Load the datafile

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m
```

```
import warnings
warnings.filterwarnings('ignore')
```

Import Packages

```
# IMPORT PACKAGES
import pandas as pd
import matplotlib.pyplot as plt
```

Merging Second Data file training and testing datasets

```
# Load the datasets

data_test_kale = pd.read_csv('/content/drive/MyDrive/CERTIFICATES/Datafiles/churn-bigml-2
data_train_kale = pd.read_csv('/content/drive/MyDrive/CERTIFICATES/Datafiles/churn-bigml-

# Concatenate the two datasets
combined_data = pd.concat([data_test_kale, data_train_kale], ignore_index=True)

duplicate_rows = combined_data[combined_data.duplicated()]

if duplicate_rows.empty:
    print("No duplicate rows found.")
else:
    print("Duplicate rows found:")
    print(duplicate_rows)



# Save the unique combined dataset to a CSV file
# unique_combined_data.to_csv('/content/drive/MyDrive/CERTIFICATES/Datafiles/unique_combi
```

```
No duplicate rows found.
```

Combining both the datasets

```

```

```
# Load the datasets
data_1_dataworld = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/customer_data_edit
data_2_kale = pd.read_csv('/content/drive/MyDrive/CERTIFICATES/Datafiles/unique_combined_

# Concatenate the two datasets
combined_data_full = pd.concat([data_1_dataworld, data_2_kale], ignore_index=True)

duplicate_rows = combined_data[combined_data.duplicated()]

if duplicate_rows.empty:
    print("No duplicate rows found.")
else:
    print("Duplicate rows found:")
    print(duplicate_rows)



# Remove duplicate rows
unique_combined_data = combined_data.drop_duplicates()

# Save the unique combined dataset to a CSV file
# combined_data_full.to_csv('/content/drive/MyDrive/CERTIFICATES/Datafiles/combined_data_
```

```
No duplicate rows found.
```

```
combined_data_full.shape
```

```
(16225, 23)
```

```
data=combined_data_full.copy()
```

```
data.head()
```

	recordID	state	account_length	area_code	international_plan	voice_mail_plan	n
0	1.0	HI	101	510	no	no	
1	2.0	MT	137	510	no	no	
2	3.0	OH	103	408	no	yes	
3	4.0	NM	99	415	no	no	
4	5.0	SC	108	415	no	no	

5 rows × 23 columns

```
data.dtypes
```

```
recordID                        float64
state                            object
```

```
account_length                  int64
area_code                       int64
international_plan             object
voice_mail_plan                object
number_vmail_messages           int64
total_day_minutes             float64
total_day_calls                 int64
total_day_charge              float64
total_eve_minutes             float64
total_eve_calls                 int64
total_eve_charge              float64
total_night_minutes           float64
total_night_calls               int64
total_night_charge            float64
total_intl_minutes            float64
total_intl_calls                int64
total_intl_charge             float64
number_customer_service_calls   int64
churn                          object
customer_id                   float64
State                          object
dtype: object
```

Drop the irrerelavant columns

```
# Drop the specified columns from the dataset
data = data.drop(['recordID', 'state', 'area_code', 'customer_id', 'State'], axis=1)

# Display the first 5 rows of the updated dataset
data.head()
```

	account_length	international_plan	voice_mail_plan	number_vmail_messages	total_
0	101	no	no	0	
1	137	no	no	0	
2	103	no	yes	29	
3	99	no	no	0	
4	108	no	no	0	

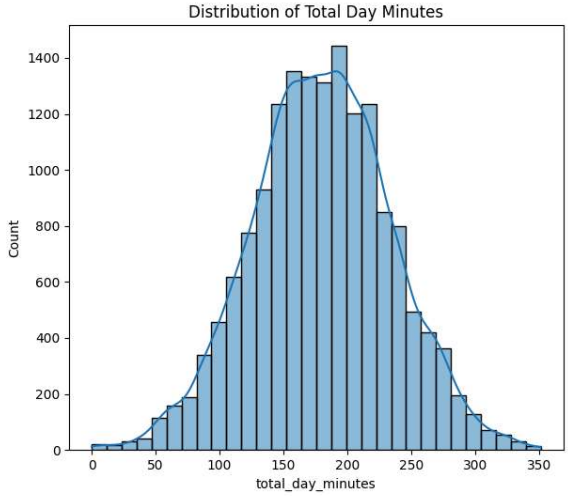
```
data.dtypes
```

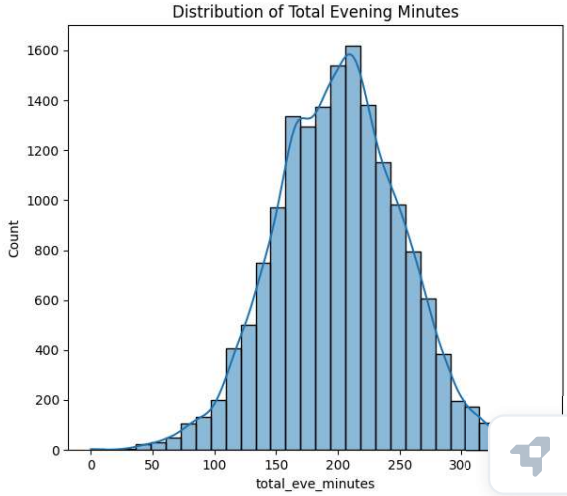
```
account_length                  int64
international_plan             object
voice_mail_plan                object
number_vmail_messages           int64
total_day_minutes             float64
total_day_calls                 int64
total_day_charge              float64
total_eve_minutes             float64
total_eve_calls                 int64
total_eve_charge              float64
```

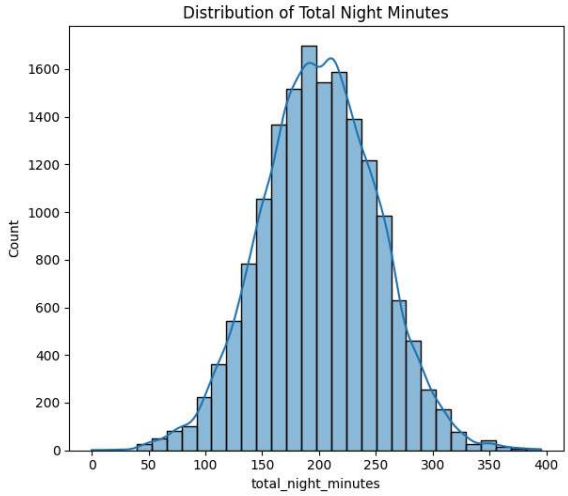
```
total_night_minutes             float64
total_night_calls                 int64
total_night_charge              float64
total_intl_minutes              float64
total_intl_calls                  int64
total_intl_charge               float64
number_customer_service_calls     int64
churn                            object
dtype: object
```

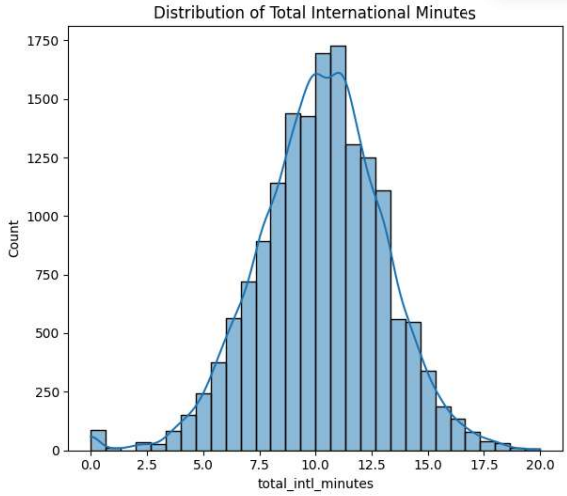
Visualizations

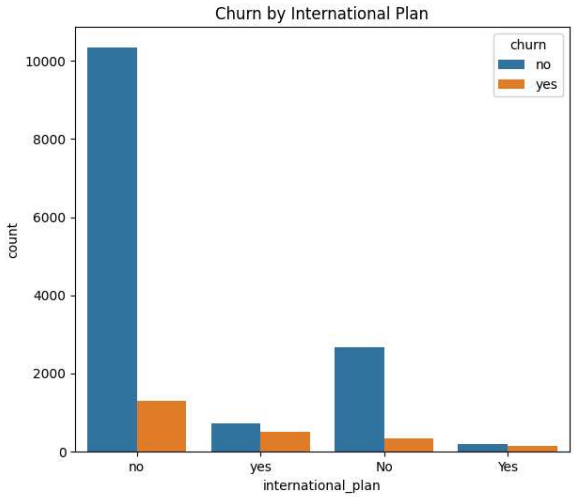
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Visualizations
fig, axes = plt.subplots(3, 2, figsize=(14, 18))

# Histograms for call details
sns.histplot(data['total_day_minutes'], bins=30, kde=True, ax=axes[0, 0])
axes[0, 0].set_title('Distribution of Total Day Minutes')

sns.histplot(data['total_eve_minutes'], bins=30, kde=True, ax=axes[0, 1])
axes[0, 1].set_title('Distribution of Total Evening Minutes')

sns.histplot(data['total_night_minutes'], bins=30, kde=True, ax=axes[1, 0])
axes[1, 0].set_title('Distribution of Total Night Minutes')

sns.histplot(data['total_intl_minutes'], bins=30, kde=True, ax=axes[1, 1])
axes[1, 1].set_title('Distribution of Total International Minutes')

# Bar chart for churn rates by international plan
sns.countplot(x='international_plan', hue='churn', data=data, ax=axes[2, 0])
axes[2, 0].set_title('Churn by International Plan')

# Correlation heatmap
corr = data.select_dtypes(include=[np.number]).corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".1f", ax=axes[2, 1])
axes[2, 1].set_title('Correlation Heatmap')

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

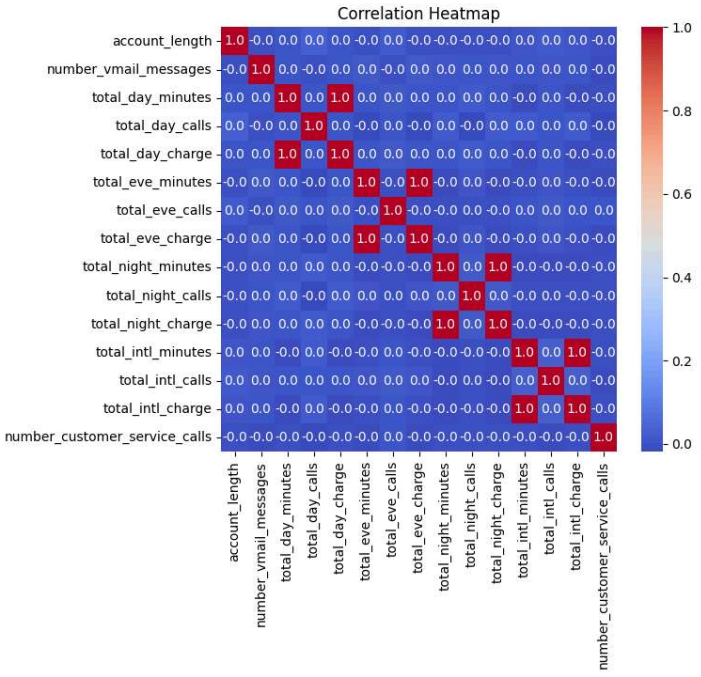

Distribution of Total Day Minutes
Count
total_day_minutes


Distribution of Total Evening Minutes
Count
total_eve_minutes


Distribution of Total Night Minutes
Count
total_night_minutes


Distribution of Total International Minutes
Count
total_intl_minutes


Churn by International Plan
churn
no
yes
count
no
yes
No
Yes
international_plan


Correlation Heatmap
account_length
number_vmail_messages
total_day_minutes
total_day_calls
total_day_charge
total_eve_minutes
total_eve_calls
total_eve_charge
total_night_minutes
total_night_calls
total_night_charge
total_intl_minutes
total_intl_calls
total_intl_charge
number_customer_service_calls

Missing Values

```
# Step 1: Handling Missing Values
# Checking for any missing values in the dataset
missing_data = data.isnull().sum()
missing_data
```

```
account_length                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
number_customer_service_calls   0
churn                           0
dtype: int64
```

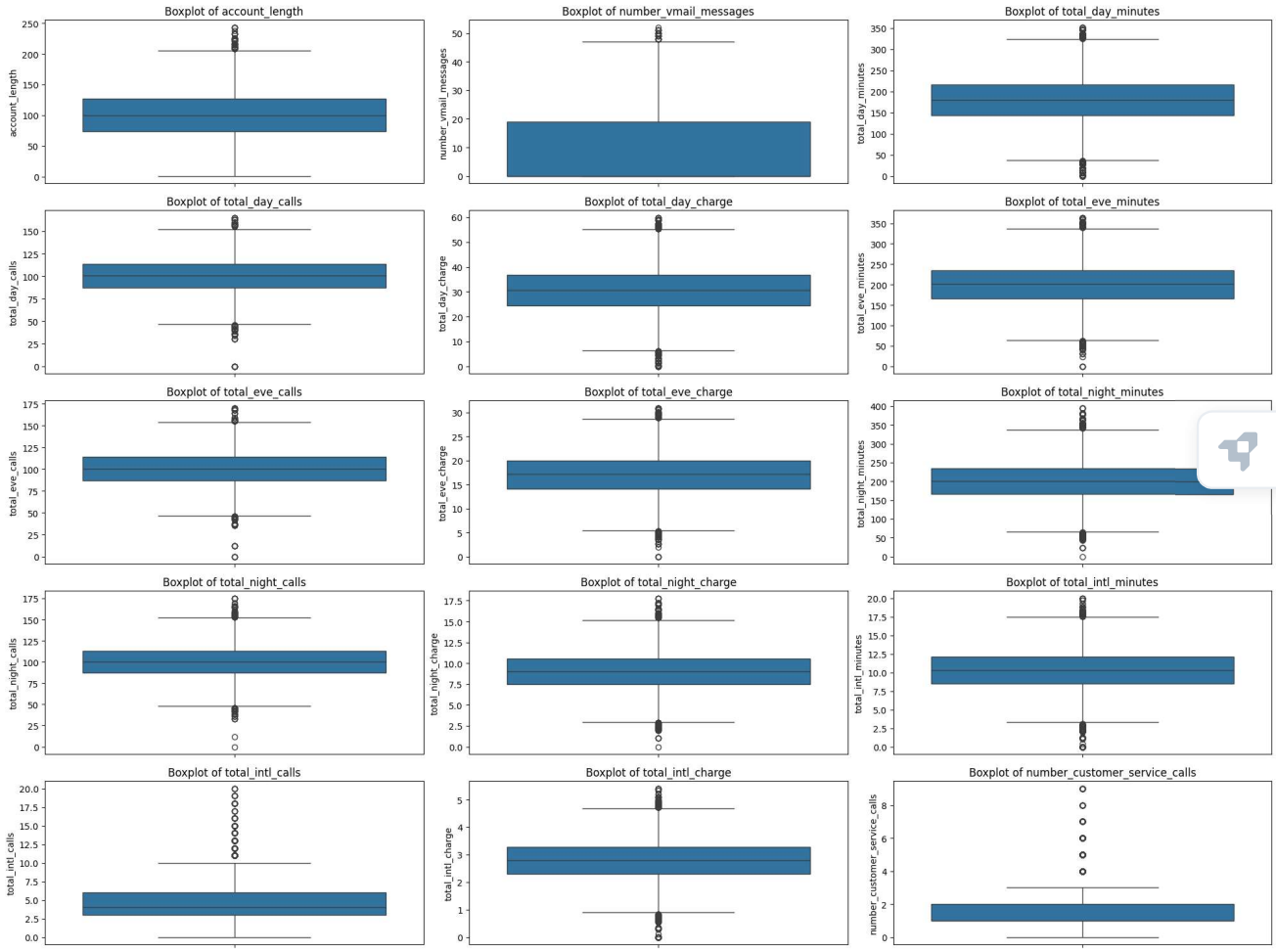
Data Type Conversions

```
# Step 2: Data Type Conversions
# Correcting data types: converting 'yes'/'no' to binary format for 'international_plan'
data['international_plan'] = data['international_plan'].map({'yes': 1, 'no': 0})
data['voice_mail_plan'] = data['voice_mail_plan'].map({'yes': 1, 'no': 0})
# Output the number of missing values per column and the head of the dataframe to see the
data.head()
```

	account_length	international_plan	voice_mail_plan	number_vmail_messages	total_
0	101	0.0	0.0	0	
1	137	0.0	0.0	0	
2	103	0.0	1.0	29	
3	99	0.0	0.0	0	
4	108	0.0	0.0	0	

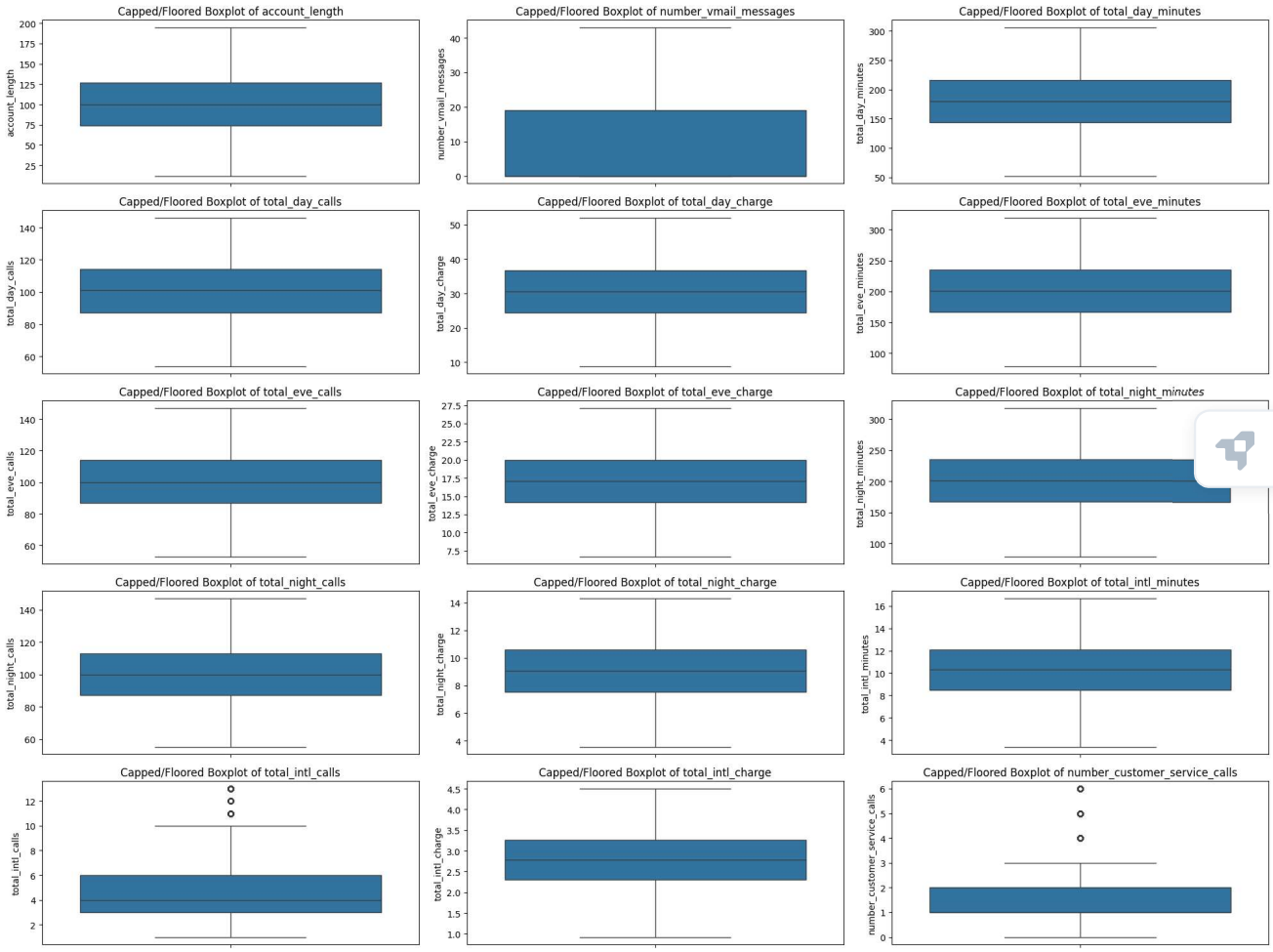
Checking for outliers using Box plot

```
import seaborn as sns
import matplotlib.pyplot as plt

# Identifying outliers using boxplots for key numerical columns
numerical_columns = ['account_length', 'number_vmail_messages', 'total_day_minutes',
                     'total_day_calls', 'total_day_charge', 'total_eve_minutes',
                     'total_eve_calls', 'total_eve_charge', 'total_night_minutes',
                     'total_night_calls', 'total_night_charge', 'total_intl_minutes',
                     'total_intl_calls', 'total_intl_charge', 'number_customer_service_ca

# Plotting boxplots for the numerical variables to identify outliers visually
plt.figure(figsize=(20, 15))
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(5, 3, i)
    sns.boxplot(y=data[col])
    plt.title(f'Boxplot of {col}')

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


Boxplot of account_length
account_length
Boxplot of number_vmail_messages
number_vmail_messages
Boxplot of total_day_minutes
total_day_minutes
Boxplot of total_day_calls
total_day_calls
Boxplot of total_day_charge
total_day_charge
Boxplot of total_eve_minutes
total_eve_minutes
Boxplot of total_eve_calls
total_eve_calls
Boxplot of total_eve_charge
total_eve_charge
Boxplot of total_night_minutes
total_night_minutes
Boxplot of total_night_calls
total_night_calls
Boxplot of total_night_charge
total_night_charge
Boxplot of total_intl_minutes
total_intl_minutes
Boxplot of total_intl_calls
total_intl_calls
Boxplot of total_intl_charge
total_intl_charge
Boxplot of number_customer_service_calls
number_customer_service_calls

Handling outliers - using capping and flooring method

```
import numpy as np

# Reapplying capping and flooring for each numerical column at the 1st and 99th percentil
for column in numerical_columns:
    # Calculate the 1st and 99th percentiles
    lower_bound = data[column].quantile(0.01)
    upper_bound = data[column].quantile(0.99)

    # Cap and floor the outliers
    data[column] = np.where(data[column] > upper_bound, upper_bound, data[column])
    data[column] = np.where(data[column] < lower_bound, lower_bound, data[column])

# Checking if the capping and flooring has been applied by replotting the boxplots
plt.figure(figsize=(20, 15))
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(5, 3, i)
    sns.boxplot(y=data[col])
    plt.title(f'Capped/Floored Boxplot of {col}')

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


Capped/Floored Boxplot of account_length
account_length
Capped/Floored Boxplot of number_vmail_messages
number_vmail_messages
Capped/Floored Boxplot of total_day_minutes
total_day_minutes
Capped/Floored Boxplot of total_day_calls
total_day_calls
Capped/Floored Boxplot of total_day_charge
total_day_charge
Capped/Floored Boxplot of total_eve_minutes
total_eve_minutes
Capped/Floored Boxplot of total_eve_calls
total_eve_calls
Capped/Floored Boxplot of total_eve_charge
total_eve_charge
Capped/Floored Boxplot of total_night_minutes
total_night_minutes
Capped/Floored Boxplot of total_night_calls
total_night_calls
Capped/Floored Boxplot of total_night_charge
total_night_charge
Capped/Floored Boxplot of total_intl_minutes
total_intl_minutes
Capped/Floored Boxplot of total_intl_calls
total_intl_calls
Capped/Floored Boxplot of total_intl_charge
total_intl_charge
Capped/Floored Boxplot of number_customer_service_calls
number_customer_service_calls

Normalization

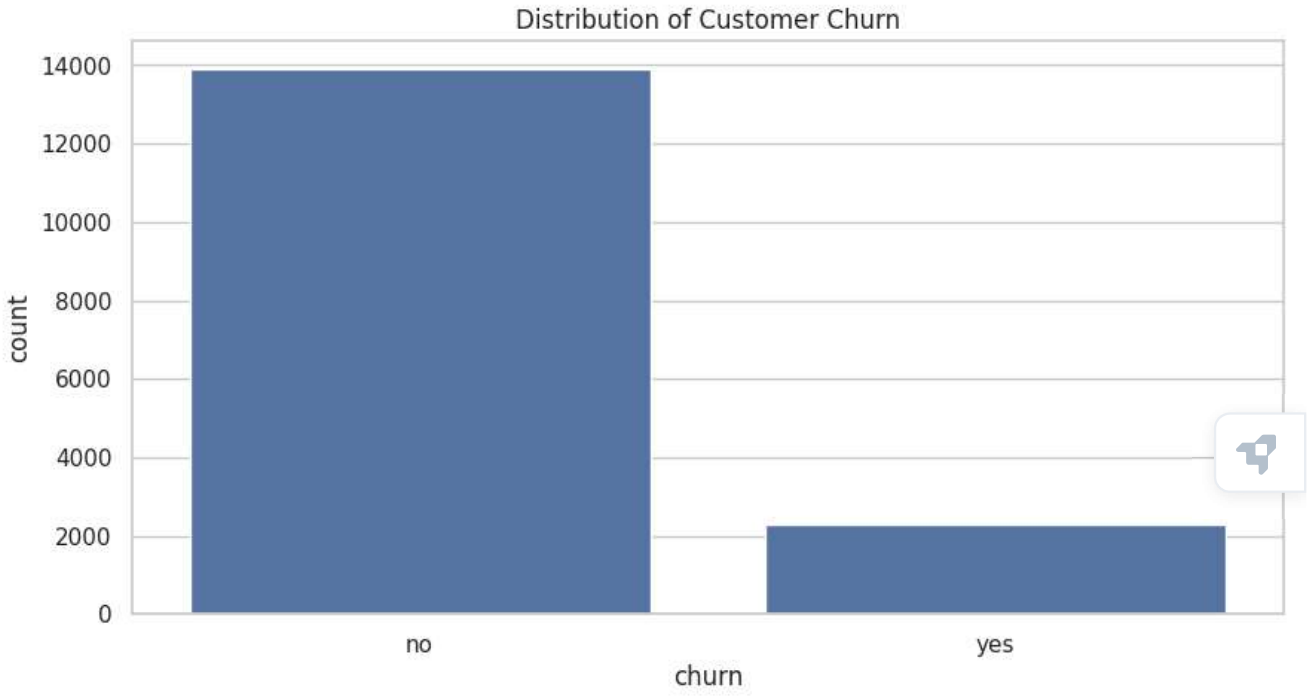
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Creating scaler objects
standard_scaler = StandardScaler()
minmax_scaler = MinMaxScaler()

# Selecting numerical columns for scaling (excluding categorical one-hot encoded columns)
numerical_columns = ['international_plan', 'voice_mail_plan']

# Applying Standardization
data_standardized = data.copy()
data_standardized[numerical_columns] = standard_scaler.fit_transform(data[numerical_colum

# Applying Min-Max Scaling
data_minmax_scaled = data.copy()
data_minmax_scaled[numerical_columns] = minmax_scaler.fit_transform(data[numerical_column

# Displaying the first few rows of the standardized and min-max scaled data
data_standardized_head = data_standardized.head()
data_minmax_scaled_head = data_minmax_scaled.head()

data_standardized_head, data_minmax_scaled_head
```

```
      2              294.7             95.0              50.10               237.3
      3              216.8            123.0              36.86               126.4
      4              197.4             78.0              33.56               124.0

         total_eve_calls  total_eve_charge  total_night_minutes  total_night_calls  \
      0             73.0             18.01                236.0               73.0
      1            139.0             20.81                 94.2               81.0
      2            105.0             20.17                300.3              127.0
      3             88.0             10.74                220.6               82.0
      4            101.0             10.54                204.5              107.0

         total_night_charge  total_intl_minutes  total_intl_calls  \
      0               10.62                10.6               3.0
      1                4.24                 9.5               7.0
      2               13.51                13.7               6.0
      3                9.93                15.7               2.0
      4                9.20                 7.7               4.0

         total_intl_charge  number_customer_service_calls churn
      0               2.86                            3.0    no
      1               2.57                            0.0    no
```

```
   total_day_minutes  total_day_calls  total_day_charge  total_eve_minutes  \
0               70.9            123.0             12.05              211.9
1              223.6             86.0             38.01              244.8
2              294.7             95.0             50.10              237.3
3              216.8            123.0             36.86              126.4
4              197.4             78.0             33.56              124.0

   total_eve_calls  total_eve_charge  total_night_minutes  total_night_calls  \
0             73.0             18.01                236.0               73.0
1            139.0             20.81                 94.2               81.0
2            105.0             20.17                300.3              127.0
3             88.0             10.74                220.6               82.0
4            101.0             10.54                204.5              107.0

   total_night_charge  total_intl_minutes  total_intl_calls  \
0               10.62                10.6               3.0
1                4.24                 9.5               7.0
2               13.51                13.7               6.0
3                9.93                15.7               2.0
4                9.20                 7.7               4.0

   total_intl_charge  number_customer_service_calls churn
0               2.86                            3.0    no
1               2.57                            0.0    no
2               3.70                            1.0    no
3               4.24                            1.0    no
4               2.08                            2.0    no  )
```

Checking the data balance in churn column

```
import matplotlib.pyplot as plt
import seaborn as sns

# Set the aesthetic style of the plots
sns.set(style="whitegrid")

# Distribution of customer churn
plt.figure(figsize=(10, 5))
sns.countplot(x='churn', data=data)
plt.title('Distribution of Customer Churn')



plt.show()
```



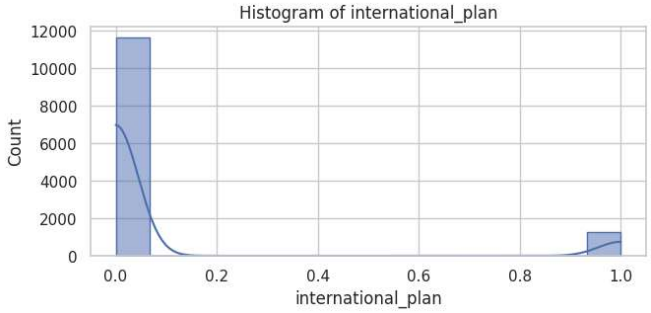
Handling Data Imbalance using SMOTE METHOD

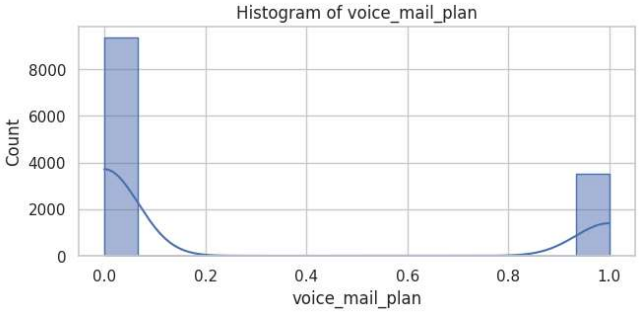
```
import pandas as pd
from sklearn.impute import SimpleImputer
from imblearn.over_sampling import SMOTE

# Setting up the feature matrix and target vector
X = data.drop('churn', axis=1)
y = data['churn']

# Encoding categorical variables using one-hot encoding
X = pd.get_dummies(X)

# Handle missing values using SimpleImputer
imputer = SimpleImputer(strategy='mean')
X_imputed = imputer.fit_transform(X)

# Initializing SMOTE
smote = SMOTE()

# Resampling the dataset
X_resampled, y_resampled = smote.fit_resample(X_imputed, y)

# Checking the new class distribution
new_churn_distribution = pd.Series(y_resampled).value_counts(normalize=True)
new_churn_distribution
```

```
churn
no     0.5
yes    0.5
Name: proportion, dtype: float64
```

Visualizations

```
# Generating histograms for numerical variables
plt.figure(figsize=(20, 15))
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(5, 3, i)
    sns.histplot(data[col], kde=True, element='step')
    plt.title(f'Histogram of {col}')

plt.tight_layout()
plt.show()

# Summary statistics for numerical variables
summary_statistics = data[numerical_columns].describe()

# Displaying summary statistics
summary_statistics
```





	international_plan	voice_mail_plan
count	12892.000000	12892.000000
mean	0.096261	0.273038
std	0.294961	0.445537
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	1.000000
max	1.000000	1.000000

Logistic regression model

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
from sklearn.impute import SimpleImputer

# Prepare the data
X = data.drop('churn', axis=1)
y = data['churn'].apply(lambda x: 1 if x == 'yes' else 0)  # Convert target to binary

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Handling missing values
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)

# Initialize and train the Logistic Regression model
logistic_model = LogisticRegression(random_state=42)
logistic_model.fit(X_train_scaled, y_train)

# Predicting the test set results
y_pred = logistic_model.predict(X_test_scaled)

# Evaluating the model
accuracy_logistic = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print("Accuracy:", accuracy_logistic)
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", report)
```

```
Accuracy: 0.8542372881355932
Confusion Matrix:
 [[2680   84]
 [ 389   92]]
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.97      0.92      2764
           1       0.52      0.19      0.28       481

    accuracy                           0.85      3245
   macro avg       0.70      0.58      0.60      3245
weighted avg       0.82      0.85      0.82      3245
```

Hyper parameter tuning for logistic regression model

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Handling missing values
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)

# Define the model and parameters grid
param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear', 'saga']  # 'saga' supports both l1 and l2 penalty
}

# Setting up the GridSearchCV
grid_search = GridSearchCV(estimator=LogisticRegression(random_state=42),
                           param_grid=param_grid,
                           cv=3,  # 3-fold cross-validation
                           scoring='accuracy',  # You can choose other metrics
                           verbose=1)

# Fit grid search
grid_search.fit(X_train_scaled, y_train)

# Best parameters and best score
print("Best Parameters:", grid_search.best_params_)
print("Best Score:", grid_search.best_score_)

# Evaluate the model with best parameters on the test set
best_lr = grid_search.best_estimator_
y_pred = best_lr.predict(X_test_scaled)
print("Accuracy on Test Set:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Fitting 3 folds for each of 20 candidates, totalling 60 fits
Best Parameters: {'C': 0.01, 'penalty': 'l2', 'solver': 'saga'}
Best Score: 0.8668721805898395
Accuracy on Test Set: 0.8585516178736518
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.98      0.92      2764
           1       0.57      0.18      0.27       481
```

```
          accuracy                           0.86      3245
         macro avg       0.72      0.58      0.60      3245
      weighted avg       0.83      0.86      0.83      3245
```

Ensamble method using Stacking classifier

```
from sklearn.ensemble import StackingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report


# Handling missing values
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)

# Define base models
base_models = [
    ('lr', LogisticRegression(random_state=42)),
    ('rf', RandomForestClassifier(n_estimators=100, random_state=42)),
    ('svc', SVC(probability=True, random_state=42))
]

# Define a meta-model
meta_model = LogisticRegression(random_state=42)

# Create the stacking ensemble
stacked_model = StackingClassifier(estimators=base_models, final_estimator=meta_model, cv

# Train the stacked model
stacked_model.fit(X_train_scaled, y_train)

# Predict the test set results
y_pred = stacked_model.predict(X_test_scaled)

# Evaluate the model
accuracy_ensamble = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_ensamble)
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.9910631741140216
Classification Report:
```

```
                   precision    recall  f1-score   support

               0       0.99      1.00      0.99      2764
               1       1.00      0.94      0.97       481

        accuracy                           0.99      3245
       macro avg       0.99      0.97      0.98      3245
    weighted avg       0.99      0.99      0.99      3245
```

Random forest model

```
from sklearn.ensemble import RandomForestClassifier

# Initialize the Random Forest model
random_forest_model = RandomForestClassifier(n_estimators=100, criterion='gini', max_dept

# Train the model on the scaled training data
random_forest_model.fit(X_train_scaled, y_train)

# Predicting the test set results
y_pred_rf = random_forest_model.predict(X_test_scaled)

# Evaluating the model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
report_rf = classification_report(y_test, y_pred_rf)

print(accuracy_rf)
print(conf_matrix_rf)
print(report_rf)
```

```
0.9882896764252697
[[2763    1]
 [  37  444]]
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      2764
           1       1.00      0.92      0.96       481

    accuracy                           0.99      3245
   macro avg       0.99      0.96      0.98      3245
weighted avg       0.99      0.99      0.99      3245
```

Hyper parameter tuning for random forest model

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split



# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Handling missing values
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)

# Setting up the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_leaf': [1, 2, 4]
}

# Setting up the GridSearchCV
grid_search = GridSearchCV(estimator=RandomForestClassifier(random_state=42),
                           param_grid=param_grid,
                           cv=5,  # 5-fold cross-validation
                           scoring='accuracy',  # Metric of choice
                           verbose=1,
                           n_jobs=-1)  # Use all available cores

# Running Grid Search
grid_search.fit(X_train_scaled, y_train)

# Best parameters and best accuracy
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_params)
print("Best Score:", best_score)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
Best Parameters: {'max_depth': None, 'min_samples_leaf': 1, 'n_estimators': 100}
Best Score: 0.9880585516178735
```

Gradient Boosting classifier

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler


# Handling missing values
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)

# Initialize the Gradient Boosting Classifier
gbm_model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=3,
gbm_model.fit(X_train_scaled, y_train)

# Predict the test set results
y_pred_gbm = gbm_model.predict(X_test_scaled)

# Evaluate the model
accuracy_gbm = accuracy_score(y_test, y_pred_gbm)
conf_matrix_gbm = confusion_matrix(y_test, y_pred_gbm)
report_gbm = classification_report(y_test, y_pred_gbm)

print("Accuracy:", accuracy_gbm)
print("Confusion Matrix:\n", conf_matrix_gbm)
print("Classification Report:\n", report_gbm)
```

```
Accuracy: 0.9624036979969184
Confusion Matrix:
 [[2748   16]
 [ 106  375]]
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.99      0.98      2764
           1       0.96      0.78      0.86       481

    accuracy                           0.96      3245
   macro avg       0.96      0.89      0.92      3245
weighted avg       0.96      0.96      0.96      3245
```

Hyper parameter tuning for Gradient Boosting Classifier

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split


# Handling missing values
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)

# Define the model and parameters grid
param_grid = {
    'n_estimators': [100, 150],
    'learning_rate': [0.1, 0.05],
    'max_depth': [3, 4],
    'min_samples_split': [2, 4],
    'min_samples_leaf': [1, 2]
}

gbm = GradientBoostingClassifier(random_state=42)
grid_search = GridSearchCV(estimator=gbm, param_grid=param_grid, cv=3, scoring='accuracy'

# Fit grid search
grid_search.fit(X_train_scaled, y_train)

# Best parameters and best score
print("Best Parameters:", grid_search.best_params_)
print("Best Score:", grid_search.best_score_)

# Evaluate the model with best parameters on the test set
best_gbm = grid_search.best_estimator_
y_pred = best_gbm.predict(X_test_scaled)
print("Accuracy on Test Set:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Fitting 3 folds for each of 32 candidates, totalling 96 fits
Best Parameters: {'learning_rate': 0.1, 'max_depth': 4, 'min_samples_leaf': 2, 'min_s
Best Score: 0.9725733435292515
Accuracy on Test Set: 0.9728813559322034
Classification Report:
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      2764
           1       0.99      0.82      0.90       481

    accuracy                           0.97      3245
   macro avg       0.98      0.91      0.94      3245
weighted avg       0.97      0.97      0.97      3245
```

Support Vector Classifier Model

```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Handling missing values
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)

# Initialize the Support Vector Classifier
svm_model = SVC(C=1.0, kernel='rbf', gamma='scale', random_state=42)

# Train the SVM on the scaled training data
svm_model.fit(X_train_scaled, y_train)

# Predict the test set results
y_pred_svm = svm_model.predict(X_test_scaled)

# Evaluate the model
accuracy_svm = accuracy_score(y_test, y_pred_svm)
conf_matrix_svm = confusion_matrix(y_test, y_pred_svm)
report_svm = classification_report(y_test, y_pred_svm)

print("Accuracy:", accuracy_svm)
print("Confusion Matrix:\n", conf_matrix_svm)
print("Classification Report:\n", report_svm)
```

```
Accuracy: 0.9565485362095532
Confusion Matrix:
 [[2746   18]
 [ 123  358]]
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.99      0.97      2764
           1       0.95      0.74      0.84       481

    accuracy                           0.96      3245
   macro avg       0.95      0.87      0.91      3245
weighted avg       0.96      0.96      0.95      3245
```

Hyper parameter tuning for Support Vector Classifier

```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split


# Handling missing values
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)
# Define the model and parameters grid
param_grid = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf', 'poly', 'sigmoid'],
    'gamma': ['scale', 'auto']
}

# Setting up the GridSearchCV
grid_search = GridSearchCV(estimator=SVC(random_state=42), param_grid=param_grid, cv=3, s

# Fit grid search
grid_search.fit(X_train_scaled, y_train)

# Best parameters and best score
print("Best Parameters:", grid_search.best_params_)
print("Best Score:", grid_search.best_score_)

# Evaluate the model with best parameters on the test set
best_svm = grid_search.best_estimator_
y_pred = best_svm.predict(X_test_scaled)
print("Accuracy on Test Set:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Best Parameters: {'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}
Best Score: 0.968027918609164
Accuracy on Test Set: 0.9722650231124808
Classification Report:
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      2764
           1       0.98      0.83      0.90       481

    accuracy                           0.97      3245
   macro avg       0.97      0.91      0.94      3245
weighted avg       0.97      0.97      0.97      3245
```