D208 Performance Assessment Task 2

This is the code for my d208 performance assessment task 2. Student id: 012047746

A1. Research Question

For this performance assessment, my research question is "What binary qualitative variables most significantly contribute to Churn?". This is an important question to ask because understanding what factors contribute to Churn can allow the business to focus on customers that provide higher revenue for the company.

A2. State Objectives and Goals for Analysis

The goal of this analysis is to gain greater insight into what factors directly correlate with MonthlyCharge. In this analysis, I will be using logistic regression modeling. Using logistic regression, we can identify what variables correlate with a single qualitative variable. The objective is to finish this analysis with a list of binary qualitative variables that signficantly correlate with Churn.

B1. Assumptions

There are four assumptions of a multiple logistic regression model that we should consider. These are:

- The dependant variable is binary, For example, with churn as my dependent variable, I can only predict a yes or a no with logarithmic regression.
- We have to watch out for multicollinearity. This means that none of the independent variables can be significantly related with one another, or the regression model will be inaccurate
- Logistic regression requires a large sample size to be sufficiently accurate
- The logistic regression requires that the independent variables must be independent of one another. That they have no repeated measurements or shared date.

B2. Programming Language and Benefits

The programming language that I used for this analysis is Python. Two reasons why I am using this language are:

- I am familiar with the language. I am not as comfortable with using R and understand how to code in Python. This will make the project completion more timely and efficient.

- Access to python libraries that can do multiple linear regression. There are a widespread list of libraries that I can use to finish my analysis for this project. This flexibility assists in timely

The libraries that I will be using in this analysis are as follows:

- Pandas: This library is essential to import the CSV and apply analysis to the data.
- numpy: We use numpy to use arrays and set up the dataframe to be used for statistical analysis
- scipy.stats: We use scipy for many of the statistical models. For instance using zscores in order to detect outliers
- matplotlib: We use matplotlib for visualization such as histograms
- statsmodels.api: We use statsmodel to run our multiple logistic regression model. We also use this for our VIF

Import Libraries

In [25]:
```
# import the libraries
import pandas as pd
from pandas import DataFrame
import numpy as np
import scipy.stats as stats
import matplotlib.pyplot as plt
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.compat import lzip
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
```

B3. Justification of Using Regression

Logistic regression is an appropriate technique to use for this analysis because the research question focuses on a dependant qualitative variable. In logistic regression, it is important that the dependent variable is a binary qualitative variable. In our research question, we are focusing on churn, which is a binary (Yes or No) variable as our depednent variable. Because churn is the dependent variable, logistic regression must be used. Linear regression would not be usable in this case because that requires a quantiative variable as the dependent variable.

C1. Data Cleaning

For my data cleaning, I am going to start by focusing on null data, outliers, and duplicates. We can start by importing our data from a CSV. I am also going to drop all the numerical variables since we are only focusing on qualitative variables for this analysis. This means dropping CaseOrder, Population, Children, Age, Income, Outage_sec_perweek, Email, Contacts, Yearly_equip_failure, Tenure, MonthlyCharge, Bandwidth_GB_Year, Item1, Item2, Item3, Item4, Item5, Item6, Item7, and Item8. I will also convert the numeric to varchar so they are counted by the code as qualitative rather than quantitative. I also drop customer_id and interaction because these are unique values, and that cateogry is already covered by UID.

In [26]:
```
df = pd.read_csv('churn_clean.csv')
```

In [27]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   CaseOrder             10000 non-null  int64  
 1   Customer_id           10000 non-null  object 
 2   Interaction           10000 non-null  object 
 3   UID                   10000 non-null  object 
 4   City                  10000 non-null  object 
 5   State                 10000 non-null  object 
 6   County                10000 non-null  object 
 7   Zip                   10000 non-null  int64  
 8   Lat                   10000 non-null  float64
 9   Lng                   10000 non-null  float64
 10  Population            10000 non-null  int64  
 11  Area                  10000 non-null  object 
 12  TimeZone              10000 non-null  object 
 13  Job                   10000 non-null  object 
 14  Children              10000 non-null  int64  
 15  Age                   10000 non-null  int64  
 16  Income                10000 non-null  float64
 17  Marital               10000 non-null  object 
 18  Gender                10000 non-null  object 
 19  Churn                 10000 non-null  object 
 20  Outage_sec_perweek    10000 non-null  float64
 21  Email                 10000 non-null  int64  
 22  Contacts              10000 non-null  int64  
 23  Yearly_equip_failure  10000 non-null  int64  
 24  Techie                10000 non-null  object 
 25  Contract              10000 non-null  object 
 26  Port_modem            10000 non-null  object 
 27  Tablet                10000 non-null  object 
 28  InternetService       10000 non-null  object 
 29  Phone                 10000 non-null  object 
 30  Multiple              10000 non-null  object 
 31  OnlineSecurity        10000 non-null  object 
 32  OnlineBackup          10000 non-null  object 
 33  DeviceProtection      10000 non-null  object 
 34  TechSupport           10000 non-null  object 
 35  StreamingTV           10000 non-null  object 
 36  StreamingMovies       10000 non-null  object 
 37  PaperlessBilling      10000 non-null  object 
 38  PaymentMethod         10000 non-null  object 
 39  Tenure                10000 non-null  float64
 40  MonthlyCharge         10000 non-null  float64
 41  Bandwidth_GB_Year     10000 non-null  float64
 42  Item1                 10000 non-null  int64  
 43  Item2                 10000 non-null  int64  
 44  Item3                 10000 non-null  int64  
 45  Item4                 10000 non-null  int64  
 46  Item5                 10000 non-null  int64  
 47  Item6                 10000 non-null  int64  
 48  Item7                 10000 non-null  int64  
 49  Item8                 10000 non-null  int64  
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

Treating Nulls

We begin by checking the dataframe for nulls. We can use .isnlull().sum() to look through the variables and see if there is any missing data. Using this function we can see that there are no nulls present in the data.

In [28]:
```
df.isnull().sum()
```

Out[28]:
```
CaseOrder              0
Customer_id            0
Interaction            0
UID                    0
City                   0
State                  0
County                 0
Zip                    0
Lat                    0
Lng                    0
Population             0
Area                   0
TimeZone               0
Job                    0
Children               0
Age                    0
Income                 0
Marital                0
Gender                 0
Churn                  0
Outage_sec_perweek     0
Email                  0
Contacts               0
Yearly_equip_failure   0
Techie                 0
Contract               0
Port_modem             0
Tablet                 0
InternetService        0
Phone                  0
Multiple               0
OnlineSecurity         0
OnlineBackup           0
DeviceProtection       0
TechSupport            0
StreamingTV            0
StreamingMovies        0
PaperlessBilling       0
PaymentMethod          0
Tenure                 0
MonthlyCharge          0
Bandwidth_GB_Year      0
Item1                  0
Item2                  0
Item3                  0
Item4                  0
Item5                  0
Item6                  0
Item7                  0
Item8                  0
dtype: int64
```

Finding & Treating Duplicates

Next, we will check to see if there are any duplicates in the data. We can do this by using .duplicated().value_counts() which will output a true or false depending on whether or not duplicates exist within the dataframe. We can see from the output of false 10,000 times that there are no duplicates within the data.

In [29]:
```
df.duplicated().value_counts()
```

Out[29]:
```
False    10000
dtype: int64
```

Finding & Treating Outliers

Because we are not dealing with quantitative variables in this analysis, there are no outliers that we can detect using z-scores.

C2. Data Exploration (EDA)

To get out summary statistics, we can use the describe function. I use a for loop to run the .describe() function and get summary statistics of all the variables. Its also important to note that all outliers have been removed.

- UID: This is another unique id, we should consider dropping the customer_id and interaction since they are effectively the all the same.
- City: We can see that there 6058 unique cities, the most common city is Houston
- State: There are 52 unique states. The top one is texas.
- County: There 1620 unique counties.
- Zip: There are 8583 unique zip codes. The most commonly occuring is 32340 4 times.
- Lat: There are 8563 unique lat values.
- Lng: There are 8630 unique lng values.
- Area: There are 3 types of areas.
- TimeZone: There 25 unique timezones, with the most being in New York timezone
- Job: There are 629 unique occip
- Marital: Marital has 5 different categories
- Gender: There are 3 gender categories]
- Churn: This is a binary variable with either yes or no values.
- Techie: This is a binary variable with either yes or no values.
- Contract: There are 3 contract types.
- Port_modem: This is a binary variable with either yes or no values.
- Tablet: This is a binary variable with either yes or no values.
- InternetService: This is a binary variable with either yes or no values.
- Phone: This is a binary variable with either yes or no values.
- Multiple:This is a binary variable with either yes or no values.

- OnlineSecurity: This is a binary variable with either yes or no values.
- OnlineBackup: This is a binary variable with either yes or no values.
- DeviceProtection: This is a binary variable with either yes or no values.
- TechSupport: This is a binary variable with either yes or no values.
- StreamingTV: This is a binary variable with either yes or no values.
- StreamingMovies: This is a binary variable with either yes or no values.
- PaperlessBilling: This is a binary variable with either yes or no values.
- PaymentMethod: There are 4 payment methods

In [30]:
```
dfq = df[['Churn','Techie','Port_modem','Tablet','Phone','Multiple','OnlineSecu
```

In [31]:
```
dfq_c = ['Churn','Techie','Port_modem','Tablet','Phone','Multiple','OnlineSecu
# run a for loop that goes through and uses .describe()
for column in dfq_c:
    print('Variable: ', column,'\n', df[column].describe(),'\n')
```

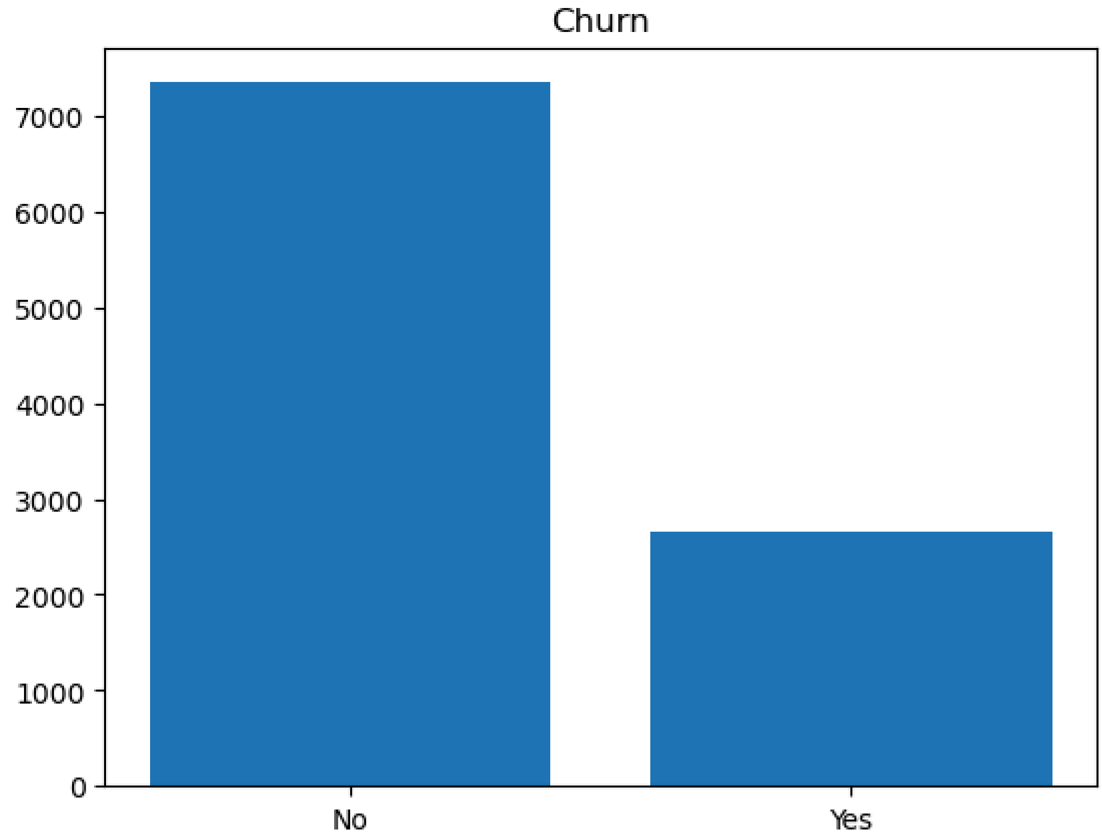
```
Variable:  Churn
 count     10000
unique         2
top           No
freq        7350
Name: Churn, dtype: object

Variable:  Techie
 count     10000
unique         2
top           No
freq        8321
Name: Techie, dtype: object

Variable:  Port_modem
 count     10000
unique         2
top           No
freq        5166
Name: Port_modem, dtype: object

Variable:  Tablet
 count     10000
unique         2
top           No
freq        7009
Name: Tablet, dtype: object

Variable:  Phone
 count     10000
unique         2
top          Yes
freq        9067
Name: Phone, dtype: object

Variable:  Multiple
 count     10000
unique         2
top           No
freq        5392
Name: Multiple, dtype: object

Variable:  OnlineSecurity
 count     10000
unique         2
top           No
freq        6424
Name: OnlineSecurity, dtype: object

Variable:  OnlineBackup
 count     10000
unique         2
top           No
freq        5494
Name: OnlineBackup, dtype: object

Variable:  DeviceProtection
 count     10000
unique         2
top           No
```

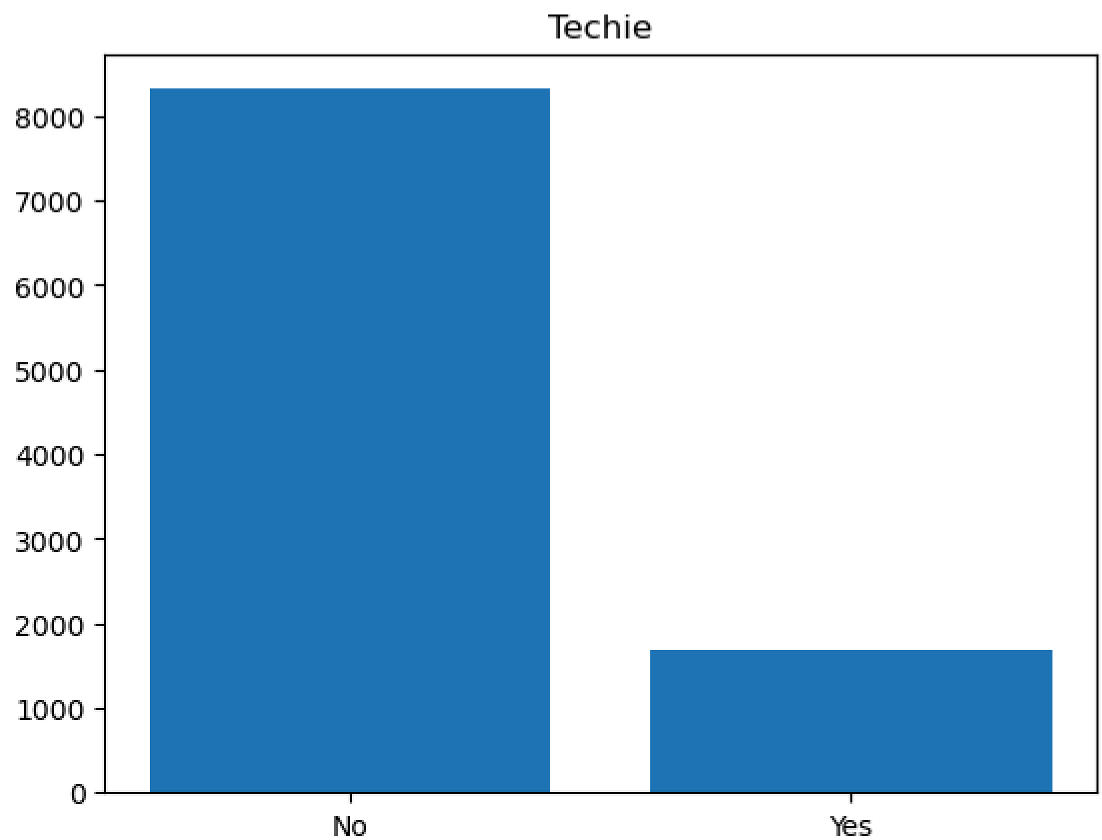
```
freq        5614
Name: DeviceProtection, dtype: object

Variable:  TechSupport
 count     10000
unique        2
top          No
freq       6250
Name: TechSupport, dtype: object

Variable:  StreamingTV
 count     10000
unique        2
top          No
freq       5071
Name: StreamingTV, dtype: object

Variable:  StreamingMovies
 count     10000
unique        2
top          No
freq       5110
Name: StreamingMovies, dtype: object

Variable:  PaperlessBilling
 count     10000
unique        2
top         Yes
freq       5882
Name: PaperlessBilling, dtype: object
```

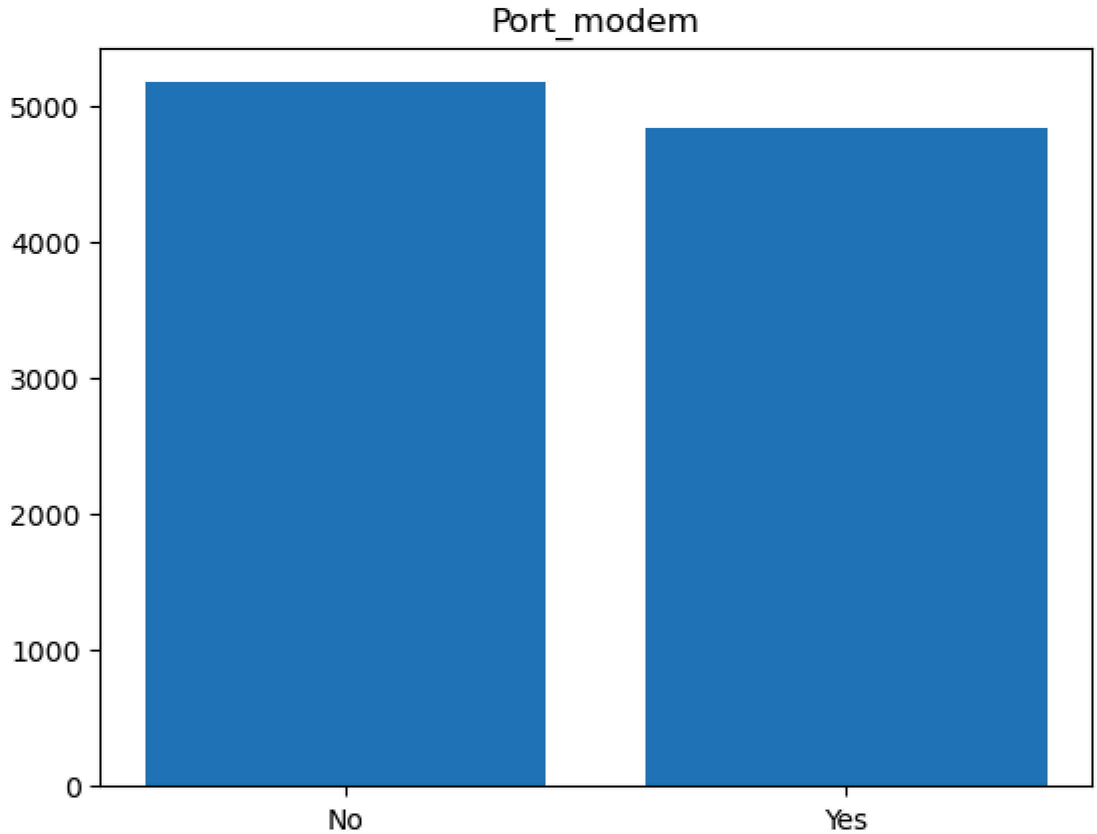
C3. Visualizations

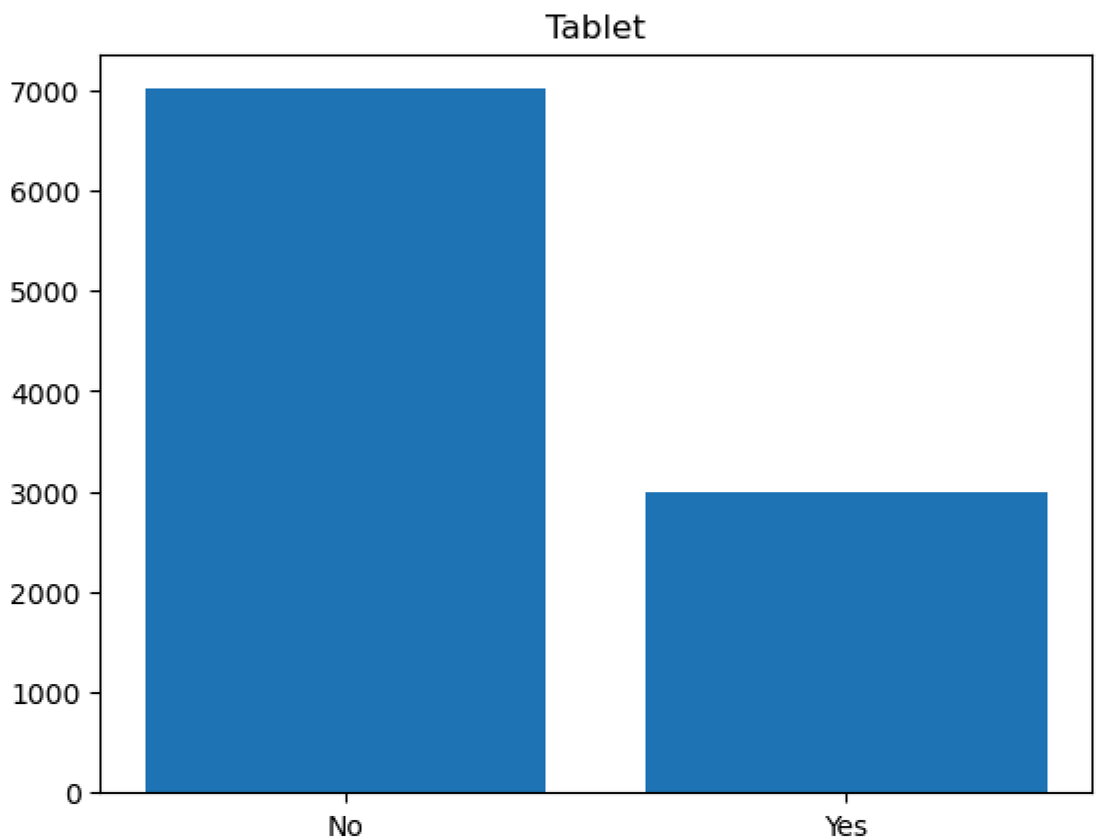
For my univariate visualizations, we can look at the distributions of all of the variables using the actual values this time rather than the z-scores. Since we are using quantitative variables for the logistic regression analysis, I generate stack bar graphs for each of the variables for my bivariate visualizations. For these bar plots, I don't include any visualizations for those with entirely unique values as there is no point to creating that graph, and ones that had over 10 different value types.

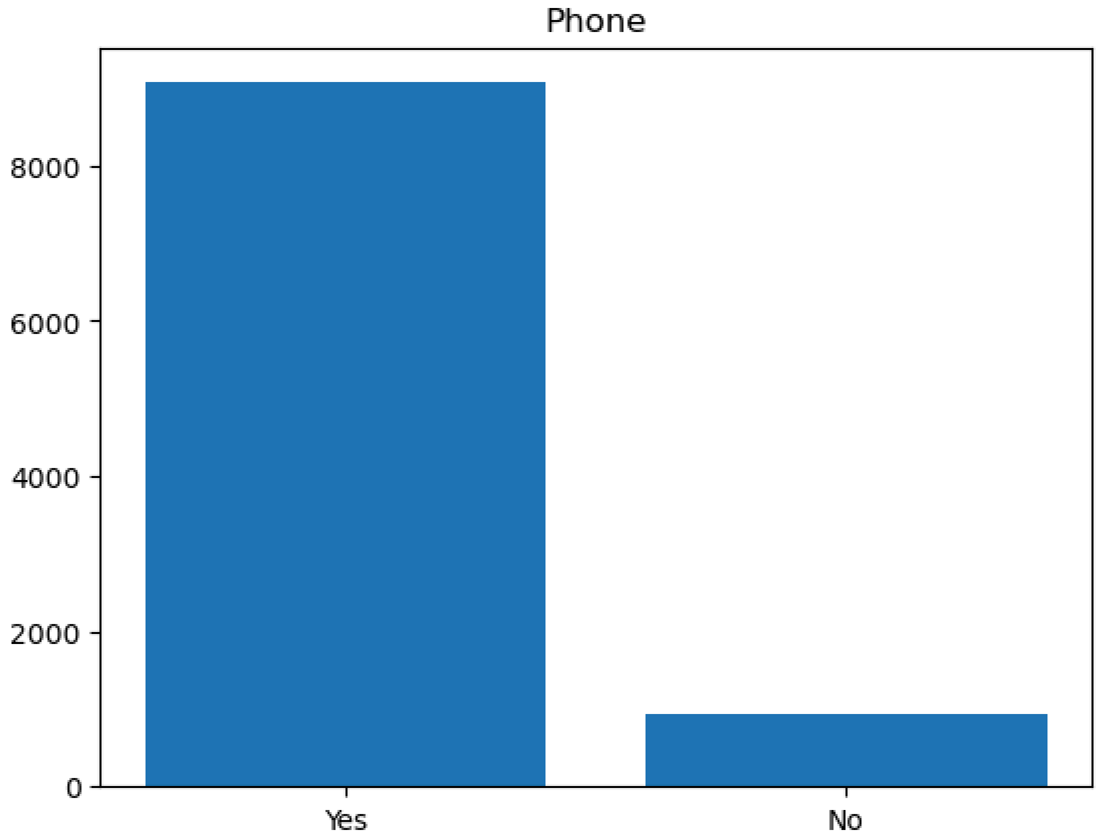
In [32]:
```
# graph our univariate visualizations
for column in dfq_c:
    # create variables for plot
    column_count = df[column].value_counts()
    plt.bar(column_count.index, column_count.values)

    #titles
    plt.title(column)

    # show plot
    plt.show()
```

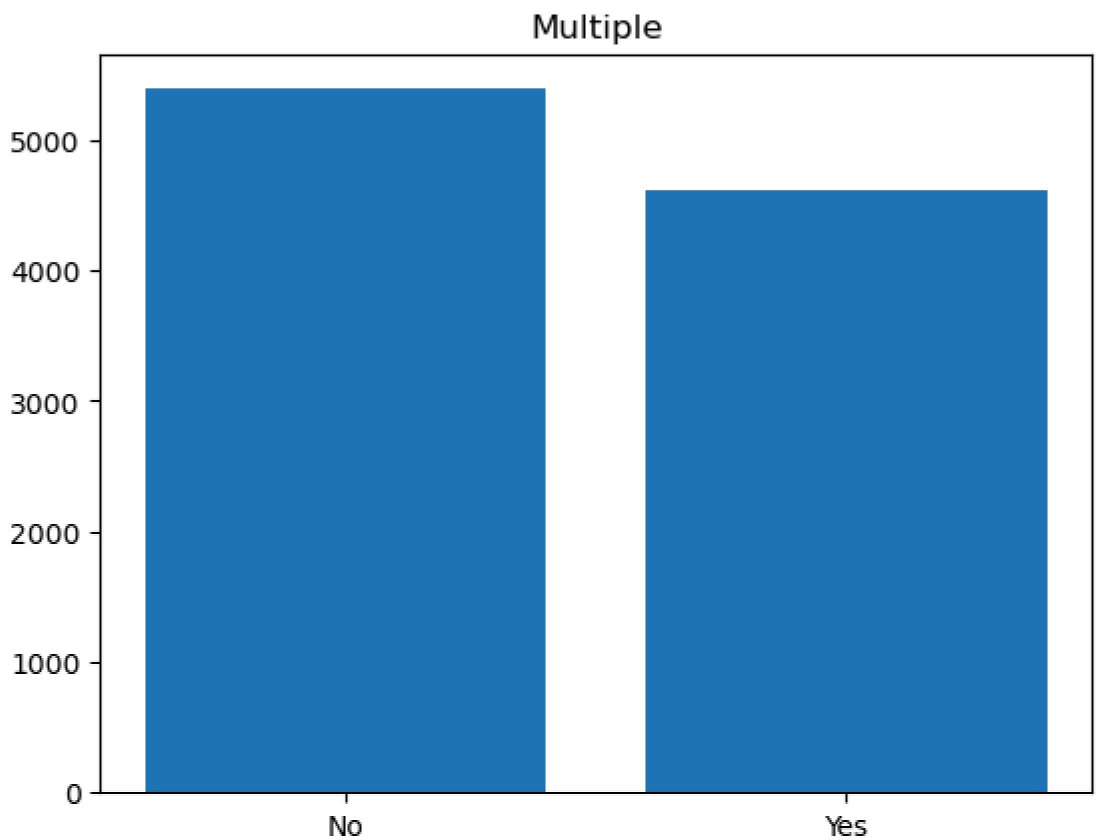

Churn
7000
6000
5000
4000
3000
2000
1000
0
No
Yes

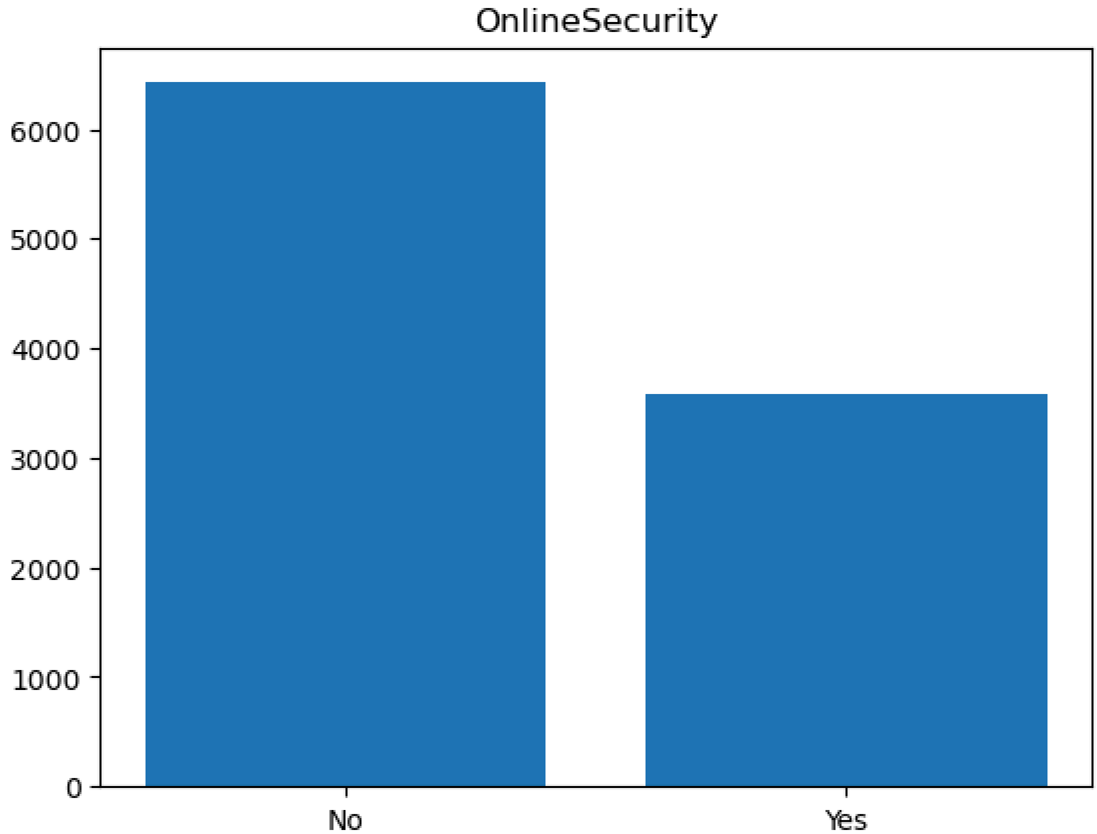

Techie
8000
7000
6000
5000
4000
3000
2000
1000
0
No
Yes

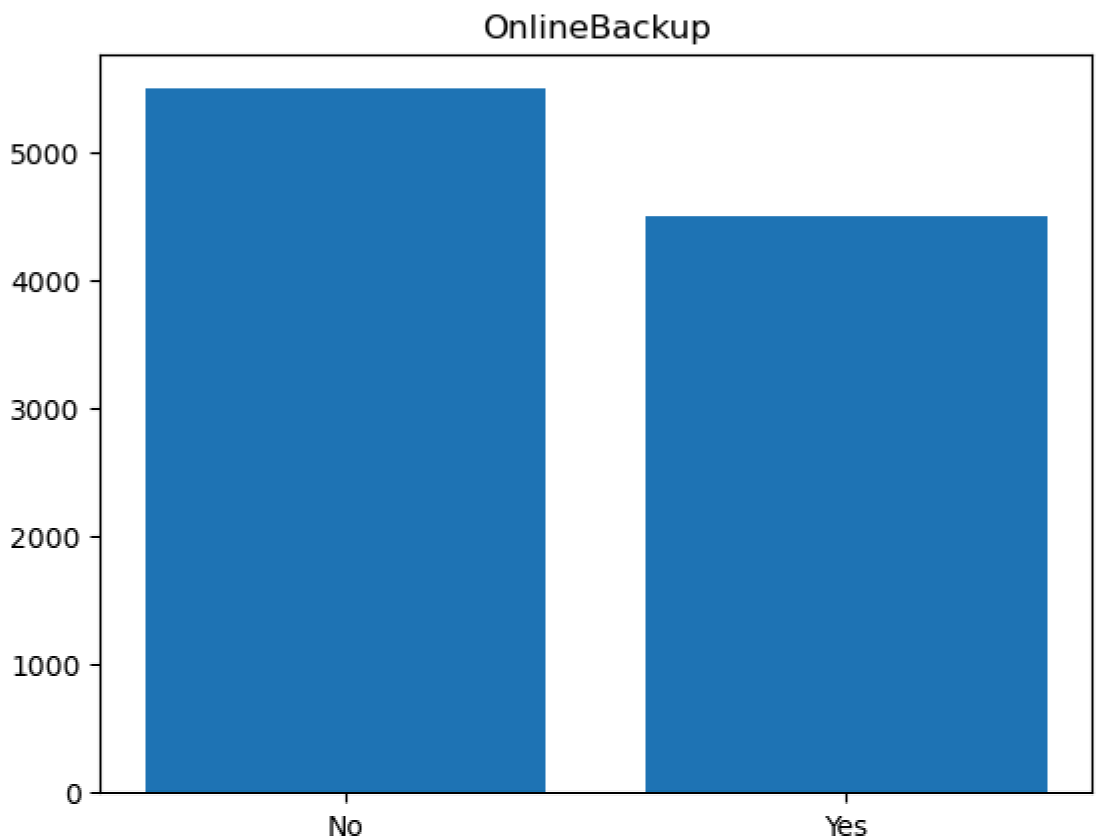

Port_modem
5000
4000
3000
2000
1000
0
No
Yes

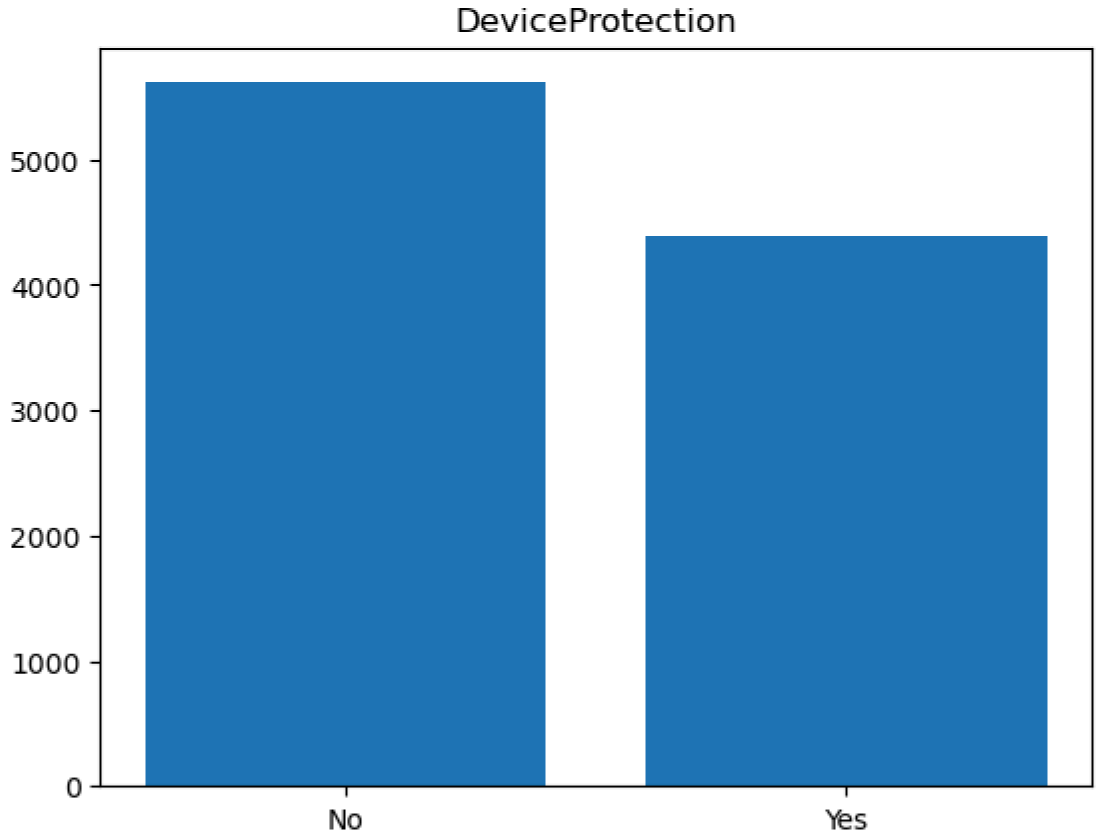

Tablet
7000
6000
5000
4000
3000
2000
1000
0
No
Yes

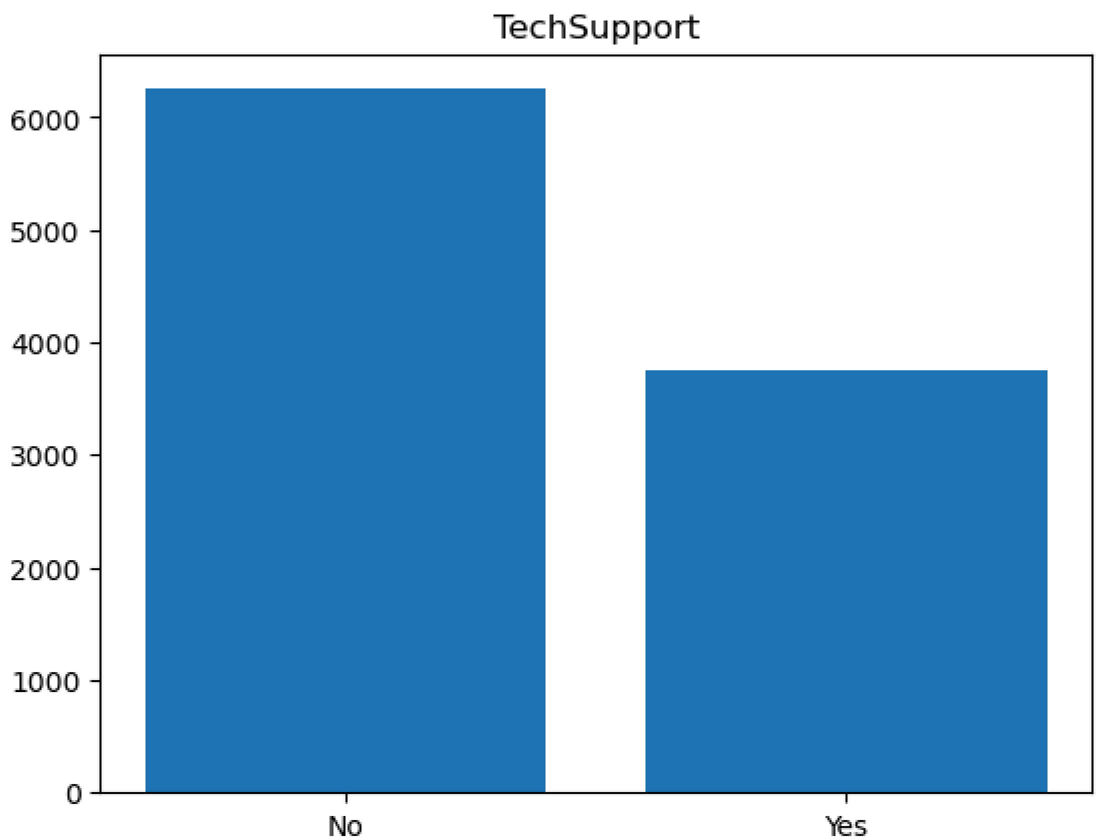

Phone
8000
6000
4000
2000
0
Yes
No

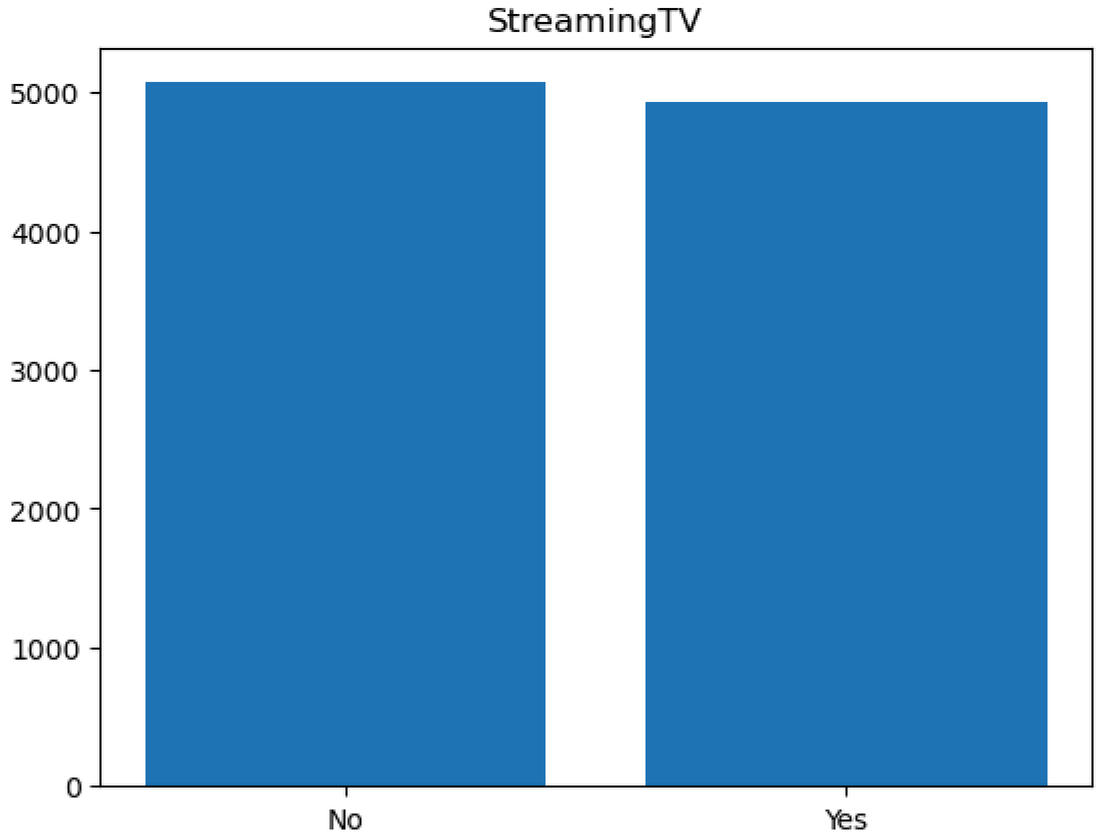

Multiple
5000
4000
3000
2000
1000
0
No
Yes

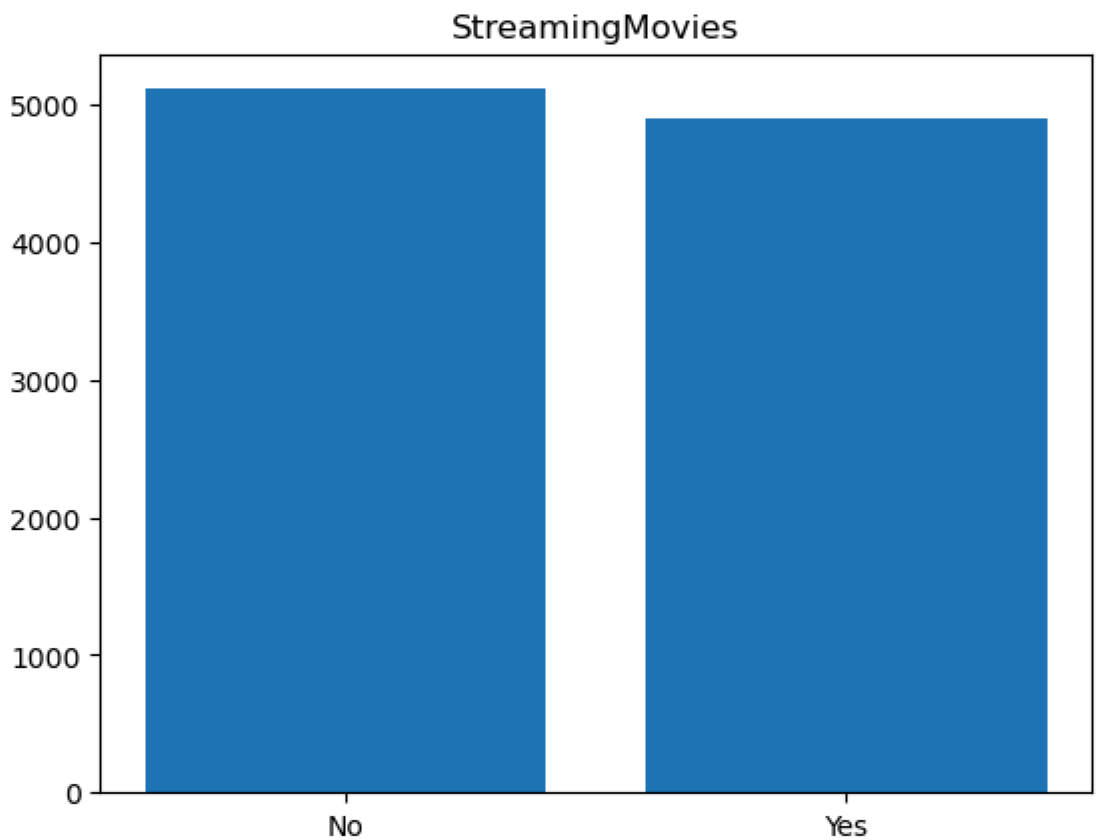

OnlineSecurity
6000
5000
4000
3000
2000
1000
0
No
Yes

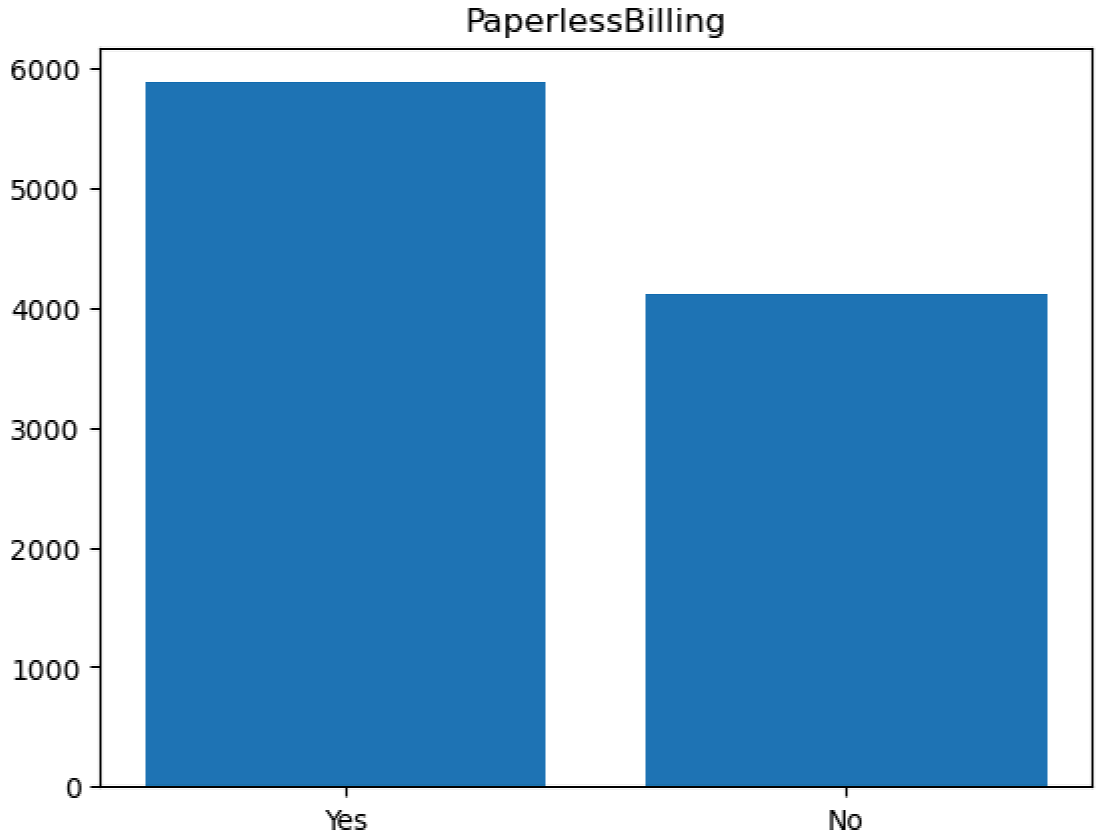

OnlineBackup
5000
4000
3000
2000
1000
0
No
Yes


DeviceProtection
5000
4000
3000
2000
1000
0
No
Yes

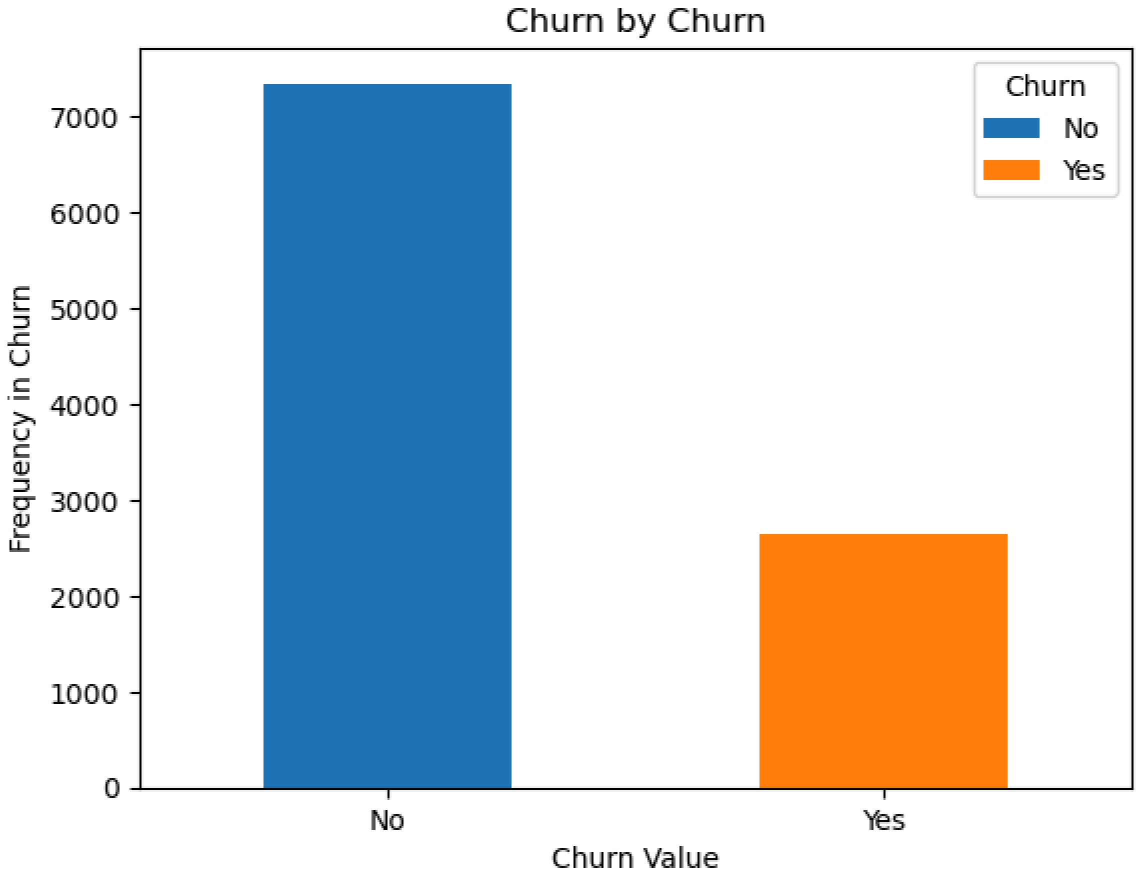

TechSupport
6000
5000
4000
3000
2000
1000
0
No
Yes

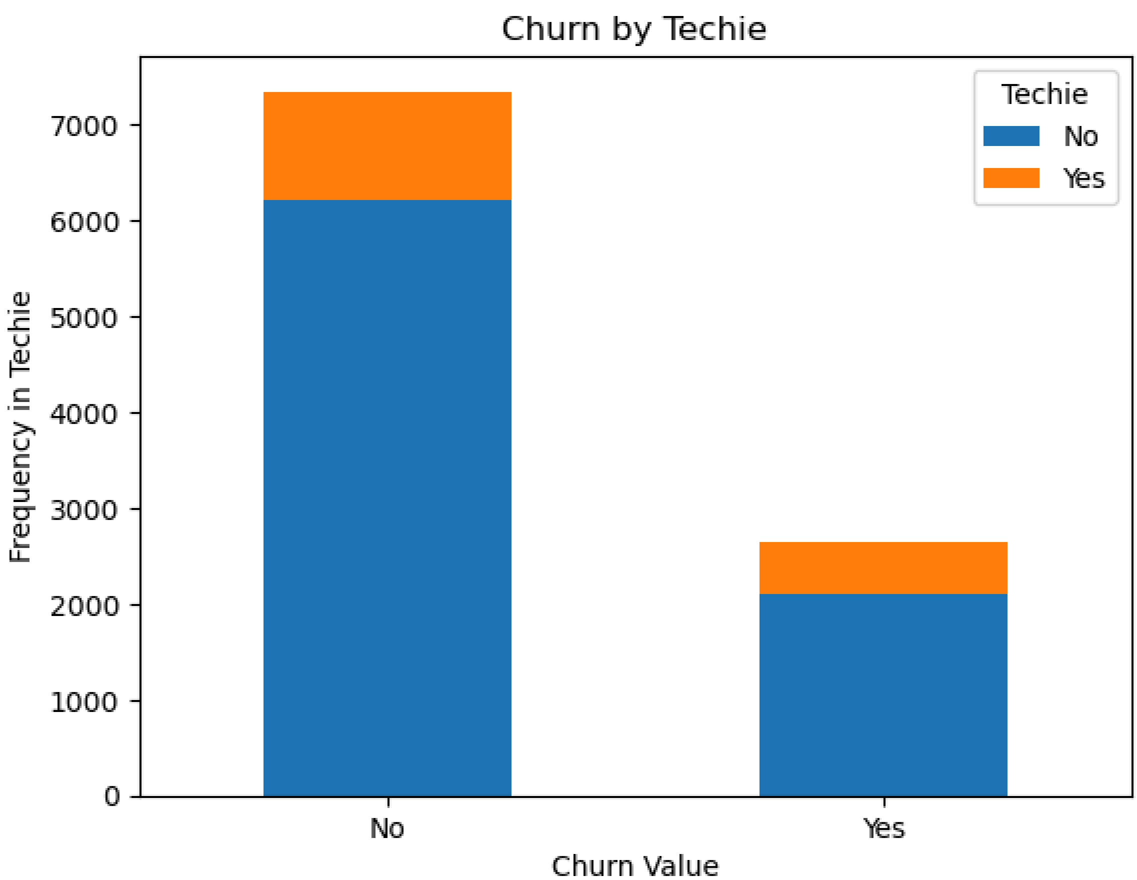

StreamingTV
0
1000
2000
3000
4000
5000
No
Yes

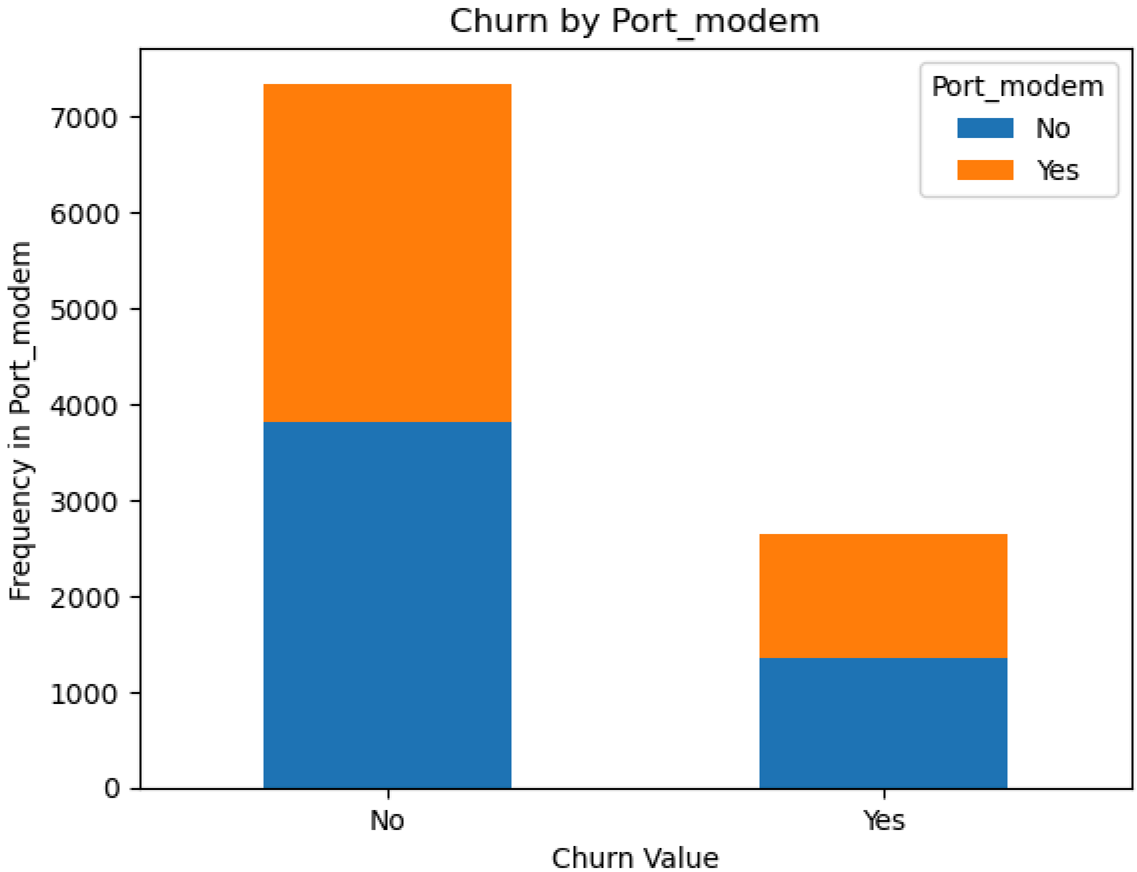

StreamingMovies
0
1000
2000
3000
4000
5000
No
Yes

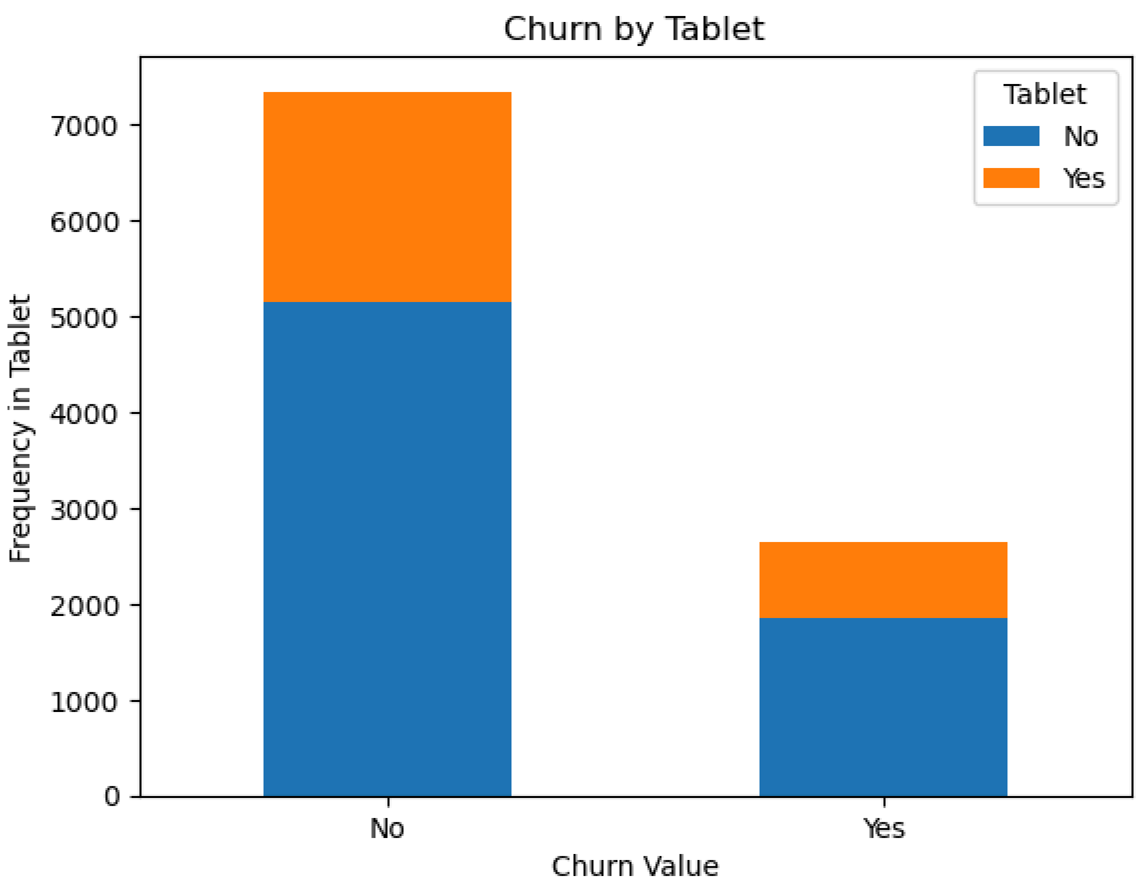


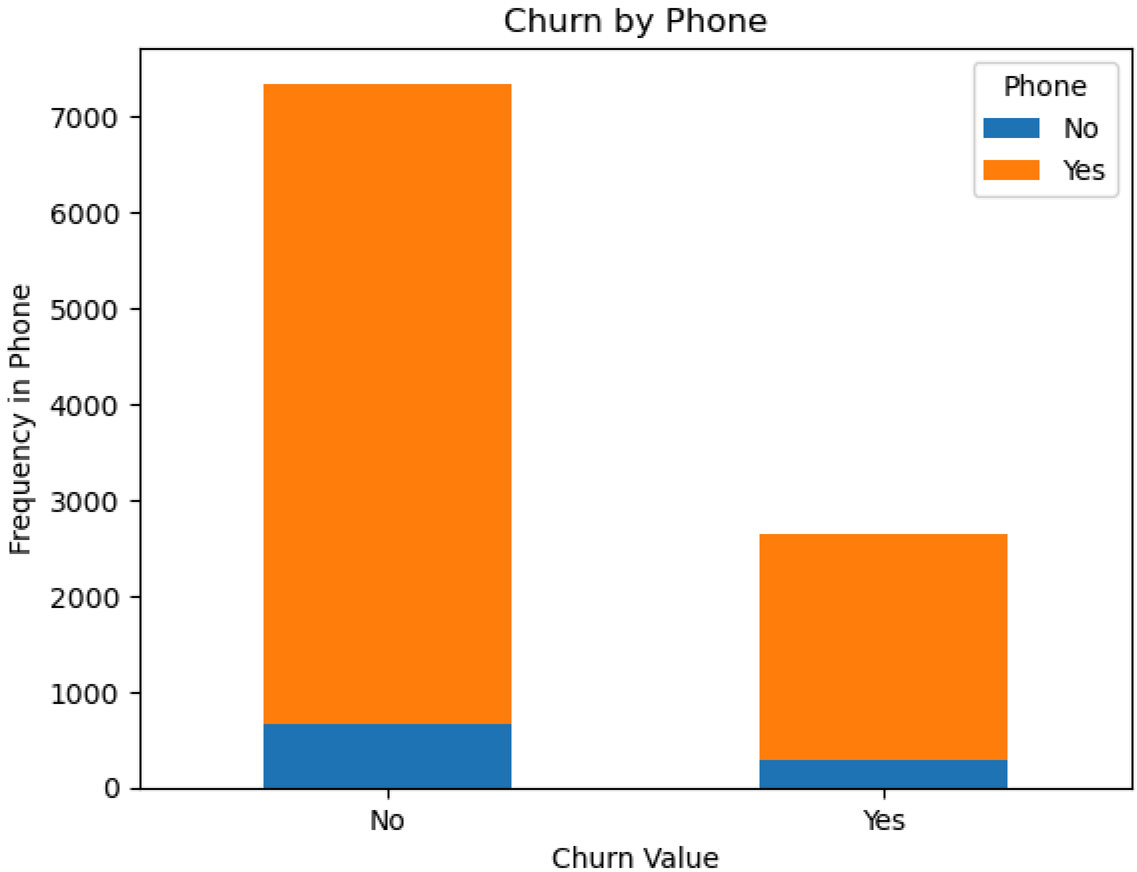
In [33]:
```
# graph our bivariate visualizations
for column in dfq_c:
    # create crosstab
    crosstab = pd.crosstab(df['Churn'], df[column])

    # plot stack bar chart
    crosstab.plot(kind='bar', stacked=True)

    # customize chart
    plt.title('Churn by ' + column)
    plt.xlabel('Churn Value')
    plt.ylabel('Frequency in ' + column)
    plt.xticks(rotation=0)  # Optional: rotate x-axis labels

    # show plot
    plt.show()
```

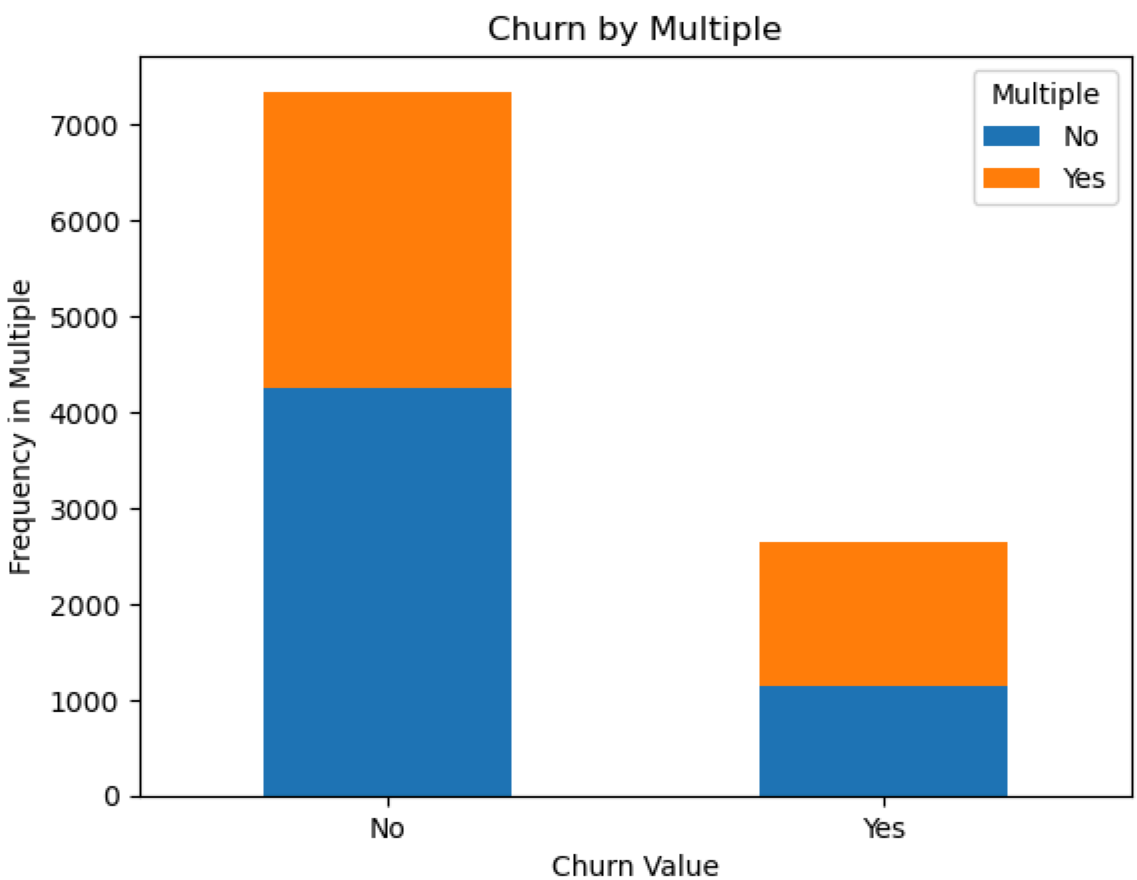

Churn by Churn
Churn
No
Yes
Frequency in Churn
7000
6000
5000
4000
3000
2000
1000
0
No
Yes
Churn Value

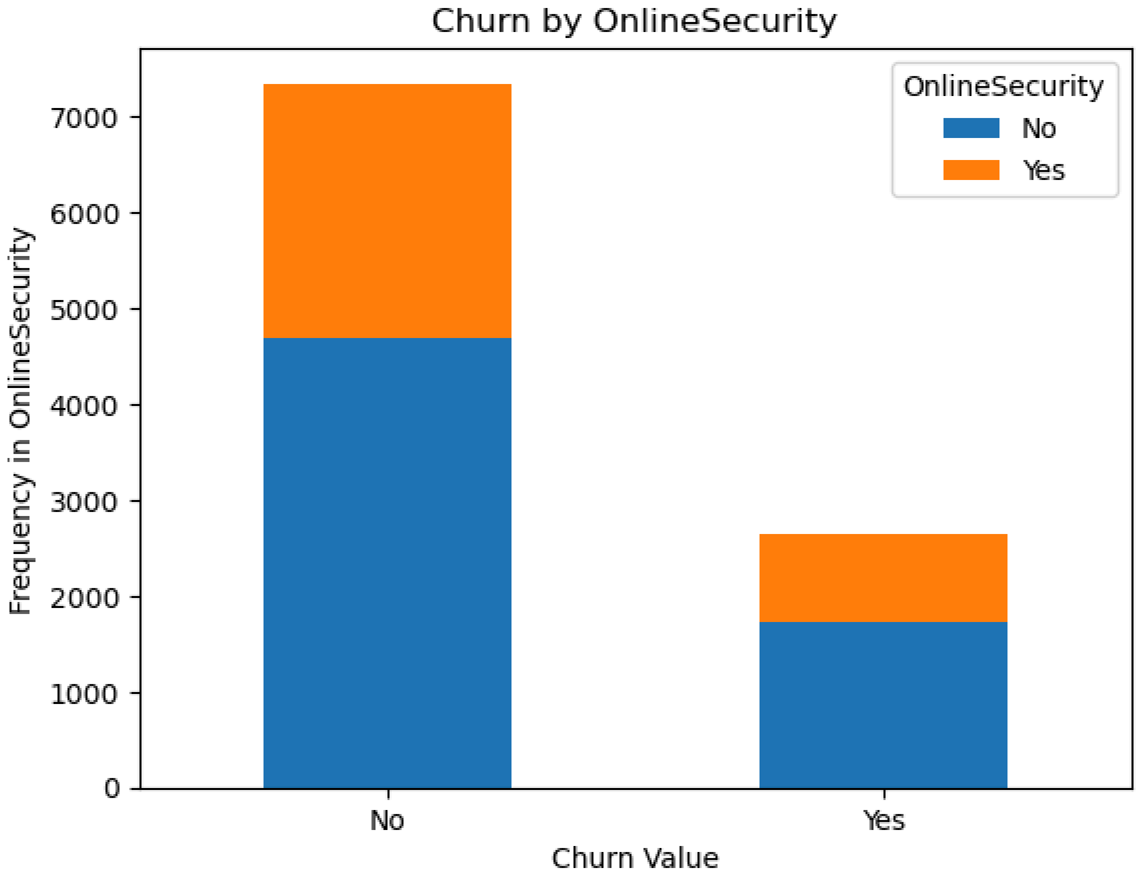

Churn by Techie
Techie
No
Yes
Frequency in Techie
7000
6000
5000
4000
3000
2000
1000
0
No
Yes
Churn Value

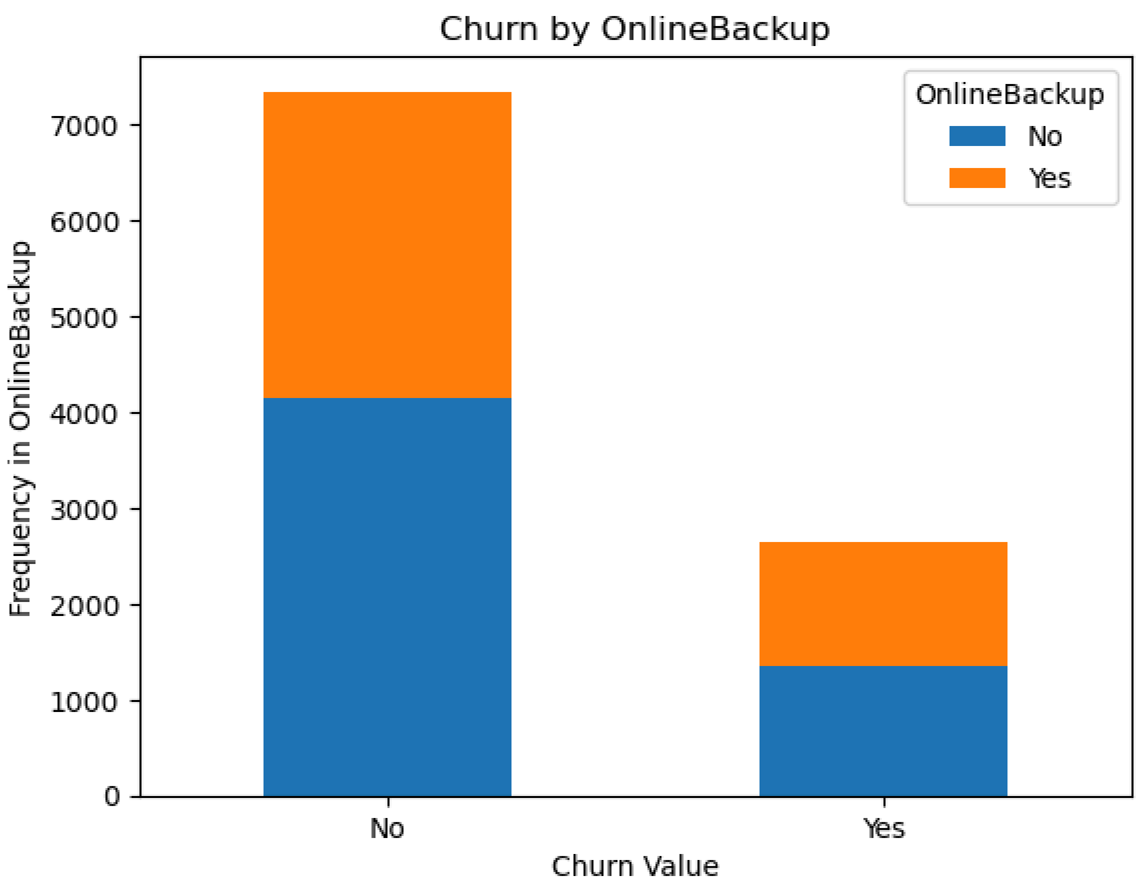

Churn by Port_modem
Port_modem
No
Yes
Frequency in Port_modem
0
1000
2000
3000
4000
5000
6000
7000
No
Yes
Churn Value

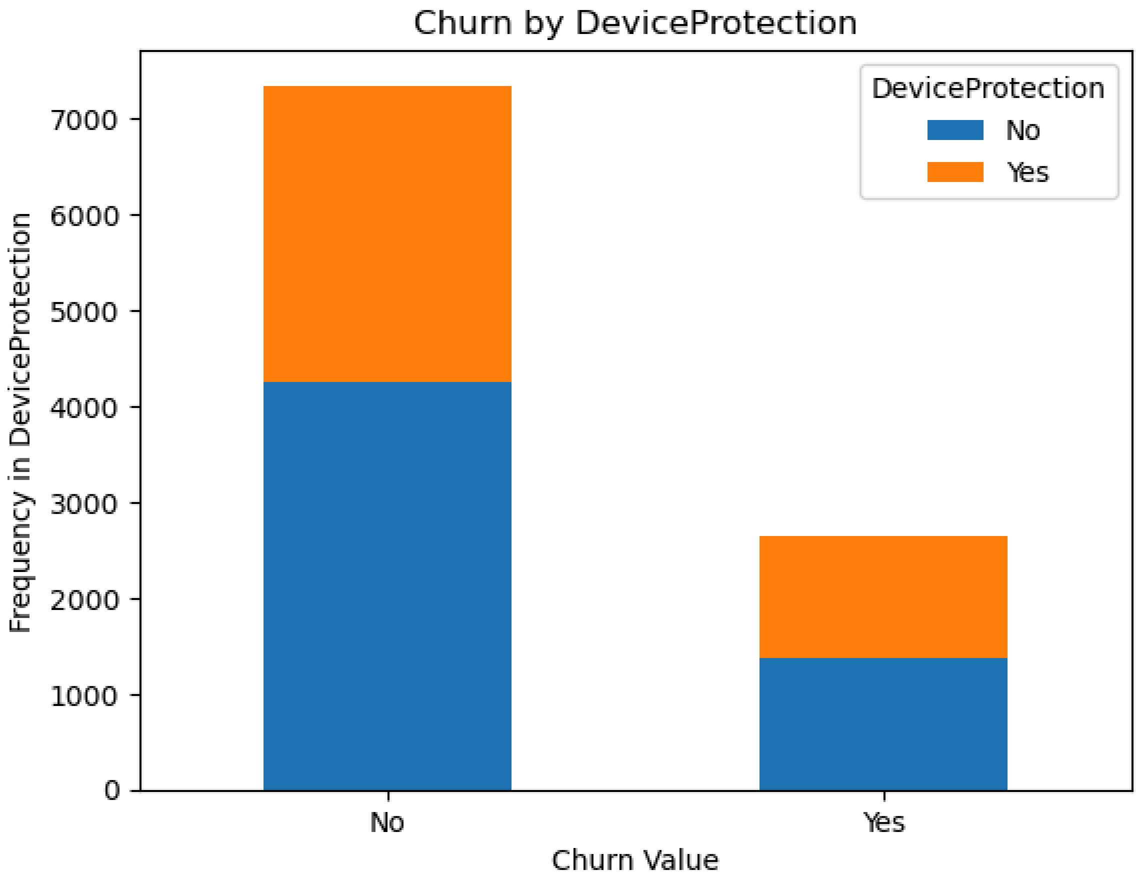

Churn by Tablet
Tablet
No
Yes
Frequency in Tablet
0
1000
2000
3000
4000
5000
6000
7000
No
Yes
Churn Value

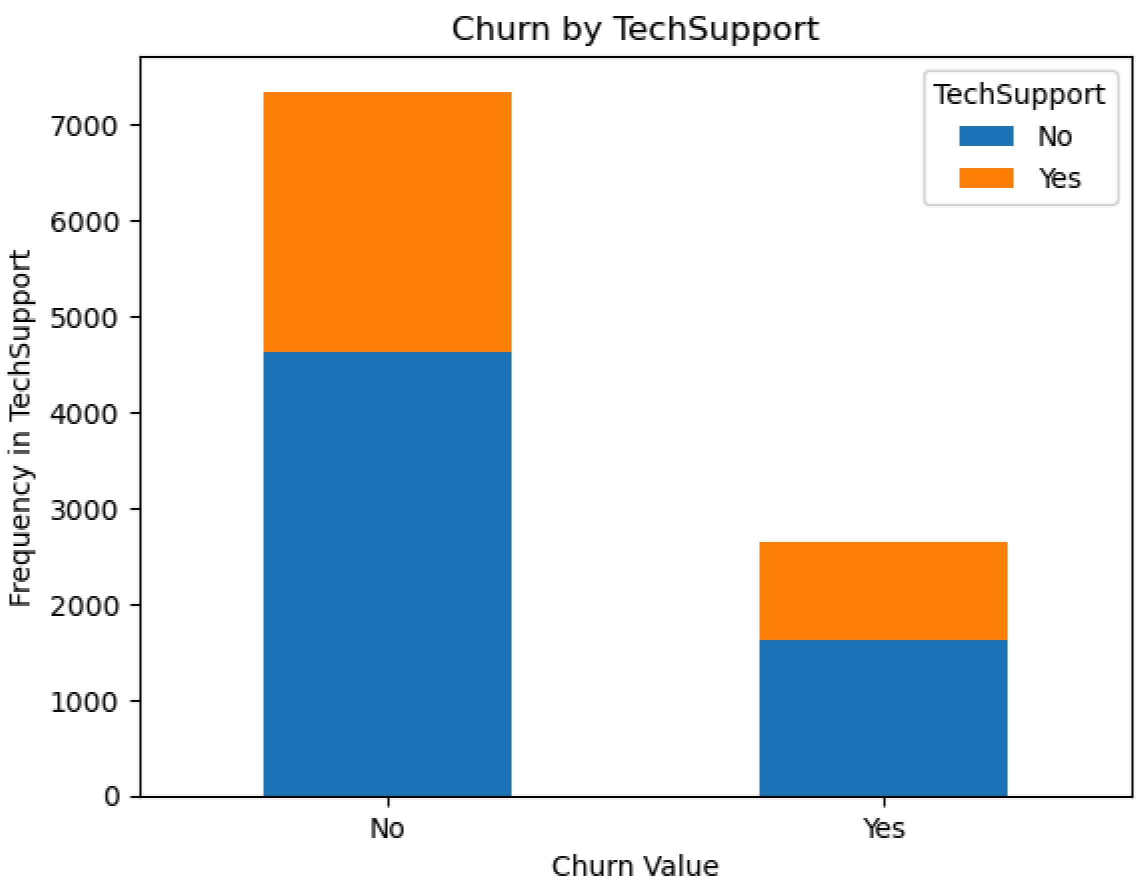

Churn by Phone
Phone
No
Yes
7000
6000
5000
4000
3000
2000
1000
0
Frequency in Phone
No
Yes
Churn Value

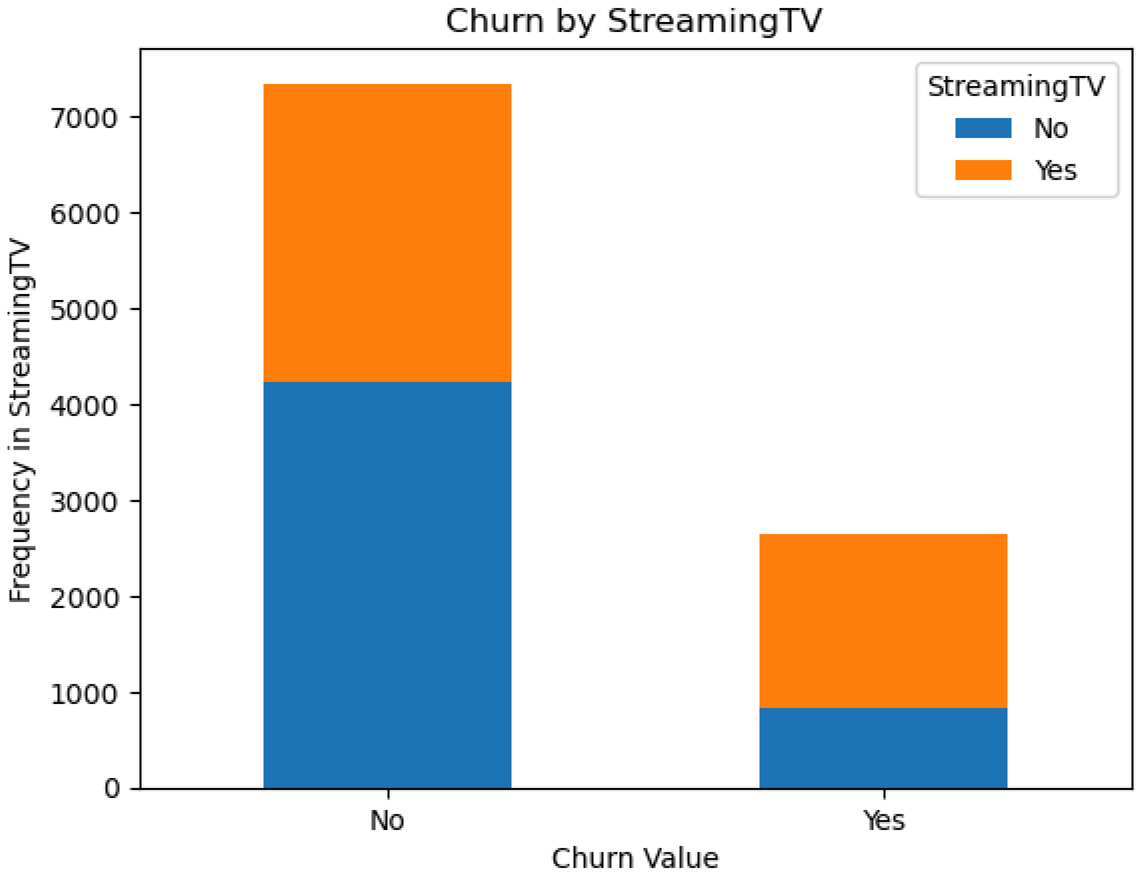

Churn by Multiple
Multiple
No
Yes
7000
6000
5000
4000
3000
2000
1000
0
Frequency in Multiple
No
Yes
Churn Value

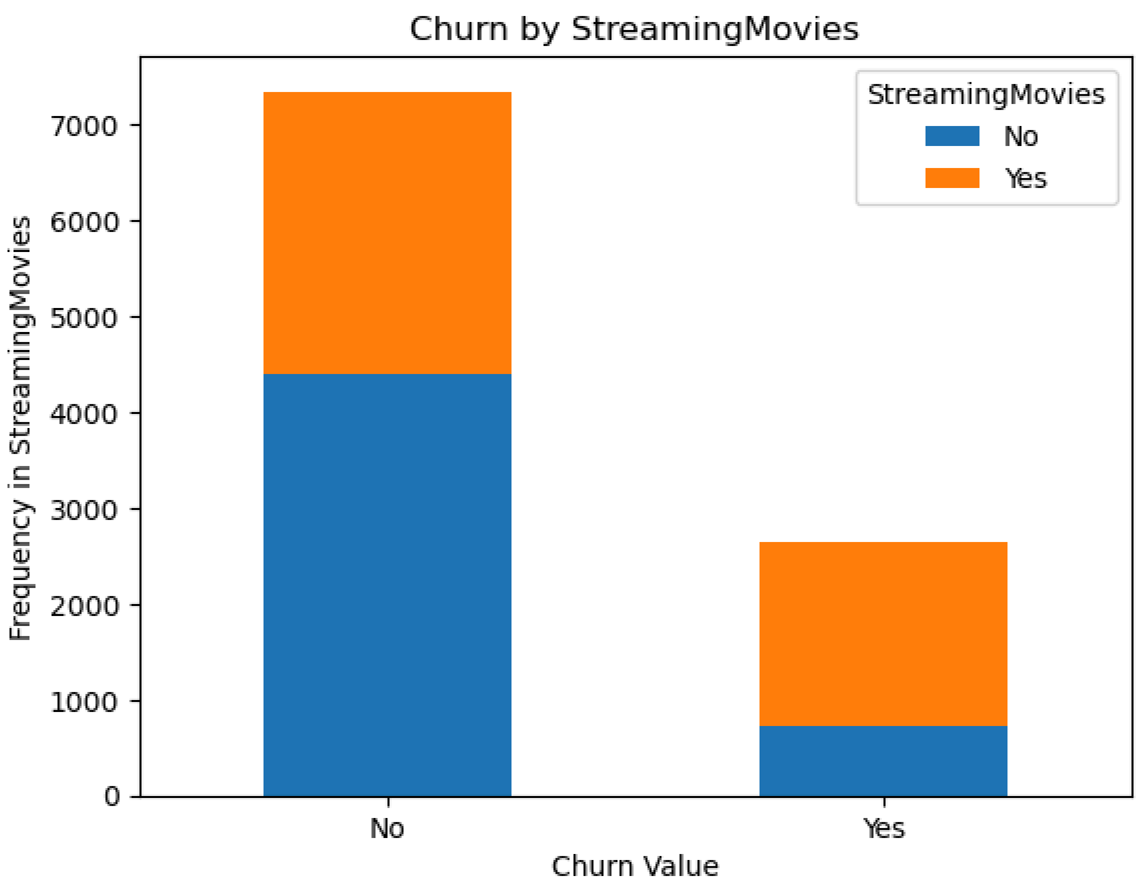

Churn by OnlineSecurity
OnlineSecurity
No
Yes
Frequency in OnlineSecurity
7000
6000
5000
4000
3000
2000
1000
0
No
Yes
Churn Value

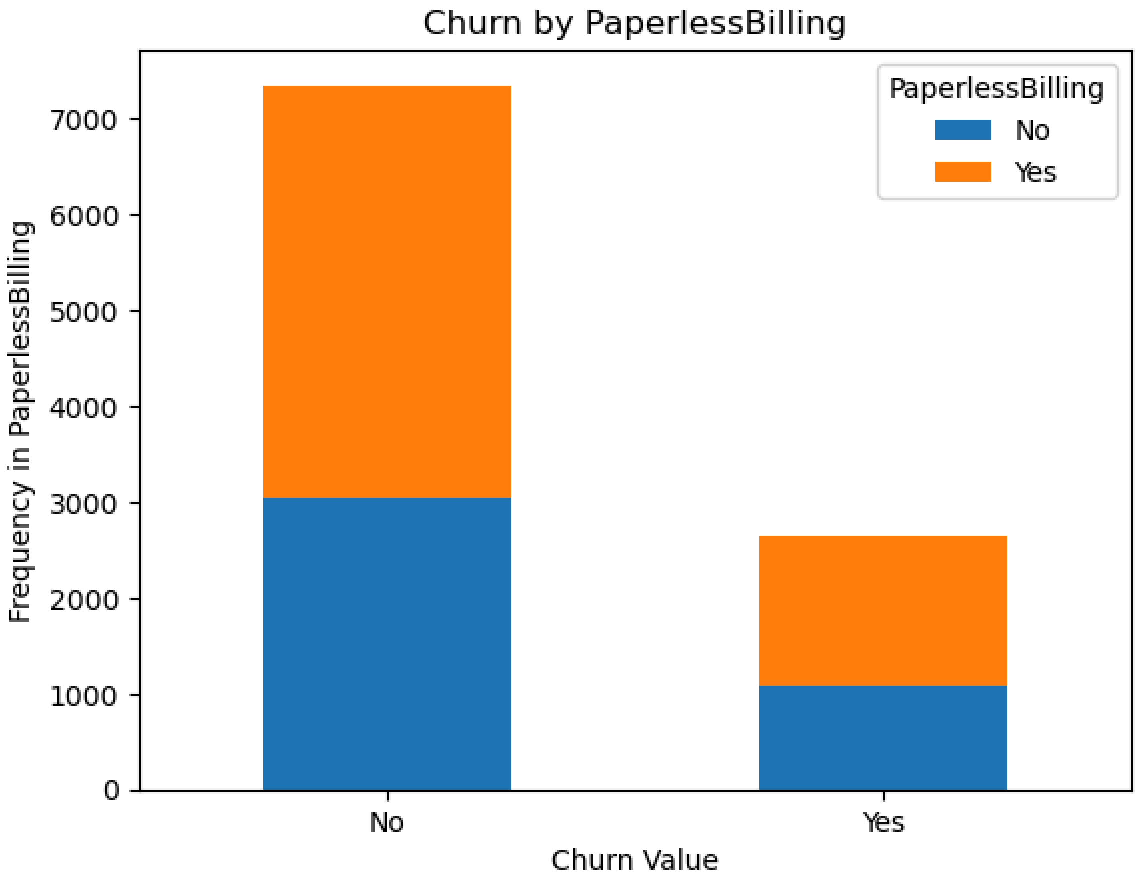

Churn by OnlineBackup
OnlineBackup
No
Yes
Frequency in OnlineBackup
7000
6000
5000
4000
3000
2000
1000
0
No
Yes
Churn Value


Churn by DeviceProtection
DeviceProtection
No
Yes
Frequency in DeviceProtection
0
1000
2000
3000
4000
5000
6000
7000
No
Yes
Churn Value


Churn by TechSupport
TechSupport
No
Yes
Frequency in TechSupport
0
1000
2000
3000
4000
5000
6000
7000
No
Yes
Churn Value


Churn by StreamingTV
StreamingTV
No
Yes
Frequency in StreamingTV
0
1000
2000
3000
4000
5000
6000
7000
No
Yes
Churn Value


Churn by StreamingMovies
StreamingMovies
No
Yes
Frequency in StreamingMovies
0
1000
2000
3000
4000
5000
6000
7000
No
Yes
Churn Value



C4. Data Wrangling

Due to the variables that were selected, no re-expression of categorical variables was necessary. I kep my analysis strictly to the qualitative variables for this test.

For the data transformations, I removed the 2 variables that were extra unique ids.

C5. Prepared Dataset

In [34]:
```
dfq.to_csv('prepared_data_task2.csv')
```

D1. Initialize Model

In [35]:
```
d = []
dfq2 = pd.DataFrame(d)

for column in dfq_c:
    dfq2[column] = dfq[column].map({'Yes': 1,'No': 0})
```

In [36]:
```
dfq2
```

Out[36]:

	Churn	Techie	Port_modem	Tablet	Phone	Multiple	OnlineSecurity	OnlineBackup	Dev
0	0	0	1	1	1	0	1	1	
1	1	1	0	1	1	1	1	0	
2	0	1	1	0	1	1	0	0	
3	0	1	0	0	1	0	1	0	
4	1	0	1	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	
9995	0	0	1	1	1	1	0	1	
9996	0	0	0	0	1	1	1	1	
9997	0	0	0	0	1	1	1	1	
9998	0	0	0	1	0	1	0	0	
9999	0	0	1	0	1	1	1	1	

10000 rows × 13 columns

In [43]:

```
# set the dependent variable as churn and the independent variables as X
y = dfq2['Churn']
X = dfq2.drop('Churn', axis=1)

# fit the model to x and Y
model = sm.Logit(y, X)
results = model.fit()

#print the results
print(results.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.532037
         Iterations 6
                           Logit Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9988
Method:                           MLE   Df Model:                           11
Date:                Fri, 21 Jun 2024   Pseudo R-squ.:                 0.07987
Time:                        07:27:01   Log-Likelihood:                -5320.4
converged:                       True   LL-Null:                       -5782.2
Covariance Type:            nonrobust   LLR p-value:                4.968e-191
==============================================================================
======
                       coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
------
Techie               0.2355      0.062      3.804      0.000       0.114
0.357
Port_modem          -0.2720      0.046     -5.855      0.000      -0.363
-0.181
Tablet              -0.2480      0.052     -4.734      0.000      -0.351
-0.145
Phone               -1.6726      0.058    -28.883      0.000      -1.786
-1.559
Multiple             0.3387      0.046      7.294      0.000       0.248
0.430
OnlineSecurity      -0.3360      0.050     -6.738      0.000      -0.434
-0.238
OnlineBackup        -0.0404      0.047     -0.865      0.387      -0.132
0.051
DeviceProtection    -0.0625      0.047     -1.338      0.181      -0.154
0.029
TechSupport         -0.1460      0.048     -3.012      0.003      -0.241
-0.051
StreamingTV          0.8042      0.047     17.157      0.000       0.712
0.896
StreamingMovies      1.1091      0.048     23.149      0.000       1.015
1.203
PaperlessBilling    -0.3485      0.046     -7.576      0.000      -0.439
-0.258
==============================================================================
======
```

D2. & D3. Model Reduction Method and Justification

For my model reduction method, I am going to use Backwards Stepwise Elimination (BSE). In the process of BSE, you iteratively remove the predictors with p-value greater than .05. This method repeats until there are no values greater than .05. We can start by checking which variables have greater than .05 p-value. This includes "OnlineBackup" and "DeviceProtection"

In [38]:
```
# drop online backup and device protection
dfq_c3 = ['Churn','Techie','Port_modem','Tablet','Phone','Multiple','OnlineSecu
```

In [39]:
```
d = []
dfq3 = pd.DataFrame(d)

for column in dfq_c3:
    dfq3[column] = dfq[column].map({'Yes': 1,'No': 0})
```

In [40]:
```
dfq3
```

Out[40]:

	Churn	Techie	Port_modem	Tablet	Phone	Multiple	OnlineSecurity	TechSupport	Strea
0	0	0	1	1	1	0	1	0	
1	1	1	0	1	1	1	1	0	
2	0	1	1	0	1	1	0	0	
3	0	1	0	0	1	0	1	0	
4	1	0	1	0	0	0	0	1	
...	...	...	...	...	...	...	...	...	
9995	0	0	1	1	1	1	0	0	
9996	0	0	0	0	1	1	1	0	
9997	0	0	0	0	1	1	1	0	
9998	0	0	0	1	0	1	0	1	
9999	0	0	1	0	1	1	1	0	

10000 rows × 11 columns

In [44]:
```
# set the dependent variable as churn and the independent variables as X
y = dfq3['Churn']
X = dfq3.drop('Churn', axis=1)

# fit the model to x and Y
model = sm.Logit(y, X)
results2 = model.fit()

#print the results
print(results2.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.532171
         Iterations 6
                           Logit Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9990
Method:                           MLE   Df Model:                            9
Date:                Fri, 21 Jun 2024   Pseudo R-squ.:                 0.07964
Time:                        07:27:08   Log-Likelihood:                -5321.7
converged:                       True   LL-Null:                       -5782.2
Covariance Type:            nonrobust   LLR p-value:                1.835e-192
==============================================================================
======
                       coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
------
Techie               0.2302      0.062      3.723      0.000       0.109
0.351
Port_modem          -0.2776      0.046     -5.992      0.000      -0.368
-0.187
Tablet              -0.2509      0.052     -4.793      0.000      -0.354
-0.148
Phone               -1.6954      0.056    -30.196      0.000      -1.805
-1.585
Multiple             0.3331      0.046      7.194      0.000       0.242
0.424
OnlineSecurity      -0.3415      0.050     -6.864      0.000      -0.439
-0.244
TechSupport         -0.1501      0.048     -3.103      0.002      -0.245
-0.055
StreamingTV          0.7984      0.047     17.083      0.000       0.707
0.890
StreamingMovies      1.1024      0.048     23.095      0.000       1.009
1.196
PaperlessBilling    -0.3568      0.046     -7.808      0.000      -0.446
-0.267
==============================================================================
======
```

E1. Model Comparison

For logistic regression, we can compare the two models using the LLR p-value. The LLR p-value for the first model is 4.968e-191. The LLR p-value for the second model is 1.835e-192. The LLR p-value helps us understand the certainty we can have in our results. For the first model there is only a 1.835e-192 chance that our results are invalid, but using the backwards stepwise elimination, we increase the accuracy of our model. 4.968e-191 is a whole decimal point smaller than the previous model, which was already significantly accurate enough.

E2. & E3. Output and Calculations

To find the residual standard error, we can use the following function: results.bse.

This is useful as the smaller the residual standard error, the better the regression model fits the dataset. We can see that income is the smallest and the best fit in terms of fitting for the dataset.

In [42]:
```
print(results2.bse)
```

```
Techie              0.061827
Port_modem          0.046325
Tablet              0.052351
Phone               0.056146
Multiple            0.046300
OnlineSecurity      0.049755
TechSupport         0.048393
StreamingTV         0.046734
StreamingMovies     0.047733
PaperlessBilling    0.045698
dtype: float64
```

F1. Regression Equation, Coefficients, etc.

Regression Equation

We can make a regression equation from the summary of the reduced model. This is the dependent variable (y) is equal to (x_n) times the coefficients added together. This means our regression equation is:

$$ {y_{Churn}} = 0.2302*x_{Techie} - 0.2776*x_{Port\ modem} - 0.2509*x_{Tablet} - 1.6954*x_{Phone} + 0.3331*x_{Multiple} - 0.3415*x_{OnlineSecurity} - 0.1501*x_{TechSupport} + 0.7984*x_{StreamingTV} + 1.1024*x_{StreamingMovies} - 0.3568*x_{PaperlessBilling} $$

Coefficients

- The coefficient for "Techie" (0.2302) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn increases by 0.2302.
- The coefficient for "Port Modem" (-0.2776) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn decreases by 0.2776.
- The coefficient for "Tablet" (-0.2509) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn decreases by 0.2509.
- The coefficient for "Phone" (-1.6954) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn decreases by 1.6954.

- The coefficient for "Multiple" (0.3331) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn increases by 0.3331.

- The coefficient for "OnlineSecurity" (-0.3415) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn decreases by 0.3415.

- The coefficient for "TechSupport" (-0.1501) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn decreases by 0.1501.

- The coefficient for "StreamingTV" (0.7984) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn increases by 0.7984.

- The coefficient for "StreamingMovies" (1.1024) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn increases by 1.1024

- The coefficient for "PaperlessBilling" (-0.3568) indicates that, holding all other variables constant, for every one unit increase in the population, the chance to churn decreases by 0.3568.

Statistical Significance & Practical Signficance of Reduced Model

The model is statistically significant because the LLR p-value is less than 5%. For the second model it is 4.968e-191

Disadvantages

One problem is that the basis of a logistic regression model assumes that there is no multicollinearity. A futher analysis could be done that checks VIF for whether or not there is multicollinearity.

F2. Recommendations

The recommendations based off of the model that was created are to focus on understanding why the highest coefficient items play such a significant affect on Churn. This can help us understand why some customers may be staying with the business more than others, and perhaps allow us to target those high value customers. For instance, questions like "Why would the StreamingMovies be positively correlated?" Exploring questions like these allows us to understand the data further, and understand how we can optimize business decisions for higher paying customers. We could also ask questions like

"Why does being techie make a customer more likely to churn? Is it because they understand the limitation of the technology or comeptitors' deals better?"

H. Third Party Sources of Code

No third party sources of code used

I. Sources

Adjusted R-squared. Corporate Finance Institute. (2023, November 21). https://corporatefinanceinstitute.com/resources/data-science/adjusted-r-squared/

Grover, J. (2021, March 28). Short python code for Backward Elimination with detailed explanation. Medium. https://groverjatin.medium.com/short-python-code-for-backward-elimination-with-detailed-explanation-52894a9a7880

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