Information

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Part I: Research Question

This project uses the data that was previously cleaned in the Jupyter Notebook "Data Cleaning". The objective of this analysis is to use the majority of the data set provided in the course to determine how customer churn might be predicted using logistic regression. I will be performing calculations that will reduce the available features to siginficant variables that affect customer churn. I hope to obtain a strong predictive model to assist the telecommunications company with decisions on how to avoid the loss of customers.

A1. Research Questions

What feature features are most significant that affect customer churn?

A2. Objectives & Goals:

Stakeholders in the company will benefit from this analysis by identifying what factors are heavily responsible for customer churn. This will provide insight for decisions in whether or not to expand customer data limits, provide unlimited (or metered) media streaming, improve customer experience, or any other factors that will reduce customer churn.

B1. Assumptions of Logistic Regression

- Response varaible is binary. There only two possible outcomes.
- Observations are Independent. Observations are indpendent of each other.
- There is No Multicollinearity Among Explanatory Variables. Two or more are not highly correlated with each other
- There is a Linear Relationship Between Explanatory Variables and the Logit of the Response Variable
- The Sample Size is Sufficiently Large.
- It is the logarithmithic of the odds of achieving 1. (Linear Relationship between explanatory variables and logit variables)

https://www.statology.org/assumptions-of-logistic-regression/

B2 Tool Benefits:

I will use the Python, since I use it at work to perform EDAs and clean data. I'll be using jupyter notebook, since it allows me to use markdowns to answer questions and program at the same time. To save time, I will be using several data science Python libraries to simply the problem. The following will be used:

- NumPy - to work with arrays
- Pandas - used to create dataframes.
- Matplotlib - plotting charts
- Scikit-learn - for PCA, Machine Learning, and Normalization.
- SciPy - used for mathematical transformations.
- Seaborn - visualization of more complex graphs

B3. Appropriateness of Logistic Regression

Logistic regression is an appropriate technique to analyze the research question because or dependent variable is binomial, Yes or No. We want to find out what the likelihood of customer churn is for individual customers, based on a list of independent variables (area type, job, children, age, income, etc.). It will improve our understanding of increased probability of churn as we include or remove different independent variables & find out whether or not they have a positive or negative relationship to our target variable.

C1 Data Goals

This project uses the data that was previously cleaned in the Data Cleaning Assignment. The majority of the data set is used to determine the amount of average amount of data used, in GB, in a year by the customer. I plan to reduce the list of variables not by what might intuitively belong together, but by looking at numerical calculations that suggest which variables are significant to answering the research question. With variables, I aim to get a predictive model to assist the telecommunications company to predict customers and target customers who use the most

The following steps will be taken to prepare the data for analysis:

1. Import data to pandas dataframe
2. Determine variable types and those which may require further investigation
3. Convert binary variables to yes = 1 and no = 0
4. Investigate potential categorical variables using bar charts, then convert categorical values to dummy variables
5. Drop columns that will not be used in regression analysis

My approach will include:

1. Import data to pandas dataframe

2. Determine variable types and those which may require further investigation
3. Convert binary variables to yes = 1 and no = 0
4. Investigate potential categorical variables using bar charts, then convert categorical values to dummy variables
5. Drop columns that will not be used in regression analysis
6. Find outliers that may create or hide statistical significance using histograms.
7. Subsitute missing data with meaningful measures of central tendency (mean, median or mode)

Important to the process is the variable of "Bandwidth_GB_Year" (the average yearly amount of data used, in GB, per customer) which will be our target variable.

When analyzing the data we will examine the following continuous predictor variables:

- Children
- Income
- Outage_sec_perweek
- Email
- Contacts
- Yearly_equip_failure
- MonthlyCharge
- Bandwidth_GB_Year

We will also examine the following categorical predictor variables:

- Churn: Whether the customer discontinued service within the last month (yes, no)
- Techie: Whether the customer considers themselves technically inclined (based on customer questionnaire when they signed up for services) (yes, no)
- Contract: The contract term of the customer (month-to-month, one year, two year)
- Port_modem: Whether the customer has a portable modem (yes, no)
- Tablet: Whether the customer owns a tablet such as iPad, Surface, etc. (yes, no)
- InternetService: Customer’s internet service provider (DSL, fiber optic, None)
- Phone: Whether the customer has a phone service (yes, no)
- Multiple: Whether the customer has multiple lines (yes, no)
- OnlineSecurity: Whether the customer has an online security add-on (yes, no)
- OnlineBackup: Whether the customer has an online backup add-on (yes, no)
- DeviceProtection: Whether the customer has device protection add-on (yes, no)
- TechSupport: Whether the customer has a technical support add-on (yes, no)
- StreamingTV: Whether the customer has streaming TV (yes, no)
- StreamingMovies: Whether the customer has streaming movies (yes, no)

We will also examine ordinal predictor variables from the survey responses from customers. In the surveys, customers rated eight customer service factors on a scale from 1 to 8.

- Item1: Timely response
- Item2: Timely fixes
- Item3: Timely replacements
- Item4: Reliability
- Item5: Options
- Item6: Respectful response
- Item7: Courteous exchange

C2 Summary Statistics

Logistic regression is an appropriate technique to analyze the research question because or dependent variable is binomial, Yes or No. We want to find out what the likelihood of customer churn is for individual customers, based on a list of independent variables (area type, job, children, age, income, etc.). It will improve our understanding of increased probability of churn as we include or remove different independent variables & find out whether or not they have a positive or negative relationship to our target variable.

C3. Steps to Prepare the Data

The following steps will be taken to prepare the data for analysis:

1. Import data to pandas dataframe
2. Determine variable types and those which may require further investigation
3. Convert binary variables to yes = 1 and no = 0
4. Investigate potential categorical variables using bar charts, then convert categorical values to dummy variables
5. Drop columns that will not be used in logistic regression

This project uses the data that was previously cleaned in the Jupyter Notebook "Data Cleaning". The objective of this analysis is to use the majority of the data set provided in the course to determine how customer churn might be predicted using logistic regression. I will be performing calculations that will reduce the available features to those variables which will be significant in answering the research question "Which factors can help predict whether a customer will end their contract (churn)?". I hope to obtain a strong predictive model to assist the telecommunications company with decisions on how to avoid the loss of customers.

Steps to Prepare the Data

The following steps will be taken to prepare the data for analysis:

1. Import data to pandas dataframe
2. Determine variable types and those which may require further investigation
3. Convert binary variables to yes = 1 and no = 0
4. Investigate potential categorical variables using bar charts, then convert categorical values to dummy variables using one-hot encoding
5. Drop columns that will not be used in logistic regression

Step 1

In [2]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import cross_val_predict, train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from sklearn.metrics import classification_report
import warnings
warnings.filterwarnings('ignore') # Ignore warning messages for readability
```

In [3]:
```
# Read in dataset and view head
df = pd.read_csv('churn_use.csv')
pd.options.display.max_columns = None
df.head()
```

Out[3]:

	CaseOrder	Customer_id	Interaction	UID	City	State
0	1	K409198	aa90260b-4141-4a24-8e36-b04ce1f4f77b	e885b299883d4f9fb18e39c75155d990	Point Baker	AK
1	2	S120509	fb76459f-c047-4a9d-8af9-e0f7d4ac2524	f2de8bef964785f41a2959829830fb8a	West Branch	MI
2	3	K191035	344d114c-3736-4be5-98f7-c72c281e2d35	f1784cfa9f6d92ae816197eb175d3c71	Yamhill	OR
3	4	D90850	abfa2b40-2d43-4994-b15a-989b8c79e311	dc8a365077241bb5cd5ccd305136b05e	Del Mar	CA
4	5	K662701	68a861fd-0d20-4e51-a587-8a90407ee574	aabb64a116e83fdc4befc1fbab1663f9	Needville	TX

Step 2

In [4]:
```
# View list of columns, data types, and missing values
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
```

Convert to Binary and Dummy Variables

In [5]:
```
df2 = df.copy()
```

In [6]:
```
# Convert binary variables into yes = 1, no = 0 (ref 1)
cols = ['Churn', 'Techie', 'Port_modem', 'Tablet', 'Phone', 'Multiple', 'Onli
df[cols] = df[cols].replace(to_replace = ['No', 'Yes'], value = [0, 1])
```

In [7]:

```
# Create separate variables for each categorical value, with a 1 if the value
df = pd.get_dummies(data=df, columns=['Area', 'Marital', 'Gender', 'Contract',
```

In [8]:

```
# Drop columns not needed for analysis
drops = ['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'State', '(
df = df.drop(drops, axis = 1)
```

In [9]:

```
df.rename(columns = {'Item1':'TimelyResponse',
                    'Item2':'Fixes',
                     'Item3':'Replacements',
                     'Item4':'Reliability',
                     'Item5':'Options',
                     'Item6':'Respectfulness',
                     'Item7':'Courteous',
                     'Item8':'Listening'},
          inplace=True)
```

In [10]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 56 columns):
 #   Column                                Non-Null Count  Dtype  
---  ------                                --------------  -----  
 0   Zip                                   10000 non-null  int64  
 1   Lat                                   10000 non-null  float64
 2   Lng                                   10000 non-null  float64
 3   Population                            10000 non-null  int64  
 4   Children                              10000 non-null  int64  
 5   Age                                   10000 non-null  int64  
 6   Income                                10000 non-null  float64
 7   Churn                                 10000 non-null  int64  
 8   Outage_sec_perweek                    10000 non-null  float64
 9   Email                                 10000 non-null  int64  
 10  Contacts                              10000 non-null  int64  
 11  Yearly_equip_failure                  10000 non-null  int64  
 12  Techie                                10000 non-null  int64  
 13  Port_modem                            10000 non-null  int64  
 14  Tablet                                10000 non-null  int64  
 15  Phone                                 10000 non-null  int64  
 16  Multiple                              10000 non-null  int64  
 17  OnlineSecurity                        10000 non-null  int64  
 18  OnlineBackup                          10000 non-null  int64  
 19  DeviceProtection                      10000 non-null  int64  
 20  TechSupport                           10000 non-null  int64  
 21  StreamingTV                           10000 non-null  int64  
 22  StreamingMovies                       10000 non-null  int64  
 23  PaperlessBilling                      10000 non-null  int64  
 24  Tenure                                10000 non-null  float64
 25  MonthlyCharge                         10000 non-null  float64
 26  Bandwidth_GB_Year                     10000 non-null  float64
 27  TimelyResponse                        10000 non-null  int64  
 28  Fixes                                 10000 non-null  int64  
 29  Replacements                          10000 non-null  int64  
 30  Reliability                           10000 non-null  int64  
 31  Options                               10000 non-null  int64  
 32  Respectfulness                        10000 non-null  int64  
```

```
 33  Courteous                                 10000 non-null  int64
 34  Listening                                 10000 non-null  int64
 35  Area_Rural                                10000 non-null  uint8
 36  Area_Suburban                             10000 non-null  uint8
 37  Area_Urban                                10000 non-null  uint8
 38  Marital_Divorced                          10000 non-null  uint8
 39  Marital_Married                           10000 non-null  uint8
 40  Marital_Never Married                     10000 non-null  uint8
 41  Marital_Separated                         10000 non-null  uint8
 42  Marital_Widowed                           10000 non-null  uint8
 43  Gender_Female                             10000 non-null  uint8
 44  Gender_Male                               10000 non-null  uint8
 45  Gender_Nonbinary                          10000 non-null  uint8
 46  Contract_Month-to-month                   10000 non-null  uint8
 47  Contract_One year                         10000 non-null  uint8
 48  Contract_Two Year                         10000 non-null  uint8
 49  PaymentMethod_Bank Transfer(automatic)    10000 non-null  uint8
 50  PaymentMethod_Credit Card (automatic)     10000 non-null  uint8
 51  PaymentMethod_Electronic Check            10000 non-null  uint8
 52  PaymentMethod_Mailed Check                10000 non-null  uint8
 53  InternetService_DSL                       10000 non-null  uint8
 54  InternetService_Fiber Optic               10000 non-null  uint8
 55  InternetService_None                      10000 non-null  uint8
dtypes: float64(7), int64(28), uint8(21)
```

C4. Visualizations

Univariate Visualizations

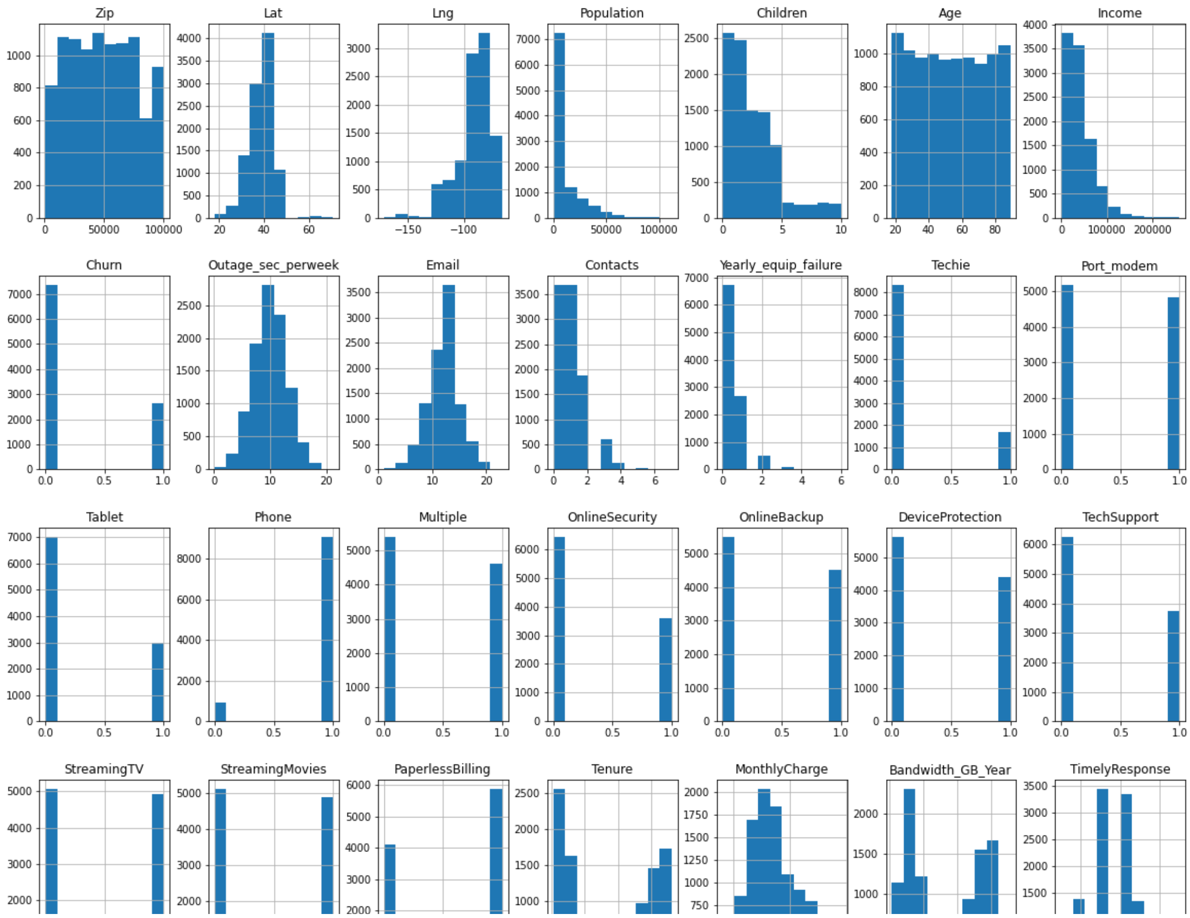
In [11]:

```
df.hist(figsize=(20, 35))
```

Out[11]:

```
array([[<AxesSubplot:title={'center':'Zip'}>,
        <AxesSubplot:title={'center':'Lat'}>,
        <AxesSubplot:title={'center':'Lng'}>,
        <AxesSubplot:title={'center':'Population'}>,
        <AxesSubplot:title={'center':'Children'}>,
        <AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'Income'}>],
       [<AxesSubplot:title={'center':'Churn'}>,
        <AxesSubplot:title={'center':'Outage_sec_perweek'}>,
        <AxesSubplot:title={'center':'Email'}>,
        <AxesSubplot:title={'center':'Contacts'}>,
        <AxesSubplot:title={'center':'Yearly_equip_failure'}>,
        <AxesSubplot:title={'center':'Techie'}>,
        <AxesSubplot:title={'center':'Port_modem'}>],
       [<AxesSubplot:title={'center':'Tablet'}>,
        <AxesSubplot:title={'center':'Phone'}>,
        <AxesSubplot:title={'center':'Multiple'}>,
        <AxesSubplot:title={'center':'OnlineSecurity'}>,
        <AxesSubplot:title={'center':'OnlineBackup'}>,
        <AxesSubplot:title={'center':'DeviceProtection'}>,
        <AxesSubplot:title={'center':'TechSupport'}>],
       [<AxesSubplot:title={'center':'StreamingTV'}>,
        <AxesSubplot:title={'center':'StreamingMovies'}>,
        <AxesSubplot:title={'center':'PaperlessBilling'}>,
        <AxesSubplot:title={'center':'Tenure'}>,
        <AxesSubplot:title={'center':'MonthlyCharge'}>,
        <AxesSubplot:title={'center':'Bandwidth_GB_Year'}>,
        <AxesSubplot:title={'center':'TimelyResponse'}>],
       [<AxesSubplot:title={'center':'Fixes'}>,
        <AxesSubplot:title={'center':'Replacements'}>,
```

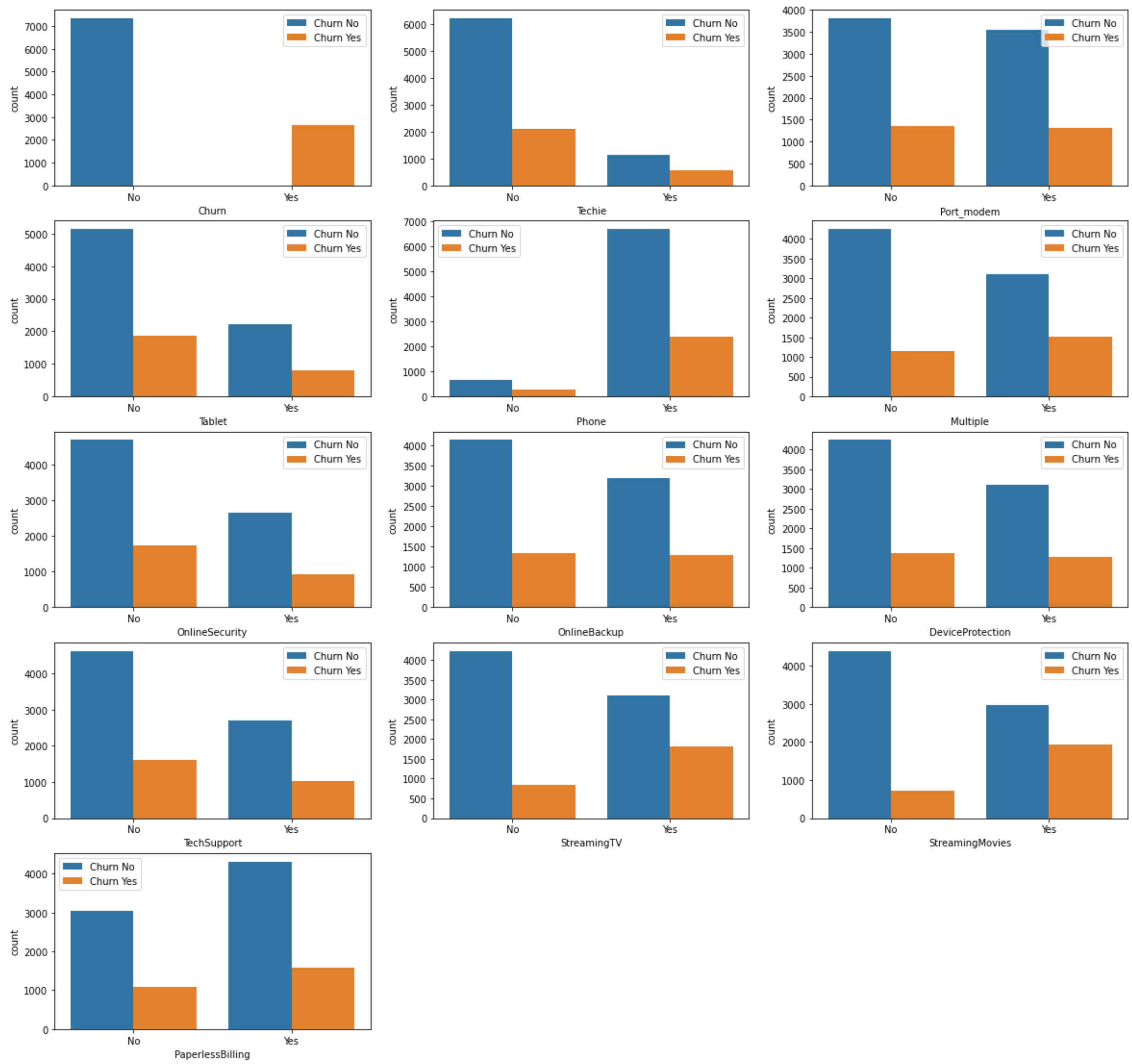
```
        <AxesSubplot:title={'center':'Reliability'}>,
        <AxesSubplot:title={'center':'Options'}>,
        <AxesSubplot:title={'center':'Respectfulness'}>,
        <AxesSubplot:title={'center':'Courteous'}>,
        <AxesSubplot:title={'center':'Listening'}>],
       [<AxesSubplot:title={'center':'Area_Rural'}>,
        <AxesSubplot:title={'center':'Area_Suburban'}>,
        <AxesSubplot:title={'center':'Area_Urban'}>,
        <AxesSubplot:title={'center':'Marital_Divorced'}>,
        <AxesSubplot:title={'center':'Marital_Married'}>,
        <AxesSubplot:title={'center':'Marital_Never Married'}>,
        <AxesSubplot:title={'center':'Marital_Separated'}>],
       [<AxesSubplot:title={'center':'Marital_Widowed'}>,
        <AxesSubplot:title={'center':'Gender_Female'}>,
        <AxesSubplot:title={'center':'Gender_Male'}>,
        <AxesSubplot:title={'center':'Gender_Nonbinary'}>,
        <AxesSubplot:title={'center':'Contract_Month-to-month'}>,
        <AxesSubplot:title={'center':'Contract_One year'}>,
        <AxesSubplot:title={'center':'Contract_Two Year'}>],
       [<AxesSubplot:title={'center':'PaymentMethod_Bank Transfer(automatic)'}
>,
        <AxesSubplot:title={'center':'PaymentMethod_Credit Card (automatic)'}
>,
        <AxesSubplot:title={'center':'PaymentMethod_Electronic Check'}>,
        <AxesSubplot:title={'center':'PaymentMethod_Mailed Check'}>,
        <AxesSubplot:title={'center':'InternetService_DSL'}>,
        <AxesSubplot:title={'center':'InternetService_Fiber Optic'}>,
        <AxesSubplot:title={'center':'InternetService_None'}>]],
```



Bivariate Visualizations

In [12]:

```
# Split bar charts for binary variables by Churn
df_bin = df[['Churn', 'Techie', 'Port_modem', 'Tablet', 'Phone', 'Multiple',
             'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
count=1
plt.subplots(figsize=(20, 80))
for i in df_bin.columns:
    plt.subplot(20,3,count)
    ax = sns.countplot(x = i, hue = 'Churn', data = df_bin)
    legend_labels, _= ax.get_legend_handles_labels()
    ax.legend(legend_labels, ['Churn No','Churn Yes'])
    ax.set_xticklabels(('No', 'Yes'))
    count+=1
plt.show();
```

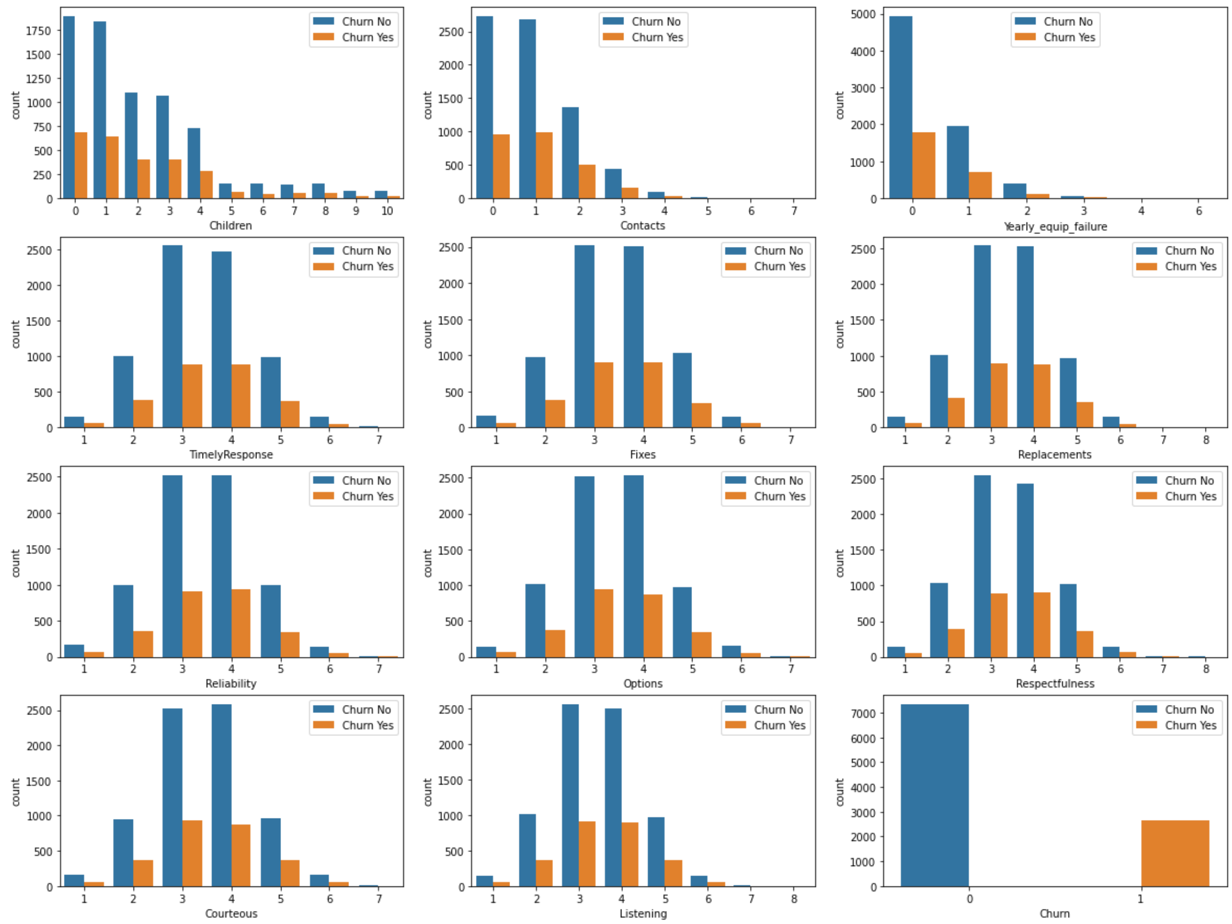


In [13]:

```
# Display plots for all discrete value variables by Churn

# Split bar charts for binary variables by Churn
df_dis = df[['Children', 'Contacts', 'Yearly_equip_failure', 'TimelyResponse',
             'Reliability', 'Options', 'Respectfulness', 'Courteous', 'Listen
count=1
plt.subplots(figsize=(20, 80))
for i in df_dis.columns:
    plt.subplot(20,3,count)
    ax = sns.countplot(x = i, hue = 'Churn', data = df_dis)
    legend_labels, _= ax.get_legend_handles_labels()
    ax.legend(legend_labels, ['Churn No','Churn Yes'])

    count+=1
plt.show();
```



In [14]:

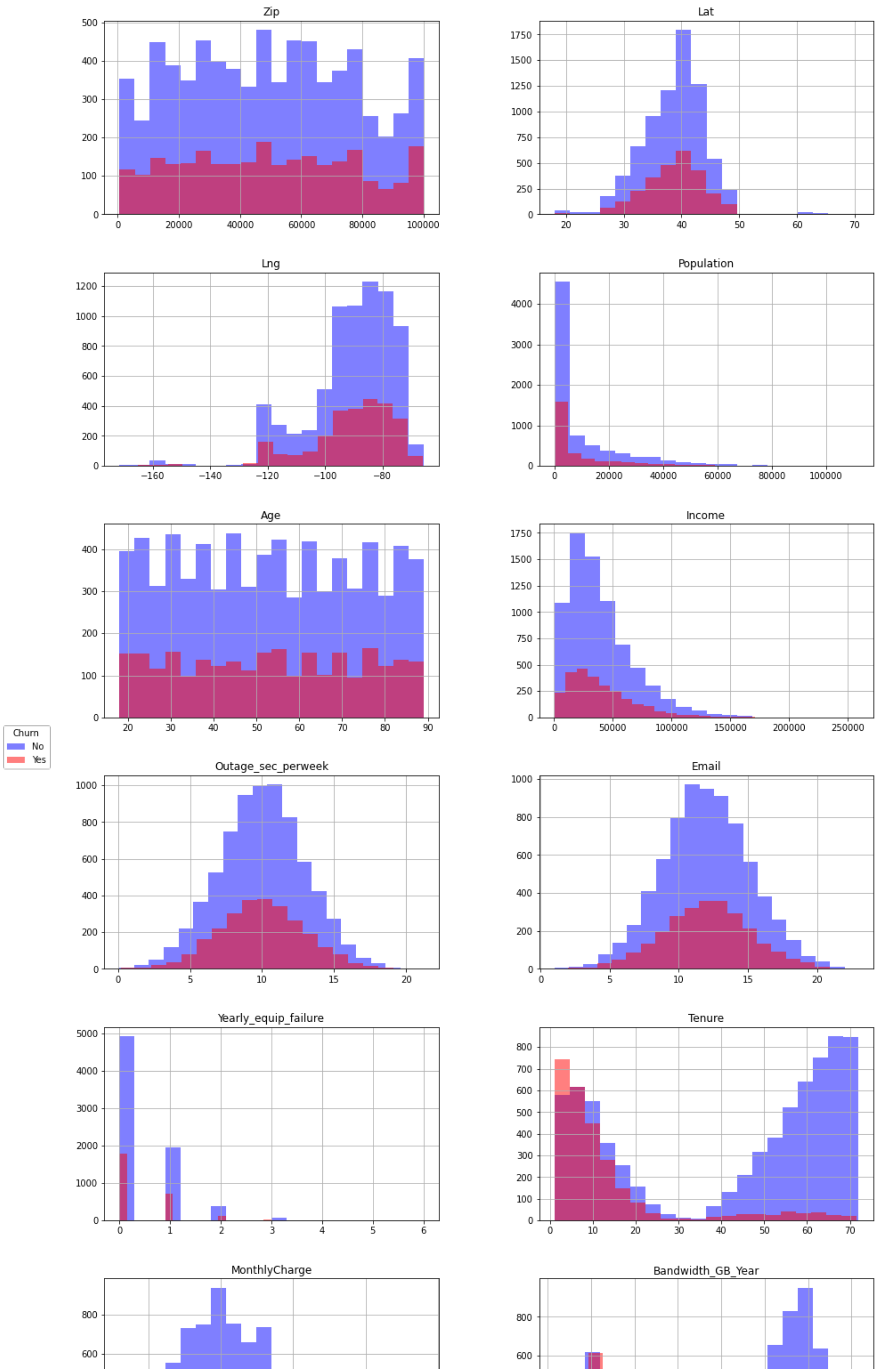
```
# Display histograms for continuous variables by Churn

# Array of columns to use
numerical_features = ['Zip', 'Lat', 'Lng', 'Population', 'Age', 'Income', 'Out
                      'Yearly_equip_failure', 'Tenure', 'MonthlyCharge', 'Banc

# Labels for chart
sub_labels = ["No", "Yes"]

# Split hisogram by churn
fig, ax = plt.subplots(6, 2, figsize=(15, 30))
no = df[df.Churn == 0][numerical_features].hist(bins=20, color="blue", alpha=(
yes = df[df.Churn == 1][numerical_features].hist(bins=20, color="red", alpha=(

# Create labels and ledgend
fig.legend([no, yes], labels=sub_labels, loc="center left", borderaxespad=0.1,
plt.subplots_adjust(left=0.1)
plt.show();
```

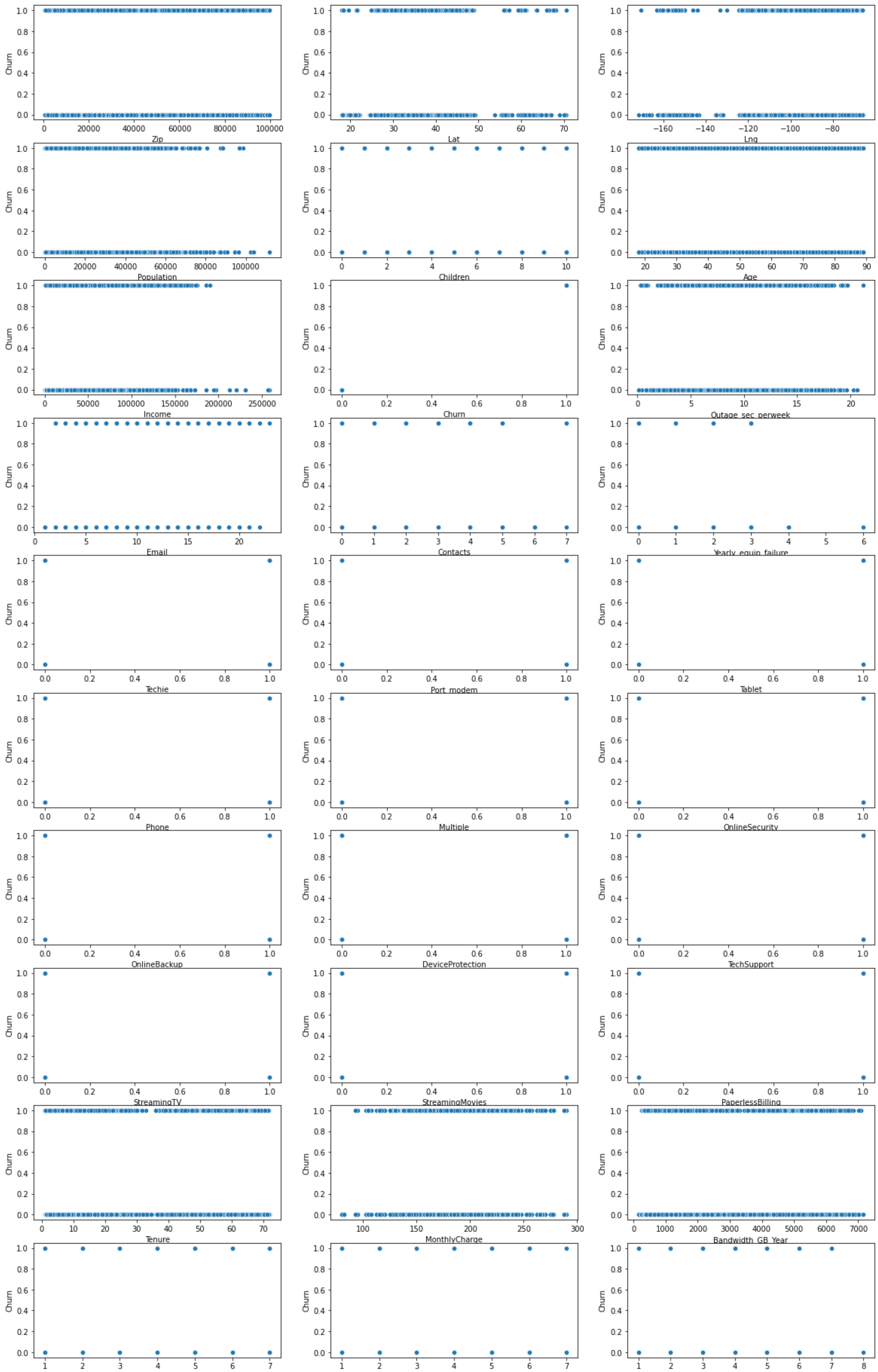

Zip
Lat
Lng
Population
Age
Income
Churn
No
Yes
Outage_sec_perweek
Email
Yearly_equip_failure
Tenure
MonthlyCharge
Bandwidth_GB_Year

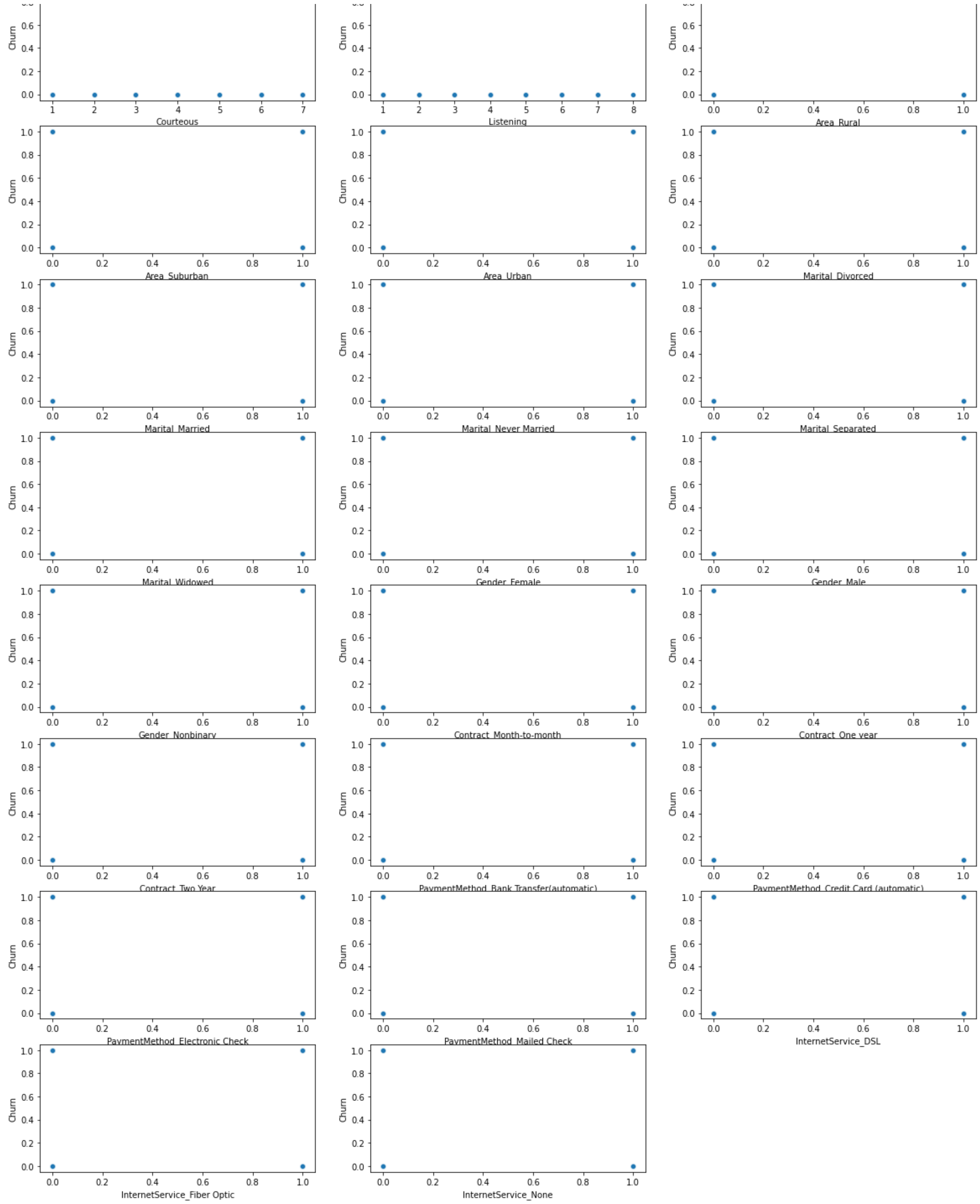
Bivariate Statistics

In [15]:

```
count=1
plt.subplots(figsize=(20, 80))
for i in df.columns:
    plt.subplot(24,3,count)
    sns.scatterplot(df[i], df["Churn"])
    count+=1

plt.show()
```


Churn
Zip
Lat
Lng
Population
Children
Age
Income
Churn
Outage sec perweek
Email
Contacts
Yearly equip failure
Techie
Port modem
Tablet
Phone
Multiple
OnlineSecurity
OnlineBackup
DeviceProtection
TechSupport
StreamingTV
StreamingMovies
PaperlessBilling
Tenure
MonthlyCharge
Bandwidth GB Year



Prepared Data

In [16]:

```
# Save cleaned dataframe to CSV
df.to_csv('churn_clean_data_final.csv', index = False, encoding = 'utf-8')
```

D1. Initial Model

In [17]:

```
# Set up input matrix and response variable
Xinit = df.drop('Churn', axis = 1)
y = df[['Churn']].values
```

In [18]:

```
y.shape
```

Out[18]:

```
(10000, 1)
```

In [19]:

```
# Veiw number of independent variables
print ("There are", Xinit.shape[1], "independent variables in the initial mode
```

```
There are 55 independent variables in the initial model.
```

In [20]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 56 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Zip                                   10000 non-null  int64
 1   Lat                                   10000 non-null  float64
 2   Lng                                   10000 non-null  float64
 3   Population                            10000 non-null  int64
 4   Children                              10000 non-null  int64
 5   Age                                   10000 non-null  int64
 6   Income                                10000 non-null  float64
 7   Churn                                 10000 non-null  int64
 8   Outage_sec_perweek                    10000 non-null  float64
 9   Email                                 10000 non-null  int64
 10  Contacts                              10000 non-null  int64
 11  Yearly_equip_failure                  10000 non-null  int64
 12  Techie                                10000 non-null  int64
 13  Port_modem                            10000 non-null  int64
 14  Tablet                                10000 non-null  int64
 15  Phone                                 10000 non-null  int64
 16  Multiple                              10000 non-null  int64
 17  OnlineSecurity                        10000 non-null  int64
 18  OnlineBackup                          10000 non-null  int64
 19  DeviceProtection                      10000 non-null  int64
 20  TechSupport                           10000 non-null  int64
 21  StreamingTV                           10000 non-null  int64
 22  StreamingMovies                       10000 non-null  int64
 23  PaperlessBilling                      10000 non-null  int64
 24  Tenure                                10000 non-null  float64
 25  MonthlyCharge                         10000 non-null  float64
 26  Bandwidth_GB_Year                     10000 non-null  float64
 27  TimelyResponse                        10000 non-null  int64
 28  Fixes                                 10000 non-null  int64
 29  Replacements                          10000 non-null  int64
```

```
 30  Reliability                            10000 non-null  int64
 31  Options                                10000 non-null  int64
 32  Respectfulness                         10000 non-null  int64
 33  Courteous                              10000 non-null  int64
 34  Listening                              10000 non-null  int64
 35  Area_Rural                             10000 non-null  uint8
 36  Area_Suburban                          10000 non-null  uint8
 37  Area_Urban                             10000 non-null  uint8
 38  Marital_Divorced                       10000 non-null  uint8
 39  Marital_Married                        10000 non-null  uint8
 40  Marital_Never Married                  10000 non-null  uint8
 41  Marital_Separated                      10000 non-null  uint8
 42  Marital_Widowed                        10000 non-null  uint8
 43  Gender_Female                          10000 non-null  uint8
 44  Gender_Male                            10000 non-null  uint8
 45  Gender_Nonbinary                       10000 non-null  uint8
 46  Contract_Month-to-month                10000 non-null  uint8
 47  Contract_One year                      10000 non-null  uint8
 48  Contract_Two Year                      10000 non-null  uint8
 49  PaymentMethod_Bank Transfer(automatic) 10000 non-null  uint8
 50  PaymentMethod_Credit Card (automatic)  10000 non-null  uint8
 51  PaymentMethod_Electronic Check         10000 non-null  uint8
 52  PaymentMethod_Mailed Check             10000 non-null  uint8
 53  InternetService_DSL                    10000 non-null  uint8
 54  InternetService_Fiber Optic            10000 non-null  uint8
 55  InternetService_None                   10000 non-null  uint8
dtypes: float64(7), int64(28), uint8(21)
memory usage: 2.9 MB
```

In [21]:

```
# Add y-intercept, create model, and view summary
Xcinit = sm.add_constant(Xinit)
logistic_regression = sm.Logit(y,Xcinit)
fitted_model1 = logistic_regression.fit()
fitted_model1.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.217085
         Iterations 9
```

Out[21]:

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9949
Method:	MLE	**Df Model:**	50
Date:	Tue, 07 Sep 2021	**Pseudo R-squ.:**	0.6246
Time:	22:51:55	**Log-Likelihood:**	-2170.9
converged:	True	**LL-Null:**	-5782.2
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.0031	nan	nan	nan	nan	nan
Zip	3.632e-07	3.35e-06	0.109	0.914	-6.2e-06	6.92e-06
Lat	0.0035	0.008	0.461	0.645	-0.011	0.018
Lng	-0.0013	0.006	-0.211	0.833	-0.013	0.011

Population	-1.473e-07	2.8e-06	-0.053	0.958	-5.64e-06	5.35e-06
Children	-0.0055	0.137	-0.040	0.968	-0.274	0.263
Age	0.0028	0.015	0.194	0.846	-0.026	0.032
Income	3.996e-07	1.38e-06	0.290	0.772	-2.3e-06	3.1e-06
Outage_sec_perweek	-0.0027	0.013	-0.207	0.836	-0.028	0.023
Email	-0.0094	0.013	-0.739	0.460	-0.034	0.016
Contacts	0.0626	0.039	1.603	0.109	-0.014	0.139
Yearly_equip_failure	-0.0349	0.061	-0.570	0.569	-0.155	0.085
Techie	1.0981	0.103	10.673	0.000	0.896	1.300
Port_modem	0.1432	0.077	1.849	0.064	-0.009	0.295
Tablet	-0.0509	0.085	-0.602	0.547	-0.217	0.115
Phone	-0.2988	0.133	-2.246	0.025	-0.560	-0.038
Multiple	0.3602	0.202	1.787	0.074	-0.035	0.755
OnlineSecurity	-0.2935	0.312	-0.942	0.346	-0.905	0.317
OnlineBackup	-0.1173	0.181	-0.649	0.516	-0.471	0.237
DeviceProtection	-0.1085	0.234	-0.465	0.642	-0.566	0.349
TechSupport	-0.2144	0.173	-1.237	0.216	-0.554	0.125
StreamingTV	1.1137	0.510	2.184	0.029	0.114	2.113
StreamingMovies	1.2743	0.363	3.506	0.000	0.562	1.987
PaperlessBilling	0.1659	0.079	2.105	0.035	0.011	0.320
Tenure	-0.1687	0.363	-0.465	0.642	-0.880	0.542
MonthlyCharge	0.0394	0.014	2.850	0.004	0.012	0.067
Bandwidth_GB_Year	0.0006	0.004	0.143	0.886	-0.008	0.009
TimelyResponse	-0.0189	0.055	-0.346	0.730	-0.126	0.088
Fixes	-0.0041	0.052	-0.078	0.938	-0.106	0.098
Replacements	0.0206	0.047	0.438	0.662	-0.072	0.113
Reliability	-0.0301	0.042	-0.716	0.474	-0.113	0.052
Options	-0.0362	0.044	-0.816	0.415	-0.123	0.051
Respectfulness	-0.0193	0.045	-0.427	0.670	-0.108	0.069
Courteous	-0.0025	0.043	-0.058	0.954	-0.087	0.082
Listening	-0.0140	0.040	-0.347	0.729	-0.093	0.065
Area_Rural	-1.3840	1.92e+06	-7.2e-07	1.000	-3.77e+06	3.77e+06
Area_Suburban	-1.4321	1.87e+06	-7.65e-07	1.000	-3.67e+06	3.67e+06
Area_Urban	-1.3326	1.89e+06	-7.03e-07	1.000	-3.71e+06	3.71e+06

Marital_Divorced	-0.3846	5.46e+05	-7.05e-07	1.000	-1.07e+06	1.07e+06
Marital_Married	-0.2796	5.51e+05	-5.07e-07	1.000	-1.08e+06	1.08e+06
Marital_Never Married	-0.3707	5.46e+05	-6.79e-07	1.000	-1.07e+06	1.07e+06
Marital_Separated	-0.2662	5.48e+05	-4.86e-07	1.000	-1.07e+06	1.07e+06
Marital_Widowed	-0.1241	5.36e+05	-2.32e-07	1.000	-1.05e+06	1.05e+06
Gender_Female	-1.1031	1.16e+06	-9.53e-07	1.000	-2.27e+06	2.27e+06
Gender_Male	-0.8757	1.03e+06	-8.47e-07	1.000	-2.03e+06	2.03e+06
Gender_Nonbinary	-1.1811	1.05e+06	-1.13e-06	1.000	-2.05e+06	2.05e+06
Contract_Month-to-month	1.2958	8.75e+05	1.48e-06	1.000	-1.72e+06	1.72e+06
Contract_One year	-2.1189	8.75e+05	-2.42e-06	1.000	-1.72e+06	1.72e+06
Contract_Two Year	-2.2223	8.76e+05	-2.54e-06	1.000	-1.72e+06	1.72e+06
PaymentMethod_Bank Transfer(automatic)	-0.6822	2.01e+06	-3.39e-07	1.000	-3.94e+06	3.94e+06
PaymentMethod_Credit Card (automatic)	-0.4729	2.01e+06	-2.35e-07	1.000	-3.94e+06	3.94e+06
PaymentMethod_Electronic Check	-0.0514	2.01e+06	-2.56e-08	1.000	-3.94e+06	3.94e+06
PaymentMethod_Mailed Check	-0.4430	2.01e+06	-2.2e-07	1.000	-3.94e+06	3.94e+06
InternetService_DSL	-0.0934	nan	nan	nan	nan	nan
InternetService_Fiber Optic	-2.0076	nan	nan	nan	nan	nan

In [22]:

```
# View prediction
clf = LogisticRegression()
clf.fit(Xinit, y.astype(int))
y_clf = clf.predict(Xinit)
print(classification_report(y, y_clf))
```

```
              precision    recall  f1-score   support

           0       0.86      0.91      0.89      7350
           1       0.71      0.59      0.64      2650

    accuracy                           0.83     10000
   macro avg       0.78      0.75      0.76     10000
weighted avg       0.82      0.83      0.82     10000
```

D2 Model Reduction

The model has several variables, with p-values over 0.5, that may be causing inaccurate predictions. These include variables are irrelevant to whether a customer is likely to churn and should be removed. The variables need to be checked for relevance. We also need to check these variables for multicollinearity whihc may be affecting the results.

In [23]:

```
# Use recursive feature elimination to choose most important features (ref 6)
model = LogisticRegression()
rfe = RFE(model, 11)
rfe = rfe.fit(Xinit, y)
print(rfe.support_)
print(rfe.ranking_)
f = rfe.get_support(1) # the most important features
Xfin = Xinit[Xinit.columns[f]] # final features`
```

```
[False False False False False False False False False False False  True
 False False False False False  True  True False  True  True False False
 False False False False False False False False False False False False
 False False False False False False  True False False  True  True  True
 False False  True False  True False False]
[43 24 35 44 34 36 45 21 42 33 17  1 41 10  4 32  8  1  1  3  1  1  9 14
 28 39 29 37 27 19 20 23 22 18 16 15 40  7  6  5 38 26  1 31  2  1  1  1
 11 12  1 13  1 25 30]
```

In [24]:

```
# Look for evidence of Variance Inflation Factors (ref 7) causing multicollin

# VIF dataframe
vif_data = pd.DataFrame()
vif_data["feature"] = Xfin.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(Xfin.values, i)
                          for i in range(len(Xfin.columns))]

print(vif_data)
```

```
                           feature       VIF
0                           Techie  1.000742
1                     OnlineBackup  1.000229
2                 DeviceProtection  1.001364
3                      StreamingTV  1.001122
4                  StreamingMovies  1.000657
5                    Gender_Female  1.001250
6          Contract_Month-to-month  4.198087
7                Contract_One year  2.258283
8                Contract_Two Year  2.411442
9   PaymentMethod_Electronic Check  1.000559
10             InternetService_DSL  1.000234
```

All variable VIF scores are below the recommended score of 5. There is no evidence for multicollinearity. However, even though it is below 5, contract_month_to_month is showing signs of multicollinearity. We will drop it from the model.

In [25]:

```
Xfin = Xfin.drop(columns='Contract_Month-to-month', axis=1)
```

In [26]:

```
# Re-run the model
Xcfin = sm.add_constant(Xfin)
logistic_regression = sm.Logit(y,Xcfin)
fitted_model2 = logistic_regression.fit()
fitted_model2.summary()
```

```
Optimization terminated successfully.
```

```
         Current function value: 0.446443
```

Out[26]:

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9989
Method:	MLE	**Df Model:**	10
Date:	Tue, 07 Sep 2021	**Pseudo R-squ.:**	0.2279
Time:	22:51:58	**Log-Likelihood:**	-4464.4
converged:	True	**LL-Null:**	-5782.2
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.7468	0.082	-33.460	0.000	-2.908	-2.586
Techie	0.5077	0.067	7.527	0.000	0.376	0.640
OnlineBackup	0.3132	0.053	5.939	0.000	0.210	0.417
DeviceProtection	0.3043	0.053	5.767	0.000	0.201	0.408
StreamingTV	1.4226	0.056	25.555	0.000	1.313	1.532
StreamingMovies	1.7039	0.057	30.034	0.000	1.593	1.815
Gender_Female	-0.1414	0.053	-2.689	0.007	-0.244	-0.038
Contract_One year	-1.5911	0.076	-20.990	0.000	-1.740	-1.443
Contract_Two Year	-1.7426	0.075	-23.350	0.000	-1.889	-1.596
PaymentMethod_Electronic Check	0.1711	0.055	3.104	0.002	0.063	0.279
InternetService_DSL	0.5931	0.054	10.882	0.000	0.486	0.700

In [27]:

```
# Split the data to be used in final model evaluation
X_train, X_test, y_train, y_test = train_test_split(Xfin, y.astype(float), tes
```

In [28]:

```
Xcfin = sm.add_constant(X_train)
logistic_regression = sm.Logit(y_train,Xcfin)
fitted_model2 = logistic_regression.fit()
fitted_model2.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.439120
         Iterations 7
```

Out[28]:

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	7000
Model:	Logit	**Df Residuals:**	6989
Method:	MLE	**Df Model:**	10
Date:	Tue, 07 Sep 2021	**Pseudo R-squ.:**	0.2303

Time:	22:51:58	**Log-Likelihood:**	-3073.8
converged:	True	**LL-Null:**	-3993.5
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.7750	0.099	-27.973	0.000	-2.969	-2.581
Techie	0.5209	0.082	6.334	0.000	0.360	0.682
OnlineBackup	0.2617	0.064	4.113	0.000	0.137	0.386
DeviceProtection	0.2892	0.064	4.539	0.000	0.164	0.414
StreamingTV	1.4706	0.068	21.687	0.000	1.338	1.604
StreamingMovies	1.7229	0.068	25.170	0.000	1.589	1.857
Gender_Female	-0.1577	0.064	-2.483	0.013	-0.282	-0.033
Contract_One year	-1.5752	0.092	-17.196	0.000	-1.755	-1.396
Contract_Two Year	-1.7606	0.090	-19.571	0.000	-1.937	-1.584
PaymentMethod_Electronic Check	0.1513	0.066	2.281	0.023	0.021	0.281

In [29]:

```
# View prediction
clf = LogisticRegression()
clf.fit(X_train, y_train.astype(int))
y_clf = clf.predict(X_test)
print(classification_report(y_test, y_clf))
```

```
              precision    recall  f1-score   support

         0.0       0.79      0.92      0.85      2153
         1.0       0.66      0.37      0.47       847

    accuracy                           0.77      3000
   macro avg       0.72      0.65      0.66      3000
weighted avg       0.75      0.77      0.74      3000
```

In [30]:

```
print ("There are", Xfin.shape[1], "independent variables in the final model.'
```

```
There are 10 independent variables in the final model.
```

E1. Model Comparison

Using recursive feature elimination, I identified the first 7 variables. This method uses model accuracy to identify which combination of attributes most contribute to predicting the target variable (Brownlee, 2020).

To check for multicollinearity, I used variance inflation factors. Given that the VIF scores for the reduced 7 variables were less than 4, this suggests that

Finally taking a look at the reduced model, I chose to remove all remaining variables which had p-scores above the 0.05 threshold. This final step ensured that all remaining independent variables were significant. I began with 55 independent variables, which was then reduced to six remaining variables.

My initial model had better scores for the target descriptive statistics than the reduced model. The initial model would predict churn correctly 70% of the time, while the reduced model was 36%. The initial model was likely to catch actual cases of churn 59% of the time, while the reduced model was only 38% of the time. The combined F1 score was also higher on the initial model at 64% compared to 45% on the reduced model. Finally, the overall accuracy of the initial model was also slightly higher at 83% compared to the reduced model at 76%.

In [31]:

```
# View prediction (initial)
clf = LogisticRegression()
clf.fit(Xinit, y.astype(int))
y_clf = clf.predict(Xinit)
print(classification_report(y, y_clf))
```

```
              precision    recall  f1-score   support

           0       0.86      0.91      0.89      7350
           1       0.71      0.59      0.64      2650

    accuracy                           0.83     10000
   macro avg       0.78      0.75      0.76     10000
weighted avg       0.82      0.83      0.82     10000
```

In [32]:

```
# View prediction (reduced)
clf = LogisticRegression()
clf.fit(X_train, y_train.astype(int))
y_clf = clf.predict(X_test)
print(classification_report(y_test, y_clf))
```

```
              precision    recall  f1-score   support

         0.0       0.79      0.92      0.85      2153
         1.0       0.66      0.37      0.47       847

    accuracy                           0.77      3000
   macro avg       0.72      0.65      0.66      3000
weighted avg       0.75      0.77      0.74      3000
```

E3. Code

See above for code

F1. Results

The equation of the final regression model is: y =
-2.76+0.5209(Techie)+0.2617(OnlineBackup)+0.2892(DeviceProtection)+1.4706(StreamingTV)+1.7229
0.1577(Gender_Female)-1.5752(Contract_One year)-1.7606(Contract_Two Year)-

0.1513(PaymentMethod_Electronic Check)+0.5948(InternetService_DSL).

In this equation, -2.76 is the y intercept value on the y-axis. Each coefficient(slope) of the predictor variables describes how much the target variable is estimated to change if all other variables remain constant (Massaron). If DeviceProtection increased by one unit, the mean value of Churn would increase by 0.2892. The Contract_Two Year and streaming movies seems to have the largest effect on churn negatively by 1.76 and postively by 1.722 respectively.

P-values for for most variables are statistically significant at 0.000, with low multicolinearity (McKinney), as evidenced by the the low Variance Inflation Factor scores under 5. Confusion matrix suggests that overall accuracy of the model stays high, even when cross validated using test train split, with an only a small drop of 0.05 from 0.83 to 0.77 from the original model to the trained model.

Data limitations include the data set is small (only 10,000 rows) and that it is not adjusted for seasonality. Seasonality could be affecting times of the year that customers churn more frequently. For example, we could have higher churn during the holidays, since customers would be interested in trying new services. We should also identify if ther are seasons of lower churn during different times of the year.

F2 Recommendations

Structurally, the model is good enough to deploy to a production environment for predictive analytics to predict churn. However, before this can be done, it would be important to label/identify when the customer exactly churned. Seasonality is important for retail businesses like telecommunications companies, and identifying periods of time that a customer is likely to churn is just as important as knowing if they will churn. Without the date of when the customer churned, we have no context of when they churned. If the model is adjusted for seasonality, or is run individually for certain seasons, the model would generate an accurate result. These adjustments would be useful for creating a model that departments such as retention, marketing, and customer service could use.

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Third Party Code

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