D206- Data Cleaning Performance Assessment

Western Governs University

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Part I: Research Question and Variables

Section A. Research Question

Do customers experiencing the most outages with their service and equipment failure increase the cancellation of service?

Section B. Required Variables

The following variables were in the churn data set:

Variable Name	Data Type	Description	Example
Case Order	Qualitative	Placeholder for order of data	15
Customer_id		Distinct customer identification	H68068
Interaction	Qualitative	Specific identification # for each customer interaction	8dc7ad15-2f59-4c77-9640-6f2c0000b3fc
City	Qualitative	Customer city of residence	Hillside
State	Qualitative	Customer state of residence	IL
County	Qualitative	Customer county of residence	Cook
Zip	Qualitative	Customer zip code of residence	60612
Lat	Qualitative	GPS coordinates of residence	41.86752
Lng	Qualitative	GPS coordinates of residence	-87.90222
Population	Quantitative	Population of customer residence	8165
Area	Qualitative	Area type (rural, urban, suburban)	Urban
TimeZone	Qualitative	Time zone of customer residence	America/Chicago
Job	Qualitative	Customer job title	Automotive engineer
Children	Quantitative	Number of children of customer	5
Age	Quantitative	Age of customer	30
Education	Qualitative	Customer highest level of education	Associate's Degree
Employment	Qualitative	Customer employment status	Full Time
Income	Quantitative	Customer annual income reported	64256.81
Martial	Qualitative	Customer marital status	Separated
Gender	Qualitative	Customer gender	Male
Churn	Qualitative	If the customer discontinued services in the last month	Yes
Outage_sec_perweek	Quantitative	Avg number of seconds per week of system outages in customer's neighborhood	12.63069124
Email	Quantitative	Number of emails sent to customer over past year	10
Contacts	Quantitative	Number of times customer contacted technical support	3

Yearly_equip_failure	Quantitative	Number of times customer's equipment failed and replaced	0
Techie	Qualitative	If customer considers themselves technically inclined	No
Contract	Qualitative	Contract term of the customer	Month-to-month
Port_modem	Qualitative	If customer have portable modem	No
Tablet	Qualitative	If customer own a tablet	No
InternetService	Qualitative	Customer's internet service provider	DSL
Phone	Qualitative	If customer has phone service	No
Multiple	Qualitative	If customer has multiple lines	Yes
OnlineSecurity	Qualitative	If customer has online security add-on	No
OnlineBackup	Qualitative	If customer has online backup add-on	No
DeviceProtection	Qualitative	If customer has device protection add-on	No
TechSupport	Qualitative	If customer has technical support add-on	Yes
StreamingTV	Qualitative	If customer has streaming TV	No
StreamingMovies	Qualitative	If customer has streaming movies	No
PaperlessBilling	Qualitative	If customer has paperless billing	Yes
PaymentMethod	Qualitative	Customer's payment method	Bank Transfer(automatic)
Tenure	Quantitative	# of months customer has stayed with provider	10.06019902
MonthlyCharge	Quantitative	Amount charged to customer monthly	160.8055418
Bandwidth_GB_Year	Quantitative	Avg amount of data customer used (GB) in a year	1948.694497
		Below are survey responses of importance of various factors/surfaces on a scale of 1 to 8 (1 =mostly important; 8 = least important):	
Item1	Qualitative	Survey response- Timely response	1
Item2	Qualitative	Survey response- Timely fixes	3
Item3	Qualitative	Survey response- Timely replacements	4
Item4	Qualitative	Survey response- Reliability	2
Item5	Qualitative	Survey response- Options	3
Item6	Qualitative	Survey response- Respectful response	4
Item7	Qualitative	Survey response- Courteous exchange	4
Item8	Qualitative	Survey response-Evidence of active listening	2

Part II: Data-Cleaning Plan (Detection)

Section C1: Plan to find Anomalies

Python was used to detect duplicate data, missing values, outliers, and any other data quality issues in the churn data set. Utilizing the "import pandas as pd" command Panda was imported into Python. The read_cvs() function was used to read the churn data on my local hard drive. This file was assigned to the variable "df" for easy reference. To determine the data types included in the churn data the df.info(file_path). The data type of each variable is needed information due to certain functions working only with specific functions. This includes the column names and the number of non-null values for each column. Once datatypes are known the data could be cleaned. Cleaning data included detecting duplicates, and identifying missing values and outlies.

To determine if there were duplicate entries in the data the df.duplicated() function was completed. This function returns columns with TRUE or FALSE values. If the column returnes a TRUE value there are duplicate records but if a FALSE value is returned there are no duplicates. The results of this function indicated all FALSE values meaning there were no duplicates values in the data set. To verify and count all entries that were FALSE the print(df.duplicated().value_counts()) was used. If duplicates were present the df.drop_duplicates() function could have been used to drop duplicate values.

The next step included determining if there were missing values. Missing values are usually represented in the form of nan, null, or none in the dataset. The df.isnull().sum() function was used. This function counted how many missing values were present in each column. The following columns included missing values: children, age, income, techie, phone, tech support, tenure, bandwidth_GB_year. A visualization of the missing data was completed using the missingno package. The install missigno and import missigno were used to import into jupyter notebook. The function msno.matrix(df) was used to create a visualization of the missing data. The matplotlib package was also imported to serve as a visualization of the data. The function plt.hist(df) was used as an additional visual to create a histogram and to examine the distribution of the missing values in the children, age, and income columns of the data set. This function was only performed on the children, age, tenure, bandwidth_gb_year, and income columns because it can only be applied to quantitative data. Once distribution was shown in each histogram the imputation methods could be determined.

The columns techie, phone, and techsupport also had missing data. These columns have qualitative data consisting of YES/NO values. Ordinal encoding was used to re-express values as numeric values. The function mapping_dict = {'No': 0, 'Yes': 1}, df['Churn'] = df['Churn'].replace(mapping_dict) was used to reassign values to 0 and 1. The function plt.hist(df[') was then used to visualize the missing data like previous numeric categories.

Univariate imputation was then used to treat missing values for all quantitative data. The mean and median were calculated to replace missing values. The function df.isnull().sum() was then used again to verify the above columns with missing values had been treated. Once duplicate and missing values were detected and treated outliers were then determined for all quantitative variables. All the quantitative variables from the churn data were plotted on boxplots to visualize outliers. For those variables that did not show obvious outliers z-scores were computed. This was completed after importing the seaborn library with the function boxplot=seaborn.boxplot(). The exact number of outliers was determined using the z-values since the boxplot could not provide an exact number. Outliers were then treated using the retention method).

Lastly, PCA was performed with the numerical variables from the data set for increased data compression and visualization.

Section C2: Justification of Approach

The methods discussed above were used to clean the raw data set of the churn data. Cleaning data is important in drawing accurate conclusions when analyzing data. It allows for different sorting options, filtering, and modification to the data set. Using the methods above helps detect duplicates while maintaining the integrity of the data. It is necessary to detect and treat duplicate data because duplicate entries can lead to miscalculations or misrepresentations of the data. When detecting missing values (represented in the form of nan, null, or none) the df.isnull().sum() function counts the missing values. This gives a count of the missing values for each variable. The missingno function allows for visualizations of the missing data in each variable. The library matplotlib.pyplot allows for visualization (i.e. box plots, z-scores, scatterplots, and histograms) of the functions imputed. Methods such as calculating the mean and mode can fix missing data and provide a better representation of the data. This allows one to know the exact location of the missing data for treatment.

Outliers need to be detected and treated because outliers can provide incorrect/inconsistent collusions from the data. Outliers come from data entry errors, measurement errors, experimental errors, sampling errors, or novelties in the data (Lacrose & Lacrose, 2019). Box plots, z-scores, and histograms were used to detach outliers. The scipy.stats function was used to calculate z-cores. Different methods of visualization were used based on the number of outliers. When outliers were not readily visible from box plots z-scores were values to determine value and volume. There were two types of data from this data set, quantitative and qualitative data. Qualitative or categorical data (i.e. yes/no) requires re-expression or encoding of numbers to perform statical modeling. (Lacrose & Lacrose, 2019). Ordinal encoding was thus used to transform categorical data into nominal data. Education was a qualitative data variable that need to be transformed into a quantitative data set. A numerical value was assigned by creating a data dictionary and mapping the categorical responses to a numeric value, making it easier to operate on. For columns such as churn, techie, and tablet which are yes/no answers, we can assign binary values through re-expression to make them easier to work with when creating visual tools.

Section C3: Justification of Tools

Data cleaning for the churn data set was completed utilizing Python. Python is an open-sourced programing language used for analysis and development. Python has a consistent syntax that makes coding and debugging user-friendly for beginners. Python is flexible and has the ability to import packages and to tailor data. The following packages were imported and used for their advantages.

Packages/Libraries	Purpose
pandas	Main package for data uploading and manipulation
numpy	Main package for working with arrays
Matplotlib.pyplot	Visualization
Missingno	Missing values visualization
Seaborn	Advanced visualiziation
scipy.stats	Normalization and statistics
sklearn.decompositionimport PCA	PCA analysis

Section C4: Provide the Code

The following functions were used for the detection of duplicates, missing data, and outliers. Also, see detailed code attached.

1. *Loading Data*:
```
File_path = "/Users/igmark/Desktop/WGU Data Files/churn_raw_data.csv"
df = pd.read_csv(file_path)
```

2. *Determine data types:*
```
df.info(file_path)
```

3. *Detecting duplicates:*
```
df.duplicated()
```

4. *Missing data:*
```
df.isnull().sum() – detection
msno.matrix(df) – visualization
plt.hist(df[''])- visualiziation
```

5. *Detecting Outliers:*
```
boxplot=seaborn.boxplot(x='Population',data=df)
df['Z_Score_Population'] = stats.zscore(df['Population'])
df[['Population','Z_Score_Population']].head()
plt.hist(df['Z_Score_Population'])
plt.show()

boxplot=seaborn.boxplot(x='Email',data=df)
df['Z_Score_Email'] = stats.zscore(df['Email'])
df[['Email,'Z_Score_Email']].head()
plt.hist(df['Z_Score_Email'])
```

```
plt.show()
boxplot=seaborn.boxplot(x='Children',data=df)
df['Z_Score_Children'] = stats.zscore(df['Children'])
df[[' Children ','Z_Score_Children']].head()
plt.hist(df['Z_Score_Children'])
plt.show()

boxplot=seaborn.boxplot(x='Age',data=df)
df['Z_Score_Age'] = stats.zscore(df['Age'])
df[['Age','Z_Score_Age']].head()
plt.hist(df['Z_Score_Age'])
plt.show()

boxplot=seaborn.boxplot(x='Income',data=df)
df['Z_Score_Income'] = stats.zscore(df['Income'])
df[['Income','Z_Score_Income']].head()
plt.hist(df['Z_Score_Income'])
plt.show()

boxplot=seaborn.boxplot(x=' Outage_sec_perweek',data=df)
df['Z_Score_Outage_sec_perweek'] = stats.zscore(df['Outage_sec_perweek'])
df[["Outage_sec_perweek",'Z_Score_Outage_sec_perweek']].head()
plt.hist(df['Z_Score_Outage_sec_perweek'])
plt.show()


boxplot=seaborn.boxplot(x='Contacts,data=df)
df['Z_Score_Contacts'] = stats.zscore(df['Contacts'])
df[[' Contacts,'Z_Score_Contacts']].head()
plt.hist(df['Z_Score_Contacts'])
plt.show()

boxplot=seaborn.boxplot(x='Yearly_equip_failure', data=df)
df['Z_Score_Yearly_equip_failure'] = stats.zscore(df['Yearly_equip_failure'])
df[[' Yearly_equip_failure",'Z_Score_Yearly_equip_failure']].head()
plt.hist(df['Z_Score_Yearly_equip_failure'])
plt.show()

boxplot=seaborn.boxplot(x= ‘Tenure’, data=df)
df['Z_Score_Tenure'] = stats.zscore(df['Tenure'])
df[[' Tenure','Z_Score_Tenure']].head()
plt.hist(df['Z_Score_Tenure'])
plt.show()

boxplot=seaborn.boxplot(x= ‘MonthlyCharge’, data=df)
df['Z_Score_MonthlyCharge'] = stats.zscore(df['MonthlyCharge'])
```

```
df[[' MonthlyCharge",'Z_Score_MonthlyCharge']].head()
plt.hist(df['Z_Score_MonthlyCharge'])
plt.show()


boxplot=seaborn.boxplot(x= ‘'Bandwidth_GB_Year'’, data=df)
df['Z_Score_Bandwidth_GB_Year'] = stats.zscore(df['Bandwidth_GB_Year'])
df[["Bandwidth_GB_Year' ','Z_Score_Bandwidth_GB_Year']].head()
plt.hist(df['Z_Score_Bandwidth_GB_Year'])
plt.show()
```

6. *Expressing values for ‘Education’ and ‘Churn’:*

```
dict_ed = {"Education_num":
{"Regular High School Diploma": 0,
"Bachelor's Degree": 1,
"Some College, 1 or More Years, No Degree": 2,
 "9th Grade to 12th Grade, No Diploma":3,
"Master's Degree": 4,
"Associate's Degree": 5,
 "Some College, Less than 1 Year": 6,
 "Nursery School to 8th Grade": 7,
"GED or Alternative Credential": 8,
"Professional School Degree": 9
"No Schooling Completed": 10,
"Doctorate Degree": 11}}
df["Education_num"] = df["Education"]
df.replace(dict_ed, inplace = True)
counts = df["Education_num"].value_counts()
print(counts)
plt.hist(df['Education'])


mapping_dict = {'No': 0, 'Yes': 1}
df['Churn'] = df['Churn'].replace(mapping_dict)
print(df.head())
```

7. *Expressing the number of outliers and values for outliers:*

```
zscores = df[['Population', 'Z_Score_Population']]
data = df[['Population']]
num_outliers, outliers = count_and_value_outliers(zscores, data)
print("Number of outliers:", num_outliers)
print("Outlier values:", outliers)

df_outliers = df.query('(Z_Score_Children > 3) | (Z_Score_Children < -3)')
print("Number of outliers:", df_outliers.shape[0])
```

```
print("Outlier values:", df_outliers['Children'].to_dict().values())

df_outliers = df.query('(Z_Score_Income > 3) | (Z_Score_Income < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Income'].to_dict().values())

df_outliers = df.query('(Z_Score_Outage_sec_perweek > 3) |
(Z_Score_Outage_sec_perweek < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Outage_sec_perweek'].to_dict().values())

df_outliers = df.query('(Z_Score_Email > 3) | (Z_Score_Email < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Email'].to_dict().values())

df_outliers = df.query('(Z_Score_Contacts > 3) | (Z_Score_Contacts < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Contacts'].to_dict().values())

df_outliers = df.query('(Z_Score_Yearly_equip_failure > 3) |
(Z_Score_Yearly_equip_failure < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Yearly_equip_failure'].to_dict().values())

df_outliers = df.query('(Z_Score_MonthlyCharge > 3) | (Z_Score_MonthlyCharge
< -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['MonthlyCharge'].to_dict().values())
```

Part III: Data Cleaning (Treatment)

Section D1: Cleaning Findings

The data cleaning process began by determining the data types with the function df.info(file_path). The following data types were present in the churn data set:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 52 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             10000 non-null  int64
 1   CaseOrder              10000 non-null  int64
 2   Customer_id            10000 non-null  object
```

```
 3   Interaction           10000 non-null  object
 4   City                  10000 non-null  object
 5   State                 10000 non-null  object
 6   County                10000 non-null  object
 7   Zip                   10000 non-null  int64
 8   Lat                   10000 non-null  float64
 9   Lng                   10000 non-null  float64
 10  Population            10000 non-null  int64
 11  Area                  10000 non-null  object
 12  Timezone              10000 non-null  object
 13  Job                   10000 non-null  object
 14  Children              7505 non-null   float64
 15  Age                   7525 non-null   float64
 16  Education             10000 non-null  object
 17  Employment            10000 non-null  object
 18  Income                7510 non-null   float64
 19  Marital               10000 non-null  object
 20  Gender                10000 non-null  object
 21  Churn                 10000 non-null  object
 22  Outage_sec_perweek    10000 non-null  float64
 23  Email                 10000 non-null  int64
 24  Contacts              10000 non-null  int64
 25  Yearly_equip_failure  10000 non-null  int64
 26  Techie                7523 non-null   object
 27  Contract              10000 non-null  object
 28  Port_modem            10000 non-null  object
 29  Tablet                10000 non-null  object
 30  InternetService       10000 non-null  object
 31  Phone                 8974 non-null   object
 32  Multiple              10000 non-null  object
 33  OnlineSecurity        10000 non-null  object
 34  OnlineBackup          10000 non-null  object
 35  DeviceProtection      10000 non-null  object
 36  TechSupport           9009 non-null   object
 37  StreamingTV           10000 non-null  object
 38  StreamingMovies       10000 non-null  object
 39  PaperlessBilling      10000 non-null  object
 40  PaymentMethod         10000 non-null  object
 41  Tenure                9069 non-null   float64
 42  MonthlyCharge         10000 non-null  float64
 43  Bandwidth_GB_Year     8979 non-null   float64
 44  item1                 10000 non-null  int64
 45  item2                 10000 non-null  int64
 46  item3                 10000 non-null  int64
 47  item4                 10000 non-null  int64
 48  item5                 10000 non-null  int64
 49  item6                 10000 non-null  int64
 50  item7                 10000 non-null  int64
 51  item8                 10000 non-null  int64
dtypes: float64(9), int64(15), object(28)
```

There were 9 floats, 15 integers, and 28 strings present in the data set. Different data types have different methods for handling missing values (Lacrose & Lacrose, 2019). Duplicates in the data set could then be determined with function df.duplicated(). This function provided TRUE/FALSE values, where TRUE means duplicates were present and FALSE means duplicates were not present (Lacrose & Lacrose, 2019). The results below indicate there were no duplicate data entries in the data set.

```
0       False
1       False
2       False
3       False
4       False
        ...
9995    False
9996    False
9997    False
9998    False
9999    False
Length: 10000, dtype: bool
```

Missing values were then detected using the df.isnull().sum(). The following variables had missing values.

Variable	**# of Missing Values**
Children	2495
Age	2475
Income	2490
Techie	2477
Phone	1026
TechSupport	991
Tenure	931
Bandwidth_GB_Year	1021

Missing data could also be visualized by importing the library and using the function: import missingno as msno msno.matrix(df).

Box plots and z-scores were used to detect outliers in the data set. Outliers were detected from all the quantitative variables in the data set. The quantitative variables included Population, Children, Age, Income, Outage_sec_perweek, Email, Contacts, Yearly_equip_failure, Tenure, MonthlyCharge, and Bandwidth_GB_Year. Box plots were completed for each of the individual variables after importing the seaborn library with the function: import seaborn boxplot=seaborn.boxplot(x='Children',data=df). See attached code for each variable. After examining the box plots of each variable the following variables that exhibited outliers were Population, Children, Income, Outage_sec_perweek, Email, Contacts, Yearly_equip_failure, and MonthlyCharge. To determine the number and values of the outliers in these variables z-scores were then taken. Values for each are printed in the code attached.

Variable	**# of Outliers**
Population	219
Children	302
Income	193
Outage_sec_perweek	491
Email	12
Contacts	165
Yearly_equip_failure	94
MonthlyCharge	3

Data wrangling includes transforming the data type into another format more appropriate for use. The re-expression of categorical data to numeric data allows for easier filtration and manipulation of the raw data. The variable 'Education' was originally expressed as categorical data. When the variable transformed into numeric data the following results were shown:

```
0    2421 Regular High School Diploma
1    1703 Bachelor's Degree
2    1562 Some College, 1 or More Years, No Degree
3     870 9th Grade to 12th Grade, No Diploma
4     764 Master's Degree
5     760 Associate's Degree
6     652 Some College, Less than 1 Year
7     449 Nursery School to 8th Grade
8     387 GED or Alternative Credential
9     198 Professional School Degree
10    118 No Schooling Completed
11    116 Doctorate Degree

Name: Education_num, dtype: int64
```

Section D2: Justification of Mitigation Methods

There were no duplicates in the data set so the treatment of the data focused on treating the missing values and outliers. To treat missing values univariate statistical imputation was completed by calculating the mean median, or mode. This technique was used for replacing the missing values in order to retain most of the data from the original data set (Lacrose & Lacrose, 2019).

The function df.isnull().sum() was then ran again to verify missing data was removed.
Result:

```
Unnamed: 0                0
CaseOrder                 0
Customer_id               0
Interaction               0
City                      0
State                     0
County                    0
Zip                       0
Lat                       0
Lng                       0
Population                0
Area                      0
Timezone                  0
Job                       0
Children                  0
Age                       0
Education                 0
Employment                0
Income                    0
Marital                   0
Gender                    0
Churn                     0
Outage_sec_perweek        0
Email                     0
Contacts                  0
Yearly_equip_failure      0
Techie                    0
Contract                  0
Port_modem                0
Tablet                    0
InternetService           0
Phone                     0
Multiple                  0
OnlineSecurity            0
OnlineBackup              0
DeviceProtection          0
TechSupport               0
```

```
StreamingTV                  0
StreamingMovies              0
PaperlessBilling             0
PaymentMethod                0
Tenure                       0
MonthlyCharge                0
Bandwidth_GB_Year            0
item1                        0
item2                        0
item3                        0
item4                        0
item5                        0
item6                        0
item7                        0
item8                        0
Z_Score_Population           0
Z_Score_Children         10000
dtype: int64
```

After using box plots and z-scores to identify the outliers the Inter Quantile Range (IQR) was used to treat the outliers. The IQR is a measure of variability based on dividing a set into quartiles. The IQR is the range between the first quartile (25^{th} percentile) and the third quartile (75^{th} percentile) of the data (D, 2022).. The IQR identifies values that are significantly higher or lower than the majority of the data (D, 2022). The ICR was computed on the following variables Population, Children, Income, Outage_sec_perweek, Email, Contacts, Yearly_equip_failure, and MonthlyCharge due to data shown on the box plots as outliers. The following code was used to determine the outliers in each variable ('population' is shown below, all other variables seen in code attached).

```
import numpy as np
outliers = []
def detect_outliers_iqr(data):
    data = sorted(data)
    q1 = np.percentile(data, 25)
    q3 = np.percentile(data, 75)
    IQR = q3-q1
    lwr_bound = q1-(1.5*IQR)
    upr_bound = q3+(1.5*IQR)
    for i in data:
        if (i<lwr_bound or i>upr_bound):
            outliers.append(i)
    return outliers
```

```
Population_column = df['Population']
Population_outliers = detect_outliers_iqr(Population_column)
print("Outliers from IQR method: ", Population_outliers)
```

A new array was then created for each variable. Example code below. New arrays for each variable seen in code attached.

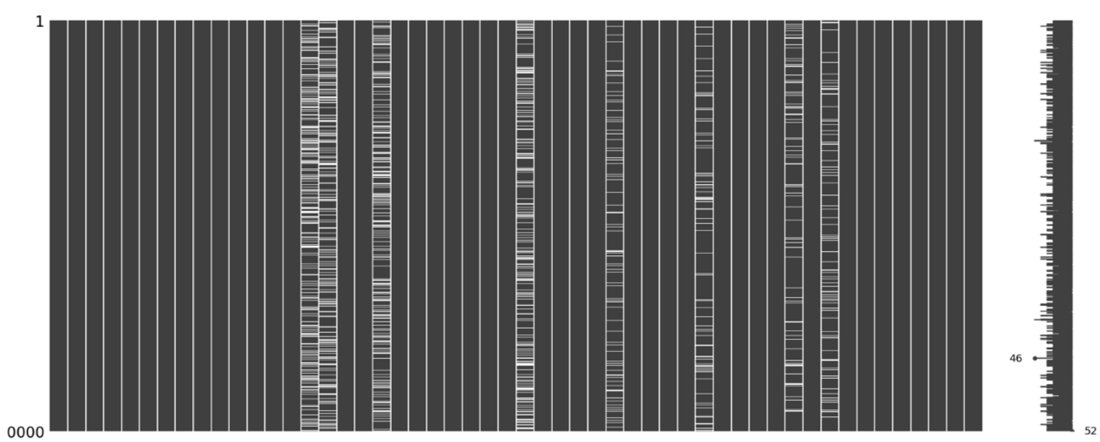
```
tenth_percentile = np.percentile(df['Population'], 10)
ninetieth_percentile = np.percentile(df['Population'], 90)
b = np.where(df['Population']<tenth_percentile, tenth_percentile,
df['Population'])
b = np.where(b>ninetieth_percentile, ninetieth_percentile, b)
print("New array:",b)
```

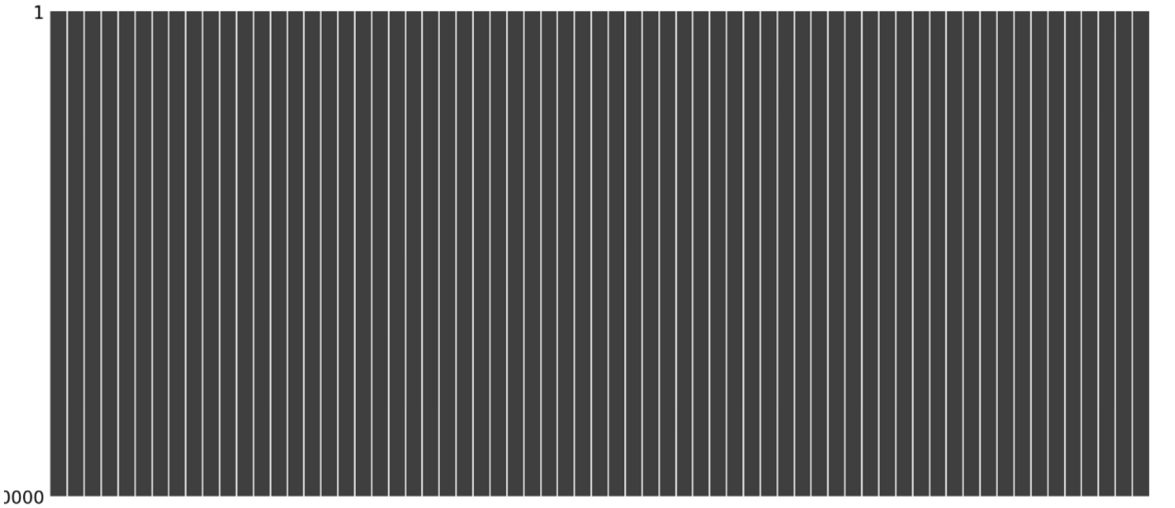
Once a new array is created a box plot was then created for each variable to verify the removal of all outliers.

```
df['Population_without_outliers'] = b
plt.figure(figsize=(8,3))
seaborn.boxplot(x=df['Population_without_outliers'])
plt.show()
```

Section D3: Summary of the Outcomes

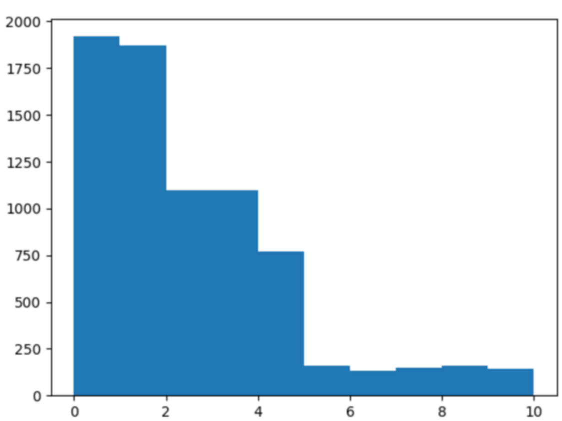
Visualizations are used to get a better view of duplicate data, missing data, and outliers. Visuals allow one to quickly identify patterns and trends. Visuals also easily detect the presence of unusual or unexpected values. Missing data was visualized with function: msno.matrix(df) prior to the treatment of the data and after the treatment of the missing data to verify no missing data remained in the data set.

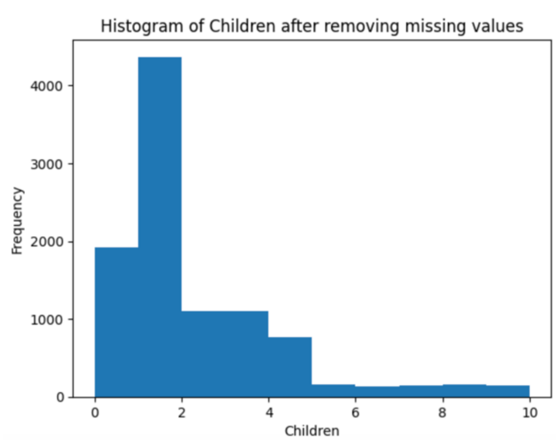




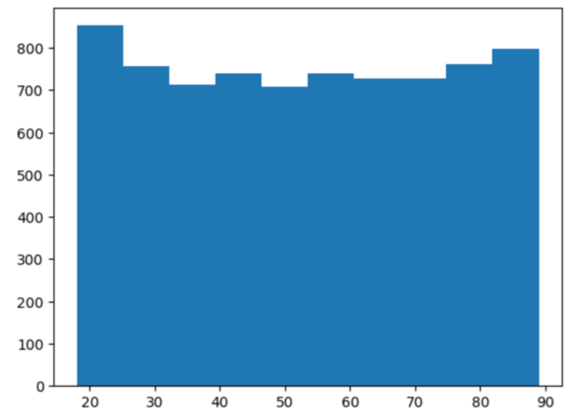
After determining the location of the missing data the treatment of the missing values could be done. Missing data was treated by replacing them with mean or medium. Each variable could be visualized with a histogram to view the distribution of the data variable. A histogram was created for the variable ‘children’, ‘age’, and ‘income’. The original distribution of the variable was viewed prior to and after the removal of the missing data. This was done to ensure the distribution of data was maintained after treatment.

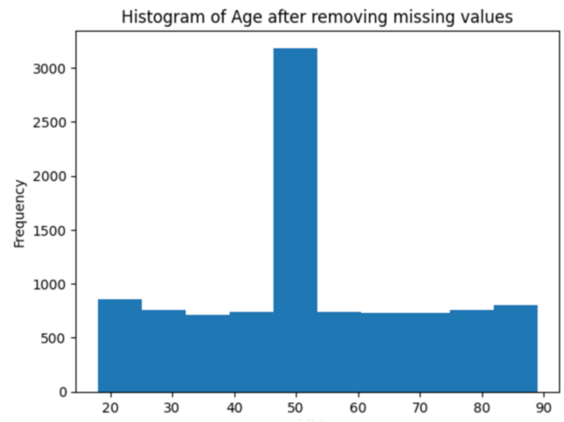
‘Children’:



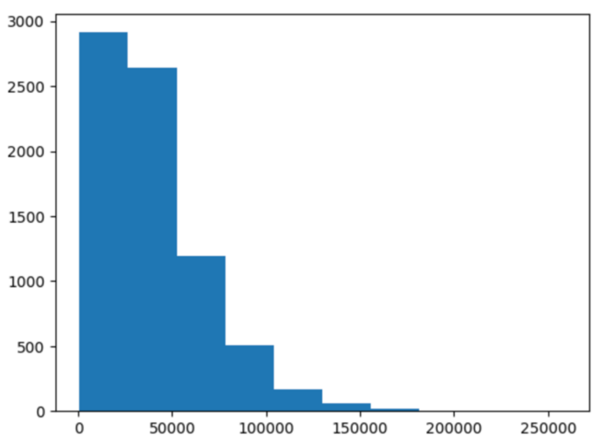


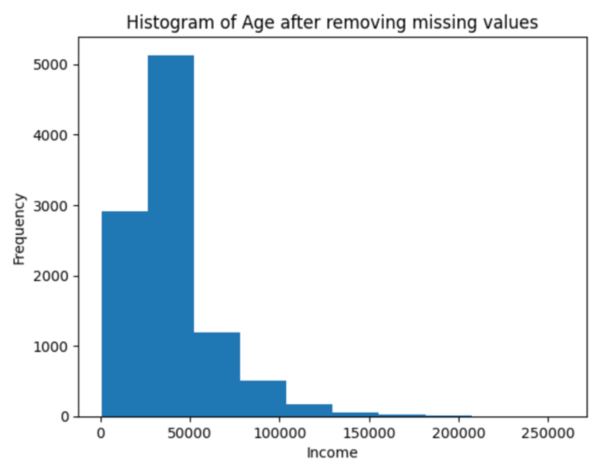
‘Age’:





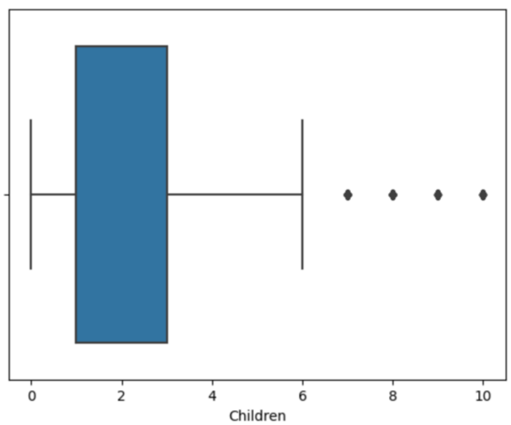
‘Income’ :

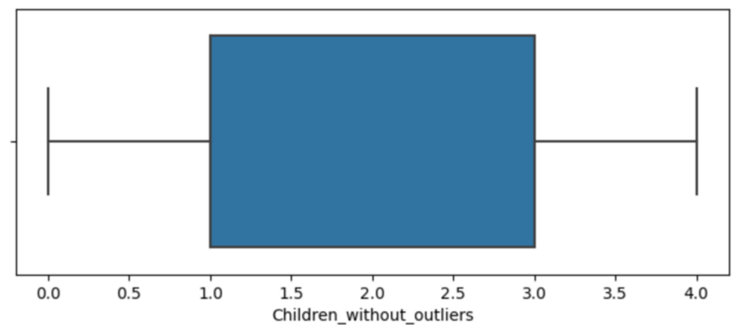




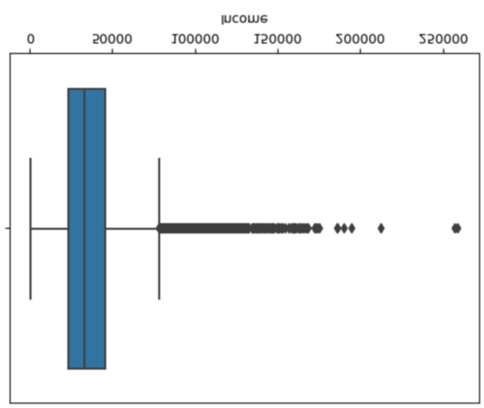
Outliers were then detected and treated. Outliers could not be adequately detected prior to addressing missing data because the presence of missing values could affect the calculation of measures of central tendency and could lead to a distortion of the data and affect the imputation methods used to fill in the missing values (Bonthu, 2022). Outliers were detected using box plots. Once box plots were created and outliers were visible z-cores were then calculated. From the z-scores, the IQR was calculated to remove outliers. An example of this can be seen by examining the variables ‘children’, ‘income’ and ‘population’. before and after outliers are removed.

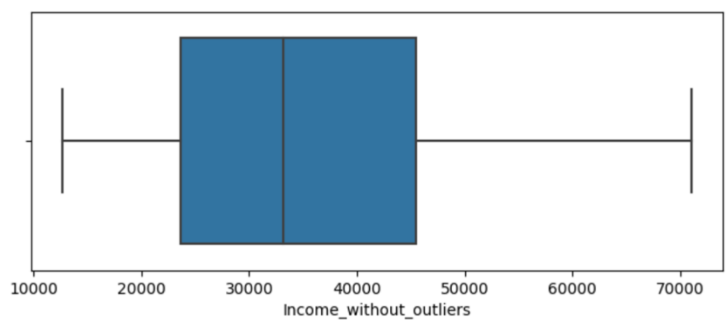
‘Children’:



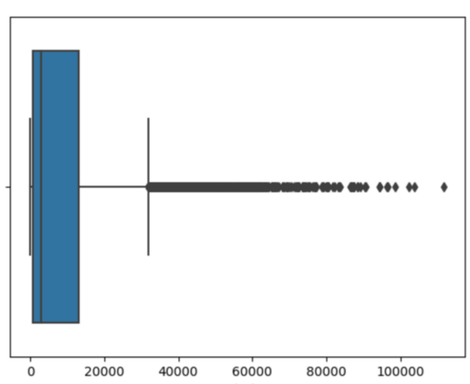


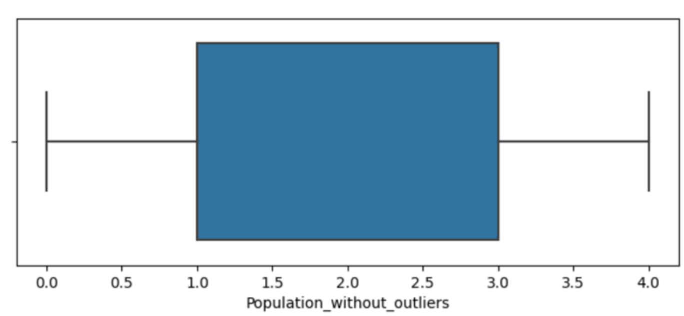
‘Income’:





‘Population’:





Section D4: Mitigation Code

The following functions were used for the treatment of missing data, and outliers. See detailed code attached.

1. *Treat the missing values:*
```
df['Children'].fillna(df['Children'].median(), inplace=True)
df['Age'].fillna(df['Age'].mean(),inplace=True)
df['Income'].fillna(df['Income'].median(), inplace=True)
df['Tenure'].fillna(df['Tenure'].mean(),inplace=True)
df['Bandwidth_GB_Year'].fillna(df['Bandwidth_GB_Year'].mean(),inplace=True)
df['Techie'].fillna(df['Techie'].mode().iat[0], inplace=True)
df['Phone'].fillna(df['Phone'].mode().iat[0], inplace=True)
df['TechSupport'].fillna(df['TechSupport'].mode().iat[0], inplace=True)
```

2. *Code to view histograms before & after removing missing data:*
```
#plt.hist(df['Children'])
plt.hist(df['Children'])
plt.xlabel('Children')
plt.ylabel('Frequency')
plt.title('Histogram of Children after removing missing values')
plt.show()

#plt.hist(df['Age'])
plt.hist(df['Age'])
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.title('Histogram of Age after removing missing values')
plt.show()

#plt.hist(df['Income'])
plt.hist(df['Income'])
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.title('Histogram of Age after removing missing values')
plt.show()
```

3. Verifying missing data:
```
msno.matrix(df)
boxplot=seaborn.boxplot(x='Population',data=df)
boxplot=seaborn.boxplot(x='Children',data=df)
boxplot=seaborn.boxplot(x='Age',data=df)
boxplot=seaborn.boxplot(x='Income',data=df)
boxplot=seaborn.boxplot(x='Outage_sec_perweek',data=df)
boxplot=seaborn.boxplot(x='Email',data=df)
```

```
boxplot=seaborn.boxplot(x='Contacts',data=df)
boxplot=seaborn.boxplot(x='Yearly_equip_failure',data=df)
boxplot=seaborn.boxplot(x='Tenure',data=df)
boxplot=seaborn.boxplot(x='Bandwidth_GB_Year',data=df)
```

4. Determining z-scores:

```
df['Z_Score_Population'] = stats.zscore(df['Population'])
df[['Population','Z_Score_Population']].head()
zscores = df[['Population', 'Z_Score_Population']]
data = df[['Population']]
num_outliers, outliers = count_and_value_outliers(zscores, data)
print("Number of outliers:", num_outliers)
print("Outlier values:", outliers)

df['Z_Score_Children'] = stats.zscore(df['Children'])
df[['Children','Z_Score_Children']].head()
df_outliers = df.query('(Z_Score_Children > 3) | (Z_Score_Children < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Children'].to_dict().values())


df['Z_Score_Income'] = stats.zscore(df['Income'])
df[['Children','Z_Score_Income']].head()
df_outliers = df.query('(Z_Score_Income > 3) | (Z_Score_Income < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Income'].to_dict().values())

df['Z_Score_Outage_sec_perweek'] = stats.zscore(df['Outage_sec_perweek'])
df[['Children','Z_Score_Outage_sec_perweek']].head()
df_outliers = df.query('(Z_Score_Outage_sec_perweek > 3) |
(Z_Score_Outage_sec_perweek < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Outage_sec_perweek'].to_dict().values())

df['Z_Score_Email'] = stats.zscore(df['Email'])
df[['Email','Z_Score_Email']].head()
df_outliers = df.query('(Z_Score_Email > 3) | (Z_Score_Email < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Email'].to_dict().values())

df['Z_Score_Contacts'] = stats.zscore(df['Contacts'])
df[['Contacts','Z_Score_Contacts']].head()
df_outliers = df.query('(Z_Score_Contacts > 3) | (Z_Score_Contacts < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Contacts'].to_dict().values())
```

```
df['Z_Score_Yearly_equip_failure'] = stats.zscore(df['Yearly_equip_failure'])
df[['Yearly_equip_failure','Z_Score_Yearly_equip_failure']].head()
df_outliers = df.query('(Z_Score_Yearly_equip_failure > 3) |
(Z_Score_Yearly_equip_failure < -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['Yearly_equip_failure'].to_dict().values())
boxplot=seaborn.boxplot(x='MonthlyCharge',data=df)

df['Z_Score_MonthlyCharge'] = stats.zscore(df['MonthlyCharge'])
df[['MonthlyCharge','Z_Score_MonthlyCharge']].head()
df_outliers = df.query('(Z_Score_MonthlyCharge > 3) | (Z_Score_MonthlyCharge
< -3)')
print("Number of outliers:", df_outliers.shape[0])
print("Outlier values:", df_outliers['MonthlyCharge'].to_dict().values())
```

5. *Treating Outliers Ihe following was the treatment of the 'Population' variable only. See attached code for all other variables with outliers.* (D, 2022).

```
outliers = []
def detect_outliers_iqr(data):
    data = sorted(data)
    q1 = np.percentile(data, 25)
    q3 = np.percentile(data, 75)
    IQR = q3-q1
    lwr_bound = q1-(1.5*IQR)
    upr_bound = q3+(1.5*IQR)
    for i in data:
        if (i<lwr_bound or i>upr_bound):
            outliers.append(i)
    return outliers

Population_column = df['Population']
Population_outliers = detect_outliers_iqr(Population_column)
print("Outliers from IQR method: ", Population_outliers)

tenth_percentile = np.percentile(df['Population'], 10)
ninetieth_percentile = np.percentile(df['Population'], 90)
b = np.where(df['Population']<tenth_percentile, tenth_percentile, df['Population'])
b = np.where(b>ninetieth_percentile, ninetieth_percentile, b)
print("New array:",b)

df['Population_without_outliers'] = b
plt.figure(figsize=(8,3))
seaborn.boxplot(x=df['Population_without_outliers'])
plt.show()
```

Section D5: Cleaning Data

See the attached file of the cleaned data set.

Code used to extract file:

```
df.to_csv(r'/Users/igmark/Desktop/WGU Data Files/churn_clean_data.csv')
```

Section D6: Limitations

Data cleaning is an important step in the data analysis process. This step is required to obtain an accurate picture of data outcomes. However, data cleaning can have limitations. One limitation of the data learning process is that it is time consuming. The data cleaning process requires a significant amount of time and resources to identify and clean data issues (Lacrose & Lacrose, 2019). Human error is also a limitation of data cleaning. Human error is related to a lack of standardization and subjectivity. There is no set methodology to clean data. Different methods can be used by different analysts and different data sets required different methods for cleaning data.

A limitation of utilizing the imputation method in replacing missing values includes possible distortion or distribution of the data (Lacrose & Lacrose, 2019). Limitations in removing outliers after detection could significantly reduce the sample size and eliminate data points from the observation that may be considered valuable (Lacrose & Lacrose, 2019).

Section D7. Impact of the Limitations

Challenges data analysts may encounter if they were to take the recently cleaned churn data set to analyze include getting inaccurate and inconsistent results. Human error can lead to incorrectly cleaning data. Due to the cleaning process not being standardized data cleaning can be subjective and lead to inconsistencies in results. Removing outliers and/or using imputation methods can lead to the loss of or incomplete data can limit the scope of the data.

Part IV: PCA

Section E1: Principal Components

Principal component analysis (PCA) is a statistical technique used to analyze the structure of a dataset by identifying patterns in the data (Mirshra et al. 2016). The goal of PCA is to identify a new set of uncorrelated variables that can explain variability in the data. PCA can only be completed with quantitative variables after missing data has been treated.

Code used for analysis:

```
from sklearn.decomposition import PCA
test_pca = df[['Age', 'Children','Income', 'Population', 'Outage_sec_perweek', 'Email',
'Contacts', 'Tenure', 'Bandwidth_GB_Year', 'Yearly_equip_failure']]
test_pca_normalized=(test_pca-test_pca.mean())/test_pca.std()
pca = PCA(n_components=test_pca.shape[1])
pca.fit(test_pca_normalized)
PCA(n_components=11)
test_pca2=pd.DataFrame(pca.transform(test_pca_normalized),columns=['PC1','PC2','PC3
', 'PC4', 'PC5', 'PC6', 'PC7', 'PC8', 'PC9', 'PC10'])
loadings = pd.DataFrame(pca.components_.T, columns=['PC1','PC2','PC3','PC4', 'PC5',
'PC6', 'PC7', 'PC8', 'PC9', 'PC10'], index=test_pca_normalized.columns)
print(test_pca2)
print(loadings)
```

PCA loading matrix:

```
                           PC1       PC2       PC3       PC4       PC5  \
Age                  -0.012401 -0.405349  0.385572 -0.256712 -0.177452
Children             -0.002073  0.559482 -0.124791  0.150532  0.177974
Income                0.006513  0.192609  0.451732  0.048109  0.730838
Population            0.000072 -0.345206 -0.330627  0.270479  0.315663
Outage_sec_perweek    0.018301  0.082482 -0.437642 -0.471634  0.362991
Email                -0.028571 -0.285364 -0.487123  0.387448  0.065333
Contacts              0.004088 -0.484051  0.029825 -0.346052  0.381535
Tenure                0.706356 -0.024595  0.009394  0.018649 -0.015609
Bandwidth_GB_Year     0.706801  0.003214 -0.010849  0.015950 -0.000423
Yearly_equip_failure  0.011158  0.207966 -0.304089 -0.585711 -0.145686

                           PC6       PC7       PC8       PC9      PC10
Age                   0.036752  0.583446  0.428641 -0.252066  0.021273
Children              0.086755  0.527043 -0.229328 -0.528049 -0.018443
Income                0.112020  0.109345  0.186350  0.403887  0.001567
Population            0.615141 -0.192537  0.285319 -0.319125 -0.000472
Outage_sec_perweek   -0.483976 -0.100266  0.412777 -0.179833 -0.010961
Email                -0.224092  0.528975 -0.014264  0.442509  0.005332
Contacts             -0.033971  0.056590 -0.689678 -0.139431 -0.003792
Tenure               -0.001465  0.019989  0.007402  0.010178 -0.706552
Bandwidth_GB_Year    -0.003916  0.011344 -0.009033 -0.002492  0.706978
Yearly_equip_failure  0.560852  0.197968 -0.034091  0.380732 -0.002803
```

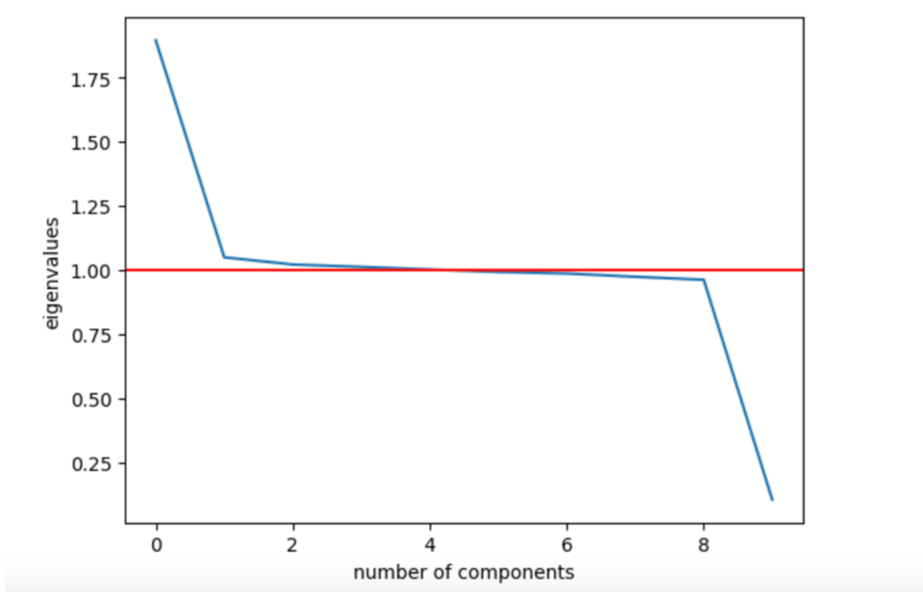
Section E2: Criteria Used

According to the Kaiser Rule, the number of components to retain from PCA is equal to the number of eigenvalues greater than one (Lacrose & Lacrose, 2019). An eigenvalue greater than one suggests that the corresponding principal component captures meaningful information from the data. PCA below one is not significant. The larger the PCA the more significant it is in explaining variations in the dataset. A visual of the PCA using eigenvalues can be seen on a scree plot. Thus PCA 1, 2, and 3 should be kept.

Code for Eigenvalues:

```
cov_matrix=np.dot(test_pca_normalized.T, test_pca_normalized) / test_pca.shape[0]
eigenvalues=[np.dot(eigenvector.T, np.dot(cov_matrix, eigenvector))for eigenvector in
pca.components_]
plt.plot(eigenvalues)
plt.xlabel('number of components')
plt.ylabel('eigenvalues')
plt.axhline(y=1, color="red")
plt.show()
```

Scree Plot:



Section E3: Benefits

PCA can be beneficial in examining patterns in a data set. One benefit of PCA is that it reduces the dimensionally of a dataset leading to easier visualizations and interpretation. PCA removed noise and irrelevant information from the data resulting in a cleaner data set (Mirshra et al. 2016). PCA also results in the ability to see uncorrelated variables. The scree plot indicates PC 1, 2, and 3 are the most significant or correlated. The PCA loading matrix shows the principal components that have positive and negative relationships between variables. The principal component and corresponding variables with a positive relationship are correlated. The variables that are contributed to each principal component are listed below:

Variable	**Contributing PC**
Age	PC3
Children	PC2
Income	PC1, PC2, PC3
Population	PC1
Outage_sec_perweek	PC1, PC2
Email	PC2
Contacts	PC1, PC3
Tenure	PC1, PC3
Bandwidth_GB_Year	PC1, PC2, PC3
Yearly_equip_failure	PC1, PC2

Section F: Panopto Video

Link for Panopto Video:

https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=5de3730a-c507-4b28-a208-afa701616723#

Section G: Third-Party Code References

Bonthu, H. (2022, November 30). *Detecting and Treating Outliers | Treating the odd one out!* Analytics Vidhya. https://www.analyticsvidhya.com/blog/2021/05/detecting-and-treating-outliers-treating-the-odd-one-out/

D, V. A. (2022, October 10). *Python Boxplot – How to create and interpret boxplots (also find outliers and summarize distributions)*. Machine Learning Plus. https://www.machinelearningplus.com/plots/python-boxplot/

Section H: References

Larose, C. D., & Larose, D. T. (2019).Data science using Python and R. John Wiley& Sons. ISBN: 978-1-119-52684-1

Mishra, S. P., Sarkar, U. K., Taraphder, S., Datta, S. K., Swain, D. P., Saikhom, R., Panda, S., & Laishram, M. (2016). Multivariate Statistical Data Analysis- Principal Component Analysis (PCA) -. *International Journal of Livestock Research*, *7*(5), 60–78. https://www.bibliomed.org/?mno=261590