# Streaming Subscription Churn

## Scientific Question: "What key user behaviors and subscription patterns contribute to customer churn in music streaming services?"

## Refined Scientific Question: "How do user age, listening behavior, and engagement with the platform (e.g., subscription pauses, song skipping, and notification clicks) influence the likelihood of churn in music streaming services?"

Ideas: predictive model to determine future subscription, and you can also use advanced statistical methods to detect if there are any factors that influenced the subscription

## Exploring the Dataset

In [51]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

# Load the dataset
train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")

# 1. Understand the Dataset's Structure
print("Shape of dataset:", train.shape)
print("\nData types:\n", train.dtypes)
print("\nFirst 5 rows:\n", train.head())

# 2. Check for Missing Data & Data Quality
print("\nMissing values per column:\n", train.isnull().sum())
print("\nNumber of duplicate rows:", train.duplicated().sum())
```

```
Shape of dataset: (125000, 20)

Data types:
 customer_id                   int64
age                          int64
location                    object
subscription_type           object
payment_plan                object
num_subscription_pauses      int64
payment_method              object
customer_service_inquiries  object
signup_date                  int64
weekly_hours               float64
average_session_length     float64
song_skip_rate             float64
weekly_songs_played          int64
weekly_unique_songs          int64
num_favorite_artists         int64
num_platform_friends         int64
num_playlists_created        int64
num_shared_playlists         int64
notifications_clicked        int64
churned                      int64
dtype: object

First 5 rows:
    customer_id  age    location subscription_type payment_plan  \
0            1   32     Montana              Free       Yearly
1            2   64  New Jersey              Free      Monthly
2            3   51  Washington           Premium       Yearly
3            4   63  California            Family       Yearly
4            5   54  Washington            Family      Monthly

   num_subscription_pauses payment_method customer_service_inquiries  \
0                        2         Paypal                     Medium
1                        3         Paypal                        Low
2                        2    Credit Card                       High
3                        4      Apple Pay                     Medium
4                        3         Paypal                       High

   signup_date  weekly_hours  average_session_length  song_skip_rate  \
0        -1606     22.391362              105.394516        0.176873
1        -2897     29.294210               52.501115        0.981811
2         -348     15.400312               24.703696        0.048411
3        -2894     22.842084               83.595480        0.035691
4          -92     23.151163               52.578266        0.039738

   weekly_songs_played  weekly_unique_songs  num_favorite_artists  \
0                  169                  109                    18
1                   55                  163                    44
2                  244                  117                    20
3                  442                  252                    47
4                  243                  230                    41

   num_platform_friends  num_playlists_created  num_shared_playlists  \
0                    32                     52                    35
```

```
1                  33                      12                     25
2                 129                      50                     28
3                 120                      55                     17
4                  66                      40                     32

   notifications_clicked  churned
0                     46        0
1                     37        1
2                     38        0
3                     24        0
4                     47        0

Missing values per column:
 customer_id                  0
age                          0
location                     0
subscription_type            0
payment_plan                 0
num_subscription_pauses      0
payment_method               0
customer_service_inquiries   0
signup_date                  0
weekly_hours                 0
average_session_length       0
song_skip_rate               0
weekly_songs_played          0
weekly_unique_songs          0
num_favorite_artists         0
num_platform_friends         0
num_playlists_created        0
num_shared_playlists         0
notifications_clicked        0
churned                      0
dtype: int64

Number of duplicate rows: 0
```

In our training data set, we hae 125000 rows and 20 columns. In our test data set, we have 75000 and 19 columns. In both the training data set and the test data set, we have no missing values. We get the summary statistics to obtain some values of our data set that could be important to note. In our location, subscription, payment_plan, and payment_method, they are all categorical variables. We have both numerical and categorical varaibles in our dataset. We have no missing values and no duplicates in our dataset.

# Exploratory Data Analysis (EDA)

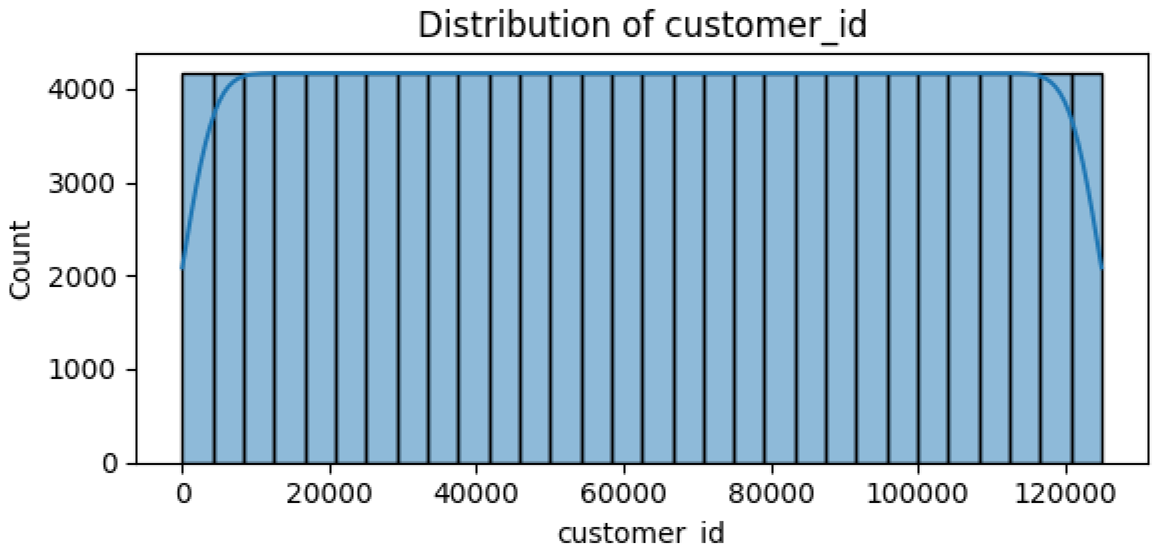
## Univariate Exploration

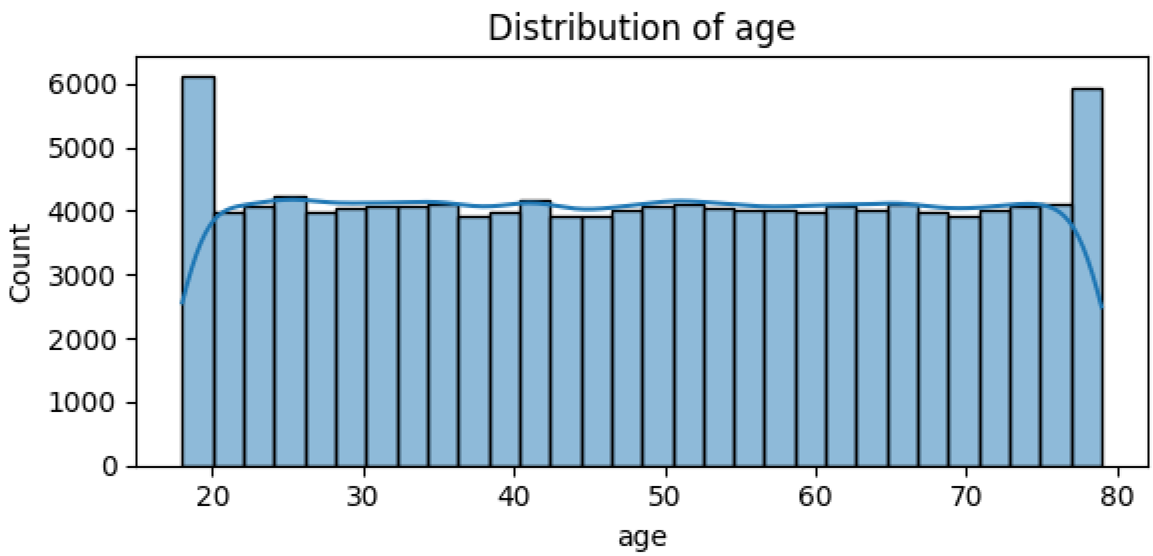
In [55]:
```
num_cols = train.select_dtypes(include=['int64', 'float64']).columns
cat_cols = train.select_dtypes(include=['object']).columns

#numerical variables: summary stats
print("\nNumerical Summary:\n", train[num_cols].describe())
```

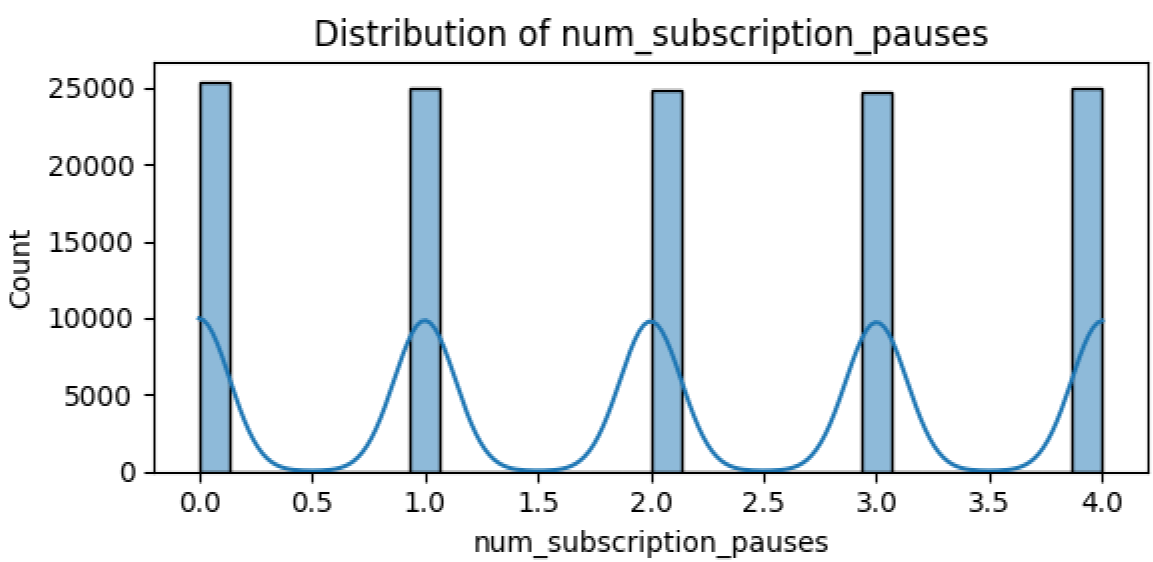
```
#histograms for each numerical variables
for col in num_cols:
    plt.figure(figsize=(6, 3))
    sns.histplot(train[col], kde=True, bins=30)
    plt.title(f"Distribution of {col}")
    plt.tight_layout()
    plt.show()

# outliers box plots for numerical variabels
for col in num_cols:
    plt.figure(figsize=(6, 3))
    sns.boxplot(x=train[col])
    plt.title(f"Boxplot of {col}")
    plt.tight_layout()
    plt.show()
'''
Q1 = train[col].quantile(0.25)
Q3 = train[col].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
outliers = train[(train[col] < lower_bound) | (train[col] > upper_bound)]
print(f"{col}: {len(outliers)} outliers")
'''
from scipy.stats import skew

#skewness for each numerical column
for col in num_cols.drop('customer_id'):
    skewness = skew(train[col])
    print(f"{col} | Skewness: {skewness:.2f}")



#checking for normality:
import scipy.stats as stats
import matplotlib.pyplot as plt

# QQ plot for each numerical variable to check for normality
for col in num_cols.drop('customer_id'):  # Skip 'customer_id' as it's not r
    plt.figure(figsize=(6, 6))
    stats.probplot(train[col], dist="norm", plot=plt)
    plt.title(f"QQ Plot of {col}")
    plt.tight_layout()
    plt.show()

#categorical variables
#frequency tables categorical variables
for col in cat_cols:
    print(f"\nFrequency table for {col}:")
    print(train[col].value_counts(normalize=True))

#proportions visualization: Useful for imbalanced categories
for col in cat_cols:
    plt.figure(figsize=(8, 5))
    ax = sns.countplot(data=train, x=col, order=train[col].value_counts().ir
```

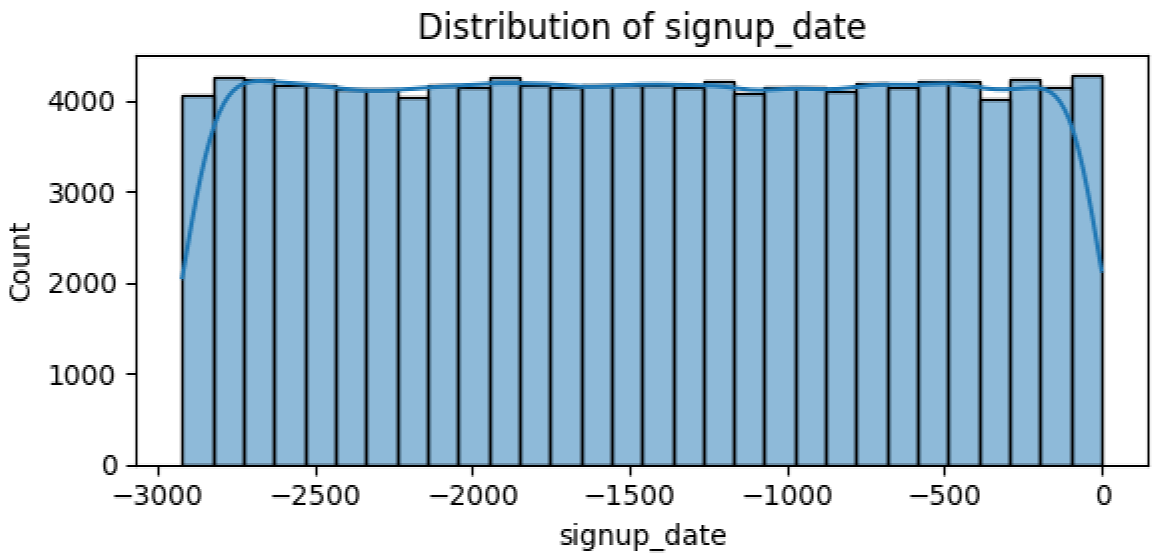
```
    plt.title(f"Count Plot of {col}")
    plt.xticks(rotation=45)

    # Add percentages
    total = len(train[col])
    for p in ax.patches:
        percentage = f'{100 * p.get_height() / total:.1f}%'
        ax.annotate(percentage, (p.get_x() + p.get_width() / 2, p.get_height
                    ha='center', va='bottom', fontsize=10)

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

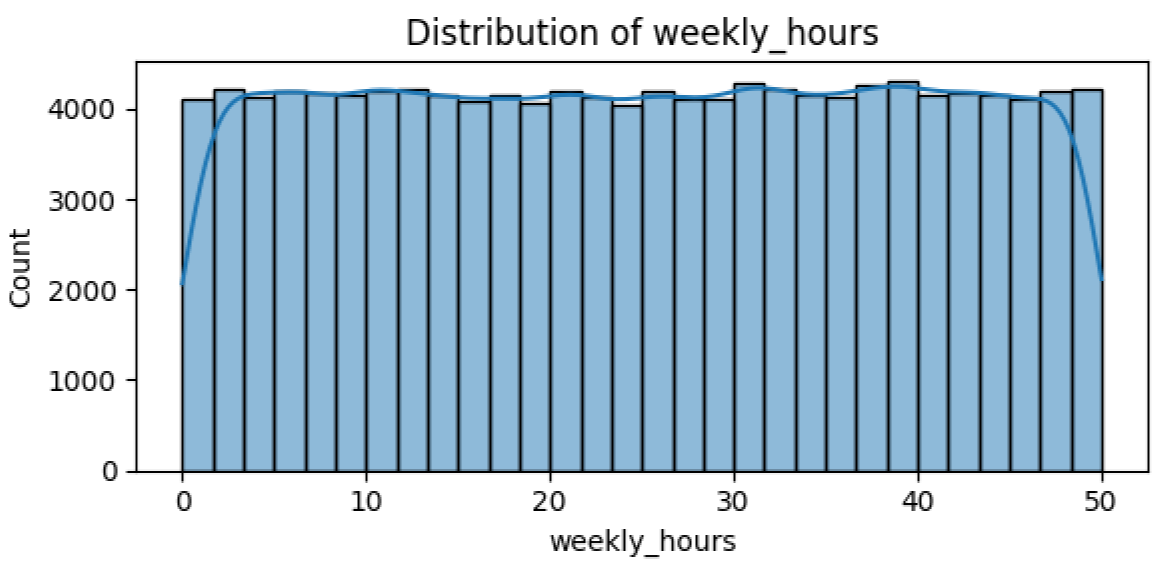
```
Numerical Summary:
          customer_id            age  num_subscription_pauses    signup_date  \
count  125000.000000  125000.000000            125000.000000  125000.000000
mean    62500.500000      48.414136                 1.991144   -1460.678936
std     36084.536162      17.901042                 1.417201     844.132871
min         1.000000      18.000000                 0.000000   -2922.000000
25%     31250.750000      33.000000                 1.000000   -2190.000000
50%     62500.500000      48.000000                 2.000000   -1462.000000
75%     93750.250000      64.000000                 3.000000    -728.000000
max    125000.000000      79.000000                 4.000000      -1.000000

        weekly_hours  average_session_length  song_skip_rate  \
count  125000.000000           125000.000000   125000.000000
mean       25.036985               60.421725        0.500802
std        14.447487               34.383782        0.288706
min         0.000068                1.000526        0.000006
25%        12.472667               30.644177        0.250974
50%        25.116710               60.340977        0.501162
75%        37.570328               90.234158        0.751110
max        49.999943              119.996501        0.999970

       weekly_songs_played  weekly_unique_songs  num_favorite_artists  \
count        125000.000000        125000.000000         125000.000000
mean            250.823928           150.783344             24.499888
std             143.327606            85.794952             14.445979
min               3.000000             3.000000              0.000000
25%             127.000000            76.000000             12.000000
50%             251.000000           150.000000             25.000000
75%             375.000000           225.000000             37.000000
max             499.000000           299.000000             49.000000

       num_platform_friends  num_playlists_created  num_shared_playlists  \
count         125000.000000          125000.000000         125000.000000
mean              99.713240              49.458048             24.554224
std               57.681372              28.935305             14.454823
min                0.000000               0.000000              0.000000
25%               50.000000              24.000000             12.000000
50%              100.000000              49.000000             25.000000
75%              150.000000              75.000000             37.000000
max              199.000000              99.000000             49.000000

       notifications_clicked        churned
count          125000.000000  125000.000000
mean               24.446848       0.513392
std                14.422850       0.499823
min                 0.000000       0.000000
25%                12.000000       0.000000
50%                24.000000       1.000000
75%                37.000000       1.000000
max                49.000000       1.000000
```

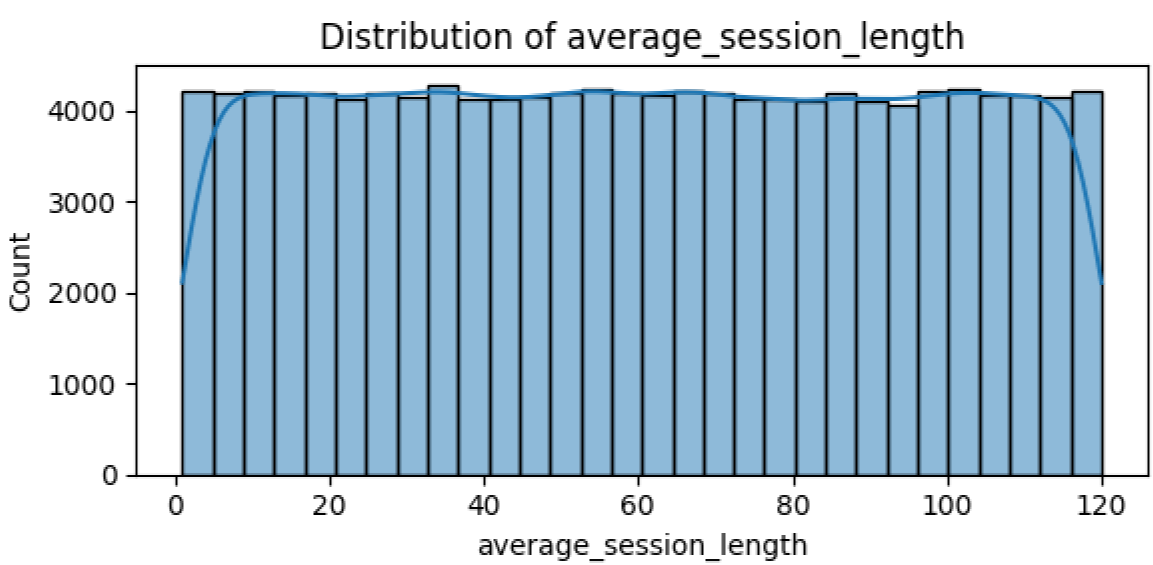

Distribution of customer_id
Count
4000
3000
2000
1000
0
0
20000
40000
60000
80000
100000
120000
customer_id

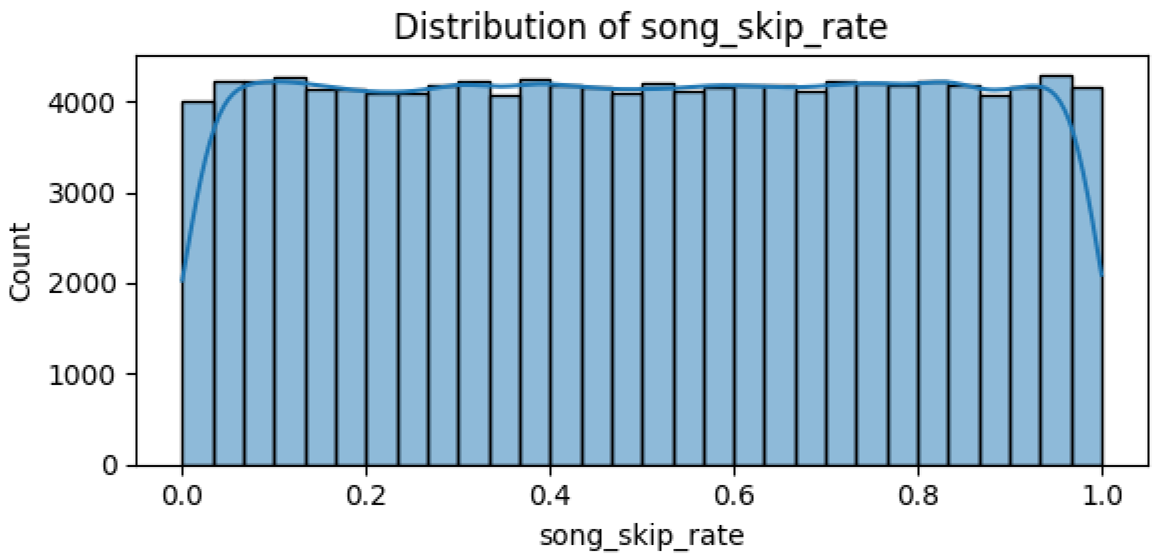

Distribution of age
Count
6000
5000
4000
3000
2000
1000
0
20
30
40
50
60
70
80
age

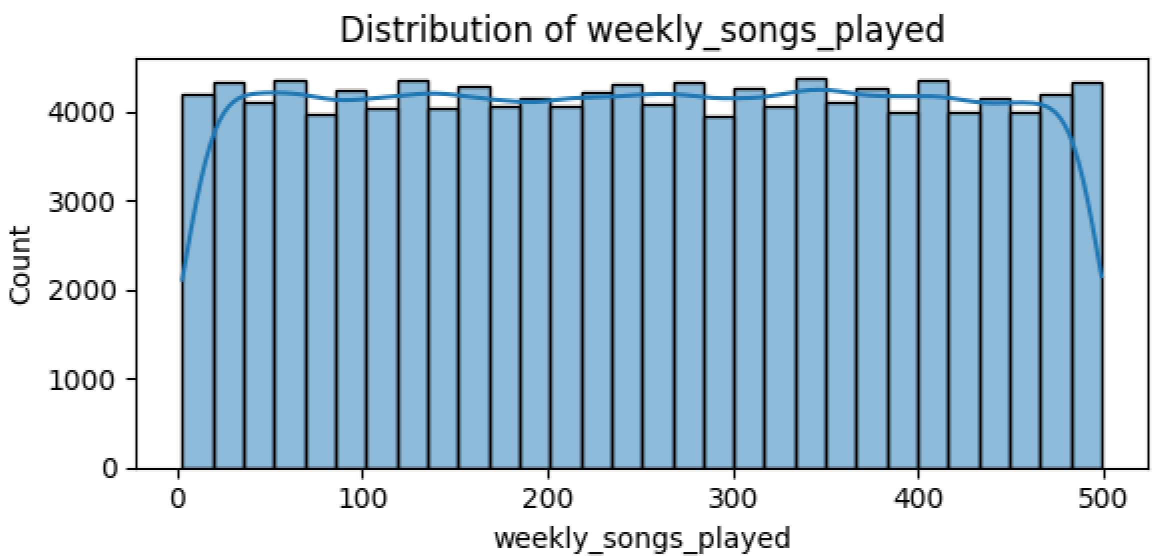

Distribution of num_subscription_pauses
Count
25000
20000
15000
10000
5000
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
num_subscription_pauses

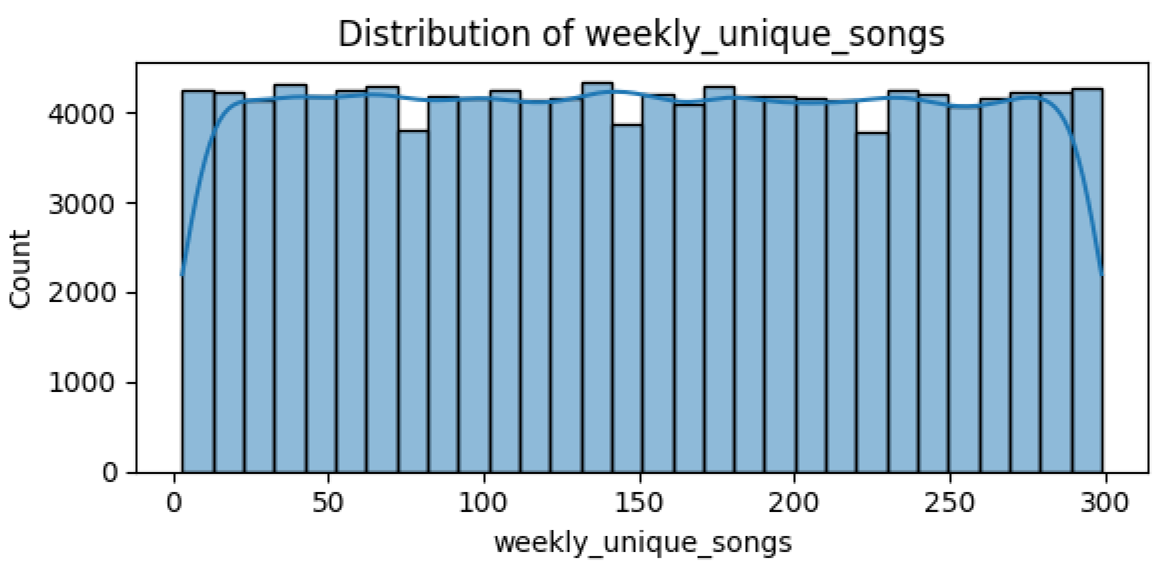

Distribution of signup_date
Count
4000
3000
2000
1000
0
−3000
−2500
−2000
−1500
−1000
−500
0
signup_date

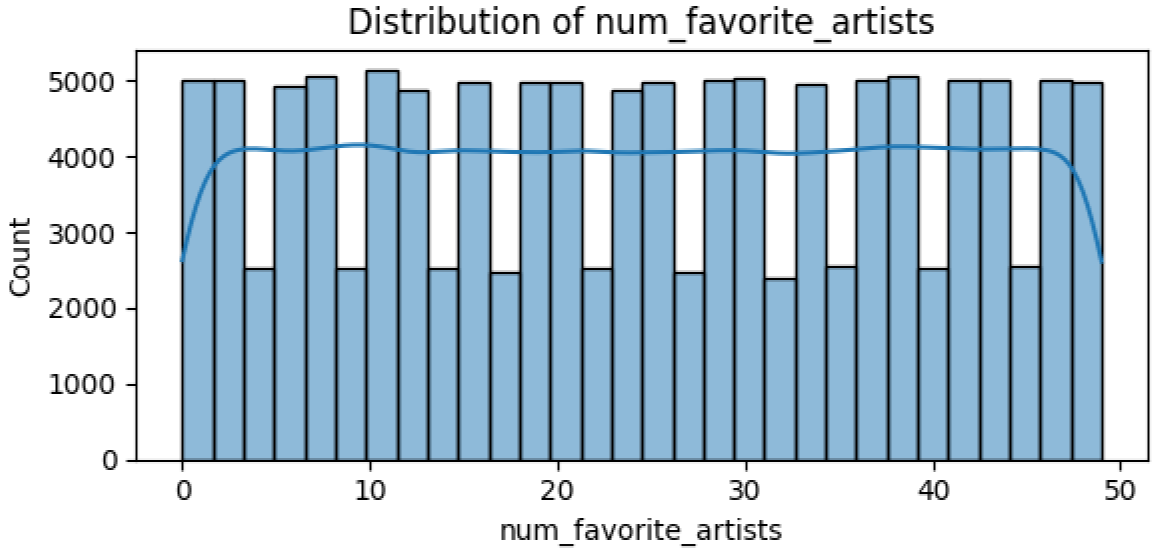

Distribution of weekly_hours
Count
4000
3000
2000
1000
0
0
10
20
30
40
50
weekly_hours

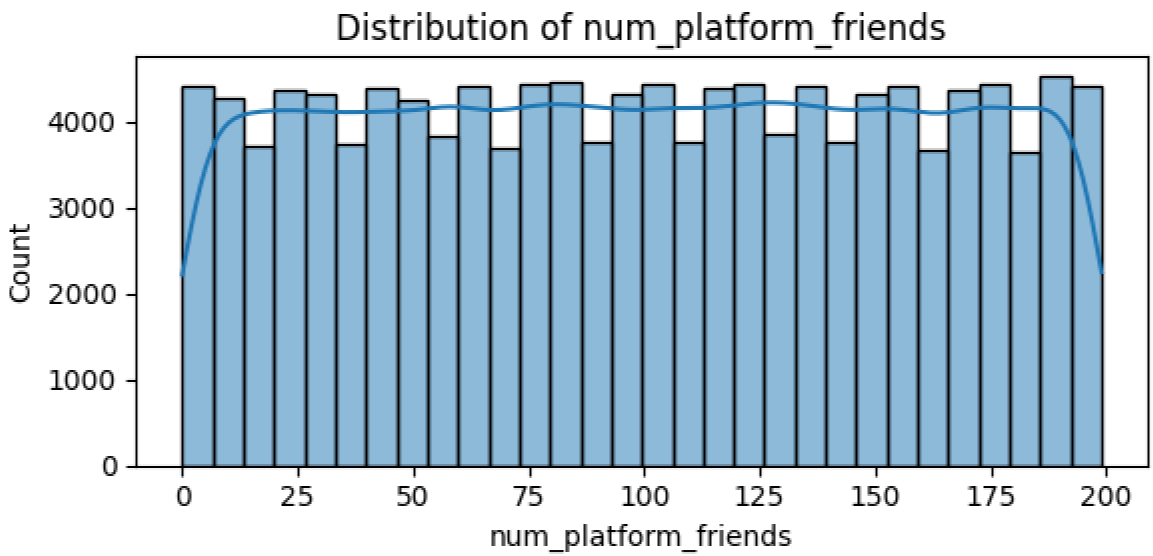

Distribution of average_session_length
Count
4000
3000
2000
1000
0
0
20
40
60
80
100
120
average_session_length

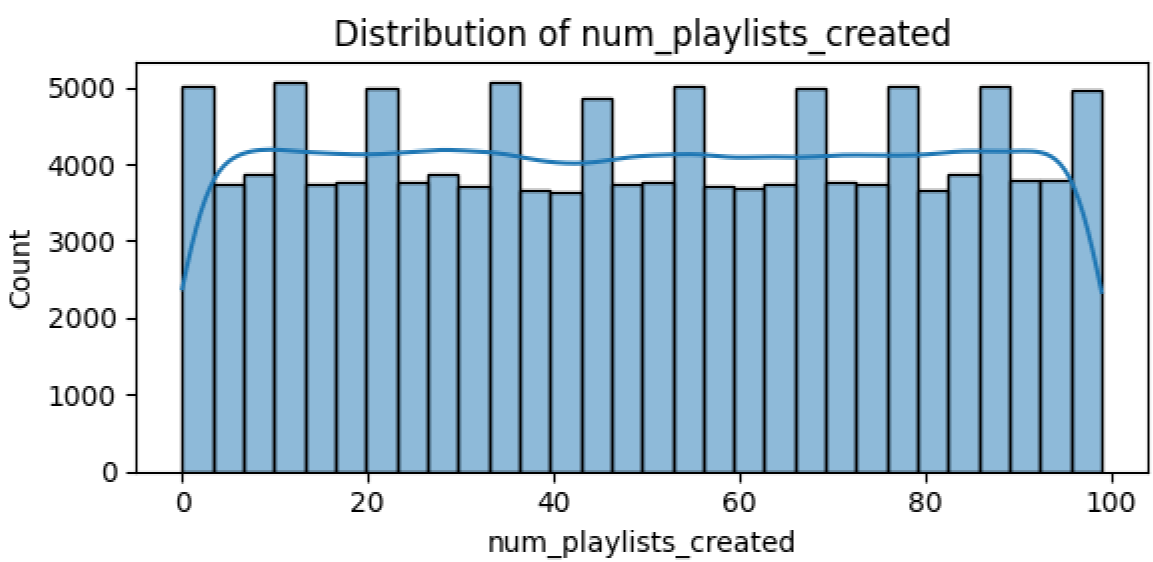

Distribution of song_skip_rate
Count
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
song_skip_rate

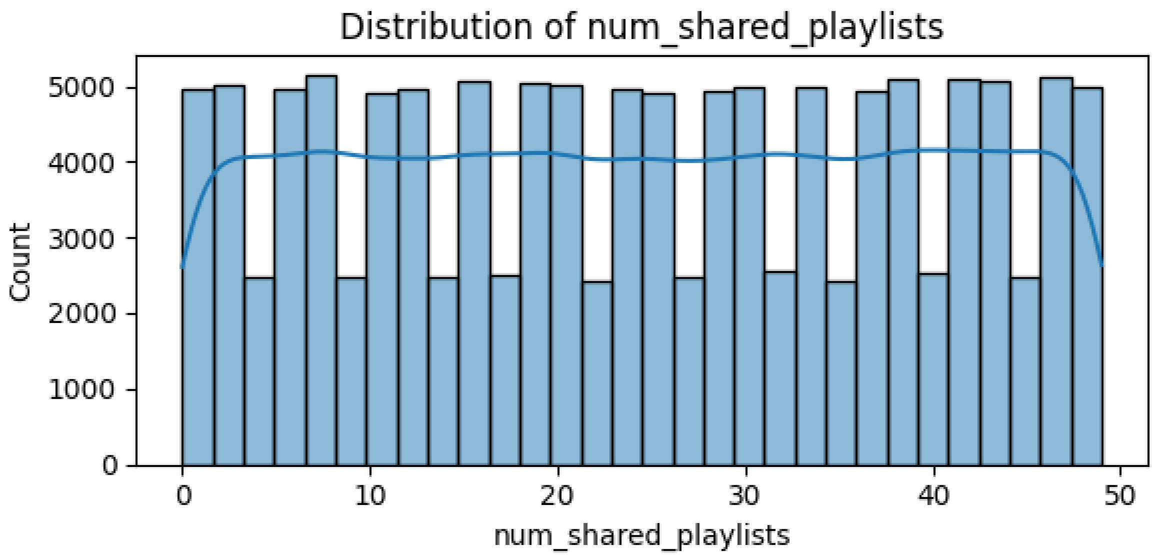

Distribution of weekly_songs_played
Count
4000
3000
2000
1000
0
0
100
200
300
400
500
weekly_songs_played

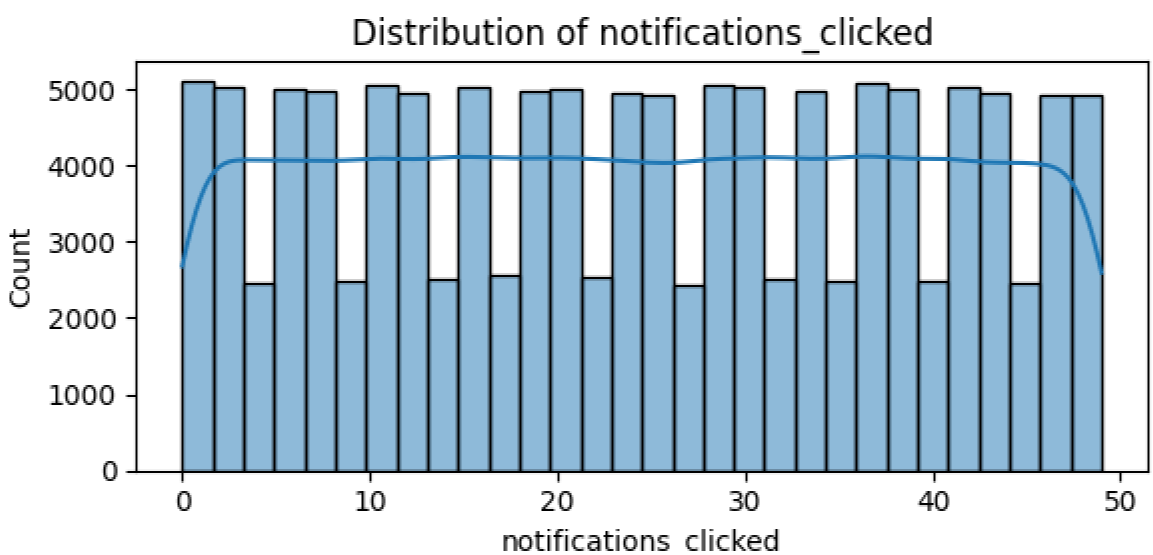

Distribution of weekly_unique_songs
Count
4000
3000
2000
1000
0
0
50
100
150
200
250
300
weekly_unique_songs

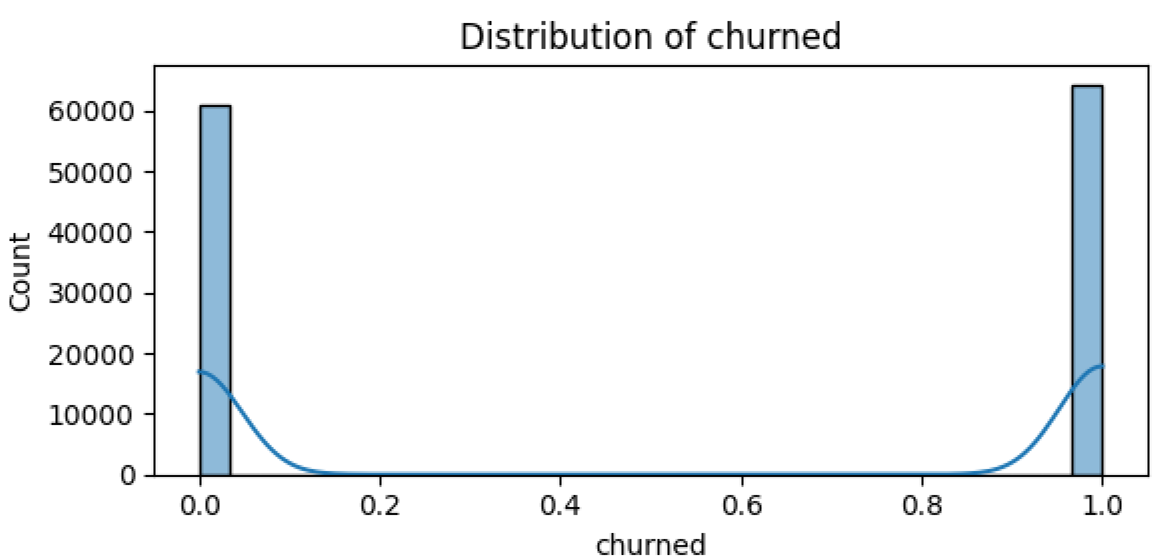

Distribution of num_favorite_artists
Count
0
1000
2000
3000
4000
5000
0
10
20
30
40
50
num_favorite_artists

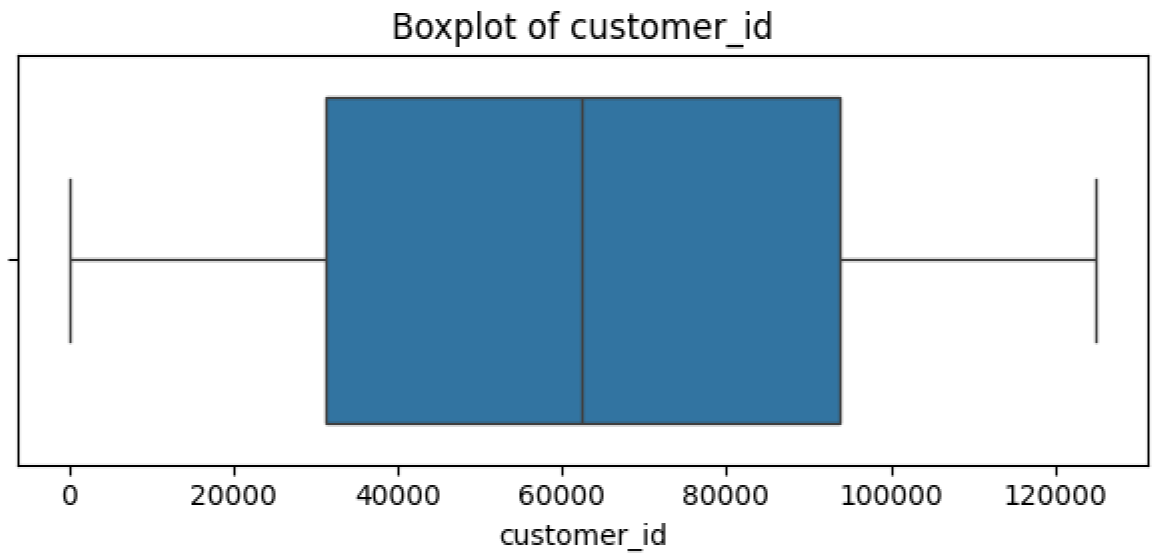

Distribution of num_platform_friends
Count
0
1000
2000
3000
4000
0
25
50
75
100
125
150
175
200
num_platform_friends

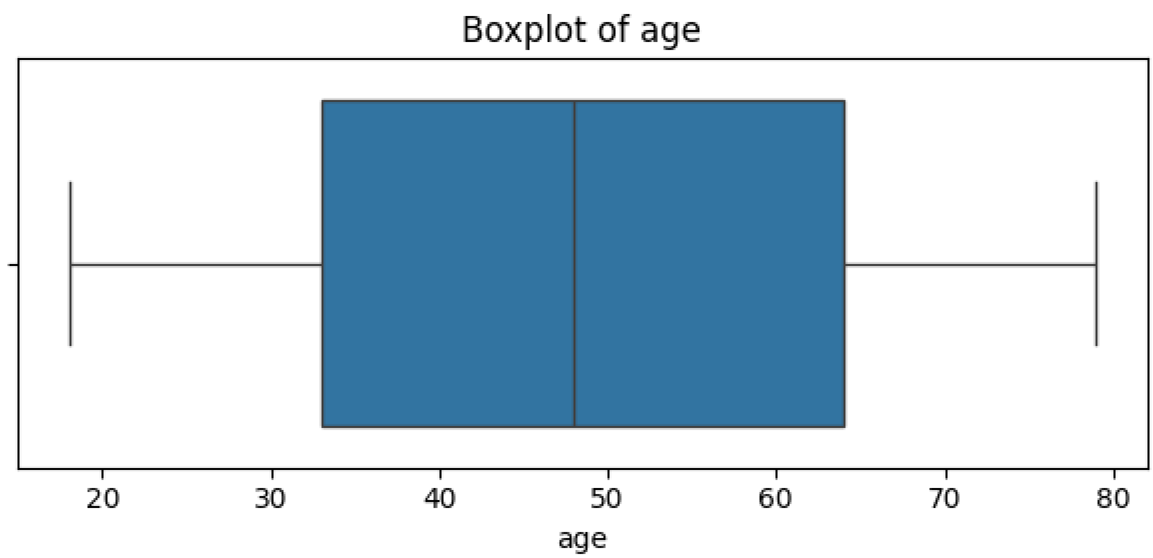

Distribution of num_playlists_created
Count
0
1000
2000
3000
4000
5000
0
20
40
60
80
100
num_playlists_created

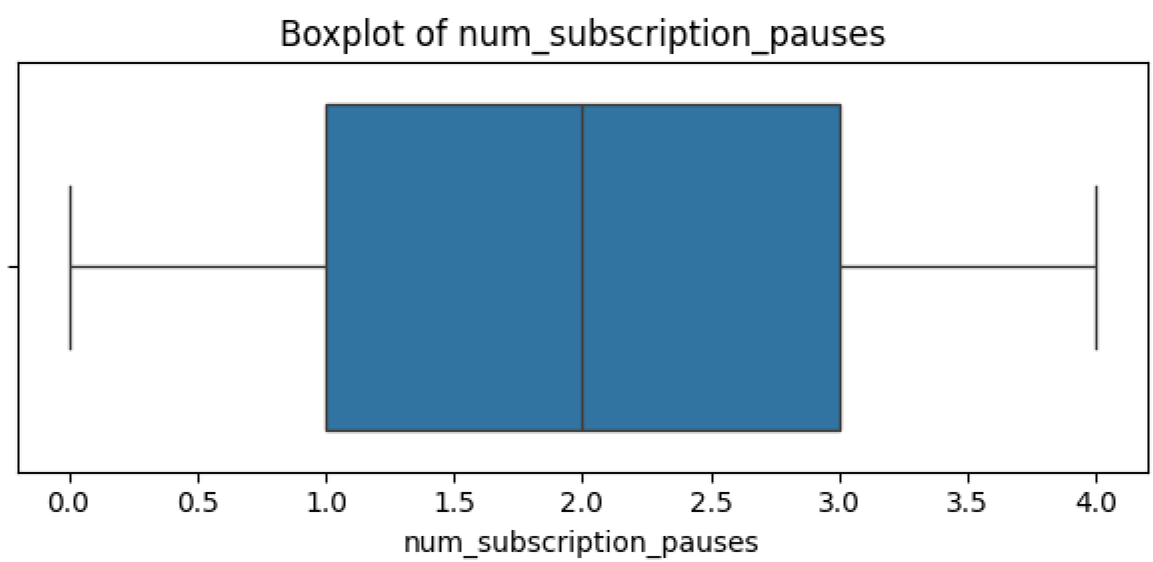

Distribution of num_shared_playlists
Count
num_shared_playlists
0
1000
2000
3000
4000
5000
0
10
20
30
40
50

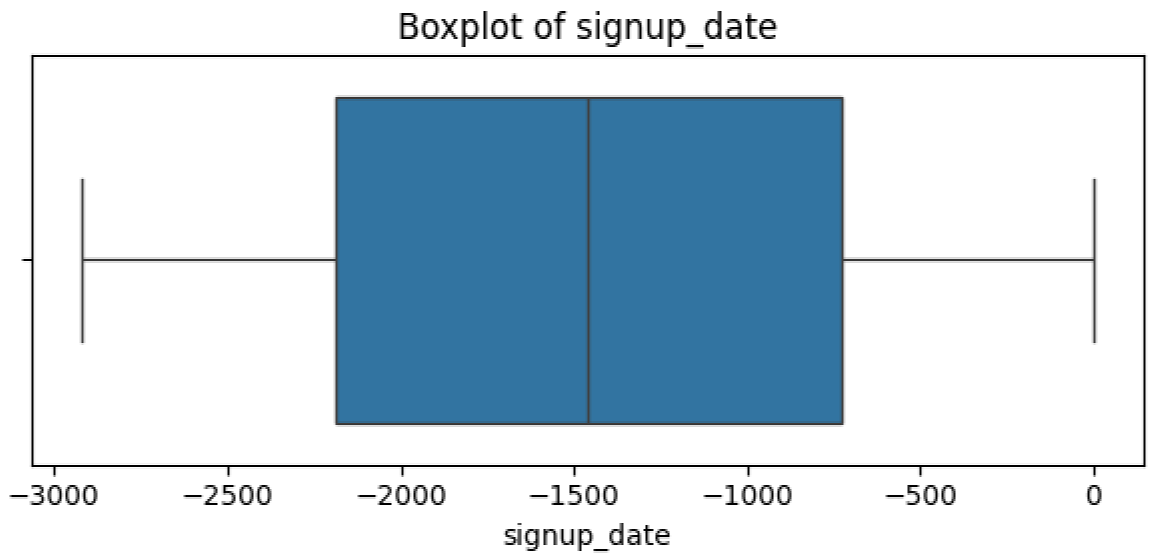

Distribution of notifications_clicked
Count
notifications_clicked
0
1000
2000
3000
4000
5000
0
10
20
30
40
50

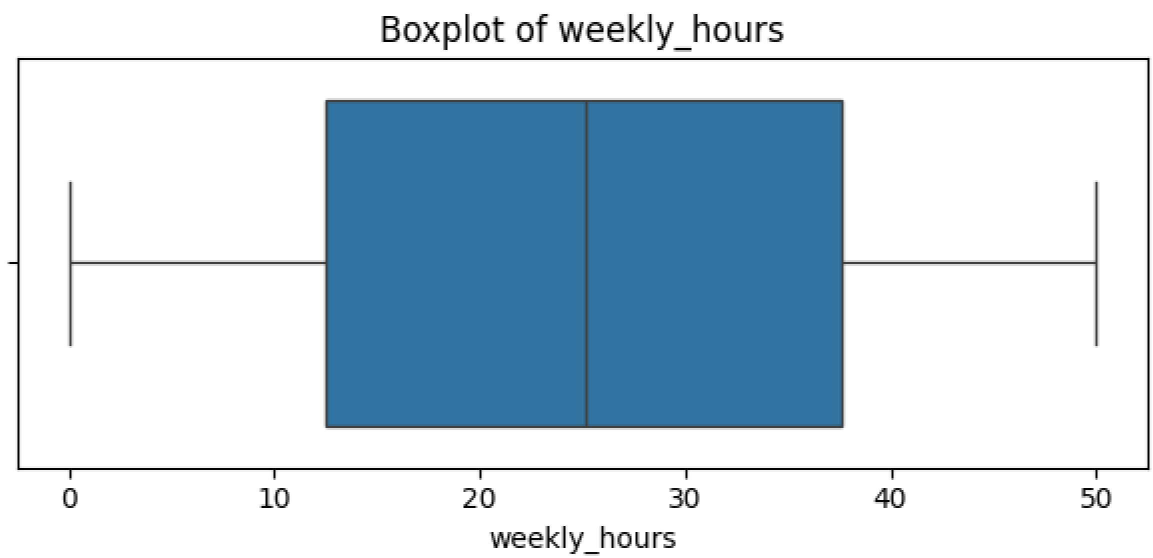

Distribution of churned
Count
churned
0
10000
20000
30000
40000
50000
60000
0.0
0.2
0.4
0.6
0.8
1.0

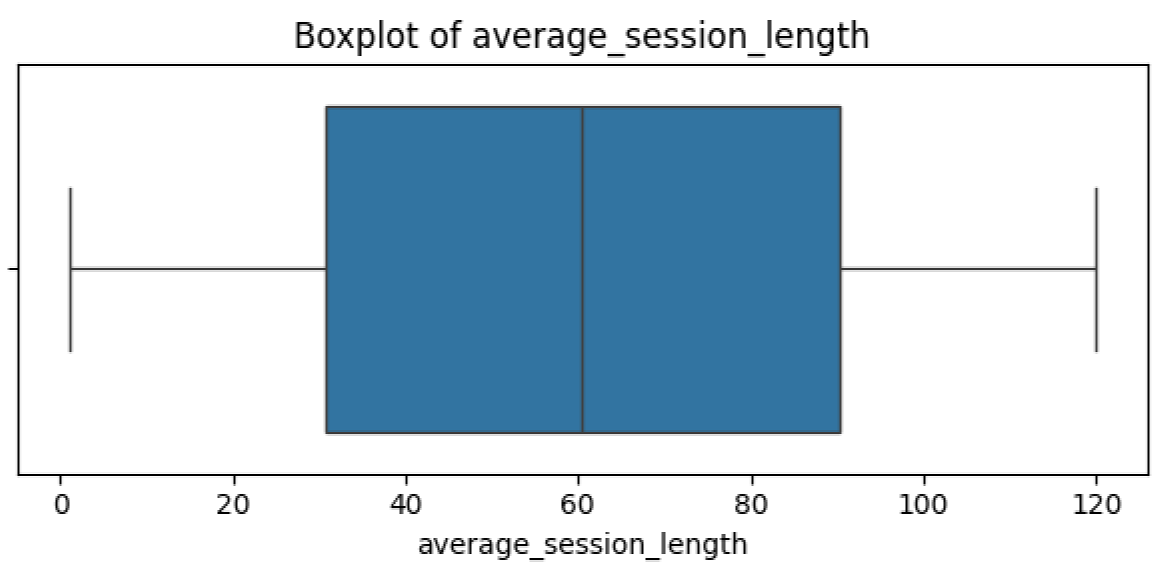

Boxplot of customer_id
0
20000
40000
60000
80000
100000
120000
customer_id

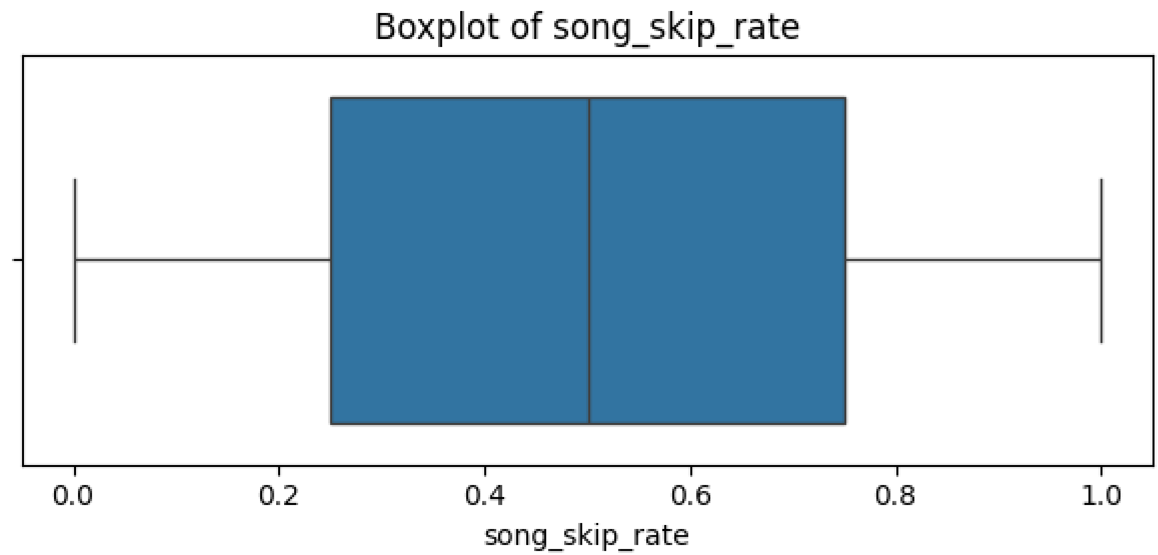

Boxplot of age
20
30
40
50
60
70
80
age

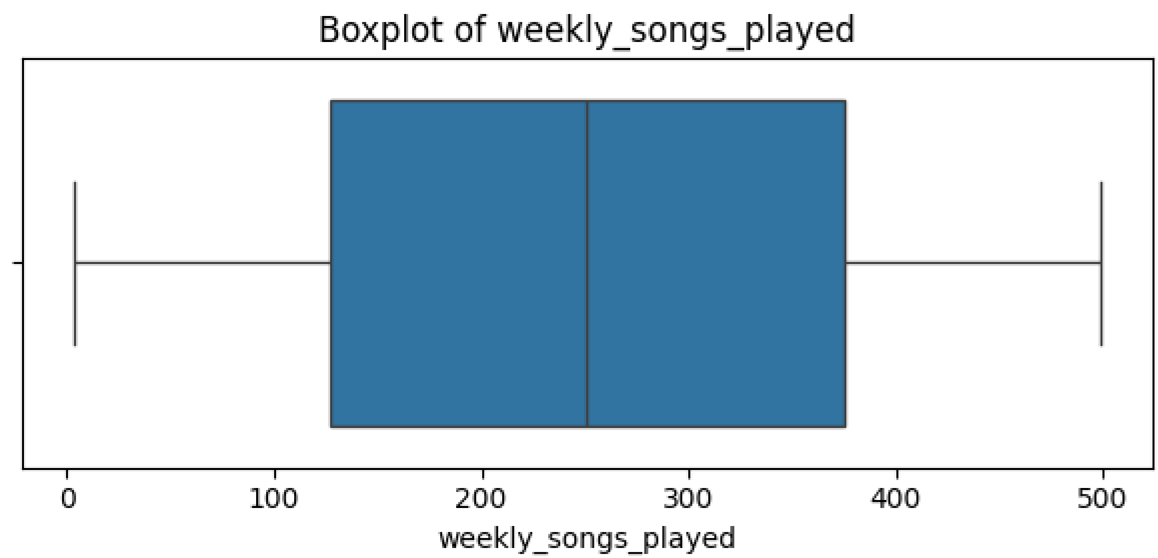

Boxplot of num_subscription_pauses
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
num_subscription_pauses

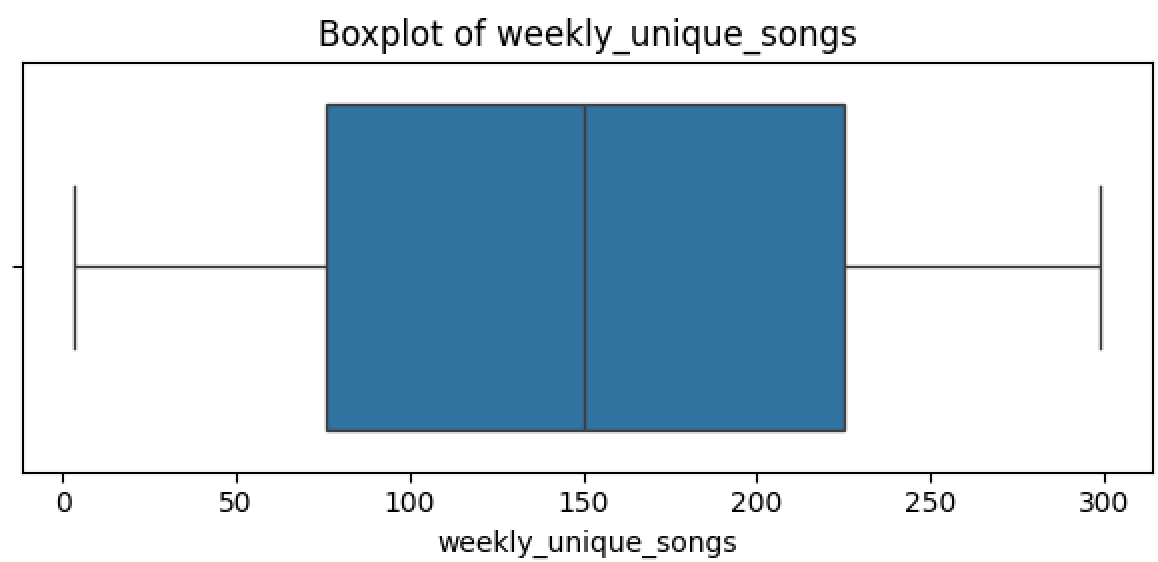

Boxplot of signup_date
−3000
−2500
−2000
−1500
−1000
−500
0
signup_date

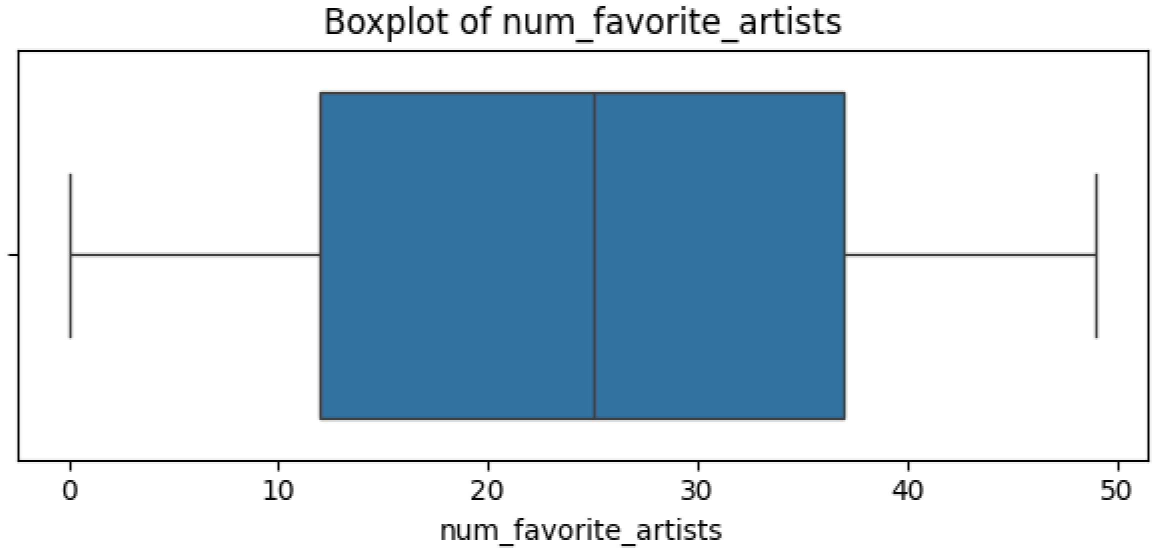

Boxplot of weekly_hours
0
10
20
30
40
50
weekly_hours

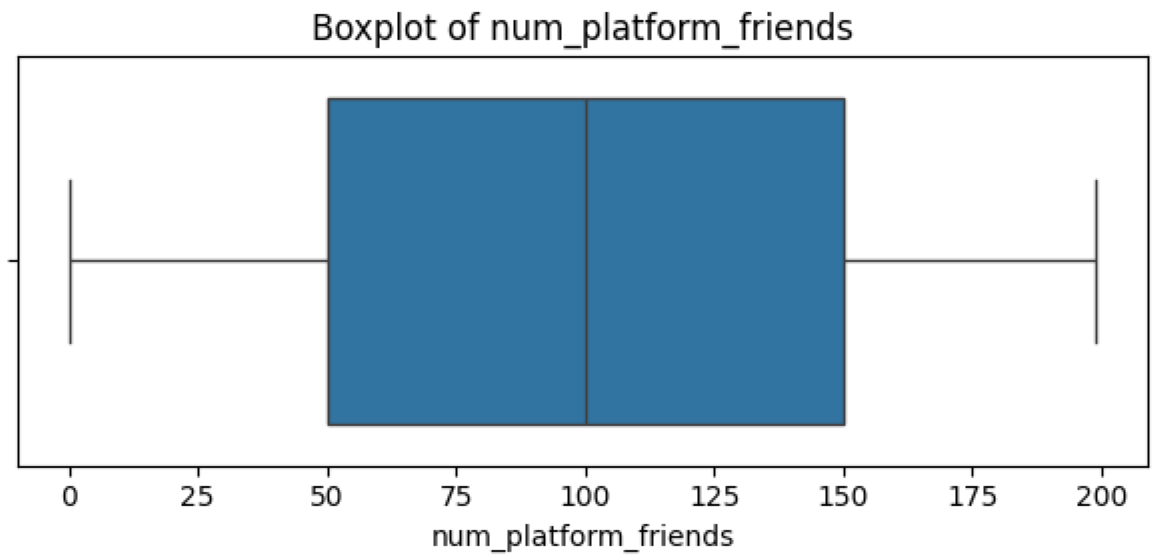

Boxplot of average_session_length
0
20
40
60
80
100
120
average_session_length

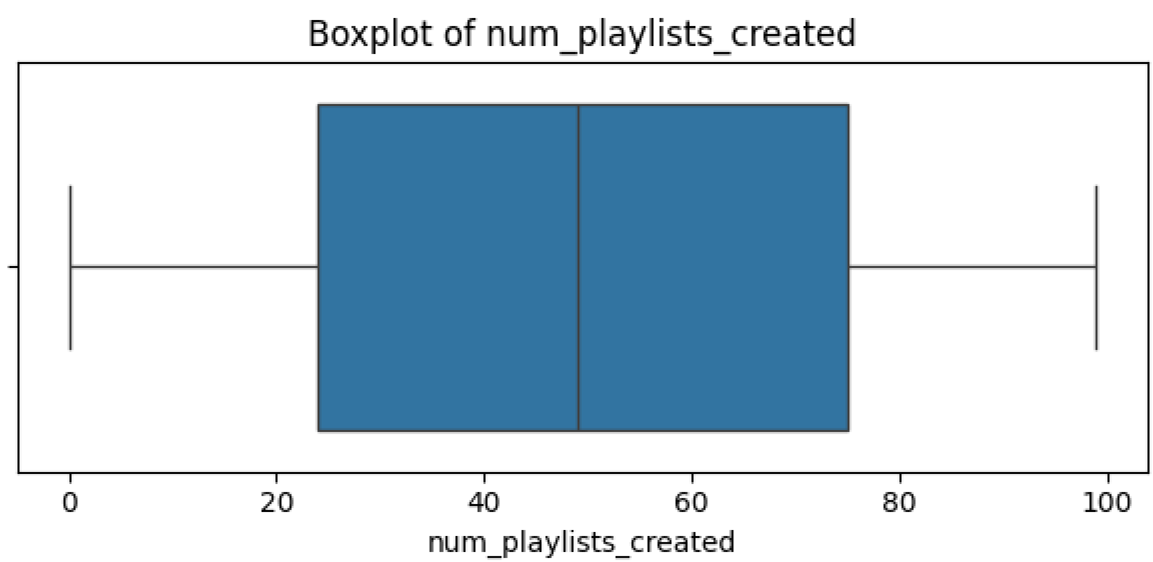

Boxplot of song_skip_rate
0.0
0.2
0.4
0.6
0.8
1.0
song_skip_rate

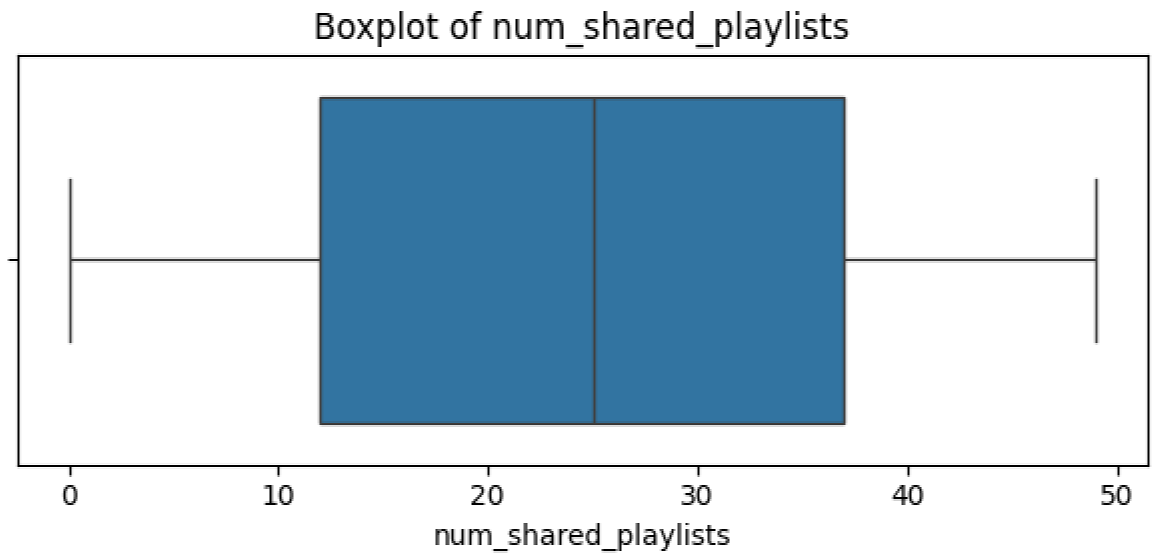

Boxplot of weekly_songs_played
0
100
200
300
400
500
weekly_songs_played

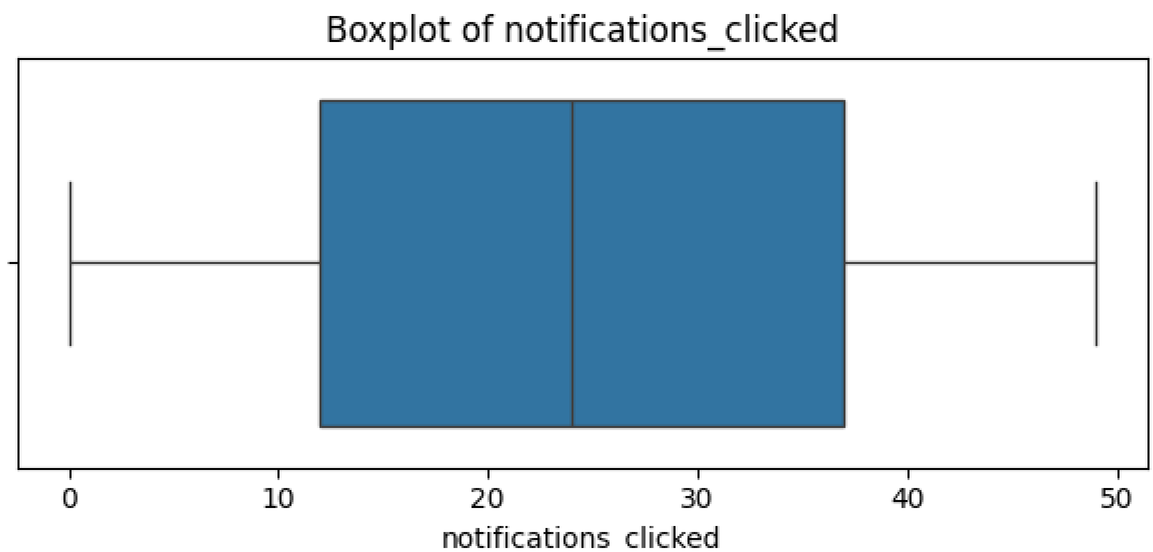

Boxplot of weekly_unique_songs
0
50
100
150
200
250
300
weekly_unique_songs

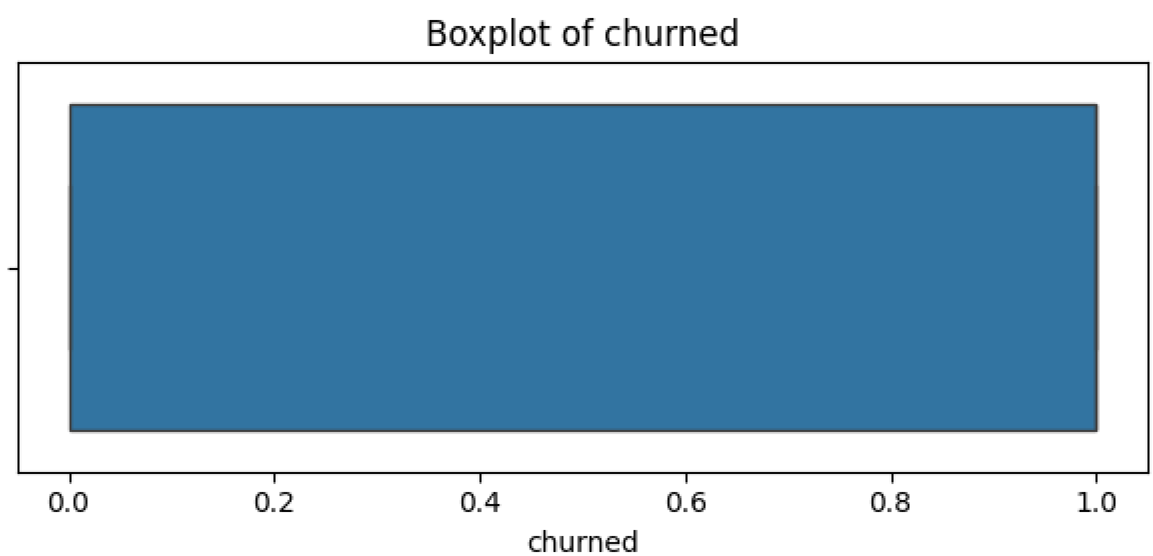

Boxplot of num_favorite_artists
0
10
20
30
40
50
num_favorite_artists


Boxplot of num_platform_friends
0
25
50
75
100
125
150
175
200
num_platform_friends

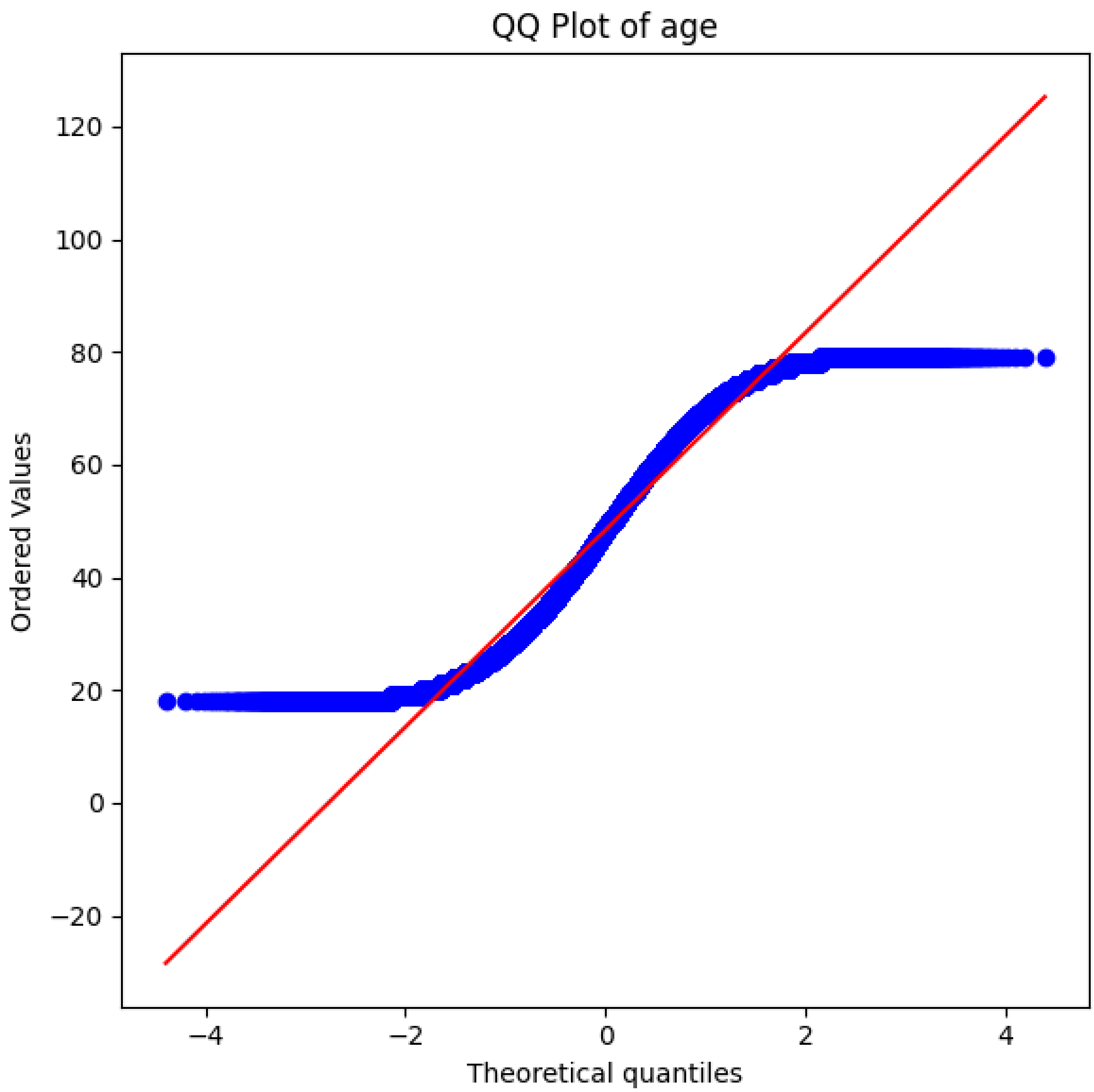

Boxplot of num_playlists_created
0
20
40
60
80
100
num_playlists_created

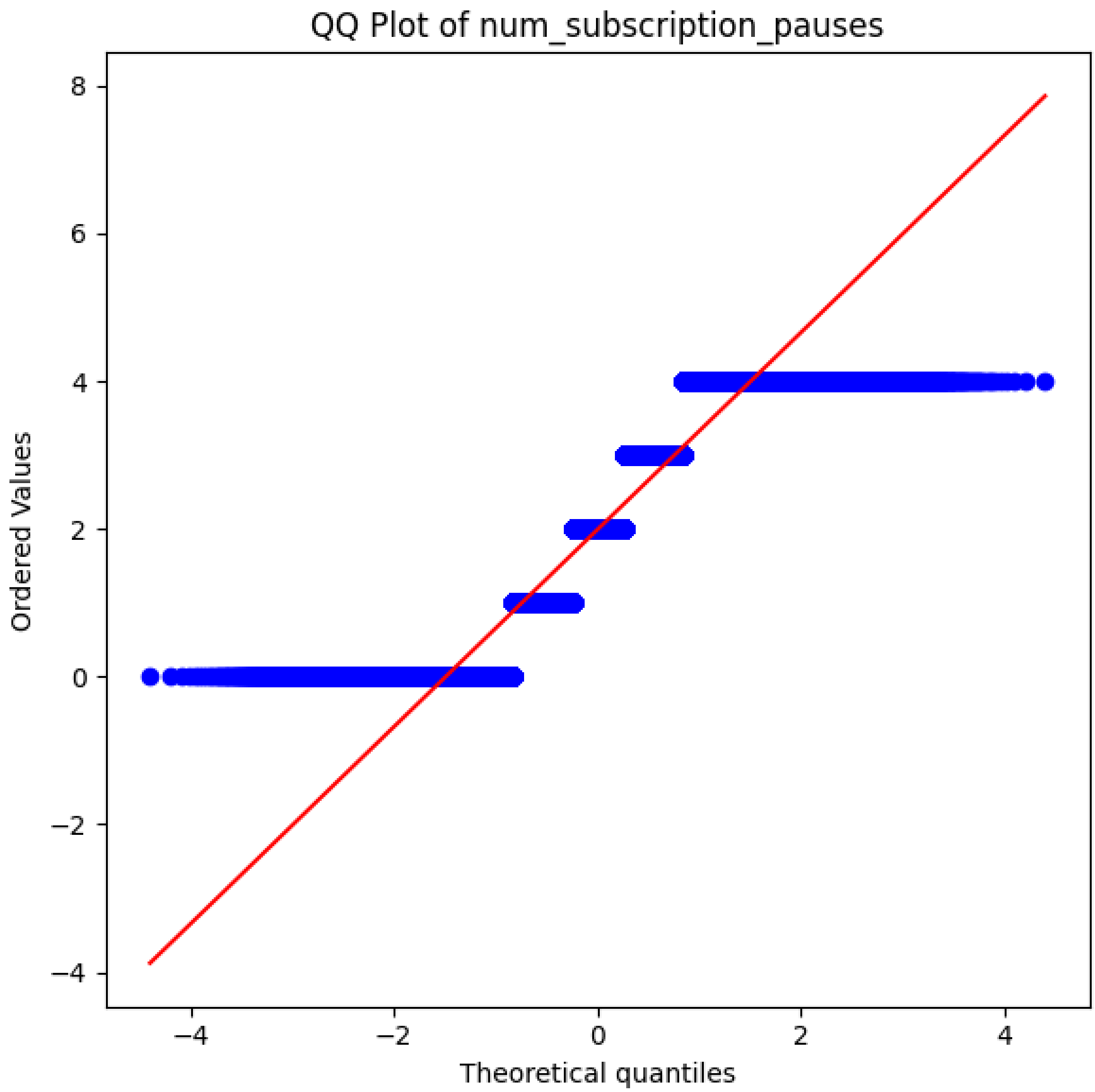

Boxplot of num_shared_playlists
0
10
20
30
40
50
num_shared_playlists

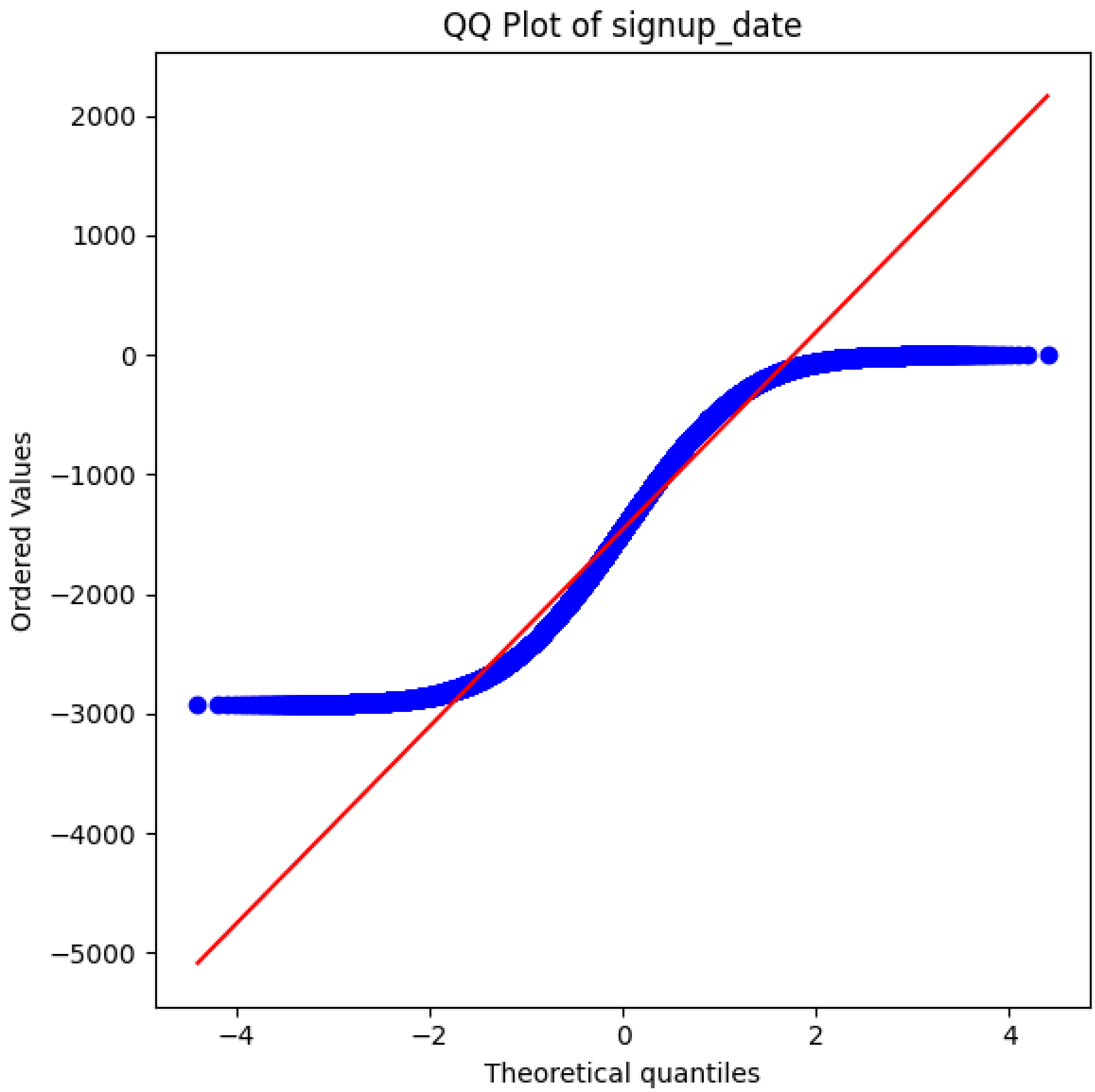

Boxplot of notifications_clicked
0
10
20
30
40
50
notifications_clicked

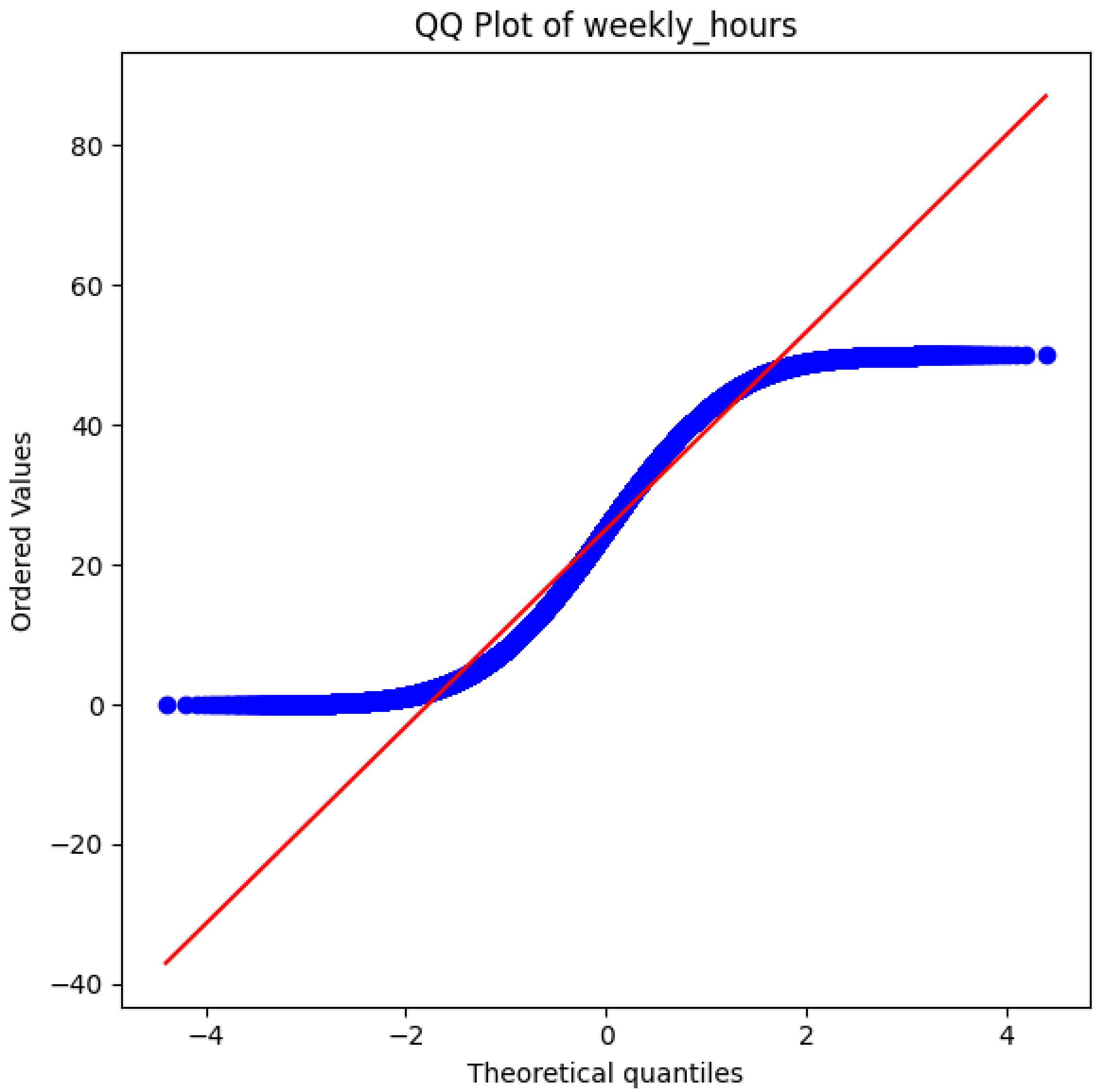

Boxplot of churned
0.0
0.2
0.4
0.6
0.8
1.0
churned

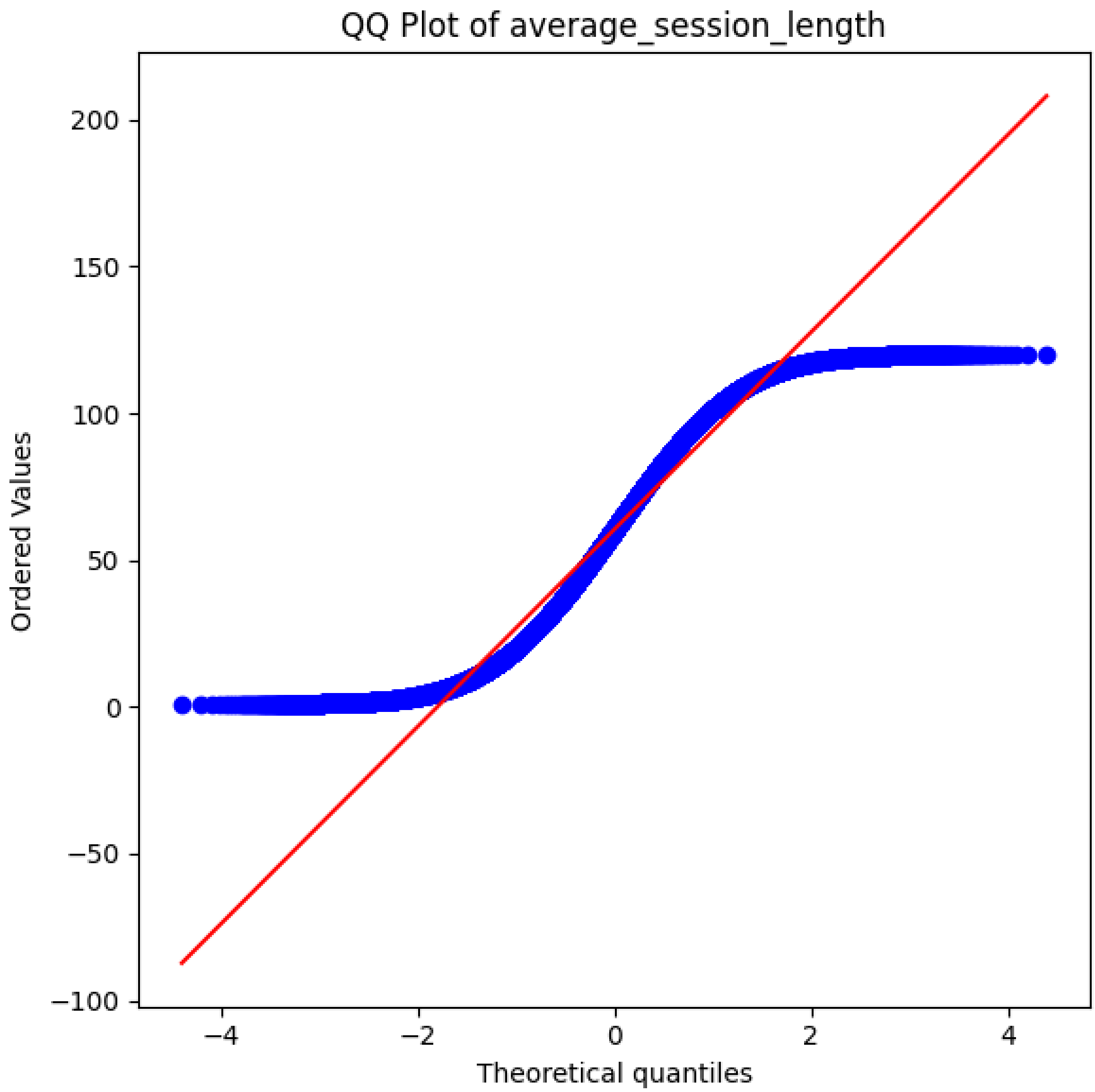
```
age | Skewness: 0.01
num_subscription_pauses | Skewness: 0.01
signup_date | Skewness: 0.00
weekly_hours | Skewness: -0.00
average_session_length | Skewness: 0.00
song_skip_rate | Skewness: -0.00
weekly_songs_played | Skewness: 0.00
weekly_unique_songs | Skewness: 0.01
num_favorite_artists | Skewness: -0.00
num_platform_friends | Skewness: -0.00
num_playlists_created | Skewness: 0.00
num_shared_playlists | Skewness: -0.00
notifications_clicked | Skewness: 0.00
churned | Skewness: -0.05
```

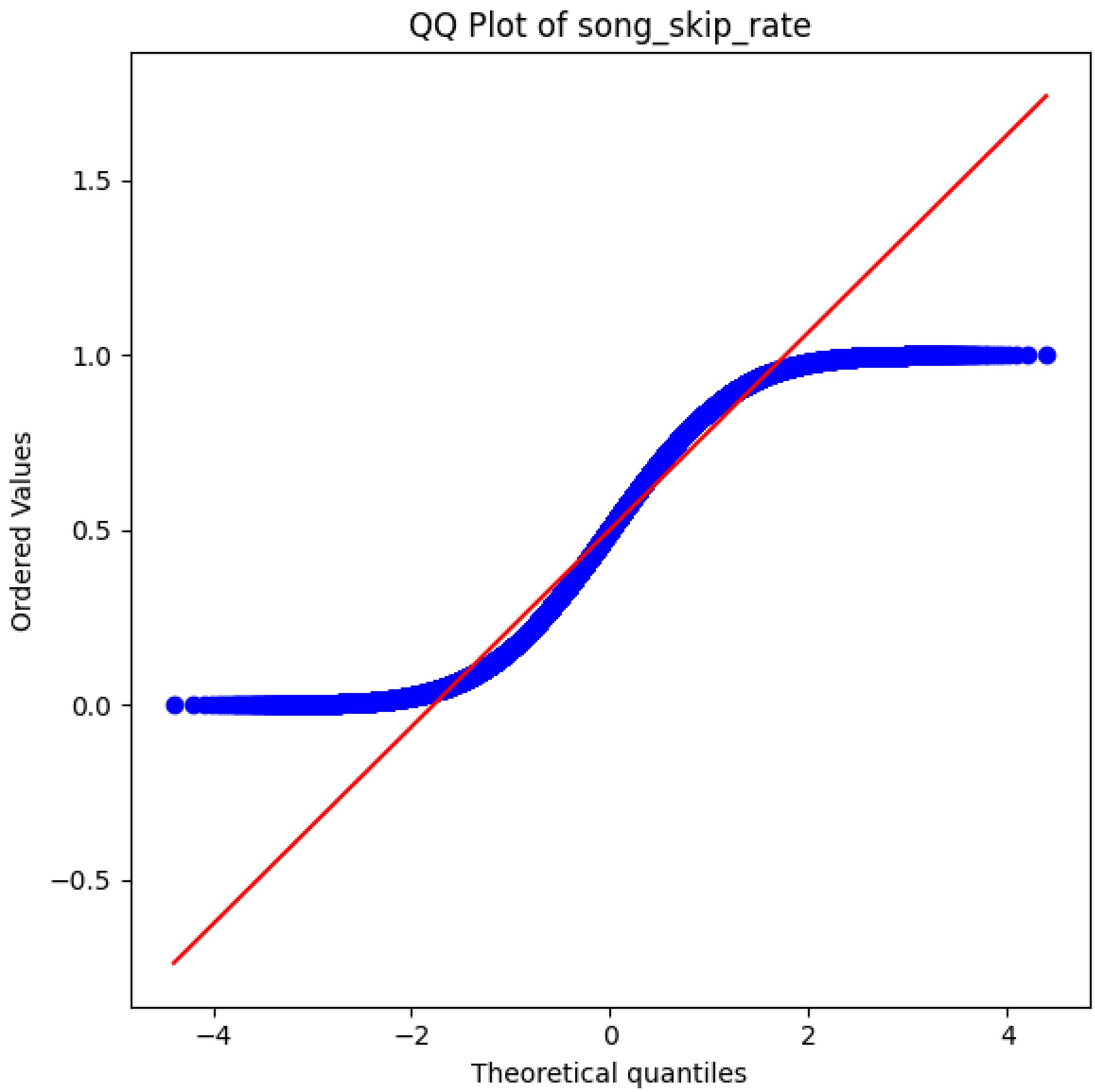


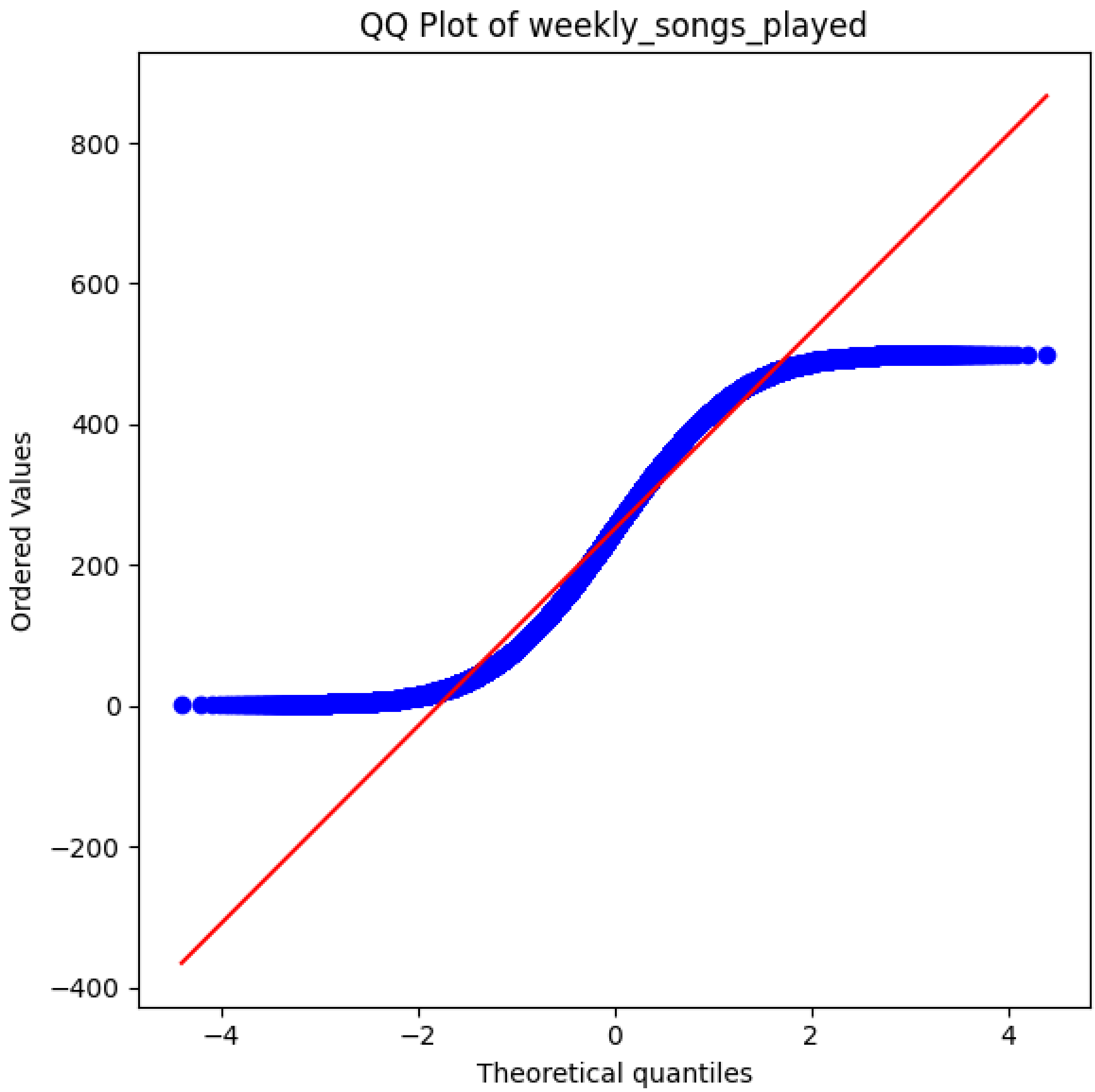

QQ Plot of num_subscription_pauses
Ordered Values
8
6
4
2
0
−2
−4
Theoretical quantiles
−4
−2
0
2
4

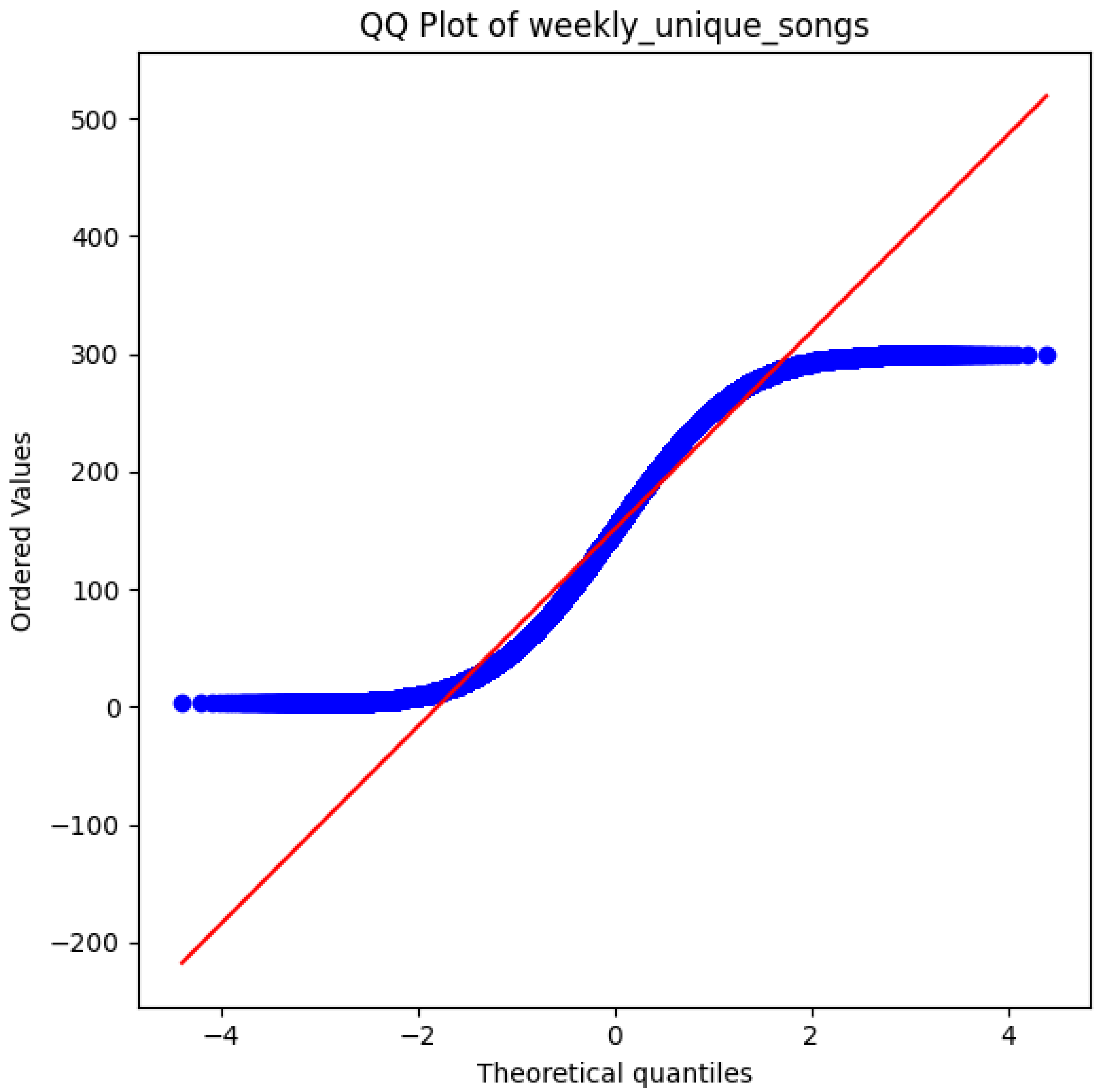

QQ Plot of signup_date
2000
1000
0
−1000
−2000
−3000
−4000
−5000
Ordered Values
−4
−2
0
2
4
Theoretical quantiles

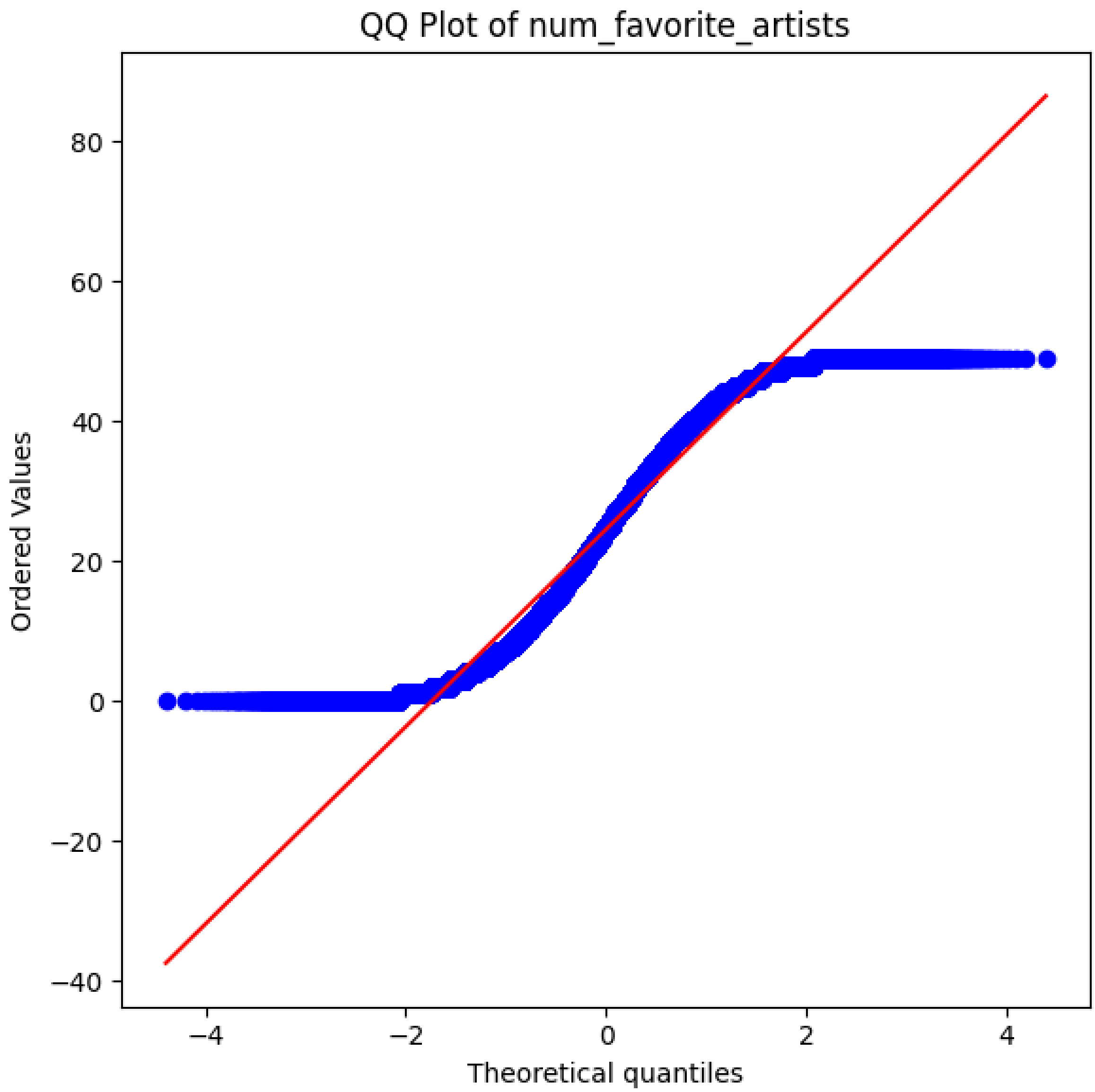

QQ Plot of weekly_hours
80
60
40
20
0
−20
−40
Ordered Values
−4
−2
0
2
4
Theoretical quantiles

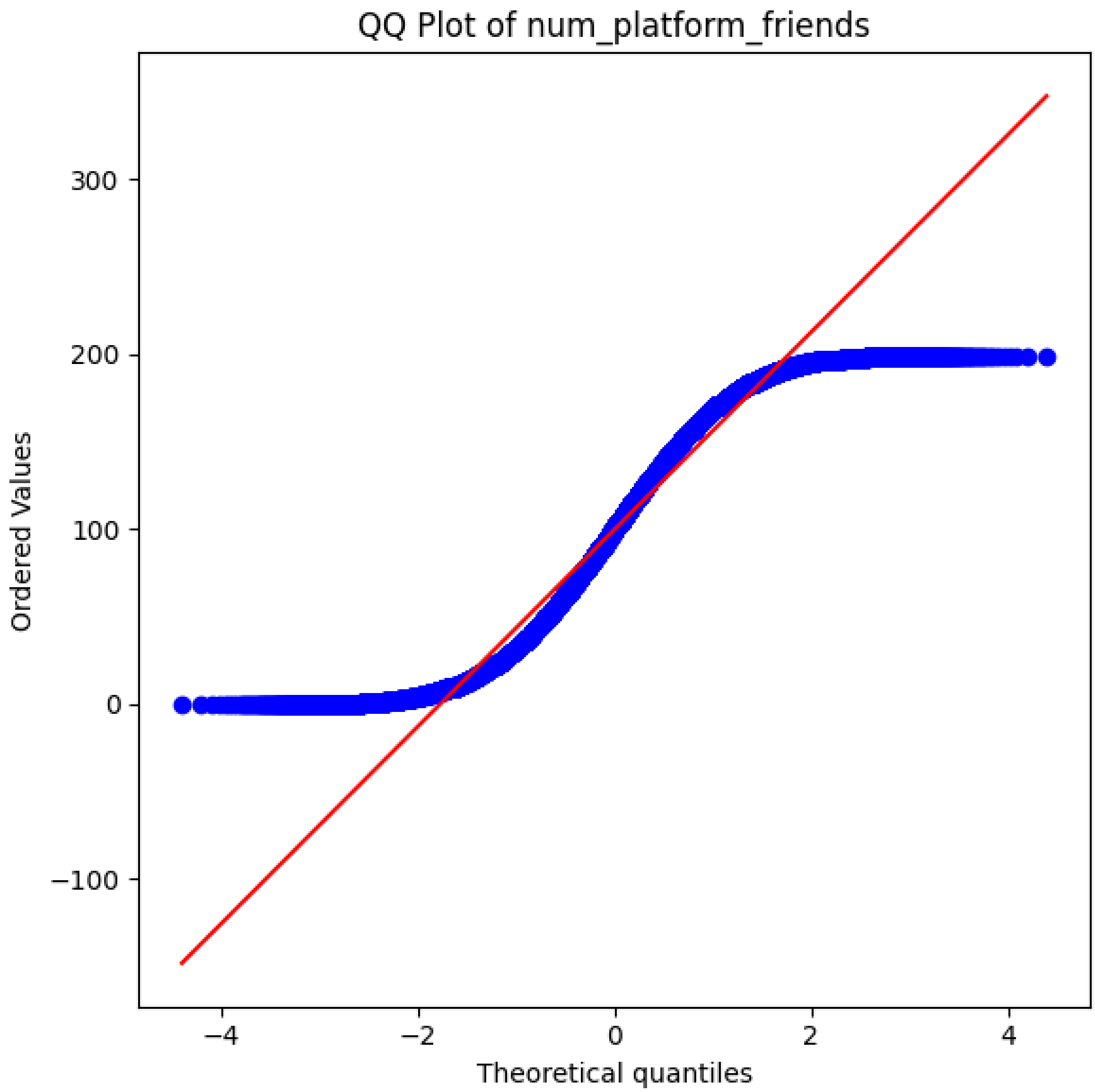

QQ Plot of average_session_length
Ordered Values
Theoretical quantiles
200
150
100
50
0
−50
−100
−4
−2
0
2
4

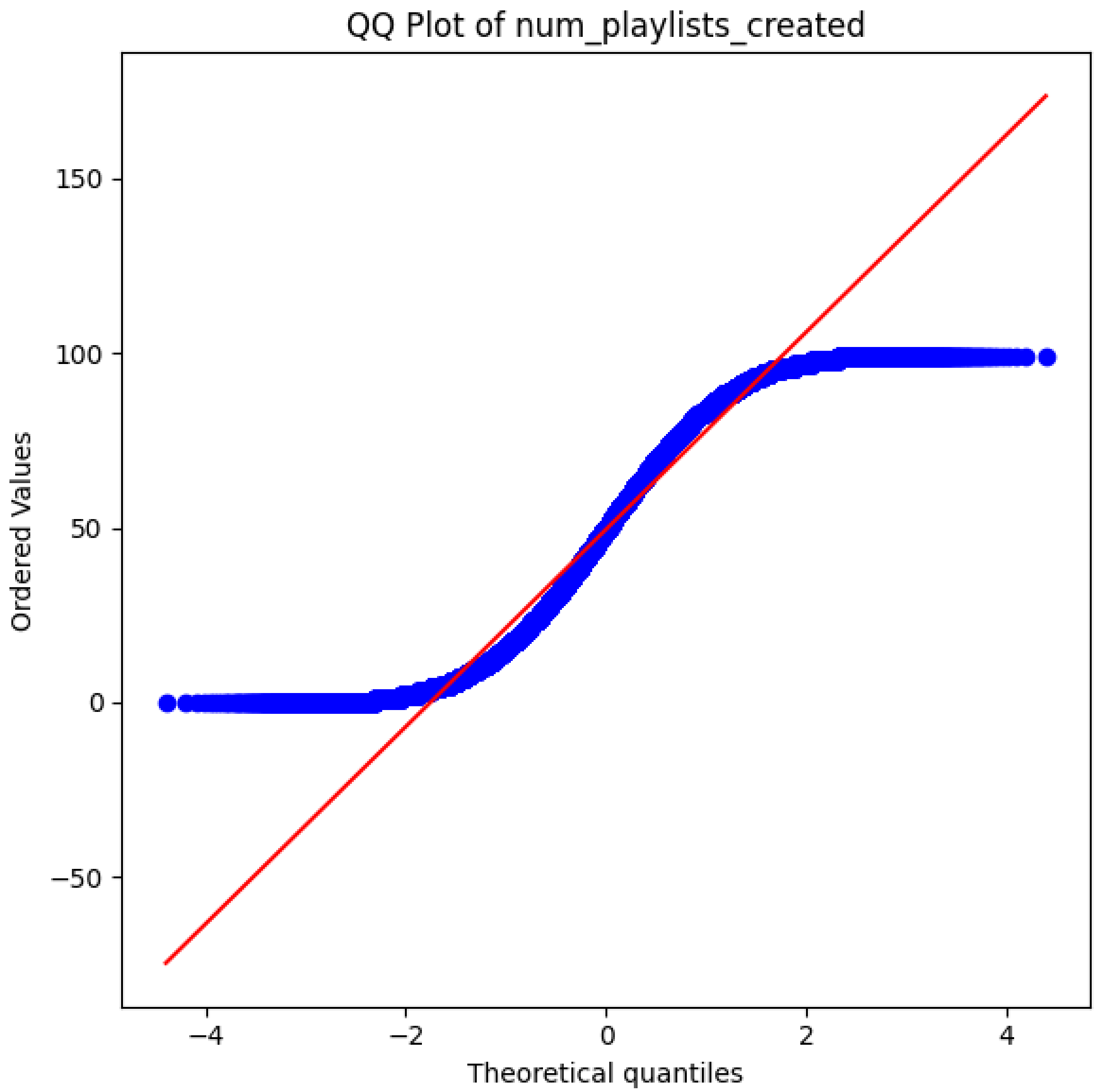

QQ Plot of song_skip_rate
Ordered Values
Theoretical quantiles
1.5
1.0
0.5
0.0
−0.5
−4
−2
0
2
4

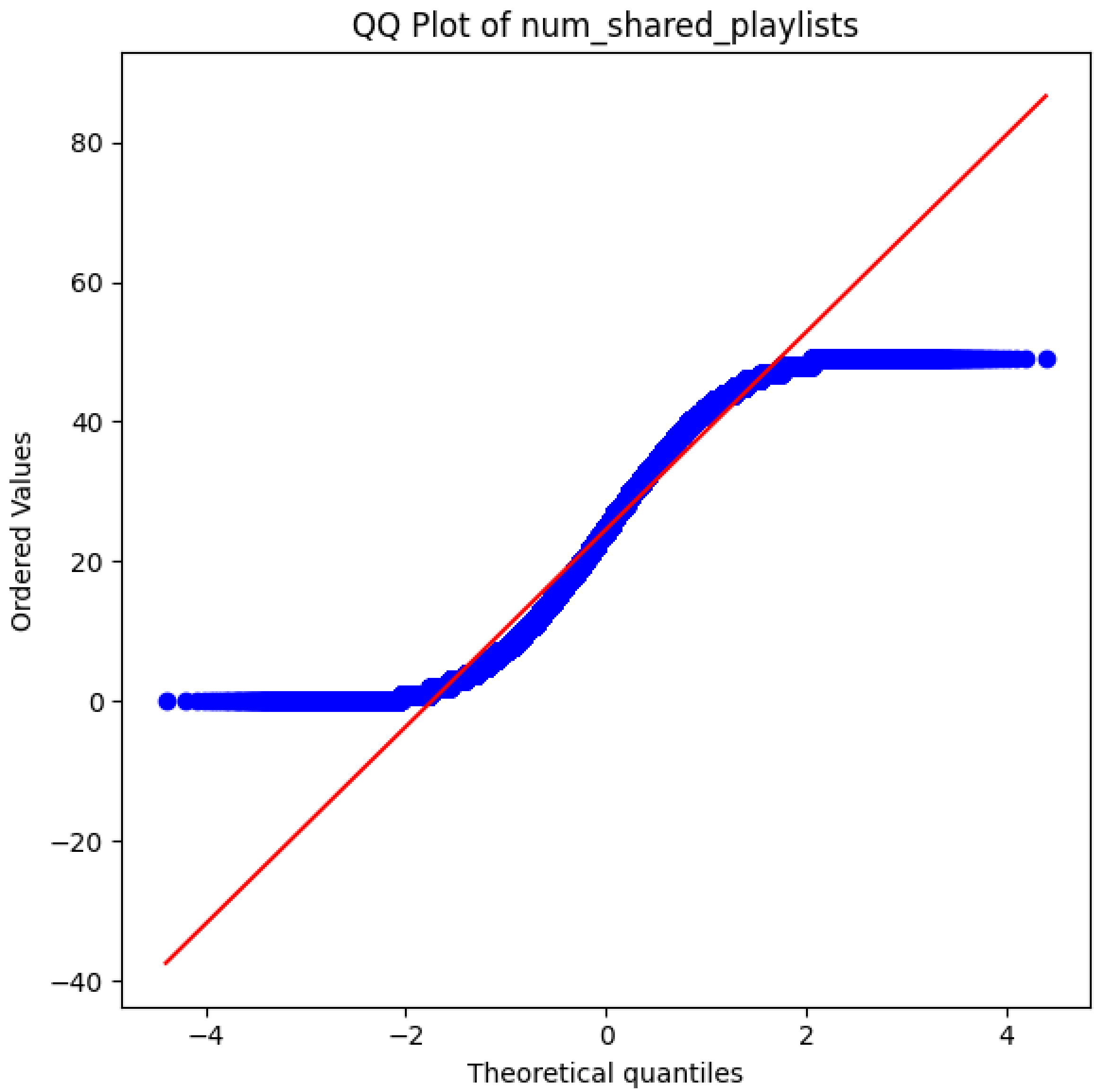

QQ Plot of weekly_songs_played
Ordered Values
Theoretical quantiles
800
600
400
200
0
−200
−400
−4
−2
0
2
4

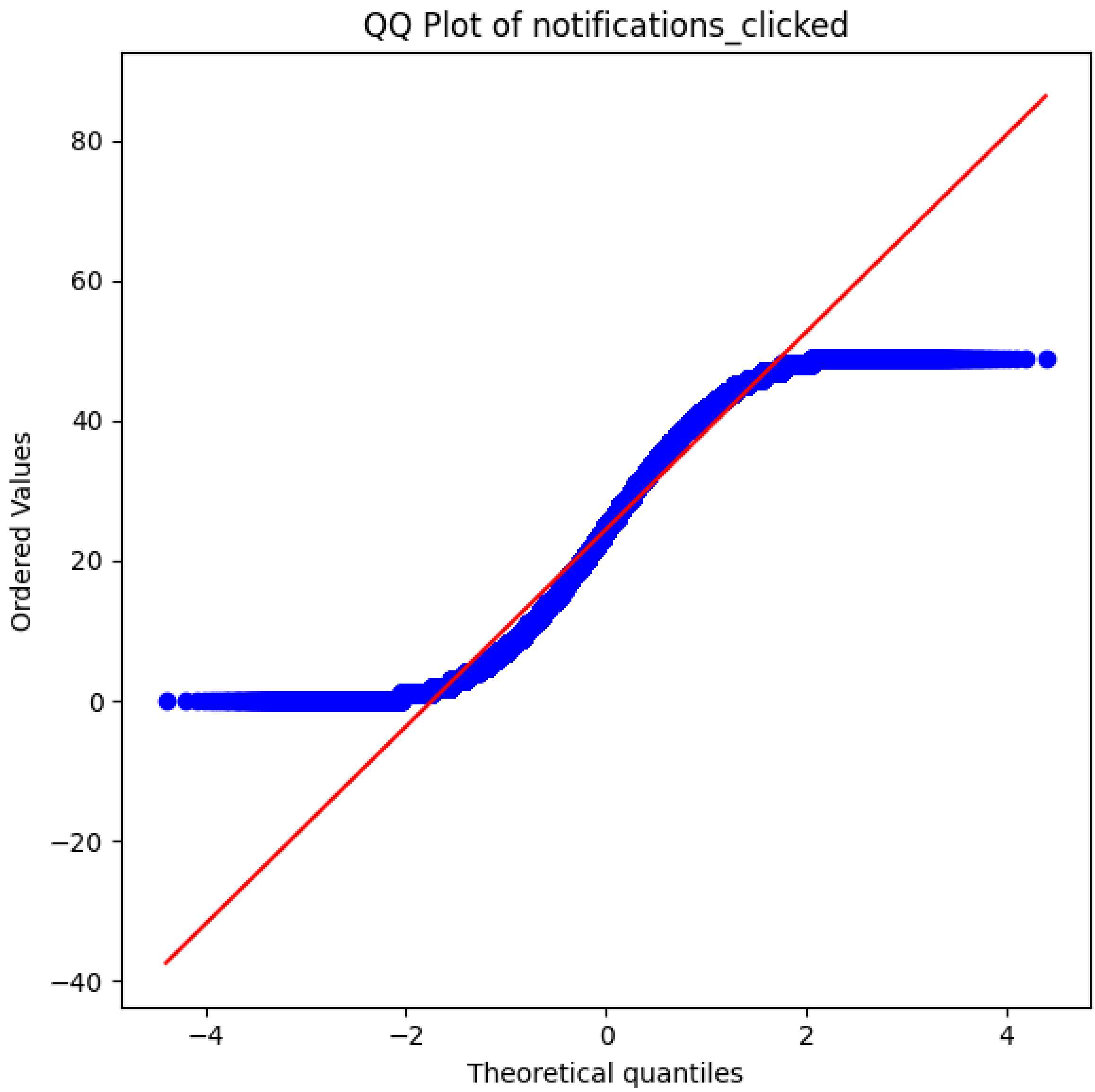

QQ Plot of weekly_unique_songs
500
400
300
200
100
0
−100
−200
Ordered Values
−4
−2
0
2
4
Theoretical quantiles

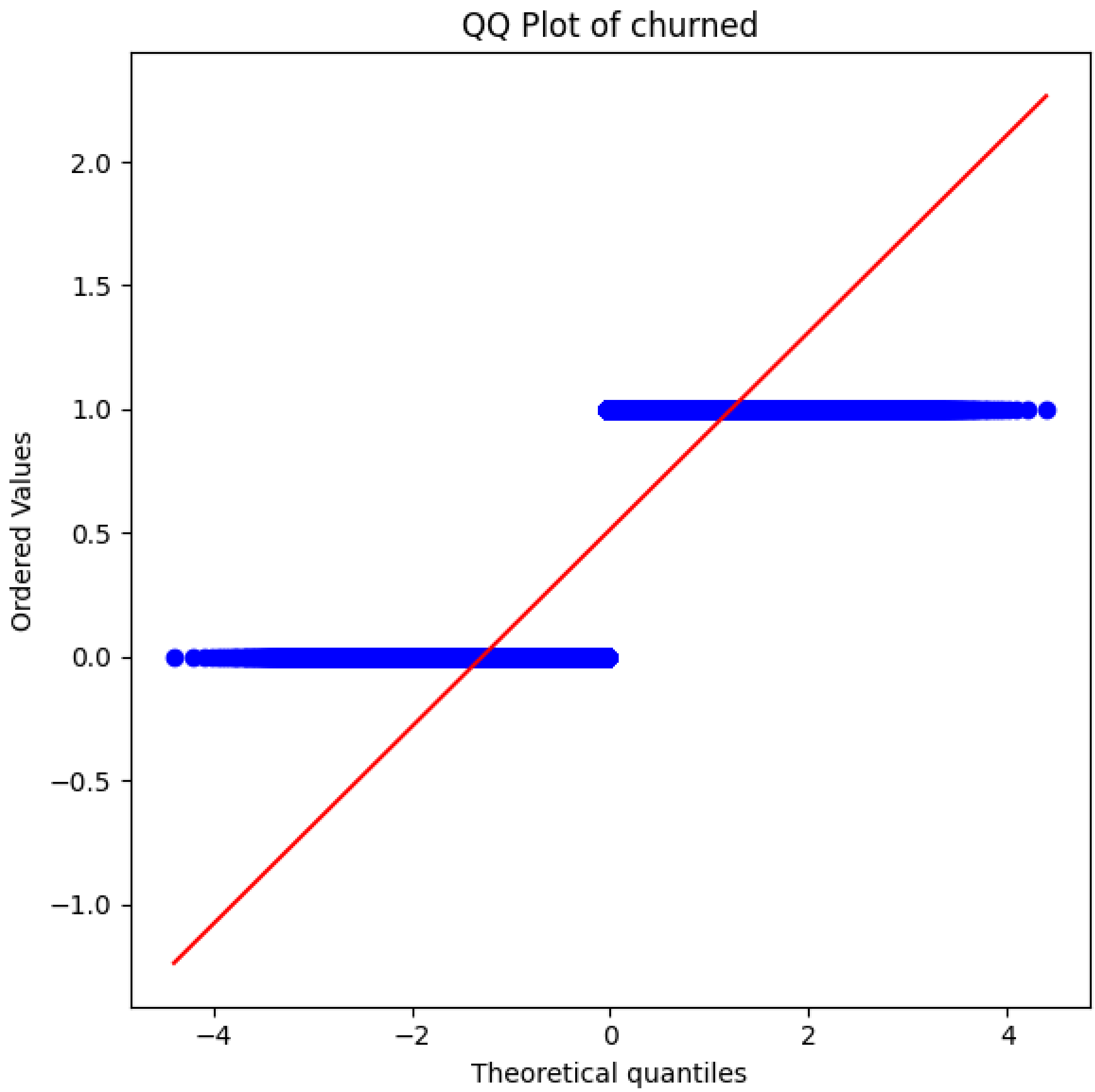

QQ Plot of num_favorite_artists
Ordered Values
Theoretical quantiles
80
60
40
20
0
−20
−40
−4
−2
0
2
4


QQ Plot of num_platform_friends
Ordered Values
300
200
100
0
−100
−4
−2
0
2
4
Theoretical quantiles

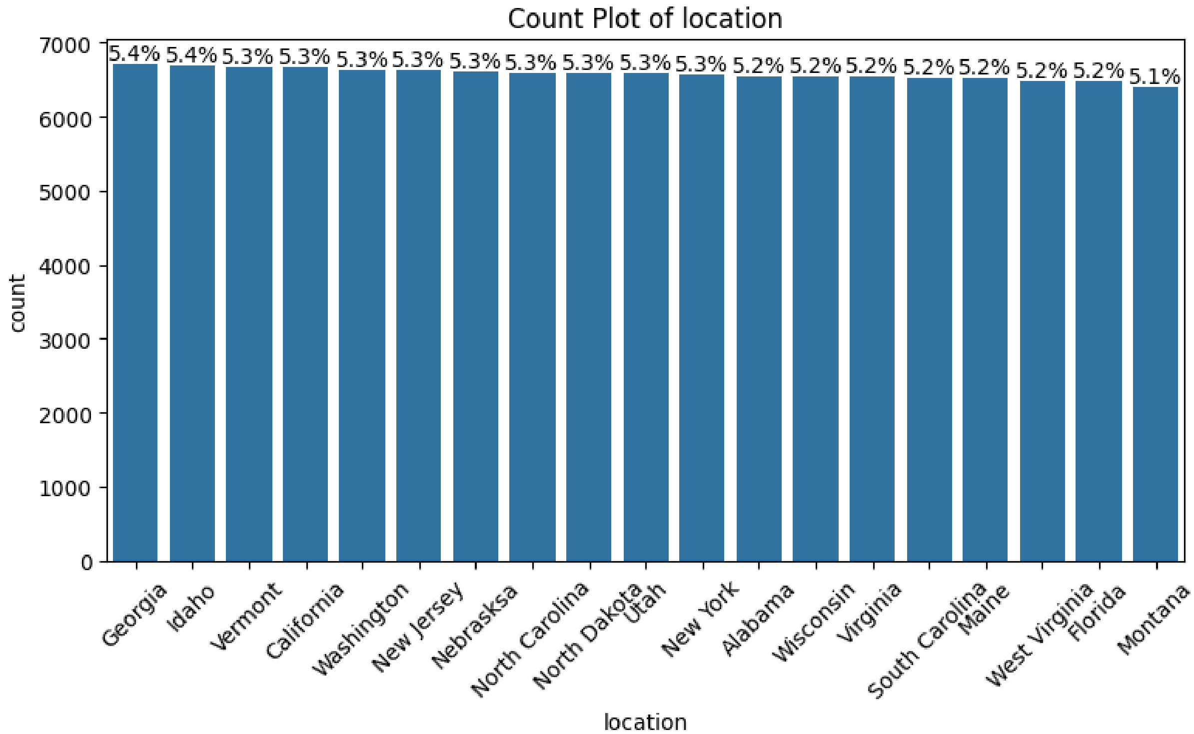

QQ Plot of num_playlists_created
Ordered Values
Theoretical quantiles
150
100
50
0
−50
−4
−2
0
2
4

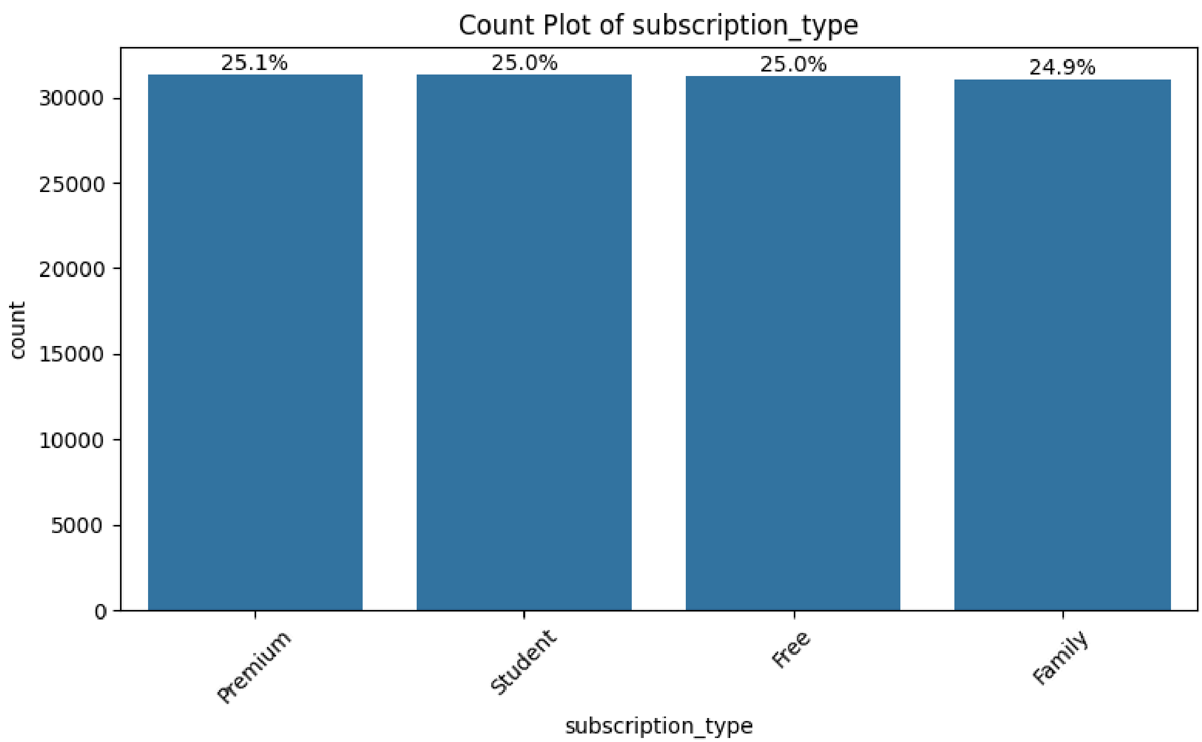

QQ Plot of num_shared_playlists
Ordered Values
Theoretical quantiles
80
60
40
20
0
−20
−40
−4
−2
0
2
4

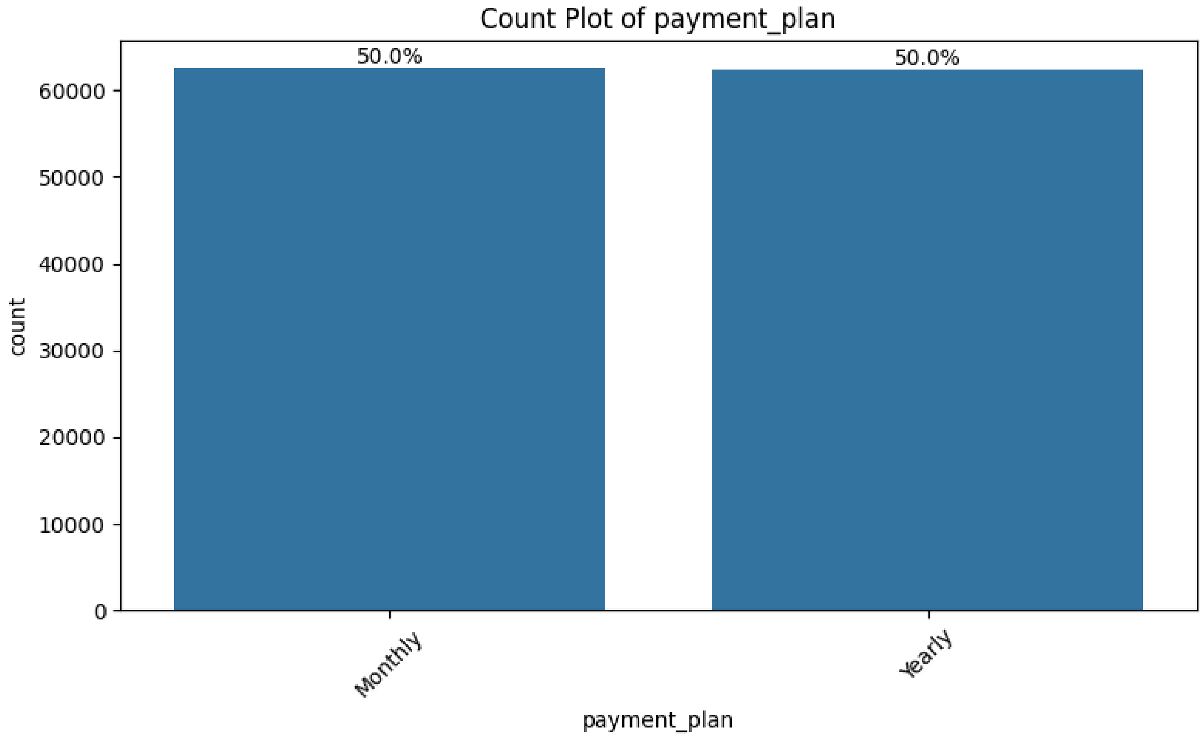

QQ Plot of notifications_clicked
Ordered Values
Theoretical quantiles
80
60
40
20
0
−20
−40
−4
−2
0
2
4

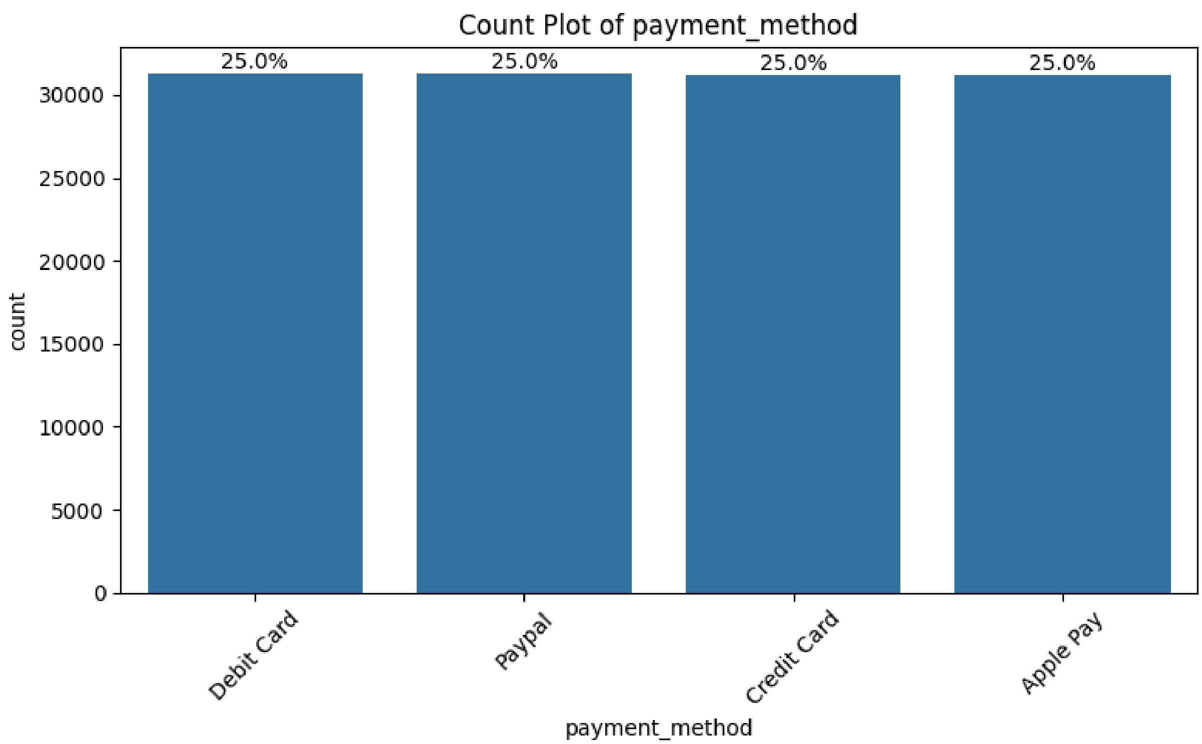

QQ Plot of churned
Ordered Values
Theoretical quantiles
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−4
−2
0
2
4

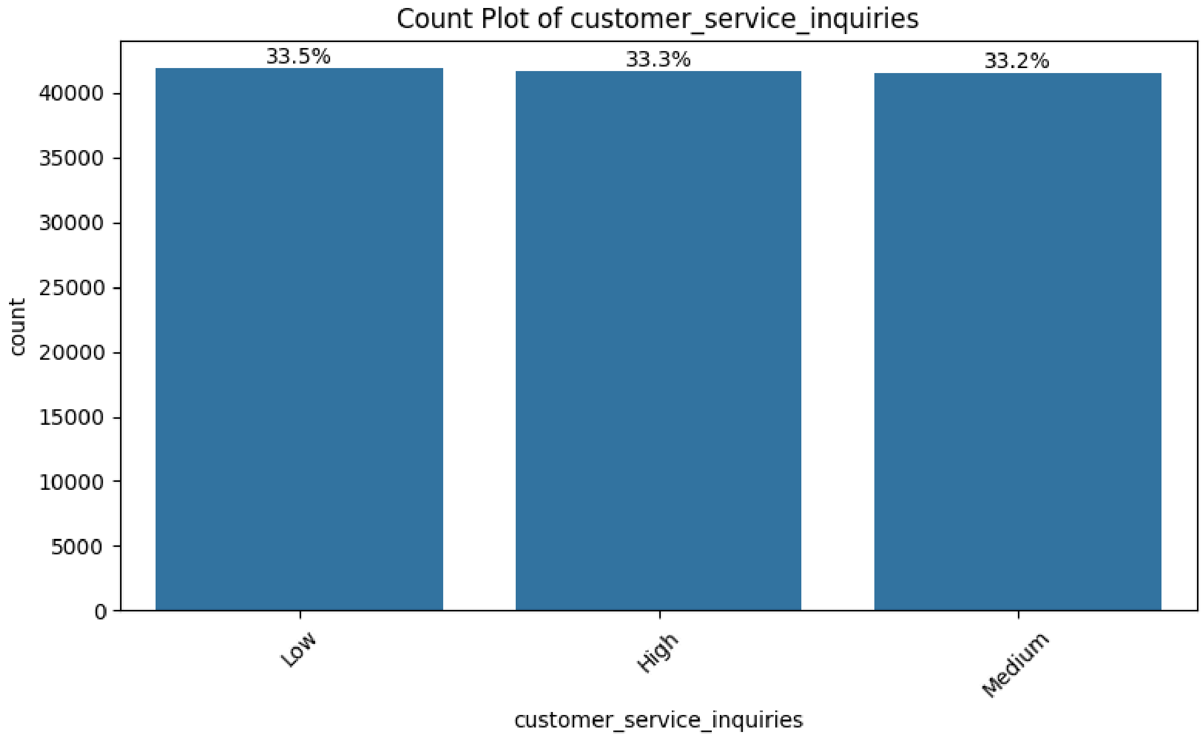
```
Frequency table for location:
location
Georgia           0.053640
Idaho             0.053576
Vermont           0.053408
California        0.053320
Washington        0.053104
New Jersey        0.053072
Nebrasksa         0.052808
North Carolina    0.052664
North Dakota      0.052616
Utah              0.052616
New York          0.052592
Alabama           0.052440
Wisconsin         0.052424
Virginia          0.052328
South Carolina    0.052272
Maine             0.052184
West Virginia     0.051888
Florida           0.051840
Montana           0.051208
Name: proportion, dtype: float64

Frequency table for subscription_type:
subscription_type
Premium    0.250832
Student    0.250440
Free       0.250152
Family     0.248576
Name: proportion, dtype: float64

Frequency table for payment_plan:
payment_plan
Monthly    0.500496
Yearly     0.499504
Name: proportion, dtype: float64

Frequency table for payment_method:
payment_method
Debit Card     0.250336
Paypal         0.250256
Credit Card    0.249704
Apple Pay      0.249704
Name: proportion, dtype: float64

Frequency table for customer_service_inquiries:
customer_service_inquiries
Low       0.334984
High      0.332664
Medium    0.332352
Name: proportion, dtype: float64
```


Count Plot of location
count
location
Georgia
Idaho
Vermont
California
Washington
New Jersey
Nebrasksa
North Carolina
North Dakota
Utah
New York
Alabama
Wisconsin
Virginia
South Carolina
Maine
West Virginia
Florida
Montana
5.4%
5.4%
5.3%
5.3%
5.3%
5.3%
5.3%
5.3%
5.3%
5.3%
5.3%
5.2%
5.2%
5.2%
5.2%
5.2%
5.2%
5.2%
5.1%


Count Plot of subscription_type
count
subscription_type
Premium
Student
Free
Family
25.1%
25.0%
25.0%
24.9%


Count Plot of payment_plan
50.0%
50.0%
count
0
10000
20000
30000
40000
50000
60000
Monthly
Yearly
payment_plan


Count Plot of payment_method
25.0%
25.0%
25.0%
25.0%
count
0
5000
10000
15000
20000
25000
30000
Debit Card
Paypal
Credit Card
Apple Pay
payment_method




## Numerical Univariate Analysis:

### Distribution shape: Normality? Skewness? Heavy tails?

The distribution shape for the numerical variables are roughly symmetrical. Checking normality using the QQ plot, age, signup_date, weekly hours, average_session_length, song_skip_rate, weekly_songs_played, weekly_unique_songs, num_favorite_artists, num_platform_friends, num_playlists_created, num_shared_playlists, and notifications_clicked numerical variables, they all roughly followed the normality line, but have heavily deviated tails. num_subscription is piecewise because there can only be integers for pausing subscription and churned is also piecewise since it is a binary variable.

### Summary stats: Mean, median, std dev, IQR, range

Age: Mean: 48.41, Standard Deviation: 17.90, Range: 18 to 79, 25th Percentile (Q1): 33, 50th Percentile (Median): 48, 75th Percentile (Q3): 64.

The age distribution is moderately spread with a significant portion of customers aged between 33 and 64 years.

Number of Subscription Pauses: Mean: 1.99, Standard Deviation: 1.42, Range: 0 to 4 pauses

This feature indicates that most customers have paused their subscriptions once or twice.

Signup Date: Mean: -1460.68 (Days since a reference point), Standard Deviation: 844.13, Range: -2922 to -1

The signup date reflects the number of days since a certain reference date, with most signups occurring closer to the reference date.

Weekly Hours: Mean: 25.04, Standard Deviation: 14.45, Range: 0.000068 to 50, 25th Percentile (Q1): 12.47, 50th Percentile (Median): 25.12, 75th Percentile (Q3): 37.57

Weekly hours vary significantly, with most users engaging in 12 to 37 hours of activity each week.

Average Session Length: Mean: 60.42 minutes, Standard Deviation: 34.38, Range: 1 to 119.99 minutes, 25th Percentile (Q1): 30.64, 50th Percentile (Median): 60.34, 75th Percentile (Q3): 90.23

Average session lengths are spread across a wide range, with most sessions lasting between 30 to 90 minutes.

Song Skip Rate: Mean: 0.50, Standard Deviation: 0.29, Range: 0.000006 to 1, 25th Percentile (Q1): 0.25, 50th Percentile (Median): 0.50, 75th Percentile (Q3): 0.75

The song skip rate is close to 50% on average, indicating that many users skip roughly half of the songs they listen to.

Weekly Songs Played: Mean: 250.82, Standard Deviation: 143.33, Range: 3 to 499 songs, 25th Percentile (Q1): 127, 50th Percentile (Median): 251, 75th Percentile (Q3): 375

This feature shows a wide distribution, with most users playing between 127 and 375 songs per week.

Weekly Unique Songs: Mean: 150.78, Standard Deviation: 85.79, Range: 3 to 299 unique songs, 25th Percentile (Q1): 76, 50th Percentile (Median): 150, 75th Percentile (Q3): 225

Most users play between 76 and 225 unique songs per week.

Number of Favorite Artists: Mean: 24.50, Standard Deviation: 14.45, Range: 0 to 49, 25th Percentile (Q1): 12, 50th Percentile (Median): 25, 75th Percentile (Q3): 37

Users generally have between 12 and 37 favorite artists, with a few having no favorite artists.

Number of Platform Friends: Mean: 99.71, Standard Deviation: 57.68, Range: 0 to 199, 25th Percentile (Q1): 50, 50th Percentile (Median): 100, 75th Percentile (Q3): 150

The number of platform friends shows significant variation, with most users having between 50 and 150 friends.

Number of Playlists Created: Mean: 49.46, Standard Deviation: 28.94, Range: 0 to 99 playlists, 25th Percentile (Q1): 24, 50th Percentile (Median): 49, 75th Percentile (Q3): 75

Users typically create between 24 and 75 playlists.

Number of Shared Playlists:, Mean: 24.55, Standard Deviation: 14.45, Range: 0 to 49 shared playlists, 25th Percentile (Q1): 12, 50th Percentile (Median): 25, 75th Percentile (Q3): 37

Most users have between 12 and 37 shared playlists.

Notifications Clicked: Mean: 24.45, Standard Deviation: 14.42, Range: 0 to 49 clicked notifications, 25th Percentile (Q1): 12, 50th Percentile (Median): 24, 75th Percentile (Q3): 37

Users generally click between 12 and 37 notifications.

Churned (Target Variable): Mean: 0.51 (indicating that roughly 51% of users have churned), Standard Deviation: 0.50, Range: 0 to 1, 25th Percentile (Q1): 0, 50th Percentile (Median): 1, 75th Percentile (Q3): 1

The churn variable indicates a near even distribution between users who churned (1) and those who did not (0).

### Outliers: Use boxplots or z-scores/IQR rule

Using box plots to check if there are any outliers within any numerical variables, we can see that there are no outliers. This was also validated using IQR to check for outliers.

## Categorical Univariate Analysis:

### Frequency tables

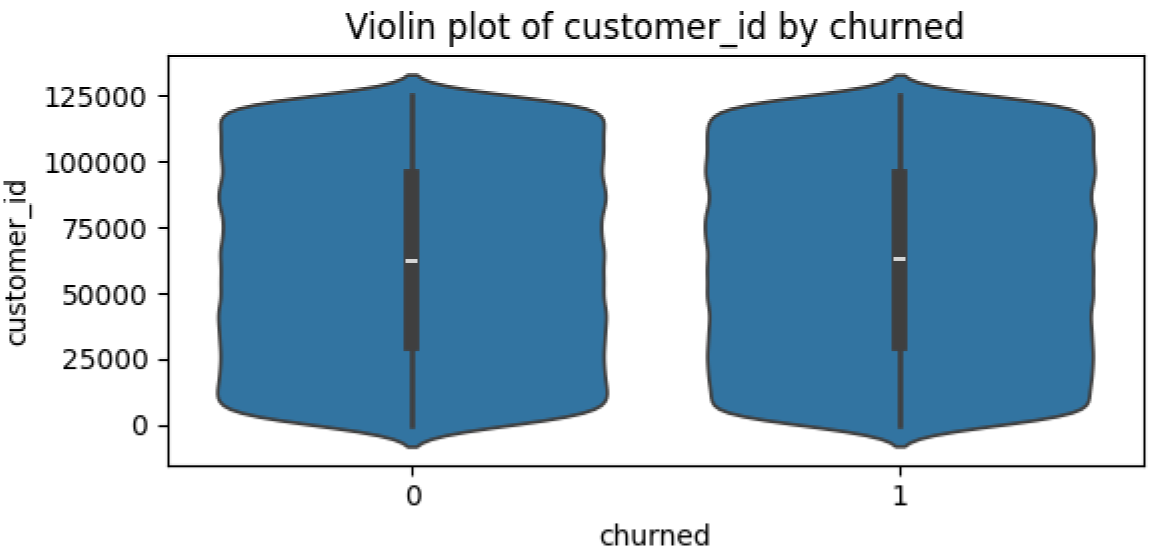
We use frequency tables to check the proportions of the categorical variables to see if there are any imbalanced categories. For the location variable, we can see that the proportions range from 5.1% to 5.4%. This means we have a roughly balanced category for location. For subscription types it ranges from 24.9% to 25.1%, indicating a balanced category. Payment plan and Payment method are all equal, so we have balanced categories for these variables. For customer service inquiries, it ranges from 33.2% to 33.5%, so we have roughly a balanced category.

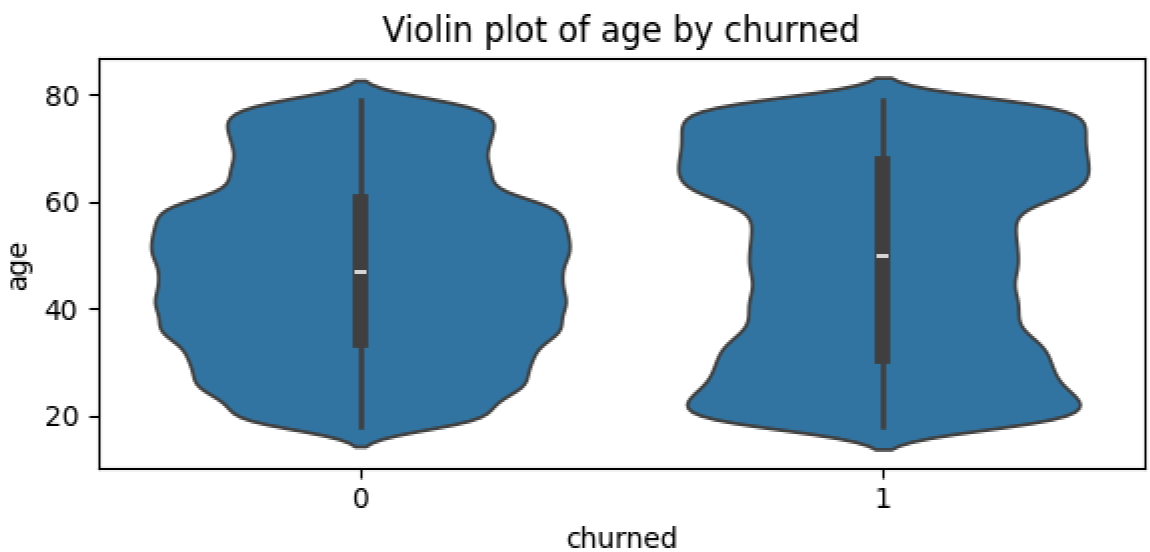
### Proportions: Useful for imbalanced categories

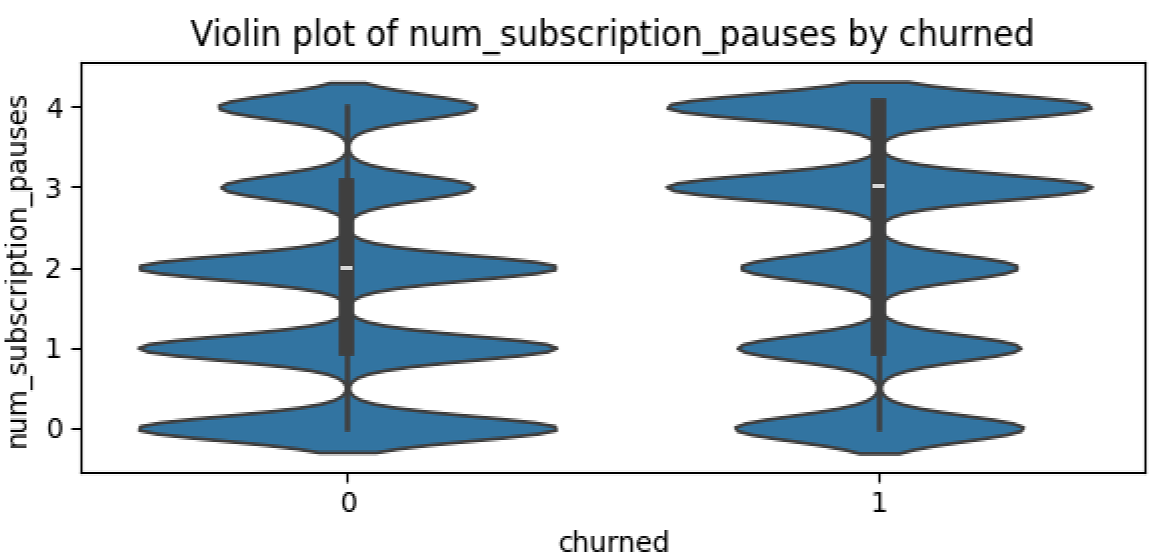
Using a bar chart with percentages, we can better visualize the proportions of each categorical variable.

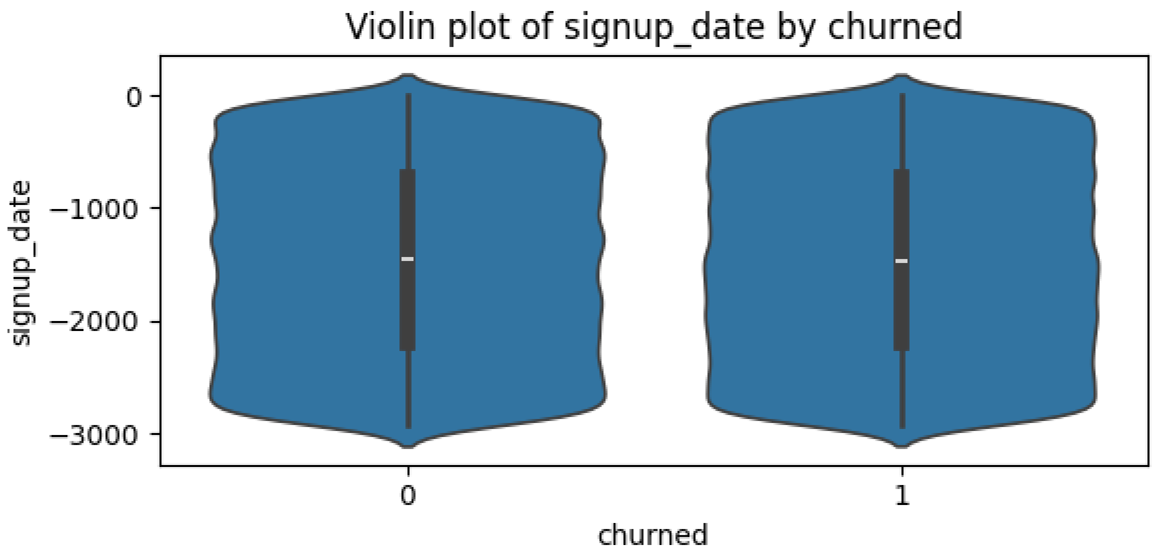
## Bivariate Exploration (with the target variable)

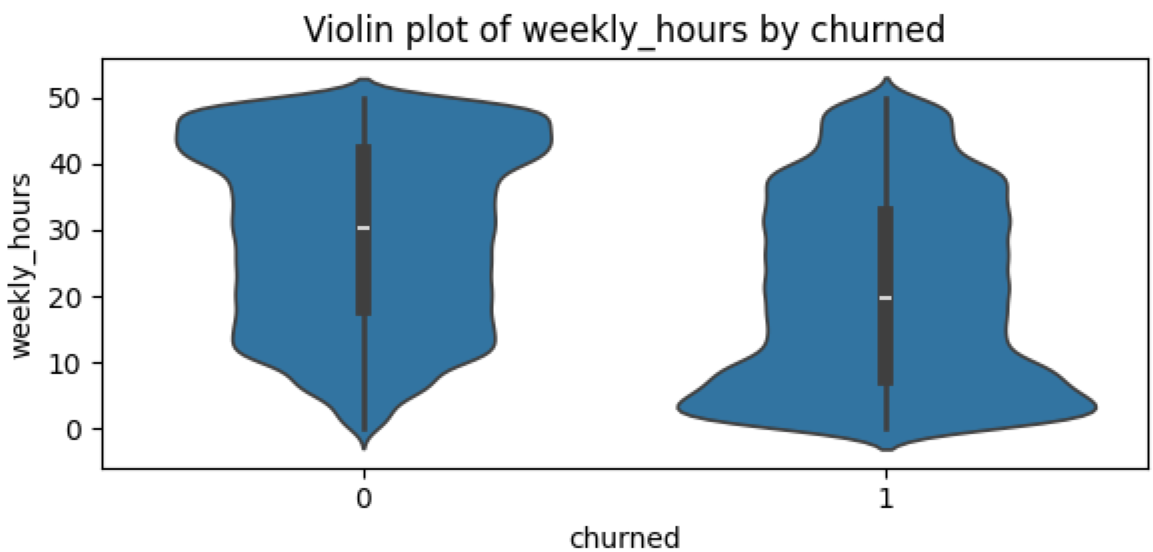
In [58]:
```
# Numerical vs Categorical: Violin chart of numerical features by churn
import seaborn as sns
import matplotlib.pyplot as plt

for col in num_cols:
    plt.figure(figsize=(6, 3))
    sns.violinplot(x='churned', y=col, data=train)
    plt.title(f"Violin plot of {col} by churned")
    plt.tight_layout()
    plt.show()

# Categorical vs Categorical: Contingency table
import pandas as pd
for col in cat_cols:
    if col != 'churned':
        contingency_table = pd.crosstab(train[col], train['churned'], margir
        print(f"\nContingency Table for {col} vs churned:")
        print(contingency_table)
```

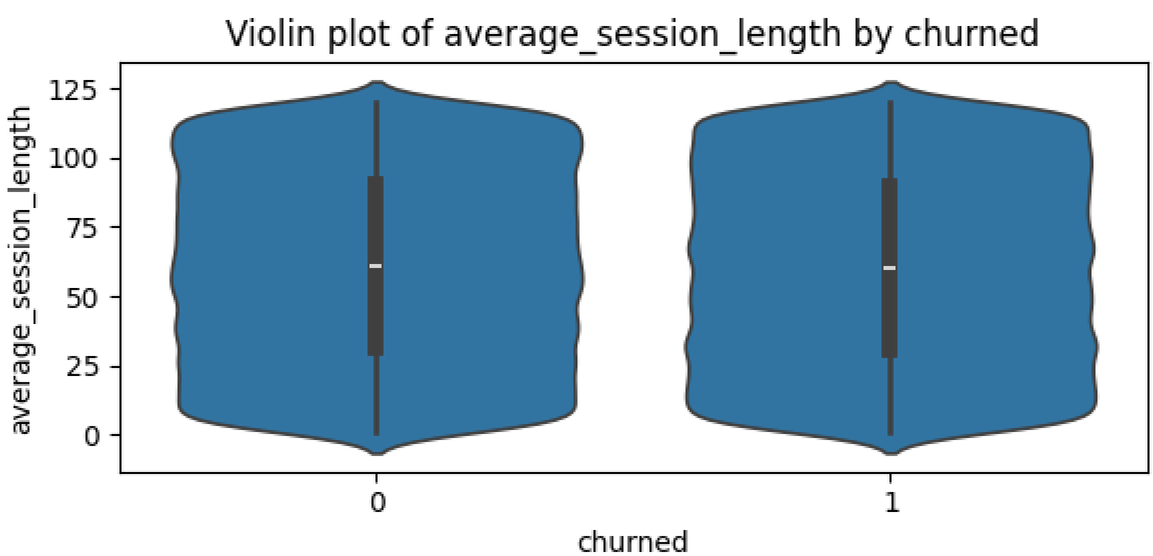

Violin plot of customer_id by churned
customer_id
125000
100000
75000
50000
25000
0
0
1
churned

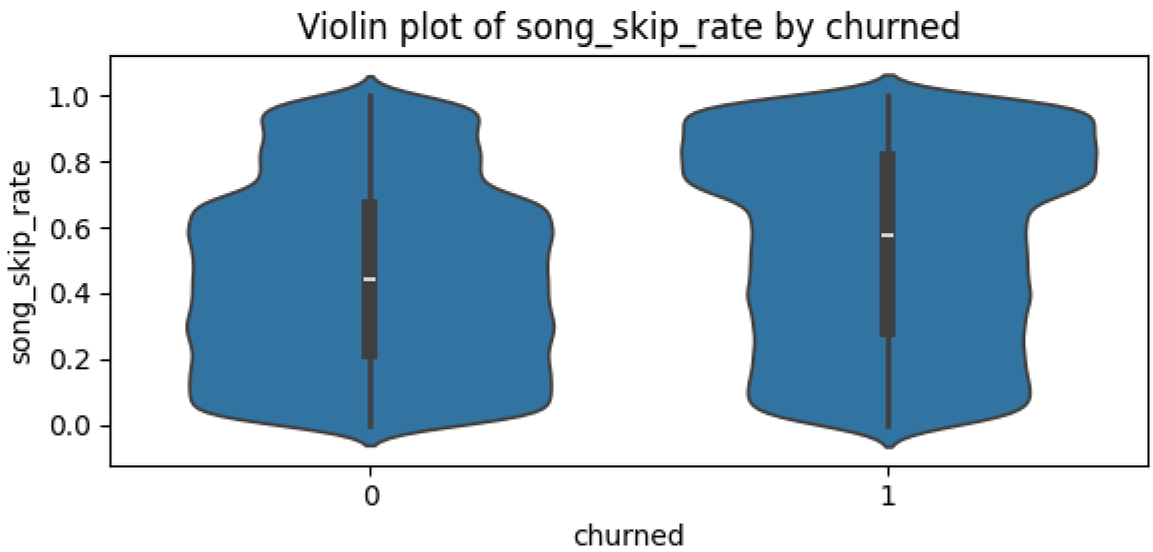

Violin plot of age by churned
age
80
60
40
20
0
1
churned

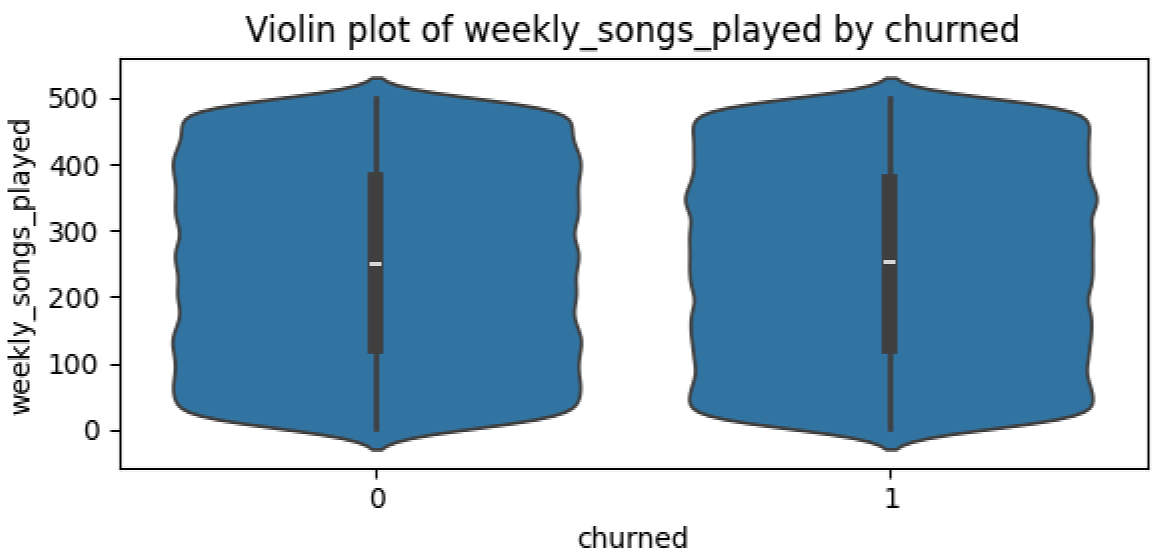

Violin plot of num_subscription_pauses by churned
num_subscription_pauses
4
3
2
1
0
0
1
churned

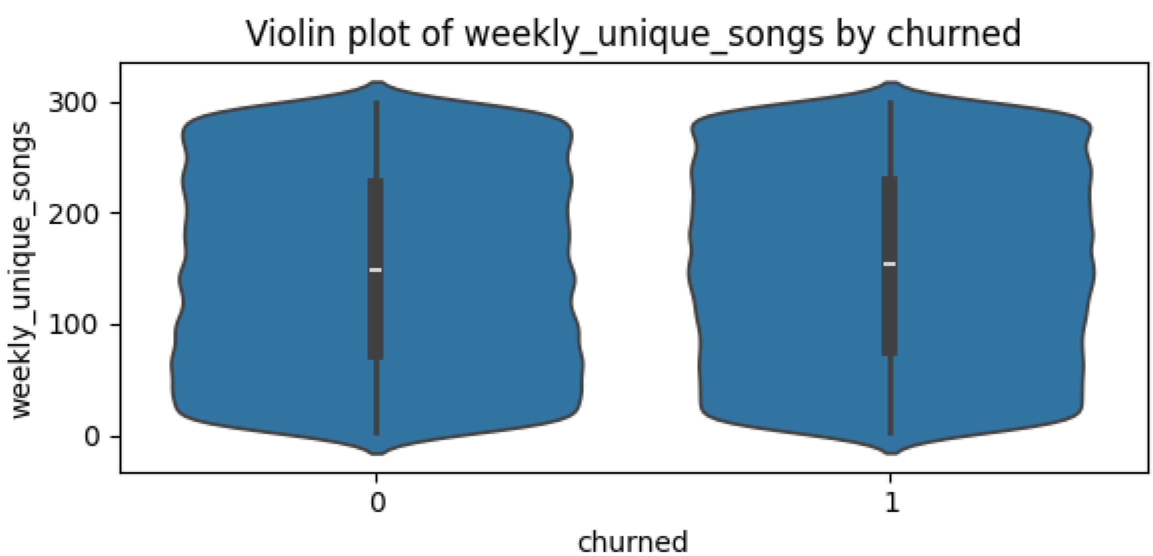

Violin plot of signup_date by churned
signup_date
0
−1000
−2000
−3000
0
1
churned

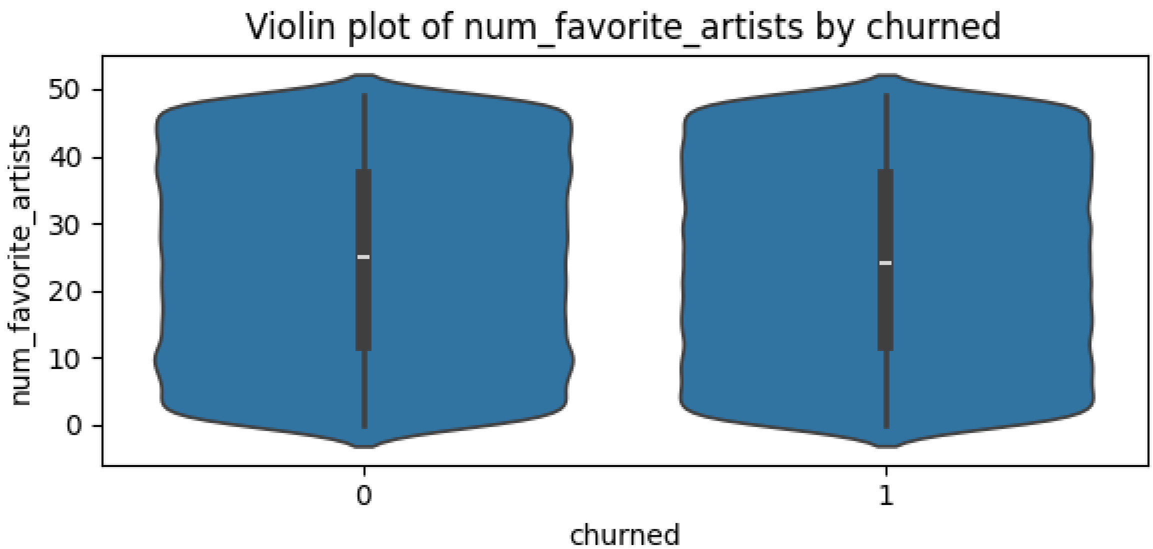

Violin plot of weekly_hours by churned
weekly_hours
50
40
30
20
10
0
0
1
churned

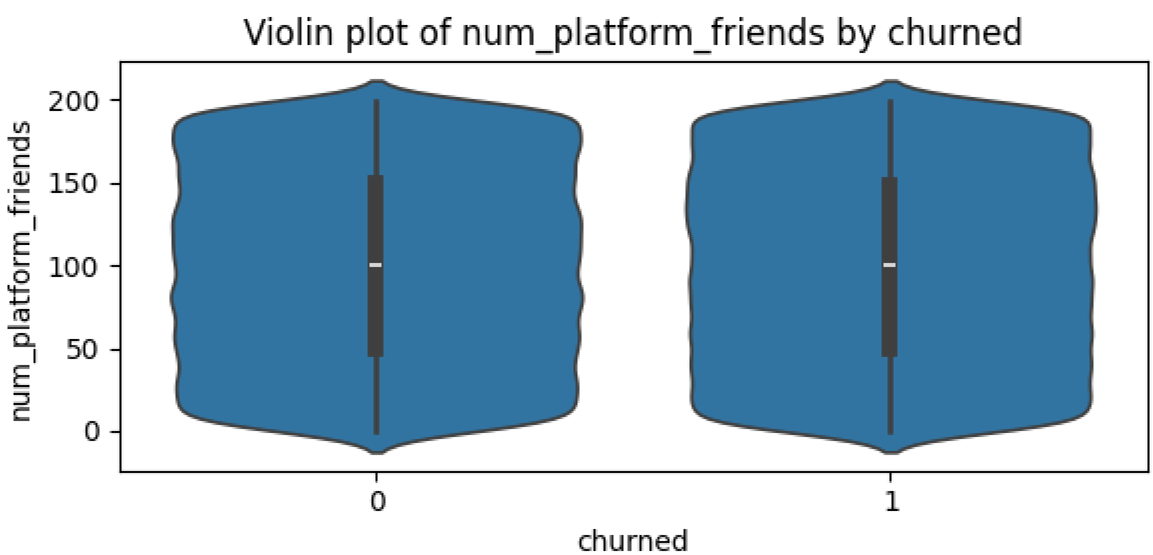

Violin plot of average_session_length by churned
average_session_length
125
100
75
50
25
0
0
1
churned

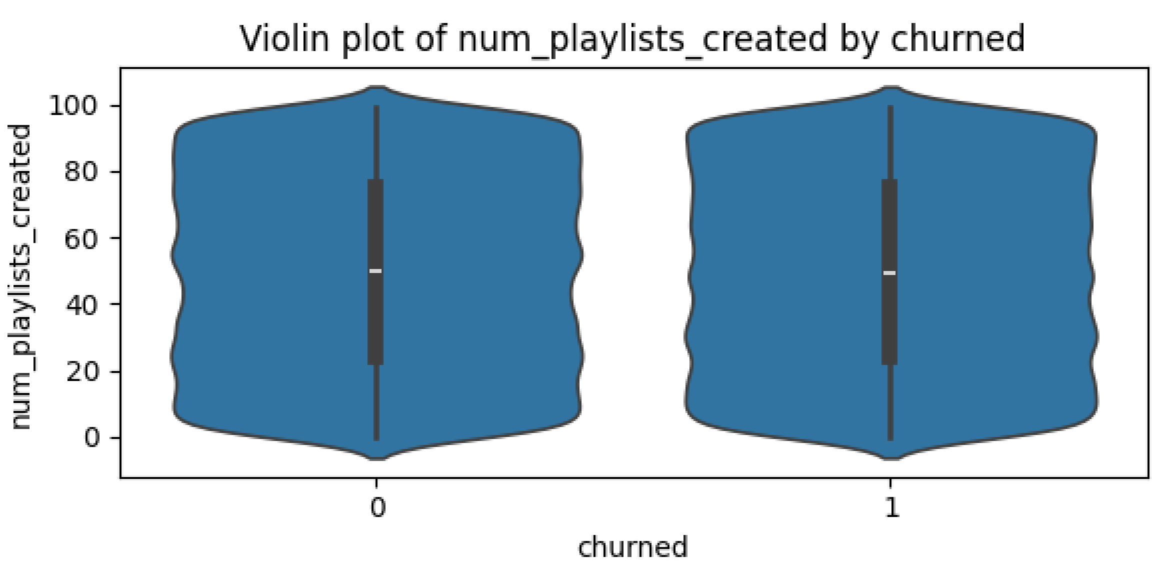

Violin plot of song_skip_rate by churned
song_skip_rate
1.0
0.8
0.6
0.4
0.2
0.0
0
1
churned

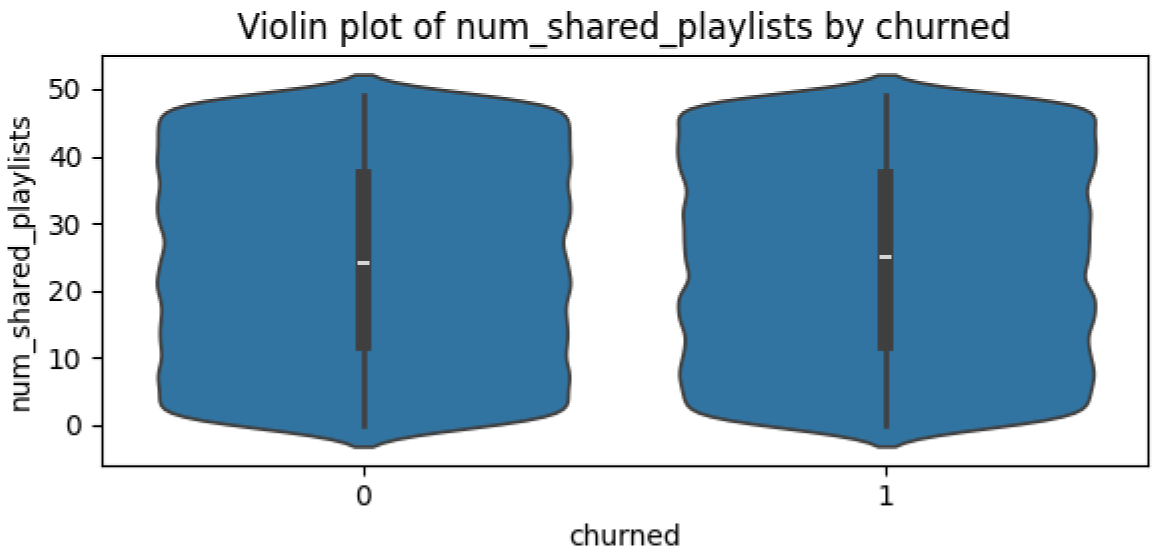

Violin plot of weekly_songs_played by churned
weekly_songs_played
500
400
300
200
100
0
0
1
churned

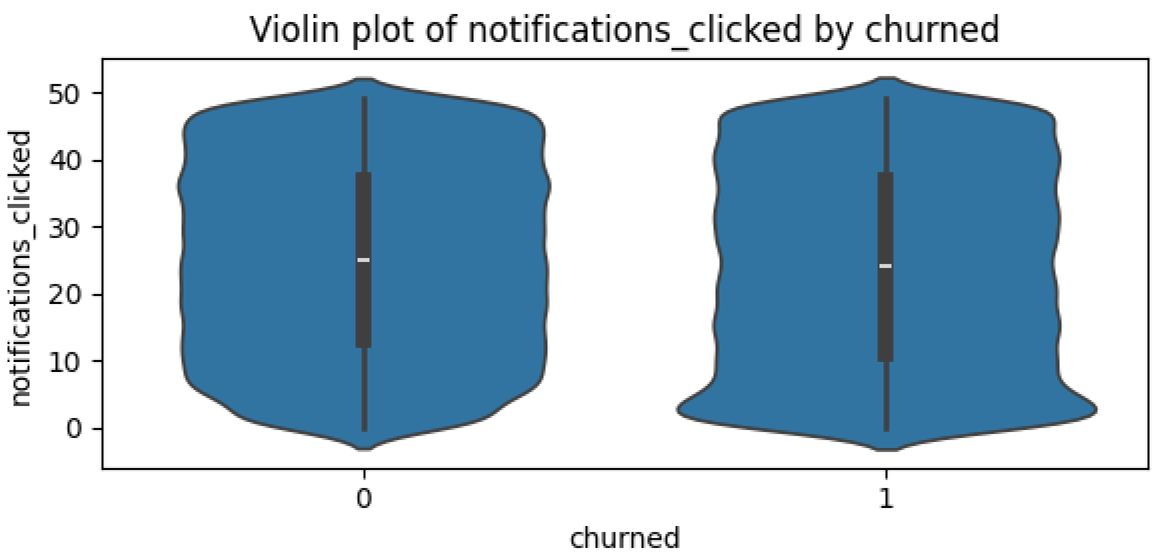

Violin plot of weekly_unique_songs by churned
weekly_unique_songs
300
200
100
0
0
1
churned

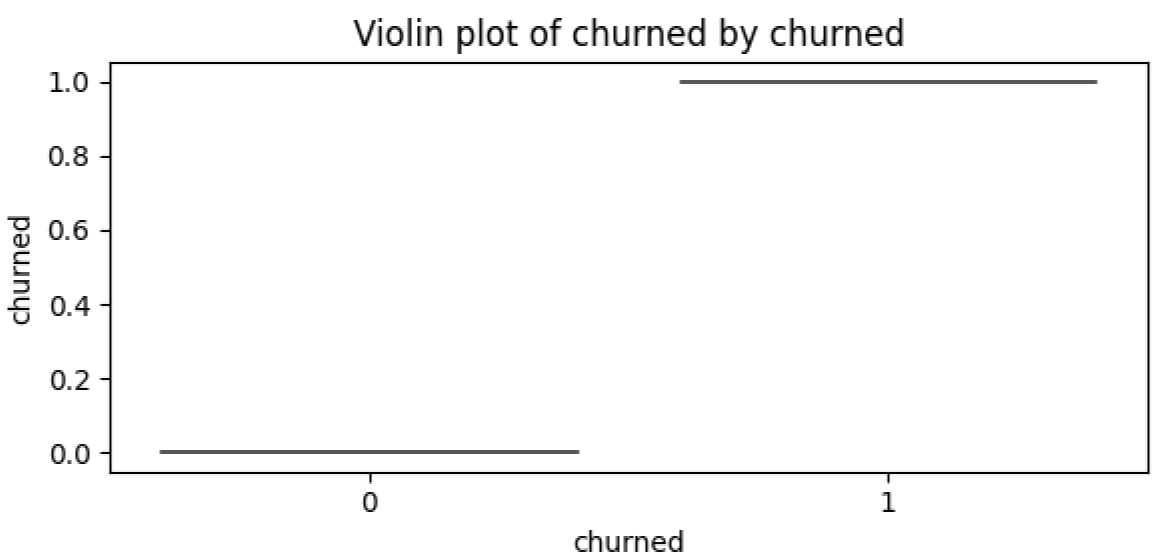

Violin plot of num_favorite_artists by churned
num_favorite_artists
0
10
20
30
40
50
0
1
churned


Violin plot of num_platform_friends by churned
num_platform_friends
0
50
100
150
200
0
1
churned


Violin plot of num_playlists_created by churned
num_playlists_created
0
20
40
60
80
100
0
1
churned


Violin plot of num_shared_playlists by churned
num_shared_playlists
0
10
20
30
40
50
0
1
churned


Violin plot of notifications_clicked by churned
notifications_clicked
0
10
20
30
40
50
0
1
churned


Violin plot of churned by churned
churned
0.0
0.2
0.4
0.6
0.8
1.0
0
1
churned

```
Contingency Table for location vs churned:
churned             0      1   Total
location
Alabama          3209   3346    6555
California       3240   3425    6665
Florida          3187   3293    6480
Georgia          3208   3497    6705
Idaho            3273   3424    6697
Maine            3227   3296    6523
Montana          3121   3280    6401
Nebrasksa        3215   3386    6601
New Jersey       3205   3429    6634
New York         3217   3357    6574
North Carolina   3203   3380    6583
North Dakota     3183   3394    6577
South Carolina   3159   3375    6534
Utah             3191   3386    6577
Vermont          3234   3442    6676
Virginia         3233   3308    6541
Washington       3204   3434    6638
West Virginia    3153   3333    6486
Wisconsin        3164   3389    6553
Total           60826  64174  125000

Contingency Table for subscription_type vs churned:
churned                 0      1   Total
subscription_type
Family              20327  10745   31072
Free                 6439  24830   31269
Premium             20722  10632   31354
Student             13338  17967   31305
Total               60826  64174  125000

Contingency Table for payment_plan vs churned:
churned           0      1   Total
payment_plan
Monthly       30401  32161   62562
Yearly        30425  32013   62438
Total         60826  64174  125000

Contingency Table for payment_method vs churned:
churned             0      1   Total
payment_method
Apple Pay       15015  16198   31213
Credit Card     15355  15858   31213
Debit Card      15177  16115   31292
Paypal          15279  16003   31282
Total           60826  64174  125000

Contingency Table for customer_service_inquiries vs churned:
churned                         0      1   Total
customer_service_inquiries
High                        10673  30910   41583
Low                         29762  12111   41873
Medium                      20391  21153   41544
Total                       60826  64174  125000
```

## Numerical vs Categorical:

### Age vs. Churned

From the violin chart, we can see that there are more churned subscriptions for 20 years and younger than not churned. From ages 20-40, we can see that there are more people not churning their subscription. For ages 40-60, there are more people not churning their subscription compared to those who are 40-60 that are churning their subscription. However, there is a large drop of 60-80 year olds in density for not churned subscription. The violin plot density shows that there were more 60-80 year olds churning their subcription.

### Number of Subscription Pauses vs. Churned

There are more people who have not churned their subcription that have 0, 1, and 2 numbers of subscription pauses. There are more people who have churned their subscription after pausing their subscription 3 and 4 times.

### Sign up Dates vs. Churned

They are roughly equal. Sign-up dates do not affect customers churning or not churning their subscription.

### Weekly Hours vs. Churned

For customers who had a 0-10 average number of weekly listening hours, there were more customers churning their subscription. From 10-40 average number of weekly listening hours, it was roughly the same for both churned and not churned subscriptions, indicating that the customers didn't feel the need to churn or not churn their subscription. However, from 40-50 average number of weekly listening hours, there were more people not churning their subscription.

### Average Session Length vs. Churned

For average length of each music listening session (in hours), there wasn't any significant differences between churning or not churning their subscription, suggesting that the average length of music listening sessions didn't help customers to determine to churn or not churn their subscription.

### Song Skip Rate vs. Churned

From about 0.1 - 0.7 percentage of songs the user does not finish, there were slighlty more customers that didn't churn their subscription. For 0.7 to 1.0 percentage of songs the user does not finish, therer were more customers that churned their subscription.

### Weekly Songs Played vs. Churned

For average number of songs the user plays in a week, the violin charts were very similar, indicating that customers didn't really churn or not churn their subscription based on this variable.

### Weekly Unique Songs vs. Churned

For 0-100 average number of unique songs the user plays in a week, there was slightly more customers that did not churn their subscription. From 100-300 average number of unique songs the user plays in a week, they are roughly the same so customers didn't churn or not churn their subcription based on this.

### Number of Favorite Artists vs. Churned

For number of artists the user set as favorite artists, there wasn't any significant difference in customers churning or not churning their subscription.

### Number of Platform Friends vs. Churned

For number of user connections in the app, there wasn't any significant difference in customers churning or not churning their subscription.

### Number of Playlists Created vs. Churned

For number of playlists the user created, there wasn't any significant difference in customers churning or not churning their subscription.

### Number of Shared Playlists vs. Churned

For number of playlists that are shared publicly, there wasn't any significant difference in customers churning or not churning their subscription.

### Notifications Clicked vs. Churned

For about 0-5 of number of in-app notifications clicked on, more customers churned their subscription. From 5-50, the violin chart looked similar, so after 5 notications clicked on, people didn't care to churn or not churn their subscription.

## Categorical vs Categorical:

### Location vs. Churned

For example, Alabama has 3,209 non-churned users and 3,346 churned users, with a total of 6,555 users. California has 3,240 non-churned and 3,425 churned users, with a total of 6,665 users. States like Georgia, Florida, and New York show similar patterns, with churn rates varying across locations.the location variable demonstrates diverse churn rates, providing a potential area for further investigation regarding geographical influences on user behavior.

### Subscription Type vs. Churned

The Family subscription plan has 20,327 non-churned users and 10,745 churned users, indicating a lower churn rate compared to other plans. The Free subscription plan has a higher churn rate, with 6,439 non-churned users and 24,830 churned users. Premium and Student plans exhibit a mixed distribution of churned and non-churned users, with Student showing a higher churn count (17,967 churned users vs. 13,338 non-churned users). These results suggest that users with a Free subscription are more likely to churn compared to other subscription types, which could be indicative of the value proposition or engagement level associated with each plan.

### Payment Plan vs. Churned

Monthly payment plan users are more likely to churn, with 30,401 non-churned and 32,161 churned users (a churn rate of approximately 51.3%). Yearly payment plan users show a slightly lower churn rate, with 30,425 non-churned and 32,013 churned users (a churn rate of approximately 51.3%). Both plans have a similar distribution of churned and non-churned users, suggesting that the payment plan may not be a strong differentiator in terms of churn behavior.

### Payment Method vs. Churned

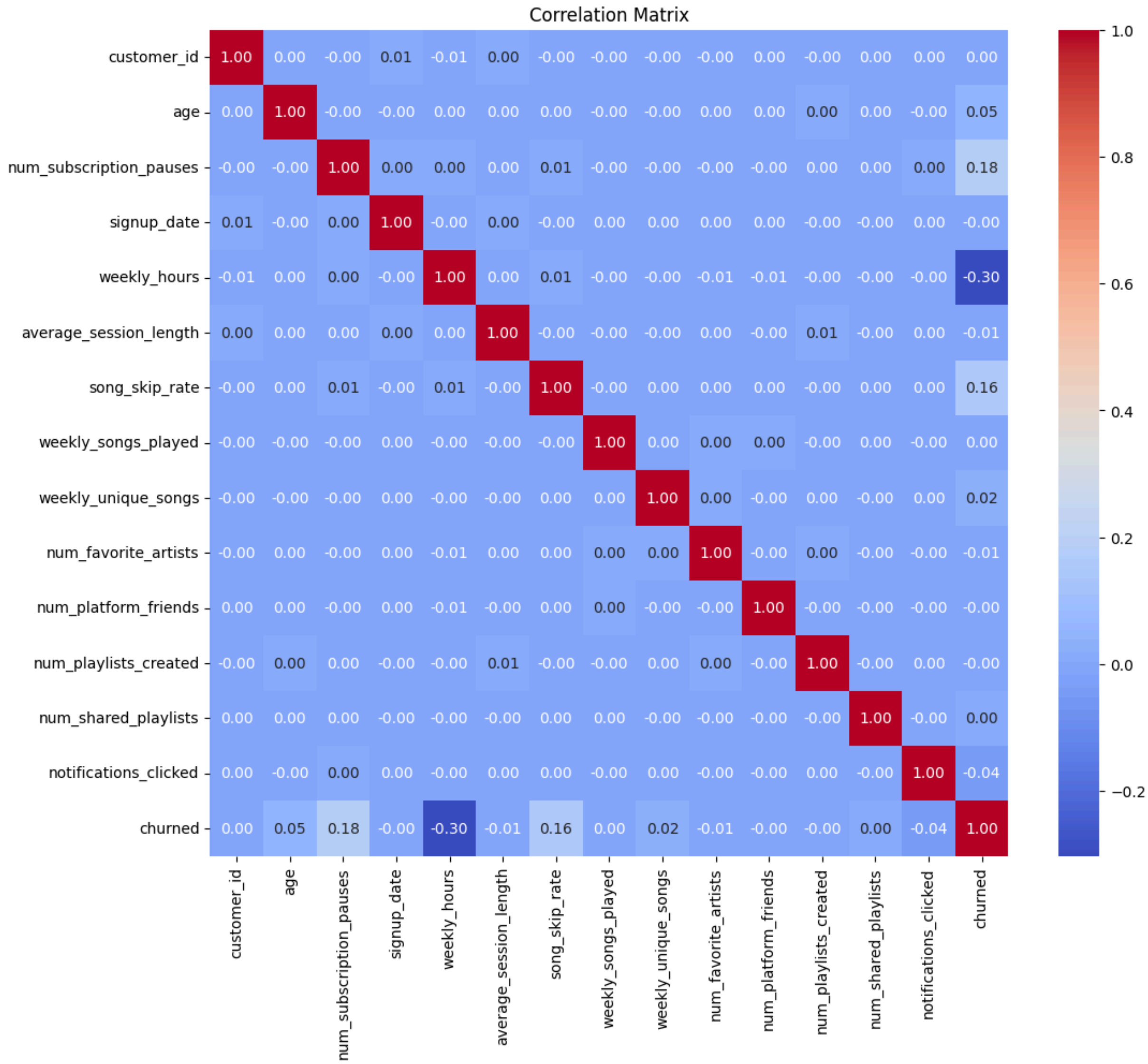
Apple Pay has 15,015 non-churned and 16,198 churned users, indicating a relatively balanced distribution. Credit Card, Debit Card, and Paypal users show similar distributions, with no notable differences in churn rates across the payment methods. The payment method does not seem to significantly affect churn, with all methods showing relatively equal distributions of churned and non-churned users.

### Customer Service Inquiries vs. Churned

High customer service inquiries show a significant churn rate, with 10,673 non-churned and 30,910 churned users, indicating that users who have higher levels of interaction with customer service are more likely to churn. Medium and Low customer service inquiries show varying churn distributions, with Medium having a higher churn count compared to Low inquiries. These results suggest that users who experience more frequent or intensive customer service interactions are more likely to churn, highlighting the potential role of customer satisfaction and service quality in influencing churn behavior.

## Multivariate Patterns: Correlation Matrix

In [91]:
```
plt.figure(figsize=(12, 10))
corr = train[num_cols].corr()
sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm')
plt.title("Correlation Matrix")
plt.show()
#pair plot
```



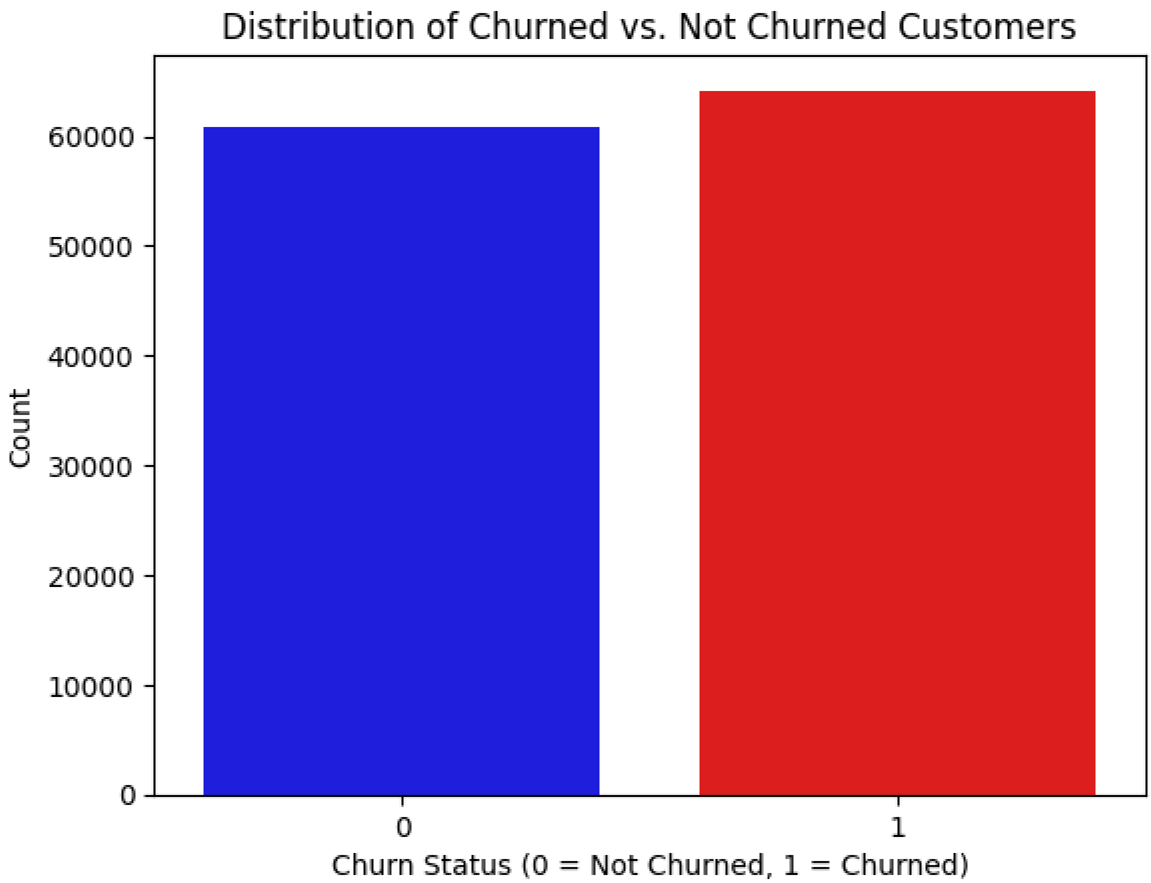
the number of times the user has paused their subscription (max 2) and percentage of songs the user does not finish is very slightly positively correlated with churned with values 0.18 and 0.16 respectively. These factors show a very mild tendency to increase with churned users. This suggests that users who pause their subscriptions more frequently or skip more songs may be slightly more likely to churn, but the relationship is not strong.The average number of weekly listening hours is strongly negatively correlated with churned with a value of -0.30. This indicates that users who listen to more hours per week are less likely to churn, showing a stronger, inverse relationship.

In [64]:
```
import seaborn as sns
import matplotlib.pyplot as plt

num_cols = ['age', 'num_subscription_pauses', 'weekly_hours', 'average_sessi
            'song_skip_rate', 'weekly_songs_played', 'weekly_unique_songs',
            'num_favorite_artists', 'num_platform_friends', 'num_playlists_c
            'num_shared_playlists', 'notifications_clicked']

sns.pairplot(train[num_cols + ['churned']], hue='churned', diag_kind='kde',
plt.suptitle('Pairplot of Numerical Features by Churned Status', y=1.02)
plt.show()
```

Out[64]:
```
'\nimport seaborn as sns\nimport matplotlib.pyplot as plt\n\n# List of nume
rical columns\nnum_cols = [\'age\', \'num_subscription_pauses\', \'weekly_h
ours\', \'average_session_length\', \n            \'song_skip_rate\', \'wee
kly_songs_played\', \'weekly_unique_songs\', \n            \'num_favorite_a
rtists\', \'num_platform_friends\', \'num_playlists_created\', \n
\'num_shared_playlists\', \'notifications_clicked\']\n\n# Creating a pairpl
ot for the numerical columns, with \'churned\' as hue\nsns.pairplot(train[n
um_cols + [\'churned\']], hue=\'churned\', diag_kind=\'kde\', markers=["o",
"s"])\nplt.suptitle(\'Pairplot of Numerical Features by Churned Status\', y
=1.02)\nplt.show()\n'
```

In [65]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

#churn distribution
sns.countplot(x="churned", data=train, palette=["blue", "red"])

plt.xlabel("Churn Status (0 = Not Churned, 1 = Churned)")
plt.ylabel("Count")
plt.title("Distribution of Churned vs. Not Churned Customers")

plt.show()

# values of not churned and churned customers
churn_counts = train["churned"].value_counts()
print(churn_counts)
```

```
/var/folders/j8/vpgy5cl96b93692bcgcpxrwh0000gn/T/ipykernel_34074/3162382379.
py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the
same effect.

  sns.countplot(x="churned", data=train, palette=["blue", "red"])
```




```
churned
1    64174
0    60826
Name: count, dtype: int64
```

From the barplot, we can observe that there are a total of 64174 of churned customers. There are a total of 60826 of not churned customers. Since the churned and non-churned classes are close in proportion (about 51% vs. 49%), the dataset is not highly imbalanced—it is fairly balanced, so we don't have to consider using a class weight.

## Sub-Questions Based from EDA:

### Age & Churn: Does user age significantly affect the likelihood of churn, and are younger or older users more prone to leaving the service?

### Listening Time & Churn: Is there a threshold of weekly listening hours below which users are more likely to churn?

### Subscription Pauses & Churn: Does a higher number of subscription pauses indicate a higher risk of churn?

### Engagement & Churn: Do users who interact less with notifications have higher churn rates?

### Skip Rate & Churn: Is there a correlation between higher song skip rates and increased churn?

# Hypothesis Testing

From EDA, we can see that the variables: age, num_subscription_pauses, weekly_hours, song_skip_rate, and notifications_clicked, have some significance, so we will be doing hypothesis testing on these variables specifically. However, I decided to look at all of the variables to see if there were any that could've been significant that I missed. We do this by doing Mann-Whitney test and using Bonferroni to adjust the p-value.

Feom EDA of categorical variables: customer_service_inquiries and subscription_type, have some signficance, but we will look at all hypothesis testing in case there are more categorical variables that are significant. We will do this doing the Chi-squared test and the Bonferroni Correction.

In [71]:
```
#Hypothesis testing for numerical values

from scipy.stats import mannwhitneyu
import statsmodels.stats.multitest as smm

key_vars = ['age', 'num_subscription_pauses', 'weekly_hours', 'average_sessi
    'song_skip_rate', 'weekly_songs_played', 'weekly_unique_songs',
    'num_favorite_artists', 'num_platform_friends', 'num_playlists_created',
    'num_shared_playlists', 'notifications_clicked']
p_values = []

#Mann-Whitney test
for var in key_vars:
    churned = train[train['churned'] == 1][var]
    not_churned = train[train['churned'] == 0][var]
    stat, p = mannwhitneyu(churned, not_churned, alternative='two-sided')
    p_values.append(p)
    print(f"{var}: raw p-value = {p:.5f}")

#Bonferroni
rejected, corrected_pvals, _, _ = smm.multipletests(p_values, method='bonfer
print("\nBonferroni-adjusted results:")
for var, p_corr, reject in zip(key_vars, corrected_pvals, rejected):
    result = "Significant" if reject else "Not significant"
    print(f"{var}: adjusted p = {p_corr:.5f} → {result}")

#For categorical variables Hypothesis testing

from scipy.stats import chi2_contingency

cat_vars = [col for col in cat_cols if col != 'churned']
cat_pvals = []

print("\nChi-Square Tests (Categorical Variables):")
for var in cat_vars:
    table = pd.crosstab(train[var], train['churned'])
    chi2, p, dof, expected = chi2_contingency(table)
    cat_pvals.append(p)
    print(f"{var} | Chi2 p-value: {p:.5f}")

# Bonferroni
```

```
rejected_cat, corrected_cat_pvals, _, _ = smm.multipletests(cat_pvals, metho
print("\nBonferroni-adjusted p-values (categorical):")
for var, p_corr, reject in zip(cat_vars, corrected_cat_pvals, rejected_cat):
    print(f"{var}: {p_corr:.5f} | Significant: {reject}")
```

```
age: raw p-value = 0.00000
num_subscription_pauses: raw p-value = 0.00000
weekly_hours: raw p-value = 0.00000
average_session_length: raw p-value = 0.02140
song_skip_rate: raw p-value = 0.00000
weekly_songs_played: raw p-value = 0.75058
weekly_unique_songs: raw p-value = 0.00000
num_favorite_artists: raw p-value = 0.05723
num_platform_friends: raw p-value = 0.29197
num_playlists_created: raw p-value = 0.44088
num_shared_playlists: raw p-value = 0.17528
notifications_clicked: raw p-value = 0.00000

Bonferroni-adjusted results:
age: adjusted p = 0.00000 → Significant
num_subscription_pauses: adjusted p = 0.00000 → Significant
weekly_hours: adjusted p = 0.00000 → Significant
average_session_length: adjusted p = 0.25681 → Not significant
song_skip_rate: adjusted p = 0.00000 → Significant
weekly_songs_played: adjusted p = 1.00000 → Not significant
weekly_unique_songs: adjusted p = 0.00000 → Significant
num_favorite_artists: adjusted p = 0.68677 → Not significant
num_platform_friends: adjusted p = 1.00000 → Not significant
num_playlists_created: adjusted p = 1.00000 → Not significant
num_shared_playlists: adjusted p = 1.00000 → Not significant
notifications_clicked: adjusted p = 0.00000 → Significant

Chi-Square Tests (Categorical Variables):
location | Chi2 p-value: 0.97771
subscription_type | Chi2 p-value: 0.00000
payment_plan | Chi2 p-value: 0.63721
payment_method | Chi2 p-value: 0.04302
customer_service_inquiries | Chi2 p-value: 0.00000

Bonferroni-adjusted p-values (categorical):
location: 1.00000 | Significant: False
subscription_type: 0.00000 | Significant: True
payment_plan: 1.00000 | Significant: False
payment_method: 0.21512 | Significant: False
customer_service_inquiries: 0.00000 | Significant: True
```

Bonferroni is adjusting for false positives by dividing the significance level of alpha by the number of tests.

## Numerical Variables Hypothesis Testing:

For the numerical variables, we get that age, num_subscription_pauses, weekly_hours, song_skip_rate, weekly_unique_songs, and notifications_clicked were all signficant variables.

Age: Churn likelihood varies significantly by age group num_subscription_pauses: Frequent pauses, suggests higher churn risk

weekly_hours: Low weekly listening hours correlate with churn

song_skip_rate: Higher skip rates means higher churn

weekly_unique_songs: Lower unique songs relates to churn

notifications_clicked: Less interaction means higher churn risk.

### Categorical Variables Hypothesis Testing:

For categorical variables, we get subscription_type and customer_service_inquires are significant variables.

subscription_type: Strongly associated with churn

customer_service_inquires: More inquiries correlate with churn.

# Modeling (Baseline Model - Logistic Regression Model)

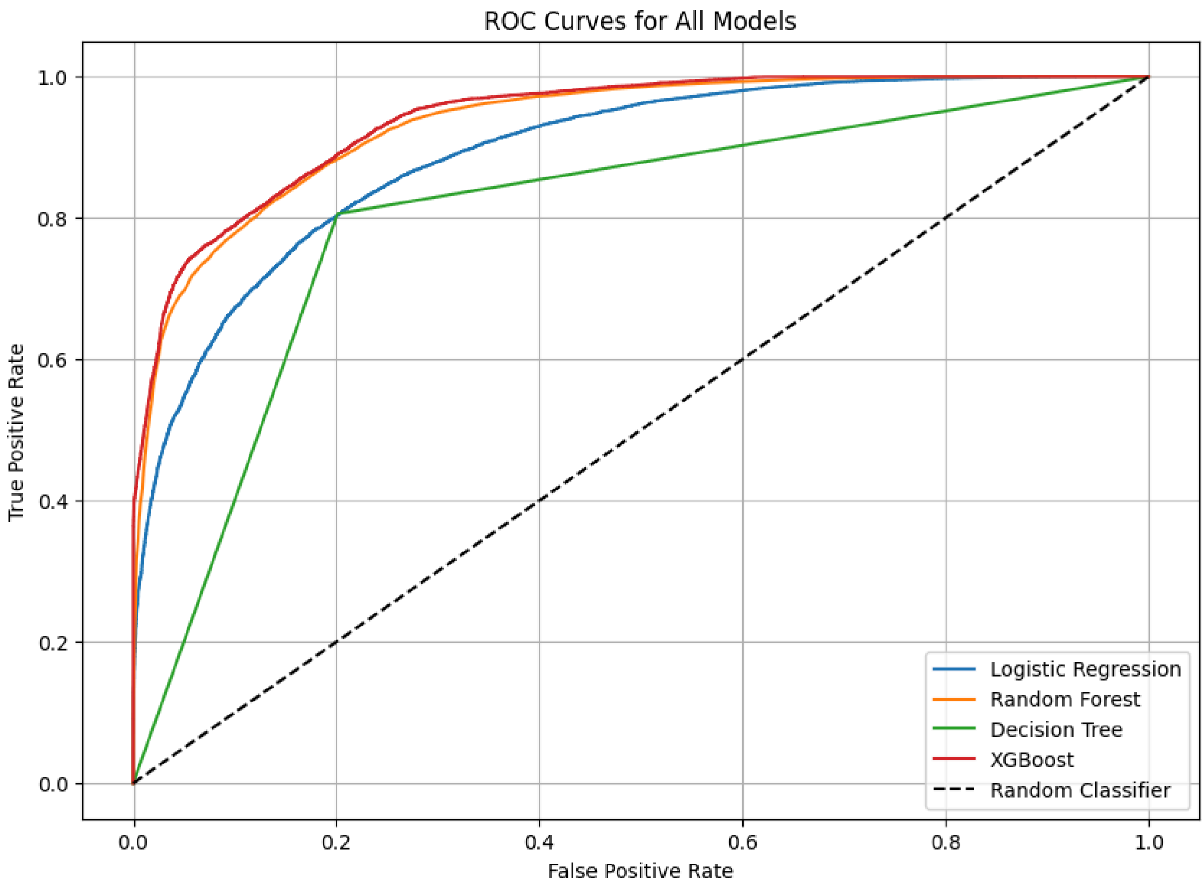
In [74]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report, roc_auc_s
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
import matplotlib.pyplot as plt

train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")

target = 'churned'
features = [col for col in train.columns if col != target]

X = train[features]
y = train[target]
X_test = test[features]

#encode categorical columns
X = pd.get_dummies(X)
X_test = pd.get_dummies(X_test)

#align train and test columns
X, X_test = X.align(X_test, join='left', axis=1, fill_value=0)

#split training data into train and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, rando

#scale the numeric features
scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

models = {
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=4
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'XGBoost': XGBClassifier(use_label_encoder=False, eval_metric='logloss',
}

plt.figure(figsize=(10, 7))

for name, model in models.items():
    print(f"\n{name}")
    model.fit(X_train_scaled, y_train)

    val_preds = model.predict(X_val_scaled)
    val_probs = model.predict_proba(X_val_scaled)[:, 1]

    print("Accuracy:", accuracy_score(y_val, val_preds))
    print("ROC AUC:", roc_auc_score(y_val, val_probs))
    print(classification_report(y_val, val_preds))

    #ROC curve
    fpr, tpr, _ = roc_curve(y_val, val_probs)
    plt.plot(fpr, tpr, label=name)

#ROC plot
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves for All Models")
plt.legend()
plt.grid()
plt.show()
```

```
Logistic Regression
Accuracy: 0.80132
ROC AUC: 0.8910406374025547
              precision    recall  f1-score   support

           0       0.80      0.80      0.80     12163
           1       0.81      0.81      0.81     12837

    accuracy                           0.80     25000
   macro avg       0.80      0.80      0.80     25000
weighted avg       0.80      0.80      0.80     25000


Random Forest
Accuracy: 0.84228
ROC AUC: 0.9327352948140593
              precision    recall  f1-score   support

           0       0.84      0.83      0.84     12163
           1       0.84      0.85      0.85     12837

    accuracy                           0.84     25000
   macro avg       0.84      0.84      0.84     25000
weighted avg       0.84      0.84      0.84     25000


Decision Tree
Accuracy: 0.8024
ROC AUC: 0.802303755745512
              precision    recall  f1-score   support

           0       0.80      0.80      0.80     12163
           1       0.81      0.81      0.81     12837

    accuracy                           0.80     25000
   macro avg       0.80      0.80      0.80     25000
weighted avg       0.80      0.80      0.80     25000


XGBoost
```

```
/opt/anaconda3/lib/python3.12/site-packages/xgboost/training.py:183: UserWar
ning: [20:12:09] WARNING: /Users/runner/work/xgboost/xgboost/src/learner.cc:
738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

```
Accuracy: 0.84508
ROC AUC: 0.9397535799956898
              precision    recall  f1-score   support

           0       0.84      0.84      0.84     12163
           1       0.85      0.85      0.85     12837

    accuracy                           0.85     25000
   macro avg       0.84      0.85      0.84     25000
weighted avg       0.85      0.85      0.85     25000
```




## Logistic Regression:

Accuracy: 80.132%

ROC AUC: 0.891

F1-Score (Class 1): 0.81

## Random Forest

Accuracy: 84.23%

ROC AUC: 0.933

F1-Score (Class 1): 0.85

## Decision Tree

Accuracy: 80.24%

ROC AUC: 0.802

F1-Score (Class 1): 0.81

### XGBoost

Accuracy: 84.51%

ROC AUC: 0.940

F1-Score (Class 1): 0.85

Conclusion: XGBoost has the best accuracy (84.51%) and ROC AUC (0.940), making it the best-performing model here. Random Forest is also a strong contender, with very similar performance to XGBoost but slightly lower in AUC (0.933). Logistic Regression is a bit behind but still solid with good balance between precision and recall. Decision Tree seems to underperform compared to the other models, both in terms of accuracy and ROC AUC.

do AISC or BISC for feature selection. Once you get the features then fit the logistic regression on this. More advanced plots will have a plot that will show the feature selected variables. In the report you can compare the features with the feature selected variables and hypothesis testing varibales. Then do the EDA on whichever gives the lower amount of feature selected variables. Do EDA on those features instead.

For the report, do it in the structure of how the scientific papers do it.

# Logistic Regression AIC Feature Selection

In [146…

```
#AIC

import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score, classification_re
from sklearn.preprocessing import StandardScaler
from statsmodels.tools import add_constant
import statsmodels.api as sm
from itertools import combinations

train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")

X_train = train.drop(columns=['churned'])
y_train = train['churned']

#convert categorical variables
X_train = pd.get_dummies(X_train, drop_first=True)
X_test = pd.get_dummies(X_test, drop_first=True)

#align columns in case test and train
X_train, X_test = X_train.align(X_test, join='left', axis=1, fill_value=0)
```

```
#standardize numeric features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

#dataFrame to use with statsmodels
X_train_df = pd.DataFrame(X_train_scaled, columns=X_train.columns)
X_train_df = add_constant(X_train_df)

# AIC-based Stepwise Feature Selection
def stepwise_selection(X, y, criterion='aic'):
    initial_features = []
    remaining_features = list(X.columns)
    best_score = np.inf
    selected_features = []

    while remaining_features:
        scores_with_candidates = []
        for candidate in remaining_features:
            features = selected_features + [candidate]
            model = sm.Logit(y, X[features]).fit(disp=0)
            score = model.aic if criterion == 'aic' else model.bic
            scores_with_candidates.append((score, candidate))

        scores_with_candidates.sort()
        best_new_score, best_candidate = scores_with_candidates[0]

        if best_new_score < best_score:
            remaining_features.remove(best_candidate)
            selected_features.append(best_candidate)
            best_score = best_new_score
        else:
            break

    return selected_features
print("AIC - Logistic Regression")

selected_features = stepwise_selection(X_train_df, y_train, criterion='aic')
print("Selected Features:", selected_features)

selected_features_clean = [feat for feat in selected_features if feat != 'co

#final logistic regression
final_model = LogisticRegression(max_iter=1000)
final_model.fit(X_train[selected_features_clean], y_train)

#predict and evaluate
y_pred = final_model.predict(X_val[selected_features_clean])

from sklearn.metrics import accuracy_score, classification_report
print("Accuracy:", accuracy_score(y_val, y_pred))
print(classification_report(y_val, y_pred))
```

```
AIC - Logistic Regression
Selected Features: ['subscription_type_Free', 'customer_service_inquiries_Lo
w', 'weekly_hours', 'num_subscription_pauses', 'customer_service_inquiries_M
edium', 'subscription_type_Student', 'song_skip_rate', 'age', 'notifications
_clicked', 'const', 'weekly_unique_songs', 'payment_method_Credit Card', 'nu
m_favorite_artists', 'location_Virginia', 'average_session_length']
Accuracy: 0.80208
              precision    recall  f1-score   support

           0       0.80      0.80      0.80     12163
           1       0.81      0.81      0.81     12837

    accuracy                           0.80     25000
   macro avg       0.80      0.80      0.80     25000
weighted avg       0.80      0.80      0.80     25000
```

## Logistic Regression BIC Feature Selection

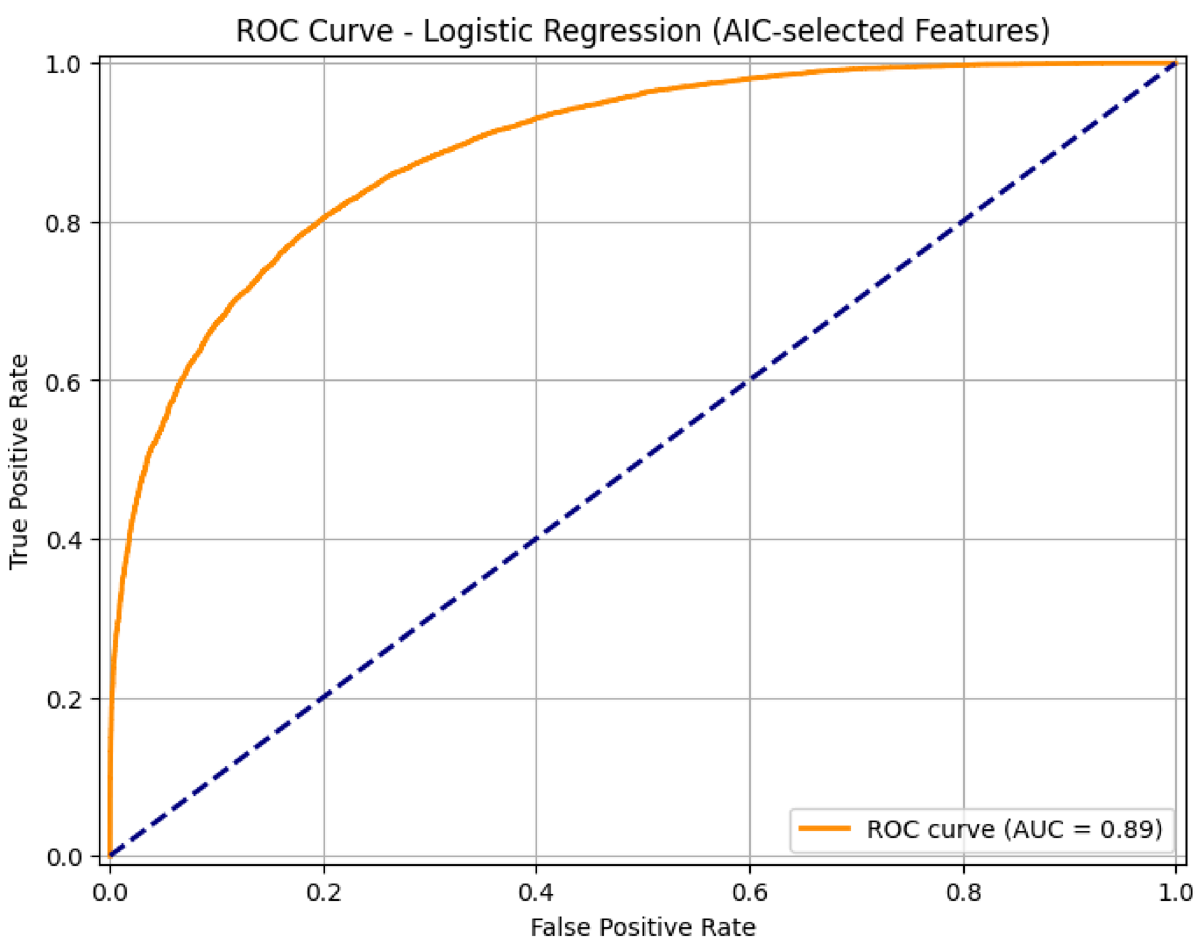
In [148…

```python
#BIC

import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score, classification_re
from sklearn.preprocessing import StandardScaler
from statsmodels.tools import add_constant
import statsmodels.api as sm
from itertools import combinations

train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")

X_train = train.drop(columns=['churned'])
y_train = train['churned']

#convert categorical variables
X_train = pd.get_dummies(X_train, drop_first=True)
X_test = pd.get_dummies(X_test, drop_first=True)

#align columns in case test and train
X_train, X_test = X_train.align(X_test, join='left', axis=1, fill_value=0)

#standardize numeric features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

#dataFrame to use with statsmodels
X_train_df = pd.DataFrame(X_train_scaled, columns=X_train.columns)
X_train_df = add_constant(X_train_df)

#AIC-based Stepwise Feature Selection (BIC)
def stepwise_selection(X, y, criterion='bic'):
    initial_features = []
```

```
    remaining_features = list(X.columns)
    best_score = np.inf
    selected_features = []

    while remaining_features:
        scores_with_candidates = []
        for candidate in remaining_features:
            features = selected_features + [candidate]
            model = sm.Logit(y, X[features]).fit(disp=0)
            score = model.aic if criterion == 'bic' else model.bic
            scores_with_candidates.append((score, candidate))

        scores_with_candidates.sort()
        best_new_score, best_candidate = scores_with_candidates[0]

        if best_new_score < best_score:
            remaining_features.remove(best_candidate)
            selected_features.append(best_candidate)
            best_score = best_new_score
        else:
            break

    return selected_features

print("BIC - Logistic Regression")

selected_features = stepwise_selection(X_train_df, y_train, criterion='aic')
print("Selected Features:", selected_features)

selected_features_clean = [feat for feat in selected_features if feat != 'co

#fit final logistic regression
final_model = LogisticRegression(max_iter=1000)
final_model.fit(X_train[selected_features_clean], y_train)

#predict and evaluate
y_pred = final_model.predict(X_val[selected_features_clean])

from sklearn.metrics import accuracy_score, classification_report
print("Accuracy:", accuracy_score(y_val, y_pred))
print(classification_report(y_val, y_pred))

#ROC
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt

#predicted probabilities for the positive class
y_val_probs = final_model.predict_proba(X_val[selected_features_clean])[:, 1

#ROC curve and AUC
fpr, tpr, thresholds = roc_curve(y_val, y_val_probs)
roc_auc = roc_auc_score(y_val, y_val_probs)

#ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_a
```

```
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([-0.01, 1.01])
plt.ylim([-0.01, 1.01])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Logistic Regression (AIC-selected Features)')
plt.legend(loc="lower right")
plt.grid()
plt.show()
```

```
BIC - Logistic Regression
Selected Features: ['subscription_type_Free', 'customer_service_inquiries_Lo
w', 'weekly_hours', 'num_subscription_pauses', 'customer_service_inquiries_M
edium', 'subscription_type_Student', 'song_skip_rate', 'age', 'notifications
_clicked', 'const', 'weekly_unique_songs']
Accuracy: 0.80212
              precision    recall  f1-score   support

           0       0.80      0.80      0.80     12163
           1       0.81      0.81      0.81     12837

    accuracy                           0.80     25000
   macro avg       0.80      0.80      0.80     25000
weighted avg       0.80      0.80      0.80     25000
```

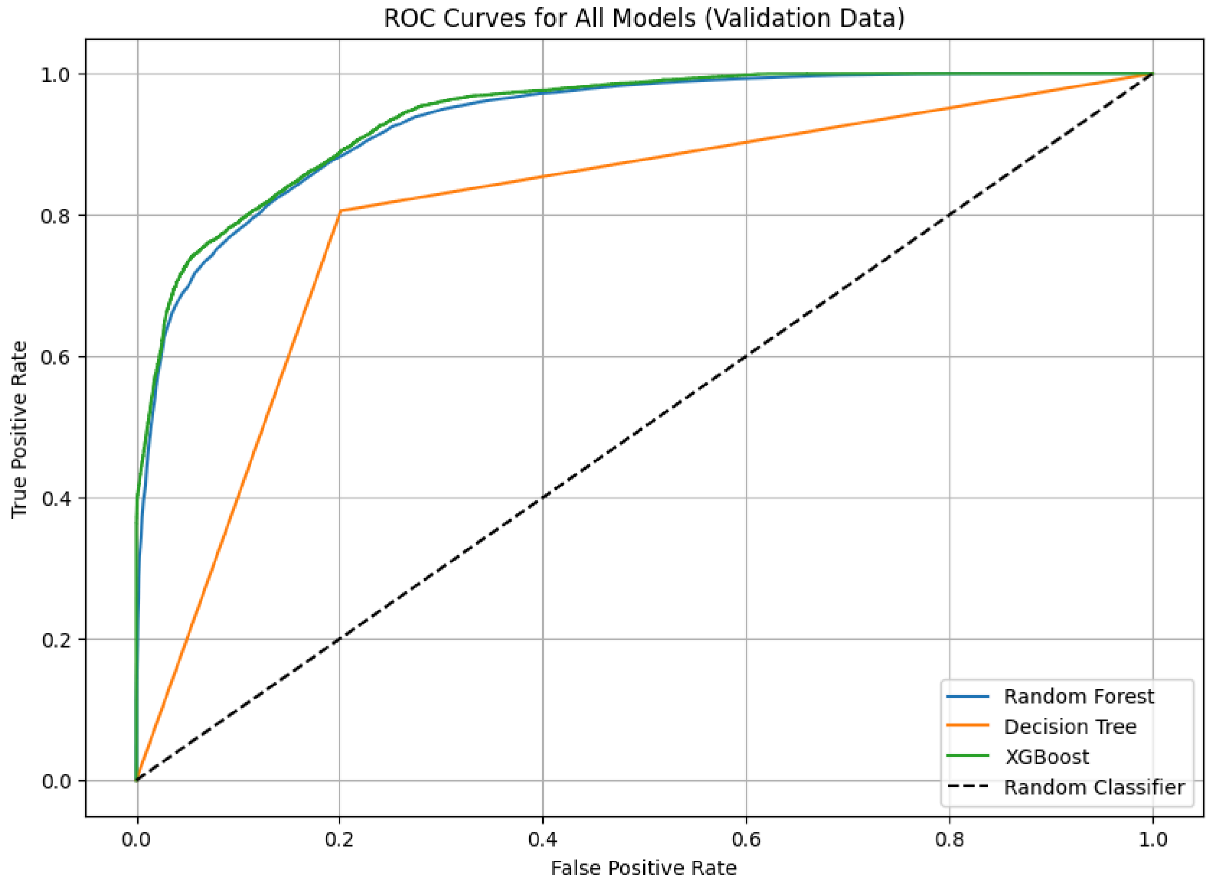


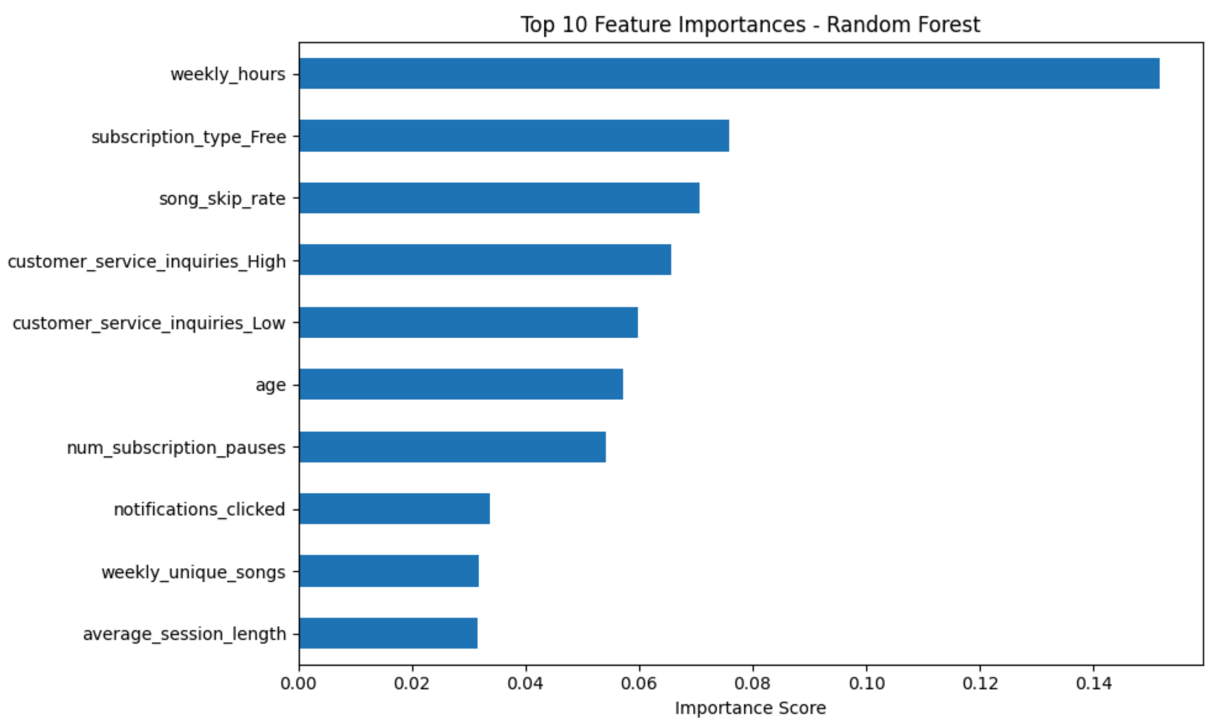
# Other Models with Evaluation on test data

In [9]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report, roc_auc_s
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
import matplotlib.pyplot as plt

train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")

target = 'churned'
features = [col for col in train.columns if col != target]

X = train[features]
y = train[target]
X_test = test.copy()

X = pd.get_dummies(X)
X_test = pd.get_dummies(X_test)

X, X_test = X.align(X_test, join='left', axis=1, fill_value=0)

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, rando

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

models = {
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=4
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'XGBoost': XGBClassifier(use_label_encoder=False, eval_metric='logloss',
}

plt.figure(figsize=(10, 7))

test_predictions = {}

for name, model in models.items():
    print(f"\n{name}")
    model.fit(X_train_scaled, y_train)

    val_preds = model.predict(X_val_scaled)
    val_probs = model.predict_proba(X_val_scaled)[:, 1]
    print("Validation Results:")
    print("  Accuracy:", accuracy_score(y_val, val_preds))
    print("  ROC AUC:", roc_auc_score(y_val, val_probs))
```

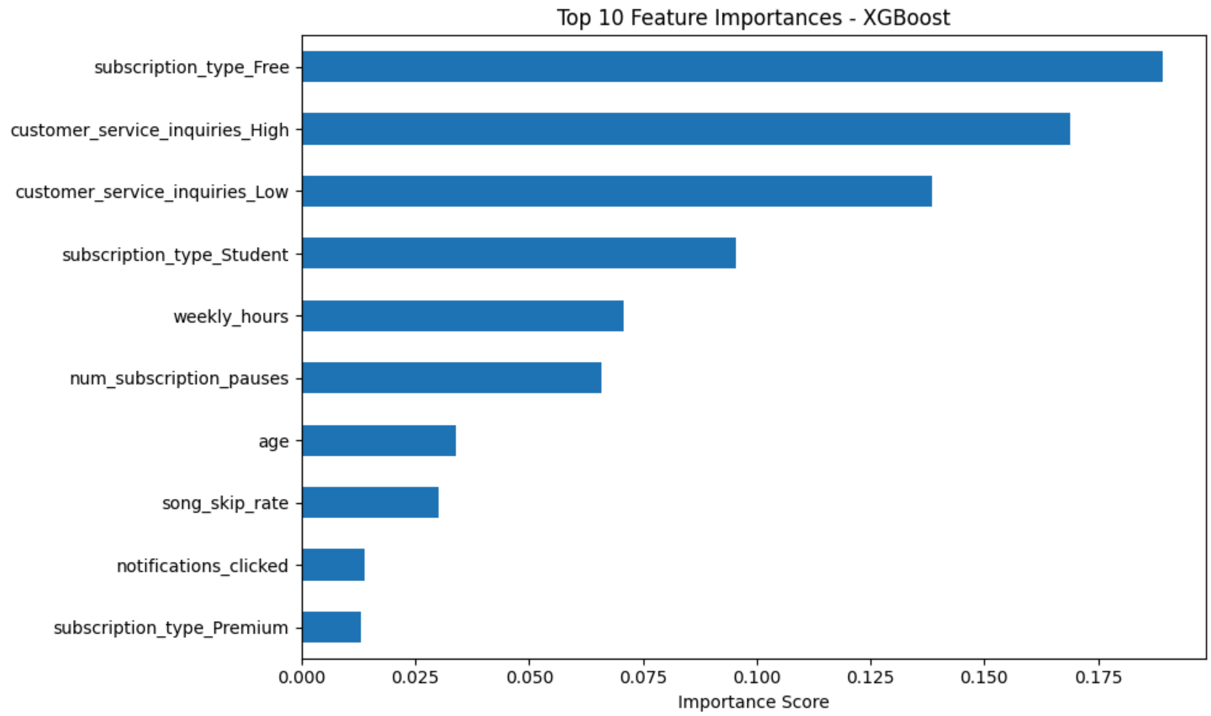
```
    print("  Classification Report:\n", classification_report(y_val, val_pre

    fpr, tpr, _ = roc_curve(y_val, val_probs)
    plt.plot(fpr, tpr, label=name)

    test_preds = model.predict(X_test_scaled)
    test_probs = model.predict_proba(X_test_scaled)[:, 1]
    test_predictions[name] = {
        'predicted_label': test_preds,
        'predicted_probability': test_probs
    }

plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves for All Models (Validation Data)")
plt.legend()
plt.grid()
plt.show()

rf_model = models['Random Forest']
rf_model.fit(X_train_scaled, y_train)

rf_importances = rf_model.feature_importances_
rf_feat_imp_series = pd.Series(rf_importances, index=X.columns).sort_values(

plt.figure(figsize=(10, 6))
rf_feat_imp_series.head(10).plot(kind='barh')
plt.gca().invert_yaxis()
plt.title("Top 10 Feature Importances - Random Forest")
plt.xlabel("Importance Score")
plt.tight_layout()
plt.show()

xgb_model = models['XGBoost']
xgb_model.fit(X_train_scaled, y_train)

xgb_importances = xgb_model.feature_importances_
xgb_feat_imp_series = pd.Series(xgb_importances, index=X.columns).sort_value

plt.figure(figsize=(10, 6))
xgb_feat_imp_series.head(10).plot(kind='barh')
plt.gca().invert_yaxis()
plt.title("Top 10 Feature Importances - XGBoost")
plt.xlabel("Importance Score")
plt.tight_layout()
plt.show()
```

```
Random Forest
Validation Results:
  Accuracy: 0.84228
  ROC AUC: 0.9327352948140593
  Classification Report:
               precision    recall  f1-score   support

           0       0.84      0.83      0.84     12163
           1       0.84      0.85      0.85     12837

    accuracy                           0.84     25000
   macro avg       0.84      0.84      0.84     25000
weighted avg       0.84      0.84      0.84     25000


Decision Tree
Validation Results:
  Accuracy: 0.8024
  ROC AUC: 0.802303755745512
  Classification Report:
               precision    recall  f1-score   support

           0       0.80      0.80      0.80     12163
           1       0.81      0.81      0.81     12837

    accuracy                           0.80     25000
   macro avg       0.80      0.80      0.80     25000
weighted avg       0.80      0.80      0.80     25000


XGBoost
/opt/anaconda3/lib/python3.12/site-packages/xgboost/training.py:183: UserWar
ning: [22:28:15] WARNING: /Users/runner/work/xgboost/xgboost/src/learner.cc:
738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
Validation Results:
  Accuracy: 0.84508
  ROC AUC: 0.9397535799956898
  Classification Report:
               precision    recall  f1-score   support

           0       0.84      0.84      0.84     12163
           1       0.85      0.85      0.85     12837

    accuracy                           0.85     25000
   macro avg       0.84      0.85      0.84     25000
weighted avg       0.85      0.85      0.85     25000
```




```
/opt/anaconda3/lib/python3.12/site-packages/xgboost/training.py:183: UserWar
ning: [22:28:28] WARNING: /Users/runner/work/xgboost/xgboost/src/learner.cc:
738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```


Top 10 Feature Importances - XGBoost
subscription_type_Free
customer_service_inquiries_High
customer_service_inquiries_Low
subscription_type_Student
weekly_hours
num_subscription_pauses
age
song_skip_rate
notifications_clicked
subscription_type_Premium
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
Importance Score