##Setting directory In [1]: import os os.chdir('C:/Users/TOTAGOUSER4/Documents/Totago Technologies/Data Science/Projects/BCG') **Datasets** In [2]: import pandas as pd cust data = pd.read csv('ml case training data.csv') price_data = pd.read_csv('ml_case_training_hist_data.csv') churn_data = pd.read_csv('ml_case_training_output.csv') #Customer Dataset In [3]: cust data.head(10) Out[3]: channel_sales cons_12m activity_new campaign_disc_ele id 48ada52261e7cf58715202705a0451c9 esoiiifxdlbkcsluxmfuacbdckommixw Imkebamcaaclubfxadlmueccxoimlema 309275 24011ae4ebbe3035111d65fa7c15bc57 NaN foosdfpfkusacimwkcsosbicdxkicaua NaN d29c2c54acc38ff3c0614d0a653813dd NaN 4660 NaN NaN 764c75f661154dac3a6c254cd082ea7d 544 NaN NaN foosdfpfkusacimwkcsosbicdxkicaua bba03439a292a1e166f80264c16191cb Imkebamcaaclubfxadlmueccxoimlema NaN NaN 1584 568bb38a1afd7c0fc49c77b3789b59a3 sfisfxfcocfpcmckuekokxuseixdaoeu foosdfpfkusacimwkcsosbicdxkicaua NaN 121335 149d57cf92fc41cf94415803a877cb4b NaN 4425 NaN NaN 1aa498825382410b098937d65c4ec26d 8302 NaN NaN usilxuppasemubllopkaafesmlibmsdf 7ab4bf4878d8f7661dfc20e9b8e18011 sscfoipxikopfskekuobeuxkxmwsuucb NaN foosdfpfkusacimwkcsosbicdxkicaua 45097 01495c955be7ec5e7f3203406785aae0 NaN NaN foosdfpfkusacimwkcsosbicdxkicaua 29552 10 rows × 32 columns In [4]: **#Pricing Data** price data.head(10) Out[4]: price_date price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix **0** 038af19179925da21a25619c5a24b745 2015-01-01 0.151367 0.0 0.0 44.266931 0.0 0.0 038af19179925da21a25619c5a24b745 2015-02-01 0.151367 0.0 0.0 44.266931 0.0 0.0 0.0 0.0 **2** 038af19179925da21a25619c5a24b745 2015-03-01 0.151367 0.0 44.266931 0.0 038af19179925da21a25619c5a24b745 2015-04-01 0.149626 0.0 0.0 44.266931 0.0 0.0 0.0 0.0 0.0 038af19179925da21a25619c5a24b745 2015-05-01 0.149626 44.266931 0.0 038af19179925da21a25619c5a24b745 2015-06-01 0.149626 0.0 0.0 44.266930 0.0 0.0 038af19179925da21a25619c5a24b745 2015-07-01 0.150321 0.0 0.0 44,444710 0.0 0.0 038af19179925da21a25619c5a24b745 0.145859 0.0 0.0 44.444710 0.0 0.0 038af19179925da21a25619c5a24b745 2015-09-01 0.0 44.444710 0.0 0.0 0.145859 0.0 038af19179925da21a25619c5a24b745 2015-10-01 0.145859 0.0 0.0 44.444710 0.0 In [5]: #Churn data churn_data.head(10) Out[5]: id churn 48ada52261e7cf58715202705a0451c9 24011ae4ebbe3035111d65fa7c15bc57 1 d29c2c54acc38ff3c0614d0a653813dd 764c75f661154dac3a6c254cd082ea7d bba03439a292a1e166f80264c16191cb 568bb38a1afd7c0fc49c77b3789b59a3 149d57cf92fc41cf94415803a877cb4b 7 1aa498825382410b098937d65c4ec26d 7ab4bf4878d8f7661dfc20e9b8e18011 01495c955be7ec5e7f3203406785aae0 **Data Cleaning** Dealing with missing data In [6]: #Checking for null values in Customer Details Dataset cust_data.isnull().sum() Out[6]: id activity_new 9545 16096 campaign_disc_ele channel_sales 4218 cons 12m 0 cons_gas_12m 0 0 cons_last_month 0 date_activ date end date_first_activ date_modif_prod date_renewal 40 forecast_base_bill_ele 12588 forecast_base_bill_year 12588 12588 forecast_bill_12m forecast_cons 12588 forecast_cons_12m forecast_cons_year 126 forecast_discount_energy forecast_meter_rent_12m 0 forecast_price_energy_p1 126 126 forecast_price_energy_p2 forecast_price_pow_p1 126 0 has gas imp_cons 13 margin_gross_pow_ele 13 margin_net_pow_ele nb prod act 0 15 net margin 0 num years antig 87 origin up 3 pow max dtype: int64 Columns with null values - activity_new, campaign_disc_ele, channel_sales, date_end, date_first_activ, date_modif_prod, date_renewal, forecast_base_bill_ele, forecast_base_bill_year, forecast_bill_12m, forecast_cons, forecast_discount_energy, forecast_price_energy_p1, forecast_price_energy_p2, forecast_price_pow_p1, margin_gross_pow_ele, margin_net_pow_ele, net_margin, origin_up, pow_max #Checking for null values in Price Dataset price_data.isnull().sum() Out[7]: id 0 price_date price_p1_var 1359 1359 price p2 var price_p3_var 1359 price_p1_fix 1359 price_p2_fix 1359 price p3 fix 1359 dtype: int64 Columns with missing data - price_p1_var, price_p2_var, price_p3_var, price_p1_fix, price_p2_fix, price_p3_fix In [8]: #Checking for null values in Churn Dataset churn_data.isnull().sum() Out[8]: id 0 churn dtype: int64 No nulls here In [9]: #Converting the dates to datetime import datetime for a in ['date_activ', 'date_end', 'date_first_activ', 'date_modif_prod', 'date_renewal']: cust_data[a] = pd.to_datetime(cust_data[a], format='%Y %m %d ') cust data.head(10) Out[9]: activity_new campaign_disc_ele channel_sales cons_12m 48ada52261e7cf58715202705a0451c9 esoiiifxdlbkcsluxmfuacbdckommixw NaN Imkebamcaaclubfxadlmueccxoimlema 309275 24011ae4ebbe3035111d65fa7c15bc57 NaN foosdfpfkusacimwkcsosbicdxkicaua 0 NaN d29c2c54acc38ff3c0614d0a653813dd NaN NaN 4660 NaN 764c75f661154dac3a6c254cd082ea7d NaN NaN foosdfpfkusacimwkcsosbicdxkicaua 544 bba03439a292a1e166f80264c16191cb Imkebamcaaclubfxadlmueccxoimlema NaN 1584 568bb38a1afd7c0fc49c77b3789b59a3 sfisfxfcocfpcmckuekokxuseixdaoeu foosdfpfkusacimwkcsosbicdxkicaua 121335 NaN 149d57cf92fc41cf94415803a877cb4b NaN NaN 4425 NaN 1aa498825382410b098937d65c4ec26d NaN usilxuppasemubllopkaafesmlibmsdf 8302 NaN 7ab4bf4878d8f7661dfc20e9b8e18011 sscfoipxikopfskekuobeuxkxmwsuucb NaN foosdfpfkusacimwkcsosbicdxkicaua 45097 01495c955be7ec5e7f3203406785aae0 29552 NaN foosdfpfkusacimwkcsosbicdxkicaua NaN 10 rows × 32 columns In [10]: #Checking the data type cust_data.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 16096 entries, 0 to 16095 Data columns (total 32 columns): Non-Null Count Dtype Column 0 id 16096 non-null object activity_new 6551 non-null object 0 non-null campaign_disc_ele float64 11878 non-null object 3 channel_sales cons_12m 16096 non-null int64 cons_gas_12m 16096 non-null int64 cons last month 16096 non-null int64 7 date_activ 16096 non-null datetime64[ns] 15939 non-null datetime64[ns] datetime64[ns] datetime64[ns] datetime64[ns] date_end date_first_activ 10 date modif_prod 11 date_renewal 16056 non-null datetime64[ns]
12 forecast_base_bill_ele 3508 non-null float64 13 forecast_base_bill_year 3508 non-null float64 14 forecast_bill_12m 3508 non-null float64 15 forecast_cons 3508 non-null float64 16 forecast_cons_12m 16096 non-null float64 17 forecast_cons_year 16096 non-null int64 18 forecast_discount_energy 15970 non-null float64 19 forecast_meter_rent_12m 16096 non-null float64 20 forecast_price_energy_p1 15970 non-null float64 21 forecast_price_energy_p2 15970 non-null float64 22 forecast_price_pow_p1 15970 non-null float64 23 has_gas 16096 non-null object 16096 non-null float64 24 imp_cons 25 margin_gross_pow_ele 16083 non-null float64 16083 non-null float64 26 margin_net_pow_ele 27 nb_prod_act 16096 non-null int64 28 net_margin 16081 non-null float64 29 num_years_antig 16096 non-null int64 30 origin_up 16009 non-null object 31 pow_max 16093 non-null float64 dtypes: datetime64[ns](5), float64(16), int64(6), object(5) memory usage: 3.9+ MB In [11]: # Filling up nulls in Customer Details Dataset #Filling with zeros for col in ['forecast_base_bill_ele', 'forecast_base_bill_year', 'forecast_bill_12m', 'forecast_cons', 'forecast_discount_energy', 'forecast_price_energy_p1', 'forecast_price_energy_p2', 'forecast_price_pow _p1', 'margin_gross_pow_ele', 'margin_net_pow_ele', 'net_margin', 'pow_max']: cust_data[col].fillna(0, inplace = True) #Filling with null keyword for col in ['channel_sales', 'origin_up']: cust_data[col].fillna('Null', inplace = True) #Filling Dates with activation date for col in ['date_end', 'date_first_activ', 'date_modif_prod', 'date_renewal']: cust_data[col].fillna(cust_data['date_activ'], inplace = True) #Dropping Some columns cust_data.drop(columns=['activity_new', 'campaign_disc_ele',], inplace=True) cust data.head(10) Out[11]: id channel_sales cons_12m cons_gas_12m cons_last_month date_activ date_er 2012-11-48ada52261e7cf58715202705a0451c9 Imkebamcaaclubfxadlmueccxoimlema 07 2013-06-2016-0 24011ae4ebbe3035111d65fa7c15bc57 foosdfpfkusacimwkcsosbicdxkicaua 54946 2009-08-2016-0 d29c2c54acc38ff3c0614d0a653813dd 4660 21 2010-04-2016-0 764c75f661154dac3a6c254cd082ea7d foosdfpfkusacimwkcsosbicdxkicaua 16 2010-03bba03439a292a1e166f80264c16191cb Imkebamcaaclubfxadlmueccxoimlema 1584 30 2010-04-2016-0 12400 568bb38a1afd7c0fc49c77b3789b59a3 foosdfpfkusacimwkcsosbicdxkicaua 121335 2010-01-2016-0 149d57cf92fc41cf94415803a877cb4b 4425 13 2011-12-2016-1 7 1aa498825382410b098937d65c4ec26d 8302 usilxuppasemubllopkaafesmlibmsdf 09 2011-12-2016-1 7ab4bf4878d8f7661dfc20e9b8e18011 45097 foosdfpfkusacimwkcsosbicdxkicaua 02 2016-0 2010-04-01495c955be7ec5e7f3203406785aae0 29552 1260 foosdfpfkusacimwkcsosbicdxkicaua 21 10 rows × 30 columns In [12]: # Filling up nulls in Price Dataset for col in ['price p1 var', 'price p2 var', 'price p3 var', 'price p1 fix', 'price p2 fix', 'price p3 f price_data[col].fillna(0, inplace = True) price data.head(10) Out[12]: price_date price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix **0** 038af19179925da21a25619c5a24b745 2015-01-01 0.151367 0.0 0.0 44.266931 0.0 0.0 44.266931 1 038af19179925da21a25619c5a24b745 2015-02-01 0.151367 0.0 0.0 0.0 0.0 2 038af19179925da21a25619c5a24b745 2015-03-01 0.0 0.151367 0.0 0.0 44.266931 0.0 3 038af19179925da21a25619c5a24b745 2015-04-01 0.149626 0.0 0.0 44.266931 0.0 0.0 4 038af19179925da21a25619c5a24b745 2015-05-01 0.149626 0.0 0.0 44.266931 0.0 0.0 **5** 038af19179925da21a25619c5a24b745 2015-06-01 0.149626 0.0 44.266930 0.0 0.0 0.0 0.150321 0.0 6 038af19179925da21a25619c5a24b745 2015-07-01 0.0 0.0 44.444710 0.0 **7** 038af19179925da21a25619c5a24b745 2015-08-01 0.145859 0.0 0.0 44.444710 0.0 0.0 8 038af19179925da21a25619c5a24b745 2015-09-01 0.145859 0.0 44.444710 0.0 0.0 9 038af19179925da21a25619c5a24b745 2015-10-01 0.145859 0.0 0.0 44.444710 0.0 In [13]: #Cross checking nulls and checking variable types for Customer Details Dataset cust_data.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 16096 entries, 0 to 16095 Data columns (total 30 columns): Non-Null Count Dtype Column ----------0 id 16096 non-null object 16096 non-null object 1 channel_sales cons 12m 16096 non-null int64 3 cons_gas_12m 16096 non-null int64 4 cons last month 16096 non-null int64 5 date activ 16096 non-null datetime64[ns] date end 16096 non-null datetime64[ns] date first activ 16096 non-null datetime64[ns] 8 date_modif_prod 16096 non-null datetime64[ns] 9 date_renewal 16096 non-null datetime64[ns] 10 forecast_base_bill_ele 16096 non-null float64 11 forecast_base_bill_year 16096 non-null float64 12 forecast_bill_12m 16096 non-null float64 13 forecast_cons 16096 non-null float64 14 forecast cons 12m 16096 non-null float64 15 forecast_cons_year 16096 non-null int64 16 forecast_discount_energy 16096 non-null float64 forecast_meter_rent_12m 16096 non-null float64 17 forecast_price_energy_p1 16096 non-null 19 forecast_price_energy_p2 16096 non-null float64 20 forecast_price_pow_p1 16096 non-null float64 16096 non-null object 21 has_gas 16096 non-null float64 22 imp cons 16096 non-null float64 23 margin_gross_pow_ele 24 margin_net_pow_ele 16096 non-null float64 25 nb_prod_act 16096 non-null int64 16096 non-null float64 26 net_margin 27 num_years_antig 16096 non-null int64 28 origin_up 16096 non-null object 29 pow max 16096 non-null float64 dtypes: datetime64[ns](5), float64(15), int64(6), object(4)memory usage: 3.7+ MB In [14]: #Cross checking nulls and checking variable types for price Dataset <class 'pandas.core.frame.DataFrame'> RangeIndex: 193002 entries, 0 to 193001 Data columns (total 8 columns): Non-Null Count Dtype Column 0 193002 non-null object id 1 price date 193002 non-null object 2 price_p1_var 193002 non-null float64 3 price_p2_var 193002 non-null float64 price_p3_var 193002 non-null float64 price_p1_fix 193002 non-null float64 price_p2_fix 193002 non-null float64 7 price_p3_fix 193002 non-null float64 dtypes: float64(6), object(2) memory usage: 11.8+ MB In []: **Data Analysis** In [15]: #For better visualization import matplotlib and seaborn import matplotlib.pyplot as plt plt.style.use('classic') %matplotlib inline import numpy as np import seaborn as sns sns.set() Looking at the rate of those who are also gas clients. In [16]: #Histogram showing number of customers that have gas plt.hist(cust_data['has_gas'], alpha=1.0) plt.title('Customers that are Gas Clients') plt.ylabel('Number of Customers', fontdict = None, labelpad = None) plt.xlabel('True/False', fontdict = None, labelpad = None) plt.plot() Out[16]: [] Customers that are Gas Clients 14000 12000 Number of Customers 10000 8000 6000 4000 2000 True/False From the histogram above, we see that a few of the customers are also gas clients. Now lets compare that to those that churn. In [17]: plt.hist(churn_data['churn'], alpha=1.0) plt.title('Customer Churn Rate') plt.ylabel('Number of Customers', fontdict = None, labelpad = None) plt.xlabel('Churn (No-0, Yes-1)', fontdict = None, labelpad = None) plt.plot() Out[17]: [] Customer Churn Rate 16000 14000 12000 Number of Customers 10000 8000 6000 4000 2000 0 0.2 0.0 Churn (No-0, Yes-1) A few Customers have churned. Which means that many Customers havent churned Now Lets compare the Electricity and gas Consumption for the past 12 months. In [18]: #Electricity Consumption in the past 12 months plt.plot(cust data['cons 12m'], alpha=1.0) plt.title('Electricity Consumption in Past 12 Months') plt.ylabel('Number of Customers', fontdict = None, labelpad = None) plt.xlabel('Electricity Consumption', fontdict = None, labelpad = None) plt.plot() Out[18]: [] Electricity Consumption in Past 12 Months 2.0 1.5 Number of Customers 1.0 0.5 -0.54000 6000 8000 10000 12000 14000 16000 18000 Electricity Consumption #Gas Consumption in the Past 12 Montus plt.plot(cust_data['cons_gas_12m'], alpha=1.0) plt.title('Gas Consumption in Past 12 Months') plt.ylabel('Number of Customers', fontdict = None, labelpad = None) plt.xlabel('Gas Consumption', fontdict = None, labelpad = None) plt.plot() Out[19]: [] Gas Consumption in Past 12 Months 5000000 4000000 Number of Customers 3000000 2000000 1000000 -10000002000 4000 6000 8000 10000 12000 14000 16000 18000 Gas Consumption **Merge the Dataset** In [20]: #dropping the price date, so as to group the data by id price_dataset = price_data.drop(['price_date'], axis = 1) #grouping the data by id, and summing the prices new price data = price dataset.groupby(["id"]).sum() new_price_data.head(10) Out[20]: price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix id 1.245525 0002203ffbb812588b632b9e628cc38d 1.492061 0.877924 488.420789 293.052462 195.368327 0004351ebdd665e6ee664792efc4fd13 1.757118 0.000000 0.000000 532.625404 0.000000 0.000000 0010bcc39e42b3c2131ed2ce55246e3c 2.178702 0.000000 0.000000 543.836520 0.000000 0.000000 487.769130 0010ee3855fdea87602a5b7aba8e42de 1.425085 1.179509 0.828384 292.661462 195.107656 0.000000 531.203164 00114d74e963e47177db89bc70108537 1.775110 0.000000 0.000000 0.000000 00126c87cf78d7604278f0a9adeb689e 1.193008 0.843651 1.437678 487.932042 292.759214 195.172828 0013f326a839a2f6ad87a1859952d227 1.512911 1.266503 0.899048 488.746620 293.247960 195.498660 00184e957277eeef733a7b563fdabd06 1.771648 0.000000 0.000000 531.203164 0.000000 0.000000 001987ed9dbdab4efa274a9c7233e1f4 1.473067 1.227485 0.876366 487.769126 292.661464 195.107662 0.000000 3.209391 0.000000 0019baf3ed1242cd99b3cb592030446f 0.000000 0.000000 695.543164 In [21]: #Join Price data to cust data. Data = pd.merge(cust data, new price data, left on = 'id', right on = 'id', indicator = True) Data.head(10) Out[21]: id channel_sales cons_12m cons_gas_12m cons_last_month date_activ date_er 2016-1 2012-11-48ada52261e7cf58715202705a0451c9 ImkebamcaaclubfxadImueccxoimlema 309275 10025 2016-0 24011ae4ebbe3035111d65fa7c15bc57 foosdfpfkusacimwkcsosbicdxkicaua 2009-08-2016-0 2 d29c2c54acc38ff3c0614d0a653813dd Null 4660 0 21 2010-04-2016-0 3 764c75f661154dac3a6c254cd082ea7d foosdfpfkusacimwkcsosbicdxkicaua 544 16 2010-03-2016-0 bba03439a292a1e166f80264c16191cb Imkebamcaaclubfxadlmueccxoimlema 1584 0 0 30 2016-0 2010-04-5 568bb38a1afd7c0fc49c77b3789b59a3 foosdfpfkusacimwkcsosbicdxkicaua 121335 12400 80 2016-0 2010-01-6 149d57cf92fc41cf94415803a877cb4b Null 4425 0 526 13 2011-12-2016-1 1aa498825382410b098937d65c4ec26d usilxuppasemubllopkaafesmlibmsdf 8302 1998 2016-1 2011-12-8 7ab4bf4878d8f7661dfc20e9b8e18011 foosdfpfkusacimwkcsosbicdxkicaua 45097 0 02 2010-04-2016-0 01495c955be7ec5e7f3203406785aae0 foosdfpfkusacimwkcsosbicdxkicaua 29552 1260 21 10 rows × 37 columns In [22]: #Join churn data. Dataset = pd.merge(Data, churn_data, left_on = 'id', right_on = 'id') Dataset.head(10) Out[22]: id channel sales cons_12m cons_gas_12m cons_last_month date_eı date_activ 2012-11-2016-1 48ada52261e7cf58715202705a0451c9 Imkebamcaaclubfxadlmueccxoimlema 309275 10025 07 2013-06-2016-0 24011ae4ebbe3035111d65fa7c15bc57 foosdfpfkusacimwkcsosbicdxkicaua 0 54946 0 15 2009-08-2016-0 d29c2c54acc38ff3c0614d0a653813dd Null 4660 0 0 21 2010-04-2016-0 764c75f661154dac3a6c254cd082ea7d foosdfpfkusacimwkcsosbicdxkicaua 544 0 0 16 2010-03-2016-0 bba03439a292a1e166f80264c16191cb Imkebamcaaclubfxadlmueccxoimlema 1584 0 30 2010-04-2016-0 5 568bb38a1afd7c0fc49c77b3789b59a3 foosdfpfkusacimwkcsosbicdxkicaua 121335 0 12400 08 2010-01-2016-0 149d57cf92fc41cf94415803a877cb4b Null 4425 0 526 13 2016-1 2011-12-1aa498825382410b098937d65c4ec26d usilxuppasemubllopkaafesmlibmsdf 8302 0 1998 09 2016-1 2011-12-8 7ab4bf4878d8f7661dfc20e9b8e18011 foosdfpfkusacimwkcsosbicdxkicaua 45097 02 2010-04-2016-0 01495c955be7ec5e7f3203406785aae0 foosdfpfkusacimwkcsosbicdxkicaua 29552 0 1260 21 10 rows × 38 columns **Feature Engineering** In [23]: #Checking for nulls Dataset.isnull().sum() Out[23]: id 0 0 channel sales cons 12m 0 0 cons_gas_12m cons last month 0 date activ date end date_first_activ date_modif_prod date_renewal forecast base bill ele forecast_base_bill_year forecast_bill_12m forecast_cons forecast cons 12m forecast_cons_year forecast discount energy forecast_meter_rent_12m 0 forecast price energy pl forecast_price_energy_p2 0 forecast_price_pow_p1 has_gas imp cons margin_gross_pow_ele margin_net_pow_ele nb_prod_act net_margin num_years_antig 0 origin_up 0 pow_max price_p1_var price p2 var price_p3_var 0 price_p1_fix 0 price_p2_fix 0 price_p3_fix 0 0 _merge churn dtype: int64 no null values In [24]: Dataset.info() <class 'pandas.core.frame.DataFrame'> Int64Index: 16096 entries, 0 to 16095 Data columns (total 38 columns): Column Non-Null Count Dtype 0 16096 non-null object channel_sales 1 16096 non-null object 16096 non-null int64 2 cons_12m 3 cons_gas_12m 16096 non-null int64 cons last month 16096 non-null int64 16096 non-null datetime64[ns] date activ 16096 non-null datetime64[ns] 6 date_end 16096 non-null datetime64[ns] 7 date_first_activ 16096 non-null datetime64[ns] date modif prod date_renewal 16096 non-null datetime64[ns] 10 forecast_base_bill_ele 16096 non-null float64 11 forecast_base_bill_year 16096 non-null float64 12 forecast_bill_12m 16096 non-null float64 13 forecast_cons 16096 non-null float64 14 forecast_cons_12m 16096 non-null float64 15 forecast_cons_year 16096 non-null int64 16 forecast_discount_energy 16096 non-null float64 17 forecast_meter_rent_12m 16096 non-null float64 18 forecast_price_energy_p1 16096 non-null float64 19 forecast price energy p2 16096 non-null float64 16096 non-null float64 20 forecast_price_pow_p1 21 has_gas 16096 non-null object 16096 non-null float64 22 imp cons 16096 non-null float64 23 margin gross pow ele 16096 non-null float64 margin net pow ele int64 25 nb_prod_act 16096 non-null 16096 non-null float64 26 net margin 27 num years antig 16096 non-null int64 28 origin up 16096 non-null object 29 pow max 16096 non-null float64 16096 non-null float64 30 price p1 var 16096 non-null float64 31 price p2 var 16096 non-null float64 32 price_p3_var 33 price_p1_fix 16096 non-null float64 16096 non-null float64 34 price_p2_fix 35 price p3 fix 16096 non-null float64 merge 16096 non-null category 37 churn 16096 non-null int64 dtypes: category(1), datetime64[ns](5), float64(21), int64(7), object(4) memory usage: 4.7+ MB Data types are fine Now, Let's generate some features. Features needed; Features present are; channel_sales, cons_12m, cons_gas_12m, cons_last_month, forecast_cons_12m, forecast_cons_year, forecast_discount_energy, forecast_meter_rent_12m, forecast_price_energy_p1, forecast_price_energy_p2, forecast_price_pow_p1, has_gas, imp_cons, margin_gross_pow_ele, margin_net_pow_ele, nb_prod_act, net_margin, num_years_antig, origin_up, pow_max, price_p1_var, price_p2_var, price_p3_var, price_p1_fix, price_p2_fix, price_p3_fix Features to be generated; num_years_renewal (time before contract renewal), avg_month_elec (Average consuption of electricity per month), avg_month_gas (Average consumption of gas per month), In [25]: #generating Average consuption of electricity per month Dataset['avg month elec'] = round(Dataset['cons 12m']/12, 2) #generating Average consumption of gas per month Dataset['avg month gas'] = round(Dataset['cons gas 12m']/12, 2) # generating time before contract renewal Dataset['num years renewal'] = ((Dataset['date renewal']).dt.year - (Dataset['date activ']).dt.year) Dataset.head(10) Out[25]: id channel_sales cons_12m cons_gas_12m cons_last_month date_activ date_er 2012-11-2016-1 48ada52261e7cf58715202705a0451c9 Imkebamcaaclubfxadlmueccxoimlema 309275 10025 07 2013-06-2016-0 24011ae4ebbe3035111d65fa7c15bc57 foosdfpfkusacimwkcsosbicdxkicaua 54946 0 15 2009-08-2016-0 d29c2c54acc38ff3c0614d0a653813dd Null 4660 0 21 2010-04-2016-0 764c75f661154dac3a6c254cd082ea7d foosdfpfkusacimwkcsosbicdxkicaua 544 0 16 2010-03-2016-0 bba03439a292a1e166f80264c16191cb Imkebamcaaclubfxadlmueccxoimlema 1584 30 2010-04-2016-0 568bb38a1afd7c0fc49c77b3789b59a3 foosdfpfkusacimwkcsosbicdxkicaua 121335 0 12400 80 2010-01-2016-0 149d57cf92fc41cf94415803a877cb4b 4425 526 13 2011-12-2016-1 7 1aa498825382410b098937d65c4ec26d usilxuppasemubllopkaafesmlibmsdf 8302 1998 09 2011-12-2016-1 7ab4bf4878d8f7661dfc20e9b8e18011 foosdfpfkusacimwkcsosbicdxkicaua 45097 02 2010-04-2016-0 01495c955be7ec5e7f3203406785aae0 foosdfpfkusacimwkcsosbicdxkicaua 29552 1260 21 10 rows × 41 columns Feature Selection In [26]: #Feature Selection features = Dataset[['channel_sales', 'cons_12m', 'cons_gas_12m', 'cons_last_month', 'forecast_cons_12m' , 'forecast cons year', 'forecast discount energy', 'forecast meter rent 12m', 'forecast price energy p1', 'foreca st_price_energy_p2', 'forecast_price_pow_p1', 'has_gas', 'imp_cons', 'margin_gross_pow_ele', 'margin_net_pow_el e', 'nb_prod_act', 'net_margin', 'num_years_antig', 'origin_up', 'pow_max', 'price_p1_var', 'price_p2_var', 'price_p3_var', 'price_p1_fix', 'price_p2_fix', 'price_p3_fix', 'num_years_renewal', 'avg_month_elec', 'av g month gas']] target = Dataset['churn']