Data_Cleaning

April 12, 2021

Building a churn model to understand whether price sensitivity is the largest driver of churn has potential

- Historical customer data: Customer data such as usage, sign up date, forecasted usage etc
- Historical pricing data: variable and fixed pricing data
- Churn indicator: whether each customer has churned or not

Thesed datasets are otherwise identical and have historical price data and customer data.

0.1 Exploratory Data Analysis & Data Cleaning

- Section **??**
  - Pandas Build-in functions
  - Dataframe sample display
  - Merging datasets
- Section **??**
  - Data Types
  - Data statistics
  - Mssing data
- Section **??**
  - Deep diving in specific parameters

- Visualizing variable distribution
- Section ??
  - Missing data/Empty values
  - Duplicates
- Section ??
  - Dates
  - Negative Data
  - Missing Data
- Section ??

[561]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno

pd.set_option('display.max_rows', None, 'display.max_columns', None)

%matplotlib inline
sns.set_theme(style="whitegrid")

import warnings
warnings.filterwarnings('ignore')

import os
import pickle
```

1. Loading data

Field name	Description	Field name	Description
id	contact id	forecast_price_energy_p1	forecasted energy price for 1st period
activity_new	category of the company's activity	forecast_price_energy_p2	forecasted energy price for 2nd period
campaign_disc_ele	code of the electricity campaign the customer last subscribed to	forecast_price_pow_p1	forecasted power price for 1st period
channel_sales	code of the sales channel	has_gas	indicated if client is also a gas client
cons_12m	electricity consumption of the past 12 months	imp_cons	current paid consumption
cons_gas_12m	gas consumption of the past 12 months	margin_gross_pow_ele	gross margin on power subscription
cons_last_month	electricity consumption of the last month	margin_net_pow_ele	net margin on power subscription
date_activ	date of activation of the contract	nb_prod_act	number of active products and services
date_end	registered date of the end of the contract	net_margin	total net margin
date_first_activ	date of first contract of the client	num_years_antig	antiquity of the client (in number of years)
date_modif_prod	date of last modification of the product	origin_up	code of the electricity campaign the customer first subscribed to
date_renewal	date of the next contract renewal	pow_max	subscribed power
forecast_base_bill_ele	forecasted electricity bill baseline for next month	price_date	reference date
forecast_base_bill_year	forecasted electricity bill baseline for calendar year	price_p1_var	price of energy for the 1st period
forecast_bill_12m	forecasted electricity bill baseline for 12 months	price_p2_var	price of energy for the 2nd period
forecast_cons	forecasted electricity consumption for next month	price_p3_var	price of energy for the 3rd period
forecast_cons_12m	forecasted electricity consumption for next 12 months	price_p1_fix	price of power for the 1st period
forecast_cons_year	forecasted electricity consumption for next calendar year	price_p2_fix	price of power for the 2nd period
forecast_discount_energy	forecasted value of current discount	price_p3_fix	price of power for the 3rd period
forecast_meter_rent_12m	forecasted bill of meter rental for the next 12 months	churned	has the client churned over the next 3 months

[498]:
```
# loading data
features_raw = pd.read_csv('data/ml_case_training_data.csv')
churn_raw = pd.read_csv('data/ml_case_training_output.csv')
price_raw = pd.read_csv('data/ml_case_training_hist_data.csv')
```

[499]:
```python
# copying data
features = features_raw.copy()
churn = churn_raw. copy()
price = price_raw.copy()
```

[500]:
```python
# feature data display
features.head(2)
```

[500]:
```
                                 id                     activity_new  \
0  48ada52261e7cf58715202705a0451c9  esoiiifxdlbkcsluxmfuacbdckommixw
1  24011ae4ebbe3035111d65fa7c15bc57                              NaN

  campaign_disc_ele                     channel_sales  cons_12m  \
0               NaN  lmkebamcaaclubfxadlmueccxoimlema    309275
1               NaN  foosdfpfkusacimwkcsosbicdxkicaua         0

   cons_gas_12m  cons_last_month  date_activ    date_end date_first_activ  \
0             0            10025  2012-11-07  2016-11-06              NaN
1         54946                0  2013-06-15  2016-06-15              NaN

  date_modif_prod date_renewal  forecast_base_bill_ele  \
0      2012-11-07   2015-11-09                     NaN
1             NaN   2015-06-23                     NaN

   forecast_base_bill_year  forecast_bill_12m  forecast_cons  \
0                      NaN                NaN            NaN
1                      NaN                NaN            NaN

   forecast_cons_12m  forecast_cons_year  forecast_discount_energy  \
0            26520.3               10025                       0.0
1                0.0                   0                       0.0

   forecast_meter_rent_12m  forecast_price_energy_p1  \
0                   359.29                  0.095919
1                     1.78                  0.114481

   forecast_price_energy_p2  forecast_price_pow_p1 has_gas  imp_cons  \
0                  0.088347              58.995952       f     831.8
1                  0.098142              40.606701       t       0.0

   margin_gross_pow_ele  margin_net_pow_ele  nb_prod_act  net_margin  \
0                -41.76              -41.76            1     1732.36
1                 25.44               25.44            2      678.99

   num_years_antig                       origin_up  pow_max
0                3  ldkssxwpmemidmecebumciepifcamkci  180.000
1                3  lxidpiddsbxsbosboudacockeimpuepw   43.648
```

[501]:

```
# churn data display
churn.head(2)
```

[501]:

```
                                 id  churn
0  48ada52261e7cf58715202705a0451c9      0
1  24011ae4ebbe3035111d65fa7c15bc57      1
```

[502]:

```
# price data display
price.head(2)
```

[502]:

```
                                 id  price_date  price_p1_var  price_p2_var  \
0  038af19179925da21a25619c5a24b745  2015-01-01      0.151367           0.0
1  038af19179925da21a25619c5a24b745  2015-02-01      0.151367           0.0

   price_p3_var  price_p1_fix  price_p2_fix  price_p3_fix
0           0.0     44.266931           0.0           0.0
1           0.0     44.266931           0.0           0.0
```

[503]:

```
# merging feature data and churn data
# merge two dataframes
client = features.merge(churn, on = 'id')
client.head()
```

[503]:

```
                                 id                      activity_new  \
0  48ada52261e7cf58715202705a0451c9  esoiiifxdlbkcsluxmfuacbdckommixw
1  24011ae4ebbe3035111d65fa7c15bc57                               NaN
2  d29c2c54acc38ff3c0614d0a653813dd                               NaN
3  764c75f661154dac3a6c254cd082ea7d                               NaN
4  bba03439a292a1e166f80264c16191cb                               NaN

   campaign_disc_ele                     channel_sales  cons_12m  \
0                NaN  lmkebamcaaclubfxadlmueccxoimlema    309275
1                NaN  foosdfpfkusacimwkcsosbicdxkicaua         0
2                NaN                               NaN      4660
3                NaN  foosdfpfkusacimwkcsosbicdxkicaua       544
4                NaN  lmkebamcaaclubfxadlmueccxoimlema      1584

   cons_gas_12m  cons_last_month  date_activ    date_end date_first_activ  \
0             0            10025  2012-11-07  2016-11-06              NaN
1         54946                0  2013-06-15  2016-06-15              NaN
2             0                0  2009-08-21  2016-08-30              NaN
3             0                0  2010-04-16  2016-04-16              NaN
4             0                0  2010-03-30  2016-03-30              NaN

  date_modif_prod date_renewal  forecast_base_bill_ele  \
0      2012-11-07   2015-11-09                     NaN
1             NaN   2015-06-23                     NaN
```

```
2     2009-08-21  2015-08-31                         NaN
3     2010-04-16  2015-04-17                         NaN
4     2010-03-30  2015-03-31                         NaN

   forecast_base_bill_year  forecast_bill_12m  forecast_cons  \
0                      NaN                NaN            NaN
1                      NaN                NaN            NaN
2                      NaN                NaN            NaN
3                      NaN                NaN            NaN
4                      NaN                NaN            NaN

   forecast_cons_12m  forecast_cons_year  forecast_discount_energy  \
0           26520.30               10025                       0.0
1               0.00                   0                       0.0
2             189.95                   0                       0.0
3              47.96                   0                       0.0
4             240.04                   0                       0.0

   forecast_meter_rent_12m  forecast_price_energy_p1  \
0                   359.29                  0.095919
1                     1.78                  0.114481
2                    16.27                  0.145711
3                    38.72                  0.165794
4                    19.83                  0.146694

   forecast_price_energy_p2  forecast_price_pow_p1 has_gas  imp_cons  \
0                  0.088347              58.995952       f     831.8
1                  0.098142              40.606701       t       0.0
2                  0.000000              44.311378       f       0.0
3                  0.087899              44.311378       f       0.0
4                  0.000000              44.311378       f       0.0

   margin_gross_pow_ele  margin_net_pow_ele  nb_prod_act  net_margin  \
0                -41.76              -41.76            1     1732.36
1                 25.44               25.44            2      678.99
2                 16.38               16.38            1       18.89
3                 28.60               28.60            1        6.60
4                 30.22               30.22            1       25.46

   num_years_antig                       origin_up  pow_max  churn
0                3  ldkssxwpmemidmecebumciepifcamkci  180.000      0
1                3  lxidpiddsbxsbosboudacockeimpuepw   43.648      1
2                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.800      0
3                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.856      0
4                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.200      0
```

2. General statistics of datasets

Data Type we look at the datatype of client, we could tell that there are four data related columns `date_activ`, `date_end`, `date_first_activ`, `date_modif_prod`, and `date_renewal` has the wrong datatype of object, we will convert these to datetime datetype later.

For the price dataset, the `price_date` has the wrong datatype as well, we will convert it later.

[504]:
```
pd.DataFrame({'data_type': client.dtypes})
```

[504]:

	data_type
id	object
activity_new	object
campaign_disc_ele	float64
channel_sales	object
cons_12m	int64
cons_gas_12m	int64
cons_last_month	int64
date_activ	object
date_end	object
date_first_activ	object
date_modif_prod	object
date_renewal	object
forecast_base_bill_ele	float64
forecast_base_bill_year	float64
forecast_bill_12m	float64
forecast_cons	float64
forecast_cons_12m	float64
forecast_cons_year	int64
forecast_discount_energy	float64
forecast_meter_rent_12m	float64
forecast_price_energy_p1	float64
forecast_price_energy_p2	float64
forecast_price_pow_p1	float64
has_gas	object
imp_cons	float64
margin_gross_pow_ele	float64
margin_net_pow_ele	float64
nb_prod_act	int64
net_margin	float64
num_years_antig	int64
origin_up	object
pow_max	float64
churn	int64

[505]:
```
pd.DataFrame({'data_type': price.dtypes})
```

[505]:

	data_type
id	object
price_date	object

```
price_p1_var    float64
price_p2_var    float64
price_p3_var    float64
price_p1_fix    float64
price_p2_fix    float64
price_p3_fix    float64
```

Data Statistics For the client data, we obtain a lot of information about the dataset we are dealing with. - The minimum `consumption` and `forecasts` for electricity and gas (yearly and monthly) are negative. This could mean that the client comapnies are producing energy and therefore energy should be 'returned', although it is unlikly and we will consider it as corrupted data - The `campaign_disc_ele` is an empty column. We verify it by running. assert client.campaign_disc_ele.isnull().sum() == client.shape[0] - Highly skewed data when we look at histplot

For the price data, it looks overall good. We might be consider that negative value on fix price columns. One more time, this might be corrupted data and we will change them to positive when cleaning the data.

[506]:
```python
assert client.campaign_disc_ele.isnull().sum() == client.shape[0]
```

[507]:
```python
client.describe()
```

[507]:
```
       campaign_disc_ele       cons_12m   cons_gas_12m  cons_last_month  \
count                0.0   1.609600e+04   1.609600e+04     1.609600e+04
mean                 NaN   1.948044e+05   3.191164e+04     1.946154e+04
std                  NaN   6.795151e+05   1.775885e+05     8.235676e+04
min                  NaN  -1.252760e+05  -3.037000e+03    -9.138600e+04
25%                  NaN   5.906250e+03   0.000000e+00     0.000000e+00
50%                  NaN   1.533250e+04   0.000000e+00     9.010000e+02
75%                  NaN   5.022150e+04   0.000000e+00     4.127000e+03
max                  NaN   1.609711e+07   4.188440e+06     4.538720e+06

       forecast_base_bill_ele  forecast_base_bill_year  forecast_bill_12m  \
count             3508.000000              3508.000000        3508.000000
mean               335.843857               335.843857        3837.441866
std                649.406000               649.406000        5425.744327
min               -364.940000              -364.940000       -2503.480000
25%                  0.000000                 0.000000        1158.175000
50%                162.955000               162.955000        2187.230000
75%                396.185000               396.185000        4246.555000
max              12566.080000             12566.080000       81122.630000

       forecast_cons  forecast_cons_12m  forecast_cons_year  \
count    3508.000000       16096.000000        16096.000000
mean      206.845165        2370.555949         1907.347229
std       455.634288        4035.085664         5257.364759
```

```
min         0.000000      -16689.260000      -85627.000000
25%         0.000000         513.230000           0.000000
50%        42.215000        1179.160000         378.000000
75%       228.117500        2692.077500        1994.250000
max      9682.890000      103801.930000      175375.000000

       forecast_discount_energy  forecast_meter_rent_12m  \
count              15970.000000             16096.000000
mean                   0.991547                70.309945
std                    5.160969                79.023251
min                    0.000000              -242.960000
25%                    0.000000                16.230000
50%                    0.000000                19.440000
75%                    0.000000               131.470000
max                   50.000000              2411.690000

       forecast_price_energy_p1  forecast_price_energy_p2  \
count              15970.000000              15970.000000
mean                   0.135901                  0.052951
std                    0.026252                  0.048617
min                    0.000000                  0.000000
25%                    0.115237                  0.000000
50%                    0.142881                  0.086163
75%                    0.146348                  0.098837
max                    0.273963                  0.195975

       forecast_price_pow_p1      imp_cons  margin_gross_pow_ele  \
count           15970.000000  16096.000000          16083.000000
mean               43.533496    196.123447             22.462276
std                 5.212252    494.366979             23.700883
min                -0.122184  -9038.210000           -525.540000
25%                40.606701      0.000000             11.960000
50%                44.311378     44.465000             21.090000
75%                44.311378    218.090000             29.640000
max                59.444710  15042.790000            374.640000

       margin_net_pow_ele   nb_prod_act    net_margin  num_years_antig  \
count        16083.000000  16096.000000  16081.000000     16096.000000
mean            21.460318      1.347788    217.987028         5.030629
std             27.917349      1.459808    366.742030         1.676101
min           -615.660000      1.000000  -4148.990000         1.000000
25%             11.950000      1.000000     51.970000         4.000000
50%             20.970000      1.000000    119.680000         5.000000
75%             29.640000      1.000000    275.810000         6.000000
max            374.640000     32.000000  24570.650000        16.000000

            pow_max         churn
```

```
count  16093.000000  16096.000000
mean      20.604131      0.099093
std       21.772421      0.298796
min        1.000000      0.000000
25%       12.500000      0.000000
50%       13.856000      0.000000
75%       19.800000      0.000000
max      500.000000      1.000000
```

[508]:
```
price.describe()
```

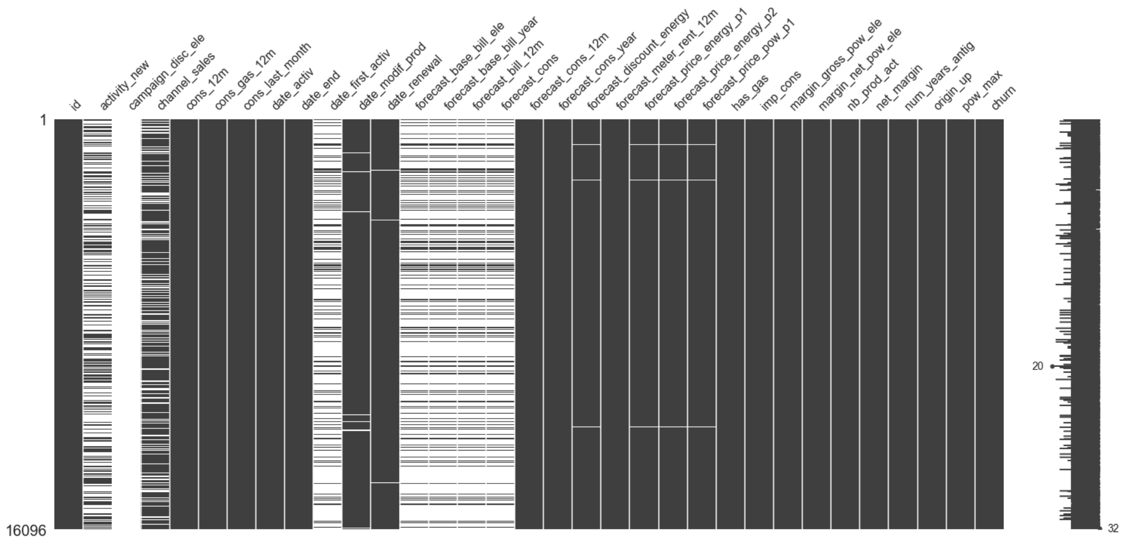
[508]:
```
         price_p1_var   price_p2_var   price_p3_var   price_p1_fix  \
count   191643.000000  191643.000000  191643.000000  191643.000000
mean         0.140991       0.054412       0.030712      43.325546
std          0.025117       0.050033       0.036335       5.437952
min          0.000000       0.000000       0.000000      -0.177779
25%          0.125976       0.000000       0.000000      40.728885
50%          0.146033       0.085483       0.000000      44.266930
75%          0.151635       0.101780       0.072558      44.444710
max          0.280700       0.229788       0.114102      59.444710

         price_p2_fix   price_p3_fix
count   191643.000000  191643.000000
mean        10.698201       6.455436
std         12.856046       7.782279
min         -0.097752      -0.065172
25%          0.000000       0.000000
50%          0.000000       0.000000
75%         24.339581      16.226389
max         36.490692      17.458221
```

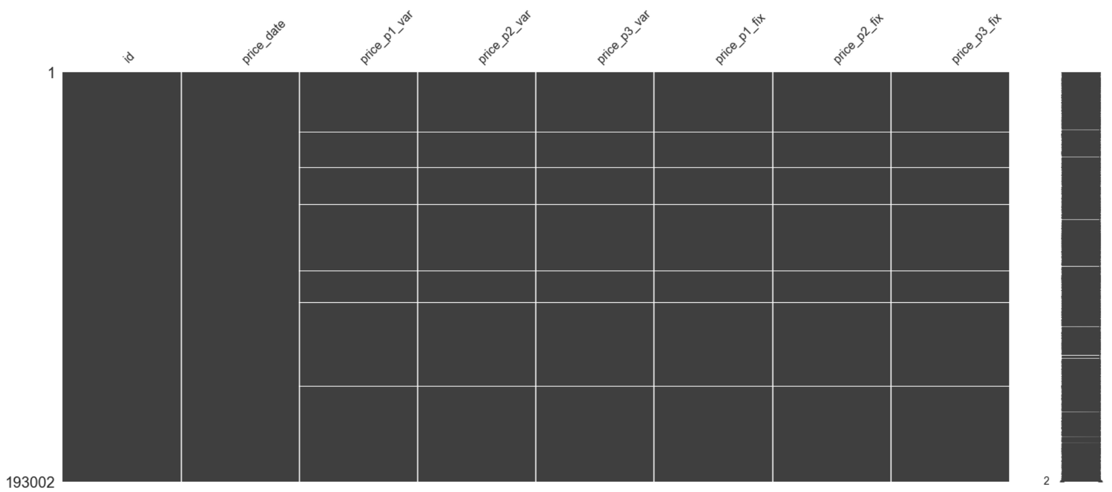
Missing data we also conconered we have a lot of missing data so we can check how much of our data is missing

For client data, these are 6 columns having more than 75% of missing values. we will remove these columns from the dataset `campaign_disc_ele`, `date_first_activ`, `forecast_base_bill_ele`, `forecast_base_bill_year`,`forecast_bill_12m`,`forecast_cons`.

The price data is qualified overall.

[509]:
```
msno.matrix(client);
msno.matrix(price);
```





```
[510]: pd.DataFrame({'Data_Type' : (client.isnull().sum()/client.shape[0])*100})
```

```
[510]:                       Data_Type
       id                     0.000000
       activity_new          59.300447
       campaign_disc_ele    100.000000
       channel_sales         26.205268
       cons_12m               0.000000
       cons_gas_12m           0.000000
       cons_last_month        0.000000
       date_activ             0.000000
       date_end               0.012425
```

```
date_first_activ           78.205765
date_modif_prod             0.975398
date_renewal                0.248509
forecast_base_bill_ele     78.205765
forecast_base_bill_year    78.205765
forecast_bill_12m          78.205765
forecast_cons              78.205765
forecast_cons_12m           0.000000
forecast_cons_year          0.000000
forecast_discount_energy    0.782803
forecast_meter_rent_12m     0.000000
forecast_price_energy_p1    0.782803
forecast_price_energy_p2    0.782803
forecast_price_pow_p1       0.782803
has_gas                     0.000000
imp_cons                    0.000000
margin_gross_pow_ele        0.080765
margin_net_pow_ele          0.080765
nb_prod_act                 0.000000
net_margin                  0.093191
num_years_antig             0.000000
origin_up                   0.540507
pow_max                     0.018638
churn                       0.000000
```

[511]:
```
pd.DataFrame({'Data_Type' : (price.isnull().sum()/price.shape[0])*100})
```

[511]:
```
              Data_Type
id             0.000000
price_date     0.000000
price_p1_var   0.704138
price_p2_var   0.704138
price_p3_var   0.704138
price_p1_fix   0.704138
price_p2_fix   0.704138
price_p3_fix   0.704138
```

Data Visulization Let's take deeper insight on some features.

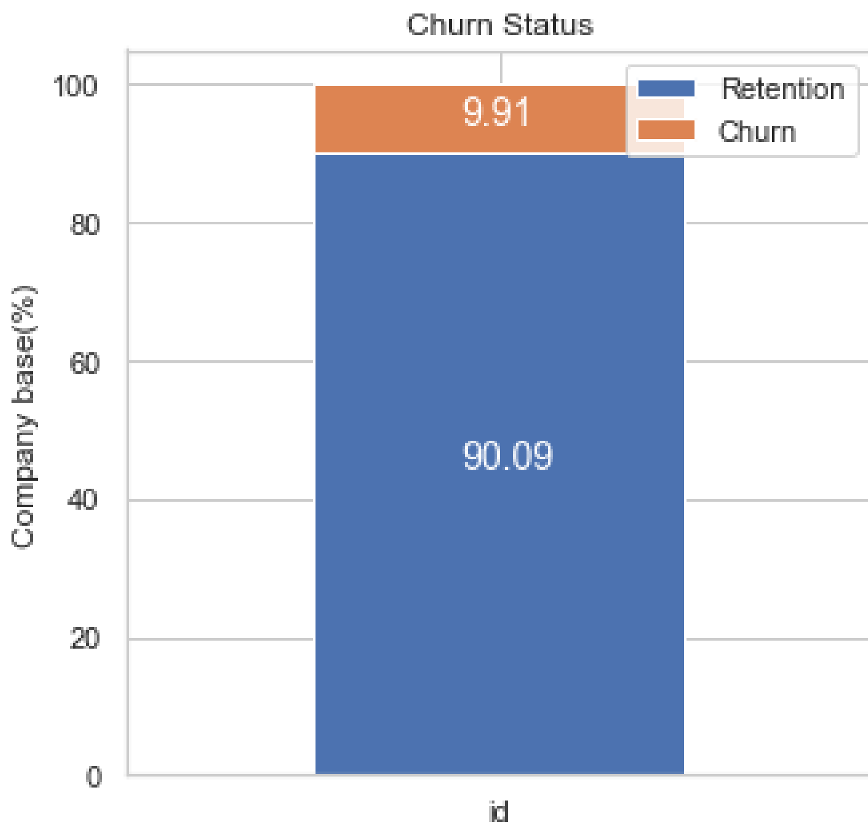
Churn About 10% of the of total customers have churned.

[512]:
```
def plot_stacked_bars(df, title_, size_ = (18, 10), rot_ = 0, legend_ = 'upper␣
↪right'):
    '''
    Plot stacked bars with annotations
    '''
    ax = df.plot(kind = 'bar',
```

```
                stacked = True,
                figsize = size_,
                rot = rot_,
                title = title_)
    # annotate bars
    annotate_stacked_bars(ax, textsize = 14)
    # rename legend
    plt.legend(['Retention', 'Churn'], loc=legend_)
    # labels
    plt.ylabel('Company base(%)')
    plt.show()

def annotate_stacked_bars(ax, pad = 0.99, colour = 'white', textsize = 13):
    '''
    Add Value annotations to the bar
    '''
    # Iterate over the plotted rectanges/bars
    for p in ax.patches:
        # calculate annotation
        value = str(round(p.get_height(), 2))
        # if value is 0 do not annotate
        if value == '0.0':
            continue
        ax.annotate(value, ((p.get_x() + p.get_width()/2)*pad - 0.05, (p.
 ↪get_y() + p.get_height()/2)*pad),
                    color = colour, size = textsize)
```

[513]:
```
client_total = client.groupby(client['churn']).count()
client_perc = client_total/client_total.sum()*100
client_perc = client_perc[['id']].transpose()
```

[514]:
```
plot_stacked_bars(client_perc, 'Churn Status', (5, 5))
```



SME activity Let's show the activity distribution of the companies as well as the sales channel.

Intuitively this might be an important predictive feature for energy consumption.

The distribution of the classes over the labeled data despite the lack of 60% of the entries

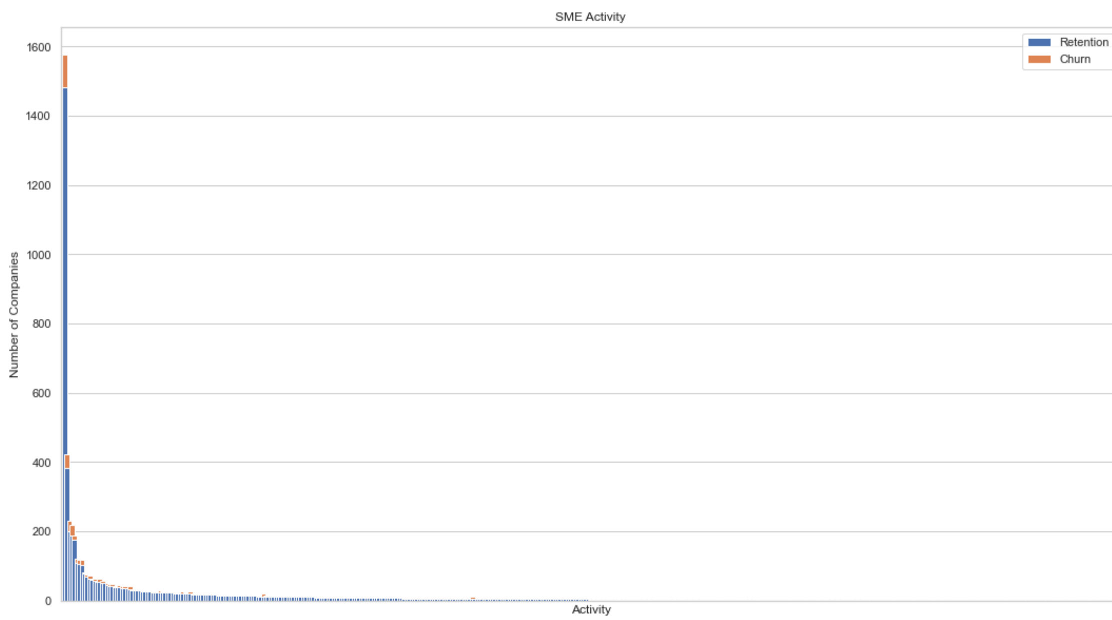
We see churn is not specifically related to any SME category in particular.

How will the SME activity influence our predictive model? > Our predictive modelis likely to struggle accurately predicting the SME activity due to the large number of categories and low number of companies belonging to each category.

[515]:
```
churn_by_activity = client.groupby(['activity_new', 'churn'])['id']\
.count()\
.unstack(level = 1)\
.fillna(0)\
.sort_values(by = [0], ascending = False)
```

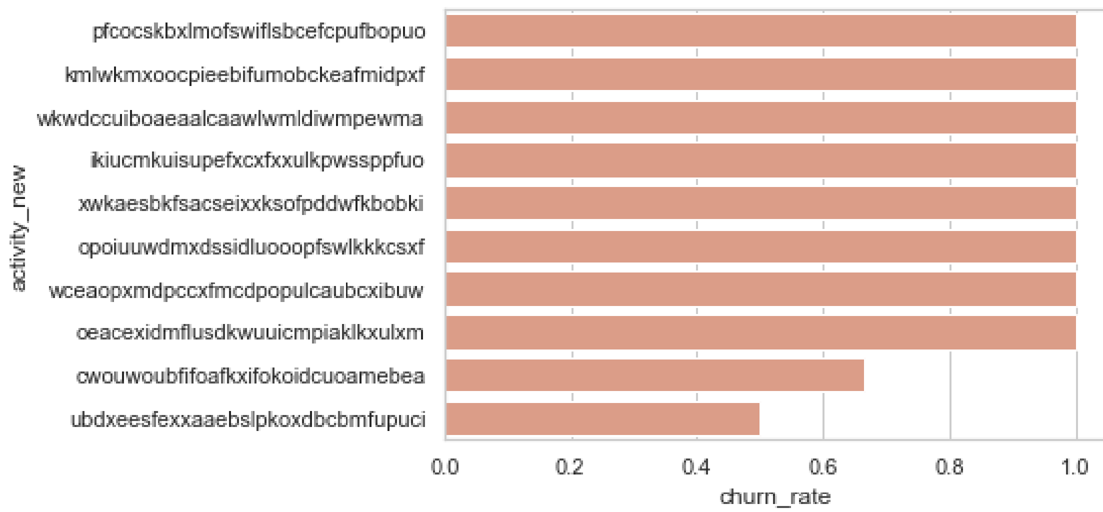
[516]:
```
churn_by_activity.plot(kind = 'bar',
                       figsize = (18, 10),
                       width = 2,
                       stacked = True,
```

```
                          title = 'SME Activity');
# labels
plt.ylabel('Number of Companies')
plt.xlabel('Activity')
# rename legend
plt.legend(['Retention', 'Churn'], loc = 'upper right')
# Remove the label for the xticks as the categories are encoded and we cant␣
 ↪draw any meaning from them yet
plt.xticks([])
plt.show();
```



[517]:
```
# high churn rate by activity
churn_by_activity['total_companies'] = churn_by_activity[0] +␣
 ↪churn_by_activity[1]
churn_by_activity['churn_rate'] = churn_by_activity[1]/
 ↪churn_by_activity['total_companies']
top_churn_rate_by_activity = churn_by_activity\
.sort_values(by = 'churn_rate', ascending = False)[['churn_rate']]\
.head(10).reset_index()
```

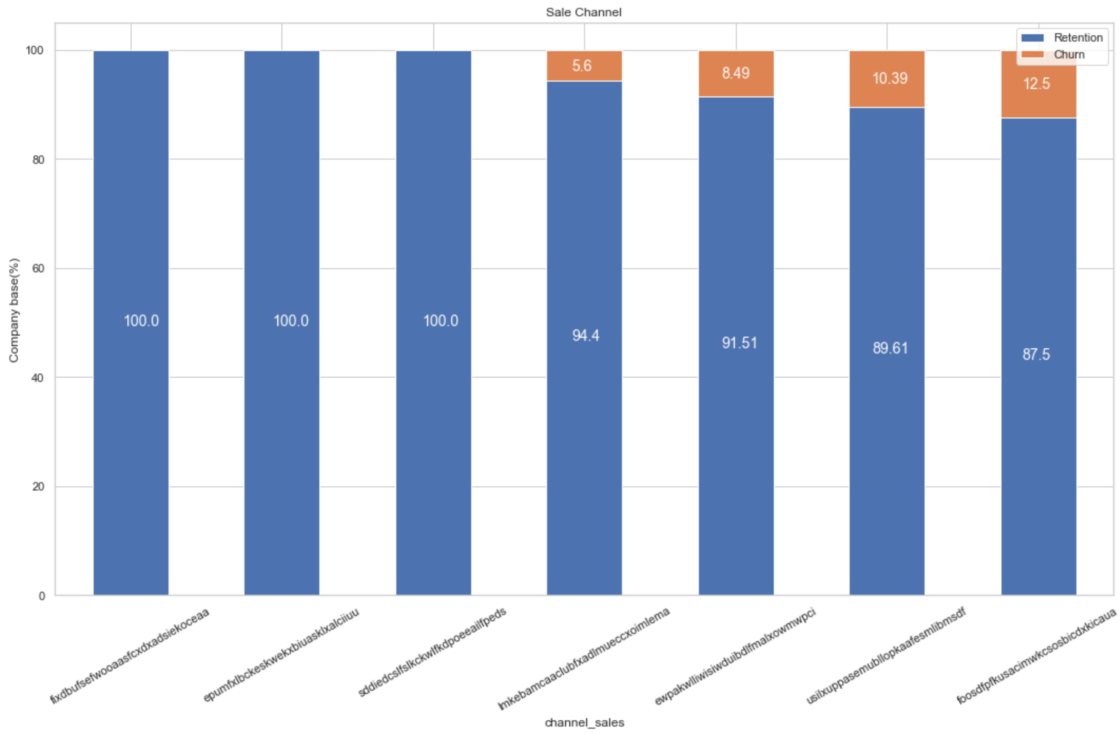
[518]:
```
sns.barplot(data = top_churn_rate_by_activity, x = 'churn_rate', y =␣
 ↪'activity_new', color = '#E9967A');
plt.show();
```



Sales Channel There are 7 different sale channel, but lack of 26.205268% entries. The sales channel seems to be an important feature when predicting the churning of a user. It is not the same if the sales were through email or telephone. We will plot the categories, despite the fact that data

[519]:
```
churn_by_channel = client.groupby(['channel_sales', 'churn'])['id'].count().
↪unstack(level = 1).fillna(0).sort_values(by = [0])
total = churn_by_channel[0] + churn_by_channel[1]
churn_by_channel[0] = churn_by_channel[0]/total*100
churn_by_channel[1] = churn_by_channel[1]/total*100

churn_by_channel = churn_by_channel.sort_values(by = [0], ascending = False)
```

[520]:
```
plot_stacked_bars(churn_by_channel, 'Sale Channel', rot_ = 30)
```



[521]:
```
churn_by_channel['total'] = total
churn_by_channel
```

[521]:
```
churn                                     0          1   total
channel_sales
fixdbufsefwooaasfcxdxadsiekoceaa  100.000000   0.000000     2.0
epumfxlbckeskwekxbiuasklxalciiuu  100.000000   0.000000     4.0
sddiedcslfslkckwlfkdpoeeailfpeds  100.000000   0.000000    12.0
lmkebamcaaclubfxadlmueccxoimlema   94.404245   5.595755  2073.0
ewpakwlliwisiwduibdlfmalxowmwpci   91.511387   8.488613   966.0
usilxuppasemubllopkaafesmlibmsdf   89.612188  10.387812  1444.0
foosdfpfkusacimwkcsosbicdxkicaua   87.501694  12.498306  7377.0
```

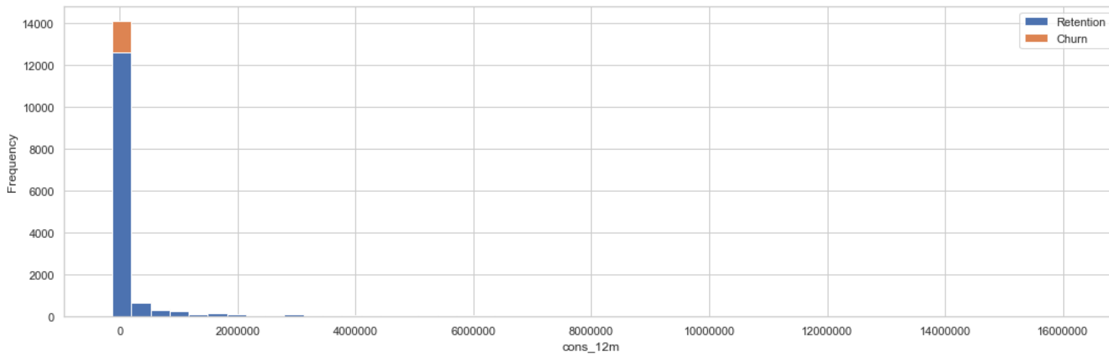
Consumption Let's see the distribution of the consumption over the year and over the month

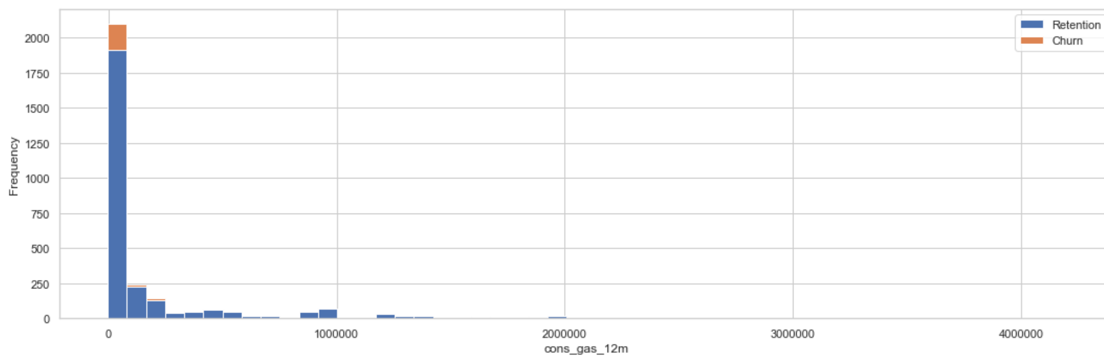
We can clearl see in here that the consumption data is highly skewed to the right, presenting a very long right-tail towards the higher values of the distribution. The values on the higher end and lower end of the distribution of data based on a five number summary. It can tell us if oue data is symmetrical, how tightly our data is grouped, and if and how data is skewed.

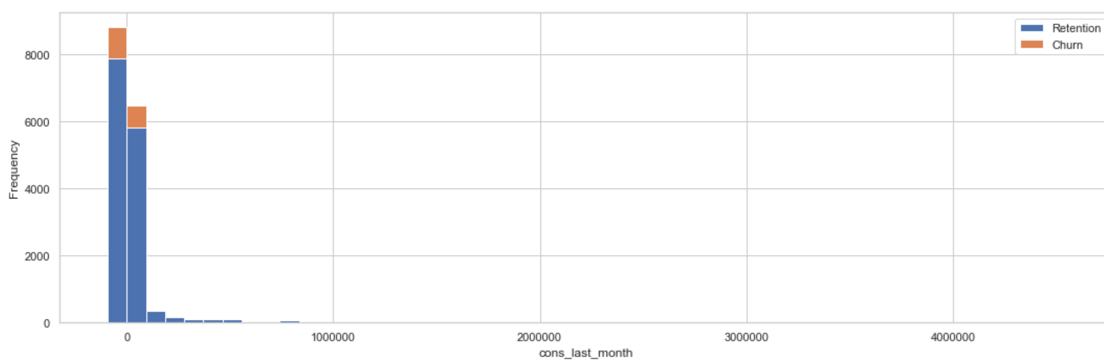
[522]:
```
consumption = client[['id', 'cons_12m', 'cons_gas_12m', 'cons_last_month',␣
↪'has_gas', 'imp_cons', 'churn']]
```

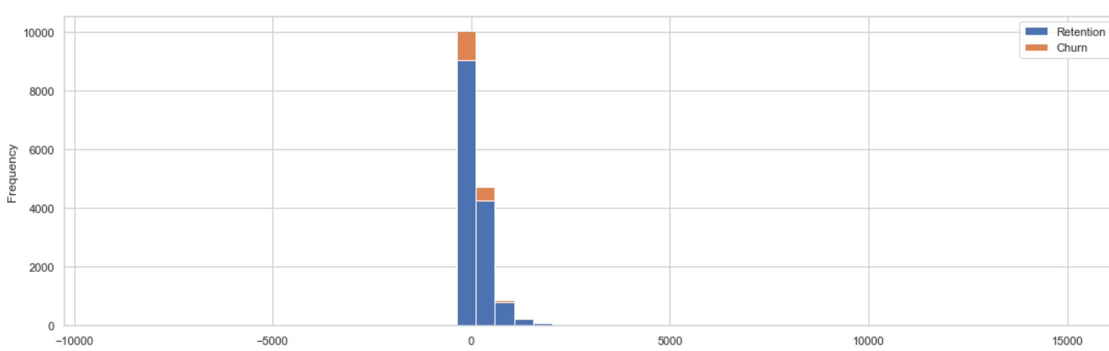
[523]:
```
def plot_distribution(dataframe, column, ax, bins_ = 50):
    '''
    Plot variable distribution in a stcked histogram of churned or related␣
↪company
    '''
    # create a temporal dataframe with the data to be plot
    temp = pd.DataFrame({'Retention': dataframe[dataframe['churn'] ==␣
↪0][column],
                         'Churn': dataframe[dataframe['churn'] == 1][column]})
    # plot the histogram
    temp[['Retention', 'Churn']].plot(kind = 'hist', bins = bins_, ax = ax,␣
↪stacked = True)
    # X-axis label
    ax.set_xlabel(column)
    # change the x-axis to the plain style
    ax.ticklabel_format(style = 'plain', axis = 'x')
```

[524]:
```
fig, axs = plt.subplots(nrows = 4, figsize = (18, 25))
# plot histogram
plot_distribution(client, 'cons_12m', ax = axs[0])
# Note that the gas consumption must have gas contract
plot_distribution(client[client['has_gas'] == 't'], 'cons_gas_12m', ax = axs[1])
plot_distribution(client, 'cons_last_month', ax = axs[2])
plot_distribution(client, 'imp_cons', ax = axs[3])
```





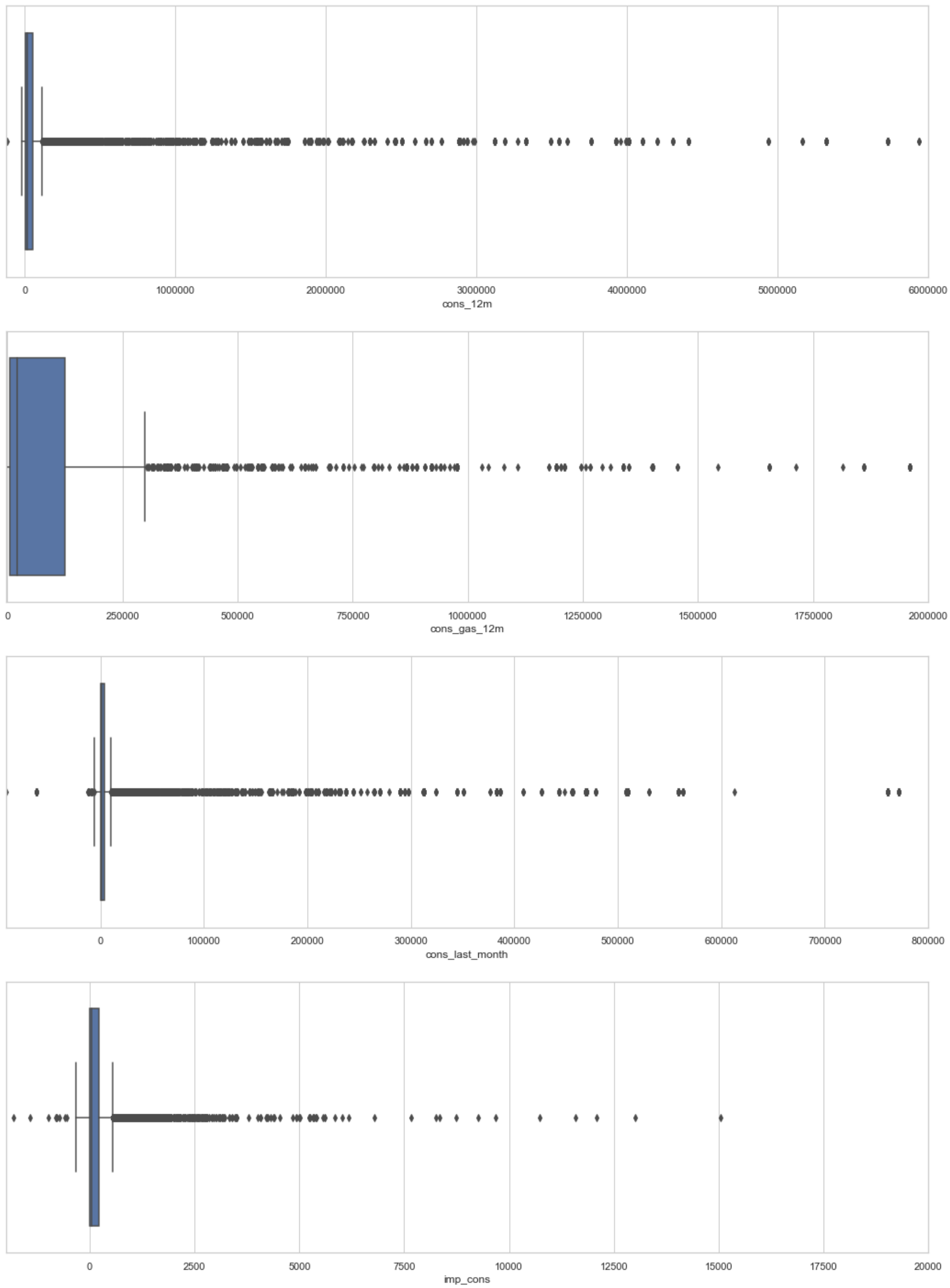




It is very clear now that we have a highly skewed distribution, and several outliers. We will deal woth the skewness and outliers in the data cleaning.

[525]:
```python
fig, axs = plt.subplots(nrows = 4, figsize = (18, 25))
# plot histogram
sns.boxplot(client['cons_12m'], ax = axs[0])
sns.boxplot(client[client['has_gas']=='t']['cons_gas_12m'], ax = axs[1])
sns.boxplot(client['cons_last_month'], ax = axs[2])
sns.boxplot(client['imp_cons'], ax = axs[3])

for ax in axs:
    ax.ticklabel_format(style = 'plain', axis = 'x')
# set x-axis limit
axs[0].set_xlim(-125276, 6000000)
axs[1].set_xlim(-3037, 2000000)
axs[2].set_xlim(-91386, 800000)
axs[3].set_xlim(-2000, 20000)
```

[525]: (-2000.0, 20000.0)

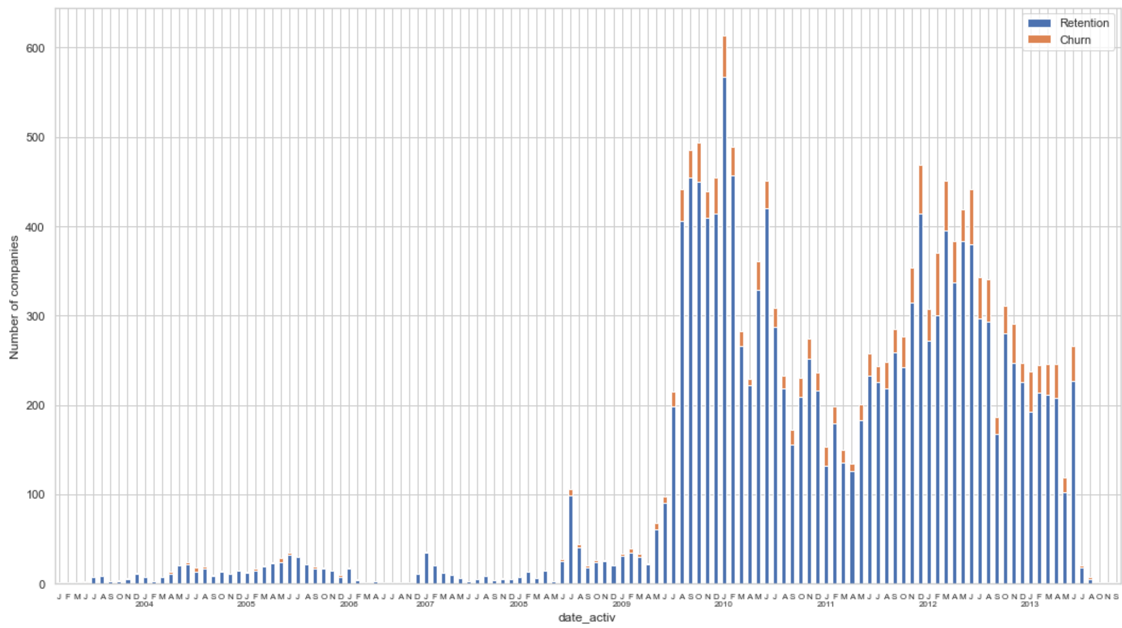


Dates We look at some feature over time. First, we convert the date columns to the datetime datatype.

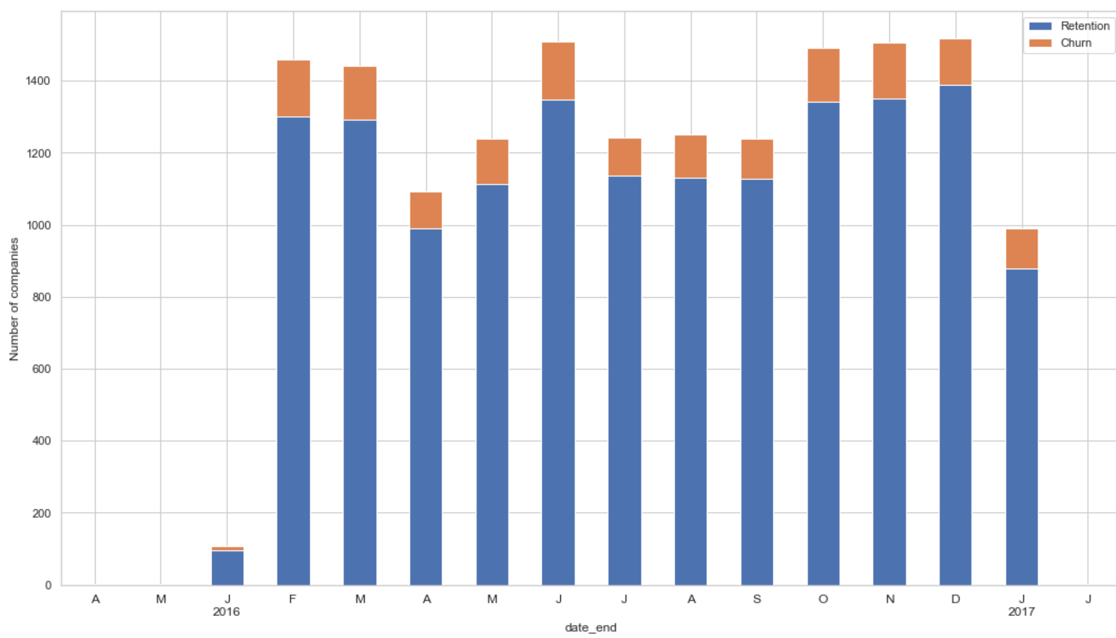
[526]:
```
client['date_activ'] = pd.to_datetime(client['date_activ'])
client['date_end'] = pd.to_datetime(client['date_end'])
client['date_first_activ'] = pd.to_datetime(client['date_first_activ'])
client['date_modif_prod'] = pd.to_datetime(client['date_modif_prod'])
client['date_renewal'] = pd.to_datetime(client['date_renewal'])
```

[527]:
```
def plot_dates(dataframe, column, fontsize_ = 12):
    '''
    Plot monthly churn and retention distribution
    '''
    # group by month
    temp = dataframe\
    .groupby([pd.Grouper(key = column, freq = 'M'), 'churn'])['id']\
    .count()\
    .unstack(level = 1)\
    .fillna(0)
    ax = temp.plot(kind = 'bar', stacked = True, figsize = (18, 10), rot = 0);
    # change x-axis labels to months
    ax.set_xticklabels(map(lambda x: line_format(x), temp.index))
    # change xlabel size
    plt.xticks(fontsize = fontsize_)
    # rename y-axis
    plt.ylabel('Number of companies')
    # rename legend
    plt.legend(['Retention', 'Churn'], loc = 'upper right')
    plt.show()


def line_format(label):
    '''
    Convert time label to the format of pandas line plot
    '''
    month = label.month_name()[:1]
    if label.month_name() == 'January':
        month += f'\n{label.year}'
    return month
```

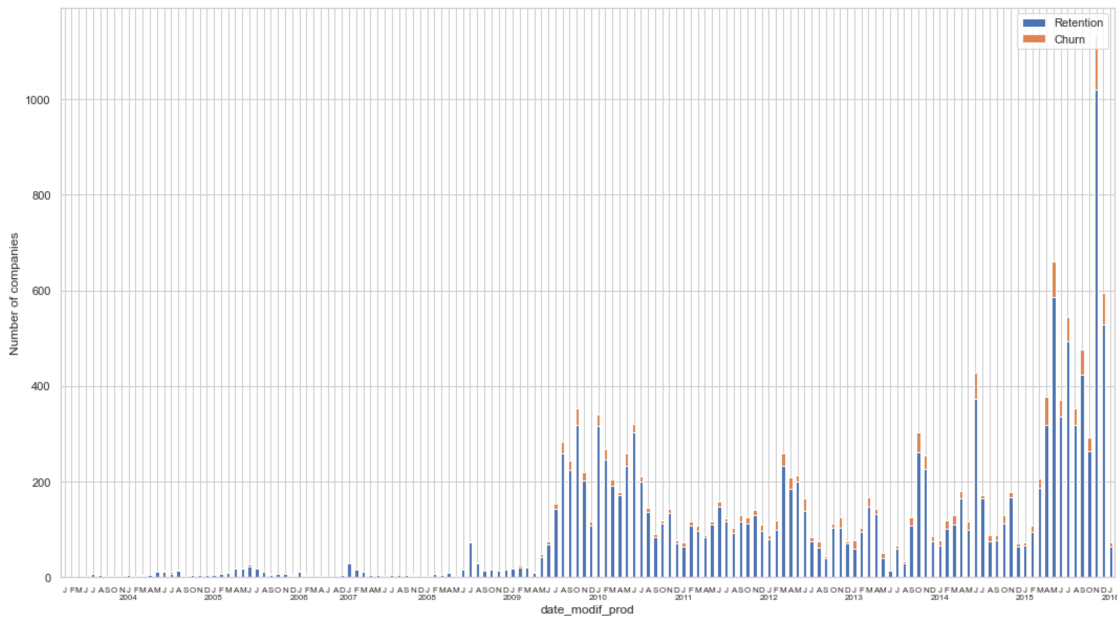
[528]:
```
plot_dates(client,'date_activ', fontsize_ = 8);
```



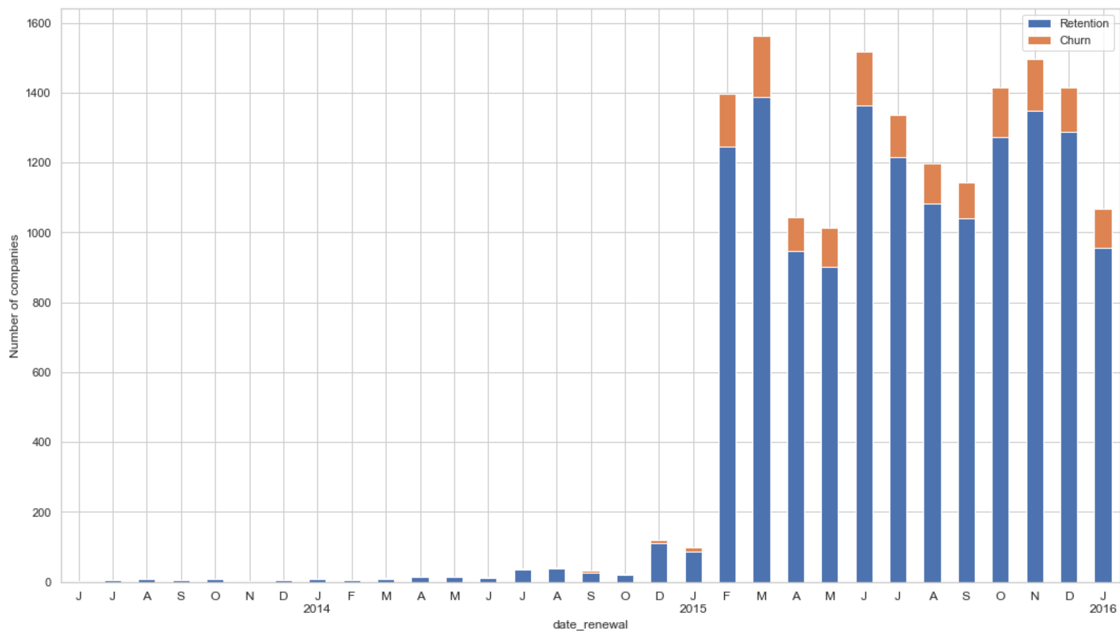

```
[529]: plot_dates(client,'date_end');
```




```
[530]: plot_dates(client, 'date_modif_prod', fontsize_ = 8)
```



[531]:
```
plot_dates(client, 'date_renewal')
```

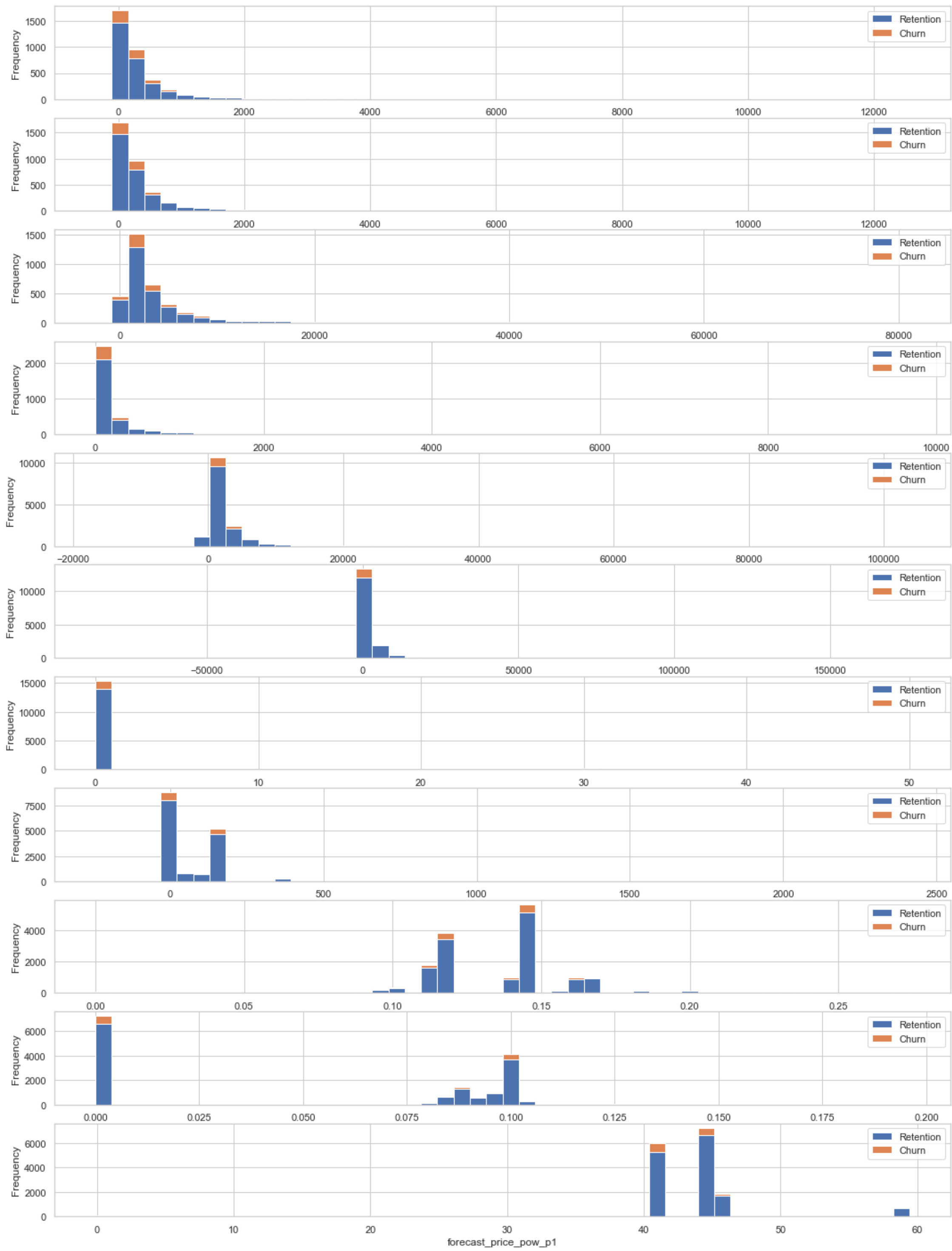


Forecast Similarly to the consumption plots, we can observe that a lot of the variables are highly skewed to the right, creating a very long tail on the higher values

We will make some transformations to correct for this skewness.

[532]:
```
temp = client[[c for c in client if (c.startswith('forecast')) | (c == 'id') |␣
↪(c == 'churn')]]
```

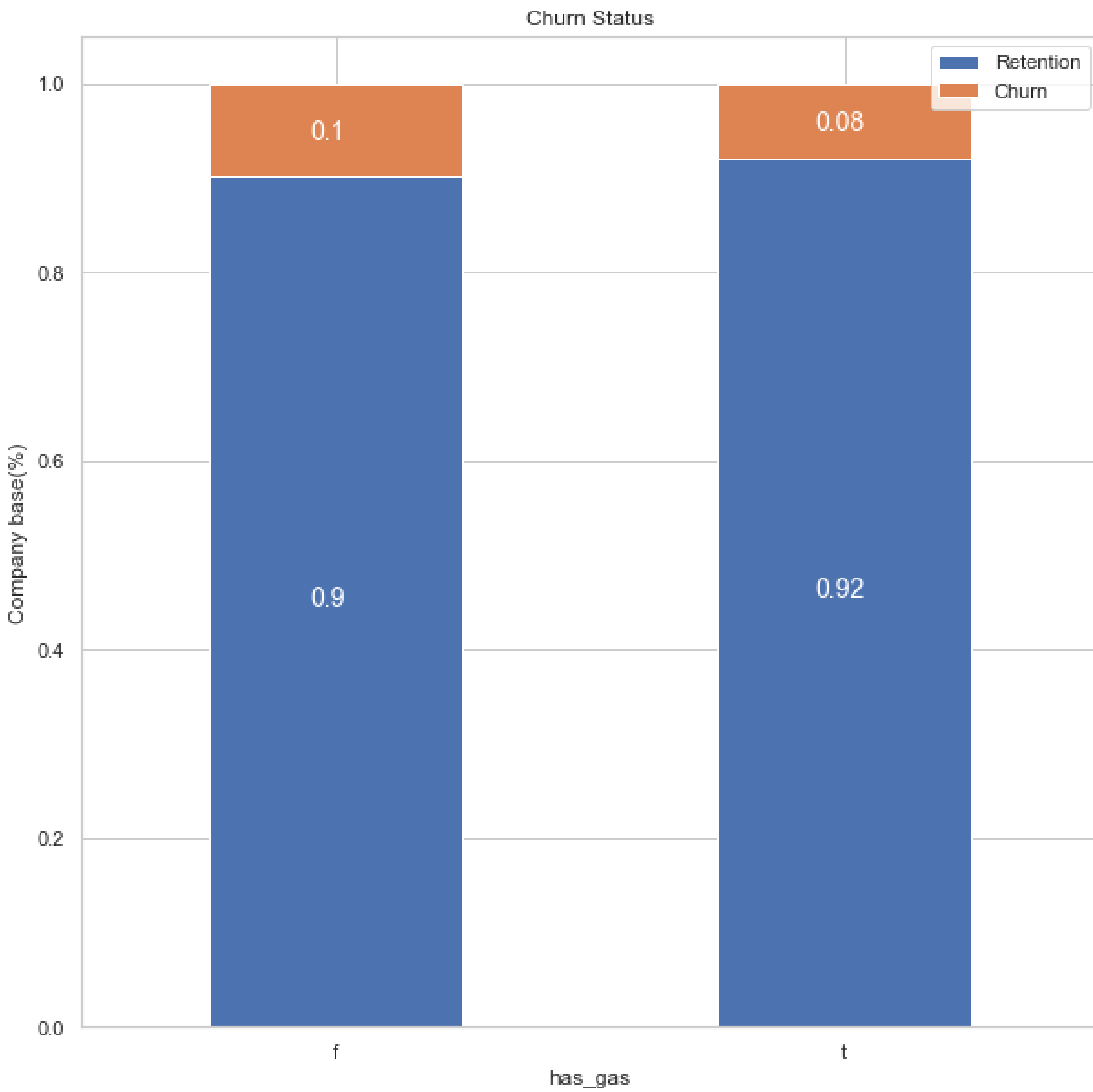
[533]:
```
fig, axs = plt.subplots(nrows = 11, figsize = (18, 25))

for idx, c in enumerate(temp.columns[temp.columns.map(lambda x: x.
↪startswith('forecast'))]):
    plot_distribution(temp, c, ax = axs[idx])

#plot_distribution(client, 'forecast_base_bill_ele', ax = axs[0])
```



Contact Types

[534]:
```
temp = client.groupby(['has_gas', 'churn'])['id'].count()
temp2 = temp.groupby(level = 0).apply(lambda x: np.round(x/x.sum(), 2)).
↪unstack(level = 1)
```

[535]:
```
plot_stacked_bars(temp2, 'Churn Status', (10, 10))
```

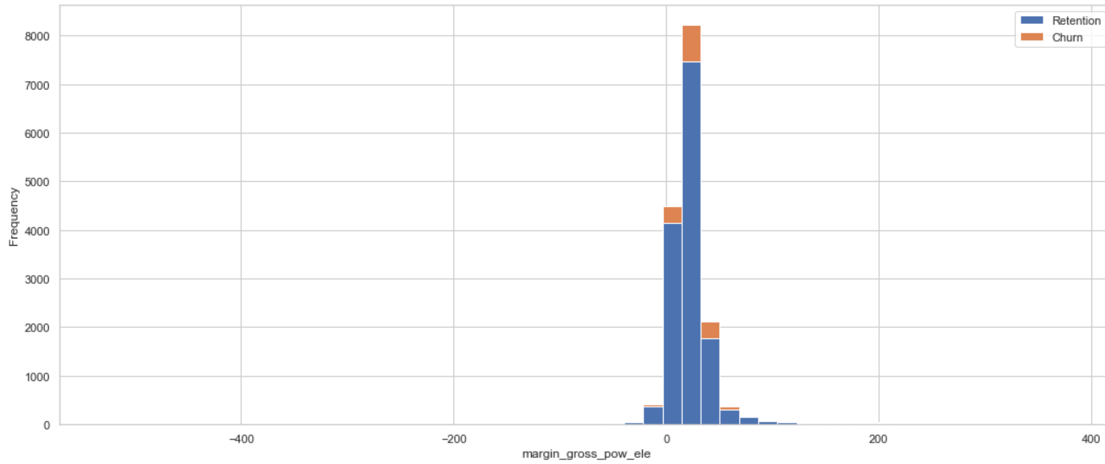


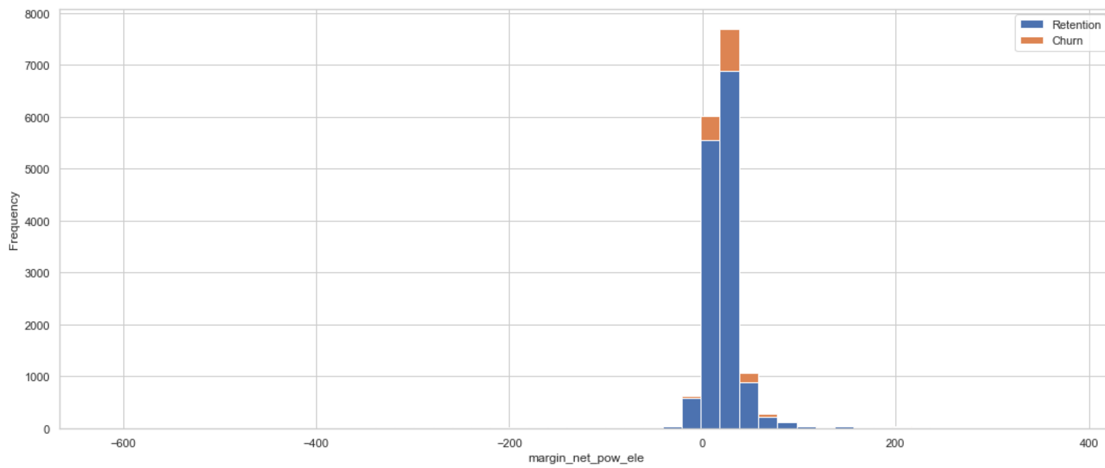
Margins Margin seems right skewed as well with a few outliers as well.

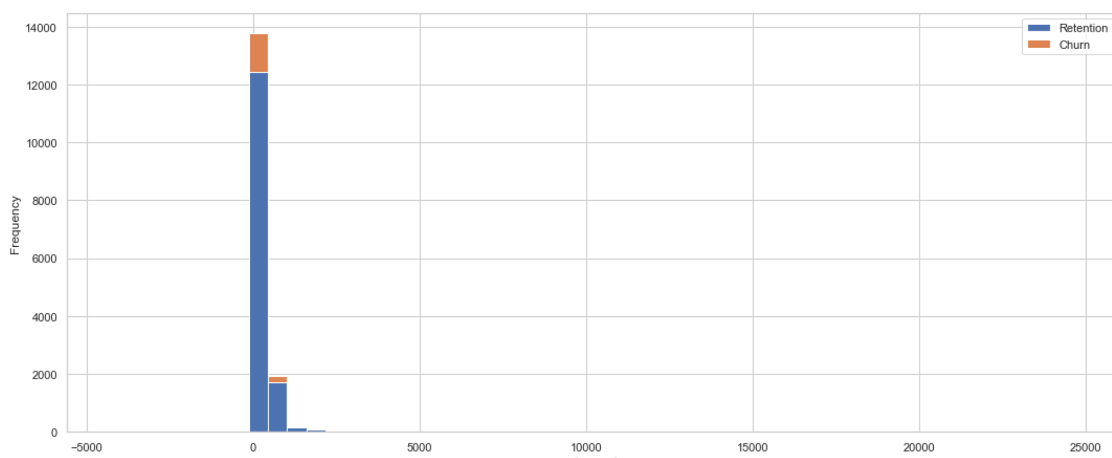
[537]:
```
margin = client[['id', 'margin_gross_pow_ele', 'margin_net_pow_ele',␣
↪'net_margin', 'churn']]
```

[538]:
```
fig, axs = plt.subplots(nrows = 3, figsize = (18, 25))
plot_distribution(margin, 'margin_gross_pow_ele', axs[0])
```

```
plot_distribution(margin, 'margin_net_pow_ele', axs[1])
plot_distribution(margin, 'net_margin', axs[2])
```

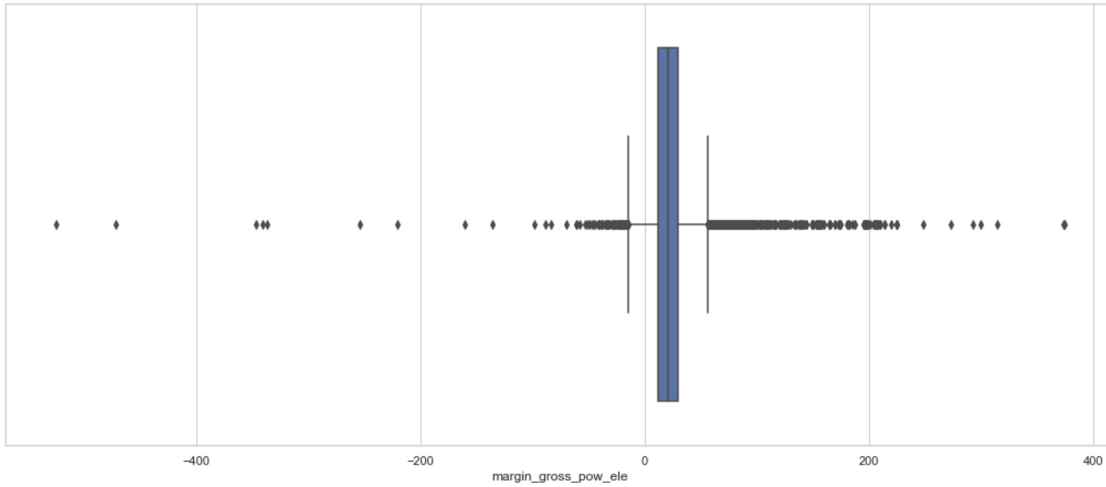


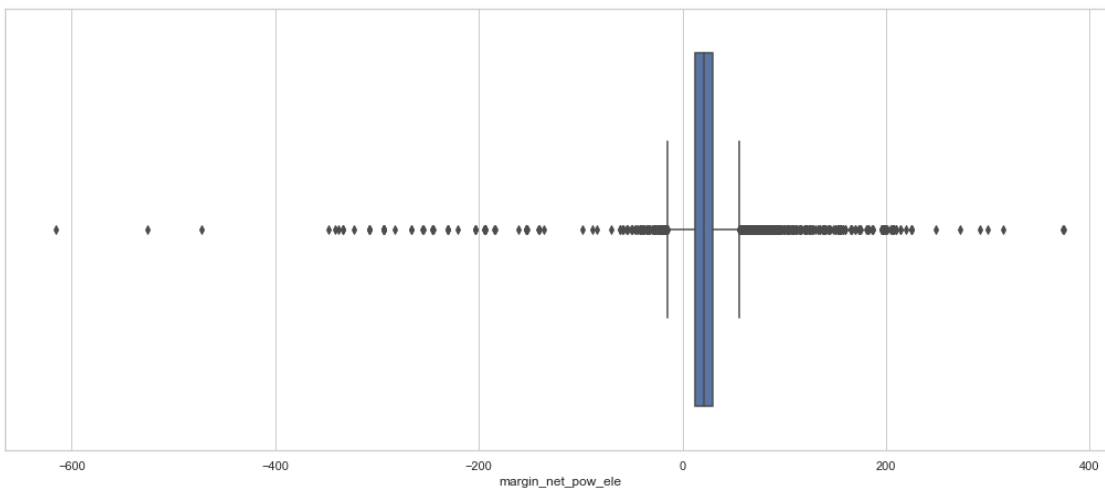


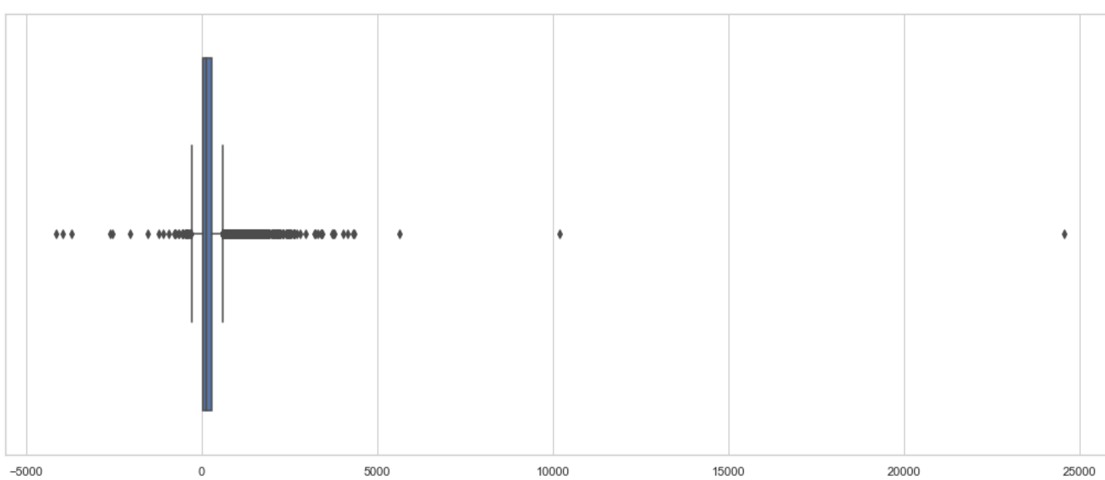


[539]:

```
fig, axs = plt.subplots(nrows = 3, figsize = (18, 25))
sns.boxplot(margin['margin_gross_pow_ele'], ax = axs[0]);
sns.boxplot(margin['margin_net_pow_ele'], ax = axs[1]);
sns.boxplot(margin['net_margin'], ax = axs[2]);
```



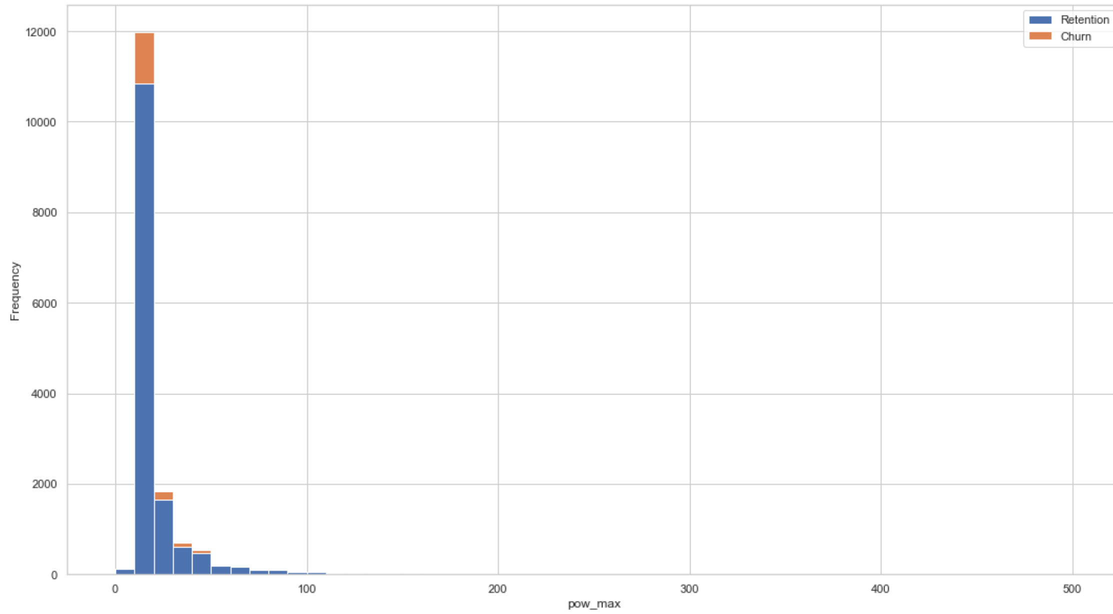




Subscribed Power

[540]:
```
power = client[['id', 'pow_max', 'churn']].fillna(0)
```

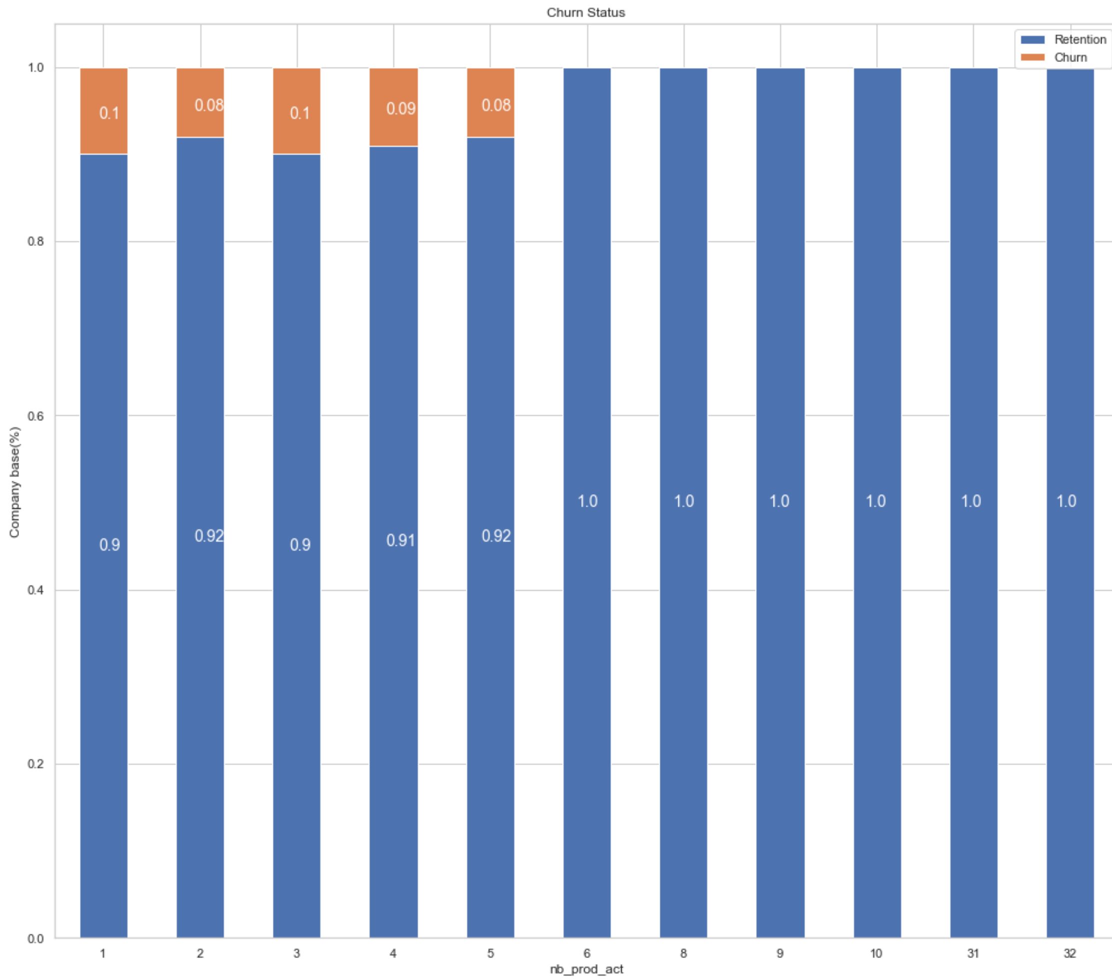
[541]:
```
fig, axs = plt.subplots(nrows = 1, figsize = (18, 10))
plot_distribution(power, 'pow_max', axs);
```



Others

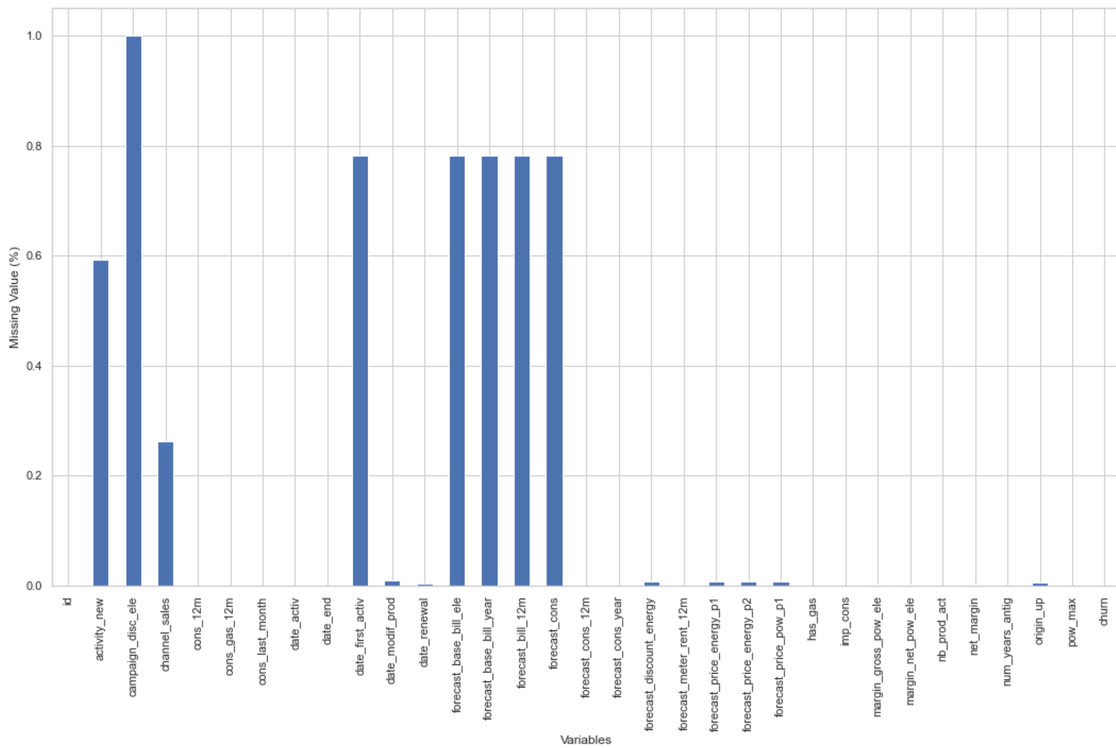
[542]:
```
other = client[['id', 'nb_prod_act', 'num_years_antig', 'origin_up', 'churn']]
```

[543]:
```
nb_prod_act = other.groupby(['nb_prod_act', 'churn'])['id'].count()
nb_prod_act = nb_prod_act.groupby(level = 0).apply(lambda x: np.round(x/x.
↪sum(), 2)).unstack(level = 1)
plot_stacked_bars(nb_prod_act, 'Churn Status', (17, 15))
```



4. Data Cleaning For simplicity we will remove the variables with more than 60% of the values missing. 'We might re-use some of these variables if our model is not good enough'.

[544]:
```
(client.isnull().sum()/client.shape[0]).plot(kind = 'bar', figsize = (18, 10));
plt.xlabel('Variables')
plt.ylabel('Missing Value (%)')
plt.show();
```



[545]:
```
client_low_missing = client[client.columns[client.apply(lambda x: (x.isnull().
↪sum()/client.shape[0]) < 0.6)]]
```

[546]:
```
pd.DataFrame({'dtype': client_low_missing.dtypes, 'missing_perc':␣
↪client_low_missing.apply(lambda x: (100*x.isnull().sum()/client_low_missing.
↪shape[0]))})
```

[546]:

	dtype	missing_perc
id	object	0.000000
activity_new	object	59.300447
channel_sales	object	26.205268
cons_12m	int64	0.000000
cons_gas_12m	int64	0.000000
cons_last_month	int64	0.000000
date_activ	datetime64[ns]	0.000000
date_end	datetime64[ns]	0.012425
date_modif_prod	datetime64[ns]	0.975398
date_renewal	datetime64[ns]	0.248509
forecast_cons_12m	float64	0.000000
forecast_cons_year	int64	0.000000
forecast_discount_energy	float64	0.782803
forecast_meter_rent_12m	float64	0.000000
forecast_price_energy_p1	float64	0.782803

```
forecast_price_energy_p2          float64       0.782803
forecast_price_pow_p1             float64       0.782803
has_gas                            object       0.000000
imp_cons                          float64       0.000000
margin_gross_pow_ele              float64       0.080765
margin_net_pow_ele                float64       0.080765
nb_prod_act                         int64       0.000000
net_margin                        float64       0.093191
num_years_antig                     int64       0.000000
origin_up                          object       0.540507
pow_max                           float64       0.018638
churn                               int64       0.000000
```

Duplicates We want to make sure all the data we have is unique and we doont have any duplicates rows.

[547]:
```
client_low_missing[client_low_missing.duplicated()]
```

[547]:
```
Empty DataFrame
Columns: [id, activity_new, channel_sales, cons_12m, cons_gas_12m,
cons_last_month, date_activ, date_end, date_modif_prod, date_renewal,
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, churn]
Index: []
```

5. Formatting Data #### Missing dates These could be several ways in which we could deal with missing dates. One way, we could 'engineer' the dates from known values. For example, the `date_renewal` is usually the same date as the `date_modif_prod` but one year ahead. The simplest way, we will replace the missing values with the median (the frequent date). For numerical values, the built-in function `.median()` can be used, but will not work for dates or strings, so we will use a workaroound using `.value_counts()`

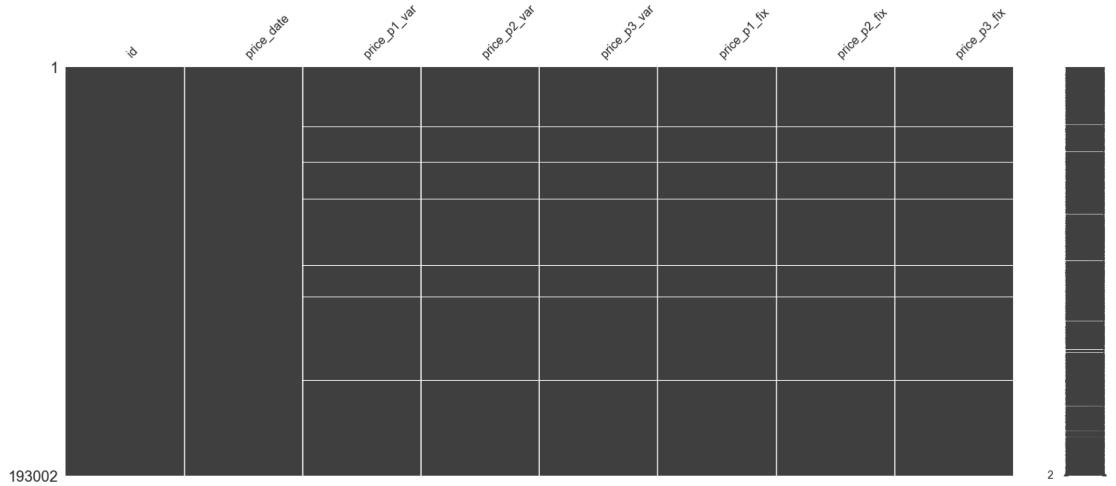
> Althoough we are directly the values in here, it is usually best practice to make a binary flag that indicates when data is missing because this is informative in itself.

[548]:
```
client_low_missing.loc[client_low_missing['date_modif_prod'].isnull(),␣
↪'date_modif_prod'] = client_low_missing['date_modif_prod']\
.value_counts()\
.index[0]

client_low_missing.loc[client_low_missing['date_end'].isnull(), 'date_end'] =␣
↪client_low_missing['date_end']\
.value_counts()\
.index[0]
```

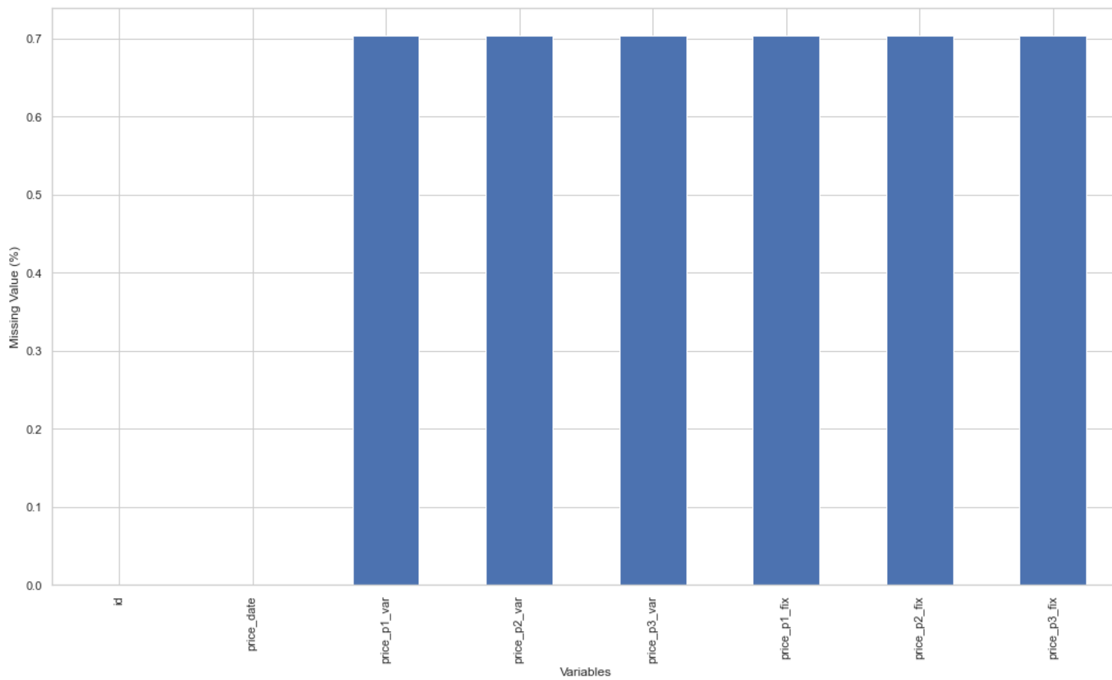
```
client_low_missing.loc[client_low_missing['date_renewal'].isnull(),␣
 ↪'date_renewal'] = client_low_missing['date_renewal']\
.value_counts()\
.index[0]
```

Missing data We might have some prices missing for soome companies and months

[549]:
```
msno.matrix(price);
```



[550]:
```
(100*price.isnull().sum()/price.shape[0]).plot(kind = 'bar', figsize = (18,␣
 ↪10));
plt.xlabel('Variables')
plt.ylabel('Missing Value (%)')
plt.show();
```



[551]:
```
price.loc[price['price_p1_var'].isnull(), 'price_p1_var'] =␣
 ↪price['price_p1_var'].median()
price.loc[price['price_p2_var'].isnull(), 'price_p2_var'] =␣
 ↪price['price_p2_var'].median()
price.loc[price['price_p3_var'].isnull(), 'price_p3_var'] =␣
 ↪price['price_p3_var'].median()
price.loc[price['price_p1_fix'].isnull(), 'price_p1_fix'] =␣
 ↪price['price_p1_fix'].median()
price.loc[price['price_p2_fix'].isnull(), 'price_p2_fix'] =␣
 ↪price['price_p2_fix'].median()
price.loc[price['price_p3_fix'].isnull(), 'price_p3_fix'] =␣
 ↪price['price_p3_fix'].median()
```

Formating dates (history prrice)

[552]:
```
price['price_date'] = pd.to_datetime(price['price_date'])
```

Negative Data let's take a look at the historical price data

We can see that there are neagtive values forr `price_p1_fix`, `price_p2_fix`, `price_p3_fix`. Further exploring on those we can see there are only about 10 entries which are negative. This is more likely to be due to corrputed data rather than a 'price' discount. We will replace the negtive values with medium

[553]:
```
price.describe()
```

[553]:

	price_p1_var	price_p2_var	price_p3_var	price_p1_fix
count	193002.000000	193002.000000	193002.000000	193002.000000
mean	0.141027	0.054630	0.030496	43.332175
std	0.025032	0.049924	0.036298	5.419345
min	0.000000	0.000000	0.000000	-0.177779
25%	0.125976	0.000000	0.000000	40.728885
50%	0.146033	0.085483	0.000000	44.266930
75%	0.151635	0.101673	0.072558	44.444710
max	0.280700	0.229788	0.114102	59.444710

	price_p2_fix	price_p3_fix
count	193002.000000	193002.000000
mean	10.622871	6.409981
std	12.841899	7.773595
min	-0.097752	-0.065172
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	24.339581	16.226389
max	36.490692	17.458221

[554]:
```
price[(price.price_p1_fix < 0) |(price.price_p2_fix < 0) | (price.price_p3_fix␣
↪< 0)]
```

[554]:

	id	price_date	price_p1_var
23138	951d99fe07ca94c2139f43bc37095139	2015-03-01	0.125976
28350	f7bdc6fa1067cd26fd80bfb9f3fca28f	2015-03-01	0.131032
98575	9b523ad5ba8aa2e524dcda5b3d54dab2	2015-02-01	0.129444
113467	cfd098ee6c567eb32374c77d20571bc7	2015-02-01	0.123086
118467	51d7d8a0bf6b8bd94f8c1de7942c66ea	2015-07-01	0.128132
125819	decc0a647016e183ded972595cd2b9fb	2015-03-01	0.124937
128761	cc214d7c05de3ee17a7691e274ac488e	2015-06-01	0.124675
141011	2a4ed325054472e03cdcc9a34693be4b	2015-02-01	0.167317
160827	395a6f41bbd1a0f23a64f00645264e78	2015-04-01	0.121352
181811	d4a84ff4ec620151ef05bdef0cf27eab	2015-05-01	0.125976

	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix	price_p3_fix
23138	0.103395	0.071536	-0.162916	-0.097749	-0.065166
28350	0.108896	0.076955	-0.162916	-0.097749	-0.065166
98575	0.106863	0.075004	-0.162916	-0.097749	-0.065166
113467	0.100505	0.068646	-0.162916	-0.097749	-0.065166
118467	0.105996	0.074056	-0.162912	-0.097752	-0.065172
125819	0.102814	0.069071	-0.162916	-0.097749	-0.065166
128761	0.102539	0.070596	-0.162912	-0.097752	-0.065172
141011	0.083347	0.000000	-0.177779	0.000000	0.000000
160827	0.098771	0.066912	-0.162916	-0.097749	-0.065166
181811	0.103395	0.071536	-0.162916	-0.097749	-0.065166

[556]:
```
price.loc[price['price_p1_fix'] < 0, 'price_p1_fix'] = price['price_p1_fix'].
 ↪median()
price.loc[price['price_p2_fix'] < 0, 'price_p2_fix'] = price['price_p2_fix'].
 ↪median()
price.loc[price['price_p3_fix'] < 0, 'price_p3_fix'] = price['price_p3_fix'].
 ↪median()
```

6 Pickling save the data

[557]:
```
price.head(2)
```

[557]:
```
                                 id price_date  price_p1_var  price_p2_var  \
0  038af19179925da21a25619c5a24b745 2015-01-01      0.151367           0.0
1  038af19179925da21a25619c5a24b745 2015-02-01      0.151367           0.0

   price_p3_var  price_p1_fix  price_p2_fix  price_p3_fix
0           0.0     44.266931           0.0           0.0
1           0.0     44.266931           0.0           0.0
```

[559]:
```
client_low_missing.head()
```

[559]:
```
                                 id                      activity_new  \
0  48ada52261e7cf58715202705a0451c9  esoiiifxdlbkcsluxmfuacbdckommixw
1  24011ae4ebbe3035111d65fa7c15bc57                               NaN
2  d29c2c54acc38ff3c0614d0a653813dd                               NaN
3  764c75f661154dac3a6c254cd082ea7d                               NaN
4  bba03439a292a1e166f80264c16191cb                               NaN

                      channel_sales  cons_12m  cons_gas_12m  cons_last_month  \
0  lmkebamcaaclubfxadlmueccxoimlema    309275             0            10025
1  foosdfpfkusacimwkcsosbicdxkicaua         0         54946                0
2                               NaN      4660             0                0
3  foosdfpfkusacimwkcsosbicdxkicaua       544             0                0
4  lmkebamcaaclubfxadlmueccxoimlema      1584             0                0

  date_activ   date_end date_modif_prod date_renewal  forecast_cons_12m  \
0 2012-11-07 2016-11-06      2012-11-07   2015-11-09           26520.30
1 2013-06-15 2016-06-15      2015-11-01   2015-06-23               0.00
2 2009-08-21 2016-08-30      2009-08-21   2015-08-31             189.95
3 2010-04-16 2016-04-16      2010-04-16   2015-04-17              47.96
4 2010-03-30 2016-03-30      2010-03-30   2015-03-31             240.04

   forecast_cons_year  forecast_discount_energy  forecast_meter_rent_12m  \
0               10025                       0.0                   359.29
1                   0                       0.0                     1.78
2                   0                       0.0                    16.27
3                   0                       0.0                    38.72
```

```
4                   0                        0.0                     19.83

   forecast_price_energy_p1  forecast_price_energy_p2  forecast_price_pow_p1  \
0                  0.095919                  0.088347              58.995952
1                  0.114481                  0.098142              40.606701
2                  0.145711                  0.000000              44.311378
3                  0.165794                  0.087899              44.311378
4                  0.146694                  0.000000              44.311378

  has_gas  imp_cons  margin_gross_pow_ele  margin_net_pow_ele  nb_prod_act  \
0       f     831.8                -41.76              -41.76            1
1       t       0.0                 25.44               25.44            2
2       f       0.0                 16.38               16.38            1
3       f       0.0                 28.60               28.60            1
4       f       0.0                 30.22               30.22            1

   net_margin  num_years_antig                         origin_up  pow_max  \
0     1732.36                3  ldkssxwpmemidmecebumciepifcamkci  180.000
1      678.99                3  lxidpiddsbxsbosboudacockeimpuepw   43.648
2       18.89                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.800
3        6.60                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.856
4       25.46                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.200

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

[568]:
```
if not os.path.exists(os.path.join('../BCG', 'processed_data')):
    os.makedirs(os.path.join('../BCG', 'processed_data'))
```

[569]:
```
pickle_train_dir = os.path.join('../BCG', 'processed_data', 'client_low_missing.
 ↪pkl')
pickle_history_dir = os.path.join('../BCG', 'processed_data', 'history_price.
 ↪pkl')
```

[570]:
```
pd.to_pickle(client_low_missing, pickle_train_dir)
pd.to_pickle(price, pickle_history_dir)
```