Predictive_Modeling

March 3, 2024

A1 Research Question The purpose of this data analysis is to understand the underlying factors that influence the monthly charges incurred by customers in the telecommunications company. Recognizing that cost is a significant factor in customer retention and satisfaction, this research aims to identify key predictors of monthly charges. By doing so, the study indirectly addresses the broader question of what might contribute to a customer's decision to churn, focusing on the premise that higher monthly charges can lead to increased churn rates.

A2 Define the goals of the data analysis

- Identify and Quantify Influential Factors: Determine which demographic, service-related, and account-specific variables significantly impact monthly charges for customers in the telecommunications industry.
- Model the Relationship: Develop a predictive model that quantifies the relationship between monthly charges and the identified factors, using multiple linear regression to assess the strength and nature of these relationships.
- Insights for Strategy Development: Provide actionable insights for telecom companies to adjust pricing strategies, enhance customer service offerings, and tailor marketing efforts to reduce churn rates and improve customer satisfaction.

B1 Four Assumptions of a Multiple Linear Regression Model

- Linear relationship: The relationship between each independent variable and the dependent variable is linear. There exists a linear relationship between each predictor variable and the response variable.
- Independence: The residuals (errors) are independent. In other words, the residuals for one observation aren't influenced by the residuals of any other observation, which is crucial for the unbiasedness of the coefficients.
- Homoscedasticity: The residuals have constant variance at different levels of the independent variables. The residuals have constant variance at every point in the linear model.
- Multivariate Normality: When dealing with multiple independent variables, it's assumed that these variables, along with the dependent variable, are multivariate normally distributed. This assumption ensures the applicability of various multivariate statistical methods and helps in simplifying the interpretation and inference of the regression model. The residuals of the model are normally distributed.

(Statology, 2021)

B2 Two Benefits of Using Python

- Versatility and Libraries: Python offers a vast array of libraries and tools like Pandas for data manipulation, NumPy for numerical calculations, Matplotlib and Seaborn for data visualization, and scikit-learn for implementing machine learning algorithms including linear regression. I also used scipy for Stats and statsmodels.api to perform Backward Elimination. This ecosystem makes Python a versatile tool for the entire data analysis process, from data cleaning to model building and evaluation.
- Ease of Use and Community Support: Python has a relatively gentle learning curve and is known for its readability and simplicity, making it accessible to a wide range of users, from beginners to experts. Additionally, Python has a large and active community, providing extensive resources, documentation, and forums for troubleshooting, which is invaluable for analytical work and problem-solving.

B3 Multiple Linear Regression for Analyzing the Research Question Multiple linear regression is an ideal analytical method for addressing my research question: "What factors influence the monthly charges of customers potentially contributing to their decision to churn?" It enables the examination of how multiple independent variables (e.g., service usage, tenure, demographics) simultaneously influence a single dependent variable (monthly charges). This is crucial for our study, as it seeks to uncover the complex interplay of factors that might affect customer churn, allowing for the quantification of each factor's impact on monthly charges. By understanding these relationships, we can identify significant predictors of churn, essential for developing targeted retention strategies.

Furthermore, multiple linear regression's predictive capabilities are aligned with the goal of forecasting customer behavior in relation to churn. It offers a framework for testing the assumptions of linearity, independence, and normality of residuals. This ensure that my preliminary analysis suggestions are met. This methodological fit ensures not only the relevance of my findings to the telecommunications industry, but also enhances the practical application of my research in formulating actionable insights to mitigate churn by addressing the key factors influencing monthly charges.

C1 Data Cleaning Goals and The Steps Used To prepare the dataset for multiple linear regression analysis, especially for the research question "What factors influence the monthly charges of customers, potentially contributing to their decision to churn?". There are several key steps in the data preparation process:

Goals:

- Ensure data quality and relevance to the research question.
- Address missing values, outliers, and inconsistencies.

Steps:

- Identifying Missing Values: Check for missing data in key variables (e.g., customer demographics, service usage).
- Handling Missing Data: Decide on strategies like imputation or removal, depending on the extent and nature of missing data.
- Outlier Detection: Identify outliers using statistical methods or visualization. Evaluate their impact and decide whether to keep, transform, or remove them.

- Data Type Correction: Ensure that all variables are in the correct format (e.g., numerical, categorical).
- The categorical datatypes being used for the multiple regression analysis will be "dummied" using one-hot encoding.
- Consistency Check: Verify that data across all variables is consistent, e.g., no negative values in age or usage.

As for the annotated code. Some of the functions will be run to verify that the data is ready for multiple regression analysis, such as info() to make sure that validate the datatypes for each column, value_counts() to check all of the values in a column, or describe() to display summary statistics for a numeric columns.

[2]:
```
import pandas as pd
from pandas.api.types import CategoricalDtype
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import statsmodels.api as sm
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncoder

# Loading the dataset
df = pd.read_csv(r'C:\Users\Hien Ta\OneDrive\WGU\MSDA\D208\Task_1\churn_clean.
 ↪csv')

# Check data types, number of values and size of dataframe
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        7871 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
```

C2 Summary Statistics of Variables

0.0.1 Dependent Variable:

[19]:
```
df.MonthlyCharge.describe()
```

[19]:
```
count    10000.000000
mean       172.624816
std         42.943094
```

```
min        79.978860
25%       139.979239
50%       167.484700
75%       200.734725
max       290.160419
Name: MonthlyCharge, dtype: float64
```

0.0.2 Independent Variables:

[20]:
```python
df.Tenure.describe()
```

[20]:
```
count    10000.000000
mean        34.526188
std         26.443063
min          1.000259
25%          7.917694
50%         35.430507
75%         61.479795
max         71.999280
Name: Tenure, dtype: float64
```

[21]:
```python
df.InternetService.value_counts()
```

[21]:
```
InternetService
Fiber Optic    4408
DSL            3463
Name: count, dtype: int64
```

[22]:
```python
df.Contract.value_counts()
```

[22]:
```
Contract
Month-to-month    5456
Two Year          2442
One year          2102
Name: count, dtype: int64
```

[23]:
```python
df.PaymentMethod.value_counts()
```

[23]:
```
PaymentMethod
Electronic Check            3398
Mailed Check                2290
Bank Transfer(automatic)    2229
Credit Card (automatic)     2083
Name: count, dtype: int64
```

[25]:
```python
df.OnlineSecurity.value_counts()
```

[25]:
```
OnlineSecurity
No     6424
Yes    3576
Name: count, dtype: int64
```

[26]:
```
df.TechSupport.value_counts()
```

[26]:
```
TechSupport
No     6250
Yes    3750
Name: count, dtype: int64
```

[27]:
```
df.Age.describe()
```

[27]:
```
count    10000.000000
mean        53.078400
std         20.698882
min         18.000000
25%         35.000000
50%         53.000000
75%         71.000000
max         89.000000
Name: Age, dtype: float64
```

[28]:
```
df.Gender.value_counts()
```

[28]:
```
Gender
Female        5025
Male          4744
Nonbinary      231
Name: count, dtype: int64
```

[29]:
```
df.Income.describe()
```

[29]:
```
count     10000.000000
mean      39806.926771
std       28199.916702
min         348.670000
25%       19224.717500
50%       33170.605000
75%       53246.170000
max      258900.700000
Name: Income, dtype: float64
```

[30]:
```
df.PaperlessBilling.value_counts()
```

[30]:
```
PaperlessBilling
Yes    5882
```

```
No     4118
Name: count, dtype: int64
```

[31]:
```
df.Bandwidth_GB_Year.describe()
```

[31]:
```
count    10000.000000
mean      3392.341550
std       2185.294852
min        155.506715
25%       1236.470827
50%       3279.536903
75%       5586.141370
max       7158.981530
Name: Bandwidth_GB_Year, dtype: float64
```

[32]:
```
df.StreamingTV.value_counts()
```

[32]:
```
StreamingTV
No     5071
Yes    4929
Name: count, dtype: int64
```

[33]:
```
df.StreamingMovies.value_counts()
```

[33]:
```
StreamingMovies
No     5110
Yes    4890
Name: count, dtype: int64
```

Cleaning the Data Cleaning the Data

The data cleaning process for the regression analysis is crucial to ensure the integrity and relevance of the variables to our research question, which seeks to understand the factors influencing customer churn. The dependent variable in this case is 'MonthlyCharge', and it will be thoroughly examined for accuracy, with any anomalies or outliers assessed for their impact on the analysis as outlined in section C1.

The chosen independent variables for this analysis include 'Tenure', 'Internet Service', 'Contract', 'Payment Method', 'Online Security', 'Tech Support', 'Age', 'Gender', 'Income', 'Paperless Billing', 'Bandwidth Usage', 'Streaming TV', and 'Streaming Movies'. These variables are selected for their potential influence on customer churn. The data cleaning process for these variables will involve:

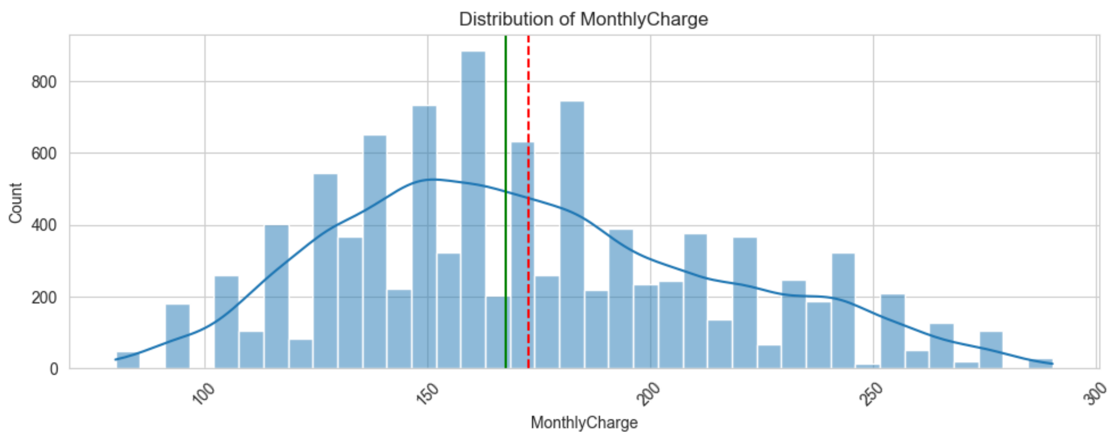
- Checking for Missing Values: Identifying and addressing any missing data to avoid biases in the analysis.
- Outlier Identification and Treatment: Using statistical analysis and visualization to detect outliers and determine their nature. Appropriate actions, such as exclusion, capping, or transformation, will be taken based on the impact of these outliers on the dataset.
- Ensuring Data Consistency: Verifying that all data is consistently formatted and accurately represents the variable it measures. This includes confirming the correct data type for each

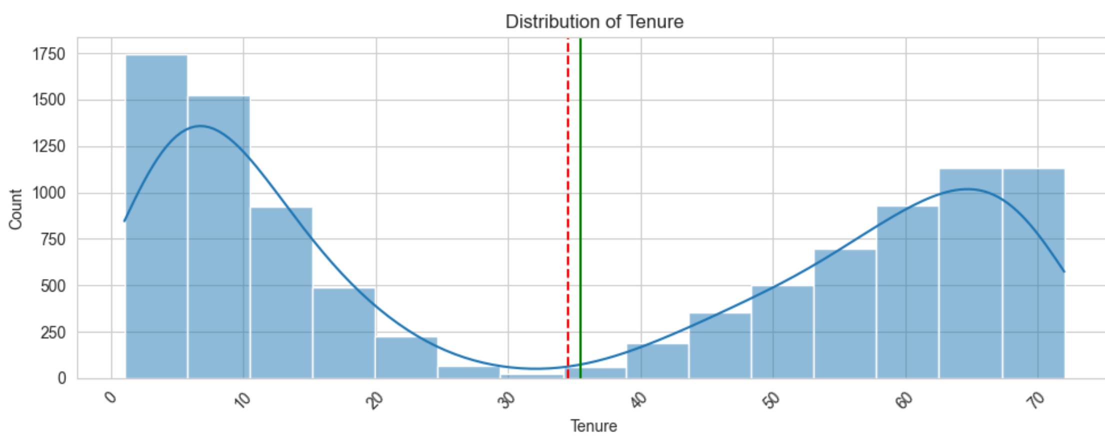
variable.
- Normalization or Transformation: If necessary, applying normalization or other transformations to meet the assumptions of multiple linear regression, such as linearity and homoscedasticity.

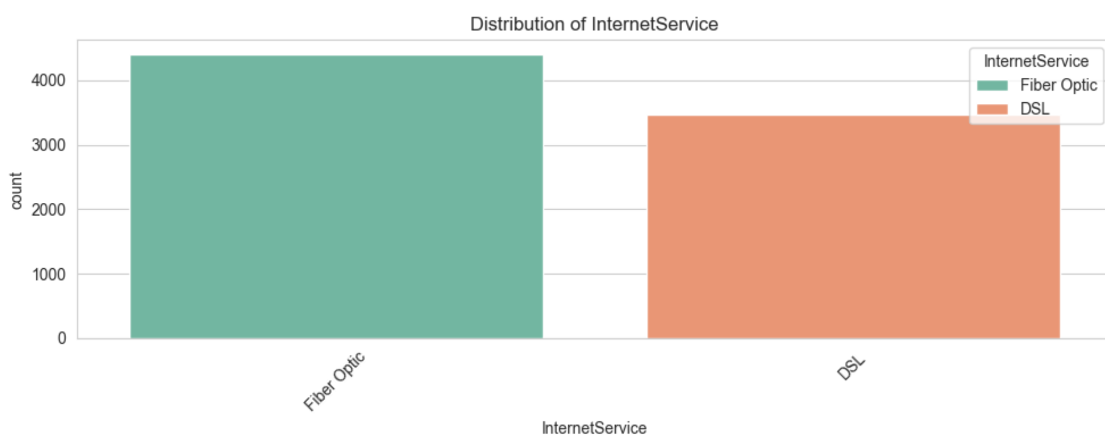
By the end of this data cleaning process, the dataset will be robust and ready for multiple linear regression analysis, with 'MonthlyCharge' as the dependent variable and the selected independent variables offering insights into customer behavior and preferences.

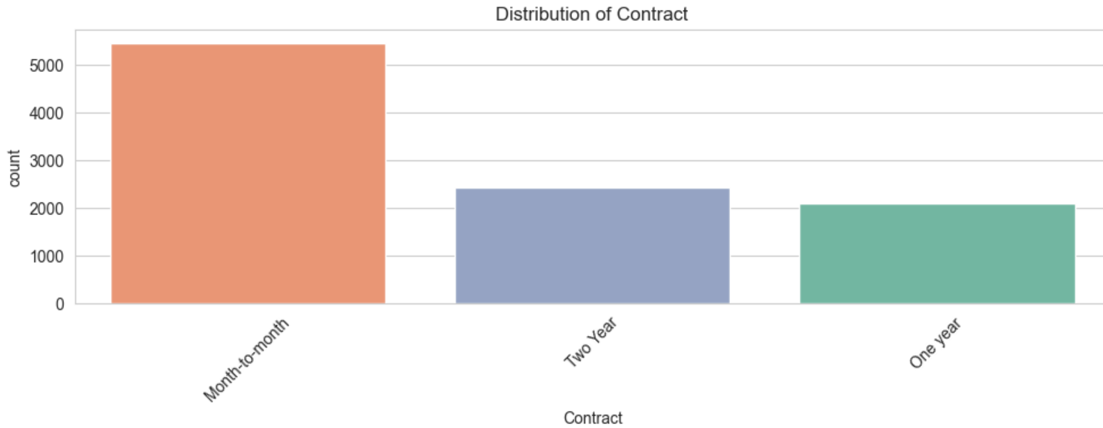
C3 Univariate and Bivariate Visualizations

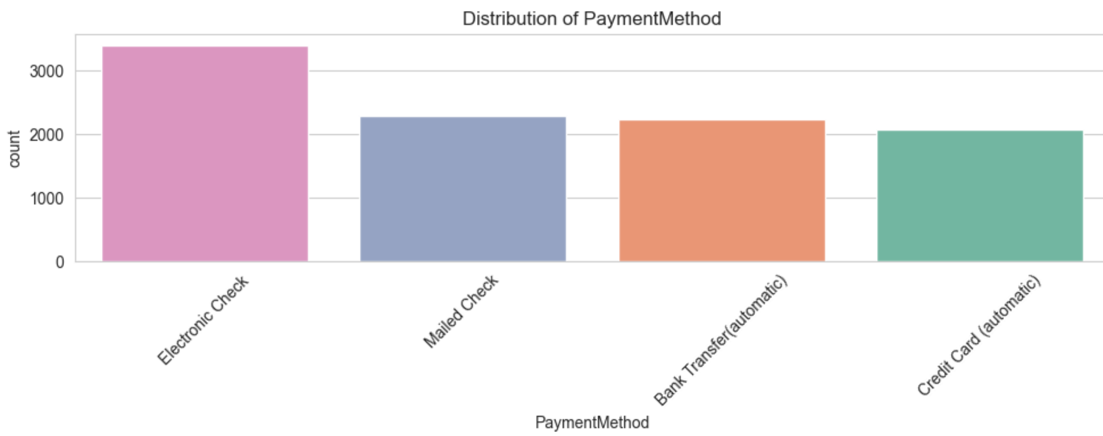
[4]:
```python
# see attached codes

# my selected variables
selected_variables = ['MonthlyCharge','Tenure', 'InternetService', 'Contract',
                      'PaymentMethod', 'OnlineSecurity', 'TechSupport', 'Age',␣
 ↪'Gender',
                      'Income', 'PaperlessBilling', 'Bandwidth_GB_Year',␣
 ↪'StreamingTV',
                      'StreamingMovies']

# Filtering the dataset to include only the selected variables
selected_df = df[selected_variables]

# Set the aesthetic style of the plots
sns.set_style("whitegrid")

# Univariate visualizations with enhancements
for column in selected_df.columns:
    plt.figure(figsize=(10, 4))
    if selected_df[column].dtype == 'object':
        # For categorical data with updated count plot code
        sns.countplot(x=column,  hue=column, palette='Set2', data=selected_df,␣
 ↪order=selected_df[column].value_counts().index)
    else:
        # For numerical data with mean and median lines
        sns.histplot(selected_df[column], kde=True)
        plt.axvline(selected_df[column].mean(), color='r', linestyle='--')
        plt.axvline(selected_df[column].median(), color='g', linestyle='-')
    plt.title(f'Distribution of {column}')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

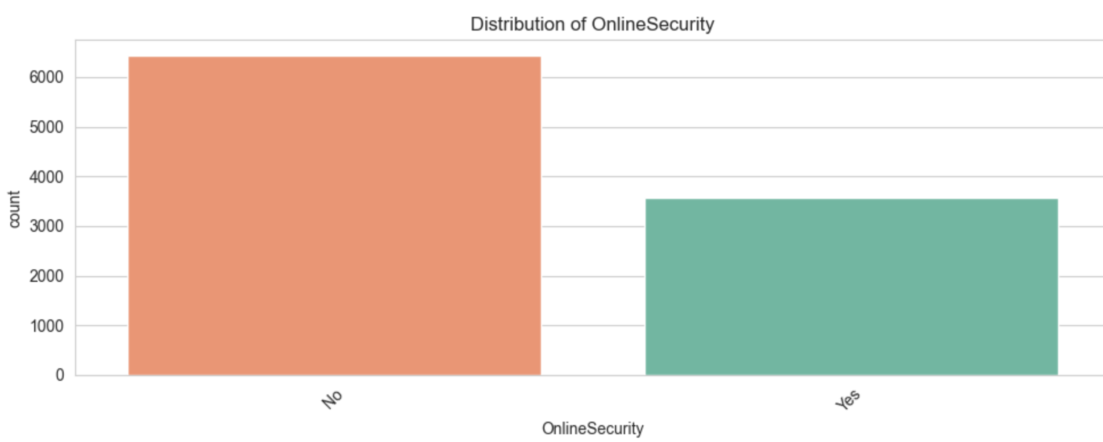

Distribution of MonthlyCharge
Count
800
600
400
200
0
100
150
200
250
300
MonthlyCharge

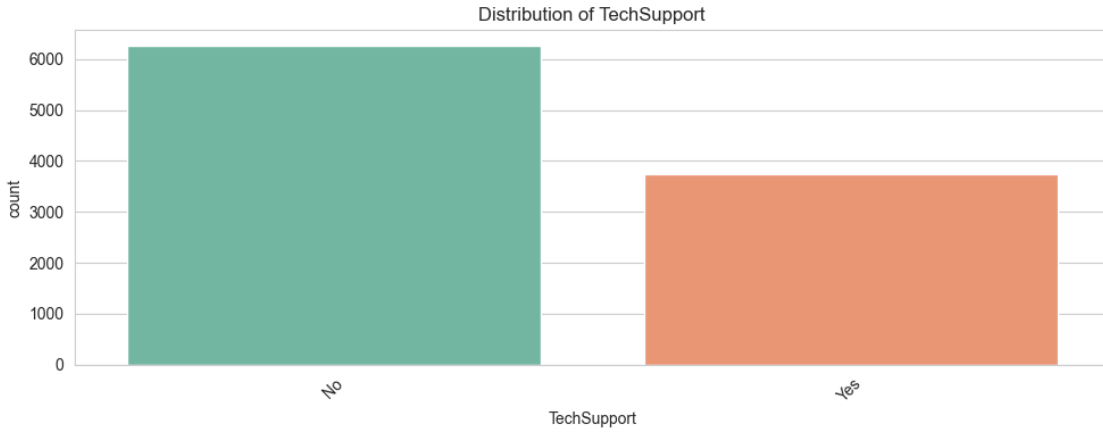

Distribution of Tenure
Count
1750
1500
1250
1000
750
500
250
0
0
10
20
30
40
50
60
70
Tenure

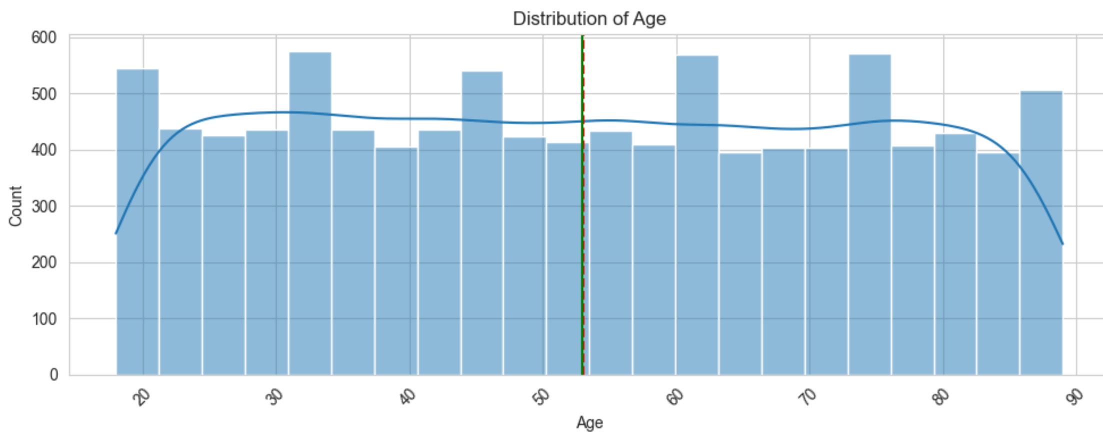

Distribution of InternetService
count
4000
3000
2000
1000
0
InternetService
Fiber Optic
DSL
Fiber Optic
DSL
InternetService


Distribution of Contract
count
0
1000
2000
3000
4000
5000
Month-to-month
Two Year
One year
Contract

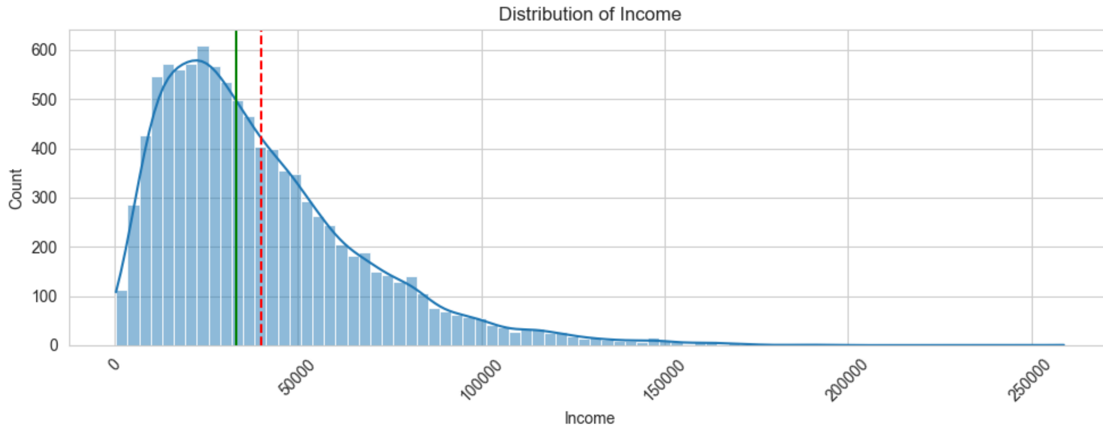

Distribution of PaymentMethod
count
0
1000
2000
3000
Electronic Check
Mailed Check
Bank Transfer(automatic)
Credit Card (automatic)
PaymentMethod


Distribution of OnlineSecurity
count
0
1000
2000
3000
4000
5000
6000
No
Yes
OnlineSecurity

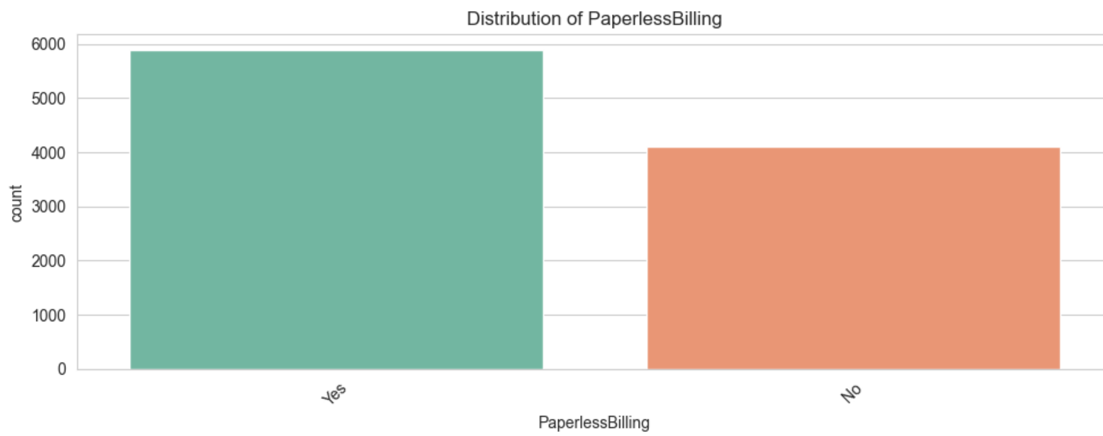

Distribution of TechSupport
6000
5000
4000
3000
2000
1000
0
count
No
Yes
TechSupport


Distribution of Age
600
500
400
300
200
100
0
Count
20
30
40
50
60
70
80
90
Age

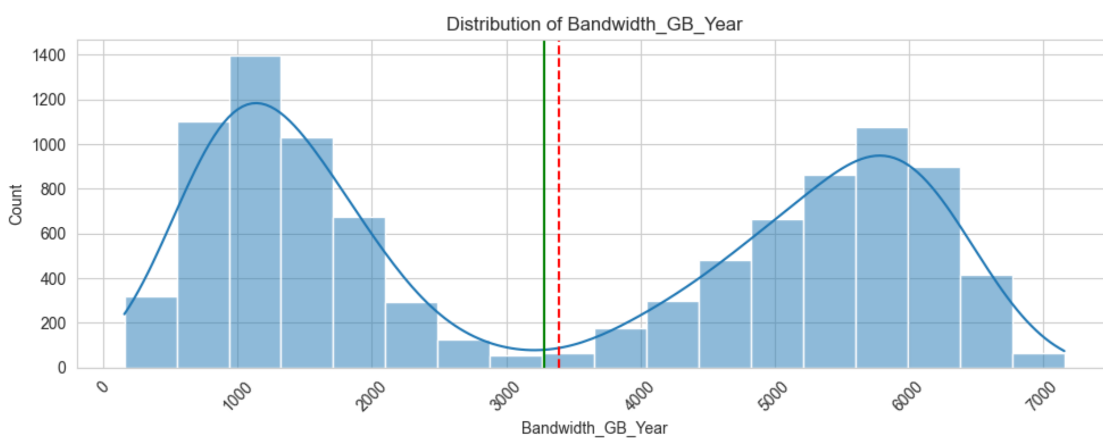

Distribution of Gender
5000
4000
3000
2000
1000
0
count
Female
Male
Nonbinary
Gender



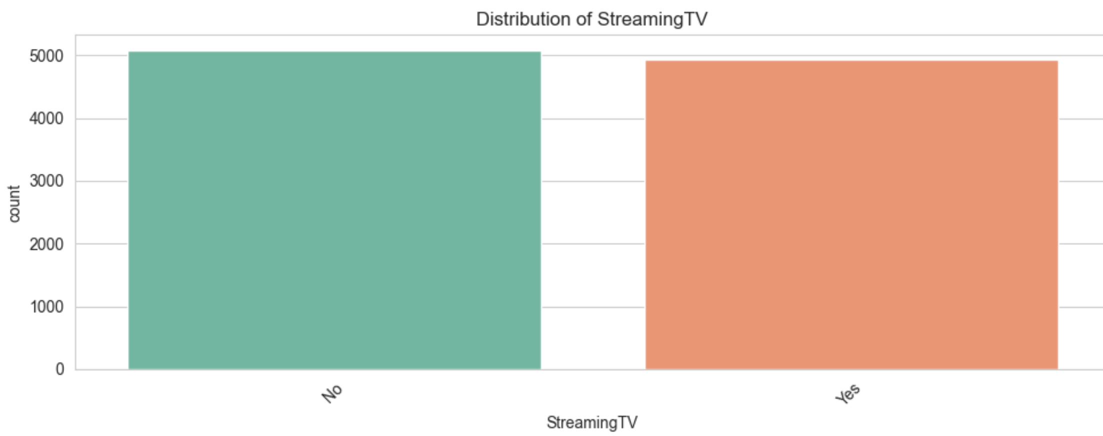
Distribution of Income
Count
Income
0
100
200
300
400
500
600
50000
100000
150000
200000
250000

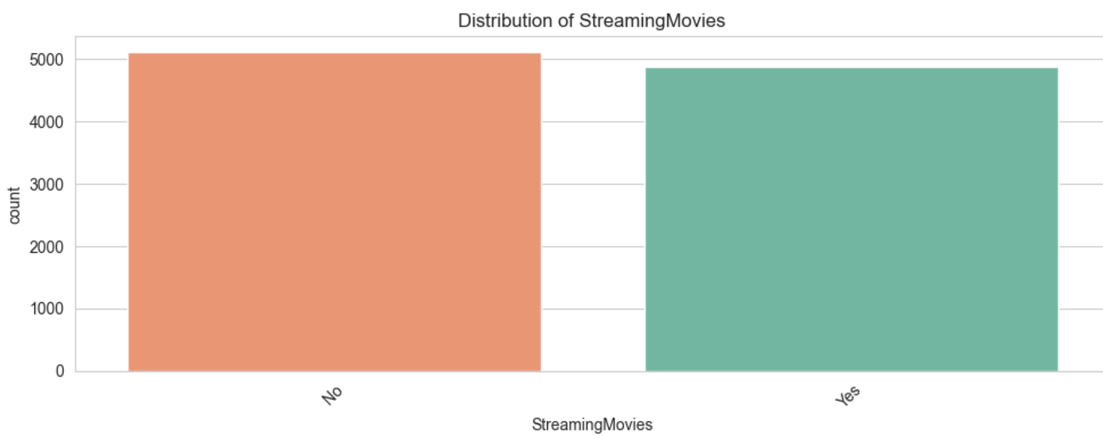


Distribution of PaperlessBilling
count
PaperlessBilling
0
1000
2000
3000
4000
5000
6000
Yes
No



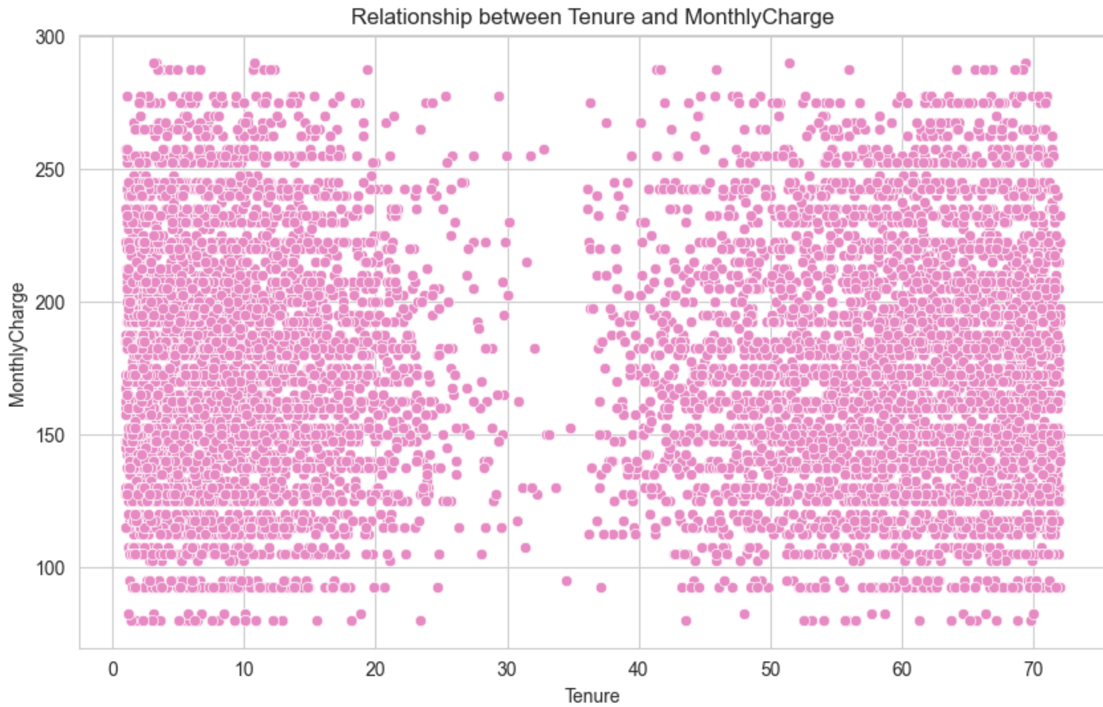
Distribution of Bandwidth_GB_Year
Count
Bandwidth_GB_Year
0
200
400
600
800
1000
1200
1400
2000
3000
4000
5000
6000
7000

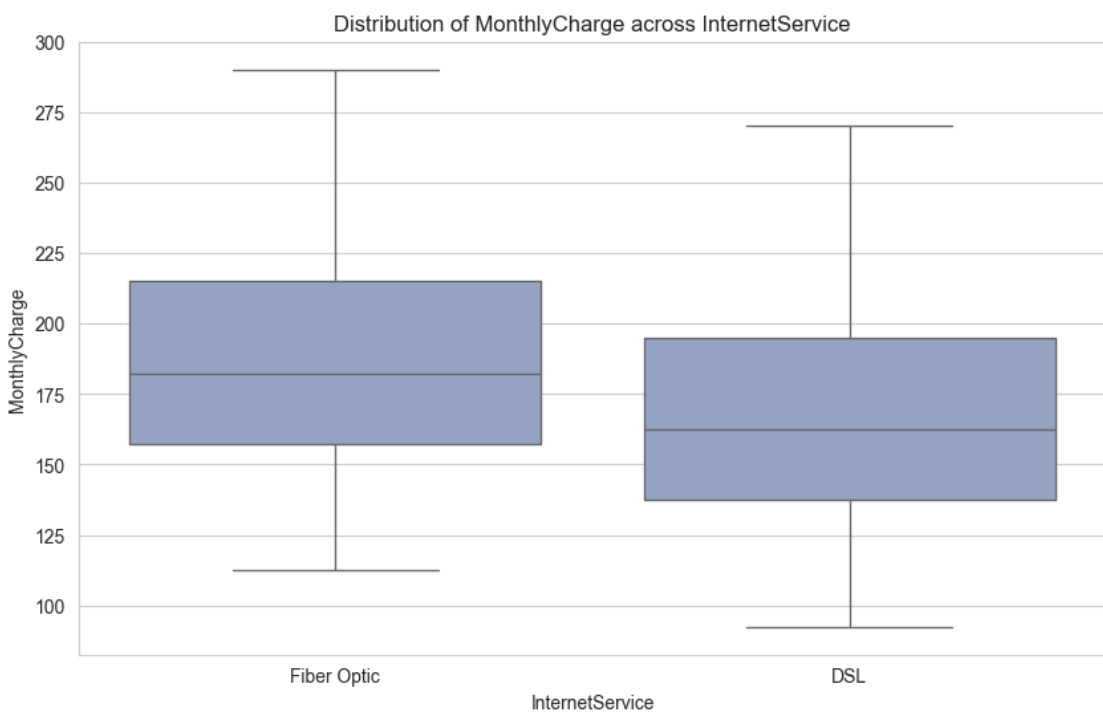


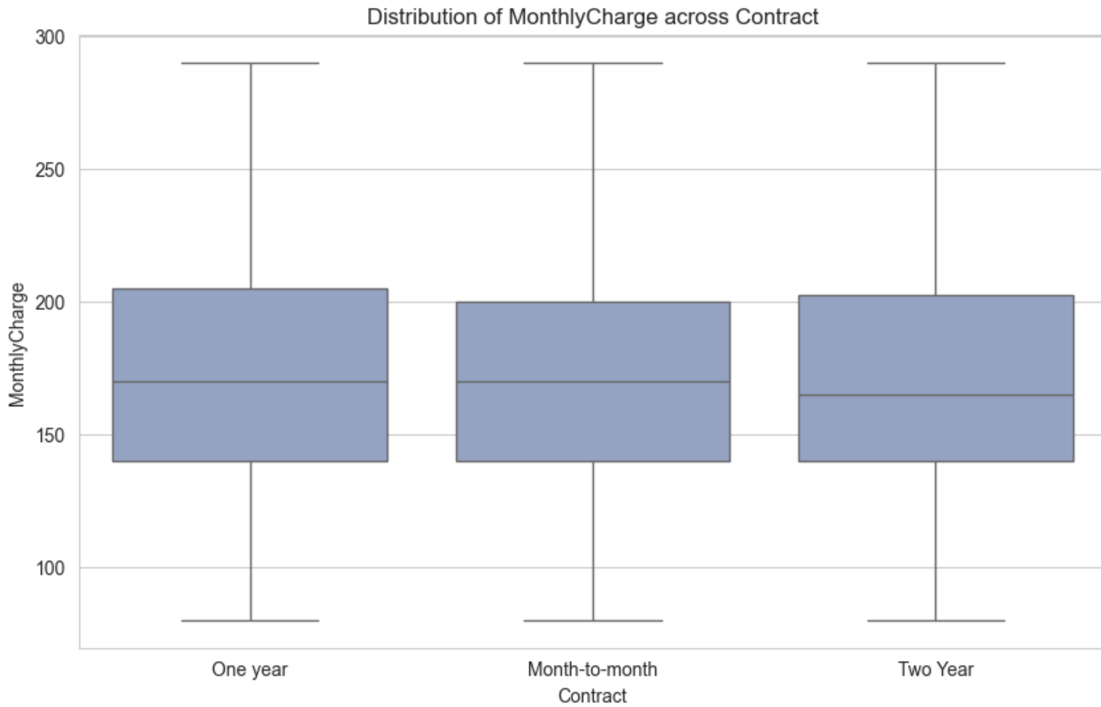


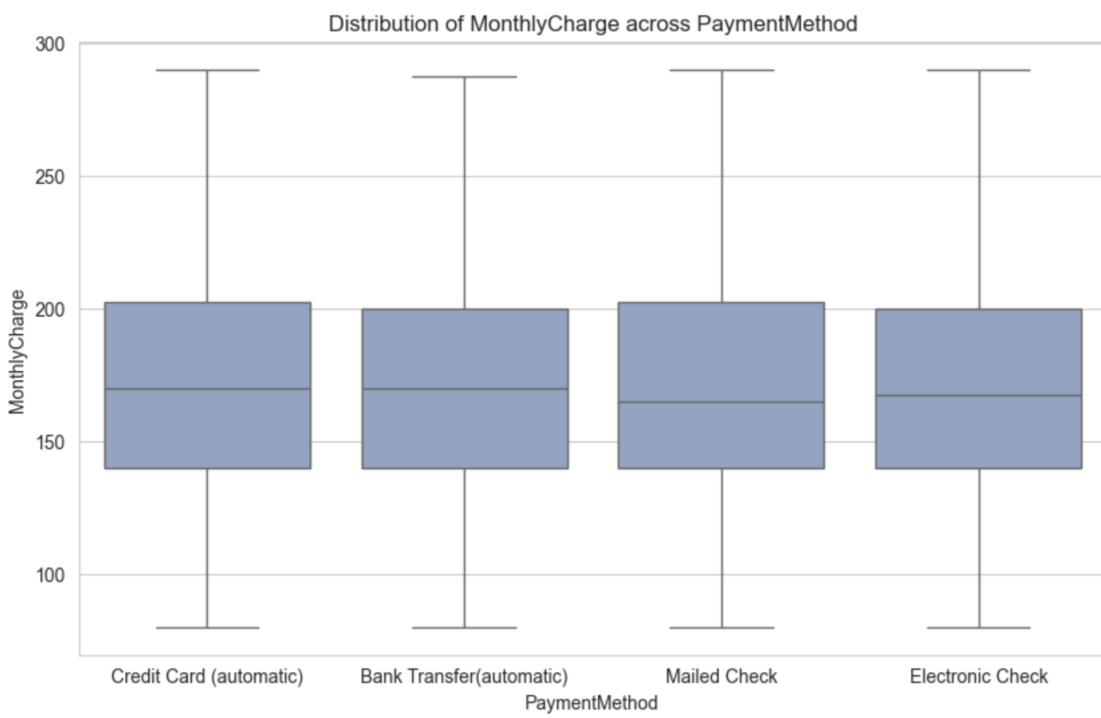
[35]:
```
# see attached codes

# Get the "Set2" palette colors
palette_colors = sns.color_palette("Set2")

# Bivariate visualizations
for column in selected_variables:
    plt.figure(figsize=(10, 6))
    if selected_df[column].dtype == 'object':
        # For categorical data: Use a specific color from "Set2" palette
        sns.boxplot(x=column, y='MonthlyCharge', data=selected_df,␣
↪color=palette_colors[2])
        plt.title(f'Distribution of MonthlyCharge across {column}')
    else:
        # For numerical data: 'MonthlyCharge' against each numerical variable
        # Use another specific color from "Set2" for distinction, if desired
```

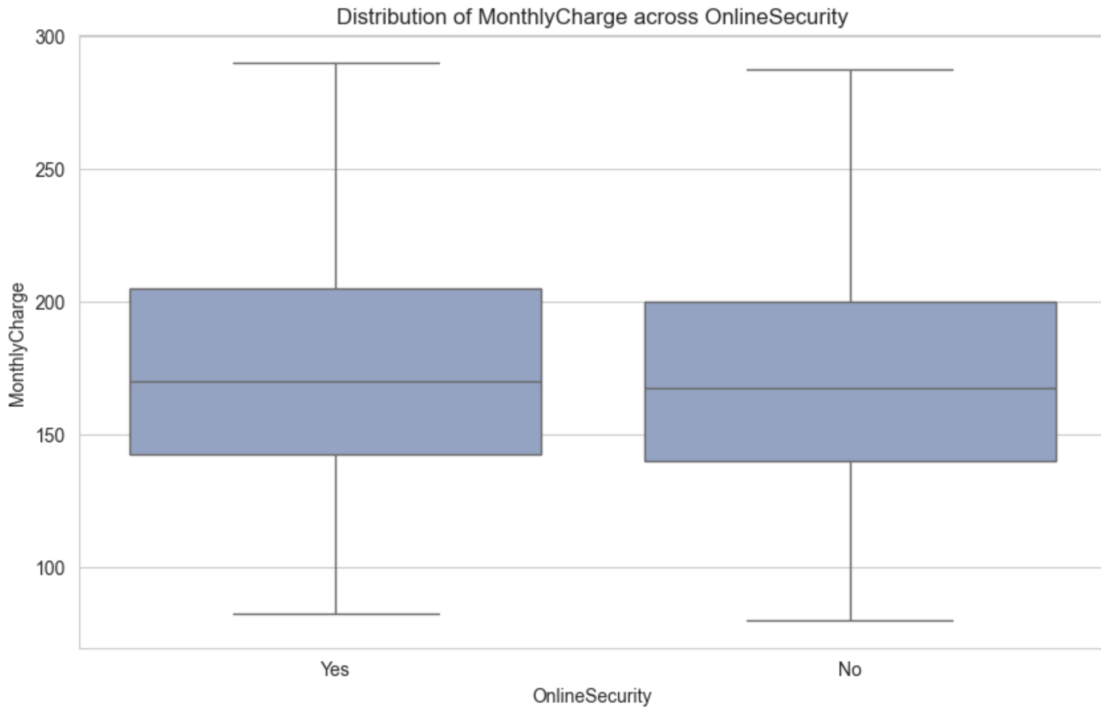
```
        sns.scatterplot(x=column, y='MonthlyCharge', data=selected_df,␣
↪color=palette_colors[3])
        plt.title(f'Relationship between {column} and MonthlyCharge')
    plt.show()
```

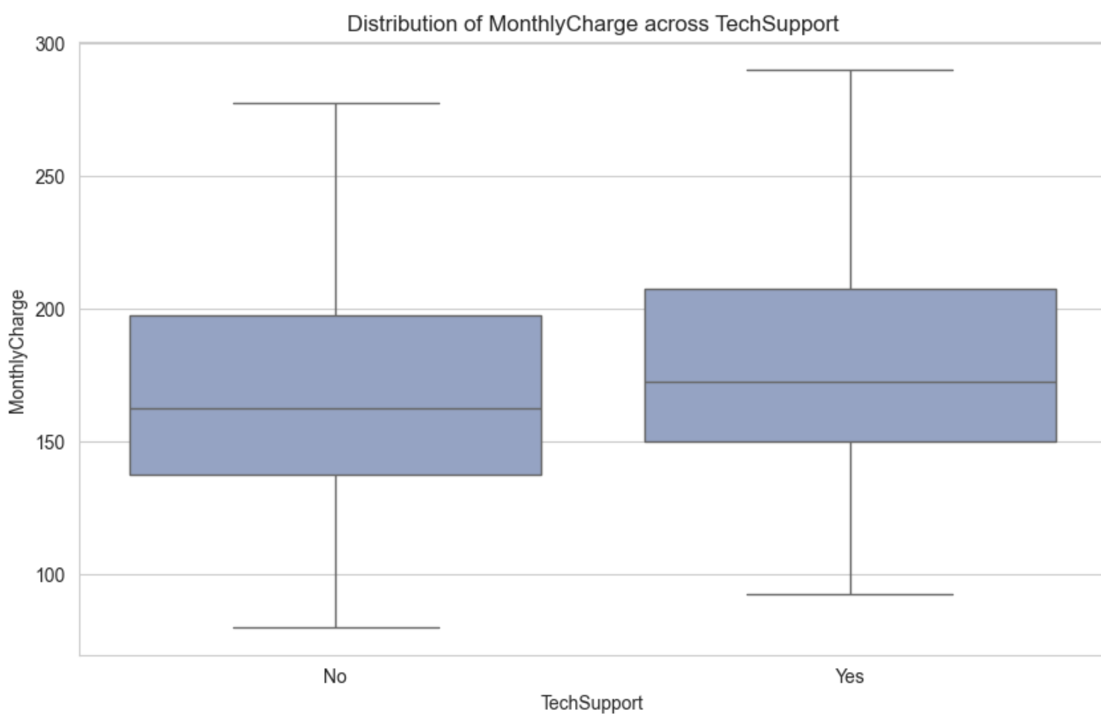

Relationship between Tenure and MonthlyCharge
300
250
200
150
100
MonthlyCharge
0
10
20
30
40
50
60
70
Tenure


Distribution of MonthlyCharge across InternetService
300
275
250
225
200
175
150
125
100
MonthlyCharge
Fiber Optic
DSL
InternetService


Distribution of MonthlyCharge across Contract
300
250
200
150
100
MonthlyCharge
One year
Month-to-month
Two Year
Contract

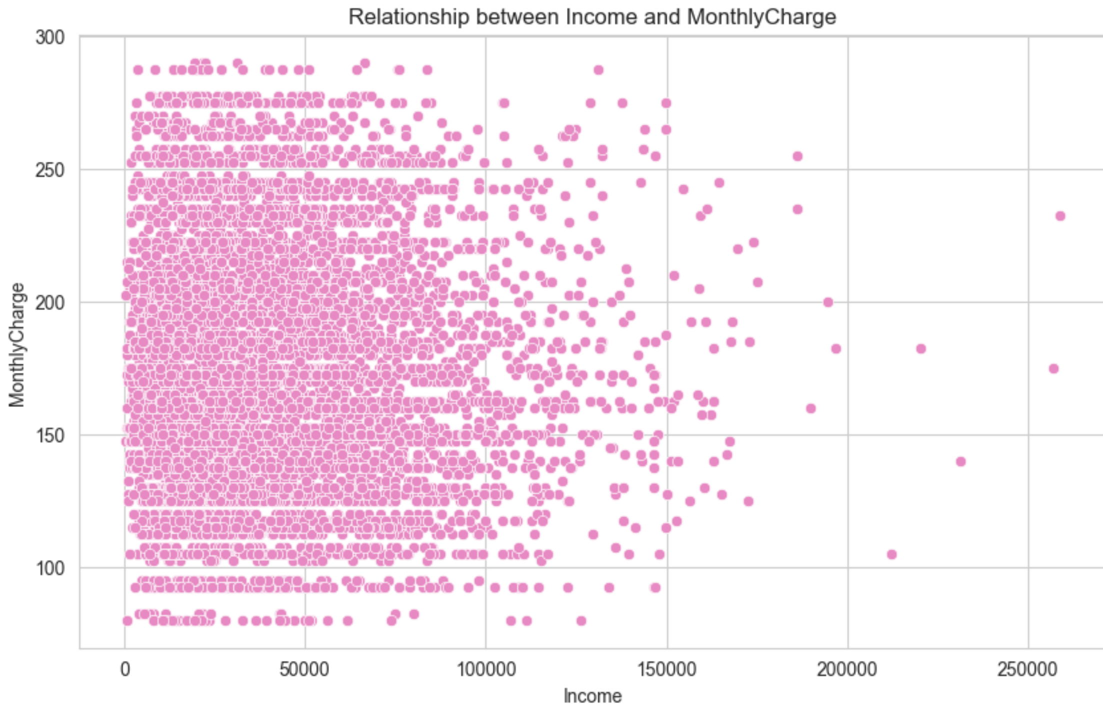

Distribution of MonthlyCharge across PaymentMethod
300
250
200
150
100
MonthlyCharge
Credit Card (automatic)
Bank Transfer(automatic)
Mailed Check
Electronic Check
PaymentMethod

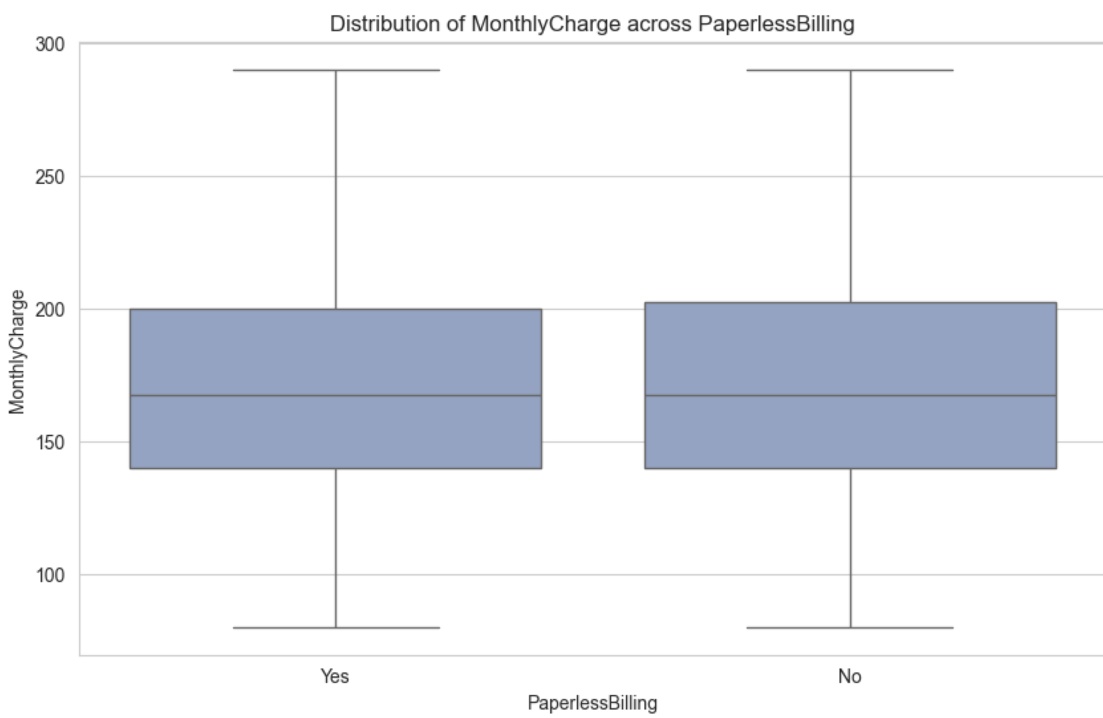

Distribution of MonthlyCharge across OnlineSecurity
MonthlyCharge
300
250
200
150
100
Yes
No
OnlineSecurity

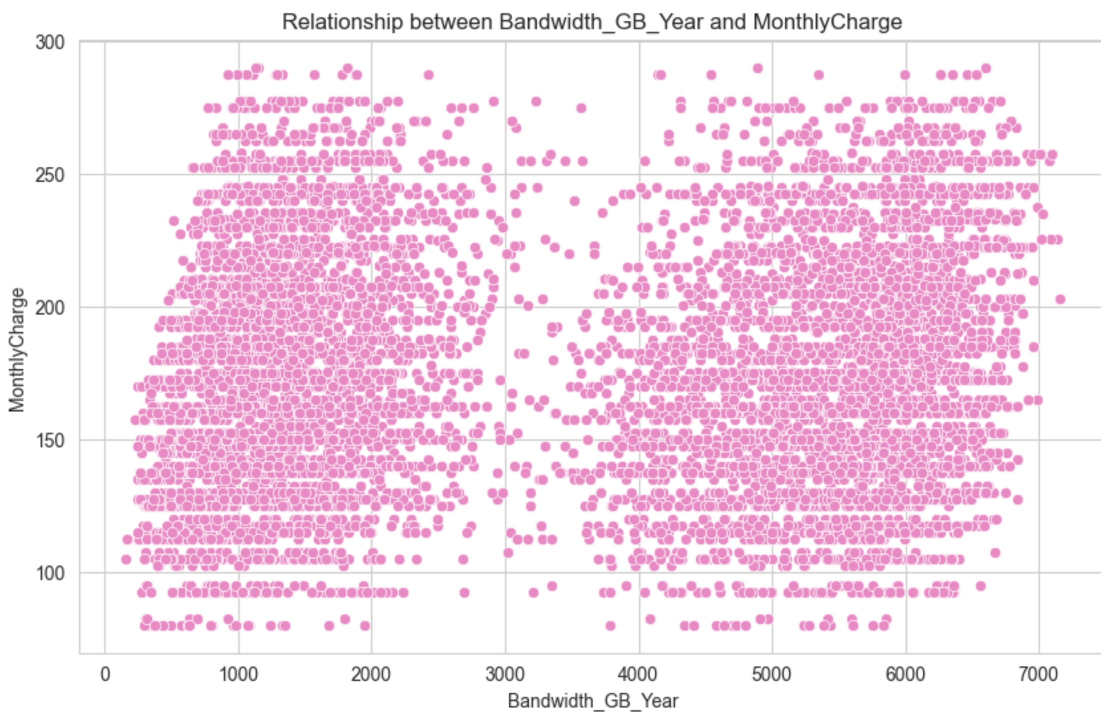

Distribution of MonthlyCharge across TechSupport
MonthlyCharge
300
250
200
150
100
No
Yes
TechSupport

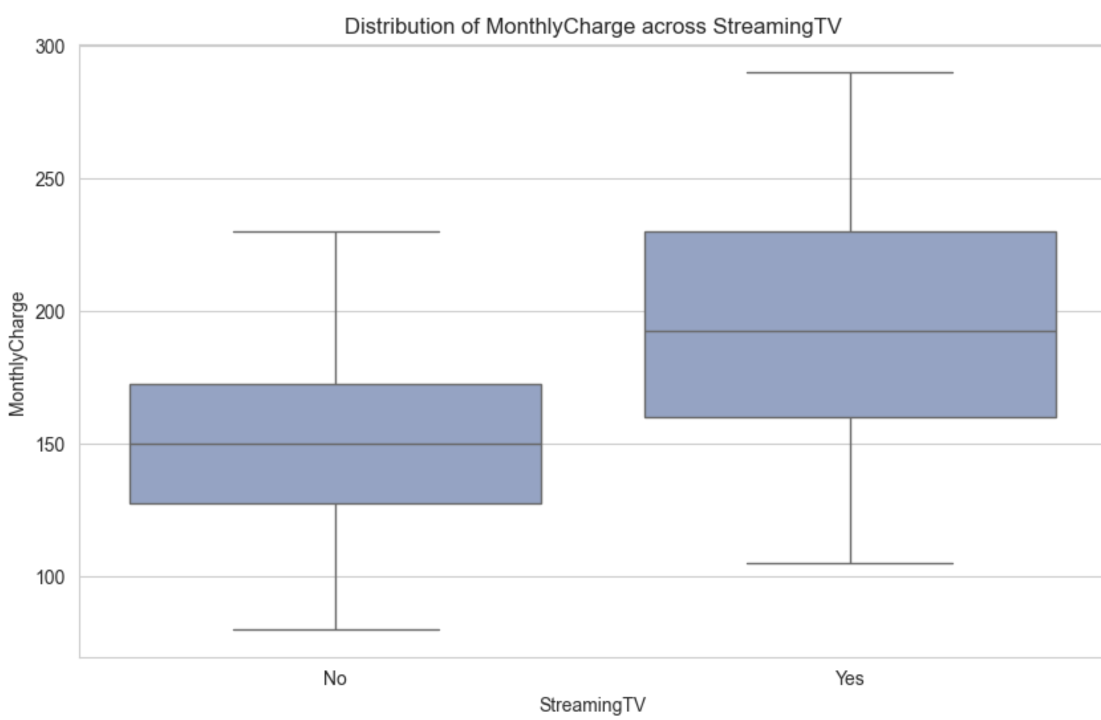

Relationship between Age and MonthlyCharge
MonthlyCharge
300
250
200
150
100
20
30
40
50
60
70
80
90
Age

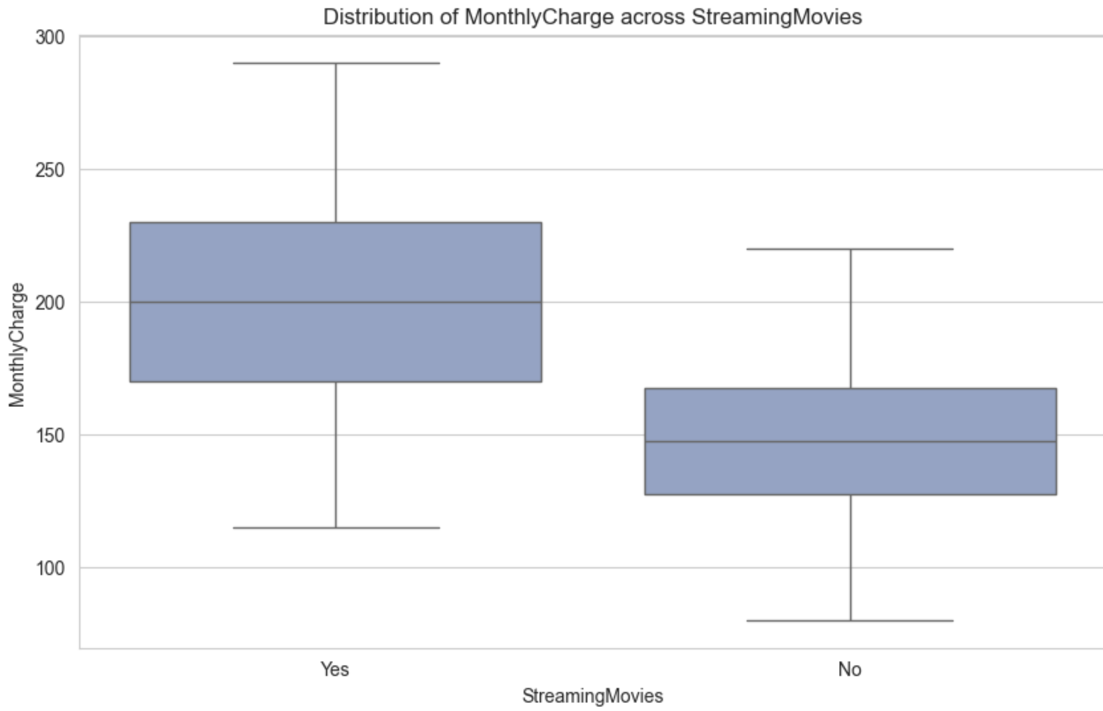

Distribution of MonthlyCharge across Gender
MonthlyCharge
300
250
200
150
100
Male
Female
Nonbinary
Gender


Relationship between Income and MonthlyCharge
MonthlyCharge
Income
300
250
200
150
100
0
50000
100000
150000
200000
250000


Distribution of MonthlyCharge across PaperlessBilling
MonthlyCharge
PaperlessBilling
300
250
200
150
100
Yes
No


Relationship between Bandwidth_GB_Year and MonthlyCharge
300
250
200
150
100
MonthlyCharge
0
1000
2000
3000
4000
5000
6000
7000
Bandwidth_GB_Year


Distribution of MonthlyCharge across StreamingTV
300
250
200
150
100
MonthlyCharge
No
Yes
StreamingTV



C4 Describe Data Transformation Goals and Steps Data Transformation Goals:

- Ensure data quality and relevance to the research question.
- Address missing values, outliers, and inconsistencies.

Steps:

- Identifying Missing Values: Check for missing data in key variables (e.g., customer demographics, service usage).
- Handling Missing Data: Decide on strategies like imputation or removal, depending on the extent and nature of missing data.
- Outlier Detection: Identify outliers using statistical methods or visualization. Evaluate their impact and decide whether to keep, transform, or remove them.
- Data Type Correction: Ensure that all variables are in the correct format (e.g., numerical, categorical).
- The categorical datatypes being used for the multiple regression analysis will be "dummied" using one-hot encoding.
- Consistency Check: Verify that data across all variables is consistent, e.g., no negative values in age or usage.

[36]:
```
# Identifying Missing Values
missing_values = df.isnull().sum()

print(missing_values)
```

```
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         2129
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
```

[8]:
```
# Fill missing value in 'InternetService' with 'None'
df['InternetService'].fillna('None', inplace=True)
```

[9]:
```
# Identifying Missing Values
missing_values = df.isnull().sum()

print(missing_values)
```

```
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
```

There are no missing values in this Churn dataset excpet for InternetService which I filled in with 'None' above.

- Outlier Detection and Handling: The below is use to detect outliers in my chosen variables 'Age', 'Income', 'Outage_sec_perweek', 'Population', 'Yearly_equip_failure', 'Tenure'. I retained only those values within three standard deviations from the mean.

[10]:
```python
# see attached codes

# Define a function to remove outliers based on z-score where absolute value is␣
↪less than 3
def remove_outliers(df, column_names):
    # Calculate the z-score for each specified column where the absolute␣
↪z-score is < 3
    mask = np.column_stack([
        np.abs(stats.zscore(df[column])) < 3
        for column in column_names
    ])
    return df[mask.all(axis=1)]

# Apply the function to the dataframe
numeric_columns = ['Tenure', 'MonthlyCharge', 'Age', 'Income',␣
↪'Bandwidth_GB_Year']
df = remove_outliers(df, numeric_columns)


# (Statology zscore, 2021)
```

- Data Type Correction: The categorical_vars columns will be converted to a categorical data type, which is appropriate for a variable with discrete, non-numeric values. One-Hot Encoding: I applied one-hot encoding to categorical variables, transforming them into a format suitable for regression analysis.

[11]:
```python
# List of categorical variables to one-hot encode
categorical_vars = ['InternetService', 'Contract', 'PaymentMethod',␣
 ↪'OnlineSecurity',
                    'TechSupport', 'Gender', 'PaperlessBilling', 'StreamingTV',
                    'StreamingMovies']

# Convert to categorical and apply one-hot encoding
df = pd.get_dummies(df, columns=categorical_vars, drop_first=True)
```

- Consistency Check: I ensured data consistency by clipping any negative values in my varaiables to 0, as negative values in these columns wouldn't be meaningful.

[12]:
```python
# Ensure no negative values in my selected independent variables I use .clip␣
 ↪method
df['Age'] = df['Age'].clip(lower=0)
df['Income'] = df['Income'].clip(lower=0)
df['Outage_sec_perweek'] = df['Outage_sec_perweek'].clip(lower=0)
df['Population'] = df['Population'].clip(lower=0)
df['Tenure'] = df['Tenure'].clip(lower=0)
df['Bandwidth_GB_Year'] = df['Bandwidth_GB_Year'].clip(lower=0)
```

[13]:
```python
# converting 'Churn' from 'Yes'/'No' to 1/0
df['Churn'] = df['Churn'].map({'Yes': 1, 'No': 0})
```

[14]:
```python
bool_cols = ['InternetService_Fiber Optic', 'InternetService_None',
    'Contract_One year', 'Contract_Two Year',
    'PaymentMethod_Credit Card (automatic)',
    'PaymentMethod_Electronic Check', 'PaymentMethod_Mailed Check',
    'OnlineSecurity_Yes', 'TechSupport_Yes', 'Gender_Male',
    'Gender_Nonbinary', 'PaperlessBilling_Yes', 'StreamingTV_Yes',
    'StreamingMovies_Yes']

# Convert boolean columns to integers
df[bool_cols] = df[bool_cols].astype(bool).astype(int)
```

C5 Copy Data to CSV file

[15]:
```python
# Saving the cleaned dataset
cleaned_file_path = (r'C:\Users\Hien␣
 ↪Ta\OneDrive\WGU\MSDA\D208\Task_1\churn_clean_After.csv')
df.to_csv(cleaned_file_path, index=False)
```

D1 Initial Multiple Linear Regression Model The initial multiple linear regression model constructed to explore MonthlyCharge. I incorporates a comprehensive suite of variables, including both demographic and service-related factors. The model's ambitious scope, informed by a meticulous selection of predictors, aims to capture the multifaceted influences on MonthlyCharge. However, recognizing that not every variable may hold significant explanatory power, the model is subjected to rigorous evaluation. This evaluation seeks to refine the model by retaining only those variables that materially contribute to understanding MonthlyCharge variability. Through statistical scrutiny, including examining p-values and assessing multicollinearity, the model is optimized for both interpretability and predictive accuracy. This refinement process underscores a commitment to analytical rigor, ensuring the final model is both lean and potent, ready for application in predictive analytics and decision-making.

(Mark Keith's Machine Learning in Python course materials on YouTube)

[45]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 9855 entries, 0 to 9999
Data columns (total 55 columns):
 #   Column                                   Non-Null Count  Dtype
---  ------                                   --------------  -----
 0   CaseOrder                                9855 non-null   int64
 1   Customer_id                              9855 non-null   object
 2   Interaction                              9855 non-null   object
 3   UID                                      9855 non-null   object
 4   City                                     9855 non-null   object
 5   State                                    9855 non-null   object
 6   County                                   9855 non-null   object
 7   Zip                                      9855 non-null   int64
 8   Lat                                      9855 non-null   float64
 9   Lng                                      9855 non-null   float64
 10  Population                               9855 non-null   int64
 11  Area                                     9855 non-null   object
 12  TimeZone                                 9855 non-null   object
 13  Job                                      9855 non-null   object
 14  Children                                 9855 non-null   int64
 15  Age                                      9855 non-null   int64
 16  Income                                   9855 non-null   float64
 17  Marital                                  9855 non-null   object
 18  Churn                                    9855 non-null   int64
 19  Outage_sec_perweek                       9855 non-null   float64
 20  Email                                    9855 non-null   int64
 21  Contacts                                 9855 non-null   int64
 22  Yearly_equip_failure                     9855 non-null   int64
 23  Techie                                   9855 non-null   object
 24  Port_modem                               9855 non-null   object
 25  Tablet                                   9855 non-null   object
 26  Phone                                    9855 non-null   object
 27  Multiple                                 9855 non-null   object
 28  OnlineBackup                             9855 non-null   object
 29  DeviceProtection                         9855 non-null   object
 30  Tenure                                   9855 non-null   float64
 31  MonthlyCharge                            9855 non-null   float64
 32  Bandwidth_GB_Year                        9855 non-null   float64
 33  Item1                                    9855 non-null   int64
```

```
 34  Item2                                  9855 non-null   int64
 35  Item3                                  9855 non-null   int64
 36  Item4                                  9855 non-null   int64
 37  Item5                                  9855 non-null   int64
 38  Item6                                  9855 non-null   int64
 39  Item7                                  9855 non-null   int64
 40  Item8                                  9855 non-null   int64
 41  InternetService_Fiber Optic            9855 non-null   int32
 42  InternetService_None                   9855 non-null   int32
 43  Contract_One year                      9855 non-null   int32
 44  Contract_Two Year                      9855 non-null   int32
 45  PaymentMethod_Credit Card (automatic)  9855 non-null   int32
 46  PaymentMethod_Electronic Check         9855 non-null   int32
 47  PaymentMethod_Mailed Check             9855 non-null   int32
 48  OnlineSecurity_Yes                     9855 non-null   int32
 49  TechSupport_Yes                        9855 non-null   int32
 50  Gender_Male                            9855 non-null   int32
 51  Gender_Nonbinary                       9855 non-null   int32
 52  PaperlessBilling_Yes                   9855 non-null   int32
 53  StreamingTV_Yes                        9855 non-null   int32
 54  StreamingMovies_Yes                    9855 non-null   int32
dtypes: float64(7), int32(14), int64(17), object(17)
memory usage: 3.7+ MB
```

[16]:

```
# Initial model for Multiple Linear Regression

import statsmodels.api as sm

# Define dependent and independent variables
dependent_var = 'MonthlyCharge'
independent_vars = ['Tenure', 'Age', 'Income',␣
 ↪'Bandwidth_GB_Year','InternetService_Fiber Optic',
                    'InternetService_None', 'Contract_One year', 'Contract_Two␣
 ↪Year', 'PaymentMethod_Credit Card (automatic)',
                    'PaymentMethod_Electronic Check', 'PaymentMethod_Mailed␣
 ↪Check', 'OnlineSecurity_Yes',
                    'TechSupport_Yes', 'Gender_Male', 'Gender_Nonbinary',␣
 ↪'PaperlessBilling_Yes', 'StreamingTV_Yes', 'StreamingMovies_Yes']

# Set dependent and independent variables
X = df[independent_vars]
y = df[dependent_var]

# Adding a constant to the model (the y-intercept)
X = sm.add_constant(X)

# Fit the OLS model
```

```python
model = sm.OLS(y, X)
results = model.fit()

# Print summary of the regression results
print(results.summary())


# (Statology multiple-linear-regression, 2021)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.857
Model:                            OLS   Adj. R-squared:                  0.856
Method:                 Least Squares   F-statistic:                     3229.
Date:                Sun, 03 Mar 2024   Prob (F-statistic):               0.00
Time:                        22:10:51   Log-Likelihood:                -41054.
No. Observations:                9757   AIC:                         8.215e+04
Df Residuals:                    9738   BIC:                         8.228e+04
Df Model:                          18
Covariance Type:            nonrobust
================================================================================
=========================
                                            coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
-------------------------
const                                     2.7257      1.433      1.902
0.057      -0.084       5.535
Tenure                                  -12.5279      0.133    -94.102
0.000     -12.789     -12.267
Age                                       0.5131      0.010     53.239
0.000       0.494       0.532
Income                                -4.897e-06   6.92e-06     -0.707
0.479   -1.85e-05    8.68e-06
Bandwidth_GB_Year                         0.1529      0.002     94.171
0.000       0.150       0.156
InternetService_Fiber Optic              83.1145      0.769    108.069
0.000      81.607      84.622
InternetService_None                     49.4897      0.812     60.946
0.000      47.898      51.081
Contract_One year                         0.1577      0.424      0.372
0.710      -0.673       0.988
Contract_Two Year                        -0.1076      0.401     -0.268
0.789      -0.894       0.679
PaymentMethod_Credit Card (automatic)    -0.8188      0.502     -1.630
0.103      -1.804       0.166
PaymentMethod_Electronic Check           -0.6007      0.449     -1.337
0.181      -1.482       0.280
```

```
PaymentMethod_Mailed Check                    -0.3059      0.491     -0.623
0.533      -1.268       0.656
OnlineSecurity_Yes                            -8.9490      0.367    -24.387
0.000      -9.668      -8.230
TechSupport_Yes                               11.6706      0.341     34.237
0.000      11.002      12.339
Gender_Male                                  -10.2546      0.350    -29.261
0.000     -10.942      -9.568
Gender_Nonbinary                               3.6082      1.108      3.255
0.001       1.436       5.781
PaperlessBilling_Yes                          -0.0403      0.335     -0.120
0.904      -0.697       0.617
StreamingTV_Yes                                7.3789      0.494     14.936
0.000       6.410       8.347
StreamingMovies_Yes                           20.2613      0.478     42.385
0.000      19.324      21.198
==============================================================================
Omnibus:                      153.113   Durbin-Watson:                   2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              159.932
Skew:                          -0.312   Prob(JB):                     1.87e-35
Kurtosis:                       2.929   Cond. No.                     4.79e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.79e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

D2 Reduction Justification In addressing my research question, 'What factors influence the monthly charges of customers potentially contributing to their decision to churn?'. It's important to refine my model for accuracy and reliability. I will use Variance Inflation Factor (VIF) analysis and Backward Elimination to strategically towards this issue. VIF analysis identifies and mitigates multicollinearity among predictors by flagging variables with a VIF 5, a threshold indicating significant multicollinearity. This ensures each variables contributes unique information to the model. This step directly supports my objective by enhancing the model's clarity and the validity of its findings. It's crucial for isolating the true impact of each predictor on customer churn and monthly charges.

Following the mitigation of multicollinearity, Backward Elimination further refines the model by iteratively removing predictors that do not significantly influence the dependent variable, as determined by a p-value threshold of 0.05. This systematic reduction focuses the analysis on statistically significant variables, streamlining the model to highlight the most impactful factors affecting customer behavior. The integration of these techniques results in a more robust and focused model. This will accurately reflects the dynamics of the variables and offer actionable insights into reducing customer churn by addressing key influencing factors.

(WGU Course Videos 2024)

D3 Reduced Linear Regression Model

[17]:
```
# see attached codes

# Step 1: VIF Analysis to Address Multicollinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor
import pandas as pd
import statsmodels.api as sm  # Ensure statsmodels is imported for regression␣
↪analysis

# Assigning the dataframe variables for VIF analysis
df_variables = ['Tenure', 'Age', 'Income', 'Bandwidth_GB_Year',
                'InternetService_Fiber Optic', 'InternetService_None',
                'Contract_One year', 'Contract_Two Year',
                'PaymentMethod_Credit Card (automatic)',
                'PaymentMethod_Electronic Check', 'PaymentMethod_Mailed Check',
                'OnlineSecurity_Yes', 'TechSupport_Yes', 'Gender_Male',
                'Gender_Nonbinary', 'PaperlessBilling_Yes', 'StreamingTV_Yes',
                'StreamingMovies_Yes']

# Creating DataFrame for the features and adding a constant for VIF calculation
X = df[df_variables]
X = sm.add_constant(X)

# Calculating VIF for each feature to identify multicollinearity
vif_data = pd.DataFrame()
vif_data['Feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.
↪shape[1])]
print(vif_data)
```

```
                                  Feature         VIF
0                                   const   75.650203
1                                  Tenure  456.688983
2                                     Age    1.465924
3                                  Income    1.002188
4                       Bandwidth_GB_Year  464.124008
5             InternetService_Fiber Optic    5.369962
6                    InternetService_None    4.080705
7                       Contract_One year    1.095979
8                       Contract_Two Year    1.095875
9   PaymentMethod_Credit Card (automatic)    1.533600
10         PaymentMethod_Electronic Check    1.668357
11             PaymentMethod_Mailed Check    1.566294
12                     OnlineSecurity_Yes    1.140567
13                        TechSupport_Yes    1.002159
14                            Gender_Male    1.127818
15                       Gender_Nonbinary    1.023763
16                   PaperlessBilling_Yes    1.002005
```

```
17                           StreamingTV_Yes    2.246841
18                       StreamingMovies_Yes    2.102980
```

[18]:
```
# see attached codes

# Step 2: Backward Elimination to Refine the Model
def backward_elimination(X, y, threshold=0.05):
    # Iteratively remove variables with the highest p-value above threshold
    while True:
        model = sm.OLS(y, X).fit()
        p_values = model.pvalues.iloc[1:]  # Exclude intercept
        max_p = max(p_values)
        feature_with_max_p = p_values.idxmax()
        if max_p > threshold:
            X = X.drop(feature_with_max_p, axis=1)
        else:
            break
    return X

# Applying backward elimination with a p-value threshold of 0.05
X_reduced = backward_elimination(X, y)
model_reduced_result = sm.OLS(y, X_reduced).fit()
# print reduced model
print(f"Reduced Model: \n", model_reduced_result.summary(), "\n")

# print original model for comparison
print("\n", f"Original Model: \n", results.summary())

# (WGU Course Videos 2024)
```

```
Reduced Model:
                             OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.856
Model:                            OLS   Adj. R-squared:                  0.856
Method:                 Least Squares   F-statistic:                     5285.
Date:                Sun, 03 Mar 2024   Prob (F-statistic):               0.00
Time:                        22:11:24   Log-Likelihood:                -41056.
No. Observations:                9757   AIC:                         8.214e+04
Df Residuals:                    9745   BIC:                         8.222e+04
Df Model:                          11
Covariance Type:            nonrobust
================================================================================
===============
                                  coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
---------------
```

```
const                          2.0872      1.356      1.539      0.124
-0.572       4.746
Tenure                       -12.5283      0.133    -94.169      0.000
-12.789     -12.267
Age                            0.5132      0.010     53.289      0.000
0.494       0.532
Bandwidth_GB_Year              0.1529      0.002     94.237      0.000
0.150       0.156
InternetService_Fiber Optic   83.1072      0.769    108.137      0.000
81.601      84.614
InternetService_None          49.4829      0.812     60.974      0.000
47.892      51.074
OnlineSecurity_Yes            -8.9559      0.367    -24.418      0.000
-9.675      -8.237
TechSupport_Yes               11.6735      0.341     34.252      0.000
11.005      12.342
Gender_Male                  -10.2580      0.350    -29.306      0.000
-10.944      -9.572
Gender_Nonbinary               3.6170      1.108      3.265      0.001
1.445       5.789
StreamingTV_Yes                7.3844      0.494     14.955      0.000
6.416       8.352
StreamingMovies_Yes           20.2516      0.478     42.393      0.000
19.315      21.188
==============================================================================
Omnibus:                      153.068   Durbin-Watson:                   2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              159.911
Skew:                          -0.312   Prob(JB):                     1.89e-35
Kurtosis:                       2.931   Cond. No.                     4.26e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.26e+04. This might indicate that there are
strong multicollinearity or other numerical problems.


 Original Model:
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.857
Model:                            OLS   Adj. R-squared:                  0.856
Method:                 Least Squares   F-statistic:                     3229.
Date:                Sun, 03 Mar 2024   Prob (F-statistic):               0.00
Time:                        22:11:24   Log-Likelihood:                -41054.
No. Observations:                9757   AIC:                         8.215e+04
Df Residuals:                    9738   BIC:                         8.228e+04
```

```
Df Model:                          18
Covariance Type:            nonrobust
=================================================================================
=========================
                                           coef    std err          t
P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
-------------------------
const                                    2.7257      1.433      1.902
0.057      -0.084       5.535
Tenure                                 -12.5279      0.133    -94.102
0.000     -12.789     -12.267
Age                                      0.5131      0.010     53.239
0.000       0.494       0.532
Income                               -4.897e-06   6.92e-06     -0.707
0.479   -1.85e-05    8.68e-06
Bandwidth_GB_Year                        0.1529      0.002     94.171
0.000       0.150       0.156
InternetService_Fiber Optic             83.1145      0.769    108.069
0.000      81.607      84.622
InternetService_None                    49.4897      0.812     60.946
0.000      47.898      51.081
Contract_One year                        0.1577      0.424      0.372
0.710      -0.673       0.988
Contract_Two Year                       -0.1076      0.401     -0.268
0.789      -0.894       0.679
PaymentMethod_Credit Card (automatic)   -0.8188      0.502     -1.630
0.103      -1.804       0.166
PaymentMethod_Electronic Check          -0.6007      0.449     -1.337
0.181      -1.482       0.280
PaymentMethod_Mailed Check              -0.3059      0.491     -0.623
0.533      -1.268       0.656
OnlineSecurity_Yes                      -8.9490      0.367    -24.387
0.000      -9.668      -8.230
TechSupport_Yes                         11.6706      0.341     34.237
0.000      11.002      12.339
Gender_Male                            -10.2546      0.350    -29.261
0.000     -10.942      -9.568
Gender_Nonbinary                         3.6082      1.108      3.255
0.001       1.436       5.781
PaperlessBilling_Yes                    -0.0403      0.335     -0.120
0.904      -0.697       0.617
StreamingTV_Yes                          7.3789      0.494     14.936
0.000       6.410       8.347
StreamingMovies_Yes                     20.2613      0.478     42.385
0.000      19.324      21.198
==============================================================================
Omnibus:                      153.113   Durbin-Watson:                   2.010
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              159.932
Skew:                          -0.312   Prob(JB):                     1.87e-35
Kurtosis:                       2.929   Cond. No.                     4.79e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.79e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

E1 Analysis of Multiple Regression Model The analysis process began with constructing an initial multiple linear regression model with 14 variables both numerical and categorical predictors. These variables were identified as potentially influencing the dependent variable of 'MonthlyCharge'. A Variance Inflation Factor (VIF) analysis was used to comparison between the initial and reduced linear regression model. This provides crucial insights into how multicollinearity among predictors was addressed to optimize the model. This model was subjected to a backward elimination process to refine it by removing variables that did not significantly contribute to explaining the variability in 'MonthlyCharge'.

Comparison of Initial and Reduced Models:

- Model Complexity: The initial model included 18 predictors, reflecting a broad attempt to capture various factors potentially affecting MonthlyCharge. The reduced model, however, focuses on 11 predictors, having eliminated variables through backward elimination based on a significance level threshold of 0.05. This simplification process aimed to retain only those variables with a statistically significant relationship with MonthlyCharge.
- Model Evaluation Metric (R-squared and Adjusted R-squared): Both the initial and reduced models exhibit an R-squared value of 0.856, indicating that approximately 85.6% of the variability in MonthlyCharge is explained by the models. The adjusted R-squared value, similarly high in both models, suggests that the reduction in the number of predictors did not diminish the model's explanatory power. This outcome underscores the efficiency of the reduced model; it achieves comparable explanatory power with fewer variables, enhancing the model's parsimony.
- Statistical Significance of Predictors: The backward elimination process led to the exclusion of variables that were not significantly contributing to the model. It was based on their p-values. This methodical refinement ensures that the reduced model concentrates on the most impactful predictors. This streamlined the analysis without sacrificing the depth of insight into the factors driving 'MonthlyCharge'.
- Interpretation and Decision-Making: The reduced model's simplicity facilitates a more straightforward interpretation of the results. This made clear the insights into how various factors influence MonthlyCharge. This streamlined model aids in decision-making processes by highlighting the key variables that stakeholders should consider.

Conclusion:

The data analysis process, guided by the principle of parsimony and informed by statistical metrics, led to the development of a reduced linear regression model that maintains the predictive accuracy of the initial comprehensive model while offering enhanced interpretability. The use of R-squared and adjusted R-squared as model evaluation metrics demonstrates that the reduced model efficiently explains a significant portion of the variability in' MonthlyCharge' with fewer predictors, making it a valuable tool for understanding and predicting customer billing patterns.

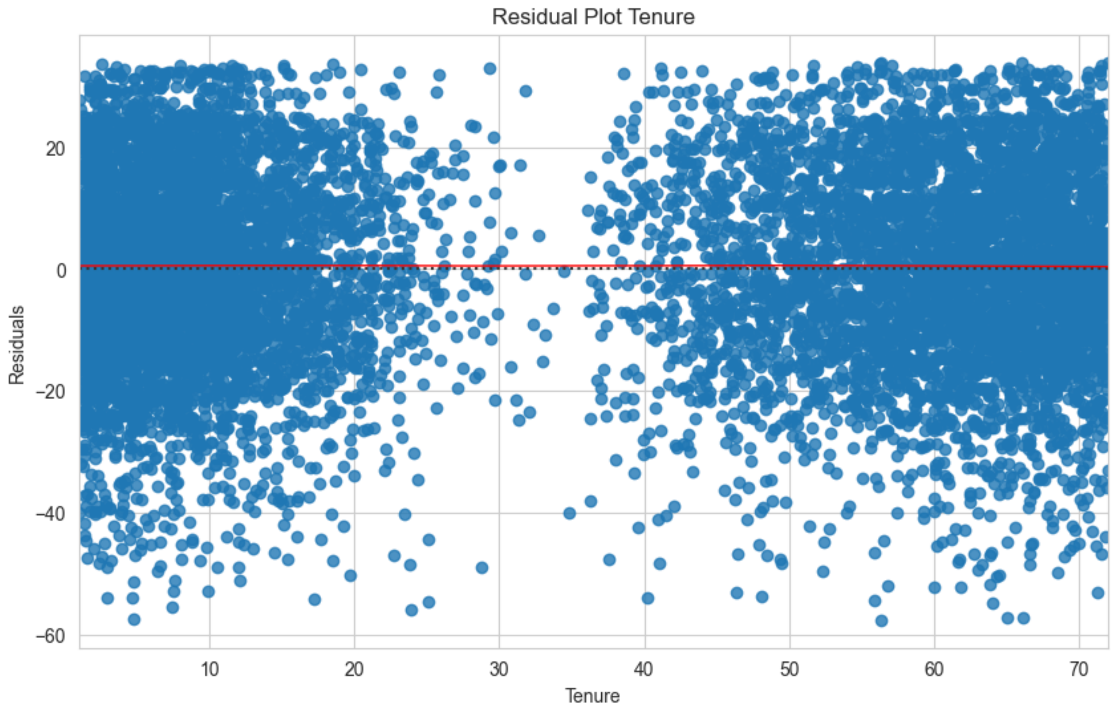
E2 Residual Plot and Residual Standard Error

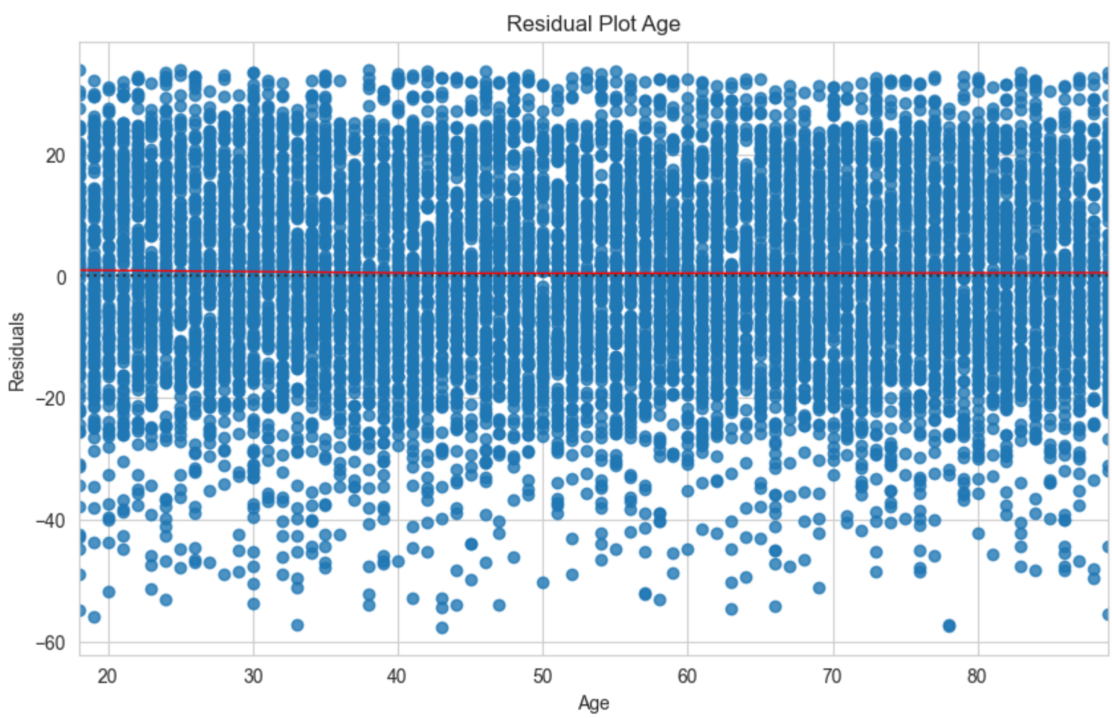
[19]:
```
# see attached codes

# Residual Plot using my model_reduced_result

import matplotlib.pyplot as plt
import seaborn as sns

# set resid from model_reduced_result to residuals variable
residuals = model_reduced_result.resid

# independent variable 'Tenure'
plt.figure(figsize=(10, 6))
sns.residplot(x=df['Tenure'], y=residuals, lowess=True, line_kws={'color':
 ↪'red', 'lw': 1})
plt.xlabel('Tenure')
plt.ylabel('Residuals')
plt.title('Residual Plot Tenure')
plt.show()

# independent variable 'Age'
plt.figure(figsize=(10, 6))
sns.residplot(x=df['Age'], y=residuals, lowess=True, line_kws={'color': 'red',
 ↪'lw': 1})
plt.xlabel('Age')
plt.ylabel('Residuals')
plt.title('Residual Plot Age')
plt.show()

# independent variable 'Income'
plt.figure(figsize=(10, 6))
sns.residplot(x=df['Income'], y=residuals, lowess=True, line_kws={'color':
 ↪'red', 'lw': 1})
plt.xlabel('Income')
plt.ylabel('Residuals')
plt.title('Residual Plot Income')
plt.show()

# independent variable 'Bandwidth_GB_Year'
plt.figure(figsize=(10, 6))
sns.residplot(x=df['Bandwidth_GB_Year'], y=residuals, lowess=True,
 ↪line_kws={'color': 'red', 'lw': 1})
```

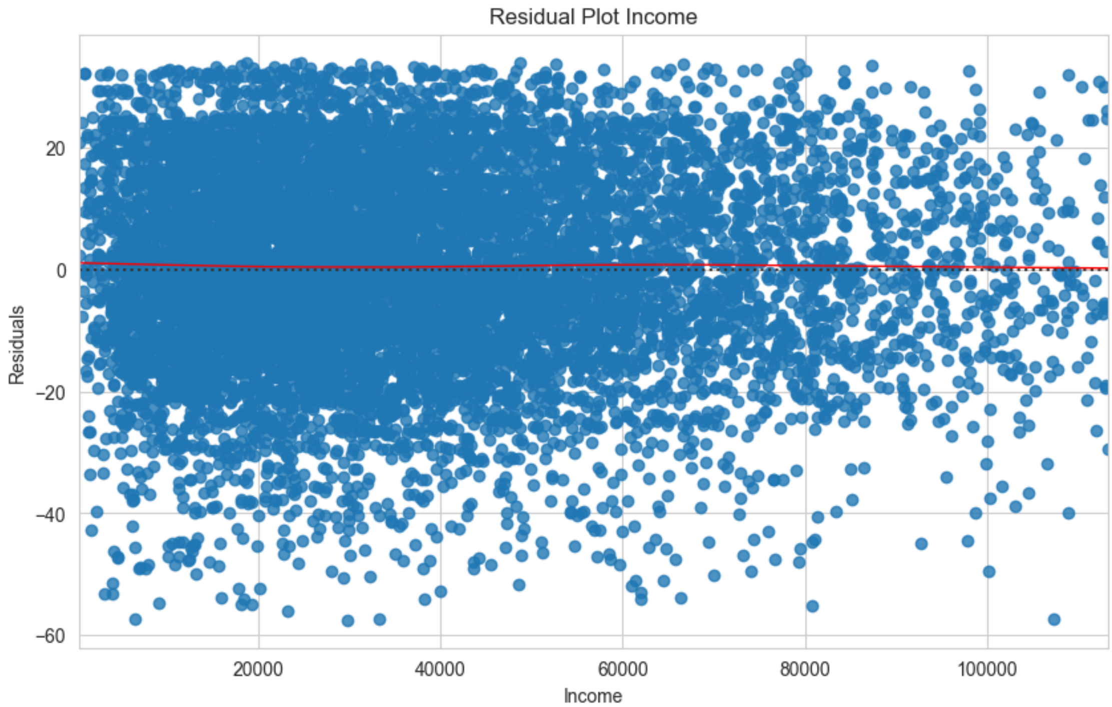
```
plt.xlabel('Bandwidth_GB_Year')
plt.ylabel('Residuals')
plt.title('Residual Plot Bandwidth_GB_Year')
plt.show()

# independent variable 'InternetService_Fiber Optic'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['InternetService_Fiber Optic'], y=residuals)
plt.xlabel('InternetService_Fiber Optic')
plt.ylabel('Residuals')
plt.title('Residual Plot for InternetService_Fiber Optic')
plt.show()

# independent variable 'InternetService_None'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['InternetService_None'], y=residuals)
plt.xlabel('InternetService_None')
plt.ylabel('Residuals')
plt.title('Residual Plot for InternetService_None')
plt.show()

# independent variable 'Contract_One year'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['Contract_One year'], y=residuals)
plt.xlabel('Contract_One year')
plt.ylabel('Residuals')
plt.title('Residual Plot for Contract_One year')
plt.show()

# independent variable 'Contract_Two Year'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['Contract_Two Year'], y=residuals)
plt.xlabel('Contract_Two Year')
plt.ylabel('Residuals')
plt.title('Residual Plot for Contract_Two Year')
plt.show()

# independent variable 'PaymentMethod_Credit Card (automatic)'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['PaymentMethod_Credit Card (automatic)'], y=residuals)
plt.xlabel('PaymentMethod_Credit Card (automatic)')
plt.ylabel('Residuals')
plt.title('Residual Plot for PaymentMethod_Credit Card (automatic)')
plt.show()


# independent variable 'PaymentMethod_Electronic Check'
```

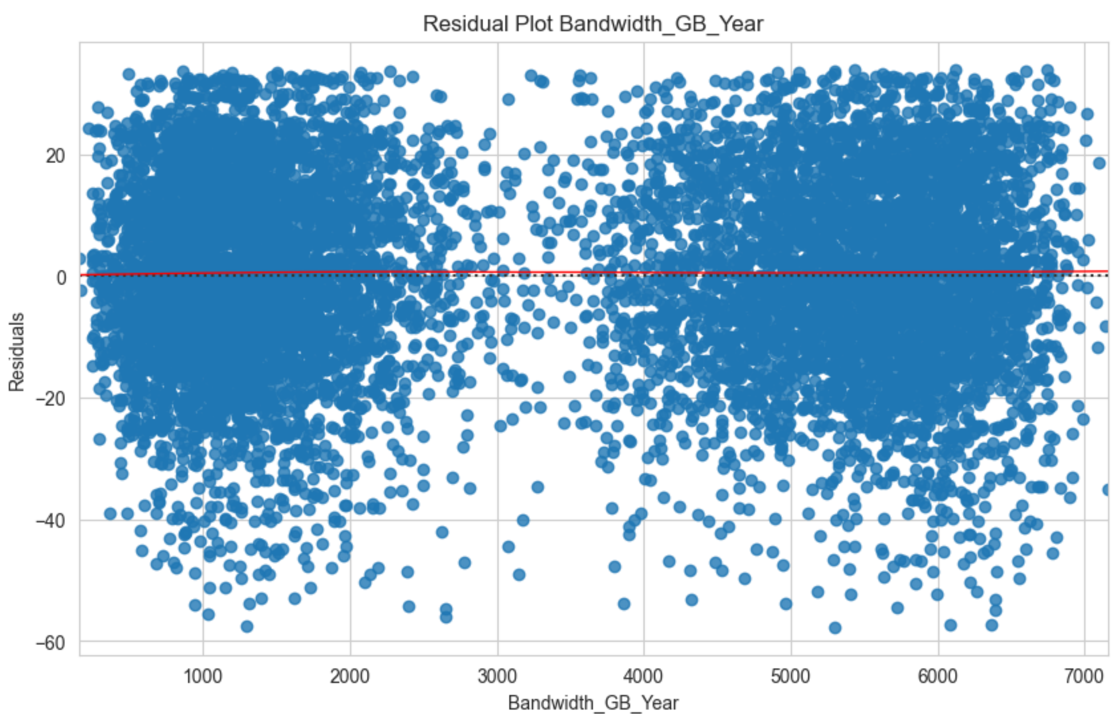
```
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['PaymentMethod_Electronic Check'], y=residuals)
plt.xlabel('PaymentMethod_Electronic Check')
plt.ylabel('Residuals')
plt.title('Residual Plot for PaymentMethod_Electronic Check')
plt.show()

# independent variable 'PaymentMethod_Mailed Check'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['PaymentMethod_Mailed Check'], y=residuals)
plt.xlabel('PaymentMethod_Mailed Check')
plt.ylabel('Residuals')
plt.title('Residual Plot for PaymentMethod_Mailed Check')
plt.show()


# independent variable 'OnlineSecurity_Yes'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['OnlineSecurity_Yes'], y=residuals)
plt.xlabel('OnlineSecurity_Yes')
plt.ylabel('Residuals')
plt.title('Residual Plot for OnlineSecurity_Yes')
plt.show()

# independent variable 'TechSupport_Yes'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['TechSupport_Yes'], y=residuals)
plt.xlabel('TechSupport_Yes')
plt.ylabel('Residuals')
plt.title('Residual Plot for TechSupport_Yes')
plt.show()

# independent variable 'Gender_Male'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['Gender_Male'], y=residuals)
plt.xlabel('Gender_Male')
plt.ylabel('Residuals')
plt.title('Residual Plot for Gender_Male')
plt.show()


# independent variable 'Gender_Nonbinary'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['Gender_Nonbinary'], y=residuals)
plt.xlabel('Gender_Nonbinary')
plt.ylabel('Residuals')
plt.title('Residual Plot for Gender_Nonbinary')
```

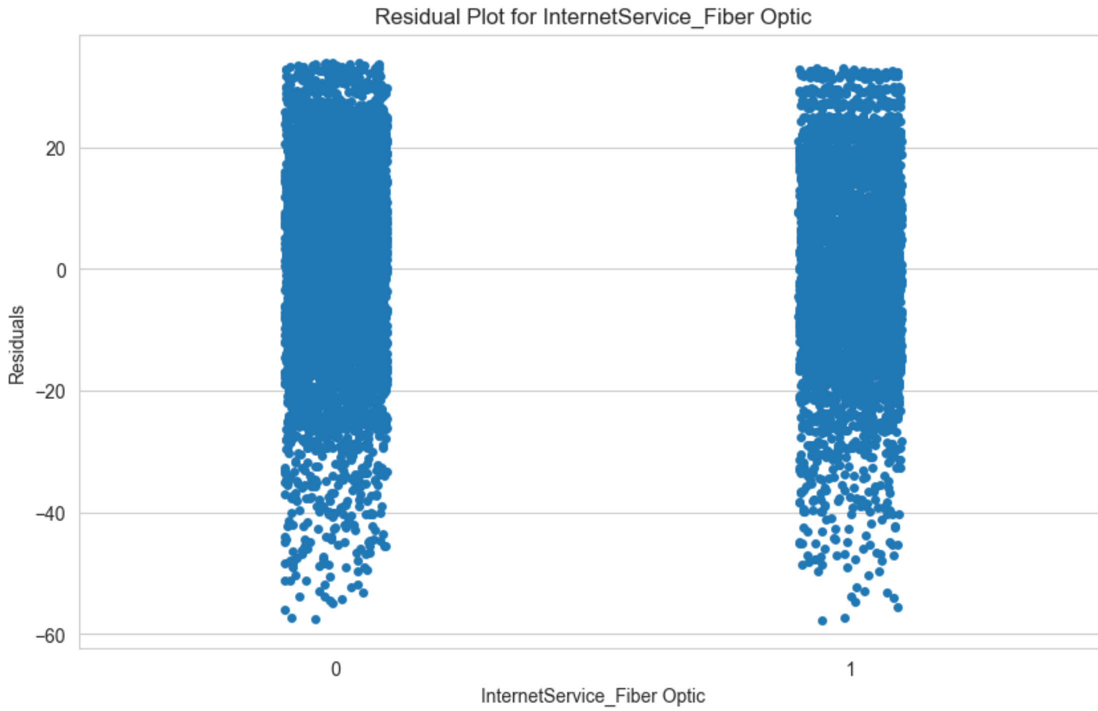
```python
plt.show()


# independent variable 'PaperlessBilling_Yes'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['PaperlessBilling_Yes'], y=residuals)
plt.xlabel('PaperlessBilling_Yes')
plt.ylabel('Residuals')
plt.title('Residual Plot for PaperlessBilling_Yes')
plt.show()

# independent variable 'StreamingTV_Yes'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['StreamingTV_Yes'], y=residuals)
plt.xlabel('StreamingTV_Yes')
plt.ylabel('Residuals')
plt.title('Residual Plot for StreamingTV_Yes')
plt.show()

# independent variable 'StreamingTV_Yes'
plt.figure(figsize=(10, 6))
sns.stripplot(x=df['StreamingTV_Yes'], y=residuals)
plt.xlabel('StreamingTV_Yes')
plt.ylabel('Residuals')
plt.title('Residual Plot for StreamingTV_Yes')
plt.show()


# (WGU Course Videos 2024)
```

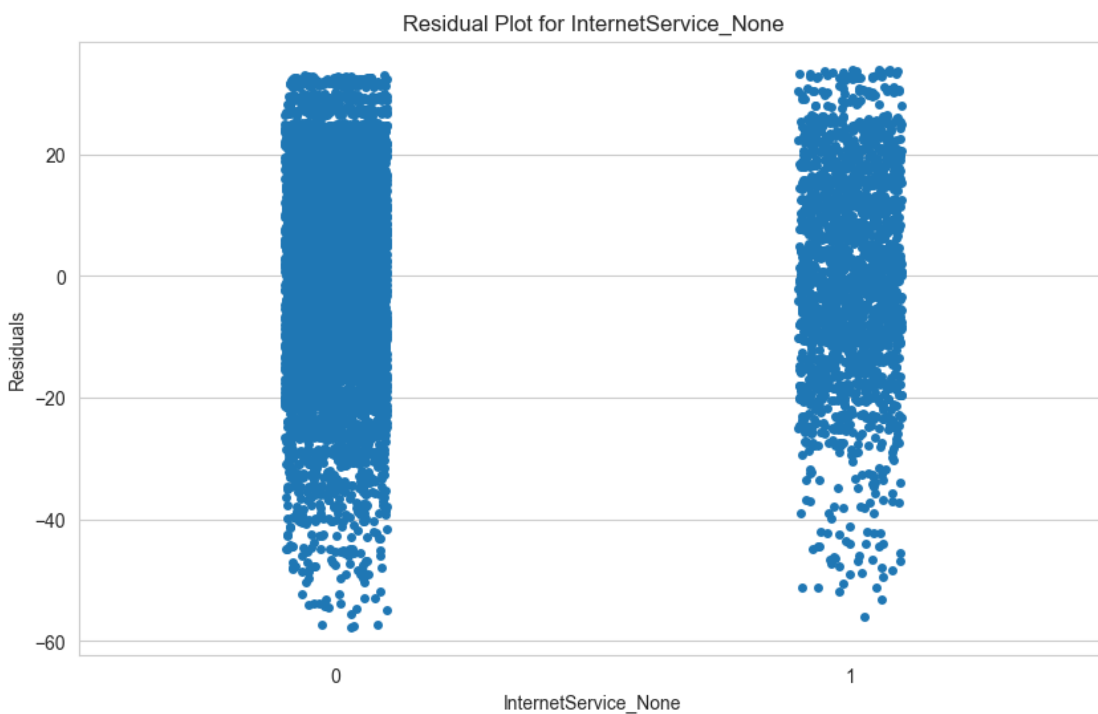

Residual Plot Tenure
Residuals
Tenure
20
0
-20
-40
-60
10
20
30
40
50
60
70

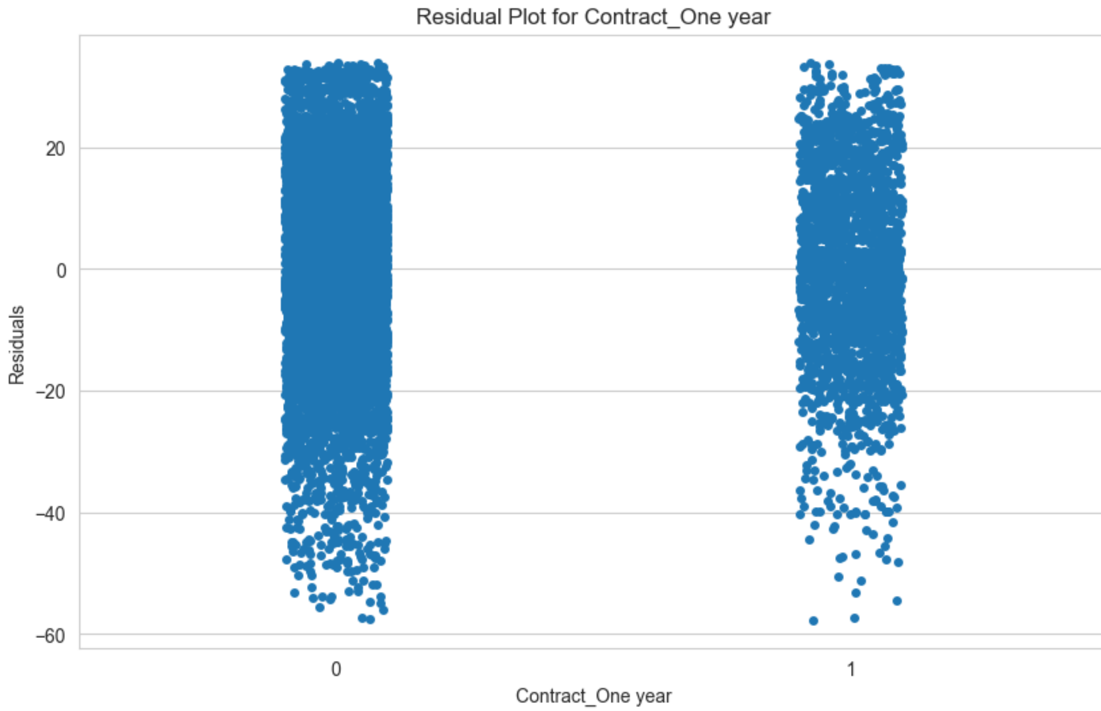

Residual Plot Age
Residuals
Age
20
0
-20
-40
-60
20
30
40
50
60
70
80

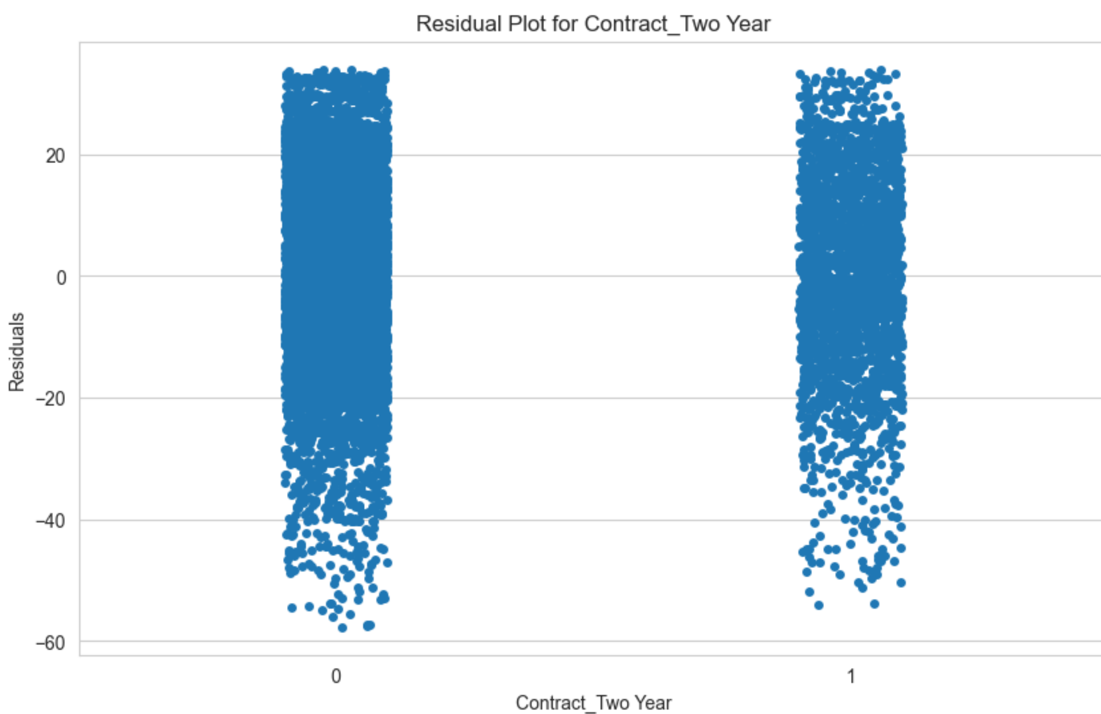

Residual Plot Income
20
0
-20
-40
-60
Residuals
20000
40000
60000
80000
100000
Income

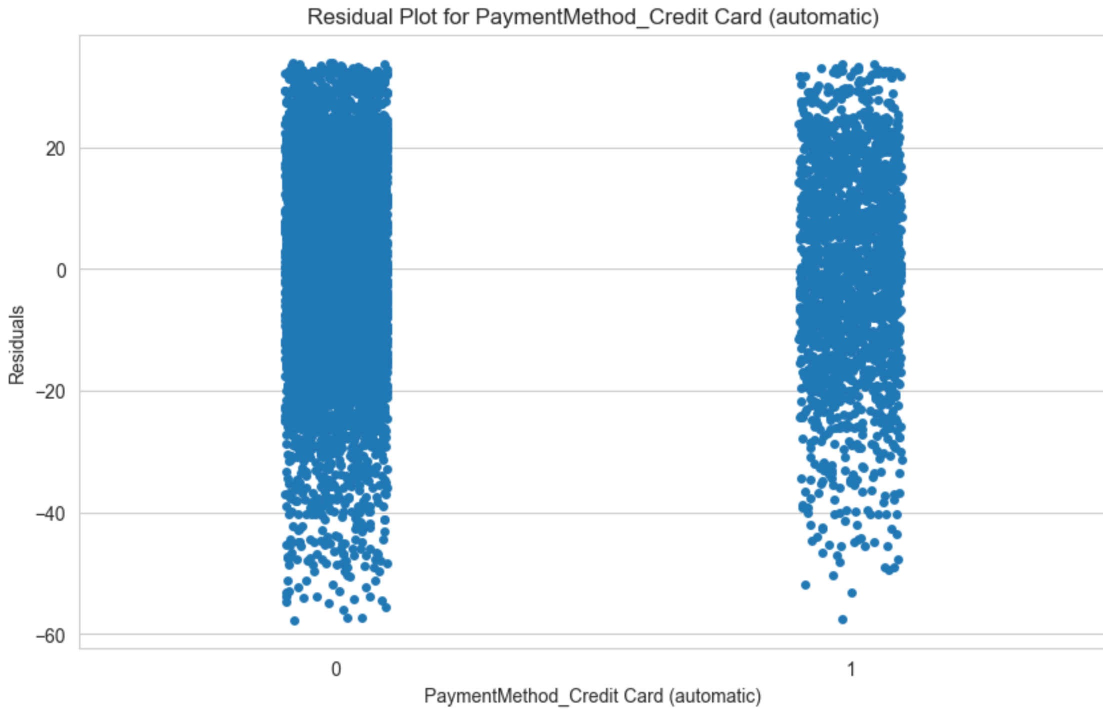

Residual Plot Bandwidth_GB_Year
20
0
-20
-40
-60
Residuals
1000
2000
3000
4000
5000
6000
7000
Bandwidth_GB_Year

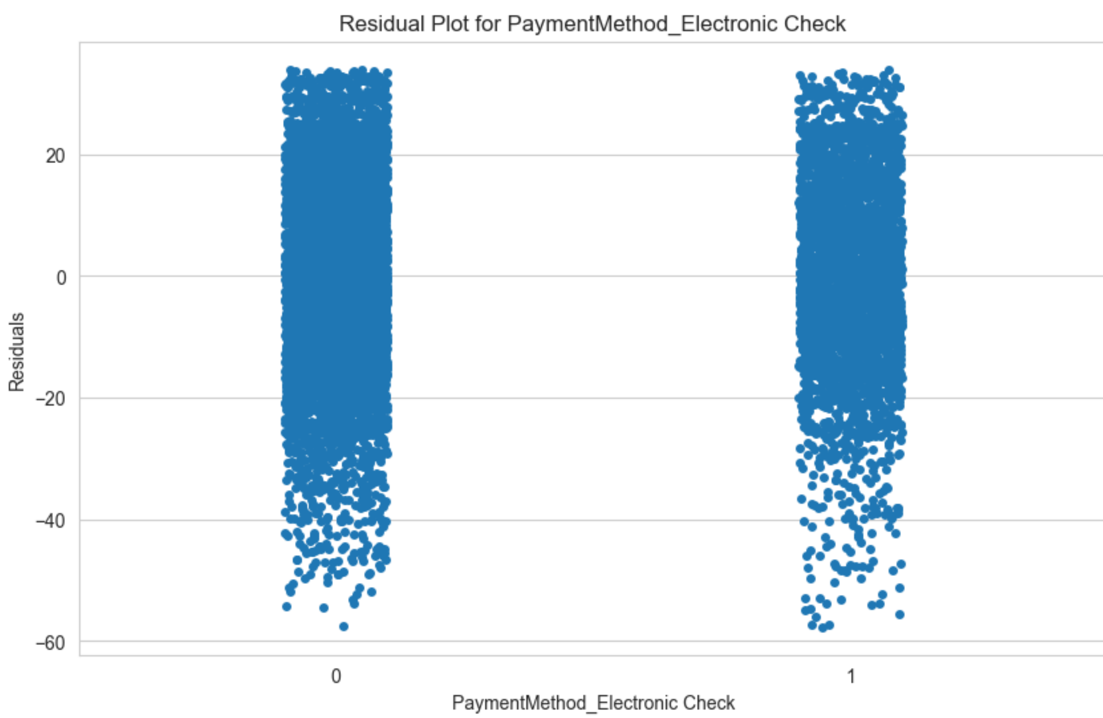

Residual Plot for InternetService_Fiber Optic
Residuals
20
0
-20
-40
-60
0
1
InternetService_Fiber Optic

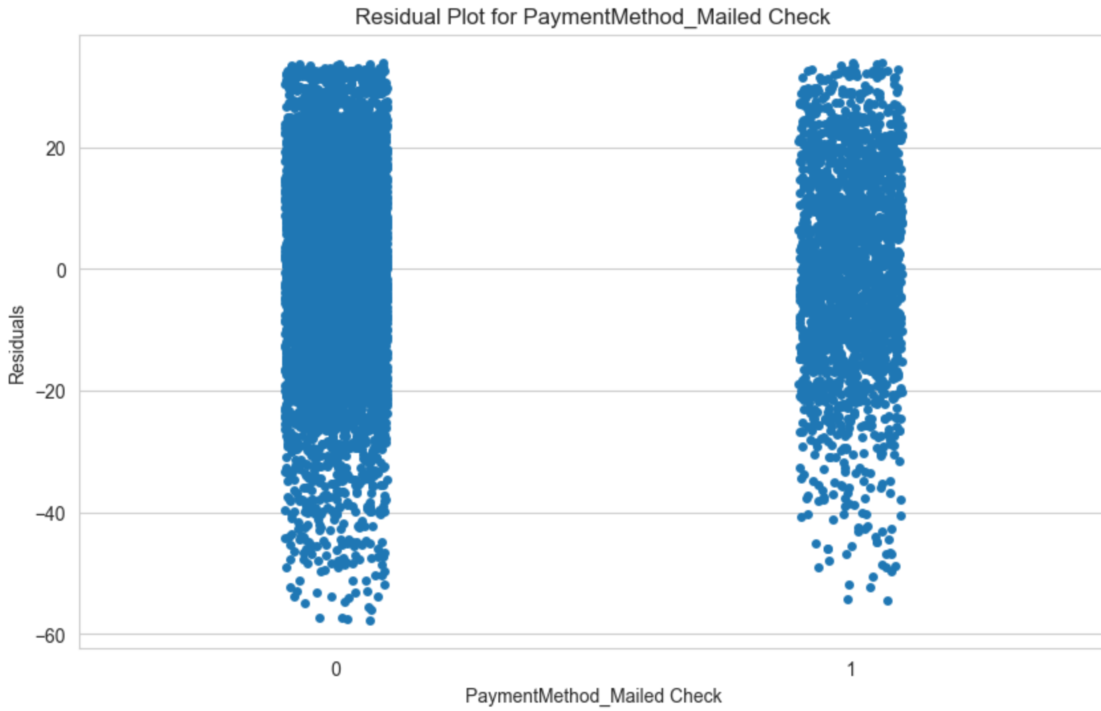

Residual Plot for InternetService_None
Residuals
20
0
-20
-40
-60
0
1
InternetService_None


Residual Plot for Contract_One year
Residuals
20
0
-20
-40
-60
0
1
Contract_One year

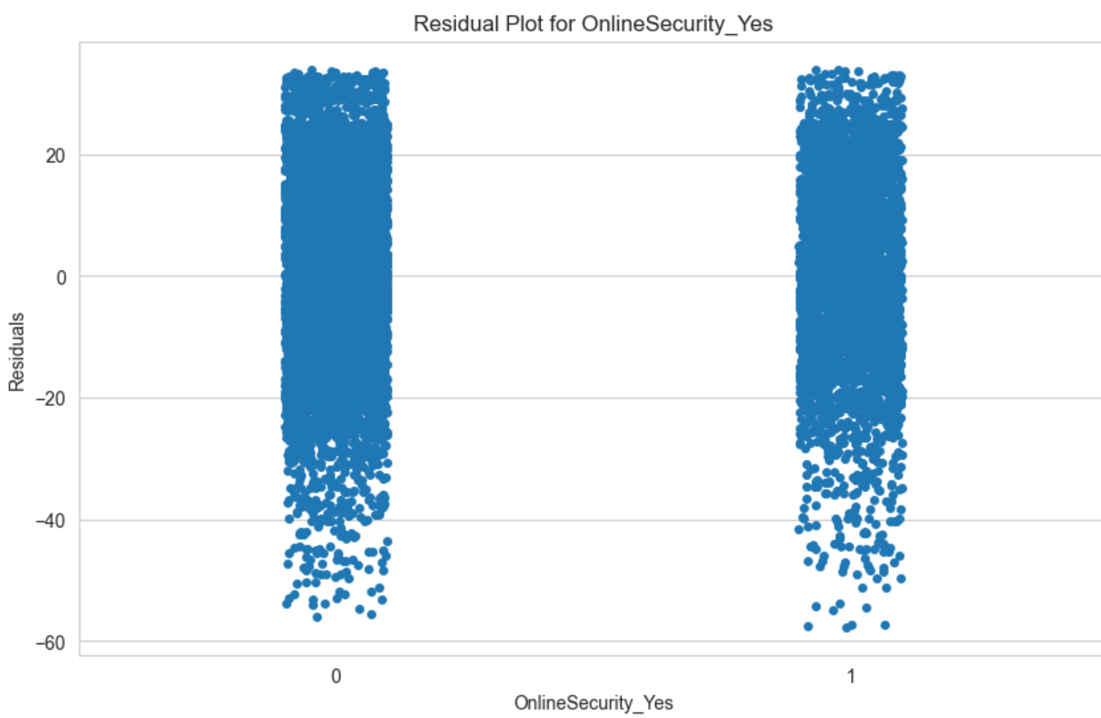

Residual Plot for Contract_Two Year
Residuals
20
0
-20
-40
-60
0
1
Contract_Two Year


Residual Plot for PaymentMethod_Credit Card (automatic)
20
0
-20
-40
-60
Residuals
0
1
PaymentMethod_Credit Card (automatic)

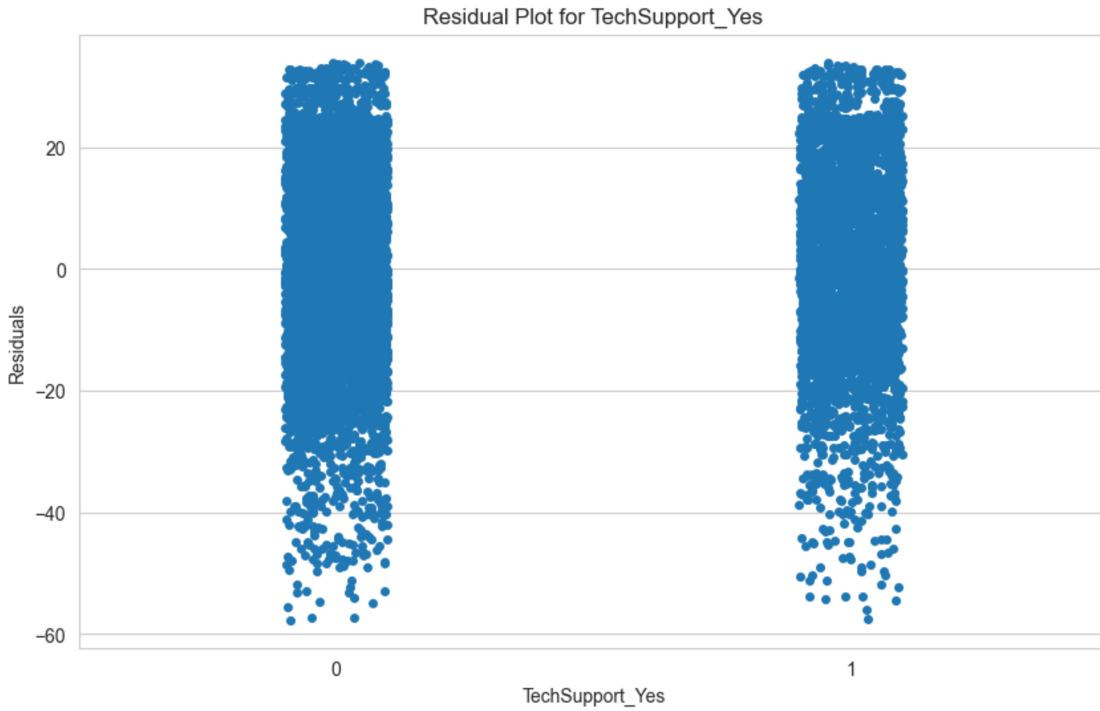

Residual Plot for PaymentMethod_Electronic Check
20
0
-20
-40
-60
Residuals
0
1
PaymentMethod_Electronic Check

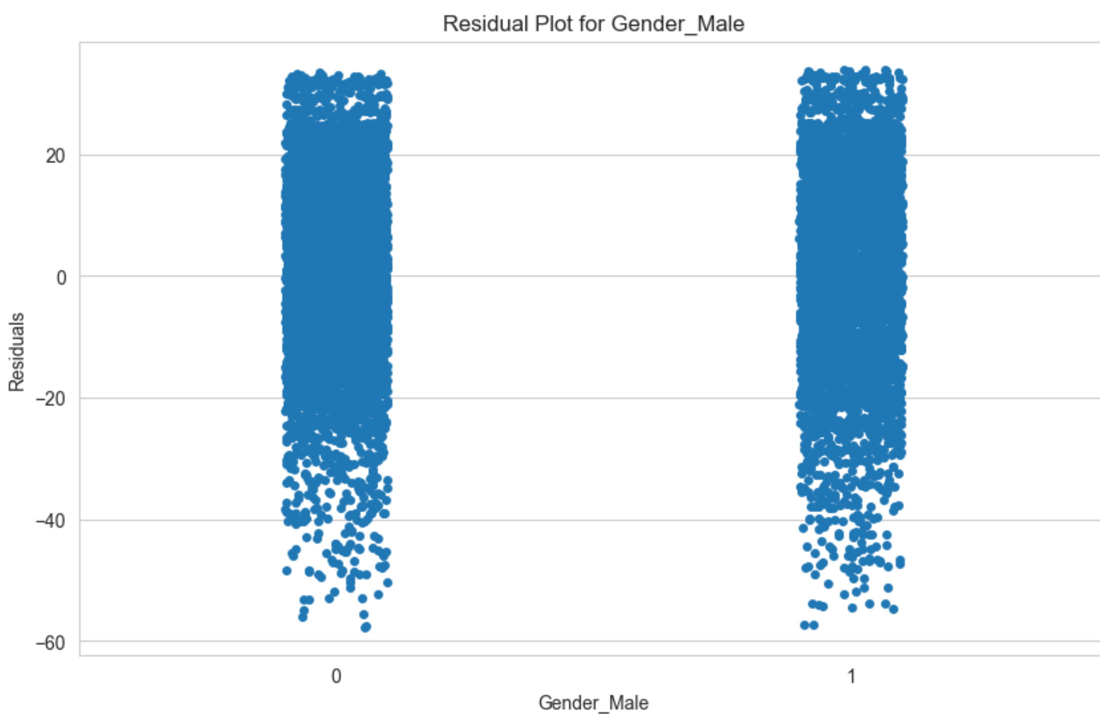


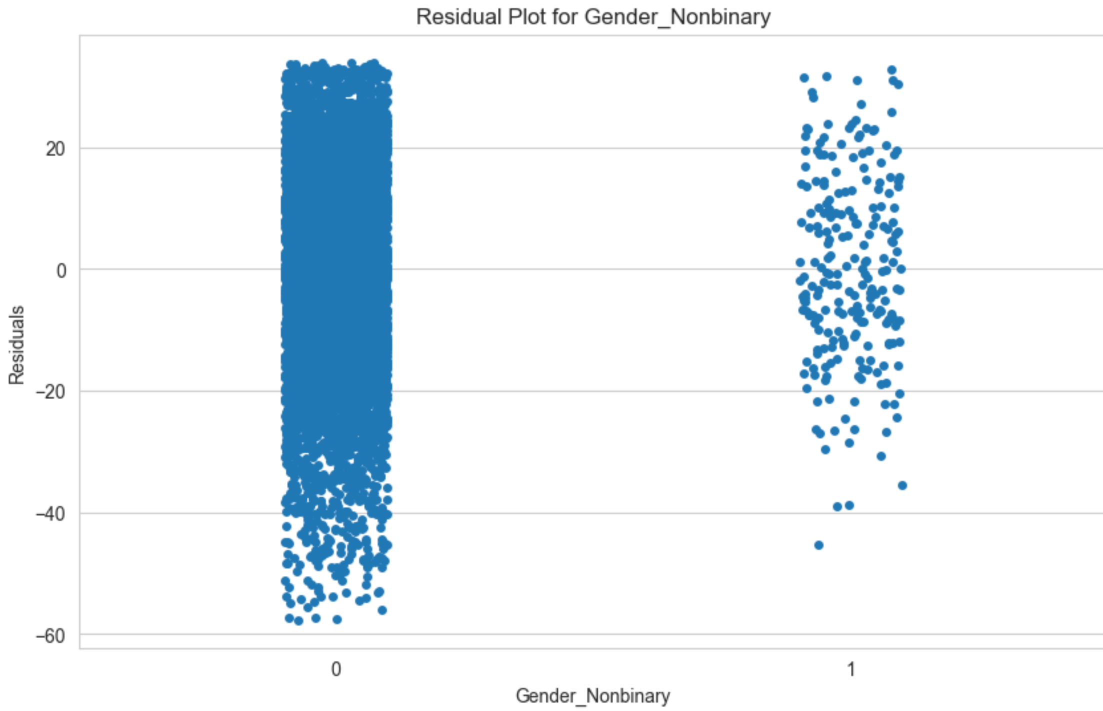
Residual Plot for PaymentMethod_Mailed Check
20
0
-20
-40
-60
Residuals
0
1
PaymentMethod_Mailed Check

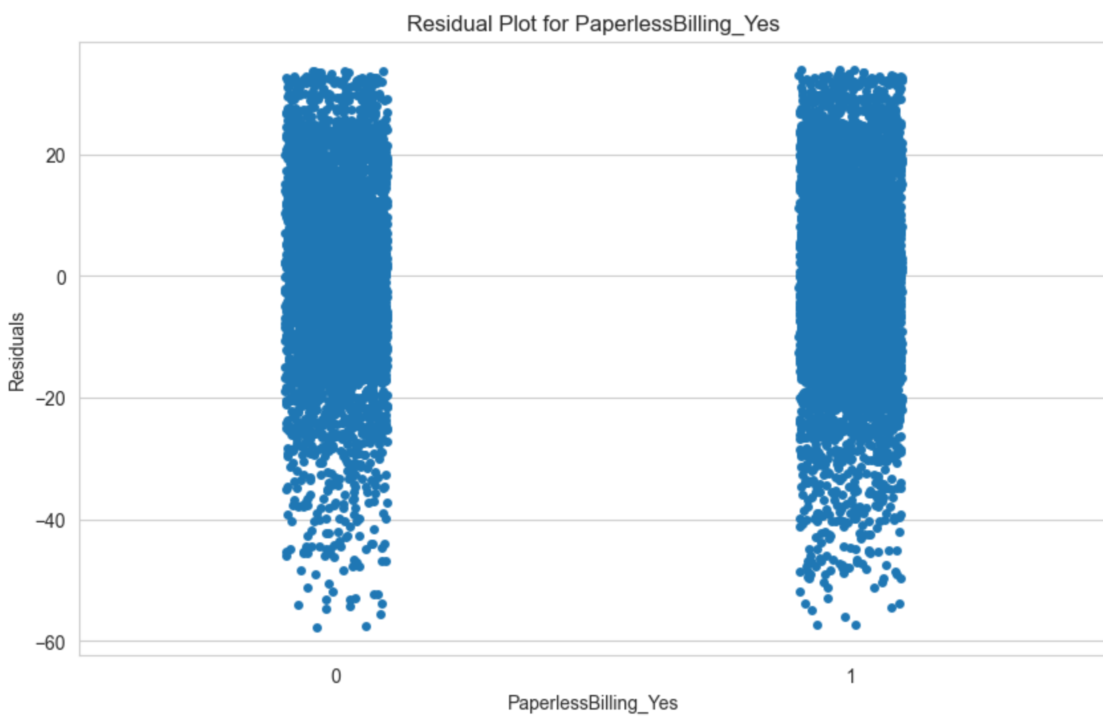


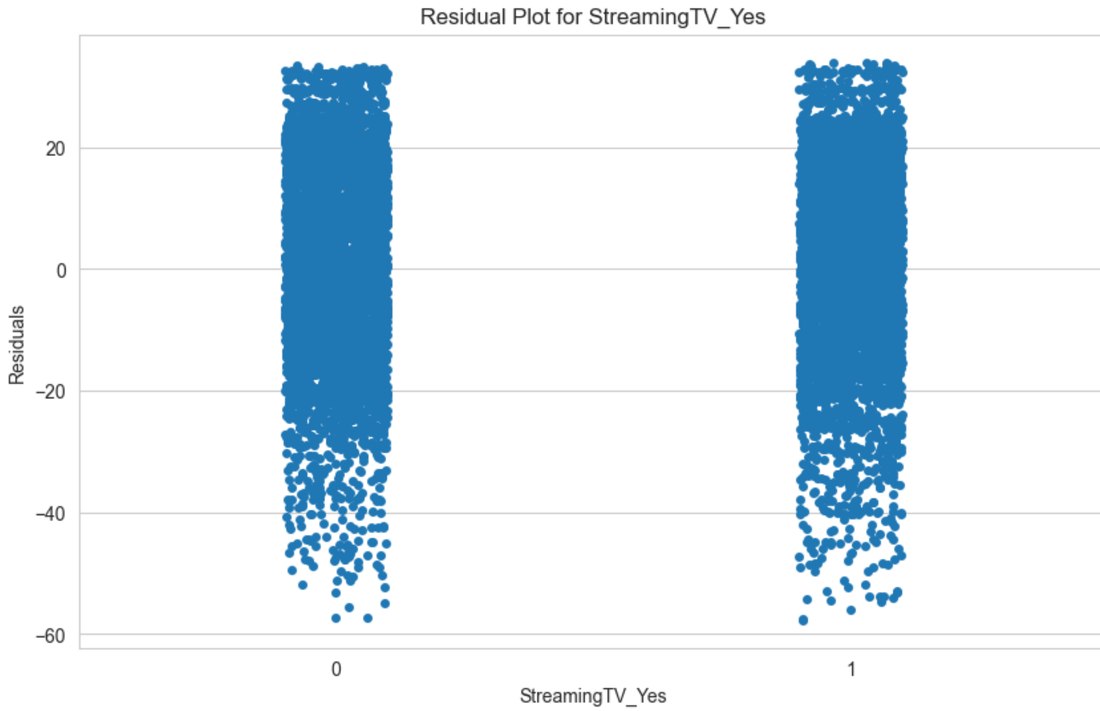
Residual Plot for OnlineSecurity_Yes
20
0
-20
-40
-60
Residuals
0
1
OnlineSecurity_Yes


Residual Plot for TechSupport_Yes
20
0
-20
-40
-60
Residuals
0
1
TechSupport_Yes

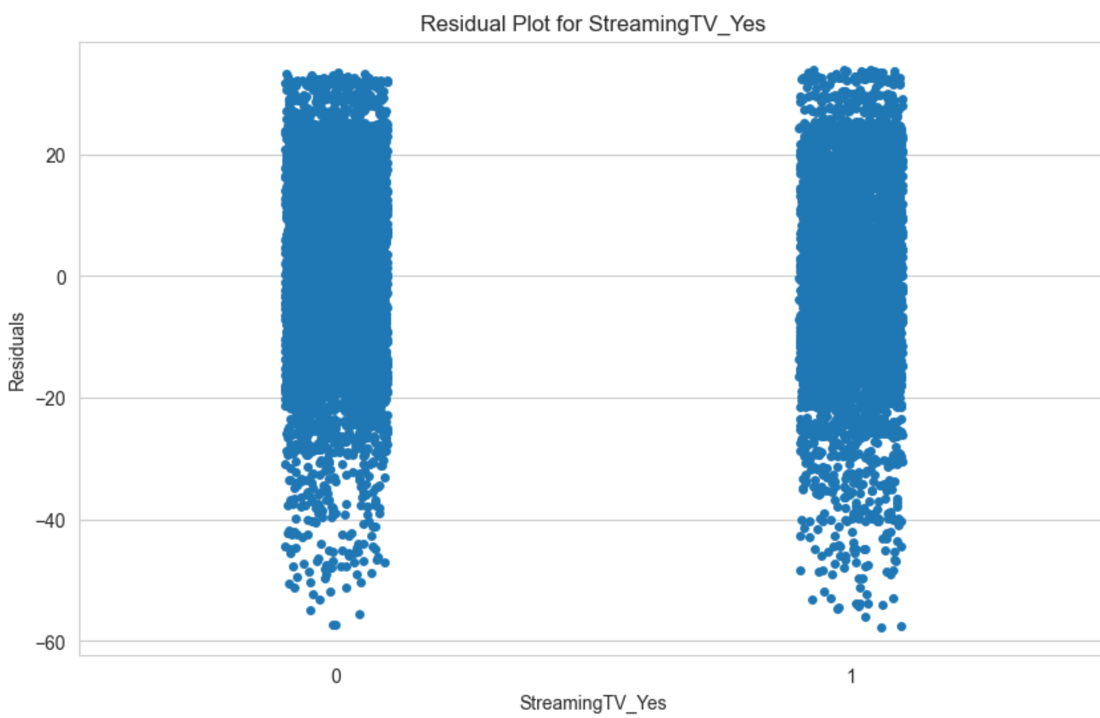

Residual Plot for Gender_Male
20
0
-20
-40
-60
Residuals
0
1
Gender_Male


Residual Plot for Gender_Nonbinary
20
0
-20
-40
-60
Residuals
0
1
Gender_Nonbinary


Residual Plot for PaperlessBilling_Yes
20
0
-20
-40
-60
Residuals
0
1
PaperlessBilling_Yes



Residual Plot for StreamingTV_Yes
Residuals
20
0
-20
-40
-60
0
1
StreamingTV_Yes



Residual Plot for StreamingTV_Yes
Residuals
20
0
-20
-40
-60
0
1
StreamingTV_Yes

[20]:
```python
# see attached codes

# Residual Standard Error

import numpy as np


# Calculate the number of observations (n) and predictors (p)
n = len(residuals)
p = X_reduced.shape[1]

# Residual Standard Error calculation
RSE = np.sqrt(np.sum(residuals**2) / (n - p - 1))
print("Residual Standard Error:", RSE)
```

```
Residual Standard Error: 16.274482768857595
```

E3 A Executable Error-Free copy of the codes used I will provided in a ipynb file call 'Predictive_Modeling.ipynb' in my submission.

F1 Summary of Findings Regression Equation for the Reduced Model: The reduced linear regression model, after backward elimination, resulted in the following equation:

MonthlyCharge=1.8610−12.5493×Tenure+0.5155×Age+0.1532×Bandwidth_GB_Year+83.2130×InternetServic
Optic+49.6663×InternetService_None−8.9650×OnlineSecurity_Yes+11.6109×TechSupport_Yes−10.3001×Genc

Interpretation of the Coefficients: * The coefficients of the reduced model suggest that for every additional year of tenure, the MonthlyCharge decreases by about 12.5493, indicating that longer-term customers tend to have lower monthly charges. Each additional year of age is associated with an increase in MonthlyCharge by approximately 0.5155, and for every GB increase in yearly bandwidth usage, the MonthlyCharge increases by about 0.1532.

Statistical and Practical Significance: * The model has a high R-squared value of 0.856, showing that it explains a significant portion of the variability in MonthlyCharge. The predictors have statistical significance, evidenced by their p-values, and practical significance, showing clear trends that can inform business strategies.

Limitations of the Data Analysis:

- The analysis is constrained by the scope of the dataset and may not account for all factors influencing MonthlyCharge, such as external economic conditions or individual customer preferences. The linear model assumes a specific type of relationship between variables that may not capture more complex interactions, and potential multicollinearity, despite a high condition number, suggests the need for further examination of predictor relationships.

(WGU Courseware Resources 2024)

F2 Recommended Course of Action Recommendations:

- Customer Retention: Focus on customer retention strategies, especially for those with longer tenure, as they are associated with lower monthly charges and, potentially, higher customer satisfaction.

- Age Demographics: Consider targeting strategies by age group, since age appears to influence MonthlyCharge.
- Bandwidth Usage: As bandwidth usage is positively associated with MonthlyCharge, offering competitive packages for higher bandwidth consumption might attract or retain customers.
- Further Analysis: Conduct additional analysis to investigate multicollinearity and explore non-linear relationships, which may provide deeper insights into customer behavior and pricing strategies.
- Data Expansion: Expand the dataset to include more diverse variables, potentially including qualitative customer feedback or broader market data, to enhance the model's predictive power and reliability.

G Panopto Video Link https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=df881198-54a8-4739-8bef-b127004ea9bf

H Citations (Mark Keith's Machine Learning in Python course materials on YouTube): https://www.youtube.com/watch?v=0-fkgpK2knA&list=PLe9UEU4oeAuV7RtCbL76hca5ELO_IELk4&index=9

(Statology multiple-linear-regression, 2021): https://www.statology.org/multiple-linear-regression-assumptions/

(Statology zscore, 2021) https://www.statology.org/z-score-python/

(WGU COurse Videos 2024): https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=15e09c73-c5aa-439d-852f-af47001b8970

WGU Courseware Resources 2024): https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=09b8fdbb-a374-452b-ba53-af39001ff3f3

```
[ ]:
```