Churn Model

April 30, 2022

0.1 Churn Prediction

Build a basic churn prediction model based on this data – predict the probability of customer churn in the next 6 month from the latest date. The approach would matter here, not the accuracy. You should clearly explain what are the data sanity checks you'll do, what parameters will you use to compare the models, how to measure the accuracy of the model – basically the entire end to end model cycle.

0.1.1

It is difficult to acquire new customers than to retain existing ones.

[248]:
```
import pandas as pd
import numpy as np

import os
import datetime as dt
import utility_functions as uf

#Plotting related libraries
import matplotlib.pyplot as plt

#Modelling related libraries
from sklearn.linear_model import LogisticRegression as LR
from sklearn.model_selection import train_test_split
import joblib

#Model Evaluation Libraries
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.metrics import confusion_matrix, f1_score
```

[4]:
```
#Read the UK related clean data
uk_data_NA_free_cust = pd.read_csv(os.getcwd() + '/Statistics/UK_data_NA_free.
↪csv')

#Unique customers = 3,950
uk_data_NA_free_cust.shape #(3,61,878 X 14)
```

[4]: (361878, 14)

[5]:
```
RFM_data = pd.read_csv(os.getcwd() + '/Final_Data.csv')
if('Unnamed: 0' in RFM_data.columns):
    RFM_data = RFM_data.drop('Unnamed: 0', axis=1)
RFM_data.head()
```

[5]:
```
   CustomerID  Days_SinceLastTxn  InvoiceNo Counts  Total Amount  R_Rank  \
0     13113.0               3794                40      10510.00    16.0
1     15804.0               3794                19       3848.55    16.0
2     13777.0               3794                41      25748.35    16.0
3     17581.0               3794                31      10736.11    16.0
4     12748.0               3794               224      29072.10    16.0

   F_Rank  M_Rank  R_Rank_nrm  R_Rank_score  F_Rank_nrm  F_Rank_score  \
0    35.0    71.0         0.0             0    0.010133             0
1   149.0   311.0         0.0             0    0.044107             0
2    32.5    29.0         0.0             0    0.009388             0
3    55.0    67.0         0.0             0    0.016093             0
4     1.0    22.0         0.0             0    0.000000             0

   M_Rank_nrm  M_Rank_score  RFM_score  Customer_Segments     Customer Tags
0    0.017726             0          0                  2  Churned Customer
1    0.078501             0          0                  2  Churned Customer
2    0.007090             0          0                  2  Churned Customer
3    0.016713             0          0                  2  Churned Customer
4    0.005318             0          0                  2  Churned Customer
```

[6]:
```
#3950
RFM_data.shape
```

[6]: (3950, 16)

[7]:
```
#Ignore the variables 'M_Rank_score', 'R_Rank_score', 'F_Rank_score'
RFM_data[['M_Rank_score', 'R_Rank_score', 'F_Rank_score']].describe()
```

[7]:
```
       M_Rank_score  R_Rank_score  F_Rank_score
count   3950.000000   3950.000000   3950.000000
mean       0.000253      0.003544      0.300759
std        0.015911      0.059436      0.458646
min        0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000
75%        0.000000      0.000000      1.000000
max        1.000000      1.000000      1.000000
```

[8]:
```
#Drop the variables ['M_Rank_score', 'R_Rank_score', 'F_Rank_score']
print(RFM_data.shape)
score_cols = ['M_Rank_score', 'R_Rank_score', 'F_Rank_score']
```

```
if(set(score_cols).intersection(set(RFM_data.columns)) == set(score_cols)):
    RFM_data = RFM_data.drop(score_cols, axis=1)

print(RFM_data.shape)
```

```
(3950, 16)
(3950, 13)
```

0.2 Target Tagging

[9]:
```
customer_tags = {0: 'New Customer', 1:'Best Customer', \
                 2:'Churned Customer', 3:'Risk of Leaving'}

RFM_data['Customer Tags'] = RFM_data['Customer_Segments'].map(customer_tags)

cust_seg_obj = uf.GetStats(RFM_data[['CustomerID', 'Customer Tags']])

cust_seg_obj.categorical_distribution('Customer Tags')
```

[9]:

	Category	Counts	Percentage
0	Best Customer	1153	29.19
3	Churned Customer	1123	28.43
1	New Customer	918	23.24
2	Risk of Leaving	756	19.14

[10]:
```
rfm_stats_obj = uf.GetStats(RFM_data)
rfm_stats = rfm_stats_obj.driver()
rfm_stats
```

[10]:

	Features	Missing Value Count	Missing Value Percentage \
0	CustomerID	0	0.0
1	Days_SinceLastTxn	0	0.0
2	InvoiceNo Counts	0	0.0
3	Total Amount	0	0.0
4	R_Rank	0	0.0
5	F_Rank	0	0.0
6	M_Rank	0	0.0
7	R_Rank_nrm	0	0.0
8	F_Rank_nrm	0	0.0
9	M_Rank_nrm	0	0.0
10	RFM_score	0	0.0
11	Customer_Segments	0	0.0
12	Customer Tags	0	0.0

	Data Types	count	mean	std	min	25% \
0	float64	3950.0	15562.029367	1576.848325	12346.00	14208.250000

1	int64	3950.0	3885.323038	100.236848	3794.00	3810.000000
2	int64	3950.0	5.027089	8.717306	1.00	1.000000
3	float64	3950.0	1713.385669	6548.608224	-4287.63	282.255000
4	float64	3950.0	1975.500000	1140.333924	16.00	965.000000
5	float64	3950.0	1975.500000	1119.520204	1.00	1108.000000
6	float64	3950.0	1975.500000	1140.411104	1.00	988.250000
7	float64	3950.0	0.498918	0.290346	0.00	0.241630
8	float64	3950.0	0.588437	0.333637	0.00	0.329906
9	float64	3950.0	0.500000	0.288785	0.00	0.250000
10	int64	3950.0	0.304557	0.468458	0.00	0.000000
11	int64	3950.0	1.434684	1.045756	0.00	1.000000
12	object	NaN	NaN	NaN	NaN	NaN

	50%	75%	max	# Categories
0	15571.500000	16913.750000	18287.00	NaN
1	3844.000000	3937.000000	4167.00	NaN
2	3.000000	5.000000	224.00	NaN
3	627.060000	1521.782500	256438.49	NaN
4	1991.500000	2962.500000	3943.50	NaN
5	1801.500000	3356.500000	3356.50	NaN
6	1975.500000	2962.750000	3950.00	NaN
7	0.502992	0.750223	1.00	NaN
8	0.536582	1.000000	1.00	NaN
9	0.500000	0.750000	1.00	NaN
10	0.000000	1.000000	2.00	NaN
11	1.000000	2.000000	3.00	NaN
12	NaN	NaN	NaN	4.0

0.3 Independent Variables

1. Days_SinceLastTxn
2. InvoiceNo Counts
3. Total Amount

0.4 Dependent Variable

Customer Tags

[11]:
```
independent_vars = ['Days_SinceLastTxn', 'InvoiceNo Counts', 'Total Amount']
target_var = 'Customer Tags'
RFM_data[['CustomerID'] + independent_vars + [target_var]].head()
```

[11]:

	CustomerID	Days_SinceLastTxn	InvoiceNo Counts	Total Amount \
0	13113.0	3794	40	10510.00
1	15804.0	3794	19	3848.55
2	13777.0	3794	41	25748.35
3	17581.0	3794	31	10736.11

```
4     12748.0                3794               224       29072.10

      Customer Tags
0   Churned Customer
1   Churned Customer
2   Churned Customer
3   Churned Customer
4   Churned Customer
```

0.5 Predict Churn Probability

Strategy:-

Present:- Churn tags for the customers (given the recent date's input)

Get their input details 6 Months before recent date. This will serve as input for the model. Customer Tags for the recent date will serve as output.

Training Data, Testing Data and Validation Data

[12]:
```
#Read the recency file
recency = pd.read_csv(os.getcwd() + "/Statistics/Recency_Customers.csv")
recency.head()
```

[12]:
```
   Unnamed: 0  CustomerID  Days_SinceLastTxn  Years_SinceLastTxn  \
0           0     13113.0               3794           10.394521
1           1     15804.0               3794           10.394521
2           2     13777.0               3794           10.394521
3           3     17581.0               3794           10.394521
4           4     12748.0               3794           10.394521

   Months_SinceLastTxn
0           124.734247
1           124.734247
2           124.734247
3           124.734247
4           124.734247
```

[13]:
```
#Days_SinceLastTxn = Days(Today's Date - InvoiceDate_new)
def get_prior_date(Invoice_date, n_months=6):
    '''
    Input:-
    Invoice_date:- Format is datetime
    n_months:- The number of months
    This function will get the date n_months before the Invoice_date date.
    '''
    if(type(Invoice_date) != dt.datetime):
        Invoice_date = Invoice_date.to_pydatetime()
```

```
    calculated_days = n_months*30 + (1*n_months//2) - 1 #Alternate 30, 31 days␣
↪months
    prior_date = Invoice_date - dt.timedelta(days=calculated_days)

    #Ignore time present in the date
    prior_date = dt.datetime(prior_date.year, prior_date.month, prior_date.day)

    return prior_date

#Date before 6 months from today
get_prior_date(dt.datetime.now(), 6)
```

[13]:
```
datetime.datetime(2021, 10, 30, 0, 0)
```

[14]:
```
#Get the input fields 6 months before current date
uk_data_NA_free_cust.head(3)
#Months since last transaction
#Necessary Columns
'''
['CustomerID', 'Quantity', 'UnitPrice', ]
'''
```

[14]:
```
"\n['CustomerID', 'Quantity', 'UnitPrice', ]\n"
```

[15]:
```
#6-Months prior date
customer_grp = uk_data_NA_free_cust.groupby('CustomerID')#CustomerID is the␣
↪index
```

0.6 R

[161]:
```
class RFM_Prior_Date():
    '''
    Input:-
    df:- A set of records belonging to a particular customer
    Return:-
    R:- Compute fields related to Recency for the customer
    F:- Compute fields related to Frequency for the customer
    M:- Compute fields related to Monetary for the customer
    '''
    def __init__(self, df, months=6):
        self.data = df
        self.months_before = months

    def get_prior_date(self, Invoice_date, n_months=6):
        '''
        This function will get the date n_months before the Invoice_date date.
        Input:-
```

```
        Invoice_date:- Format is datetime
        n_months:- The number of months

        Return:-
        prior_date:- The date n_months before the Invoice_date date.
        '''
        if(type(Invoice_date) != dt.datetime):
            Invoice_date = Invoice_date.to_pydatetime()

        calculated_days = n_months*30 + (1*n_months//2) - 1 #Alternate 30, 31␣
↪days months
        prior_date = Invoice_date - dt.timedelta(days=calculated_days)

        #Ignore time present in the date
        prior_date = dt.datetime(prior_date.year, prior_date.month, prior_date.
↪day)

        return prior_date

    def get_prior_date_records(self, df_grp):

        '''
        Input:-
        df_grp:- The records corresponding to a particular customer

        Return:-
        prior_data:- The data corresonding to previous date
        prior_date_today:- The provious date before today's date
        The prior_date_today will be needed for date calculations in the past.
        '''

        global customers_with_prior_record #Add the customerID whose 6 months␣
↪prior record exists

        df_grp['InvoiceDateExclusive'] = df_grp['InvoiceDateExclusive'].
↪apply(pd.to_datetime)
        df_grp = df_grp.sort_values(by='InvoiceDate_new', ascending=False)

        #Create a month variable. Compare 6 months prior using this variable
        df_grp['Months'] = list(map(lambda invoice_dt:int(str(invoice_dt).
↪split()[0].split('-')[1]),\
                                    df_grp['InvoiceDateExclusive'].tolist()))

        df_grp = df_grp.reset_index()
        current_date = df_grp.loc[0, 'InvoiceDateExclusive']

        #Get the current date 6 months before today
```

```
        prior_date = self.get_prior_date(current_date, self.months_before)
        prior_date_today = self.get_prior_date(pd.Timestamp(dt.datetime.now()))␣
↪#Current Date 6 months before

        prior_data = df_grp.loc[df_grp['Months']==int(str(prior_date).
↪split()[0].split('-')[1]), :]
        return prior_data, prior_date_today

    #R
    def get_recency(self, df_grp):
        '''
        Input:-
        df_grp:- The records corresponding to a particular customer

        Return:-
        Record with 1 row
        prior_recency:- The most recent row for that customer
        '''
        #Get previous date's data
        prior_recency, prior_date_today = self.get_prior_date_records(df_grp)

        #If 6 months prior record exists
        if(prior_recency.shape[0]>0):
            #-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#
            prior_recency = pd.DataFrame(prior_recency)

            #Sort in descending order of InvoiceDate_new
            prior_recency = prior_recency.sort_values(by='InvoiceDate_new',␣
↪ascending=False)

            #Time since the last transaction = Current Date - Maximum Invoice␣
↪Date
            prior_recency['TimeSinceLastTxn'] = prior_date_today -␣
↪prior_recency['InvoiceDateExclusive']#.apply(lambda dt:dt.to_pydatetime())

            #Extract days from the above
            prior_recency['Days_SinceLastTxn'] =␣
↪prior_recency['TimeSinceLastTxn'].apply(lambda diff:diff.days)
            prior_recency['Years_SinceLastTxn'] =␣
↪prior_recency['Days_SinceLastTxn']/365
            prior_recency['Months_SinceLastTxn'] =␣
↪prior_recency['Years_SinceLastTxn']*12

            #Get the latest row. First row of the sorted df in descending order␣
↪of 'TimeSinceLastTxn'
```

```
            prior_recency = prior_recency.sort_values(by='TimeSinceLastTxn',␣
↪ascending=False)

            #Most recent transactions(InvoiceDate_new) will be at the top
            prior_recency = pd.DataFrame(prior_recency.iloc[0,:]).T #Latest␣
↪record

            prior_recency = prior_recency.reset_index()
            customers_with_prior_record.add(prior_recency.loc[0, 'CustomerID'])␣
↪#Add the customer to the set

        return prior_recency

    #F
    def get_frequency(self, df_grp):
        '''
        Input:-
        df_grp:- The records corresponding to a particular customer

        Return:-
        Record with 1 row
        prior_frequency:- The frequency count for that customer
        '''
        #Get previous date's data and count of Invoices then for each customer
        prior_frequency, prior_date_today = self.get_prior_date_records(df_grp)

        if(prior_frequency.shape[0]>0):
            #Count Unique Invoices for each customer
            unique_invoices_count = len(np.unique(prior_frequency['InvoiceNo']))

            prior_frequency = prior_frequency.reset_index()

            customer_id = prior_frequency.loc[0, 'CustomerID']

            prior_frequency =  pd.DataFrame({'CustomerID':[customer_id], \
                                            'InvoiceNo Counts':
↪[unique_invoices_count]},\
                                           columns = ['CustomerID', 'InvoiceNo␣
↪Counts'])
            return prior_frequency[['CustomerID', 'InvoiceNo Counts']]

    #M
    def get_monetary(self, df_grp):
        '''
        Input:-
        df_grp:- The records corresponding to a particular customer
```

```
        Return:-
        Record with 1 row
        prior_monetary:- The total amount spent by the customer
        '''
        #Get previous date's data and count of Invoices then for each customer
        prior_monetary, prior_date_today = self.get_prior_date_records(df_grp)
        if(prior_monetary.shape[0]>0):
            total_amount_sum = sum(df_grp['Total Amount'])#, max(df['Total␣
↪Amount'])]))

            prior_monetary = prior_monetary.reset_index()
            customer_id = prior_monetary.loc[0, 'CustomerID']

            prior_monetary = pd.DataFrame({'CustomerID':[customer_id], \
                                            'Total Amount Sum':
↪[total_amount_sum]},\
                                          columns = ['CustomerID', 'Total␣
↪Amount Sum'])

            return prior_monetary[['CustomerID', 'Total Amount Sum']]

    def remove_unwanted_cols(self, data):
        #Remove unwanted columns created as a result of .reset_index()
        for unwanted_col in ['index', 'Unnamed: 0', 'level_0']:
            if(unwanted_col in data.columns):
                data = data.drop(unwanted_col, axis=1)

        if('CustomerID' in data.index):
            if('CustomerID' in data.columns):
                data = data.drop('CustomerID', axis=1)

            data = data.reset_index()

        #print(data)
        return data

    def driver(self):
        #Group the data basis the CustomerID
        customer_grp = self.data.groupby('CustomerID')

        #Apply R,F and M on each of the groups
        prior_recency = customer_grp.apply(lambda df:self.get_recency(df))

        prior_frequency = customer_grp.apply(lambda df:self.get_frequency(df))

        prior_monetary = customer_grp.apply(lambda df:self.get_monetary(df))
```

```
        #Remove unwanted columns created as a conscequence of .reset_index
        RFM_data_frames = [prior_recency, prior_frequency, prior_monetary]
        prior_recency, prior_frequency, prior_monetary = list(map(
                                                            self.
↪remove_unwanted_cols, RFM_data_frames))
        print("Data Shapes:- \nR:-{}\nF:-{}\nM:-{}" .format(prior_recency.
↪shape, \
                                                               prior_frequency.
↪shape,\
                                                               prior_monetary.
↪shape))
        return prior_recency, prior_frequency, prior_monetary
        '''
        #Merge the frequency and recency data
        RFM = pd.merge(prior_recency, prior_frequency, on='CustomerID',␣
↪how='left')
        return RFM
        '''
```

[162]:
```
RFM_object = RFM_Prior_Date(uk_data_NA_free_cust)
prior_recency, prior_frequency, prior_monetary = RFM_object.driver()
```

```
Data Shapes:-
R:-(764, 18)
F:-(764, 2)
M:-(764, 2)
```

[172]:
```
prior_monetary.head()
```

[172]:

		CustomerID	Total Amount Sum
CustomerID			
12747.0	0	12747.0	4196.01
12748.0	0	12748.0	29072.10
12823.0	0	12823.0	1759.50
12826.0	0	12826.0	1468.12
12839.0	0	12839.0	5583.62

[182]:
```
from functools import reduce
'''

dfs = [df1, df2, df3, df4, df5, df6]
df_final = reduce(lambda left,right: pd.
↪merge(left,right,on='some_common_column_name'), dfs)

'''
def joining_RFM_data(R, F, M):
    def remove_unwanted_cols(data):
```

```
        #data = data.reset_index()
        #Remove unwanted columns created as a result of .reset_index()
        if('CustomerID' in data.columns):
            data = data.drop('CustomerID', axis=1)
            data = data.reset_index()
            for unwanted_col in ['index', 'Unnamed: 0', 'level_0', 'level_1']:
                if(unwanted_col in data.columns):
                    data = data.drop(unwanted_col, axis=1)

        return data

    F = remove_unwanted_cols(prior_frequency)
    R = remove_unwanted_cols(prior_recency)
    M = remove_unwanted_cols(prior_monetary)

    dfs = [R, F, M]
    RFM = reduce(lambda left, right: pd.merge(left, right, on='CustomerID'),␣
↪dfs)
    return RFM
```

[187]:
```
RFM_prior = joining_RFM_data(prior_recency, prior_frequency, prior_monetary)

#Write the Modelling data to a file
RFM_prior.to_csv(os.getcwd() + '/Modelling/modelling_data.csv')
RFM_prior.head()
```

[187]:
```
   CustomerID InvoiceNo StockCode                         Description Quantity  \
0     12747.0    558265     22424              ENAMEL BREAD BIN CREAM        1
1     12748.0    555620     22436          12 COLOURED PARTY BALLOONS       20
2     12823.0    548245     48138                 DOORMAT UNION FLAG       60
3     12826.0    556681     84077  WORLD WAR 2 GLIDERS ASSTD DESIGNS       48
4     12839.0    556229     20712          JUMBO BAG WOODLAND ANIMALS       10

       InvoiceDate UnitPrice         Country          InvoiceNo_Date  \
0  6/28/2011 10:06     12.75  United Kingdom  558265_6/28/2011 10:06
1   6/6/2011 11:46      0.65  United Kingdom   555620_6/6/2011 11:46
2  3/30/2011 10:36      7.65  United Kingdom  548245_3/30/2011 10:36
3   6/14/2011 9:41      0.29  United Kingdom   556681_6/14/2011 9:41
4   6/9/2011 14:43      2.08  United Kingdom   556229_6/9/2011 14:43

  InvoiceDateExclusive InvoiceTimeExclusive      InvoiceDate_new Total Amount  \
0           2011-06-28                10:06  2011-06-28 10:06:00        12.75
1           2011-06-06                11:46  2011-06-06 11:46:00           13
2           2011-03-30                10:36  2011-03-30 10:36:00          459
3           2011-06-14                 9:41  2011-06-14 09:41:00        13.92
4           2011-06-09                14:43  2011-06-09 14:43:00         20.8
```

```
  Months TimeSinceLastTxn Days_SinceLastTxn Years_SinceLastTxn  \
0      6        3777 days              3777            10.3479
1      6        3799 days              3799            10.4082
2      3        3867 days              3867            10.5945
3      6        3791 days              3791            10.3863
4      6        3796 days              3796               10.4

  Months_SinceLastTxn  InvoiceNo Counts  Total Amount Sum
0             124.175                 1           4196.01
1             124.899                16          29072.10
2             127.134                 1           1759.50
3             124.636                 2           1468.12
4               124.8                 1           5583.62
```

0.7 Modelling

Input is 6 months before the current date.

Target(Customer Tags) is current target present in RFM_data prepared during part 1.

[190]:
```
#Map the target class which is 6 months ahead for each of the 764 customers

RFM_prior = pd.merge(RFM_prior, RFM_data[['CustomerID', target]], \
                     on='CustomerID', how='left')

#Target Distribution
modelling_data_stats_obj = uf.GetStats(RFM_prior)
modelling_data_stats_obj.categorical_distribution('Customer Tags')
```

[190]:
```
           Category  Counts  Percentage
3  Churned Customer     531       69.50
1      New Customer     187       24.48
2   Risk of Leaving      31        4.06
0     Best Customer      15        1.96
```

0.7.1 Modelling Data Statistics

[191]:
```
modelling_data_stats_obj.driver()
```

[191]:
```
              Features  Missing Value Count  Missing Value Percentage  \
0           CustomerID                    0                       0.0
1      InvoiceDate_new                    0                       0.0
2     Total Amount Sum                    0                       0.0
3     InvoiceNo Counts                    0                       0.0
4  Months_SinceLastTxn                    0                       0.0
5   Years_SinceLastTxn                    0                       0.0
```

```
6      Days_SinceLastTxn                    0                       0.0
7       TimeSinceLastTxn                    0                       0.0
8                 Months                    0                       0.0
9           Total Amount                    0                       0.0
10  InvoiceTimeExclusive                    0                       0.0
11             InvoiceNo                    0                       0.0
12  InvoiceDateExclusive                    0                       0.0
13        InvoiceNo_Date                    0                       0.0
14               Country                    0                       0.0
15             UnitPrice                    0                       0.0
16           InvoiceDate                    0                       0.0
17              Quantity                    0                       0.0
18           Description                    0                       0.0
19             StockCode                    0                       0.0
20         Customer Tags                    0                       0.0

         Data Types  count          mean           std       min       25%  \
0           float64  764.0  15541.700262   1581.888356  12747.00  14188.25
1            object    NaN           NaN           NaN       NaN       NaN
2           float64  764.0   4993.985825  13874.843717    -24.05   1054.14
3             int64  764.0      1.723822      1.353955      1.00      1.00
4            object    NaN           NaN           NaN       NaN       NaN
5            object    NaN           NaN           NaN       NaN       NaN
6            object    NaN           NaN           NaN       NaN       NaN
7   timedelta64[ns]    NaN           NaN           NaN       NaN       NaN
8            object    NaN           NaN           NaN       NaN       NaN
9            object    NaN           NaN           NaN       NaN       NaN
10           object    NaN           NaN           NaN       NaN       NaN
11           object    NaN           NaN           NaN       NaN       NaN
12   datetime64[ns]    NaN           NaN           NaN       NaN       NaN
13           object    NaN           NaN           NaN       NaN       NaN
14           object    NaN           NaN           NaN       NaN       NaN
15           object    NaN           NaN           NaN       NaN       NaN
16           object    NaN           NaN           NaN       NaN       NaN
17           object    NaN           NaN           NaN       NaN       NaN
18           object    NaN           NaN           NaN       NaN       NaN
19           object    NaN           NaN           NaN       NaN       NaN
20           object    NaN           NaN           NaN       NaN       NaN

          50%         75%        max  # Categories
0   15539.500  16878.2500   18283.00           NaN
1         NaN         NaN        NaN         759.0
2    2202.315   4416.5525  256438.49           NaN
3       1.000      2.0000      16.00           NaN
4         NaN         NaN        NaN         131.0
5         NaN         NaN        NaN         131.0
6         NaN         NaN        NaN         131.0
```

```
7           NaN          NaN         NaN           NaN
8           NaN          NaN         NaN           7.0
9           NaN          NaN         NaN         285.0
10          NaN          NaN         NaN         404.0
11          NaN          NaN         NaN         764.0
12          NaN          NaN         NaN           NaN
13          NaN          NaN         NaN         764.0
14          NaN          NaN         NaN           1.0
15          NaN          NaN         NaN          80.0
16          NaN          NaN         NaN         759.0
17          NaN          NaN         NaN          56.0
18          NaN          NaN         NaN         513.0
19          NaN          NaN         NaN         509.0
20          NaN          NaN         NaN           4.0
```

[198]:

```
#Convert the columns to their correct data types
for col in ['Months_SinceLastTxn', 'Years_SinceLastTxn', 'Days_SinceLastTxn']:
    RFM_prior[col] = pd.to_numeric(RFM_prior[col])

RFM_prior['InvoiceDate_new'] = pd.to_datetime(RFM_prior['InvoiceDate_new'])

RFM_prior[['Months_SinceLastTxn', 'Years_SinceLastTxn', \
           'Days_SinceLastTxn', 'InvoiceDate_new']].dtypes
```

[198]:

```
Months_SinceLastTxn           float64
Years_SinceLastTxn            float64
Days_SinceLastTxn               int64
InvoiceDate_new        datetime64[ns]
dtype: object
```

[226]:

```
independent_variables = ['Months_SinceLastTxn', 'Years_SinceLastTxn', \
                         'Days_SinceLastTxn', 'Total Amount Sum']
RFM_prior[['CustomerID'] + independent_variables + [target]].head()
```

[226]:

```
   CustomerID  Months_SinceLastTxn  Years_SinceLastTxn  Days_SinceLastTxn  \
0     12747.0           124.175342           10.347945               3777
1     12748.0           124.898630           10.408219               3799
2     12823.0           127.134247           10.594521               3867
3     12826.0           124.635616           10.386301               3791
4     12839.0           124.800000           10.400000               3796

   Total Amount Sum     Customer Tags
0           4196.01  Churned Customer
1          29072.10  Churned Customer
2           1759.50      New Customer
3           1468.12  Churned Customer
4           5583.62  Churned Customer
```

[227]:
```
#Binary Classification --> Churn or not Churn
RFM_prior['Target'] = RFM_prior['Customer Tags'].apply(lambda target_class:1␣
↪if(target_class=='Churned Customer') \
                                    else 0)
```

[228]:
```
modelling_data_stats_obj = uf.GetStats(RFM_prior)
modelling_data_stats_obj.categorical_distribution('Target')
```

[228]:

	Category	Counts	Percentage
1	1	531	69.5
0	0	233	30.5

[244]:
```
#Split the data into train and test sets #764 Observations
#Train Size = , Test Size =
X_train, X_test, y_train, y_test = train_test_split(RFM_prior[['CustomerID'] +␣
↪independent_variables],\
                                                    RFM_prior['Target'],\
                                        test_size = 0.15)

train_data = pd.concat([X_train, y_train], axis=1)
test_data = pd.concat([X_test, y_test], axis=1)

print("Train Data Shape:- {}\nTest Data Shape:- {}" .format(train_data.shape, \
                                                          test_data.shape))
```

```
Train Data Shape:- (649, 6)
Test Data Shape:- (115, 6)
```

[230]:
```
train_data.head()
```

[230]:

	CustomerID	Months_SinceLastTxn	Years_SinceLastTxn	Days_SinceLastTxn	\
762	18260.0	130.553425	10.879452	3971	
341	15199.0	126.509589	10.542466	3848	
137	13798.0	124.898630	10.408219	3799	
214	14336.0	125.983562	10.498630	3832	
234	14507.0	125.852055	10.487671	3828	

	Total Amount Sum	Customer Tags
762	2595.00	New Customer
341	1268.70	New Customer
137	36351.42	Churned Customer
214	1614.91	Churned Customer
234	1368.18	Churned Customer

[231]:
```
test_data.head()
```

[231]:
```
     CustomerID  Months_SinceLastTxn  Years_SinceLastTxn  Days_SinceLastTxn  \
565     16837.0           126.016438           10.501370               3833
331     15132.0           125.326027           10.443836               3812
146     13871.0           125.556164           10.463014               3819
362     15367.0           126.838356           10.569863               3858
504     16515.0           126.871233           10.572603               3859

     Total Amount Sum     Customer Tags
565           3167.73  Churned Customer
331            977.93  Churned Customer
146           6389.80  Churned Customer
362           1867.69      New Customer
504           1627.13      New Customer
```

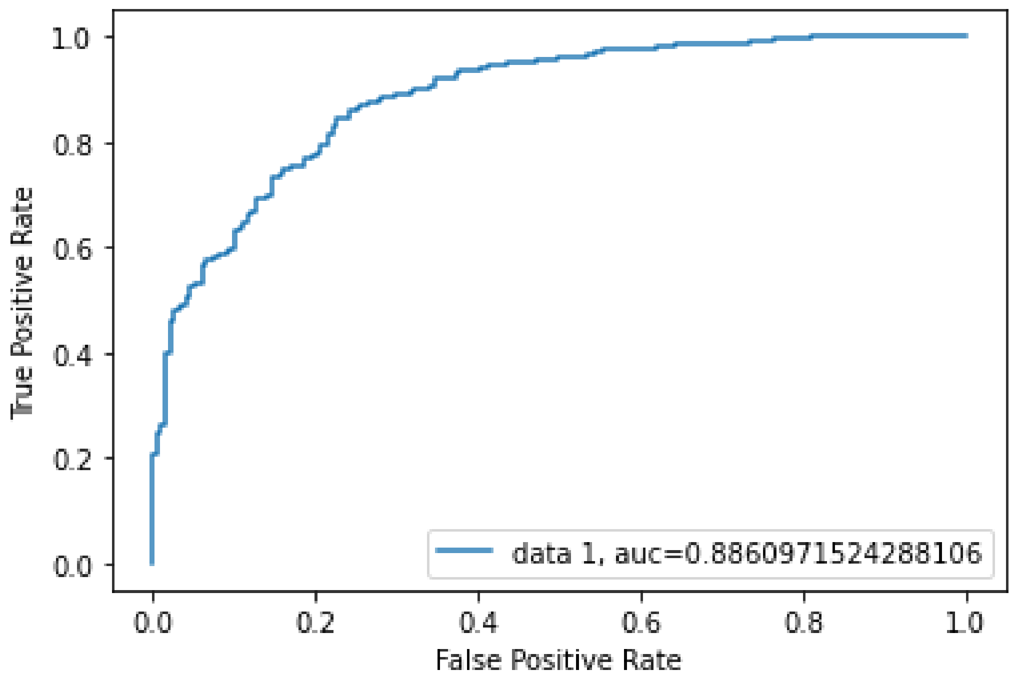
[259]:
```
class Modeling():

    def __init__(self, X_train, X_test, y_train, y_test, model,␣
 ↪name_of_classifier):
        self.X_train = X_train
        self.X_test = X_test
        self.y_train = y_train
        self.y_test = y_test
        self.model = model
        self.clf_name = name_of_classifier

    def auc_roc(self, train_test='train'):
        if(train_test!='train'):
            print("Testing Data")
            X_data = self.X_test
            y_data = self.y_test
        else:
            print("Training Data")
            X_data = self.X_train
            y_data = self.y_train

        predicted_probability = self.model.predict_proba(X_data)

        fpr, tpr, _ = roc_curve(y_data,  predicted_probability[::,1])
        auc = roc_auc_score(y_data, predicted_probability[::,1])
        plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
        plt.legend(loc=4)
        plt.xlabel("False Positive Rate")
        plt.ylabel("True Positive Rate")
        plt.savefig("AUC " + self.clf_name + ".png")
        plt.show()

    def evaluate(self, CM, train_test='train'):
```

```
        accuracy = CM.diagonal().sum()/CM.sum()
        precision = CM[0][0]/(CM[0][0] + CM[0][1])
        recall = CM[0][0]/(CM[0][0] + CM[1][0])
        f_measure = (2*precision*recall)/(precision+recall)
        if(train_test=='train'):
            print("Training Data")
        else:
            print("Testing Data")

        print(CM)
        print("Accuracy:- {:.2f}\nPrecision:- {:.2f}\nRecall:- {:.
↪2f}\nF-measure:- {:.2f}" \
              .format(accuracy*100, precision*100, recall*100, f_measure*100))

    def prediction(self, f=1):
        #X_train, X_test, y_train, y_test = train_test_split(self.X, self.y,␣
↪test_size=test_size/100, random_state=42)

        #Fit the model
        model = self.model.fit(self.X_train, self.y_train)

        #Predict on test set
        predicted_train, predicted_test = model.predict(self.X_train), model.
↪predict(self.X_test)

        #Results
        result_test = pd.DataFrame({'Actual':self.y_test.ravel(), 'Predicted':
↪predicted_test.ravel()}, columns=['Actual','Predicted'])
        result_train = pd.DataFrame({'Actual':self.y_train.ravel(), 'Predicted':
↪predicted_train.ravel()}, columns=['Actual','Predicted'])

        #Save the model
        joblib.dump(model, os.getcwd() + "/Modelling/" + self.clf_name + ".pkl")

        #Print the AUC_ROC curve
        self.auc_roc() #Train
        self.auc_roc('test') #Test

        #Evaluate the model
        CM_train = confusion_matrix(self.y_train.ravel(), predicted_train.
↪ravel(), labels=None, sample_weight=None)
        self.evaluate(CM_train)

        CM_test = confusion_matrix(self.y_test.ravel(), predicted_test.ravel(),␣
↪labels=None, sample_weight=None)
        self.evaluate(CM_test, "test")
```

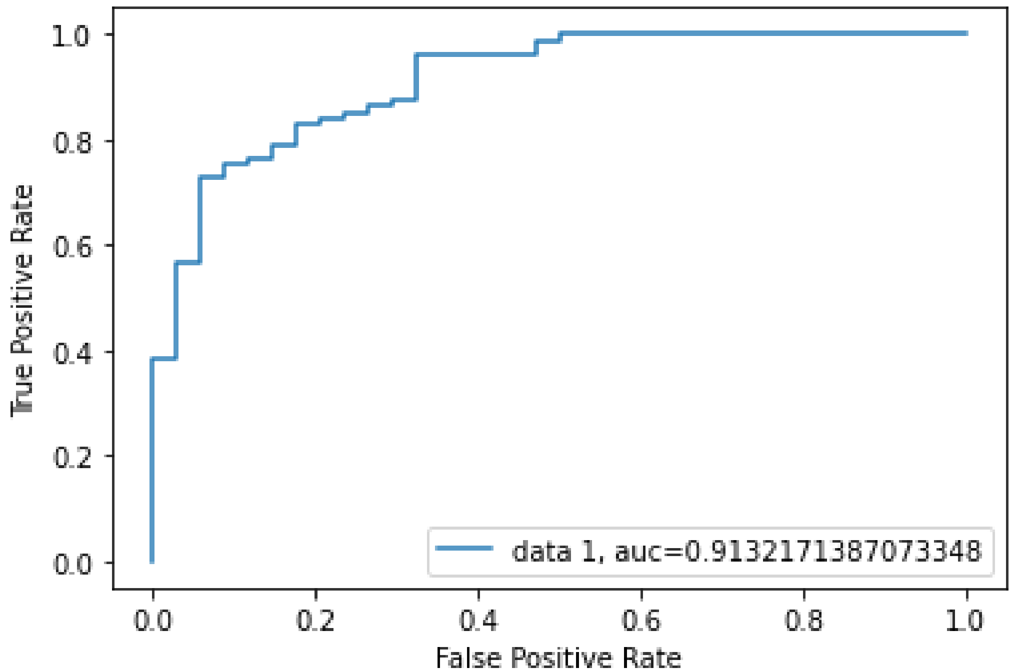
[260]:
```
lr = LR()

logistic_model = lr.fit(X_train[independent_variables], y_train.tolist())
test_prediction = logistic_model.predict(X_train[independent_variables])

train_prediction = logistic_model.predict(X_test[independent_variables])
```

[261]:
```
logistic_model = Modeling(X_train, X_test, y_train, y_test, lr, 'Logistic␣
↪Regression')
logistic_model.prediction()
```

Training Data



Testing Data




```
Training Data
[[146  53]
 [ 59 391]]
Accuracy:- 82.74
Precision:- 73.37
Recall:- 71.22
F-measure:- 72.28
Testing Data
[[23 11]
 [10 71]]
Accuracy:- 81.74
Precision:- 67.65
Recall:- 69.70
F-measure:- 68.66
```

[ ]:

[ ]:

[ ]: