ClusterChamps_Marketing_Phase2

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0.0.1 Group Cluster Champs Final Project Phase 2

Topic- Marketing Campaign Analysis

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2 Import Libraries and Dataset

[1]:
```
import os
import pandas as pd
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
import matplotlib.pylab as plt
import matplotlib.pyplot as plt
from dmba import plotDecisionTree, classificationSummary, regressionSummary
from sklearn.linear_model import LinearRegression, Lasso, Ridge, LassoCV,␣
↪BayesianRidge
import matplotlib.pylab as plt
import seaborn as sns
from pathlib import Path
import statsmodels.formula.api as sm
from sklearn import linear_model
```

```
from sklearn import metrics
from sklearn.naive_bayes import GaussianNB
from sklearn.impute import KNNImputer
%matplotlib inline
from pathlib import Path
from scipy import stats
```

```
no display found. Using non-interactive Agg backend
```

[2]:
```
# read data file
df= pd.read_csv('marketing_campaign.csv', delimiter = ';')
df.head(10)
```

[2]:
```
     ID  Year_Birth   Education Marital_Status   Income  Kidhome  Teenhome  \
0  5524        1957  Graduation         Single  58138.0        0         0
1  2174        1954  Graduation         Single  46344.0        1         1
2  4141        1965  Graduation       Together  71613.0        0         0
3  6182        1984  Graduation       Together  26646.0        1         0
4  5324        1981         PhD        Married  58293.0        1         0
5  7446        1967      Master       Together  62513.0        0         1
6   965        1971  Graduation       Divorced  55635.0        0         1
7  6177        1985         PhD        Married  33454.0        1         0
8  4855        1974         PhD       Together  30351.0        1         0
9  5899        1950         PhD       Together   5648.0        1         1

  Dt_Customer  Recency  MntWines  …  NumWebVisitsMonth  AcceptedCmp3  \
0  2012-09-04       58       635  …                  7             0
1  2014-03-08       38        11  …                  5             0
2  2013-08-21       26       426  …                  4             0
3  2014-02-10       26        11  …                  6             0
4  2014-01-19       94       173  …                  5             0
5  2013-09-09       16       520  …                  6             0
6  2012-11-13       34       235  …                  6             0
7  2013-05-08       32        76  …                  8             0
8  2013-06-06       19        14  …                  9             0
9  2014-03-13       68        28  …                 20             1

   AcceptedCmp4  AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  Complain  \
0             0             0             0             0         0
1             0             0             0             0         0
2             0             0             0             0         0
3             0             0             0             0         0
4             0             0             0             0         0
5             0             0             0             0         0
6             0             0             0             0         0
7             0             0             0             0         0
8             0             0             0             0         0
```

```
9              0              0              0              0          0

   Z_CostContact  Z_Revenue  Response
0              3         11         1
1              3         11         0
2              3         11         0
3              3         11         0
4              3         11         0
5              3         11         0
6              3         11         0
7              3         11         0
8              3         11         1
9              3         11         0

[10 rows x 29 columns]
```

[3]:
```
# Get total number of rows and columns
df.shape
```

[3]: (2240, 29)

2.0.1 Drop 'ID' column

The ID column will not give us any useful information so we will drop it.

[4]:
```
# drop ID coloumn
df = df.drop(['ID'], axis = 1)
```

3 Exploratory Data Analysis

We will do an exploratory analysis on the dataset, to summarize it and also get an understanding of what we are working with.

3.0.1 1 a. Target Variable

As per the dataset, the column Response (target) in itself is one of the campaigns (last campaign). So, in total there are 6 campaigns.

Let's create a target variable called 'Customer_Response' where the value will be 1 if the customer responds to any of the 6 campaigns and 0 if the customer has not responded to any campaign.

[5]:
```
df['Customer_Response'] = np.where(df[['AcceptedCmp1', 'AcceptedCmp2',␣
↪'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'Response']].sum(axis=1) >=␣
↪1, 1, 0)
```

[6]:
```python
# Renaming the 6th campaign name to intuitive column name
df.rename(columns={'Response': 'AcceptedCmp6'}, inplace=True)
```

3.0.2 Frequency of the target variable.

[7]:
```python
df['Customer_Response'].value_counts()
```

[7]:
```
0    1631
1     609
Name: Customer_Response, dtype: int64
```

Explanation: 1631 is the number of instances for 0, which tells that there are 1631 customers who have not responded to the any of the campaign.

609 is the number of instances for 1, which tells that there are 609 customers who have responded to atleast one of the campaign.

We can also see that creating the 'Customer_Reponse' variable reduced the number of '0's and provides a holoistic view if the customers ever accepted the offers through the campaigns.

As new target variable i.e 'Customer_response' is created from the 6 campaigns , there is no more use of the 6 campaign columns, so we can drop it.

Also dropping column 'Z_CostContact' & 'Z_Revenue' as they are constant variables.

[8]:
```python
df = df.drop(['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3', 'AcceptedCmp4',␣
↪'AcceptedCmp5', 'AcceptedCmp6', 'Z_CostContact', 'Z_Revenue'], axis = 1)
```

3.0.3 1 b. Missing Values

Checking the type of data to understand what all columns it contains and of what types and whether they contain any value or not.

[9]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 21 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Year_Birth           2240 non-null   int64
 1   Education            2240 non-null   object
 2   Marital_Status       2240 non-null   object
 3   Income               2216 non-null   float64
 4   Kidhome              2240 non-null   int64
 5   Teenhome             2240 non-null   int64
```

```
 6   Dt_Customer          2240 non-null   object
 7   Recency              2240 non-null   int64
 8   MntWines             2240 non-null   int64
 9   MntFruits            2240 non-null   int64
 10  MntMeatProducts      2240 non-null   int64
 11  MntFishProducts      2240 non-null   int64
 12  MntSweetProducts     2240 non-null   int64
 13  MntGoldProds         2240 non-null   int64
 14  NumDealsPurchases    2240 non-null   int64
 15  NumWebPurchases      2240 non-null   int64
 16  NumCatalogPurchases  2240 non-null   int64
 17  NumStorePurchases    2240 non-null   int64
 18  NumWebVisitsMonth    2240 non-null   int64
 19  Complain             2240 non-null   int64
 20  Customer_Response    2240 non-null   int64
dtypes: float64(1), int64(17), object(3)
memory usage: 367.6+ KB
```

So we see that we have 3 categorical variables and 26 numerical variables. We can also see that there are missing values in the column ‘Income’. We will do missing value treatment later.

[10]:
```python
# Recalculating the missing values in the dataset
df.isnull().sum()
```

[10]:
```
Year_Birth              0
Education               0
Marital_Status          0
Income                 24
Kidhome                 0
Teenhome                0
Dt_Customer             0
Recency                 0
MntWines                0
MntFruits               0
MntMeatProducts         0
MntFishProducts         0
MntSweetProducts        0
MntGoldProds            0
NumDealsPurchases       0
NumWebPurchases         0
NumCatalogPurchases     0
NumStorePurchases       0
NumWebVisitsMonth       0
Complain                0
Customer_Response       0
dtype: int64
```

Only ‘Income’ valriable has missing values. There are 24 missing values for the ‘Income’ variable.

Let's understand more about column 'Income'.

[11]:
```
df["Income"].describe()
```

[11]:
```
count      2216.000000
mean      52247.251354
std       25173.076661
min        1730.000000
25%       35303.000000
50%       51381.500000
75%       68522.000000
max      666666.000000
Name: Income, dtype: float64
```

Explanation: Handling missing values can be done in few ways-

We can delete the entire column containing null-values.

Delete the rows containing null-values or can impute the mean value.

So, here we are treating the missing values in 'Income' column by Imputation method. Imputation fills in the missing value with some number. The imputed value won't be exactly right in most cases, but it usually gives more accurate models than dropping the column entirely.

[12]:
```
missing_col = ['Income']
#Technique : Using mean to impute the missing values
for i in missing_col:
    df.loc[df.loc[:,i].isnull(),i]=df.loc[:,i].mean()
```

[13]:
```
print("count of NULL values after imputation\n")
df.isnull().sum()
```

```
count of NULL values after imputation
```

[13]:
```
Year_Birth             0
Education              0
Marital_Status         0
Income                 0
Kidhome                0
Teenhome               0
Dt_Customer            0
Recency                0
MntWines               0
MntFruits              0
MntMeatProducts        0
MntFishProducts        0
MntSweetProducts       0
MntGoldProds           0
```

```
NumDealsPurchases       0
NumWebPurchases         0
NumCatalogPurchases     0
NumStorePurchases       0
NumWebVisitsMonth       0
Complain                0
Customer_Response       0
dtype: int64
```

Now there are no null values after imputation

[14]:
```
# Calculating number of Zeroes in each of the columns to find anomalies if any␣
↪(such as high number of zeroes in Year_Birth)
df.isin([0]).sum()
```

[14]:
```
Year_Birth                 0
Education                  0
Marital_Status             0
Income                     0
Kidhome                 1293
Teenhome                1158
Dt_Customer                0
Recency                   28
MntWines                  13
MntFruits                400
MntMeatProducts            1
MntFishProducts          384
MntSweetProducts         419
MntGoldProds              61
NumDealsPurchases         46
NumWebPurchases           49
NumCatalogPurchases      586
NumStorePurchases         15
NumWebVisitsMonth         11
Complain                2219
Customer_Response       1631
dtype: int64
```

Based on above table, there are no anomalies found in terms of '0's in the variables

3.0.4 1 b. Checking for duplicates

Let's check for duplicate rows and drop them if necessary. Then we'll do a recount of duplicates to double check that they were dropped.

[15]:
```
# duplicate count
df.duplicated().sum()
```

[15]: 189

[16]:
```
# drop duplicates and reset index
df = df.drop_duplicates().reset_index(drop = True)
```

[17]:
```
# The duplicated values are indicated as True values in the resulting Series
df.duplicated().sum()
```

[17]: 0

Explanation After performing the action to remove duplicates the total number of rows are still 2240 which tells that there are no duplicate values in the dataset.

3.0.5 1 c. Variable Relationships

[18]:
```
df.shape
```

[18]: (2051, 21)

[19]:
```
# Statistical summary of data frame
df.describe([.01,.1,.2,.3,.4,.5,.6,.7,.8,.9,.99])
```

[19]:
```
        Year_Birth         Income      Kidhome     Teenhome      Recency  \
count  2051.000000    2051.000000  2051.000000  2051.000000  2051.000000
mean   1968.798147   52337.652381     0.445636     0.508532    48.972696
std      11.970297   25382.967842     0.537695     0.546653    29.005100
min    1893.000000    1730.000000     0.000000     0.000000     0.000000
1%     1945.000000    7500.000000     0.000000     0.000000     0.000000
10%    1952.000000   24336.000000     0.000000     0.000000     9.000000
20%    1957.000000   32313.000000     0.000000     0.000000    19.000000
30%    1962.000000   38547.000000     0.000000     0.000000    29.000000
40%    1966.000000   45072.000000     0.000000     0.000000    39.000000
50%    1970.000000   52034.000000     0.000000     0.000000    49.000000
60%    1973.000000   58025.000000     1.000000     1.000000    59.000000
70%    1976.000000   65031.000000     1.000000     1.000000    70.000000
80%    1979.000000   71670.000000     1.000000     1.000000    79.000000
90%    1984.000000   79761.000000     1.000000     1.000000    89.000000
99%    1992.000000   94557.000000     2.000000     2.000000    98.000000
max    1996.000000  666666.000000     2.000000     2.000000    99.000000

          MntWines    MntFruits  MntMeatProducts  MntFishProducts  \
count  2051.000000  2051.000000      2051.000000      2051.000000
mean    302.902974    26.227694       167.313506        37.300341
std     335.657543    39.743769       227.513616        54.591382
min       0.000000     0.000000         0.000000         0.000000
```

1%	1.000000	0.000000	2.000000	0.000000
10%	6.000000	0.000000	7.000000	0.000000
20%	16.000000	1.000000	12.000000	2.000000
30%	34.000000	2.000000	20.000000	3.000000
40%	84.000000	4.000000	35.000000	7.000000
50%	173.000000	8.000000	67.000000	12.000000
60%	283.000000	14.000000	108.000000	20.000000
70%	415.000000	25.000000	175.000000	37.000000
80%	576.000000	44.000000	292.000000	65.000000
90%	817.000000	82.000000	501.000000	120.000000
99%	1285.000000	172.000000	923.000000	226.000000
max	1493.000000	199.000000	1725.000000	259.000000

	MntSweetProducts	MntGoldProds	NumDealsPurchases	NumWebPurchases	\
count	2051.000000	2051.000000	2051.000000	2051.000000	
mean	27.128230	43.893223	2.333496	4.098489	
std	41.621742	52.186942	1.934272	2.799138	
min	0.000000	0.000000	0.000000	0.000000	
1%	0.000000	0.000000	0.000000	0.000000	
10%	0.000000	3.000000	1.000000	1.000000	
20%	1.000000	6.000000	1.000000	2.000000	
30%	2.000000	11.000000	1.000000	2.000000	
40%	5.000000	16.000000	1.000000	3.000000	
50%	8.000000	24.000000	2.000000	4.000000	
60%	14.000000	34.000000	2.000000	4.000000	
70%	26.000000	46.000000	3.000000	5.000000	
80%	44.000000	72.000000	3.000000	6.000000	
90%	89.000000	122.000000	5.000000	8.000000	
99%	178.500000	228.000000	10.000000	11.000000	
max	263.000000	362.000000	15.000000	27.000000	

	NumCatalogPurchases	NumStorePurchases	NumWebVisitsMonth	Complain	\
count	2051.000000	2051.000000	2051.000000	2051.000000	
mean	2.657728	5.767918	5.319844	0.009751	
std	2.936044	3.238302	2.440130	0.098290	
min	0.000000	0.000000	0.000000	0.000000	
1%	0.000000	1.000000	1.000000	0.000000	
10%	0.000000	2.000000	2.000000	0.000000	
20%	0.000000	3.000000	3.000000	0.000000	
30%	1.000000	3.000000	4.000000	0.000000	
40%	1.000000	4.000000	5.000000	0.000000	
50%	2.000000	5.000000	6.000000	0.000000	
60%	2.000000	6.000000	6.000000	0.000000	
70%	4.000000	7.000000	7.000000	0.000000	
80%	5.000000	9.000000	7.000000	0.000000	
90%	7.000000	11.000000	8.000000	0.000000	
99%	11.000000	13.000000	9.000000	0.000000	

```
max              28.000000          13.000000          20.000000     1.000000

       Customer_Response
count        2051.000000
mean            0.274013
std             0.446124
min             0.000000
1%              0.000000
10%             0.000000
20%             0.000000
30%             0.000000
40%             0.000000
50%             0.000000
60%             0.000000
70%             0.000000
80%             1.000000
90%             1.000000
99%             1.000000
max             1.000000
```

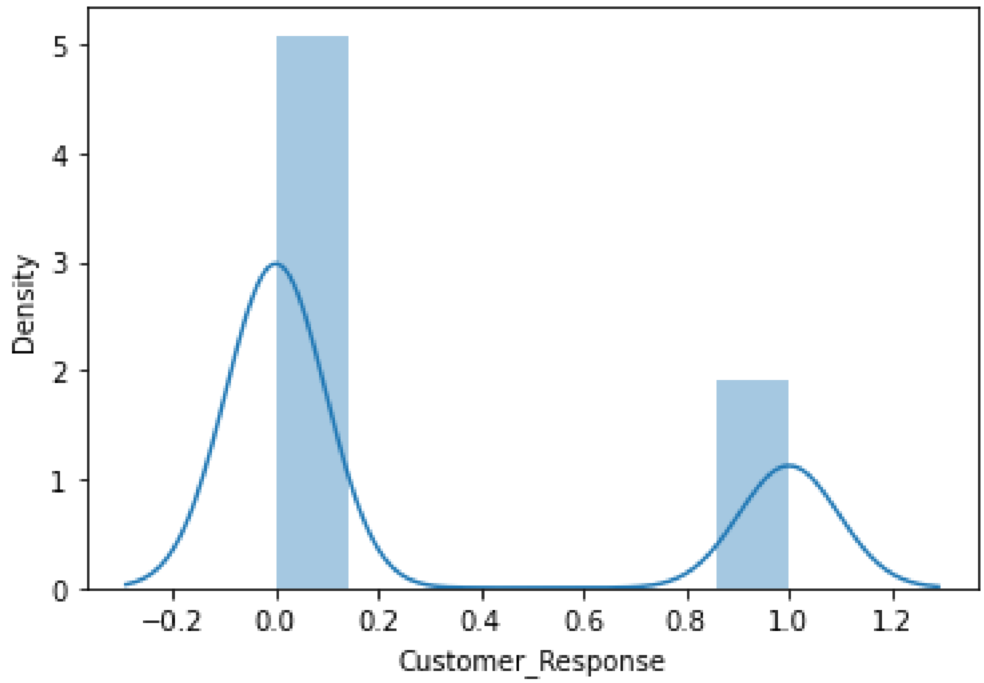
To understand the relationship between dependent variable and independent variables, here creating plot and heatmap.

[20]:
```python
predictors = [ 'Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Dt_Customer', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',␣
 ↪'Complain']

outcome = 'Customer_Response'
```

[21]:
```python
sns.distplot(df['Customer_Response'])
```

```
/Users/akhilapamukuntla/opt/anaconda3/lib/python3.8/site-
packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[21]:
```
<AxesSubplot:xlabel='Customer_Response', ylabel='Density'>
```



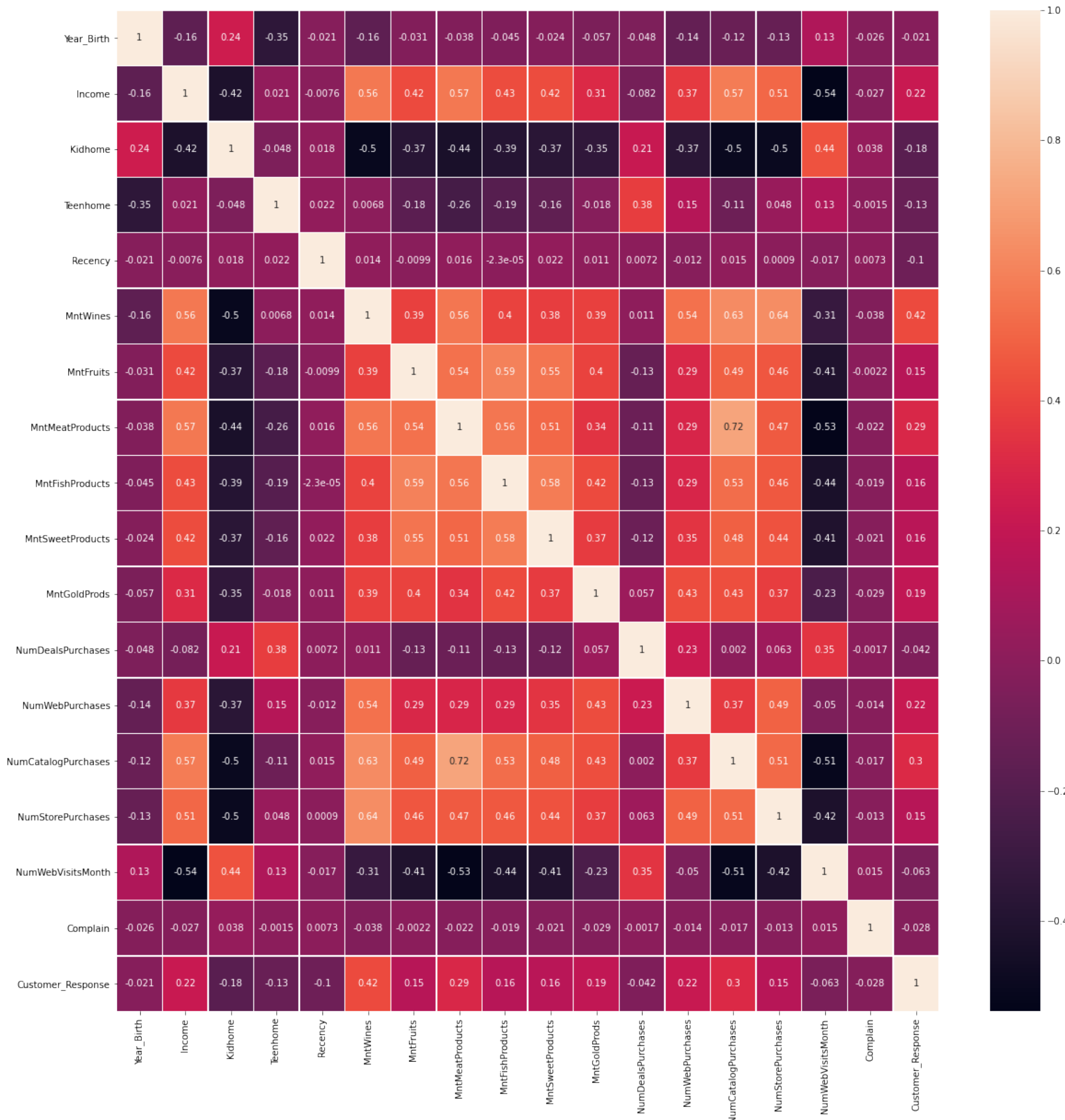
Above graph shows the ratio between the customers who responded to any of the campaigns and those who never responded to any campaign

[22]:
```
df['Customer_Response'].sum()
```

[22]: 562

Heatmap

[23]:
```
df_small = df.iloc[:,:29]
correlation_mat = df_small.corr()
fig, ax = plt.subplots(figsize=(20,20))
sns.heatmap(correlation_mat, annot = True, linewidths=.5)
plt.show()
```



Explanation Each square of the heatmap shows correlation between the variables on each axis. Values closer to zero means there is no linear trend between the two variables. The close to 1 correlation is positively correlated. Taking positive 0.4 as the benchmark, we can check, which variables have more postive corelarion with other variables.

3.0.6 1 d. Outliers:

Here identifying the outliers with interquartile range

[24]:
```
#Sorting the dataset
# 50th percentile is median
sorted(df)
Q1=df.quantile(0.25)
Q3=df.quantile(0.75)
IQR=Q3-Q1
print(IQR)
```

```
Year_Birth              18.0
Income               32516.5
Kidhome                  1.0
Teenhome                 1.0
Recency                 50.0
MntWines               479.5
MntFruits               31.5
MntMeatProducts        213.0
MntFishProducts         47.0
MntSweetProducts        32.5
MntGoldProds            47.0
NumDealsPurchases        2.0
NumWebPurchases          4.0
NumCatalogPurchases      4.0
NumStorePurchases        5.0
NumWebVisitsMonth        4.0
Complain                 0.0
Customer_Response        1.0
dtype: float64
```

[25]:
```
((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).sum()
```

```
<ipython-input-25-40a85132028f>:1: FutureWarning: Automatic reindexing on
DataFrame vs Series comparisons is deprecated and will raise ValueError in a
future version.  Do `left, right = left.align(right, axis=1, copy=False)` before
e.g. `left == right`
  ((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).sum()
<ipython-input-25-40a85132028f>:1: FutureWarning: Automatic reindexing on
DataFrame vs Series comparisons is deprecated and will raise ValueError in a
future version.  Do `left, right = left.align(right, axis=1, copy=False)` before
e.g. `left == right`
  ((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).sum()
```

[25]:
```
Complain               20
Customer_Response       0
Dt_Customer             0
Education               0
Income                  8
Kidhome                 0
```

```
Marital_Status          0
MntFishProducts       202
MntFruits             211
MntGoldProds          187
MntMeatProducts       174
MntSweetProducts      223
MntWines               34
NumCatalogPurchases    22
NumDealsPurchases      77
NumStorePurchases       0
NumWebPurchases         4
NumWebVisitsMonth       8
Recency                 0
Teenhome                0
Year_Birth              3
dtype: int64
```

Explanation: There are different outlier treatments like by calculating mean and median, but one of the most commonly used approach is calculating percentile value and replacing the outliers with that percentile value.

Here the complain variable do not require an outlier treatment as it has binary values(1, 0).

As the next step, will understand the outliers with visualization starting with 'Income' variable. And after doing the outlier treatment we will again find the relationship between variables.

[26]:
```
#Shows the skewness value of Income and also summary statistics
print(df['Income'].skew())
df['Income'].describe([.01,.1,.2,.3,.4,.5,.6,.7,.8,.9,.99])
```

```
7.120444939794689
```

[26]:
```
count     2051.000000
mean     52337.652381
std      25382.967842
min       1730.000000
1%        7500.000000
10%      24336.000000
20%      32313.000000
30%      38547.000000
40%      45072.000000
50%      52034.000000
60%      58025.000000
70%      65031.000000
80%      71670.000000
90%      79761.000000
99%      94557.000000
```

```
max      666666.000000
Name: Income, dtype: float64
```

Explanation: The skewness value of 7.12 shows that the variable 'Income' has right-skewes distribution, indicating the presence of extreme values.

Based on research, skewness value greater than 3.5 shows skewness. https://stats.stackexchange.com/questions/436274/performing-t-test-on-highly-skewed-financial-data-outlier-treatment#:~:text=After%20treating%20for%20outliers%2C%20most,and%20%2B1.5%20max%20is%

3.0.7 Outliers Treatment

Quantile-based Flooring and Capping

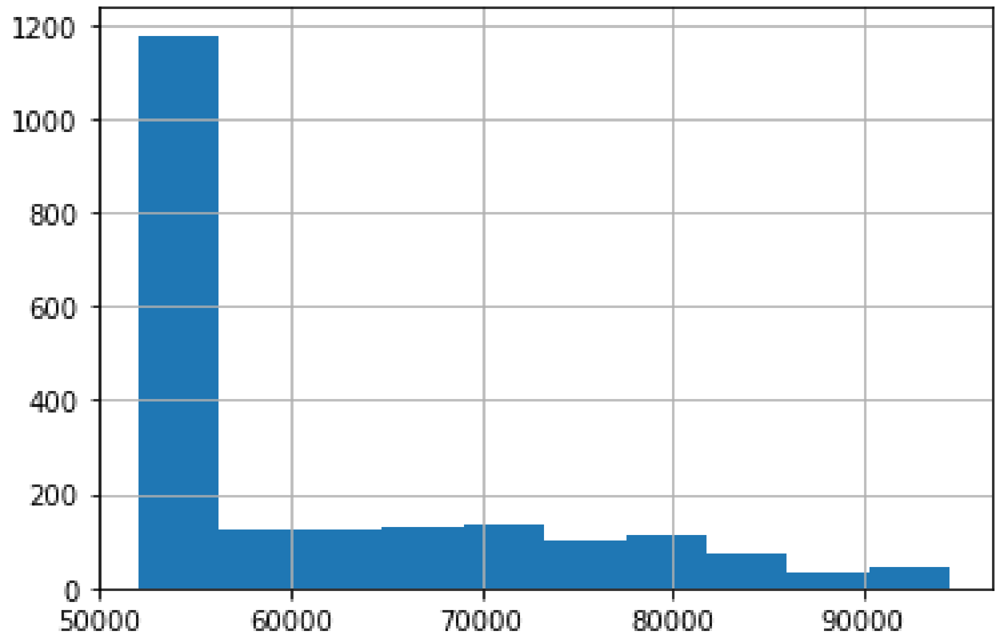
[27]:
```python
print(df['Income'].quantile(0.5))
print(df['Income'].quantile(0.99))
```

```
52034.0
94557.0
```

[28]:
```python
# Now we will remove the outliers of 'Income' and calculate the skewness value again
df["Income"] = np.where(df["Income"] <df['Income'].quantile(0.5), df['Income'].quantile(0.5),df['Income'])
df["Income"] = np.where(df["Income"] >df['Income'].quantile(0.99), df['Income'].quantile(0.99),df['Income'])
print(df['Income'].skew())
df.Income.hist()
```

```
1.1653097906825942
```

[28]:
```
<AxesSubplot:>
```



[29]:
```
#Outlier treatment for "MntMeatProducts"
print(df['MntMeatProducts'].quantile(0.1))
print(df['MntMeatProducts'].quantile(0.99))
```

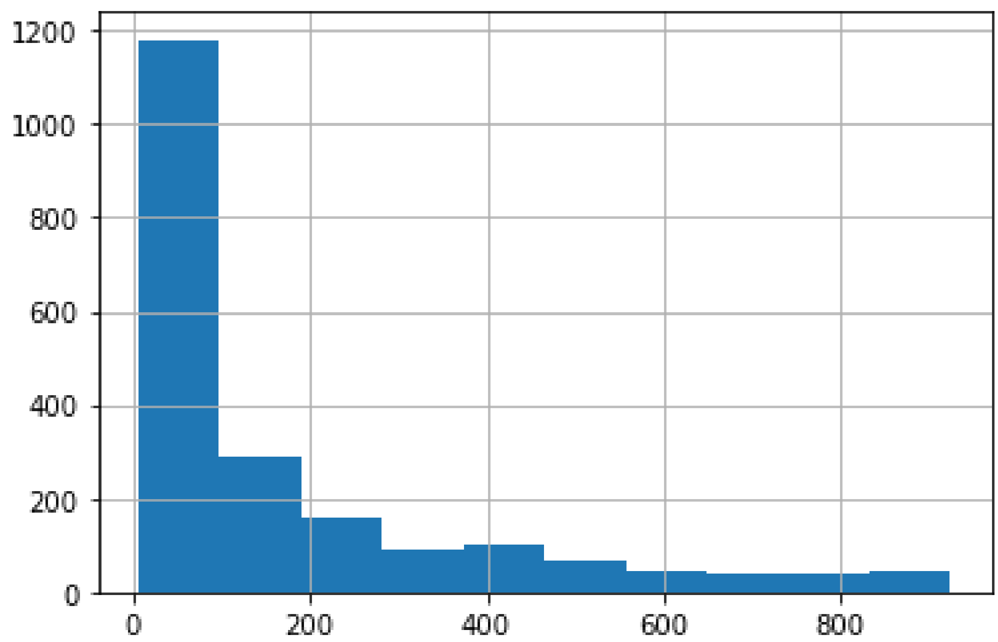
```
7.0
923.0
```

[30]:
```
df["MntMeatProducts"] = np.where(df["MntMeatProducts"] <df['MntMeatProducts'].
 ↪quantile(0.1), df['MntMeatProducts'].quantile(0.1),df['MntMeatProducts'])
df["MntMeatProducts"] = np.where(df["MntMeatProducts"] >df['MntMeatProducts'].
 ↪quantile(0.99), df['MntMeatProducts'].quantile(0.99),df['MntMeatProducts'])
```

[31]:
```
#After treatment SKewness and distribution of data points through histogram.
print(df['MntMeatProducts'].skew())
df.MntMeatProducts.hist()
```

```
1.7238773596047992
```

[31]: <AxesSubplot:>




```
[32]: #Outlier treatment for "NumWebPurchases"
print(df['NumWebPurchases'].quantile(0.01))
print(df['NumWebPurchases'].quantile(0.99))
```

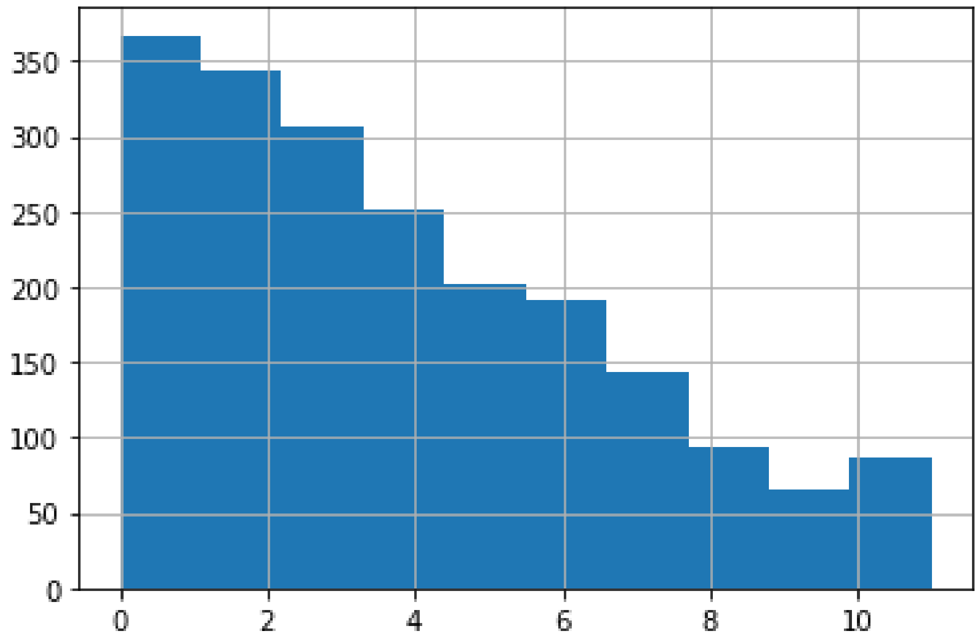
```
0.0
11.0
```

```
[33]: df["NumWebPurchases"] = np.where(df["NumWebPurchases"] <df['NumWebPurchases'].
 ↪quantile(0.01), df['NumWebPurchases'].quantile(0.01),df['NumWebPurchases'])
df["NumWebPurchases"] = np.where(df["NumWebPurchases"] >df['NumWebPurchases'].
 ↪quantile(0.99), df['NumWebPurchases'].quantile(0.99),df['NumWebPurchases'])
```

```
[34]: #After treatment SKewness and distribution of data points through histogram.
print(df['NumWebPurchases'].skew())
df.NumWebPurchases.hist()
```

```
0.70144368248077
```

```
[34]: <AxesSubplot:>
```




```
[35]: print(df['NumCatalogPurchases'].quantile(0.01))
      print(df['NumCatalogPurchases'].quantile(0.99))
```

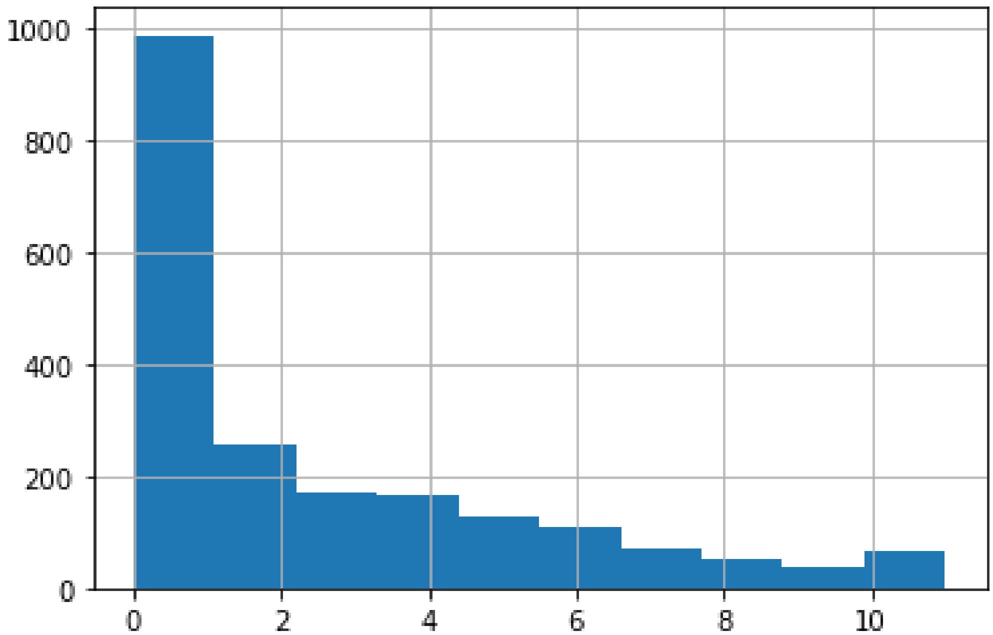
```
0.0
11.0
```

```
[36]: df["NumCatalogPurchases"] = np.where(df["NumCatalogPurchases"]␣
       ↪<df['NumCatalogPurchases'].quantile(0.01), df['NumCatalogPurchases'].
       ↪quantile(0.01),df['NumCatalogPurchases'])
      df["NumCatalogPurchases"] = np.where(df["NumCatalogPurchases"]␣
       ↪>df['NumCatalogPurchases'].quantile(0.99), df['NumCatalogPurchases'].
       ↪quantile(0.99),df['NumCatalogPurchases'])
```

```
[37]: print(df['NumCatalogPurchases'].skew())
      df.NumCatalogPurchases.hist()
```

```
1.1344367713369197
```

```
[37]: <AxesSubplot:>
```



[38]:
```
print(df['NumWebVisitsMonth'].quantile(0.01))
print(df['NumWebVisitsMonth'].quantile(0.99))
```

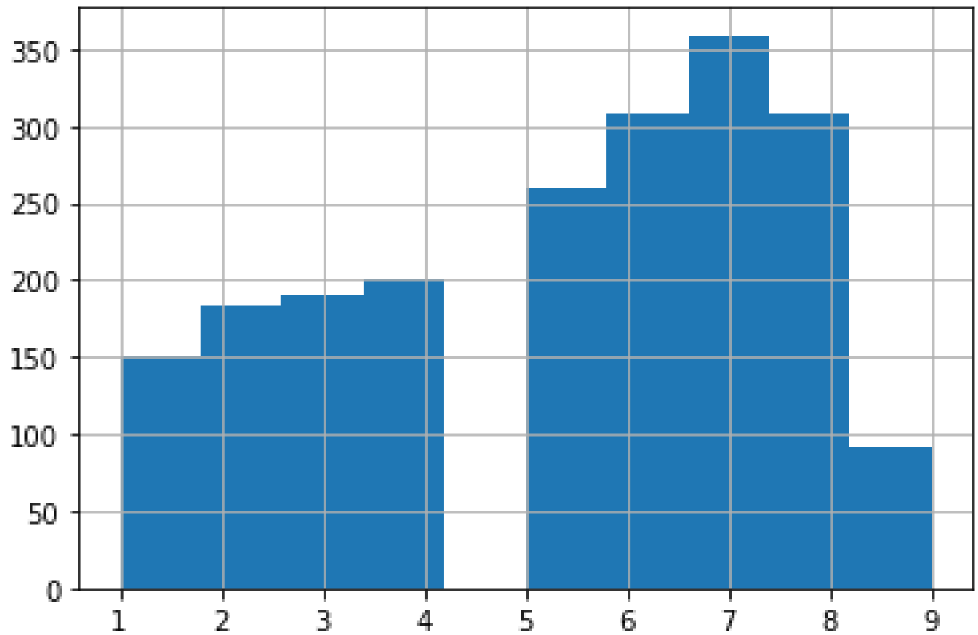
```
1.0
9.0
```

[39]:
```
df["NumWebVisitsMonth"] = np.where(df["NumWebVisitsMonth"]␣
↪<df['NumWebVisitsMonth'].quantile(0.01),df['NumWebVisitsMonth'].quantile(0.
↪01),df['NumWebVisitsMonth'])
df["NumWebVisitsMonth"] = np.where(df["NumWebVisitsMonth"]␣
↪>df['NumWebVisitsMonth'].quantile(0.99), df['NumWebVisitsMonth'].quantile(0.
↪99),df['NumWebVisitsMonth'])
```

[40]:
```
print(df['NumWebVisitsMonth'].skew())
df.NumWebVisitsMonth.hist()
```

```
-0.3320145683081151
```

[40]: <AxesSubplot:>



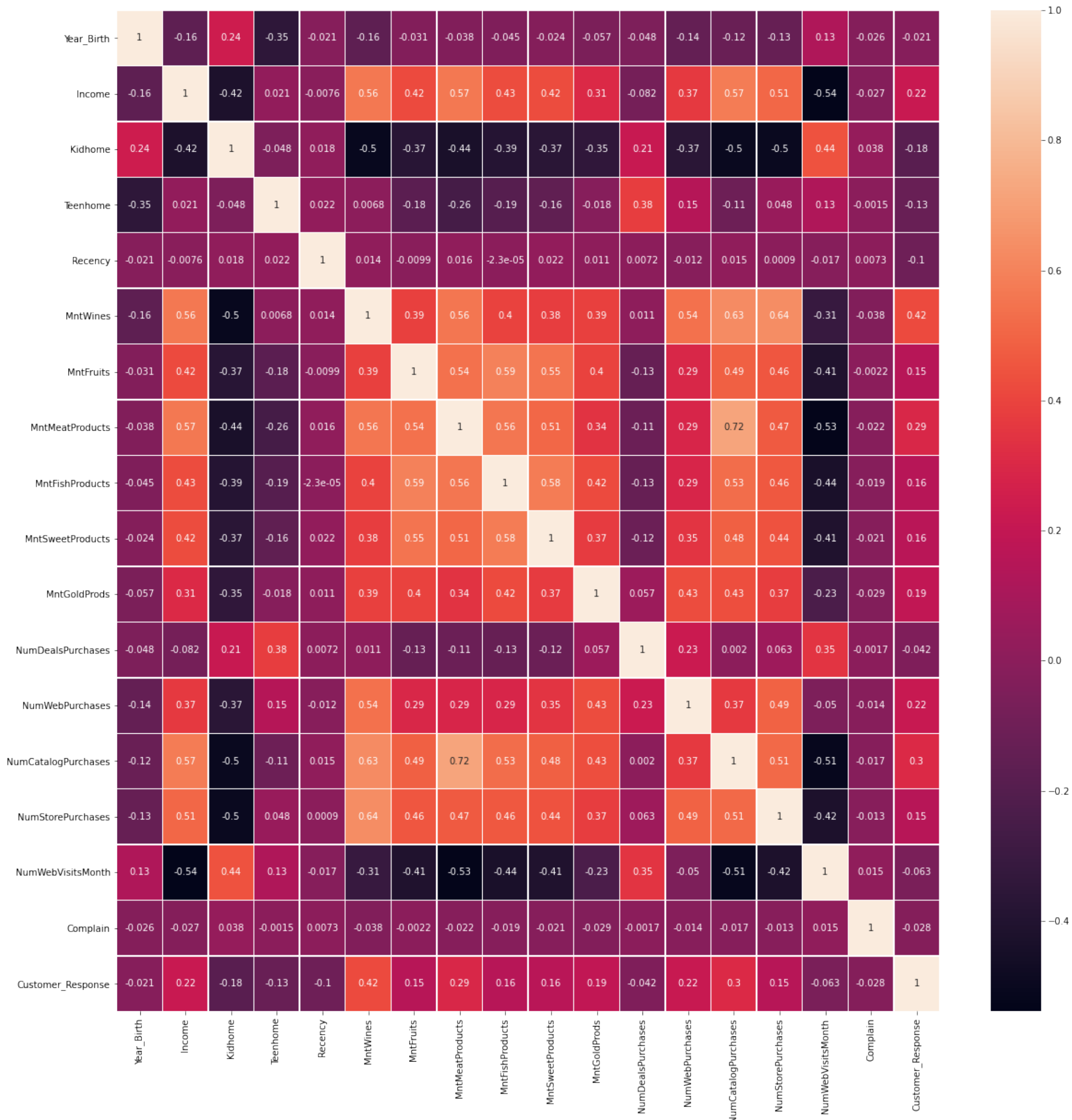
Explanation: So, after the outlier treatment the number of rows are same as before.

[41]:
```
df.shape
```

[41]: (2051, 21)

3.0.8 Correlation Matrix after Outlier Treatment

[42]:
```
df_after = df.iloc[:,:29]
correlation_mat = df_small.corr()
fig, ax = plt.subplots(figsize=(20,20))
sns.heatmap(correlation_mat, annot = True, linewidths=.5)
plt.show()
```



3.0.9 Understanding columns of dataset

Listed unique values in the column ‘Marital_Status’, to understand the types of it.

[43]:
```
df.Marital_Status.unique()
```

[43]:
```
array(['Single', 'Together', 'Married', 'Divorced', 'Widow', 'Alone',
       'Absurd', 'YOLO'], dtype=object)
```

From Business perspective, accepted Marital Status coule be single, married, together(not married), divorced, and widow. Apart from these marital status, the rest ‘Alone’, ‘YOLO’, ‘Absurd’ can be considered as ‘Single’.

So replacing the data cells which have ‘Alone’, ‘YOLO’, ‘Absurd’ with ‘Single’.

[44]:
```
df['Marital_Status'] = df['Marital_Status'].
↪replace(['Absurd','YOLO','Alone'],['Single','Single','Single'])
```

[45]:
```
df.Marital_Status.unique()
```

[45]:
```
array(['Single', 'Together', 'Married', 'Divorced', 'Widow'], dtype=object)
```

Now, to understand the types of Education that respondents have in the dataset, listed unique values in the ‘Education’ column

[46]:
```
df.Education.unique()
```

[46]:
```
array(['Graduation', 'PhD', 'Master', 'Basic', '2n Cycle'], dtype=object)
```

Education has degree ‘2n Cycle’ and ‘Masters’ which means the same so we will change that

[47]:
```
df['Education'].value_counts().index.sort_values(ascending=True)
```

[47]:
```
Index(['2n Cycle', 'Basic', 'Graduation', 'Master', 'PhD'], dtype='object')
```

[48]:
```
df['Education'] = df["Education"].replace('2n Cycle', "Master")
```

4 2. Baseline Model

4.0.1 Explanation

Here we’ll run a baseline model without feature engineering to get an idea of the predictive power of some models. We decided to use a variety of models to compare and contrast. The models are Logistic Regression, Support Vector Machines, Stoachasic Gradient Descent, K-nearest neighbor Classifer, Decision Trees, Multi-Layer Perception Classifier, and Naive Bayes. We will run them all at the same time and compare the performence metrics of each.

[49]:
```
# specify attributes and target column
predictors =␣
↪['Year_Birth','Education','Income','Kidhome','Teenhome','Recency','MntWines','MntFruits','M
            ␣
↪'MntFishProducts','MntSweetProducts','MntGoldProds','NumDealsPurchases',
            ␣
↪'NumCatalogPurchases','NumStorePurchases','NumWebVisitsMonth','Complain']
outcome = 'Customer_Response'
```

[50]:
```
X = pd.get_dummies(df[predictors], drop_first=True)
y = df[outcome]
```

[51]:
```
# Import all models
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.linear_model import SGDClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.naive_bayes import GaussianNB

# List all the models to be fitted
models_store = [LogisticRegression(random_state=0, max_iter=1000),
                SVC(gamma='auto'),
                SGDClassifier(max_iter=1000, tol=1e-3),
                KNeighborsClassifier(n_neighbors=3),
                DecisionTreeClassifier(random_state=0),
                MLPClassifier(random_state=1, max_iter=1000),
                GaussianNB()]

# String values of the models
models_names = ['LogisticRegression',
                'SVC',
                'SGD',
                'KNNClassifer',
                'DecisionTree',
                'MLPClassifer',
                'GaussianNB']
```

[52]:
```
from sklearn.model_selection import cross_validate

#empty array to hold peformance of all model
acc_storage = []
prec_storage = []
recall_storage = []
f1_storage = []

#loop through all models and run each one according to the pipeline steps
for model in models_store:

    #performance metrics
    # get mean of each performance metric during cross validation
    scores = cross_validate(model, X, y, cv = 4, scoring = ('accuracy',␣
 ↪'precision', 'recall', 'f1'))
    acc_avg_score = scores['test_accuracy'].mean()
    prec_avg_score = scores['test_precision'].mean()
    recall_avg_score = scores['test_recall'].mean()
    f1_avg_score = scores['test_f1'].mean()
```

```
    # get the ranges
    acc_performance = str(round(acc_avg_score,5)) + ' +/- ' +␣
↪str(round((scores['test_accuracy'].max()-acc_avg_score),5))
    prec_performance = str(round(prec_avg_score,5)) + ' +/- ' +␣
↪str(round((scores['test_precision'].max()-prec_avg_score),5))
    recall_performance = str(round(recall_avg_score,5)) + ' +/- ' +␣
↪str(round((scores['test_recall'].max()-recall_avg_score),5))
    f1_performance = str(round(f1_avg_score,5)) + ' +/- ' +␣
↪str(round((scores['test_f1'].max()-f1_avg_score),5))

    acc_storage.append(acc_performance)
    prec_storage.append(prec_performance)
    recall_storage.append(recall_performance)
    f1_storage.append(f1_performance)

#display performance
df_metric = pd.DataFrame(data = {'Models' : models_names,
                                 'accuracy' : acc_storage,
                                 'precision' : prec_storage,
                                 'recall' : recall_storage,
                                 'f1': f1_storage})

df_metric.sort_values(by = 'accuracy', ascending = False)
```

```
/Users/akhilapamukuntla/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1245: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[52]:

```
                Models             accuracy            precision  \
0  LogisticRegression  0.78206 +/- 0.00895  0.67795 +/- 0.06118
2                 SGD  0.75134 +/- 0.03424  0.43355 +/- 0.22961
3       KNNClassifer  0.73379 +/- 0.01475  0.52045 +/- 0.03745
1                 SVC  0.72257 +/- 0.00452    0.3625 +/- 0.6375
6          GaussianNB  0.71331 +/- 0.01574  0.48091 +/- 0.02259
4        DecisionTree  0.71039 +/- 0.01476  0.47214 +/- 0.02786
5       MLPClassifer  0.64023 +/- 0.12975  0.53031 +/- 0.12683

                recall                   f1
0  0.40203 +/- 0.05897  0.50193 +/- 0.03526
2  0.40099 +/- 0.19901  0.41131 +/- 0.14683
3  0.41097 +/- 0.02875  0.45824 +/- 0.02238
1  0.00533 +/- 0.00181  0.01042 +/- 0.00367
6  0.54977 +/- 0.03179  0.51234 +/- 0.00339
4  0.49107 +/- 0.04794    0.48127 +/- 0.0375
5  0.46017 +/- 0.51855  0.39935 +/- 0.03875
```

So far, it looks like logistic regression is the best.

5 4. Feature engineering

This will help improve the performance of our models. It will increase the predictive power of our algorithm

5.0.1 Column Adjustments for ML

Reset the indexing of the dataset to avoid any issues when using loops.

[53]:
```
df = df.reset_index(drop = True)
```

Adding age of the customer to better undnerstand the demographics, dropping the Year_Birth col since we now have age

[54]:
```
df['Age'] = 2021 - df['Year_Birth']

df.drop('Year_Birth', axis=1, inplace=True)
```

Dt_Customer represents the date since the customer has been with the company

[55]:
```
import datetime as dt

# Change Dt_Customer to Num_days_cust
# Get todays date
df['DateTimeToday'] = dt.datetime.today()

# convert date string to DateTime format
df['DateTimeConvert'] = pd.to_datetime(df['Dt_Customer'],format='%Y-%m-%d')

# Get difference in days
df['DateTimeDifference'] = df['DateTimeToday'] - df['DateTimeConvert']

# Initialize difference in int column
df['DaysCustomer'] = 0

# Convert days difference to int
for x in range(len(df)):
    df.at[x, 'DaysCustomer'] = df['DateTimeDifference'][x].days
```

Customer Spending - Sum of all products

We should remove all the other cols, since the aggregate spending should be enough. Unless we want to analyse spending on each product

[56]:
```
df['Spending']=df['MntWines']+df['MntFruits']+df['MntMeatProducts']+df['MntFishProducts']+df['
```

Added a Martial Status to indicate if the person is Alone, Couple or Married

[57]:
```
df['Marital_Status']=df['Marital_Status'].replace({'Divorced':'Alone','Single':
↪'Alone','Married':'In couple','Together':'In couple','Absurd':
↪'Alone','Widow':'Alone'})
```

5.0.2 Dummy Code

5.0.3 Explanation

ML models do not handle categorical data in text form well. We need to transform the categorical columns into multiple true/false columns for the domains in each column.

[58]:
```
# dummy code
df_dummied = pd.get_dummies(df, columns=['Education', 'Marital_Status'],␣
↪prefix_sep='_', drop_first=True)
df_dummied.head(5)
```

[58]:
```
    Income  Kidhome  Teenhome Dt_Customer  Recency  MntWines  MntFruits  \
0  58138.0        0         0  2012-09-04       58       635         88
1  52034.0        1         1  2014-03-08       38        11          1
2  71613.0        0         0  2013-08-21       26       426         49
3  52034.0        1         0  2014-02-10       26        11          4
4  58293.0        1         0  2014-01-19       94       173         43

   MntMeatProducts  MntFishProducts  MntSweetProducts  …  Age  \
0            546.0              172                88  …   64
1              7.0                2                 1  …   67
2            127.0              111                21  …   56
3             20.0               10                 3  …   37
4            118.0               46                27  …   40

               DateTimeToday  DateTimeConvert        DateTimeDifference  \
0 2021-05-02 16:31:09.415500       2012-09-04 3162 days 16:31:09.415500
1 2021-05-02 16:31:09.415500       2014-03-08 2612 days 16:31:09.415500
2 2021-05-02 16:31:09.415500       2013-08-21 2811 days 16:31:09.415500
3 2021-05-02 16:31:09.415500       2014-02-10 2638 days 16:31:09.415500
4 2021-05-02 16:31:09.415500       2014-01-19 2660 days 16:31:09.415500

   DaysCustomer  Spending  Education_Graduation  Education_Master  \
0          3162    1617.0                     1                 0
1          2612      28.0                     1                 0
2          2811     776.0                     1                 0
3          2638      53.0                     1                 0
4          2660     422.0                     0                 0

   Education_PhD Marital_Status_In couple
```

```
0          0                0
1          0                0
2          0                1
3          0                1
4          1                1

[5 rows x 28 columns]
```

5.0.4 Standard Scale

Sometimes large values or small values in numerical data can have exponential effects on the outcome. We can normalize the numerical columns to overcome them.

[59]:
```python
from sklearn import preprocessing

# Specify columns, exclude categorical and target variable
df_numerical = df_dummied[['Income',
       'Recency', 'MntWines', 'MntFruits', 'MntMeatProducts',
       'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
       'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
       'NumStorePurchases', 'NumWebVisitsMonth', 'Complain',
       'Age', 'DaysCustomer', 'Spending']]

# Column names
names = df_numerical.columns

# Initialize scaler
scaler = preprocessing.StandardScaler()

# Fit data
scaled_num_df = scaler.fit_transform(df_numerical)
scaled_num_df = pd.DataFrame(scaled_num_df, columns=names)
```

[60]:
```python
# add back in categorical and target variables

df_add = df_dummied[['Kidhome', 'Teenhome', 'Customer_Response',
       'Education_Graduation', 'Education_Master', 'Education_PhD',
       'Marital_Status_In couple']]

df_scaled = pd.concat([scaled_num_df, df_add], axis=1)
```

5.0.5 Add Cluster Column

We want to try to incorporate unsupervised machine learning into our supervised machine learning problem. We can use clustering to create a new column and predicts the cluster of customers who have similar behaviour. This will be additional information in our end supervised machine learning models.

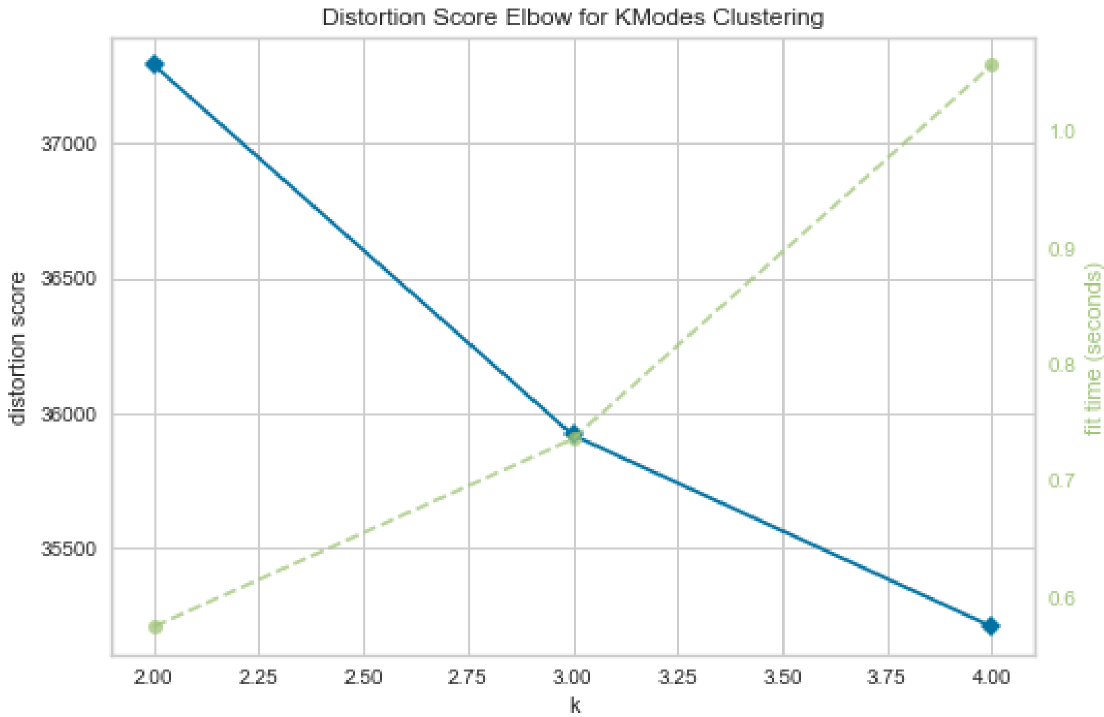
[61]:
```
# add clustering column
# remove target label
df_for_cluster = df_scaled[['Income', 'Recency', 'MntWines', 'MntFruits',␣
↪'MntMeatProducts',
        'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
        'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
        'NumStorePurchases', 'NumWebVisitsMonth', 'Complain', 'Age',
        'DaysCustomer', 'Spending', 'Kidhome', 'Teenhome',
        'Education_Graduation', 'Education_Master', 'Education_PhD',
        'Marital_Status_In couple']]
```

[62]:
```
# Elbow Method for K modes to select optimal number of clusters
from yellowbrick.cluster import KElbowVisualizer
from kmodes.kmodes import KModes

model = KModes( init = 'Cao', n_init = 1, verbose=1)
# k is range of number of clusters.
visualizer = KElbowVisualizer(model, k=(2,5), timings= True)
visualizer.fit(df_for_cluster)        # Fit data to visualizer
visualizer.show()        # Finalize and render figure
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations…
Run 1, iteration: 1/100, moves: 89, cost: 31070.0
Run 1, iteration: 2/100, moves: 5, cost: 31070.0
Init: initializing centroids
Init: initializing clusters
Starting iterations…
Run 1, iteration: 1/100, moves: 235, cost: 30445.0
Run 1, iteration: 2/100, moves: 10, cost: 30445.0
Init: initializing centroids
Init: initializing clusters
Starting iterations…
Run 1, iteration: 1/100, moves: 339, cost: 29729.0
Run 1, iteration: 2/100, moves: 17, cost: 29729.0
```

```
/Users/akhilapamukuntla/opt/anaconda3/lib/python3.8/site-
packages/yellowbrick/utils/kneed.py:155: YellowbrickWarning: No 'knee' or 'elbow
point' detected This could be due to bad clustering, no actual clusters being
formed etc.
  warnings.warn(warning_message, YellowbrickWarning)
/Users/akhilapamukuntla/opt/anaconda3/lib/python3.8/site-
packages/yellowbrick/cluster/elbow.py:343: YellowbrickWarning: No 'knee' or
'elbow' point detected, pass `locate_elbow=False` to remove the warning
```

```
  warnings.warn(warning_message, YellowbrickWarning)
```



[62]:
```
<AxesSubplot:title={'center':'Distortion Score Elbow for KModes Clustering'},
xlabel='k', ylabel='distortion score'>
```

[63]:
```python
# Take a look at the clusters
# K-Modes with optimal number of clusters
km_cao = KModes(n_clusters=3, init = 'Cao', n_init = 1, verbose=1)
fitClusters_cao = km_cao.fit_predict(df_scaled) # predict cluster

clusterCentroidsDf = pd.DataFrame(km_cao.cluster_centroids_)
clusterCentroidsDf.columns = df_scaled.columns
pd.options.display.max_columns = None

clusterCentroidsDf
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations…
Run 1, iteration: 1/100, moves: 182, cost: 31103.0
Run 1, iteration: 2/100, moves: 87, cost: 31074.0
Run 1, iteration: 3/100, moves: 7, cost: 31074.0
```

[63]:
```
     Income   Recency  MntWines  MntFruits  MntMeatProducts  MntFishProducts  \
0 -0.736286  0.242337 -0.887737  -0.660081        -0.729027        -0.683431
1 -0.736286 -1.309492 -0.893697  -0.584579        -0.729027        -0.683431
2 -0.736286  0.897554 -0.896677  -0.660081        -0.729027        -0.646786

   MntSweetProducts  MntGoldProds  NumDealsPurchases  NumWebPurchases  \
0         -0.651939     -0.822115          -0.689573        -0.781083
1         -0.651939     -0.611283          -0.172456        -0.781083
2         -0.627907     -0.707116          -0.689573        -0.403786

   NumCatalogPurchases  NumStorePurchases  NumWebVisitsMonth  Complain  \
0            -0.951271          -0.854952           0.310237 -0.099234
1            -0.589227          -0.546073           0.745460 -0.099234
2            -0.589227          -1.163831           0.745460 -0.099234

        Age  DaysCustomer  Spending  Kidhome  Teenhome  Customer_Response  \
0 -0.601790     -1.507249 -0.974584      0.0       1.0                0.0
1 -0.518230     -0.536404 -0.909398      1.0       0.0                0.0
2 -0.434669     -1.536969 -0.961212      1.0       0.0                0.0

   Education_Graduation  Education_Master  Education_PhD  \
0                   1.0               0.0            0.0
1                   0.0               1.0            0.0
2                   1.0               0.0            0.0

   Marital_Status_In couple
0                       1.0
1                       0.0
2                       1.0
```

[64]:
```
# Combine df and predicted cluter to one df
pred_df = df_scaled.reset_index()
clustersDf = pd.DataFrame(fitClusters_cao)
clustersDf.columns = ['cluster_predicted']
combinedDf = pd.concat([pred_df, clustersDf], axis = 1).reset_index()
combinedDf = combinedDf.drop(['index', 'level_0'], axis = 1)
```

5.0.6 Adjust Unbalanced Target Variable Values

As we seen in the exploratory data analysis, our target variable is highly skewed and contains mostly 0 values. This will not be enough information to predict the 1 values. We can upscale the 1 values to match the 0 values. Using Synethic Memory Oversampling Technique, we can create more 1 values. This technique does not simply duplicate more 1 values but synethizes them or creates 1 values that are similar to existing 1 values.

[65]:
```
combinedDf.columns
```

```
[65]: Index(['Income', 'Recency', 'MntWines', 'MntFruits', 'MntMeatProducts',
        'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
        'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
        'NumStorePurchases', 'NumWebVisitsMonth', 'Complain', 'Age',
        'DaysCustomer', 'Spending', 'Kidhome', 'Teenhome', 'Customer_Response',
        'Education_Graduation', 'Education_Master', 'Education_PhD',
        'Marital_Status_In couple', 'cluster_predicted'],
       dtype='object')
```

```
[66]: # adjust unbalanced dataset using SMOTE
from imblearn.over_sampling import SMOTE
smt = SMOTE()

X_b4_sampling = combinedDf[['Income', 'Recency', 'MntWines', 'MntFruits',␣
 ↪'MntMeatProducts',
       'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
       'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
       'NumStorePurchases', 'NumWebVisitsMonth', 'Complain', 'Age',
       'DaysCustomer', 'Spending', 'Kidhome', 'Teenhome',
       'Education_Graduation', 'Education_Master', 'Education_PhD',
       'Marital_Status_In couple', 'cluster_predicted']]
y_b4_sampling = combinedDf['Customer_Response']

X_upsampled, y_upsampled = smt.fit_resample(X_b4_sampling, y_b4_sampling)
```

5.1 3. Feature Importance

A feature importance ranking method we can use is Recursive Feature Elimination where the model is initially run with all the variables. Then an importance coefficient is obtained for each variable. Then the least important features are removed from the model. We can specify how many features we want to keep. Since Logistic Regression was our top performing model, we will use that as the base of RFE.

```
[67]: from sklearn.feature_selection import RFE

# the model
model = LogisticRegression(max_iter=1000)

#run RFE
rfe = RFE(model, 1)
rfe = rfe.fit(X_upsampled, y_upsampled)

#display the ranking of each variable
series1 = pd.Series(X_upsampled.columns.values)
series2 = pd.Series(rfe.ranking_)
```

```
rank = pd.DataFrame(data={'Variables': series1, 'Ranking' : series2})
rank.sort_values(by='Ranking')
```

```
/Users/akhilapamukuntla/opt/anaconda3/lib/python3.8/site-
packages/sklearn/utils/validation.py:70: FutureWarning: Pass
n_features_to_select=1 as keyword args. From version 1.0 (renaming of 0.25)
passing these as positional arguments will result in an error
  warnings.warn(f"Pass {args_msg} as keyword args. From version "
```

[67]:

	Variables	Ranking
20	Education_Master	1
19	Education_Graduation	2
21	Education_PhD	3
2	MntWines	4
18	Teenhome	5
22	Marital_Status_In couple	6
11	NumStorePurchases	7
10	NumCatalogPurchases	8
12	NumWebVisitsMonth	9
1	Recency	10
17	Kidhome	11
0	Income	12
5	MntFishProducts	13
16	Spending	14
3	MntFruits	15
15	DaysCustomer	16
13	Complain	17
7	MntGoldProds	18
6	MntSweetProducts	19
14	Age	20
9	NumWebPurchases	21
8	NumDealsPurchases	22
4	MntMeatProducts	23
23	cluster_predicted	24

5.1.1 Explanation:

If we specify that we want to the 20 most important variables, we can see that the following columns are of least importance: NumDealsPurchases, NumWebPurchases, MntSweetProducts, and cluster_predicted.

6 7. Model Building

Explanation Here we will run the model again with adjustments made through feature engineering.

[68]:

```
# shuffle data before model

# put dataframe back together
combinedDf3 = pd.concat([X_upsampled, y_upsampled], axis = 1).reset_index()
combinedDf3 = combinedDf3.drop(['index'], axis = 1)

# shuffle data
df_shuffled = combinedDf3.sample(frac = 1).reset_index()
df_shuffled = df_shuffled.drop(['index'], axis = 1)

# redefine train and target
X2 = df_shuffled[['Income', 'Recency', 'MntWines', 'MntFruits',␣
↪'MntMeatProducts',
       'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
       'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
       'NumStorePurchases', 'NumWebVisitsMonth', 'Complain', 'Age',
       'DaysCustomer', 'Spending', 'Kidhome', 'Teenhome',
       'Education_Graduation', 'Education_Master', 'Education_PhD',
       'Marital_Status_In couple', 'cluster_predicted']]

y2 = df_shuffled['Customer_Response']
```

[69]:

```
# Rerun model with new features and changes

X3 = X2
y3 = y2

# List all the models to be fitted
models_store = [LogisticRegression(random_state=0, max_iter=1000),
                SVC(gamma='auto'),
                SGDClassifier(max_iter=1000, tol=1e-3),
                KNeighborsClassifier(n_neighbors=3),
                DecisionTreeClassifier(random_state=0),
                MLPClassifier(random_state=1, max_iter=1000),
                GaussianNB()]

# String values of the models
models_names = ['LogisticRegression',
                'SVC',
                'SGD',
                'KNNClassifer',
                'DecisionTree',
                'MLPClassifer',
                'GaussianNB']

#empty array to hold peformance of all model
acc_storage2 = []
```

```
prec_storage2 = []
recall_storage2 = []
f1_storage2 = []

#loop through all models and run each one according to the pipeline steps
for model in models_store:

    #performance metrics
    scores = cross_validate(model, X3, y3, cv = 4, scoring = ('accuracy',␣
↪'precision', 'recall', 'f1'))
    acc_avg_score = scores['test_accuracy'].mean()
    prec_avg_score = scores['test_precision'].mean()
    recall_avg_score = scores['test_recall'].mean()
    f1_avg_score = scores['test_f1'].mean()


    acc_performance = str(round(acc_avg_score,5)) + ' +/- ' +␣
↪str(round((scores['test_accuracy'].max()-acc_avg_score),5))
    prec_performance = str(round(prec_avg_score,5)) + ' +/- ' +␣
↪str(round((scores['test_precision'].max()-prec_avg_score),5))
    recall_performance = str(round(recall_avg_score,5)) + ' +/- ' +␣
↪str(round((scores['test_recall'].max()-recall_avg_score),5))
    f1_performance = str(round(f1_avg_score,5)) + ' +/- ' +␣
↪str(round((scores['test_f1'].max()-f1_avg_score),5))

    acc_storage2.append(acc_performance)
    prec_storage2.append(prec_performance)
    recall_storage2.append(recall_performance)
    f1_storage2.append(f1_performance)

#display performance
df_metric = pd.DataFrame(data = {'Models' : models_names,
                                 'accuracy' : acc_storage2,
                                 'precision' : prec_storage2,
                                 'recall' : recall_storage2,
                                 'f1': f1_storage2})

df_metric.sort_values(by = 'accuracy', ascending = False)
```

[69]:

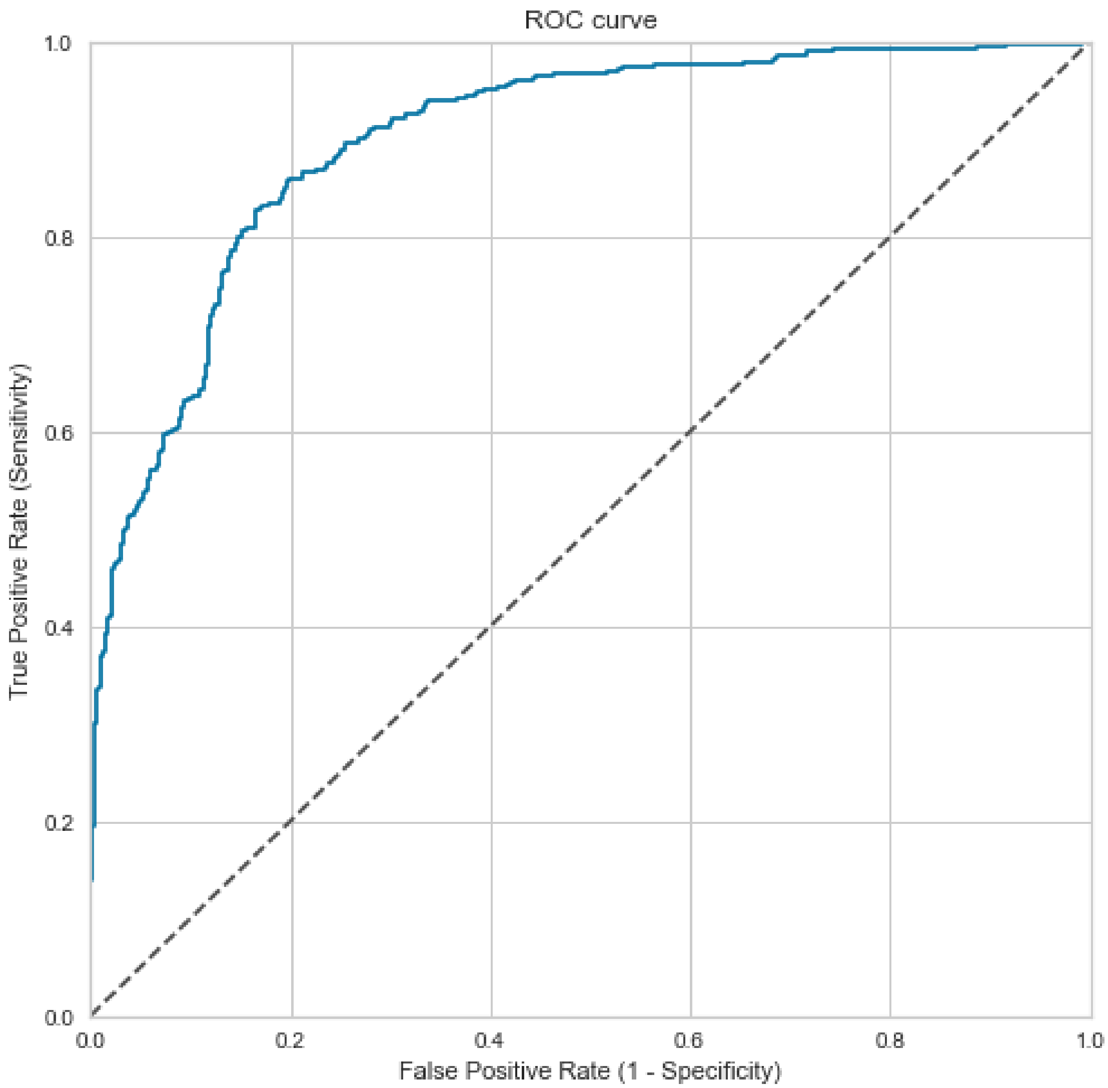
```
                Models             accuracy            precision  \
5         MLPClassifer  0.85191 +/- 0.00715  0.84159 +/- 0.00517
3         KNNClassifer  0.81464 +/- 0.01355   0.75563 +/- 0.0136
1                  SVC   0.79919 +/- 0.0086   0.80457 +/- 0.0254
4         DecisionTree  0.77636 +/- 0.01799  0.77245 +/- 0.03775
0   LogisticRegression  0.76561 +/- 0.01694  0.78445 +/- 0.02881
2                  SGD  0.70785 +/- 0.03175  0.76021 +/- 0.02337
6           GaussianNB  0.65513 +/- 0.02004   0.6766 +/- 0.02278
```

```
                recall                      f1
5  0.86702 +/- 0.00932  0.85411 +/- 0.00718
3  0.93015 +/- 0.00819  0.83384 +/- 0.01157
1  0.79113 +/- 0.01048  0.79759 +/- 0.00352
4  0.78576 +/- 0.02607  0.77853 +/- 0.01044
0    0.73338 +/- 0.022  0.75788 +/- 0.01837
2  0.60781 +/- 0.08305  0.67438 +/- 0.05161
6    0.59367 +/- 0.031   0.6323 +/- 0.02099
```

[70]:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc

#split the data
X_train, X_test, y_train, y_test = train_test_split(X3, y3, test_size=0.3,␣
 ↪random_state=0)

#the model
model = MLPClassifier(random_state=1, max_iter=1000)

#fit and predict
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
y_pred_quant = model.predict_proba(X_test)[:, 1]

#ROC graph x and y axis
fpr, tpr, thresholds = roc_curve(y_test, y_pred_quant)
print('AUC:', round((auc(fpr, tpr))*100,2), '%')

#plot the ROC graph
fig, ax = plt.subplots(figsize = (8,8))
ax.plot(fpr, tpr)
ax.plot([0, 1], [0, 1], transform=ax.transAxes, ls="--", c=".3")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.rcParams['font.size'] = 12
plt.title('ROC curve')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.grid(True)
```

```
AUC: 89.98 %
```



7 5. Parameter Optimization

Since the MLP model was the top performing model, we wll attempt to further enhance our performance by adjusting the paramters. We can use run the model multiple times with different parameter values and see the changes in each run.

[71]:
```
# Optimize Parameters of top performing model

# Intialize gridsearch
from sklearn.model_selection import GridSearchCV

tuning_parameters = [{'hidden_layer_sizes': [100, 300],
```

```
                          'activation': ['relu','identity'],
                          'solver': ['adam'],
                          'alpha': [1e-4, 1e-5],
                          'max_iter': [1000],
                          'random_state': [1]}]

model = GridSearchCV(MLPClassifier(), tuning_parameters, scoring='accuracy',cv␣
 ↪= 4)

model.fit(X3, y3)

# Display gridsearch
pd.options.display.max_columns = None
pd.options.display.max_rows = None
df_gridsearch = pd.DataFrame(model.cv_results_)
df_gridsearch
```

[71]:

```
   mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
0      20.430053      9.519978         0.003492        0.000161
1      15.173626      1.297968         0.007543        0.006631
2      10.840248      2.352475         0.003605        0.001304
3      13.303691      1.913005         0.004442        0.001034
4       0.764103      0.221806         0.002757        0.000353
5       0.698101      0.041480         0.003298        0.000245
6       0.846102      0.087911         0.002911        0.000212
7       0.704868      0.039106         0.002895        0.000046

  param_activation param_alpha param_hidden_layer_sizes param_max_iter  \
0             relu      0.0001                      100           1000
1             relu      0.0001                      300           1000
2             relu     0.00001                      100           1000
3             relu     0.00001                      300           1000
4         identity      0.0001                      100           1000
5         identity      0.0001                      300           1000
6         identity     0.00001                      100           1000
7         identity     0.00001                      300           1000

  param_random_state param_solver  \
0                  1         adam
1                  1         adam
2                  1         adam
3                  1         adam
4                  1         adam
5                  1         adam
6                  1         adam
7                  1         adam
```

```
                                              params  split0_test_score  \
0  {'activation': 'relu', 'alpha': 0.0001, 'hidde…           0.855034
1  {'activation': 'relu', 'alpha': 0.0001, 'hidde…           0.856376
2  {'activation': 'relu', 'alpha': 1e-05, 'hidden…           0.861745
3  {'activation': 'relu', 'alpha': 1e-05, 'hidden…           0.849664
4  {'activation': 'identity', 'alpha': 0.0001, 'h…           0.751678
5  {'activation': 'identity', 'alpha': 0.0001, 'h…           0.754362
6  {'activation': 'identity', 'alpha': 1e-05, 'hi…           0.751678
7  {'activation': 'identity', 'alpha': 1e-05, 'hi…           0.754362

   split1_test_score  split2_test_score  split3_test_score  mean_test_score  \
0           0.859060           0.840054           0.853495         0.851911
1           0.861745           0.842742           0.868280         0.857286
2           0.855034           0.842742           0.850806         0.852582
3           0.859060           0.840054           0.869624         0.854601
4           0.766443           0.748656           0.778226         0.761251
5           0.762416           0.750000           0.771505         0.759571
6           0.766443           0.748656           0.778226         0.761251
7           0.762416           0.750000           0.771505         0.759571

   std_test_score  rank_test_score
0        0.007141                4
1        0.009395                1
2        0.006891                3
3        0.010972                2
4        0.011889                5
5        0.008205                7
6        0.011889                5
7        0.008205                7
```

Using accuracy as the performance metric to evalute, we see that 'mean_test_score' does not vary too much if at all.