Lora Milam

Western Governors University

D209 Data Mining I

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D209 Performance Assessment Task 1

1 Research Question

Lora Milam Masters Data Analytics (7/4/2022) Program Mentor:d209@wgu.edu

1.1 Question

The questions posed for this assessment will be: what customers are at a high risk of churn? Which customer characteristics are most significant to churn? These questions will be answered by the k-nearest neighbor(KNN) classification method.

1.2 Objective

Stakeholders in the company could benefit from further analysis of these fields and the correlation between these fields and the likelihood of a customer being at a high risk of churn. Future findings could provide valuable information for marketing teams to improve the customer's experience and decrease churn rate by utilizing these characteristics and past user experience.

2 Method Justification

2.1 Explanation of Classification Method

The KNN algorithm stores all applicable scenarios and labels them new cases of its most common K-nearest neighbors. KNN will find and categorize the most similar data points in the training set. A *k* amount of data points will be chosen by the model. The test set will be used to analyze the model's ability to determine the correct classification. The model will determine the classification by utilizing the dominant class's characteristics to assign the new data point a label.

The expected outcome is that the test set data points will be categorized by their closest neighbors.

2.2 Summary of Assumption

One assumption that this method makes is that the Euclidean distance between the data point of interest and the dominant class of its *k* nearest neighbors are similar enough to be grouped together and classifying the data point of interest as that of the dominant class (Chakure).

2.3 Packages and Libraries

The packages and/or libraries chosen for this assessment are as follows:

- Pandas
- Numpy
- Matplotlib
- Seaborn
- Scikit-learn

Pandas, Numpy, and Matplotlib provide mathematical and statistical packages to read, score and visualize data. Seaborn provides more in-depth and easy to read graphs, matrices, and plots. Scikit-learn efficiently provides methods to split, fit, predict and apply metrics for machine learning models.

3 Data Preparation

3.1 Data Preparation Goals

One preprocessing goal for this assessment is to impute numerical dummy variables for features that are populated with character string objects. Specifically, there are alot of variables that are populated with binary character string objects (yes/no) which can be imputed with numerical objects (1/0).

3.2 Initial Dataset Variables

Variable	**Description**
CaseOrder:	- Categorical
Customer_id:	- Categorical
Interaction:	- Categorical
UID:	- Categorical
City:	- Categorical

State:	- Categorical
County:	- Categorical
Zip:	- Categorical
Lat:	- Continuous
Lng:	- Continuous
Population:	- Categorical
Area:	- Categorical
Timezone:	- Categorical
Job:	- Categorical
Children:	- Continuous
Age:	- Categorical
Income:	- Continuous
Marital:	- Categorical
Gender:	- Categorical
Churn	- Categorical
Outage_sec_perweek:	- Continuous
Email:	- Continuous
Contacts:	- Continuous
Yearly_equip_failure:	- Continuous

Techie:	- Categorical
Contract:	- Categorical
Port_modem:	- Categorical
Tablet:	- Categorical
InternetService:	- Categorical
Phone:	- Categorical
Multiple:	- Categorical
OnlineSecurity:	- Categorical
OnlineBackup:	- Categorical
DeviceProtection:	- Categorical
TechSupport:	- Categorical
StreamingTV:	- Categorical
StreamingMovies:	- Categorical
PaperlessBilling:	- Categorical
PaymentMethod:	- Categorical
Tenure:	- Continuous
MonthlyCharge:	- Continuous
Bandwidth_GB_Year:	- Continuous
Item1:	- Categorical
Item2:	- Categorical

Item3:	- Categorical
Item4:	- Categorical
Item5:	- Categorical
Item6:	- Categorical
Item7:	- Categorical
Item8:	- Categorical

3.3 Data Preparation Steps

The preparation steps are as follows:

- Read data into Python using the read_csv command provided by Pandas
- Get a better understanding of the input data by using info and describe methods
- Determine if there is a possibility for misspellings, unintuitive variable names and /or missing values
- Determine if there are outliers that may disrupt the model by using histograms and box plots
- Impute missing data with measures of central tendency(mean, median, or mode) or remove outliers that have a significant difference then the standard deviation
- Remove less meaningful variables
- Save cleaned dataset as “churn_clean.csv” for future use.

In [1]:
```
# Imports
# General
import numpy as np
import pandas as pd
from pandas import Series, DataFrame

# Visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Scikit-learn
import sklearn
from sklearn import datasets
from sklearn import preprocessing
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import classification_report
```

In [2]:
```
# Load data set into Pandas dataset
churn_df = pd.read_csv('churn.csv', index_col = 0)
```

In [3]:
```
# Look at dataset variables
churn_df.columns
```

Out[3]:
```
Index(['Customer_id', 'Interaction', 'UID', 'City', 'State', 'County', 'Zip',
       'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job', 'Children',
       'Age', 'Income', 'Marital', 'Gender', 'Churn', 'Outage_sec_perweek',
       'Email', 'Contacts', 'Yearly_equip_failure', 'Techie', 'Contract',
       'Port_modem', 'Tablet', 'InternetService', 'Phone', 'Multiple',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'PaperlessBilling', 'PaymentMethod',
       'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year', 'Item1', 'Item2',
       'Item3', 'Item4', 'Item5', 'Item6', 'Item7', 'Item8'],
      dtype='object')
```

In [4]:
```
# Look at dimensions of dataset
churn_df.shape
```

Out[4]:
```
(10000, 49)
```

In [5]:
```
# Look at some of the entries of dataset
churn_df.head()
```

Out[5]:

CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat	Lng	Population	...	MonthlyCha
1	K409198	aa90260b-4141-4a24-8e36-b04ce1f4f77b	e885b299883d4f9fb18e39c75155d990	Point Baker	AK	Prince of Wales-Hyder	99927	56.25100	-133.37571	38	...	172.455
2	S120509	fb76459f-c047-4a9d-8af9-e0f7d4ac2524	f2de8bef964785f41a2959829830fb8a	West Branch	MI	Ogemaw	48661	44.32893	-84.24080	10446	...	242.632
3	K191035	344d114c-3736-4be5-98f7-c72c281e2d35	f1784cfa9f6d92ae816197eb175d3c71	Yamhill	OR	Yamhill	97148	45.35589	-123.24657	3735	...	159.947
4	D90850	abfa2b40-2d43-4994-b15a-989b8c79e311	dc8a365077241bb5cd5ccd305136b05e	Del Mar	CA	San Diego	92014	32.96687	-117.24798	13863	...	119.956
5	K662701	68a861fd-0d20-4e51-a587-8a90407ee574	aabb64a116e83fdc4befc1fbab1663f9	Needville	TX	Fort Bend	77461	29.38012	-95.80673	11352	...	149.948

5 rows × 49 columns

In [6]:
```
# Look at dataframe info
churn_df.info
```

Out[6]:
```
<bound method DataFrame.info of            Customer_id                             Interaction  \
CaseOrder
1              K409198  aa90260b-4141-4a24-8e36-b04ce1f4f77b
2              S120509  fb76459f-c047-4a9d-8af9-e0f7d4ac2524
3              K191035  344d114c-3736-4be5-98f7-c72c281e2d35
4               D90850  abfa2b40-2d43-4994-b15a-989b8c79e311
5              K662701  68a861fd-0d20-4e51-a587-8a90407ee574
...                ...                                   ...
9996           M324793  45deb5a2-ae04-4518-bf0b-c82db8dbe4a4
9997           D861732  6e96b921-0c09-4993-bbda-a1ac6411061a
9998           I243405  e8307ddf-9a01-4fff-bc59-4742e03fd24f
9999           I641617  3775ccfc-0052-4107-81ae-9657f81ecdf3
10000           T38070  9de5fb6e-bd33-4995-aec8-f01d0172a499

                                      UID          City State  \
CaseOrder
1           e885b299883d4f9fb18e39c75155d990   Point Baker    AK
2           f2de8bef964785f41a2959829830fb8a   West Branch    MI
3           f1784cfa9f6d92ae816197eb175d3c71       Yamhill    OR
4           dc8a365077241bb5cd5ccd305136b05e       Del Mar    CA
5           aabb64a116e83fdc4befc1fbab1663f9     Needville    TX
...                                      ...           ...   ...
9996        9499fb4de537af195d16d046b79fd20a   Mount Holly    VT
9997        c09a841117fa81b5c8e19afec2760104   Clarksville    TN
9998        9c41f212d1e04dca84445019bbc9b41c      Mobeetie    TX
9999        3e1f269b40c235a1038863ecf6b7a0df    Carrollton    GA
10000       0ea683a03a3cd544aefe8388aab16176  Clarkesville    GA

                          County    Zip       Lat        Lng  Population  ...  \
CaseOrder                                                                 ...
1          Prince of Wales-Hyder  99927  56.25100 -133.37571          38  ...
2                        Ogemaw  48661  44.32893  -84.24080       10446  ...
3                       Yamhill  97148  45.35589 -123.24657        3735  ...
4                     San Diego  92014  32.96687 -117.24798       13863  ...
5                     Fort Bend  77461  29.38012  -95.80673       11352  ...
...                         ...    ...       ...        ...         ...  ...
9996                    Rutland   5758  43.43391  -72.78734         640  ...
9997                 Montgomery  37042  36.56907  -87.41694       77168  ...
9998                    Wheeler  79061  35.52039 -100.44180         406  ...
9999                    Carroll  30117  33.58016  -85.13241       35575  ...
10000                 Habersham  30523  34.70783  -83.53648       12230  ...

           MonthlyCharge Bandwidth_GB_Year Item1  Item2  Item3  Item4 Item5  \
CaseOrder
1             172.455519         904.536110     5      5      5      3     4
2             242.632554         800.982766     3      4      3      3     4
3             159.947583        2054.706961     4      4      2      4     4
4             119.956840        2164.579412     4      4      4      2     5
5             149.948316         271.493436     4      4      4      3     4
...                  ...                ...   ...    ...    ...    ...   ...
9996          159.979400        6511.252601     3      2      3      3     4
9997          207.481100        5695.951810     4      5      5      4     4
9998          169.974100        4159.305799     4      4      4      4     4
9999          252.624000        6468.456752     4      4      6      4     3
10000         217.484000        5857.586167     2      2      3      3     3

           Item6 Item7  Item8
CaseOrder
1              4     3      4
2              3     4      4
3              3     3      3
4              4     3      3
5              4     4      5
...          ...   ...    ...
9996           3     2      3
9997           5     2      5
9998           4     4      5
9999           3     5      4
10000          3     4      1

[10000 rows x 49 columns]>
```

In [7]:
```
# Look at stats of dataframe
churn_df.describe()
```

Out[7]:

	Zip	Lat	Lng	Population	Children	Age	Income	Outage_sec_perweek	Email	Contacts	..
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.0000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	..
mean	49153.319600	38.757567	-90.782536	9756.562400	2.0877	53.078400	39806.926771	10.001848	12.016000	0.994200	..
std	27532.196108	5.437389	15.156142	14432.698671	2.1472	20.698882	28199.916702	2.976019	3.025898	0.988466	..
min	601.000000	17.966120	-171.688150	0.000000	0.0000	18.000000	348.670000	0.099747	1.000000	0.000000	..
25%	26292.500000	35.341828	-97.082812	738.000000	0.0000	35.000000	19224.717500	8.018214	10.000000	0.000000	..
50%	48869.500000	39.395800	-87.918800	2910.500000	1.0000	53.000000	33170.605000	10.018560	12.000000	1.000000	..
75%	71866.500000	42.106908	-80.088745	13168.000000	3.0000	71.000000	53246.170000	11.969485	14.000000	2.000000	..
max	99929.000000	70.640660	-65.667850	111850.000000	10.0000	89.000000	258900.700000	21.207230	23.000000	7.000000	..

8 rows × 22 columns

In [8]:
```
# Look at data types of variables
churn_df.dtypes
```

Out[8]:
```
Customer_id             object
Interaction             object
UID                     object
City                    object
State                   object
County                  object
Zip                      int64
Lat                    float64
Lng                    float64
Population               int64
Area                    object
TimeZone                object
Job                     object
Children                 int64
Age                      int64
Income                 float64
Marital                 object
Gender                  object
Churn                   object
Outage_sec_perweek     float64
Email                    int64
Contacts                 int64
Yearly_equip_failure     int64
Techie                  object
Contract                object
Port_modem              object
Tablet                  object
InternetService         object
Phone                   object
Multiple                object
OnlineSecurity          object
OnlineBackup            object
DeviceProtection        object
TechSupport             object
StreamingTV             object
StreamingMovies         object
PaperlessBilling        object
PaymentMethod           object
Tenure                 float64
MonthlyCharge          float64
Bandwidth_GB_Year      float64
Item1                    int64
Item2                    int64
Item3                    int64
Item4                    int64
Item5                    int64
Item6                    int64
Item7                    int64
Item8                    int64
dtype: object
```

In [9]:
```
# Rename unintuitive variable names
churn_df = churn_df.rename(columns = {'Item1':'TimelyResponse',
                          'Item2':'Fixes',
                          'Item3':'Replacements',
                          'Item4':'Reliability',
                          'Item5':'Options',
                          'Item6':'Respectfulness',
                          'Item7':'Courteous',
                          'Item8':'Listening'})
```

In [10]:
```
# Look at the dataset variables again
churn_df.columns
```

Out[10]:
```
Index(['Customer_id', 'Interaction', 'UID', 'City', 'State', 'County', 'Zip',
       'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job', 'Children',
       'Age', 'Income', 'Marital', 'Gender', 'Churn', 'Outage_sec_perweek',
       'Email', 'Contacts', 'Yearly_equip_failure', 'Techie', 'Contract',
       'Port_modem', 'Tablet', 'InternetService', 'Phone', 'Multiple',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'PaperlessBilling', 'PaymentMethod',
       'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year', 'TimelyResponse',
       'Fixes', 'Replacements', 'Reliability', 'Options', 'Respectfulness',
       'Courteous', 'Listening'],
      dtype='object')
```

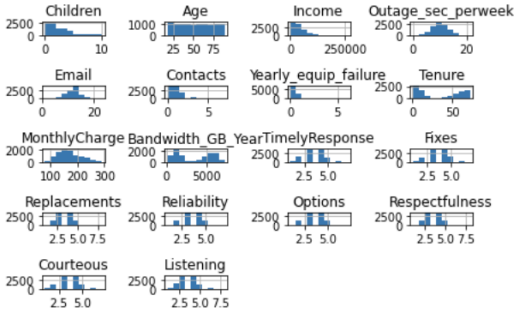
In [11]:
```
# Remove less relevant fields from stats description
churn_df = churn_df.drop(columns=['Customer_id', 'Interaction', 'UID', 'City', 'State',
                                  'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job',
                                  'Marital'])
churn_df.shape
```

Out[11]:
```
(10000, 35)
```

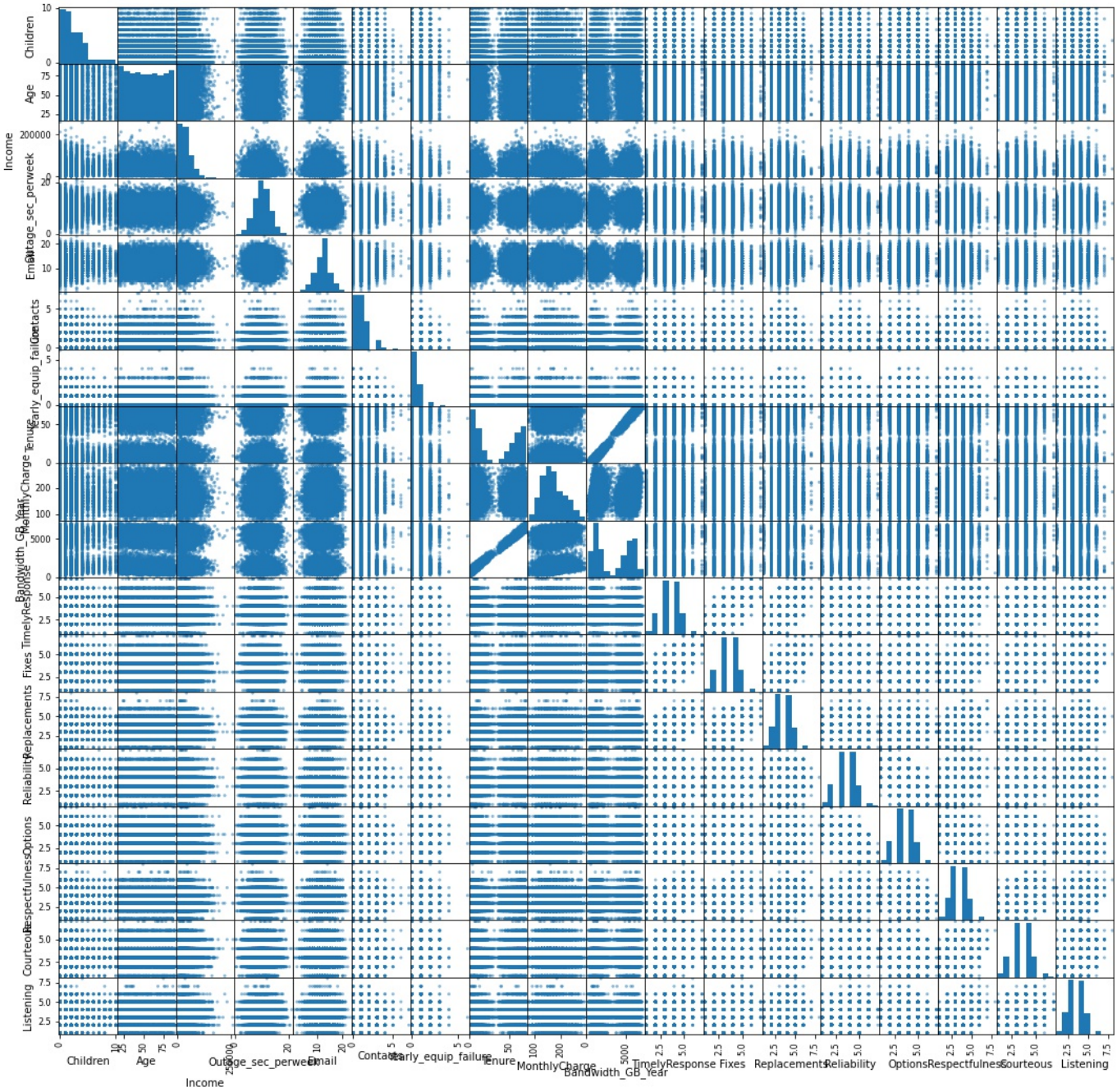
In [12]:
```
churn_df.columns
```

Out[12]:
```
Index(['Children', 'Age', 'Income', 'Gender', 'Churn', 'Outage_sec_perweek',
       'Email', 'Contacts', 'Yearly_equip_failure', 'Techie', 'Contract',
       'Port_modem', 'Tablet', 'InternetService', 'Phone', 'Multiple',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'PaperlessBilling', 'PaymentMethod',
       'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year', 'TimelyResponse',
       'Fixes', 'Replacements', 'Reliability', 'Options', 'Respectfulness',
       'Courteous', 'Listening'],
      dtype='object')
```

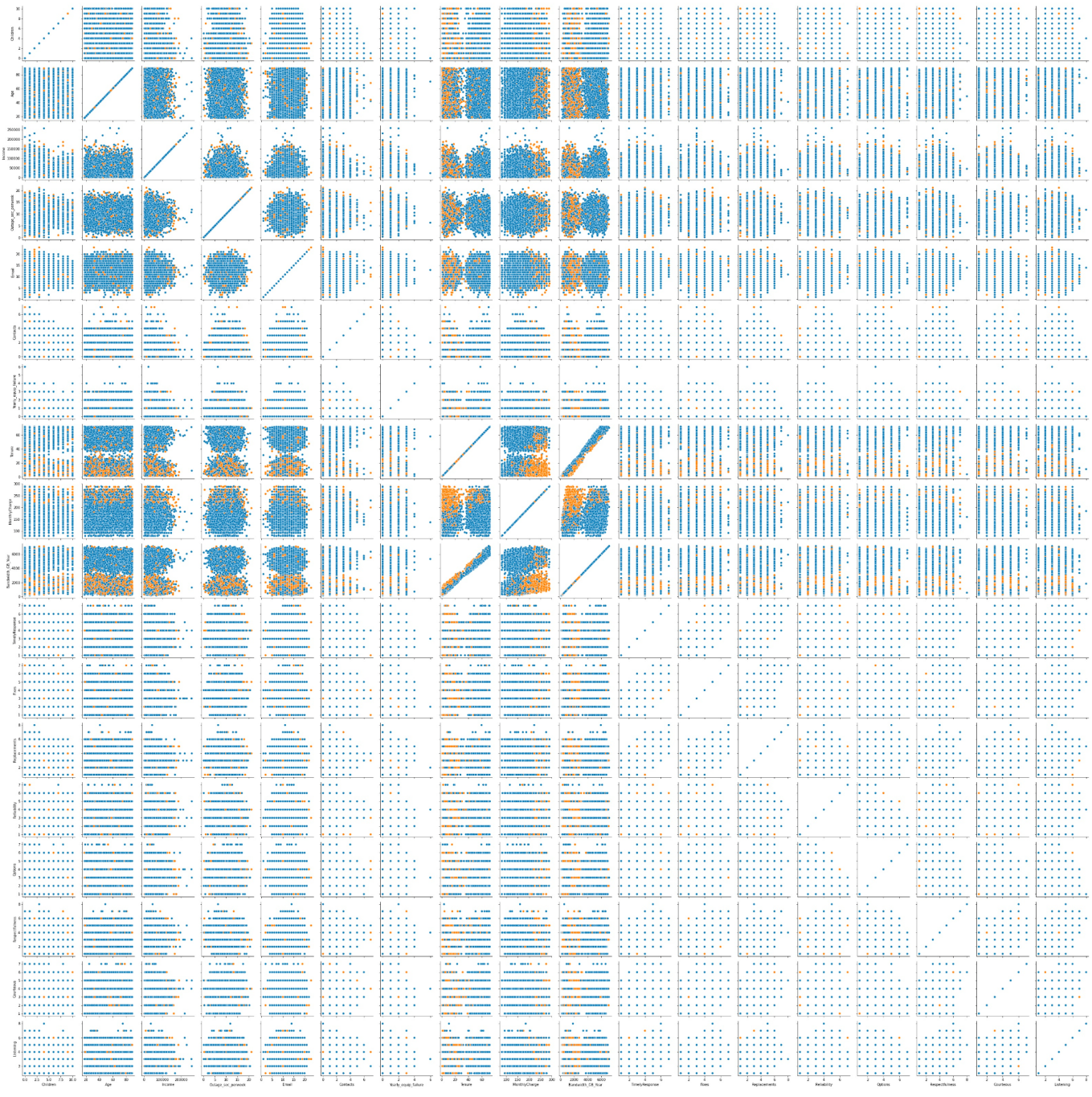
In [13]:
```
# Examine continous variables by creating histograms
churn_df[['Children', 'Age', 'Income', 'Outage_sec_perweek',
       'Email', 'Contacts', 'Yearly_equip_failure',
       'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year', 'TimelyResponse',
       'Fixes', 'Replacements', 'Reliability', 'Options', 'Respectfulness',
       'Courteous', 'Listening']].hist()
plt.savefig('churn_pyplot.jpg')
plt.tight_layout()
```



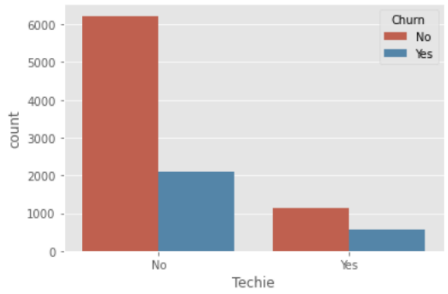
In [14]:
```
# Examine a scatter matrix for any potential relationships
churn_numeric = churn_df[['Children', 'Age', 'Income', 'Outage_sec_perweek',
       'Email', 'Contacts', 'Yearly_equip_failure',
       'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year', 'TimelyResponse',
       'Fixes', 'Replacements', 'Reliability', 'Options', 'Respectfulness',
       'Courteous', 'Listening']]
pd.plotting.scatter_matrix(churn_numeric, figsize = [18,18])
plt.savefig('numeric_scatter_matrix.jpg')
```



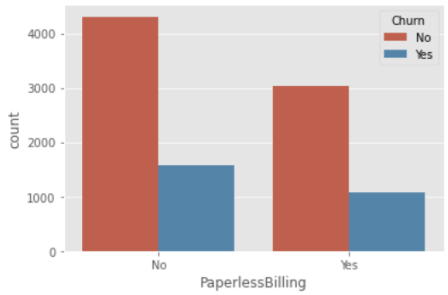
In [15]:
```
# Examine a scatter matrix with the target variable as the hue
g = sns.PairGrid(churn_df, hue = "Churn")
g.map(sns.scatterplot)
plt.savefig('churn_scatter_matrix.jpg')
```


Children
Age
Income
Outage_sec_perweek
Email
Contacts
Yearly_equip_failure
Tenure
MonthlyCharge
Bandwidth_GB_Year
TimelyResponse
Fixes
Replacements
Reliability
Options
RespectfulResponse
Courteous
Listening

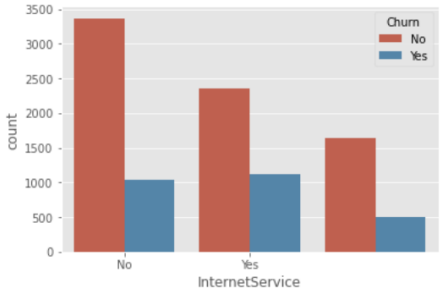
In [16]:
```
# Examine binary categoricals using ggplot's countplot
plt.style.use('ggplot')
plt.figure()
sns.countplot(x='Techie', hue='Churn', data=churn_df)
plt.xticks([0,1],['No','Yes'])
plt.show()
```



In [17]:
```
plt.figure()
sns.countplot(x='PaperlessBilling', hue='Churn', data=churn_df)
plt.xticks([0,1],['No','Yes'])
plt.show()
```

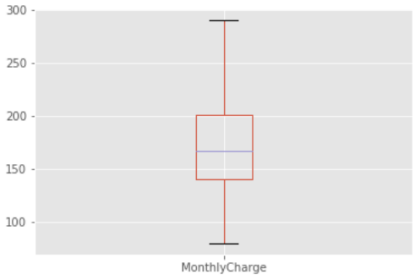


In [18]:
```
plt.figure()
sns.countplot(x='InternetService', hue='Churn', data=churn_df)
plt.xticks([0,1],['No','Yes'])
plt.show()
```



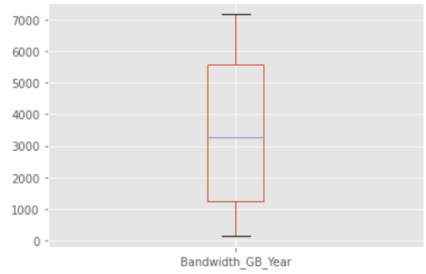
In [19]:
```
# Examine boxplots or variables
churn_df.boxplot(column='MonthlyCharge')
```

Out[19]: <AxesSubplot:>



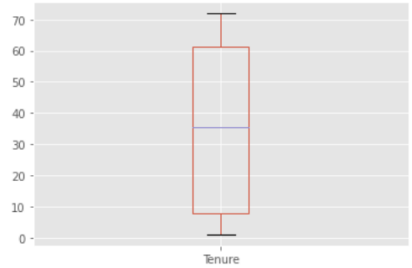
In [20]:
```
churn_df.boxplot(column='Bandwidth_GB_Year')
```

Out[20]: <AxesSubplot:>



In [21]:
```
churn_df.boxplot(column='Tenure')
```

Out[21]: <AxesSubplot:>



Anomalies

- Anomalies have been removed from the dataset. There are no remaining outliers

In [22]:
```
# Determine if there is any missing data
data_nulls = churn_df.isnull().sum()
print(data_nulls)
```

```
Children                0
Age                     0
Income                  0
Gender                  0
Churn                   0
Outage_sec_perweek      0
Email                   0
Contacts                0
Yearly_equip_failure    0
Techie                  0
Contract                0
Port_modem              0
Tablet                  0
InternetService         0
Phone                   0
Multiple                0
OnlineSecurity          0
OnlineBackup            0
DeviceProtection        0
TechSupport             0
StreamingTV             0
StreamingMovies         0
PaperlessBilling        0
PaymentMethod           0
Tenure                  0
MonthlyCharge           0
Bandwidth_GB_Year       0
TimelyResponse          0
Fixes                   0
Replacements            0
Reliability             0
Options                 0
Respectfulness          0
Courteous               0
Listening               0
dtype: int64
```

In [23]:
```
# Impute binary categoricals as numerics
data = churn_df['Churn']
churn_dict = {
    "No":0,"Yes":1
}
# Churn variable
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['Churn'] = data
# Techie variable
data = churn_df['Techie']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['Techie'] = data
# Port_modem variable
data = churn_df['Port_modem']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['Port_modem'] = data
# Tablet variable
data = churn_df['Tablet']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['Tablet'] = data
# Phone variable
data = churn_df['Phone']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['Phone'] = data
# Multiple variable
data = churn_df['Multiple']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['Multiple'] = data
# OnlineSecurity variable
data = churn_df['OnlineSecurity']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['OnlineSecurity'] = data
# OnlineBackup variable
data = churn_df['OnlineBackup']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['OnlineBackup'] = data
# DeviceProtection variable
data = churn_df['DeviceProtection']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['DeviceProtection'] = data
# TechSupport variable
data = churn_df['TechSupport']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['TechSupport'] = data
# StreamingTV variable
data = churn_df['StreamingTV']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['StreamingTV'] = data
# StreamingMovies variable
data = churn_df['StreamingMovies']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['StreamingMovies'] = data
# PaperlessBilling variable
data = churn_df['PaperlessBilling']
for k,v in churn_dict.items():
    data = data.replace(k,v)
churn_df['PaperlessBilling'] = data
```

In [24]:
```
churn_df.head()
```

Out[24]:

CaseOrder	Children	Age	Income	Gender	Churn	Outage_sec_perweek	Email	Contacts	Yearly_equip_failure	Techie	...	MonthlyCharge	Bandwidth_GB_Year
1	0	68	28561.99	Male	0	7.978323	10	0	1	0	...	172.455519	904.536110
2	1	27	21704.77	Female	1	11.699080	12	0	1	1	...	242.632554	800.982766
3	4	50	9609.57	Female	0	10.752800	9	0	1	1	...	159.947583	2054.706961
4	1	48	18925.23	Male	0	14.913540	15	2	0	1	...	119.956840	2164.579412
5	0	83	40074.19	Male	1	8.147417	16	2	1	0	...	149.948316	271.493436

5 rows × 35 columns

In [25]:
```
# Look at data types of variables
churn_df.dtypes
```

Out[25]:
```
Children                  int64
Age                       int64
Income                  float64
Gender                   object
Churn                     int64
Outage_sec_perweek      float64
Email                     int64
Contacts                  int64
Yearly_equip_failure      int64
Techie                    int64
Contract                 object
Port_modem                int64
Tablet                    int64
InternetService          object
Phone                     int64
Multiple                  int64
OnlineSecurity            int64
OnlineBackup              int64
DeviceProtection          int64
TechSupport               int64
StreamingTV               int64
StreamingMovies           int64
PaperlessBilling          int64
PaymentMethod            object
Tenure                  float64
MonthlyCharge           float64
Bandwidth_GB_Year       float64
TimelyResponse            int64
Fixes                     int64
Replacements              int64
Reliability               int64
Options                   int64
Respectfulness            int64
Courteous                 int64
Listening                 int64
dtype: object
```

In [26]:
```
# Create dumby variables for the remaining non-numeric variables:
# Gender, Contract, InternetService, PaymentMethod
# Drop original column
# Exclude redundant values: ex. gender is categorized as male or female, the value 'prefer not to answer' can be identi

# Gender
dmy = pd.get_dummies(churn_df['Gender'])
dmy = dmy.iloc[:,:-1]
churn_df = pd.concat([churn_df,dmy],axis=1)
churn_df = churn_df.drop(columns = 'Gender')

# Contract
dmy = pd.get_dummies(churn_df['Contract'])
churn_df = pd.concat([churn_df,dmy],axis=1)
churn_df = churn_df.drop(columns = 'Contract')

# InternetService
dmy = pd.get_dummies(churn_df['InternetService'])
churn_df = pd.concat([churn_df,dmy],axis=1)
churn_df = churn_df.drop(columns = 'InternetService')

# PaymentMethod
dmy = pd.get_dummies(churn_df['PaymentMethod'])
churn_df = pd.concat([churn_df,dmy],axis=1)
churn_df = churn_df.drop(columns = 'PaymentMethod')
```

In [27]:
```
# Move Churn to the end of the dataframe to set as terget
Churn = churn_df[['Churn']]
churn_df.pop("Churn")
churn_df['Churn'] = Churn

df = churn_df.columns
print(df)
churn_df.head()
```

```
Index(['Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email', 'Contacts',
       'Yearly_equip_failure', 'Techie', 'Port_modem', 'Tablet', 'Phone',
       'Multiple', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'PaperlessBilling',
       'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year', 'TimelyResponse',
       'Fixes', 'Replacements', 'Reliability', 'Options', 'Respectfulness',
       'Courteous', 'Listening', 'Female', 'Male', 'Month-to-month',
       'One year', 'Two Year', 'DSL', 'Fiber Optic', 'None',
       'Bank Transfer(automatic)', 'Credit Card (automatic)',
       'Electronic Check', 'Mailed Check', 'Churn'],
      dtype='object')
```

Out[27]:

CaseOrder	Children	Age	Income	Outage_sec_perweek	Email	Contacts	Yearly_equip_failure	Techie	Port_modem	Tablet	...	One year	Two Year	DSL	Fiber Optic	None
1	0	68	28561.99	7.978323	10	0	1	0	1	1	...	1	0	0	1	0
2	1	27	21704.77	11.699080	12	0	1	1	0	1	...	0	0	0	1	0
3	4	50	9609.57	10.752800	9	0	1	1	1	0	...	0	1	1	0	0
4	1	48	18925.23	14.913540	15	2	0	1	0	0	...	0	1	1	0	0
5	0	83	40074.19	8.147417	16	2	1	0	1	0	...	0	0	0	1	0

5 rows × 43 columns

In [28]:
```
# List variables for analysis
var = (list(churn_df.columns[:-1]))
print('Variables for analysis include: \n', var)
```

```
Variables for analysis include:
 ['Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email', 'Contacts', 'Yearly_equip_failure', 'Techie', 'Port_mod
em', 'Tablet', 'Phone', 'Multiple', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingT
V', 'StreamingMovies', 'PaperlessBilling', 'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year', 'TimelyResponse', 'Fixes',
 'Replacements', 'Reliability', 'Options', 'Respectfulness', 'Courteous', 'Listening', 'Female', 'Male', 'Month-to-mon
th', 'One year', 'Two Year', 'DSL', 'Fiber Optic', 'None', 'Bank Transfer(automatic)', 'Credit Card (automatic)', 'El
ectronic Check', 'Mailed Check']
```

In [29]:
```
# Save clean dataset
churn_df.to_csv('clean_churn.csv')
```

3.4 Prepared Dataset

This can be found in the attached file named “clean_churn.csv”.

4 Analysis

In [30]:
```
# Re-import fully numeric prepared dataset
churn_df = pd.read_csv('clean_churn.csv')

# Set predictor variables and target variable
X = churn_df.drop('Churn',axis=1).values
y = churn_df['Churn'].values
```

In [31]:
```
# Import model, splitting method and metrics from sklearn
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score, train_test_split
```

4.1 Train/Test Split

The training and test sets can be found in the attached files named "training_set.csv" and "testing_set.csv".

In [32]:
```
# Set the seed
seed = 1313

# Create training and test sets
X_train,X_test,y_train,y_test = train_test_split(X, y, test_size = .2, random_state = seed)
```

In [33]:
```
# Convert training and seting sets to Dataframe for export
X_train_df = pd.DataFrame(X_train, columns = ['x','Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email', 'Contacts
y_train_df = pd.DataFrame(y_train, columns = ['Churn'])
X_test_df = pd.DataFrame(X_test, columns = ['x','Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email', 'Contacts',
y_test_df = pd.DataFrame(y_test, columns = ['Churn'])
X_train_df
```

Out[33]:

	x	Children	Age	Income	Outage_sec_perweek	Email	Contacts	Yearly_equip_failure	Techie	Port_modem	...	Listening	Female	Male	Month-to-month
0	1971.0	1.0	86.0	20926.46	3.577497	13.0	0.0	0.0	0.0	0.0	...	3.0	1.0	0.0	0.0
1	4101.0	2.0	67.0	39176.98	8.341450	15.0	1.0	0.0	0.0	1.0	...	5.0	1.0	0.0	0.0
2	9942.0	1.0	80.0	5821.59	14.678300	9.0	0.0	0.0	0.0	0.0	...	2.0	0.0	1.0	0.0
3	2325.0	0.0	58.0	9352.62	13.197550	13.0	3.0	1.0	0.0	0.0	...	3.0	1.0	0.0	0.0
4	8066.0	0.0	63.0	20189.82	8.383716	6.0	1.0	0.0	0.0	1.0	...	4.0	0.0	1.0	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
7995	3820.0	0.0	50.0	20931.13	11.411930	12.0	1.0	1.0	0.0	1.0	...	4.0	0.0	1.0	1.0
7996	5959.0	9.0	36.0	38900.92	11.352260	7.0	1.0	0.0	1.0	1.0	...	4.0	0.0	1.0	0.0
7997	5803.0	1.0	19.0	27844.19	7.227551	8.0	2.0	0.0	0.0	1.0	...	4.0	0.0	1.0	0.0
7998	6324.0	4.0	50.0	70152.92	10.304880	8.0	0.0	2.0	0.0	0.0	...	5.0	1.0	0.0	0.0
7999	9073.0	4.0	73.0	71134.21	9.067273	18.0	0.0	0.0	1.0	0.0	...	3.0	0.0	1.0	1.0

8000 rows × 40 columns

In [34]:
```
# Save training and testing sets
training_set = pd.concat([X_train_df,y_train_df], axis = 1)
testing_set = pd.concat([X_test_df, y_test_df], axis = 1)

training_set.pop('x')
testing_set.pop('x')

# Export sets
training_set.to_csv('training_set')
testing_set.to_csv('testing_set')
```

In [35]:
```
# Instantiate KNN model
knn = KNeighborsClassifier(n_neighbors = 13)

# Fit the data to the model
knn.fit(X_train,y_train)

#Predict outcomes from test set
y_pred = knn.predict(X_test)
```

4.2 Analysis Technique

In [36]:
```
# Print initial accuracy score of knn model
print('Initial accuracy score of KNN model: ', accuracy_score(y_test,y_pred))
```

```
Initial accuracy score of KNN model:  0.7285
```

In [37]:
```
# Compute classification metrics
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.85      0.82      1470
           1       0.49      0.40      0.44       530

    accuracy                           0.73      2000
   macro avg       0.64      0.62      0.63      2000
weighted avg       0.71      0.73      0.72      2000
```

In [38]:
```
# Create pipeline object and scale dataframe
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score

# Set steps for pipeline object
steps = [('scaler', StandardScaler()),
        ('knn', KNeighborsClassifier())]

# Instantiate pipeline
pipeline = Pipeline(steps)

# Split dataframe
X_train_scaled, X_test_scaled, y_train_scaled, y_test_scaled = train_test_split(X, y, test_size = .2, random_state = se

# Scale dataframe with pipline object
knn_scaled = pipeline.fit(X_train_scaled, y_train_scaled)

# Predict from scaled dataframe
y_pred_scaled = pipeline.predict(X_test_scaled)
```

In [39]:
```
# Print new accuracy score of scaled KNN model
print('New accuracy score of KNN model: ', accuracy_score(y_test_scaled,y_pred_scaled))
```

```
New accuracy score of KNN model:  0.835
```

In [40]:
```
# Compute classification metrics of scaled KNN model
print(classification_report(y_test_scaled,y_pred_scaled))
```

```
              precision    recall  f1-score   support

           0       0.87      0.91      0.89      1470
           1       0.72      0.62      0.67       530

    accuracy                           0.83      2000
   macro avg       0.79      0.77      0.78      2000
weighted avg       0.83      0.83      0.83      2000
```

In [41]:
```
# Import sklearn confusion matrix, then make a confusion matrix
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred)
conf_matrix
```

Out[41]:
```
array([[1243,  227],
       [ 316,  214]])
```

In [42]:
```
conf_matrix = confusion_matrix(y_test_scaled, y_pred_scaled)
conf_matrix
```

Out[42]:
```
array([[1340,  130],
       [ 200,  330]])
```

5 Data Summary and Implications

5.1 Accuracy and AUC

Thanks to scaling, the model improved performance from an Accuracy of 0.73 to 0.84 and Precision of 0.80 to 0.87. The area under the curve of the scaled KNN model is a decent score of 0.8082.

In [43]:
```
# Import GridSearchCV for cross validation of model
from sklearn.model_selection import GridSearchCV

# Set up grid parametes
grid_param = {'n_neighbors': np.arange(1,50)}

# Re-instantiate KNN for cross validation
knn = KNeighborsClassifier()

# Instantiate GridSearch cross validation
knn_gridcv = GridSearchCV(knn, grid_param, cv = 5)

# Fit to model
knn_gridcv.fit(X_train, y_train)

# Print best params
print('Best parameters for this KNN model: {}'.format(knn_gridcv.best_params_))
```

```
Best parameters for this KNN model: {'n_neighbors': 22}
```

In [44]:
```
# Generate model best score
print('Best score for this KNN model: {:.3f}'.format(knn_gridcv.best_score_))
```

```
Best score for this KNN model: 0.735
```

In [45]:
```
# Import ROC AUC metrics
from sklearn.metrics import roc_auc_score

# Fit to data
knn_gridcv.fit(X,y)

# Predicted probabilities
y_pred_prob = knn_gridcv.predict_proba(X_test)[:,1]

# Print AUC score
print("The Area under curve (AUC) on validation dataset is: {:.4f}".format(roc_auc_score(y_test, y_pred_prob)))
```

```
The Area under curve (AUC) on validation dataset is: 0.8082
```

In [46]:
```
# Compute cross-validated AUC scores: cv_auc
cv_auc = cross_val_score(knn_gridcv, X, y, cv=5, scoring='roc_auc')

# Print list of AUC scores
print("AUC scores computed using 5-fold cross-validation: {}".format(cv_auc))
```

```
AUC scores computed using 5-fold cross-validation: [0.68120909 0.17406045 0.96370684 0.96560711 0.58834745]
```

In [47]:
```
#
```

5.2 Results and Implications

The scaled KNN model predicts about 80% correctly. This means that 20% of the time, the model predicts incorrectly. Breaking it down even more, the model predicts 87% of churned customers correctly and 73% of non-churned customers correctly. This means that 13% of the predicted churned customers are actually non-churned and 27% of the predicted non-churned customers are actually churned. Though this model is relatively accurate, the inaccurate predictions could cost time and resources by incorrectly depicting where those resources should be directed to. Depending on the implications of marketing costs versus loss of customers, it could be argued that marketing someone who doesn't plan to churn is less impactful than losing a customer due to not marketing them. With this assumption, it would be most beneficial to increase the accuracy of the correctly identified potential churned customers.

5.3 Limitations of Analysis

One limitation of this analysis is that it is very memory intensive and computationally expensive. This means that it takes a long time to complete the process.

5.4 Recommended Course of Action

The recommended course of action would be to further analyze the data to determine if there is a better combination of variables(more or less) to further strengthen the model.

6 Supporting Documents

6.1 Video

This can be found within the attached file ‘Panopto Recording’.

6.2 Sources for Third-Party Code

Chakure, A. (2019, July 6). K-Nearest Neighbors (KNN) algorithm. Medium. Retrieved July 4, 2022, from https://medium.datadriveninvestor.com/k-nearest-neighbors-knn-algorithm-bd375d14eec7

6.3 Sources

Straw, Eric. (2022). D209 Data Mining I . Salt Lake City ; Western Governors University.

Western Governors University. (n.d.). D207 D208 D209 Medical Data Considerations and Dictionary. Salt Lake City.