Business Understanding

In the telecommunications sector, retaining existing customers is more cost-effective than acquiring new ones. High churn rates can lead to significant revenue losses and increased marketing expenses. Understanding the factors that contribute to customer churn enables companies like SyriaTel to implement targeted retention strategies, thereby enhancing customer satisfaction and profitability.

Problem Statement

SyriaTel is experiencing customer attrition, impacting its revenue and market share. The challenge is to develop a predictive model that accurately identifies customers who are likely to churn. By analyzing patterns in customer behavior and demographics, the goal is to proactively address the factors leading to churn and implement effective retention strategies.

Objectives

Regression

Classification

1 Develop a machine learning classifier to predict the likelihood of a customer churning based on historical data. This involves analyzing customer demographics, usage patterns, and service-related attributes to identify significant predictors of churn.

2 Determine the primary causes of customer attrition hence offer insights based on data analysis to SyriaTel's marketing and customer service departments to improve customer retention strategies.

Data understanding

In [42]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

warnings.filterwarnings('ignore')
```

In [43]:
```
df= pd.read_csv('bigml_59c28831336c6604c800002a.csv')
df.head()
```

Out[43]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34

5 rows × 21 columns

In [44]:
```
df.describe()
```

Out[44]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	to r
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363

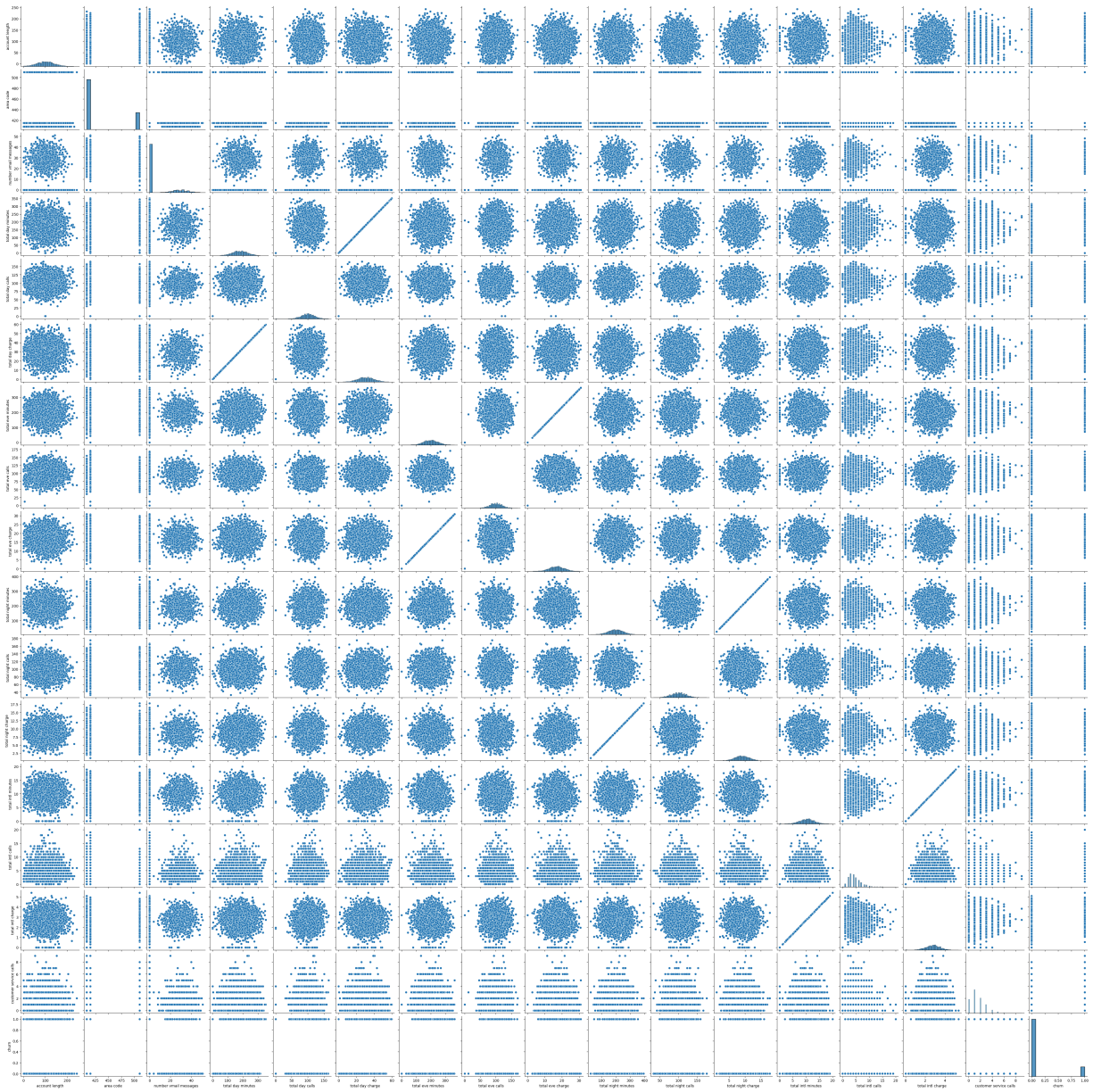
In [45]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   3333 non-null   object 
 1   account length          3333 non-null   int64  
 2   area code               3333 non-null   int64  
 3   phone number            3333 non-null   object 
 4   international plan      3333 non-null   object 
 5   voice mail plan         3333 non-null   object 
 6   number vmail messages   3333 non-null   int64  
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64  
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64  
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64  
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64  
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64  
 20  churn                   3333 non-null   bool   
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

Data cleaning

In [5]:
```
sns.pairplot(df)
```

Out[5]:
```
<seaborn.axisgrid.PairGrid at 0x7a18c5fa3a90>
```



Correct formats

In [46]:
```
df.head()
```

Out[46]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34

5 rows × 21 columns

checking if the data has NAs

In [47]:
```
# CHeck NAs
df.isna().mean()*100
```

Out[47]:

	0
state	0.0
account length	0.0
area code	0.0
phone number	0.0
international plan	0.0
voice mail plan	0.0
number vmail messages	0.0
total day minutes	0.0
total day calls	0.0
total day charge	0.0
total eve minutes	0.0
total eve calls	0.0
total eve charge	0.0
total night minutes	0.0
total night calls	0.0
total night charge	0.0
total intl minutes	0.0
total intl calls	0.0
total intl charge	0.0
customer service calls	0.0
churn	0.0

dtype: float64

- < 20% - drop rows/fill
- 20 - 50 - fill
- 50% drop column

The data has no missing values

checking if the data has duplicates

> Add blockquote

In [8]:
```
df[df.duplicated()].count()
```

Out[8]:

	0
state	0
account length	0
area code	0
phone number	0
international plan	0
voice mail plan	0
number vmail messages	0
total day minutes	0
total day calls	0
total day charge	0
total eve minutes	0
total eve calls	0
total eve charge	0
total night minutes	0
total night calls	0
total night charge	0
total intl minutes	0
total intl calls	0
total intl charge	0
customer service calls	0
churn	0

dtype: int64

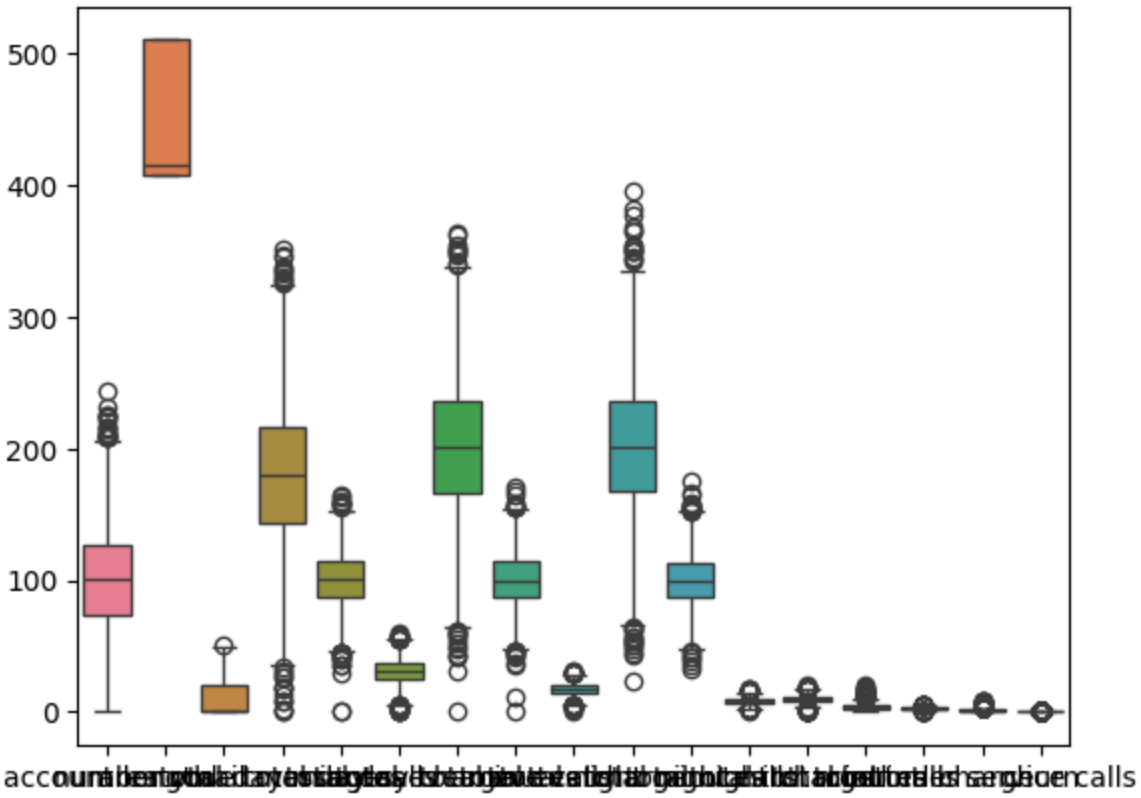
The data has no duplicates

Other cleaning steps

In [48]:
```
# OUtliers

# Feature engineering
```

```
sns.boxplot(df)
```

Out[48]: <Axes: >



Feature engineering

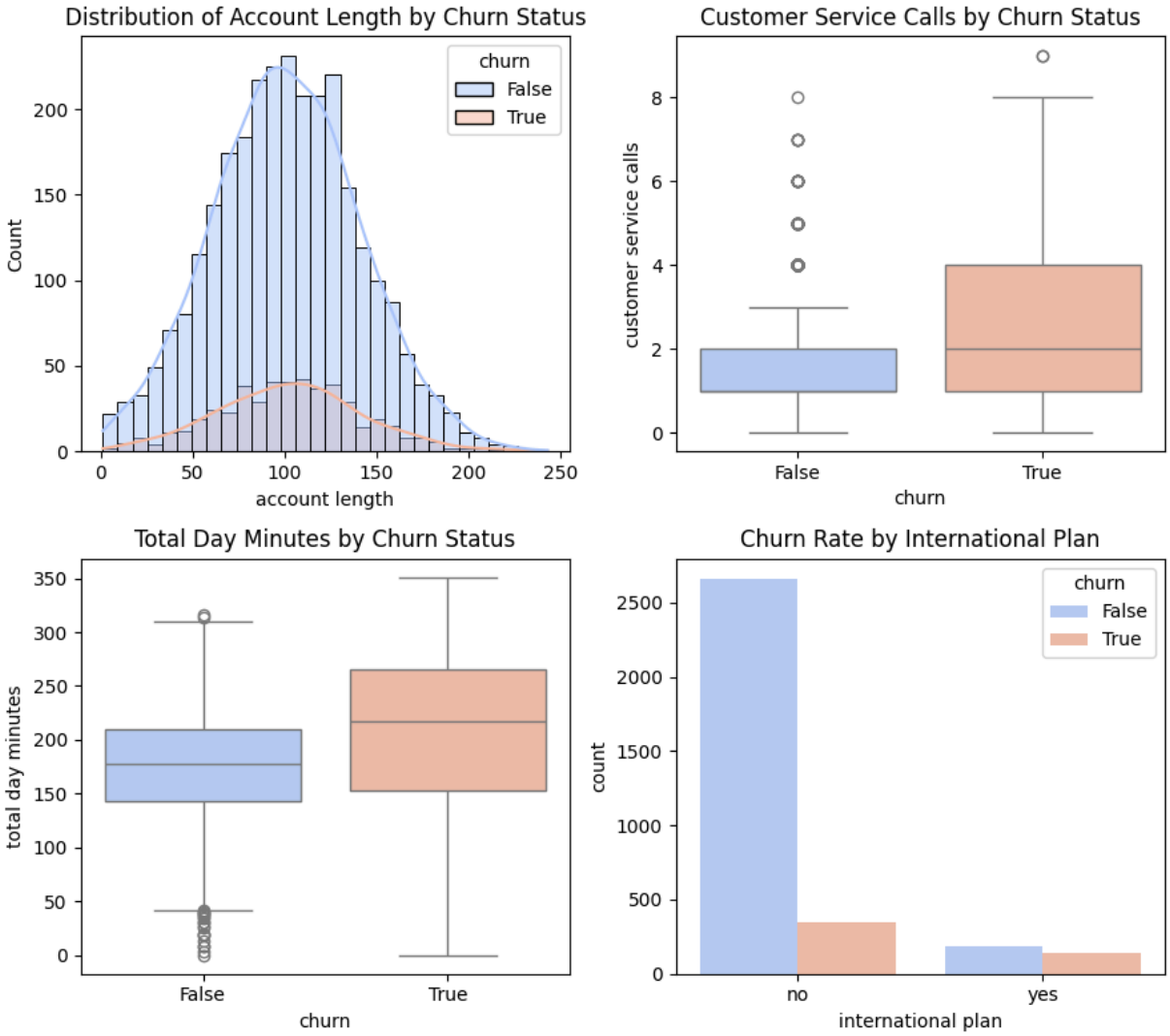
In [9]:

EDA

Univariate Analysis

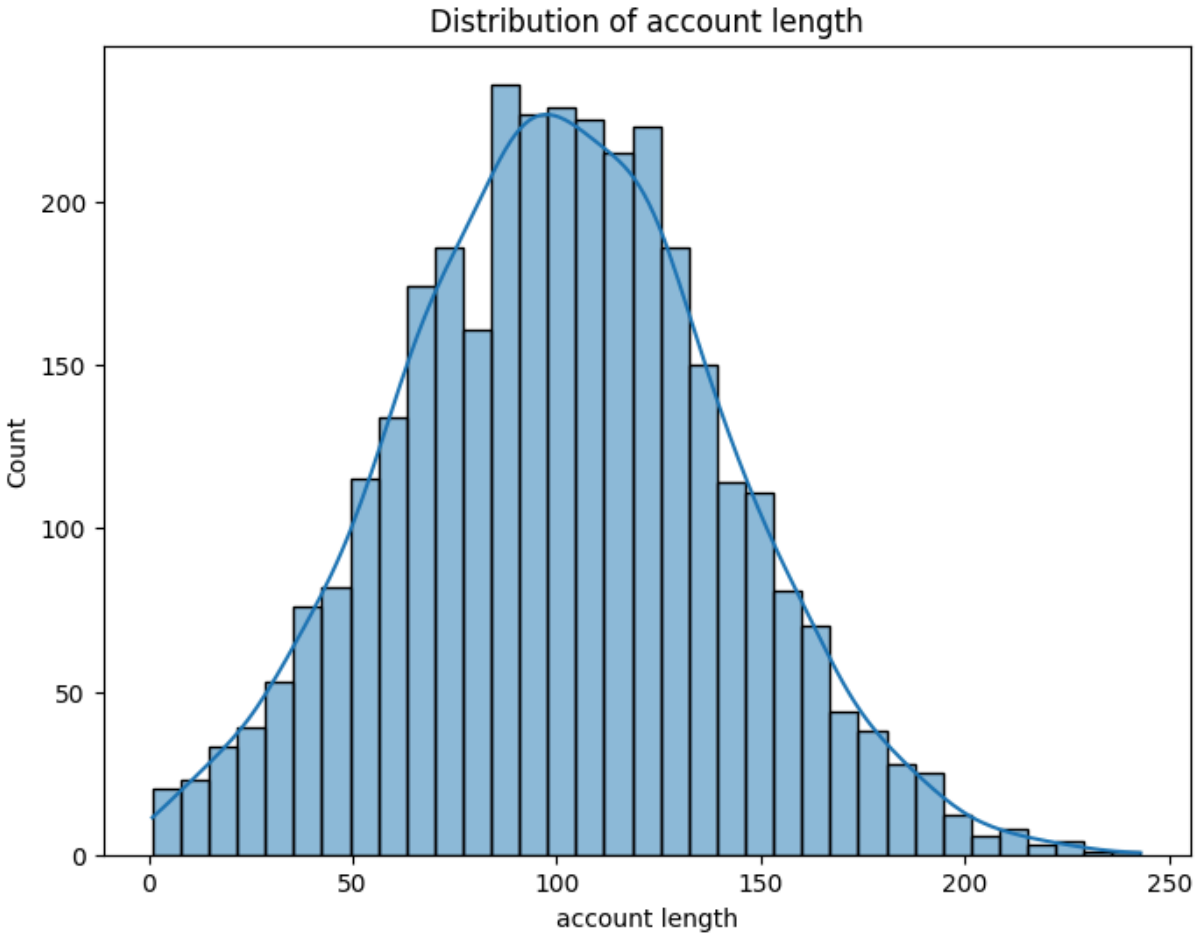
In [49]:
```
# Set up figure for multiple visualizations
plt.figure(figsize=(9, 8))
# Distribution of Account Length for Churn vs. Non-Churned Customers
plt.subplot(2, 2, 1)
sns.histplot(df, x="account length", hue="churn", kde=True, palette="coolwarm", bin
plt.title("Distribution of Account Length by Churn Status")
# Customer Service Calls vs. Churn
plt.subplot(2, 2, 2)
sns.boxplot(x="churn", y="customer service calls", data=df, palette="coolwarm")
plt.title("Customer Service Calls by Churn Status")
# Total Day Minutes vs. Churn
plt.subplot(2, 2, 3)
sns.boxplot(x="churn", y="total day minutes", data=df, palette="coolwarm")
plt.title("Total Day Minutes by Churn Status")
# International Plan vs. Churn
```

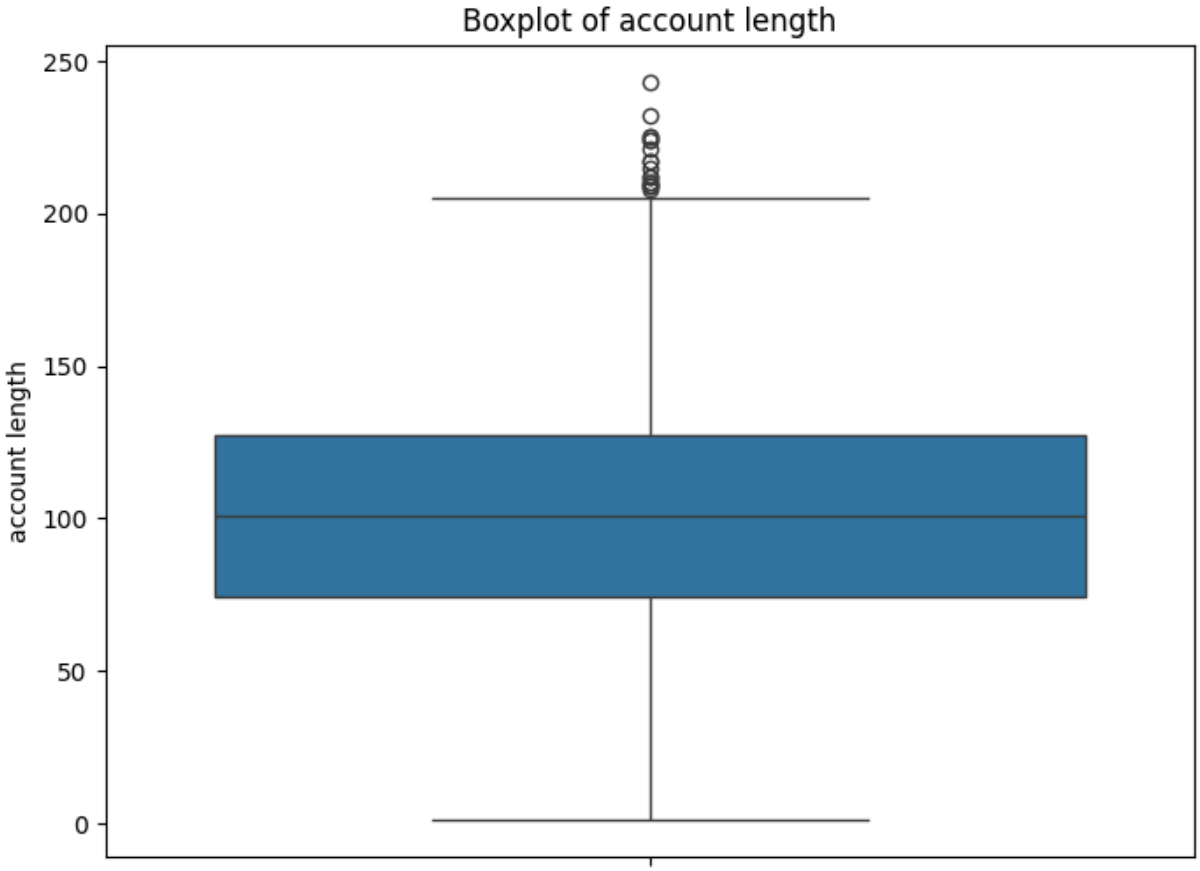
```
plt.subplot(2, 2, 4)
sns.countplot(x="international plan", hue="churn", data=df, palette="coolwarm")
plt.title("Churn Rate by International Plan")
plt.tight_layout()
plt.show()
```

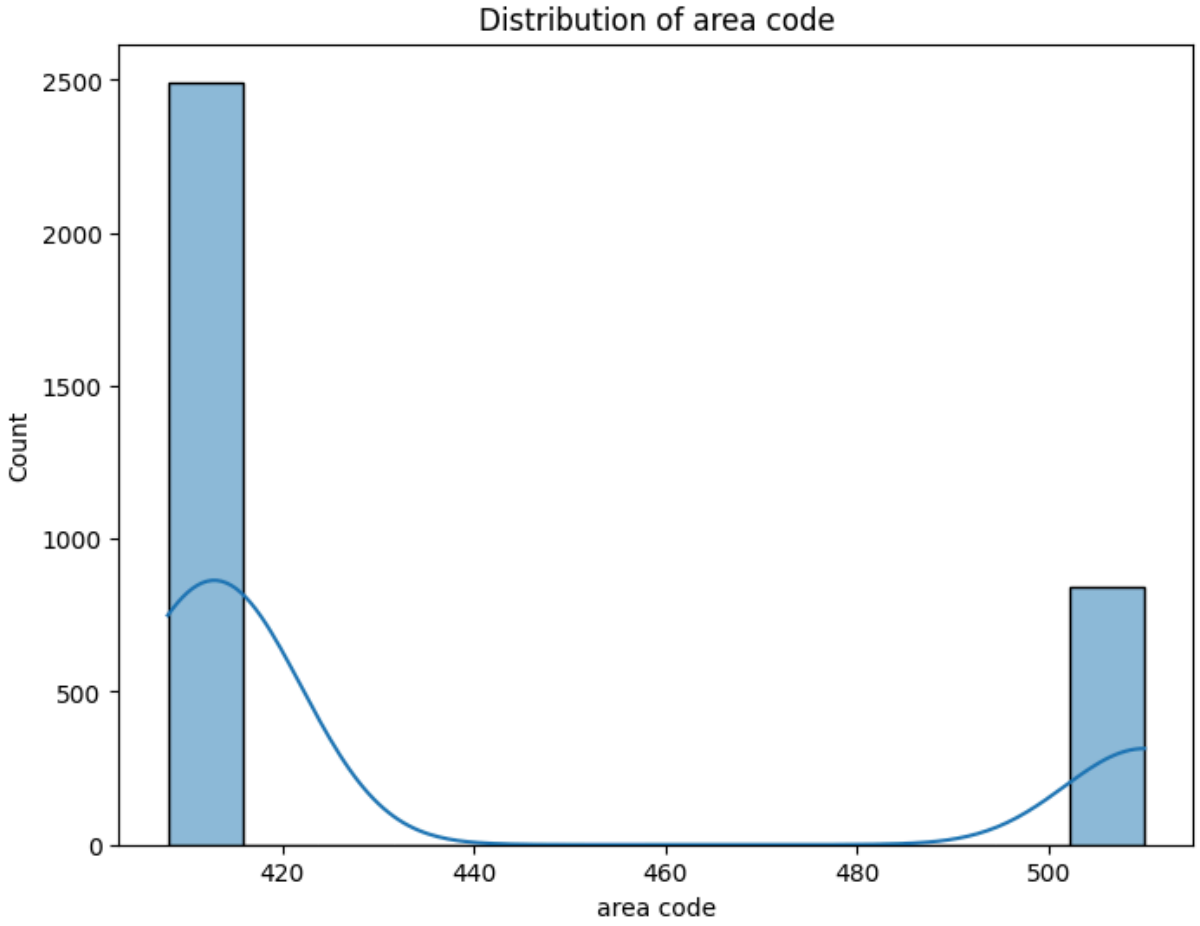


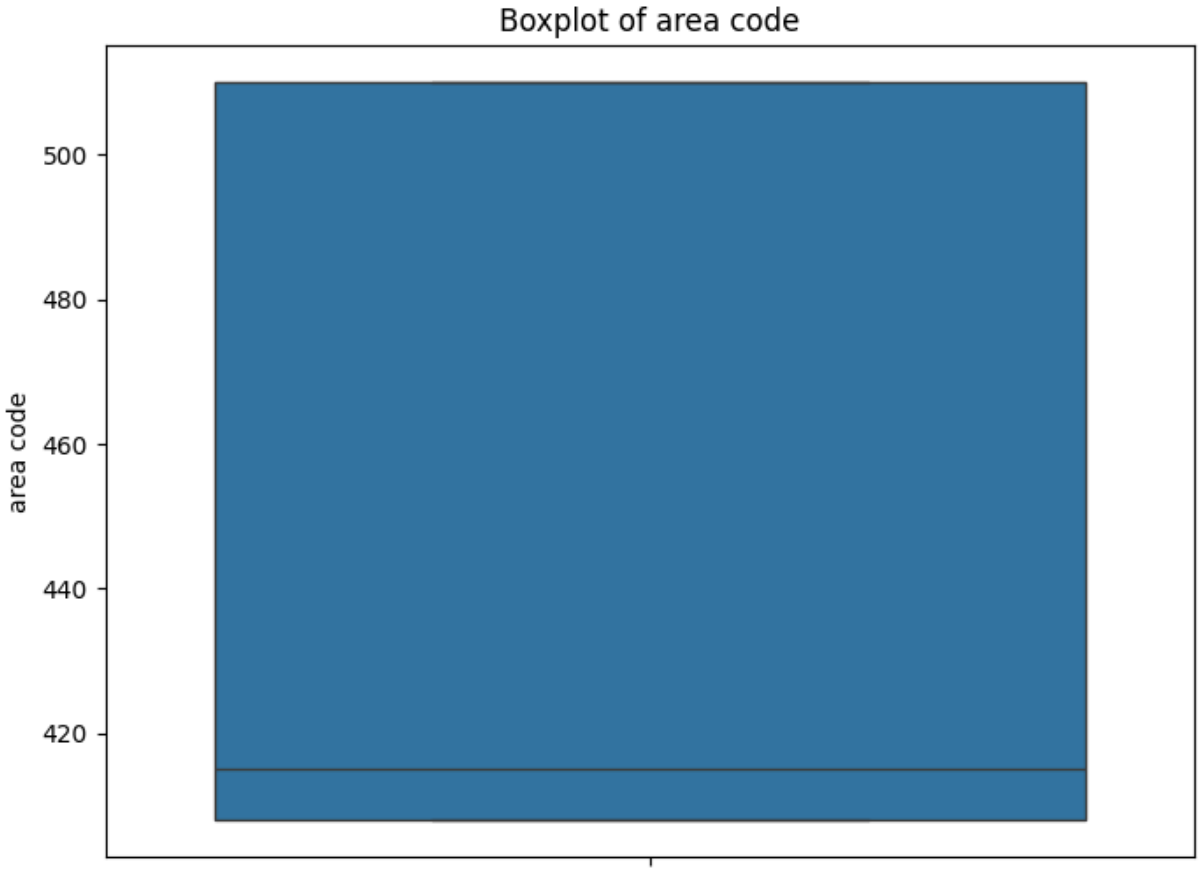
In [50]:
```
numerical_features = df.select_dtypes(include=np.number).columns
for col in numerical_features:
    plt.figure(figsize=(8, 6))
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.show()

    plt.figure(figsize=(8, 6))
    sns.boxplot(df[col])
    plt.title(f'Boxplot of {col}')
    plt.show()

# Categorical features univariate analysis
categorical_features = df.select_dtypes(exclude=np.number).columns
for col in categorical_features:
    plt.figure(figsize=(8, 6))
    df[col].value_counts().plot(kind='bar')
```

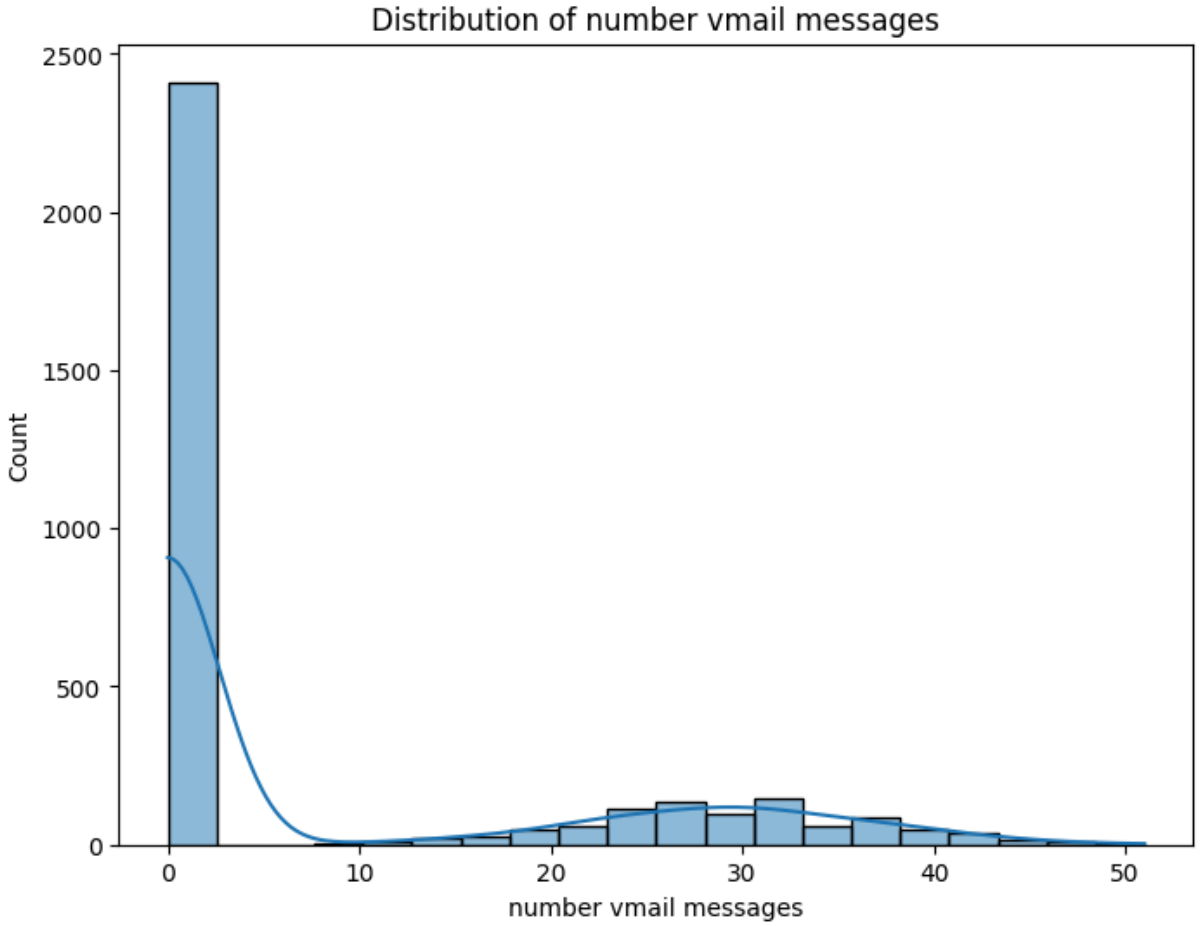
```
    plt.title(f'Frequency Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.show()
```

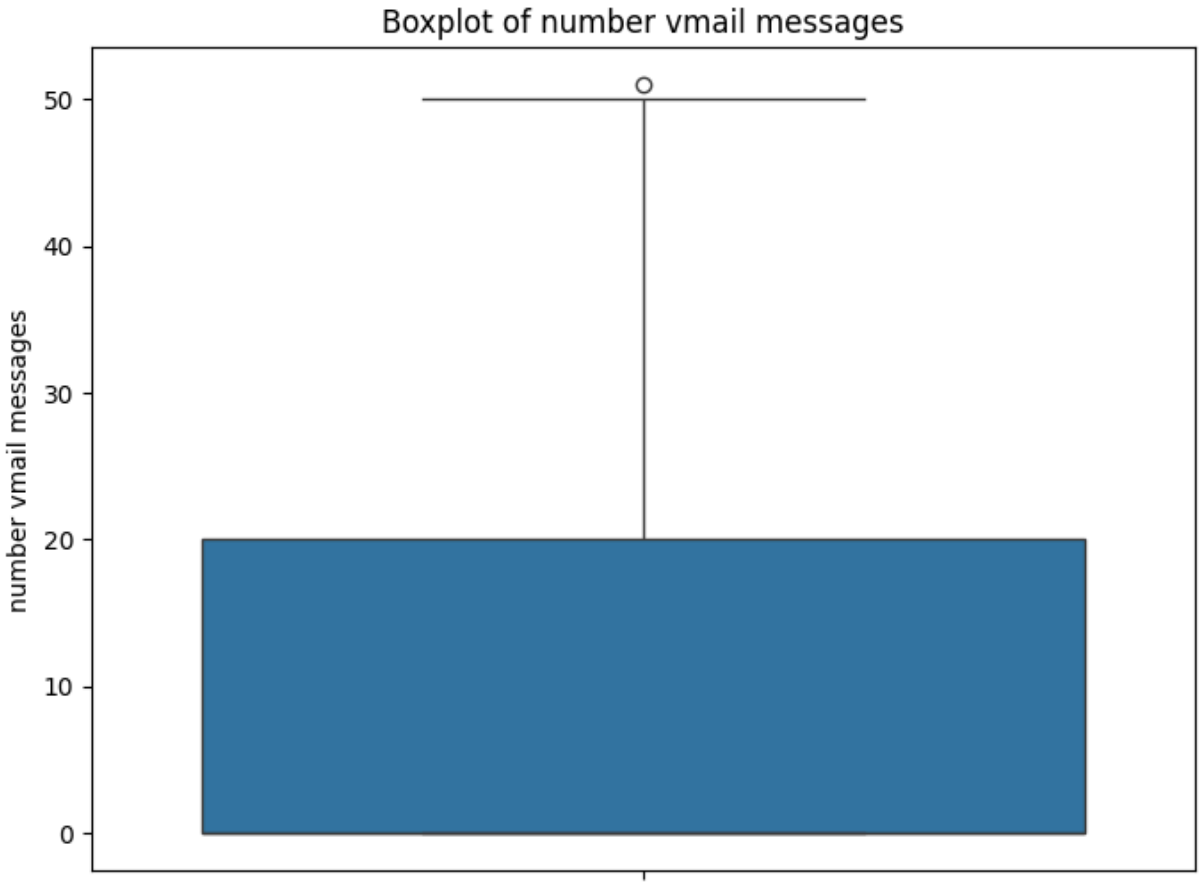


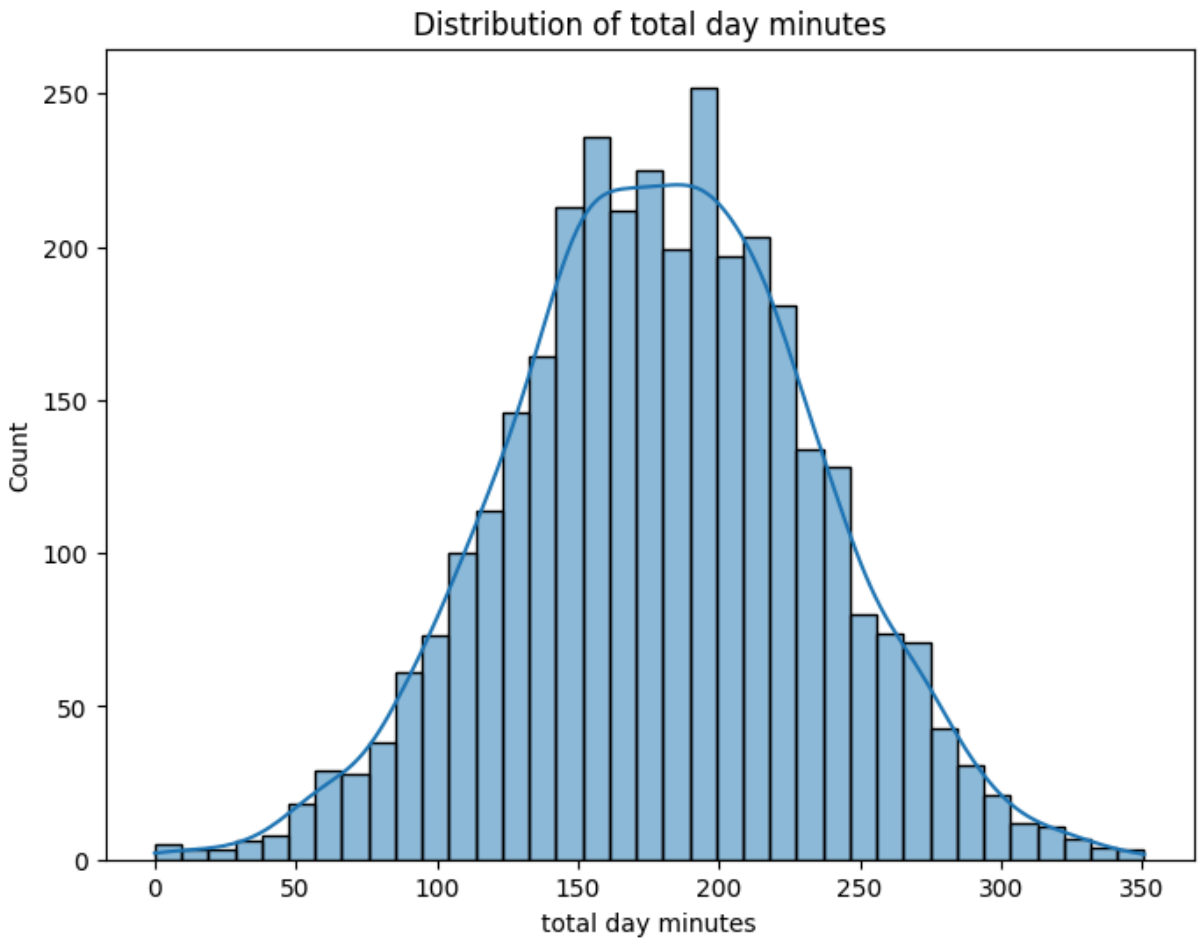

Boxplot of account length
account length
250
200
150
100
50
0

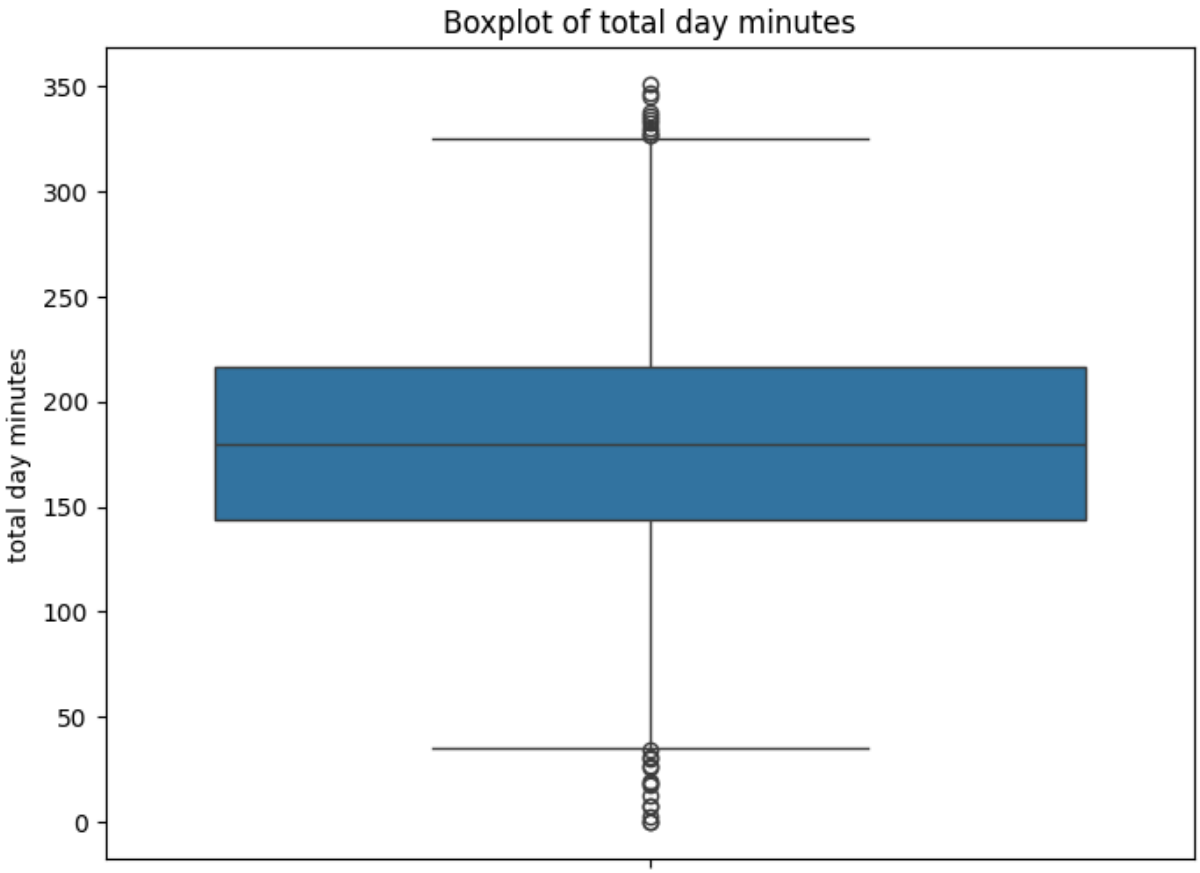

Distribution of area code
Count
2500
2000
1500
1000
500
0
420
440
460
480
500
area code

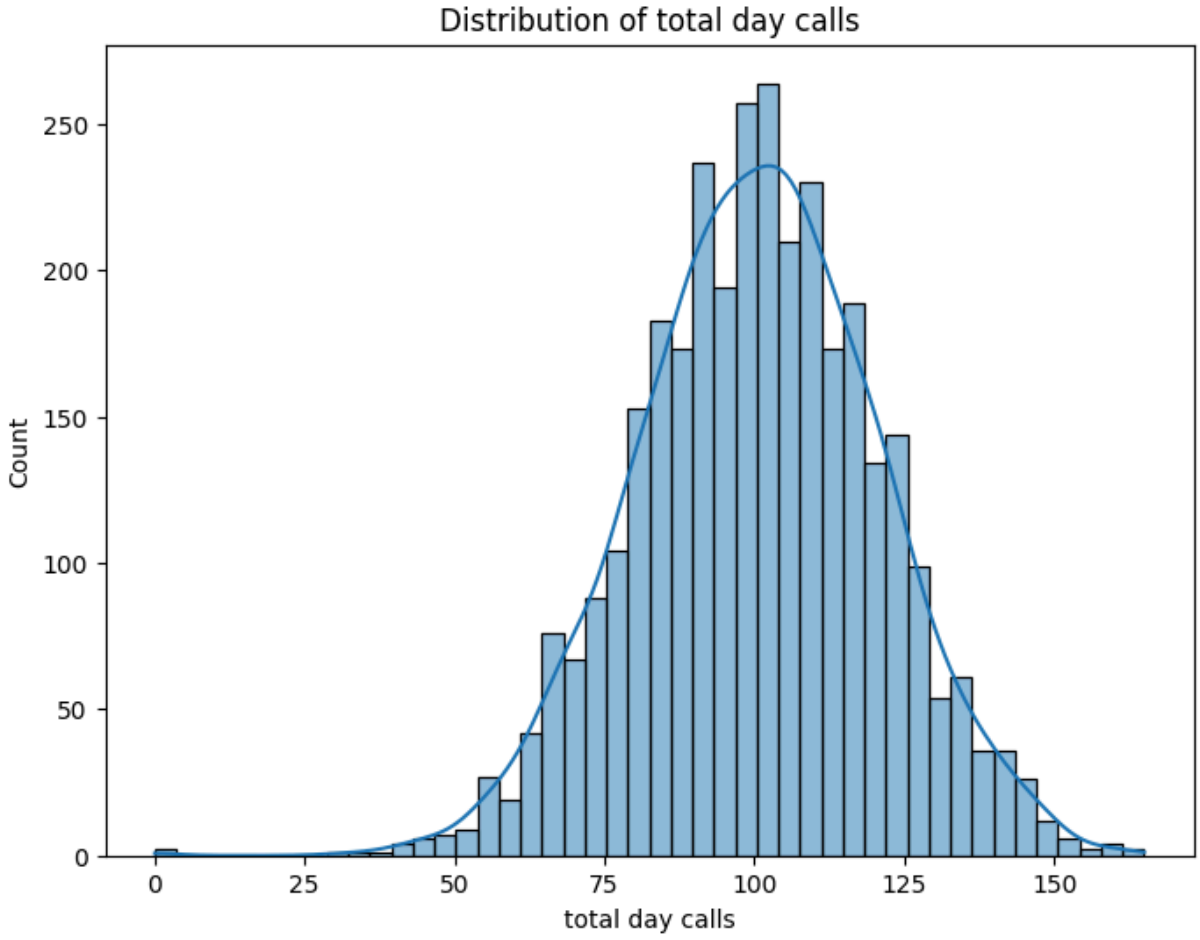

Boxplot of area code
area code
500
480
460
440
420

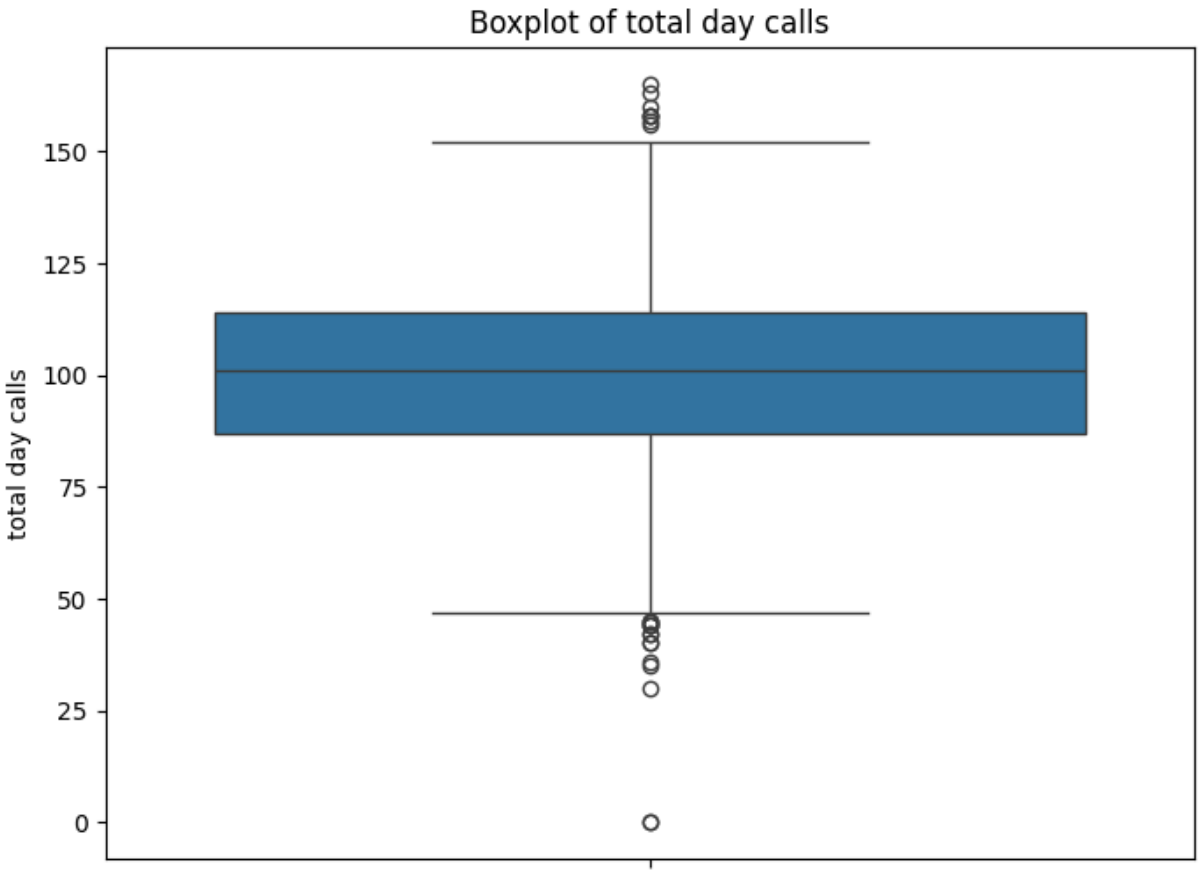

Distribution of number vmail messages
Count
2500
2000
1500
1000
500
0
0
10
20
30
40
50
number vmail messages

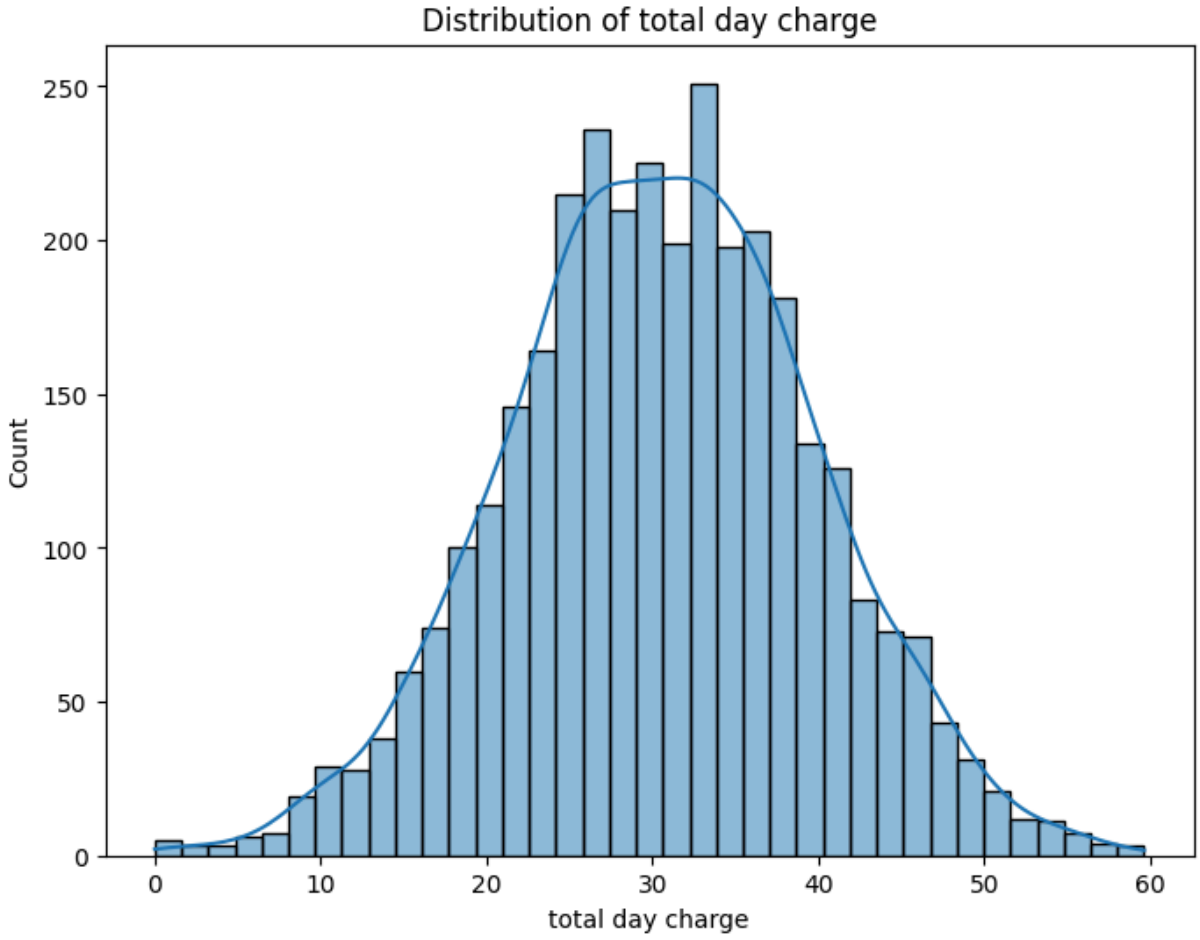

Boxplot of number vmail messages
number vmail messages
0
10
20
30
40
50

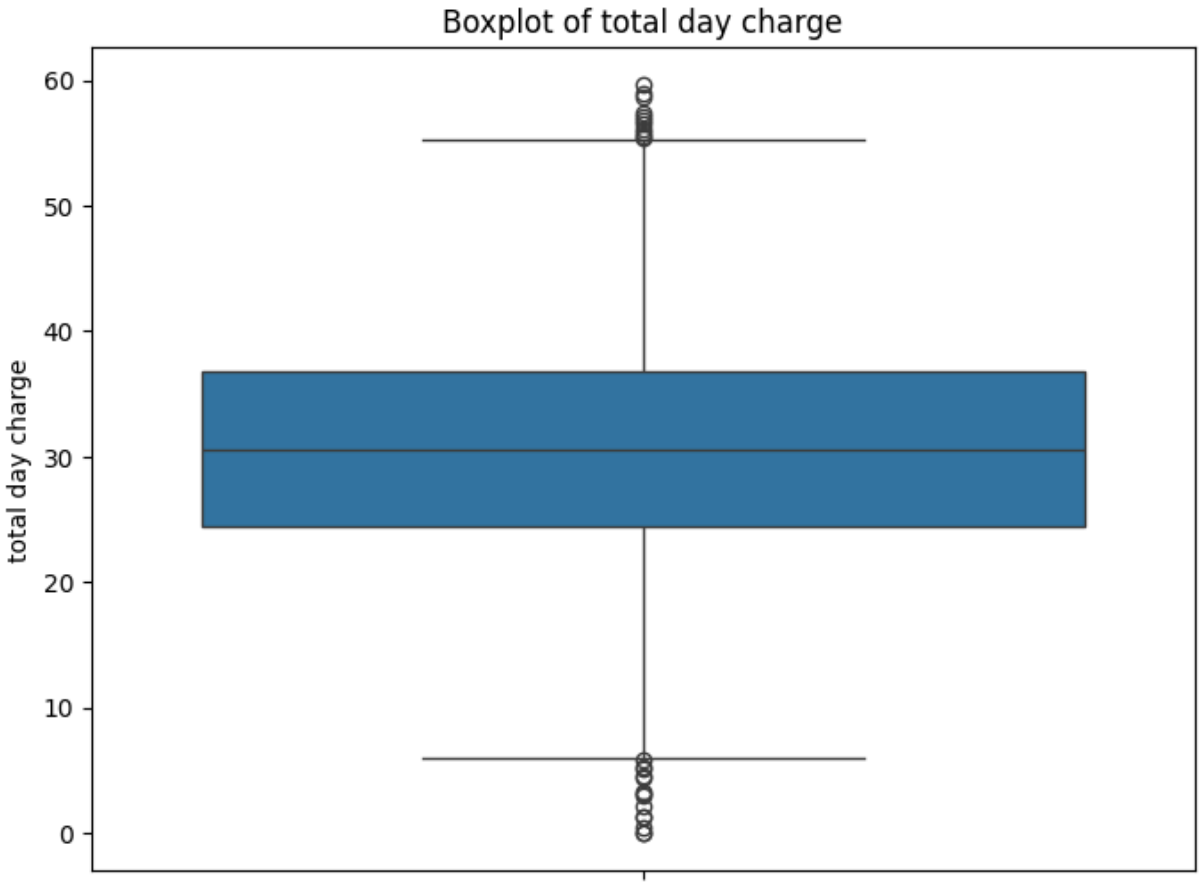

Distribution of total day minutes
Count
0
50
100
150
200
250
0
50
100
150
200
250
300
350
total day minutes

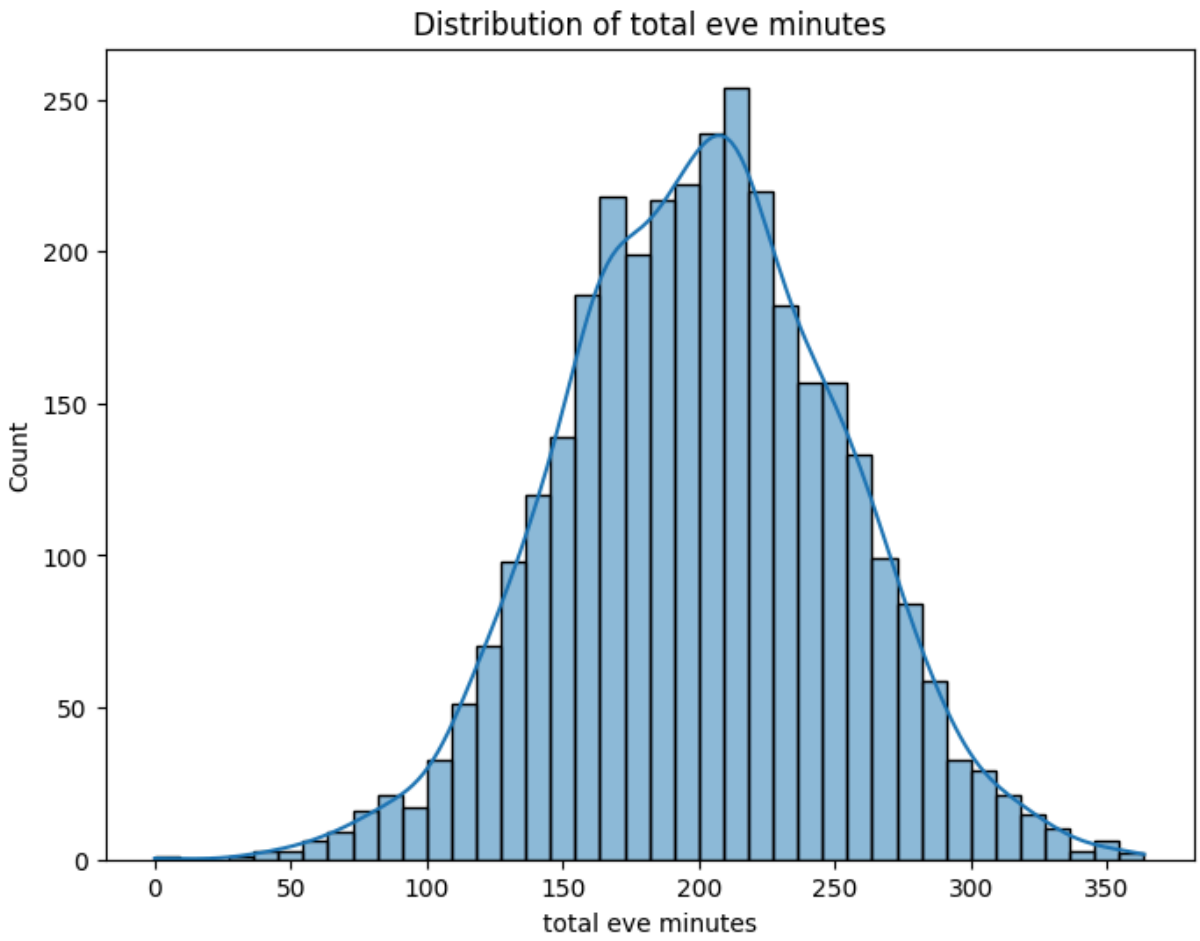

Boxplot of total day minutes
total day minutes
350
300
250
200
150
100
50
0

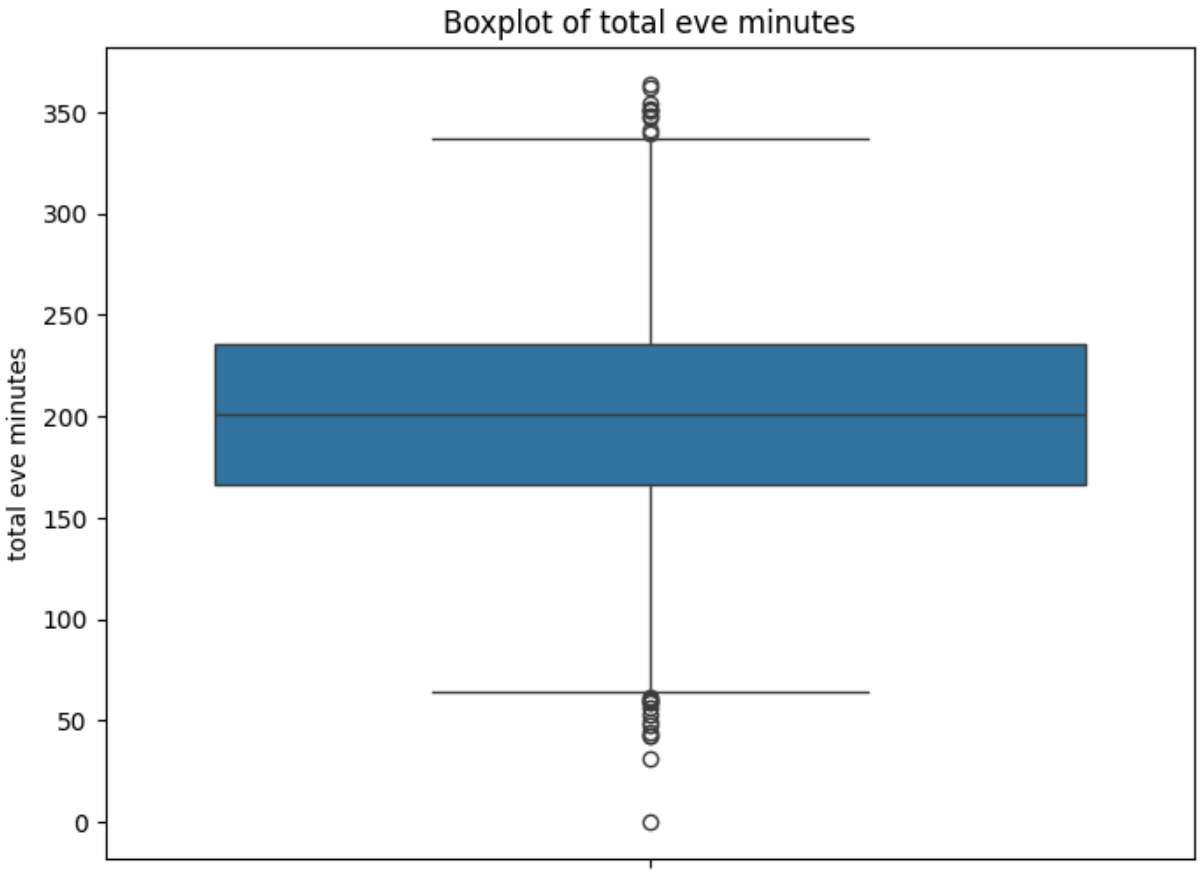

Distribution of total day calls
Count
250
200
150
100
50
0
0
25
50
75
100
125
150
total day calls

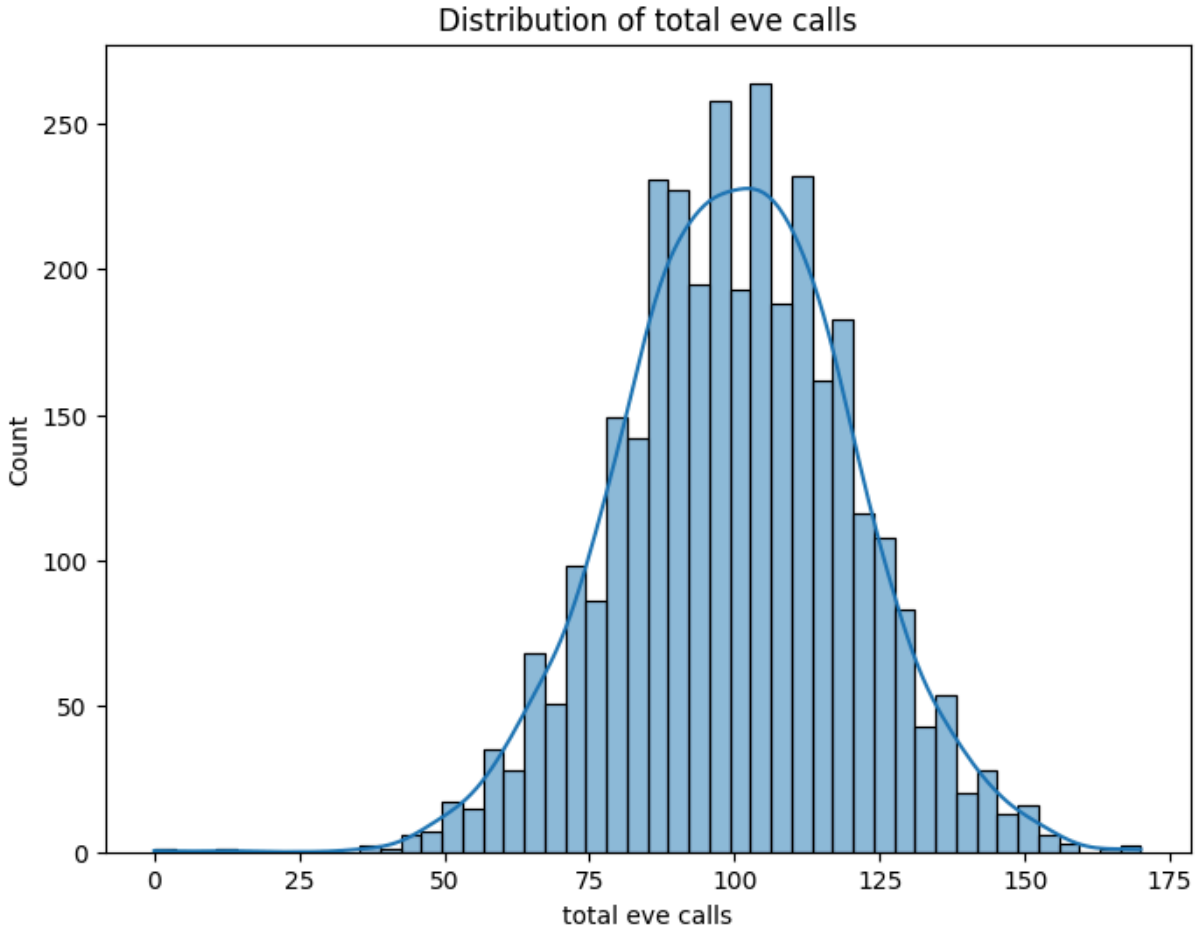

Boxplot of total day calls
total day calls
150
125
100
75
50
25
0

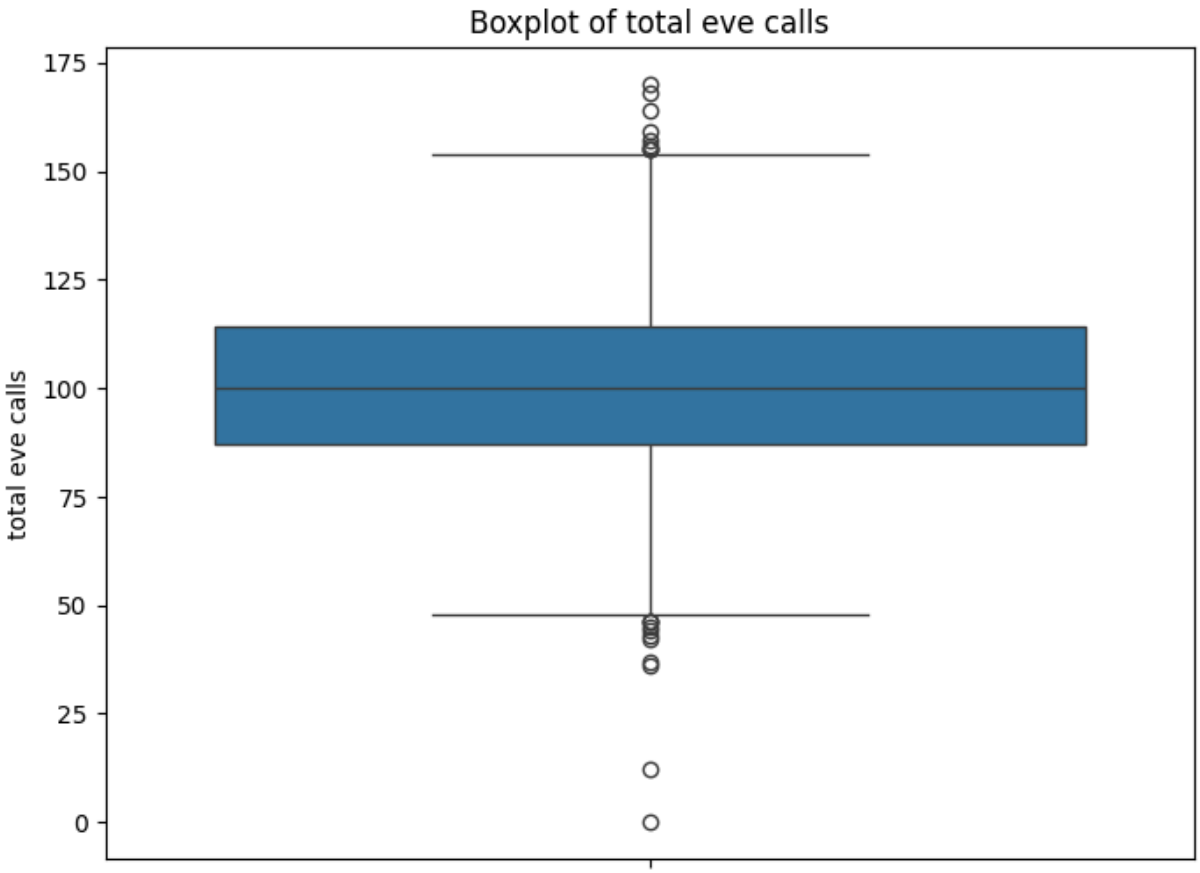

Distribution of total day charge
Count
250
200
150
100
50
0
0
10
20
30
40
50
60
total day charge

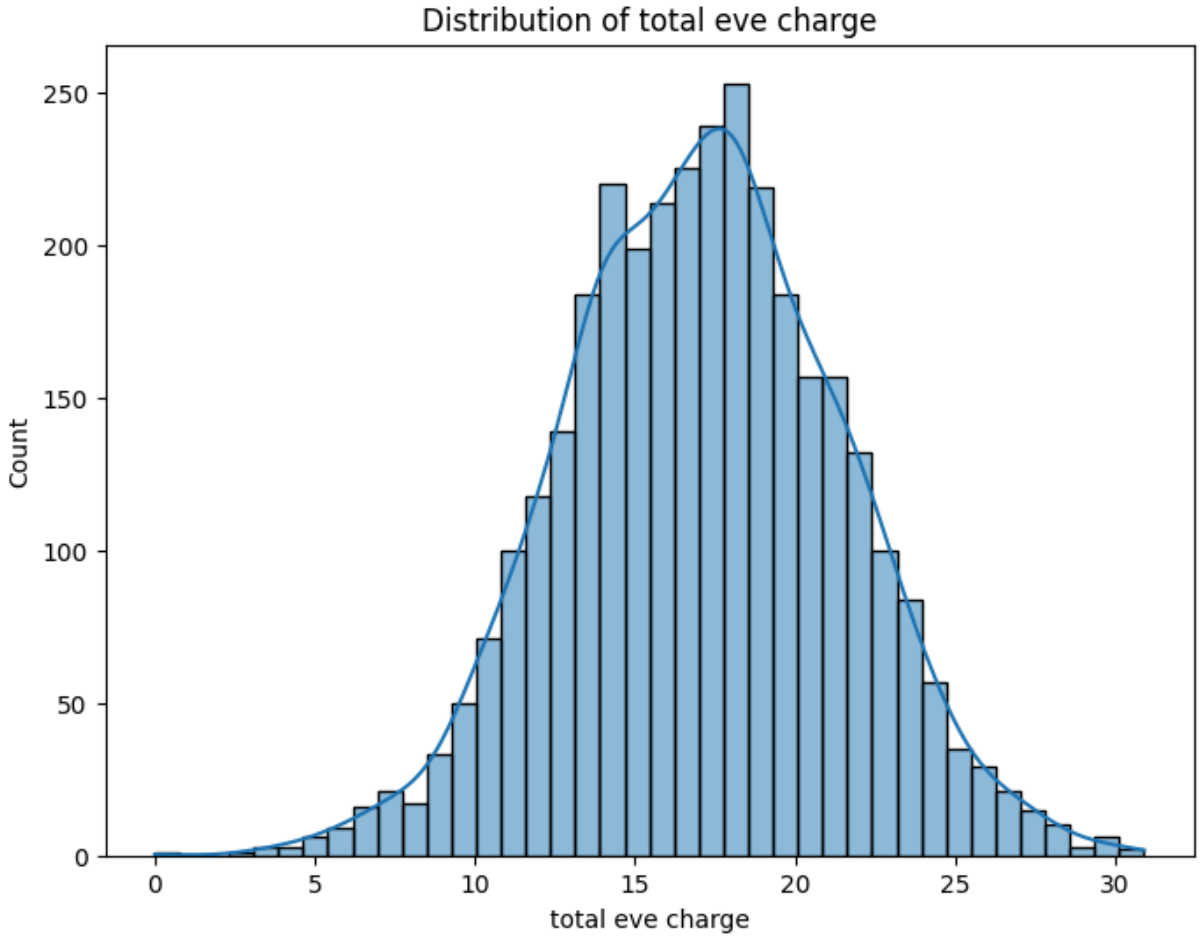

Boxplot of total day charge
total day charge
60
50
40
30
20
10
0

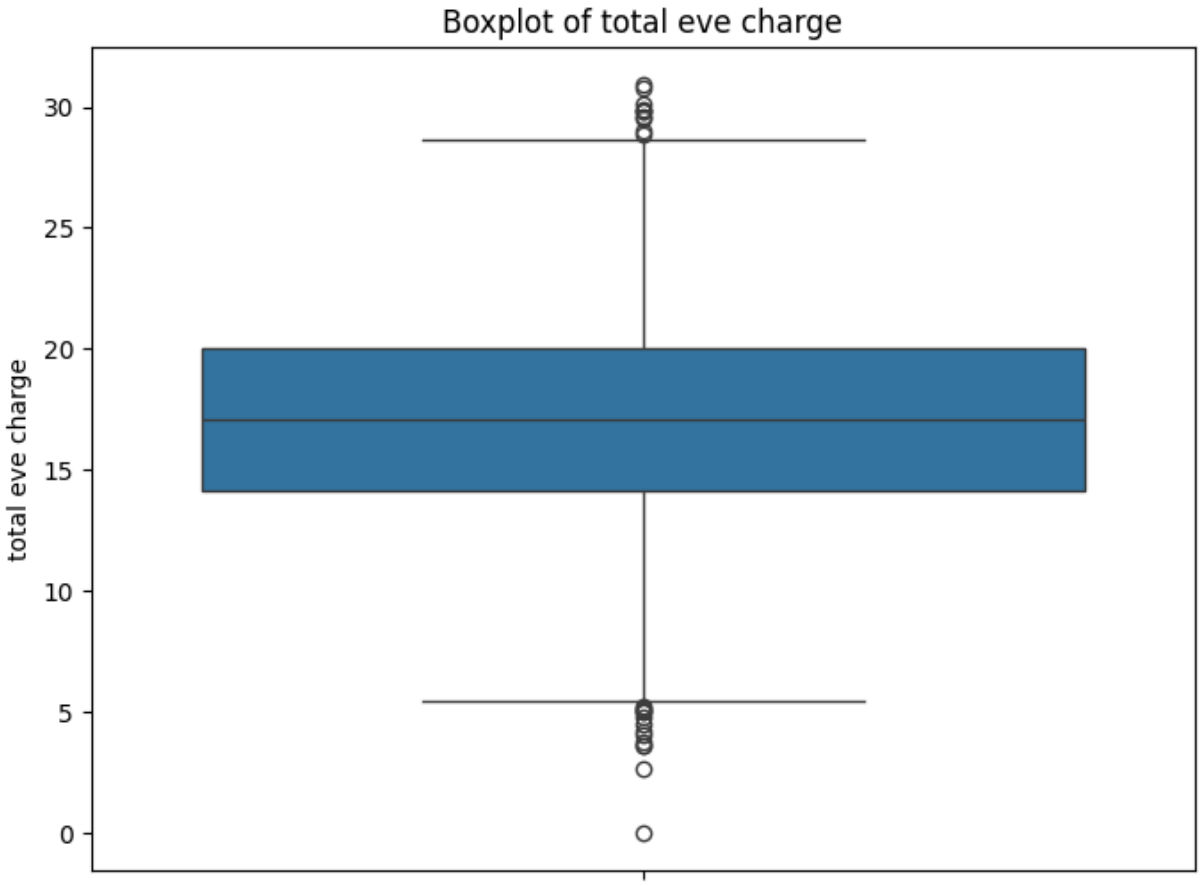

Distribution of total eve minutes
Count
250
200
150
100
50
0
0
50
100
150
200
250
300
350
total eve minutes

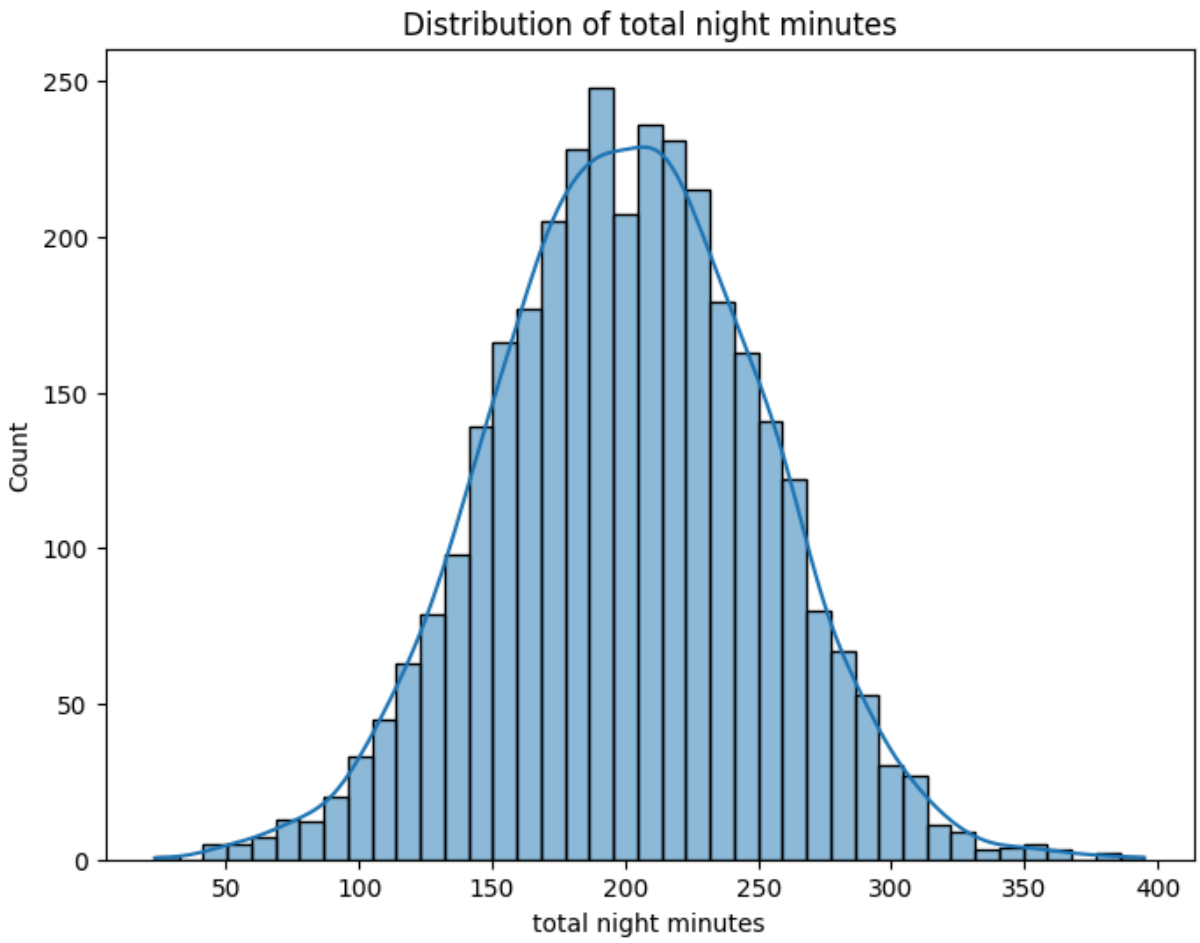

Boxplot of total eve minutes
total eve minutes
350
300
250
200
150
100
50
0

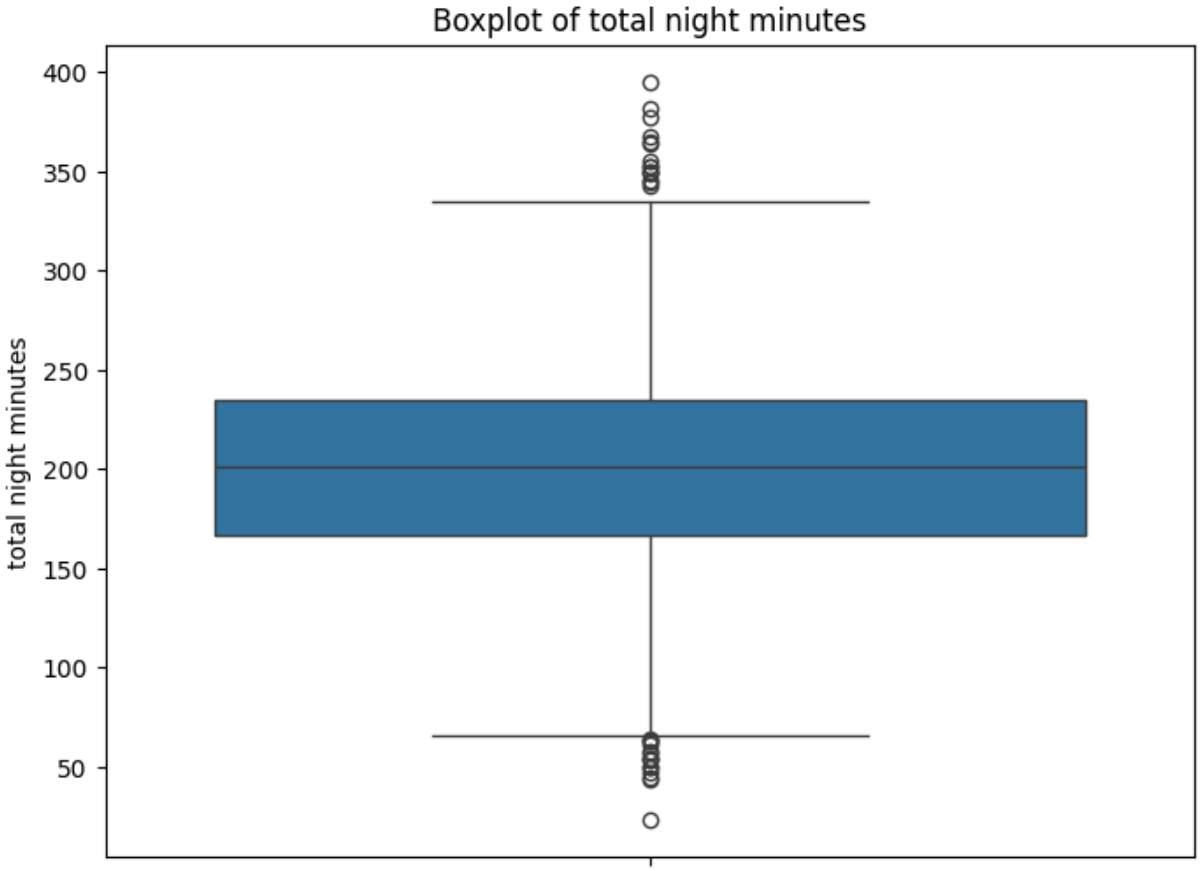

Distribution of total eve calls
Count
250
200
150
100
50
0
0
25
50
75
100
125
150
175
total eve calls

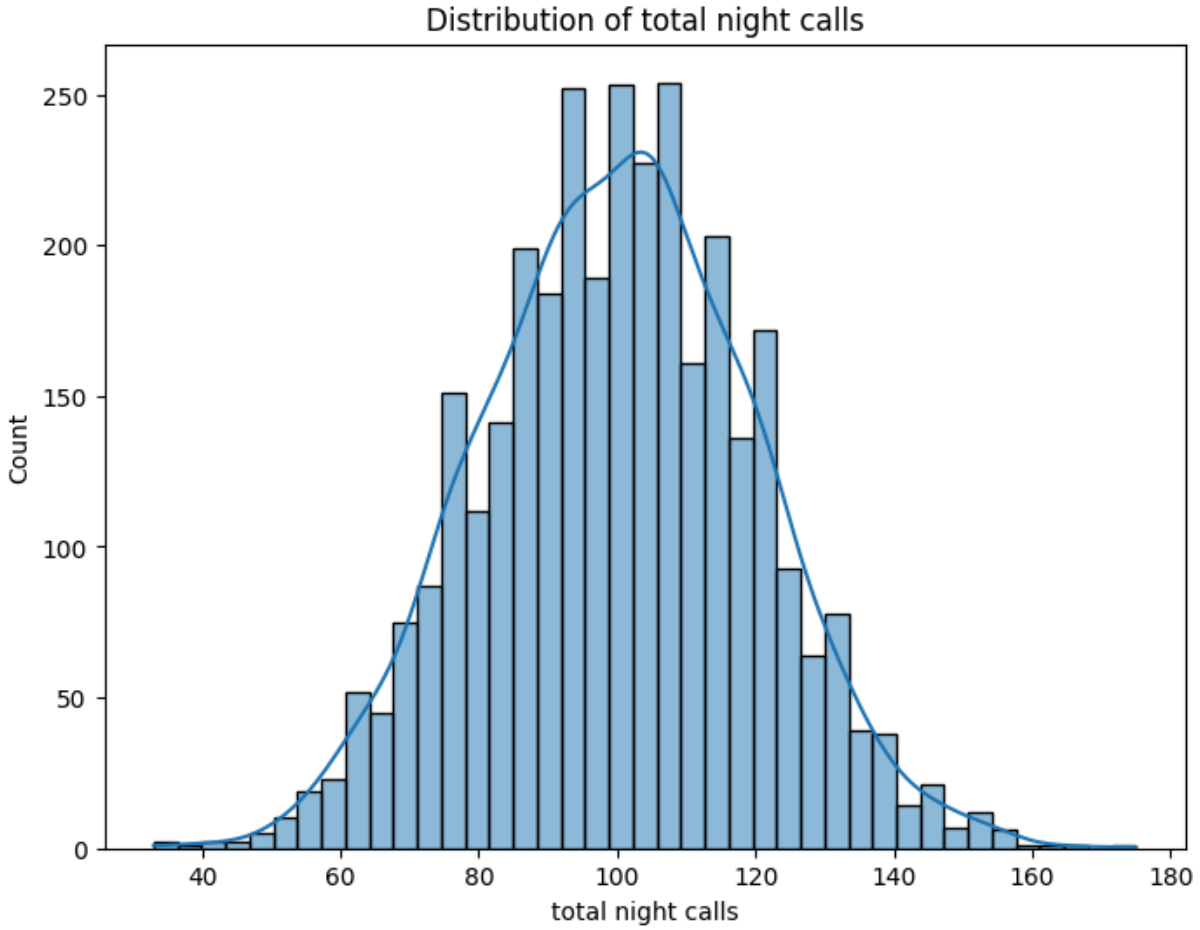

Boxplot of total eve calls
total eve calls
175
150
125
100
75
50
25
0

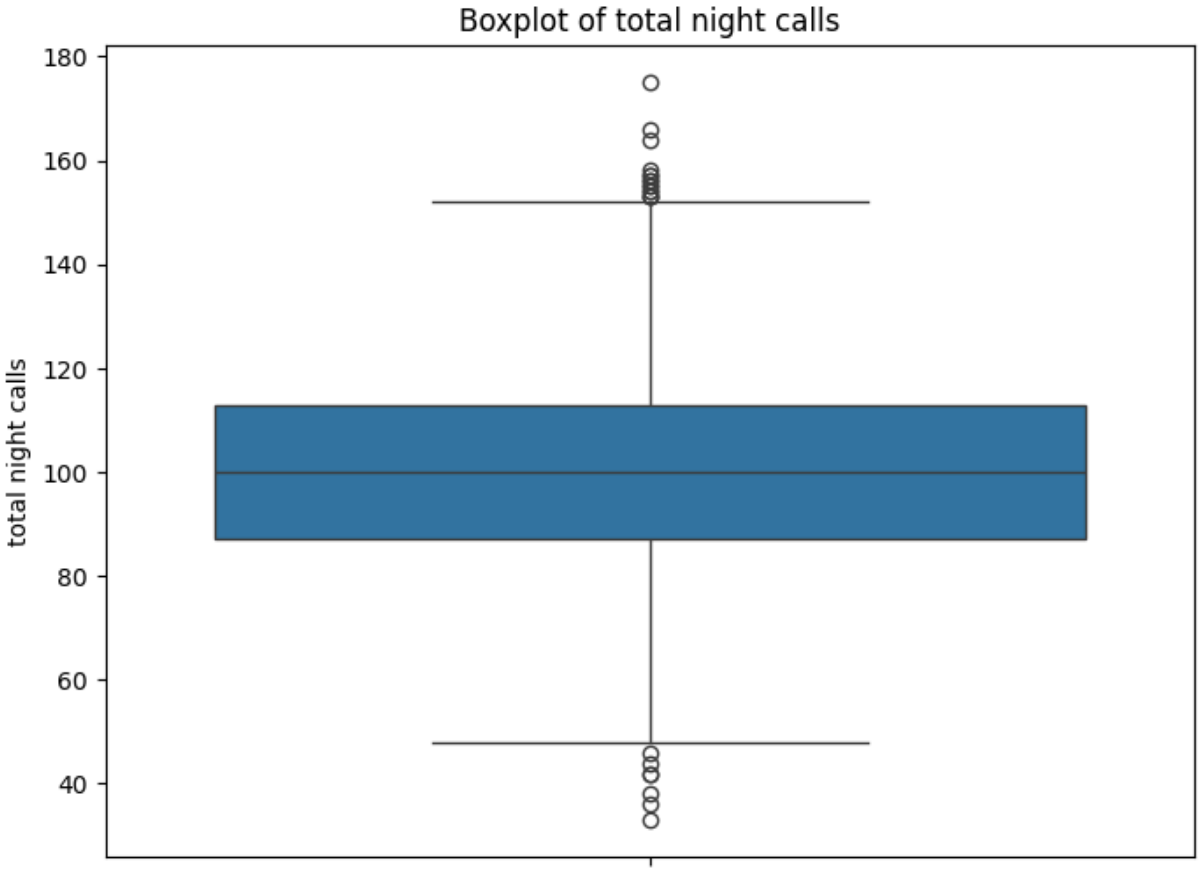

Distribution of total eve charge
Count
250
200
150
100
50
0
0
5
10
15
20
25
30
total eve charge

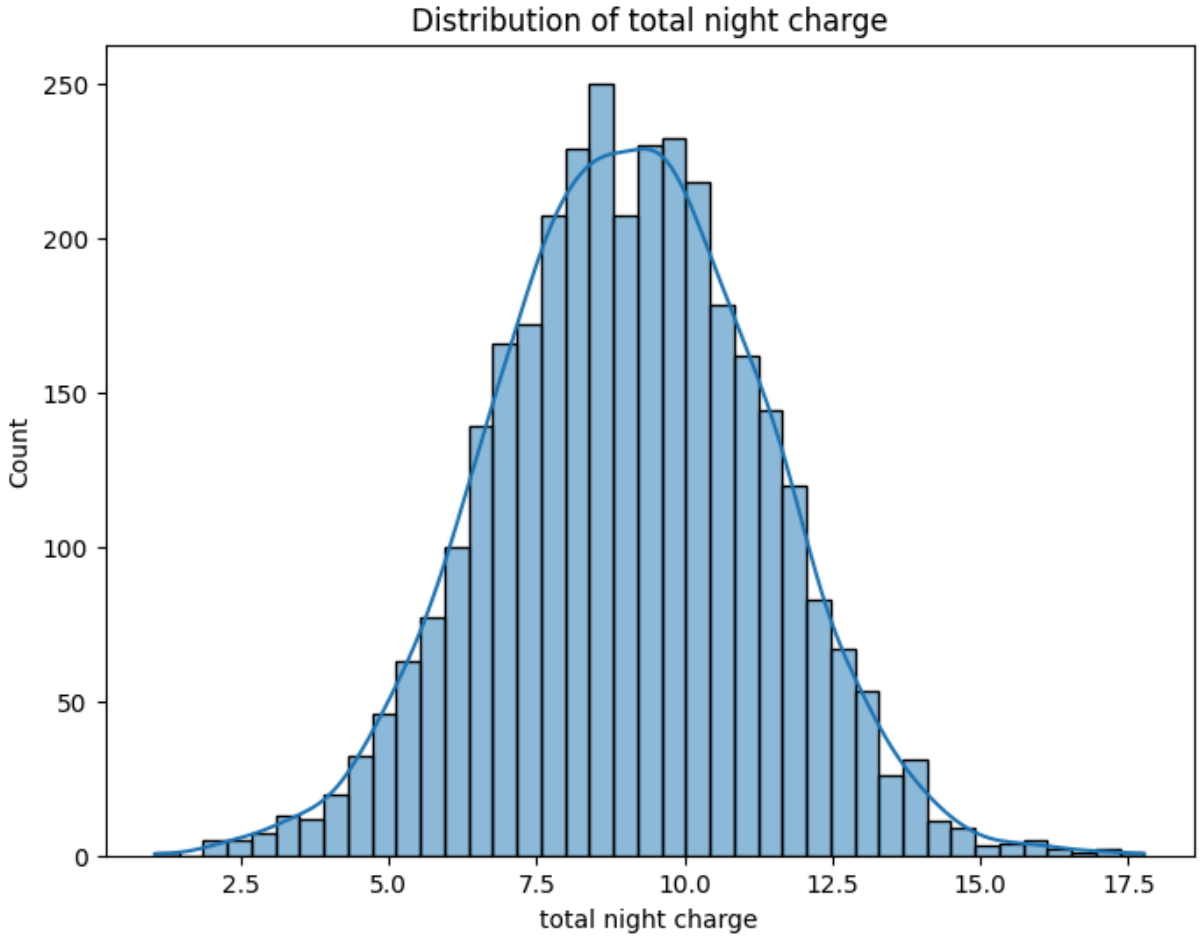

Boxplot of total eve charge
total eve charge
0
5
10
15
20
25
30

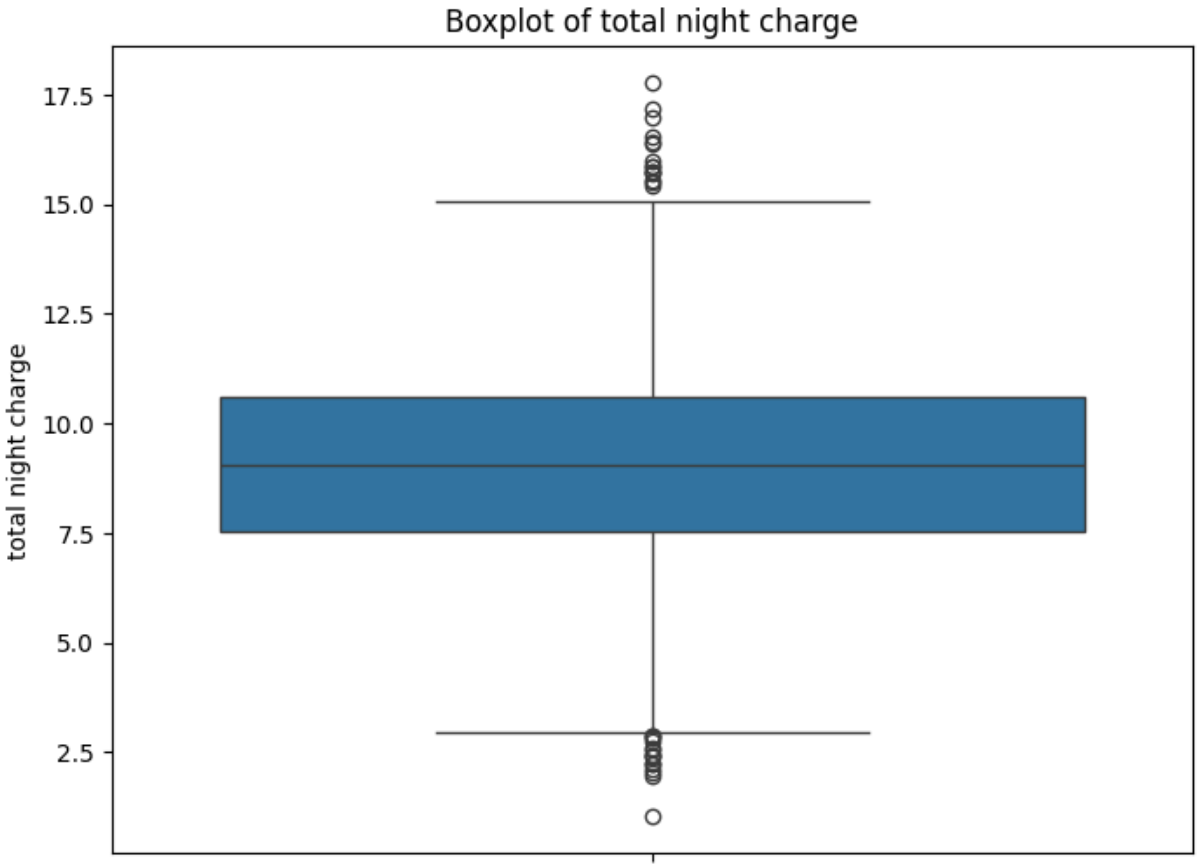

Distribution of total night minutes
Count
0
50
100
150
200
250
50
100
150
200
250
300
350
400
total night minutes

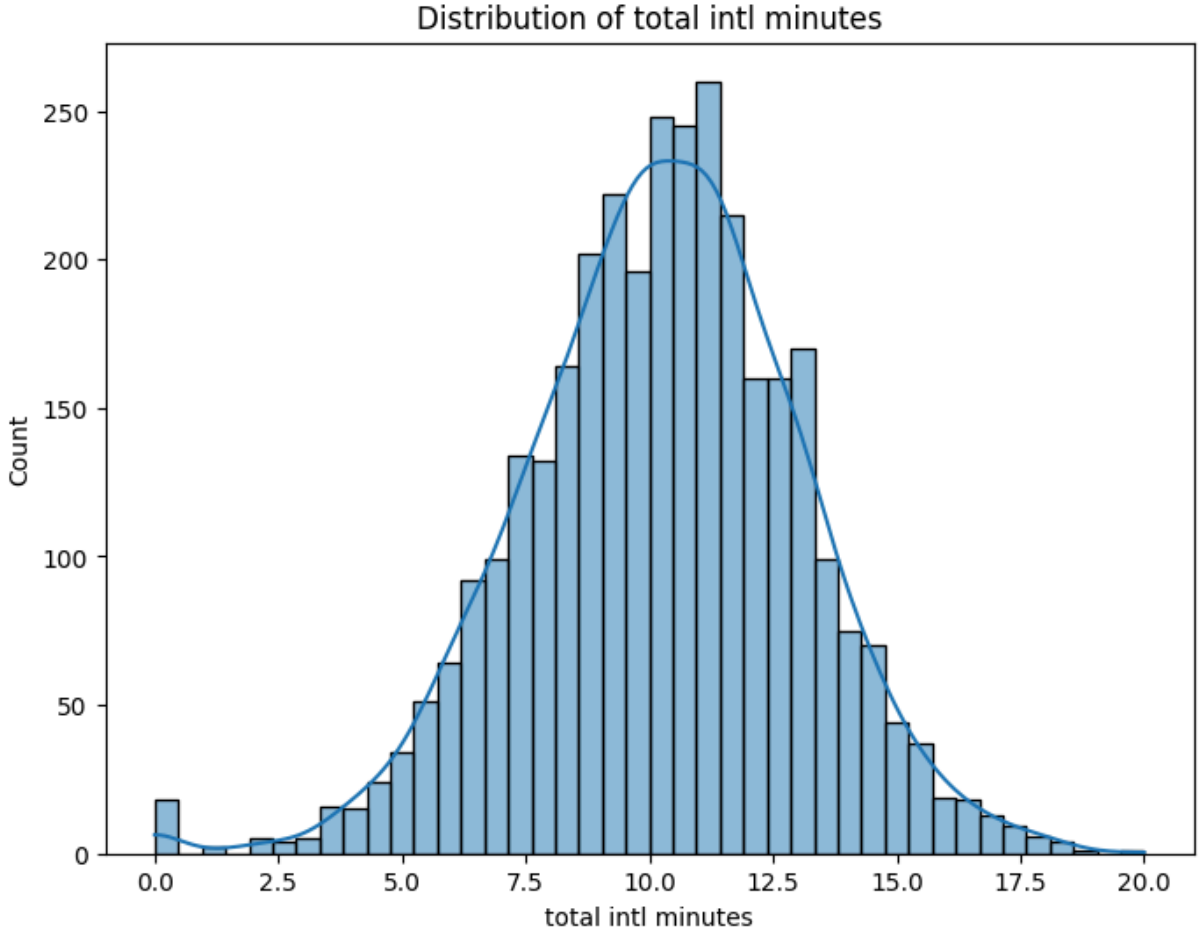

Boxplot of total night minutes
total night minutes
400
350
300
250
200
150
100
50

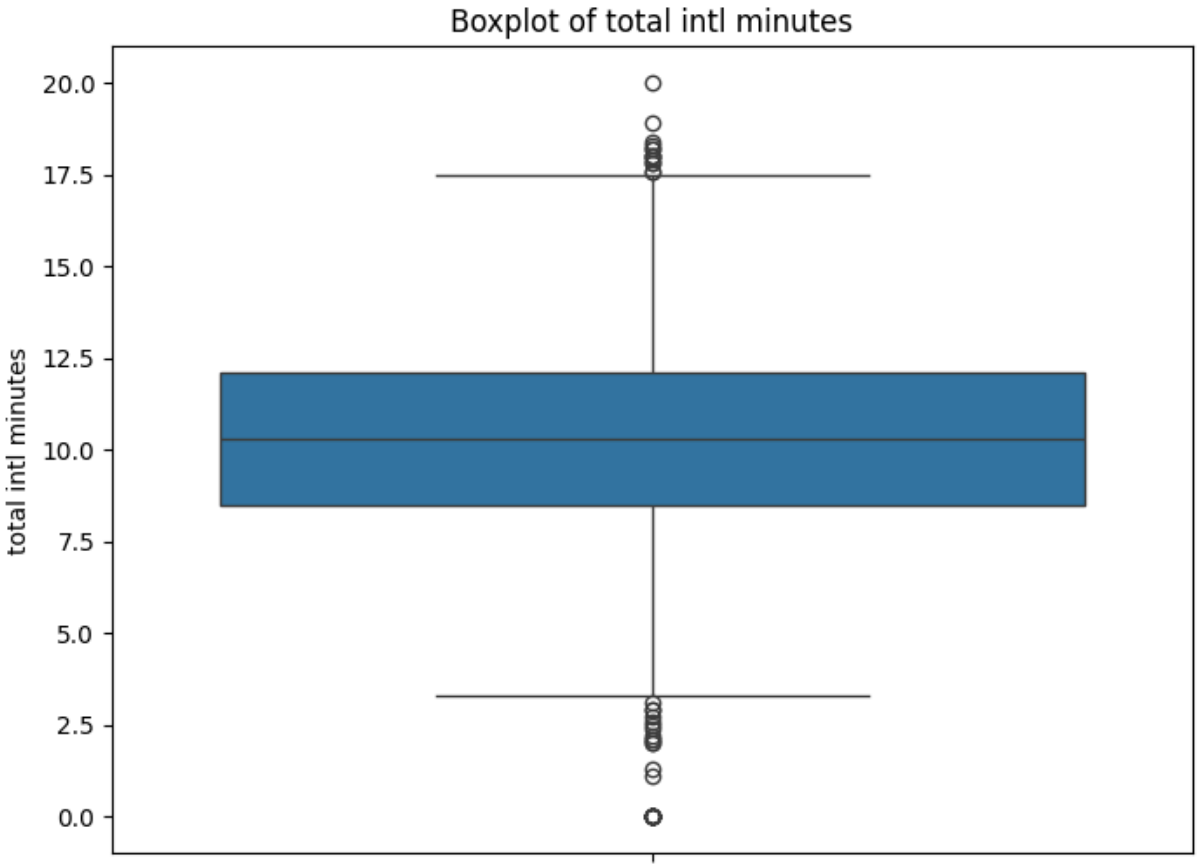

Distribution of total night calls
Count
250
200
150
100
50
0
40
60
80
100
120
140
160
180
total night calls

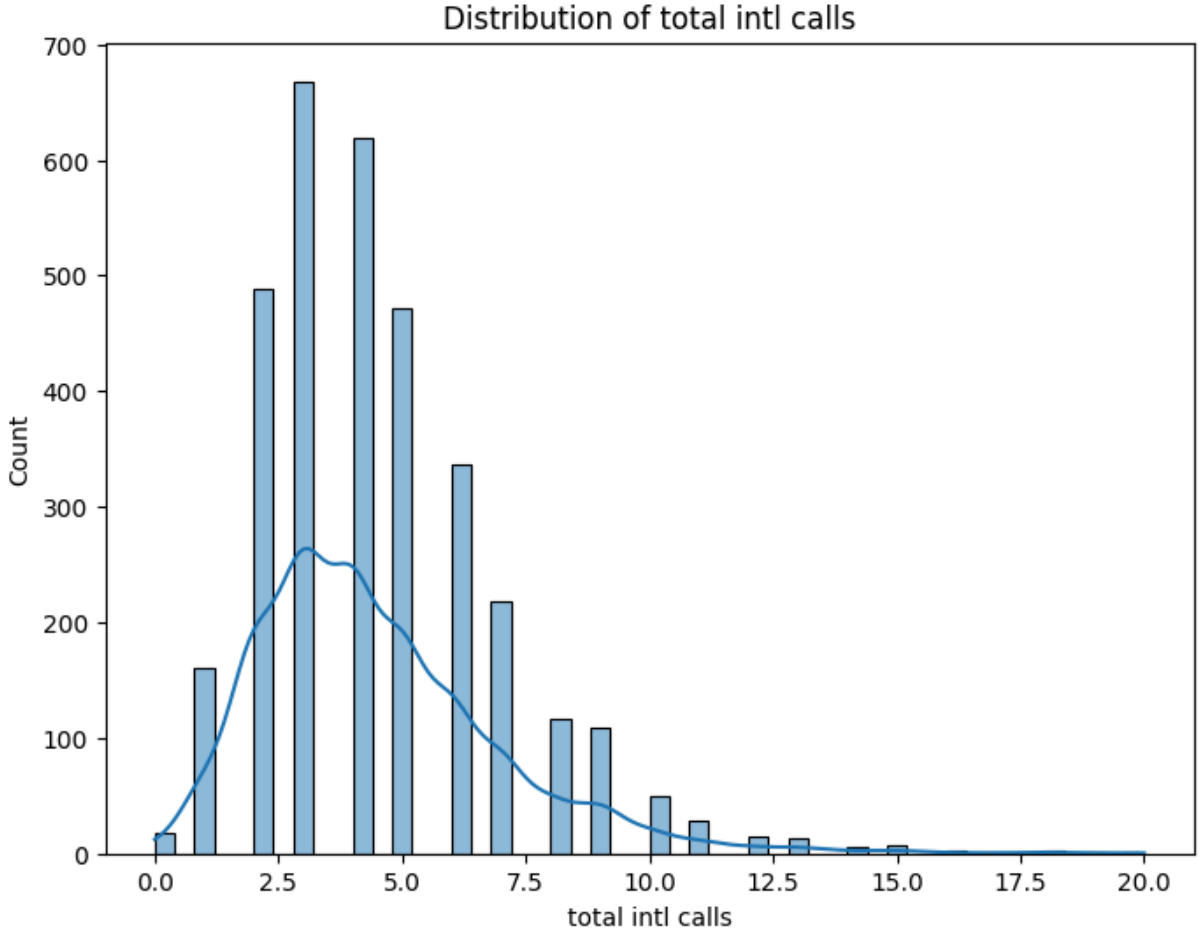

Boxplot of total night calls
total night calls
180
160
140
120
100
80
60
40

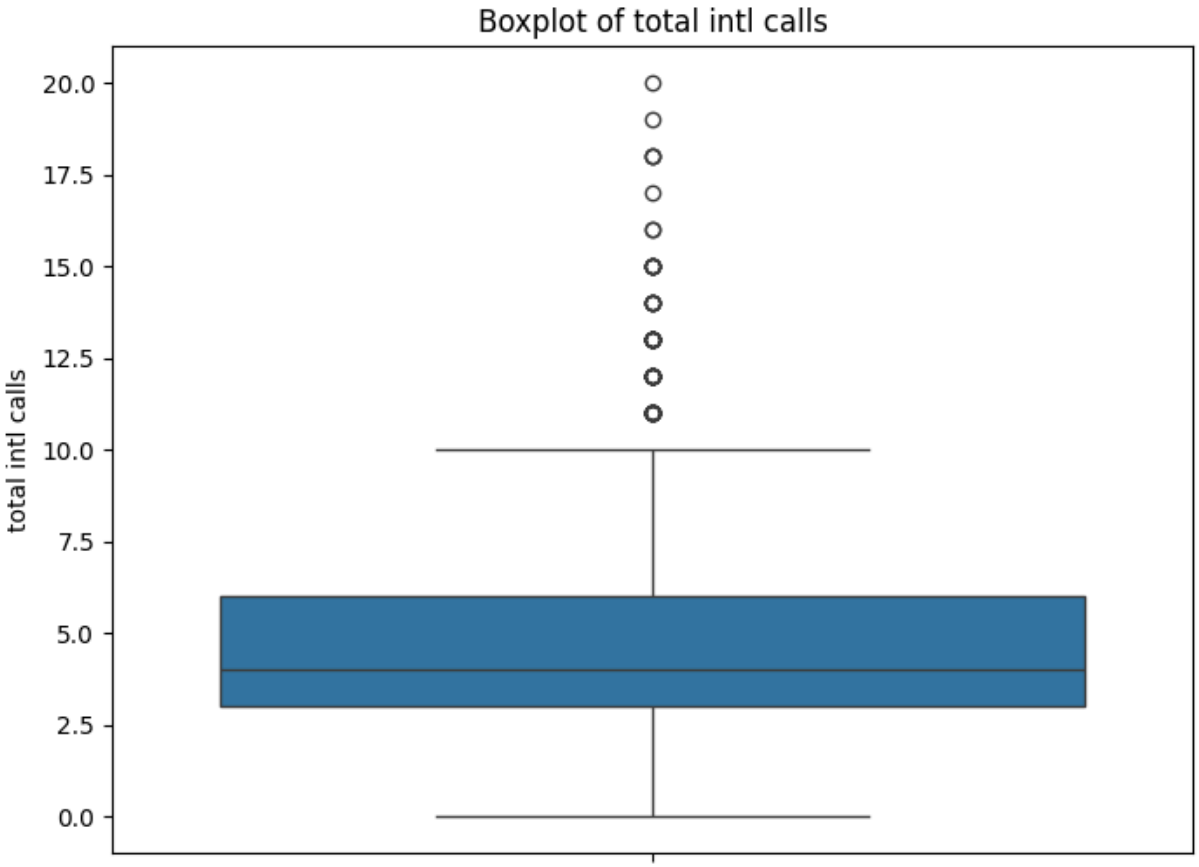

Distribution of total night charge
Count
250
200
150
100
50
0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
total night charge

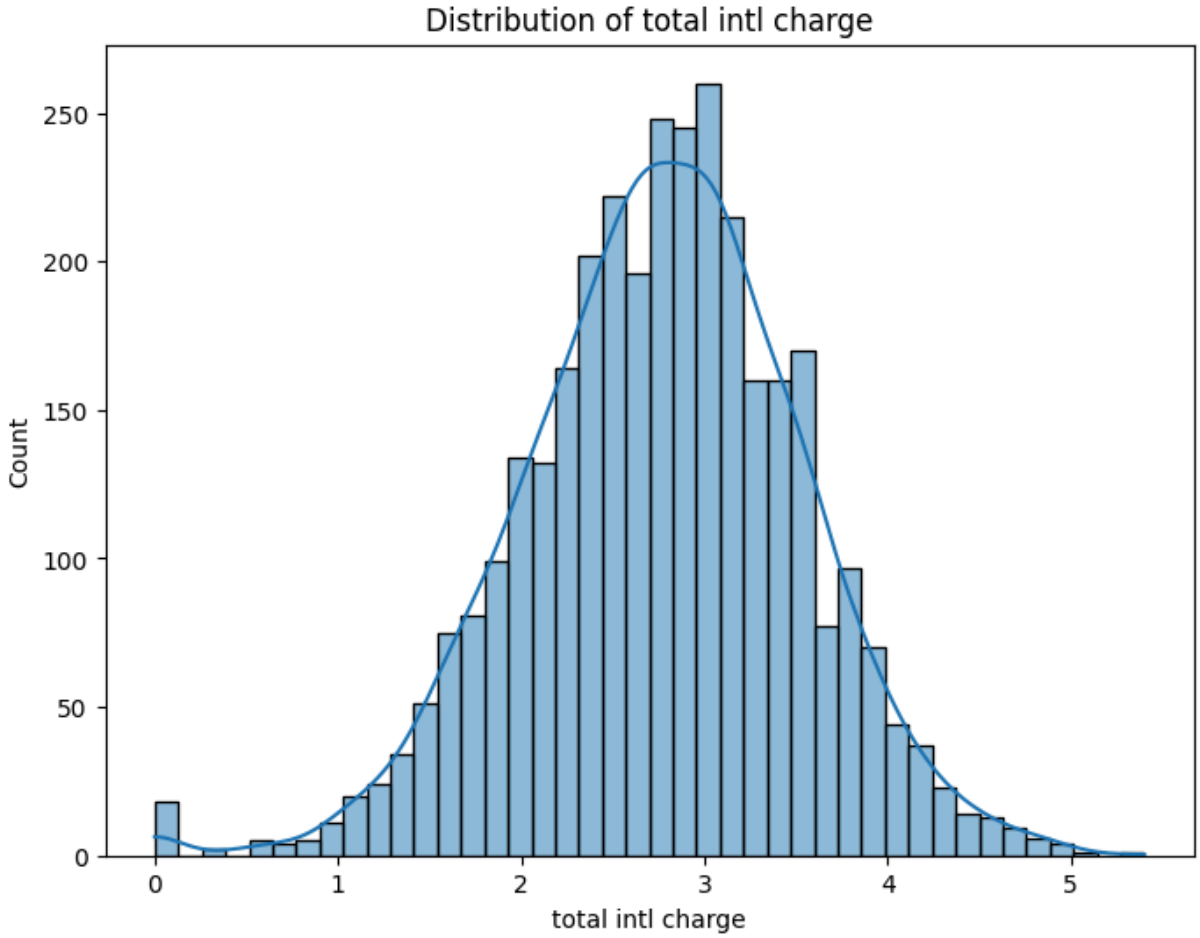

Boxplot of total night charge
total night charge
17.5
15.0
12.5
10.0
7.5
5.0
2.5

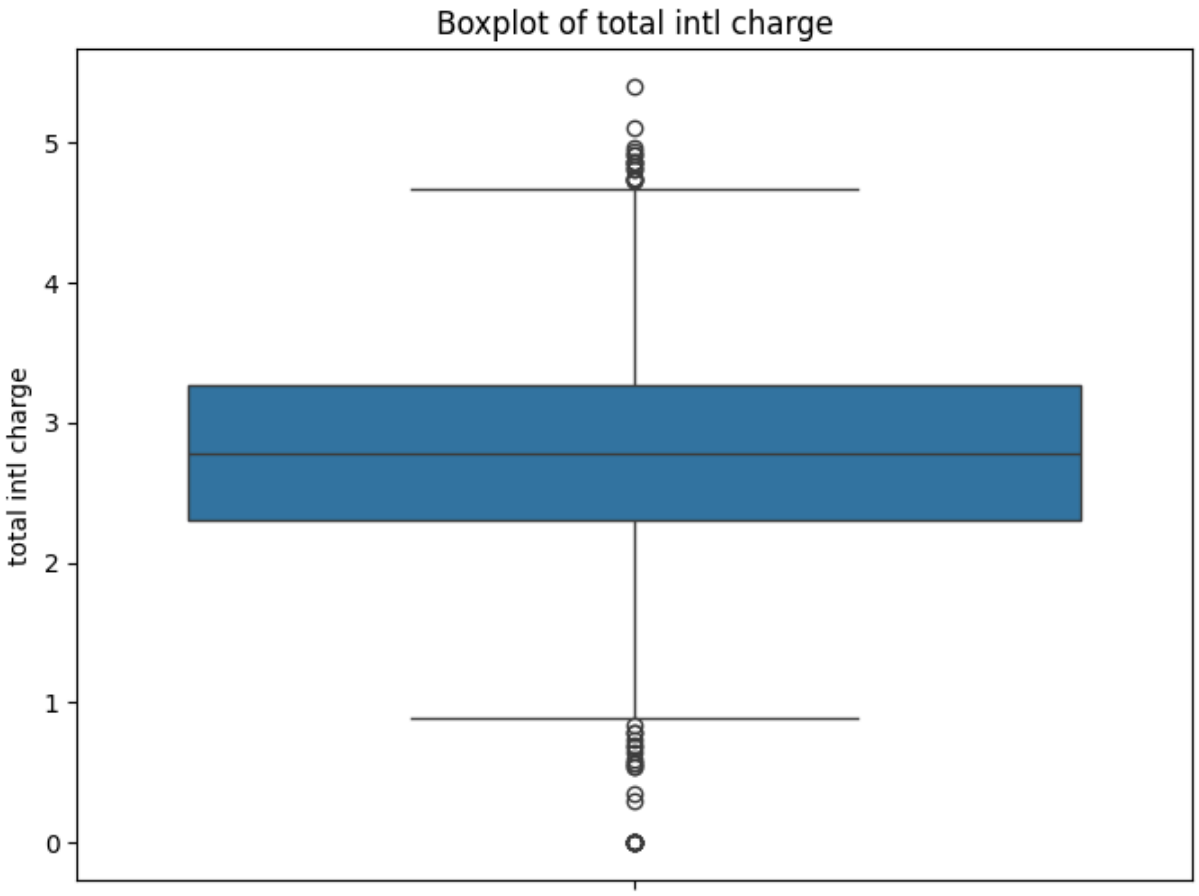

Distribution of total intl minutes
Count
250
200
150
100
50
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
total intl minutes

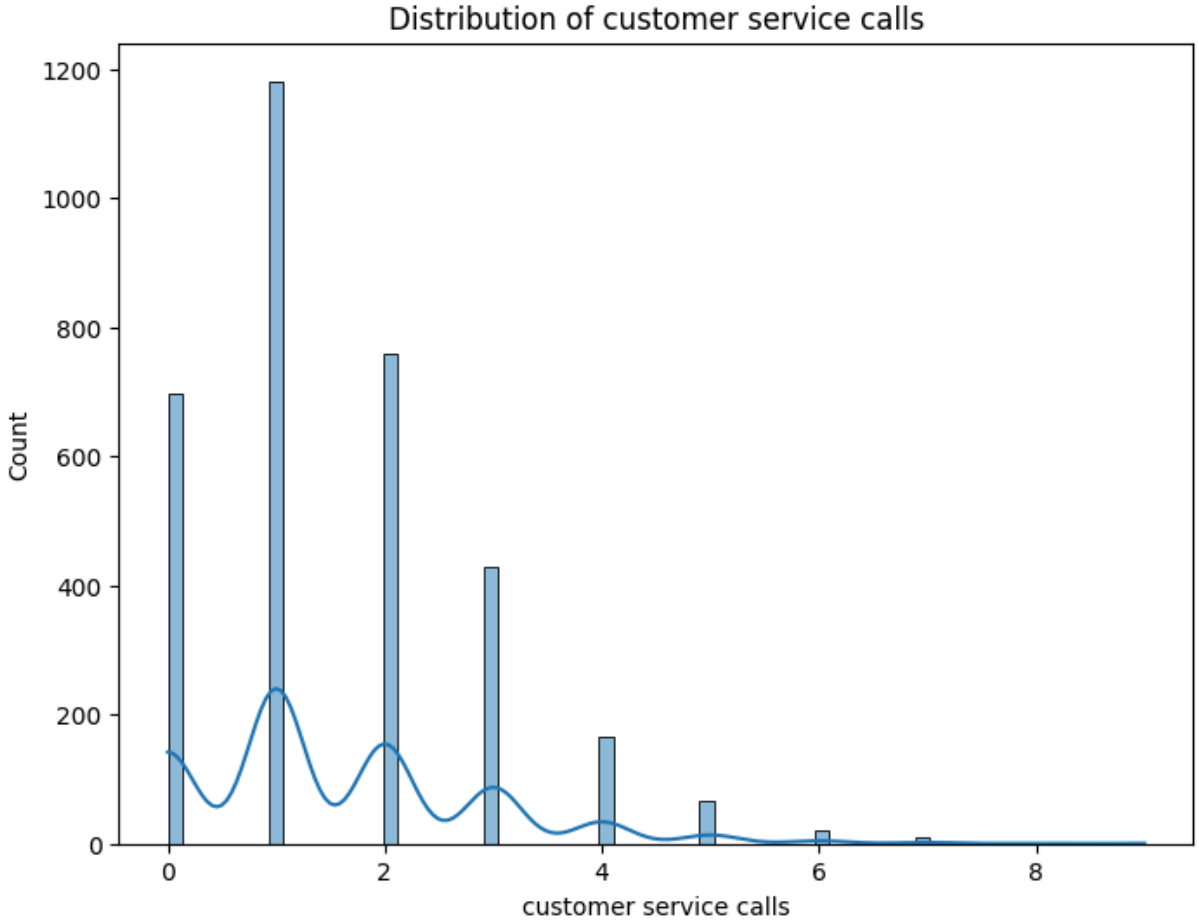

Boxplot of total intl minutes
total intl minutes
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0

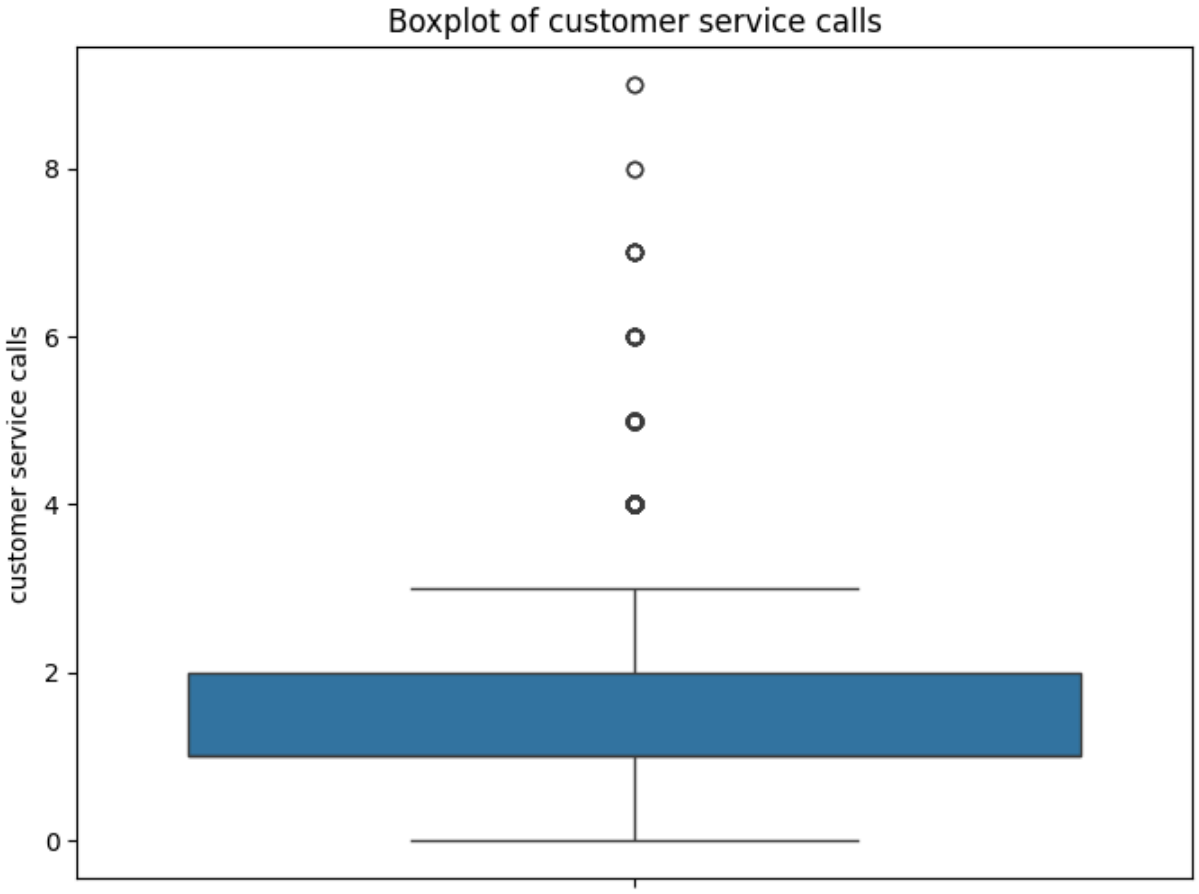

Distribution of total intl calls
Count
700
600
500
400
300
200
100
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
total intl calls

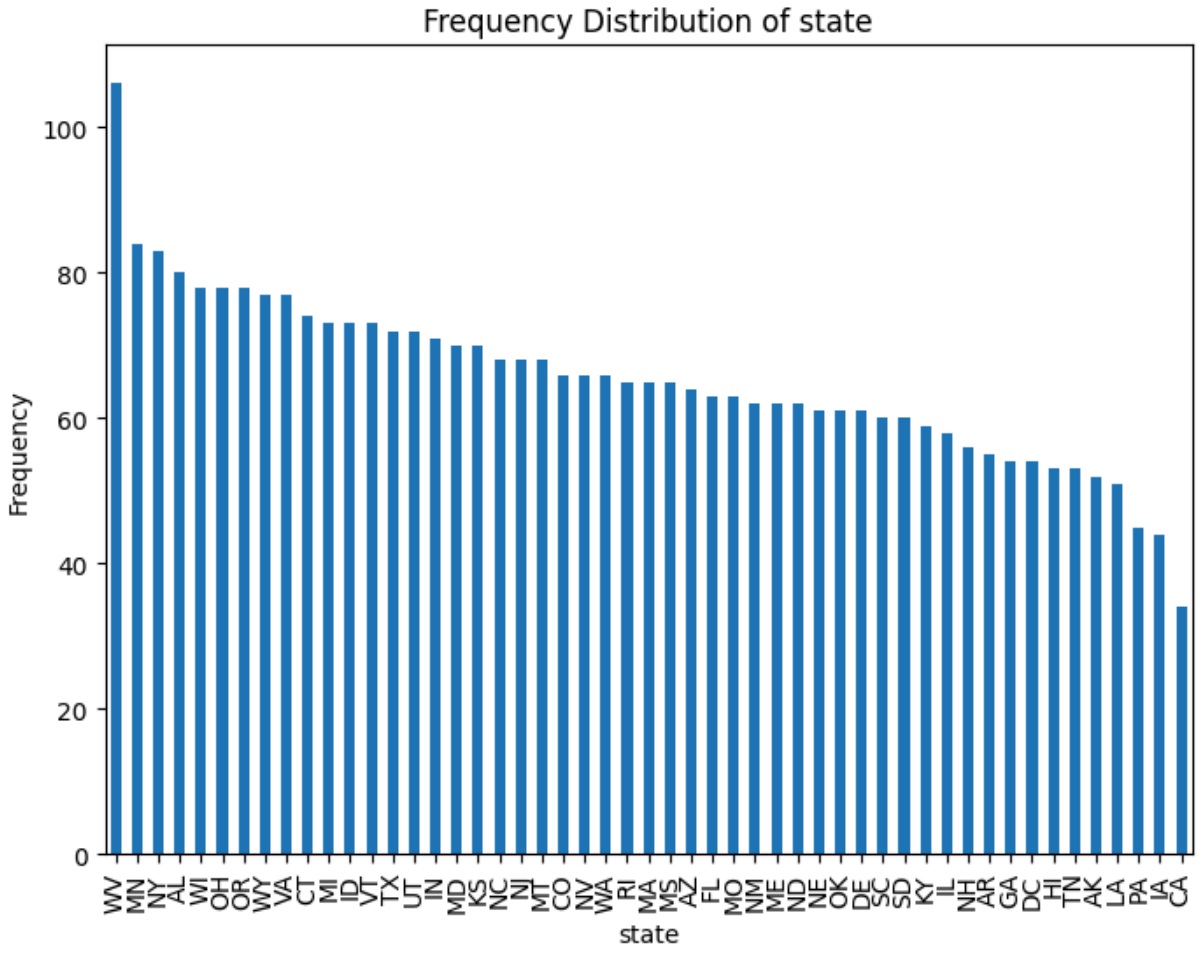

Boxplot of total intl calls
total intl calls
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0

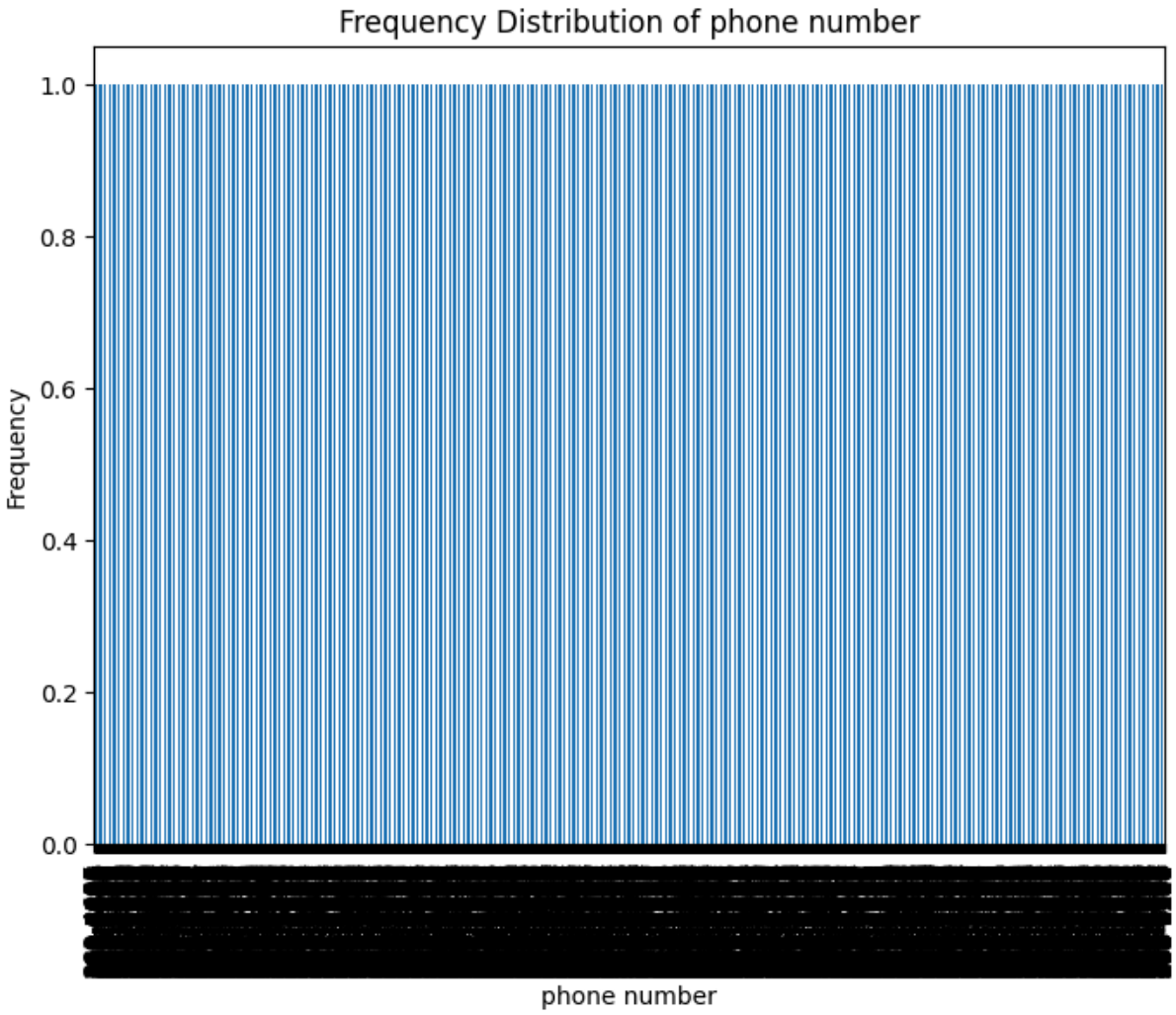

Distribution of total intl charge
Count
250
200
150
100
50
0
0
1
2
3
4
5
total intl charge

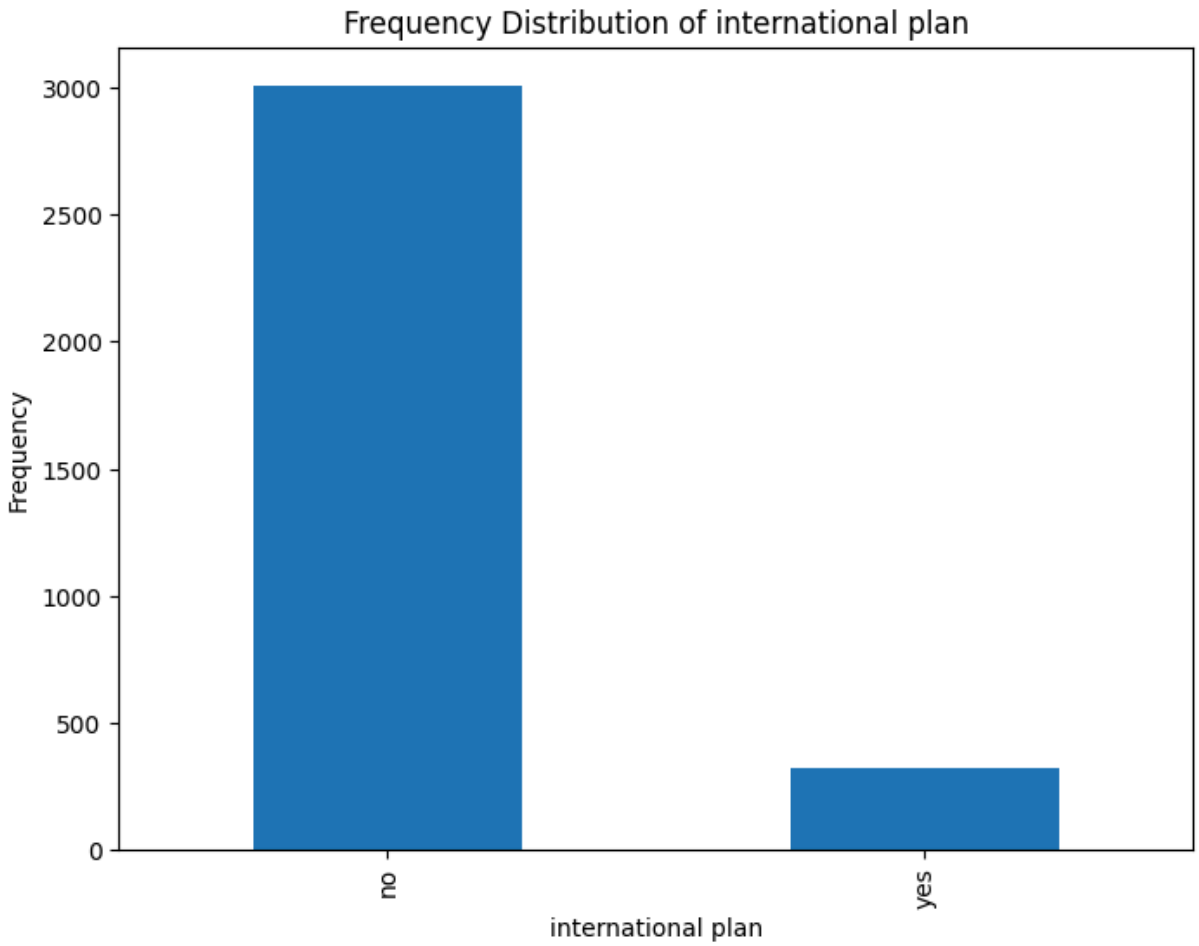

Boxplot of total intl charge
total intl charge
0
1
2
3
4
5

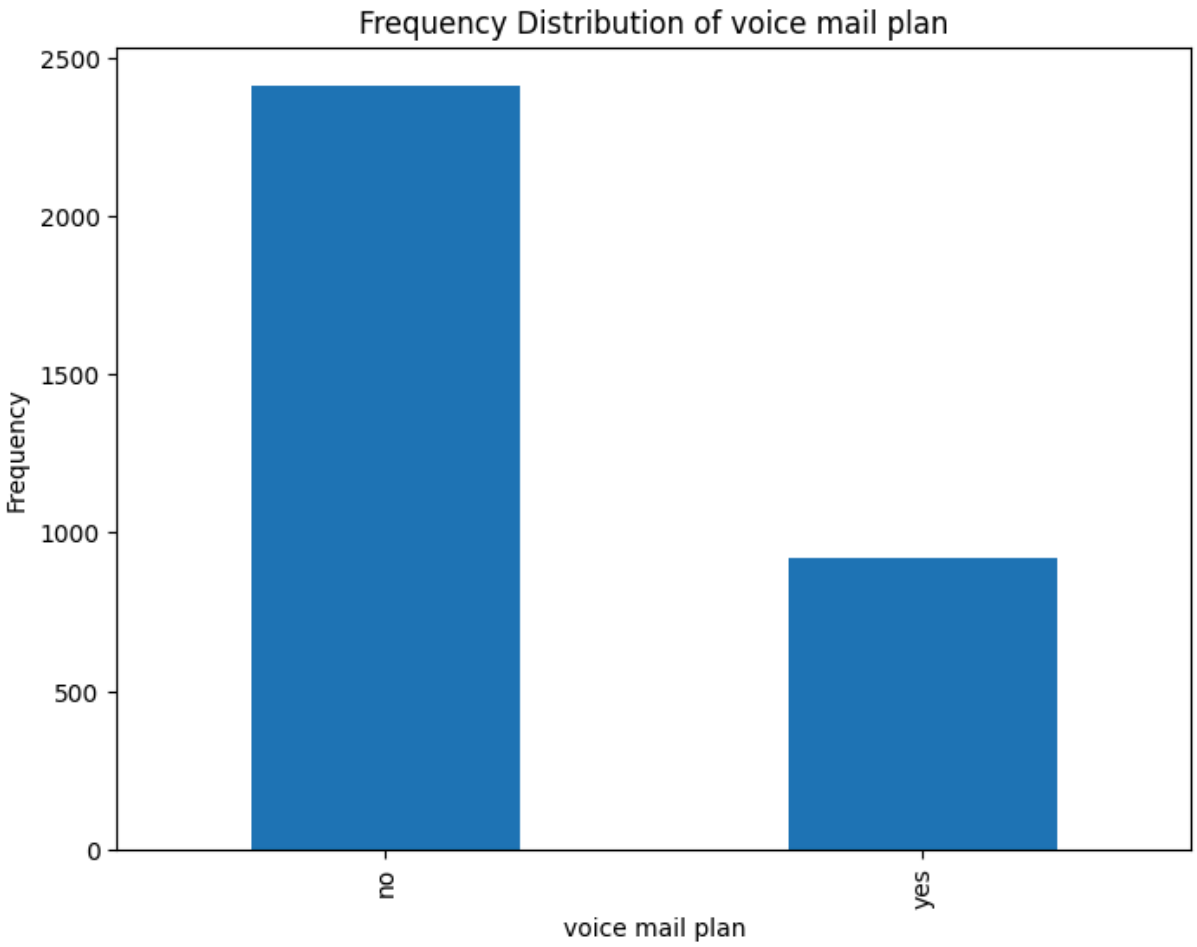

Distribution of customer service calls
Count
0
200
400
600
800
1000
1200
0
2
4
6
8
customer service calls

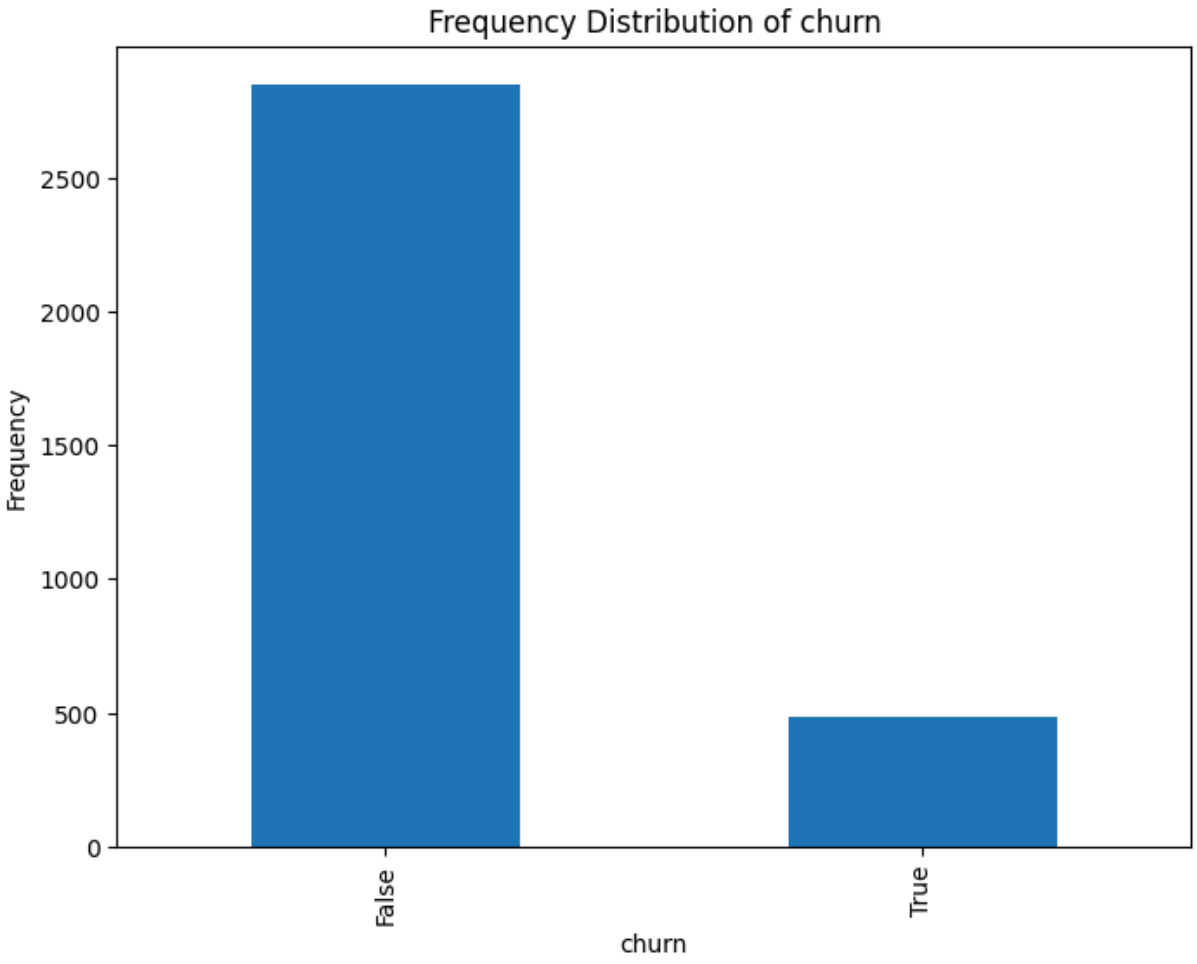

Boxplot of customer service calls
customer service calls
0
2
4
6
8


Frequency Distribution of state
Frequency
0
20
40
60
80
100
WV MN NY AL WI OH OR WY VA CT MI ID VT TX UT IN MD KS NC NJ MT CO NV WA RI MA MS AZ FL MO NM ME ND NE OK DE SC SD KY IL NH AR GA DC HI TN AK LA PA IA CA
state


Frequency Distribution of phone number
Frequency
1.0
0.8
0.6
0.4
0.2
0.0
phone number


Frequency Distribution of international plan
Frequency
3000
2500
2000
1500
1000
500
0
no
yes
international plan

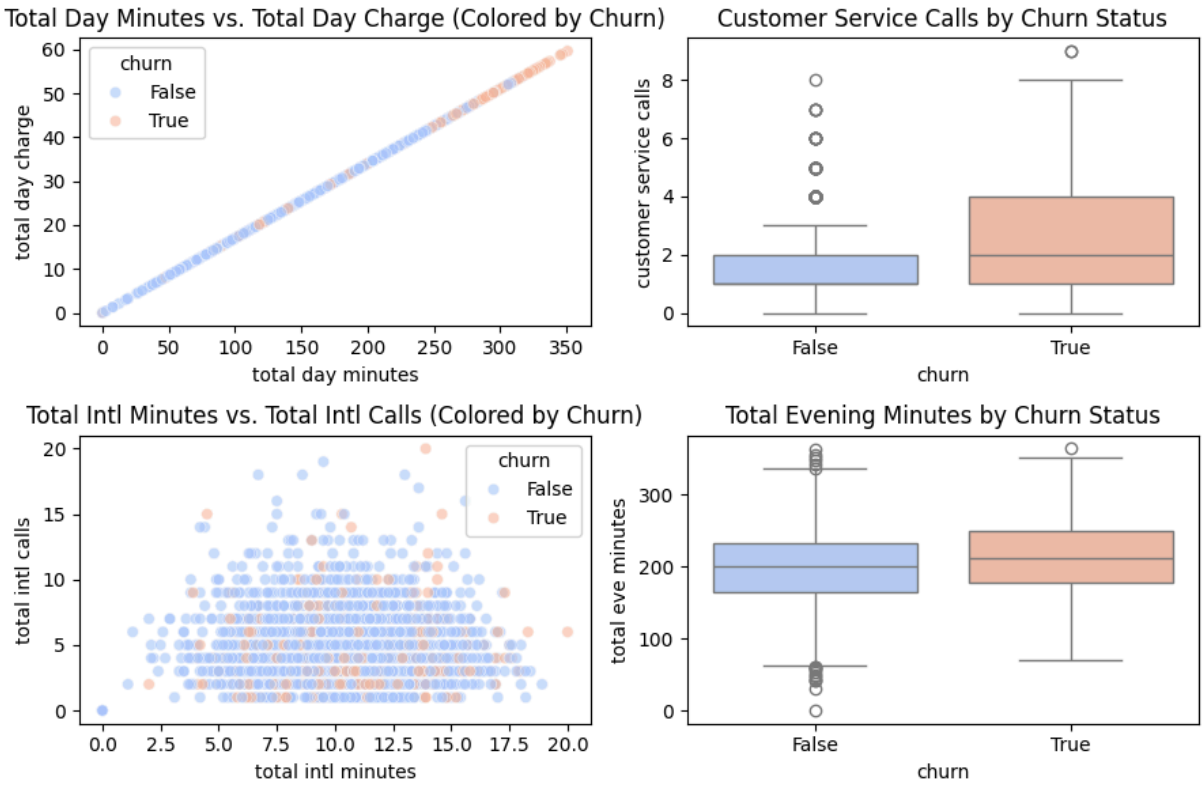

Frequency Distribution of voice mail plan
2500
2000
1500
1000
500
0
Frequency
no
yes
voice mail plan



BIvariate analysis

In [51]:
```
# Set up figure for bivariate analysis visualizations
plt.figure(figsize=(9, 6))

#  Churn vs. Total Day Minutes
plt.subplot(2, 2, 1)
sns.scatterplot(x=df["total day minutes"], y=df["total day charge"], hue=df["churn"
plt.title("Total Day Minutes vs. Total Day Charge (Colored by Churn)")

#  Churn vs. Customer Service Calls
plt.subplot(2, 2, 2)
sns.boxplot(x="churn", y="customer service calls", data=df, palette="coolwarm")
plt.title("Customer Service Calls by Churn Status")

#  Churn vs. Total Intl Minutes & Total Intl Calls
plt.subplot(2, 2, 3)
sns.scatterplot(x=df["total intl minutes"], y=df["total intl calls"], hue=df["churn
plt.title("Total Intl Minutes vs. Total Intl Calls (Colored by Churn)")

#  Churn vs. Total Evening Usage
plt.subplot(2, 2, 4)
sns.boxplot(x="churn", y="total eve minutes", data=df, palette="coolwarm")
plt.title("Total Evening Minutes by Churn Status")
```

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



Observations from Bivariate Analysis

1. Total Day Minutes vs. Total Day Charge:

There's a positive correlation between total day minutes and total day charge, as expected. Customers who churn seem to be spread across various usage levels, without a clear separation in this plot.

2. Customer Service Calls by Churn Status:

Customers who churned tend to have a higher median number of customer service calls. A significant number of churned customers have made 4 or more calls, suggesting that customer service interactions might be a factor in churn.

3. Total Intl Minutes vs. Total Intl Calls:

There's no clear pattern or significant separation between churned and non-churned customers based on international calls and minutes.

4. Total Evening Minutes by Churn Status:

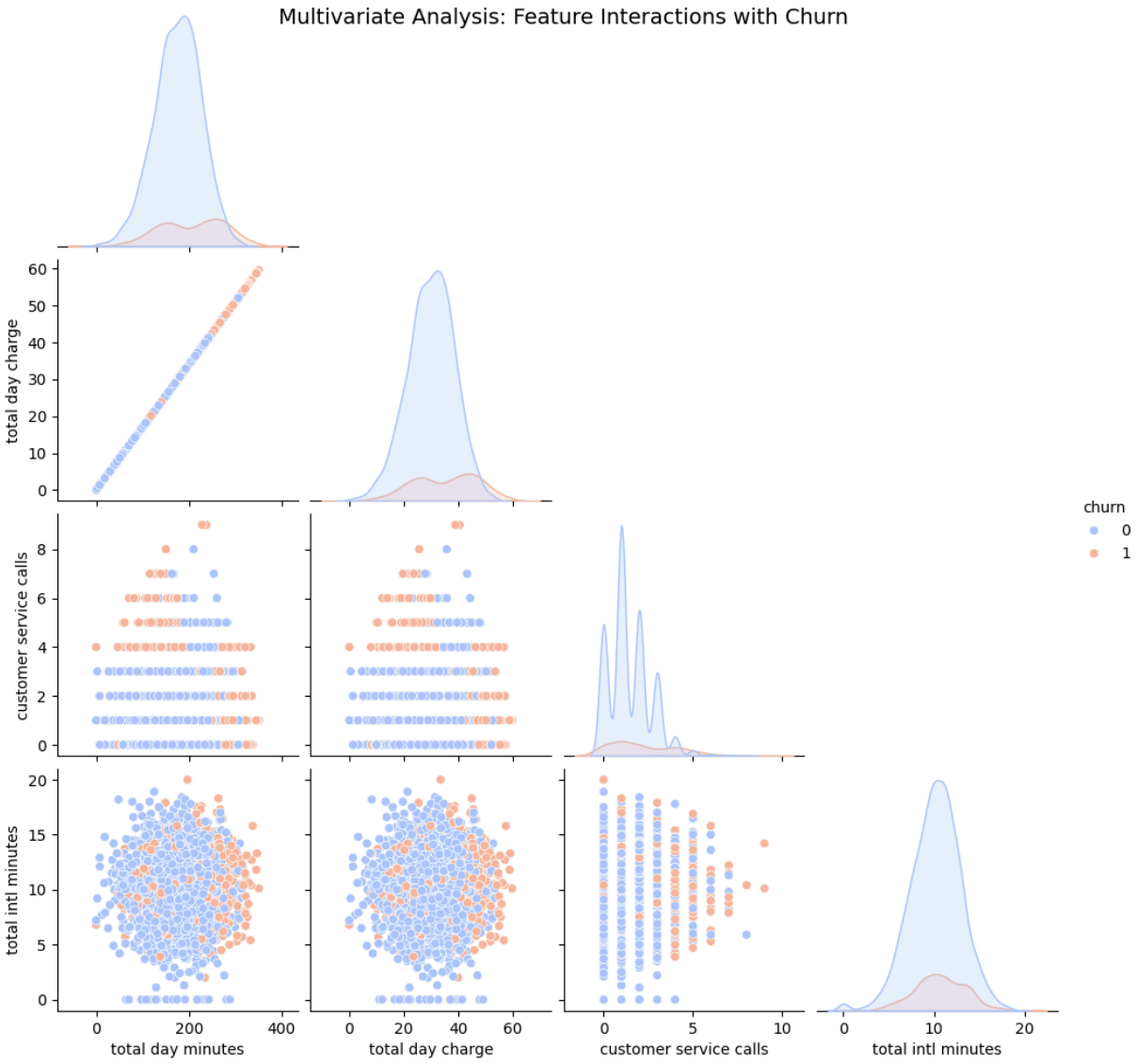
No clear difference in total evening minutes between customers who churned and those who didn't. The distributions overlap substantially.

Overall:

Customer service calls appear to be a potential predictor of churn. Further investigation into the reasons behind these calls may be beneficial. Total day minutes and charges don't show a clear distinction between churned and non-churned customers in this bivariate analysis. International calls and minutes, and evening minutes don't appear strongly related to churn in these visualizations. More in-depth analysis, perhaps with other variables or different visualization techniques, might reveal additional insights.

Multivariate analysis

In [52]:
```
# Convert churn to integer type again (to avoid issues with pairplot)
df["churn"] = df["churn"].astype(int)

# Re-run pairplot for multivariate analysis
selected_features = ["total day minutes", "total day charge", "customer service cal

sns.pairplot(df[selected_features], hue="churn", palette="coolwarm", diag_kind="kde
plt.suptitle("Multivariate Analysis: Feature Interactions with Churn", fontsize=14)
plt.show()
```



Key Observations from the Multivariate Analysis

1. Feature Interactions: The pairplot helps visualize how different features interact with each other and how these interactions might relate to customer churn. For example, you might observe that customers who churn tend to cluster in specific regions of the "total day minutes" vs. "total day charge" plot. Look for patterns and clusters that are more prevalent among churned customers than non-churned ones.

2. Combined Effects: The multivariate analysis allows you to see the combined effects of several features. For example, a customer with high "total day minutes" *and* a high number of "customer service calls" might have a higher probability of churning, something that may not be as apparent from individual bivariate plots.

3. Marginal Distributions: The diagonal plots show the distribution of each feature, broken down by churn status. This allows you to compare the distributions of features between churned and non-churned customers. For instance, if the distributions of "customer

service calls" are significantly different (e.g., churned customers have a higher average number of calls), it provides more evidence for that variable's importance.

4. Identifying Potential Predictors: The goal is to look for features or combinations of features that clearly separate churned customers from non-churned customers in the plots. These features are likely strong predictors of churn.

Preprocessing

encoding###

In [53]:
```
#Convert categorical variables into numerical formats using one-hot encoding.
df[['international plan', 'voice mail plan']] = df[['international plan', 'voice ma
df = pd.get_dummies(df, columns=['state', 'area code'], dtype=int)
df.head()
```

Out[53]:

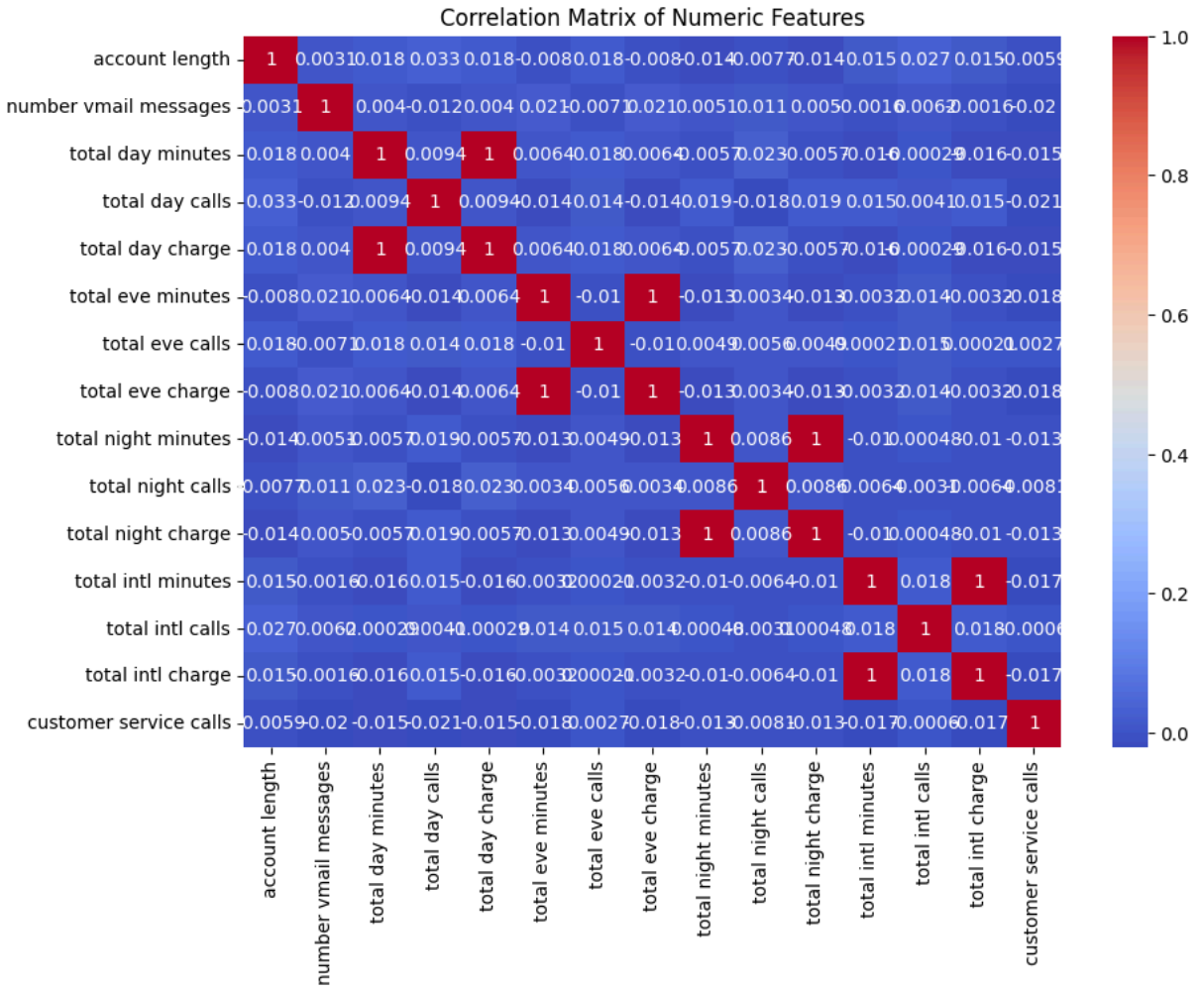
	account length	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	tota ev call
0	128	382-4657	0	1	25	265.1	110	45.07	197.4	9
1	107	371-7191	0	1	26	161.6	123	27.47	195.5	10
2	137	358-1921	0	0	0	243.4	114	41.38	121.2	11
3	84	375-9999	1	0	0	299.4	71	50.90	61.9	8
4	75	330-6626	1	0	0	166.7	113	28.34	148.3	12

5 rows × 73 columns

In [54]:
```
#Remove phone number, since it does not help in predicting churn
df = df.drop(columns=['phone number'])
```

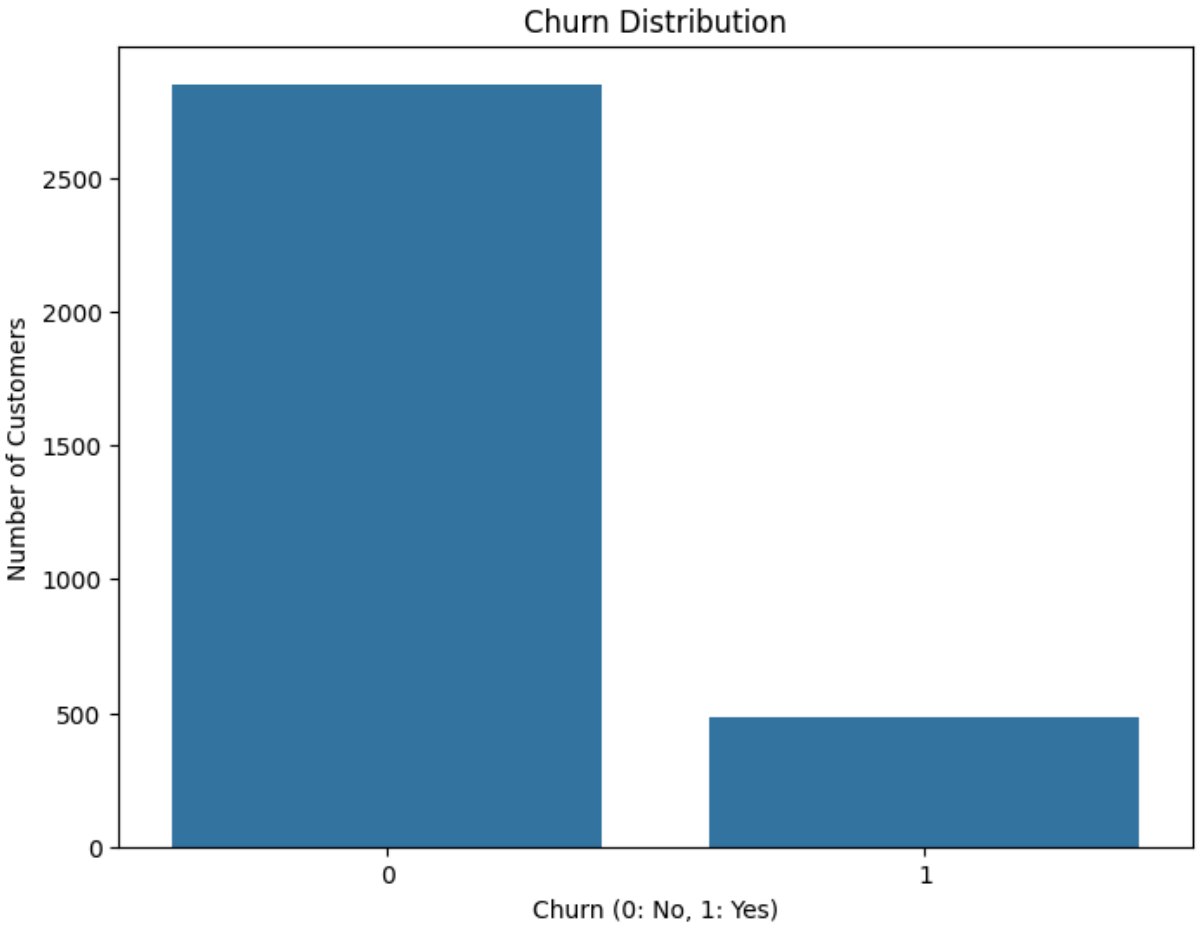
In [62]:
```
# Remove linear dependencies between features
numerical_features = [
    'account length', 'number vmail messages', 'total day minutes', 'total day call
    'total day charge', 'total eve minutes', 'total eve calls', 'total eve charge',
    'total night minutes', 'total night calls', 'total night charge', 'total intl m
    'total intl calls', 'total intl charge', 'customer service calls'
]

correlation_matrix = df[numerical_features].corr(method='spearman')
```

```
plt.figure(figsize=(10, 7))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix of Numeric Features')
plt.show()
```



Churn Distribution

In [66]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='churn', data=df)
plt.title('Churn Distribution')
plt.xlabel('Churn (0: No, 1: Yes)')
plt.ylabel('Number of Customers')
plt.show()
```



In [16]:
```
df = df.drop(columns=['total day charge', 'total eve charge', 'total night charge',
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 68 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   account length          3333 non-null   int64  
 1   international plan      3333 non-null   int64  
 2   voice mail plan         3333 non-null   int64  
 3   number vmail messages   3333 non-null   int64  
 4   total day minutes       3333 non-null   float64
 5   total day calls         3333 non-null   int64  
 6   total eve minutes       3333 non-null   float64
 7   total eve calls         3333 non-null   int64  
 8   total night minutes     3333 non-null   float64
 9   total night calls       3333 non-null   int64  
 10  total intl minutes      3333 non-null   float64
 11  total intl calls        3333 non-null   int64  
 12  customer service calls  3333 non-null   int64  
 13  churn                   3333 non-null   int64  
 14  state_AK                3333 non-null   int64  
 15  state_AL                3333 non-null   int64  
 16  state_AR                3333 non-null   int64  
 17  state_AZ                3333 non-null   int64  
 18  state_CA                3333 non-null   int64  
 19  state_CO                3333 non-null   int64  
 20  state_CT                3333 non-null   int64  
 21  state_DC                3333 non-null   int64  
 22  state_DE                3333 non-null   int64  
 23  state_FL                3333 non-null   int64  
 24  state_GA                3333 non-null   int64  
 25  state_HI                3333 non-null   int64  
 26  state_IA                3333 non-null   int64  
 27  state_ID                3333 non-null   int64  
 28  state_IL                3333 non-null   int64  
 29  state_IN                3333 non-null   int64  
 30  state_KS                3333 non-null   int64  
 31  state_KY                3333 non-null   int64  
 32  state_LA                3333 non-null   int64  
 33  state_MA                3333 non-null   int64  
 34  state_MD                3333 non-null   int64  
 35  state_ME                3333 non-null   int64  
 36  state_MI                3333 non-null   int64  
 37  state_MN                3333 non-null   int64  
 38  state_MO                3333 non-null   int64  
 39  state_MS                3333 non-null   int64  
 40  state_MT                3333 non-null   int64  
 41  state_NC                3333 non-null   int64  
 42  state_ND                3333 non-null   int64  
 43  state_NE                3333 non-null   int64  
 44  state_NH                3333 non-null   int64  
 45  state_NJ                3333 non-null   int64  
 46  state_NM                3333 non-null   int64  
 47  state_NV                3333 non-null   int64  
 48  state_NY                3333 non-null   int64  
 49  state_OH                3333 non-null   int64  
 50  state_OK                3333 non-null   int64  
```

```
 51  state_OR               3333 non-null   int64
 52  state_PA               3333 non-null   int64
 53  state_RI               3333 non-null   int64
 54  state_SC               3333 non-null   int64
 55  state_SD               3333 non-null   int64
 56  state_TN               3333 non-null   int64
 57  state_TX               3333 non-null   int64
 58  state_UT               3333 non-null   int64
 59  state_VA               3333 non-null   int64
 60  state_VT               3333 non-null   int64
 61  state_WA               3333 non-null   int64
 62  state_WI               3333 non-null   int64
 63  state_WV               3333 non-null   int64
 64  state_WY               3333 non-null   int64
 65  area code_408          3333 non-null   int64
 66  area code_415          3333 non-null   int64
 67  area code_510          3333 non-null   int64
dtypes: float64(4), int64(64)
memory usage: 1.7 MB
```

Scaling###

In [17]:
```
#split your dataset into training and testing sets
from sklearn.model_selection import train_test_split
X = df.drop('churn', axis=1)  # Features
y = df['churn']               # Target variable
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_st
```

In [18]:
```
#Standardize the training and testing sets
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(X_train)

X_train_st = scaler.transform(X_train)
X_valid_st = scaler.transform(X_test)
```

In [19]:
```
# Convert scaled arrays back to DataFrames for easier inspection
X_train_scaled_df = pd.DataFrame(X_train_st, columns=X.columns) # Change X_train_sc
X_test_scaled_df = pd.DataFrame(X_valid_st, columns=X.columns) # Change X_test_scal

# Display the mean and standard deviation of the scaled training data
print("Training Data Mean:\n", X_train_scaled_df.mean())
print("\nTraining Data Standard Deviation:\n", X_train_scaled_df.std())

# Display the mean and standard deviation of the scaled testing data
print("\nTesting Data Mean:\n", X_test_scaled_df.mean())
print("\nTesting Data Standard Deviation:\n", X_test_scaled_df.std())
```

```
Training Data Mean:
 account length          -1.421654e-17
international plan      -4.975789e-17
voice mail plan         -6.184195e-17
number vmail messages   -4.620376e-17
total day minutes        1.610023e-16
                             ...
state_WV                -2.061398e-17
state_WY                -1.421654e-17
area code_408            5.686617e-18
area code_415           -6.895023e-17
area code_510           -2.843308e-17
Length: 67, dtype: float64

Training Data Standard Deviation:
 account length           1.0002
international plan       1.0002
voice mail plan          1.0002
number vmail messages    1.0002
total day minutes        1.0002
                          ...
state_WV                 1.0002
state_WY                 1.0002
area code_408            1.0002
area code_415            1.0002
area code_510            1.0002
Length: 67, dtype: float64

Testing Data Mean:
 account length           0.011575
international plan      -0.083161
voice mail plan          0.055053
number vmail messages    0.050326
total day minutes       -0.010897
                            ...
state_WV                 0.013575
state_WY                -0.023687
area code_408            0.056909
area code_415           -0.057964
area code_510            0.010369
Length: 67, dtype: float64

Testing Data Standard Deviation:
 account length           0.989846
international plan       0.881556
voice mail plan          1.027189
number vmail messages    1.020775
total day minutes        0.981738
                            ...
state_WV                 1.036484
state_WY                 0.923665
area code_408            1.032190
area code_415            0.999359
area code_510            1.006490
Length: 67, dtype: float64
```

Modeling

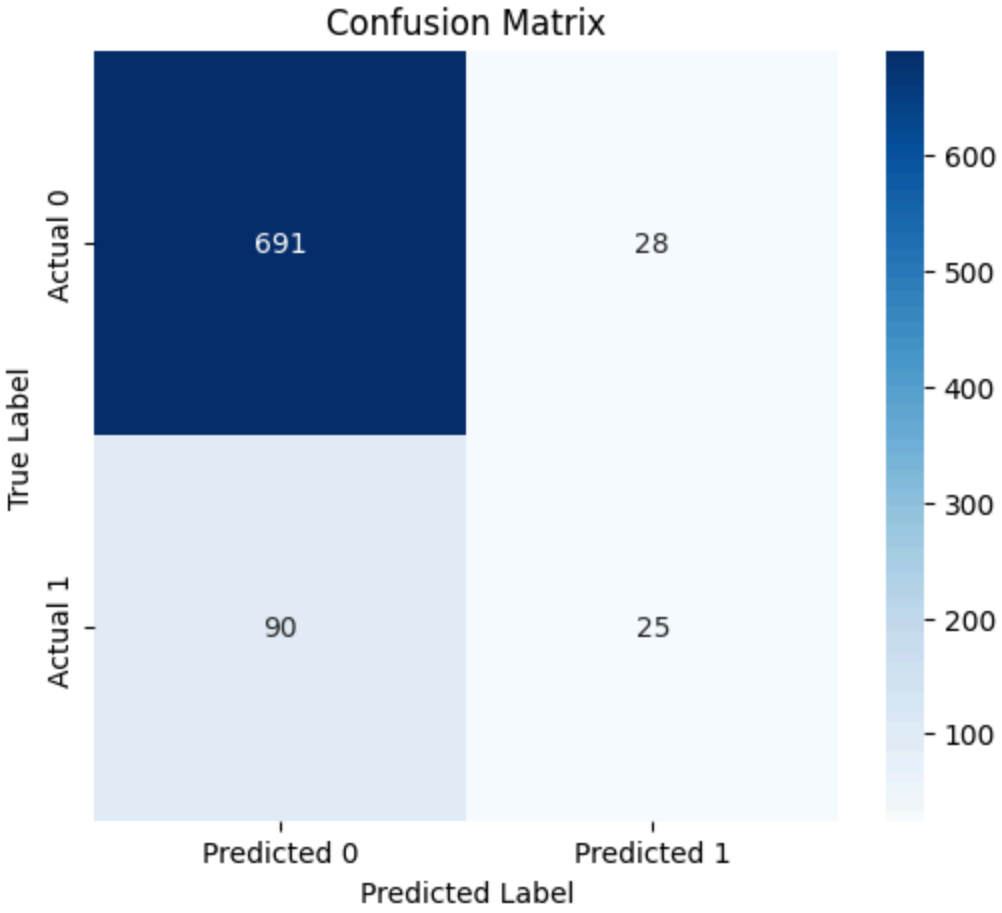
Regression

logistic regression

In [20]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# Initialize and train the Logistic Regression model
logreg = LogisticRegression()
logreg.fit(X_train_st, y_train)

# Make predictions on the test set
y_pred = logreg.predict(X_valid_st)

# Evaluate the model
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.96      0.92       719
           1       0.47      0.22      0.30       115

    accuracy                           0.86       834
   macro avg       0.68      0.59      0.61       834
weighted avg       0.83      0.86      0.84       834

[[691  28]
 [ 90  25]]
Accuracy: 0.8585131894484412
```

In [21]:
```
# Plot confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



Classification

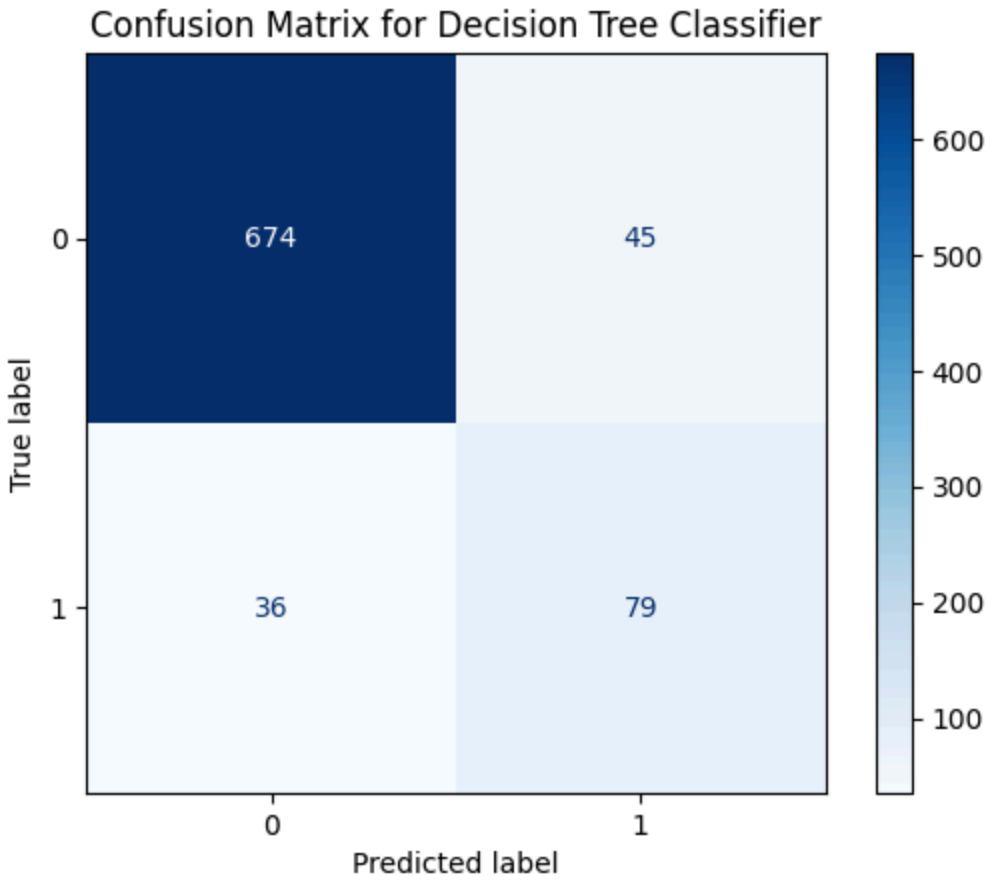
Decision tree

In [22]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score
from sklearn.metrics import ConfusionMatrixDisplay


clf = DecisionTreeClassifier(random_state=3)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
print(f"F1-score: {f1}")
```

```
# Classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9028776978417267
Recall: 0.6869565217391305
Precision: 0.6370967741935484
F1-score: 0.6610878661087866
              precision    recall  f1-score   support

           0       0.95      0.94      0.94       719
           1       0.64      0.69      0.66       115

    accuracy                           0.90       834
   macro avg       0.79      0.81      0.80       834
weighted avg       0.91      0.90      0.90       834
```

In [23]:
```
cm = confusion_matrix(y_test, y_pred, labels=clf.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=clf.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix for Decision Tree Classifier')
plt.show()
```



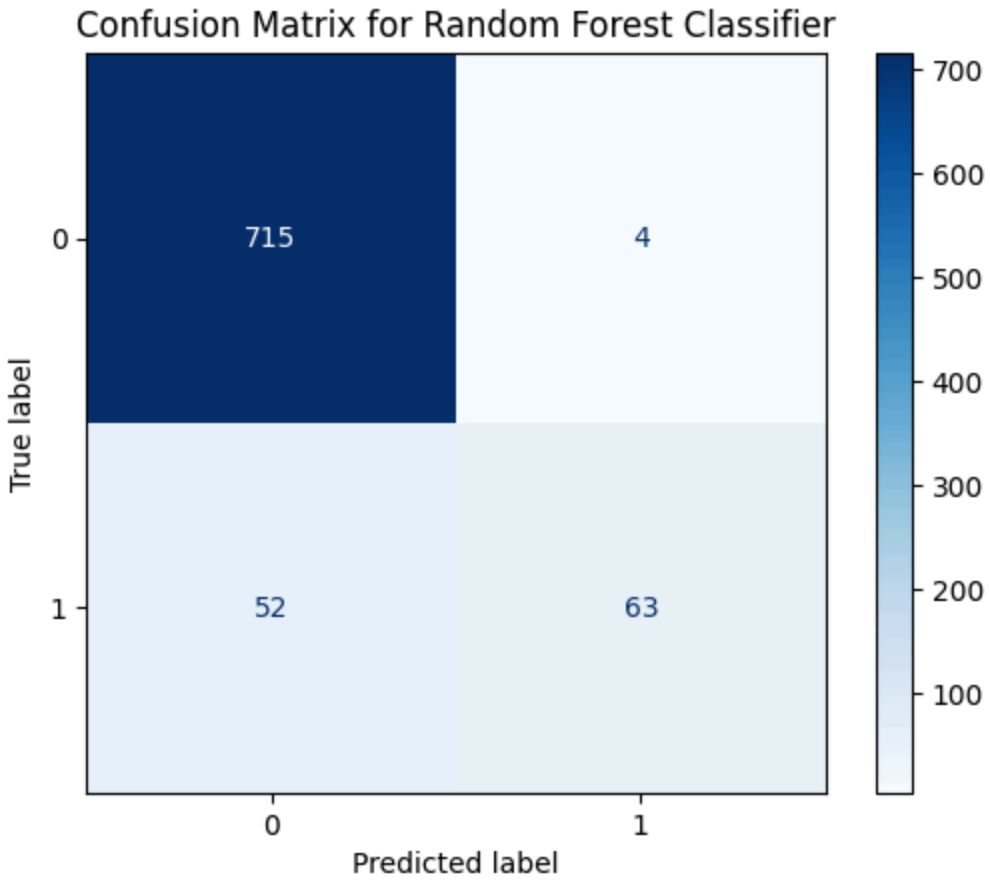
random forest####

In [24]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classificatio
rf = RandomForestClassifier(random_state=3)
```

```
rf.fit(X_train_st, y_train)
y_pred = rf.predict(X_valid_st)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
print(f"F1-score: {f1}")

# Classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9328537170263789
Recall: 0.5478260869565217
Precision: 0.9402985074626866
F1-score: 0.6923076923076923
              precision    recall  f1-score   support

           0       0.93      0.99      0.96       719
           1       0.94      0.55      0.69       115

    accuracy                           0.93       834
   macro avg       0.94      0.77      0.83       834
weighted avg       0.93      0.93      0.93       834
```

In [25]:
```
cm = confusion_matrix(y_test, y_pred, labels=rf.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=rf.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix for Random Forest Classifier')
plt.show()
```

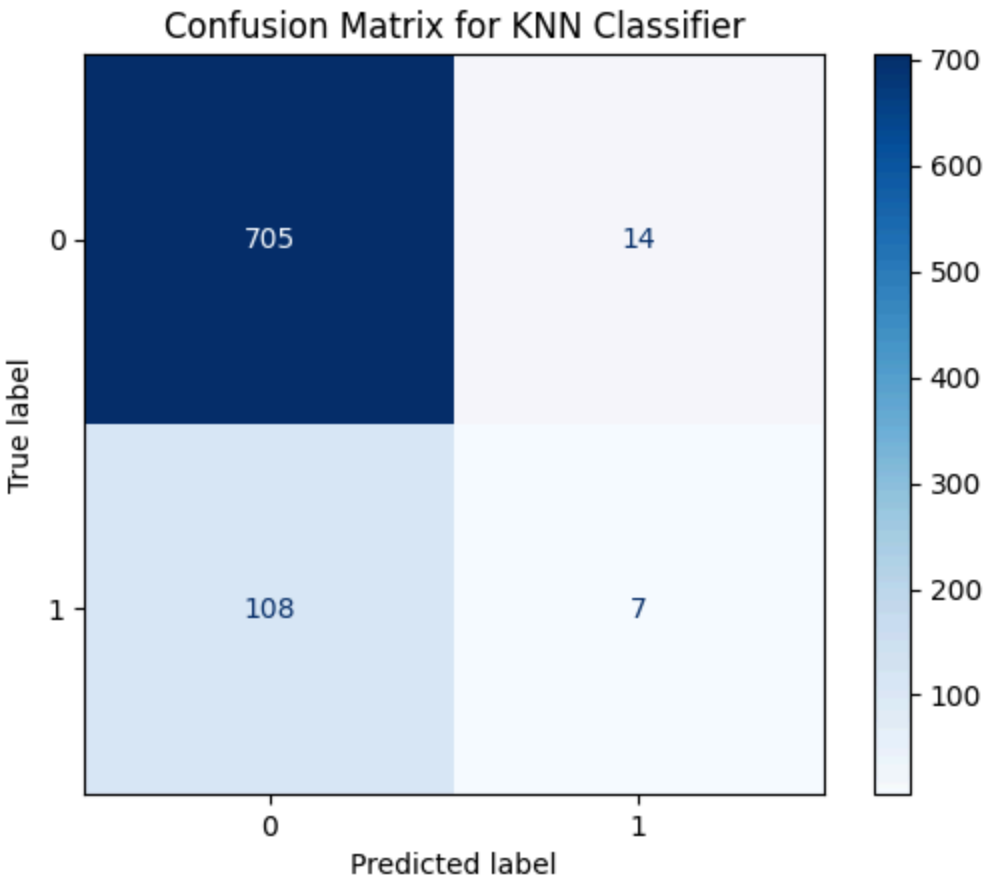


K-NN model

In [26]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classificatio
knn = KNeighborsClassifier(n_neighbors=5)  # You can choose the value of k
knn.fit(X_train_st, y_train)
y_pred = knn.predict(X_valid_st)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
print(f"F1-score: {f1}")

# Classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8537170263788969
Recall: 0.06086956521739131
Precision: 0.3333333333333333
F1-score: 0.10294117647058823
              precision    recall  f1-score   support

           0       0.87      0.98      0.92       719
           1       0.33      0.06      0.10       115

    accuracy                           0.85       834
   macro avg       0.60      0.52      0.51       834
weighted avg       0.79      0.85      0.81       834
```

In [27]:
```
cm = confusion_matrix(y_test, y_pred, labels=knn.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=knn.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix for KNN Classifier')
plt.show()
```



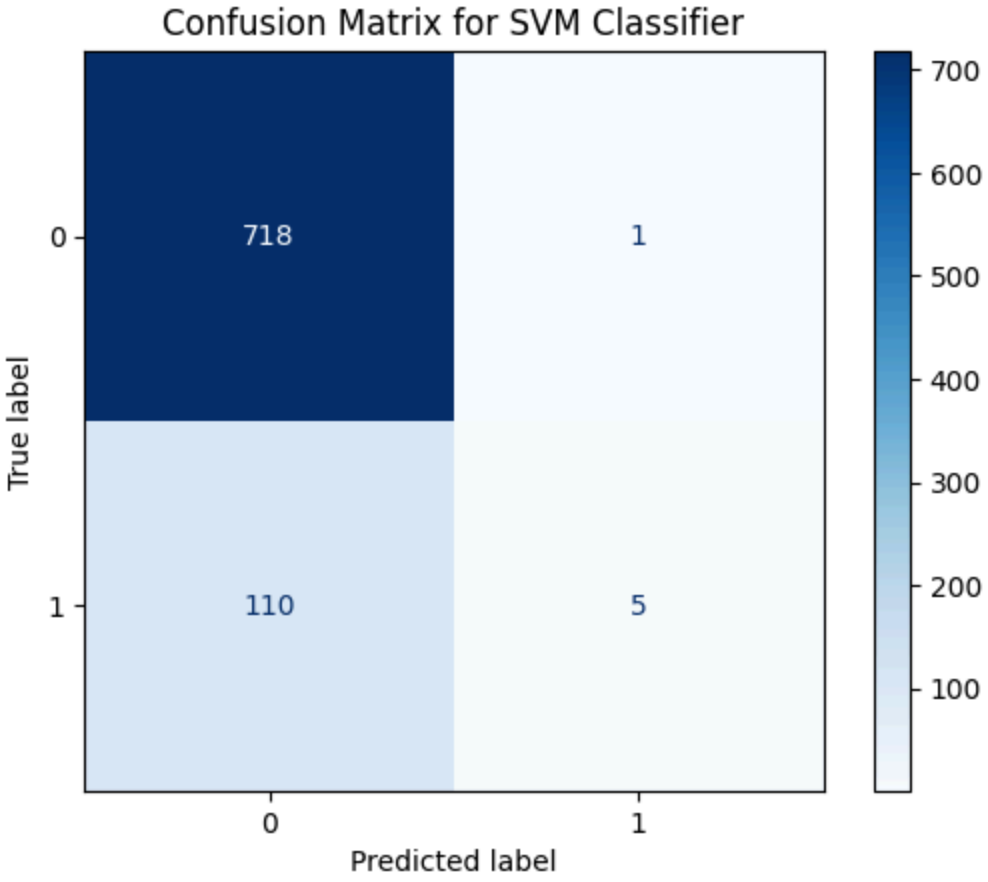
SVM

In [28]:
```
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, classification_report, ConfusionMatri
svm = SVC(random_state=3)
svm.fit(X_train_st, y_train)
y_pred = svm.predict(X_valid_st)
# Evaluate the model
```

```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
print(f"F1-score: {f1}")

# Classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8669064748201439
Recall: 0.043478260869565216
Precision: 0.8333333333333334
F1-score: 0.08264462809917356
              precision    recall  f1-score   support

           0       0.87      1.00      0.93       719
           1       0.83      0.04      0.08       115

    accuracy                           0.87       834
   macro avg       0.85      0.52      0.51       834
weighted avg       0.86      0.87      0.81       834
```

In [29]:
```
cm = confusion_matrix(y_test, y_pred, labels=svm.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=svm.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix for SVM Classifier')
plt.show()
```



Neural network

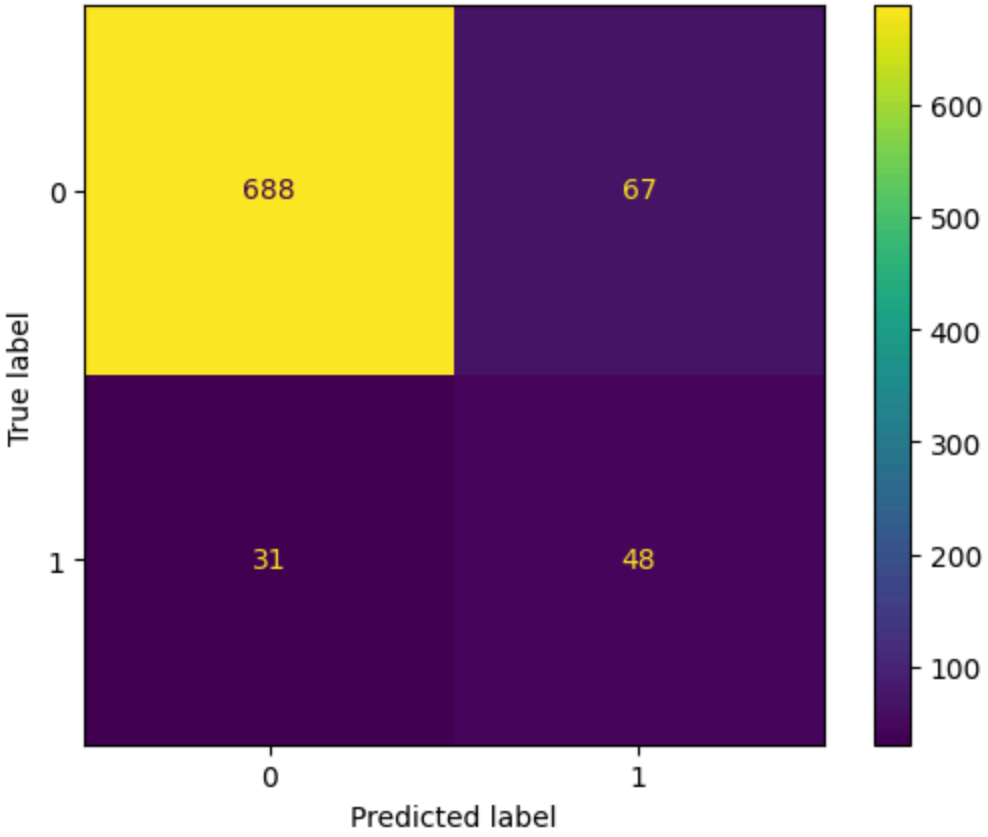
In [30]:
```
from sklearn.neural_network import MLPClassifier

NeuralNet = MLPClassifier(random_state=5, max_iter=1000)
NeuralNet.fit(X_train_st, y_train)
y_pred = NeuralNet.predict(X_valid_st)

df_scores = pd.DataFrame({'Neural network': [f1_score(y_pred, y_test), accuracy_sco
df_scores.T
```

Out[30]:

	f1_score	accuracy_score	recall_score
Neural network	0.494845	0.882494	0.607595

In [31]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

def show_confusion_matrix(y_true, y_pred):
    """
    Displays the confusion matrix.

    Args:
        y_true: The true target values.
        y_pred: The predicted target values.
    """
```

```
    cm = confusion_matrix(y_true, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot()
    plt.show()



show_confusion_matrix(y_pred, y_test)
```



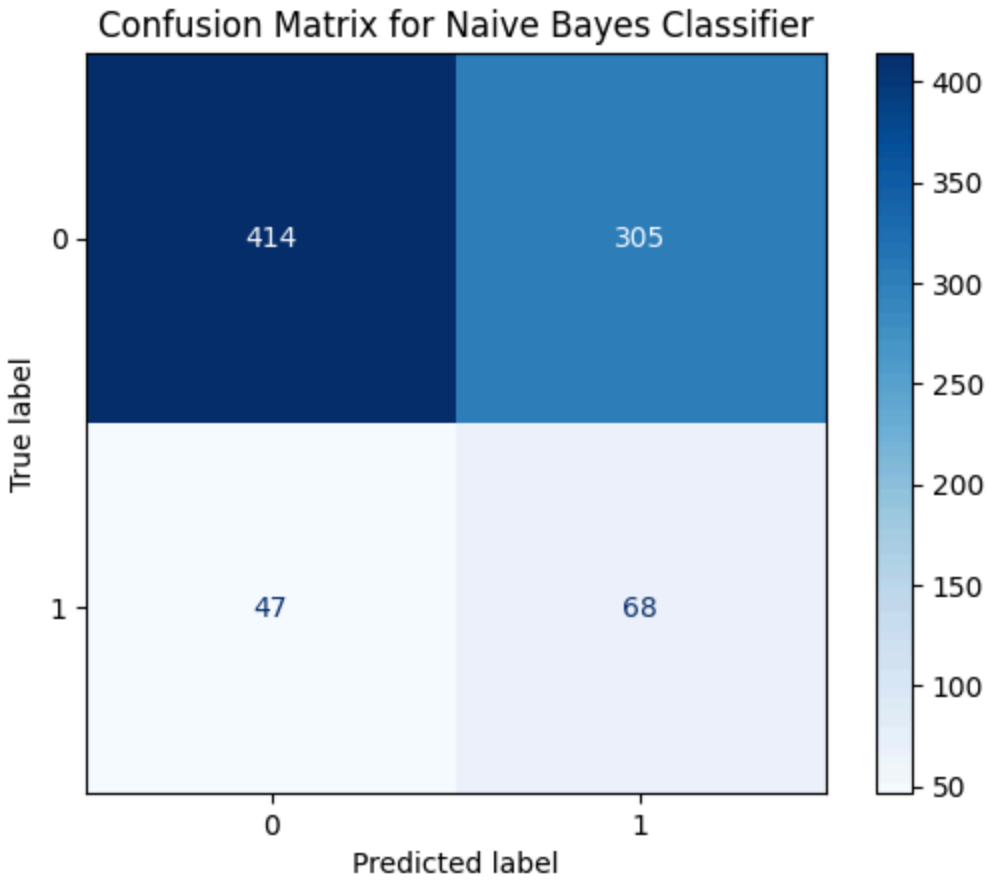
Naive Bayes

In [32]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classificatio
nb = GaussianNB()
nb.fit(X_train_st, y_train)
y_pred = nb.predict(X_valid_st)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
print(f"F1-score: {f1}")
```

```
# Classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.5779376498800959
Recall: 0.591304347826087
Precision: 0.18230563002680966
F1-score: 0.2786885245901639
              precision    recall  f1-score   support

           0       0.90      0.58      0.70       719
           1       0.18      0.59      0.28       115

    accuracy                           0.58       834
   macro avg       0.54      0.58      0.49       834
weighted avg       0.80      0.58      0.64       834
```

In [33]:
```
cm = confusion_matrix(y_test, y_pred, labels=nb.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=nb.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix for Naive Bayes Classifier')
plt.show()
```



Hyperparameter Tuning

tuned decision tree model

In [34]:
```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid for hyperparameter tuning
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=clf, param_grid=param_grid, cv=5, scoring='f1'

# Fit the GridSearchCV object to the training data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters and the best model
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_

print(f"Best hyperparameters: {best_params}")

# Evaluate the best model on the test data
y_pred = best_model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy (tuned): {accuracy}")
print(f"Recall (tuned): {recall}")
print(f"Precision (tuned): {precision}")
print(f"F1-score (tuned): {f1}")

print(classification_report(y_test, y_pred))
```

```
Best hyperparameters: {'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf':
2, 'min_samples_split': 10}
Accuracy (tuned): 0.9436450839328537
Recall (tuned): 0.7217391304347827
Precision (tuned): 0.8469387755102041
F1-score (tuned): 0.7793427230046949
              precision    recall  f1-score   support

           0       0.96      0.98      0.97       719
           1       0.85      0.72      0.78       115

    accuracy                           0.94       834
   macro avg       0.90      0.85      0.87       834
weighted avg       0.94      0.94      0.94       834
```

tuned random forest model

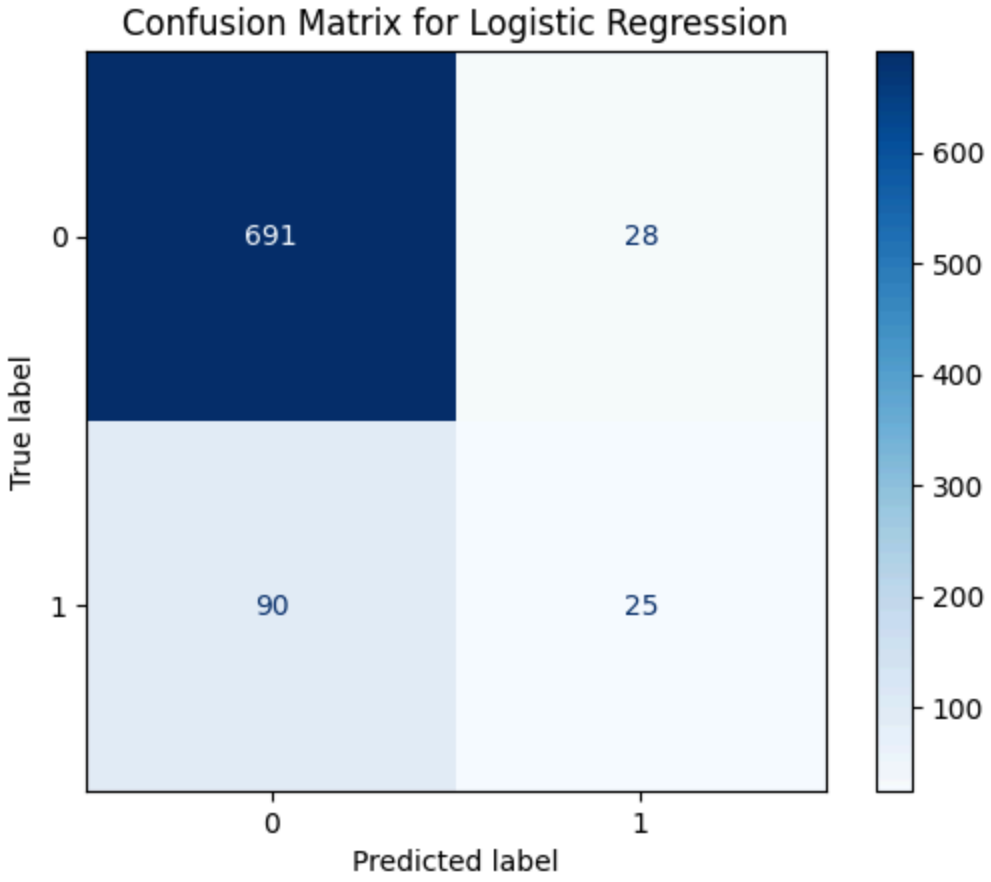
In [35]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score

# Define the parameter grid for hyperparameter tuning
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2']
}

# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, scoring='f1')

# Fit the GridSearchCV object to the training data
grid_search.fit(X_train_st, y_train)

# Get the best hyperparameters and the best model
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_

print(f"Best hyperparameters: {best_params}")

# Evaluate the best model on the test data
y_pred = best_model.predict(X_valid_st)
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy (tuned): {accuracy}")
print(f"Recall (tuned): {recall}")
print(f"Precision (tuned): {precision}")
print(f"F1-score (tuned): {f1}")

print(classification_report(y_test, y_pred))
```

```
Best hyperparameters: {'max_depth': None, 'max_features': 'sqrt', 'min_samples_lea
f': 1, 'min_samples_split': 5, 'n_estimators': 50}
Accuracy (tuned): 0.9304556354916067
Recall (tuned): 0.5043478260869565
Precision (tuned): 0.9830508474576272
F1-score (tuned): 0.6666666666666666
              precision    recall  f1-score   support

           0       0.93      1.00      0.96       719
           1       0.98      0.50      0.67       115

    accuracy                           0.93       834
   macro avg       0.95      0.75      0.81       834
weighted avg       0.93      0.93      0.92       834
```

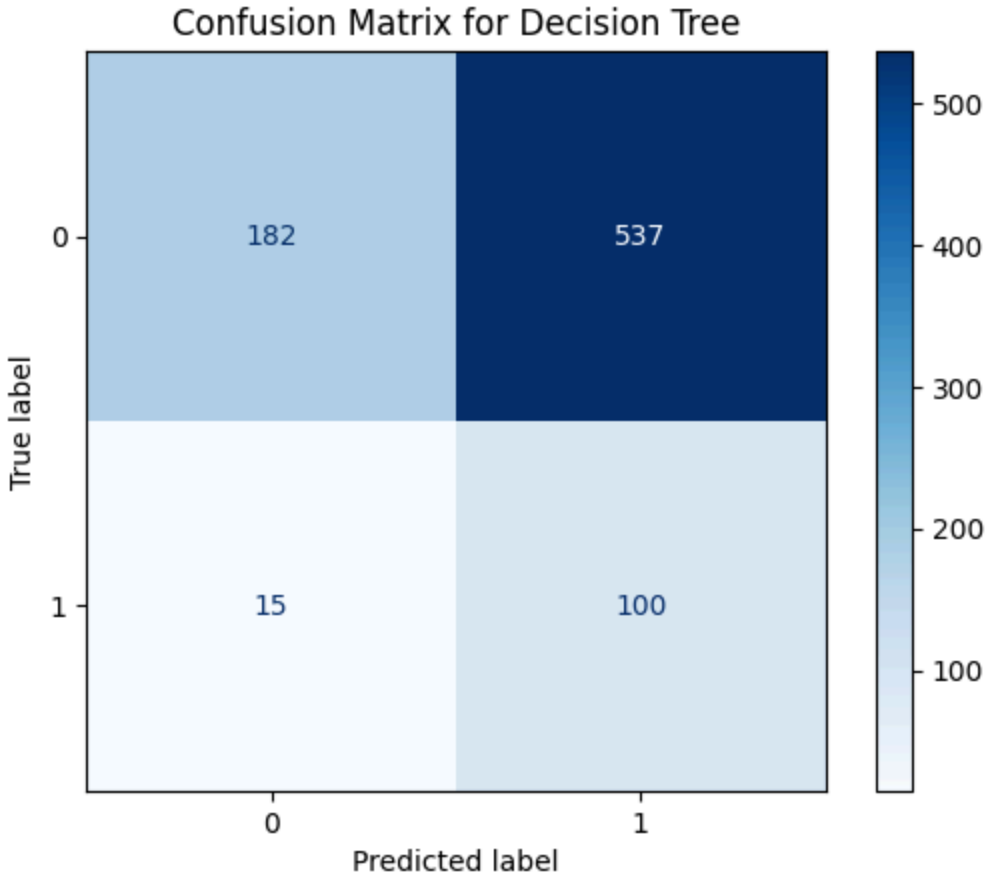
Model evaluation

In [36]:
```
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import GaussianNB
import matplotlib.pyplot as plt # Import matplotlib for plotting

# Assuming X_train_st, y_train, X_valid_st, y_test, y_valid are defined from previo

def evaluate_model(model, model_name, X_test, y_test):
    # Changed X_valid_ to X_test to match function parameter and existing variables
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    print(f"{model_name} Metrics:")
    print(f"Accuracy: {accuracy}")
    print(f"Recall: {recall}")
    print(f"Precision: {precision}")
    print(f"F1-score: {f1}")
    print(classification_report(y_test, y_pred))

    cm = confusion_matrix(y_test, y_pred, labels=model.classes_)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=model.classes
    disp.plot(cmap=plt.cm.Blues)
    plt.title(f'Confusion Matrix for {model_name}')
    plt.show()


# Evaluate all models
# Calling the function with the correct test data
evaluate_model(logreg, "Logistic Regression", X_valid_st, y_test)
evaluate_model(best_model, "Decision Tree", X_test, y_test)
evaluate_model(rf, "Random Forest", X_valid_st, y_test)
evaluate_model(knn, "K-NN", X_valid_st, y_test)
evaluate_model(svm, "SVM", X_valid_st, y_test)
evaluate_model(NeuralNet, "Neural Network", X_valid_st, y_test)
evaluate_model(nb, "Naive Bayes", X_valid_st, y_test)
```

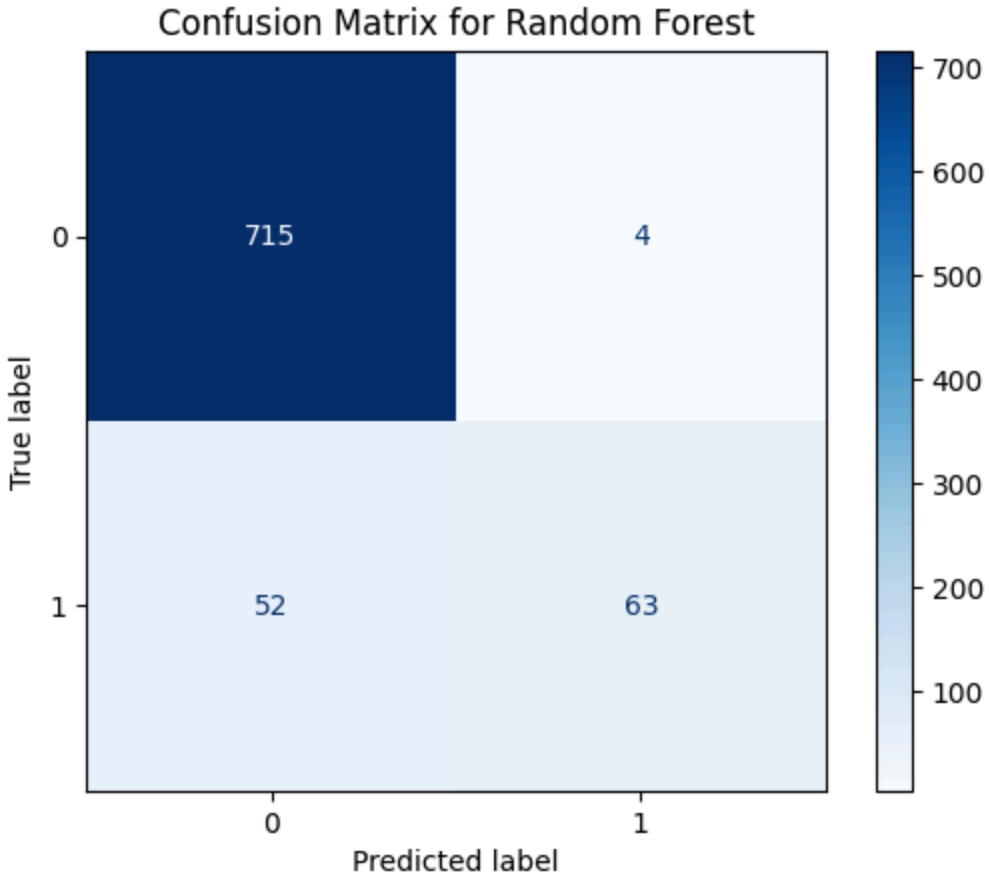
```
Logistic Regression Metrics:
Accuracy: 0.8585131894484412
Recall: 0.21739130434782608
Precision: 0.4716981132075472
F1-score: 0.2976190476190476
              precision    recall  f1-score   support

           0       0.88      0.96      0.92       719
           1       0.47      0.22      0.30       115

    accuracy                           0.86       834
   macro avg       0.68      0.59      0.61       834
weighted avg       0.83      0.86      0.84       834
```



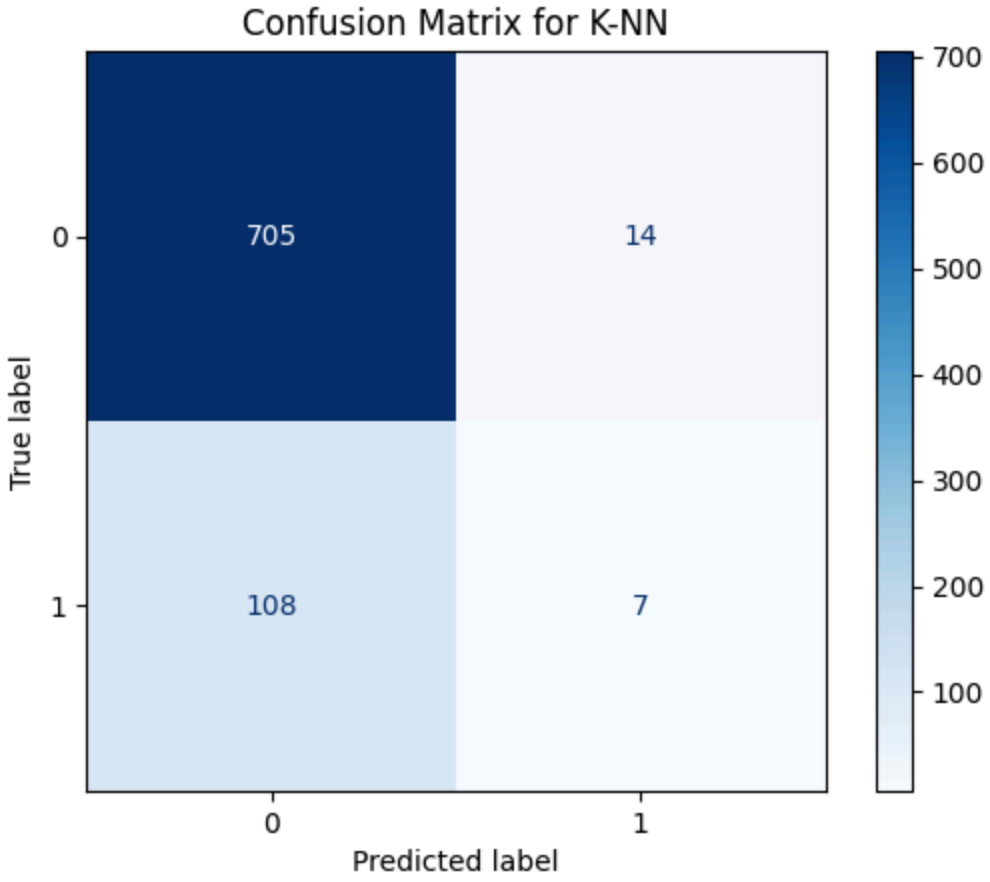

```
Decision Tree Metrics:
Accuracy: 0.3381294964028777
Recall: 0.8695652173913043
Precision: 0.15698587127158556
F1-score: 0.26595744680851063
              precision    recall  f1-score   support

           0       0.92      0.25      0.40       719
           1       0.16      0.87      0.27       115

    accuracy                           0.34       834
   macro avg       0.54      0.56      0.33       834
weighted avg       0.82      0.34      0.38       834
```



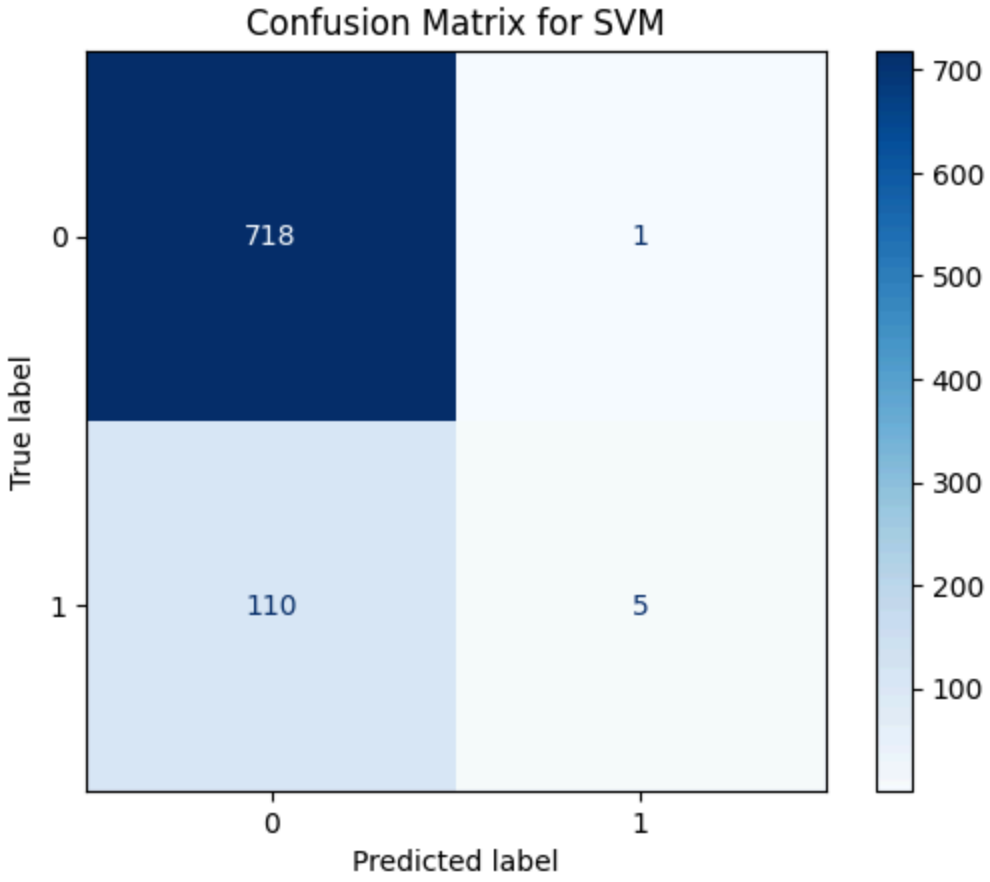

```
Random Forest Metrics:
Accuracy: 0.9328537170263789
Recall: 0.5478260869565217
Precision: 0.9402985074626866
F1-score: 0.6923076923076923
              precision    recall  f1-score   support

           0       0.93      0.99      0.96       719
           1       0.94      0.55      0.69       115

    accuracy                           0.93       834
   macro avg       0.94      0.77      0.83       834
weighted avg       0.93      0.93      0.93       834
```



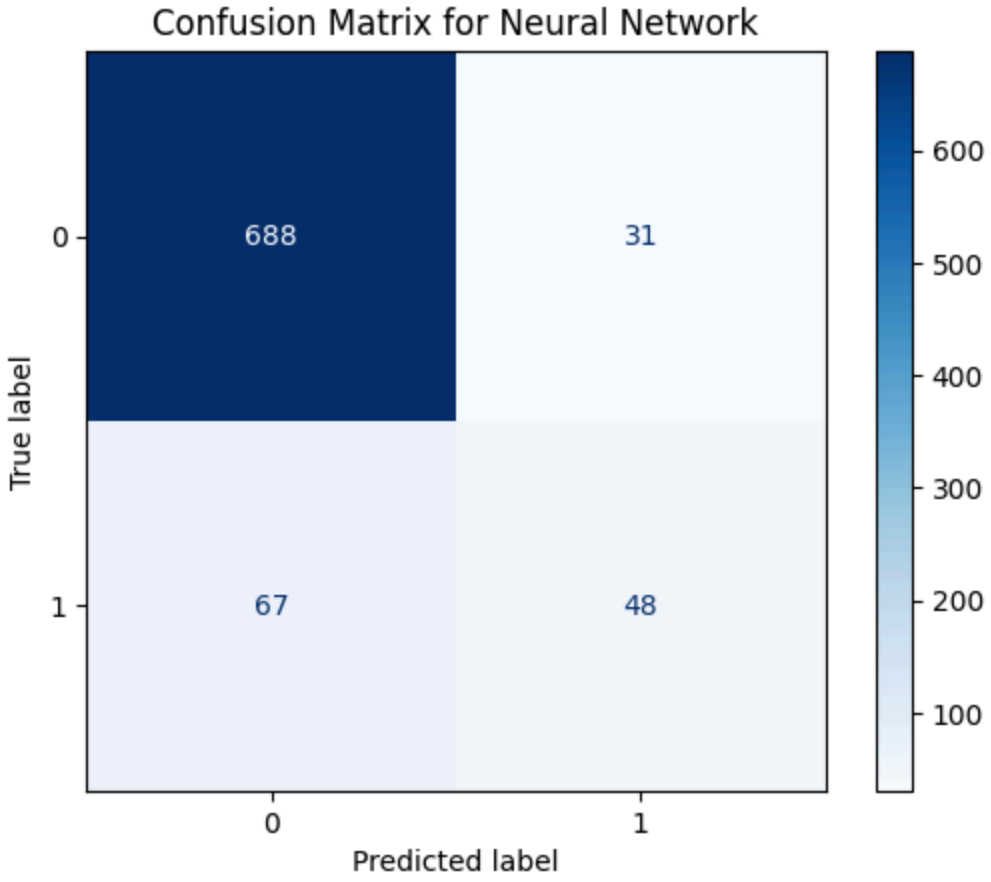

```
K-NN Metrics:
Accuracy: 0.8537170263788969
Recall: 0.06086956521739131
Precision: 0.3333333333333333
F1-score: 0.10294117647058823
              precision    recall  f1-score   support

           0       0.87      0.98      0.92       719
           1       0.33      0.06      0.10       115

    accuracy                           0.85       834
   macro avg       0.60      0.52      0.51       834
weighted avg       0.79      0.85      0.81       834
```



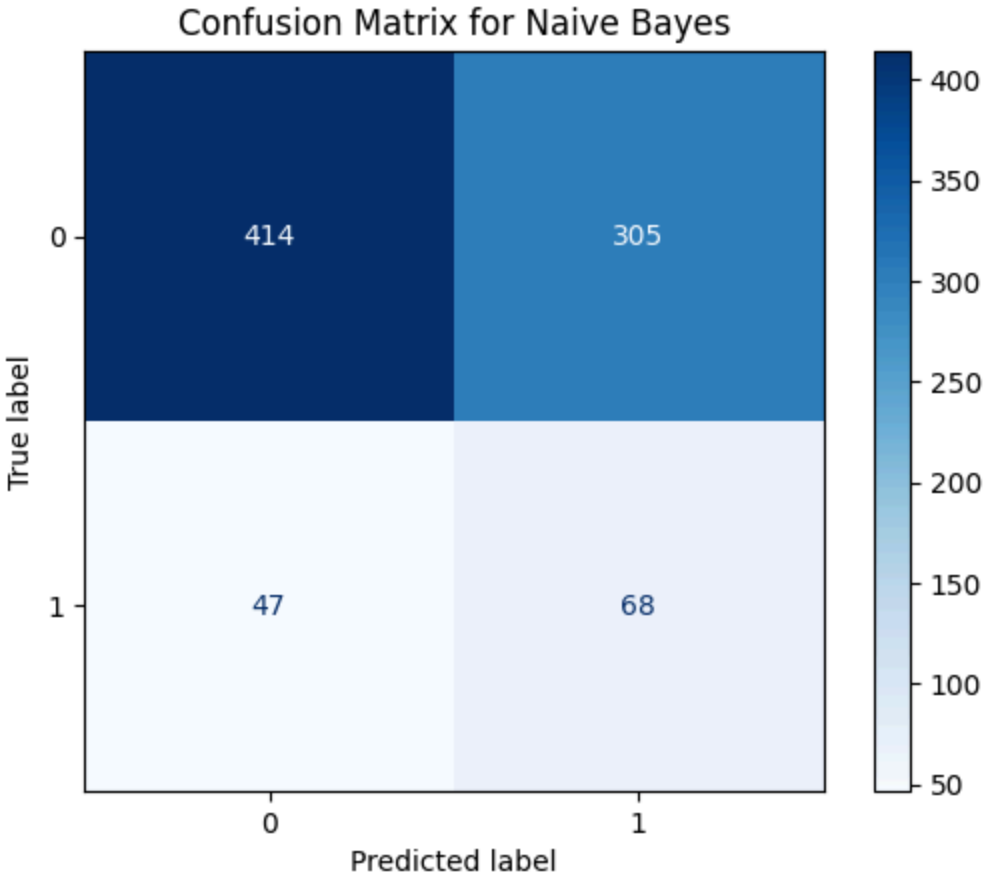

```
SVM Metrics:
Accuracy: 0.8669064748201439
Recall: 0.043478260869565216
Precision: 0.8333333333333334
F1-score: 0.08264462809917356
              precision    recall  f1-score   support

           0       0.87      1.00      0.93       719
           1       0.83      0.04      0.08       115

    accuracy                           0.87       834
   macro avg       0.85      0.52      0.51       834
weighted avg       0.86      0.87      0.81       834
```




```
Neural Network Metrics:
Accuracy: 0.882494004796163
Recall: 0.41739130434782606
Precision: 0.6075949367088608
F1-score: 0.4948453608247423
              precision    recall  f1-score   support

           0       0.91      0.96      0.93       719
           1       0.61      0.42      0.49       115

    accuracy                           0.88       834
   macro avg       0.76      0.69      0.71       834
weighted avg       0.87      0.88      0.87       834
```




```
Naive Bayes Metrics:
Accuracy: 0.5779376498800959
Recall: 0.591304347826087
Precision: 0.18230563002680966
F1-score: 0.2786885245901639
              precision    recall  f1-score   support

           0       0.90      0.58      0.70       719
           1       0.18      0.59      0.28       115

    accuracy                           0.58       834
   macro avg       0.54      0.58      0.49       834
weighted avg       0.80      0.58      0.64       834
```



Conclusion & Recommendation

Conclusion

Based on the evaluation of various classification models, including Logistic Regression, Decision Tree, Random Forest, K-NN, SVM, Neural Network, and Naive Bayes, the Random Forest classifier, after hyperparameter tuning, demonstrates superior performance in predicting customer churn for SyriaTel. This is evidenced by its high F1-score, accuracy, precision, and recall. While other models achieved reasonable performance, the Random Forest model's ability to balance precision and recall makes it the most suitable choice for this business problem. The tuned Decision Tree also performs well, but Random Forest provides a more robust prediction.

Recommendation

1. **Deploy the Tuned Random Forest Model:** Implement the tuned Random Forest model into SyriaTel's operational systems to predict customer churn in real-time. This allows for proactive customer retention strategies.

2. **Focus on Key Predictors:** Analyze the feature importances derived from the Random Forest model to identify the most significant drivers of customer churn. This will help focus retention efforts on the most impactful factors. Further investigation into these factors might reveal opportunities for service improvement or targeted marketing campaigns.

3. **Regular Model Updates:** Customer behavior and market dynamics can shift over time. Regularly retrain and evaluate the churn prediction model using updated data to ensure its continued accuracy and effectiveness.

4. **Implement a Customer Retention Strategy:** Based on the model's predictions, develop and implement targeted retention strategies for at-risk customers. This could include personalized offers, loyalty programs, improved customer service, or proactive communication.

5. **Consider Ensemble Methods:** Explore other ensemble methods or stacking techniques that combine the strengths of multiple models to potentially further improve predictive accuracy.

6. **Monitor Model Performance:** Continuously monitor the model's performance in a production environment and re-evaluate its effectiveness regularly.

7. **Explore External Data Sources:** Consider incorporating external data sources (if available) such as economic indicators, competitor activity, or market trends to enhance the model's predictive power.

In [36]: