Churn in SyriaTel

Overview

This dataset provides customer data from a telecommunications company, aiming to predict churn, i.e., whether a customer will stop using the service. It includes demographic and usage-related features such as call duration during different times (day, evening, night), customer service calls, and whether the customer has specific plans like international or voicemail. The target variable, churn, is binary (Yes/No). Initial analysis reveals key trends: customers with high service interactions or unusual usage patterns may be more likely to churn. The dataset offers opportunities for understanding customer behavior and identifying actionable insights to improve retention strategies.

Business Understanding

The dataset pertains to SyriaTel telecommunications company seeking to understand and reduce customer churn. Churn, defined as customers leaving the service and reduce customer churn. Churn, defined as customers leaving the service, significantly impacts revenue and profitability. Key business objectives include identifying factors contributing to churn, such as call usage patterns, subscription plans, and customer interactions, to predict at-risk customers. This analysis aims to uncover actionable insights to improve customer retention strategies, enhance service offerings, and focus on critical features like international plan subscriptions, daytime call usage, and customer service interactions to reduce churn rates and improve customer satisfaction.

1.Problem Definition

- **Objective**: Develop a predictive model to determine whether a customer will churn (binary classification: Yes/No) based on customer usage patterns, interaction with the company, and plan features.

- **Outcome**: Provide actionable insights to SyriaTel to reduce customer churn by identifying high-risk customers and enabling targeted retention strategies.

- **Metric for Success**: Evaluate the model's performance using metrics such as:

  - **Accuracy**: Measures overall correctness but may not address class imbalance.
  - **Precision**: Useful when minimizing false positives (e.g., targeting non-churners for retention campaigns is costly).
  - **Recall**: Important to identify as many churners as possible (minimizing false negatives).
  - **F1-Score**: Balances Precision and Recall, suitable for imbalanced datasets.
  - **AUC-ROC**: Evaluates the tradeoff between true positive and false positive rates across thresholds.

2. Data Collection

- *Source*: This project utilizes a dataset obtained from Kaggle, which includes customer details such as demographics, account attributes, and usage metrics critical for predicting churn.
- *File Format*: CSV (Comma-Separated Values).
- *Dataset Link: *(https://www.kaggle.com/datasets/becksddf/churn-in-telecoms-dataset).

3.1. Data Understanding

Data understanding lets us explore and analyze our churn data to gain insights into its structure, content, and relationships. It involves looking at the types of data and what the columns entail, identifying patterns, checking for missing values, and understanding the distribution of variables. The goal is to familiarize ourselves with the data before any analysis or modeling, ensuring that we can make informed decisions and address any issues, such as imbalances or outliers, that might affect the results.

In [207…

```python
#importing necessary libraries

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_
```

In [208…

```python
# Read data from csv file & create dataframe. Checking the first 5 rows.
df_churn = pd.read_csv('churn_file.csv')
df_churn
```

Out[208…

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

3333 rows × 21 columns

In [209…

```
df_churn.describe()
```

Out[209…

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

In [210…

```
df_churn.info()
```

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

In [211

In [211…

```
df_churn.columns
```

Out[211…

```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', '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',
       'customer service calls', 'churn'],
      dtype='object')
```

1. **state**: The state in which the customer resides.
2. **account length**: The duration (in months) the customer has had an account with the service provider.
3. **area code**: The area code associated with the customer's phone number.
4. **phone number**: The customer's phone number.
5. **international plan**: A binary indicator (yes/no) of whether the customer has an international calling plan.
6. **voice mail plan**: A binary indicator (yes/no) of whether the customer has a voicemail plan.
7. **number vmail messages**: The total number of voicemail messages received by the customer.
8. **total day minutes**: The total number of minutes the customer spent on daytime calls.
9. **total day calls**: The total number of daytime calls made by the customer.
10. **total day charge**: The total charge for daytime calls made by the customer.
11. **total eve minutes**: The total number of minutes the customer spent on evening calls.
12. **total eve calls**: The total number of evening calls made by the customer.
13. **total eve charge**: The total charge for evening calls made by the customer.
14. **total night minutes**: The total number of minutes the customer spent on nighttime calls.
15. **total night calls**: The total number of nighttime calls made by the customer.
16. **total night charge**: The total charge for nighttime calls made by the customer.
17. **total intl minutes**: The total number of minutes the customer spent on international calls.
18. **total intl calls**: The total number of international calls made by the customer.
19. **total intl charge**: The total charge for international calls made by the customer.
20. **customer service calls**: The total number of calls the customer made to customer service.
21. **churn**: A binary indicator (1/0) representing whether the customer has churned (left the service) or not.

In [212…

```
df_churn.shape
```

Out[212…

```
(3333, 21)
```

3.2. Data Preparation

Data Preparation/Data cleaning will focus on preparing the dataset for exploratory data analysis (EDA) and modeling. The steps include:

- Identifying and removing duplicate rows.
- Handling missing/NAN values to ensure data consistency.
- Eliminating irrelevant columns that do not contribute meaningfully to the analysis.

In [213…

```
# Check for duplicated rows, no duplicated rows to deal with.
df_churn.duplicated().sum()
```

Out[213…

```
0
```

In [214…

```
# Checking for missing values, no missing values.

df_churn.isnull().sum()
```

Out[214…

```
state                     0
account length            0
area code                 0
phone number              0
international plan        0
voice mail plan           0
number vmail messages     0
total day minutes         0
total day calls           0
total day charge          0
total eve minutes         0
total eve calls           0
total eve charge          0
total night minutes       0
total night calls         0
total night charge        0
total intl minutes        0
total intl calls          0
total intl charge         0
customer service calls    0
churn                     0
dtype: int64
```

In [215…

```
# Removing customer phone number feature as it is contact information to the

df_churn.drop(['phone number','area code','state'],axis=1,inplace=True)
df_churn.head()
```

Out[215…

	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls
0	128	no	yes	25	265.1	110	45.07	197.4	99

1	107	no	yes	26	161.6	123	27.47	195.5	103
2	137	no	no	0	243.4	114	41.38	121.2	110
3	84	yes	no	0	299.4	71	50.90	61.9	88
4	75	yes	no	0	166.7	113	28.34	148.3	122

We then check the number of categorical columns we have remaining and the relationship between our target, Churn, and the columns

In [216…

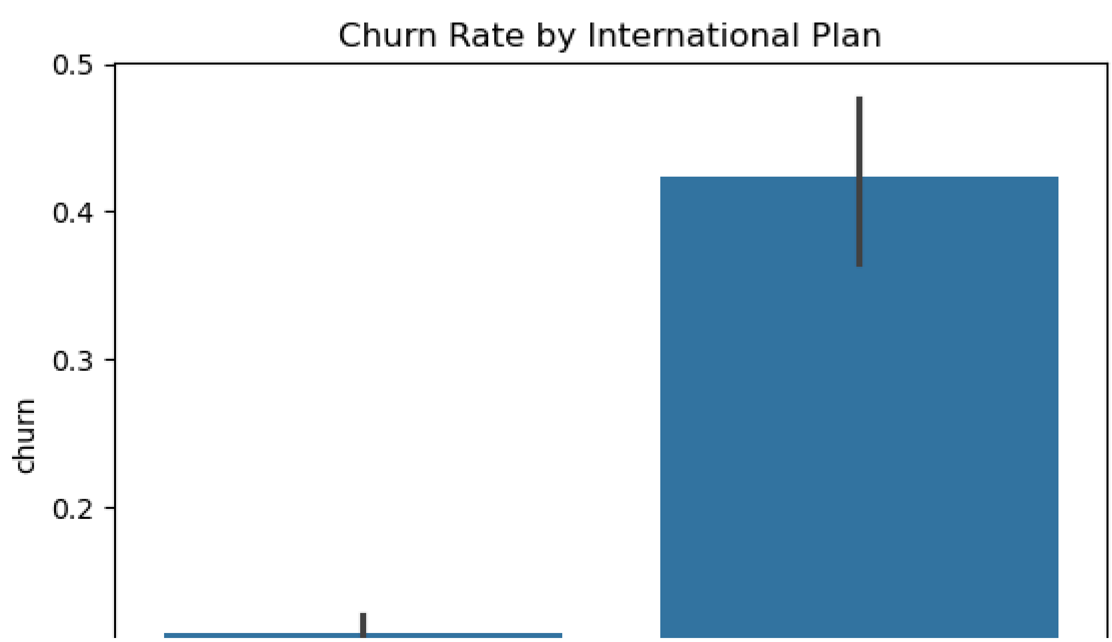
```
categoricals = df_churn.select_dtypes("object")

for col in categoricals:
    print(df_churn[col].value_counts(), "\n")
```

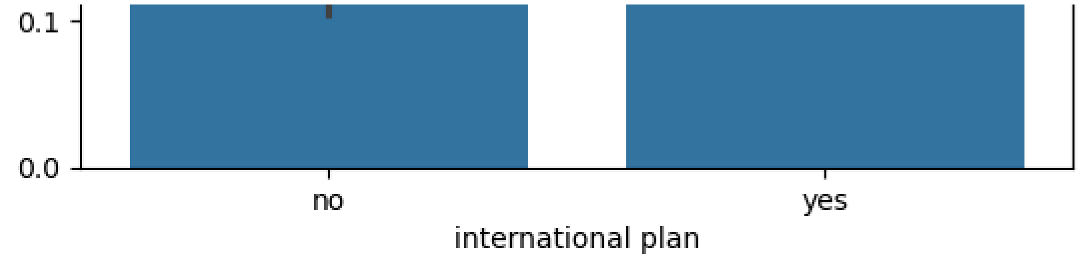
```
international plan
no     3010
yes     323
Name: count, dtype: int64

voice mail plan
no     2411
yes     922
Name: count, dtype: int64
```

In [217…

```
print(df_churn.groupby('international plan')['churn'].mean())
sns.barplot(x='international plan', y='churn', data=df_churn)
plt.title('Churn Rate by International Plan')
plt.show()
```

```
international plan
no     0.114950
yes    0.424149
Name: churn, dtype: float64
```

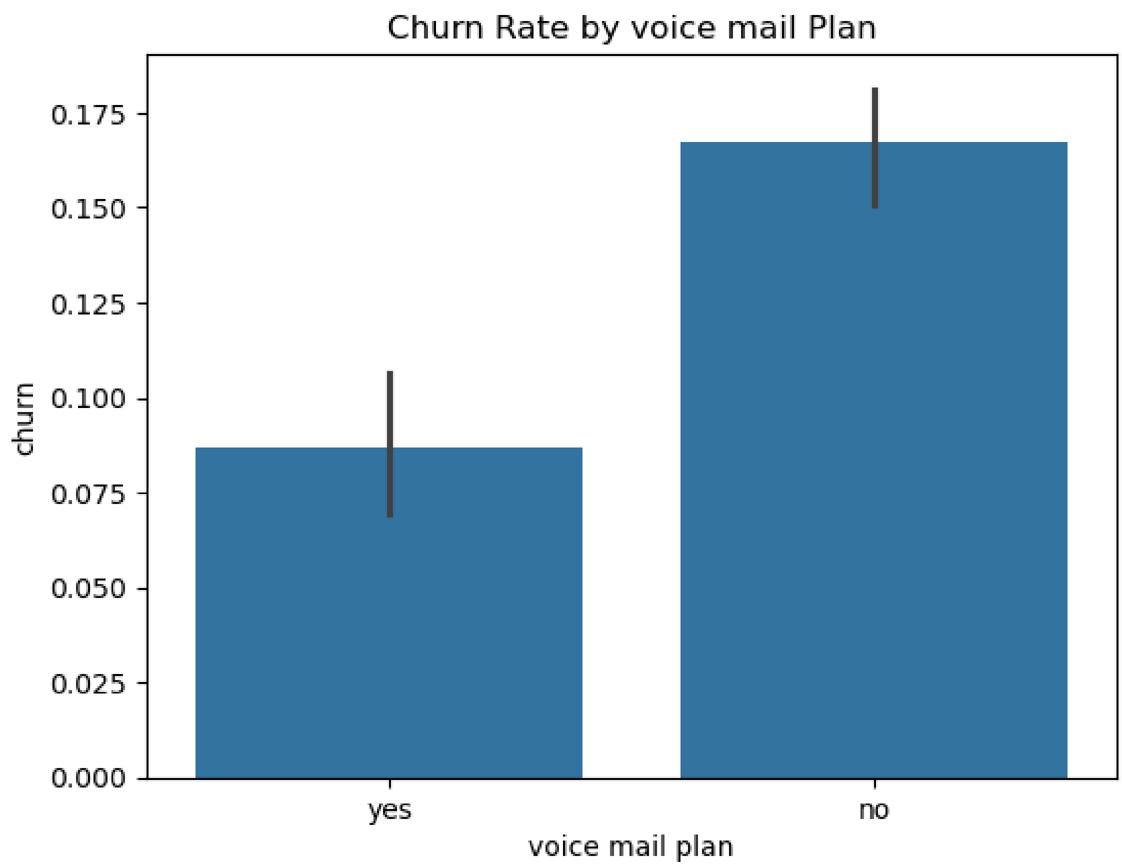




In [218…

```
print(df_churn.groupby('voice mail plan')['churn'].mean())
sns.barplot(x='voice mail plan', y='churn', data=df_churn)
plt.title('Churn Rate by voice mail Plan')
plt.show()
```

```
voice mail plan
no     0.167151
yes    0.086768
Name: churn, dtype: float64
```



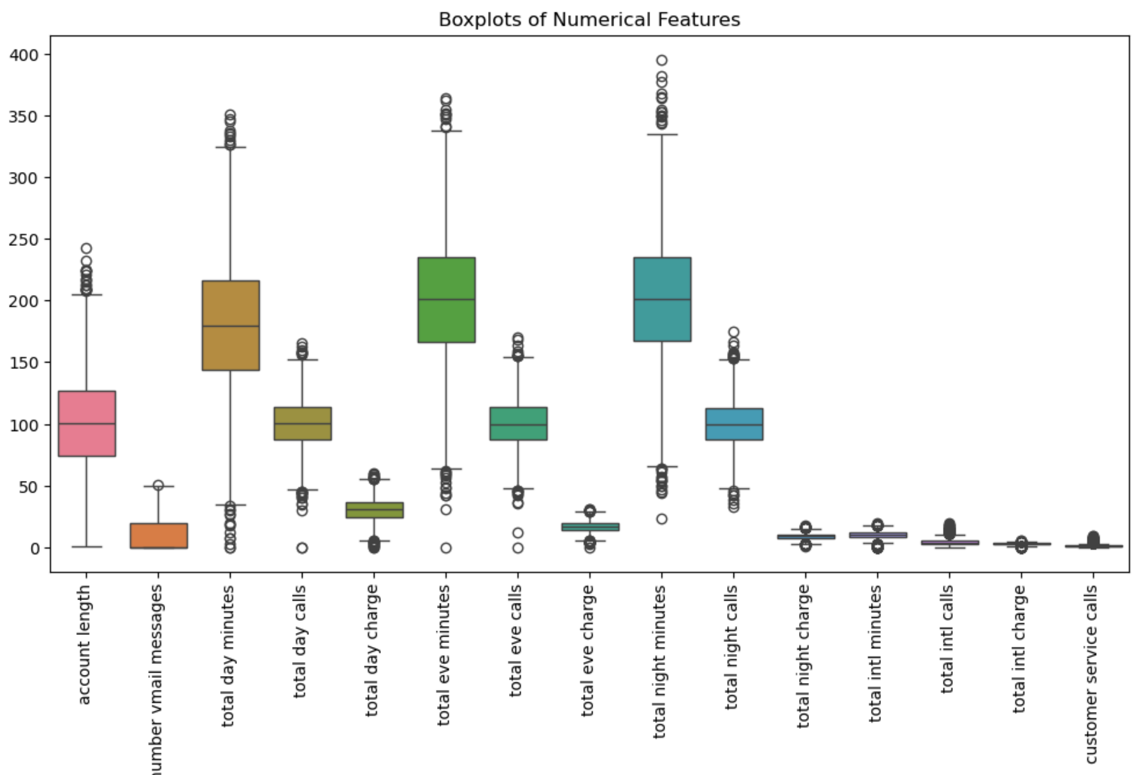
3.3 EDA

Exploratory Data Analysis (EDA) on our dataset will involve examining the churn data to understand the underlying patterns, relationships, and characteristics of the features before building any predictive models. This includes analyzing the distribution of numerical variables (e.g., total day minutes, total night calls), understanding categorical features (e.g., international plan, voice mail plan), identifying potential outliers or anomalies, checking for missing data, and exploring correlations between features. EDA also involves visualizing the data using tools like histograms, boxplots, and correlation heatmaps to uncover trends or patterns that could influence customer churn prediction, ultimately helping to make informed decisions about data preparation and modeling strategies.

We then generate boxplots to detect outliers in numerical features, helping visualize data distribution and identify extreme values that could impact analysis or modeling. By highlighting outliers, it guides data cleaning steps such as removing, transforming, or imputing extreme values and informs decisions about scaling or normalizing features to ensure consistency.

In [219…

```
# Detecting outliers for numerical features using boxplots
plt.figure(figsize=(12, 6))
sns.boxplot(data=df_churn.select_dtypes(include='number'))
plt.title("Boxplots of Numerical Features")
plt.xticks  (rotation = 90)
plt.show()
```



In [220…

```
def remove_outliers(df_churn, columns):
    for col in columns:
        # Calculate Q1 (25th percentile) and Q3 (75th percentile)
        Q1 = df_churn[col].quantile(0.25)
        Q3 = df_churn[col].quantile(0.75)
        IQR = Q3 - Q1  # Interquartile Range

        # Define lower and upper bounds for detecting outliers
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Filter out outliers
        df_churn = df_churn[(df_churn[col] >= lower_bound) & (df_churn[col] <
```

```
    return df_churn

# List of columns to check for outliers (excluding 'Churn')
feature_columns = [col for col in df_churn.columns if col != 'Churn' and df_c

# Apply the function to remove outliers
df_churn = remove_outliers(df_churn, feature_columns)
df_churn
```

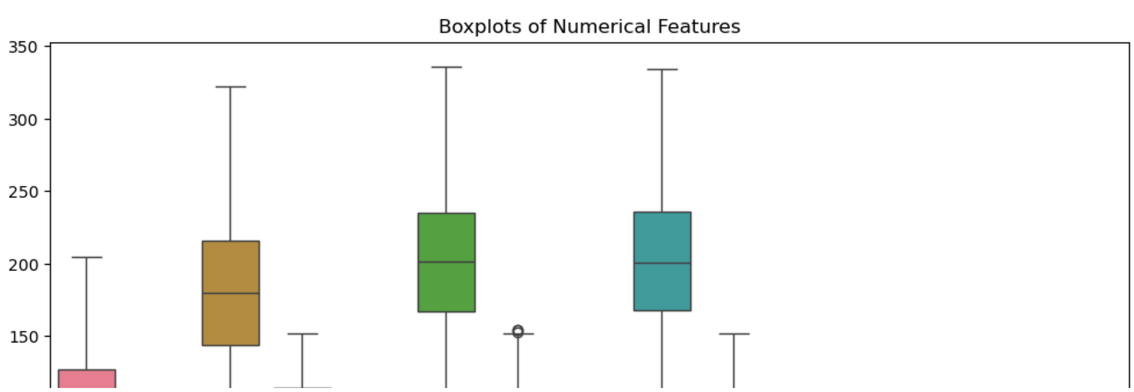
Out[220…

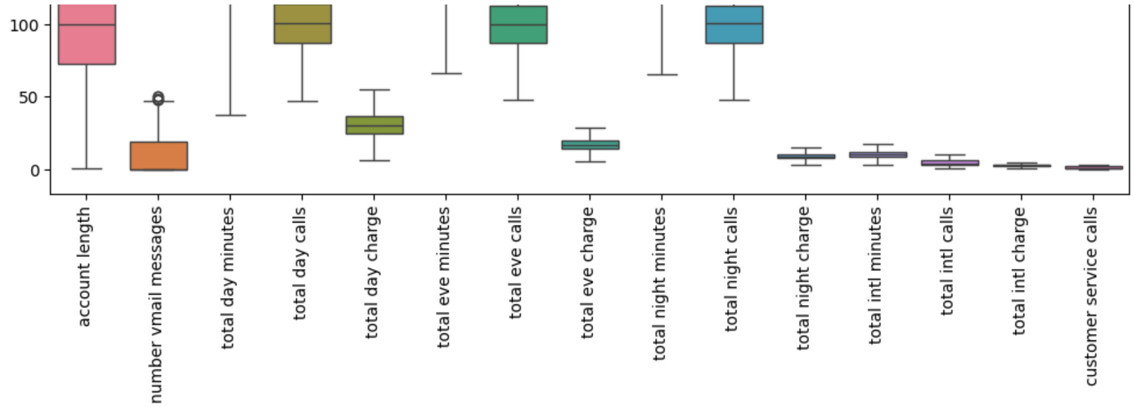
	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	tota ev call
0	128	no	yes	25	265.1	110	45.07	197.4	9
1	107	no	yes	26	161.6	123	27.47	195.5	10
2	137	no	no	0	243.4	114	41.38	121.2	11
4	75	yes	no	0	166.7	113	28.34	148.3	12
5	118	yes	no	0	223.4	98	37.98	220.6	10
...	...	...	...	...	...	...	...	...	.
3328	192	no	yes	36	156.2	77	26.55	215.5	12
3329	68	no	no	0	231.1	57	39.29	153.4	5
3330	28	no	no	0	180.8	109	30.74	288.8	5
3331	184	yes	no	0	213.8	105	36.35	159.6	8
3332	74	no	yes	25	234.4	113	39.85	265.9	8

2797 rows × 18 columns

In [ ]:

```
# Detecting outliers for the numerical features using boxplots
plt.figure(figsize=(12, 6))
sns.boxplot(data=df_churn.select_dtypes(include='number'))
plt.title("Boxplots of Numerical Features")
plt.xticks  (rotation = 90)
plt.show()
```





Next we convert the categorical values "yes" and "no" in the `'international plan'` and `'voice mail plan'` columns into numerical representations (1 for "yes" and 0 for "no"). This transformation makes the data suitable for machine learning algorithms, which typically require numerical inputs. By applying this mapping, the code prepares these categorical features for modeling while maintaining the information they represent.

In [222…

```
# Map 'yes' to 1 and 'no' to 0 in the 'international plan' and 'voice mail' c
df_churn['international plan'] = df_churn['international plan'].map({'yes': 1
df_churn['voice mail plan'] = df_churn['voice mail plan'].map({'yes': 1, 'no'

# Display the first few rows of the updated DataFrame
df_churn.head()
```

Out[222…

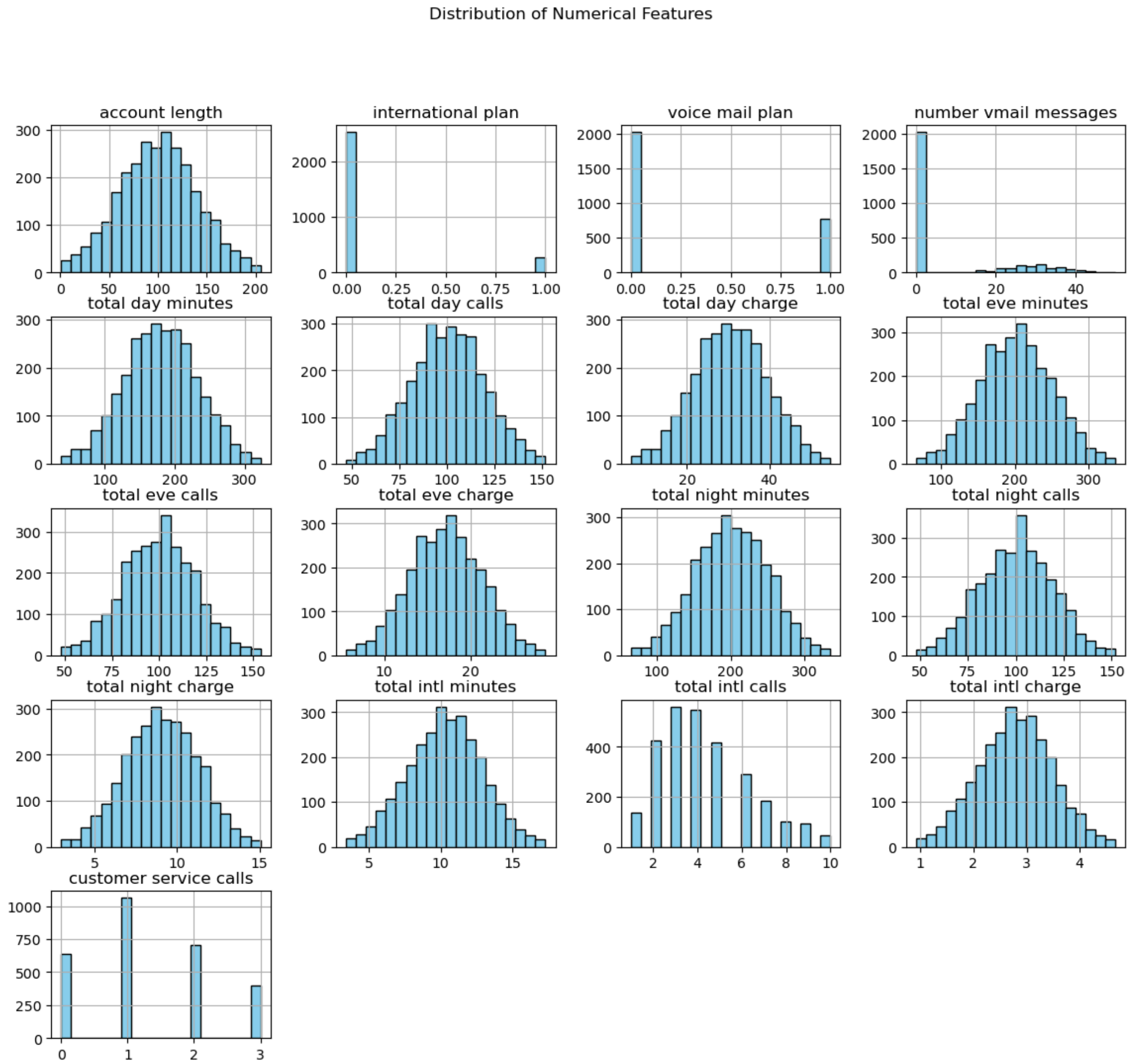
	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls
0	128	0	1	25	265.1	110	45.07	197.4	99
1	107	0	1	26	161.6	123	27.47	195.5	103
2	137	0	0	0	243.4	114	41.38	121.2	110
4	75	1	0	0	166.7	113	28.34	148.3	122
5	118	1	0	0	223.4	98	37.98	220.6	101

Next we check numerical features in the `df_churn` dataset to analyze their distributions. This helps identify patterns such as skewness, outliers, data spread, and concentration of values, while also revealing potential data quality issues. Such insights guide decisions on data transformations or scaling needed for effective modeling.

In [223…

```
# Visualize distributions for Numerical features using histograms
df_churn.hist(bins=20, figsize=(14, 12), color='skyblue', edgecolor='black')
plt.suptitle("Distribution of Numerical Features")
```

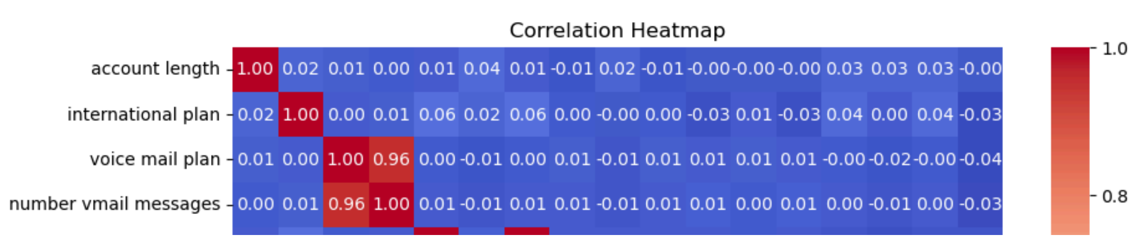
```
plt.show()
```

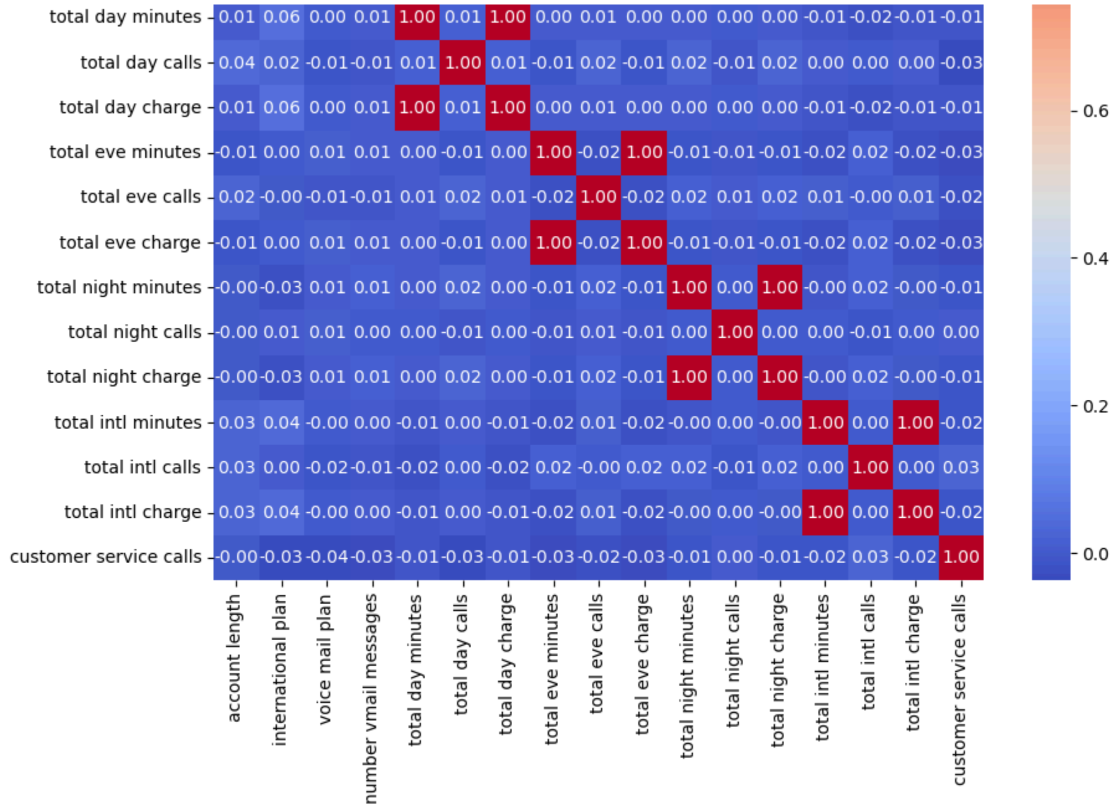


Then we identify highly correlated columns with a correlation greater than 0.9, which are considered highly redundant, and drop them from the dataset. The goal is to reduce multicollinearity and simplify the dataset by removing highly correlated features that may not provide additional useful information for modeling.

In [224…

```
# Correlation heatmap for the numerical columns
numeric_columns = df_churn.select_dtypes(include=['number']).columns

plt.figure(figsize=(10, 8))
sns.heatmap(df_churn[numeric_columns].corr(), annot=True, cmap='coolwarm', fm
plt.title("Correlation Heatmap")
plt.show()
```

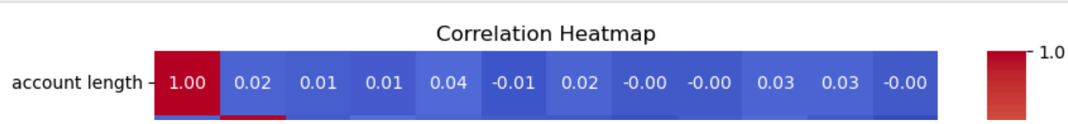


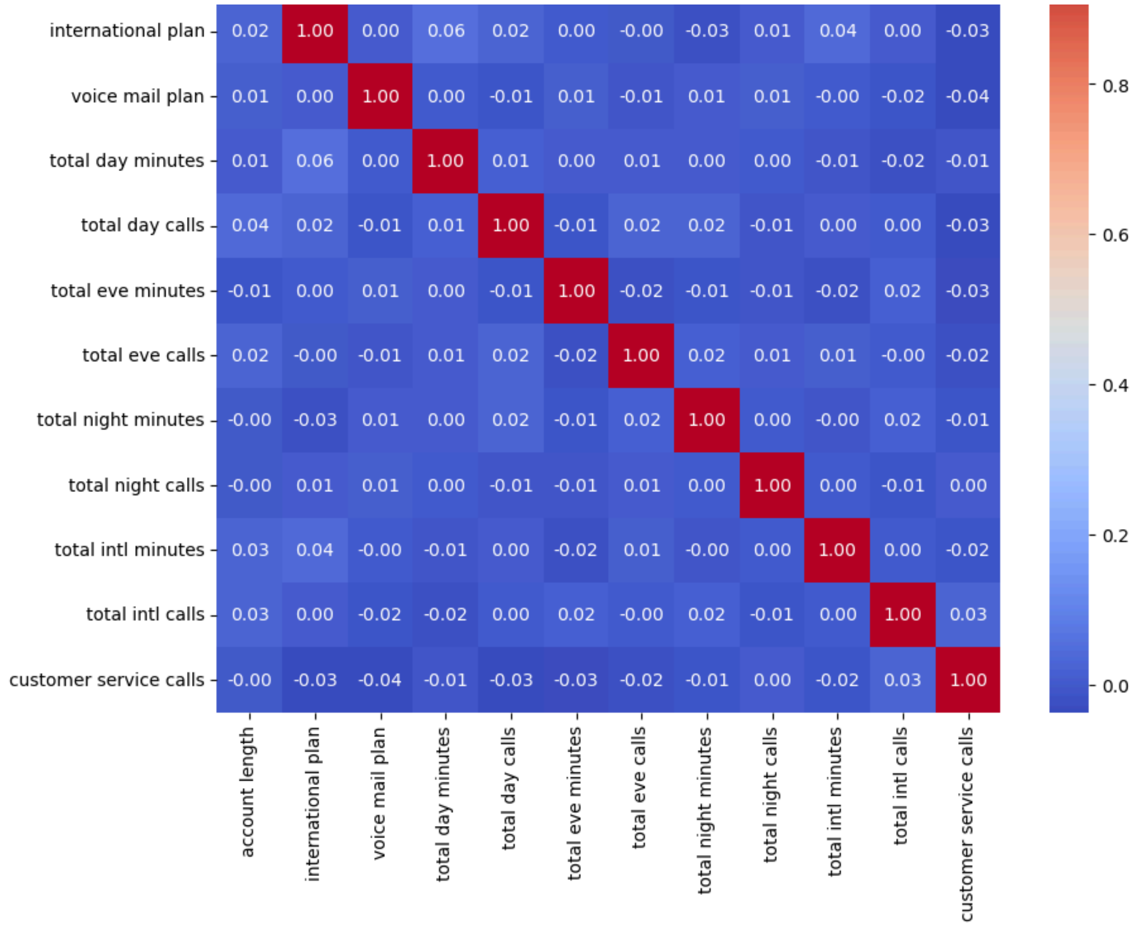


```
In [225…
import numpy as np
import pandas as pd

# Calculate the correlation matrix
corr_matrix = df_churn.corr().abs()

# Identify upper triangle of the correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(boo

# Find columns with correlation > 0.9
to_drop = [column for column in upper.columns if any(upper[column] > 0.9)]

# Drop the columns
df_churn = df_churn.drop(columns=to_drop)

print("Dropped columns:", to_drop)
```

```
Dropped columns: ['number vmail messages', 'total day charge', 'total eve charg
e', 'total night charge', 'total intl charge']
```

```
In [226…
# Correlation heatmap for the numerical columns
numeric_columns = df_churn.select_dtypes(include=['number']).columns

plt.figure(figsize=(10, 8))
sns.heatmap(df_churn[numeric_columns].corr(), annot=True, cmap='coolwarm', fm
plt.title("Correlation Heatmap")
plt.show()
```





Transforming churn values into 0s and 1s so the data is compatible with the models enabling them to perform calculations and predictions. Many algorithms, especially classification models (e.g., logistic regression, decision trees, and random forests), require numeric inputs for target variables.

In [ ]:

```
# transforming churn values into 0s and 1s
df_churn['churn'].value_counts()
df_churn['churn'] = df_churn['churn'].map({True: 1, False: 0}).astype('int')
df_churn.head(20)
```

Out[ ]:

	account length	international plan	voice mail plan	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	total night calls	m
0	128	0	1	265.1	110	197.4	99	244.7	91	
1	107	0	1	161.6	123	195.5	103	254.4	103	
2	137	0	0	243.4	114	121.2	110	162.6	104	
4	75	1	0	166.7	113	148.3	122	186.9	121	
5	118	1	0	223.4	98	220.6	101	203.9	118	
7	147	1	0	157.0	79	103.1	94	211.8	96	
9	141	1	1	258.6	84	222.0	111	326.4	97	
11	74	0	0	187.7	127	163.4	148	196.0	94	

12	168	0	0	128.8	96	104.9	71	141.1	128	
13	95	0	0	156.6	88	247.6	75	192.3	115	
16	85	0	1	196.4	139	280.9	90	89.3	75	
17	93	0	0	190.7	114	218.2	111	129.6	121	
18	76	0	1	189.7	66	212.8	65	165.7	108	
19	73	0	0	224.4	90	159.5	88	192.8	74	
20	147	0	0	155.1	117	239.7	93	208.8	133	
23	111	0	0	110.4	103	137.3	102	189.6	105	
24	132	0	0	81.1	86	245.2	72	237.0	115	
25	174	0	0	124.3	76	277.1	112	250.7	115	
26	57	0	1	213.0	115	191.1	112	182.7	115	
27	54	0	0	134.3	73	155.5	100	102.1	68	

4.0 Modelling

Now we make predictions and decisions based on data thru Modelling. After inputting data into a chosen model it will learn patterns or relationships within the data. The model's performance is assessed using evaluation metrics. The goal of modeling is to create a predictive model that generalizes well to new, unseen data, enabling it to make accurate predictions or classifications.

In [228…

```
# In order to standardise the range of features to ensure they all contribute
from sklearn.preprocessing import MinMaxScaler # to scale the numeric feature
transformer = MinMaxScaler()

def scaling(columns):
    return transformer.fit_transform(df_churn[columns].values.reshape(-1,1))

for i in df_churn.select_dtypes(include=[np.number]).columns:
    df_churn[i] = scaling(i)
df_churn.head()
```

Out[228…

	account length	international plan	voice mail plan	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	
0	0.622549	0.0	1.0	0.798455	0.600000	0.486667	0.481132	0.665428	0
1	0.519608	0.0	1.0	0.435042	0.723810	0.479630	0.518868	0.701487	0
2	0.666667	0.0	0.0	0.722261	0.638095	0.204444	0.584906	0.360223	0

4	0.362745	1.0	0.0	0.452949	0.628571	0.304815	0.698113	0.450558	0
5	0.573529	1.0	0.0	0.652037	0.485714	0.572593	0.500000	0.513755	0

In [229…

```
# Define X and y
y =df_churn['churn']
X = df_churn.drop(['churn'],axis=1)

# Split the data into training and test sets

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=17)
print(y_train.value_counts(),'\n\n', y_test.value_counts())
```

```
churn
0.0    1874
1.0     223
Name: count, dtype: int64

 churn
0.0    619
1.0     81
Name: count, dtype: int64
```

This gives an overview of how the target variable (churn) is distributed across both training and test sets, showing how balanced or imbalanced the data is for each class (e.g., the number of churn vs. non-churn instances). It can also be a guidance as to whether further techniques like class balancing are needed.

In [230…

```
# importing the necessary libraries
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression(fit_intercept=False, C=1e16, solver='liblinear')
logreg.fit(X_train, y_train)
```

Out[230…

```
LogisticRegression(C=1e+16, fit_intercept=False, solver='liblinear')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Here we get the trained logistic regression model that has been fitted to the training data. The model will learn the relationship between the features (X_train) and the target (y_train), with no regularization applied due to the very high value of C.

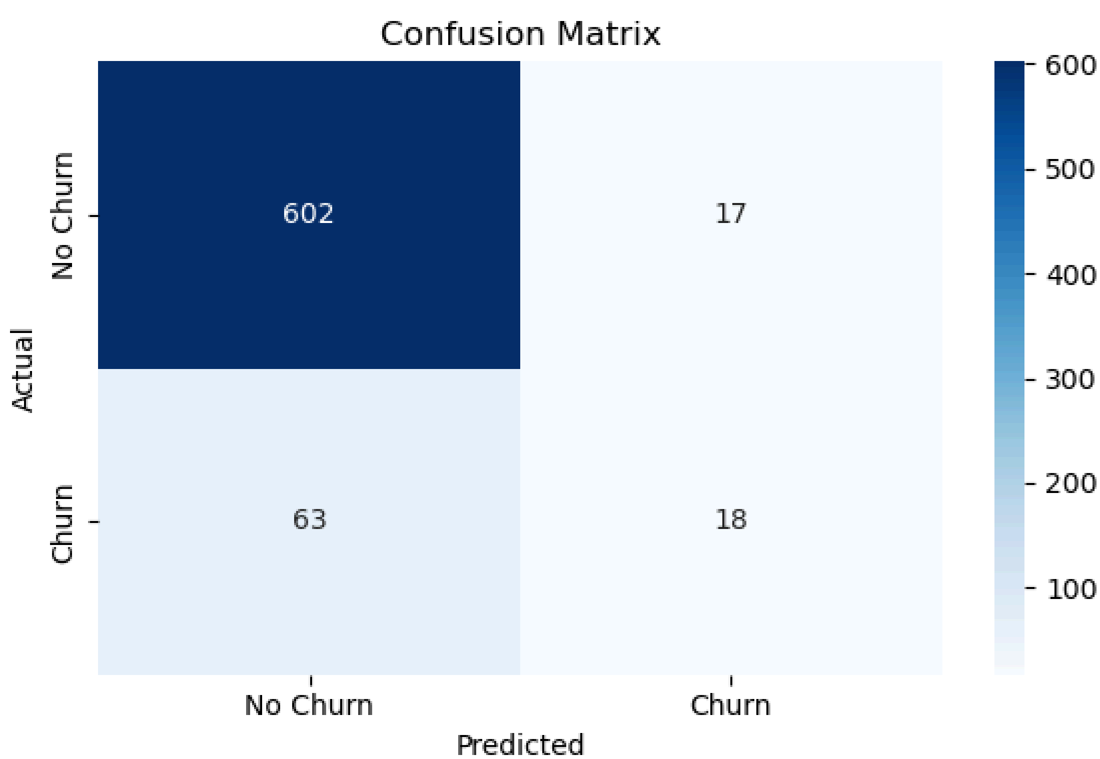
In [231…

```
# Importing the relevant function and  defining y_pred

from sklearn.metrics import mean_squared_error

# Generate predictions using baseline_model and X_train
y_pred = logreg.predict(X_test)
```

In [232…

```python
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Print classification metrics
print("**************** LOGISTIC REGRESSION CLASSIFIER MODEL RESULTS ********
print(classification_report(y_test, y_pred, target_names=['No Churn', 'Churn'

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

# Plot Confusion Matrix
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Churn', '
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.tight_layout()
plt.show()
```

```
**************** LOGISTIC REGRESSION CLASSIFIER MODEL RESULTS ****************
              precision    recall  f1-score   support

    No Churn       0.91      0.97      0.94       619
       Churn       0.51      0.22      0.31        81

    accuracy                           0.89       700
   macro avg       0.71      0.60      0.62       700
weighted avg       0.86      0.89      0.87       700
```



The confusion matrix indicates the performance of the model as follows:

- **True Negatives (No Churn correctly predicted)**: 602 instances were correctly

- **True Negatives (No Churn correctly predicted)**: 602 instances were correctly classified as "No Churn."
- **False Positives (Predicted Churn but was No Churn)**: 17 instances were incorrectly classified as "Churn" when they were actually "No Churn."
- **False Negatives (Predicted No Churn but was Churn)**: 63 instances were incorrectly classified as "No Churn" when they were actually "Churn."
- **True Positives (Churn correctly predicted)**: 18 instances were correctly classified as "Churn."

Overall, the model performs well for identifying "No Churn" instances but struggles significantly with identifying "Churn," as evidenced by the high number of false negatives. This suggests a potential imbalance in the dataset or room for improvement in model sensitivity towards the "Churn" class.

In [233...

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1

# Calculate and print key metrics
print("**************** LOGISTIC REGRESSION CLASSIFIER MODEL RESULTS ********
print(f"Accuracy: {accuracy_score(y_test, y_pred):.5f}")
print(f"Precision: {precision_score(y_test, y_pred):.5f}")
print(f"Recall: {recall_score(y_test, y_pred):.5f}")
print(f"F1 Score: {f1_score(y_test, y_pred):.5f}")
```

```
**************** LOGISTIC REGRESSION CLASSIFIER MODEL RESULTS ****************
Accuracy: 0.88571
Precision: 0.51429
Recall: 0.22222
F1 Score: 0.31034
```

The Logistics Regressionmodel performance metrics are as follows:

Accuracy (0.88571): The model accurately predicted 88% of all instances. Precision (0.51429): Of the cases predicted as "Churn," 51% were correct. Recall (0.22222): The model successfully identified only 22% of the actual "Churn" cases. F1 Score (0.31034): The low F1 score reflects poor overall performance in detecting "Churn," balancing both precision and recall.

These metrics are particularly useful for imbalanced datasets, as Accuracy alone may not reflect the model's ability to correctly identify the minority class ("Churn"). In this case, the metrics will highlight that while the model performs well in predicting "No Churn," it has lower Recall and F1 Score for "Churn," indicating room for improvement in recognizing this minority class.

In [236...

```
from sklearn.ensemble import RandomForestClassifier
from imblearn.over_sampling import SMOTE
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1
from sklearn.model_selection import train_test_split


# Apply SMOTE to handle class imbalance
```

```
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)

# Train the Random Forest model
model = RandomForestClassifier(random_state=42)
model.fit(X_resampled, y_resampled)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate performance
print("*************** RANDOM FOREST CLASSIFIER RESULTS ***************")
print(f"Accuracy: {accuracy_score(y_test, y_pred):.5f}")
print(f"Precision: {precision_score(y_test, y_pred):.5f}")
print(f"Recall: {recall_score(y_test, y_pred):.5f}")
print(f"F1 Score: {f1_score(y_test, y_pred):.5f}")
```

```
*************** RANDOM FOREST CLASSIFIER RESULTS ***************
Accuracy: 0.93000
Precision: 0.68182
Recall: 0.74074
F1 Score: 0.71006
```

The Random Forest model which has SMOTE applied to it clearly outperforms the Logistic Regression baseline in all metrics. While Logistic Regression shows acceptable accuracy, its poor recall and F1 score highlight its inability to effectively detect "Churn." In contrast, Random Forest demonstrates strong performance across all metrics, making it a much better choice for this problem, especially if identifying "Churn" is critical.

In [237…

```
from sklearn.ensemble import RandomForestClassifier
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1

# Handle class imbalance with SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)

# Define the Random Forest model
rf = RandomForestClassifier(random_state=42)

# Define the hyperparameters grid
param_grid = {
    'n_estimators': [50, 100, 200],            # Number of trees in the fores
    'max_depth': [None, 10, 20, 30],          # Maximum depth of the tree
    'min_samples_split': [2, 5, 10],          # Minimum number of samples req
    'min_samples_leaf': [1, 2, 4],            # Minimum number of samples req
    'bootstrap': [True, False]                # Whether bootstrap samples are
}

# Apply GridSearchCV
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, scoring
grid_search.fit(X_resampled, y_resampled)

# Best hyperparameters and model
```

```
best_rf = grid_search.best_estimator_
print("Best Hyperparameters:", grid_search.best_params_)

# Make predictions with the best model
y_pred = best_rf.predict(X_test)

# Evaluate the tuned model
print("**************** TUNED RANDOM FOREST CLASSIFIER RESULTS **************
print(f"Accuracy: {accuracy_score(y_test, y_pred):.5f}")
print(f"Precision: {precision_score(y_test, y_pred):.5f}")
print(f"Recall: {recall_score(y_test, y_pred):.5f}")
print(f"F1 Score: {f1_score(y_test, y_pred):.5f}")
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
Best Hyperparameters: {'bootstrap': False, 'max_depth': None, 'min_samples_lea
f': 1, 'min_samples_split': 2, 'n_estimators': 200}
**************** TUNED RANDOM FOREST CLASSIFIER RESULTS ****************
Accuracy: 0.94000
Precision: 0.75325
Recall: 0.71605
F1 Score: 0.73418
```

The tuned Random Forest model achieves excellent performance across all metrics, significantly improving the detection of "Churn" compared to earlier models like Logistic Regression. It effectively balances precision and recall, making it reliable for applications where identifying churners accurately is critical for business strategy. The chosen hyperparameters likely enhanced the model's ability to generalize and capture the complexities of the data.

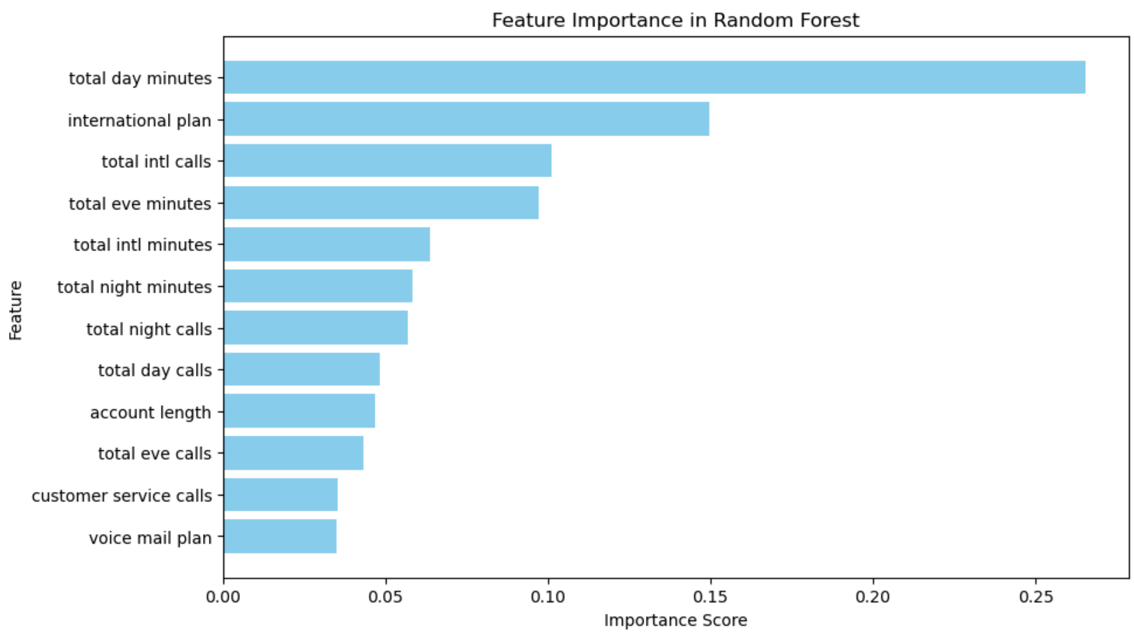
Hyperparameter tuning marginally improved overall performance, with a higher accuracy, precision, and F1 score compared to the baseline. While recall slightly decreased, the improvement in precision ensures that the tuned model is more reliable and consistent in its predictions. This makes the tuned Random Forest classifier a more robust choice, especially in scenarios prioritizing reduced false positives without sacrificing much recall.

In [241…

```
import pandas as pd
import matplotlib.pyplot as plt


# Get feature importances
feature_importances = best_rf.feature_importances_

# Create a DataFrame to visualize
feature_importance_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)

# Display feature importances
print(feature_importance_df)

# Plot feature importances
```

```python
plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.title("Feature Importance in Random Forest")
plt.gca().invert_yaxis()  # Invert y-axis for better readability
plt.show()
```

```
                  Feature  Importance
3        total day minutes    0.265457
1       international plan    0.149616
10        total intl calls    0.101183
5        total eve minutes    0.097269
9       total intl minutes    0.063487
7      total night minutes    0.058100
8        total night calls    0.056699
4          total day calls    0.048233
0           account length    0.046843
6          total eve calls    0.043025
11  customer service calls    0.035230
2          voice mail plan    0.034858
```



The **feature importance scores** indicate how much each feature contributes to the Random Forest model's predictions. Here's an explanation of the results:

Top Contributors:

- **`total day minutes` (0.265):** This feature has the highest importance, meaning the total minutes a customer spends on daytime calls is the most critical factor in predicting churn.
- **`international plan` (0.150):** Whether a customer has subscribed to an international plan is the second most influential factor, reflecting its impact on churn decisions.
- **`total intl calls` (0.101):** The total number of international calls made is another significant factor, showing its relevance in customer churn behavior.

Less Significant Features:

- **Call and account-related features** like `total day calls` (0.048), `account length` (0.047), and `total eve calls` (0.043) have lower importance, suggesting they are less predictive of churn compared to the top features.
- **`customer service calls` (0.035):** While low, this feature still has some influence, as frequent interactions with customer service might be a signal of dissatisfaction.
- **`voice mail plan` (0.035):** This feature has minimal impact, indicating it is not a major factor in predicting churn.

Summary:

The model emphasizes **call usage patterns (minutes and international calls)** and **subscription plans** (international plan) as the primary predictors of churn. Features like account length, voice mail plan, and customer service calls have relatively less influence. These insights could guide strategies for churn reduction by focusing on optimizing services related to the most critical features.

In [238…

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1
from imblearn.over_sampling import SMOTE
import numpy as np

# Handle class imbalance with SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)

# Define the Decision Tree model
dt = DecisionTreeClassifier(random_state=42)

# Define the hyperparameter space for Randomized Search
param_dist = {
    'criterion': ['gini', 'entropy'],            # Splitting criterion
    'max_depth': [None, 10, 20, 30, 50],         # Maximum depth of the tree
    'min_samples_split': [2, 5, 10, 20],         # Minimum samples to split a
    'min_samples_leaf': [1, 2, 4, 10],           # Minimum samples at a leaf
    'max_features': [None, 'sqrt', 'log2'],      # Number of features to cons
    'splitter': ['best', 'random']               # Strategy for choosing the
}

# Apply RandomizedSearchCV
random_search = RandomizedSearchCV(
    estimator=dt,
    param_distributions=param_dist,
    n_iter=100,                  # Number of parameter settings sampled
    scoring='f1',                # Use F1 score to evaluate performance
    cv=5,                        # 5-fold cross-validation
    random_state=42,             # Ensures reproducibility
    verbose=2,
    n_jobs=-1                    # Use all available processors
)
random_search.fit(X_resampled, y_resampled)
```

```
random_search.fit(X_resampled, y_resampled)

# Best hyperparameters and model
best_dt = random_search.best_estimator_
print("Best Hyperparameters:", random_search.best_params_)

# Make predictions with the best model
y_pred = best_dt.predict(X_test)

# Step 7: Evaluate the tuned model
print("*************** TUNED DECISION TREE RESULTS ***************")
print(f"Accuracy: {accuracy_score(y_test, y_pred):.5f}")
print(f"Precision: {precision_score(y_test, y_pred):.5f}")
print(f"Recall: {recall_score(y_test, y_pred):.5f}")
print(f"F1 Score: {f1_score(y_test, y_pred):.5f}")
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
Best Hyperparameters: {'splitter': 'best', 'min_samples_split': 5, 'min_samples
_leaf': 1, 'max_features': None, 'max_depth': 30, 'criterion': 'entropy'}
*************** TUNED DECISION TREE RESULTS ***************
Accuracy: 0.86143
Precision: 0.43846
Recall: 0.70370
F1 Score: 0.54028
```

The Decision Tree shows lower accuracy and precision compared to Random Forest, with a higher recall. It's prone to overfitting due to its single tree structure, which could explain the imbalance between precision and recall. The Random Forest performs well across all metrics, with high accuracy and reasonable precision and recall. Its ensemble nature (using multiple trees) helps in reducing overfitting and improving stability.

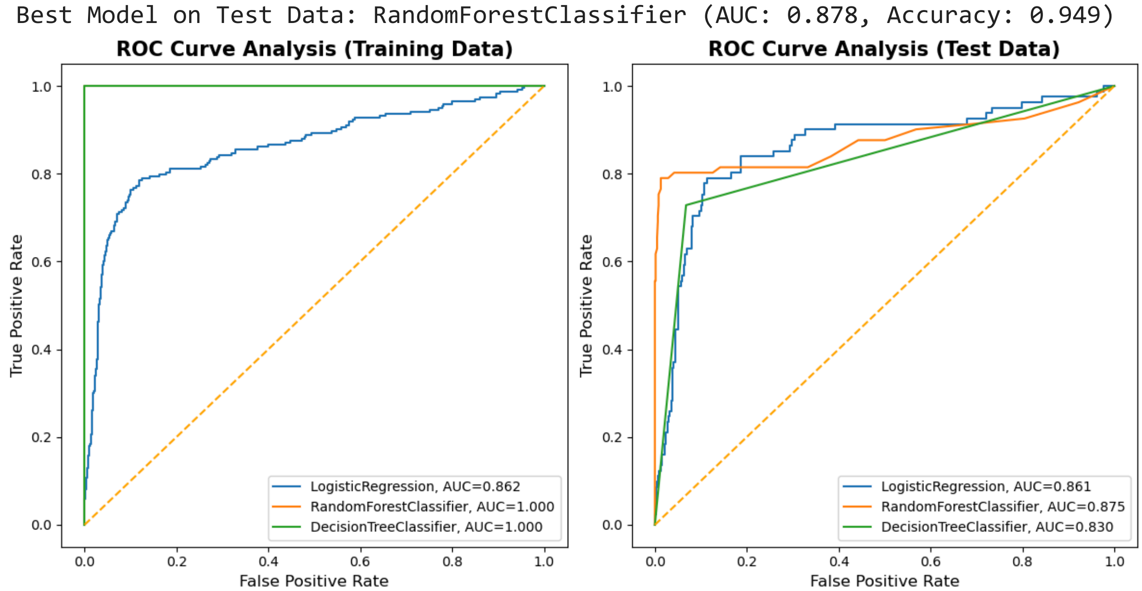
In [239…

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score, accuracy_score
import matplotlib.pyplot as plt
import pandas as pd

# Define classifiers
classifiers = [
    LogisticRegression(max_iter=1000),  # Increased max_iter for Logistic Reg
    RandomForestClassifier(),
    DecisionTreeClassifier()
]

# Define result tables for training and test data
train_result_table = pd.DataFrame(columns=['classifiers', 'auc', 'accuracy'])
test_result_table = pd.DataFrame(columns=['classifiers', 'auc', 'accuracy'])

# Train the models and record the results
for cls in classifiers:
    model = cls.fit(X_train, y_train)

    # Training data predictions
    y_train_proba = model.predict_proba(X_train)[:, 1]
```

```python
    y_train_pred = model.predict(X_train)
    train_auc = roc_auc_score(y_train, y_train_proba)
    train_accuracy = accuracy_score(y_train, y_train_pred)

    # Test data predictions
    y_test_proba = model.predict_proba(X_test)[:, 1]
    y_test_pred = model.predict(X_test)
    test_auc = roc_auc_score(y_test, y_test_proba)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Append results for training and test data
    train_result_table = pd.concat([train_result_table,
                                    pd.DataFrame({'classifiers': [cls.__clas
                                                  'auc': [train_auc],
                                                  'accuracy': [train_accurac
                                   ignore_index=True)
    test_result_table = pd.concat([test_result_table,
                                   pd.DataFrame({'classifiers': [cls.__class
                                                 'auc': [test_auc],
                                                 'accuracy': [test_accuracy]
                                  ignore_index=True)

# Identify the best model for training and test data
best_train_model = train_result_table.loc[train_result_table['auc'].idxmax()]
best_test_model = test_result_table.loc[test_result_table['auc'].idxmax()]

# Display comparison results
print("*************** MODEL COMPARISON RESULTS ***************")
print("Training Data:")
print(train_result_table)
print("\nBest Model on Training Data: {} (AUC: {:.3f}, Accuracy: {:.3f})".for
    best_train_model['classifiers'], best_train_model['auc'], best_train_mode

print("\nTest Data:")
print(test_result_table)
print("\nBest Model on Test Data: {} (AUC: {:.3f}, Accuracy: {:.3f})".format(
    best_test_model['classifiers'], best_test_model['auc'], best_test_model['

# Plot ROC curves for training and test data
plt.figure(figsize=(12, 6))

# Training ROC curves
plt.subplot(1, 2, 1)
plt.title('ROC Curve Analysis (Training Data)', fontweight='bold', fontsize=1
for cls in classifiers:
    model = cls.fit(X_train, y_train)
    y_train_proba = model.predict_proba(X_train)[:, 1]
    fpr, tpr, _ = roc_curve(y_train, y_train_proba)
    auc = roc_auc_score(y_train, y_train_proba)
    plt.plot(fpr, tpr, label="{}, AUC={:.3f}".format(cls.__class__.__name__,
plt.plot([0, 1], [0, 1], color='orange', linestyle='--')
plt.xlabel("False Positive Rate", fontsize=12)
plt.ylabel("True Positive Rate", fontsize=12)
plt.legend(prop={'size': 10}, loc='lower right')

# Test ROC curves
plt.subplot(1, 2, 2)
plt.title('ROC Curve Analysis (Test Data)', fontweight='bold', fontsize=15)
for cls in classifiers:
    model = cls.fit(X_train, y_train)
    y_test_proba = model.predict_proba(X_test)[:, 1]
```

```python
    y_test_proba = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_test_proba)
    auc = roc_auc_score(y_test, y_test_proba)
    plt.plot(fpr, tpr, label="{}, AUC={:.3f}".format(cls.__class__.__name__,
plt.plot([0, 1], [0, 1], color='orange', linestyle='--')
plt.xlabel("False Positive Rate", fontsize=12)
plt.ylabel("True Positive Rate", fontsize=12)
plt.legend(prop={'size': 10}, loc='lower right')

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

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_15772\3760878546.py:36: FutureWarni
ng: The behavior of DataFrame concatenation with empty or all-NA entries is dep
recated. In a future version, this will no longer exclude empty or all-NA colum
ns when determining the result dtypes. To retain the old behavior, exclude the
relevant entries before the concat operation.
  train_result_table = pd.concat([train_result_table,
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_15772\3760878546.py:41: FutureWarni
ng: The behavior of DataFrame concatenation with empty or all-NA entries is dep
recated. In a future version, this will no longer exclude empty or all-NA colum
ns when determining the result dtypes. To retain the old behavior, exclude the
relevant entries before the concat operation.
  test_result_table = pd.concat([test_result_table,
*************** MODEL COMPARISON RESULTS ***************
Training Data:
              classifiers       auc  accuracy
0      LogisticRegression  0.862025  0.901288
1  RandomForestClassifier  1.000000  1.000000
2  DecisionTreeClassifier  1.000000  1.000000

Best Model on Training Data: RandomForestClassifier (AUC: 1.000, Accuracy: 1.00
0)

Test Data:
              classifiers       auc  accuracy
0      LogisticRegression  0.860986  0.885714
1  RandomForestClassifier  0.877889  0.948571
2  DecisionTreeClassifier  0.819542  0.908571

Best Model on Test Data: RandomForestClassifier (AUC: 0.878, Accuracy: 0.949)
```



Of the three models (Logistic Regression, Random Forest, and Decision Tree) based on their AUC and accuracy scores for both training and test data we can conclude as