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.
- Place Bandwidth_GB_Year at end of dataframe
- Finally, the prepared dataset will be extracted & provided as "churn_prepared.csv"

[1]:
```
# 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>
```

[2]:
```
# 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
%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')
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
public API at pandas.testing instead.
  import pandas.util.testing as tm
```

[3]:
```
# 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
```

[4]:
```
# Load data set into Pandas dataframe
churn_df = pd.read_csv('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)
```

[5]:
```
# Display Churn dataframe
churn_df
```

[5]:
```
      CaseOrder Customer_id  ... Courteous Listening
0             1     K409198  ...         3         4
1             2     S120509  ...         4         4
2             3     K191035  ...         3         3
3             4      D90850  ...         3         3
4             5     K662701  ...         4         5
...         ...         ...  ...       ...       ...
9995       9996     M324793  ...         2         3
9996       9997     D861732  ...         2         5
9997       9998     I243405  ...         4         5
9998       9999     I641617  ...         5         4
9999      10000      T38070  ...         4         1

[10000 rows x 50 columns]
```

[6]:
```
# 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')
```

[7]:
```
# Find number of records and columns of dataset
churn_df.shape
```

[7]:
```
(10000, 50)
```

[8]:
```
# Describe Churn dataset statistics
churn_df.describe()
```

[8]:
```
         CaseOrder           Zip  ...     Courteous     Listening
count  10000.00000  10000.000000  ...  10000.000000  10000.000000
mean    5000.50000  49153.319600  ...      3.509500      3.495600
std     2886.89568  27532.196108  ...      1.028502      1.028633
min        1.00000    601.000000  ...      1.000000      1.000000
25%     2500.75000  26292.500000  ...      3.000000      3.000000
50%     5000.50000  48869.500000  ...      4.000000      3.000000
75%     7500.25000  71866.500000  ...      4.000000      4.000000
max    10000.00000  99929.000000  ...      7.000000      8.000000

[8 rows x 23 columns]
```

[9]:
```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',␣
 ↪'PaymentMethod'])
churn_df.describe()
```

[9]:
```
         Children           Age  ...     Courteous     Listening
count  10000.0000  10000.000000  ...  10000.000000  10000.000000
mean       2.0877     53.078400  ...      3.509500      3.495600
std        2.1472     20.698882  ...      1.028502      1.028633
min        0.0000     18.000000  ...      1.000000      1.000000
25%        0.0000     35.000000  ...      3.000000      3.000000
50%        1.0000     53.000000  ...      4.000000      3.000000
75%        3.0000     71.000000  ...      4.000000      4.000000
max       10.0000     89.000000  ...      7.000000      8.000000

[8 rows x 18 columns]
```

[10]:
```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
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.

[11]:
```
churn_df['DummyGender'] = [1 if v == 'Male' else 0 for v in churn_df['Gender']]
churn_df['DummyChurn'] = [1 if v == 'Male' else 0 for v in churn_df['Churn']]
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']]
```

[12]:
```
# Drop original categorical features from dataframe
churn_df = churn_df.drop(columns=['Gender', 'Churn', 'Techie', 'Contract',␣
↪'Port_modem', 'Tablet',
                                  'InternetService', 'Phone', 'Multiple',␣
↪'OnlineSecurity',
                                  'OnlineBackup', 'DeviceProtection',␣
↪'TechSupport',
                                  'StreamingTV', 'StreamingMovies',␣
↪'PaperlessBilling'])
churn_df.describe()
```

[12]:
```
         Children          Age  ...  DummyStreamingTV  DummyPaperlessBilling
count  10000.0000  10000.000000  ...      10000.000000           10000.000000
mean       2.0877     53.078400  ...          0.492900               0.588200
std        2.1472     20.698882  ...          0.499975               0.492184
min        0.0000     18.000000  ...          0.000000               0.000000
25%        0.0000     35.000000  ...          0.000000               0.000000
50%        1.0000     53.000000  ...          0.000000               1.000000
75%        3.0000     71.000000  ...          1.000000               1.000000
max       10.0000     89.000000  ...          1.000000               1.000000

[8 rows x 33 columns]
```

[13]:
```
df = churn_df.columns
print(df)
```

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

[14]:
```
# Move Bandwidth_GB_Year to end of dataset as target
churn_df = churn_df[['Children', 'Age', 'Income', 'Outage_sec_perweek',␣
↪'Email', 'Contacts',
```

```
       'Yearly_equip_failure', 'Tenure', 'MonthlyCharge',
        'TimelyResponse', 'Fixes', 'Replacements',
       'Reliability', 'Options', 'Respectfulness', 'Courteous', 'Listening',
       'DummyGender', 'DummyChurn', 'DummyTechie', 'DummyContract',
       'DummyPort_modem', 'DummyTablet', 'DummyInternetService', 'DummyPhone',
       'DummyMultiple', 'DummyOnlineSecurity', 'DummyOnlineBackup',
       'DummyDeviceProtection', 'DummyTechSupport', 'DummyStreamingTV',
       'DummyPaperlessBilling', 'Bandwidth_GB_Year']]
```

[15]:
```
df = churn_df.columns
print(df)
```

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

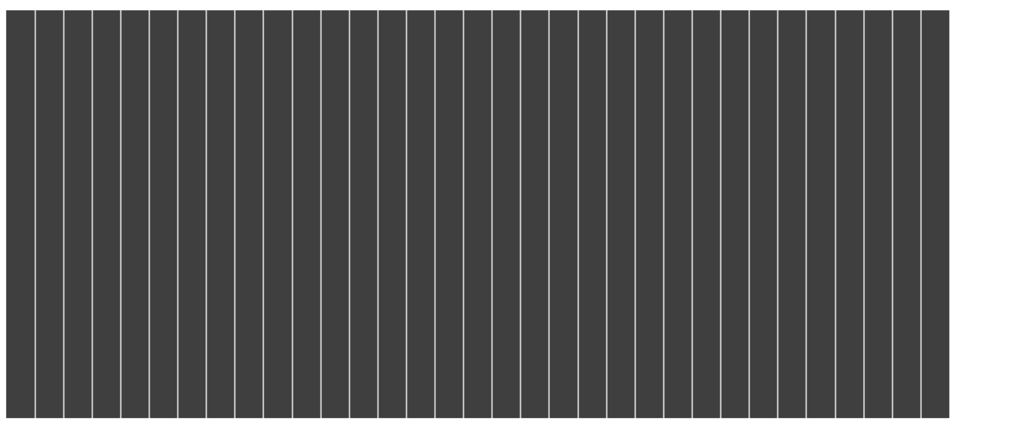
1.1.10 C4. Visualizations:

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

[16]:
```
# 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);
```

```
Requirement already satisfied: missingno in /usr/local/lib/python3.7/dist-
packages (0.4.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages
(from missingno) (1.19.5)
Requirement already satisfied: seaborn in /usr/local/lib/python3.7/dist-packages
(from missingno) (0.11.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages
(from missingno) (1.4.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-
```

```
packages (from missingno) (3.2.2)
Requirement already satisfied: pandas>=0.23 in /usr/local/lib/python3.7/dist-
packages (from seaborn->missingno) (1.1.5)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7
/dist-packages (from matplotlib->missingno) (2.8.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib->missingno) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7
/dist-packages (from matplotlib->missingno) (1.3.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->missingno) (2.4.7)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-
packages (from pandas>=0.23->seaborn->missingno) (2018.9)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.1->matplotlib->missingno) (1.15.0)
```

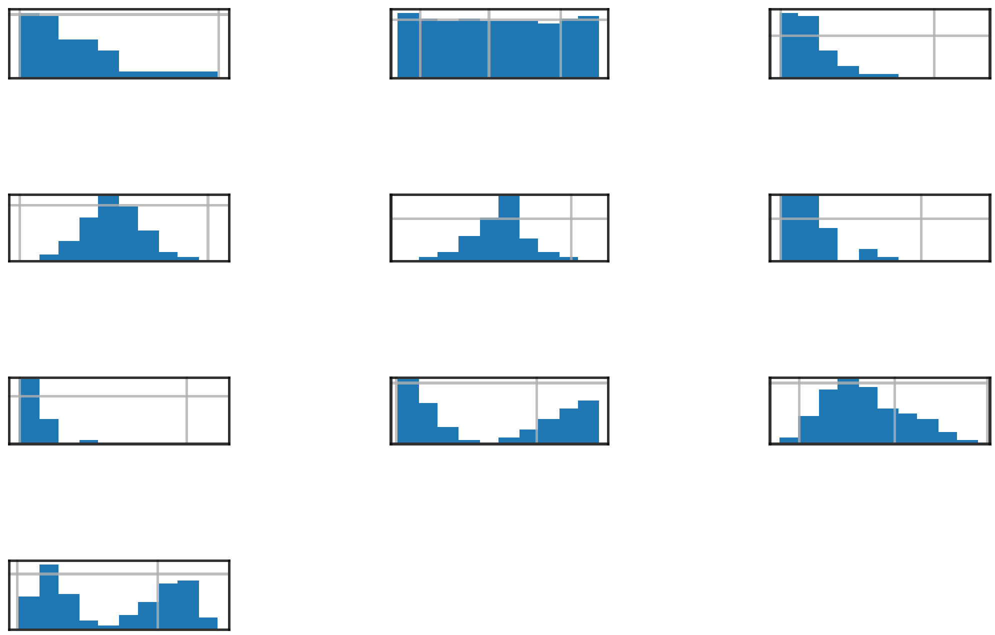


[17]:
```
'''No need to impute an missing values as the dataset appears complete/
 ↪cleaned'''
# Impute missing fields for variables Children, Age, Income, Tenure and␣
 ↪Bandwidth_GB_Year with median or mean
# churn_df['Children'] = churn_df['Children'].fillna(churn_df['Children'].
 ↪median())
# churn_df['Age'] = 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())
```

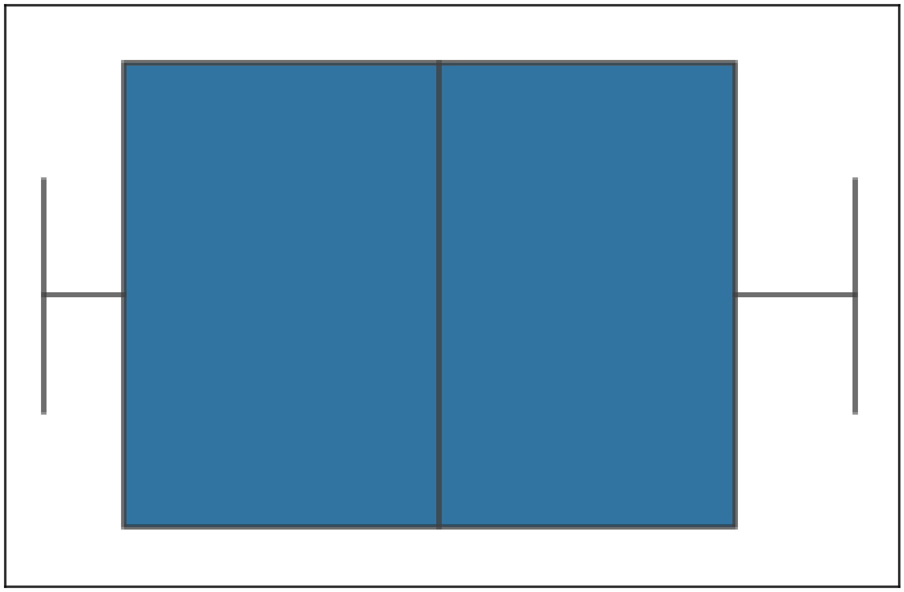
[17]:
```
'No need to impute an missing values as the dataset appears complete/cleaned'
```

1.2 Univariate Statistics

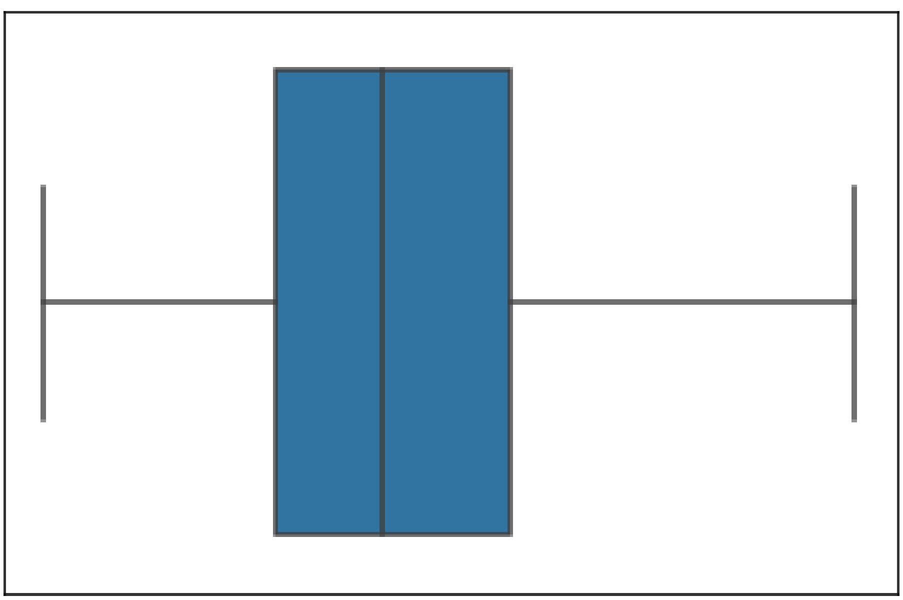
[18]:
```
# Create histograms of contiuous variables
churn_df[['Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email',
          'Contacts', 'Yearly_equip_failure', 'Tenure', 'MonthlyCharge',
          'Bandwidth_GB_Year']].hist()
plt.savefig('churn_pyplot.jpg')
plt.tight_layout()
```



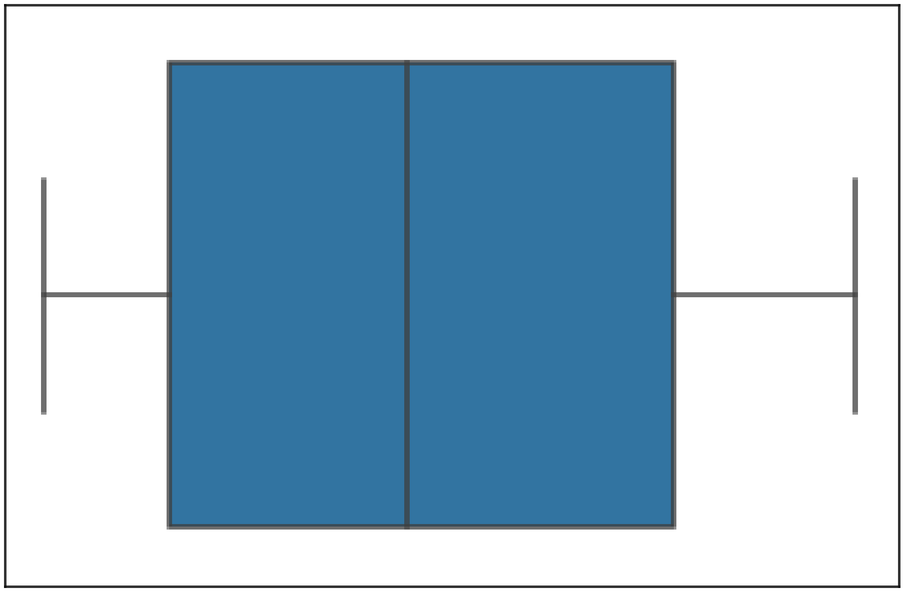
[19]:
```
# Create Seaborn boxplots for continuous variables
sns.boxplot('Tenure', data = churn_df)
plt.show()
```



[20]:
```
sns.boxplot('MonthlyCharge', data = churn_df)
plt.show()
```



[21]:
```
sns.boxplot('Bandwidth_GB_Year', data = churn_df)
plt.show()
```

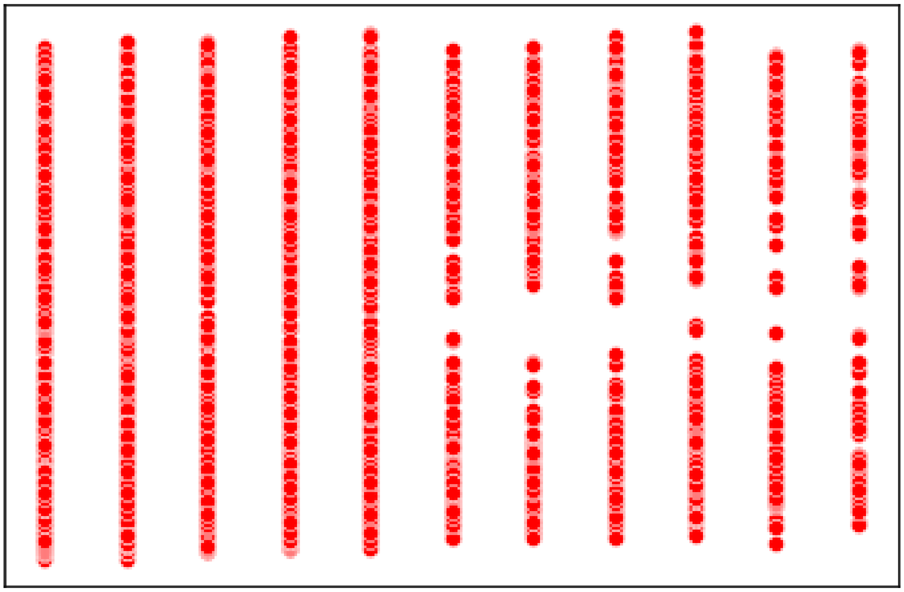


1.2.1 It appears that anomolies have been removed from the dataset present "churn_clean.csv" as there are no remaining outliers.

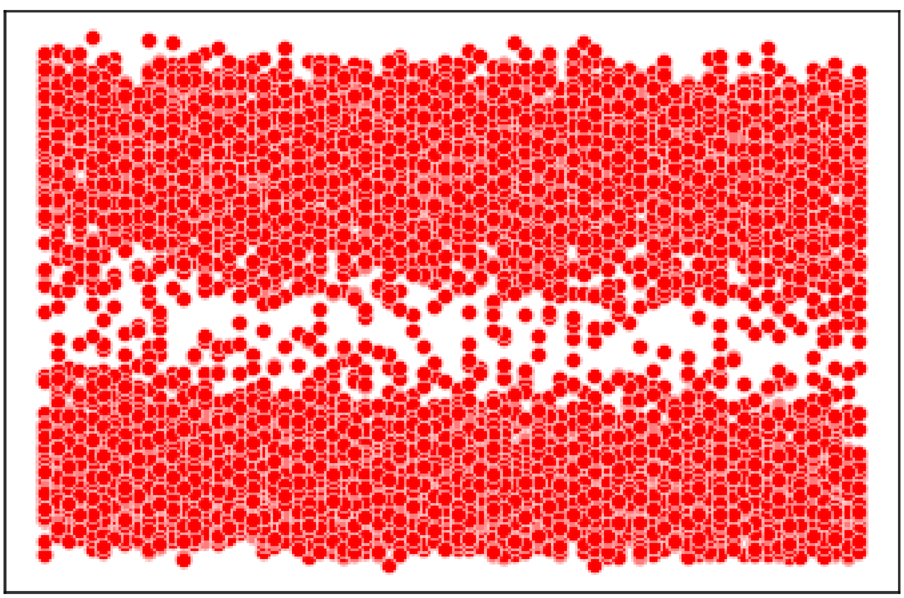
1.3 Bivariate Statistics

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.

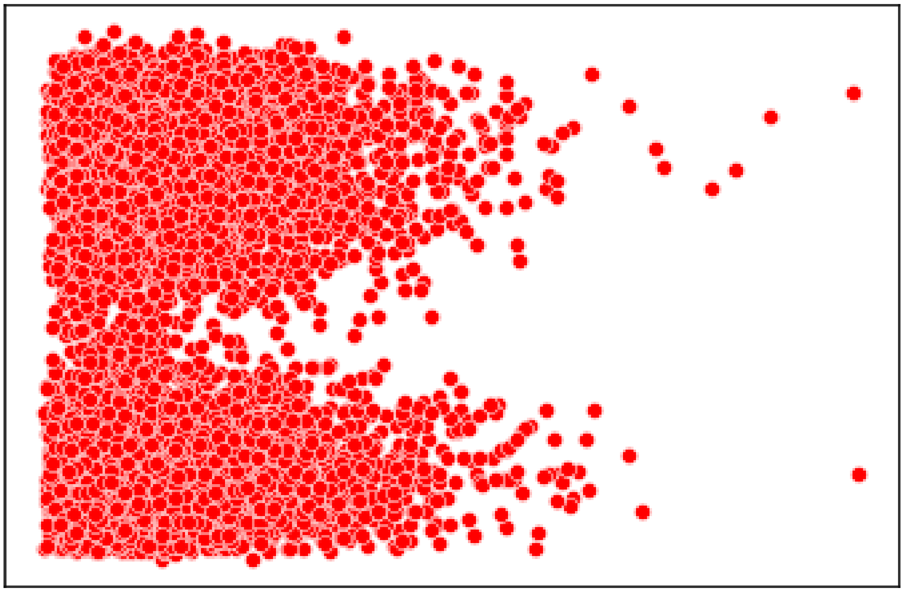
[22]:
```
# Run scatterplots to show direct or inverse relationships between target &␣
↪independent variables
sns.scatterplot(x=churn_df['Children'], y=churn_df['Bandwidth_GB_Year'],␣
↪color='red')
plt.show();
```



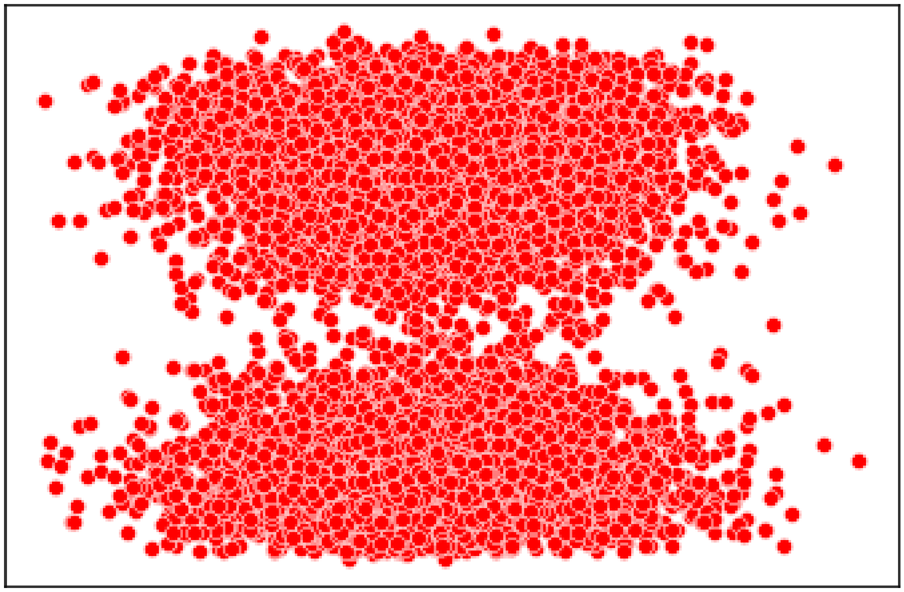
[23]:
```
sns.scatterplot(x=churn_df['Age'], y=churn_df['Bandwidth_GB_Year'], color='red')
plt.show();
```



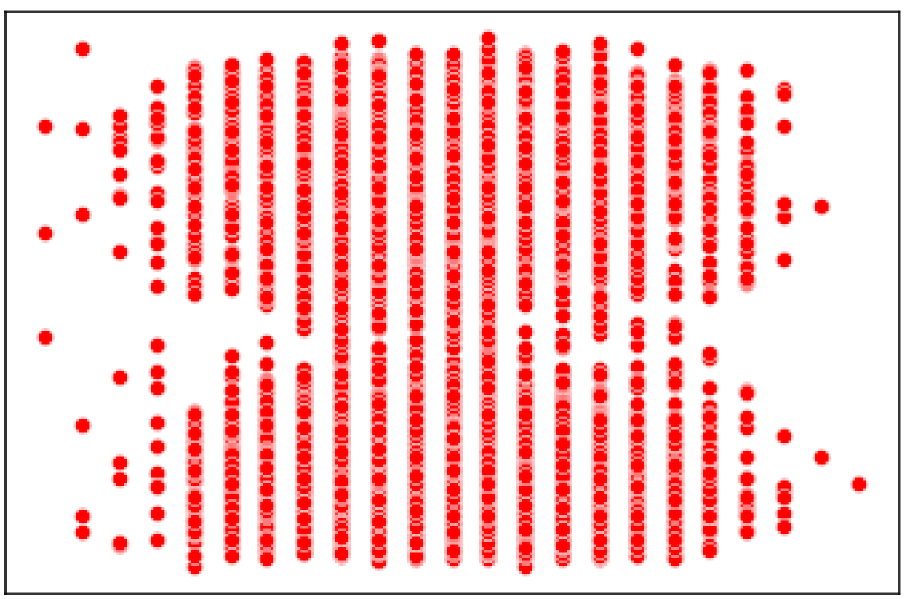
[24]:
```
sns.scatterplot(x=churn_df['Income'], y=churn_df['Bandwidth_GB_Year'],␣
 ↪color='red')
plt.show();
```



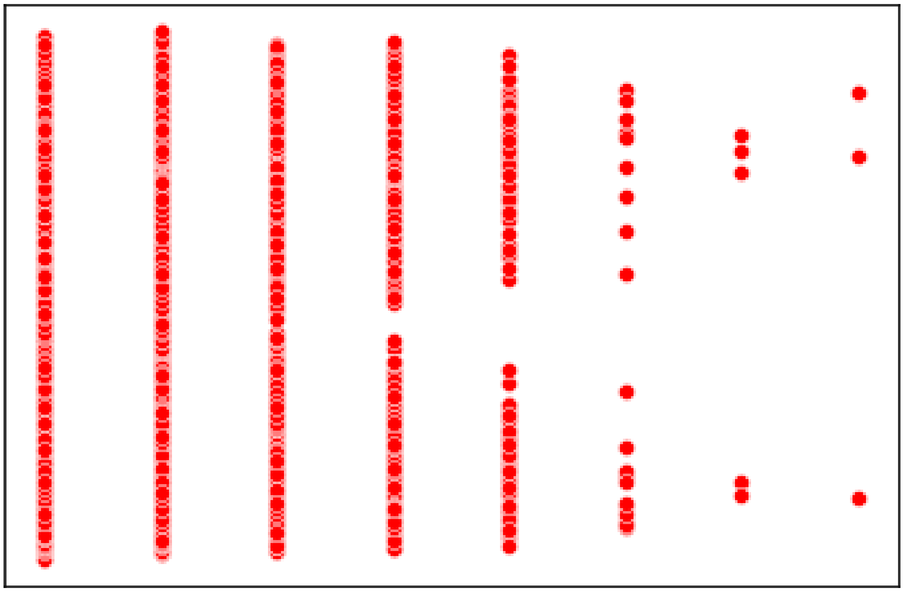
[25]:
```
sns.scatterplot(x=churn_df['Outage_sec_perweek'],␣
 ↪y=churn_df['Bandwidth_GB_Year'], color='red')
plt.show();
```



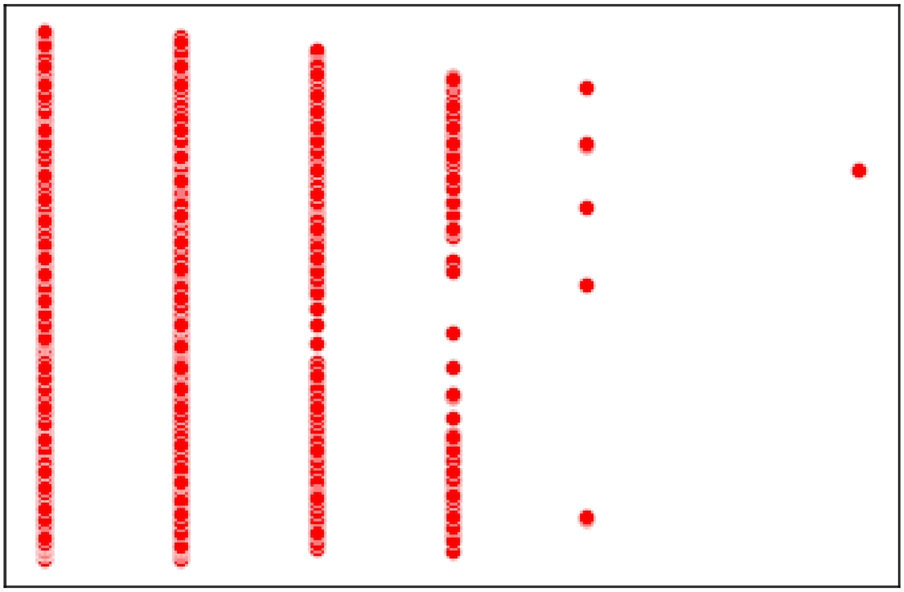
[26]:
```
sns.scatterplot(x=churn_df['Email'], y=churn_df['Bandwidth_GB_Year'],␣
  ↪color='red')
plt.show();
```



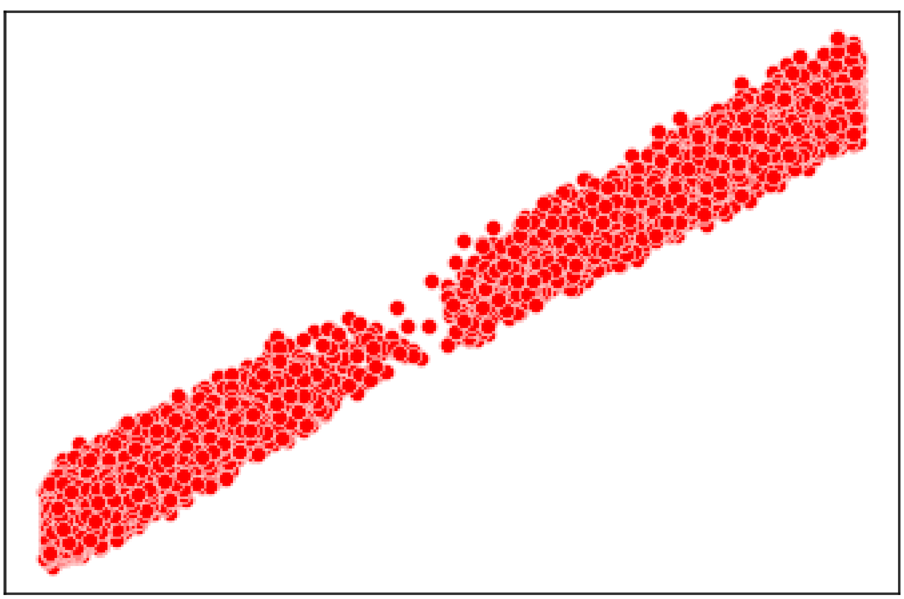
[27]:
```
sns.scatterplot(x=churn_df['Contacts'], y=churn_df['Bandwidth_GB_Year'],␣
 ↪color='red')
plt.show();
```



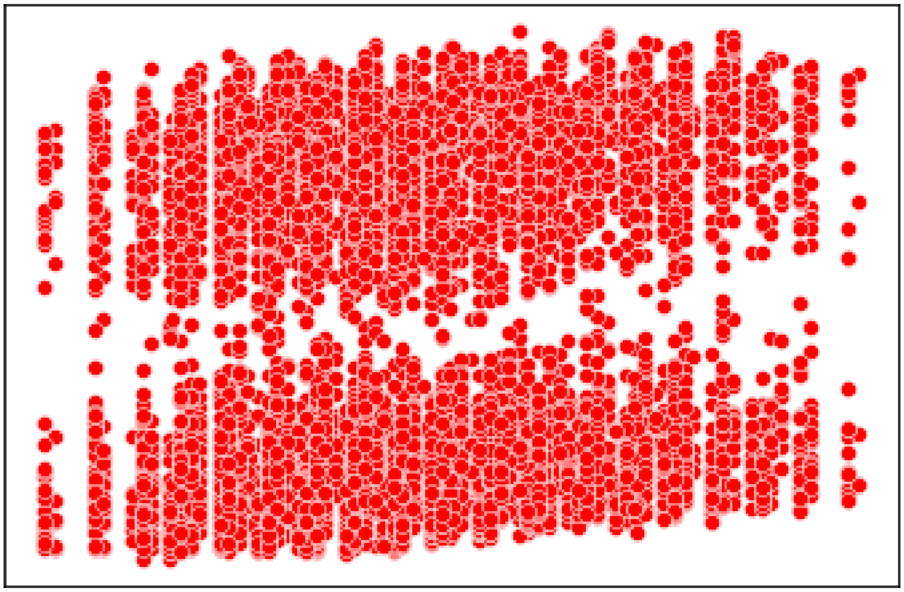
[28]:
```
sns.scatterplot(x=churn_df['Yearly_equip_failure'],␣
 ↪y=churn_df['Bandwidth_GB_Year'], color='red')
plt.show();
```



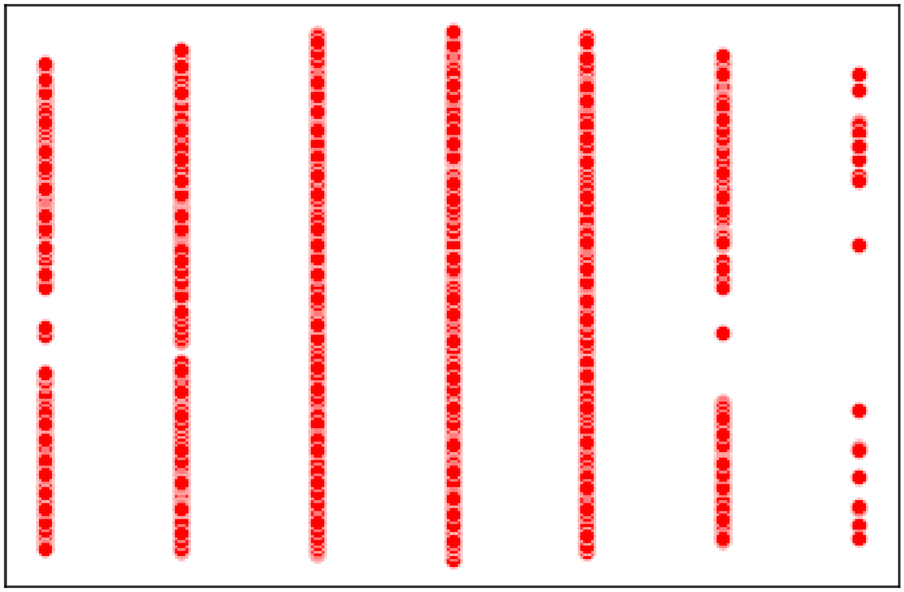
[29]:
```
sns.scatterplot(x=churn_df['Tenure'], y=churn_df['Bandwidth_GB_Year'],
    color='red')
plt.show();
```



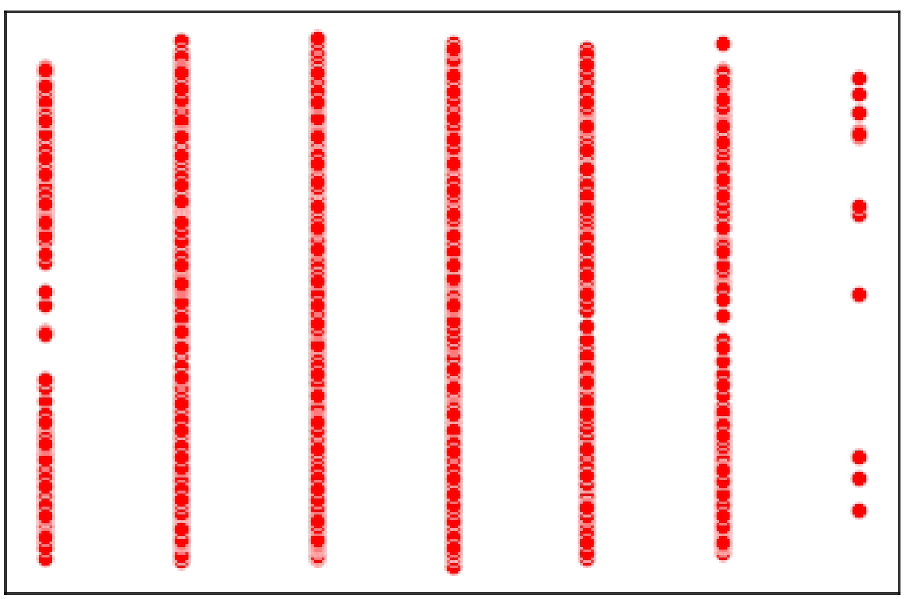
[30]:
```
sns.scatterplot(x=churn_df['MonthlyCharge'], y=churn_df['Bandwidth_GB_Year'],␣
 ↪color='red')
plt.show();
```



[31]:
```
sns.scatterplot(x=churn_df['TimelyResponse'], y=churn_df['Bandwidth_GB_Year'],␣
 ↪color='red')
plt.show();
```



[32]:
```
sns.scatterplot(x=churn_df['Fixes'], y=churn_df['Bandwidth_GB_Year'],␣
 ↪color='red')
plt.show();
```



[33]:
```
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.

[34]:
```
# Extract Clean dataset
churn_df.to_csv('churn_prepared.csv')
```

1.3.3 D1. Initial Model

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

[35]:
```
"""Develop the initial estimated regression equation that could be used to␣
 ↪predict the Bandwidth_GB_Year, given the only 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:                Thu, 15 Jul 2021   Prob (F-statistic):               0.00
Time:                        00:48:12   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.
```

[36]:
```python
churn_df_dummies = churn_df.columns
print(churn_df_dummies)
```

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

1.3.4 Now, let's run a model including all encoded categorical dummy variables.

[37]:
```
"""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:                Thu, 15 Jul 2021   Prob (F-statistic):               0.00
```

```
Time:                        00:48:28   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

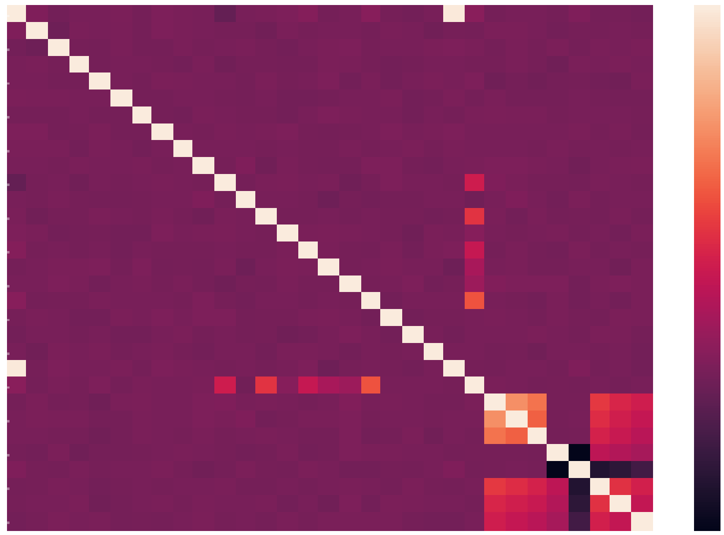
1.3.6 Based on an R2 value = 0.989. So, 99% of the variation is explained by this model. The condition number is large which might suggest strong multicolinnearity. Apparently, we do not need all of these variables to explain the variance. So, let's run a heatmap for bivariate analysis & a principal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

1.3.7 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.

[38]:
```
# 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']]
```

[39]:
```
# Run Seaborn heatmap
sns.heatmap(churn_bivariate.corr(), annot=False)
plt.show()
```



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

[40]:
```
churn_bivariate = churn_df[['Bandwidth_GB_Year', 'Children',
                            'Tenure', 'TimelyResponse', 'Fixes',
                            'Replacements', 'Respectfulness',
                            'Courteous', 'Listening']]

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

1.3.9 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. I also add children intuitively because children always add cost & using the p-value for children is 0.000, & therefore statistically significant.

1.3.10 So, the reduced regression equation will include the continuous variable of tenure & the categorical of children as well ad the the ordinal categorical independent variables of fixes & replacements.

1.3.11 D3. Reduced Multiple Regression Model

[41]:
```
# Run reduced OLS multiple regression
churn_df['intercept'] = 1
lm_bandwidth_reduced = sm.OLS(churn_df['Bandwidth_GB_Year'],␣
 ↪churn_df[['Children', 'Tenure', 'Fixes', 'Replacements', 'intercept']]).fit()
print(lm_bandwidth_reduced.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:                Thu, 15 Jul 2021   Prob (F-statistic):               0.00
Time:                        00:48:57   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.
```

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

1.3.13 Reduced Multiple Linear Regression Model

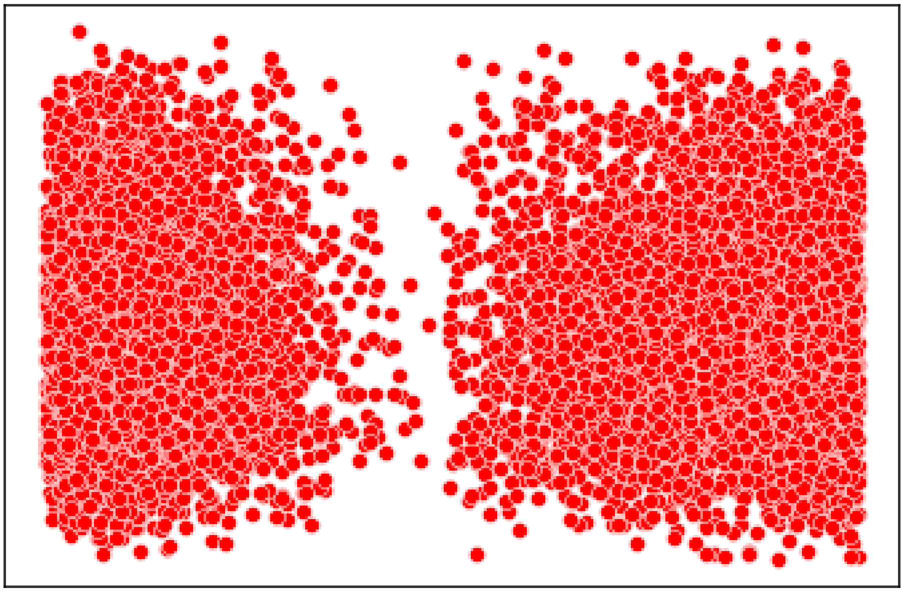
With 4 indpendent variables: y = 497.78 + 31.18 * Children + 81.94 * Tenure + 1.07 * Fixes - 3.66 * Replacements

1.3.14 E1. Model Comparison

1.3.15 Residual Plot

[42]:
```
churn_df = pd.read_csv('churn_prepared.csv')
churn_df['intercept'] = 1
residuals = churn_df['Bandwidth_GB_Year'] - lm_bandwidth_reduced.
 ↪predict(churn_df[['Children', 'Tenure', 'Fixes',␣
 ↪'Replacements','intercept']])
sns.scatterplot(x=churn_df['Tenure'],y=residuals,color='red')
```

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



1.3.16 E2. Output & Calculations

Calculations & code output above.

1.3.17 E3. Code

All code for analysis include above.

1.3.18 F1. Results

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

The final multiple regression equation with 4 indpendent variables:

y = 497.78 + 31.18 * Children + 81.94 * Tenure + 1.07 * Fixes - 3.66 * Replacements

The coefficients suggest that for every 1 unit of:

Children - Bandwidth_GB_Year will increase 31.18 units
Tenure - Bandwidth_GB_Year will increase 81.94 units
Fixes - Bandwidth_GB_Year will increase 1.07 units

```
        <li>Replacements -  - Bandwidth_GB_Year will decrease 3.66 units</li>
    </ul>
</li>
<li>
P-values for Children & Tenure are statistically significant at 0.000, while p-values for Fixes
</li>
<li>
The limitations of this analysis are that the data set is a bit small & that perhaps more years
</li>
```

1.3.19 F2. Recommendations

For the purposes of this analysis & to make the time spent on the analysis acceptable & provide actionable information:
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. This would include making sure that fixes to customer problems are prompt & that the equipment provided is high quality to avoid fewer replacements of equipment.

1.3.20 G. Video

link

1.3.21 H. Sources for Third-Party Code

Kaggle. (2018, May 01). Bivariate plotting with pandas. Kaggle. https://www.kaggle.com/residentmario/bivariate-plotting-with-pandas#

Sree. (2020, October 26). Predict Customer Churn in Python. Towards Data Science. https://towardsdatascience.com/predict-customer-churn-in-python-e8cd6d3aaa7

Wikipedia. (2021, May 31). Bivariate Analysis. https://en.wikipedia.org/wiki/Bivariate_analysis#:~:text=Biv

1.3.22 I. Sources

Ahmad, A. K., Jafar, A & Aljoumaa, K. (2019, March 20). Customer churn prediction in telecom using machine learning in big data platform. Journal of Big Data. https://journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0191-6

Altexsoft. (2019, March 27). Customer Churn Prediction Using Machine Learning: Main Approaches and Models. Altexsoft. https://www.altexsoft.com/blog/business/customer-churn-prediction-for-subscription-businesses-using-machine-learning-main-approaches-and-models/

Bruce, P., Bruce A. & Gedeck P. (2020). Practical Statistics for Data Scientists. O'Reilly.

CBTNuggets. (2018, September 20). Why Data Scientists Love Python. https://www.cbtnuggets.com/blog/technology/data/why-data-scientists-love-python

Freedman, D. Pisani, R. & Purves, R. (2018). Statistics. W. W. Norton & Company, Inc.

Frohbose, F. (2020, November 24). Machine Learning Case Study: Telco Customer Churn Prediction. Towards Data Science. https://towardsdatascience.com/machine-learning-case-study-telco-customer-churn-prediction-bc4be03c9e1d

Griffiths, D. (2009). A Brain-Friendly Guide: Head First Statistics. O'Reilly.

Grus, J. (2015). Data Science from Scratch. O'Reilly.
Massaron, L. & Boschetti, A. (2016). Regression Analysis with Python. Packt Publishing.
McKinney, W. (2018). Python for Data Analysis. O'Reilly.
Rossant, C. (2018). IPython Interactive Computing & Visualization Cookbook, 2nd Edition. Packt Publishing.
Rossant, C. (2015). Learning IPython Interactive Computing & Visualization, 2nd Edition. Packt Publishing.
VanderPlas, J. (2017). Python Data Science Handbook. O'Reilly.

[ ]:
```
!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')
```

```
--2021-07-15 00:50:15--  https://raw.githubusercontent.com/brpy/colab-
pdf/master/colab_pdf.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)...
185.199.111.133, 185.199.108.133, 185.199.109.133, ...
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.111.133|: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

2021-07-15 00:50:15 (25.9 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.


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Extracting templates from packages: 100%
```

[ ]:
```
```