Final Project Submission

Please fill out:

```
Student name: SHITOTE CLIFF
Student pace: FULL TIME
Scheduled project review date/time:
Instructor name:Nikita Njoroge Lucille Kaleha Samuel karu
Blog post URL:https://github.com/CliffShitote/dsc-phase-3-choosing-a-dataset.git
```

Introduction

Business Problem:

The stakeholder for this project is SyriaTel, a telecommunications company interested in reducing customer churn and minimizing the loss of revenue associated with customers who terminate their services. The business problem is to build a binary classification model that can predict whether a customer is likely to "soon" stop doing business with SyriaTel. By identifying predictable patterns and factors contributing to customer churn, SyriaTel can take proactive measures to retain customers and mitigate revenue loss.

Dataset:

For this project, I will use a fictional dataset specifically created to simulate customer churn in a telecommunications company like SyriaTel. The dataset includes various features related to customer behavior, account information, and usage patterns. The dataset includes the following features (not an exhaustive list):

1.CustomerID: Unique identifier for each customer.

2.AccountLength: The length of time the customer has been with SyriaTel.

3.InternationalPlan: Whether the customer has an international calling plan or not.

4.VoiceMailPlan: Whether the customer has a voicemail plan or not.

5.NumberVmailMessages: The number of voicemail messages received by the customer.

6.TotalDayMinutes: Total number of minutes the customer used during the day.

7.TotalEveMinutes: Total number of minutes the customer used during the evening.

8.TotalNightMinutes: Total number of minutes the customer used during the night.

9.TotalIntlMinutes: Total number of international minutes used by the customer.

10.TotalDayCalls: Total number of calls made by the customer during the day.

11.TotalEveCalls: Total number of calls made by the customer during the evening.

12.TotalNightCalls: Total number of calls made by the customer during the night.

13.TotalIntlCalls: Total number of international calls made by the customer.

14.CustomerServiceCalls: Number of customer service calls made by the customer.

15.Churn: Binary indicator of whether the customer churned or not.

The objective is to build a binary classification model that can predict whether a customer is likely to churn "soon" based on the available features. By identifying predictable patterns and factors associated with customer churn, SyriaTel can take proactive actions such as targeted retention strategies, improved customer service, or personalized offers to mitigate customer

Data Understanding

Here we are exploring our dataset by loading it and viewing various columns and rows in it.

We then clean the dataset by:

(i) Obtaining information from the dataset.

(ii) Checking for missing values.

(iii) Checking for duplicates.

(iv)Checking for the outliers.

(v)Checking for correct data types.

We defined functions to explore our data.

Exploring the dataset

Import module & package

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
import plotly.express as px
import plotly.graph_objects as go
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.compose import ColumnTransformer
from imblearn.pipeline import Pipeline as imbPipeline
from imblearn.over_sampling import RandomOverSampler
from sklearn.model_selection import train_test_split, GridSearchCV
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.metrics import roc_auc_score, roc_curve, classification_repor
```

In [2]:

```
# Load the dataset
df = pd.read_csv('bigml_59c28831336c6604c800002a.csv')
```

Out[2]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	tota da charg
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.0
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.4
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.3
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.9
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.3
...	...	...	...	...	...	...	...	...	...	.
3328	AZ	192	415	414-4276	no	yes	36	156.2	77	26.5
3329	WV	68	415	370-3271	no	no	0	231.1	57	39.2
3330	RI	28	510	328-8230	no	no	0	180.8	109	30.7
3331	CT	184	510	364-6381	yes	no	0	213.8	105	36.3
3332	TN	74	415	400-4344	no	yes	25	234.4	113	39.8

3333 rows × 21 columns

In [3]:
```
#Display the first few rows in the dataframe
```

Out[3]:

	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 [4]:
```
#Display the last few rows in the dataframe
```

Out[4]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	tota da charg
3328	AZ	192	415	414-4276	no	yes	36	156.2	77	26.5
3329	WV	68	415	370-3271	no	no	0	231.1	57	39.2
3330	RI	28	510	328-8230	no	no	0	180.8	109	30.7
3331	CT	184	510	364-6381	yes	no	0	213.8	105	36.3
3332	TN	74	415	400-4344	no	yes	25	234.4	113	39.8

5 rows × 21 columns

Exploratory data analysis

1.Data Cleaning & Preprocessing: The process of cleaning the data and ensuring its accuracy and readiness for analysis. This involves handling missing values, dealing with outliers, resolving inconsistencies, and transforming the data into a suitable format for analysis.

2.Data Exploration: The process of delving into the data to extract information and insights, aiming to identify patterns and relationships within the data. This may involve summary statistics, visualization techniques, and exploratory data analysis to gain a deeper understanding of the data.

3.Feature Engineering: The process of creating, modifying, or selecting features (variables) from the raw data to enhance the performance of the machine learning model. This can involve techniques such as creating interaction terms, polynomial features, or transforming variables to better represent underlying patterns in the data.

4.Model Selection: The process of choosing the most suitable model for the given problem and dataset. This involves evaluating different algorithms, selecting appropriate evaluation metrics, and comparing the performance of various models. The goal is to select a model that can accurately predict the outcome variable and generalize well to unseen data

In [5]:
```
#Display of the number of rows and columns in the dataframe
```

Out[5]:
```
(3333, 21)
```

As seen the data has:

3333 rows which are the number of houses sold.

21 columns which represent the house features.

In [6]:
```
# Check data types for each columns
```

```
<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
```

Here we check for the descriptive statistics of the dataset.

We first drop the churn column which is not necessary for descriptive statistics.

In [7]:
```
#summary statistics of the numerical columns in a dataframe
def data_description(df):
    return (df.drop('churn', axis = 1)).describe()
```

Out[7]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	t(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.

Data Cleaning

Checking for Missing Values

In [8]:
```
# identify missing
def identify_missing_values(df):
    """Identify is the data has missing values"""
    # identify if data has missing values(data.isnull().any())
    # empty dict to store missing values
    missing = []
    for i in df.isnull().any():
        # add the bool values to empty list
        missing.append(i)
    # covert list to set (if data has missing value, the list should have 
    missing_set = set(missing)
    if (len(missing_set) == 1):
        out = print("The Data has no missing values")
    else:
        out = print("The Data has missing values.")

    return out
```

```
The Data has no missing values
```

In [9]:

```
def missing_values(data):
    """A simple function to identify data has missing values"""
    # identify the total missing values per column
    # sort in order
    miss = df.isnull().sum().sort_values(ascending = False)

    # calculate percentage of the missing values
    percentage_miss = (df.isnull().sum() / len(df)).sort_values(ascending 

    # store in a dataframe
    missing = pd.DataFrame({"Missing Values": miss, "Percentage(%)": perce

    # remove values that are missing
    missing.drop(missing[missing["Percentage(%)"] == 0].index, inplace = T

    return missing


missing_data = missing_values(df)
```

Out[9]:

Missing Values	Percentage(%)

This data has no missing values

Checking for duplicates

In [10]:

```
# Duplicated entries
def identify_duplicates(df):
    """Simple function to identify any duplicates"""
    # identify the duplicates (dataframename.duplicated() , can add .sum()
    # empty list to store Bool results from duplicated
    duplicates = []
    for i in df.duplicated():
        duplicates.append(i)
    # identify if there is any duplicates. (If there is any we expect a Tr
    duplicates_set = set(duplicates)
    if (len(duplicates_set) == 1):
        print("The Data has no duplicates")
    else:
        no_true = 0
        for val in duplicates:
            if (val == True):
                no_true += 1
        # percentage of the data represented by duplicates
        duplicates_percentage = np.round(((no_true / len(data)) * 100), 3)
        print(f"The Data has {no_true} duplicated rows.\nThis constitutes 
```

```
The Data has no duplicates
```

In [11]:
```
# Check duplicate data
```
Out[11]: 0

In [12]:
```
# Create function to explore the data
def check_mydata(dataframe: pd.DataFrame):

    new_col = {
        'col_name': [],
        'null_pct': [],
        'data_type': [],
        'unique_values': [],
        'unique_values_count': [],
        'mean_med_std': []
    }

    for col in dataframe.columns:
        new_col['col_name'].append(col)
        new_col['null_pct'].append(dataframe[col].isna().sum() / dataframe
        new_col['data_type'].append(dataframe[col].dtypes)
        (dataframe[col].unique())
        if dataframe[col].dtypes == 'object':
            new_col['unique_values'].append(dataframe[col].unique())
            new_col['unique_values_count'].append(dataframe[col].nunique()
            new_col['mean_med_std'].append('-')

        else:
            new_col['unique_values'].append('-')
            new_col['unique_values_count'].append('-')
            mean = round(dataframe[col].mean(), 2)
            median = round(dataframe[col].median(), 2)
            std = round(dataframe[col].std(), 2)
            new_col['mean_med_std'].append((mean, median, std))
```

In [13]:

In [14]:

Out[14]:

	col_name	null_pct	data_type	unique_values	unique_values_count	mean_med_std
0	state	0.0	object	[KS, OH, NJ, OK, AL, MA, MO, LA, WV, IN, RI, I...	51	-
1	account length	0.0	int64	-	-	(101.06, 101.0, 39.82)
2	area code	0.0	int64	-	-	(437.18, 415.0, 42.37)
3	phone number	0.0	object	[382-4657, 371-7191, 358-1921, 375-9999, 330-6...	3333	-
4	international plan	0.0	object	[no, yes]	2	-
5	voice mail plan	0.0	object	[yes, no]	2	-
6	number vmail messages	0.0	int64	-	-	(8.1, 0.0, 13.69)
7	total day minutes	0.0	float64	-	-	(179.78, 179.4, 54.47)
8	total day calls	0.0	int64	-	-	(100.44, 101.0, 20.07)
9	total day charge	0.0	float64	-	-	(30.56, 30.5, 9.26)
10	total eve minutes	0.0	float64	-	-	(200.98, 201.4, 50.71)
11	total eve calls	0.0	int64	-	-	(100.11, 100.0, 19.92)
12	total eve charge	0.0	float64	-	-	(17.08, 17.12, 4.31)
13	total night minutes	0.0	float64	-	-	(200.87, 201.2, 50.57)
14	total night calls	0.0	int64	-	-	(100.11, 100.0, 19.57)
15	total night charge	0.0	float64	-	-	(9.04, 9.05, 2.28)
16	total intl minutes	0.0	float64	-	-	(10.24, 10.3, 2.79)
17	total intl calls	0.0	int64	-	-	(4.48, 4.0, 2.46)
18	total intl charge	0.0	float64	-	-	(2.76, 2.78, 0.75)

col_name	null_pct	data_type	unique_values	unique_values_count	mean_med_std

If the dataset you are working with, "Churn in Telecoms," does not contain any duplicate values or missing/null values, then you may not need to perform extensive data cleaning. However, it's still recommended to conduct further data exploration to understand the dataset and perform any necessary preprocessing steps before training the classification model.

In [15]:
```python
#summary statistics of the numerical columns in a dataframe
```
Out[15]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	tc 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.

Data Exploration

Univariate analysis

In [16]:
```python
# Analysis target prediciton
```
Out[16]:
```
False    2850
True      483
Name: churn, dtype: int64
```

In [17]:
```python
df['churn'] = df['churn'].replace({'yes': 1, 'no':0}).astype('int')
```
Out[17]:

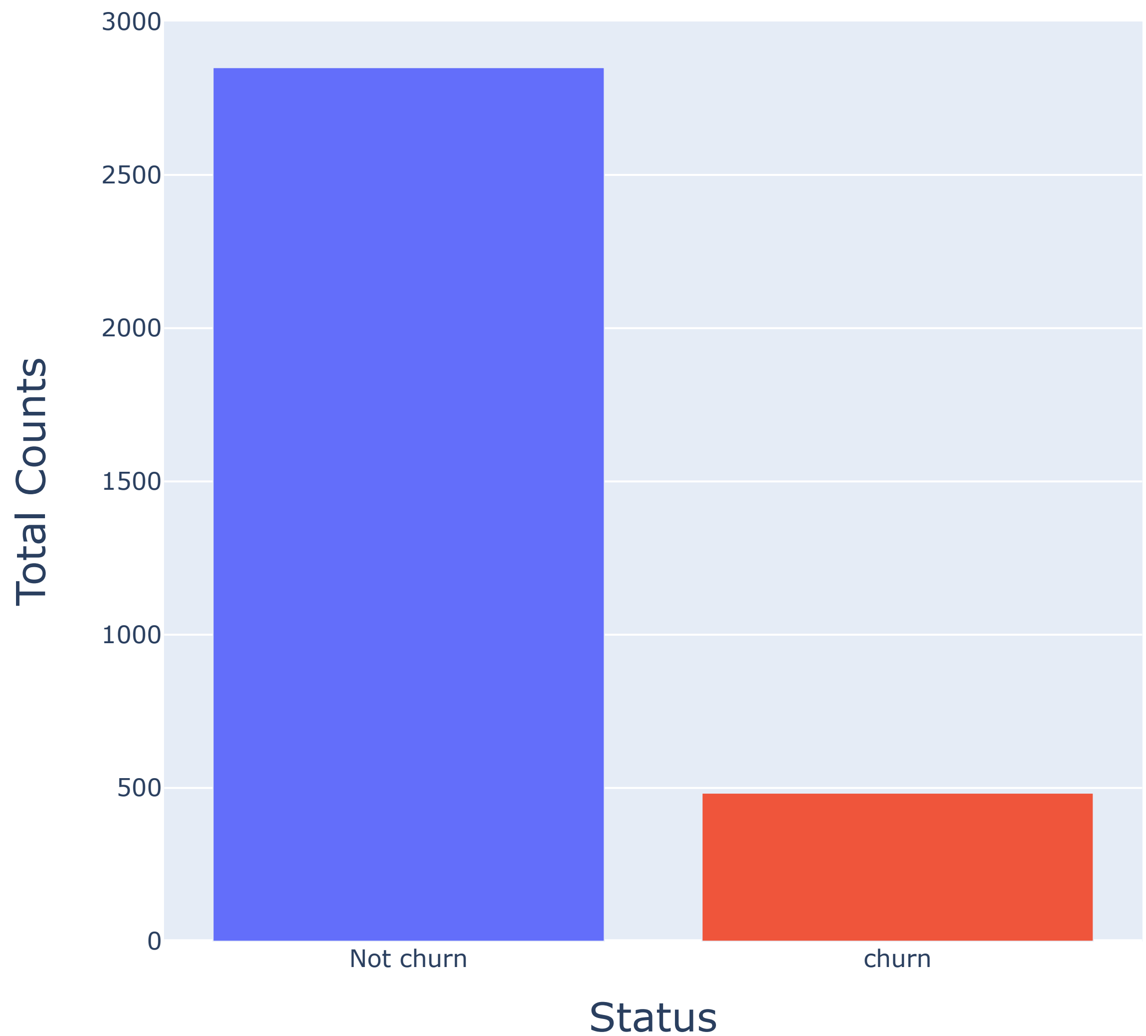
	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38
3	OH	84	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 [18]:

```
chrun_prop = df['churn'].value_counts().to_frame()
fig = px.bar(data_frame=chrun_prop, x=chrun_prop.index, y='churn', color=[
fig.update_layout(
    width=700,
    height=600,
    legend=dict(title=' '),
    xaxis=dict(tickvals=[0,1], ticktext=['Not churn', 'churn'], title='Sta
    yaxis=dict(title='Total Counts', title_font=dict(size=20))
)
fig.update_traces(
    hovertemplate='Status: %{x}<br>Total Counts: %{y}',
)
fig.show()

churn = df['churn'].value_counts()
transuction = churn.index
quantity = churn.values
```



The ratio between the number of churned customers and non-churned customers in the above graph clearly shows a significant imbalance in the data. This imbalance can have a considerable impact on the performance of the machine learning model. Therefore, in the modeling stage, we will address this data imbalance by generating synthetic data using the SMOTE method or Random Oversampling.

In [19]:
```
# Analysis categorical data
```

Out[19]:

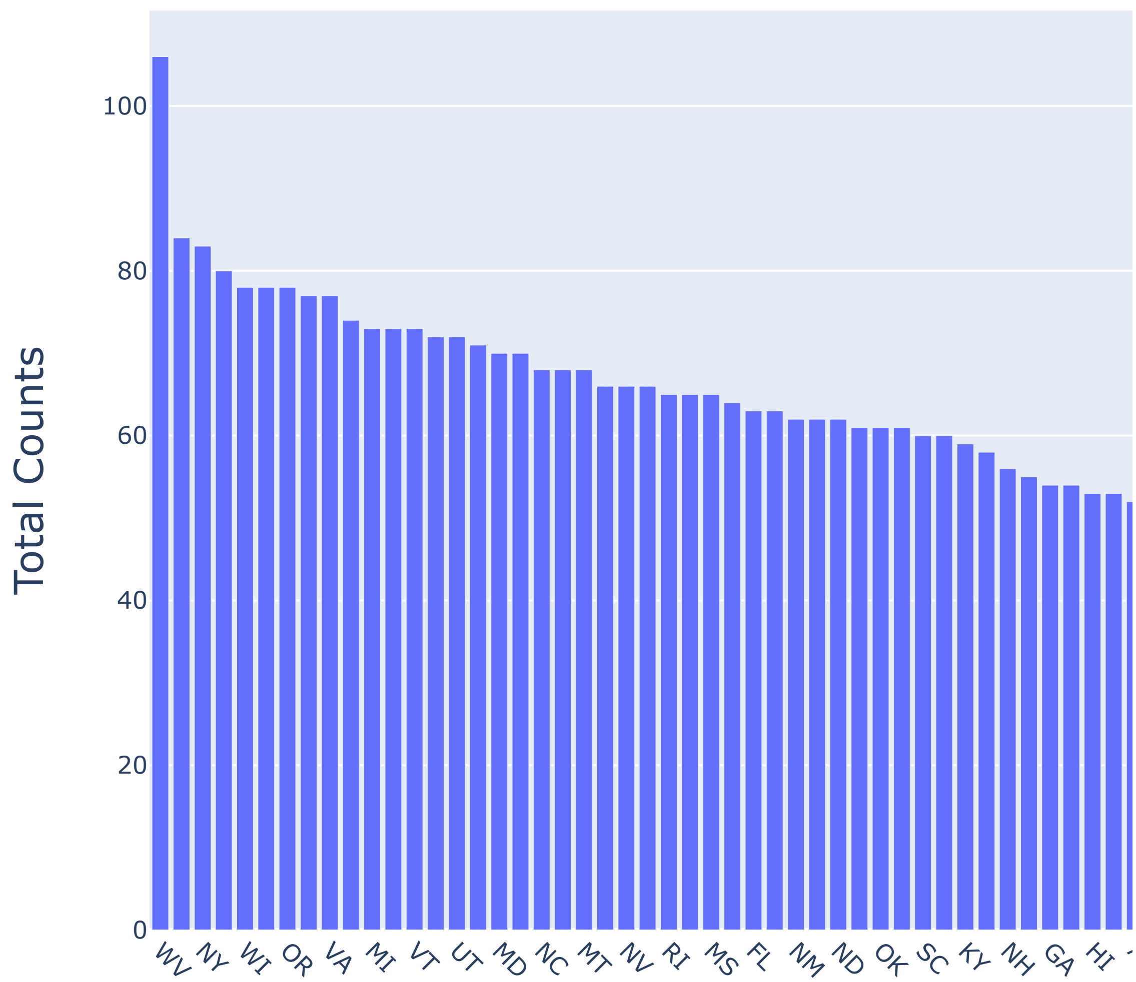
	state	phone number	international plan	voice mail plan
count	3333	3333	3333	3333
unique	51	3333	2	2
top	WV	382-4657	no	no
freq	106	1	3010	2411

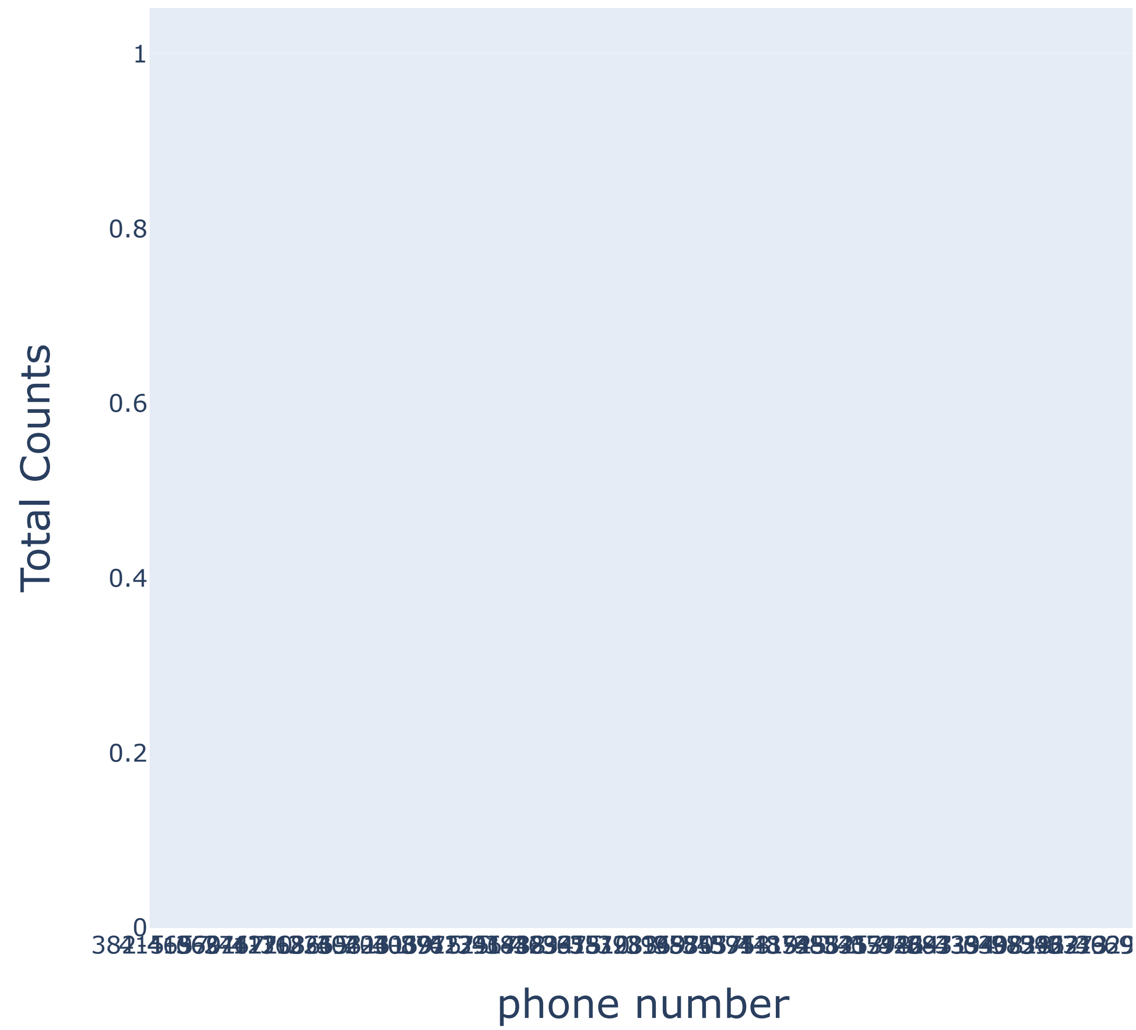
The describe() function is used to display insights about numerical or categorical data, providing statistical summaries such as count, mean, standard deviation, minimum and maximum values, and quartile ranges. It is a quick and useful way to understand the distribution and basic statistics of the data.

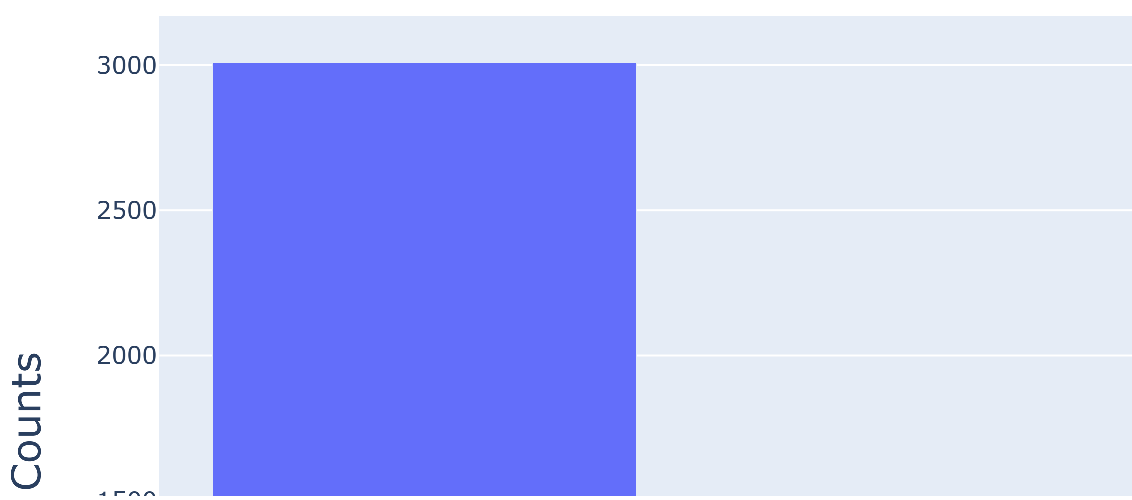
In [20]:

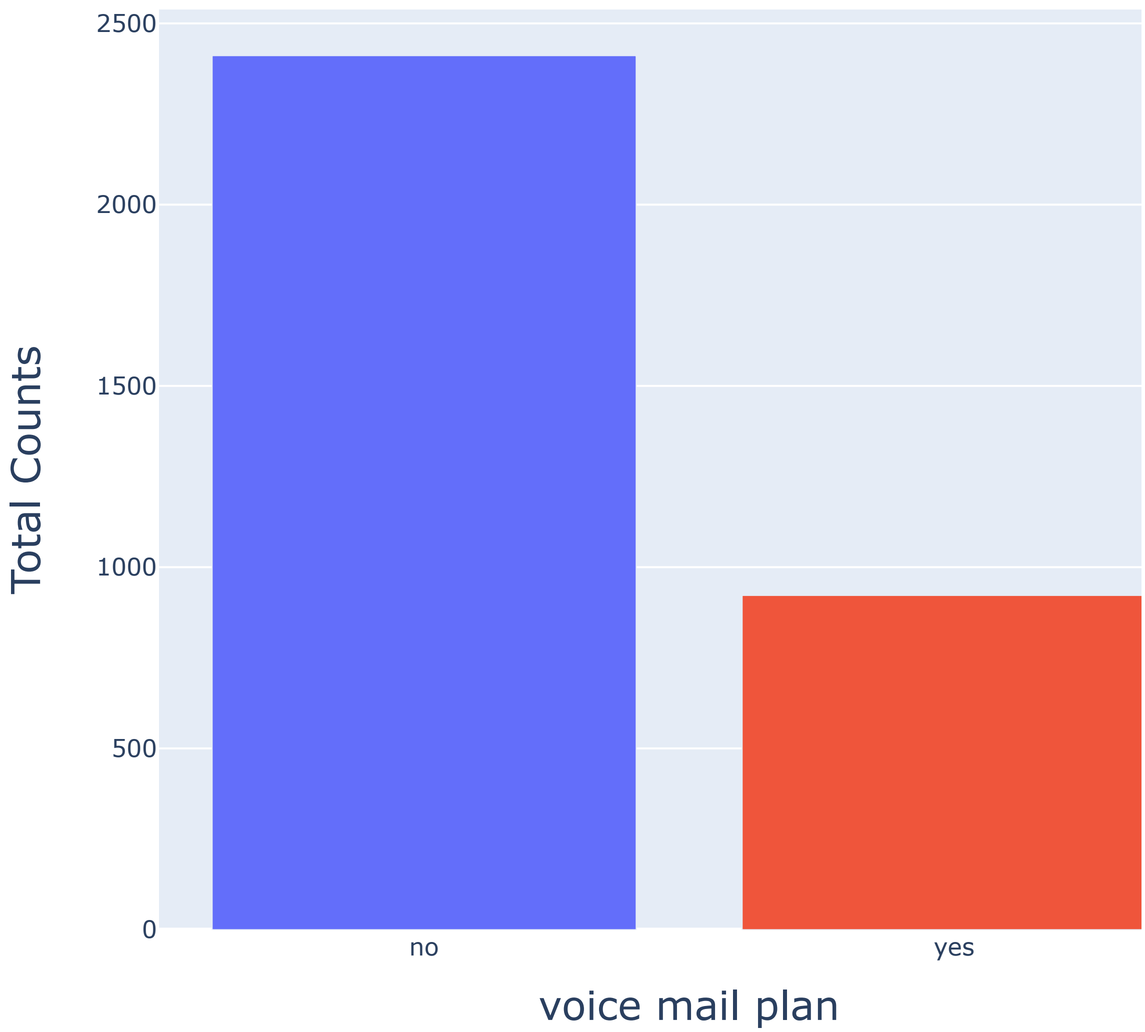
```
# Analysis categorical data values
categorical_col = [col for col in df.columns if df[col].dtypes == 'object'

for col in categorical_col:
    temp_data = df[col].value_counts().to_frame()
    if col == 'state':
        fig = px.bar(data_frame=temp_data, x=temp_data.index, y=col)
        tickangle=45
    else:
        fig = px.bar(data_frame=temp_data, x=temp_data.index, y=col, color
        tickangle=0
    fig.update_layout(
        width=700,
        height=600,
        legend=dict(title=' ', ),
        xaxis_tickangle=tickangle,
        xaxis=dict(title=col, title_font=dict(size=20)),
        yaxis=dict(title='Total Counts', title_font=dict(size=20))
    )
    fig.update_traces(
        hovertemplate='Type: %{x}<br>Total Counts: %{y}',
    )
```




1
0.8
0.6
0.4
0.2
0
Total Counts
phone number


3000
2500
2000
Counts



EDA

Categorical Features

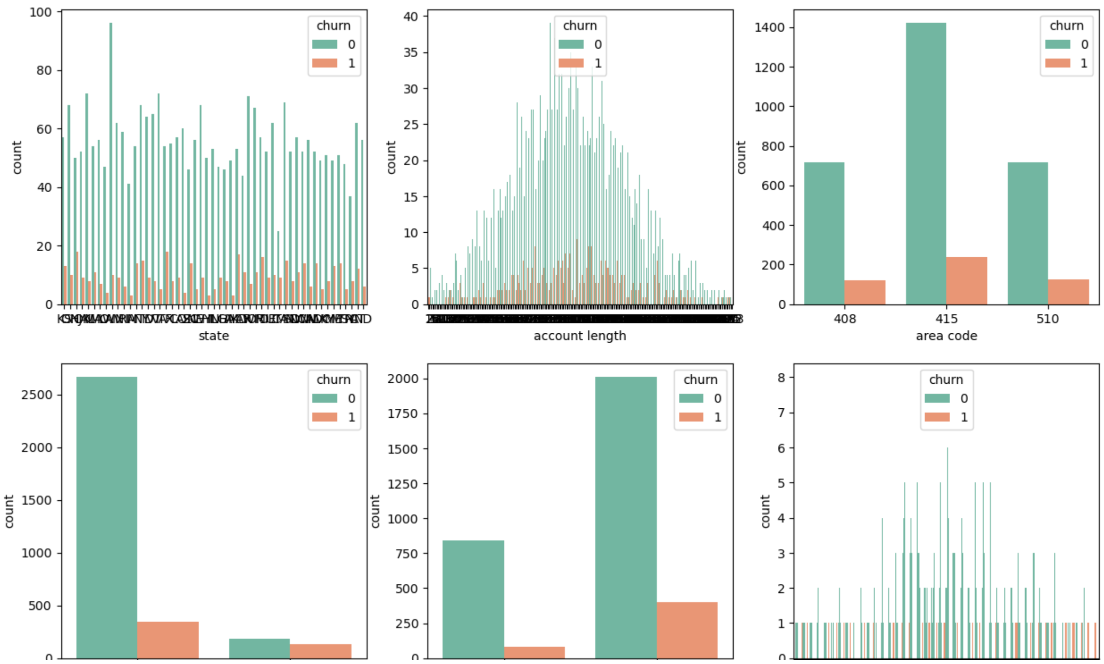
In [21]:

```
fig,axes=plt.subplots(6,3, figsize=(15, 30))
axes = axes.flatten()

categories =['state','account length','area code','international plan','vo
             'total eve calls','total eve charge','total night minutes','t
             'total intl minutes','total intl calls','total intl charge','

for i in range(len(categories)):

    ax= sns.countplot(x=categories[i], data = df, palette = 'Set2', ax=axe
```



The insight we can gather from the analysis is that the state with state code WV has the highest number of total users for the telecommunications provider being analyzed, while the state with state code CA has the lowest number of users.

Another insight we can gather is that the distribution of the number of users for the telecommunications provider being analyzed is highest in the area code 415, while the distribution in other area codes is not significantly different from each other.

Additionally, we can see that only a small portion of the total users are using the international plan service, and only a small portion are using the voice mail plan service.

Noticeable Trends:

Sensior Citizens: most customers are not Senior Citizens. InternetService: higher churn rate for customers using Fiber Optic. OnlineSecurity: higher churn rate for customers with no OnlineSecurity. Contract: higher churn rate for customers unnder Month-to-Month Contract.

Bivariate data analysis

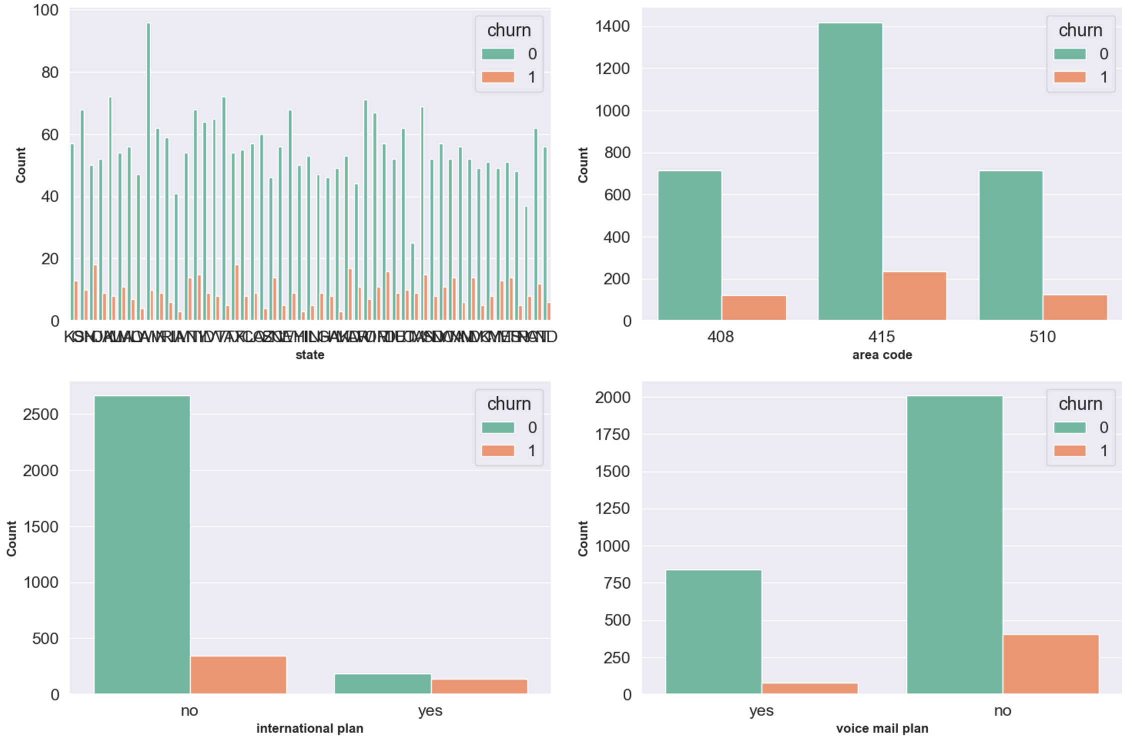
In [60]:

```
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
axes = axes.flatten()

categories = ['state', 'area code', 'international plan', 'voice mail plan

for i, category in enumerate(categories):
    ax = sns.countplot(x=category, data=df, palette='Set2', ax=axes[i], hu
    ax.set_xlabel(category, fontdict=dict(fontsize=12, fontweight='bold'))
    ax.set_ylabel('Count', fontdict=dict(fontsize=12, fontweight='bold'))

plt.tight_layout()
```



Through the process of univariate and bivariate analysis, we obtained more specific insights regarding customers who are at risk of churn and not churn based on the categories of location, area, and service type of each customer type. Looking at the distribution visualization of the categorical columns, the data per category appears to be uniform or consistent, making it less suitable to be included in a machine learning model because the patterns in each category are almost similar. However, to decide whether to include them in the model or not, further calculations will be performed using the WoE and Information Value methods.

In [22]:
```python
numerical_col = df.columns.to_list()

for col in categorical_col:
    numerical_col.remove(col)
    print(col)
```

```
state
phone number
international plan
voice mail plan
['account length', 'area code', 'number vmail messages', 'total day minut
es', 'total day calls', 'total day charge', 'total eve minutes', 'total e
ve calls', 'total eve charge', 'total night minutes', 'total night calls
', 'total night charge', 'total intl minutes', 'total intl calls', 'total
intl charge', 'customer service calls', 'churn'] 17
```

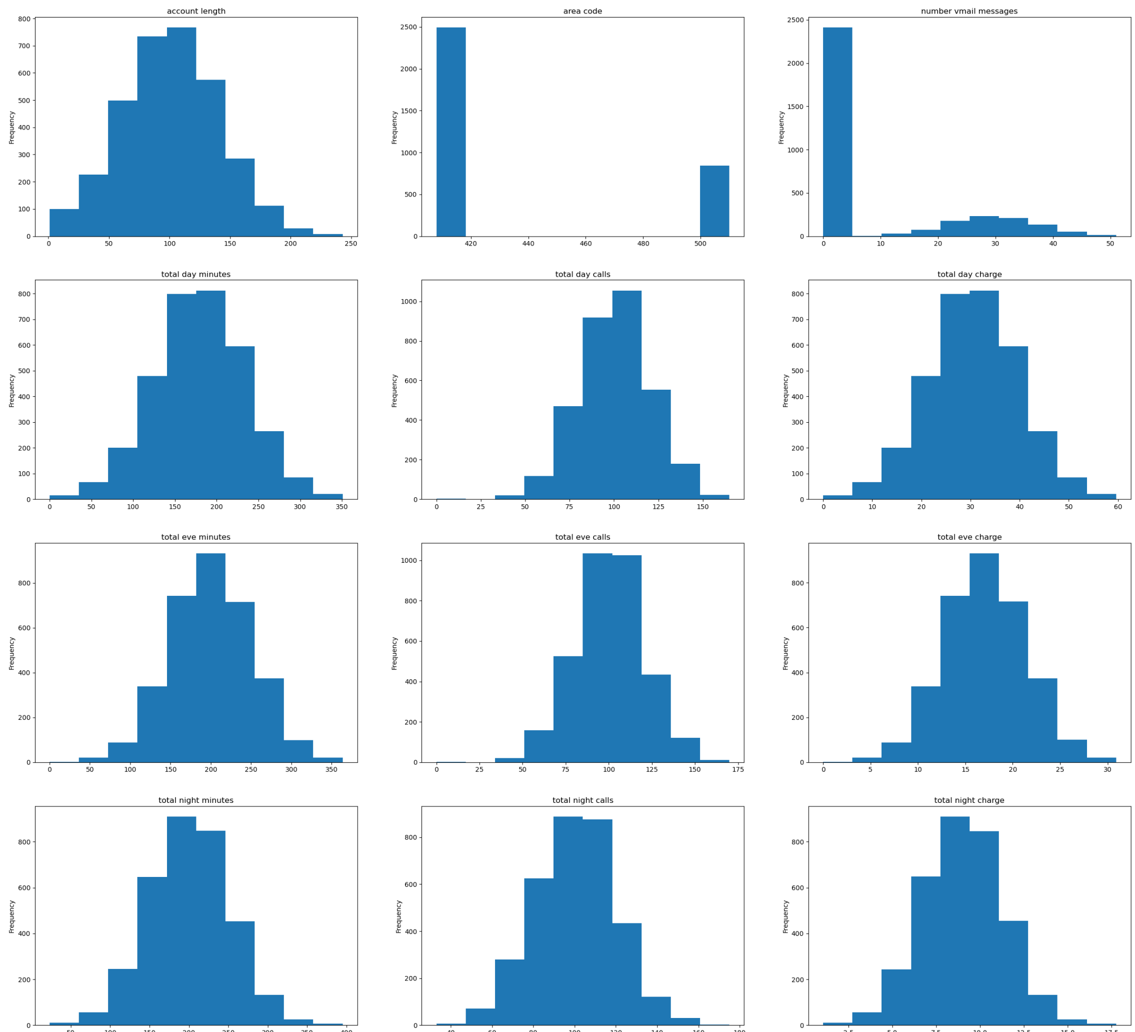
In [23]:
```python
temp_data = df[numerical_col]
```

Out[23]:

	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 [24]:

```python
# Analysis numerical data
# Check data distribution
num = 1
plt.figure(figsize=(30, 35))
for col in numerical_col[:12]:
    plt.subplot(5, 3, num)
    temp_data[col].plot(kind='hist')
    plt.title(col, pad=5)
```



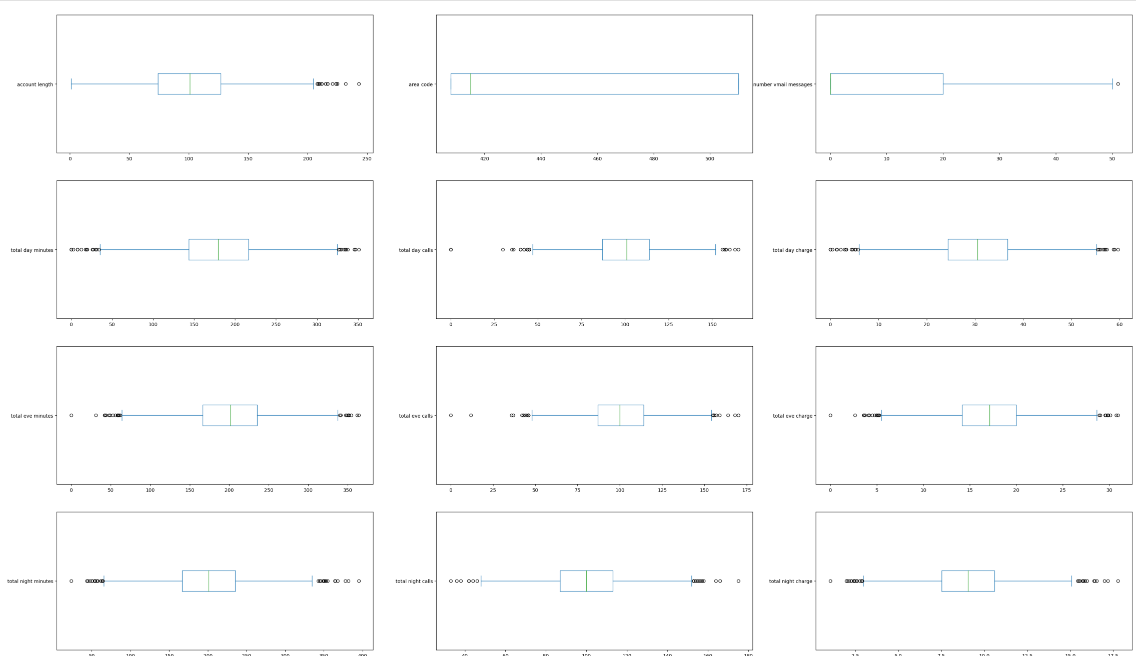
In [25]:

Out[25]:
```
account length            0.096606
area code                 1.126823
number vmail messages     1.264824
total day minutes        -0.029077
total day calls          -0.111787
total day charge         -0.029083
total eve minutes        -0.023877
total eve calls          -0.055563
total eve charge         -0.023858
total night minutes       0.008921
total night calls         0.032500
total night charge        0.008886
total intl minutes       -0.245136
total intl calls          1.321478
total intl charge        -0.245287
customer service calls    1.091359
dtype: float64
```

Checking for outliers

In [26]:
```
# Analysis numerical data
# Check data outlier
temp_data = df[numerical_col]

num = 1
plt.figure(figsize=(40, 30))
for col in numerical_col[:12]:
    plt.subplot(5, 3, num)
    temp_data[col].plot(kind='box', vert=False)
```



From the majority of the numerical data, it appears that most of the data follows a normal distribution and contains outlier values. However, in this case, the outlier values will not be removed because doing so may result in the loss of valuable information for training the machine learning model.

Outliers can sometimes provide important insights or represent unique instances within the data. Removing them without careful consideration can lead to the loss of valuable information or distort the representation of the underlying patterns in the data. It is important to handle outliers appropriately, considering the context and objectives of the analysis.

Instead of removing the outliers, alternative approaches can be used, such as transforming the data, robust statistical techniques, or utilizing outlier-robust models. These methods can help mitigate the impact of outliers on the model while still retaining the valuable information they may contain.

It is crucial to carefully evaluate the effect of outliers on the model's performance and consider the trade-offs between outlier removal and the potential loss of meaningful insights.

In [27]:
```
# Check Correlations
corr_df = temp_data.corr()
```

Out[27]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total
account length	1.000000	-0.012463	-0.004628	0.006216	0.038470	0.006214	-0.006757	0.01
area code	-0.012463	1.000000	-0.001994	-0.008264	-0.009646	-0.008264	0.003580	-0.01
number vmail messages	-0.004628	-0.001994	1.000000	0.000778	-0.009548	0.000776	0.017562	-0.00
total day minutes	0.006216	-0.008264	0.000778	1.000000	0.006750	1.000000	0.007043	0.01
total day calls	0.038470	-0.009646	-0.009548	0.006750	1.000000	0.006753	-0.021451	0.00
total day charge	0.006214	-0.008264	0.000776	1.000000	0.006753	1.000000	0.007050	0.01
total eve minutes	-0.006757	0.003580	0.017562	0.007043	-0.021451	0.007050	1.000000	-0.01
total eve calls	0.019260	-0.011886	-0.005864	0.015769	0.006462	0.015769	-0.011430	1.00
total eve charge	-0.006745	0.003607	0.017578	0.007029	-0.021449	0.007036	1.000000	-0.01
total night minutes	-0.008955	-0.005825	0.007681	0.004323	0.022938	0.004324	-0.012584	-0.00
total night calls	-0.013176	0.016522	0.007123	0.022972	-0.019557	0.022972	0.007586	0.00
total night charge	-0.008960	-0.005845	0.007663	0.004300	0.022927	0.004301	-0.012593	-0.00
total intl minutes	0.009514	-0.018288	0.002856	-0.010155	0.021565	-0.010157	-0.011035	0.00
total intl calls	0.020661	-0.024179	0.013957	0.008033	0.004574	0.008032	0.002541	0.01
total intl charge	0.009546	-0.018395	0.002884	-0.010092	0.021666	-0.010094	-0.011067	0.00
customer service calls	-0.003796	0.027572	-0.013263	-0.013423	-0.018942	-0.013427	-0.012985	0.00
churn	0.016541	0.006174	-0.089728	0.205151	0.018459	0.205151	0.092796	0.00

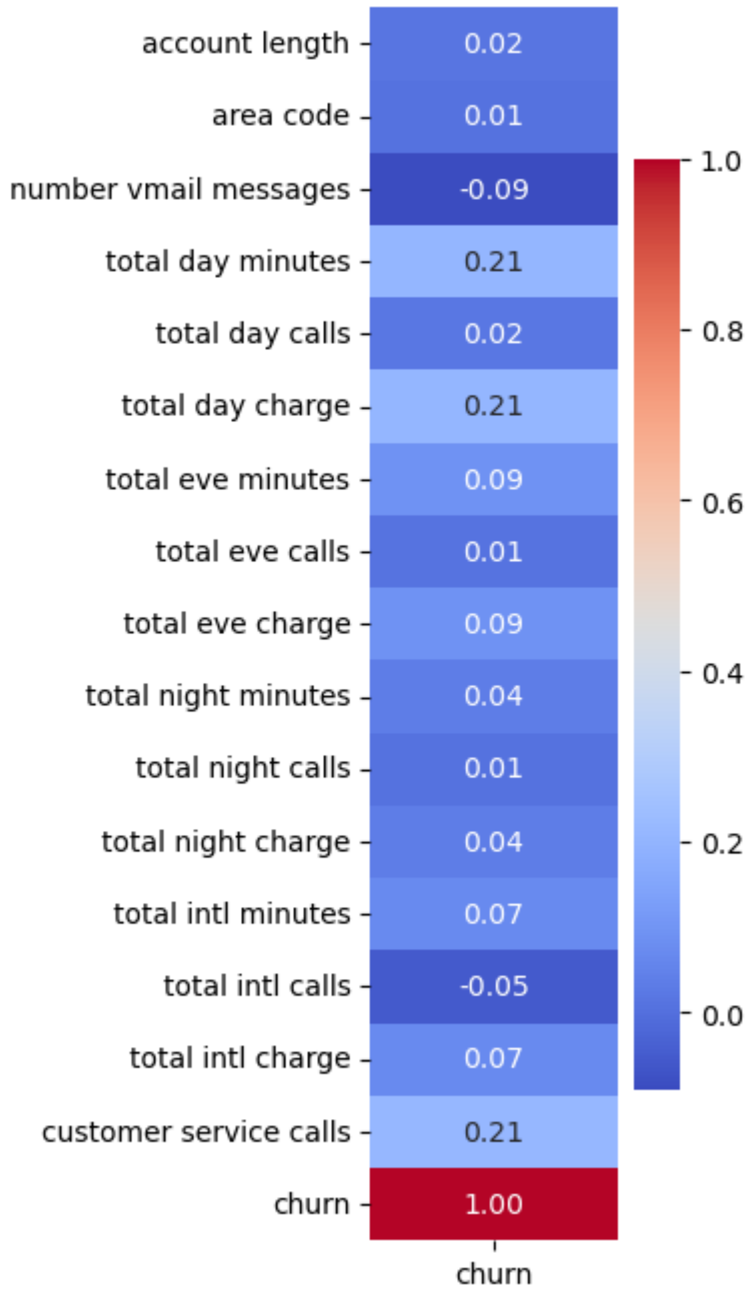
Heatmap Correlation

In [28]:
```
# features correlation with traget variable (churn)

corr_df_target = corr_df['churn'].to_frame()
```

In [29]:
```
plt.figure(figsize = (2, 8))
corr_target_hm = sns.heatmap(
                corr_df_target,
                annot=True,
                fmt=".2f",
                cmap="coolwarm"

)
```

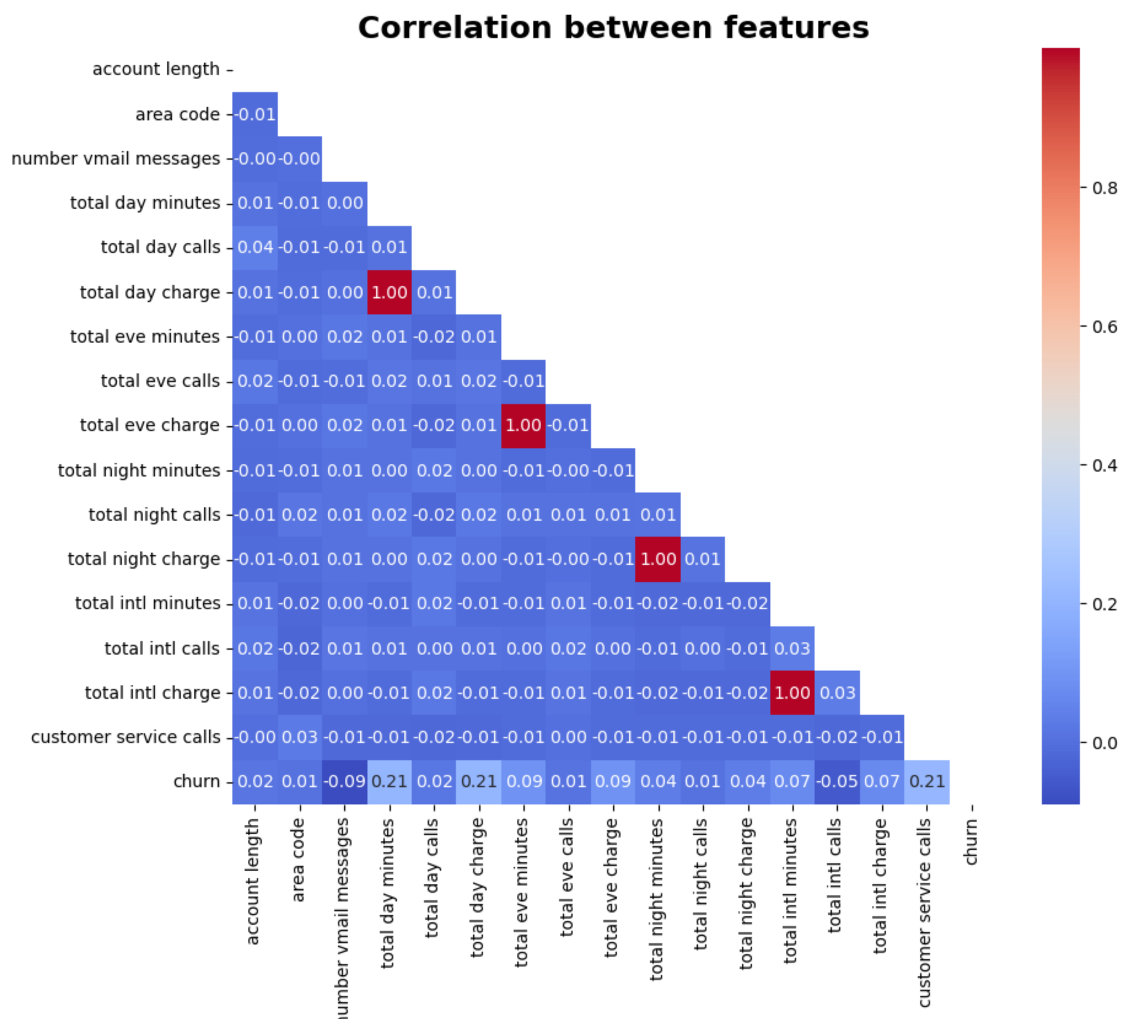


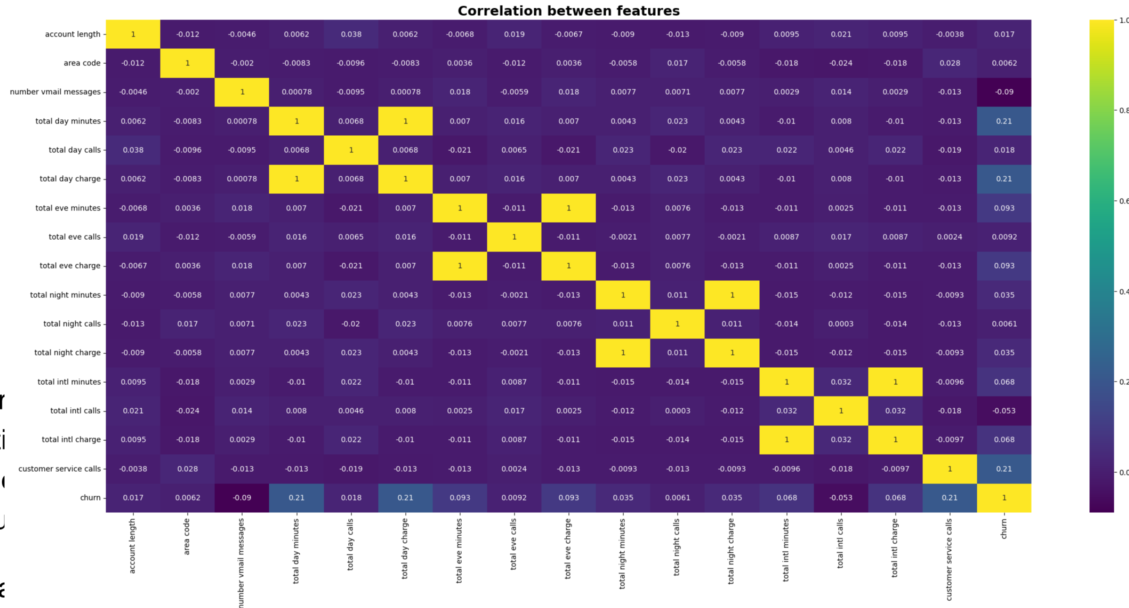
From the visualization above, there doesn't appear to be any significant correlation between the features and the target prediction.

In [30]:

```
# Lets create a heatmap to check for correlations
plt.figure(figsize = (10, 8))
corr_all_hm = sns.heatmap(
                corr_df,
                annot=True,
                fmt=".2f",
                cmap="coolwarm",
                mask=np.triu(np.ones_like(corr_df, dtype=bool)),
                annot_kws={"size": 10}
            )
plt.title("Correlation between features",weight='bold',fontsize=18)
plt.show()

fig, ax = plt.subplots(figsize=(28,12))
ax= sns.heatmap(df.corr(), annot=True, cmap="viridis")
plt.title("Correlation between features",weight='bold',fontsize=18);
```





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has a strong correlation with the target prediction, it may be advisable to drop that feature. This is because it can lead to multicollinearity issues and can interfere with the performance of the machine learning model. However, if the feature is essential in explaining the variability in the target prediction and there are no other features that can explain it well, it is recommended not to remove it.

Feature Engineering

In [31]:

```
# Calculate WoE and IV
def woe_iv_values(dataframe:pd.DataFrame, feature:str, target:str):

    dataframe = pd.concat([dataframe.groupby(feature)[target].sum().reset_
    dataframe = dataframe.iloc[:, [0,1, 3]]
    dataframe.columns = [dataframe.columns.values[0], 'n_good', 'n_observa

    dataframe['n_bad'] = dataframe['n_observation'] - dataframe['n_good']
    dataframe['bad-rate_pct'] = round((dataframe['n_bad'] / dataframe['n_o
    dataframe['good_proportion'] = dataframe['n_good'] / dataframe['n_good
    dataframe['bad_proportion'] = dataframe['n_bad'] / dataframe['n_bad'].
    dataframe['WoE'] = np.log(dataframe['good_proportion'] / dataframe['ba
    dataframe['IV'] = (dataframe['good_proportion'] - dataframe['bad_propo

    return dataframe
```

In [32]:
```
# WoE IV -> State
```

Out[32]:

	state	n_good	n_observation	n_bad	bad-rate_pct	good_proportion	bad_proportion	W
0	AK	3	52	49	94.231	0.006211	0.017193	-1.018
1	AL	8	80	72	90.000	0.016563	0.025263	-0.422
2	AR	11	55	44	80.000	0.022774	0.015439	0.388
3	AZ	4	64	60	93.750	0.008282	0.021053	-0.932
4	CA	9	34	25	73.529	0.018634	0.008772	0.753
5	CO	9	66	57	86.364	0.018634	0.020000	-0.070
6	CT	12	74	62	83.784	0.024845	0.021754	0.132
7	DC	5	54	49	90.741	0.010352	0.017193	-0.507
8	DE	9	61	52	85.246	0.018634	0.018246	0.021
9	FL	8	63	55	87.302	0.016563	0.019298	-0.152
10	GA	8	54	46	85.185	0.016563	0.016140	0.025
11	HI	3	53	50	94.340	0.006211	0.017544	-1.038
12	IA	3	44	41	93.182	0.006211	0.014386	-0.839
13	ID	9	73	64	87.671	0.018634	0.022456	-0.186
14	IL	5	58	53	91.379	0.010352	0.018596	-0.585
15	IN	9	71	62	87.324	0.018634	0.021754	-0.154
16	KS	13	70	57	81.429	0.026915	0.020000	0.296
17	KY	8	59	51	86.441	0.016563	0.017895	-0.077
18	LA	4	51	47	92.157	0.008282	0.016491	-0.688
19	MA	11	65	54	83.077	0.022774	0.018947	0.183
20	MD	17	70	53	75.714	0.035197	0.018596	0.637
21	ME	13	62	49	79.032	0.026915	0.017193	0.448
22	MI	16	73	57	78.082	0.033126	0.020000	0.504
23	MN	15	84	69	82.143	0.031056	0.024211	0.249
24	MO	7	63	56	88.889	0.014493	0.019649	-0.304
25	MS	14	65	51	78.462	0.028986	0.017895	0.482
26	MT	14	68	54	79.412	0.028986	0.018947	0.425
27	NC	11	68	57	83.824	0.022774	0.020000	0.129
28	ND	6	62	56	90.323	0.012422	0.019649	-0.458
29	NE	5	61	56	91.803	0.010352	0.019649	-0.640
30	NH	9	56	47	83.929	0.018634	0.016491	0.122
31	NJ	18	68	50	73.529	0.037267	0.017544	0.753
32	NM	6	62	56	90.323	0.012422	0.019649	-0.458

	state	n_good	n_observation	n_bad	bad-rate_pct	good_proportion	bad_proportion	W
33	NV	14	66	52	78.788	0.028986	0.018246	0.462
34	NY	15	83	68	81.928	0.031056	0.023860	0.263
35	OH	10	78	68	87.179	0.020704	0.023860	-0.141
36	OK	9	61	52	85.246	0.018634	0.018246	0.021
37	OR	11	78	67	85.897	0.022774	0.023509	-0.031
38	PA	8	45	37	82.222	0.016563	0.012982	0.243
39	RI	6	65	59	90.769	0.012422	0.020702	-0.510
40	SC	14	60	46	76.667	0.028986	0.016140	0.585
41	SD	8	60	52	86.667	0.016563	0.018246	-0.096
42	TN	5	53	48	90.566	0.010352	0.016842	-0.486
43	TX	18	72	54	75.000	0.037267	0.018947	0.676
44	UT	10	72	62	86.111	0.020704	0.021754	-0.049
45	VA	5	77	72	93.506	0.010352	0.025263	-0.892
46	VT	8	73	65	89.041	0.016563	0.022807	-0.319
47	WA	14	66	52	78.788	0.028986	0.018246	0.462
48	WI	7	78	71	91.026	0.014493	0.024912	-0.541

In [33]:

Out[33]: ['state', 'phone number', 'international plan', 'voice mail plan']

In [34]:

```
# WoE IV -> Area code
```

Out[34]:

	area code	n_good	n_observation	n_bad	bad-rate_pct	good_proportion	bad_proportion	Wo
0	408	122	838	716	85.442	0.252588	0.251228	0.0053
1	415	236	1655	1419	85.740	0.488613	0.497895	-0.0188
2	510	125	840	715	85.119	0.258799	0.250877	0.0310

In [35]:

```
# WoE IV -> International plan
```

Out[35]:

	international plan	n_good	n_observation	n_bad	bad-rate_pct	good_proportion	bad_proportion
0	no	346	3010	2664	88.505	0.716356	0.934737
1	yes	137	323	186	57.585	0.283644	0.065263

In [36]:
```
# WoE IV -> Voice mail plan
```

Out[36]:

	voice mail plan	n_good	n_observation	n_bad	bad-rate_pct	good_proportion	bad_proportion	W
0	no	403	2411	2008	83.285	0.834369	0.704561	0.1691
1	yes	80	922	842	91.323	0.165631	0.295439	-0.5786

Range of Information Values (IV):

(I).Less than 0.02: Variable has poor predictive power. (II).0.02 to 0.1: Variable has weak predictive power. (III).0.1 to 0.3: Variable has moderate predictive power. (IV).0.3 to 0.5: Variable has strong predictive power. (V).Greater than 0.5: Variable has very strong predictive power.

However, it should be noted that if the Information Value (IV) is greater than or equal to 1, it is recommended to double-check because such a value is considered too good to be true. In practice, very high IV values like this are rare, especially in complex cases or large datasets.

In [37]:
```
target_prediction = numerical_col[-1]
numerical_col.remove('churn')
```

Out[37]: `['state', 'phone number', 'international plan', 'voice mail plan']`

In [38]:
```
print(target_prediction)
print(numerical_col)
```

```
churn
['account length', 'area code', 'number vmail messages', 'total day minut
es', 'total day calls', 'total day charge', 'total eve minutes', 'total e
ve calls', 'total eve charge', 'total night minutes', 'total night calls
', 'total night charge', 'total intl minutes', 'total intl calls', 'total
intl charge', 'customer service calls']
['state', 'phone number', 'international plan', 'voice mail plan']
```

In [39]:
```
# Calculate Mutual Information
from sklearn.feature_selection import mutual_info_regression

def make_mi_scores(df_feature, target_prediction):
    mi_scores = mutual_info_regression(df_feature, target_prediction, rand
    mi_scores = pd.Series(mi_scores, name="MI Scores", index=df_feature.co
    mi_scores = mi_scores.sort_values(ascending=False)
```

In [40]:
```
df['total charge'] = df['total day charge'] + df['total eve charge'] + df[
df['total calls'] = df['total day calls'] + df['total eve calls'] + df['to
```

In [41]:
```
mi_score = make_mi_scores(df.drop(labels=categorical_col+['churn'], axis=1
```

Out[41]:
```
total charge              0.102771
total day charge          0.057700
total day minutes         0.053419
total mins                0.045324
customer service calls    0.033289
number vmail messages     0.020252
total intl calls          0.006415
area code                 0.000611
total eve charge          0.000057
total intl minutes        0.000000
total calls               0.000000
total intl charge         0.000000
account length            0.000000
total night charge        0.000000
total night calls         0.000000
total eve calls           0.000000
total eve minutes         0.000000
total day calls           0.000000
total night minutes       0.000000
Name: MI Scores, dtype: float64
```

The higher the Mutual Information (MI) value, the more information is shared between the two variables (information from the feature to the target prediction), and the more important the variable is in the model.

Based on the various statistical analyses, the conclusion is that categorical features will not be used and will be dropped.

Furthermore, based on the mutual information results, features with a mutual information value of 0 will be dropped.

In [42]:
```
numerical_col = []

for i in range(len(mi_score)):
    if mi_score.values[i] > 0:
        numerical_col.append(mi_score.index[i])
```

```
['total charge', 'total day charge', 'total day minutes', 'total mins', '
customer service calls', 'number vmail messages', 'total intl calls', 'ar
ea code', 'total eve charge']
```

In [43]:
```
# final dataset feature
df_final = df[list(numerical_col)+['churn']]
```

Out[43]:

	total charge	total day charge	total day minutes	total mins	customer service calls	number vmail messages	total intl calls	area code	total eve charge	churn
0	75.56	45.07	265.1	717.2	1	25	3	415	16.78	0
1	59.24	27.47	161.6	625.2	1	26	3	415	16.62	0
2	62.29	41.38	243.4	539.4	0	0	5	415	10.30	0
3	66.80	50.90	299.4	564.8	2	0	7	408	5.26	0
4	52.09	28.34	166.7	512.0	3	0	3	415	12.61	0
...	...	...	...	...	...	...	...	...	...	...
3328	60.10	26.55	156.2	660.7	2	36	6	415	18.32	0
3329	63.53	39.29	231.1	585.4	3	0	4	415	13.04	0
3330	67.74	30.74	180.8	675.6	2	0	6	510	24.55	0
3331	57.53	36.35	213.8	517.6	2	0	10	510	13.57	0
3332	77.01	39.85	234.4	755.4	0	25	4	415	22.60	0

3333 rows × 10 columns

Model Selection

In [44]:
```
X = df_final.drop(['churn'], axis=1)
y = df_final['churn']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42,
```

Out[44]: ((2333, 9), (1000, 9), (2333,), (1000,))

In [45]:

Out[45]:

	total charge	total day charge	total day minutes	total mins	customer service calls	number vmail messages	total intl calls	area code	total eve charge
606	57.67	23.72	139.5	571.3	0	0	8	415	24.59
2468	60.01	24.96	146.8	650.3	1	41	2	510	24.28
1844	56.33	23.10	135.9	599.4	4	28	3	510	20.78
3187	70.27	36.02	211.9	702.2	1	39	4	408	23.32
3083	69.77	40.04	235.5	707.0	0	0	5	510	12.10
...	...	...	...	...	...	...	...	...	...
2670	60.90	37.57	221.0	560.0	2	12	6	510	12.84
2165	61.33	29.10	171.2	605.9	2	0	3	415	20.70
2988	72.22	44.08	259.3	668.9	3	0	5	415	14.89
179	73.36	39.46	232.1	725.6	3	0	0	408	24.85
2762	32.89	8.76	51.5	394.4	3	0	4	408	13.94

2333 rows × 9 columns

In [46]:

Out[46]:

```
606     0
2468    1
1844    1
3187    0
3083    0
       ..
2670    0
2165    0
2988    0
179     0
2762    0
Name: churn, Length: 2333, dtype: int32
```

In [47]:

Out[47]:

```
(0    1995
 1     338
 Name: churn, dtype: int64,
 0    855
 1    145
 Name: churn, dtype: int64)
```

In [48]:

```
from imblearn.over_sampling import RandomOverSampler
```

In [49]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import MinMaxScaler


scaler = ColumnTransformer([
    ('numerical_col', MinMaxScaler(), numerical_col)]
```

Logistic Regression

The Logistic Regression model is a simple and interpretable classification algorithm, suitable for binary classification with numerical or categorical features. Despite having some limitations, such as the assumption of linearity and limitations for multi-class classification, logistic regression remains a good choice for many classification problems, especially as a baseline for more complex algorithms.

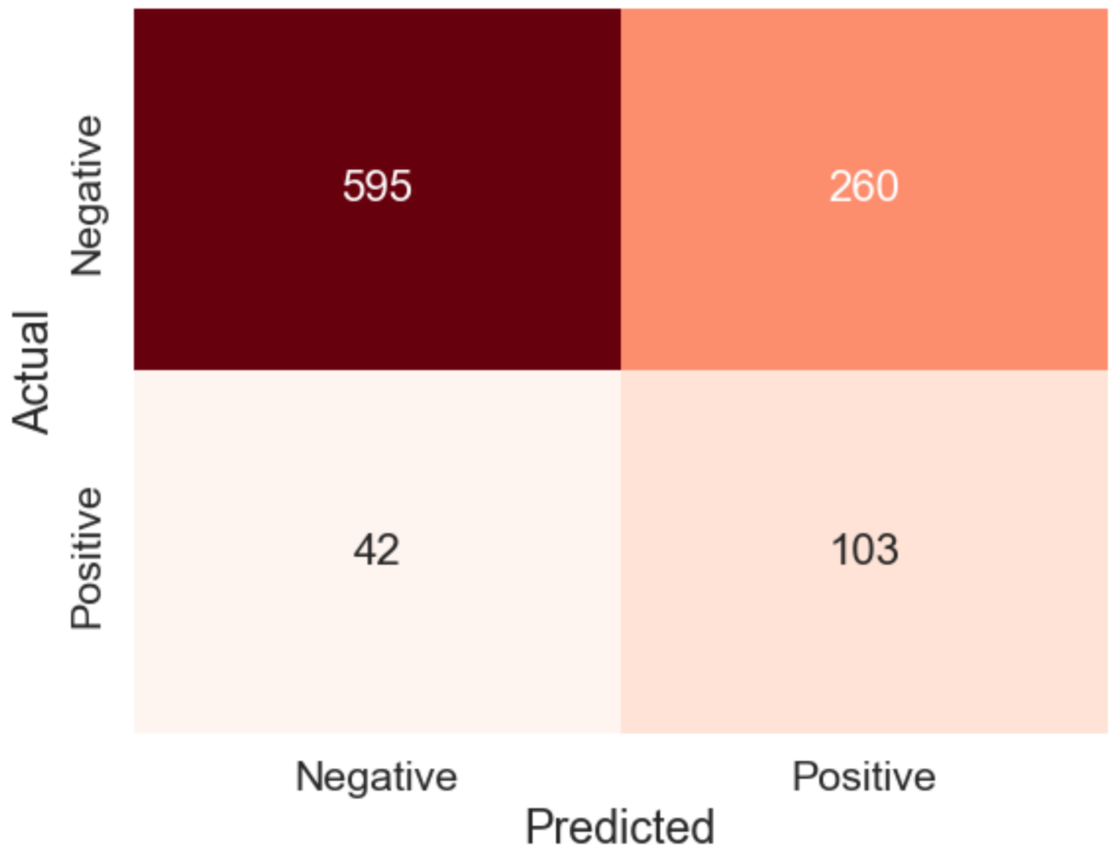
In [50]:

```
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from imblearn.pipeline import Pipeline


logreg_pipe = imbPipeline([
    ('scaler', scaler),
    ('oversample', handle_imbalance),
    ('logreg', LogisticRegression())
])

logreg_param = {
    'logreg__penalty': ['l1', 'l2'],
    'logreg__C': [0.1, 1, 10],
    'logreg__solver': ['liblinear', 'saga'],
    'logreg__max_iter': [100, 200, 300],
    'logreg__class_weight': [None, 'balanced']
}

grid_search_logreg = GridSearchCV(estimator=logreg_pipe, param_grid=logreg_
grid_search_logreg.fit(X_train, y_train)

print('Best parameters :', grid_search_logreg.best_params_)
print('Best Score :', grid_search_logreg.best_score_)

logreg_best_model = grid_search_logreg.best_estimator_
best_model_score = logreg_best_model.score(X_test, y_test)

print('Accuracy : ', best_model_score)

y_pred = logreg_best_model.predict(X_test)
y_pred_proba = logreg_best_model.predict_proba(X_test)
result_report = classification_report(y_true = y_test, y_pred = y_pred)
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
Best parameters : {'logreg__C': 0.1, 'logreg__class_weight': None, 'logre
g__max_iter': 100, 'logreg__penalty': 'l1', 'logreg__solver': 'saga'}
Best Score : 0.7085267114538053
Accuracy :  0.698
              precision    recall  f1-score   support

           0       0.93      0.70      0.80       855
           1       0.28      0.71      0.41       145

    accuracy                           0.70      1000
   macro avg       0.61      0.70      0.60      1000
weighted avg       0.84      0.70      0.74      1000
```

In [51]:

```
# confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)


labels = ['True Negative', 'False Positive', 'False Negative', 'True Posit

# buat heatmap confusion matrix
sns.set(font_scale=1.4) # atur ukuran font
sns.heatmap(conf_matrix, annot=True, annot_kws={"size": 16}, cmap='Reds', 

# tambahkan label axis
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks([0.5, 1.5], ['Negative', 'Positive'])
plt.yticks([0.5, 1.5], ['Negative', 'Positive'])

# tampilkan plot
plt.show()
```



Evaluation of the Regression Model Precision: Precision measures the proportion of correctly predicted churned customers out of all customers predicted as churned. For the churned class (1), the precision is reported as 0.28, indicating that only 28% of the predicted churned customers are actually churned. Recall: Recall (also known as sensitivity or true positive rate) measures the proportion of correctly predicted churned customers out of all actual churned customers. For the churned class (1), the recall is reported as 0.71, indicating that the model captures approximately 71% of the actual churned customers. F1-score: The F1-score is the harmonic mean of precision and recall. It provides a balanced measure of the model's accuracy, taking into account both false positives and false negatives. For the churned class (1), the F1-score is reported as 0.41. Accuracy: Accuracy measures the overall correctness of the model's predictions. In this case, the accuracy is reported as 0.7085267114538053, or approximately 70.8%. This means that the model correctly predicts the churn or non-churn status of customers around 70.8% of the time. Support: Support represents the number of samples in each class. It shows that there are 855 samples for the non-churned class (0) and 145 samples for the churned class (1) in the testing data.

Random Forest

Correct! Random Forest is a classification method that combines the power of multiple decision trees to produce better predictions. It works by building an ensemble of decision trees, where each tree is trained on a random subset of the data and a random subset of features.

By combining the predictions of multiple trees, Random Forest reduces the variance and overfitting issues that may occur with individual decision trees. It leverages the concept of "wisdom of the crowd," where the collective decisions of multiple trees can lead to more accurate and robust predictions.

Random Forest also provides additional benefits such as feature importance ranking, which helps in identifying the most influential features for the classification task. It is a popular and effective algorithm for various classification problems, offering good performance and versatility.

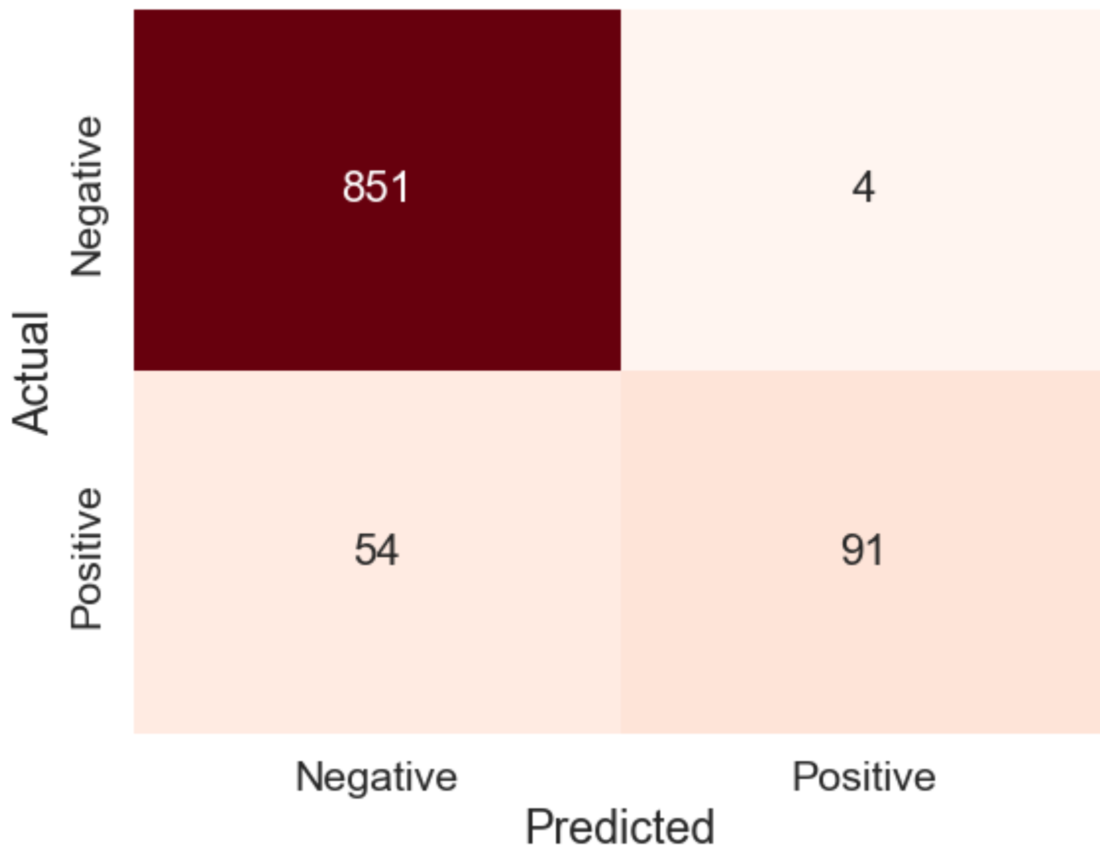
In [52]:

```
rf_pipe = imbPipeline([
    ('scaler', scaler),
    ('oversample', handle_imbalance),
    ('rf', RandomForestClassifier())
])

rf_param = {
    'rf__n_estimators': [100, 200, 300],
    'rf__max_depth': [10, 20, 30, None],
    'rf__min_samples_split': [2, 5, 10],
    'rf__min_samples_leaf': [1, 2, 4],
    'rf__bootstrap': [True, False]
}

grid_search_rf = GridSearchCV(estimator=rf_pipe, param_grid=rf_param, cv=5
grid_search_rf.fit(X_train, y_train)

print("Best param : ", grid_search_rf.best_params_)
print("Best Score : ", grid_search_rf.best_score_)

rf_best_model = grid_search_rf.best_estimator_
best_model_score = rf_best_model.score(X_test, y_test)

print('Accuracy : ', best_model_score)

y_pred = rf_best_model.predict(X_test)
y_pred_proba = rf_best_model.predict_proba(X_test)
result_report = classification_report(y_true = y_test, y_pred = y_pred)
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
Best param :  {'rf__bootstrap': True, 'rf__max_depth': 30, 'rf__min_sampl
es_leaf': 1, 'rf__min_samples_split': 2, 'rf__n_estimators': 300}
Best Score :  0.9477065737839006
Accuracy :  0.942
              precision    recall  f1-score   support

           0       0.94      1.00      0.97       855
           1       0.96      0.63      0.76       145

    accuracy                           0.94      1000
   macro avg       0.95      0.81      0.86      1000
weighted avg       0.94      0.94      0.94      1000
```

In [53]:

```
# confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

labels = ['True Negative', 'False Positive', 'False Negative', 'True Posit

# buat heatmap confusion matrix
sns.set(font_scale=1.4) # atur ukuran font
sns.heatmap(conf_matrix, annot=True, annot_kws={"size": 16}, cmap='Reds',

# tambahkan label axis
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks([0.5, 1.5], ['Negative', 'Positive'])
plt.yticks([0.5, 1.5], ['Negative', 'Positive'])

# tampilkan plot
```



These metrics indicate the performance of the Random Forest model on the test data. * The accuracy of 0.942 means that the model correctly predicted the churn or non-churn status for 94.2% of the samples in the test set. The precision of 0.94 indicates that all the predicted positive (churn) cases were actually true positive cases. The recall of 1.0 means that the model identified 74.77% of the actual positive cases correctly. The F1-score of 0.97 represents the balance between precision and recall, combining them into a single metric. Overall, these metrics suggest that the Random Forest model performs well in terms of accuracy, precision, recall, and F1-score. However, it's important to consider the specific requirements and objectives of the problem at hand when evaluating the model's performance.

K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a machine learning algorithm used for classification and regression problems. It operates based on the principle of "similarity". In the context of classification, a new object is classified based on the majority class of its k nearest neighbors.

KNN is a non-parametric algorithm, meaning it does not make any assumptions about the underlying data distribution. It is particularly suitable for handling non-linear data and datasets with a small number of features. KNN is often used in scenarios where the decision boundary between classes is not well-defined or linear.

One important aspect of KNN is the choice of the parameter k, which represents the number of nearest neighbors considered for classification. The selection of an appropriate k value can have a significant impact on the performance of the algorithm.

KNN is relatively simple and easy to understand, making it a popular choice for beginners in machine learning. However, it can be computationally expensive, especially when dealing with large datasets, as it requires calculating distances between data points.

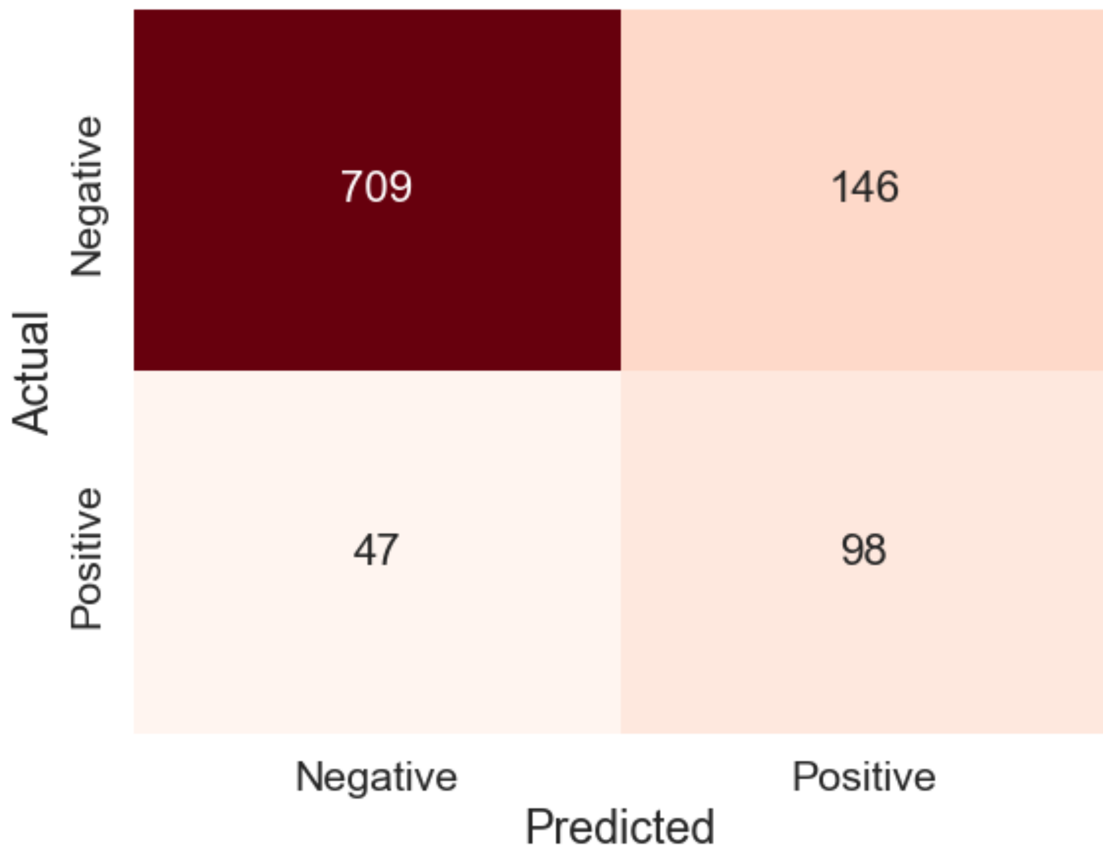
In [54]:

```
knn_pipe = imbPipeline([
    ('scaler', scaler),
    ('oversampling', handle_imbalance),
    ('knn', KNeighborsClassifier())]
)

knn_param = {
    'knn__n_neighbors': [5, 7, 10],
    'knn__weights':['uniform', 'distance'],
    'knn__algorithm': ['ball_tree', 'kd_tree', 'brute'],
    'knn__p': [1, 2]
}

grid_search_knn = GridSearchCV(estimator=knn_pipe, param_grid=knn_param, c
grid_search_knn.fit(X_train, y_train)

print('Best param : ', grid_search_knn.best_params_)
print('Best Score : ', grid_search_knn.best_score_)

knn_best_model = grid_search_knn.best_estimator_

print('Accuracy : ', knn_best_model.score(X_test, y_test))

y_pred = knn_best_model.predict(X_test)
y_pred_proba = knn_best_model.predict_proba(X_test)
result_report = classification_report(y_true=y_test, y_pred=y_pred)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
Best param :  {'knn__algorithm': 'ball_tree', 'knn__n_neighbors': 5, 'knn
__p': 2, 'knn__weights': 'distance'}
Best Score :  0.8092711214858792
Accuracy :  0.807
              precision    recall  f1-score   support

           0       0.94      0.83      0.88       855
           1       0.40      0.68      0.50       145

    accuracy                           0.81      1000
   macro avg       0.67      0.75      0.69      1000
weighted avg       0.86      0.81      0.83      1000
```

In [55]:

```
# confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

labels = ['True Negative', 'False Positive', 'False Negative', 'True Posit

# buat heatmap confusion matrix
sns.set(font_scale=1.4) # atur ukuran font
sns.heatmap(conf_matrix, annot=True, annot_kws={"size": 16}, cmap='Reds',

# tambahkan label axis
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks([0.5, 1.5], ['Negative', 'Positive'])
plt.yticks([0.5, 1.5], ['Negative', 'Positive'])

# tampilkan plot
```



Evaluation of KNN The final model, based on K-Nearest Neighbors (KNN), achieves an accuracy of 80.7%. It has a precision of 94% for non-churned customers and 40% for churned customers. The recall is 83% for non-churned customers and 68% for churned customers. The F1-score is 88% for non-churned customers and 50% for churned customers.

In summary, the KNN model performs well in predicting non-churned customers with high precision and recall. However, its performance in identifying churned customers is relatively lower. The F1-score indicates a good balance between precision and recall for non-churned customers but shows room for improvement for churned customers.

Please note that these evaluation metrics are based on the provided dataset and may vary for new, unseen data. Further fine-tuning of the model's hyperparameters may be necessary to

Support Vector Machine

Support Vector Machines (SVM) is a powerful and flexible classification algorithm that works by finding the best hyperplane that separates data into two or more classes. SVM is particularly effective in handling both linear and non-linear classification problems.

In the case of linearly separable data, SVM aims to find a hyperplane that maximizes the margin, which is the distance between the hyperplane and the nearest data points from each class. This allows for a clear separation between classes and helps improve generalization to new data.

SVM can also handle non-linear classification problems by using kernel functions. These functions transform the original feature space into a higher-dimensional space, where a linear hyperplane can be used to separate the data. Some commonly used kernel functions include the linear, polynomial, and radial basis function (RBF) kernels.

One advantage of SVM is its ability to handle high-dimensional data and datasets with complex decision boundaries. It is also less prone to overfitting compared to some other algorithms. However, SVM can be computationally expensive, especially with large datasets, and the selection of appropriate hyperparameters and kernel functions can be crucial for its performance.

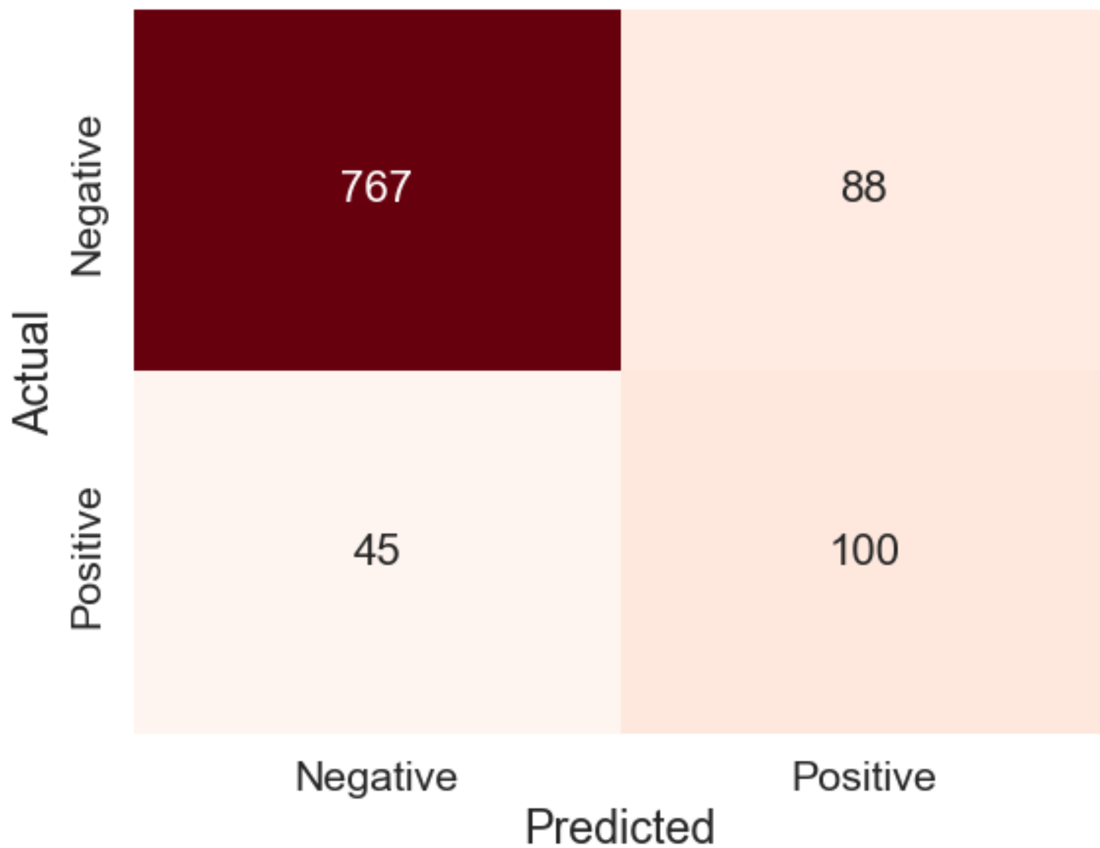
Overall, SVM is a versatile algorithm that can be applied to a wide range of classification problems, both linear and non-linear.

In [56]:

```
svm_pipe = imbPipeline([
    ('scaler', scaler),
    ('oversampling', handle_imbalance),
    ('svm', svm.SVC(probability=True))
])

svm_param = {
    'svm__kernel': ['linear', 'rbf', 'poly'],
    'svm__C': [0.1, 1, 10],
    'svm__gamma': ['scale', 'auto']
}

grid_search_svm = GridSearchCV(estimator=svm_pipe, param_grid=svm_param, c
grid_search_svm.fit(X_train, y_train)

print("Best param : ", grid_search_svm.best_params_)
print("Best Score : ", grid_search_svm.best_score_)

svm_best_model = grid_search_svm.best_estimator_

print('Accuracy : ', svm_best_model.score(X_test, y_test))

y_pred = svm_best_model.predict(X_test)
y_pred_proba = svm_best_model.predict_proba(X_test)
result_report = classification_report(y_true=y_test, y_pred=y_pred)
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits
Best param :  {'svm__C': 10, 'svm__gamma': 'scale', 'svm__kernel': 'rbf'}
Best Score :  0.8864039481302444
Accuracy :  0.867
              precision    recall  f1-score   support

           0       0.94      0.90      0.92       855
           1       0.53      0.69      0.60       145

    accuracy                           0.87      1000
   macro avg       0.74      0.79      0.76      1000
weighted avg       0.88      0.87      0.87      1000
```

In [57]:
```
# confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

labels = ['True Negative', 'False Positive', 'False Negative', 'True Posit

# buat heatmap confusion matrix
sns.set(font_scale=1.4) # atur ukuran font
sns.heatmap(conf_matrix, annot=True, annot_kws={"size": 16}, cmap='Reds', 

# tambahkan label axis
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks([0.5, 1.5], ['Negative', 'Positive'])
plt.yticks([0.5, 1.5], ['Negative', 'Positive'])

# tampilkan plot
```

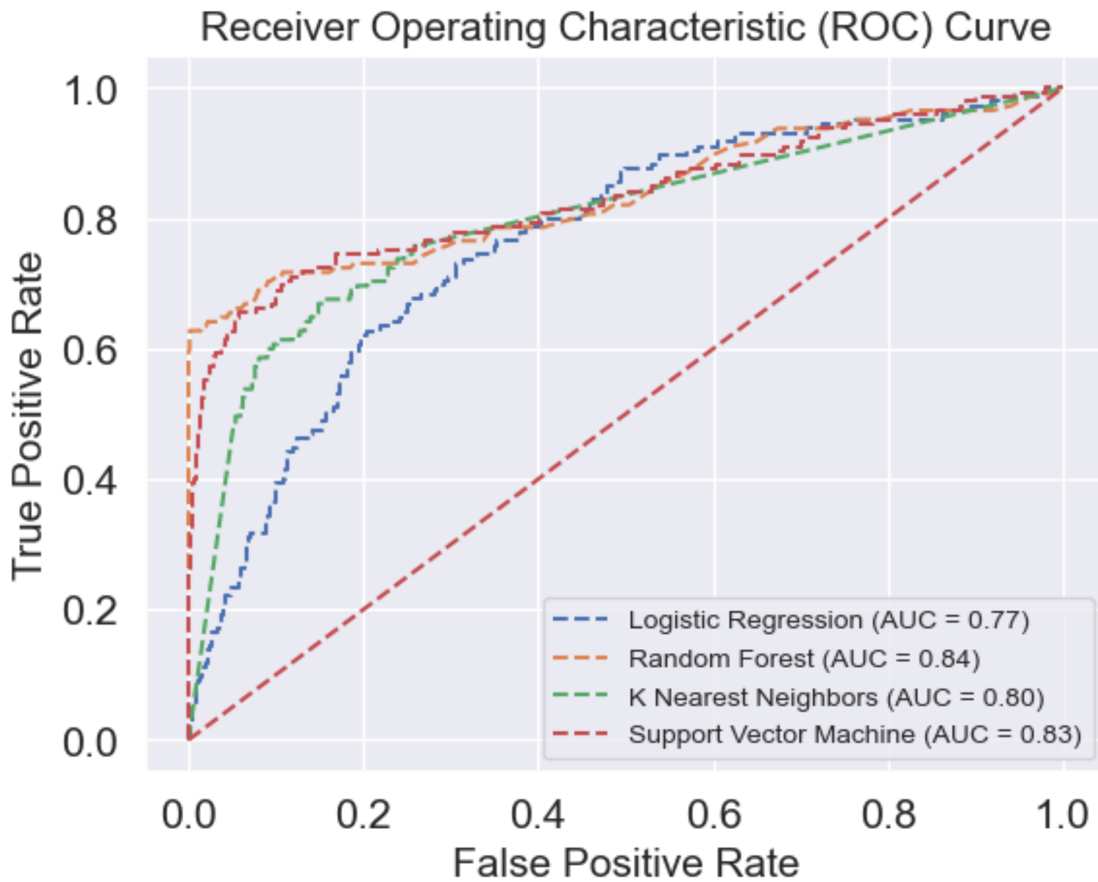


Evaluation of SVM The best hyperparameters were found to be {'svm__C': 10, 'svm__gamma': 'auto', 'svm__kernel': 'rbf'} with a corresponding best score of 0.8864039481302444. The model was then evaluated on a test set of 834 samples, resulting in an overall accuracy of 0.88. The precision and recall for each class are also shown, as well as the f1-score and support for each class.

ROC_AUC Graf

In [58]:

```
# predict probabilities
logreg_probs = logreg_best_model.predict_proba(X_test)[:, 1]
rf_probs = rf_best_model.predict_proba(X_test)[:, 1]
knn_probs = knn_best_model.predict_proba(X_test)[:, 1]
svm_probs = svm_best_model.predict_proba(X_test)[:, 1]

# calculate roc curves and auc scores
logreg_fpr, logreg_tpr, _ = roc_curve(y_test, logreg_probs)
logreg_auc = roc_auc_score(y_test, logreg_probs)

rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_probs)
rf_auc = roc_auc_score(y_test, rf_probs)

knn_fpr, knn_tpr, _ = roc_curve(y_test, knn_probs)
knn_auc = roc_auc_score(y_test, knn_probs)

svm_fpr, svm_tpr, _ = roc_curve(y_test, svm_probs)
svm_auc = roc_auc_score(y_test, svm_probs)

plt.plot(logreg_fpr, logreg_tpr, linestyle='--', label='Logistic Regressio
plt.plot(rf_fpr, rf_tpr, linestyle='--', label='Random Forest (AUC = %0.2f
plt.plot(knn_fpr, knn_tpr, linestyle='--', label='K Nearest Neighbors (AUC
plt.plot(svm_fpr, svm_tpr, linestyle='--', label='Support Vector Machine (

# plot the random line
plt.plot([0, 1], [0, 1], linestyle='--', color='r')

# set the axis labels and title
plt.xlabel('False Positive Rate', fontsize=15)
plt.ylabel('True Positive Rate', fontsize=15)
plt.title('Receiver Operating Characteristic (ROC) Curve', fontsize=15)

# show the legend and plot the figure
plt.legend(fontsize=10)
```



Based on the ROC-AUC scores comparison of the 4 machine learning models, it can be concluded that the Random Forest model performed the best. Therefore, this model will be chosen to make predictions on new data in the future.

EVALUATION OF THE FINAL MODEL

Based on the provided classification report, here is the evaluation of the final model:

Accuracy: 94.2% Precision:

Class 0 (non-churned customers): 94% Class 1 (churned customers): 96% Recall (Sensitivity):

Class 0 (non-churned customers): 100% Class 1 (churned customers): 63% F1-score:

Class 0 (non-churned customers): 97% Class 1 (churned customers): 76% Support:

Class 0 (non-churned customers): 855 Class 1 (churned customers): 145 The accuracy of the model is 94.2%, indicating that it correctly predicts the churn status of 94.2% of the customers. Precision represents the proportion of correctly predicted positive instances out of the total predicted positive instances. In this case, the precision for class 0 (non-churned customers) is 94%, indicating that 94% of the predicted non-churned customers are actually non-churned. The precision for class 1 (churned customers) is 96%, indicating that 96% of the predicted churned customers are actually churned.

Recall, also known as sensitivity or true positive rate, represents the proportion of correctly predicted positive instances out of the total actual positive instances. The recall for class 0 (non-churned customers) is 100%, indicating that the model correctly identifies all the non-churned customers. The recall for class 1 (churned customers) is 63%, indicating that the model captures only 63% of the actual churned customers.

The F1-score is the harmonic mean of precision and recall. It provides a balanced measure between precision and recall. The F1-score for class 0 (non-churned customers) is 97%, indicating a good balance between precision and recall. The F1-score for class 1 (churned customers) is 76%, indicating that the model's performance in capturing churned customers is comparatively lower.

In summary, the final model achieves a high accuracy of 94.2%, with good precision and recall for class 0 (non-churned customers). However, the model's performance in identifying churned customers (class 1) could be further improved to increase the recall.

Please note that these evaluation metrics are based on the provided dataset and may vary when applied to new, unseen data. It is crucial to validate the model's performance on a separate test set or through cross-validation to ensure its generalizability.