Data Cleaning Code

November 15, 2021

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Part I: Research Question

A. Question to address

What variables in the dataset can help predict which customers are most likely to discontinue service?

B. Variables description

```
import pandas as pd

# Import CSV file to Pythondf.
churn = pd.read_csv('churn_raw_data.csv')

churn.shape             # Return the rows x columns of dataset
churn.info()            # Print summary of dataframe
```

Running the above code, the output shows that the dataset contains 52 variables and 10,000 records. The variable we are interested in is `Churn`, whether the customer discontinued service within the last month. The dataset also includes services that each customer signed up for, customer account information, and customer demographics. The data types of the variables are `int64`, `object`, and `float64`.

Part II: Data Cleaning Plan

C1. Plan to identify anomalies

My plan to find the anomalies include the following steps:

- Learn about the dataset and its characteristics.
- Explore measures of central tendency (mean, median, mode) and potential outliers.
- Summarize and visualize missing values for possible patterns.
- Impute missing data.

C2. Approach to assess data quality

To assess the data quality, I need to answer the following questions:

- Is the data accurate?
- How much data is missing?

- Is the data in the correct format?
- Are there duplicates?

The most difficult question to answer is about data accuracy since I do not have a baseline to compare this dataset against. The other questions can be answered through exploration of the data. Finding out how much data is missing will help me to avoid poor estimations and analysis based on incomplete data (Donthi, 2021). Incorrect formatting is another issue that can cause problems with processing data. Having a lot of duplicates can also skew the results of the analysis.

C3. Language and libraries

For the analysis of the data, I will use Python. It is a powerful general purpose programming language with an easy to read syntax. It also provides specialized libraries for working with data science projects.

A. Nehme (2021) recommended the following Python libraries for data cleaning:

- `pandas` - data manipulation and analysis.
- `numpy` - math functions and multidimensional arrays and matrices support.
- `matplotlib` - data visualization.
- `missingno` - missing data visualization.
- `scikit-learn` - machine learning models.

C4. Code to identify anomalies

[26]:
```python
import pandas as pd
import missingno as msno
import matplotlib.pyplot as plt

# Import CSV to dataframe
churn = pd.read_csv('churn_raw_data.csv')
```

[27]:
```python
# Return the rows x columns of dataset
churn.shape
```

[27]:
```
(10000, 52)
```

[28]:
```python
# Print summary of dataframe
churn.info()
```

```
<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)
memory usage: 4.0+ MB
```

```
[29]: # See first 5 rows
churn.head()
```

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

          City State                County    Zip       Lat        Lng  …  \
0  Point Baker    AK  Prince of Wales-Hyder  99927  56.25100 -133.37571  …
1  West Branch    MI                Ogemaw  48661  44.32893  -84.24080  …
2      Yamhill    OR               Yamhill  97148  45.35589 -123.24657  …
3      Del Mar    CA             San Diego  92014  32.96687 -117.24798  …
4    Needville    TX             Fort Bend  77461  29.38012  -95.80673  …

   MonthlyCharge Bandwidth_GB_Year item1 item2  item3  item4 item5 item6  \
0     171.449762        904.536110     5     5      5      3     4     4
1     242.948015        800.982766     3     4      3      3     4     3
2     159.440398       2054.706961     4     4      2      4     4     3
3     120.249493       2164.579412     4     4      4      2     5     4
4     150.761216        271.493436     4     4      4      3     4     4

   item7 item8
0      3     4
1      4     4
2      3     3
3      3     3
4      4     5

[5 rows x 52 columns]
```

```
[30]: # Get statistics of numeric columns
churn.describe()
```

```
[30]:        Unnamed: 0    CaseOrder           Zip           Lat           Lng  \
count  10000.00000  10000.00000  10000.000000  10000.000000  10000.000000
mean    5000.50000   5000.50000  49153.319600     38.757567    -90.782536
std     2886.89568   2886.89568  27532.196108      5.437389     15.156142
min        1.00000      1.00000    601.000000     17.966120   -171.688150
25%     2500.75000   2500.75000  26292.500000     35.341828    -97.082812
50%     5000.50000   5000.50000  48869.500000     39.395800    -87.918800
75%     7500.25000   7500.25000  71866.500000     42.106908    -80.088745
max    10000.00000  10000.00000  99929.000000     70.640660    -65.667850

          Population     Children           Age         Income  \
```

```
count   10000.000000  7505.000000  7525.000000   7510.000000
mean     9756.562400     2.095936    53.275748  39936.762226
std     14432.698671     2.154758    20.753928  28358.469482
min         0.000000     0.000000    18.000000    740.660000
25%       738.000000     0.000000    35.000000  19285.522500
50%      2910.500000     1.000000    53.000000  33186.785000
75%     13168.000000     3.000000    71.000000  53472.395000
max    111850.000000    10.000000    89.000000 258900.700000

       Outage_sec_perweek  …  MonthlyCharge  Bandwidth_GB_Year  \
count        10000.000000  …   10000.000000        8979.000000
mean            11.452955  …     174.076305        3398.842752
std              7.025921  …      43.335473        2187.396807
min             -1.348571  …      77.505230         155.506715
25%              8.054362  …     141.071078        1234.110529
50%             10.202896  …     169.915400        3382.424000
75%             12.487644  …     203.777441        5587.096500
max             47.049280  …     315.878600        7158.982000

              item1         item2         item3         item4         item5  \
count  10000.000000  10000.000000  10000.000000  10000.000000  10000.000000
mean       3.490800      3.505100      3.487000      3.497500      3.492900
std        1.037797      1.034641      1.027977      1.025816      1.024819
min        1.000000      1.000000      1.000000      1.000000      1.000000
25%        3.000000      3.000000      3.000000      3.000000      3.000000
50%        3.000000      4.000000      3.000000      3.000000      3.000000
75%        4.000000      4.000000      4.000000      4.000000      4.000000
max        7.000000      7.000000      8.000000      7.000000      7.000000

              item6         item7         item8
count  10000.000000  10000.000000  10000.000000
mean       3.497300      3.509500      3.495600
std        1.033586      1.028502      1.028633
min        1.000000      1.000000      1.000000
25%        3.000000      3.000000      3.000000
50%        3.000000      4.000000      3.000000
75%        4.000000      4.000000      4.000000
max        8.000000      7.000000      8.000000

[8 rows x 24 columns]
```

[31]:
```python
# Get statistics of non-numeric columns
churn.describe(include=object)
```

[31]:
```
       Customer_id                           Interaction   City  State  \
count        10000                                 10000  10000  10000
unique       10000                                 10000   6058     52
```

```
top        K409198  aa90260b-4141-4a24-8e36-b04ce1f4f77b  Houston     TX
freq             1                                     1       34    603

              County      Area         Timezone                       Job  \
count          10000     10000            10000                     10000
unique          1620         3               25                       639
top       Washington  Suburban  America/New_York  Occupational psychologist
freq             111      3346             4072                        30

                          Education Employment  … Phone Multiple  \
count                         10000      10000  …  8974    10000
unique                           12          5  …     2        2
top       Regular High School Diploma  Full Time  …   Yes       No
freq                           2421       5992  …  8128     5392

       OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV  \
count           10000        10000            10000        9009       10000
unique              2            2                2           2           2
top                No           No               No          No          No
freq             6424         5494             5614        5635        5071

       StreamingMovies PaperlessBilling     PaymentMethod
count            10000            10000             10000
unique               2                2                 4
top                 No              Yes  Electronic Check
freq              5110             5882              3398

[4 rows x 28 columns]
```

[32]:

```python
# Check if there is any duplicate across all columns
duplicates = churn.duplicated().any()

# No duplicate found
duplicates
```

[32]: False

[33]:

```python
# Print unique values of each categorical column
# Print total if there are more than 15 unique values
for column in churn:
    if churn[column].dtype == object:
        print(column)
        uniques = churn[column].unique()
        if len(uniques) > 15:
            print(f'- {len(uniques)}')
        else:
            print(f'- {churn[column].unique()}')
```

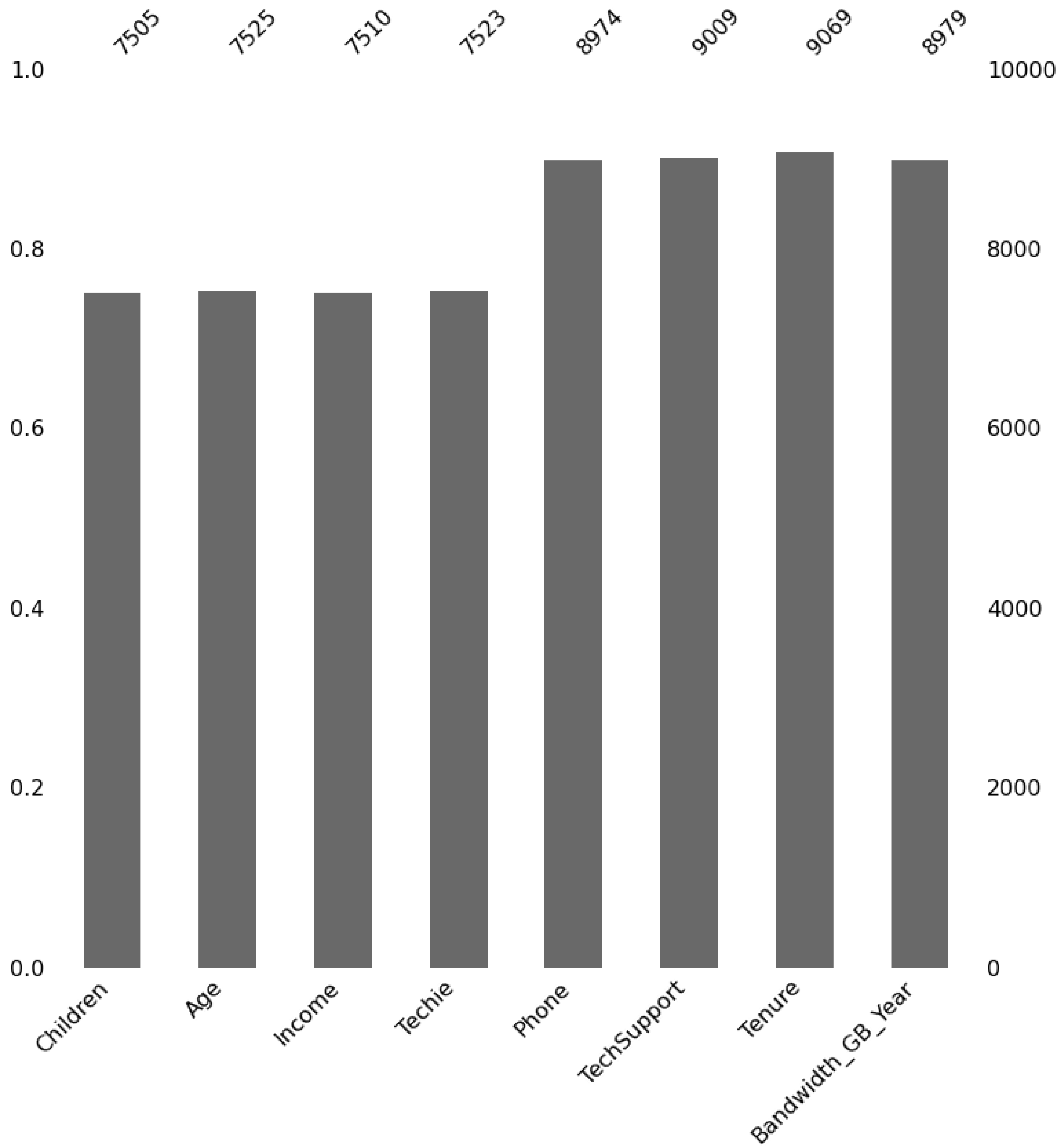
```
Customer_id
- 10000
Interaction
- 10000
City
- 6058
State
- 52
County
- 1620
Area
- ['Urban' 'Suburban' 'Rural']
Timezone
- 25
Job
- 639
Education
- ["Master's Degree" 'Regular High School Diploma' 'Doctorate Degree'
 'No Schooling Completed' "Associate's Degree" "Bachelor's Degree"
 'Some College, Less than 1 Year' 'GED or Alternative Credential'
 'Some College, 1 or More Years, No Degree'
 '9th Grade to 12th Grade, No Diploma' 'Nursery School to 8th Grade'
 'Professional School Degree']
Employment
- ['Part Time' 'Retired' 'Student' 'Full Time' 'Unemployed']
Marital
- ['Widowed' 'Married' 'Separated' 'Never Married' 'Divorced']
Gender
- ['Male' 'Female' 'Prefer not to answer']
Churn
- ['No' 'Yes']
Techie
- ['No' 'Yes' nan]
Contract
- ['One year' 'Month-to-month' 'Two Year']
Port_modem
- ['Yes' 'No']
Tablet
- ['Yes' 'No']
InternetService
- ['Fiber Optic' 'DSL' 'None']
Phone
- ['Yes' 'No' nan]
Multiple
- ['No' 'Yes']
OnlineSecurity
- ['Yes' 'No']
OnlineBackup
```

```
- ['Yes' 'No']
DeviceProtection
- ['No' 'Yes']
TechSupport
- ['No' 'Yes' nan]
StreamingTV
- ['No' 'Yes']
StreamingMovies
- ['Yes' 'No']
PaperlessBilling
- ['Yes' 'No']
PaymentMethod
- ['Credit Card (automatic)' 'Bank Transfer(automatic)' 'Mailed Check'
 'Electronic Check']
```

[34]:
```
# Explore columns with missing values similar to the 'nan' results above
churn_null = churn.isnull()
null_sums = churn_null.sum()

# Add missing column names to a list print out missing percentage
print('Total and percentage of missing values per column')
cols_missing = []
for column, missing in null_sums.items():
    if missing > 0:
        print(f'{column}: {missing} - {round((missing / 10000) * 100, )}%')
        cols_missing.append(column)
```

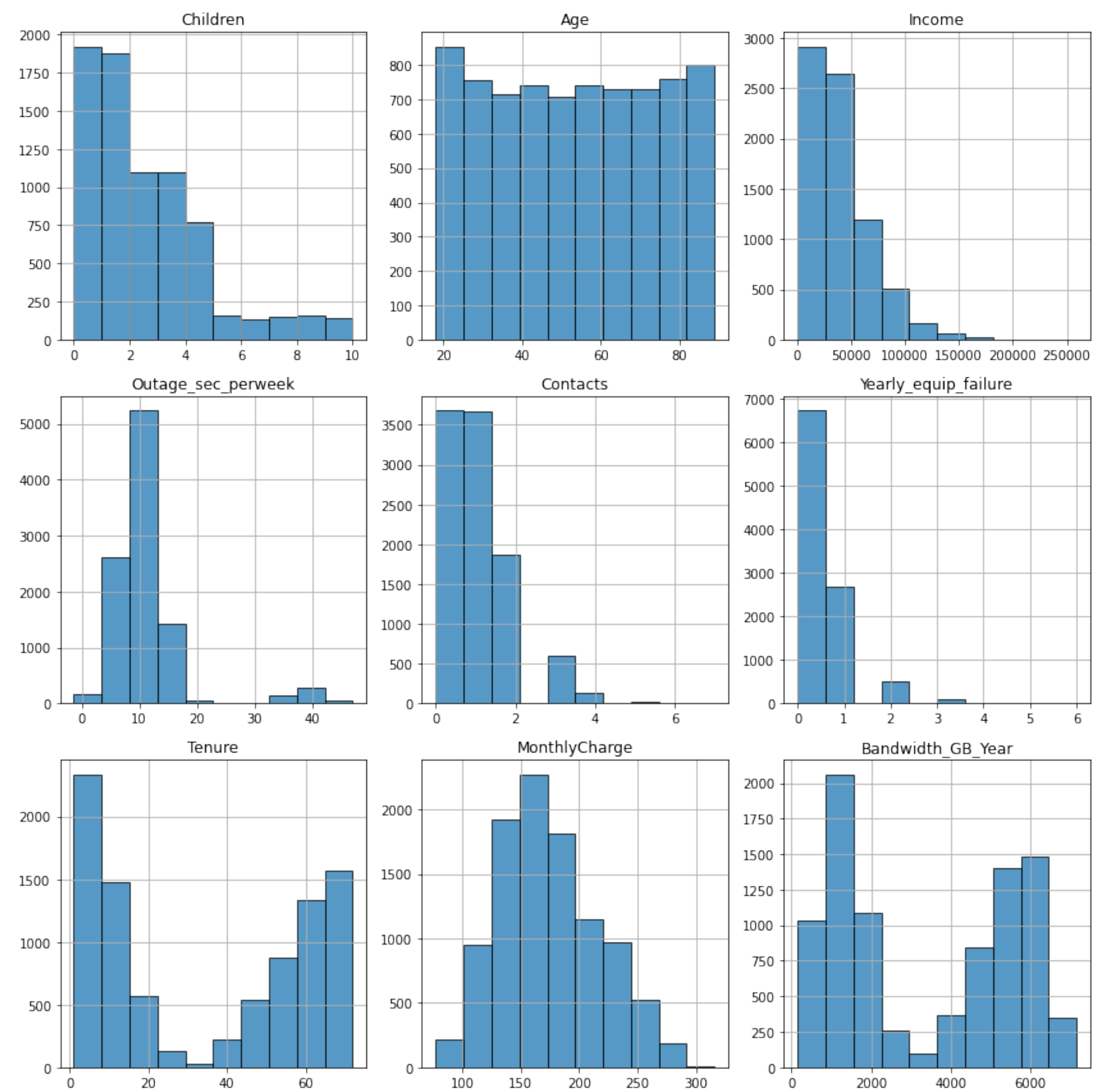
```
Total and percentage of missing values per column
Children: 2495 - 25%
Age: 2475 - 25%
Income: 2490 - 25%
Techie: 2477 - 25%
Phone: 1026 - 10%
TechSupport: 991 - 10%
Tenure: 931 - 9%
Bandwidth_GB_Year: 1021 - 10%
```

[35]:
```
# Copy missing columns to new dataframe
churn_missing = churn[cols_missing].copy()

# Visualize missing data
msno.bar(churn_missing, figsize=(12, 12))
plt.show()
```

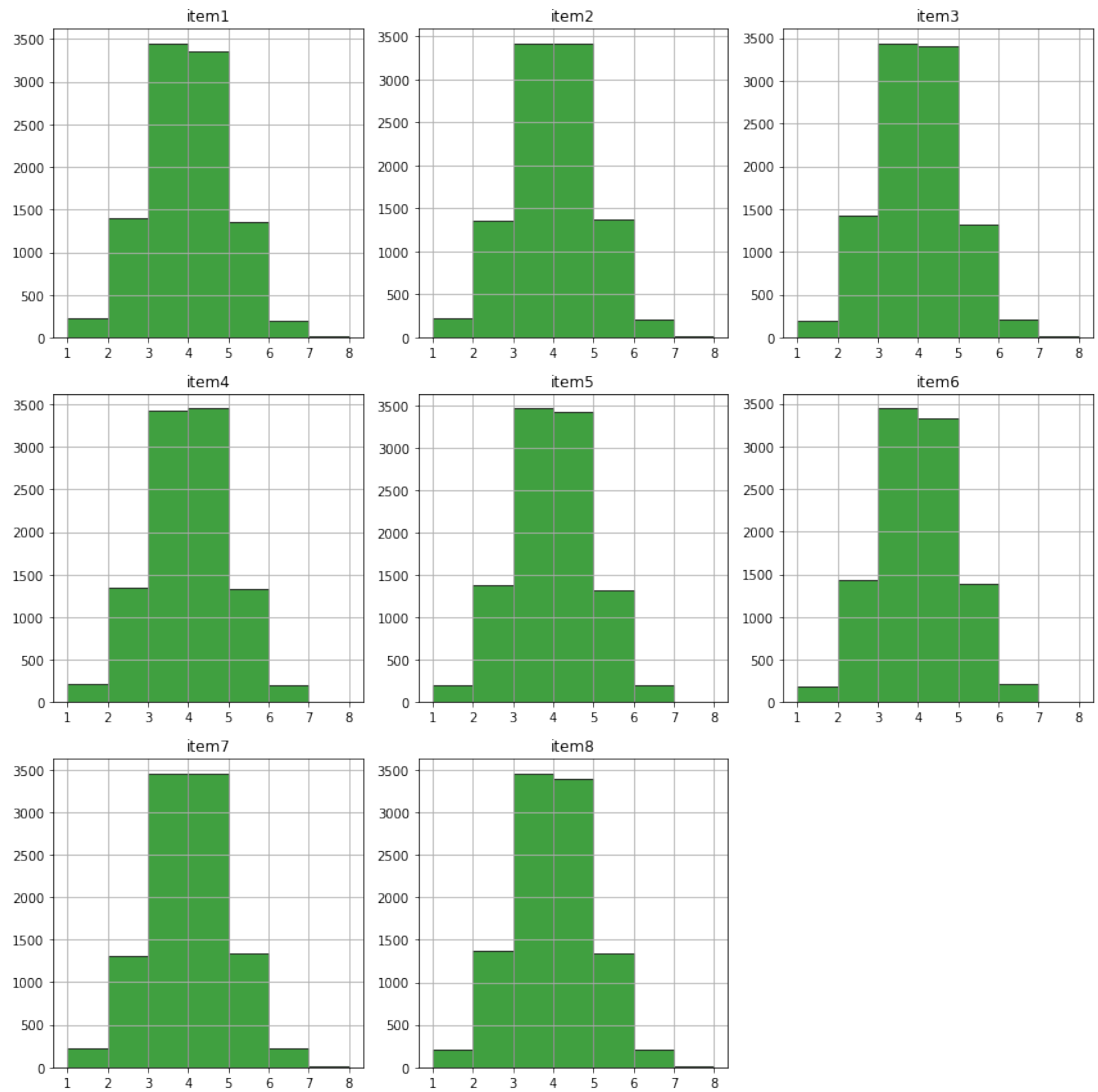


[36]:
```
"""
Author: Brad Solomon
Date: 2021
Title: Python Histogram Plotting: NumPy, Matplotlib, Pandas & Seaborn
Type: Source code
Web: https://realpython.com/python-histograms/
"""

# Plot the histograms of interesting numeric columns to see patterns
```

```
churn[['Children', 'Age', 'Income', 'Outage_sec_perweek', 'Contacts',␣
↪'Yearly_equip_failure', 'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year']].
↪hist(figsize=(12, 12),
                                                                          ␣
↪                                                                 ␣
↪ec='black',
                                                                          ␣
↪                                                                 alpha=0.
↪75)
plt.tight_layout()
plt.show()
```

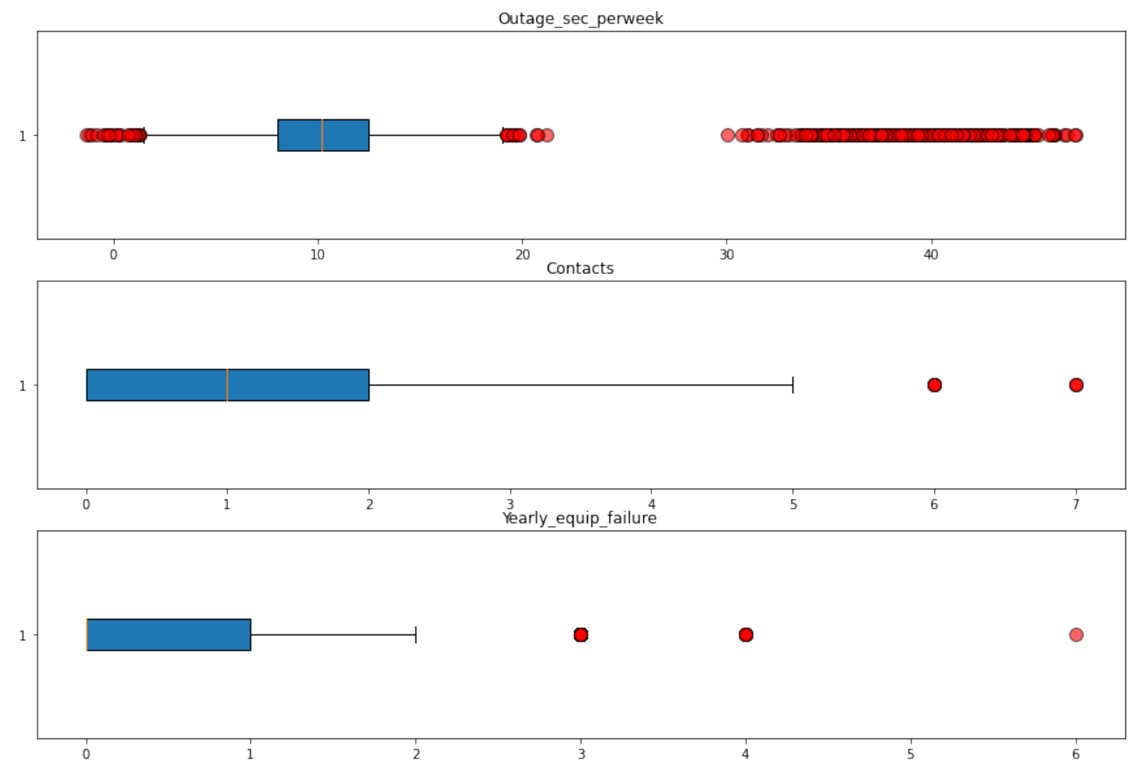


[37]:
```python
# Plot survey responses
churn[[f'item{i}' for i in range(1, 9)]].hist(figsize=(12, 12),
                                             ec='black',
                                             alpha=0.75,
                                             color='green',
                                             bins=[1, 2, 3, 4, 5, 6, 7, 8])
plt.tight_layout()
plt.show()
```



[38]:
```python
"""
Author: Python Pool
Date: 2021
Title: Matplotlib Boxplot With Customization in Python
```

```python
Type: Source Code
Web: https://www.pythonpool.com/matplotlib-boxplot/
"""

# Verify columns with outliers using boxplots
fig, ax = plt.subplots(3, 1, figsize=(15, 10))
for index, column in enumerate(['Outage_sec_perweek', 'Contacts', 'Yearly_equip_failure']):
    ax[index].boxplot(
        churn[column],
        vert=False,
        patch_artist=True,
        flierprops=dict(markerfacecolor='red', markersize=10, linestyle='none', alpha=0.6)
    )
    ax[index].set_title(column)
plt.show()
```



Part III: Data Cleaning

D1. Describe findings

There are several anomalies in the dataset:

- Columns `Unnamed: 0` and `CaseOrder` are the same.
- Unclear column names for survey responses.
- Negative values in `Outage_sec_perweek`, where the minimum should only be zero.
- Multiple columns are missing from 9% to 25% of their data.
- Based on the histograms and boxplots, there are outliers for `Outage_sec_perweek`, `Contacts`, and `Yearly_equip_failure`.

D2. Mitigation methods

My approach for dealing with the anomalies will be:

- Drop `Unnamed: 0` column since it's a duplicate of `CaseOrder`.
- Rename survey responses to something easier to understand.
- Change the negative values in `Outage_sec_perweek` to 0 to enforce proper range (Nehme, 2021).
- Use K-Nearest Neighbor algorithm to predict missing values based on values of neighboring columns (Donthi, 2021).
- Leave the outliers alone since they might provide important insights for later analysis.

D3. Outcome summary

The outcome of each data cleaning step is:

- `Unnamed: 0` column dropped from the dataframe.
- Survey items are easier to understand.
- The minimum for `Outage_sec_perweek` is set to 0.
- Missing values are imputed using KNN algorithm. Categorical values are ordinally encoded before imputation.

D4. Code for mitigation

[39]:
```
# Drop 'Unnamed: 0' column
churn = churn.drop('Unnamed: 0', axis=1)
```

[40]:
```
# Rename survey responses columns
churn.rename(columns={
    'item1': 'SurveyResponse',
    'item2': 'SurveyFixes',
    'item3': 'SurveyReplacements',
    'item4': 'SurveyReliability',
    'item5': 'SurveyOptions',
    'item6': 'SurveyRespect',
    'item7': 'SurveyCourteous',
    'item8': 'SurveyListening'
}, inplace=True)
```

[41]:
```
# Set negative values in Outage_sec_perweek to 0
churn.loc[churn['Outage_sec_perweek'] < 0, 'Outage_sec_perweek'] = 0
```

[42]:
```
import numpy as np
from sklearn.impute import KNNImputer
```

```
# Split missing columns into numeric and categorical
num_missing = churn_missing[['Children', 'Age', 'Income', 'Tenure',␣
 ↪'Bandwidth_GB_Year']].copy()
cat_missing = churn_missing[['Techie', 'Phone', 'TechSupport']].copy()

# Impute numeric columns
knn = KNNImputer()
num_missing.iloc[:, :] = knn.fit_transform(num_missing)

num_missing.describe()
```

[42]:

```
           Children          Age         Income        Tenure  \
count  10000.000000  10000.00000   10000.000000  10000.000000
mean       2.045900     52.99086   39976.469551     34.539410
std        1.917549     18.62637   25328.964531     25.539056
min        0.000000     18.00000     740.660000      1.000259
25%        1.000000     39.20000   22838.322500      8.574026
50%        1.800000     52.40000   35629.102000     34.369232
75%        3.000000     67.00000   50947.115000     60.367002
max       10.000000     89.00000  258900.700000     71.999280

       Bandwidth_GB_Year
count       10000.000000
mean         3388.508002
std          2108.192078
min           155.506715
25%          1290.549139
50%          3349.915681
75%          5476.439000
max          7158.982000
```

[43]:

```
"""
Author: Suraj Donthi
Date: 2021
Title: Imputing categorical values
Type: Source code
Web: https://campus.datacamp.com/courses/dealing-with-missing-data-in-python/
 ↪advanced-imputation-techniques?ex=4
"""

from sklearn.preprocessing import OrdinalEncoder

# Perform ordinal encoding for missing categorical columns
ordinal_dict = {}
for column in cat_missing:
    # Create ordinal encoder for column
```

```
    ordinal_dict[column] = OrdinalEncoder()
    col = cat_missing[column]

    # Select non-null values and encode them
    col_not_null = col[col.notnull()]
    reshaped_vals = col_not_null.values.reshape(-1, 1)
    encoded_vals = ordinal_dict[column].fit_transform(reshaped_vals)

    # Store the encoded values back in the column
    cat_missing.loc[col.notnull(), column] = np.squeeze(encoded_vals)

# Impute missing values
cat_missing.iloc[:, :] = np.round(knn.fit_transform(cat_missing))

# Convert encoded columns back to categorical
for column in cat_missing:
    reshaped = cat_missing[column].values.reshape(-1, 1)
    cat_missing[column] = ordinal_dict[column].inverse_transform(reshaped)

cat_missing.describe()
```

[43]:

	Techie	Phone	TechSupport
count	10000	10000	10000
unique	2	2	2
top	No	Yes	No
freq	8743	9154	6413

D5. Copy of clean data

[44]:
```
# Create copy of churn data
churn_clean = churn.copy(deep=True)

# Replace missing columns with imputed ones
for column in churn_missing:
    if column in num_missing:
        churn_clean[column] = num_missing[column]
    elif column in cat_missing:
        churn_clean[column] = cat_missing[column]

churn_clean.to_csv('churn_clean.csv')
```

[45]:
```
# Check the cleaned data by importing and display summary of imputed columns
cleaned_data = pd.read_csv('churn_clean.csv')

cleaned_data[['Children', 'Age', 'Income', 'Tenure', 'Bandwidth_GB_Year',␣
 ↪'Techie', 'Phone', 'TechSupport']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Children           10000 non-null  float64
 1   Age                10000 non-null  float64
 2   Income             10000 non-null  float64
 3   Tenure             10000 non-null  float64
 4   Bandwidth_GB_Year  10000 non-null  float64
 5   Techie             10000 non-null  object
 6   Phone              10000 non-null  object
 7   TechSupport        10000 non-null  object
dtypes: float64(5), object(3)
memory usage: 625.1+ KB
```

D6. Limitations of data cleaning

Without knowing where the data came from or how it was collected, I have to assume some uncertainty when working with it. While KNN algorithm is better than using the mean or median for imputing values (Donthi, 2021), , it does not replace real data. By imputing the values, I might lose some insight when performing analysis with the imputed values. To properly clean the data, I would need help from a domain expert, someone who understands churn in both the company and the industry. Since I'm not familiar with the industry, my data cleaning process might be very different than someone who understands the industry well.

D7. Effects of limitation on research question

Given that the dataset was missing a lot of data, the conclusion drawn from this data needs to be scrutinized before decisions are made from imputed values (Nehme, 2021). Predicting which customers are at high risk of churn require some degree of caution. It can be very costly for the company to predict the wrong segment of customers to retain, leading to ineffective marketing. It's also possible for the company to focus on the wrong metrics for customer retention based on erroneous data. There are also some variables in the data that need more consideration since their correlations with churn are unclear at the moment.

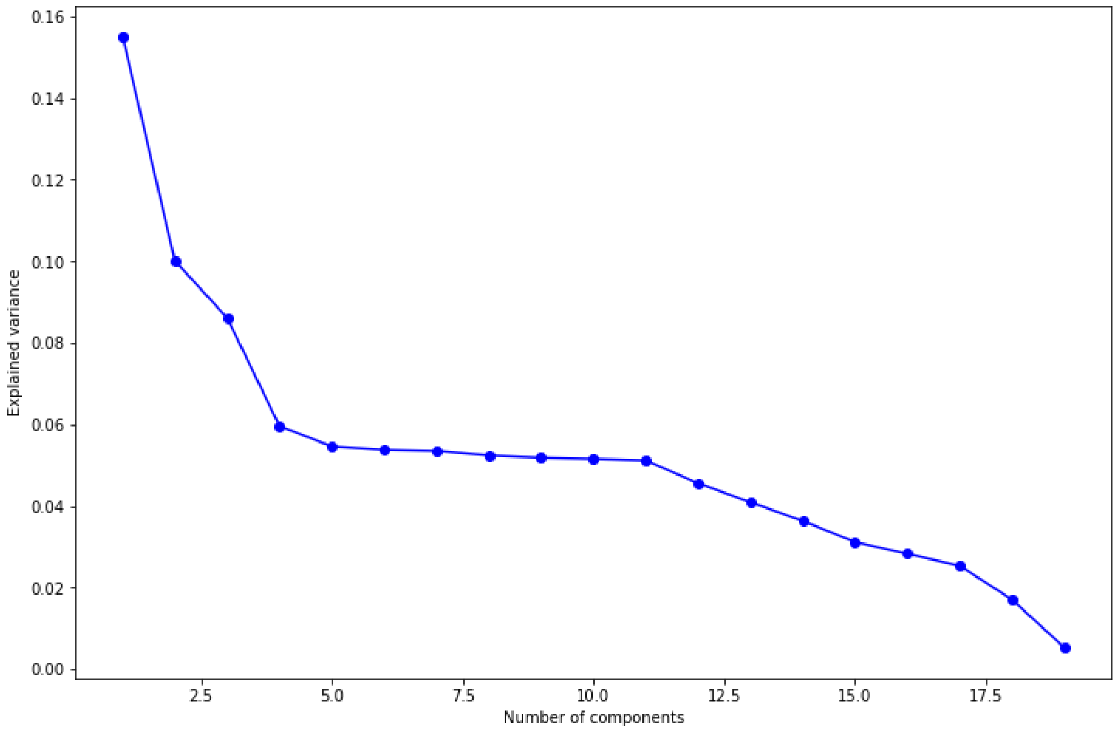
[46]:
```python
# Create dataframe with only numeric columns for PCA
churn_cp = churn_clean.select_dtypes(include=['int64', 'float64'])

# Drop columns that are not meaningful
churn_cp = churn_cp.drop(['CaseOrder', 'Zip', 'Lat', 'Lng'], axis=1)

churn_cp.head()
```

[46]:
```
   Population  Children   Age     Income  Outage_sec_perweek  Email  Contacts  \
0          38       1.2  68.0  28561.990            6.972566     10         0
1       10446       1.0  27.0  21704.770           12.014541     12         0
2        3735       4.0  50.0  45759.278           10.245616      9         0
3       13863       1.0  48.0  18925.230           15.206193     15         2
4       11352       0.0  83.0  40074.190            8.960316     16         2
```

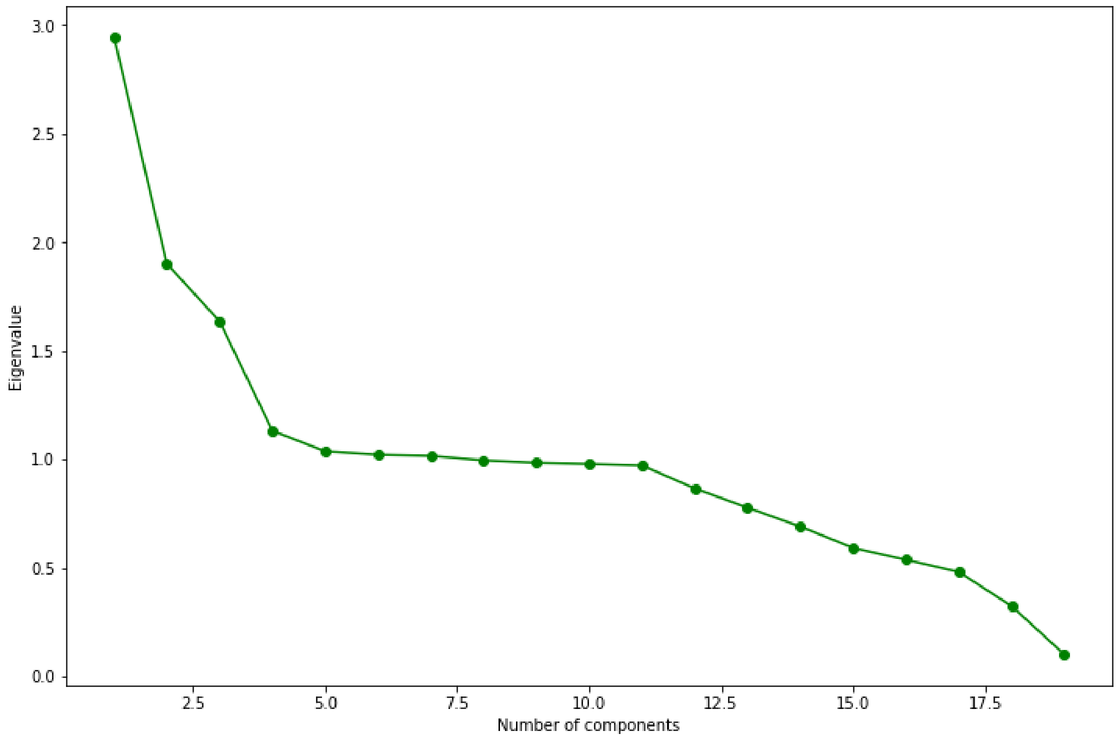
```
   Yearly_equip_failure     Tenure  MonthlyCharge  Bandwidth_GB_Year  \
0                     1   6.795513     171.449762         904.536110
1                     1   1.156681     242.948015         800.982766
2                     1  15.754144     159.440398        2054.706961
3                     0  17.087227     120.249493        2164.579412
4                     1   1.670972     150.761216         271.493436

   SurveyResponse  SurveyFixes  SurveyReplacements  SurveyReliability  \
0               5            5                   5                  3
1               3            4                   3                  3
2               4            4                   2                  4
3               4            4                   4                  2
4               4            4                   4                  3

   SurveyOptions  SurveyRespect  SurveyCourteous  SurveyListening
0              4              4                3                4
1              4              3                4                4
2              4              3                3                3
3              5              4                3                3
4              4              4                4                5
```

[47]:
```
"""
Author: Keiona Middleton
Date: 2021
Title: How to perform PCA in Python
Type: Source code
Web: https://cgp-oex.wgu.edu/lti_provider/courses/course-v1:WGUx+D206x+2021_T3/
 ↪block-v1:
 ↪WGUx+D206x+2021_T3+type@vertical+block@3f0422d47d8b4a3eaec25de3bced8bf8
"""

from sklearn.decomposition import PCA

# Normalize data
churn_normalized = (churn_cp - churn_cp.mean()) / churn_cp.std()

# Extract all components for analysis
pca = PCA(n_components=churn_cp.shape[1])
pca.fit(churn_normalized)

# Converts 19 variables into dataset of 19 components
pca_cols = [f'PC{i}' for i in range(1, 20)]      # Create list of component␣
 ↪names 'PC1' to 'PC19'
churn_pca = pd.DataFrame(pca.transform(churn_normalized),
                         columns=pca_cols)
```

```python
# Scree plot of PCA with each additional component variance
pc_values = np.arange(pca.n_components_) + 1
plt.figure(figsize=(12, 8))
plt.plot(pc_values, pca.explained_variance_ratio_, 'o-', color='blue')
plt.xlabel('Number of components')
plt.ylabel('Explained variance')
plt.show()
```



[48]:
```python
# Extract eigenvalues from dataset
cov_matrix = np.dot(churn_normalized.T, churn_normalized) / churn_cp.shape[0]
eigenvalues = [np.dot(eigenvector.T, np.dot(cov_matrix, eigenvector)) for␣
 ↪eigenvector in pca.components_]

# Plot eigenvalues
plt.figure(figsize=(12, 8))
plt.plot(pc_values, eigenvalues, 'o-', color='green')
plt.xlabel('Number of components')
plt.ylabel('Eigenvalue')
plt.show()
```



[49]:
```python
# Table output of loadings for the components
loadings = pd.DataFrame(pca.components_.T,
                        columns=pca_cols,
                        index=churn_cp.columns)
loadings
```

[49]:

	PC1	PC2	PC3	PC4	PC5 \
Population	-0.002126	-0.000453	0.015690	-0.044868	-0.460027
Children	0.003095	0.012553	0.004845	0.011792	0.421564
Age	0.005289	-0.008653	-0.014067	-0.056497	0.051788
Income	0.000406	0.026147	0.014560	-0.006958	0.114120
Outage_sec_perweek	-0.013174	0.016744	-0.047773	0.703619	0.010886
Email	0.008630	-0.022362	-0.003666	0.055706	-0.499512
Contacts	-0.008565	-0.000282	-0.009801	-0.008902	-0.309932
Yearly_equip_failure	-0.007685	0.017058	0.006632	0.056346	0.495476
Tenure	-0.010849	0.700531	-0.073350	-0.059601	-0.023359
MonthlyCharge	-0.000559	0.044965	-0.025080	0.696056	-0.048205
Bandwidth_GB_Year	-0.012615	0.702102	-0.078281	-0.008758	-0.012278
SurveyResponse	0.458796	0.032644	0.280102	0.032057	0.010777
SurveyFixes	0.434080	0.044668	0.281116	0.018523	0.002328
SurveyReplacements	0.400724	0.036816	0.280686	-0.010283	-0.013250
SurveyReliability	0.145661	-0.053416	-0.566751	-0.031787	-0.003018
SurveyOptions	-0.175523	0.067532	0.586020	0.026249	-0.015021

```
SurveyRespect         0.405060 -0.013150 -0.183604  0.005018 -0.006709
SurveyCourteous       0.358304 -0.006069 -0.180813 -0.031803  0.011792
SurveyListening       0.308741 -0.016078 -0.132101  0.028892 -0.005769

                          PC6       PC7       PC8       PC9      PC10  \
Population           -0.158561  0.107099  0.729421  0.046957  0.106960
Children             -0.414608  0.311922 -0.175497  0.512950  0.339433
Age                   0.459666  0.613717 -0.025014  0.169097 -0.559523
Income                0.386314 -0.530936  0.226829  0.699160 -0.081200
Outage_sec_perweek    0.000618 -0.035980  0.069240  0.014744  0.030149
Email                -0.333894  0.273176 -0.076051  0.445199 -0.126064
Contacts              0.561927  0.231294 -0.190770  0.055106  0.699880
Yearly_equip_failure  0.089111  0.317711  0.573607 -0.094018  0.187278
Tenure                0.001832  0.010757 -0.002293 -0.010241 -0.020274
MonthlyCharge         0.060946  0.036933 -0.065864 -0.025081 -0.069746
Bandwidth_GB_Year    -0.021574  0.008498 -0.012761 -0.004181  0.005750
SurveyResponse        0.000905  0.007292  0.003301 -0.013699  0.019661
SurveyFixes           0.020153  0.009658 -0.015558 -0.002410  0.003798
SurveyReplacements   -0.027931 -0.004126 -0.009081 -0.027810 -0.012818
SurveyReliability     0.000443 -0.008382  0.006269 -0.031082 -0.004963
SurveyOptions         0.029561  0.006610 -0.009244 -0.011694 -0.015676
SurveyRespect         0.003374  0.008938  0.014247  0.014941  0.014856
SurveyCourteous       0.008325 -0.019559 -0.028750  0.052351  0.044482
SurveyListening       0.030224 -0.006635  0.055473 -0.034340 -0.060296

                         PC11      PC12      PC13      PC14      PC15  \
Population           -0.446193 -0.014801 -0.061320  0.020601 -0.016653
Children             -0.372158  0.009287  0.036773 -0.046451 -0.014709
Age                  -0.214528  0.104919 -0.072154  0.014209 -0.003069
Income                0.042847 -0.056917  0.002122 -0.051703 -0.002525
Outage_sec_perweek    0.023587  0.692611 -0.117754  0.011810 -0.012325
Email                 0.578073 -0.038336  0.065146 -0.017915 -0.016313
Contacts              0.029897  0.017236  0.038945 -0.036829 -0.003329
Yearly_equip_failure  0.501887 -0.124765  0.030201  0.005490 -0.014937
Tenure                0.017391  0.039345  0.000411 -0.007265  0.007949
MonthlyCharge        -0.143934 -0.685115  0.047218  0.010463 -0.014067
Bandwidth_GB_Year    -0.001585 -0.009198  0.011018  0.003327  0.002187
SurveyResponse        0.008390 -0.008013 -0.071120 -0.118479 -0.047430
SurveyFixes          -0.006463 -0.000031 -0.112110 -0.169856 -0.066158
SurveyReplacements    0.022081 -0.011836 -0.176501 -0.247545 -0.145847
SurveyReliability     0.009143 -0.024202 -0.180151 -0.477840 -0.444332
SurveyOptions        -0.004841  0.041377  0.129460  0.059700 -0.209737
SurveyRespect         0.009247 -0.003978 -0.061852  0.064204  0.757673
SurveyCourteous       0.018457 -0.022811 -0.161773  0.807284 -0.377386
SurveyListening      -0.069925  0.119793  0.915859 -0.025113 -0.112988

                         PC16      PC17      PC18      PC19
```

```
Population            0.000779 -0.004951 -0.002278 -0.000272
Children              0.013368  0.022523 -0.005728 -0.024382
Age                  -0.017409  0.010475  0.017236  0.021007
Income               -0.007898  0.012777  0.005285  0.004322
Outage_sec_perweek   -0.017055  0.010844 -0.004232 -0.000537
Email                 0.006996 -0.016869  0.001158  0.002413
Contacts             -0.025880  0.020654 -0.000704 -0.000614
Yearly_equip_failure -0.000625  0.006623 -0.021210 -0.000405
Tenure               -0.014183  0.007800  0.003097 -0.704827
MonthlyCharge         0.000258  0.021226 -0.013417 -0.048510
Bandwidth_GB_Year     0.002832 -0.010185  0.010384  0.706642
SurveyResponse        0.023999 -0.239656  0.792887 -0.006345
SurveyFixes           0.068930 -0.591542 -0.573519 -0.002684
SurveyReplacements   -0.392388  0.676032 -0.177546  0.018473
SurveyReliability     0.431204  0.086404  0.017657 -0.002076
SurveyOptions         0.694894  0.261050 -0.042670 -0.004053
SurveyRespect         0.404606  0.226563 -0.063876  0.000992
SurveyCourteous       0.067671  0.065179 -0.041271 -0.006966
SurveyListening      -0.042895  0.046252 -0.042857 -0.001540
```

[50]:
```python
# Percentage of variance explained by number of components
print('Percentage of variance explained by number of components:')
for index, var in enumerate(pca.explained_variance_ratio_.cumsum()):
    print(f'- PC{index + 1}: {round(var * 100, 2)}%')
```

```
Percentage of variance explained by number of components:
- PC1: 15.52%
- PC2: 25.53%
- PC3: 34.14%
- PC4: 40.1%
- PC5: 45.56%
- PC6: 50.94%
- PC7: 56.29%
- PC8: 61.53%
- PC9: 66.71%
- PC10: 71.87%
- PC11: 76.99%
- PC12: 81.55%
- PC13: 85.64%
- PC14: 89.27%
- PC15: 92.39%
- PC16: 95.22%
- PC17: 97.76%
- PC18: 99.47%
- PC19: 100.0%
```

E1. Principal components

The scree and eigenvalue plots showed that the dataset contained 11 principal components: Population, Children, Age, Income, Outage_sec_perweek, Email, Contacts, Yearly_equip_failure, Tenure, MonthlyCharge, and Bandwidth_GB_Year.

E2. Identifying the principal components

To identify the principal components, I performed a Principal Component Analysis on the numeric columns that provided statistical insight from the dataset. I graphed the scree plot to look at how much variance can be explained based on the number of components. The first 11 components together explained 76.99% of the total variability. For additional information, I extracted and plotted the eigenvalues of all the components. The eigenvalue plot showed that first 11 components had eigenvalues greater than one. The eigenvalue criterion states that only components with eigenvalue greater than one should be retained because each component should explain at least one predictor's worth of variability (Larose, 2019, p. 188). The last eight components did not provide additional value when analyzing churn rate and can be reduced from the dataset.

E3. Benefits of PCA

The results of the PCA showed that the dataset had 11 principal components. Focusing on these components will help the most when attempting to explain the variability in the data. The last eight components, the survey responses, did not provide additional insight into the dataset. As such, they can be reduced from the data. This result is not a surprise since customer retention can be made up of multiple different components. There is not a single component that will predict the churn rate with certainty. However, knowing which components to focus on would save the company time and money from analyzing the unimportant variables.

Part IV: Supporting Documents

F. Panopto recording

https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=37f4a481-e095-431a-8105-ade1013d4e8e

G. Third-party code sources

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Zach, B. (2021, September 18). How to Create a Scree Plot in Python. [Weblog]. https://www.statology.org/scree-plot-python/

H. References

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