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```
# install libraries
!python -m pip install --upgrade pip -q
!pip install pandas numpy matplotlib seaborn scikit-learn openpyxl -q
!pip install notebook -q
!pip install nbconvert -q
!pip install tabulate -q
```

Lloyd Bank EDA

Bottom Line Up Front

- Discovered through clustering that our **Most** valuable customers in Group 6 and 8 churn with a Churn Rate at rates higher than average.
- Group 6 spend 0.44 above average but churn at 0.21
- Group 8 spend 0.36 above average but churn at 0.27
- They are our most valuable customers and we cannot figure out why they are leaving, because the features we rely on have such poor correlation a coin flip is better at predicting churn.
- The group with the lowest churn is our **Least** Valuable customers. They spend the least.
- The data is all over the place, and no single feature seems to correlate to the why they churn at such a high clip. Further analysis is required.

Project Overview

Objective: First Critical Steps to build a predictive model for customer churn. Gather all relevant data, and then conduct an EDA and prepare the data set for model development. Key Results:

Business Problem: We need to predict which of our customers are likely to churn.

Goal: Conduct exploratory data analysis and translate findings into a predictive model that can predict which customers are going to churn. Methodology and Justification.

Tools Used: Python for data cleaning, manipulation, analysis, and visualization Reason: Python has libraries that are suited for the assignment. Pandas is used to manipulate the data, numpy for calculation, matplotlib and seaborn for data visualization, sklearn for machine learning model, and datetime to calculate date ranges in days.

```python
#import libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')
```

Identify and Gathering Steps:

- Downloaded the data from the excel files, and the uploaded a copy using pd.read_excel as it is an excel file.
- Kept the names the same as the sheets for consistency across the board.
- Printed the head of each Sheet and compared to original dataset for accuracy and to ensure consistency and nothing is lost

```python
# Set Display Options
pd.set_option('display.max_columns', None) # Set option to display all columns
pd.set_option('display.float_format', '{:.2f}'.format) # Set float format to 2 decimal places

Churn_Status = pd.read_excel('Customer_Churn_Data_Large.xlsx', sheet_name='Churn_Status')
Customer_Demographics = pd.read_excel('Customer_Churn_Data_Large.xlsx', sheet_name='Customer_Demographics')
Transaction_History = pd.read_excel('Customer_Churn_Data_Large.xlsx', sheet_name='Transaction_History')
Customer_Service = pd.read_excel('Customer_Churn_Data_Large.xlsx', sheet_name='Customer_Service')
Online_Activity = pd.read_excel('Customer_Churn_Data_Large.xlsx', sheet_name='Online_Activity')


# Display first few rows of each dataset
print("Churn Status:")
print(Churn_Status.head())
print("\nCustomer Demographics:")
print(Customer_Demographics.head())
print("\nTransaction History:")
print(Transaction_History.head())
print("\nCustomer Service:")
print(Customer_Service.head())
print("\nOnline Activity:")
print(Online_Activity.head())
```

```python
# Display info of each dataset to understand structure and data types
print(Customer_Demographics.info())
print(Transaction_History.info())
print(Churn_Status.info())
print(Customer_Service.info())
print(Online_Activity.info())
```

```
Churn Status:
   CustomerID  ChurnStatus
0           1            0
1           2            1
2           3            0
3           4            0
4           5            0

Customer Demographics:
   CustomerID  Age Gender MaritalStatus IncomeLevel
0           1   62      M        Single         Low
1           2   65      M       Married         Low
2           3   18      M        Single         Low
3           4   21      M       Widowed         Low
4           5   21      M      Divorced      Medium

Transaction History:
   CustomerID  TransactionID TransactionDate  AmountSpent
ProductCategory
0           1           7194      2022-03-27       416.50
Electronics
1           2           7250      2022-08-08        54.96
Clothing
2           2           9660      2022-07-25       197.50
Electronics
3           2           2998      2022-01-25       101.31
Furniture
4           2           1228      2022-07-24       397.37
Clothing

Customer Service:
   CustomerID  InteractionID InteractionDate InteractionType
ResolutionStatus
0           1           6363      2022-03-31         Inquiry
Resolved
1           2           3329      2022-03-17         Inquiry
Resolved
2           3           9976      2022-08-24         Inquiry
Resolved
3           4           7354      2022-11-18         Inquiry
Resolved
4           4           5393      2022-07-03         Inquiry
```

```
Unresolved

Online Activity:
   CustomerID LastLoginDate  LoginFrequency ServiceUsage
0           1    2023-10-21              34   Mobile App
1           2    2023-12-05               5      Website
2           3    2023-11-15               3      Website
3           4    2023-08-25               2      Website
4           5    2023-10-27              41      Website
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   CustomerID     1000 non-null   int64 
 1   Age            1000 non-null   int64 
 2   Gender         1000 non-null   object
 3   MaritalStatus  1000 non-null   object
 4   IncomeLevel    1000 non-null   object
dtypes: int64(2), object(3)
memory usage: 39.2+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5054 entries, 0 to 5053
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype         
---  ------           --------------  -----         
 0   CustomerID       5054 non-null   int64         
 1   TransactionID    5054 non-null   int64         
 2   TransactionDate  5054 non-null   datetime64[ns]
 3   AmountSpent      5054 non-null   float64       
 4   ProductCategory  5054 non-null   object        
dtypes: datetime64[ns](1), float64(1), int64(2), object(1)
memory usage: 197.6+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   CustomerID   1000 non-null   int64
 1   ChurnStatus  1000 non-null   int64
dtypes: int64(2)
memory usage: 15.8 KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1002 entries, 0 to 1001
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype 
```

```
---  ------            -------------  -----
 0   CustomerID        1002 non-null   int64
 1   InteractionID     1002 non-null   int64
 2   InteractionDate   1002 non-null   datetime64[ns]
 3   InteractionType   1002 non-null   object
 4   ResolutionStatus  1002 non-null   object
dtypes: datetime64[ns](1), int64(2), object(2)
memory usage: 39.3+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype
---  ------          -------------  -----
 0   CustomerID      1000 non-null   int64
 1   LastLoginDate   1000 non-null   datetime64[ns]
 2   LoginFrequency  1000 non-null   int64
 3   ServiceUsage    1000 non-null   object
dtypes: datetime64[ns](1), int64(2), object(1)
memory usage: 31.4+ KB
None
```

Data Cleaning Process

- Created a backup of the original raw data
- Created a Transaction_Summary based on Transaction_History grouped by CustomerID to create a single column per customer rather than multiple columns.
- Grouped by minimum and Maximum transaction, the amount of transactions, and the total spent per customers, also calculated the LoyaltyLength by subtracting the most recent transaction date by the first transaction date.

All these are new columns that are added to a table and dropped all null values from Transaction_Summary I don’t need to analyze customers who haven’t spend any money.

Documentation: All cleaning steps are documented with inline comments.

- For the Customer_Service, and InteractionType, I created unique columns again to make sure there is one column per CustomerID as it has a one to many relationship with InteractionType. 1 customer can put in multiple Interaction or have none, The summary dataframe groups it by feedback, inquiry or complaint and if it was resolved or not each has its own columns assigned to that customer.
- For customers with no values the Nan are filled with 0 rather than dropping the column
- For customer with no demographics or churn status or online activity, they Nan Values were dropped.
- The result was we started with 1000 rows and ended up with 1000 rows.
- Customer_Data is a new table that groups all these tables and columns together using a merge and inner join for the Churn_Status and the Demographics on the CustomerID because they are the key place holders. Then a left join with Transaction_Summary, Customer_Service_Summary, and the Online_Activity.

- Consolidated all the data into Customer_Data and encoded the non_numeric columns to prepare for learning model.

Data Quality Assessment (ROCCC):

- Reliable: Direct from mock company data
- Original: First-party company data
- Comprehensive: Contains all necessary variables for analysis
- Current: Static dataset (not real-time)
- Cited: Well-documented source

Limitations:

- Data does not indicate if feedback is positive or negative which is a valid metric in measuring which customers churn.
- Data is not dynamic/real-time
- Limited to a point-in-time snapshot

```
# Create New Columns based on Transaction History of each "CustomerID"
Transaction_Summary = Transaction_History.groupby('CustomerID').agg(
    TotalSpent = ("AmountSpent", "sum"), # Create column for total
transaction amount
    MinTransaction = ("AmountSpent", "min"), # Create column for
minimum transaction amount
    MaxTransaction = ("AmountSpent", "max"), # Create column for
maximum transaction amount
    TransactionFrequency = ("AmountSpent", "count"), # Create column
for frequency of transactions
    MostRecentTransaction = ("TransactionDate", "max"), # Create
column for most recent transaction date
    FirstTransaction = ("TransactionDate", "min") # Create column for
first transaction date
).reset_index()

# Create column for length of relationship based on first transaction
and most recent transaction
Transaction_Summary['LoyaltyLength'] =
(Transaction_Summary['MostRecentTransaction'] -
Transaction_Summary['FirstTransaction']).dt.days
Transaction_Summary = Transaction_Summary.fillna(0)  # Fill any NaN
values with 0

# Check to make sure all is right with the cosmos thus far
display(Transaction_Summary.head())

   CustomerID  TotalSpent  MinTransaction  MaxTransaction  \
0           1      416.50          416.50          416.50
1           2     1547.42           54.96          397.37
2           3     1702.98           51.07          419.95
3           4      917.29           44.22          382.39
4           5     2001.49           69.86          475.69
```

```
   TransactionFrequency MostRecentTransaction FirstTransaction
LoyaltyLength
0                     1            2022-03-27       2022-03-27
0
1                     7            2022-11-19       2022-01-09
314
2                     6            2022-10-08       2022-02-11
239
3                     5            2022-12-27       2022-05-22
219
4                     8            2022-12-21       2022-02-21
303
```

```
Interaction_Types = Customer_Service['InteractionType'].unique() #
Make a List of the different interaction types

summaries = [] # Create an empty list to hold the summaries of each
interaction type

for interaction_type in Interaction_Types: # for loop that loops
through each interaction type and creates a summary dataframe
    type_summary =
Customer_Service[Customer_Service['InteractionType'] ==
interaction_type].groupby('CustomerID').agg(**{ # group by CustomerID
and aggregate the data
        f"{interaction_type}Count": ('InteractionType', 'count'), # f
string to create dynamic column names
        f"{interaction_type}Resolved": ("ResolutionStatus", lambda x:
(x == 'Resolved').sum())
    }).reset_index()

    type_summary[f"{interaction_type}Unresolved"] =
type_summary[f"{interaction_type}Count"] -
type_summary[f"{interaction_type}Resolved"] # since we cant add or
subtract in the agg function, we create a new column for unresolved
interactions by subtracting resolved from total count

    summaries.append(type_summary) # append the summary dataframe to
the list

# Merge all interaction summaries into a single dataframe
Customer_Service_Summary = summaries[0] # start with the first summary
for i in range(1, len(summaries)): # loop through the rest of the
summaries
    Customer_Service_Summary = pd.merge(Customer_Service_Summary,
summaries[i], on='CustomerID', how='outer') # merge on CustomerID with
an outer join to keep all customers

#fill NaN values with 0s for customers who did not have certain
```

```
interaction types
Customer_Service_Summary = Customer_Service_Summary.fillna(0)
# Check to make sure all is right with the cosmos thus far
display(Customer_Service_Summary.head())
```

```
   CustomerID  InquiryCount  InquiryResolved  InquiryUnresolved  \
0           1          1.00             1.00               0.00
1           2          1.00             1.00               0.00
2           3          1.00             1.00               0.00
3           4          2.00             1.00               1.00
4           6          0.00             0.00               0.00

   FeedbackCount  FeedbackResolved  FeedbackUnresolved  ComplaintCount
\
0           0.00              0.00                0.00            0.00

1           0.00              0.00                0.00            0.00

2           0.00              0.00                0.00            0.00

3           0.00              0.00                0.00            0.00

4           1.00              1.00                0.00            0.00


   ComplaintResolved  ComplaintUnresolved
0               0.00                 0.00
1               0.00                 0.00
2               0.00                 0.00
3               0.00                 0.00
4               0.00                 0.00
```

```
# Address Nan values in individual datasets before merging
Customer_Demographics = Customer_Demographics.dropna()
Churn_Status = Churn_Status.dropna()
Online_Activity = Online_Activity.dropna()

#  Merge Customer Demographics, Transaction Summary, Customer Service
Summary, Online Activity, and Churn Status into a single dataframe
Customer_Data = pd.merge(Customer_Demographics, Churn_Status,
on='CustomerID', how = 'inner')
Customer_Data = pd.merge(Customer_Data, Transaction_Summary,
on='CustomerID', how = 'left').fillna(0) # Fill NaN values with 0 for
customers with no transactions
Customer_Data = pd.merge(Customer_Data, Customer_Service_Summary,
on='CustomerID', how = 'left').fillna(0) # Fill NaN values with 0 for
customers with no customer service interactions
Customer_Data = pd.merge(Customer_Data, Online_Activity,
on='CustomerID', how = 'left')
```

Analysis Steps:

1. ***Descriptive Statistics***

- Used the describe().T function to calculate mean, median, standard deviation, minimum, 25% quartile, median 75% quartile, maximum, and then the skew and kurtosis as well for all numeric variables.
- Calculated skew and kurtosis to determine distribution shapes, and see where the outliers mostly are, and to determine where to use StandardScale or RobustScale when calculating z scores.
- Calculated the churn_rate to check for balance.

1. ***Relationship Analysis***

- Correlation analysis between variables and churn_rate. -Visualization with bar graph and box plots to confirm correlation calculations, check for outliers and confirm statistical information.

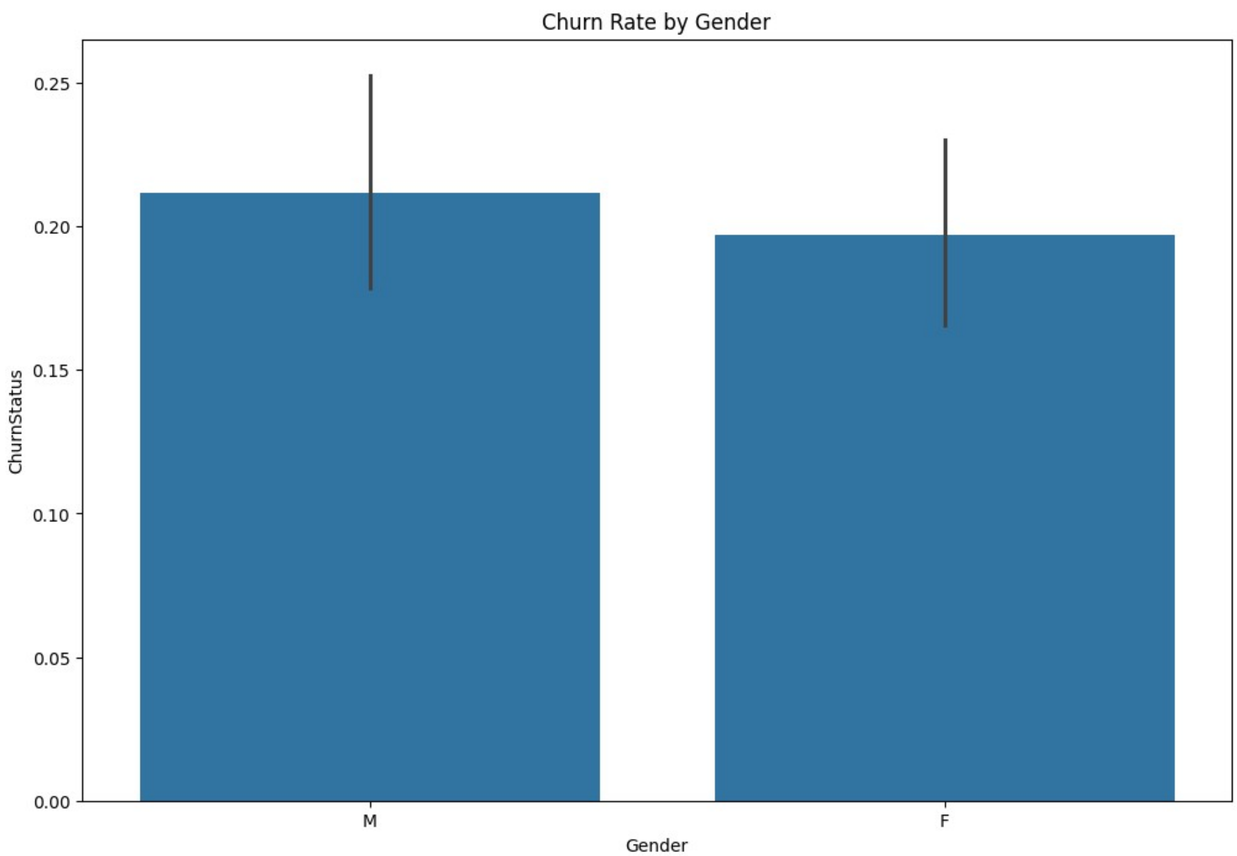
```
#Create a table to summarize numerical features
description =
Customer_Data.select_dtypes(include='number').describe().T
description['skew'] =
Customer_Data.select_dtypes(include='number').skew()
description['kurtosis'] =
Customer_Data.select_dtypes(include='number').kurtosis()
description.round(2)

# Final check to make sure all is right with the cosmos thus far
print(Customer_Data.info())
display(Customer_Data.head())
display(description)

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   CustomerID             1000 non-null   int64
 1   Age                    1000 non-null   int64
 2   Gender                 1000 non-null   object
 3   MaritalStatus          1000 non-null   object
 4   IncomeLevel            1000 non-null   object
 5   ChurnStatus            1000 non-null   int64
 6   TotalSpent             1000 non-null   float64
 7   MinTransaction         1000 non-null   float64
 8   MaxTransaction         1000 non-null   float64
 9   TransactionFrequency   1000 non-null   int64
 10  MostRecentTransaction  1000 non-null   datetime64[ns]
 11  FirstTransaction       1000 non-null   datetime64[ns]
 12  LoyaltyLength          1000 non-null   int64
 13  InquiryCount           1000 non-null   float64
 14  InquiryResolved        1000 non-null   float64
```

```
 15  InquiryUnresolved      1000 non-null   float64
 16  FeedbackCount          1000 non-null   float64
 17  FeedbackResolved       1000 non-null   float64
 18  FeedbackUnresolved     1000 non-null   float64
 19  ComplaintCount         1000 non-null   float64
 20  ComplaintResolved      1000 non-null   float64
 21  ComplaintUnresolved    1000 non-null   float64
 22  LastLoginDate          1000 non-null   datetime64[ns]
 23  LoginFrequency         1000 non-null   int64
 24  ServiceUsage           1000 non-null   object
dtypes: datetime64[ns](3), float64(12), int64(6), object(4)
memory usage: 195.4+ KB
None

   CustomerID  Age Gender MaritalStatus IncomeLevel  ChurnStatus
TotalSpent  \
0           1   62      M        Single         Low            0
416.50
1           2   65      M       Married         Low            1
1547.42
2           3   18      M        Single         Low            0
1702.98
3           4   21      M       Widowed         Low            0
917.29
4           5   21      M      Divorced      Medium            0
2001.49

   MinTransaction  MaxTransaction  TransactionFrequency
MostRecentTransaction  \
0          416.50          416.50                     1
2022-03-27
1           54.96          397.37                     7
2022-11-19
2           51.07          419.95                     6
2022-10-08
3           44.22          382.39                     5
2022-12-27
4           69.86          475.69                     8
2022-12-21

  FirstTransaction  LoyaltyLength  InquiryCount  InquiryResolved  \
0       2022-03-27              0          1.00             1.00
1       2022-01-09            314          1.00             1.00
2       2022-02-11            239          1.00             1.00
3       2022-05-22            219          2.00             1.00
4       2022-02-21            303          0.00             0.00

   InquiryUnresolved  FeedbackCount  FeedbackResolved
FeedbackUnresolved  \
0               0.00           0.00              0.00
```

```
0.00
1               0.00           0.00                 0.00
0.00
2               0.00           0.00                 0.00
0.00
3               1.00           0.00                 0.00
0.00
4               0.00           0.00                 0.00
0.00

   ComplaintCount  ComplaintResolved  ComplaintUnresolved
LastLoginDate  \
0            0.00               0.00                 0.00    2023-10-
21
1            0.00               0.00                 0.00    2023-12-
05
2            0.00               0.00                 0.00    2023-11-
15
3            0.00               0.00                 0.00    2023-08-
25
4            0.00               0.00                 0.00    2023-10-
27

   LoginFrequency ServiceUsage
0              34   Mobile App
1               5      Website
2               3      Website
3               2      Website
4              41      Website

                      count    mean    std   min    25%     50%
75%  \
CustomerID          1000.00  500.50 288.82  1.00 250.75  500.50
750.25
Age                 1000.00   43.27  15.24 18.00  30.00   43.00
56.00
ChurnStatus         1000.00    0.20   0.40  0.00   0.00    0.00
0.00
TotalSpent          1000.00 1267.07 738.59  9.80 626.68 1232.88
1791.90
MinTransaction      1000.00  107.07 101.08  5.18  32.80   74.62
146.40
MaxTransaction      1000.00  390.18 107.38  9.80 342.86  429.93
468.50
TransactionFrequency 1000.00    5.05   2.60  1.00   3.00    5.00
7.00
LoyaltyLength       1000.00  208.11 109.96  0.00 137.75  240.00
294.25
InquiryCount        1000.00    0.31   0.52  0.00   0.00    0.00
1.00
```

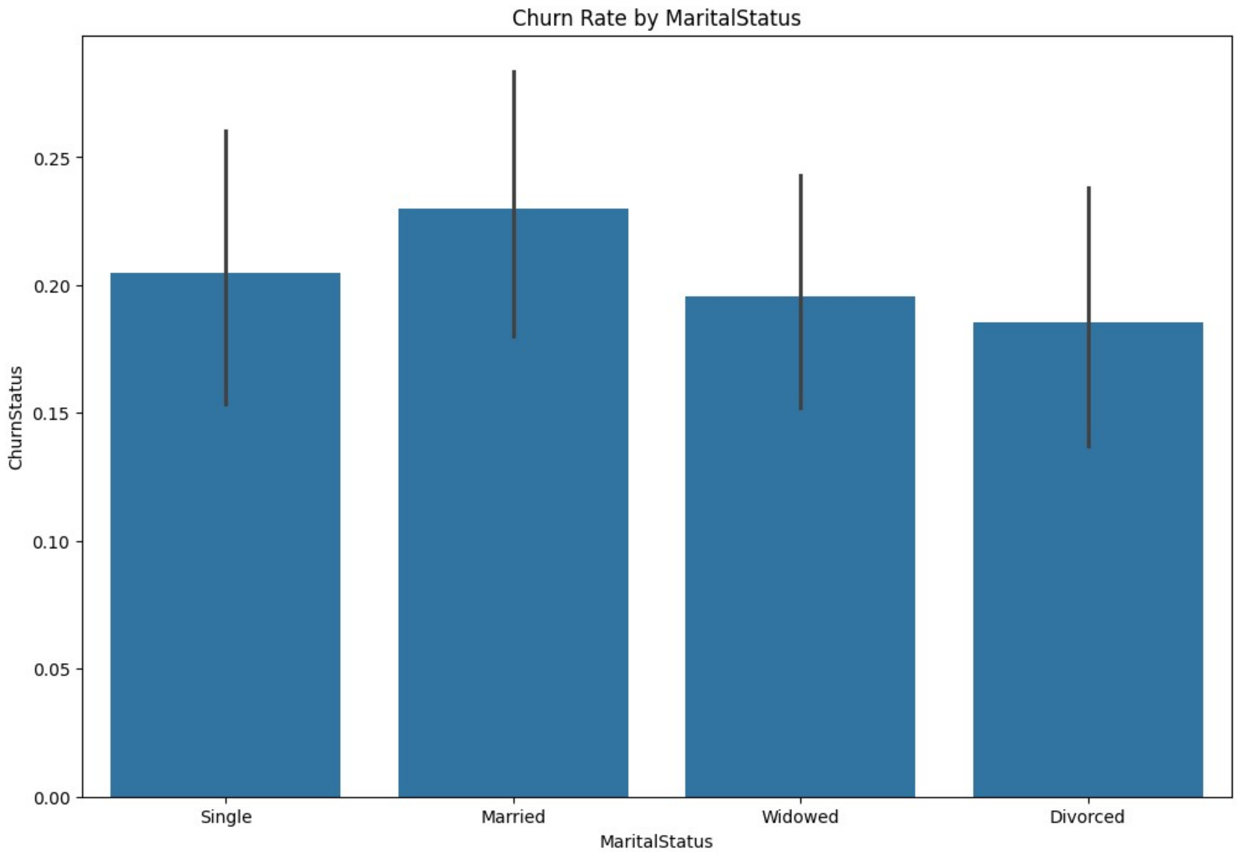
```
InquiryResolved       1000.00    0.17   0.40  0.00   0.00    0.00
0.00
InquiryUnresolved     1000.00    0.14   0.36  0.00   0.00    0.00
0.00
FeedbackCount         1000.00    0.36   0.58  0.00   0.00    0.00
1.00
FeedbackResolved      1000.00    0.20   0.43  0.00   0.00    0.00
0.00
FeedbackUnresolved    1000.00    0.16   0.39  0.00   0.00    0.00
0.00
ComplaintCount        1000.00    0.34   0.55  0.00   0.00    0.00
1.00
ComplaintResolved     1000.00    0.16   0.38  0.00   0.00    0.00
0.00
ComplaintUnresolved   1000.00    0.18   0.41  0.00   0.00    0.00
0.00
LoginFrequency        1000.00   25.91  14.06  1.00  13.75   27.00
38.00

                          max  skew  kurtosis
CustomerID            1000.00  0.00     -1.20
Age                     69.00  0.01     -1.21
ChurnStatus              1.00  1.47      0.17
TotalSpent            3386.04  0.27     -0.79
MinTransaction         496.99  1.60      2.39
MaxTransaction         499.86 -1.51      1.90
TransactionFrequency     9.00 -0.06     -1.24
LoyaltyLength          361.00 -0.73     -0.70
InquiryCount             2.00  1.43      1.09
InquiryResolved          2.00  2.20      4.01
InquiryUnresolved        2.00  2.35      4.41
FeedbackCount            2.00  1.38      0.88
FeedbackResolved         2.00  1.93      2.79
FeedbackUnresolved       2.00  2.33      4.71
ComplaintCount           2.00  1.38      0.95
ComplaintResolved        2.00  2.31      4.55
ComplaintUnresolved      2.00  2.14      3.79
LoginFrequency          49.00 -0.13     -1.18

# Count how many customers churned vs. did not churn
churn_counts = Customer_Data['ChurnStatus'].value_counts()
print(churn_counts)
# Calculate churn rate
churn_rate = (churn_counts[1] / churn_counts.sum()) * 100  #
Percentage of customers who churned
print(f"Churn Rate: {churn_rate:.2f}%")

ChurnStatus
0    796
1    204
```

```
Name: count, dtype: int64
Churn Rate: 20.40%

# For Loop to calculate churn rates for categorical variables
categorical_columns =
Customer_Data.select_dtypes(include='object').columns

for col in categorical_columns:
    churn_rates = Customer_Data.groupby(col)['ChurnStatus'].mean()
    print(churn_rates)
    plt.figure(figsize=(12, 8))
    sns.barplot(x=col, y='ChurnStatus', data=Customer_Data)
    plt.title(f'Churn Rate by {col}')
    plt.show()

Gender
F   0.20
M   0.21
Name: ChurnStatus, dtype: float64
```

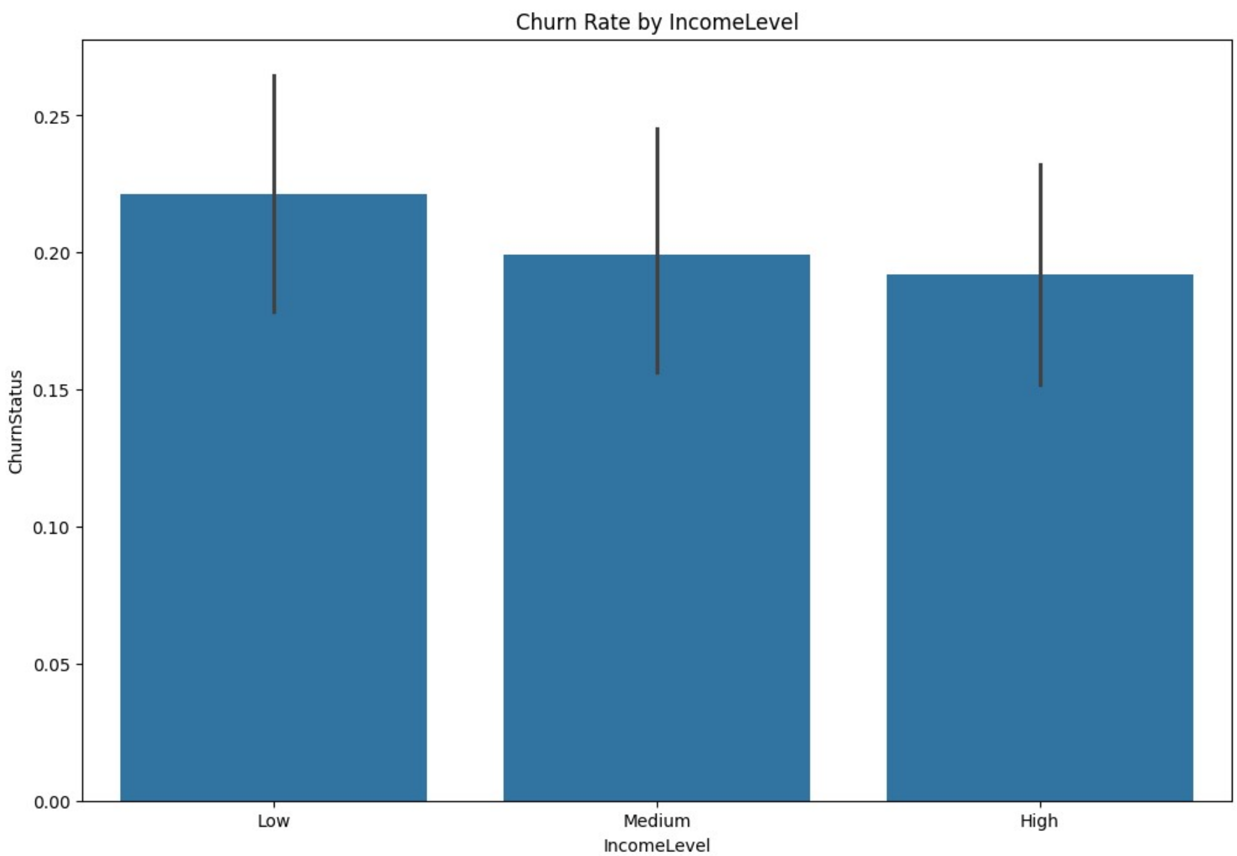



```
MaritalStatus
Divorced   0.19
Married    0.23
```

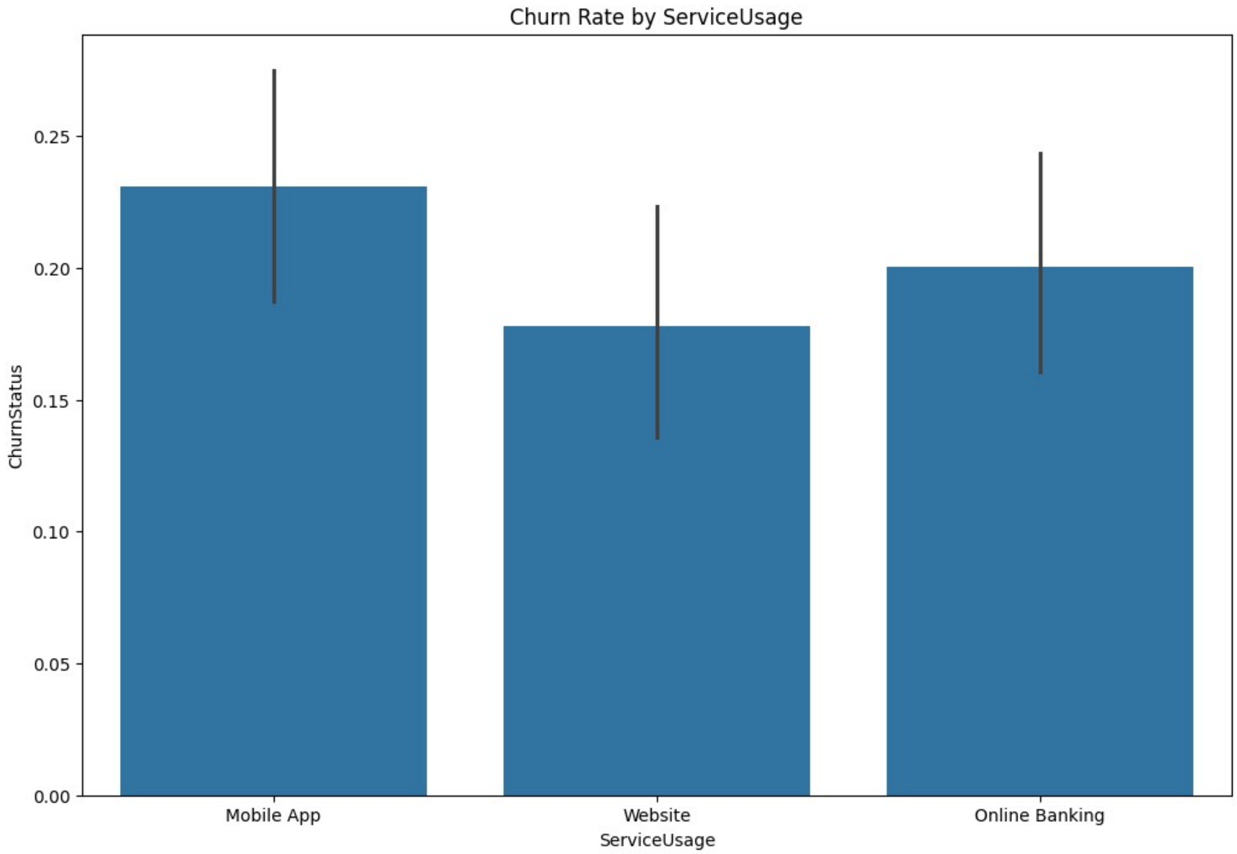
```
Single      0.20
Widowed     0.20
Name: ChurnStatus, dtype: float64
```



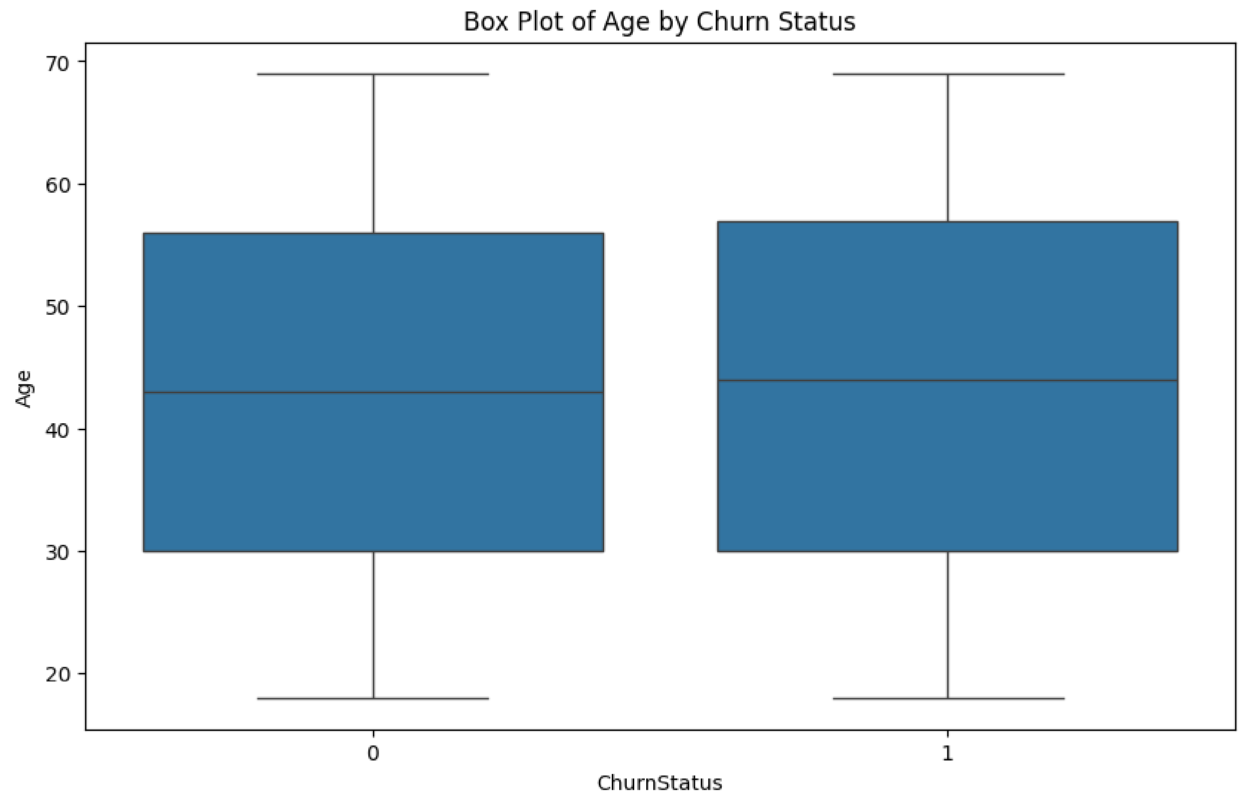

```
IncomeLevel
High      0.19
Low       0.22
Medium    0.20
Name: ChurnStatus, dtype: float64
```

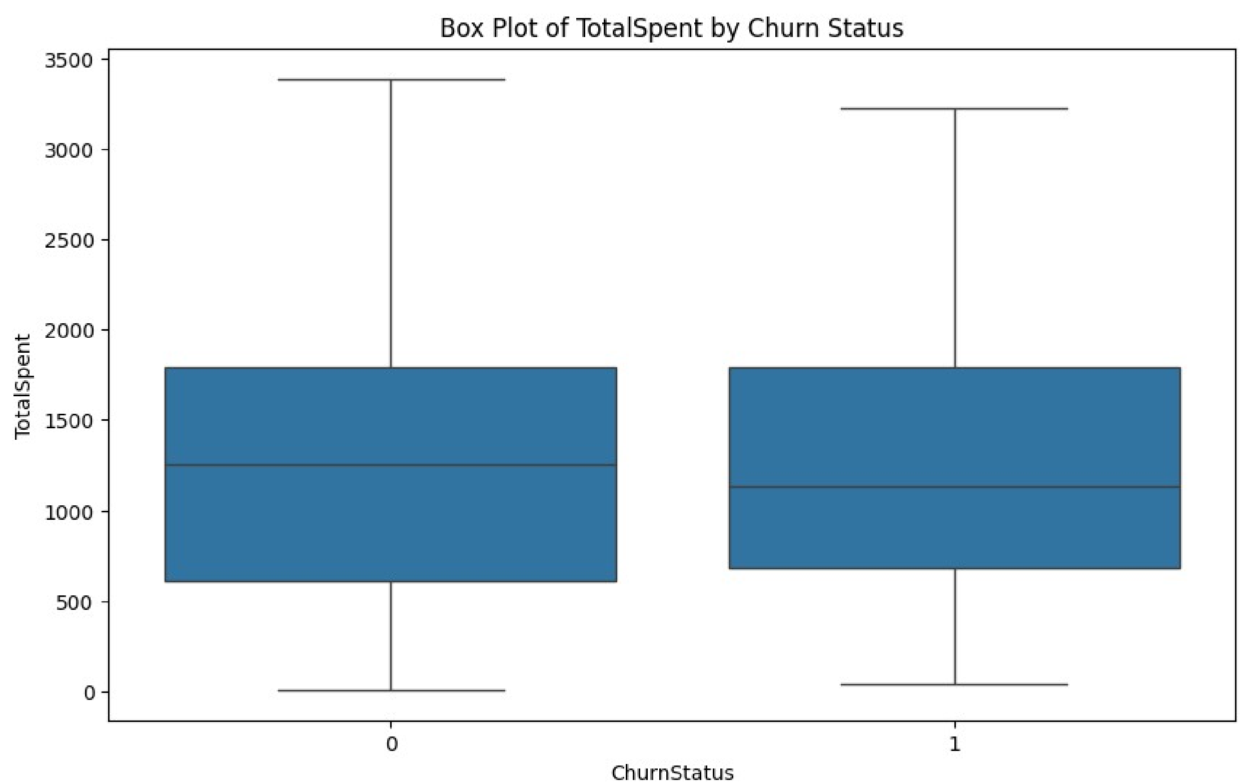



```
ServiceUsage
Mobile App        0.23
Online Banking    0.20
Website           0.18
Name: ChurnStatus, dtype: float64
```

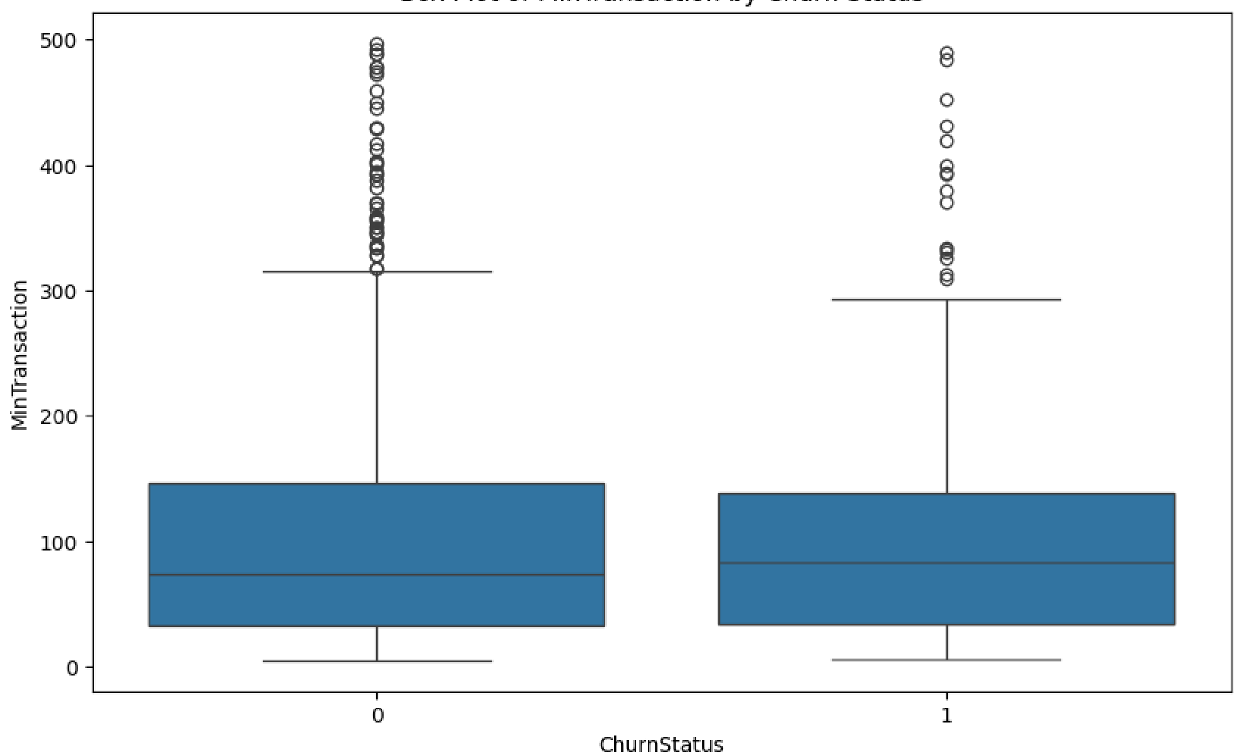



```
# For Loop to plot box plots for the numerical variables against churn status
numerical_columns = Customer_Data.select_dtypes(include='number').columns.drop(['ChurnStatus','CustomerID'])
for col in numerical_columns:
    plt.figure(figsize=(10, 6))
    sns.boxplot(x='ChurnStatus', y=col, data=Customer_Data)
    plt.title(f'Box Plot of {col} by Churn Status')
    plt.show()
```

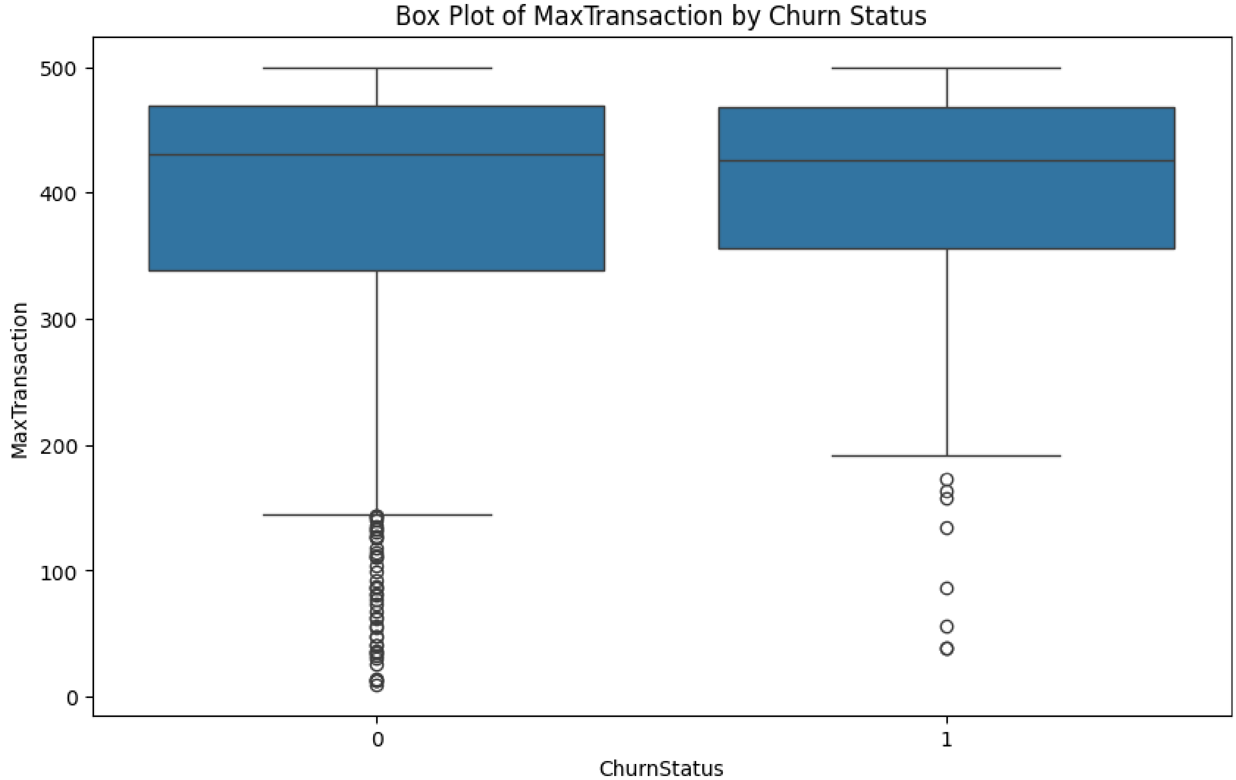

Box Plot of Age by Churn Status
Age
70
60
50
40
30
20
0
1
ChurnStatus

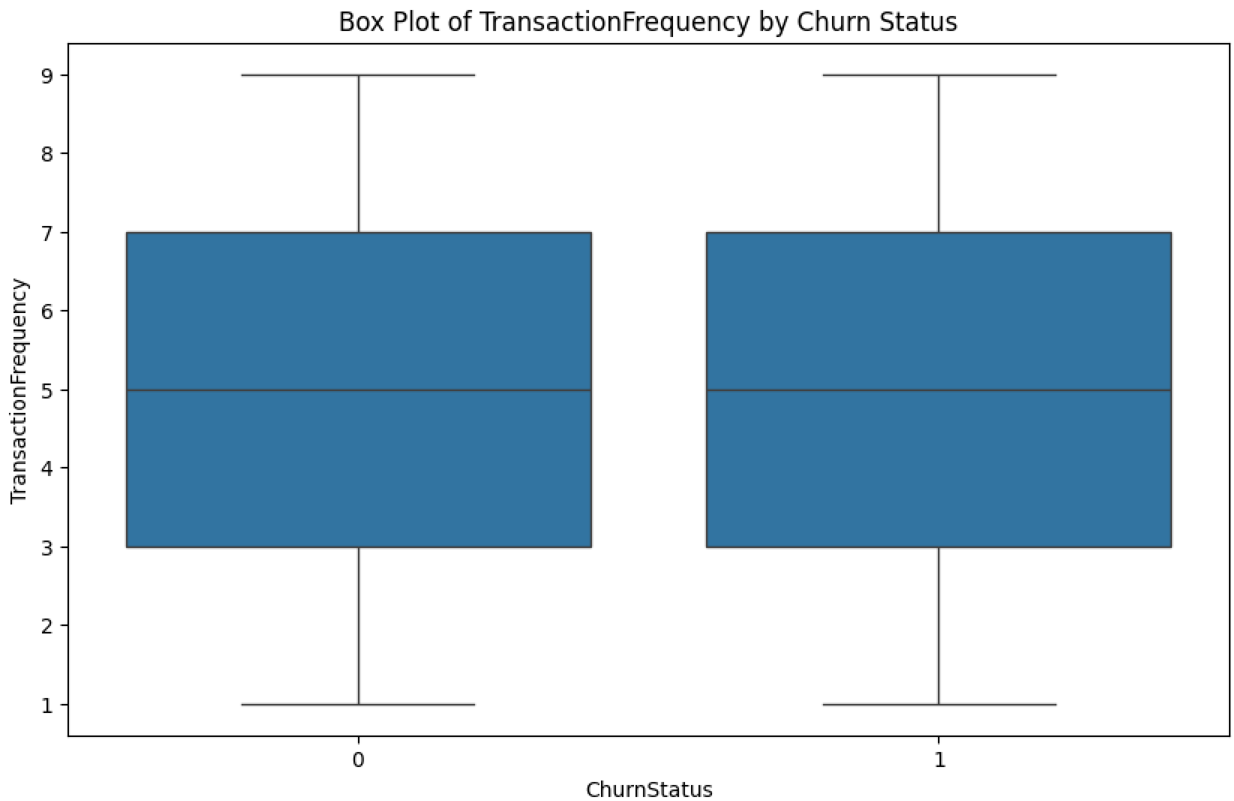

Box Plot of TotalSpent by Churn Status
TotalSpent
3500
3000
2500
2000
1500
1000
500
0
0
1
ChurnStatus

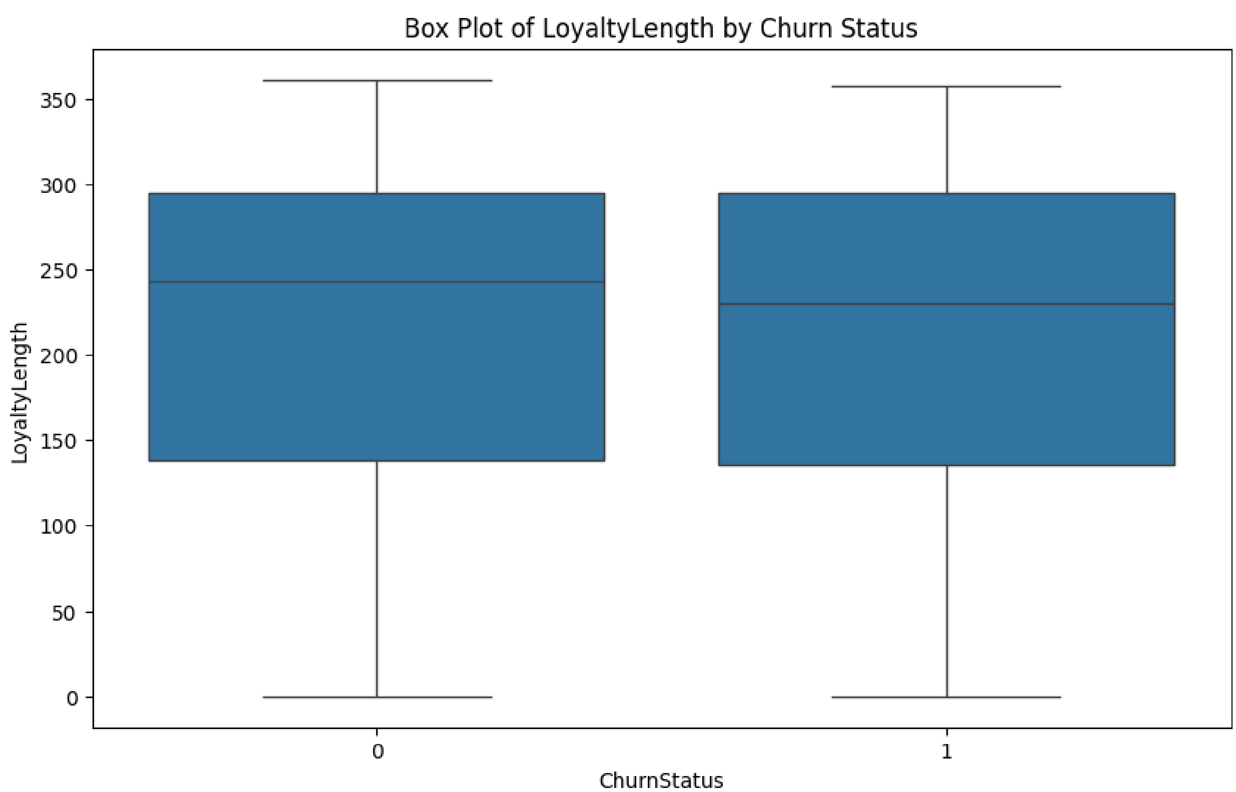
Box Plot of MinTransaction by Churn Status

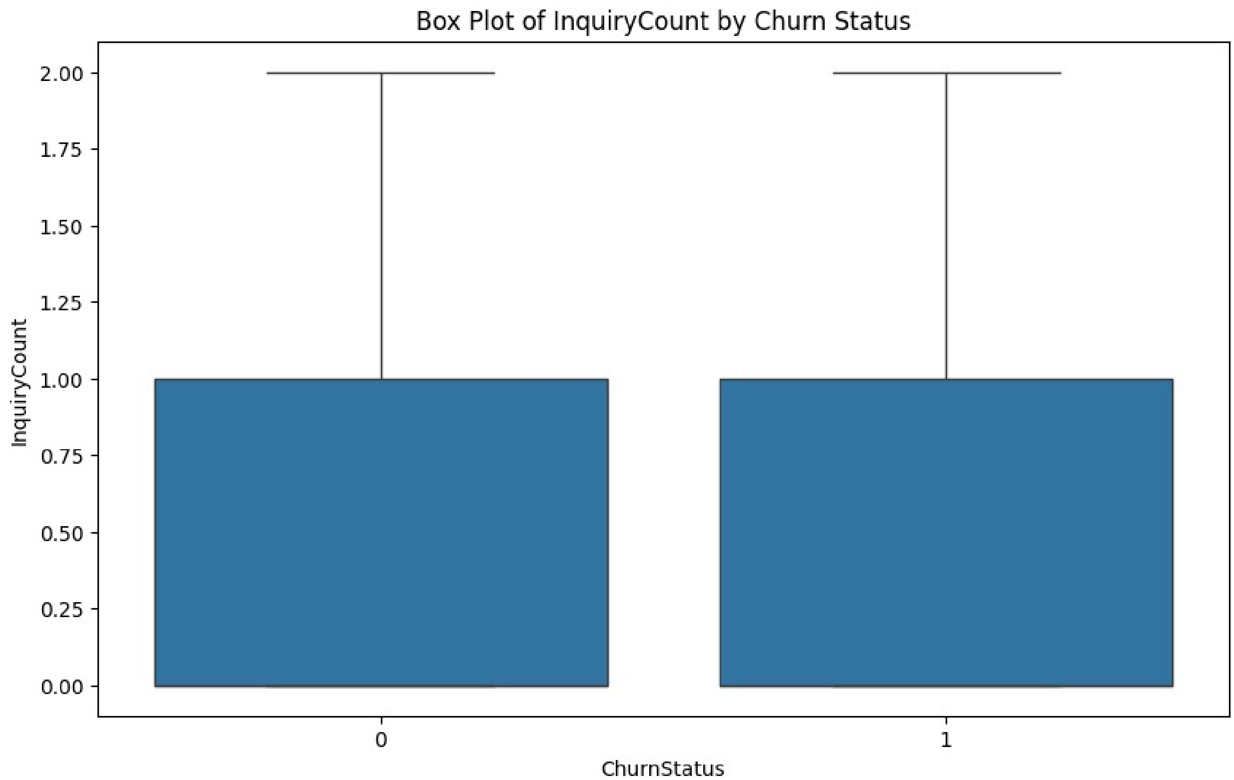


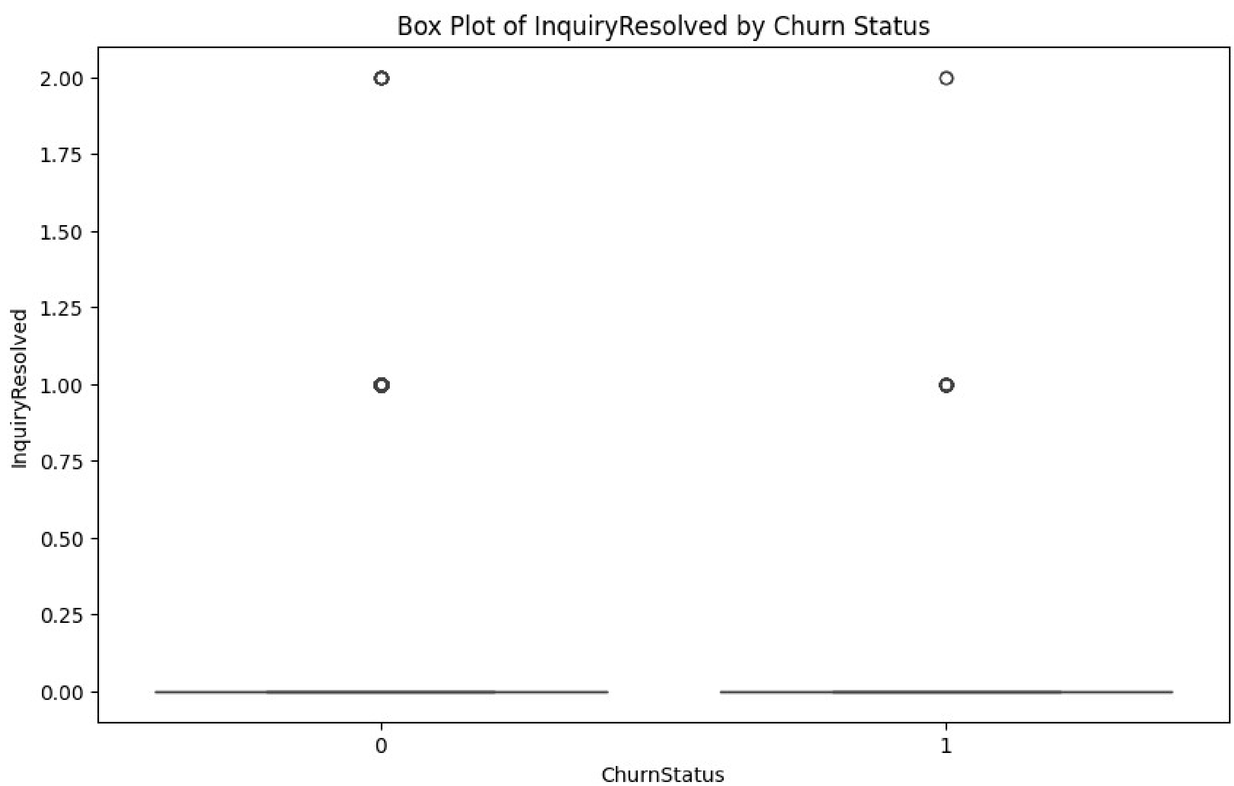
Box Plot of MaxTransaction by Churn Status

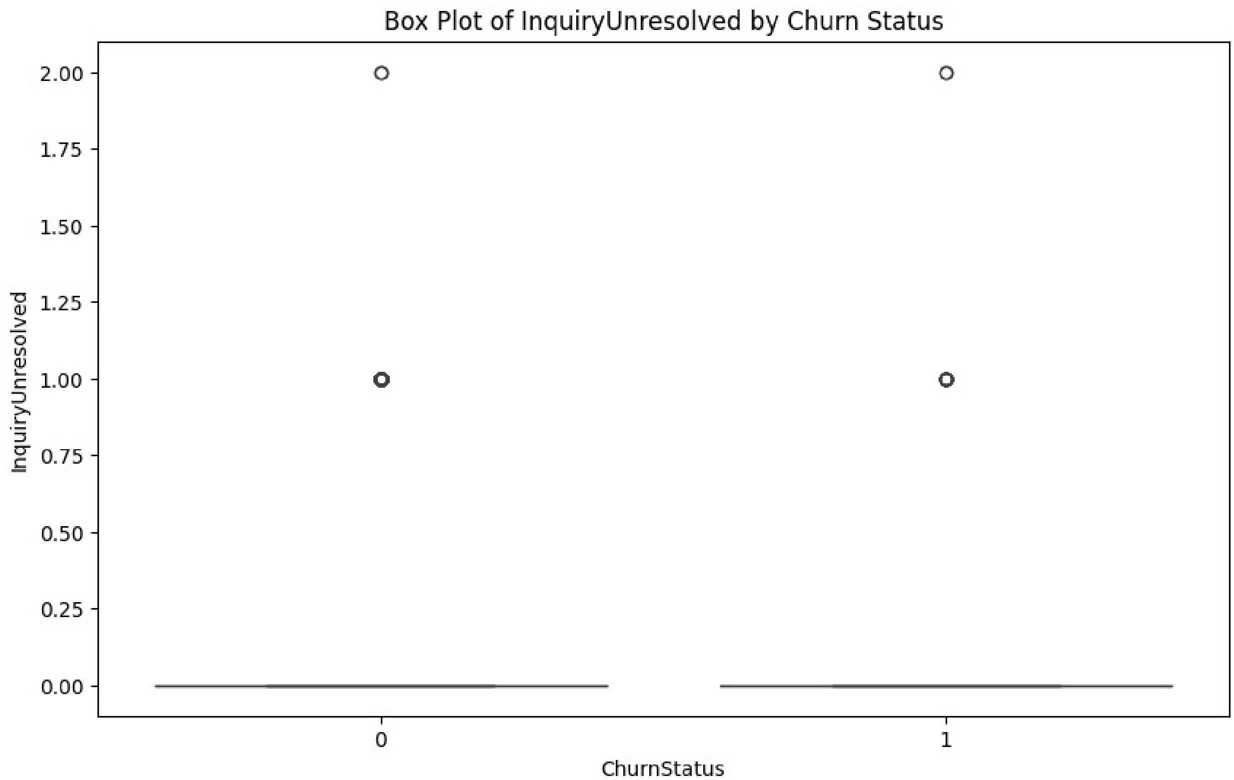


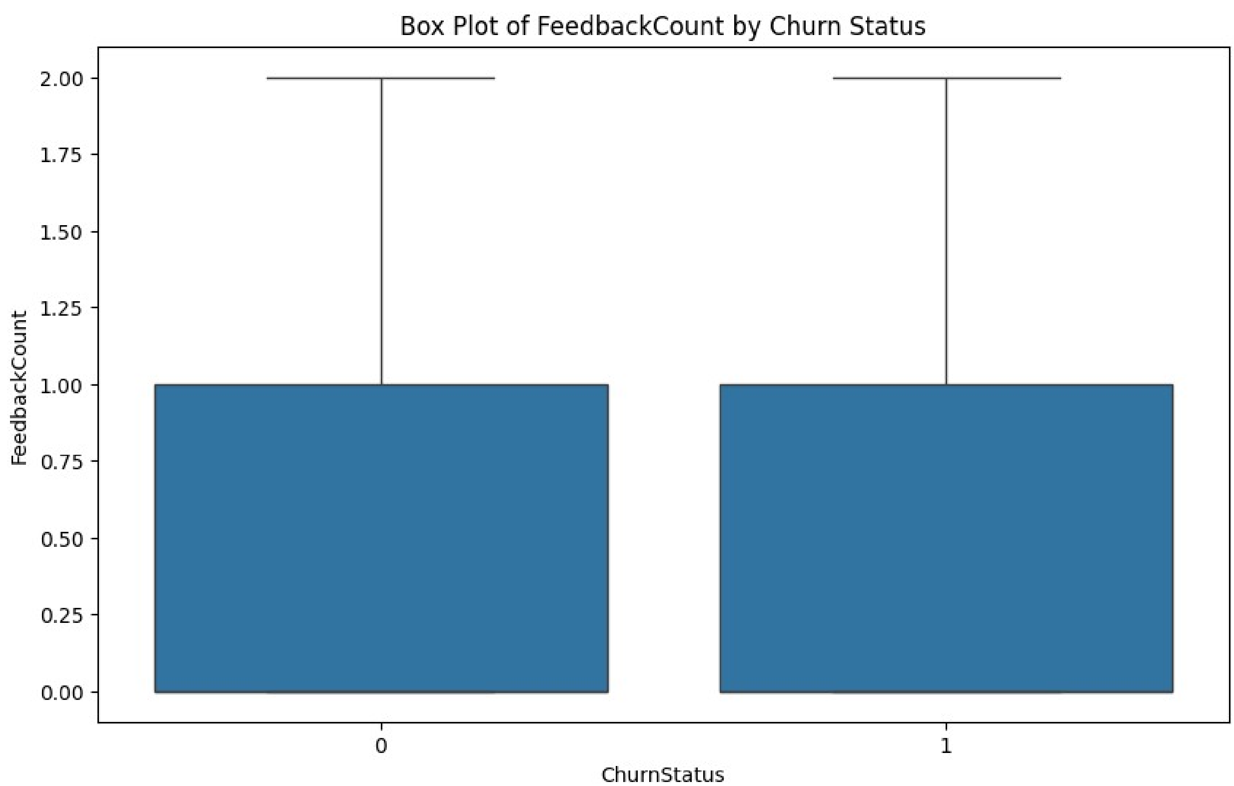

Box Plot of TransactionFrequency by Churn Status
TransactionFrequency
ChurnStatus
0
1
9
8
7
6
5
4
3
2
1

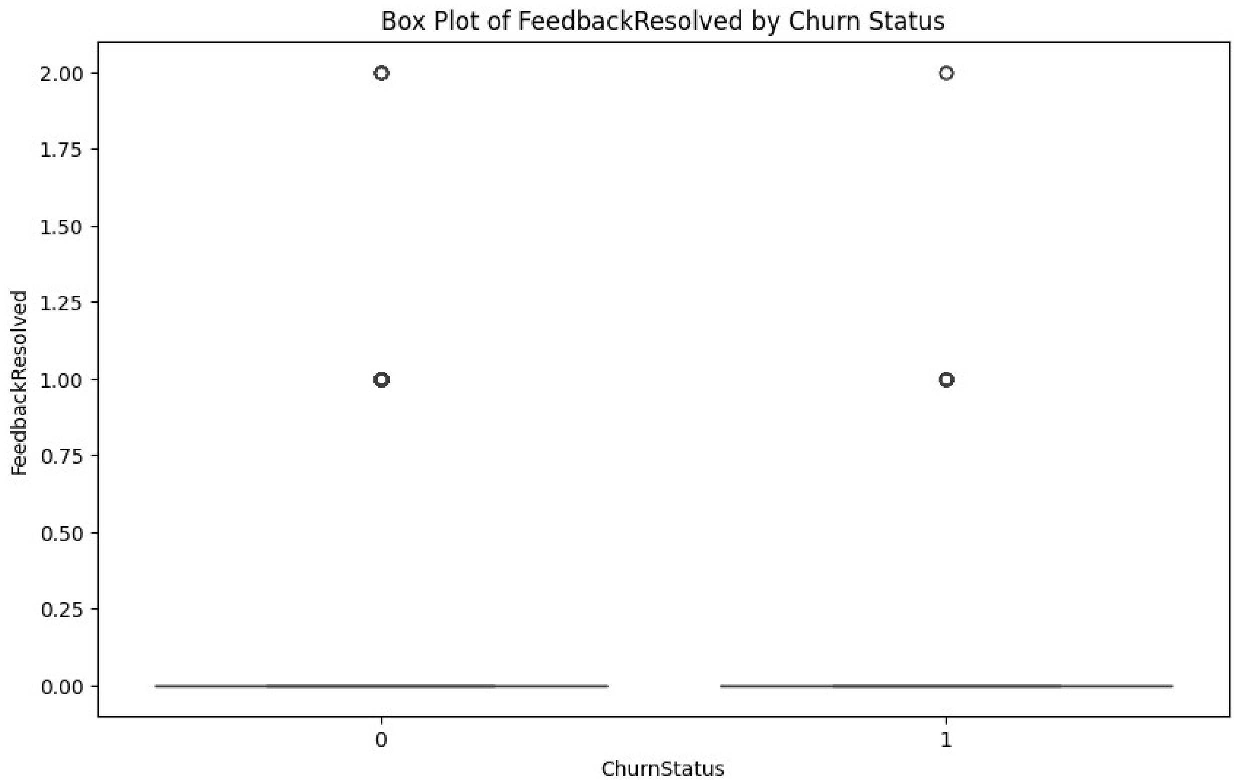

Box Plot of LoyaltyLength by Churn Status
LoyaltyLength
ChurnStatus
0
1
350
300
250
200
150
100
50
0

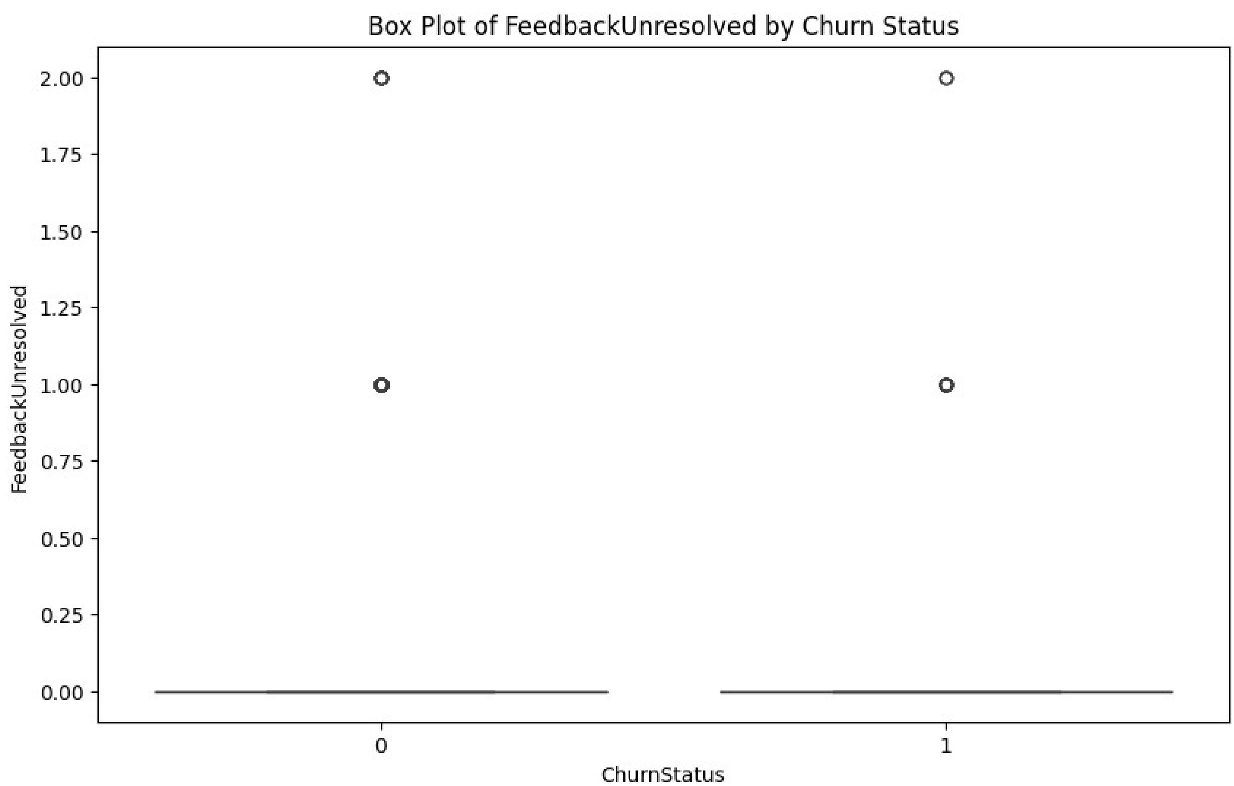

Box Plot of InquiryCount by Churn Status
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
InquiryCount
0
1
ChurnStatus

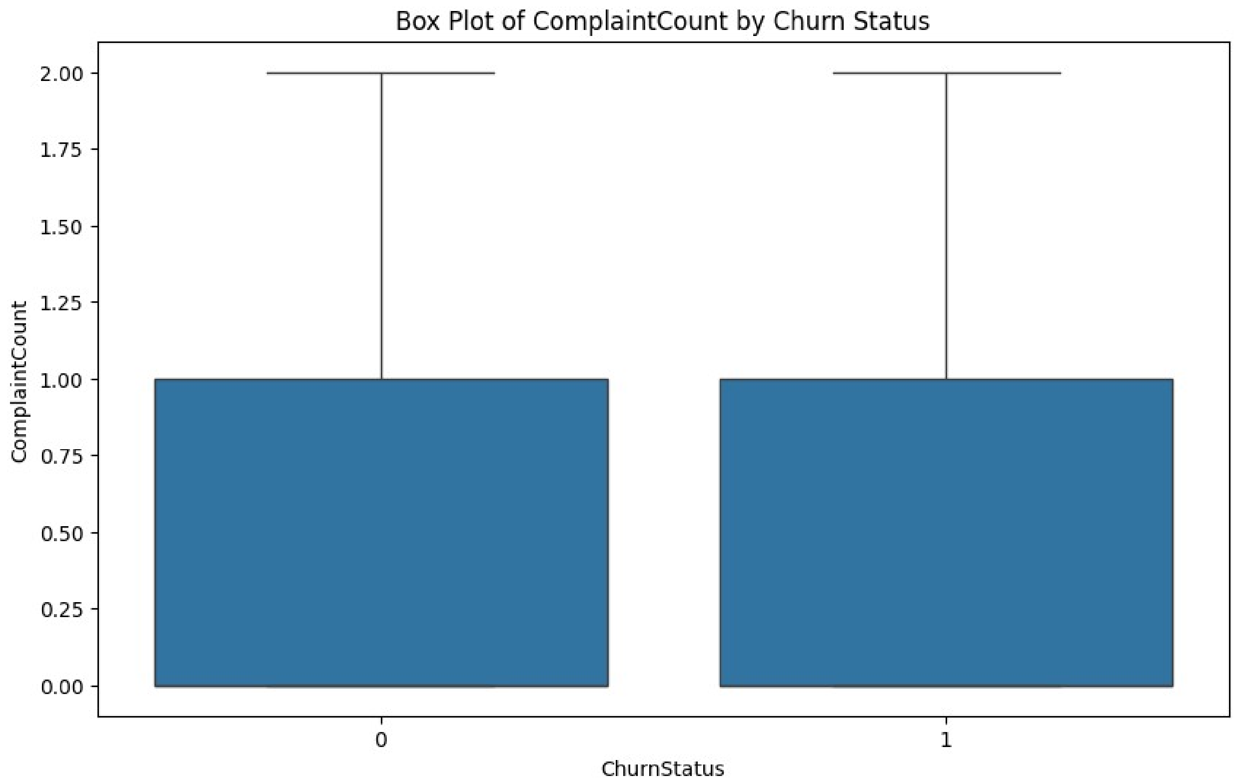

Box Plot of InquiryResolved by Churn Status
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
InquiryResolved
0
1
ChurnStatus

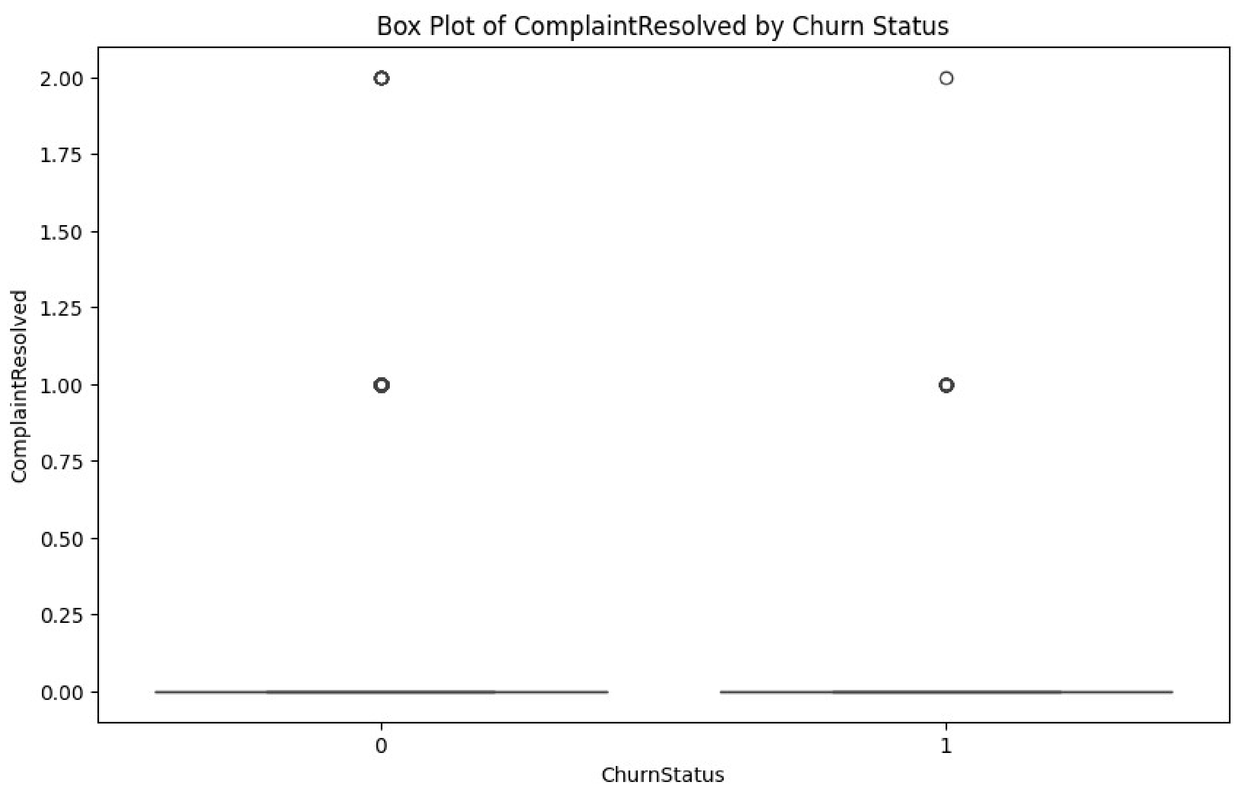

Box Plot of InquiryUnresolved by Churn Status
InquiryUnresolved
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
1
ChurnStatus

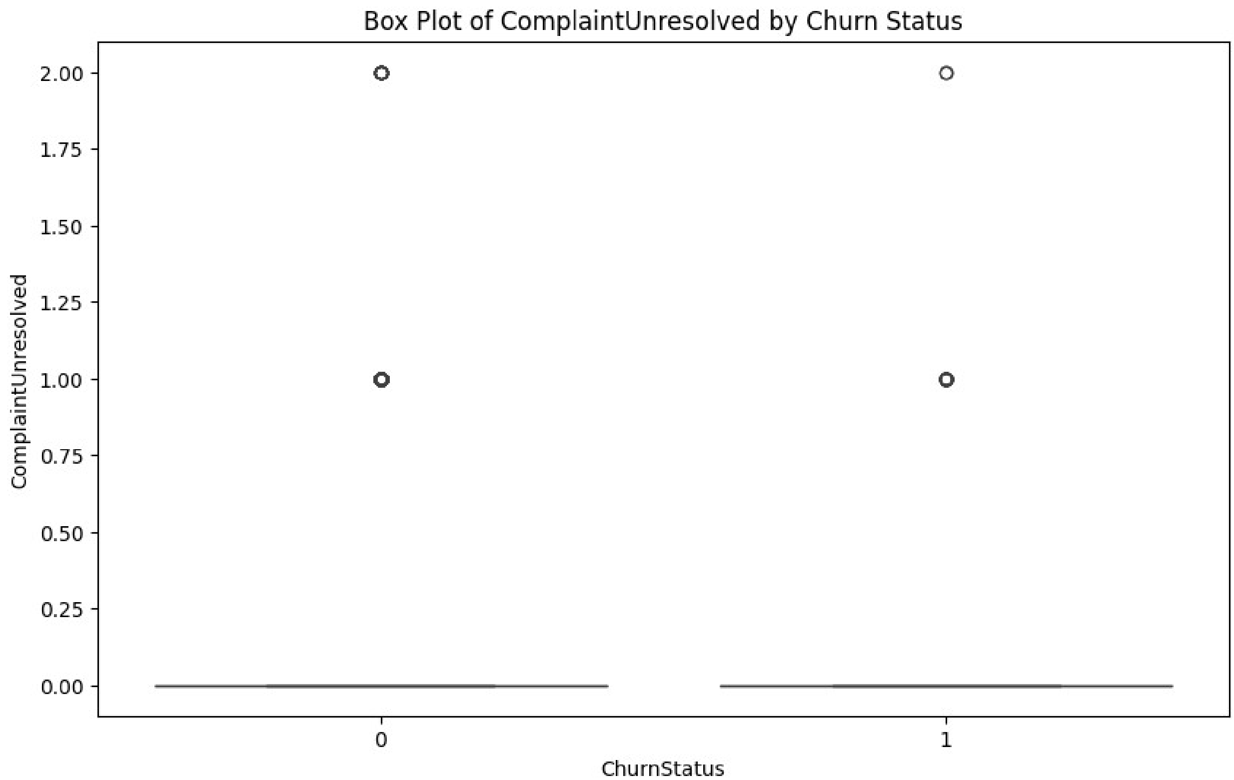

Box Plot of FeedbackCount by Churn Status
FeedbackCount
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
1
ChurnStatus

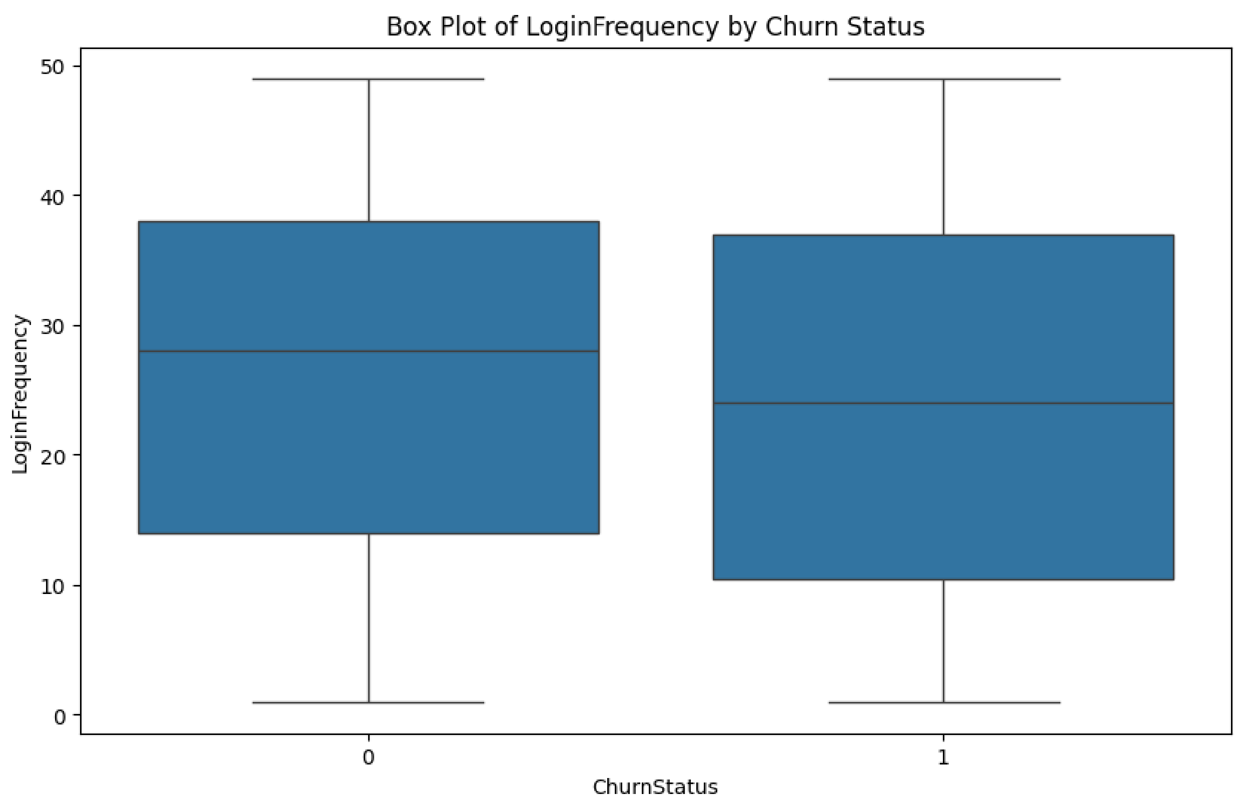

Box Plot of FeedbackResolved by Churn Status
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
FeedbackResolved
0
1
ChurnStatus


Box Plot of FeedbackUnresolved by Churn Status
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
FeedbackUnresolved
0
1
ChurnStatus


Box Plot of ComplaintCount by Churn Status
ComplaintCount
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
1
ChurnStatus


Box Plot of ComplaintResolved by Churn Status
ComplaintResolved
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
1
ChurnStatus





Encode categorical data to numbers to prep for algorithm

```python
# Encode categorical variables using mapping for the IncomeLevel as
order matters.

Customer_Data['IncomeLevel'] = Customer_Data['IncomeLevel'].map({
    'Low': 1,
    'Medium': 2,
    'High': 3
    })

display(Customer_Data.head())
```

```
   CustomerID  Age Gender MaritalStatus  IncomeLevel  ChurnStatus
TotalSpent  \
0           1   62      M        Single            1            0
416.50
1           2   65      M       Married            1            1
1547.42
2           3   18      M        Single            1            0
1702.98
3           4   21      M       Widowed            1            0
917.29
4           5   21      M      Divorced            2            0
2001.49

   MinTransaction  MaxTransaction  TransactionFrequency
MostRecentTransaction  \
0          416.50          416.50                     1
2022-03-27
1           54.96          397.37                     7
2022-11-19
2           51.07          419.95                     6
2022-10-08
3           44.22          382.39                     5
2022-12-27
4           69.86          475.69                     8
2022-12-21

  FirstTransaction  LoyaltyLength  InquiryCount  InquiryResolved  \
0       2022-03-27              0          1.00             1.00
1       2022-01-09            314          1.00             1.00
2       2022-02-11            239          1.00             1.00
3       2022-05-22            219          2.00             1.00
4       2022-02-21            303          0.00             0.00

   InquiryUnresolved  FeedbackCount  FeedbackResolved
FeedbackUnresolved  \
0               0.00           0.00              0.00
0.00
1               0.00           0.00              0.00
0.00
```

```
2              0.00         0.00            0.00
0.00
3              1.00         0.00            0.00
0.00
4              0.00         0.00            0.00
0.00

   ComplaintCount  ComplaintResolved  ComplaintUnresolved
LastLoginDate  \
0            0.00               0.00                 0.00    2023-10-
21
1            0.00               0.00                 0.00    2023-12-
05
2            0.00               0.00                 0.00    2023-11-
15
3            0.00               0.00                 0.00    2023-08-
25
4            0.00               0.00                 0.00    2023-10-
27

   LoginFrequency ServiceUsage
0              34   Mobile App
1               5      Website
2               3      Website
3               2      Website
4              41      Website
```

```python
# Encode Gender using one-hot encoding since order does not matter

isMale = pd.get_dummies(Customer_Data['Gender'], drop_first=True)
Customer_Data['Gender'] = isMale
Customer_Data['Gender'] = Customer_Data['Gender'].astype(int) # Change
from true to an integer 1

# Rename Columns for clarity
Customer_Data = Customer_Data.rename(columns={'Gender': 'isMale'})

# Drop the date columns as they have served their purpose
Customer_Data = Customer_Data.drop(columns=['MostRecentTransaction',
'FirstTransaction', 'LastLoginDate'])

display(Customer_Data.head())
```

```
   CustomerID  Age  isMale MaritalStatus  IncomeLevel  ChurnStatus  \
0           1   62       1        Single            1            0
1           2   65       1       Married            1            1
2           3   18       1        Single            1            0
3           4   21       1       Widowed            1            0
4           5   21       1      Divorced            2            0

   TotalSpent  MinTransaction  MaxTransaction  TransactionFrequency  \
```

```
0     416.50          416.50          416.50                     1
1    1547.42           54.96          397.37                     7
2    1702.98           51.07          419.95                     6
3     917.29           44.22          382.39                     5
4    2001.49           69.86          475.69                     8

   LoyaltyLength  InquiryCount  InquiryResolved  InquiryUnresolved  \
0              0          1.00             1.00               0.00
1            314          1.00             1.00               0.00
2            239          1.00             1.00               0.00
3            219          2.00             1.00               1.00
4            303          0.00             0.00               0.00

   FeedbackCount  FeedbackResolved  FeedbackUnresolved  ComplaintCount
\
0           0.00              0.00                0.00            0.00

1           0.00              0.00                0.00            0.00

2           0.00              0.00                0.00            0.00

3           0.00              0.00                0.00            0.00

4           0.00              0.00                0.00            0.00


   ComplaintResolved  ComplaintUnresolved  LoginFrequency ServiceUsage

0               0.00                 0.00              34   Mobile App

1               0.00                 0.00               5      Website

2               0.00                 0.00               3      Website

3               0.00                 0.00               2      Website

4               0.00                 0.00              41      Website
```

```
# Encode all the other categorical variables using one-hot encoding
Customer_Data = pd.get_dummies(Customer_Data,
columns=['MaritalStatus', 'ServiceUsage'], dtype=int)
display(Customer_Data.head())
Customer_Data.info()
```

```
   CustomerID  Age  isMale  IncomeLevel  ChurnStatus  TotalSpent  \
0           1   62       1            1            0      416.50
1           2   65       1            1            1     1547.42
2           3   18       1            1            0     1702.98
3           4   21       1            1            0      917.29
4           5   21       1            2            0     2001.49
```

```
   MinTransaction  MaxTransaction  TransactionFrequency  LoyaltyLength
\
0          416.50          416.50                     1              0

1           54.96          397.37                     7            314

2           51.07          419.95                     6            239

3           44.22          382.39                     5            219

4           69.86          475.69                     8            303


   InquiryCount  InquiryResolved  InquiryUnresolved  FeedbackCount  \
0          1.00             1.00               0.00           0.00
1          1.00             1.00               0.00           0.00
2          1.00             1.00               0.00           0.00
3          2.00             1.00               1.00           0.00
4          0.00             0.00               0.00           0.00

   FeedbackResolved  FeedbackUnresolved  ComplaintCount
ComplaintResolved  \
0              0.00                0.00            0.00
0.00
1              0.00                0.00            0.00
0.00
2              0.00                0.00            0.00
0.00
3              0.00                0.00            0.00
0.00
4              0.00                0.00            0.00
0.00

   ComplaintUnresolved  LoginFrequency  MaritalStatus_Divorced  \
0                 0.00              34                       0
1                 0.00               5                       0
2                 0.00               3                       0
3                 0.00               2                       0
4                 0.00              41                       1

   MaritalStatus_Married  MaritalStatus_Single  MaritalStatus_Widowed
\
0                      0                     1                      0

1                      1                     0                      0

2                      0                     1                      0

3                      0                     0                      1
```

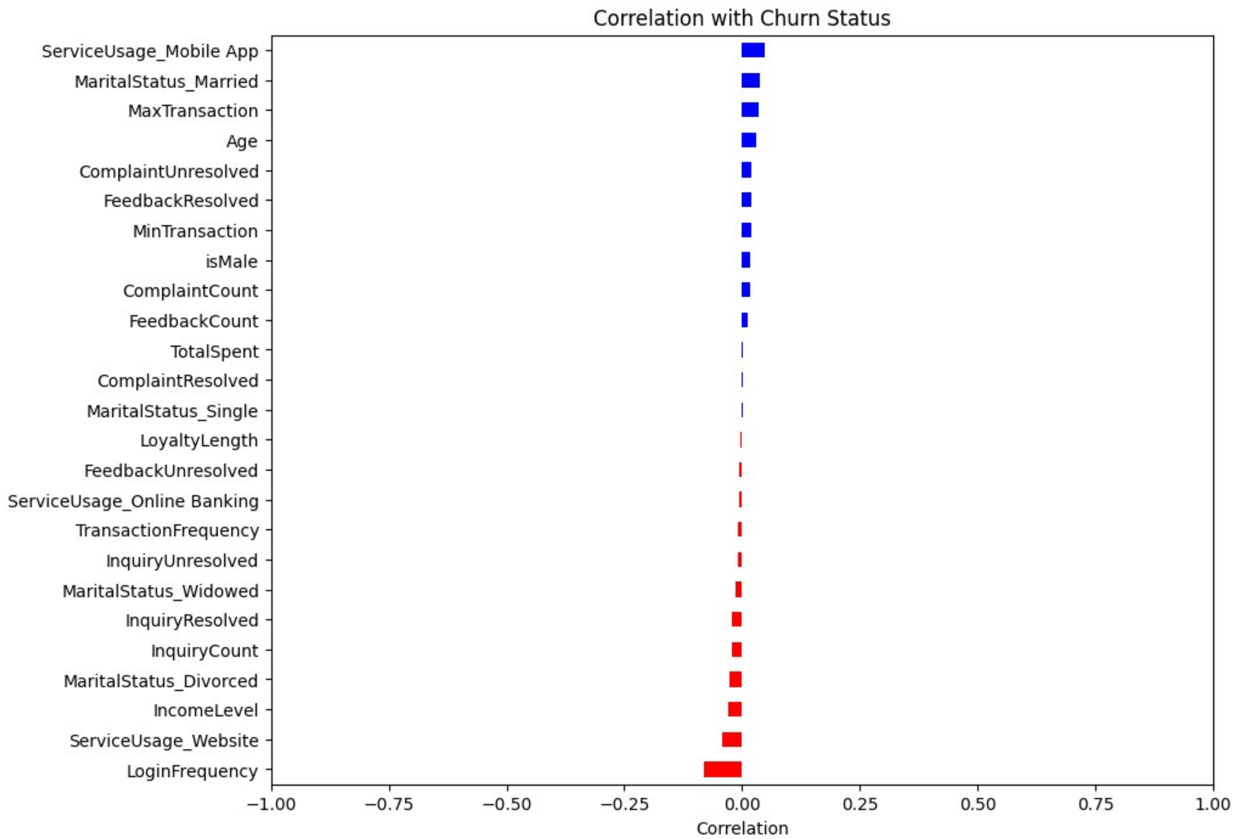
```
4                       0                     0                       0


   ServiceUsage_Mobile App  ServiceUsage_Online Banking
ServiceUsage_Website
0                         1                            0
0
1                         0                            0
1
2                         0                            0
1
3                         0                            0
1
4                         0                            0
1

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 27 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   CustomerID                   1000 non-null   int64
 1   Age                          1000 non-null   int64
 2   isMale                       1000 non-null   int64
 3   IncomeLevel                  1000 non-null   int64
 4   ChurnStatus                  1000 non-null   int64
 5   TotalSpent                   1000 non-null   float64
 6   MinTransaction               1000 non-null   float64
 7   MaxTransaction               1000 non-null   float64
 8   TransactionFrequency         1000 non-null   int64
 9   LoyaltyLength                1000 non-null   int64
 10  InquiryCount                 1000 non-null   float64
 11  InquiryResolved              1000 non-null   float64
 12  InquiryUnresolved            1000 non-null   float64
 13  FeedbackCount                1000 non-null   float64
 14  FeedbackResolved             1000 non-null   float64
 15  FeedbackUnresolved           1000 non-null   float64
 16  ComplaintCount               1000 non-null   float64
 17  ComplaintResolved            1000 non-null   float64
 18  ComplaintUnresolved          1000 non-null   float64
 19  LoginFrequency               1000 non-null   int64
 20  MaritalStatus_Divorced       1000 non-null   int64
 21  MaritalStatus_Married        1000 non-null   int64
 22  MaritalStatus_Single         1000 non-null   int64
 23  MaritalStatus_Widowed        1000 non-null   int64
 24  ServiceUsage_Mobile App      1000 non-null   int64
 25  ServiceUsage_Online Banking  1000 non-null   int64
 26  ServiceUsage_Website         1000 non-null   int64
dtypes: float64(12), int64(15)
memory usage: 211.1 KB
```

```
# Export to excel for submission

Customer_Data.to_excel('Customer_Data_Cleaned.xlsx', index=False)

# Used StandardScaler() to calculate z scores so all numeric values
hold the same weight.
from sklearn.preprocessing import StandardScaler

# Identify columns to scale drop non-numeric and target variable as
well as CustomerID
columns_to_scale =
Customer_Data.select_dtypes(include='number').columns.drop(['CustomerI
D', 'ChurnStatus'])

# Scale them
scaler = StandardScaler()
scaled_values = scaler.fit_transform(Customer_Data[columns_to_scale])
Customer_Data[columns_to_scale] =
scaler.fit_transform(Customer_Data[columns_to_scale])

display(Customer_Data.head())

   CustomerID   Age  isMale  IncomeLevel  ChurnStatus  TotalSpent  \
0           1  1.23    1.03        -1.25            0       -1.15
1           2  1.43    1.03        -1.25            1        0.38
2           3 -1.66    1.03        -1.25            0        0.59
3           4 -1.46    1.03        -1.25            0       -0.47
4           5 -1.46    1.03        -0.03            0        0.99

   MinTransaction  MaxTransaction  TransactionFrequency  LoyaltyLength
\
0            3.06            0.25                 -1.56          -1.89

1           -0.52            0.07                  0.75           0.96

2           -0.55            0.28                  0.36           0.28

3           -0.62           -0.07                 -0.02           0.10

4           -0.37            0.80                  1.13           0.86


   InquiryCount  InquiryResolved  InquiryUnresolved  FeedbackCount  \
0          1.34             2.09              -0.39          -0.62
1          1.34             2.09              -0.39          -0.62
2          1.34             2.09              -0.39          -0.62
3          3.27             2.09               2.41          -0.62
4         -0.59            -0.42              -0.39          -0.62

   FeedbackResolved  FeedbackUnresolved  ComplaintCount
```

```
ComplaintResolved  \
0              -0.47                   -0.41            -0.61              -
0.41
1              -0.47                   -0.41            -0.61              -
0.41
2              -0.47                   -0.41            -0.61              -
0.41
3              -0.47                   -0.41            -0.61              -
0.41
4              -0.47                   -0.41            -0.61              -
0.41

   ComplaintUnresolved  LoginFrequency  MaritalStatus_Divorced  \
0                 -0.44            0.58                   -0.57
1                 -0.44           -1.49                   -0.57
2                 -0.44           -1.63                   -0.57
3                 -0.44           -1.70                   -0.57
4                 -0.44            1.07                    1.74

   MaritalStatus_Married  MaritalStatus_Single  MaritalStatus_Widowed
\
0                  -0.59                  1.91                  -0.62

1                   1.68                 -0.52                  -0.62

2                  -0.59                  1.91                  -0.62

3                  -0.59                 -0.52                   1.62

4                  -0.59                 -0.52                  -0.62


   ServiceUsage_Mobile App  ServiceUsage_Online Banking
ServiceUsage_Website
0                     1.39                        -0.73
-0.67
1                    -0.72                        -0.73
1.50
2                    -0.72                        -0.73
1.50
3                    -0.72                        -0.73
1.50
4                    -0.72                        -0.73
1.50
```

```python
# Check Correlation of numerical features with Churn Status

churn_corr = Customer_Data.select_dtypes(include='number').corr()
['ChurnStatus'].drop(['ChurnStatus', 'CustomerID']).sort_values() #
include all numerical values -ChurnStatus and CustoomeID
```

```
plt.figure(figsize=(10, 8))
churn_corr.plot(kind='barh', color=['red' if x < 0 else 'blue' for x
in churn_corr]) # a horizontal bar plot with red for negative
correlation and blue for positive correlation
plt.title('Correlation with Churn Status')
plt.xlabel('Correlation')
plt.xlim(-1, 1)
plt.show()
```

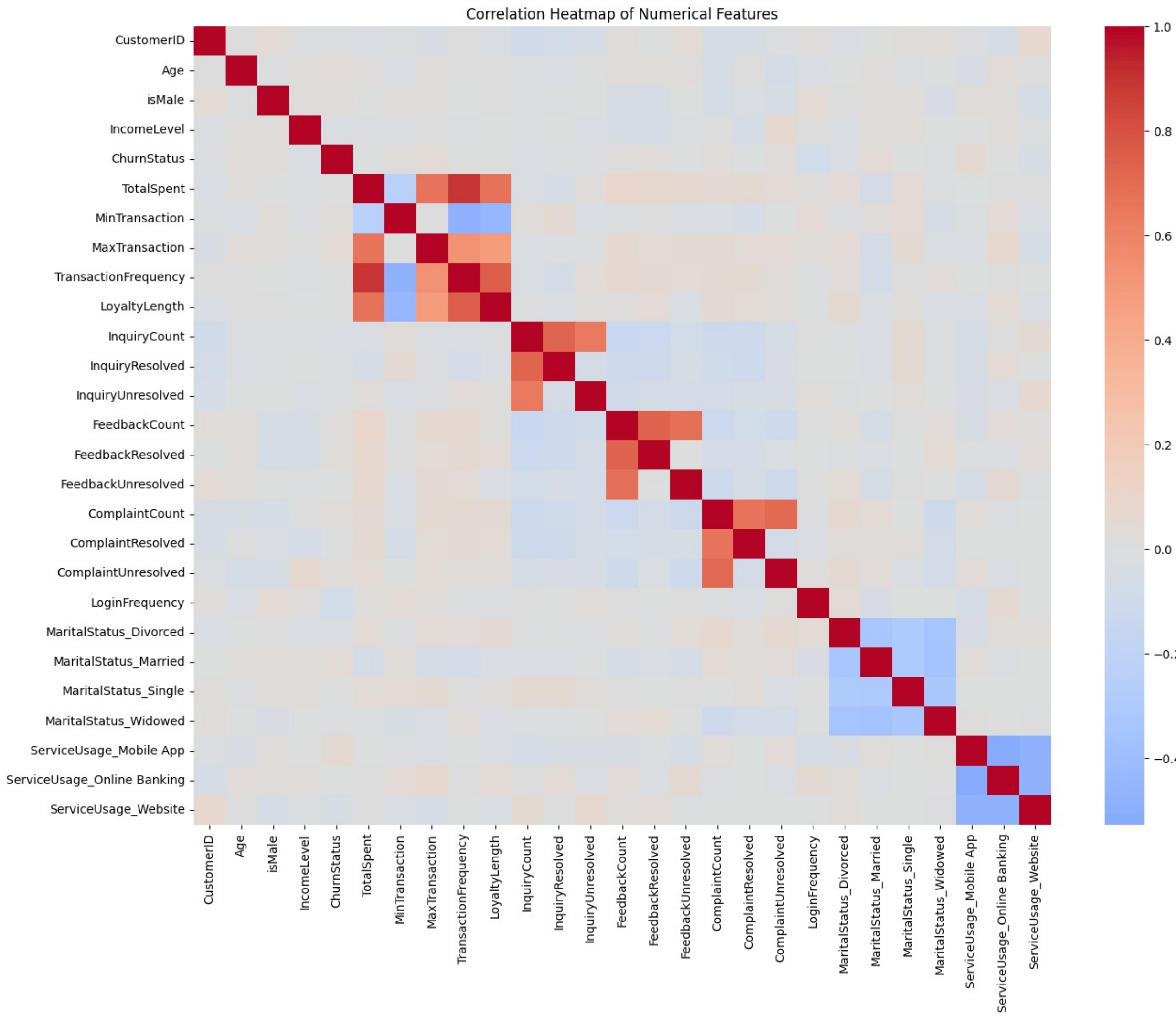


Observation:

There is little to no correlation with any of the features to ChurnStatus the strongest correlation is LoginFrequency at approximately 0.08. It might as well be nothing.

```
# do a correlation heatmap to see how features correlate with each
other
plt.figure(figsize=(16, 12))
correlation_matrix =
Customer_Data.select_dtypes(include='number').corr() # select only
numerical columns
sns.heatmap(correlation_matrix, annot=False, cmap='coolwarm',
center=0)
```

```
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



Observation

There is little to no correlation with any of the features with each other.

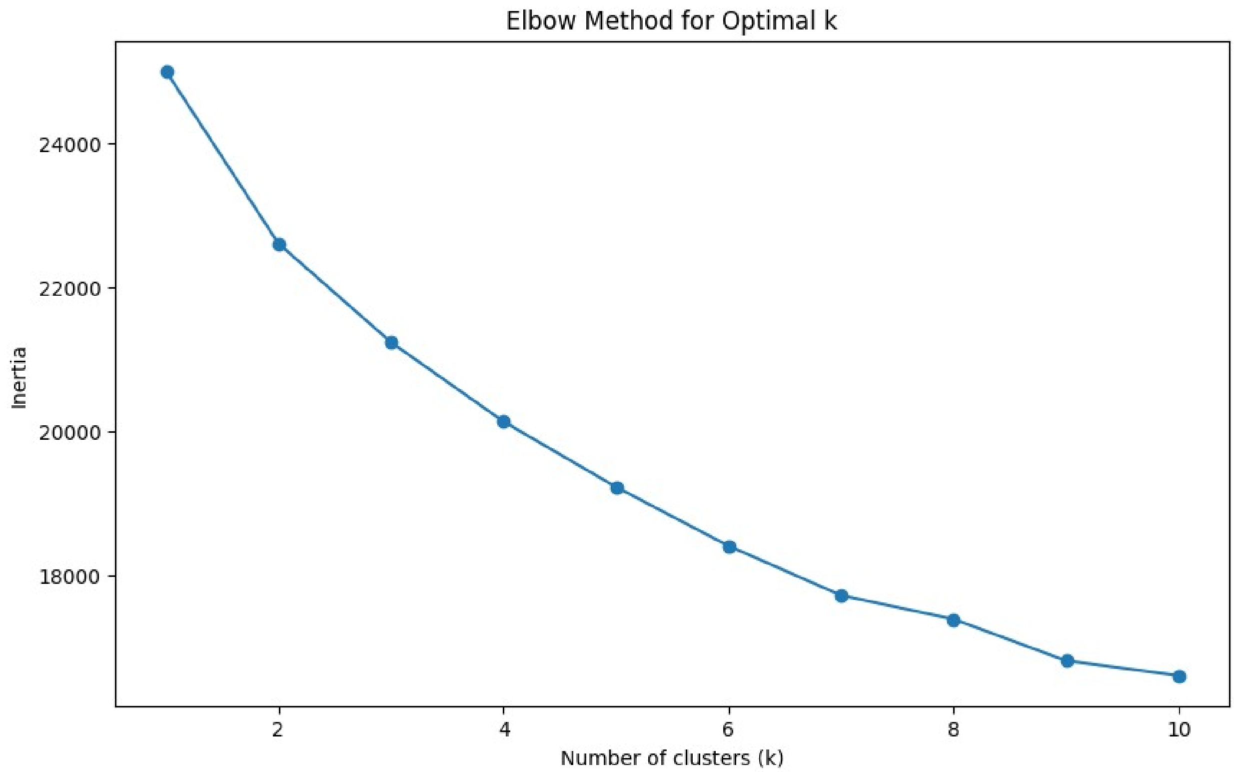
Why It Matters: This indicates a systemic issue with data collection that must be addressed. The data we collect is next to useless for driving any meaningful business decision.

```
display(Customer_Data.head())

   CustomerID   Age  isMale  IncomeLevel  ChurnStatus  TotalSpent  \
0           1  1.23    1.03        -1.25            0       -1.15
1           2  1.43    1.03        -1.25            1        0.38
2           3 -1.66    1.03        -1.25            0        0.59
3           4 -1.46    1.03        -1.25            0       -0.47
4           5 -1.46    1.03        -0.03            0        0.99
```

```
   MinTransaction  MaxTransaction  TransactionFrequency  LoyaltyLength
\
0            3.06            0.25                 -1.56          -1.89

1           -0.52            0.07                  0.75           0.96

2           -0.55            0.28                  0.36           0.28

3           -0.62           -0.07                 -0.02           0.10

4           -0.37            0.80                  1.13           0.86


   InquiryCount  InquiryResolved  InquiryUnresolved  FeedbackCount  \
0          1.34             2.09              -0.39          -0.62
1          1.34             2.09              -0.39          -0.62
2          1.34             2.09              -0.39          -0.62
3          3.27             2.09               2.41          -0.62
4         -0.59            -0.42              -0.39          -0.62

   FeedbackResolved  FeedbackUnresolved  ComplaintCount
ComplaintResolved  \
0             -0.47               -0.41           -0.61                  -
0.41
1             -0.47               -0.41           -0.61                  -
0.41
2             -0.47               -0.41           -0.61                  -
0.41
3             -0.47               -0.41           -0.61                  -
0.41
4             -0.47               -0.41           -0.61                  -
0.41

   ComplaintUnresolved  LoginFrequency  MaritalStatus_Divorced  \
0                -0.44            0.58                   -0.57
1                -0.44           -1.49                   -0.57
2                -0.44           -1.63                   -0.57
3                -0.44           -1.70                   -0.57
4                -0.44            1.07                    1.74

   MaritalStatus_Married  MaritalStatus_Single  MaritalStatus_Widowed
\
0                  -0.59                  1.91                  -0.62

1                   1.68                 -0.52                  -0.62

2                  -0.59                  1.91                  -0.62

3                  -0.59                 -0.52                   1.62
```

```
4                      -0.59                      -0.52                      -0.62


   ServiceUsage_Mobile App  ServiceUsage_Online Banking
ServiceUsage_Website
0                     1.39                           -0.73
-0.67
1                    -0.72                           -0.73
1.50
2                    -0.72                           -0.73
1.50
3                    -0.72                           -0.73
1.50
4                    -0.72                           -0.73
1.50
```

```
# Cluster Analysis to identify customer segments to see if we can
identify any patterns among churners vs non-churners

from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
# Select features for clustering (excluding CustomerID and
ChurnStatus)
features =
Customer_Data.select_dtypes(include='number').drop(columns=['CustomerI
D', 'ChurnStatus'])
# Determine optimal number of clusters using Elbow Method
inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(features)
    inertia.append(kmeans.inertia_)
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), inertia, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.show()
```




```
# Create combined unresolved interactions column
Customer_Data['TotalUnresolved'] =
(Customer_Data['FeedbackUnresolved'] +

Customer_Data['ComplaintUnresolved'] +

Customer_Data['InquiryUnresolved'])

# Now run clustering and aggregate
kmeans = KMeans(n_clusters=9, random_state=42, n_init=10)
Customer_Data['Cluster'] = kmeans.fit_predict(features)

cluster_summary = Customer_Data.groupby('Cluster').agg(
    Count = ('CustomerID', 'count'),
    Age = ('Age', 'mean'),
    TotalUnresolved = ('TotalUnresolved', 'mean'),
    TotalSpent = ('TotalSpent', 'mean'),
    TransactionFrequency = ('TransactionFrequency', 'mean'),
    LoyaltyLength = ('LoyaltyLength', 'mean'),
    LoginFrequency = ('LoginFrequency', 'mean'),
    ChurnRate = ('ChurnStatus', 'mean')
).reset_index()

display(cluster_summary)
```

```
   Cluster  Count   Age  TotalUnresolved  TotalSpent  
TransactionFrequency  \
0        0    115  0.01            -0.50        0.22                  
0.25   
1        1    118 -0.07            -0.50        0.10                  
0.10   
2        2    108 -0.01            -0.41       -1.38                 -
1.28   
3        3    234  0.07            -1.23        0.32                  
0.41   
4        4     92 -0.16             1.79        0.32                  
0.23   
5        5     79 -0.19            -0.31       -1.06                 -
1.43   
6        6     78  0.12             1.63        0.44                  
0.35   
7        7    114  0.02             2.27        0.30                  
0.36   
8        8     62  0.19            -1.23        0.36                  
0.41   

   LoyaltyLength  LoginFrequency  ChurnRate  
0           0.26           -0.05       0.22  
1           0.24           -0.04       0.19  
2          -1.30            0.01       0.16  
3           0.45           -0.06       0.19  
4           0.30            0.11       0.24  
5          -1.62            0.06       0.20  
6           0.23            0.11       0.21  
7           0.35            0.03       0.20  
8           0.31           -0.02       0.27  
```

Observations: Group 6 and 8 Churns at a 21% and 27% respectively.

Why It Matters: These are number 1 and number 2 biggest spenders on average. The reason they churn is undetermined because the features have such low correlation. Further investigation is required.

```python
# Compare the high-churn vs low-churn clusters
high_churn = Customer_Data[Customer_Data['Cluster'] == 3].mean()
low_churn = Customer_Data[Customer_Data['Cluster'] == 4].mean()

comparison = pd.DataFrame({
    'High Churn (Cluster 3)': high_churn.drop('CustomerID'),
    'Low Churn (Cluster 4)': low_churn.drop('CustomerID'),
    'Difference': high_churn - low_churn
}).round(2)

print(comparison.drop('CustomerID'))
```

```
                             High Churn (Cluster 3)  Low Churn
(Cluster 4)  \
Age                                            0.07                  -
0.16
ChurnStatus                                    0.19
0.24
Cluster                                        3.00
4.00
ComplaintCount                                -0.61
1.44
ComplaintResolved                             -0.41                  -
0.41
ComplaintUnresolved                           -0.44
2.29
FeedbackCount                                 -0.62
0.05
FeedbackResolved                              -0.47
0.17
FeedbackUnresolved                            -0.41                  -
0.11
IncomeLevel                                    0.05
0.16
InquiryCount                                  -0.59                  -
0.59
InquiryResolved                               -0.42                  -
0.42
InquiryUnresolved                             -0.39                  -
0.39
LoginFrequency                                -0.06
0.11
LoyaltyLength                                  0.45
0.30
MaritalStatus_Divorced                        -0.00
0.13
MaritalStatus_Married                         -0.04
0.10
MaritalStatus_Single                          -0.00                  -
0.05
MaritalStatus_Widowed                          0.04                  -
0.18
MaxTransaction                                 0.35
0.29
MinTransaction                                -0.33                  -
0.01
ServiceUsage_Mobile App                        0.09
0.13
ServiceUsage_Online Banking                   -0.07
0.04
ServiceUsage_Website                          -0.02                  -
0.17
```

```
TotalSpent                                      0.32
0.32
TotalUnresolved                                -1.23
1.79
TransactionFrequency                            0.41
0.23
isMale                                          0.10                   -
0.02

                             Difference
Age                                0.23
ChurnStatus                       -0.05
Cluster                           -1.00
ComplaintCount                    -2.05
ComplaintResolved                  0.00
ComplaintUnresolved               -2.72
FeedbackCount                     -0.67
FeedbackResolved                  -0.64
FeedbackUnresolved                -0.30
IncomeLevel                       -0.11
InquiryCount                      -0.00
InquiryResolved                   -0.00
InquiryUnresolved                  0.00
LoginFrequency                    -0.17
LoyaltyLength                      0.16
MaritalStatus_Divorced            -0.13
MaritalStatus_Married             -0.14
MaritalStatus_Single               0.04
MaritalStatus_Widowed              0.22
MaxTransaction                     0.06
MinTransaction                    -0.32
ServiceUsage_Mobile App           -0.04
ServiceUsage_Online Banking       -0.11
ServiceUsage_Website               0.15
TotalSpent                         0.00
TotalUnresolved                   -3.03
TransactionFrequency               0.18
isMale                             0.12
```