D208 Performance Assessment Task 1

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0.0.1 A. Purpose of Analysis

A1. Research Question. Which independent variables had the most significant impact on customers' `MonthlyCharge`?

A2. Objectives The objective of the analysis was to identify which independent variables significantly affected `MonthlyCharge`. Customers who were price sensitive would be more likely to churn if their monthly payments were too high. By determining which variables influenced `MonthlyCharge`, stakeholders could run various marketing campaigns to reduce cost for customers. This analysis could also lead to a better understanding of how the dependent variable changes based on the independent variables.

0.0.2 B. Multiple Regression Description

B1. Summarize Assumptions To perform multiple linear regression, five assumptions must be met (Bobbitt, 2021b):

1. Linear relationship between independent and dependent variable.
2. Independent variables are not highly correlated with each other.
3. Observations are independent.
4. Residuals have constant variance.
5. Residuals are normally distributed.

B2. Tool Benefits I chose Python for this project because it is a flexible and powerful programming language. The syntax was also easy to read. On top of that, Python had a great ecosystem of libraries that made data analysis tasks much easier (Rane, 2021). The libraries used in this project were:

- `NumPy`: high-performance numerical computation.
- `Pandas`: fats and flexible dataframes.
- `Matplotlib` and `Seaborn`: data visualizations.
- `Statsmodels`: classes and functions for different statistical models.

The environment for this project was Conda, an open-source package manager and environment management system.

B3. Multiple Regression Justification Multiple linear regression (MLR) could explain the relationship between multiple independent variables against one dependent variable (Bevans, 2020). This statistical technique could provide a more accurate representation of exactly how the dependent variable changes through a linear model. I wanted to use MLR to find out which independent variables are most significant to the dependent variable. By creating a linear regression model based on these variables, I could adjust the independent variables to see how they affect `MonthlyCharge`.

0.0.3 C. Data Preparation Process

C1. Preparation Goals The goals of data preparation included:

- Learn about the dataset and its variables.
- Explore measures of central tendency (mean, median, and mode).
- Check for missing data and handle them as necessary.
- Visualize data through univariate and bivariate plots.
- Remove highly correlated columns for MLR.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

churn = pd.read_csv('churn_clean.csv')
churn_cp = churn.copy(deep=True)
```

[2]:
```
churn_cp.head()
```

[2]:
```
   CaseOrder Customer_id                           Interaction  \
0          1     K409198  aa90260b-4141-4a24-8e36-b04ce1f4f77b
1          2     S120509  fb76459f-c047-4a9d-8af9-e0f7d4ac2524
2          3     K191035  344d114c-3736-4be5-98f7-c72c281e2d35
3          4      D90850  abfa2b40-2d43-4994-b15a-989b8c79e311
4          5     K662701  68a861fd-0d20-4e51-a587-8a90407ee574

                                UID         City State                 County  \
0  e885b299883d4f9fb18e39c75155d990  Point Baker    AK  Prince of Wales-Hyder
1  f2de8bef964785f41a2959829830fb8a  West Branch    MI                 Ogemaw
2  f1784cfa9f6d92ae816197eb175d3c71      Yamhill    OR                Yamhill
3  dc8a365077241bb5cd5ccd305136b05e      Del Mar    CA              San Diego
4  aabb64a116e83fdc4befc1fbab1663f9   Needville    TX              Fort Bend

     Zip       Lat        Lng  …  MonthlyCharge Bandwidth_GB_Year Item1  \
0  99927  56.25100 -133.37571  …     172.455519        904.536110     5
1  48661  44.32893  -84.24080  …     242.632554        800.982766     3
2  97148  45.35589 -123.24657  …     159.947583       2054.706961     4
3  92014  32.96687 -117.24798  …     119.956840       2164.579412     4
```

```
4  77461  29.38012  -95.80673  …     149.948316        271.493436     4

  Item2  Item3  Item4  Item5 Item6 Item7 Item8
0     5      5      3      4     4     3     4
1     4      3      3      4     3     4     4
2     4      2      4      4     3     3     3
3     4      4      2      5     4     3     3
4     4      4      3      4     4     4     5

[5 rows x 50 columns]
```

C2. Summary Statistics The original dataset contained 10,000 rows and 50 columns. 23 columns were dropped from the dataset because they were not relevant to the MLR. The first twelve dropped columns were customer demographic data: `CaseOrder`, `Customer_id`, `Interaction`, `UID`, `City`, `State`, `County`, `Zip`, `Lat`, `Lng`, `Area`, `TimeZone`, `Job`, `Marital`, and `PaymentMethod`. Each of these demographic columns contained multiple unique categorical values that would generate too many dummy variables. The last eight dropped columns were survey responses, `Item1` through `Item8`, that were not significant to the target dependent variable.

The prepared dataset contained 26 independent variables and one dependent variable. The target dependent variable is `MonthlyCharge`, the amount charged to the customer monthly. The mean of this variable is 172.62 with a standard deviation of 42.94.

The eleven continuous independent variables are: `Population`, `Children`, `Age`, `Income`, `Outage_sec_perweek`, `Email`, `Contacts`, `Yearly_equip_failure`, `Tenure`, `MonthlyCharge`, and `Bandwidth_GB_Year`.

The sixteen categorical independent variables are: `Gender`, `Churn`, `Techie`, `Contract`, `Port_modem`, `Tablet`, `InternetService`, `Phone`, `Multiple`, `OnlineSecurity`, `OnlineBackup`, `DeviceProtection`, `TechSupport`, `StreamingTV`, `StreamingMovies`, and `PaperlessBilling`.

[4]:
```
churn_cp['MonthlyCharge'].describe()
```

[4]:
```
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
```

[3]:
```
# Drop customer demographic and survey columns that are not important to the
↪regression analysis
```

```
churn_cp.drop(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City',␣
↪'State', 'County', 'Zip', 'Lat', 'Lng', 'Area', 'TimeZone', 'Job',␣
↪'Marital', 'PaymentMethod', 'Item1', 'Item2', 'Item3', 'Item4', 'Item5',␣
↪'Item6', 'Item7', 'Item8'], axis=1, inplace=True)

churn_cp.head()
```

[3]:
```
   Population  Children  Age    Income  Gender Churn  Outage_sec_perweek  \
0          38         0   68  28561.99    Male    No            7.978323
1       10446         1   27  21704.77  Female   Yes           11.699080
2        3735         4   50   9609.57  Female    No           10.752800
3       13863         1   48  18925.23    Male    No           14.913540
4       11352         0   83  40074.19    Male   Yes            8.147417

   Email  Contacts  Yearly_equip_failure  … OnlineSecurity OnlineBackup  \
0     10         0                     1  …            Yes          Yes
1     12         0                     1  …            Yes           No
2      9         0                     1  …             No           No
3     15         2                     0  …            Yes           No
4     16         2                     1  …             No           No

  DeviceProtection TechSupport StreamingTV StreamingMovies PaperlessBilling  \
0               No          No          No             Yes              Yes
1               No          No         Yes             Yes              Yes
2               No          No          No             Yes              Yes
3               No          No         Yes              No              Yes
4               No         Yes         Yes              No               No

      Tenure MonthlyCharge Bandwidth_GB_Year
0   6.795513    172.455519        904.536110
1   1.156681    242.632554        800.982766
2  15.754144    159.947583       2054.706961
3  17.087227    119.956840       2164.579412
4   1.670972    149.948316        271.493436

[5 rows x 27 columns]
```

[5]:
```
# Check statistics of continuous variables
churn_cp.describe()
```

[5]:
```
         Population    Children           Age         Income  \
count  10000.000000  10000.0000  10000.000000   10000.000000
mean    9756.562400      2.0877     53.078400   39806.926771
std    14432.698671      2.1472     20.698882   28199.916702
min        0.000000      0.0000     18.000000     348.670000
25%      738.000000      0.0000     35.000000   19224.717500
50%     2910.500000      1.0000     53.000000   33170.605000
```

```
75%     13168.000000      3.0000     71.000000   53246.170000
max    111850.000000     10.0000     89.000000  258900.700000

       Outage_sec_perweek         Email      Contacts  Yearly_equip_failure  \
count        10000.000000  10000.000000  10000.000000          10000.000000
mean            10.001848     12.016000      0.994200              0.398000
std              2.976019      3.025898      0.988466              0.635953
min              0.099747      1.000000      0.000000              0.000000
25%              8.018214     10.000000      0.000000              0.000000
50%             10.018560     12.000000      1.000000              0.000000
75%             11.969485     14.000000      2.000000              1.000000
max             21.207230     23.000000      7.000000              6.000000

             Tenure  MonthlyCharge  Bandwidth_GB_Year
count  10000.000000   10000.000000       10000.000000
mean      34.526188     172.624816        3392.341550
std       26.443063      42.943094        2185.294852
min        1.000259      79.978860         155.506715
25%        7.917694     139.979239        1236.470827
50%       35.430507     167.484700        3279.536903
75%       61.479795     200.734725        5586.141370
max       71.999280     290.160419        7158.981530
```

[6]:
```
# Check statistics of categorical variable
churn_cp.describe(include=object)
```

[6]:
```
        Gender  Churn Techie        Contract Port_modem Tablet  \
count    10000  10000  10000           10000      10000  10000
unique       3      2      2               3          2      2
top     Female     No     No  Month-to-month         No     No
freq      5025   7350   8321            5456       5166   7009

       InternetService  Phone Multiple OnlineSecurity OnlineBackup  \
count            10000  10000    10000          10000        10000
unique               3      2        2              2            2
top        Fiber Optic    Yes       No             No           No
freq              4408   9067     5392           6424         5494

       DeviceProtection TechSupport StreamingTV StreamingMovies  \
count             10000       10000       10000           10000
unique                2           2           2               2
top                  No          No          No              No
freq               5614        6250        5071            5110

       PaperlessBilling
count             10000
unique                2
```

```
top                    Yes
freq                  5882
```

C3. Preparation Steps The steps used to prepare the data are:

1. Get an overview of the imported data.
2. Drop columns unnecessary for the MLR.
3. Check statistics of continuous and categorical variables.
4. Check for any duplicate or missing values.
5. Plot univariate and bivariate plots.
6. Encode categorical variables into numerical values.
7. Run a heatmap and drop highly correlated columns.
8. Calculate VIF and drop columns with VIF > 5.

[7]:
```
# Check if there is any duplicates
churn_cp.duplicated().any()
```

[7]: False

[8]:
```
# Check if there is any missing values
churn_cp.isnull().values.any()
```

[8]: False

C4. Generate Visualizations

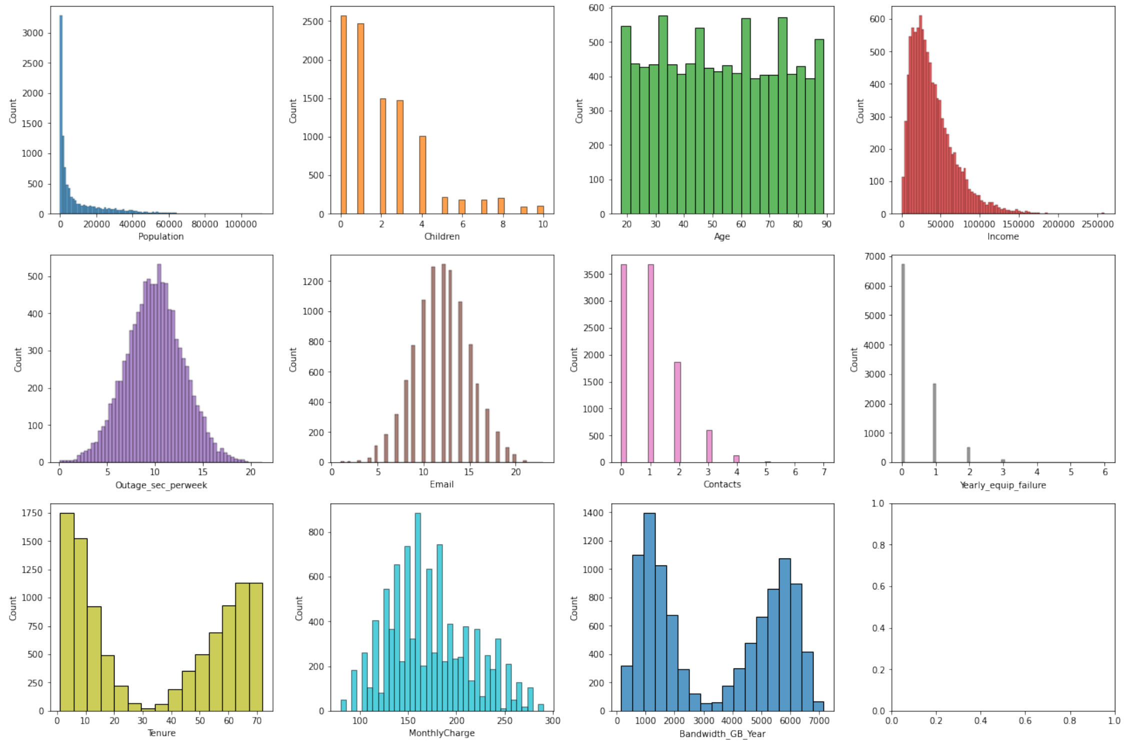
[9]:
```
# Plot histograms for continuous columns
continuous = churn_cp.select_dtypes(include='number').columns.tolist()

fig, axes = plt.subplots(3, 4, figsize=(18, 12))
palette1 = sns.color_palette()

# Adapted from seaborn documentation (Waskom, 2022)
# https://seaborn.pydata.org/tutorial/color_palettes.html
x = 0
y = 0
color = 0
for col in continuous:
    if color == 10:
        color = 0
    if y == 4:
        x += 1
        y = 0
    sns.histplot(ax=axes[x, y], data=churn_cp[col], color=palette1[color])
    color += 1
    y += 1

plt.tight_layout()
```

```python
plt.show()
```



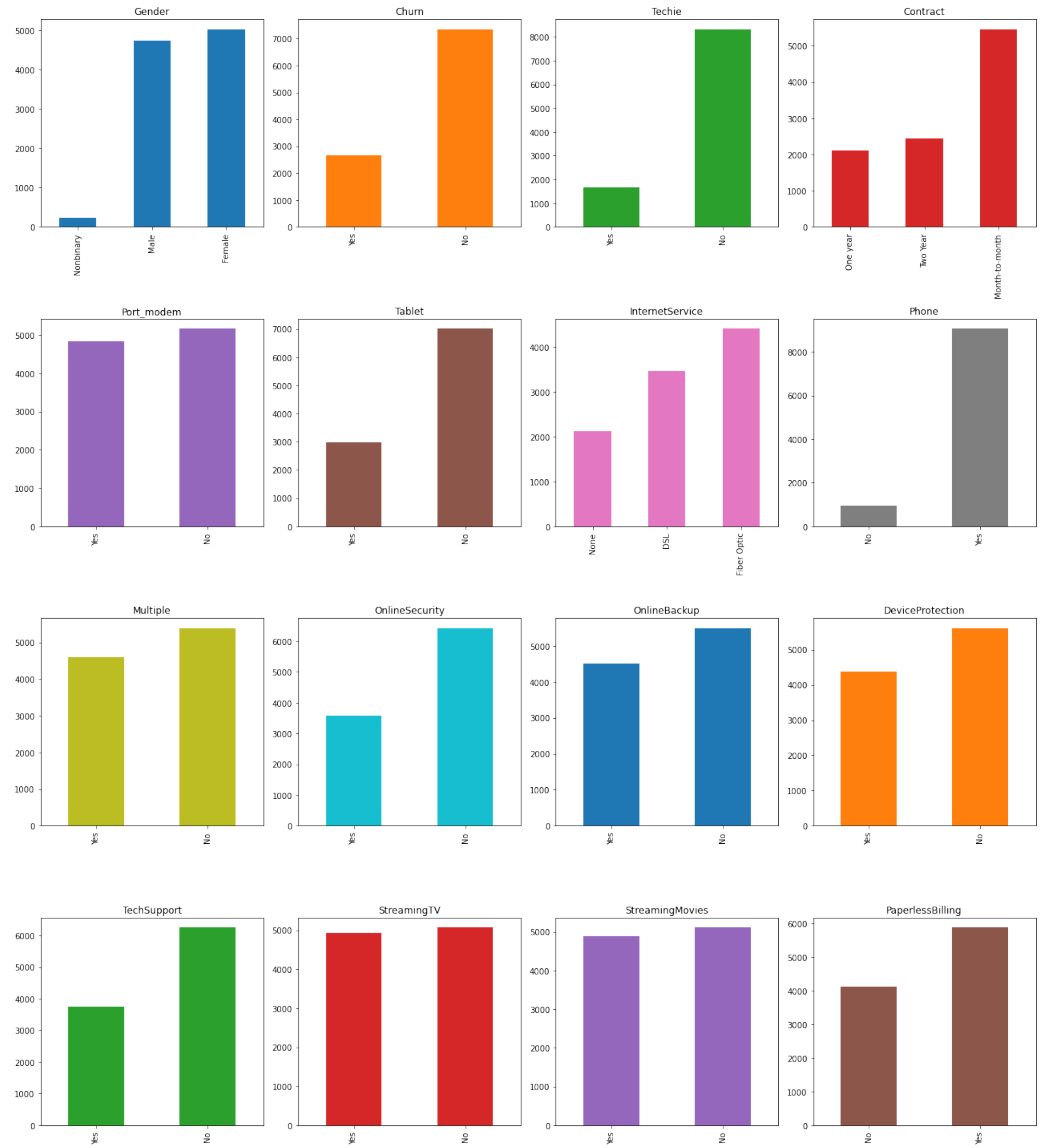
[10]:

```python
# Plot barplots for categorical columns
categorical = churn_cp.select_dtypes(include='object').columns.tolist()

fig, axes = plt.subplots(4, 4, figsize=(18, 20))
palette2 = sns.color_palette('tab10')

x = 0
y = 0
color = 0
for col in categorical:
    if color == 10:
        color = 0
    if y == 4:
        x += 1
        y = 0
    count = churn_cp[col].value_counts().sort_values()
    axes[x, y].set_title(col)
    count.plot.bar(ax=axes[x, y], color=palette2[color])
    color += 1
    y += 1
```

```
plt.tight_layout()
plt.show()
```



[11]:
```
# Generate bivariate pairplots
g = sns.PairGrid(churn_cp)
g.map_upper(sns.scatterplot, color='#333C83')
g.map_diag(sns.histplot, color='#F24A72')
g.map_lower(sns.scatterplot, color='#006778')
plt.show()
```

[12]:
```
# Convert categorical columns into dummy variables
churn_dmy = pd.get_dummies(churn_cp, drop_first=True)

# Replace space in column names with underscore
churn_dmy.columns = churn_dmy.columns.str.replace(' ', '_')

churn_dmy.describe()
```

[12]:
```
         Population    Children           Age         Income  \
count  10000.000000  10000.0000  10000.000000   10000.000000
mean    9756.562400      2.0877     53.078400   39806.926771
std    14432.698671      2.1472     20.698882   28199.916702
min        0.000000      0.0000     18.000000     348.670000
```

25%	738.000000	0.0000	35.000000	19224.717500
50%	2910.500000	1.0000	53.000000	33170.605000
75%	13168.000000	3.0000	71.000000	53246.170000
max	111850.000000	10.0000	89.000000	258900.700000

	Outage_sec_perweek	Email	Contacts	Yearly_equip_failure	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	10.001848	12.016000	0.994200	0.398000	
std	2.976019	3.025898	0.988466	0.635953	
min	0.099747	1.000000	0.000000	0.000000	
25%	8.018214	10.000000	0.000000	0.000000	
50%	10.018560	12.000000	1.000000	0.000000	
75%	11.969485	14.000000	2.000000	1.000000	
max	21.207230	23.000000	7.000000	6.000000	

	Tenure	MonthlyCharge	…	InternetService_None	Phone_Yes	\
count	10000.000000	10000.000000	…	10000.000000	10000.000000	
mean	34.526188	172.624816	…	0.212900	0.906700	
std	26.443063	42.943094	…	0.409378	0.290867	
min	1.000259	79.978860	…	0.000000	0.000000	
25%	7.917694	139.979239	…	0.000000	1.000000	
50%	35.430507	167.484700	…	0.000000	1.000000	
75%	61.479795	200.734725	…	0.000000	1.000000	
max	71.999280	290.160419	…	1.000000	1.000000	

	Multiple_Yes	OnlineSecurity_Yes	OnlineBackup_Yes	\
count	10000.000000	10000.000000	10000.000000	
mean	0.460800	0.357600	0.450600	
std	0.498486	0.479317	0.497579	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	
75%	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	

	DeviceProtection_Yes	TechSupport_Yes	StreamingTV_Yes	\
count	10000.000000	10000.000000	10000.000000	
mean	0.438600	0.375000	0.492900	
std	0.496241	0.484147	0.499975	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	
75%	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	

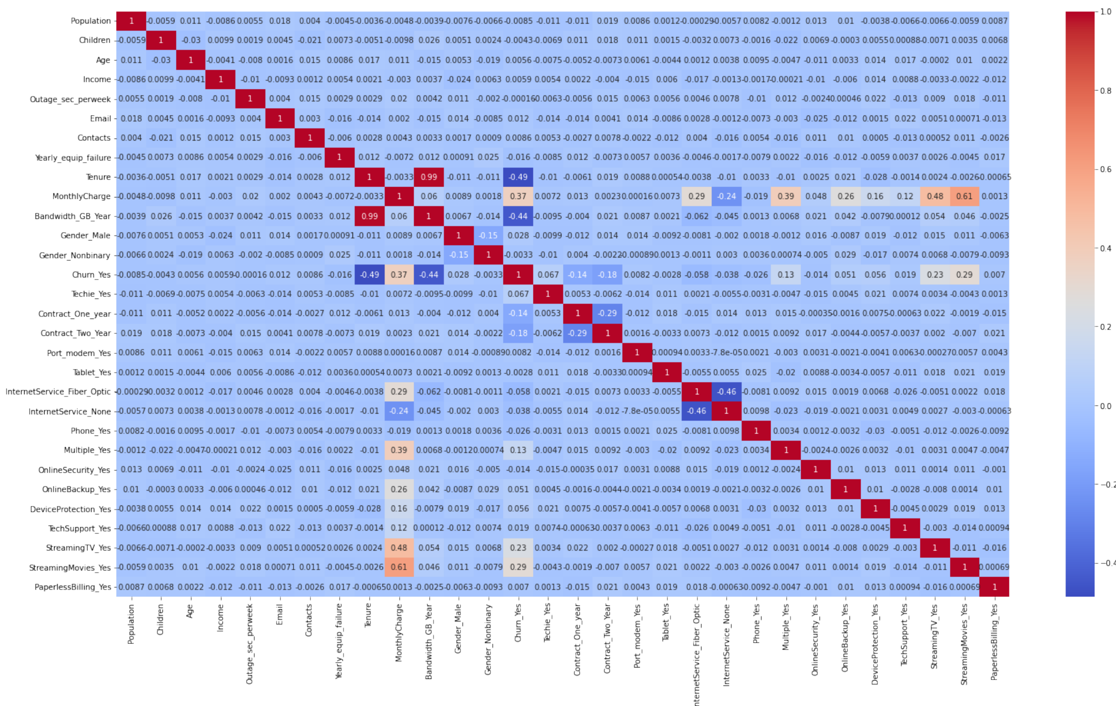
	StreamingMovies_Yes	PaperlessBilling_Yes
count	10000.000000	10000.000000

```
mean            0.489000            0.588200
std             0.499904            0.492184
min             0.000000            0.000000
25%             0.000000            0.000000
50%             0.000000            1.000000
75%             1.000000            1.000000
max             1.000000            1.000000

[8 rows x 30 columns]
```

[13]:
```python
# Run a correlation matrix
churn_corr = churn_dmy.corr()

# Plot a heatmap of the correlations
plt.figure(figsize=(26, 14))
sns.heatmap(churn_corr, annot=True, xticklabels=churn_corr.columns,␣
 ↪yticklabels=churn_corr.columns, cmap='coolwarm')
plt.show()
```



[14]:
```python
# Drop highly correlated columns
churn_dmy.drop(['Bandwidth_GB_Year', 'Tenure'], axis=1, inplace=True)

churn_dmy.head()
```

[14]:
```
   Population  Children  Age    Income  Outage_sec_perweek  Email  Contacts  \
0          38         0   68  28561.99            7.978323     10         0
1       10446         1   27  21704.77           11.699080     12         0
2        3735         4   50   9609.57           10.752800      9         0
3       13863         1   48  18925.23           14.913540     15         2
4       11352         0   83  40074.19            8.147417     16         2

   Yearly_equip_failure  MonthlyCharge  Gender_Male  …  \
0                     1     172.455519            1  …
1                     1     242.632554            0  …
2                     1     159.947583            0  …
3                     0     119.956840            1  …
4                     1     149.948316            1  …

   InternetService_None  Phone_Yes  Multiple_Yes  OnlineSecurity_Yes  \
0                     0          1             0                   1
1                     0          1             1                   1
2                     0          1             1                   0
3                     0          1             0                   1
4                     0          0             0                   0

   OnlineBackup_Yes  DeviceProtection_Yes  TechSupport_Yes  StreamingTV_Yes  \
0                 1                     0                0                0
1                 0                     0                0                1
2                 0                     0                0                0
3                 0                     0                0                1
4                 0                     0                1                1

   StreamingMovies_Yes  PaperlessBilling_Yes
0                    1                     1
1                    1                     1
2                    1                     1
3                    0                     1
4                    0                     0

[5 rows x 28 columns]
```

[15]:
```python
# Adapted from Detecting Multicollinearity with VIF (GeeksforGeeks, 2020)
# https://www.geeksforgeeks.org/detecting-multicollinearity-with-vif-python/

# Create independent variables set
X = churn_dmy.drop('MonthlyCharge', axis=1)

# VIF dataframe
vif = pd.DataFrame()
vif['Variables'] = X.columns
```

```
# Calculating VIF for each variable
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(len(X.
 ↪columns))]

vif
```

[15]:

	Variables	VIF
0	Population	1.452552
1	Children	1.919980
2	Age	6.799319
3	Income	2.881564
4	Outage_sec_perweek	10.106537
5	Email	12.448311
6	Contacts	1.988874
7	Yearly_equip_failure	1.384885
8	Gender_Male	1.925507
9	Gender_Nonbinary	1.046806
10	Churn_Yes	1.811674
11	Techie_Yes	1.205180
12	Contract_One_year	1.455095
13	Contract_Two_Year	1.542198
14	Port_modem_Yes	1.915201
15	Tablet_Yes	1.424275
16	InternetService_Fiber_Optic	2.237575
17	InternetService_None	1.598786
18	Phone_Yes	8.980119
19	Multiple_Yes	1.879134
20	OnlineSecurity_Yes	1.544828
21	OnlineBackup_Yes	1.804321
22	DeviceProtection_Yes	1.777888
23	TechSupport_Yes	1.590844
24	StreamingTV_Yes	2.097631
25	StreamingMovies_Yes	2.158125
26	PaperlessBilling_Yes	2.372637

[16]:

```
# Get a list of variables with VIF > 5
high_vif = vif[vif['VIF'] > 5]
high_vif = high_vif['Variables'].tolist()

# Drop columns with high VIF
churn_dmy.drop(high_vif, axis=1, inplace=True)

churn_dmy.head()
```

[16]:

	Population	Children	Income	Contacts	Yearly_equip_failure	\
0	38	0	28561.99	0	1	
1	10446	1	21704.77	0	1	

```
2       3735          4   9609.57         0                      1
3      13863          1  18925.23         2                      0
4      11352          0  40074.19         2                      1

   MonthlyCharge  Gender_Male  Gender_Nonbinary  Churn_Yes  Techie_Yes  …  \
0     172.455519            1                 0          0           0  …
1     242.632554            0                 0          1           1  …
2     159.947583            0                 0          0           1  …
3     119.956840            1                 0          0           1  …
4     149.948316            1                 0          1           0  …

   InternetService_Fiber_Optic  InternetService_None  Multiple_Yes  \
0                            1                     0             0
1                            1                     0             1
2                            0                     0             1
3                            0                     0             0
4                            1                     0             0

   OnlineSecurity_Yes  OnlineBackup_Yes  DeviceProtection_Yes  \
0                   1                 1                     0
1                   1                 0                     0
2                   0                 0                     0
3                   1                 0                     0
4                   0                 0                     0

   TechSupport_Yes  StreamingTV_Yes  StreamingMovies_Yes  PaperlessBilling_Yes
0                0                0                    1                     1
1                0                1                    1                     1
2                0                0                    1                     1
3                0                1                    0                     1
4                1                1                    0                     0

[5 rows x 24 columns]
```

C5. Copy of Prepared Data

[17]:
```
# Create a copy of the prepared data
churn_dmy.to_csv('churn_prepare.csv', index=False)
```

0.0.4 D. Compare Initial and Reduced Models

D1. Construct Initial Model

[18]:
```
Y = churn_dmy['MonthlyCharge']
X = churn_dmy.drop('MonthlyCharge', axis=1)

X = sm.add_constant(X)
model = sm.OLS(Y, X).fit()
```

```python
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.959
Model:                            OLS   Adj. R-squared:                  0.959
Method:                 Least Squares   F-statistic:                 1.006e+04
Date:                Tue, 26 Apr 2022   Prob (F-statistic):               0.00
Time:                        15:27:29   Log-Likelihood:                -35859.
No. Observations:               10000   AIC:                         7.177e+04
Df Residuals:                    9976   BIC:                         7.194e+04
Df Model:                          23
Covariance Type:            nonrobust
================================================================================
===============
                                  coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
---------------
const                          83.6796      0.372    225.111      0.000
82.951      84.408
Population                   1.089e-06   6.06e-06      0.180      0.857
-1.08e-05     1.3e-05
Children                        0.0062      0.041      0.151      0.880
-0.074       0.086
Income                       3.311e-06    3.1e-06      1.067      0.286
-2.77e-06    9.39e-06
Contacts                       -0.0462      0.089     -0.522      0.602
-0.220       0.127
Yearly_equip_failure           -0.0985      0.138     -0.716      0.474
-0.368       0.171
Gender_Male                    -0.2929      0.177     -1.652      0.099
-0.640       0.055
Gender_Nonbinary               -0.8302      0.589     -1.410      0.159
-1.985       0.324
Churn_Yes                       2.5025      0.229     10.946      0.000
2.054       2.951
Techie_Yes                      0.2383      0.235      1.015      0.310
-0.222       0.698
Contract_One_year               0.8026      0.231      3.474      0.001
0.350       1.255
Contract_Two_Year               0.7724      0.220      3.503      0.000
0.340       1.205
Port_modem_Yes                 -0.2277      0.175     -1.301      0.193
-0.571       0.115
Tablet_Yes                     -0.1759      0.191     -0.920      0.358
-0.551       0.199
```

```
InternetService_Fiber_Optic    20.0524      0.200    100.419      0.000
19.661      20.444
InternetService_None          -12.6692      0.242    -52.409      0.000
-13.143     -12.195
Multiple_Yes                   32.2933      0.178    181.711      0.000
31.945      32.642
OnlineSecurity_Yes              2.7101      0.183     14.837      0.000
2.352       3.068
OnlineBackup_Yes               22.4526      0.176    127.456      0.000
22.107      22.798
DeviceProtection_Yes           12.4009      0.177     70.193      0.000
12.055      12.747
TechSupport_Yes                12.5063      0.181     69.165      0.000
12.152      12.861
StreamingTV_Yes                41.6656      0.181    229.564      0.000
41.310      42.021
StreamingMovies_Yes            51.6903      0.184    280.210      0.000
51.329      52.052
PaperlessBilling_Yes            0.1430      0.178      0.804      0.421
-0.206       0.492
==============================================================================
Omnibus:                    35663.845   Durbin-Watson:                   1.997
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1567.455
Skew:                           0.021   Prob(JB):                         0.00
Kurtosis:                       1.061   Cond. No.                     3.34e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.34e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[19]:

```python
# Residuals of the initial model
model.resid
```

[19]:

```
0       -8.374701
1        7.842365
2       -8.603571
3       -8.950703
4       -9.891661
           …
9995     9.738315
9996    -8.382081
9997     8.484229
9998    10.235932
9999    -7.420766
```

```
Length: 10000, dtype: float64
```

D2. Variable Selection Procedure

[20]:
```python
# Get a list of variables with p > 0.05
high_p = []
for col in churn_dmy.columns:
    if col == 'MonthlyCharge':
        pass
    else:
        p_val = model.pvalues[col]
        if p_val > 0.05:
            print(f'{col}: {p_val:.2f}')
            high_p.append(col)
```

```
Population: 0.86
Children: 0.88
Income: 0.29
Contacts: 0.60
Yearly_equip_failure: 0.47
Gender_Male: 0.10
Gender_Nonbinary: 0.16
Techie_Yes: 0.31
Port_modem_Yes: 0.19
Tablet_Yes: 0.36
PaperlessBilling_Yes: 0.42
```

[21]:
```python
# Perform backward selection by dropping columns with high p-values
churn_dmy.drop(high_p, axis=1, inplace=True)

churn_dmy.head()
```

[21]:
```
   MonthlyCharge  Churn_Yes  Contract_One_year  Contract_Two_Year  \
0     172.455519          0                  1                  0
1     242.632554          1                  0                  0
2     159.947583          0                  0                  1
3     119.956840          0                  0                  1
4     149.948316          1                  0                  0

   InternetService_Fiber_Optic  InternetService_None  Multiple_Yes  \
0                            1                     0             0
1                            1                     0             1
2                            0                     0             1
3                            0                     0             0
4                            1                     0             0

   OnlineSecurity_Yes  OnlineBackup_Yes  DeviceProtection_Yes  \
0                   1                 1                     0
```

```
1                    1                 0                     0
2                    0                 0                     0
3                    1                 0                     0
4                    0                 0                     0

   TechSupport_Yes  StreamingTV_Yes  StreamingMovies_Yes
0                0                0                    1
1                0                1                    1
2                0                0                    1
3                0                1                    0
4                1                1                    0
```

[22]:
```
# Drop variables that have coefficients < 3
churn_dmy.drop(['Churn_Yes', 'Contract_One_year', 'Contract_Two_Year',␣
 ↪'OnlineSecurity_Yes'], axis=1, inplace=True)
```

D3. Reduced Regression Model

[23]:
```
Y = churn_dmy['MonthlyCharge']
X = churn_dmy.drop('MonthlyCharge', axis=1)

X = sm.add_constant(X)
reduced_model = sm.OLS(Y, X).fit()
print(reduced_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.957
Model:                            OLS   Adj. R-squared:                  0.957
Method:                 Least Squares   F-statistic:                 2.793e+04
Date:                Tue, 26 Apr 2022   Prob (F-statistic):               0.00
Time:                        15:28:50   Log-Likelihood:                -36031.
No. Observations:               10000   AIC:                         7.208e+04
Df Residuals:                    9991   BIC:                         7.214e+04
Df Model:                           8
Covariance Type:            nonrobust
================================================================================
===============
                                  coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
---------------
const                          84.8067      0.251    338.393      0.000
84.315      85.298
InternetService_Fiber_Optic    19.8588      0.202     98.365      0.000
19.463      20.254
InternetService_None          -12.9291      0.245    -52.810      0.000
-13.409     -12.449
```

```
Multiple_Yes                   32.5912      0.178    182.735      0.000
32.242      32.941
OnlineBackup_Yes               22.5885      0.179    126.453      0.000
22.238      22.939
DeviceProtection_Yes           12.5566      0.179     70.089      0.000
12.205      12.908
TechSupport_Yes                12.5919      0.184     68.557      0.000
12.232      12.952
StreamingTV_Yes                42.1879      0.178    237.303      0.000
41.839      42.536
StreamingMovies_Yes            52.3453      0.178    294.327      0.000
51.997      52.694
==============================================================================
Omnibus:                    36028.412   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1541.892
Skew:                           0.023   Prob(JB):                         0.00
Kurtosis:                       1.077   Cond. No.                         6.04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

[24]:
```
# Residuals of the reduced model
reduced_model.resid
```

[24]:
```
0       -7.143755
1       10.842737
2       -9.795579
3       -7.037777
4       -9.496975
          …
9995     7.436309
9996    -7.108647
9997    10.128885
9998     8.242267
9999    -7.263100
Length: 10000, dtype: float64
```

0.0.5 E. Analyze Dataset

E1. Explain Analysis Process **Variable Selection Logic**

The process of backward selection removed the variables with high p-values in the initial model. The stopping rule is the p-value threshold of 0.05 (JMP, 2019). Another factor to consider with these variables was that their coefficients were extremely small. Take `Population` in the initial model for example, the p-value of this variable was 0.857 and its coefficient was 1.089e-06. Removing this variable had minimal effect on the model. Other variables with high p-value also tend to have coefficients that were lower than +-1. These variables do not significantly affect the accuracy of the model.

Model Evaluation Metric

[25]:
```
# Check values of R-squared
initial_r2 = model.rsquared_adj
reduced_r2 = reduced_model.rsquared_adj

print(f'Adjusted R-squared:\n- Initial: {initial_r2:.3f}\n- Reduced:␣
↪{reduced_r2:.3f}')
```

```
Adjusted R-squared:
- Initial: 0.959
- Reduced: 0.957
```

The first metric to look at is the Adjusted R-squared. This score is a measure of how much variation in the dependent variable is explained by only the independent variables that actually affect the dependent variable (Glen, 2021). The score on the reduced model was 0.957 while the initial model was 0.959. That was a minimal loss in explained variation despite reducing the number of independent variables from 25 to 8.

[26]:
```
# Check values of RMSE
initial_rmse = np.sqrt(model.mse_resid)
reduced_rmse = np.sqrt(reduced_model.mse_resid)

print(f'RMSE:\n- Initial: {initial_rmse:.2f}\n- Reduced: {reduced_rmse:.2f}')
```

```
RMSE:
- Initial: 8.74
- Reduced: 8.89
```

The second metric is the Root Mean Square Error (RMSE). This value is the measure of accuracy for the regression model. It is based on the average distance between the observed and predicted data values (Bobbit, 2021a). The initial model RMSE was 8.74 while the reduced model was 8.88. The slight increase in RMSE was due to the reduction of predictor variables. Overall it should not affect the accuracy of the reduced model.

Residual Plot

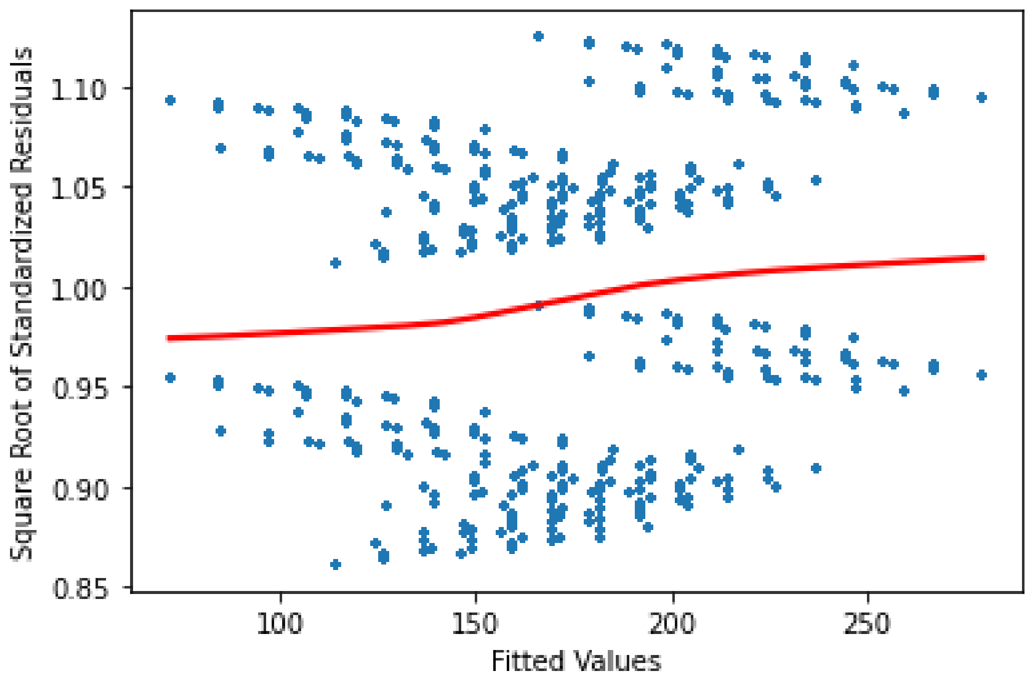
The scale-location plot below showed the square root of the standardized residuals versus the fitted values. This plot indicates whether the size of the residuals get bigger or smaller (Broeck, 2022). Since the residuals appear to be randomly scattered, there did not seem to be a problem with heteroscedasticity.

[27]:
```
# Adapted from Assessing Model Fit (Broeck, 2022)
# https://app.datacamp.com/learn/courses/
↪introduction-to-regression-with-statsmodels-in-python

# Create a scale-location plot
```

```
reduced_model_norm_resid = reduced_model.get_influence().
 ↪resid_studentized_internal
reduced_model_norm_resid_sqrt = np.sqrt(np.abs(reduced_model_norm_resid))
sns.regplot(x=reduced_model.fittedvalues, y=reduced_model_norm_resid_sqrt,␣
 ↪lowess=True, marker='+', line_kws={'color': 'red'}, scatter_kws={'s': 15})

plt.xlabel('Fitted Values')
plt.ylabel('Square Root of Standardized Residuals')
plt.show()
```



E2. Analysis Output The output and calculations of both the model and the reduced model are found in sections D1 through D3. The initial model's residuals can be found at the end of section D1. The reduced model's residuals can be found at the end of section D3.

The reduced model's predictions are below:

[28]:
```
predictions = reduced_model.get_prediction()
predictions.summary_frame()
```

[28]:

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	\
0	179.599274	0.246765	179.115564	180.082984	162.172045	
1	231.789817	0.245958	231.307691	232.271944	214.362632	
2	169.743162	0.255481	169.242368	170.243956	152.315450	
3	126.994617	0.250331	126.503918	127.485316	109.567192	
4	159.445291	0.256945	158.941628	159.948954	142.017497	

```
…           …          …              …              …            …
9995  152.543091  0.269429    152.014957    153.071226    135.114573
9996  214.589747  0.258382    214.083266    215.096228    197.161871
9997  159.845215  0.250246    159.354681    160.335748    142.417795
9998  244.381733  0.265728    243.860853    244.902614    226.953433
9999  224.747100  0.256063    224.245165    225.249036    207.319356

      obs_ci_upper
0       197.026503
1       249.217003
2       187.170873
3       144.422042
4       176.873086
…              …
9995    169.971610
9996    232.017623
9997    177.272634
9998    261.810034
9999    242.174845

[10000 rows x 6 columns]
```

E3. Code for MLR The code that ran the MLR could be found in section D1 for the initial model and D3 for the reduced model.

0.0.6 F. Summarize Findings

F1. Results of Analysis **Regression Equation**

[29]:
```python
# Lists of variables and their coefficients
cols = churn_dmy.columns.tolist()
coefs = reduced_model.params.tolist()

# Create equation string for the reduced model
equation = f'y = {coefs[0]:.2f}'
for col, coef in zip(cols[1:], coefs[1:]):
    equation += f' + ({coef:.2f} * {col})'

print(f'Regression Equation:\n{equation}')
```

```
Regression Equation:
y = 84.81 + (19.86 * InternetService_Fiber_Optic) + (-12.93 *
InternetService_None) + (32.59 * Multiple_Yes) + (22.59 * OnlineBackup_Yes) +
(12.56 * DeviceProtection_Yes) + (12.59 * TechSupport_Yes) + (42.19 *
StreamingTV_Yes) + (52.35 * StreamingMovies_Yes)
```

Interpretation of Coefficients

The majority of the coefficients in the model are positive. This is in line with the fact that having additional services and add-ons cost more money. The only negative coefficient was not having an internet service. This makes sense because the highest coefficients were streaming movies, streaming TV, and having multiple lines. All of those high cost services required the internet.

Model Significance

All of the independent variables in the equation are statistically significant. This means that the relationships between these variables and `MonthlyCharge` are statistically significant. Changes in these independent variables are associated with changes in the dependent variable when applied to the population (Frost, 2021). At the same time, there could be other factors that could influence either the coefficients or the p-values of these variables. The original dataset contained many independent variables that were reduced for the analysis. This would be an important case where having domain expertise will help the analysis identify the important variables.

Limitations of Analysis

There were multiple limitations to this analysis. The first was mentioned above, where reducing too many variables could have affected the accuracy of the final result. The second was that creating dummy variables for the categorical columns could have created some redundancy. The data generated from these dummy variables could have created some bias in the model, leading to some inaccuracy. These dummy variables also made it difficult to plot residuals versus fitted values because their values were either zero or one, not continuous.

F2. Recommendations Based on the model, the variables with the highest coefficients were streaming movies, streaming TV, and having multiple lines. Given that the mean `MonthlyCharge` was 172.62, customers who had all of mentioned additional services and add-ons would be paying significantly more than the average. This could lead to more churn for customers sensitive to high prices. To counteract this, stakeholders had multiple options:

1. Lowering the basic cost of service. This basic cost was the constant of 84.81, the price that customers paid without any of the additional variables involved. This constant alone is almost half of the mean monthly payment.
2. Lowering the costs of services and add-ons. The model indicated that having multiple lines and streaming services were expensive. Lowering the costs of these services could lead to better customer retention. The loss in profit could be made up by spreading it over the additional tenure of the customers.
3. Creating packages for customers who had these services together. Customers who had multiple services together would be less likely to leave if they are paying less by bundling these services together.

0.0.7 G. Panopto Recording

Link: https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=2cbfe92e-1314-4338-a99b-ae830088f19a

0.0.8 H. Third-Party Code

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0.0.9 I. References

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