EDA and Data cleaning

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0. Import packages

Load the necessary packages

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
import datetime
import pickle
```

In [2]:
```
# Show plots in jupyter notebook
%matplotlib inline
```

In [3]:
```
# Set plot style
sns.set(color_codes=True)
```

In [4]:
```
# Set maximum number of columns to be displayed
pd.set_option('display.max_columns', 100)
```

---

1. Loading data

Data directory

Explicitly show how paths are indicated

In [5]:
```
DATA_DIR = os.path.join("..", "ml_case_data")
TRAINING_DATA = os.path.join(DATA_DIR, "ml_case_training_data.csv")
HISTORY_DATA = os.path.join(DATA_DIR, "ml_case_training_hist_data.csv")
CHURN_DATA = os.path.join(DATA_DIR, "ml_case_training_output.csv")
```

Load data into a dataframe

Data file are in `csv` format, hence we can use the built-in functions form pandas `pd.read_csv(filename)`

In [6]:
```
train_data = pd.read_csv(TRAINING_DATA)
churn_data = pd.read_csv(CHURN_DATA)
history_data = pd.read_csv(HISTORY_DATA)
```

We will also print the first `3` rows to the screen. Just to see what the first dataset looks like

In [7]:
```
# Show first 3 rows
train_data.head(3)
```

Out[7]:

	id	activity_new	campaign_disc_ele	channel_sales	cons_12m	cons_gas_12
0	48ada52261e7cf58715202705a0451c9	esoiiifxdlbkcsluxmfuacbdckommixw	NaN	lmkebamcaaclubfxadlmueccxoimlema	309275	
1	24011ae4ebbe3035111d65fa7c15bc57	NaN	NaN	foosdfpfkusacimwkcsosbicdxkicaua	0	5494
2	d29c2c54acc38ff3c0614d0a653813dd	NaN	NaN	NaN	4660	

From above we can already see that there are a lot of `NaN` values. We will replace or remove those values later.

The first `3` rows of the dataframe also show us that there is numeric data and categorical data, which we will need to transform to the right form

In [8]:
```
churn_data.head(3)
```

Out[8]:

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

It seems the churn data is in the correct format as it shows `0` for `not churned` and `1` for `churned`

In [9]:
```
history_data.head(3)
```

Out[9]:

	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

For the historic data, a lot of values are zeros

Combining two dataframes

We loaded data in two different pandas dataframes. Nonetheless, we might be interested in putting the data into a single dataframe to access it more easily. We can merge the two dataframes on a common column (`id`) using the function `pd.merge()` from pandas.

In [10]:
```
train = pd.merge(train_data, churn_data, on="id")
```

Let's take a look at the new `train` dataframe, this time at the last `5` rows.

```
In [11]: train.tail(5)
```

Out[11]:

	id	activity_new	campaign_disc_ele	channel_sales	cons_12m	cons_gas_12m	cons_last_mon
16091	18463073fb097fc0ac5d3e040f356987	NaN	NaN	foosdfpfkusacimwkcsosbicdxkicaua	32270	47940	
16092	d0a6f71671571ed83b2645d23af6de00	NaN	NaN	foosdfpfkusacimwkcsosbicdxkicaua	7223	0	1
16093	10e6828ddd62cbcf687cb74928c4c2d2	NaN	NaN	foosdfpfkusacimwkcsosbicdxkicaua	1844	0	1
16094	1cf20fd6206d7678d5bcafd28c53b4db	NaN	NaN	foosdfpfkusacimwkcsosbicdxkicaua	131	0	
16095	563dde550fd624d7352f3de77c0cdfcd	NaN	NaN	NaN	8730	0	

2. General statistics of a dataframe

Data types

Often, it is useful to understand what data we are dealing with, as the data types might end up causing errors into our analysis at a later stage.

Below, we can quickly see the dates in our dataset are not `datetime` types yet, which means we might need to convert them. In addition, we can see that the `churn` is full of integers so we can keep it in that form.

Note: We've transformed the output to a dataframe to facilitate visualization

In [12]:
```
pd.DataFrame({"Data type":train.dtypes})
```

Out[12]:

	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

In [13]:
```
pd.DataFrame({"Data type":history_data.dtypes})
```

Out[13]:

	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

Dataframe statistics

Let's also look at the basic statistics of the data.

In [14]:
```
train.describe()
```

Out[14]:

	campaign_disc_ele	cons_12m	cons_gas_12m	cons_last_month	forecast_base_bill_ele	forecast_base_bill_year	forecast_bill_12m	forecast_co
count	0.0	1.609600e+04	1.609600e+04	1.609600e+04	3508.000000	3508.000000	3508.000000	3508.0000
mean	NaN	1.948044e+05	3.191164e+04	1.946154e+04	335.843857	335.843857	3837.441866	206.8451
std	NaN	6.795151e+05	1.775885e+05	8.235676e+04	649.406000	649.406000	5425.744327	455.6342
min	NaN	-1.252760e+05	-3.037000e+03	-9.138600e+04	-364.940000	-364.940000	-2503.480000	0.0000
25%	NaN	5.906250e+03	0.000000e+00	0.000000e+00	0.000000	0.000000	1158.175000	0.0000
50%	NaN	1.533250e+04	0.000000e+00	9.010000e+02	162.955000	162.955000	2187.230000	42.2150
75%	NaN	5.022150e+04	0.000000e+00	4.127000e+03	396.185000	396.185000	4246.555000	228.1175
max	NaN	1.609711e+07	4.188440e+06	4.538720e+06	12566.080000	12566.080000	81122.630000	9682.8900

From above we can obtain a lot of information about the dataset we are dealing with. Some key facts include:

> 1. The minimum `consumption` and `forecasts` for electricity and gas (yearly and monthly) are negative. This could mean that the client companies are producing energy and therefore energy should be "returned", although it is unlikely and we will consider it as corrupted data.
> 2. The `campaign_disc_ele` is an empty column. We verify it by running
>
> ```
> train["campaign_disc_ele"].isnull().values.all()
> ```
>
> 3. Highly skewed data when we look at the percentiles.

In [15]:
```
history_data.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	43.325546	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

For this dataset, it looks overall good.

We might be a bit concerned about the negative values in the `fix price` column. One more time, this might be corruped data and we will change them to positive when cleaning the data.

Missing data

We are also concerned we have a lot of missing data so we can check how much of our data is missing.

Note: We've transformed the output to a dataframe to facilitate visualization. This will be used for data cleaning in the next exercise.

In [16]:
```
pd.DataFrame({"Missing values (%)": train.isnull().sum()/len(train.index)*100})
```

Out[16]:

	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
churn	0.000000

Some of the columns might need to be removed since they have more than `75%` of the data missing

In [17]:
```
pd.DataFrame({"Missing values (%)": history_data.isnull().sum()/len(history_data.index)*100})
```

Out[17]:

	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

In this case the missing data is very small, so we might be able to easily replace the missing values with approximations

---

3. Data visualization

Deep diving a little bit on the main parameters

Churn

Let's see the churning rate

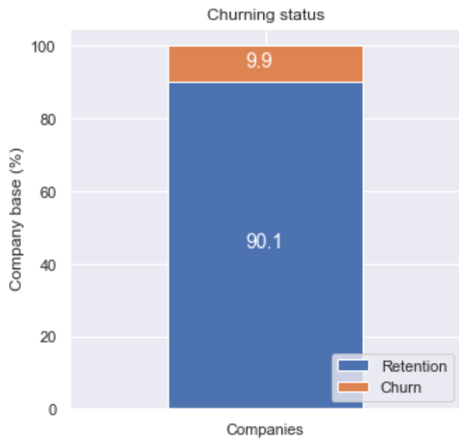
In [18]:
```
churn = train[["id","churn"]]
```

In [19]:
```
# Rename columns for visualization purposes
churn.columns = ["Companies", "churn"]
```

In [20]:
```
def plot_stacked_bars(dataframe, title_, size_=(18, 10), rot_=0, legend_="upper right"):
    """
    Plot stacked bars with annotations
    """
    ax = dataframe.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 bars
    """
    # Iterate over the plotted rectangles/bars
    for p in ax.patches:
        # Calculate annotation
        value = str(round(p.get_height(),1))
        # 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,
                   )
```

In [21]:
```
churn_total = churn.groupby(churn["churn"]).count()
churn_percentage = churn_total/churn_total.sum()*100
```

In [22]:
```
plot_stacked_bars(churn_percentage.transpose(),"Churning status", (5,5), legend_="lower right")
```



About `10%` of the of total customers have churned. (This sounds about right)

SME activity

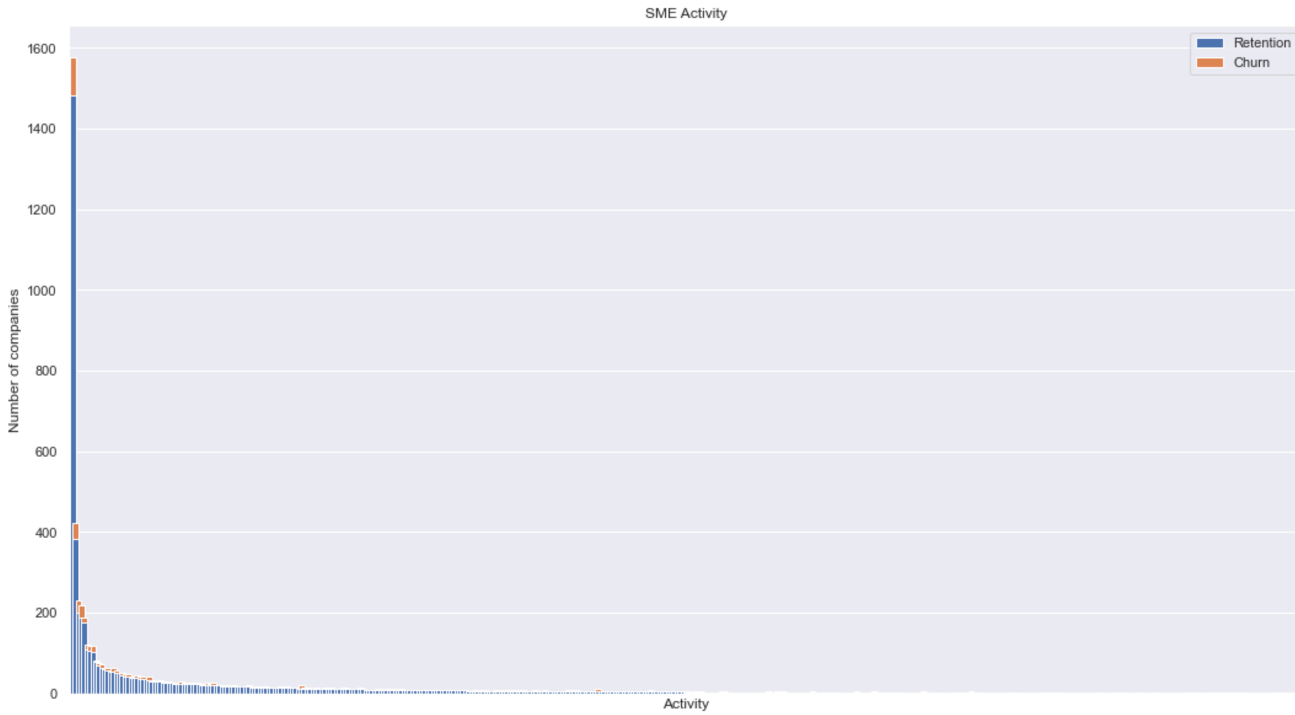
Let's show the activity distribution of the companies as well as the sales channel.

Intuitively this might be an important predictive feature for energy consumption

In [23]:
```
activity = train[["id","activity_new", "churn"]]
```

In [24]:
```
activity = activity.groupby([activity["activity_new"],
                             activity["churn"]])["id"].count().unstack(level=1).sort_values(by=[0], ascending=Fal
```

In [25]:
```
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 can't draw any meaning from them yet
plt.xticks([])
plt.show()
```



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 cateogry in particular.

Note: Not showing the labels in the x-axis to facilitate visualization

If we take a look at the values percentage-wise

In [26]:
```
activity_total = activity.fillna(0)[0]+activity.fillna(0)[1]
activity_percentage = activity.fillna(0)[1]/(activity_total)*100
pd.DataFrame({"Percentage churn": activity_percentage,
              "Total companies": activity_total }).sort_values(by="Percentage churn",
                                                               ascending=False).head(10)
```

Out[26]:

	Percentage churn	Total companies
activity_new		
xwkaesbkfsacseixxksofpddwfkbobki	100.000000	1.0
wkwdccuiboaeaalcaawlwmldiwmpewma	100.000000	1.0
ikiucmkuisupefxcxfxxulkpwssppfuo	100.000000	1.0
opoiuuwdmxdssidluooopfswlkkkcsxf	100.000000	1.0
pfcocskbxlmofswiflsbcefcpufbopuo	100.000000	2.0
oeacexidmflusdkwuuicmpiaklkxulxm	100.000000	1.0
wceaopxmdpccxfmcdpopulcaubcxibuw	100.000000	1.0
kmlwkmxoocpieebifumobckeafmidpxf	100.000000	1.0
cwouwoubfifoafkxifokoidcuoamebea	66.666667	3.0
wfiuolfffsekuoimxdsasfwcmwssewoi	50.000000	4.0

If sorted by activity some companies have churned a `100%` but this is due to the fact that only a few companies belong to that activity.

How will the SME activity influence our predictive model?

> Our predictive model is likely to struggle accurately predicting the the SME activity due to the large number of categories and low number of companies belonging to each category.

Sales channel

The sales channel seems to be an important feature when predecting the churning of a user. It is not the same if the sales were through email or telephone.

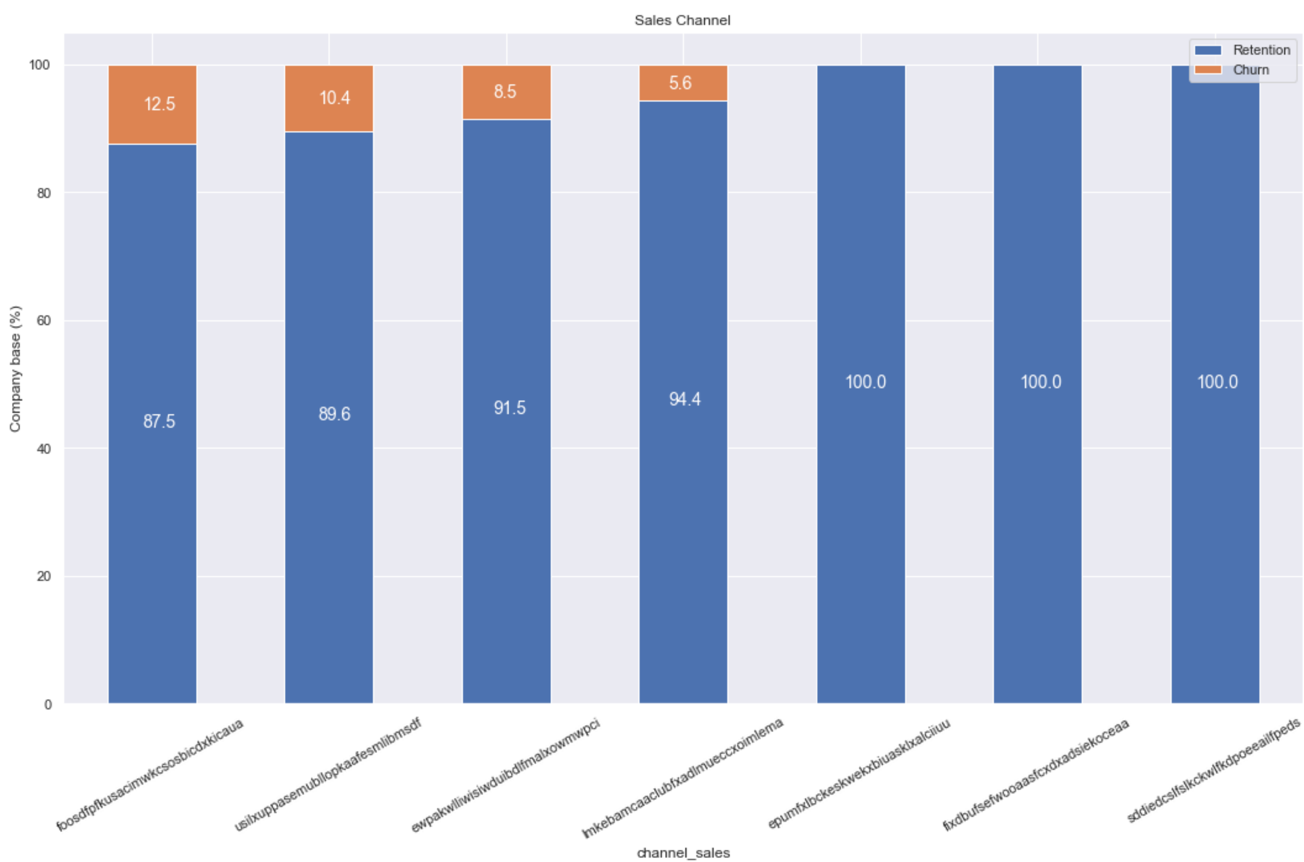
In [27]:
```
channel = train[["id","channel_sales", "churn"]]
```

In [28]:
```
channel = channel.groupby([channel["channel_sales"],
                           channel["churn"]])["id"].count().unstack(level=1).fillna(0)
```

In [29]:
```
channel_churn = (channel.div(channel.sum(axis=1), axis=0)*100).sort_values(by=[1], ascending=False)
```

We will plot the categories, despite the fact that data is available for only `75%` of the dataset.

In [30]:
```
plot_stacked_bars(channel_churn, "Sales Channel", rot_=30)
```



Nothing out of the normal form this graph above.

If we look at it percentage-wise

In [31]:
```
channel_total = channel.fillna(0)[0]+channel.fillna(0)[1]
channel_percentage = channel.fillna(0)[1]/(channel_total)*100
pd.DataFrame({"Churn percentage": channel_percentage,
              "Total companies": channel_total }).sort_values(by="Churn percentage",
                                                              ascending=False).head(10)
```

Out[31]:

channel_sales	Churn percentage	Total companies
foosdfpfkusacimwkcsosbicdxkicaua	12.498306	7377.0
usilxuppasemubllopkaafesmlibmsdf	10.387812	1444.0
ewpakwlliwisiwduibdlfmalxowmwpci	8.488613	966.0
lmkebamcaaclubfxadlmueccxoimlema	5.595755	2073.0
epumfxlbckeskwekxbiuasklxalciiuu	0.000000	4.0
fixdbufsefwooaasfcxdxadsiekoceaa	0.000000	2.0
sddiedcslfslkckwlfkdpoeeailfpeds	0.000000	12.0

Consumption

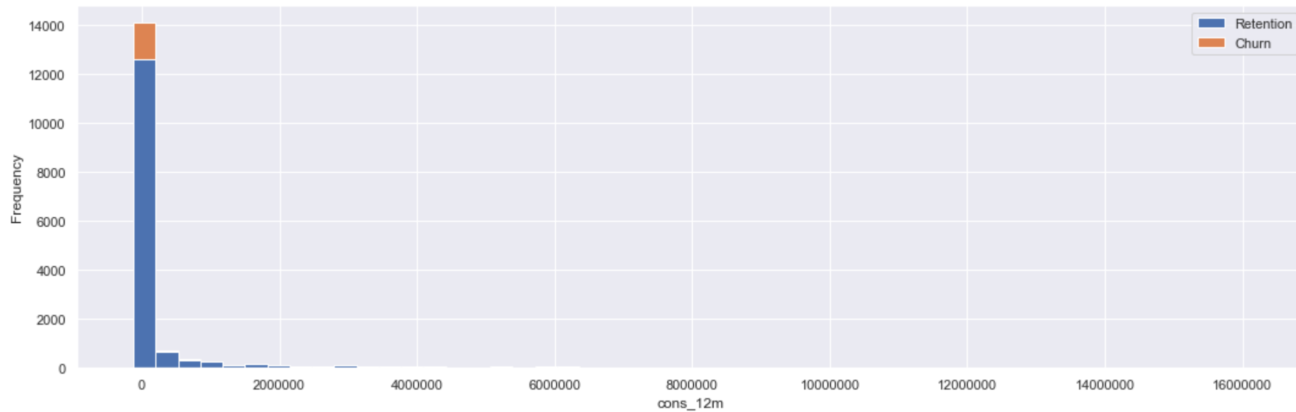
Let's see the distribution of the consumption over the last year and last month

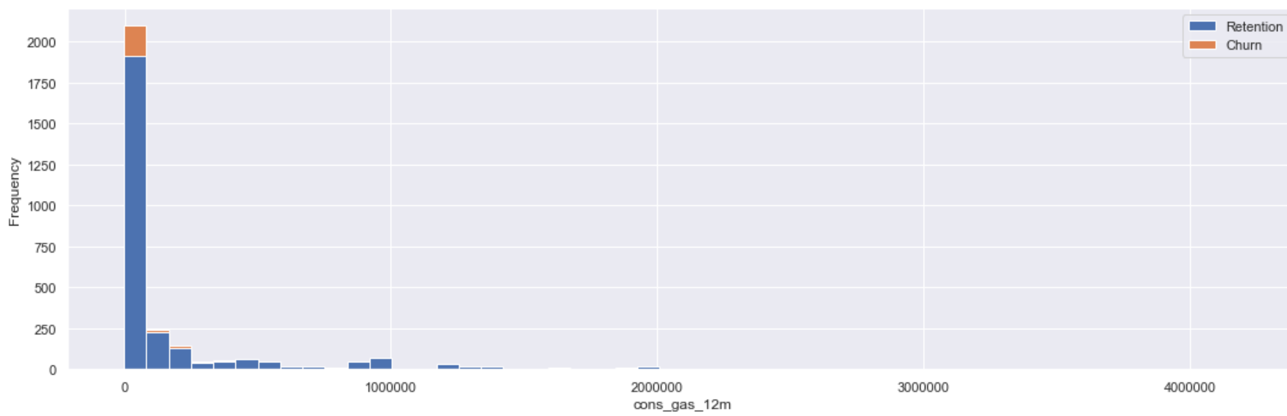
In [32]:
```
consumption = train[["id","cons_12m", "cons_gas_12m","cons_last_month", "imp_cons", "has_gas", "churn"]]
```

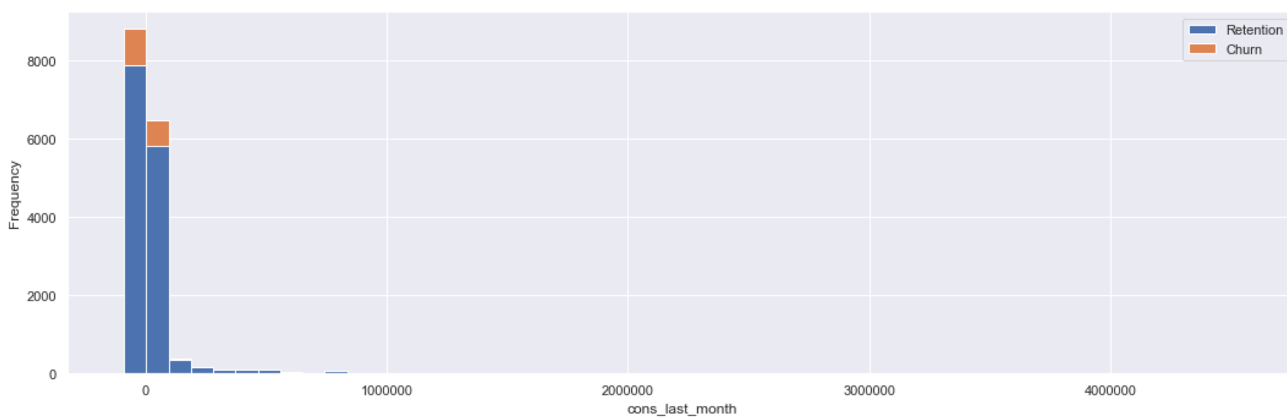
The most straight forward to visualise and identify the distribution of uni-variate data is through histograms

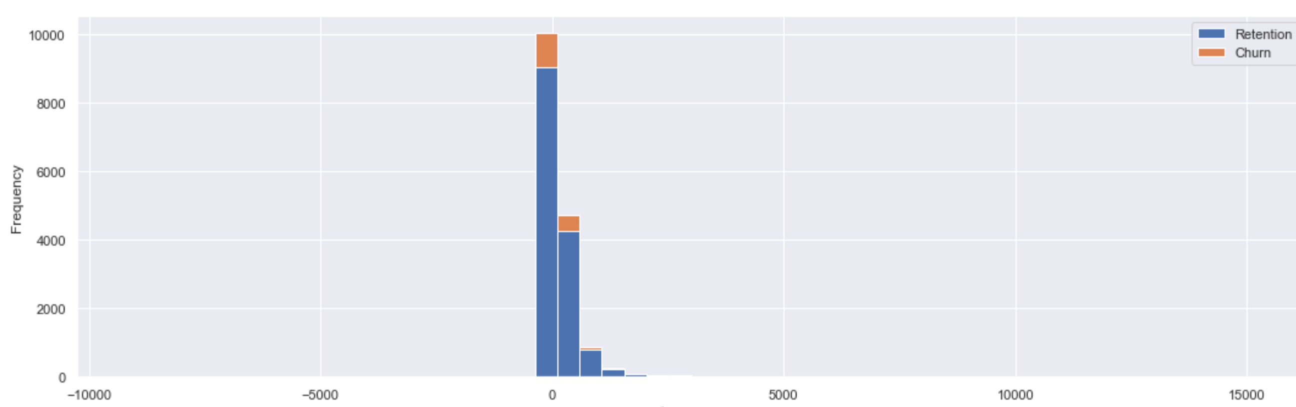
In [33]:
```
def plot_distribution(dataframe, column, ax, bins_=50):
    """
    Plot variable distirbution in a stacked histogram of churned or retained company
    """
    # Create a temporal dataframe with the data to be plot
    temp = pd.DataFrame({"Retention": dataframe[dataframe["churn"]==0][column],
                         "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 plain style
    ax.ticklabel_format(style='plain', axis='x')
```

In [34]:
```
fig, axs = plt.subplots(nrows=4, figsize=(18,25))
# Plot histogram
plot_distribution(consumption, "cons_12m", axs[0])
# Note that the gas consumption must have gas contract
plot_distribution(consumption[consumption["has_gas"] == "t"], "cons_gas_12m", axs[1])
plot_distribution(consumption, "cons_last_month", axs[2])
plot_distribution(consumption, "imp_cons", axs[3])
```





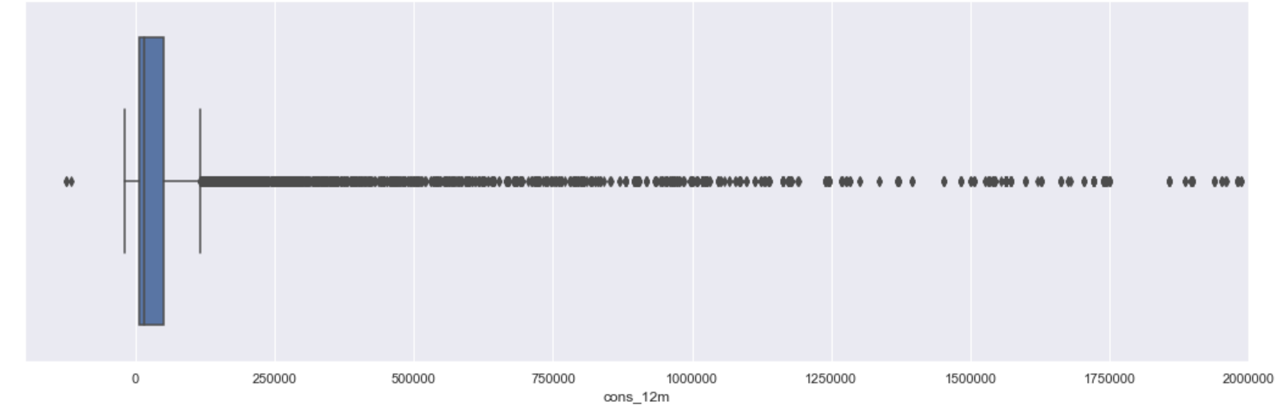


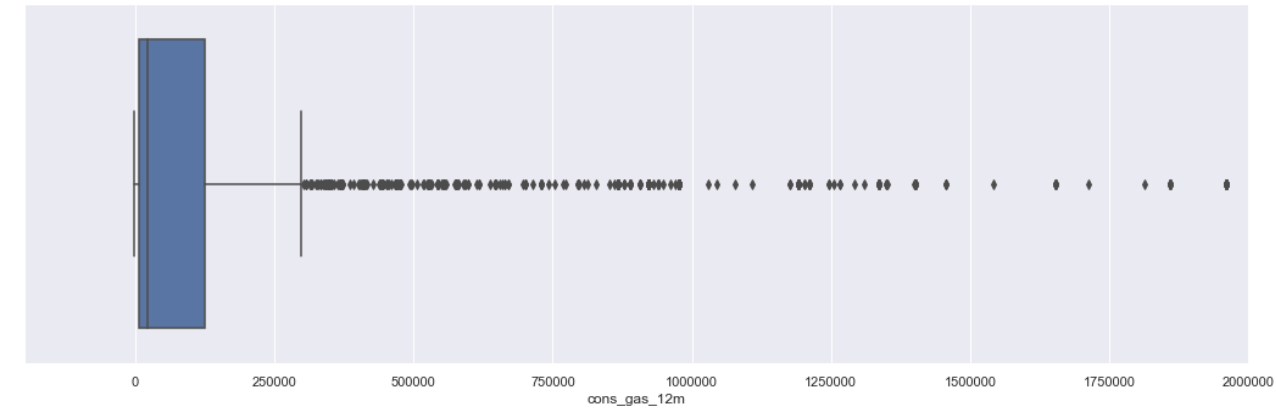


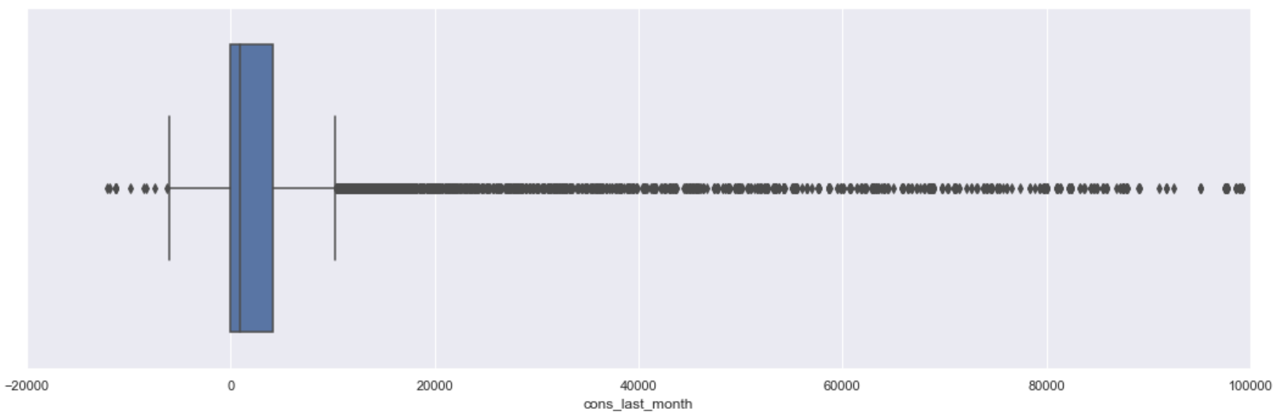
We can clearly see in here that the consumption data is highly *skewed to the right*, presenting a very long right-tail towards the higher values of the distribution.

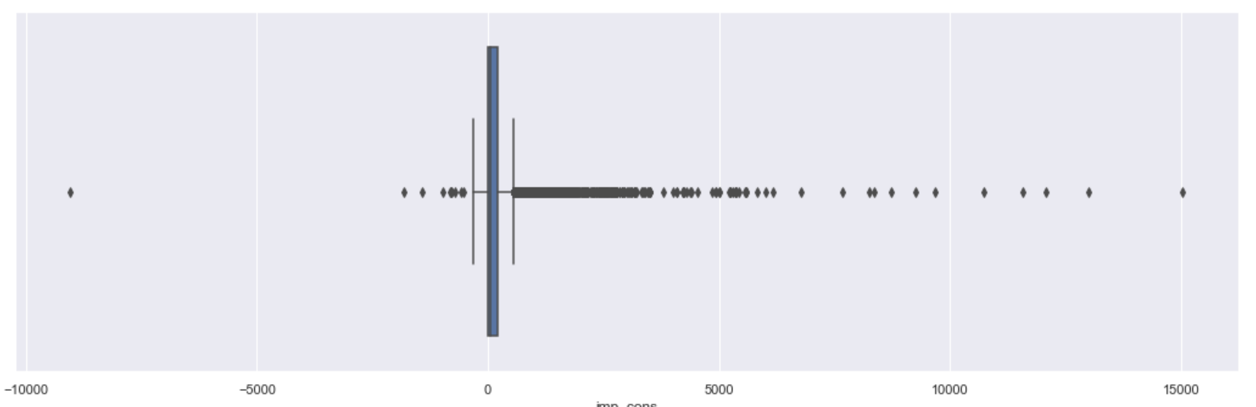
The values on the higher end and lower ends of the distribution are likely to be outliers. We can use a standard plot to visualise the outliers in more detail. A boxplot is a standardized way of displaying the distribution of data based on a five number summary (“minimum”, first quartile (Q1), median, third quartile (Q3), and “maximum”). It can tell us about our outliers and what their values are. It can also tell us if our data is symmetrical, how tightly our data is grouped, and if and how our data is skewed.

In [35]:
```
fig, axs = plt.subplots(nrows=4, figsize=(18,25))
# Plot histogram
sns.boxplot(consumption["cons_12m"], ax=axs[0])
sns.boxplot(consumption[consumption["has_gas"] == "t"]["cons_gas_12m"], ax=axs[1])
sns.boxplot(consumption["cons_last_month"], ax=axs[2])
sns.boxplot(consumption["imp_cons"], ax=axs[3])
# Remove scientific notation
for ax in axs:
    ax.ticklabel_format(style='plain', axis='x')
# Set x-axis limit
axs[0].set_xlim(-200000, 2000000)
axs[1].set_xlim(-200000, 2000000)
axs[2].set_xlim(-20000, 100000)
plt.show()
```









It is very clear now that we have a highly skewed distribution, and several outliers.

We will deal with the skewness and outliers in the next exercise (`Data cleaning`)

Dates

In [36]:

```
dates = train[["id","date_activ","date_end", "date_modif_prod","date_renewal","churn"]].copy()
```

In [37]:

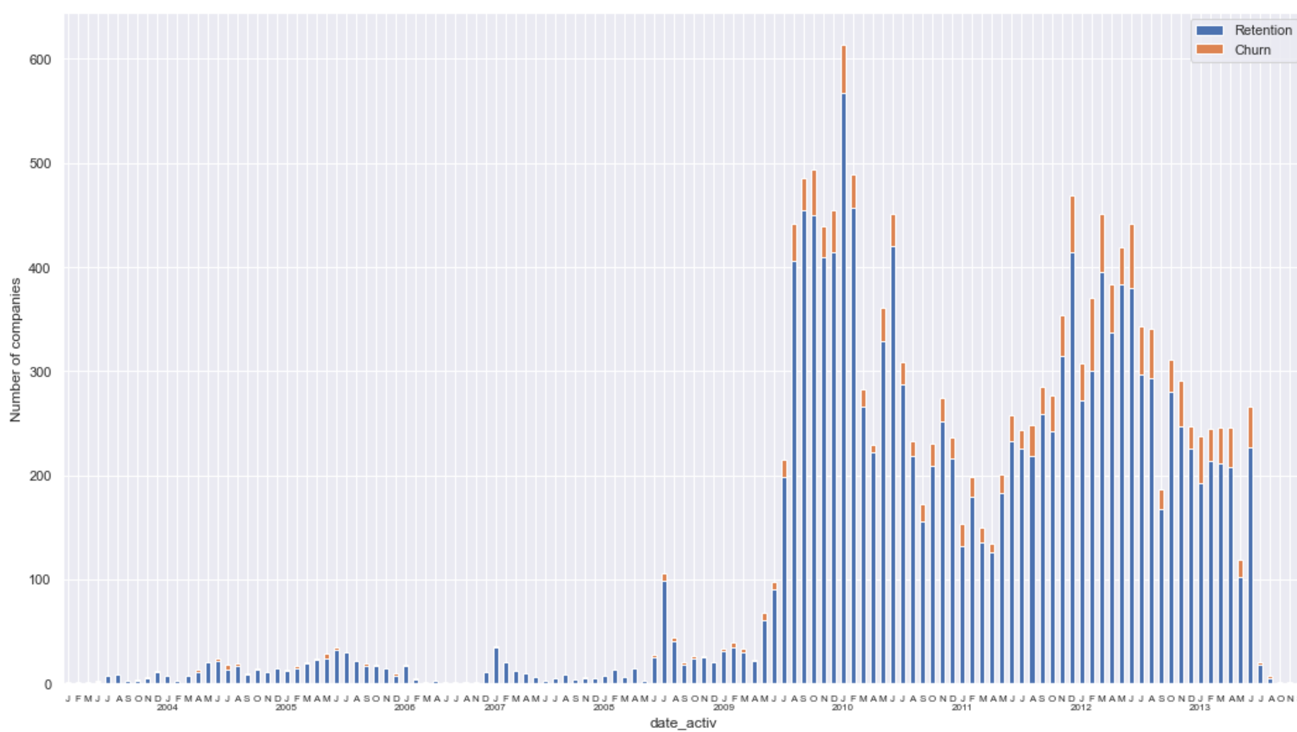
```
# Transform date columns to datetime type
dates["date_activ"] = pd.to_datetime(dates["date_activ"], format='%Y-%m-%d')
dates["date_end"] = pd.to_datetime(dates["date_end"], format='%Y-%m-%d')
dates["date_modif_prod"] = pd.to_datetime(dates["date_modif_prod"], format='%Y-%m-%d')
dates["date_renewal"] = pd.to_datetime(dates["date_renewal"], format='%Y-%m-%d')
```

In [38]:

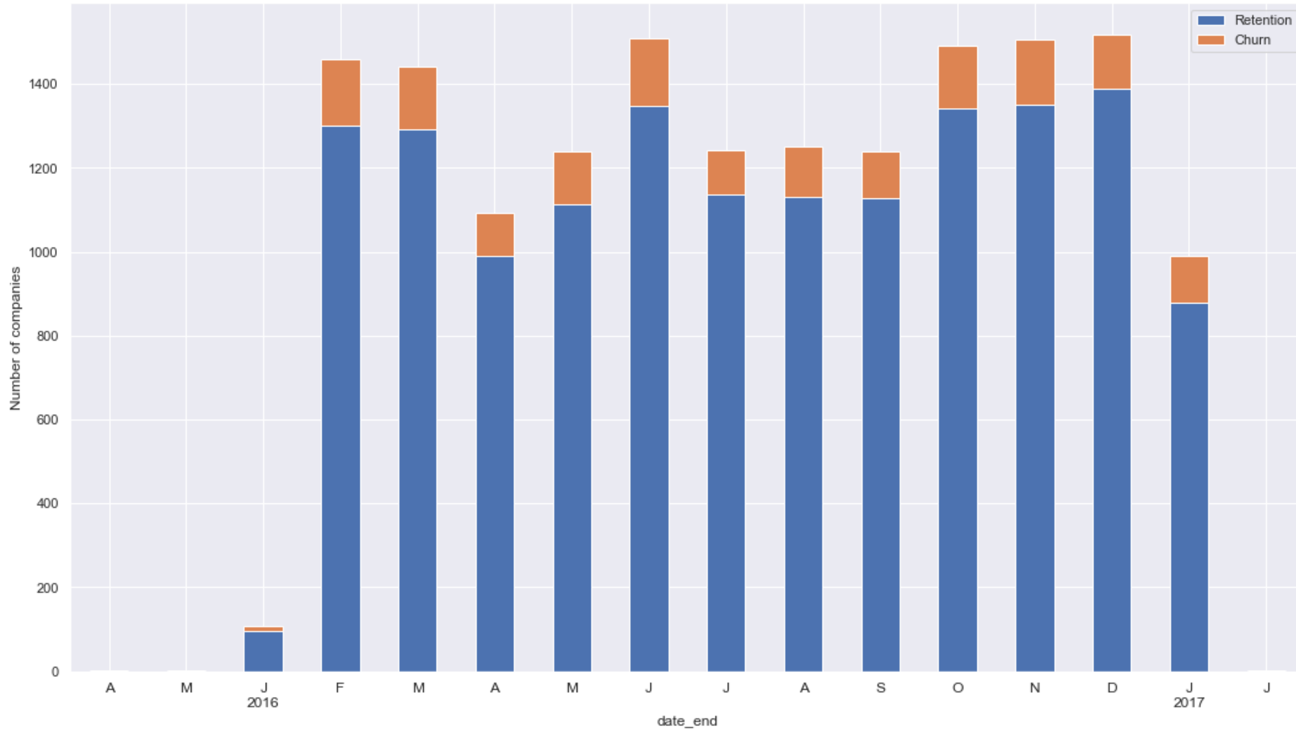
```
def plot_dates(dataframe, column, fontsize_=12):
    """
    Plot monthly churn and retention distribution
    """
    # Group by month
    temp = dataframe[[column,
                      "churn",
                      "id"]].set_index(column).groupby([pd.Grouper(freq='M'), "churn"]).count().unstack(level=1)
    # Plot
    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
```

In [39]:

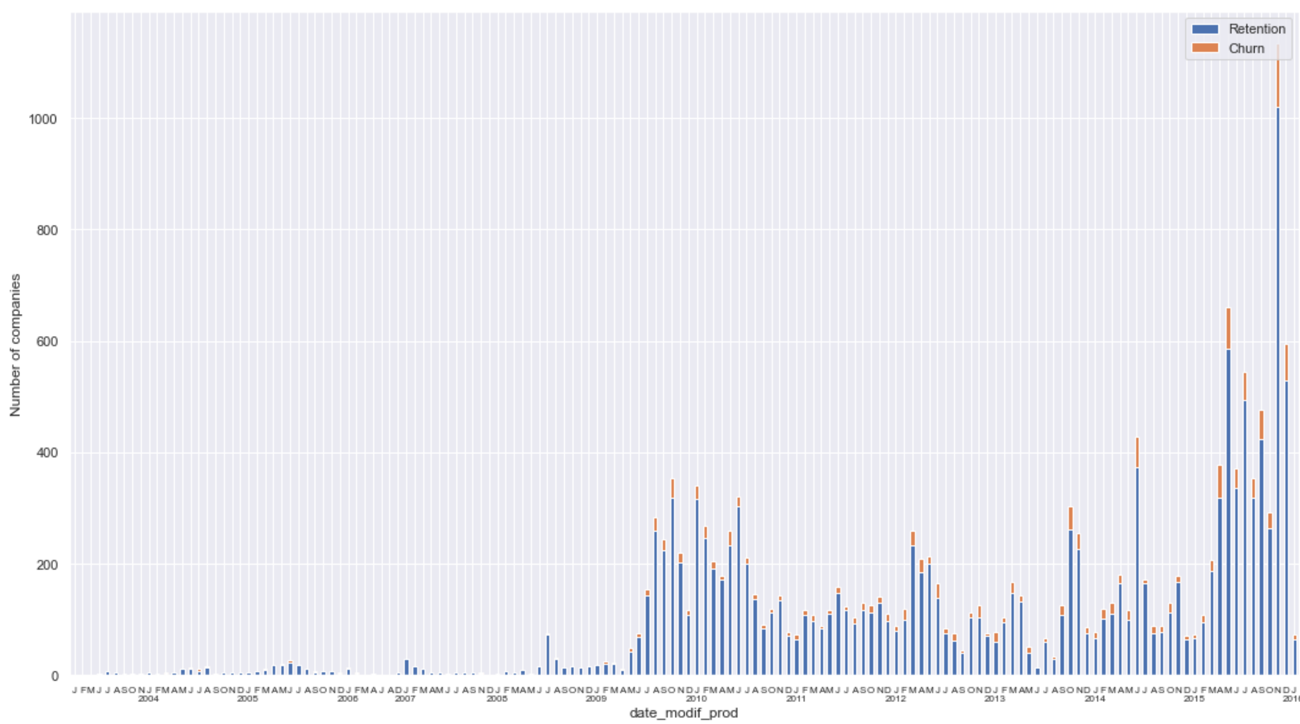
```
plot_dates(dates, "date_activ", fontsize_=8)
```



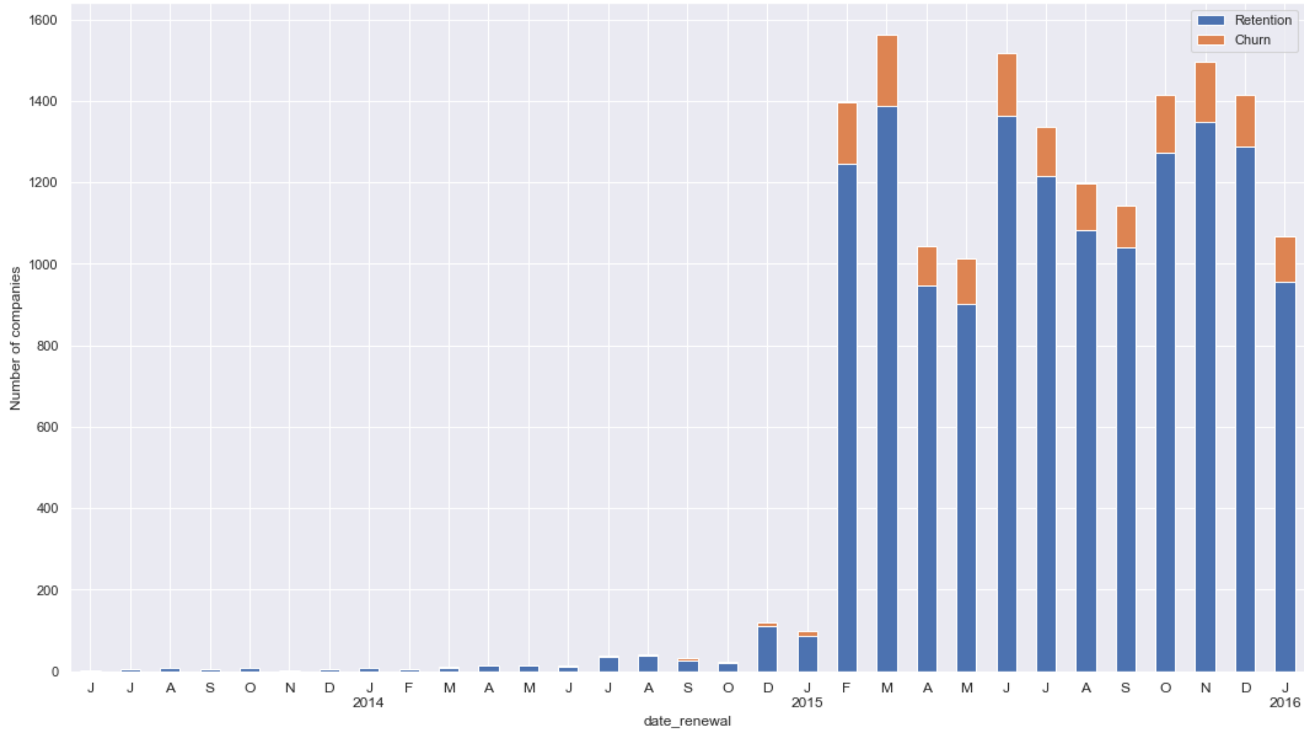
```
In [40]: plot_dates(dates, "date_end")
```




```
In [41]: plot_dates(dates, "date_modif_prod", fontsize_=8)
```



```
In [42]: plot_dates(dates, "date_renewal")
```

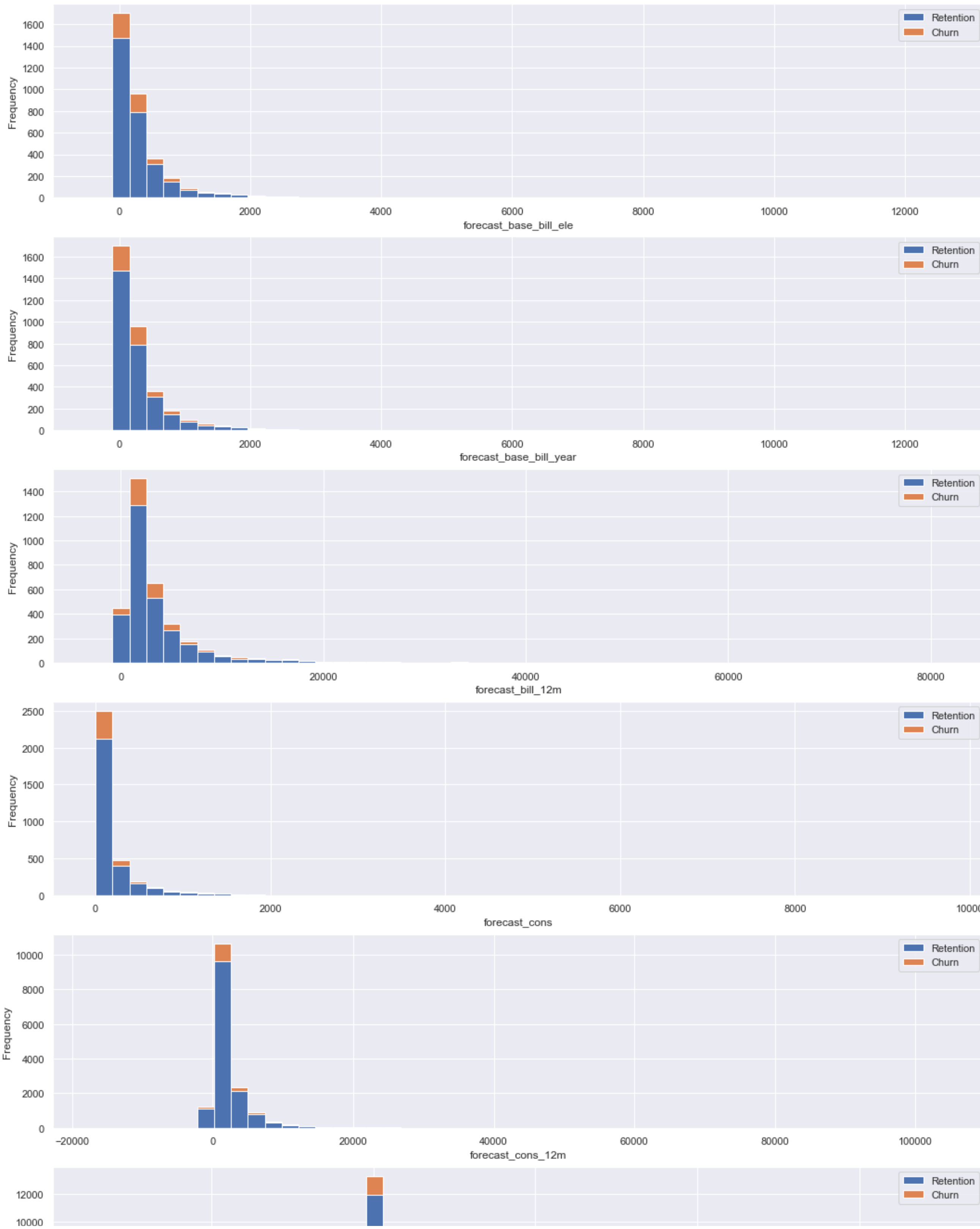


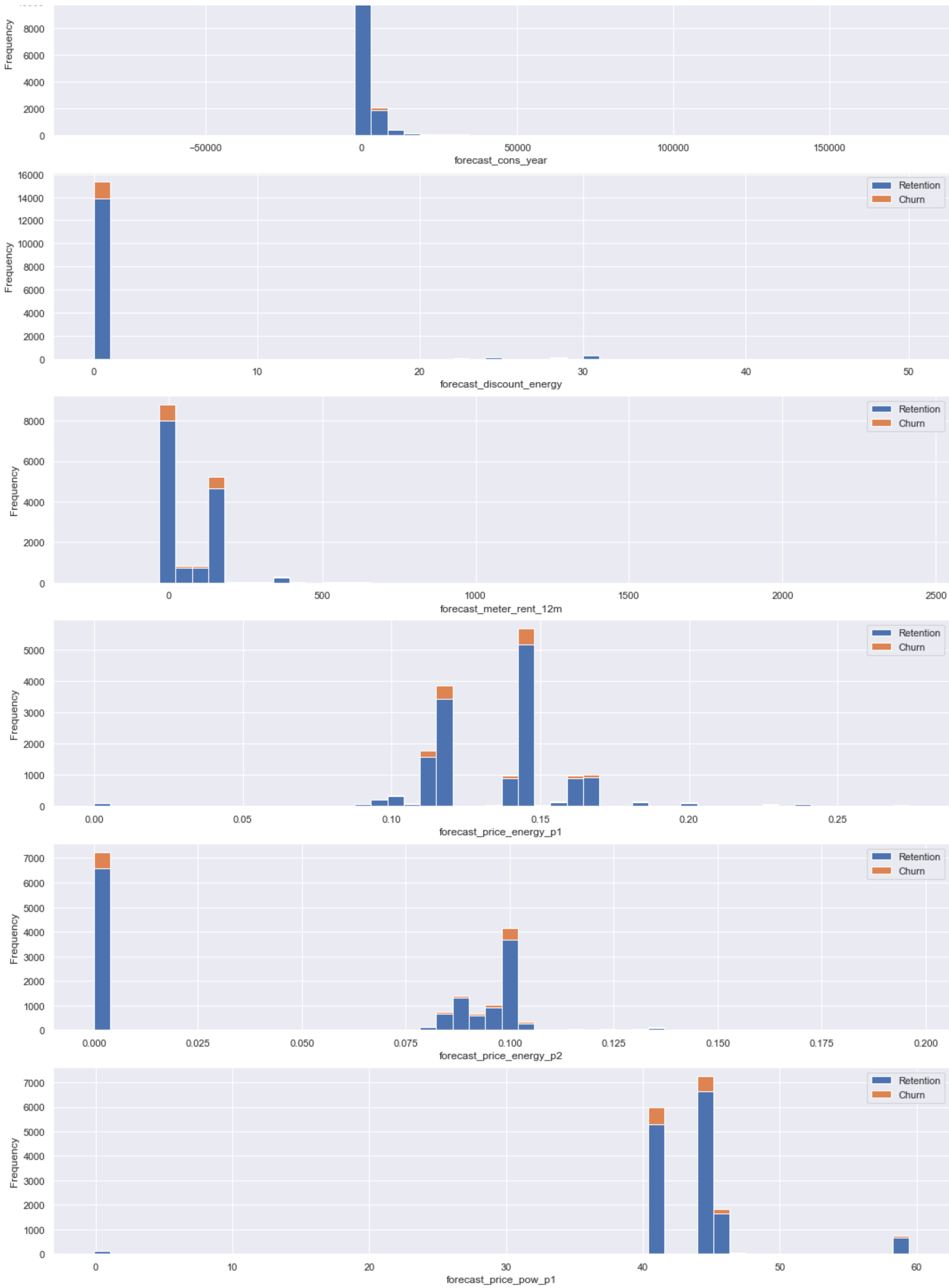
As a remark in here, we can visualize the distribution of churned companies according to the date. However, this does not provide us with any useful insight. We will create a new feature using the raw dates provided in the next exercise.

Forecast

```
In [43]: forecast = train[["id","forecast_base_bill_ele","forecast_base_bill_year",
                   "forecast_bill_12m","forecast_cons","forecast_cons_12m",
                   "forecast_cons_year","forecast_discount_energy","forecast_meter_rent_12m",
                   "forecast_price_energy_p1","forecast_price_energy_p2",
                   "forecast_price_pow_p1","churn"]]
```

In [44]:
```python
fig, axs = plt.subplots(nrows=11, figsize=(18,50))
# Plot histogram
plot_distribution(train, "forecast_base_bill_ele", axs[0])
plot_distribution(train, "forecast_base_bill_year", axs[1])
plot_distribution(train, "forecast_bill_12m", axs[2])
plot_distribution(train, "forecast_cons", axs[3])
plot_distribution(train, "forecast_cons_12m", axs[4])
plot_distribution(train, "forecast_cons_year", axs[5])
plot_distribution(train, "forecast_discount_energy", axs[6])
plot_distribution(train, "forecast_meter_rent_12m", axs[7])
plot_distribution(train, "forecast_price_energy_p1", axs[8])
plot_distribution(train, "forecast_price_energy_p2", axs[9])
plot_distribution(train, "forecast_price_pow_p1", axs[10])
```





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

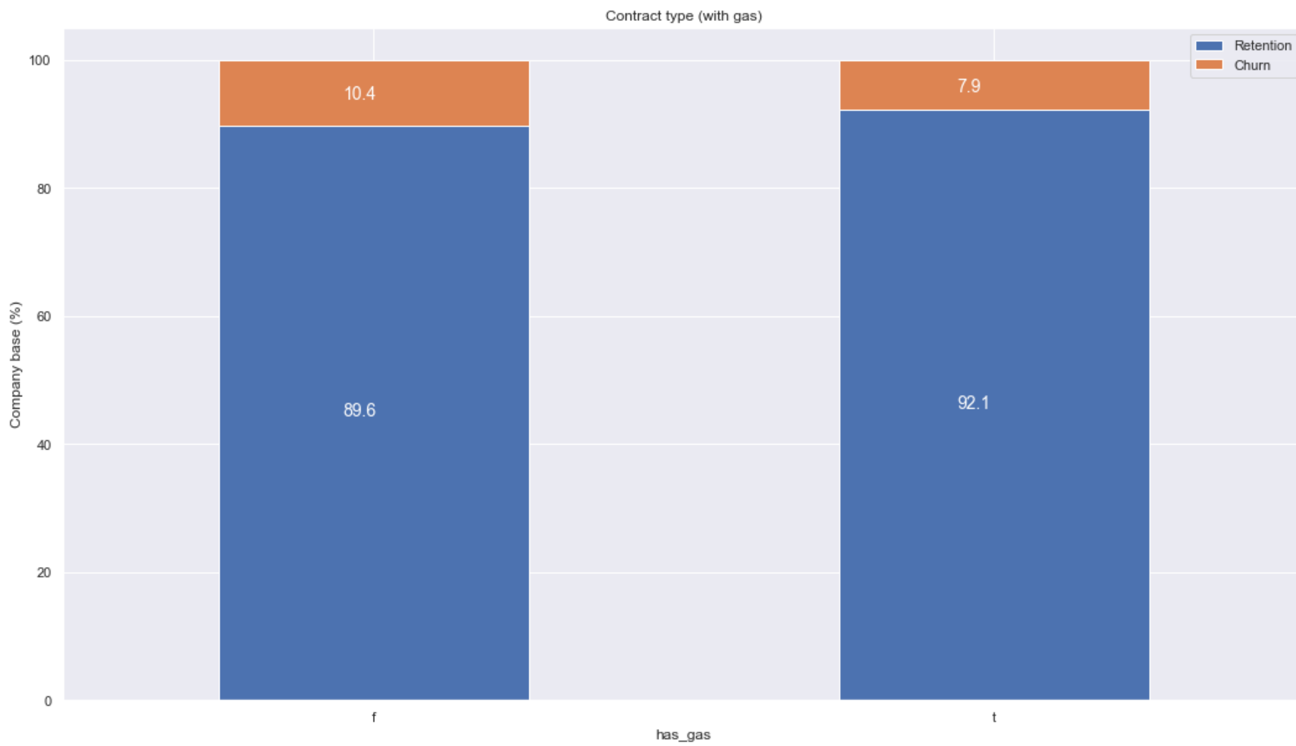
Contract type (electricity, gas)

In [45]:
```
contract_type = train[["id", "has_gas", "churn"]]
```

In [46]:
```
contract = contract_type.groupby([contract_type["churn"],
                                  contract_type["has_gas"]])["id"].count().unstack(level=0)
```

In [47]:
```
contract_percentage = (contract.div(contract.sum(axis=1), axis=0)*100).sort_values(by=[1], ascending=False)
```

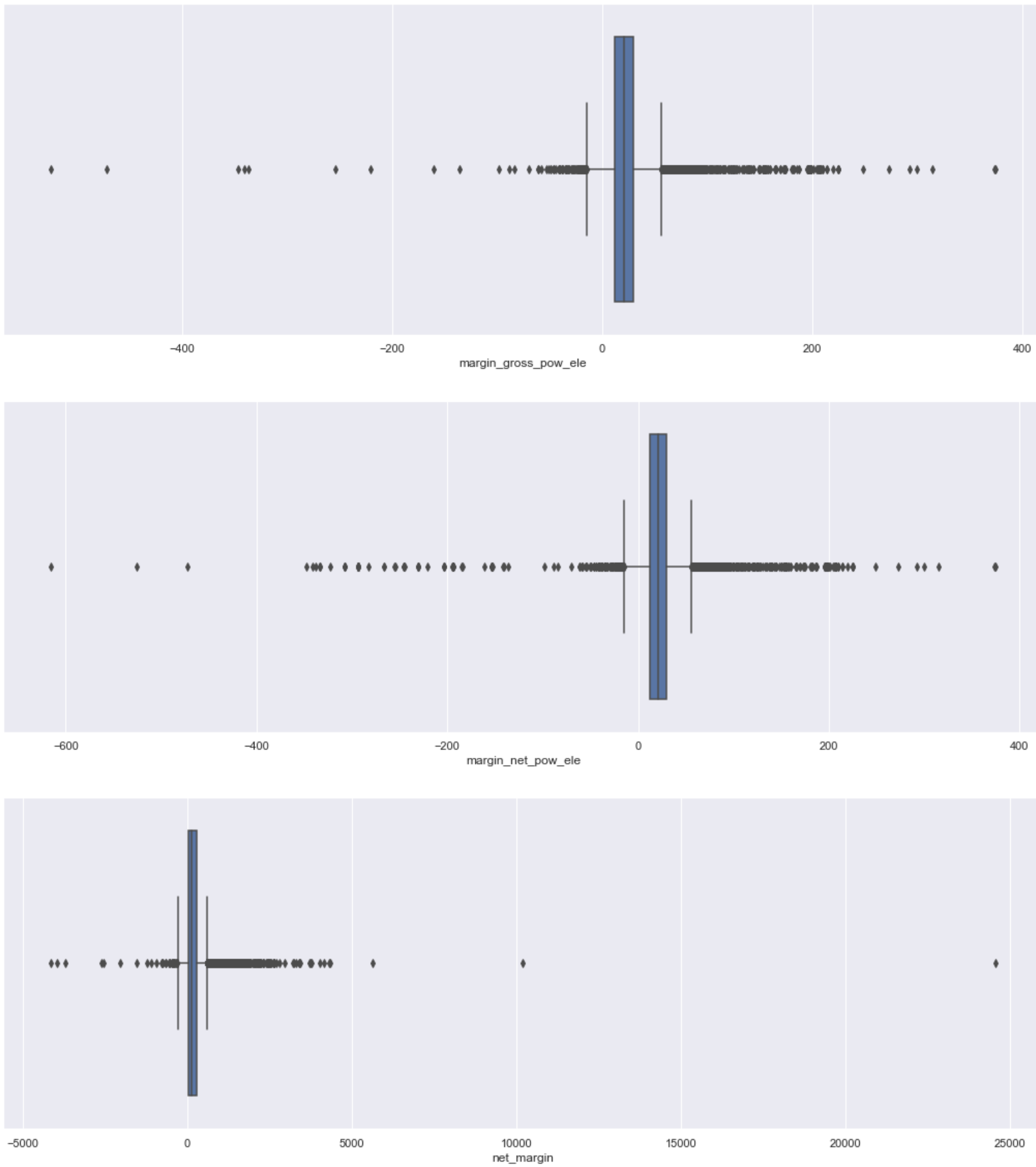
In [48]:
```
plot_stacked_bars(contract_percentage, "Contract type (with gas)")
```



Margins

In [49]:
```
margin = train[["id","margin_gross_pow_ele","margin_net_pow_ele","net_margin"]]
```

In [50]:
```
fig, axs = plt.subplots(nrows=3, figsize=(18,20))
# Plot histogram
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])

# Remove scientific notation
axs[0].ticklabel_format(style='plain', axis='x')
axs[1].ticklabel_format(style='plain', axis='x')
axs[2].ticklabel_format(style='plain', axis='x')
plt.show()
```

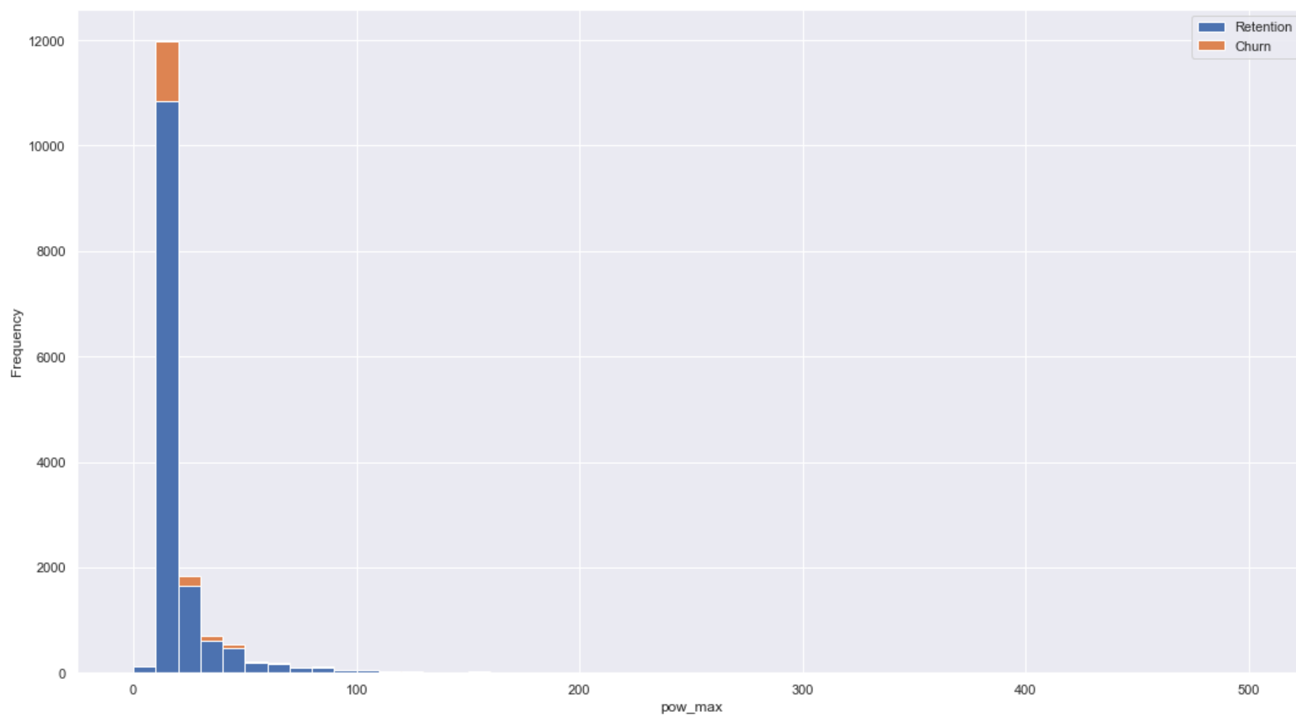


We can observe a few outliers in here as well.

Subscribed power

In [51]:
```
power = train[["id","pow_max", "churn"]].fillna(0)
```

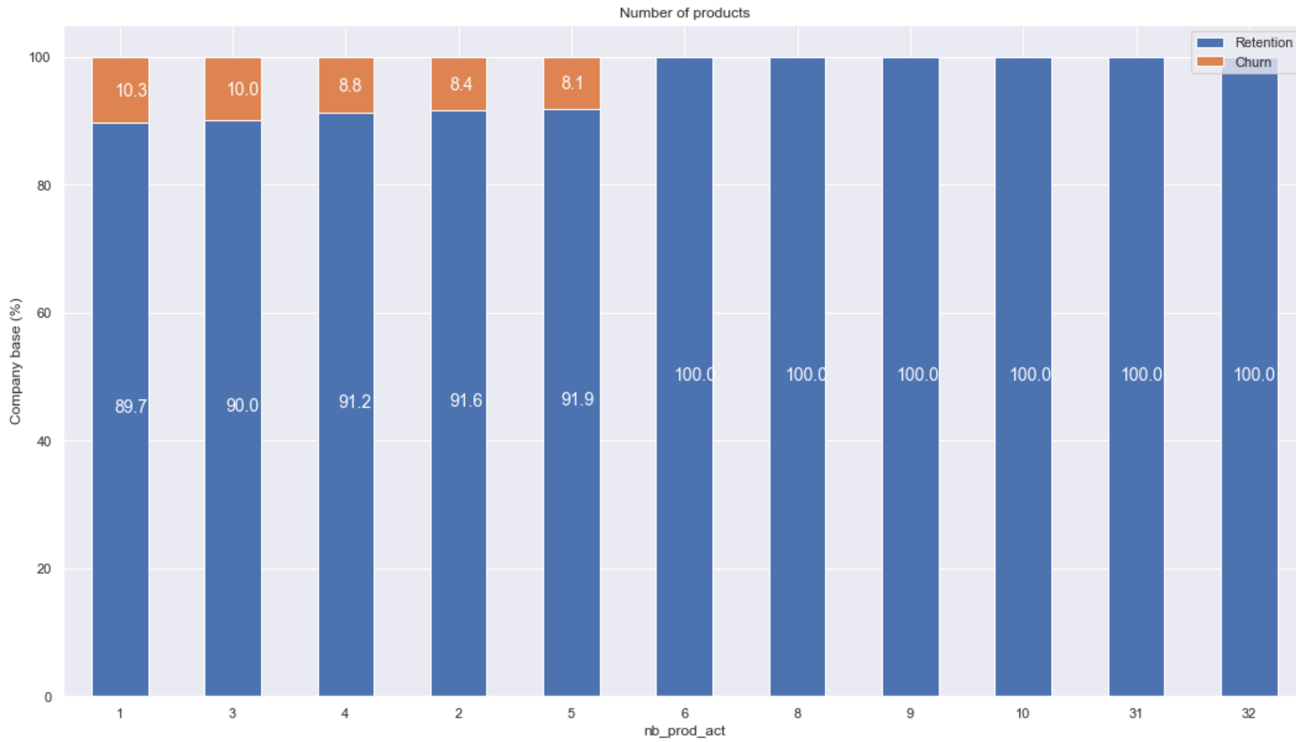
In [52]:
```
fig, axs = plt.subplots(nrows=1, figsize=(18,10))
plot_distribution(power, "pow_max", axs)
```



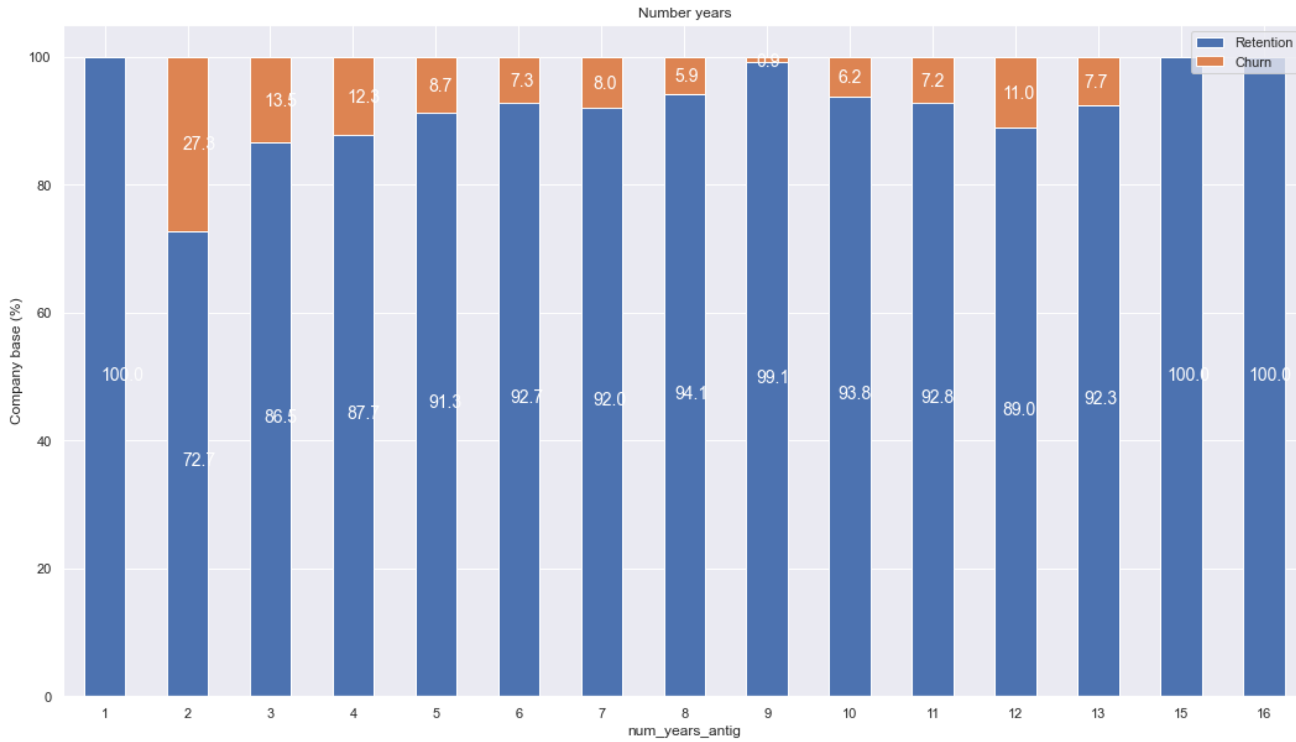
Others

In [53]:
```
others = train[["id","nb_prod_act","num_years_antig", "origin_up", "churn"]]
```

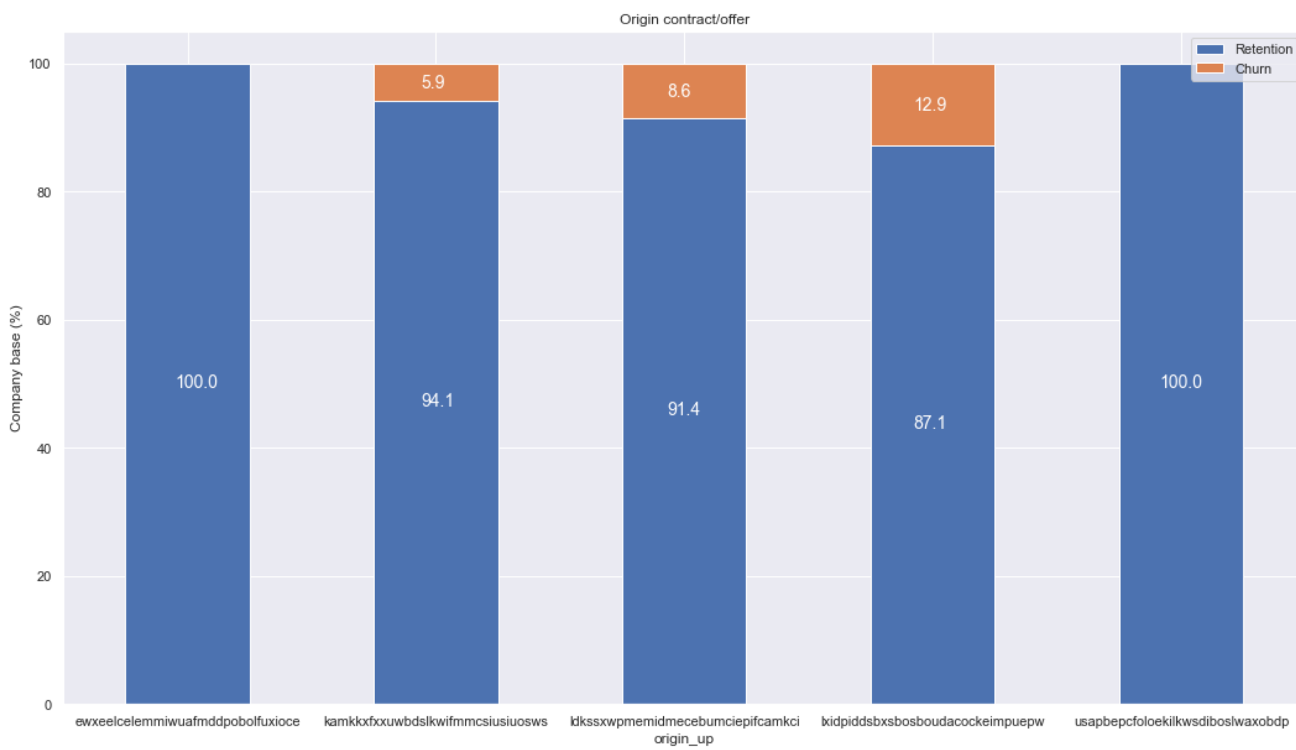
In [54]:
```
products = others.groupby([others["nb_prod_act"],others["churn"]])["id"].count().unstack(level=1)
products_percentage = (products.div(products.sum(axis=1), axis=0)*100).sort_values(by=[1], ascending=False)
plot_stacked_bars(products_percentage, "Number of products")
```



In [55]:
```
years_antig = others.groupby([others["num_years_antig"],others["churn"]])["id"].count().unstack(level=1)
years_antig_percentage = (years_antig.div(years_antig.sum(axis=1), axis=0)*100)
plot_stacked_bars(years_antig_percentage, "Number years")
```



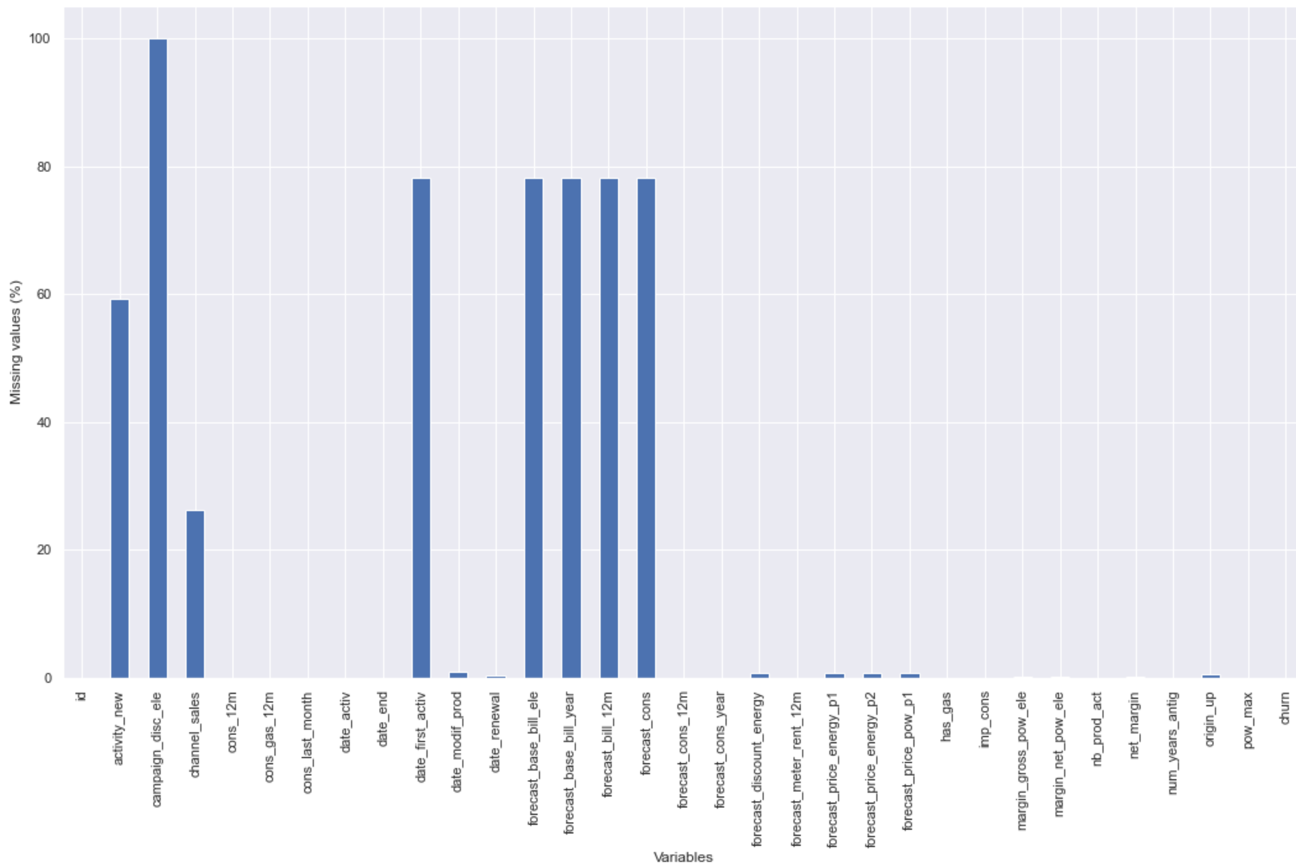
In [56]:
```
origin = others.groupby([others["origin_up"],others["churn"]])["id"].count().unstack(level=1)
origin_percentage = (origin.div(origin.sum(axis=1), axis=0)*100)
plot_stacked_bars(origin_percentage, "Origin contract/offer")
```



4. Data cleaning

Missing data

In [57]:
```
# Plot missing data
(train.isnull().sum()/len(train.index)*100).plot(kind="bar", figsize=(18,10))
# Set axis labels
plt.xlabel("Variables")
plt.ylabel("Missing values (%)")
plt.show()
```



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.

In [58]:
```
train.drop(columns=["campaign_disc_ele", "date_first_activ",
                    "forecast_base_bill_ele","forecast_base_bill_year",
                    "forecast_bill_12m", "forecast_cons"], inplace=True)
```

Notice how the columns that we removed do not appear in the dataframe anymore.

Note: Showing the columns as a separate dataframe to facilitate visualization

In [59]:
```
pd.DataFrame({"Dataframe columns": train.columns})
```

Out[59]:

	Dataframe columns
0	id
1	activity_new
2	channel_sales
3	cons_12m
4	cons_gas_12m
5	cons_last_month
6	date_activ
7	date_end
8	date_modif_prod
9	date_renewal
10	forecast_cons_12m
11	forecast_cons_year
12	forecast_discount_energy
13	forecast_meter_rent_12m
14	forecast_price_energy_p1
15	forecast_price_energy_p2
16	forecast_price_pow_p1
17	has_gas
18	imp_cons
19	margin_gross_pow_ele
20	margin_net_pow_ele
21	nb_prod_act
22	net_margin
23	num_years_antig
24	origin_up
25	pow_max
26	churn

Duplicates

We want to make sure all the data we have is unique and we don't have any duplicated rows. For that, we're going to use the `.duplicated()` function in pandas.

This will tell us if there are any duplicated rows.

In [60]:
```
train[train.duplicated()]
```

Out[60]:

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

5. Formatting data

Missing dates

There could be several ways in which we could deal with the 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 most frequent date). For numerical values, the built-in function `.median()` can be used, but this will not work for dates or strings, so we will use a workaround using `.value counts()`

```python
In [61]: train.loc[train["date_modif_prod"].isnull(),"date_modif_prod"] = train["date_modif_prod"].value_counts().index[0]
         train.loc[train["date_end"].isnull(),"date_end"] = train["date_end"].value_counts().index[0]
         train.loc[train["date_renewal"].isnull(),"date_renewal"] = train["date_renewal"].value_counts().index[0]
```

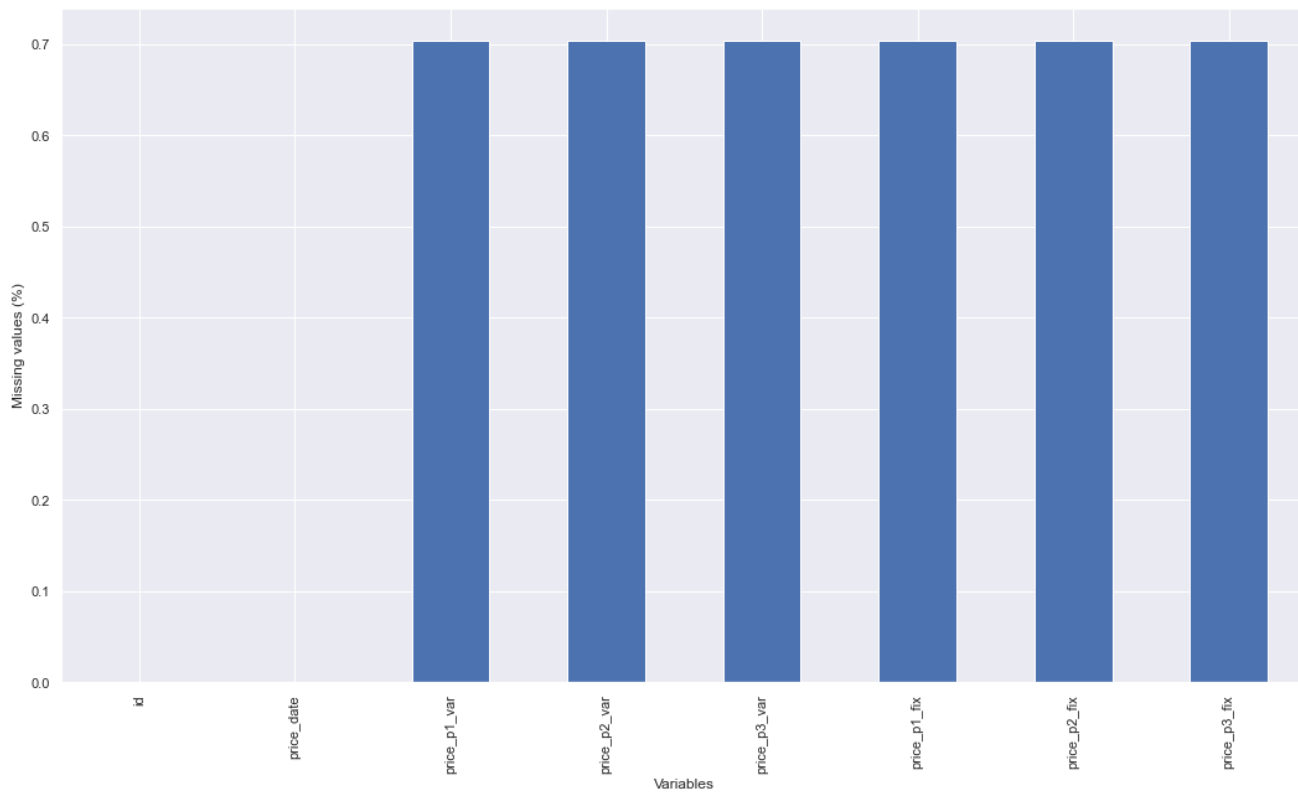
> Although we are directly replacing the values in here, it is usually best practice to make a binary flag that indicates when data is missing because this is informative in itself.

Missing data

We might have some prices missing for some companies and months

```python
In [62]: missing_data_percentage = history_data.isnull().sum()/len(history_data.index)*100
```

```python
In [63]: missing_data_percentage.plot(kind="bar", figsize=(18,10))
         # Set labels
         plt.xlabel("Variables")
         plt.ylabel("Missing values (%)")
         plt.show()
```



There is not much data missing. Instead of removing the entries that are empty we will simply substitute them with the `median`.

Note: We could use something slightly more complicated such as using the `mean` of the previous and following months to calculate the value of the missing month since the data does not vary much.

In [64]:
```
history_data[history_data.isnull().any(axis=1)]
```

Out[64]:

	id	price_date	price_p1_var	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix	price_p3_fix
75	ef716222bbd97a8bdfcbb831e3575560	2015-04-01	NaN	NaN	NaN	NaN	NaN	NaN
221	0f5231100b2febab862f8dd8eaab3f43	2015-06-01	NaN	NaN	NaN	NaN	NaN	NaN
377	2f93639de582fadfbe3e86ce1c8d8f35	2015-06-01	NaN	NaN	NaN	NaN	NaN	NaN
413	f83c1ab1ca1d1802bb1df4d72820243c	2015-06-01	NaN	NaN	NaN	NaN	NaN	NaN
461	3076c6d4a060e12a049d1700d9b09cf3	2015-06-01	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...
192767	2dc2c9a9f6e6896d9a07d7bcbb9d0ce9	2015-06-01	NaN	NaN	NaN	NaN	NaN	NaN
192788	e4053a0ad6c55e4665e8e9adb9f75db5	2015-03-01	NaN	NaN	NaN	NaN	NaN	NaN
192875	1a788ca3bfb16ce443dcf7d75e702b5d	2015-06-01	NaN	NaN	NaN	NaN	NaN	NaN
192876	1a788ca3bfb16ce443dcf7d75e702b5d	2015-07-01	NaN	NaN	NaN	NaN	NaN	NaN
192886	d625f9e90d4af9986197444361e99235	2015-05-01	NaN	NaN	NaN	NaN	NaN	NaN

1359 rows × 8 columns

In [65]:
```
history_data.loc[history_data["price_p1_var"].isnull(),"price_p1_var"] = history_data["price_p1_var"].median()
history_data.loc[history_data["price_p2_var"].isnull(),"price_p2_var"] = history_data["price_p2_var"].median()
history_data.loc[history_data["price_p3_var"].isnull(),"price_p3_var"] = history_data["price_p3_var"].median()
history_data.loc[history_data["price_p1_fix"].isnull(),"price_p1_fix"] = history_data["price_p1_fix"].median()
history_data.loc[history_data["price_p2_fix"].isnull(),"price_p2_fix"] = history_data["price_p2_fix"].median()
history_data.loc[history_data["price_p3_fix"].isnull(),"price_p3_fix"] = history_data["price_p3_fix"].median()
```

Formatting dates (train data)

In order to use the dates in our churn prediction model we are going to change the representation of these dates. Instead of using the date itself, we will be transforming it in number of months. In order to make this transformation we need to change the dates to `datetime` and create a `reference date` which will be January 2016 (see notes)

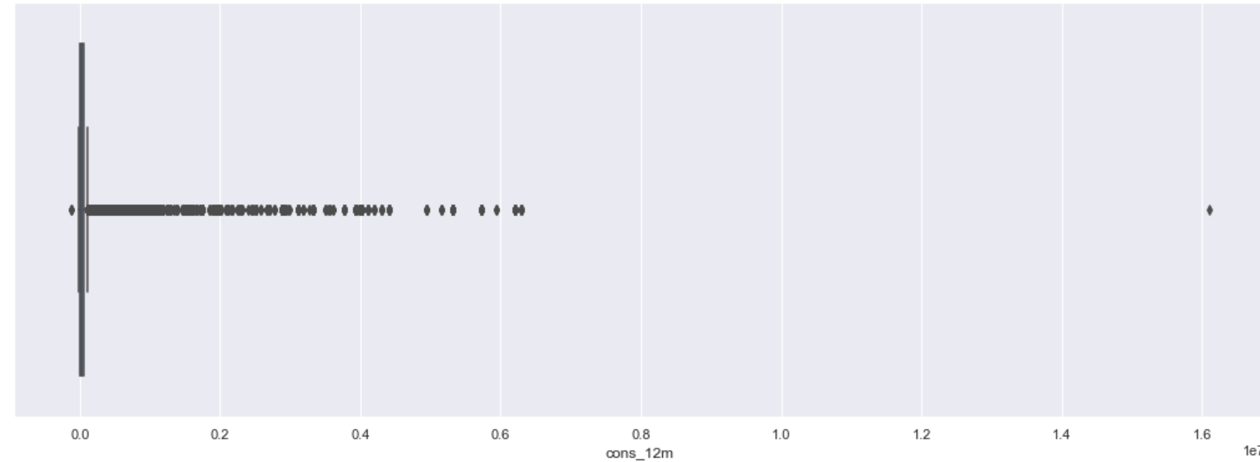
Note: See more information in the feature engineering notebook

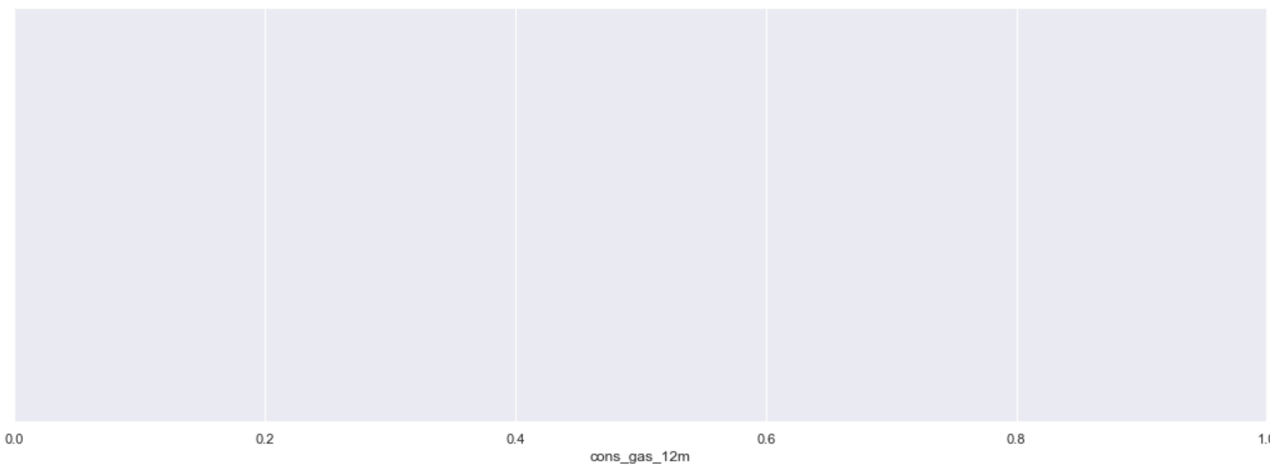
In [66]:
```
# Transform date columns to datetime type
train["date_activ"] = pd.to_datetime(train["date_activ"], format='%Y-%m-%d')
train["date_end"] = pd.to_datetime(train["date_end"], format='%Y-%m-%d')
train["date_modif_prod"] = pd.to_datetime(train["date_modif_prod"], format='%Y-%m-%d')
train["date_renewal"] = pd.to_datetime(train["date_renewal"], format='%Y-%m-%d')
```

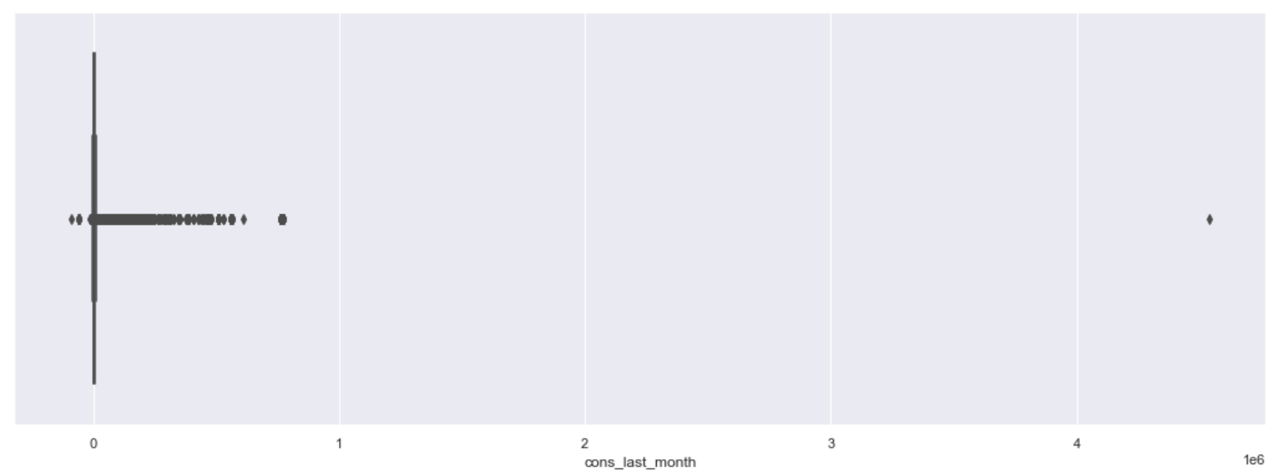
Formating dates (history data)

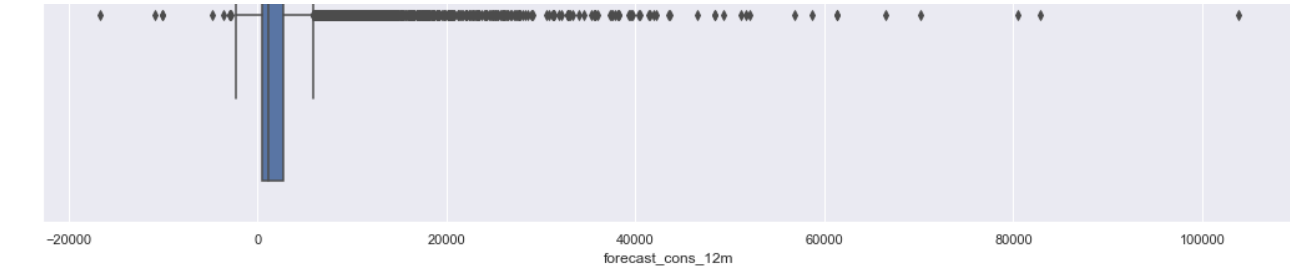
In [67]:
```
history_data["price_date"] = pd.to_datetime(history_data["price_date"], format='%Y-%m-%d')
```

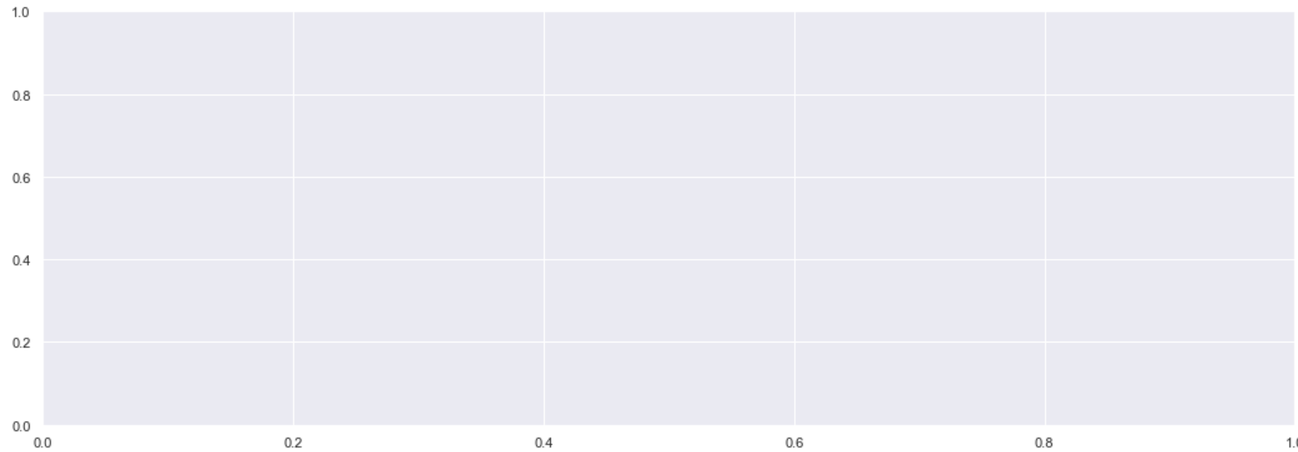
In [68]:
```python
fig, axs = plt.subplots(nrows=7, figsize=(18,50))
# Plot boxplots
sns.boxplot((train["cons_12m"].dropna()), ax=axs[0])
sns.boxplot((train[train["has_gas"]==1]["cons_gas_12m"].dropna()), ax=axs[1])
sns.boxplot((train["cons_last_month"].dropna()), ax=axs[2])
sns.boxplot((train["forecast_cons_12m"].dropna()), ax=axs[3])
#sns.boxplot((train["forecast_cons_year"].dropna()), ax=axs[4])
sns.boxplot((train["forecast_meter_rent_12m"].dropna()), ax=axs[5])
sns.boxplot((train["imp_cons"].dropna()), ax=axs[6])
plt.show()
```

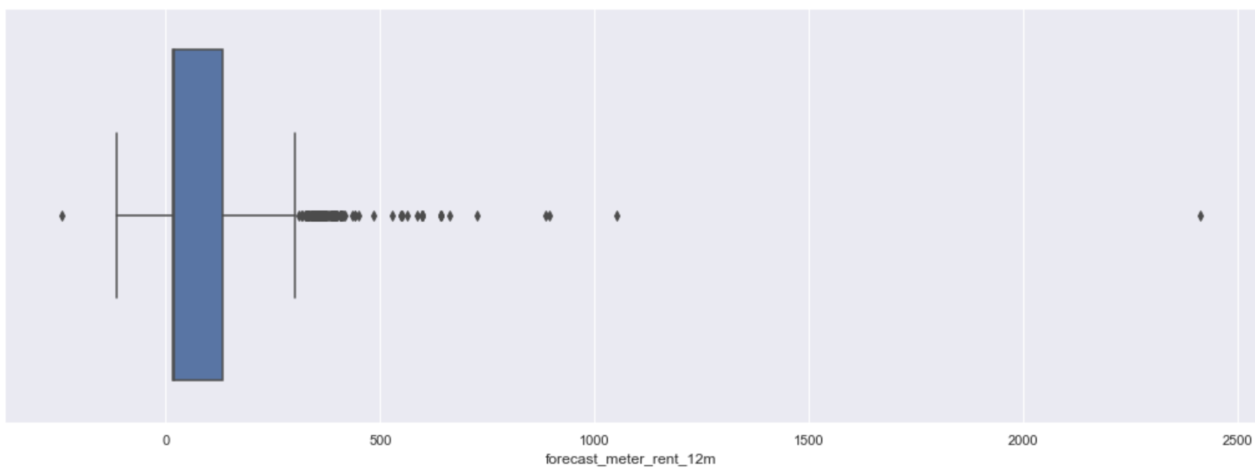


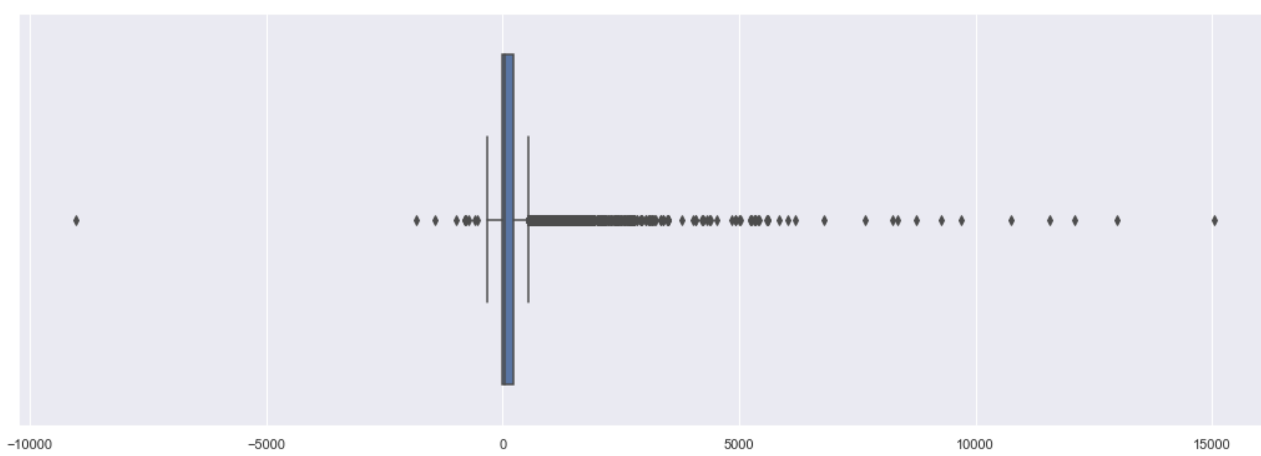












Negative data

Let's take a look a the historical price data.

In [69]:
```
history_data.describe()
```

Out[69]:

	price_p1_var	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix	price_p3_fix
count	193002.000000	193002.000000	193002.000000	193002.000000	193002.000000	193002.000000
mean	0.141027	0.054630	0.030496	43.332175	10.622871	6.409981
std	0.025032	0.049924	0.036298	5.419345	12.841899	7.773595
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	0.101673	0.072558	44.444710	24.339581	16.226389
max	0.280700	0.229788	0.114102	59.444710	36.490692	17.458221

We can see that there are negative values for `price_p1_fix` , `price_p2_fix` and `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 corrupted data rather than a "price discount".

We will replace the negative values with the `median` (most frequent value)

In [70]:
```
history_data[(history_data.price_p1_fix < 0) | (history_data.price_p2_fix < 0) | (history_data.price_p3_fix < 0)]
```

Out[70]:

	id	price_date	price_p1_var	price_p2_var	price_p3_var	price_p1_fix	price_p2_fix	price_p3_fix
23138	951d99fe07ca94c2139f43bc37095139	2015-03-01	0.125976	0.103395	0.071536	-0.162916	-0.097749	-0.065166
28350	f7bdc6fa1067cd26fd80bfb9f3fca28f	2015-03-01	0.131032	0.108896	0.076955	-0.162916	-0.097749	-0.065166
98575	9b523ad5ba8aa2e524dcda5b3d54dab2	2015-02-01	0.129444	0.106863	0.075004	-0.162916	-0.097749	-0.065166
113467	cfd098ee6c567eb32374c77d20571bc7	2015-02-01	0.123086	0.100505	0.068646	-0.162916	-0.097749	-0.065166
118467	51d7d8a0bf6b8bd94f8c1de7942c66ea	2015-07-01	0.128132	0.105996	0.074056	-0.162912	-0.097752	-0.065172
125819	decc0a647016e183ded972595cd2b9fb	2015-03-01	0.124937	0.102814	0.069071	-0.162916	-0.097749	-0.065166
128761	cc214d7c05de3ee17a7691e274ac488e	2015-06-01	0.124675	0.102539	0.070596	-0.162912	-0.097752	-0.065172
141011	2a4ed325054472e03cdcc9a34693be4b	2015-02-01	0.167317	0.083347	0.000000	-0.177779	0.000000	0.000000
160827	395a6f41bbd1a0f23a64f00645264e78	2015-04-01	0.121352	0.098771	0.066912	-0.162916	-0.097749	-0.065166
181811	d4a84ff4ec620151ef05bdef0cf27eab	2015-05-01	0.125976	0.103395	0.071536	-0.162916	-0.097749	-0.065166

In [71]:
```
history_data.loc[history_data["price_p1_fix"] < 0,"price_p1_fix"] = history_data["price_p1_fix"].median()
history_data.loc[history_data["price_p2_fix"] < 0,"price_p2_fix"] = history_data["price_p2_fix"].median()
history_data.loc[history_data["price_p3_fix"] < 0,"price_p3_fix"] = history_data["price_p3_fix"].median()
```

8. Pickling

Pickling is useful for applications where we need some degree of persistency in our data. Our program's state data can be saved to disk, so we can continue working on it later on.

Make directory `processed_data` if it does not exist already

In [72]:
```
if not os.path.exists(os.path.join("..", "processed_data")):
    os.makedirs(os.path.join("..", "processed_data"))
```

In [73]:
```
PICKLE_TRAIN_DIR = os.path.join("..", "processed_data", "train_data.pkl")
PICKLE_HISTORY_DIR = os.path.join("..", "processed_data", "history_data.pkl")
```

In [74]:
```
pd.to_pickle(train, PICKLE_TRAIN_DIR)
pd.to_pickle(history_data, PICKLE_HISTORY_DIR)
```

In [ ]: