Credit Score Analysis - Jupyter Notebook

Importing essential libraries

In [239…
```
import pandas as pd

import matplotlib.pyplot as plt
from matplotlib import cm
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns

import ast
import numpy as np

from scipy.stats import chi2_contingency
from scipy.stats import f_oneway, ttest_ind

from sklearn.utils import resample
from sklearn.cluster import KMeans
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_curve, auc, roc_auc_score,
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split

import statsmodels.api as sm
from statsmodels.tools import add_constant
```

Importing data and storing in a dataframe

In [239…
```
data = pd.read_csv('credit-score-classification-cleaned-dataset/credit_score_cleaned_train.csv')
data.head()
```

Out[239…

	id	customer_id	month	name	age	ssn	occupation	annual_income	monthly_inhand_salary	total_emi_per_month
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.120	1824.843	49.575
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.120	1824.843	49.575
2	0x1604	CUS_0xd40	March	Aaron Maashoh	23	821-00-0265	Scientist	19114.120	1824.843	49.575
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.120	1824.843	49.575
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.120	1824.843	49.575

Exploratory Data Analysis

Looking at the type of each attribute in the dataframe

In [239…
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 28 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  int64  
 5   ssn                       100000 non-null  object 
 6   occupation                100000 non-null  object 
 7   annual_income             100000 non-null  float64
 8   monthly_inhand_salary     100000 non-null  float64
 9   total_emi_per_month       100000 non-null  float64
 10  num_bank_accounts         100000 non-null  int64  
 11  num_credit_card           100000 non-null  int64  
 12  interest_rate             100000 non-null  int64  
 13  num_of_loan               100000 non-null  int64  
 14  type_of_loan              100000 non-null  object 
 15  delay_from_due_date       100000 non-null  int64  
 16  num_of_delayed_payment    100000 non-null  int64  
 17  changed_credit_limit      100000 non-null  float64
 18  num_credit_inquiries      100000 non-null  int64  
 19  credit_mix                100000 non-null  object 
 20  outstanding_debt          100000 non-null  float64
 21  credit_utilization_ratio  100000 non-null  float64
 22  credit_history_age        100000 non-null  int64  
 23  payment_of_min_amount     100000 non-null  object 
 24  amount_invested_monthly   100000 non-null  float64
 25  payment_behaviour         100000 non-null  object 
 26  monthly_balance           100000 non-null  float64
 27  credit_score              100000 non-null  int64  
dtypes: float64(8), int64(10), object(10)
memory usage: 21.4+ MB
```

Checking for null values

In [239…
```
nullCounts = data.isnull().sum()
print(nullCounts)
```

```
id                          0
customer_id                 0
month                       0
name                        0
age                         0
ssn                         0
occupation                  0
annual_income               0
monthly_inhand_salary       0
total_emi_per_month         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
amount_invested_monthly     0
payment_behaviour           0
monthly_balance             0
credit_score                0
dtype: int64
```

Checking for duplicates

In [239…
```
duplicate_rows = data[data.duplicated()]
print(f"Number of duplicate rows: {duplicate_rows.shape[0]}")
```

```
Number of duplicate rows: 0
```

Examining the mean and standard deviations of each numerical attribute to get an idea of their distributions

In [239…
```
data.describe().T
```

Out[239...

	count	mean	std	min	25%	50%	75%	max
age	100000.000	33.309	10.765	14.000	24.000	33.000	42.000	56.000
annual_income	100000.000	50505.123	38299.422	7005.930	19342.972	36999.705	71683.470	179987.280
monthly_inhand_salary	100000.000	4198.772	3187.494	303.645	1626.762	3096.378	5961.745	15204.634
total_emi_per_month	100000.000	107.044	130.035	0.000	29.197	66.403	146.827	3776.000
num_bank_accounts	100000.000	5.369	2.593	0.000	3.000	5.000	7.000	11.000
num_credit_card	100000.000	5.534	2.067	0.000	4.000	5.000	7.000	11.000
interest_rate	100000.000	14.532	8.741	1.000	7.000	13.000	20.000	34.000
num_of_loan	100000.000	3.533	2.446	0.000	2.000	3.000	5.000	9.000
delay_from_due_date	100000.000	21.069	14.860	-5.000	10.000	18.000	28.000	67.000
num_of_delayed_payment	100000.000	13.334	6.271	0.000	9.000	14.000	18.000	28.000
changed_credit_limit	100000.000	10.389	6.790	-6.490	5.320	9.400	14.860	36.970
num_credit_inquiries	100000.000	5.773	3.861	0.000	3.000	5.000	8.000	17.000
outstanding_debt	100000.000	1426.220	1155.129	0.230	566.072	1166.155	1945.963	4998.070
credit_utilization_ratio	100000.000	32.285	5.117	20.000	28.053	32.306	36.497	50.000
credit_history_age	100000.000	221.207	99.681	1.000	144.000	219.000	302.000	404.000
amount_invested_monthly	100000.000	637.633	2043.334	0.000	74.594	135.952	266.178	10000.000
monthly_balance	100000.000	403.120	214.015	0.008	270.189	337.114	471.571	1602.041
credit_score	100000.000	0.888	0.675	0.000	0.000	1.000	1.000	2.000

Examining the number of unique catgeories in each categorical attribute

In [239...
```
data.describe(include="object").T
```

Out[239...

	count	unique	top	freq
id	100000	100000	0x1602	1
customer_id	100000	12500	CUS_0xd40	8
month	100000	8	January	12500
name	100000	10139	Langep	48
ssn	100000	12500	821-00-0265	8
occupation	100000	15	Lawyer	7096
type_of_loan	100000	6261	['No Loan']	11408
credit_mix	100000	3	Standard	45848
payment_of_min_amount	100000	2	Yes	59432
payment_behaviour	100000	6	Low_spent_Small_value_payments	27588

Dropping id, name and ssn columns since they are not revlevant to this analysis

In [239...
```
columnsToDrop = ['id', 'name', 'ssn']
data = data.drop(columns=columnsToDrop)
```

Dropping customers that have ages lower than 18 since thier credit scores are reliant on thier parents which is a corner case that this analysis is not interested in

In [239...
```
filteredData = data[data['age'] < 18]
numCustomersToRemove = filteredData['customer_id'].nunique()
print(numCustomersToRemove)
```

```
788
```

In [239...
```
customersToRemove = filteredData['customer_id'].unique()
data = data[~data['customer_id'].isin(customersToRemove)]
data['customer_id'].nunique()
```

Out[239... 11712

Dropping customers that have no bank accounts but have a monthly balance greater than 0 which is not possible

In [240...
```
filteredData = data[(data['num_bank_accounts'] == 0) & (data['monthly_balance'] > 0)]
numCustomersToRemove = filteredData['customer_id'].nunique()

print(numCustomersToRemove)
```

```
563
```

In [240…
```
customersToRemove = filteredData['customer_id'].unique()
data = data[~data['customer_id'].isin(customersToRemove)]
data['customer_id'].nunique()
```

Out[240… 11149

Checking if credit_history_age is lesser than the number of years from age 18 to current age of the customer

In [240…
```
filteredData = data[(data['credit_history_age']//12) > (data['age']-18)]
print(filteredData[['age', 'credit_history_age']])
numCustomersToRemove = filteredData['customer_id'].nunique()
print(numCustomersToRemove)
```

```
       age  credit_history_age
0       23                 265
1       23                 266
2       23                 267
3       23                 268
4       23                 269
...    ...                 ...
99995   25                 378
99996   25                 379
99997   25                 380
99998   25                 381
99999   25                 382

[46537 rows x 2 columns]
5935
```

Credit_history_age has majority erroneous data since most of the customers have a credit history age greater than the duration from age 18 to their current age which is not possible hence this column is dropped

In [240…
```
data = data.drop('credit_history_age', axis=1)
data.head()
```

Out[240…

	customer_id	month	age	occupation	annual_income	monthly_inhand_salary	total_emi_per_month	num_bank_accounts	nu
0	CUS_0xd40	January	23	Scientist	19114.120	1824.843	49.575	3	
1	CUS_0xd40	February	23	Scientist	19114.120	1824.843	49.575	3	
2	CUS_0xd40	March	23	Scientist	19114.120	1824.843	49.575	3	
3	CUS_0xd40	April	23	Scientist	19114.120	1824.843	49.575	3	
4	CUS_0xd40	May	23	Scientist	19114.120	1824.843	49.575	3	

Label encoding credit_mix to numerical data and storing it in a new column: CreditMixNum. (Bad -> 0, Standard -> 1, Good -> 2)

In [240…
```
uniqueCreditMix = data['credit_mix'].unique()
print("Unique credit mix in the dataset:", sorted(uniqueCreditMix))
```

```
Unique credit mix in the dataset: ['Bad', 'Good', 'Standard']
```

In [240…
```
creditMixMapping = {'Bad': 0, 'Standard': 1, 'Good': 2}
data['creditMixNum'] = data['credit_mix'].map(creditMixMapping)

print(data[['credit_mix', 'creditMixNum']].head())
```

```
  credit_mix  creditMixNum
0       Good             2
1       Good             2
2       Good             2
3       Good             2
4       Good             2
```

Label encoding payment_of_min_amount to numerical data and storing it in a new colum called paymentMinAmountNum (No -> 0, Yes -> 1). 0 denotes a customer who does not pay just the minimum amount and instead pays more, whereas 1 denotes a customer who pays just the minimum amount

In [240…
```
uniquePaymentMinAmt = data['payment_of_min_amount'].unique()
print("Unique payment of min amount in the dataset:", sorted(uniquePaymentMinAmt))
```

```
Unique payment of min amount in the dataset: ['No', 'Yes']
```

In [240…
```
PaymentMinAmtMapping = {'No': 0, 'Yes': 1}
data['paymentMinAmountNum'] = data['payment_of_min_amount'].map(PaymentMinAmtMapping)

print(data[['payment_of_min_amount', 'paymentMinAmountNum']].head())
```

```
  payment_of_min_amount  paymentMinAmountNum
0                    No                    0
1                    No                    0
2                    No                    0
3                    No                    0
4                    No                    0
```

Converting type_of_loan entries from string to list of strings to make it usable

In [240…
```
data['type_of_loan'] = data['type_of_loan'].apply(ast.literal_eval)
```

Checking if num_of_loans matches with the length of type of loans taken

In [240…
```
def countValidLoans(loanList):
    count = 0
    for loan in loanList:
        if loan != 'No Loan':
            count += 1
    return count

mismatchedRows = data[data['num_of_loan'] != data['type_of_loan'].apply(countValidLoans)]

print(f"Number of rows with mismatched loan counts: {len(mismatchedRows)}")
```

```
Number of rows with mismatched loan counts: 0
```

Storing the unique loan types in a list

In [241…
```
uniqueLoanTypes = set()

for loans in data['type_of_loan']:
    for loan in loans:
        uniqueLoanTypes.add(loan)

loanTypes = list(uniqueLoanTypes)
print(loanTypes)
```

```
['Student Loan', 'Mortgage Loan', 'Home Equity Loan', 'Debt Consolidation Loan', 'No Loan', 'Payday Loan', 'Auto Loa
n', 'Credit-Builder Loan', 'Personal Loan', 'Not Specified']
```

Getting count of the different types of loan in each credit score

In [241…
```
loanDict = {}

for creditScore in data['credit_score'].unique():
    creditScoreData = data[data['credit_score'] == creditScore]
    loanCounts = {}
    for loans in creditScoreData['type_of_loan']:
        for loan in loans:
            if loan in loanCounts:
                loanCounts[loan] += 1
            else:
                loanCounts[loan] = 1
    loanDict[creditScore] = loanCounts

print(loanDict)
```

```
{2: {'Auto Loan': 3566, 'Credit-Builder Loan': 4101, 'Personal Loan': 3659, 'Home Equity Loan': 3802, 'Not Specifie
d': 3993, 'No Loan': 3013, 'Debt Consolidation Loan': 3574, 'Payday Loan': 3897, 'Mortgage Loan': 3845, 'Student Loa
n': 3888}, 1: {'Auto Loan': 16927, 'Credit-Builder Loan': 18131, 'Personal Loan': 17644, 'Home Equity Loan': 17504,
'Not Specified': 17529, 'No Loan': 6137, 'Student Loan': 16822, 'Debt Consolidation Loan': 17522, 'Payday Loan': 179
62, 'Mortgage Loan': 17225}, 0: {'Not Specified': 13374, 'Auto Loan': 13043, 'Student Loan': 13698, 'Personal Loan':
13361, 'Payday Loan': 14101, 'Home Equity Loan': 13286, 'No Loan': 1130, 'Mortgage Loan': 13418, 'Debt Consolidation
Loan': 13424, 'Credit-Builder Loan': 13600}}
```

In [241…
```
flattenedData = []

for creditScore, loans in loanDict.items():
    for loan, count in loans.items():
        flattenedData.append({
            'credit_score': creditScore,
            'loan_type': loan,
            'loan_count': count
        })

loanData = pd.DataFrame(flattenedData)
```

```
print(loanData)
```

```
    credit_score               loan_type  loan_count
0              2               Auto Loan        3566
1              2     Credit-Builder Loan        4101
2              2           Personal Loan        3659
3              2        Home Equity Loan        3802
4              2           Not Specified        3993
5              2                 No Loan        3013
6              2  Debt Consolidation Loan        3574
7              2             Payday Loan        3897
8              2           Mortgage Loan        3845
9              2            Student Loan        3888
10             1               Auto Loan       16927
11             1     Credit-Builder Loan       18131
12             1           Personal Loan       17644
13             1        Home Equity Loan       17504
14             1           Not Specified       17529
15             1                 No Loan        6137
16             1            Student Loan       16822
17             1  Debt Consolidation Loan       17522
18             1             Payday Loan       17962
19             1           Mortgage Loan       17225
20             0           Not Specified       13374
21             0               Auto Loan       13043
22             0            Student Loan       13698
23             0           Personal Loan       13361
24             0             Payday Loan       14101
25             0        Home Equity Loan       13286
26             0                 No Loan        1130
27             0           Mortgage Loan       13418
28             0  Debt Consolidation Loan       13424
29             0     Credit-Builder Loan       13600
```

Examining the unique credit score values in the target column: credit_score

In [241…
```
uniqueScores = data['credit_score'].unique()
print("Unique credit scores in the dataset:", sorted(uniqueScores))
```

```
Unique credit scores in the dataset: [0, 1, 2]
```

There are three possible credit scores classes. 0 which referes to Poor, 1 which referes to Standard and 2 which refers to Good.

Evaluating distribution of Credit Scores

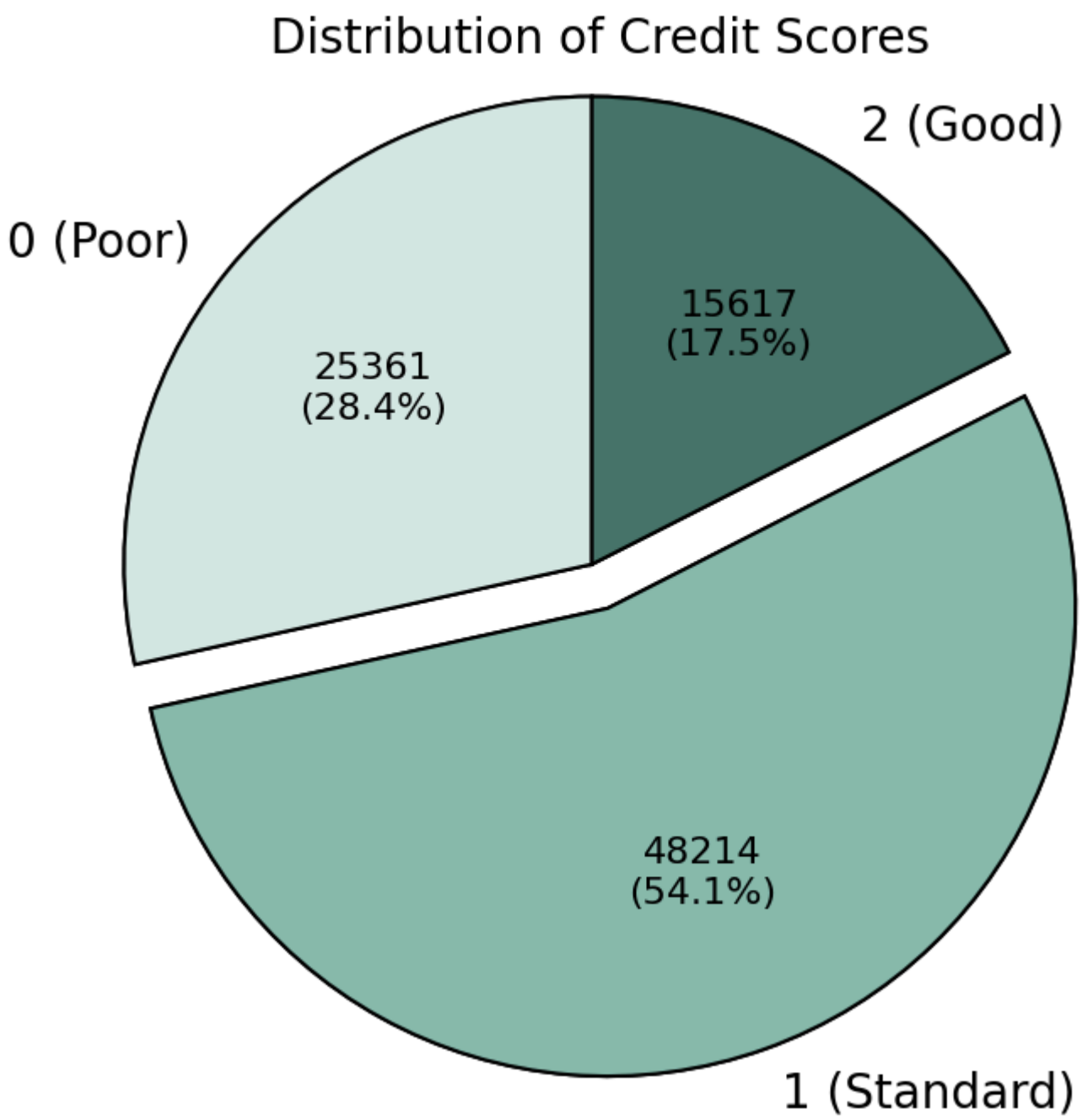
In [241…
```
scoreCounts = data['credit_score'].value_counts()
scorePercentages = data['credit_score'].value_counts(normalize=True) * 100
scoreSummary = pd.DataFrame({
    'Count': scoreCounts,
    'Percentage (%)': scorePercentages
})

print("Credit score counts and percentages:\n", scoreSummary.sort_index())
```

```
Credit score counts and percentages:
    Count  Percentage (%)
0  25361          28.434
1  48214          54.056
2  15617          17.509
```

Plotting a pie chart illustrating the distribution of credit scores in the data. This figure is mentioned in the report

In [241…
```
labels = ['0 (Poor)', '1 (Standard)', '2 (Good)']
colors = ['#d6e7e4', '#87bbae', '#48756a']
explode = (0, 0.1, 0)

def autopct_func(pct, allvals):
    absolute = int(round(pct / 100. * sum(allvals)))
    return f'{absolute}\n({pct:.1f}%)'

plt.figure(figsize=(8, 8))

plt.pie(scoreCounts.sort_index(),
        autopct=lambda pct: autopct_func(pct, scoreCounts.sort_index()),
        startangle=90,
        colors=colors,
        textprops={'color': 'black', 'fontsize': 16},
        wedgeprops={'edgecolor': 'black', 'linewidth': 1.5},
        explode=explode)

plt.pie(scoreCounts.sort_index(),
        labels=labels,
        startangle=90,
        colors=colors,
        textprops={'color': 'black', 'fontsize': 20},
        wedgeprops={'edgecolor': 'black', 'linewidth': 1.5},
```

```
        explode=explode)

plt.title('Distribution of Credit Scores', fontsize=20, color='black')
plt.axis('equal')
plt.gca().set_facecolor('#f0f0f0')
plt.savefig('graphs/credit_score_distribution.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Data is slightly unbalanced with the majority class being Standard (1) with 54.1%, followed by Poor (0) with 28.4% and then Good (2) with 17.5%.

Count of unique customers

In [241…
```
uniqueCustomers = data['customer_id'].nunique()
print(f"Number of unique customer IDs: {uniqueCustomers}")
```

```
Number of unique customer IDs: 11149
```

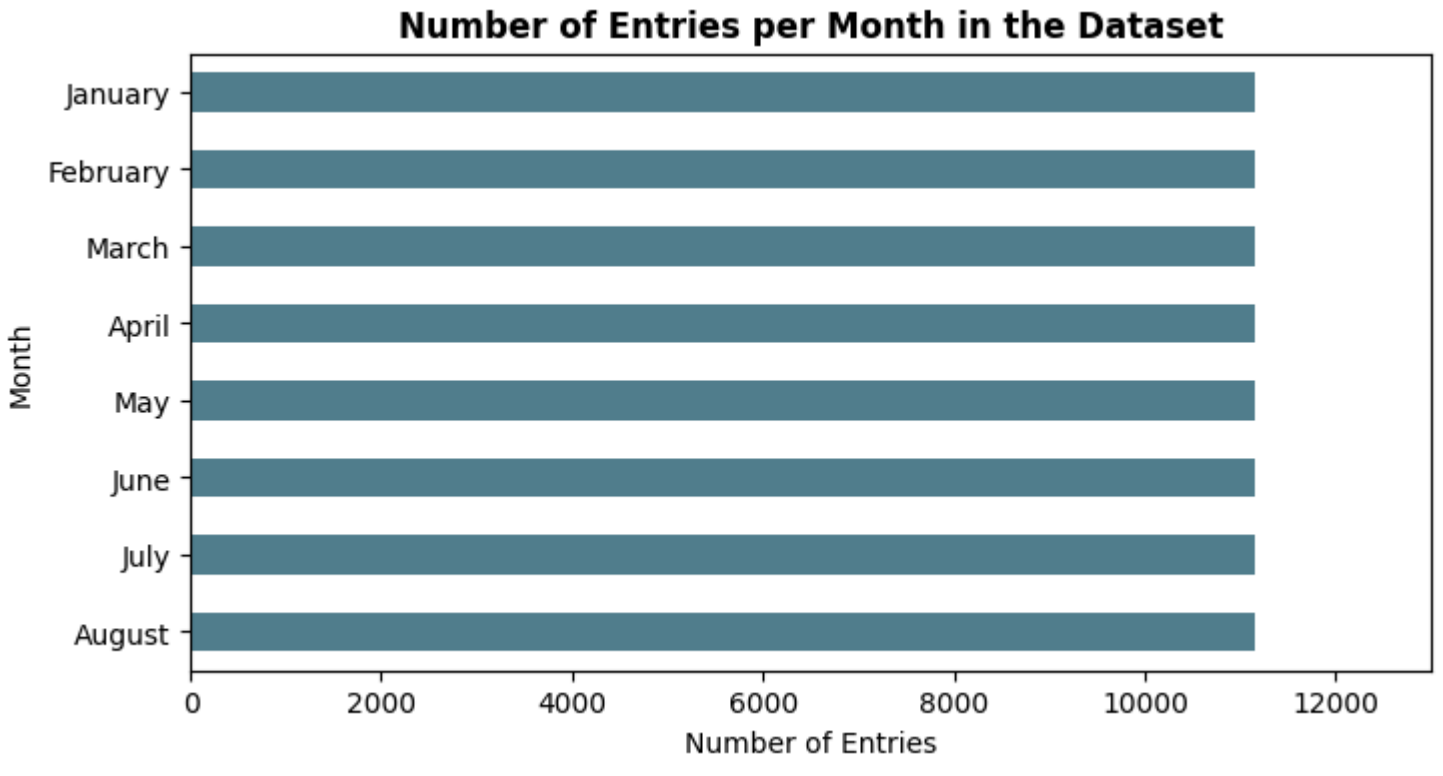
After initial data preparation, the dataset contains data on 11149 customers.

Looking at the unique month values

In [241…
```
uniqueMonths = data['month'].unique()
print("Unique months in the dataset:", uniqueMonths)
```

```
Unique months in the dataset: ['January' 'February' 'March' 'April' 'May' 'June' 'July' 'August']
```

In [241…
```
monthCounts = data['month'].value_counts()

plt.figure(figsize=(8, 4))
sns.barplot(
    x=monthCounts.values,
    y=monthCounts.index,
    color='#498699',
    width=0.5)

plt.xlim(0, 13000)
plt.xlabel("Number of Entries")
plt.ylabel("Month")
plt.title("Number of Entries per Month in the Dataset", fontsize=12, fontweight="bold")
plt.show()
```

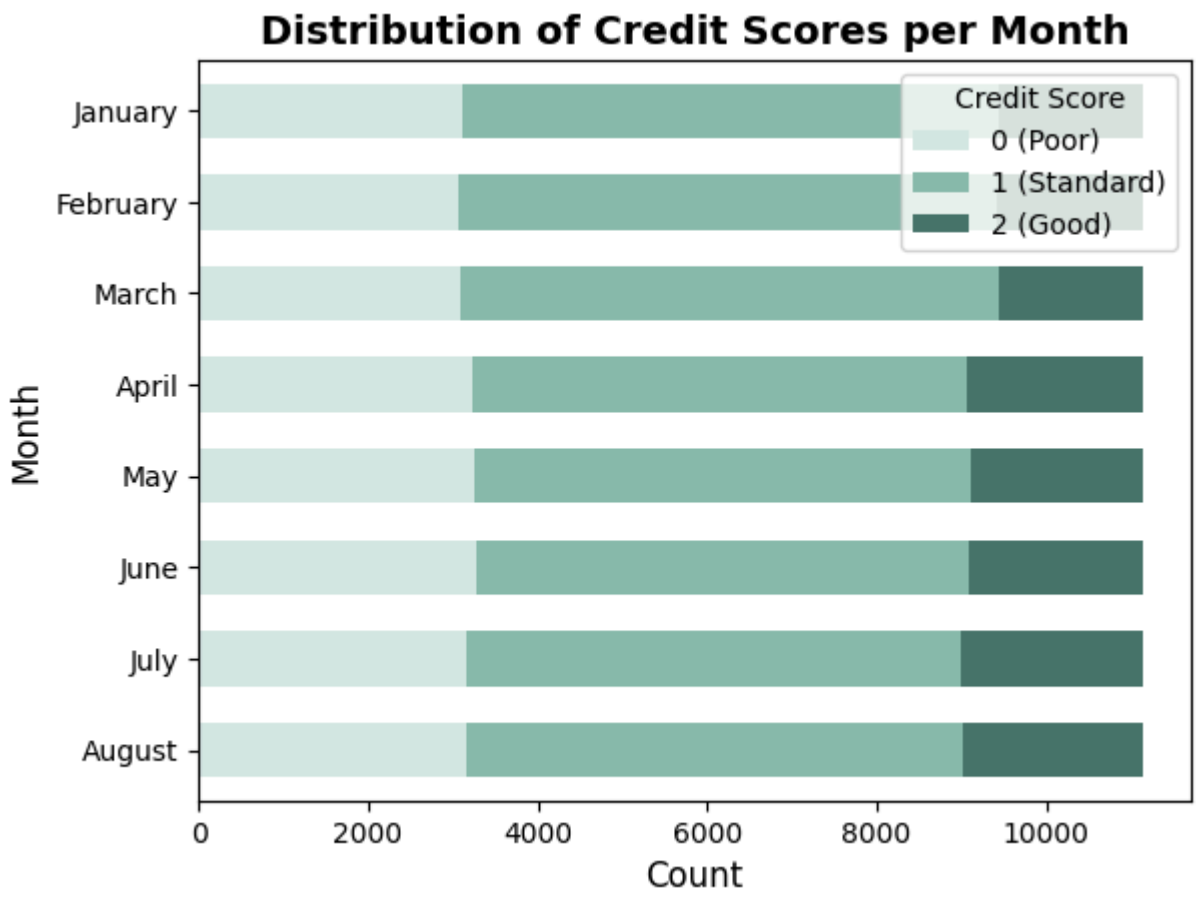


There is data for each customer over 8 months from January to August.

Examining the distribution of credit scores in each month

In [241…
```
monthOrder = ['August', 'July', 'June', 'May', 'April', 'March', 'February', 'January']
data['orderedMonth'] = pd.Categorical(data['month'], categories=monthOrder)

monthScoreDistribution = data.groupby(['orderedMonth', 'credit_score']).size().unstack(fill_value=0)

plt.figure(figsize=(10, 6))
monthScoreDistribution.plot(kind='barh', stacked=True, width=0.6, color=['#d6e7e4', '#87bbae', '#48756a'])
plt.title("Distribution of Credit Scores per Month", fontsize=14, fontweight="bold")
plt.xlabel("Count", fontsize=12)
plt.ylabel("Month", fontsize=12)
plt.legend(labels=["0 (Poor)", "1 (Standard)", "2 (Good)"], title="Credit Score", loc="upper right")
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



The distribution of credit scores is similar for every month. Standard has the highest percentage of credit scores across every month followed by Poor and then Good.

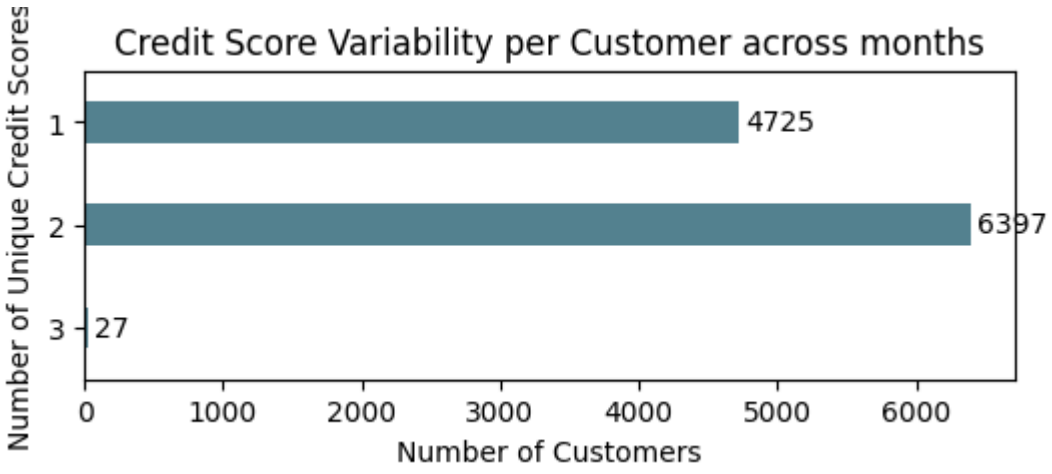
Checking if the customer credit score remains same or varies across the 8 months (January-August)

In [242…
```
creditScoreVariability = data.groupby('customer_id')['credit_score'].nunique()
varyingCreditScores = creditScoreVariability[creditScoreVariability > 1]

print(f"Number of customers with varying credit scores: {len(varyingCreditScores)}")
```

```
Number of customers with varying credit scores: 6424
```

In [242…
```
variabilityCounts = creditScoreVariability.value_counts().sort_index()

plt.figure(figsize=(6, 2))
sns.barplot(
```

```
    x=variabilityCounts.values,
    y=variabilityCounts.index.astype(str),
    color='#498699',
    width=0.4
)

for index, value in enumerate(variabilityCounts.values):
    plt.text(value + 50, index, str(value), va='center', ha='left', fontsize=10)

plt.title("Credit Score Variability per Customer across months", fontsize=12)
plt.ylabel("Number of Unique Credit Scores", fontsize=10)
plt.xlabel("Number of Customers", fontsize=10)
plt.show()
```

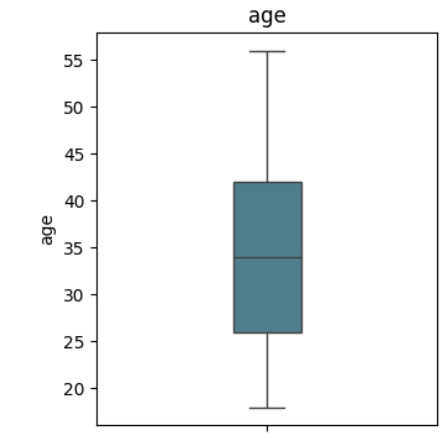


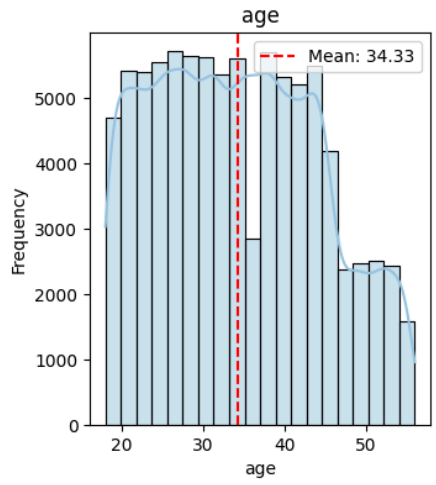
4725 customers maintain same the credit score across the 8 months whereas 6397 customers go from one score to another and 27 customers change across all three credit scores.

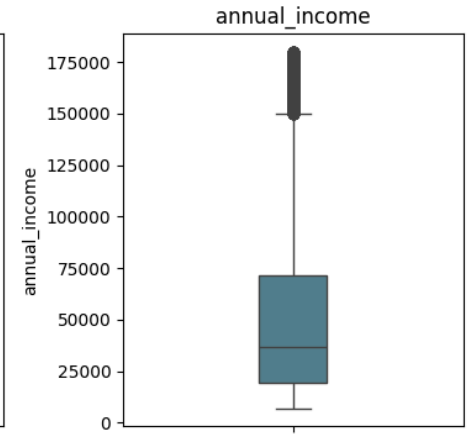
Univariate Analysis of Numerical Variables. Analyzing their distributions using boxplots and histograms

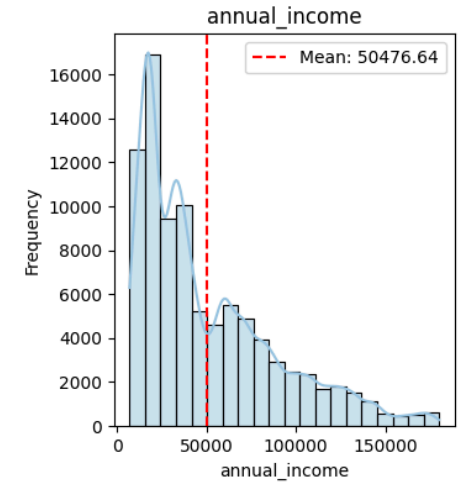
In [242…

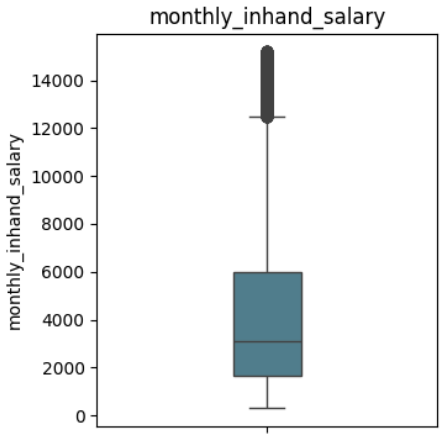
```
numericColumns = data.select_dtypes(include='number').columns
numPlots = len(numericColumns)
rows = (numPlots // 2) + 1
cols = 4
fig, axes = plt.subplots(rows, cols, figsize=(15, rows * 4))
axes = axes.flatten()

for i, col in enumerate(numericColumns):

    sns.boxplot(data=data, y=col, ax=axes[2 * i], color="#498699",  width=0.2)
    axes[2 * i].set_title(f'{col}', fontsize=12)
    axes[2 * i].set_ylabel(col, fontsize=10)

    sns.histplot(data=data, x=col, ax=axes[2 * i + 1], color="#98c5e1", kde=True, bins=20)
    mean_value = data[col].mean()
    axes[2 * i + 1].axvline(mean_value, color='red', linestyle='--', label=f'Mean: {mean_value:.2f}')
    axes[2 * i + 1].legend()
    axes[2 * i + 1].set_title(f'{col}', fontsize=12)
    axes[2 * i + 1].set_xlabel(col, fontsize=10)
    axes[2 * i + 1].set_ylabel('Frequency', fontsize=10)


for j in range(2 * numPlots, len(axes)):
    fig.delaxes(axes[j])

plt.subplots_adjust(wspace=0.6, hspace=0.4)
plt.tight_layout()
plt.show()
```

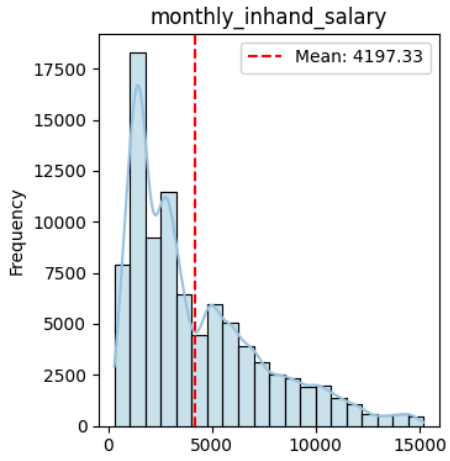


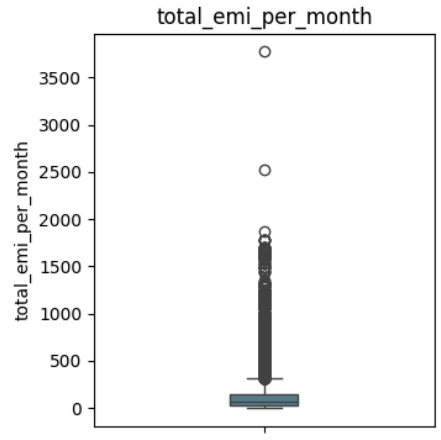


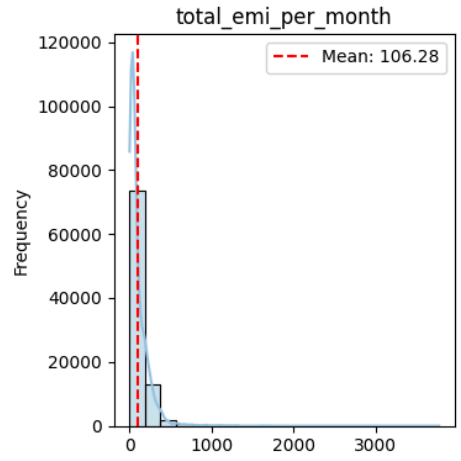


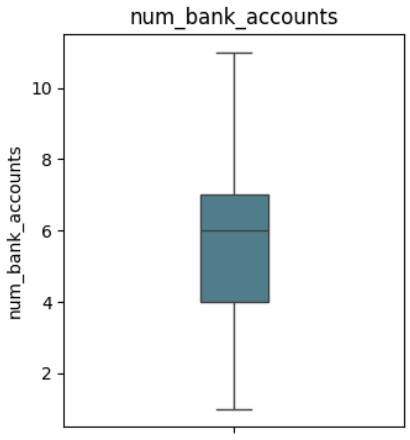


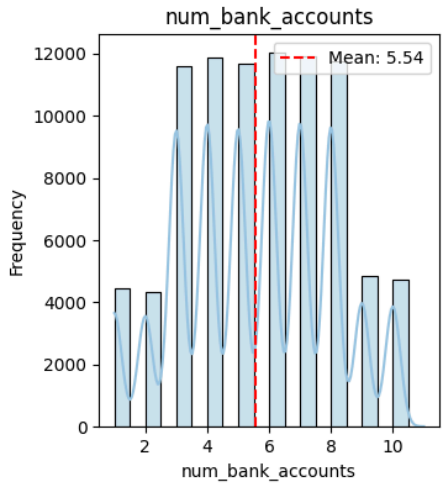


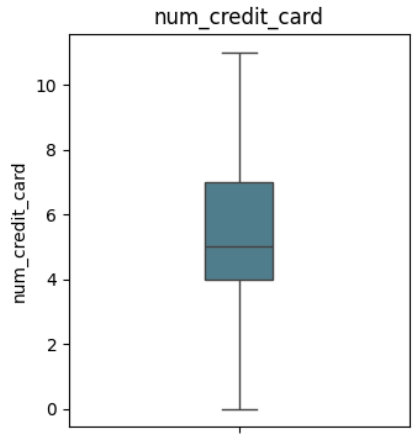


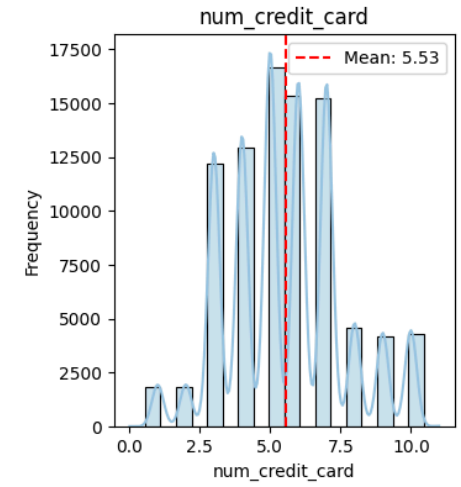


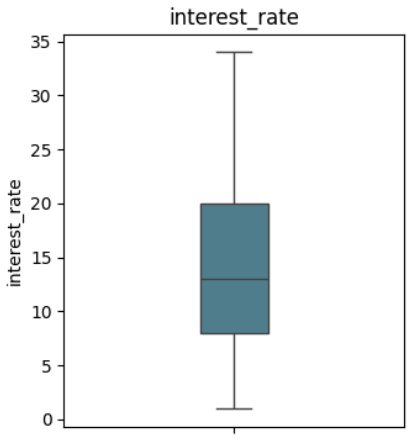


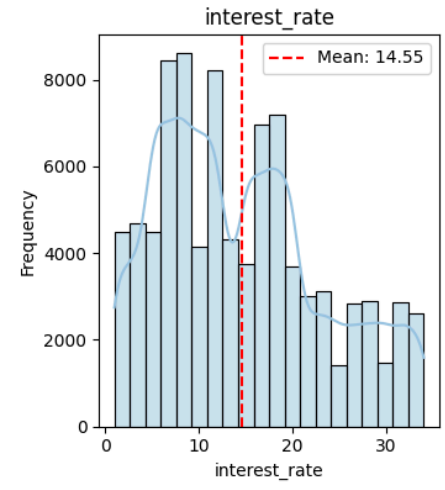


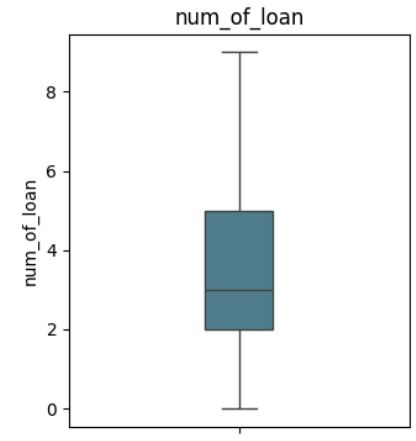


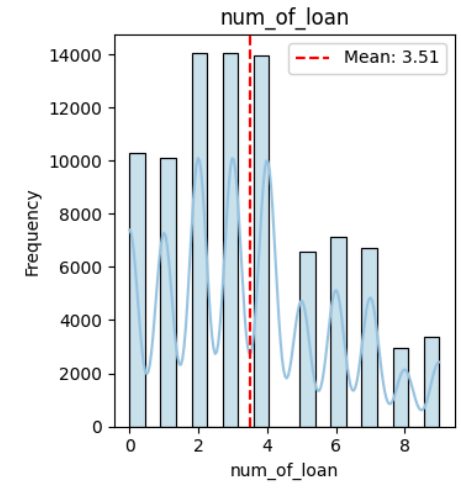


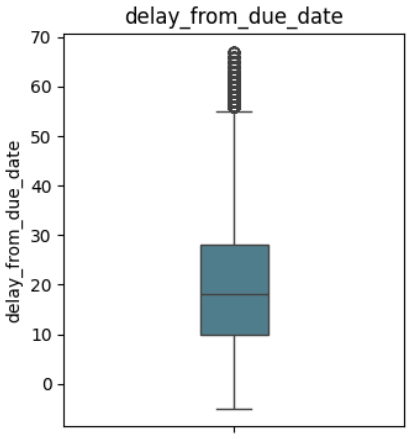


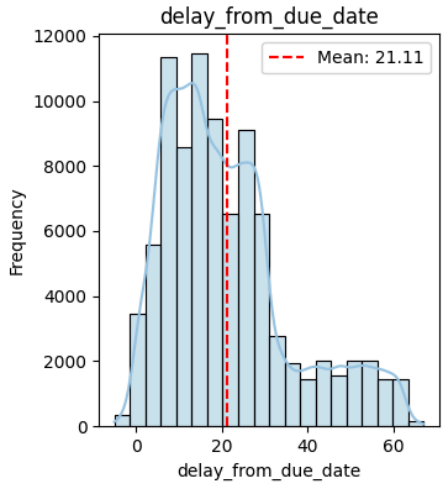


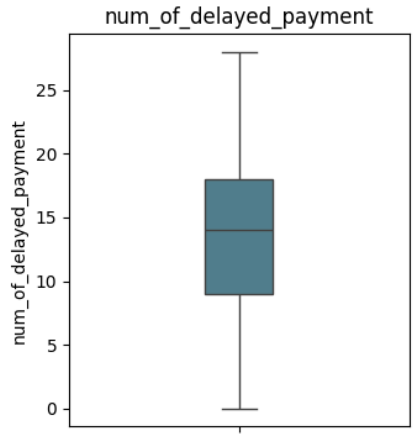


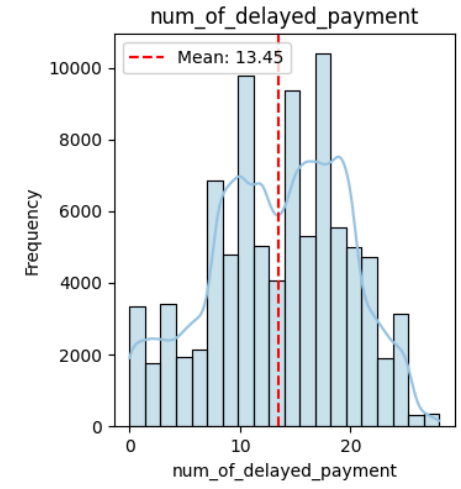


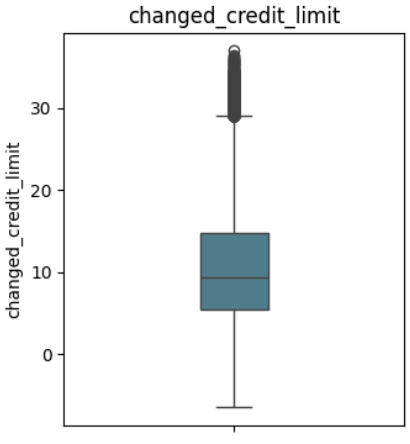


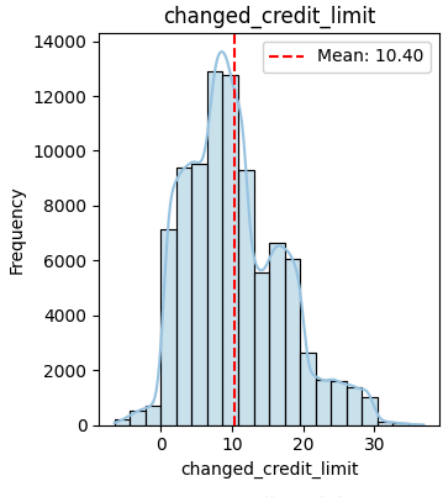


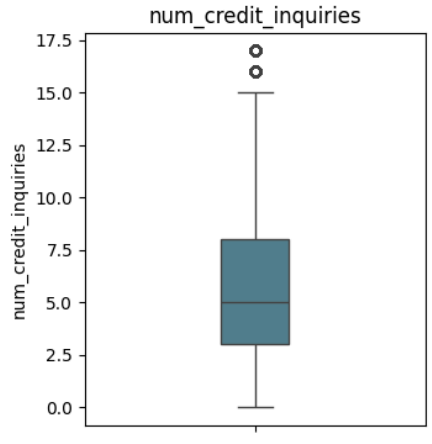


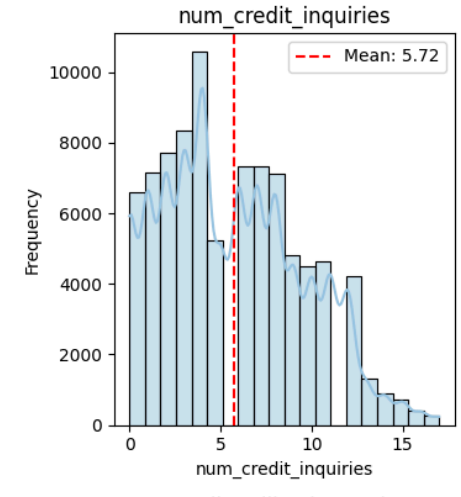










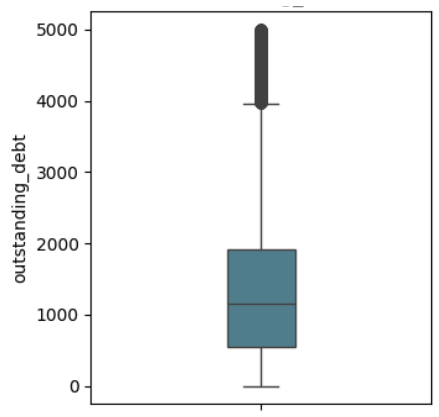


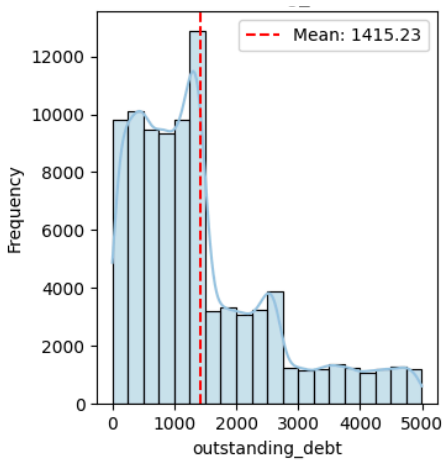
outstanding_debt

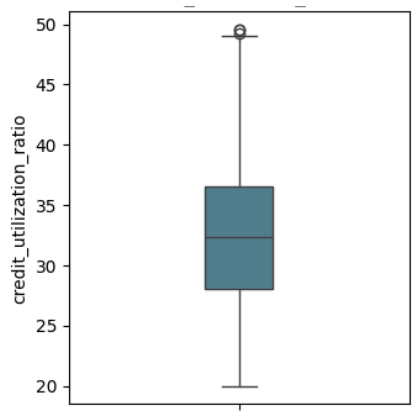
outstanding_debt

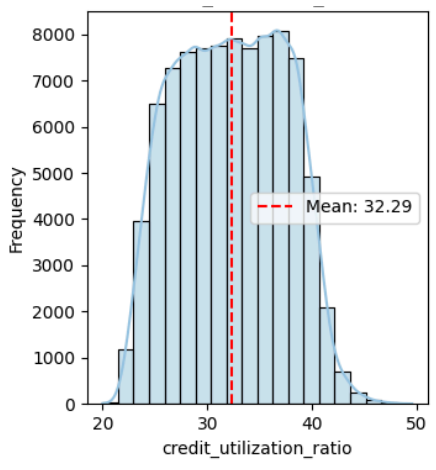
credit_utilization_ratio

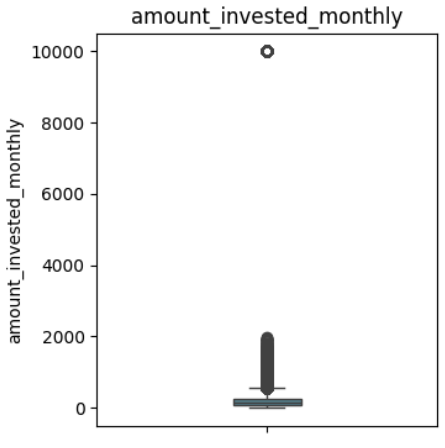
credit_utilization_ratio

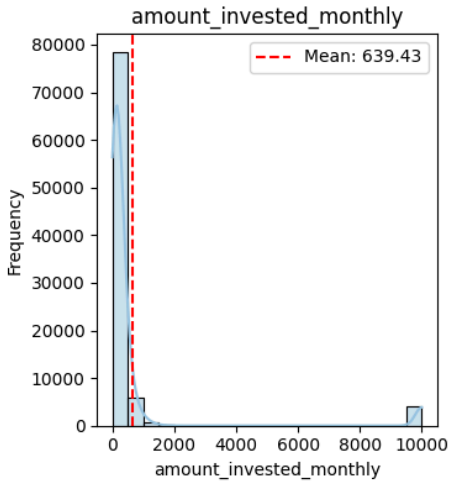


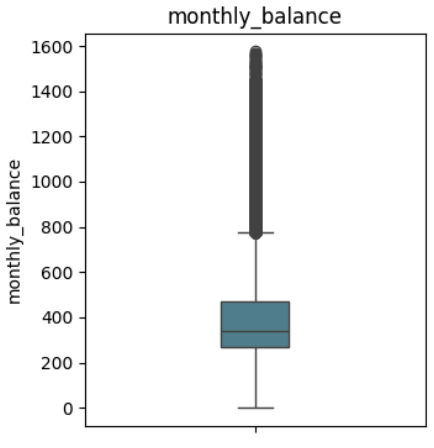


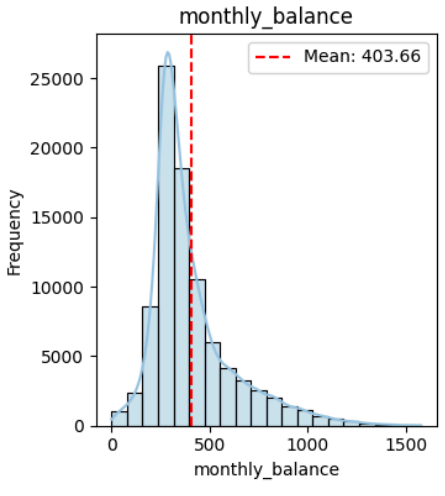


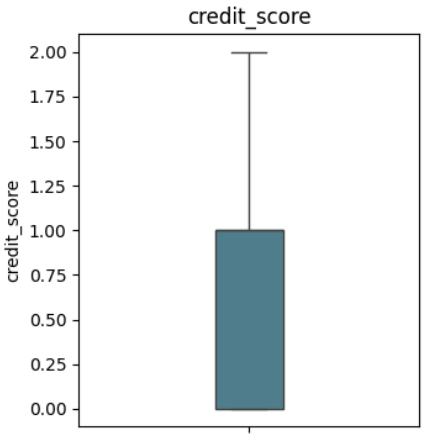


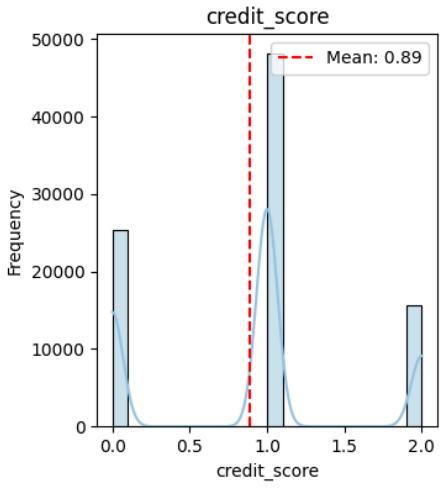


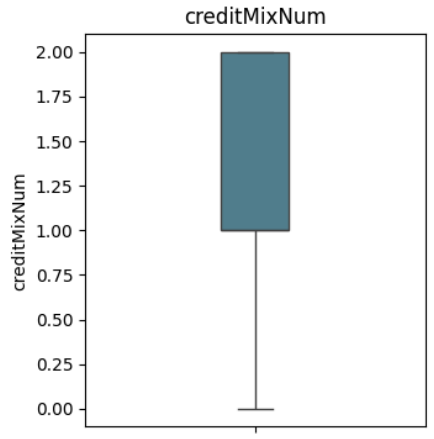


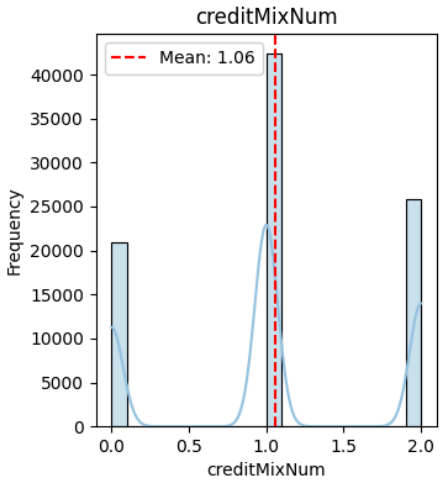


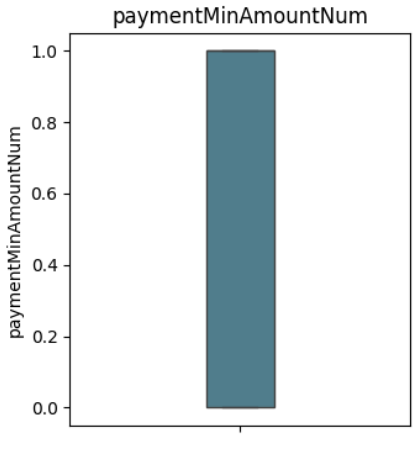


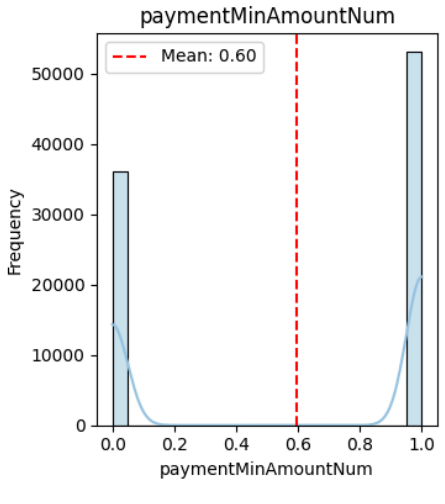












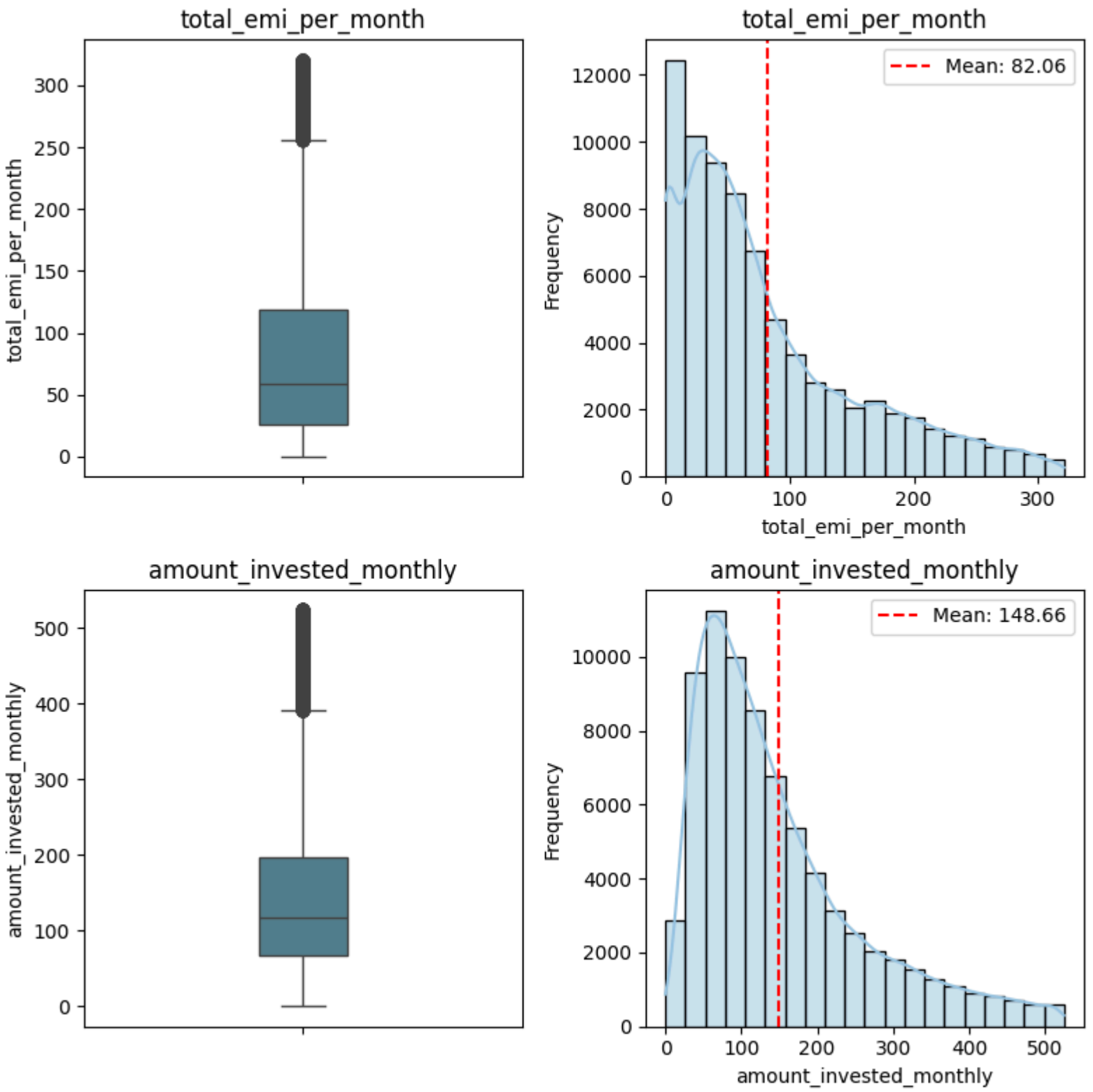
Variables such as age, num_bank_accounts, num_credit_card, num_of_delayed_payments, changed_credit_limit and credit_utlization_ratio are somewhat normally distributed with their means close to the centre. Interest_rate, num_of_loans, delay_from_due_date, num_credit_inquiries are slightly right-skewed. Variables annual_income, monthly_inhand_salary, total_emi_per_month, outstanding_debt, amount_invested_monthly and monthly_balance are heavily right skewed. Total_emi_per_month and amount_invested_monthly have outliers which will be removed.

Removing outliers from total_emi_per_month and amount_invested_monthly, and plotting them again

In [242…

```
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

data = remove_outliers(data, 'total_emi_per_month')
data = remove_outliers(data, 'amount_invested_monthly')

columnsToPlot = ['total_emi_per_month', 'amount_invested_monthly']
rows = 2
cols = 2
fig, axes = plt.subplots(rows, cols, figsize=(8, rows * 4))
axes = axes.flatten()


for i, col in enumerate(columnsToPlot):
```

```
    sns.boxplot(data=data, y=col, ax=axes[2 * i], color="#498699",  width=0.2)
    axes[2 * i].set_title(f'{col}', fontsize=12)
    axes[2 * i].set_ylabel(col, fontsize=10)

    sns.histplot(data=data, x=col, ax=axes[2 * i + 1], color="#98c5e1", kde=True, bins=20)
    mean_value = data[col].mean()
    axes[2 * i + 1].axvline(mean_value, color='red', linestyle='--', label=f'Mean: {mean_value:.2f}')
    axes[2 * i + 1].legend()
    axes[2 * i + 1].set_title(f'{col}', fontsize=12)
    axes[2 * i + 1].set_xlabel(col, fontsize=10)
    axes[2 * i + 1].set_ylabel('Frequency', fontsize=10)


for j in range(2 * 2, len(axes)):
    fig.delaxes(axes[j])

plt.subplots_adjust(wspace=0.6, hspace=0.4)
plt.tight_layout()
plt.show()
```



Both of them have a right-skewed distribution

In [242…
```
uniqueCustomers = data['customer_id'].nunique()
print(f"Number of unique customer IDs: {uniqueCustomers}")
```

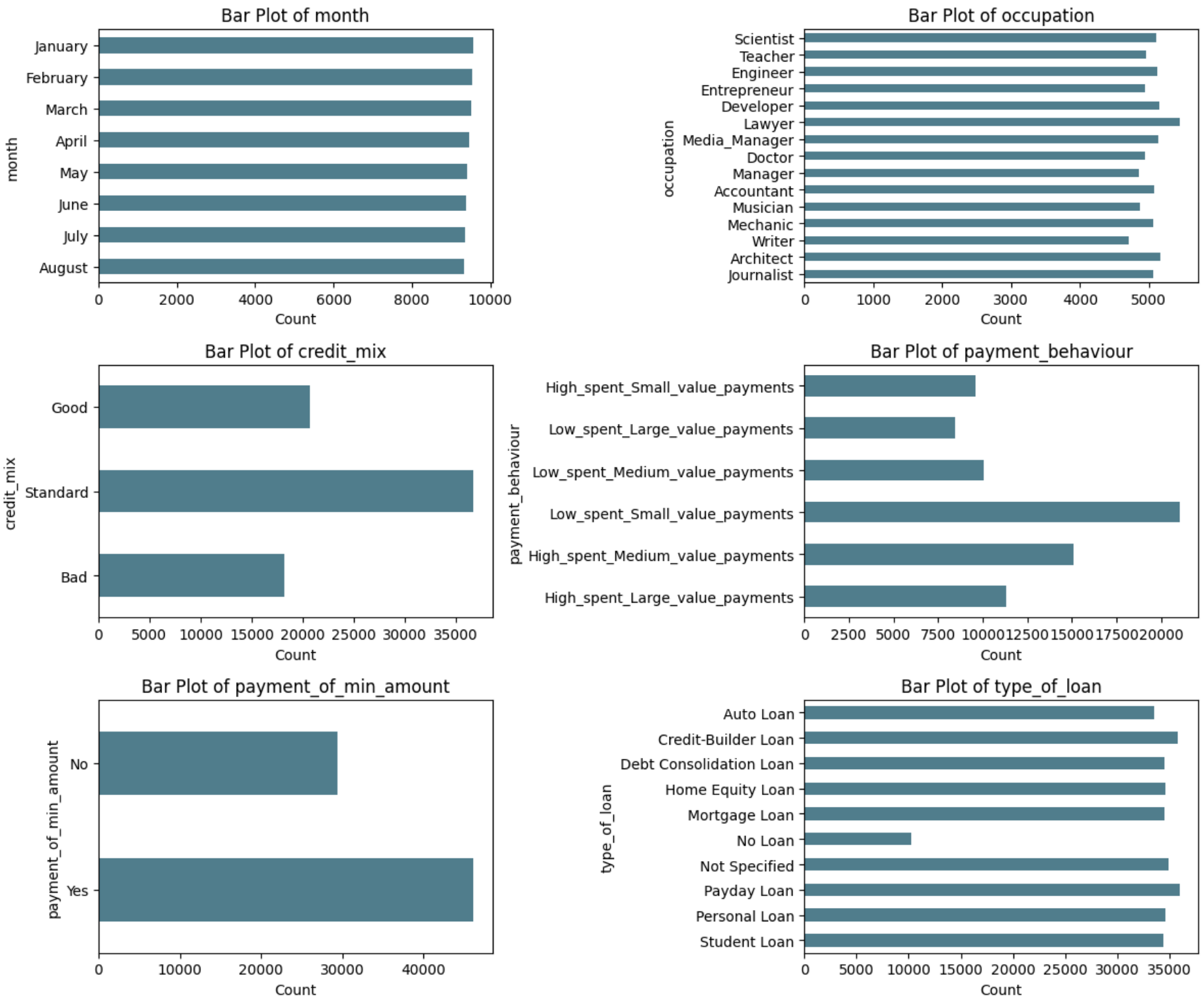
```
Number of unique customer IDs: 10720
```

After removing outliers, the dataset contains 10720 customers.

Univariate Analysis of Categorical Variables using barcharts

In [242…
```
categoricalColumns = ['month', 'occupation', 'credit_mix', 'payment_behaviour', 'payment_of_min_amount']
dataFiltered = data[categoricalColumns]
numPlots = len(categoricalColumns)
rows = (numPlots // 2) + 1
cols = 2
fig, axes = plt.subplots(rows, cols, figsize=(12, 10))
axes = axes.flatten()
```

```
for i, col in enumerate(categoricalColumns):
    sns.countplot(data=dataFiltered, y=col, ax=axes[i], color='#498699', width=0.5, legend=False, orient='h')
    axes[i].set_title(f'Bar Plot of {col}', fontsize=12)
    axes[i].set_ylabel(col, fontsize=10)
    axes[i].set_xlabel('Count', fontsize=10)

loanTypeCounts = loanData.groupby('loan_type')['loan_count'].sum().reset_index()
sns.barplot(x='loan_count', y='loan_type', data=loanTypeCounts, ax=axes[numPlots], color='#498699', width=0.5)
axes[numPlots].set_title('Bar Plot of type_of_loan', fontsize=12)
axes[numPlots].set_xlabel('Count', fontsize=10)
axes[numPlots].set_ylabel('type_of_loan', fontsize=10)

for j in range(numPlots+1, len(axes)):
    fig.delaxes(axes[j])

plt.subplots_adjust(wspace=0.6, hspace=0.4)
plt.tight_layout()
plt.show()
```



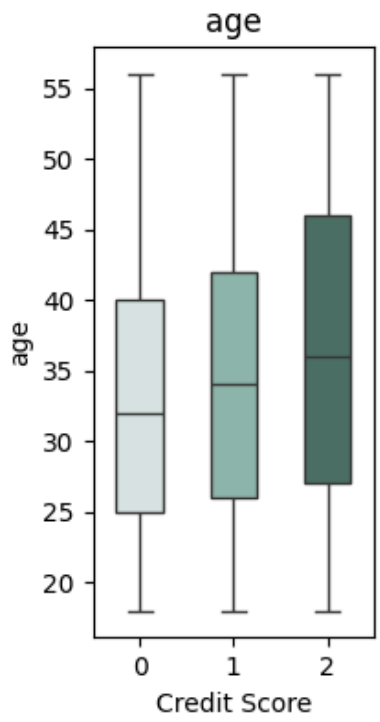
There is an almost even distribution in month, occupation and type_of_loan (except for no loan). In credit_mix, standard has the highest count whereas in payment_behaviour, low_spent_small_value_payments has the highest count. In payment_of_min_amount, Yes is the majority class which means that most of the times, customers paid just the minimum amount required for that month.

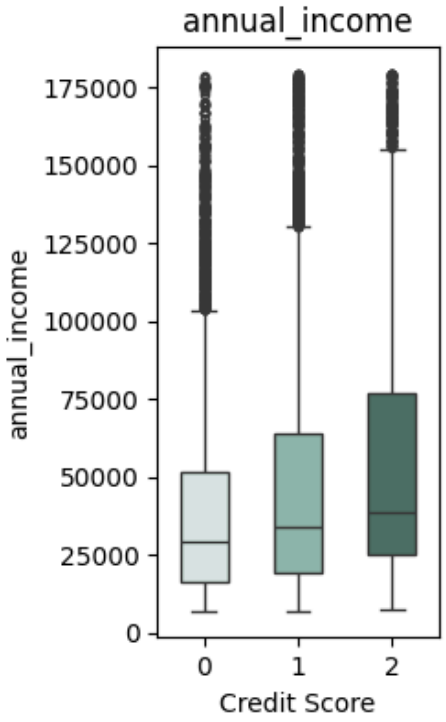
Comparing relationship between numerical columns and credit scores. Analysing how the distribution of numerical columns varies in each credit score category using box plots

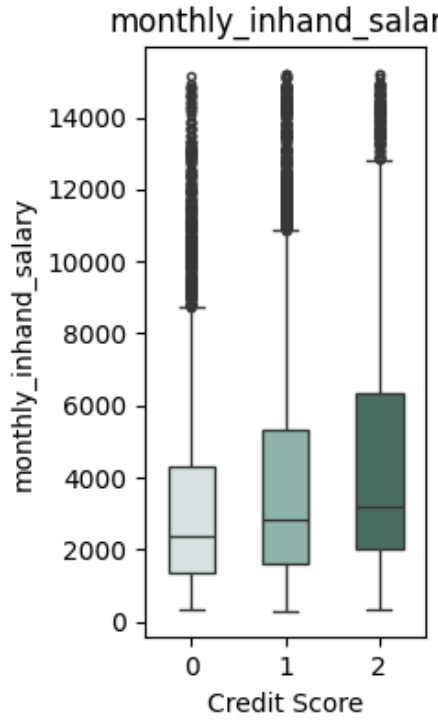
In [242…

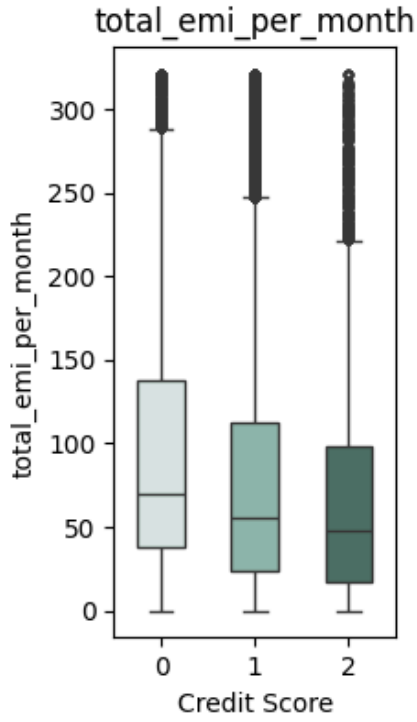
```
numericColumns = data.select_dtypes(include='number').columns.drop('credit_score')
customPalette = {0: "#d6e7e4", 1: "#87bbae", 2: "#48756a"}
flierprops = dict(markersize=3)

numPlots = len(numericColumns)
nCols = 4
nRows = (numPlots // 2) + 1
fig, axes = plt.subplots(nRows, nCols, figsize=(10, nRows * 4))
axes=axes.flatten()

for i, col in enumerate(numericColumns):
    sns.boxplot(data=data, x='credit_score', y=col, ax=axes[i], hue='credit_score', palette=customPalette, width=0.
    axes[i].set_title(f'{col}', fontsize=12)
```

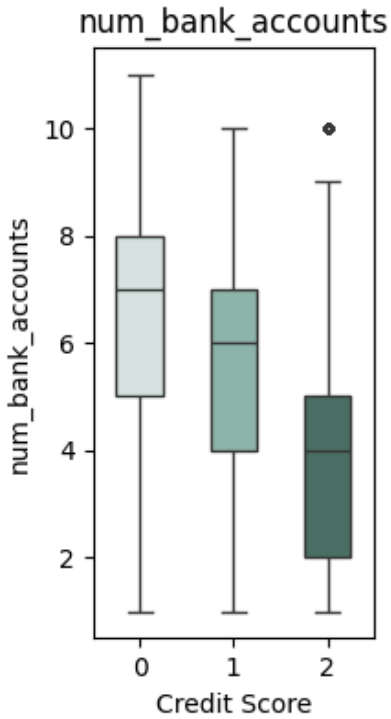
```
    axes[i].set_xlabel('Credit Score')
    axes[i].set_ylabel(col)

for j in range(numPlots, len(axes)):
    axes[j].set_visible(False)

plt.subplots_adjust(hspace=0.4, wspace=5)
plt.tight_layout()
plt.show()
```

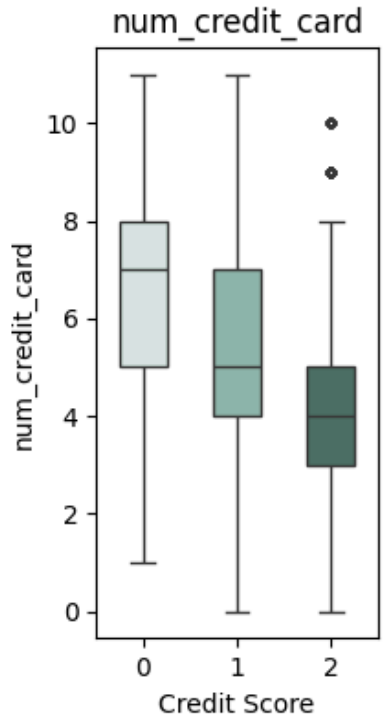


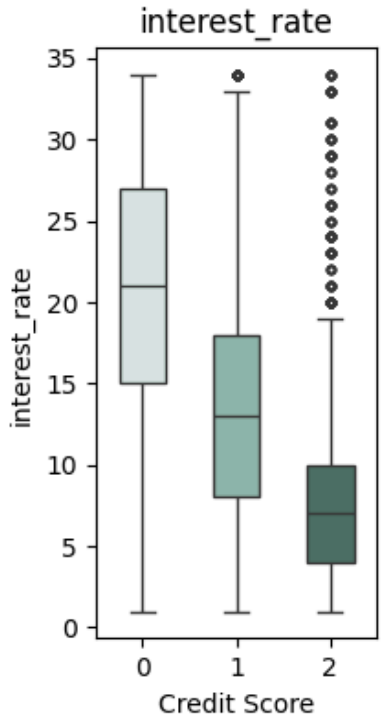


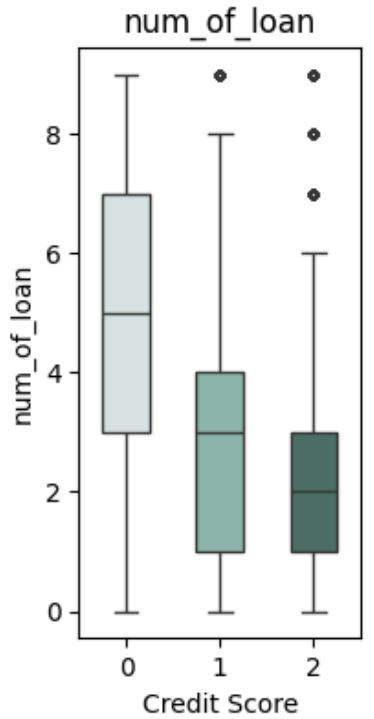


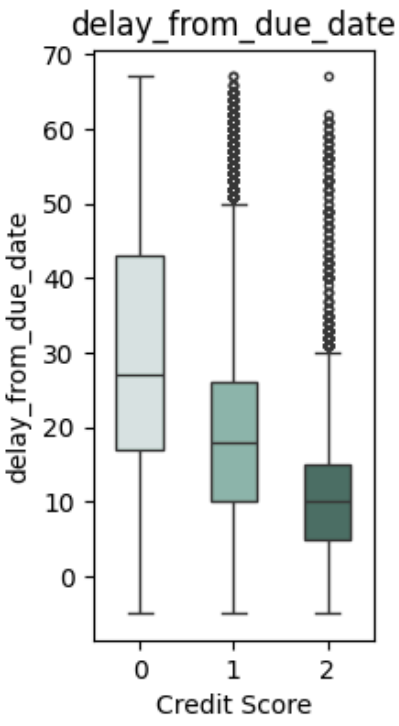


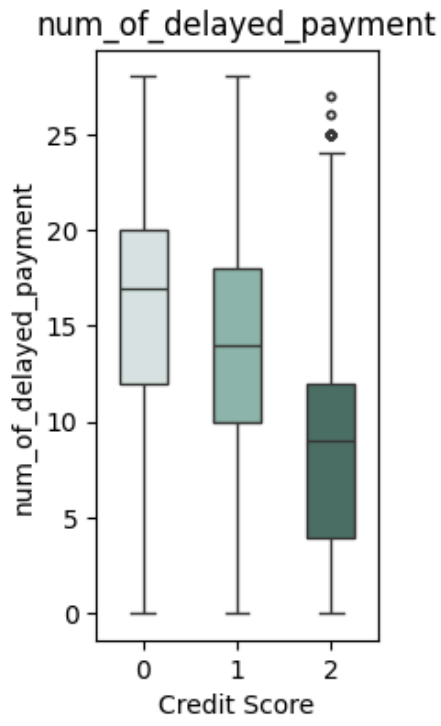


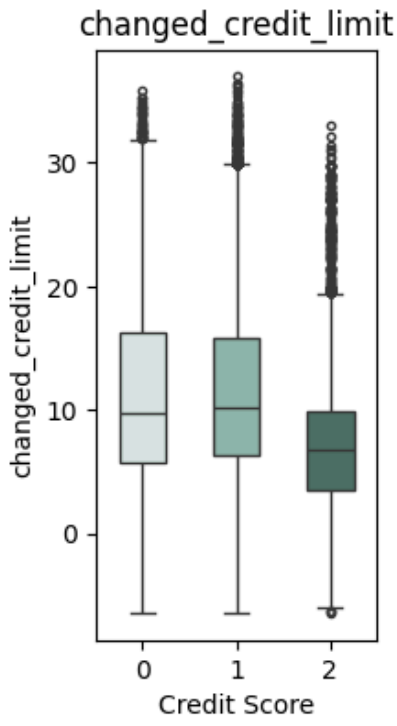


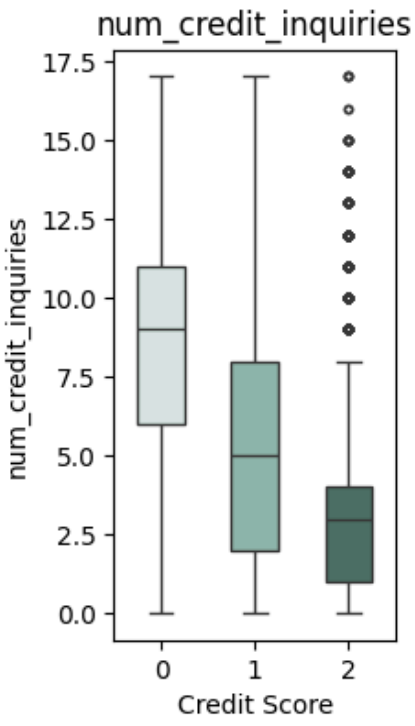


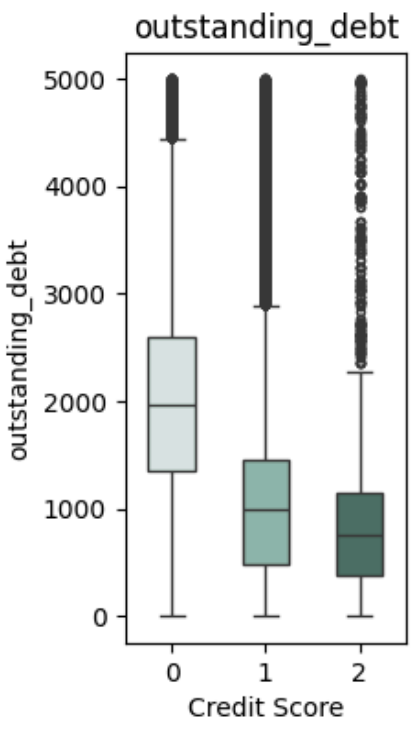


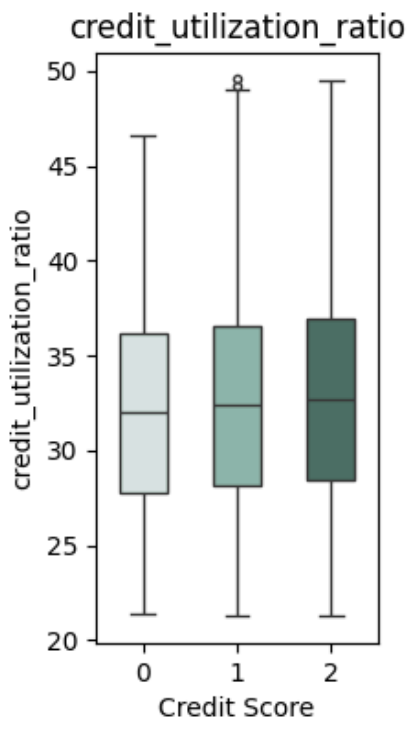


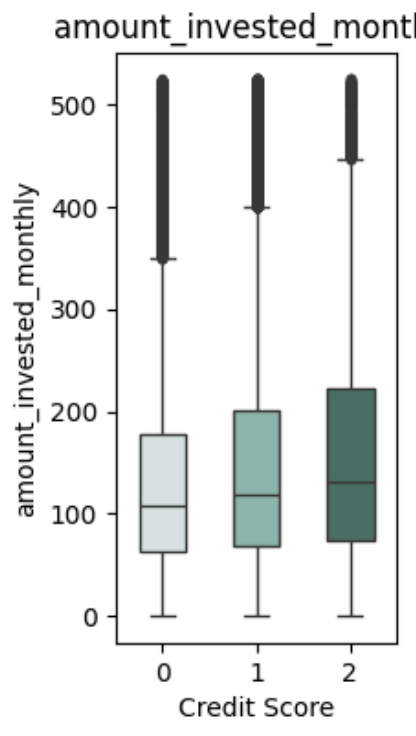


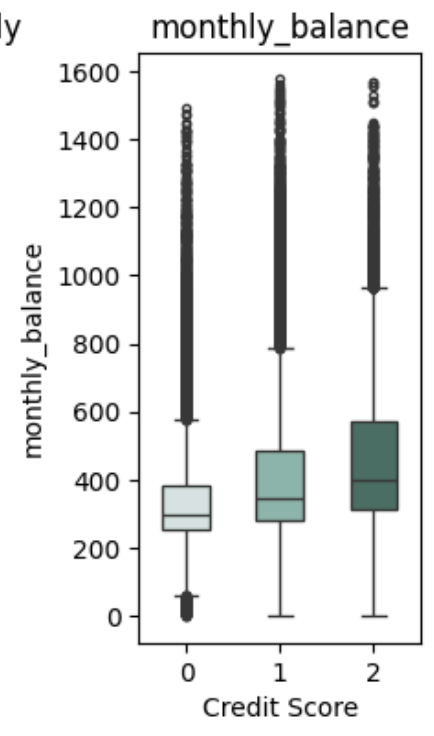




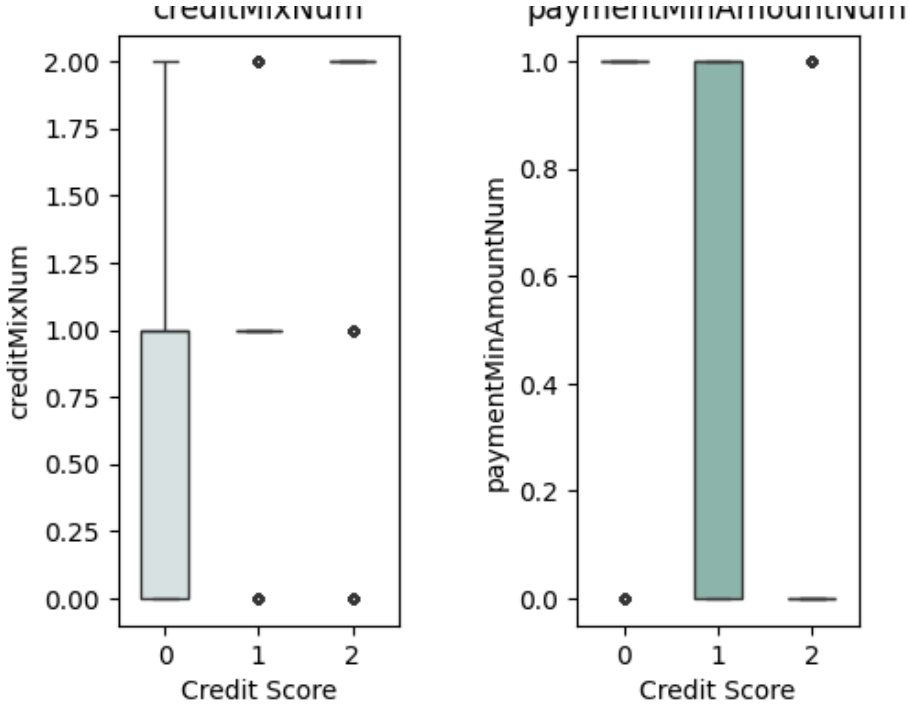








creditMixNum paymentMinAmountNum

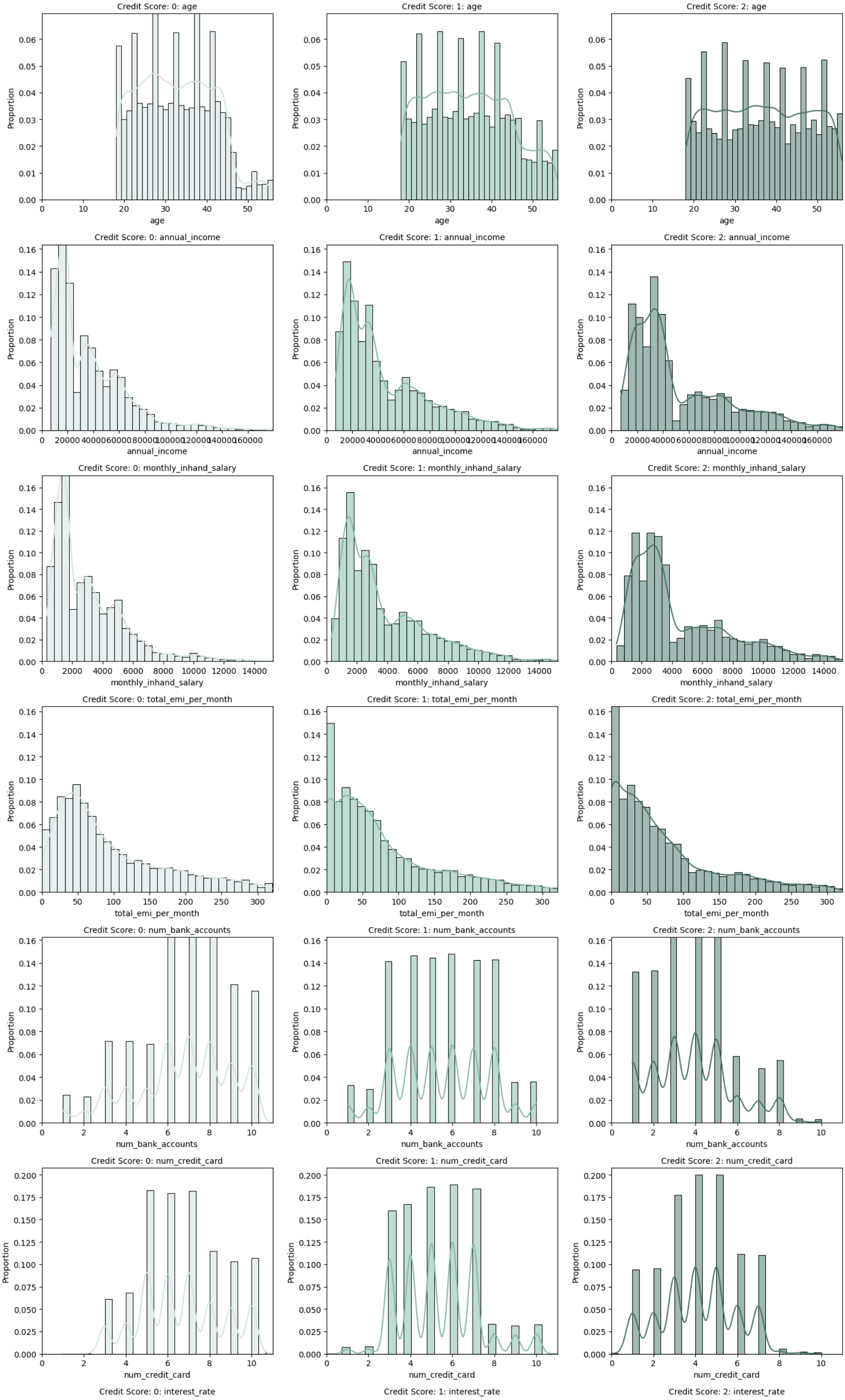


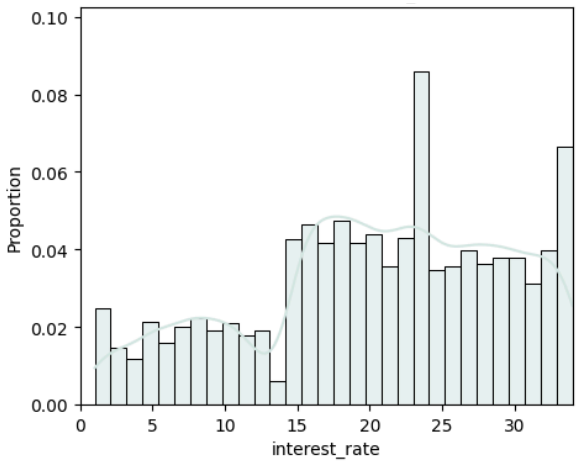
The mean values of age, annual_income, monthly_in_hand salary, amount_invested_monthly and monthly_balance increase as the credit score increase. Whereas the mean values of total_emi_per_month, num_bank_accounts, num_credit_card, interest_rate, num_of_loan, delay_from_due_date (in days), num_of_delayed_payments, num_credit_inquiries, outstanding_debt decrease as the credit score increases. For changed_credit_limit and credit_utilization_ratio the mean values relatively stay the same across the credit scores.

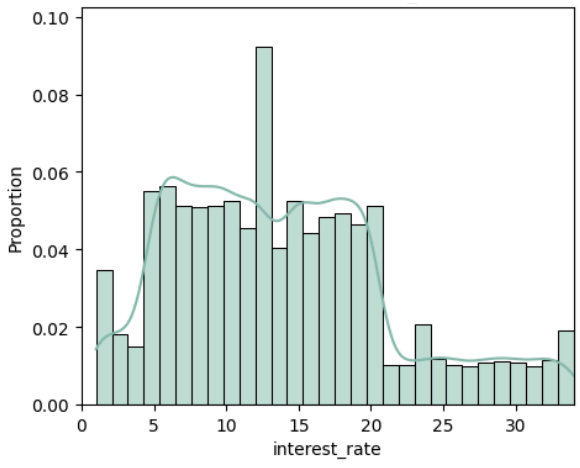
Comparing distributions of numerical columns in each credit score using histograms. For every numeric column, the proportion of values in each credit score category is shown instead of the absolute count so that they can be fairly compared

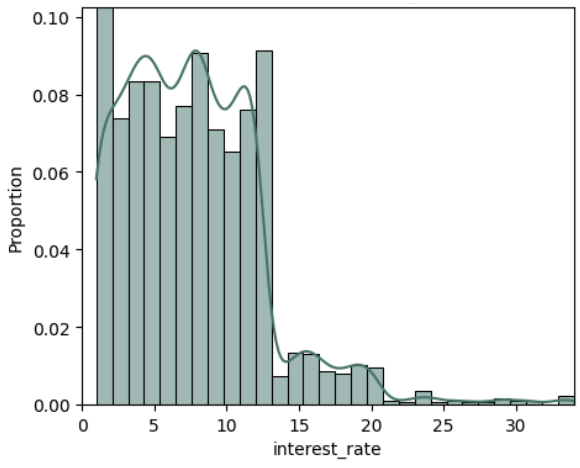
In [242…

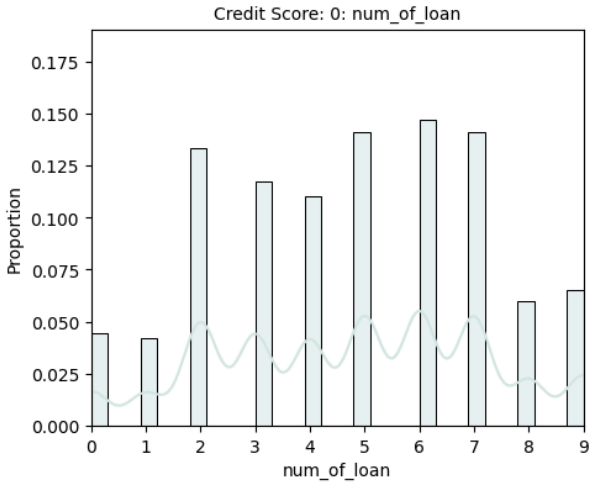
```
creditScores = {0: "Credit Score: 0", 1: "Credit Score: 1", 2: "Credit Score: 2"}

globalXLimits = {}
globalYLimits = {}

# Getting the limits for the y-axis for each numeric column by setting it equal to the value of the biggest bin in
# across all credit scores and dividing it by the sum of all the bins and adding a buffer to leave some space on to
for i, col in enumerate(numericColumns):
    xMax = data[col].max()
    yMax = 0
    yMaxPercent = 0
    _, bins, _ = plt.hist(data[col], bins=30)
    plt.close()
    for score in creditScores.keys():
        counts = [0] * (len(bins) - 1)
        for i in range(len(bins) - 1):
            counts[i] = sum((data[data['credit_score'] == score][col] >= bins[i]) & (data[data['credit_score'] == s
        if yMax < max(counts):
            yMax = max(counts)
            yMaxPercent = yMax/sum(counts)

    buffer = yMaxPercent*0.1
    globalXLimits[col] = (0, xMax)
    globalYLimits[col] = (0, yMaxPercent+buffer)


nCols = 3
nRows = len(numericColumns)
fig, axes = plt.subplots(nRows, nCols, figsize=(15, nRows * 4))
axes = axes.reshape(nRows, nCols)

for i, col in enumerate(numericColumns):
    for j, score in enumerate(creditScores.keys()):
        sns.histplot(
            data=data[data['credit_score'] == score],
            x=col,
            kde=True,
            stat="probability",
            color={0: '#d6e7e4', 1: '#87bbae', 2: '#48756a'}[score],
            ax=axes[i, j],
            bins=30
        )
        axes[i, j].set_title(f'{creditScores[score]}: {col}', fontsize=10)
        axes[i, j].set_ylabel('Proportion')
        axes[i, j].set_xlabel(col)
        axes[i, j].set_xlim(globalXLimits[col])
        axes[i, j].set_ylim(globalYLimits[col])

plt.tight_layout()
plt.show()
```

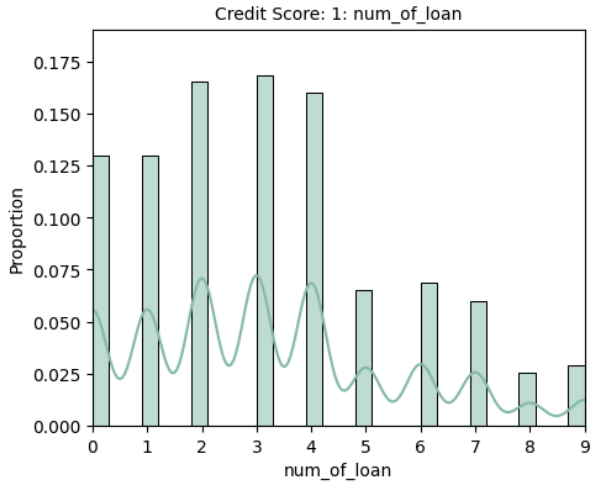

Credit Score: 0: age
Credit Score: 1: age
Credit Score: 2: age
Credit Score: 0: annual_income
Credit Score: 1: annual_income
Credit Score: 2: annual_income
Credit Score: 0: monthly_inhand_salary
Credit Score: 1: monthly_inhand_salary
Credit Score: 2: monthly_inhand_salary
Credit Score: 0: total_emi_per_month
Credit Score: 1: total_emi_per_month
Credit Score: 2: total_emi_per_month
Credit Score: 0: num_bank_accounts
Credit Score: 1: num_bank_accounts
Credit Score: 2: num_bank_accounts
Credit Score: 0: num_credit_card
Credit Score: 1: num_credit_card
Credit Score: 2: num_credit_card
Credit Score: 0: interest_rate
Credit Score: 1: interest_rate
Credit Score: 2: interest_rate
Proportion
age
annual_income
monthly_inhand_salary
total_emi_per_month
num_bank_accounts
num_credit_card
interest_rate

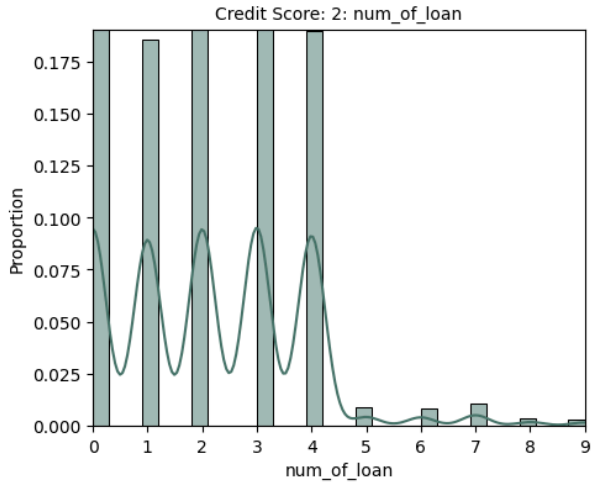

Proportion
interest_rate

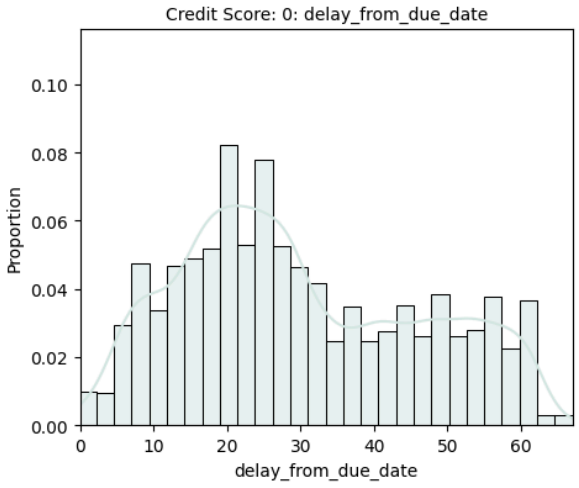

Proportion
interest_rate

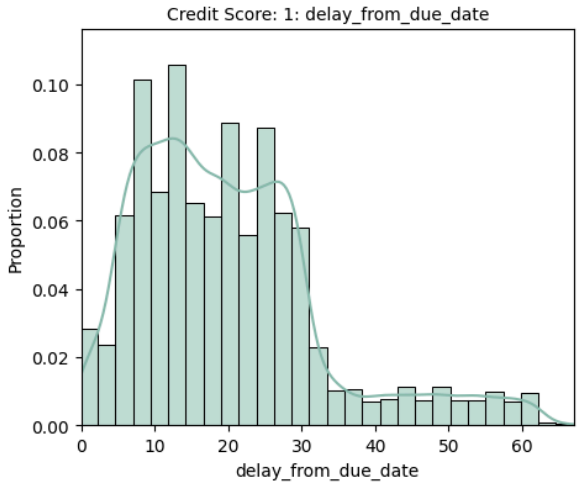

Proportion
interest_rate

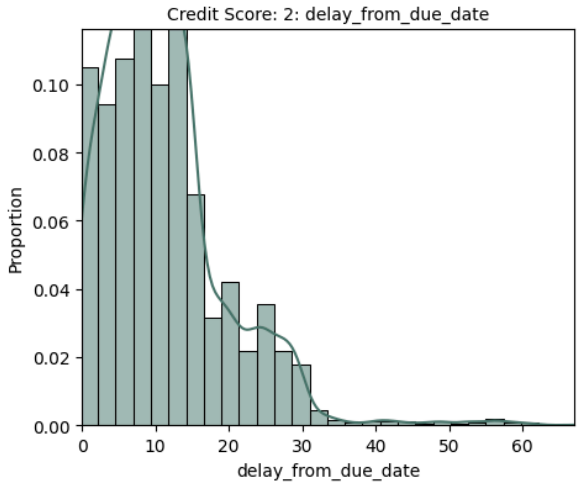

Credit Score: 0: num_of_loan
Proportion
num_of_loan

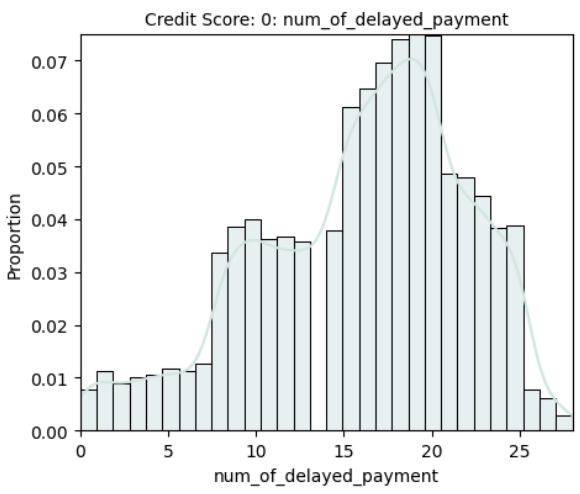

Credit Score: 1: num_of_loan
Proportion
num_of_loan

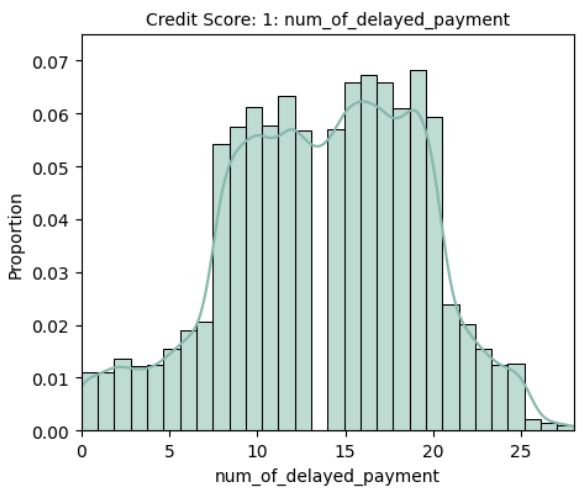

Credit Score: 2: num_of_loan
Proportion
num_of_loan

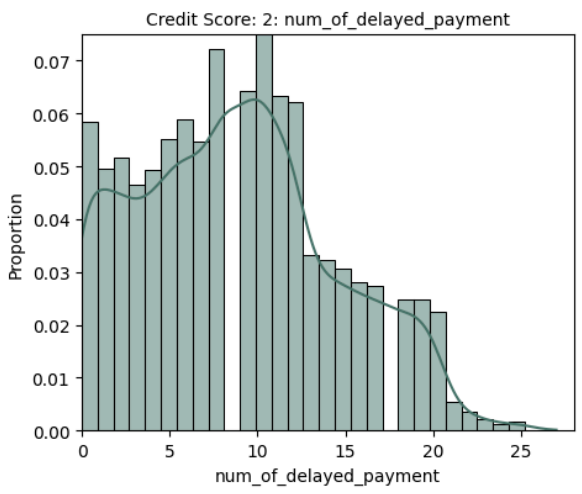

Credit Score: 0: delay_from_due_date
Proportion
delay_from_due_date

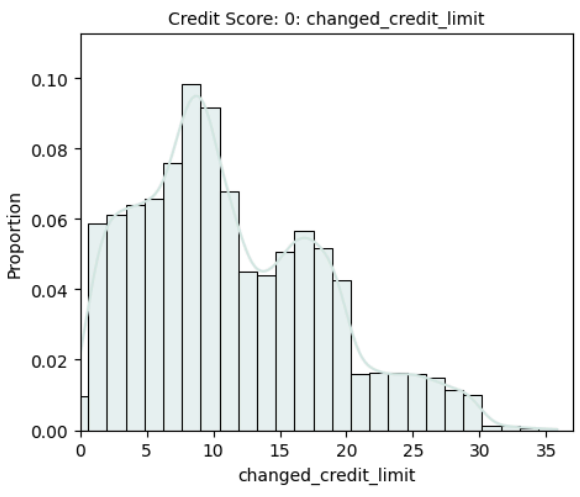

Credit Score: 1: delay_from_due_date
Proportion
delay_from_due_date

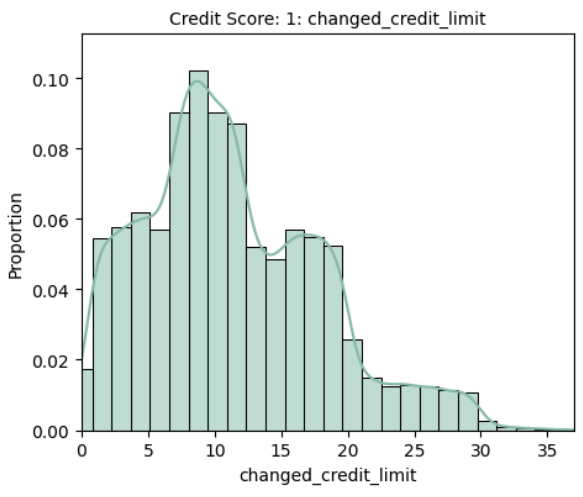

Credit Score: 2: delay_from_due_date
Proportion
delay_from_due_date

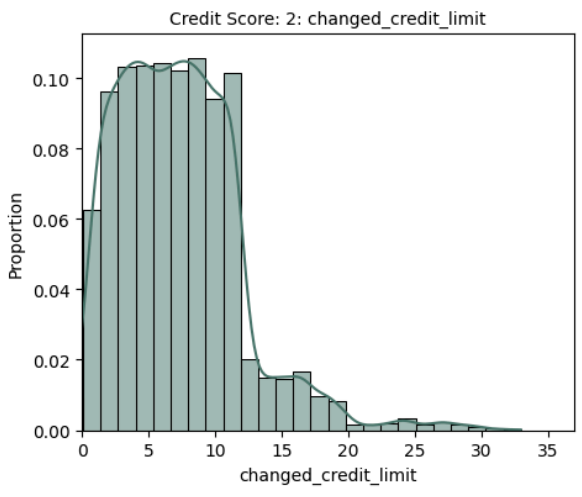

Credit Score: 0: num_of_delayed_payment
Proportion
num_of_delayed_payment

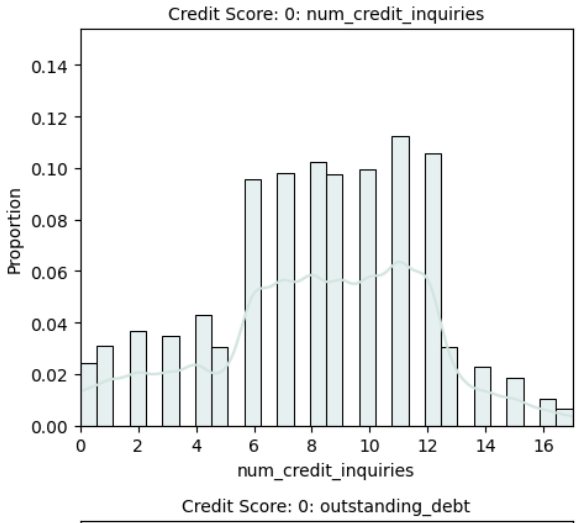

Credit Score: 1: num_of_delayed_payment
Proportion
num_of_delayed_payment

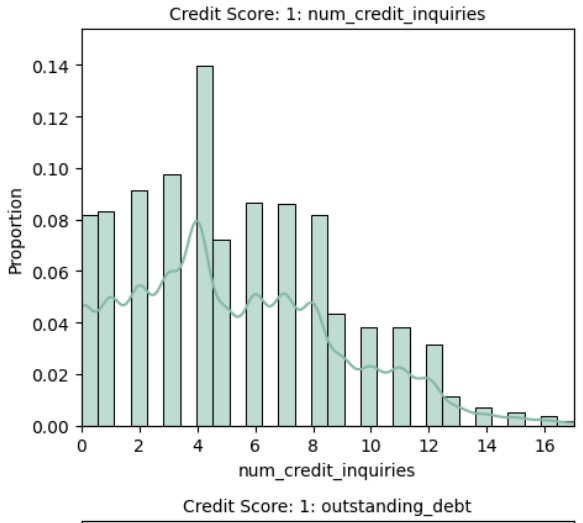

Credit Score: 2: num_of_delayed_payment
Proportion
num_of_delayed_payment

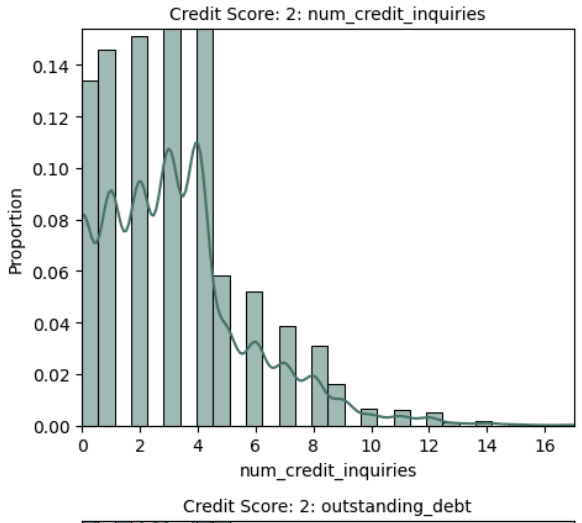

Credit Score: 0: changed_credit_limit
Proportion
changed_credit_limit

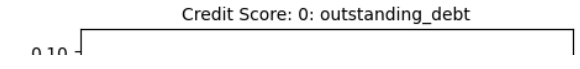

Credit Score: 1: changed_credit_limit
Proportion
changed_credit_limit

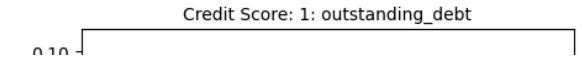

Credit Score: 2: changed_credit_limit
Proportion
changed_credit_limit

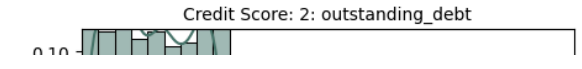

Credit Score: 0: num_credit_inquiries
Proportion
num_credit_inquiries

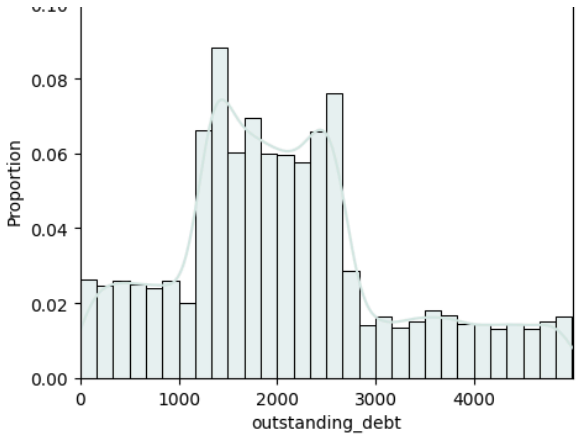

Credit Score: 1: num_credit_inquiries
Proportion
num_credit_inquiries


Credit Score: 2: num_credit_inquiries
Proportion
num_credit_inquiries

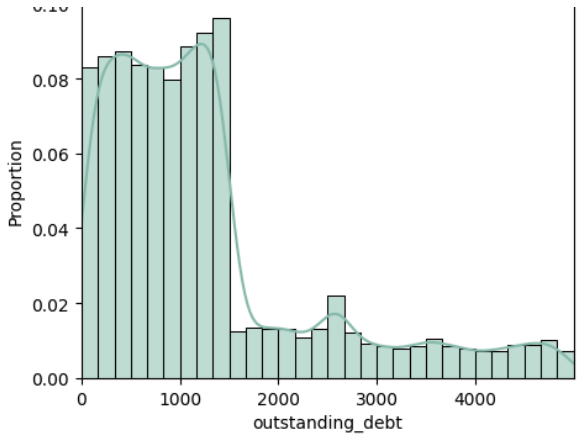

Credit Score: 0: outstanding_debt


Credit Score: 1: outstanding_debt

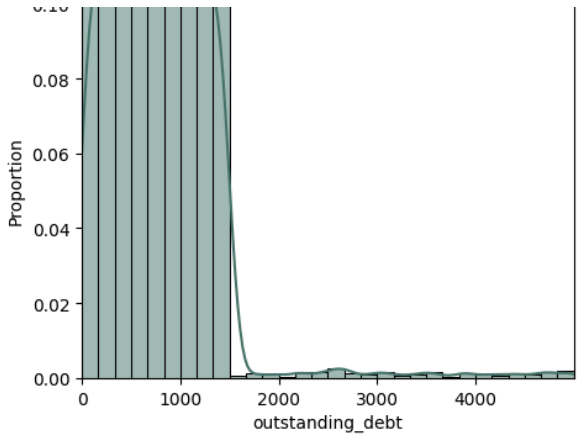

Credit Score: 2: outstanding_debt



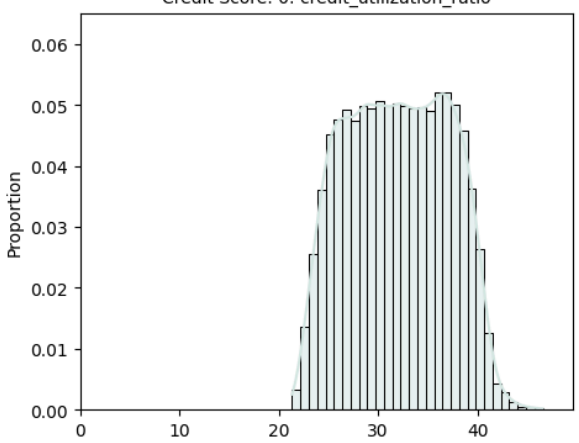
Credit Score: 0: credit_utilization_ratio



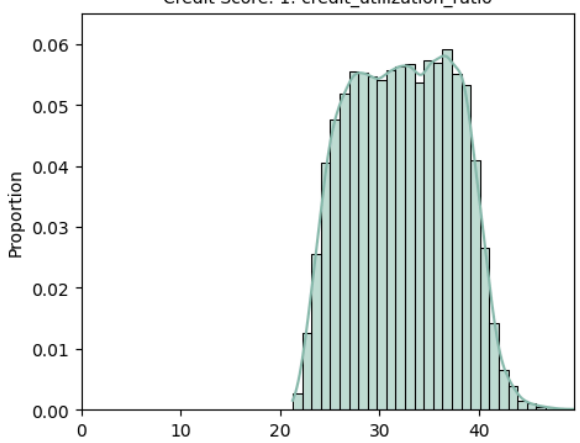
Credit Score: 1: credit_utilization_ratio



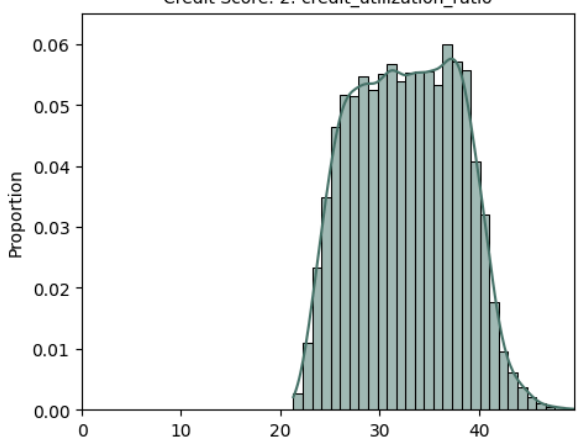
Credit Score: 2: credit_utilization_ratio



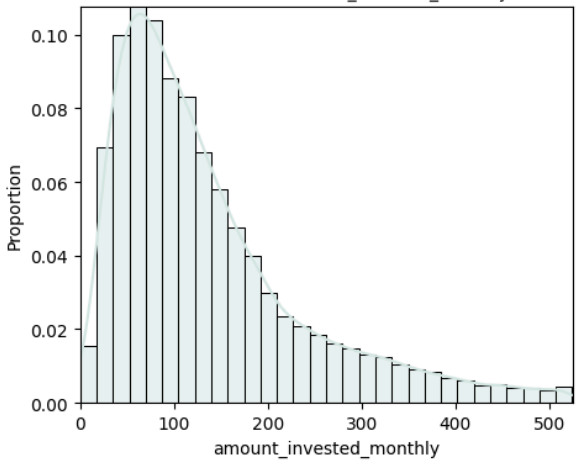
Credit Score: 0: amount_invested_monthly



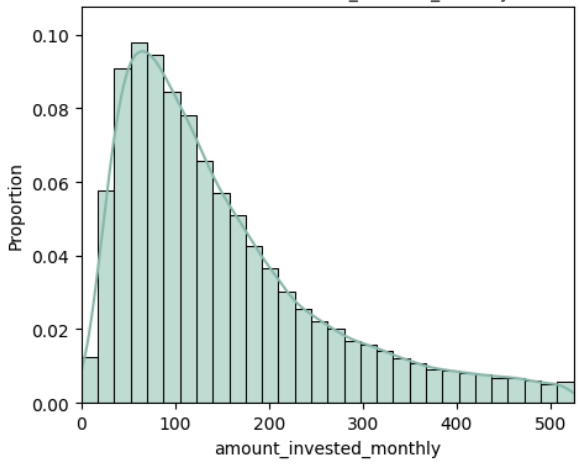
Credit Score: 1: amount_invested_monthly



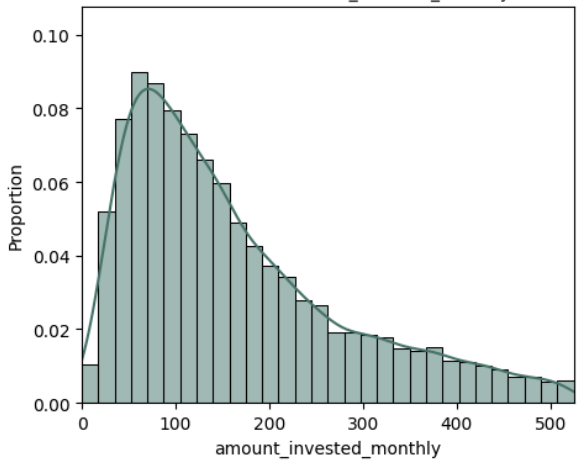
Credit Score: 2: amount_invested_monthly



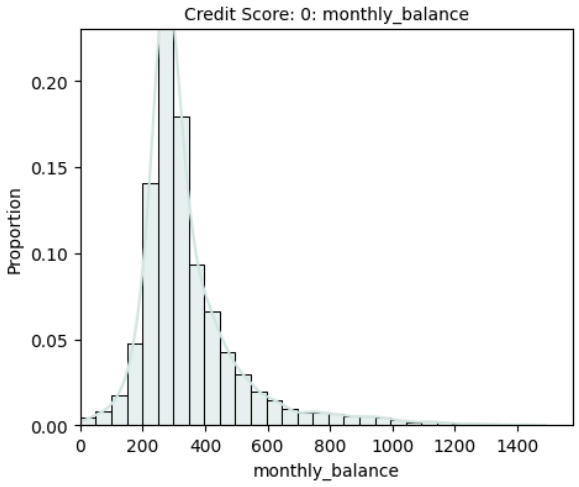
Credit Score: 0: monthly_balance



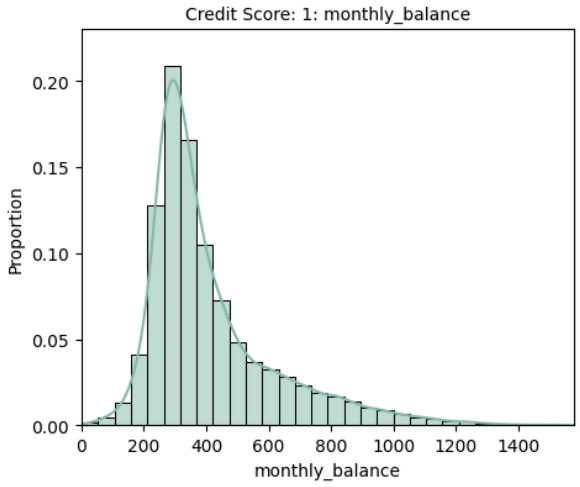
Credit Score: 1: monthly_balance



Credit Score: 2: monthly_balance

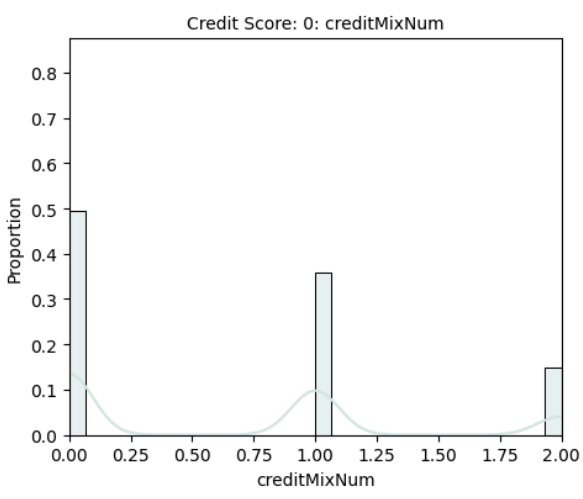


Credit Score: 0: creditMixNum

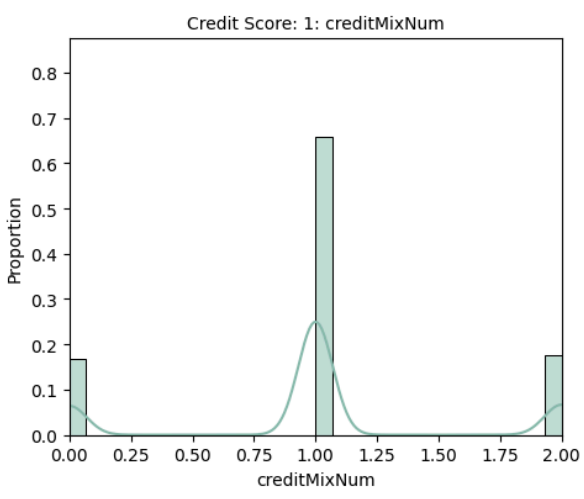


Credit Score: 1: creditMixNum

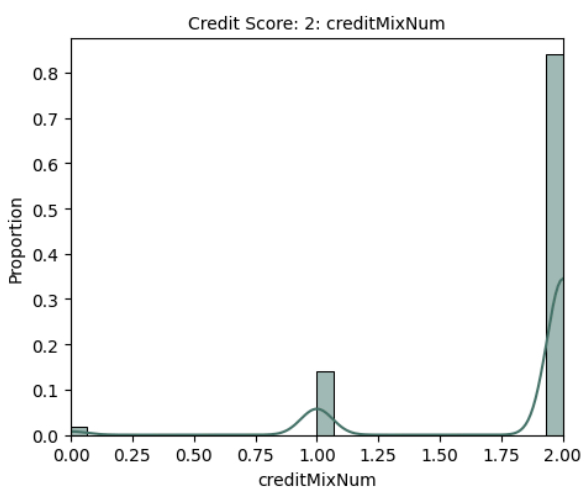
Credit Score: 2: creditMixNum



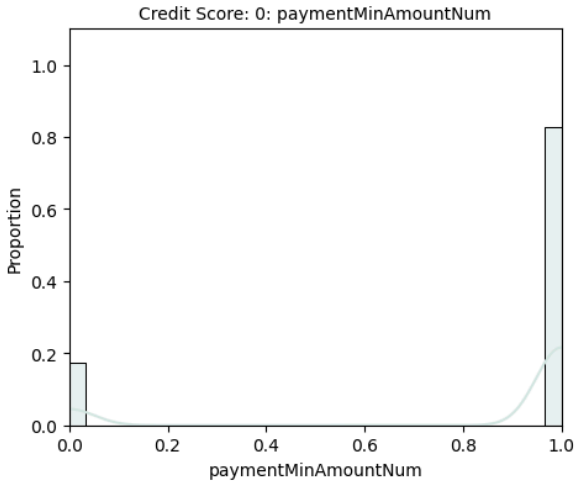
Credit Score: 0: paymentMinAmountNum

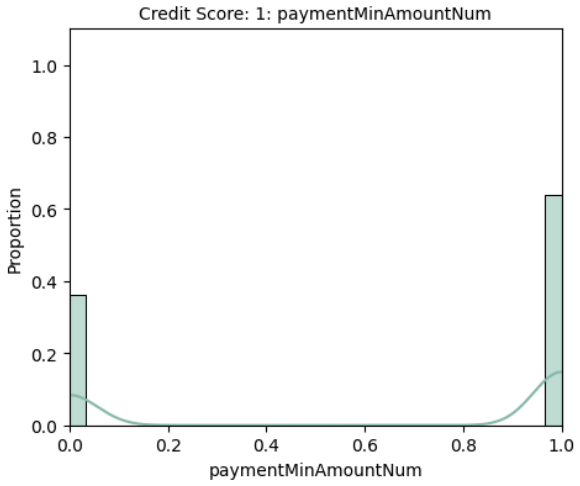


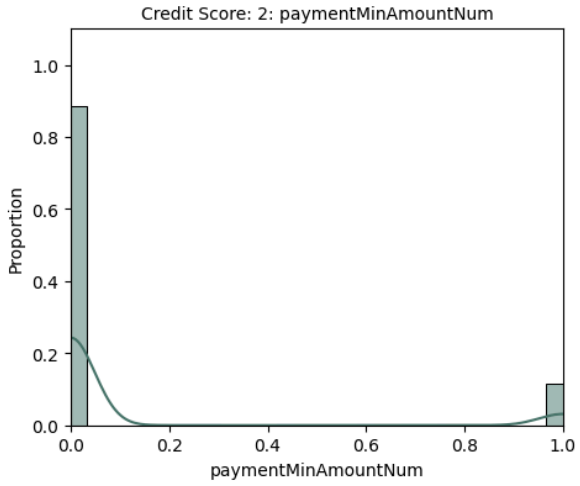
Credit Score: 1: paymentMinAmountNum



Credit Score: 2: paymentMinAmountNum





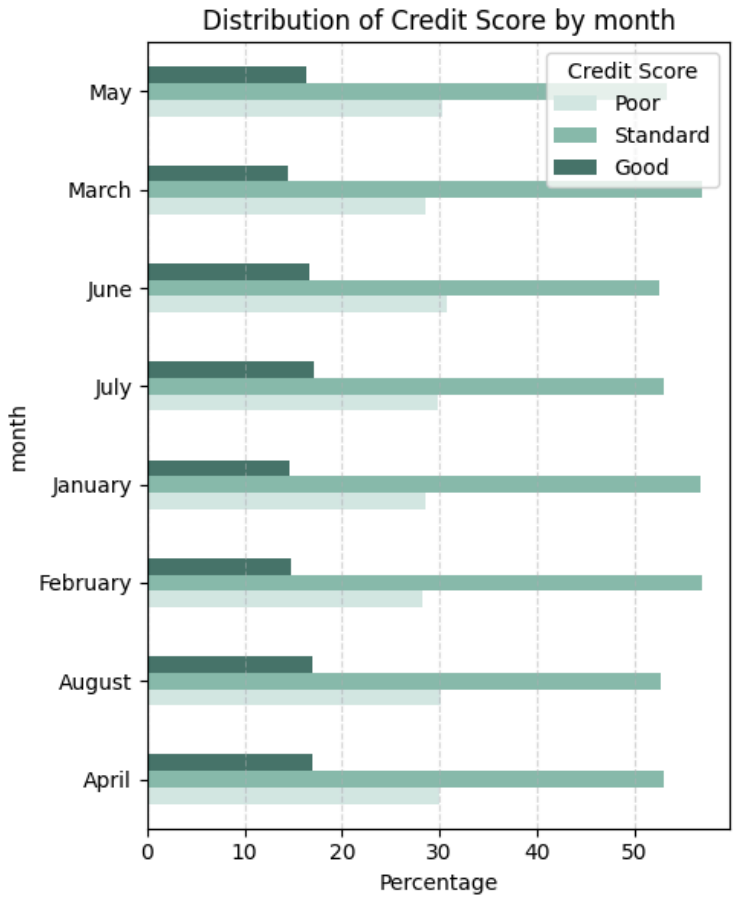


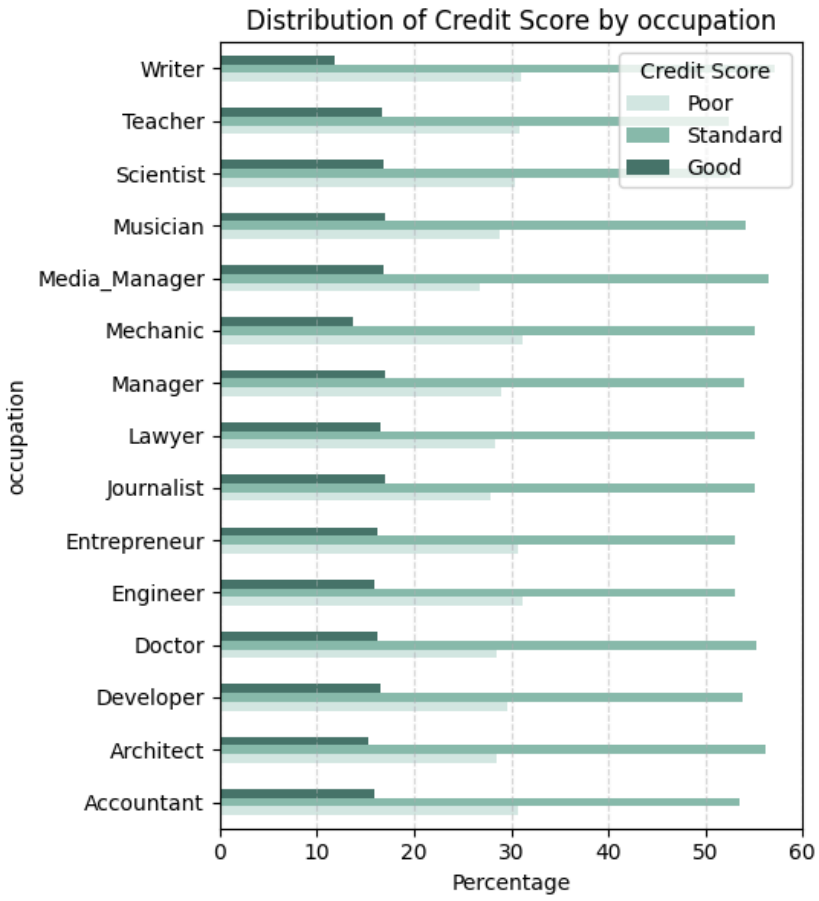
For the age column, out of all the customers with a good credit score, there is a higher proportion of customers above the age of 45 as compared to the customers with a poor and standard credit score. Moreover, a greater proportion of customers with a good credit have fewer bank accounts as compared to the ones with a poor and standard score. A greater proportion of customers with a good credit score have a lower interest rate as compared to the ones with a poor and standard score but this may be because they are eligible for lower interest rates. A large proportion of good credit score customers also take fewer loans. They also have shorter delays from the due date and lesser delayed payments as well. Moreover, almost all of the customers with a good credit score have either no outstanding debt or debt less than 1500 whereas customers with a standard or poor credit score do have higher outstanding debts. Credit utilization rate is similar across the credit scores.

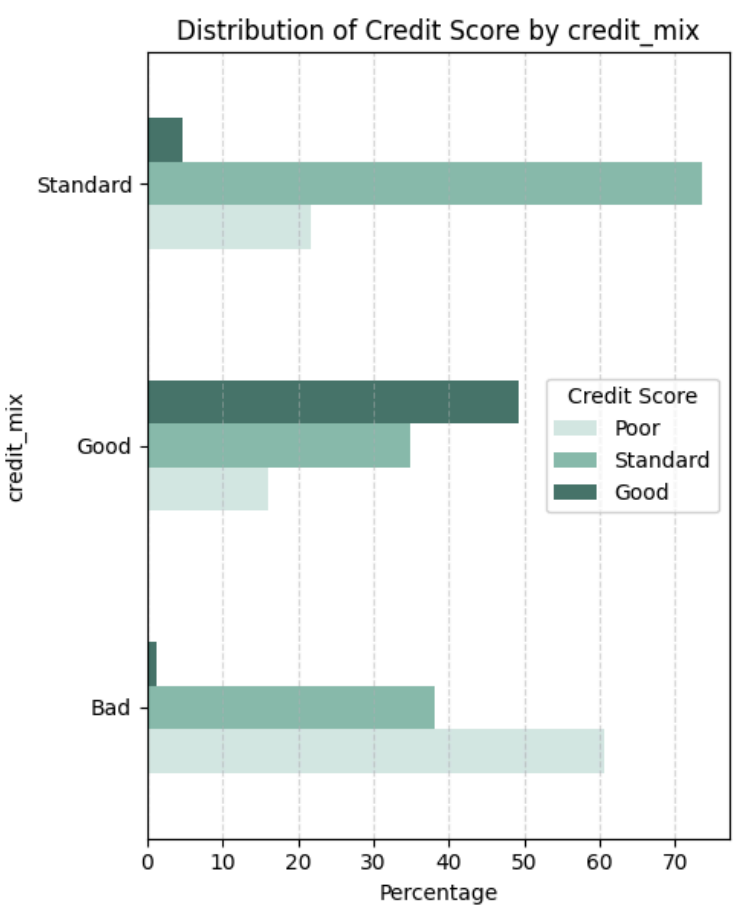
Analyzing thr relationships between categorical columns and credit scores using bar charts

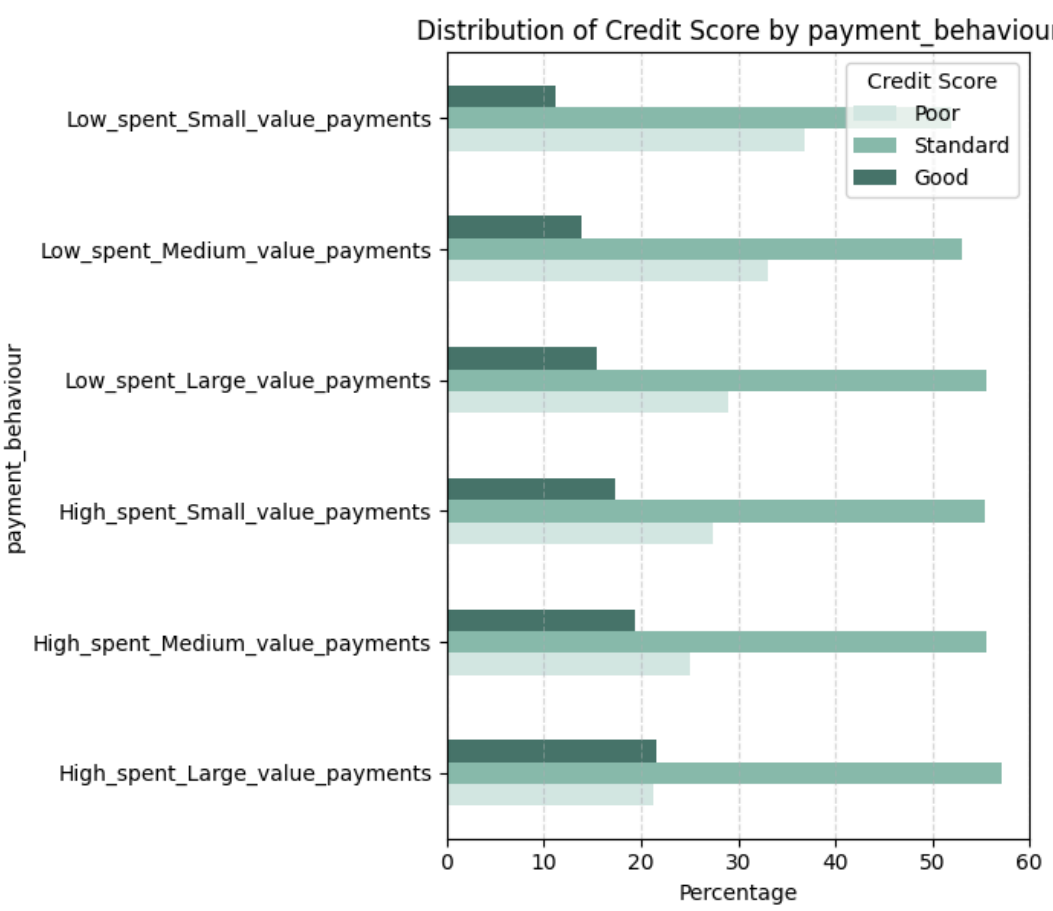
In [242…

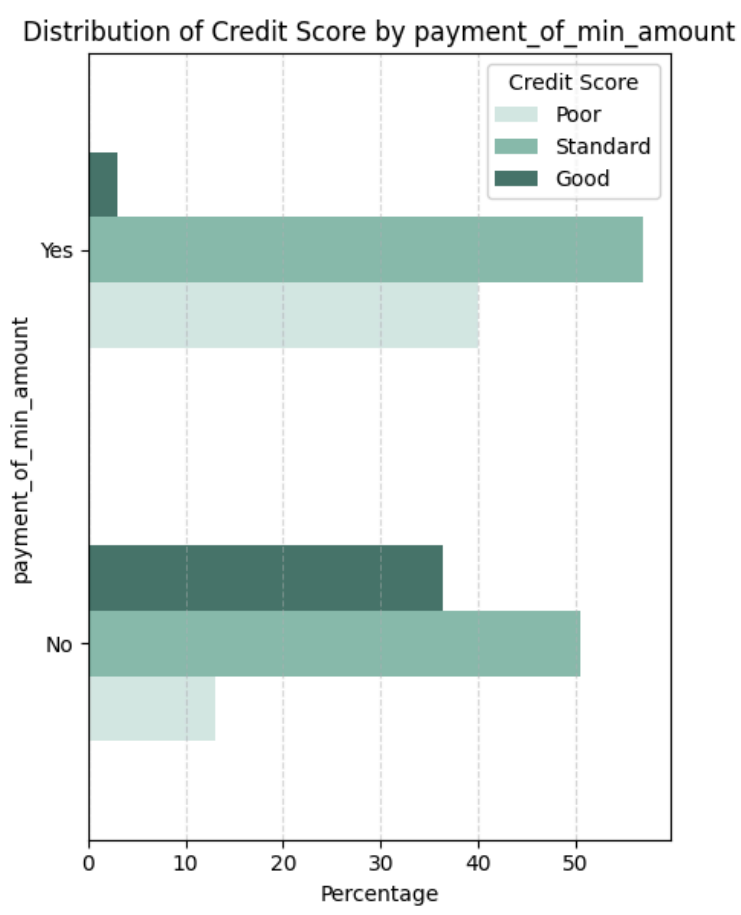
```
categoricalColumns = ['month', 'occupation', 'credit_mix', 'payment_behaviour', 'payment_of_min_amount']
dataFiltered = data[categoricalColumns]
customPalette = {0: "#d6e7e4", 1: "#87bbae", 2: "#48756a"}

numPlots = len(categoricalColumns)
nCols = 2
nRows = (numPlots + 1) // nCols
fig, axes = plt.subplots(nRows, nCols, figsize=(12, nRows * 6))
axes = axes.flatten()

for i, col in enumerate(categoricalColumns):
    cross_tab = pd.crosstab(data[col], data['credit_score'], normalize='index') * 100
    cross_tab.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], ax=axes[i])
    axes[i].set_title(f'Distribution of Credit Score by {col}', fontsize=12)
    axes[i].set_xlabel('Percentage')
    axes[i].set_ylabel(col)
    axes[i].legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
    axes[i].grid(True, axis='x', linestyle='--', alpha=0.5)

loanDataSum = loanData.groupby('loan_type')['loan_count'].sum()
loanDataPercentage = loanData.pivot_table(index='loan_type', columns='credit_score', values='loan_count', aggfunc='
loanDataPercentage = loanDataPercentage.div(loanDataSum, axis=0) * 100
loanDataPercentage.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], ax=axes[numPlots])
axes[numPlots].set_title('Distribution of Credit Score by type_of_loan', fontsize=12)
axes[numPlots].set_xlabel('Percentage')
axes[numPlots].set_ylabel('type_of_loan')
axes[numPlots].legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
axes[numPlots].grid(True, axis='x', linestyle='--', alpha=0.5)


for j in range(numPlots+1, len(axes)):
    axes[j].set_visible(False)

plt.subplots_adjust(hspace=0.4, wspace=0.4)
plt.tight_layout()
plt.show()
```

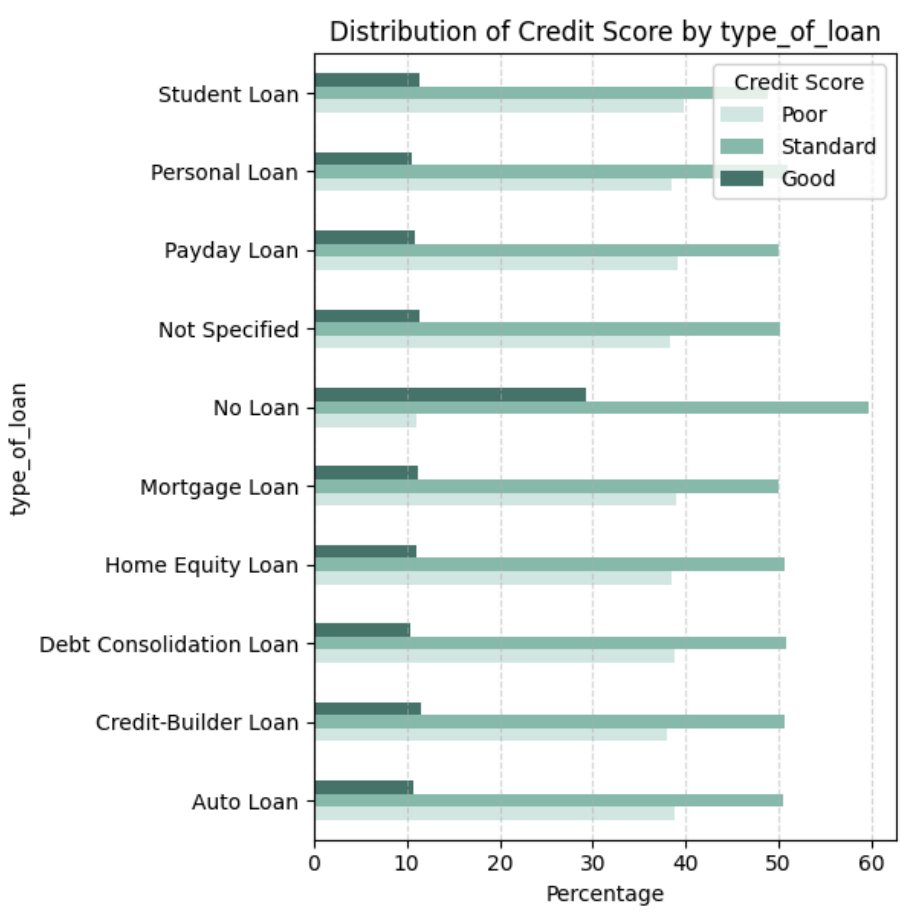










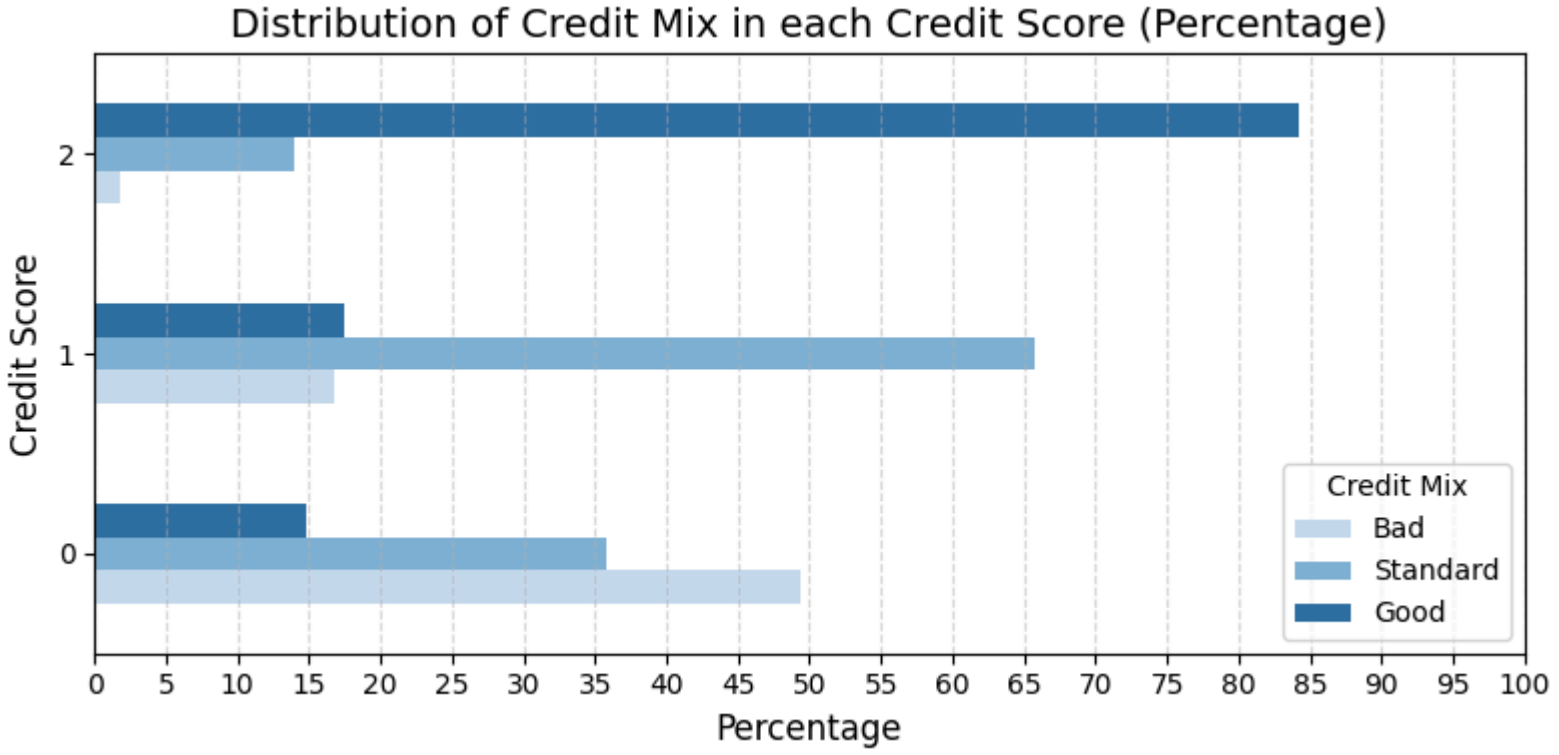


Distribution of credit score across month, occupation, payment_behaviour and type_of_loan is similar in which 1 (standard) is the majority in every category followed by 0 (poor) and then 2 (good). However in the No Loan class in type_of_loan, 1 (standard) is followed by 2 (good) which is higher than 0 (poor). In credit_mix, the majority class relates to the credit score. In Good credit mix, the majority class is 2 (good), in Standard credit mix, the majority class is 1 (standard) whereas in Bad credit mix, the majority class is 0 (poor). In payment_of_min_amount, customers who did not pay just the minimum amount and paid more have a majority of 1 (standard) credit

scores, closely followed by 2 (good) credit scores and a few 0 (poor) credit scores. However, those who paid just the minimum amount, also have a majority of 1 (standard) credit scores but followed by 0 (poor) credit scores and with a very few 2 (good) credit scores.

Analyzing the distribution of credit_mix within each credit score

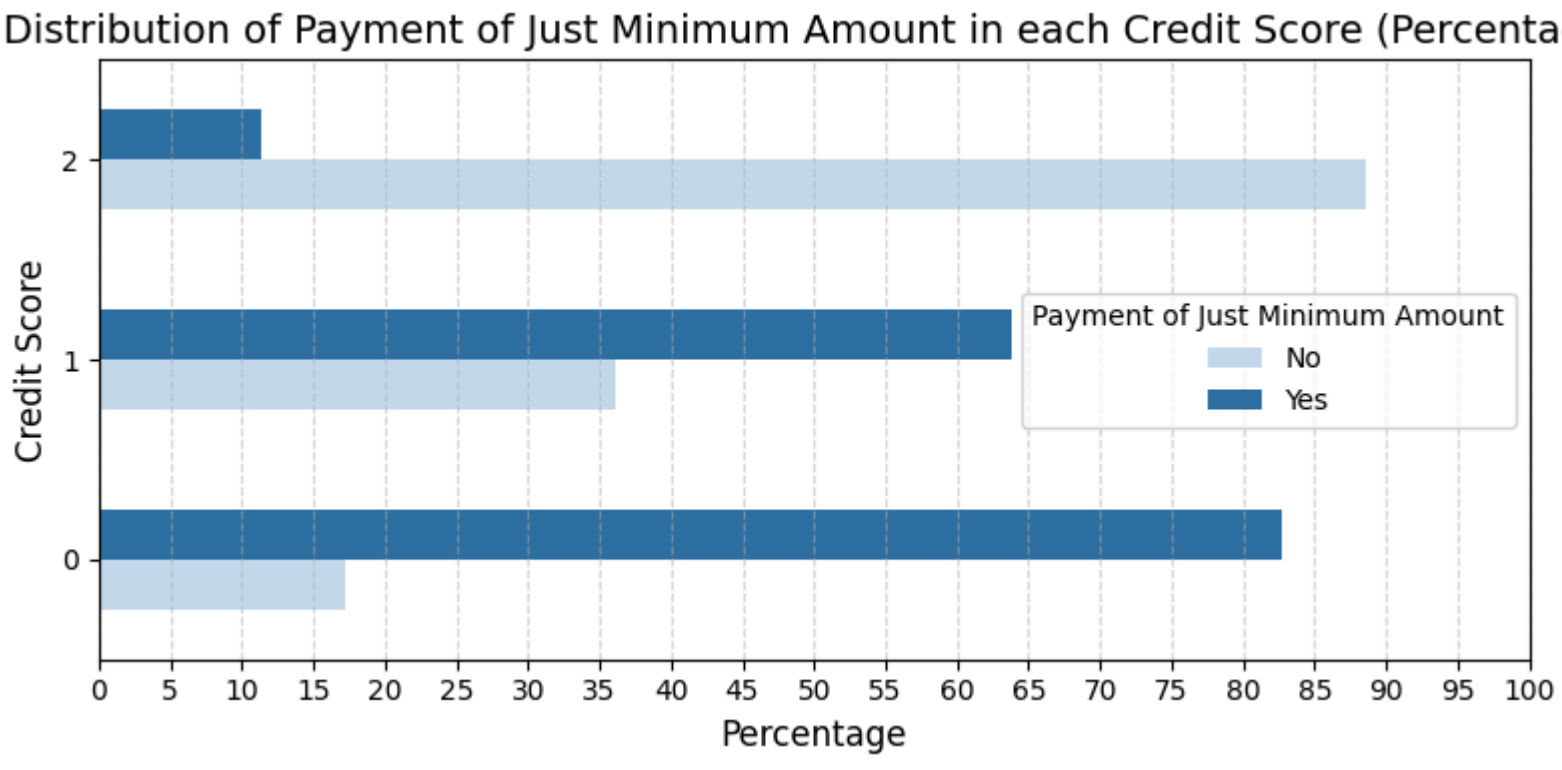
In [242…
```
creditMixDistribution = data.groupby(['credit_score', 'credit_mix']).size().unstack(fill_value=0)

creditMixSums = creditMixDistribution.sum(axis=1)
creditMixDistributionNormalized = creditMixDistribution.div(creditMixSums, axis=0)
creditMixDistributionPercent = creditMixDistributionNormalized * 100

creditMixDistributionPercent = creditMixDistributionPercent[['Bad', 'Standard', 'Good']]

creditMixDistributionPercent.plot(kind='barh', figsize=(8, 4), color=['#c7dbed', '#81afd3', '#3171a2'])
plt.title('Distribution of Credit Mix in each Credit Score (Percentage)', fontsize=14)
plt.ylabel('Credit Score', fontsize=12)
plt.xlabel('Percentage', fontsize=12)
plt.legend(title='Credit Mix', fontsize=10)
plt.xticks(range(0, 101, 5), rotation=0)
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```



The figure shows that around 50% of the customers who have a 0 (poor) credit score have a bad credit mix. More than 60% of the customers who have a standard credit mix have a 1 (standard) credit score. Lastly more than 80% of the customers who have a 2 (good) score have a good credit mix as well.

Analyzing the distribution of payment_of_min_amount within each credit score

In [243…
```
minAmtPaymentDistributionPercent = pd.crosstab(data['credit_score'], data['payment_of_min_amount'], normalize='inde

minAmtPaymentDistributionPercent.plot(kind='barh', figsize=(8, 4), color=['#c7dbed', '#3171a2'])
plt.title('Distribution of Payment of Just Minimum Amount in each Credit Score (Percentage)', fontsize=14)
plt.ylabel('Credit Score', fontsize=12)
plt.xlabel('Percentage', fontsize=12)
plt.legend(title='Payment of Just Minimum Amount', fontsize=10)
plt.xticks(range(0, 101, 5), rotation=0)
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```

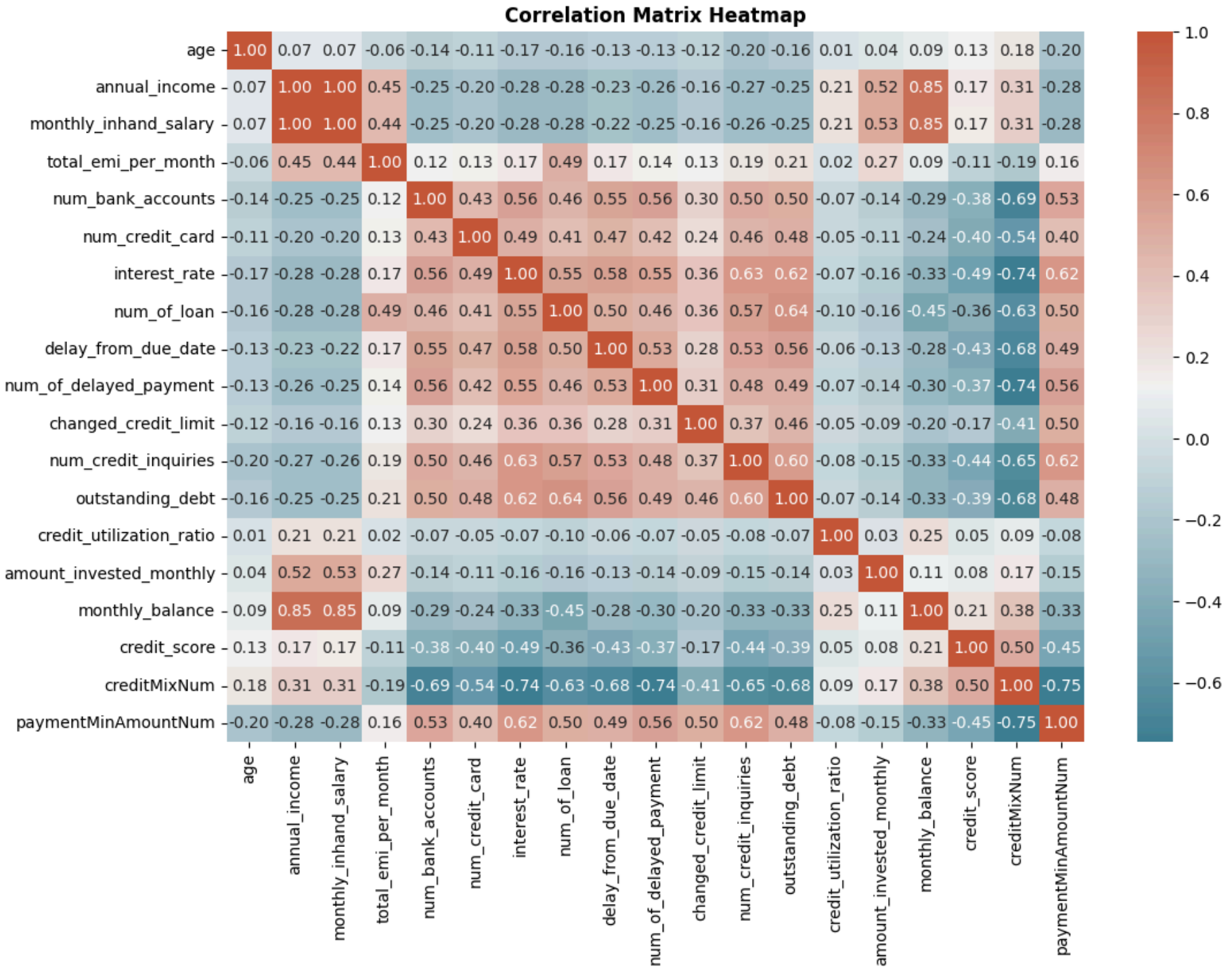


According to the figure, more then 80% of the customers with a 0 (poor) credit score and more than 60% of the customers with a 1 (standard) credit score paid just the minimum amount. Whereas more than 85% of the customers with a 2 (good) credit score did not pay just the minimum amount and paid more than that.

Analyzing correlations between the variables using a correlation matrix

In [243…

```
numericColumns = []

for col in data.select_dtypes(include='number').columns:
    if col not in loanTypes:
        numericColumns.append(col)


correlationMatrix = data[numericColumns].corr()

plt.figure(figsize=(12, 8))
sns.heatmap(correlationMatrix, annot=True, cmap=sns.diverging_palette(220, 20, as_cmap=True), fmt='.2f', cbar=True,
            xticklabels=correlationMatrix.columns, yticklabels=correlationMatrix.columns)

plt.title('Correlation Matrix Heatmap', fontsize=12, fontweight="bold")
plt.show()
```



Displaying the correlation of each numerical variables with the class column (credit_score), sorted according to the absolute value of the correlation

In [243…

```
correlationWithCreditScore = correlationMatrix['credit_score'].sort_values(key=lambda x: x.abs(), ascending=False)

correlationTable = correlationWithCreditScore.reset_index()
correlationTable.columns = ['Column', 'Correlation with Credit Score']
correlationTableDF = pd.DataFrame(correlationTable)
correlationTableDF
```

Out[243...

	Column	Correlation with Credit Score
0	credit_score	1.000
1	creditMixNum	0.503
2	interest_rate	-0.490
3	paymentMinAmountNum	-0.445
4	num_credit_inquiries	-0.445
5	delay_from_due_date	-0.426
6	num_credit_card	-0.403
7	outstanding_debt	-0.385
8	num_bank_accounts	-0.384
9	num_of_delayed_payment	-0.366
10	num_of_loan	-0.361
11	monthly_balance	0.211
12	annual_income	0.168
13	monthly_inhand_salary	0.167
14	changed_credit_limit	-0.165
15	age	0.127
16	total_emi_per_month	-0.113
17	amount_invested_monthly	0.081
18	credit_utilization_ratio	0.047

Anova test to check which numerical variables have a significant relation with credit score. Followed by eta squared to check effect size. The code for correlation_ratio is cited from (Kiryl, 2021). Complete citation is in the references section at the end of this notebook

1. 0.01 - Small effect size
2. 0.06 - Medium effect size
3. 0.14 or higher - Large effect size (Bobbitt, 2020)

In [ ]:
```
def correlation_ratio(categories, values):
    categories = np.array(categories)
    values = np.array(values)

    ssw = 0
    ssb = 0
    for category in set(categories):
        subgroup = values[np.where(categories == category)[0]]
        ssw += sum((subgroup-np.mean(subgroup))**2)
        ssb += len(subgroup)*(np.mean(subgroup)-np.mean(values))**2

    return (ssb / (ssb + ssw))

results = {}

for column in numericColumns:
    if column != 'credit_score':
        groupData = []
        for score in data['credit_score'].unique():
            groupData.append(data[data['credit_score'] == score][column].tolist())

        f_stat, p_value = f_oneway(groupData[0], groupData[1], groupData[2])
        results[column] = {'F-statistic': f_stat, 'p-value': p_value}

        if (p_value <= 0.05):
            etaSquared = correlation_ratio(data['credit_score'], data[column])
            results[column]['etaSquared'] = etaSquared


resultsDF = pd.DataFrame(results).T
resultsDF.sort_values('etaSquared', ascending=False, inplace=True)

resultsDF
```

Out[ ]:

	F-statistic	p-value	etaSquared
creditMixNum	14553.874	0.000	0.278
interest_rate	11940.755	0.000	0.240
paymentMinAmountNum	11041.741	0.000	0.226
num_credit_inquiries	9547.115	0.000	0.202
delay_from_due_date	8403.175	0.000	0.182
num_credit_card	7312.740	0.000	0.162
outstanding_debt	6878.150	0.000	0.154
num_bank_accounts	6709.186	0.000	0.151
num_of_delayed_payment	6427.954	0.000	0.145
num_of_loan	5778.282	0.000	0.133
changed_credit_limit	1917.378	0.000	0.048
monthly_balance	1755.574	0.000	0.044
annual_income	1099.084	0.000	0.028
monthly_inhand_salary	1083.676	0.000	0.028
age	627.651	0.000	0.016
total_emi_per_month	518.059	0.000	0.014
amount_invested_monthly	251.754	0.000	0.007
credit_utilization_ratio	82.542	0.000	0.002

Chi Square test to check which categorical variables are associated or independent to the credit score. Followed by Cramer's V to check the level of association.

Using Cramers V to find the level of asociation between categorical columns and credit score. The function for cramers v corrected stat is cited from (Eunicien & Lee, 2021). Complete citation is in the references section at the end of this notebook

1. "0.00 to 0.20: The result is weak. Although the result is statistically significant, the fields are only weakly associated."
2. "0.20 to 0.60: The result is moderate. The fields are moderately associated."
3. "0.60 to 1.00: The result is strong. The fields are strongly associated." (IBM, 2024)

In [ ]:
```
def cramersCorrectedStat(confusionMatrix):
    """ calculate Cramers V statistic for categorial-categorial association.
        uses correction from Bergsma and Wicher,
        Journal of the Korean Statistical Society 42 (2013): 323-328
    """
    chi2 = chi2_contingency(confusionMatrix)[0]
    n = confusionMatrix.sum().sum()
    phi2 = chi2/n
    r,k = confusionMatrix.shape
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    return np.sqrt(phi2corr / min( (kcorr-1), (rcorr-1)))


results = {}

for col in categoricalColumns:
    contingencyTable = pd.crosstab(data['credit_score'], data[col])
    chi2, p, _, _ = chi2_contingency(contingencyTable)
    results[col] = {'chi2': chi2, 'p-value': p}

    if (p <= 0.05):
        results[col]["cramer's v"] = cramersCorrectedStat(contingencyTable)


contingencyTable = pd.crosstab(loanData['credit_score'], loanData['loan_type'], values=loanData['loan_count'], aggf
chi2, p, _, _ = chi2_contingency(contingencyTable)
results['type_of_loan'] = {'chi2': chi2, 'p-value': p}

if (p <= 0.05):
    results['type_of_loan']["cramer's v"] = cramersCorrectedStat(contingencyTable)

resultsDF = pd.DataFrame(results).T
resultsDF.sort_values("cramer's v", ascending=False, inplace=True)
resultsDF
```

Out[ ]:

	chi2	p-value	cramer's v
payment_of_min_amount	17090.737	0.000	0.475
credit_mix	32538.092	0.000	0.464
payment_behaviour	1553.138	0.000	0.101
type_of_loan	5180.361	0.000	0.089
occupation	160.750	0.000	0.030
month	125.971	0.000	0.027

Out of all the categorical columns, payment_of_min_amount and credit_mix have a moderate association with credit score.

After analyzing the data and looking at how FICO uses features to rank credit scores (Demyanyk, 2010), this study will examine the influences of two domains on credit score. They are debt management and payment behaviour. According to this paper (Hayashi & Stavins, 2012), demographic factors also have a tendency to influence credit scores hence the study will also examine the effect of a customer's demographic factors on their credit score.

Aggregating relevant features and credit scores for customer segmentation

In [243…

```
customerData = data.groupby('customer_id').agg({
    'outstanding_debt': 'mean',
    'num_of_loan': 'mean',
    'num_credit_card': 'mean',
    'delay_from_due_date': 'mean',
    'num_of_delayed_payment': 'mean',
    'paymentMinAmountNum': 'mean',
    'age': 'mean',
    'annual_income': 'mean',
    'credit_score': 'mean'
}).reset_index()

# Feature Columns
customerData['num_of_loan'] = customerData['num_of_loan'].round().astype(int)
customerData['num_credit_card'] = customerData['num_credit_card'].round().astype(int)
customerData['delay_from_due_date'] = customerData['delay_from_due_date'].round().astype(int)
customerData['num_of_delayed_payment'] = customerData['num_of_delayed_payment'].round().astype(int)
customerData['paymentMinAmountNum'] = customerData['paymentMinAmountNum'].round().astype(int)
customerData['age'] = customerData['age'].round().astype(int)
customerData['annual_income'] = customerData['annual_income'].round().astype(int)

# Target Colunn
customerData['credit_score'] = customerData['credit_score'].round().astype(int)

customerData.head()
```

Out[243…

	customer_id	outstanding_debt	num_of_loan	num_credit_card	delay_from_due_date	num_of_delayed_payment	paymentMinAr
0	CUS_0x1009	202.680	4	5	7	18	
1	CUS_0x100b	1030.200	0	4	13	7	
2	CUS_0x1011	473.140	3	3	27	14	
3	CUS_0x1013	1233.510	3	3	13	9	
4	CUS_0x1015	340.220	0	4	8	9	

Checking the credit score class distribution after aggregating

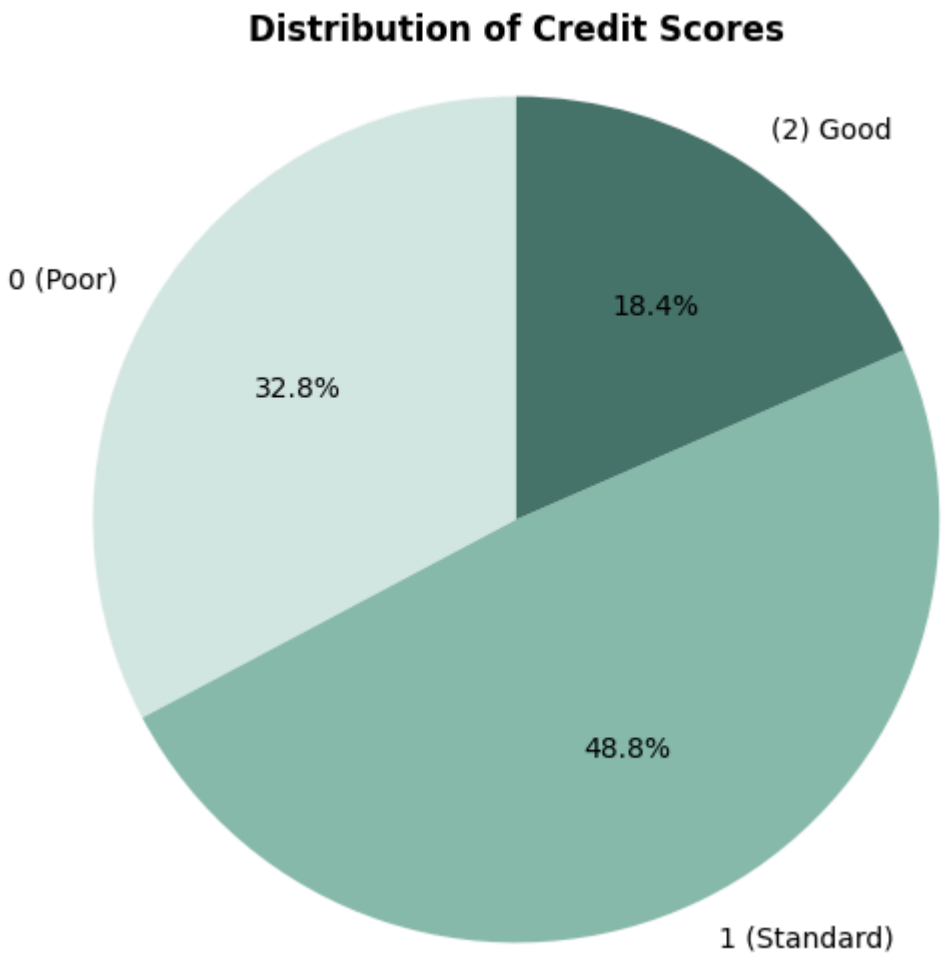
In [243…

```
scoreCounts = customerData['credit_score'].value_counts()
scorePercentages = customerData['credit_score'].value_counts(normalize=True) * 100
scoreSummary = pd.DataFrame({
    'Count': scoreCounts,
    'Percentage (%)': scorePercentages
})


print("Credit score counts and percentages:\n", scoreSummary.sort_index())
```

```
Credit score counts and percentages:
    Count  Percentage (%)
0   3512          32.761
1   5231          48.797
2   1977          18.442
```

In [243…

```
plt.figure(figsize=(6, 6))
plt.pie(scoreCounts.sort_index(), labels=['0 (Poor)', '1 (Standard)', '(2) Good'], autopct='%1.1f%%', startangle=90
plt.title("Distribution of Credit Scores", fontsize=12, fontweight="bold")
plt.axis('equal')
plt.show()
```



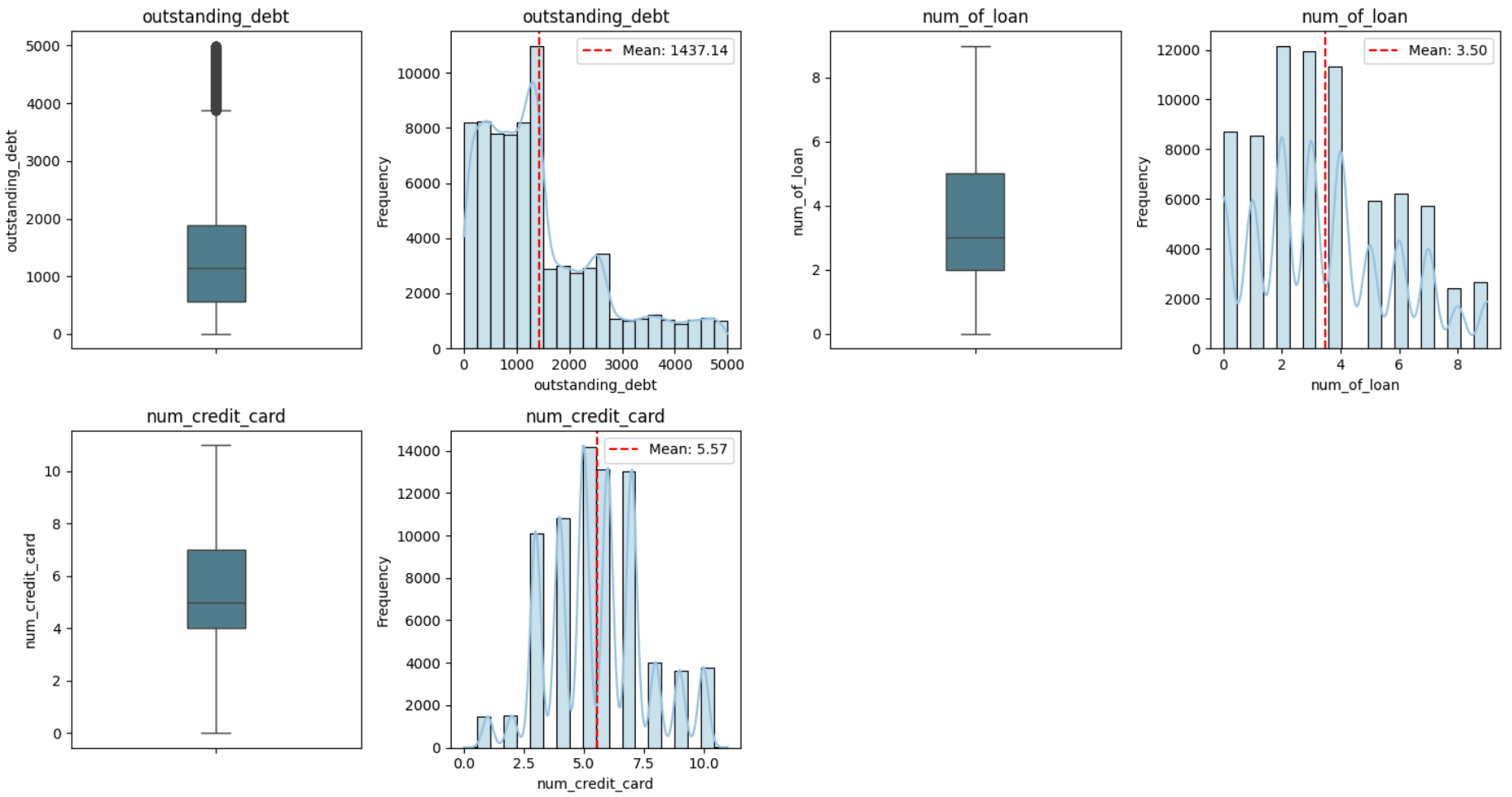
Checking the correlation of variables after aggregation

In [243…
```
correlationMatrix = customerData.corr(numeric_only=True)

plt.figure(figsize=(12, 8))
sns.heatmap(correlationMatrix, annot=True, cmap=sns.diverging_palette(220, 20, as_cmap=True), fmt='.2f', cbar=True,
            xticklabels=correlationMatrix.columns, yticklabels=correlationMatrix.columns)

plt.title('Correlation Matrix Heatmap', fontsize=12, fontweight="bold")
plt.show()
```

First Research Question: How do specific debt management features impact the likelihood of an individual achieving a good credit score?

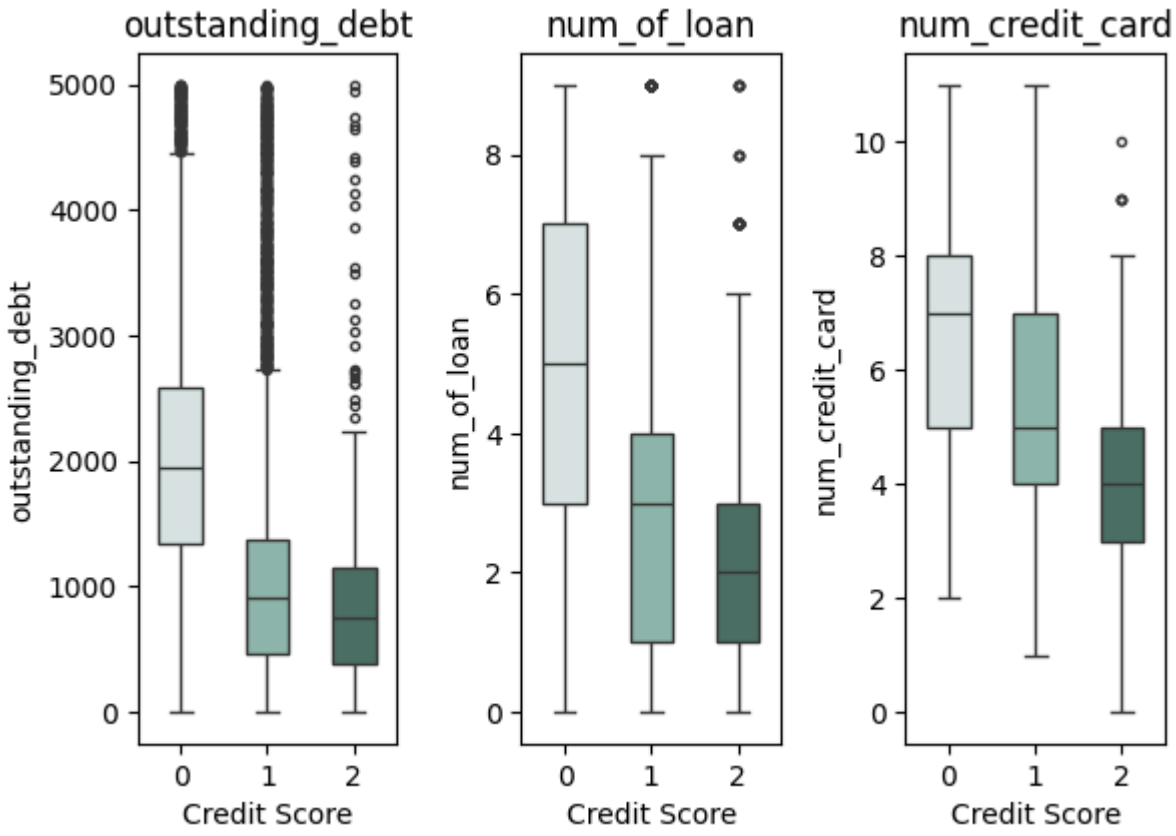
Analyzing the distribution of debt management features using box plots and histograms

In [243…
```
debtManagementColumns = ['outstanding_debt', 'num_of_loan', 'num_credit_card']

numPlots = len(debtManagementColumns)
rows = (numPlots // 2) + 1
cols = 4

fig, axes = plt.subplots(rows, cols, figsize=(15, rows * 4))
axes = axes.flatten()

for i, col in enumerate(debtManagementColumns):
    sns.boxplot(data=customerData, y=col, ax=axes[2 * i], color="#498699",  width=0.2)
    axes[2 * i].set_title(f'{col}', fontsize=12)
    axes[2 * i].set_ylabel(col, fontsize=10)

    sns.histplot(data=data, x=col, ax=axes[2 * i + 1], color="#98c5e1", kde=True, bins=20)
    mean_value = data[col].mean()
    axes[2 * i + 1].axvline(mean_value, color='red', linestyle='--', label=f'Mean: {mean_value:.2f}')
    axes[2 * i + 1].legend()

    axes[2 * i + 1].set_title(f'{col}', fontsize=12)
    axes[2 * i + 1].set_xlabel(col, fontsize=10)
    axes[2 * i + 1].set_ylabel('Frequency', fontsize=10)

for j in range(2 * numPlots, len(axes)):
    fig.delaxes(axes[j])

plt.subplots_adjust(wspace=0.6, hspace=0.4)
plt.tight_layout()
plt.show()
```



Analyzing the distributon of debt management features in each credit score class using box plots. This is included in the report

In [244…
```
customPalette = {0: "#d6e7e4", 1: "#87bbae", 2: "#48756a"}
flierprops = dict(markersize=3)

fig, axes = plt.subplots(rows, cols, figsize=(8, rows * 4))
axes = axes.flatten()

for i, col in enumerate(debtManagementColumns):
    sns.boxplot(data=customerData, x='credit_score', y=col, ax=axes[i], hue='credit_score', palette=customPalette,
    axes[i].set_title(f'{col}', fontsize=12)
    axes[i].set_xlabel('Credit Score')
    axes[i].set_ylabel(col)

for j in range(numPlots, len(axes)):
    axes[j].set_visible(False)

plt.subplots_adjust(hspace=0.4, wspace=5)
plt.tight_layout()
plt.savefig('graphs/debtManagement(EDA).png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Anova test to check if there is significance difference between the debt management attributes of customers belonging to different credit scores. Followed by eta squared to check effect size. This is included in the report

In [244…

```
def correlation_ratio(categories, values):
    categories = np.array(categories)
    values = np.array(values)

    ssw = 0
    ssb = 0
    for category in set(categories):
        subgroup = values[np.where(categories == category)[0]]
        ssw += sum((subgroup-np.mean(subgroup))**2)
        ssb += len(subgroup)*(np.mean(subgroup)-np.mean(values))**2

    return (ssb / (ssb + ssw))

results = {}

for column in debtManagementColumns:
    groupData = []
    for score in customerData['credit_score'].unique():
        groupData.append(customerData[customerData['credit_score'] == score][column].tolist())

    f_stat, p_value = f_oneway(groupData[0], groupData[1], groupData[2])
    results[column] = {'F-statistic': f_stat, 'p-value': p_value}

    if (p_value <= 0.05):
        etaSquared = correlation_ratio(customerData['credit_score'], customerData[column])
        results[column]['etaSquared'] = etaSquared


resultsDF = pd.DataFrame(results).T
resultsDF.sort_values('etaSquared', ascending=False, inplace=True)

resultsDF
```

Out[244…

	F-statistic	p-value	etaSquared
num_credit_card	1294.554	0.000	0.195
outstanding_debt	1228.893	0.000	0.187
num_of_loan	1006.234	0.000	0.158

Customer Segmentation based on Debt Management variables using K Mean Clustering

Features for clustering: Outstanding debt and number of loans

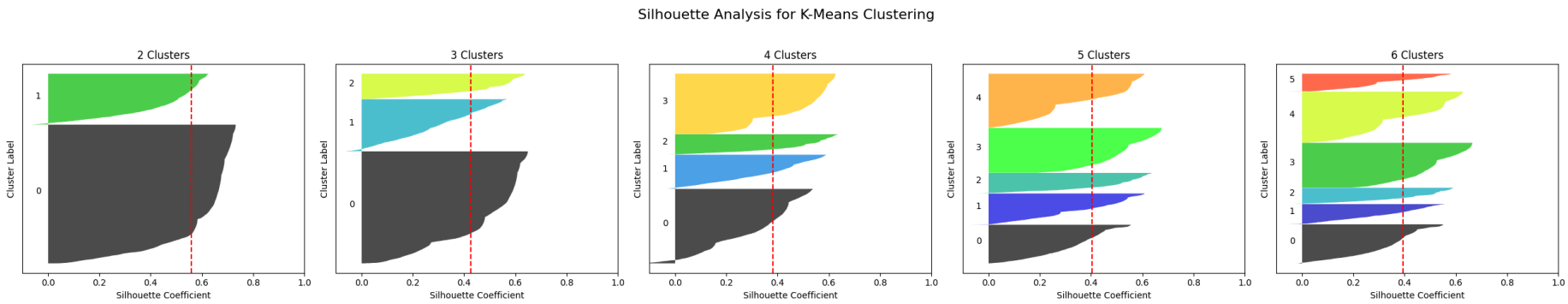
Using Silhoutte Score to find ideal number of clusters. This code for Silhoutte analysis is influenced by (Scikit-Learn, 2024). Full reference is mentioned at the end of this notebook.

In [244…

```
features = ['outstanding_debt', 'num_of_loan']
scaler = StandardScaler()
debtManagementScaled = scaler.fit_transform(customerData[features])

clusterRange = range(2, 7)
fig, axes = plt.subplots(1, 5, figsize=(25, 5))
fig.suptitle("Silhouette Analysis for K-Means Clustering", fontsize=16)
```

```
for i, nClusters in enumerate(clusterRange):
    ax = axes[i]
    kmeans = KMeans(n_clusters=nClusters, random_state=42, n_init='auto')
    clusterLabels = kmeans.fit_predict(debtManagementScaled)
    silhouetteAvg = silhouette_score(debtManagementScaled, clusterLabels)
    silhouetteValues = silhouette_samples(debtManagementScaled, clusterLabels)
    print(f"Number of Clusters: {nClusters}, Silhouette Score: {silhouetteAvg:.4f}")
    y_lower = 10
    for i in range(nClusters):
        ithClusterSilhouetteValues = silhouetteValues[clusterLabels == i]
        ithClusterSilhouetteValues.sort()
        size_cluster_i = ithClusterSilhouetteValues.shape[0]
        y_upper = y_lower + size_cluster_i
        color = plt.cm.nipy_spectral(float(i) / nClusters)
        ax.fill_betweenx(np.arange(y_lower, y_upper), 0, ithClusterSilhouetteValues, facecolor=color, alpha=0.7)
        ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
        y_lower = y_upper + 10

    ax.set_title(f"{nClusters} Clusters")
    ax.axvline(x=silhouetteAvg, color="red", linestyle="--")
    ax.set_xlabel("Silhouette Coefficient")
    ax.set_xlim([-0.1, 1])
    ax.set_ylabel("Cluster Label")
    ax.set_yticks([])

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

```
Number of Clusters: 2, Silhouette Score: 0.5588
Number of Clusters: 3, Silhouette Score: 0.4256
Number of Clusters: 4, Silhouette Score: 0.3821
Number of Clusters: 5, Silhouette Score: 0.4039
Number of Clusters: 6, Silhouette Score: 0.3934
```



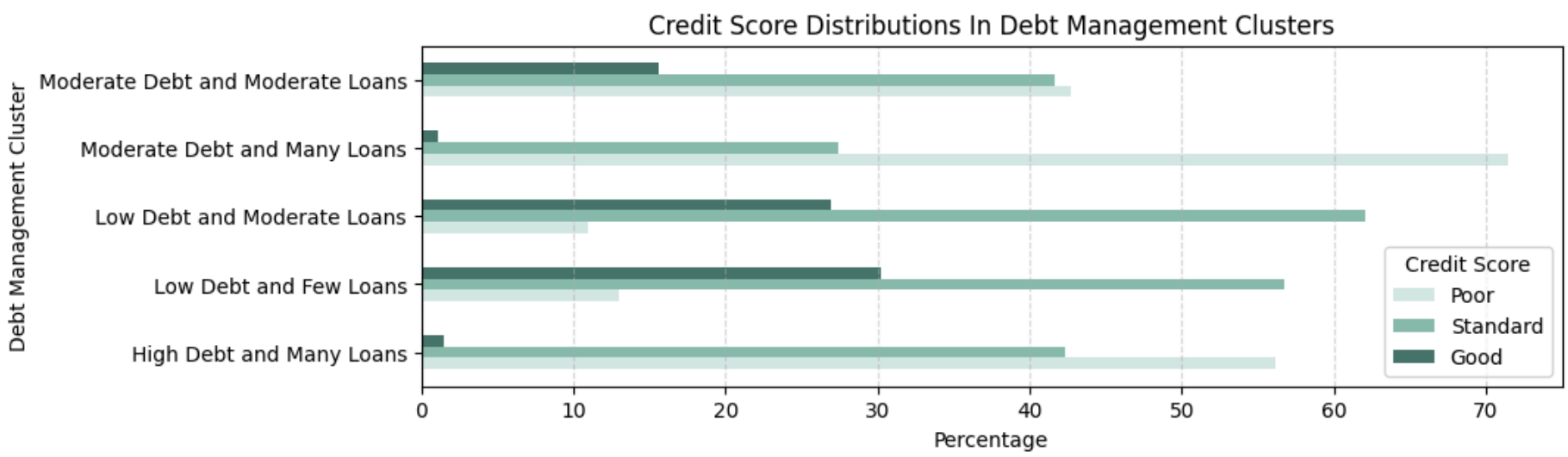
Although 5 clusters has a lower silhoutte score than 2 and 3, it is selected because the thickness of the silhoutte plots with 5 clusters are more balanced

In [244…

```
dataClusters = customerData.copy()
kmeans = KMeans(n_clusters=5, random_state=42, n_init='auto')
dataClusters['debt_management_cluster'] = kmeans.fit_predict(debtManagementScaled)
customLabels = {
    0: "Moderate Debt and Moderate Loans",
    1: "Moderate Debt and Many Loans",
    2: "High Debt and Many Loans",
    3: "Low Debt and Few Loans",
    4: "Low Debt and Moderate Loans",
}
dataClusters['debt_management_cluster'] = dataClusters['debt_management_cluster'].map(customLabels)
plt.figure(figsize=(8, 6))
sns.scatterplot(x=dataClusters['outstanding_debt'], y=dataClusters['num_of_loan'], hue=dataClusters['debt_managemen
plt.title('Debt Management Clusters')
plt.xlabel('Outstanding Debt')
plt.ylabel('Number of Loans')
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```

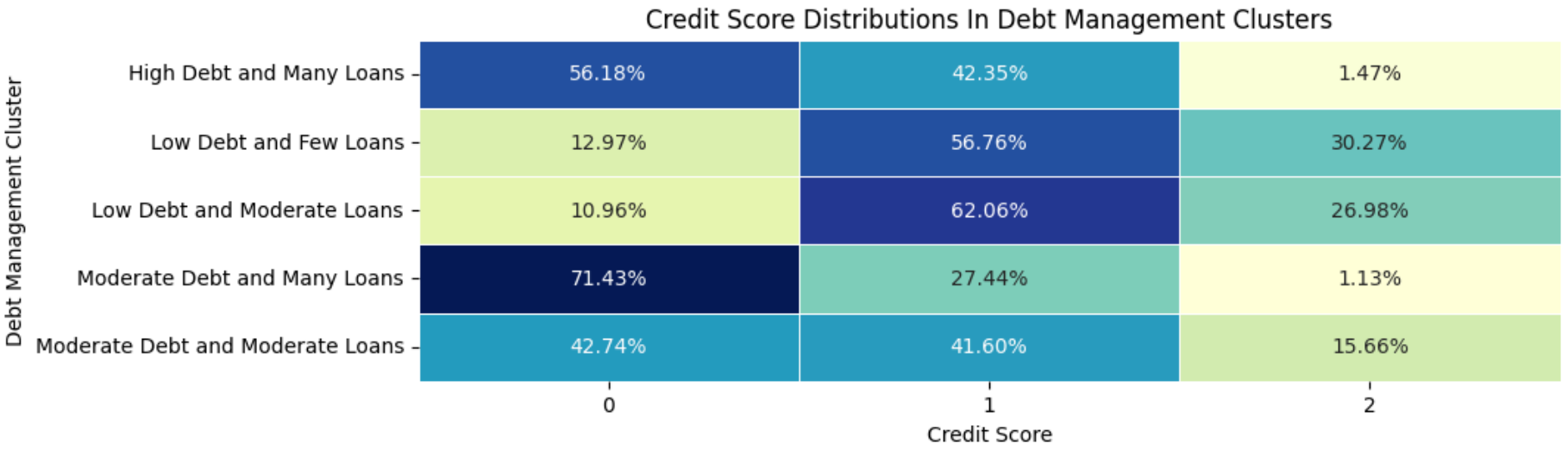
Displaying the distribution of credit scores in each cluster as a bar graph

In [244…
```
clusterScoreDistribution = pd.crosstab(dataClusters['debt_management_cluster'], dataClusters['credit_score'], norma

clusterScoreDistribution.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], figsize=(10, 3))
plt.title('Credit Score Distributions In Debt Management Clusters')
plt.xlabel('Percentage')
plt.ylabel('Debt Management Cluster')
plt.legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.show()
```



Displaying the distribution of credit scores in each cluster as a heatmap

In [244…
```
clusterScoreDistribution = clusterScoreDistribution.round(2)
annotations = clusterScoreDistribution.applymap(lambda x: f"{x:.2f}%")

plt.figure(figsize=(10, 3))
sns.heatmap(clusterScoreDistribution, annot=annotations, cmap='YlGnBu', cbar=False, fmt='', linewidths=.5)

plt.title('Credit Score Distributions In Debt Management Clusters')
plt.ylabel('Debt Management Cluster')
plt.xlabel('Credit Score')
plt.show()
```



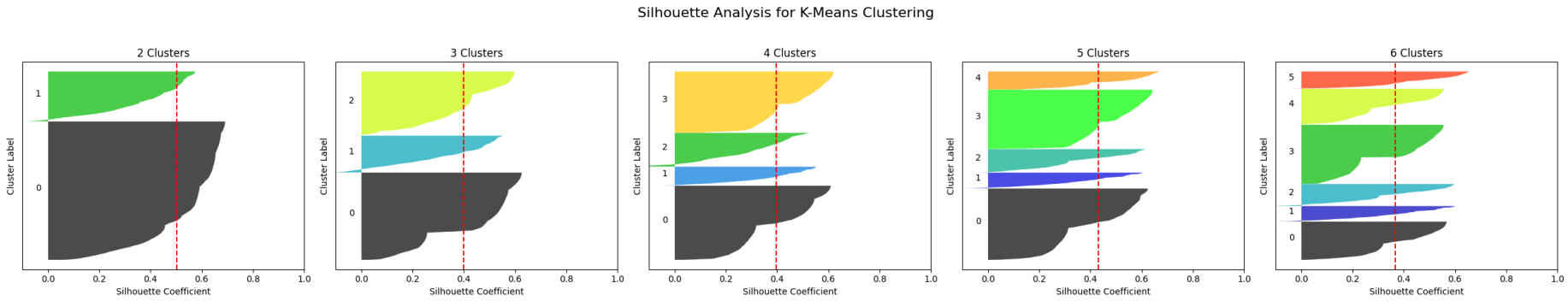
Features for clustering: Outstanding debt and number of credit cards

Using Silhoutte Score to find ideal number of clusters

In [244…

```
features = ['outstanding_debt', 'num_credit_card']
scaler = StandardScaler()
debtManagementScaled = scaler.fit_transform(customerData[features])

clusterRange = range(2, 7)
fig, axes = plt.subplots(1, 5, figsize=(25, 5))
fig.suptitle("Silhouette Analysis for K-Means Clustering", fontsize=16)

for i, nClusters in enumerate(clusterRange):
    ax = axes[i]
    kmeans = KMeans(n_clusters=nClusters, random_state=42, n_init='auto')
    clusterLabels = kmeans.fit_predict(debtManagementScaled)
    silhouetteAvg = silhouette_score(debtManagementScaled, clusterLabels)
    silhouetteValues = silhouette_samples(debtManagementScaled, clusterLabels)
    print(f"Number of Clusters: {nClusters}, Silhouette Score: {silhouetteAvg:.4f}")
    y_lower = 10
    for i in range(nClusters):
        ithClusterSilhouetteValues = silhouetteValues[clusterLabels == i]
        ithClusterSilhouetteValues.sort()
        size_cluster_i = ithClusterSilhouetteValues.shape[0]
        y_upper = y_lower + size_cluster_i
        color = plt.cm.nipy_spectral(float(i) / nClusters)
        ax.fill_betweenx(np.arange(y_lower, y_upper), 0, ithClusterSilhouetteValues, facecolor=color, alpha=0.7)
        ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
        y_lower = y_upper + 10

    ax.set_title(f"{nClusters} Clusters")
    ax.axvline(x=silhouetteAvg, color="red", linestyle="--")
    ax.set_xlabel("Silhouette Coefficient")
    ax.set_xlim([-0.1, 1])
    ax.set_ylabel("Cluster Label")
    ax.set_yticks([])

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

```
Number of Clusters: 2, Silhouette Score: 0.5025
Number of Clusters: 3, Silhouette Score: 0.3993
Number of Clusters: 4, Silhouette Score: 0.3965
Number of Clusters: 5, Silhouette Score: 0.4313
Number of Clusters: 6, Silhouette Score: 0.3682
```



5 clusters is selected over 2 clusters despite having a lower silhoutte score because in 2 clusters, the silhoutte plot of cluster 0 is too thick

In [244…

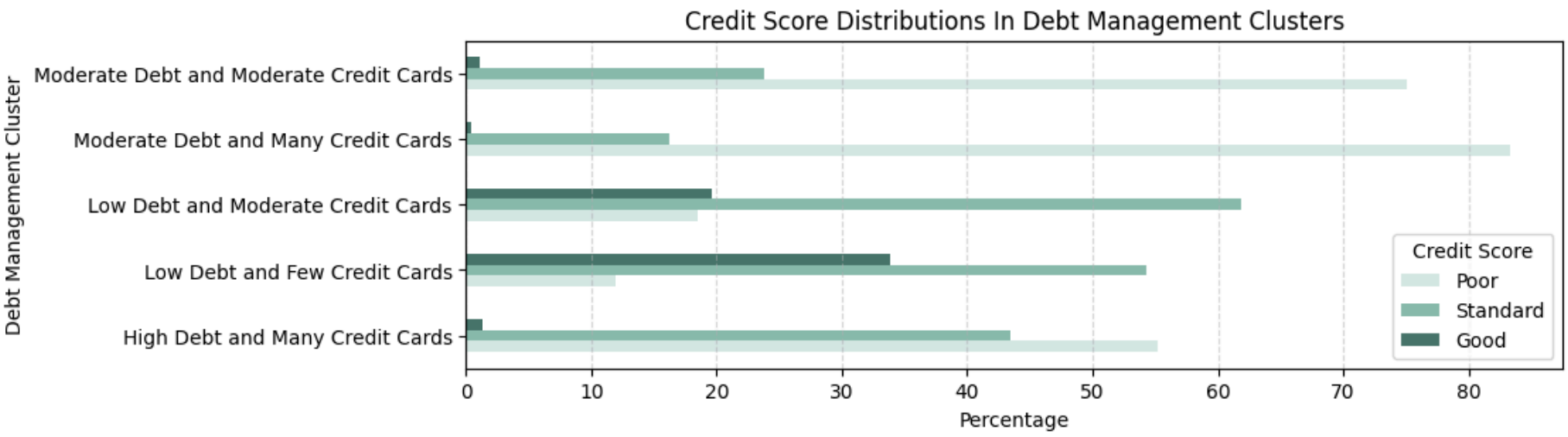
```
kmeans = KMeans(n_clusters=5, random_state=42, n_init='auto')
dataClusters['debt_management_cluster'] = kmeans.fit_predict(debtManagementScaled)
customLabels = {
    0: "Low Debt and Moderate Credit Cards",
    1: "High Debt and Many Credit Cards",
    2: "Moderate Debt and Moderate Credit Cards",
    3: "Low Debt and Few Credit Cards",
    4: "Moderate Debt and Many Credit Cards",
}
dataClusters['debt_management_cluster'] = dataClusters['debt_management_cluster'].map(customLabels)
```

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x=dataClusters['outstanding_debt'], y=dataClusters['num_credit_card'], hue=dataClusters['debt_manag
plt.title('Debt Management Clusters')
plt.xlabel('Outstanding Debt')
plt.ylabel('Number of Credit Cards')
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```

Displaying the distribution of credit scores in each cluster as a bar graph

In [244…

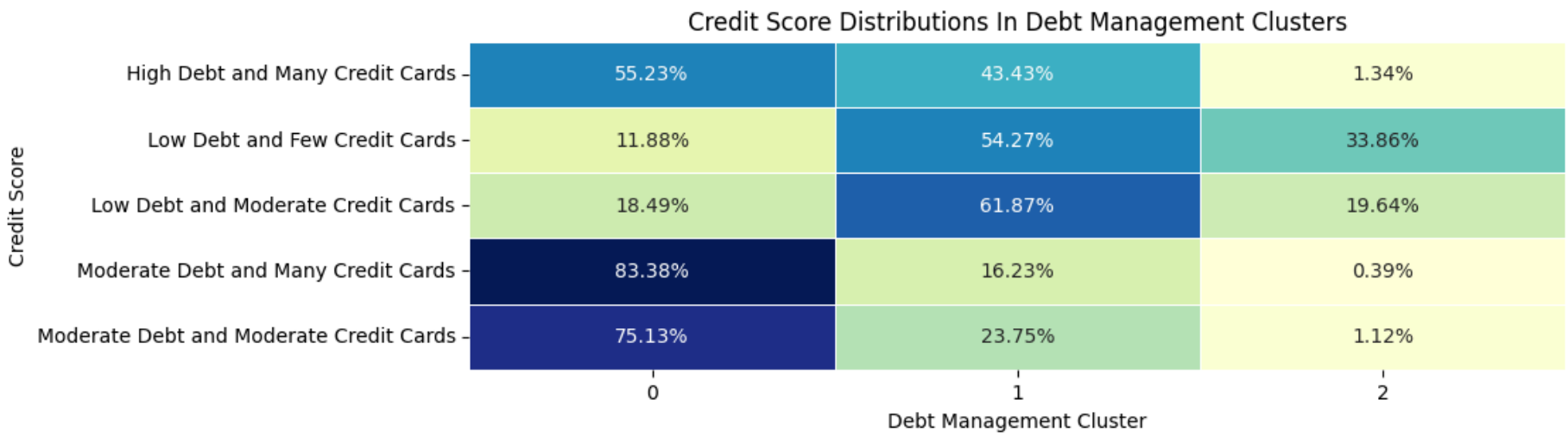
```
clusterScoreDistribution = pd.crosstab(dataClusters['debt_management_cluster'], dataClusters['credit_score'], norma

clusterScoreDistribution.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], figsize=(10, 3))
plt.title('Credit Score Distributions In Debt Management Clusters')
plt.xlabel('Percentage')
plt.ylabel('Debt Management Cluster')
plt.legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.show()
```



Displaying the distribution of credit scores in each cluster as a heatmap

In [244…

```
clusterScoreDistribution = clusterScoreDistribution.round(2)
annotations = clusterScoreDistribution.applymap(lambda x: f"{x:.2f}%")

plt.figure(figsize=(10, 3))
sns.heatmap(clusterScoreDistribution, annot=annotations, cmap='YlGnBu', cbar=False, fmt='', linewidths=.5)

plt.title('Credit Score Distributions In Debt Management Clusters')
plt.xlabel('Debt Management Cluster')
plt.ylabel('Credit Score')
plt.show()
```

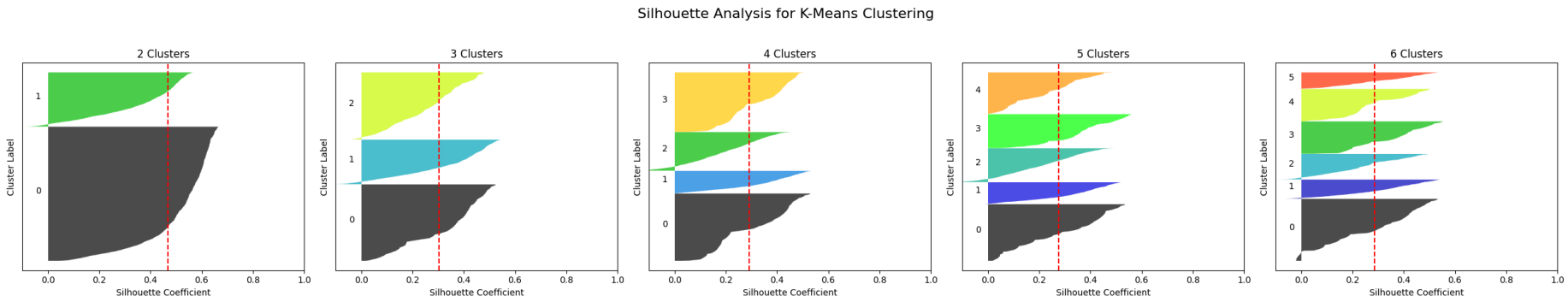


Clustering with all 3 variables (outstanding debt, number of loans and number of credit cards) belonging to debt management

Using Silhoutte Score to find ideal number of clusters

In [245…
```
features = ['outstanding_debt', 'num_of_loan', 'num_credit_card']
scaler = StandardScaler()
debtManagementScaled = scaler.fit_transform(customerData[features])

clusterRange = range(2, 7)
fig, axes = plt.subplots(1, 5, figsize=(25, 5))
fig.suptitle("Silhouette Analysis for K-Means Clustering", fontsize=16)

for i, nClusters in enumerate(clusterRange):
    ax = axes[i]
    kmeans = KMeans(n_clusters=nClusters, random_state=42, n_init='auto')
    clusterLabels = kmeans.fit_predict(debtManagementScaled)
    silhouetteAvg = silhouette_score(debtManagementScaled, clusterLabels)
    silhouetteValues = silhouette_samples(debtManagementScaled, clusterLabels)
    print(f"Number of Clusters: {nClusters}, Silhouette Score: {silhouetteAvg:.4f}")
    y_lower = 10
    for i in range(nClusters):
        ithClusterSilhouetteValues = silhouetteValues[clusterLabels == i]
        ithClusterSilhouetteValues.sort()
        size_cluster_i = ithClusterSilhouetteValues.shape[0]
        y_upper = y_lower + size_cluster_i
        color = plt.cm.nipy_spectral(float(i) / nClusters)
        ax.fill_betweenx(np.arange(y_lower, y_upper), 0, ithClusterSilhouetteValues, facecolor=color, alpha=0.7)
        ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
        y_lower = y_upper + 10

    ax.set_title(f"{nClusters} Clusters")
    ax.axvline(x=silhouetteAvg, color="red", linestyle="--")
    ax.set_xlabel("Silhouette Coefficient")
    ax.set_xlim([-0.1, 1])
    ax.set_ylabel("Cluster Label")
    ax.set_yticks([])

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

```
Number of Clusters: 2, Silhouette Score: 0.4691
Number of Clusters: 3, Silhouette Score: 0.3028
Number of Clusters: 4, Silhouette Score: 0.2907
Number of Clusters: 5, Silhouette Score: 0.2752
Number of Clusters: 6, Silhouette Score: 0.2849
```

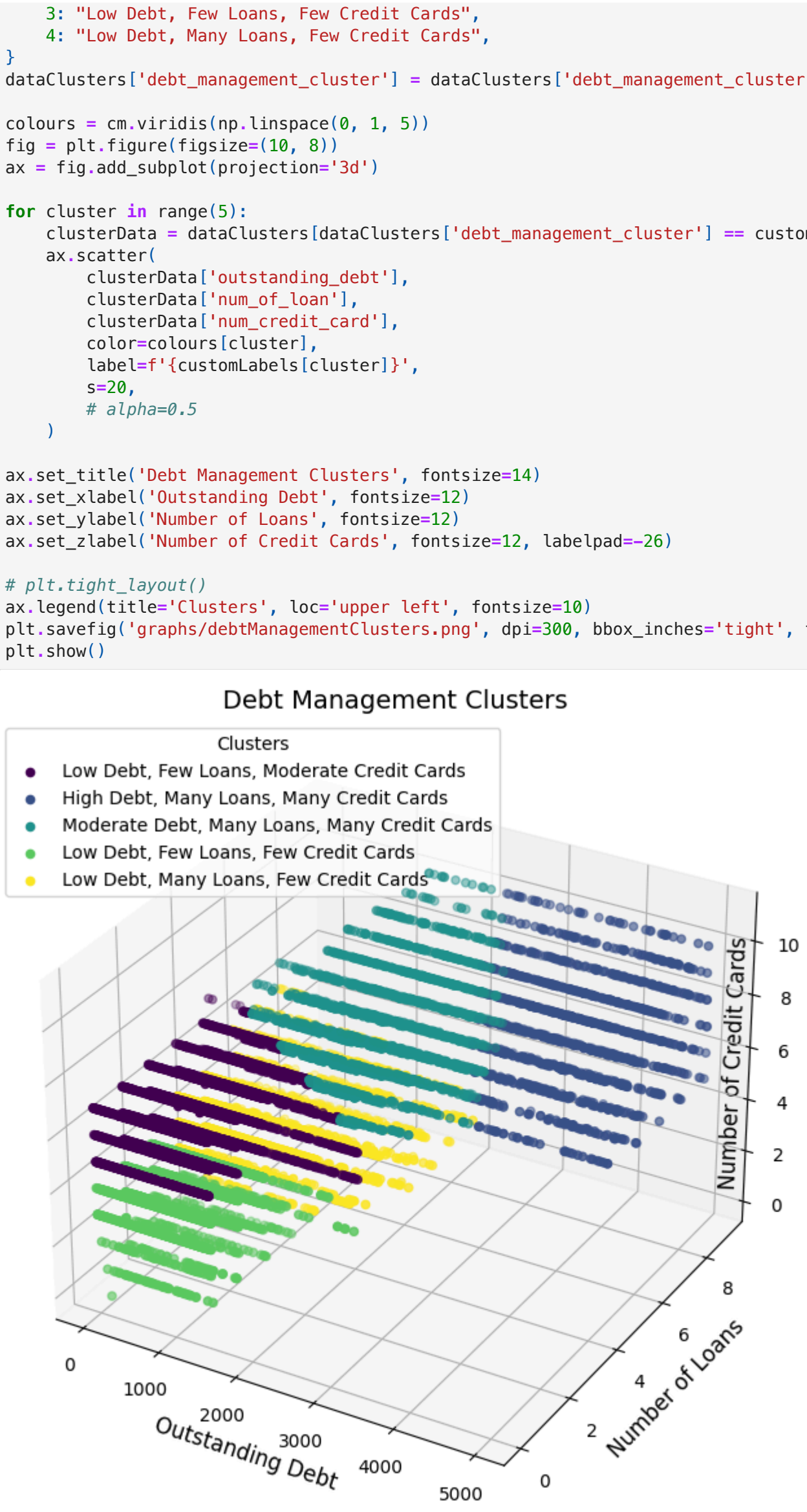


Even though 5 clusters has a lower silhoutte score, it is selected because the thickness of the silhoutte plots with 5 clusters is reasonably balanced

This cluster plot is included in the report. The code for 3d scatterplots has been influenced by (GeeksforGeeks, 2020) and (Matplotlib, 2014). Complete citations at the end of the notebook

In [ ]:
```
kmeans = KMeans(n_clusters=5, random_state=42, n_init='auto')
dataClusters = customerData.copy()
dataClusters['debt_management_cluster'] = kmeans.fit_predict(debtManagementScaled)
customLabels = {
    0: "Low Debt, Few Loans, Moderate Credit Cards",
    1: "High Debt, Many Loans, Many Credit Cards",
    2: "Moderate Debt, Many Loans, Many Credit Cards",
```

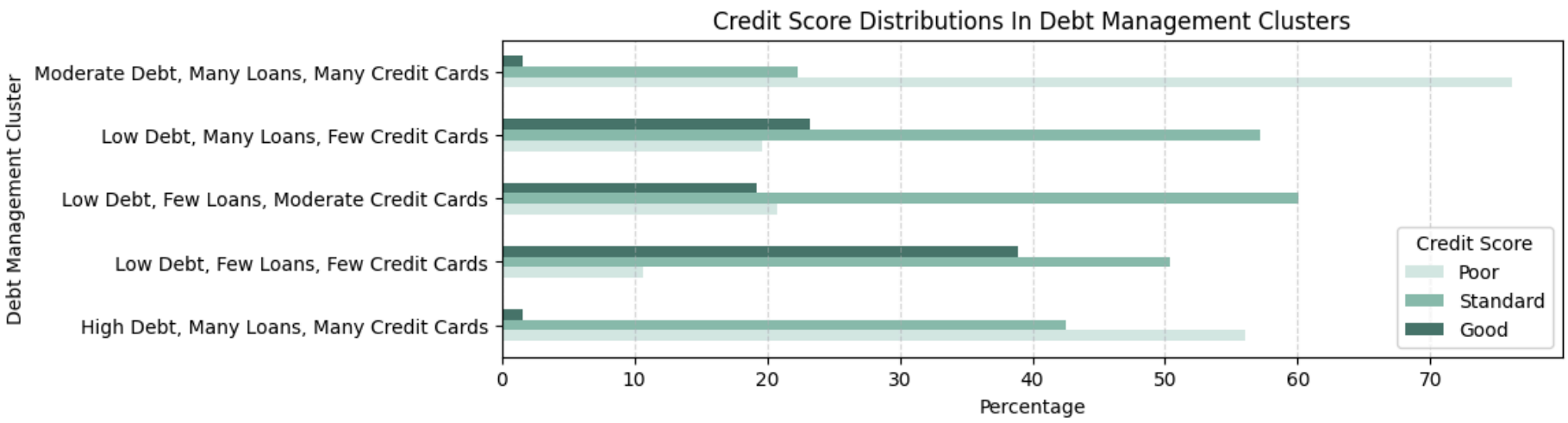
```
    3: "Low Debt, Few Loans, Few Credit Cards",
    4: "Low Debt, Many Loans, Few Credit Cards",
}
dataClusters['debt_management_cluster'] = dataClusters['debt_management_cluster'].map(customLabels)

colours = cm.viridis(np.linspace(0, 1, 5))
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(projection='3d')

for cluster in range(5):
    clusterData = dataClusters[dataClusters['debt_management_cluster'] == customLabels[cluster]]
    ax.scatter(
        clusterData['outstanding_debt'],
        clusterData['num_of_loan'],
        clusterData['num_credit_card'],
        color=colours[cluster],
        label=f'{customLabels[cluster]}',
        s=20,
        # alpha=0.5
    )

ax.set_title('Debt Management Clusters', fontsize=14)
ax.set_xlabel('Outstanding Debt', fontsize=12)
ax.set_ylabel('Number of Loans', fontsize=12)
ax.set_zlabel('Number of Credit Cards', fontsize=12, labelpad=-26)

# plt.tight_layout()
ax.legend(title='Clusters', loc='upper left', fontsize=10)
plt.savefig('graphs/debtManagementClusters.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Displaying the distribution of credit scores in each cluster as a bar graph

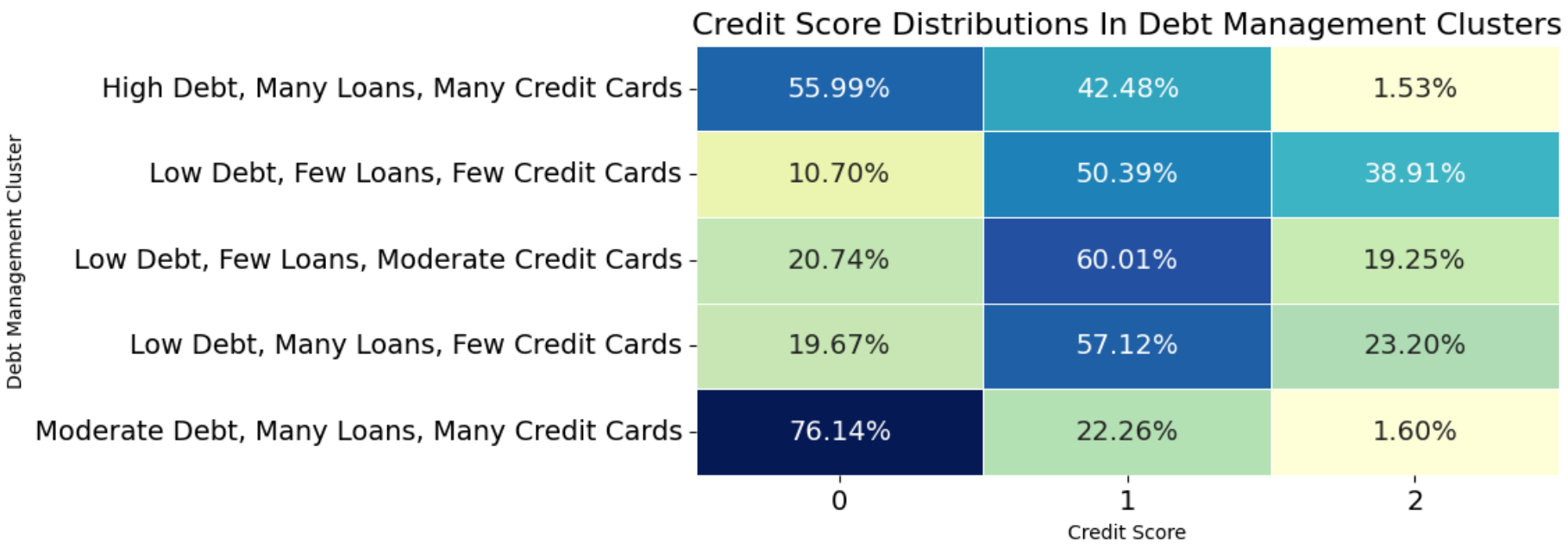
In [245…

```
clusterScoreDistribution = pd.crosstab(dataClusters['debt_management_cluster'], dataClusters['credit_score'], norma

clusterScoreDistribution.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], figsize=(10, 3))
plt.title('Credit Score Distributions In Debt Management Clusters')
plt.xlabel('Percentage')
plt.ylabel('Debt Management Cluster')
plt.legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.show()
```



Displaying the distribution of credit scores in each cluster as a heatmap. This plot is included in the report

In [245…
```
clusterScoreDistribution = clusterScoreDistribution.round(2)
annotations = clusterScoreDistribution.applymap(lambda x: f"{x:.2f}%")

plt.figure(figsize=(8, 4))
sns.heatmap(clusterScoreDistribution, annot=annotations, cmap='YlGnBu', cbar=False, fmt='', linewidths=.5, annot_kw

plt.title('Credit Score Distributions In Debt Management Clusters', fontsize=16)
plt.ylabel('Debt Management Cluster')
plt.xlabel('Credit Score')
plt.yticks(fontsize=14)
plt.xticks(fontsize=14)
plt.savefig('graphs/debtManagementResults.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Logistic Regression to predict credit score using debt management varialbes to quantify their impact

In [245…
```
x = customerData[['outstanding_debt', 'num_credit_card', 'num_of_loan']]
y = customerData['credit_score']

xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size=0.2, random_state=42)
```

In [245…
```
scaler = StandardScaler()
xTrain = scaler.fit_transform(xTrain)
xTest = scaler.transform(xTest)
```

In [245…
```
model = LogisticRegression(multi_class='multinomial')
result = model.fit(xTrain, yTrain)
```

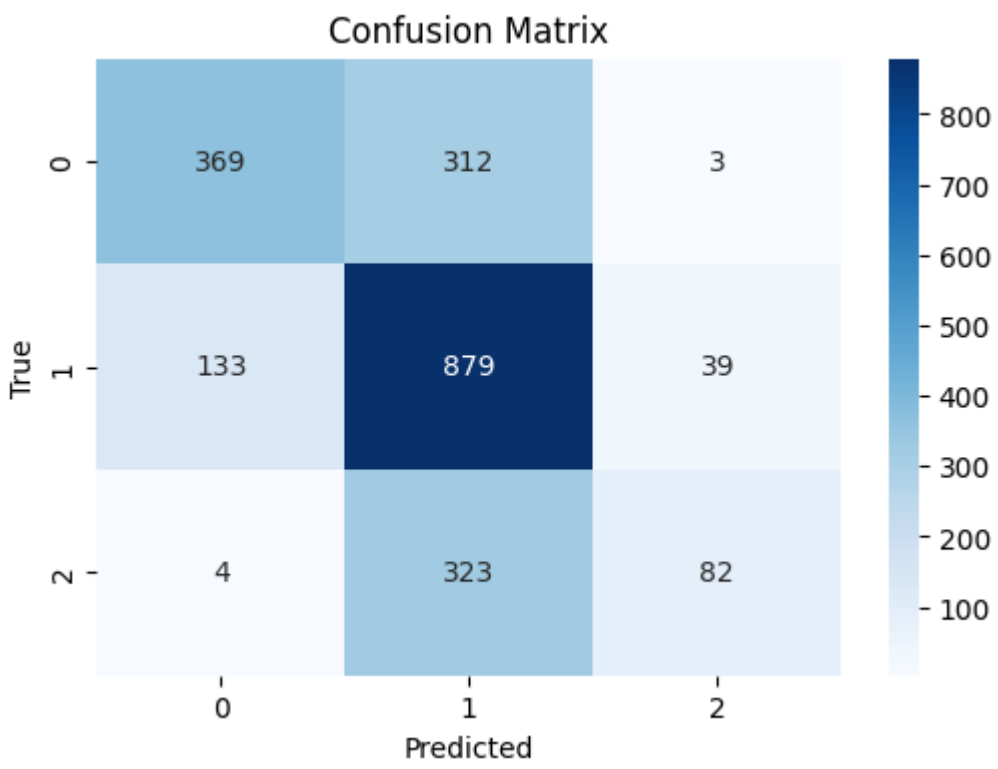
In [245…
```
yPred = model.predict(xTest)
accuracy = accuracy_score(yTest, yPred)
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Accuracy: 62.03%
```

In [245…
```
classNames = [f"Credit Score {className}" for className in model.classes_]

coefficients_df = pd.DataFrame(
    model.coef_.T,
    index=x.columns,
    columns= classNames)

print(coefficients_df)
```

```
                 Credit Score 0  Credit Score 1  Credit Score 2
outstanding_debt           0.427           0.005          -0.432
num_credit_card            0.529           0.079          -0.608
num_of_loan                0.294           0.037          -0.331
```

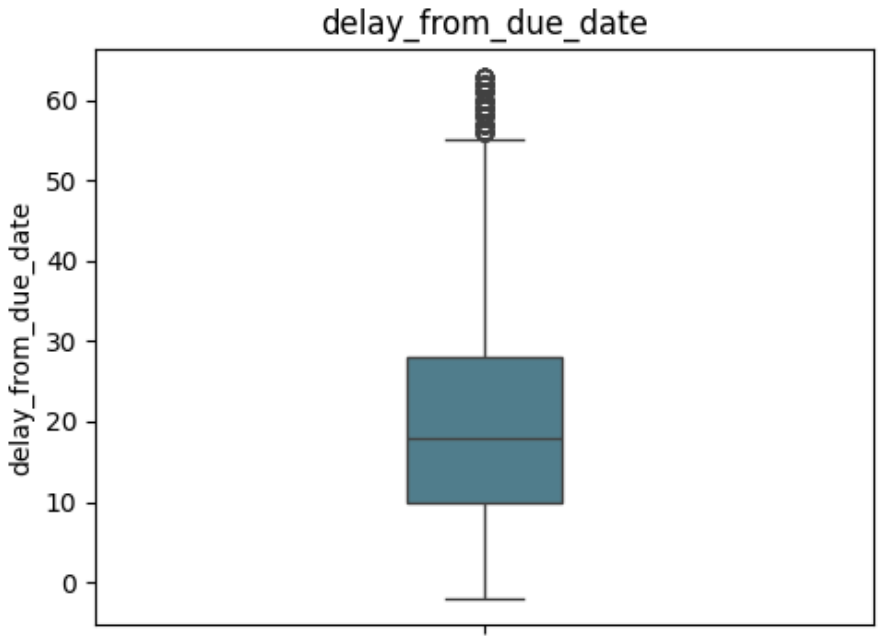
In [245…
```
confusionMatrix = confusion_matrix(yTest, yPred)

plt.figure(figsize=(6, 4))
sns.heatmap(confusionMatrix, annot=True, fmt='d', cmap='Blues', xticklabels=model.classes_, yticklabels=model.class
plt.title("Confusion Matrix")
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

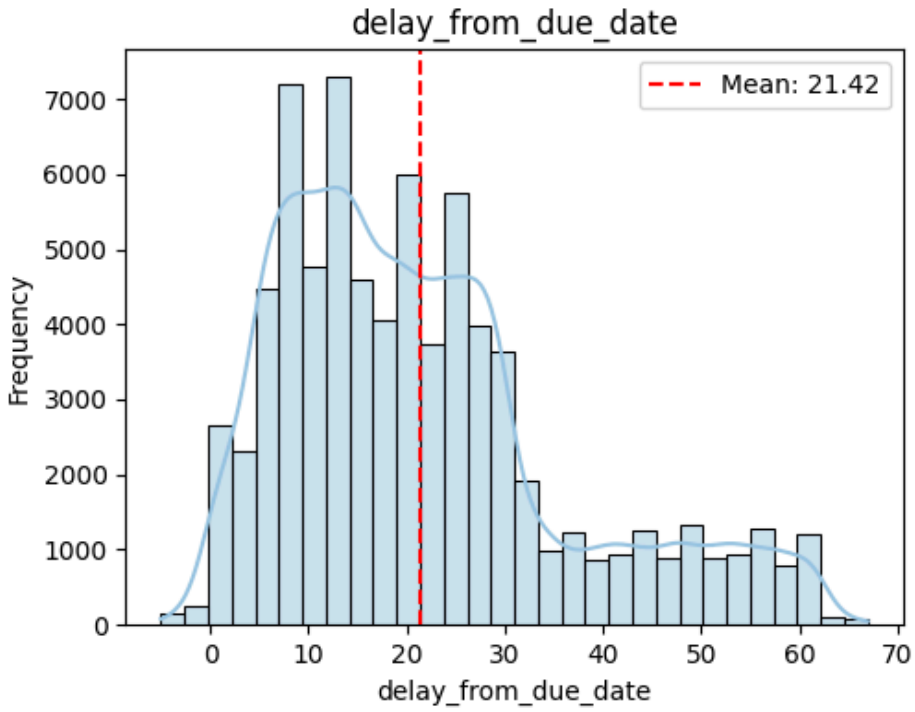


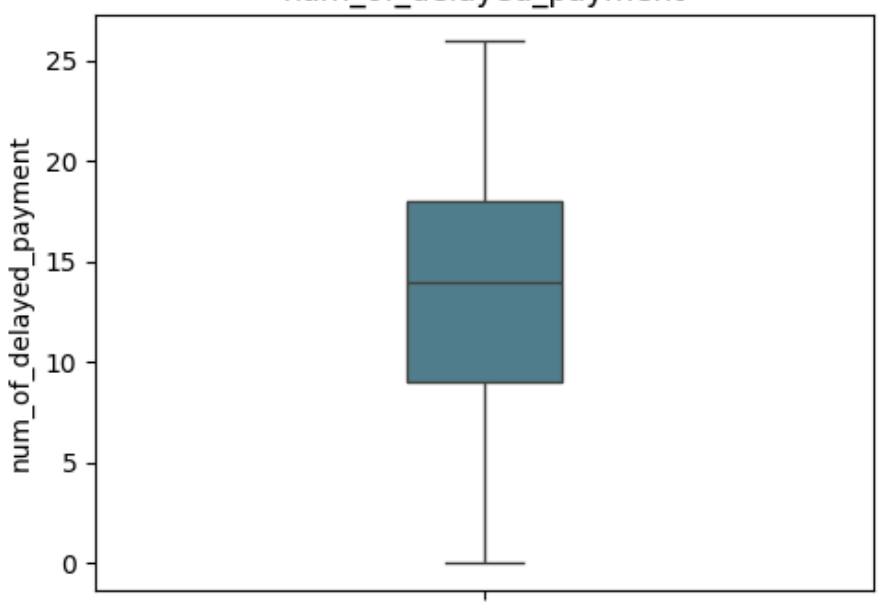
Second Research Question: What is the relationship between an individual's payment behavior and their credit score?

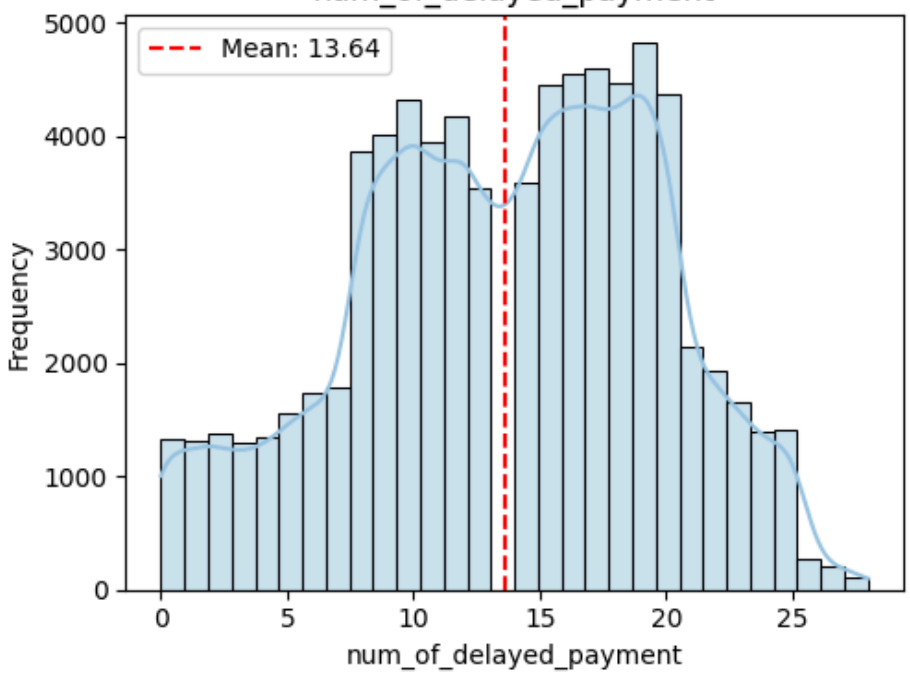
Analyzing the distribution of payment behaviour features using boxplots and histograms

In [246…
```
paymentBehaviourColumns = ['delay_from_due_date', 'num_of_delayed_payment']

numPlots = len(paymentBehaviourColumns)
rows = 2
cols = 2

fig, axes = plt.subplots(rows, cols, figsize=(10, rows * 4))
axes = axes.flatten()

for i, col in enumerate(paymentBehaviourColumns):
    sns.boxplot(data=customerData, y=col, ax=axes[2 * i], color="#498699",  width=0.2)
    axes[2 * i].set_title(f'{col}', fontsize=12)
    axes[2 * i].set_ylabel(col, fontsize=10)

    sns.histplot(data=data, x=col, ax=axes[2 * i + 1], color="#98c5e1", kde=True, bins=30)
    mean_value = data[col].mean()
    axes[2 * i + 1].axvline(mean_value, color='red', linestyle='--', label=f'Mean: {mean_value:.2f}')
    axes[2 * i + 1].legend()

    axes[2 * i + 1].set_title(f'{col}', fontsize=12)
    axes[2 * i + 1].set_xlabel(col, fontsize=10)
    axes[2 * i + 1].set_ylabel('Frequency', fontsize=10)

for j in range(2 * numPlots, len(axes)):
    fig.delaxes(axes[j])

plt.subplots_adjust(wspace=0.6, hspace=0.4)
plt.tight_layout()
plt.show()
```





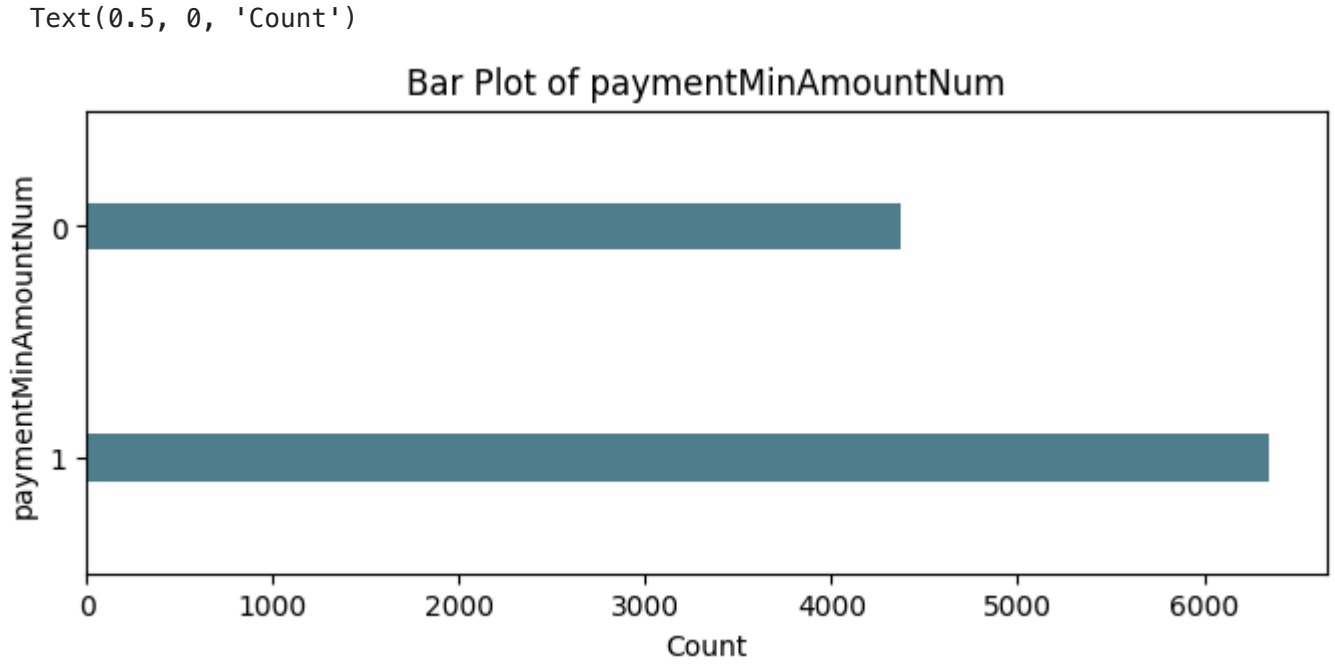




Examining the number of customers who paid just the minimum amount (1) and the customers who did not pay just the minimum amount and paid more (0)

In [246…
```
plt.figure(figsize=(8, 3))
sns.countplot(data=customerData, y='paymentMinAmountNum', color='#498699', width=0.2, legend=False, orient='h')
plt.title('Bar Plot of paymentMinAmountNum', fontsize=12)
plt.ylabel('paymentMinAmountNum', fontsize=10)
plt.xlabel('Count', fontsize=10)
```

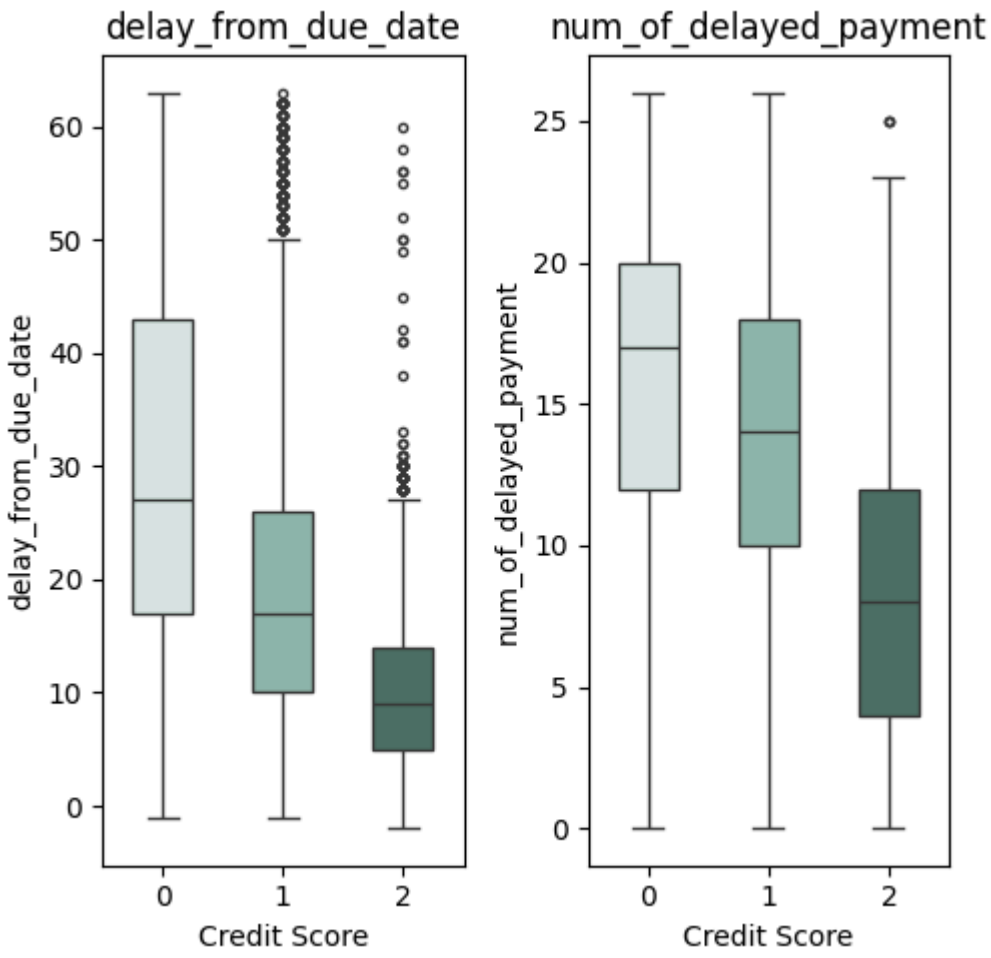
Out[246… `Text(0.5, 0, 'Count')`



Comparing the distributions of payment behaviour features in each credit score class using box plots. This is included in the report

In [246…
```
customPalette = {0: "#d6e7e4", 1: "#87bbae", 2: "#48756a"}
flierprops = dict(markersize=3)

fig, axes = plt.subplots(1, 2, figsize=(5, 5))
axes = axes.flatten()

for i, col in enumerate(paymentBehaviourColumns):
    sns.boxplot(data=customerData, x='credit_score', y=col, ax=axes[i], hue='credit_score', palette=customPalette,
    axes[i].set_title(f'{col}', fontsize=12)
    axes[i].set_xlabel('Credit Score')
```

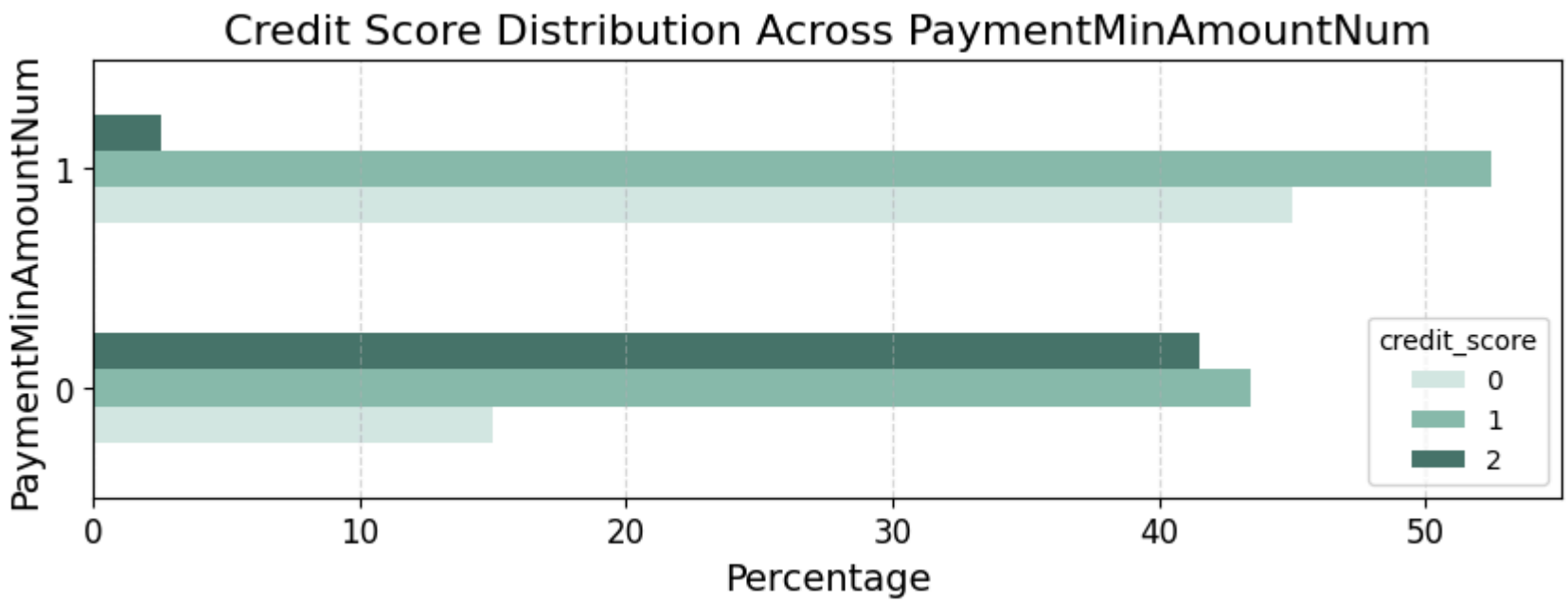
```
    axes[i].set_ylabel(col)

for j in range(numPlots, len(axes)):
    axes[j].set_visible(False)

plt.subplots_adjust(hspace=0.4, wspace=8)
plt.tight_layout()
plt.savefig('graphs/paymentBehaviour(EDA).png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Comparing the distribution of credit scores in the category of customers who paid just the minimum amount and the category of customers who paid more then just the minimum amount. This is included in the report

In [246…

```
paymentMinAmountDistribution = pd.crosstab(customerData['paymentMinAmountNum'], customerData['credit_score'], norma

paymentMinAmountDistribution.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], figsize=(10, 3))
plt.title('Credit Score Distribution Across PaymentMinAmountNum', fontsize=16)
plt.xlabel('Percentage', fontsize=14)
plt.ylabel('PaymentMinAmountNum', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.savefig('graphs/paymentBehaviour(EDA)v2.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Anova test to check if there is significance difference between the payment behaviour attributes of customers belonging to different credit scores. Followed by eta squared to check effect size. This is includd in the report

In [246…

```
results = {}

for column in paymentBehaviourColumns:
    groupData = []
    for score in customerData['credit_score'].unique():
        groupData.append(customerData[customerData['credit_score'] == score][column].tolist())

    f_stat, p_value = f_oneway(groupData[0], groupData[1], groupData[2])
```

```
    results[column] = {'F-statistic': f_stat, 'p-value': p_value}

    if (p_value <= 0.05):
        etaSquared = correlation_ratio(customerData['credit_score'], customerData[column])
        results[column]['etaSquared'] = etaSquared


resultsDF = pd.DataFrame(results).T
resultsDF.sort_values('etaSquared', ascending=False, inplace=True)

resultsDF
```

Out [246…

	F-statistic	p-value	etaSquared
delay_from_due_date	1540.769	0.000	0.223
num_of_delayed_payment	1175.577	0.000	0.180

Chi Square test to check if paymentMinAmountNum is associated or independent to the credit score. Followed by Cramer's V to check the level of association. This is included in the report

In [246…

```
results = {}
contingencyTable = pd.crosstab(customerData['credit_score'], customerData['paymentMinAmountNum'])
chi2, p, _, _ = chi2_contingency(contingencyTable)
results['paymentMinAmountNum'] = {'chi2': chi2, 'p-value': p}

if (p <= 0.05):
    results['paymentMinAmountNum']["cramer's v"] = cramersCorrectedStat(contingencyTable)

print(results)
```

```
{'paymentMinAmountNum': {'chi2': 2879.7318747499944, 'p-value': 0.0, "cramer's v": 0.5181410680112958}}
```

Customer Segmentation based on Payment Behaviour using K Mean Clustering

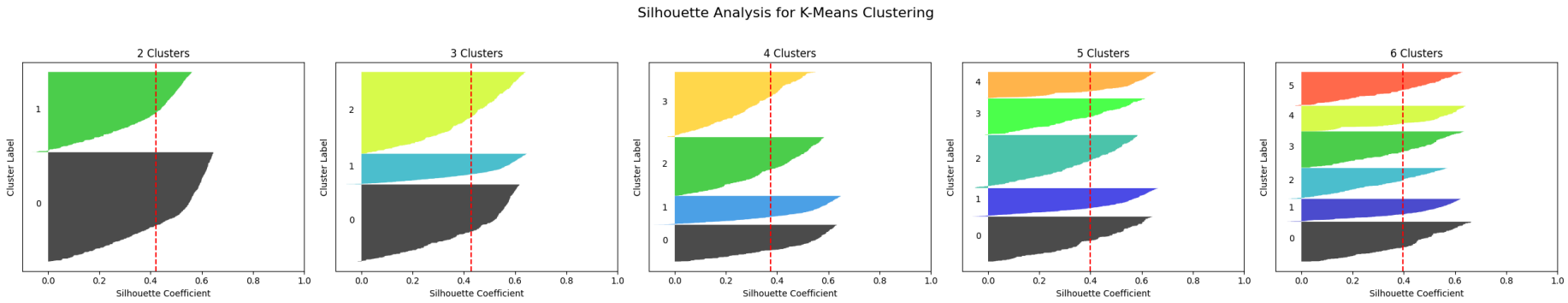
Features for clustering: Delay from due date and number of delayed payments

Using Silhoutte Score to find ideal number of clusters

In [246…

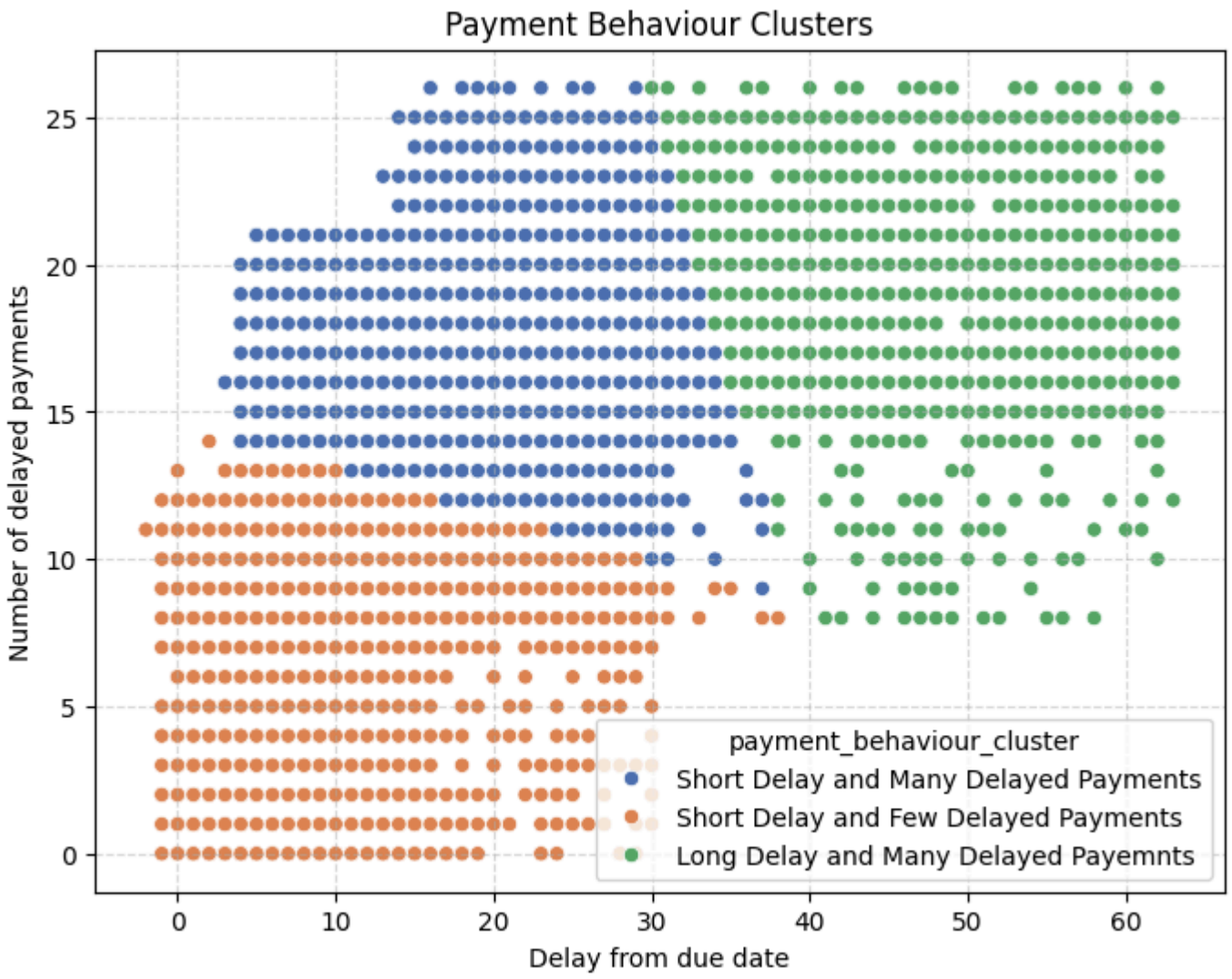
```
features = ['delay_from_due_date', 'num_of_delayed_payment']
scaler = StandardScaler()
paymentBehaviourScaled = scaler.fit_transform(customerData[features])

clusterRange = range(2, 7)
fig, axes = plt.subplots(1, 5, figsize=(25, 5))
fig.suptitle("Silhouette Analysis for K-Means Clustering", fontsize=16)

for i, nClusters in enumerate(clusterRange):
    ax = axes[i]
    kmeans = KMeans(n_clusters=nClusters, random_state=42, n_init='auto')
    clusterLabels = kmeans.fit_predict(paymentBehaviourScaled)
    silhouetteAvg = silhouette_score(paymentBehaviourScaled, clusterLabels)
    silhouetteValues = silhouette_samples(paymentBehaviourScaled, clusterLabels)
    print(f"Number of Clusters: {nClusters}, Silhouette Score: {silhouetteAvg:.4f}")
    y_lower = 10
    for i in range(nClusters):
        ithClusterSilhouetteValues = silhouetteValues[clusterLabels == i]
        ithClusterSilhouetteValues.sort()
        size_cluster_i = ithClusterSilhouetteValues.shape[0]
        y_upper = y_lower + size_cluster_i
        color = plt.cm.nipy_spectral(float(i) / nClusters)
        ax.fill_betweenx(np.arange(y_lower, y_upper), 0, ithClusterSilhouetteValues, facecolor=color, alpha=0.7)
        ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
        y_lower = y_upper + 10

    ax.set_title(f"{nClusters} Clusters")
    ax.axvline(x=silhouetteAvg, color="red", linestyle="--")
    ax.set_xlabel("Silhouette Coefficient")
    ax.set_xlim([-0.1, 1])
    ax.set_ylabel("Cluster Label")
    ax.set_yticks([])

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

```
Number of Clusters: 2, Silhouette Score: 0.4218
Number of Clusters: 3, Silhouette Score: 0.4275
Number of Clusters: 4, Silhouette Score: 0.3754
Number of Clusters: 5, Silhouette Score: 0.3993
Number of Clusters: 6, Silhouette Score: 0.3959
```



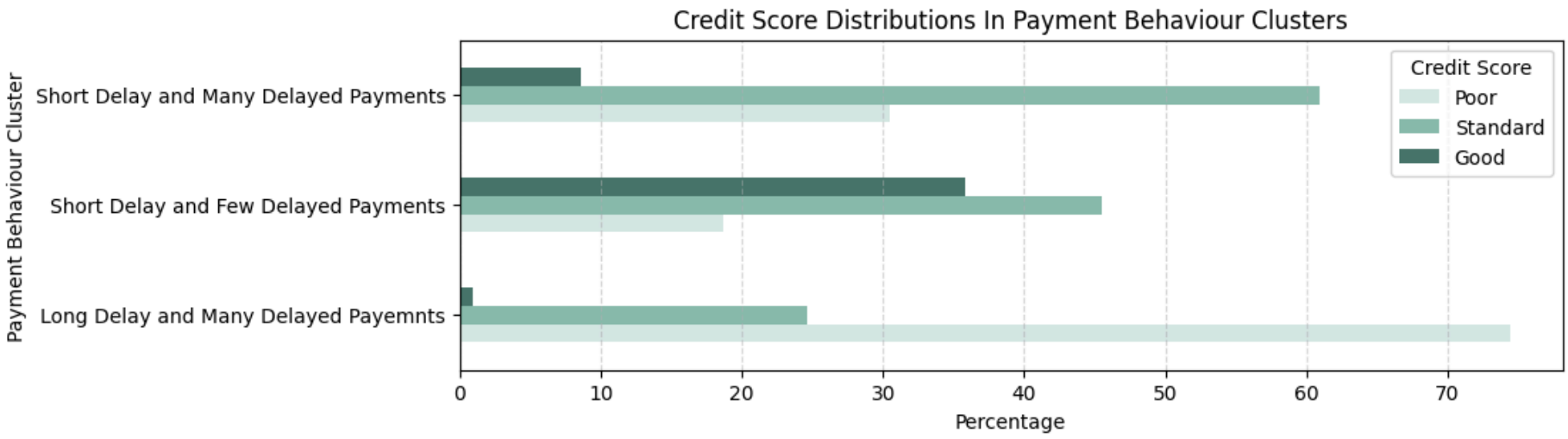
3 clusters is selected since it has the highest silhoutte score and reasonable thickness of the silhoutte plots

In [246…
```
kmeans = KMeans(n_clusters=3, random_state=42, n_init='auto')
dataClusters['payment_behaviour_cluster'] = kmeans.fit_predict(paymentBehaviourScaled)
customLabels = {
    0: "Short Delay and Few Delayed Payments",
    1: "Long Delay and Many Delayed Payemnts",
    2: "Short Delay and Many Delayed Payments"
}
dataClusters['payment_behaviour_cluster'] = dataClusters['payment_behaviour_cluster'].map(customLabels)

plt.figure(figsize=(8, 6))
sns.scatterplot(x=dataClusters['delay_from_due_date'], y=dataClusters['num_of_delayed_payment'], hue=dataClusters['
plt.title('Payment Behaviour Clusters')
plt.xlabel('Delay from due date')
plt.ylabel('Number of delayed payments')
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```



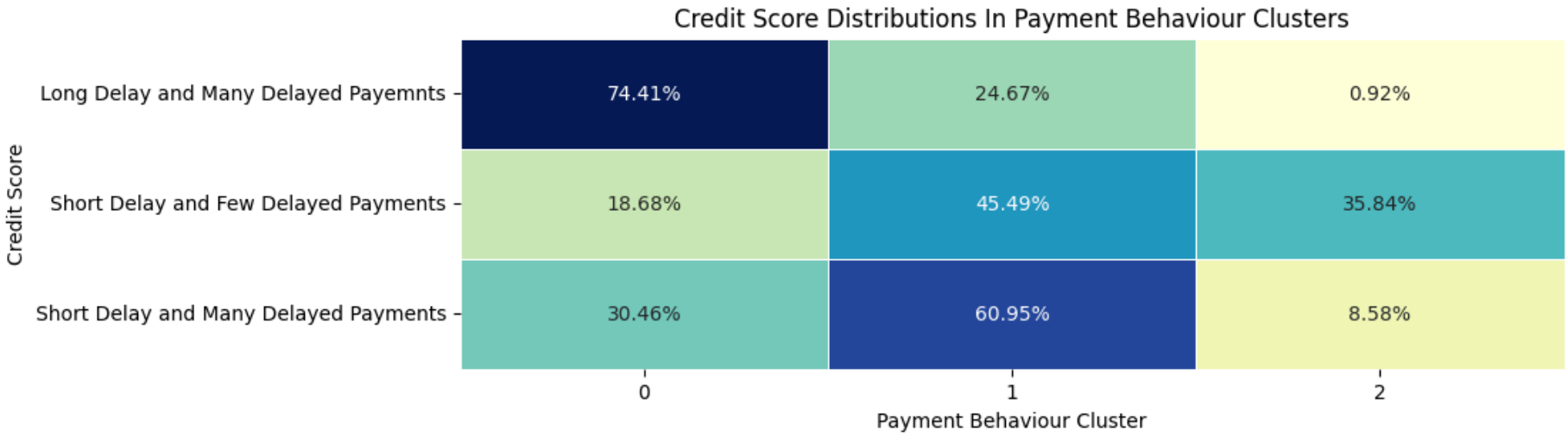
Displaying the distribution of credit scores in each cluster as a bar graph

In [246…
```
clusterScoreDistribution = pd.crosstab(dataClusters['payment_behaviour_cluster'], dataClusters['credit_score'], nor

clusterScoreDistribution.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], figsize=(10, 3))
plt.title('Credit Score Distributions In Payment Behaviour Clusters')
plt.xlabel('Percentage')
plt.ylabel('Payment Behaviour Cluster')
plt.legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.show()
```



Displaying the distribution of credit scores in each cluster as a heatmap

In [246…
```
clusterScoreDistribution = clusterScoreDistribution.round(2)
annotations = clusterScoreDistribution.applymap(lambda x: f"{x:.2f}%")

plt.figure(figsize=(10, 3))
sns.heatmap(clusterScoreDistribution, annot=annotations, cmap='YlGnBu', cbar=False, fmt='', linewidths=.5)

plt.title('Credit Score Distributions In Payment Behaviour Clusters')
plt.xlabel('Payment Behaviour Cluster')
plt.ylabel('Credit Score')
plt.show()
```

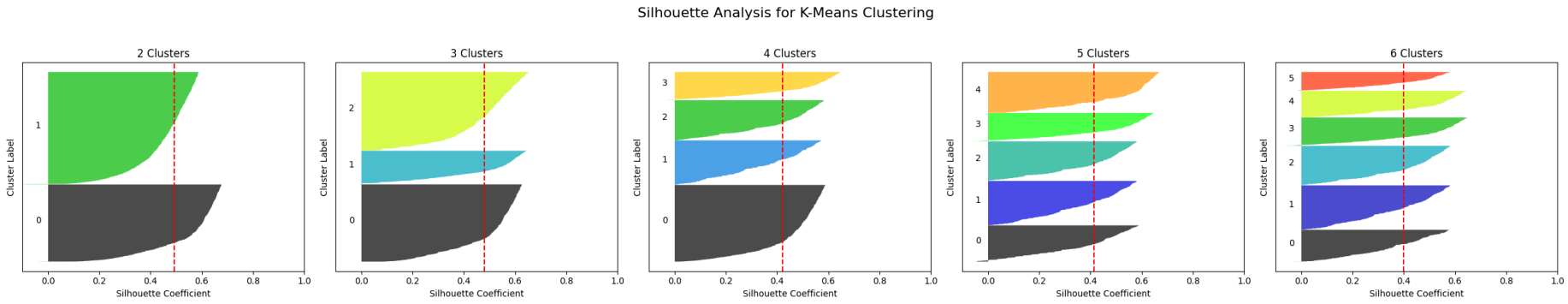


Clustering with all 3 variables of payment behaviour: delay from due date, number of delayed payments and payment of just the minimum amount

Using Silhoutte Score to find ideal number of clusters

In [247…
```
features = ['delay_from_due_date', 'num_of_delayed_payment', 'paymentMinAmountNum']
scaler = StandardScaler()
paymentBehaviourScaled = scaler.fit_transform(customerData[features])

clusterRange = range(2, 7)
fig, axes = plt.subplots(1, 5, figsize=(25, 5))
fig.suptitle("Silhouette Analysis for K-Means Clustering", fontsize=16)

for i, nClusters in enumerate(clusterRange):
    ax = axes[i]
    kmeans = KMeans(n_clusters=nClusters, random_state=42, n_init='auto')
    clusterLabels = kmeans.fit_predict(paymentBehaviourScaled)
    silhouetteAvg = silhouette_score(paymentBehaviourScaled, clusterLabels)
    silhouetteValues = silhouette_samples(paymentBehaviourScaled, clusterLabels)
    print(f"Number of Clusters: {nClusters}, Silhouette Score: {silhouetteAvg:.4f}")
    y_lower = 10
    for i in range(nClusters):
        ithClusterSilhouetteValues = silhouetteValues[clusterLabels == i]
        ithClusterSilhouetteValues.sort()
        size_cluster_i = ithClusterSilhouetteValues.shape[0]
        y_upper = y_lower + size_cluster_i
        color = plt.cm.nipy_spectral(float(i) / nClusters)
        ax.fill_betweenx(np.arange(y_lower, y_upper), 0, ithClusterSilhouetteValues, facecolor=color, alpha=0.7)
        ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
        y_lower = y_upper + 10

    ax.set_title(f"{nClusters} Clusters")
    ax.axvline(x=silhouetteAvg, color="red", linestyle="--")
    ax.set_xlabel("Silhouette Coefficient")
    ax.set_xlim([-0.1, 1])
    ax.set_ylabel("Cluster Label")
    ax.set_yticks([])

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

```
Number of Clusters: 2, Silhouette Score: 0.4929
Number of Clusters: 3, Silhouette Score: 0.4794
Number of Clusters: 4, Silhouette Score: 0.4212
Number of Clusters: 5, Silhouette Score: 0.4136
Number of Clusters: 6, Silhouette Score: 0.3998
```

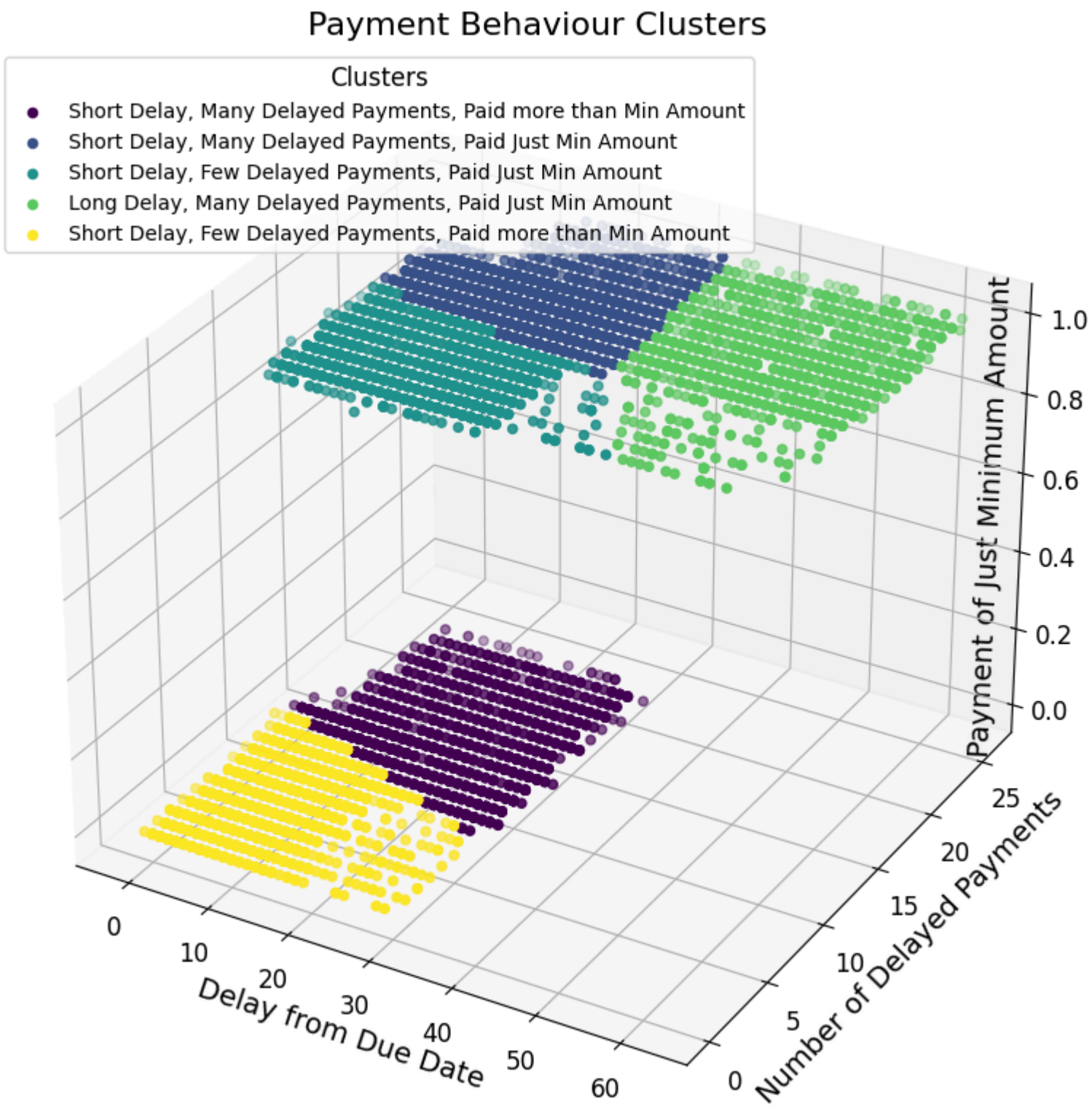


5 clusters is selected despite having a lower silhoutte score since the silhoutte plots have balanced thickness

Clustering using all three variables of payment behaviour. This is included in the report

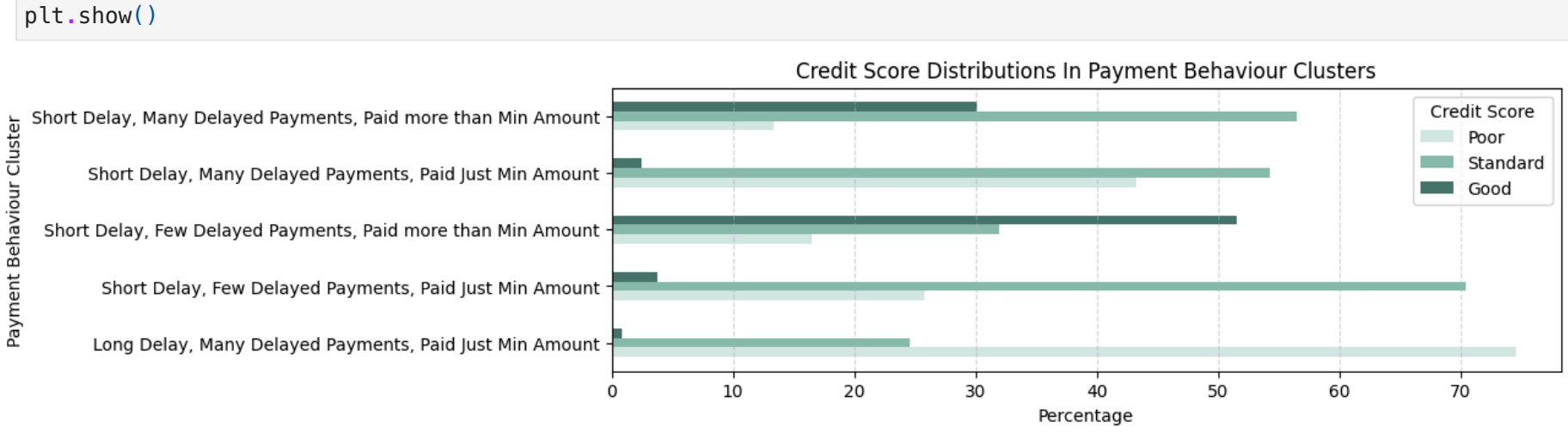
In [247…

```
kmeans = KMeans(n_clusters=5, random_state=42, n_init='auto')
dataClusters['payment_behaviour_cluster'] = kmeans.fit_predict(paymentBehaviourScaled)
customLabels = {
    0: "Short Delay, Many Delayed Payments, Paid more than Min Amount",
    1: "Short Delay, Many Delayed Payments, Paid Just Min Amount",
    2: "Short Delay, Few Delayed Payments, Paid Just Min Amount",
    3: "Long Delay, Many Delayed Payments, Paid Just Min Amount",
    4: "Short Delay, Few Delayed Payments, Paid more than Min Amount"
}
dataClusters['payment_behaviour_cluster'] = dataClusters['payment_behaviour_cluster'].map(customLabels)

colours = cm.viridis(np.linspace(0, 1, 5))
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(projection='3d')

for cluster in range(5):
    clusterData = dataClusters[dataClusters['payment_behaviour_cluster'] == customLabels[cluster]]
    ax.scatter(
        clusterData['delay_from_due_date'],
        clusterData['num_of_delayed_payment'],
        clusterData['paymentMinAmountNum'],
        color=colours[cluster],
        label=customLabels[cluster],
        s=20,
        # alpha=0.5
    )

ax.set_title('Payment Behaviour Clusters', fontsize=16)
ax.set_xlabel('Delay from Due Date', fontsize=14)
ax.set_ylabel('Number of Delayed Payments', fontsize=14)
ax.set_zlabel('Payment of Just Minimum Amount', fontsize=14, labelpad=-30)
ax.tick_params(axis='x', labelsize=12)
ax.tick_params(axis='y', labelsize=12)
ax.tick_params(axis='z', labelsize=12)
ax.legend(title='Clusters', loc='upper left', title_fontsize=12, fontsize=10)
plt.tight_layout()
plt.savefig('graphs/paymentBehaviourClusters.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Displaying the distribution of credit scores in each cluster using a bar graph

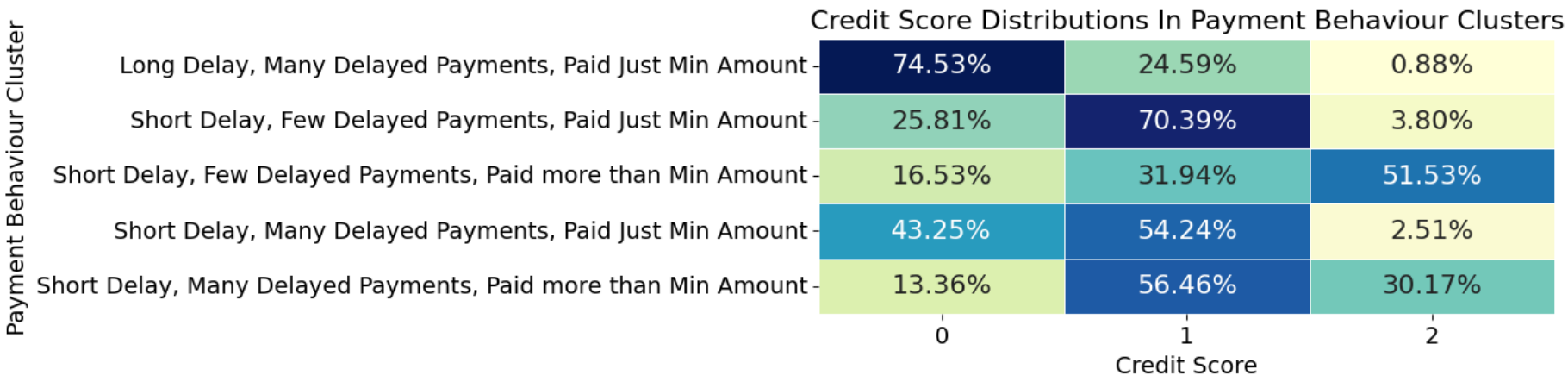
In [247…
```
clusterScoreDistribution = pd.crosstab(dataClusters['payment_behaviour_cluster'], dataClusters['credit_score'], nor

clusterScoreDistribution.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], figsize=(10, 3))
plt.title('Credit Score Distributions In Payment Behaviour Clusters')
plt.xlabel('Percentage')
plt.ylabel('Payment Behaviour Cluster')
plt.legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.show()
```



Displaying the distribution of credit scores in each cluster using a heatmap

In [247…
```
clusterScoreDistribution = clusterScoreDistribution.round(2)
annotations = clusterScoreDistribution.applymap(lambda x: f"{x:.2f}%")

plt.figure(figsize=(8, 3))
sns.heatmap(clusterScoreDistribution, annot=annotations, cmap='YlGnBu', cbar=False, fmt='', linewidths=.5, annot_kw

plt.title('Credit Score Distributions In Payment Behaviour Clusters', fontsize=16)
plt.ylabel('Payment Behaviour Cluster', fontsize=14)
plt.xlabel('Credit Score', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
```

```
plt.savefig('graphs/paymentBehaviourResults.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Logistic Regression to predict credit score using payment behaviour varialbes to quantify their impact.

In [247…
```
x = customerData[['delay_from_due_date', 'num_of_delayed_payment', 'paymentMinAmountNum']]
y = customerData['credit_score']

xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size=0.2, random_state=42)
```

In [247…
```
scaler = StandardScaler()
xTrain = scaler.fit_transform(xTrain)
xTest = scaler.transform(xTest)
```

In [247…
```
model = LogisticRegression(multi_class='multinomial')
result = model.fit(xTrain, yTrain)
```

In [247…
```
yPred = model.predict(xTest)
accuracy = accuracy_score(yTest, yPred)
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Accuracy: 63.15%
```

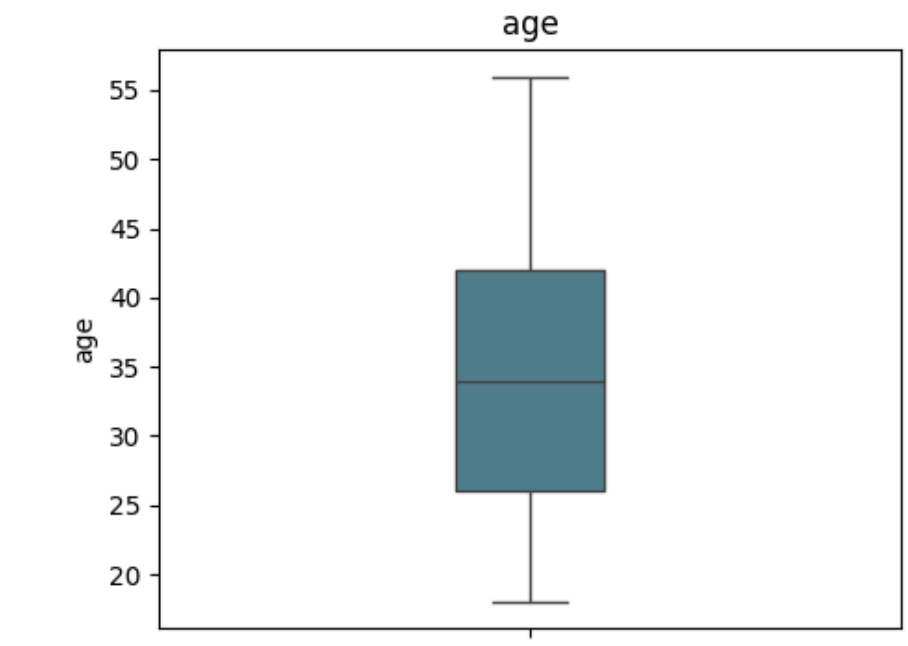
In [247…
```
classNames = [f"Credit Score {className}" for className in model.classes_]

coefficients_df = pd.DataFrame(
    model.coef_.T,
    index=x.columns,
    columns= classNames)

print(coefficients_df)
```

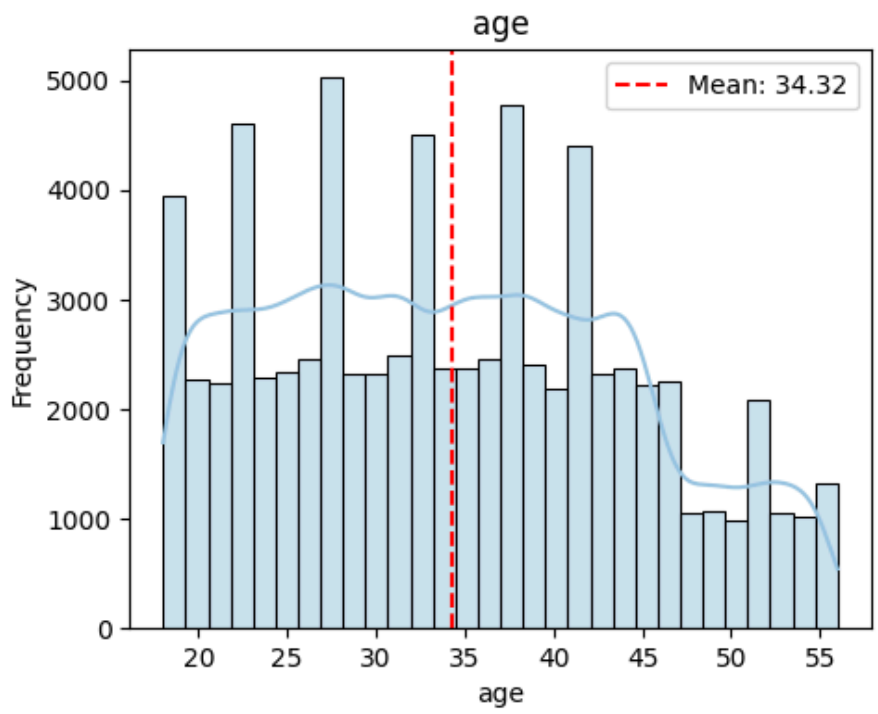
```
                        Credit Score 0  Credit Score 1  Credit Score 2
delay_from_due_date              0.689          -0.018          -0.671
num_of_delayed_payment           0.119           0.079          -0.199
paymentMinAmountNum              0.449           0.345          -0.794
```

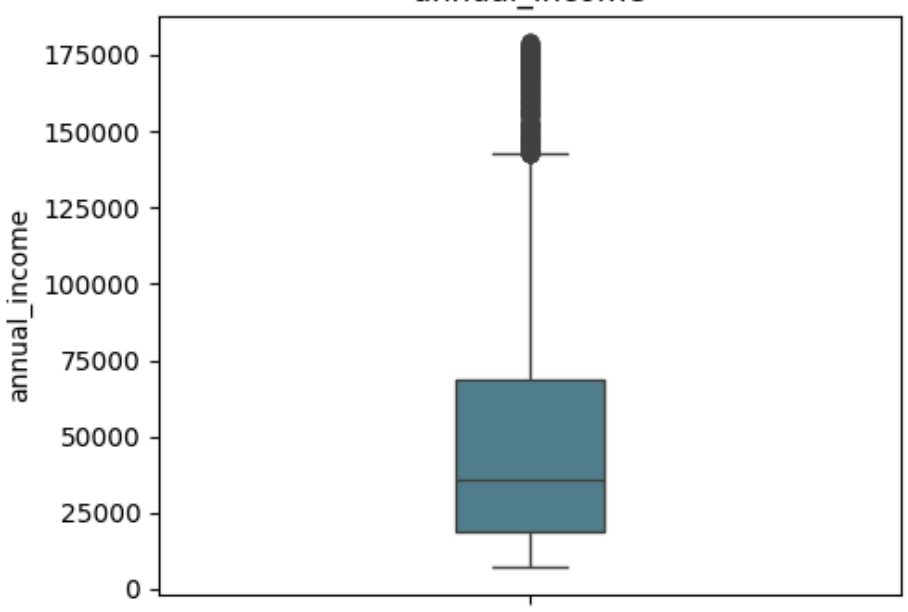
Third Research Question: To what extent do demographic factors such as age and income influence an individual's credit score?

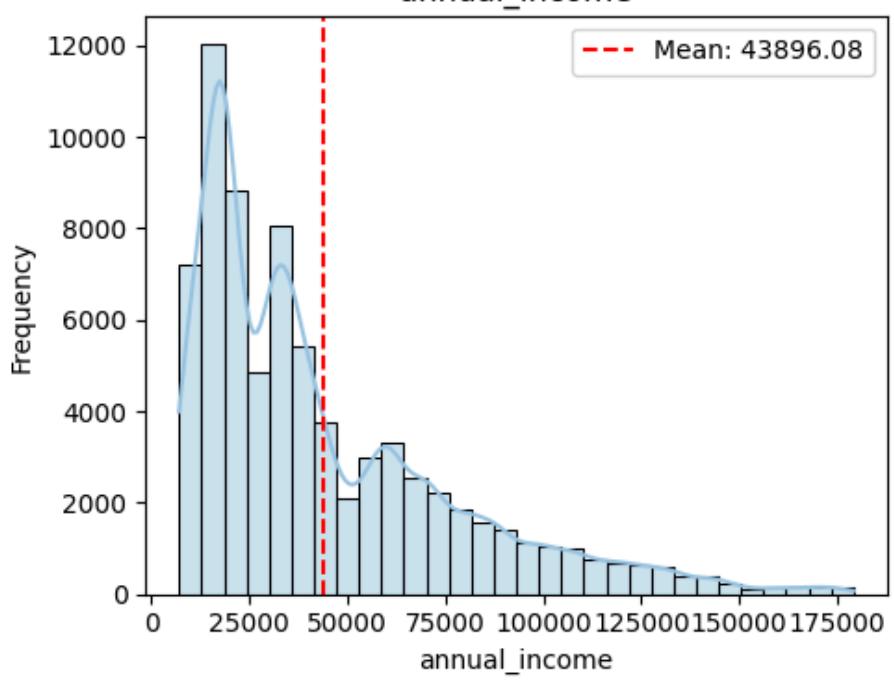
Analyzing the distribution of age and annual income using boxplots and histograms

In [247…
```
demographicFactorsColumns = ['age', 'annual_income']

numPlots = len(demographicFactorsColumns)
rows = 2
cols = 2

fig, axes = plt.subplots(rows, cols, figsize=(10, rows * 4))
axes = axes.flatten()

for i, col in enumerate(demographicFactorsColumns):
    sns.boxplot(data=customerData, y=col, ax=axes[2 * i], color="#498699",  width=0.2)
    axes[2 * i].set_title(f'{col}', fontsize=12)
    axes[2 * i].set_ylabel(col, fontsize=10)

    sns.histplot(data=data, x=col, ax=axes[2 * i + 1], color="#98c5e1", kde=True, bins=30)
    mean_value = data[col].mean()
    axes[2 * i + 1].axvline(mean_value, color='red', linestyle='--', label=f'Mean: {mean_value:.2f}')
    axes[2 * i + 1].legend()

    axes[2 * i + 1].set_title(f'{col}', fontsize=12)
    axes[2 * i + 1].set_xlabel(col, fontsize=10)
    axes[2 * i + 1].set_ylabel('Frequency', fontsize=10)

for j in range(2 * numPlots, len(axes)):
    fig.delaxes(axes[j])

plt.subplots_adjust(wspace=0.6, hspace=0.4)
plt.tight_layout()
plt.show()
```





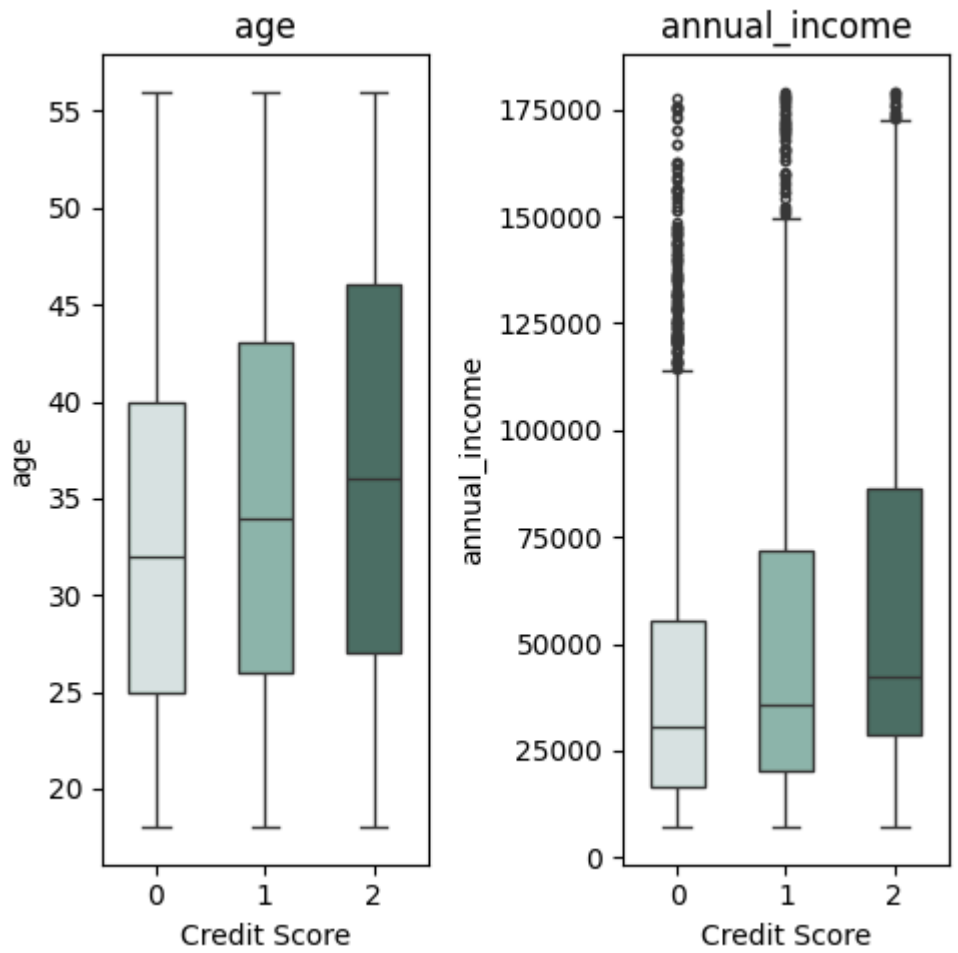




Comparing the distributions of age and annual income in each credit score class using boxplots. This is included in the report

In [248…

```
customPalette = {0: "#d6e7e4", 1: "#87bbae", 2: "#48756a"}
flierprops = dict(markersize=3)

fig, axes = plt.subplots(1, 2, figsize=(5, 5))
axes = axes.flatten()

for i, col in enumerate(demographicFactorsColumns):
    sns.boxplot(data=customerData, x='credit_score', y=col, ax=axes[i], hue='credit_score', palette=customPalette,
    axes[i].set_title(f'{col}', fontsize=12)
    axes[i].set_xlabel('Credit Score')
    axes[i].set_ylabel(col)

for j in range(numPlots, len(axes)):
    axes[j].set_visible(False)

plt.subplots_adjust(hspace=0.4, wspace=8)
plt.tight_layout()
plt.savefig('graphs/demographicFactors(EDA).png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Anova test to check if there is significance difference between the demographic factors attributes of customers belonging to different credit scores. Followed by eta squared to check effect size. This is included in the report

In [248…
```
results = {}

for column in demographicFactorsColumns:
    groupData = []
    for score in customerData['credit_score'].unique():
        groupData.append(customerData[customerData['credit_score'] == score][column].tolist())

    f_stat, p_value = f_oneway(groupData[0], groupData[1], groupData[2])
    results[column] = {'F-statistic': f_stat, 'p-value': p_value}

    if (p_value <= 0.05):
        etaSquared = correlation_ratio(customerData['credit_score'], customerData[column])
        results[column]['etaSquared'] = etaSquared


resultsDF = pd.DataFrame(results).T
resultsDF.sort_values('etaSquared', ascending=False, inplace=True)

resultsDF
```

Out[248…

	F-statistic	p-value	etaSquared
annual_income	220.063	0.000	0.039
age	98.551	0.000	0.018

Customer Segmentation based on Demographic Factors using K Mean Clustering

Clustering using both demographic factors: age and annual income

Using Silhoutte Score to find ideal number of clusters

In [248…
```
features = ['age', 'annual_income']
scaler = StandardScaler()
demographicFactorsScaled = scaler.fit_transform(customerData[features])

clusterRange = range(2, 7)
fig, axes = plt.subplots(1, 5, figsize=(25, 5))
fig.suptitle("Silhouette Analysis for K-Means Clustering", fontsize=16)

for i, nClusters in enumerate(clusterRange):
    ax = axes[i]
    kmeans = KMeans(n_clusters=nClusters, random_state=42, n_init='auto')
    clusterLabels = kmeans.fit_predict(demographicFactorsScaled)
    silhouetteAvg = silhouette_score(demographicFactorsScaled, clusterLabels)
    silhouetteValues = silhouette_samples(demographicFactorsScaled, clusterLabels)
    print(f"Number of Clusters: {nClusters}, Silhouette Score: {silhouetteAvg:.4f}")
    y_lower = 10
    for i in range(nClusters):
        ithClusterSilhouetteValues = silhouetteValues[clusterLabels == i]
        ithClusterSilhouetteValues.sort()
        size_cluster_i = ithClusterSilhouetteValues.shape[0]
```

```
        y_upper = y_lower + size_cluster_i
        color = plt.cm.nipy_spectral(float(i) / nClusters)
        ax.fill_betweenx(np.arange(y_lower, y_upper), 0, ithClusterSilhouetteValues, facecolor=color, alpha=0.7)
        ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
        y_lower = y_upper + 10

    ax.set_title(f"{nClusters} Clusters")
    ax.axvline(x=silhouetteAvg, color="red", linestyle="--")
    ax.set_xlabel("Silhouette Coefficient")
    ax.set_xlim([-0.1, 1])
    ax.set_ylabel("Cluster Label")
    ax.set_yticks([])

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

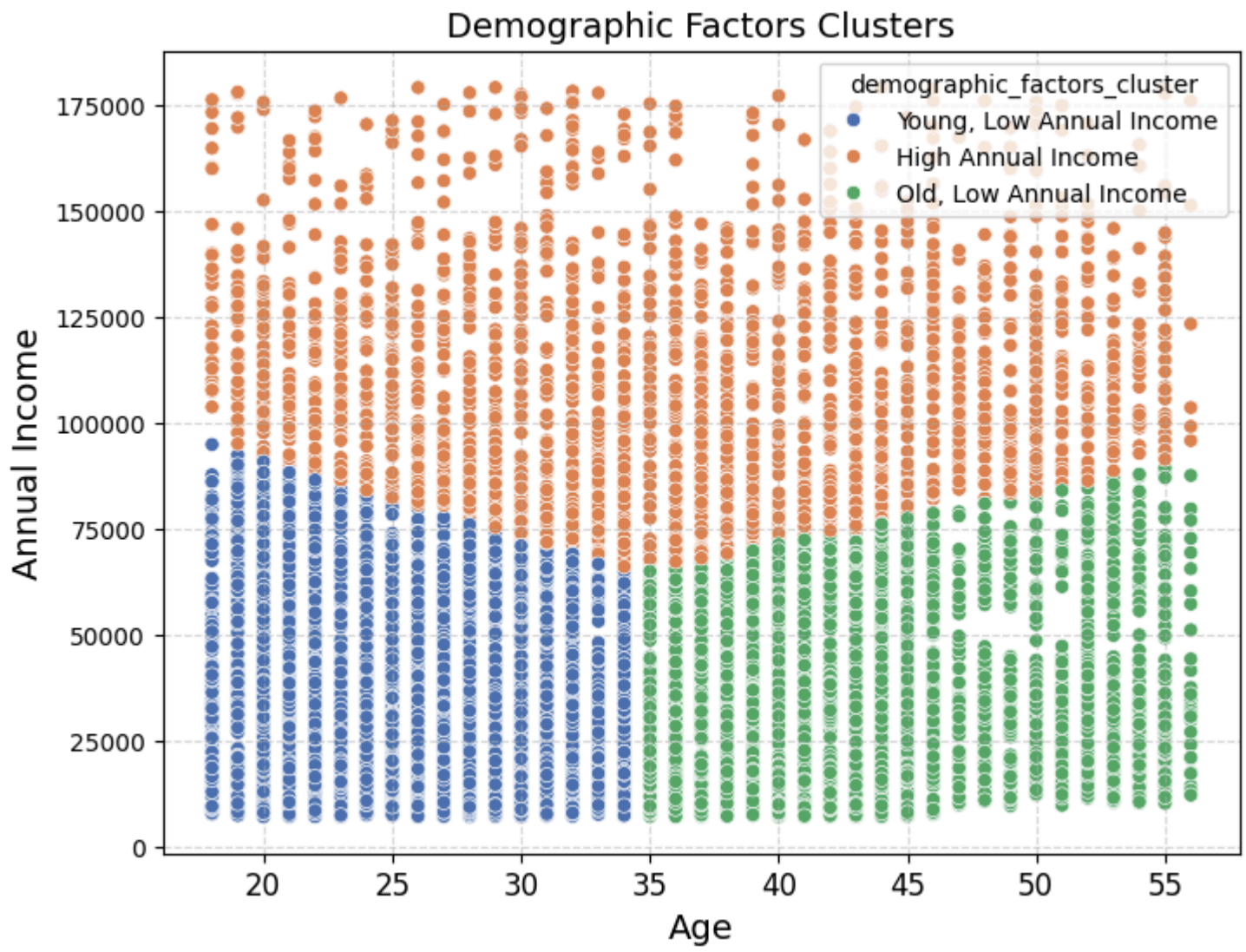
```
Number of Clusters: 2, Silhouette Score: 0.3629
Number of Clusters: 3, Silhouette Score: 0.4190
Number of Clusters: 4, Silhouette Score: 0.3617
Number of Clusters: 5, Silhouette Score: 0.3673
Number of Clusters: 6, Silhouette Score: 0.3768
```


3 clusters is selected since it has the highest silhoutte score and reasonable silhoutte plot thickness

Clustering using age and annual income. This is included in the report

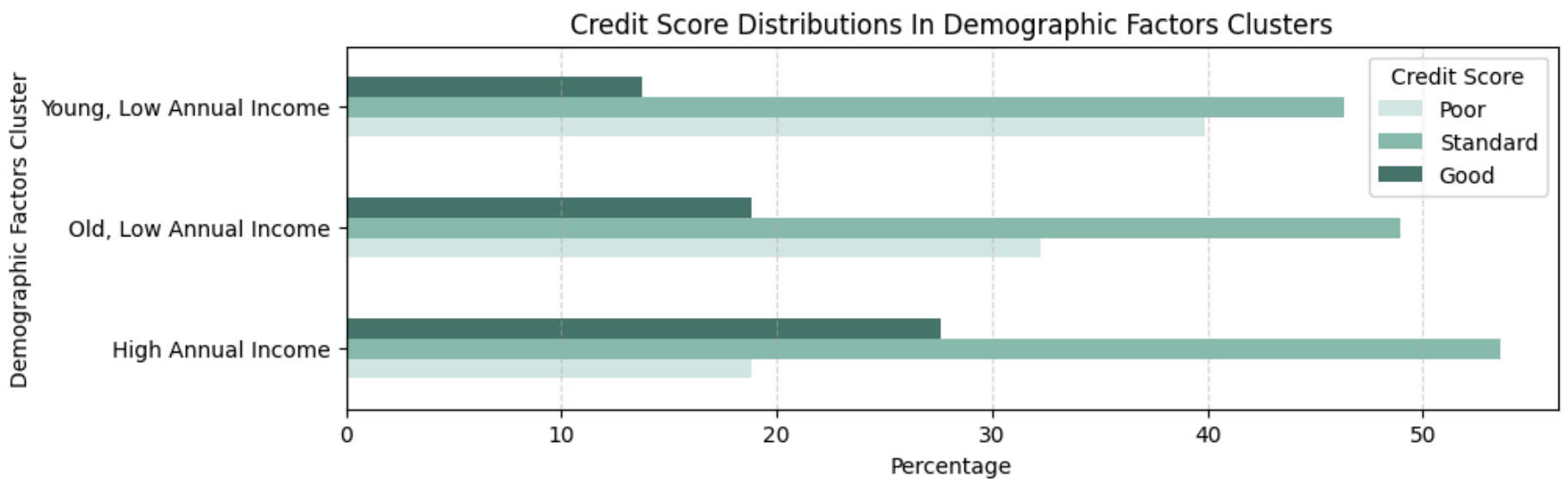
In [248…

```
# dataClusters = customerData.copy()
kmeans = KMeans(n_clusters=3, random_state=42, n_init='auto')
dataClusters['demographic_factors_cluster'] = kmeans.fit_predict(demographicFactorsScaled)
customLabels = {
    0: "Old, Low Annual Income",
    1: "Young, Low Annual Income",
    2: "High Annual Income"
}
dataClusters['demographic_factors_cluster'] = dataClusters['demographic_factors_cluster'].map(customLabels)

plt.figure(figsize=(8, 6))
sns.scatterplot(x=dataClusters['age'], y=dataClusters['annual_income'], hue=dataClusters['demographic_factors_clust
plt.title('Demographic Factors Clusters', fontsize = 14)
plt.xlabel('Age', fontsize=14)
plt.ylabel('Annual Income', fontsize=14)
plt.xticks(fontsize = 12)
plt.xticks(fontsize = 12)
plt.grid(True, linestyle='--', alpha=0.5)
plt.savefig('graphs/demographicFactorsClusters.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



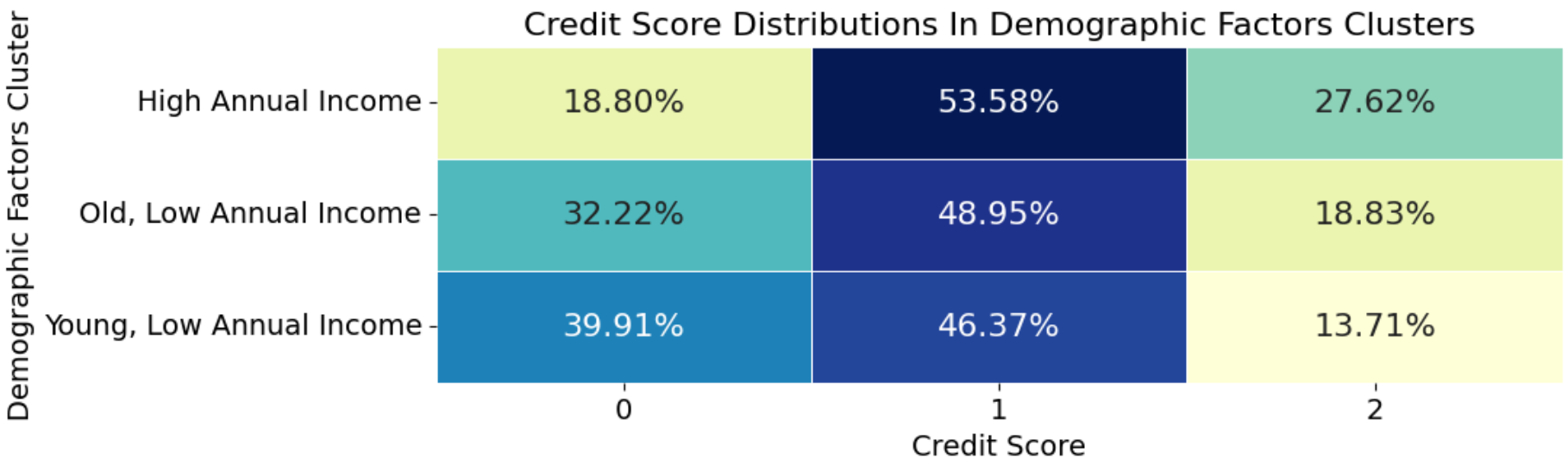
Analyzing the distribution of credit scores in each cluster using a bar graph

In [248…
```
clusterScoreDistribution = pd.crosstab(dataClusters['demographic_factors_cluster'], dataClusters['credit_score'], n

clusterScoreDistribution.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], figsize=(10, 3))
plt.title('Credit Score Distributions In Demographic Factors Clusters')
plt.xlabel('Percentage')
plt.ylabel('Demographic Factors Cluster')
plt.legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.show()
```



Analyzing the distribution of credit scores in each cluster using a heatmap. This is included in the report

In [248…
```
clusterScoreDistribution = clusterScoreDistribution.round(2)
annotations = clusterScoreDistribution.applymap(lambda x: f"{x:.2f}%")

plt.figure(figsize=(10, 3))
sns.heatmap(clusterScoreDistribution, annot=annotations, cmap='YlGnBu', cbar=False, fmt='', linewidths=.5, annot_kw

plt.title('Credit Score Distributions In Demographic Factors Clusters', fontsize=16)
plt.ylabel('Demographic Factors Cluster', fontsize=14)
plt.xlabel('Credit Score', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.savefig('graphs/demographicFactorsResults.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Logistic Regression to predict credit score using demographics factors to quantify their impact.

In [248…
```
x = customerData[['age', 'annual_income']]
y = customerData['credit_score']

xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size=0.2, random_state=42)
```

In [248…
```
scaler = StandardScaler()
xTrain = scaler.fit_transform(xTrain)
xTest = scaler.transform(xTest)
```

In [248…
```
model = LogisticRegression(multi_class='multinomial')
result = model.fit(xTrain, yTrain)
```

In [248…
```
yPred = model.predict(xTest)
accuracy = accuracy_score(yTest, yPred)
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Accuracy: 49.35%
```

In [249…
```
classNames = [f"Credit Score {className}" for className in model.classes_]

coefficients_df = pd.DataFrame(
    model.coef_.T,
    index=x.columns,
    columns= classNames)

print(coefficients_df)
```

```
              Credit Score 0  Credit Score 1  Credit Score 2
age                   -0.185           0.003           0.182
annual_income         -0.284           0.029           0.255
```

Feature Engineering using PCA on debt management variables to combine them into one component

In [249…
```
scaler = StandardScaler()
debtManagementScaled = scaler.fit_transform(customerData[['outstanding_debt', 'num_of_loan', 'num_credit_card']])

pca = PCA(n_components=1)
debtManagementComponent = pca.fit_transform(debtManagementScaled)
customerData['debtManagementComponent'] = debtManagementComponent
print(f"Explained Variance Ratio: {pca.explained_variance_ratio_}")
print(f"PCA Loadings: {pca.components_}")
customerData.head()
```

```
Explained Variance Ratio: [0.67607054]
PCA Loadings: [[0.6130833  0.59114397 0.524097  ]]
```

Out[249…

	customer_id	outstanding_debt	num_of_loan	num_credit_card	delay_from_due_date	num_of_delayed_payment	paymentMinAr
0	CUS_0x1009	202.680	4	5	7	18	
1	CUS_0x100b	1030.200	0	4	13	7	
2	CUS_0x1011	473.140	3	3	27	14	
3	CUS_0x1013	1233.510	3	3	13	9	
4	CUS_0x1015	340.220	0	4	8	9	

Feature Engineering using PCA on payment behaviour variables to combine them into one component

In [249…
```
scaler = StandardScaler()
paymentBehaviourScaled = scaler.fit_transform(customerData[['delay_from_due_date', 'num_of_delayed_payment', 'payme

pca = PCA(n_components=1)
paymentBehaviourComponent = pca.fit_transform(paymentBehaviourScaled)
customerData['paymentBehaviourComponent'] = paymentBehaviourComponent
print(f"Explained Variance Ratio: {pca.explained_variance_ratio_}")
```

```
print(f"PCA Loadings: {pca.components_}")
customerData.head()
```

```
Explained Variance Ratio: [0.69227479]
PCA Loadings: [[0.56370799 0.59153227 0.57647452]]
```

Out[249…

	customer_id	outstanding_debt	num_of_loan	num_credit_card	delay_from_due_date	num_of_delayed_payment	paymentMinAr
0	CUS_0x1009	202.680	4	5	7	18	
1	CUS_0x100b	1030.200	0	4	13	7	
2	CUS_0x1011	473.140	3	3	27	14	
3	CUS_0x1013	1233.510	3	3	13	9	
4	CUS_0x1015	340.220	0	4	8	9	

Feature Engineering using PCA on demographic factors to combine them into one component

In [249…

```
scaler = StandardScaler()
demographicFactorsScaled = scaler.fit_transform(customerData[['age', 'annual_income']])

pca = PCA(n_components=1)
demographicFactorsComponent = pca.fit_transform(demographicFactorsScaled)
customerData['demographicFactorsComponent'] = demographicFactorsComponent
print(f"Explained Variance Ratio: {pca.explained_variance_ratio_}")
print(f"PCA Loadings: {pca.components_}")
customerData.head()
```

```
Explained Variance Ratio: [0.53652232]
PCA Loadings: [[0.70710678 0.70710678]]
```

Out[249…

	customer_id	outstanding_debt	num_of_loan	num_credit_card	delay_from_due_date	num_of_delayed_payment	paymentMinAr
0	CUS_0x1009	202.680	4	5	7	18	
1	CUS_0x100b	1030.200	0	4	13	7	
2	CUS_0x1011	473.140	3	3	27	14	
3	CUS_0x1013	1233.510	3	3	13	9	
4	CUS_0x1015	340.220	0	4	8	9	

Since the explained variance ratio is low for demographic factors component, feature engineering is also done using weighted sum of age and annual income

In [249…

```
customerData['demographicFactorsComponent'] = (
    0.5 * demographicFactorsScaled[:, 0] +
    0.5 * demographicFactorsScaled[:, 1]
)

customerData.head()
```

Out[249…

	customer_id	outstanding_debt	num_of_loan	num_credit_card	delay_from_due_date	num_of_delayed_payment	paymentMinAr
0	CUS_0x1009	202.680	4	5	7	18	
1	CUS_0x100b	1030.200	0	4	13	7	
2	CUS_0x1011	473.140	3	3	27	14	
3	CUS_0x1013	1233.510	3	3	13	9	
4	CUS_0x1015	340.220	0	4	8	9	

K Mean Clustering for Customer Segmentation using feature engineered debt management component, payment behaviour component and demographic factors component

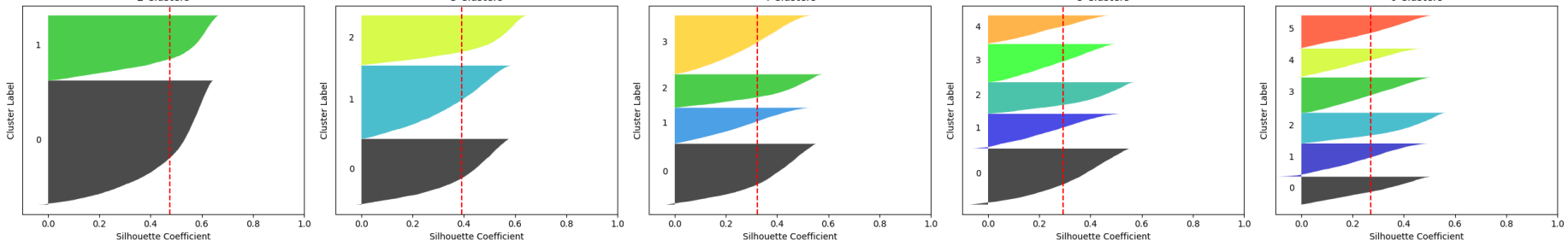
Using Silhoutte Score to find the ideal number of clusters

In [249…

```
features = customerData[['debtManagementComponent', 'paymentBehaviourComponent', 'demographicFactorsComponent']]

clusterRange = range(2, 7)
fig, axes = plt.subplots(1, 5, figsize=(25, 5))
fig.suptitle("Silhouette Analysis for K-Means Clustering", fontsize=16)

for i, nClusters in enumerate(clusterRange):
    ax = axes[i]
    kmeans = KMeans(n_clusters=nClusters, random_state=42, n_init='auto')
    clusterLabels = kmeans.fit_predict(features)
    silhouetteAvg = silhouette_score(features, clusterLabels)
    silhouetteValues = silhouette_samples(features, clusterLabels)
    print(f"Number of Clusters: {nClusters}, Silhouette Score: {silhouetteAvg:.4f}")
    y_lower = 10
    for i in range(nClusters):
        ithClusterSilhouetteValues = silhouetteValues[clusterLabels == i]
```

```
        ithClusterSilhouetteValues.sort()
        size_cluster_i = ithClusterSilhouetteValues.shape[0]
        y_upper = y_lower + size_cluster_i
        color = plt.cm.nipy_spectral(float(i) / nClusters)
        ax.fill_betweenx(np.arange(y_lower, y_upper), 0, ithClusterSilhouetteValues, facecolor=color, alpha=0.7)
        ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
        y_lower = y_upper + 10

    ax.set_title(f"{nClusters} Clusters")
    ax.axvline(x=silhouetteAvg, color="red", linestyle="--")
    ax.set_xlabel("Silhouette Coefficient")
    ax.set_xlim([-0.1, 1])
    ax.set_ylabel("Cluster Label")
    ax.set_yticks([])

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

```
Number of Clusters: 2, Silhouette Score: 0.4745
Number of Clusters: 3, Silhouette Score: 0.3905
Number of Clusters: 4, Silhouette Score: 0.3220
Number of Clusters: 5, Silhouette Score: 0.2930
Number of Clusters: 6, Silhouette Score: 0.2705
```

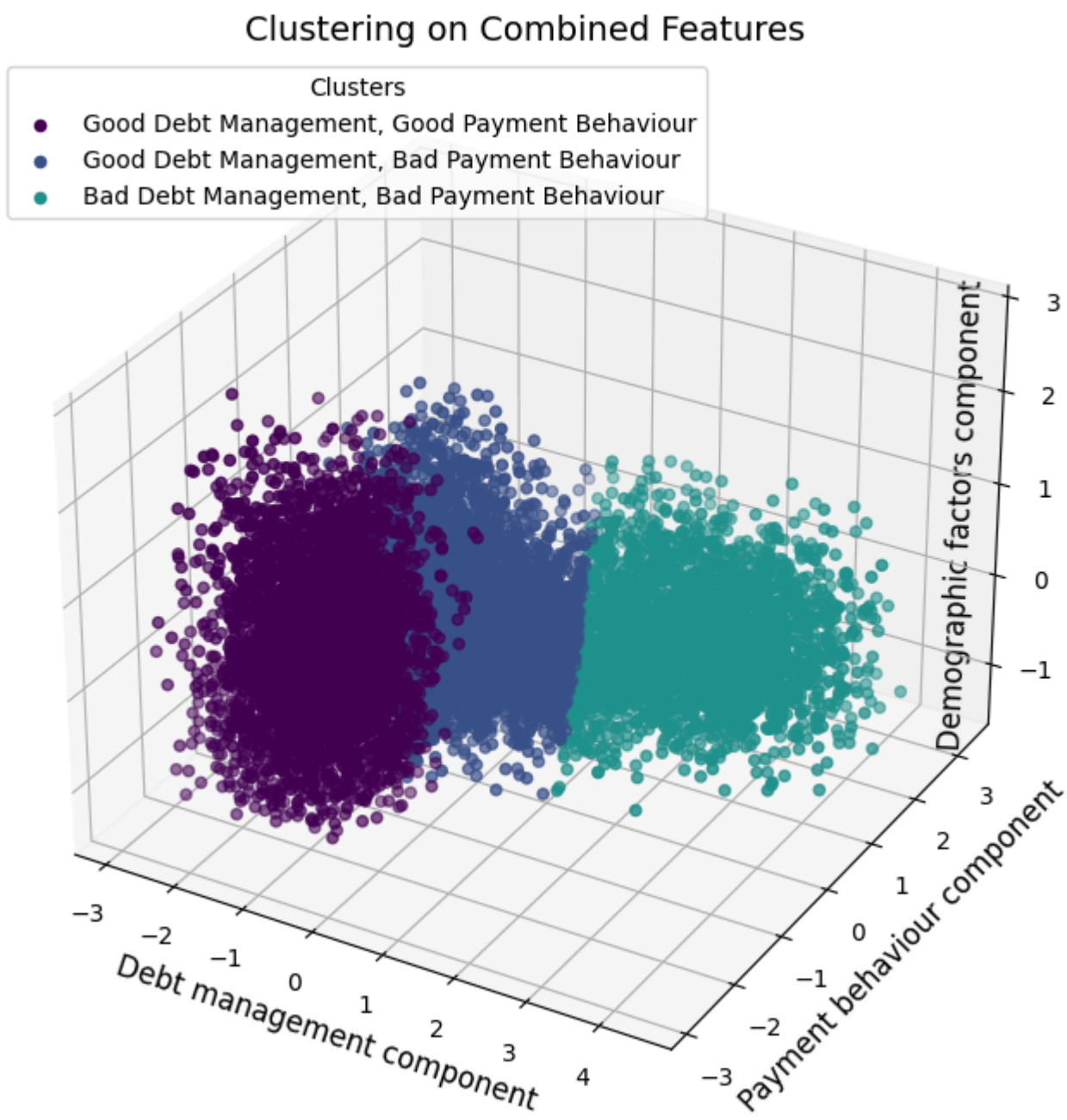


3 clusters is selected over 2 clusters because in 2 clusters, the silhotte plot for cluster 0 is too thick

Clustering using the debt management component, payment behaviour component and demographic factors component. This is included in the report

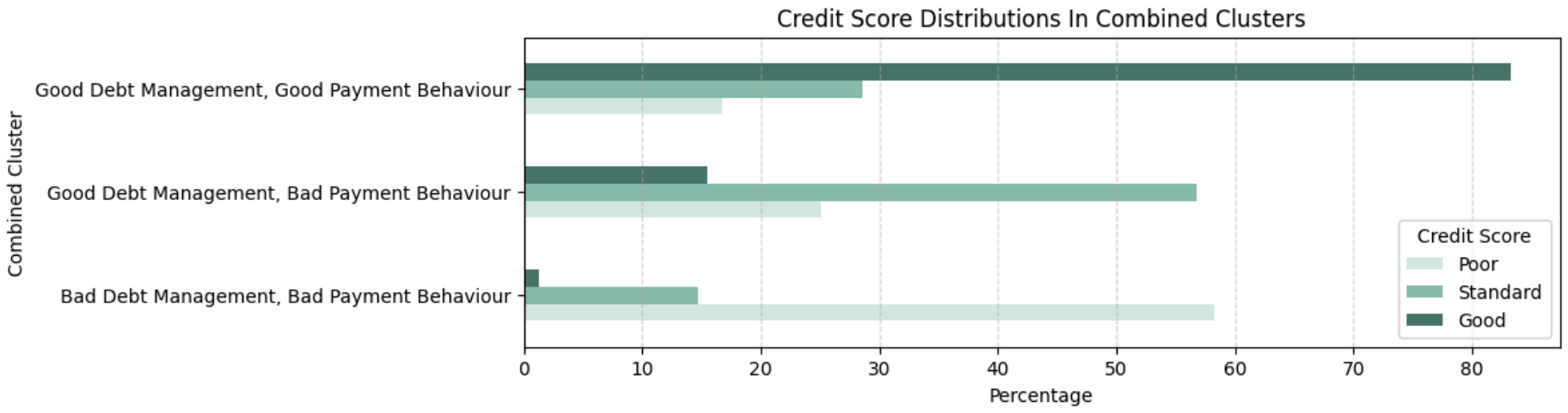
In [249…

```
kmeans = KMeans(n_clusters=3, random_state=42, n_init='auto')
dataClusters = customerData.copy()
dataClusters['combined_cluster'] = kmeans.fit_predict(features)
customLabels = {
    0: "Good Debt Management, Good Payment Behaviour",
    1: "Good Debt Management, Bad Payment Behaviour",
    2: "Bad Debt Management, Bad Payment Behaviour"
}
dataClusters['combined_cluster'] = dataClusters['combined_cluster'].map(customLabels)

colours = cm.viridis(np.linspace(0, 1, 5))
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(projection='3d')

for cluster in range(3):
    clusterData = dataClusters[dataClusters['combined_cluster'] == customLabels[cluster]]
    ax.scatter(
        clusterData['debtManagementComponent'],
        clusterData['paymentBehaviourComponent'],
        clusterData['demographicFactorsComponent'],
        color=colours[cluster],
        label=customLabels[cluster],
        s=20,
        # alpha=0.5
    )

ax.set_title('Clustering on Combined Features', fontsize=14)
ax.set_xlabel('Debt management component', fontsize=12)
ax.set_ylabel('Payment behaviour component', fontsize=12)
ax.set_zlabel('Demographic factors component', fontsize=12, labelpad=-30)
ax.legend(title='Clusters', loc='upper left', fontsize=10)
plt.savefig('graphs/combinedClusters.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



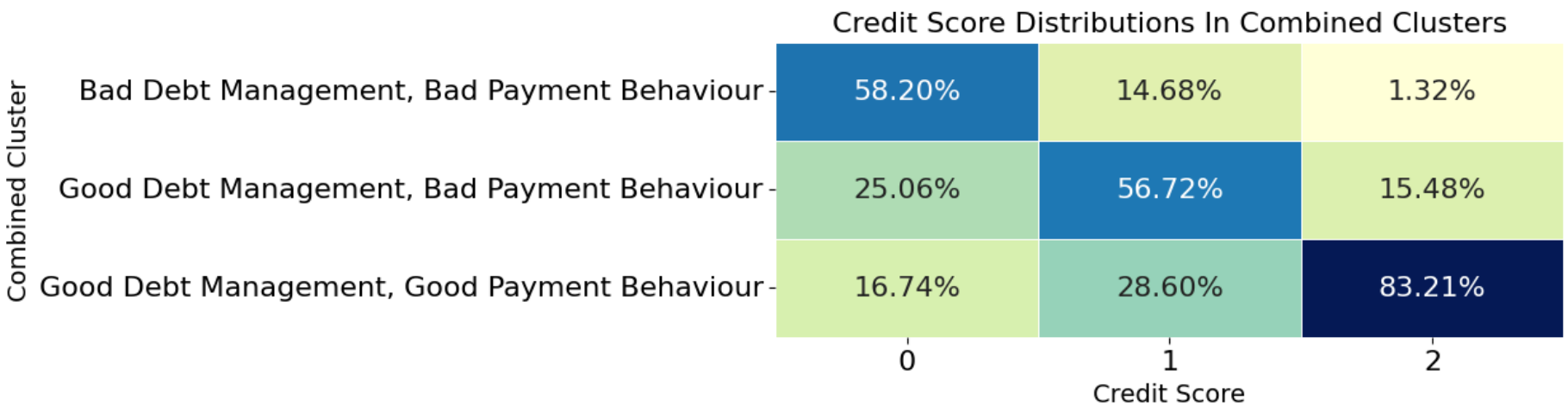
Analyzing the distribution of credit scores in each cluster using a bar graph

In [249…
```
clusterScoreDistribution = pd.crosstab(dataClusters['combined_cluster'], dataClusters['credit_score'], normalize='c

clusterScoreDistribution.plot(kind='barh', color=['#d6e7e4', '#87bbae', '#48756a'], figsize=(10, 3))
plt.title('Credit Score Distributions In Combined Clusters')
plt.xlabel('Percentage')
plt.ylabel('Combined Cluster')
plt.legend(title='Credit Score', labels=['Poor', 'Standard', 'Good'])
plt.grid(True, axis='x', linestyle='--', alpha=0.5)
plt.show()
```



Analyzing the distribution of credit scores in each cluster using a heatmap. This is included in the report

In [249…
```
clusterScoreDistribution = clusterScoreDistribution.round(2)
annotations = clusterScoreDistribution.applymap(lambda x: f"{x:.2f}%")

plt.figure(figsize=(8, 3))
sns.heatmap(clusterScoreDistribution, annot=annotations, cmap='YlGnBu', cbar=False, fmt='', linewidths=.5, annot_kw

plt.title('Credit Score Distributions In Combined Clusters', fontsize=16)
plt.ylabel('Combined Cluster', fontsize=14)
plt.xlabel('Credit Score', fontsize=14)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.savefig('graphs/combinedResults.png', dpi=300, bbox_inches='tight', transparent=True)
plt.show()
```



Logistic Regression across featured engineered debt management, payment behaviour and demographic factors to quantify their impact

In [249…
```
x = customerData[['debtManagementComponent', 'paymentBehaviourComponent', 'demographicFactorsComponent']]
y = customerData['credit_score']

xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size=0.2, random_state=42)
```

In [250…
```
model = LogisticRegression(multi_class='multinomial')
result = model.fit(xTrain, yTrain)
```

In [250…
```
yPred = model.predict(xTest)
accuracy = accuracy_score(yTest, yPred)
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Accuracy: 66.65%
```

Comparing the coefficients of each component. This is included in the report

In [250…
```
classNames = [f"Credit Score {className}" for className in model.classes_]

coefficientsDF = pd.DataFrame(
    model.coef_.T,
    index=x.columns,
    columns= classNames)

coefficientsDF
```

Out[250…

	Credit Score 0	Credit Score 1	Credit Score 2
debtManagementComponent	0.483	-0.084	-0.399
paymentBehaviourComponent	0.410	0.328	-0.738
demographicFactorsComponent	-0.015	0.048	-0.032

Converting the log odds to odd ratios for interpretability. This is inlcuded in the report

In [250…
```
oddsRatios = np.exp(coefficientsDF)
oddsRatios.columns = pd.MultiIndex.from_product([["Odds Ratios"], coefficientsDF.columns])
oddsRatios
```

Out[250…

	Odds Ratios		
	Credit Score 0	Credit Score 1	Credit Score 2
debtManagementComponent	1.622	0.919	0.671
paymentBehaviourComponent	1.507	1.388	0.478
demographicFactorsComponent	0.985	1.049	0.968

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