Data Modeling D208 - Multiple Linear Regression

Overview

We will review a telecom churn dataset and develop a predictive model using Multiple Linear Regression. This dataset contains 10,000 records of telecom customers with various datapoints.

The usual focus is on churn (whether or not a customer leaves), but we will be focusing on a continuous variable instead. This will be more appropriate to demonstrate Multiple Linear Regression.

Our focus will be on the bandwidth usage of the customers. If we can predict that, we could either A) focus on bringing in new customers that would use less data or B) know when we need to expand our infrastructure to handle new usage demands.

Multiple regression is helpful when trying to predict the value of a dependent (target) continuous variable based on two or more independent variables. It also allows us to use varying weights on each independent variables, so they have different levels of impact on the dependent variable predictions.

Objectives & Goals

We will look for variables that show correlation with data usage and then perform analysis to determine if we can predict usage for new or potential customers. We will split the dataset into train and test segments so we can test the level of success.

Primary assumptions of multiple regression models -

- The dependent variable is continuous
- Variables being used have a normal distribution
- An assumption of a linear relationship between the outcome and predictor variables
- The variance of error terms is similar across variables (Homoscedasticity)
- Indepenent variables involved do not have a high level of correlation (Multicollinearity)

    My goal during will be developing a clean dataset that contains relevant variables, develop the model, and describe the results.

Plan

I will be using Python for my analysis. There are many benefits of using Python for data science, including but not limited to -

- It is possible to use Python for full application development, so the project can always be expanded or integrated into other Python projects
- The pandas dataframe and its methods make dealing with tabular data very straightforward
- The syntax of Python feels closer to other programming languages than R, and that makes it easier for me to understand
- Python is a relatively easy language to pick up
- Other libraries including MatPlotLib, NumPy, and SciKitLearn offer vast support for operations involving data analysis and data science

I will use the following steps during this analysis -

1. Examine the dataset
2. Determine the intial set of variables I want to use
3. Change any qualitive variables into quantitive form
4. Normalize any variables (only if necessary)
5. Inspect for outliers and distributions
6. Determine a course of action if there are excessive or special case outliers that might need removal
7. Execute the model
8. Re-evaluate variables included
9. Re-execute the model (only if variables were removed)

10. Describe the resulting correlation (could be R or R2, algrebraic equation that describes the relationship, or any other relevant information discovered)

Exploratory Data Analysis

Review the dataset and remove/transform variables

In [1]:
```
import pandas as pd
import numpy as np
df = pd.read_csv('data/churn_clean.csv')
df.info()
```

```
<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       10000 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
```

It looks like all the values are non-null, so this is a complete dataset and we should not need to remove empty records.

Next, I will to remove variables that either have no relevance to bandwith, cannot be converted to a scaled quantitive value, or might have an obvious correlation but not be helpful when looking at new customers.

In [2]:
```
df.drop(columns=['Lat','Lng','Area','Outage_sec_perweek','Contacts','CaseOrder','Customer_id','Interaction','UID','Ci
df.sample(10)
```

Out[2]:

	Population	Children	Age	Income	Marital	Gender	Email	Yearly_equip_failure	Techie	Port_modem	...	Phone	Multiple	Onli
7476	331	1	86	33294.80	Never Married	Male	9	2	No	Yes	...	Yes	Yes	

	Population	Children	Age	Income	Marital	Gender	Email	Yearly_equip_failure	Techie	Port_modem	...	Phone	Multiple	Onli
7283	1136	1	86	54539.52	Widowed	Male	12	0	No	Yes	...	Yes	Yes	
439	22	2	43	31920.88	Married	Male	10	1	No	Yes	...	Yes	Yes	
659	4478	0	43	33731.69	Separated	Male	14	0	No	No	...	Yes	No	
4358	35157	3	26	20223.80	Never Married	Male	13	1	No	Yes	...	Yes	Yes	
6714	4444	1	21	25091.72	Divorced	Nonbinary	15	0	Yes	Yes	...	Yes	No	
7010	163	4	66	31965.59	Married	Female	4	0	No	No	...	Yes	Yes	
5839	5307	2	77	22328.55	Married	Male	12	0	No	No	...	Yes	No	
7116	12659	1	89	40422.38	Widowed	Female	13	0	No	No	...	Yes	Yes	
4657	34135	0	23	62214.19	Never Married	Female	13	0	No	No	...	Yes	No	

10 rows × 22 columns

Next, we need to convert the categorical columns into numeric values so the model can include them.

In [3]:
```
df.Marital.value_counts()
```

Out[3]:
```
Divorced         2092
Widowed          2027
Separated        2014
Never Married    1956
Married          1911
Name: Marital, dtype: int64
```

In [4]:
```
# create a list of conditions
conditions = [(df['Marital'] == "Divorced")
            , (df['Marital'] == "Widowed")
            , (df['Marital'] == "Separated")
            , (df['Marital'] == "Never Married")
            , (df['Marital'] == "Married")]
# create a list of the values
values = [1,2,3,4,5]

df['MaritalClass'] = np.select(conditions, values)
df.MaritalClass.value_counts()
```

Out[4]:
```
1    2092
2    2027
3    2014
4    1956
5    1911
Name: MaritalClass, dtype: int64
```

In [5]:
```
df.Gender.value_counts()
```

Out[5]:
```
Female       5025
Male         4744
Nonbinary     231
Name: Gender, dtype: int64
```

In [6]:
```
# create a list of conditions
conditions = [(df['Gender'] == "Female")
            , (df['Gender'] == "Male")
            , (df['Gender'] == "Nonbinary")]
# create a list of the values
values = [1,2,3]

df['GenderClass'] = np.select(conditions, values)
df.GenderClass.value_counts()
```

Out[6]:
```
1    5025
2    4744
3     231
Name: GenderClass, dtype: int64
```

In [7]:
```
df.InternetService.value_counts()
```

Out[7]:
```
Fiber Optic    4408
DSL            3463
None           2129
Name: InternetService, dtype: int64
```

In [8]:
```
# create a list of conditions
conditions = [(df['InternetService'] == "Fiber Optic")
            , (df['InternetService'] == "DSL")
```

```
            , (df['InternetService'] == "None")]
# create a list of the values
values = [1,2,3]

df['InternetServiceClass'] = np.select(conditions, values)
df.InternetServiceClass.value_counts()
```

Out[8]:
```
1    4408
2    3463
3    2129
Name: InternetServiceClass, dtype: int64
```

In [9]:
```
# handle all yes/no variables
# create a list of the values

def convertBinaryField(df, fieldName):
  conditions = [(df[fieldName] == "Yes")
            , (df[fieldName] == "No")]
  values = (0,1)
  df[fieldName + 'Class'] = np.select(conditions, values)

convertBinaryField(df, 'Techie')
convertBinaryField(df, 'Port_modem')
convertBinaryField(df, 'Tablet')
convertBinaryField(df, 'Phone')
convertBinaryField(df, 'Multiple')
convertBinaryField(df, 'OnlineSecurity')
convertBinaryField(df, 'OnlineBackup')
convertBinaryField(df, 'DeviceProtection')
convertBinaryField(df, 'TechSupport')
convertBinaryField(df, 'StreamingTV')
convertBinaryField(df, 'StreamingMovies')
convertBinaryField(df, 'PaperlessBilling')
```

In [10]:
```
df.drop(columns=['Marital','Gender','InternetService','Techie','Port_modem','Tablet','Phone','Multiple','OnlineSecuri
```

In [11]:
```
df.head()
```

Out[11]:

	Population	Children	Age	Income	Email	Yearly_equip_failure	Bandwidth_GB_Year	MaritalClass	GenderClass	InternetServiceClass	...
0	38	0	68	28561.99	10	1	904.536110	2	2	1	...
1	10446	1	27	21704.77	12	1	800.982766	5	1	1	...
2	3735	4	50	9609.57	9	1	2054.706961	2	1	2	...
3	13863	1	48	18925.23	15	0	2164.579412	5	2	2	...
4	11352	0	83	40074.19	16	1	271.493436	3	2	1	...

5 rows × 22 columns

In [12]:
```
df.describe().T
```

Out[12]:

	count	mean	std	min	25%	50%	75%	max
Population	10000.0	9756.562400	14432.698671	0.000000	738.000000	2910.500000	13168.000000	111850.00000
Children	10000.0	2.087700	2.147200	0.000000	0.000000	1.000000	3.000000	10.00000
Age	10000.0	53.078400	20.698882	18.000000	35.000000	53.000000	71.000000	89.00000
Income	10000.0	39806.926771	28199.916702	348.670000	19224.717500	33170.605000	53246.170000	258900.70000
Email	10000.0	12.016000	3.025898	1.000000	10.000000	12.000000	14.000000	23.00000
Yearly_equip_failure	10000.0	0.398000	0.635953	0.000000	0.000000	0.000000	1.000000	6.00000
Bandwidth_GB_Year	10000.0	3392.341550	2185.294852	155.506715	1236.470827	3279.536903	5586.141369	7158.98153
MaritalClass	10000.0	2.956700	1.413444	1.000000	2.000000	3.000000	4.000000	5.00000
GenderClass	10000.0	1.520600	0.543880	1.000000	1.000000	1.000000	2.000000	3.00000
InternetServiceClass	10000.0	1.772100	0.775772	1.000000	1.000000	2.000000	2.000000	3.00000
TechieClass	10000.0	0.832100	0.373796	0.000000	1.000000	1.000000	1.000000	1.00000
Port_modemClass	10000.0	0.516600	0.499749	0.000000	0.000000	1.000000	1.000000	1.00000
TabletClass	10000.0	0.700900	0.457887	0.000000	0.000000	1.000000	1.000000	1.00000
PhoneClass	10000.0	0.093300	0.290867	0.000000	0.000000	0.000000	0.000000	1.00000
MultipleClass	10000.0	0.539200	0.498486	0.000000	0.000000	1.000000	1.000000	1.00000
OnlineSecurityClass	10000.0	0.642400	0.479317	0.000000	0.000000	1.000000	1.000000	1.00000

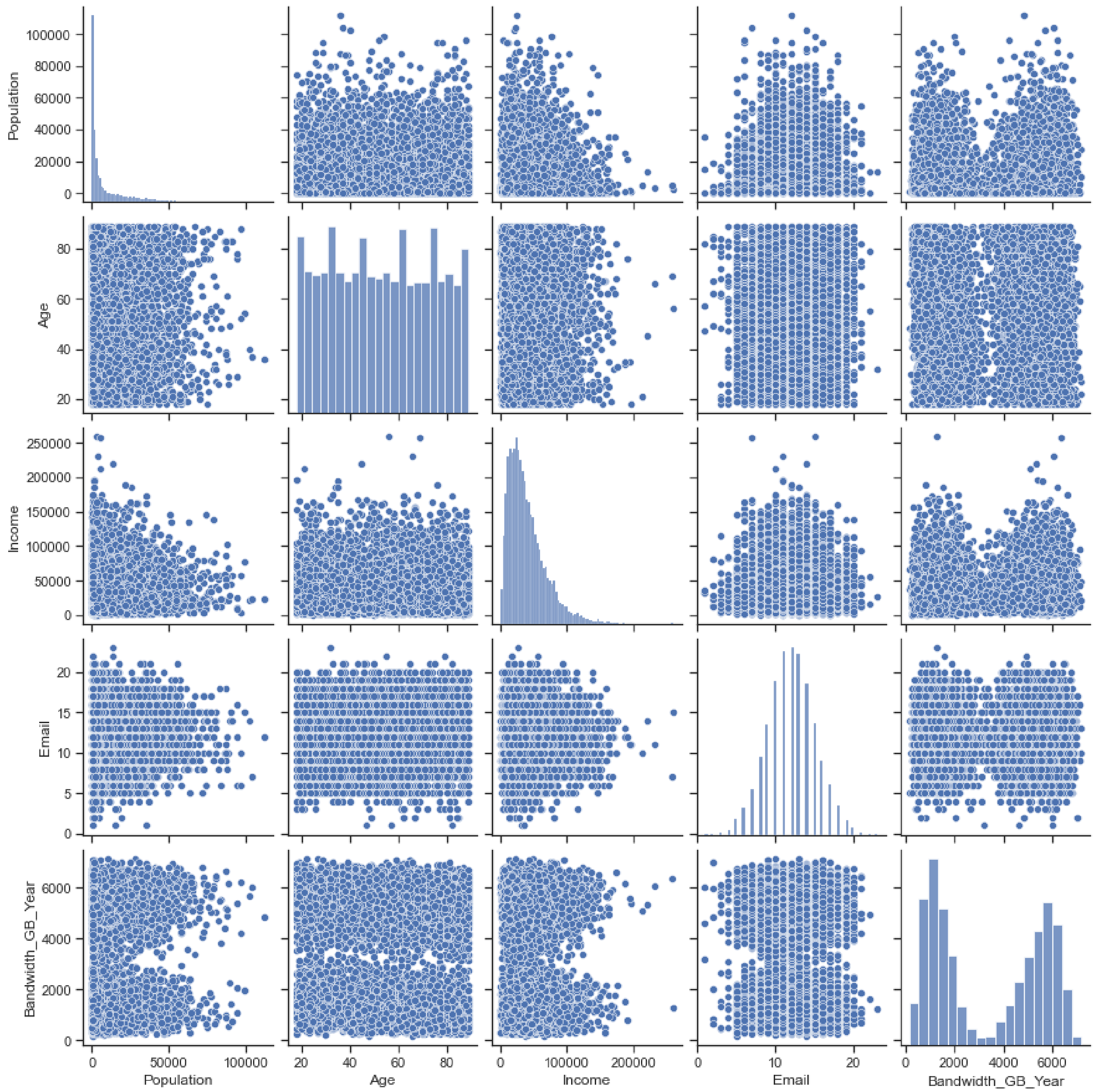
	count	mean	std	min	25%	50%	75%	max
OnlineBackupClass	10000.0	0.549400	0.497579	0.000000	0.000000	1.000000	1.000000	1.00000
DeviceProtectionClass	10000.0	0.561400	0.496241	0.000000	0.000000	1.000000	1.000000	1.00000
TechSupportClass	10000.0	0.625000	0.484147	0.000000	0.000000	1.000000	1.000000	1.00000
StreamingTVClass	10000.0	0.507100	0.499975	0.000000	0.000000	1.000000	1.000000	1.00000
StreamingMoviesClass	10000.0	0.511000	0.499904	0.000000	0.000000	1.000000	1.000000	1.00000
PaperlessBillingClass	10000.0	0.411800	0.492184	0.000000	0.000000	0.000000	1.000000	1.00000

We will look at an overview of some of the relationships between the more continuous variables. This view also shows the distribution of each variable (down the diagonal).

In [13]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme(style="ticks")

sns.pairplot(df[["Population","Age","Income","Email","Bandwidth_GB_Year"]])
```

Out[13]: <seaborn.axisgrid.PairGrid at 0x7ff5b307e5b0>



Review Summary Statistics

In [14]:
```
df.describe().T
```

Out[14]:

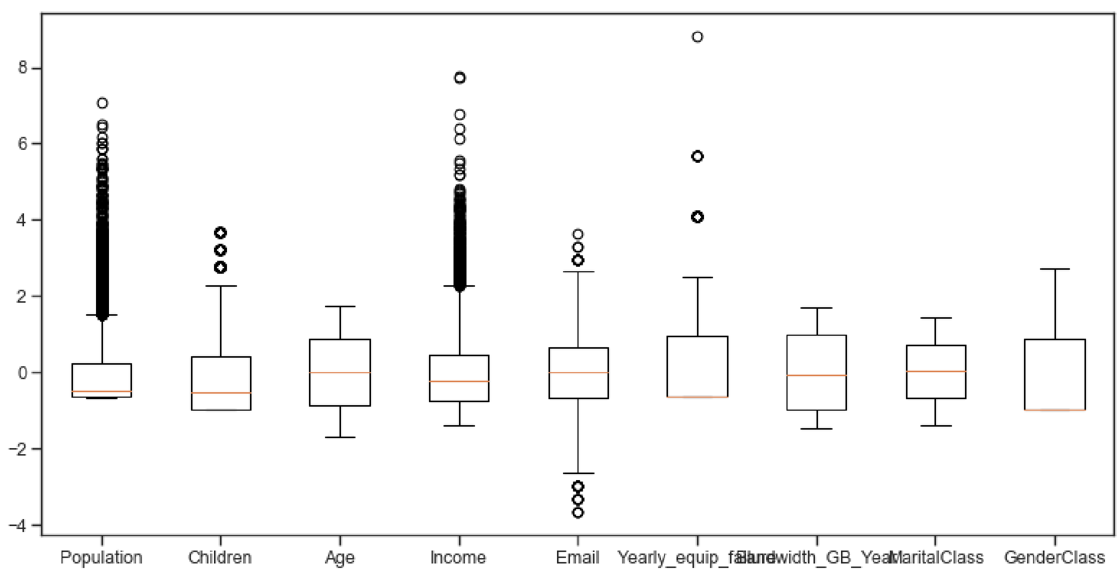
	count	mean	std	min	25%	50%	75%	max
Population	10000.0	9756.562400	14432.698671	0.000000	738.000000	2910.500000	13168.000000	111850.00000
Children	10000.0	2.087700	2.147200	0.000000	0.000000	1.000000	3.000000	10.00000
Age	10000.0	53.078400	20.698882	18.000000	35.000000	53.000000	71.000000	89.00000
Income	10000.0	39806.926771	28199.916702	348.670000	19224.717500	33170.605000	53246.170000	258900.70000
Email	10000.0	12.016000	3.025898	1.000000	10.000000	12.000000	14.000000	23.00000
Yearly_equip_failure	10000.0	0.398000	0.635953	0.000000	0.000000	0.000000	1.000000	6.00000
Bandwidth_GB_Year	10000.0	3392.341550	2185.294852	155.506715	1236.470827	3279.536903	5586.141369	7158.98153
MaritalClass	10000.0	2.956700	1.413444	1.000000	2.000000	3.000000	4.000000	5.00000
GenderClass	10000.0	1.520600	0.543880	1.000000	1.000000	1.000000	2.000000	3.00000
InternetServiceClass	10000.0	1.772100	0.775772	1.000000	1.000000	2.000000	2.000000	3.00000
TechieClass	10000.0	0.832100	0.373796	0.000000	1.000000	1.000000	1.000000	1.00000
Port_modemClass	10000.0	0.516600	0.499749	0.000000	0.000000	1.000000	1.000000	1.00000
TabletClass	10000.0	0.700900	0.457887	0.000000	0.000000	1.000000	1.000000	1.00000
PhoneClass	10000.0	0.093300	0.290867	0.000000	0.000000	0.000000	0.000000	1.00000
MultipleClass	10000.0	0.539200	0.498486	0.000000	0.000000	1.000000	1.000000	1.00000
OnlineSecurityClass	10000.0	0.642400	0.479317	0.000000	0.000000	1.000000	1.000000	1.00000
OnlineBackupClass	10000.0	0.549400	0.497579	0.000000	0.000000	1.000000	1.000000	1.00000
DeviceProtectionClass	10000.0	0.561400	0.496241	0.000000	0.000000	1.000000	1.000000	1.00000
TechSupportClass	10000.0	0.625000	0.484147	0.000000	0.000000	1.000000	1.000000	1.00000
StreamingTVClass	10000.0	0.507100	0.499975	0.000000	0.000000	1.000000	1.000000	1.00000
StreamingMoviesClass	10000.0	0.511000	0.499904	0.000000	0.000000	1.000000	1.000000	1.00000
PaperlessBillingClass	10000.0	0.411800	0.492184	0.000000	0.000000	0.000000	1.000000	1.00000

Look for outliers and determine course of action

In [15]:
```
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from matplotlib.pyplot import figure

figure(figsize=(12, 6), dpi=80)

standardization = StandardScaler(with_mean=True, with_std=True)
Xs = standardization.fit_transform(df)
labels = df.columns
boxplot = plt.boxplot(Xs[:, 0:9], labels=labels[0:9])
```



The only variable with extreme outliers appears to be Yearly_equip_failure. Since this variable would not be a key descriptor for new customers, we will remove it from the dataset and therefore avoid any possible issues due to its outliers.

In [16]:
```
df.drop(columns='Yearly_equip_failure', inplace=True)
```

Normalization

Since there is a large variance on the min/max of variables, we will now normalize variables that go beyond the 0 to 1 range.

In [17]:
```
from sklearn import preprocessing

x = df.values #returns a numpy array
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(x)
df = pd.DataFrame(x_scaled, columns=df.columns)
df.describe().T
```

Out[17]:

	count	mean	std	min	25%	50%	75%	max
Population	10000.0	0.087229	0.129036	0.0	0.006598	0.026021	0.117729	1.0
Children	10000.0	0.208770	0.214720	0.0	0.000000	0.100000	0.300000	1.0
Age	10000.0	0.494062	0.291534	0.0	0.239437	0.492958	0.746479	1.0
Income	10000.0	0.152612	0.109069	0.0	0.073007	0.126945	0.204591	1.0
Email	10000.0	0.500727	0.137541	0.0	0.409091	0.500000	0.590909	1.0
Bandwidth_GB_Year	10000.0	0.462176	0.312030	0.0	0.154347	0.446069	0.775420	1.0
MaritalClass	10000.0	0.489175	0.353361	0.0	0.250000	0.500000	0.750000	1.0
GenderClass	10000.0	0.260300	0.271940	0.0	0.000000	0.000000	0.500000	1.0
InternetServiceClass	10000.0	0.386050	0.387886	0.0	0.000000	0.500000	0.500000	1.0
TechieClass	10000.0	0.832100	0.373796	0.0	1.000000	1.000000	1.000000	1.0
Port_modemClass	10000.0	0.516600	0.499749	0.0	0.000000	1.000000	1.000000	1.0
TabletClass	10000.0	0.700900	0.457887	0.0	0.000000	1.000000	1.000000	1.0
PhoneClass	10000.0	0.093300	0.290867	0.0	0.000000	0.000000	0.000000	1.0
MultipleClass	10000.0	0.539200	0.498486	0.0	0.000000	1.000000	1.000000	1.0
OnlineSecurityClass	10000.0	0.642400	0.479317	0.0	0.000000	1.000000	1.000000	1.0
OnlineBackupClass	10000.0	0.549400	0.497579	0.0	0.000000	1.000000	1.000000	1.0
DeviceProtectionClass	10000.0	0.561400	0.496241	0.0	0.000000	1.000000	1.000000	1.0
TechSupportClass	10000.0	0.625000	0.484147	0.0	0.000000	1.000000	1.000000	1.0
StreamingTVClass	10000.0	0.507100	0.499975	0.0	0.000000	1.000000	1.000000	1.0
StreamingMoviesClass	10000.0	0.511000	0.499904	0.0	0.000000	1.000000	1.000000	1.0
PaperlessBillingClass	10000.0	0.411800	0.492184	0.0	0.000000	0.000000	1.000000	1.0

In [18]:
```
# Save the dataset for submission
df.to_csv('data/prepped_churn.csv')
```

Initial check for correlation

Now we will create a heatmap to view correlation.

In [19]:
```
df.corr()
```

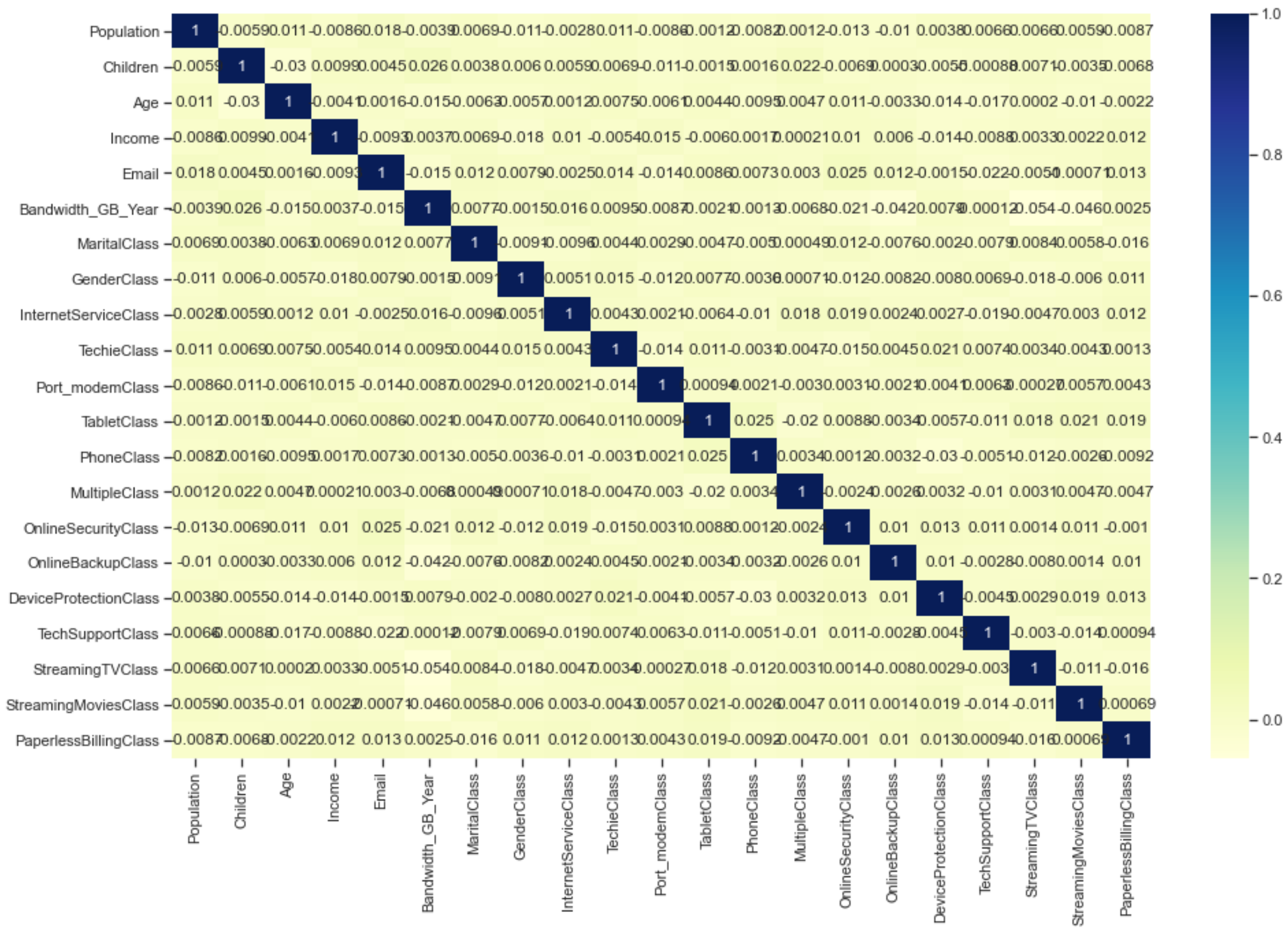
Out[19]:

	Population	Children	Age	Income	Email	Bandwidth_GB_Year	MaritalClass	GenderClass	InternetServi
Population	1.000000	-0.005877	0.010538	-0.008639	0.017962	-0.003902	0.006903	-0.010659	-0.
Children	-0.005877	1.000000	-0.029732	0.009942	0.004479	0.025585	0.003822	0.006032	0.
Age	0.010538	-0.029732	1.000000	-0.004091	0.001588	-0.014724	-0.006345	-0.005660	0
Income	-0.008639	0.009942	-0.004091	1.000000	-0.009267	0.003674	0.006896	-0.018436	0.
Email	0.017962	0.004479	0.001588	-0.009267	1.000000	-0.014579	0.011643	0.007882	-0
Bandwidth_GB_Year	-0.003902	0.025585	-0.014724	0.003674	-0.014579	1.000000	0.007698	-0.001469	0.
MaritalClass	0.006903	0.003822	-0.006345	0.006896	0.011643	0.007698	1.000000	-0.009052	-0.
GenderClass	-0.010659	0.006032	-0.005660	-0.018436	0.007882	-0.001469	-0.009052	1.000000	0.
InternetServiceClass	-0.002849	0.005876	0.001194	0.010208	-0.002451	0.016050	-0.009639	0.005084	1.
TechieClass	0.011483	0.006884	0.007531	-0.005442	0.014047	0.009455	0.004410	0.014801	0.
Port_modemClass	-0.008577	-0.011283	-0.006081	0.014977	-0.014196	-0.008688	0.002929	-0.012297	0.
TabletClass	-0.001225	-0.001494	0.004384	-0.005999	0.008579	-0.002129	-0.004715	0.007676	-0.
PhoneClass	-0.008196	0.001629	-0.009521	0.001677	0.007281	-0.001332	-0.005011	-0.003616	-0.

	Population	Children	Age	Income	Email	Bandwidth_GB_Year	MaritalClass	GenderClass	InternetServi
MultipleClass	0.001241	0.021969	0.004674	0.000214	0.002966	-0.006823	0.000493	0.000710	0
OnlineSecurityClass	-0.012549	-0.006937	0.011213	0.010385	0.024908	-0.021006	0.011833	-0.012021	0
OnlineBackupClass	-0.010352	0.000297	-0.003309	0.005974	0.011763	-0.041740	-0.007552	-0.008195	0.
DeviceProtectionClass	0.003795	-0.005477	-0.014489	-0.014073	-0.001520	0.007856	-0.001984	-0.008022	0
TechSupportClass	0.006606	-0.000878	-0.017155	-0.008835	-0.022119	-0.000120	-0.007947	0.006931	-0.
StreamingTVClass	0.006590	0.007106	0.000197	0.003324	-0.005099	-0.054314	0.008431	-0.017640	-0.
StreamingMoviesClass	0.005882	-0.003461	-0.010125	0.002186	-0.000711	-0.045600	0.005840	-0.005983	0.
PaperlessBillingClass	-0.008656	-0.006828	-0.002247	0.012049	0.012632	0.002470	-0.015625	0.010898	0

21 rows × 21 columns

In [20]:
```python
plt.figure(figsize=(16,10))
sns.heatmap(df.corr(), annot=True, cmap='YlGnBu');
```



There appears to be very little correlation among variables.

Model Creation

Separate the dependent and independent variables

In [21]:
```python
# Move the dependent variable to the end
cols = list(df)
cols.insert(0, cols.pop(cols.index('Bandwidth_GB_Year')))
df = df.loc[:, cols]

# Dependent (Target) Variable:
y = df['Bandwidth_GB_Year']
# Independent Variables:
X = df.iloc[:, 1:]
variables = X.columns
```

Fit the data into a model

In [22]:
```
import statsmodels.api as sm
Xc = sm.add_constant(X)
linear_regression = sm.OLS(y,Xc)
fitted_model = linear_regression.fit()
fitted_model.summary()
```

Out[22]:

OLS Regression Results

Dep. Variable:	Bandwidth_GB_Year	**R-squared:**	0.009
Model:	OLS	**Adj. R-squared:**	0.007
Method:	Least Squares	**F-statistic:**	4.532
Date:	Sun, 28 Mar 2021	**Prob (F-statistic):**	6.54e-11
Time:	15:14:18	**Log-Likelihood:**	-2497.1
No. Observations:	10000	**AIC:**	5036.
Df Residuals:	9979	**BIC:**	5188.
Df Model:	20		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.5202	0.020	25.795	0.000	0.481	0.560
Population	-0.0087	0.024	-0.362	0.718	-0.056	0.039
Children	0.0367	0.014	2.530	0.011	0.008	0.065
Age	-0.0152	0.011	-1.427	0.154	-0.036	0.006
Income	0.0112	0.029	0.394	0.693	-0.045	0.067
Email	-0.0322	0.023	-1.420	0.156	-0.077	0.012
MaritalClass	0.0075	0.009	0.850	0.395	-0.010	0.025
GenderClass	-0.0041	0.011	-0.359	0.719	-0.027	0.018
InternetServiceClass	0.0131	0.008	1.636	0.102	-0.003	0.029
TechieClass	0.0076	0.008	0.914	0.360	-0.009	0.024
Port_modemClass	-0.0053	0.006	-0.854	0.393	-0.018	0.007
TabletClass	6.387e-05	0.007	0.009	0.993	-0.013	0.013
PhoneClass	-0.0019	0.011	-0.181	0.857	-0.023	0.019
MultipleClass	-0.0046	0.006	-0.735	0.462	-0.017	0.008
OnlineSecurityClass	-0.0129	0.006	-1.986	0.047	-0.026	-0.000
OnlineBackupClass	-0.0264	0.006	-4.219	0.000	-0.039	-0.014
DeviceProtectionClass	0.0058	0.006	0.924	0.356	-0.007	0.018
TechSupportClass	-0.0006	0.006	-0.095	0.924	-0.013	0.012
StreamingTVClass	-0.0346	0.006	-5.559	0.000	-0.047	-0.022
StreamingMoviesClass	-0.0288	0.006	-4.629	0.000	-0.041	-0.017
PaperlessBillingClass	0.0013	0.006	0.208	0.835	-0.011	0.014

Omnibus:	42344.249	**Durbin-Watson:**	0.177
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1246.812
Skew:	0.069	**Prob(JB):**	1.81e-271
Kurtosis:	1.276	**Cond. No.**	23.4

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Findings: Our model does not seem to work very well based on the R2 of 0.009.

Remove columns and try again

We can use eigenvectors to detect high associated fields and remove them to lessen their impact on the model.

In [23]:
```
corr = np.corrcoef(X, rowvar=0)
eigenvalues, eigenvectors = np.linalg.eig(corr)
print(eigenvalues)
```

```
[0.9186545  0.93204632 1.06669323 1.06359777 1.05405348 1.05275256
 1.04736495 0.94666042 1.0355902  0.95828003 0.9627079  1.0203008
 1.01480109 1.0049031  1.00265996 0.99561056 0.97416908 0.97715253
 0.98881531 0.98318619]
```

There aren't stark outliers, but the biggest outlier seems to be the first grouping (0.919). We can now look at the values inside of it to determine what is causing it to shift.

In [24]:
```
print (eigenvectors[:,0])
```

```
[ 0.18163847 -0.04992078 -0.29495116 -0.16159492 -0.35418445 -0.10991424
 -0.00162073 -0.26413157  0.30304777  0.01922044 -0.11811569 -0.11905896
  0.08462459  0.45971953 -0.00512182 -0.33840414 -0.39593338 -0.01884499
 -0.0457646   0.17753006]
```

In [25]:
```
variables[13], variables[16]
```

Out[25]:
```
('OnlineSecurityClass', 'TechSupportClass')
```

It is being driven by the columns at index 13 and 16. These correspond to OnlineSecurityClass and TechSupportClass. These will now be removed from the model.

In [26]:
```
variables[13], variables[16]
```

Out[26]:
```
('OnlineSecurityClass', 'TechSupportClass')
```

Also, looking at the P major values, it appears as thought most variables are insignificant, with the exception of Children, OnlineSecurity, OnlineBackup, StreamingTV, and StreamingMovies.

We will now remove all but those 5 columns and create another model.

In [27]:
```
df.drop(columns=['Population', 'Age', 'Income', 'Email', 'MaritalClass', 'InternetServiceClass', 'TechieClass', 'Port
```

Create a revised model

In [28]:
```
# Dependent (Target) Variable:
y = df['Bandwidth_GB_Year']
# Independent Variables:
X = df.iloc[:, 1:]
variables = X.columns
```

In [29]:
```
import statsmodels.api as sm
Xc = sm.add_constant(X)
linear_regression = sm.OLS(y,Xc)
fitted_model = linear_regression.fit()
fitted_model.summary()
```

Out[29]:

OLS Regression Results

Dep. Variable:	Bandwidth_GB_Year	**R-squared:**	0.008
Model:	OLS	**Adj. R-squared:**	0.007
Method:	Least Squares	**F-statistic:**	15.95
Date:	Sun, 28 Mar 2021	**Prob (F-statistic):**	1.10e-15
Time:	15:14:18	**Log-Likelihood:**	-2502.6
No. Observations:	10000	**AIC:**	5017.
Df Residuals:	9994	**BIC:**	5060.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.5092	0.008	61.830	0.000	0.493	0.525
Children	0.0373	0.014	2.579	0.010	0.009	0.066
OnlineSecurityClass	-0.0129	0.006	-1.990	0.047	-0.026	-0.000
OnlineBackupClass	-0.0263	0.006	-4.207	0.000	-0.039	-0.014
StreamingTVClass	-0.0345	0.006	-5.548	0.000	-0.047	-0.022

StreamingMoviesClass	-0.0286	0.006	-4.599	0.000	-0.041	-0.016

Omnibus:	42359.615	**Durbin-Watson:**	0.177
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1246.134
Skew:	0.068	**Prob(JB):**	2.54e-271
Kurtosis:	1.276	**Cond. No.**	7.47

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

An example of running the model with SKLearn

In [30]:
```
from sklearn.linear_model import LinearRegression
reg = LinearRegression()
reg.fit(X, y)
print('Model intercept: ', reg.intercept_)
print('Model coefficients: ', reg.coef_)
```

```
Model intercept:  0.5092296100697045
Model coefficients:  [ 0.03733834 -0.0129101  -0.02628877 -0.03450453 -0.02860165]
```

Results

Our **Adjusted R2 is very low at 0.007**, even after-fine tuning the dataset. This would not be very helpful in predicting data usage. Unfortunately, it is sometimes found that a model cannot be created to accurately predict target variables. This can be due to a lack of relevant data points, unclean/incomplete data, or many other factors.

The calculation for our model is
y = 0.509 + 0.0373Children + -0.0129Security + -0.0263Backup + -0.0345TV + -0.0286Movies

---

Reference

Theory

Model Assumptions - https://www.statisticssolutions.com/assumptions-of-multiple-linear-regression/

Code Examples

Multiple Linear Regression - https://www.kaggle.com/akdagmelih/multiplelinear-regression-fish-weight-estimation

Normalizing Variables - https://stackoverflow.com/questions/26414913/normalize-columns-of-pandas-data-frame

Plot Sizing - https://stackoverflow.com/questions/332289/how-do-you-change-the-size-of-figures-drawn-with-matplotlib