Reducing Telecom Customer Churn: A Predictive Analytics Approach

Problem Statement:

Customer churn is an enormous challenge for telecom firms as consumers switch to competitors or end their contracts early. The task is to create predictive models capable of identifying and comprehending the aspects contributing to client attrition. This project will address the following questions:

1. What are the primary factors influencing telecom customer churn?

2. Can we create an accurate predictive model to anticipate which customers would churn?

3. How may this information be used to build targeted retention tactics and lower client churn?

Background:

Customer retention is crucial in the telecommunications sector since it is exceptionally competitive and consumer-centric. The rising cost of client acquisition and the possible revenue loss associated with churn have increased the importance of solving this issue. The origins of this problem may be traced back to the rising availability of telecom service providers, which provides consumers with more options, as well as customers' growing expectations for improved service quality, competitive pricing, and tailored experiences.

Significance:

Reduced telecom customer turnover is critical for various reasons, including:

1. Economic Impact: Customer turnover results in considerable revenue loss since gaining new customers is more expensive than maintaining existing ones.

2. Market Competition: The telecom sector is very competitive, with several service providers competing for clients. Reduced turnover can provide you with a competitive edge.

3. Customer happiness: Churn is a reflection of discontent with services, and resolving it leads to increased customer happiness and loyalty.

4. Data-Driven Insights: Using predictive analytics to understand consumer behavior better may help telecom firms customize their services and marketing efforts more successfully.

Contribution:

This initiative has the potential to benefit the telecom industry significantly:

1. Predictive Modeling: By developing accurate predictive models, this project will provide telecom companies with valuable insight into which customers are at risk of churning, allowing for pre-emptive retention efforts.

2. Data-Driven Decision-Making: The initiative will enable telecom firms to make data-driven choices by identifying and prioritizing the most significant churn drivers.

3. Cost Savings: Lowering churn rates can result in significant cost savings since businesses can devote more energy to maintaining existing customers rather than constantly gaining new ones.

4. Improved Customer Experience: Addressing churn reasons improves the customer experience, which can lead to long-term loyalty and advocacy.

Data Source:

This study's dataset was taken from Kaggle, a library of publicly available datasets for different data science and machine learning projects. The dataset was chosen for its relevance to the topic at hand, forecasting client attrition. Here are the data source's specifics:

- **Source:** Kaggle / IBM Sample Data Sets

- **Dataset Name**: Telco Customer Churn

- **Description**: This dataset contains customer information about their churn behavior and numerous factors such as subscribed services, customer account details, and demographic information.

Rationale for Dataset Selection

The necessity for a comprehensive dataset that could be utilized to investigate client retention tactics drove the choice to use this dataset. Customers who departed within the last month are included in the dataset, as are the services they signed up for, account information, and demographic information. It has about 7000 rows and 21 columns, which provides a big enough sample size for significant data analysis and predictive modeling.

In summary, the dataset utilized in this study was obtained from IBM Sample Data Sets and was selected due to its relevance to customer churn analysis. It satisfied the criterion of having sufficient records (over 2000 rows) and the relevant columns to satisfy the Phase 1 objectives.

Data Cleaning

- **Dealing with missing data**
    - We have missing data in the column 'OnlineSecurity.'

```
# Checking for missing data
data.isnull().sum()
```

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity     17
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

    - Column OnlineSecurity is categorical data and 50% of the people have No as the categorical value so replacing missing values with No. Using the mode of the column for data imputation.

```python
data['OnlineSecurity'] = data['OnlineSecurity'].fillna(data['OnlineSecurity'].mode()[0])
```

```python
data.isnull().sum()
```

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

We have no more missing values!

➢ **Removing Duplicate Entries**

Checking for duplicate entries in data

```
data.duplicated().value_counts()
```

```
False    7043
True       29
dtype: int64
```

We have found some duplicate rows in the data so removing these rows by drop_duplicate()

```
# Removing the duplicate rows
data.drop_duplicates(inplace=True)
```

```
data.duplicated().value_counts()
```

```
False    7043
dtype: int64
```

```
data.duplicated().value_counts()
```

```
False    7043
dtype: int64
```

All duplicate rows removed!

➢ **Fixing Inconsistencies in column**

```
# Currently datatype of column totalcharges is of the 'object' datatype
# Changing it to float
data['TotalCharges'] = data['TotalCharges'].astype('float64')
data.info()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_8864\1981693660.py in <module>
      1 # Currently datatype of column totalcharges is of the 'object' datatype
      2 # Changing it to float
----> 3 data['TotalCharges'] = data['TotalCharges'].astype('float64')
      4 data.info()

C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\generic.py in astype(self, dt
   5910         else:
   5911             # else, only a single dtype is given
-> 5912             new_data = self._mgr.astype(dtype=dtype, copy=copy, errors=error
   5913             return self._constructor(new_data).__finalize__(self, method="as
   5914

C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\internals\managers.py in asty
    417
    418     def astype(self: T, dtype, copy: bool = False, errors: str = "raise") ->
--> 419         return self.apply("astype", dtype=dtype, copy=copy, errors=errors)
    420
    421     def convert(

C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\internals\managers.py in appl
lures, **kwargs)
    302                     applied = b.apply(f, **kwargs)
```

This means we have some erroneous entries in totalcharges that are of string type instead numeric

Fixing that

```
data['TotalCharges'].map(type).value_counts()
```

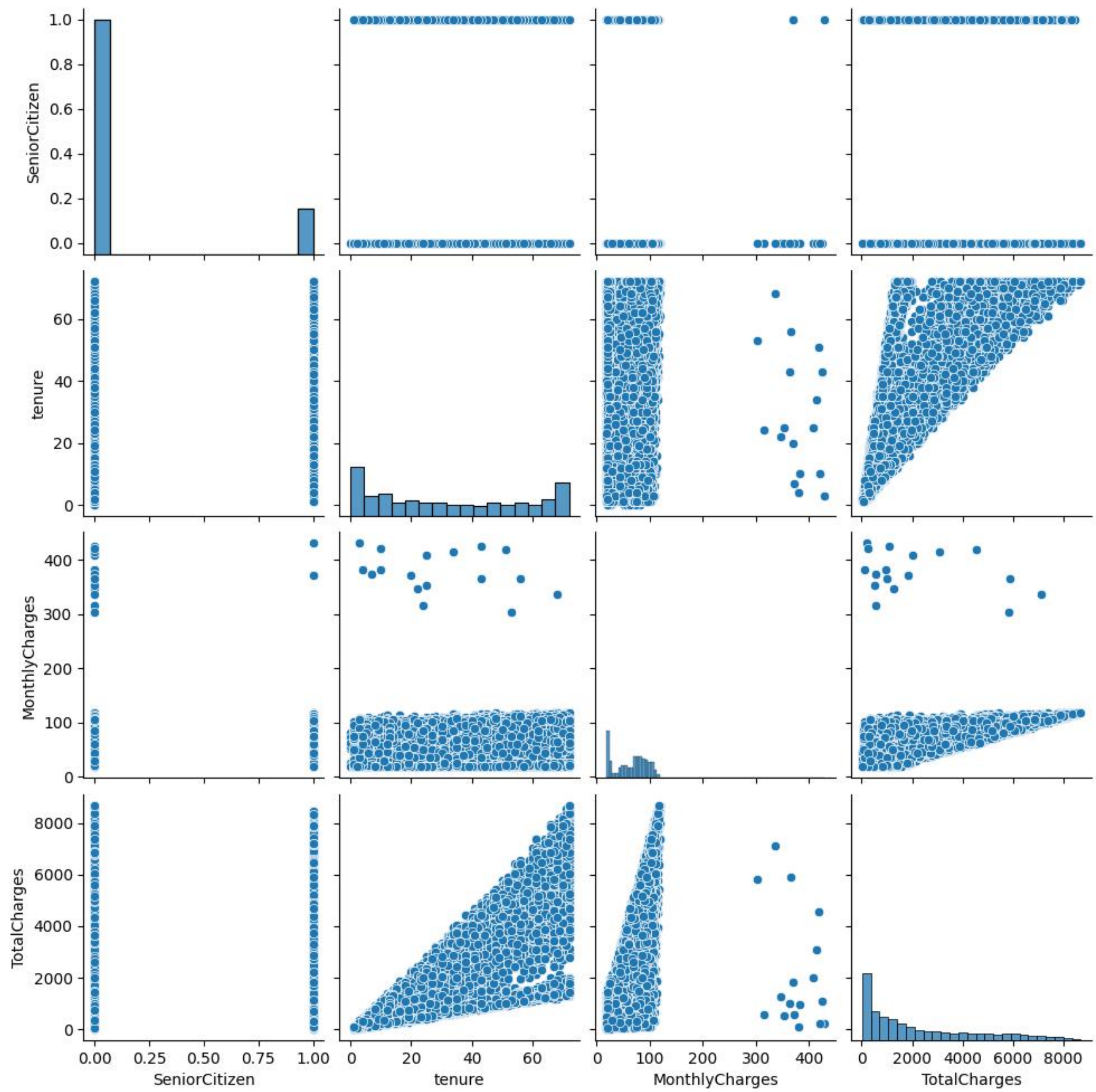
```
<class 'str'>    7043
Name: TotalCharges, dtype: int64
```

```
data['TotalCharges'] = pd.to_numeric(data['TotalCharges'], errors='coerce', downcast='float')
```

```
data['TotalCharges'].map(type).value_counts()
```

```
<class 'float'>    7043
Name: TotalCharges, dtype: int64
```

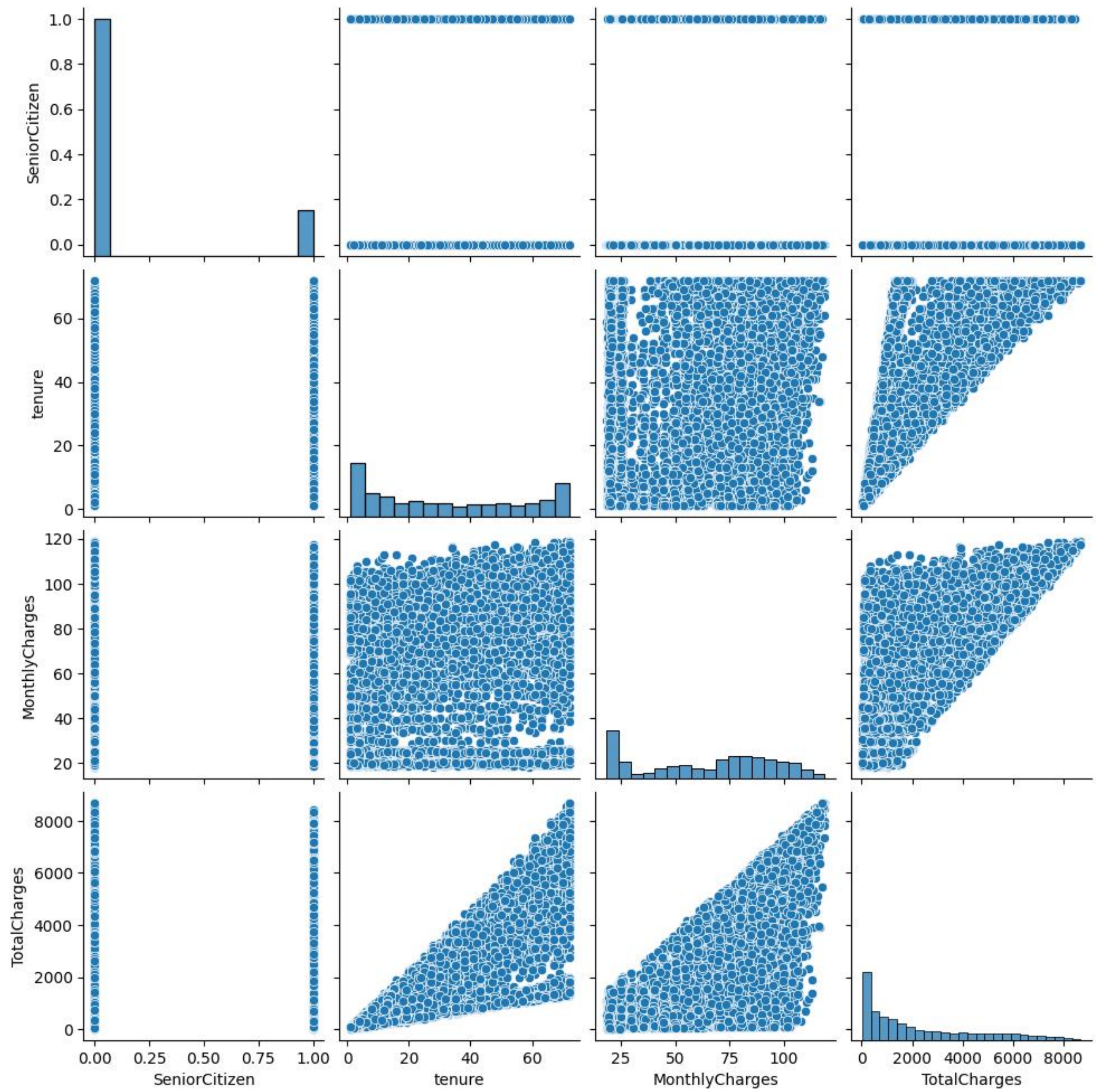
- **Removing Outliers**
  - We have outliers in our data, which are arising due to high-paying customers.
  - This can negatively affect our predictive analysis during the modeling phase, thus removing these outlier customers.



```
# Montlycharges seems to be contributing to the outlier entries
# all entries with monthly charges above 300 are outliers
# so removing all such entries
max_value = data['MonthlyCharges'].max()
outliers = data['MonthlyCharges'].between(300, max_value)
data = data[~outliers]
data.dropna(axis = 0, inplace=True)
data.isnull().sum()
# data = data[~outliers]
# data.reset_index(drop=True, inplace=True)
```

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

- After removing outliers, our graph looks like this:



➢ Addressing Inconsistencies in Categorical Data

- Multiple columns have redundant category names that can be merged into one. This will reduce the complexity of the data.

- Before:

```
data.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupp
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	

5 rows × 21 columns

Column "MultipleLines" Category Merge

```
column = 'MultipleLines'
data[column].value_counts()
```

```
No                  3379
Yes                 2956
No phone service     680
Name: MultipleLines, dtype: int64
```

```
data.loc[data[column] == 'No phone service', column] = 'No'
data[column].value_counts()
```

```
No     4059
Yes    2956
Name: MultipleLines, dtype: int64
```

Column "OnlineSecurity" Category Merge

```
column = 'OnlineSecurity'
data[column].value_counts()
```

```
No                     3499
Yes                    2006
No internet service    1510
Name: OnlineSecurity, dtype: int64
```

```
data.loc[data[column] == 'No internet service', column] = 'No'
data[column].value_counts()
```

```
No     5009
Yes    2006
Name: OnlineSecurity, dtype: int64
```

Column "OnlineBackup"Category Merge

```
column = 'OnlineBackup'
data[column].value_counts()
```

```
No                     3082
Yes                    2419
No internet service    1514
Name: OnlineBackup, dtype: int64
```

```
data.loc[data[column] == 'No internet service', column] = 'No'
data[column].value_counts()
```

```
No     4596
Yes    2419
Name: OnlineBackup, dtype: int64
```

Column "DeviceProtection" Category Merge

```
column = 'DeviceProtection'
data[column].value_counts()
```

```
No                     3088
Yes                    2413
No internet service    1514
Name: DeviceProtection, dtype: int64
```

```
data.loc[data[column] == 'No internet service', column] = 'No'
data[column].value_counts()
```

```
No     4602
Yes    2413
Name: DeviceProtection, dtype: int64
```

Column "TechSupport" Category Merge

```
column = 'TechSupport'
data[column].value_counts()
```

```
No                     3463
Yes                    2038
No internet service    1514
Name: TechSupport, dtype: int64
```

```
data.loc[data[column] == 'No internet service', column] = 'No'
data[column].value_counts()
```

```
No     4977
Yes    2038
Name: TechSupport, dtype: int64
```

Column "StreamingTV" Category Merge

```
column = 'StreamingTV'
data[column].value_counts()
```

```
No                     2803
Yes                    2698
No internet service    1514
Name: StreamingTV, dtype: int64
```

```
data.loc[data[column] == 'No internet service', column] = 'No'
data[column].value_counts()
```

```
No     4317
Yes    2698
Name: StreamingTV, dtype: int64
```

Column "StreamingMovies" Category Merge

```
column = 'StreamingMovies'
data[column].value_counts()
```

```
No                     2775
Yes                    2726
No internet service    1514
Name: StreamingMovies, dtype: int64
```

```
data.loc[data[column] == 'No internet service', column] = 'No'
data[column].value_counts()
```

```
No     4289
Yes    2726
Name: StreamingMovies, dtype: int64
```

- **Label Encoding Categorical Columns**

Label Encoding Categorical Columns

Column: Partner

```
column = 'Partner'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     3628
Yes    3387
Name: Partner, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    3628
1    3387
Name: Partner, dtype: int64
```

Column: Dependents

```
column = 'Dependents'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     4923
Yes    2092
Name: Dependents, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    4923
1    2092
Name: Dependents, dtype: int64
```

Column: PhoneService

```
column = 'PhoneService'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
Yes    6335
No      680
Name: PhoneService, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
1    6335
0     680
Name: PhoneService, dtype: int64
```

Column: MultipleLines

```
column = 'MultipleLines'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     4059
Yes    2956
Name: MultipleLines, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    4059
1    2956
Name: MultipleLines, dtype: int64
```

Column: OnlineSecurity

```
column = 'OnlineSecurity'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     5009
Yes    2006
Name: OnlineSecurity, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    5009
1    2006
Name: OnlineSecurity, dtype: int64
```

Column: OnlineBackup

```
column = 'OnlineBackup'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     4596
Yes    2419
Name: OnlineBackup, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    4596
1    2419
Name: OnlineBackup, dtype: int64
```

Column: DeviceProtection

```
column = 'DeviceProtection'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     4602
Yes    2413
Name: DeviceProtection, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    4602
1    2413
Name: DeviceProtection, dtype: int64
```

Column: TechSupport

```
column = 'TechSupport'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     4977
Yes    2038
Name: TechSupport, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    4977
1    2038
Name: TechSupport, dtype: int64
```

Column: StreamingTV

```
column = 'StreamingTV'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     4317
Yes    2698
Name: StreamingTV, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    4317
1    2698
Name: StreamingTV, dtype: int64
```

Column: StreamingMovies

```
column = 'StreamingMovies'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     4289
Yes    2726
Name: StreamingMovies, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    4289
1    2726
Name: StreamingMovies, dtype: int64
```

Column: PaperlessBilling

```
column = 'PaperlessBilling'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
Yes    4158
No     2857
Name: PaperlessBilling, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
1    4158
0    2857
Name: PaperlessBilling, dtype: int64
```

Column: Churn

```
column = 'Churn'
mapping = {'Yes': 1, 'No': 0}
data[column].value_counts()
```

```
No     5150
Yes    1865
Name: Churn, dtype: int64
```

```
data[column] = data[column].map(mapping)
data[column].value_counts()
```

```
0    5150
1    1865
Name: Churn, dtype: int64
```

```
data.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupp
0	7590-VHVEG	Female	0	1	0	1	0	0	DSL	0	...	0	
1	5575-GNVDE	Male	0	0	0	34	1	0	DSL	1	...	1	
2	3668-QPYBK	Male	0	0	0	2	1	0	DSL	1	...	0	
3	7795-CFOCW	Male	0	0	0	45	0	0	DSL	1	...	1	
4	9237-HQITU	Female	0	0	0	2	1	0	Fiber optic	0	...	0	

5 rows × 21 columns

- **Binary Encoding for gender**

Label Encoding for gender:

Binary encoding gender to make it similar to column having data of isMale?

```
mapping = {'Male': 1, 'Female': 0}
data['gender'].value_counts()
```

```
Male      3543
Female    3472
Name: gender, dtype: int64
```

```
data['gender'] = data['gender'].map(mapping)
data['gender'].value_counts()
```

```
1    3543
0    3472
Name: gender, dtype: int64
```

- **One - Hot Encoding**
  - One-hot encoding is essential for classification jobs because it converts categorical data into a format machine-learning algorithms can understand. To make predictions in classification tasks, algorithms require numerical input characteristics, which one-hot encoding does by expressing category variables as binary columns. Each category is transformed into a distinct binary column, allowing the algorithm to consider each individually without indicating any ordinal connection. This encoding prevents the algorithm from assigning unwanted meaning or hierarchy to the categories and increases the model's ability to catch patterns and generate accurate predictions on categorical data.

One-hot encoding for column InternetService

```
# Converting categorical to numerical: Fetching categories of Internet Service
data['InternetService'].value_counts()
```

```
Fiber optic    3086
DSL            2415
No             1514
Name: InternetService, dtype: int64
```

```
# Performing one-hot encoding
data = pd.get_dummies(data, columns=['InternetService'], prefix='InternetService')

# Move the new three columns to its position 9
columns = data.columns.tolist()
columns = columns[:8] + columns[-3:] + columns[8:-3]
data = data[columns]

# Renaming newly created columns
mapping = {'InternetService_DSL': 'IntrntSrvc_DSL',
           'InternetService_Fiber optic': 'IntrntSrvc_FiberOptic',
           'InternetService_No': 'IntrntSrvc_No'}
data.rename(columns = mapping, inplace=True)

# New columns after one hot encoding
data.iloc[:5,8:11]
```

	IntrntSrvc_DSL	IntrntSrvc_FiberOptic	IntrntSrvc_No
0	1	0	0
1	1	0	0
2	1	0	0
3	1	0	0
4	0	1	0

One-hot encoding for column Contract

```
# Convert categorical to numerical: Fetching categories of Contract
data['Contract'].value_counts()
```

```
Month-to-month    3864
Two year          1683
One year          1468
Name: Contract, dtype: int64
```

```
# Performing one-hot encoding
data = pd.get_dummies(data, columns=['Contract'], prefix='Contract')

# Move the new three columns to its position 18
columns = data.columns.tolist()
columns = columns[:17] + columns[-3:] + columns[17:-3]
data = data[columns]

# Renaming newly created columns
mapping = {'Contract_Month-to-month': 'Contract_Monthly',
           'Contract_One year': 'Contract_OneYear',
           'Contract_Two year': 'Contract_TwoYear'}
data.rename(columns = mapping, inplace=True)

# New columns after one hot encoding
data.iloc[:5,17:20]
```

	Contract_Monthly	Contract_OneYear	Contract_TwoYear
0	1	0	0
1	0	1	0
2	1	0	0
3	0	1	0
4	1	0	0

One-hot encoding for column PaymentMethod

```
# Convert categorical to numerical: Fetching categories of Payment Method
data['PaymentMethod'].value_counts()
```

```
Electronic check             2357
Mailed check                 1602
Bank transfer (automatic)    1538
Credit card (automatic)      1518
Name: PaymentMethod, dtype: int64
```

```
# Performing one-hot encoding
data = pd.get_dummies(data, columns=['PaymentMethod'], prefix='PaymentMethod')

# Move the new four columns to its position 22
columns = data.columns.tolist()
columns = columns[:21] + columns[-4:] + columns[21:-4]
data = data[columns]

# Renaming newly created columns
mapping = {'PaymentMethod_Bank transfer (automatic)': 'PayMthd_BankTransfer',
           'PaymentMethod_Credit card (automatic)': 'PayMthd_CreditCard',
           'PaymentMethod_Electronic check': 'PayMthd_ElectronicCheck',
           'PaymentMethod_Mailed check': 'PayMthd_MailedCheck'}
data.rename(columns = mapping, inplace=True)

# New columns after one hot encoding
data.iloc[:5,21:25]
```

	PayMthd_BankTransfer	PayMthd_CreditCard	PayMthd_ElectronicCheck	PayMthd_MailedCheck
0	0	0	1	0
1	0	0	0	1
2	0	0	0	1
3	1	0	0	0
4	0	0	1	0

- **Typecasting Categorical columns to data type 'category'**

  - Since many of our columns are of the categorical type, storing them as 'object' type is poor practice, thus converting them to the dtype 'category.'

  - Before

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7015 entries, 0 to 7042
Data columns (total 28 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   customerID              7015 non-null   object
 1   gender                  7015 non-null   int64
 2   SeniorCitizen           7015 non-null   int64
 3   Partner                 7015 non-null   int64
 4   Dependents              7015 non-null   int64
 5   tenure                  7015 non-null   int64
 6   PhoneService            7015 non-null   int64
 7   MultipleLines           7015 non-null   int64
 8   IntrntSrvc_DSL          7015 non-null   uint8
 9   IntrntSrvc_FiberOptic   7015 non-null   uint8
 10  IntrntSrvc_No           7015 non-null   uint8
 11  OnlineSecurity          7015 non-null   int64
 12  OnlineBackup            7015 non-null   int64
 13  DeviceProtection        7015 non-null   int64
 14  TechSupport             7015 non-null   int64
 15  StreamingTV             7015 non-null   int64
 16  StreamingMovies         7015 non-null   int64
 17  Contract_Monthly        7015 non-null   uint8
 18  Contract_OneYear        7015 non-null   uint8
 19  Contract_TwoYear        7015 non-null   uint8
 20  PaperlessBilling        7015 non-null   int64
 21  PayMthd_BankTransfer    7015 non-null   uint8
 22  PayMthd_CreditCard      7015 non-null   uint8
 23  PayMthd_ElectronicCheck 7015 non-null   uint8
 24  PayMthd_MailedCheck     7015 non-null   uint8
 25  MonthlyCharges          7015 non-null   float64
 26  TotalCharges            7015 non-null   float32
 27  Churn                   7015 non-null   int64
dtypes: float32(1), float64(1), int64(15), object(1), uint8(10)
memory usage: 1.3+ MB
```

- After

```
categorical_columns = ['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'PhoneService',
                       'MultipleLines', 'OnlineSecurity','OnlineSecurity', 'OnlineBackup',
                       'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
                       'PaperlessBilling','Churn']
for col in categorical_columns:
    data[col] = data[col].astype('category')
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7015 entries, 0 to 7042
Data columns (total 28 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   customerID              7015 non-null   object
 1   gender                  7015 non-null   category
 2   SeniorCitizen           7015 non-null   category
 3   Partner                 7015 non-null   category
 4   Dependents              7015 non-null   category
 5   tenure                  7015 non-null   int64
 6   PhoneService            7015 non-null   category
 7   MultipleLines           7015 non-null   category
 8   IntrntSrvc_DSL          7015 non-null   uint8
 9   IntrntSrvc_FiberOptic   7015 non-null   uint8
 10  IntrntSrvc_No           7015 non-null   uint8
 11  OnlineSecurity          7015 non-null   category
 12  OnlineBackup            7015 non-null   category
 13  DeviceProtection        7015 non-null   category
 14  TechSupport             7015 non-null   category
 15  StreamingTV             7015 non-null   category
 16  StreamingMovies         7015 non-null   category
 17  Contract_Monthly        7015 non-null   uint8
 18  Contract_OneYear        7015 non-null   uint8
 19  Contract_TwoYear        7015 non-null   uint8
 20  PaperlessBilling        7015 non-null   category
 21  PayMthd_BankTransfer    7015 non-null   uint8
 22  PayMthd_CreditCard      7015 non-null   uint8
 23  PayMthd_ElectronicCheck 7015 non-null   uint8
 24  PayMthd_MailedCheck     7015 non-null   uint8
 25  MonthlyCharges          7015 non-null   float64
 26  TotalCharges            7015 non-null   float32
 27  Churn                   7015 non-null   category
dtypes: category(14), float32(1), float64(1), int64(1), object(1), uint8(10)
memory usage: 670.8+ KB
```

- **Datatype downcasting**
  - Storing data such as int64,float64, etc., not only requires more space but also increases processing times.
  - In such scenarios, downcasting will stop the wastage of space and improve data processing times during the training phases of our predictive models.
  - Before:

```
data['tenure'] = data['tenure'].astype('int8')
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7015 entries, 0 to 7042
Data columns (total 28 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   customerID               7015 non-null   object
 1   gender                   7015 non-null   category
 2   SeniorCitizen            7015 non-null   category
 3   Partner                  7015 non-null   category
 4   Dependents               7015 non-null   category
 5   tenure                   7015 non-null   int8
 6   PhoneService             7015 non-null   category
 7   MultipleLines            7015 non-null   category
 8   IntrntSrvc_DSL           7015 non-null   uint8
 9   IntrntSrvc_FiberOptic    7015 non-null   uint8
 10  IntrntSrvc_No            7015 non-null   uint8
 11  OnlineSecurity           7015 non-null   category
 12  OnlineBackup             7015 non-null   category
 13  DeviceProtection         7015 non-null   category
 14  TechSupport              7015 non-null   category
 15  StreamingTV              7015 non-null   category
 16  StreamingMovies          7015 non-null   category
 17  Contract_Monthly         7015 non-null   uint8
 18  Contract_OneYear         7015 non-null   uint8
 19  Contract_TwoYear         7015 non-null   uint8
 20  PaperlessBilling         7015 non-null   category
 21  PayMthd_BankTransfer     7015 non-null   uint8
 22  PayMthd_CreditCard       7015 non-null   uint8
 23  PayMthd_ElectronicCheck  7015 non-null   uint8
 24  PayMthd_MailedCheck      7015 non-null   uint8
 25  MonthlyCharges           7015 non-null   float64
 26  TotalCharges             7015 non-null   float32
 27  Churn                    7015 non-null   category
dtypes: category(14), float32(1), float64(1), int8(1), object(1), uint8(10)
memory usage: 622.8+ KB
```

- After:

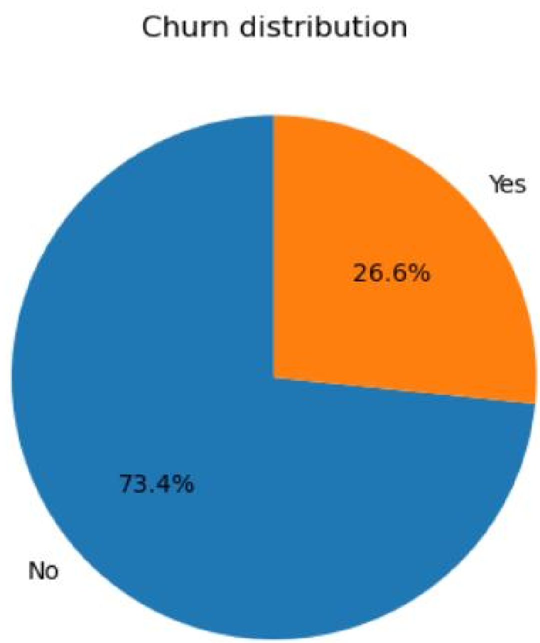
```
data['MonthlyCharges'] = data['MonthlyCharges'].astype('float16')
data['TotalCharges'] = data['TotalCharges'].astype('float16')
data['customerID'] = data['customerID'].astype('string')
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7015 entries, 0 to 7042
Data columns (total 28 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   customerID               7015 non-null   string
 1   gender                   7015 non-null   category
 2   SeniorCitizen            7015 non-null   category
 3   Partner                  7015 non-null   category
 4   Dependents               7015 non-null   category
 5   tenure                   7015 non-null   int8
 6   PhoneService             7015 non-null   category
 7   MultipleLines            7015 non-null   category
 8   IntrntSrvc_DSL           7015 non-null   uint8
 9   IntrntSrvc_FiberOptic    7015 non-null   uint8
 10  IntrntSrvc_No            7015 non-null   uint8
 11  OnlineSecurity           7015 non-null   category
 12  OnlineBackup             7015 non-null   category
 13  DeviceProtection         7015 non-null   category
 14  TechSupport              7015 non-null   category
 15  StreamingTV              7015 non-null   category
 16  StreamingMovies          7015 non-null   category
 17  Contract_Monthly         7015 non-null   uint8
 18  Contract_OneYear         7015 non-null   uint8
 19  Contract_TwoYear         7015 non-null   uint8
 20  PaperlessBilling         7015 non-null   category
 21  PayMthd_BankTransfer     7015 non-null   uint8
 22  PayMthd_CreditCard       7015 non-null   uint8
 23  PayMthd_ElectronicCheck  7015 non-null   uint8
 24  PayMthd_MailedCheck      7015 non-null   uint8
 25  MonthlyCharges           7015 non-null   float16
 26  TotalCharges             7015 non-null   float16
 27  Churn                    7015 non-null   category
dtypes: category(14), float16(2), int8(1), string(1), uint8(10)
memory usage: 568.0 KB
```

EDA

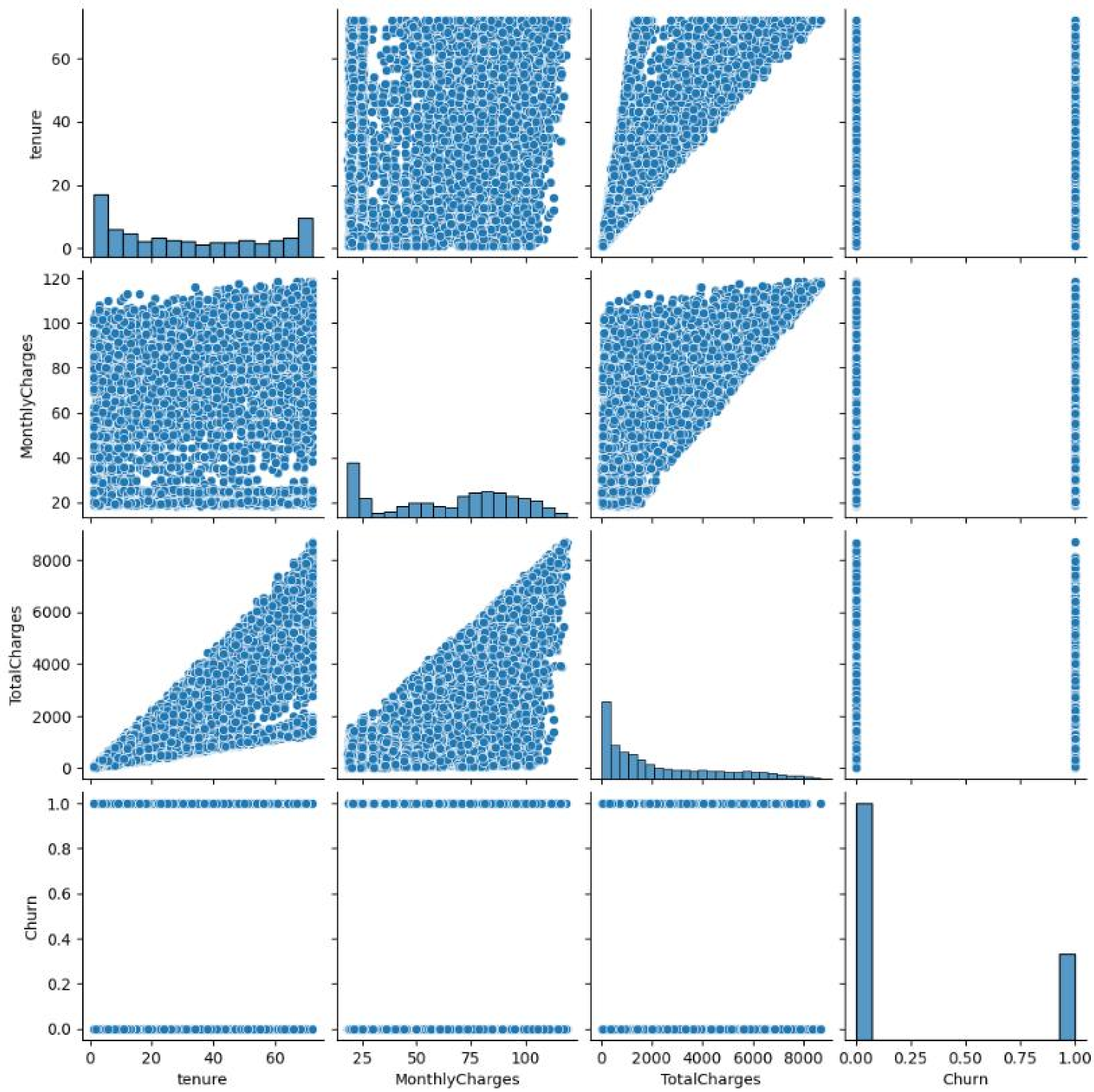
Exploratory Data Analysis (EDA) for the Telecom Customer churn dataset comprises initial data exploration, pattern identification, and understanding of significant factors affecting customer retention, i.e., customer churn. EDA provides insights such as the distribution of churn, correlations between features, and possible predictors for the churn utilizing graphical representations, analysis of data, and various plots, charts, and graphs.

- ## Churn Distribution



We can see from the churn distribution pie chart that 26.6% of customers churned while the rest 73.4% of the customers stayed with the company. It can be induced from this pie chart that more than a quarter of the customers have left in the past month.

- **Pair plots of some crucial features**



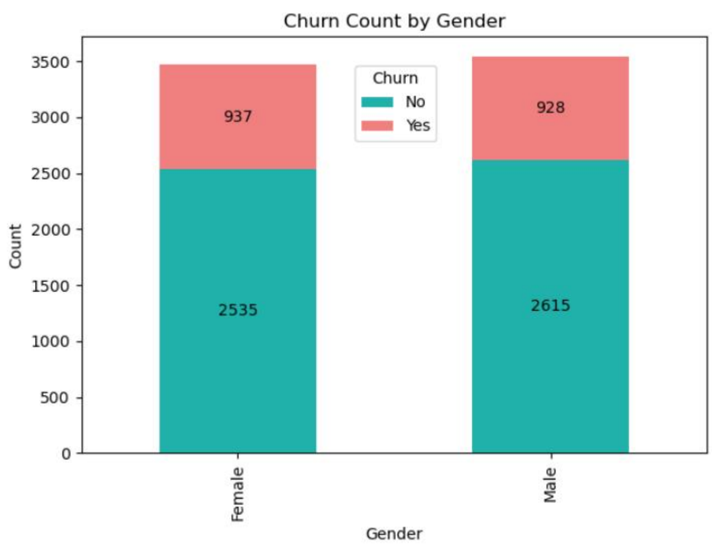
- ## Customer's analysis

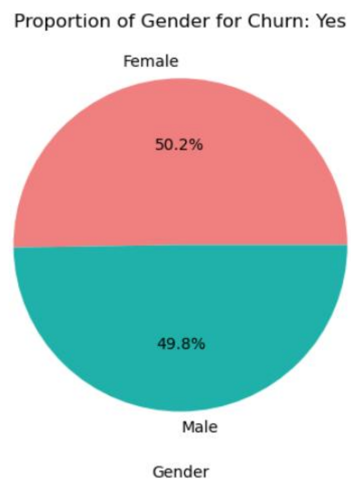
The data has various features of the Customer. These features include their:

- **Gender**: Customer is male or female
- **Dependent**: Does the Customer have dependents or not
- **Partner**: Does the Customer have a partner or not
- **Senior Citizen**: Is the Customer is a senior citizen or not

Analyzing each feature separately:

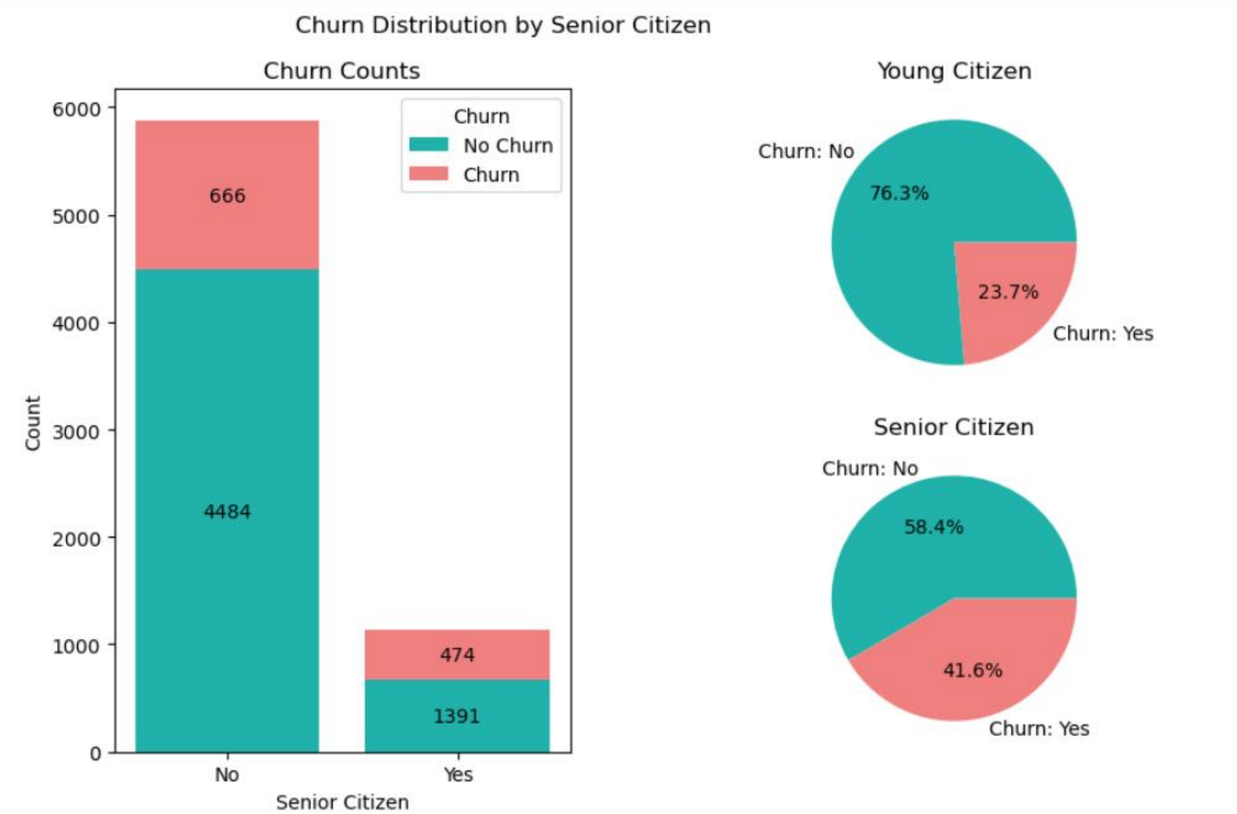
- **Churn distribution by Gender**





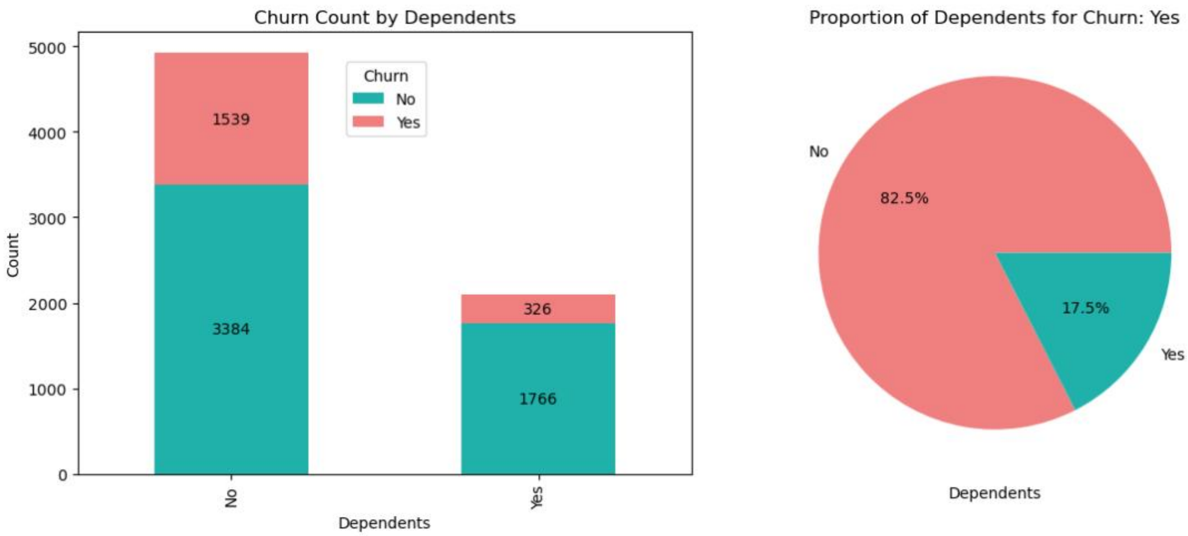
No particular trend was observed based on Gender for churn prediction. Both the genders are equally likely to churn.

- **Churn distribution by Senior Citizen**



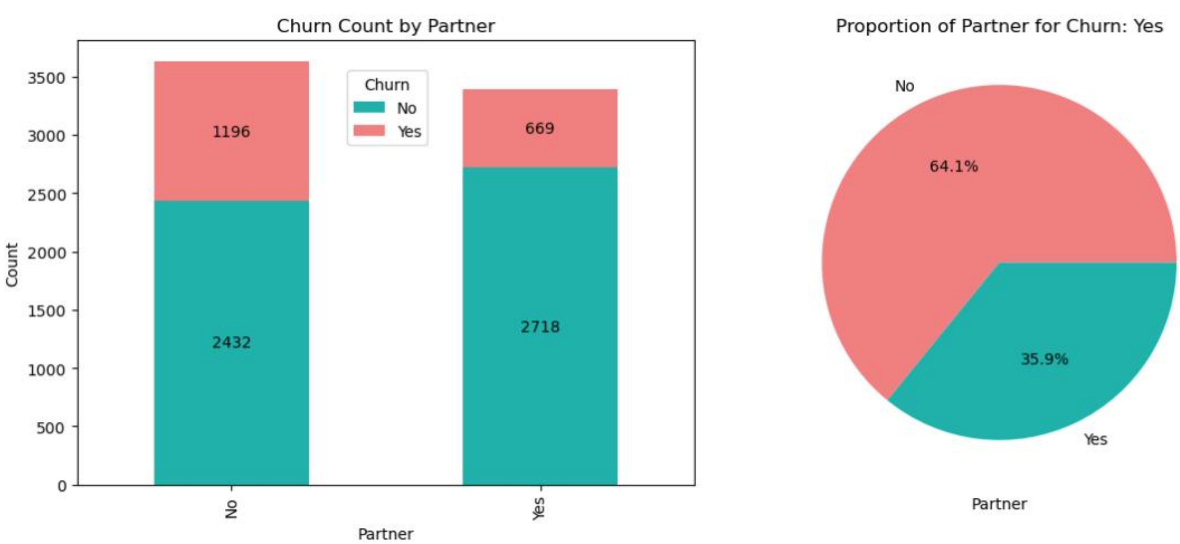
The bar plot unmistakably illustrates that young people, as opposed to senior citizens, have a higher contribution to churn in terms of count. However, the pie charts reveal a distinct pattern when we examine each category individually. Approximately 42% of senior citizens left, nearly double that of young citizens who left (Senior Citizens = No).

- **Churn distribution by Dependent**



The majority of the customers do not have dependents and customers who do not appear more likely to churn than those who have dependents.

- **Churn distribution by Partner**



Customers who do not have partners (single) appear to contribute more towards the churn.

- ## Insights from Customer's Analysis

  It was discovered that gender and relationship status are pretty evenly distributed within the client base, with approximate percentage values based on the study. While females have a somewhat greater turnover rate, this difference is modest and may not be statistically significant.

  When diving further into the details, though, a noteworthy tendency emerges. Younger consumers, consumers without partners, and consumers without dependents have a greater turnover rate. Based on the data study, these specific categories of the consumer population stand out as being more prone to churn.

  Our findings, in particular, highlight the importance of non-senior citizens without partners or dependents as a separate client niche worthy of consideration when developing customer retention tactics.

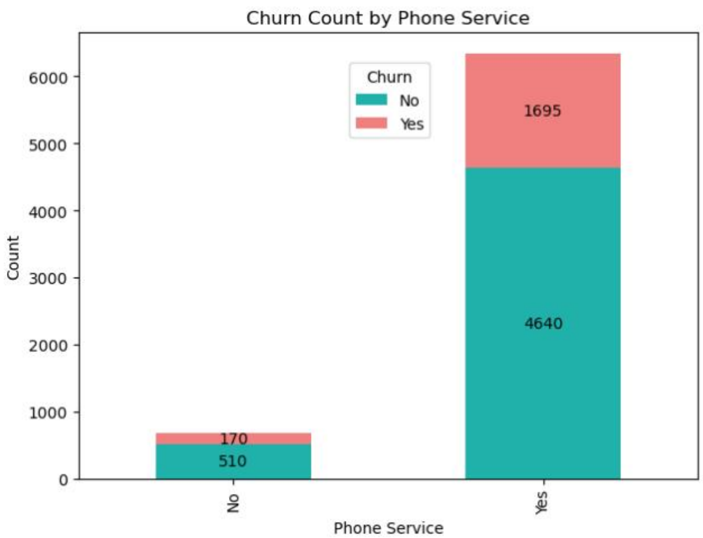
- # Customer’s Subscription Service Analysis

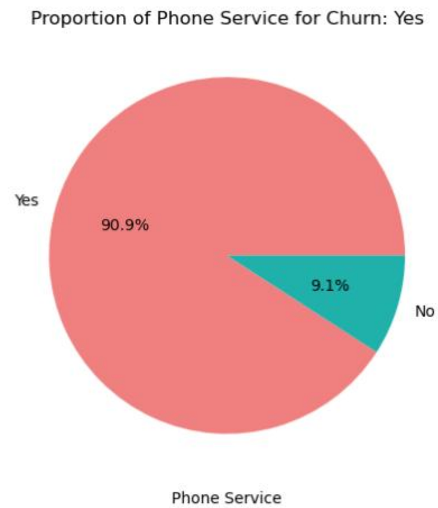
The dataset has various details of the various services subscribed by the Customer.
These subscription services include various columns as follows:

- **Phone Service**: Does the Customer have phone service or not
- **Multiple Lines**: Does the Customer have multiple lines or not if he has phone service
- **Online Security**: Does the Customer has online security or not if he has internet service
- **Online Backup**: Does the Customer have online backup or not if he has internet service
- **Device Protection**: Does the Customer have device protection or not if he has internet service
- **Tech Support**: Does the Customer have tech support or not if he has internet service
- **Streaming TV**: Does the Customer have streaming TV or not if he has internet service
- **Streaming Movies**: Does the Customer have streaming movies or not if he has internet service

Analyzing each feature separately:

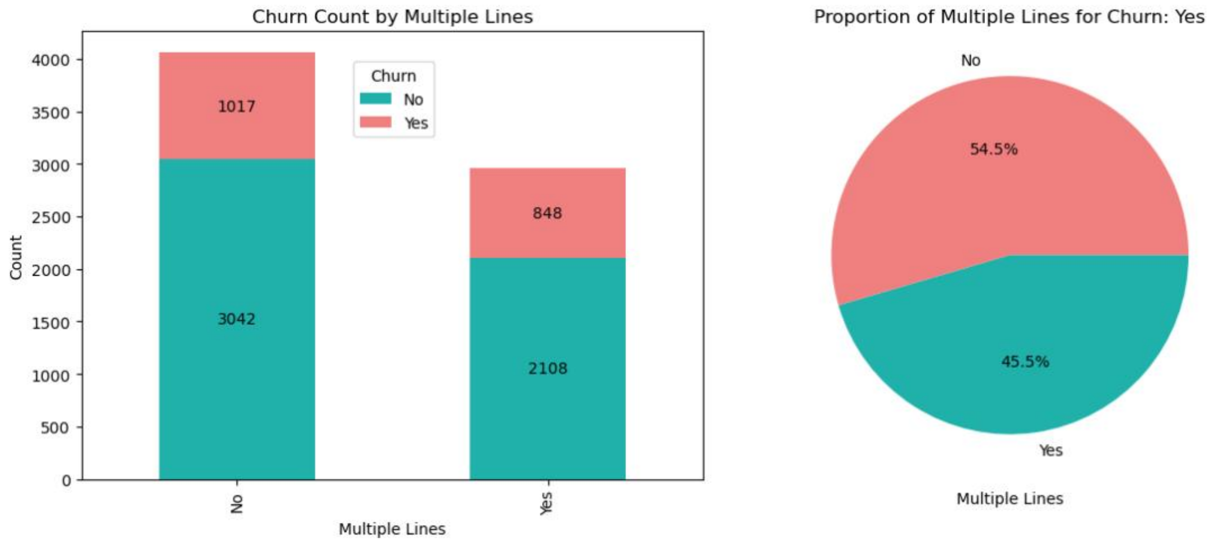
- **Churn distribution by Phone Service**





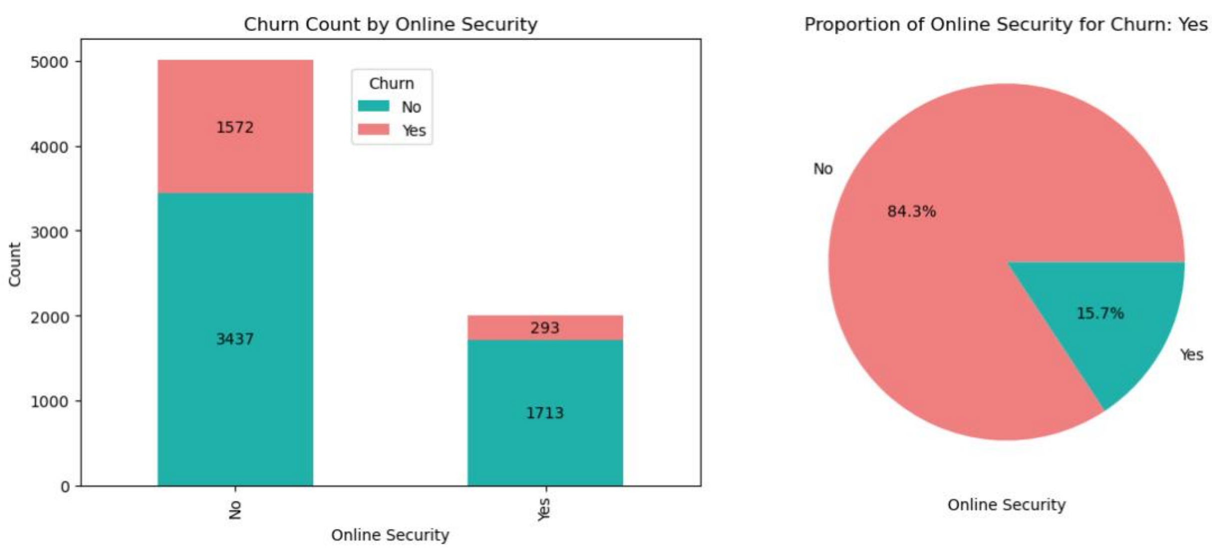
More than 90% of the customers have phone service.

- **Churn distribution by Multiple Lines**



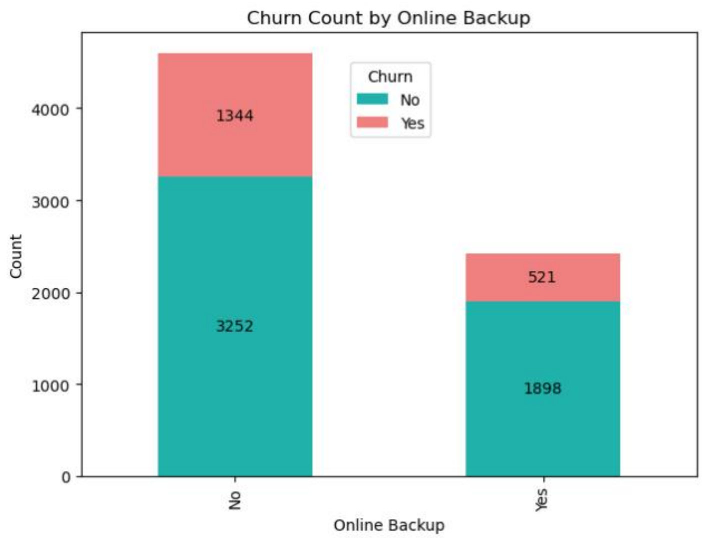
Customers who do not have multiple lines are more likely to be retained than those with multiple lines.

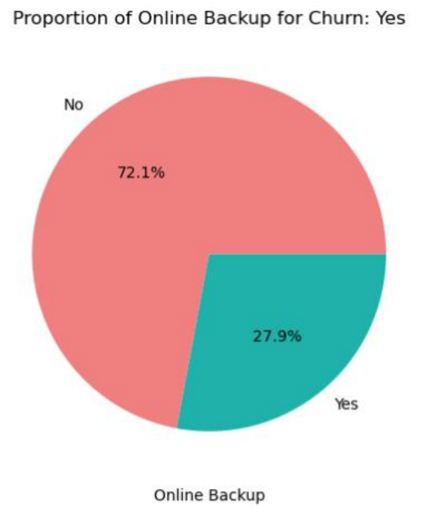
- **Churn distribution by Online Security**



Roughly 5 out of 7 customers need online security, and these customers have higher chances of churning than those with online security.

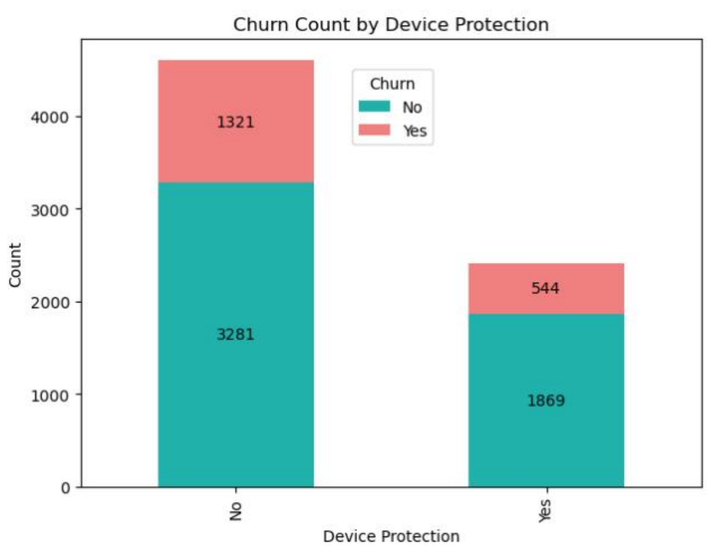
- **Churn distribution by Online Backup**

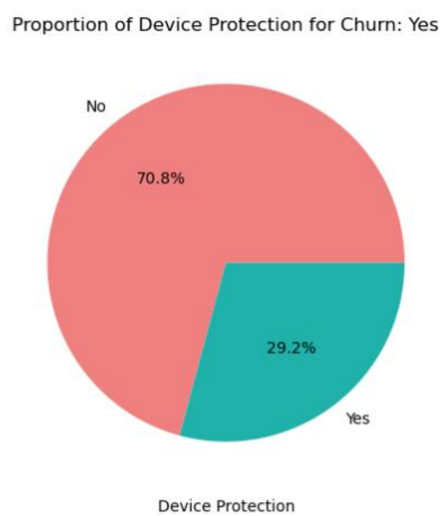




Just like Online security, customers who do not have online backup are churning more.

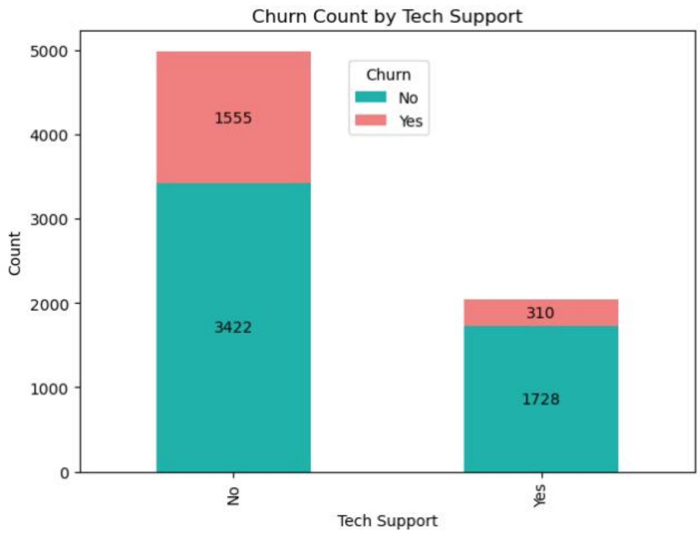
- **Churn distribution by Device Protection**

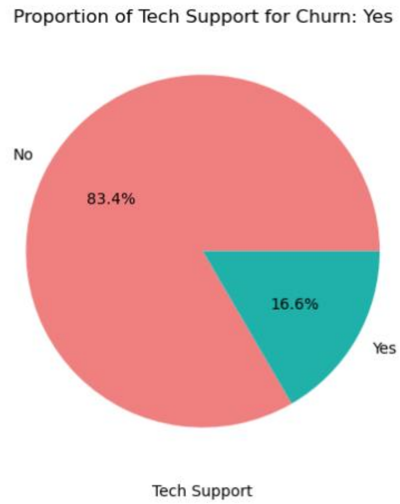




More than half of the customers do not have device protection, and such customers are more likely to churn.

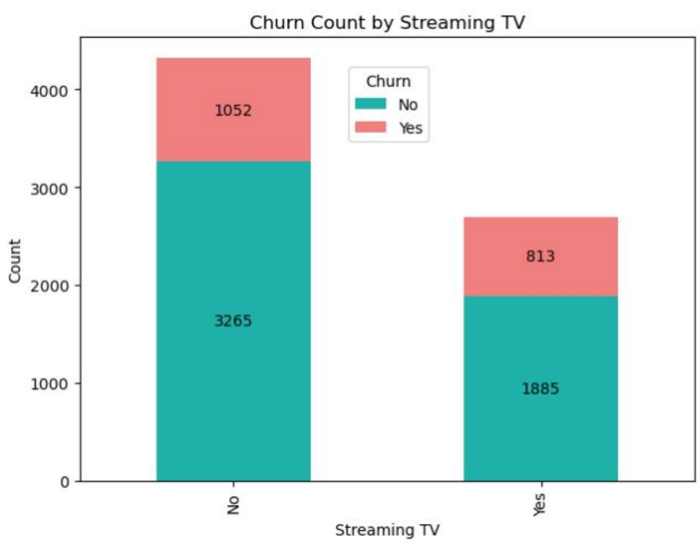
- **Churn distribution by Tech Support**

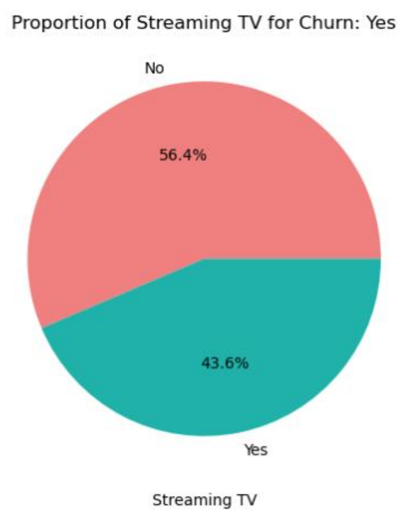




Approximately 5 out of 7 customers opt for something other than tech support. These customers are more likely to churn.

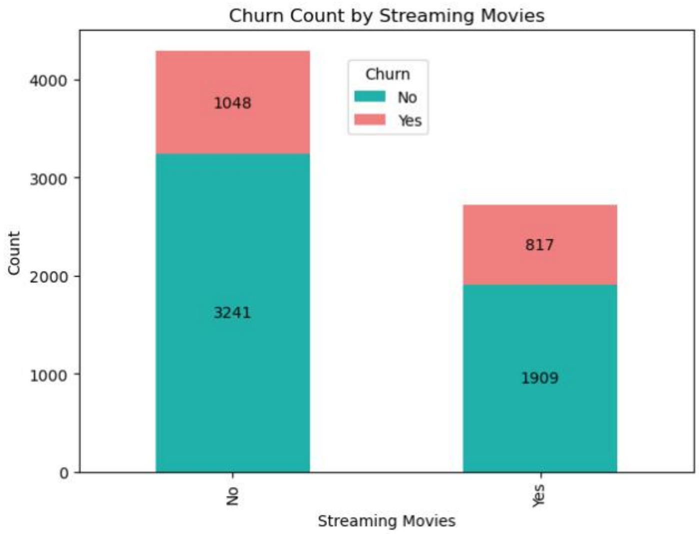
- **Churn distribution by Streaming TV**

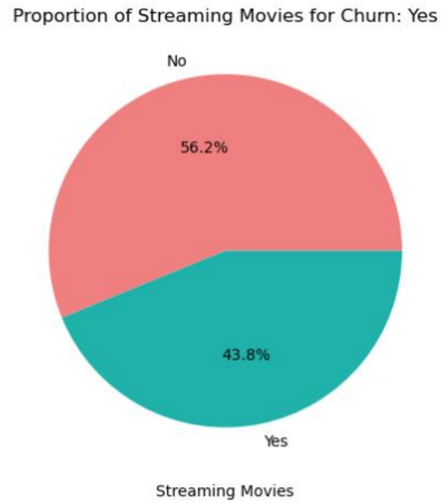




More than half of the customers (exactly 61.5%) do not have Streaming TV service, and such customers are slightly more likely to churn than the rest.

- **Churn distribution by Streaming Movies**





For Streaming Movies, the same trend can be observed as streaming TV, where more than half (precisely 61.1%) of customers do not have Streaming Movies and are slightly more likely to churn.

- **Insights from Customer Subscription Service**

Our examination of customer service subscriptions found substantial differences among different service offerings. Notably, the following tendencies may be identified:

- **Dependency on Phone Service**: It should be noted that clients need phone service to have several lines. Phone services are used by about 90.3% of our consumers, and they have a higher turnover rate. This discovery may point to the necessity for more investigation into the causes of this unanticipated trend.

- **Fibre Optic Internet and Churn:** Customers who have chosen fiber optic as their internet service provider are more likely to churn. This can be attributable to various variables, including prospective price increases, greater competition, customer service quality, and other underlying causes. Notably, fiber optic connection is substantially more expensive than DSL, which may contribute to customer turnover.

- **Reduced Turnover Services:** Customers who have subscribed to extra services such as OnlineSecurity, OnlineBackup, DeviceProtection, and TechSupport, however, are less likely to churn. These services are essential to client retention, stressing their importance in customer retention tactics.

- **Neutrality of Streaming Services**: Surprisingly, the availability of streaming service subscribers does not predict attrition. This service is evenly distributed among consumers who select both "yes" and "no" choices, indicating that it is not a significant churn factor.

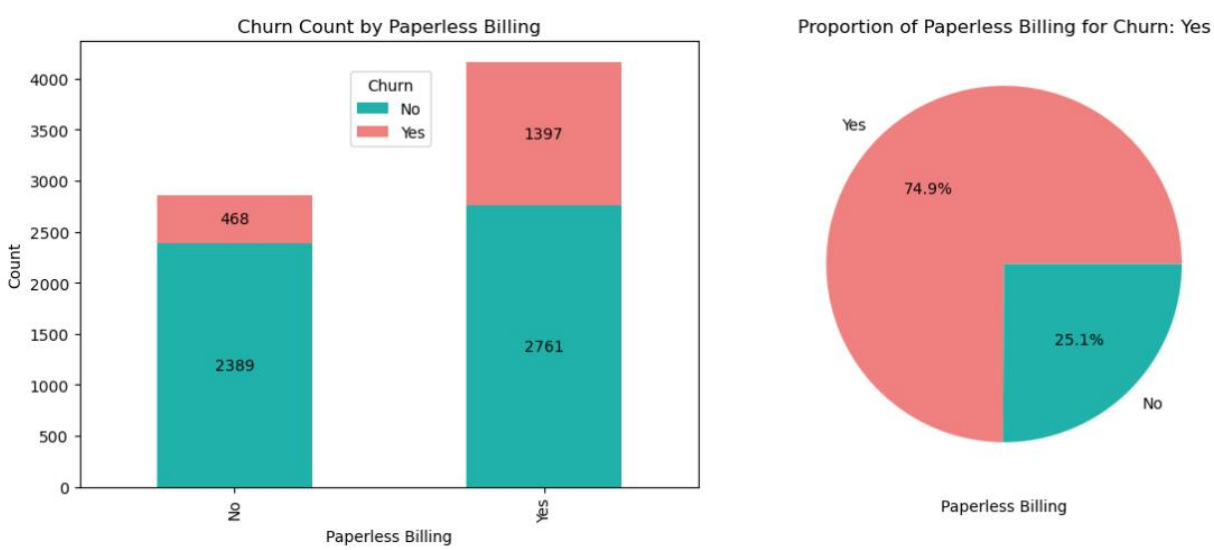
- ## Customer's Contract and Payment Analysis

The data includes the Customer's contract duration and payment details.
These features include below columns:

- **Paperless Billing**: Does the Customer have paperless billing or not
- **Internet Services**: Customer's internet services provider (DSL et al., No ISP)
- **Contract**: Customer's contract term (Month-to-Month, One Year, Two Year)
- **Payment Method**: Customer's Payment method (Electronic et al. (automatic), credit card (automatic))

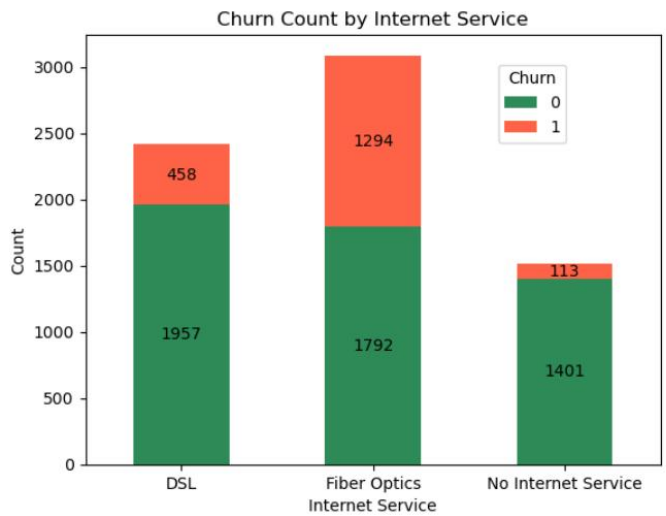
Analyzing each feature separately:

- **Churn distribution by Paperless Billing**



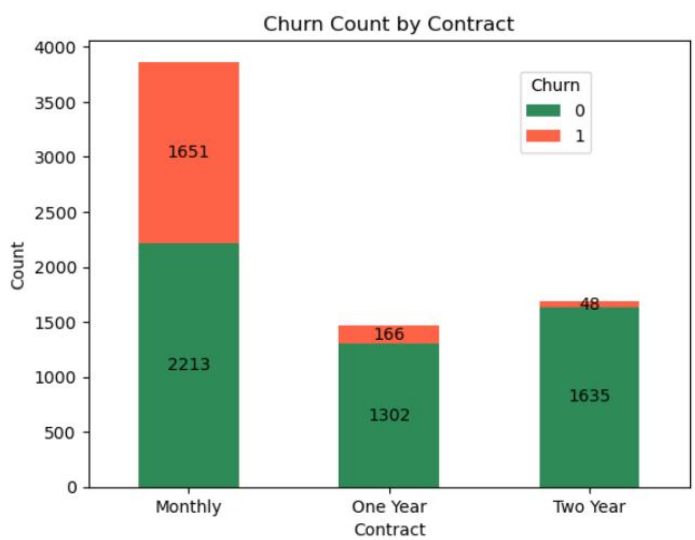
Nearly 6 out of 10 customers have gone for paperless billing. These customers are more likely to churn.

- **Churn distribution by Internet Services**



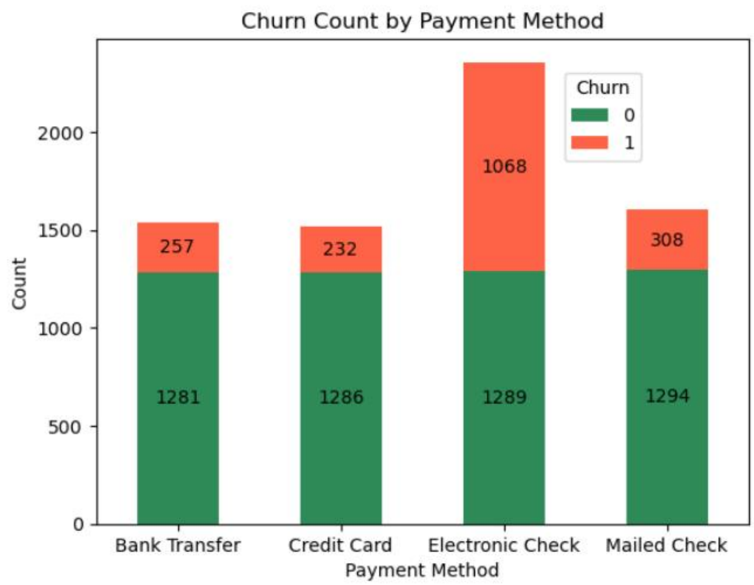
Customers who have Fiber Optics churned the most compared to people with DSL. However, people with no internet service are much less likely to churn.

- **Churn distribution by Contract**



Customers prefer short-term contracts (monthly contracts) to longer-term ones (one-year and two-year contracts). These short-term customers are majorly contributing to the churn. Customers with more extended Contract with the company are significantly less likely to churn.

- **Churn distribution by Payment Method**



Customers who pay through the Electronic check are more likely to churn than the rest of the payment methods.

- **Insights from Customer Contract and Payment**

Our examination of Customer's payment and contracts with the company revealed below trends:

- **Contract Length and Churn:** One intriguing finding is the negative association between contract length and turnover rate. Customers who have shorter contract terms are more likely to leave. On the other hand, those with longer-term obligations face extra obstacles when seeking to cancel early. This research emphasizes the need to develop long-term client connections to lower churn rates since such ties appear more robust.

- **The Impact of Paperless Billing:** It is worth noting that clients who choose paperless billing have a greater turnover rate. Paperless billing has been implemented by about 59.2% of our clients. The reasons for this correlation need further examination since it gives insight into consumer billing preferences and habits.

- **Electronic Checks and Churn**: According to one fascinating result, customers who pay with electronic checks are more likely to churn. This payment type is popular among our clients. Understanding the causes behind this correlation might be critical in devising ways to decrease attrition among electronic check consumers.

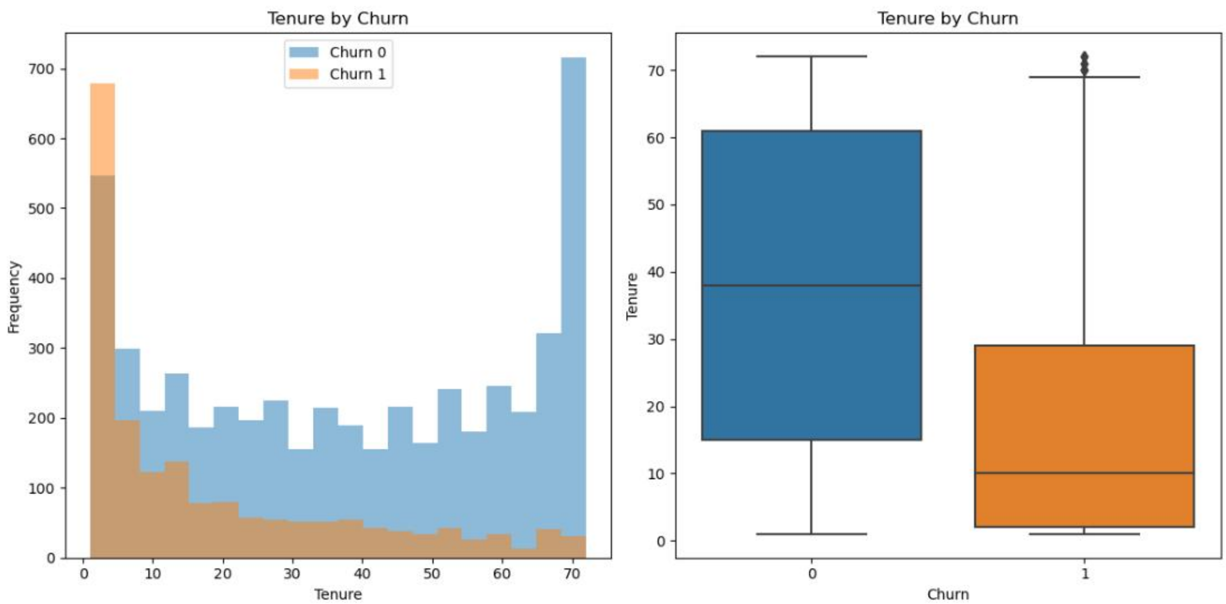
- ## Customer’s account information analysis

The data has features related to the account information of the Customer. These features include their:

- **Tenure**: Number of months the Customer has stayed with the company
- **Monthly Charge**: The amount charged to the Customer monthly
- **Total Charge**: The total amount charged to the Customer

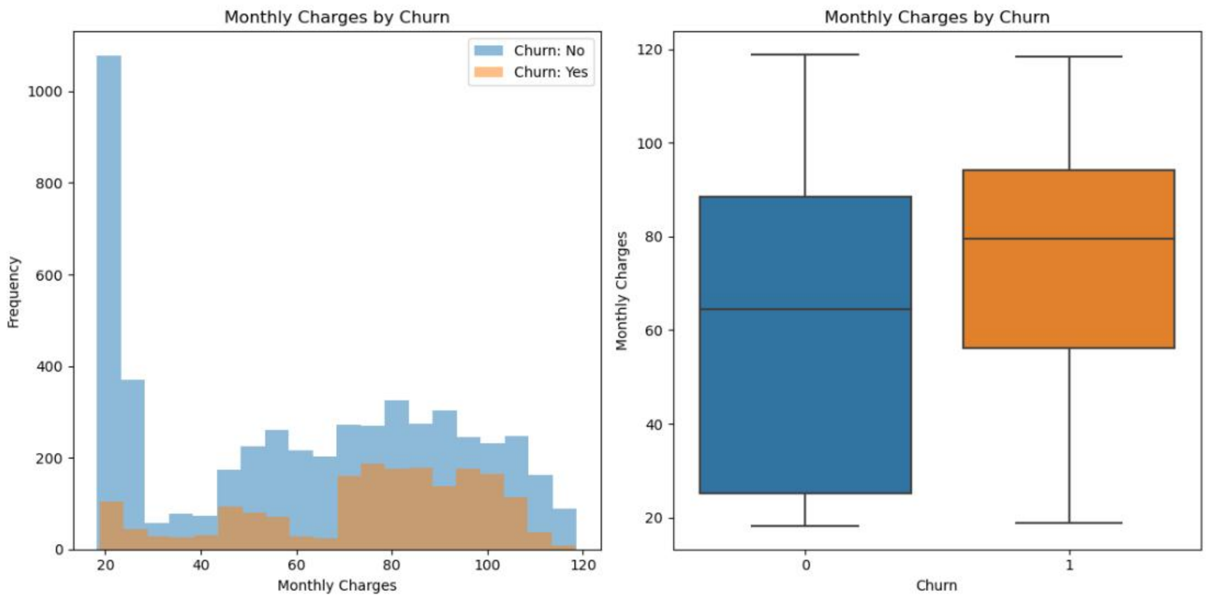
Analyzing each feature separately:

- **Churn distribution by Tenure**



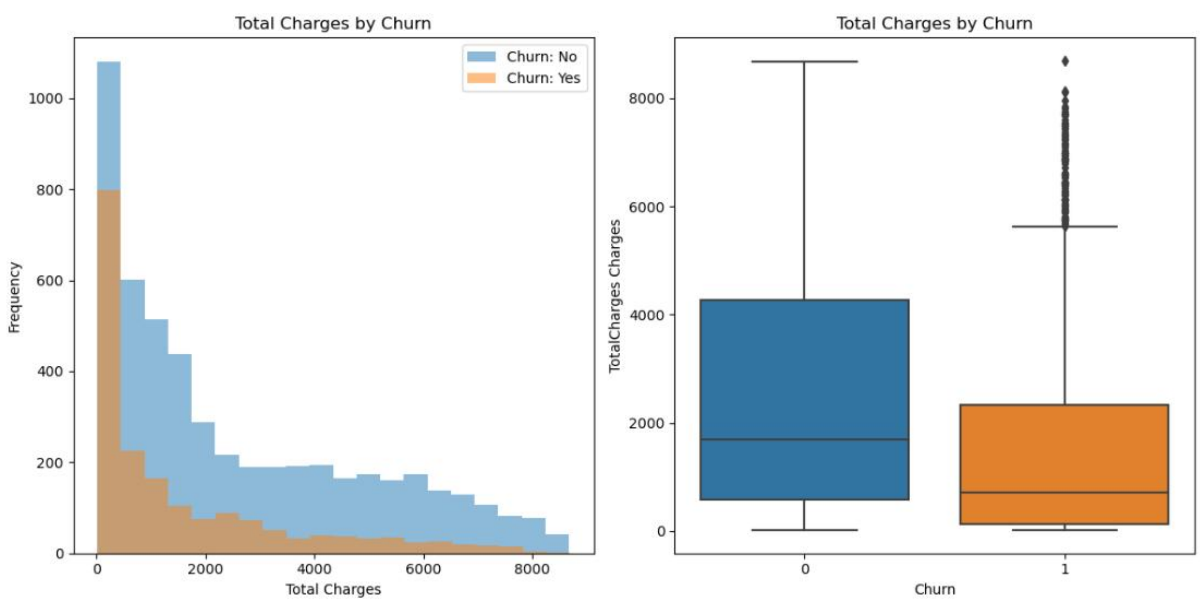
It is evident from the graphs that once people stay more than 20 years, then they are less likely to churn based on the Tenure of the customers compared to their churn rate.

- **Churn distribution by Monthly Charge**



Monthly charges are directly proportional to the churn rate, meaning the lower the monthly charges the Customer pays, the less likely the Customer is to churn.

- **Churn distribution by Total Charge**



The churn rate is inversely proportional to the total charges the Customer pays. That is, the higher the total charges paid by the Customer lower the chances of their churning.

- **Insights from Customer account information**

  Our examination of the Customer's account information has shown the below trends:

  - **Tenure Distribution:** The customer tenure histogram shows a right-skewed distribution, indicating that most consumers have only been with the telecom business for the first few months (0-9 months). This realization emphasizes the significance of efficiently maintaining consumers throughout their first few months of involvement.

  - **Churn Timing**: Surprisingly, the most significant percentage of churn happens within the first few months (0-9 months). This discovery underscores the critical period during which customer retention efforts should be concentrated to minimize churn rates effectively.

  - **Early Churn Concentration**: One significant conclusion is that around 75% of consumers who eventually quit the Telco firm do so during their first 30 months of employment. This statistic emphasizes the importance of early client interaction and satisfaction in developing long-term connections.

  - **Monthly Fees and Churn:** Our examination of the monthly charge histogram indicates an interesting pattern. Customers who pay more significant monthly fees are more likely to leave. This implies that discounts, promotions, or competitive pricing effectively motivate customers to stay loyal. Pricing methods that consider these findings may be beneficial in keeping consumers.