D209_Performance_Assessment

Classification Analysis

DATA MINIG I – D209

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# Performance Evaluation of Classification Analysis – NVM2, D209

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# Part I:

## A1. Analytical Question:

Which consumers are most likely to leave? What are the most important customer features/variables in terms of churn? We are using the K-Nearest Neighbors algorithm for this analysis.

## A2. Goals and Objectives:

Knowing something with any degree of certainty will benefit everyone in the organization, which customers are most likely to churn, as this will provide weight to selling enhanced services to consumers with these traits and previous user experiences.

# Part II:

## B. Justification for the method

### B1. Assumptions Summary: Classification Analysis

The method keeps track of all existing samples and classifies new ones using K-nearest neighbors "majority vote". In the training data, KNN will find the data points that are the most comparable. A total of k data points will be chosen by the model. The closest data points' dominant classes will advise how to create a data point of interest should be categorized. The generalizability of the model's outcomes will subsequently be tested using test data.
Our test data points will be categorized according to their closest hyperspace neighbors, which is one of the expected outcomes.

### B2. Method Assumption Summary

The strategy presupposes that the data point of interest and its closest neighbors are sufficiently comparable to classify them as the same, given a certain Euclidean distance (Grant, p. 3)[1].

### B3. Advantages/Benefit of the Tool

**Tools will be used:**

For this assessment, I'll use Python because the study will be supported by Jupyter notebooks in Python and IPython. Python includes many established data science and machine learning tools, straightforward, and extensible programming style, and grammar. Python is cross-platform, so it will function whether the analysis is viewed on a Windows PC or a MacBook laptop. When compared to other programming languages such as R or MATLAB, it is quick (Massaron, p. 8[2]). In addition, Python is often regarded in popular media as the most widely used programming language for data science and media (CBTNuggets, p. 1). [3]

**NumPy** used to work with arrays,
**Pandas** used to load datasets,
**Matplotlib** used to plot charts,
**Scikit-learn** used for machine learning model classes,
**SciPy** used for mathematical problems, specifically linear algebra transformations, and
**Seaborn** used for a high-level interface and appealing visualizations.
Using the Pandas library and its accompanying "read csv" function to transform our data as a dataframe is a quick, exact example of loading a dataset and constructing a variable efficiently: imported pandas as pd, df(dataframe) = pd.read csv('ChurnData.csv')

# Part III: Data Objectives:

## C1. The following will be part of my strategy:

1. Using Pandas' read csv command, read the data collection into python programming.
2. Examine the data structure for a better understanding of the data collection process.
3. Using the variable "churn df" to name the dataset, and "df" to name the data frame's subsequent usable slices.
4. Check for misspellings, strange variable names, and data that is missing.
5. Identify outliers that may create or obscure statistical significance using histograms.
6. Computing replaces missing data with relevant central tendency measures (mean, median, or mode) or just Outliers a few standard deviations above the mean are removed.

Using "Bandwidth GB Year" (the average) is a dependent variable of yearly quantity of data consumed, per customer, in GB), it will be our long- term target variable, is the most important to our decision-making process. To construct a model that will give us an indication of data a customer may use given the quantities utilized by known customers given their individual data points for selected predictor variables, on our given dataset, we must first train and then test our machine.

The categorical variables (all binary Predictor except for categorical variable with two values, "Yes"/ "No," were stated) may be shown to be significant: * Churn: Whether the consumer stopped using the service in the previous month (yes, no)* Techie: Whether or not the customer perceives themselves to be technically savvy (as determined by a customer questionnaire completed * Contract (at the time of signing up for services) (yes, no):The customer's contract term (one year , two years or month-on-month). * Port_modem: consumer using a portable modem (yes/no) * the consumer possesses a tablet, such as or a Surface or an iPad (yes, no) * Internet Service: The internet service provider for the customer (DSL, fiber optic, None) * Phone: Is there a phone service for the consumer (yes, no)? * Multiple: If the customer has more than one line (yes, no) * Online Security: Whether the consumer has an add-on for online security (yes, no) * Online Backup: Whether the consumer has purchased an add-on for internet backup (yes, no) * Device Protection: Is any consumer device protection add-on? (Yes, no) * Tech Support: Is there a technical assistance add-on for the customer (yes, no) * Streaming TV: Whether the consumer has access to streaming television (yes, no) * Streaming Movies: If the customer has access to on-demand movies (yes, no).

In the decisionmaking process, discrete ordinal predictor variables created from consumer surve y responses about various customer service attributes could be valuable. Customers in the surve ys provided ordinal numerical data by rating eight customer service aspects on a scale of 8 to 1 (8 being the most essential and 1 being the least important):

- Item1: Evidence of active listening
- Item2: Courteous exchange
- Item3: Respectful response
- Item4: Options
- Item5: Reliability
- Item6: Timely replacements
- Item7: Timely fixes
- Item8: Timely response

## C2. Statistics in Brief:

The dataset has 50 original columns and 10,000 records, as shown in the Python pandas data frame techniques are as follows.

Especial user IDs and statics categorical variables (‘Customer id’,'Case Order, 'Interaction, 'City,'State,'County,'Zip,'Lat,'UID, 'Area,'Lng’,'PaymentMethod','Population, 'TimeZone,'Job,'Marital) not included in the data frame for this research. In addition, binomial "Yes"or "No" / "Male"or"Female" variables encoded to 1 or 0. This left 34 numerical independent predictor factors, including the target variable, to be determined. There appeared to be no nulls, NAs, or missing data points in the dataset, indicating that it had been well cleaned. Ordinary distributions were discovered for "Outage sec per week,” Email" and "Monthly

Charge," using histograms and boxplots as calculate the central tendency. There were no more outliers in the cleaned dataset. In a scatterplot, histograms for "Bandwidth_GB_Year" and "Tenure" displayed bimodal distributions, indicating a straight linear relationship. 53 years old customers are average (with standard deviation of 20 years), had two children (with a standard deviation of two children), had an income of $39,806 (There were 10 outage-seconds every week, with a standard deviation of around 30,000, 12 times email was marked, called technical assistance few times, had fewer than one annual equipment fault, has been with the organization for almost months of 34.5, has a monthly charges of about 173, and uses 3,392 GBs.

## C3. Data Preparation Procedures:

- Create a Python data frame from a dataset.
- Rename the survey's columns/variables to make them more clearly identifiable (ex: "Item1" to "Timely_Response").
- Obtain a description of the data frame, including its structure (columns and rows) and data types.
- Look for the summary statistics.
- Remove the data frame's non-vital identifying (ex: "Customer id" and ex: zip code) are demographic columns.
- Search records for missing data and fill in the blanks, Outliers that are several standard deviations above the mean should be removed with the central tendency (mean/median/mode)/ delete the outliers that are more than a standard deviation above the mean.
- Make a list of dummy variables to encode category, yes/no data points into 1/0 number values
- Create a visual representation of univariate and bivariate data.
- At the end of the data frame, add Bandwidth GB Year.
- The prepared dataset will be extracted and delivered as "churn prepared.csv" at the end.

**1. Include standard imports all the required references:**

```
# Increase Jupyter display cell-width
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:75% !important; }</style>"))
```

```
<IPython.core.display.HTML object>
```

```python
# Standard data science imports
import numpy as np
import pandas as pd
from pandas import Series, DataFrame

# Visualization libraries
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
```

2. **Change font and color of the Matplotlib:**

```python
# Change color of Matplotlib font
import matplotlib as mpl
COLOR = 'white'
mpl.rcParams['text.color'] = COLOR
mpl.rcParams['axes.labelcolor'] = COLOR
mpl.rcParams['xtick.color'] = COLOR
mpl.rcParams['ytick.color'] = COLOR
```

3. **Imports the Ignore warning codes:**

```python
# Ignore Warning Code
import warnings
warnings.filterwarnings('ignore')
```

4. **Load the churn data frame into pandas:**

```python
In [8]: # Load data set into Pandas dataframe
        churn_df = pd.read_csv('C:\Rekha\churn_clean.csv', index_col=0)
```

5. **To examine the data frame columns:**

```
# Examine the features of the dataset
churn_df.columns
```

```
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')
```

6. **To List the records & columns of dataset:**

```
# Get an idea of dataset size
churn_df.shape
```

```
(10000, 49)
```

7. **List the churn data set statics:**

```
# Examine first few records of dataset
churn_df.head()
```

| CaseOrder | Customer_id | Interaction | UID | City | State | County | Zip | Lat | Lng | Population | ... | MonthlyCharge | Bandwidth_GB_Year | Item1 | Item2 | Item3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | K409198 | aa90260b-4141-4a24-8e36-b04ce1f4f77b | e885b299883d4f9fb18e39c75155d990 | Point Baker | AK | Prince of Wales-Hyder | 99927 | 56.25100 | -133.37571 | 38 | ... | 172.455519 | 904.536110 | 5 | 5 | 5 |
| 2 | S120509 | fb76459f-c047-4a9d-8af9-e0f7d4ac2524 | f2de8bef964785f41a2959829830fb8a | West Branch | MI | Ogemaw | 48661 | 44.32893 | -84.24080 | 10446 | ... | 242.632554 | 800.982766 | 3 | 4 | 3 |
| 3 | K191035 | 344d114c-3736-4be5-98f7-c72c281e2d35 | f1784cfa9f6d92ae816197eb175d3c71 | Yamhill | OR | Yamhill | 97148 | 45.35589 | -123.24657 | 3735 | ... | 159.947583 | 2054.706961 | 4 | 4 | 2 |
| 4 | D90850 | abfa2b40-2d43-4994-b15a-989b8c79e311 | dc8a365077241bb5cd5ccd305136b05e | Del Mar | CA | San Diego | 92014 | 32.96687 | -117.24798 | 13863 | ... | 119.956840 | 2164.579412 | 4 | 4 | 4 |
| 5 | K662701 | 68a861fd-0d20-4e51-a587-8a90407ee574 | aabb64a116e83fdc4befc1fbab1663f9 | Needville | TX | Fort Bend | 77461 | 29.38012 | -95.80673 | 11352 | ... | 149.948316 | 271.493436 | 4 | 4 | 4 |

5 rows × 49 columns

## 8. To List the data frame info:

```
# View DataFrame info
churn_df.info
```

```
<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]>
```

## 9. Dataset with data points:

```
# Provide an initial look at extant dataset
churn_df.head()
```

| CaseOrder | Customer_id | Interaction | UID | City | State | County | Zip | Lat | Lng | Population | ... | MonthlyCharge | Bandwidth_GB_Year | Item1 | Item2 | Item3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | K409198 | aa90260b-4141-4a24-8e36-b04ce1f4f77b | e885b299883d4f9fb18e39c75155d990 | Point Baker | AK | Prince of Wales-Hyder | 99927 | 56.25100 | -133.37571 | 38 | ... | 172.455519 | 904.536110 | 5 | 5 | 5 |
| 2 | S120509 | fb76459f-c047-4a9d-8af9-e0f7d4ac2524 | f2de8bef964785f41a2959829830fb8a | West Branch | MI | Ogemaw | 48661 | 44.32893 | -84.24080 | 10446 | ... | 242.632554 | 800.982766 | 3 | 4 | 3 |
| 3 | K191035 | 344d114c-3736-4be5-98f7-c72c281e2d35 | f1784cfa9f6d92ae816197eb175d3c71 | Yamhill | OR | Yamhill | 97148 | 45.35589 | -123.24657 | 3735 | ... | 159.947583 | 2054.706961 | 4 | 4 | 2 |
| 4 | D90850 | abfa2b40-2d43-4994-b15a-989b8c79e311 | dc8a365077241bb5cd5ccd305136b05e | Del Mar | CA | San Diego | 92014 | 32.96687 | -117.24798 | 13863 | ... | 119.956840 | 2164.579412 | 4 | 4 | 4 |
| 5 | K662701 | 68a861fd-0d20-4e51-a587-8a90407ee574 | aabb64a116e83fdc4befc1fbab1663f9 | Needville | TX | Fort Bend | 77461 | 29.38012 | -95.80673 | 11352 | ... | 149.948316 | 271.493436 | 4 | 4 | 4 |

5 rows × 49 columns

## 10. To List the churn data set statics:

```
# Get an overview of descriptive statistics
churn_df.describe()
```

| | Zip | Lat | Lng | Population | Children | Age | Income | Outage_sec_perweek | Email | Contacts | ... | MonthlyCharge | Bandwidth_GB_Year | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.0000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | ... | 10000.000000 | 10000.000000 | 10000.0 |
| **mean** | 49153.319600 | 38.757567 | -90.782536 | 9756.562400 | 2.0877 | 53.078400 | 39806.926771 | 10.001848 | 12.016000 | 0.994200 | ... | 172.624816 | 3392.341550 | 3.4 |
| **std** | 27532.196108 | 5.437389 | 15.156142 | 14432.698671 | 2.1472 | 20.698882 | 28199.916702 | 2.976019 | 3.025898 | 0.988466 | ... | 42.943094 | 2185.294852 | 1.0 |
| **min** | 601.000000 | 17.966120 | -171.688150 | 0.000000 | 0.0000 | 18.000000 | 348.670000 | 0.099747 | 1.000000 | 0.000000 | ... | 79.978860 | 155.506715 | 1.0 |
| **25%** | 26292.500000 | 35.341828 | -97.082812 | 738.000000 | 0.0000 | 35.000000 | 19224.717500 | 8.018214 | 10.000000 | 0.000000 | ... | 139.979239 | 1236.470827 | 3.0 |
| **50%** | 48869.500000 | 39.395800 | -87.918800 | 2910.500000 | 1.0000 | 53.000000 | 33170.605000 | 10.018560 | 12.000000 | 1.000000 | ... | 167.484700 | 3279.536903 | 3.0 |
| **75%** | 71866.500000 | 42.106908 | -80.088745 | 13168.000000 | 3.0000 | 71.000000 | 53246.170000 | 11.969485 | 14.000000 | 2.000000 | ... | 200.734725 | 5586.141370 | 4.0 |
| **max** | 99929.000000 | 70.640660 | -65.667850 | 111850.000000 | 10.0000 | 89.000000 | 258900.700000 | 21.207230 | 23.000000 | 7.000000 | ... | 290.160419 | 7158.981530 | 7.0 |

8 rows × 22 columns

## 11. List the data types:

```
# Get data types of features
churn_df.dtypes
```

```
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
```

**12 Change the names of the last eight survey columns to better describe the variables:**

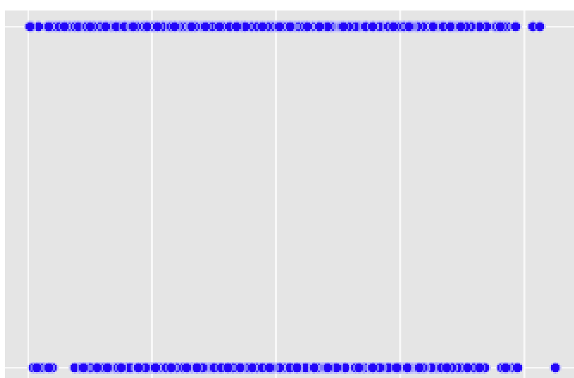
```
# Rename last 8 survey columns for better description of variables
churn_df.rename(columns = {'Item1':'Timely_Response',
'Item2':'Timely_Fixes',
'Item3':'Timely_Replacements',
'Item4':'Reliability',
'Item5':'Options',
'Item6':'Respectful_Response',
'Item7':'Courteous_exchange',
'Item8':'Active_Listening'},
inplace=True)
```

## 13 Histograms of continuous variables & categorical variables:

```
 # Create histograms of contiuous variables & categorical variables
churn_df[['Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email',
'Contacts', 'Yearly_equip_failure', 'Tenure', 'MonthlyCharge',
'Bandwidth_GB_Year','Timely_Response','Courteous_exchange']].hist()
plt.savefig('churn_pyplot.jpg')
plt.tight_layout()
```

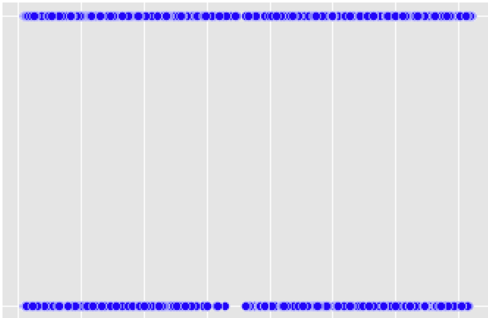
## 14 Scatterplot:

```
# Create a scatterplot to get an idea of correlations between potentially related variables
sns.scatterplot(x=churn_df['Outage_sec_perweek'], y=churn_df['Churn'], color='blue')
plt.show();
```



## 15 Scatterplot:

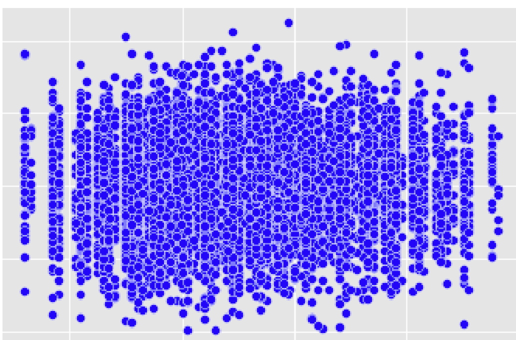
```
# Create a scatterplot to get an idea of correlations between potentially related variables
sns.scatterplot(x=churn_df['Tenure'], y=churn_df['Churn'], color='blue')
plt.show();
```



---

## 16 Scatterplot:

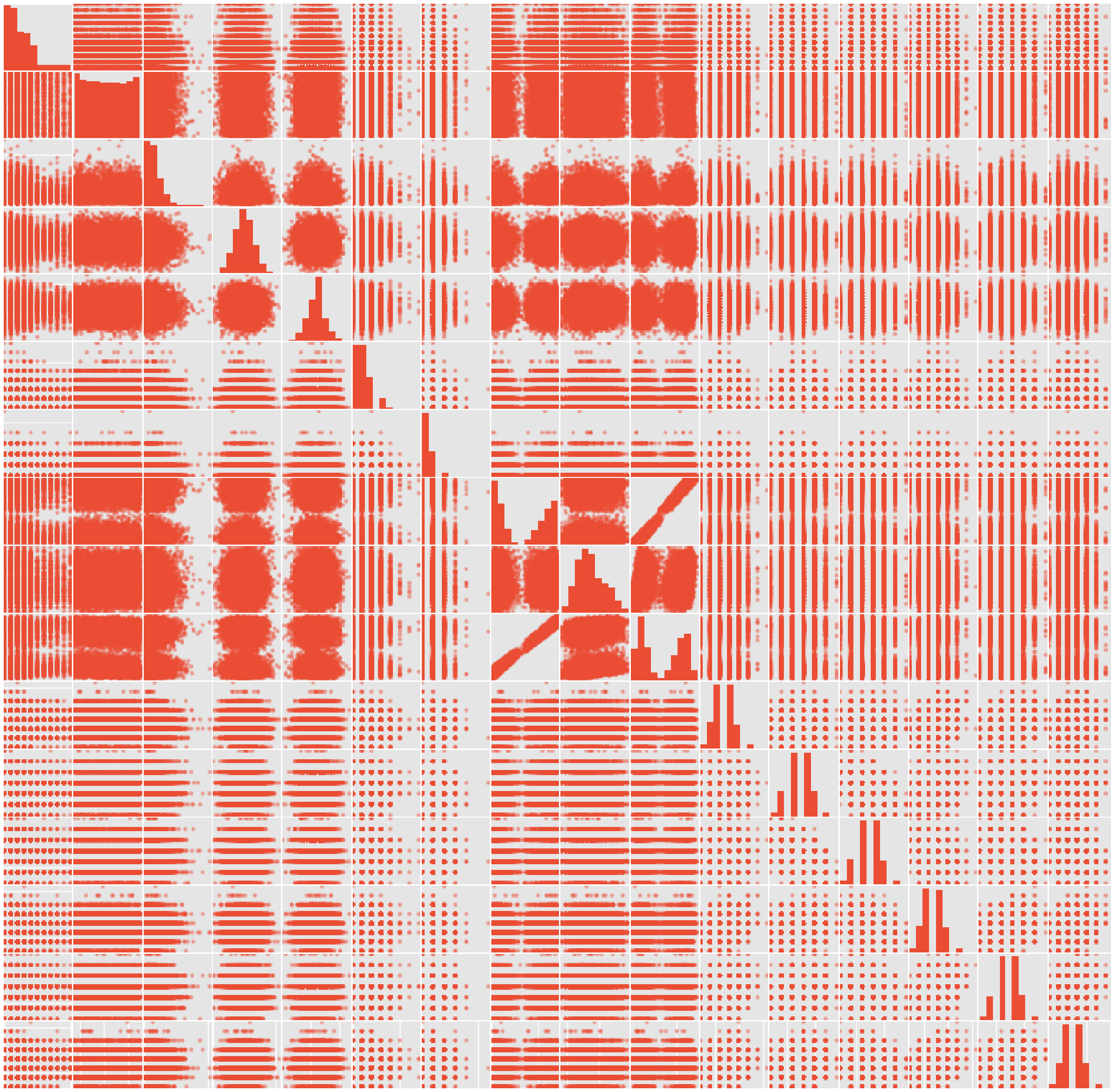
```
# Create a scatterplot to get an idea of correlations between potentially related variables
sns.scatterplot(x=churn_df['MonthlyCharge'], y=churn_df['Outage_sec_perweek'], color='blue')
plt.show();
```



---

## 17 Scatter Matrix:

```
# Provide a scatter matrix of numeric variables for high level overview of potential relationships & distributions
churn_numeric = churn_df[['Children', 'Age', 'Income', 'Outage_sec_perweek',
 'Email', 'Contacts','Yearly_equip_failure', 'Tenure',
 'MonthlyCharge', 'Bandwidth_GB_Year', 'Timely_Replacements',
 'Reliability', 'Options', 'Respectful_Response','Courteous_exchange',
 'Active_Listening']]
pd.plotting.scatter_matrix(churn_numeric, figsize = [15, 15]);
```

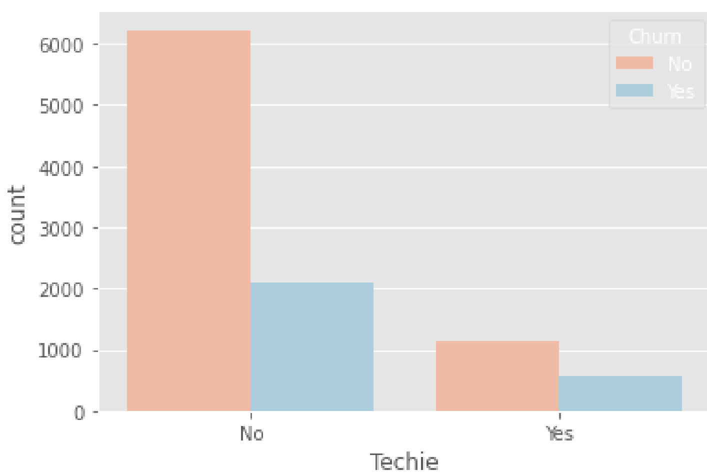


## 18 Scatterplot

```
# Create individual scatterplot for viewing relationship of key financial featurte against target variable
sns.scatterplot(x = churn_df['MonthlyCharge'], y = churn_df['Churn'], color='red')
plt.show();
```

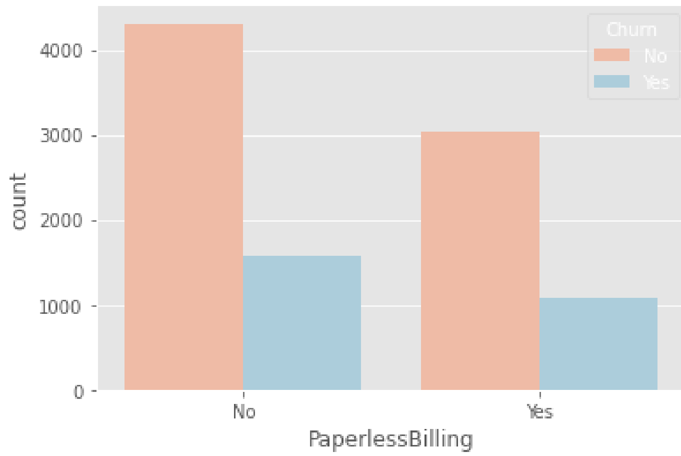
## 19 Set **plot style to ggplot**

```
# Set plot style to ggplot for aesthetics & R style
plt.style.use('ggplot')
# Countplot more useful than scatter_matrix when features of dataset are binary
plt.figure()
sns.countplot(x='Techie', hue='Churn', data=churn_df, palette='RdBu')
plt.xticks([0,1], ['No', 'Yes'])
plt.show()
```



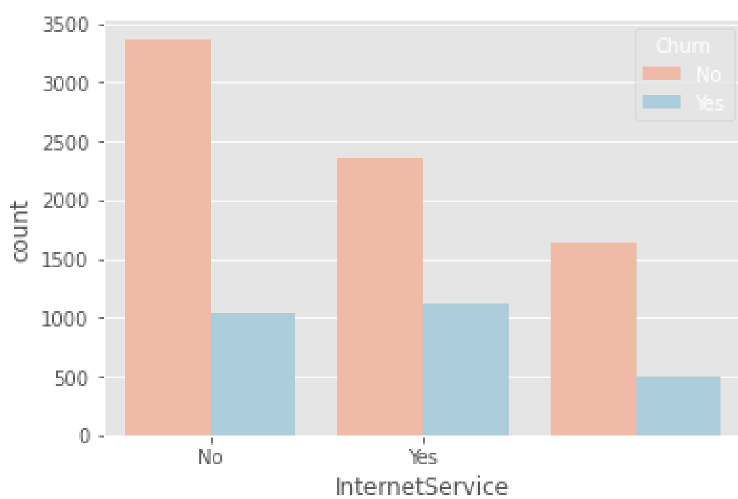
## 20 Countplot

```python
# Countplot more useful than scatter_matrix when features of dataset are binary
plt.figure()
sns.countplot(x='PaperlessBilling', hue='Churn', data=churn_df, palette='RdBu')
plt.xticks([0,1], ['No', 'Yes'])
plt.show()
```




## 21 Countplot

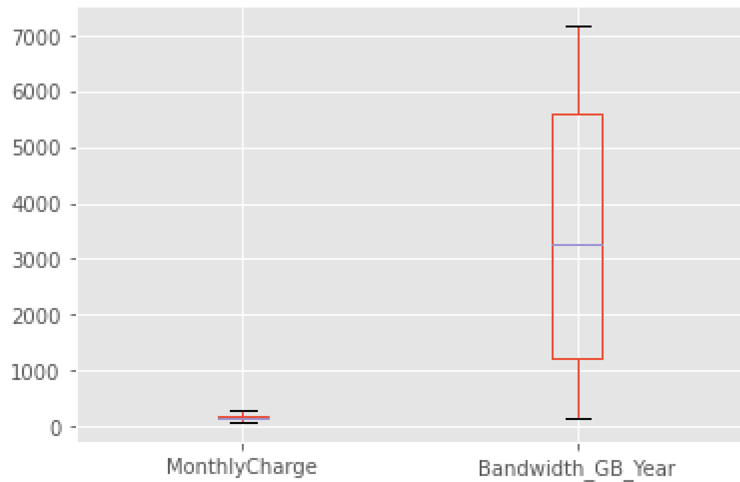
```python
# Countplot more useful than scatter_matrix when features of dataset are binary
plt.figure()
sns.countplot(x='InternetService', hue='Churn', data=churn_df, palette='RdBu')
plt.xticks([0,1], ['No', 'Yes'])
plt.show()
```



**22** Boxplot

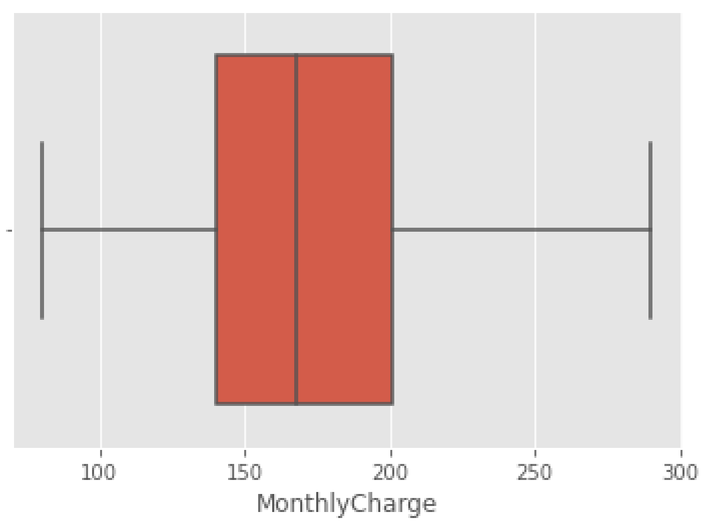
```
# Create multiple boxplots for continuous & categorical variables
churn_df.boxplot(column=['MonthlyCharge','Bandwidth_GB_Year'])
```

```
<AxesSubplot:>
```



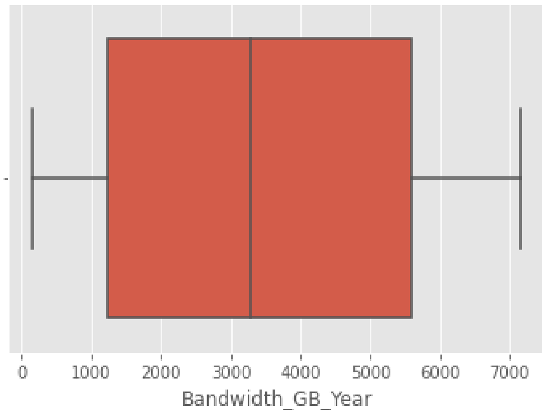

**23** Boxplot

```
# Create Seaborn boxplots for continuous & categorical variables
sns.boxplot('MonthlyCharge', data = churn_df)
plt.show()
```



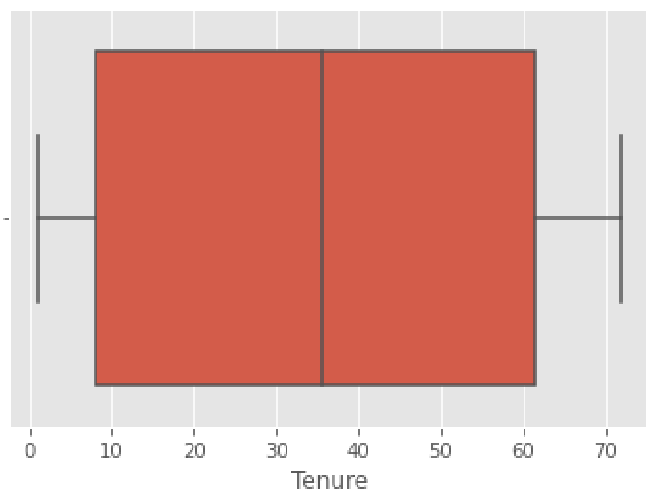
24 Seaborn boxplot

```
# Create Seaborn boxplots for continuous & categorical variables
sns.boxplot('Bandwidth_GB_Year', data = churn_df)
plt.show()
```




**25 Seaborn boxplot**

```
# Create Seaborn boxplots for continuous variables
sns.boxplot('Tenure', data = churn_df)
plt.show()
```




**Anomalies**

Anomalies appear to have been removed from the provided dataset, churn clean.csv. There are no more anomalies.

26 Discover missing data points:

```
# Discover missing data points within dataset
data_nulls = churn_df.isnull().sum()
print(data_nulls)
```

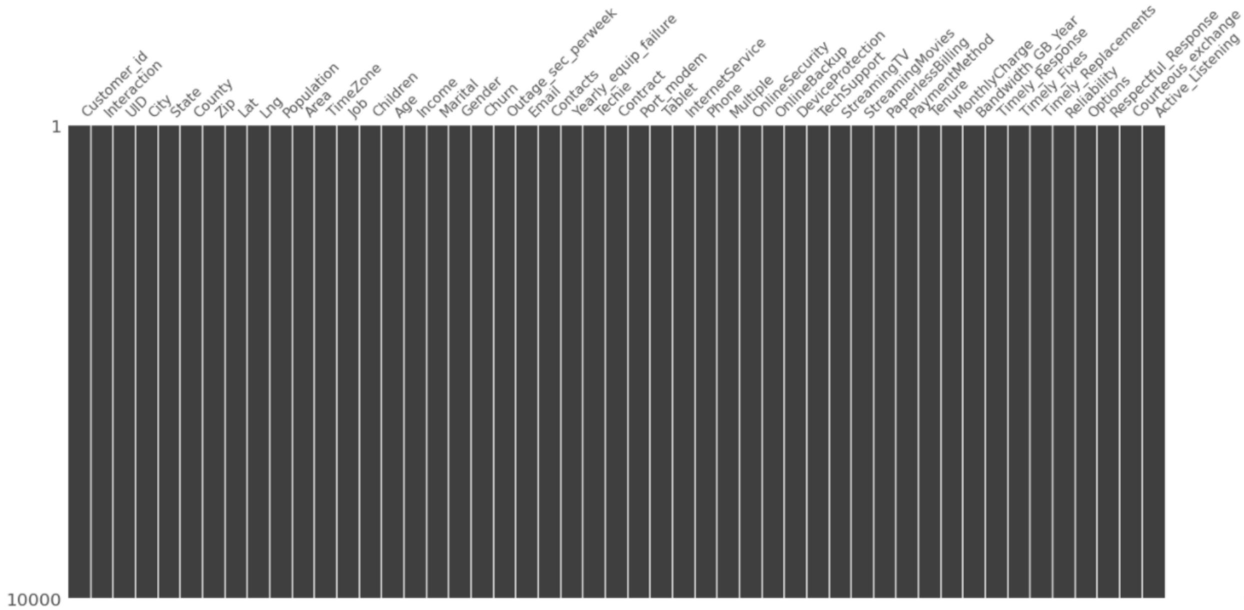
```
Customer_id             0
Interaction             0
UID                     0
City                    0
State                   0
County                  0
Zip                     0
Lat                     0
Lng                     0
Population              0
Area                    0
TimeZone                0
Job                     0
Children                0
Age                     0
Income                  0
Marital                 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
Timely_Response          0
Timely_Fixes             0
Timely_Replacements      0
Reliability              0
Options                  0
Respectful_Response      0
Courteous_exchange       0
Active_Listening         0
dtype: int64
```

27 Check for missing data

```
# Check for missing data & visualize missing values in dataset
# Install appropriate library
!pip install missingno
# Importing the libraries
import missingno as msno
# Visualize missing values as a matrix
msno.matrix(churn_df);
"""(GeeksForGeeks, p. 1)"""
```

```
Requirement already satisfied: missingno in c:\users\kaila\anaconda3\lib\site-packages (0.5.0)
Requirement already satisfied: scipy in c:\users\kaila\anaconda3\lib\site-packages (from missingno) (1.6.2)
Requirement already satisfied: matplotlib in c:\users\kaila\anaconda3\lib\site-packages (from missingno) (3.3.4)
Requirement already satisfied: seaborn in c:\users\kaila\anaconda3\lib\site-packages (from missingno) (0.11.1)
Requirement already satisfied: numpy in c:\users\kaila\anaconda3\lib\site-packages (from missingno) (1.20.1)
Requirement already satisfied: pillow>=6.2.0 in c:\users\kaila\anaconda3\lib\site-packages (from matplotlib->missingno) (8.2.0)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\kaila\anaconda3\lib\site-packages (from matplotlib->missingno) (2.8.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in c:\users\kaila\anaconda3\lib\site-packages (from matplotlib->missingno) (2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\kaila\anaconda3\lib\site-packages (from matplotlib->missingno) (1.3.1)
Requirement already satisfied: cycler>=0.10 in c:\users\kaila\anaconda3\lib\site-packages (from matplotlib->missingno) (0.10.0)
Requirement already satisfied: six in c:\users\kaila\anaconda3\lib\site-packages (from cycler>=0.10->matplotlib->missingno) (1.15.0)
Requirement already satisfied: pandas>=0.23 in c:\users\kaila\anaconda3\lib\site-packages (from seaborn->missingno) (1.2.4)
Requirement already satisfied: pytz>=2017.3 in c:\users\kaila\anaconda3\lib\site-packages (from pandas>=0.23->seaborn->missingno) (2021.1)

'(GeeksForGeeks, p. 1)'
```




## 28 Encode Binary Categorical

```python
# Encode binary categorical variables with dummies
churn_df['DummyGender'] = [1 if v == 'Male' else 0 for v in churn_df['Gender']]
churn_df['DummyChurn'] = [1 if v == 'Yes' else 0 for v in churn_df['Churn']] ### If the customer left (churned) they get a '1'
churn_df['DummyTechie'] = [1 if v == 'Yes' else 0 for v in churn_df['Techie']]
churn_df['DummyContract'] = [1 if v == 'Two Year' else 0 for v in churn_df['Contract']]
churn_df['DummyPort_modem'] = [1 if v == 'Yes' else 0 for v in churn_df['Port_modem']]
churn_df['DummyTablet'] = [1 if v == 'Yes' else 0 for v in churn_df['Tablet']]
churn_df['DummyInternetService'] = [1 if v == 'Fiber Optic' else 0 for v in churn_df['InternetService']]
churn_df['DummyPhone'] = [1 if v == 'Yes' else 0 for v in churn_df['Phone']]
churn_df['DummyMultiple'] = [1 if v == 'Yes' else 0 for v in churn_df['Multiple']]
churn_df['DummyOnlineSecurity'] = [1 if v == 'Yes' else 0 for v in churn_df['OnlineSecurity']]
churn_df['DummyOnlineBackup'] = [1 if v == 'Yes' else 0 for v in churn_df['OnlineBackup']]
churn_df['DummyDeviceProtection'] = [1 if v == 'Yes' else 0 for v in churn_df['DeviceProtection']]
churn_df['DummyTechSupport'] = [1 if v == 'Yes' else 0 for v in churn_df['TechSupport']]
churn_df['DummyStreamingTV'] = [1 if v == 'Yes' else 0 for v in churn_df['StreamingTV']]
churn_df['StreamingMovies'] = [1 if v == 'Yes' else 0 for v in churn_df['StreamingMovies']]
churn_df['DummyPaperlessBilling'] = [1 if v == 'Yes' else 0 for v in churn_df['PaperlessBilling']]
```

## 29 Drop original categorical features

```python
# Drop original categorical features from dataframe
churn_df = churn_df.drop(columns=['Gender', 'Churn', 'Techie', 'Contract', 'Port_modem', 'Tablet',
 'InternetService', 'Phone', 'Multiple', 'OnlineSecurity',
 'OnlineBackup', 'DeviceProtection', 'TechSupport',
 'StreamingTV', 'StreamingMovies', 'PaperlessBilling'])
```

## 30 Churn Head

```
churn_df.head()
```

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

5 rows × 48 columns

## 31 Remove categorical variables

```
# Remove less meaningful categorical variables from dataset to provide fully numerical dataframe for further analysis
churn_df = churn_df.drop(columns=['Customer_id', 'Interaction', 'UID',
'City', 'State', 'County', 'Zip', 'Lat', 'Lng',
'Area', 'TimeZone', 'Job', 'Marital', 'PaymentMethod'])
churn_df.head()
```

| CaseOrder | Population | Children | Age | Income | Outage_sec_perweek | Email | Contacts | Yearly_equip_failure | Tenure | MonthlyCharge | ... | DummyTablet | DummyInternetService | DummyPhone | DummyMultip |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 38 | 0 | 68 | 28561.99 | 7.978323 | 10 | 0 | 1 | 6.795513 | 172.455519 | ... | 1 | 1 | 1 | |
| 2 | 10446 | 1 | 27 | 21704.77 | 11.699080 | 12 | 0 | 1 | 1.156681 | 242.632554 | ... | 1 | 1 | 1 | |
| 3 | 3735 | 4 | 50 | 9609.57 | 10.752800 | 9 | 0 | 1 | 15.754144 | 159.947583 | ... | 0 | 0 | 1 | |
| 4 | 13863 | 1 | 48 | 18925.23 | 14.913540 | 15 | 2 | 0 | 17.087227 | 119.956840 | ... | 0 | 0 | 1 | |
| 5 | 11352 | 0 | 83 | 40074.19 | 8.147417 | 16 | 2 | 1 | 1.670972 | 149.948316 | ... | 0 | 1 | 0 | |

5 rows × 34 columns

## 32 Move DummyChurn

```
# Move DummyChurn to end of dataset to set as target
churn_df = churn_df[['Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email', 'Contacts',
'Yearly_equip_failure', 'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year',
'Timely_Response', 'Timely_Fixes', 'Timely_Replacements',
'Reliability', 'Options', 'Respectful_Response', 'Courteous_exchange', 'Active_Listening',
'DummyGender', 'DummyTechie', 'DummyContract',
'DummyPort_modem', 'DummyTablet', 'DummyInternetService', 'DummyPhone',
'DummyMultiple', 'DummyOnlineSecurity', 'DummyOnlineBackup',
'DummyDeviceProtection', 'DummyTechSupport', 'DummyStreamingTV',
'DummyPaperlessBilling', 'DummyChurn',]]
churn_df.head()
```

| CaseOrder | Children | Age | Income | Outage_sec_perweek | Email | Contacts | Yearly_equip_failure | Tenure | MonthlyCharge | Bandwidth_GB_Year | ... | DummyInte |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 68 | 28561.99 | 7.978323 | 10 | 0 | 1 | 6.795513 | 172.455519 | 904.536110 | ... | |
| 2 | 1 | 27 | 21704.77 | 11.699080 | 12 | 0 | 1 | 1.156681 | 242.632554 | 800.982766 | ... | |
| 3 | 4 | 50 | 9609.57 | 10.752800 | 9 | 0 | 1 | 15.754144 | 159.947583 | 2054.706961 | ... | |
| 4 | 1 | 48 | 18925.23 | 14.913540 | 15 | 2 | 0 | 17.087227 | 119.956840 | 2164.579412 | ... | |
| 5 | 0 | 83 | 40074.19 | 8.147417 | 16 | 2 | 1 | 1.670972 | 149.948316 | 271.493436 | ... | |

5 rows × 33 columns

### 33 List features

```
# List features for analysis
features = (list(churn_df.columns[:-1]))
print('Features for analysis include: \n', features)
```

```
Features for analysis include:
 ['Children', 'Age', 'Income', 'Outage_sec_perweek', 'Email', 'Contacts', 'Yearly_equip_failure', 'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year', 'Timely_Response',
'Timely_Fixes', 'Timely_Replacements', 'Reliability', 'Options', 'Respectful_Response', 'Courteous_exchange', 'Active_Listening', 'DummyGender', 'DummyTechie', 'Dumm
yContract', 'DummyPort_modem', 'DummyTablet', 'DummyInternetService', 'DummyPhone', 'DummyMultiple', 'DummyOnlineSecurity', 'DummyOnlineBackup', 'DummyDeviceProtecti
on', 'DummyTechSupport', 'DummyStreamingTV', 'DummyPaperlessBilling']
```

## C4: Dataset that has been cleaned

```
# Extract Clean dataset
churn_df.to_csv('C:\Rekha\churn_prepared.csv')
```

# Part IV: Analysis

```
# Re-read fully numerical prepared dataset
churn_df = pd.read_csv('C:\Rekha\churn_prepared.csv')
# Set predictor features & target variable
X = churn_df.drop('DummyChurn', axis=1).values
y = churn_df['DummyChurn'].values
```

```
# Import model, splitting method & 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
```

## D. Analysis and Comparison of Models

### D1. Data Segmentation:

```
# Set seed for reproducibility
SEED = 1
# Create training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = SEED)
```

```
# Instantiate KNN model
knn = KNeighborsClassifier(n_neighbors = 7)
# Fit data to KNN model
knn.fit(X_train, y_train)
# Predict outcomes from test set
y_pred = knn.predict(X_test)
```

## D2. Calculations for Output and Intermediate:

```
# Print initial accuracy score of KNN model
print('Initial accuracy score KNN model: ', accuracy_score(y_test, y_pred))
```

```
Initial accuracy score KNN model:  0.7145
```

```
# Compute classification metrics
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      0.83      0.81      1442
           1       0.49      0.40      0.44       558

    accuracy                           0.71      2000
   macro avg       0.63      0.62      0.62      2000
weighted avg       0.70      0.71      0.71      2000
```

## D3: Execution of Code:

```
# Create pipeline object & 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 = 0.2, random_state = SEED)
# Scale dateframe with pipeline object
knn_scaled = pipeline.fit(X_train_scaled, y_train_scaled)
# Predict from scaled dataframe
y_pred_scaled = pipeline.predict(X_test_scaled)
```

```
# Print new accuracy score of scaled KNN model
print('New accuracy score of scaled KNN model: {:0.3f}'.format(accuracy_score(y_test_scaled, y_pred_scaled)))
```

```
New accuracy score of scaled KNN model: 0.790
```

```
# Compute classification metrics after scaling
print(classification_report(y_test_scaled, y_pred_scaled))
```

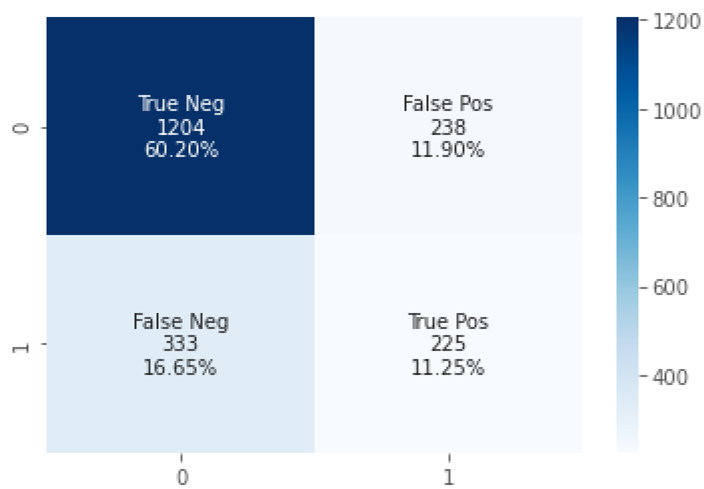
```
              precision    recall  f1-score   support

           0       0.84      0.88      0.86      1442
           1       0.64      0.56      0.60       558

    accuracy                           0.79      2000
   macro avg       0.74      0.72      0.73      2000
weighted avg       0.78      0.79      0.79      2000
```

```python
# Import sklearn confusion_matrix & generate results
from sklearn.metrics import confusion_matrix
cf_matrix = confusion_matrix(y_test, y_pred)
print(cf_matrix)
```

```
[[1204  238]
 [ 333  225]]
```

```python
# Create a visually more intuitive confusion matrix
"""(Dennis, pg. 1)"""
group_names = ['True Neg', 'False Pos', 'False Neg', 'True Pos']
group_counts = ["{0:0.0f}".format(value) for value in
cf_matrix.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in
cf_matrix.flatten()/np.sum(cf_matrix)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
zip(group_names,group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(cf_matrix, annot=labels, fmt='', cmap='Blues')
```

```
<AxesSubplot:>
```



## Part V:

Scaling the model raised accuracy and precision from 0.71 to 0.79 and 0.78 to 0.84, respectively. 0.7959 is a good score for the area under the curve.

### E1. Perform the following AUC & Accuracy model

```
# Import GridSearchCV for cross validation of model
from sklearn.model_selection import GridSearchCV

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

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

# Instantiate GridSearch cross validation
knn_cv = GridSearchCV(knn , param_grid, cv=5)

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

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

```
Best parameters for this KNN model: {'n_neighbors': 6}
```

```
# Generate model best score
print('Best score for this KNN model: {:.3f}'.format(knn_cv.best_score_))
```

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

```
# Import ROC AUC metrics for explaining the area under the curve
from sklearn.metrics import roc_auc_score

# Fit it to the data
knn_cv.fit(X, y)

# Compute predicted probabilities: y_pred_prob
y_pred_prob = knn_cv.predict_proba(X_test)[:,1]

# Compute and 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: 0.7959
```

```
# Compute cross-validated AUC scores: cv_auc
cv_auc = cross_val_score(knn_cv, 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]
```

### E2. Conclusions and Implications:

Attached the calculations and code outputs.

### E3. Constraints/Limitations:

"When utilizing the k-nearest neighbors' technique, you can alter the value of k to get drastically different results. You determine the value of k by experimenting with different values and evaluating the model's prediction abilities. This means you'll need to create, validate, and test a number of models " (Grant, pg. 1).

This indicates that if we select a different KNN, our very random choice of k = 7 nearest neighbors could have radically different results. Perhaps it should be the 6 closest neighbors, as we discovered in our cross-validation grid search.
It also looks to be memory- and computationally taxing. To put it another way, it takes a long time to compute.

### E4. Plan of Action:

It's vital for marketers and decision-makers to recognize that the accuracy of our prediction factors is low, with an after-scaling result of 0.84. We should look at the qualities that are frequent with people leaving the company and strive to reduce the likelihood that they would occur with any future consumer. This means that as more of the company's services are subscribed by the customers, including a second port modem or online backup, they will receive a discount, they have a lower chance of leaving. Certainly, providing more services to clients and improving their experience with the company is in the company's best interests. supporting customers in comprehending all the services available to them as a subscriber, It's more than just a mobile phone service.

# Part VI: Documentary Evidence

## F. Panopto video recording:

https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=1962cf6d-5187-48d0-a6c6-ae06000c0fd2

## G. Third Party Evidence:

Practiced code: Bivariate plotting with pandas
URL: https://www.kaggle.com

Practiced code: GeeksforGeeks (July 4th, 2019)
URL: https://www.geeksforgeeks.org/python-visualize-missing-values-nanvalues-using-missingno-library/

Practiced code: Dennis. T. (July 25th, 2019)
Confusion Matrix Visualization. Medium.
URL: https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30fea/

Article: Predict Customer Churn in Python.
URL: https://towardsdatascience.com/

LinkedIn: https://www.linkedin.com/learning/python-statistics-essential-training/introducing-pandas?u=2045532

## H. References:

[1] Grant p. (July21, 2019) Introducing K-nearest Neighbors. https://towardsdatascience.com/introducing-k-nearest-neighbors-7bcd10f938c5

[2] Massaron, L. & Boschetti, A. (2016). Regression Analysis with Python. Packt Publishing.

[3] CBTNuggets. (2018, September 20). Why Data Scientists Love Python.