Bank Customer Behaviour Prediction

We have been provided the data from a credit card processor company which has approximately 20000 records of the same number of users which are represented by their IDs to keep their privacy. The data is of customer credit card/debit card spend of three months(April, May & June) and we have to predict their expected average spend in the coming 3 months (July, August & September). We have been provided a separate dataset that has the average of three month (July, August & September) for some entries and not all which we have to predict based on the previous month data and other factors in the dataset. The entries we have been provided can be our training dataset and we have to match our predicted average with the actual values. The model with the lowest Root Mean Square Percentage Error (RMSPE) will be selected.

Step 1: Setting up the work environment

We will download the necessary packages and obtain the datasets. We wil have a quick overview of the datatypes.

In [64]:
```
#getting packages
import pandas as pd        # For data manipulation and analysis
import numpy as np         # For numerical operations
import matplotlib.pyplot as plt    # For basic data visualization
import seaborn as sns      # For advanced data visualization
from scipy import stats # For statistics
from sklearn.linear_model import LinearRegression #For linear regression
from sklearn.metrics import mean_squared_error, make_scorer   #For Error measurement
from sklearn.model_selection import train_test_split #for model training and testing
from sklearn.metrics import r2_score #for model efficiency
from sklearn.linear_model import Ridge #for ridge regularization
from sklearn.linear_model import Lasso #for lasso regularization
from sklearn.tree import DecisionTreeRegressor #for decision tree regression
from sklearn.ensemble import RandomForestRegressor #for random forest regression
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV  #for Hyperparameter tuning
```

In [2]:
```
#getting the dataset

bcd= pd.read_excel('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Bank customer analysis\\CustomerBe
bcd.head()
```

Out[2]:

	ID	cc_cons_apr	dc_cons_apr	cc_cons_may	dc_cons_may	cc_cons_jun	dc_cons_jun	cc_count_apr	cc_count_may	cc_count_jun	...	credit_
0	17051	3412.60	2909.34	1077.36	3084.50	4615.97	6693.0	19.0	10	2	...	
1	11491	18133.76	3877.00	6123.78	5597.43	64620.00	6117.0	4.0	60	1	...	
2	7433	6363.65	735.49	8799.00	13768.00	38266.00	2638.0	2.0	83	47	...	
3	14606	12765.66	4429.16	16745.86	6360.00	29063.97	3711.0	12.0	2	16	...	
4	8381	27819.70	1944.00	7006.50	2228.50	1096.25	1065.0	15.0	13	61	...	

5 rows × 39 columns

In [3]:
```
#examining the dataset
bcd.shape
```

Out[3]:
```
(20000, 39)
```

In [4]:
```
#seeing datatypes
bcd.dtypes
```

Out[4]:
```
ID                          int64
cc_cons_apr               float64
dc_cons_apr               float64
cc_cons_may               float64
dc_cons_may               float64
cc_cons_jun               float64
dc_cons_jun               float64
cc_count_apr              float64
cc_count_may                int64
cc_count_jun                int64
dc_count_apr                int64
dc_count_may                int64
dc_count_jun                int64
card_lim                    int64
personal_loan_active        int64
vehicle_loan_active         int64
personal_loan_closed      float64
vehicle_loan_closed         int64
investment_1              float64
investment_2              float64
investment_3              float64
investment_4              float64
debit_amount_apr          float64
credit_amount_apr         float64
debit_count_apr           float64
credit_count_apr            int64
max_credit_amount_apr     float64
debit_amount_may          float64
credit_amount_may         float64
credit_count_may            int64
debit_count_may             int64
max_credit_amount_may     float64
debit_amount_jun          float64
credit_amount_jun         float64
credit_count_jun            int64
debit_count_jun             int64
max_credit_amount_jun     float64
loan_enq                   object
emi_active                float64
dtype: object
```

Step 2: Data cleaning/formatting

We are going to remove abnormally high/low values from the dataset in order to make sure we can take out better insights from the data. The columns in the dataset are going to be converted into proper format and all irregulairties would be removed.

In [5]:
```
#seeing missing values
bcd.isnull().sum()
```

Out[5]:
```
ID                         0
cc_cons_apr                0
dc_cons_apr                0
cc_cons_may                1
dc_cons_may                0
cc_cons_jun                0
dc_cons_jun                1
cc_count_apr               1
cc_count_may               0
cc_count_jun               0
dc_count_apr               0
dc_count_may               0
dc_count_jun               0
card_lim                   0
personal_loan_active       0
vehicle_loan_active        0
personal_loan_closed       1
vehicle_loan_closed        0
investment_1               0
investment_2               0
investment_3               2
investment_4               0
debit_amount_apr           0
credit_amount_apr          0
debit_count_apr            1
credit_count_apr           0
max_credit_amount_apr      0
debit_amount_may           0
credit_amount_may          0
credit_count_may           0
debit_count_may            0
max_credit_amount_may      0
debit_amount_jun           0
credit_amount_jun          0
credit_count_jun           0
debit_count_jun            0
max_credit_amount_jun      0
loan_enq                   2
emi_active                 1
dtype: int64
```

In [6]:
```
#dropping null values
bcd=bcd.dropna()
bcd
```

Out[6]:

	ID	cc_cons_apr	dc_cons_apr	cc_cons_may	dc_cons_may	cc_cons_jun	dc_cons_jun	cc_count_apr	cc_count_may	cc_count_jun	...	cr
0	17051	3412.600	2909.34	1077.36	3084.50	4615.97	6693.00	19.0	10	2	...	
1	11491	18133.760	3877.00	6123.78	5597.43	64620.00	6117.00	4.0	60	1	...	
2	7433	6363.650	735.49	8799.00	13768.00	38266.00	2638.00	2.0	83	47	...	
3	14606	12765.660	4429.16	16745.86	6360.00	29063.97	3711.00	12.0	2	16	...	
4	8381	27819.700	1944.00	7006.50	2228.50	1096.25	1065.00	15.0	13	61	...	
...	...	...	...	...	...	...	...	...	...	...	...	...
19995	12512	4641.500	5979.58	6008.61	4410.00	41743.00	1884.00	26.0	1	4	...	
19996	14224	4994.450	2805.37	23214.00	5870.00	1041.00	1008.73	37.0	56	50	...	
19997	18740	3262.145	2871.00	7335.25	11774.04	4130.00	1413.00	12.0	77	1	...	
19998	18134	12824.010	4866.00	12242.48	284.00	15132.77	37911.00	67.0	1	4	...	
19999	12413	26218.000	6615.00	2832.00	4642.00	1314.64	11355.00	7.0	1	84	...	

19993 rows × 39 columns

In [7]:
```
#Dropping irrelevant columns
columns_to_drop = ['loan_enq', 'personal_loan_active','vehicle_loan_active','personal_loan_closed','vehicle_loa

# Drop the specified columns
bcd = bcd.drop(columns=columns_to_drop)

# Display the modified DataFrame
bcd.head()
```

Out[7]:

	ID	cc_cons_apr	dc_cons_apr	cc_cons_may	dc_cons_may	cc_cons_jun	dc_cons_jun	cc_count_apr	cc_count_may	cc_count_jun	...	credit_
0	17051	3412.60	2909.34	1077.36	3084.50	4615.97	6693.0	19.0	10	2	...	
1	11491	18133.76	3877.00	6123.78	5597.43	64620.00	6117.0	4.0	60	1	...	
2	7433	6363.65	735.49	8799.00	13768.00	38266.00	2638.0	2.0	83	47	...	
3	14606	12765.66	4429.16	16745.86	6360.00	29063.97	3711.0	12.0	2	16	...	
4	8381	27819.70	1944.00	7006.50	2228.50	1096.25	1065.0	15.0	13	61	...	

5 rows × 34 columns

In [8]:
```
#making the data type appropriate
bcd['ID'] = bcd['ID'].astype(str)
```

In [9]:
```
#seeing new datatypes
bcd.dtypes
```

Out[9]:
```
ID                         object
cc_cons_apr               float64
dc_cons_apr               float64
cc_cons_may               float64
dc_cons_may               float64
cc_cons_jun               float64
dc_cons_jun               float64
cc_count_apr              float64
cc_count_may                int64
cc_count_jun                int64
dc_count_apr                int64
dc_count_may                int64
dc_count_jun                int64
card_lim                    int64
investment_1              float64
investment_2              float64
investment_3              float64
investment_4              float64
debit_amount_apr          float64
credit_amount_apr         float64
debit_count_apr           float64
credit_count_apr            int64
max_credit_amount_apr     float64
debit_amount_may          float64
credit_amount_may         float64
credit_count_may            int64
debit_count_may             int64
max_credit_amount_may     float64
debit_amount_jun          float64
credit_amount_jun         float64
credit_count_jun            int64
debit_count_jun             int64
max_credit_amount_jun     float64
emi_active                float64
dtype: object
```

In [10]:
```
#function to handle outliers


def handle_extreme_values_iqr(data, variables, multiplier=1.5):

    modified_data = data.copy()

    for variable in variables:
        Q1 = data[variable].quantile(0.25)
        Q3 = data[variable].quantile(0.75)
        IQR = Q3 - Q1

        lower_bound = Q1 - multiplier * IQR
        upper_bound = Q3 + multiplier * IQR


        modified_data[variable] = data[variable].apply(lambda x: x if lower_bound <= x <= upper_bound else data

    return modified_data
```

In [11]:
```
#handling outliers for numerical variables

variables_to_handle = [
    'cc_cons_apr', 'dc_cons_apr', 'cc_cons_may', 'dc_cons_may', 'cc_cons_jun', 'dc_cons_jun',
    'cc_count_apr', 'cc_count_may', 'cc_count_jun',
    'dc_count_apr', 'dc_count_may', 'dc_count_jun',
    'card_lim',
    'investment_1', 'investment_2', 'investment_3', 'investment_4',
    'debit_amount_apr', 'credit_amount_apr', 'debit_count_apr', 'credit_count_apr', 'max_credit_amount_apr',
    'debit_amount_may', 'credit_amount_may', 'credit_count_may', 'debit_count_may', 'max_credit_amount_may',
    'debit_amount_jun', 'credit_amount_jun', 'credit_count_jun', 'debit_count_jun', 'max_credit_amount_jun',
    'emi_active'
]

bcd = handle_extreme_values_iqr(bcd, variables_to_handle)
bcd
```

Out[11]:

	ID	cc_cons_apr	dc_cons_apr	cc_cons_may	dc_cons_may	cc_cons_jun	dc_cons_jun	cc_count_apr	cc_count_may	cc_count_jun	...	cr
0	17051	3412.600	2909.34	1077.36	3084.50	4615.97	6693.00	19.0	10.0	2.0	...	
1	11491	18133.760	3877.00	6123.78	5597.43	6656.80	6117.00	4.0	60.0	1.0	...	
2	7433	6363.650	735.49	8799.00	13768.00	6656.80	2638.00	2.0	83.0	47.0	...	
3	14606	12765.660	4429.16	16745.86	6360.00	29063.97	3711.00	12.0	2.0	16.0	...	
4	8381	27819.700	1944.00	7006.50	2228.50	1096.25	1065.00	15.0	13.0	61.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	...
19995	12512	4641.500	5979.58	6008.61	4410.00	6656.80	1884.00	26.0	1.0	4.0	...	
19996	14224	4994.450	2805.37	23214.00	5870.00	1041.00	1008.73	37.0	56.0	50.0	...	
19997	18740	3262.145	2871.00	7335.25	11774.04	4130.00	1413.00	12.0	77.0	1.0	...	
19998	18134	12824.010	4866.00	12242.48	284.00	15132.77	3326.00	67.0	1.0	4.0	...	
19999	12413	26218.000	6615.00	2832.00	4642.00	1314.64	11355.00	7.0	1.0	84.0	...	

19993 rows × 34 columns

Step 3:Feature engineering

We are going to combine and modify existing variables to help us explore newer patterns and relationships. Our aim is to find out what affects the credit card consumption of the customers

In [12]:
```
#making new feature total customer investment
bcd['total_customer_investment']=bcd['investment_1']+bcd['investment_2']+bcd['investment_3']+bcd['investment_4'
```

In [13]:
```
#transaction count monthly
bcd['trans_cnt_apr']=bcd['cc_count_apr']+bcd['dc_count_apr']
bcd['trans_cnt_may']=bcd['cc_count_may']+bcd['dc_count_may']
bcd['trans_cnt_jun']=bcd['cc_count_jun']+bcd['dc_count_jun']
```

In [14]:
```
#  Credit Card Utilization Monthly Rate
bcd['card_utilization_apr'] = bcd['credit_amount_apr'] / bcd['max_credit_amount_apr']
bcd['card_utilization_may'] = bcd['credit_amount_may'] / bcd['max_credit_amount_may']
bcd['card_utilization_jun'] = bcd['credit_amount_jun'] / bcd['max_credit_amount_jun']
```

In [15]:
```
# Credit card utilization ratio per individual
bcd['Credit_Card_Utilization_Ratio'] = (bcd['cc_count_apr'] + bcd['cc_count_may'] + bcd['cc_count_jun']) / (bcd
```

In [16]:
```
#removing obsolete features
obsolete_columns = ['cc_count_apr','dc_count_apr','cc_count_may','dc_count_may','cc_count_jun','dc_count_jun',
                    'credit_amount_apr','max_credit_amount_apr','credit_amount_may','max_credit_amount_may',
                    'credit_amount_jun','max_credit_amount_jun','investment_1','investment_2','investment_3','i
                   'cc_count_apr','cc_count_may','cc_count_jun','card_lim']

bcd.drop(columns=obsolete_columns, inplace=True)


bcd.head()
```

Out[16]:

	ID	cc_cons_apr	dc_cons_apr	cc_cons_may	dc_cons_may	cc_cons_jun	dc_cons_jun	debit_amount_apr	debit_count_apr	credit_count_apr
0	17051	3412.60	2909.34	1077.36	3084.50	4615.97	6693.0	25210.23	103.0	36.0
1	11491	18133.76	3877.00	6123.78	5597.43	6656.80	6117.0	30937.00	40.0	35.0
2	7433	6363.65	735.49	8799.00	13768.00	6656.80	2638.0	12940.25	11.0	3.0
3	14606	12765.66	4429.16	16745.86	6360.00	29063.97	3711.0	78122.15	42.0	26.0
4	8381	27819.70	1944.00	7006.50	2228.50	1096.25	1065.0	6855.71	46.0	35.0

5 rows × 25 columns

In [17]:
```
#examining new dataset
bcd.dtypes
```

Out[17]:
```
ID                                object
cc_cons_apr                      float64
dc_cons_apr                      float64
cc_cons_may                      float64
dc_cons_may                      float64
cc_cons_jun                      float64
dc_cons_jun                      float64
debit_amount_apr                 float64
debit_count_apr                  float64
credit_count_apr                 float64
debit_amount_may                 float64
credit_count_may                 float64
debit_count_may                  float64
debit_amount_jun                 float64
credit_count_jun                 float64
debit_count_jun                    int64
emi_active                       float64
total_customer_investment        float64
trans_cnt_apr                    float64
trans_cnt_may                    float64
trans_cnt_jun                    float64
card_utilization_apr             float64
card_utilization_may             float64
card_utilization_jun             float64
Credit_Card_Utilization_Ratio    float64
dtype: object
```

Step 4:Exploratory Data Analysis

We can explore the dataset to get some sample insights and get to know what is happening. Charts will be used to provide key insights.

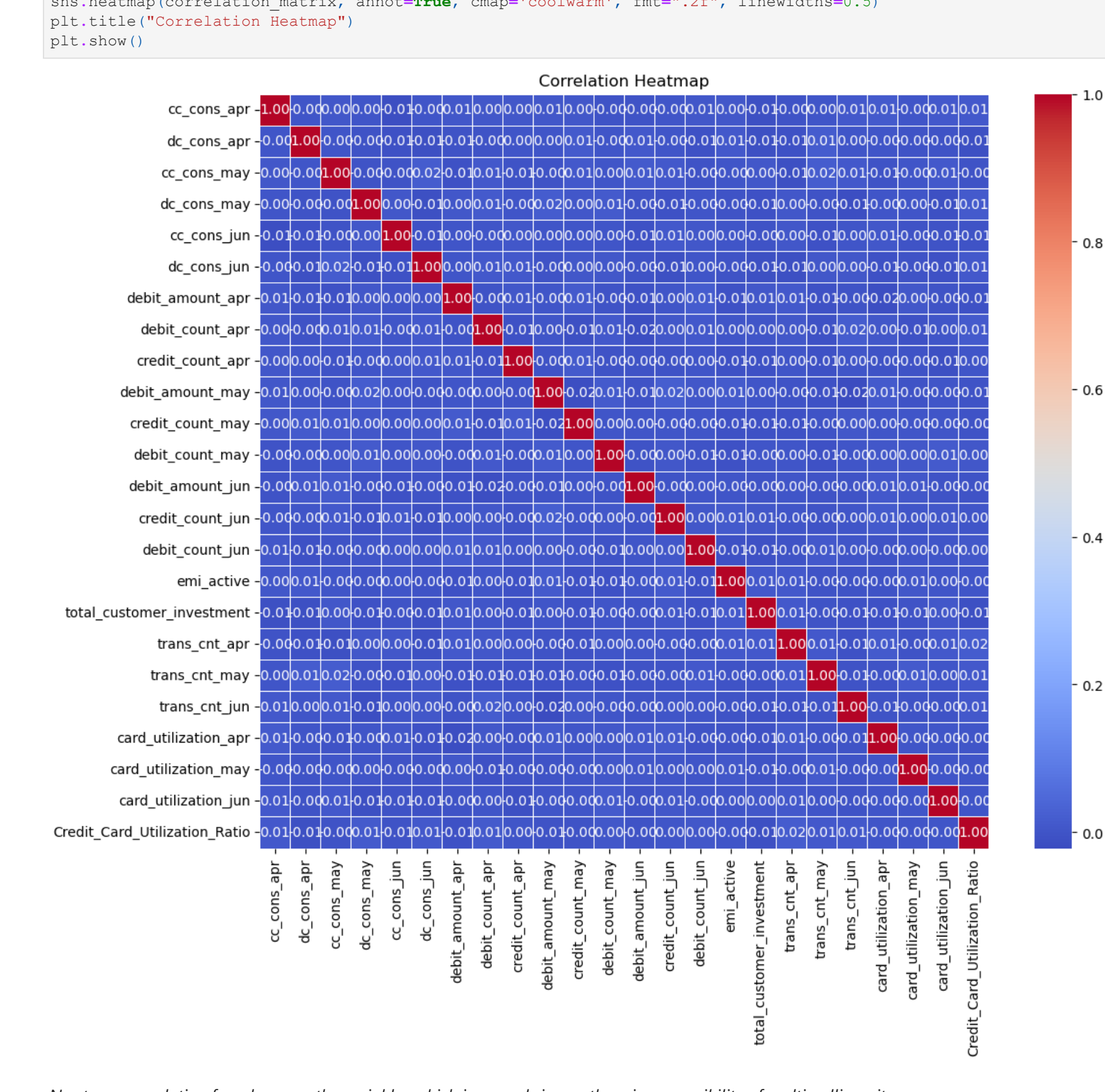
In [18]:
```
# Correlation matrix
selected_variables = bcd[['cc_cons_apr', 'dc_cons_apr', 'cc_cons_may', 'dc_cons_may', 'cc_cons_jun',
                          'dc_cons_jun', 'debit_amount_apr', 'debit_count_apr', 'credit_count_apr',
                          'debit_amount_may', 'credit_count_may', 'debit_count_may', 'debit_amount_jun',
                          'credit_count_jun', 'debit_count_jun', 'emi_active', 'total_customer_investment',
                          'trans_cnt_apr', 'trans_cnt_may', 'trans_cnt_jun', 'card_utilization_apr',
                          'card_utilization_may', 'card_utilization_jun', 'Credit_Card_Utilization_Ratio']]

# Calculate the correlation matrix
correlation_matrix = selected_variables.corr()
correlation_matrix
```

Out[18]:

	cc_cons_apr	dc_cons_apr	cc_cons_may	dc_cons_may	cc_cons_jun	dc_cons_jun	debit_amount_apr	debit_count_apr
cc_cons_apr	1.000000	-0.001275	0.004917	0.000080	-0.014216	-0.000528	0.005683	0.002309
dc_cons_apr	-0.001275	1.000000	-0.000803	-0.004023	-0.006619	-0.010639	-0.005637	-0.002008
cc_cons_may	0.004917	-0.000803	1.000000	-0.002010	-0.001732	0.016929	-0.008218	0.006594
dc_cons_may	0.000080	-0.004023	-0.002010	1.000000	0.004554	-0.012510	0.002463	0.010275
cc_cons_jun	-0.014216	-0.006619	-0.001732	0.004554	1.000000	-0.006032	0.000919	-0.001655
dc_cons_jun	-0.000528	-0.010639	0.016929	-0.012510	-0.006032	1.000000	0.002009	0.007764
debit_amount_apr	0.005683	-0.005637	-0.008218	0.002463	0.000919	0.002009	1.000000	-0.004088
debit_count_apr	0.002309	-0.002008	0.006594	0.010275	-0.001655	0.007764	-0.004088	1.000000
credit_count_apr	0.002384	0.002238	-0.005534	-0.000416	0.003518	0.008216	0.005121	-0.009258
debit_amount_may	0.006166	0.001733	-0.004004	0.017780	0.000497	-0.003704	-0.000274	0.002183
credit_count_may	0.004962	0.011687	0.007574	0.002609	0.001737	0.003540	0.010622	-0.010651
debit_count_may	-0.002987	-0.001056	0.000755	0.012380	0.001677	0.003923	-0.002348	0.009912
debit_amount_jun	-0.002675	0.010105	0.011248	-0.004335	-0.006457	-0.002188	-0.009081	-0.017451
credit_count_jun	-0.001527	-0.000962	0.010145	-0.008598	0.009133	-0.011623	0.001570	0.003546
debit_count_jun	0.005076	-0.008494	-0.002557	-0.000246	0.002539	0.001351	0.014925	0.007836
emi_active	0.004577	0.008298	-0.000655	-0.004041	0.000558	-0.002844	-0.007553	0.001472
total_customer_investment	-0.010084	-0.012977	0.004311	-0.009223	-0.002129	-0.013059	0.005414	0.000465
trans_cnt_apr	-0.003899	-0.006507	-0.013047	0.004395	0.004365	-0.011500	0.006823	0.003614
trans_cnt_may	0.000251	0.014846	0.017725	-0.002889	-0.007078	0.004006	-0.006631	-0.007309
trans_cnt_jun	0.009876	0.001338	0.007400	-0.014242	0.000143	0.002707	-0.001943	0.015748
card_utilization_apr	0.011331	-0.000304	-0.005396	-0.001061	0.005441	-0.006388	-0.015463	0.002351
card_utilization_may	-0.000113	-0.002418	-0.001411	0.000174	-0.003373	-0.003798	0.003836	-0.006587
card_utilization_jun	0.008657	-0.002367	0.007293	-0.012344	-0.005121	-0.008001	-0.002425	0.001853
Credit_Card_Utilization_Ratio	0.008048	-0.012454	-0.002805	0.011316	-0.005241	0.009788	-0.008037	0.011270

24 rows × 24 columns

In [19]:
```
# Create a heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```

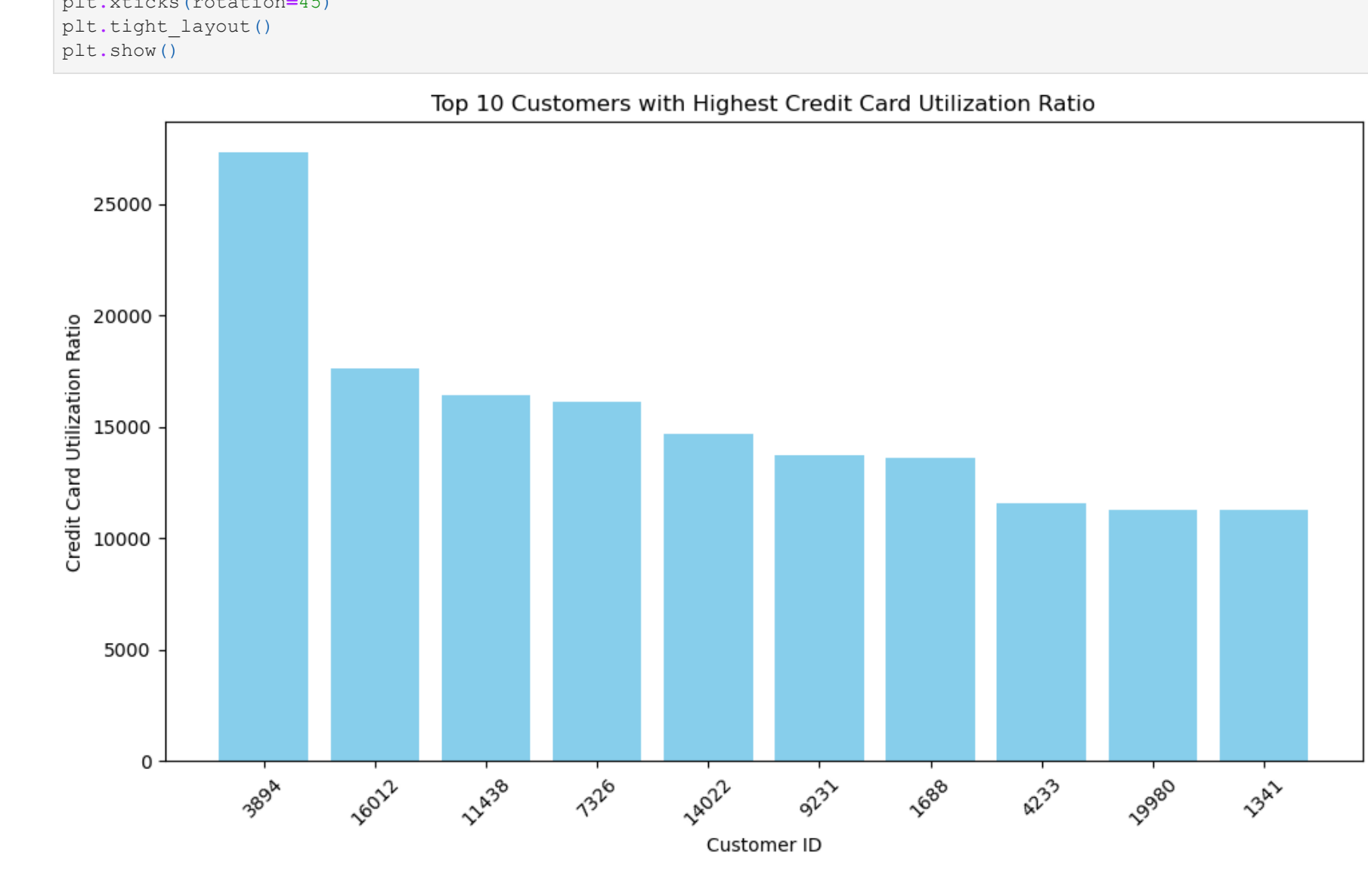


No strong correlation found among the variables which is a good sign as there is no possibility of multi-collinearity

In [20]:
```
#Seeing the IDs with highest utilization ratio
sorted_df = bcd.sort_values(by='Credit_Card_Utilization_Ratio', ascending=False)


top_10_ids = sorted_df[['ID', 'Credit_Card_Utilization_Ratio']].head(10)


print(top_10_ids)
```

```
          ID  Credit_Card_Utilization_Ratio
18220   3894                        27300.0
10316  16012                        17600.0
12321  11438                        16400.0
1657    7326                        16100.0
17668  14022                        14700.0
8533    9231                        13700.0
13302   1688                        13600.0
9844    4233                        11600.0
16896  19980                        11300.0
18350   1341                        11300.0
```

In [21]:
```
# Chart vizualization of the top 10 IDs with highest utilization ratio
plt.figure(figsize=(10, 6))
plt.bar(top_10_ids['ID'], top_10_ids['Credit_Card_Utilization_Ratio'], color='skyblue')
plt.xlabel('Customer ID')
plt.ylabel('Credit Card Utilization Ratio')
plt.title('Top 10 Customers with Highest Credit Card Utilization Ratio')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

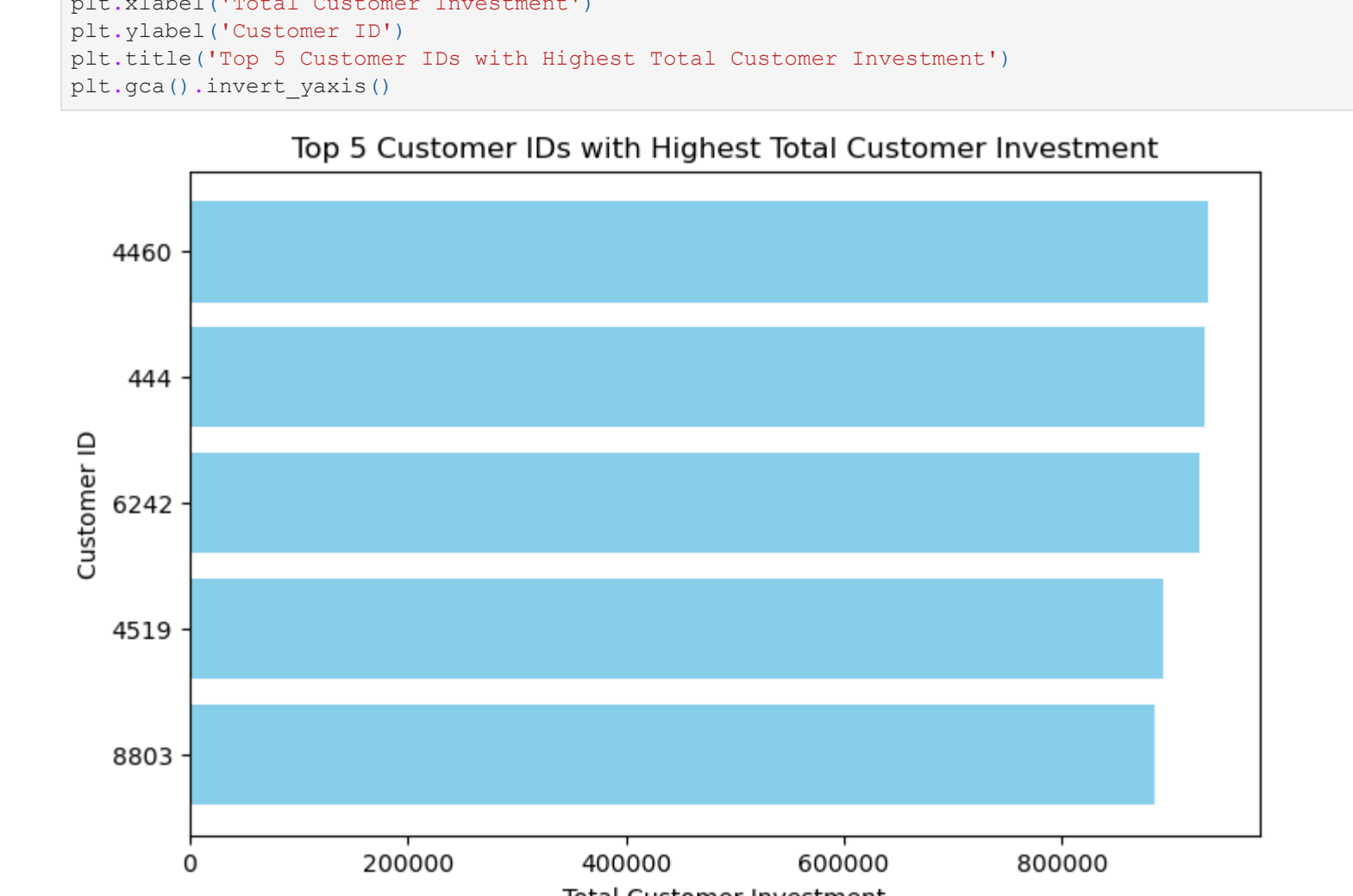


This ratio is supposed to be in decimals but it is whole number which is strange. Actually they are card defaulters whose limit is zero but however they have managed to spend a substantial amount with their credit card which can be attributed to the lapse of the bank authorities.(The formula had plus 1 in the denominator to catch them!)

In [22]:
```
#Top 5 highest investors
sorted_df = bcd.sort_values(by='total_customer_investment', ascending=False)

# Get the top 5 IDs with the highest customer investment
top_5_investment_ids = sorted_df[['ID', 'total_customer_investment']].head(5)

# Print or display the result
print(top_5_investment_ids)
```

```
         ID  total_customer_investment
16320  4460               934423.25000
10260   444               930183.12023
19589  6242               926843.37000
2876   4519               892290.20000
6810   8803               884849.37000
```

In [23]:
```
# Chart vizualization of the top 5 IDs with highest investment
plt.figure(figsize=(8, 5))
plt.barh(top_5_investment_ids['ID'], top_5_investment_ids['total_customer_investment'], color='skyblue')
plt.xlabel('Total Customer Investment')
plt.ylabel('Customer ID')
plt.title('Top 5 Customer IDs with Highest Total Customer Investment')
plt.gca().invert_yaxis()
```



These are the IDs with the highest investment and care must be taken to retain these customers

Step 5: Model Building

Now it is time to build a regression model that is going to use the independent variables to predict the customer spend of July, August and September. The model with highest R squared value will be used.

In [24]:
```
# Loading the validation dataset
ccp = pd.read_excel('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Bank customer analysis\\CreditCon
ccp.head()
```

Out[24]:

	ID	cc_cons
0	12554	20014.0
1	17645	10173.0
2	7604	16095.0
3	1590	7707.0
4	16556	96408.0

In [25]:
```
#making the data type appropriate
ccp['ID'] = ccp['ID'].astype(str)
```

In [26]:
```
# Assuming 'ID' is the common column
merged_df = bcd.merge(ccp[['ID', 'cc_cons']], on='ID', how='left')
merged_df.head()
```

Out[26]:

	ID	cc_cons_apr	dc_cons_apr	cc_cons_may	dc_cons_may	cc_cons_jun	dc_cons_jun	debit_amount_apr	debit_count_apr	credit_count_apr
0	17051	3412.60	2909.34	1077.36	3084.50	4615.97	6693.0	25210.23	103.0	36.0
1	11491	18133.76	3877.00	6123.78	5597.43	6656.80	6117.0	30937.00	40.0	35.0
2	7433	6363.65	735.49	8799.00	13768.00	6656.80	2638.0	12940.25	11.0	3.0
3	14606	12765.66	4429.16	16745.86	6360.00	29063.97	3711.0	78122.15	42.0	26.0
4	8381	27819.70	1944.00	7006.50	2228.50	1096.25	1065.0	6855.71	46.0	35.0

5 rows × 26 columns

In [27]:
```
# Splitting data into known and missing values
known_data = merged_df[merged_df['cc_cons'].notna()]
missing_data = merged_df[merged_df['cc_cons'].isna()]
```

In [28]:
```
#selecting feature and target variables
X  = known_data[['cc_cons_apr', 'dc_cons_apr', 'cc_cons_may', 'dc_cons_may', 'cc_cons_jun', 'dc_cons_jun',
        'debit_amount_apr', 'debit_count_apr', 'credit_count_apr', 'debit_amount_may', 'credit_count_may',
        'debit_count_may', 'debit_amount_jun', 'credit_count_jun', 'debit_count_jun', 'emi_active',
        'total_customer_investment', 'trans_cnt_apr', 'trans_cnt_may', 'trans_cnt_jun',
        'card_utilization_apr', 'card_utilization_may', 'card_utilization_jun',
        'Credit_Card_Utilization_Ratio']]

y = known_data['cc_cons']
```

In [29]:
```
# Root Mean Square Percentage Error (RMSPE)
def rmspe(y_true, y_pred):
    return np.sqrt(np.mean(((y_true - y_pred) / y_true) ** 2)) * 100
```

In [30]:
```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
```

In [31]:
```
# Train your model (e.g., Linear Regression)
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[31]:
```
▾ LinearRegression
LinearRegression()
```

In [32]:
```
# Making predictions on the test set
y_pred_lin = model.predict(X_test)
```

In [33]:
```
# Calculate RMSPE for linear regression model
rmspe_value = rmspe(y_test, y_pred_lin)
print("RMSPE on Test Set:", rmspe_value)
```

```
RMSPE on Test Set: 10656.049078046442
```

In [34]:
```
# Ridge Regression model
ridge_model = Ridge(alpha=1.0)
ridge_model.fit(X_train, y_train)
```

Out[34]:
```
▾ Ridge
Ridge()
```

In [35]:
```
#  predictions on the test set
y_pred_ridge = ridge_model.predict(X_test)
```

In [36]:
```
# Calculate RMSPE for Ridge Regression model
rmspe_value = rmspe(y_test, y_pred_ridge)
print("RMSPE on Test Set:", rmspe_value)
```

```
RMSPE on Test Set: 10656.048912840028
```

In [37]:
```
# Lasso Regression model
lasso_model = Lasso(alpha=1.0)
lasso_model.fit(X_train, y_train)
```

Out[37]:
```
▾ Lasso
Lasso()
```

In [38]:
```
# predictions on the test set
y_pred_lasso = lasso_model.predict(X_test)
```

In [39]:
```
# Calculate RMSPE for Lasso Regression model
rmspe_value = rmspe(y_test, y_pred_lasso)
print("RMSPE on Test Set:", rmspe_value)
```

```
RMSPE on Test Set: 10656.011804731375
```

In [40]:
```
# Decision Tree Regression model
tree_model = DecisionTreeRegressor(max_depth=5)
tree_model.fit(X_train, y_train)
```

Out[40]:
```
▾     DecisionTreeRegressor
DecisionTreeRegressor(max_depth=5)
```

In [41]:
```
# predictions on the test set
y_pred_tree = tree_model.predict(X_test)
```

In [42]:
```
# Calculate RMSPE for Decision Tree Regression model
rmspe_value = rmspe(y_test, y_pred_tree)
print("RMSPE on Test Set:", rmspe_value)
```

```
RMSPE on Test Set: 10112.220502139253
```

In [43]:
```
# Random Forest Regression model
rf_model = RandomForestRegressor(n_estimators=400)
rf_model.fit(X_train, y_train)
```

Out[43]:
```
▾       RandomForestRegressor
RandomForestRegressor(n_estimators=400)
```

In [44]:
```
# predictions on the test set
y_pred_rf = rf_model.predict(X_test)
```

In [45]:
```
# Calculate RMSPE for Random Forest Regression mode
rmspe_value = rmspe(y_test, y_pred_rf)
print("RMSPE on Test Set:", rmspe_value)
```

```
RMSPE on Test Set: 14118.07642945612
```

After trying every available regression model, we are unable to get good results as they are in negative,so the next step of hyperparameter tuning needs to be taken

Step 6:Hyperparameter Tuning

In this step, we are going to upgrade the Decision Tree regressor model so that it is able to select the best hyper parameters which would help it predict the target variable. We have selected the Decision Tree regressor model because it has the lowest error.

In [73]:
```
# Defining the hyperparameters and their possible values
param_dist = {
    'max_depth': [None] + list(np.arange(10, 110, 10)),
    'min_samples_split': [2, 5, 10, 20, 30, 40, 50],
    'min_samples_leaf': [1, 2, 4, 8, 16],
    'max_features': ['auto', 'sqrt', 'log2'],
    'criterion': ['mse', 'friedman_mse', 'mae'],
    'splitter': ['best', 'random'],
    'min_weight_fraction_leaf': [0.0, 0.1, 0.2, 0.3, 0.4],
    'max_leaf_nodes': [None] + list(np.arange(10, 110, 10)),
    'min_impurity_decrease': [0.0, 0.1, 0.2, 0.3, 0.4],
    'random_state': [42]
}
```

In [74]:
```
# Decision Tree Regressor
dtree = DecisionTreeRegressor(random_state=42)
```

In [75]:
```
# scorer based on RMSE
scoring = make_scorer(rmspe, greater_is_better=False)
```

In [76]:
```
# RandomizedSearchCV object
random_search = RandomizedSearchCV(
    estimator=dtree,
    param_distributions=param_dist,
    n_iter=50,  # Adjust the number of iterations
    cv=5,
    scoring=scoring,
    n_jobs=-1  # Use all available CPU cores for parallel processing
)
```

In [77]:
```
# Fitting the GridSearchCV object to training data
random_search.fit(X_train, y_train)
```

```
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\model_selection\_search.py:953: UserWarning: One or mor
e of the test scores are non-finite: [-inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf
 -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf
 -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf -inf
 -inf -inf -inf -inf -inf -inf -inf -inf]
  warnings.warn(
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\model_selection\_search.py:962: RuntimeWarning: invalid
value encountered in subtract
  (array - array_means[:, np.newaxis]) ** 2, axis=1, weights=weights
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\tree\_classes.py:306: FutureWarning: `max_features='aut
o'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_feat
ures=1.0'`.
  warnings.warn(
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\tree\_classes.py:404: FutureWarning: Criterion 'mae' wa
s deprecated in v1.0 and will be removed in version 1.2. Use `criterion='absolute_error'` which is equivalent.
  warnings.warn(
```

Out[77]:
```
▸        RandomizedSearchCV
▸ estimator: DecisionTreeRegressor
      ▸ DecisionTreeRegressor
```

In [78]:
```
# Getting the best hyperparameters from the grid search
best_params = random_search.best_params_
print("Best Hyperparameters:", best_params)
```

```
Best Hyperparameters: {'splitter': 'random', 'random_state': 42, 'min_weight_fraction_leaf': 0.0, 'min_samples_
split': 2, 'min_samples_leaf': 2, 'min_impurity_decrease': 0.0, 'max_leaf_nodes': 90, 'max_features': 'auto',
'max_depth': 70, 'criterion': 'mae'}
```

In [80]:
```
# Putting the best hyperparameters in Decision Tree Regressor
best_dtree = DecisionTreeRegressor(**best_params)
```

In [81]:
```
# Train the model on the training data
best_dtree.fit(X_train, y_train)
```

```
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\tree\_classes.py:306: FutureWarning: `max_features='aut
o'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_feat
ures=1.0'`.
  warnings.warn(
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\tree\_classes.py:404: FutureWarning: Criterion 'mae' wa
s deprecated in v1.0 and will be removed in version 1.2. Use `criterion='absolute_error'` which is equivalent.
  warnings.warn(
```

Out[81]:
```
▾                     DecisionTreeRegressor
DecisionTreeRegressor(criterion='mae', max_depth=70, max_features='auto',
                      max_leaf_nodes=90, min_samples_leaf=2, random_state=42,
                      splitter='random')
```

In [82]:
```
# Make predictions on the test data
y_pred_best_dtree = best_dtree.predict(X_test)
```

In [83]:
```
# Calculate RMSE on the test data
rmspe_value = rmspe(y_test, y_pred_best_dtree)
print("RMSPE on Test Set:", rmspe_value)
```

```
RMSPE on Test Set: 5549.876172232738
```

We can see that after Hyperparameter tuning we are able to bring down the error to almost half the original value and hence we must select this model to predict the missing values.

Step 7:Model validation

This is the final step in this exercise and in this step we are going to predict the missing values of the dataset using the decision tree regressor model we perfected through hyperparameter tuning.

In [89]:
```
#getting the dependent variables
X_missing = missing_data[['cc_cons_apr', 'dc_cons_apr', 'cc_cons_may', 'dc_cons_may', 'cc_cons_jun', 'dc_cons_j
        'debit_amount_apr', 'debit_count_apr', 'credit_count_apr', 'debit_amount_may', 'credit_count_may',
        'debit_count_may', 'debit_amount_jun', 'credit_count_jun', 'debit_count_jun', 'emi_active',
        'total_customer_investment', 'trans_cnt_apr', 'trans_cnt_may', 'trans_cnt_jun',
        'card_utilization_apr', 'card_utilization_may', 'card_utilization_jun',
        'Credit_Card_Utilization_Ratio']]
```

In [90]:
```

# Predict the missing values
missing_data['cc_cons'] = best_dtree.predict(X_missing)
missing_data['cc_cons']
```

```
C:\Users\sujoydutta\AppData\Local\Temp\ipykernel_12120\1594784132.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  missing_data['cc_cons'] = best_dtree.predict(X_missing)
```

Out[90]:
```
14995    12708.0
14996    11711.0
14997    13396.5
14998    12708.0
14999    13396.5
          ...
19988    13396.5
19989    12708.0
19990    12171.5
19991    13396.5
19992    12708.0
Name: cc_cons, Length: 4998, dtype: float64
```

In [ ]:
```
# Output data frame with predicted values
output_df = missing_data[['ID', 'cc_cons']]
output_df.head()
```

In [95]:
```
# Making the final dataset
final_data = pd.concat([known_data, output_df], axis=0)

# Reset the index of the final DataFrame
final_data.reset_index(drop=True, inplace=True)
```

In [96]:
```
# Saving the final DataFrame to an Excel file
final_data.to_excel('final_data_with_missing_predictions.xlsx', index=False)
```

In [ ]: