WGU D212 Data Mining II

Task 1 - Clustering Techniques

Ednalyn C. De Dios

August 24, 2023

Environment

- Python: 3.9.9
- Jupyter: 7.0.2

Part I - Research Question

A1. Propose one relevant question and choose a clustering technique.

> ***What are the different groups within the organization's customer base?***

We will endeavor to answer the above question by using the K-means method.

A2. Define one goal of the data analysis.

The ultimate goal of this data analysis is to reduce operating costs by increasing the efficiency of the organization's marketing efforts. We will use the K-means clustering technique identify the different groups within the organization's customer base and segment them accordingly. The organization will benefit from knowing the similarities and differences between customer groups because the knowledge will greatly influence how marketing is conducted. This will inform the decisions of stakeholders in matters where customer retention is involved, for example. Knowing which group a particular customer belong in will provide the organization with advanced insight towards that customer's characteristics or behavior. Thereby increasing the effective of marketing campaigns.

This goal is within the scope of the scenario and is represented in the available data.

Part II - Method Justification

B1. Explain how the clustering technique you chose analyzes the selected dataset. Include expected outcomes.

I chose K-means it's relatively easy to implement, scales to large data sets, and guarantees convergence. (Google.com, 2023). K-means works by taking data points as input and groups them into groups or k number of clusters.It starts the training process of grouping by selecting a number of starting center points called centroids. The algorithm then takes each data point and assigns them to the nearest centroid. Based on the new assignments, the centroids are then recalculated and the whole process repeats until they converge.

I expect the model to show the groupings of k number of clusters that are similar to each other (the data points are similar, not necessarily the clusters themselves.) I also expect a summary of the model's performance, such as silhoutte score.

B2. Summarize one assumption of the chosen clustering technique.

One core assumption of K-means is that the "scales of different variables are specified so they can be reasonably combined using sum-of-squares as the measure to be minimised" (Henry, 2022). In other words, using K-means assumes that the radius of each cluster is the same.

B3. List the packages or libraries you have chosen for Python or R, and justify how each item on the list supports the analysis.

The packages/libraries I've chosen are:

- sys: for running the executable file (d209_task1.py)
- random: set random seed for reproducibility of the experiment
- pandas: for manipulating dataframes
- numpy: for performing mathematical computations
- matplotlib and seaborn: for visualizations
- Image: display image from a URL
- StandardScaler: to scale the data set
- kmeans: clustering algorithm
- silhoutte_score: evaluating the model

Part III - Data Preparation

C1. Describe one data preprocessing goal relevant to the clustering technique from part A1.

One preprocessing goal is to standardize the variables to satisfy the spherical assumption of k-means. We will accomplish this using StandardScaler.

C2. Identify the initial data set variables that you will use to analyze the classification question from part A1, and classify each variable as continuous or categorical.

Independent Variables:

- Children, Continuous, Quantitative
- Age, Continuous, Quantitative
- Income, Continuous, Quantitative
- Tenure, Continuous, Quantitative
- MonthlyCharge, Continuous, Quantitative
- Bandwidth_GB_Year, Continuous, Quantitative

C3. Explain each of the steps used to prepare the data for the analysis. Identify the code segment for each step.

- Load and view the data

  > use pandas to read the csv use head or tail methods use info()

- Remove irrelevant data for the analysis

  > use the drop method

- Perform data cleaning

  > remove duplicates, missing values, outliers

- Pre-process data

  > scale the features

- Perform K-means clustering

  > determine optimal number of k clusters select best model get characteristics evaluate model

In [1]:
```python
# setting the random seed for reproducibility
import random
random.seed(493)

# for manipulating dataframes
import pandas as pd
import numpy as np

# for visualizations
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid")
from IPython.display import Image

# for modeling
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# to print out all the outputs of the cell
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

# set display options
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
pd.set_option('display.max_colwidth', None)
```

In [2]:
```python
# read the csv file
df = pd.read_csv('churn_clean.csv')
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   CaseOrder             10000 non-null  int64  
 1   Customer_id           10000 non-null  object 
 2   Interaction           10000 non-null  object 
 3   UID                   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              10000 non-null  int64  
 15  Age                   10000 non-null  int64  
 16  Income                10000 non-null  float64
 17  Marital               10000 non-null  object 
 18  Gender                10000 non-null  object 
 19  Churn                 10000 non-null  object 
 20  Outage_sec_perweek    10000 non-null  float64
 21  Email                 10000 non-null  int64  
 22  Contacts              10000 non-null  int64  
 23  Yearly_equip_failure  10000 non-null  int64  
 24  Techie                10000 non-null  object 
 25  Contract              10000 non-null  object 
 26  Port_modem            10000 non-null  object 
 27  Tablet                10000 non-null  object 
 28  InternetService       7871 non-null   object 
 29  Phone                 10000 non-null  object 
 30  Multiple              10000 non-null  object 
 31  OnlineSecurity        10000 non-null  object 
 32  OnlineBackup          10000 non-null  object 
 33  DeviceProtection      10000 non-null  object 
 34  TechSupport           10000 non-null  object 
 35  StreamingTV           10000 non-null  object 
 36  StreamingMovies       10000 non-null  object 
 37  PaperlessBilling      10000 non-null  object 
 38  PaymentMethod         10000 non-null  object 
 39  Tenure                10000 non-null  float64
 40  MonthlyCharge         10000 non-null  float64
 41  Bandwidth_GB_Year     10000 non-null  float64
 42  Item1                 10000 non-null  int64  
 43  Item2                 10000 non-null  int64  
 44  Item3                 10000 non-null  int64  
 45  Item4                 10000 non-null  int64  
 46  Item5                 10000 non-null  int64  
 47  Item6                 10000 non-null  int64  
 48  Item7                 10000 non-null  int64  
 49  Item8                 10000 non-null  int64  
```

```
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

Out[2]:

	CaseOrder	Customer_id	Interaction	UID	City	S
0	1	K409198	aa90260b-4141-4a24-8e36-b04ce1f4f77b	e885b299883d4f9fb18e39c75155d990	Point Baker	
1	2	S120509	fb76459f-c047-4a9d-8af9-e0f7d4ac2524	f2de8bef964785f41a2959829830fb8a	West Branch	
2	3	K191035	344d114c-3736-4be5-98f7-c72c281e2d35	f1784cfa9f6d92ae816197eb175d3c71	Yamhill	
3	4	D90850	abfa2b40-2d43-4994-b15a-989b8c79e311	dc8a365077241bb5cd5ccd305136b05e	Del Mar	
4	5	K662701	68a861fd-0d20-4e51-a587-8a90407ee574	aabb64a116e83fdc4befc1fbab1663f9	Needville	

In [3]:

```
columns = ['Children',
           'Age',
           'Income',
           'MonthlyCharge',
            'Bandwidth_GB_Year',
           'Tenure']
```

In [4]:

```
for col in columns:
    # show outliers
    plt.boxplot(df[col])
    fig = plt.figure(figsize =(10, 7))
```

Out[4]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x223e6f0fd90>,
  <matplotlib.lines.Line2D at 0x223e6f2e070>],
 'caps': [<matplotlib.lines.Line2D at 0x223e6f2e310>,
  <matplotlib.lines.Line2D at 0x223e6f2e5b0>],
 'boxes': [<matplotlib.lines.Line2D at 0x223e6f0faf0>],
 'medians': [<matplotlib.lines.Line2D at 0x223e6f2e850>],
 'fliers': [<matplotlib.lines.Line2D at 0x223e6f2eaf0>],
 'means': []}
```

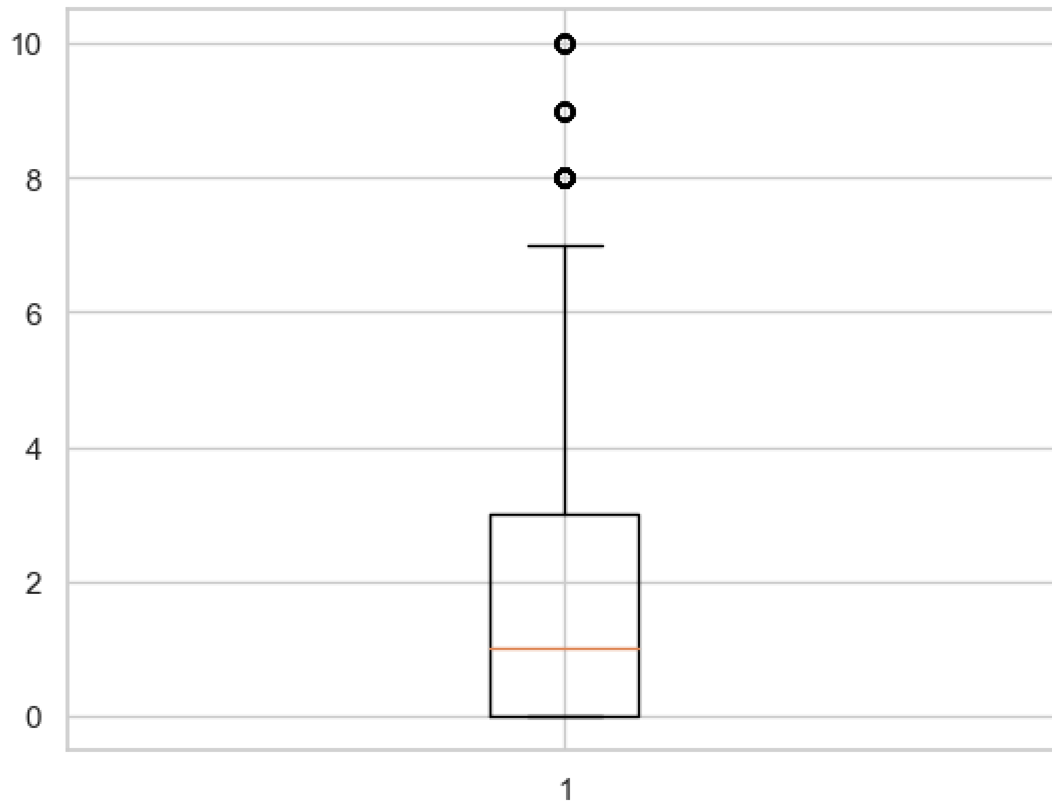
```
Out[4]: {'whiskers': [<matplotlib.lines.Line2D at 0x223e6f75af0>,
          <matplotlib.lines.Line2D at 0x223e6f75d90>],
         'caps': [<matplotlib.lines.Line2D at 0x223e6f75f10>,
          <matplotlib.lines.Line2D at 0x223e6f881f0>],
         'boxes': [<matplotlib.lines.Line2D at 0x223e6f75850>],
         'medians': [<matplotlib.lines.Line2D at 0x223e6f88490>],
         'fliers': [<matplotlib.lines.Line2D at 0x223e6f88730>],
         'means': []}
```

```
Out[4]: {'whiskers': [<matplotlib.lines.Line2D at 0x223e6fcf610>,
          <matplotlib.lines.Line2D at 0x223e6fcf760>],
         'caps': [<matplotlib.lines.Line2D at 0x223e6fcfa30>,
          <matplotlib.lines.Line2D at 0x223e6fcfcd0>],
         'boxes': [<matplotlib.lines.Line2D at 0x223e6fcf370>],
         'medians': [<matplotlib.lines.Line2D at 0x223e6fcff70>],
         'fliers': [<matplotlib.lines.Line2D at 0x223e6fdc250>],
         'means': []}
```

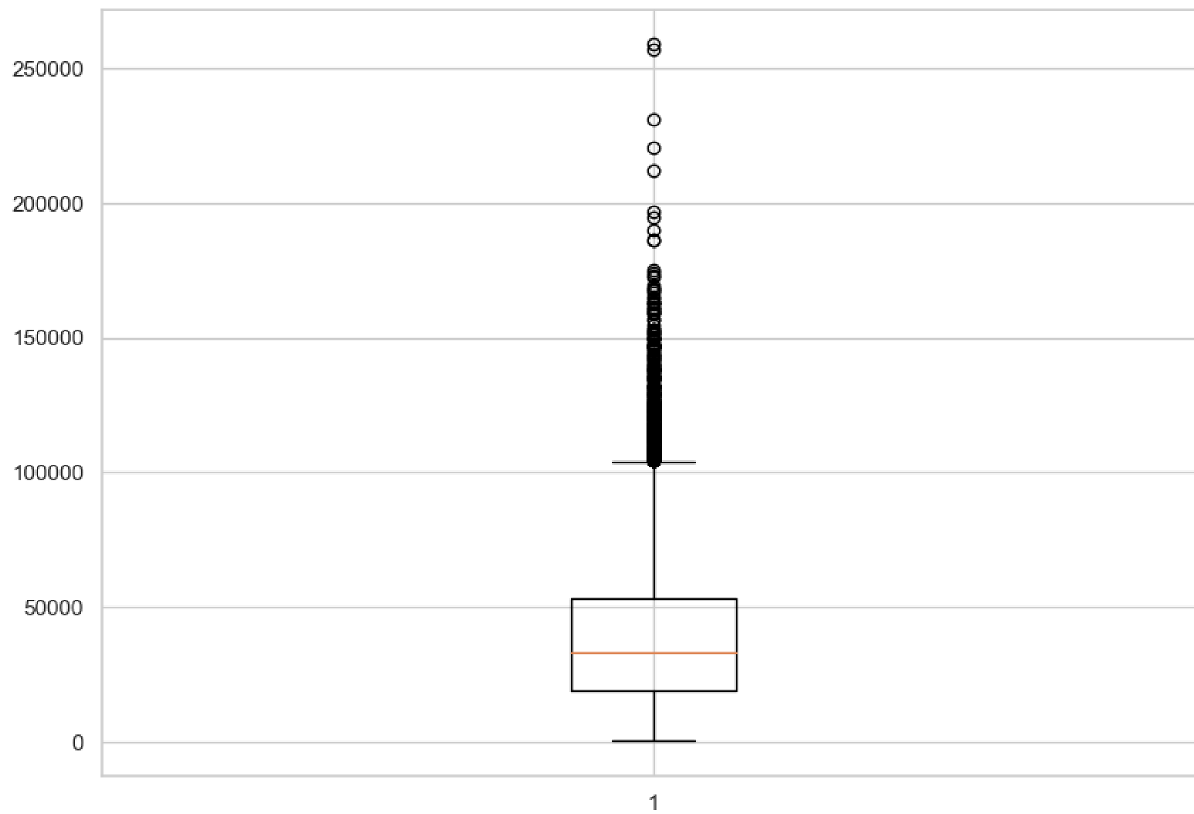
```
Out[4]: {'whiskers': [<matplotlib.lines.Line2D at 0x223e7013eb0>,
          <matplotlib.lines.Line2D at 0x223e7024070>],
         'caps': [<matplotlib.lines.Line2D at 0x223e7024310>,
          <matplotlib.lines.Line2D at 0x223e70245b0>],
         'boxes': [<matplotlib.lines.Line2D at 0x223e7013c10>],
         'medians': [<matplotlib.lines.Line2D at 0x223e7024850>],
         'fliers': [<matplotlib.lines.Line2D at 0x223e7024af0>],
         'means': []}
```

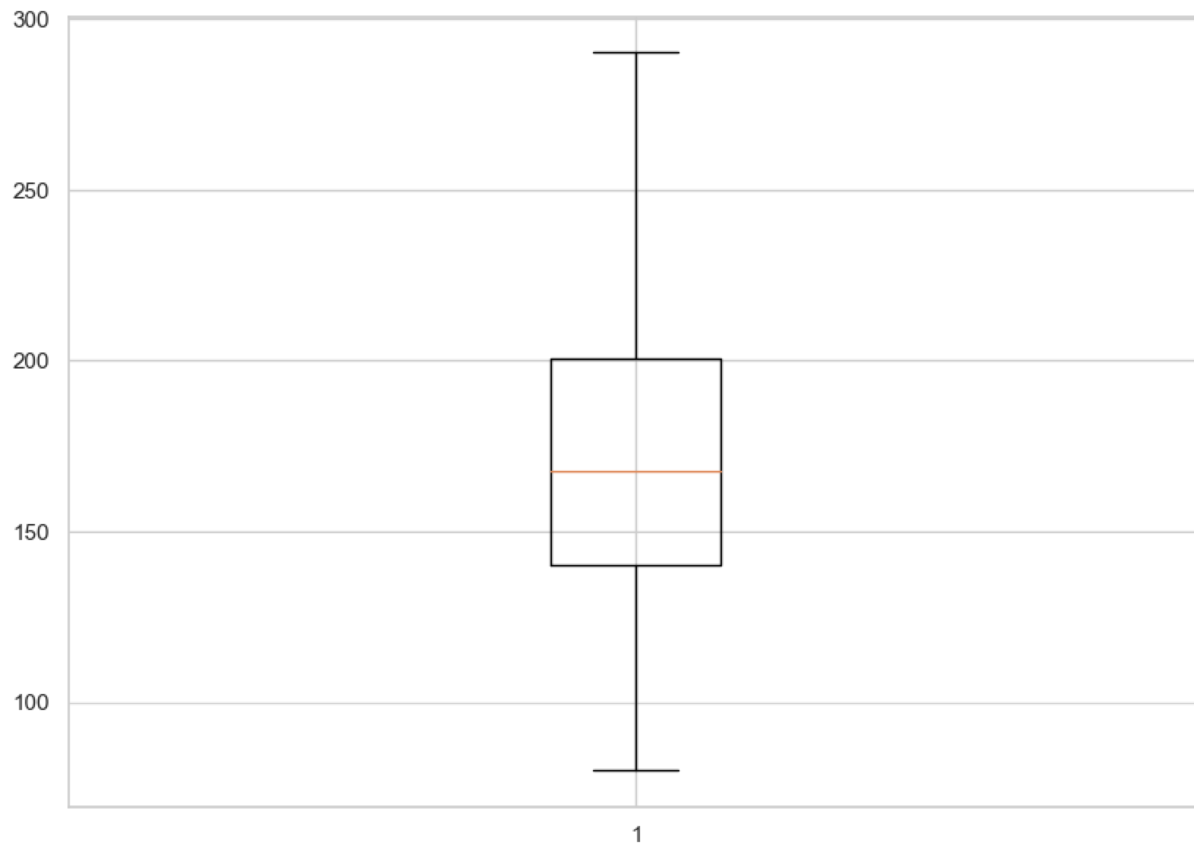
```
Out[4]: {'whiskers': [<matplotlib.lines.Line2D at 0x223e7069940>,
          <matplotlib.lines.Line2D at 0x223e7069be0>],
         'caps': [<matplotlib.lines.Line2D at 0x223e7069e80>,
          <matplotlib.lines.Line2D at 0x223e7079160>],
         'boxes': [<matplotlib.lines.Line2D at 0x223e70697c0>],
         'medians': [<matplotlib.lines.Line2D at 0x223e7079400>],
         'fliers': [<matplotlib.lines.Line2D at 0x223e70796a0>],
         'means': []}
```

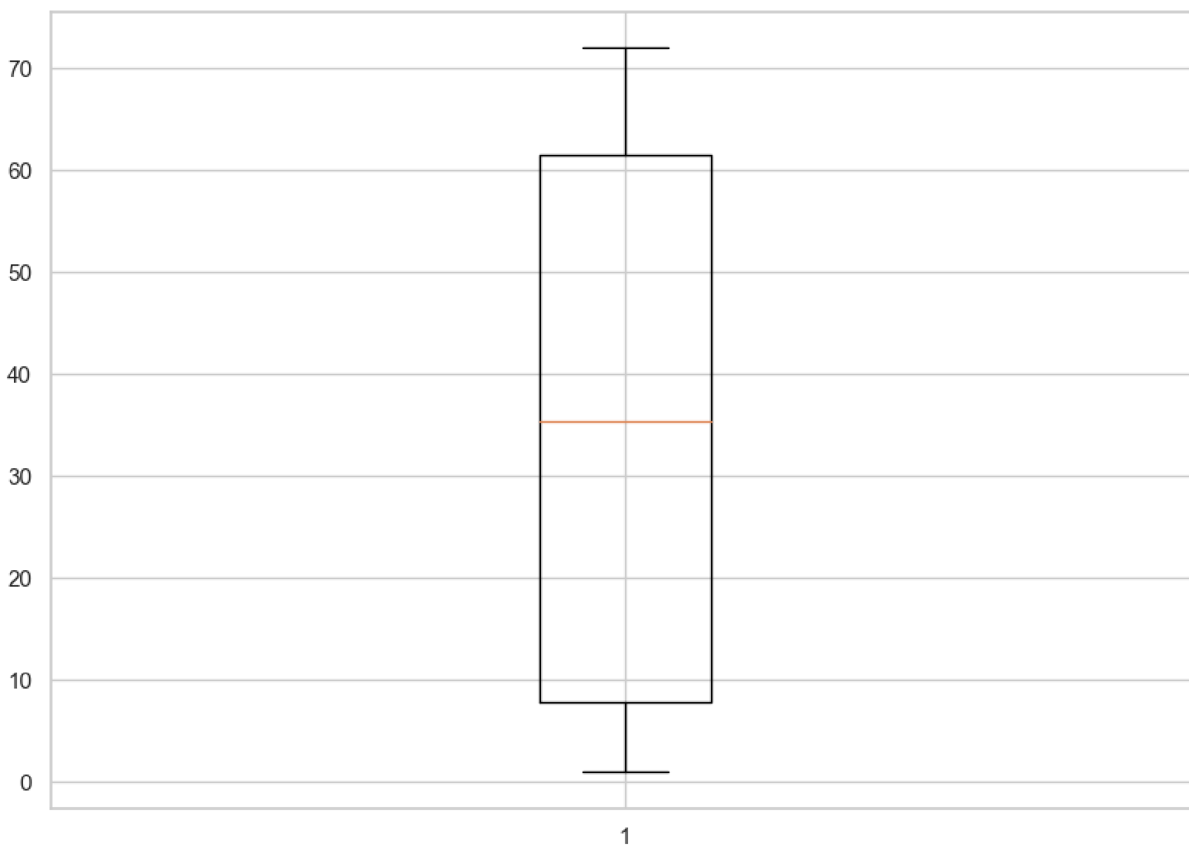
```
Out[4]: {'whiskers': [<matplotlib.lines.Line2D at 0x223e70bd4c0>,
          <matplotlib.lines.Line2D at 0x223e70bd760>],
         'caps': [<matplotlib.lines.Line2D at 0x223e70bda00>,
          <matplotlib.lines.Line2D at 0x223e70bdca0>],
         'boxes': [<matplotlib.lines.Line2D at 0x223e70bd340>],
         'medians': [<matplotlib.lines.Line2D at 0x223e70bdf40>],
         'fliers': [<matplotlib.lines.Line2D at 0x223e70cb220>],
         'means': []}
```


10
8
6
4
2
0
1


90
80
70
60
50
40
30
20
1


250000
200000
150000
100000
50000
0
1


300
250
200
150
100
1




```
<Figure size 1000x700 with 0 Axes>
```

In [5]:
```
# remove outliers in "Children"
df = df[df['Children'] < 8]
df.shape
```

Out[5]: (9599, 50)

In [6]:
```
# drop unnecessary columns not used in the analysis
df = df[columns]
```

In [7]:
```
# select rows that are duplicated based on all columns
dup = df[df.duplicated()]

# find out how many rows are duplicated
dup.shape
```

Out[7]: (0, 6)

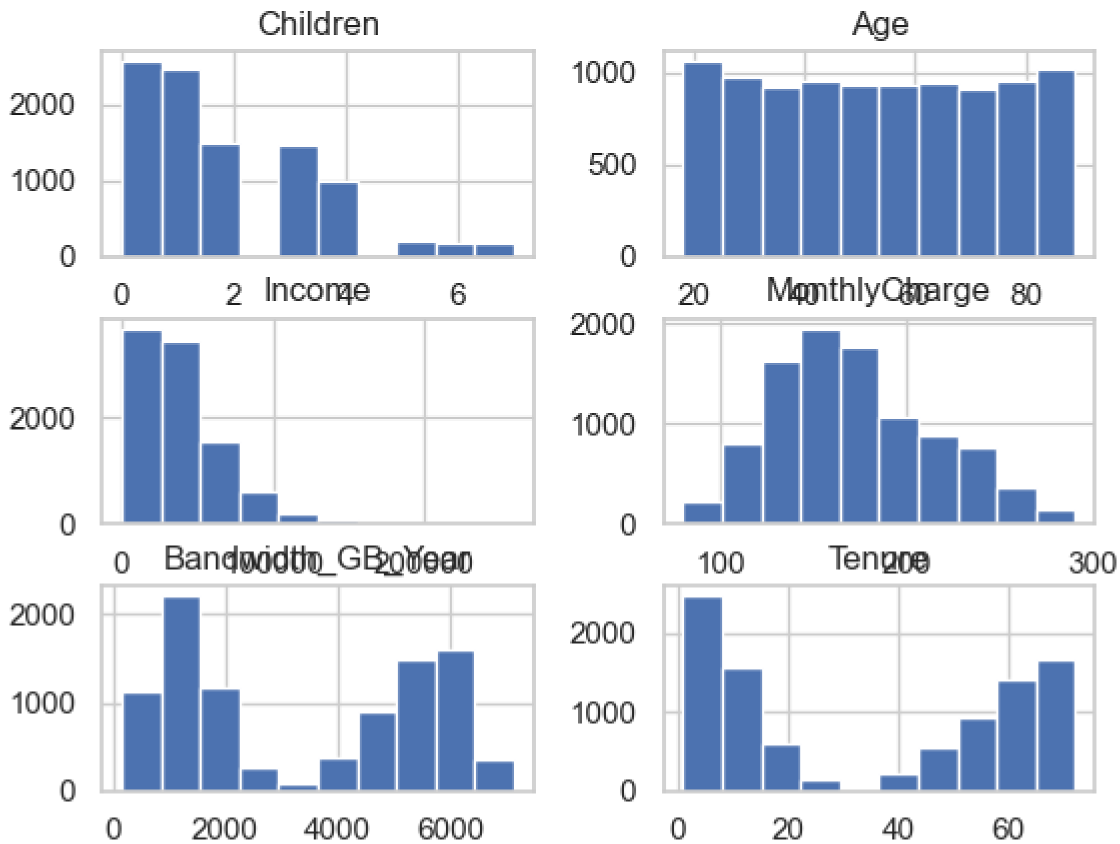
In [8]:
```
def show_missing(df):
    """
    Takes a dataframe and returns a dataframe with stats
    on missing and null values with their percentages.
    """
    null_count = df.isnull().sum()
    null_percentage = (null_count / df.shape[0]) * 100
    empty_count = pd.Series(((df == ' ') | (df == '')).sum())
    empty_percentage = (empty_count / df.shape[0]) * 100
    nan_count = pd.Series(((df == 'nan') | (df == 'NaN')).sum())
    nan_percentage = (nan_count / df.shape[0]) * 100
    dfx = pd.DataFrame({'num_missing': null_count, 'missing_percentage': null_perce
                        'num_empty': empty_count, 'empty_percentage': empty_percen
                        'nan_count': nan_count, 'nan_percentage': nan_percentage})
    return dfx

show_missing(df)
```

Out[8]:

	num_missing	missing_percentage	num_empty	empty_percentage	nan
Children	0	0.0	0	0.0	
Age	0	0.0	0	0.0	
Income	0	0.0	0	0.0	
MonthlyCharge	0	0.0	0	0.0	
Bandwidth_GB_Year	0	0.0	0	0.0	
Tenure	0	0.0	0	0.0	

In [9]:
```
# make historgrams and save the plot
df[columns].hist()
```

Out[9]:
```
array([[<Axes: title={'center': 'Children'}>,
        <Axes: title={'center': 'Age'}>],
       [<Axes: title={'center': 'Income'}>,
        <Axes: title={'center': 'MonthlyCharge'}>],
       [<Axes: title={'center': 'Bandwidth_GB_Year'}>,
        <Axes: title={'center': 'Tenure'}>]], dtype=object)
```



In [10]:
```python
df.head()
```

Out[10]:

	Children	Age	Income	MonthlyCharge	Bandwidth_GB_Year	Tenure
0	0	68	28561.99	172.455519	904.536110	6.795513
1	1	27	21704.77	242.632554	800.982766	1.156681
2	4	50	9609.57	159.947583	2054.706961	15.754144
3	1	48	18925.23	119.956840	2164.579412	17.087227
4	0	83	40074.19	149.948316	271.493436	1.670972

In [11]:
```python
# scale the data
scaler = StandardScaler()

# apply scaler() to all the continuous column
scaled = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)

scaled.head()
```

Out[11]:

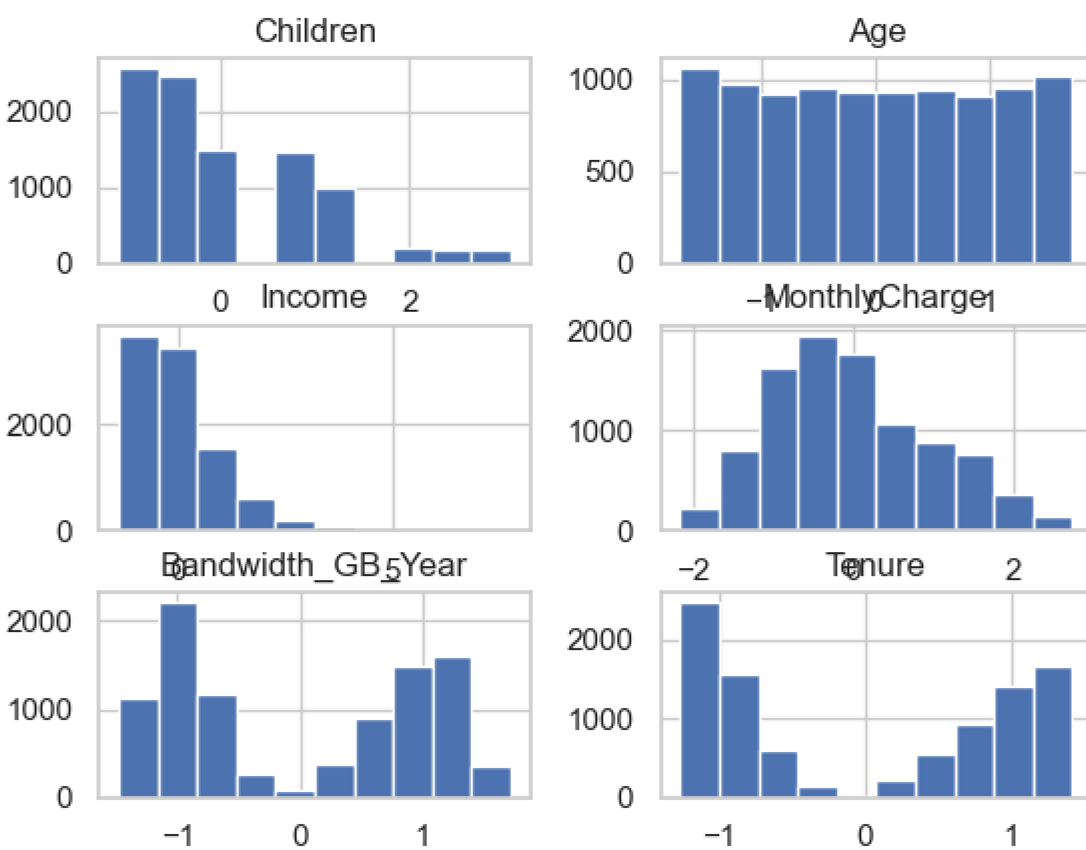
	Children	Age	Income	MonthlyCharge	Bandwidth_GB_Year	Tenure
0	-1.071056	0.713714	-0.398974	-0.006432	-1.135196	-1.049171
1	-0.479476	-1.270369	-0.642528	1.629571	-1.182594	-1.262376
2	1.295264	-0.157347	-1.072124	-0.298023	-0.608743	-0.710444
3	-0.479476	-0.254131	-0.741251	-1.230307	-0.558452	-0.660040
4	-1.071056	1.439598	0.009914	-0.531131	-1.424951	-1.242931

In [12]:

```
# make historgrams and save the plot
scaled[columns].hist()
```

Out[12]:

```
array([[<Axes: title={'center': 'Children'}>,
        <Axes: title={'center': 'Age'}>],
       [<Axes: title={'center': 'Income'}>,
        <Axes: title={'center': 'MonthlyCharge'}>],
       [<Axes: title={'center': 'Bandwidth_GB_Year'}>,
        <Axes: title={'center': 'Tenure'}>]], dtype=object)
```



C4. Provide a copy of the cleaned dataset.

In [13]:

```
# save the prepared data set
df.to_csv('churn_prepared1.csv', index=False)
```

Part IV - Analysis

D1. Describe the analysis technique you used to appropriately analyze the data. Include screenshots of the intermediate calculations you performed.

Multiple k-means models were used to conduct the analysis. Each model had a different number of k clusters, ranging from 1 to 10. The inertia score was plotted against the number of k clusters for each model, and the elbow method, the optimal number of k clusters was selected through visual inspection of the graph.

The selected number of k clusters was two and scikit learn's implementation of k-means clustering was used to label each data point's cluster. The cluster labels were then assigned back to the unscaled dataframe and aggregated by mean, median, and standard deviation. Finally, the characteristics of each centroids were displayed and reviewed.

D2. Provide the code used to perform the clustering technique from part D1.

In [14]:
```python
# determine the best value for k
inertia = np.array([])
k_vals = range(1,10)

for k in k_vals:
    kmeans = KMeans(n_clusters=k, random_state=493)
    kmeans.fit(scaled)
    inertia = np.append(inertia, kmeans.inertia_)

inertia_vals = pd.DataFrame(inertia, index=k_vals, columns=['Inertia'])
```

Out[14]:
```
▾ KMeans
KMeans(n_clusters=1, random_state=493)
```

Out[14]:
```
▾ KMeans
KMeans(n_clusters=2, random_state=493)
```

Out[14]:
```
▾ KMeans
KMeans(n_clusters=3, random_state=493)
```

Out[14]:
```
▾ KMeans
KMeans(n_clusters=4, random_state=493)
```

Out[14]:

```
KMeans
KMeans(n_clusters=5, random_state=493)
```

Out[14]:

```
KMeans
KMeans(n_clusters=6, random_state=493)
```

Out[14]:

```
KMeans
KMeans(n_clusters=7, random_state=493)
```

Out[14]:

```
KMeans
KMeans(random_state=493)
```

Out[14]:

```
KMeans
KMeans(n_clusters=9, random_state=493)
```

In [15]:

```python
# plot the inertia values
sns.barplot(x=inertia_vals.index, y=inertia_vals.Inertia, alpha=0.25)
sns.lineplot(x=inertia_vals.index-1, y=inertia_vals.Inertia, marker='o', markersize
plt.title('Elbow Method')
plt.xticks(inertia_vals.index-1)
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
for i in inertia_vals.index:
    plt.text(
        x=i-1,
        y=inertia_vals.Inertia[i]+1000,
        s=round(inertia_vals.Inertia[i], 2)
    )
plt.grid(alpha=0.25)
```

Out[15]:

```
<Axes: ylabel='Inertia'>
```

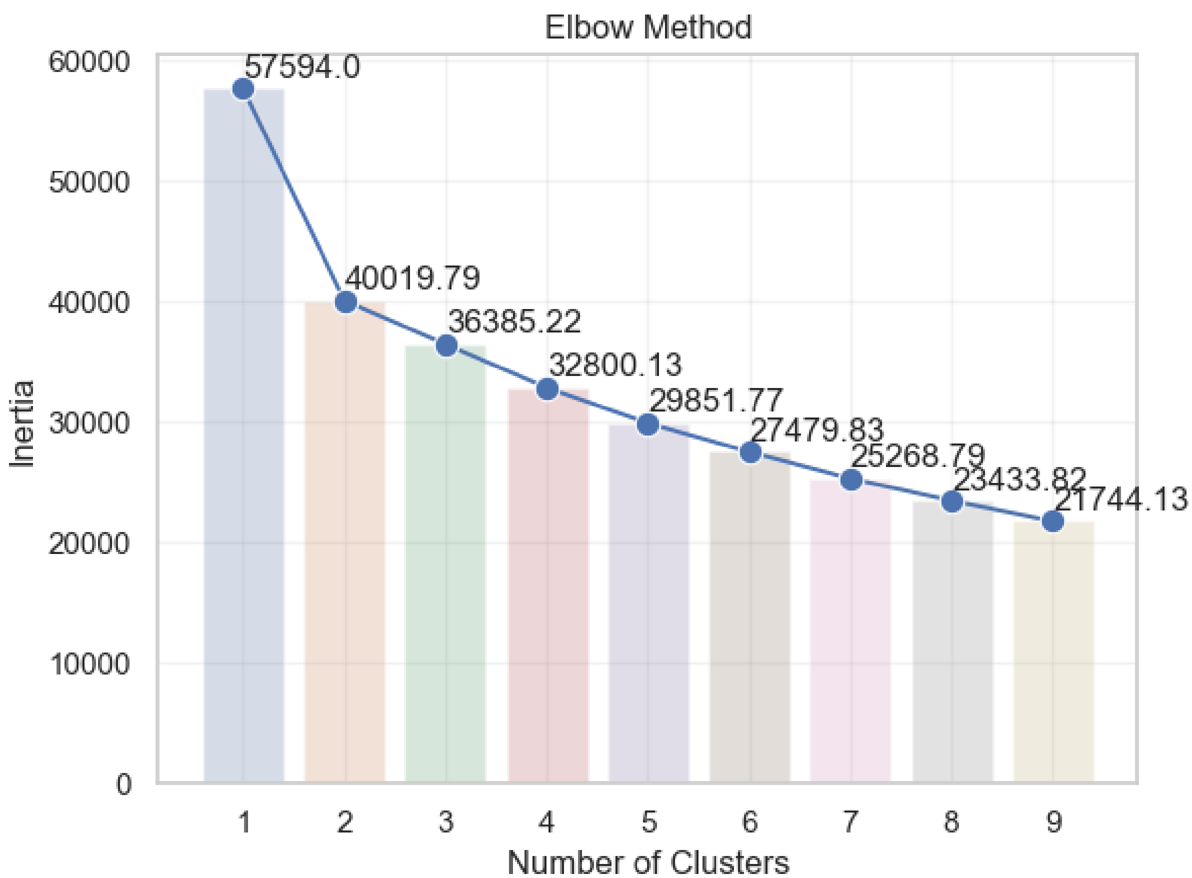
Out[15]:

```
<Axes: ylabel='Inertia'>
```

Out[15]:

```
Text(0.5, 1.0, 'Elbow Method')
```

```
Out[15]: ([<matplotlib.axis.XTick at 0x223e89b0910>,
           <matplotlib.axis.XTick at 0x223e89b0310>,
           <matplotlib.axis.XTick at 0x223e7ce6b20>,
           <matplotlib.axis.XTick at 0x223e7d43490>,
           <matplotlib.axis.XTick at 0x223e7cff7f0>,
           <matplotlib.axis.XTick at 0x223e831af70>,
           <matplotlib.axis.XTick at 0x223e81a1e50>,
           <matplotlib.axis.XTick at 0x223e819ef10>,
           <matplotlib.axis.XTick at 0x223e81947c0>],
          [Text(0, 0, '1'),
           Text(1, 0, '2'),
           Text(2, 0, '3'),
           Text(3, 0, '4'),
           Text(4, 0, '5'),
           Text(5, 0, '6'),
           Text(6, 0, '7'),
           Text(7, 0, '8'),
           Text(8, 0, '9')])

Out[15]: Text(0.5, 0, 'Number of Clusters')

Out[15]: Text(0, 0.5, 'Inertia')

Out[15]: Text(0, 58593.99999999997, '57594.0')

Out[15]: Text(1, 41019.79419385704, '40019.79')

Out[15]: Text(2, 37385.21592901777, '36385.22')

Out[15]: Text(3, 33800.13300225327, '32800.13')

Out[15]: Text(4, 30851.765052565588, '29851.77')

Out[15]: Text(5, 28479.832289387083, '27479.83')

Out[15]: Text(6, 26268.785976365332, '25268.79')

Out[15]: Text(7, 24433.821092213588, '23433.82')

Out[15]: Text(8, 22744.129180902477, '21744.13')
```



In [16]:
```
# do k-means clustering
n_clusters = 2
kmeans = KMeans(n_clusters=n_clusters, random_state=493)
kmeans.fit(scaled)
```

Out[16]:

KMeans

KMeans(n_clusters=2, random_state=493)

In [17]:
```
# get predictions
predictions = kmeans.fit_predict(scaled)

# calculate the silhouette score
silhouette = silhouette_score(scaled, predictions)
print(f'Silhouette Score: {silhouette}, {n_clusters} clusters')
```

```
Silhouette Score: 0.29897803408788926, 2 clusters
```

In [18]:
```
# assign cluster labels
df['Cluster'] = kmeans.labels_ + 1
```

In [19]:
```
# calculate cluster summary
cluster = df.groupby('Cluster').agg(['mean', 'median', 'std']).transpose()
cluster.columns = ['Cluster 1', 'Cluster 2']
cluster
```

Out[19]:

		Cluster 1	Cluster 2
Children	**mean**	1.811446	1.809554
	median	1.000000	1.000000
	std	1.696421	1.684673
Age	**mean**	53.695109	52.806842
	median	54.000000	53.000000
	std	20.661250	20.662434
Income	**mean**	39974.132903	39615.565920
	median	33056.020000	33348.015000
	std	28456.884915	27853.631809
MonthlyCharge	**mean**	172.655381	172.807601
	median	167.456400	169.937833
	std	43.105339	42.692882
Bandwidth_GB_Year	**mean**	5463.462849	1301.088811
	median	5574.461345	1224.665872
	std	748.306325	568.844865
Tenure	**mean**	59.922603	9.106950
	median	61.417660	7.890303
	std	8.456071	6.028835

In [20]:

```
# get the centroids
centroids = pd.DataFrame(
    scaler.inverse_transform(kmeans.cluster_centers_),
    index=['Cluster 1', 'Cluster 2'],
    columns=df.columns[:-1]
)
```

In [21]:

```
# view the centroids
print('Cluster Centroids:\n')
for i in centroids.index:
    print(i)
    for col in centroids.columns:
        print(f'{col}: {round(centroids[col][i], 2)}')
    print()
```

```
Cluster Centroids:

Cluster 1
Children: 1.81
Age: 53.7
Income: 39974.13
MonthlyCharge: 172.66
Bandwidth_GB_Year: 5463.46
Tenure: 59.92

Cluster 2
Children: 1.81
Age: 52.81
Income: 39615.57
MonthlyCharge: 172.81
Bandwidth_GB_Year: 1301.09
Tenure: 9.11
```

In [24]:

```
# plot the centroids
centr_x = [sum(df[df.Cluster==1].index)/len(df[df.Cluster==1]),
           sum(df[df.Cluster==2].index)/len(df[df.Cluster==2])]

titles = [
    'Number of Children',
    'Age',
    'Income',
    'Monthly Charge',
    'Bandwidth',
    'Tenure',
]
y_labels = [
    '',
    '',
    '',
    '','',
    '',
]
fig, ax = plt.subplots(1, 6)
plt.suptitle('Cluster Characteristics and Centroids')
plt.rcParams['figure.figsize'] = (12,6)
plt.tight_layout()
for i in range(6):
    sns.scatterplot(x=df.index, y=df[df.columns[i]], hue=df.Cluster, ax=ax[i], lege
    sns.scatterplot(x=centr_x, y=centroids[centroids.columns[i]], ax=ax[i])
    ax[i].set_title(titles[i])
    ax[i].set_ylabel(y_labels[i])
```

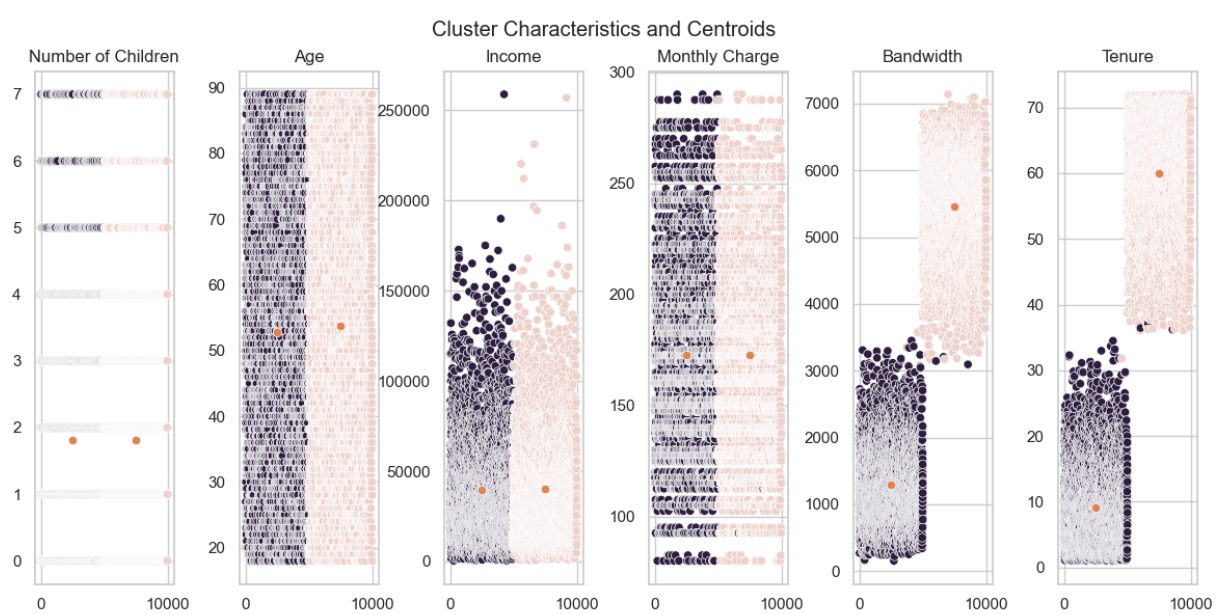
Out[24]: `Text(0.5, 0.98, 'Cluster Characteristics and Centroids')`

Out[24]: `<Axes: ylabel='Children'>`

Out[24]: `<Axes: ylabel='Children'>`

Out[24]: `Text(0.5, 1.0, 'Number of Children')`

```
Out[24]: Text(109.87499999999999, 0.5, '')
Out[24]: <Axes: ylabel='Age'>
Out[24]: <Axes: ylabel='Age'>
Out[24]: Text(0.5, 1.0, 'Age')
Out[24]: Text(269.3035714285715, 0.5, '')
Out[24]: <Axes: ylabel='Income'>
Out[24]: <Axes: ylabel='Income'>
Out[24]: Text(0.5, 1.0, 'Income')
Out[24]: Text(428.7321428571429, 0.5, '')
Out[24]: <Axes: ylabel='MonthlyCharge'>
Out[24]: <Axes: ylabel='MonthlyCharge'>
Out[24]: Text(0.5, 1.0, 'Monthly Charge')
Out[24]: Text(588.1607142857143, 0.5, '')
Out[24]: <Axes: ylabel='Bandwidth_GB_Year'>
Out[24]: <Axes: ylabel='Bandwidth_GB_Year'>
Out[24]: Text(0.5, 1.0, 'Bandwidth')
Out[24]: Text(747.5892857142858, 0.5, '')
Out[24]: <Axes: ylabel='Tenure'>
Out[24]: <Axes: ylabel='Tenure'>
Out[24]: Text(0.5, 1.0, 'Tenure')
Out[24]: Text(907.0178571428572, 0.5, '')
```



Part V - Data Summary and Implications

E1. Explain the accuracy of your clustering technique.

The final model with 2 clusters was evaluated using the silhoutte score. A silhoutte score is "a measure of how well each data point fits within its assigned cluster" (Castillo, 2023). The silhoutte score is near 0, indicative of overlapping clusters (Banerji, 2021).

E2. Discuss the results and implications of your clustering analysis.

The twp most distinctive characteristics of the two clusters were the amount of bandwidth per year in gigabytes and tenure. Cluster 1's bandwidth is 5,463.46 GB while Cluster 2's bandwidth is only 1,301.09 GB. Respectively, Cluster 1's and Cluster 2's tenure were 59.92 and 9.11. Everything else, including the number of children, age, income, and monthly charge, were pretty much similar in values. This leads me to believe that customers with the longest tenure tend to be the heavy users of bandwidth as well.

The implication of this is the materialization of customer segments: heavy and light users of bandwidth.

E3. Discuss one limitation of your data analysis.

One big limitation of this analysis is the exclusion of categorical variables because k-means clustering can only handle continuous variables. One categorical variable in mind is contract types. Previous analysis of the data set indicated that those customers with month-to-month contract types are more likely to churn than those with one and two-year contract types. As such, future analysis should utilize other clustering techniques that can deal with both continuous and categorical variables.

E4. Recommend a course of action for the real-world organizational situation from part A1 based on your results and implications discussed in part E2.

An easy course of action for the organization is for the marketing department to make use of the newly discovered customer segments. For example, a marketing campaign can be designed to target light users of bandwidth and upsell them some streaming services.

Bundling services is also an option. The point is that the more bandwidth a customer uses, the more likely that they are going to stick around.

Part VI - Video Demonstration

F. Panopto recording

URL: https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=8fe99cc7-78d5-4f14-bcd2-b068006d2bfa

G. Record the web sources used to acquire data or segments of third-party code to support the analysis. Ensure the web sources are reliable.

- https://github.com/ecdedios/code-snippets/blob/main/notebooks/master.ipynb
- https://www.analyticsvidhya.com/blog/2020/10/a-simple-explanation-of-k-means-clustering
- https://github.com/jlopez873/Telecom_Churn_Analysis_Using_Clustering_Techniques_Kmean

H. Acknowledge sources, using in-text citations and references, for content that is quoted, paraphrased, or summarized.

- https://developers.google.com/machine-learning/clustering/algorithm/advantages-disadvantages
- https://stats.stackexchange.com/questions/576812/what-are-the-k-means-algorithm-assumptions
- https://javilopezcastillo.medium.com/telecom-churn-analysis-using-clustering-techniques-for-customer-segmentation-4cdb7318f672
- https://www.analyticsvidhya.com/blog/2021/05/k-mean-getting-the-optimal-number-of-clusters

In [23]:
```
print('Successful run!')
```

```
Successful run!
```