Telco Customer Churn Analysis

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Course: Software Development for Data Science
Assignment: Coursework 2
Program: MSc Financial Technology

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1. Business Understanding

Customer churn is the rate at which customers stop doing business with a specific organization (Frankenfield, 2022). This is is especially important for company's as it essentially measures a company's ability to retain customers. Its helpful to not only look at the churn rate as what will be identified in this analysis but also compare it to the company's growth rate (which will not be covered in this project). This is because if the churn rate is higher than the growth rate then the company is losing customers faster than it is gaining them.

In the competitive space of telecommunications (telco) companies, customer churn is a key metric that companies use to evaluate their performance as it impacts their profitability and brand recognition (Wagh, et al., 2024). According to Wagh, et al., (2024), he states that in some cases, the cost of acquiring a new customer is 5x more expensive than retaining an existing customer. This is why it is important for companies to identify the key factors that lead to customers churning. Several factors can lead to a business churning customers such as high prices, poor customer service, poor product quality and much more.

Despite this project not being able to identify the exact reason why customers churn such as an increase in prices or a competitor offering new services, it will try identify the key factors that lead to customers churning. This will be done by building a model that will predict whether a customer will churn or not.

1.1. Objectives

The main objective of this coursework project is to build a model that can identify customers who are at risk of churning. This will be done by answering the following questions:

- What is the churn rate of the company?
- What is the average tenure of customers?
- What is the average monthly charges of customers?
- What are the key factors that dictate whether a customer will churn or not?
- How do churn rates vary across different customer demographics?

1.2. Success Criteria

1. Successfully predict whether a customer will churn or not with an accuracy of 90% or higher on unseen data.
2. Identify the key factors that dictate whether a customer will churn or not.
3. Aim for a precision score of 0.85 or higher to reduce the number of false positives.
4. Aim for a recall score of 0.85 or higher to reduce the number of false negatives.

Methodology To achieve these goals, the coursework will involve the following steps which is in line with the CRISP-DM methodology (Smart Vision, 2020):

> - Business Understanding
> - Data Understanding
> - Data Preparation
> - Modelling
> - Evaluation

For this coursework we will not deploy the model, but we will evaluate the model and make recommendations based on the results.

2. Data Understanding

The dataset we've been provided with is a Telco customer churn data from California, USA. The data is available at [Telco Customer Churn - Kaggle]() and has 7,043 customers with multiple features from `OnlineSecurity`, `Contract` type, `Charges`, `Dependents` amongst many more. The target variable is the `Churn` column which is a binary variable with Yes or No values.

This section will include:

> - Data Collection
> - Data Description
> - Data Exploration
> - Data Quality

Load Libraries

```
# Data Analysis
import pandas as pd
import numpy as np

# Data Visualization
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno

# Data Preprocessing
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Data Modelling
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier

# Data Evaluation
from sklearn.metrics import RocCurveDisplay, confusion_matrix, classification_rep

# Data Sampling
from imblearn.over_sampling import SMOTE

# Styling & Settings
sns.set_style("whitegrid")
# pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
%matplotlib inline
```

Load Data

```
df = pd.read_csv("Telco-Customer-Churn.csv")
print(df.shape)
df.head()
```

Show hidden output

We can see a high-level overview of our data and what each of the columns may contain. We can also see that there are 7,043 rows and 21 columns.

Summary of the data

```
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
```

We can see that all columns have the same number of non-null values which is 7,043. This means that there are no missing values in the dataset.

We can also see `TotalCharges` is an object type and not a numerical type. We will need to convert this to a numerical type in the next section.

```
# Summary statistics (numerical)
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

Based of the above summary statistics we can see the we do not have any inacurrate outliers in our dataset as the minimum and maximum values are within the expected range

```
# Summary statistics (categorical)
df.describe(include=['O'])
```

	customerID	gender	Partner	Dependents	PhoneService	MultipleLines	I
count	7043	7043	7043	7043	7043	7043	
unique	7043	2	2	2	2	3	
top	7590-VHVEG	Male	No	No	Yes	No	
freq	1	3555	3641	4933	6361	3390	

Data Description

Below is a description of each column in the dataset. This will help us understand what each column represents and what type of data it contains.

Column Name	Description
Senior Citizen	Whether the customer is a senior citizen or not
Tenure	Number of months the customer has stayed with the company
Monthly Charges	The amount charged to the customer monthly
CustomerID	Customer ID
Gender	Is the customer male or female
Partner	Whether the customer has a partner or not
Dependents	Whether the customer has dependents or not
Phone Service	Whether the customer has a phone service or not
Multiple Lines	Whether the customer has multiple lines or not
Internet Service	Customer's internet service provider (DSL, Fiber optic, No)
Online Security	Whether the customer has online security or not
Online Backup	Whether the customer has online backup or not
Device Protection	Whether the customer has device protection or not
Tech Support	Whether the customer has tech support or not
Streaming TV	Whether the customer has streaming TV or not
Streaming Movies	Whether the customer has streaming movies or not
Contract	The contract term of the customer (Month-to-month, One year, Two year)
Paperless Billing	Whether the customer has paperless billing or not
Payment Method	The customer's payment method (Electronic check, Mailed check, Bank transfer (automatic), Credit card (au
Total Charges	The total amount charged to the customer
Churn	Whether the customer churned or not (Yes or No)

We can see that we have 2 columns that have incorrect data types:

- `SeniorCitizen` should be a categorical variable
- `TotalCharges` should be a numerical variable

Data Exploration

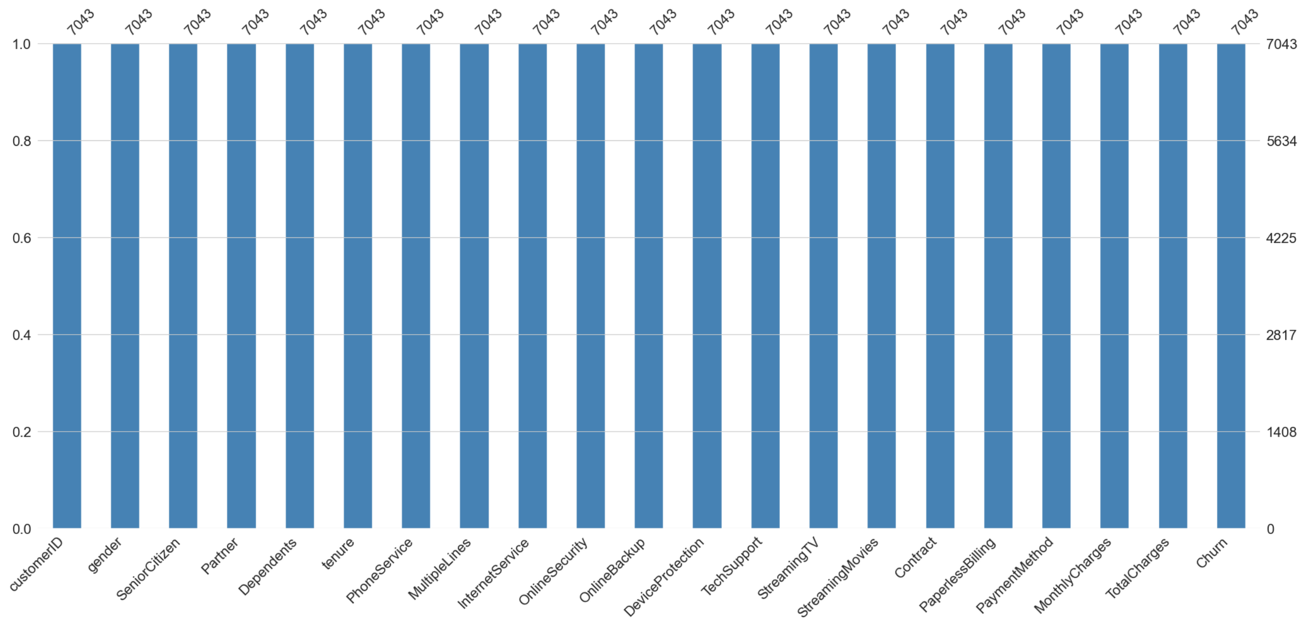
In this section we will explore the data to get a better understanding of the data and identify any issues with the data. We will also look at the distribution of the data and identify any outliers.

Missing Values

```
df.isna().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
```

```
msno.bar(df, color="steelblue");
```



From the above chart we can see that there are no missing values in the dataset. However, we can see that there are 11 missing values in the `TotalCharges` column. This is most likely because the column is an object type and not a numerical type. We will convert this column to a numerical type in the next section.

Duplicates

```
df.duplicated().any().sum()
```

```
0
```

```
df['customerID'].duplicated().sum()
```

```
0
```

Based of the 2 code cells above we can see that no row in our data has duplicated values. In addition we did a further check to make sure there are no duplicated customerIDs which is the unique identifier for each customer. This is good as we don't have to worry about removing any duplicated rows.

Data Type Consistency

```
df.dtypes
```

```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

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

```
dtype('float64')
```

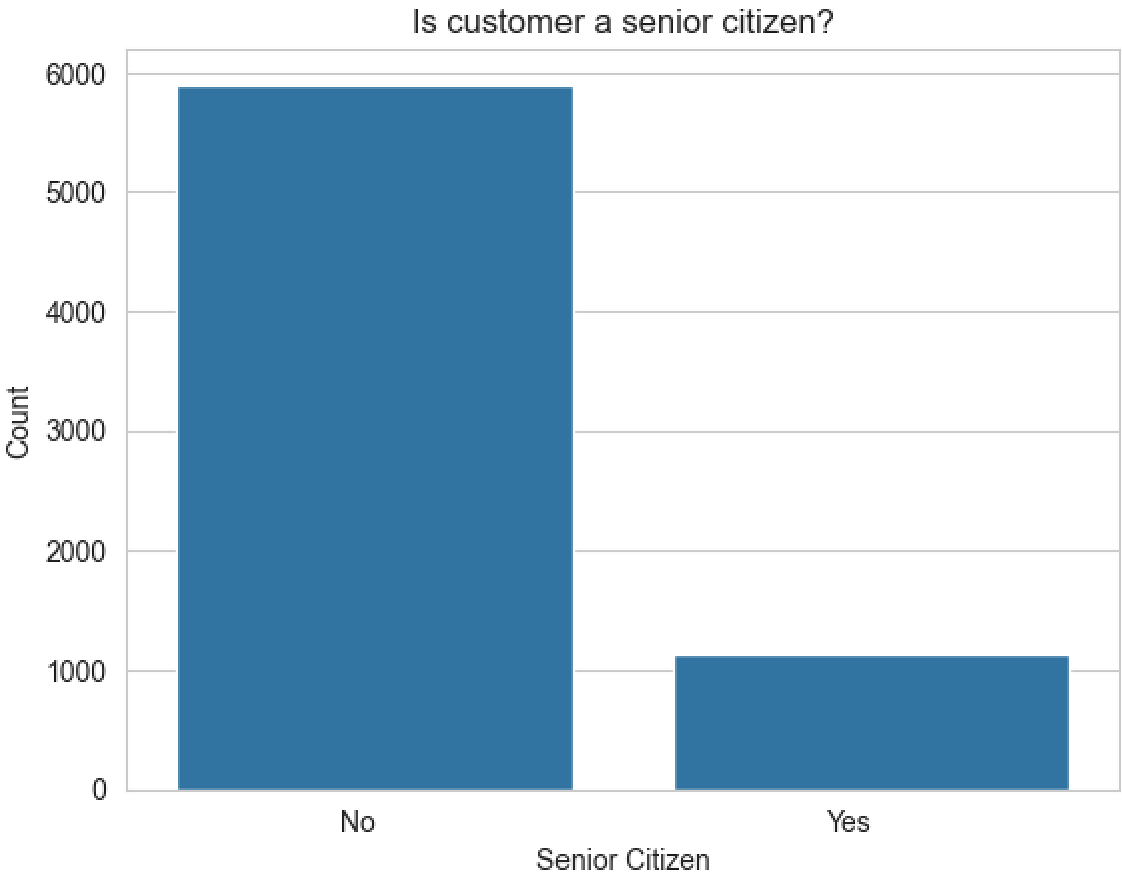
Univariate Analysis

```
def plot_categorical(df:pd.DataFrame, col:str, title:str, xlabel:str, ylabel:str,
    """
    Function to plot categorical data

    :param df: Name of the dataframe
    :param col: Column of intereset
    :param title:  Title of the plot
    :param xlabel: X label of the plot
    :param ylabel: Y label of the plot
    """

    # Map binary variables to Yes or No
    mapping = {0: 'No', 1: 'Yes'}
    if df[col].dtype == 'int64':
        df[col] = df[col].map(mapping)

    # Print summary stats
    print("Data Statistics:")
    print(df[col].value_counts())

    # sns.countplot(x=df[col], data=df)
    sns.barplot(x=df[col].value_counts().index, y=df[col].value_counts())
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.xticks(rotation=txt_rotation, ha="right")
    plt.show();
```

Senior Citizen

```
plot_categorical(df=df, col="SeniorCitizen", title="Is customer a senior citizen?
                 xlabel="Senior Citizen", ylabel="Count")
```

```
Data Statistics:
SeniorCitizen
No     5901
Yes    1142
Name: count, dtype: int64
```

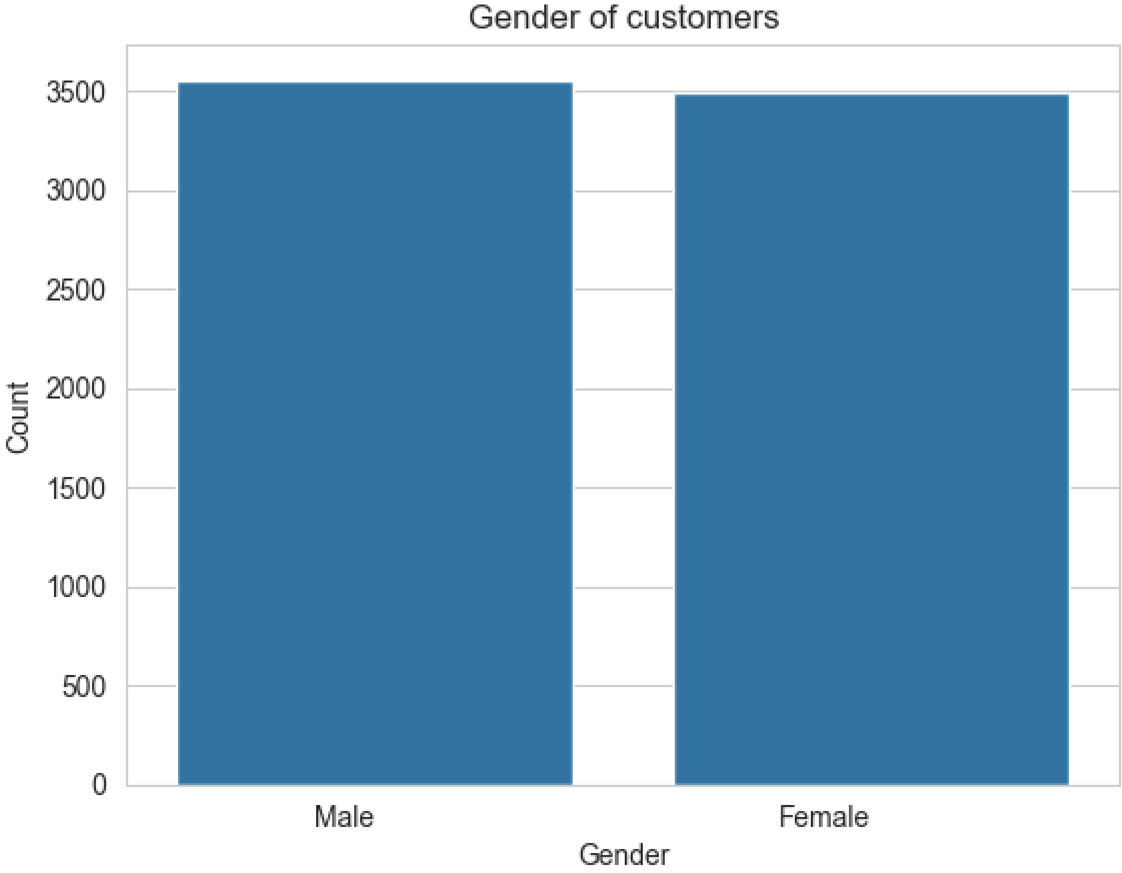


Within our dataset, we have slightly over 1,000 senior citizens and just about 6,000 non-senior citizens. This shows that the majority of the telco's customers are not senior citizens which is good for their business as they can effectively capture the younger market.

Gender

```
plot_categorical(df=df, col="gender", title="Gender of customers", xlabel="Gender
```

```
Data Statistics:
gender
Male      3555
Female    3488
Name: count, dtype: int64
```

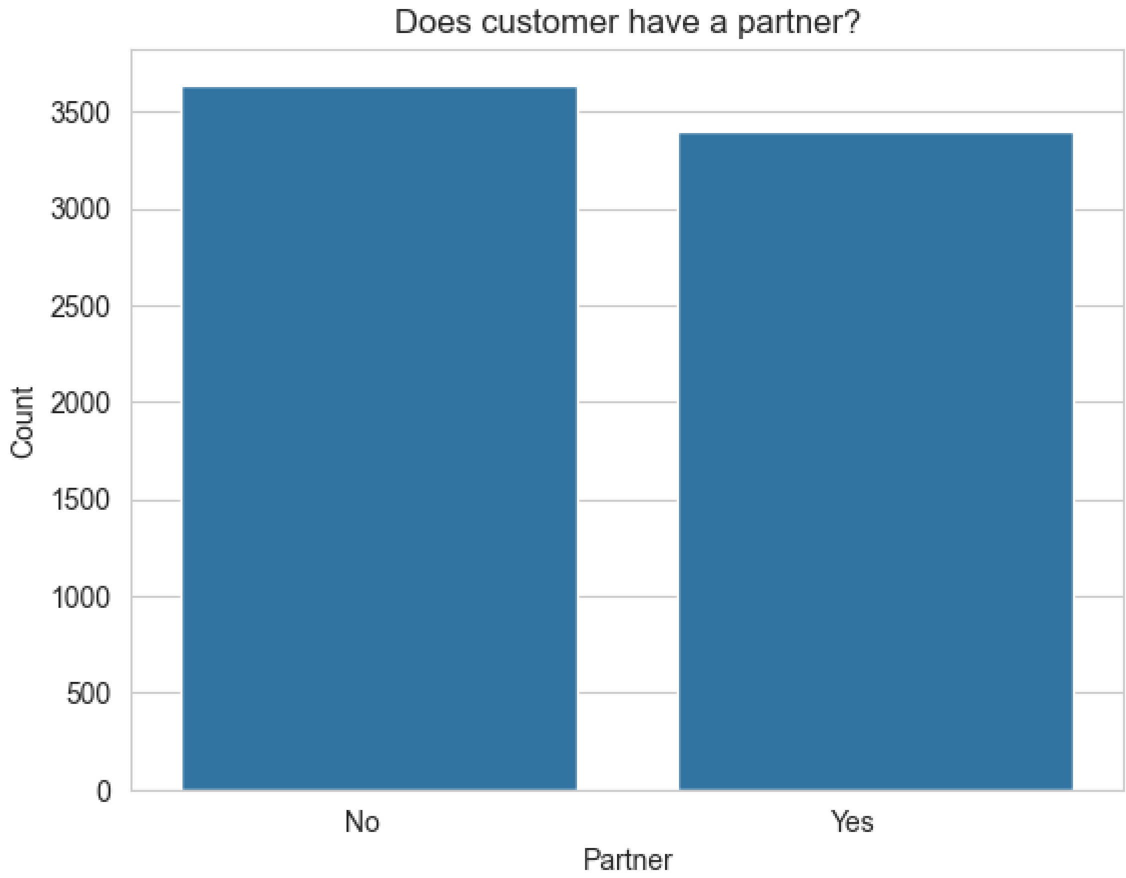


The dataset is very close to being evenly split between male and female customers at 3,500.

Partner

```
plot_categorical(df=df, col="Partner", title="Does customer have a partner?", xla
```

```
Data Statistics:
Partner
No     3641
Yes    3402
Name: count, dtype: int64
```

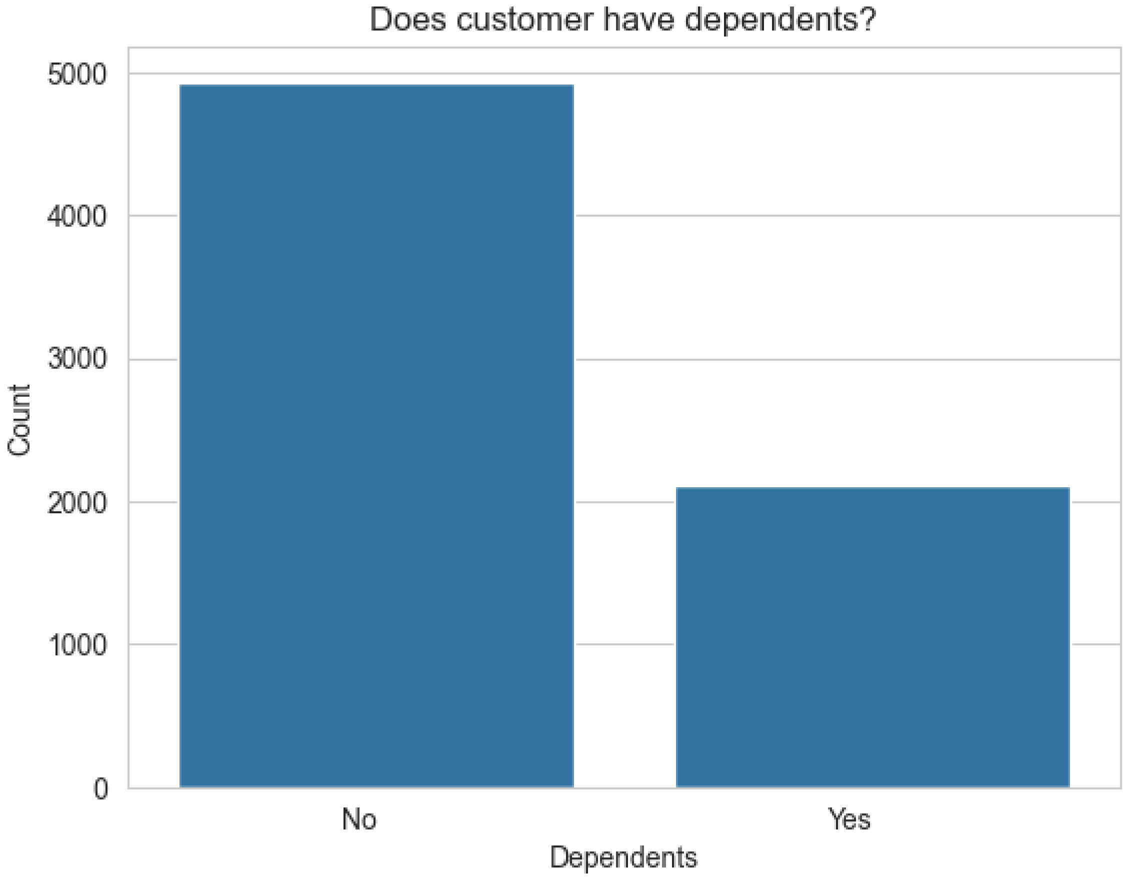


The dataset is also very close to being evenly split between customers who have a partner and those who don't.

Dependents

```
plot_categorical(df=df, col="Dependents", title="Does customer have dependents?",
                 xlabel="Dependents", ylabel="Count")
```

```
Data Statistics:
Dependents
No     4933
Yes    2110
Name: count, dtype: int64
```

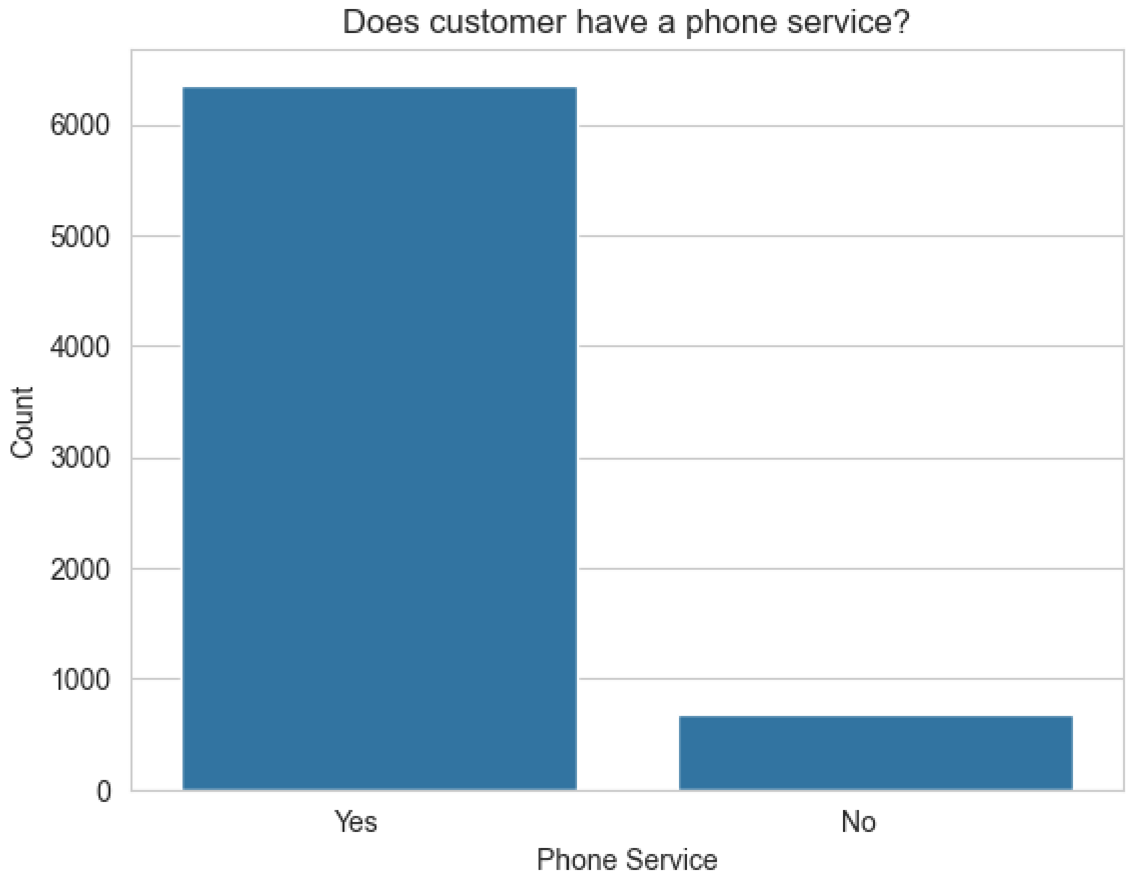


Most of the customers do not have dependents which could be closely linked to the low number of senior citizens in the dataset.

Phone Service

```
plot_categorical(df=df, col="PhoneService", title="Does customer have a phone ser
                 xlabel="Phone Service", ylabel="Count")
```

```
Data Statistics:
PhoneService
Yes    6361
No      682
Name: count, dtype: int64
```

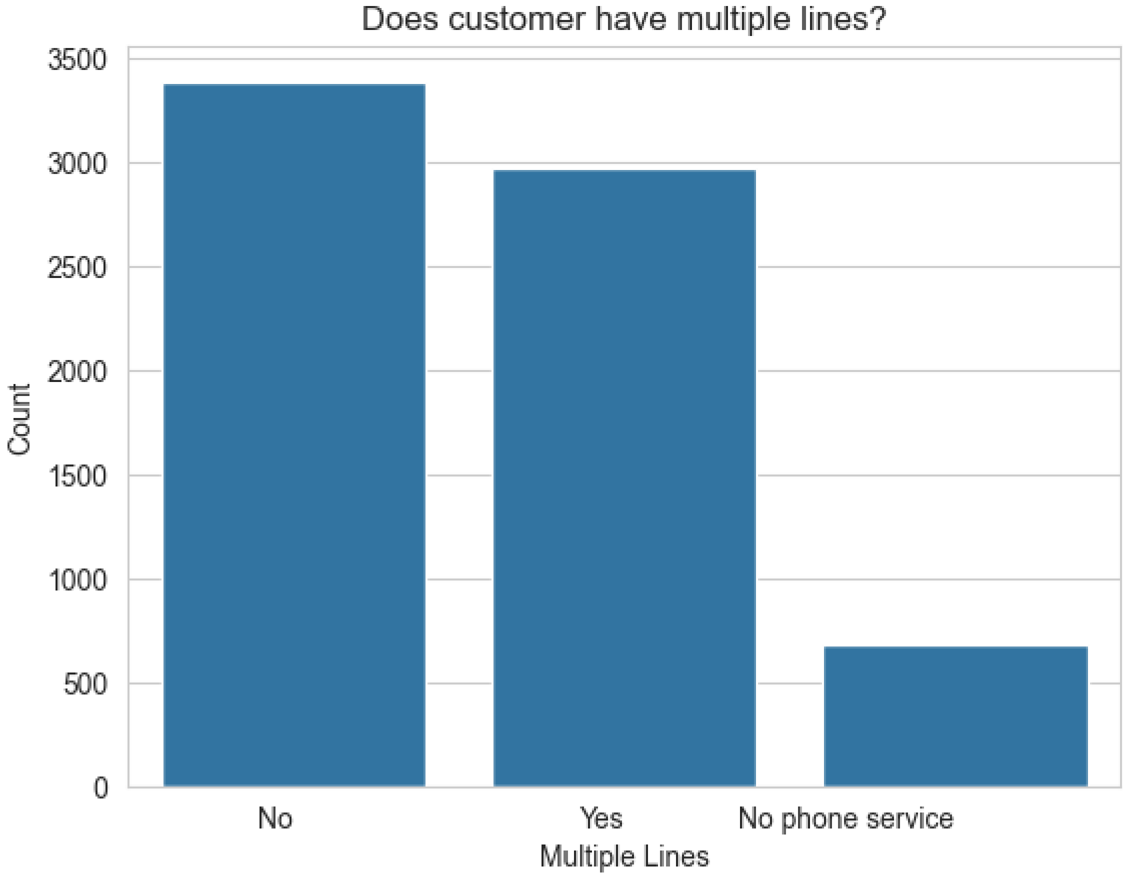


The majority of the customers have a phone service which is good for the telco as they can offer them other services such as Internet service, device protection or other services. The disparity between the customers who have a phone service and those who don't is quite large which was to be expected.

Multiple Lines

```
plot_categorical(df=df, col="MultipleLines", title="Does customer have multiple l
                 xlabel="Multiple Lines", ylabel="Count")
```

```
Data Statistics:
MultipleLines
No                  3390
Yes                 2971
No phone service     682
Name: count, dtype: int64
```

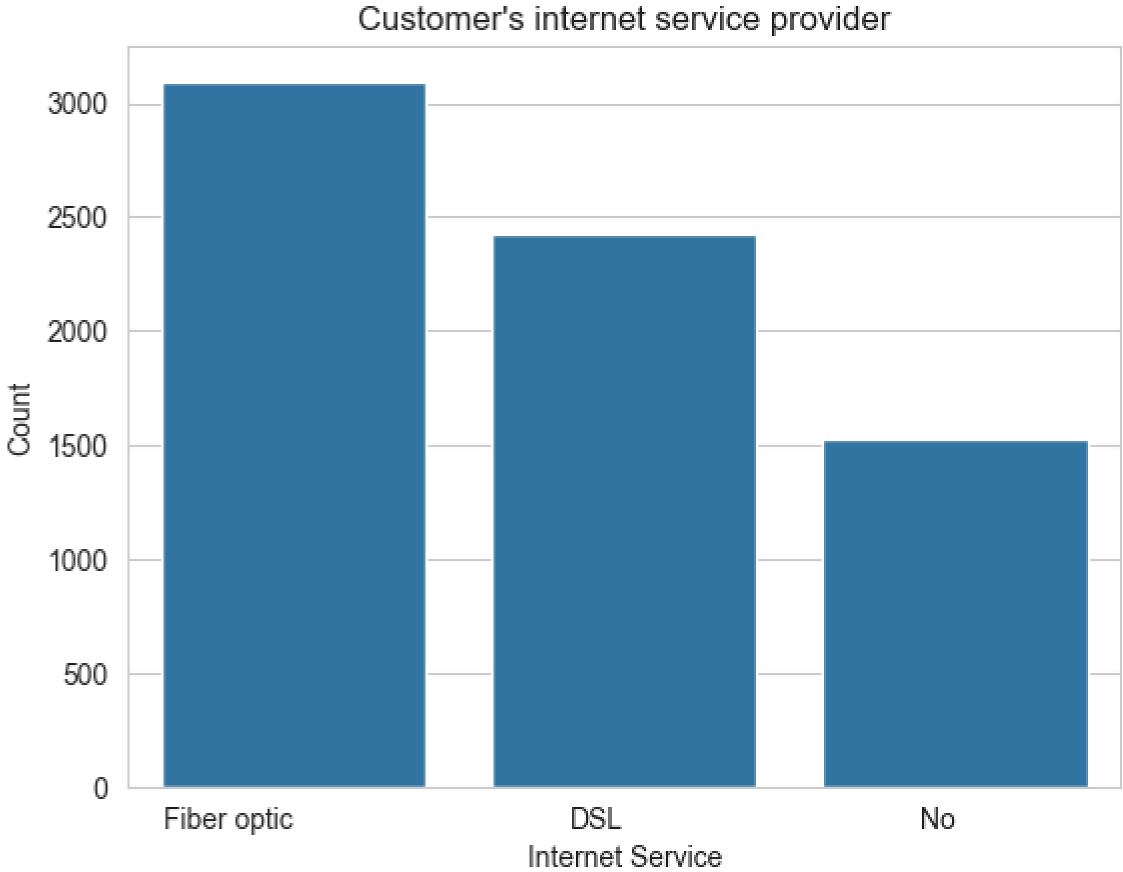


The majority of the customers do not have multiple lines which is to be expected as most customers will usually have only one line. However, what's interesting is that nearly 3,000 customers have multiple lines which is a large number. In addition, over 500 customers have no phone service which was unexpected.

Internet Service

```
plot_categorical(df=df, col="InternetService", title="Customer's internet service
                 xlabel="Internet Service", ylabel="Count")
```

```
Data Statistics:
InternetService
Fiber optic    3096
DSL            2421
No             1526
Name: count, dtype: int64
```



The majority of the customers have `Fiber Optic` internet service, this could be due to higher internet speeds or lower prices. The number of customers who have `DSL` is also quite high at just about 2,500 which is good for competition and maintaining a healthy market share.

Online Security

```
plot_categorical(df=df, col="OnlineSecurity", title="Does customer have online se
                 xlabel="Online Security", ylabel="Count")
```

```
Data Statistics:
OnlineSecurity
No                     3498
Yes                    2019
No internet service    1526
Name: count, dtype: int64
```

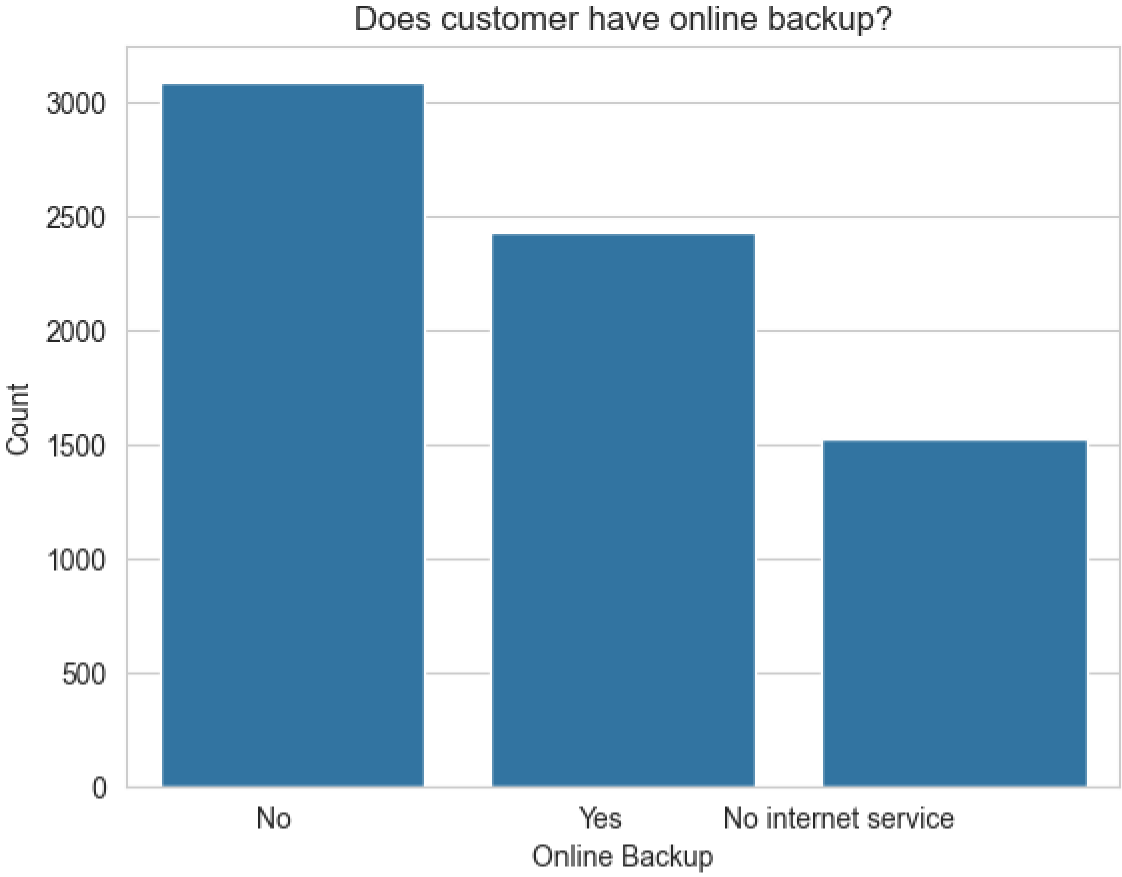
This column indicates whether a customer has subscribed to additional online security service provided by the company. Approximately 3,500 customers do not have online security compared to 2,000 who have. What's interesting is that about 1,500 have been categorizes as not having an internet service.

This could be either miscategorized as if they didn't have an internet service, one would have expected them to have been categorized as `No`

Online Backup

```
plot_categorical(df=df, col="OnlineBackup", title="Does customer have online back
                 xlabel="Online Backup", ylabel="Count")
```

```
Data Statistics:
OnlineBackup
No                     3088
Yes                    2429
No internet service    1526
Name: count, dtype: int64
```

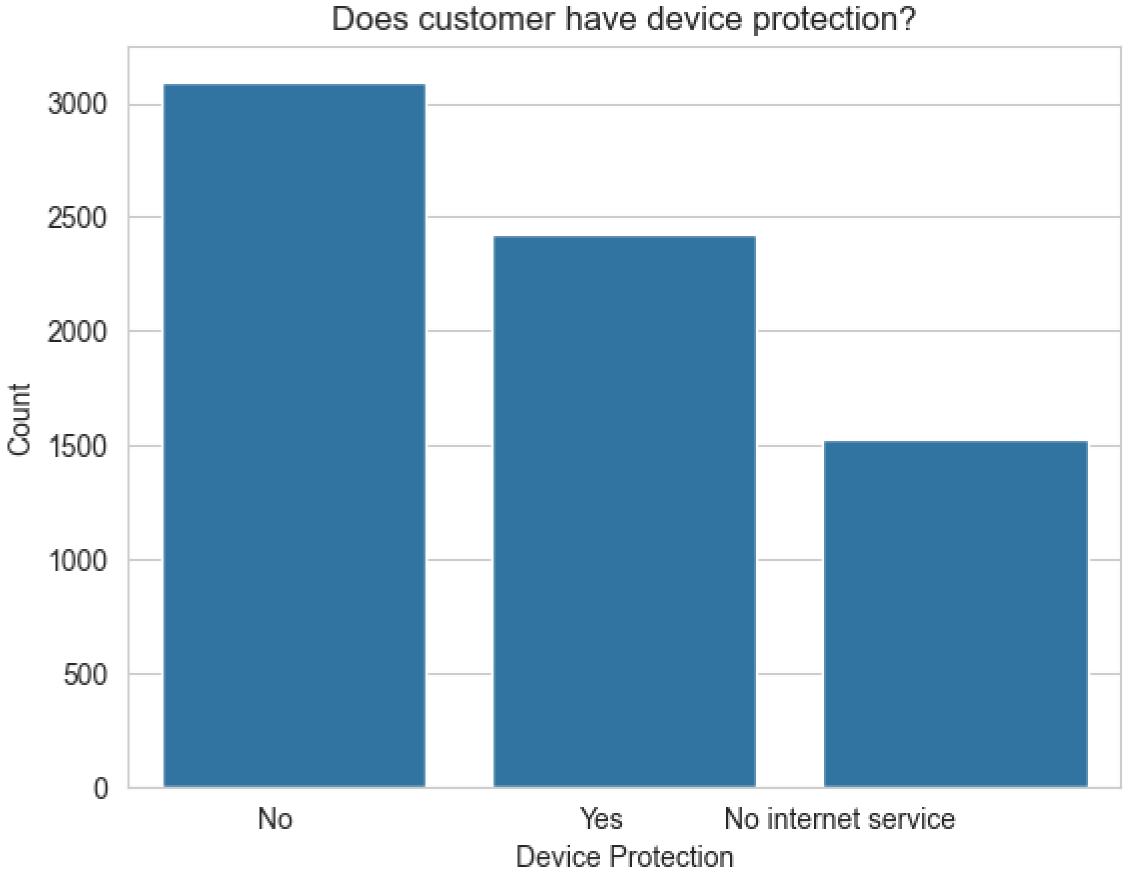


Slightly over 3,000 customers have not subscribed to an additional online backup service from the telco company compared to 2,000 who have. As this is a paid for service, the telco company may consider this service when looking at their churn rate.

Device Protection

```
plot_categorical(df=df, col="DeviceProtection", title="Does customer have device
                 xlabel="Device Protection", ylabel="Count")
```

```
Data Statistics:
DeviceProtection
No                     3095
Yes                    2422
No internet service    1526
Name: count, dtype: int64
```

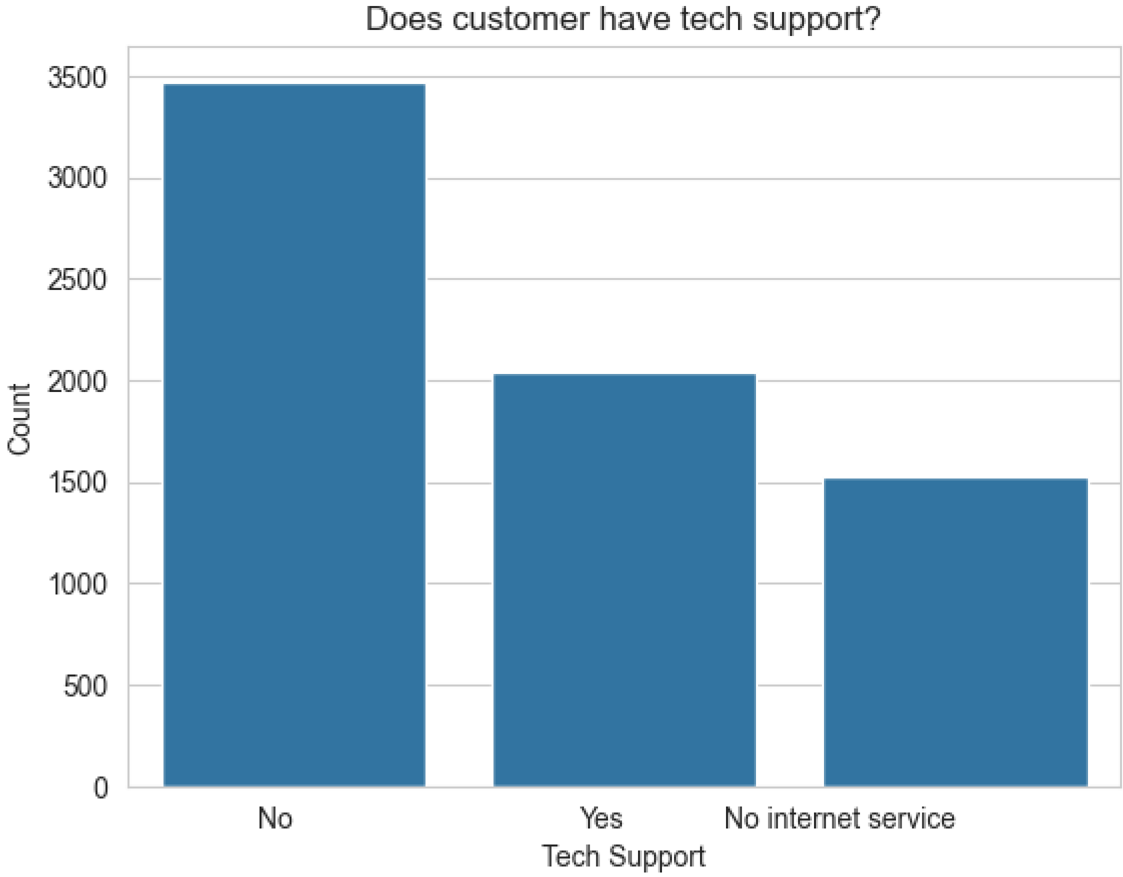


The above chart indicates the number of customers who have subscribed to an additional device protection service from the telco company. The number of customers who have not subscribed to this service is slightly over 3,000 compared to about 2,500 who have. This can be a good indicator for the telco company to see if they can improve their device protection service to attract more customers.

Tech Support

```
plot_categorical(df=df, col="TechSupport", title="Does customer have tech support
                 xlabel="Tech Support", ylabel="Count")
```

```
Data Statistics:
TechSupport
No                     3473
Yes                    2044
No internet service    1526
Name: count, dtype: int64
```

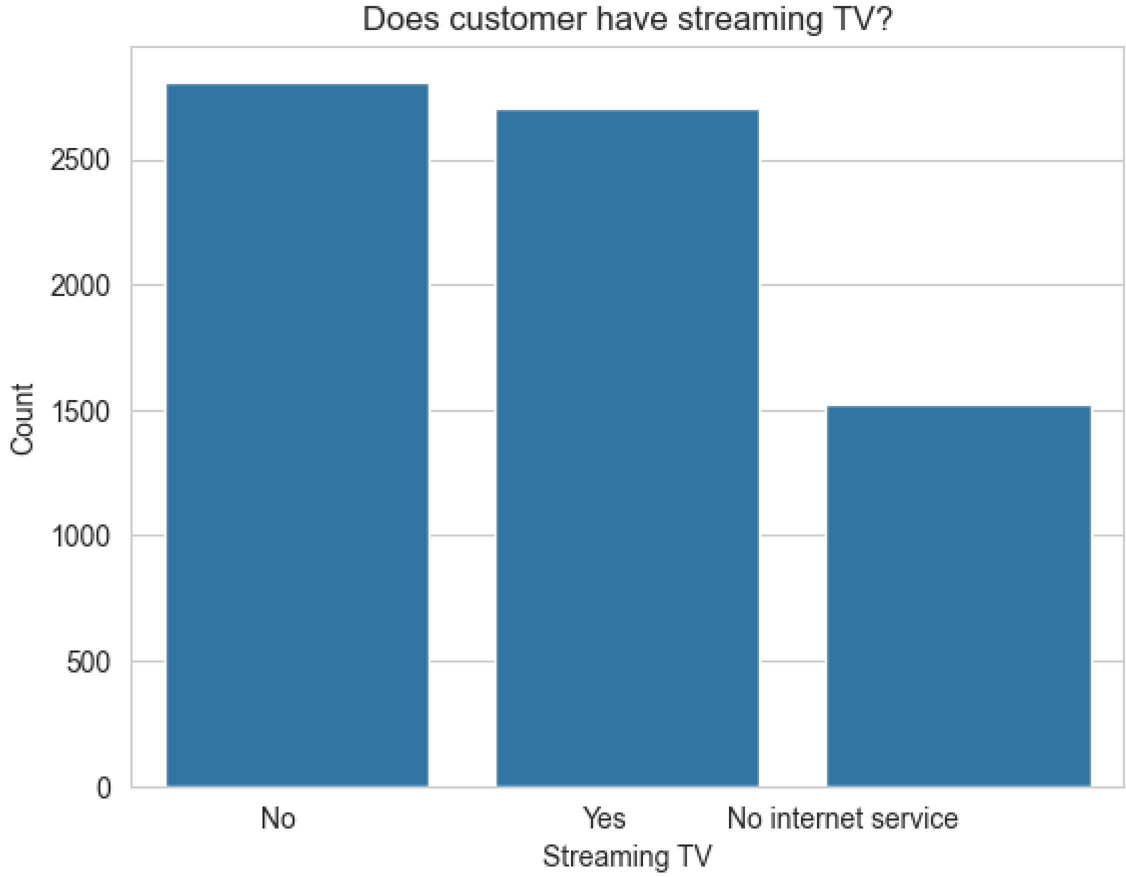


This chart shows the proportion of customer who have subscribed to an additional tech support service from the telco company. The number of customers who have not subscribed to this service is slightly below 3,500 compared to about 2,000 who have. This can be a good indicator for the telco company to see if they can improve their tech support service to attract more customers either by improving the service or reducing the price.

Streaming TV

```
plot_categorical(df=df, col="StreamingTV", title="Does customer have streaming TV
                 xlabel="Streaming TV", ylabel="Count")
```

```
Data Statistics:
StreamingTV
No                     2810
Yes                    2707
No internet service    1526
Name: count, dtype: int64
```



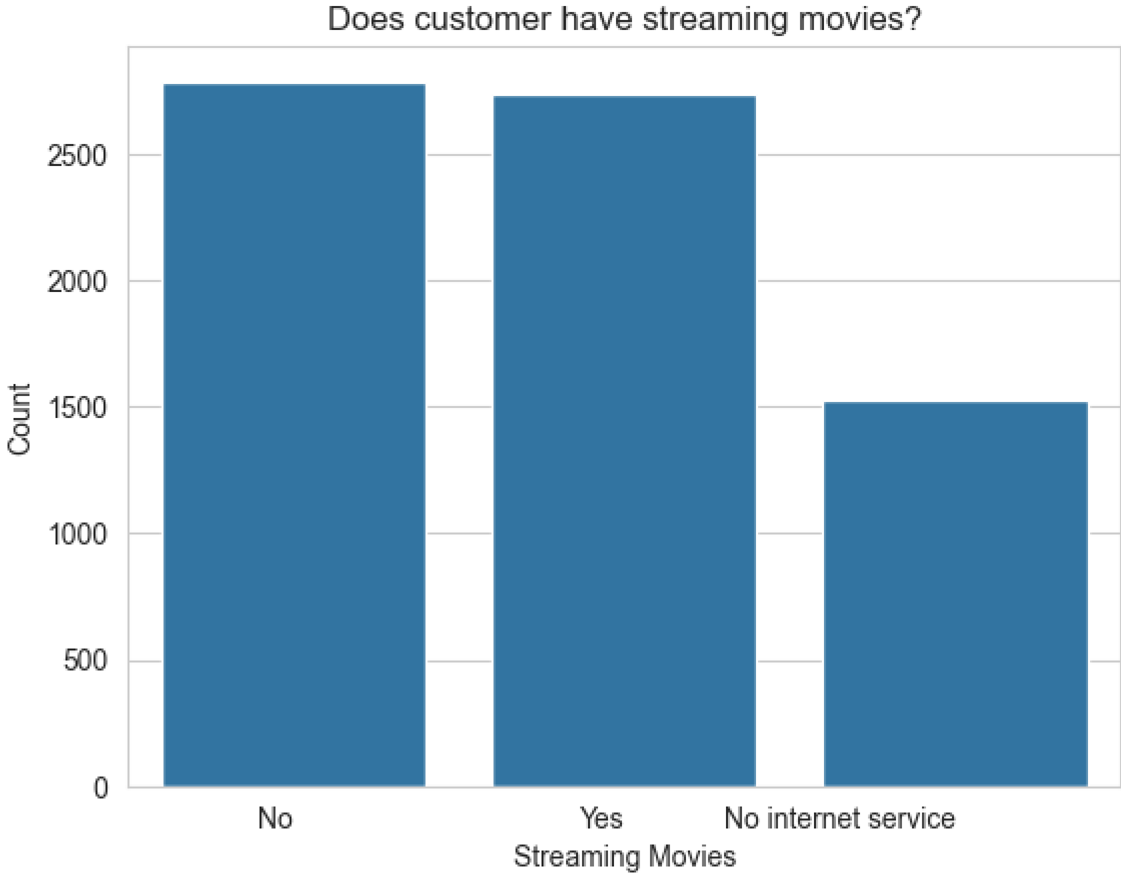
The amount of telco customers who didn't use the telco's services to stream TV from a 3rd party provider is approximately 2,800 customers which is evenly split with the ones who did. However, as this is not a paid for service, the telco company may not be too concerned about this as they are not losing out on revenue.

Streaming Movies

Double-click (or enter) to edit

```
plot_categorical(df=df, col="StreamingMovies", title="Does customer have streamin
                 xlabel="Streaming Movies", ylabel="Count")
```

```
Data Statistics:
StreamingMovies
No                     2785
Yes                    2732
No internet service    1526
Name: count, dtype: int64
```

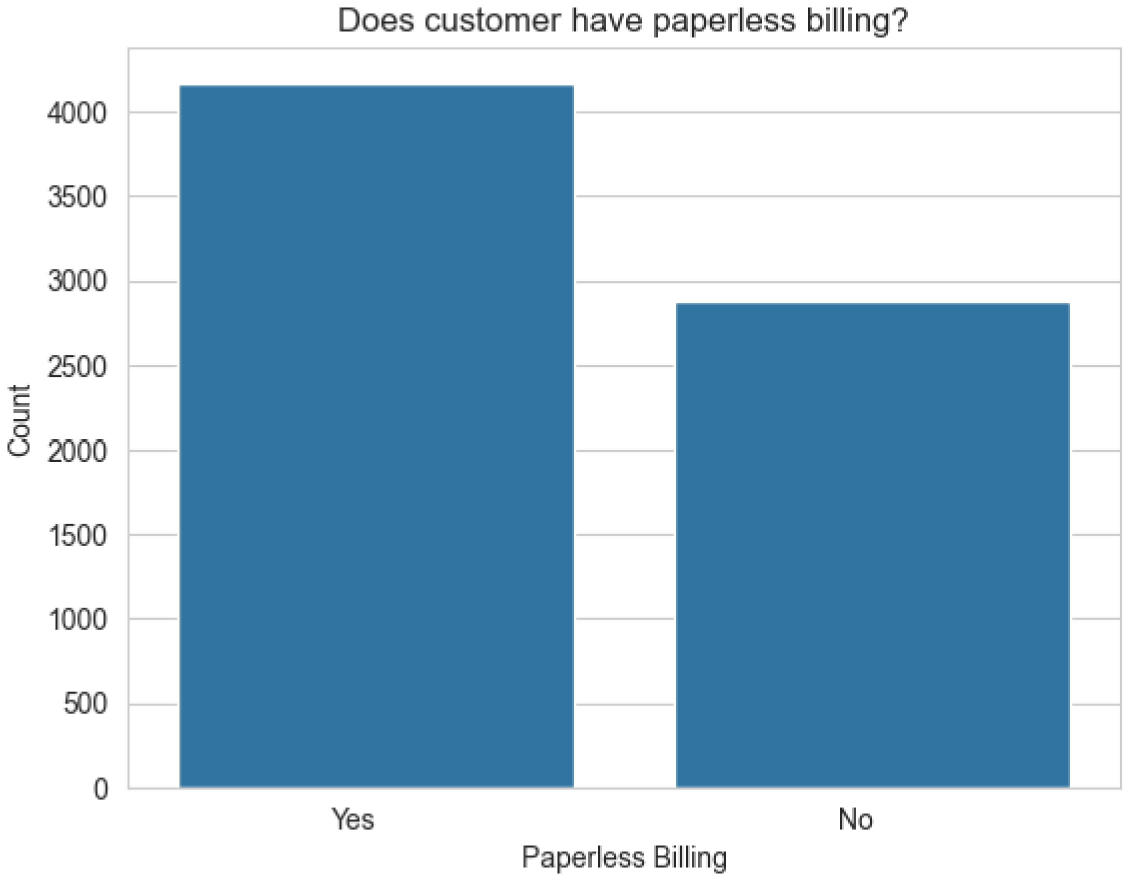


There's an even split between the customers who use the telco's services for streaming movies and those who don't at around 2,700 customers. However, about 1,500 customers have been categorized as not having an internet service and can't use the telco's service for streaming movies. As this is also not a paid for service, the telco company may not be too concerned about this as they are not losing out any revenue from these customers.

Billing Type

```
plot_categorical(df=df, col="PaperlessBilling", title="Does customer have paperle
                 xlabel="Paperless Billing", ylabel="Count")
```

```
Data Statistics:
PaperlessBilling
Yes    4171
No     2872
Name: count, dtype: int64
```

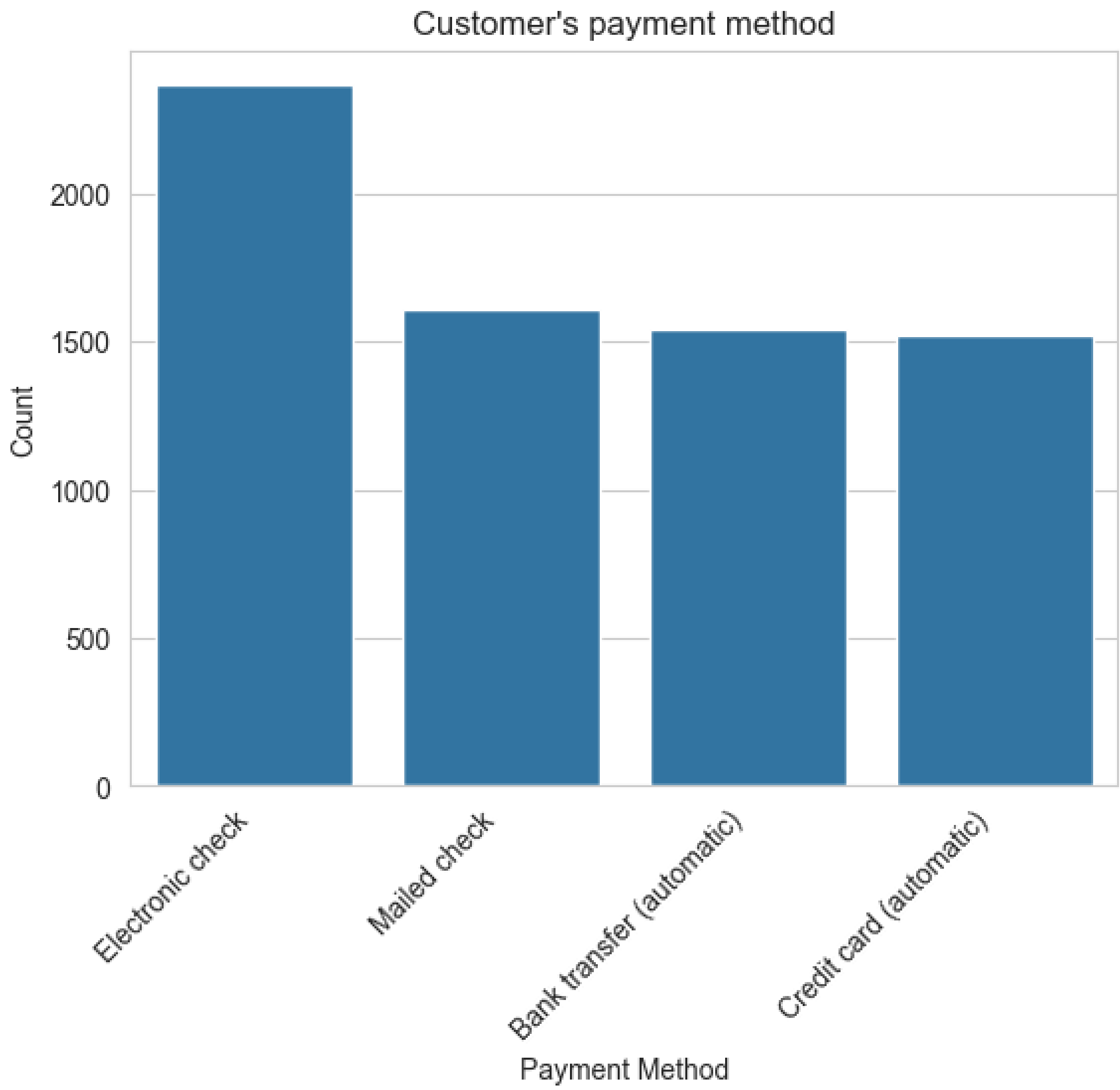


The majority of the customers have paperless billing which is to be expected as it is more convenient for customers and the company. However, the number of customers who do not have paperless billing is quite high at 2,872 customers.

Payment Method

```
plot_categorical(df=df, col="PaymentMethod", title="Customer's payment method",
                 xlabel="Payment Method", ylabel="Count", txt_rotation=45)
```

```
Data Statistics:
PaymentMethod
Electronic check             2365
Mailed check                 1612
Bank transfer (automatic)    1544
Credit card (automatic)      1522
Name: count, dtype: int64
```

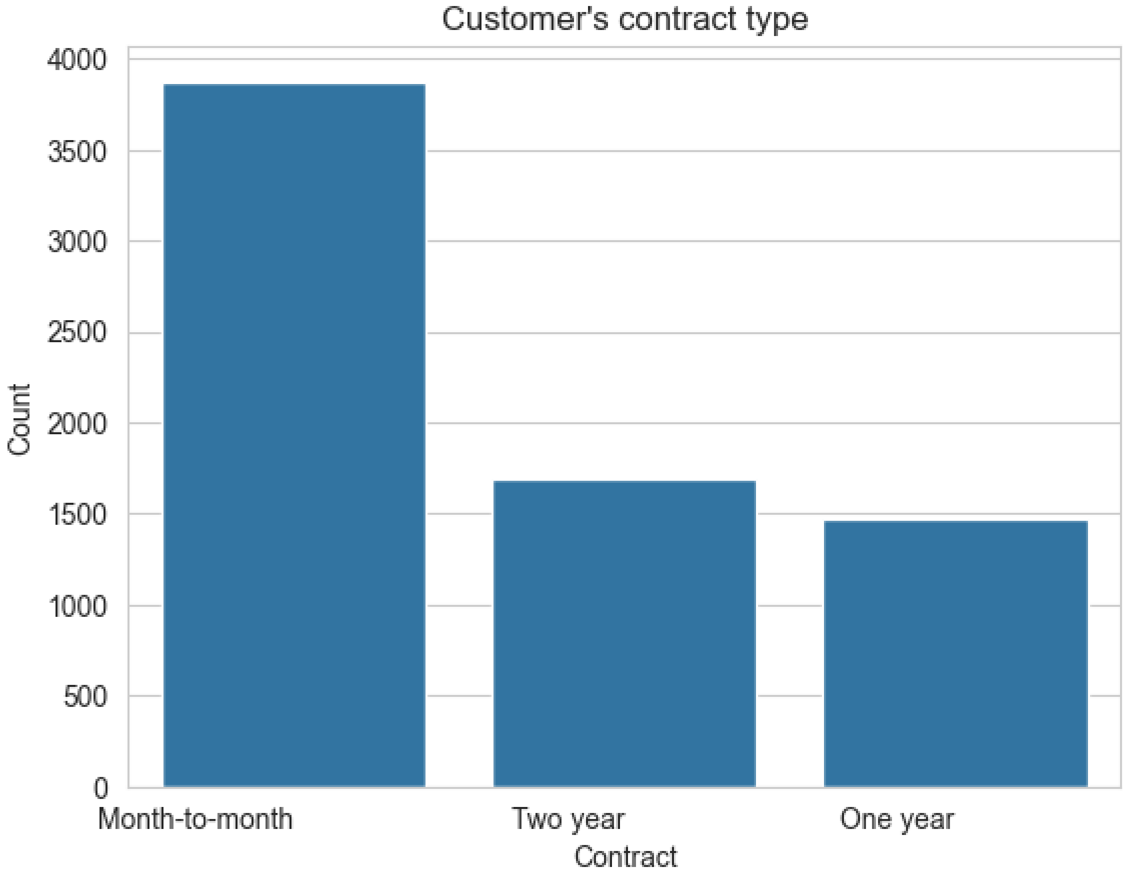


The most common payment method is electronic check with over 2,000 customers. This wasn't expected as one would expect for a telco company in California, USA to have more customers paying via credit card or bank transfer.

Contract Type

```
plot_categorical(df=df, col="Contract", title="Customer's contract type",
                 xlabel="Contract", ylabel="Count")
```

```
Data Statistics:
Contract
Month-to-month    3875
Two year          1695
One year          1473
Name: count, dtype: int64
```

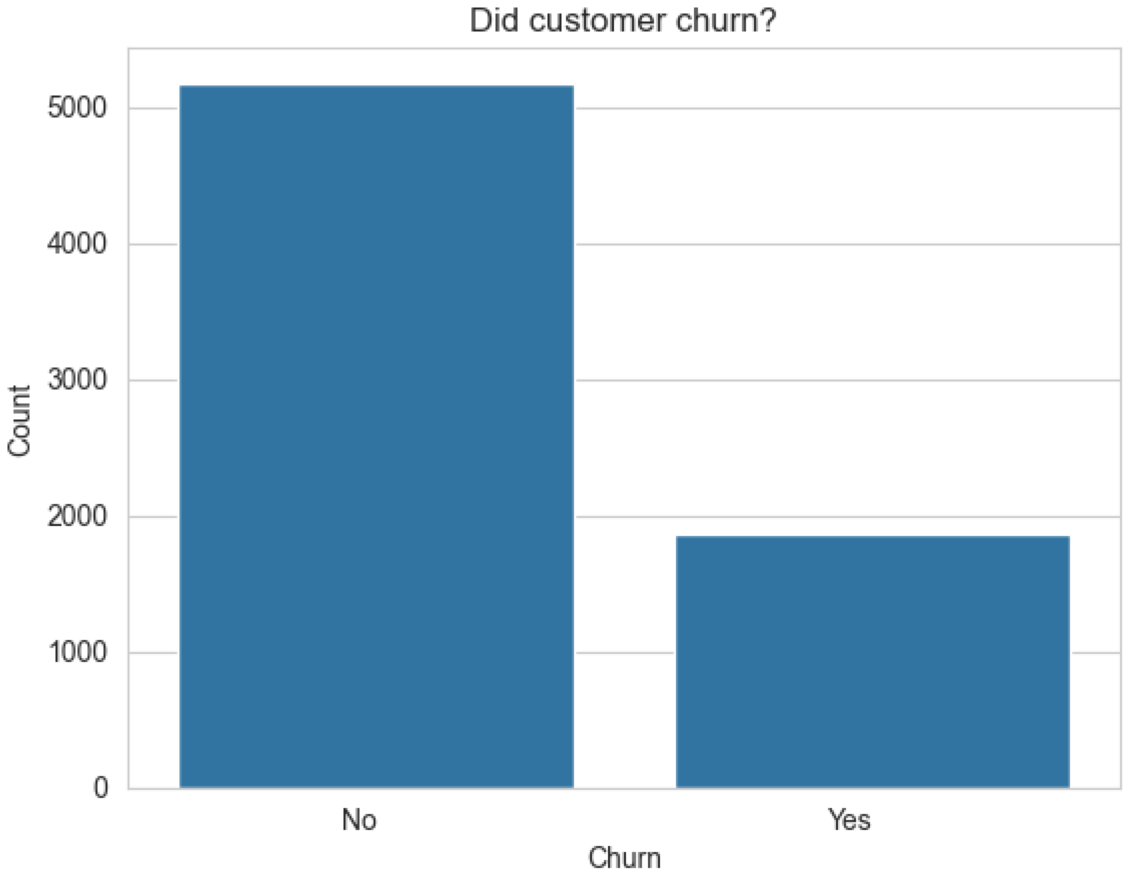


Most of the telco customers are on a month-to-month contract which is to expected as not most people would want to be tied down to long-term contracts. What is interesting is that there are nearly 2,000 customers on a two-year contract which is more than the one-year contract customers which is not what one would expect.

Churn

```
plot_categorical(df=df, col="Churn", title="Did customer churn?",
                 xlabel="Churn", ylabel="Count")
```

```
Data Statistics:
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```



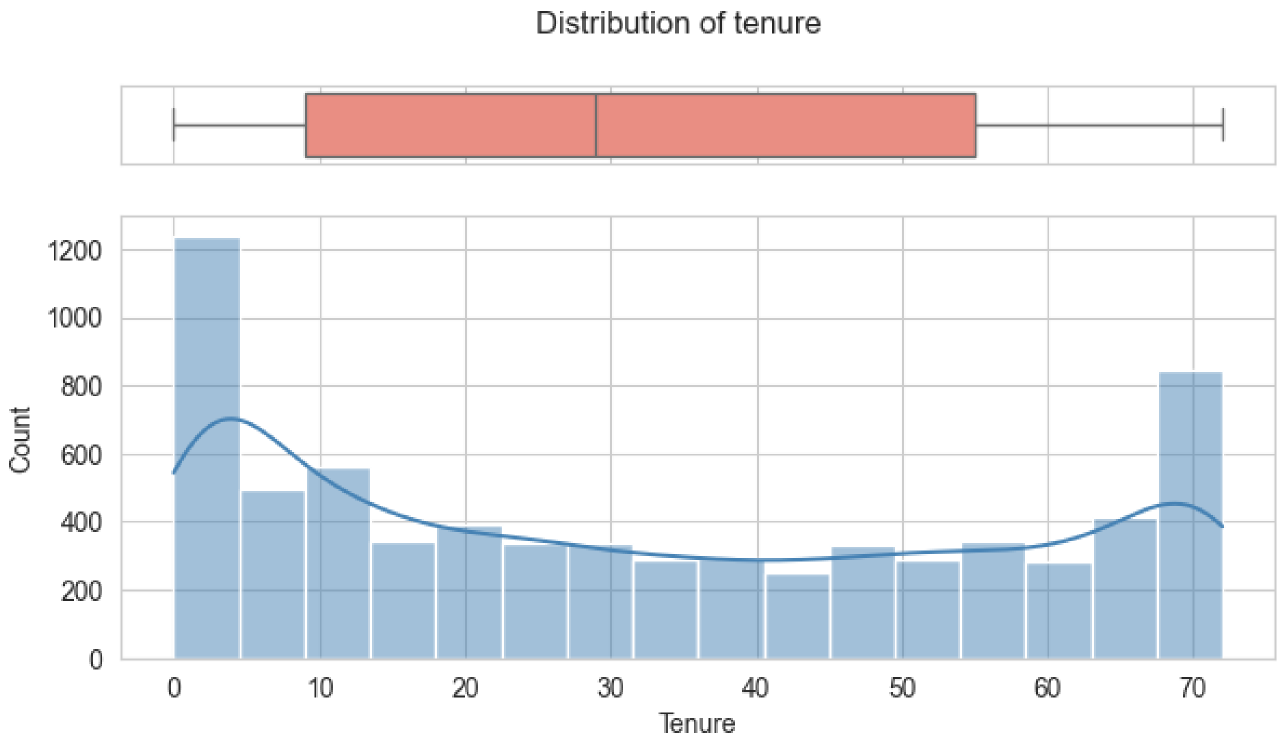
From the graph above we can see that nearly 5,000 customers did not churn compared to about 2,000 who did. This is a good sign for the telco company as they have a high retention rate. However, the challenge this may bring during modelling is the class imbalance between the churned and non-churned customers.

```
def plot_numerical(df:pd.DataFrame, columns:str, title:str, xlabel:str, ylabel:st
    """
    This function plot the distribution of the stated columns in a dataframe.

    :param df: Dataframe to be used
    :param columns: Columns for visualizing
    :param title: Title for distribution
    :param xlabel: X label
    :param ylabel: Y label
    """
    print("Summary statistics:")
    print(df[columns].describe())

    fig, (ax_box, ax_hist) = plt.subplots(nrows=2, ncols=1,
                                          sharex=True, figsize=(8,4),
                                          gridspec_kw={"height_ratios": (.15, .85
    sns.boxplot(df[columns], ax=ax_box, color="salmon", orient="h")
    sns.histplot(df[columns], ax=ax_hist, color="steelblue", kde=kde)

    plt.xlabel(xlabel)
    plt.ylabel(ylabel)

    plt.suptitle(title)
```

Tenure

```
plot_numerical(df=df, columns="tenure", title="Distribution of tenure",
               xlabel="Tenure", ylabel="Count")
```

```
Summary statistics:
count    7043.000000
mean       32.371149
std        24.559481
min         0.000000
25%         9.000000
50%        29.000000
75%        55.000000
max        72.000000
Name: tenure, dtype: float64
```



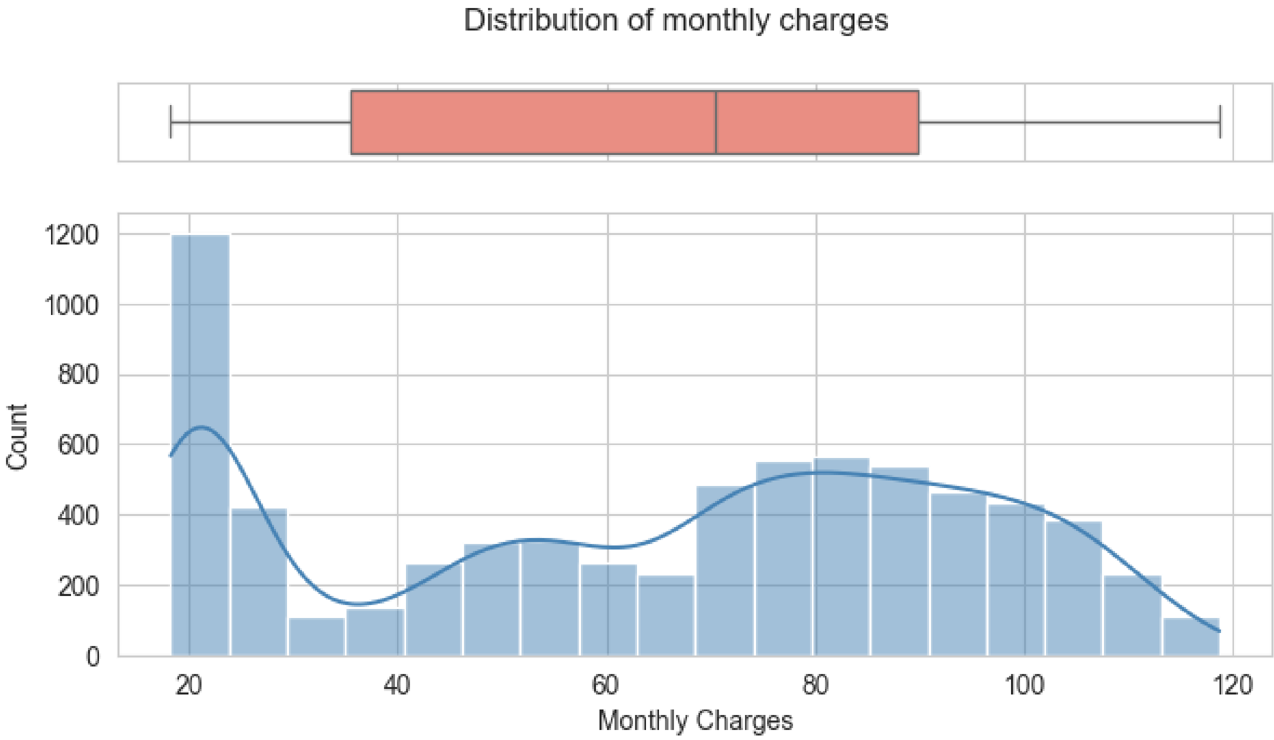
The above distribution shows the total months a customer has been with the telco company. We can see that the average tenure is 32 months with the median being approximately 29 months.

The distribution also has twin peaks at 0 months and 70 months.

Monthly Charges

```
plot_numerical(df=df, columns="MonthlyCharges", title="Distribution of monthly ch
               xlabel="Monthly Charges", ylabel="Count")
```

```
Summary statistics:
count    7043.000000
mean       64.761692
std        30.090047
min        18.250000
25%        35.500000
50%        70.350000
75%        89.850000
max       118.750000
Name: MonthlyCharges, dtype: float64
```

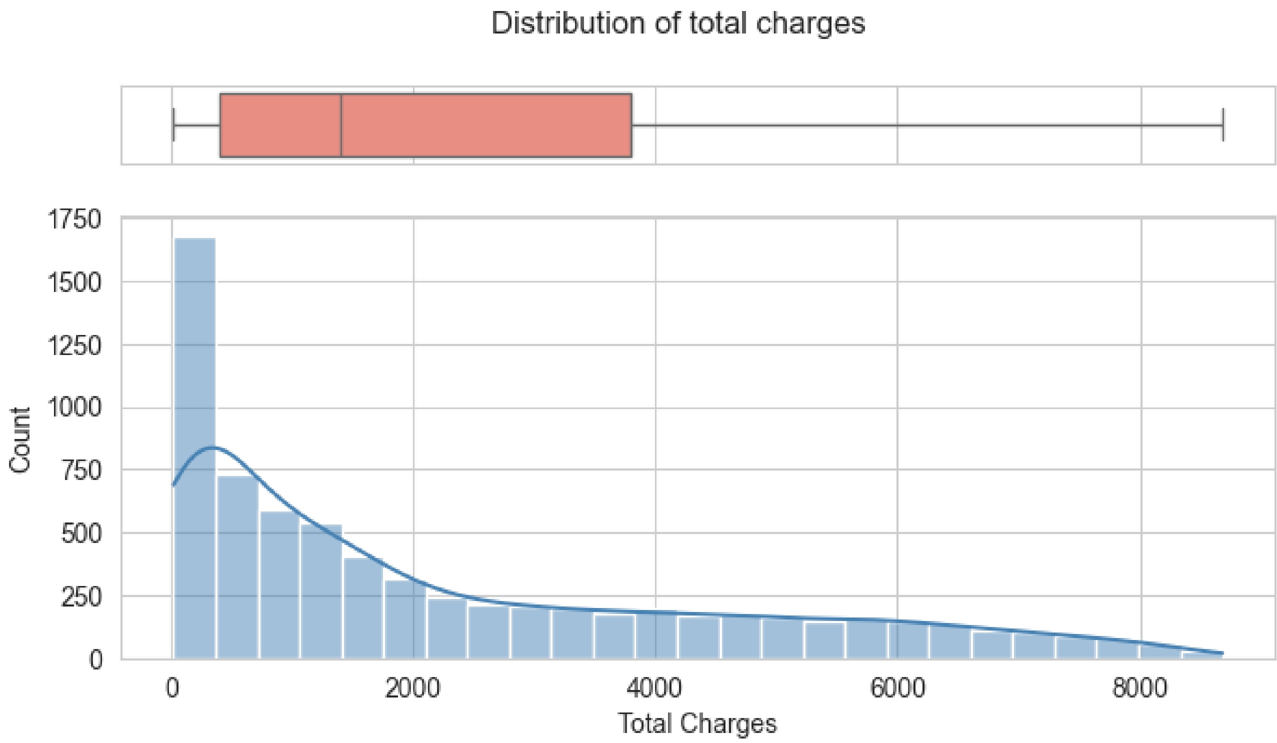


The above distribution shows the customers current total monthly charge for all their services from the company. The distribution is interestingly shaped as there is a peak at 20 dollars then a dip before another peak at 80 dollars. The average monthly charge is 64.76 dollars and a maximum of 118.75 dollars which is quite high.

Total Charges

```
plot_numerical(df=df, columns="TotalCharges", title="Distribution of total charge
               xlabel="Total Charges", ylabel="Count")
```

```
Summary statistics:
count    7032.000000
mean     2283.300441
std      2266.771362
min        18.800000
25%       401.450000
50%      1397.475000
75%      3794.737500
max      8684.800000
Name: TotalCharges, dtype: float64
```



The above distribution shows the total amount charged to customers. The distribution is skewed to the right with the 75% of the customers being charged between USD 401 - USD3794.7 (Q1 - Q3). The averagge total charge is USD 2,283 however approximately 25% of the customers are charged less than USD 401.

Bivariate Analysis

In this section we will look at the relationship between the target variable and the other variables in the dataset. This will help us identify which variables have a strong relationship with the target variable and which ones don't.

```
totalcount = df["SeniorCitizen"].value_counts()
print(totalcount)
groupcount = df.groupby(["SeniorCitizen", "Churn"])["SeniorCitizen"].count().unst
groupcount
```

```
SeniorCitizen
No     5901
Yes    1142
Name: count, dtype: int64
```

Churn	No	Yes
SeniorCitizen		
No	4508	1393
Yes	666	476

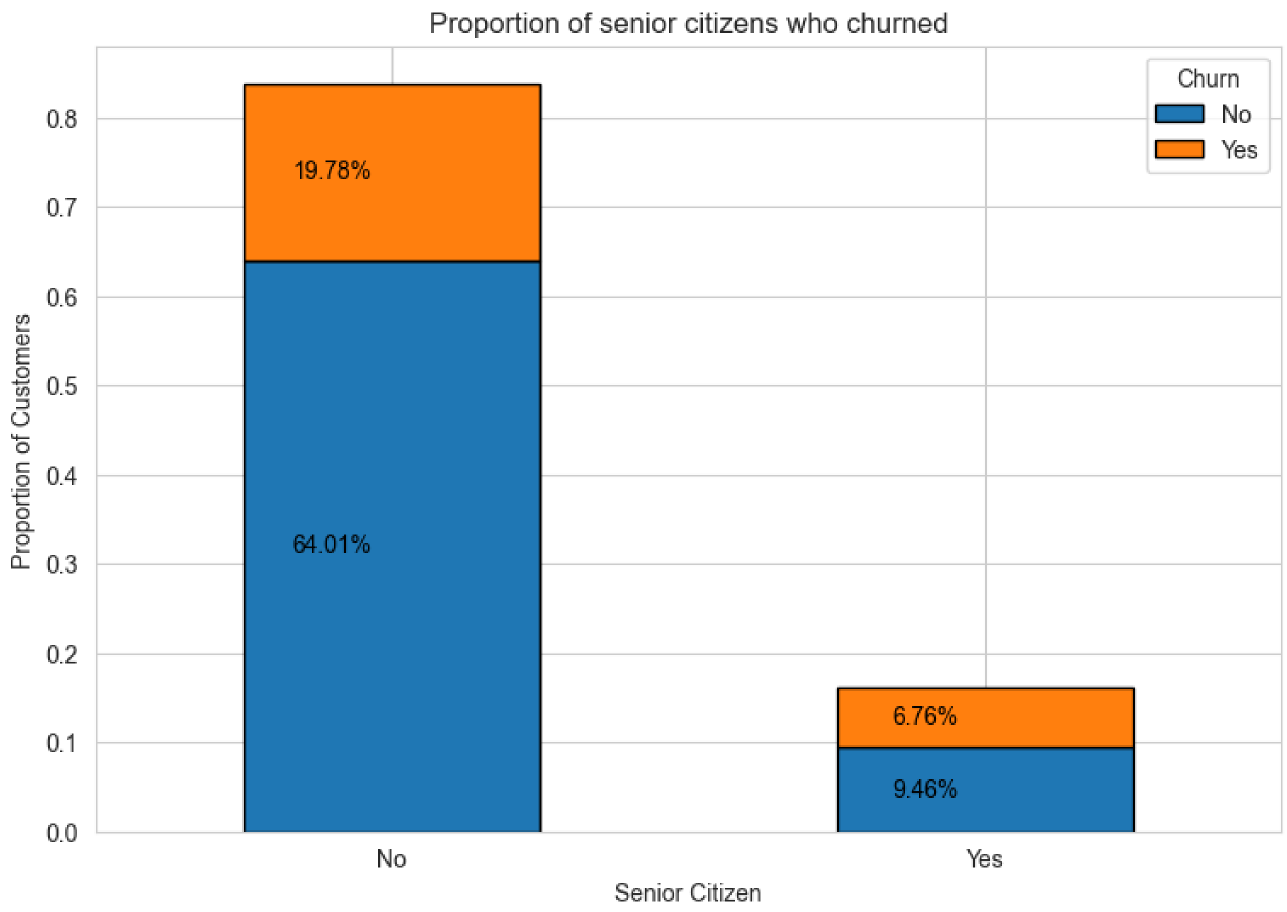
```
group_proportions = groupcount.div(len(df), axis=0)
group_proportions
```

Churn	No	Yes
SeniorCitizen		
No	0.640068	0.197785
Yes	0.094562	0.067585

```
def plot_bivariate(df: pd.DataFrame, x: str, title: str, xlabel: str, ylabel: str
                   hue: str = None, rotation: int = 0):
    """
    This function plots the relationship between the target variable and another

    :param df: Dataframe to be used
    :param x: X variable
    :param title: Title for distribution
    :param xlabel: X label
    :param ylabel: Y label
    :param hue: Hue variable
    """
    # Calculate proportions relative to the entire dataset
    total_counts = df[x].value_counts().sort_values(ascending=False)
    group_counts = df.groupby([x, hue])[x].count().unstack()
    proportions = group_counts.div(len(df), axis=0)

    # Create subplots
    fig, ax = plt.subplots(figsize=(9, 6))

    # Plotting the grouped bar chart
    ax = proportions.plot(kind='bar', stacked=True, edgecolor='black', ax=ax)

    # Adding annotation
    for i, (index, row) in enumerate(proportions.iterrows()):
        for j, value in enumerate(row):
            x_pos = i + j * 0 - 0.1 * (len(row) - 1)  # Adjust the position for h
            y_pos = row.head(j + 1).sum() - value / 2
            proportion_text = f"{value:.2%}"
            ax.text(x_pos, y_pos, proportion_text, ha='center', va='center', colo

    # Customize the plot
    ax.set_title(title)
    ax.set_xlabel(xlabel)
    ax.set_ylabel(ylabel)
    ax.set_xticks(range(len(total_counts)))
    ax.set_xticklabels(total_counts.index, rotation=rotation, ha="center")
    ax.legend(title=hue)

    # Show the plot
    plt.show()
```

Senior Citizens

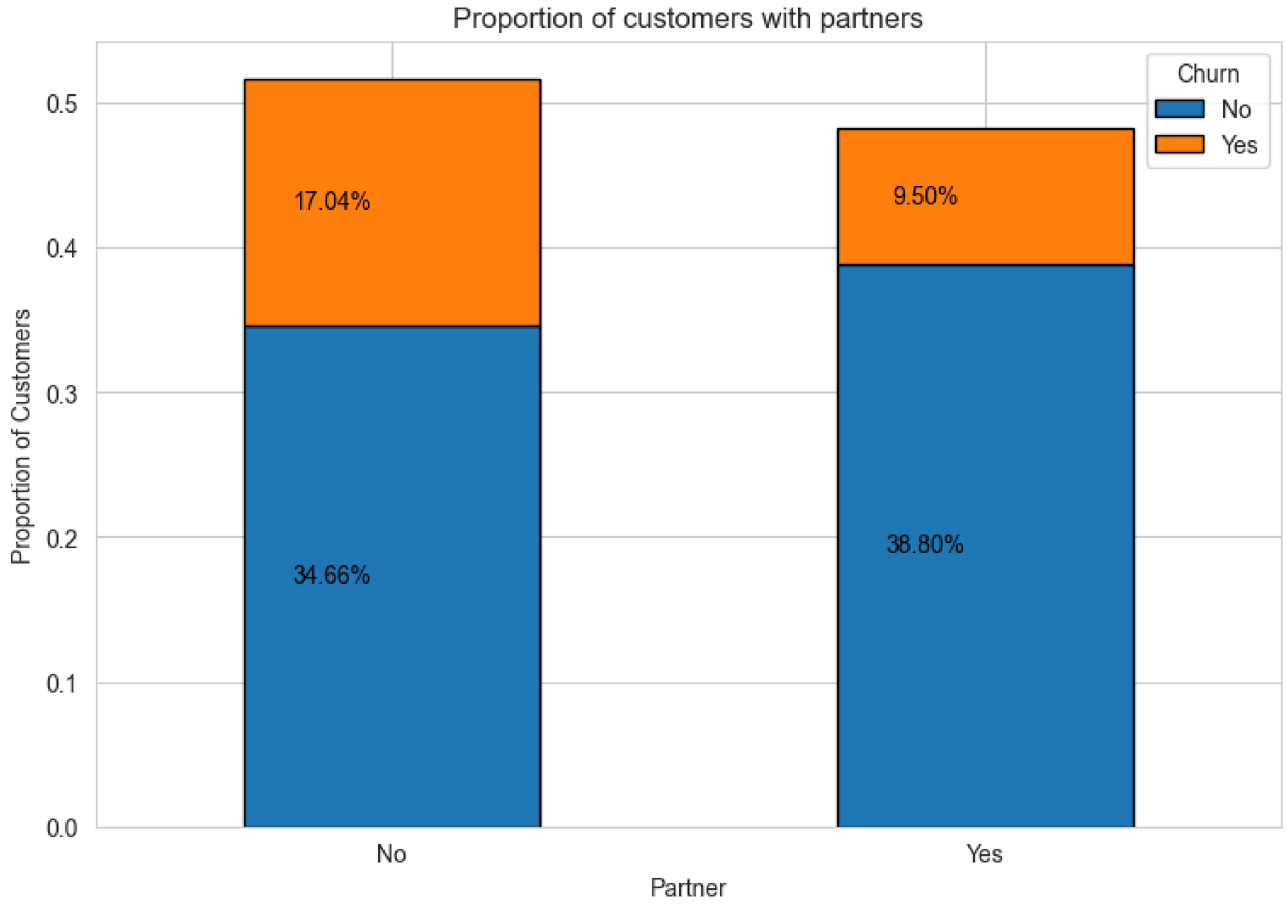
```
plot_bivariate(df=df, x="SeniorCitizen", title="Proportion of senior citizens who
               xlabel="Senior Citizen", ylabel="Proportion of Customers", hue="Ch
```



From the above chart we can see out of the customers who were registered as non-senior citizens 64.01% did not churn while 19.78% churned. However, the proportion of senior customers who churned vs didn't churn is quite similar at 9.46% vs 6.76%

Partner

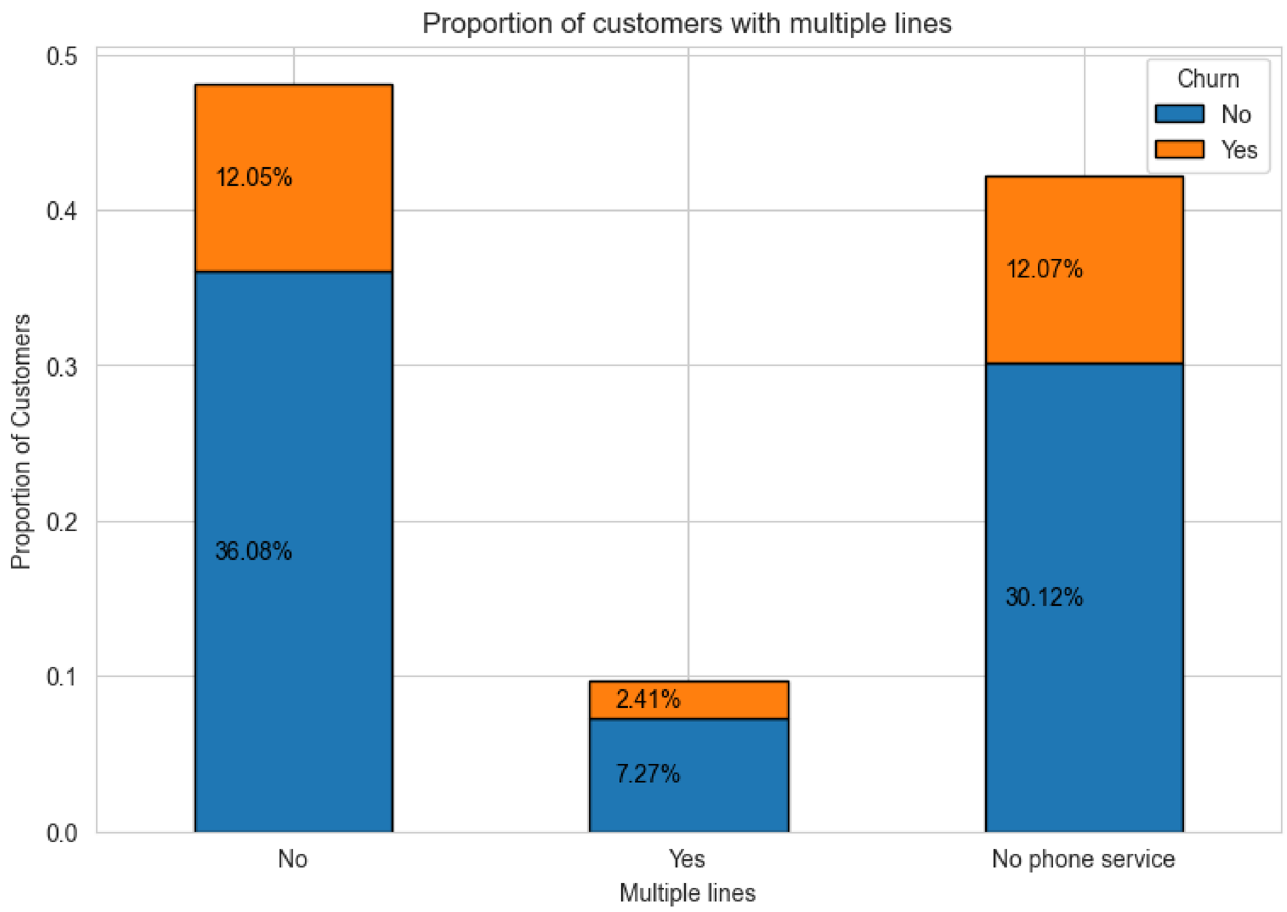
```
plot_bivariate(df=df, x="Partner", title="Proportion of customers with partners",
               xlabel="Partner", ylabel="Proportion of Customers", hue="Churn")
```



From the above chart we can see that the proportion of customers who didn't have a partner and churned is 17.04% of the total customers compared ot 9.50% who had a partner and churned. This would indicate that customers who have a partner are less likely to churn compared to those who don't, however, looking at the proportion of customers who didn't churn, the difference is not that significant.

Multiple Lines

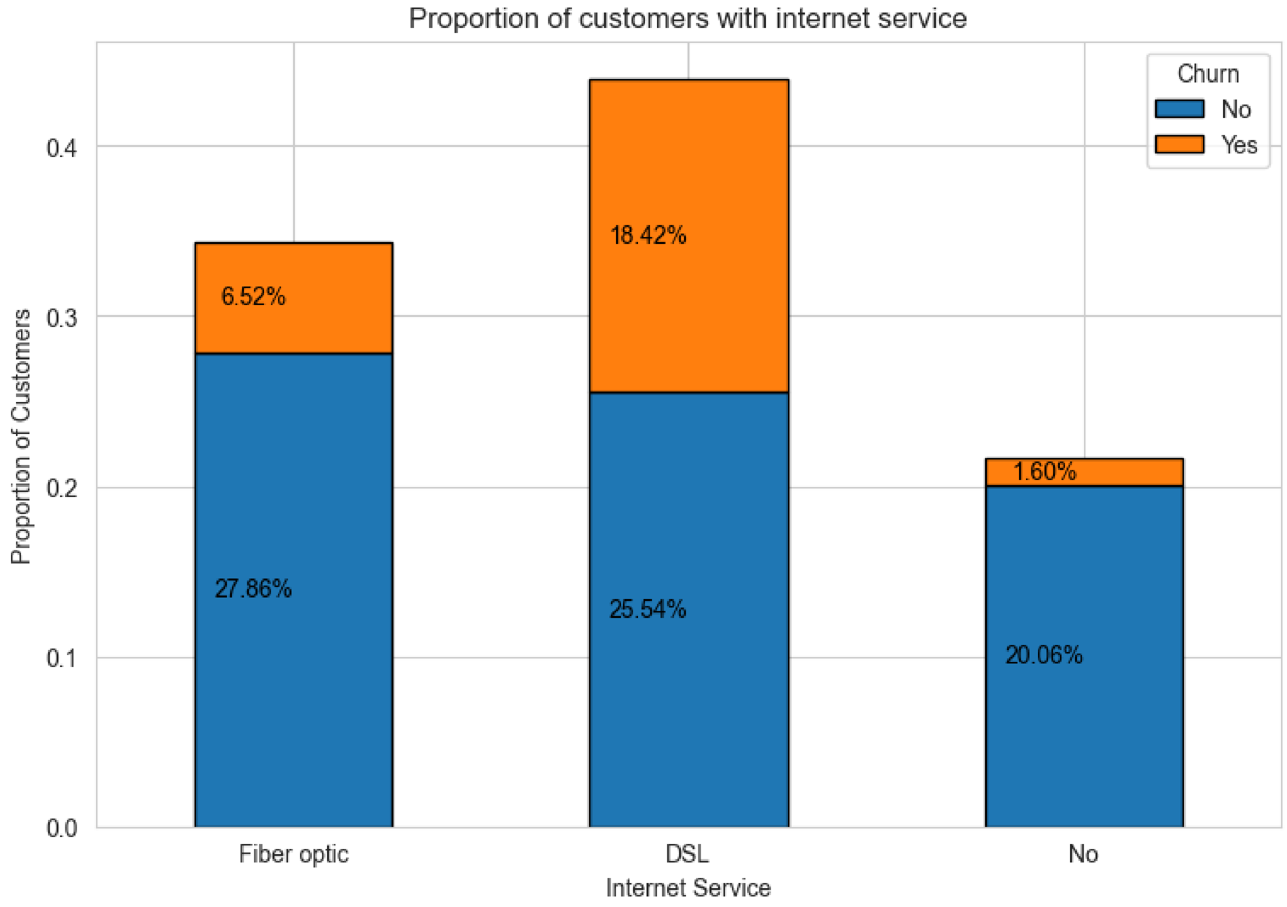
```
plot_bivariate(df=df, x="MultipleLines", title="Proportion of customers with mult
               xlabel="Multiple lines", ylabel="Proportion of Customers", hue="Ch
```



From the above chart we can see that the customers who are most likely to churn either have not subscribed to a phone service of haven't subscribed to multiple lines from the telco company.

Internet Service

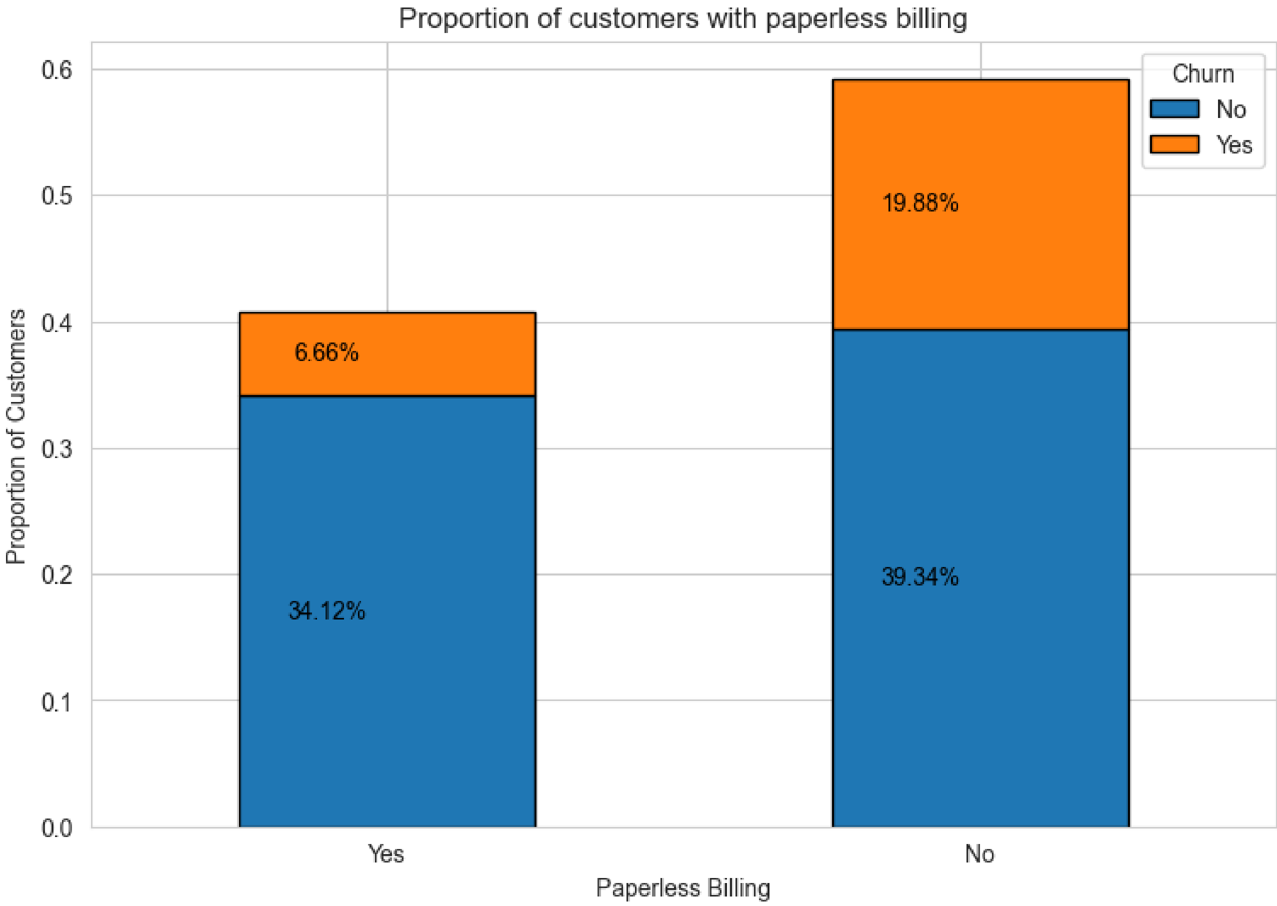
```
plot_bivariate(df=df, x="InternetService", title="Proportion of customers with in
               xlabel="Internet Service", ylabel="Proportion of Customers", hue="
```



Looking at the above chart we can see that there's a higher chance for a customer to churn if they have subscribed to a DSL internet service. What's interesting is that there are more customers using DSL internet service over Fiber optic service which is up to 100x faster (Socket, n.d.). This could be due to the price of the DSL service being lower than the Fiber optic service.

Billing Type

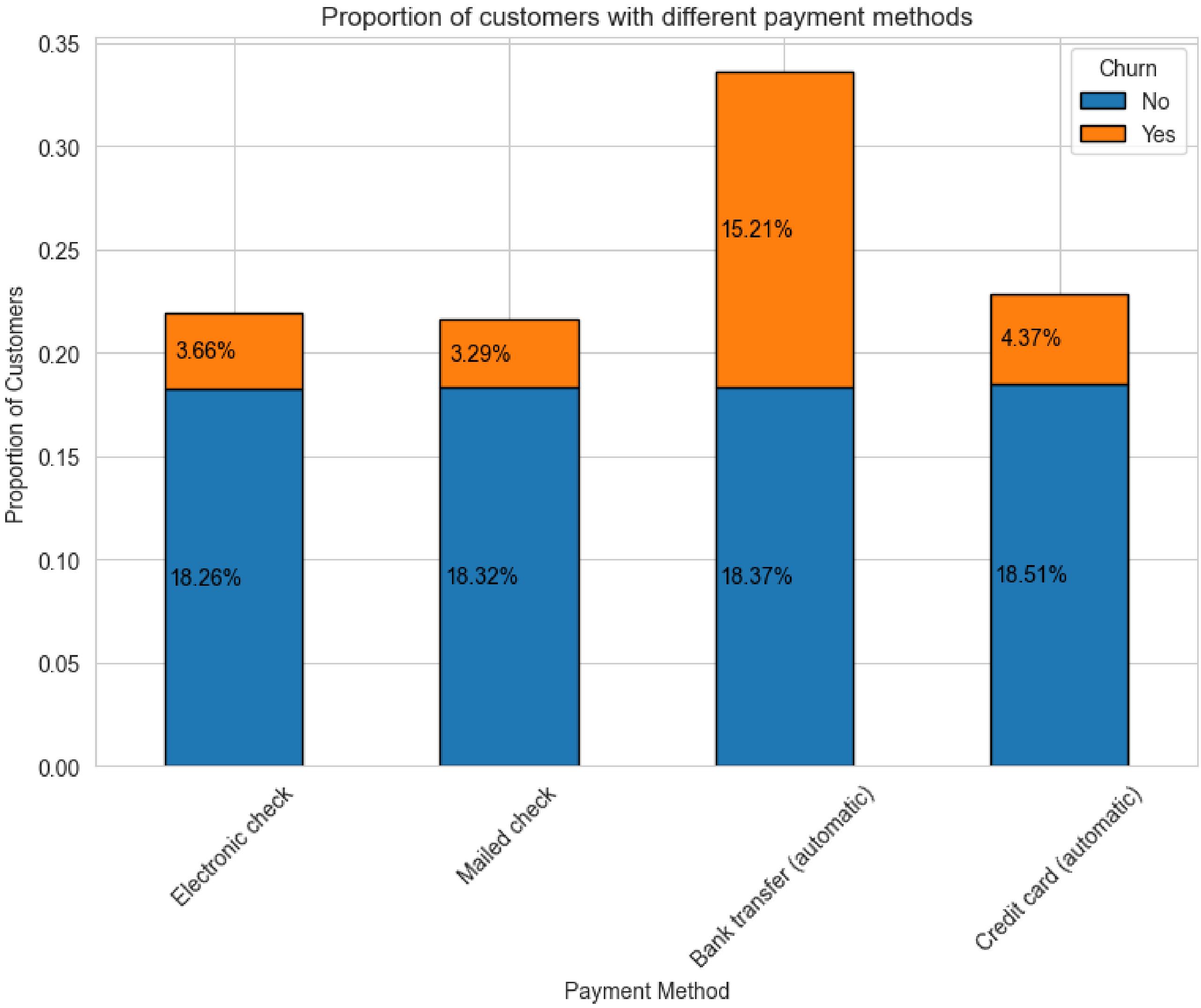
```
plot_bivariate(df=df, x="PaperlessBilling", title="Proportion of customers with p
               xlabel="Paperless Billing", ylabel="Proportion of Customers", hue=
```



From the above chart we can see taht the customers who have not subscribed to paperless billing are more likely to churn (19.88%) compared to those who have paperless billing (6.66%). This could be due to the fact that customers who have paperless billing are more likely to be on a contract and have subscribed to other services from the telco company.

Payment Method

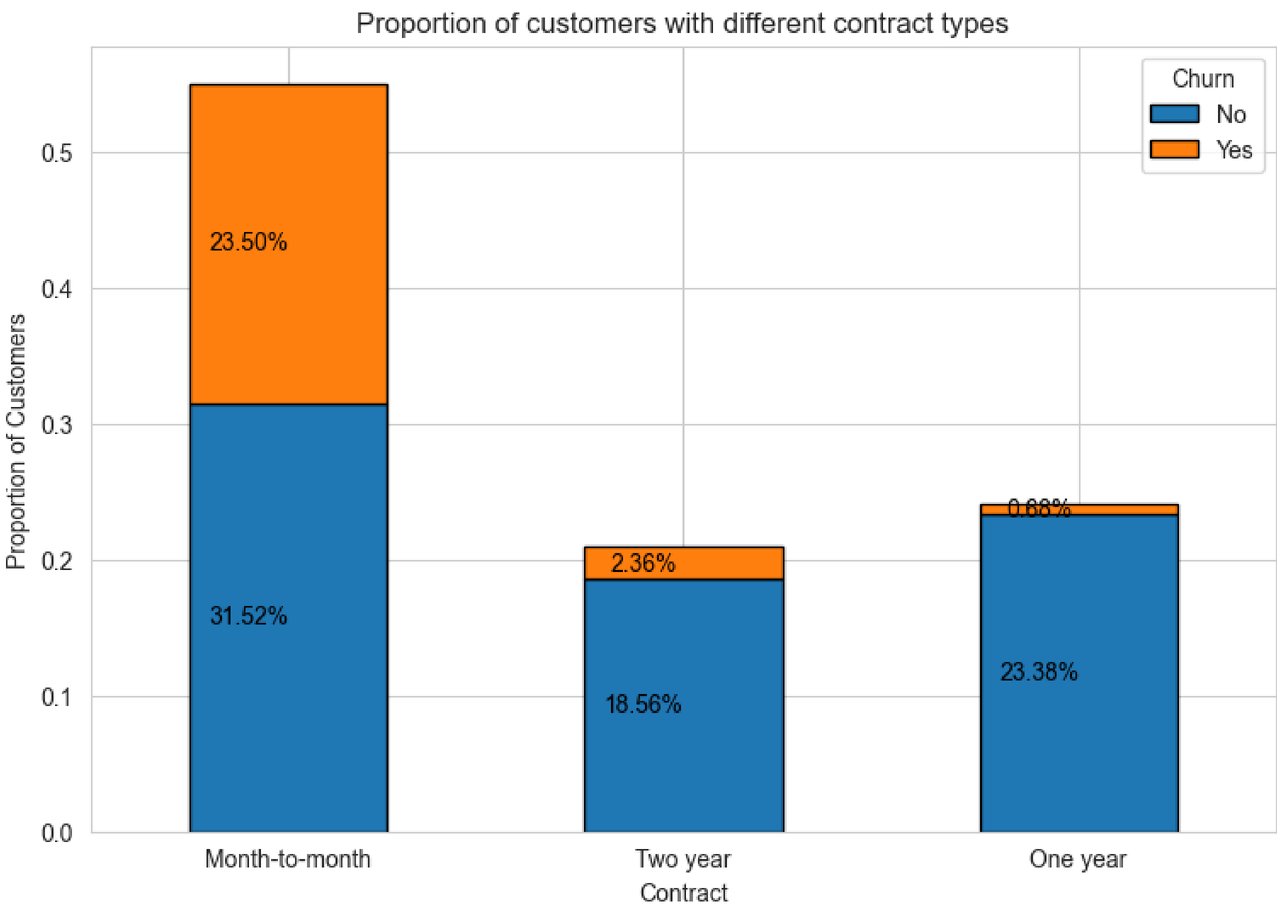
```
plot_bivariate(df=df, x="PaymentMethod", title="Proportion of customers with diff
               xlabel="Payment Method", ylabel="Proportion of Customers", hue="Ch
               rotation=45)
```



From the above chart we can see that customers who paid via an automated bank transfer were at a higher risk of churning (15.21%) compared to the other payment methods.

Contract Type

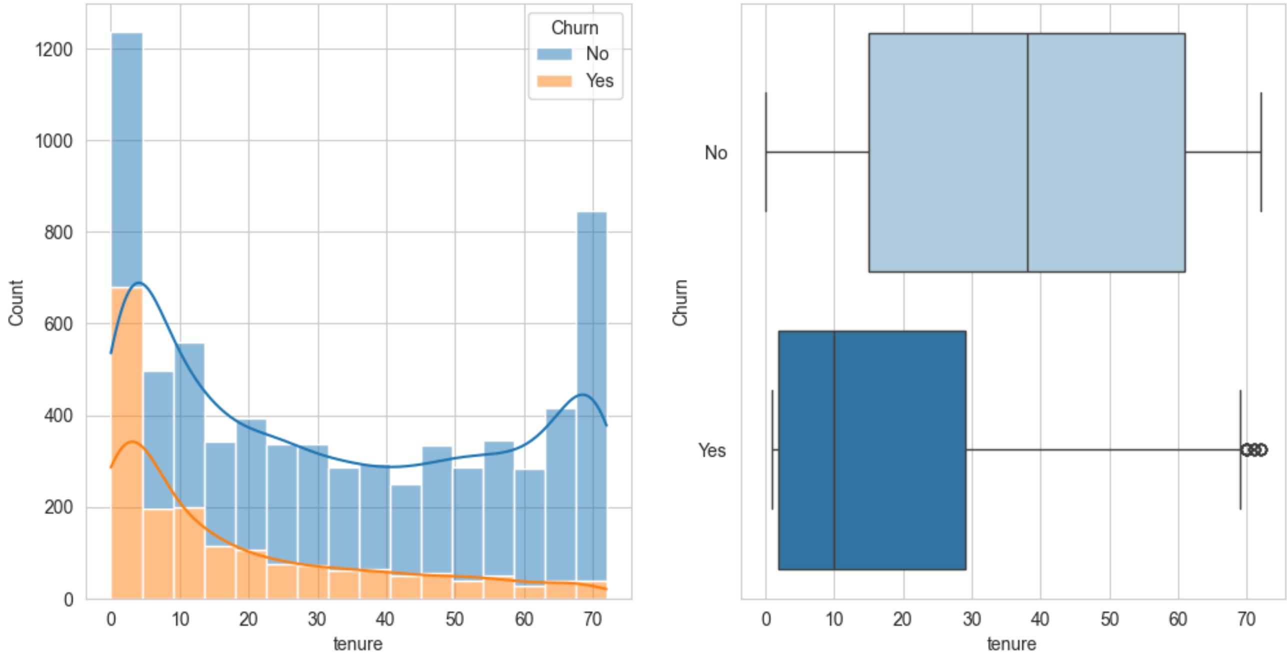
```
plot_bivariate(df=df, x="Contract", title="Proportion of customers with different
               xlabel="Contract", ylabel="Proportion of Customers", hue="Churn")
```



From the above chart we can see that customers who were on a month-to-month contract were at a higher risk of churning (23.50%) compared to those on a one-year contract (0.88%) and two-year contract (2.36%). This is to be expected as customers on a month-to-month contract are not tied down to a long-term contract and can easily switch to another provider which is not a good sign for the telco company.

Tenure

```
fig, (ax1, ax2) = plt.subplots(nrows=1,
                               ncols=2,
                               figsize=(12, 6))

sns.histplot(x="tenure", hue="Churn", data=df, multiple="stack",
             kde=True, ax=ax1)
sns.boxplot(x="tenure", y="Churn", data=df, hue="Churn",
            palette="Paired", ax=ax2);
```



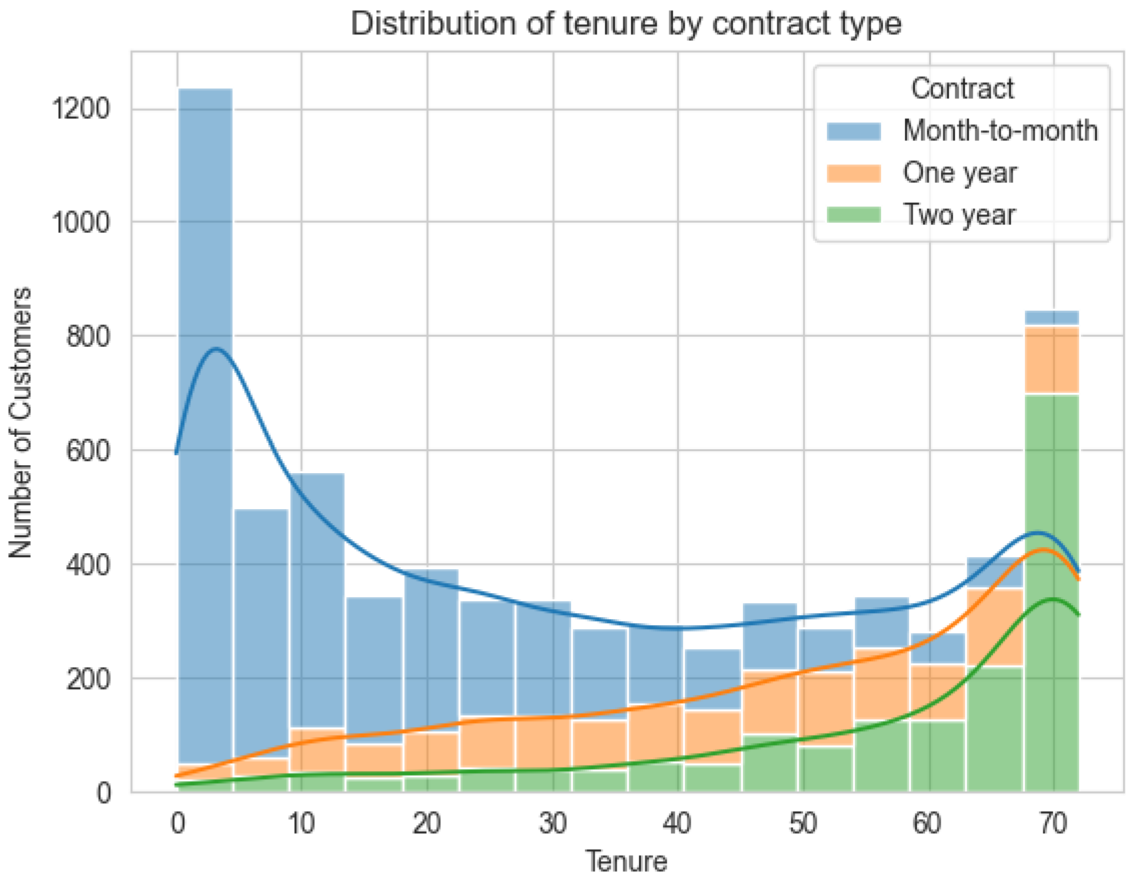
From the box plot we can see on average customers who churned had a lower overall tenure with the telco (2-30 months) compared to those who didn't churn (15-60months). Despite the overall trend there are a few customers who churned after being with the telco for approximately 70+ months.

Looking at the histogram above, we can see that the longer a customer stayed with the telco company, they were less likely to churn. This is to be expected as the longer a customer stays with a company, the more likely they won't churn.

Understanding the factors that made the customers churn after being with the telco for so long could be very beneficial for the company as they can try to improve their services to reduce the number of customers who churn after being with them for so long.

Contract Type & Tenure

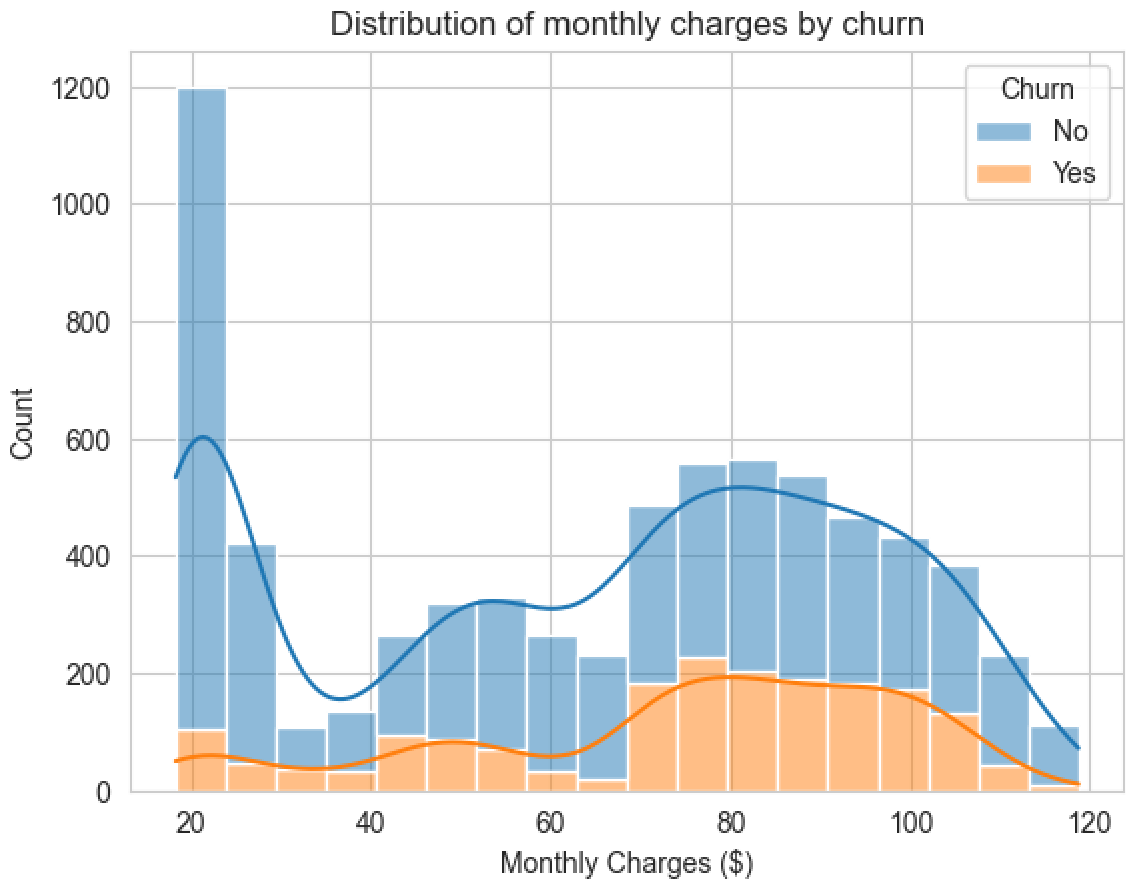
```
sns.histplot(x="tenure", hue="Contract", data=df, multiple="stack",
             kde=True)
plt.title("Distribution of tenure by contract type")
plt.xlabel("Tenure")
plt.ylabel("Number of Customers");
```



Looking at the distribution above we can see that the longer the customers tenure with the telco, they are more likely to be on a two-year contract compared to a one-year or month-to-month contract. This is to be expected as customers who have been with the telco for a long time are more likely to be loyal and pick a long-term contract that may offer them a discount or other benefits.

Monthly Charges

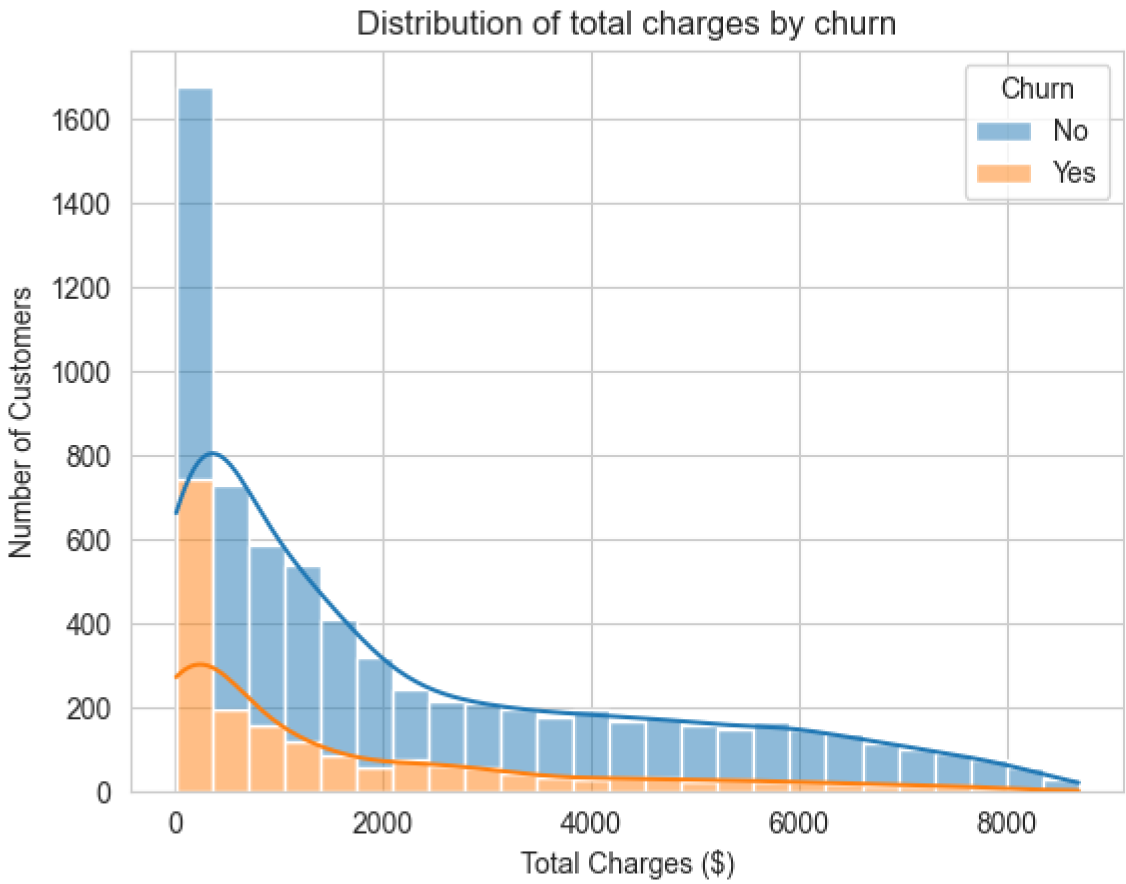
```
sns.histplot(x="MonthlyCharges", hue="Churn", data=df, multiple="stack",
             kde=True)
plt.title("Distribution of monthly charges by churn")
plt.xlabel("Monthly Charges ($)");
```



From the above distribution we can see the number of customers who churned increased between 70-100 dollars. This could be due to the fact that customers who are paying more are more likely to churn as they may be able to get a better deal from another provider or get cash strapped and not be able to afford the service anymore.

Total Charges

```
sns.histplot(x="TotalCharges", hue="Churn", data=df, multiple="stack",
             kde=True)
plt.title("Distribution of total charges by churn")
plt.xlabel("Total Charges ($)")
plt.ylabel("Number of Customers");
```



From the above distribution we can see that the number of customers who churned decreased as the total charges increased. This is to be expected as the higher the total charges, fewer customers will be able to afford as well as the ones who may churn may not want to pay more and more for the service.

3. Data Preparation

In this section we will prepare the data for modelling. This will include:

> - Selecting features
> - Encoding categorical variables
> - Dropping unnecessary columns
> - Correlation analysis

```
df1 = df.copy()
df1.head()
```

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

Selecting/ Dropping Features

We will drop `customerID` as it is a unique identifier for each customer, in addition we will drop `gender` as it is not a useful feature for modelling.

```
# Dropping customerID column
df1.drop(["customerID","gender", "PaymentMethod"], axis=1, inplace=True)
df1.head()
```

	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	No	Yes	No	1	No	No phone service	
1	No	No	No	34	Yes	No	
2	No	No	No	2	Yes	No	
3	No	No	No	45	No	No phone service	
4	No	No	No	2	Yes	No	

Based of [IBM Telco Data (additional)]() we will drop columns that the telco doesn't charge its customers it is not a useful feature for modelling.

```
free_to_use = ["StreamingTV", "StreamingMovies"]
df1.drop(free_to_use, axis=1, inplace=True)
df1.head()
```

	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	No	Yes	No	1	No	No phone service	
1	No	No	No	34	Yes	No	
2	No	No	No	2	Yes	No	
3	No	No	No	45	No	No phone service	
4	No	No	No	2	Yes	No	

Dropping missing rows

```
df1.isna().sum()
```

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

```
df1.dropna(inplace=True)
df1.isna().sum()
```

```
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
Contract            0
PaperlessBilling    0
MonthlyCharges      0
TotalCharges        0
```

```
Churn               0
dtype: int64
```

We decided to drop the missing rows as there were only 11 rows with missing values which is a very small number compared to the total number of rows in the dataset. In addition, we can see that the missing values are in the `TotalCharges` column which is a numerical column. As the number of missing values is very small, we can drop these rows without affecting the distribution of the data.

Encoding Categorical Variables

```
# Selecting categorical columns
cat_cols = df1.select_dtypes(include="object").columns.tolist()
cat_cols
```

```
['SeniorCitizen',
 'Partner',
 'Dependents',
 'PhoneService',
 'MultipleLines',
 'InternetService',
 'OnlineSecurity',
 'OnlineBackup',
 'DeviceProtection',
 'TechSupport',
 'Contract',
 'PaperlessBilling',
 'Churn']
```

```
# Encoding categorical columns
label_encoder = LabelEncoder()

for col in cat_cols:
    df1[col] = label_encoder.fit_transform(df1[col])

df1.head()
```

	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	0	1	0	1	0	1	
1	0	0	0	34	1	0	
2	0	0	0	2	1	0	
3	0	0	0	45	0	1	
4	0	0	0	2	1	0	

```
df1["Contract"].value_counts()
```

```
Contract
0    3875
2    1685
1    1472
Name: count, dtype: int64
```

```
df["Contract"].value_counts()
```

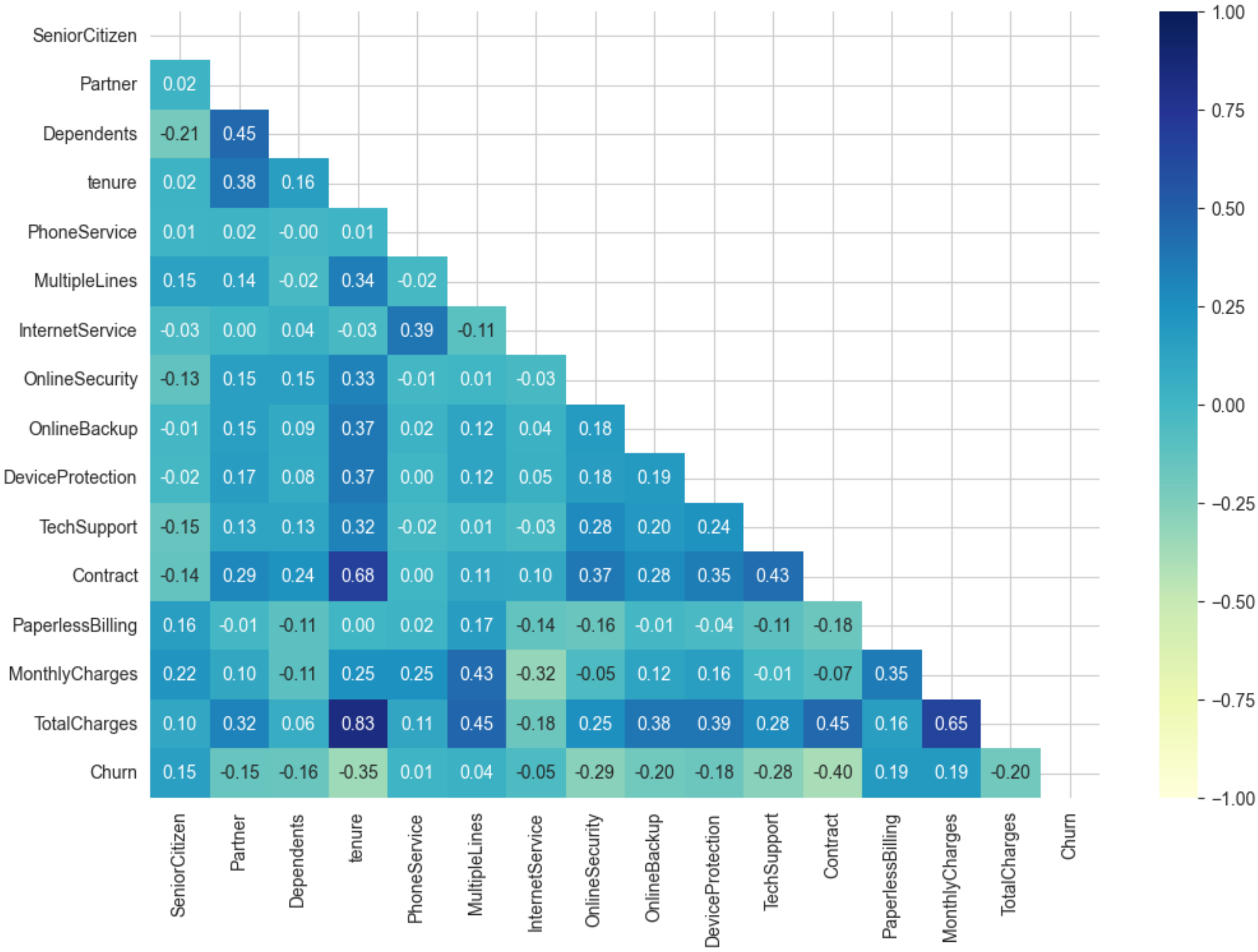
```
Contract
Month-to-month    3875
Two year          1695
One year          1473
Name: count, dtype: int64
```

From the above 3 code cells we can see that the features within our dataframe have been encoded correctly. We can see that the `Contract` column has been encoded as follows:

> - Month-to-month = 0
> - One year = 1
> - Two year = 2

Correlation Analysis

```
# Correlation matrix
corr = df1.corr()

# Plotting heatmap
plt.figure(figsize=(12,8))
mask = np.triu(np.ones_like(corr))
sns.heatmap(corr, annot=True,
            cmap="YlGnBu",
            mask=mask,
            fmt=".2f",
            vmin=-1,
            vmax=1);
```



From the above correlation matrix we can see that there are no strong correlations between the features and the target variable. Based of the heatmap we will remove `PhoneService`, `MultipleLines` and `InternetService` as they have a correlation of 0.01, 0.04 and -0.05 respectively which is very low and may not add any useful insights for modelling.

```
# Dropping addditional features
df1.drop(["PhoneService", "MultipleLines", "InternetService"], axis=1, inplace=Tr
df1.head()
```

	SeniorCitizen	Partner	Dependents	tenure	OnlineSecurity	OnlineBackup	De
0	0	1	0	1	0	2	
1	0	0	0	34	2	0	
2	0	0	0	2	2	2	
3	0	0	0	45	2	0	
4	0	0	0	2	0	0	

4. Modelling

The goal for this coursework project is to build a model that can identify customers who are at risk of churning based on the features we have in our dataset. The `churn` column is our target variable and is a binary variable of "Yes" or "No" values. As what we are trying to predict is a binary model and not continuous values e.g. a number, we will use a classification model.

In this section we will build a model that will predict whether a customer will churn or not. We will use the following models and compare their performance:

> - KNN Classifier
> - Logistic Regression
> - Random Forest Classifier

```
df2 = df1.copy()

# Splitting data into features and target
X = df2.drop("Churn", axis=1)
y = df2["Churn"]

X.shape, y.shape
```

```
((7032, 12), (7032,))
```

```
# Splitting data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.1,
                                                    stratify=y,
                                                    random_state=42)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((6328, 12), (704, 12), (6328,), (704,))
```

```
# Split train data into train and validation sets
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
                                                   test_size=0.2,
                                                   stratify=y_train,
                                                   random_state=42)

X_train.shape, X_val.shape, y_train.shape, y_val.shape
```

```
((5062, 12), (1266, 12), (5062,), (1266,))
```

We decided to specify stratify as the target variable `Churn` is imbalanced. This will ensure that the train, validation and test sets have the same proportion of churned and non-churned customers. This will help us avoid any class imbalance issues when modelling.

We split the data into 3 sets as follows:

> - Train set: 70% of the data
> - Validation set: 20% of the data
> - Test set: 10% of the data

This is because we want the train data for training the model, the validation data for tuning the model and the test data for evaluating the model. We will use the validation data to tune the hyperparameters of the model and the test data to evaluate the model.

```
# Weight to deal with imbalanced dataset
weightage = dict(1/df2["Churn"].value_counts())
weightage
```

```
{0: 0.0001936858415649816, 1: 0.0005350454788657035}
```

Double-click (or enter) to edit

KNN Classifier

We chose KNN classifier as it is a simple model that can be used for classification problems. In addition, it is a non-parametric model which means it doesn't make any assumptions about the data.

```
# Build KNN Model
knn = KNeighborsClassifier()

# Fit model to train data
knn.fit(X_train, y_train)

# Make predictions on validation data
knn_base = knn.score(X_val, y_val)
knn_base
```

```
0.7614533965244866
```

The KNN model has an accuracy of 0.75 on the validation data. This is a good start but we will need to tune the hyperparameters to improve the model.

KNN Hyperparameter Tuning

```
np.random.seed(1234)
knn_train_scores = []
knn_val_scores = []

# Create a list of different values for n_neighbors
neighbors = range(1, 21) # 1 to 20

# Loop through different neighbors values
for i in neighbors:
    knn.set_params(n_neighbors = i) # set neighbors value

    # Fit the algorithm
    knn.fit(X_train, y_train)

    # Update the  scores
    knn_train_scores.append(knn.score(X_train, y_train))
    knn_val_scores.append(knn.score(X_val, y_val))
```

```
knn_train_scores, knn_val_scores
```

```
([0.9964440932437771,
  0.8690241011457922,
  0.8656657447649151,
  0.8374160410904781,
  0.8332674832082181,
  0.8251679178190439,
  0.8194389569340181,
  0.8208218095614381,
  0.8192414065586725,
  0.8212169103121296,
  0.818846305807981,
  0.8176610035559068,
  0.816080600553141,
  0.8127222441722639,
  0.8109442907941525,
```

```
        0.8069932832872383,
        0.8073883840379297,
        0.8071908336625839,
        0.8052153299091268,
        0.8064006321612011],
       [0.7124802527646129,
        0.7456556082148499,
        0.7424960505529226,
        0.7701421800947867,
        0.7614533965244866,
        0.7709320695102686,
        0.7669826224328594,
        0.7725118483412322,
        0.7756714060031595,
        0.7748815165876777,
        0.7819905213270142,
        0.7772511848341233,
        0.778041074249605,
        0.7740916271721959,
        0.7772511848341233,
        0.7756714060031595,
        0.7812006319115324,
        0.7725118483412322,
        0.7717219589257504,
        0.7717219589257504])
```

```
# Plotting the train and validation scores
plt.plot(neighbors, knn_train_scores, label="Train score")
plt.plot(neighbors, knn_val_scores, label="Validation score")
plt.xticks(np.arange(1, 21, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")
plt.legend()

print(f"Maximum KNN score on the test data: {max(knn_val_scores)*100:.2f}%")
knn_tuned = max(knn_val_scores)
```

```
Maximum KNN score on the test data: 78.20%
```