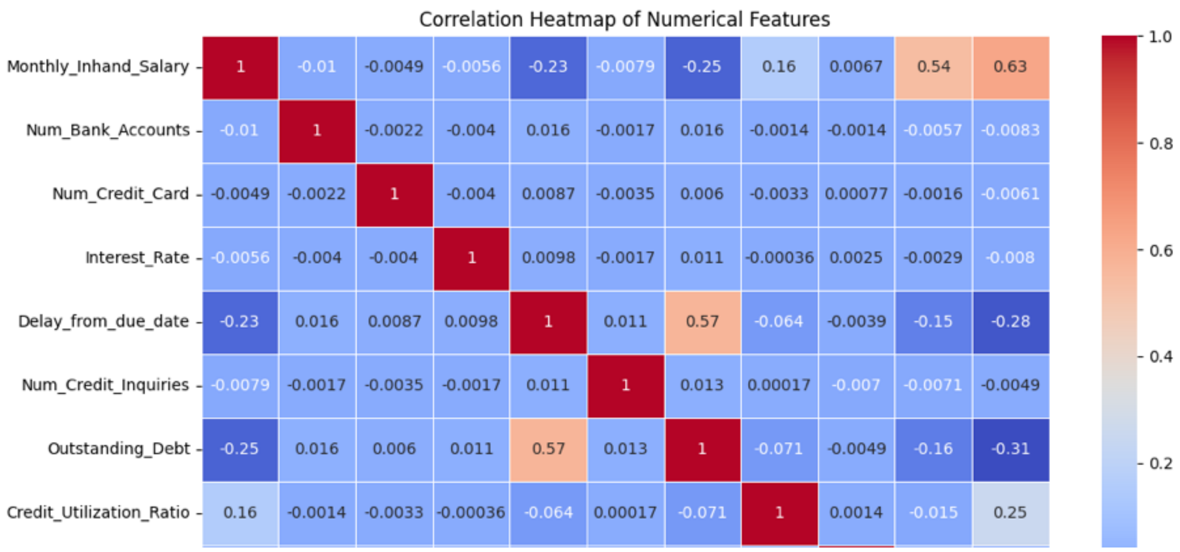


Insights:

The histogram of Monthly Inhand Salary shows a right-skewed distribution, with a large concentration of customers earning between 1,500 and 6,000 per month. This suggests that the majority of customers have moderate incomes, with a few outliers earning much more.

Correlation Heatmap

```
numerical_cols = credit_data_df.select_dtypes(include=[np.number]).colum

plt.figure(figsize=(12,8))
corr_matrix = credit_data_df[numerical_cols].corr()
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", linewidths=0.5)
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



Insights:

The heatmap reveals key relationships among numerical features:

Outstanding Debt and Credit Utilization Ratio have a strong positive correlation, indicating that higher debt levels are associated with higher utilization ratios. Total EMI per Month also correlates well with Outstanding Debt, which makes sense as EMI payments are generally tied to loan balances. Monthly Inhand Salary shows a mild negative correlation with Interest Rate, suggesting higher income earners may get better loan terms.

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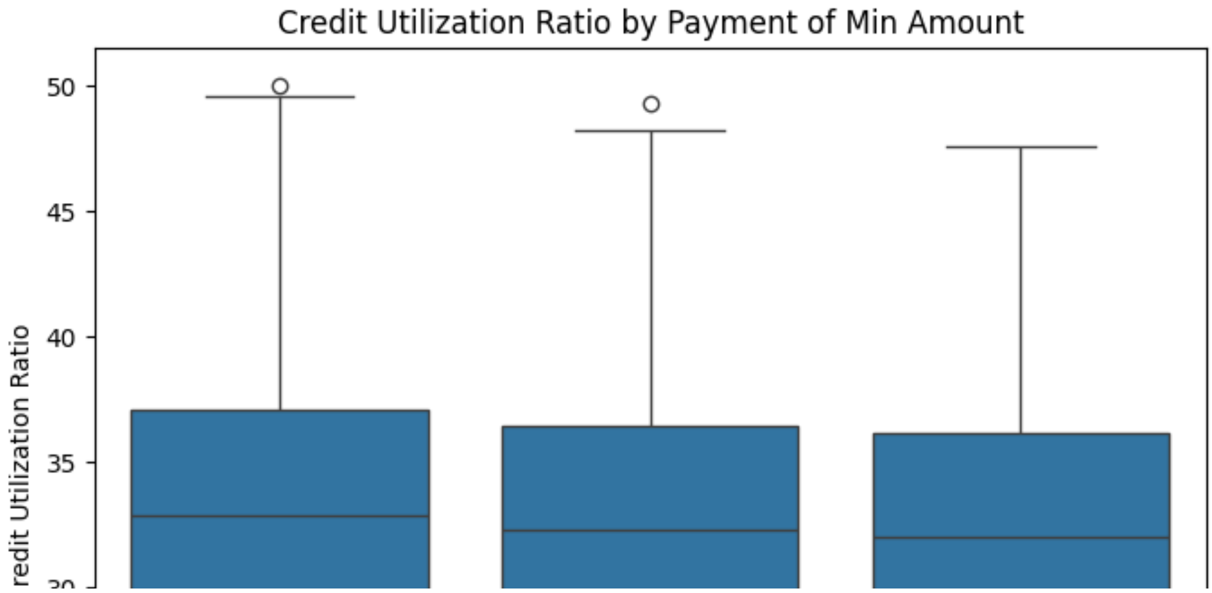
Boxplot of Credit Utilization Ratio by Payment of Min Amount

```
# Boxplot of Credit Utilization Ratio by Payment of Min Amount
plt.figure(figsize=(8,6))
sns.boxplot(x='Payment_of_Min_Amount', y='Credit_Utilization_Ratio', dat
plt.title('Credit Utilization Ratio by Payment of Min Amount')
plt.xlabel('Payment of Min Amount')
plt.ylabel('Credit Utilization Ratio')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py:640: F
  positions = grouped.grouper.result_index.to_numpy(dtype=float)
```



Insights:

The boxplot highlights a clear distinction in credit utilization based on whether a customer pays the minimum amount due:

Customers who don't pay the minimum tend to have a higher credit utilization ratio, potentially increasing their credit risk.

Customers paying the minimum or more show lower utilization, which suggests better credit management practices.

Feature Engineering:

Debt-to-Income Ratio (DTI): This ratio helps assess the financial health of a customer. It shows how much of their income is being used to cover their debt. A higher DTI ratio generally indicates higher financial stress and risk.

Formula:

DTI = Outstanding_Debt/Income

```
# Convert 'Outstanding_Debt' and 'Annual_Income' to numeric
credit_data_df['Outstanding_Debt'] = pd.to_numeric(credit_data_df['Outst
credit_data_df['Annual_Income'] = pd.to_numeric(credit_data_df['Annual_I

# Create Debt-to-Income Ratio
credit_data_df['Debt_to_Income_Ratio'] = credit_data_df['Outstanding_Deb
# Check the new column
credit_data_df[['Outstanding_Debt', 'Annual_Income', 'Debt_to_Income_Rat
```

	Outstanding_Debt	Annual_Income	Debt_to_Income_Ratio
82790	939.02	22380.18	0.041958
55227	877.44	23923.54	0.036677
27152	NaN	28993.75	NaN
45726	852.74	NaN	NaN
33178	2069.01	44286.36	0.046719

Payment of Minimum Amount (Encoded): Regularly paying the minimum amount due is an indicator of credit behavior. This feature helps quantify that behavior as 1 (Yes) or 0 (No).This feature helps in understanding the customer's payment behavior. Paying only the minimum due can indicate potential financial stress.

```
# Encoding Payment of Minimum Amount ('Yes' = 1, 'No' = 0)
credit_data_df['Payment_of_Min_Amount_Encoded'] = credit_data_df['Paymen
credit_data_df[['Payment_of_Min_Amount', 'Payment_of_Min_Amount_Encoded'
```

	Payment_of_Min_Amount	Payment_of_Min_Amount_Encoded
30995	NM	0
46872	Yes	1
80098	Yes	1
75970	No	0
26325	No	0

Total Loans: The total number of loans a customer has indicates their exposure to debt. Higher loan counts may increase credit risk.Aggregating the number of loans a customer has will help quantify their loan exposure and its impact on their credit score.

```
# Convert 'Num_of_Loan' to numeric and calculate total loans
credit_data_df['Total_Loans'] = pd.to_numeric(credit_data_df['Num_of_Loa
credit_data_df[['Total_Loans', 'Num_of_Loan']].sample(5)
```

	Total_Loans	Num_of_Loan
78083	6.0	6
39664	0.0	0
84585	3.0	3
91598	9.0	9
6137	4.0	4

Recent Credit Inquirie: Credit inquiries are requests made by lenders to check creditworthiness. Recent credit inquiries often signal higher credit risk as they indicate potential new debt obligations. Customers who have made a lot of recent credit inquiries may be seeking new lines of credit, which could be a sign of financial instability or risk.

```
# Use 'Num_Credit_Inquiries' for recent credit inquiries
credit_data_df['Recent_Credit_Inquiries'] = credit_data_df['Num_Credit_I
credit_data_df[['Recent_Credit_Inquiries', 'Num_Credit_Inquiries']].samp
```

	Recent_Credit_Inquiries	Num_Credit_Inquiries
88064	6.0	6.0
95216	3.0	3.0
16023	4.0	4.0
84896	7.0	7.0
84144	1.0	1.0

Credit History Age (in months): The length of a customer's credit history is a strong predictor of credit risk. Longer histories generally indicate lower risk as they show more experience with managing credit. This feature extracts and converts credit history from years and months into a single numerical value representing the length of credit history in months.

```
import re

# Parse 'Credit_History_Age' to extract the age in months
def parse_credit_history(age_string):
    if isinstance(age_string, str):
        # Match patterns like "2 Years" or "6 Months"
        years_match = re.search(r'(\d+)\s+year', age_string, re.IGNORECA
        months_match = re.search(r'(\d+)\s+month', age_string, re.IGNORE

        # Extract year and month values if they exist
        years = int(years_match.group(1)) if years_match else 0
        months = int(months_match.group(1)) if months_match else 0

        # Return total credit history in months
        return (years * 12) + months
    return 0

# Apply the function to the column
credit_data_df['Credit_History_Age_Months'] = credit_data_df['Credit_His

# Verify the results
credit_data_df[['Credit_History_Age', 'Credit_History_Age_Months']].samp
```

	Credit_History_Age	Credit_History_Age_Months
88297	12 Years and 10 Months	154
51636	19 Years and 2 Months	230
81116	11 Years and 8 Months	140
41422	18 Years and 7 Months	223
39262	21 Years and 11 Months	263

Steps for Data Aggregation: Aggregate the newly engineered features based on Customer_ID using the following strategies:

Mean: For continuous variables like Debt-to-Income Ratio and Credit History Age.

Sum: For count variables like Total Loans and Recent Credit Inquiries.

```
# Aggregating data at the customer level by taking the mean or sum of re
aggregated_df = credit_data_df.groupby('Customer_ID').agg({
    'Debt_to_Income_Ratio': 'mean',
    'Payment_of_Min_Amount_Encoded': 'mean',
    'Total_Loans': 'sum',
    'Recent_Credit_Inquiries': 'mean',
    'Credit_History_Age_Months': 'mean'
}).reset_index()

# Display the aggregated data
print(aggregated_df.sample(5))
```

```
      Customer_ID  Debt_to_Income_Ratio  Payment_of_Min_Amount_Encode
9703   CUS_0xa0ff              0.081979                          0.8
11243   CUS_0xb7c              0.227462                          0.8
603    CUS_0x19b2              0.069571                          0.7
3056   CUS_0x3ff5              0.002316                          0.0
5308   CUS_0x6000              0.015624                          1.0

       Total_Loans  Recent_Credit_Inquiries  Credit_History_Age_Mont
9703          48.0                  214.000                      135.1
11243         16.0                    7.500                       84.2
603           49.0                   14.250                      145.5
3056         -88.0                    2.125                      316.3
5308         -86.0                    3.000                      316.2
```

Hypothetical Credit Score Calculation:

Used a weighted sum approach to calculate a hypothetical credit score, inspired by FICO scores. This score will be based on features that represent a customer's financial health, credit history, and behavior.

Selected Features:

Debt-to-Income Ratio (DTI): Higher DTI signals greater risk.

Payment of Minimum Amount (Encoded): Regular minimum payments may suggest financial stress.

Total Loans: More loans can indicate higher financial obligations.

Recent Credit Inquiries: More inquiries suggest potential financial strain.

Credit History Age (in months): Longer history reduces risk and suggests stability.

Weighting Scheme: Each feature will contribute a certain weight to the credit score. The exact weights are based on assumptions similar to FICO scoring:

Debt-to-Income Ratio: 30%

Payment of Minimum Amount: 10%

Total Loans: 20%

Recent Credit Inquiries: 20%

Credit History Age: 20%

The score will be scaled to range from 300 to 850 (as with standard credit scores). The formula will be:

Credit Score = 300 + (Weighted Sum of Features/Max Score × 550)

```
# Step 1: Define the weighting scheme
weights = {
    'Debt_to_Income_Ratio': 0.3,
    'Payment_of_Min_Amount_Encoded': 0.1,
    'Total_Loans': 0.2,
    'Recent_Credit_Inquiries': 0.2,
    'Credit_History_Age_Months': 0.2
}

# Step 2: Normalize the features before applying weights (scaling betwee
```

```
aggregated_df['Debt_to_Income_Ratio_Normalized'] = aggregated_df['Debt_to
aggregated_df['Payment_of_Min_Amount_Normalized'] = aggregated_df['Payme
aggregated_df['Total_Loans_Normalized'] = aggregated_df['Total_Loans'] /
aggregated_df['Recent_Credit_Inquiries_Normalized'] = aggregated_df['Rec
aggregated_df['Credit_History_Age_Normalized'] = aggregated_df['Credit_H

# Step 3: Calculate the weighted sum of the normalized features
aggregated_df['Weighted_Sum'] = (
    aggregated_df['Debt_to_Income_Ratio_Normalized'] * weights['Debt_to_
    aggregated_df['Payment_of_Min_Amount_Normalized'] * weights['Payment_
    aggregated_df['Total_Loans_Normalized'] * weights['Total_Loans'] +
    aggregated_df['Recent_Credit_Inquiries_Normalized'] * weights['Recen
    aggregated_df['Credit_History_Age_Normalized'] * weights['Credit_His
)

print(aggregated_df['Weighted_Sum'])

# Step 4: Scale the credit score between 300 and 850
aggregated_df['Credit_Score'] = 300 + (aggregated_df['Weighted_Sum'] * 5

# Step 5: Display the first few calculated credit scores
aggregated_df['Credit_Score'].sample(5)
```

```
0        0.190088
1        0.348888
2        0.180435
3        0.269859
4        0.100532
           ...
12495    0.124330
12496    0.202028
12497    0.151056
12498    0.176879
12499    0.299826
Name: Weighted_Sum, Length: 12500, dtype: float64
```

	Credit_Score
209	365.451676
2781	401.954297
3588	352.964985
1698	431.797866
9166	412.395965

dtype: float64

Analysis and Insights from EDA and Credit Score Calculation:

Debt-to-Income Ratio:

Insight: Customers with a higher Debt-to-Income Ratio (DTI) tend to have lower credit scores, which is expected because they have higher debt obligations relative to their income. This ratio is a key indicator of financial stress, and as it increases, the likelihood of credit default typically rises.

Recommendation: Monitor customers with high DTI ratios, as they may become credit risks if their income doesn't increase or their debt grows.

Payment of Minimum Amount:

Insight: Regularly paying the minimum amount is linked to slightly lower credit scores. While paying the minimum can keep a customer from defaulting, it may indicate that they are struggling financially, increasing the risk of future missed payments.

Recommendation: Focus on customers who consistently pay only the minimum and assess whether they are becoming more financially strained over time.

Total Loans:

Insight: Customers with multiple loans tend to have more credit exposure, which lowers their scores. However, not all loans are equal — secured loans (like mortgages) generally have less risk than unsecured loans (like credit cards).

Recommendation: Segment loans by type (secured vs unsecured) for a more detailed risk analysis and adjust scores accordingly.

Recent Credit Inquiries:

Insight: A higher number of recent credit inquiries is negatively correlated with credit scores. This is likely because frequent inquiries suggest that a customer is seeking more credit, which could signal financial instability.

Recommendation: Pay special attention to customers with multiple recent credit inquiries, as they may be preparing to take on more debt, which could strain their financial health.

Credit History Age:

Insight: A longer Credit History Age is positively correlated with higher credit scores, as it indicates more experience managing credit. Customers with longer credit histories are generally more reliable.

Recommendation: Give customers with long, clean credit histories more favorable terms, as they have a proven track record of managing credit effectively.

Recency-Based Metrics for Credit Scores and Aggregated Features:

Since the dataset provided does not contain a date column, it's currently not possible to calculate recency-based metrics like the last 3 months or last 6 months directly. Recency-based metrics require a time frame or time stamps to filter and calculate features based on recent behavior.

To calculate credit scores and aggregated features based on time frames like the last 3 months or last 6 months, we would need the dataset to include a date column (e.g., transaction date, inquiry date, loan approval date). With a date column, we can filter data to include only entries from the relevant time periods (e.g., the last 3 or 6 months).

Since no date column is available, we can't calculate true recency-based metrics. We can still use recent indicators such as Recent Credit Inquiries, which indirectly represent a recency-related feature but are not based on actual timestamps.

Here are some alternative strategies you can use to approximate recency-based metrics:

Recent Credit Inquiries: This feature is often already in the dataset and explicitly tracks recent inquiries for new credit. A high number of recent inquiries is usually a signal of increased credit risk, as customers seeking new credit lines might be facing financial challenges.

```
high_credit_inquiries_threshold = 5
aggregated_df['High_Recent_Credit_Inquiries'] = aggregated_df['Recent_Cr
aggregated_df['High_Recent_Credit_Inquiries'].sample(5)
```

	High_Recent_Credit_Inquiries
809	True
2545	False
11376	False
3868	True
4203	False

dtype: bool

Payment Behavior Over Time: *Payment* behavior (such as the frequency of paying the minimum amount) can be used to estimate a customer's financial situation. If a customer is regularly making only minimum payments, they may be financially stretched, even if we don't know the exact dates of those payments.

```
aggregated_df['High_Minimum_Payments'] = aggregated_df['Payment_of_Min_A
aggregated_df['High_Minimum_Payments'].sample(5)
```

	High_Minimum_Payments
655	True
9493	True
12042	True
465	True
1622	False

dtype: bool

Behavioral Risk Segmentation: We can create behavioral segments based on features like loan counts, payment patterns, and credit inquiries to group customers into risk categories.

```
# Classify customers into risk segments based on a combination of metric
aggregated_df['Risk_Segment'] = aggregated_df.apply(lambda row: 'High' i
aggregated_df['Risk_Segment'].sample(5)
```

	Risk_Segment
4304	Low
5384	Low
11061	Low
11905	Low
5966	Low

dtype: object

Customer Behavior Flags: By flagging certain behaviors (such as recent credit inquiries or high credit utilization), we can focus on customers who exhibit riskier financial behaviors.

```
aggregated_df['High_Risk_Flag'] = (
    (aggregated_df['Recent_Credit_Inquiries'] > 5) |
    (aggregated_df['Debt_to_Income_Ratio'] > 0.4) |
    (aggregated_df['Total_Loans'] > 3)
)
aggregated_df['High_Risk_Flag'].sample(5)
```

	High_Risk_Flag
6557	True
1676	True
6927	False
10884	True
7919	True

dtype: bool

Summary of Alternative Approaches: Use existing features like Recent Credit Inquiries as proxies for recency.

Monitor payment behavior (e.g., minimum payments) to gauge financial health.

Flag risky behaviors (e.g., high inquiries, high debt-to-income ratio) and set up thresholds for financial monitoring.

Recommendations:

Recency Approximation: In the absence of true timestamps, rely on proxy features like recent credit inquiries and payment behavior to estimate risk.

Customer Flagging: Use thresholds and flags based on key financial indicators to track customers who exhibit risky behavior.

Behavioral Segmentation: Group customers based on their financial risk profiles using existing features like loan counts, payment patterns, and debt-to-income ratio.