Customer Churn Prediction - Telco

1.0 Business Understanding

1.1 Introduction

Customer churn is a significant problem in the telecom industry as it results in reduced profit margin and negatively impacting long-term sustainability. Churn, which refers to customers discontinuing their service and moving to a competitor, can be driven by various factors such as charges, customer service quality, network coverage, and the competitiveness of offerings. The implications of high churn rates are multifaceted:

- Reduced Profit Margin: Acquiring new customers often costs more than retaining existing ones due to marketing expenses, promotional offers, and the operational costs of setting up new accounts. When customers leave, the company not only loses the revenue these customers would have generated but also the investment made in acquiring them.
- Investment Recovery: Telecommunications companies make significant upfront investments in infrastructure and customer acquisition. Customer longevity is crucial for recovering these investments. High churn rates shorten the average customer lifespan, jeopardizing the return on these investments.
- Brand Reputation: High churn rates can signal dissatisfaction, potentially damaging the company's reputation. This perception can make it more challenging to attract new customers and retain existing ones.
- Operational Efficiency: High churn rates can lead to inefficiencies in resource allocation and operations. Companies may find themselves in a constant cycle of trying to replace lost customers, diverting resources from improving services and innovating.

In the rapidly evolving commercial landscape, organizations continuously strive to carve out a competitive edge—profit maximization and customer loyalty being the twin pillars of sustainable growth. Advanced analytics and machine learning now stand at the forefront of this quest, transforming raw data into a strategic asset. Among these technologies, churn analysis classification models exemplify a critical tool in the modern business arsenal, offering not just insights but actionable foresight.

Classification in machine learning and statistics entails a supervised learning approach where the computer program learns from provided data to make new observations or classifications. The primary objective is to determine the class or category into which new data points will fall. In this project, an elaborate analysis will be conducted to train at least seven models for predicting customer churn in a telecom company. This analysis will adhere to the **CRISP-DM framework**, ensuring a structured and systematic approach to model development and evaluation.

In conclusion, as companies navigate the complexities of the modern market, the use of machine learning in churn analysis emerges not just as a technical enhancement, but as a fundamental component of a robust strategic framework aimed at nurturing customer loyalty and driving financial performance. The forward-thinking enterprises that can best harness these capabilities will likely lead the pack in realizing the twin goals of enhanced profitability and sustained customer engagement.

1.2 Project Objective

The primary objective of this project is to develop a classification model for churn analysis to aid in customer retention efforts. Churn analysis focuses on predicting whether customers are likely to leave or continue their relationship with the company. By identifying customers at risk of churning, the company can take proactive measures to retain them, thus increasing revenue and profit margins.

1.3 Data Description

The project will utilize historical data encompassing various customer attributes, transactional details, and behavioral patterns. These may include demographic information, purchase history, engagement metrics, customer service interactions, and any other relevant data points. The dataset will be sufficiently large and diverse to capture the complexities of customer behavior across different segments.

1.4 Methodology

The project will employ a supervised learning approach, specifically classification algorithms, to train predictive models. These models will learn from past instances of churn and non-churn events to classify new customers accordingly. Various classification algorithms such as logistic regression, decision trees, random forests, and gradient boosting will be explored to identify the most effective model for the given dataset.

1.5 Key Deliverables

1. Churn Prediction Model: A robust machine learning model capable of accurately predicting customer churn based on input features.
2. Feature Importance Analysis: Identification of the most influential factors driving churn, providing actionable insights for targeted retention strategies.
3. Model Evaluation: Rigorous evaluation of model performance using appropriate metrics such as accuracy, precision, recall, and F1-score. The model will be validated using techniques like cross-validation and holdout validation to ensure generalizability.
4. Deployment Strategy: Recommendations for integrating the churn prediction model into the company's existing systems or workflows for real-time monitoring and intervention.

1.6 Success metrics

- `Good:` accurately predicting churn at least 75% measured with the harmonic f1-score metric.
- `Excellent:` accurately predicting churn at least 80%.

1.7 Hypothesis

Hypothesis 1

`Null Hypothesis (Ho):` There is no significant difference in churn rates between customers with shorter and longer tenure.

`Alternative Hypothesis (Ha):` There is a significant difference in churn rates between customers with shorter and longer tenure.

Hypothesis 2

`Null Hypothesis (Ho):` There is no significant difference in churn rates between customers with higher and lower monthly charge.

`Alternative Hypothesis (Ha):` There is a significant difference in churn rates between customers with higher and lower monthly charge.

1.8 Business Questions

1. What is the average tenure of customers who churned compared to those who stayed?
2. Do customers with partners or dependents have a lower churn rate?
3. How does the presence of multiple lines affect customer churn?
4. Is there a correlation between the contract term (Contract) and customer churn?
5. What are the common payment methods (Payment Method) among customers who churned?
6. How does the availability of tech-related services (e.g., OnlineSecurity, TechSupport) impact churn rates?
7. What percentage of customers who churned had streaming services (StreamingTV, StreamingMovies)?
8. Is there a difference in churn rates between senior citizens and non-senior citizens?
9. How does the total amount charged to customers (TotalCharges) correlate with churn behavior?
10. How does the contract affect churn rates?

NB:

This notebook embrases plotly's philosophy for visualizations and implicitly carries the limitation of no native in power BI and no renderings on github. Kindly, run the notebook to see the visualizations. Screenshots and PDF is also attached for convenience.

2.0 Data Understanding 🔍

2.1 Prerequisites

- Doing necessary installations

In [1]:
```
# Install necessary packages in quiet mode

%pip install --quiet pandas matplotlib seaborn plotly pyodbc python-dotenv
scikit-learn imbalanced-learn catboost lightgbm xgboost
```

```
Note: you may need to restart the kernel to use updated packages.
```

- Import needed packages

In [2]:
```
# Environmental variables
from dotenv import dotenv_values

# Microsoft Open Database Connectivity (ODBC) library
import pyodbc

# Data handling
import numpy as np
import pandas as pd

# Regular expression
import re

# Type hinting
from typing import Callable, Dict, ValuesView, List, Any, Union

# Get signature of a function
import inspect

# Visualization
import plotly.express as px
from plotly.subplots import make_subplots
import plotly.graph_objects as go

# Statistical tests
from scipy.stats import mannwhitneyu, fisher_exact, chi2_contingency

# PCA
from sklearn.decomposition import PCA

# Feature Processing
from imblearn.over_sampling import SMOTE # Balance class distribution
from sklearn.impute import SimpleImputer
from sklearn.feature_selection import mutual_info_classif, SelectKBest, chi
2  # Univariate Selection using KBest
from sklearn.model_selection import train_test_split, GridSearchCV, Stratif
iedKFold
from sklearn.preprocessing import RobustScaler, LabelEncoder, OneHotEncode
r, FunctionTransformer
from sklearn.pipeline import Pipeline
from imblearn.pipeline import Pipeline as imPipeline
from sklearn.compose import ColumnTransformer

# Modelling
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from catboost import CatBoostClassifier
import lightgbm as lgb
from xgboost import XGBClassifier
from sklearn import svm
from sklearn.neighbors import KNeighborsClassifier

# Save model
import joblib
import json
from sklearn.base import BaseEstimator
import neptune

# Evaluation - Cross Validation & Hyperparameters Fine-tuning
```

```python
from sklearn.metrics import f1_score, confusion_matrix, classification_repo
rt, roc_curve, auc

# Set pandas to display all columns
pd.set_option("display.max_columns", None)

# Suppress the scientific notation
pd.set_option("display.float_format", lambda x: '%.2f' % x)

# Disable warnings
import warnings
warnings.filterwarnings('ignore')

# Other packages
import os

print("🛬 Imported all packages.", "Warnings hidden. 👻")
```

🛬 Imported all packages. Warnings hidden. 👻

2.2 Data reading

In [3]:
```python
BASE_DIR = '../'
ENV_FILE = os.path.join(BASE_DIR, '.env')
SECOND_FILE = os.path.join(BASE_DIR, 'data/untouched/LP2_Telco-churn-second
-2000.csv')
TEST_FILE = os.path.join(BASE_DIR, 'data/untouched/Telco-churn-last-2000.xl
sx')
TRAIN_FILE = os.path.join(BASE_DIR, 'data/untouched/df_train.csv')
TRAIN_FILE_CLEANED = os.path.join(BASE_DIR, 'data/cleaned/df_train.csv')
SAVE_MODELS = os.path.join(BASE_DIR, 'models/')
```

2.2.1 First Data Set

The first data was from a database management system, that is MIRCORSOFT SQL SERVER. Connection was made to the database using an Open Database Connectivity standard library, pyodbc.
The database contains the first 3000 records of the dataset

In [4]:
```python
# Load environment variables from .env file into a dictionary
environment_variables = dotenv_values(ENV_FILE)

# Get the values for the credentials you set in the '.env' file
database = environment_variables.get("DATABASE")
table = environment_variables.get("TABLE")
server = environment_variables.get("SERVER")
username = environment_variables.get("USERNAME")
password = environment_variables.get("PASSWORD")
neptune_api_token = environment_variables.get("NEPTUNE_API_TOKEN")

# Create a connection string# Create a connection string
connection_string = f"DRIVER={{SQL Server}};SERVER={server};DATABASE={datab
ase};UID={username};PWD={password};MARS_Connection=yes;MinProtocolVersion=T
LSv1.2;"
```

In [5]:
```python
# Use the connect method of the pyodbc library and pass in the connection s
tring.
# This will connect to the server and might take a few seconds to be comple
te.
# Check your internet connection if it takes more time than necessary
connection = pyodbc.connect(connection_string)
```

In [6]:
```python
# Select the all rows from database table
query = f"SELECT * FROM {table}"

first_dataset = pd.read_sql(query, connection)
```

In [7]:
```python
first_dataset.head()
```

Out[7]:

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

In [8]:
```
first_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        3000 non-null   object 
 1   gender            3000 non-null   object 
 2   SeniorCitizen     3000 non-null   bool   
 3   Partner           3000 non-null   bool   
 4   Dependents        3000 non-null   bool   
 5   tenure            3000 non-null   int64  
 6   PhoneService      3000 non-null   bool   
 7   MultipleLines     2731 non-null   object 
 8   InternetService   3000 non-null   object 
 9   OnlineSecurity    2349 non-null   object 
 10  OnlineBackup      2349 non-null   object 
 11  DeviceProtection  2349 non-null   object 
 12  TechSupport       2349 non-null   object 
 13  StreamingTV       2349 non-null   object 
 14  StreamingMovies   2349 non-null   object 
 15  Contract          3000 non-null   object 
 16  PaperlessBilling  3000 non-null   bool   
 17  PaymentMethod     3000 non-null   object 
 18  MonthlyCharges    3000 non-null   float64
 19  TotalCharges      2995 non-null   float64
 20  Churn             2999 non-null   object 
dtypes: bool(5), float64(2), int64(1), object(13)
memory usage: 389.8+ KB
```

In [9]:
```
first_dataset.isna().sum()
```

Out[9]:
```
customerID            0
gender                0
SeniorCitizen         0
Partner               0
Dependents            0
tenure                0
PhoneService          0
MultipleLines       269
InternetService       0
OnlineSecurity      651
OnlineBackup        651
DeviceProtection    651
TechSupport         651
StreamingTV         651
StreamingMovies     651
Contract              0
PaperlessBilling      0
PaymentMethod         0
MonthlyCharges        0
TotalCharges          5
Churn                 1
dtype: int64
```

In [10]:
```
first_dataset.shape
```

Out[10]:
```
(3000, 21)
```

2.2.2 Second Data Set

- The second part of the data is hosted on this [GitHub Repository (https://github.com/Azubi-Africa/Career_Accelerator_LP2-Classifcation/tree/main)](https://github.com/Azubi-Africa/Career_Accelerator_LP2-Classifcation/tree/main) in a file called [LP2_Telco-churn-second-2000.csv (https://raw.githubusercontent.com/Azubi-Africa/Career_Accelerator_LP2-Classifcation/main/LP2_Telco-churn-second-2000.csv)](https://raw.githubusercontent.com/Azubi-Africa/Career_Accelerator_LP2-Classifcation/main/LP2_Telco-churn-second-2000.csv).

In [11]:
```
# Load dataset
url = 'https://github.com/D0nG4667/telco_customer_churn_prediction/blob/mai
n/data/untouched/LP2_Telco-churn-second-2000.csv'

# Read the csv file
try:
    second_dataset = pd.read_csv(url)
except Exception as e:
    second_dataset = pd.read_csv(SECOND_FILE)
```

In [12]:
```
second_dataset.head()
```

Out[12]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLin
0	5600-PDUJF	Male	0	No	No	6	Yes	N
1	8292-TYSPY	Male	0	No	No	19	Yes	N
2	0567-XRHCU	Female	0	Yes	Yes	69	No	No phoi servi
3	1867-BDVFH	Male	0	Yes	Yes	11	Yes	Y
4	2067-QYTCF	Female	0	Yes	No	64	Yes	Y

In [13]:
```
second_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2043 entries, 0 to 2042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        2043 non-null   object 
 1   gender            2043 non-null   object 
 2   SeniorCitizen     2043 non-null   int64  
 3   Partner           2043 non-null   object 
 4   Dependents        2043 non-null   object 
 5   tenure            2043 non-null   int64  
 6   PhoneService      2043 non-null   object 
 7   MultipleLines     2043 non-null   object 
 8   InternetService   2043 non-null   object 
 9   OnlineSecurity    2043 non-null   object 
 10  OnlineBackup      2043 non-null   object 
 11  DeviceProtection  2043 non-null   object 
 12  TechSupport       2043 non-null   object 
 13  StreamingTV       2043 non-null   object 
 14  StreamingMovies   2043 non-null   object 
 15  Contract          2043 non-null   object 
 16  PaperlessBilling  2043 non-null   object 
 17  PaymentMethod     2043 non-null   object 
 18  MonthlyCharges    2043 non-null   float64
 19  TotalCharges      2043 non-null   object 
 20  Churn             2043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 335.3+ KB
```

In [14]:
```
second_dataset.shape
```

Out[14]: (2043, 21)

2.2.3 Testing Data Set

- The final 2000 records of the data set needed for this project can be found in this OneDrive (https://azubiafrica-my.sharepoint.com/:f:/g/personal/teachops_azubiafrica_org/EnSl-bZ6lyNJsy6nLuOVcigB28t8r9YFEEquv_CJMgkm9w?e=kxD5m1).
- The file is named Telco-churn-last-2000.xlsx (https://azubiafrica-my.sharepoint.com/:x:/r/personal/teachops_azubiafrica_org/_layouts/15/Doc.aspx?sourcedoc=%7B4BFB3536-A4A1-43C9-8F4F-79741606114C%7D&file=Telco-churn-last-2000.xlsx&action=default&mobileredirect=true).
- This is the test dataset. This Dataset will be used for testing the accuracy of your models.

In [15]:
```
url = 'https://github.com/D0nG4667/telco_customer_churn_prediction/raw/main/data/untouched/Telco-churn-last-2000.xlsx'

# Read the excel file
try:
    df_test = pd.read_excel(url)
except Exception as e:
    df_test = pd.read_excel(TEST_FILE)
```

In [16]:
```
df_test.head()
```

Out[16]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLin
0	7613-LLQFO	Male	0	No	No	12	Yes	Y
1	4568-TTZRT	Male	0	No	No	9	Yes	N
2	9513-DXHDA	Male	0	No	No	27	Yes	N
3	2640-PMGFL	Male	0	No	Yes	27	Yes	Y
4	3801-HMYNL	Male	0	Yes	Yes	1	Yes	N

In [17]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        2000 non-null   object 
 1   gender            2000 non-null   object 
 2   SeniorCitizen     2000 non-null   int64  
 3   Partner           2000 non-null   object 
 4   Dependents        2000 non-null   object 
 5   tenure            2000 non-null   int64  
 6   PhoneService      2000 non-null   object 
 7   MultipleLines     2000 non-null   object 
 8   InternetService   2000 non-null   object 
 9   OnlineSecurity    2000 non-null   object 
 10  OnlineBackup      2000 non-null   object 
 11  DeviceProtection  2000 non-null   object 
 12  TechSupport       2000 non-null   object 
 13  StreamingTV       2000 non-null   object 
 14  StreamingMovies   2000 non-null   object 
 15  Contract          2000 non-null   object 
 16  PaperlessBilling  2000 non-null   object 
 17  PaymentMethod     2000 non-null   object 
 18  MonthlyCharges    2000 non-null   float64
 19  TotalCharges      2000 non-null   object 
dtypes: float64(1), int64(2), object(17)
memory usage: 312.6+ KB
```

In [18]:
```
df_test.shape
```

Out[18]: (2000, 20)

2.2.4 Train Data Set

- Create the train concatenated dataset
- Concatenate first_dataset and second_dataset

In [19]:
```
# Checking if the first and second Dataset have the same column names for e
asy concatenation

if all(first_dataset.columns == second_dataset.columns):
    print("The DataFrames have the same column names.")
else:
    print("The DataFrames do not have the same column names.")
```

```
The DataFrames have the same column names.
```

In [20]:
```
# Train Data set
df_train = pd.concat([first_dataset, second_dataset], ignore_index=True)
```

2.2.5 Data Dictionary

In [21]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        5043 non-null   object 
 1   gender            5043 non-null   object 
 2   SeniorCitizen     5043 non-null   int64  
 3   Partner           5043 non-null   object 
 4   Dependents        5043 non-null   object 
 5   tenure            5043 non-null   int64  
 6   PhoneService      5043 non-null   object 
 7   MultipleLines     4774 non-null   object 
 8   InternetService   5043 non-null   object 
 9   OnlineSecurity    4392 non-null   object 
 10  OnlineBackup      4392 non-null   object 
 11  DeviceProtection  4392 non-null   object 
 12  TechSupport       4392 non-null   object 
 13  StreamingTV       4392 non-null   object 
 14  StreamingMovies   4392 non-null   object 
 15  Contract          5043 non-null   object 
 16  PaperlessBilling  5043 non-null   object 
 17  PaymentMethod     5043 non-null   object 
 18  MonthlyCharges    5043 non-null   float64
 19  TotalCharges      5038 non-null   object 
 20  Churn             5042 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 827.5+ KB
```

The following describes the columns present in the dataset for this project.

- **Gender**: Whether the customer is a male or a female
- **SeniorCitizen**: Whether a customer is a senior citizen or not
- **Partner**: Whether the customer has a partner or not (Yes, No)
- **Dependents**: Whether the customer has dependents or not (Yes, No)
- **Tenure**: Number of months the customer has stayed with the company
- **Phone Service**: Whether the customer has a phone service or not (Yes, No)
- **MultipleLines**: Whether the customer has multiple lines or not
- **InternetService**: Customer's internet service provider (DSL, Fiber Optic, No)
- **OnlineSecurity**: Whether the customer has online security or not (Yes, No, No Internet)
- **OnlineBackup**: Whether the customer has online backup or not (Yes, No, No Internet)
- **DeviceProtection**: Whether the customer has device protection or not (Yes, No, No internet service)
- **TechSupport**: Whether the customer has tech support or not (Yes, No, No internet)
- **StreamingTV**: Whether the customer has streaming TV or not (Yes, No, No internet service)
- **StreamingMovies**: Whether the customer has streaming movies or not (Yes, No, No Internet service)
- **Contract**: The contract term of the customer (Month-to-Month, One year, Two year)
- **PaperlessBilling**: Whether the customer has paperless billing or not (Yes, No)
- **Payment Method**: The customer's payment method (Electronic check, mailed check, Bank transfer(automatic), Credit card(automatic))
- **MonthlyCharges**: The amount charged to the customer monthly
- **TotalCharges**: The total amount charged to the customer
- **Churn**: Whether the customer churned or not (Yes or No)

2.3 Verify Data Quality

In [22]:
```
# Save the DataFrame to a CSV file
try:
    df_train.to_csv(TRAIN_FILE, index=False)
except Exception as e:
    print(e)
```

In [23]:
```
df_train.head()
```

Out[23]:

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

2.3.1 Missing values in columns

In [24]:
```
df_train.isna().sum()
```

Out[24]:
```
customerID           0
gender               0
SeniorCitizen        0
Partner              0
Dependents           0
tenure               0
PhoneService         0
MultipleLines      269
InternetService      0
OnlineSecurity     651
OnlineBackup       651
DeviceProtection   651
TechSupport        651
StreamingTV        651
StreamingMovies    651
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges         5
Churn                1
dtype: int64
```

Key Findings:

1. **Missing Data:**
   - The dataset contains missing values in several columns: `MultipleLines` , `OnlineSecurity` , `OnlineBackup` , `DeviceProtection` , `TechSupport` , `StreamingTV` , `StreamingMovies` , `TotalCharges` , and `Churn` .
     - `MultipleLines` : 269 missing values
     - `OnlineSecurity` , `OnlineBackup` , `DeviceProtection` , `TechSupport` , `StreamingTV` , `StreamingMovies` : 651 missing values each
     - `TotalCharges` : 5 missing values
     - `Churn` : 1 missing value
   - Addressing these missing values is crucial to ensure the accuracy and reliability of subsequent analyses.
2. **Service Subscriptions:**
   - A significant number of customers have missing values for additional services such as `MultipleLines` , `OnlineSecurity` , `OnlineBackup` , `DeviceProtection` , `TechSupport` , `StreamingTV` , and `StreamingMovies` . This suggests potential issues with data collection or customer preferences.
   - Further investigation into the reasons for missing data in these columns is recommended to understand if it is due to customers not opting for these services or data recording errors.
3. **Churn Rate:**
   - The `Churn` column contains one missing value, indicating that one customer's churn status is not recorded. Accurate recording of churn status is essential for evaluating customer retention strategies and predicting future churn.
4. **Numerical features - Tenure, Monthly Charges and TotalCharges:**
   - `Tenure` and `MonthlyCharges` exhibit no missing values, indicating complete data for these important variables.
   - However, there are five missing values in the `TotalCharges` column, which should be addressed to maintain data integrity.
   - These numerical features are not on the same scale.

Recommendations:

1. **Data Imputation and Scaling:**
   - Employ appropriate techniques such as mean or median or mode imputation to address missing values in the dataset, particularly in columns related to service subscriptions (`MultipleLines` , `OnlineSecurity` , etc.) and churn status (`Churn`). Condsider dropping rows containing missing values Churn value.
   - Validate imputation methods to ensure they do not introduce bias or distort the underlying patterns in the data.
   - Scale the numerical feautures using Robust Scaling so that outliers in `TotalCharges` do not unduly influence the scaling process.
2. **Data Quality Assurance:**
   - Conduct a thorough review of data collection processes to identify and rectify issues leading to missing values.

- Implement robust mechanisms for recording and validating customer data to minimize future instances of missing or erroneous data.

3. **Churn Analysis:**

   - Analyze churn patterns and factors influencing churn, such as tenure, service subscriptions, and billing information, to develop targeted retention strategies.
   - Utilize predictive modeling techniques to forecast future churn and proactively implement measures to mitigate it.

4. **Customer Segmentation:**

   - Segment customers based on demographic characteristics, service subscriptions, and tenure to tailor marketing efforts and service offerings to specific customer needs and preferences.
   - Personalize communication and incentives to enhance customer engagement and loyalty.

Assumptions:

1. **`MultipleLines`** Implies multiple phone services
2. No **`InternetService`** implies No `OnlineSecurity` , `OnlineBackup` , `DeviceProtection` , `TechSupport` , `StreamingTV` , and `StreamingMovies`

2.3.2 Train Dataset Info

In [25]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        5043 non-null   object
 1   gender            5043 non-null   object
 2   SeniorCitizen     5043 non-null   int64
 3   Partner           5043 non-null   object
 4   Dependents        5043 non-null   object
 5   tenure            5043 non-null   int64
 6   PhoneService      5043 non-null   object
 7   MultipleLines     4774 non-null   object
 8   InternetService   5043 non-null   object
 9   OnlineSecurity    4392 non-null   object
 10  OnlineBackup      4392 non-null   object
 11  DeviceProtection  4392 non-null   object
 12  TechSupport       4392 non-null   object
 13  StreamingTV       4392 non-null   object
 14  StreamingMovies   4392 non-null   object
 15  Contract          5043 non-null   object
 16  PaperlessBilling  5043 non-null   object
 17  PaymentMethod     5043 non-null   object
 18  MonthlyCharges    5043 non-null   float64
 19  TotalCharges      5038 non-null   object
 20  Churn             5042 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 827.5+ KB
```

Dataset Description:

- **Total Entries:** 5043
- **Data Columns:** 21
- **Data Types:**
  - Object: 18 columns
  - Integer: 2 columns
  - Float: 1 column

Key Observations:

1. **Categorical Variables:**

   - Majority of the columns are categorical, representing customer attributes such as gender, partner status, dependents, phone service, internet service, contract type, paperless billing, payment method, and churn status.

2. **Numerical Variables:**

   - `Tenure` : Represents the duration of the customer's subscription tenure.
   - `MonthlyCharges` : Indicates the monthly charges incurred by the customer.
   - `TotalCharges` : Represents the total charges incurred by the customer. It is noteworthy that this column is currently classified as an object datatype, which may require conversion for accurate numerical analysis.

Recommendations:

1. **Data Cleaning:**

   - Address missing values by employing appropriate imputation techniques tailored to each column's characteristics.
   - Convert the `TotalCharges` column to a numerical datatype (float64) for accurate numerical analysis.

2. **Exploratory Data Analysis (EDA):**

   - Conduct thorough exploratory analysis to understand the distribution of categorical variables, identify trends, and unveil potential relationships between variables.
   - Explore the impact of demographic factors, service subscriptions, and billing information on churn rate to derive actionable insights for retention strategies.

3. **Feature Engineering:**

   - Engineer new features or derive meaningful insights from existing ones to enhance model performance and predictive accuracy.
   - Consider creating aggregate metrics or customer segmentation based on usage patterns or tenure to refine predictive models.

2.3.3 Unique Values Summary

In [26]:
```
def unique_value_summary(df):
    """
    Generate a summary table of unique values for each column in a DataFram
e.

    Parameters:
    - df: pandas DataFrame

    Returns:
    - summary_df: pandas DataFrame containing the summary
    """
    # Initialize a list to store our summaries
    unique_values_summary = []

    # Iterate over each column in the DataFrame
    for column in df.columns:
        unique_values = df[column].unique()  # Get unique values for the co
lumn
        unique_count = len(unique_values)    # Count of unique values

        # Append the summary to our list
        unique_values_summary.append({
            'Column': column,
            'Unique Values Count': unique_count,
            'Unique Values': unique_values
        })

    # Convert the summaries list to a DataFrame for better readability
    summary_df = pd.DataFrame(unique_values_summary)

    return summary_df
```

In [27]:
```
# Set display option for max column width to 100
pd.set_option('display.max_colwidth', 100)

# Check the unique value across columns
unique_value_summary(df_train)
```

Out[27]:

	Column	Unique Values Count	Unique Values
0	customerID	5043	[7590-VHVEG, 5575-GNVDE, 3668-QPYBK, 7795-CFOCW, 9237-HQITU, 9305-CDSKC, 1452-KIOVK, 6713-OKOMC,...
1	gender	2	[Female, Male]
2	SeniorCitizen	2	[0, 1]
3	Partner	4	[True, False, No, Yes]
4	Dependents	4	[False, True, No, Yes]
5	tenure	73	[1, 34, 2, 45, 8, 22, 10, 28, 62, 13, 16, 58, 49, 25, 69, 52, 71, 21, 12, 30, 47, 72, 17, 27, 5,...
6	PhoneService	4	[False, True, Yes, No]
7	MultipleLines	6	[None, False, True, No, No phone service, Yes]
8	InternetService	3	[DSL, Fiber optic, No]
9	OnlineSecurity	6	[False, True, None, No, Yes, No internet service]
10	OnlineBackup	6	[True, False, None, No, Yes, No internet service]
11	DeviceProtection	6	[False, True, None, No, Yes, No internet service]
12	TechSupport	6	[False, True, None, Yes, No, No internet service]
13	StreamingTV	6	[False, True, None, No, Yes, No internet service]
14	StreamingMovies	6	[False, True, None, No, Yes, No internet service]
15	Contract	3	[Month-to-month, One year, Two year]
16	PaperlessBilling	4	[True, False, Yes, No]
17	PaymentMethod	4	[Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic)]
18	MonthlyCharges	2069	[29.850000381469727, 56.95000076293945, 53.849998474121094, 42.29999923706055, 70.69999694824219...
19	TotalCharges	4885	[29.850000381469727, 1889.5, 108.1500015258789, 1840.75, 151.64999389648438, 820.5, 1949.4000244...
20	Churn	5	[False, True, None, No, Yes]

In [28]:
```
# Set display option for max column width back to default 50
pd.set_option('display.max_colwidth', 50)
```

Key Observations:

1. **CustomerID:**
   - There are 5043 unique customer IDs present in the dataset.
   - Values are not relevant
2. **Gender:**
   - Two unique values are observed: "Female" and "Male".
3. **SeniorCitizen:**
   - Two unique values are observed: 0 and 1, representing whether a customer is a senior citizen or not.
4. **Partner:**
   - Four unique values are observed: "True", "False", "No", and "Yes".
5. **Dependents:**
   - Four unique values are observed: "False", "True", "No", and "Yes".
6. **Tenure:**
   - There are 73 unique values observed, representing the duration of customer tenure in months.
7. **PhoneService:**
   - Four unique values are observed: "False", "True", "Yes", and "No".
8. **MultipleLines:**
   - Six unique values are observed, including "None", "False", "True", "No", "No phone service", and "Yes".
9. **InternetService:**
   - Three unique values are observed: "DSL", "Fiber optic", and "No".
10. **OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies:**
    - Each of these columns exhibits six unique values, including "False", "True", "None", "No", "Yes", and "No internet service".
11. **Contract:**
    - Three unique values are observed: "Month-to-month", "One year", and "Two year".
12. **PaperlessBilling:**
    - Four unique values are observed: "True", "False", "Yes", and "No".
13. **PaymentMethod:**
    - Four unique values are observed: "Electronic check", "Mailed check", "Bank transfer (automatic)", and "Credit card (automatic)".
14. **MonthlyCharges:**
    - There are 2069 unique values observed, representing the monthly charges incurred by customers.
15. **TotalCharges:**
    - There are 4885 unique values observed for total charges incurred by customers.
16. **Churn:**
    - Five unique values are observed: "False", "True", "None", "No", and "Yes".

Recommendations:

- Drop the `CustomerID` column.
- The count of unique values tend to be highest in numerical columns.
- Standardize the unique values of categorical columns to allow for consistency by casting to "Yes" or "No" where implied. Therefore, False, 0, "No phone service" and "No internet service" becomes "No", while True and 1 becomes "Yes".
- "None" values are actually missing or null values so replace NULL with pd.NA
- Consider visualization techniques such as histograms, bar plots, or box plots to gain deeper insights into the distribution of categorical and numerical variables.

2.4 Cleaning 🧹

2.4.1 Handle Duplicates

- Check duplicates in train dataset

In [29]:
```
count_duplicates = df_train.duplicated().sum()

print(f'There are {count_duplicates} duplicates in the dataset.')
```

```
There are 0 duplicates in the dataset.
```

- Drop duplicated from train dataset

In [30]:
```
# Drop duplicated from train dataset
if count_duplicates > 0 :
    df_train.drop_duplicates(inplace=True)
```

2.4.2 Standardize Column Names

- Use snake case
  - Insert underscores at the boundary between a lowercase letter followed by an uppercase letter, excluding consecutive capital letters thereby converting a camel case string into snake case.

```
In [31]: # Regular expression to split by capital letters without consecutive capitals:
# (?<!^)(?=[A-Z][a-z]) - Matches boundary between uppercase letter and lowercase letter.
# | - Alternation operator.
# (?<=[a-z])(?=[A-Z]) - Matches boundary between lowercase letter and uppercase letter.

pattern = r'(?<!^)(?=[A-Z][a-z])|(?<=[a-z])(?=[A-Z])'

df_train.columns = [re.sub(pattern, '_', column).lower() for column in df_train.columns] # Train

df_test.columns = [re.sub(pattern, '_', column).lower() for column in df_test.columns] # Test
```

```
In [32]: df_train
```

Out[32]:

	customer_id	gender	senior_citizen	partner	dependents	tenure	phone_service	multip
0	7590-VHVEG	Female	0	True	False	1	False	
1	5575-GNVDE	Male	0	False	False	34	True	
2	3668-QPYBK	Male	0	False	False	2	True	
3	7795-CFOCW	Male	0	False	False	45	False	
4	9237-HQITU	Female	0	False	False	2	True	
...	...	...	...	...	...	...	...	
5038	6840-RESVB	Male	0	Yes	Yes	24	Yes	
5039	2234-XADUH	Female	0	Yes	Yes	72	Yes	
5040	4801-JZAZL	Female	0	Yes	Yes	11	No	N
5041	8361-LTMKD	Male	1	Yes	No	4	Yes	
5042	3186-AJIEK	Male	0	No	No	66	Yes	

5043 rows × 21 columns

2.4.3 Drop `customer_id` column

```
In [33]: try:
    df_train.drop(columns='customer_id', inplace=True)
    df_test.drop(columns='customer_id', inplace=True)
except Exception as e:
    print(e)
```

```
In [34]: df_train.columns
```

```
Out[34]: Index(['gender', 'senior_citizen', 'partner', 'dependents', 'tenure',
       'phone_service', 'multiple_lines', 'internet_service',
       'online_security', 'online_backup', 'device_protection', 'tech_support',
       'streaming_tv', 'streaming_movies', 'contract', 'paperless_billing',
       'payment_method', 'monthly_charges', 'total_charges', 'churn'],
      dtype='object')
```

2.4.4 Fix inconsistent representation of missing values

```
In [35]: df_train.isna().sum()
```

```
Out[35]: gender                0
senior_citizen        0
partner               0
dependents            0
tenure                0
phone_service         0
multiple_lines      269
internet_service      0
online_security     651
online_backup       651
device_protection   651
tech_support        651
streaming_tv        651
streaming_movies    651
contract              0
paperless_billing     0
payment_method        0
monthly_charges       0
total_charges         5
churn                 1
dtype: int64
```

- Replace 'None' string values or NULL with pd.NA NaN element-wise allowing for consistent representation of missing values

```
In [36]: # Function replace None with Pandas NaN
def replace_none(value):
    like_nan = {'none', ''}
    if pd.isnull(value) or (isinstance(value, str) and (value.lower().strip() in like_nan)):
        value = pd.NA

    return value

# Apply the function to all columns
df_train = df_train.applymap(replace_none) # element-wise
```

In [37]:
```
df_train.isna().sum()
```

Out[37]:
```
gender                0
senior_citizen        0
partner               0
dependents            0
tenure                0
phone_service         0
multiple_lines      269
internet_service      0
online_security     651
online_backup       651
device_protection   651
tech_support        651
streaming_tv        651
streaming_movies    651
contract              0
paperless_billing     0
payment_method        0
monthly_charges       0
total_charges         8
churn                 1
dtype: int64
```

- `total_charges` column now has 3 more correctly identified missing values that were initial empty strings.

2.4.5 Fix Datatypes

- Check dataset info

In [38]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 20 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             5043 non-null   object 
 1   senior_citizen     5043 non-null   int64  
 2   partner            5043 non-null   object 
 3   dependents         5043 non-null   object 
 4   tenure             5043 non-null   int64  
 5   phone_service      5043 non-null   object 
 6   multiple_lines     4774 non-null   object 
 7   internet_service   5043 non-null   object 
 8   online_security    4392 non-null   object 
 9   online_backup      4392 non-null   object 
 10  device_protection  4392 non-null   object 
 11  tech_support       4392 non-null   object 
 12  streaming_tv       4392 non-null   object 
 13  streaming_movies   4392 non-null   object 
 14  contract           5043 non-null   object 
 15  paperless_billing  5043 non-null   object 
 16  payment_method     5043 non-null   object 
 17  monthly_charges    5043 non-null   float64
 18  total_charges      5035 non-null   object 
 19  churn              5042 non-null   object 
dtypes: float64(1), int64(2), object(17)
memory usage: 788.1+ KB
```

- Convert the `total_charges` column to a numerical datatype (Float64) for accurate numerical analysis.

In [39]:
```
# The 'total_charges' column datatype should be numerical float handling missing values gracefuly with Float64
df_train['total_charges'] = pd.to_numeric(df_train['total_charges'], errors = 'coerce')

df_test['total_charges'] = pd.to_numeric(df_test['total_charges'], errors = 'coerce')
```

In [40]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 20 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             5043 non-null   object 
 1   senior_citizen     5043 non-null   int64  
 2   partner            5043 non-null   object 
 3   dependents         5043 non-null   object 
 4   tenure             5043 non-null   int64  
 5   phone_service      5043 non-null   object 
 6   multiple_lines     4774 non-null   object 
 7   internet_service   5043 non-null   object 
 8   online_security    4392 non-null   object 
 9   online_backup      4392 non-null   object 
 10  device_protection  4392 non-null   object 
 11  tech_support       4392 non-null   object 
 12  streaming_tv       4392 non-null   object 
 13  streaming_movies   4392 non-null   object 
 14  contract           5043 non-null   object 
 15  paperless_billing  5043 non-null   object 
 16  payment_method     5043 non-null   object 
 17  monthly_charges    5043 non-null   float64
 18  total_charges      5035 non-null   float64
 19  churn              5042 non-null   object 
dtypes: float64(2), int64(2), object(16)
memory usage: 788.1+ KB
```

- Convert the `senior_citizen` column to a string datatype (str).

In [41]:
```
df_train['senior_citizen'] = df_train.senior_citizen.astype(str)
```

- Check the dataset info again

In [42]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 20 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             5043 non-null   object 
 1   senior_citizen     5043 non-null   object 
 2   partner            5043 non-null   object 
 3   dependents         5043 non-null   object 
 4   tenure             5043 non-null   int64  
 5   phone_service      5043 non-null   object 
 6   multiple_lines     4774 non-null   object 
 7   internet_service   5043 non-null   object 
 8   online_security    4392 non-null   object 
 9   online_backup      4392 non-null   object 
 10  device_protection  4392 non-null   object 
 11  tech_support       4392 non-null   object 
 12  streaming_tv       4392 non-null   object 
 13  streaming_movies   4392 non-null   object 
 14  contract           5043 non-null   object 
 15  paperless_billing  5043 non-null   object 
 16  payment_method     5043 non-null   object 
 17  monthly_charges    5043 non-null   float64
 18  total_charges      5035 non-null   float64
 19  churn              5042 non-null   object 
dtypes: float64(2), int64(1), object(17)
memory usage: 788.1+ KB
```

2.4.6 Categorical columns cleaning

- Standardize the unique values of categorical columns to allow for consistency by casting to "Yes" or "No" where implied.
- False, 0, "No phone service" and "No internet service" becomes "No", while True and 1 becomes "Yes".

In [43]:
```
def clean_with_corrections(df: pd.DataFrame, column_names: list, correction
s: dict) -> pd.DataFrame:
    """
    Make corrections in values of columns in dataframe based on a dictionar
y of corrections.

    Parameters:
    - df (DataFrame): A pandas DataFrame containing the data.
    - column_names (list): The lis of column names in the DataFrame to corr
ect.
    - corrections (dict): A dictionary where keys are misspelled words and
values are their correct forms.

    Returns:
    - DataFrame: The DataFrame with corrected values in the specified colum
n.
    """
    # Create a copy of the DataFrame to avoid modifying the original
    corrected_df = df.copy()

    for column_name in column_names:
        # Iterate over each correction
        for correction, keywords in corrections.items():
            # Replace misspelled values with correct form
            corrected_df[column_name] = corrected_df[column_name].apply(lam
bda x: correction if (pd.notna(x) and str(x) in keywords) else x)

    return corrected_df
```

In [44]:
```
# Get the categoricals
categoricals = df_train.select_dtypes(include=['object', 'category']).colum
ns.tolist()
categoricals
```

Out[44]:
```
['gender',
 'senior_citizen',
 'partner',
 'dependents',
 'phone_service',
 'multiple_lines',
 'internet_service',
 'online_security',
 'online_backup',
 'device_protection',
 'tech_support',
 'streaming_tv',
 'streaming_movies',
 'contract',
 'paperless_billing',
 'payment_method',
 'churn']
```

In [45]:
```
df_train[categoricals].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   gender             5043 non-null   object
 1   senior_citizen     5043 non-null   object
 2   partner            5043 non-null   object
 3   dependents         5043 non-null   object
 4   phone_service      5043 non-null   object
 5   multiple_lines     4774 non-null   object
 6   internet_service   5043 non-null   object
 7   online_security    4392 non-null   object
 8   online_backup      4392 non-null   object
 9   device_protection  4392 non-null   object
 10  tech_support       4392 non-null   object
 11  streaming_tv       4392 non-null   object
 12  streaming_movies   4392 non-null   object
 13  contract           5043 non-null   object
 14  paperless_billing  5043 non-null   object
 15  payment_method     5043 non-null   object
 16  churn              5042 non-null   object
dtypes: object(17)
memory usage: 669.9+ KB
```

In [46]:
```
# Define the corrections dictionary for categorical columns
corrections = {
    "No": ["False", "0", "No phone service", "No internet service"],
    "Yes": ["True", "1"]
}

# Apply the correction function to company_brand column
df_train = clean_with_corrections(df_train, categoricals, corrections)
```

In [47]:
```
unique_value_summary(df_train[categoricals])
```
Out[47]:

	Column	Unique Values Count	Unique Values
0	gender	2	[Female, Male]
1	senior_citizen	2	[No, Yes]
2	partner	2	[Yes, No]
3	dependents	2	[No, Yes]
4	phone_service	2	[No, Yes]
5	multiple_lines	3	[<NA>, No, Yes]
6	internet_service	3	[DSL, Fiber optic, No]
7	online_security	3	[No, Yes, <NA>]
8	online_backup	3	[Yes, No, <NA>]
9	device_protection	3	[No, Yes, <NA>]
10	tech_support	3	[No, Yes, <NA>]
11	streaming_tv	3	[No, Yes, <NA>]
12	streaming_movies	3	[No, Yes, <NA>]
13	contract	3	[Month-to-month, One year, Two year]
14	paperless_billing	2	[Yes, No]
15	payment_method	4	[Electronic check, Mailed check, Bank transfer...
16	churn	3	[No, Yes, <NA>]

- Looks, good. Less Redundancy, More Consistent representation of values

In [48]:
```
df_train.isna().sum()
```
Out[48]:
```
gender                0
senior_citizen        0
partner               0
dependents            0
tenure                0
phone_service         0
multiple_lines      269
internet_service      0
online_security     651
online_backup       651
device_protection   651
tech_support        651
streaming_tv        651
streaming_movies    651
contract              0
paperless_billing     0
payment_method        0
monthly_charges       0
total_charges         8
churn                 1
dtype: int64
```

2.5 Visualizations

2.5.1 Visualizing Characteristics of the Dataset

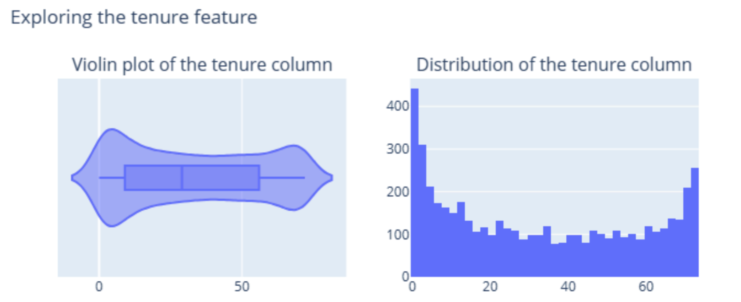
In [49]:
```
# Define the target column
target = 'churn'
```

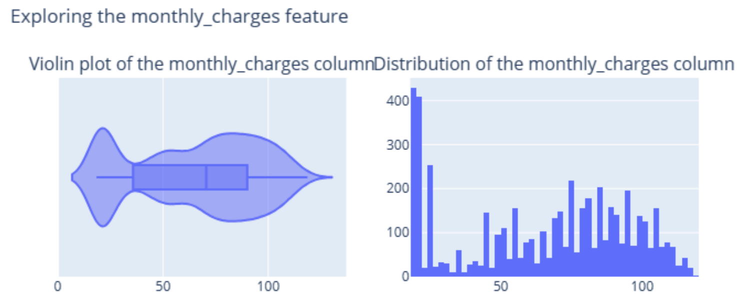
2.5.1.1 Numericals

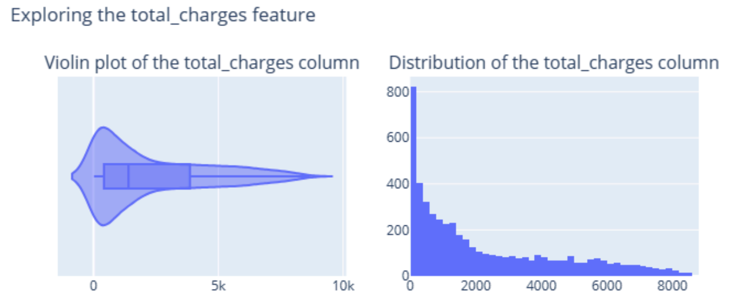
In [50]:
```
# Create a list of the numeric variables
# numericals = [column for column in df_train.columns if df_train[column].d
type != "O"]
numericals = df_train.select_dtypes(include=['number']).columns.tolist()
numericals
```
Out[50]:
```
['tenure', 'monthly_charges', 'total_charges']
```

2.5.1.1.1 Univariate

In [51]:
```
# Visualize their distributions
for column in df_train[numericals].columns:
    fig1 = px.violin(df_train, x=column, box=True)

    fig2 = px.histogram(df_train, x=column)

    # Create a subplot layout with 1 row and 2 columns
    fig = make_subplots(rows=1, cols=2, subplot_titles=(f"Violin plot of th
e {column} column",
                                                     f"Distribution of the
{column} column"))

    # Add traces from fig1 to the subplot
    for trace in fig1.data:
        fig.add_trace(trace, row=1, col=1)

    # Add traces from fig2 to the subplot
    for trace in fig2.data:
        fig.add_trace(trace, row=1, col=2)

    # Update layout
    fig.update_layout(title_text=f"Exploring the {column} feature",
                      showlegend=True,
                      legend_title_text=target
    )

    fig.show()
```

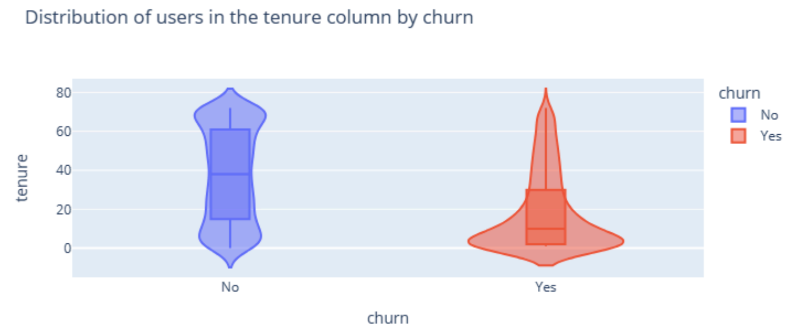


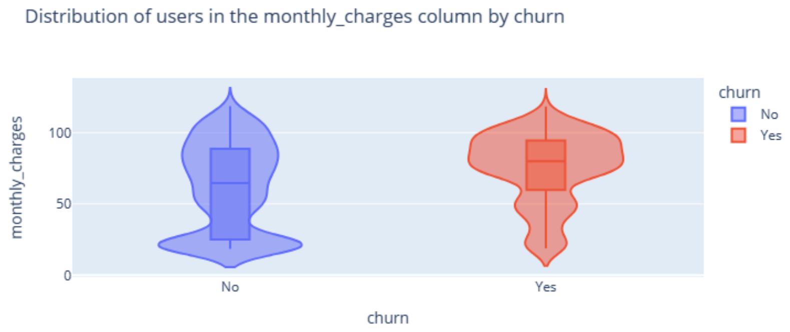


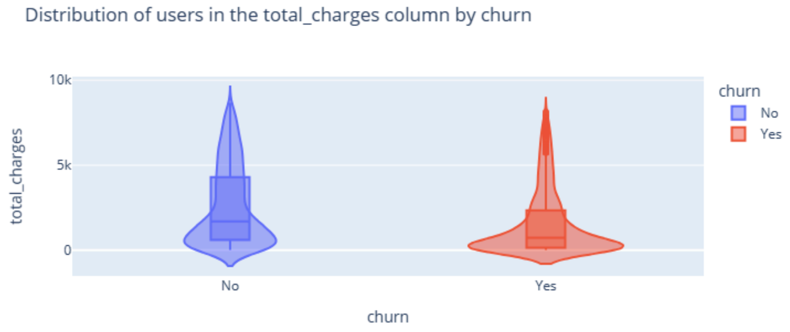


2.5.1.1.2 Bivariate

In [52]:
```
for column in numericals:
    # Visualizing the distribution of the numericals in the columns by chur
n
    fig = px.violin(
        df_train,
        x=target,
        y=column,
        color=target,
        box=True,
        title=f"Distribution of users in the {column} column by churn"
    )

    fig.show()
```







Key Insights

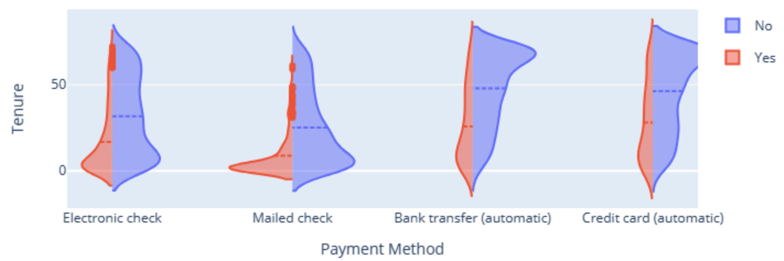
`Tenure:` Analysis of customer tenure reveals a diverse pattern of engagement with the company. The majority of customers exhibit relatively short tenure, with many staying for less than 10 months. However, there is an interesting outlier observed, indicating a small but notable spike in customer loyalty, with some individuals remaining with the company for up to 72 months.

`Monthly Charges:` Examination of monthly charges illustrates a right-skewed distribution, with a significant portion of customers being charged around
$70.55 monthly, as indicated by the median. However, there is substantial variability in charges beyon$
18.40 to
$118.65. This variability suggests diverse pricing plans or additional services catering to different cust$
$most of the customers who churn have monthly charges above$
70.00.

`Total Charges:` The analysis of total charges reveals a concentration within the range of $18.80 to$2000.00. This indicates that the majority of customers have accumulated charges within this bracket. However, there are also notable instances of higher total charges up to $8,670.10, suggesting variations in usage, additional services, or other factors influencing overall expenditure.

2.5.1.1.3 Multivariate

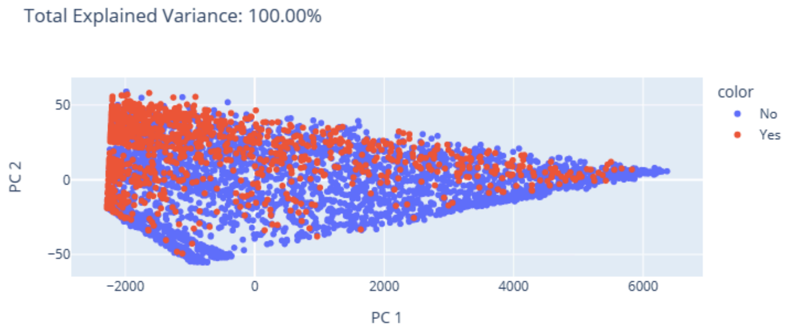
In [53]:
```
fig = go.Figure()

fig.add_trace(
    go.Violin(
        x=df_train['payment_method'][ df_train['churn'] == 'No' ],
        y=df_train['tenure'][ df_train['churn'] == 'No' ],
        legendgroup='No', scalegroup='No', name='No',
        side='positive'
    )
)

fig.add_trace(
    go.Violin(
        x=df_train['payment_method'][ df_train['churn'] == 'Yes' ],
        y=df_train['tenure'][ df_train['churn'] == 'Yes' ],
        legendgroup='Yes', scalegroup='Yes', name='Yes',
        side='negative'
    )
)

fig.update_traces(meanline_visible=True)
fig.update_layout(
    xaxis_title='Payment Method',
    yaxis_title='Tenure',
    violingap=0,
    violinmode='overlay'
)
fig.show()
```



Key Insight

- Customers retention implying longer tenure is influenced by automatic payment methods- bank transfer and credit card. Customers who make payments automatically are less likely to churn compared to those who use check payment methods- electronic and mailed.

In [54]:
```
pca = PCA(n_components=2)

X = df_train[numericals+[target]].dropna()

components = pca.fit_transform(X.drop(columns=target))

total_var = pca.explained_variance_ratio_.sum() * 100

fig = px.scatter(
    components, x=0, y=1, color=X['churn'],
    title=f'Total Explained Variance: {total_var:.2f}%',
    labels={'0': 'PC 1', '1': 'PC 2'}
)
fig.show()
```



Key Insights

The PCA plot above visualizes the relationships between customers churn based on their tenure, monthly charges, and total charges. The plot displays the first two principal components, which capture the most significant sources of variance in the dataset.

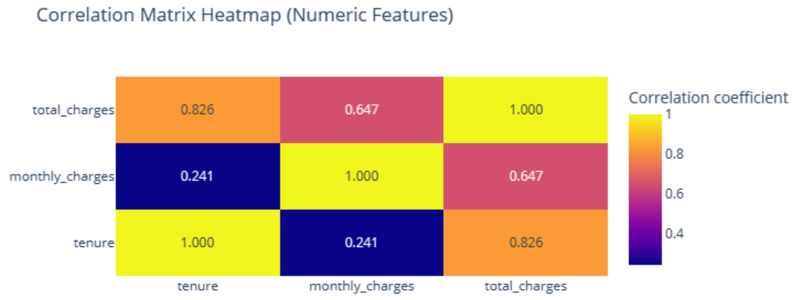
`Direction of Data Points:` Each point on the plot represents an individual customer. The direction and distance between points reflect similarities or differences in their tenure and charges.

`Clusters and Patterns:` Clusters or groupings of points suggest similarities among customers. For instance, a dense cluster in one area of the plot may indicate a group of customers with similar tenure and charge characteristics, such as long-term customers with high monthly and total charges.

`Outliers:` Points that are far from the main cluster(s) may represent outliers—customers with unique characteristics compared to the rest of the dataset. These outliers could be customers with exceptionally high or low charges relative to their tenure.

`Variance Explained:` The first two components explain a significant portion of the total variance 100.0%, suggesting the visualization of the dataset's structure in two dimensions is effective.

In [55]:
```
# Calculate correlation matrix
numeric_correlation_matrix = df_train[numericals].corr()

# Create heatmap trace
heatmap_trace = go.Heatmap(
    z=numeric_correlation_matrix.values,
    x=numeric_correlation_matrix.columns,
    y=numeric_correlation_matrix.index,
    colorbar=dict(title='Correlation coefficient'),
    texttemplate='%{z:.3f}',
)

# Create figure
fig = go.Figure(data=[heatmap_trace])

# Update layout
fig.update_layout(
    title='Correlation Matrix Heatmap (Numeric Features)',
)

# Show plot
fig.show()
```



Key Insights

- Tenure has a strong positive correlation (0.826) with total_charges while its correlation (0.241) with monthly_charges is weak. Although, monthly_charges and total_charges have a strong positive correlation (0.647) but less than (0.826).
- Due to the limited number of numeric features, none of them will be dropped prior to modelling.

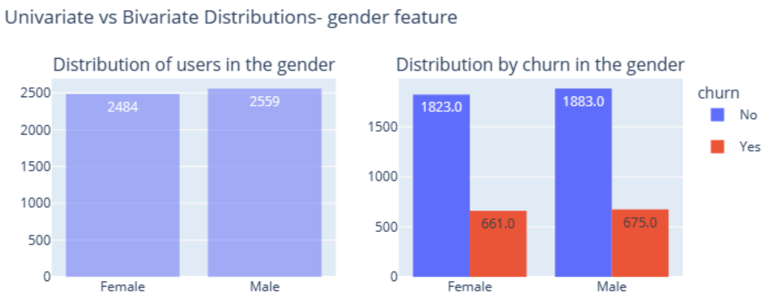
2.5.1.2 Categoricals

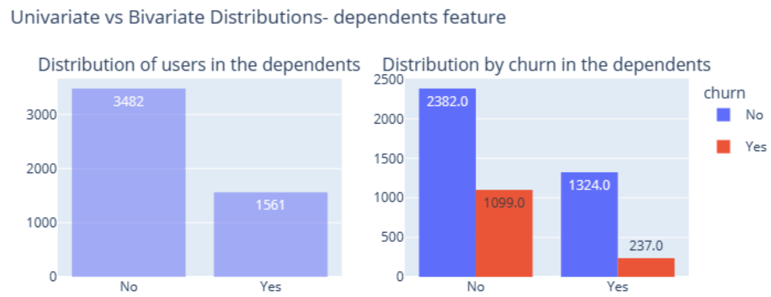
In [56]:
```
df_train[categoricals].info()
```

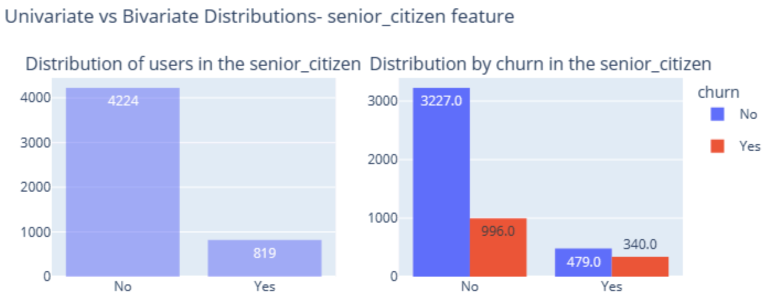
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   gender             5043 non-null   object
 1   senior_citizen     5043 non-null   object
 2   partner            5043 non-null   object
 3   dependents         5043 non-null   object
 4   phone_service      5043 non-null   object
 5   multiple_lines     4774 non-null   object
 6   internet_service   5043 non-null   object
 7   online_security    4392 non-null   object
 8   online_backup      4392 non-null   object
 9   device_protection  4392 non-null   object
 10  tech_support       4392 non-null   object
 11  streaming_tv       4392 non-null   object
 12  streaming_movies   4392 non-null   object
 13  contract           5043 non-null   object
 14  paperless_billing  5043 non-null   object
 15  payment_method     5043 non-null   object
 16  churn              5042 non-null   object
dtypes: object(17)
memory usage: 669.9+ KB
```

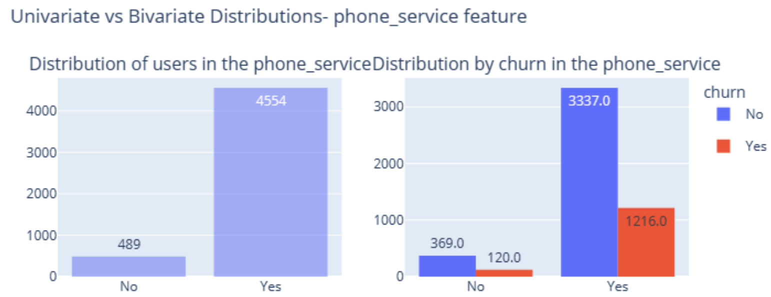
2.5.1.2.1 Univariate and Bivariate

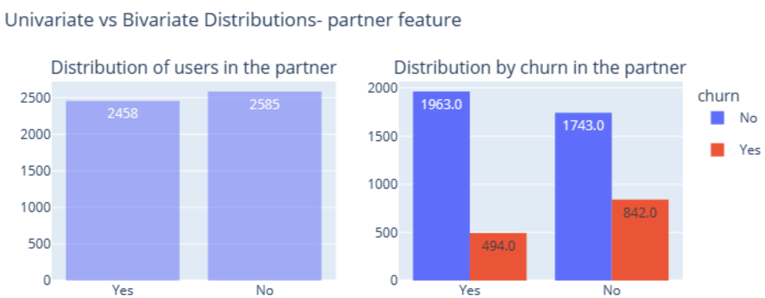
In [57]:
```
# Visualizing the distribution of the columns with categorical values and w
ith respect to churn
for column in categoricals:
    if column != target:  # Exclude the 'churn' column
        # Visualizing the distribution of the categories in the columns
        fig1 = px.histogram(df_train, x=column, text_auto=True, opacity=0.
5,
                            title=f"Distribution of users in the {column} colum
n")

        # Visualizing the distribution of the categories in the columns by
churn
        fig2 = px.histogram(df_train, x=column, color=target, text_auto=".1
f",
                            title=f"Distribution of users in the {column} colum
n by churn")

        # Create a subplot layout with 1 row and 2 columns
        fig = make_subplots(rows=1, cols=2, subplot_titles=(f"Distribution
of users in the {column}",
                                                            f"Distribution by c
hurn in the {column}"))

        # Add traces from fig1 to the subplot
        for trace in fig1.data:
            fig.add_trace(trace, row=1, col=1)

        # Add traces from fig2 to the subplot
        for trace in fig2.data:
            fig.add_trace(trace, row=1, col=2)

        # Update layout
        fig.update_layout(title_text=f"Univariate vs Bivariate Distribution
s- {column} feature",
                          showlegend=True,
                          legend_title_text=target
        )

        fig.show()
    else:
        # Visualizing the distribution of the target variable
        fig = px.histogram(df_train, x=column, text_auto=True, color=colum
n,
                            title=f"Distribution of users in the {column} colum
n")
        fig.show()
```

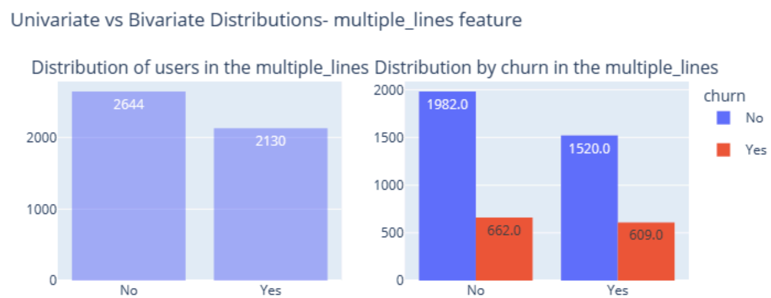

Univariate vs Bivariate Distributions- gender feature
Distribution of users in the gender
Distribution by churn in the gender
churn
No
Yes
2484
2559
1823.0
661.0
1883.0
675.0
Female
Male

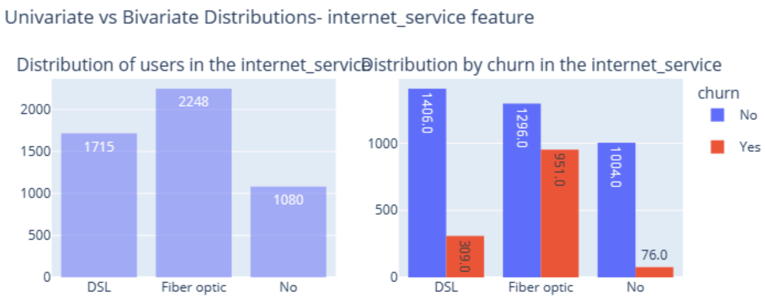

Univariate vs Bivariate Distributions- dependents feature
Distribution of users in the dependents
Distribution by churn in the dependents
churn
No
Yes
3482
1561
2382.0
1099.0
1324.0
237.0
No
Yes

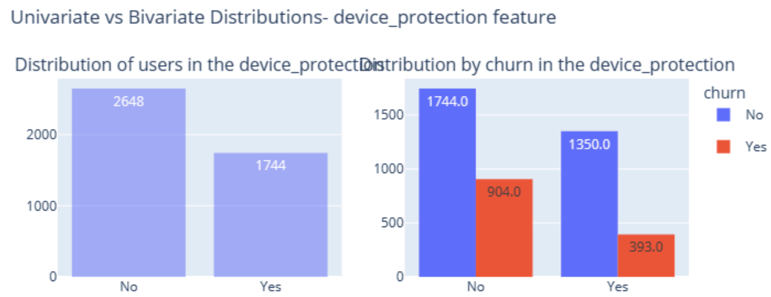

Univariate vs Bivariate Distributions- senior_citizen feature
Distribution of users in the senior_citizen
Distribution by churn in the senior_citizen
churn
No
Yes
4224
819
3227.0
996.0
479.0
340.0
No
Yes

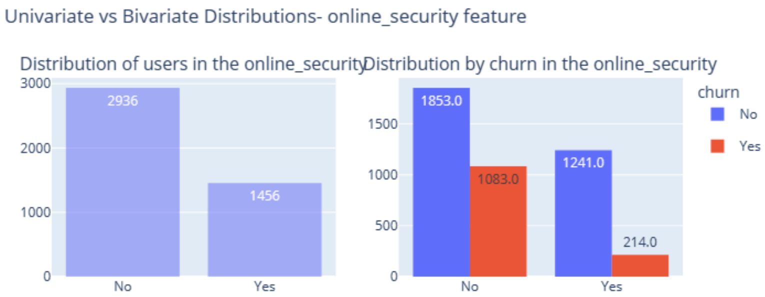

Univariate vs Bivariate Distributions- phone_service feature
Distribution of users in the phone_service
Distribution by churn in the phone_service
churn
No
Yes
489
4554
369.0
120.0
3337.0
1216.0
No
Yes

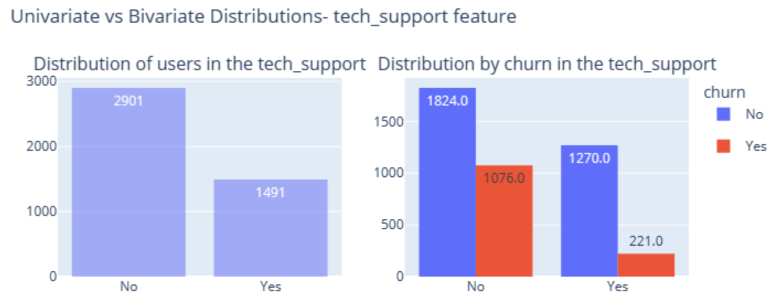

Univariate vs Bivariate Distributions- partner feature
Distribution of users in the partner
Distribution by churn in the partner
churn
No
Yes
2458
2585
1963.0
494.0
1743.0
842.0
Yes
No

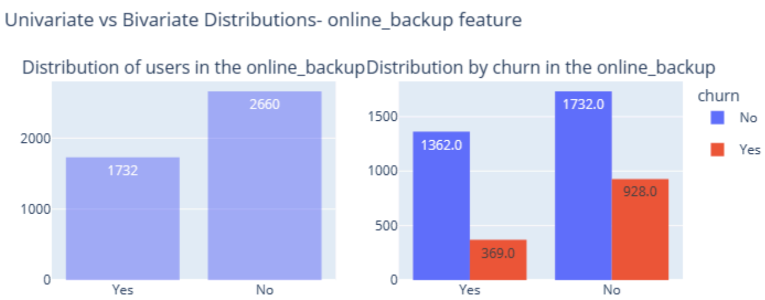

Univariate vs Bivariate Distributions- multiple_lines feature
Distribution of users in the multiple_lines
Distribution by churn in the multiple_lines
churn
No
Yes
2644
2130
1982.0
662.0
1520.0
609.0
No
Yes

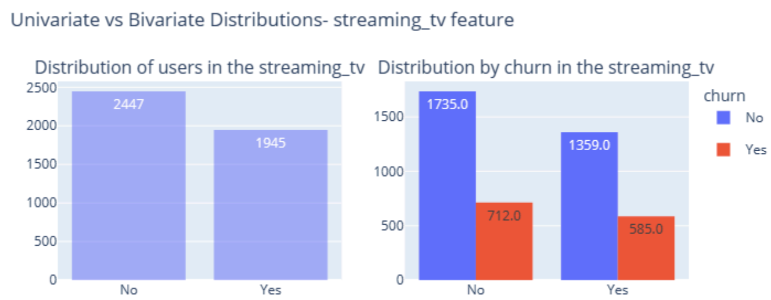

Univariate vs Bivariate Distributions- internet_service feature
Distribution of users in the internet_service
Distribution by churn in the internet_service
1715
2248
1080
DSL
Fiber optic
No
1406.0
309.0
1296.0
951.0
1004.0
76.0
churn
No
Yes

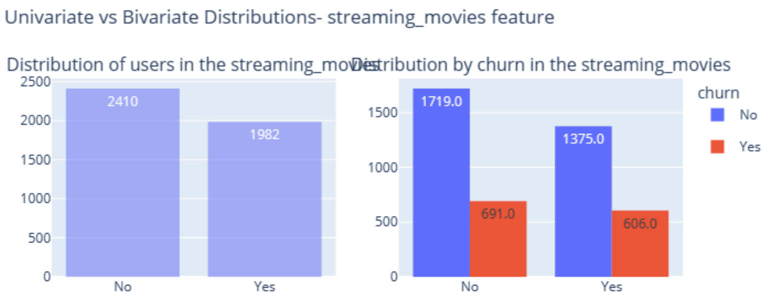

Univariate vs Bivariate Distributions- device_protection feature
Distribution of users in the device_protection
Distribution by churn in the device_protection
2648
1744
No
Yes
1744.0
904.0
1350.0
393.0
churn
No
Yes

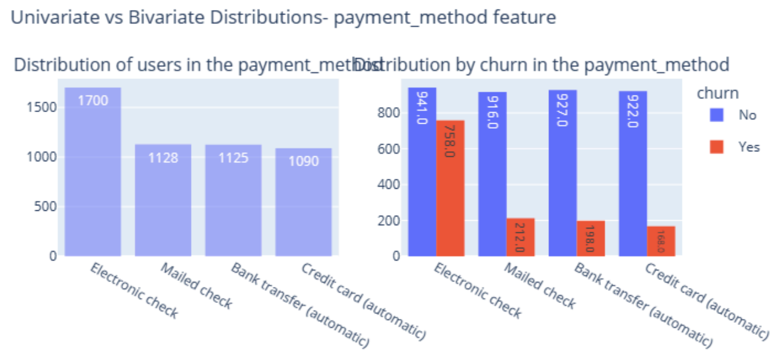

Univariate vs Bivariate Distributions- online_security feature
Distribution of users in the online_security
Distribution by churn in the online_security
2936
1456
No
Yes
1853.0
1083.0
1241.0
214.0
churn
No
Yes

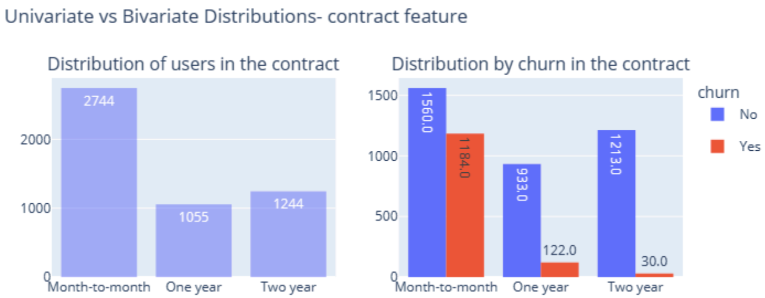

Univariate vs Bivariate Distributions- tech_support feature
Distribution of users in the tech_support
Distribution by churn in the tech_support
2901
1491
No
Yes
1824.0
1076.0
1270.0
221.0
churn
No
Yes

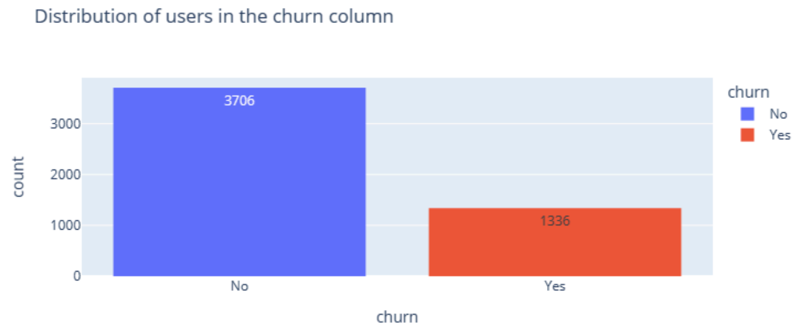

Univariate vs Bivariate Distributions- online_backup feature
Distribution of users in the online_backup
Distribution by churn in the online_backup
1732
2660
Yes
No
1362.0
369.0
1732.0
928.0
churn
No
Yes

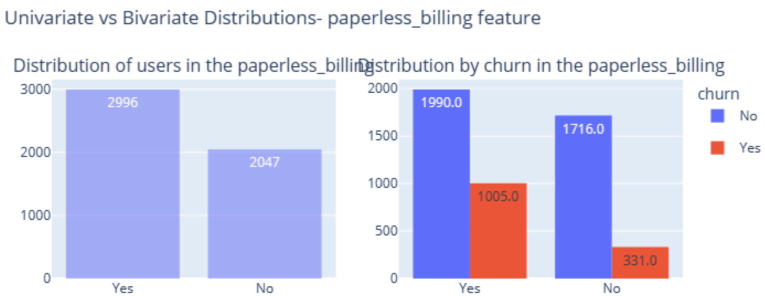

Univariate vs Bivariate Distributions- streaming_tv feature
Distribution of users in the streaming_tv
Distribution by churn in the streaming_tv
2447
1945
No
Yes
1735.0
712.0
1359.0
585.0
churn
No
Yes


Univariate vs Bivariate Distributions- streaming_movies feature
Distribution of users in the streaming_movies
Distribution by churn in the streaming_movies
2410
1982
1719.0
691.0
1375.0
606.0
No
Yes
churn
No
Yes


Univariate vs Bivariate Distributions- payment_method feature
Distribution of users in the payment_method
Distribution by churn in the payment_method
1700
1128
1125
1090
941.0
758.0
916.0
212.0
927.0
198.0
922.0
168.0
Electronic check
Mailed check
Bank transfer (automatic)
Credit card (automatic)
churn
No
Yes


Univariate vs Bivariate Distributions- contract feature
Distribution of users in the contract
Distribution by churn in the contract
2744
1055
1244
1560.0
1184.0
933.0
122.0
1213.0
30.0
Month-to-month
One year
Two year
churn
No
Yes


Distribution of users in the churn column
count
3706
1336
No
Yes
churn
churn
No
Yes


Univariate vs Bivariate Distributions- paperless_billing feature
Distribution of users in the paperless_billing
Distribution by churn in the paperless_billing
2996
2047
1990.0
1005.0
1716.0
331.0
Yes
No
churn
No
Yes

Key Insights

`Gender:` Male customers slightly outnumber female customers.

`Partner:` The proportion of customers with or without partners is approximately equal.

`Dependents:` There are more customers without dependent members compared to those with dependents.

`Phone Service:` The majority of customers do not have phone service, outnumbering those who do.

`Internet Service:` Customers with internet service predominantly opt for DSL or Fiber optic connections.

`MultipleLines, InternetService, OnlineSecurity, OnlineBackup, TechSupport` : A consistent pattern emerges across these features, with most customers preferring not to access these features.

`StreamingMovies and StreamingTV:` Similar barplots indicate an equal preference among customers for having or not having these services.

`Contract:` Customers generally prefer month-to-month contracts over longer-term options such as two-year or one-year contracts.

`Paperless Billing:` The majority of customers prefer paperless billing, utilizing various forms of banking transactions, with Electronic Check being the most common.

Churn Analysis- Customers more likely to churn:

- Those without partners.
- Those without dependents.
- Those with phone service.
- Those using fiber optic internet service.
- Those not subscribing to extra services like Online Backup or Online Security.
- Those on a month-to-month contract basis.
- Those using Electronic Check as their payment method.

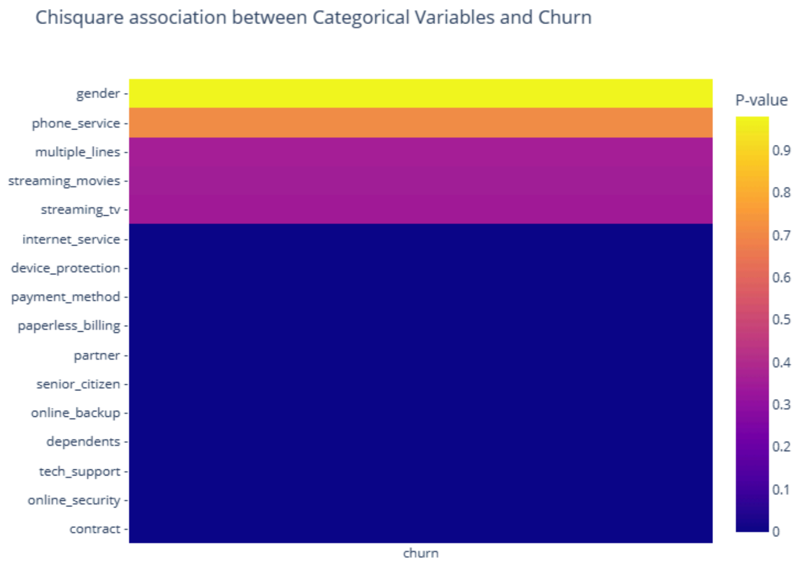
Recommendations:

- Vodafone could enhance the electronic check payment method experience to ensure convenience and ease of use for customers, potentially reducing churn rates.
- Consider improve customer experience and offer discount on family plans, phone services and cross selling other services with online security and backup.
- More investigation into customer experience with fiber optic connections should be engaged. A questionnaire or survey approach may be a good start.

2.5.1.2.2 Multivariate

In [58]:
```
#  Association between categorical variables and churn

# Drop missing values in the categoricals df_train
df_train_categoricals = df_train[categoricals].dropna()

# Convert categorical variables to numerical labels
label_encoder = LabelEncoder()
df_train_cat_viz = df_train_categoricals.apply(label_encoder.fit_transform)

# Use the Chi-squared test to calculate p-values
chi2_values, p_values = chi2(df_train_cat_viz.drop(target, axis=1), df_trai
n_cat_viz[target])

# Create a DataFrame to store p-values
chi2_results = pd.DataFrame(p_values, index=df_train_categoricals.drop(targ
et, axis=1).columns, columns=[target])

# Sort chi2_results by churn p_values
chi2_results = chi2_results.sort_values(by=target, ascending=False)
```

In [59]:
```python
# Sort chi2_results by churn p_values
chi2_results = chi2_results.sort_values(by=target, ascending=True)

# Display the heatmap of p-values
fig = go.Figure(
  data=go.Heatmap(
    z=chi2_results.values,
    x=chi2_results.columns,
    y=chi2_results.index+' -',
    colorbar=dict(title='P-value'),
    hovertemplate='%{y} %{x}: p=%{z}',
#     texttemplate='%{z}',
  )
)

fig.update_layout(
    title = 'Chisquare association between Categorical Variables and Churn',
    width = 900,
    height = 600
)

fig.show()
```



Key Insights

`Significant Variables:` The majority of the variables exhibit a p-value of 0.00, indicating a significant association with churn. These variables include contract type, online security, tech support, dependents, online backup, senior citizen status, partner status, paperless billing, payment method, device protection, and internet service.

`Non-Significant Variables:` Variables such as streaming TV, streaming movies, multiple lines, phone service, and gender have p-values above the typical significance threshold of 0.05. While streaming TV, streaming movies, and multiple lines have relatively low p-values, indicating some association with churn, they may not be as influential as the other variables in predicting churn.

Impact on Modeling Churn Prediction:

`Significant Variables:` Variables with significant p-values are crucial for modeling churn prediction as they provide valuable information about customer behavior and preferences. The variables will be incorporated into the churn prediction model to improve its performance in identifying customers at risk of churn.

`Non-Significant Variables:` While non-significant variables may still have some predictive power, their impact on the overall churn prediction model may be limited. It's essential to prioritize variables with significant associations with churn when building the predictive model to ensure its robustness and reliability. Considerations will be made to create new features from these non-significant features.

2.6 Save datasets as flat files

In [60]:
```python
# Final merged dataset with cleaned column names and cleaned column values
try:
    df_train.to_csv(TRAIN_FILE_CLEANED, index=False)
except Exception as e:
    print(e)
```

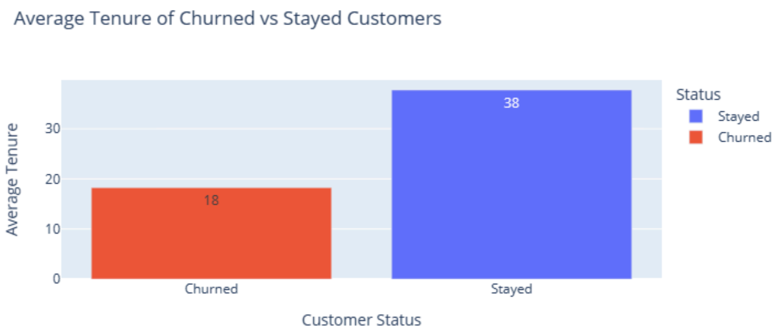
2.7 Business Questions 💼

2.7.1. What is the average tenure of customers who churned compared to those who stayed?

In [61]:
```
# Separate customers who churned from those who stayed
mask = df_train['churn'] == 'Yes'

churned_customers = df_train[mask]
stayed_customers = df_train[~mask]

# Calculate the average tenure for each group
avg_tenure_churned = churned_customers['tenure'].mean()
avg_tenure_stayed = stayed_customers['tenure'].mean()

# Compare the average tenure of the two groups
print(f"Average tenure of churned customers: {avg_tenure_churned:.0f}")
print(f"Average tenure of stayed customers: {avg_tenure_stayed:.0f}")
```

```
Average tenure of churned customers: 18
Average tenure of stayed customers: 38
```

In [62]:
```
# Data
customer_status = ['Stayed', 'Churned']
average_tenure = [avg_tenure_stayed, avg_tenure_churned]

# Creating the bar plot
fig = px.bar(
    x=customer_status,
    y=average_tenure,
    labels={'x': 'Customer Status', 'y': 'Average Tenure', 'color': 'Statu
s'},
    title='Average Tenure of Churned vs Stayed Customers',
    color=customer_status,
    category_orders={'x': customer_status[::-1]}
)

# Adding data labels
fig.update_traces(texttemplate='%{y:.2s}', textposition='inside')

# fig.update_layout(hovermode="x")

# Show plot
fig.show()
```



Key Insights

`Customer Status:` The x-axis represents the status of customers, with two categories: "Churned" and "Stayed." These categories indicate whether customers have churned (left bar) or stayed (right bar).

`Average Tenure:` The y-axis shows the average tenure in months. It measures the average duration that customers, either churned or stayed, have been with the company.

`Churned Customers:` The left bar represents churned customers. On average, churned customers have a tenure of 18 months, indicated by the height of the bar.

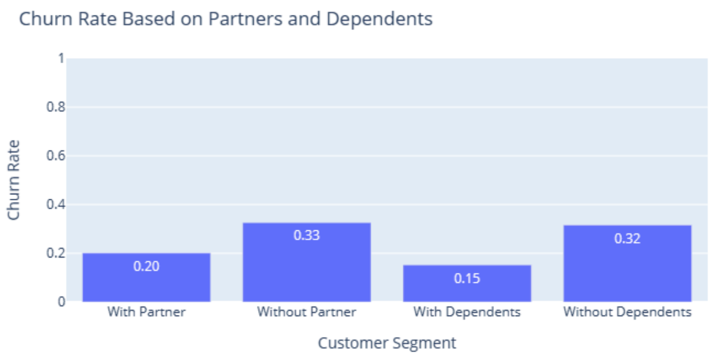
`Stayed Customers:` The right bar represents customers who stayed with the company. On average, these customers have a significantly higher tenure of 38 months, shown by the taller bar compared to churned customers.

The bar chart clearly illustrates the stark difference in tenure between churned and stayed customers. Stayed customers have, on average, a much longer tenure compared to churned customers. This insight suggests that customer retention efforts may be effective, as evidenced by the longer tenure of stayed customers. However, it also indicates potential issues in customer retention strategies or satisfaction levels, as some customers have churned relatively quickly. Further analysis may be needed to understand the factors influencing customer churn and retention.

2.7.2. Do customers with partners or dependents have a lower churn rate?

In [63]:
```
# Calculate churn rate for customers with partners
partner_churn_rate = df_train[df_train['partner'] == 'Yes']['churn'].value_
counts(normalize=True)['Yes']

# Calculate churn rate for customers without partners
no_partner_churn_rate = df_train[df_train['partner'] == 'No']['churn'].valu
e_counts(normalize=True)['Yes']

# Calculate churn rate for customers with dependents
dependent_churn_rate = df_train[df_train['dependents'] == 'Yes']['churn'].v
alue_counts(normalize=True)['Yes']

# Calculate churn rate for customers without dependents
no_dependent_churn_rate = df_train[df_train['dependents'] == 'No']['chur
n'].value_counts(normalize=True)['Yes']
```

```
In [64]: # Data
segments = ['With Partner', 'Without Partner', 'With Dependents', 'Without Dependents']
churn_rates = [partner_churn_rate, no_partner_churn_rate, dependent_churn_rate, no_dependent_churn_rate]

# Create the bar plot using Plotly Express
fig = px.bar(
    x=segments,
    y=churn_rates,
    text=[f'{rate:.2f}' for rate in churn_rates]
)

# Add title and axis labels
fig.update_layout(
    title='Churn Rate Based on Partners and Dependents',
    xaxis_title='Customer Segment',
    yaxis_title='Churn Rate'
)

# Set y-axis limits from 0 to 1
fig.update_yaxes(range=[0, 1])

# Show plot
fig.show()
```



Key Insights

`Customer Segments:` The x-axis represents different customer segments: "With Partner," "Without Partner," "With Dependents," and "Without Dependents." These segments categorize customers based on their household composition.

`Churn Rate:` The y-axis indicates the churn rate, which represents the proportion of customers within each segment who have discontinued their services or stopped their subscriptions over a specific period.

`With Partner:` The first bar corresponds to customers who have partners. Their churn rate is approximately 20.11%.

`Without Partner:` The second bar represents customers without partners. They exhibit a slightly higher churn rate of around 32.57%.

`With Dependents:` The third bar illustrates customers with dependents. Their churn rate is notably lower at about 15.18%.

`Without Dependents:` The last bar signifies customers without dependents, who have a churn rate of approximately 31.57%.

Comparing the churn rates across different customer segments, it's evident that customers with partners or dependents generally have lower churn rates compared to those without. Specifically, customers with dependents have the lowest churn rate among the segments analyzed, indicating higher loyalty or satisfaction levels within this group. This insight suggests that targeting strategies towards customers with partners or dependents may help reduce churn and enhance customer retention efforts. Further analysis could delve into understanding the specific needs and preferences of these customer segments to tailor retention strategies effectively.

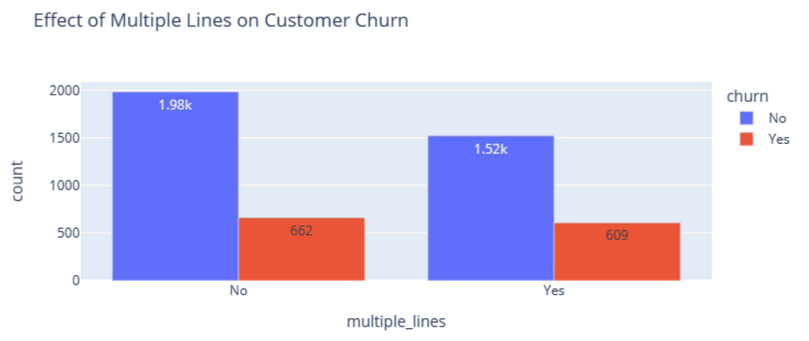
2.7.3. How does the presence of multiple lines affect customer churn?

```
In [65]: # Calculating churn rate by presence of multiple lines
churn_rate_multiple_lines = df_train.groupby('multiple_lines')['churn'].value_counts().reset_index()
churn_rate_multiple_lines
```

Out[65]:

	multiple_lines	churn	count
0	No	No	1982
1	No	Yes	662
2	Yes	No	1520
3	Yes	Yes	609

In [66]:
```python
# Create a bar chart
fig = px.bar(
    churn_rate_multiple_lines,
    x='multiple_lines',
    y='count',
    color='churn',
    title="Effect of Multiple Lines on Customer Churn",
    barmode='group'
)

# Adding data labels
fig.update_traces(texttemplate='%{y:.3s}', textposition='inside')

fig.show()
```



In [67]:
```python
# Calculating churn rate by presence of multiple lines
churn_rate_ml_normalized = df_train.groupby('multiple_lines')['churn'].valu
e_counts(normalize=True).unstack()
print("Churn Rate by Presence of Multiple Lines:")
print(churn_rate_ml_normalized)

# Chi-square test for association between multiple lines and churn
chi2, p_val, _, _ = chi2_contingency(pd.crosstab(df_train['multiple_line
s'], df_train['churn'], dropna=True))
print("\nChi-square Test Results for Multiple Lines and Churn:")
print("Chi-square value:", chi2)
print("p-value:", p_val)
```

```
Churn Rate by Presence of Multiple Lines:
churn            No  Yes
multiple_lines
No             0.75 0.25
Yes            0.71 0.29

Chi-square Test Results for Multiple Lines and Churn:
Chi-square value: 7.499396411455509
p-value: 0.006171967510333475
```

Key Insights

Chi-square value: 7.50

p-value: 0.0062

`Presence of Multiple Lines:` The analysis assesses how the presence of multiple lines, such as additional phone lines or services, influences customer churn.

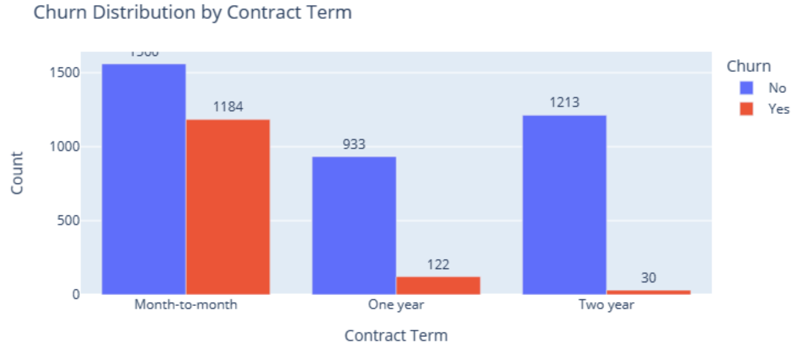
`Chi-square value:` The calculated chi-square value of 7.50 indicates the degree of association between the presence of multiple lines and customer churn.

`p-value:` With a p-value of 0.0062, the test suggests that there is a statistically significant relationship between the presence of multiple lines and customer churn.

It is evident that the presence of multiple lines significantly affects customer churn. This suggests that customers with multiple lines may exhibit different churn behaviors compared to those with a single line. Further analysis could explore the specific reasons behind this relationship, such as the satisfaction levels with additional services, pricing structures, or the quality of service provided across multiple lines.

2.7.4 Is there a correlation between the contract term (Contract) and customer churn?

In [68]:
```
churn_contract = df_train.groupby('contract')['churn'].value_counts().reset
_index()

fig = px.bar(churn_contract, x='contract', y='count', color='churn', barmod
e='group')

fig.update_layout(
    title='Churn Distribution by Contract Term',
    xaxis_title='Contract Term',
    yaxis_title='Count',
    legend_title='Churn',
)

# Adding data labels
fig.update_traces(texttemplate='%{y}', textposition='outside')

fig.show()
```



In [69]:
```
# Calculating churn rate by contract term
churn_rate_contract = df_train.groupby('contract')['churn'].value_counts(no
rmalize=True).unstack()
print("\nChurn Rate by Contract Term:")
print(churn_rate_contract)

# Chi-square test for association between contract term and churn
chi2, p_val, _, _ = chi2_contingency(pd.crosstab(df_train['contract'], df_t
rain['churn']))
print("\nChi-square Test Results for Contract Term and Churn:")
print("Chi-square value:", chi2)
print("p-value:", p_val)
```

```
Churn Rate by Contract Term:
churn             No  Yes
contract
Month-to-month 0.57 0.43
One year       0.88 0.12
Two year       0.98 0.02

Chi-square Test Results for Contract Term and Churn:
Chi-square value: 881.6208905118242
p-value: 3.617895846412 33e-192
```

Key Insights

The bar chart visualizes the churn rates across different contract terms. Each contract term category ("Month-to-month", "One year", and "Two year") has two bars corresponding to churned ("Yes") and non-churned ("No") customers.

- In the "Month-to-month" category, there are 1184 churned customers (Yes) and 1560 non-churned customers (No).
- In the "One year" category, there are 122 churned customers (Yes) and 933 non-churned customers (No).
- In the "Two year" category, there are 30 churned customers (Yes) and 1213 non-churned customers (No).

`Churn Rate by Contract Term:`

- **Month-to-month**: Churn rate of 43% for "Yes" and 57% for "No".
- **One year**: Churn rate of 12% for "Yes" and 88% for "No".
- **Two year**: Churn rate of 2% for "Yes" and 98% for "No".

`Chi-square Test Results`

- **Chi-square value**: 881.62
- **p-value**: < 0.001 (3.62e-192)

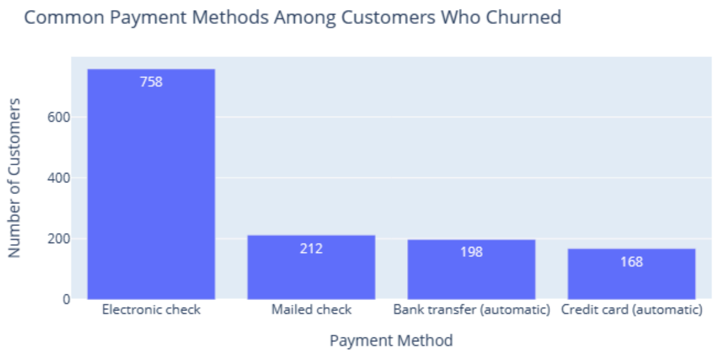
The chi-square test results indicate a highly significant relationship between the contract term and customer churn. With a p-value much less than the conventional significance level of 0.05, there's strong evidence to reject the null hypothesis, suggesting that there is indeed a correlation between the contract term and customer churn.

Further analysis shows that customers with shorter contract terms, such as month-to-month contracts, exhibit significantly higher churn rates compared to those with longer contract terms, such as one year or two years. This finding suggests that customers with longer-term contracts are more likely to stay with the service provider, potentially due to factors such as commitment, loyalty incentives, or reduced price sensitivity.

This correlation informs strategic decisions for customer retention efforts, such as targeted promotions or incentives to encourage longer-term contract commitments and reduce churn rates. Additionally, it emphasizes the importance of offering flexible contract options and ensuring customer satisfaction throughout the contract duration to mitigate churn risk effectively.

2.7.5 What are the common payment methods (Payment Method) among customers who churned?

In [70]:
```
churned_customers = df_train[df_train['churn'] == 'Yes']
common_payment_methods = churned_customers['payment_method'].value_counts()

fig = px.bar(x=common_payment_methods.index, y=common_payment_methods.value
s)

fig.update_layout(
    title='Common Payment Methods Among Customers Who Churned',
    xaxis_title='Payment Method',
    yaxis_title='Number of Customers'
)

# Adding data labels
fig.update_traces(texttemplate='%{y}', textposition='inside')

fig.show()
```



Key Insights

`Payment Methods:`

- Electronic check: 758
- Mailed check: 212
- Bank transfer (automatic): 198
- Credit card (automatic): 168

`Common Payment Methods Among Churned Customers:`

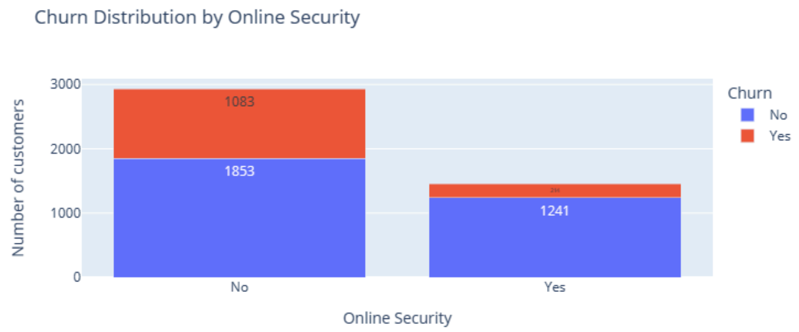
- Among customers who churned, the most common payment method is Electronic check, with a count of 758.
- The second most common payment method among churned customers is Mailed check, with a count of 212.
- Bank transfer (automatic) and Credit card (automatic) are less common among churned customers, with counts of 198 and 168, respectively.

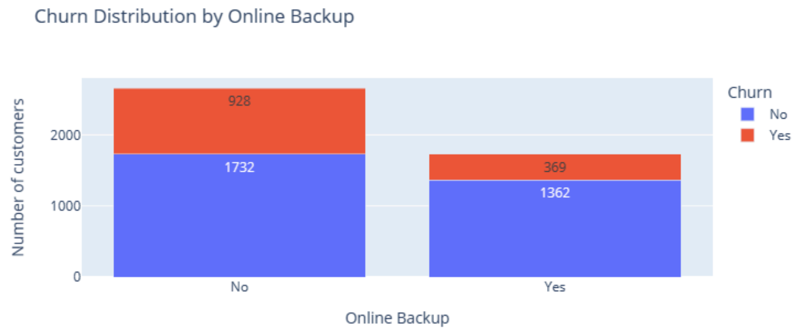
It is evident that Electronic check is the most prevalent payment method among churned customers, followed by Mailed check. This suggests potential areas for improvement in payment processing systems or incentives for customers to use more convenient or reliable payment methods, which could potentially help reduce churn rates.

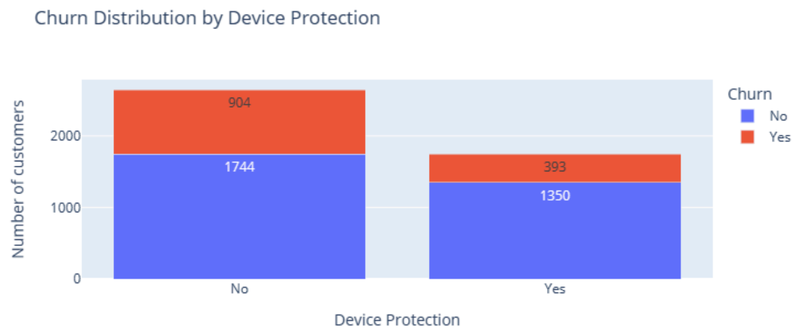
2.7.6 How does the availability of online-related services (e.g., OnlineSecurity, TechSupport) impact churn rates?

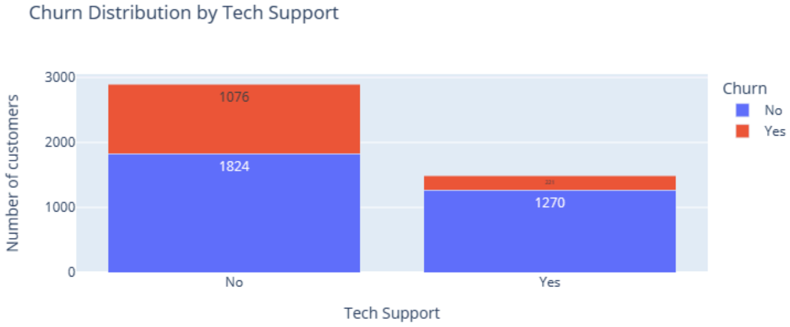
In [71]:
```
online_service_group = {}

online_related_services = ['online_security', 'online_backup', 'device_prot
ection', 'tech_support', 'streaming_tv', 'streaming_movies']

for col in online_related_services:
       online_service_group[col] = df_train.groupby([col]+['churn'])['chur
n'].count()
```

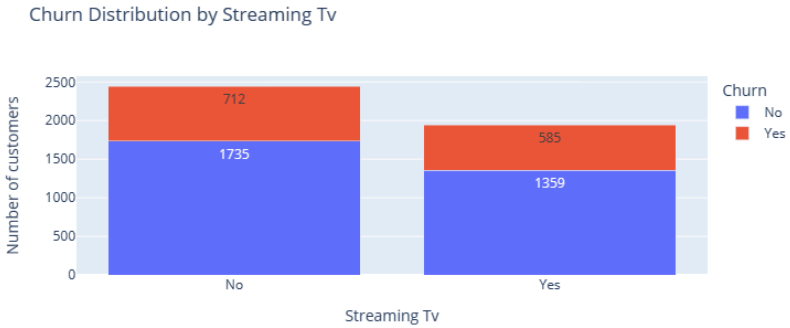
```
In [72]: for col in online_service_group.keys():
    # Convert series data to DataFrame
    online_service_group_df = online_service_group.get(col).unstack().reset
_index()
    col_text = col.title().replace('_', ' ')

    # Create a stacked bar chart using Plotly Express
    fig = px.bar(online_service_group_df, x=col, y=['No', 'Yes'], barmode
='stack',
                 labels={'variable': 'Churn', col: col_text, 'value': 'Numbe
r of customers'},
                 title=f'Churn Distribution by {col_text}')

    # Adding data labels
    fig.update_traces(texttemplate='%{y}', textposition='inside')

    fig.show()
```

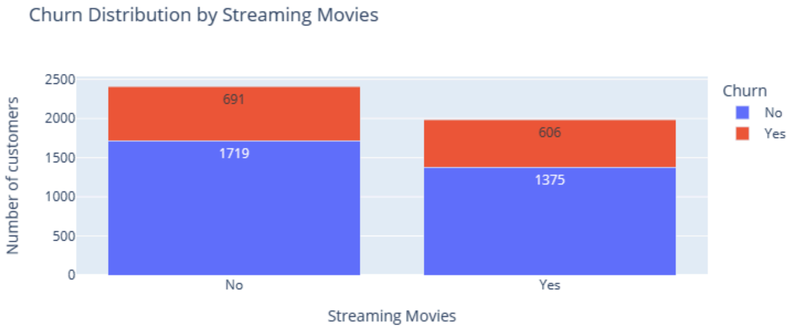












Key Insights

`Online Security:`

- Among customers without online security, 1083 churned and 1853 stayed, while among customers with online security, 214 churned and 1241 stayed.

`Online Backup:`

- Among customers without online backup, 928 churned and 1732 stayed, while among customers with online backup, 369 churned and 1362 stayed.

`Device Protection:`

- Among customers without device protection, 904 churned and 1744 stayed, while among customers with device protection, 393 churned and 1350 stayed.

`Tech Support:`

- Among customers without tech support, 1076 churned and 1824 stayed, while among customers with tech support, 221 churned and 1270 stayed.

`Streaming TV:`

- Among customers without streaming TV, 712 churned and 1735 stayed, while among customers with streaming TV, 585 churned and 1359 stayed.

`Streaming Movies:`

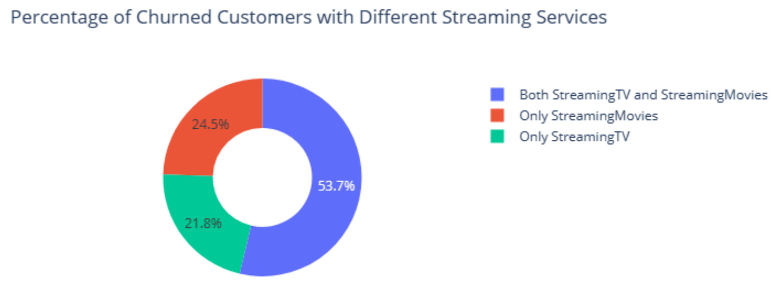
- Among customers without streaming movies, 691 churned and 1719 stayed, while among customers with streaming movies, 606 churned and 1375 stayed.

It is evident that the availability of online-related services does impact churn rates. In most cases, customers without these services exhibit higher churn rates compared to those with access to them. This suggests that online-related services may play a role in customer retention. Further exploration into the specific features and quality of these services could provide insights into strategies for reducing churn and enhancing customer satisfaction within the telecommunications industry. In addition, marketing online related services to customers so they make a subscription would likely improve customer retention.

2.7.7 What percentage of customers who churned had streaming services (StreamingTV, StreamingMovies)?

In [73]:

```
# Filter the train data to include only churned customers
churned_customers = df_train[df_train['churn'] == 'Yes']

# Calculate the number of churned customers with different streaming servic
es
streaming_tv_churned_count = len(churned_customers[(churned_customers['stre
aming_tv'] == 'Yes') & (churned_customers['streaming_movies'] == 'No')])
streaming_movies_churned_count = len(churned_customers[(churned_customers
['streaming_tv'] == 'No') & (churned_customers['streaming_movies'] == 'Ye
s')])
both_streaming_churned_count = len(churned_customers[(churned_customers['st
reaming_tv'] == 'Yes') & (churned_customers['streaming_movies'] == 'Yes')])

# Calculate the total number of churned customers
total_churned_customers = len(churned_customers)

# Calculate the percentage of churned customers for each category
percentage_streaming_tv_churned = (streaming_tv_churned_count / total_churn
ed_customers) * 100
percentage_streaming_movies_churned = (streaming_movies_churned_count / tot
al_churned_customers) * 100
percentage_both_streaming_churned = (both_streaming_churned_count / total_c
hurned_customers) * 100

# Create plot data
data = {
    'Streaming Services': ['Only StreamingTV', 'Only StreamingMovies', 'Bot
h StreamingTV and StreamingMovies'],
    'Percentage of Churned Customers': [percentage_streaming_tv_churned, pe
rcentage_streaming_movies_churned, percentage_both_streaming_churned]
}
df_plot = pd.DataFrame(data)

# Create a donut chart using Plotly Express
fig = px.pie(
    df_plot,
    values='Percentage of Churned Customers',
    names='Streaming Services',
    hole=0.5,
    title='Percentage of Churned Customers with Different Streaming Service
s'
)

fig.show()
```



Key Insights

Streaming Services and Churn Percentage:

`Only StreamingTV:` 12.65%

`Only StreamingMovies:` 14.22%

`Both StreamingTV and StreamingMovies:` 31.14%

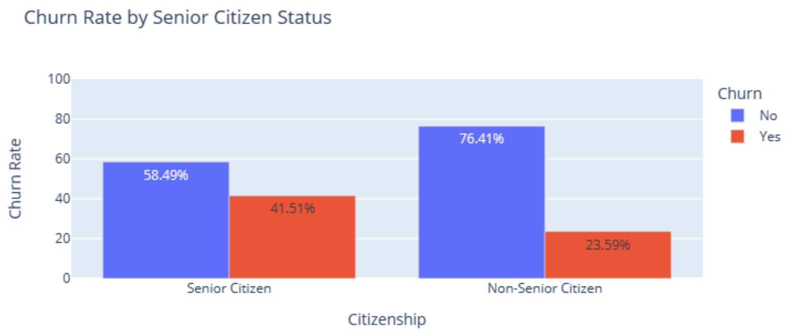
The data shows that customers who had both Streaming TV and Streaming Movies services exhibited the highest churn rate at 31.14%. Customers who had only Streaming Movies or only Streaming TV services had lower churn rates at 14.22% and 12.65% respectively.

This suggests that customers who had access to both Streaming TV and Streaming Movies services were more likely to churn compared to those who had access to only one of these services.

Notably, it is important to consider the combined impact of multiple streaming services on churn rates when developing retention strategies. Further exploration into the reasons behind the higher churn rate among customers with both services could provide valuable insights for targeted retention efforts, potentially involving service improvements or personalized offers to enhance customer loyalty and reduce churn.

2.7.8 Is there a difference in churn rates between senior citizens and non-senior citizens?

In [74]:
```
# Calculate churn rates for senior and non-senior citizens
senior_churn_rate = df_train[df_train['senior_citizen'] == 'Yes']['churn'].value_counts(normalize=True)*100
non_senior_churn_rate = df_train[df_train['senior_citizen'] == 'No']['churn'].value_counts(normalize=True)*100

# Create DataFrame for the churn rates
data = {
    'Churn': senior_churn_rate.index,
    'Senior Citizen': senior_churn_rate.values,
    'Non-Senior Citizen': non_senior_churn_rate.values
}
df_plot = pd.DataFrame(data)

# Melt the DataFrame to have 'Senior Citizen' and 'Non-Senior Citizen' as a single column for Plotly Express
df_plot = df_plot.melt(id_vars='Churn', var_name='Citizenship', value_name='Churn Rate')

# Create a grouped bar chart using Plotly Express
fig = px.bar(
    df_plot,
    x='Citizenship',
    y='Churn Rate',
    color='Churn',
    barmode='group',
    labels={'Churn': 'Churn', 'Churn Rate': 'Churn Rate', 'Citizenship': 'Citizenship'},
    title='Churn Rate by Senior Citizen Status'
)

# Adding data labels
fig.update_traces(texttemplate='%{y:.2f}%', textposition='inside')

# Update layout to set y-axis range from 0 to 100
fig.update_layout(yaxis=dict(range=[0, 100]))

fig.show()
```



Key Insights

- **Churn Rates by Citizenship**:

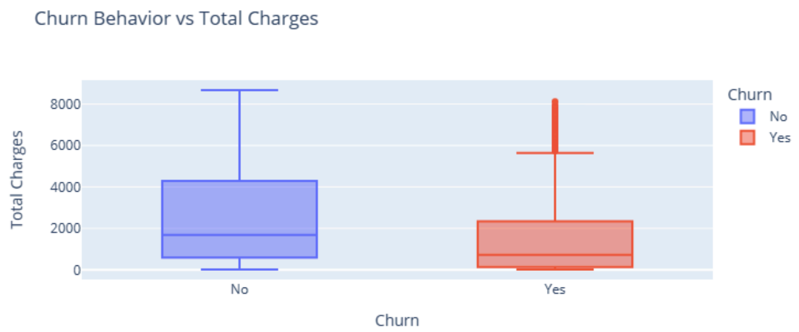
  `Senior Citizen:`
  - Churn Rate (Yes): 41.51%
  - Churn Rate (No): 58.49%

  `Non-Senior Citizen:`
  - Churn Rate (Yes): 23.59%
  - Churn Rate (No): 76.41%
- The data indicates notable differences in churn rates between senior citizens and non-senior citizens.
- Senior citizens have a churn rate of 41.51%, while non-senior citizens have a lower churn rate of 23.59%.

There is an observable difference in churn rates between senior citizens and non-senior citizens. Senior citizens exhibit a higher churn rate compared to non-senior citizens, suggesting potential differences in preferences, needs, or satisfaction levels between these demographic groups. These differences can inform targeted retention strategies tailored to the unique characteristics and preferences of each demographic group, thereby helping to mitigate churn and enhance customer satisfaction within the telecommunications industry.

2.7.9 How does the total amount charged to customers (TotalCharges) relate with churn behavior?

In [75]:
```
fig = px.box(df_train, x='churn', y='total_charges', color='churn',
             labels={'churn': 'Churn', 'total_charges': 'Total Charges'},
             title='Churn Behavior vs Total Charges')

fig.update_layout(xaxis={'categoryorder':'array', 'categoryarray':['No', 'Yes']})  # Ensure the order of x-axis categories

fig.show()
```



```
In [76]: churned_total_charges = df_train[df_train['churn'] == 'Yes']['total_charges']
not_churned_total_charges = df_train[df_train['churn'] == 'No']['total_charges']

# Perform Mann-Whitney U test
u_statistic, p_value = mannwhitneyu(churned_total_charges, not_churned_total_charges, alternative='two-sided', nan_policy='omit')

# Print the results
print("Mann-Whitney U Test Results:")
print(f"U-statistic: {u_statistic}")
print(f"P-value: {p_value}")
```

```
Mann-Whitney U Test Results:
U-statistic: 1735257.0
P-value: 1.2635460045211262e-58
```

Key Insights

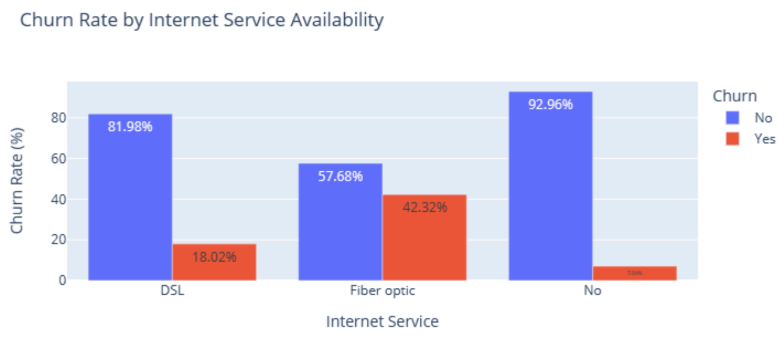
- **Churn Behavior**:
  - Churn (No): Median Total Charges - $1681.83
  - Churn (Yes): Median Total Charges - $725.60, there is evidence of potential outliers.
- Churned customers have a lower mean total charge ($725.60) compared to non - churned customers$(1681.83).

There appears to be a relationship between the total amount charged to customers and churn behavior. Churned customers tend to have lower total charges compared to non-churned customers, suggesting that lower total charges may be associated with higher churn rates. This highlights the importance of monitoring and optimizing pricing strategies, as well as providing value-added services to enhance customer satisfaction and reduce churn within the telecommunications industry.

The Mann-Whitney U Test results reveal a statistically significant difference between the total amount charged to customers (TotalCharges) and churn behavior. With a remarkably low p-value of 1.26e-58, the test suggests strong evidence to reject the null hypothesis, indicating that there is indeed a significant difference in total charges between churned and non-churned customers. This suggests that total charges play a significant role in determining churn behavior, with lower total charges potentially associated with higher churn rates. This may be due to the fact that most customers who churn spend less tenure with the company. And less tenure implies lower total charges- a factor of monthly charges and tenure. Telecom companies should consider optimizing their pricing strategies and offering value-added services to enhance customer satisfaction and reduce churn, particularly for customers with lower total charges.

2.7.10 How does the availability of internet service impact customer churn rates?

```
In [77]: # Calculate churn rates for each type of internet service
internet_churn_rate = df_train.groupby('internet_service')['churn'].value_counts(normalize=True) * 100

# Create DataFrame for the churn rates
df_plot = internet_churn_rate.reset_index(name='Churn Rate')

# Create a grouped bar chart using Plotly Express
fig = px.bar(
    df_plot,
    x='internet_service',
    y='Churn Rate',
    color='churn',
    barmode='group',
    labels={'churn': 'Churn', 'Churn Rate': 'Churn Rate (%)', 'internet_service': 'Internet Service'},
    title='Churn Rate by Internet Service Availability'
)

# Adding data labels
fig.update_traces(texttemplate='%{y:.2f}%', textposition='inside')

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




```
In [78]: # Create a contingency table
contingency_table = pd.crosstab(df_train['internet_service'], df_train['churn'])

# Perform chi-square test of independence
chi2, p_value, _, _ = chi2_contingency(contingency_table)

# Print the results
print("Chi-square Test of Independence Results:")
print(f"Chi-square value: {chi2}")
print(f"P-value: {p_value}")
```

```
Chi-square Test of Independence Results:
Chi-square value: 562.2698920653917
P-value: 8.028682205375917e-123
```

Key Insights

- **Churn Rate by Internet Service**:
  - DSL:
    - Churn Rate (No): 81.98%
    - Churn Rate (Yes): 18.02%
  - Fiber optic:
    - Churn Rate (No): 57.68%
    - Churn Rate (Yes): 42.32%
  - No Internet Service:
    - Churn Rate (No): 92.96%
    - Churn Rate (Yes): 7.04%
- **Chi-square Test Results**:
  - Chi-square value: 562.27
  - P-value: 8.03e-123

The availability of internet service significantly influences customer churn rates, as indicated by the Chi-square test's extremely low p-value. Customers with Fiber optic internet service have a higher churn rate (42.32%) compared to those with DSL (18.02%) or no internet service (7.04%). This suggests that the type of internet service offered plays a crucial role in customer retention. Telecom companies should assess the quality and reliability of different internet service options and consider strategies to enhance customer satisfaction and loyalty, particularly for customers with Fiber optic internet service, to mitigate churn risk effectively.

2.8 Hypothesis Testing

- Set the significance level

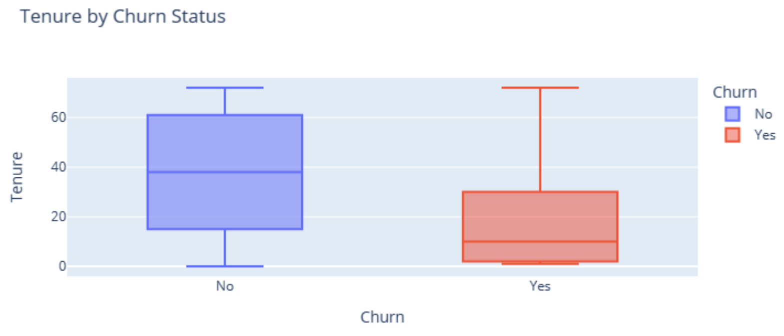
In [79]:
```
# State the significance level
alpha = 0.05
```

Hypothesis 1

`Null Hypothesis (Ho):` There is no significant difference in churn rates between customers with shorter and longer tenure.

`Alternative Hypothesis (Ha):` There is a significant difference in churn rates between customers with shorter and longer tenure.

In [80]:
```
# Create Box Plot
fig = px.box(
    df_train,
    x='churn',
    y='tenure',
    color='churn',
    title='Tenure by Churn Status',
    labels={'churn': 'Churn', 'tenure': 'Tenure'},
)

# Show plot
fig.show()
```



In [81]:
```
# Encode 'churn' column into numeric values
median_tenure_df = df_train[['tenure', 'churn']]

# Drop rows with NaN values in the 'tenure' column
median_tenure_df = median_tenure_df.dropna()

median_tenure_df['churn_numeric'] = median_tenure_df['churn'].replace({'Ye
s': 1, 'No': 0})

# Calculate the median value for tenure
median_tenure = median_tenure_df['tenure'].median()

# Divide the data into two categories
long_tenure = median_tenure_df[median_tenure_df['tenure'] >= median_tenure]
['churn_numeric']
short_tenure = median_tenure_df[median_tenure_df['tenure'] < median_tenure]
['churn_numeric']

# Perform Fisher's exact test
odds_ratio, p_value = fisher_exact(
    [[long_tenure.sum(), short_tenure.sum()],
    [len(long_tenure), len(short_tenure)]]
)

# Print the test statistic (odds ratio) and p-value
print("Odds ratio:", odds_ratio)
print("P-value:", p_value)

# Compare p-value to the significance level
if p_value < alpha:
    print("Reject Null Hypothesis: There is a significant difference in chu
rn rates between customers with shorter and longer tenure.")
else:
    print("Fail to Reject Null Hypothesis: There is no significant differen
ce in churn rates between customers with shorter and longer tenure.")
```

```
Odds ratio: 0.33645634422753296
P-value: 2.86729849545336840e-62
Reject Null Hypothesis: There is a significant difference in churn rates be
tween customers with shorter and longer tenure.
```

Key Insights

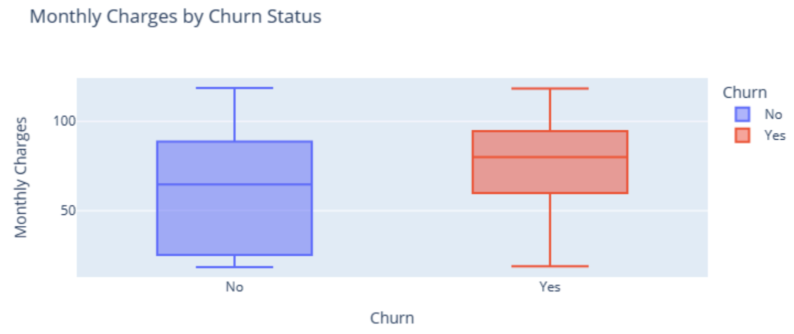
At the significance level(5%), there is sufficient evidence to conclude that the median churn rate of customers with shorter tenure differs significantly from the churn rate of customers with longer tenure. Therefore, there is strong evidence that customers with shorter tenure will likely churn as observed in the box plot.

Hypothesis 2

`Null Hypothesis (Ho):` There is no significant difference in churn rates between customers with higher and lower monthly charge.

`Alternative Hypothesis (Ha):` There is a significant difference in churn rates between customers with higher and lower monthly charge.

In [82]:
```
# Create Box Plot
fig = px.box(
    df_train,
    x='churn',
    y='monthly_charges',
    color='churn',
    title='Monthly Charges by Churn Status',
    labels={'churn': 'Churn', 'monthly_charges': 'Monthly Charges'},
)

# Show plot
fig.show()
```



In [83]:
```python
# Encode 'churn' column into numeric values
monthly_charges_df= df_train[['monthly_charges', 'churn']]

# Drop rows with NaN values in the 'monthly_charges' column
monthly_charges_df = monthly_charges_df.dropna()

monthly_charges_df['churn_numeric'] = monthly_charges_df['churn'].replace
({'Yes': 1, 'No': 0})

# Calculate the median value for monthlycharge
median_monthlycharge = monthly_charges_df['monthly_charges'].median()

# Divide the data into two categories
high_monthlycharge = monthly_charges_df[monthly_charges_df['monthly_charge
s'] >= median_monthlycharge]['churn_numeric']
low_monthlycharge = monthly_charges_df[monthly_charges_df['monthly_charge
s'] < median_monthlycharge]['churn_numeric']

# Perform Mann-Whitney U test
statistic, p_value = mannwhitneyu(high_monthlycharge, low_monthlycharge, na
n_policy='omit')

# Print the test statistic (U statistic) and p-value
print("Mann-Whitney U statistic:", statistic)
print("P-value:", p_value)

# Compare p-value to the significance level
if p_value < alpha:
    print("Reject Null Hypothesis: There is a significant difference in chu
rn rates between customers with higher and lower monthly charge.")
else:
    print("Fail to Reject Null Hypothesis: There is no significant differen
ce in churn rates between customers with higher and lower monthly charge.")
```

```
Mann-Whitney U statistic: 3742937.0
P-value: 1.9514908320378217e-46
Reject Null Hypothesis: There is a significant difference in churn rates be
tween customers with higher and lower monthly charge.
```

Key Insights

At the significance level(5%), there is sufficient evidence to conclude that the median churn rate of customers with lower monthly charge differs significantly from the churn rate of customers with higher monthly charge. Therefore, there is strong evidence that customers with higher monthly charge will likely churn as observed in the box plot.

3.0 Data Preparation 🛠️

3.1 Check for balanced dataset

In [84]:
```python
class_counts = df_train[target].value_counts().reset_index()
class_counts.columns = ['churn_class', 'count']
class_counts
```

Out[84]:

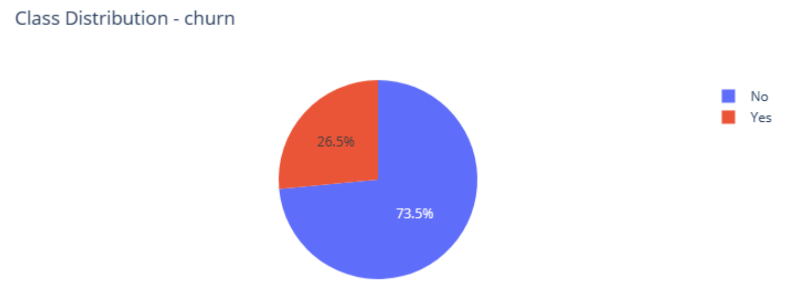
	churn_class	count
0	No	3706
1	Yes	1336

In [85]:
```python
class_ratio =  class_counts.copy()
class_ratio['ratio'] = class_ratio['count'].apply(lambda x: x*100/class_cou
nts['count'].sum())
class_ratio.drop(columns='count', inplace=True)
class_ratio
```

Out[85]:

	churn_class	ratio
0	No	73.50
1	Yes	26.50

In [86]:
```python
# Visualizing the class distribution of the target variable
fig = px.pie(class_ratio, values='ratio', names='churn_class', title='Class
Distribution - churn')
fig.show()
```



3.2 Split Data into X and y then into train and eval for training and evaluation

In [87]:
```
df_train.isna().sum()
```

Out[87]:
```
gender                 0
senior_citizen         0
partner                0
dependents             0
tenure                 0
phone_service          0
multiple_lines       269
internet_service       0
online_security      651
online_backup        651
device_protection    651
tech_support         651
streaming_tv         651
streaming_movies     651
contract               0
paperless_billing      0
payment_method         0
monthly_charges        0
total_charges          8
churn                  1
dtype: int64
```

Drop single row with missing value in target column instead of fill with mode to prevent data leakage.

In [88]:
```
df_train.dropna(subset='churn', inplace=True)
```

In [89]:
```
# Split the data into X and y
X = df_train.drop(columns=[target])
y = df_train[[target]]
```

In [90]:
```
# Split the X and y into train and eval
X_train, X_eval, y_train, y_eval =  train_test_split(X, y, train_size=0.8,
random_state=2024, stratify=y)
(X_train.shape, y_train.shape), (X_eval.shape, y_eval.shape), (df_test.shap
e)
```

Out[90]:
```
(((4033, 19), (4033, 1)), ((1009, 19), (1009, 1)), (2000, 19))
```

In [91]:
```
# Ensure the dimensions match
assert X_train.shape[1] == X_eval.shape[1], "Number of features doesn't mat
ch"
```

In [92]:
```
data_split_size = pd.DataFrame({
    'data': ['train', 'evaluation'],
    'size': [y_train.shape[0], y_eval.shape[0]]
})
data_split_size
```

Out[92]:

	data	size
0	train	4033
1	evaluation	1009

In [93]:
```
encoder = LabelEncoder()

y_train_encoded = encoder.fit_transform(y_train)
y_eval_encoded = encoder.transform(y_eval)
```

3.3 Creating pipelines- imputation, encoding, scaling, and transformation

3.3.1 Pipeline for the numerical features

In [94]:
```
numerical_features = numericals
```

In [95]:
```
df_train[numerical_features].isna().sum()
```

Out[95]:
```
tenure             0
monthly_charges    0
total_charges      8
dtype: int64
```

In [96]:
```
# Infer values of missing total charges in the numerical columns through Fu
nction Transformer
def infer_missing_total_charge(df):
    # Creating a mask variable for the missing values in the column for tot
alcharges
    mask = df['total_charges'].isna()

    # Filling the missing values of total_charge with the values of the mon
thly_charge times tenure
    monthly_charges = df.loc[mask,'monthly_charges']

    # If tenure is 0, times by 1 or tenure = 1
    tenure = df.loc[mask,'tenure'].apply(lambda x: x+1 if x==0 else x)

    df['total_charges'].fillna(monthly_charges*tenure, inplace=True)

    return df
```

In [97]:
```
numerical_pipeline = Pipeline(
    steps = [
            ('infer_missing_total_charge', FunctionTransformer(func=infer_missing_total_charge)), # Handle total_charge with precision
            ('imputer', SimpleImputer(strategy='median')), # Handle missing values
            ('scaler', RobustScaler())                    # Scale numerics
          ]
)

numerical_pipeline
```

Out[97]:
```
Pipeline
  FunctionTransformer
  SimpleImputer
  RobustScaler
```

3.3.2 Pipeline for categorical features

In [98]:
```
df_train.isna().sum()
```

Out[98]:
```
gender                 0
senior_citizen         0
partner                0
dependents             0
tenure                 0
phone_service          0
multiple_lines       269
internet_service       0
online_security      651
online_backup        651
device_protection    651
tech_support         651
streaming_tv         651
streaming_movies     651
contract               0
paperless_billing      0
payment_method         0
monthly_charges        0
total_charges          8
churn                  0
dtype: int64
```

In [99]:
```
# Categorical features
categorical_features = [column for column in categoricals if column not in target]
```

In [100]:
```
def infer_missing_multiple_lines(df):
    mask = df['multiple_lines'].isna()

    # Get the values of the phone_service for missing multiple_lines
    phone_service = df.loc[mask,'phone_service']

    # If phone_service is not available or No, then the value for multiple_lines is also No otherwise the value for multiple_lines remains missing
    multiple_lines = phone_service.apply(lambda x: x if x=='No' else pd.NA)

    df['multiple_lines'].fillna(multiple_lines, inplace=True)

    return df
```

In [101]:
```
# Services columns
services = ['online_security', 'online_backup', 'device_protection', 'tech_support', 'streaming_tv', 'streaming_movies']
```

- Feature engineering

In [102]:
```
def feature_creation(X):
    # After imputation
    df_copy = pd.DataFrame(X, columns=categorical_features)

    # Create new feature in phone_service column- single or multiple lines,
drop multiple_lines column
    # Create 'call_service' column if it doesn't exist
    if 'call_service' not in df_copy.columns:
        conditions = [
            (df_copy['multiple_lines'] == 'Yes') & (df_copy['phone_servic
e'] == 'Yes'),
            (df_copy['multiple_lines'] == 'No') & (df_copy['phone_service']
== 'Yes')
        ]
        choices = ['Multiplelines', 'Singleline']
        df_copy['call_service'] = np.select(conditions, choices, default='N
o')

    # Create new feature from services column- security_service and streami
ng_service
    # Create 'security_service' column if it doesn't exist
    if 'security_service' not in df_copy.columns:
        conditions = [
            (df_copy['online_security'] == 'Yes') & (df_copy['online_backu
p'] == 'Yes') & (df_copy['device_protection'] == 'Yes') & (df_copy['tech_su
pport'] == 'Yes'),
            (df_copy['online_security'] == 'Yes') & (df_copy['online_backu
p'] == 'Yes') & (df_copy['device_protection'] == 'No') & (df_copy['tech_sup
port'] == 'No'),
            (df_copy['online_security'] == 'No') & (df_copy['online_backu
p'] == 'No') & (df_copy['device_protection'] == 'Yes') & (df_copy['tech_sup
port'] == 'No'),
            (df_copy['online_security'] == 'No') & (df_copy['online_backu
p'] == 'No') & (df_copy['device_protection'] == 'No') & (df_copy['tech_supp
ort'] == 'Yes')
        ]
        choices = ['Fullsecurity', 'Securitybackup', 'Deviceprotection', 'T
echsupport']
        df_copy['security_service'] = np.select(conditions, choices, defaul
t='No')

    # Create 'streaming_service' column if it doesn't exist
    if 'streaming_service' not in df_copy.columns:
        # streaming_service feature
        conditions = [
            (df_copy['streaming_tv'] == 'Yes') & (df_copy['streaming_movie
s'] == 'Yes'), # Fullservice
            (df_copy['streaming_tv'] == 'Yes') & (df_copy['streaming_movie
s'] == 'No'), # Tv
            (df_copy['streaming_tv'] == 'No') & (df_copy['streaming_movie
s'] == 'Yes') # Movies
        ]
        choices = ['Fullservice', 'Tv', 'Movies']
        df_copy['streaming_service'] = np.select(conditions, choices, defau
lt='No')

    # Drop redundant feature columns- multiple_lines, services
    columns = ['phone_service', 'multiple_lines'] + services

    df_copy.drop(columns=columns, inplace=True, errors='ignore')

    return df_copy
```

- Handle missing values in 'online_security', 'online_backup', 'device_protection', 'tech_support', 'streaming_tv', 'streaming_movies' with precision. If internet_service is unavailable or No, the aforementioned services is also unavailable or No

In [103]:
```
def infer_missing_services(df):
    for service in services:
        mask = df[service].isna()

        # Get the values of the internet_service for missing service column
        internet_service = df.loc[mask,'internet_service']

        # If internet_service is not available or No, then the value for mu
ltiple_lines is also No otherwise the value for multiple_lines remains miss
ing
        fill_service = internet_service.apply(lambda x: x if x=='No' else p
d.NA)

        df[service].fillna(fill_service, inplace=True)

    return df
```

In [104]:
```
# Pipeline for the categorical columns excluding target column

categorical_pipeline = Pipeline(
    steps = [
        ('infer_missing_multiple_lines', FunctionTransformer(func=infer_mis
sing_multiple_lines)), # Handle multiple_lines with precision
        ('infer_missing_services', FunctionTransformer(func=infer_missing_s
ervices)), # Handle services with precision
        ('imputer', SimpleImputer(strategy='most_frequent')),
        ('feature_creation', FunctionTransformer(func=feature_creation)), #
Handle feature creation of categorical features
        ('encoder', OneHotEncoder(drop='first', sparse_output=False, handle
_unknown='ignore'))
    ]
)

categorical_pipeline
```

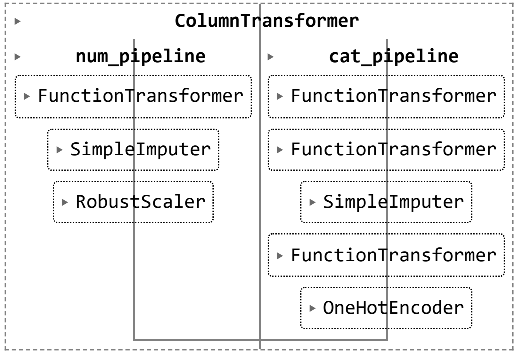
Out[104]:

```
Pipeline
FunctionTransformer
FunctionTransformer
SimpleImputer
FunctionTransformer
OneHotEncoder
```

3.3.3 Create the preprocessing pipeline

In [105]:
```
# Create the preprocessing pipeline - preprocessor for feature columns
preprocessor = ColumnTransformer(
    transformers = [
        ('num_pipeline', numerical_pipeline, numerical_features),
        ('cat_pipeline', categorical_pipeline, categorical_features),
    ],
    remainder='drop'
)

preprocessor
```

Out[105]:



In [106]:
```
categorical_features_new=[feature for feature in categorical_features if feature not in services+['phone_service','multiple_lines',,]] + ['call_service', 'security_service', 'streaming_service']
categorical_features_new
```

Out[106]:
```
['gender',
 'senior_citizen',
 'partner',
 'dependents',
 'internet_service',
 'contract',
 'paperless_billing',
 'payment_method',
 'call_service',
 'security_service',
 'streaming_service']
```

In [107]:
```
unique_value_summary(df_test)
```

Out[107]:

	Column	Unique Values Count	Unique Values
0	gender	2	[Male, Female]
1	senior_citizen	2	[0, 1]
2	partner	2	[No, Yes]
3	dependents	2	[No, Yes]
4	tenure	73	[12, 9, 27, 1, 24, 14, 32, 11, 38, 54, 29, 44,...
5	phone_service	2	[Yes, No]
6	multiple_lines	3	[Yes, No, No phone service]
7	internet_service	3	[Fiber optic, No, DSL]
8	online_security	3	[No, No internet service, Yes]
9	online_backup	3	[No, No internet service, Yes]
10	device_protection	3	[No, No internet service, Yes]
11	tech_support	3	[No, No internet service, Yes]
12	streaming_tv	3	[Yes, No internet service, No]
13	streaming_movies	3	[No, No internet service, Yes]
14	contract	3	[Month-to-month, One year, Two year]
15	paperless_billing	2	[Yes, No]
16	payment_method	4	[Electronic check, Mailed check, Credit card (...
17	monthly_charges	986	[84.45, 20.4, 81.7, 79.5, 89.15, 20.3, 74.95, ...
18	total_charges	1930	[1059.55, 181.8, 2212.55, 2180.55, 89.15, 459....

4.0 Modelling & Evaluation 💡

Models

1. AdaBoostClassifier
2. CatBoostClassifier
3. DecisionTreeClassifier
4. KNeighborsClassifier
5. LogisticRegression
6. RandomForestClassifier
7. Support Vector Machines
8. XGBClassifier
9. Lightgbm

- Create a models list

In [108]:
```python
random_state = 2024
n_jobs = -1
verbose = 0

models = [
    AdaBoostClassifier(random_state=random_state),
    CatBoostClassifier(random_state=random_state, verbose=verbose),
    DecisionTreeClassifier(random_state=random_state),
    KNeighborsClassifier(n_neighbors=10),
    LogisticRegression(random_state=random_state, verbose=verbose),
    RandomForestClassifier(random_state=random_state, n_jobs=n_jobs, verbos
e=verbose),
    svm.SVC(random_state=random_state, probability=True),
    XGBClassifier(random_state=random_state, n_jobs=n_jobs, verbose=verbos
e),
    lgb.LGBMClassifier(random_state=random_state, verbose=verbose)
]
```

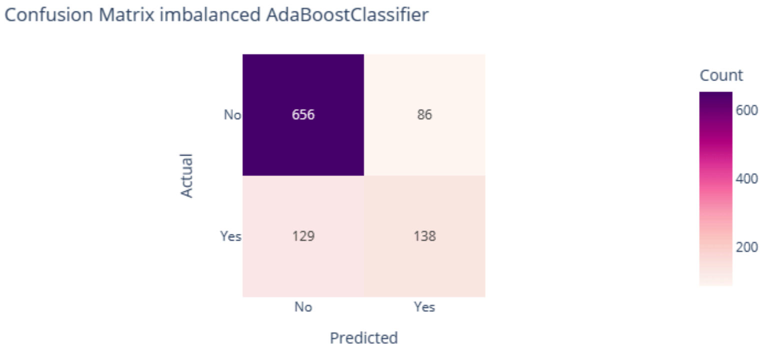
- Create a function to model and return comparative model evaluation scores
- Use F1 Score because of the uneven class distribution (imbalanced classes)

In [109]:
```python
# Set the metric
metric= f1_score

# Get the target class
target_class = y_eval[target].unique().tolist() # encoder.classes_

# Function to calculate and compare F1 Score
def evaluate_models(models=models, X_eval=X_eval, y_eval_encoded=y_eval_enc
oded, target_class=target_class, balanced=False):
     # Creating dictionary for the models
    trained_models = {}

    # Create an empty DataFrame for metrics
    metrics_table = pd.DataFrame(columns=['model_name', 'accuracy', 'precis
ion', 'recall', 'f1_score'])

    for model in models:
        if balanced:
            text = 'balanced'
            final_pipeline = imPipeline(
                steps=[
                    ('preprocessor', preprocessor),
                    ('smote_sampler', SMOTE(random_state=random_state)),
                    ('feature-selection', SelectKBest(mutual_info_classif,
k='all')),
                    ('classifier', model)
                ]
            )
        else:
            text = 'imbalanced'
            final_pipeline = Pipeline(
                steps=[
                    ('preprocessor', preprocessor),
                    # ('feature-selection', SelectKBest(mutual_info_classi
f, k='all')),
                    ('classifier', model)
                ]
            )

        # Fit final pipeline to training data
        final_pipeline.fit(X_train, y_train_encoded)

        # Predict and calculate performance scores
        y_pred = final_pipeline.predict(X_eval)

        # Calculate classification report metrics
        metrics = classification_report(y_eval_encoded, y_pred, target_name
s=target_class, output_dict=True)
        metrics_print = classification_report(y_eval_encoded, y_pred, targe
t_names=target_class)

        # Print classification report
        model_name = final_pipeline['classifier'].__class__.__name__
        print(f"This is the classification report of the {text} {model_nam
e} model\n{metrics_print}\n")

        # Extract metrics for the current model
        accuracy = metrics['accuracy']
        precision = metrics['weighted avg']['precision']
        recall = metrics['weighted avg']['recall']
```

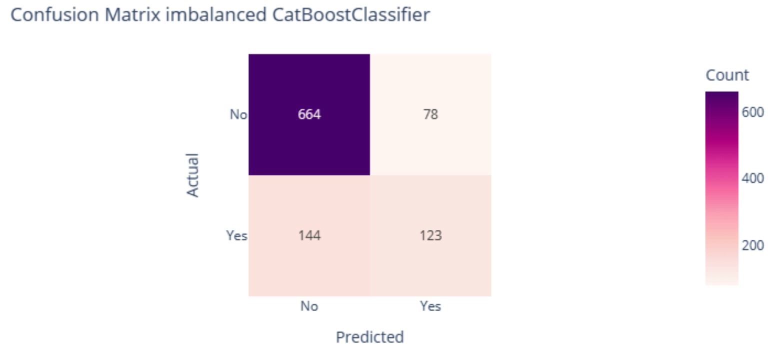
```python
        f1_score = metrics['weighted avg']['f1-score']

        # Add metrics to metrics_table
        metrics_table.loc[len(metrics_table)] = [model_name, accuracy, prec
ision, recall, f1_score]

        # Defining the Confusion Matrix
        model_conf_mat = confusion_matrix(y_eval_encoded, y_pred)
        model_conf_mat = pd.DataFrame(model_conf_mat).reset_index(drop=Tru
e)
        print(f"Below is the confusion matrix for the {text} {model_name} m
odel")

        # Use Plotly Express to create the confusion matrix heatmap
        fig = px.imshow(
            model_conf_mat,
            labels=dict(x='Predicted', y='Actual', color='Count'),
            x=target_class,  # Prediction labels
            y=target_class,  # Actual labels
            text_auto=True,  # Automatically add text in each cell
            color_continuous_scale='RdPu'  # Color scale
        )

        # Add title and adjust layout
        fig.update_layout(
            title=f'Confusion Matrix {text} {model_name}',
            xaxis_nticks=len(model_conf_mat),  # Adjust ticks to match numb
er of classes
            yaxis_nticks=len(model_conf_mat),
        )

        # Show plot
        fig.show()

        # Store trained model
        trained_model_name = 'trained_' + text.strip() + '_' + str(model_na
me).lower()
        trained_models[trained_model_name] = final_pipeline

        print('\n', '-----   -----'*12, '\n',  '-----   -----'*12, '\n')

    # Display the metrics table
    print(f"\nModel evaluation summary report: {text} dataset")
    metrics_table.set_index('model_name', inplace=True)
    metrics_table.sort_values(by=['f1_score', 'precision', 'recall', 'accur
acy'], ascending=False, inplace=True)

    return metrics_table, trained_models
```

In [110]:
```python
# Run the function to train models and return performances
models_eval, trained_models = evaluate_models()
models_eval
```

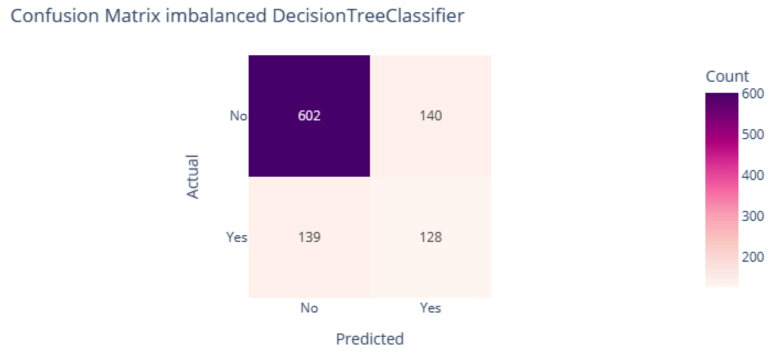
```
This is the classification report of the imbalanced AdaBoostClassifier mode
l
              precision    recall  f1-score   support

          No       0.84      0.88      0.86       742
         Yes       0.62      0.52      0.56       267

    accuracy                           0.79      1009
   macro avg       0.73      0.70      0.71      1009
weighted avg       0.78      0.79      0.78      1009


Below is the confusion matrix for the imbalanced AdaBoostClassifier model
```



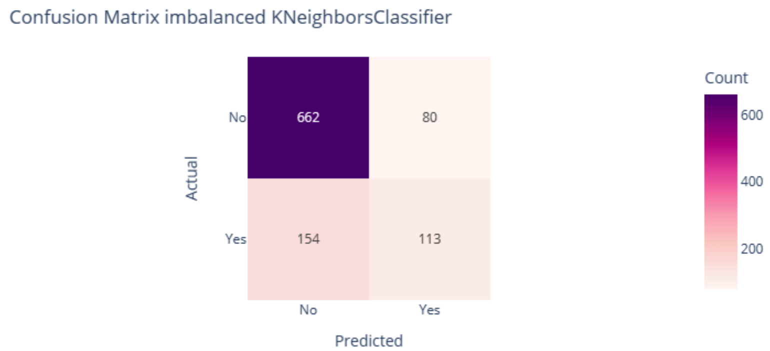

```
 -----   ----------   ----------   ----------   ----------   ----------   -
---------   ----------   ----------   ----------   ----------   ----------
-----
 -----   ----------   ----------   ----------   ----------   ----------   -
---------   ----------   ----------   ----------   ----------  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

This is the classification report of the imbalanced CatBoostClassifier mode
l
              precision    recall  f1-score   support

          No       0.82      0.89      0.86       742
         Yes       0.61      0.46      0.53       267

    accuracy                           0.78      1009
   macro avg       0.72      0.68      0.69      1009
weighted avg       0.77      0.78      0.77      1009


Below is the confusion matrix for the imbalanced CatBoostClassifier model
```




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

This is the classification report of the imbalanced DecisionTreeClassifier
model
              precision    recall  f1-score   support

          No       0.81      0.81      0.81       742
         Yes       0.48      0.48      0.48       267

    accuracy                           0.72      1009
   macro avg       0.65      0.65      0.65      1009
weighted avg       0.72      0.72      0.72      1009


Below is the confusion matrix for the imbalanced DecisionTreeClassifier mod
el
```



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

This is the classification report of the imbalanced KNeighborsClassifier mo
del
              precision    recall  f1-score   support

          No       0.81      0.89      0.85       742
         Yes       0.59      0.42      0.49       267

    accuracy                           0.77      1009
   macro avg       0.70      0.66      0.67      1009
weighted avg       0.75      0.77      0.75      1009


Below is the confusion matrix for the imbalanced KNeighborsClassifier model
```




```
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-----

This is the classification report of the imbalanced LogisticRegression mode
l
              precision    recall  f1-score   support

          No       0.83      0.89      0.86       742
         Yes       0.62      0.51      0.56       267

    accuracy                           0.79      1009
   macro avg       0.73      0.70      0.71      1009
weighted avg       0.78      0.79      0.78      1009


Below is the confusion matrix for the imbalanced LogisticRegression model
```

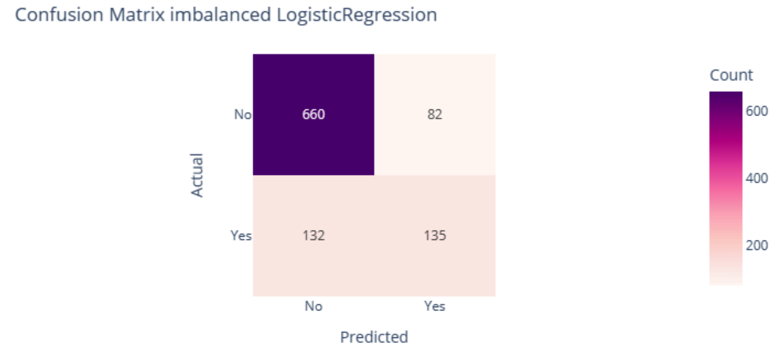


```
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-----

This is the classification report of the imbalanced RandomForestClassifier
model
              precision    recall  f1-score   support

          No       0.83      0.89      0.86       742
         Yes       0.61      0.49      0.55       267

    accuracy                           0.78      1009
   macro avg       0.72      0.69      0.70      1009
weighted avg       0.77      0.78      0.78      1009


Below is the confusion matrix for the imbalanced RandomForestClassifier mod
el
```

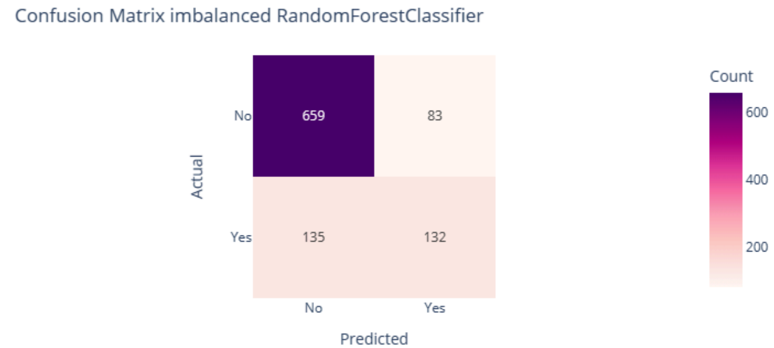

```
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-----
```
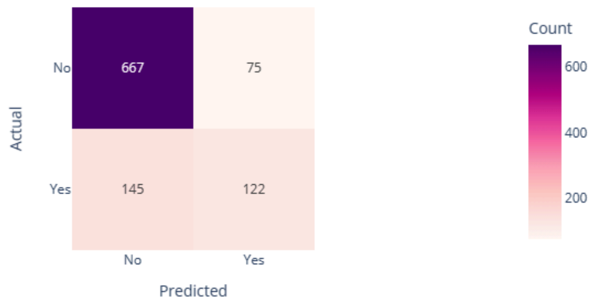
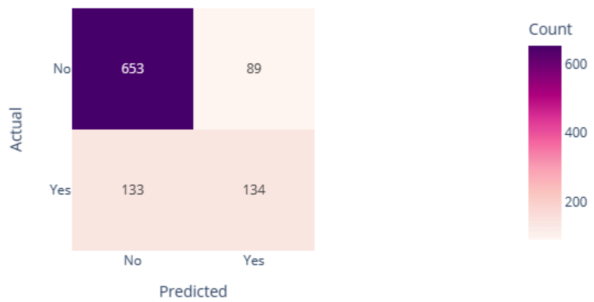
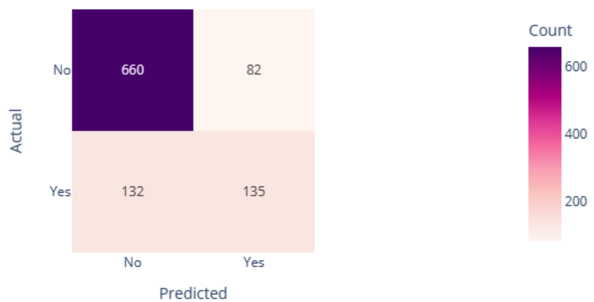

Confusion Matrix imbalanced SVC



Confusion Matrix imbalanced XGBClassifier



Confusion Matrix imbalanced LGBMClassifier




```
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-----
```

```
Model evaluation summary report: imbalanced dataset
```

Out[110]:

model_name	accuracy	precision	recall	f1_score
AdaBoostClassifier	0.79	0.78	0.79	0.78
LogisticRegression	0.79	0.78	0.79	0.78
LGBMClassifier	0.79	0.78	0.79	0.78
RandomForestClassifier	0.78	0.77	0.78	0.78
XGBClassifier	0.78	0.77	0.78	0.77
SVC	0.78	0.77	0.78	0.77
CatBoostClassifier	0.78	0.77	0.78	0.77
KNeighborsClassifier	0.77	0.75	0.77	0.75
DecisionTreeClassifier	0.72	0.72	0.72	0.72

Training Models on a Balanced Data Set

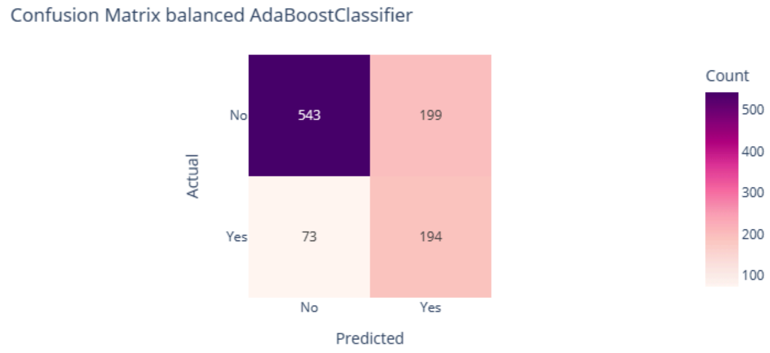
In [111]:
```python
# Run the function to train models and return performances on a balanced dataset
balanced_models_eval, balanced_trained_models = evaluate_models(balanced=True)
balanced_models_eval
```

```
This is the classification report of the balanced AdaBoostClassifier model
              precision    recall  f1-score   support

          No       0.88      0.73      0.80       742
         Yes       0.49      0.73      0.59       267

    accuracy                           0.73      1009
   macro avg       0.69      0.73      0.69      1009
weighted avg       0.78      0.73      0.74      1009


Below is the confusion matrix for the balanced AdaBoostClassifier model
```




```
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-----

This is the classification report of the balanced CatBoostClassifier model
              precision    recall  f1-score   support

          No       0.86      0.84      0.85       742
         Yes       0.58      0.61      0.60       267

    accuracy                           0.78      1009
   macro avg       0.72      0.73      0.72      1009
weighted avg       0.78      0.78      0.78      1009


Below is the confusion matrix for the balanced CatBoostClassifier model
```
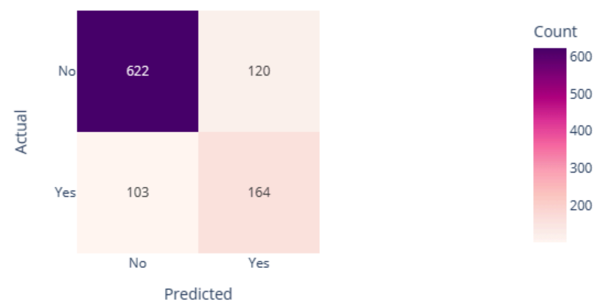

Confusion Matrix balanced CatBoostClassifier




```
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-----

This is the classification report of the balanced DecisionTreeClassifier mo
del
              precision    recall  f1-score   support

          No       0.81      0.80      0.81       742
         Yes       0.47      0.48      0.48       267

    accuracy                           0.72      1009
   macro avg       0.64      0.64      0.64      1009
weighted avg       0.72      0.72      0.72      1009


Below is the confusion matrix for the balanced DecisionTreeClassifier model
```
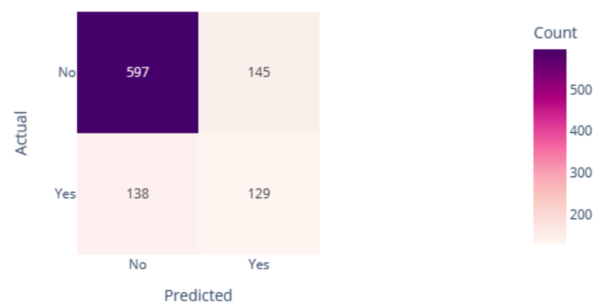

Confusion Matrix balanced DecisionTreeClassifier




```
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-----

This is the classification report of the balanced KNeighborsClassifier mode
l
              precision    recall  f1-score   support

          No       0.89      0.71      0.79       742
         Yes       0.48      0.75      0.58       267

    accuracy                           0.72      1009
   macro avg       0.68      0.73      0.68      1009
weighted avg       0.78      0.72      0.73      1009


Below is the confusion matrix for the balanced KNeighborsClassifier model
```
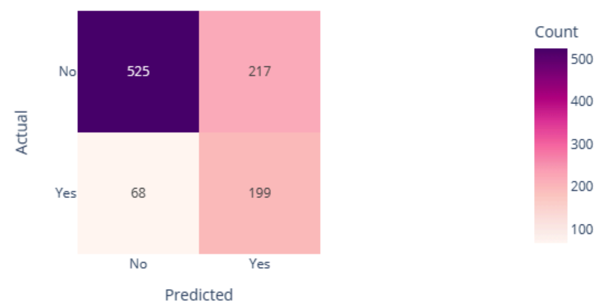

Confusion Matrix balanced KNeighborsClassifier




```
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-----

This is the classification report of the balanced LogisticRegression model
              precision    recall  f1-score   support

          No       0.90      0.73      0.81       742
         Yes       0.51      0.78      0.62       267

    accuracy                           0.74      1009
   macro avg       0.71      0.76      0.71      1009
weighted avg       0.80      0.74      0.76      1009


Below is the confusion matrix for the balanced LogisticRegression model
```

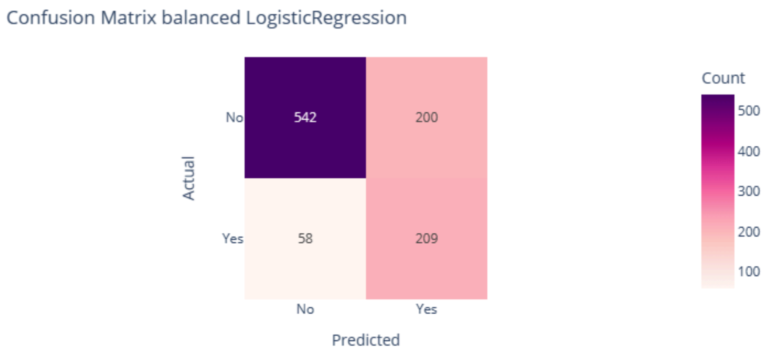


```
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-----
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---------   ----------   ----------   ----------   ----------   ----------
-----

This is the classification report of the balanced RandomForestClassifier mo
del
              precision    recall  f1-score   support

          No       0.85      0.84      0.84       742
         Yes       0.57      0.60      0.58       267

    accuracy                           0.77      1009
   macro avg       0.71      0.72      0.71      1009
weighted avg       0.78      0.77      0.77      1009


Below is the confusion matrix for the balanced RandomForestClassifier model
```

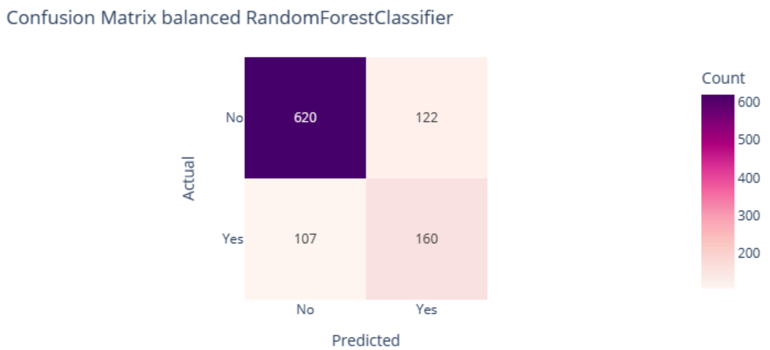


```
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-----
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-----

This is the classification report of the balanced SVC model
              precision    recall  f1-score   support

          No       0.88      0.78      0.83       742
         Yes       0.54      0.71      0.61       267

    accuracy                           0.76      1009
   macro avg       0.71      0.75      0.72      1009
weighted avg       0.79      0.76      0.77      1009


Below is the confusion matrix for the balanced SVC model
```

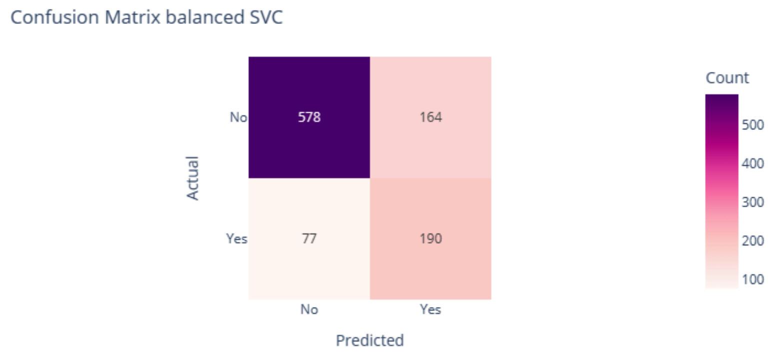


```
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-----
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-----

This is the classification report of the balanced XGBClassifier model
              precision    recall  f1-score   support

          No       0.84      0.83      0.83       742
         Yes       0.54      0.55      0.54       267

    accuracy                           0.76      1009
   macro avg       0.69      0.69      0.69      1009
weighted avg       0.76      0.76      0.76      1009


Below is the confusion matrix for the balanced XGBClassifier model
```

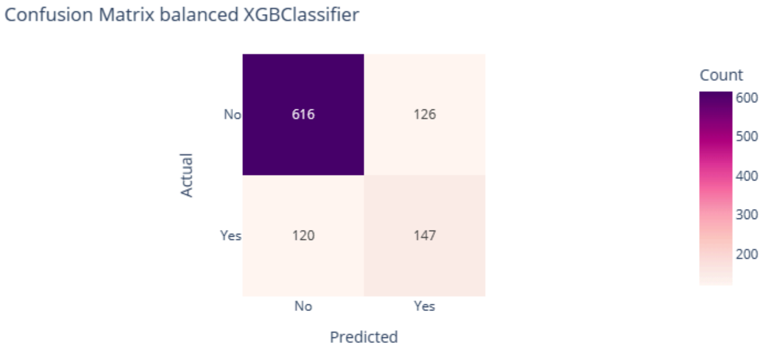


```
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-----
```
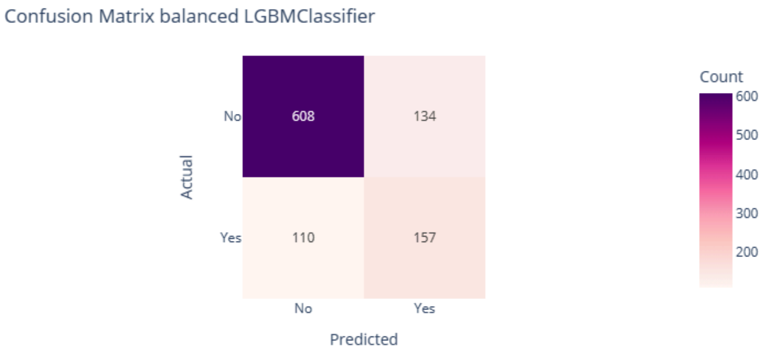

```
This is the classification report of the balanced LGBMClassifier model
              precision    recall  f1-score   support

          No       0.85      0.82      0.83       742
         Yes       0.54      0.59      0.56       267

    accuracy                           0.76      1009
   macro avg       0.69      0.70      0.70      1009
weighted avg       0.77      0.76      0.76      1009
```

```
Below is the confusion matrix for the balanced LGBMClassifier model
```




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

```
Model evaluation summary report: balanced dataset
```

Out[111]:

model_name	accuracy	precision	recall	f1_score
CatBoostClassifier	0.78	0.78	0.78	0.78
RandomForestClassifier	0.77	0.78	0.77	0.77
SVC	0.76	0.79	0.76	0.77
LGBMClassifier	0.76	0.77	0.76	0.76
LogisticRegression	0.74	0.80	0.74	0.76
XGBClassifier	0.76	0.76	0.76	0.76
AdaBoostClassifier	0.73	0.78	0.73	0.74
KNeighborsClassifier	0.72	0.78	0.72	0.73
DecisionTreeClassifier	0.72	0.72	0.72	0.72

Compare model evaluation report on imbalanced and balanced dataset

In [112]:
```python
eval_before_after_balance_models = pd.merge(
    models_eval[['accuracy']],
    balanced_models_eval[['accuracy']],
    left_index=True,
    right_index=True,
    how='inner',
    suffixes=('_before', '_after')
).sort_values(ascending=False, by=['accuracy_before'])

eval_before_after_balance_models
```

Out[112]:

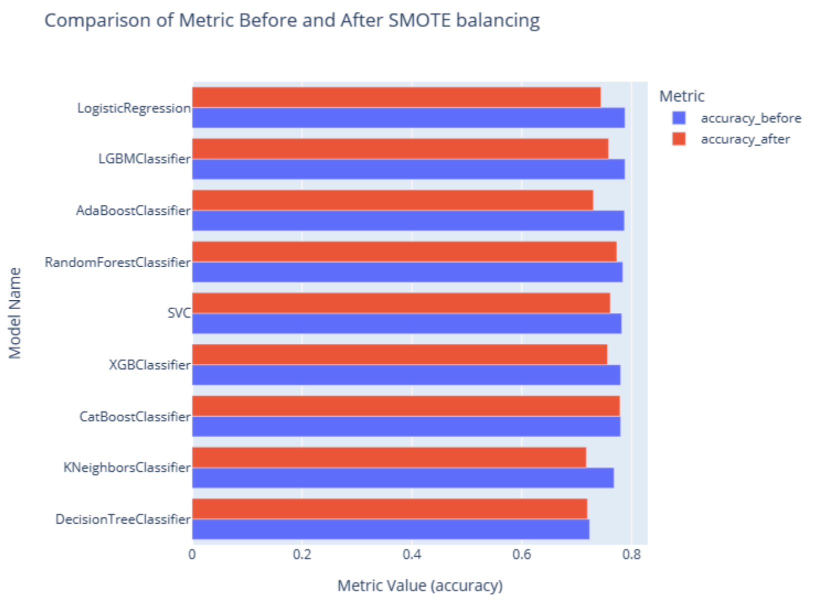
model_name	accuracy_before	accuracy_after
LogisticRegression	0.79	0.74
LGBMClassifier	0.79	0.76
AdaBoostClassifier	0.79	0.73
RandomForestClassifier	0.78	0.77
SVC	0.78	0.76
XGBClassifier	0.78	0.76
CatBoostClassifier	0.78	0.78
KNeighborsClassifier	0.77	0.72
DecisionTreeClassifier	0.72	0.72

In [113]:
```python
# Melt the dataframe
df_melted_bal = (
    eval_before_after_balance_models
    .reset_index()
    .melt(id_vars='model_name', var_name='metric', value_name='value')
    .sort_values(ascending=False, by=['value'])
)

category_orders = {
    'model_name': df_melted_bal.model_name,
    'metric': ['accuracy_before', 'accuracy_after']
}

# Make the plot
fig = px.bar(
    df_melted_bal,
    x='value',
    y='model_name',
    color='metric',
    barmode='group',
    title='Comparison of Metric Before and After SMOTE balancing',
    labels={'value': 'Metric Value (accuracy)', 'model_name': 'Model Name',
'metric': 'Metric'},
    category_orders=category_orders,
    orientation='h',
    height=600
)

# Show plot
fig.show()
```



- In general, the models performed better on the imbalanced dataset before smote balancing was applied. Therefore, the imbalanced pipeline will be used for further evaluation, hyperparameter tuning and analysis.

In [114]:
```python
def info(models: Union[ValuesView[Pipeline], List[Pipeline]], metric: Callable[..., float], **kwargs) -> List[Dict[str, Any]]:
    """
    Generates a list of dictionaries, each containing a model's name and a specified performance metric.

    Parameters:
    - models (List[Pipeline]): A list of model pipeline instances.
    - metric (Callable[..., float]): A function used to evaluate the model's performance. Expected to accept
      parameters like `y_true`, `y_pred`, and `average`, and return a float.
    - **kwargs: Additional keyword arguments to be passed to the metric function or any other function calls inside `info`. Can pass

    Returns:
    - List[Dict[str, Any]]: A list of dictionaries with model names and their evaluated metrics.
    """
    def get_metric(model, kwargs):

        # Add default kwargs for callable metric to kwargs. Consider is they are present in kwargs
        if 'X_train' and 'y_train_encoded' in kwargs:
            model.fit(kwargs[X_train], kwargs[y_train_encoded])
        else:
            # Fit final pipeline to training data
            model.fit(X_train, y_train_encoded)

        if 'y_eval_encoded' in kwargs:
            kwargs['y_true'] = kwargs['y_eval_encoded']
        else:
            kwargs['y_true'] = y_eval_encoded

        if 'X_eval' in kwargs:
            kwargs['y_pred'] = model.predict(kwargs[X_eval])
        else:
            kwargs['y_pred'] = model.predict(X_eval)

        # Sanitize the metric arguments, use only valid metric parameters
        kwargs = {k: value for k, value in kwargs.items() if k in inspect.signature(metric).parameters.keys()}

        return metric(**kwargs)

    info_metric = [
        {
            'model_name': model['classifier'].__class__.__name__,
            f'Metric ({metric.__name__}_{kwargs['average'] if 'average' in kwargs else ''})': get_metric(model, kwargs),
        } for model in models
    ]

    return info_metric
```

- Get the info of the trained models

In [115]:
```
info_models_before_tuning = info(trained_models.values(), metric, average
='weighted')
info_models_before_tuning
```

Out[115]:
```
[{'model_name': 'AdaBoostClassifier',
  'Metric (f1_score_weighted)': 0.7805874303142074},
 {'model_name': 'CatBoostClassifier',
  'Metric (f1_score_weighted)': 0.7691502531804332},
 {'model_name': 'DecisionTreeClassifier',
  'Metric (f1_score_weighted)': 0.7236537974046441},
 {'model_name': 'KNeighborsClassifier',
  'Metric (f1_score_weighted)': 0.754940917133973},
 {'model_name': 'LogisticRegression',
  'Metric (f1_score_weighted)': 0.7804102032433796},
 {'model_name': 'RandomForestClassifier',
  'Metric (f1_score_weighted)': 0.7759472428811512},
 {'model_name': 'SVC', 'Metric (f1_score_weighted)': 0.7704262907519801},
 {'model_name': 'XGBClassifier',
  'Metric (f1_score_weighted)': 0.7732695620810294},
 {'model_name': 'LGBMClassifier',
  'Metric (f1_score_weighted)': 0.7804102032433796}]
```

In [116]:
```
column_to_sort = [column for column in info_models_before_tuning[0].keys()
if f'{metric.__name__}' in column]
pd.DataFrame(info_models_before_tuning).sort_values(ascending=False, by=col
umn_to_sort)
```

Out[116]:

	model_name	Metric (f1_score_weighted)
0	AdaBoostClassifier	0.78
4	LogisticRegression	0.78
8	LGBMClassifier	0.78
5	RandomForestClassifier	0.78
7	XGBClassifier	0.77
6	SVC	0.77
1	CatBoostClassifier	0.77
3	KNeighborsClassifier	0.75
2	DecisionTreeClassifier	0.72

4.1 Hyperparameter tuning- GridSearch

4.1.1 Define hyperparameters to search

In [117]:
```
# Define the hyperparameters to search

param_grids = {
    0: { # ada_boost
        'classifier__n_estimators': [10, 50],
        'classifier__learning_rate':  [0.1, 0.5, 1],
        'classifier__algorithm': ['SAMME', 'SAMME.R'],
    },
    1: { # cat_boost
        'classifier__n_estimators': [10, 50],
        'classifier__learning_rate':  [0.1, 0.5, 1],
    },
    2: { # decision_tree
        'classifier__max_depth': [None, 10, 20, 30],
        'classifier__min_samples_split': [2, 5, 10],
    },
    3: { # knn
        'classifier__n_neighbors': [3, 5, 7, 9, 11],
        'classifier__leaf_size': [20, 30, 40],
    },
    4: { # log_regression
        'classifier__C': [0.1, 1, 10],
        'classifier__solver' : ['lbfgs', 'liblinear', 'newton-cg', 'newton-
cholesky', 'sag', 'saga'],
        'classifier__max_iter': [100, 200, 300],
    },
    5: { # random_forest
        'classifier__n_estimators': [10, 50],
        'classifier__max_depth': [None, 10, 20],
    },
    6: { # svm
        'classifier__C': [0.1, 1, 10],
        'classifier__kernel': ['linear', 'poly', 'rbf', 'sigmoid', 'precomp
uted'],
        'classifier__decision_function_shape': ['ovo', 'ovr'],
    },
    7: { # xgb
        'classifier__n_estimators': [10, 50],
        'classifier__max_depth': [5, 10, 20],
    },
    8: { # lgb
        'classifier__num_leaves': [20, 40],
        'classifier__n_estimators': [10, 50],
        'classifier__max_depth': [3, 5],
    }
}

param_grids= {models[k].__class__.__name__: v for k, v in param_grids.items
()}
param_grids.keys()
```

Out[117]:
```
dict_keys(['AdaBoostClassifier', 'CatBoostClassifier', 'DecisionTreeClassif
ier', 'KNeighborsClassifier', 'LogisticRegression', 'RandomForestClassifie
r', 'SVC', 'XGBClassifier', 'LGBMClassifier'])
```

In [118]:
```python
params = {}
search_histories = {}

for model in models:
    final_pipeline = Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('classifier', model)
    ])

    model_name = model.__class__.__name__

    param_grid = param_grids[model_name]

    # Create a StratifiedKFold object
    skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=random_sta
te)

    searcher = GridSearchCV(
        estimator = final_pipeline,
        param_grid = param_grid,
        cv = skf, # StratifiedKFold for imbalanced dataset
        scoring = ['f1_weighted', 'f1', 'accuracy', 'balanced_accuracy', 'p
recision', 'recall', 'roc_auc'],
        refit = 'f1_weighted', # True if one scoring. Refit model with the
best scoring- using f1_weighted in this case
        verbose = 3, # verbose=3 # Show the steps as output
        n_jobs = -1
    )

    searcher.fit(X_train, y_train_encoded)
    search_history = pd.DataFrame(searcher.cv_results_)
    params[model_name] = searcher
    search_histories[model_name] = search_history

for model_name, search in params.items():
    print(f'Best hyperparamters for {model_name}:{search.best_params_}')
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Fitting 5 folds for each of 12 candidates, totalling 60 fits
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Fitting 5 folds for each of 54 candidates, totalling 270 fits
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Fitting 5 folds for each of 30 candidates, totalling 150 fits
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Fitting 5 folds for each of 8 candidates, totalling 40 fits
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
Best hyperparamters for AdaBoostClassifier:{'classifier__algorithm': 'SAMM
E.R', 'classifier__learning_rate': 0.5, 'classifier__n_estimators': 50}
```

```
Best hyperparamters for CatBoostClassifier:{'classifier__learning_rate': 0.
1, 'classifier__n_estimators': 50}
Best hyperparamters for DecisionTreeClassifier:{'classifier__max_depth': 1
0, 'classifier__min_samples_split': 10}
Best hyperparamters for KNeighborsClassifier:{'classifier__leaf_size': 20,
'classifier__n_neighbors': 11}
Best hyperparamters for LogisticRegression:{'classifier__C': 1, 'classifier
__max_iter': 100, 'classifier__solver': 'lbfgs'}
Best hyperparamters for RandomForestClassifier:{'classifier__max_depth': 1
0, 'classifier__n_estimators': 50}
Best hyperparamters for SVC:{'classifier__C': 10, 'classifier__decision_fun
ction_shape': 'ovo', 'classifier__kernel': 'linear'}
Best hyperparamters for XGBClassifier:{'classifier__max_depth': 5, 'classif
ier__n_estimators': 10}
Best hyperparamters for LGBMClassifier:{'classifier__max_depth': 5, 'classi
fier__n_estimators': 50, 'classifier__num_leaves': 40}
```

In [119]:

```
# Get the performance of each model with the best hyperparameters
def get_best_models(params):
    best_models = {}
    best_scores = {}
    for model_name, search in params.items():
        best_model = search.best_estimator_
        best_model_score = search.best_score_
        best_models[model_name] = best_model
        best_scores[model_name] = best_model_score
    return best_models, best_scores

best_models, best_scores = get_best_models(params)
```

In [120]:

```
info_models_before_tuning
```

Out[120]:

```
[{'model_name': 'AdaBoostClassifier',
  'Metric (f1_score_weighted)': 0.7805874303142074},
 {'model_name': 'CatBoostClassifier',
  'Metric (f1_score_weighted)': 0.7691502531804332},
 {'model_name': 'DecisionTreeClassifier',
  'Metric (f1_score_weighted)': 0.7236537974046441},
 {'model_name': 'KNeighborsClassifier',
  'Metric (f1_score_weighted)': 0.754940917133973},
 {'model_name': 'LogisticRegression',
  'Metric (f1_score_weighted)': 0.7804102032433796},
 {'model_name': 'RandomForestClassifier',
  'Metric (f1_score_weighted)': 0.7759472428811512},
 {'model_name': 'SVC', 'Metric (f1_score_weighted)': 0.7704262907519801},
 {'model_name': 'XGBClassifier',
  'Metric (f1_score_weighted)': 0.7732695620810294},
 {'model_name': 'LGBMClassifier',
  'Metric (f1_score_weighted)': 0.7804102032433796}]
```

In [121]:

```
info_models_after_tuning = info(models=best_models.values(), metric=metric,
average='weighted')
info_models_after_tuning
```

```
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

Out[121]:

```
[{'model_name': 'AdaBoostClassifier',
  'Metric (f1_score_weighted)': 0.7855279660687892},
 {'model_name': 'CatBoostClassifier',
  'Metric (f1_score_weighted)': 0.782097618947286},
 {'model_name': 'DecisionTreeClassifier',
  'Metric (f1_score_weighted)': 0.7494383522998187},
 {'model_name': 'KNeighborsClassifier',
  'Metric (f1_score_weighted)': 0.7604208289000768},
 {'model_name': 'LogisticRegression',
  'Metric (f1_score_weighted)': 0.7804102032433796},
 {'model_name': 'RandomForestClassifier',
  'Metric (f1_score_weighted)': 0.7704262907519801},
 {'model_name': 'SVC', 'Metric (f1_score_weighted)': 0.7717166956437632},
 {'model_name': 'XGBClassifier',
  'Metric (f1_score_weighted)': 0.7712299806292581},
 {'model_name': 'LGBMClassifier',
  'Metric (f1_score_weighted)': 0.773623310997827}]
```

In [122]:

```
column_to_sort = [column for column in info_models_after_tuning[0].keys() i
f f'{metric.__name__}' in column]
pd.DataFrame(info_models_after_tuning).sort_values(ascending=False, by=colu
mn_to_sort)
```

Out[122]:

	model_name	Metric (f1_score_weighted)
0	AdaBoostClassifier	0.79
1	CatBoostClassifier	0.78
4	LogisticRegression	0.78
8	LGBMClassifier	0.77
6	SVC	0.77
7	XGBClassifier	0.77
5	RandomForestClassifier	0.77
3	KNeighborsClassifier	0.76
2	DecisionTreeClassifier	0.75

In [123]:

```
info_models_before_tuning
```

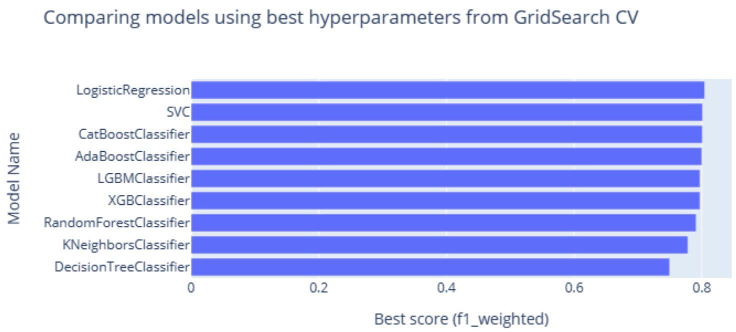
Out[123]:

```
[{'model_name': 'AdaBoostClassifier',
  'Metric (f1_score_weighted)': 0.7805874303142074},
 {'model_name': 'CatBoostClassifier',
  'Metric (f1_score_weighted)': 0.7691502531804332},
 {'model_name': 'DecisionTreeClassifier',
  'Metric (f1_score_weighted)': 0.7236537974046441},
 {'model_name': 'KNeighborsClassifier',
  'Metric (f1_score_weighted)': 0.754940917133973},
 {'model_name': 'LogisticRegression',
  'Metric (f1_score_weighted)': 0.7804102032433796},
 {'model_name': 'RandomForestClassifier',
  'Metric (f1_score_weighted)': 0.7759472428811512},
 {'model_name': 'SVC', 'Metric (f1_score_weighted)': 0.7704262907519801},
 {'model_name': 'XGBClassifier',
  'Metric (f1_score_weighted)': 0.7732695620810294},
 {'model_name': 'LGBMClassifier',
  'Metric (f1_score_weighted)': 0.7804102032433796}]
```

In [124]:
```
pd.DataFrame(info_models_before_tuning).sort_values(ascending=False, by=col
umn_to_sort)
```
Out[124]:

	model_name	Metric (f1_score_weighted)
0	AdaBoostClassifier	0.78
4	LogisticRegression	0.78
8	LGBMClassifier	0.78
5	RandomForestClassifier	0.78
7	XGBClassifier	0.77
6	SVC	0.77
1	CatBoostClassifier	0.77
3	KNeighborsClassifier	0.75
2	DecisionTreeClassifier	0.72

In [125]:
```
# Create a DataFrame to use with Plotly Express
df_best_models = pd.DataFrame(best_scores.items(), columns=['model_name',
'f1_score'])

df_best_models = df_best_models.sort_values(by='f1_score', ascending=True)

# Create the bar chart using Plotly Express
fig = px.bar(
    df_best_models, x='f1_score', y='model_name',
    labels={'f1_score': 'Best score (f1_weighted)', 'model_name': 'Model Na
me'},
    title='Comparing models using best hyperparameters from GridSearch CV',
    orientation='h'
)

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



- It is evident that `CatBoostClassifier` is the best model after hyperparameter tuning over taking `LogisticRegression` which is now 3rd place. The top five(5) models are `CatBoostClassifier`, `LGBMClassifier`, `LogisticRegression`, `AdaBoostClassifier`, and `SVC`.

In [126]:
```
df_best_models
```
Out[126]:

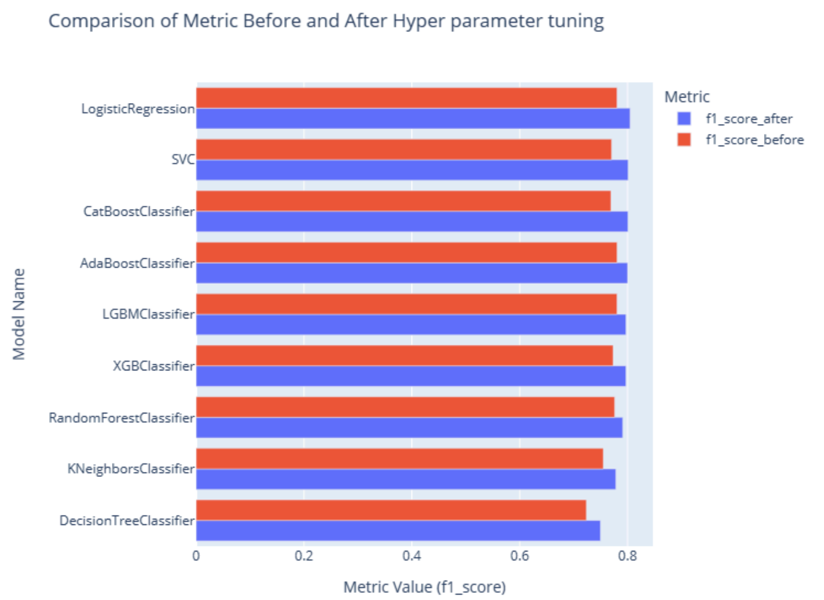
	model_name	f1_score
2	DecisionTreeClassifier	0.75
3	KNeighborsClassifier	0.78
5	RandomForestClassifier	0.79
7	XGBClassifier	0.80
8	LGBMClassifier	0.80
0	AdaBoostClassifier	0.80
1	CatBoostClassifier	0.80
6	SVC	0.80
4	LogisticRegression	0.80

In [127]:
```
metric_before_after_tuning_models = pd.merge(
    models_eval[['f1_score']].reset_index(),
    df_best_models,
    on='model_name',
    how='inner',
    suffixes=('_before', '_after')
).sort_values(ascending=False, by='f1_score_after')

metric_before_after_tuning_models
```
Out[127]:

	model_name	f1_score_before	f1_score_after
1	LogisticRegression	0.78	0.80
5	SVC	0.77	0.80
6	CatBoostClassifier	0.77	0.80
0	AdaBoostClassifier	0.78	0.80
2	LGBMClassifier	0.78	0.80
4	XGBClassifier	0.77	0.80
3	RandomForestClassifier	0.78	0.79
7	KNeighborsClassifier	0.75	0.78
8	DecisionTreeClassifier	0.72	0.75

Compare models before and after hyperparameter tuning using f1 score (weighted) metric

In [128]:
```python
# Melt the dataframe
df_melted_tuning = (
    metric_before_after_tuning_models
    .melt(id_vars='model_name', var_name='metric', value_name='value')
    .sort_values(ascending=False, by=['value'])
)

category_orders = {
    'model_name': df_melted_tuning.model_name,
    'metric':['f1_score_after', 'f1_score_before']
}

# Make the plot
fig = px.bar(
    df_melted_tuning,
    x='value',
    y='model_name',
    color='metric',
    barmode='group',
    title='Comparison of Metric Before and After Hyper parameter tuning',
    labels={'value': f'Metric Value ({metric.__name__})', 'model_name': 'Mo
del Name', 'metric': 'Metric'},
    category_orders=category_orders,
    orientation='h',
    height=600
)

# Show plot
fig.show()
```



- In general, the models performed better after hyper parametrer tuning. Therefore, the models with their best hyperparameters will be used for further evaluation, modeling, testing and analysis.

In [129]:
```python
mask = df_best_models['f1_score'] == df_best_models['f1_score'].max()
best_model_score = df_best_models[mask]
best_model_name = best_model_score['model_name'].iloc[0]
best_model = best_models[best_model_name]
best_model
```

Out[129]:
```
Pipeline
preprocessor: ColumnTransformer
num_pipeline                cat_pipeline
FunctionTransformer         FunctionTransformer
SimpleImputer               FunctionTransformer
RobustScaler                SimpleImputer
                            FunctionTransformer
                            OneHotEncoder
LogisticRegression
```

4.1.2 Evaluate the best model on the evaluation set

In [130]:
```python
X_eval.head()
```

Out[130]:

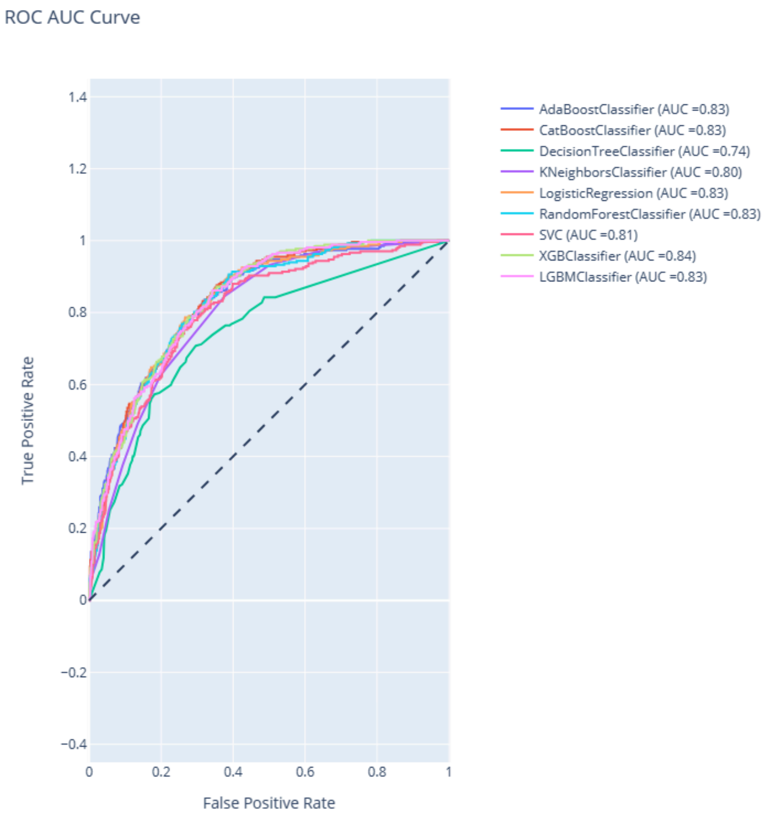
	gender	senior_citizen	partner	dependents	tenure	phone_service	multiple_lines	inter
3920	Female	Yes	No	No	26	Yes	No	
2545	Female	No	Yes	Yes	62	Yes	No	
812	Female	No	Yes	No	42	Yes	Yes	
4748	Female	Yes	No	No	1	Yes	No	
1904	Male	No	No	No	56	Yes	Yes	

In [131]:
```
X_eval.isna().sum()
```
Out[131]:
```
gender                0
senior_citizen        0
partner               0
dependents            0
tenure                0
phone_service         0
multiple_lines       61
internet_service      0
online_security     134
online_backup       134
device_protection   134
tech_support        134
streaming_tv        134
streaming_movies    134
contract              0
paperless_billing     0
payment_method        0
monthly_charges       0
total_charges         1
dtype: int64
```

In [132]:
```
y_eval_pred = best_model.predict(X_eval)
print(f'Classification report of the best model- {best_model_name}\n\n{classification_report(y_true=y_eval_encoded, y_pred=y_eval_pred, target_names=target_class)}')
```
```
Classification report of the best model- LogisticRegression

              precision    recall  f1-score   support

          No       0.83      0.89      0.86       742
         Yes       0.62      0.51      0.56       267

    accuracy                           0.79      1009
   macro avg       0.73      0.70      0.71      1009
weighted avg       0.78      0.79      0.78      1009
```

4.1.3 Plot the ROC-AUC Curve for all models

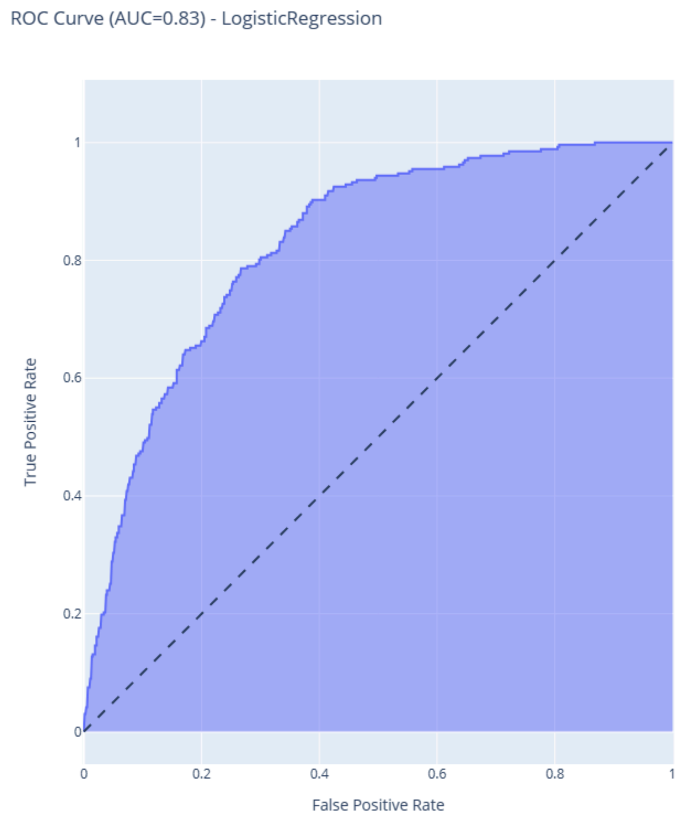
In [133]:
```
fig = go.Figure()

# Add confusion matrix to all pipelines
all_confusion_matrix = {}

# Add ROC data for all pipelines
all_roc_data = {}

for model_name, pipeline in best_models.items():
    y_score = pipeline.predict_proba(X_eval)[:, 1]

    fpr, tpr, thresholds = roc_curve(y_eval_encoded, y_score)

    roc_auc = auc(fpr, tpr)

    roc_data_df = pd.DataFrame({'False Positive rate': fpr, 'True Positive Rate': tpr, 'Thresholds': thresholds})

    all_roc_data[model_name] = roc_data_df


    # Generate the confusion matrix
    y_pred = pipeline.predict(X_eval)

    conf_matrix = confusion_matrix(y_eval_encoded, y_pred)

    all_confusion_matrix[model_name] = conf_matrix

    fig.add_trace(go.Scatter(x=fpr, y=tpr, mode='lines', name=f'{model_name} (AUC ={roc_auc:.2f})'))

    fig.update_layout(
        title=f'ROC AUC Curve',
        xaxis_title='False Positive Rate',
        yaxis_title='True Positive Rate',
        legend=dict(
            x=1.02,
            y=0.98
        ),
        yaxis=dict(scaleanchor="x", scaleratio=1),
        xaxis=dict(constrain='domain'),
        width=1024,
        height=800
)

fig.add_shape(
    type='line', line=dict(dash='dash'),
    x0=0, x1=1, y0=0, y1=1
)


fig.show()
```



- Plot the ROC AUC Curve for the best model

In [134]:
```
# Compute ROC curve
fpr, tpr, thresholds = roc_curve(y_eval_encoded, best_model.predict_proba(X
_eval)[:, 1])
roc_auc = auc(fpr, tpr)
```

In [135]:
```
fig = px.area(
    x=fpr,
    y=tpr,
    title=f'ROC Curve (AUC={auc(fpr, tpr):.2f}) - {best_model_name}',
    labels=dict(x='False Positive Rate', y='True Positive Rate'),
    width=800,
    height=800
)
fig.add_shape(
    type='line',
    line=dict(dash='dash'),
    x0=0,
    x1=1,
    y0=0,
    y1=1
)

fig.update_yaxes(scaleanchor="x", scaleratio=1)
fig.update_xaxes(constrain='domain')
fig.show()
```



In [136]:
```
all_confusion_matrix[best_model_name]
```
Out[136]:
```
array([[660,  82],
       [132, 135]], dtype=int64)
```

In [137]:
```
all_roc_data[best_model_name].tail(50).style.format("{:.9f}")
```

Out[137]:

	False Positive rate	True Positive Rate	Thresholds
244	0.409703504	0.910112360	0.164851692
245	0.413746631	0.910112360	0.161788909
246	0.413746631	0.913857678	0.161514659
247	0.415094340	0.913857678	0.161154612
248	0.415094340	0.917602996	0.161126255
249	0.423180593	0.917602996	0.157075845
250	0.423180593	0.921348315	0.156569297
251	0.424528302	0.921348315	0.156456135
252	0.424528302	0.925093633	0.156057560
253	0.444743935	0.925093633	0.142087284
254	0.444743935	0.928838951	0.141636495
255	0.455525606	0.928838951	0.131662488
256	0.455525606	0.932584270	0.131597075
257	0.463611860	0.932584270	0.128752886
258	0.463611860	0.936329588	0.128057543
259	0.494609164	0.936329588	0.104969320
260	0.494609164	0.940074906	0.104420745
261	0.497304582	0.940074906	0.103403074
262	0.497304582	0.943820225	0.103100382
263	0.533692722	0.943820225	0.087625595
264	0.533692722	0.947565543	0.086775164
265	0.552560647	0.947565543	0.081037211
266	0.552560647	0.951310861	0.077524550
267	0.557951482	0.951310861	0.075491393
268	0.557951482	0.955056180	0.075479325
269	0.611859838	0.955056180	0.060140966
270	0.611859838	0.958801498	0.059512601
271	0.637466307	0.958801498	0.050683099
272	0.637466307	0.962546816	0.050566373
273	0.644204852	0.962546816	0.048478893
274	0.644204852	0.966292135	0.047034847
275	0.646900270	0.966292135	0.045095908
276	0.646900270	0.970037453	0.044771999
277	0.652291105	0.970037453	0.042584097
278	0.652291105	0.973782772	0.042549237
279	0.673854447	0.973782772	0.037771182
280	0.673854447	0.977528090	0.037442747
281	0.712938005	0.977528090	0.029204169
282	0.712938005	0.981273408	0.028860051
283	0.722371968	0.981273408	0.027893894
284	0.722371968	0.985018727	0.027893058
285	0.776280323	0.985018727	0.019980136
286	0.776280323	0.988764045	0.019808464
287	0.804582210	0.988764045	0.015972081
288	0.804582210	0.992509363	0.015971026
289	0.807277628	0.992509363	0.015325745
290	0.807277628	0.996254682	0.015256002
291	0.867924528	0.996254682	0.009660294
292	0.867924528	1.000000000	0.009645357
293	1.000000000	1.000000000	0.001923647

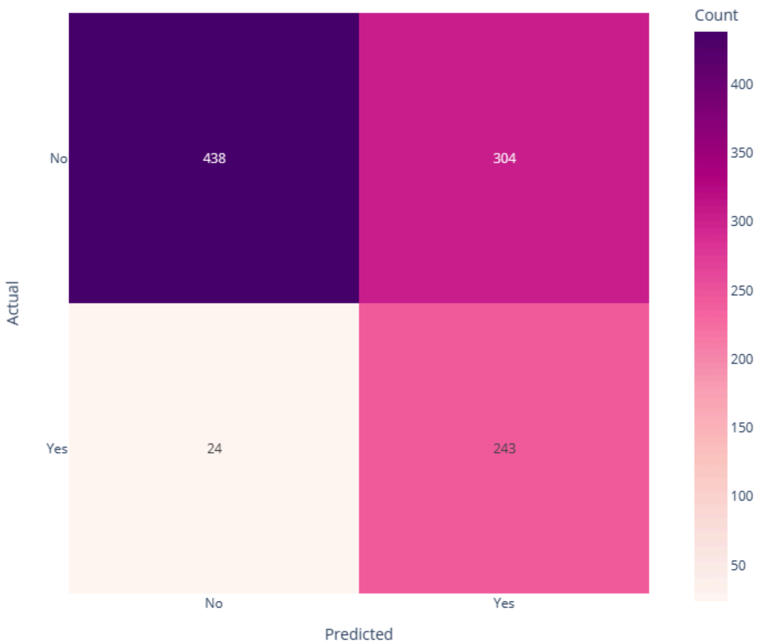
In [138]:

```
threshold = 0.164851692 # STrue Positive Rate 0.910112360

y_pred_proba = best_model.predict_proba(X_eval)[:,1]

binary_predictions = (y_pred_proba > threshold).astype(int)
threshold_matrix = confusion_matrix(y_eval_encoded, binary_predictions)
threshold_matrix
```

Out[138]:

```
array([[438, 304],
       [ 24, 243]], dtype=int64)
```

In [139]:
```python
# Create a heatmap using Plotly Express
fig = px.imshow(
            threshold_matrix,
            labels=dict(x='Predicted', y='Actual', color='Count'),
            x=target_class,  # Prediction labels
            y=target_class,  # Actual labels
            text_auto=True,  # Automatically add text in each cell
            color_continuous_scale='RdPu',  # Color scale
            width=700,
            height=700
        )

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



Key Insights

Notably, all the models have a good AUC score of over 0.70 with the best model- logistic regression having an excellent score of 0.83.

`True Negatives (TN):` The model correctly predicted 438 customers who did not churn. This indicates the model's ability to identify customers who are likely to remain with the service.

`False Positives (FP):` The model incorrectly predicted that 304 customers would churn, though they did not. This type of error might lead to unnecessary retention efforts, potentially increasing operational costs.

`False Negatives (FN):` There were 24 instances where the model failed to identify customers who eventually churned. This represents a missed opportunity to potentially retain these customers through targeted interventions.

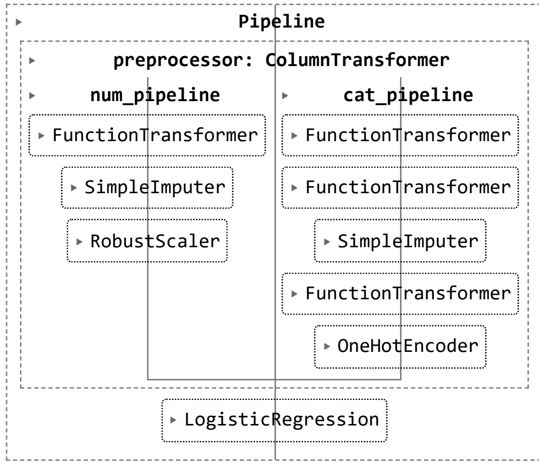
`True Positives (TP):` The model successfully identified 243 customers who churned. Recognizing these customers allows the company to focus retention strategies effectively.

In conclusion, after choosing a threshold of 0.164851692 for the best model, it showed a strong ability to identify customers who are likely to churn high true positive rate (high recall), it does so at the expense of a significant number of false positives (low precision).

4.1.4 Feature importances of the best model

In [140]:
```python
best_model
```

Out[140]:



In [141]:
```python
# Get the numerical feature names after transformation
numerical_features_transformed = best_model.named_steps['preprocessor'].named_transformers_['num_pipeline'].named_steps['scaler'].get_feature_names_out(numerical_features)
numerical_features_transformed
```

Out[141]:
```
array(['tenure', 'monthly_charges', 'total_charges'], dtype=object)
```

In [142]:
```python
# Get the categorical feature names after transformation
categorical_features_transformed = best_model.named_steps['preprocessor'].named_transformers_['cat_pipeline'].named_steps['encoder'].get_feature_names_out(categorical_features_new)
categorical_features_transformed
```

Out[142]:
```
array(['gender_Male', 'senior_citizen_Yes', 'partner_Yes',
       'dependents_Yes', 'internet_service_Fiber optic',
       'internet_service_No', 'contract_One year', 'contract_Two year',
       'paperless_billing_Yes', 'payment_method_Credit card (automatic)',
       'payment_method_Electronic check', 'payment_method_Mailed check',
       'call_service_No', 'call_service_Singleline',
       'security_service_Fullsecurity', 'security_service_No',
       'security_service_Securitybackup', 'security_service_Techsupport',
       'streaming_service_Movies', 'streaming_service_No',
       'streaming_service_Tv'], dtype=object)
```

In [143]:
```python
# Get the feature names after transformation
feature_columns = np.concatenate((numerical_features_transformed, categorical_features_transformed))

# Remove unwanted prefixes and get the last part
# feature_columns = np.array([col.split('__')[-1] for col in feature_columns])

# Display the feature columns
print("Feature Columns:", feature_columns)
```

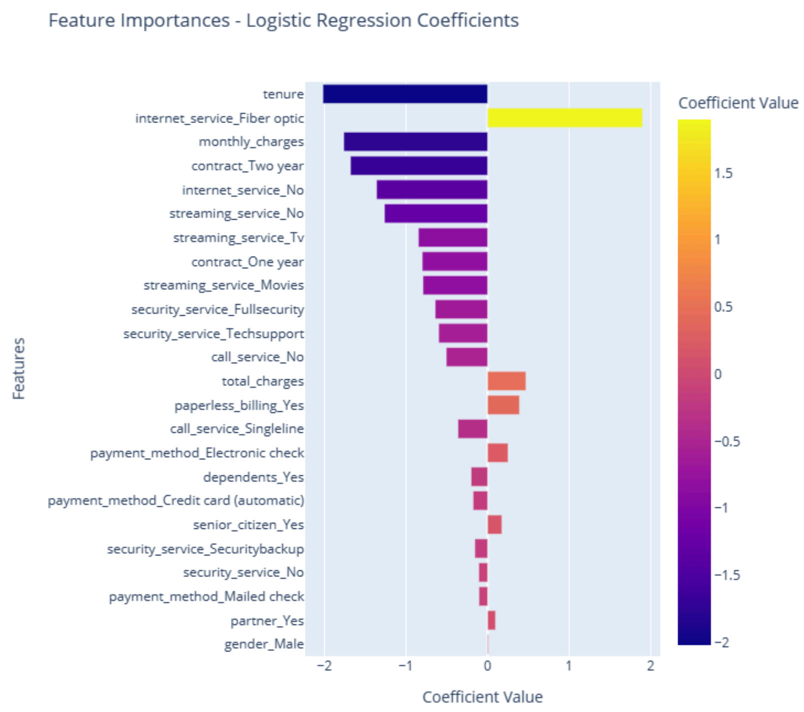
```
Feature Columns: ['tenure' 'monthly_charges' 'total_charges' 'gender_Male'
 'senior_citizen_Yes' 'partner_Yes' 'dependents_Yes'
 'internet_service_Fiber optic' 'internet_service_No' 'contract_One year'
 'contract_Two year' 'paperless_billing_Yes'
 'payment_method_Credit card (automatic)'
 'payment_method_Electronic check' 'payment_method_Mailed check'
 'call_service_No' 'call_service_Singleline'
 'security_service_Fullsecurity' 'security_service_No'
 'security_service_Securitybackup' 'security_service_Techsupport'
 'streaming_service_Movies' 'streaming_service_No' 'streaming_service_Tv']
```

In [144]:
```python
# Access the coefficients since best model is logistic regression
coefficients = best_model.named_steps['classifier'].coef_[0]

coefficients_df = pd.DataFrame({'Feature': feature_columns, 'Coefficient': coefficients})

# Magnitude of impact
coefficients_df['Absolute Coefficient'] = np.abs(coefficients_df['Coefficient'])
coefficients_df.sort_values(by="Absolute Coefficient", ascending=True, inplace=True)

coefficients_df
```

Out[144]:

	Feature	Coefficient	Absolute Coefficient
3	gender_Male	0.01	0.01
5	partner_Yes	0.10	0.10
14	payment_method_Mailed check	-0.10	0.10
18	security_service_No	-0.11	0.11
19	security_service_Securitybackup	-0.16	0.16
4	senior_citizen_Yes	0.17	0.17
12	payment_method_Credit card (automatic)	-0.18	0.18
6	dependents_Yes	-0.20	0.20
13	payment_method_Electronic check	0.25	0.25
16	call_service_Singleline	-0.36	0.36
11	paperless_billing_Yes	0.39	0.39
2	total_charges	0.47	0.47
15	call_service_No	-0.51	0.51
20	security_service_Techsupport	-0.60	0.60
17	security_service_Fullsecurity	-0.64	0.64
21	streaming_service_Movies	-0.79	0.79
9	contract_One year	-0.80	0.80
23	streaming_service_Tv	-0.85	0.85
22	streaming_service_No	-1.26	1.26
8	internet_service_No	-1.36	1.36
10	contract_Two year	-1.68	1.68
1	monthly_charges	-1.76	1.76
7	internet_service_Fiber optic	1.90	1.90
0	tenure	-2.02	2.02

In [145]:
```python
# Create a horizontal bar chart using Plotly Express
fig = px.bar(
    coefficients_df,
    x='Coefficient',
    y='Feature',
    orientation='h',  # Set orientation to horizontal
    title='Feature Importances - Logistic Regression Coefficients',
    labels={'Coefficient': 'Coefficient Value', 'Feature': 'Features'},
    height=700,
    color='Coefficient'
)


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



Understanding Feature Importances in Customer Churn Prediction

Overview

We leveraged logistic regression, our best-performing model, to discern the most influential factors predicting customer behavior within our dataset. The coefficients extracted from the model, denoted as "feature importances," elucidate the impact of each variable on the likelihood of customer actions, such as churn or retention.

Key Findings

1. Tenure:

- **Impact**: This feature exhibits the most substantial negative impact on the outcome (-2.02).
- **Interpretation**: Longer tenure diminishes the probability of churn, suggesting that established customers are more inclined to remain with the service.

2. Contract Type:

- **Month-to-Month Contracts**: Positively correlated with the outcome (+0.647), indicating higher volatility or turnover among short-term customers.
- **Two-Year Contracts**: Displays a significant negative coefficient (-1.68), signifying enhanced customer retention and stability.

3. Internet Service:

- **Fiber Optic Services**: Positively influences the outcome (+1.90), potentially reflecting heightened expectations or distinct service experiences.
- **No Internet Service**: Exhibits a negative coefficient (-1.36), lowering the likelihood of churn, possibly due to reduced engagement with services.

4. Billing and Payment Methods:

- **Electronic Checks**: Positively associated with the outcome (+0.25), suggesting a potential link to more transient or less satisfied customer segments.
- **Mailed Checks**: Shows a negative coefficient (-0.10), albeit with lesser significance, indicating a different customer behavior pattern.

5. Add-On Services:

- Features such as **security services**, **call services**, and **streaming services** display varying impacts. Their presence tends to either increase or decrease the likelihood of churn, underscoring their influence on customer satisfaction and retention.

Implications and Recommendations

- **Customer Retention**: Strengthen retention strategies by enhancing service offerings for long-tenure customers, particularly those with stable contract setups like two-year agreements.
- **Service Improvement**: Investigate the significant impact of fiber optic services on customer behavior, focusing on improving service quality or customer support for these users.
- **Payment Flexibility**: Consider promoting automatic payment methods, which appear to be associated with more stable customer behavior, potentially enhancing overall customer satisfaction and retention.

- **Targeted Marketing**: Tailor marketing strategies to address the specific needs of different customer segments, particularly focusing on those with month-to-month contracts or using electronic checks.

The most important features for predicting churn are whether a customer has fibre optic internet service, a contract term of two years and tenure. Other features such as monthly charges, total charges, contract of one year, electronic check payment method, whethether a customer has streaming movies, tech support and online security services are also important although around half the most important features.

4.1.5 Test the best model on unknown dataset (df_test)

In [146]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             2000 non-null   object 
 1   senior_citizen     2000 non-null   int64  
 2   partner            2000 non-null   object 
 3   dependents         2000 non-null   object 
 4   tenure             2000 non-null   int64  
 5   phone_service      2000 non-null   object 
 6   multiple_lines     2000 non-null   object 
 7   internet_service   2000 non-null   object 
 8   online_security    2000 non-null   object 
 9   online_backup      2000 non-null   object 
 10  device_protection  2000 non-null   object 
 11  tech_support       2000 non-null   object 
 12  streaming_tv       2000 non-null   object 
 13  streaming_movies   2000 non-null   object 
 14  contract           2000 non-null   object 
 15  paperless_billing  2000 non-null   object 
 16  payment_method     2000 non-null   object 
 17  monthly_charges    2000 non-null   float64
 18  total_charges      1997 non-null   float64
dtypes: float64(2), int64(2), object(15)
memory usage: 297.0+ KB
```

In [147]:
```
predicted_churn = best_model.predict(df_test)
predicted_churn
```

Out[147]:
```
array([1, 0, 0, ..., 0, 0, 0])
```

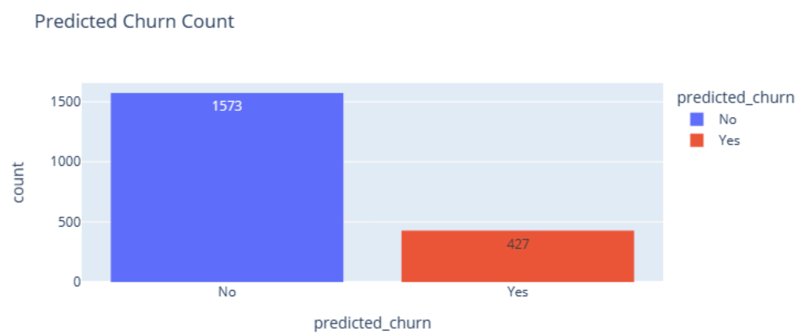
In [148]:
```
# Create the predicted_churn column
df_test['predicted_churn'] = encoder.inverse_transform(predicted_churn)
df_test.head()
```

Out[148]:

	gender	senior_citizen	partner	dependents	tenure	phone_service	multiple_lines	internet_
0	Male	0	No	No	12	Yes	Yes	Fi
1	Male	0	No	No	9	Yes	No	
2	Male	0	No	No	27	Yes	No	
3	Male	0	No	Yes	27	Yes	Yes	Fi
4	Male	0	Yes	Yes	1	Yes	No	Fi

4.1.6 Visualize the predicted churn

In [149]:
```
fig = px.histogram(
    df_test, x='predicted_churn',
    title='Predicted Churn Count',
    color='predicted_churn',
    category_orders={'predicted_churn': target_class}
)

# # Update the layout to add count values on top of each bar
fig.update_traces(texttemplate='%{y}', textposition='inside')

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



4.1.7 Save the model

- Using joblib

In [150]:
```
for model_name, pipeline in best_models.items():
    joblib.dump(model_name, SAVE_MODELS+f'joblib/{model_name}.joblib')

    joblib.dump(encoder, SAVE_MODELS+'joblib/encoder.joblib')
```

- Using json

In [151]:
```
class PipelineEncoder(json.JSONEncoder):
    """Custom JSON encoder to handle scikit-learn pipeline"""
    def default(self, obj):
        if isinstance(obj, Pipeline):
            # Serialize pipeline steps
            steps = [(name, type(estimator).__name__) for name, estimator i
n obj.steps]
            return {'__class__': 'Pipeline', 'steps': steps}
        elif isinstance(obj, BaseEstimator):
            # Serialize individual transformers or estimators
            return {'__class__': type(obj).__name__, 'parameters': obj.get_
params()}
        return json.JSONEncoder.default(self, obj)


for model_name, pipeline in best_models.items():
    filename = SAVE_MODELS+f'json/{model_name}.json'
    with open(filename, 'w') as file:
        json.dump(pipeline, file, cls=PipelineEncoder, indent=4, separators
=(',', ': '), ensure_ascii=False)
```

- Using neptune to save the best model

In [152]:
```
# Initialize model
model = neptune.init_model(
    name=f"{best_model_name} Churn Prediction Model",
    key="MOD",
    project="modelia/customer-churn-prediction",
    api_token=neptune_api_token, # your credentials
)

# Assign the classification model metadata to model object
model_info = {"size_limit": 7.09, "size_units": "KB"}
model["model"] = model_info

# Upload the model to registry
try:
    model["model/signature"].upload(SAVE_MODELS+f'joblib/{best_model_name}.
joblib')
except Exception as e:
    print({e})
```

```
[neptune] [info   ] Neptune initialized. Open in the app: https://app.neptu
ne.ai/modelia/customer-churn-prediction/m/TELCO-MOD
```

Made with 💖 Gabriel Okundaye (https://www.linkedin.com/in/dr-gabriel-okundaye) & Light ✨