Logistic Regression Churn Prediction

June 8, 2022

1 Logistic Regression Churn Prediction Model

1.1 Importing Libraries

[1]:
```
from sklearn import linear_model
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
import scipy
from scipy import stats
import matplotlib.pyplot as plt
import plotly.express as px
```

1.2 Data Inspection & Cleaning

[2]:
```
#Importing the dataset and looking at the attributes of the dataset

df = pd.read_csv('data_regression.csv')
df.columns
```

[2]:
```
Index(['year', 'customer_id', 'phone_no', 'gender', 'age',
       'no_of_days_subscribed', 'multi_screen', 'mail_subscribed',
       'weekly_mins_watched', 'minimum_daily_mins', 'maximum_daily_mins',
       'weekly_max_night_mins', 'videos_watched', 'maximum_days_inactive',
       'customer_support_calls', 'churn'],
      dtype='object')
```

[3]:
```
df.head(10)
```

[3]:
```
   year  customer_id  phone_no  gender  age  no_of_days_subscribed  \
0  2015       100198  409-8743  Female   36                     62
1  2015       100643  340-5930  Female   39                    149
2  2015       100756  372-3750  Female   65                    126
3  2015       101595  331-4902  Female   24                    131
4  2015       101653  351-8398  Female   40                    191
```

```
5  2015       101953  329-6603     NaN   31                      65
6  2015       103051  416-1845     NaN   54                      59
7  2015       103225  348-7193  Female   40                      50
8  2015       103408  413-4039    Male   61                     205
9  2015       103676  338-5207    Male   31                      63

  multi_screen mail_subscribed  weekly_mins_watched  minimum_daily_mins  \
0           no              no               148.35                12.2
1           no              no               294.45                 7.7
2           no              no                87.30                11.9
3           no             yes               321.30                 9.5
4           no              no               243.00                10.9
5           no              no               193.65                12.7
6           no              no               239.25                10.2
7           no              no               196.65                 5.6
8           no             yes               263.70                 7.8
9           no              no               316.80                12.3

   maximum_daily_mins  weekly_max_night_mins  videos_watched  \
0               16.81                     82               1
1               33.37                     87               3
2                9.89                     91               1
3               36.41                    102               4
4               27.54                     83               7
5               21.95                    111               6
6               27.12                    106               4
7               22.29                     88               9
8               29.89                     64               5
9               35.90                     58               2

   maximum_days_inactive  customer_support_calls  churn
0                    4.0                       1    0.0
1                    3.0                       2    0.0
2                    4.0                       5    1.0
3                    3.0                       3    0.0
4                    3.0                       1    0.0
5                    4.0                       4    1.0
6                    NaN                       0    0.0
7                    NaN                       5    1.0
8                    3.0                       2    0.0
9                    4.0                       0    0.0
```

We can see that the gender and maximum_days_inactive is having the NAN values. Gender, screen, and mail are categorical variables. There are also other behavioural variables like weekly_mins_wathced, minimum_daily_mins, maximum_daily_mins, weekly_max_night_mins, videos_watched, maximum_days_inactive, customer_support_calls, and churn.

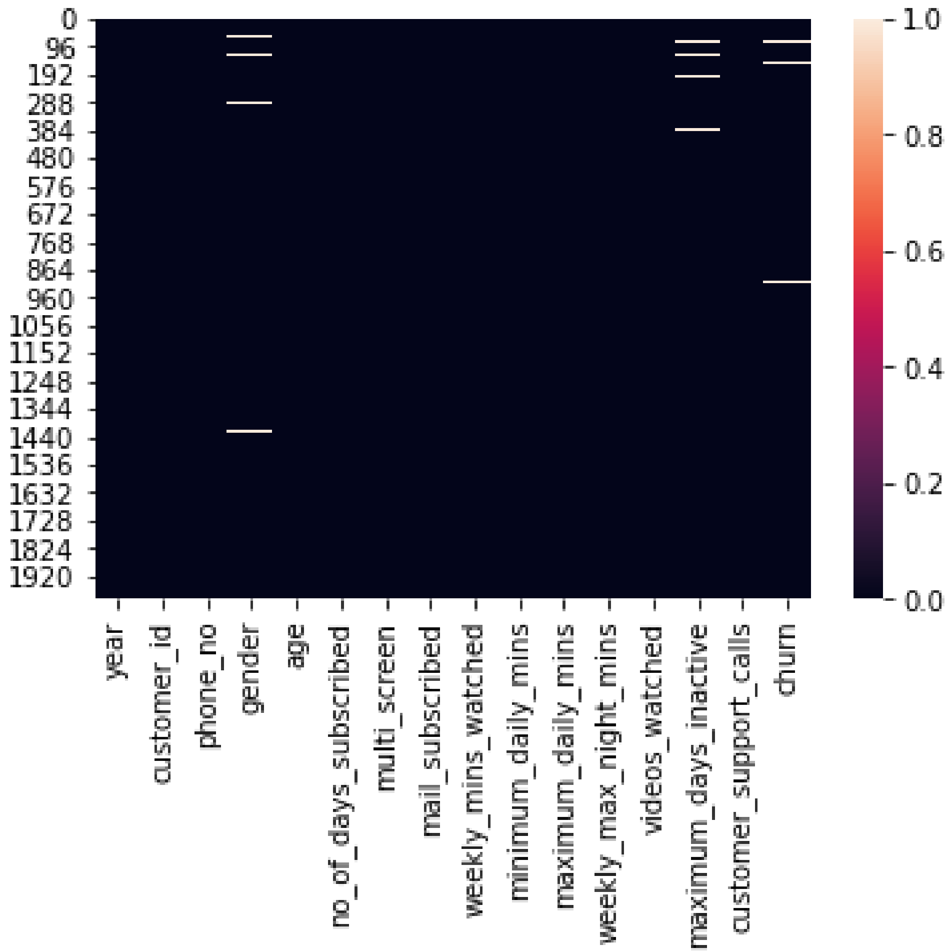
[4]:
```
#Defining Inspection and Cleaning function

def inspection(df):

    import pandas as pd
    import seaborn as sns

    print('Types of variables we are working with: ')
    print(df.dtypes, "\n")

    print('Total number of samples with missing values')
    print(df.isnull().any(axis=1).sum(), "\n")

    print('Total missing variables per attribute/column')
    print(df.isnull().sum(), "\n")

    print('Map of missing values')
    sns.heatmap(df.isnull())
```

[5]:
```
inspection(df)
```

```
Types of variables we are working with:
year                        int64
customer_id                 int64
phone_no                   object
gender                     object
age                         int64
no_of_days_subscribed       int64
multi_screen               object
mail_subscribed            object
weekly_mins_watched       float64
minimum_daily_mins        float64
maximum_daily_mins        float64
weekly_max_night_mins       int64
videos_watched              int64
maximum_days_inactive     float64
customer_support_calls      int64
churn                     float64
dtype: object

Total number of samples with missing values
82

Total missing variables per attribute/column
year                       0
customer_id                0
phone_no                   0
```

```
gender                    24
age                        0
no_of_days_subscribed      0
multi_screen               0
mail_subscribed            0
weekly_mins_watched        0
minimum_daily_mins         0
maximum_daily_mins         0
weekly_max_night_mins      0
videos_watched             0
maximum_days_inactive     28
customer_support_calls     0
churn                     35
dtype: int64
```

```
Map of missing values
```



From the heatmap, it doesn't seems like that there is lot of missing data. There are some values for Churn coloumn which are missing. Mostly, those are in the first 1000 samples. Few values of gneder and maximum_days_inactive are also missing. These can be seen in first half of the data. There is not much missing data, but again we need to get rid of the data which is holding null values. So, we will remove all the rows with missing values from the data frame.

[6]:
```
#Using dropna to remove missing values

df = df.dropna()
df
```

[6]:
```
      year  customer_id  phone_no  gender  age  no_of_days_subscribed  \
0     2015       100198  409-8743  Female   36                     62
1     2015       100643  340-5930  Female   39                    149
2     2015       100756  372-3750  Female   65                    126
3     2015       101595  331-4902  Female   24                    131
4     2015       101653  351-8398  Female   40                    191
…     …             …         …       …  …                      …
1990  2015       993714  364-1969    Male   32                     61
1991  2015       993815  387-5891    Male   49                     50
1992  2015       994954  329-3222  Female   42                    119
1996  2015       998086  383-9255    Male   45                    127
1999  2015       999961  414-1496    Male   37                     73

     multi_screen mail_subscribed  weekly_mins_watched  minimum_daily_mins  \
0              no              no               148.35                12.2
1              no              no               294.45                 7.7
2              no              no                87.30                11.9
3              no             yes               321.30                 9.5
4              no              no               243.00                10.9
…             …               …                   …                   …
1990           no              no                67.50                 9.8
1991          yes             yes               460.65                 8.0
1992           no             yes               176.70                 7.6
1996           no              no               273.45                 9.3
1999           no              no               326.70                10.3

      maximum_daily_mins  weekly_max_night_mins  videos_watched  \
0                  16.81                     82               1
1                  33.37                     87               3
2                   9.89                     91               1
3                  36.41                    102               4
4                  27.54                     83               7
…                    …                     …              …
1990                7.65                     94               6
1991               52.21                    109               3
1992               20.03                     76               3
1996               30.99                    116               3
```

```
1999               37.03                         89               6

      maximum_days_inactive  customer_support_calls  churn
0                       4.0                       1    0.0
1                       3.0                       2    0.0
2                       4.0                       5    1.0
3                       3.0                       3    0.0
4                       3.0                       1    0.0
…                     …                       …    …
1990                    3.0                       2    0.0
1991                    3.0                       0    0.0
1992                    3.0                       3    0.0
1996                    3.0                       1    0.0
1999                    3.0                       1    1.0

[1918 rows x 16 columns]
```

[7]:

```
df.describe()
```

[7]:

```
         year    customer_id          age  no_of_days_subscribed  \
count  1918.0    1918.000000  1918.000000            1918.000000
mean   2015.0  562267.639208    38.659020             100.065693
std       0.0  257172.549309    10.150896              39.923242
min    2015.0  100198.000000    18.000000               1.000000
25%    2015.0  341491.750000    32.000000              73.000000
50%    2015.0  579594.500000    37.000000              99.000000
75%    2015.0  778377.250000    43.000000             127.000000
max    2015.0  999961.000000    82.000000             243.000000

       weekly_mins_watched  minimum_daily_mins  maximum_daily_mins  \
count          1918.000000         1918.000000         1918.000000
mean            269.919291           10.180553           30.591413
std              80.541705            2.771199            9.128036
min               0.000000            0.000000            0.000000
25%             218.587500            8.400000           24.775000
50%             269.550000           10.200000           30.550000
75%             324.000000           12.000000           36.720000
max             526.200000           20.000000           59.640000

       weekly_max_night_mins  videos_watched  maximum_days_inactive  \
count            1918.000000     1918.000000            1918.000000
mean              100.400938        4.484880               3.247132
std                19.569822        2.477764               0.805840
min                42.000000        0.000000               0.000000
25%                87.000000        3.000000               3.000000
50%               101.000000        4.000000               3.000000
75%               114.000000        6.000000               4.000000
```

```
max                175.000000       19.000000                  6.000000

       customer_support_calls         churn
count             1918.000000  1918.000000
mean                 1.539625     0.131908
std                  1.300553     0.338479
min                  0.000000     0.000000
25%                  1.000000     0.000000
50%                  1.000000     0.000000
75%                  2.000000     0.000000
max                  9.000000     1.000000
```

Attribute year is having a zero standard deviation because all the elements of attribute year are same, i.e. the year 2015. The dataset contains only the data about the customers who were there on the platform during the year 2015. There are 1918 rows, i.e. 1918 customers in total. This is after we remove the null values from the dataset. Age of the customer varies from 18 to 82. The main attribute used to describe if the customer churned or not is based on maximum days the customer was inactive. The minimum value for this attribute is 0, which is reasonable as some of the customers may not be inactive on the platform, but the maximum value is 6, i.e. some of the customers were inactive for longer time and result into getting churned. This description says a lot about the customers, i.e. the average customers were of age 38-39 and on a average 0.13% of customers are getting churned.

[8]:
```
#Printing the correlation matrix
corr = df.corr()
corr
```

[8]:
```
                        year  customer_id       age  no_of_days_subscribed  \
year                     NaN          NaN       NaN                    NaN
customer_id              NaN     1.000000  0.021881              -0.019180
age                      NaN     0.021881  1.000000               0.035426
no_of_days_subscribed    NaN    -0.019180  0.035426               1.000000
weekly_mins_watched      NaN    -0.010410  0.019586              -0.002089
minimum_daily_mins       NaN     0.040254 -0.008557               0.015247
maximum_daily_mins       NaN    -0.010415  0.019598              -0.002095
weekly_max_night_mins    NaN     0.000648  0.015150               0.001290
videos_watched           NaN     0.061229 -0.003876               0.012856
maximum_days_inactive    NaN     0.047551  0.001507               0.017720
customer_support_calls   NaN    -0.034940 -0.002848               0.011272
churn                    NaN    -0.054260  0.015982               0.009627

                        weekly_mins_watched  minimum_daily_mins  \
year                                    NaN                 NaN
customer_id                       -0.010410            0.040254
age                                0.019586           -0.008557
no_of_days_subscribed             -0.002089            0.015247
weekly_mins_watched                1.000000           -0.015180
```

```
minimum_daily_mins              -0.015180            1.000000
maximum_daily_mins               1.000000           -0.015178
weekly_max_night_mins            0.039856            0.011446
videos_watched                   0.027869            0.046493
maximum_days_inactive           -0.012410            0.931296
customer_support_calls          -0.031239           -0.003817
churn                            0.165991            0.072308

                        maximum_daily_mins  weekly_max_night_mins  \
year                                   NaN                    NaN
customer_id                      -0.010415               0.000648
age                               0.019598               0.015150
no_of_days_subscribed            -0.002095               0.001290
weekly_mins_watched               1.000000               0.039856
minimum_daily_mins               -0.015178               0.011446
maximum_daily_mins                1.000000               0.039858
weekly_max_night_mins             0.039858               1.000000
videos_watched                    0.027870              -0.003355
maximum_days_inactive            -0.012410               0.032647
customer_support_calls           -0.031250              -0.013568
churn                             0.165989               0.006029

                        videos_watched  maximum_days_inactive  \
year                               NaN                    NaN
customer_id                   0.061229               0.047551
age                          -0.003876               0.001507
no_of_days_subscribed         0.012856               0.017720
weekly_mins_watched           0.027869              -0.012410
minimum_daily_mins            0.046493               0.931296
maximum_daily_mins            0.027870              -0.012410
weekly_max_night_mins        -0.003355               0.032647
videos_watched                1.000000               0.026169
maximum_days_inactive         0.026169               1.000000
customer_support_calls       -0.009850              -0.006362
churn                        -0.018457               0.046809

                        customer_support_calls     churn
year                                       NaN       NaN
customer_id                          -0.034940 -0.054260
age                                  -0.002848  0.015982
no_of_days_subscribed                 0.011272  0.009627
weekly_mins_watched                  -0.031239  0.165991
minimum_daily_mins                   -0.003817  0.072308
maximum_daily_mins                   -0.031250  0.165989
weekly_max_night_mins                -0.013568  0.006029
videos_watched                       -0.009850 -0.018457
maximum_days_inactive                -0.006362  0.046809
```

```
customer_support_calls                    1.000000  0.212678
churn                                     0.212678  1.000000
```

1.3 Encoding Categorical Variables

[9]:
```
df.head(5)
```

[9]:
```
   year  customer_id  phone_no  gender  age  no_of_days_subscribed  \
0  2015       100198  409-8743  Female   36                     62
1  2015       100643  340-5930  Female   39                    149
2  2015       100756  372-3750  Female   65                    126
3  2015       101595  331-4902  Female   24                    131
4  2015       101653  351-8398  Female   40                    191

  multi_screen mail_subscribed  weekly_mins_watched  minimum_daily_mins  \
0           no              no               148.35                12.2
1           no              no               294.45                 7.7
2           no              no                87.30                11.9
3           no             yes               321.30                 9.5
4           no              no               243.00                10.9

   maximum_daily_mins  weekly_max_night_mins  videos_watched  \
0               16.81                     82               1
1               33.37                     87               3
2                9.89                     91               1
3               36.41                    102               4
4               27.54                     83               7

   maximum_days_inactive  customer_support_calls  churn
0                    4.0                       1    0.0
1                    3.0                       2    0.0
2                    4.0                       5    1.0
3                    3.0                       3    0.0
4                    3.0                       1    0.0
```

We can see our dataset has 3 categorical variables, i.e. gender, multi_screen, and mail_subscribed. We can look at the unique values of each attribute as follows

[10]:
```
df.gender.unique()
```

[10]:
```
array(['Female', 'Male'], dtype=object)
```

[11]:
```
df.multi_screen.unique()
```

[11]:
```
array(['no', 'yes'], dtype=object)
```

[12]:
```
df.mail_subscribed.unique()
```

[12]: array(['no', 'yes'], dtype=object)

[13]:
```
#Function for encoding categorical variables using scikit learn function called␣
↪as ordinal encoder

def enc_cat (df, variables):
    from sklearn.preprocessing import OrdinalEncoder
    ord_enc = OrdinalEncoder()

    for v in variables:
        name = v+'_code'
        df[name] = ord_enc.fit_transform(df[[v]])
        print('The encoded values for ' + v +' are: ')
        print(df[name].unique())
```

[14]:
```
enc_cat(df, ['gender', 'multi_screen', 'mail_subscribed'])
```

```
The encoded values for gender are:
[0. 1.]
The encoded values for multi_screen are:
[0. 1.]
The encoded values for mail_subscribed are:
[0. 1.]
```

[15]:
```
df
```

[15]:
```
      year  customer_id  phone_no  gender  age  no_of_days_subscribed  \
0     2015       100198  409-8743  Female   36                     62
1     2015       100643  340-5930  Female   39                    149
2     2015       100756  372-3750  Female   65                    126
3     2015       101595  331-4902  Female   24                    131
4     2015       101653  351-8398  Female   40                    191
…     …          …        …         …   …                   …
1990  2015       993714  364-1969    Male   32                     61
1991  2015       993815  387-5891    Male   49                     50
1992  2015       994954  329-3222  Female   42                    119
1996  2015       998086  383-9255    Male   45                    127
1999  2015       999961  414-1496    Male   37                     73

     multi_screen mail_subscribed  weekly_mins_watched  minimum_daily_mins  \
0              no              no               148.35                12.2
1              no              no               294.45                 7.7
2              no              no                87.30                11.9
3              no             yes               321.30                 9.5
4              no              no               243.00                10.9
…             …               …                 …                  …
1990           no              no                67.50                 9.8
```

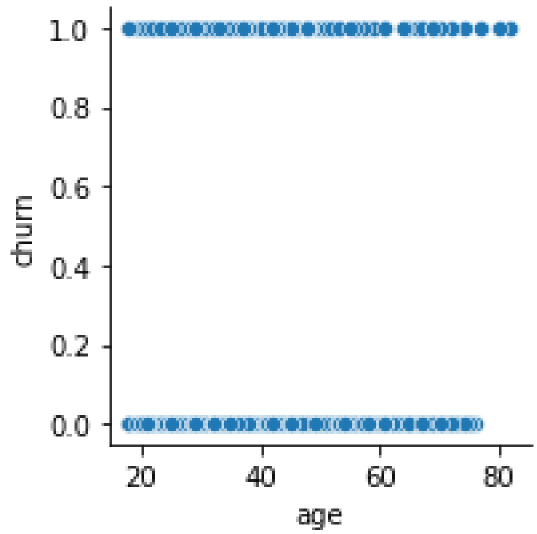
```
1991        yes         yes         460.65         8.0
1992         no         yes         176.70         7.6
1996         no          no         273.45         9.3
1999         no          no         326.70        10.3

      maximum_daily_mins  weekly_max_night_mins  videos_watched  \
0                  16.81                     82               1
1                  33.37                     87               3
2                   9.89                     91               1
3                  36.41                    102               4
4                  27.54                     83               7
…                    …                    …              …
1990                7.65                     94               6
1991               52.21                    109               3
1992               20.03                     76               3
1996               30.99                    116               3
1999               37.03                     89               6

      maximum_days_inactive  customer_support_calls  churn  gender_code  \
0                       4.0                       1    0.0          0.0
1                       3.0                       2    0.0          0.0
2                       4.0                       5    1.0          0.0
3                       3.0                       3    0.0          0.0
4                       3.0                       1    0.0          0.0
…                     …                     …    …          …
1990                    3.0                       2    0.0          1.0
1991                    3.0                       0    0.0          1.0
1992                    3.0                       3    0.0          0.0
1996                    3.0                       1    0.0          1.0
1999                    3.0                       1    1.0          1.0

      multi_screen_code  mail_subscribed_code
0                   0.0                   0.0
1                   0.0                   0.0
2                   0.0                   0.0
3                   0.0                   1.0
4                   0.0                   0.0
…                   …                    …
1990                0.0                   0.0
1991                1.0                   1.0
1992                0.0                   1.0
1996                0.0                   0.0
1999                0.0                   0.0

[1918 rows x 19 columns]
```

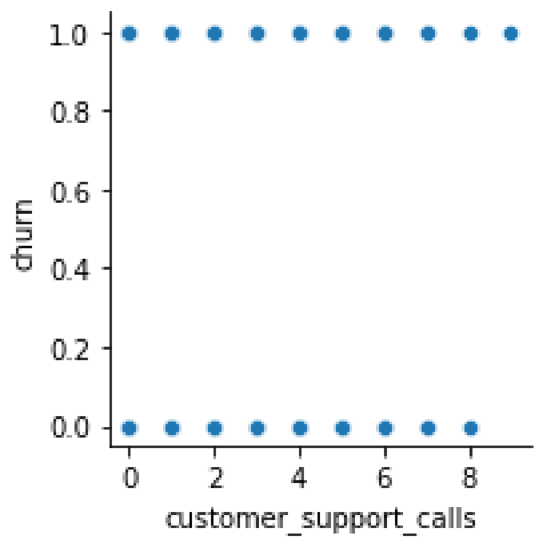
We can see that three new variables are created at the end of the dataframe called as gender_code, multi_screen_code, and mail_subscribed_code. All of those have only two types of values, i.e. 0 & 1.

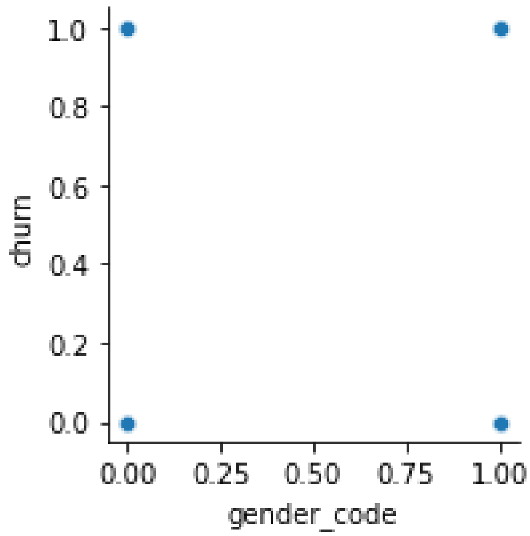
1.4 Exploratory Data Analysis

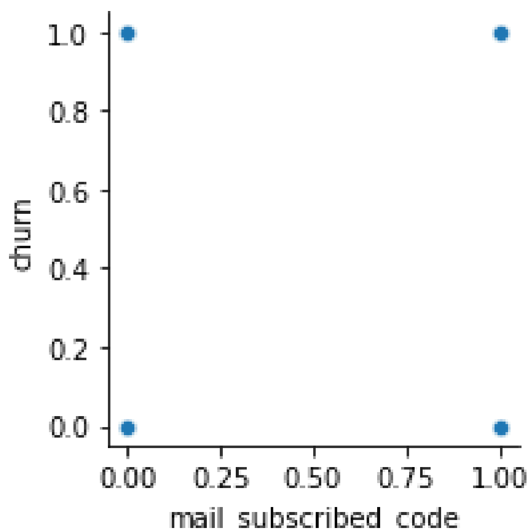
[16]:
```
#Function to return scatterplots of all the variables in the dataset against␣
↪the classification variable

def plot1(df, cols_to_exclude, class_col):

    import numpy as np
    import seaborn as sns
    import warnings

    warnings.filterwarnings('ignore')

    #cleaning up of non-numerical columns
    cols = df.select_dtypes(include=np.number).columns.tolist() #finding all␣
↪the numerical cols from df
    X = df[cols]                                                 #creating df␣
↪only with numerical cols
    X = X[X.columns.difference(cols_to_exclude)]                 #removing␣
↪columns to exclude

    #function dataframe.columns.difference give the complement of the values␣
↪that we provide as argument.
    #here we are providing the cols to be excluded list as arg, so it will␣
↪return all other cols other than those

    for col in X.columns.difference([class_col]):                #selecting all␣
↪cols in list except the churn col
        g = sns.FacetGrid(df)

        #Facetgrid maps dataset onto multiple axes arrayed in a grid of rows or␣
↪columns that correspond to levels of variables
        #in the dataset. Here we have only two variables compared at a time, so␣
↪it is not using hue.

        #Applying a plot function to each facet's subset of the data
        g.map(sns.scatterplot, col, class_col)
```

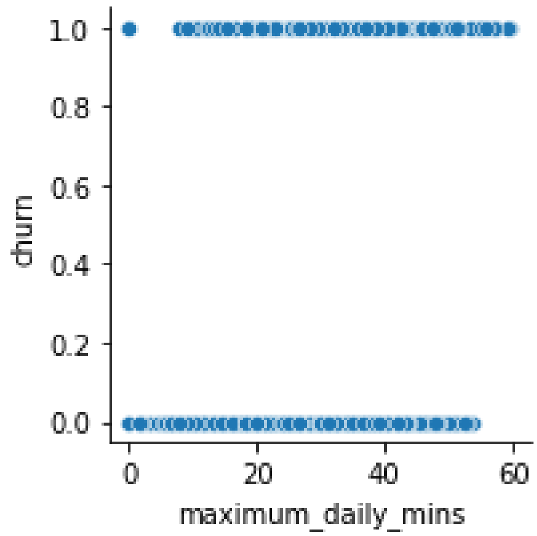
[17]:
```
plot1(df, ['customer_id', 'phone_no', 'year'], 'churn')
```

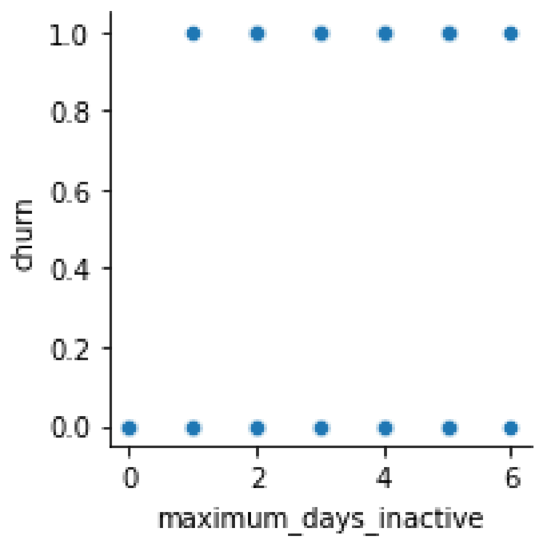

1.0
0.8
0.6
0.4
0.2
0.0
churn
20
40
60
80
age

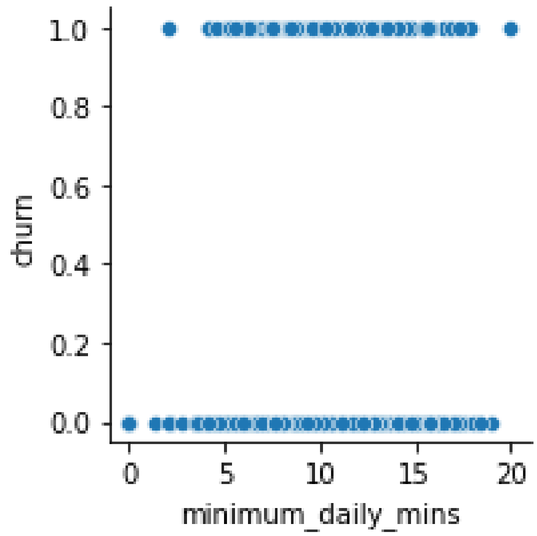

1.0
0.8
0.6
0.4
0.2
0.0
churn
0
2
4
6
8
customer_support_calls

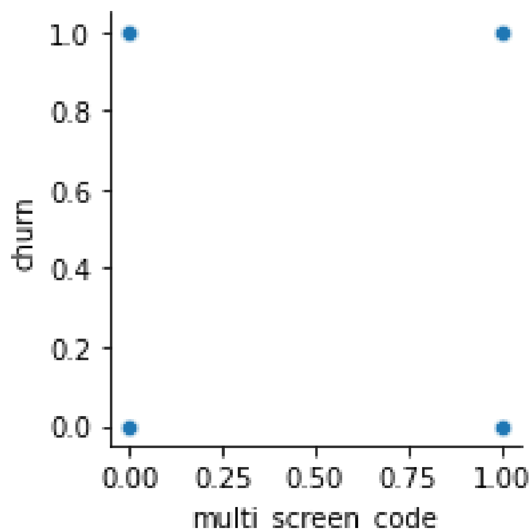

1.0
0.8
0.6
0.4
0.2
0.0
churn
0.00
0.25
0.50
0.75
1.00
gender_code

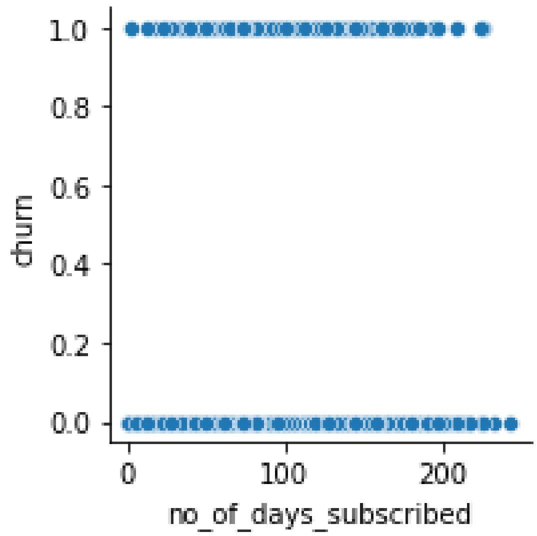

1.0
0.8
0.6
0.4
0.2
0.0
churn
0.00
0.25
0.50
0.75
1.00
mail_subscribed_code

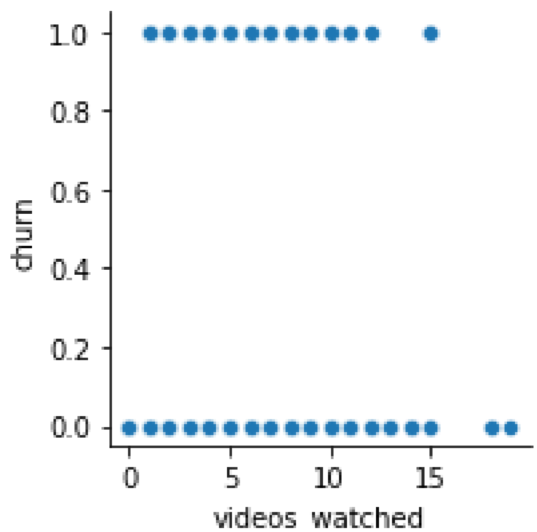

1.0
0.8
0.6
0.4
0.2
0.0
churn
0
20
40
60
maximum_daily_mins

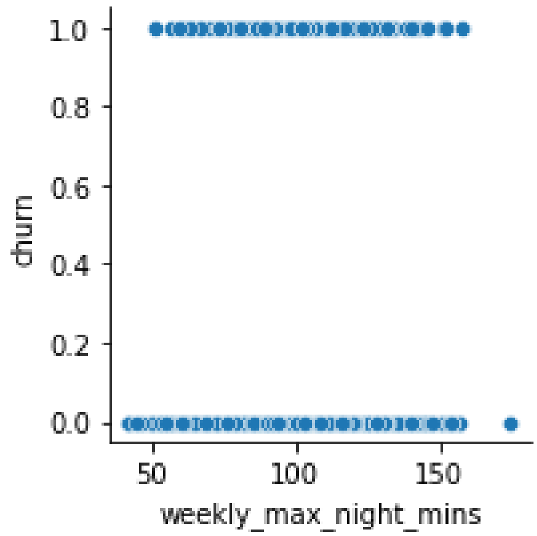

1.0
0.8
0.6
0.4
0.2
0.0
churn
0
2
4
6
maximum_days_inactive

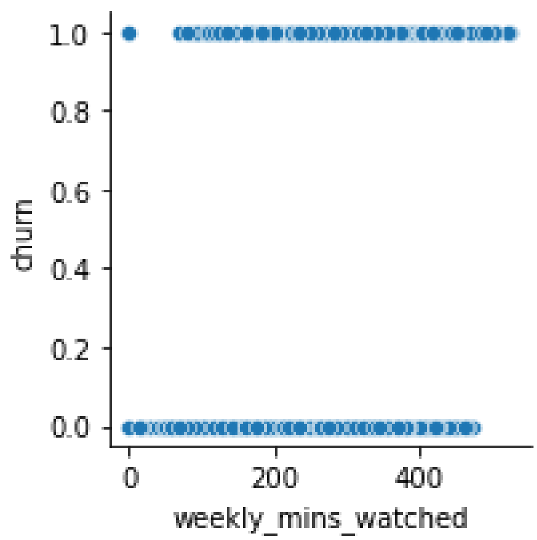

1.0
0.8
0.6
0.4
0.2
0.0
churn
0
5
10
15
20
minimum_daily_mins


1.0
0.8
0.6
0.4
0.2
0.0
churn
0.00
0.25
0.50
0.75
1.00
multi_screen_code


1.0
0.8
0.6
0.4
0.2
0.0
churn
0
100
200
no_of_days_subscribed


1.0
0.8
0.6
0.4
0.2
0.0
churn
0
5
10
15
videos_watched



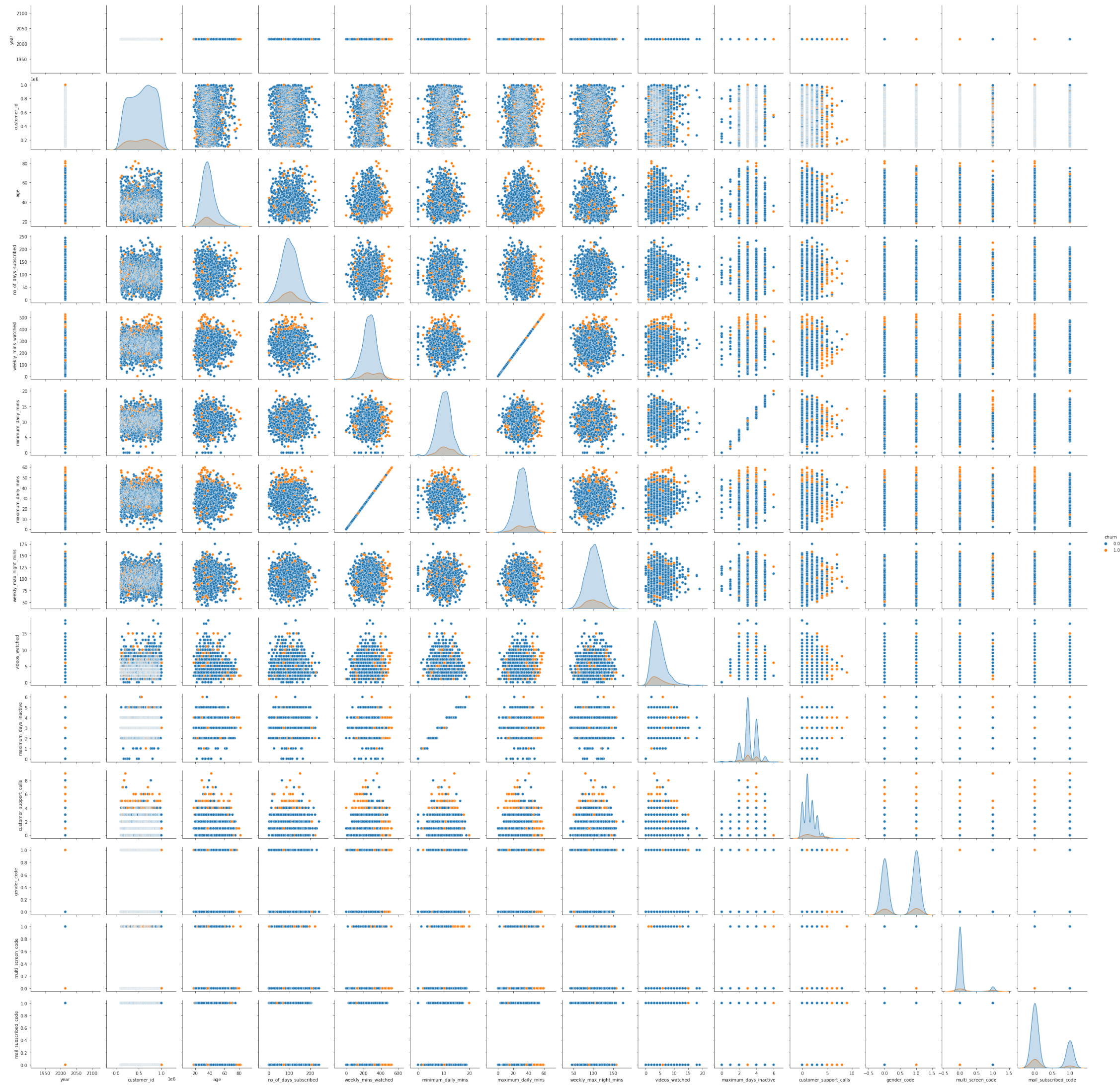


Unfortunately, it can be seen from the graph that there aren't a many obvious patterns when it comes to logistic regression. For example, if we see tha above graph for churn vs weekly__mins__watched, we can see that people that churn and do not churn are all ober the scale. Similarly, the graph for weekly__max__night__mins, videos__watched, no__of__days__subscribed, minimum__daily__mins, etc have when compared with churn.

[18]:
```
#Function to return the pair-plots of classification variable versus all other␣
↪variables

def plot2(df, class_col, cols_to_exclude):
```

```
    import numpy as np
    import seaborn as sns

    #cleaning up of non-numerical columns
    cols = df.select_dtypes(include=np.number).columns.tolist() #finding all␣
↪the numerical cols from df
    X = df[cols]                                                 #creating df␣
↪only with numerical cols
    X = X[X.columns.difference(cols_to_exclude)]                 #removing␣
↪columns to exclude

    #function dataframe.columns.difference give the complement of the values␣
↪that we provide as argument.
    #here we are providing the cols to be excluded list as arg, so it will␣
↪return all other cols other than those

    sns.pairplot(df, hue = class_col)
```

```
[19]: plot2(df, class_col='churn', cols_to_exclude=['customer_id', 'phone_no',␣
↪'year'])
```



This is the pair-plot of all the variables against each other. The diagonal graphs are all histograms. The one with orange dots are the customers who got churned and the blue ones were not churned.

For example, if we check the graph of weekkly_mins_watched versus weekly_max_night_mins, we can see that more people got churned when weekly_mins_watched went beyond a certain limit. This can be an explanation for the situation where people are coming on the platform to watch one particular series and then are getting churned.

Similarly, if we see the graph of maximum_daily_mins and weekly_mins_watched we can see that there is a linear relation which is growing increasingly. As the people are on the platform for few weeks their daily watch time is also increasing and most of them are getting churned when they are on the platform for long time or beyond some limit.

Also, when we see the relation between other variables and the encoded variables it will only show data points at values 0 and 1. This is because these variables were encoded with the values 0 and 1.

There is one more relation which is noticeable, i.e. as the minimum_daily_mins are increasing from 0 to 20 the maximum_days_inactive count is increasing from 0 to 6. Some people still stay on the platform and some of them get churned.

1.5 Running Logistic Regression

1.5.1 1. Running model using statsmodels.api

[22]:
```
def logistic_regression(df, class_col, cols_to_exclude):

    #cleaning the dataframe for logistic regression with the columns which␣
 ↪we're not using, i.e. phone no, customer_id, & year
    cols = df.select_dtypes(include=np.number).columns.tolist()
    X = df[cols]
    X = X[X.columns.difference(cols_to_exclude)]
    X = X[X.columns.difference([class_col])]

    #We're running the logistic regression here using two ways:
    # 1. Using statsmodels.api library which bring the coeff with itself and is␣
 ↪easy to visualize
    # 2. Using sklearn for logistic regression

    # 1.
    import statsmodels.api as sm
    y = df[class_col]
    logit_1 = sm.Logit(y, X)
    result_1 = logit_1.fit()
    print(result_1.summary2())
```

[23]:
```
logistic_regression(df, class_col = 'churn', cols_to_exclude=['customer_id',␣
 ↪'phone_no', 'year'])
```

```
Optimization terminated successfully.
         Current function value: 0.336585
         Iterations 7
                            Results: Logit
=======================================================================
Model:                Logit             Pseudo R-squared:   0.137
Dependent Variable:   churn             AIC:                1315.1404
Date:                 2022-06-08 18:53  BIC:                1381.8488
No. Observations:     1918              Log-Likelihood:     -645.57
Df Model:             11                LL-Null:            -748.02
Df Residuals:         1906              LLR p-value:        7.1751e-38
Converged:            1.0000            Scale:              1.0000
No. Iterations:       7.0000
-----------------------------------------------------------------------
                        Coef.  Std.Err.    z     P>|z|    [0.025   0.975]
-----------------------------------------------------------------------
```

```
age                    -0.0208   0.0068 -3.0739 0.0021  -0.0340 -0.0075
customer_support_calls  0.4246   0.0505  8.4030 0.0000   0.3256  0.5237
gender_code            -0.2144   0.1446 -1.4824 0.1382  -0.4979  0.0691
mail_subscribed_code   -0.7529   0.1798 -4.1873 0.0000  -1.1053 -0.4005
maximum_daily_mins     -3.7125  25.2522 -0.1470 0.8831 -53.2058 45.7809
maximum_days_inactive  -0.7870   0.2473 -3.1828 0.0015  -1.2716 -0.3024
minimum_daily_mins      0.2075   0.0727  2.8555 0.0043   0.0651  0.3499
multi_screen_code       1.9511   0.1831 10.6562 0.0000   1.5923  2.3100
no_of_days_subscribed  -0.0045   0.0018 -2.5572 0.0106  -0.0080 -0.0011
videos_watched         -0.0948   0.0317 -2.9954 0.0027  -0.1569 -0.0328
weekly_max_night_mins  -0.0169   0.0032 -5.3119 0.0000  -0.0231 -0.0107
weekly_mins_watched     0.4248   2.8619  0.1484 0.8820  -5.1844  6.0340
======================================================================
```

We can see that the model iterated 7 times to reach the best optimization. Maximum number of iterations using Logit for statsmodels.api is 35, after this optimization fails. The value of log-likelihood is -645.57, i.e. we get our best logistic regression model at this value of LL. Also, the Psuedo R-squared value is very low, i.e. 13.7% which is not good and it says that our choice of model is not good.

According to the p-values, gender_code, maximum_daily_mins, and weekly_mins_watched are not significant.

[24]:
```
#Interpreting coefficients of age

import math
math.exp(-0.0208)
```

[24]: 0.9794148279480585

This means that an addition of year in customers age increases the odds of churning by 0.97. This is not a lot.

[25]:
```
#Interpreting coefficients of multi_screen_code

import math
math.exp(1.9511)
```

[25]: 7.036423390843554

This shows that having a multi_scree_code changes the odd of churning by 7.03% and also the p-value of this attribute shows that it is very significant as it is 0.0000.

1.5.2 2. Running model using sklearn

[31]:
```
def prep_model(df, class_col, cols_to_exclude):

    from sklearn.model_selection import train_test_split
```

```
    import numpy as np

    #cleaning the dataframe for logistic regression with the columns which␣
↪we're not using, i.e. phone no, customer_id, & year
    cols = df.select_dtypes(include=np.number).columns.tolist()
    X = df[cols]
    X = X[X.columns.difference(cols_to_exclude)]
    X = X[X.columns.difference([class_col])]

    y = df[class_col]

    #Declaring globally so that we can call this variables outside this␣
↪function also.
    global X_train, X_test, y_train, y_test

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
↪random_state = 0)
```

[32]:
```
def running_model(X_train, X_test, y_train, y_test):

    from sklearn.linear_model import LogisticRegression
    from sklearn.metrics import roc_auc_score, classification_report

    #Defining the logistic model globally to use it outside the function
    global logreg

    #Fitting the logistic regression model from sklearn
    logreg = LogisticRegression(random_state = 13)
    logreg.fit(X_train, y_train)

    #Predicting y values
    global y_pred #Defining globally to use outside the function

    y_pred = logreg.predict(X_test)

    logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))

    print(classification_report(y_test, y_pred))
    print('The area under the curve is: %0.2f'%logit_roc_auc)
```

1.6 Model Evaluation

[33]:
```
prep_model(df, class_col='churn', cols_to_exclude=['customer_id', 'phone_no',␣
↪'year'])
```

[34]:
```
running_model(X_train, X_test, y_train, y_test)
```

```
              precision    recall  f1-score   support

         0.0       0.90      0.98      0.94       513
         1.0       0.47      0.13      0.20        63

    accuracy                           0.89       576
   macro avg       0.69      0.55      0.57       576
weighted avg       0.85      0.89      0.86       576

The area under the curve is: 0.55
```

First we executed the prep_model function to define our training and test sets as per the function. Then we executed running_model function using the training and testing sets.

The precision, recall and f1-score for our prediction is not that good as per the model. Infact the accuracy is very good, so that means our model is predicting properly which customers are not getting churned, but it is not predicting that accuractely which customers are getting churned. Also, the area under the curve is 0.55 which is not that good as the worst model has 0.5 AUC.

[35]:

```
#Confusion matrix

def conf_mat(y_test, y_pred):
    from sklearn.metrics import confusion_matrix

    confusion_matrix = confusion_matrix(y_test, y_pred)
    print(confusion_matrix)

    tn, fp, fn, tp = confusion_matrix.ravel()
    print('TN: %0.2f'%tn)
    print('FP: %0.2f'%fn)
    print('FN: %0.2f'%fn)
    print('TP: %0.2f'%tp)
```

[40]:

```
#ROC Curve

def roc_cur(logreg, X_test, y_test):
    import matplotlib.pyplot as plt
    from sklearn.metrics import roc_auc_score
    from sklearn.metrics import roc_curve

    logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))

    fpr, tpr, thresholds = roc_curve(y_test, logreg.predict(X_test))

    #Creating Graph
    plt.figure()
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
```

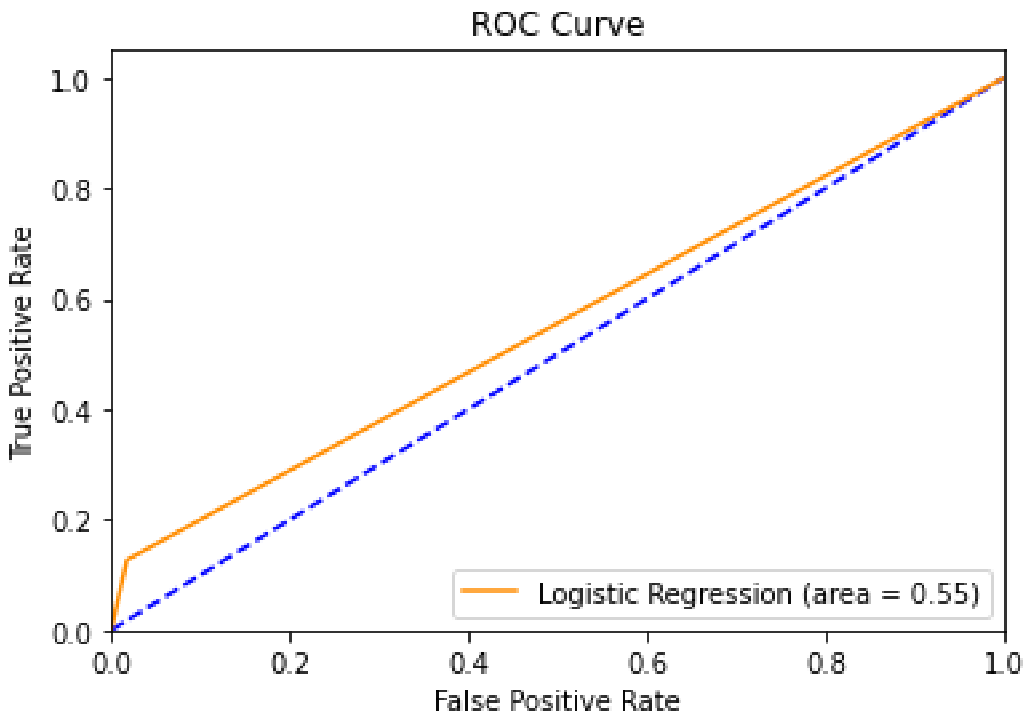
```
    #Plotting the worst ROC model
    plt.plot([0, 1], [0, 1], 'b--')

    #Plotting the logistic regression which we have built
    plt.plot(fpr, tpr, color='darkorange', label='Logistic Regression (area =␣
↪%0.2f)'%logit_roc_auc)

    #Adding labels and titles
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend(loc='lower right')
    plt.savefig('LogROC')
    plt.show()
```

[38]:
```
conf_mat(y_test, y_pred)
```

```
[[504   9]
 [ 55   8]]
TN: 504.00
FP: 55.00
FN: 55.00
TP: 8.00
```

Our TN = 504, TP = 8, this is the reason our model is not good.

[41]:
```
roc_cur(logreg, X_test, y_test)
```



This curve shows that our logistic regression model is not very far from the worst model, hence our model choice is not that good.

1.7 Dealing with Class Imbalance

[42]:
```
df['churn'].describe()
```

[42]:
```
count    1918.000000
mean        0.131908
std         0.338479
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000
Name: churn, dtype: float64
```

In this project we're trying to predict how many customers are getting churned from the platform. So, the churn attribute is our dependent variable. When we describe this attribute we can see that our mean is 0.13, i.e. 13% which says that amount of people getting churned for the year 2015 are only 13%. This bring in the issue of class imbalance and for the same reason our model doesn't works well on this dataset.

1. Dealing with class imbalance using class_weight = balanced in LogisticRegression function of sklearn

[43]:
```
def run_model_bweights(X_train, X_test, y_train, y_test):

    from sklearn.linear_model import LogisticRegression
    from sklearn.metrics import roc_auc_score, classification_report

    #Defining the logistic model globally to use it outside the function
    global logreg

    #Fitting the logistic regression model from sklearn
    logreg = LogisticRegression(random_state = 13, class_weight = 'balanced')␣
↪#here we're adding an extra attribute for balanced class weights
    logreg.fit(X_train, y_train)

    #Predicting y values
    global y_pred #Defining globally to use outside the function

    y_pred = logreg.predict(X_test)

    logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))

    print(classification_report(y_test, y_pred))
    print('The area under the curve is: %0.2f'%logit_roc_auc)
```

Using class_weight = 'balanced' the model either decreases the weight of the majority class or increases the weight of the minority class.

[44]:
```
run_model_bweights(X_train, X_test, y_train, y_test)
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.74      0.84       513
         1.0       0.27      0.78      0.40        63

    accuracy                           0.74       576
   macro avg       0.62      0.76      0.62       576
weighted avg       0.89      0.74      0.79       576

The area under the curve is: 0.76
```

Now, we can see that our results are more better. We have lower precision and better recall, as a result, the AUC is 76%. This is a better model than the one which we executed above. Our F1-Score increased, but the accuracy had a dip of few percentages.

2. Dealing with class imbalance using class_weight = w as argument in LogisticRegression function of sklearn to pass our own tuned weights

[45]:
```
def run_model_aweights(X_train, X_test, y_train, y_test, w):

    from sklearn.linear_model import LogisticRegression
    from sklearn.metrics import roc_auc_score, classification_report

    #Defining the logistic model globally to use it outside the function
    global logreg

    #Fitting the logistic regression model from sklearn

    #here we're adding an extra attribute for our own passed class weights
    logreg = LogisticRegression(random_state = 13, class_weight = w)
    logreg.fit(X_train, y_train)

    #Predicting y values
    global y_pred #Defining globally to use outside the function

    y_pred = logreg.predict(X_test)

    logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))

    print(classification_report(y_test, y_pred))
    print('The area under the curve is: %0.2f'%logit_roc_auc)
```

[51]:
```
run_model_aweights(X_train, X_test, y_train, y_test, {0:90, 1:10})
```

```
              precision    recall  f1-score   support

         0.0       0.89      1.00      0.94       513
         1.0       1.00      0.02      0.03        63

    accuracy                           0.89       576
   macro avg       0.95      0.51      0.49       576
weighted avg       0.90      0.89      0.84       576

The area under the curve is: 0.51
```

Now, we can see our precision is really good, recall, F1-score and AUC is not good, but accuracy is better than earlier one.

3. Dealing with class imbalance using bootstraps for minority/majority class or re-sampling from majority/minority class

[53]:
```
def adjust_imbalance(X_train, y_train, class_col):

    from sklearn.utils import resample #used to resample array or matrix in␣
↪consistent way
    import pandas as pd
```

```
    X = pd.concat([X_train, y_train], axis=1)

    #seperating 2 classes
    class0 = X[X[class_col]==0]
    class1 = X[X[class_col]==1]

    #Case 1 - bootstrapping from minority class - used to convert the minority␣
↪class into the size of majority class
    if len(class1) < len(class0):
        resampled = resample(class1, replace=True, n_samples=len(class0),␣
↪random_state=10)
        resampled_df = pd.concat([resampled, class0])

    #Case 2 -  Resampling from the majority class - used to cut cases from␣
↪majority class until it has size of minority class
    else:
        resampled = resample(class1, replace=False, n_samples=len(calss0),␣
↪random_state=10)
        resampled_df = pd.concat([resampled, class0])

    return resampled_df
```

Above function will generate a resampled dataframe and we can run the model on resampled dataframe.

[54]:
```
resampled_df = adjust_imbalance(X_train, y_train, class_col = 'churn')
```

[56]:
```
prep_model(resampled_df, class_col = 'churn', cols_to_exclude = ['customer_id',␣
↪'phone_no', 'year'])
running_model(X_train, X_test, y_train, y_test)
```

```
              precision    recall  f1-score   support

         0.0       0.67      0.75      0.71       339
         1.0       0.73      0.65      0.69       353

    accuracy                           0.70       692
   macro avg       0.70      0.70      0.70       692
weighted avg       0.70      0.70      0.70       692

The area under the curve is: 0.70
```

This method gives us less accuracy but better AUC. The precision, recall and f1-score is also good here.

4. Dealing with class imbalance using smote

```python
[71]: #Synthetic Minority Optimization Technique. Generated new instances from␣
 ↪existing minority cases that supply as input.

def prep_model_smote(df, class_col, cols_to_exclude):

    from sklearn.model_selection import train_test_split
    import numpy as np
    from imblearn.over_sampling import SMOTE

    #cleaning the dataframe for logistic regression with the columns which␣
 ↪we're not using, i.e. phone no, customer_id, & year
    cols = df.select_dtypes(include=np.number).columns.tolist()
    X = df[cols]
    X = X[X.columns.difference(cols_to_exclude)]
    X = X[X.columns.difference([class_col])]

    y = df[class_col]

    #Declaring globally so that we can call this variables outside this␣
 ↪function also.
    global X_train, X_test, y_train, y_test

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
 ↪random_state = 0)

    sm = SMOTE(random_state=0, sampling_strategy=1.0)
    X_train, y_train = sm.fit_sample(X_train, y_train)
```

```python
[72]: prep_model_smote(df, class_col = 'churn', cols_to_exclude = ['customer_id',␣
 ↪'phone_no', 'year'])
running_model(X_train, X_test, y_train, y_test)
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.72      0.82       513
         1.0       0.25      0.76      0.37        63

    accuracy                           0.72       576
   macro avg       0.60      0.74      0.60       576
weighted avg       0.88      0.72      0.77       576

The area under the curve is: 0.74
```

Using this technique we get area under the curve of 76%, but with lower precision and higher recall.

1.8 Feature Selection

We will try to select best features for our model to increase the accuracy of our model with efficieny. This is beneficial when datasets are large and we can build the best model with less features.

1. Feature Selection using Variance Threshold selection We only get features which pass a certain variance threshold

[79]:
```
class_col = 'churn'
cols_to_exlcude = ['customer_id', 'phone_no', 'year']

def var_threshold_selection(df, cols_to_exclude, class_col, threshold):

    from sklearn.feature_selection import VarianceThreshold
    import numpy as np
    from sklearn import preprocessing

    #cleaning the dataframe for logistic regression with the columns which␣
 ↪we're not using, i.e. phone no, customer_id, & year
    cols = df.select_dtypes(include=np.number).columns.tolist()
    X = df[cols]
    X = X[X.columns.difference(cols_to_exclude)]
    X = X[X.columns.difference([class_col])]

    #Scaling Variables
    scaler = preprocessing.StandardScaler().fit(X)
    X_scaled = scaler.transform(X)
    var_thr = VarianceThreshold(threshold = threshold) #removing both constant␣
 ↪and quasi-constant
    var_thr.fit(X_scaled)
    var_thr.get_support()

    global selected_cols
    selected_cols = X.columns[var_thr.get_support()]

    print('The selected features are: ')
    print(list(selected_cols))
```

[83]:
```
var_threshold_selection(df, cols_to_exclude=['customer_id', 'phone_no',␣
 ↪'year'], class_col = 'churn', threshold = 1)
```

```
The selected features are:
['maximum_daily_mins', 'maximum_days_inactive', 'weekly_mins_watched']
```

[84]:
```
prep_model(resampled_df, class_col = 'churn', cols_to_exclude=['customer_id',␣
 ↪'phone_no', 'year',
                                                                 'gender', 'age',␣
 ↪'no_of_days_subscribed',
```

```
'multi_screen',␣
↪'mail_subscribed', 'minimum_daily_mins',                                                            ␣
↪'weekly_max_night_mins', 'videos_watched',                                                          ␣
↪'customer_support_calls', 'churn', 'gender_code',                                                   ␣
↪'multi_screen_code', 'mail_subscribed_code'])
running_model(X_train, X_test, y_train, y_test)
```

```
              precision    recall  f1-score   support

         0.0       0.57      0.62      0.59       339
         1.0       0.60      0.55      0.57       353

    accuracy                           0.58       692
   macro avg       0.58      0.58      0.58       692
weighted avg       0.59      0.58      0.58       692

The area under the curve is: 0.58
```

This is not that good technique of feature selection as the threshold is not tuned properly and many columns are getting dropped. There is better technique than this which is called as RFE. Above model is similar to the previous one and did not brought a lot of imporvement.

2. Feature Selection using Recursive Feature Eliminations (RFE) This method exectues several models with different features and eliminates them one by one to see the optimal amount of features.

[89]:
```
def rfe_selection(df, cols_to_exclude, class_col, model):

    import warnings
    warnings.filterwarnings('ignore')

    from sklearn.feature_selection import RFE
    import numpy as np

    #cleaning the dataframe for logistic regression with the columns which␣
↪we're not using, i.e. phone no, customer_id, & year
    cols = df.select_dtypes(include=np.number).columns.tolist()
    X = df[cols]
    X = X[X.columns.difference(cols_to_exclude)]
    X = X[X.columns.difference([class_col])]
    y = df[class_col]

    rfe = RFE(model)
    rfe = rfe.fit(X, y)
```

```
    global selected_cols
    selected_cols = X.columns[rfe.support_]

    print('The selected features are: ')
    print(list(selected_cols))
```

[90]:
```
rfe_selection(df, cols_to_exclude=['customer_id', 'phone_no', 'year'],␣
 ↪class_col = 'churn', model=logreg)
```

```
The selected features are:
['customer_support_calls', 'gender_code', 'mail_subscribed_code',
'maximum_days_inactive', 'minimum_daily_mins', 'multi_screen_code']
```

[92]:
```
prep_model(resampled_df, class_col = 'churn', cols_to_exclude=['customer_id',␣
 ↪'phone_no', 'year',
                                                                   'gender', 'age',␣
 ↪'no_of_days_subscribed',
                                                                   'multi_screen',␣
 ↪'mail_subscribed',
                                                                  ␣
 ↪'weekly_max_night_mins', 'gender_code',
                                                                  ␣
 ↪'multi_screen_code', 'mail_subscribed_code'])
running_model(X_train, X_test, y_train, y_test)
```

```
              precision    recall  f1-score   support

         0.0       0.69      0.71      0.70       339
         1.0       0.71      0.69      0.70       353

    accuracy                           0.70       692
   macro avg       0.70      0.70      0.70       692
weighted avg       0.70      0.70      0.70       692

The area under the curve is: 0.70
```

This model gives more better result than the earlier one, these results are very much similar to the one where we used resampled_df. It gives the similar results with very less features. So, it's a better model.

1.9 Saving and Running the Model

[96]:
```
import pickle
pickle.dump(logreg, open('model1.pk1', 'wb')) #use to dump the logreg model␣
 ↪into the file name mentioned in the command
```

[94]:

```python
model = pickle.load(open('model1.pk1', 'rb'))
```

[97]:

```python
model.predict(X_test) #Sample Prediction
```

[97]:

```
array([1., 0., 0., 1., 1., 0., 1., 1., 0., 0., 1., 1., 1., 1., 0., 0., 1.,
       1., 0., 1., 1., 1., 1., 0., 0., 0., 0., 1., 1., 0., 0., 1., 1., 0.,
       1., 1., 1., 0., 0., 1., 0., 1., 0., 1., 1., 1., 0., 1., 1., 1., 0.,
       1., 0., 1., 1., 1., 1., 0., 0., 0., 1., 0., 0., 0., 1., 0., 0., 0.,
       1., 1., 0., 1., 1., 0., 0., 0., 1., 0., 1., 0., 0., 1., 0., 1., 1.,
       1., 1., 1., 1., 1., 1., 1., 1., 1., 0., 0., 1., 0., 1., 0., 0., 0.,
       1., 1., 1., 1., 0., 0., 1., 1., 0., 1., 0., 1., 1., 1., 1., 0., 1.,
       1., 0., 1., 1., 0., 1., 0., 0., 0., 0., 1., 0., 1., 1., 0., 0., 1.,
       1., 1., 1., 0., 1., 1., 0., 1., 0., 0., 1., 1., 0., 1., 0., 1., 0.,
       0., 0., 1., 0., 1., 1., 0., 0., 1., 0., 1., 0., 1., 0., 0., 1., 0.,
       1., 0., 1., 1., 0., 1., 1., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 1., 0., 1., 0., 1., 1., 1., 0., 1., 1., 0., 0., 1., 0., 1.,
       1., 1., 1., 0., 0., 0., 0., 0., 1., 0., 1., 1., 0., 0., 0., 0., 1.,
       0., 1., 0., 0., 0., 0., 1., 1., 1., 1., 1., 0., 1., 0., 0., 0., 1.,
       1., 1., 0., 1., 1., 1., 1., 0., 1., 0., 1., 1., 0., 1., 0., 0., 1.,
       1., 1., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0.,
       1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 0.,
       0., 1., 0., 1., 1., 1., 1., 0., 0., 0., 1., 1., 1., 0., 1., 0., 0.,
       0., 0., 1., 1., 0., 1., 0., 1., 1., 0., 0., 1., 0., 0., 1., 0., 0.,
       1., 1., 0., 1., 1., 1., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0.,
       1., 0., 0., 1., 1., 1., 1., 1., 1., 0., 0., 1., 1., 1., 1., 0., 0.,
       1., 1., 0., 1., 1., 0., 1., 1., 1., 0., 0., 1., 1., 1., 0., 0., 0.,
       0., 0., 1., 1., 0., 0., 1., 0., 0., 1., 0., 1., 1., 1., 0., 0., 0.,
       0., 1., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 1., 1.,
       1., 1., 1., 1., 1., 1., 0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 1.,
       0., 1., 0., 1., 0., 1., 0., 0., 1., 0., 1., 0., 0., 0., 0., 1., 1.,
       1., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 1.,
       0., 0., 1., 1., 1., 1., 1., 1., 0., 0., 1., 1., 0., 0., 1., 1., 1.,
       1., 1., 1., 1., 0., 1., 0., 0., 1., 0., 1., 1., 0., 1., 0., 1., 0.,
       1., 1., 1., 0., 0., 1., 0., 0., 1., 0., 0., 1., 1., 0., 0., 1., 1.,
       0., 1., 1., 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 1., 0., 0., 0.,
       0., 0., 0., 1., 1., 0., 1., 1., 0., 1., 0., 1., 1., 1., 1., 0., 1.,
       1., 0., 0., 0., 0., 1., 1., 1., 1., 1., 1., 0., 0., 1., 1., 1., 1.,
       0., 0., 0., 1., 1., 0., 0., 0., 1., 0., 1., 0., 0., 1., 1., 1., 1.,
       1., 0., 0., 1., 1., 0., 0., 1., 0., 1., 0., 1., 0., 1., 0., 1., 1.,
       1., 1., 0., 1., 0., 0., 1., 0., 0., 1., 0., 1., 1., 1., 0., 0., 0.,
       1., 1., 0., 1., 0., 0., 0., 0., 0., 1., 1., 0., 1., 0., 0., 1., 1.,
       1., 0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 1., 0., 0., 0., 1., 0.,
       1., 0., 1., 1., 1., 0., 0., 1., 0., 0., 1., 0., 1., 1., 1., 0., 0.,
       1., 0., 1., 0., 0., 0., 0., 0., 1., 1., 1., 0., 1., 1., 1., 0., 1.,
       0., 0., 0., 0., 0., 1., 1., 0., 0., 1., 1., 1.])
```