Step 1: Importing Required Libraries

We start by importing the fundamental libraries required for data analysis and manipulation:

- `pandas` for handling tabular data,
- `numpy` for numerical operations.
- `matplotlib.pyplot` and `seaborn` for data visualization.
- `sklearn` for data preprocessing, model training, and model evaluation.
- `imblearn` for handling class imbalance.

These will serve as the core tools for our preprocessing and modeling pipeline.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
```

Step 2: Loading the Telco Customer Churn Dataset

We load the dataset using `pandas.read_csv()`. This dataset includes details about telecom customers, including their demographics, services they've subscribed to, and whether or not they have churned (i.e., left the company).

This is the raw data on which we will perform cleaning, analysis, and build predictive models.

```
df = pd.read_csv('Dataset/WA_Fn-UseC_-Telco-Customer-Churn.csv')
```

Step 3: Initial Data Exploration

To understand the data structure, we use:

- `df.shape` to check dataset size,
- `df.head()` to preview records,
- `df.info()` to identify data types and nulls,
- `df.describe()` to view statistics of numeric fields.

This helps us identify issues like incorrect data types, missing values, and outliers.

```
df.shape
```

```
(7043, 21)

df.head()

   customerID  gender  SeniorCitizen Partner Dependents  tenure
PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1
No
1  5575-GNVDE    Male              0      No         No      34
Yes
2  3668-QPYBK    Male              0      No         No       2
Yes
3  7795-CFOCW    Male              0      No         No      45
No
4  9237-HQITU  Female              0      No         No       2
Yes

      MultipleLines InternetService OnlineSecurity  ...
DeviceProtection  \
0  No phone service             DSL             No  ...
No
1                No             DSL            Yes  ...
Yes
2                No             DSL            Yes  ...
No
3  No phone service             DSL            Yes  ...
Yes
4                No     Fiber optic             No  ...
No

  TechSupport StreamingTV StreamingMovies        Contract
PaperlessBilling  \
0          No          No              No  Month-to-month
Yes
1          No          No              No        One year
No
2          No          No              No  Month-to-month
Yes
3         Yes          No              No        One year
No
4          No          No              No  Month-to-month
Yes

               PaymentMethod MonthlyCharges  TotalCharges Churn
0           Electronic check          29.85         29.85    No
1               Mailed check          56.95        1889.5    No
2               Mailed check          53.85        108.15   Yes
3  Bank transfer (automatic)          42.30       1840.75    No
4           Electronic check          70.70        151.65   Yes
```

```
[5 rows x 21 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

```
df.describe()
```

```
       SeniorCitizen       tenure  MonthlyCharges
count    7043.000000  7043.000000     7043.000000
mean        0.162147    32.371149       64.761692
std         0.368612    24.559481       30.090047
min         0.000000     0.000000       18.250000
25%         0.000000     9.000000       35.500000
50%         0.000000    29.000000       70.350000
75%         0.000000    55.000000       89.850000
max         1.000000    72.000000      118.750000
```

Step 4: Data Cleaning

4.1 Convert 'TotalCharges' to Numeric

The `TotalCharges` column was incorrectly loaded as an object due to presence of blank entries.
We use `pd.to_numeric(errors='coerce')` to convert it to float, coercing invalid entries to NaN.

```
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors =
'coerce')

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

```
customerID           0
gender               0
SeniorCitizen        0
Partner              0
Dependents           0
tenure               0
PhoneService         0
MultipleLines        0
InternetService      0
OnlineSecurity       0
OnlineBackup         0
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
```

4.2 Handle Missing Values

After conversion, 11 rows had `NaN` values in `TotalCharges`.
Since these are very few and likely represent customers with very short tenure, we safely drop them using `df.dropna()`.

```
df.dropna(subset = ['TotalCharges'], inplace = True)
```

4.3 Validate Cleaned Data

We verify:

- Data shape has changed to 7032 rows,
- No missing values remain,
- Data types are correct,
- Summary statistics make sense.

At this point, the dataset is clean and ready for analysis.

```
df.shape
```

```
(7032, 21)
```

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

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7032 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7032 non-null   object
 1   gender            7032 non-null   object
 2   SeniorCitizen     7032 non-null   int64
 3   Partner           7032 non-null   object
 4   Dependents        7032 non-null   object
 5   tenure            7032 non-null   int64
 6   PhoneService      7032 non-null   object
```

```
 7   MultipleLines     7032 non-null   object 
 8   InternetService   7032 non-null   object 
 9   OnlineSecurity    7032 non-null   object 
 10  OnlineBackup      7032 non-null   object 
 11  DeviceProtection  7032 non-null   object 
 12  TechSupport       7032 non-null   object 
 13  StreamingTV       7032 non-null   object 
 14  StreamingMovies   7032 non-null   object 
 15  Contract          7032 non-null   object 
 16  PaperlessBilling  7032 non-null   object 
 17  PaymentMethod     7032 non-null   object 
 18  MonthlyCharges    7032 non-null   float64
 19  TotalCharges      7032 non-null   float64
 20  Churn             7032 non-null   object 
dtypes: float64(2), int64(2), object(17)
memory usage: 1.2+ MB
```

```
df.describe()
```

```
       SeniorCitizen       tenure  MonthlyCharges  TotalCharges
count    7032.000000  7032.000000     7032.000000   7032.000000
mean        0.162400    32.421786       64.798208   2283.300441
std         0.368844    24.545260       30.085974   2266.771362
min         0.000000     1.000000       18.250000     18.800000
25%         0.000000     9.000000       35.587500    401.450000
50%         0.000000    29.000000       70.350000   1397.475000
75%         0.000000    55.000000       89.862500   3794.737500
max         1.000000    72.000000      118.750000   8684.800000
```

4.4 Check for Uniqueness of `customerID`

Before proceeding to analysis, it's important to ensure that the `customerID` column — which acts as the unique identifier for each customer — contains only unique values.

This step helps verify data integrity by checking for any duplicate entries that may have been mistakenly included in the dataset. Duplicates in a primary key column could lead to incorrect assumptions or bias in model training and analysis.

We use the `duplicated()` method to find any repeated customer IDs. If the number of duplicated records is zero, we can safely confirm the uniqueness of the `customerID` column.

```
duplicate_ids = df[df.duplicated('customerID', keep = False)]
duplicate_ids.shape[0]
```

```
0
```

Step 5: Exploratory Data Analysis (EDA)

5.1 Check Target Variable Distribution: `Churn`

We begin EDA by examining the target variable `Churn`. This tells us whether the dataset is balanced or imbalanced in terms of the customers who have churned (left the service) versus those who have not.

A balanced target means we have roughly equal numbers of churned and non-churned customers. A class imbalance can significantly affect model performance. For example, if 80% of the customers have not churned, a model could just predict "No" for everything and still be 80% accurate — but that wouldn't be useful!

Hence, checking the class distribution early helps us plan ahead for model evaluation and training strategies.

We will:

- Use `value_counts()` to see the exact numbers.

```
# Count churn values
df['Churn'].value_counts()

Churn
No     5163
Yes    1869
Name: count, dtype: int64
```

5.2 Visualize Target Variable Distribution: `Churn`

While numerical counts give an idea of churn distribution, visualizing it helps quickly spot class imbalance, which is crucial for model building.

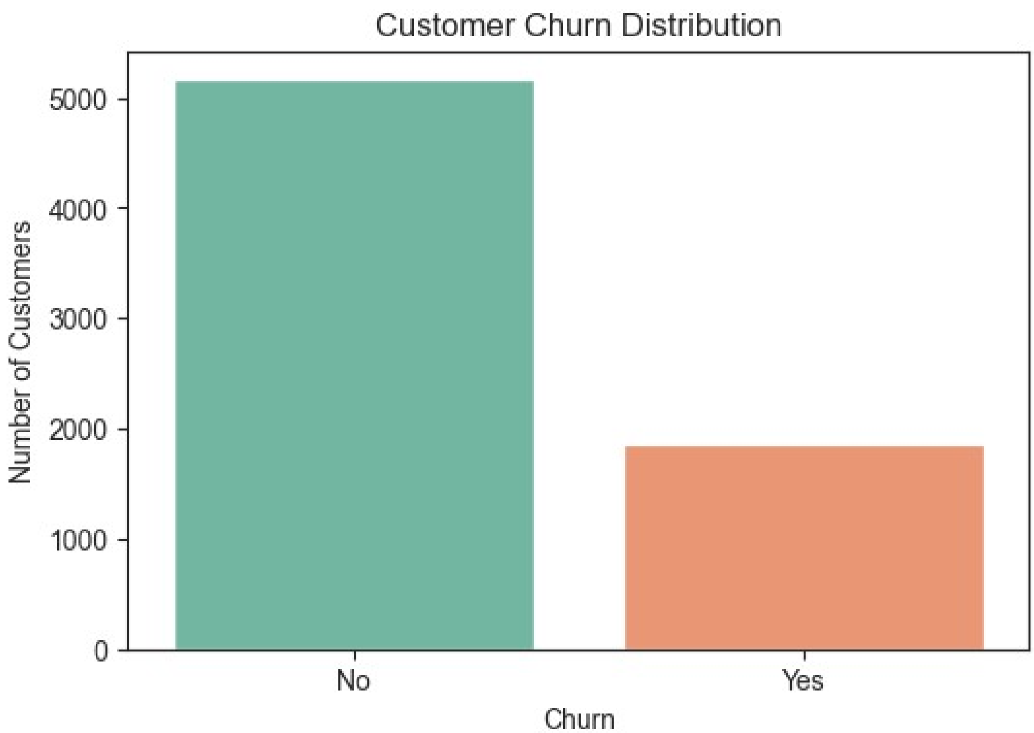
A bar plot of the `Churn` column will visually show how many customers stayed (`No`) and how many left (`Yes`). This is an important part of EDA because:

- A large imbalance (e.g., too many `No`s compared to `Yes`s) can bias machine learning models.
- We might need to apply balancing techniques (like oversampling, undersampling, or class weighting) later during training.
- It sets the stage for understanding churn trends among other variables.

We will use Seaborn's `countplot()` to display this class distribution.

```
sns.set_style("ticks")
plt.figure(figsize = (6, 4))
sns.countplot(data=df, x='Churn', hue='Churn', palette='Set2',
legend=False)
plt.title('Customer Churn Distribution')
plt.xlabel('Churn')
```

```
plt.ylabel('Number of Customers')
plt.show()
```



5.3 Calculate Churn Class Percentages

To better understand the class imbalance, we calculate the percentage of customers who churned (`Yes`) and who did not (`No`). This numeric insight complements the visual plot and helps in identifying the degree of imbalance in the target variable.

We use the `value_counts(normalize=True)` function, which returns the relative frequencies of each class as proportions. Multiplying by 100 converts these to percentages.

```
churn_percentages = df['Churn'].value_counts(normalize = 'True') * 100
print(churn_percentages)
```

```
Churn
No     73.421502
Yes    26.578498
Name: proportion, dtype: float64
```

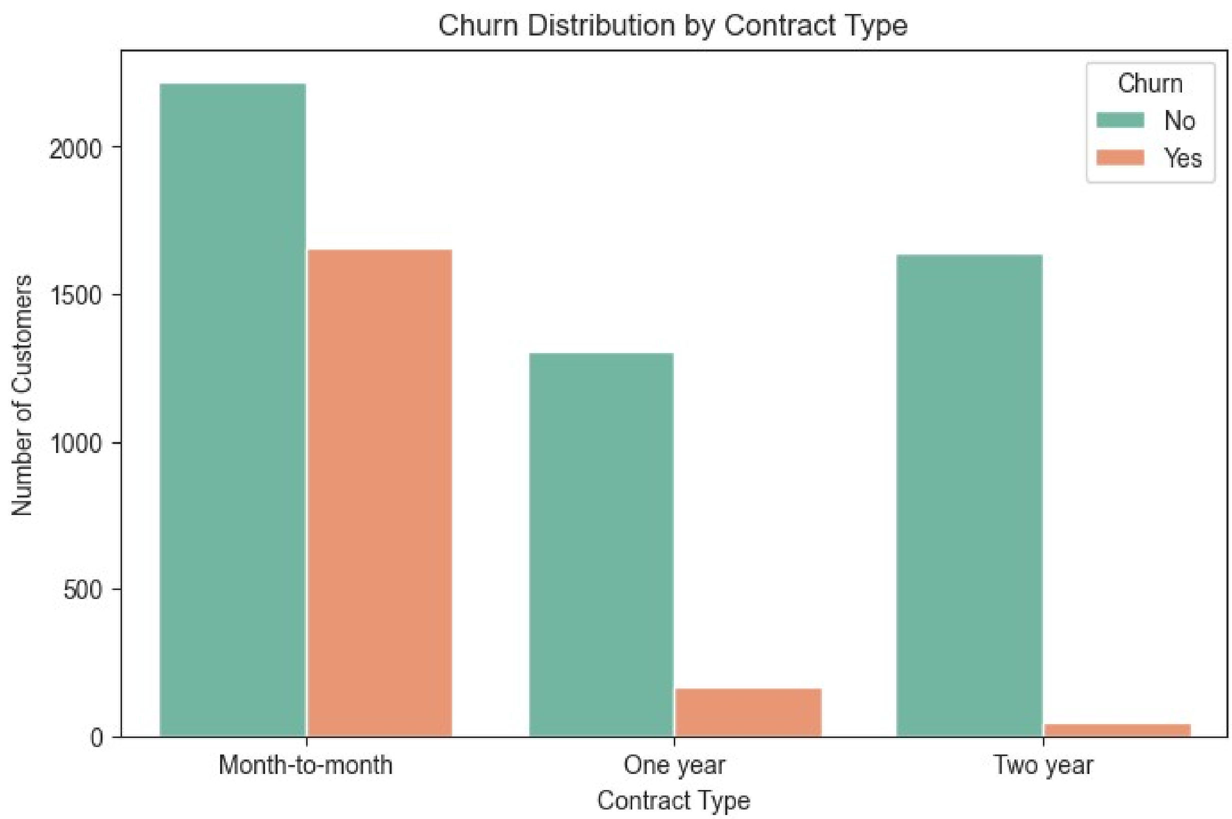
5.4 Analyze Categorical Features: `Contract` vs `Churn`

We investigate how churn varies across different contract types.

- The `Contract` feature indicates the duration of the customer's contract (e.g., month-to-month, one year, two year).

- Customers with month-to-month contracts typically show higher churn.
- Visualizing this relationship helps identify important predictors for churn.

```
sns.set_style("ticks")
plt.figure(figsize = (8, 5))
sns.countplot(data = df, x = 'Contract', hue = 'Churn', palette =
'Set2')
plt.title('Churn Distribution by Contract Type')
plt.xlabel('Contract Type')
plt.ylabel('Number of Customers')
plt.legend(title='Churn')
plt.show()
```



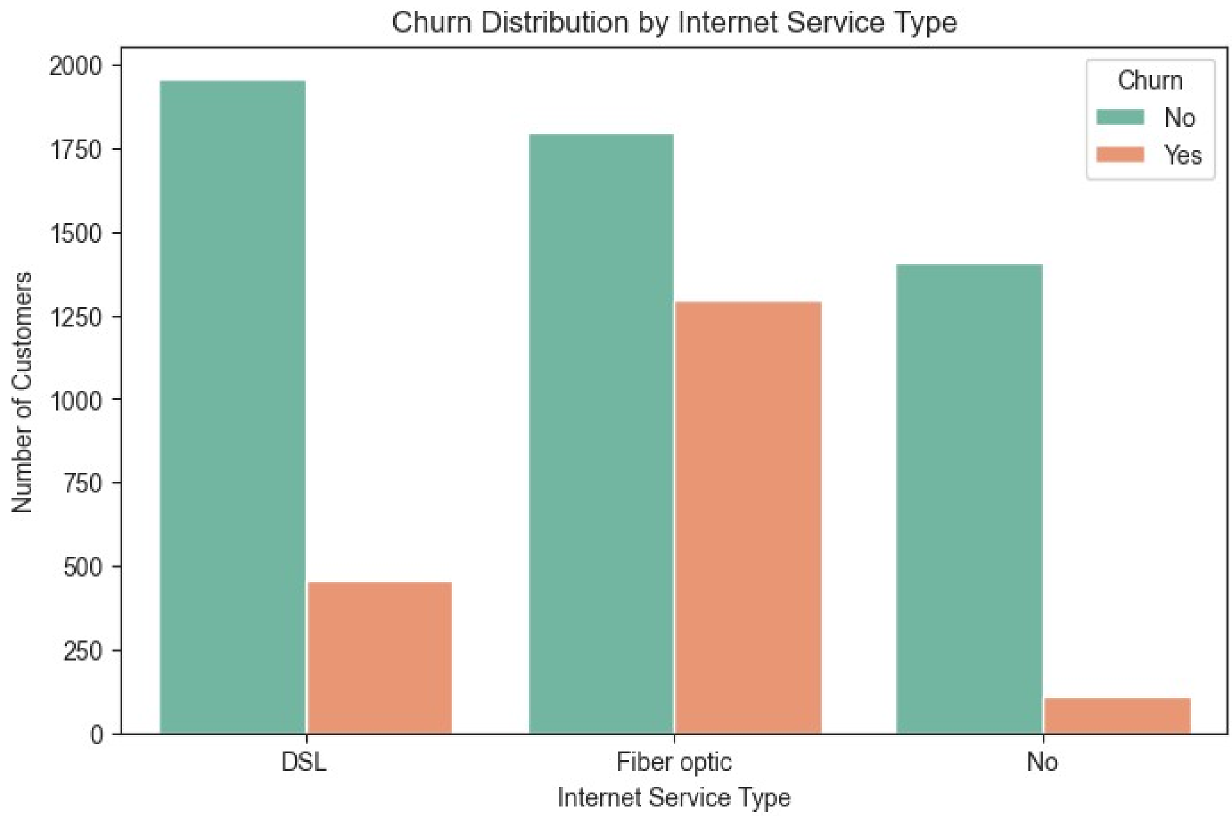
5.5 Churn Distribution by Internet Service Type

We analyze how customer churn varies by the type of internet service they use. This may reveal whether certain services (like fiber optic) are more associated with customer loss.

A countplot with `hue='Churn'` will show how many customers stayed or left for each internet service category (`DSL`, `Fiber optic`, `No`).

```
sns.set_style('ticks')
plt.figure(figsize = (8, 5))
sns.countplot(data = df, x = 'InternetService', hue = 'Churn', palette
```

```
= 'Set2')
plt.title('Churn Distribution by Internet Service Type')
plt.xlabel('Internet Service Type')
plt.ylabel('Number of Customers')
plt.legend(title='Churn')
plt.show()
```



5.6 Churn by `OnlineSecurity`

The `OnlineSecurity` feature tells us whether a customer subscribed to an online security service. This service is typically considered a value-add for internet users.

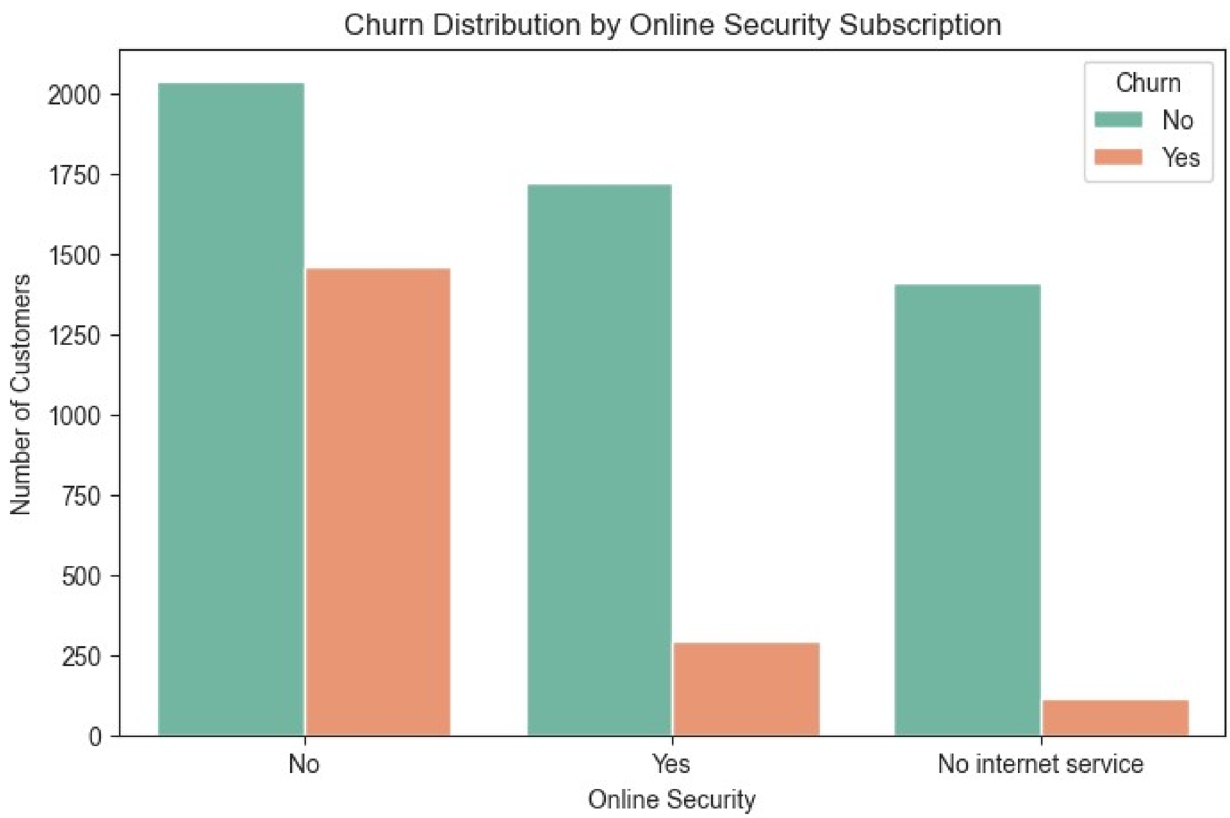
Analyzing churn across this feature helps us understand:

- Whether having **security protection** correlates with customer loyalty.
- Whether **not having security** might be associated with higher churn.
- The behavior of customers with **no internet service** (a third category).

This can give insight into how value-added services might reduce churn.

```
sns.set_style('ticks')
plt.figure(figsize = (8, 5))
sns.countplot(data = df, x = 'OnlineSecurity', hue = 'Churn', palette
= 'Set2')
```

```
plt.title('Churn Distribution by Online Security Subscription')
plt.xlabel('Online Security')
plt.ylabel('Number of Customers')
plt.legend(title='Churn')
plt.show()
```



5.7 Analyze Churn with Other Service Features

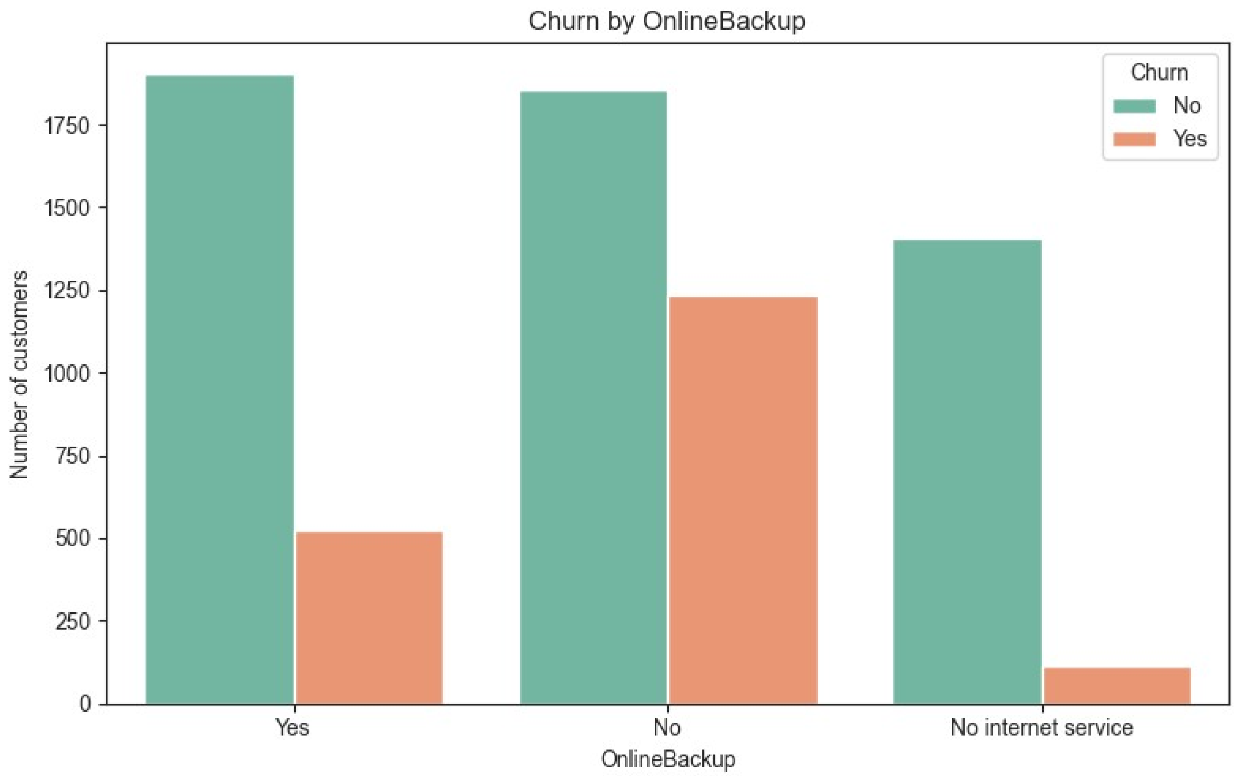
To deepen our understanding of customer churn behavior, we now explore other service-related features like:

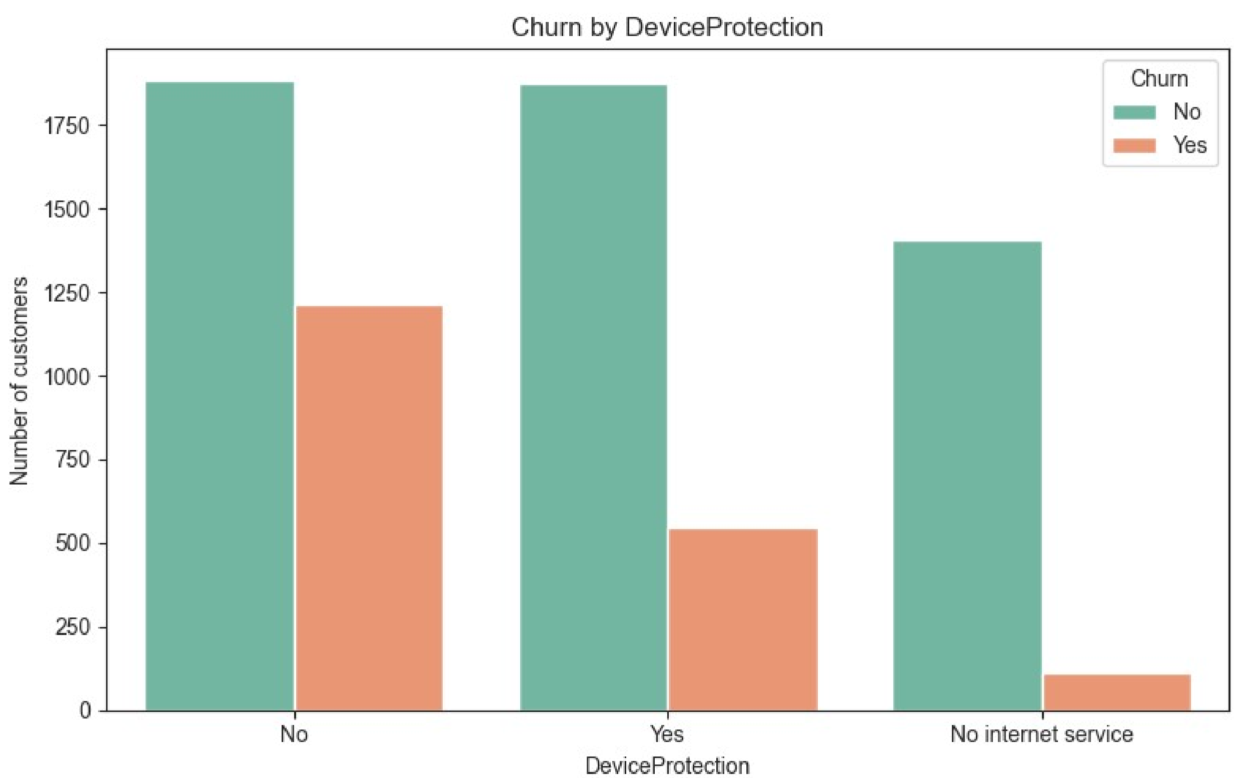
- Online Backup
- Device Protection
- Tech Support
- Streaming TV
- Streaming Movies

These optional services may influence customer satisfaction. Customers who **don't use these services** might be **more likely to churn**, either because they are less engaged or didn't see enough value in the subscription.

We will visualize each of these against the `Churn` column to look for such patterns.

```
service_features = ['OnlineBackup', 'DeviceProtection', 'TechSupport',
'StreamingTV', 'StreamingMovies']

n_features = len(service_features)
n_cols = 1
n_rows = n_features
fig, axes = plt.subplots(n_rows, n_cols, figsize=(8, n_rows * 5))
axes = axes.flatten()


for i, feature in enumerate(service_features):
    ax = axes[i]
    sns.countplot(data=df, x=feature, hue='Churn', palette='Set2',
ax=ax)
    ax.set_title(f'Churn by {feature}')
    ax.set_ylabel('Number of customers')
    ax.legend(title='Churn')

for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

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


Churn by OnlineBackup
Number of customers
0
250
500
750
1000
1250
1500
1750
Yes
No
No internet service
OnlineBackup
Churn
No
Yes


Churn by DeviceProtection
Number of customers
0
250
500
750
1000
1250
1500
1750
No
Yes
No internet service
DeviceProtection
Churn
No
Yes


Churn by TechSupport
2000
Churn
No
Yes

5.8 Explore Numerical Features vs Churn

Understanding how numerical features like `tenure`, `MonthlyCharges`, and `TotalCharges` relate to customer churn helps us detect behavioral trends.

We'll use **boxplots** and **histograms** to compare distributions of these features across churned and non-churned customers.

5.8.1 Churn vs Tenure: Boxplot

The `tenure` feature shows how long a customer has stayed with the company.

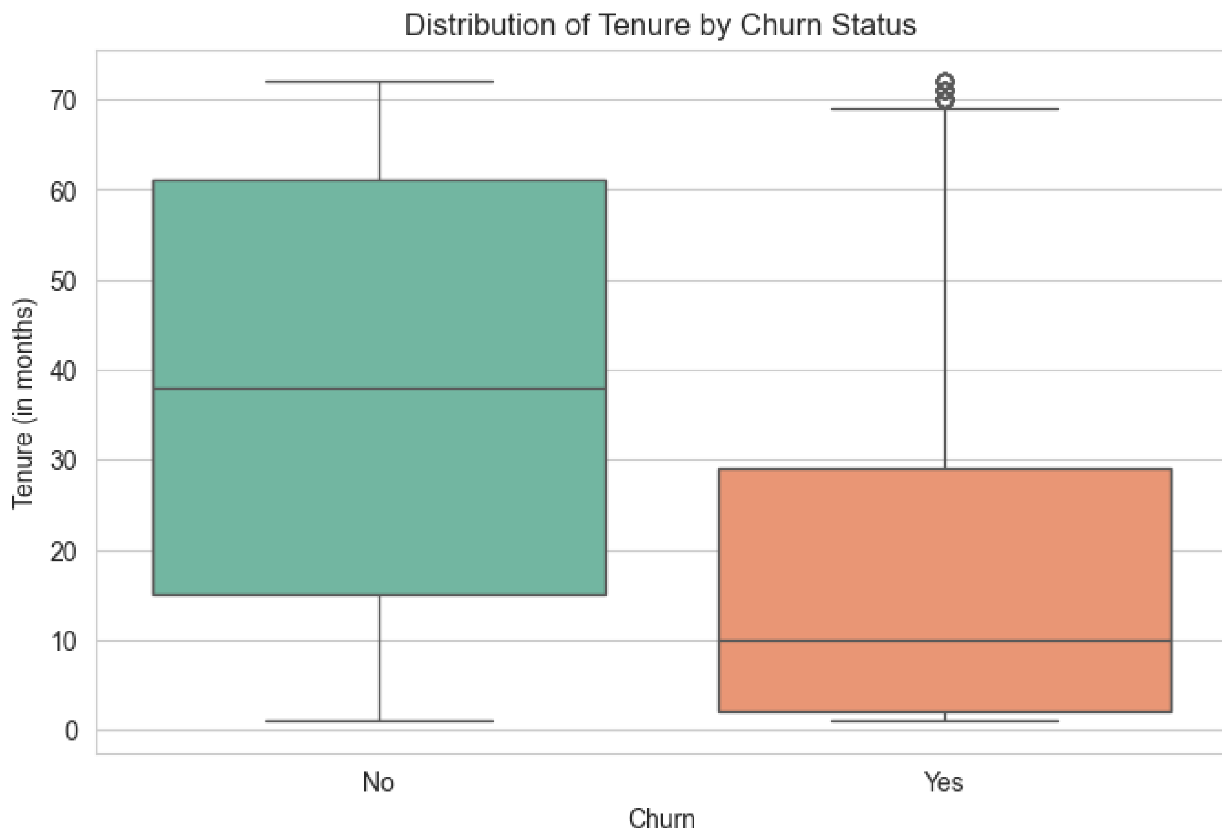
By plotting it against churn, we can see whether customers who left typically had shorter tenures compared to those who stayed.

This boxplot helps visualize:

- Median tenure
- Range and spread
- Outliers in both churn classes

We expect churned customers to have **lower median tenure**.

```
sns.set_style('whitegrid')
plt.figure(figsize = (8, 5))
sns.boxplot(data = df, x = 'Churn', y = 'tenure', hue = 'Churn',
palette = 'Set2', dodge = False)
plt.title('Distribution of Tenure by Churn Status')
plt.xlabel('Churn')
plt.ylabel('Tenure (in months)')
plt.show()
```

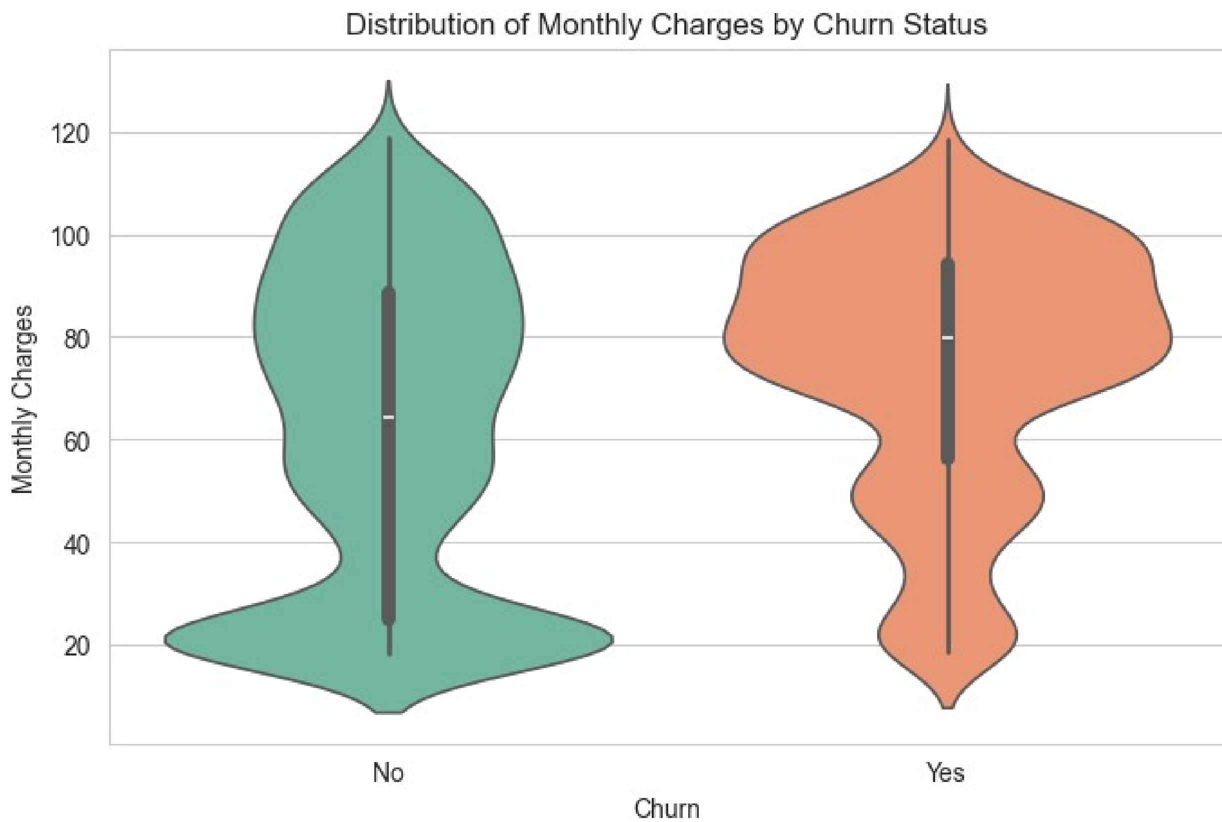


5.8.2 Explore Monthly Charges Distribution by Churn

To understand how the monthly charges differ between customers who churn and those who do not, we use a violin plot.

This visualization helps us see the distribution, density, median, and spread of monthly charges for each churn class, highlighting if customers with certain charge ranges are more likely to churn.

```
sns.set_style('whitegrid')
plt.figure(figsize = (8, 5))
sns.violinplot(data = df, x = 'Churn', y = 'MonthlyCharges', hue =
'Churn', palette = 'Set2', dodge = False)
plt.title('Distribution of Monthly Charges by Churn Status')
plt.xlabel('Churn')
plt.ylabel('Monthly Charges')
plt.show()
```

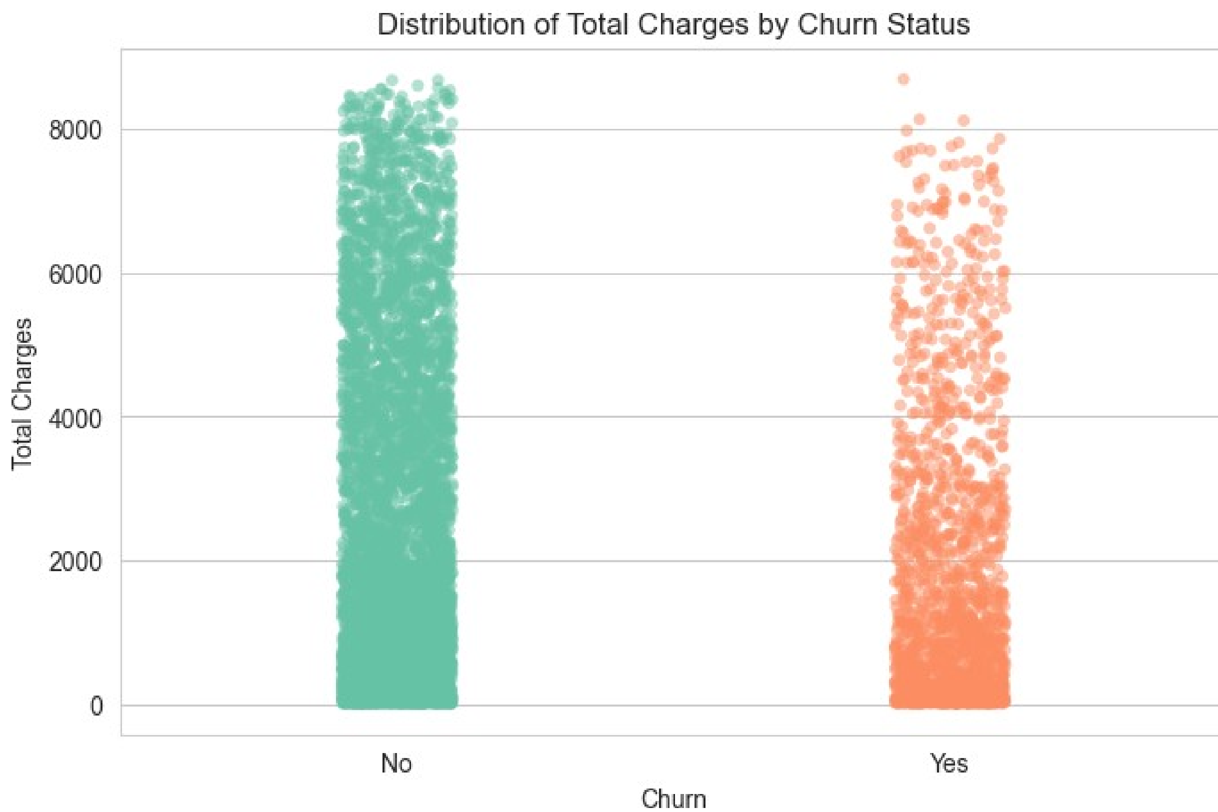


5.8.3 – Strip Plot for TotalCharges vs Churn

We use a strip plot to visualize the distribution of `TotalCharges` for churned and non-churned customers. This helps in identifying patterns, density, and any outliers that may not be clearly visible in box or violin plots. Although it's prone to overlapping points, it provides raw insight into the distribution of individual data points.

This visual will help us determine if there's any significant difference in the `TotalCharges` variable between the two churn groups.

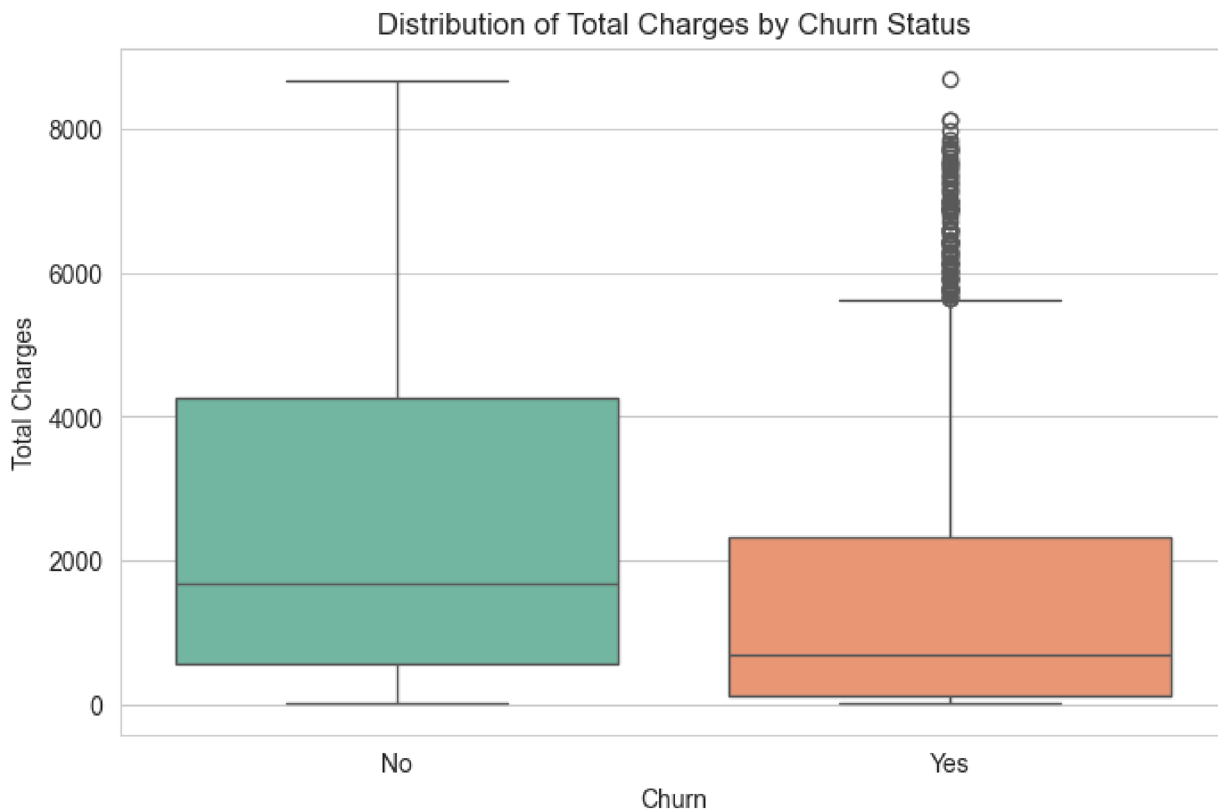
```
sns.set_style('whitegrid')
plt.figure(figsize = (8, 5))
sns.stripplot(data = df, x = 'Churn', y = 'TotalCharges', hue =
'Churn', palette = 'Set2', dodge = False, alpha = 0.5, jitter = True)
plt.title('Distribution of Total Charges by Churn Status')
plt.xlabel('Churn')
plt.ylabel('Total Charges')
plt.show()
```



5.8.4 Box Plot – Distribution of Total Charges by Churn

This box plot shows the distribution of `TotalCharges` for churned and retained customers. It helps us understand the central tendency and spread of total charges for both categories, along with any outliers. This can reveal patterns like whether high-spending customers are more or less likely to churn.

```
sns.set_style('whitegrid')
plt.figure(figsize = (8, 5))
sns.boxplot(data = df, x = 'Churn', y = 'TotalCharges', hue = 'Churn',
palette = 'Set2', dodge = False)
plt.title('Distribution of Total Charges by Churn Status')
plt.xlabel('Churn')
plt.ylabel('Total Charges')
plt.show()
```



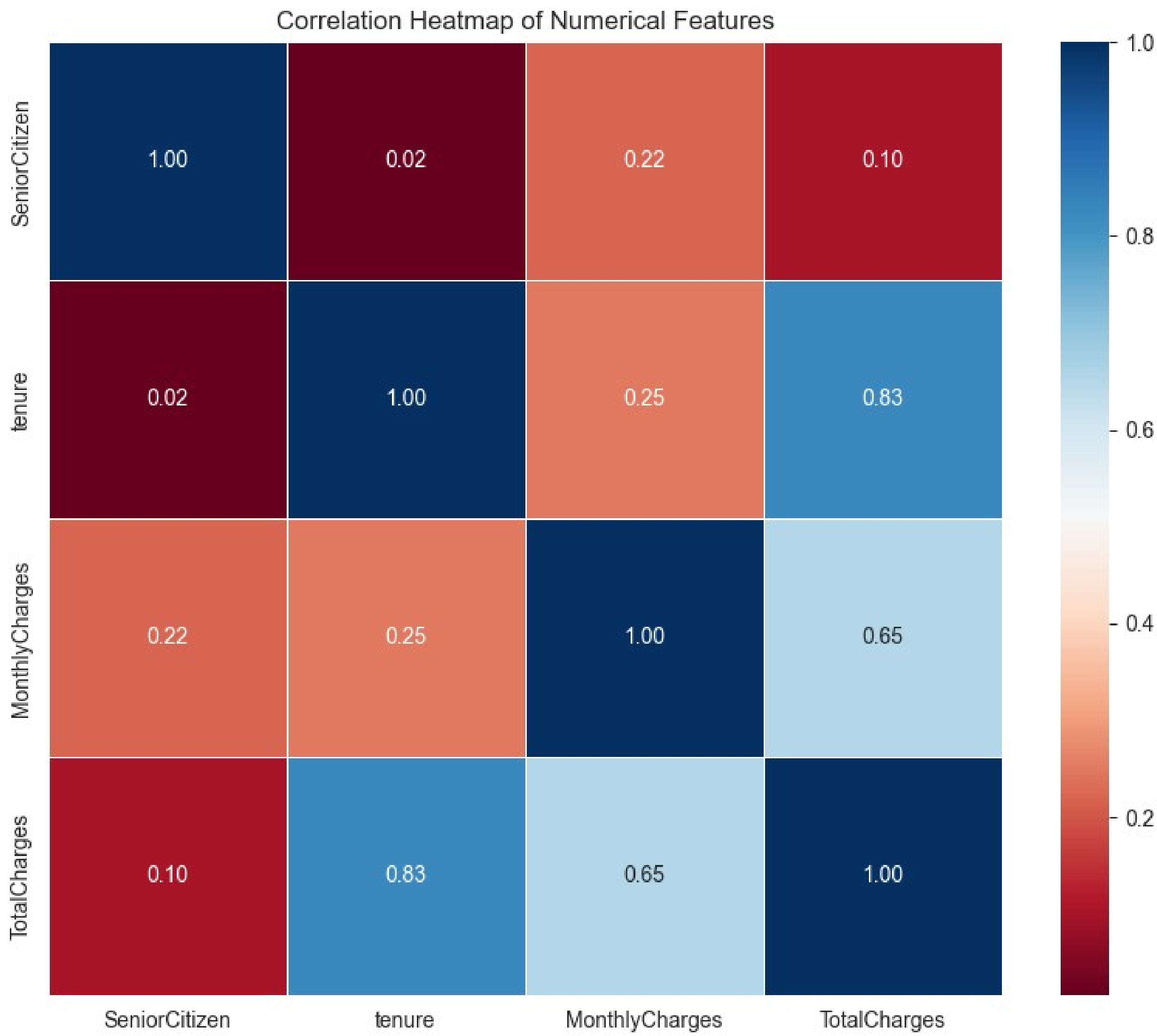
5.9 Correlation Heatmap of Numerical Features

To understand the linear relationships between numerical features, we plot a correlation heatmap. This helps identify multicollinearity and spot features that are strongly correlated with each other. This is especially useful when selecting features for model building.

```
numerical_features = df.select_dtypes(include = ['int64', 'float64'])
corr_matrix = numerical_features.corr()
print("Correlation Matrix:\n")
print(corr_matrix)
```

```
Correlation Matrix:

                SeniorCitizen    tenure  MonthlyCharges  TotalCharges
SeniorCitizen        1.000000  0.015683        0.219874      0.102411
tenure               0.015683  1.000000        0.246862      0.825880
MonthlyCharges       0.219874  0.246862        1.000000      0.651065
TotalCharges         0.102411  0.825880        0.651065      1.000000
```

```
sns.set_style('white')
plt.figure(figsize = (10, 8))
sns.heatmap(corr_matrix, annot = True, cmap = 'RdBu', fmt = '.2f',
square = True, linewidth = 0.5)
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



5.10 Distribution of Numerical Features by Churn Status

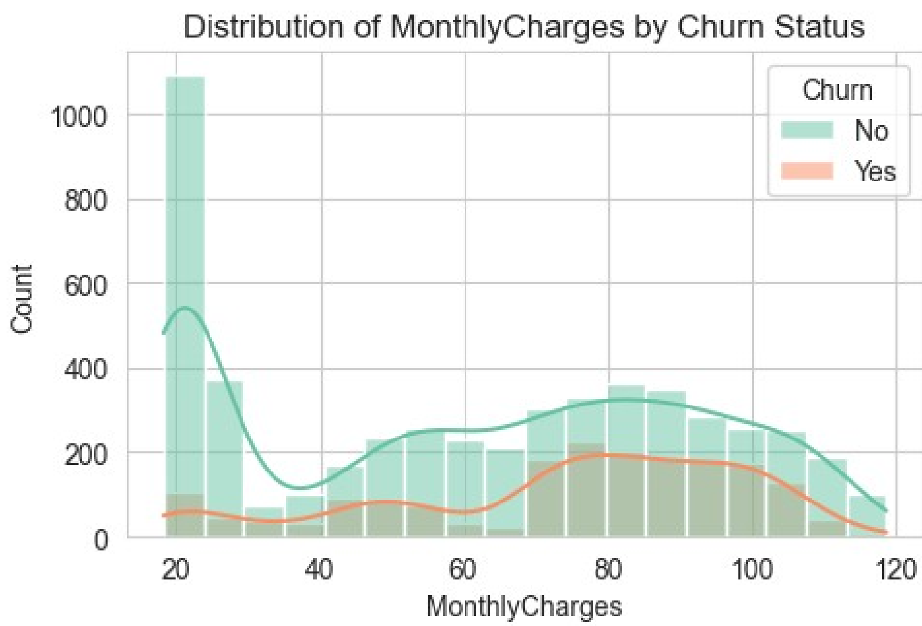
To better understand how the numerical features are distributed across churn categories, we plot histograms for each key numerical feature: **MonthlyCharges**, **TotalCharges**, and **tenure**.

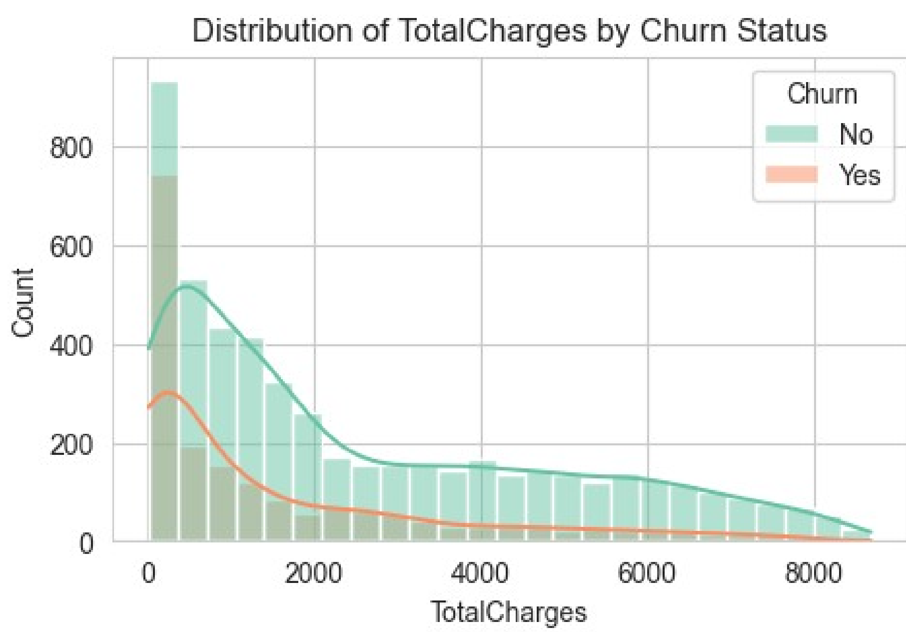
These histograms show the count of customers for each range of feature values, separated by churn status (`Yes` or `No`). Including a kernel density estimate (KDE) curve helps us see the distribution shape more smoothly.

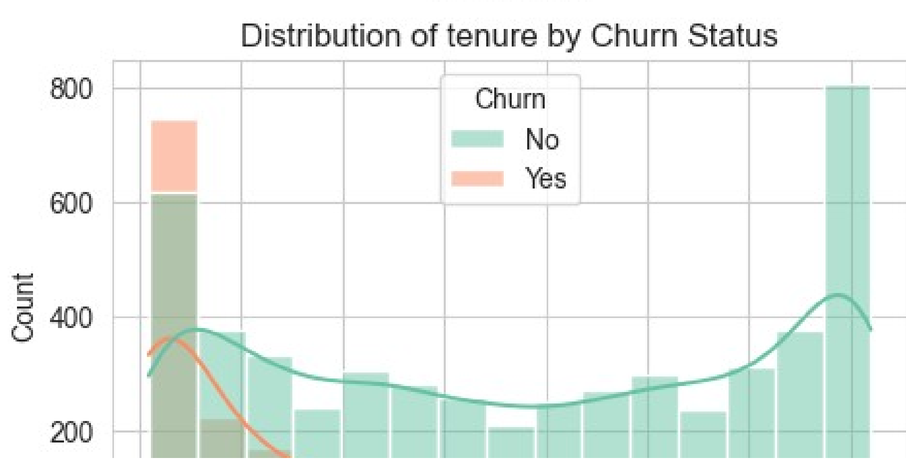
By analyzing these plots, we can observe patterns such as whether churned customers tend to have higher monthly charges or longer tenure, which can guide feature selection and model building.

```
sns.set_style('whitegrid')
num_features = ['MonthlyCharges', 'TotalCharges', 'tenure']
```

```
plt.figure(figsize=(5, 10))
for i, feature in enumerate(num_features, 1):
    plt.subplot(len(num_features), 1, i)
    sns.histplot(data=df, x=feature, hue='Churn', kde=True,
palette='Set2')
    plt.title(f'Distribution of {feature} by Churn Status')
    plt.xlabel(feature)
    plt.ylabel('Count')

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


Distribution of MonthlyCharges by Churn Status
Churn
No
Yes
Count
0
200
400
600
800
1000
20
40
60
80
100
120
MonthlyCharges


Distribution of TotalCharges by Churn Status
Churn
No
Yes
Count
0
200
400
600
800
0
2000
4000
6000
8000
TotalCharges

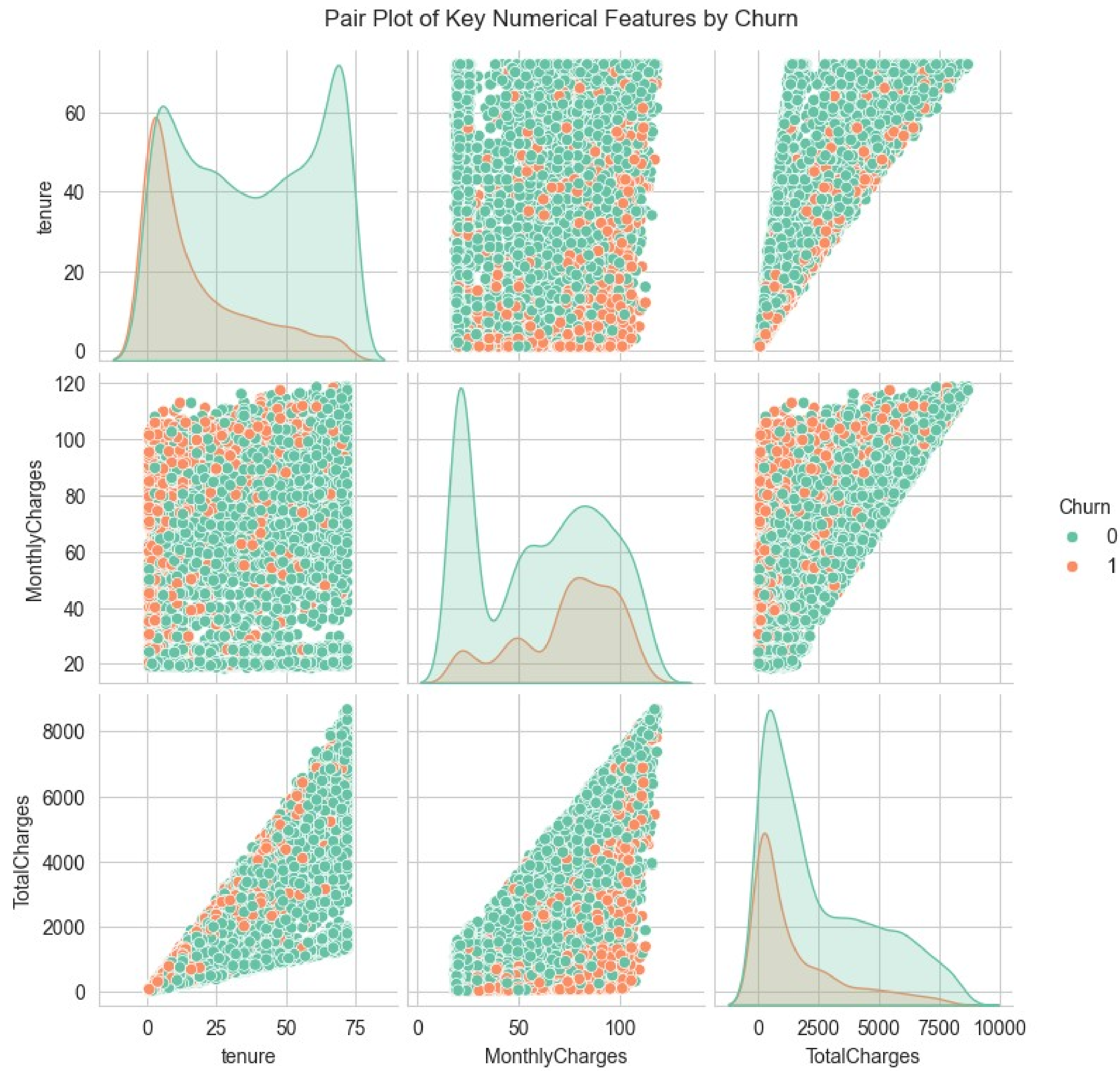

Distribution of tenure by Churn Status
Churn
No
Yes
Count
200
400
600
800

5.11 Pair Plot of Key Numerical Features

To visualize relationships between numerical features and how they vary with churn, we use a pair plot. This allows us to explore feature interactions and spot patterns or clusters that may differentiate churned and non-churned customers.

- The diagonal shows distributions of each individual feature by churn status.
- Off-diagonal scatter plots show how feature pairs relate, colored by churn.
- This helps in identifying potential trends, separation between churn classes, and correlation among features.

```
num_features = ['tenure', 'MonthlyCharges', 'TotalCharges', 'Churn']

# Convert 'Churn' to numeric for coloring in the pair plot
df_pairplot = df.copy()
df_pairplot['Churn'] = df_pairplot['Churn'].map({'Yes': 1, 'No': 0})

sns.pairplot(df_pairplot[num_features], hue='Churn', palette='Set2')
plt.suptitle("Pair Plot of Key Numerical Features by Churn", y=1.02)
plt.show()
```



Step 6: Data Preprocessing and Feature Engineering

6.1 Dropping Irrelevant Identifier Column

The `customerID` column uniquely identifies each customer but holds no predictive value for churn. Including such identifiers in the model can introduce noise or lead to overfitting. Therefore, we drop it from the dataset.

```
df.drop('customerID', axis = 1, inplace = True)
```

6.2 Identifying Categorical and Numerical Features

To begin preprocessing, we classify our dataset columns into:

- **Categorical Features:** These represent categories or groups, usually of type `object` (e.g., gender, Contract).
- **Numerical Features:** These are numeric values, usually of type `int64` or `float64` (e.g., tenure, MonthlyCharges).

This distinction helps us decide the right transformations for each group.

```
# Separate categorical and numerical columns
categorical_features =
df.select_dtypes(include=['object']).columns.tolist()
numerical_features = df.select_dtypes(include=['int64',
'float64']).columns.tolist()

print("Categorical Features:\n", categorical_features)
print("\nNumerical Features:\n", numerical_features)

Categorical Features:
 ['gender', 'Partner', 'Dependents', 'PhoneService', 'MultipleLines',
'InternetService', 'OnlineSecurity', 'OnlineBackup',
'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
'Contract', 'PaperlessBilling', 'PaymentMethod', 'Churn']

Numerical Features:
 ['SeniorCitizen', 'tenure', 'MonthlyCharges', 'TotalCharges']
```

6.3 Encode Categorical Variables

We apply:

- Label Encoding to binary categorical variables (e.g., Yes/No, Male/Female),
- One-Hot Encoding to multi-class categorical variables (e.g., InternetService, Contract).

Label Encoding is efficient for binary variables and avoids unnecessary dimensionality.
One-Hot Encoding avoids misleading ordering for multi-class variables.

```
# Label encode binary categorical features (excluding the target
feature)
binary_cols = ['gender', 'Partner', 'Dependents', 'PhoneService',
'PaperlessBilling']
le = LabelEncoder()
for col in binary_cols:
    df[col] = le.fit_transform(df[col])

# One-hot encode multi-class categorical features
multi_class_cols = ['MultipleLines', 'InternetService',
'OnlineSecurity', 'OnlineBackup',
                    'DeviceProtection', 'TechSupport', 'StreamingTV',
'StreamingMovies',
                    'Contract', 'PaymentMethod']
df = pd.get_dummies(df, columns = multi_class_cols, drop_first = True)
```

6.4 Encode Target Variable (Churn)

We encode the target variable `Churn` using Label Encoding:

- `Yes` → `1`
- `No` → `0`

This prepares the target for use in binary classification models.

```
df['Churn'] = le.fit_transform(df['Churn'])
```

6.5 Feature Scaling of numerical columns

Some machine learning models (like logistic regression, SVM, and KNN) are sensitive to the scale of features.

Here:

- We scale only the numerical features using **StandardScaler** (mean = 0, std = 1)
- Dummy variables from one-hot encoding and binary label-encoded columns are left unchanged
- The target variable `Churn` is **not scaled**

This ensures a uniform scale among features, improving model performance and convergence.

```
numerical_features = ['SeniorCitizen', 'tenure', 'MonthlyCharges',
'TotalCharges']
scaler = StandardScaler()
df[numerical_features] = scaler.fit_transform(df[numerical_features])
df[numerical_features].describe()
```

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7.032000e+03	7.032000e+03	7.032000e+03	7.032000e+03
mean	2.627149e-17	-1.126643e-16	6.062651e-17	-1.119064e-16
std	1.000071e+00	1.000071e+00	1.000071e+00	1.000071e+00
min	-4.403271e-01	-1.280248e+00	-1.547283e+00	-9.990692e-01
25%	-4.403271e-01	-9.542963e-01	-9.709769e-01	-8.302488e-01
50%	-4.403271e-01	-1.394171e-01	1.845440e-01	-3.908151e-01
75%	-4.403271e-01	9.199259e-01	8.331482e-01	6.668271e-01
max	2.271039e+00	1.612573e+00	1.793381e+00	2.824261e+00

Step 7: Splitting Data for Model Training and Evaluation

7.1 Separate Features and Target Variable

Before training a model, we must separate the dataset into:

- **Features (X):** All input columns used to predict churn.
- **Target (y):** The `Churn` column, which we are trying to predict.

Separate features and target

X = df.drop('Churn', axis = 1) y = df['Churn']

7.2 Split the Data into Training and Testing Sets

To evaluate model performance on unseen data:

- We split the data into **Training Set (80%)** and **Testing Set (20%)**.
- We use `train_test_split` from scikit-learn with:
  - `random_state=42` to ensure reproducibility.
  - `stratify=y` to maintain the same churn ratio in both sets

```
# Step: Splitting features and target
X = df.drop('Churn', axis=1)   # Assuming 'Churn' is your target
column
y = df['Churn']

# Step: Train-Test Split (80% train, 20% test)
# from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Print the shapes
print("Training features shape:", X_train.shape)
print("Testing features shape:", X_test.shape)
print("Training labels shape:", y_train.shape)
print("Testing labels shape:", y_test.shape)
```

```
Training features shape: (5625, 30)
Testing features shape: (1407, 30)
Training labels shape: (5625,)
Testing labels shape: (1407,)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7032 entries, 0 to 7042
Data columns (total 31 columns):
 #   Column                                             Non-Null Count  Dtype
---  ------                                             --------------  -----
 0   gender                                             7032 non-null   int32
 1   SeniorCitizen                                      7032 non-null   float64
 2   Partner                                            7032 non-null   int32
 3   Dependents                                         7032 non-null   int32
 4   tenure                                             7032 non-null   float64
 5   PhoneService                                       7032 non-null   int32
 6   PaperlessBilling                                   7032 non-null   int32
 7   MonthlyCharges                                     7032 non-null   float64
```

```
 8   TotalCharges                            7032 non-null   float64
 9   Churn                                   7032 non-null   int32
 10  MultipleLines_No phone service          7032 non-null   bool
 11  MultipleLines_Yes                       7032 non-null   bool
 12  InternetService_Fiber optic             7032 non-null   bool
 13  InternetService_No                      7032 non-null   bool
 14  OnlineSecurity_No internet service      7032 non-null   bool
 15  OnlineSecurity_Yes                      7032 non-null   bool
 16  OnlineBackup_No internet service        7032 non-null   bool
 17  OnlineBackup_Yes                        7032 non-null   bool
 18  DeviceProtection_No internet service    7032 non-null   bool
 19  DeviceProtection_Yes                    7032 non-null   bool
 20  TechSupport_No internet service         7032 non-null   bool
 21  TechSupport_Yes                         7032 non-null   bool
 22  StreamingTV_No internet service         7032 non-null   bool
 23  StreamingTV_Yes                         7032 non-null   bool
 24  StreamingMovies_No internet service     7032 non-null   bool
 25  StreamingMovies_Yes                     7032 non-null   bool
 26  Contract_One year                       7032 non-null   bool
 27  Contract_Two year                       7032 non-null   bool
 28  PaymentMethod_Credit card (automatic)   7032 non-null   bool
 29  PaymentMethod_Electronic check          7032 non-null   bool
 30  PaymentMethod_Mailed check              7032 non-null   bool
dtypes: bool(21), float64(4), int32(6)
memory usage: 841.8 KB
```

Step 8: Handling Class Imbalance

8.1 Apply `SMOTE (Synthetic Minority Over-sampling TEchnique)` on training data

In this substep, we address the class imbalance in the target variable `Churn`. Our dataset contains significantly more "No" labels than "Yes" labels, which can bias the model toward predicting "No" too often.

To correct this imbalance, we use **SMOTE**, a powerful method that generates synthetic samples for the minority class rather than simply duplicating existing rows.

SMOTE generates new, plausible examples by interpolating between existing minority class samples. This helps the model learn better patterns from the minority class, improving its predictive performance on both classes.

Applying SMOTE to the test set would distort the real-world class distribution. Since our test set is meant to simulate actual unseen data, we leave it untouched and apply SMOTE only to the training data (`X_train`, `y_train`).

We'll use `SMOTE()` from the `imblearn.over_sampling` module.

```
smote = SMOTE(random_state = 42)

# Apply SMOTE only on training data
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

print("Resampled training features shape:", X_train_resampled.shape)
print("Resampled training labels shape:", y_train_resampled.shape)

Resampled training features shape: (8260, 30)
Resampled training labels shape: (8260,)
```

8.2 Confirm balance after SMOTE

Now that we've applied SMOTE, we need to verify whether the class distribution is balanced. This step is essential to ensure that synthetic oversampling has correctly equalized the number of samples in both classes.

```
# Check class distribution after SMOTE
unique, counts = np.unique(y_train_resampled, return_counts=True)
print("Class distribution after SMOTE:")
for label, count in zip(unique, counts):
    print(f"Class {label}: {count}")

Class distribution after SMOTE:
Class 0: 4130
Class 1: 4130

pd.Series(y_train_resampled).value_counts()

Churn
0    4130
1    4130
Name: count, dtype: int64
```

Step 9: Feature Scaling on Resampled Data

Now that class imbalance has been addressed using SMOTE, we perform feature scaling on the resampled training data.

- We use **StandardScaler** to scale all features to have a mean of 0 and standard deviation of 1.
- The scaler is **fitted only on the resampled training features**.
- The same scaler is then used to **transform the test features**.
- This ensures consistency and prevents data leakage.

Feature scaling is especially important for models like Logistic Regression, SVM, and KNN which are sensitive to the scale of input features.

```
X_train_scaled = scaler.fit_transform(X_train_resampled)

X_test_scaled = scaler.transform(X_test)

print("Scaled training features shape:", X_train_scaled.shape)
print("Scaled test features shape:", X_test_scaled.shape)
```

```
Scaled training features shape: (8260, 30)
Scaled test features shape: (1407, 30)
```

```
# Initialize the model
logreg_model = LogisticRegression(max_iter=1000, random_state=42)

# Train the model on resampled training data
logreg_model.fit(X_train_scaled, y_train_resampled)

# Predict on test set
y_pred = logreg_model.predict(X_test_scaled)

# Evaluation metrics
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.7299218194740583

Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.74      0.80      1033
           1       0.49      0.70      0.58       374

    accuracy                           0.73      1407
   macro avg       0.68      0.72      0.69      1407
weighted avg       0.77      0.73      0.74      1407


Confusion Matrix:
 [[766 267]
 [113 261]]
```

Step 10: Train & Compare Multiple Models

We will now train several classifiers on our SMOTE-balanced, scaled data:

- Decision Tree
- Random Forest

- Support Vector Machine (SVM)
- K-Nearest Neighbors (KNN)

For each model, we will report:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    confusion_matrix,
    classification_report
)



models = {
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(random_state=42),
    'SVM': SVC(random_state=42),
    'KNN': KNeighborsClassifier()
}

predictions = {}
for name, model in models.items():
    model.fit(X_train_scaled, y_train_resampled)
    preds = model.predict(X_test_scaled)
    predictions[name] = preds
```

Step 11: Evaluate & Compare Models

Now we print the evaluation metrics for each model on the test set.

```python
for name, preds in predictions.items():
    print(f"=== {name} ===")
    print(f"Accuracy       : {accuracy_score(y_test,    preds):.4f}")
    print(f"Precision      : {precision_score(y_test,   preds):.4f}")
    print(f"Recall         : {recall_score(y_test,      preds):.4f}")
    print(f"F1-Score       : {f1_score(y_test,          preds):.4f}")
    print("Confusion Matrix:")
    print(confusion_matrix(y_test, preds))
    print("Classification Report:")
    print(classification_report(y_test, preds))
    print("\n" + "-"*60 + "\n")
```

```
=== Decision Tree ===
Accuracy       : 0.7292
Precision      : 0.4924
Recall         : 0.6043
F1-Score       : 0.5426
Confusion Matrix:
[[800 233]
 [148 226]]
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.77      0.81      1033
           1       0.49      0.60      0.54       374

    accuracy                           0.73      1407
   macro avg       0.67      0.69      0.68      1407
weighted avg       0.75      0.73      0.74      1407


------------------------------------------------------------

=== Random Forest ===
Accuracy       : 0.7704
Precision      : 0.5576
Recall         : 0.6604
F1-Score       : 0.6047
Confusion Matrix:
[[837 196]
 [127 247]]
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.81      0.84      1033
           1       0.56      0.66      0.60       374

    accuracy                           0.77      1407
   macro avg       0.71      0.74      0.72      1407
weighted avg       0.79      0.77      0.78      1407
```

```
------------------------------------------------------------

=== SVM ===
Accuracy       : 0.7370
Precision      : 0.5037
Recall         : 0.7299
F1-Score       : 0.5961
Confusion Matrix:
[[764 269]
 [101 273]]
Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.74      0.81      1033
           1       0.50      0.73      0.60       374

    accuracy                           0.74      1407
   macro avg       0.69      0.73      0.70      1407
weighted avg       0.78      0.74      0.75      1407


------------------------------------------------------------

=== KNN ===
Accuracy       : 0.6994
Precision      : 0.4575
Recall         : 0.7059
F1-Score       : 0.5552
Confusion Matrix:
[[720 313]
 [110 264]]
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.70      0.77      1033
           1       0.46      0.71      0.56       374

    accuracy                           0.70      1407
   macro avg       0.66      0.70      0.66      1407
weighted avg       0.76      0.70      0.72      1407


------------------------------------------------------------
```