D208_Performance_Assessment_NBM2_Task_1

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1 D208 Performance Assessment NBM2 Task 1

1.1 Multiple Regression for Predictive Modeling

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1.1.1 A1. Research Question:

How much many GBs of data will a customer use yearly? Can this be predicted accurately from a list of explanatory variables?

1.1.2 A2. Objectives & Goals:

Stakeholders in the company will benefit by knowing, with some measure of confidence, how much data a customer might predictably use. This will provide weight for decisions in whether or not to expand customer data limits, provide unlimited (or metered) media streaming & expand company cloud computing resources for increased bandwidth demands.

1.1.3 B1. Summary of Assumptions:

Assumptions of a multiple regression model include: * There is a linear relationship between the dependent variables & the independent variables. * The independent variables are not too highly correlated with each other. * yi observations are selected independently & randomly from the population. * Residuals should normally distributed with a mean of zero.

1.1.4 B2. Tool Benefits:

Python & IPython Jupyter notebooks will be used to support this analysis. Python offers very intuitive, simple & versatile programming style & syntax, as well as a large system of mature packages for data science & machine learning. Since, Python is cross-platform, it will work well whether consumers of the analysis are using Windows PCs or a MacBook laptop. It is fast when compared with other possible programming languages like R or MATLAB (Massaron, p. 8). Also, there is strong support for Python as the most popular data science programming language in popular literature & media (CBTNuggets)

1.1.5 B3. Appropriate Technique:

Multiple regression is an appropriate technique to analyze the research question because our target variable, predicting a real number of GBs per year, is a continuous variable (how much data is used). Also, perhaps there are several (versus simply one) explanatory variables (area type, job, children, age, income, etc.) that will add to our understanding when trying to predict how much data a customer will use in a given year. When adding or removing independent variables from our regression equation, we will find out whether or not they have a positive or negative relationship to our target variable & how that might affect company decisions on marketing segmentation.

1.1.6 C1. Data Goals:

My approach will include: 1. Back up my data and the process I am following as a copy to my machine and, since this is a manageable dataset, to GitHub using command line and gitbash. 2. Read the data set into Python using Pandas' read_csv command. 3. Evaluate the data struture to better understand input data. 4. Naming the dataset as a the variable "churn_df" and subsequent useful slices of the dataframe as "df". 5. Examine potential misspellings, awkward variable naming & missing data. 6. Find outliers that may create or hide statistical significance using histograms. 7. Imputing records missing data with meaningful measures of central tendency (mean, median or mode) or simply remove outliers that are several standard deviations above the mean.

Most relevant to our decision making process is the dependent variable of "Bandwidth_GB_Year" (the average yearly amount of data used, in GB, per customer) which will be our continuous target variable. We need to train & then test our machine on our given dataset to develop a model that will give us an idea of how much data a customer may use given the amounts used by known customers given their respective data points for selected predictor variables.

In cleaning the data, we may discover relevance of the continuous predictor variables: * Children * Income * Outage_sec_perweek * Email * Contacts
* Yearly_equip_failure * Tenure (the number of months the customer has stayed with the provider) * MonthlyCharge * Bandwidth_GB_Year

Likewise, we may discover relevance of the categorical predictor variables (all binary categorical with only two values, "Yes" or "No", except where noted): * Churn: Whether the customer discontinued service within the last month (yes, no) * Techie: Whether the customer considers themselves technically inclined (based on customer questionnaire when they signed up for services) (yes, no) * Contract: The contract term of the customer (month-to-month, one year, two year) * Port_modem: Whether the customer has a portable modem (yes, no) * Tablet: Whether the customer owns a tablet such as iPad, Surface, etc. (yes, no) * InternetService: Customer's internet service provider (DSL, fiber optic, None) * Phone: Whether the customer has a phone service (yes, no) * Multiple: Whether the customer has multiple lines (yes, no) * OnlineSecurity: Whether the customer has an online security add-on (yes, no) * OnlineBackup: Whether the customer has an online backup add-on (yes, no) * DeviceProtection: Whether the customer has device protection add-on (yes, no) * TechSupport: Whether the customer has a technical support add-on (yes, no) * StreamingTV: Whether the customer has streaming TV (yes, no) * StreamingMovies: Whether the customer has streaming movies (yes, no)

Finally, discrete ordinal predictor variables from the survey responses from customers regarding various customer service features may be relevant in the decision-making process. In the surveys, customers provided ordinal numerical data by rating 8 customer service factors on a scale of 1 to 8 (1 = most important, 8 = least important):

- Item1: Timely response
- Item2: Timely fixes
- Item3: Timely replacements
- Item4: Reliability
- Item5: Options
- Item6: Respectful response
- Item7: Courteous exchange
- Item8: Evidence of active listening

1.1.7 C2. Summary Statistics:

Discuss the summary statistics, including the target variable and all predictor variables that you will need to gather from the data set to answer the research question.

1.1.8 C3. Steps to Prepare Data:

- Import dataset to Python dataframe.
- Rename columns/variables of survey to easily recognizable features (ex: "Item1" to "TimelyResponse").
- Get a description of dataframe, structure (columns & rows) & data types.
- View summary statistics.
- Drop less meaningful identifying (ex: "Customer_id") & demographic columns (ex: zip code) from dataframe.
- Check for records with missing data & impute missing data with meaningful measures of central tendency (mean, median or mode) or simply remove outliers that are several standard deviations above the mean.
- Create dummy variables in order to encoded categorical, yes/no data points into 1/0 numerical values.
- View univariate & bivariate visualizations.
- Finally, the prepared dataset will be extracted & provided as "churn_prepared.csv"

[ ]:
```
# Increase Jupyter display cell-width
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:75% !important; }</style>"))
```

```
<IPython.core.display.HTML object>
```

[ ]:
```
# Standard data science imports
import numpy as np
import pandas as pd
from pandas import Series, DataFrame

# Visualization libraries
import seaborn as sns
import matplotlib.pyplot as plt
```

```python
%matplotlib inline

# Statistics packages
import pylab
from pylab import rcParams
import statsmodels.api as sm
import statistics
from scipy import stats

# Scikit-learn
import sklearn
from sklearn import preprocessing
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import classification_report


# Import chisquare from SciPy.stats
from scipy.stats import chisquare
from scipy.stats import chi2_contingency

# Ignore Warning Code
import warnings
warnings.filterwarnings('ignore')
```

[ ]:
```python
# Change color of Matplotlib font
import matplotlib as mpl

COLOR = 'white'
mpl.rcParams['text.color'] = COLOR
mpl.rcParams['axes.labelcolor'] = COLOR
mpl.rcParams['xtick.color'] = COLOR
mpl.rcParams['ytick.color'] = COLOR
```

[ ]:
```python
# Load data set into Pandas dataframe
churn_df = pd.read_csv('Data/churn_clean.csv')

# Rename last 8 survey columns for better description of variables
churn_df.rename(columns = {'Item1':'TimelyResponse',
                    'Item2':'Fixes',
                     'Item3':'Replacements',
                     'Item4':'Reliability',
                     'Item5':'Options',
                     'Item6':'Respectfulness',
                     'Item7':'Courteous',
                     'Item8':'Listening'},
          inplace=True)
```

[ ]:
```
# Display Churn dataframe
churn_df
```

[ ]:
```
      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
...         ...         ...                                   ...
9995       9996     M324793  45deb5a2-ae04-4518-bf0b-c82db8dbe4a4
9996       9997     D861732  6e96b921-0c09-4993-bbda-a1ac6411061a
9997       9998     I243405  e8307ddf-9a01-4fff-bc59-4742e03fd24f
9998       9999     I641617  3775ccfc-0052-4107-81ae-9657f81ecdf3
9999      10000      T38070  9de5fb6e-bd33-4995-aec8-f01d0172a499

                                   UID         City State  \
0     e885b299883d4f9fb18e39c75155d990  Point Baker    AK
1     f2de8bef964785f41a2959829830fb8a  West Branch    MI
2     f1784cfa9f6d92ae816197eb175d3c71      Yamhill    OR
3     dc8a365077241bb5cd5ccd305136b05e      Del Mar    CA
4     aabb64a116e83fdc4befc1fbab1663f9    Needville    TX
...                                ...          ...   ...
9995  9499fb4de537af195d16d046b79fd20a  Mount Holly    VT
9996  c09a841117fa81b5c8e19afec2760104  Clarksville    TN
9997  9c41f212d1e04dca84445019bbc9b41c      Mobeetie    TX
9998  3e1f269b40c235a1038863ecf6b7a0df   Carrollton    GA
9999  0ea683a03a3cd544aefe8388aab16176  Clarkesville    GA

                     County    Zip       Lat        Lng  ...  MonthlyCharge  \
0     Prince of Wales-Hyder  99927  56.25100 -133.37571  ...     172.455519
1                    Ogemaw  48661  44.32893  -84.24080  ...     242.632554
2                   Yamhill  97148  45.35589 -123.24657  ...     159.947583
3                 San Diego  92014  32.96687 -117.24798  ...     119.956840
4                 Fort Bend  77461  29.38012  -95.80673  ...     149.948316
...                     ...    ...       ...        ...  ...            ...
9995                Rutland   5758  43.43391  -72.78734  ...     159.979400
9996             Montgomery  37042  36.56907  -87.41694  ...     207.481100
9997                Wheeler  79061  35.52039 -100.44180  ...     169.974100
9998                Carroll  30117  33.58016  -85.13241  ...     252.624000
9999              Habersham  30523  34.70783  -83.53648  ...     217.484000

     Bandwidth_GB_Year TimelyResponse Fixes  Replacements  Reliability  \
0           904.536110              5     5             5            3
1           800.982766              3     4             3            3
2          2054.706961              4     4             2            4
3          2164.579412              4     4             4            2
```

```
4           271.493436               4     4           4            3
...                ...             ...   ...         ...          ...
9995       6511.252601               3     2           3            3
9996       5695.951810               4     5           5            4
9997       4159.305799               4     4           4            4
9998       6468.456752               4     4           6            4
9999       5857.586167               2     2           3            3

      Options Respectfulness Courteous Listening
0           4              4         3         4
1           4              3         4         4
2           4              3         3         3
3           5              4         3         3
4           4              4         4         5
...       ...            ...       ...       ...
9995        4              3         2         3
9996        4              5         2         5
9997        4              4         4         5
9998        3              3         5         4
9999        3              3         4         1

[10000 rows x 50 columns]
```

[ ]:
```python
# List of Dataframe Columns
df = churn_df.columns
print(df)
```

```
Index(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'State',
       'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job',
       'Children', 'Age', 'Income', 'Marital', 'Gender', 'Churn',
       'Outage_sec_perweek', 'Email', 'Contacts', 'Yearly_equip_failure',
       'Techie', 'Contract', 'Port_modem', 'Tablet', 'InternetService',
       'Phone', 'Multiple', 'OnlineSecurity', 'OnlineBackup',
       'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
       'PaperlessBilling', 'PaymentMethod', 'Tenure', 'MonthlyCharge',
       'Bandwidth_GB_Year', 'TimelyResponse', 'Fixes', 'Replacements',
       'Reliability', 'Options', 'Respectfulness', 'Courteous', 'Listening'],
      dtype='object')
```

[ ]:
```python
# Find number of records and columns of dataset
churn_df.shape
```

[ ]:
```
(10000, 50)
```

[ ]:
```python
# Describe Churn dataset statistics
churn_df.describe()
```

[ ]:
```
         CaseOrder           Zip           Lat           Lng    Population  \
count  10000.00000  10000.000000  10000.000000  10000.000000  10000.000000
```

```
mean    5000.50000  49153.319600     38.757567    -90.782536    9756.562400
std     2886.89568  27532.196108      5.437389     15.156142   14432.698671
min        1.00000    601.000000     17.966120   -171.688150       0.000000
25%     2500.75000  26292.500000     35.341828    -97.082813     738.000000
50%     5000.50000  48869.500000     39.395800    -87.918800    2910.500000
75%     7500.25000  71866.500000     42.106908    -80.088745   13168.000000
max    10000.00000  99929.000000     70.640660    -65.667850  111850.000000

         Children           Age         Income  Outage_sec_perweek  \
count  10000.0000  10000.000000   10000.000000        10000.000000
mean       2.0877     53.078400   39806.926771           10.001848
std        2.1472     20.698882   28199.916702            2.976019
min        0.0000     18.000000     348.670000            0.099747
25%        0.0000     35.000000   19224.717500            8.018214
50%        1.0000     53.000000   33170.605000           10.018560
75%        3.0000     71.000000   53246.170000           11.969485
max       10.0000     89.000000  258900.700000           21.207230

              Email  ...  MonthlyCharge  Bandwidth_GB_Year  TimelyResponse  \
count  10000.000000  ...   10000.000000       10000.000000    10000.000000
mean      12.016000  ...     172.624816        3392.341550        3.490800
std        3.025898  ...      42.943094        2185.294852        1.037797
min        1.000000  ...      79.978860         155.506715        1.000000
25%       10.000000  ...     139.979239        1236.470827        3.000000
50%       12.000000  ...     167.484700        3279.536903        3.000000
75%       14.000000  ...     200.734725        5586.141369        4.000000
max       23.000000  ...     290.160419        7158.981530        7.000000

              Fixes  Replacements   Reliability       Options  Respectfulness  \
count  10000.000000  10000.000000  10000.000000  10000.000000    10000.000000
mean       3.505100      3.487000      3.497500      3.492900        3.497300
std        1.034641      1.027977      1.025816      1.024819        1.033586
min        1.000000      1.000000      1.000000      1.000000        1.000000
25%        3.000000      3.000000      3.000000      3.000000        3.000000
50%        4.000000      3.000000      3.000000      3.000000        3.000000
75%        4.000000      4.000000      4.000000      4.000000        4.000000
max        7.000000      8.000000      7.000000      7.000000        8.000000

          Courteous     Listening
count  10000.000000  10000.000000
mean       3.509500      3.495600
std        1.028502      1.028633
min        1.000000      1.000000
25%        3.000000      3.000000
50%        4.000000      3.000000
75%        4.000000      4.000000
max        7.000000      8.000000
```

```
[8 rows x 23 columns]
```

[ ]:
```python
# Remove less meaningful demographic variables from statistics description
churn_df = churn_df.drop(columns=['CaseOrder', 'Customer_id', 'Interaction',␣
↪'UID', 'City',
                              'State', 'County', 'Zip', 'Lat', 'Lng',␣
↪'Population',
                              'Area', 'TimeZone', 'Job', 'Marital'])
churn_df.describe()
```

[ ]:
```
          Children           Age         Income  Outage_sec_perweek  \
count   10000.0000  10000.000000   10000.000000        10000.000000
mean        2.0877     53.078400   39806.926771           10.001848
std         2.1472     20.698882   28199.916702            2.976019
min         0.0000     18.000000     348.670000            0.099747
25%         0.0000     35.000000   19224.717500            8.018214
50%         1.0000     53.000000   33170.605000           10.018560
75%         3.0000     71.000000   53246.170000           11.969485
max        10.0000     89.000000  258900.700000           21.207230

              Email      Contacts  Yearly_equip_failure        Tenure  \
count  10000.000000  10000.000000          10000.000000  10000.000000
mean      12.016000      0.994200              0.398000     34.526188
std        3.025898      0.988466              0.635953     26.443063
min        1.000000      0.000000              0.000000      1.000259
25%       10.000000      0.000000              0.000000      7.917694
50%       12.000000      1.000000              0.000000     35.430507
75%       14.000000      2.000000              1.000000     61.479795
max       23.000000      7.000000              6.000000     71.999280

       MonthlyCharge  Bandwidth_GB_Year  TimelyResponse         Fixes  \
count   10000.000000       10000.000000    10000.000000  10000.000000
mean      172.624816        3392.341550        3.490800      3.505100
std        42.943094        2185.294852        1.037797      1.034641
min        79.978860         155.506715        1.000000      1.000000
25%       139.979239        1236.470827        3.000000      3.000000
50%       167.484700        3279.536903        3.000000      4.000000
75%       200.734725        5586.141369        4.000000      4.000000
max       290.160419        7158.981530        7.000000      7.000000

       Replacements   Reliability       Options  Respectfulness     Courteous  \
count  10000.000000  10000.000000  10000.000000    10000.000000  10000.000000
mean       3.487000      3.497500      3.492900        3.497300      3.509500
std        1.027977      1.025816      1.024819        1.033586      1.028502
min        1.000000      1.000000      1.000000        1.000000      1.000000
25%        3.000000      3.000000      3.000000        3.000000      3.000000
50%        3.000000      3.000000      3.000000        3.000000      4.000000
```

```
75%        4.000000      4.000000      4.000000         4.000000      4.000000
max        8.000000      7.000000      7.000000         8.000000      7.000000

          Listening
count  10000.000000
mean       3.495600
std        1.028633
min        1.000000
25%        3.000000
50%        3.000000
75%        4.000000
max        8.000000
```

[ ]:
```python
# Discover missing data points within dataset
data_nulls = churn_df.isnull().sum()
print(data_nulls)
```

```
Children                0
Age                     0
Income                  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
TimelyResponse          0
Fixes                   0
Replacements            0
Reliability             0
```

```
Options                  0
Respectfulness           0
Courteous                0
Listening                0
dtype: int64
```

1.1.9 Dummy variable data preparation

Turn all yes/no into dummy variables a la Performance Lab Python.

[ ]:
```
churn_df['DummyTechie'] = [1 if v == 'Yes' else 0 for v in churn_df['Techie']]
churn_df['DummyContract'] = [1 if v == 'Two Year' else 0 for v in␣
 ↪churn_df['Contract']]
churn_df['DummyPort_modem'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['Port_modem']]
churn_df['DummyTablet'] = [1 if v == 'Yes' else 0 for v in churn_df['Tablet']]
churn_df['DummyInternetService'] = [1 if v == 'Fiber Optic' else 0 for v in␣
 ↪churn_df['InternetService']]
churn_df['DummyPhone'] = [1 if v == 'Yes' else 0 for v in churn_df['Phone']]
churn_df['DummyMultiple'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['Multiple']]
churn_df['DummyOnlineSecurity'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['OnlineSecurity']]
churn_df['DummyOnlineBackup'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['OnlineBackup']]
churn_df['DummyDeviceProtection'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['DeviceProtection']]
churn_df['DummyTechSupport'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['TechSupport']]
churn_df['DummyStreamingTV'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['StreamingTV']]
churn_df['StreamingMovies'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['StreamingMovies']]
churn_df['DummyPaperlessBilling'] = [1 if v == 'Yes' else 0 for v in␣
 ↪churn_df['PaperlessBilling']]
```

[ ]:
```
# Drop original categorical features from dataframe
churn_df = churn_df.drop(columns=['Techie', 'Contract', 'Port_modem', 'Tablet',
                                  'InternetService', 'Phone', 'Multiple',␣
 ↪'OnlineSecurity',
                                  'OnlineBackup', 'DeviceProtection',␣
 ↪'TechSupport',
                                  'StreamingTV', 'StreamingMovies',␣
 ↪'PaperlessBilling'])
churn_df.describe()
```

[ ]:
```
          Children           Age        Income  Outage_sec_perweek  \
count  10000.0000  10000.000000  10000.000000        10000.000000
```

```
mean       2.0877     53.078400   39806.926771           10.001848
std        2.1472     20.698882   28199.916702            2.976019
min        0.0000     18.000000     348.670000            0.099747
25%        0.0000     35.000000   19224.717500            8.018214
50%        1.0000     53.000000   33170.605000           10.018560
75%        3.0000     71.000000   53246.170000           11.969485
max       10.0000     89.000000  258900.700000           21.207230

              Email      Contacts  Yearly_equip_failure        Tenure  \
count  10000.000000  10000.000000          10000.000000  10000.000000
mean      12.016000      0.994200              0.398000     34.526188
std        3.025898      0.988466              0.635953     26.443063
min        1.000000      0.000000              0.000000      1.000259
25%       10.000000      0.000000              0.000000      7.917694
50%       12.000000      1.000000              0.000000     35.430507
75%       14.000000      2.000000              1.000000     61.479795
max       23.000000      7.000000              6.000000     71.999280

       MonthlyCharge  Bandwidth_GB_Year  ...   DummyTablet  \
count   10000.000000       10000.000000  ...  10000.000000
mean      172.624816        3392.341550  ...      0.299100
std        42.943094        2185.294852  ...      0.457887
min        79.978860         155.506715  ...      0.000000
25%       139.979239        1236.470827  ...      0.000000
50%       167.484700        3279.536903  ...      0.000000
75%       200.734725        5586.141369  ...      1.000000
max       290.160419        7158.981530  ...      1.000000

       DummyInternetService   DummyPhone  DummyMultiple  DummyOnlineSecurity  \
count          10000.000000 10000.000000   10000.000000         10000.000000
mean               0.440800     0.906700       0.460800             0.357600
std                0.496508     0.290867       0.498486             0.479317
min                0.000000     0.000000       0.000000             0.000000
25%                0.000000     1.000000       0.000000             0.000000
50%                0.000000     1.000000       0.000000             0.000000
75%                1.000000     1.000000       1.000000             1.000000
max                1.000000     1.000000       1.000000             1.000000

       DummyOnlineBackup  DummyDeviceProtection  DummyTechSupport  \
count       10000.000000           10000.000000      10000.000000
mean            0.450600               0.438600          0.375000
std             0.497579               0.496241          0.484147
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
```

```
       DummyStreamingTV  DummyPaperlessBilling
count      10000.000000           10000.000000
mean           0.492900               0.588200
std            0.499975               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 31 columns]
```

1.1.10 C4. Visualizations:

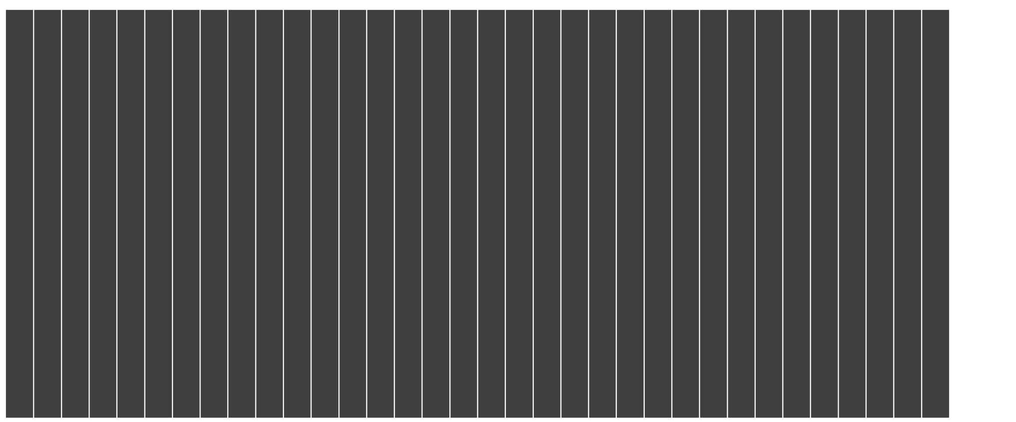
Generate univariate and bivariate visualizations of the distributions of variables in the cleaned data set. Include the target variable in your bivariate visualizations.

[ ]:
```
# Visualize missing values in dataset

# Install appropriate library
!pip install missingno

# Importing the libraries
import missingno as msno

# Visualize missing values as a matrix
msno.matrix(churn_df);
```

```
findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans.
findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans.

Requirement already satisfied: missingno in c:\users\vreed\anaconda3\lib\site-
packages (0.5.0)
Requirement already satisfied: numpy in c:\users\vreed\anaconda3\lib\site-
packages (from missingno) (1.18.1)
Requirement already satisfied: seaborn in c:\users\vreed\anaconda3\lib\site-
packages (from missingno) (0.10.0)
Requirement already satisfied: matplotlib in c:\users\vreed\anaconda3\lib\site-
packages (from missingno) (3.1.3)
Requirement already satisfied: scipy in c:\users\vreed\anaconda3\lib\site-
packages (from missingno) (1.4.1)
Requirement already satisfied: pandas>=0.22.0 in c:\users\vreed\anaconda3\lib
\site-packages (from seaborn->missingno) (1.0.1)
Requirement already satisfied: cycler>=0.10 in c:\users\vreed\anaconda3\lib
\site-packages (from matplotlib->missingno) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
c:\users\vreed\anaconda3\lib\site-packages (from matplotlib->missingno) (2.4.6)
```

```
Requirement already satisfied: python-dateutil>=2.1 in
c:\users\vreed\anaconda3\lib\site-packages (from matplotlib->missingno) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\vreed\anaconda3\lib
\site-packages (from matplotlib->missingno) (1.1.0)
Requirement already satisfied: pytz>=2017.2 in c:\users\vreed\anaconda3\lib
\site-packages (from pandas>=0.22.0->seaborn->missingno) (2019.3)
Requirement already satisfied: six in c:\users\vreed\anaconda3\lib\site-packages
(from cycler>=0.10->matplotlib->missingno) (1.14.0)
Requirement already satisfied: setuptools in c:\users\vreed\anaconda3\lib\site-
packages (from kiwisolver>=1.0.1->matplotlib->missingno) (45.2.0.post20200210)
```

```
findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans.
```



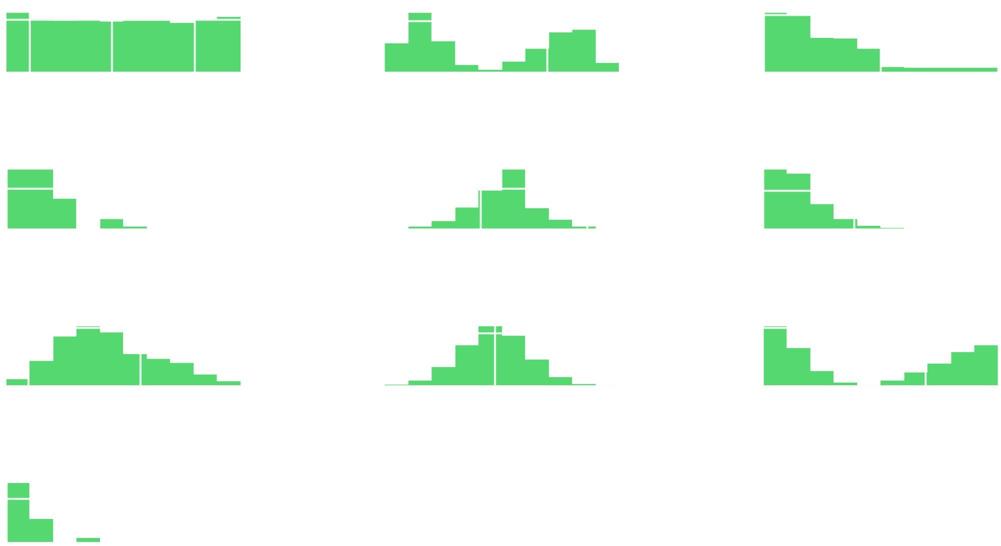
[ ]:
```
'''No need to impute an missing values as the dataset appears complete/
 ↪cleaned'''
# Impute missing fields for variables Children, Age, Income, Tenure and␣
 ↪Bandwidth_GB_Year with median or mean
# churn_df['Children'] = churn_df['Children'].fillna(churn_df['Children'].
 ↪median())
# churn_df['Age'] = churn_df['Age'].fillna(churn_df['Age'].median())
# churn_df['Income'] = churn_df['Income'].fillna(churn_df['Income'].median())
# churn_df['Tenure'] = churn_df['Tenure'].fillna(churn_df['Tenure'].median())
# churn_df['Bandwidth_GB_Year'] = churn_df['Bandwidth_GB_Year'].
 ↪fillna(churn_df['Bandwidth_GB_Year'].median())
```

[ ]:
```
'No need to impute an missing values as the dataset appears complete/cleaned'
```

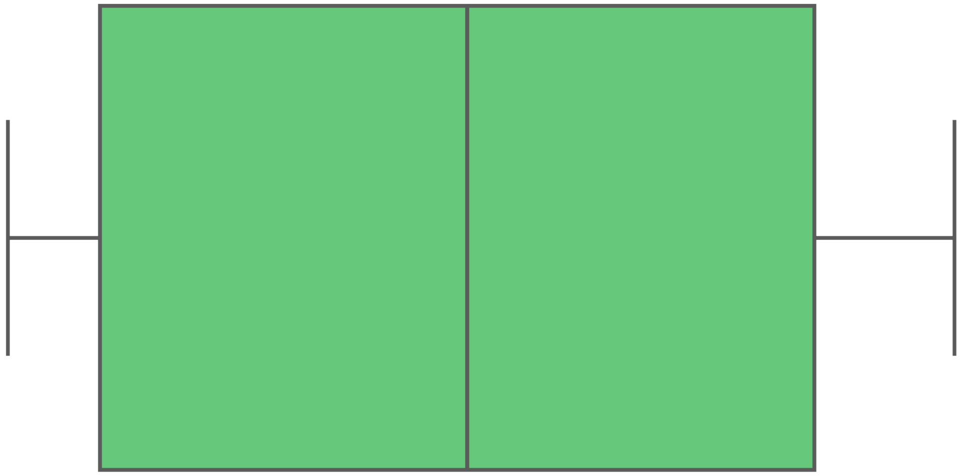
1.2 Univariate Statistics

[ ]:
```
# Create histograms of contiuous variables
churn_df[['Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email',
          'Contacts', 'Yearly_equip_failure', 'Tenure', 'MonthlyCharge',
          'Bandwidth_GB_Year']].hist()
plt.savefig('churn_pyplot.jpg')
plt.tight_layout()
```

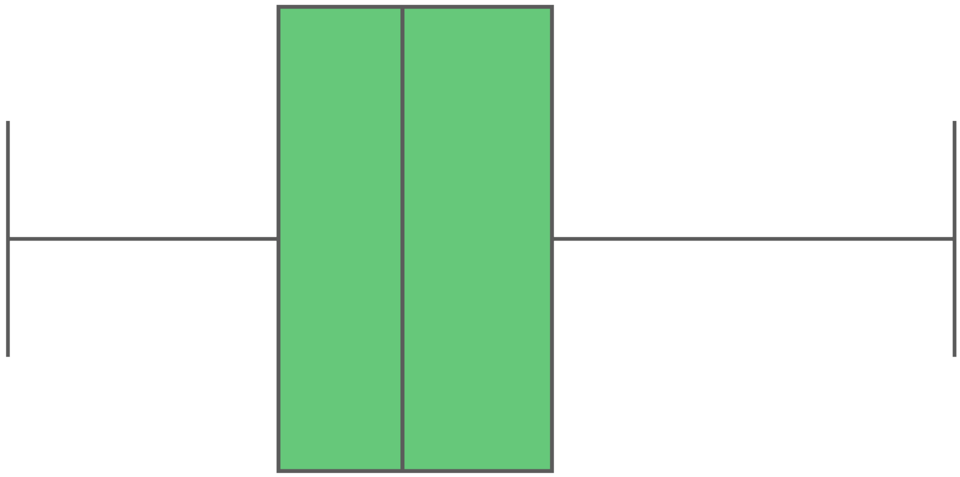
```
findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans.
findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans.
```



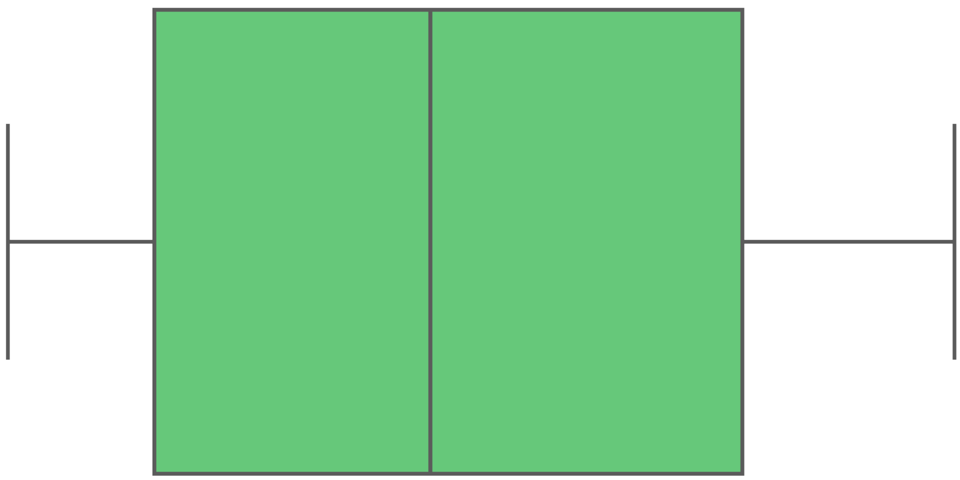
[ ]:
```
# Create Seaborn boxplots for continuous variables
sns.boxplot('Tenure', data = churn_df)
plt.show()
```



[ ]:
```
sns.boxplot('MonthlyCharge', data = churn_df)
plt.show()
```



[ ]:
```
sns.boxplot('Bandwidth_GB_Year', data = churn_df)
plt.show()
```

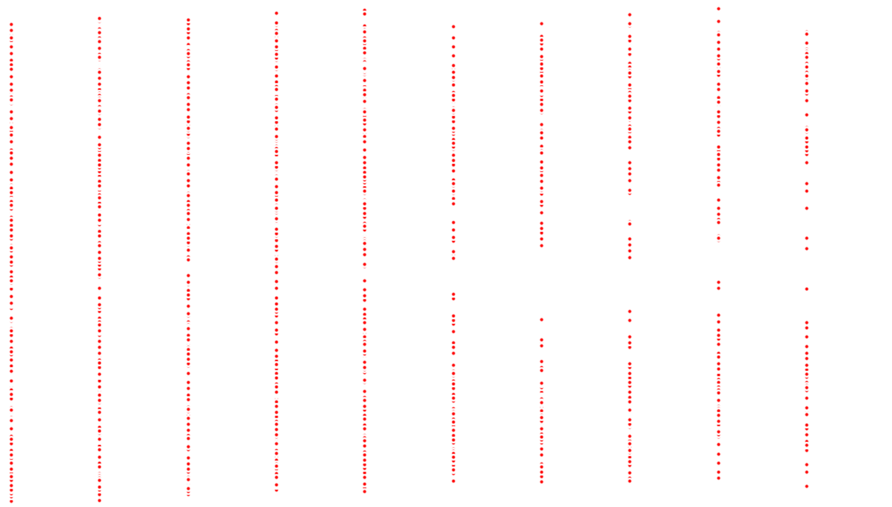


1.2.1 It appears that anomolies have been removed from the dataset present "churn_clean.csv" as there are no remaining outliers.

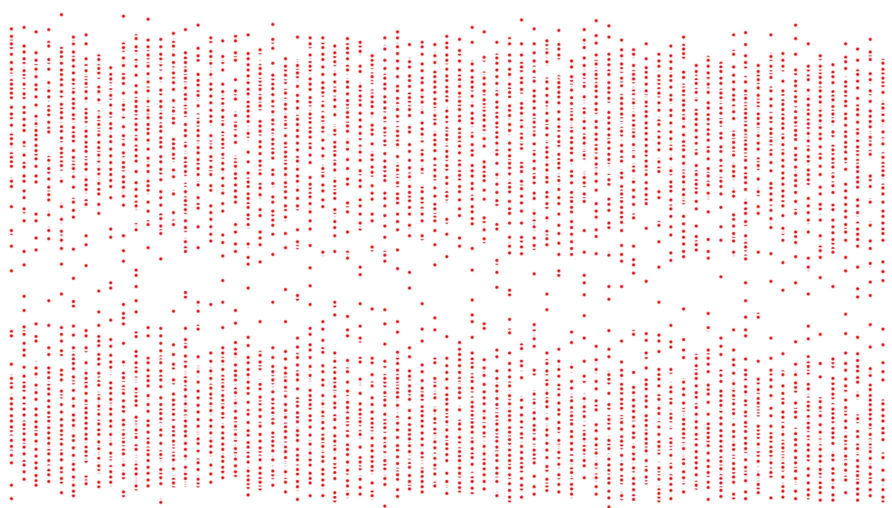
1.3 Bivariate Statistics

1.3.1 Let's run some scatterplots to get an idea of our linear relationships with our target variable of "Bandwidth_GB_Year" usage & some of the respective predictor variables.

[ ]:
```
# Run scatterplots to show direct or inverse relationships between target &␣
↪independent variables
sns.scatterplot(x=churn_df['Children'], y=churn_df['Bandwidth_GB_Year'],␣
↪color='red')
plt.show();
```

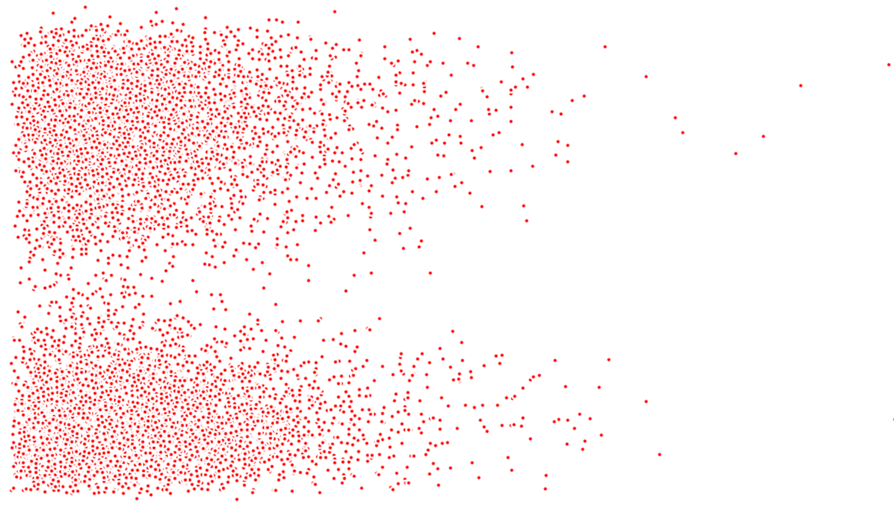


```
[ ]: sns.scatterplot(x=churn_df['Age'], y=churn_df['Bandwidth_GB_Year'], color='red')
     plt.show();
```

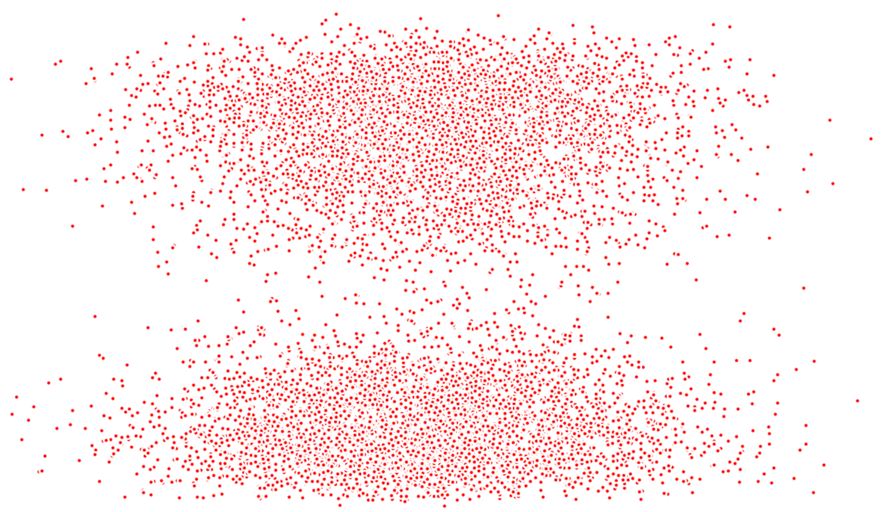


```
[ ]: sns.scatterplot(x=churn_df['Income'], y=churn_df['Bandwidth_GB_Year'],␣
      ↪color='red')
```

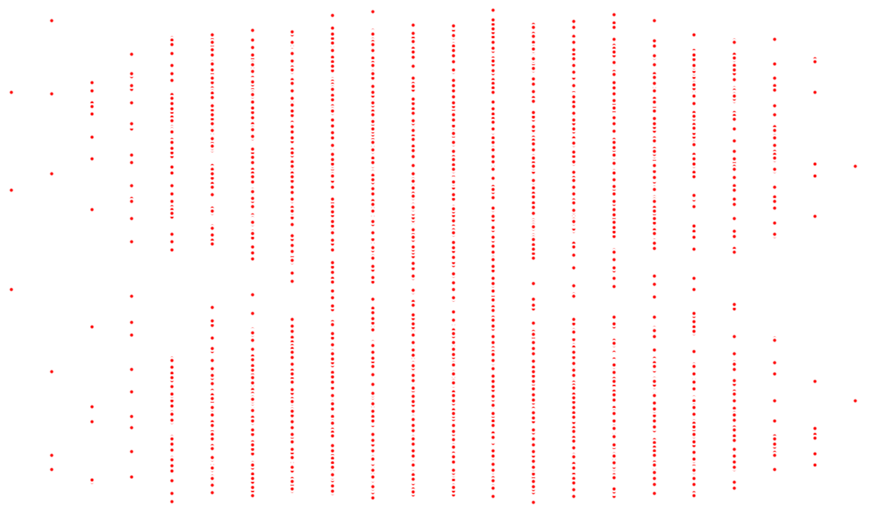
```
plt.show();
```



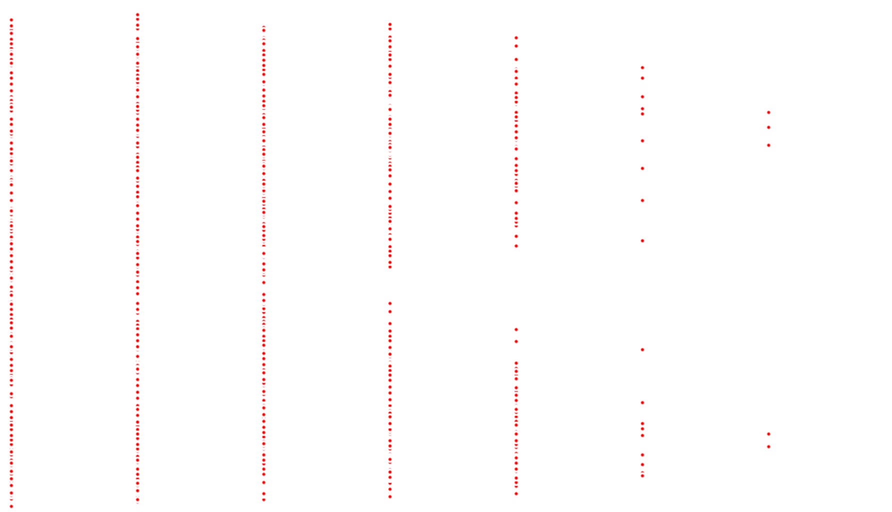
[ ]:
```
sns.scatterplot(x=churn_df['Outage_sec_perweek'],␣
 ↪y=churn_df['Bandwidth_GB_Year'], color='red')
plt.show();
```



[ ]:
```
sns.scatterplot(x=churn_df['Email'], y=churn_df['Bandwidth_GB_Year'],
 ↪color='red')
plt.show();
```

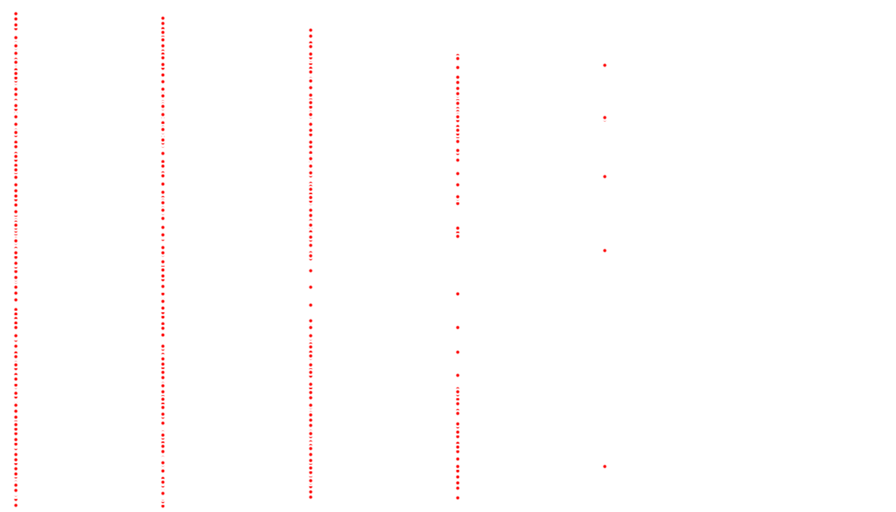


[ ]:
```
sns.scatterplot(x=churn_df['Contacts'], y=churn_df['Bandwidth_GB_Year'],
 ↪color='red')
plt.show();
```



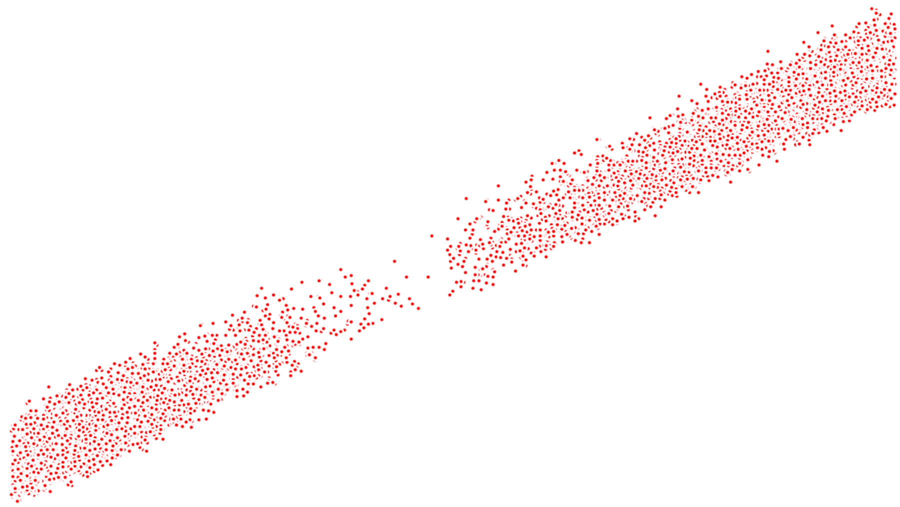
[ ]:

```
sns.scatterplot(x=churn_df['Yearly_equip_failure'], y=churn_df['Bandwidth_GB_Year'], color='red')
plt.show();
```



[ ]:

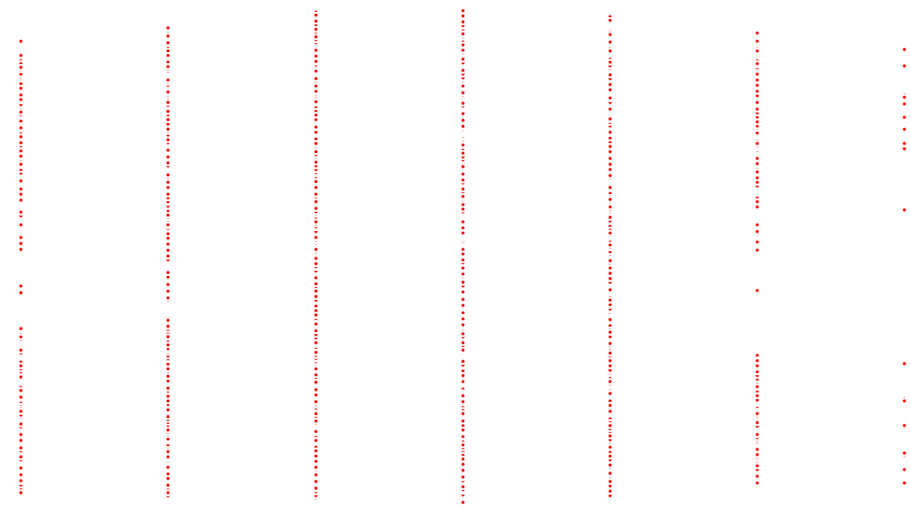
```
sns.scatterplot(x=churn_df['Tenure'], y=churn_df['Bandwidth_GB_Year'], color='red')
plt.show();
```



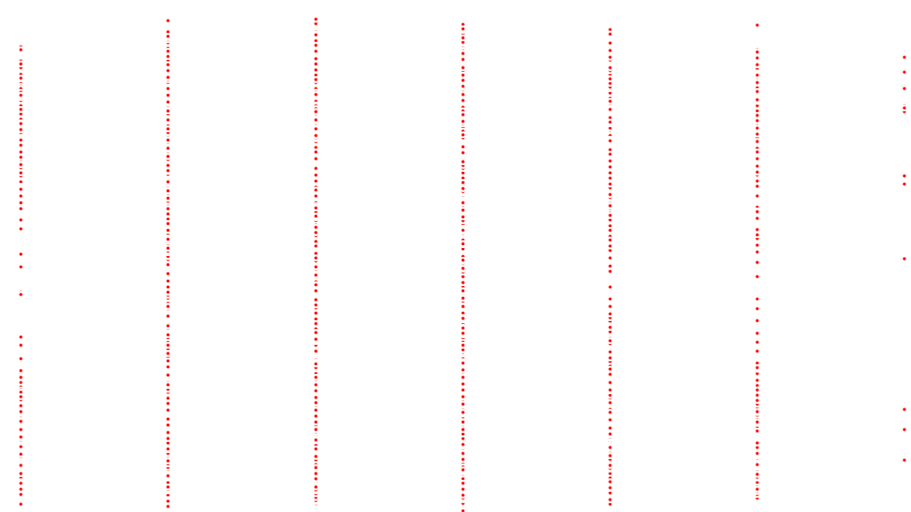
```
[ ]: sns.scatterplot(x=churn_df['MonthlyCharge'], y=churn_df['Bandwidth_GB_Year'],␣
      ↪color='red')
     plt.show();
```

```
[ ]: sns.scatterplot(x=churn_df['TimelyResponse'], y=churn_df['Bandwidth_GB_Year'],␣
      ↪color='red')
```

```
plt.show();
```



[ ]:
```
sns.scatterplot(x=churn_df['Fixes'], y=churn_df['Bandwidth_GB_Year'],␣
 ↪color='red')
plt.show();
```



[ ]:
```
sns.scatterplot(x=churn_df['DummyTechie'], y=churn_df['Bandwidth_GB_Year'], color='red')
plt.show();
```

1.3.2 C5. Prepared Dataset:

Provide a copy of the prepared data set.

[ ]:
```
# Extract Clean dataset
churn_df.to_csv('churn_prepared.csv')
```

1.3.3 Part IV: Model Comparison and Analysis

D. Compare an initial and a reduced multiple regression model by doing the following:

1. Construct an initial multiple regression model from all predictors that were identified in Part C2.
2. Justify a statistically based variable selection procedure and a model evaluation metric to reduce the initial model in a way that aligns with the research question.
3. Provide a reduced multiple regression model that includes both categorical and continuous variables.

Note: The output should include a screenshot of each model.

1.3.4 D1. Initial Model

Construct an initial multiple regression model from all predictors that were identified in Part C2.

[ ]:
```
# Develop the initial estimated regression equation that could be used to␣
 ↪predict the Bandwidth_GB_Year,
# given the continuous variables
churn_df['intercept'] = 1
lm_bandwidth = sm.OLS(churn_df['Bandwidth_GB_Year'], churn_df[['Children',␣
 ↪'Age',
                                                              'Income',
                                                             ␣
 ↪'Outage_sec_perweek',
                                                              'Email',␣
 ↪'Contacts',
                                                             ␣
 ↪'Yearly_equip_failure',
                                                              'Tenure',␣
 ↪'MonthlyCharge',
                                                             ␣
 ↪'TimelyResponse', 'Fixes',
                                                              'Replacements',␣
 ↪'Reliability',
                                                              'Options',␣
 ↪'Respectfulness',
                                                              'Courteous',␣
 ↪'Listening',
                                                              'intercept']]).
 ↪fit()
print(lm_bandwidth.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Bandwidth_GB_Year   R-squared:                       0.989
Model:                            OLS   Adj. R-squared:                  0.989
Method:                 Least Squares   F-statistic:                 5.329e+04
Date:                Mon, 12 Jul 2021   Prob (F-statistic):               0.00
Time:                        13:34:57   Log-Likelihood:                -68489.
No. Observations:               10000   AIC:                         1.370e+05
Df Residuals:                    9982   BIC:                         1.371e+05
Df Model:                          17
Covariance Type:            nonrobust
================================================================================
========
                           coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
--------
Children                30.9275      1.065     29.050      0.000      28.841
33.014
Age                     -3.3206      0.110    -30.065      0.000      -3.537
```

```
-3.104
Income                 9.976e-05    8.1e-05      1.231      0.218   -5.91e-05
0.000
Outage_sec_perweek       -0.3501      0.768     -0.456      0.649      -1.856
1.156
Email                    -0.2792      0.755     -0.370      0.712      -1.759
1.201
Contacts                  2.9707      2.312      1.285      0.199      -1.562
7.503
Yearly_equip_failure      0.9080      3.593      0.253      0.801      -6.136
7.952
Tenure                   82.0113      0.086    948.882      0.000      81.842
82.181
MonthlyCharge             3.2768      0.053     61.585      0.000       3.173
3.381
TimelyResponse           -8.8961      3.271     -2.720      0.007     -15.308
-2.484
Fixes                     3.4660      3.064      1.131      0.258      -2.541
9.473
Replacements             -0.1771      2.812     -0.063      0.950      -5.690
5.335
Reliability              -0.2697      2.515     -0.107      0.915      -5.199
4.659
Options                   2.7199      2.611      1.042      0.298      -2.398
7.838
Respectfulness            1.7157      2.689      0.638      0.523      -3.554
6.986
Courteous                -1.3482      2.543     -0.530      0.596      -6.333
3.637
Listening                 5.7844      2.420      2.390      0.017       1.040
10.529
intercept                95.8754     26.146      3.667      0.000      44.624
147.127
==============================================================================
Omnibus:                    12280.983   Durbin-Watson:                   1.979
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              968.853
Skew:                           0.449   Prob(JB):                    4.13e-211
Kurtosis:                       1.768   Cond. No.                     5.60e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.6e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
[ ]: churn_df_dummies = churn_df.columns
     print(churn_df_dummies)
```

```
Index(['Children', 'Age', 'Income', 'Gender', 'Churn', 'Outage_sec_perweek',
       'Email', 'Contacts', 'Yearly_equip_failure', 'PaymentMethod', 'Tenure',
       'MonthlyCharge', 'Bandwidth_GB_Year', 'TimelyResponse', 'Fixes',
       'Replacements', 'Reliability', 'Options', 'Respectfulness', 'Courteous',
       'Listening', 'DummyTechie', 'DummyContract', 'DummyPort_modem',
       'DummyTablet', 'DummyInternetService', 'DummyPhone', 'DummyMultiple',
       'DummyOnlineSecurity', 'DummyOnlineBackup', 'DummyDeviceProtection',
       'DummyTechSupport', 'DummyStreamingTV', 'DummyPaperlessBilling',
       'intercept'],
      dtype='object')
```

```
[ ]: """Model including all dummy variables"""
     churn_df['intercept'] = 1
     lm_bandwidth = sm.OLS(churn_df['Bandwidth_GB_Year'], churn_df[['Children',␣
      ↪'Age',
                                                                     'Income',␣
      ↪'Outage_sec_perweek',
                                                                     'Email',␣
      ↪'Contacts',
                                                                    ␣
      ↪'Yearly_equip_failure',
                                                                     'DummyTechie',␣
      ↪'DummyContract',
                                                                    ␣
      ↪'DummyPort_modem', 'DummyTablet',
                                                                    ␣
      ↪'DummyInternetService', 'DummyPhone',
                                                                     'DummyMultiple',␣
      ↪'DummyOnlineSecurity',
                                                                    ␣
      ↪'DummyOnlineBackup', 'DummyDeviceProtection',
                                                                    ␣
      ↪'DummyTechSupport', 'DummyStreamingTV',
                                                                    ␣
      ↪'DummyPaperlessBilling',
                                                                     'Tenure',␣
      ↪'MonthlyCharge',
                                                                    ␣
      ↪'TimelyResponse', 'Fixes',
                                                                     'Replacements',␣
      ↪'Reliability',
                                                                     'Options',␣
      ↪'Respectfulness',
```

```
                                                              'Courteous',␣
↪'Listening',
                                                              'intercept']]).
↪fit()
print(lm_bandwidth.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Bandwidth_GB_Year   R-squared:                       0.996
Model:                            OLS   Adj. R-squared:                  0.996
Method:                 Least Squares   F-statistic:                 8.675e+04
Date:                Mon, 12 Jul 2021   Prob (F-statistic):               0.00
Time:                        13:34:57   Log-Likelihood:                -63241.
No. Observations:               10000   AIC:                         1.265e+05
Df Residuals:                    9969   BIC:                         1.268e+05
Df Model:                          30
Covariance Type:            nonrobust
================================================================================
=========
                            coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---------
Children                 30.4177      0.631     48.226      0.000      29.181
31.654
Age                      -3.3153      0.065    -50.671      0.000      -3.444
-3.187
Income                  9.27e-06    4.8e-05      0.193      0.847   -8.48e-05
0.000
Outage_sec_perweek       -0.5259      0.455     -1.156      0.248      -1.418
0.366
Email                     0.1812      0.448      0.405      0.686      -0.696
1.058
Contacts                  2.1263      1.370      1.552      0.121      -0.559
4.811
Yearly_equip_failure      1.2859      2.129      0.604      0.546      -2.887
5.459
DummyTechie               0.6193      3.621      0.171      0.864      -6.478
7.717
DummyContract             3.9328      3.151      1.248      0.212      -2.244
10.110
DummyPort_modem           0.4710      2.707      0.174      0.862      -4.835
5.777
DummyTablet              -1.9813      2.959     -0.670      0.503      -7.781
3.819
DummyInternetService   -373.7111      2.980   -125.411      0.000    -379.552
-367.870
```

DummyPhone	-2.1515	4.658	-0.462	0.644	-11.282	6.979
DummyMultiple	-76.0773	3.153	-24.130	0.000	-82.257	-69.897
DummyOnlineSecurity	67.4949	2.830	23.850	0.000	61.948	73.042
DummyOnlineBackup	-12.6597	2.931	-4.319	0.000	-18.406	-6.914
DummyDeviceProtection	24.8879	2.807	8.867	0.000	19.386	30.390
DummyTechSupport	-52.5816	2.857	-18.405	0.000	-58.182	-46.981
DummyStreamingTV	30.4799	3.372	9.039	0.000	23.870	37.090
DummyPaperlessBilling	-2.6415	2.752	-0.960	0.337	-8.035	2.752
Tenure	81.9913	0.051	1600.655	0.000	81.891	82.092
MonthlyCharge	4.7092	0.048	97.416	0.000	4.614	4.804
TimelyResponse	-1.4340	1.939	-0.739	0.460	-5.236	2.368
Fixes	1.6837	1.817	0.927	0.354	-1.878	5.245
Replacements	-2.4128	1.666	-1.448	0.148	-5.679	0.853
Reliability	-1.5594	1.489	-1.047	0.295	-4.479	1.360
Options	0.5285	1.547	0.342	0.733	-2.504	3.561
Respectfulness	1.2322	1.593	0.774	0.439	-1.890	4.354
Courteous	0.4649	1.507	0.308	0.758	-2.490	3.419
Listening	3.1708	1.434	2.212	0.027	0.361	5.981
intercept	33.1742	16.379	2.025	0.043	1.069	65.280

==

Omnibus:	871.245	Durbin-Watson:	1.970
Prob(Omnibus):	0.000	Jarque-Bera (JB):	697.849
Skew:	-0.559	Prob(JB):	2.91e-152
Kurtosis:	2.349	Cond. No.	5.95e+05

==

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

[2] The condition number is large, 5.95e+05. This might indicate that there are strong multicollinearity or other numerical problems.

1.3.5 Initial Multiple Linear Regression Model

With 30 indpendent variables (17 continuous & 13 categorical): y = 104.85 + 30.86 * Children - 3.31 * Age + 0.00 * Income - 0.26 * Outage_sec_perweek - 0.31 * Email + 2.95 * Contacts + 0.67 * Yearly_equip_failure + 0.62 * DummyTechie + 3.93 * DummyContract + 0.47 * DummyPort_modem - 1.98 * DummyTablet - 373.71 * DummyInternetService - 2.15 * DummyPhone - 76.08 * DummyMultiple + 67.49 * DummyOnlineSecurity - 12.66 * DummyOnlineBackup + 24.89 * DummyDeviceProtection - 52.58 * DummyTechSupport + 30.48 * DummyStreamingTV - 2.64 * DummyPaperlessBilling + 82.01 * Tenure + 3.28 * MonthlyCharge - 8.9 * TimelyResponse + 3.47 * Fixes - 0.18 * Replacements - 0.27 * Reliability + 2.72 * Options + 1.72 * Respectfulness - 1.35 * Courteous + 5.78 * Listening

1.4 Must train/test?split this model!!!

[ ]:
```
"""Testing the Hypotheses of No Relationship"""
# residuals = churn_df['Bandwidth_GB_Year'] - lm_bandwidth.
↪predict(churn_df[['Tenure', 'intercept']])
# sns.scatterplot(x=churn_df['Bandwidth_GB_Year'], y=residuals, color='red')
# plt.show();
```

[ ]:
```
'Testing the Hypotheses of No Relationship'
```

1.4.1 Based on an R2 value = 0.989. So, 99% of the variation is explained by this model. The condition number is large which might suggest strong multicolinnearity. Apparently, we do not need all of these variables to explain the variance. So, let's run a heatmap for bivariate analysis & a principal component analysis in order to reduce variables.

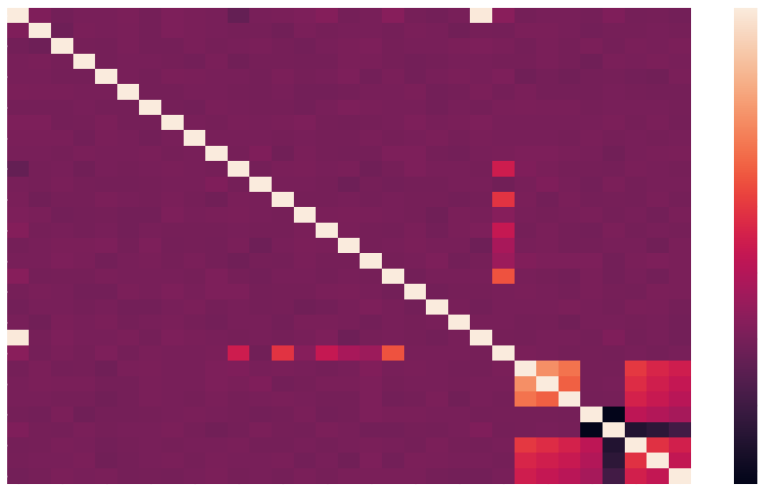
1.4.2 D2. Justification of Model Reduction

Justify a statistically based variable selection procedure and a model evaluation metric to reduce the initial model in a way that aligns with the research question.

[ ]:
```
# Create dataframe for heatmap bivariate analysis of correlation
churn_bivariate = churn_df[['Bandwidth_GB_Year', 'Children', 'Age', 'Income',
                            'Outage_sec_perweek', 'Yearly_equip_failure',␣
↪'DummyTechie', 'DummyContract',
                            'DummyPort_modem', 'DummyTablet',␣
↪'DummyInternetService',
                            'DummyPhone', 'DummyMultiple',␣
↪'DummyOnlineSecurity',
                            'DummyOnlineBackup', 'DummyDeviceProtection',
                            'DummyTechSupport', 'DummyStreamingTV',
                            'DummyPaperlessBilling','Email', 'Contacts',
                            'Tenure', 'MonthlyCharge', 'TimelyResponse',␣
↪'Fixes',
```

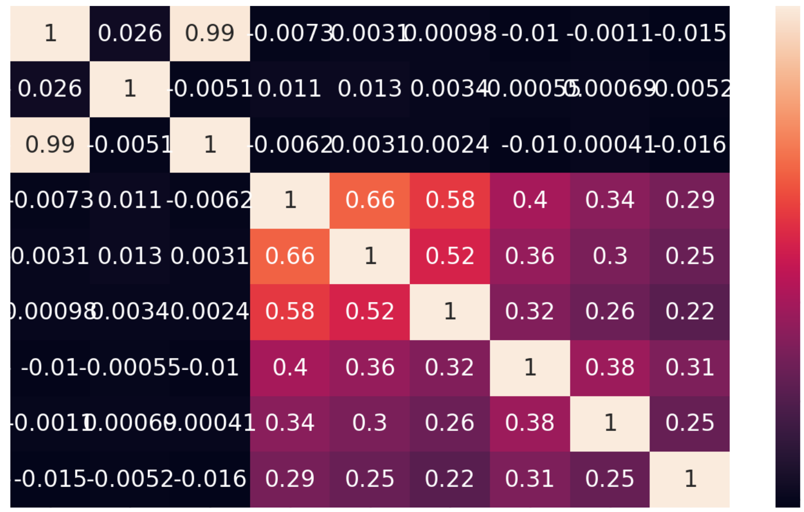
```
                            'Replacements', 'Reliability', 'Options',␣
↪'Respectfulness',
                            'Courteous', 'Listening']]
```

[ ]:
```
# Run Seaborn heatmap
sns.heatmap(churn_bivariate.corr(), annot=False)
plt.show()
```



1.4.3 Alrighty, let's try that without some demographic, contacting-customer & options variables, basically purple or darker.

[ ]:
```
churn_bivariate = churn_df[['Bandwidth_GB_Year', 'Children',
                            'Tenure', 'TimelyResponse', 'Fixes',
                            'Replacements', 'Respectfulness',
                            'Courteous', 'Listening']]

sns.heatmap(churn_bivariate.corr(), annot=True)
plt.show()
```



1.4.4 That looks a lot better.

Again, it appears that Tenure is the predictor for most of the variance. There is clearly a direct linear relationship between customer tenure with the telecom company & the amount of data (in GBs) that is being used. Let's run a multiple linear regression model on those variables with 0.50 or above & children because of its high coefficient (30.86) on the original OLS model. So, Y = bandwidth & then children, tenure, fixes, replacements.

1.4.5 D3. Reduced Multiple Regression Model

Provide a reduced multiple regression model that includes both categorical and continuous variables.

[ ]:
```
# Run reduced OLS multiple regression
churn_df['intercept'] = 1
lm_bandwidth = sm.OLS(churn_df['Bandwidth_GB_Year'], churn_df[['Children',␣
 ↪'Tenure', 'Fixes', 'Replacements', 'intercept']]).fit()
print(lm_bandwidth.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Bandwidth_GB_Year   R-squared:                       0.984
Model:                            OLS   Adj. R-squared:                  0.984
```

```
Method:                 Least Squares   F-statistic:                 1.537e+05
Date:                Mon, 12 Jul 2021   Prob (F-statistic):               0.00
Time:                        13:34:59   Log-Likelihood:                -70407.
No. Observations:               10000   AIC:                         1.408e+05
Df Residuals:                    9995   BIC:                         1.409e+05
Df Model:                           4
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Children        31.1763      1.288     24.211      0.000      28.652      33.700
Tenure          81.9518      0.105    783.845      0.000      81.747      82.157
Fixes            1.0728      3.129      0.343      0.732      -5.061       7.206
Replacements    -3.6585      3.149     -1.162      0.245      -9.831       2.514
intercept      506.7695     11.949     42.413      0.000     483.348     530.191
==============================================================================
Omnibus:                      380.733   Durbin-Watson:                   1.978
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              295.369
Skew:                           0.334   Prob(JB):                     7.27e-65
Kurtosis:                       2.488   Cond. No.                         191.
==============================================================================

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

1.4.6 Reduced Multiple Linear Regression Model

With 4 indpendent variables: y = 497.78 + 31.18 * Children + 81.94 * Tenure + 1.07 * Fixes - 3.66 * Replacements

1.4.7 Well, there it is. Removing all those other predictor variables & our model still explains 98% of the variance.

1.4.8 Part IV: E

E. Analyze the data set using your reduced multiple regression model by doing the following:

1. Explain your data analysis process by comparing the initial and reduced multiple regression models, including the following elements:
   the logic of the variable selection technique
   the model evaluation metric
   a residual plot
2. Provide the output and any calculations of the analysis you performed, including the model's residual error.

Note: The output should include the predictions from the refined model you used to perform the analysis.

3. Provide the code used to support the implementation of the multiple regression models.

1.4.9 E1. Model Comparison

Explain your data analysis process by comparing the initial and reduced multiple regression models, including the following elements:

```
<li>
the logic of the variable selection technique
</li>
<li>
the model evaluation metric
</li>
<li>
a residual plot
</li>
```

Note: Verbatim from fasttrack description of analysis of Titanic dataset, "Since male is the dummy variable, being male reduces the log odds by 2.75 while a unit increase in age reduces log odds by 0.037."

1.4.10 E2. Output & Calculations

Provide the output and any calculations of the analysis you performed, including the model's residual error.

Note: The output should include the predictions from the refined model you used to perform the analysis.

1.4.11 E3. Code

All code for analysis include above.

1.4.12 Part V: Data Summary and Implications

F. Summarize your findings and assumptions by doing the following:

1. Discuss the results of your data analysis, including the following elements:
   a regression equation for the reduced model
   an interpretation of coefficients of the statistically significant variables of the model
   the statistical and practical significance of the model
   the limitations of the data analysis
2. Recommend a course of action based on your results.

1.4.13 F1. Results

Discuss the results of your data analysis, including the following elements:

```
<li>
a regression equation for the reduced model
</li>
<li>
an interpretation of coefficients of the statistically significant variables of the model
```

```
</li>
<li>
the statistical and practical significance of the model
</li>
<li>
the limitations of the data analysis
</li>
```

1.4.14 F2. Recommendations

Clearly with such a direct linear relationship between bandwidth used yearly & tenure with the telecom company it makes sense to suggest the company do everything within marketing & customer service capability to retain the customers gained as the longer they stay with the company the more bandwidth they tend to use.

1.4.15 Part VI: Demonstration

G. Provide a Panopto video recording that includes all of the following elements:

a demonstration of the functionality of the code used for the analysis
an identification of the version of the programming environment
a comparison of the two multiple regression models you used in your analysis
an interpretation of the coefficients.

1.4.16 G. Video

link

1.4.17 H. Sources for Third-Party Code

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[ ]:
```
!wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('D208_Performance_Assessment_NBM2_Task_1.ipynb')
```

```
--2021-07-12 19:42:30--  https://raw.githubusercontent.com/brpy/colab-
pdf/master/colab_pdf.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)...
185.199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1864 (1.8K) [text/plain]
Saving to: colab_pdf.py

colab_pdf.py        100%[===================>]   1.82K  --.-KB/s    in 0s

2021-07-12 19:42:30 (33.5 MB/s) - colab_pdf.py saved [1864/1864]

Mounted at /content/drive/

WARNING: apt does not have a stable CLI interface. Use with caution in scripts.


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.

Extracting templates from packages: 100%
```