Exploratory Data Analysis & Data Cleaning

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The Datasets

`ml_case_training_output.csv` named as `pco_output` contains:

- id: contact id
- churned: has the client churned over the next 3 months

`ml_case_training_hist_data.csv` named as `pco_hist` contains the history of energy and power consumption per client:

- id: contact id
- price_date: reference date
- price_p1_var: price of energy for the 1st period
- price_p2_var: price of energy for the 2nd
- periodprice_p3_var: price of energy for the 3rd period
- price_p1_fix: price of power for the 1st period
- price_p2_fix: price of power for the 2nd period
- price_p3_fix: price of power for the 3rd period

`ml_case_training_data.csv` contains:

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

Import Libraries

In [1]:

```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt

import missingno as msno
from scipy.stats import zscore as zscore
```

Load Data

In [2]:

```
# list of dates
dt_lst = ['date_activ','date_end','date_first_activ','date_modif_prod','date_renewal']

pco_main = pd.read_csv('ml_case_training_data.csv', parse_dates=dt_lst)
pco_hist = pd.read_csv('ml_case_training_hist_data.csv', parse_dates=['price_date'])
pco_output = pd.read_csv('ml_case_training_output.csv')
pd.set_option('display.max_columns',None)
```

Main Dataset

In [3]:

```
pco_main.head()
```

Out[3]:

	id	activity_new	campaign_disc_ele	channel_sales
0	48ada52261e7cf58715202705a0451c9	esoiiifxdlbkcsluxmfuacbdckommixw	NaN	lmkebamcaaclubfxadlmueccxoimlema
1	24011ae4ebbe3035111d65fa7c15bc57	NaN	NaN	foosdfpfkusacimwkcsosbicdxkicaua
2	d29c2c54acc38ff3c0614d0a653813dd	NaN	NaN	NaN
3	764c75f661154dac3a6c254cd082ea7d	NaN	NaN	foosdfpfkusacimwkcsosbicdxkicaua
4	bba03439a292a1e166f80264c16191cb	NaN	NaN	lmkebamcaaclubfxadlmueccxoimlema

In [4]:

```
pco_main.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16096 entries, 0 to 16095
Data columns (total 32 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   id                        16096 non-null  object
 1   activity_new              6551 non-null   object
 2   campaign_disc_ele         0 non-null      float64
 3   channel_sales             11878 non-null  object
 4   cons_12m                  16096 non-null  int64
 5   cons_gas_12m              16096 non-null  int64
 6   cons_last_month           16096 non-null  int64
 7   date_activ                16096 non-null  datetime64[ns]
 8   date_end                  16094 non-null  datetime64[ns]
 9   date_first_activ          3508 non-null   datetime64[ns]
 10  date_modif_prod           15939 non-null  datetime64[ns]
 11  date_renewal              16056 non-null  datetime64[ns]
 12  forecast_base_bill_ele    3508 non-null   float64
 13  forecast_base_bill_year   3508 non-null   float64
 14  forecast_bill_12m         3508 non-null   float64
 15  forecast_cons             3508 non-null   float64
 16  forecast_cons_12m         16096 non-null  float64
 17  forecast_cons_year        16096 non-null  int64
 18  forecast_discount_energy  15970 non-null  float64
 19  forecast_meter_rent_12m   16096 non-null  float64
 20  forecast_price_energy_p1  15970 non-null  float64
 21  forecast_price_energy_p2  15970 non-null  float64
 22  forecast_price_pow_p1     15970 non-null  float64
 23  has_gas                   16096 non-null  object
 24  imp_cons                  16096 non-null  float64
 25  margin_gross_pow_ele      16083 non-null  float64
 26  margin_net_pow_ele        16083 non-null  float64
 27  nb_prod_act               16096 non-null  int64
 28  net_margin                16081 non-null  float64
 29  num_years_antig           16096 non-null  int64
 30  origin_up                 16009 non-null  object
 31  pow_max                   16093 non-null  float64
dtypes: datetime64[ns](5), float64(16), int64(6), object(5)
memory usage: 3.9+ MB
```

In [5]:

```
# Percentage of nullity by column
missing_perc = pco_main.isnull().mean() * 100
print('Percentage of Missing Values:\n', missing_perc)
```

```
Percentage of Missing Values:
 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
dtype: float64
```

In [6]:

```
# Descriptive statistics
pco_main.describe()
```

Out[6]:

	campaign_disc_ele	cons_12m	cons_gas_12m	cons_last_month	forecast_base_bill_ele	forecast_base_bill_year
count	0.0	1.609600e+04	1.609600e+04	1.609600e+04	3508.000000	3508.000000
mean	NaN	1.948044e+05	3.191164e+04	1.946154e+04	335.843857	335.843857
std	NaN	6.795151e+05	1.775885e+05	8.235676e+04	649.406000	649.406000
min	NaN	-1.252760e+05	-3.037000e+03	-9.138600e+04	-364.940000	-364.940000
25%	NaN	5.906250e+03	0.000000e+00	0.000000e+00	0.000000	0.000000
50%	NaN	1.533250e+04	0.000000e+00	9.010000e+02	162.955000	162.955000
75%	NaN	5.022150e+04	0.000000e+00	4.127000e+03	396.185000	396.185000
max	NaN	1.609711e+07	4.188440e+06	4.538720e+06	12566.080000	12566.080000

Observations

- 14 columns have negative minimum values.
- `campaign_disc_ele` column is missing completely.
- `activity_new` column is missing 59.3%.
- The `date_first_active`, `forecast_base_bill_ele`, `forecast_base_bill_year`, `forecast_bill_12m`, and `forecast_cons` columns are each missing 78.2%.

The History Dataset

In [7]:

```
pco_hist.head()
```

Out[7]:

	id	price_date	price_p1_var	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix	price_p3_fix
0	038af19179925da21a25619c5a24b745	2015-01-01	0.151367	0.0	0.0	44.266931	0.0	0.0
1	038af19179925da21a25619c5a24b745	2015-02-01	0.151367	0.0	0.0	44.266931	0.0	0.0
2	038af19179925da21a25619c5a24b745	2015-03-01	0.151367	0.0	0.0	44.266931	0.0	0.0
3	038af19179925da21a25619c5a24b745	2015-04-01	0.149626	0.0	0.0	44.266931	0.0	0.0
4	038af19179925da21a25619c5a24b745	2015-05-01	0.149626	0.0	0.0	44.266931	0.0	0.0

In [8]:

```
pco_hist.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  datetime64[ns]
 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: datetime64[ns](1), float64(6), object(1)
memory usage: 11.8+ MB
```

In [9]:

```
# Percentage of nullity by column
missing_perc = pco_hist.isnull().mean() * 100
print('Percentage of Missing Values:\n', missing_perc)
```

```
Percentage of Missing Values:
 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
dtype: float64
```

In [10]:

```
# Descriptive statistics
pco_hist.describe()
```

Out[10]:

	price_p1_var	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix	price_p3_fix
count	191643.000000	191643.000000	191643.000000	191643.000000	191643.000000	191643.000000
mean	0.140991	0.054412	0.030712	43.325546	10.698201	6.455436
std	0.025117	0.050033	0.036335	5.437952	12.856046	7.782279
min	0.000000	0.000000	0.000000	-0.177779	-0.097752	-0.065172
25%	0.125976	0.000000	0.000000	40.728885	0.000000	0.000000
50%	0.146033	0.085483	0.000000	44.266930	0.000000	0.000000
75%	0.151635	0.101780	0.072558	44.444710	24.339581	16.226389
max	0.280700	0.229788	0.114102	59.444710	36.490692	17.458221

Observations

- `price_p1_var`, `price_p2_var`, `price_p3_var`, `price_p1_fix`, `price_p2_fix`, `price_p3_fix` are missing 70.4% values.
- `price_p1_fix`, `price_p2_fix`, `price_p3_fix` contain negative values, which doesn't make sense for price of power.

The Output Dataset

In [11]:

```
pco_output.head()
```

Out[11]:

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

In [12]:

```
pco_output.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16096 entries, 0 to 16095
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   id      16096 non-null  object
 1   churn   16096 non-null  int64
dtypes: int64(1), object(1)
memory usage: 251.6+ KB
```

In [13]:

```
# Percentage of nullity by column
missing_perc = pco_output.isnull().mean() * 100
print('Percentage of Missing Values:\n', missing_perc)
```

```
Percentage of Missing Values:
 id       0.0
churn    0.0
dtype: float64
```

In [14]:

```
# Descriptive statistics
pco_output.describe()
```

Out[14]:

	churn
count	16096.000000
mean	0.099093
std	0.298796
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

Observations

- Complete dataset.

Data Cleaning and Imputation

Missing Data

Types of missingness

Missing Completely at Random (MCAR)
Missingness has no relationship between any values, observed or missing

Missing at Random (MAR)
There is a systematic relationship between missingness and other observed data, but not the missing data

Missing Not at Random (MNAR)
There is a relationship between missingness and its values, missing or non-missing

The History Dataset

In [15]:

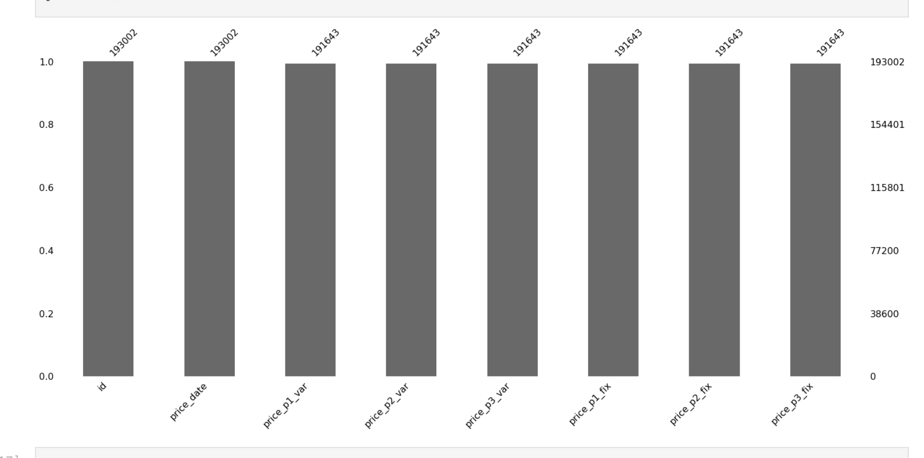
```
# Identify negative columns
negative_cols = ['price_p1_fix','price_p2_fix','price_p3_fix']
# Convert to positive the negative columns in pco_hist
pco_hist[negative_cols] = pco_hist[negative_cols].apply(abs)

pco_hist.describe()
```

Out[15]:

	price_p1_var	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix	price_p3_fix
count	191643.000000	191643.000000	191643.000000	191643.000000	191643.000000	191643.000000
mean	0.140991	0.054412	0.030712	43.325563	10.698210	6.455443
std	0.025117	0.050033	0.036335	5.437816	12.856039	7.782273
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.125976	0.000000	0.000000	40.728885	0.000000	0.000000
50%	0.146033	0.085483	0.000000	44.266930	0.000000	0.000000
75%	0.151635	0.101780	0.072558	44.444710	24.339581	16.226389
max	0.280700	0.229788	0.114102	59.444710	36.490692	17.458221

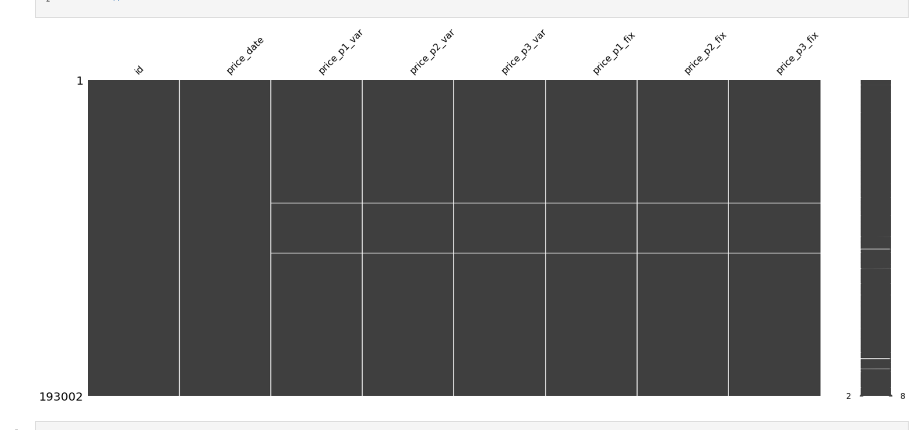
In [16]:

```
# Visualize the completeness of the dataframe
msno.bar(pco_hist)
plt.show()
```



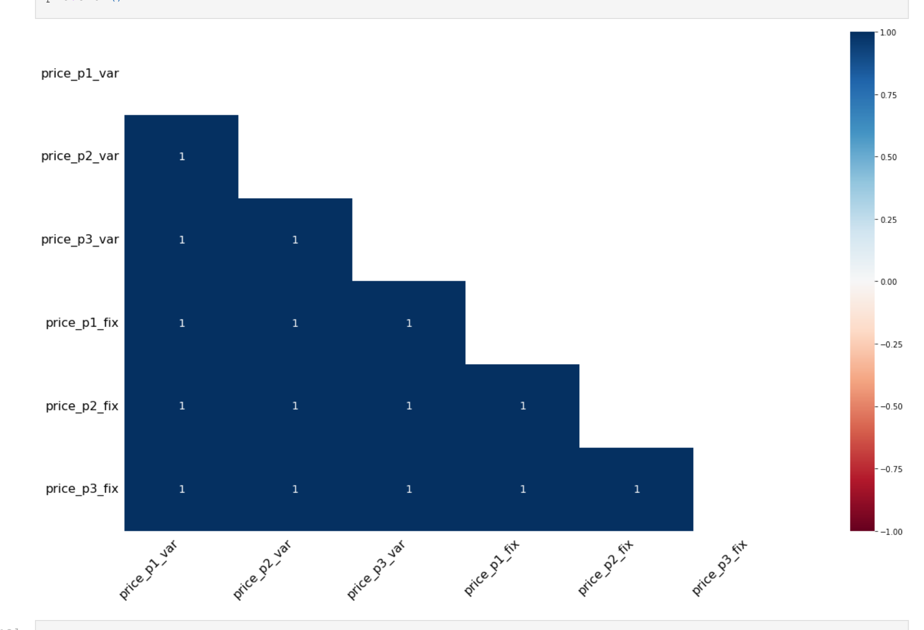
In [17]:

```
# Visualize the locations of the missing values of the dataset
sorted = pco_hist.sort_values(by = ['id','price_date'])
msno.matrix(sorted)
plt.show()
```



In [18]:

```
# Visualize the correlation between the numeric variables of the dataframe
msno.heatmap(pco_hist)
plt.show()
```



In [19]:

```
# Identify the index of the IDs containing missing values.
hist_NAN_index = pco_hist[pco_hist.isnull().any(axis=1)].index.values.tolist()

# Obtain a dataframe with the missing values
pco_hist_missing = pco_hist.iloc[hist_NAN_index,:]

# Glimpse at the NaN cases of the pco_hist dataset
pco_hist_missing.head(10)
```

Out[19]:

	id	price_date	price_p1_var	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix
75	ef716222bbd97a8bdfcbb831e3575560	2015-04-01	NaN	NaN	NaN	NaN	NaN
221	0f5231100b2febab862f8dd8eaab3f43	2015-06-01	NaN	NaN	NaN	NaN	NaN
377	2f93639de582fadfbe3e86ce1c8d8f35	2015-06-01	NaN	NaN	NaN	NaN	NaN
413	f83c1ab1ca1d1802bb1df4d72820243c	2015-06-01	NaN	NaN	NaN	NaN	NaN
461	3076c6d4a060e12a049d1700d9b09cf3	2015-06-01	NaN	NaN	NaN	NaN	NaN
471	33bb3af90650ac2e9ecac6ff2c975a6b	2015-04-01	NaN	NaN	NaN	NaN	NaN
472	33bb3af90650ac2e9ecac6ff2c975a6b	2015-05-01	NaN	NaN	NaN	NaN	NaN
475	33bb3af90650ac2e9ecac6ff2c975a6b	2015-08-01	NaN	NaN	NaN	NaN	NaN
476	33bb3af90650ac2e9ecac6ff2c975a6b	2015-09-01	NaN	NaN	NaN	NaN	NaN
874	0e90101b08183cc9548e827e4b256f47	2015-12-01	NaN	NaN	NaN	NaN	NaN

In [20]:

```
# extract the unique dates of missing data
date_lst = pco_hist_missing['price_date'].unique()
id_lst = pco_hist_missing['id'].unique()

# Create a time dataframe with the unique dates
time_df = pd.DataFrame(data=date_lst, columns=['price_date'] )

# Glimpse the time dataframe
time_df.sort_values(by=['price_date'])
```

Out[20]:

	price_date
9	2015-01-01
11	2015-02-01
8	2015-03-01
0	2015-04-01
2	2015-05-01
1	2015-06-01
10	2015-07-01
3	2015-08-01
4	2015-09-01
7	2015-10-01
6	2015-11-01
5	2015-12-01

Observations

The columns containing prices display strong positive correlation in the missingness, suggesting a case of **MNAR**.

We can use trend and cyclicality when imputing time series data.

Filling Time series data

In [21]:

```
# Make a copy of pco_hist dataset
pco_hist_ff = pco_hist.copy(deep=True)

# Print prior to imputing missing values
print(pco_hist_ff.iloc[hist_NAN_index,3:9].head())

# Fill NaNs using forward fill
pco_hist_ff.fillna(method = 'ffill', inplace=True)

print(pco_hist_ff.iloc[hist_NAN_index,3:9].head())
```

```
     price_p2_var  price_p3_var  price_p1_fix  price_p2_fix  price_p3_fix
75            NaN           NaN           NaN           NaN           NaN
221           NaN           NaN           NaN           NaN           NaN
377           NaN           NaN           NaN           NaN           NaN
413           NaN           NaN           NaN           NaN           NaN
461           NaN           NaN           NaN           NaN           NaN
     price_p2_var  price_p3_var  price_p1_fix  price_p2_fix  price_p3_fix
75       0.000000      0.000000     44.266931      0.000000      0.000000
221      0.000000      0.000000     44.266931      0.000000      0.000000
377      0.087970      0.000000     44.266931      0.000000      0.000000
413      0.102239      0.070381     40.565969     24.339581     16.226389
461      0.000000      0.000000     44.266931      0.000000      0.000000
```

In [22]:

```
# Merge output dataset with historical forward fill dataset
pco_hist_ff_merged = pco_hist_ff.merge(right=pco_output,on=['id'])
pco_hist_ff_merged.head()
```

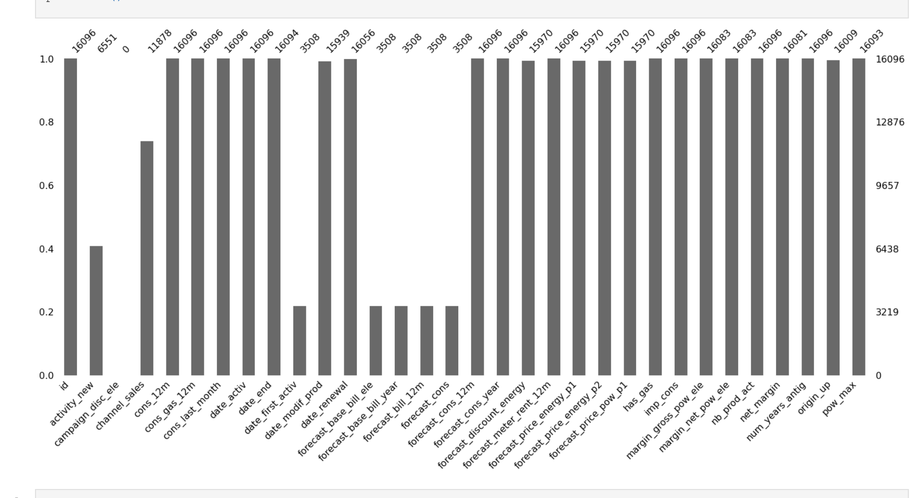
Out[22]:

	id	price_date	price_p1_var	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix	price_p3_fix
0	038af19179925da21a25619c5a24b745	2015-01-01	0.151367	0.0	0.0	44.266931	0.0	0.0
1	038af19179925da21a25619c5a24b745	2015-02-01	0.151367	0.0	0.0	44.266931	0.0	0.0
2	038af19179925da21a25619c5a24b745	2015-03-01	0.151367	0.0	0.0	44.266931	0.0	0.0
3	038af19179925da21a25619c5a24b745	2015-04-01	0.149626	0.0	0.0	44.266931	0.0	0.0
4	038af19179925da21a25619c5a24b745	2015-05-01	0.149626	0.0	0.0	44.266931	0.0	0.0

The Main Dataset

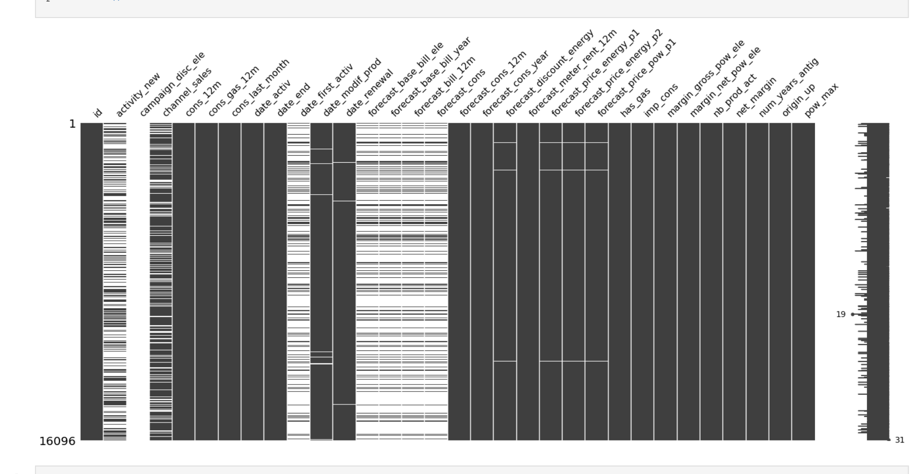
In [24]:

```
# Visualize the completeness of the dataframe
msno.bar(pco_main)
plt.show()
```



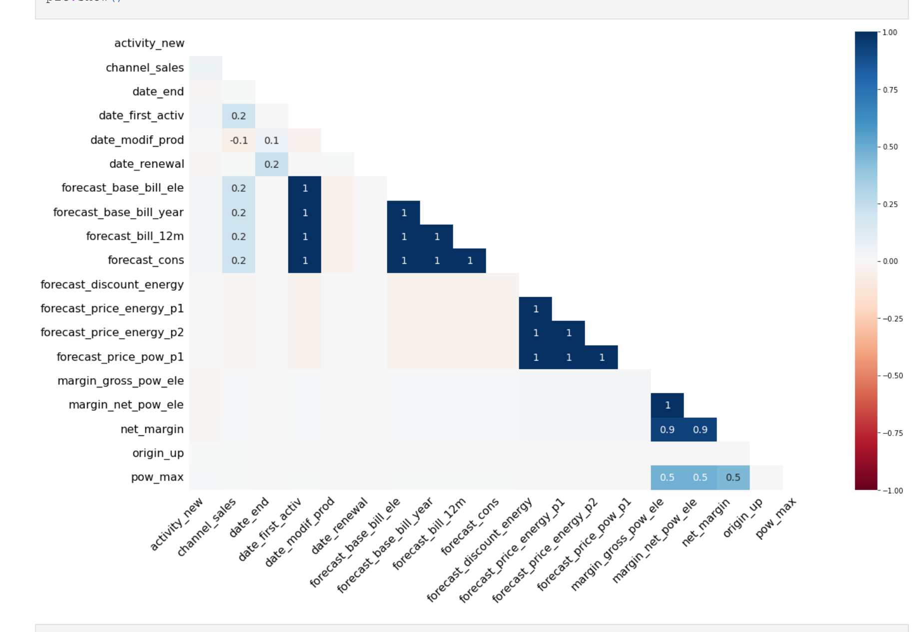
In [25]:

```
# Visualize the locations of the missing values of the dataset
msno.matrix(pco_main)
plt.show()
```



In [26]:

```
msno.heatmap(pco_main)
plt.show()
```



In [27]:

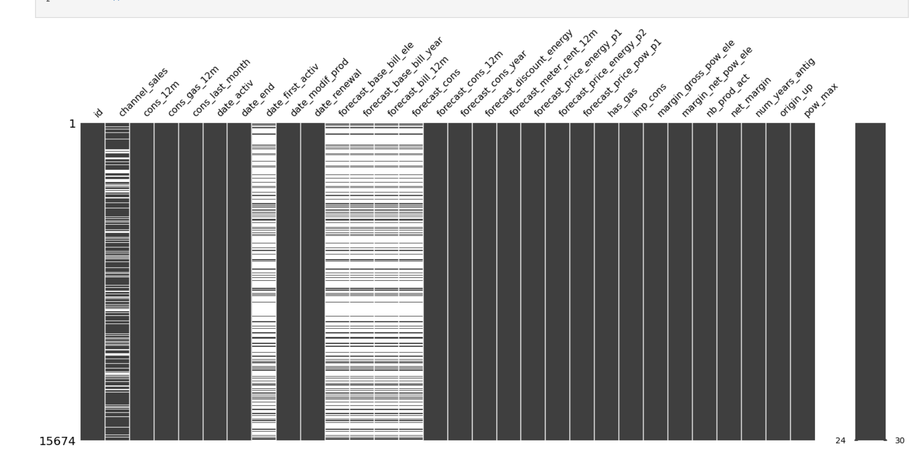
```
# Demonstrate why the date_activ column cannot replace completely date_first_activ
activity = ['date_activ','date_first_activ']

# Filter the columns of interest
pco_activity = pco_main[activity]

# Obtain only the complete cases
pco_activity_cc = pco_activity.dropna(subset=['date_first_activ'],how='any',inplace=False)

# Test whether two objects contain the same elements.
pco_activity_cc.date_activ.equals(pco_activity_cc.date_first_activ)

# Describe it
pco_activity_cc.describe(datetime_is_numeric=True)
```

Out[27]:

	date_activ	date_first_activ
count	3508	3508
mean	2011-09-03 07:45:05.131128832	2011-06-19 20:20:23.261117440
min	2003-09-23 00:00:00	2001-01-10 00:00:00
25%	2010-10-26 00:00:00	2010-08-04 18:00:00
50%	2012-01-03 00:00:00	2011-10-28 00:00:00
75%	2012-08-08 00:00:00	2012-06-22 06:00:00
max	2014-09-01 00:00:00	2014-09-01 00:00:00

In [28]:

```
# Drop the column activity_new and campaign_disc_elec
pco_main_drop = pco_main.drop(labels= ['activity_new','campaign_disc_ele'] , axis=1)

# Remove date_end date_modif_prod date_renewal origin_up pow_max margin_gross_pow_ele margin_net_pow_ele net_ma
brush = ['date_end','date_modif_prod','date_renewal','origin_up','pow_max','margin_gross_pow_ele',
         'margin_net_pow_ele', 'net_margin','forecast_discount_energy','forecast_price_energy_p1',
         'forecast_price_energy_p2','forecast_price_pow_p1']
pco_main_drop.dropna(subset=brush, how='any',inplace=True)

msno.matrix(pco_main_drop)
plt.show()
```



Observations

- `activity_new` is **MCAR** with low correlation with other variables. Can drop this column
- `campaign_disc_elec` is **MCAR**. Can drop this column. Suggests that subscribers are not subscribing through campaign offers.
- `date_first_activ` cannot replace `date_active`. **MAR**
- `net_margin` has strong correlation between `margin_gross_pow_elec` and `margin)_net_pow_ele`. Suggests multi-colinearity.
- `origin_up` and `pow_max` is **MCAR**. Can drop.
- `Forecast_base_bill_ele`, `forecast_base_bill_year`, `forecast_bill_12m` and `forecast_cons variables` are highly correlated with `date_first_activ`. **MNAR**

In [31]:

```
# Choose the columns without missing values
incomplete_cols = ['channel_sales','date_first_activ','forecast_base_bill_ele','forecast_base_bill_year','forec

complete_cols = [column_name for column_name in pco_main_drop.columns if column_name not in incomplete_cols]

pco_main_cc = pco_main_drop[complete_cols]

# Fix negative numeric variables
numeric = [column_name for column_name in pco_main_cc.columns
           if pco_main_cc[column_name].dtype == 'float64'
           or pco_main_cc[column_name].dtype == 'int64']

# Overwrite positive values on negative values
pco_main_cc[numeric] = pco_main_cc[numeric].apply(abs)

# Describe
pco_main_cc.describe()
```

```
/Applications/JupyterLab.app/Contents/Resources/jlab_server/lib/python3.8/site-packages/pandas/core/frame.py:3641: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[k1] = value[k2]
```

Out[31]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_year	forecast_discount_energy	forecast_m
count	1.567400e+04	1.567400e+04	1.567400e+04	15674.000000	15674.000000	15674.000000	
mean	1.916143e+05	3.132400e+04	1.941588e+04	2359.676441	1911.698354	0.976139	
std	6.724688e+05	1.716291e+05	8.226881e+04	3979.605687	5224.813531	5.124103	
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	
25%	5.893250e+03	0.000000e+00	0.000000e+00	514.045000	0.000000	0.000000	
50%	1.522000e+04	0.000000e+00	9.090000e+02	1178.970000	382.000000	0.000000	
75%	4.953825e+04	0.000000e+00	4.131500e+03	2677.220000	1994.750000	0.000000	
max	1.609711e+07	4.154590e+06	4.538720e+06	103801.930000	175375.000000	50.000000	

In [32]:
```python
# Convert the has_gas column to  Yes/No
pco_main_cc['has_gas'] = pco_main_cc['has_gas'].replace({'t':'Yes','f':'No'})

# Merge the main dataset with the output dataset
pco_main_cc_merged = pco_main_cc.merge(right=pco_output,on=['id'])

# Convert the churn column to Churned/Stayed
pco_main_cc_merged['churn'] = pco_main_cc_merged['churn'].replace({1:'Churned',0:'Stayed'})
```

```
/tmp/ipykernel_1269/3976640459.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  pco_main_cc['has_gas'] = pco_main_cc['has_gas'].replace({'t':'Yes','f':'No'})
```

In [33]:
```python
pco_main_cc_merged.head()
```

Out[33]:

	id	cons_12m	cons_gas_12m	cons_last_month	date_activ	date_end	date_modif_prod	date_ren
0	48ada52261e7cf58715202705a0451c9	309275	0	10025	2012-11-07	2016-11-06	2012-11-07	2015-1
1	d29c2c54acc38ff3c0614d0a653813dd	4660	0	0	2009-08-21	2016-08-30	2009-08-21	2015-0
2	764c75f661154dac3a6c254cd082ea7d	544	0	0	2010-04-16	2016-04-16	2010-04-16	2015-0
3	bba03439a292a1e166f80264c16191cb	1584	0	0	2010-03-30	2016-03-30	2010-03-30	2015-0
4	568bb38a1afd7c0fc49c77b3789b59a3	121335	0	12400	2010-04-08	2016-04-08	2010-04-08	2015-0

In [34]:
```python
# Obtain all the variables except for id
variables = [column_name for column_name in pco_main_cc_merged.columns if column_name != 'id']

# Obtain all the categorical variables except for id
categorical = [column_name for column_name in variables if pco_main_cc_merged[column_name].dtype == 'object']

# Obtain all the Date Variables
dates = [column_name for column_name in variables if pco_main_cc_merged[column_name].dtype == 'datetime64[ns]']

# Obtain all the numeric columns
numeric = [column_name for column_name in variables
           if column_name not in categorical
           and column_name != 'id'
           and column_name != 'churn'
           and column_name not in dates]
```

Data Visualization

The Output Dataset

In [52]:
```python
# Calculate the zcores of tenure
tenure_zcores = zscore(a=pco_main_cc_merged['num_years_antig'])
# Convert to absolute values
abs_tenure_zscores = np.abs(tenure_zcores)
# Extract Columns of interest
churn_tenure = pco_main_cc_merged[['churn','num_years_antig']]
# Add z-score column
churn_tenure.loc[:,'z_score'] = list(abs_tenure_zscores)
# Remove outliers
churned_tenure_filtered = churn_tenure[churn_tenure['z_score'] < 3]
# Visualize tenure by retained customer and churner
vio = sns.violinplot( y=churned_tenure_filtered["churn"], x=churned_tenure_filtered["num_years_antig"] )
# Settings
vio.set(xlabel='Years', ylabel='')
vio.set_title("Customer Attrition by Tenure")
plt.show()
```

Facts

- The median age of churners is 4 years
- Customers are more likely to churn during the 4th year than the 7th year
- The median age of retained customers is 5 years

The Main Dataset

In [37]:
```python
# Most popular electricty campaign
ele_nm = pco_main_cc_merged.loc[(pco_main_cc_merged['churn']>='Stayed') & (pco_main_cc_merged['net_margin']>0),

ele_nm.value_counts(subset=['origin_up'])
```

Out[37]:
```
origin_up
lxidpiddsbxsbosboudacockeimpuepw    6584
kamkkxfxxuwbdslkwifmmcsiusiuosws    4188
ldkssxwpmemidmecebumciepifcamkci    3201
usapbepcfoloekilkwsdiboslwaxobdp       2
ewxeelcelemmiwuafmddpobolfuxioce       1
dtype: int64
```

In [38]:
```python
# Highest netting electricity subscription campaign
print(ele_nm.groupby('origin_up')['net_margin'].agg('sum').sort_values(ascending=False))
```

```
origin_up
lxidpiddsbxsbosboudacockeimpuepw    1541159.95
ldkssxwpmemidmecebumciepifcamkci     814230.02
kamkkxfxxuwbdslkwifmmcsiusiuosws     717939.95
usapbepcfoloekilkwsdiboslwaxobdp        250.40
ewxeelcelemmiwuafmddpobolfuxioce         46.22
Name: net_margin, dtype: float64
```

Facts

- The most popular electricity campaign is `lxidpiddsbxsbosboudacockeimpuepw` which has brought 6,584 current customers. With a net margin of $1,541,159.95 in 2015.

In [39]:
```python
# Select current customers with positive net margins
top_customers = pco_main_cc_merged.loc[(pco_main_cc_merged['churn']>='Stayed') & (pco_main_cc_merged['net_margi

# Top 10 customers by net margin
top_customers.sort_values(by=['net_margin'],ascending=False).head(10)
```

Out[39]:

	id	num_years_antig	net_margin
11502	d00e8a9951b5551d8f02e45f9ed2b0dd	3	10203.50
6930	78bd1c5c0c67f2be6de89b19df5f8861	3	5625.14
13259	818b8bca0a9d7668252d46b978169325	4	4346.37
8378	a3a739686fbd5ba8b4a21ec835507b6d	4	4305.79
324	89b3406c3ba717f1b788ceeb5af9e8b9	3	4161.74
10100	93435ecb05910c7b87e0ae9dbedb2882	4	4148.99
12028	4519e6a8928a015819466fc9de0fa49e	3	4040.60
6405	933527d7a2f669af49075a2380c10ded	4	3744.72
6850	43580ef6cc40fcfd0a9b76eee17a267a	4	3716.78
13553	ee98a86efa759681cc59c7d4e0d0312f	4	3407.65

These are the most profitable customers for PowerCo in terms of net margin. Notet that most of them are within the likely tenure of attrition.

In [42]:
```
!jupyter-nbconvert --to PDFviaHTML Task_2.ipynb
```

```
[NbConvertApp] Converting notebook Task_2.ipynb to PDFviaHTML
[W:pyppeteer.chromium_downloader] Starting Chromium download. Download may take a few minutes.
100%|██████████████████████████████████████| 86.8M/86.8M [00:01<00:00, 45.2Mb/s]
[W:pyppeteer.chromium_downloader] Chromium download done.
[W:pyppeteer.chromium_downloader] chromium extracted to: /Users/simplypatrickg/Library/Application Support/pyppeteer/local-chromium/588429
[NbConvertApp] Writing 1466887 bytes to Task_2.pdf
```

In [ ]: