Data Mining & Machine Learning Final Project

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Importing Libraries

In [1]:

```
import re
import graphviz
import numpy as np
import pandas as pd
import seaborn as sns
from collections import Counter
import matplotlib.pyplot as plt
from IPython.display import display, HTML
from sklearn.preprocessing import MinMaxScaler
from sklearn.tree import DecisionTreeClassifier
from scipy.stats.contingency import association
from sklearn.neural_network import MLPClassifier
from sklearn import tree, neighbors, preprocessing
from sklearn.linear_model import LogisticRegression
from imblearn.under_sampling import RandomUnderSampler
from sklearn.naive_bayes import GaussianNB, CategoricalNB
from sklearn.model_selection import cross_validate, KFold
from imblearn.over_sampling import RandomOverSampler, SMOTE
from mlxtend.frequent_patterns import apriori, association_rules
from sklearn.neighbors import KNeighborsClassifier, LocalOutlierFactor
from scipy.stats import zscore, median_abs_deviation, chi2_contingency
from sklearn.feature_selection import f_classif, SelectKBest, SequentialFeatureSelector
from sklearn.ensemble import (RandomForestClassifier, ExtraTreesClassifier, BaggingClassifier, GradientBoost
from sklearn.metrics import (accuracy_score, precision_score, f1_score, roc_auc_score, make_scorer, recall_s
confusion_matrix)

import warnings
warnings.filterwarnings("ignore")
```

Reading The CSV File

In [2]:

```
df = pd.read_csv("train.csv")

# print out and display dataframe as tables in HTML
display(HTML(df.head().to_html()))
display(HTML(df.tail().to_html()))
```

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

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Ban
99995	0x25fe9	CUS_0x942c	April	Nicks	25	078-73-5990	Mechanic	39628.99	3359.415833	
99996	0x25fea	CUS_0x942c	May	Nicks	25	078-73-5990	Mechanic	39628.99	3359.415833	
99997	0x25feb	CUS_0x942c	June	Nicks	25	078-73-5990	Mechanic	39628.99	3359.415833	
99998	0x25fec	CUS_0x942c	July	Nicks	25	078-73-5990	Mechanic	39628.99	3359.415833	
99999	0x25fed	CUS_0x942c	August	Nicks	25	078-73-5990	Mechanic	39628.99_	3359.415833	

Describing All Columns

In [3]:
```
df.describe(include='all')
```

Out[3]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Sal
count	100000	100000	100000	90015	100000	100000	100000	100000	84998.000
unique	100000	12500	8	10139	1788	12501	16	18940	N
top	0x1602	CUS_0xd40	January	Langep	38	#F%$D@*&8	_______	36585.12	N
freq	1	8	12500	44	2833	5572	7062	16	N
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4194.170
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3183.686
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	303.645
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1625.568
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3093.745
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	5957.448
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	15204.633

11 rows × 28 columns

Data Preprocessing

Data Cleaning

In [4]:
```
# strip column names
df = df.rename(columns=lambda x: x.strip())

# create a copy first
df1=df.copy(deep=True)
print(df1.shape)

# Remove the coulumns (ID,Name, SSN) as these are personal identifiers and we already have customer_ID to id
cols_to_drop =['ID', 'Name', 'SSN']
df1=df1.drop(columns=cols_to_drop , axis=1)
```

```
(100000, 28)
```

In [5]:
```
print(df1['Type_of_Loan'].nunique())

# Drop column 'Type_of_Loan' as we have 6260 unique columns
df1=df1.drop('Type_of_Loan' , axis=1)
```

```
6260
```

Checking For Duplicate Rows

In [6]:
```
duplicate_df=df1[df1.duplicated()]

display(HTML(duplicate_df.head().to_html()))
```

Customer_ID	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Carc

Checking For Missing Values

In [7]:
```
cols = df1.columns
print('\nColumnName, DataType, MissingValues')
for i in cols:
        print(i, ',', df1[i].dtype, ',', df1[i].isnull().sum())

# Calculate percentage of missing values in the entire DataFrame
```

```
percentage_missing = round(df1.isna().sum().sum() / df1.size * 100, 1)
print("\nPercentage of Missing Values in the DataFrame: {}%".format(percentage_missing))
```

```
ColumnName, DataType, MissingValues
Customer_ID , object , 0
Month , object , 0
Age , object , 0
Occupation , object , 0
Annual_Income , object , 0
Monthly_Inhand_Salary , float64 , 15002
Num_Bank_Accounts , int64 , 0
Num_Credit_Card , int64 , 0
Interest_Rate , int64 , 0
Num_of_Loan , object , 0
Delay_from_due_date , int64 , 0
Num_of_Delayed_Payment , object , 7002
Changed_Credit_Limit , object , 0
Num_Credit_Inquiries , float64 , 1965
Credit_Mix , object , 0
Outstanding_Debt , object , 0
Credit_Utilization_Ratio , float64 , 0
Credit_History_Age , object , 9030
Payment_of_Min_Amount , object , 0
Total_EMI_per_month , float64 , 0
Amount_invested_monthly , object , 4479
Payment_Behaviour , object , 0
Monthly_Balance , object , 1200
Credit_Score , object , 0

Percentage of Missing Values in the DataFrame: 1.6%
```

In [8]:
```
# Displaying only Missing values
for i in df1.columns:
    if df1[i].isnull().sum() > 0:
        print(i, ',', df1[i].dtype, df1[i].isnull().sum())
```

```
Monthly_Inhand_Salary , float64 15002
Num_of_Delayed_Payment , object 7002
Num_Credit_Inquiries , float64 1965
Credit_History_Age , object 9030
Amount_invested_monthly , object 4479
Monthly_Balance , object 1200
```

Checking Columns Which Have Invalid Character '_'

In [9]:
```
cols = df1.columns

for col in cols:
    if df1[col].apply(lambda x: isinstance(x, str) and x.endswith("_")).any():
        print(f"Column '{col}' contains values ending with an underscore.")
```

```
Column 'Age' contains values ending with an underscore.
Column 'Occupation' contains values ending with an underscore.
Column 'Annual_Income' contains values ending with an underscore.
Column 'Num_of_Loan' contains values ending with an underscore.
Column 'Num_of_Delayed_Payment' contains values ending with an underscore.
Column 'Changed_Credit_Limit' contains values ending with an underscore.
Column 'Credit_Mix' contains values ending with an underscore.
Column 'Outstanding_Debt' contains values ending with an underscore.
Column 'Amount_invested_monthly' contains values ending with an underscore.
Column 'Monthly_Balance' contains values ending with an underscore.
```

Dealing With Underscore By Striping _ If The Value Contains _ With The Number

In [10]:
```
cols = ["Age", "Annual_Income", "Num_of_Loan", "Num_of_Delayed_Payment", "Outstanding_Debt",]

for col in cols:
    if not df1[col].isnull().all():
        df1[col] = df1[col].apply(lambda x: x.rstrip('_') if isinstance(x, str) and x.endswith("_") else x)
```

Identifying String Columns Which Are Having '_'

In [11]:
```python
cols = ['Occupation', 'Credit_Mix', 'Amount_invested_monthly', 'Monthly_Balance', 'Changed_Credit_Limit']

for col in cols:
    group_sizes = df1.groupby([col]).size()
    if any('_' in str(index) for index in group_sizes.index):
        mask = pd.Series(group_sizes.index.str.contains('_'))
        mask = mask.fillna(False)
        print(group_sizes[mask.values])
        print()
```

```
Occupation
Media_Manager    6232
_______          7062
dtype: int64

Credit_Mix
_    20195
dtype: int64

Amount_invested_monthly
__10000__    4305
dtype: int64

Monthly_Balance
__-333333333333333333333333333__    9
dtype: int64

Changed_Credit_Limit
_    2091
dtype: int64
```

Removing All Invalid Values With '_'

In [12]:
```python
# Media_Manager is valid value.

df1['Occupation'] = df1['Occupation'].replace("_______", pd.NA)
df1['Changed_Credit_Limit'] = df1['Changed_Credit_Limit'].replace("_", 'NaN')
df1['Credit_Mix'] = df1['Credit_Mix'].replace("_", pd.NA)
df1['Amount_invested_monthly'] = df1['Amount_invested_monthly'].replace("__10000__", 'NaN')
df1['Monthly_Balance'] = df1['Monthly_Balance'].replace("__-333333333333333333333333333__", 'NaN')

# checking if any underscore still exists
for col in cols:
    if df1[col].apply(lambda x: isinstance(x, str) and x.endswith("_")).any():
        print(f"Column '{col}' contains values ending with an underscore.")
```

Converting Object Type Columns Which Must Be Numerical (Float/Int Type)

In [13]:
```python
cols = ['Age','Monthly_Inhand_Salary', 'Num_Bank_Accounts', 'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan
        'Annual_Income', 'Num_of_Delayed_Payment', 'Changed_Credit_Limit', 'Outstanding_Debt', 'Total_EMI_pe
        'Amount_invested_monthly', 'Monthly_Balance']

for col in cols:
    df1[col] = pd.to_numeric(df1[col], errors='coerce')
```

Dealing With Invalid Negative Values In The Numeric Columns

In [14]:
```python
cols = ['Age', 'Num_Bank_Accounts', 'Num_of_Loan', 'Num_of_Delayed_Payment']

for col in cols:
      df1.loc[df1[col] < 0, col] = pd.NA
```

Filling Numeric Column Null Values By Median Of The Column Grouped-by Customer_Id

In [15]:
```python
cols = df1.select_dtypes(include=['number']).columns
```

```python
for col in cols:
    median_by_id = df1.groupby('Customer_ID')[col].median()
    df1[col] = df1.apply(lambda row: median_by_id[row['Customer_ID']] if pd.isna(row[col]) else row[col], ax
    print(f"Number of null values in {col}: {df1[col].isnull().sum()}")
```

```
Number of null values in Age: 0
Number of null values in Annual_Income: 0
Number of null values in Monthly_Inhand_Salary: 0
Number of null values in Num_Bank_Accounts: 0
Number of null values in Num_Credit_Card: 0
Number of null values in Interest_Rate: 0
Number of null values in Num_of_Loan: 0
Number of null values in Delay_from_due_date: 0
Number of null values in Num_of_Delayed_Payment: 0
Number of null values in Changed_Credit_Limit: 0
Number of null values in Num_Credit_Inquiries: 0
Number of null values in Outstanding_Debt: 0
Number of null values in Credit_Utilization_Ratio: 0
Number of null values in Total_EMI_per_month: 0
Number of null values in Amount_invested_monthly: 0
Number of null values in Monthly_Balance: 0
```

Identifying Invalid Characters In `Payment_Behaviour` Column

In [16]:
```python
# Define a regular expression pattern to match special characters
special_chars_pattern = re.compile(r'[^\w\s]')

# Find groups with special characters in 'Payment_Behaviour'
groups_with_special_chars = df1['Payment_Behaviour'].apply(lambda x: bool(special_chars_pattern.search(x)))

# Filter and display the group sizes of 'Payment_Behaviour' with special characters
print(df1[groups_with_special_chars].groupby('Payment_Behaviour').size())

# Dealing with categorical values (noisy data)
df1['Payment_Behaviour'] = df1['Payment_Behaviour'].replace("!@9#%8", pd.NA)
```

```
Payment_Behaviour
!@9#%8    7600
dtype: int64
```

Filling Missing/NA Categorical Value With Mode Grouped By Customer_ID (Most Frequent value grouping by customer_ID)

In [17]:
```python
# Filling Missing/NA Categorical Value With Mode Grouped By Customer_ID (Most Frequent value grouping by cus
cols = ['Occupation','Credit_Mix', 'Credit_History_Age', 'Payment_Behaviour']

for column in cols:
    mode_by_id = df1.groupby('Customer_ID')[column].transform(lambda x: x.mode()[0])
    df1[column] = df1[column].fillna(mode_by_id)
    print(f"Number of null values in {column}: {df1[column].isnull().sum()}")
```

```
Number of null values in Occupation: 0
Number of null values in Credit_Mix: 0
Number of null values in Credit_History_Age: 0
Number of null values in Payment_Behaviour: 0
```

Converting Credit_History_Age Categorical Data To Numeric

In [18]:
```python
def convert_to_months(age_str):
    years, months = age_str.split(' and ')
    years = int(years.split(' ')[0])
    months = int(months.split(' ')[0])
    return years * 12 + months

df1['Credit_History_Age_Months'] = df1['Credit_History_Age'].apply(convert_to_months)
df1 = df1.drop('Credit_History_Age', axis=1)
print(df1['Credit_History_Age_Months'])

display(HTML(df1.head().to_html()))
```

```
0        265
1        265
2        267
3        268
4        269
        ...
99995    378
99996    379
99997    380
99998    381
99999    382
Name: Credit_History_Age_Months, Length: 100000, dtype: int64
```

	Customer_ID	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_C
0	CUS_0xd40	January	23.0	Scientist	19114.12	1824.843333	3.0	
1	CUS_0xd40	February	23.0	Scientist	19114.12	1824.843333	3.0	
2	CUS_0xd40	March	23.0	Scientist	19114.12	1824.843333	3.0	
3	CUS_0xd40	April	23.0	Scientist	19114.12	1824.843333	3.0	
4	CUS_0xd40	May	23.0	Scientist	19114.12	1824.843333	3.0	

Mapping Months To Numerical As It Is Ordinal Column

Checking If Any Null Values Are Present After Preprocessing

In [19]:

```python
monthMapping={
    'January':1,
    'February':2,
    'March':3,
    'April':4,
    'May':5,
    'June':6,
    'July':7,
    'August':8
}

df1['Month'] = df1['Month'].map(monthMapping)
display(HTML(df1.head().to_html()))
```

	Customer_ID	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Ca
0	CUS_0xd40	1	23.0	Scientist	19114.12	1824.843333	3.0	
1	CUS_0xd40	2	23.0	Scientist	19114.12	1824.843333	3.0	
2	CUS_0xd40	3	23.0	Scientist	19114.12	1824.843333	3.0	
3	CUS_0xd40	4	23.0	Scientist	19114.12	1824.843333	3.0	
4	CUS_0xd40	5	23.0	Scientist	19114.12	1824.843333	3.0	

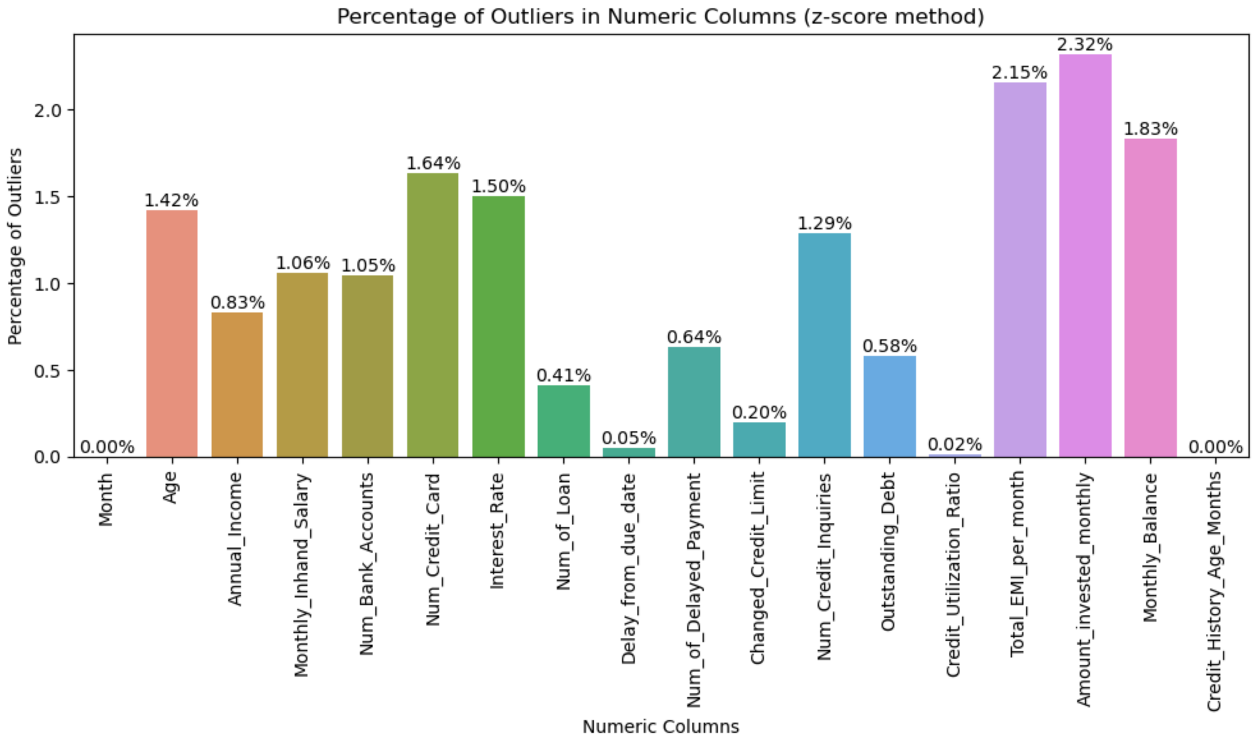
In [20]:

```python
df1.isnull().sum()
```

Out[20]:
```
Customer_ID                 0
Month                       0
Age                         0
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary       0
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
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
Payment_of_Min_Amount       0
Total_EMI_per_month         0
Amount_invested_monthly     0
Payment_Behaviour           0
Monthly_Balance             0
Credit_Score                0
Credit_History_Age_Months   0
dtype: int64
```

Displaying The Percentage Of Outliers For Each Numerical Column Based On Z-Score Method

In [21]:
```python
#Percentage of outliers in Numeric column

# Step 1: Identify numeric columns
numeric_columns = df1.select_dtypes(include=['number']).columns

# Step 2: Calculate z-scores for each numeric column
z_scores = df1[numeric_columns].apply(zscore)

# Step 3: Calculate percentage of outliers for each numeric column
outlier_percentages = {}
for column in numeric_columns:
    # Identify outliers based on absolute z-score threshold (e.g., 3)
    outliers = z_scores[abs(z_scores[column]) > 3][column]
    percentage_outliers = (len(outliers) / len(df1)) * 100

    # Store the percentage of outliers for the column
    outlier_percentages[column] = percentage_outliers

# Step 4: Plot the percentages
plt.figure(figsize=(10, 6))
ax = sns.barplot(x=list(outlier_percentages.keys()), y=list(outlier_percentages.values()))
plt.title('Percentage of Outliers in Numeric Columns (z-score method)')
plt.xlabel('Numeric Columns')
plt.ylabel('Percentage of Outliers')
plt.xticks(rotation=90)
plt.tight_layout()

# Annotate each bar with its respective percentage value
for i, percentage in enumerate(outlier_percentages.values()):
    ax.text(i, percentage, f'{percentage:.2f}%', ha='center', va='bottom')

plt.show()
```



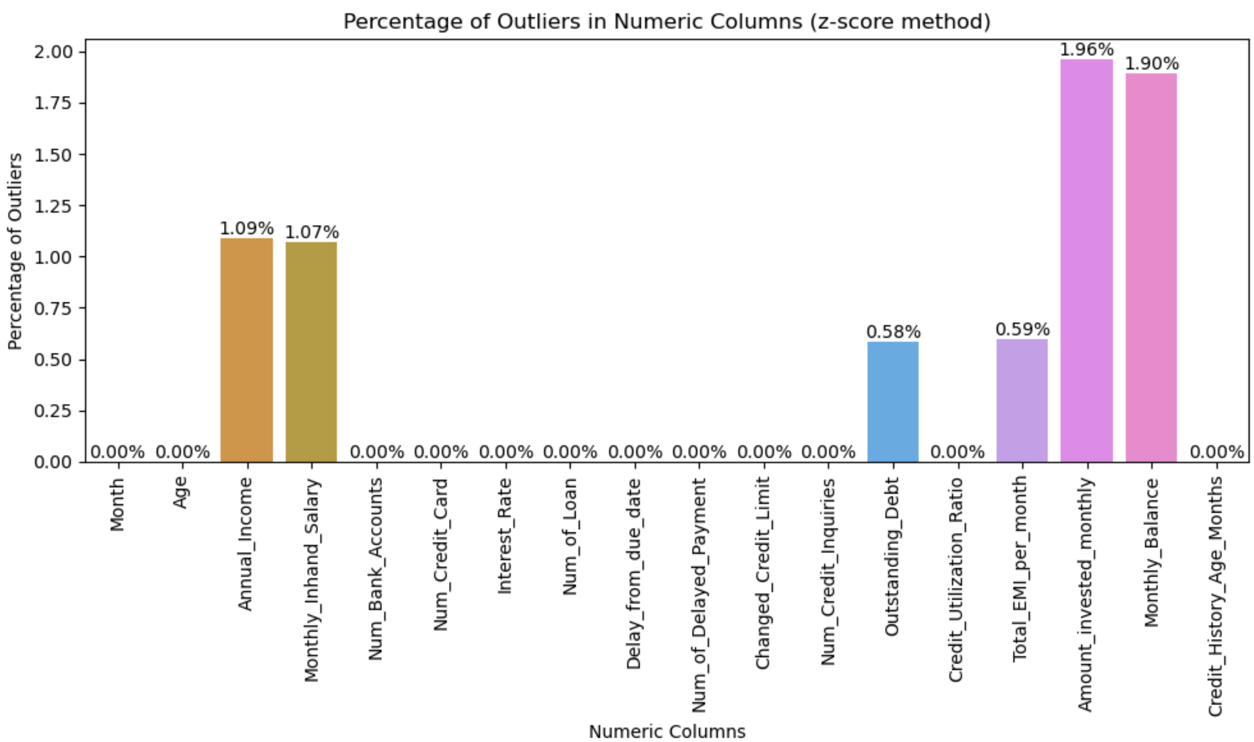
Replacing The Noisy Data With Median Of The Column Grouped By Customerid

In [22]:
```
# Dealing with Noisy Data in numeric columns (outliers which are noisy)
cols = df1.select_dtypes(include=['number']).columns

# Create an empty DataFrame to store flagged outliers
outliers_df = pd.DataFrame(columns=['Customer_ID'] + cols)

# Replace outliers with median_by_cid for each column
for col in cols:
    # Calculate the median for each column by Customer ID
    median_by_cid = df1.groupby('Customer_ID')[col].transform('median')
    median_col = df1[col].median()

    # Calculate MAD
    mad_col = np.abs(df1[col] - median_col).median()

    # Define Outlier Threshold
    threshold = 3 * mad_col
    df1[col] = np.where(np.abs(df1[col] - median_col) > threshold, median_by_cid, df1[col])
```

Checking For Outliers After Handling Noisy Data

In [23]:
```
# Step 1: Identify numeric columns
numeric_columns = df1.select_dtypes(include=['number']).columns

# Step 2: Calculate z-scores for each numeric column
z_scores = df1[numeric_columns].apply(zscore)


# Step 3: Calculate percentage of outliers for each numeric column
outlier_percentages = {}
for column in numeric_columns:
    # Identify outliers based on absolute z-score threshold (e.g., 3)
    outliers = z_scores[abs(z_scores[column]) > 3][column]
    percentage_outliers = (len(outliers) / len(df1)) * 100

    # Store the percentage of outliers for the column
    outlier_percentages[column] = percentage_outliers
```

```
# Step 4: Plot the percentages
plt.figure(figsize=(10, 6))
ax = sns.barplot(x=list(outlier_percentages.keys()), y=list(outlier_percentages.values()))
plt.title('Percentage of Outliers in Numeric Columns (z-score method)')
plt.xlabel('Numeric Columns')
plt.ylabel('Percentage of Outliers')
plt.xticks(rotation=90)
plt.tight_layout()

# Annotate each bar with its respective percentage value
for i, percentage in enumerate(outlier_percentages.values()):
    ax.text(i, percentage, f'{percentage:.2f}%', ha='center', va='bottom')

plt.show()
```



In [24]:
```
df2 = df1.copy(deep=True)
df2 = df2.drop('Customer_ID',axis=1)
```

Data Transformation

Normalizing Dataset For Outlier Detection

In [25]:
```
## Prepare a numerical feature matrix, better to be normalized

# convert all nominal variables to binary variables
df_Num=df2.copy(deep=True)
# create new binary columns
cols = ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount', 'Payment_Behaviour']

for col in cols:
    df_dummies = pd.get_dummies(df_Num[[col]], dtype=float)
    df_Num = df_Num.join(df_dummies)
    df_Num = df_Num.drop(col, axis=1)

display(df_Num.head())

display('Data Example:',HTML(df_Num.head().to_html()))

# Normalized all numerical features
# find numeric columns
```

```
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
scaler = MinMaxScaler(feature_range=(1,5))
cols_numeric = df_Num.select_dtypes(include=numerics).columns.tolist()

# min-max normalization to scale [1, 5]
df_Num[cols_numeric] = scaler.fit_transform(df_Num[cols_numeric])

df_Num=df_Num.drop("Credit_Score",axis=1)
display(HTML(df_Num.head().to_html()))
```

	Month	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Num_of_l
0	1.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
1	2.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
2	3.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
3	4.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
4	5.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	

5 rows × 46 columns

'Data Example:'

	Month	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Num_of_l
0	1.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
1	2.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
2	3.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
3	4.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
4	5.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	

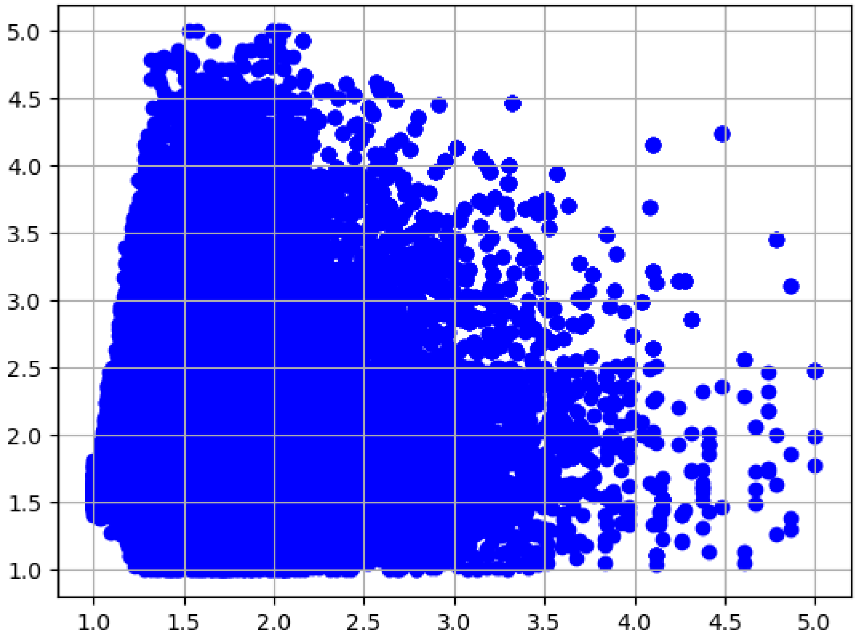
	Month	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Nu
0	1.000000	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	
1	1.571429	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	
2	2.142857	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	
3	2.714286	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	
4	3.285714	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	

Outlier Detection With Localoutlierfactor Method

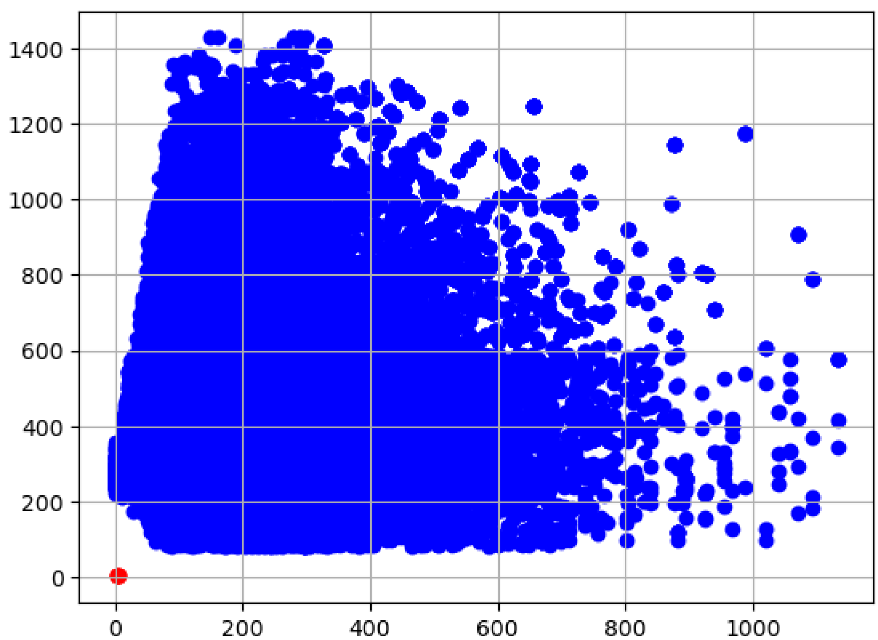
In [26]:

```
# plot data points
plt.scatter(df_Num['Amount_invested_monthly'], df_Num['Monthly_Balance'], color = "b")
plt.grid()
plt.show()

# model specification
model1 = LocalOutlierFactor(n_neighbors = 100 , metric = "euclidean")
# model fitting
y_pred = model1.fit_predict(df_Num)
# filter outlier index
outlier_index = np.where(y_pred == -1) # negative values are outliers
outlier_index = list(outlier_index[0])
print("outlier indices: ", outlier_index, 'Number of outliers: ', len(outlier_index))
# filter outlier values
outlier_values = df_Num.iloc[outlier_index]
# plot data
plt.scatter(df2['Amount_invested_monthly'], df2['Monthly_Balance'], color = "b")
```

```
# plot outlier values
plt.scatter(outlier_values['Amount_invested_monthly'], outlier_values['Monthly_Balance'], color = "r")
plt.grid()
plt.show()

print(df_Num.shape)
# remove outliers
df_Num = df_Num.drop(outlier_index, axis=0)
print(df_Num.shape)
```



```
outlier indices:  [13751, 24739, 24740, 26903, 40239, 68004, 99512] Number of outliers:  7
```



```
(100000, 45)
(99993, 45)
```

Dropping The Outliers Identified From Above Method

In [27]:
```
# df1 backup dataframe
# df2 dataframe for numerical operations

df1 = df1.drop(outlier_index, axis=0)
df2 = df2.drop(outlier_index, axis=0)
```

```
df1 = df1.reset_index(drop=True)
df2 = df2.reset_index(drop=True)
```

In [28]:
```
df2.describe(include='all')
```

Out[28]:

	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_C
count	99993.000000	99993.000000	99993	99993.000000	99993.000000	99993.000000	999
unique	NaN	NaN	15	NaN	NaN	NaN	
top	NaN	NaN	Lawyer	NaN	NaN	NaN	
freq	NaN	NaN	7094	NaN	NaN	NaN	
mean	4.499925	33.312127	NaN	50496.638189	4197.635483	5.369051	
std	2.291271	10.764209	NaN	38287.250299	3186.377110	2.593269	
min	1.000000	14.000000	NaN	7005.930000	303.645417	0.000000	
25%	2.000000	24.000000	NaN	19339.080000	1626.594167	3.000000	
50%	4.000000	33.000000	NaN	36996.830000	3095.978333	5.000000	
75%	6.000000	42.000000	NaN	71681.400000	5961.637500	7.000000	
max	8.000000	56.000000	NaN	179987.280000	15204.633333	11.000000	

11 rows × 23 columns

Taking Backup For Categorical Classifiers & Association Rules

In [29]:
```
df2_cat = df2.copy(deep=True)
```

Data Integration - Correlation Analysis

Normalizing All Numerical Columns

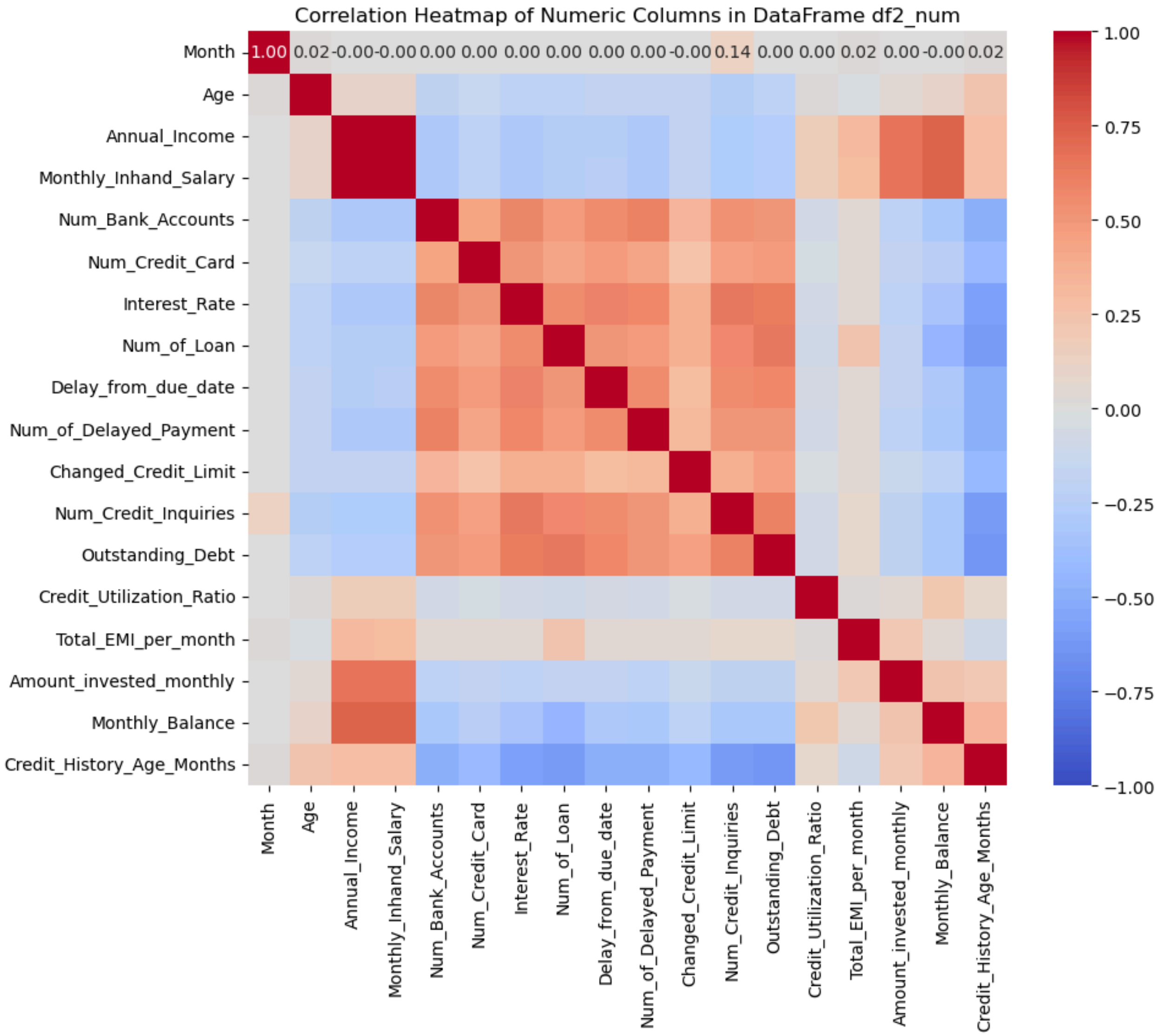
In [30]:
```
numeric_columns = df2.select_dtypes(include=['number'])

df2_num = df2.copy()
scaler = MinMaxScaler(feature_range=(1, 5))
df2_num[numeric_columns.columns] = scaler.fit_transform(df2_num[numeric_columns.columns])

display(HTML(df2_num.head().to_html()))
```

	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Inter
0	1.000000	1.857143	Scientist	1.279988	1.408348	2.090909	2.454545	
1	1.571429	1.857143	Scientist	1.279988	1.408348	2.090909	2.454545	
2	2.142857	1.857143	Scientist	1.279988	1.408348	2.090909	2.454545	
3	2.714286	1.857143	Scientist	1.279988	1.408348	2.090909	2.454545	
4	3.285714	1.857143	Scientist	1.279988	1.408348	2.090909	2.454545	

Identifying All Correlation Between Numerical Columns

In [31]:
```
numeric_columns = df2_num.select_dtypes(include=['number'])

correlation_matrix = numeric_columns.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", vmin=-1, vmax=1)
```

```
plt.title('Correlation Heatmap of Numeric Columns in DataFrame df2_num')
plt.show()
```



Displaying The Correlation Values

In [32]:
```
correlations = []

for i in range(len(correlation_matrix.columns)):
    for j in range(i+1, len(correlation_matrix.columns)):
        if abs(correlation_matrix.iloc[i, j]) > 0.5:
            correlation = (correlation_matrix.iloc[i, j], correlation_matrix.columns[i], correlation_matrix.
            correlations.append(correlation)

correlations.sort(reverse=True)

# Display sorted correlations
for correlation_strength, col1, col2 in correlations:
    print(f"Correlation between '{col1}' and '{col2}': {correlation_strength}")
```

```
Correlation between 'Annual_Income' and 'Monthly_Inhand_Salary': 0.9981931786577981
Correlation between 'Monthly_Inhand_Salary' and 'Monthly_Balance': 0.7312678295065864
Correlation between 'Annual_Income' and 'Monthly_Balance': 0.7299898792469446
Correlation between 'Monthly_Inhand_Salary' and 'Amount_invested_monthly': 0.6627806893284941
Correlation between 'Annual_Income' and 'Amount_invested_monthly': 0.6617174995194506
Correlation between 'Num_of_Loan' and 'Outstanding_Debt': 0.6387264878651886
Correlation between 'Interest_Rate' and 'Num_Credit_Inquiries': 0.6341868930751874
Correlation between 'Interest_Rate' and 'Outstanding_Debt': 0.6294166952679965
Correlation between 'Num_Bank_Accounts' and 'Num_of_Delayed_Payment': 0.6013421266600413
Correlation between 'Num_Credit_Inquiries' and 'Outstanding_Debt': 0.5983118618738731
Correlation between 'Interest_Rate' and 'Delay_from_due_date': 0.5892042766251065
Correlation between 'Num_Bank_Accounts' and 'Interest_Rate': 0.5842815116198057
Correlation between 'Delay_from_due_date' and 'Outstanding_Debt': 0.5715971213135743
Correlation between 'Interest_Rate' and 'Num_of_Delayed_Payment': 0.5714168864241729
Correlation between 'Num_of_Loan' and 'Num_Credit_Inquiries': 0.5662764911378759
Correlation between 'Num_Bank_Accounts' and 'Delay_from_due_date': 0.5605878028832653
Correlation between 'Interest_Rate' and 'Num_of_Loan': 0.5591419558684696
Correlation between 'Delay_from_due_date' and 'Num_of_Delayed_Payment': 0.5425757904654998
Correlation between 'Delay_from_due_date' and 'Num_Credit_Inquiries': 0.5408994134522189
Correlation between 'Num_Bank_Accounts' and 'Num_Credit_Inquiries': 0.5197964741634016
Correlation between 'Num_Bank_Accounts' and 'Outstanding_Debt': 0.5070618678168655
Correlation between 'Num_of_Delayed_Payment' and 'Outstanding_Debt': 0.5049665461107264
Correlation between 'Num_of_Loan' and 'Delay_from_due_date': 0.5011919534119488
Correlation between 'Num_of_Delayed_Payment' and 'Num_Credit_Inquiries': 0.5008680677298626
Correlation between 'Interest_Rate' and 'Credit_History_Age_Months': -0.5762164245955868
Correlation between 'Num_of_Loan' and 'Credit_History_Age_Months': -0.6057289772730868
Correlation between 'Num_Credit_Inquiries' and 'Credit_History_Age_Months': -0.6114512479077562
Correlation between 'Outstanding_Debt' and 'Credit_History_Age_Months': -0.6293303284871611
```

We can remove strongly correlated columns such as 'Annual_Income' and 'Monthly_Inhand_Salary'

Identifying All Correlation Between Categorical Columns By Chi-Sqaure Test

In [33]:

```python
categorical_columns = df2.select_dtypes(include=['object']).columns

# Initialize an empty DataFrame for the correlation matrix
correlation_matrix = pd.DataFrame(index=categorical_columns, columns=categorical_columns)

# Calculate the correlation for each pair of categorical columns
for col1 in categorical_columns:
    for col2 in categorical_columns:
        contingency_table = pd.crosstab(df2[col1], df2[col2])
        chi, p, dof, expects = chi2_contingency(contingency_table)
        coef = association(contingency_table)
        correlation_matrix.loc[col1, col2] = f"chi={chi:.2f}, p-value={p:.2f}, coefficient={coef:.2f}"

# Print the correlation matrix
correlation_matrix
```

Out[33]:

	Occupation	Credit_Mix	Payment_of_Min_Amount	Payment_Behaviour	Credit_Scor
Occupation	chi=1399902.00, p-value=0.00, coefficient=1.00	chi=223.87, p-value=0.00, coefficient=0.03	chi=87.16, p-value=0.00, coefficient=0.02	chi=96.33, p-value=0.02, coefficient=0.01	chi=180.46, p value=0.00 coefficient=0.0
Credit_Mix	chi=223.87, p-value=0.00, coefficient=0.03	chi=199986.00, p-value=0.00, coefficient=1.00	chi=59080.33, p-value=0.00, coefficient=0.54	chi=1678.37, p-value=0.00, coefficient=0.09	chi=40488.40 p-value=0.00 coefficient=0.4
Payment_of_Min_Amount	chi=87.16, p-value=0.00, coefficient=0.02	chi=59080.33, p-value=0.00, coefficient=0.54	chi=199986.00, p-value=0.00, coefficient=1.00	chi=1178.03, p-value=0.00, coefficient=0.08	chi=19618.62 p-value=0.00 coefficient=0.3
Payment_Behaviour	chi=96.33, p-value=0.02, coefficient=0.01	chi=1678.37, p-value=0.00, coefficient=0.09	chi=1178.03, p-value=0.00, coefficient=0.08	chi=499965.00, p-value=0.00, coefficient=1.00	chi=1531.34, p value=0.00 coefficient=0.0
Credit_Score	chi=180.46, p-value=0.00, coefficient=0.03	chi=40488.40, p-value=0.00, coefficient=0.45	chi=19618.62, p-value=0.00, coefficient=0.31	chi=1531.34, p-value=0.00, coefficient=0.09	chi=199986.00 p-value=0.00 coefficient=1.0

We can see that Credit_Mix and Credit_Score, Credit_Mix and Payment_of_Min_Amount are highly correlated.

Converting Nominal Columns To N-1 Binary Columns

In [34]:

```
cols= ['Payment_Behaviour', 'Occupation', 'Payment_of_Min_Amount', 'Credit_Mix']

for col in cols:
    df2_dummies = pd.get_dummies(df2[[col]], dtype=int)
    df2 = df2.join(df2_dummies)

df2 = df2.drop(cols, axis=1)
df2 = df2.drop(['Occupation_Doctor', 'Payment_of_Min_Amount_NM', 'Payment_Behaviour_High_spent_Large_value_p


display(HTML(df2.head().to_html()))
```

	Month	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Num_of_I
0	1.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
1	2.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
2	3.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
3	4.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
4	5.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	

Identifying The Target Data Split

In [35]:

```
df2.groupby(['Credit_Score']).size()
```

Out[35]:

```
Credit_Score
Good        17825
Poor        28997
Standard    53171
dtype: int64
```

Encoding The Target Variabe

In [36]:

```
y = df2['Credit_Score']
le = preprocessing.LabelEncoder()
le.fit(y)
y_encoded = le.transform(y)
```

```
print(y_encoded)

df2['Credit_Score'] = y_encoded
display(HTML(df2.head().to_html()))
```

```
[0 0 0 ... 1 2 1]
```

	Month	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Num_of_l
0	1.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
1	2.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
2	3.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
3	4.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	
4	5.0	23.0	19114.12	1824.843333	3.0	4.0	3.0	

Normalizing Whole Dataset

In [37]:
```
df2_std = df2.copy(deep=True)
print(df2_std.columns)

cols = df2_std.columns.drop('Credit_Score')

scaler = MinMaxScaler(feature_range=(1,5))

df2_std[cols] = scaler.fit_transform(df2_std[cols])
display(HTML(df2_std.head().to_html()))
```

```
Index(['Month', 'Age', 'Annual_Income', 'Monthly_Inhand_Salary',
       'Num_Bank_Accounts', 'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Limit',
       'Num_Credit_Inquiries', 'Outstanding_Debt', 'Credit_Utilization_Ratio',
       'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance',
       'Credit_Score', 'Credit_History_Age_Months',
       'Payment_Behaviour_High_spent_Medium_value_payments',
       'Payment_Behaviour_High_spent_Small_value_payments',
       'Payment_Behaviour_Low_spent_Large_value_payments',
       'Payment_Behaviour_Low_spent_Medium_value_payments',
       'Payment_Behaviour_Low_spent_Small_value_payments',
       'Occupation_Accountant', 'Occupation_Architect', 'Occupation_Developer',
       'Occupation_Engineer', 'Occupation_Entrepreneur',
       'Occupation_Journalist', 'Occupation_Lawyer', 'Occupation_Manager',
       'Occupation_Mechanic', 'Occupation_Media_Manager',
       'Occupation_Musician', 'Occupation_Scientist', 'Occupation_Teacher',
       'Occupation_Writer', 'Payment_of_Min_Amount_No',
       'Payment_of_Min_Amount_Yes', 'Credit_Mix_Good', 'Credit_Mix_Standard'],
      dtype='object')
```

	Month	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Nu
0	1.000000	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	
1	1.571429	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	
2	2.142857	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	
3	2.714286	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	
4	3.285714	1.857143	1.279988	1.408348	2.090909	2.454545	1.242424	

Performing Over Sampling To Handle Imbalanced Data

In [38]:
```
y = df2_std['Credit_Score']
x = df2_std.drop('Credit_Score', axis=1)

kf = KFold(n_splits=5, shuffle=True)
data_5folds = []
```

```
for train_index, test_index in kf.split(x,y):
    print("\nTRAIN:", train_index, "TEST:", test_index)
    x_train, x_test = x.iloc[train_index], x.iloc[test_index]
    y_train, y_test = y[train_index], y[test_index]
    fold = [x_train, x_test, y_train, y_test]
    data_5folds.append(fold)

for k in range(1,2):
    acc_5folds = []
    for x_train, x_test, y_train, y_test in data_5folds:
        print('\nOriginal dataset shape {}'.format(Counter(y_train)))
        ros = RandomOverSampler(random_state=100)
        ros.fit(x_train, y_train)
        x_resampled, y_resampled = ros.fit_resample(x_train, y_train)
        print('After oversampling dataset shape {}'.format(Counter(y_resampled)))
        clf=neighbors.KNeighborsClassifier(k, weights='uniform')
        clf.fit(x_resampled, y_resampled)
        y_pred = clf.predict(x_test)
        acc = accuracy_score(y_test, y_pred)
        acc_5folds.append(acc)
    print('k = ',k,'Accuracy on 5-folds: ', np.mean(acc_5folds))
```

```
TRAIN: [    0     1     2 ... 99990 99991 99992] TEST: [   16    18    20 ... 99971 99977 99983]

TRAIN: [    0     1     2 ... 99990 99991 99992] TEST: [   10    11    14 ... 99975 99976 99989]

TRAIN: [    0     2     3 ... 99985 99988 99989] TEST: [    1     7     8 ... 99990 99991 99992]

TRAIN: [    1     2     4 ... 99990 99991 99992] TEST: [    0     3     5 ... 99979 99985 99988]

TRAIN: [    0     1     3 ... 99990 99991 99992] TEST: [    2     4     6 ... 99961 99964 99968]

Original dataset shape Counter({2: 42447, 1: 23264, 0: 14283})
After oversampling dataset shape Counter({0: 42447, 2: 42447, 1: 42447})

Original dataset shape Counter({2: 42538, 1: 23335, 0: 14121})
After oversampling dataset shape Counter({0: 42538, 2: 42538, 1: 42538})

Original dataset shape Counter({2: 42585, 1: 23096, 0: 14313})
After oversampling dataset shape Counter({0: 42585, 2: 42585, 1: 42585})

Original dataset shape Counter({2: 42595, 1: 23127, 0: 14273})
After oversampling dataset shape Counter({0: 42595, 2: 42595, 1: 42595})

Original dataset shape Counter({2: 42519, 1: 23166, 0: 14310})
After oversampling dataset shape Counter({0: 42519, 2: 42519, 1: 42519})
k =  1 Accuracy on 5-folds:  0.6725270821996945
```

Data Reduction - Feature Selection Method

Performing Feature Selection Using Entropy Criteria

In [39]:

```
y = y_resampled
x = x_resampled

model = ExtraTreesClassifier(n_estimators = 200, criterion='entropy', max_depth = 20, min_samples_split = 50
                             max_leaf_nodes = 100,  min_impurity_decrease=0.0, class_weight = 'balanced', ra
model.fit(x, y)

values = model.feature_importances_.tolist()
keys = x.columns.tolist()
d = dict(zip(keys, values))

s = [(k, d[k]) for k in sorted(d, key=d.get, reverse=True)]

print('\nRanked features by Entropy importance:\n')
for k, v in s:
    if v >= 0.01:
        print(k,'\t',v)
```

```
Ranked features by Entropy importance:

Credit_Mix_Good          0.20491431990360542
Credit_Mix_Standard      0.11788392478803479
Interest_Rate    0.1011657360541914
Payment_of_Min_Amount_No         0.09984676364739106
Payment_of_Min_Amount_Yes        0.09411104150059232
Outstanding_Debt         0.0778942152621177
Num_Credit_Inquiries     0.05050907908486704
Credit_History_Age_Months        0.036994823304418833
Delay_from_due_date      0.03552430359013057
Num_Credit_Card          0.03533279277326141
Num_Bank_Accounts        0.028727027816175078
Num_of_Loan      0.0250565411930885
Month    0.02439864551266448
Num_of_Delayed_Payment   0.023001659413974154
Changed_Credit_Limit     0.010777827826620408
```

Selecting Top 10 Features From Entropy Criteria

In [40]:
```python
x_resampled_ent = x_resampled[['Credit_Mix_Good', 'Credit_Mix_Standard', 'Interest_Rate', 'Payment_of_Min_Am
                                'Payment_of_Min_Amount_No', 'Outstanding_Debt', 'Num_Credit_Inquiries', 'Del
                                'Credit_History_Age_Months', 'Num_Credit_Card']]

display(HTML(x_resampled_ent.head().to_html()))
```

	Credit_Mix_Good	Credit_Mix_Standard	Interest_Rate	Payment_of_Min_Amount_Yes	Payment_of_Min_Amount_No	Outs
0	5.0	1.0	1.242424	1.0	5.0	
1	5.0	1.0	1.242424	1.0	5.0	
2	5.0	1.0	1.242424	1.0	5.0	
3	5.0	1.0	1.242424	1.0	5.0	
4	5.0	1.0	1.242424	1.0	5.0	

Converting Numerical Data To Categorical

In [41]:
```python
display(HTML(df2_cat.head().to_html()))
```

	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Ra
0	1.0	23.0	Scientist	19114.12	1824.843333	3.0	4.0	
1	2.0	23.0	Scientist	19114.12	1824.843333	3.0	4.0	
2	3.0	23.0	Scientist	19114.12	1824.843333	3.0	4.0	
3	4.0	23.0	Scientist	19114.12	1824.843333	3.0	4.0	
4	5.0	23.0	Scientist	19114.12	1824.843333	3.0	4.0	

In [42]:
```python
num_cols = df2_cat.select_dtypes(include=['number']).columns

# Iterate over numerical columns
for col in num_cols:
    # Calculate quartiles
    q25, q50, q75 = df2_cat[col].quantile([0.25, 0.50, 0.75])
    range_labels = [f"{q25} to {q50}", f"{q50} to {q75}", f"{q75} to {df2_cat[col].max()}"]
    df2_cat[col + '_range'] = pd.cut(df2_cat[col], bins=[df2_cat[col].min(), q25, q75, df2_cat[col].max()],

    # Iterate over range labels and convert to binary
    for label in range_labels:
        df2_cat[col + f" [{label}]"] = (df2_cat[col + '_range'] == label).astype(int)

# Drop the original numerical columns and quartile range columns
```

```python
df2_cat.drop(columns=num_cols, inplace=True)
df2_cat.drop(columns=[col + '_range' for col in num_cols], inplace=True)

display(HTML(df2_cat.head().to_html()))
```

	Occupation	Credit_Mix	Payment_of_Min_Amount	Payment_Behaviour	Credit_Score	Month [2.0 to 4.0]	Month [4.0 to 6.0]	M [
0	Scientist	Good	No	High_spent_Small_value_payments	Good	0	0	
1	Scientist	Good	No	Low_spent_Large_value_payments	Good	1	0	
2	Scientist	Good	No	Low_spent_Medium_value_payments	Good	0	1	
3	Scientist	Good	No	Low_spent_Small_value_payments	Good	0	1	
4	Scientist	Good	No	High_spent_Medium_value_payments	Good	0	1	

Converting Nominal Columns To N-1 Binary Columns

In [43]:
```python
df2_NB = df2_cat.copy(deep=True)

cols= ['Payment_Behaviour', 'Occupation', 'Payment_of_Min_Amount', 'Credit_Mix']

for col in cols:
    df2_NB_dummies = pd.get_dummies(df2_NB[[col]], dtype=int)
    df2_NB = df2_NB.join(df2_NB_dummies)

df2_NB = df2_NB.drop(cols, axis=1)
df2_NB = df2_NB.drop(['Occupation_Doctor', 'Payment_of_Min_Amount_NM', 'Payment_Behaviour_High_spent_Large_v

display(HTML(df2_NB.head().to_html()))
```

	Credit_Score	Month [2.0 to 4.0]	Month [4.0 to 6.0]	Month [6.0 to 8.0]	Age [24.0 to 33.0]	Age [33.0 to 42.0]	Age [42.0 to 56.0]	Annual_Income [19339.08 to 36996.83]	Annual_Income [36996.83 to 71681.4]	Annual_Income [71681.4 to 179987.28]	Monthly_I [1626.5 3095.97
0	Good	0	0	0	1	0	0	1	0	0	
1	Good	1	0	0	1	0	0	1	0	0	
2	Good	0	1	0	1	0	0	1	0	0	
3	Good	0	1	0	1	0	0	1	0	0	
4	Good	0	1	0	1	0	0	1	0	0	

Encoding The Target Variabe

In [44]:
```python
y = df2_NB['Credit_Score']
le = preprocessing.LabelEncoder()
le.fit(y)
y_encoded = le.transform(y)

print(y_encoded)

df2_NB['Credit_Score'] = y_encoded
display(HTML(df2_NB.head().to_html()))
```

```
[0 0 0 ... 1 2 1]
```

	Credit_Score	Month [2.0 to 4.0]	Month [4.0 to 6.0]	Month [6.0 to 8.0]	Age [24.0 to 33.0]	Age [33.0 to 42.0]	Age [42.0 to 56.0]	Annual_Income [19339.08 to 36996.83]	Annual_Income [36996.83 to 71681.4]	Annual_Income [71681.4 to 179987.28]	Monthly_I [1626.5 3095.97
0	0	0	0	0	1	0	0	1	0	0	
1	0	1	0	0	1	0	0	1	0	0	
2	0	0	1	0	1	0	0	1	0	0	
3	0	0	1	0	1	0	0	1	0	0	
4	0	0	1	0	1	0	0	1	0	0	

Performing Over Sampling To Handle Imbalanced Data

In [45]:

```
y = df2_NB['Credit_Score']
x = df2_NB.drop('Credit_Score', axis=1)

kf = KFold(n_splits=5, shuffle=True)
data_5folds = []
for train_index, test_index in kf.split(x,y):
    print("\nTRAIN:", train_index, "TEST:", test_index)
    x_train, x_test = x.iloc[train_index], x.iloc[test_index]
    y_train, y_test = y[train_index], y[test_index]
    fold = [x_train, x_test, y_train, y_test]
    data_5folds.append(fold)

for k in range(1,2):
    acc_5folds = []
    for x_train, x_test, y_train, y_test in data_5folds:
        print('\nOriginal dataset shape {}'.format(Counter(y_train)))
        ros = RandomOverSampler(random_state=100)
        ros.fit(x_train, y_train)
        x_resampled_Cat, y_resampled_Cat = ros.fit_resample(x_train, y_train)
        print('After oversampling dataset shape {}'.format(Counter(y_resampled_Cat)))
        clf=neighbors.KNeighborsClassifier(k, weights='uniform')
        clf.fit(x_resampled_Cat, y_resampled_Cat)
        y_pred = clf.predict(x_test)
        acc = accuracy_score(y_test, y_pred)
        acc_5folds.append(acc)
    print('k = ',k,'Accuracy on 5-folds: ', np.mean(acc_5folds))
```

```
TRAIN: [    0     1     2 ... 99990 99991 99992] TEST: [    8    29    36 ... 99962 99963 99971]

TRAIN: [    2     3     4 ... 99990 99991 99992] TEST: [    0     1    10 ... 99961 99972 99986]

TRAIN: [    0     1     4 ... 99989 99991 99992] TEST: [    2     3     5 ... 99981 99983 99990]

TRAIN: [    0     1     2 ... 99990 99991 99992] TEST: [    4     6    20 ... 99985 99987 99989]

TRAIN: [    0     1     2 ... 99987 99989 99990] TEST: [    9    12    19 ... 99988 99991 99992]

Original dataset shape Counter({2: 42475, 1: 23165, 0: 14354})
After oversampling dataset shape Counter({0: 42475, 2: 42475, 1: 42475})

Original dataset shape Counter({2: 42593, 1: 23139, 0: 14262})
After oversampling dataset shape Counter({0: 42593, 2: 42593, 1: 42593})

Original dataset shape Counter({2: 42536, 1: 23260, 0: 14198})
After oversampling dataset shape Counter({0: 42536, 2: 42536, 1: 42536})

Original dataset shape Counter({2: 42609, 1: 23198, 0: 14188})
After oversampling dataset shape Counter({0: 42609, 2: 42609, 1: 42609})

Original dataset shape Counter({2: 42471, 1: 23226, 0: 14298})
After oversampling dataset shape Counter({0: 42471, 2: 42471, 1: 42471})
k =  1 Accuracy on 5-folds:  0.7328713085319233
```

Performing Feature Selection Using Entropy Criteria

In [46]:

```
y = y_resampled_Cat
x = x_resampled_Cat

model = ExtraTreesClassifier(n_estimators = 200, criterion='entropy', max_depth = 20, min_samples_split = 50
                             max_leaf_nodes = 100,  min_impurity_decrease=0.0, class_weight = 'balanced', ra
model.fit(x, y)

values = model.feature_importances_.tolist()
keys = x.columns.tolist()
d = dict(zip(keys, values))

s = [(k, d[k]) for k in sorted(d, key=d.get, reverse=True)]

print('\nRanked features by entropy criteria:\n')
for k, v in s:
    if v >= 0.01:
        print(k,'\t',v)
```

```
Ranked features by entropy criteria:

Credit_Mix_Good          0.1747970837544036
Interest_Rate [20.0 to 34.0]     0.10573309888120505
Credit_Mix_Standard      0.09129816544871816
Payment_of_Min_Amount_No         0.08313487485405818
Payment_of_Min_Amount_Yes        0.07355874101461542
Outstanding_Debt [1946.81 to 4998.07]    0.0658084715050524
Num_Credit_Inquiries [8.0 to 17.0]       0.05326014019018178
Delay_from_due_date [28.0 to 62.5]       0.03799445780277021
Num_Credit_Card [7.0 to 11.0]    0.025729592801005573
Credit_History_Age_Months [144.0 to 219.0]       0.0242901581818495
Num_of_Loan [5.0 to 9.0]         0.02423305620074819
Num_Credit_Card [4.0 to 5.0]     0.022918563333793645
Delay_from_due_date [10.0 to 18.0]       0.020504709396628393
Outstanding_Debt [566.08 to 1166.23]     0.019581727528502155
Credit_History_Age_Months [302.0 to 404.0]       0.01617192544397545
Interest_Rate [7.0 to 13.0]      0.015501645338284208
Interest_Rate [13.0 to 20.0]     0.014534895050689799
Changed_Credit_Limit [14.85 to 29.98]    0.012457386575239631
```

Selecting Top 10 Features From Entropy Criteria

In [47]:
```
x_resampled_ent_Cat = x_resampled_Cat[['Credit_Mix_Good', 'Credit_Mix_Standard', 'Interest_Rate [20.0 to 34.
                                       'Payment_of_Min_Amount_No', 'Outstanding_Debt [1946.81 to 4998.07]', 'Num_Cr
                                       'Delay_from_due_date [28.0 to 62.5]', 'Credit_History_Age_Months [144.0 to 2

display(HTML(x_resampled_ent_Cat.head().to_html()))
```

	Credit_Mix_Good	Credit_Mix_Standard	Interest_Rate [20.0 to 34.0]	Payment_of_Min_Amount_Yes	Payment_of_Min_Amount_No	Outs
0	1	0	0	0	1	
1	1	0	0	0	1	
2	1	0	0	0	1	
3	1	0	0	0	1	
4	1	0	0	0	1	

Classification

1) KNN Classifier

In [48]:
```
y = y_resampled
x = x_resampled_ent

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

k_values = [11, 111, 711, 1121, 1151]

for k in k_values:
    KNN_Model_1 = KNeighborsClassifier(k, metric='manhattan', weights='distance', algorithm='brute', leaf_si
    KNN_Model_1_Acc = cross_validate(KNN_Model_1, x, y, cv = 5, scoring = Metrics)

    for metric in Metrics:
        metric_scores = KNN_Model_1_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'K={k}, {metric}: {mean_score:.4f}', end=' ')
    print()
```

```
K=11, Accuracy: 0.7944 K=11, Precision_micro: 0.7944 K=11, F1_micro: 0.7944 K=11, Recall_micro: 0.7944 K=11,
AUC_micro: 0.9239
K=111, Accuracy: 0.8231 K=111, Precision_micro: 0.8231 K=111, F1_micro: 0.8231 K=111, Recall_micro: 0.8231 K=
111, AUC_micro: 0.9498
K=711, Accuracy: 0.8319 K=711, Precision_micro: 0.8319 K=711, F1_micro: 0.8319 K=711, Recall_micro: 0.8319 K=
711, AUC_micro: 0.9558
K=1121, Accuracy: 0.8331 K=1121, Precision_micro: 0.8331 K=1121, F1_micro: 0.8331 K=1121, Recall_micro: 0.833
1 K=1121, AUC_micro: 0.9567
K=1151, Accuracy: 0.8332 K=1151, Precision_micro: 0.8332 K=1151, F1_micro: 0.8332 K=1151, Recall_micro: 0.833
2 K=1151, AUC_micro: 0.9567
```

KNN Classifier With Best K Value

In [49]:
```
y = y_resampled
x = x_resampled_ent

k_values = [1121]

KNN_Model_2 = KNeighborsClassifier(k, metric='manhattan', weights='distance', algorithm='brute', leaf_size=3
```

```
Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

KNN_Model_2_Acc = cross_validate(KNN_Model_2, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = KNN_Model_2_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.8332 Precision_micro: 0.8332 F1_micro: 0.8332 Recall_micro: 0.8332 AUC_micro: 0.9567
```

Naive Bayesian Classifier

2) Categorical NB Classifier

In [50]:

```
y = y_resampled_Cat
x = x_resampled_ent_Cat

NB_Model_1 = CategoricalNB(alpha=2.0, class_prior = None, fit_prior = True, force_alpha = True, min_categori

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

NB_Model_1_Acc = cross_validate(NB_Model_1, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = NB_Model_1_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7040 Precision_micro: 0.7040 F1_micro: 0.7040 Recall_micro: 0.7040 AUC_micro: 0.8027
```

3) Gaussian NB Classifier

In [51]:

```
y = y_resampled
x = x_resampled_ent

NB_Model_2 = GaussianNB(var_smoothing = 1e-05)

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

NB_Model_2_Acc = cross_validate(NB_Model_2, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = NB_Model_2_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7015 Precision_micro: 0.7015 F1_micro: 0.7015 Recall_micro: 0.7015 AUC_micro: 0.8117
```

4) Gaussian NB Classifier Ensembled With Bagging

In [52]:
```python
y = y_resampled
x = x_resampled_ent

NB_Model_2 = GaussianNB(var_smoothing = 1e-05)

NB_Model_2_Bag = BaggingClassifier(NB_Model_2, n_estimators=100, max_samples=0.8, random_state=100)

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

NB_Model_2_Bag_Acc = cross_validate(NB_Model_2_Bag, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = NB_Model_2_Bag_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7014 Precision_micro: 0.7014 F1_micro: 0.7014 Recall_micro: 0.7014 AUC_micro: 0.8117
```

5) Decision Tree Classifier

In [53]:
```python
y = y_resampled
x = x_resampled_ent

DT_Model_1 = DecisionTreeClassifier(criterion='entropy', splitter = 'best', max_depth=5, max_leaf_nodes = 10
                            min_samples_split=1000, min_impurity_decrease=0.01, min_samples_leaf= 200, rando

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

DT_Model_1_Acc = cross_validate(DT_Model_1, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = DT_Model_1_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7101 Precision_micro: 0.7101 F1_micro: 0.7101 Recall_micro: 0.7101 AUC_micro: 0.8432
```

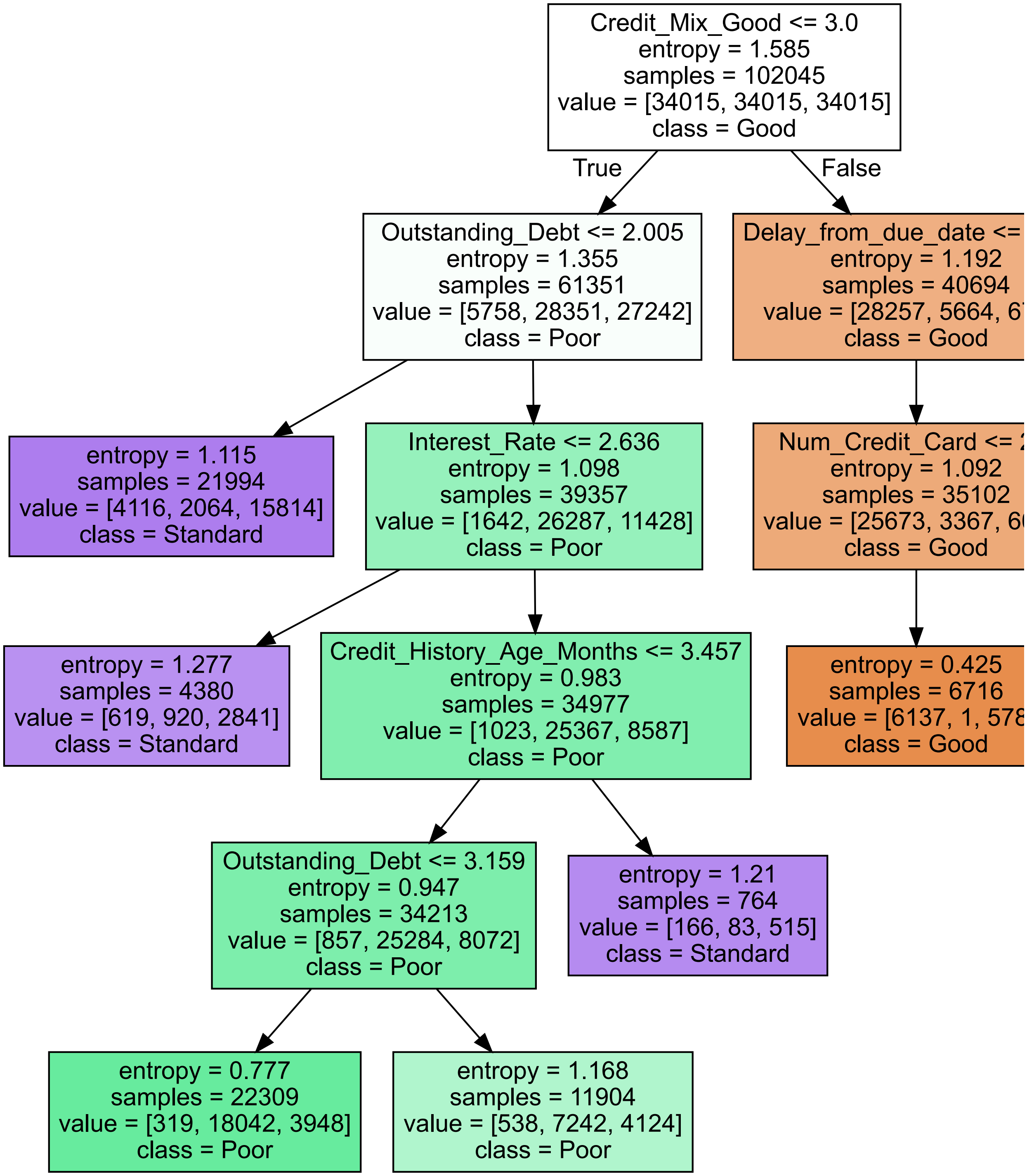
Visualizing The Tree From The Above Decision Tree Classifier

In [54]:
```python
y = y_resampled
x = x_resampled_ent

DT_Model_1 = DecisionTreeClassifier(criterion='entropy', splitter = 'best', max_depth=5, max_leaf_nodes = 10
                            min_samples_split=1000, min_impurity_decrease=0.01, min_samples_leaf= 200, rando

rst = cross_validate(DT_Model_1, x, y, cv = 5, scoring='roc_auc_ovr', return_estimator=True)

# get fitted trees for each fold
trees = rst['estimator']
# print accuracy scores for each fold
scores = rst['test_score']
print(scores)

# select the best model
best_fold_index = np.argmax(scores)
best_clf = trees[best_fold_index]
```

```
# encode labels
labels = le.inverse_transform([0,1,2])

print('features: ', x.columns.to_list())
print('labels: ', labels)

# DOT data
dot_data = tree.export_graphviz(best_clf, out_file=None, feature_names=x.columns.to_list(), class_names=labe

# Draw graph
graph_best= graphviz.Source(dot_data, format="png")
# save graph to MyDecisionTree.png
graph_best.render("MyDecisionTree")
graph_best
```

```
[0.81984798 0.83678165 0.83484312 0.83325995 0.82220525]
features:  ['Credit_Mix_Good', 'Credit_Mix_Standard', 'Interest_Rate', 'Payment_of_Min_Amount_Yes', 'Payment_
of_Min_Amount_No', 'Outstanding_Debt', 'Num_Credit_Inquiries', 'Delay_from_due_date', 'Credit_History_Age_Mon
ths', 'Num_Credit_Card']
labels:  ['Good' 'Poor' 'Standard']
```

Out[54]:



6) Decision Tree Classifier Ensembled with RandomForest

In [55]:

```
y = y_resampled
x = x_resampled_ent

DT_Model_1 = DecisionTreeClassifier(criterion='entropy', splitter = 'best', max_depth=5, max_leaf_nodes = 10
                                    min_samples_split=1000, min_impurity_decrease=0.01, min_samples_leaf= 200, rando

DT_Model_1_Bag = BaggingClassifier(base_estimator= DT_Model_1, n_estimators=100, max_samples=0.8, random_sta

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
```

```
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

DT_Model_1_Bag_Acc = cross_validate(DT_Model_1_Bag, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = DT_Model_1_Bag_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7105 Precision_micro: 0.7105 F1_micro: 0.7105 Recall_micro: 0.7105 AUC_micro: 0.8469
```

7) Decision Tree Classifier Ensembled With GradientBoosting

In [56]:
```
y = y_resampled
x = x_resampled_ent

DT_Model_1_GB = GradientBoostingClassifier(n_estimators=100, random_state= 100, learning_rate=0.2, criterion

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

DT_Model_1_GB_Acc = cross_validate(DT_Model_1_GB, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = DT_Model_1_GB_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7233 Precision_micro: 0.7233 F1_micro: 0.7233 Recall_micro: 0.7233 AUC_micro: 0.8667
```

8) Logistic Regression Classifier

In [57]:
```
y = y_resampled
x = x_resampled_ent

LR_Model_1 = LogisticRegression(penalty='l2',solver='lbfgs', max_iter=200, multi_class='ovr', C= 10, tol = 1
                         random_state= 100, dual=False, fit_intercept= True, intercept_scaling=1, class_weig

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

LR_Model_1_Acc = cross_validate(LR_Model_1, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = LR_Model_1_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7036 Precision_micro: 0.7036 F1_micro: 0.7036 Recall_micro: 0.7036 AUC_micro: 0.8267
```

9) Logistic Regression Classifier Ensembled With Bagging

In [58]:
```
y = y_resampled
x = x_resampled_ent

LR_Model_1 = LogisticRegression(penalty='l2',solver='lbfgs', max_iter=200, multi_class='ovr', C= 10, tol = 1
                         random_state= 100, dual=False, fit_intercept= True, intercept_scaling=1, class_weig
```

```python
LR_Model_1_Bag = BaggingClassifier(LR_Model_1, n_estimators=100, max_samples=0.8, random_state=100)

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

LR_Model_1_Bag_Acc = cross_validate(LR_Model_1_Bag, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = LR_Model_1_Bag_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7035 Precision_micro: 0.7035 F1_micro: 0.7035 Recall_micro: 0.7035 AUC_micro: 0.8267
```

10) Multilayer Perceptron Classifier Model 1

In [59]:
```python
y = y_resampled
x = x_resampled_ent


MLP_Model_1 = MLPClassifier(activation ='identity', solver='sgd', learning_rate_init=0.01, alpha=1e-2, hidde

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

MLP_Model_1_Acc = cross_validate(MLP_Model_1, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = MLP_Model_1_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7023 Precision_micro: 0.7023 F1_micro: 0.7023 Recall_micro: 0.7023 AUC_micro: 0.8263
```

11) Multilayer Perceptron Classifier Model 2

In [60]:
```python
y = y_resampled
x = x_resampled_ent


MLP_Model_2 = MLPClassifier(activation ='logistic', solver='lbfgs', learning_rate_init=0.001, alpha=1e-3,
                    hidden_layer_sizes=(100,), random_state=100, batch_size= 'auto', max_iter= 200)

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

MLP_Model_2_Acc = cross_validate(MLP_Model_2, x, y, cv = 5, scoring = Metrics)

for metric in Metrics:
        metric_scores = MLP_Model_2_Acc[f'test_{metric}']
        mean_score = metric_scores.mean()
        print(f'{metric}: {mean_score:.4f}', end=' ')
```

```
Accuracy: 0.7167 Precision_micro: 0.7167 F1_micro: 0.7167 Recall_micro: 0.7167 AUC_micro: 0.8567
```

Displaying Metrics For All Models

In [61]:
```
Models = [KNN_Model_2_Acc, NB_Model_1_Acc, NB_Model_2_Acc, NB_Model_2_Bag_Acc, DT_Model_1_Acc,
          DT_Model_1_Bag_Acc, DT_Model_1_GB_Acc, LR_Model_1_Acc, LR_Model_1_Bag_Acc, MLP_Model_1_Acc, MLP_Mo

Metrics = {
    'Accuracy': make_scorer(accuracy_score),
    'Precision_micro': make_scorer(precision_score, average='micro'),
    'F1_micro': make_scorer(f1_score, average='micro'),
    'Recall_micro': make_scorer(recall_score, average='micro'),
    'AUC_micro': make_scorer(roc_auc_score, average='micro', multi_class='ovr', needs_proba=True)
}

mean_metric_scores = {metric: [] for metric in Metrics}

# Iterate over each model
for mod in Models:
    # Iterate over each metric
    for metric, scorer in Metrics.items():
        # Calculate the mean score for the current metric and model
        mean_score = mod[f'test_{metric}'].mean()

        # Append the mean score to the list for the current metric
        mean_metric_scores[metric].append(mean_score)

# Create a DataFrame to display the results
results_df = pd.DataFrame(mean_metric_scores)

# Add a column for the model names
results_df['Model'] = ['KNN Classifier', 'Categorical NB Classifier', 'Gaussian NB Classifier', 'Gaussian NB
                       'Decision Tree Classifer', 'Decision Tree Classifer - Random Forest', 'Decision Tree
                       'Logistic Regression', 'Logistic Regression - Bagging', 'MLP Classifier - 1', 'MLP Cl


# Reorder columns to have 'Model' as the first column
results_df = results_df[['Model'] + list(Metrics.keys())]

# Display the DataFrame
results_df
```

Out[61]:

	Model	Accuracy	Precision_micro	F1_micro	Recall_micro	AUC_micro
0	KNN Classifier	0.833220	0.833220	0.833220	0.833220	0.956731
1	Categorical NB Classifier	0.703971	0.703971	0.703971	0.703971	0.802665
2	Gaussian NB Classifier	0.701451	0.701451	0.701451	0.701451	0.811664
3	Gaussian NB Classifier - Bagging	0.701428	0.701428	0.701428	0.701428	0.811671
4	Decision Tree Classifer	0.710145	0.710145	0.710145	0.710145	0.843195
5	Decision Tree Classifer - Random Forest	0.710545	0.710545	0.710545	0.710545	0.846853
6	Decision Tree Classifer - Gradient Boosting	0.723277	0.723277	0.723277	0.723277	0.866656
7	Logistic Regression	0.703568	0.703568	0.703568	0.703568	0.826664
8	Logistic Regression - Bagging	0.703544	0.703544	0.703544	0.703544	0.826663
9	MLP Classifier - 1	0.702266	0.702266	0.702266	0.702266	0.826315
10	MLP Classifier - 2	0.716660	0.716660	0.716660	0.716660	0.856669

Predicting The Labels in Test Dataset

In [62]:
```
df_test = pd.read_csv("test.csv")
display(HTML(df_test.head().to_html()))
```

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_B
0	0x160a	CUS_0xd40	September	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	
1	0x160b	CUS_0xd40	October	Aaron Maashoh	24	821-00-0265	Scientist	19114.12	1824.843333	
2	0x160c	CUS_0xd40	November	Aaron Maashoh	24	821-00-0265	Scientist	19114.12	1824.843333	
3	0x160d	CUS_0xd40	December	Aaron Maashoh	24_	821-00-0265	Scientist	19114.12	NaN	
4	0x1616	CUS_0x21b1	September	Rick Rothackerj	28	004-07-5839	_______	34847.84	3037.986667	

Preprocessing The Test Dataset

In [63]:
```
# strip column names
df_test = df_test.rename(columns=lambda x: x.strip())

duplicate_df_test = df_test[df_test.duplicated()]
display(HTML(duplicate_df_test.head().to_html()))
```

ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts

In [64]:
```
cols = ['Customer_ID', 'Credit_Mix', 'Interest_Rate', 'Payment_of_Min_Amount', 'Outstanding_Debt', 'Num_Cred
        'Delay_from_due_date', 'Credit_History_Age', 'Num_Credit_Card']

df2_test = df_test[cols]
display(HTML(df2_test.head().to_html()))
```

	Customer_ID	Credit_Mix	Interest_Rate	Payment_of_Min_Amount	Outstanding_Debt	Num_Credit_Inquiries	Delay_fror
0	CUS_0xd40	Good	3	No	809.98	2022.0	
1	CUS_0xd40	Good	3	No	809.98	4.0	
2	CUS_0xd40	Good	3	No	809.98	4.0	
3	CUS_0xd40	Good	3	No	809.98	4.0	
4	CUS_0x21b1	Good	6	No	605.03	5.0	

In [65]:
```
cols = df2_test.columns
print('\nColumnName, DataType, MissingValues')
for i in cols:
        print(i, ',', df2_test[i].dtype, ',', df2_test[i].isnull().sum())
```

```
ColumnName, DataType, MissingValues
Customer_ID , object , 0
Credit_Mix , object , 0
Interest_Rate , int64 , 0
Payment_of_Min_Amount , object , 0
Outstanding_Debt , object , 0
Num_Credit_Inquiries , float64 , 1035
Delay_from_due_date , int64 , 0
Credit_History_Age , object , 4470
Num_Credit_Card , int64 , 0
```

In [66]:
```
# Displaying only Missing values
for i in df2_test.columns:
    if df2_test[i].isnull().sum() > 0:
        print(i, ',', df2_test[i].dtype, df2_test[i].isnull().sum())
```

```
Num_Credit_Inquiries , float64 1035
Credit_History_Age , object 4470
```

In [67]:
```
cols = df2_test.columns

for col in cols:
    if df2_test[col].apply(lambda x: isinstance(x, str) and x.endswith("_")).any():
        print(f"Column '{col}' contains values ending with an underscore.")
```

```
Column 'Credit_Mix' contains values ending with an underscore.
Column 'Outstanding_Debt' contains values ending with an underscore.
```

In [68]:
```
cols = ["Outstanding_Debt"]

for col in cols:
    if not df2_test[col].isnull().all():
        df2_test[col] = df2_test[col].apply(lambda x: x.rstrip('_') if isinstance(x, str) and x.endswith("_"

cols = ['Credit_Mix']

for col in cols:
    group_sizes = df2_test.groupby([col]).size()
    if any('_' in str(index) for index in group_sizes.index):
        mask = pd.Series(group_sizes.index.str.contains('_'))
        mask = mask.fillna(False)
        print(group_sizes[mask.values])
        print()
```

```
Credit_Mix
_    9805
dtype: int64
```

```
In [69]: df2_test['Credit_Mix'] = df2_test['Credit_Mix'].replace("_", pd.NA)

         # checking if any underscore still exists
         for col in cols:
             if df2_test[col].apply(lambda x: isinstance(x, str) and x.endswith("_")).any():
                 print(f"Column '{col}' contains values ending with an underscore.")
```

```
In [70]: cols = ['Outstanding_Debt']

         for col in cols:
             df2_test[col] = pd.to_numeric(df2_test[col], errors='coerce')

         cols = df2_test.select_dtypes(include=['number']).columns

         for col in cols:
             median_by_id = df2_test.groupby('Customer_ID')[col].median()
             df2_test[col] = df2_test.apply(lambda row: median_by_id[row['Customer_ID']] if pd.isna(row[col]) else ro
             print(f"Number of null values in {col}: {df2_test[col].isnull().sum()}")
```

```
Number of null values in Interest_Rate: 0
Number of null values in Outstanding_Debt: 0
Number of null values in Num_Credit_Inquiries: 0
Number of null values in Delay_from_due_date: 0
Number of null values in Num_Credit_Card: 0
```

```
In [71]: cols = ['Credit_Mix', 'Credit_History_Age']

         for column in cols:
             mode_val = df2_test[column].mode()[0]
             df2_test[column] = df2_test[column].fillna(mode_val)
             print(f"Number of null values in {column}: {df2_test[column].isnull().sum()}")

         def convert_to_months(age_str):
             years, months = age_str.split(' and ')
             years = int(years.split(' ')[0])
             months = int(months.split(' ')[0])
             return years * 12 + months

         df2_test['Credit_History_Age_Months'] = df2_test['Credit_History_Age'].apply(convert_to_months)
         df2_test = df2_test.drop('Credit_History_Age', axis=1)
         print(df2_test['Credit_History_Age_Months'])

         display(HTML(df2_test.head().to_html()))
```

```
Number of null values in Credit_Mix: 0
Number of null values in Credit_History_Age: 0
0        273
1        274
2        193
3        276
4        327
        ...
49995    193
49996    383
49997    384
49998    385
49999    386
Name: Credit_History_Age_Months, Length: 50000, dtype: int64
```

	Customer_ID	Credit_Mix	Interest_Rate	Payment_of_Min_Amount	Outstanding_Debt	Num_Credit_Inquiries	Delay_fron
0	CUS_0xd40	Good	3	No	809.98	2022.0	
1	CUS_0xd40	Good	3	No	809.98	4.0	
2	CUS_0xd40	Good	3	No	809.98	4.0	
3	CUS_0xd40	Good	3	No	809.98	4.0	
4	CUS_0x21b1	Good	6	No	605.03	5.0	

In [72]:
```
cols= ['Payment_of_Min_Amount', 'Credit_Mix']

for col in cols:
    df2_test_dummies = pd.get_dummies(df2_test[[col]], dtype=int)
    df2_test = df2_test.join(df2_test_dummies)

df2_test = df2_test.drop(cols, axis=1)
df2_test = df2_test.drop(['Payment_of_Min_Amount_NM', 'Credit_Mix_Bad', 'Customer_ID'], axis=1)

display(HTML(df2_test.head().to_html()))
```

	Interest_Rate	Outstanding_Debt	Num_Credit_Inquiries	Delay_from_due_date	Num_Credit_Card	Credit_History_Age_Mc
0	3	809.98	2022.0	3	4	
1	3	809.98	4.0	3	4	
2	3	809.98	4.0	-1	4	
3	3	809.98	4.0	4	4	
4	6	605.03	5.0	3	4	

In [73]:
```
df2_test_std = df2_test.copy(deep=True)
print(df2_test_std.columns)

scaler = MinMaxScaler(feature_range=(1,5))

cols = df2_test_std.columns

df2_test_std[cols] = scaler.fit_transform(df2_test_std[cols])
display(HTML(df2_test_std.head().to_html()))
```

```
Index(['Interest_Rate', 'Outstanding_Debt', 'Num_Credit_Inquiries',
       'Delay_from_due_date', 'Num_Credit_Card', 'Credit_History_Age_Months',
       'Payment_of_Min_Amount_No', 'Payment_of_Min_Amount_Yes',
       'Credit_Mix_Good', 'Credit_Mix_Standard'],
      dtype='object')
```

	Interest_Rate	Outstanding_Debt	Num_Credit_Inquiries	Delay_from_due_date	Num_Credit_Card	Credit_History_Age_Mc
0	1.001380	1.648080	4.119167	1.444444	1.010674	3.64
1	1.001380	1.648080	1.006170	1.444444	1.010674	3.65
2	1.001380	1.648080	1.006170	1.222222	1.010674	2.83
3	1.001380	1.648080	1.006170	1.500000	1.010674	3.67
4	1.003449	1.484049	1.007713	1.444444	1.010674	4.18

In [74]:
```
df2_test_std_ent = df2_test_std[['Credit_Mix_Good', 'Credit_Mix_Standard', 'Interest_Rate', 'Payment_of_Min_
                                 'Payment_of_Min_Amount_No', 'Outstanding_Debt', 'Num_Credit_Inquiries', 'Del
                                 'Credit_History_Age_Months', 'Num_Credit_Card']]

display(HTML(df2_test_std_ent.head().to_html()))
```

	Credit_Mix_Good	Credit_Mix_Standard	Interest_Rate	Payment_of_Min_Amount_Yes	Payment_of_Min_Amount_No	Outs
0	5.0	1.0	1.001380	1.0	5.0	
1	5.0	1.0	1.001380	1.0	5.0	
2	5.0	1.0	1.001380	1.0	5.0	
3	5.0	1.0	1.001380	1.0	5.0	
4	5.0	1.0	1.003449	1.0	5.0	

In [75]:

```
y = y_resampled
x = x_resampled_ent

DT_Model_1_GB = GradientBoostingClassifier(n_estimators=100, random_state= 100, learning_rate=0.2, criterion

DT_Model_1_GB.fit(x, y)

# Make predictions on the test data
predictions = DT_Model_1_GB.predict(df2_test_std_ent)

# Analyze the predictions using the silhouette score method
silhouette = silhouette_score(df2_test_std_ent, predictions)
print(f"Silhouette Score: {silhouette:.4f}")

labels = le.inverse_transform(predictions)

df2_test_std_ent['Credit_Score'] = labels
display(HTML(df2_test_std_ent.head().to_html()))
```

```
Silhouette Score: 0.2134
```

	Credit_Mix_Good	Credit_Mix_Standard	Interest_Rate	Payment_of_Min_Amount_Yes	Payment_of_Min_Amount_No	Outs
0	5.0	1.0	1.001380	1.0	5.0	
1	5.0	1.0	1.001380	1.0	5.0	
2	5.0	1.0	1.001380	1.0	5.0	
3	5.0	1.0	1.001380	1.0	5.0	
4	5.0	1.0	1.003449	1.0	5.0	

In [76]:

```
df2_test_std_ent = df2_test_std[['Credit_Mix_Good', 'Credit_Mix_Standard', 'Interest_Rate', 'Payment_of_Min_
                                 'Payment_of_Min_Amount_No', 'Outstanding_Debt', 'Num_Credit_Inquiries', 'Del
                                 'Credit_History_Age_Months', 'Num_Credit_Card']]

display(HTML(df2_test_std_ent.head().to_html()))
```

	Credit_Mix_Good	Credit_Mix_Standard	Interest_Rate	Payment_of_Min_Amount_Yes	Payment_of_Min_Amount_No	Outs
0	5.0	1.0	1.001380	1.0	5.0	
1	5.0	1.0	1.001380	1.0	5.0	
2	5.0	1.0	1.001380	1.0	5.0	
3	5.0	1.0	1.001380	1.0	5.0	
4	5.0	1.0	1.003449	1.0	5.0	

In [77]:

```
y = y_resampled
x = x_resampled_ent

KNN_Model_2 = KNeighborsClassifier(n_neighbors= 1121, metric='manhattan', weights='distance', algorithm='bru
```

```
KNN_Model_2.fit(x, y)

# Make predictions on the test data
predictions = KNN_Model_2.predict(df2_test_std_ent)

# Analyze the predictions using the silhouette score method
silhouette = silhouette_score(df2_test_std_ent, predictions)
print(f"Silhouette Score: {silhouette:.4f}")

labels = le.inverse_transform(predictions)

df2_test_std_ent['Credit_Score'] = labels
display(HTML(df2_test_std_ent.head().to_html()))
```

```
Silhouette Score: 0.4677
```

	Credit_Mix_Good	Credit_Mix_Standard	Interest_Rate	Payment_of_Min_Amount_Yes	Payment_of_Min_Amount_No	Outs
0	5.0	1.0	1.001380	1.0	5.0	
1	5.0	1.0	1.001380	1.0	5.0	
2	5.0	1.0	1.001380	1.0	5.0	
3	5.0	1.0	1.001380	1.0	5.0	
4	5.0	1.0	1.003449	1.0	5.0	

Association Rules

In [78]:
```
display(HTML(df2_cat.head().to_html()))
```

	Occupation	Credit_Mix	Payment_of_Min_Amount	Payment_Behaviour	Credit_Score	Month [2.0 to 4.0]	Month [4.0 to 6.0]	M [(
0	Scientist	Good	No	High_spent_Small_value_payments	Good	0	0	
1	Scientist	Good	No	Low_spent_Large_value_payments	Good	1	0	
2	Scientist	Good	No	Low_spent_Medium_value_payments	Good	0	1	
3	Scientist	Good	No	Low_spent_Small_value_payments	Good	0	1	
4	Scientist	Good	No	High_spent_Medium_value_payments	Good	0	1	

Converting All Numerical Columns To Binary Based On Quadrants Like 25,50,75

In [79]:
```
df2_encoded = pd.get_dummies(df2_cat)
df2_encoded.replace({1: True, 0: False}, inplace=True)
print(df2_encoded.columns)
display(HTML(df2_encoded.head().to_html()))
```

```
Index(['Month [2.0 to 4.0]', 'Month [4.0 to 6.0]', 'Month [6.0 to 8.0]',
       'Age [24.0 to 33.0]', 'Age [33.0 to 42.0]', 'Age [42.0 to 56.0]',
       'Annual_Income [19339.08 to 36996.83]',
       'Annual_Income [36996.83 to 71681.4]',
       'Annual_Income [71681.4 to 179987.28]',
       'Monthly_Inhand_Salary [1626.594166666667 to 3095.978333333333]',
       'Monthly_Inhand_Salary [3095.978333333333 to 5961.6375]',
       'Monthly_Inhand_Salary [5961.6375 to 15204.633333333331]',
       'Num_Bank_Accounts [3.0 to 5.0]', 'Num_Bank_Accounts [5.0 to 7.0]',
       'Num_Bank_Accounts [7.0 to 11.0]', 'Num_Credit_Card [4.0 to 5.0]',
       'Num_Credit_Card [5.0 to 7.0]', 'Num_Credit_Card [7.0 to 11.0]',
       'Interest_Rate [7.0 to 13.0]', 'Interest_Rate [13.0 to 20.0]',
       'Interest_Rate [20.0 to 34.0]', 'Num_of_Loan [2.0 to 3.0]',
       'Num_of_Loan [3.0 to 5.0]', 'Num_of_Loan [5.0 to 9.0]',
       'Delay_from_due_date [10.0 to 18.0]',
       'Delay_from_due_date [18.0 to 28.0]',
       'Delay_from_due_date [28.0 to 62.5]',
       'Num_of_Delayed_Payment [9.0 to 14.0]',
       'Num_of_Delayed_Payment [14.0 to 18.0]',
       'Num_of_Delayed_Payment [18.0 to 28.0]',
       'Changed_Credit_Limit [5.34 to 9.4]',
       'Changed_Credit_Limit [9.4 to 14.85]',
       'Changed_Credit_Limit [14.85 to 29.98]',
       'Num_Credit_Inquiries [3.0 to 5.0]',
       'Num_Credit_Inquiries [5.0 to 8.0]',
       'Num_Credit_Inquiries [8.0 to 17.0]',
       'Outstanding_Debt [566.08 to 1166.23]',
       'Outstanding_Debt [1166.23 to 1946.81]',
       'Outstanding_Debt [1946.81 to 4998.07]',
       'Credit_Utilization_Ratio [28.05234445125113 to 32.30552378486248]',
       'Credit_Utilization_Ratio [32.30552378486248 to 36.486018233613954]',
       'Credit_Utilization_Ratio [36.486018233613954 to 44.96820522820443]',
       'Total_EMI_per_month [29.13133496222223 to 66.31256648622086]',
       'Total_EMI_per_month [66.31256648622086 to 145.6395523263464]',
       'Total_EMI_per_month [145.6395523263464 to 21627.11710415826]',
       'Amount_invested_monthly [73.63464644580425 to 127.5229742043934]',
       'Amount_invested_monthly [127.5229742043934 to 210.32459402415014]',
       'Amount_invested_monthly [210.32459402415014 to 1132.6696341760935]',
       'Monthly_Balance [272.6430415618064 to 339.31853676978216]',
       'Monthly_Balance [339.31853676978216 to 470.6429990645397]',
       'Monthly_Balance [470.6429990645397 to 1427.7974642624645]',
       'Credit_History_Age_Months [144.0 to 219.0]',
       'Credit_History_Age_Months [219.0 to 302.0]',
       'Credit_History_Age_Months [302.0 to 404.0]', 'Occupation_Accountant',
       'Occupation_Architect', 'Occupation_Developer', 'Occupation_Doctor',
       'Occupation_Engineer', 'Occupation_Entrepreneur',
       'Occupation_Journalist', 'Occupation_Lawyer', 'Occupation_Manager',
       'Occupation_Mechanic', 'Occupation_Media_Manager',
       'Occupation_Musician', 'Occupation_Scientist', 'Occupation_Teacher',
       'Occupation_Writer', 'Credit_Mix_Bad', 'Credit_Mix_Good',
       'Credit_Mix_Standard', 'Payment_of_Min_Amount_NM',
       'Payment_of_Min_Amount_No', 'Payment_of_Min_Amount_Yes',
       'Payment_Behaviour_High_spent_Large_value_payments',
       'Payment_Behaviour_High_spent_Medium_value_payments',
       'Payment_Behaviour_High_spent_Small_value_payments',
       'Payment_Behaviour_Low_spent_Large_value_payments',
       'Payment_Behaviour_Low_spent_Medium_value_payments',
       'Payment_Behaviour_Low_spent_Small_value_payments', 'Credit_Score_Good',
       'Credit_Score_Poor', 'Credit_Score_Standard'],
      dtype='object')
```

	Month [2.0 to 4.0]	Month [4.0 to 6.0]	Month [6.0 to 8.0]	Age [24.0 to 33.0]	Age [33.0 to 42.0]	Age [42.0 to 56.0]	Annual_Income [19339.08 to 36996.83]	Annual_Income [36996.83 to 71681.4]	Annual_Income [71681.4 to 179987.28]	Monthly_Inhand_Salary [1626.59416666667 to 3095.978333333333]
0	False	False	False	True	False	False	True	False	False	False
1	True	False	False	True	False	False	True	False	False	False
2	False	True	False	True	False	False	True	False	False	False
3	False	True	False	True	False	False	True	False	False	False
4	False	True	False	True	False	False	True	False	False	False

In [80]:
```
# Association Rules
frequent_itemsets = apriori(df2_encoded, min_support=0.1, use_colnames=True)
```

In [81]:
```
# Generate rules with confidence greater than 0.6
rules_confidence = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.5)

rules = pd.DataFrame(rules_confidence)
display(HTML(rules.head(10).to_html()))
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	con
0	(Month [4.0 to 6.0])	(Age [33.0 to 42.0])	0.500005	0.520836	0.260738	0.521471	1.001219	0.000317	1
1	(Age [33.0 to 42.0])	(Month [4.0 to 6.0])	0.520836	0.500005	0.260738	0.500614	1.001219	0.000317	1
2	(Annual_Income [19339.08 to 36996.83])	(Month [4.0 to 6.0])	0.249937	0.500005	0.124969	0.500000	0.999990	-0.000001	0
3	(Annual_Income [36996.83 to 71681.4])	(Month [4.0 to 6.0])	0.500035	0.500005	0.250018	0.500000	0.999990	-0.000003	0
4	(Month [4.0 to 6.0])	(Annual_Income [36996.83 to 71681.4])	0.500005	0.500035	0.250018	0.500030	0.999990	-0.000003	0
5	(Annual_Income [71681.4 to 179987.28])	(Month [4.0 to 6.0])	0.249947	0.500005	0.124979	0.500020	1.000030	0.000004	1
6	(Month [4.0 to 6.0])	(Monthly_Inhand_Salary [3095.978333333333 to 5961.6375])	0.500005	0.500065	0.250088	0.500170	1.000210	0.000053	1
7	(Monthly_Inhand_Salary [3095.978333333333 to 5961.6375])	(Month [4.0 to 6.0])	0.500065	0.500005	0.250088	0.500110	1.000210	0.000053	1
8	(Monthly_Inhand_Salary [5961.6375 to 15204.633333333331])	(Month [4.0 to 6.0])	0.249927	0.500005	0.124969	0.500020	1.000030	0.000004	1
9	(Num_Bank_Accounts [3.0 to 5.0])	(Month [4.0 to 6.0])	0.209855	0.500005	0.105017	0.500429	1.000848	0.000089	1

In [82]:
```
rows_to_access = [110, 474, 661, 289, 740, 367, 315, 629, 735]
Significant_Rules = rules.iloc[rows_to_access]
Significant_Rules
```

Out[82]:

	antecedents	consequents	antecedent support	consequent support	support
110	(Credit_Score_Poor)	(Age [33.0 to 42.0])	0.289990	0.520836	0.160071
474	(Num_of_Loan [5.0 to 9.0])	(Credit_Score_Poor)	0.230176	0.289990	0.120608
661	(Credit_Score_Poor)	(Credit_Utilization_Ratio [32.30552378486248 t...	0.289990	0.499995	0.145540
289	(Credit_Score_Standard)	(Num_Bank_Accounts [5.0 to 7.0])	0.531747	0.508136	0.296351
740	(Payment_Behaviour_High_spent_Medium_value_pay...	(Credit_Score_Standard)	0.193674	0.531747	0.105247
367	(Credit_Score_Standard)	(Num_Credit_Card [5.0 to 7.0])	0.531747	0.528617	0.295811
315	(Credit_Score_Good)	(Num_Credit_Card [4.0 to 5.0])	0.178262	0.322983	0.101177
629	(Credit_Score_Good)	(Outstanding_Debt [1166.23 to 1946.81])	0.178262	0.499995	0.104497
735	(Credit_Score_Good)	(Payment_of_Min_Amount_No)	0.178262	0.356625	0.136690

Three Rules on Each class of Target variable credit score

1. **(Credit_Score_Poor) → (Age [33.0 to 42.0]):**

- Support: 16.007%, Confidence: 55.199, Lift: 1.05, 8 Leverage: 0.0090
- This rule suggests 16% of the dataset supports, that when a customer has a poor credit the age is falling withinge range of 33 to 42.
- The confidence of 55.199% suggests that over half of the customers with a poor credit score also fall within the specified age range.
- The lift of 1.0598 indicates that this association is slightly more likely to occur than if the two variables were independent.

2. **(Num_of_Loan [5.0 to 9.0]) → (Credit_Score_Poor):**

- Support: 12.061%, Confidence: 52.398, Lift: 1.80, 9 Leverage: 0.0539
- This rule suggests that 12% of the dataset contain both a number of loans between 5.0 and 9.0 and a poor credit score.
- It implies that if number of loans are in this range, there is a 52% confidence that its credit score is poor.
- The lift value of 1.8069 suggests a notable likelihood of occurrence for this association compared to what would be expected if the two variables were independent.pendent.

3. **(Credit_Score_Poor) → (Credit_Utilization_Ratio [32.30552378486248 to 36.486018233613954]):**

- Support: 14.554%, Confidence: 50.188%, Lift: 1.003769, Leverage: 0.000546
- The 14.5% of the dataset in the dataset support that when a customer has a poor credit score, then their credit utilization ratio falling within the specified range.
- The confidence of 50.188% suggests that slightly over half of the customers with a poor credit score also have a credit utilization ratio within the specified range.
- The lift score of 1.003769 indicates a slightly positive association between these two groups.

4. **(Num_Bank_Accounts [5.0 to 7.0]) → (Credit_Score_Standard):**

- Support: 29.6351%, Confidence: 58.3212%, Lift: 1.096784, Leverage: 0.026151
- This association rule suggests when a customer has between 5 and 7 bank accounts, 29.6% of data supports that they will have a standard credit score.
- Furthermore, If a customer has a number of bank accounts in this range, there's a 58.3% confidence that his credit score is standard.
- The lift score of 1.096784 suggests a modestly favorable association between these two groups.

5. **(Payment_Behaviour_High_spent_Medium_value_payments) → (Credit_Score_Standard):**

- Support: 10.5247%, Confidence: 54.3427, Lift: 1.0219, 4 Leverage: 0.002262
- The 10.5% of the dataset aligns with the rule that a high spent medium value payment behaviour will have a standard credit score.
- We have 54% confidence over the customers with the specified payment behavior have a standard credit score.
- The lift of 1.021964 indicates that this association is slightly more likely to occur than if the two variables were independent.

6. **(Num_Credit_Card [5.0 to 7.0]) → (Credit_Score_Standard):**

- Support: 29.5811%, Confidence: 55.9594%, Lift: 1.052368, Leverage: 0.01472
- This rule indicates that when a customer has between 5 and 7 credit cards, they tend to have a standard credit score, nearly 29.6% of instances in the dataset support this rule.
- The confidence suggests that slightly over 55.9% of customers with this specific range of credit cards have a standard credit score.
- With a lift value of 1.052368, this association is slightly more probable than if the two variables were independent.

7. **(Credit_Score_Good) → (Outstanding_Debt [1166.23 to 1946.81]):**

- Support: 10.4497%, Confidence: 58.6199%, Lift: 1.17241, Leverage: 0.015367
- Over 10.4% of dataset supports that, when a customer has a good credit score, his outstanding debt falling within the specified range.
- Additionally, there is a 58.6% confidence that if a transaction has a good credit score, then the outstanding debt lies in the range.
- The lift score of 1.17 indicates a positive association between these two groups.

8. **(Credit_Score_Good) → (Payment_of_Min_Amount_No):**

- Support: 13.669%, Confidence: 76.6788%, Lift: 2.150125, Leverage: 0.073117
- The Customer has a good credit score tend to opt for paying the full amount instead of making minimum payments, denoting no minimum payments with a support of 13.7%.
- The confidence of 76.6788% suggests that over 76% of customers with a good credit score do not make minimum payments.

- The lift of 2.150125 indicates that this association is more than twice as likely to occur as if the two variables were independent.

9. **(Credit_Score_Good) → (Num_Credit_Card [4.0 to 5.0]):**

- Support: 10.1177%, Confidence: 56.7574%, Lift: 1.757289, Leverage: 0.043601
- This rule suggests that when a customer has a good credit score, he is having between 4 and 5 credit cards with 10.1% of dataset support.
- Furthermore, if a customer has a good credit score, there’s a 56.8% confidence that his number of credit cards is in the specified range.
- The lift score of 1.76 indicates a strong positive association between these two groups.

In [ ]:
```

```