BCG- TASK 2

July 14, 2021

1 Libraries

[350]:
```
# Data analysis and wrangling
import pandas as pd
import numpy as np

# Data visualisation
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Dates
import datetime

#remove warnings
import warnings
warnings.filterwarnings('ignore')
```

2 Import and read data

[351]:
```
churn_data=pd.read_csv('ml_case_training_output.csv')
churn_data.head()
```

[351]:

	id	churn
0	48ada52261e7cf58715202705a0451c9	0
1	24011ae4ebbe3035111d65fa7c15bc57	1
2	d29c2c54acc38ff3c0614d0a653813dd	0
3	764c75f661154dac3a6c254cd082ea7d	0
4	bba03439a292a1e166f80264c16191cb	0

[352]:
```
churn_data['churn'] = churn_data['churn'].replace({0:'stayed',1:'churned'})
churn_data.head()
```

[352]:

	id	churn
0	48ada52261e7cf58715202705a0451c9	stayed
1	24011ae4ebbe3035111d65fa7c15bc57	churned
2	d29c2c54acc38ff3c0614d0a653813dd	stayed

```
3  764c75f661154dac3a6c254cd082ea7d   stayed
4  bba03439a292a1e166f80264c16191cb   stayed
```

[353]:
```
history_data=pd.read_csv('ml_case_training_hist_data.csv')
history_data.head()
```

[353]:
```
                                 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
2  038af19179925da21a25619c5a24b745  2015-03-01      0.151367           0.0
3  038af19179925da21a25619c5a24b745  2015-04-01      0.149626           0.0
4  038af19179925da21a25619c5a24b745  2015-05-01      0.149626           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
2           0.0     44.266931           0.0           0.0
3           0.0     44.266931           0.0           0.0
4           0.0     44.266931           0.0           0.0
```

[354]:
```
training_data=pd.read_csv('ml_case_training_data.csv')
training_data.tail()
```

[354]:
```
                                     id activity_new  campaign_disc_ele  \
16091  18463073fb097fc0ac5d3e040f356987          NaN                NaN
16092  d0a6f71671571ed83b2645d23af6de00          NaN                NaN
16093  10e6828ddd62cbcf687cb74928c4c2d2          NaN                NaN
16094  1cf20fd6206d7678d5bcafd28c53b4db          NaN                NaN
16095  563dde550fd624d7352f3de77c0cdfcd          NaN                NaN

                          channel_sales  cons_12m  cons_gas_12m  \
16091  foosdfpfkusacimwkcsosbicdxkicaua     32270         47940
16092  foosdfpfkusacimwkcsosbicdxkicaua      7223             0
16093  foosdfpfkusacimwkcsosbicdxkicaua      1844             0
16094  foosdfpfkusacimwkcsosbicdxkicaua       131             0
16095                               NaN      8730             0

       cons_last_month  date_activ    date_end date_first_activ  …  \
16091                0  2012-05-24  2016-05-08              NaN  …
16092              181  2012-08-27  2016-08-27       2012-08-27  …
16093              179  2012-02-08  2016-02-07              NaN  …
16094                0  2012-08-30  2016-08-30              NaN  …
16095                0  2009-12-18  2016-12-17              NaN  …

      forecast_price_pow_p1 has_gas  imp_cons  margin_gross_pow_ele  \
16091             44.311378       t      0.00                 27.88
16092             58.995952       f     15.94                  0.00
```

```
16093          40.606701       f    18.05                 39.84
16094          44.311378       f     0.00                 13.08
16095          45.311378       f     0.00                 11.84

       margin_net_pow_ele  nb_prod_act  net_margin  num_years_antig  \
16091               27.88            2      381.77                4
16092                0.00            1       90.34                3
16093               39.84            1       20.38                4
16094               13.08            1        0.96                3
16095               11.84            1       96.34                6

                              origin_up  pow_max
16091  lxidpiddsbxsbosboudacockeimpuepw   15.000
16092  lxidpiddsbxsbosboudacockeimpuepw    6.000
16093  lxidpiddsbxsbosboudacockeimpuepw   15.935
16094  lxidpiddsbxsbosboudacockeimpuepw   11.000
16095  ldkssxwpmemidmecebumciepifcamkci   10.392

[5 rows x 32 columns]
```

[355]:
```
merge=pd.merge(churn_data, training_data, on='id')
merge.tail()
```

[355]:
```
                                     id    churn activity_new  \
16091  18463073fb097fc0ac5d3e040f356987   stayed          NaN
16092  d0a6f71671571ed83b2645d23af6de00  churned          NaN
16093  10e6828ddd62cbcf687cb74928c4c2d2  churned          NaN
16094  1cf20fd6206d7678d5bcafd28c53b4db   stayed          NaN
16095  563dde550fd624d7352f3de77c0cdfcd   stayed          NaN

       campaign_disc_ele                     channel_sales  cons_12m  \
16091                NaN  foosdfpfkusacimwkcsosbicdxkicaua     32270
16092                NaN  foosdfpfkusacimwkcsosbicdxkicaua      7223
16093                NaN  foosdfpfkusacimwkcsosbicdxkicaua      1844
16094                NaN  foosdfpfkusacimwkcsosbicdxkicaua       131
16095                NaN                               NaN      8730

       cons_gas_12m  cons_last_month  date_activ    date_end  …  \
16091         47940                0  2012-05-24  2016-05-08  …
16092             0              181  2012-08-27  2016-08-27  …
16093             0              179  2012-02-08  2016-02-07  …
16094             0                0  2012-08-30  2016-08-30  …
16095             0                0  2009-12-18  2016-12-17  …

      forecast_price_pow_p1 has_gas imp_cons  margin_gross_pow_ele  \
16091             44.311378       t     0.00                 27.88
16092             58.995952       f    15.94                  0.00
```

```
16093             40.606701       f    18.05                     39.84
16094             44.311378       f     0.00                     13.08
16095             45.311378       f     0.00                     11.84

       margin_net_pow_ele  nb_prod_act  net_margin  num_years_antig  \
16091               27.88            2      381.77                4
16092                0.00            1       90.34                3
16093               39.84            1       20.38                4
16094               13.08            1        0.96                3
16095               11.84            1       96.34                6

                            origin_up  pow_max
16091  lxidpiddsbxsbosboudacockeimpuepw   15.000
16092  lxidpiddsbxsbosboudacockeimpuepw    6.000
16093  lxidpiddsbxsbosboudacockeimpuepw   15.935
16094  lxidpiddsbxsbosboudacockeimpuepw   11.000
16095  ldkssxwpmemidmecebumciepifcamkci   10.392

[5 rows x 33 columns]
```

3 CHURN DATA

[356]:
```
churn_data.count()
```

[356]:
```
id       16096
churn    16096
dtype: int64
```

[357]:
```
churn_count=churn_data['churn'].value_counts()
print(churn_count)
```

```
stayed     14501
churned     1595
Name: churn, dtype: int64
```

It can be seen that, the number of companies that have churned out is

[358]:
```
rate_of_churn = pd.DataFrame(churn_data['churn'].value_counts() / churn_data.
 ↪shape[0] * 100)
print(rate_of_churn )
```

```
             churn
stayed   90.090706
churned   9.909294
```

It can be seen that, the number of companies that have churned out is 1595 which represent 9.9%, approximately, 10%.

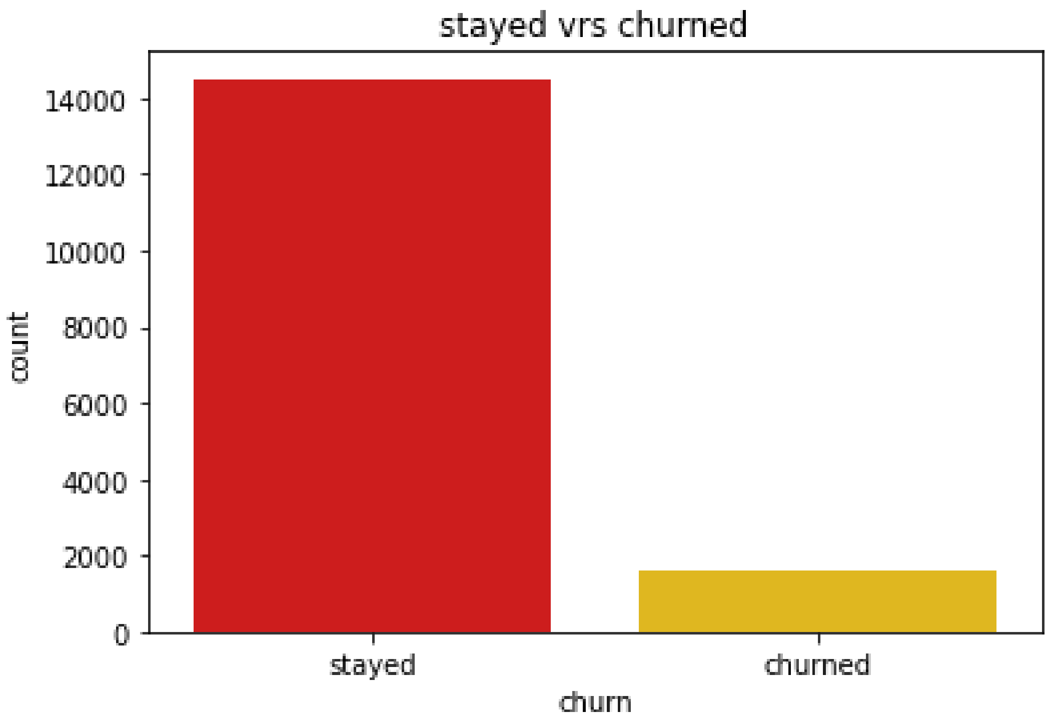
[359]:
```
#changing the column names
merge['churn'] = merge['churn'].replace({0:'stayed',1:'churned'})
merge.head()
```

[359]:
```
                                 id    churn  \
0  48ada52261e7cf58715202705a0451c9   stayed
1  24011ae4ebbe3035111d65fa7c15bc57  churned
2  d29c2c54acc38ff3c0614d0a653813dd   stayed
3  764c75f661154dac3a6c254cd082ea7d   stayed
4  bba03439a292a1e166f80264c16191cb   stayed

                       activity_new  campaign_disc_ele  \
0  esoiiifxdlbkcsluxmfuacbdckommixw                NaN
1                               NaN                NaN
2                               NaN                NaN
3                               NaN                NaN
4                               NaN                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  … forecast_price_pow_p1 has_gas imp_cons  \
0  2012-11-07  2016-11-06  …             58.995952       f    831.8
1  2013-06-15  2016-06-15  …             40.606701       t      0.0
2  2009-08-21  2016-08-30  …             44.311378       f      0.0
3  2010-04-16  2016-04-16  …             44.311378       f      0.0
4  2010-03-30  2016-03-30  …             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
0                3  ldkssxwpmemidmecebumciepifcamkci  180.000
1                3  lxidpiddsbxsbosboudacockeimpuepw   43.648
2                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.800
3                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.856
4                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.200

[5 rows x 33 columns]
```

4 Data visualization of churn

[360]:
```
sns.countplot(x= 'churn', data = churn_data, palette = 'hot')
plt.title('stayed vrs churned')
```

[360]: Text(0.5, 1.0, 'stayed vrs churned')



5 Describing data

[361]:
```
merge.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16096 entries, 0 to 16095
Data columns (total 33 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   id                        16096 non-null  object
 1   churn                     16096 non-null  object
 2   activity_new              6551 non-null   object
 3   campaign_disc_ele         0 non-null      float64
 4   channel_sales             11878 non-null  object
 5   cons_12m                  16096 non-null  int64
 6   cons_gas_12m              16096 non-null  int64
```

```
 7   cons_last_month           16096 non-null  int64
 8   date_activ                16096 non-null  object
 9   date_end                  16094 non-null  object
 10  date_first_activ          3508 non-null   object
 11  date_modif_prod           15939 non-null  object
 12  date_renewal              16056 non-null  object
 13  forecast_base_bill_ele    3508 non-null   float64
 14  forecast_base_bill_year   3508 non-null   float64
 15  forecast_bill_12m         3508 non-null   float64
 16  forecast_cons             3508 non-null   float64
 17  forecast_cons_12m         16096 non-null  float64
 18  forecast_cons_year        16096 non-null  int64
 19  forecast_discount_energy  15970 non-null  float64
 20  forecast_meter_rent_12m   16096 non-null  float64
 21  forecast_price_energy_p1  15970 non-null  float64
 22  forecast_price_energy_p2  15970 non-null  float64
 23  forecast_price_pow_p1     15970 non-null  float64
 24  has_gas                   16096 non-null  object
 25  imp_cons                  16096 non-null  float64
 26  margin_gross_pow_ele      16083 non-null  float64
 27  margin_net_pow_ele        16083 non-null  float64
 28  nb_prod_act               16096 non-null  int64
 29  net_margin                16081 non-null  float64
 30  num_years_antig           16096 non-null  int64
 31  origin_up                 16009 non-null  object
 32  pow_max                   16093 non-null  float64
dtypes: float64(16), int64(6), object(11)
memory usage: 4.2+ MB
```

It can be seen that the types of date is object, but needs to be in datetime.

[362]:
```python
merge.describe()
```

[362]:
```
       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_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
count	16093.000000

```
mean      20.604131
std       21.772421
min        1.000000
25%       12.500000
50%       13.856000
75%       19.800000
max      500.000000

[8 rows x 22 columns]
```

[363]:
```
merge['has_gas'] = merge['has_gas'].replace({'f':'No','t':'Yes'})
merge.head()
```

[363]:
```
                                 id    churn  \
0  48ada52261e7cf58715202705a0451c9   stayed
1  24011ae4ebbe3035111d65fa7c15bc57  churned
2  d29c2c54acc38ff3c0614d0a653813dd   stayed
3  764c75f661154dac3a6c254cd082ea7d   stayed
4  bba03439a292a1e166f80264c16191cb   stayed

                       activity_new  campaign_disc_ele  \
0  esoiiifxdlbkcsluxmfuacbdckommixw                NaN
1                               NaN                NaN
2                               NaN                NaN
3                               NaN                NaN
4                               NaN                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  … forecast_price_pow_p1 has_gas imp_cons  \
0  2012-11-07  2016-11-06  …              58.995952      No    831.8
1  2013-06-15  2016-06-15  …              40.606701     Yes      0.0
2  2009-08-21  2016-08-30  …              44.311378      No      0.0
3  2010-04-16  2016-04-16  …              44.311378      No      0.0
4  2010-03-30  2016-03-30  …              44.311378      No      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
0                3  ldkssxwpmemidmecebumciepifcamkci  180.000
1                3  lxidpiddsbxsbosboudacockeimpuepw   43.648
2                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.800
3                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.856
4                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.200

[5 rows x 33 columns]
```

[364]:
```python
history_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 193002 entries, 0 to 193001
Data columns (total 8 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   id            193002 non-null  object
 1   price_date    193002 non-null  object
 2   price_p1_var  191643 non-null  float64
 3   price_p2_var  191643 non-null  float64
 4   price_p3_var  191643 non-null  float64
 5   price_p1_fix  191643 non-null  float64
 6   price_p2_fix  191643 non-null  float64
 7   price_p3_fix  191643 non-null  float64
dtypes: float64(6), object(2)
memory usage: 11.8+ MB
```

[365]:
```python
history_data.describe()
```

[365]:
```
         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
```

6 Checking for missing data

[366]:
```
missing_figures_1 = history_data.isnull().sum()
missing_figures_1 = missing_figures_1[missing_figures_1 > 0]
pd.DataFrame({"missing_figures 1": missing_figures_1, "Missing_values_1(%)":␣
↪history_data.isnull().sum()/len(history_data.index)*100}).sort_values(by =␣
↪"Missing_values_1(%)", ascending = False)
```

[366]:

	missing_figures 1	Missing_values_1(%)
price_p1_fix	1359.0	0.704138
price_p1_var	1359.0	0.704138
price_p2_fix	1359.0	0.704138
price_p2_var	1359.0	0.704138
price_p3_fix	1359.0	0.704138
price_p3_var	1359.0	0.704138
id	NaN	0.000000
price_date	NaN	0.000000

[367]:
```
missing_figures = merge.isnull().sum()
missing_figures = missing_figures[missing_figures > 0]
pd.DataFrame({"missing_figures": missing_figures, "Missing values (%)": merge.
↪isnull().sum()/len(merge.index)*100}).sort_values(by = "Missing values (%)",␣
↪ascending = False)
```

[367]:

	missing_figures	Missing values (%)
campaign_disc_ele	16096.0	100.000000
date_first_activ	12588.0	78.205765
forecast_base_bill_ele	12588.0	78.205765
forecast_cons	12588.0	78.205765
forecast_bill_12m	12588.0	78.205765
forecast_base_bill_year	12588.0	78.205765
activity_new	9545.0	59.300447
channel_sales	4218.0	26.205268
date_modif_prod	157.0	0.975398
forecast_price_pow_p1	126.0	0.782803
forecast_price_energy_p2	126.0	0.782803
forecast_discount_energy	126.0	0.782803
forecast_price_energy_p1	126.0	0.782803
origin_up	87.0	0.540507
date_renewal	40.0	0.248509
net_margin	15.0	0.093191
margin_gross_pow_ele	13.0	0.080765
margin_net_pow_ele	13.0	0.080765
pow_max	3.0	0.018638

date_end	2.0	0.012425
forecast_meter_rent_12m	NaN	0.000000
forecast_cons_year	NaN	0.000000
date_activ	NaN	0.000000
has_gas	NaN	0.000000
id	NaN	0.000000
imp_cons	NaN	0.000000
cons_last_month	NaN	0.000000
cons_gas_12m	NaN	0.000000
nb_prod_act	NaN	0.000000
cons_12m	NaN	0.000000
num_years_antig	NaN	0.000000
churn	NaN	0.000000
forecast_cons_12m	NaN	0.000000

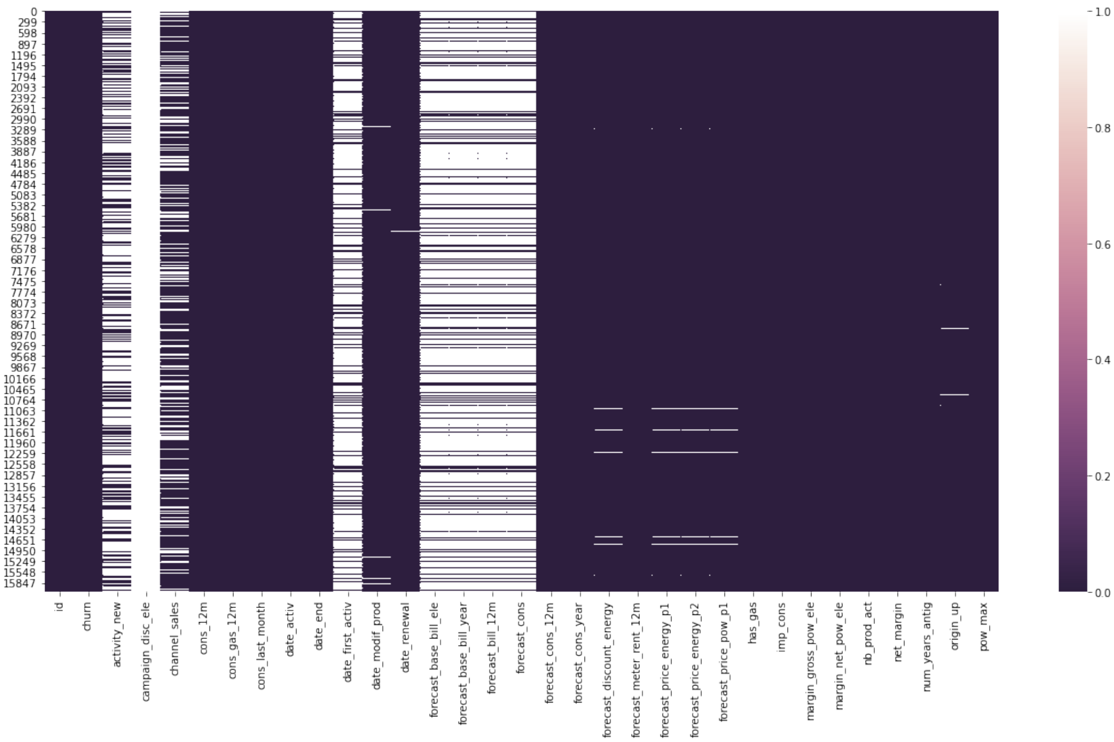
We need to drop columns with alot of missing data. Hence all columns with more than 70% missing data should be dropped

The history data looks good with less than 1% missing data.

7 Visualization of missing figures

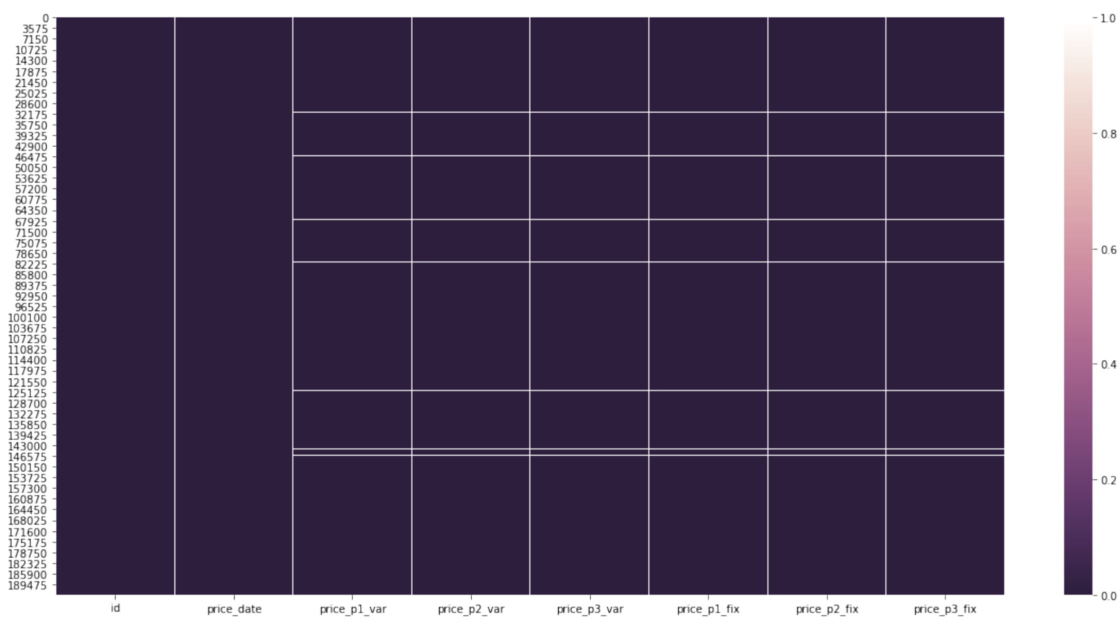
[368]:
```
plt.figure(figsize=(20, 10))
cmap = sns.cubehelix_palette(light=1, as_cmap=True, reverse=True)
sns.heatmap(merge.isnull(), cmap=cmap)
```

[368]: <AxesSubplot:>



[369]:
```
plt.figure(figsize=(20, 10))
cmap = sns.cubehelix_palette(light=1, as_cmap=True, reverse=True)
sns.heatmap(history_data.isnull(), cmap=cmap)
```

[369]: <AxesSubplot:>



[370]:
```
pip install missingno
```

```
Requirement already satisfied: missingno in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (0.4.2)
Requirement already satisfied: numpy in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from missingno)
(1.19.5)
Requirement already satisfied: matplotlib in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from missingno) (3.3.2)
Requirement already satisfied: scipy in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from missingno) (1.5.2)
Requirement already satisfied: seaborn in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from missingno)
(0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
matplotlib->missingno) (2.4.7)
Requirement already satisfied: certifi>=2020.06.20 in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
matplotlib->missingno) (2020.6.20)
Requirement already satisfied: python-dateutil>=2.1 in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
matplotlib->missingno) (2.8.1)
Requirement already satisfied: pillow>=6.2.0 in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
matplotlib->missingno) (8.0.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
matplotlib->missingno) (1.3.0)
Requirement already satisfied: cycler>=0.10 in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
matplotlib->missingno) (0.10.0)
Requirement already satisfied: six in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
cycler>=0.10->matplotlib->missingno) (1.15.0)
Requirement already satisfied: pandas>=0.23 in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
seaborn->missingno) (1.1.3)
Requirement already satisfied: pytz>=2017.2 in
/Users/barbarazen/anaconda3/lib/python3.8/site-packages (from
pandas>=0.23->seaborn->missingno) (2020.1)
Note: you may need to restart the kernel to use updated packages.
```

[371]:
```
import missingno as msno
```

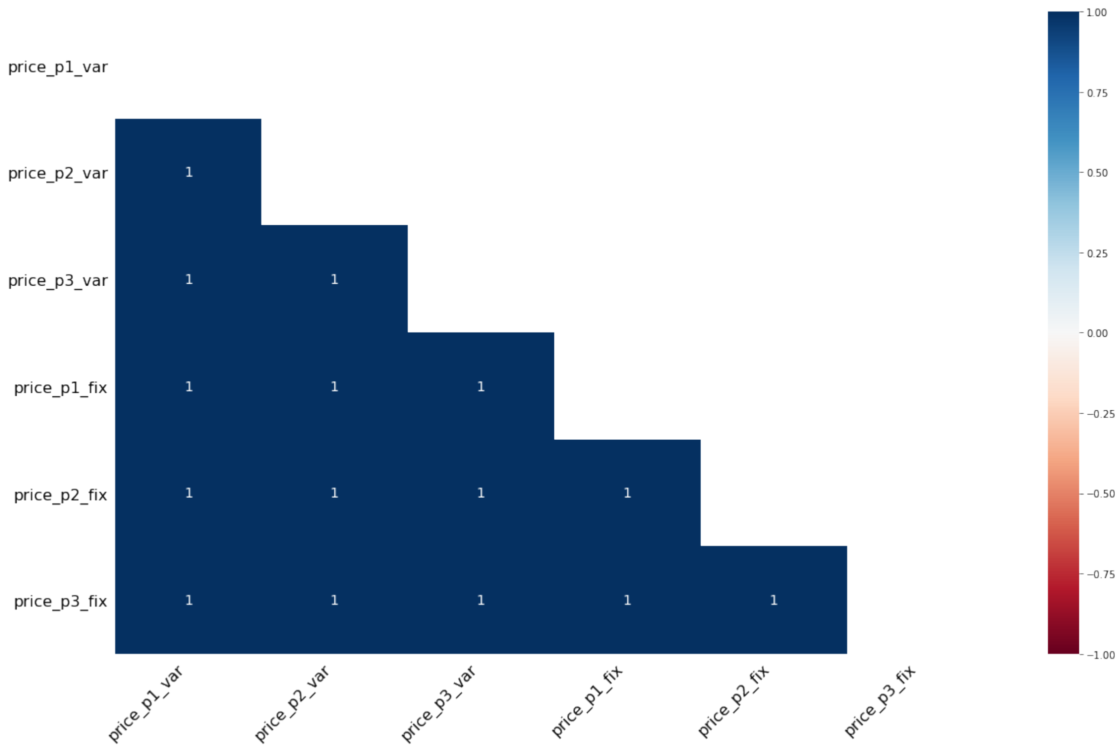
The missingno correlation heatmap measures nullity correlation: how strongly the presence or absence of one variable affects the presence of another:

Nullity correlation ranges from -1 (if one variable appears the other definitely does not) to 0 (variables appearing or not appearing have no effect on one another) to 1 (if one variable appears the other definitely also does).

Variables that are always full or always empty have no meaningful correlation, and so are silently removed from the visualization—in this case for instance the datetime and injury number columns, which are completely filled, are not included.

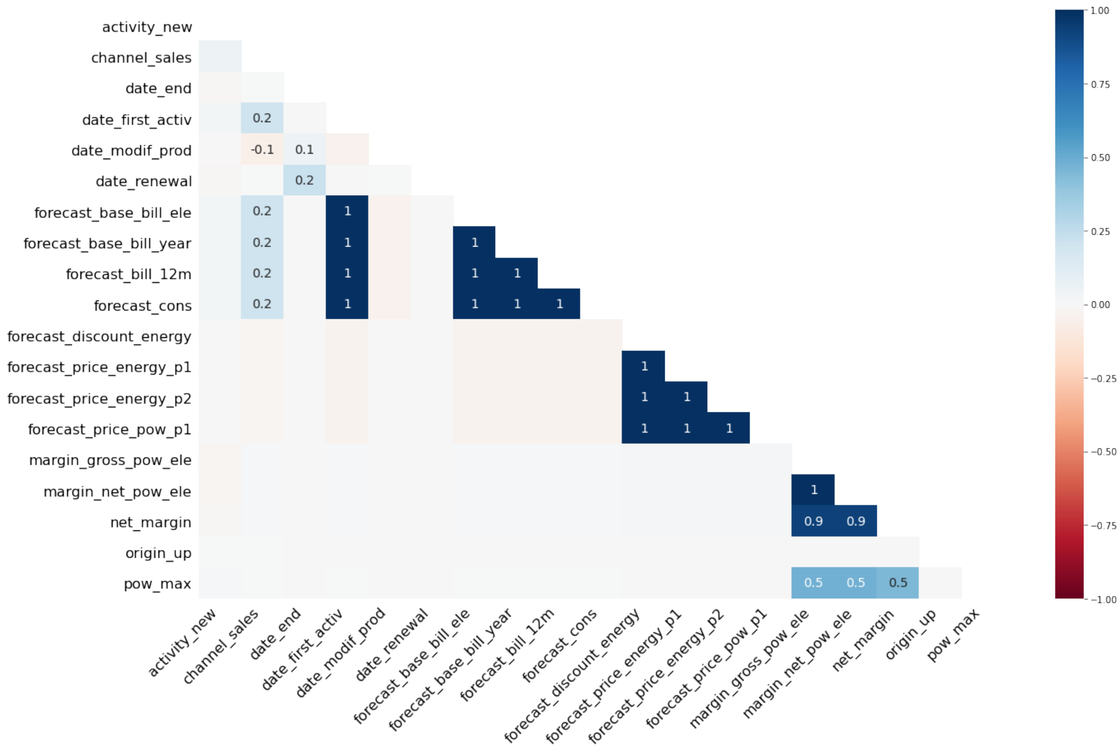
[372]:
```
msno.heatmap(history_data)
```

[372]: <AxesSubplot:>



[373]:
```
msno.heatmap(merge)
```

[373]: <AxesSubplot:>



Variables that are always full or always empty have no meaningful correlation, and so are silently removed from the visualization—in this case for instance the datetime and injury number columns, which are completely filled, are not included. It can be seen that, the columns with alot of missing data is already dropped from the correlation heatmap.

We need to drop columns with alot of missing data. Hence all columns with more than 70% missing data should be dropped

8 Dropping missing figures

[374]:
```
merge=merge.drop(columns= ["forecast_base_bill_ele", "date_first_activ",␣
↪"campaign_disc_ele", "forecast_base_bill_year", "forecast_bill_12m",␣
↪"forecast_cons", ])
merge.head()
```

[374]:
```
                                 id    churn  \
0  48ada52261e7cf58715202705a0451c9   stayed
1  24011ae4ebbe3035111d65fa7c15bc57  churned
2  d29c2c54acc38ff3c0614d0a653813dd   stayed
3  764c75f661154dac3a6c254cd082ea7d   stayed
4  bba03439a292a1e166f80264c16191cb   stayed

                       activity_new                      channel_sales  \
```

```
0  esoiiifxdlbkcsluxmfuacbdckommixw  lmkebamcaaclubfxadlmueccxoimlema
1                               NaN  foosdfpfkusacimwkcsosbicdxkicaua
2                               NaN                               NaN
3                               NaN  foosdfpfkusacimwkcsosbicdxkicaua
4                               NaN  lmkebamcaaclubfxadlmueccxoimlema

   cons_12m  cons_gas_12m  cons_last_month  date_activ    date_end  \
0    309275             0            10025  2012-11-07  2016-11-06
1         0         54946                0  2013-06-15  2016-06-15
2      4660             0                0  2009-08-21  2016-08-30
3       544             0                0  2010-04-16  2016-04-16
4      1584             0                0  2010-03-30  2016-03-30

  date_modif_prod  … forecast_price_pow_p1  has_gas  imp_cons  \
0      2012-11-07  …             58.995952       No     831.8
1             NaN  …             40.606701      Yes       0.0
2      2009-08-21  …             44.311378       No       0.0
3      2010-04-16  …             44.311378       No       0.0
4      2010-03-30  …             44.311378       No       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
0                3  ldkssxwpmemidmecebumciepifcamkci  180.000
1                3  lxidpiddsbxsbosboudacockeimpuepw   43.648
2                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.800
3                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.856
4                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.200

[5 rows x 27 columns]
```

8.1 Replacing the Missing data with the mean of the data

To start, we need to find the mean and replace the mean with the null values

[375]:
```python
#finding the mean of the data
mean_cons_12m= merge["cons_12m"].mean()
mean_cons_gas_12m= merge["cons_gas_12m"].mean()
mean_cons_last_month= merge["cons_last_month"].mean()
mean_forecast_cons_12m= merge["forecast_cons_12m"].mean()
mean_forecast_cons_year= merge["forecast_cons_year"].mean()
mean_forecast_discount_energy= merge["forecast_discount_energy"].mean()
```

```python
mean_forecast_meter_rent_12m= merge["forecast_meter_rent_12m"].mean()
mean_forecast_price_energy_p1= merge["forecast_price_energy_p1"].mean()
mean_forecast_price_energy_p2= merge["forecast_price_energy_p2"].mean()
mean_forecast_price_pow_p1= merge["forecast_price_pow_p1"].mean()
mean_imp_cons= merge["imp_cons"].mean()
mean_margin_gross_pow_ele= merge["margin_gross_pow_ele"].mean()
mean_margin_net_pow_ele= merge["margin_net_pow_ele"].mean()
mean_nb_prod_act= merge["nb_prod_act"].mean()
mean_net_margin= merge["net_margin"].mean()
mean_num_years_antig= merge["num_years_antig"].mean()
mean_pow_max= merge["pow_max"].mean()
```

[376]:

```python
merge["cons_12m"] = merge["cons_12m"].fillna(mean_cons_12m)
merge["cons_gas_12m"] = merge["cons_gas_12m"].fillna(mean_cons_gas_12m)
merge["cons_last_month"] = merge["cons_last_month"].fillna(mean_cons_last_month)
merge["forecast_cons_12m"] = merge["forecast_cons_12m"].
 ↪fillna(mean_forecast_cons_12m)
merge["forecast_cons_year"] = merge["forecast_cons_year"].
 ↪fillna(mean_forecast_cons_year)
merge["forecast_discount_energy"] = merge["forecast_discount_energy"].
 ↪fillna(mean_forecast_discount_energy)
merge["forecast_meter_rent_12m"] = merge["forecast_meter_rent_12m"].
 ↪fillna(mean_forecast_meter_rent_12m)
merge["forecast_price_energy_p1"] = merge["forecast_price_energy_p1"].
 ↪fillna(mean_forecast_price_energy_p1)
merge["forecast_price_energy_p2"] = merge["forecast_price_energy_p2"].
 ↪fillna(mean_forecast_price_energy_p2)
merge["forecast_price_pow_p1"] = merge["forecast_price_pow_p1"].
 ↪fillna(mean_forecast_price_pow_p1)
merge["imp_cons"] = merge["imp_cons"].fillna(mean_imp_cons)
merge["margin_gross_pow_ele"] = merge["margin_gross_pow_ele"].
 ↪fillna(mean_margin_gross_pow_ele)
merge["margin_net_pow_ele"] = merge["margin_net_pow_ele"].
 ↪fillna(mean_margin_net_pow_ele)
merge["nb_prod_act"] = merge["nb_prod_act"].fillna(mean_nb_prod_act)
merge["net_margin"] = merge["net_margin"].fillna(mean_net_margin)
merge["num_years_antig"] = merge["num_years_antig"].fillna(mean_num_years_antig)
merge["pow_max"] = merge["pow_max"].fillna(mean_pow_max)
```

[377]:

```python
mean_price_p1_var= history_data["price_p1_var"].mean()
mean_price_p2_var= history_data["price_p2_var"].mean()
mean_price_p3_var= history_data["price_p3_var"].mean()
mean_price_p1_fix= history_data["price_p1_fix"].mean()
mean_price_p2_fix= history_data["price_p2_fix"].mean()
mean_price_p3_fix= history_data["price_p3_fix"].mean()
```

[378]:
```
history_data["price_p1_var"] = history_data["price_p1_var"].
 ↪fillna(mean_price_p1_var)
history_data["price_p2_var"] = history_data["price_p2_var"].
 ↪fillna(mean_price_p2_var)
history_data["price_p3_var"] = history_data["price_p3_var"].
 ↪fillna(mean_price_p3_var)
history_data["price_p1_fix"] = history_data["price_p1_fix"].
 ↪fillna(mean_price_p1_fix)
history_data["price_p2_fix"] = history_data["price_p2_fix"].
 ↪fillna(mean_price_p2_fix)
history_data["price_p3_fix"] = history_data["price_p3_fix"].
 ↪fillna(mean_price_p3_fix)
```

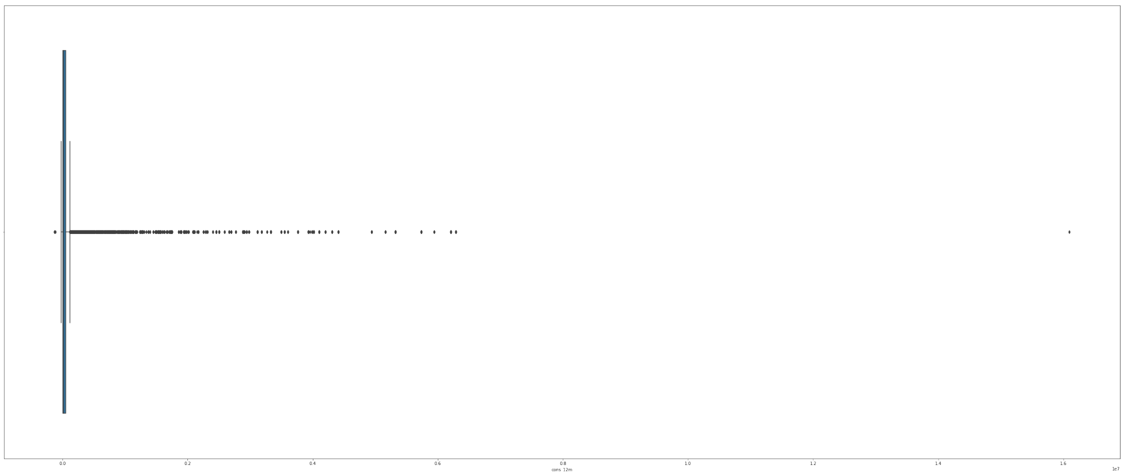
[379]:
```
merge.isnull().sum()
```

[379]:
```
id                              0
churn                           0
activity_new                 9545
channel_sales                4218
cons_12m                        0
cons_gas_12m                    0
cons_last_month                 0
date_activ                      0
date_end                        2
date_modif_prod               157
date_renewal                   40
forecast_cons_12m               0
forecast_cons_year              0
forecast_discount_energy        0
forecast_meter_rent_12m         0
forecast_price_energy_p1        0
forecast_price_energy_p2        0
forecast_price_pow_p1           0
has_gas                         0
imp_cons                        0
margin_gross_pow_ele            0
margin_net_pow_ele              0
nb_prod_act                     0
net_margin                      0
num_years_antig                 0
origin_up                      87
pow_max                         0
dtype: int64
```

9 Checking Skewness

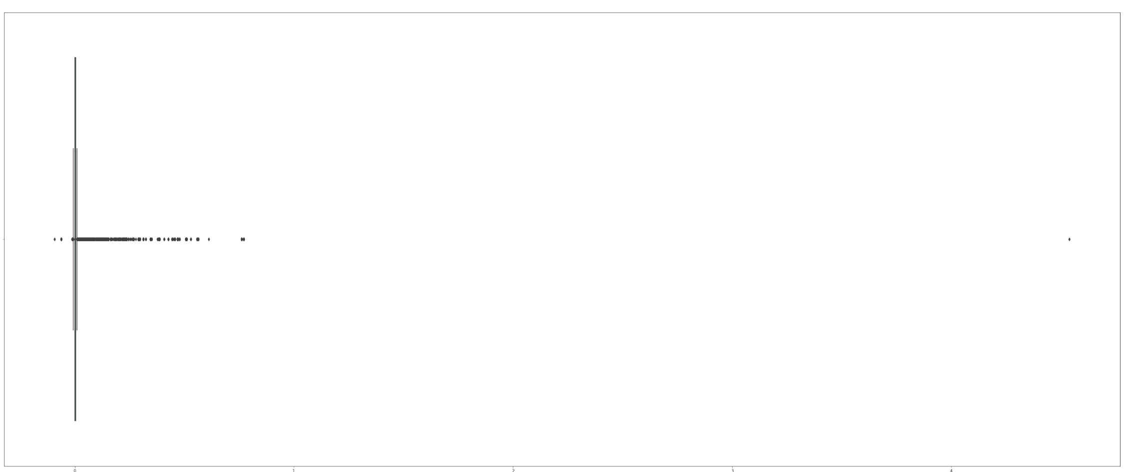
[380]:
```
fig, axs = plt.subplots(figsize=(48,20))
sns.boxplot(x=merge['cons_12m'])
```

[380]: <AxesSubplot:xlabel='cons_12m'>



[381]:
```
fig, axs = plt.subplots(figsize=(48,20))
sns.boxplot(x=merge['cons_last_month'])
```

[381]: <AxesSubplot:xlabel='cons_last_month'>

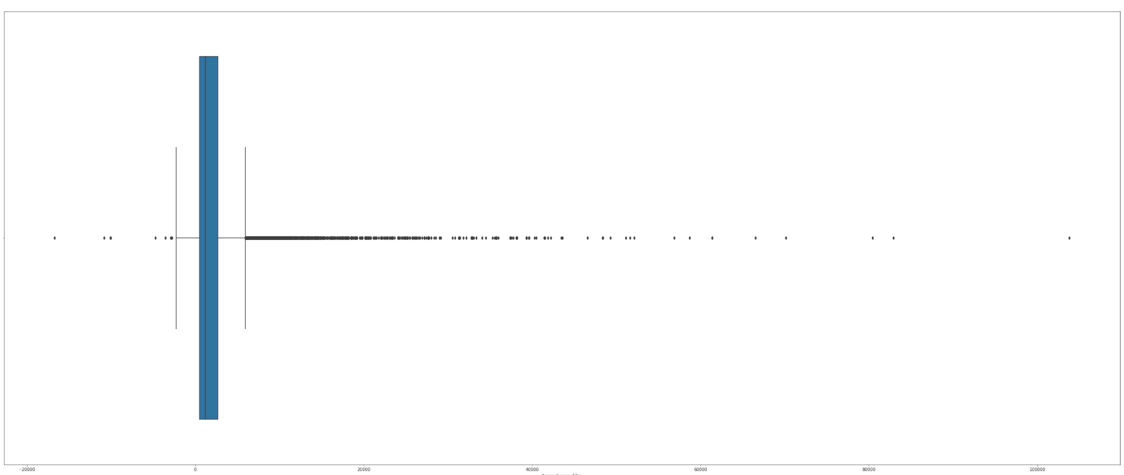


[382]:
```
fig, axs = plt.subplots(figsize=(48,20))
sns.boxplot(x=merge['cons_last_month'])
```

[382]: <AxesSubplot:xlabel='cons_last_month'>

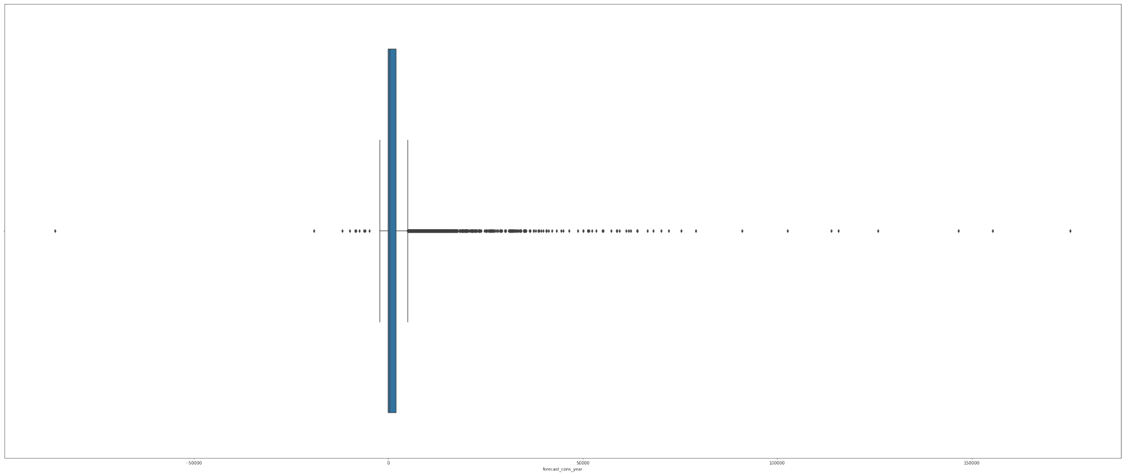
[383]:
```
fig, axs = plt.subplots(figsize=(48,20))
sns.boxplot(x=merge['forecast_cons_12m'])
```

[383]: <AxesSubplot:xlabel='forecast_cons_12m'>



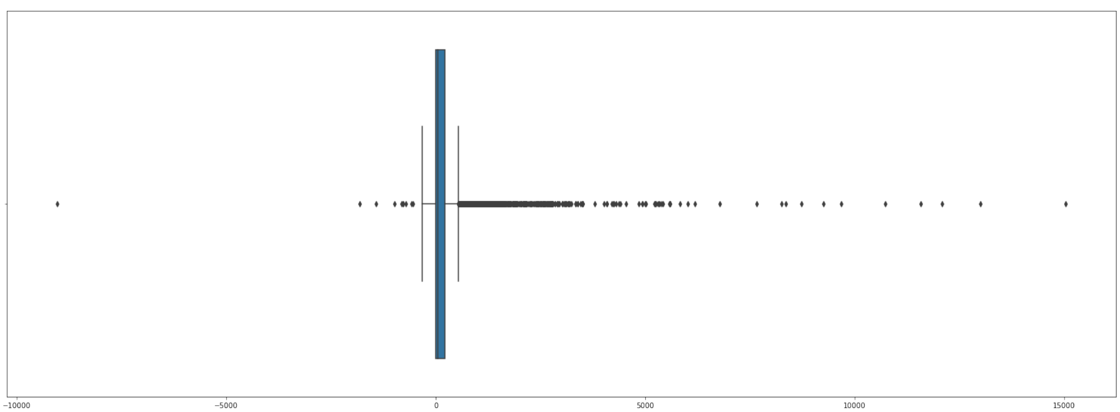
[384]:
```
fig, axs = plt.subplots(figsize=(48,20))
sns.boxplot(x=merge['forecast_cons_year'])
```

[384]: <AxesSubplot:xlabel='forecast_cons_year'>



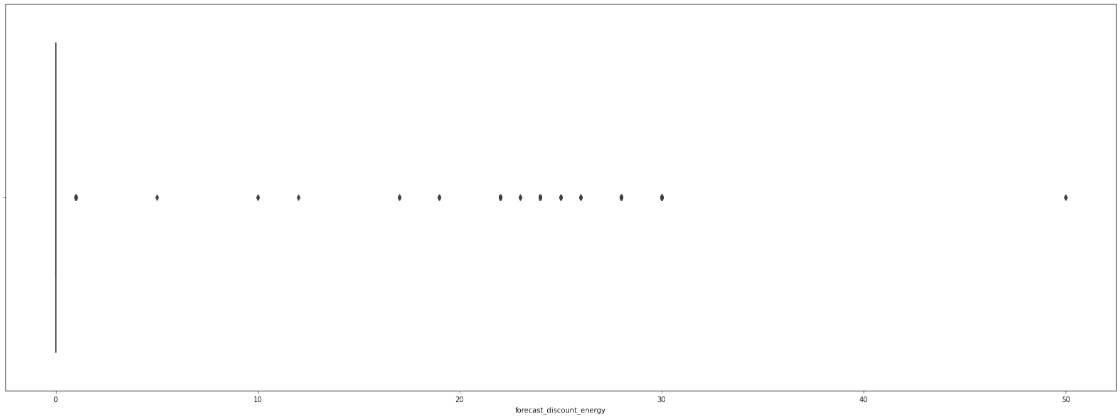
```
[385]: fig, axs = plt.subplots(figsize=(28,10))
       sns.boxplot(x=merge['imp_cons'])
```

[385]: <AxesSubplot:xlabel='imp_cons'>



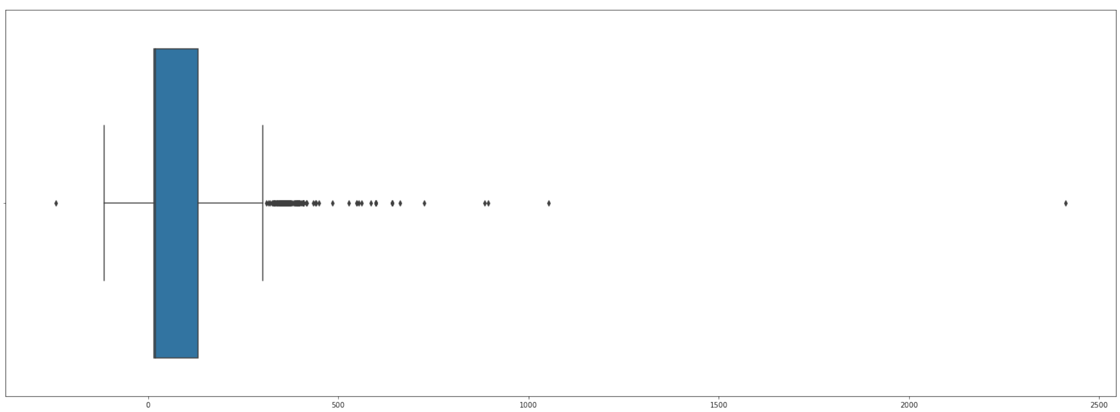

```
[386]: fig, axs = plt.subplots(figsize=(28,10))
       sns.boxplot(x=merge['forecast_discount_energy'])
```

[386]: <AxesSubplot:xlabel='forecast_discount_energy'>



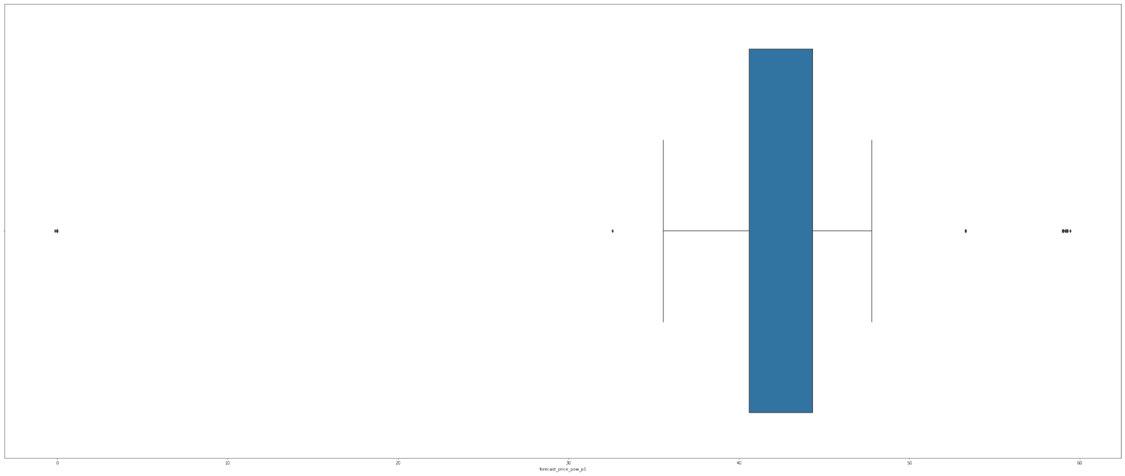

```
[387]: fig, axs = plt.subplots(figsize=(28,10))
       sns.boxplot(x=merge['forecast_meter_rent_12m'])
```

```
[387]: <AxesSubplot:xlabel='forecast_meter_rent_12m'>
```



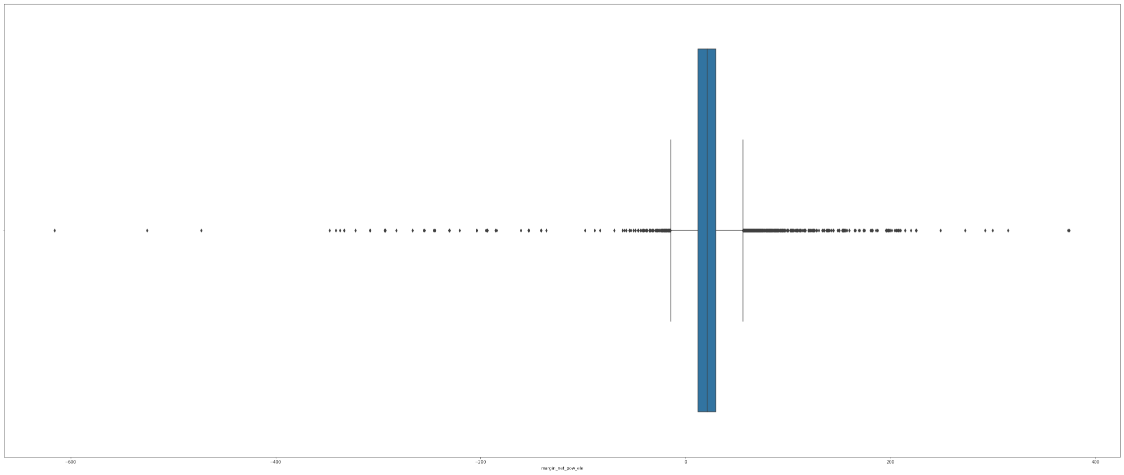

```
[388]: fig, axs = plt.subplots(figsize=(48,20))
       sns.boxplot(x=merge['forecast_price_pow_p1'])
```

```
[388]: <AxesSubplot:xlabel='forecast_price_pow_p1'>
```



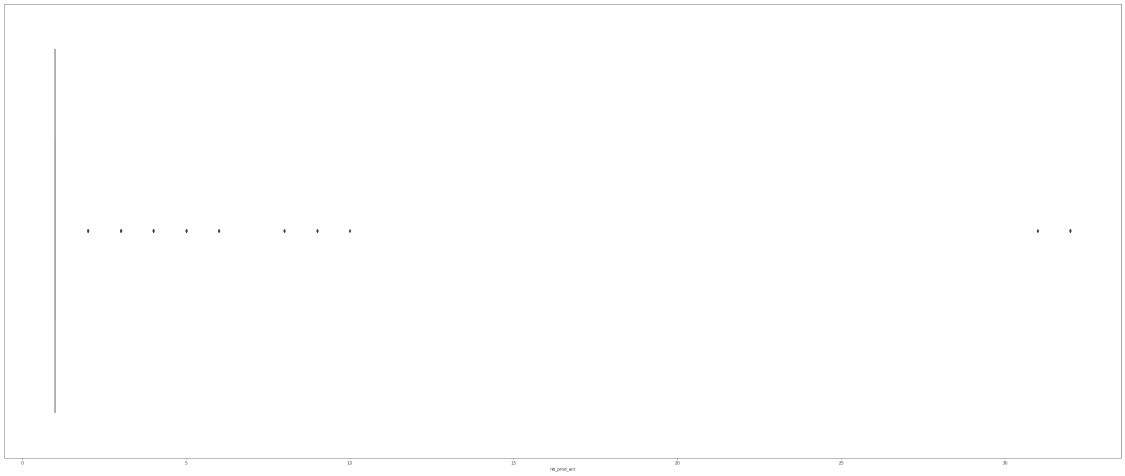
```
[389]: fig, axs = plt.subplots(figsize=(48,20))
       sns.boxplot(x=merge['margin_net_pow_ele'])
```

[389]: <AxesSubplot:xlabel='margin_net_pow_ele'>



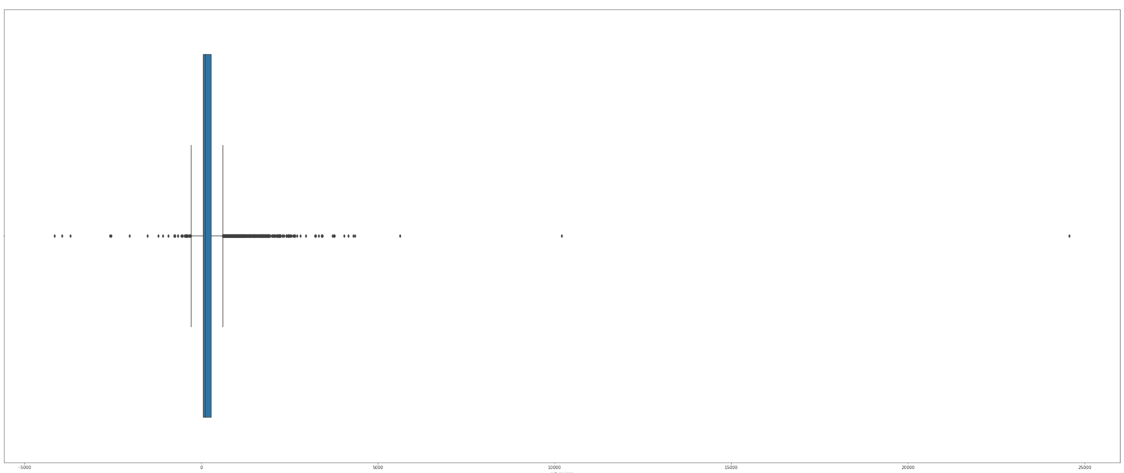
```
[390]: fig, axs = plt.subplots(figsize=(48,20))
       sns.boxplot(x=merge['nb_prod_act'])
```

[390]: <AxesSubplot:xlabel='nb_prod_act'>



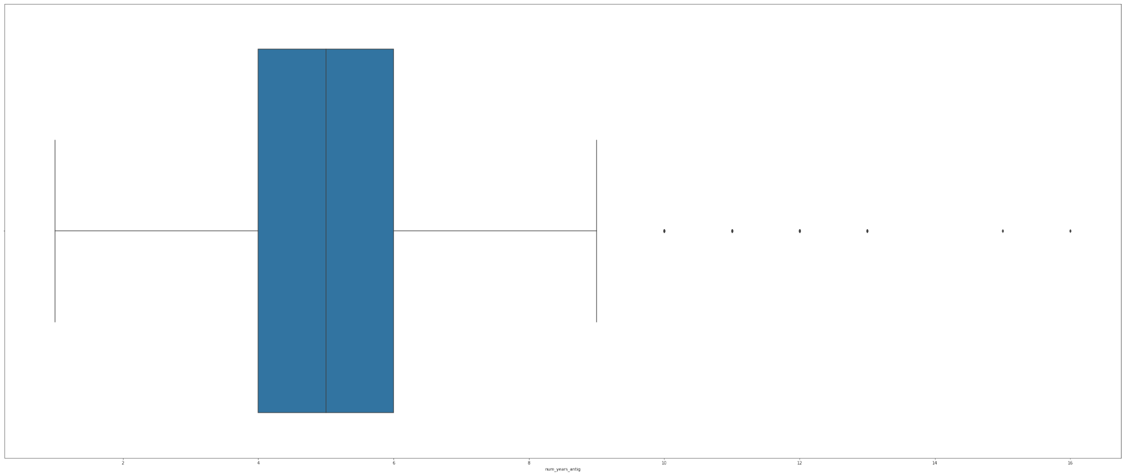
[391]:
```
fig, axs = plt.subplots(figsize=(48,20))
sns.boxplot(x=merge['net_margin'])
```

[391]: <AxesSubplot:xlabel='net_margin'>



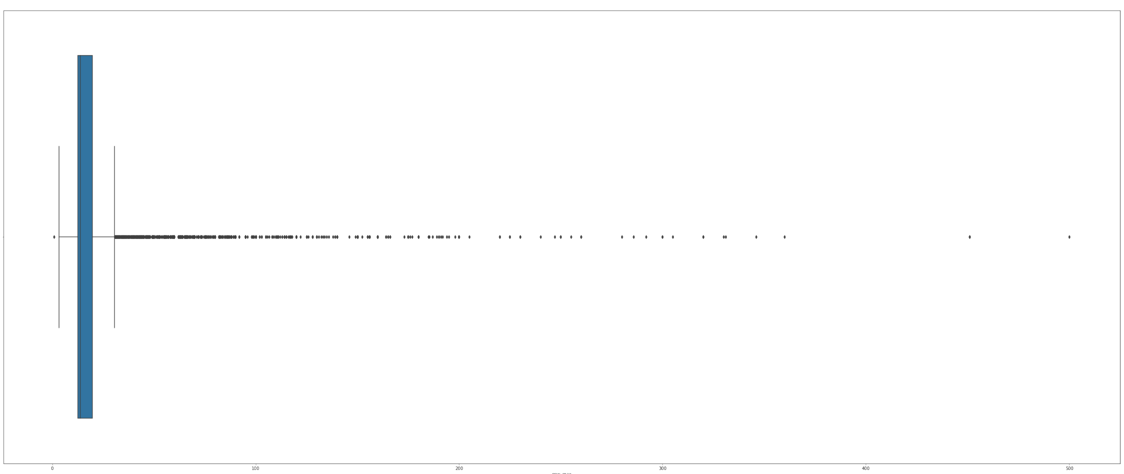
[392]:
```
fig, axs = plt.subplots(figsize=(48,20))
sns.boxplot(x=merge['num_years_antig'])
```

[392]: <AxesSubplot:xlabel='num_years_antig'>



[393]:
```
fig, axs = plt.subplots(figsize=(48,20))
sns.boxplot(x=merge['pow_max'])
```

[393]: <AxesSubplot:xlabel='pow_max'>



10 Finding factors that affect churning

Now let's find the code of the sales channel that companies suscribed to and check to see if it has correlation with the churning.

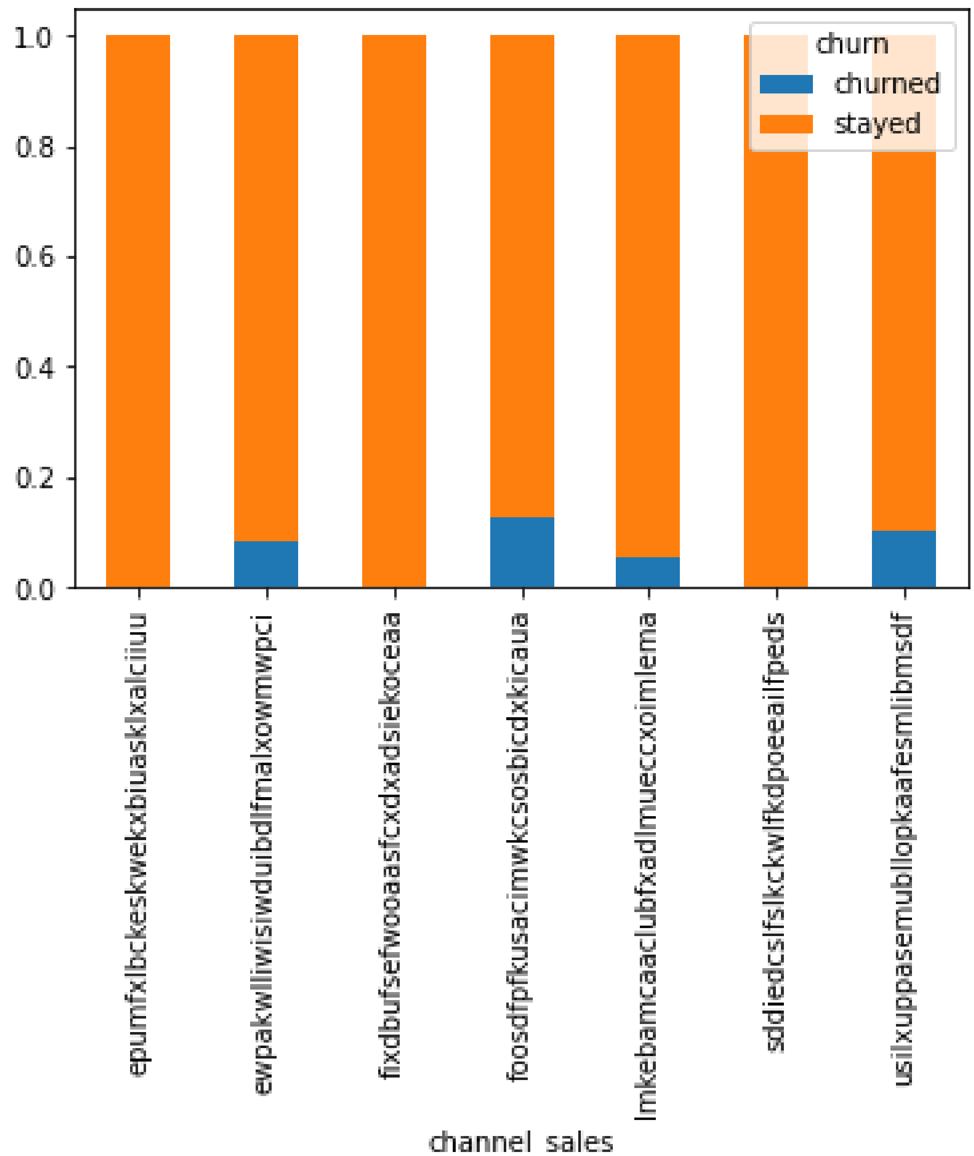
[394]:
```
channelsales_count=pd.DataFrame(merge['channel_sales'].value_counts())
print(channelsales_count)
```

```
                                  channel_sales
foosdfpfkusacimwkcsosbicdxkicaua           7377
```

```
lmkebamcaaclubfxadlmueccxoimlema          2073
usilxuppasemubllopkaafesmlibmsdf          1444
ewpakwlliwisiwduibdlfmalxowmwpci           966
sddiedcslfslkckwlfkdpoeeailfpeds            12
epumfxlbckeskwekxbiuasklxalciiuu             4
fixdbufsefwooaasfcxdxadsiekoceaa             2
```

[395]:
```
pd.crosstab(merge['channel_sales'],merge['churn'],normalize='index').plot.
↪bar(stacked=True)
```

[395]: <AxesSubplot:xlabel='channel_sales'>

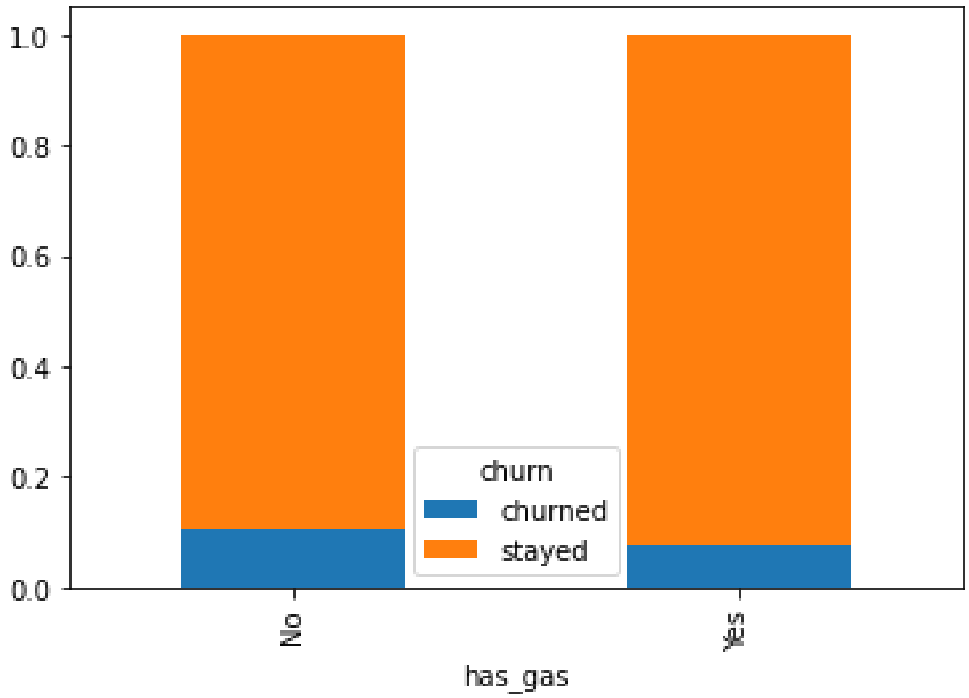


Relatively, companies with who joined the firm through 'foosdfpfkusacimwkcsosbicdxkicaua' and 'usilxuppasemubllopkaafesmlibmsdf' sales channel are more likely to churn.

Finding out if churning is dependent on whether a company has gas or not

[396]:
```
pd.crosstab(merge['has_gas'],merge['churn'],normalize='index').plot.
↪bar(stacked=True)
```

[396]:
```
<AxesSubplot:xlabel='has_gas'>
```



It can be seen that, relatively, companies without gas churned more than the companies with gas.

Finding out if churning is dependent on whether a company suscribed power or not

[397]:
```
merge.groupby(['pow_max','churn']).size().unstack().head()
```

[397]:

churn	churned	stayed
pow_max		
1.000	NaN	1.0
3.300	2.0	5.0
3.450	2.0	2.0
3.464	NaN	4.0
3.500	1.0	1.0

[398]:
```
pow_id = merge[['id','churn','pow_max']]
pow_id.head()
```

[398]:

	id	churn	pow_max
0	48ada52261e7cf58715202705a0451c9	stayed	180.000
1	24011ae4ebbe3035111d65fa7c15bc57	churned	43.648
2	d29c2c54acc38ff3c0614d0a653813dd	stayed	13.800
3	764c75f661154dac3a6c254cd082ea7d	stayed	13.856
4	bba03439a292a1e166f80264c16191cb	stayed	13.200

we need to group the pow_max into grades

[399]:
```
bins = [0,10,20,30,40,50,60,70,80,90,100,110,120,130,140,200]
```

[400]:
```
pow_id['pow_grade'] = pd.cut(pow_id['pow_max'],bins, labels=None)
pow_id.head()
```

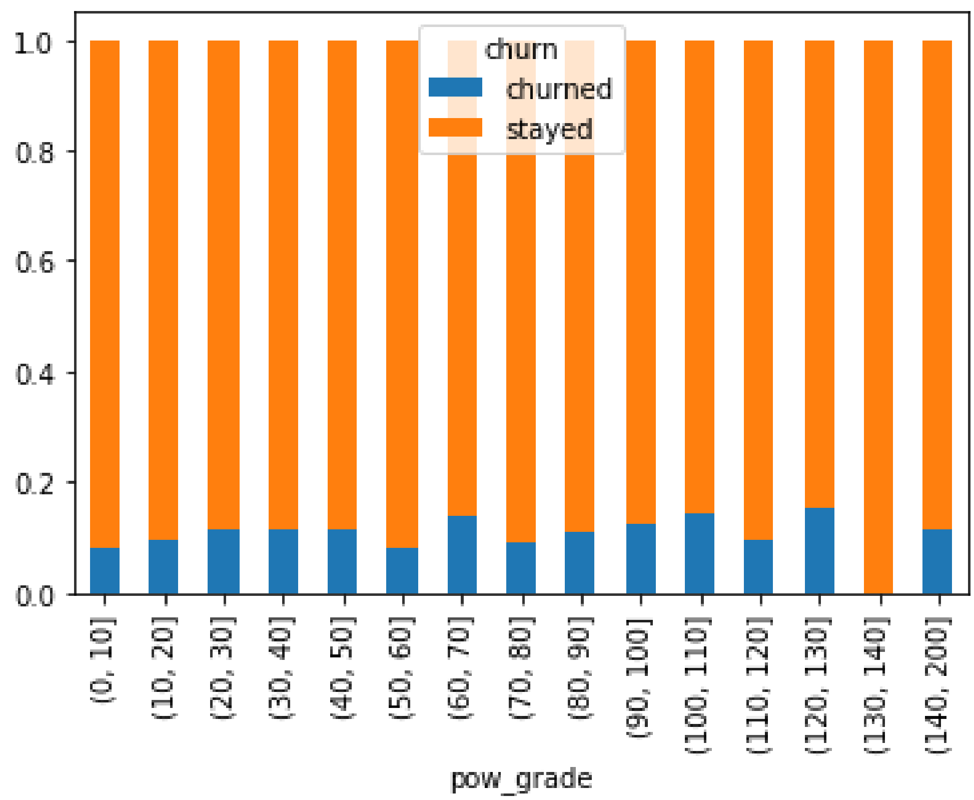
[400]:

	id	churn	pow_max	pow_grade
0	48ada52261e7cf58715202705a0451c9	stayed	180.000	(140, 200]
1	24011ae4ebbe3035111d65fa7c15bc57	churned	43.648	(40, 50]
2	d29c2c54acc38ff3c0614d0a653813dd	stayed	13.800	(10, 20]
3	764c75f661154dac3a6c254cd082ea7d	stayed	13.856	(10, 20]
4	bba03439a292a1e166f80264c16191cb	stayed	13.200	(10, 20]

[401]:
```
plt.figure(figsize = (40, 20))
pd.crosstab(pow_id['pow_grade'],pow_id['churn'],normalize='index').plot.
↪bar(stacked=True)
```

[401]: <AxesSubplot:xlabel='pow_grade'>

<Figure size 2880x1440 with 0 Axes>



Relatively, companies with (60,70), (100,110) and (120,130) suscribed power are more likely to churn.

[402]:
```
merge['date_activ'] = pd.to_datetime(merge['date_activ']).dt.to_period('m')
merge['date_end'] = pd.to_datetime(merge['date_end']).dt.to_period('m')
merge['date_modif_prod'] = pd.to_datetime(merge['date_modif_prod']).dt.
 ↪to_period('m')
merge['date_renewal'] = pd.to_datetime(merge['date_renewal']).dt.to_period('m')
```

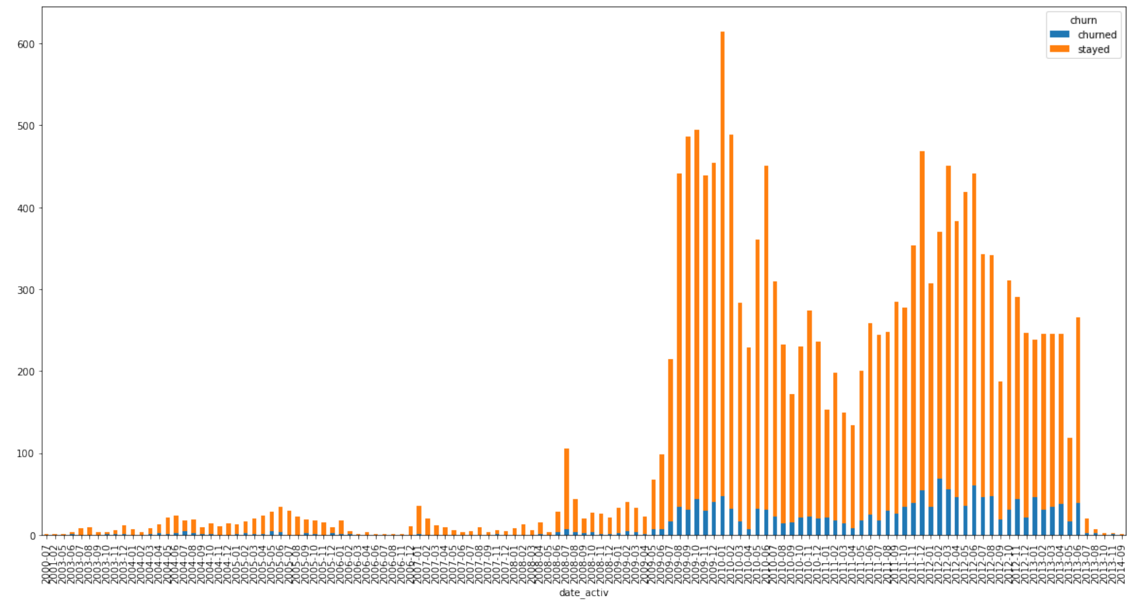
[403]:
```
merge.head()
```

[403]:
```
                                 id    churn  \
0  48ada52261e7cf58715202705a0451c9   stayed
1  24011ae4ebbe3035111d65fa7c15bc57  churned
2  d29c2c54acc38ff3c0614d0a653813dd   stayed
3  764c75f661154dac3a6c254cd082ea7d   stayed
4  bba03439a292a1e166f80264c16191cb   stayed

                       activity_new                     channel_sales  \
0  esoiiifxdlbkcsluxmfuacbdckommixw  lmkebamcaaclubfxadlmueccxoimlema
1                               NaN  foosdfpfkusacimwkcsosbicdxkicaua
2                               NaN                               NaN
```

```
3                              NaN  foosdfpfkusacimwkcsosbicdxkicaua
4                              NaN  lmkebamcaaclubfxadlmueccxoimlema

   cons_12m  cons_gas_12m  cons_last_month date_activ date_end  \
0    309275             0            10025    2012-11  2016-11
1         0         54946                0    2013-06  2016-06
2      4660             0                0    2009-08  2016-08
3       544             0                0    2010-04  2016-04
4      1584             0                0    2010-03  2016-03

  date_modif_prod  … forecast_price_pow_p1  has_gas  imp_cons  \
0         2012-11  …             58.995952       No     831.8
1             NaT  …             40.606701      Yes       0.0
2         2009-08  …             44.311378       No       0.0
3         2010-04  …             44.311378       No       0.0
4         2010-03  …             44.311378       No       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
0                3  ldkssxwpmemidmecebumciepifcamkci  180.000
1                3  lxidpiddsbxsbosboudacockeimpuepw   43.648
2                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.800
3                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.856
4                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.200

[5 rows x 27 columns]
```

[404]:
```
plt.rcParams['figure.figsize']=(20,10)
merge.groupby(['date_activ','churn']).size().unstack().plot.bar(stacked=True)
```

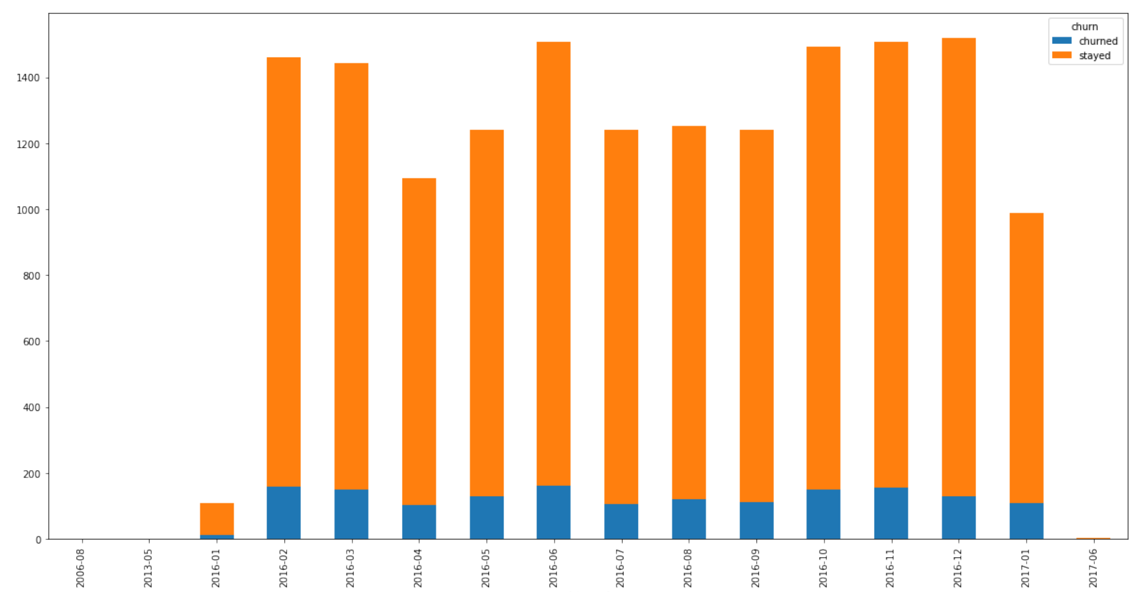
[404]: <AxesSubplot:xlabel='date_activ'>



Relatively, companies with who joined the firm through from december 2011 to 2014 are more likely to churn.

[405]:
```
plt.rcParams['figure.figsize']=(20,10)
merge.groupby(['date_end','churn']).size().unstack().plot.bar(stacked=True)
```

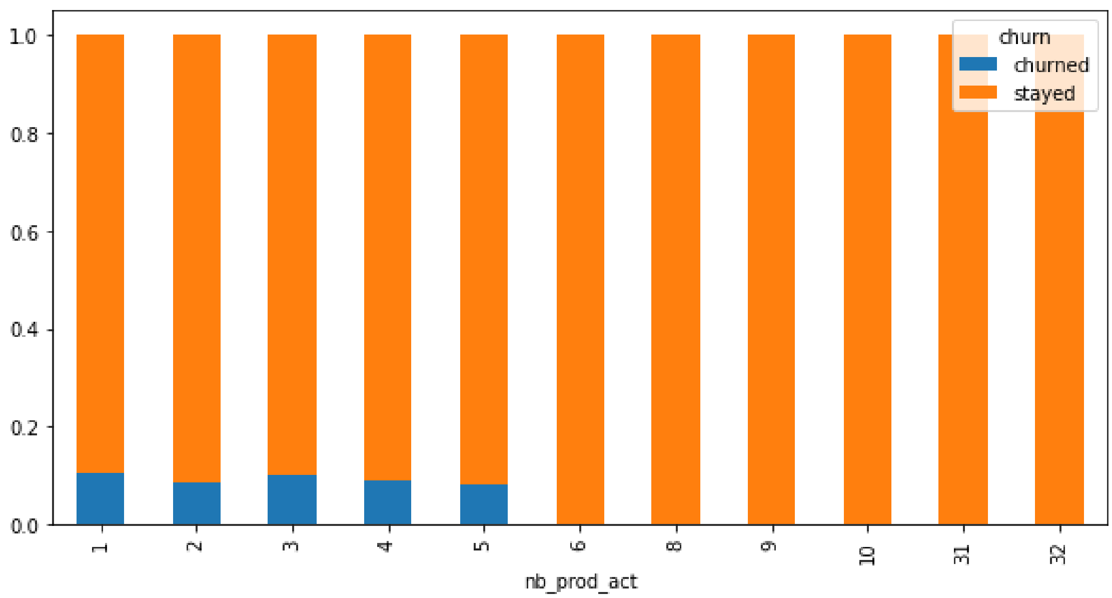
[405]: `<AxesSubplot:xlabel='date_end'>`



Active products and services

[406]:
```
plt.rcParams['figure.figsize']=(10,5)
pd.crosstab(merge['nb_prod_act'],merge['churn'],normalize='index').plot.
    ↪bar(stacked=True)
```

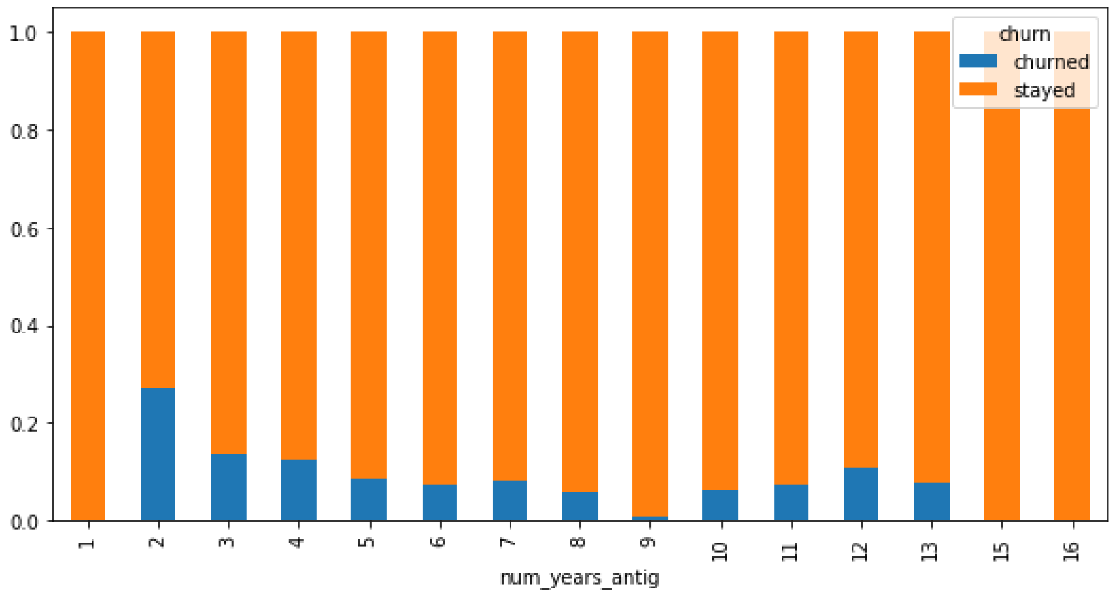
[406]: <AxesSubplot:xlabel='nb_prod_act'>



Relatively, companies with 1-5 active products and services are more likely to churn.

[407]:
```
plt.rcParams['figure.figsize']=(10,5)
pd.crosstab(merge['num_years_antig'],merge['churn'],normalize='index').plot.
    ↪bar(stacked=True)
```

[407]: <AxesSubplot:xlabel='num_years_antig'>

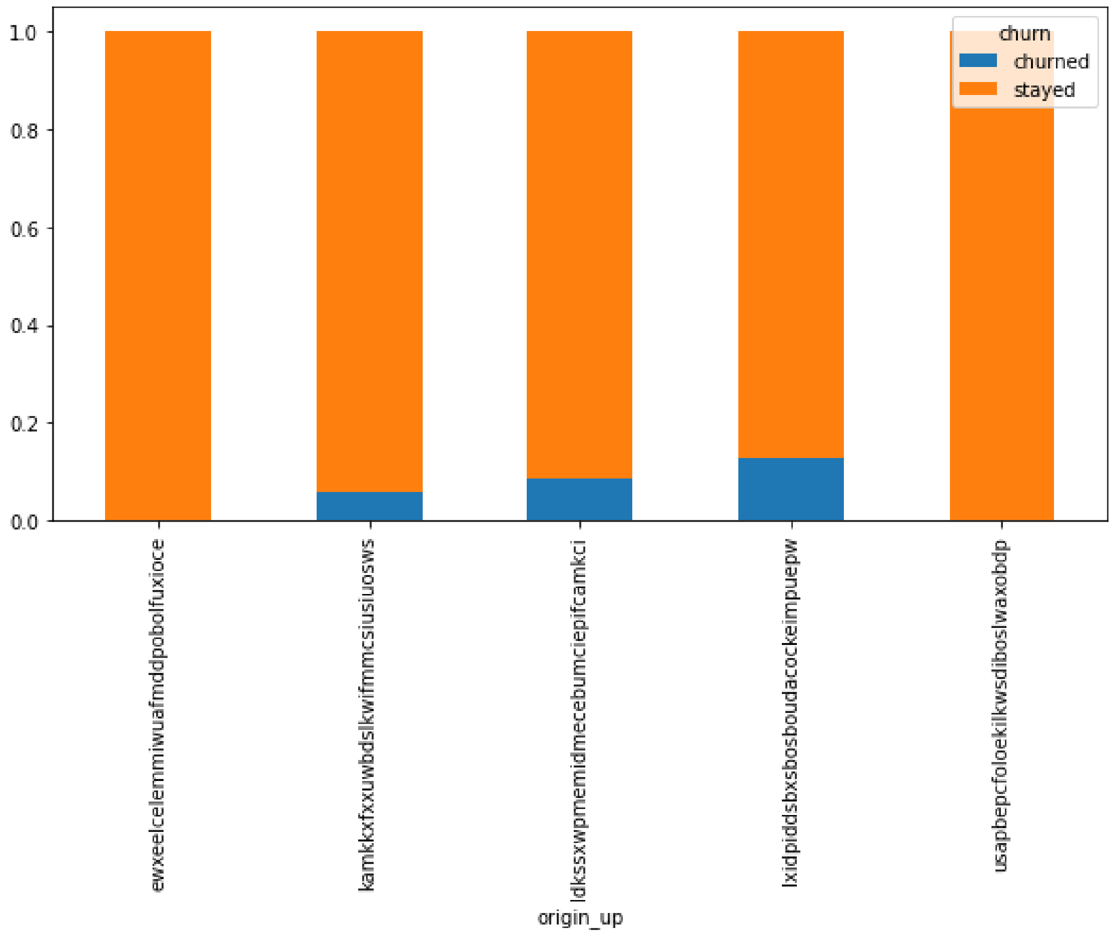


Relatively, companies are likely to churn in the second year. After, the probability for companies to churn diminishes up to the ninth year and starts rising again. By the 15th year, the companies are more likely to stay.

Code of the electricity campaign the customer first subscribed to

[408]:
```
plt.rcParams['figure.figsize']=(10,5)
pd.crosstab(merge['origin_up'],merge['churn'],normalize='index').plot.
 ↪bar(stacked=True)
```

[408]: <AxesSubplot:xlabel='origin_up'>

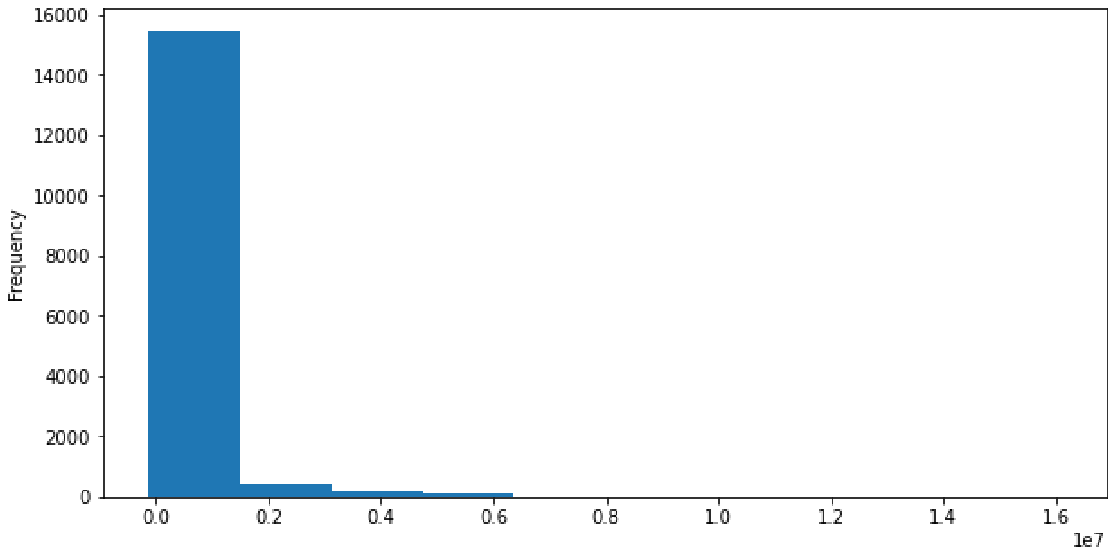


Relatively, companies that first suscribed to the code of the electricity campaign ‘lxidpiddsbx’ is likely to churn.

11 Histogram of the data

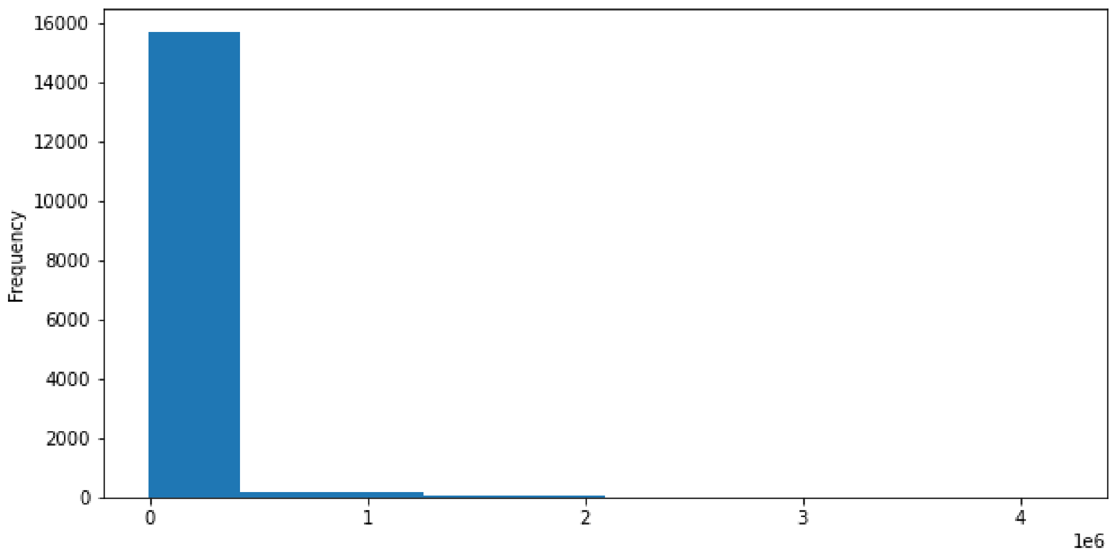
[409]:
```
merge["cons_12m"].plot.hist()
```

[409]: <AxesSubplot:ylabel='Frequency'>



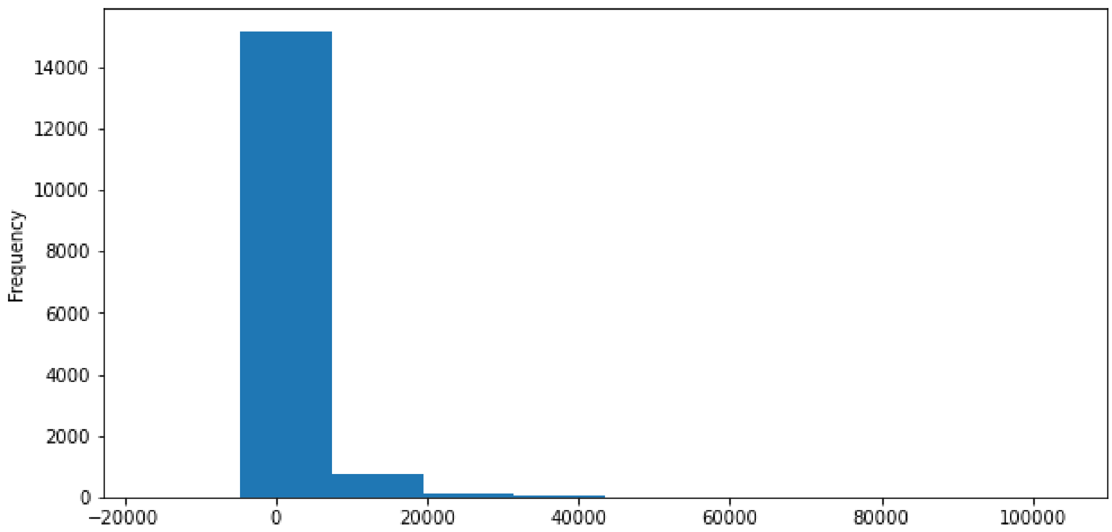
[410]:
```
merge["cons_gas_12m"].plot.hist()
```

[410]: <AxesSubplot:ylabel='Frequency'>



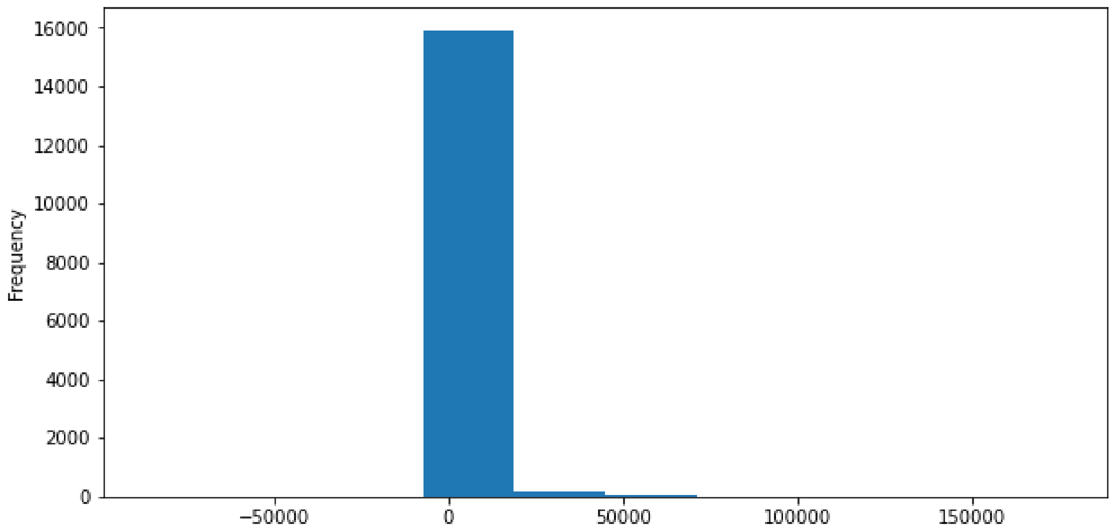
[411]:
```
merge["forecast_cons_12m"].plot.hist()
```

[411]: <AxesSubplot:ylabel='Frequency'>



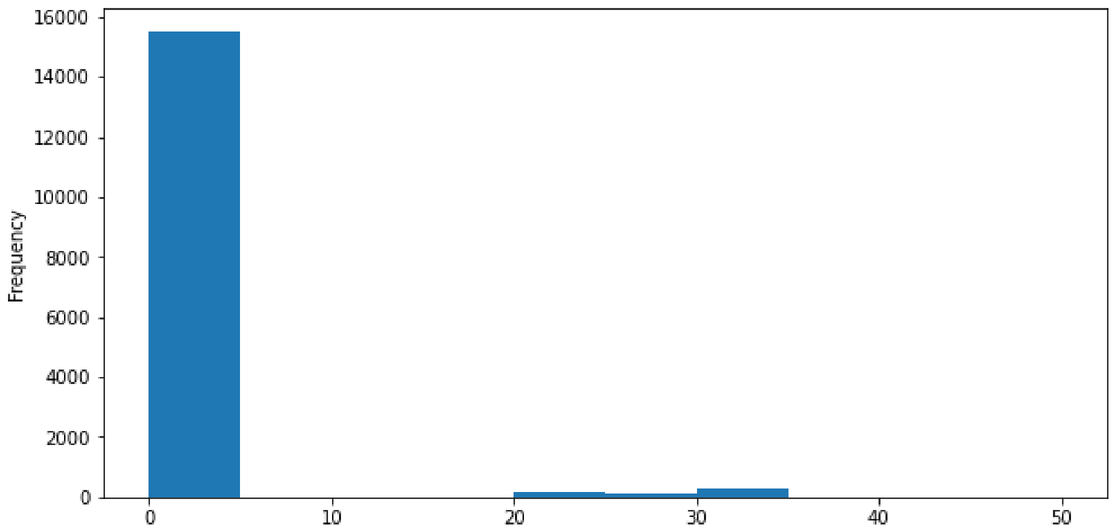

```
[412]: merge["forecast_cons_year"].plot.hist()
```

[412]: <AxesSubplot:ylabel='Frequency'>



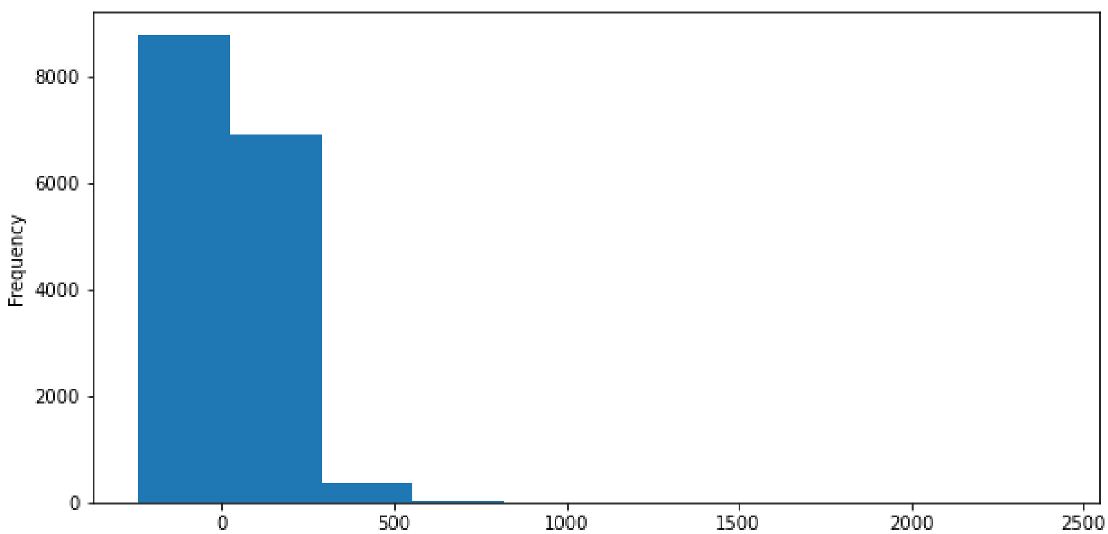

```
[413]: merge["forecast_discount_energy"].plot.hist()
```

[413]: <AxesSubplot:ylabel='Frequency'>



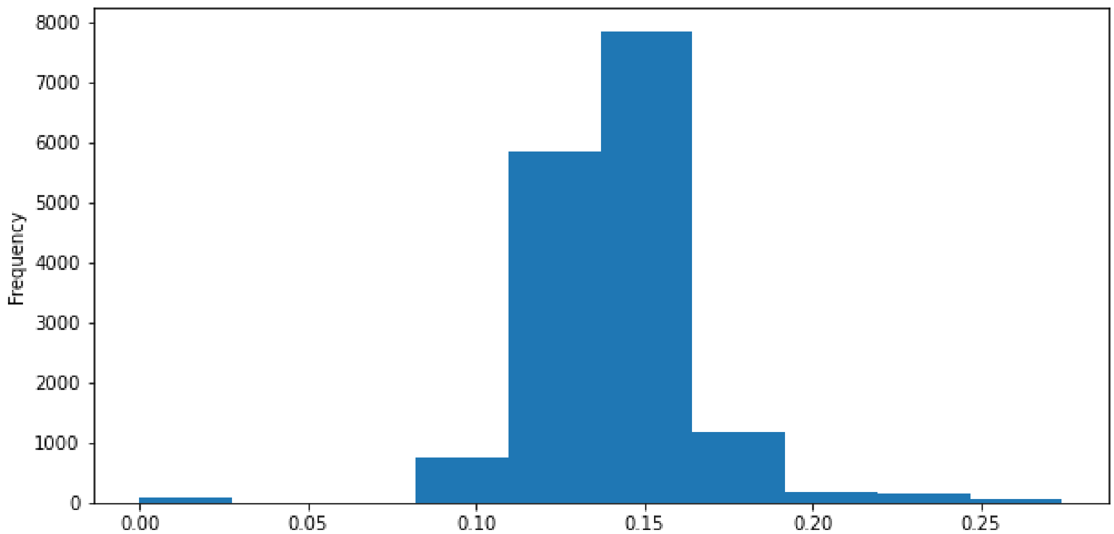
[414]:
```
merge["forecast_meter_rent_12m"].plot.hist()
```

[414]: <AxesSubplot:ylabel='Frequency'>



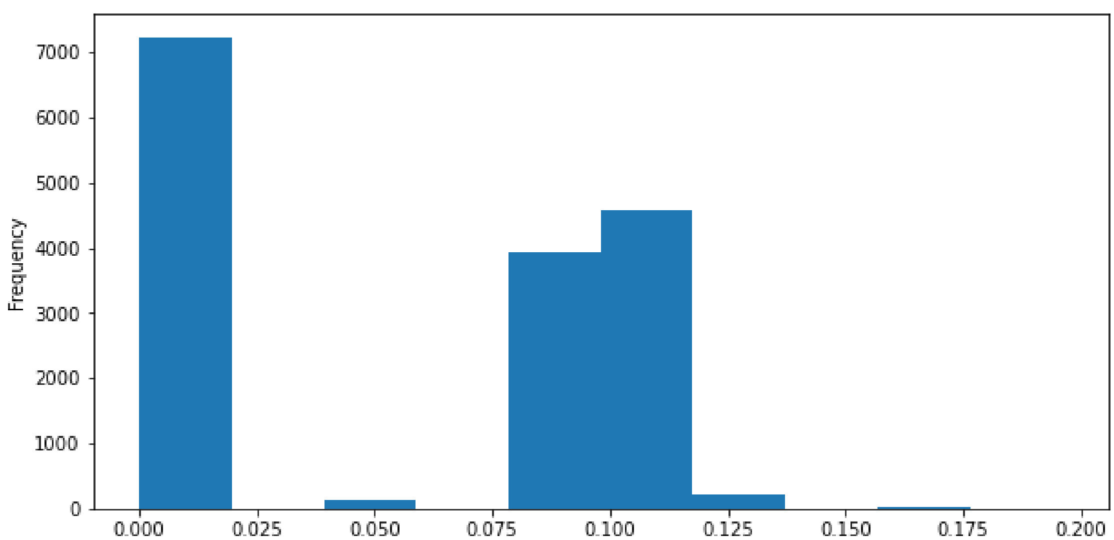
[415]:
```
merge["forecast_price_energy_p1"].plot.hist()
```

[415]: <AxesSubplot:ylabel='Frequency'>



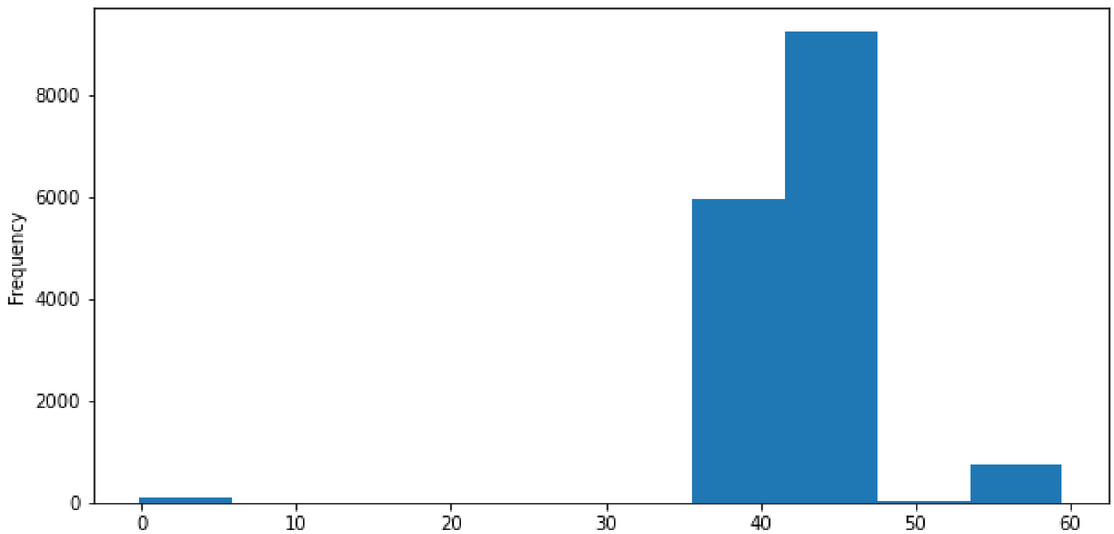
[416]:
```
merge["forecast_price_energy_p2"].plot.hist()
```

[416]: <AxesSubplot:ylabel='Frequency'>



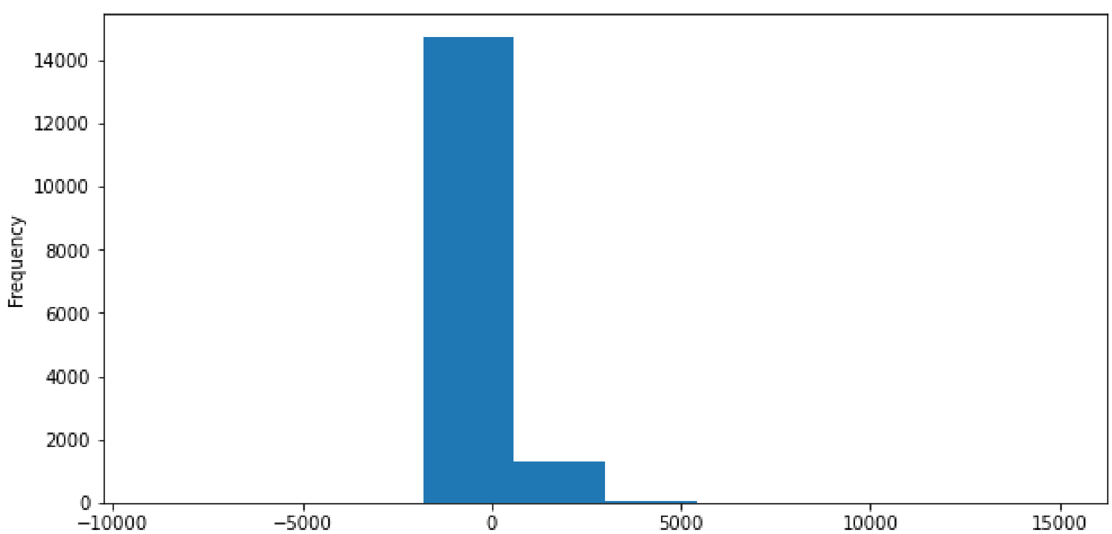
[417]:
```
merge["forecast_price_pow_p1"].plot.hist()
```

[417]: <AxesSubplot:ylabel='Frequency'>



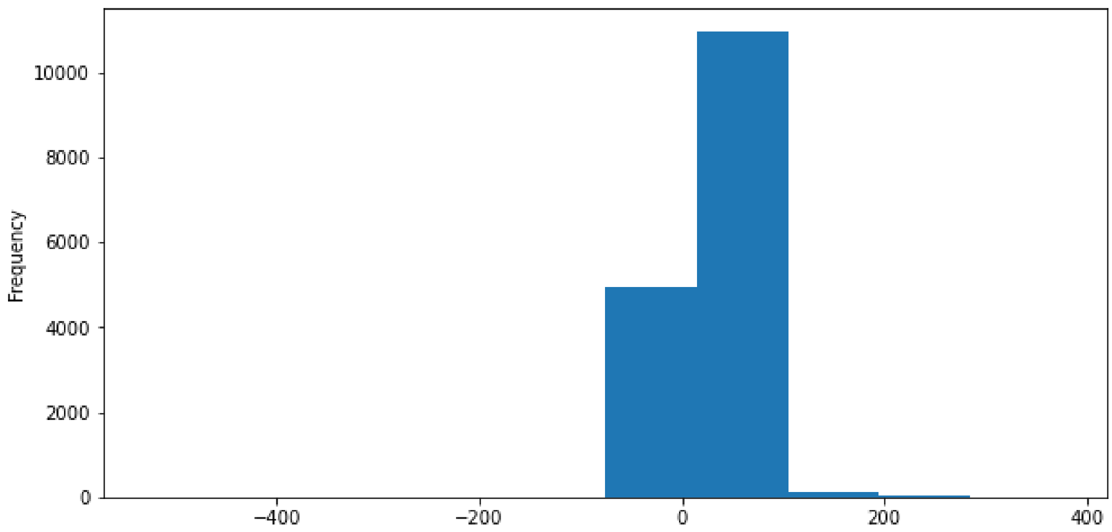
[418]:
```
merge["imp_cons"].plot.hist()
```

[418]: <AxesSubplot:ylabel='Frequency'>



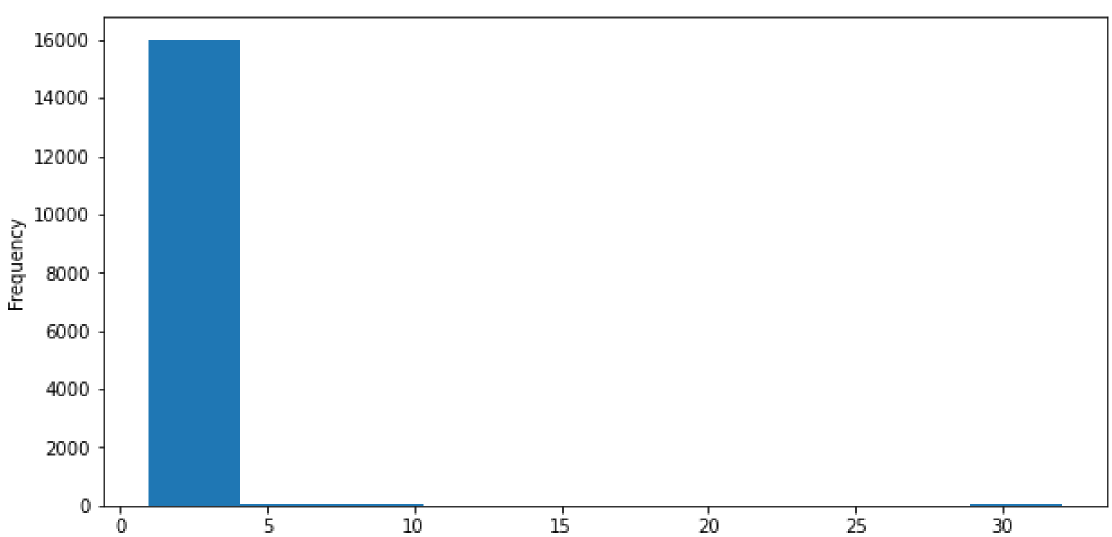
[419]:
```
merge["margin_gross_pow_ele"].plot.hist()
```

[419]: <AxesSubplot:ylabel='Frequency'>



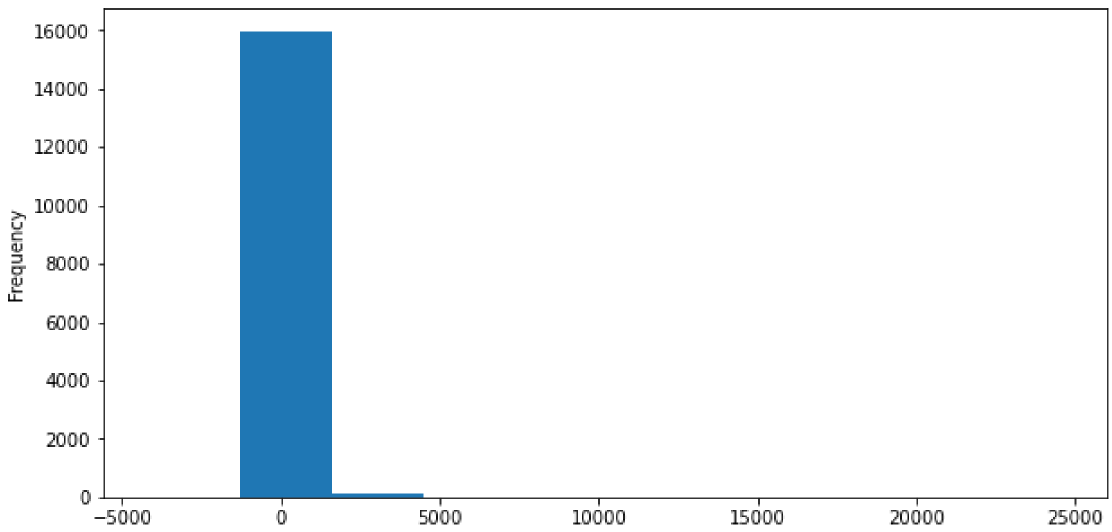
[420]:
```
merge["nb_prod_act"].plot.hist()
```

[420]: <AxesSubplot:ylabel='Frequency'>



[421]:
```
merge["net_margin"].plot.hist()
```

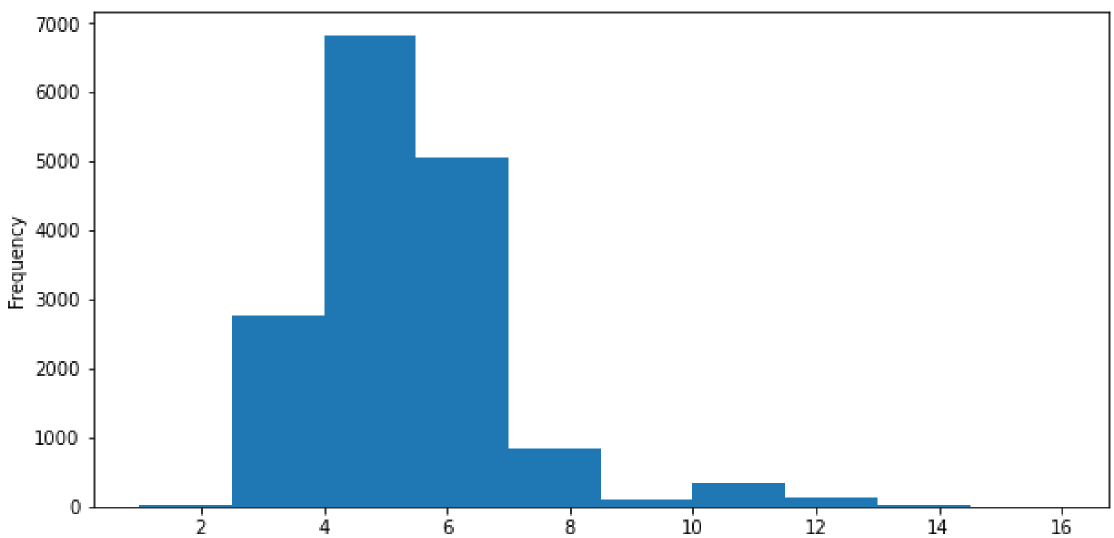
[421]: <AxesSubplot:ylabel='Frequency'>



[422]:

```
merge["num_years_antig"].plot.hist()
```

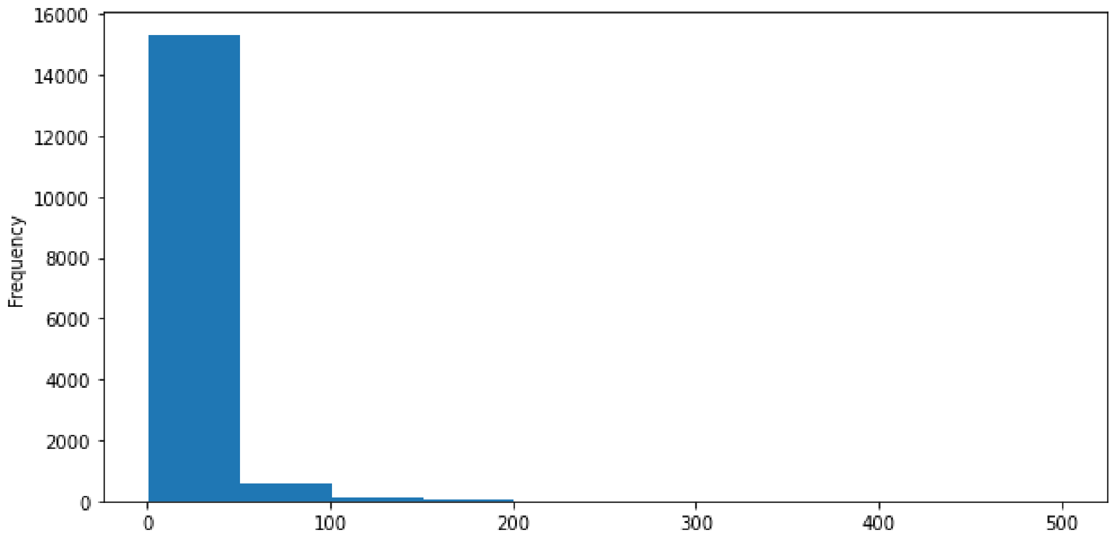
[422]: <AxesSubplot:ylabel='Frequency'>



[423]:

```
merge["pow_max"].plot.hist()
```

[423]: <AxesSubplot:ylabel='Frequency'>



It can be seen that most of the data are rightly skewed

11.1 Checking the company with the highest consumption

[424]:
```
consumption = merge[["id","cons_12m", "cons_gas_12m","cons_last_month",␣
↪"imp_cons", "has_gas", "churn"]]
```

[425]:
```
total_cons_12m = pd.DataFrame(consumption.groupby(["id", "churn"])["cons_12m"].
↪agg(["sum"]))
total_cons_12m.sort_values(ascending=False, by="sum").head()
```

[425]:

id	churn	sum
2c2abbe8998364dd500e41588d41f45f	stayed	16097108
b880901f75613c801886354abf24f30a	stayed	6286272
3cbf266f90f0419636aa9e748fa0e7f0	stayed	6286272
f3baf732b3a86a45f5aec2d4578070c0	stayed	6286272
4130bb214991c2ec4504b96d527624ca	stayed	6286272

It can be seen that ,company '2c2abbe8998364dd500e41588d41f45f' has the highest consumption of energy.

[426]:
```
merge.to_csv('merge.csv')
```