How to process :

Load and Understand the Data

Load the dataset into a pandas DataFrame and inspect its structure. Identify the columns and their data types, look for missing values, and understand the data.

Data Preprocessing

Handle missing values and outliers. Encode categorical variables into numerical format. Normalize or scale numerical features if necessary.

Exploratory Data Analysis (EDA)

Visualize distributions, correlations, and imbalances in the data. Investigate relationships between features and the target variable (customer churn).

Feature Selection

Select the most impactful features using correlation matrices, statistical tests, or feature importance scores.

Model Building

Train multiple machine learning models such as Logistic Regression, Decision Trees, Random Forests, and k-NN. Split the dataset into training and testing subsets.

Model Evaluation

Use metrics like accuracy, precision, recall, F1-score, and AUC to evaluate the models.

Model Tuning and Refinement

Optimize hyperparameters of the selected models to improve their performance.

Expandability and Business Perspective

Interpret the model's output and explain the importance of features from a business standpoint.

Load and Understand the Data

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
data=pd.read_excel('account_churn_project.xlsx')
data.head(10)
```

```
   identification         churn_flag  age gender  number_dependants  \
0       768805383  Existing Customer   45      M                  3   
1       818770008  Existing Customer   49      F                  5   
2       713982108  Existing Customer   51      M                  3   
3       769911858  Existing Customer   40      F                  4   
```

```
4      709106358  Existing Customer   40      M                  3
5      713061558  Existing Customer   44      M                  2
6      810347208  Existing Customer   51      M                  4
7      818906208  Existing Customer   32      M                  0
8      710930508  Existing Customer   37      M                  3
9      719661558  Existing Customer   48      M                  2

     education civil_status          income account_category
account_age  \
0  High School      Married     $60K - $80K             Blue
39
1     Graduate       Single  Less than $40K             Blue
44
2     Graduate      Married    $80K - $120K             Blue
36
3  High School      Unknown  Less than $40K             Blue
34
4   Uneducated      Married     $60K - $80K             Blue
21
5     Graduate      Married     $40K - $60K             Blue
36
6      Unknown      Married         $120K +             Gold
46
7  High School      Unknown     $60K - $80K           Silver
27
8   Uneducated       Single     $60K - $80K             Blue
36
9     Graduate       Single    $80K - $120K             Blue
36

   ...  inactivity  past_contacts  card_Limit  balance  open_to_use  \
0  ...           1              3       12691      777        11914
1  ...           1              2        8256      864         7392
2  ...           1              0        3418        0         3418
3  ...           4              1        3313     2517          796
4  ...           1              0        4716        0         4716
5  ...           1              2        4010     1247         2763
6  ...           1              3       34516     2264        32252
7  ...           2              2       29081     1396        27685
8  ...           2              0       22352     2517        19835
9  ...           3              3       11656     1677         9979

   change_per_quarter_amount  total_transaction_amount  \
0                       1335                      1144
1                       1541                      1291
2                       2594                      1887
3                       1405                      1171
4                       2175                       816
5                       1376                      1088
6                       1975                      1330
```

```
7                       2204                          1538
8                       3355                          1350
9                       1524                          1441

   total_transaction_count  change_per_quarter_quantity  average_use
0                       42                         1625           61
1                       33                         3714          105
2                       20                         2333            0
3                       20                         2333           76
4                       28                           25            0
5                       24                          846          311
6                       31                          722           66
7                       36                          714           48
8                       24                         1182          113
9                       32                          882          144

[10 rows x 21 columns]
```

```python
# Identify the columns and their data types
print(data.info())

# Look for missing values
print("Missing values : ")
print(data.isnull().sum())

# Understand the data (basic statistics)
print(data.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 21 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   identification               10127 non-null  int64
 1   churn_flag                   10127 non-null  object
 2   age                          10127 non-null  int64
 3   gender                       10127 non-null  object
 4   number_dependants            10127 non-null  int64
 5   education                    10127 non-null  object
 6   civil_status                 10127 non-null  object
 7   income                       10127 non-null  object
 8   account_category             10127 non-null  object
 9   account_age                  10127 non-null  int64
 10  total_num_services           10127 non-null  int64
 11  inactivity                   10127 non-null  int64
 12  past_contacts                10127 non-null  int64
 13  card_Limit                   10127 non-null  int64
 14  balance                      10127 non-null  int64
 15  open_to_use                  10127 non-null  int64
 16  change_per_quarter_amount    10127 non-null  int64
```

```
 17  total_transaction_amount     10127 non-null  int64
 18  total_transaction_count      10127 non-null  int64
 19  change_per_quarter_quantity  10127 non-null  int64
 20  average_use                  10127 non-null  int64
dtypes: int64(15), object(6)
memory usage: 1.6+ MB
None
Missing values :
identification                0
churn_flag                    0
age                           0
gender                        0
number_dependants             0
education                     0
civil_status                  0
income                        0
account_category              0
account_age                   0
total_num_services            0
inactivity                    0
past_contacts                 0
card_Limit                    0
balance                       0
open_to_use                   0
change_per_quarter_amount     0
total_transaction_amount      0
total_transaction_count       0
change_per_quarter_quantity   0
average_use                   0
dtype: int64
       identification           age  number_dependants
account_age  \
count    1.012700e+04  10127.000000       10127.000000  10127.000000

mean     7.391776e+08     46.325960           2.346203     35.928409

std      3.690378e+07      8.016814           1.298908      7.986416

min      7.080821e+08     26.000000           0.000000     13.000000

25%      7.130368e+08     41.000000           1.000000     31.000000

50%      7.179264e+08     46.000000           2.000000     36.000000

75%      7.731435e+08     52.000000           3.000000     40.000000

max      8.283431e+08     73.000000           5.000000     56.000000


       total_num_services    inactivity  past_contacts
```

```
card_Limit  \
count         10127.000000  10127.000000   10127.000000  10127.000000

mean              3.812580      2.341167       2.455317   9280.019552

std               1.554408      1.010622       1.106225   9013.924409

min               1.000000      0.000000       0.000000   1439.000000

25%               3.000000      2.000000       2.000000   2787.000000

50%               4.000000      2.000000       2.000000   5363.000000

75%               5.000000      3.000000       3.000000  13576.000000

max               6.000000      6.000000       6.000000  34516.000000


            balance   open_to_use  change_per_quarter_amount  \
count  10127.000000  10127.000000               10127.000000
mean    1162.814061   7988.004345                 689.673645
std      814.987335   9054.851654                 297.521767
min        0.000000      3.000000                   0.000000
25%      359.000000   1463.500000                 579.000000
50%     1276.000000   4199.000000                 715.000000
75%     1784.000000  11456.000000                 844.000000
max     2517.000000  34516.000000                3397.000000

       total_transaction_amount  total_transaction_count  \
count              10127.000000             10127.000000
mean                4404.086304                64.858695
std                 3397.129254                23.472570
min                  510.000000                10.000000
25%                 2155.500000                45.000000
50%                 3899.000000                67.000000
75%                 4741.000000                81.000000
max                18484.000000               139.000000

       change_per_quarter_quantity   average_use
count                 10127.000000  10127.000000
mean                    591.557322    249.842500
std                     323.649708    272.424923
min                       0.000000      0.000000
25%                     438.500000      3.500000
50%                     655.000000    132.000000
75%                     786.000000    463.000000
max                    3714.000000    999.000000
```

Data Preprocessing

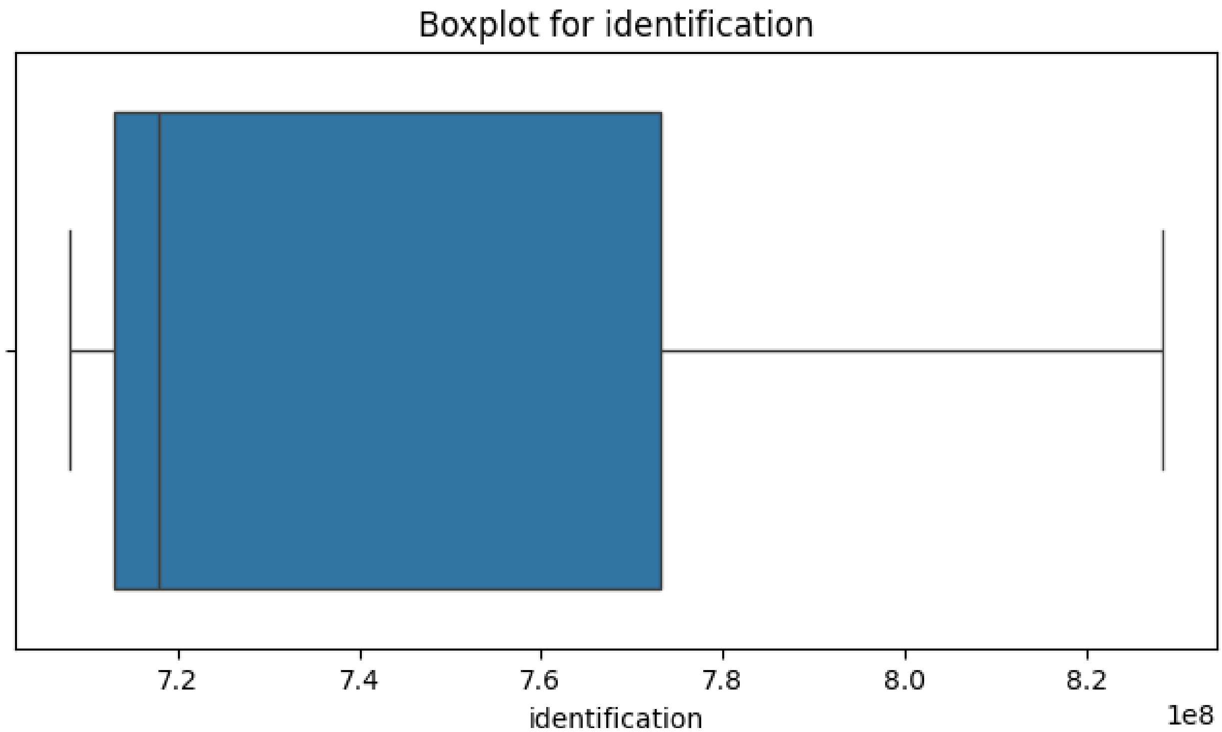
We don't have any missing value but we can still compute the following code lines to be sure

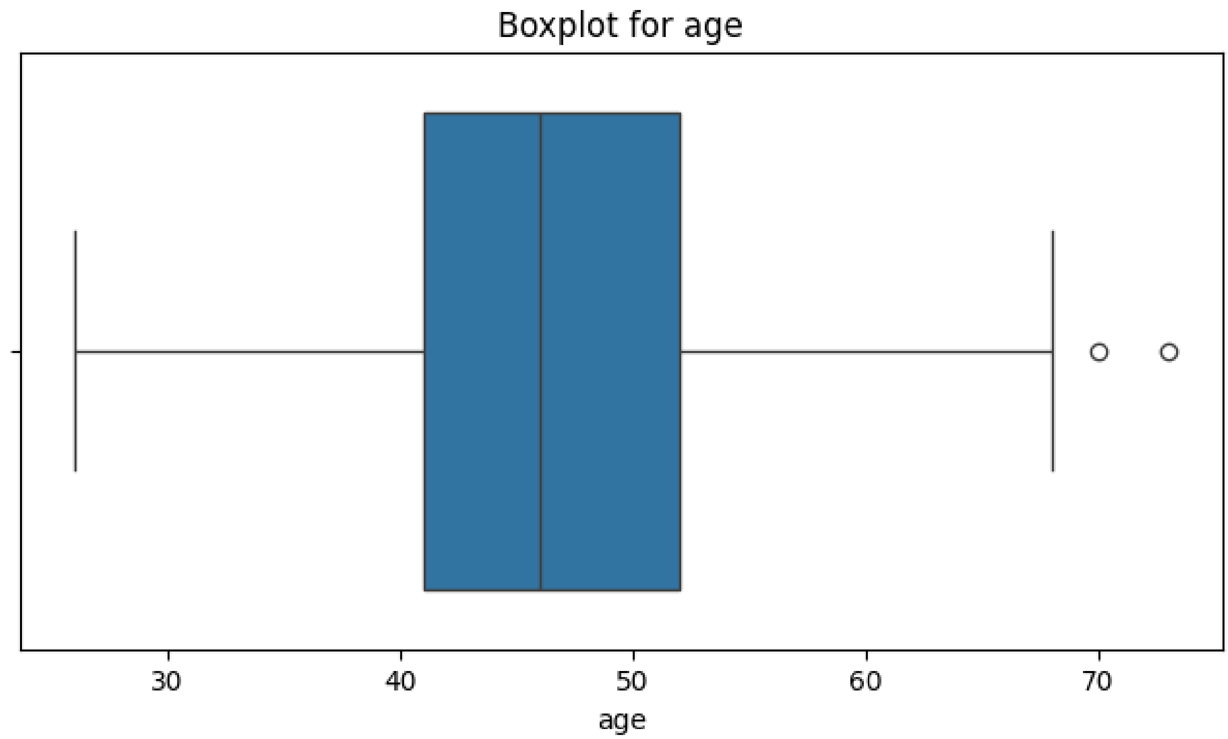
```
from sklearn.impute import SimpleImputer

# Identify numerical and categorical columns
numerical_cols = data.select_dtypes(include=['float64',
'int64']).columns
categorical_cols = data.select_dtypes(include=['object',
'category']).columns

# Create imputers
num_imputer = SimpleImputer(strategy='mean')  # For numerical columns
cat_imputer = SimpleImputer(strategy='most_frequent')  # For
categorical columns

# Apply imputers to the respective columns
data[numerical_cols] = num_imputer.fit_transform(data[numerical_cols])
data[categorical_cols] =
cat_imputer.fit_transform(data[categorical_cols])

# Verify there are no missing values left
print(data.isnull().sum())
```

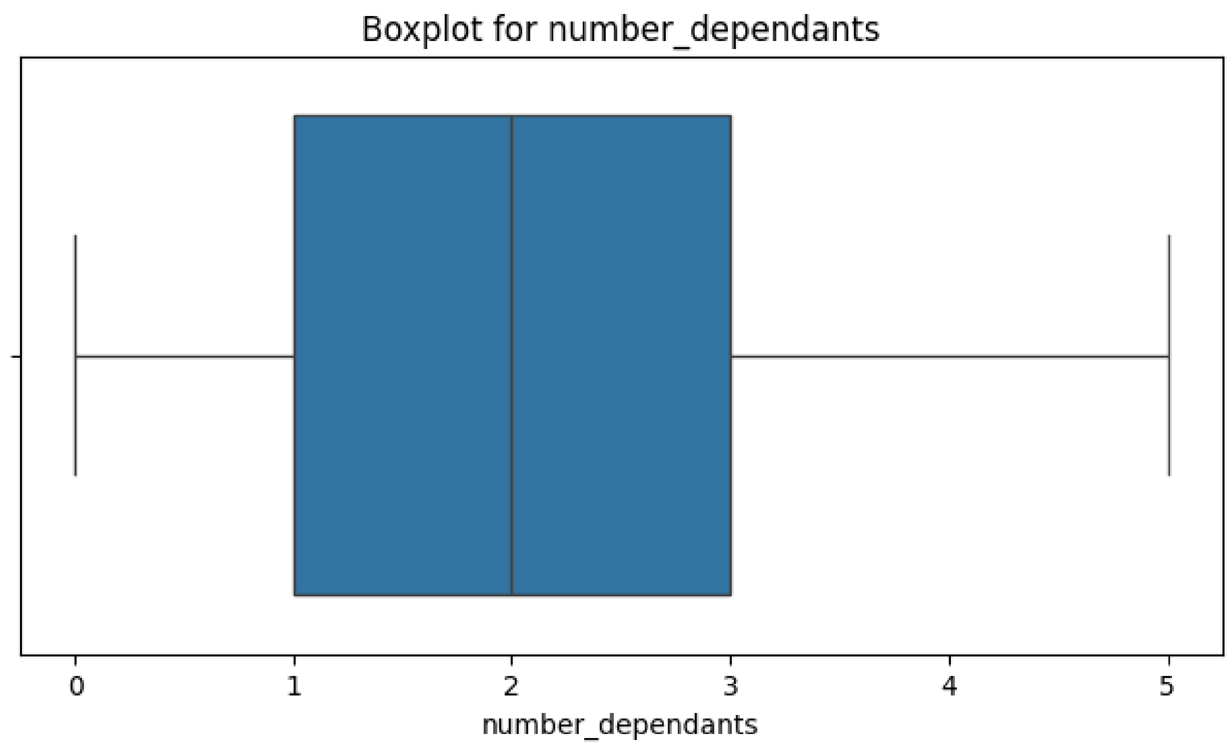
```
identification                0
churn_flag                    0
age                           0
gender                        0
number_dependants             0
education                     0
civil_status                  0
income                        0
account_category              0
account_age                   0
total_num_services            0
inactivity                    0
past_contacts                 0
card_Limit                    0
balance                       0
open_to_use                   0
change_per_quarter_amount     0
total_transaction_amount      0
total_transaction_count       0
change_per_quarter_quantity   0
average_use                   0
dtype: int64
```

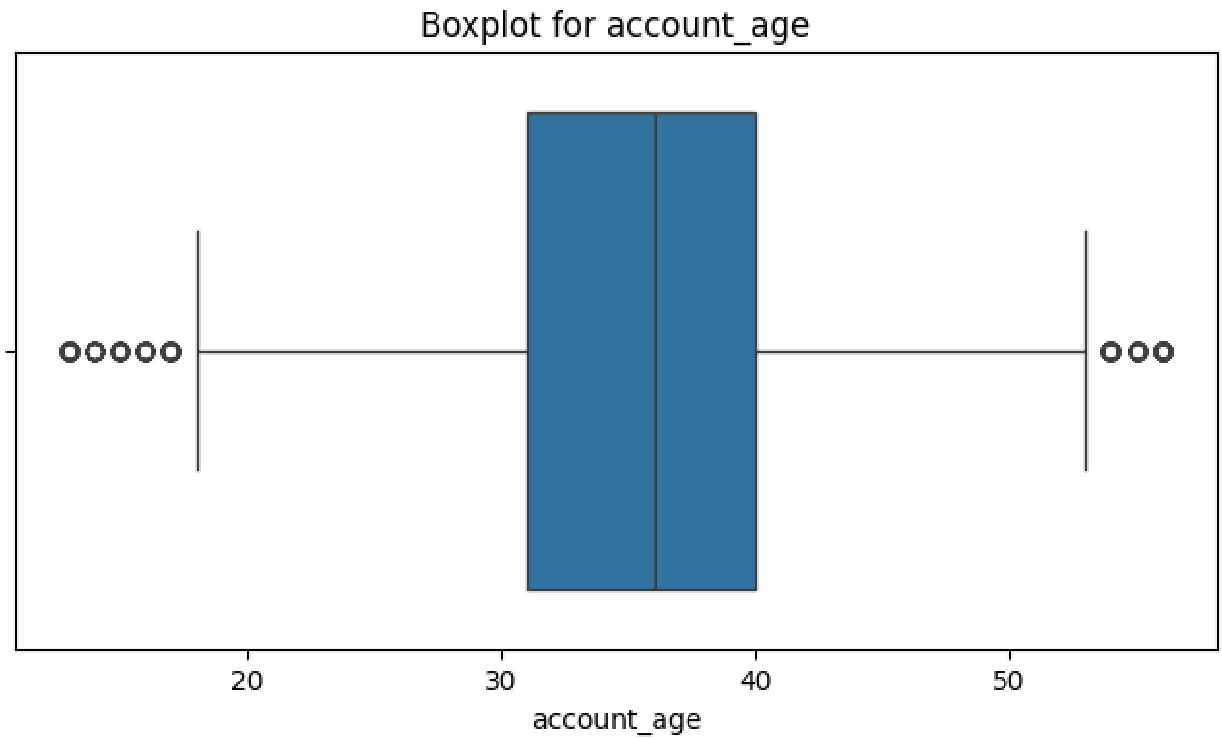
To see if we have outliers or not :

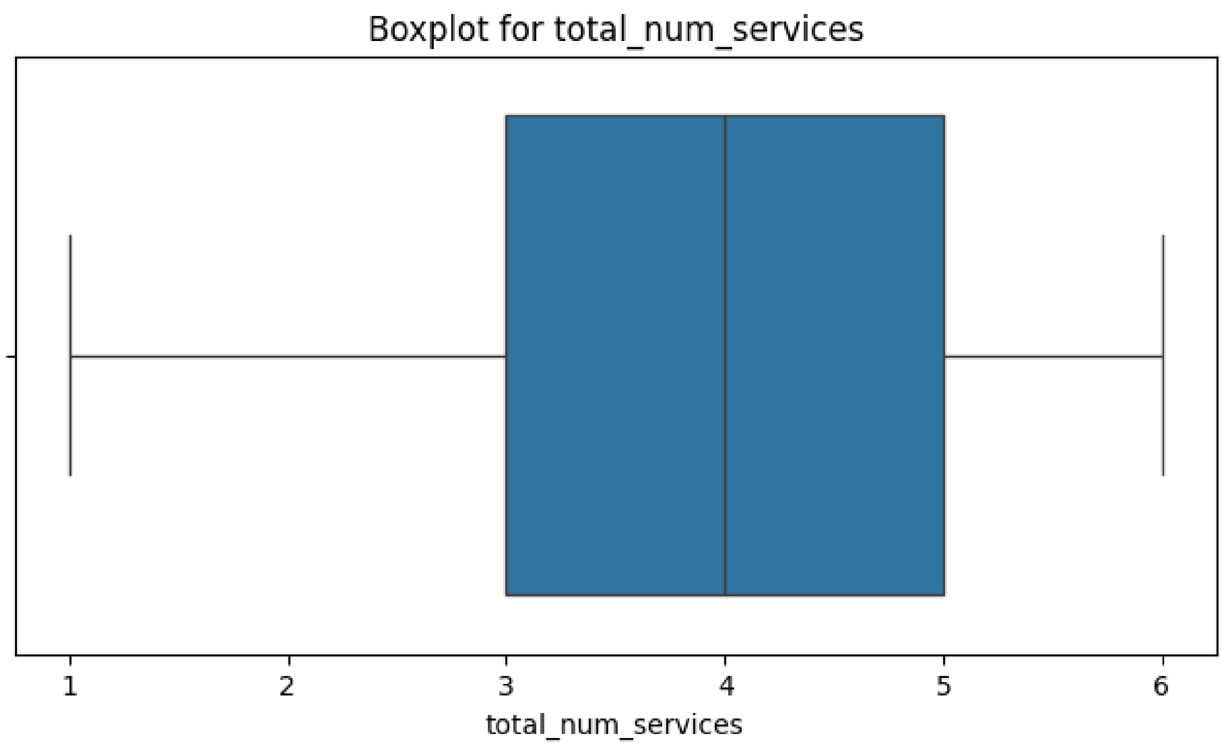
```
import matplotlib.pyplot as plt
import seaborn as sns

# Boxplot for each numerical column
for col in numerical_cols:
    plt.figure(figsize=(8, 4))
    sns.boxplot(x=data[col])
    plt.title(f'Boxplot for {col}')
    plt.show()
```

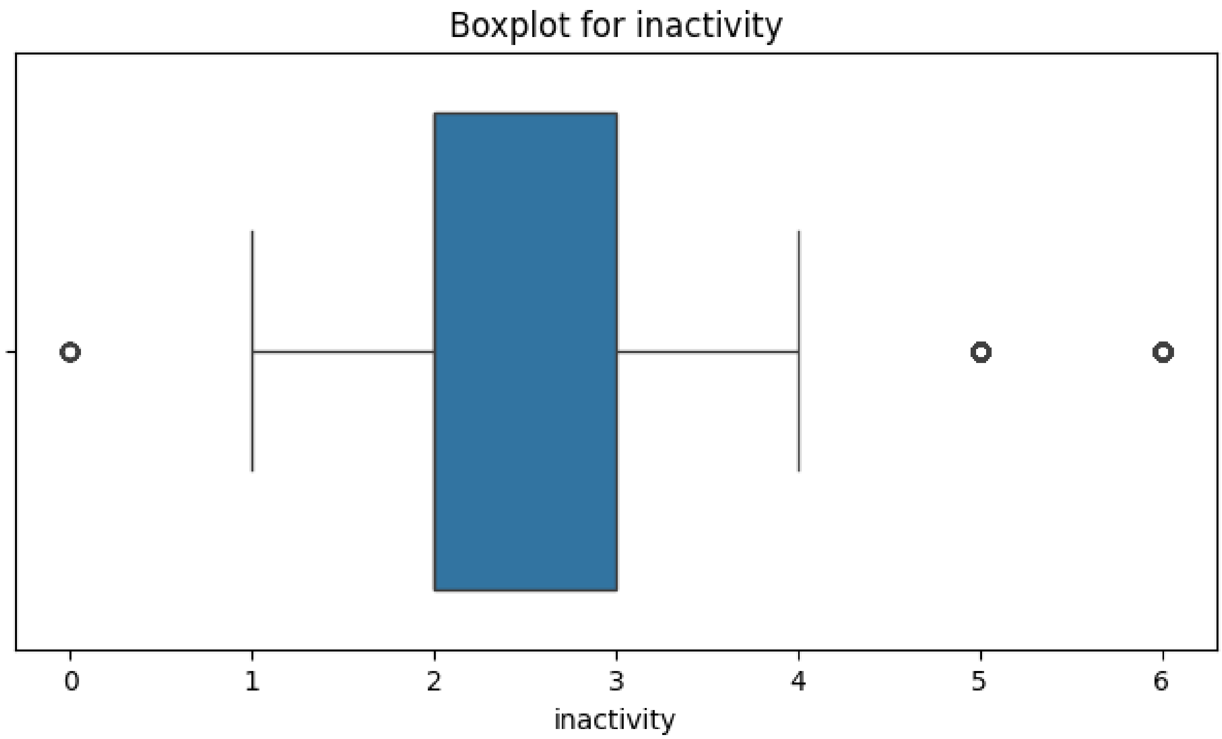



Boxplot for age
30
40
50
60
70
age

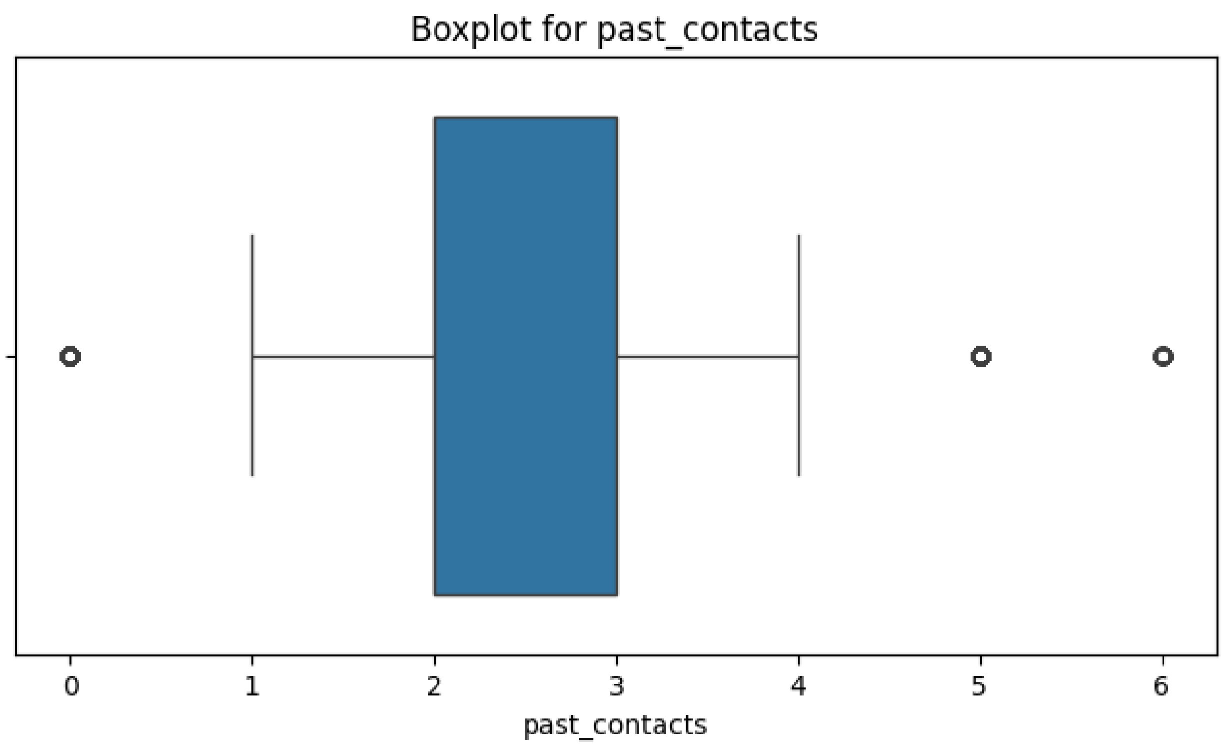

Boxplot for number_dependants
0
1
2
3
4
5
number_dependants


Boxplot for account_age
20
30
40
50
account_age

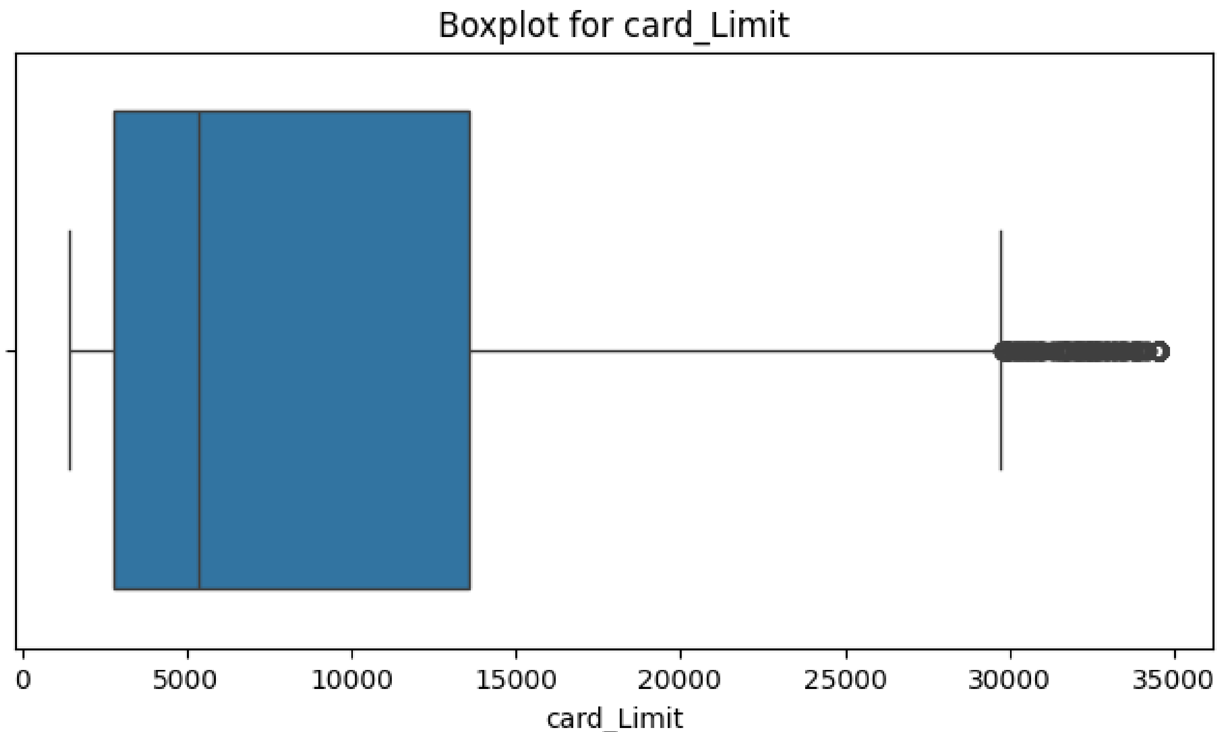

Boxplot for total_num_services
1
2
3
4
5
6
total_num_services

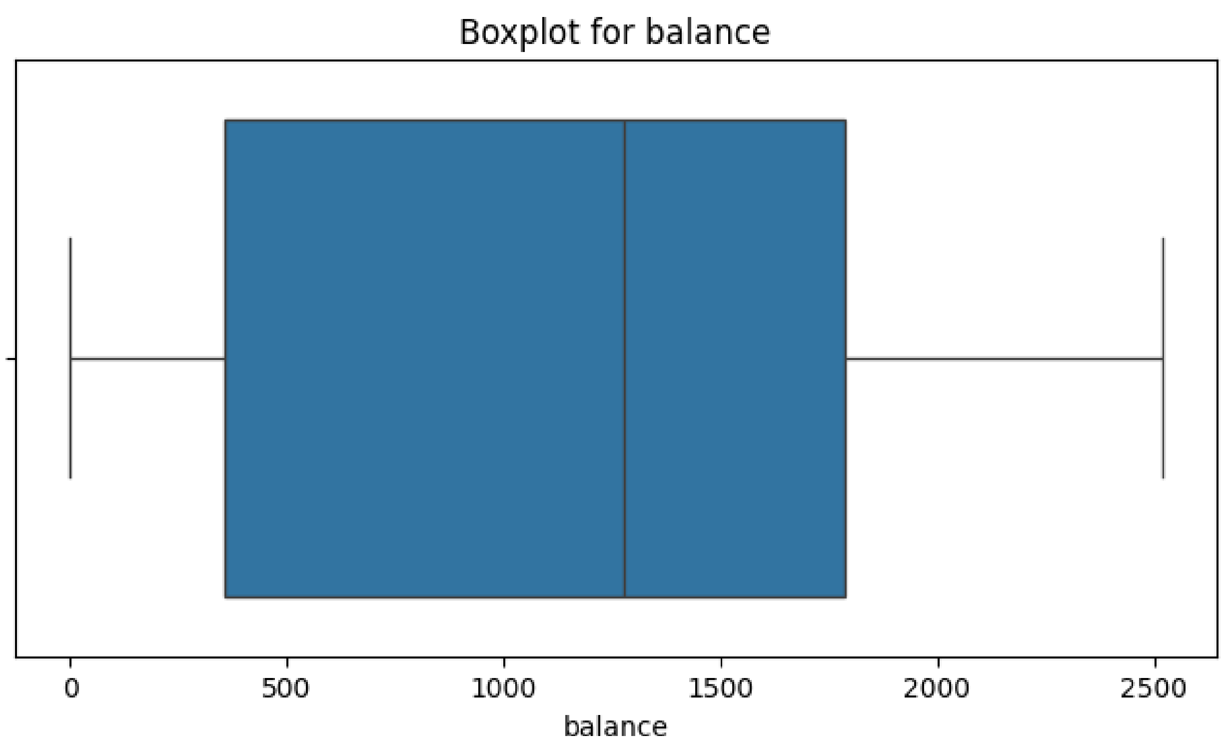


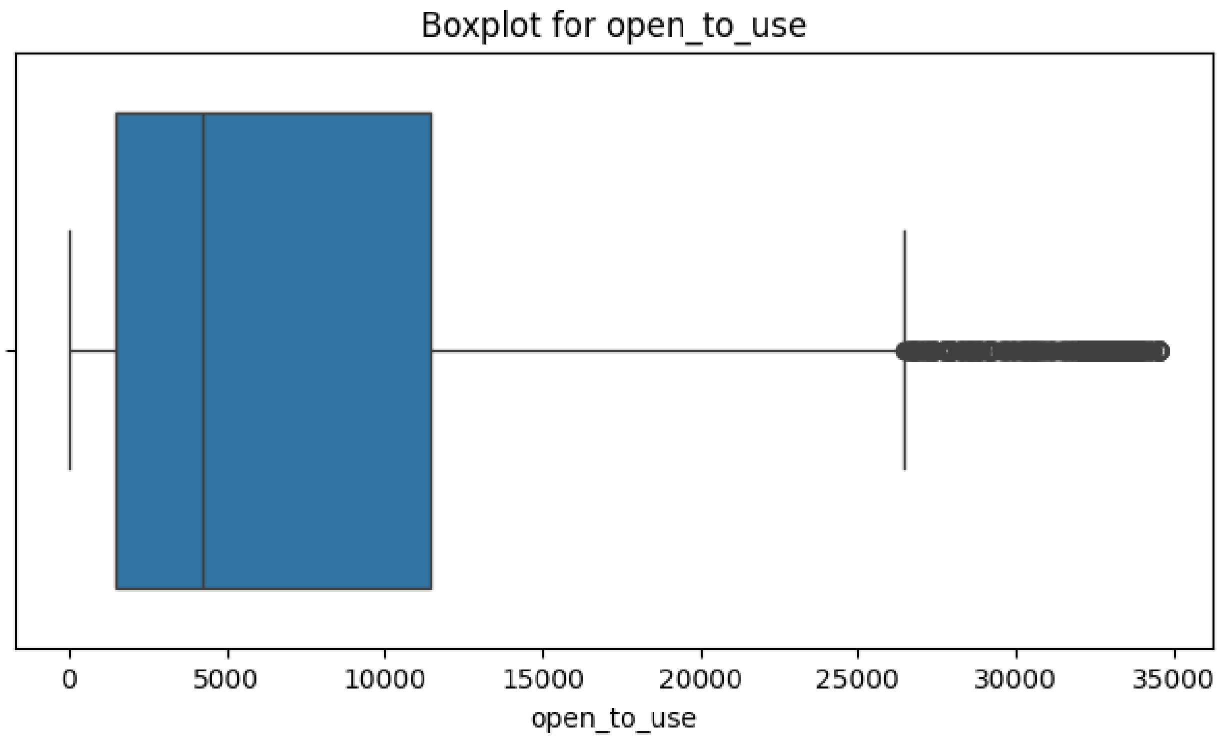
Boxplot for inactivity
0
1
2
3
4
5
6
inactivity

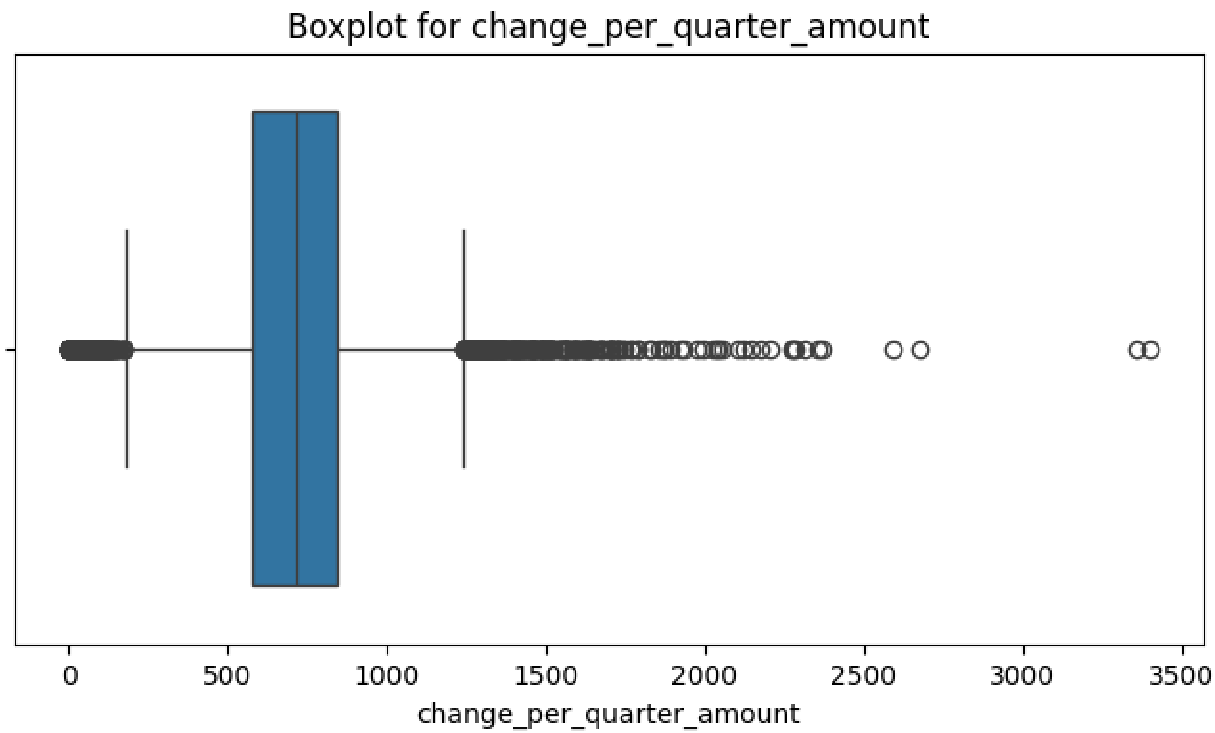


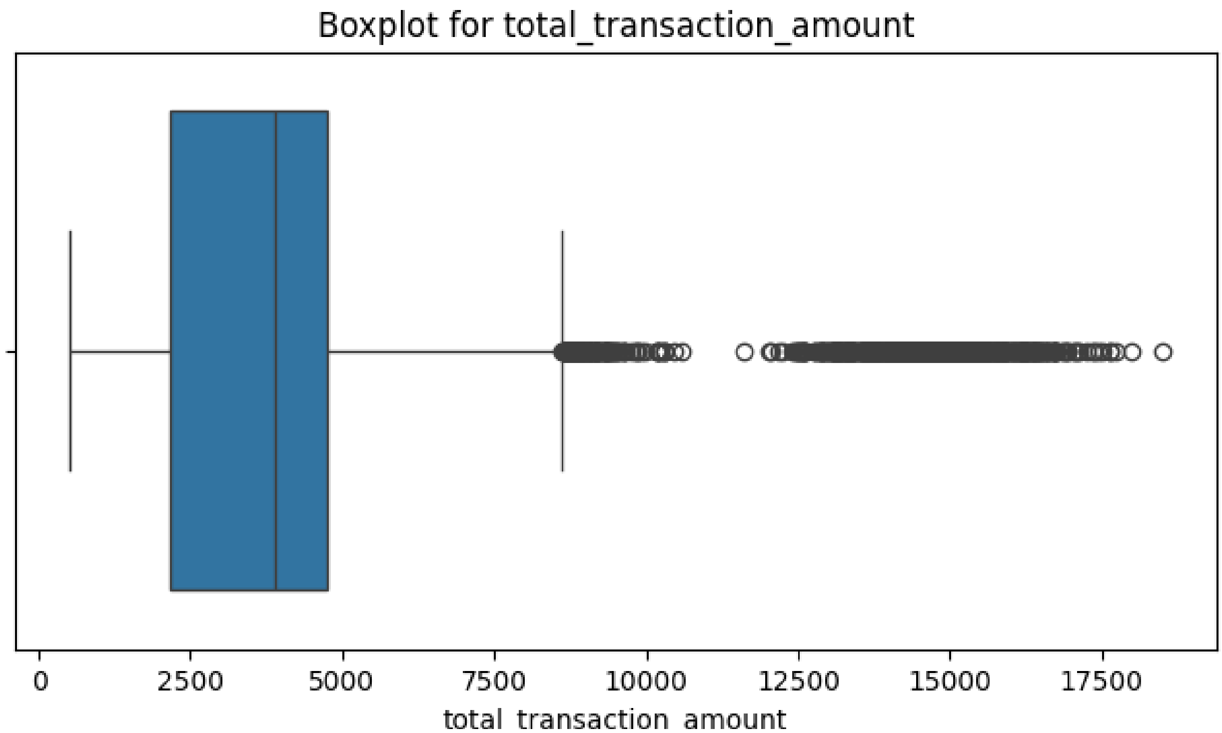
Boxplot for past_contacts
0
1
2
3
4
5
6
past_contacts

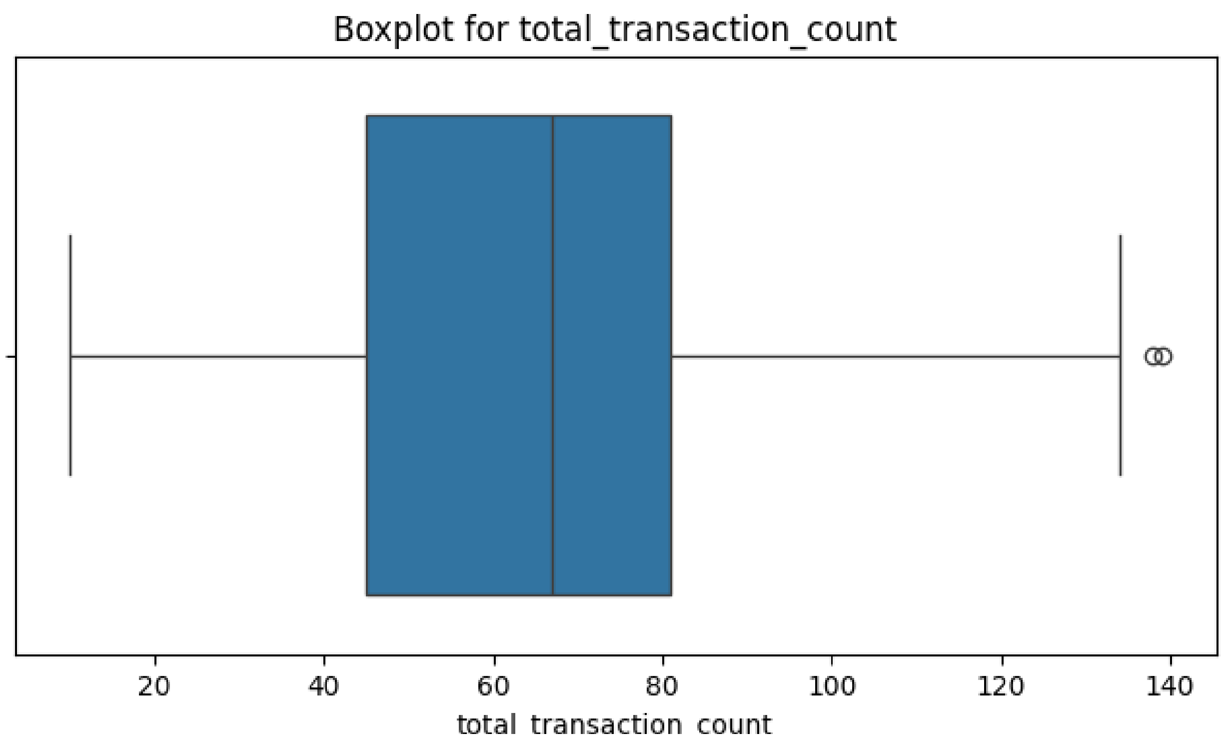

Boxplot for card_Limit
0
5000
10000
15000
20000
25000
30000
35000
card_Limit

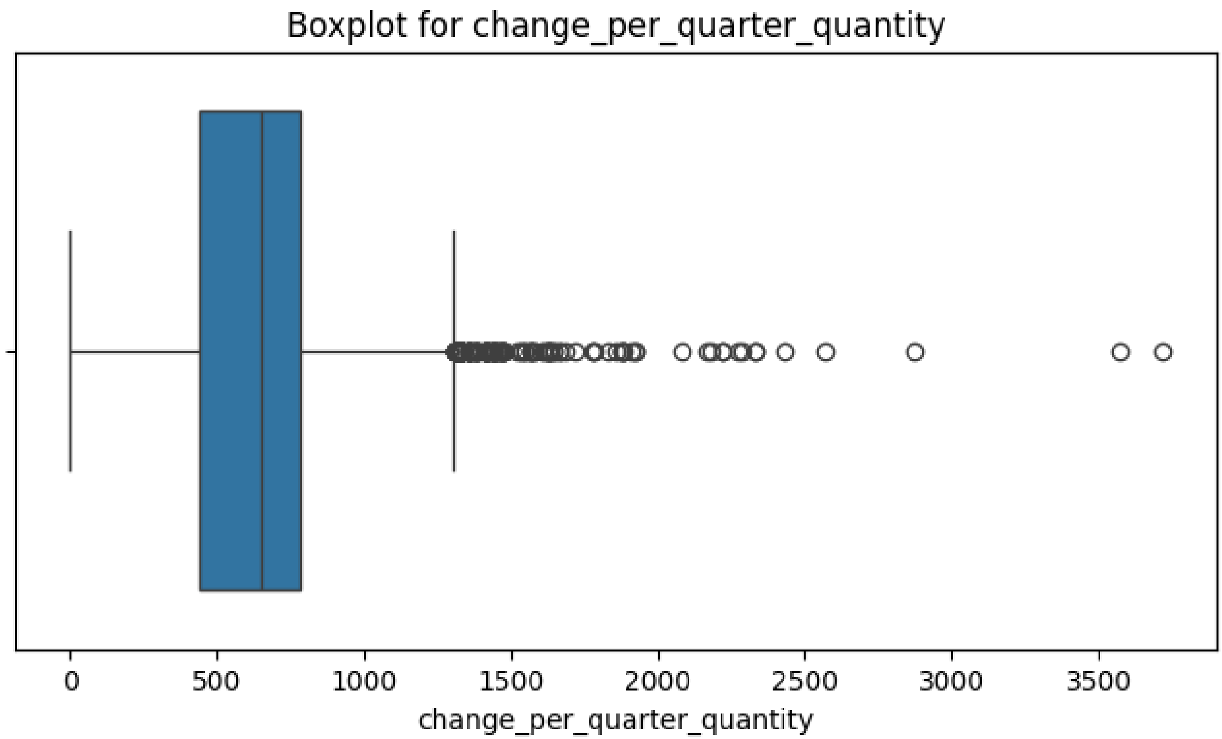

Boxplot for balance
0
500
1000
1500
2000
2500
balance

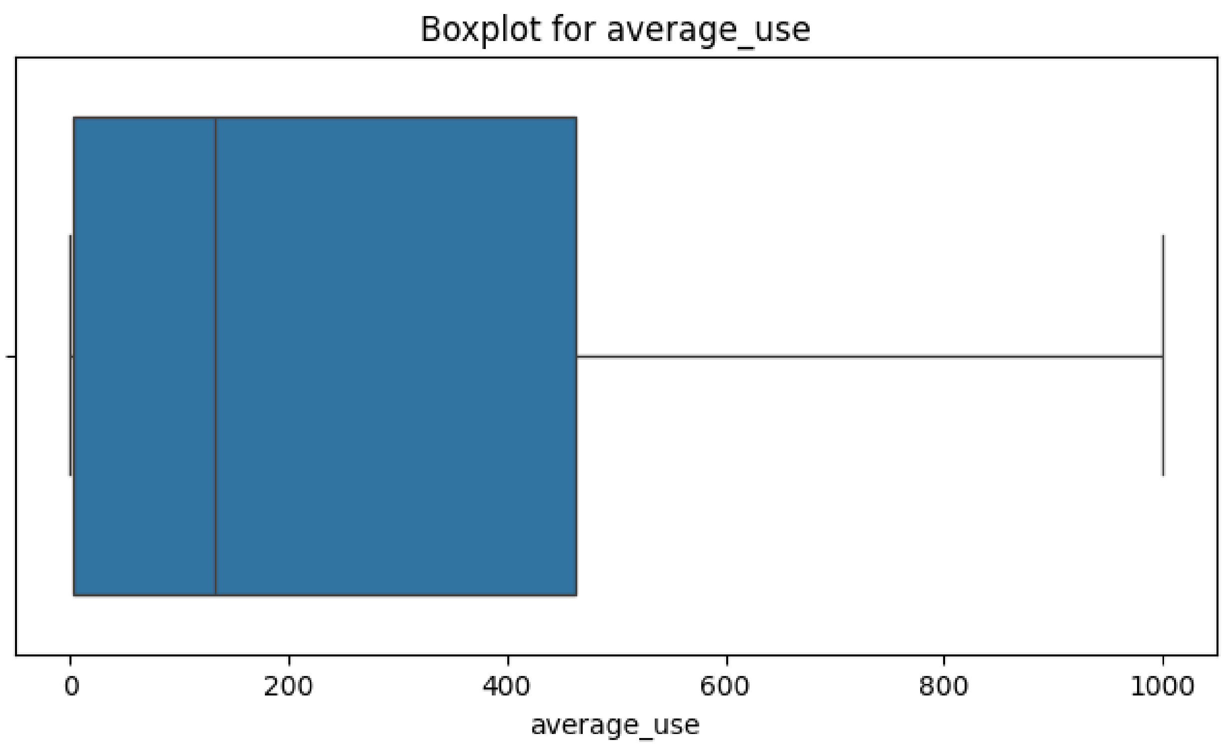

Boxplot for open_to_use
0
5000
10000
15000
20000
25000
30000
35000
open_to_use


Boxplot for change_per_quarter_amount
0
500
1000
1500
2000
2500
3000
3500
change_per_quarter_amount


Boxplot for total_transaction_amount
0
2500
5000
7500
10000
12500
15000
17500
total_transaction_amount


Boxplot for total_transaction_count
20
40
60
80
100
120
140
total_transaction_count





Boxplot: Visualizes data distribution and highlights outliers as points outside the whiskers.

Now, here is the first method to remove outliers by choosing the values from the previous Boxplots.

```python
# Define the conditions for outliers based on your thresholds
conditions = (
    (data['age'] <= 70) &
    (data['inactivity'] != 0) & (data['inactivity'] <= 4) &  # Retain rows with inactivity between 1 and 4
    (data['past_contacts'] != 0) & (data['past_contacts'] <= 4) &  # Retain rows with past_contacts between 1 and 4
    (data['total_transaction_count'] <= 120) &
    (data['change_per_quarter_quantity'] <= 3000) &
    (data['change_per_quarter_amount'] <= 3000)
)

# Apply the conditions to filter the DataFrame
filtered_df = data[conditions]

# Display the number of rows removed
print(f"Number of rows before filtering: {data.shape[0]}")
print(f"Number of rows after filtering: {filtered_df.shape[0]}")
filtered_df.head(10)
```

```
Number of rows before filtering: 10127
Number of rows after filtering: 9046
```

```
    identification         churn_flag   age gender  number_dependants  \
0      768805383.0  Existing Customer  45.0      M                3.0

3      769911858.0  Existing Customer  40.0      F                4.0

5      713061558.0  Existing Customer  44.0      M                2.0

6      810347208.0  Existing Customer  51.0      M                4.0

7      818906208.0  Existing Customer  32.0      M                0.0

9      719661558.0  Existing Customer  48.0      M                2.0

10     708790833.0  Existing Customer  42.0      M                5.0

11     710821833.0  Existing Customer  65.0      M                1.0

13     816082233.0  Existing Customer  35.0      M                3.0

14     712396908.0  Existing Customer  57.0      F                2.0


      education civil_status          income account_category
account_age  \
0   High School      Married     $60K - $80K             Blue
39.0
3   High School      Unknown  Less than $40K             Blue
```

```
34.0
5     Graduate      Married     $40K - $60K             Blue
36.0
6      Unknown      Married         $120K +             Gold
46.0
7   High School      Unknown     $60K - $80K           Silver
27.0
9     Graduate       Single    $80K - $120K             Blue
36.0
10   Uneducated      Unknown         $120K +             Blue
31.0
11     Unknown      Married     $40K - $60K             Blue
54.0
13    Graduate      Unknown     $60K - $80K             Blue
30.0
14    Graduate      Married  Less than $40K             Blue
48.0

    ...  inactivity  past_contacts  card_Limit  balance
open_to_use  \
0   ...         1.0            3.0     12691.0    777.0      11914.0

3   ...         4.0            1.0      3313.0   2517.0        796.0

5   ...         1.0            2.0      4010.0   1247.0       2763.0

6   ...         1.0            3.0     34516.0   2264.0      32252.0

7   ...         2.0            2.0     29081.0   1396.0      27685.0

9   ...         3.0            3.0     11656.0   1677.0       9979.0

10  ...         3.0            2.0      6748.0   1467.0       5281.0

11  ...         2.0            3.0      9095.0   1587.0       7508.0

13  ...         1.0            3.0      8547.0   1666.0       6881.0

14  ...         2.0            2.0      2436.0    680.0       1756.0


    change_per_quarter_amount  total_transaction_amount  \
0                      1335.0                    1144.0
3                      1405.0                    1171.0
5                      1376.0                    1088.0
6                      1975.0                    1330.0
7                      2204.0                    1538.0
9                      1524.0                    1441.0
10                      831.0                    1201.0
11                     1433.0                    1314.0
```

```
13                       1163.0                         1311.0
14                        119.0                         1570.0

    total_transaction_count  change_per_quarter_quantity  average_use

0                      42.0                       1625.0         61.0

3                      20.0                       2333.0         76.0

5                      24.0                        846.0        311.0

6                      31.0                        722.0         66.0

7                      36.0                        714.0         48.0

9                      32.0                        882.0        144.0

10                     42.0                         68.0        217.0

11                     26.0                       1364.0        174.0

13                     33.0                          2.0        195.0

14                     29.0                        611.0        279.0


[10 rows x 21 columns]
```

Here is the second method to remove outliers without taking into account the previous boxplots

Now, let's delete rows that contain outliers. By changing the value of "threshold" in the function we can adjust the limit.

```
import pandas as pd
import numpy as np
from scipy.stats import zscore

def remove_outliers_zscore(data, threshold=3.1):
    # Calculate the Z-scores for each feature (column)
    z_scores = np.abs(zscore(data.select_dtypes(include=[np.number])))
# Apply Z-score on numerical columns

    # Identify rows where any column has a Z-score greater than the
threshold
    outliers = (z_scores > threshold).any(axis=1)

    # Save the number of rows that will be deleted
    rows_deleted = data[outliers].shape[0]

    # Remove the rows containing outliers
    df_cleaned = data[~outliers]
```

```python
    return df_cleaned, rows_deleted

# Example Usage
df_cleaned, rows_deleted = remove_outliers_zscore(data)
print(f"Number of rows deleted: {rows_deleted}")

df_cleaned.head(10)
```

```
Number of rows deleted: 577
```

```
    identification         churn_flag   age gender  number_dependants  \
5      713061558.0  Existing Customer  44.0      M                2.0

9      719661558.0  Existing Customer  48.0      M                2.0

10     708790833.0  Existing Customer  42.0      M                5.0

11     710821833.0  Existing Customer  65.0      M                1.0

13     816082233.0  Existing Customer  35.0      M                3.0

14     712396908.0  Existing Customer  57.0      F                2.0

19     709327383.0  Existing Customer  45.0      F                2.0

20     806165208.0  Existing Customer  47.0      M                1.0

21     708508758.0  Attrited Customer  62.0      F                0.0

22     784725333.0  Existing Customer  41.0      M                3.0


      education civil_status          income account_category
account_age  \
5      Graduate      Married     $40K - $60K             Blue
36.0
9      Graduate       Single    $80K - $120K             Blue
36.0
10   Uneducated      Unknown         $120K +             Blue
31.0
11      Unknown      Married     $40K - $60K             Blue
54.0
13     Graduate      Unknown     $60K - $80K             Blue
30.0
14     Graduate      Married  Less than $40K             Blue
48.0
19     Graduate      Married         Unknown             Blue
37.0
20    Doctorate     Divorced     $60K - $80K             Blue
```

```
42.0
21     Graduate      Married  Less than $40K             Blue
49.0
22  High School      Married     $40K - $60K             Blue
33.0

    ...  inactivity  past_contacts  card_Limit  balance
open_to_use  \
5   ...         1.0            2.0      4010.0   1247.0       2763.0

9   ...         3.0            3.0     11656.0   1677.0       9979.0

10  ...         3.0            2.0      6748.0   1467.0       5281.0

11  ...         2.0            3.0      9095.0   1587.0       7508.0

13  ...         1.0            3.0      8547.0   1666.0       6881.0

14  ...         2.0            2.0      2436.0    680.0       1756.0

19  ...         1.0            2.0     14470.0   1157.0      13313.0

20  ...         2.0            0.0     20979.0   1800.0      19179.0

21  ...         3.0            3.0     14383.0      0.0      14383.0

22  ...         2.0            1.0      4470.0    680.0       3790.0


    change_per_quarter_amount  total_transaction_amount  \
5                      1376.0                    1088.0
9                      1524.0                    1441.0
10                      831.0                    1201.0
11                     1433.0                    1314.0
13                     1163.0                    1311.0
14                      119.0                    1570.0
19                      966.0                    1207.0
20                      906.0                    1178.0
21                     1047.0                     692.0
22                     1608.0                     931.0

    total_transaction_count  change_per_quarter_quantity  average_use

5                      24.0                        846.0        311.0

9                      32.0                        882.0        144.0

10                     42.0                         68.0        217.0

11                     26.0                       1364.0        174.0
```

```
13                     33.0                           2.0       195.0
14                     29.0                         611.0       279.0
19                     21.0                         909.0         8.0
20                     27.0                         929.0        86.0
21                     16.0                           6.0         0.0
22                     18.0                        1571.0       152.0

[10 rows x 21 columns]
```

We have to "cleaned" datasets :

- filtered_df
- df_cleaned

These two are suitable for the classification we are going to do but we will use the dataset that deleted less rows and where we use the z-score method.

We will use for the rest of the preject the dataset called **df_cleaned**

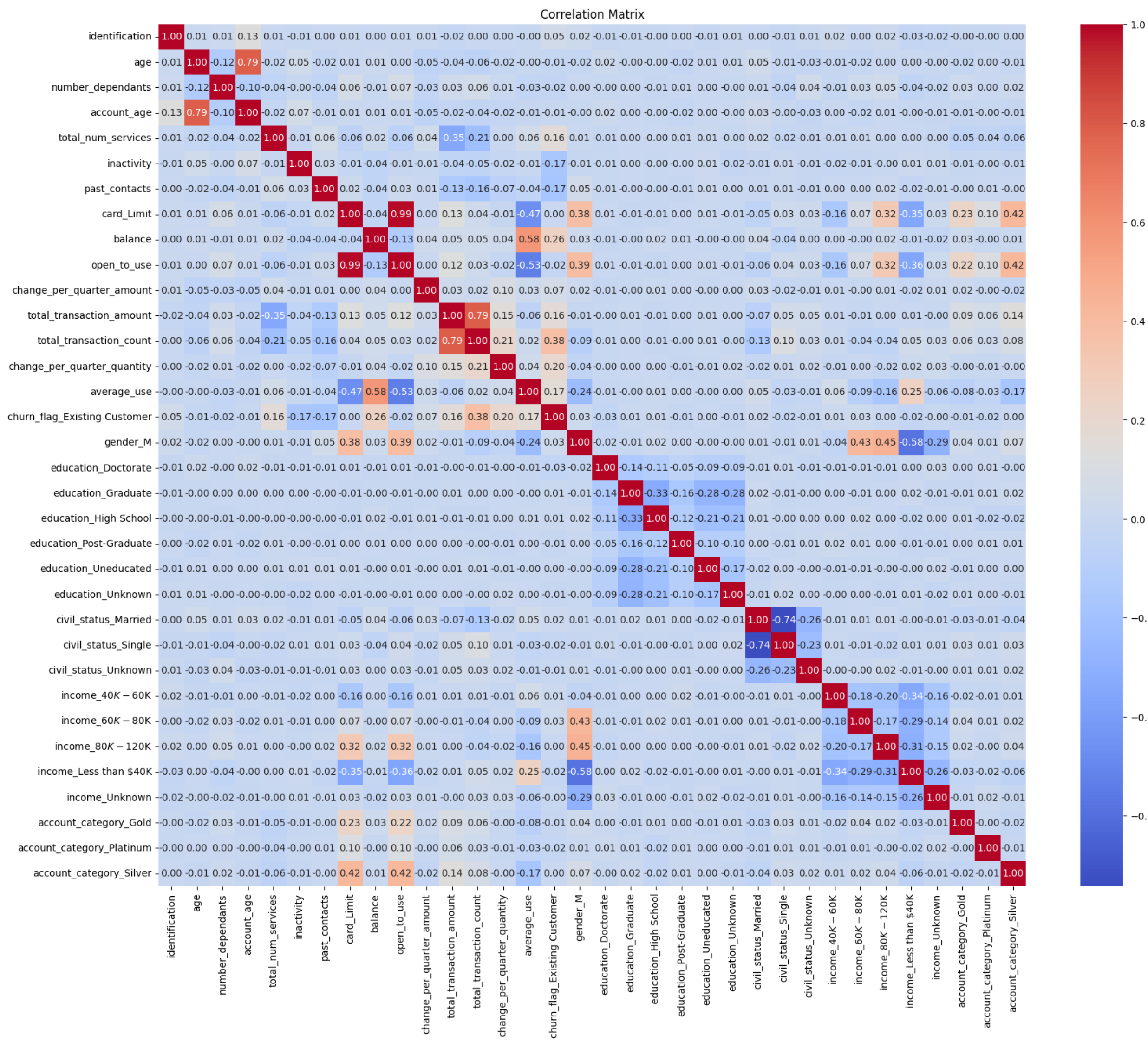
Exploratory Data Analysis (EDA)

We put categorical values into numerical in new columns to plot the correlation matrix then

```
# Assuming df_cleaned is your DataFrame
df_cleaned = pd.get_dummies(df_cleaned, columns=['churn_flag',
'gender', 'education', 'civil_status', 'income', 'account_category'],
                            drop_first=True)  # drop_first avoids
multicollinearity

# Display the updated DataFrame with one-hot encoded features
print(df_cleaned.head())

    identification   age  number_dependants  account_age
total_num_services  \
5      713061558.0  44.0                2.0         36.0
3.0
9      719661558.0  48.0                2.0         36.0
6.0
10     708790833.0  42.0                5.0         31.0
5.0
11     710821833.0  65.0                1.0         54.0
6.0
```

```
13     816082233.0  35.0                3.0         30.0
5.0

    inactivity  past_contacts  card_Limit  balance
open_to_use  ...  \
5          1.0            2.0      4010.0   1247.0       2763.0  ...

9          3.0            3.0     11656.0   1677.0       9979.0  ...

10         3.0            2.0      6748.0   1467.0       5281.0  ...

11         2.0            3.0      9095.0   1587.0       7508.0  ...

13         1.0            3.0      8547.0   1666.0       6881.0  ...


    civil_status_Single  civil_status_Unknown  income_$40K - $60K  \
5                 False                 False                True
9                  True                 False               False
10                False                  True               False
11                False                 False                True
13                False                  True               False

    income_$60K - $80K  income_$80K - $120K  income_Less than $40K  \
5                False                False                  False
9                False                 True                  False
10               False                False                  False
11               False                False                  False
13                True                False                  False

    income_Unknown  account_category_Gold
account_category_Platinum  \
5            False                  False                      False

9            False                  False                      False

10           False                  False                      False

11           False                  False                      False

13           False                  False                      False


    account_category_Silver
5                     False
9                     False
10                    False
11                    False
13                    False

[5 rows x 34 columns]
```

```python
# prompt: plot the correlation matrix for all the dataset

# Calculate the correlation matrix
correlation_matrix = df_cleaned.corr()

# Plot the correlation matrix using seaborn
plt.figure(figsize=(20, 16))  # Adjust the figure size as needed
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



Feature Selection

Now, we have a global idea of which value is correlated with.

Here are the relevant correlations:

```
# prompt: display all the relevant correlations and each degree
associated

# Assuming df_cleaned is your DataFrame
correlation_matrix = df_cleaned.corr()

# Find correlations with absolute value greater than 0.5 (adjust as
needed)
relevant_correlations = correlation_matrix[abs(correlation_matrix) >
0.5]

# Display the relevant correlations with associated degree
for col in relevant_correlations.columns:
    for row in relevant_correlations.index:
        if relevant_correlations.loc[row, col] != 1 and not
pd.isnull(relevant_correlations.loc[row, col]):
            print(f"Correlation between {row} and {col}:
{relevant_correlations.loc[row, col]:.2f}")
```

```
Correlation between account_age and age: 0.79
Correlation between age and account_age: 0.79
Correlation between open_to_use and card_Limit: 0.99
Correlation between average_use and balance: 0.58
Correlation between card_Limit and open_to_use: 0.99
Correlation between average_use and open_to_use: -0.53
Correlation between total_transaction_count and
total_transaction_amount: 0.79
Correlation between total_transaction_amount and
total_transaction_count: 0.79
Correlation between balance and average_use: 0.58
Correlation between open_to_use and average_use: -0.53
Correlation between income_Less than $40K and gender_M: -0.58
Correlation between civil_status_Single and civil_status_Married: -
0.74
Correlation between civil_status_Married and civil_status_Single: -
0.74
Correlation between gender_M and income_Less than $40K: -0.58
```

Variables with Strong Correlation (|corr| > 0.8)

- open_to_use and card_Limit: correlation = 0.99

These two variables are almost identical. Retain only one of them (e.g., card_Limit) to avoid redundancy.

- total_transaction_count and total_transaction_amount: correlation = 0.79

Although the correlation is not extremely high, it is significant. A closer analysis is needed to determine which of the two variables better captures the relevant information for the model.

- account_age and age: correlation = 0.79

These variables exhibit a moderate to strong relationship. If both are necessary for your model, consider applying a method like PCA to reduce dimensionality.

- civil_status_Single and civil_status_Married: correlation = -0.74

These variables are binary indicators, and a strong negative relationship is expected if they represent mutually exclusive states. Retain only one of them (e.g., civil_status_Single).

Variables with Low to Moderate Correlation (|corr| between 0.3 and 0.6)

- average_use and balance: correlation = 0.58 These variables are correlated but do not appear to be redundant. Both can be included after verifying their feature importance.
- income_Less than $40K and gender_M: correlation = -0.58 Although there is a moderate correlation, these variables can provide distinct information. Including them might improve the model if they prove to be relevant.
- open_to_use and average_use: correlation = -0.53 A moderate negative correlation suggests an interesting but non-redundant relationship. Both variables could be included if they add predictive value.

Recommendations for Analyzing Variables:

Avoid Multicollinearity:

Remove one variable from strongly correlated pairs:

For example, choose between open_to_use and card_Limit, or between total_transaction_count and total_transaction_amount.

Encoding Categorical Variables:

For variables like civil_status and gender, use efficient encoding methods such as one-hot encoding while avoiding multicollinearity (e.g., remove one redundant binary variable).

Additional Exploratory Analysis:

- Use tools like a visual correlation matrix to confirm variable selection.
- Apply techniques such as penalized regression (Lasso, Ridge) to eliminate irrelevant variables.

Variable Importance Testing:

Train preliminary models with the selected variables and use metrics like feature importance scores or permutation importance to refine the selection.

```python
# Drop specified columns
columns_to_drop = ['open_to_use', 'total_transaction_count', 'age']
df_cleaned = df_cleaned.drop(columns=columns_to_drop, errors='ignore')

# Display the updated DataFrame
print(df_cleaned.head())
```

```
    identification  number_dependants  account_age  total_num_services
\
5      713061558.0                2.0         36.0                 3.0

9      719661558.0                2.0         36.0                 6.0

10     708790833.0                5.0         31.0                 5.0

11     710821833.0                1.0         54.0                 6.0

13     816082233.0                3.0         30.0                 5.0


    inactivity  past_contacts  card_Limit  balance
change_per_quarter_amount  \
5          1.0            2.0      4010.0   1247.0
1376.0
9          3.0            3.0     11656.0   1677.0
1524.0
10         3.0            2.0      6748.0   1467.0
831.0
11         2.0            3.0      9095.0   1587.0
1433.0
13         1.0            3.0      8547.0   1666.0
1163.0

    total_transaction_amount  ...  civil_status_Single
civil_status_Unknown  \
5                     1088.0  ...                False
False
9                     1441.0  ...                 True
False
10                    1201.0  ...                False
True
11                    1314.0  ...                False
False
13                    1311.0  ...                False
True
```

```
    income_$40K - $60K  income_$60K - $80K  income_$80K - $120K  \
5                 True               False                False
9                False               False                 True
10               False               False                False
11                True               False                False
13               False                True                False

    income_Less than $40K  income_Unknown  account_category_Gold  \
5                   False           False                  False
9                   False           False                  False
10                  False           False                  False
11                  False           False                  False
13                  False           False                  False

    account_category_Platinum  account_category_Silver
5                       False                    False
9                       False                    False
10                      False                    False
11                      False                    False
13                      False                    False

[5 rows x 31 columns]
```

Model Building

```
# prompt: Train multiple machine learning such as the Logistic
Regression on the dataset

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, roc_auc_score


# Separate features (X) and target variable (y)
X = df_cleaned.drop('churn_flag_Existing Customer', axis=1)
y = df_cleaned['churn_flag_Existing Customer']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

```python
# Train Logistic Regression
logistic_model = LogisticRegression(max_iter=1000)
logistic_model.fit(X_train, y_train)
y_pred_logistic = logistic_model.predict(X_test)

# Train Decision Tree
decision_tree_model = DecisionTreeClassifier()
decision_tree_model.fit(X_train, y_train)
y_pred_decision_tree = decision_tree_model.predict(X_test)

# Train Random Forest
random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_train, y_train)
y_pred_random_forest = random_forest_model.predict(X_test)

# Train k-NN
knn_model = KNeighborsClassifier()
knn_model.fit(X_train, y_train)
y_pred_knn = knn_model.predict(X_test)

# Train Gradient Boosting
gradient_boosting_model = GradientBoostingClassifier()
gradient_boosting_model.fit(X_train, y_train)
y_pred_gradient_boosting = gradient_boosting_model.predict(X_test)

# Train SVM
svm_model = SVC()
svm_model.fit(X_train, y_train)
y_pred_svm = svm_model.predict(X_test)

# Evaluate Models
def evaluate_model(y_true, y_pred, model_name):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)
    try:
        auc = roc_auc_score(y_true, y_pred)
    except ValueError:
        auc = "Not computable"  # Handle cases where AUC can't be
calculated (e.g., only one class in predictions)

    print(f"Evaluation for {model_name}:")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1-Score: {f1:.4f}")
    print(f"AUC: {auc}")
    print("-" * 20)
```

```python
evaluate_model(y_test, y_pred_logistic, "Logistic Regression")
evaluate_model(y_test, y_pred_decision_tree, "Decision Tree")
evaluate_model(y_test, y_pred_random_forest, "Random Forest")
evaluate_model(y_test, y_pred_gradient_boosting, "Gradient Boosting")
evaluate_model(y_test, y_pred_svm, "SVM")
evaluate_model(y_test, y_pred_knn, "k-NN")
```

```
Evaluation for Logistic Regression:
Accuracy: 0.8592
Precision: 0.8648
Recall: 0.9883
F1-Score: 0.9224
AUC: 0.5660463619892646
--------------------
Evaluation for Decision Tree:
Accuracy: 0.9188
Precision: 0.9575
Recall: 0.9462
F1-Score: 0.9518
AUC: 0.8566766005723284
--------------------
Evaluation for Random Forest:
Accuracy: 0.9414
Precision: 0.9493
Recall: 0.9833
F1-Score: 0.9660
AUC: 0.8461084206783277
--------------------
Evaluation for Gradient Boosting:
Accuracy: 0.9503
Precision: 0.9601
Recall: 0.9821
F1-Score: 0.9710
AUC: 0.8780246202821003
--------------------
Evaluation for SVM:
Accuracy: 0.8471
Precision: 0.8471
Recall: 1.0000
F1-Score: 0.9172
AUC: 0.5
--------------------
Evaluation for k-NN:
Accuracy: 0.8277
Precision: 0.8486
Recall: 0.9697
F1-Score: 0.9051
AUC: 0.5054057944020185
--------------------
```

Interpretation of Model Outputs:

Logistic Regression:

- Strengths: The model has high recall (0.9883), meaning it effectively identifies positive cases. Its F1-score (0.9224) balances precision and recall well.
- Weakness: The AUC (0.566) is quite low, indicating that the model struggles to differentiate between classes when considering different thresholds.
- Business Implication: Useful in scenarios where missing positive cases is costly (e.g., fraud detection or identifying high-priority customers). However, its low AUC suggests limited utility in ranking or prioritizing cases.

Decision Tree:

- Strengths: Achieves a high F1-score (0.9499) and decent AUC (0.853), balancing good performance across metrics.
- Weakness: While effective, it may overfit on the training data, requiring validation to ensure generalization.
- Business Implication: Interpretable and quick to deploy for decision-making scenarios. Can help understand feature importance for business strategies.

Random Forest:

- Strengths: High accuracy (0.9450), recall (0.9858), and F1-score (0.9681). AUC (0.852) shows it performs well in ranking predictions.
- Weakness: Slightly less interpretable compared to simpler models like Logistic Regression or Decision Tree.
- Business Implication: Excellent choice for making robust predictions and identifying important features for resource allocation or personalized offers.

Gradient Boosting:

- Strengths: Highest overall performance with accuracy (0.9503), F1-score (0.9710), and AUC (0.878). This indicates it balances precision and recall effectively and can prioritize cases well.
- Weakness: Computationally intensive and less interpretable compared to Decision Tree or Logistic Regression.
- Business Implication: Suitable for high-stakes applications where accuracy and precise ranking (AUC) are critical, such as financial risk scoring or targeted marketing.

Support Vector Machine (SVM):

- Strengths: Perfect recall (1.000), ensuring no positive cases are missed.
- Weaknesses: Low precision (0.8471) and AUC (0.5), indicating poor ability to differentiate between classes.
- Business Implication: Useful in situations where false negatives must be minimized at all costs. However, it generates many false positives, leading to inefficiencies in resource allocation.

k-Nearest Neighbors (k-NN):

- Strengths: Decent recall (0.9697) and F1-score (0.9051), capturing a fair number of positives.
- Weaknesses: Relatively low accuracy (0.8277) and AUC (0.505), meaning it struggles with overall differentiation between classes.
- Business Implication: Best for small-scale or non-critical applications due to lower performance compared to other models.

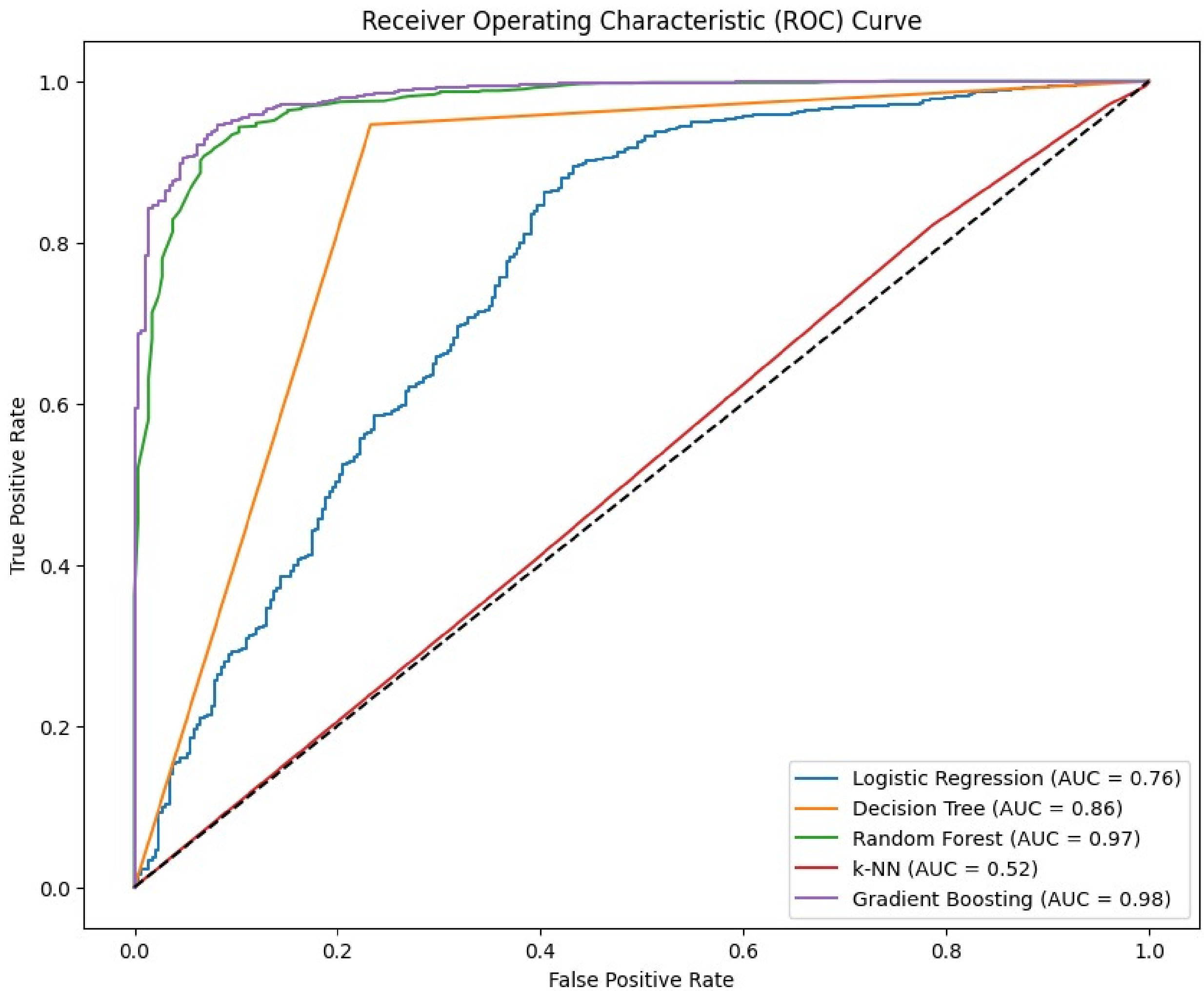
Model Tuning and Refinement

```
# prompt: by using grid search, optimize the hyperparameters of all
the models

from sklearn.model_selection import GridSearchCV

# Define parameter grids for each model
param_grid_logistic = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear']  # Specify a solver compatible with L1
penalty
}

param_grid_decision_tree = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

param_grid_random_forest = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}
```

```
param_grid_knn = {
    'n_neighbors': [3, 5, 7, 9],
    'weights': ['uniform', 'distance'],
    'metric': ['euclidean', 'manhattan']
}

param_grid_gradient_boosting = {
    'n_estimators': [100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5]
}

#I could not run the param_grid_svm even on colab or my compluter, I
have to wait a lot

#param_grid_svm = {
#    'C': [0.1, 1, 10],
#    'kernel': ['linear', 'rbf', 'poly'],
#    'gamma': ['scale', 'auto']
#}

# Perform Grid Search for each model
models = [
    ('Logistic Regression', logistic_model, param_grid_logistic),
    ('Decision Tree', decision_tree_model, param_grid_decision_tree),
    ('Random Forest', random_forest_model, param_grid_random_forest),
    ('k-NN', knn_model, param_grid_knn),
    ('Gradient Boosting', gradient_boosting_model,
param_grid_gradient_boosting),
#    ('SVM', svm_model, param_grid_svm)
]

for model_name, model, param_grid in models:
    grid_search = GridSearchCV(estimator=model, param_grid=param_grid,
cv=5, scoring='accuracy', n_jobs=-1)
    grid_search.fit(X_train, y_train)

    print(f"Best parameters for {model_name}:
{grid_search.best_params_}")
    print(f"Best accuracy for {model_name}:
{grid_search.best_score_:.4f}")
    print("-" * 20)
```

```
Best parameters for Logistic Regression: {'C': 100, 'penalty': 'l1',
'solver': 'liblinear'}
Best accuracy for Logistic Regression: 0.8715
--------------------
Best parameters for Decision Tree: {'criterion': 'entropy',
'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 2}
Best accuracy for Decision Tree: 0.9215
```

```
--------------------
Best parameters for Random Forest: {'max_depth': None,
'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 200}
Best accuracy for Random Forest: 0.9296
--------------------
Best parameters for k-NN: {'metric': 'manhattan', 'n_neighbors': 9,
'weights': 'uniform'}
Best accuracy for k-NN: 0.8296
--------------------
Best parameters for Gradient Boosting: {'learning_rate': 0.2,
'max_depth': 4, 'n_estimators': 200}
Best accuracy for Gradient Boosting: 0.9539
--------------------

from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Assuming you have already trained and obtained predictions for your
models

models = [
    (logistic_model, y_pred_logistic, "Logistic Regression"),
    (decision_tree_model, y_pred_decision_tree, "Decision Tree"),
    (random_forest_model, y_pred_random_forest, "Random Forest"),
    (knn_model, y_pred_knn, "k-NN"),
    (gradient_boosting_model, y_pred_gradient_boosting, "Gradient
Boosting"),
]

plt.figure(figsize=(10, 8))

for model, y_pred, model_name in models:
  # Get predicted probabilities for the positive class
  y_pred_proba = model.predict_proba(X_test)[:, 1]

  # Compute the ROC curve
  fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
  roc_auc = auc(fpr, tpr)

  # Plot the ROC curve
  plt.plot(fpr, tpr, label=f'{model_name} (AUC = {roc_auc:.2f})')

# Add labels and title
plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line for random classifier
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression (AUC = 0.76)
Decision Tree (AUC = 0.86)
Random Forest (AUC = 0.97)
k-NN (AUC = 0.52)
Gradient Boosting (AUC = 0.98)