Part 0: Environment Setup

Loading the Churn CSV into a data frame. I will be loading and using the following modules for this project:

In [29]:
```
import numpy as np
import pandas as pd
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

df = pd.read_csv('churn_raw_data.csv', index_col=0)
```

Part I: Research Question

A. Description of Question

In the telecommunications industry, customers can choose from multiple service providers and actively switch from one provider to another. Customer “churn” is defined as the percentage of customers who stopped using a provider’s product or service during a certain time frame. In this highly competitive market, some telecommunications industries can experience average annual churn rates as high as 25 percent. Given that it costs 10 times more to acquire a new customer than to retain an existing one, customer retention has now become even more important than customer acquisition. For many providers, retaining highly profitable customers is the number one business goal. To reduce customer churn, telecommunications companies need to predict which customers are at high risk of churn. You are an analyst on a team of analysts in a popular telecommunications company, which serves customers in all regions of the United States. You have been asked to clean the raw data set in preparation to explore the data, identify trends, and compare key metrics.

The question I will be posing: Given the cost in acquiring new customers versus maintaining current customers, which factors tend to lead to customer churn, or a higher churn rate? Some factors may include:

- service outages
- service costs too much
- not enough use of service
- too many technical problems
- low quality tech support
- not technically inclined enough paired with low quality technical support

B. Describe Variables

In this section, I will review the types of data present in the dataset, review statistics on the dataset, and describe the variables in the dataset.

Summary Statistics of the dataset with unneccessary variables:

In [2]:
```
df = df.drop(columns=['Interaction', 'CaseOrder',  'Zip', 'Lat', 'Lng', 'Techie', 'Phone
df.describe()
```

Out[2]:

	Population	Children	Age	Income	Outage_sec_perweek	Email	Contacts
count	10000.000000	7505.000000	7525.000000	7510.000000	10000.000000	10000.000000	10000.000000

mean	9756.562400	2.095936	53.275748	39936.762226	11.452955	12.016000	0.994200
std	14432.698671	2.154758	20.753928	28358.469482	7.025921	3.025898	0.988466
min	0.000000	0.000000	18.000000	740.660000	-1.348571	1.000000	0.000000
25%	738.000000	0.000000	35.000000	19285.522500	8.054362	10.000000	0.000000
50%	2910.500000	1.000000	53.000000	33186.785000	10.202896	12.000000	1.000000
75%	13168.000000	3.000000	71.000000	53472.395000	12.487644	14.000000	2.000000
max	111850.000000	10.000000	89.000000	258900.700000	47.049280	23.000000	7.000000

Shape of the dataset:

In [3]:
```
df.shape
```

Out[3]:
```
(10000, 35)
```

Object types will be categorical variables. float64 and int64 will be numerical variables.

Review of the types of data in the dataset:

In [4]:
```
df.dtypes
```

Out[4]:
```
Customer_id              object
City                     object
State                    object
County                   object
Population                int64
Area                     object
Timezone                 object
Job                      object
Children                float64
Age                     float64
Education                object
Employment               object
Income                  float64
Marital                  object
Gender                   object
Churn                    object
Outage_sec_perweek      float64
Email                     int64
Contacts                  int64
Yearly_equip_failure      int64
Contract                 object
Port_modem               object
Tablet                   object
InternetService          object
Multiple                 object
OnlineSecurity           object
OnlineBackup             object
DeviceProtection         object
StreamingTV              object
StreamingMovies          object
PaperlessBilling         object
PaymentMethod            object
Tenure                  float64
MonthlyCharge           float64
Bandwidth_GB_Year       float64
dtype: object
```

Part II

C. Cleaning Plan

In this section, I will explain the plan for cleaning the data.

My approach will be as follows:

- Identify null values
- Identify NA or zero values where that input does not make sense
- Identify areas with missing values
- Indentify method to finding typographical errors

For all of the above, I will identify an appropriate approach to managing unclean data.

Relevant techniques and specific steps to identify anomalies in the data set will be expressed in the below python code.

Finding nulls and null values

In [5]:
```
# Finding which rows have null values.
df.isnull()
```

Out[5]:

	Customer_id	City	State	County	Population	Area	Timezone	Job	Children	Age	...	OnlineSecurity
1	False	False	False	False	False	False	False	False	True	False	...	False
2	False	False	False	False	False	False	False	False	False	False	...	False
3	False	False	False	False	False	False	False	False	False	False	...	False
4	False	False	False	False	False	False	False	False	False	False	...	False
5	False	False	False	False	False	False	False	False	False	False	...	False
...	...	...	...	...	...	...	...	...	...	...	...	...
9996	False	False	False	False	False	False	False	False	False	True	...	False
9997	False	False	False	False	False	False	False	False	False	False	...	False
9998	False	False	False	False	False	False	False	False	True	True	...	False
9999	False	False	False	False	False	False	False	False	False	False	...	False
10000	False	False	False	False	False	False	False	False	False	False	...	False

10000 rows × 35 columns

It looks to be good. Let's look closer.

In [6]:
```
# Shows which specific columns have NAs in them
df.isna().any()
```

Out[6]:
```
Customer_id          False
City                 False
State                False
County               False
Population           False
Area                 False
```

```
Timezone                False
Job                     False
Children                 True
Age                      True
Education               False
Employment              False
Income                   True
Marital                 False
Gender                  False
Churn                   False
Outage_sec_perweek      False
Email                   False
Contacts                False
Yearly_equip_failure    False
Contract                False
Port_modem              False
Tablet                  False
InternetService         False
Multiple                False
OnlineSecurity          False
OnlineBackup            False
DeviceProtection        False
StreamingTV             False
StreamingMovies         False
PaperlessBilling        False
PaymentMethod           False
Tenure                   True
MonthlyCharge           False
Bandwidth_GB_Year        True
dtype: bool
```

Age, Children, Income, Tenure, Bandwidth_GB_Year all contain NA values that must be dealt with.

In [7]:
```
# How many rows, and which rows, have null data?

null_data_rows = df.isnull().sum()
print(null_data_rows)
```

```
Customer_id                0
City                       0
State                      0
County                     0
Population                 0
Area                       0
Timezone                   0
Job                        0
Children                2495
Age                     2475
Education                  0
Employment                 0
Income                  2490
Marital                    0
Gender                     0
Churn                      0
Outage_sec_perweek         0
Email                      0
Contacts                   0
Yearly_equip_failure       0
Contract                   0
Port_modem                 0
Tablet                     0
InternetService            0
Multiple                   0
OnlineSecurity             0
OnlineBackup               0
```

```
DeviceProtection           0
StreamingTV                0
StreamingMovies            0
PaperlessBilling           0
PaymentMethod              0
Tenure                   931
MonthlyCharge              0
Bandwidth_GB_Year       1021
dtype: int64
```

In [8]:
```python
# This will show rows from this dataframe that do contain missing values

df_missing_values = df.isnull().any(axis=1)
df[df_missing_values]
```

Out[8]:

	Customer_id	City	State	County	Population	Area	Timezone	Job	Ch
1	K409198	Point Baker	AK	Prince of Wales-Hyder	38	Urban	America/Sitka	Environmental health practitioner	
3	K191035	Yamhill	OR	Yamhill	3735	Urban	America/Los_Angeles	Chief Financial Officer	
6	W303516	Fort Valley	GA	Peach	17701	Urban	America/New_York	Chief Technology Officer	
7	U335188	Pioneer	TN	Scott	2535	Suburban	America/New_York	Surveyor, hydrographic	
8	V538685	Oklahoma City	OK	Oklahoma	23144	Suburban	America/Chicago	Sales promotion account executive	
...	...	...	...	...	...	...	...	...	
9995	P175475	West Kill	NY	Greene	210	Urban	America/New_York	Youth worker	
9996	M324793	Mount Holly	VT	Rutland	640	Rural	America/New_York	Sport and exercise psychologist	
9997	D861732	Clarksville	TN	Montgomery	77168	Rural	America/Chicago	Consulting civil engineer	
9998	I243405	Mobeetie	TX	Wheeler	406	Rural	America/Chicago	IT technical support officer	
10000	T38070	Clarkesville	GA	Habersham	12230	Urban	America/New_York	Personal assistant	

6544 rows × 35 columns

C3. Justification of Tools

For this project, I will use Python because of the libraries available. While R could be used, I have more experience with Python through other projects.

I used the following packages as well specifically for this project:

- numpy - for creating and manipulating matrices
- pandas - for using data frames, importing CSV, exporting CSV, and manipulating tables/rows/cells
- PCA through sci-kit learn - PCA used specifically to perform principle component analysis
- matplotlib - used to create graphs/charts for data visualization

I used Jupyter notebooks for this project because it provides for a very useful way to run, test, and write code with imediate visual results. I use it also because of the ability to create markdown documents which allows for easy visualization.

Using the above languages, tools, programs, libraries, and applications allow me to create a running-document. Additionally, to use less time creating tools for a task and more time using tools that already exists to perform a task.

Finding typos and similar mistakes

I will run unique() on select categorical rows, and use the output to determine if there are any blaring typographical errors that present themselves.

In [9]:
```
# Look at unique employment values
df['Employment'].unique()
```

Out[9]:
```
array(['Part Time', 'Retired', 'Student', 'Full Time', 'Unemployed'],
      dtype=object)
```

In [10]:
```
# Look at unique area values
df['Area'].unique()
```

Out[10]:
```
array(['Urban', 'Suburban', 'Rural'], dtype=object)
```

In [11]:
```
# Look at unique timezone values
df['Timezone'].unique()
```

Out[11]:
```
array(['America/Sitka', 'America/Detroit', 'America/Los_Angeles',
       'America/Chicago', 'America/New_York', 'America/Puerto_Rico',
       'America/Denver', 'America/Menominee', 'America/Phoenix',
       'America/Indiana/Indianapolis', 'America/Boise',
       'America/Kentucky/Louisville', 'Pacific/Honolulu',
       'America/Indiana/Petersburg', 'America/Nome', 'America/Anchorage',
       'America/Indiana/Knox', 'America/Juneau', 'America/Toronto',
       'America/Indiana/Winamac', 'America/Indiana/Vincennes',
       'America/North_Dakota/New_Salem', 'America/Indiana/Tell_City',
       'America/Indiana/Marengo', 'America/Ojinaga'], dtype=object)
```

In [12]:
```
# Look at unique education values
df['Education'].unique()
```

Out[12]:
```
array(["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'],
      dtype=object)
```

In [13]:
```
# Look at unique marital status
df['Marital'].unique()
```

Out[13]:
```
array(['Widowed', 'Married', 'Separated', 'Never Married', 'Divorced'],
      dtype=object)
```

In [14]:
```
# Look at unique gender values
df['Gender'].unique()
```

Out[14]:
```
array(['Male', 'Female', 'Prefer not to answer'], dtype=object)
```

In [15]:
```
# Look at unique payment methods
df['PaymentMethod'].unique()
```

Out[15]:
```
array(['Credit Card (automatic)', 'Bank Transfer(automatic)',
       'Mailed Check', 'Electronic Check'], dtype=object)
```

There are fields with missing values. To solve this, I will use the median value to place into blank fields

In [16]:
```
# Add median value to blank fields for the following variables/columns:
# Age, Income, Tenure, Children, Bandwidth GB Year

df['Age'] = df['Age'].fillna(df['Age'].median())

df['Income'] = df['Income'].fillna(df['Income'].median())

df['Tenure'] = df['Tenure'].fillna(df['Tenure'].median())

df['Children'] = df['Children'].fillna(df['Children'].median())

df['Bandwidth_GB_Year'] = df['Bandwidth_GB_Year'].fillna(df['Bandwidth_GB_Year'].median(
```

Part III

D: Summary of Data Cleaning Process

Duplicate Rows

In [17]:
```
# Creates a data frame that contains rows that are duplicates from other rows, and then
# displays the contents of that dataframe.

# Useful to discover if there are identical repeat rows that could skew our data innapro

duplicates = df.loc[df.duplicated()]
print(duplicates)
```

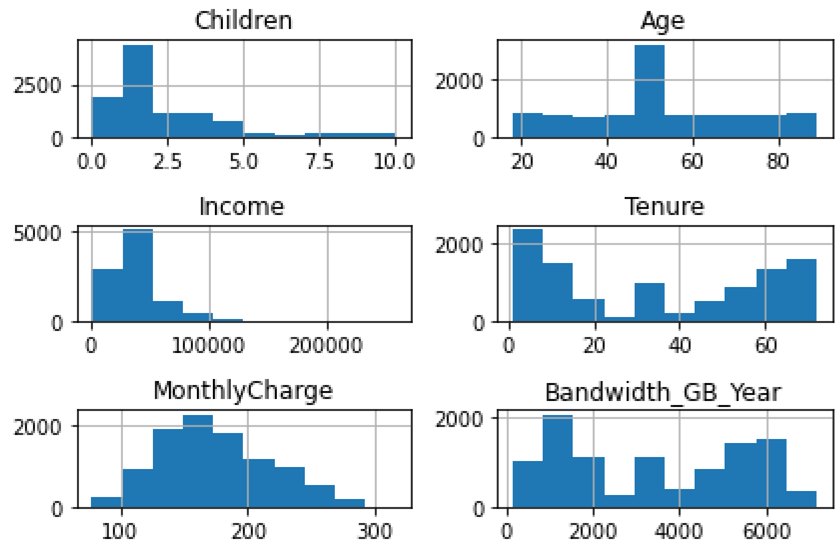
```
Empty DataFrame
Columns: [Customer_id, City, State, County, Population, Area, Timezone, Job, Children, A
ge, Education, Employment, Income, Marital, Gender, Churn, Outage_sec_perweek, Email, Co
ntacts, Yearly_equip_failure, Contract, Port_modem, Tablet, InternetService, Multiple, O
nlineSecurity, OnlineBackup, DeviceProtection, StreamingTV, StreamingMovies, PaperlessBi
lling, PaymentMethod, Tenure, MonthlyCharge, Bandwidth_GB_Year]
Index: []

[0 rows x 35 columns]
```

In the prior section, I have discovered the following data anomalies: Null values, NA values, and blank values. For the quantitative variables, I have identified that Age, Tenure, Children, Income, and Bandwidth_GB_Year all had the aforementioned anomalies. To mitigate, I placed the median value of all valid entries and used that as input for the fields. Mean could have been used, however mean would be more subject to extreme outliers and has the potential of allowing for a grossly skewed valued to influence my data set.

Anomaly Visualization and Data Visualization

Here I will visualize my key variables, and use the visualization to explore the presence of anomalies.

In [18]:
```
df[['Children', 'Age', 'Income', 'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year']].hist()
plt.savefig('churn_pyplot.jpg')
plt.tight_layout()
# plt.close()
```



On the above distributions, Monthly Charge is roughly normal, which is to be expected. The Income and Children variables approximates either a binomial distribution or a poisson distribution which is on par with expected results.

The Age variable shows a large spike around the age of 50, which makes sense due to the data replacement I made in earlier steps. Blank, NA, null, and 0 values were replaced with the median age which contributes to the visualization we see above.

Saving the cleaned dataframe to a new CSV file

In [19]:
```
df.to_csv('churned_cleaned.csv')
```

D6: Limitations of the Data

Limitations of the Churn data set include gaps data the require cleaning. For example, there are holes in data that would not be present in a real-world data set. Bandwidth-per-year is one example; internet service providers and other data companies have quick and reasonable access to this information, and most internet service providers break down your data usage monthly in your utility bill. Why this information is not present, I'm not sure - but it is reasonable to expect that it would be present in a real-world data set.

Additionally, this data set could have other variables that might be of use. For example, time of day of peak bandwidth usage or service usage. This might be of intereste to marketing. Someone who utilizing internet services during a 9-to-5 time frame might work from home, and might be more likely to purchase a higher internet package.

D7: Impact of the Limitaitons of the Data

The aforementioned limitations in the data set explained in section D6 do not accurately illustrate the impact.

An example of the impact of the data set would be for sections where impuatation was used to modify the data. Monthly Billing and Age are two examples of such. Using the median value for blank data fields in age provided a work around to conduct princople component analysis. However, by using the median value accuracy of the data is sacrificed for precision, especially in the larger picture of the data set. Using the median value for Monthly Billing might be a good metric for an accounting department wihsing to provide revenue estimates, but it does not allow for the most accurate principle component analysis when the alternative is to have accurate and inclusive data.

To prevent this, the Data Analytics department could institute finer controls on other departments as there is no reason, for example, that Monthly Billing should be missing.

E: Principle Component Analysis

E. Apply principal component analysis (PCA) to identify the significant features of the data set by doing the following:

1. List the principal components in the data set.
2. Describe how you identified the principal components of the data set.
3. Describe how the organization can benefit from the results of the PCA

PCA will be performed using the below variables:

In [20]:
```
df_pca = df[['Population','Children','Age','Income','Outage_sec_perweek','Email','Contac
```

Normalizaing the data:

In [21]:
```
df_pca_normalized=(df_pca-df_pca.mean())/df_pca.std()
```

Selecting the number of components to extract:

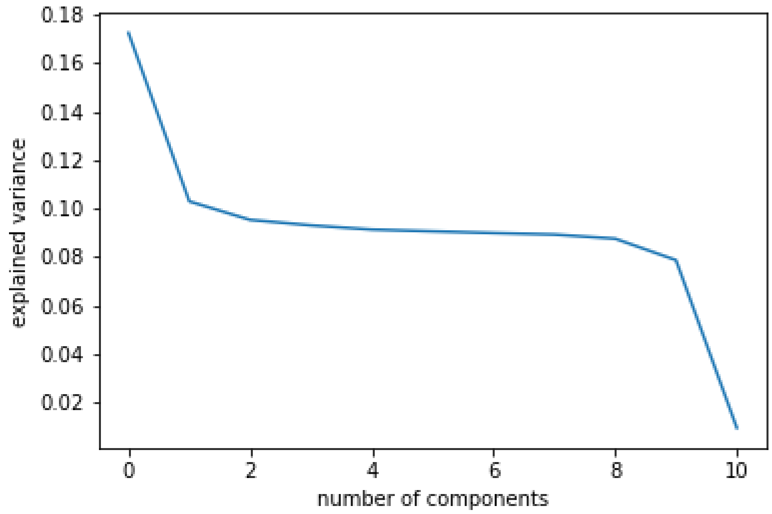
In [22]:
```
pca = PCA(n_components=df_pca.shape[1])
```

Convert the dataset of variables into dataset of components:

In [23]:
```
pca.fit(df_pca_normalized)
df_pca_components = pd.DataFrame(pca.transform(df_pca_normalized),
     columns=['PC1','PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10','PC11'])
```

Create and display Scree Plot:

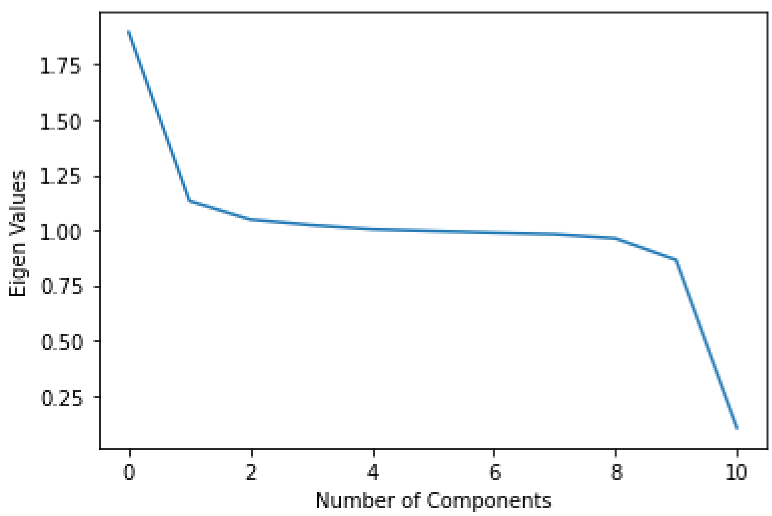
In [24]:
```
plt.plot(pca.explained_variance_ratio_)
plt.xlabel('number of components')
plt.ylabel('explained variance')
plt.show()
```



Extracting the eigenvalues:

In [25]:
```
cov_matrix = np.dot(df_pca_normalized.T, df_pca_normalized) / df_pca_components.shape[0]
eigenvalues = [np.dot(eigenvector.T, np.dot(cov_matrix, eigenvector)) for eigenvector in
```

In [26]:
```
plt.plot(eigenvalues)
plt.xlabel('Number of Components')
plt.ylabel('Eigen Values')
plt.show();
```



Choose the fewest components from the PCA:

In [27]:
```
# Select the fewest components
for pc, var in zip(['PC1','PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10','PC11']
    print(pc, var)
```

```
PC1 0.17244993159605304
PC2 0.2753495936482726
PC3 0.3706212623504477
PC4 0.46362429558505946
PC5 0.5548872112206896
PC6 0.6454219069153501
PC7 0.7352552793560467
PC8 0.8244724601975989
PC9 0.9119783436096773
PC10 0.9906307587163313
PC11 1.0000000000000002
```

From the above, 7 components account for approximately 73% of the variance. 8 components account for approximately 82% of the variance.

In [28]:
```
# Output loadings for components
loaded_components = pd.DataFrame(pca.components_.T,
                                 columns = ['PC1','PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9',
                                 index = df_pca.columns)
loaded_components
```

Out[28]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	P
Population	-0.000410	-0.055172	-0.317127	-0.384422	-0.037651	0.658501	0.434816	-0.050178	-0.3492
Children	-0.001874	0.023430	0.553580	-0.199589	0.052694	0.210905	-0.492439	0.257462	-0.5446
Age	-0.012381	-0.047600	-0.364657	0.519582	-0.102786	0.199533	-0.439573	-0.480542	-0.3239
Income	0.006197	-0.004281	0.241758	0.178934	0.767896	0.414818	0.000105	-0.210840	0.3137
Outage_sec_perweek	0.022599	0.706399	0.021625	-0.010069	0.014757	0.057495	0.053024	0.016099	0.0520
Email	-0.021292	0.057703	-0.335480	-0.526402	-0.057022	0.171801	-0.602346	-0.006356	0.4558
Contacts	0.004533	-0.007842	-0.433968	0.330427	0.246842	0.091689	-0.090491	0.789002	-0.0481
Yearly_equip_failure	0.015836	0.058207	0.302058	0.349379	-0.574507	0.515659	0.028153	0.167224	0.3768
Tenure	0.704915	-0.058213	-0.018176	-0.004509	-0.003199	-0.000671	-0.017972	-0.015981	0.0109
MonthlyCharge	0.045221	0.696325	-0.092961	0.040624	0.033253	-0.053477	0.012068	-0.068953	-0.1513
Bandwidth_GB_Year	0.706837	-0.009361	0.002069	-0.016804	0.001747	-0.003915	-0.011493	0.004921	-0.0073

E3. Benefits

The data suggests that outage_sec_perweek is a very prominent variable. Understandably so, it makes intuitive sense that a company would aim to reduce outages, but now there is actionable analysis that the company can use to make strategic moves.

Decision makers at the company can now act on data, instead of intuition alone. Tenure is also noted as an important factor, and should be noted by the company appropriately in order to reduce overall churn rate of its customer base.

Part H: Citations and References

Pandas documentation. pandas documentation - pandas 1.4.3 documentation. (n.d.). Retrieved August 25, 2022, from https://pandas.pydata.org/docs/