

In [ ]:

```
In [3]: #####          Data preparation          #####

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sys
from scipy.io import arff

from scipy.io import arff
!pip install ydata-profiling
!jupyter nbextension enable --py widgetsnbextension
!pip install matplotlib
!pip install graphviz
```

Requirement already satisfied: ydata-profiling in ./anaconda3/lib/python3.10/site-packages (4.7.0)

Requirement already satisfied: pydantic>=2 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (2.6.4)

Requirement already satisfied: scipy<1.12,>=1.4.1 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (1.11.4)

Requirement already satisfied: phik<0.13,>=0.11.1 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (0.12.4)

Requirement already satisfied: wordcloud>=1.9.1 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (1.9.3)

Requirement already satisfied: numpy<2,>=1.16.0 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (1.26.4)

Requirement already satisfied: matplotlib<3.9,>=3.2 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (3.8.3)

Requirement already satisfied: typeguard<5,>=4.1.2 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (4.1.5)

Requirement already satisfied: seaborn<0.13,>=0.10.1 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (0.12.2)

Requirement already satisfied: htmlmin==0.1.12 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (0.1.12)

Requirement already satisfied: jinja2<3.2,>=2.11.1 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (3.1.3)

Requirement already satisfied: pandas!=1.4.0,<3,>1.1 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (2.2.1)

Requirement already satisfied: imagehash==4.3.1 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (4.3.1)

Requirement already satisfied: PyYAML<6.1,>=5.0.0 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (6.0.1)

Requirement already satisfied: dacite>=1.8 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (1.8.1)

Requirement already satisfied: multimethod<2,>=1.4 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (1.11.2)

Requirement already satisfied: statsmodels<1,>=0.13.2 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (0.14.1)

Requirement already satisfied: tqdm<5,>=4.48.2 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (4.65.0)

Requirement already satisfied: requests<3,>=2.24.0 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (2.31.0)

Requirement already satisfied: numba<1,>=0.56.0 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (0.59.1)

Requirement already satisfied: visions[type\_image\_path]<0.7.7,>=0.7.5 in ./anaconda3/lib/python3.10/site-packages (from ydata-profiling) (0.7.6)

Requirement already satisfied: pillow in ./anaconda3/lib/python3.10/site-packages (from imagehash==4.3.1->ydata-profiling) (10.2.0)

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Requirement already satisfied: MarkupSafe>=2.0 in ./anaconda3/lib/python3.10/site-packages (from jinja2<3.2,>=2.11.1->ydata-profiling) (2.1.3)

Requirement already satisfied: contourpy>=1.0.1 in ./anaconda3/lib/python3.10/site-packages (from matplotlib<3.9,>=3.2->ydata-profiling) (1.2.0)

Requirement already satisfied: packaging>=20.0 in ./anaconda3/lib/python3.10/site-packages (from matplotlib<3.9,>=3.2->ydata-profiling) (23.2)

Requirement already satisfied: pyparsing>=2.3.1 in ./anaconda3/lib/python3.10/site-packages (from matplotlib<3.9,>=3.2->ydata-profiling) (3.1.2)

Requirement already satisfied: kiwisolver>=1.3.1 in ./anaconda3/lib/python3.10/site-packages (from matplotlib<3.9,>=3.2->ydata-profiling) (1.4.5)

Requirement already satisfied: fonttools>=4.22.0 in ./anaconda3/lib/python3.10/site-packages (from matplotlib<3.9,>=3.2->ydata-profiling) (4.50.0)

Requirement already satisfied: cycycler>=0.10 in ./anaconda3/lib/python3.10/site-packages (from matplotlib<3.9,>=3.2->ydata-profiling) (0.12.1)

Requirement already satisfied: python-dateutil>=2.7 in ./anaconda3/lib/python3.10/site-packages (from matplotlib<3.9,>=3.2->ydata-profiling) (2.8.2)

Requirement already satisfied: llvmlite<0.43,>=0.42.0dev0 in ./anaconda3/lib/python3.10/site-packages (from numba<1,>=0.56.0->ydata-profiling) (0.42.0)

Requirement already satisfied: tzdata>=2022.7 in ./anaconda3/lib/python3.10/site-packages (from pandas!=1.4.0,<3,>1.1->ydata-profiling) (2024.1)

Requirement already satisfied: pytz>=2020.1 in ./anaconda3/lib/python3.10/site-packages (from pandas!=1.4.0,<3,>1.1->ydata-profiling) (2023.3.post1)

Requirement already satisfied: joblib>=0.14.1 in ./anaconda3/lib/python3.10/site-packages (from phik<0.13,>=0.11.1->ydata-profiling) (1.3.2)

Requirement already satisfied: typing-extensions>=4.6.1 in ./anaconda3/lib/python3.10/site-packages (from pydantic>=2->ydata-profiling) (4.10.0)

Requirement already satisfied: annotated-types>=0.4.0 in ./anaconda3/lib/python3.10/site-packages (from pydantic>=2->ydata-profiling) (0.6.0)

Requirement already satisfied: pydantic-core==2.16.3 in ./anaconda3/lib/python3.10/site-packages (from pydantic>=2->ydata-profiling) (2.16.3)

Requirement already satisfied: urllib3<3,>=1.21.1 in ./anaconda3/lib/python3.10/site-packages (from requests<3,>=2.24.0->ydata-profiling) (2.1.0)

Requirement already satisfied: idna<4,>=2.5 in ./anaconda3/lib/python3.10/site-packages (from requests<3,>=2.24.0->ydata-profiling) (3.4)

Requirement already satisfied: charset-normalizer<4,>=2 in ./anaconda3/lib/python3.10/site-packages (from requests<3,>=2.24.0->ydata-profiling) (2.0.4)

Requirement already satisfied: certifi>=2017.4.17 in ./anaconda3/lib/python3.10/site-packages (from requests<3,>=2.24.0->ydata-profiling) (2024.2.2)

Requirement already satisfied: patsy>=0.5.4 in ./anaconda3/lib/python3.10/site-packages (from statsmodels<1,>=0.13.2->ydata-profiling) (0.5.6)

Requirement already satisfied: networkx>=2.4 in ./anaconda3/lib/python3.10/site-packages (from visions[type\_image\_path]<0.7.7,>=0.7.5->ydata-profiling) (3.2.1)

Requirement already satisfied: attrs>=19.3.0 in ./anaconda3/lib/python3.10/site-packages (from visions[type\_image\_path]<0.7.7,>=0.7.5->ydata-profiling) (23.1.0)

Requirement already satisfied: six in ./anaconda3/lib/python3.10/site-packages (from patsy>=0.5.4->statsmodels<1,>=0.13.2->ydata-profiling) (1.16.0)

Enabling notebook extension jupyter-js-widgets/extension...

– Validating: **OK**

Requirement already satisfied: matplotlib in ./anaconda3/lib/python3.10/site-packages (3.8.3)

Requirement already satisfied: fonttools>=4.22.0 in ./anaconda3/lib/python3.10/site-packages (from matplotlib) (4.50.0)

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Requirement already satisfied: pillow>=8 in ./anaconda3/lib/python3.10/site-packages (from matplotlib) (10.2.0)

Requirement already satisfied: python-dateutil>=2.7 in ./anaconda3/lib/python3.10/site-packages (from matplotlib) (2.8.2)

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Requirement already satisfied: numpy<2,>=1.21 in ./anaconda3/lib/python3.10/site-packages (from matplotlib) (1.26.4)  
 Requirement already satisfied: packaging>=20.0 in ./anaconda3/lib/python3.10/site-packages (from matplotlib) (23.2)  
 Requirement already satisfied: six>=1.5 in ./anaconda3/lib/python3.10/site-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)  
 Requirement already satisfied: graphviz in ./anaconda3/lib/python3.10/site-packages (0.20.2)

```
In [4]: import pandas as pd
        from scipy.io import arff

        data_file = "churn.arff"

        # Load ARFF file
        data, meta = arff.loadarff(data_file)

        # Convert data to DataFrame
        df = pd.DataFrame(data)

        # Decode object columns if needed
        for col in df.columns:
            if df[col].dtype == 'object':
                df[col] = df[col].str.decode('utf-8')

        # Look at loaded data and data types
        print(df.dtypes)
```

State	object
Account Length	float64
Area Code	object
Phone Number	object
Inter Plan	object
VoiceMail Plan	object
No of Vmail Mesgs	float64
Total Day Min	float64
Total Day calls	float64
Total Day Charge	float64
Total Evening Min	float64
Total Evening Calls	float64
Total Evening Charge	float64
Total Night Minutes	float64
Total Night Calls	float64
Total Night Charge	float64
Total Int Min	float64
Total Int Calls	float64
Total Int Charge	float64
No of Calls Customer Service	float64
Churn	object
dtype:	object

In [ ]:

In [ ]:

In [5]: *# Display the first few rows of the DataFrame*  
`df.head(10)`

Out[5]:

	State	Account Length	Area Code	Phone Number	Inter Plan	VoiceMail Plan	No of Vmail Mesgs	Total Day Min	Total Day calls	Total Day Charge	...
0	OH	107.0	A415	371-7191	no	yes	26.0	161.6	123.0	27.47	...
1	NJ	137.0	A415	358-1921	no	no	0.0	243.4	114.0	41.38	...
2	OH	84.0	A408	375-9999	yes	no	0.0	299.4	71.0	50.90	...
3	OK	75.0	A415	330-6626	yes	no	0.0	166.7	113.0	28.34	...
4	AL	118.0	A510	391-8027	yes	no	0.0	223.4	98.0	37.98	...
5	MA	121.0	A510	355-9993	no	yes	24.0	218.2	88.0	37.09	...
6	MO	147.0	A415	329-9001	yes	no	0.0	157.0	79.0	26.69	...
7	LA	117.0	A408	335-4719	no	no	0.0	184.5	97.0	31.37	...
8	WV	141.0	A415	330-8173	yes	yes	37.0	258.6	84.0	43.96	...
9	IN	65.0	A415	329-6603	no	no	0.0	129.1	137.0	21.95	...

10 rows x 21 columns

In [6]: *# look at meta information about data, such as null values*  
`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	float64
2	Area Code	3333 non-null	object
3	Phone Number	3333 non-null	object
4	Inter Plan	3333 non-null	object
5	VoiceMail Plan	3333 non-null	object
6	No of Vmail Mesgs	3333 non-null	float64
7	Total Day Min	3333 non-null	float64
8	Total Day calls	3333 non-null	float64
9	Total Day Charge	3333 non-null	float64
10	Total Evening Min	3333 non-null	float64
11	Total Evening Calls	3333 non-null	float64
12	Total Evening Charge	3333 non-null	float64
13	Total Night Minutes	3333 non-null	float64
14	Total Night Calls	3333 non-null	float64
15	Total Night Charge	3333 non-null	float64
16	Total Int Min	3333 non-null	float64
17	Total Int Calls	3333 non-null	float64
18	Total Int Charge	3333 non-null	float64
19	No of Calls Customer Service	3333 non-null	float64
20	Churn	3333 non-null	object

```
dtypes: float64(15), object(6)
```

```
memory usage: 546.9+ KB
```

```
In [7]: # Find max, min, mean and standard deviation of attributes.
```

```
df.describe()
```

```
Out[7]:
```

	Account Length	No of Vmail Mesgs	Total Day Min	Total Day calls	Total Day Charge	Total Evening
<b>count</b>	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000
<b>mean</b>	101.064806	8.099010	179.775098	100.435644	30.562307	200.980000
<b>std</b>	39.822106	13.688365	54.467389	20.069084	9.259435	50.713000
<b>min</b>	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
<b>25%</b>	74.000000	0.000000	143.700000	87.000000	24.430000	166.600000
<b>50%</b>	101.000000	0.000000	179.400000	101.000000	30.500000	201.400000
<b>75%</b>	127.000000	20.000000	216.400000	114.000000	36.790000	235.300000
<b>max</b>	243.000000	51.000000	350.800000	165.000000	59.640000	363.700000

```
In [8]: df.shape
```

```
Out[8]: (3333, 21)
```

```
In [9]: column_names = df.columns
column_names
```

```
Out[9]: Index(['State', 'Account Length', 'Area Code', 'Phone Number', 'Inter Plan',
              'VoiceMail Plan', 'No of Vmail Mesgs', 'Total Day Min',
              'Total Day calls', 'Total Day Charge', 'Total Evening Min',
              'Total Evening Calls', 'Total Evening Charge', 'Total Night Minute',
              'Total Night Calls', 'Total Night Charge', 'Total Int Min',
              'Total Int Calls', 'Total Int Charge', 'No of Calls Customer Service',
              'Churn'],
              dtype='object')
```

```
In [10]: # Finding missing values

df.isnull().sum()
```

```
Out[10]: State                                0
Account Length                               0
Area Code                                    0
Phone Number                                0
Inter Plan                                  0
VoiceMail Plan                              0
No of Vmail Mesgs                           0
Total Day Min                               0
Total Day calls                              0
Total Day Charge                             0
Total Evening Min                           0
Total Evening Calls                          0
Total Evening Charge                         0
Total Night Minutes                          0
Total Night Calls                           0
Total Night Charge                           0
Total Int Min                                0
Total Int Calls                              0
Total Int Charge                             0
No of Calls Customer Service                 0
Churn                                         0
dtype: int64
```

```
In [11]: # Handle duplicates

print(df.drop_duplicates(inplace=True))
```

None

```
In [12]: # Identify numerical variables

numeric_variables = df.select_dtypes(include=['int64', 'float64']).columns.tolist()

# Print the list of numerical variables

print("Numerical Variables:")
print(numeric_variables)
```

Numerical Variables:

```
['Account Length', 'No of Vmail Mesgs', 'Total Day Min', 'Total Day calls',  
'Total Day Charge', 'Total Evening Min', 'Total Evening Calls', 'Total Eveni  
ng Charge', 'Total Night Minutes', 'Total Night Calls', 'Total Night Charg  
e', 'Total Int Min', 'Total Int Calls', 'Total Int Charge', 'No of Calls Cus  
tomer Service']
```

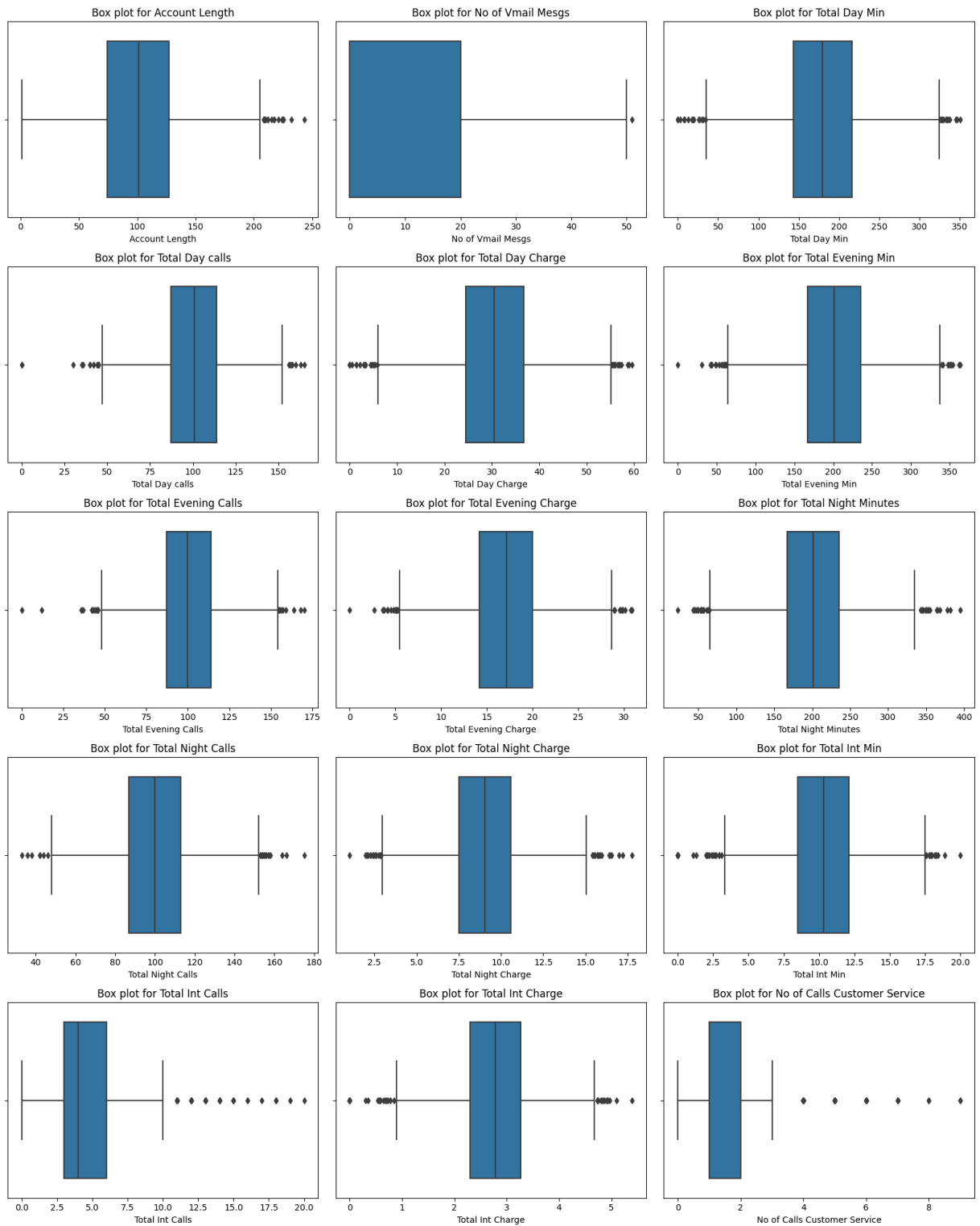
```
In [13]: # Identify categorical variables  
  
categorical_variables = df.select_dtypes(include=['object']).columns.tolist()  
  
# Print the list of categorical variables  
  
print("Categorical Variables:")  
print(categorical_variables)
```

Categorical Variables:

```
['State', 'Area Code', 'Phone Number', 'Inter Plan', 'VoiceMail Plan', 'Chur  
n']
```

```
In [14]: #Determine any outlier values(records)for numeric attributes and create box  
  
# Select numeric attributes  
numeric_attributes = df.select_dtypes(include=['int64', 'float64']).columns  
  
# Calculate the number of rows needed for the subplots  
  
num_attributes = len(numeric_attributes)  
num_rows = (num_attributes // 3) + (num_attributes % 3 > 0)  
  
# Create box plots for numeric attributes  
  
plt.figure(figsize=(16, 4 * num_rows))  
for i, column in enumerate(numeric_attributes, 1):  
    plt.subplot(num_rows, 3, i)  
    sns.boxplot(x=df[column])  
    plt.title(f'Box plot for {column}')  
  
plt.tight_layout()  
plt.show()
```





In [15]: *# To analyze the distribution of numeric attributes and create Histogram*

```
num_attributes = len(numeric_attributes)
```

```
num_cols = 3 # Number of columns in the subplot grid
```

```
num_rows = (num_attributes // num_cols) + (num_attributes % num_cols > 0)
```

```
plt.figure(figsize=(15, 5 * num_rows))

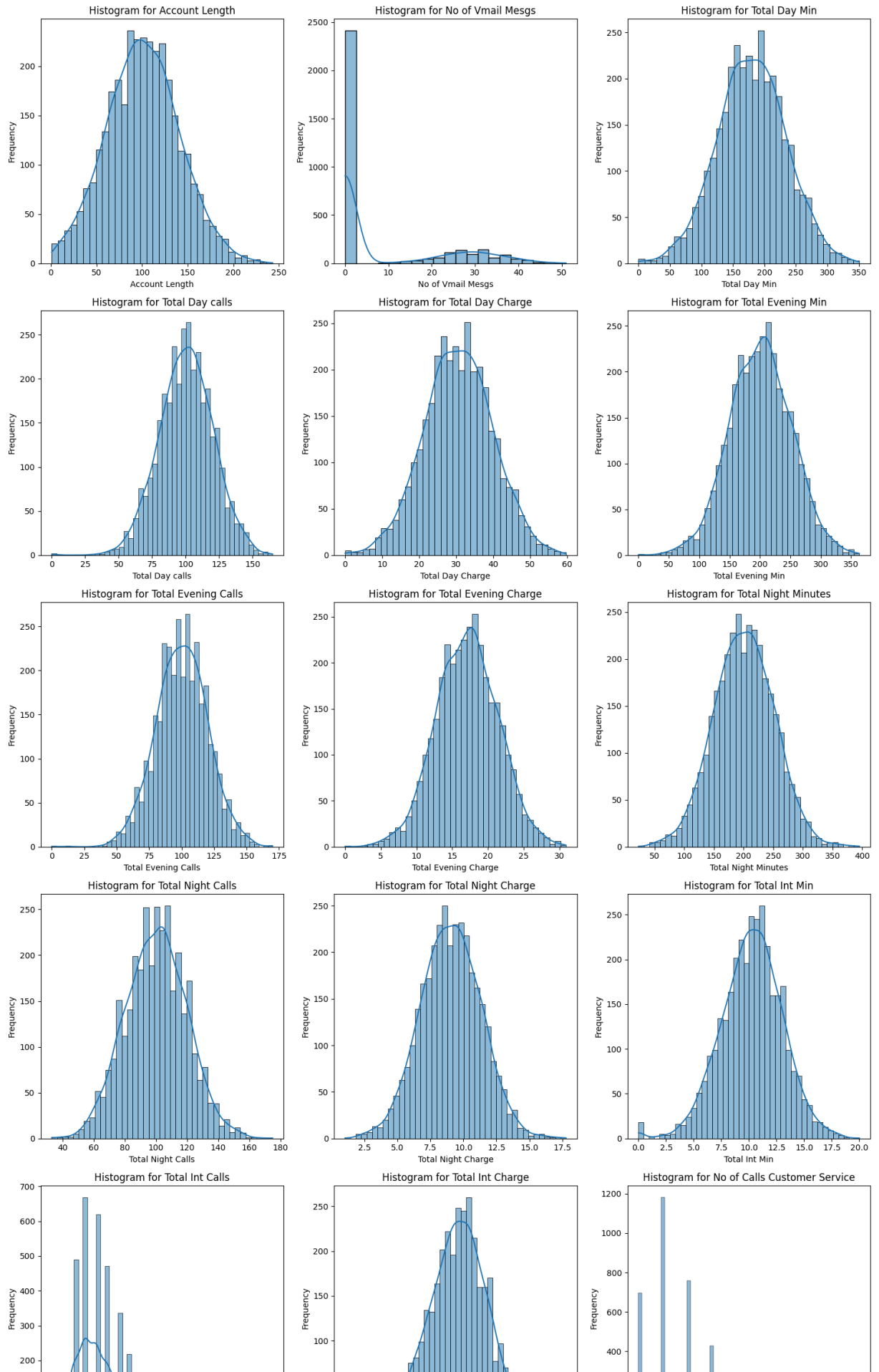
# Plot histograms for numeric attributes

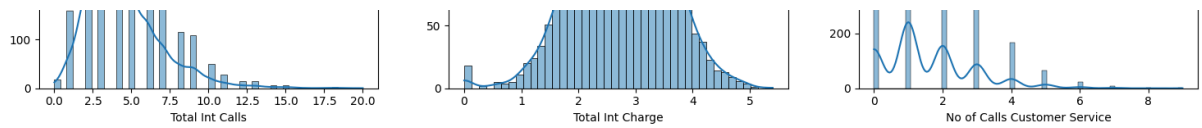
for i, column in enumerate(numeric_attributes, 1):
    plt.subplot(num_rows, num_cols, i)
    sns.histplot(df[column], kde=True)
    plt.title(f'Histogram for {column}')
    plt.xlabel(column)
    plt.ylabel('Frequency')

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

```
/Users/zhila/anaconda3/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will be removed in
a future version. Convert inf values to NaN before operating instead.
    with pd.option_context('mode.use_inf_as_na', True):
/Users/zhila/anaconda3/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will be removed in
a future version. Convert inf values to NaN before operating instead.
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/Users/zhila/anaconda3/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will be removed in
a future version. Convert inf values to NaN before operating instead.
    with pd.option_context('mode.use_inf_as_na', True):
```

```
/Users/zhila/anaconda3/lib/python3.10/site-packages/seaborn/_oldcore.py:111  
9: FutureWarning: use_inf_as_na option is deprecated and will be removed in  
a future version. Convert inf values to NaN before operating instead.  
with pd.option_context('mode.use_inf_as_na', True):
```

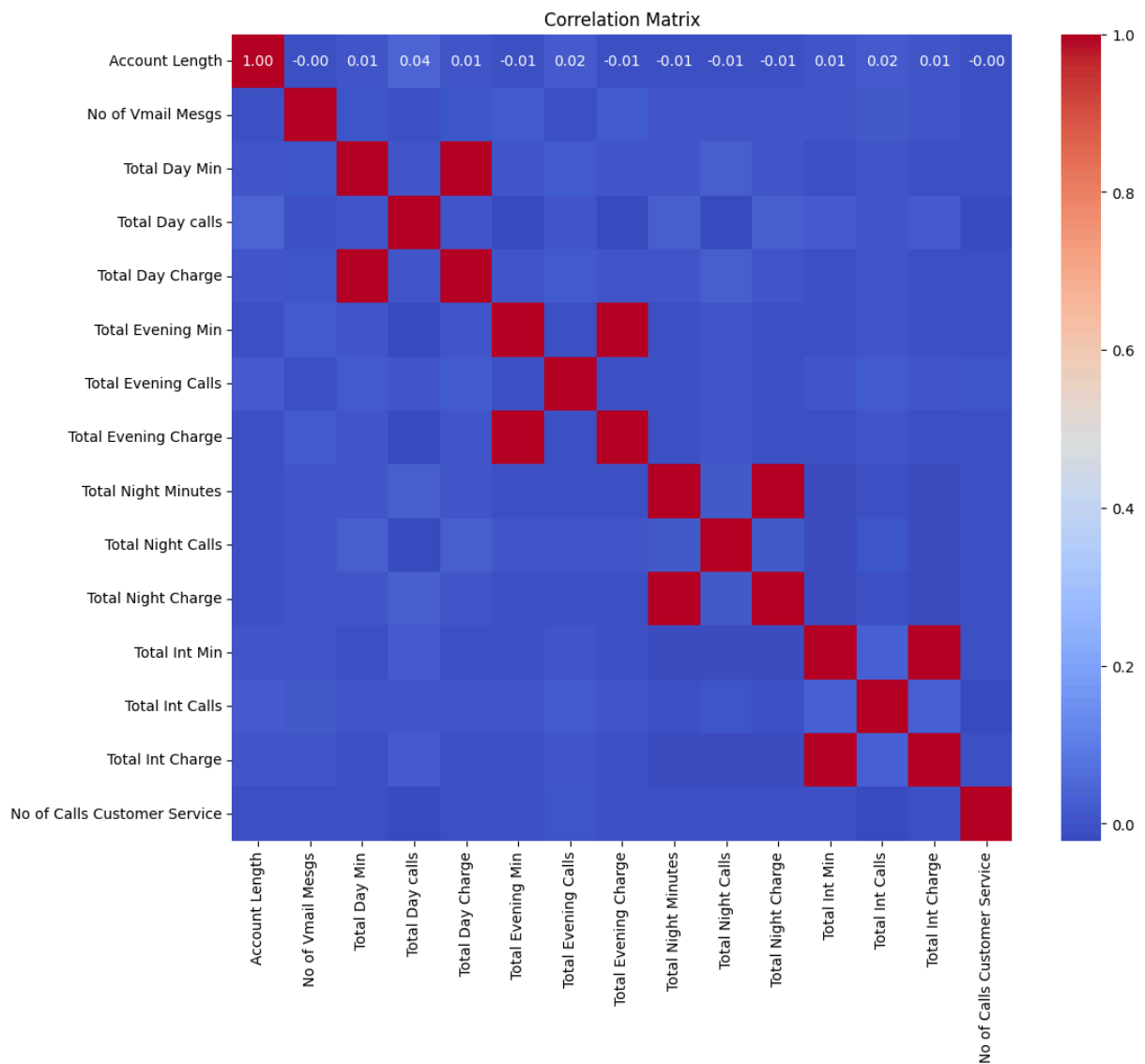




```
In [11]: # Select only numerical columns
numeric_df = df.select_dtypes(include=['float64', 'int64'])

# Calculate correlation matrix
correlation_matrix = numeric_df.corr()

# Plot correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



```
In [16]: ##### Construct contingency table and perform chi-squared test to assess a

from scipy.stats import chi2_contingency
```

```
# Contingency table
contingency_table = pd.crosstab(df['State'], df['Churn'])

# Chi-squared test
chi2, p, _, _ = chi2_contingency(contingency_table)
print(f"Chi-squared p-value: {p}")
```

Chi-squared p-value: 0.002296221552011188

In [17]: ##### Determine whether the dataset has an imbalanced class distribution ###

```
# Check the class distribution of the target variable

class_distribution = df['Churn'].value_counts()

# Print the class distribution

print("Class Distribution:")

print(class_distribution)

# Check if the dataset has an imbalanced class distribution

is_imbalanced = class_distribution.nunique() > 1

# Print the result

if is_imbalanced:
    print("The dataset has an imbalanced class distribution.")
else:
    print("The dataset has a balanced class distribution.")
```

Class Distribution:

Churn

FALSE 2850

TRUE 483

Name: count, dtype: int64

The dataset has an imbalanced class distribution.

In [18]: #Let's create a list for our categorical columns for Churn data set

```
cat_cols = ["State", "Area Code", "Phone Number", "Inter Plan", "VoiceMail F

# Create a copy of the data frame in memory with a different name
df_onehot = df.copy()

# Convert only categorical variables/features to dummy/one-hot features
df_onehot = pd.get_dummies(df_onehot, columns=cat_cols, prefix=cat_cols)

# Print the dataset
print(df_onehot)
```

```
# Create a copy of the data frame in memory with a different name
df_onehot=df.copy()

#convert only categorical variables/features to dummy/one-hot features
df_onehot = pd.get_dummies(df, columns=cat_cols, prefix = cat_cols)

#print the dataset
df_onehot
```



	Account Length	No of Vmail Mesgs	Total Day Min	Total Day calls	\
0	107.0	26.0	161.6	123.0	
1	137.0	0.0	243.4	114.0	
2	84.0	0.0	299.4	71.0	
3	75.0	0.0	166.7	113.0	
4	118.0	0.0	223.4	98.0	
...	...	...	...	...	
3328	68.0	0.0	231.1	57.0	
3329	28.0	0.0	180.8	109.0	
3330	184.0	0.0	213.8	105.0	
3331	74.0	25.0	234.4	113.0	
3332	128.0	25.0	265.1	110.0	

	Total Day Charge	Total Evening Min	Total Evening Calls	\
0	27.47	195.5	103.0	
1	41.38	121.2	110.0	
2	50.90	61.9	88.0	
3	28.34	148.3	122.0	
4	37.98	220.6	101.0	
...	...	...	...	
3328	39.29	153.4	55.0	
3329	30.74	288.8	58.0	
3330	36.35	159.6	84.0	
3331	39.85	265.9	82.0	
3332	45.07	197.4	99.0	

	Total Evening Charge	Total Night Minutes	Total Night Calls	...	\
0	16.62	254.4	103.0	...	
1	10.30	162.6	104.0	...	
2	5.26	196.9	89.0	...	
3	12.61	186.9	121.0	...	
4	18.75	203.9	118.0	...	
...	...	...	...	...	
3328	13.04	191.3	123.0	...	
3329	24.55	191.9	91.0	...	
3330	13.57	139.2	137.0	...	
3331	22.60	241.4	77.0	...	
3332	16.78	244.7	91.0	...	

	Phone Number_422-6690	Phone Number_422-7728	Phone Number_422-8268	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	
...	...	...	...	
3328	False	False	False	
3329	False	False	False	
3330	False	False	False	
3331	False	False	False	
3332	False	False	False	

	Phone Number_422-8333	Phone Number_422-8344	Phone Number_422-9964	\
0	False	False	False	
1	False	False	False	
2	False	False	False	

3	False	False	False
4	False	False	False
...	...	...	...
3328	False	False	False
3329	False	False	False
3330	False	False	False
3331	False	False	False
3332	False	False	False

	Inter	Plan_no	Inter	Plan_yes	VoiceMail	Plan_no	VoiceMail	Plan_yes
0		True		False		False		True
1		True		False		True		False
2		False		True		True		False
3		False		True		True		False
4		False		True		True		False
...		...		...		...		...
3328		True		False		True		False
3329		True		False		True		False
3330		False		True		True		False
3331		True		False		False		True
3332		True		False		False		True

[3333 rows x 3407 columns]

Out[18]:

	Account Length	No of Vmail Mesgs	Total Day Min	Total Day calls	Total Day Charge	Total Evening Min	Total Evening Calls	Total Evening Charge	Total Night Minutes	T N C
0	107.0	26.0	161.6	123.0	27.47	195.5	103.0	16.62	254.4	10
1	137.0	0.0	243.4	114.0	41.38	121.2	110.0	10.30	162.6	10
2	84.0	0.0	299.4	71.0	50.90	61.9	88.0	5.26	196.9	8
3	75.0	0.0	166.7	113.0	28.34	148.3	122.0	12.61	186.9	1
4	118.0	0.0	223.4	98.0	37.98	220.6	101.0	18.75	203.9	1
...	...	...	...	...	...	...	...	...	...	...
3328	68.0	0.0	231.1	57.0	39.29	153.4	55.0	13.04	191.3	10
3329	28.0	0.0	180.8	109.0	30.74	288.8	58.0	24.55	191.9	10
3330	184.0	0.0	213.8	105.0	36.35	159.6	84.0	13.57	139.2	1
3331	74.0	25.0	234.4	113.0	39.85	265.9	82.0	22.60	241.4	10
3332	128.0	25.0	265.1	110.0	45.07	197.4	99.0	16.78	244.7	10

3333 rows x 3407 columns

In [ ]:

In [19]:

```
#Repeat the train test set split

from sklearn.model_selection import train_test_split
```

```
class_col_name="Churn"
one_hot_feature_names=df_onehot.columns[df_onehot.columns != class_col_name]
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(df_onehot.loc[:, one_hot
```

```
In [20]: # Repeat Naive Bayes modeling
from sklearn.naive_bayes import MultinomialNB

#Create a MultiNomial NB Classifier
nb = MultinomialNB()

#Train the model using the training sets
nb.fit(X_train, y_train)

#Predict the response for test dataset
y_pred = nb.predict(X_test)
print ("Succesfully done..")
```

Succesfully done..

```
In [21]: print("Number of features used ",nb.n_features_in_)
print("Classes ",nb.classes_)
print("Number of records for classes ",nb.class_count_)
print("Log prior probability for classes ", nb.class_log_prior_)
print("Log conditional probability for each feature given a class\n",nb.featur
```

```
Number of features used 3406
Classes ['FALSE' 'TRUE']
Number of records for classes [2000. 333.]
Log prior probability for classes [-0.15400781 -1.94676778]
Log conditional probability for each feature given a class
[[-2.35240444 -4.81236658 -1.8039874 ... -9.66722848 -7.32471068
 -8.18058615]
 [-2.38746885 -5.36209714 -1.70638185 ... -8.24401576 -7.2151181
 -8.7786926 ]]
```

```
In [23]: from sklearn.metrics import confusion_matrix
cf=confusion_matrix(y_test, y_pred)
print ("Confusion Matrix")
print(cf)
tn, fp, fn, tp=cf.ravel()
print ("TP: ", tp, ", FP: ", fp, ", TN: ", tn, ", FN: ", fn)
```

```
Confusion Matrix
[[758  92]
 [ 84  66]]
TP: 66 , FP: 92 , TN: 758 , FN: 84
```

```
In [24]: from sklearn.metrics import classification_report
from sklearn import metrics

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

	precision	recall	f1-score	support
FALSE	0.90	0.89	0.90	850
TRUE	0.42	0.44	0.43	150
accuracy			0.82	1000
macro avg	0.66	0.67	0.66	1000
weighted avg	0.83	0.82	0.83	1000

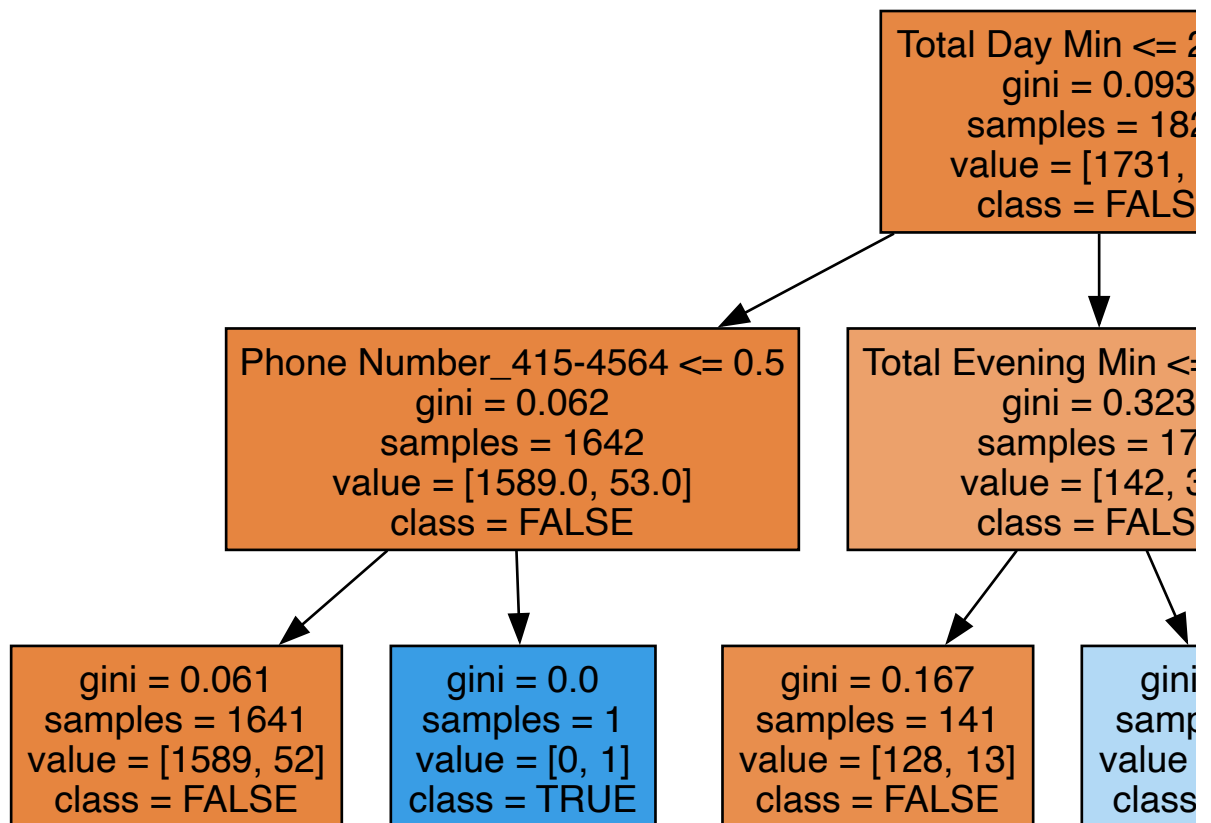
```
In [25]: from sklearn import tree
clf = tree.DecisionTreeClassifier(max_depth=5)
clf = clf.fit(X_train, y_train)
import graphviz
#Get unique class values to display on the tree
class_values=df_onehot[class_col_name].unique()
print ("class Names",class_values)

dot_data = tree.export_graphviz(clf, out_file=None,
                                feature_names=one_hot_feature_names,
                                class_names=class_values,
                                filled=True)

# Draw graph
graph = graphviz.Source(dot_data, format="png")
graph
```

```
class Names ['FALSE' 'TRUE']
```

Out [25]:



```
In [21]: # Perform prediction on the test set
y_pred = clf.predict(X_test)
```

```
In [26]: # Get classification report
from sklearn.metrics import classification_report
from sklearn import metrics

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

	precision	recall	f1-score	support
FALSE	0.90	0.89	0.90	850
TRUE	0.42	0.44	0.43	150
accuracy			0.82	1000
macro avg	0.66	0.67	0.66	1000
weighted avg	0.83	0.82	0.83	1000

```
In [27]: from ydata_profiling import ProfileReport
```

```
# Generate the data profiling report
report = ProfileReport(df)
report
```

```
Summarize dataset: 0%|          | 0/5 [00:00<?, ?it/s]
Generate report structure: 0%|          | 0/1 [00:00<?, ?it/s]
Render HTML: 0%|          | 0/1 [00:00<?, ?it/s]
```

# Overview

## Dataset statistics

Number of variables	21
Number of observations	3333
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	546.9 KiB
Average record size in memory	168.0 B

## Variable types

Text	2
Numeric	15
Categorical	1
Boolean	3

## Alerts

Inter Plan is highly imbalanced (54.1%)	Imbalance
Phone Number has unique values	Unique

Out [27]:

In [ ]:

