Subtask 1: Explorattory Data Analysis

Import packages and Datasets

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import missingno as msno
```

In [2]:
```
client_df=pd.read_csv('client_data.csv')
price_df=pd.read_csv('price_data.csv')
```

In [3]:
```
client_df.head()
```

Out[3]:

id	channel_sales	cons_12m	cons_gas_12m	cons_last_month	date_activ	date_end	date_modif_prod	date_
24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	54946	0	2013-06-15	2016-06-15	2015-11-01	20
d29c2c54acc38ff3c0614d0a653813dd	MISSING	4660	0	0	2009-08-21	2016-08-30	2009-08-21	20
764c75f661154dac3a6c254cd082ea7d	foosdfpfkusacimwkcsosbicdxkicaua	544	0	0	2010-04-16	2016-04-16	2010-04-16	20
bba03439a292a1e166f80264c16191cb	lmkebamcaaclubfxadlmueccxoimlema	1584	0	0	2010-03-30	2016-03-30	2010-03-30	20
149d57cf92fc41cf94415803a877cb4b	MISSING	4425	0	526	2010-01-13	2016-03-07	2010-01-13	20

ows × 26 columns

In [4]:
```
price_df.head()
```

Out[4]:

	id	price_date	price_off_peak_var	price_peak_var	price_mid_peak_var	price_off_peak_fix	price_peak_fix	price_mid_peak_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

Descriptive statistics of data

In [5]:
```
client_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14606 entries, 0 to 14605
Data columns (total 26 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              14606 non-null  object 
 1   channel_sales                   14606 non-null  object 
 2   cons_12m                        14606 non-null  int64  
 3   cons_gas_12m                    14606 non-null  int64  
 4   cons_last_month                 14606 non-null  int64  
 5   date_activ                      14606 non-null  object 
 6   date_end                        14606 non-null  object 
 7   date_modif_prod                 14606 non-null  object 
 8   date_renewal                    14606 non-null  object 
 9   forecast_cons_12m               14606 non-null  float64
 10  forecast_cons_year              14606 non-null  int64  
 11  forecast_discount_energy        14606 non-null  float64
 12  forecast_meter_rent_12m         14606 non-null  float64
 13  forecast_price_energy_off_peak  14606 non-null  float64
 14  forecast_price_energy_peak      14606 non-null  float64
 15  forecast_price_pow_off_peak     14606 non-null  float64
 16  has_gas                         14606 non-null  object 
 17  imp_cons                        14606 non-null  float64
 18  margin_gross_pow_ele            14606 non-null  float64
 19  margin_net_pow_ele              14606 non-null  float64
 20  nb_prod_act                     14606 non-null  int64  
 21  net_margin                      14606 non-null  float64
 22  num_years_antig                 14606 non-null  int64  
 23  origin_up                       14606 non-null  object 
 24  pow_max                         14606 non-null  float64
 25  churn                           14606 non-null  int64  
dtypes: float64(11), int64(7), object(8)
memory usage: 2.9+ MB
```

In [6]:
```
price_df.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_off_peak_var  193002 non-null  float64
 3   price_peak_var      193002 non-null  float64
 4   price_mid_peak_var  193002 non-null  float64
 5   price_off_peak_fix  193002 non-null  float64
 6   price_peak_fix      193002 non-null  float64
 7   price_mid_peak_fix  193002 non-null  float64
dtypes: float64(6), object(2)
memory usage: 11.8+ MB
```

In [7]:
```
#We need to convert the datetime related columns into datetime data types later
```

Lets look at some clients and price statistics for now

In [8]:
```
client_df.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
cons_12m	14606.0	159220.286252	573465.264198	0.0	5674.750000	14115.500000	40763.750000	6.207104e+06
cons_gas_12m	14606.0	28092.375325	162973.059057	0.0	0.000000	0.000000	0.000000	4.154590e+06
cons_last_month	14606.0	16090.269752	64364.196422	0.0	0.000000	792.500000	3383.000000	7.712030e+05
forecast_cons_12m	14606.0	1868.614880	2387.571531	0.0	494.995000	1112.875000	2401.790000	8.290283e+04
forecast_cons_year	14606.0	1399.762906	3247.786255	0.0	0.000000	314.000000	1745.750000	1.753750e+05
forecast_discount_energy	14606.0	0.966726	5.108289	0.0	0.000000	0.000000	0.000000	3.000000e+01
forecast_meter_rent_12m	14606.0	63.086871	66.165783	0.0	16.180000	18.795000	131.030000	5.993100e+02
forecast_price_energy_off_peak	14606.0	0.137283	0.024623	0.0	0.116340	0.143166	0.146348	2.739630e-01
forecast_price_energy_peak	14606.0	0.050491	0.049037	0.0	0.000000	0.084138	0.098837	1.959750e-01
forecast_price_pow_off_peak	14606.0	43.130056	4.485988	0.0	40.606701	44.311378	44.311378	5.926638e+01
imp_cons	14606.0	152.786896	341.369366	0.0	0.000000	37.395000	193.980000	1.504279e+04
margin_gross_pow_ele	14606.0	24.565121	20.231172	0.0	14.280000	21.640000	29.880000	3.746400e+02
margin_net_pow_ele	14606.0	24.562517	20.230280	0.0	14.280000	21.640000	29.880000	3.746400e+02
nb_prod_act	14606.0	1.292346	0.709774	1.0	1.000000	1.000000	1.000000	3.200000e+01
net_margin	14606.0	189.264522	311.798130	0.0	50.712500	112.530000	243.097500	2.457065e+04
num_years_antig	14606.0	4.997809	1.611749	1.0	4.000000	5.000000	6.000000	1.300000e+01
pow_max	14606.0	18.135136	13.534743	3.3	12.500000	13.856000	19.172500	3.200000e+02
churn	14606.0	0.097152	0.296175	0.0	0.000000	0.000000	0.000000	1.000000e+00

In [140]:
```
client_df.skew(numeric_only=True)
```

Out[140]:
```
cons_12m                           5.997308
cons_gas_12m                       9.597530
cons_last_month                    6.391407
forecast_cons_12m                  7.155853
forecast_cons_year                16.587990
forecast_discount_energy           5.155098
forecast_meter_rent_12m            1.505148
forecast_price_energy_off_peak    -0.119586
forecast_price_energy_peak        -0.014331
forecast_price_pow_off_peak       -4.998772
imp_cons                          13.198799
margin_gross_pow_ele               4.472632
margin_net_pow_ele                 4.473326
nb_prod_act                        8.636878
net_margin                        36.569515
num_years_antig                    1.446214
pow_max                            5.786785
churn                              2.720715
dtype: float64
```

This shows the distribution is highly skewed

In [9]:
```
price_df.describe()
```

Out[9]:

	price_off_peak_var	price_peak_var	price_mid_peak_var	price_off_peak_fix	price_peak_fix	price_mid_peak_fix
count	193002.000000	193002.000000	193002.000000	193002.000000	193002.000000	193002.000000
mean	0.141027	0.054630	0.030496	43.334477	10.622875	6.409984
std	0.025032	0.049924	0.036298	5.410297	12.841895	7.773592
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	0.101673	0.072558	44.444710	24.339581	16.226389
max	0.280700	0.229788	0.114102	59.444710	36.490692	17.458221

```
The average price of energy for the 1st period was: $0.14
The average price of energy for the 2nd period was: $0.05
The average price of energy for the 3rd period was: $0.03
```

```
The average price of energy was declining in the last year.

The average power of power for the 1st period was: $43.33
The average power of power for the 2nd period was: $10.62
The average power of power for the 3rd period was: $6.40
The average price of power was declining in the last year.
```

Creating a new dataset to see the customer churn info

In [10]:
```
churn_df=client_df[['id','churn']]
```

In [11]:
```
churn_df.head(3)
```

Out[11]:

	id	churn
0	24011ae4ebbe3035111d65fa7c15bc57	1
1	d29c2c54acc38ff3c0614d0a653813dd	0
2	764c75f661154dac3a6c254cd082ea7d	0

In [12]:
```
churn_df=churn_df.replace({0:'Stayed',1:'Churned'})
```

In [13]:
```
churn_df.head(3)
```

Out[13]:

	id	churn
0	24011ae4ebbe3035111d65fa7c15bc57	Churned
1	d29c2c54acc38ff3c0614d0a653813dd	Stayed
2	764c75f661154dac3a6c254cd082ea7d	Stayed

In [14]:
```
churn_df.to_csv('churn_data.csv')
```

Checking what % of customers churned in the last 3 months

In [15]:
```
churn_df['churn'].value_counts()
```

Out[15]:
```
Stayed     13187
Churned     1419
Name: churn, dtype: int64
```

So 1419 customers churned in the last 3 months

In [16]:
```
churn_df['churn'].value_counts()/churn_df.shape[0]*100
```

Out[16]:
```
Stayed     90.284814
Churned     9.715186
Name: churn, dtype: float64
```

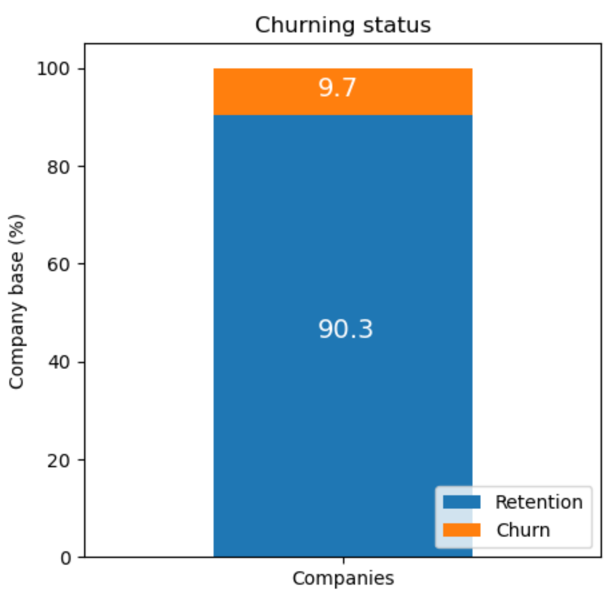
In the past 3 months : 90% of customer retention, 10% of customer churn

Subtask 2:Data Visualization

Visualizing the churning status

In [130]:
```
def plot_stacked_bars(dataframe, title_, size_=(15, 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 rectanges/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 [131]:
```
churn = client_df[['id', 'churn']]
churn.columns = ['Companies', 'churn']
churn_total = churn.groupby(churn['churn']).count()
churn_percentage = churn_total / churn_total.sum() * 100
plot_stacked_bars(churn_percentage.transpose(), "Churning status", (5, 5), legend_="lower right")
```



About 10% of customers churned over the last 3 months, sounds about right from previous calculations

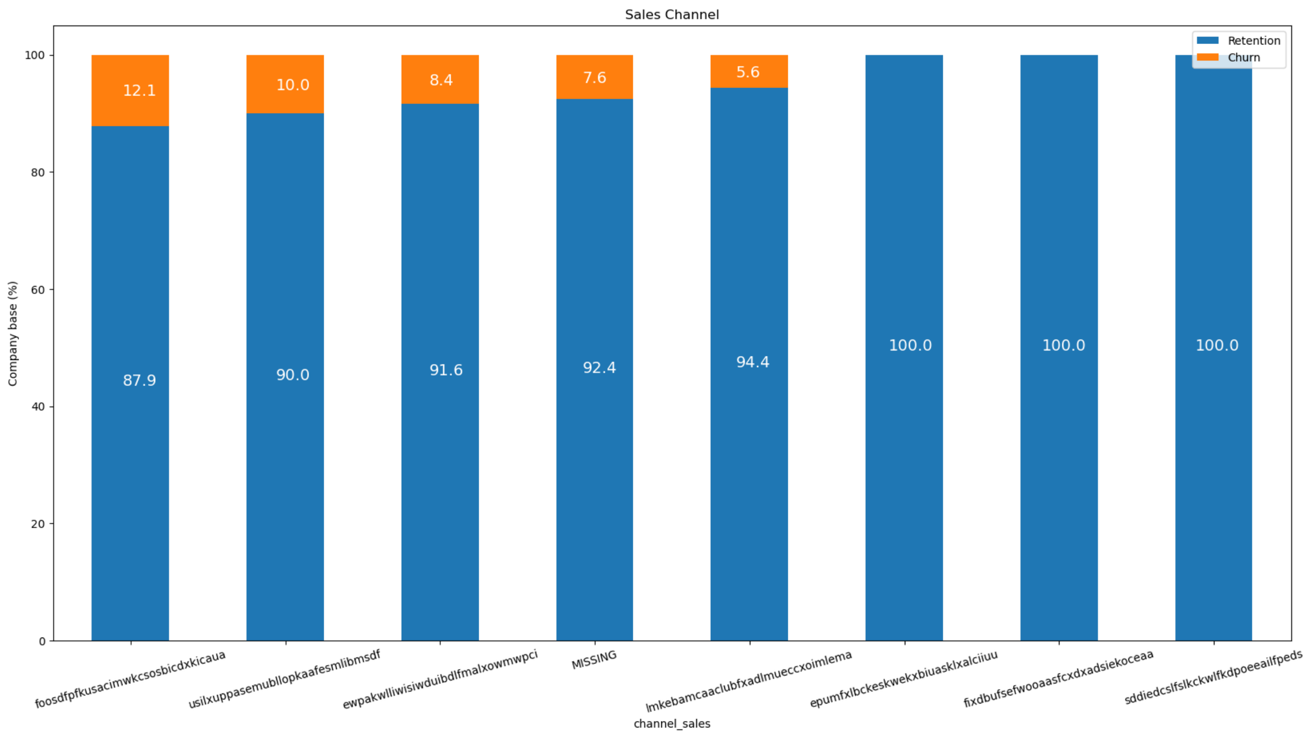
Sales Channel and churning relationship

In [132]:
```
channel=client_df[['id','channel_sales','churn']]
channel=channel.groupby([channel['channel_sales'],channel['churn']])['id'].count().unstack(level=1).fillna(0)
channel_churn=(channel.div(channel.sum(axis=1),axis=0)*100).sort_values(by=[1],ascending=False)
channel_churn
```

Out[132]:

churn	0	1
channel_sales		
foosdfpfkusacimwkcsosbicdxkicaua	87.859046	12.140954
usilxuppasemubllopkaafesmlibmsdf	89.963636	10.036364
ewpakwlliwisiwduibdlfmalxowmwpci	91.601344	8.398656
MISSING	92.402685	7.597315
lmkebamcaaclubfxadlmueccxoimlema	94.411286	5.588714
epumfxlbckeskwekxbiuasklxalciiuu	100.000000	0.000000
fixdbufsefwooaasfcxdxadsiekoceaa	100.000000	0.000000
sddiedcslfslkckwlfkdpoeeailfpeds	100.000000	0.000000

In [135]:
```
plot_stacked_bars(channel_churn,'Sales Channel',(20,10), rot_=15)
```



Interestingly, the churning customers are distributed over 5 different values of 'sales_channel', as well as the value of 'MISSING' has a churn rate of 7.6% Missing indicates a missing value and was added by the team when they were cleaning the dataset. This feature could be an important feature when it comes to building our model.

In [ ]:

Consumption

```
Lets check the consumption in the last year and month. Since the consumption data is univarient, lets use histogram to
visualize their distribution
```

In [141]:
```
client_df.head(2)
```

Out[141]:

last_month	date_activ	date_end	date_modif_prod	date_renewal	forecast_cons_12m	...	has_gas	imp_cons	margin_gross_pow_ele	margin_net_pow_ele	nb_pro
0	2013-06-15	2016-06-15	2015-11-01	2015-06-23	0.00	...	t	0.0	25.44	25.44	
0	2009-08-21	2016-08-30	2009-08-21	2015-08-31	189.95	...	f	0.0	16.38	16.38	

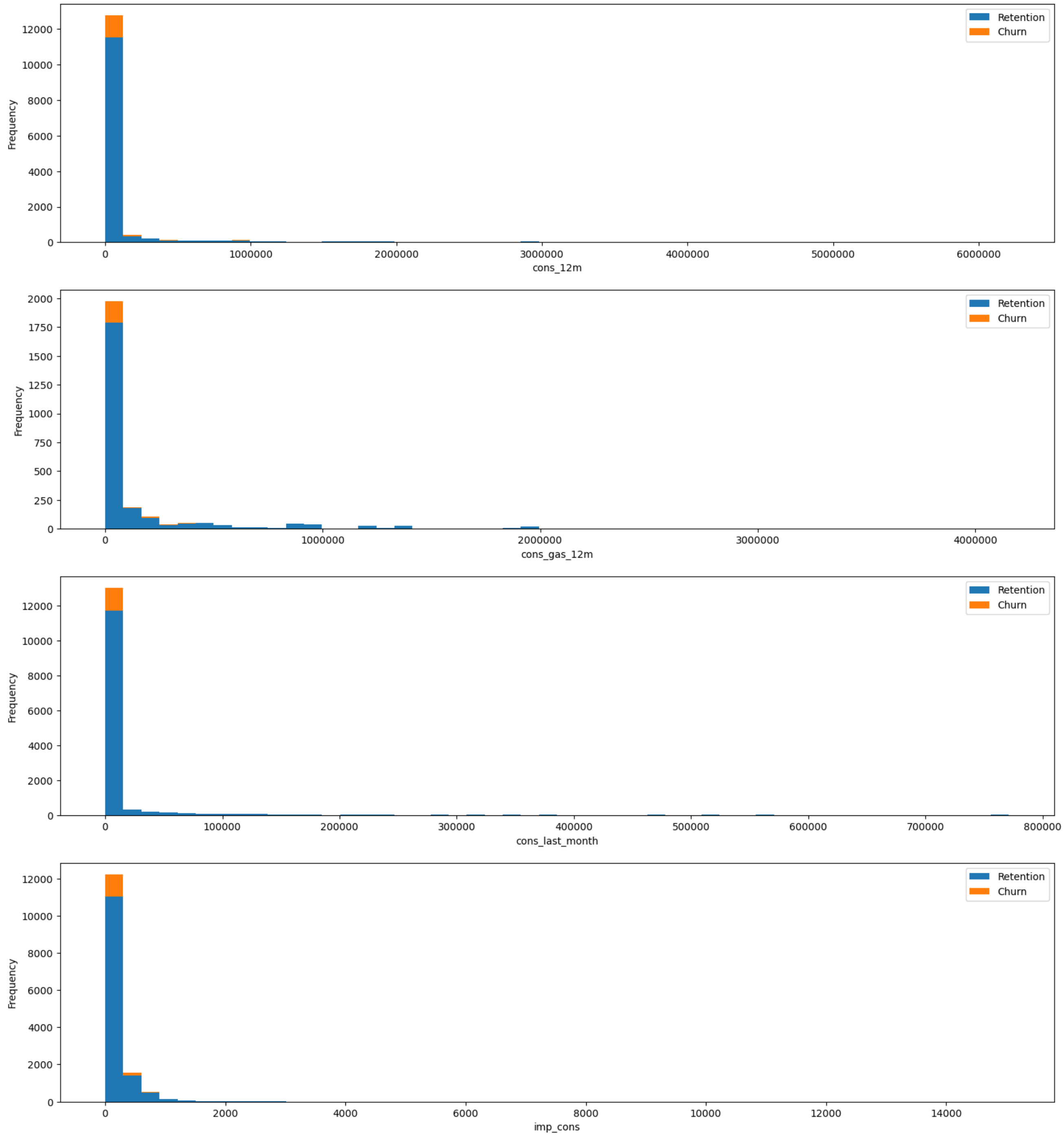
In [145]:
```
consumption=client_df[['id','cons_12m','cons_gas_12m','cons_last_month','imp_cons','has_gas','churn']]
consumption.head(3)
```

Out[145]:

	id	cons_12m	cons_gas_12m	cons_last_month	imp_cons	has_gas	churn
0	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	0.0	t	1
1	d29c2c54acc38ff3c0614d0a653813dd	4660	0	0	0.0	f	0
2	764c75f661154dac3a6c254cd082ea7d	544	0	0	0.0	f	0

In [146]:
```
def plot_distribution(dataframe,column,ax,bins_=50):
    temp=pd.DataFrame({'Retention':dataframe[dataframe['churn']==0][column],
                      'Churn':dataframe[dataframe['churn']==1][column]})
    temp[['Retention','Churn']].plot(kind='hist',bins=bins_,ax=ax,stacked=True)
    ax.set_xlabel(column)
    ax.ticklabel_format(style='plain',axis='x')
```

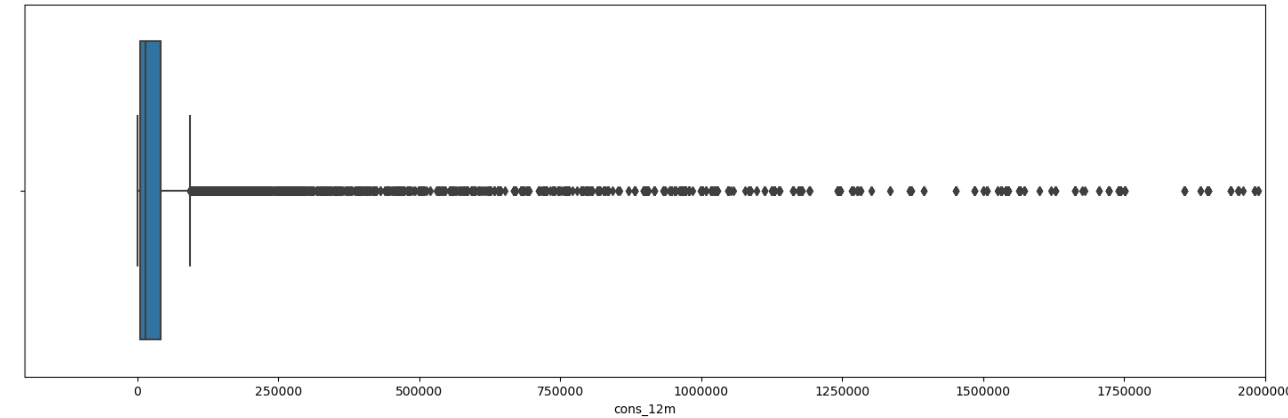
In [150]:
```
fig, axs=plt.subplots(nrows=4, figsize=(18,20))
plot_distribution(consumption,'cons_12m',axs[0])
plot_distribution(consumption[consumption['has_gas']=='t'],'cons_gas_12m',axs[1])
plot_distribution(consumption,'cons_last_month',axs[2])
plot_distribution(consumption,'imp_cons',axs[3])
```

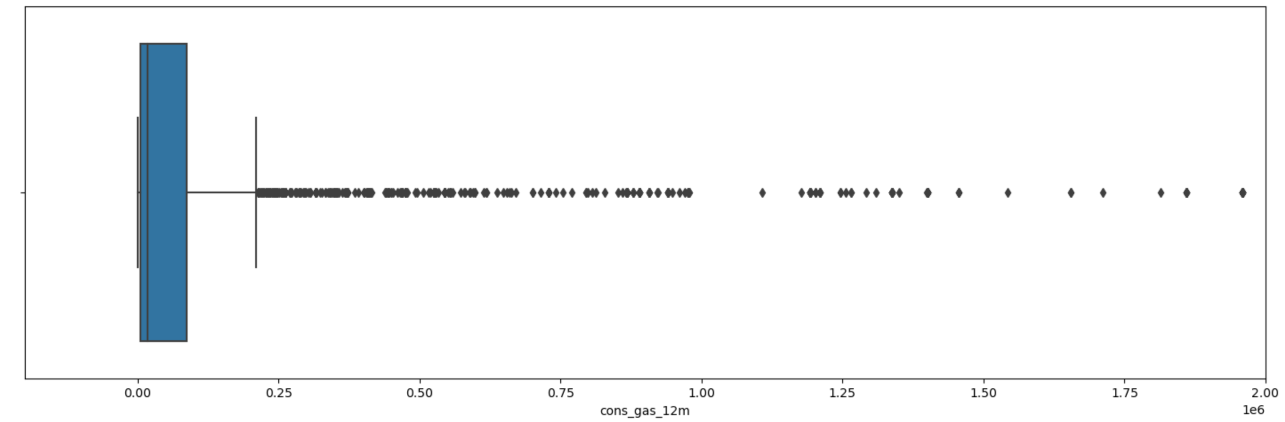


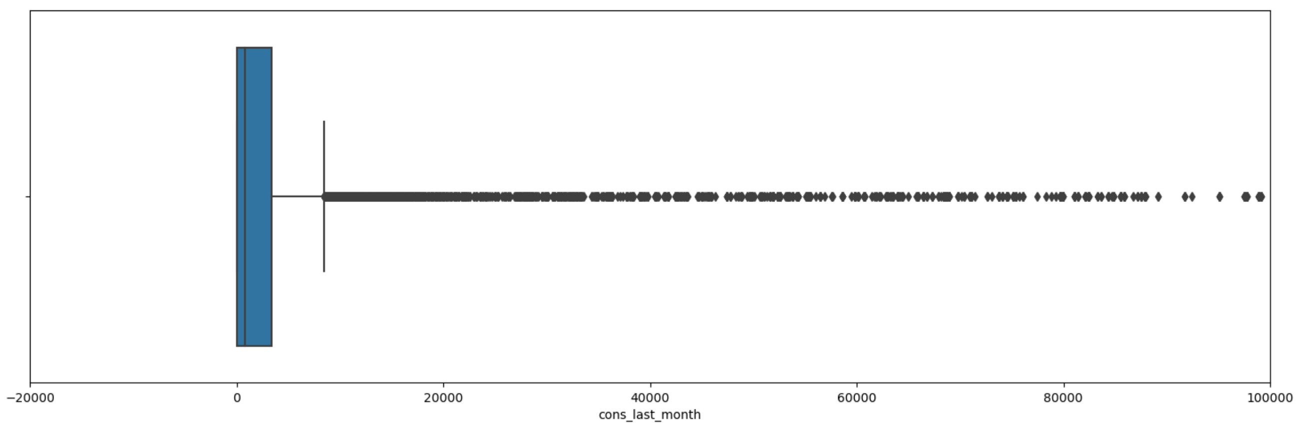
Looks like there's some possible outliers, Lets visualize the outliers

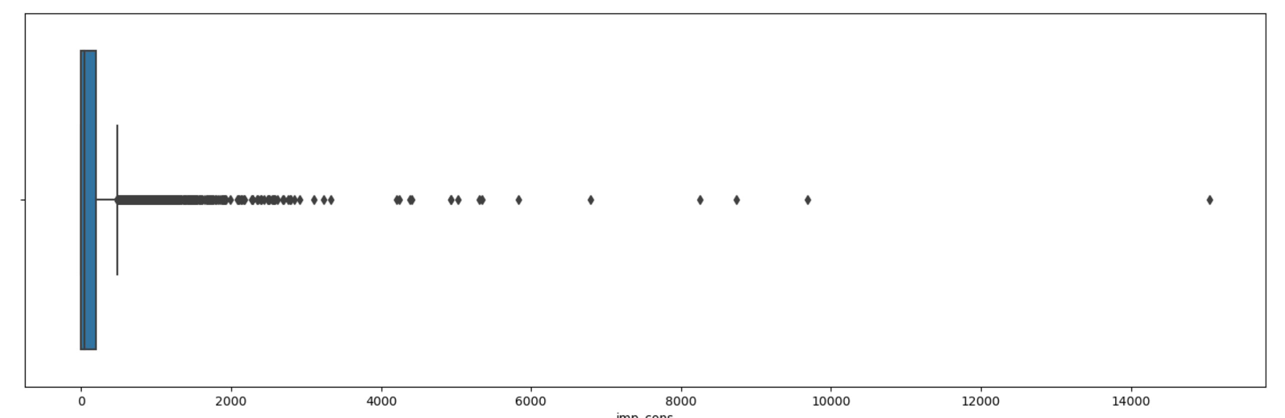
In [177]:
```
fig, axs=plt.subplots(nrows=4, figsize=(18,25))

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()
```

```
C:\Users\sudee\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\sudee\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\sudee\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\sudee\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
```









We'll try and deal with skewness and outliers later.

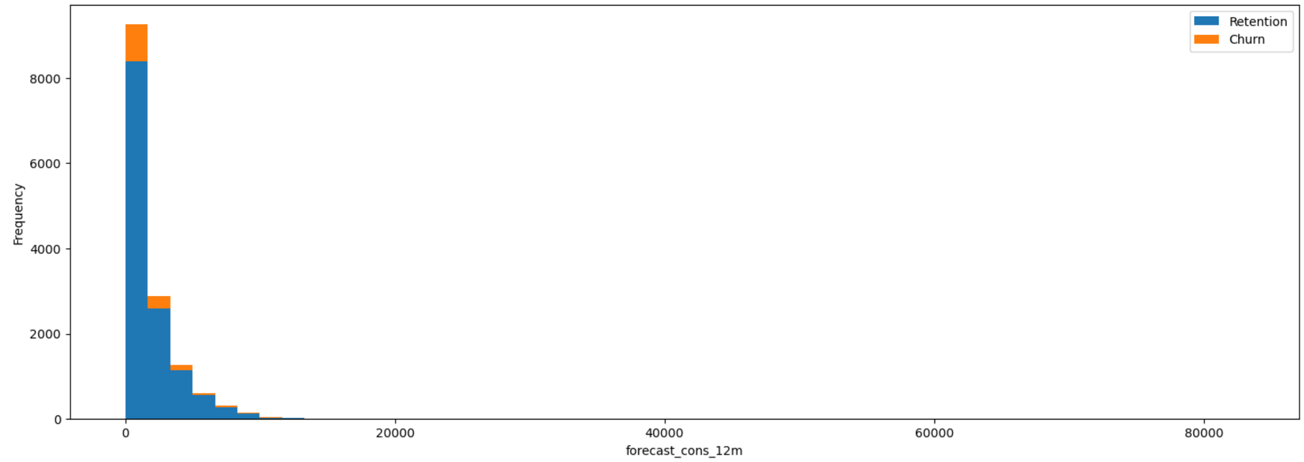
Forecast

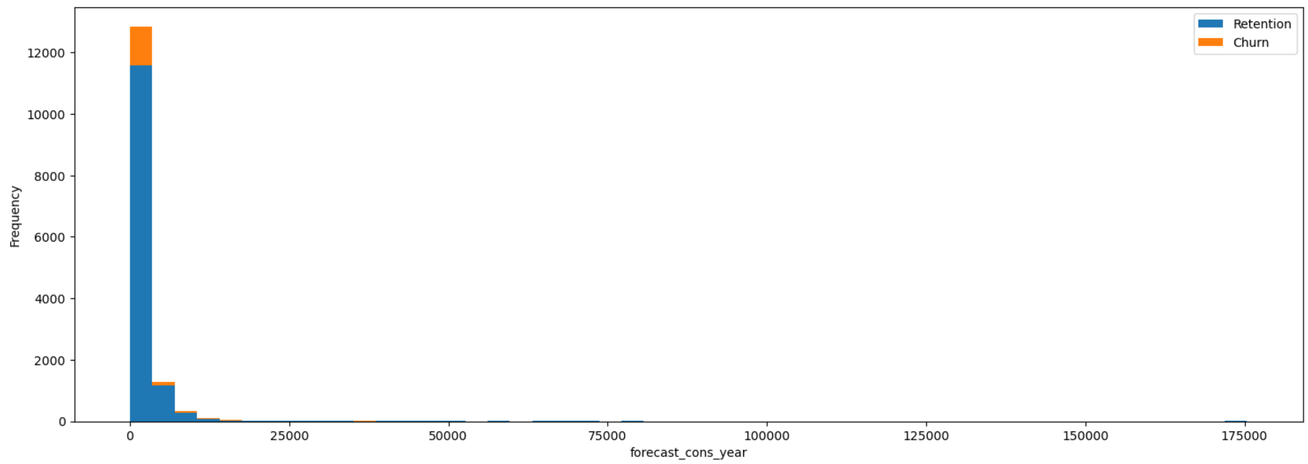
In [183]:
```
forecast = client_df[['id','forecast_cons_12m','forecast_cons_year',
                      'forecast_discount_energy','forecast_meter_rent_12m',
                      'forecast_price_energy_off_peak','forecast_price_energy_peak',
                      'forecast_price_pow_off_peak','churn']]
forecast.head(2)
```

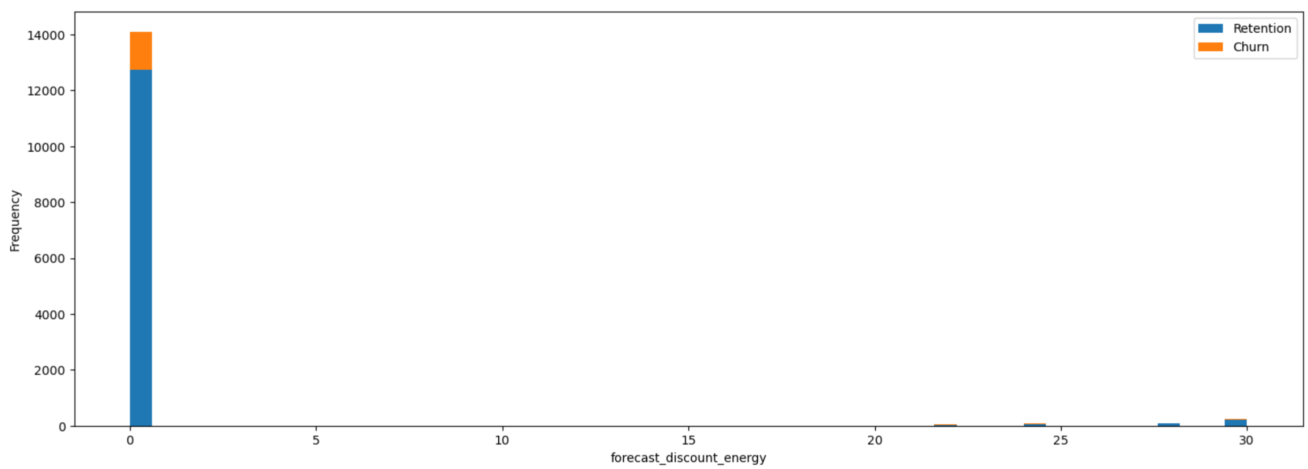
Out[183]:

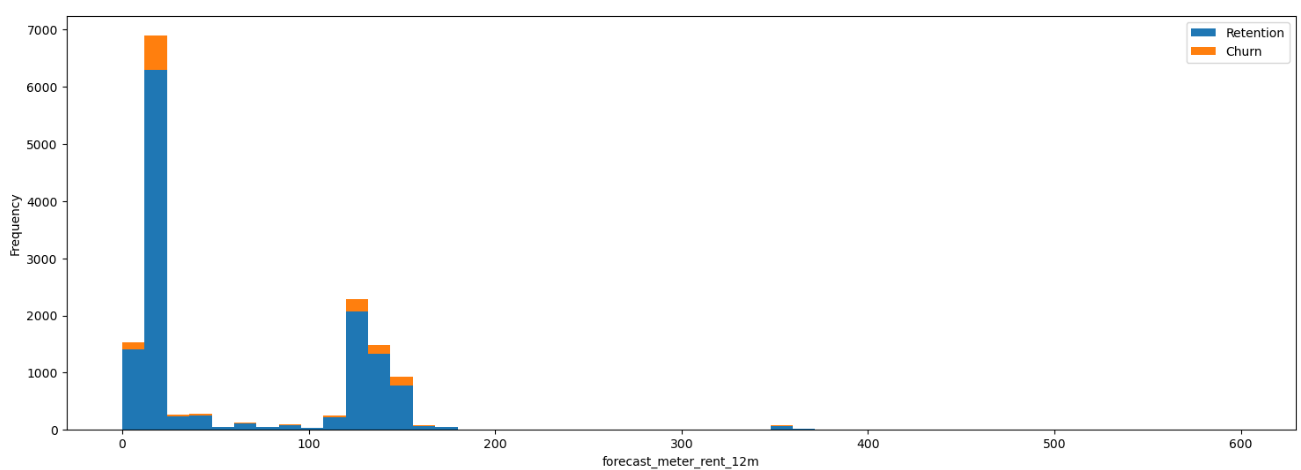
st_cons_year	forecast_discount_energy	forecast_meter_rent_12m	forecast_price_energy_off_peak	forecast_price_energy_peak	forecast_price_pow_off_peak	churn
0	0.0	1.78	0.114481	0.098142	40.606701	1
0	0.0	16.27	0.145711	0.000000	44.311378	0

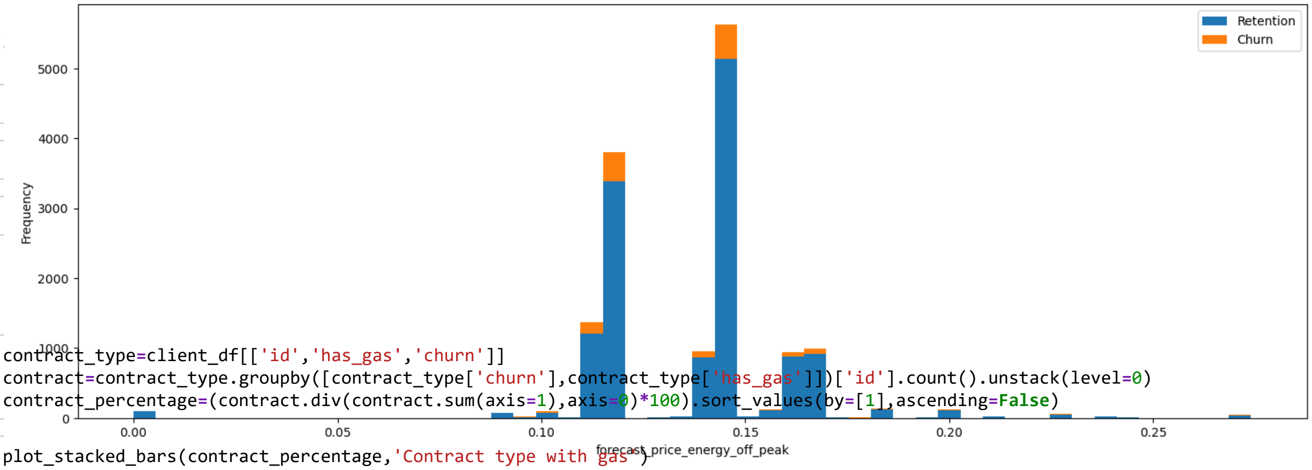
In [187]:
```
fig,axs=plt.subplots(nrows=7,figsize=(18,50))
plot_distribution(client_df,'forecast_cons_12m',axs[0])
plot_distribution(client_df,'forecast_cons_year',axs[1])
plot_distribution(client_df,'forecast_discount_energy',axs[2])
plot_distribution(client_df,'forecast_meter_rent_12m',axs[3])
plot_distribution(client_df,'forecast_price_energy_off_peak',axs[4])
plot_distribution(client_df,'forecast_price_energy_peak',axs[5])
plot_distribution(client_df,'forecast_price_pow_off_peak',axs[6])
```


Retention
Churn
Frequency
forecast_cons_12m
0
2000
4000
6000
8000
20000
40000
60000
80000


Retention
Churn
Frequency
forecast_cons_year
0
2000
4000
6000
8000
10000
12000
25000
50000
75000
100000
125000
150000
175000

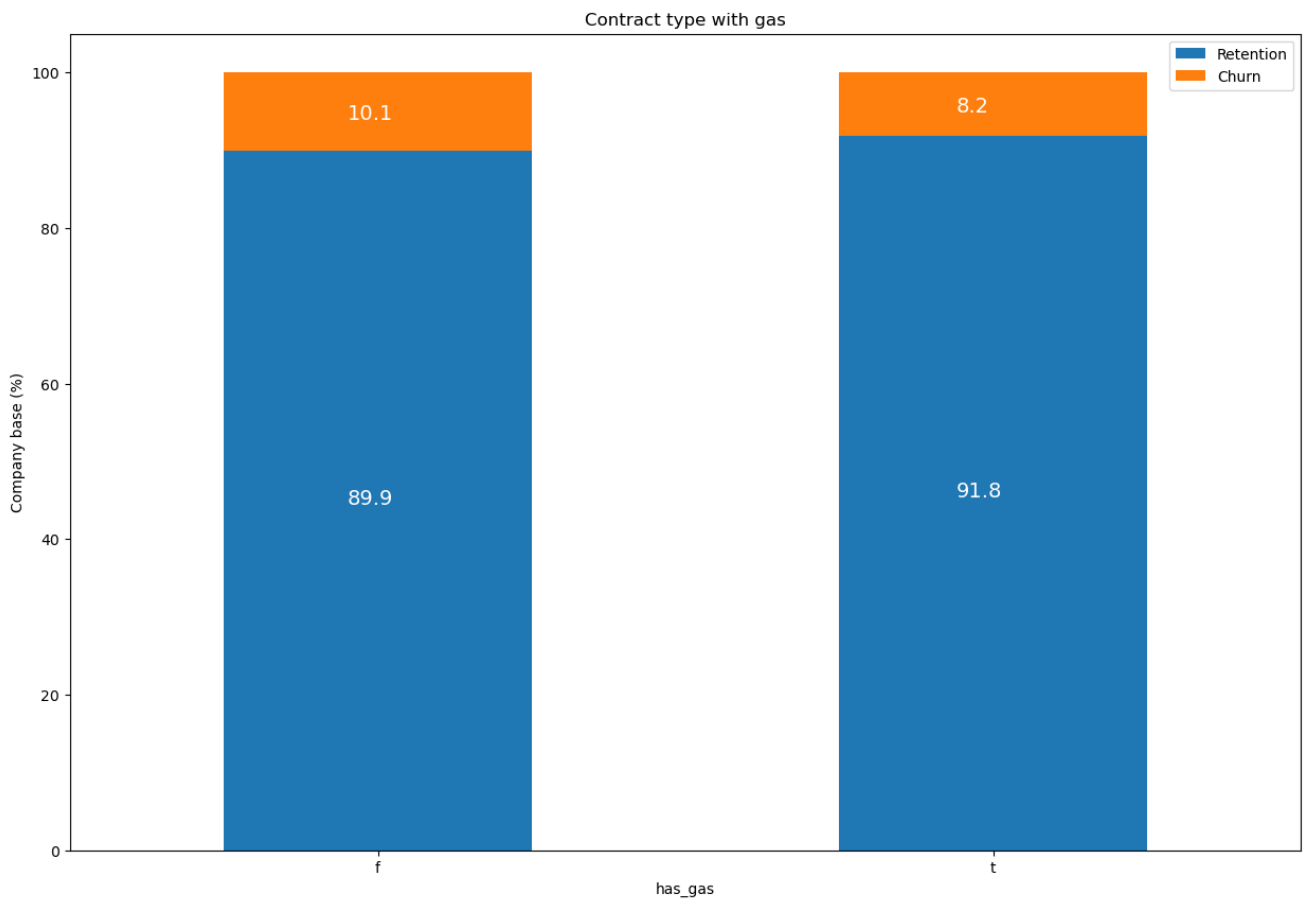

Retention
Churn
Frequency
forecast_discount_energy
0
2000
4000
6000
8000
10000
12000
14000
5
10
15
20
25
30

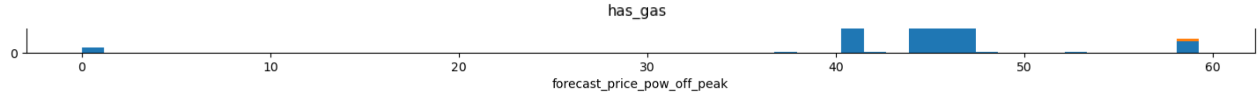

Retention
Churn
Frequency
forecast_meter_rent_12m
0
1000
2000
3000
4000
5000
6000
7000
100
200
300
400
500
600



In [196]:
```
contract_type=client_df[['id','has_gas','churn']]
contract=contract_type.groupby([contract_type['churn'],contract_type['has_gas']])['id'].count().unstack(level=0)
contract_percentage=(contract.div(contract.sum(axis=1),axis=0)*100).sort_values(by=[1],ascending=False)
```

In [197]:
```
plot_stacked_bars(contract_percentage,'Contract type with gas')
```





Margins

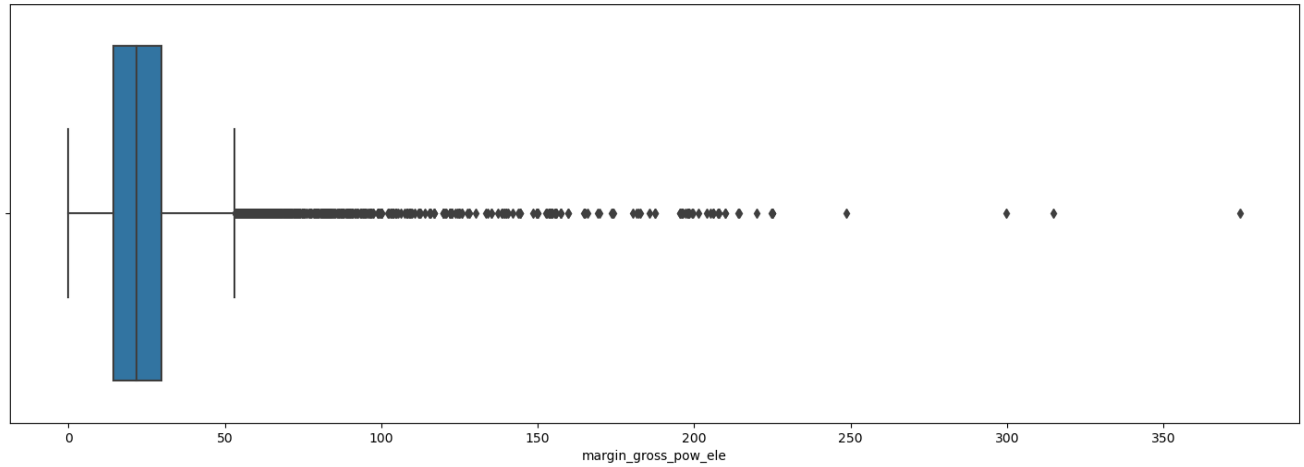
In [198]:
```
margin=client_df[['id','margin_gross_pow_ele','margin_net_pow_ele','net_margin']]
margin.head(2)
```

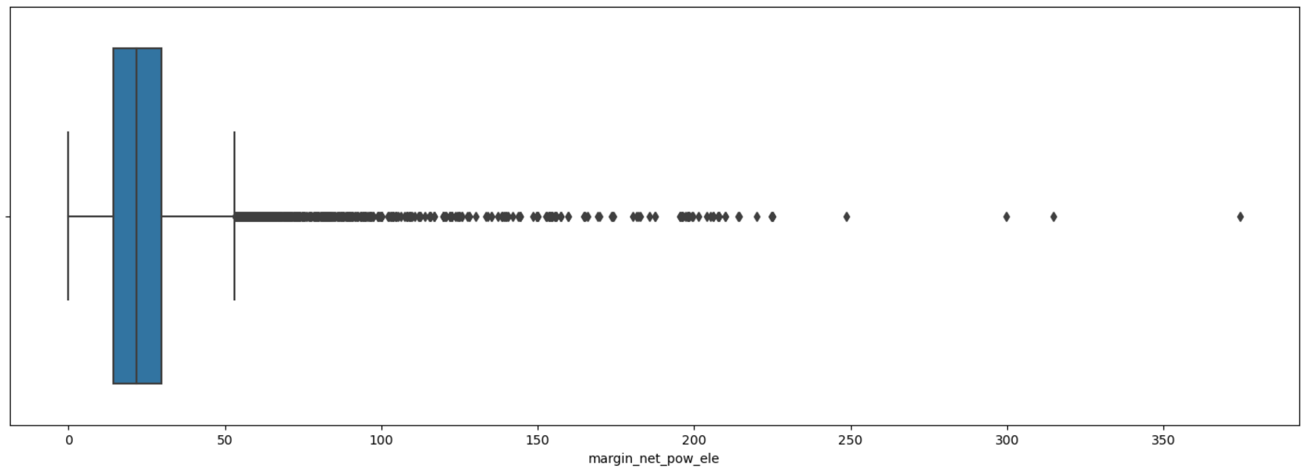
Out[198]:

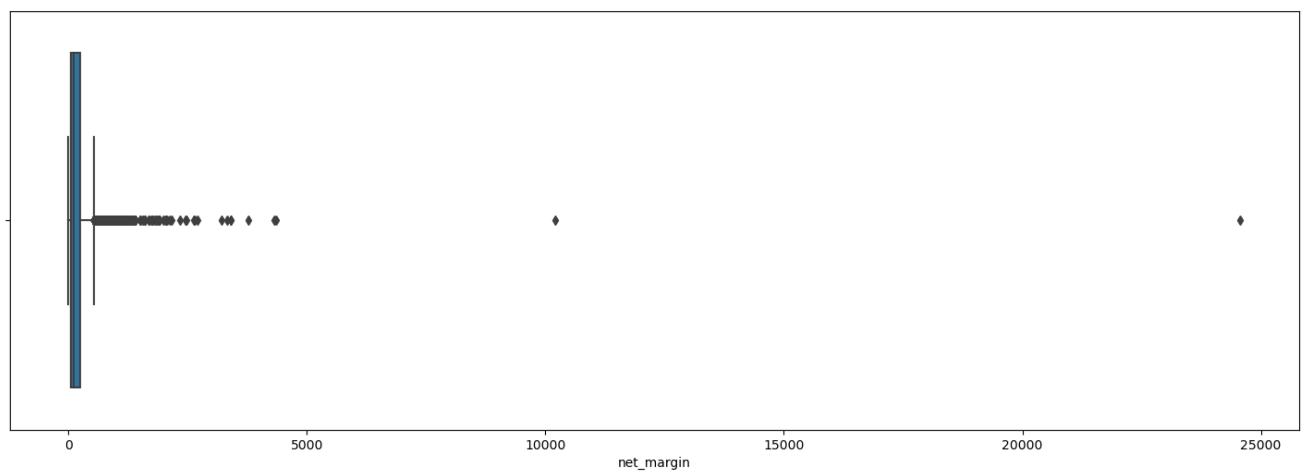
	id	margin_gross_pow_ele	margin_net_pow_ele	net_margin
0	24011ae4ebbe3035111d65fa7c15bc57	25.44	25.44	678.99
1	d29c2c54acc38ff3c0614d0a653813dd	16.38	16.38	18.89

In [201]:
```
fig, axs=plt.subplots(nrows=3,figsize=(18,20))
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])

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()
```

```
C:\Users\sudee\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\sudee\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\sudee\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
```







We have some outliers in Margin as well, we can deal with all the outliers later

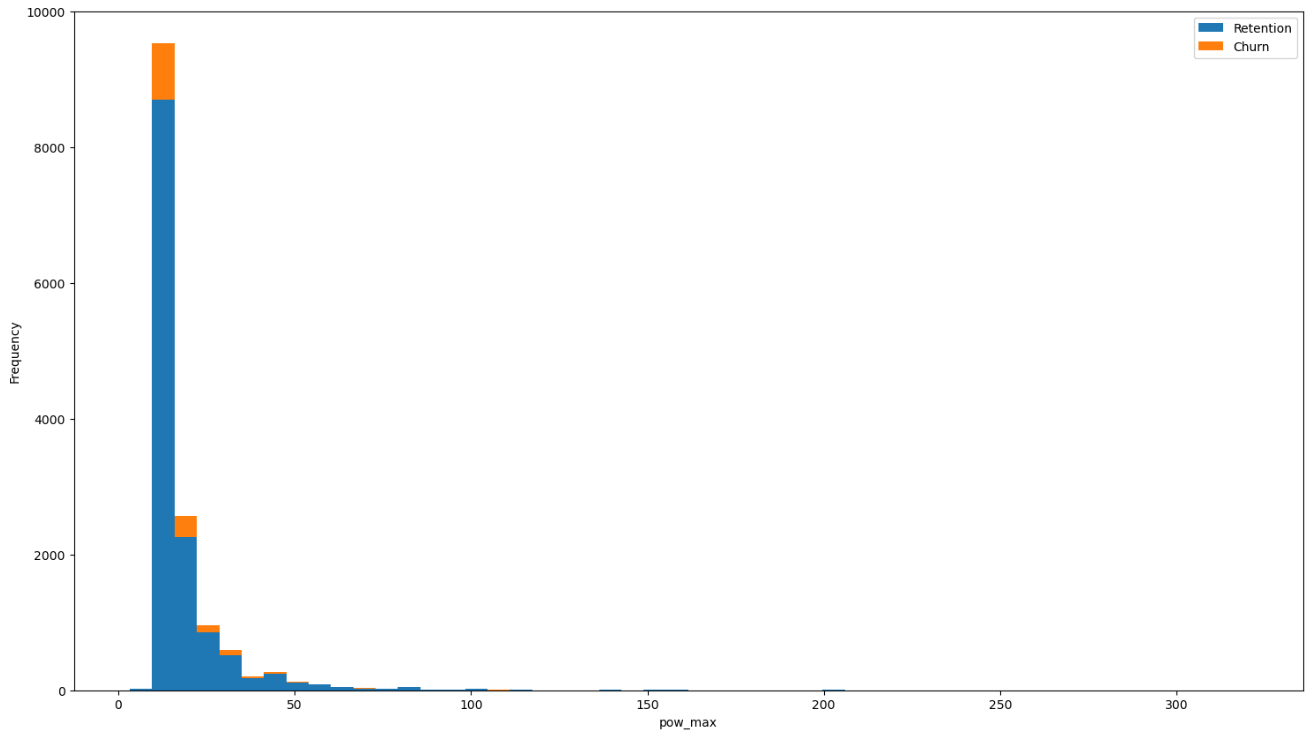
Subscribed Power

In [202]:
```
power=client_df[['id','pow_max','churn']]
power.head(2)
```

Out[202]:

	id	pow_max	churn
0	24011ae4ebbe3035111d65fa7c15bc57	43.648	1
1	d29c2c54acc38ff3c0614d0a653813dd	13.800	0

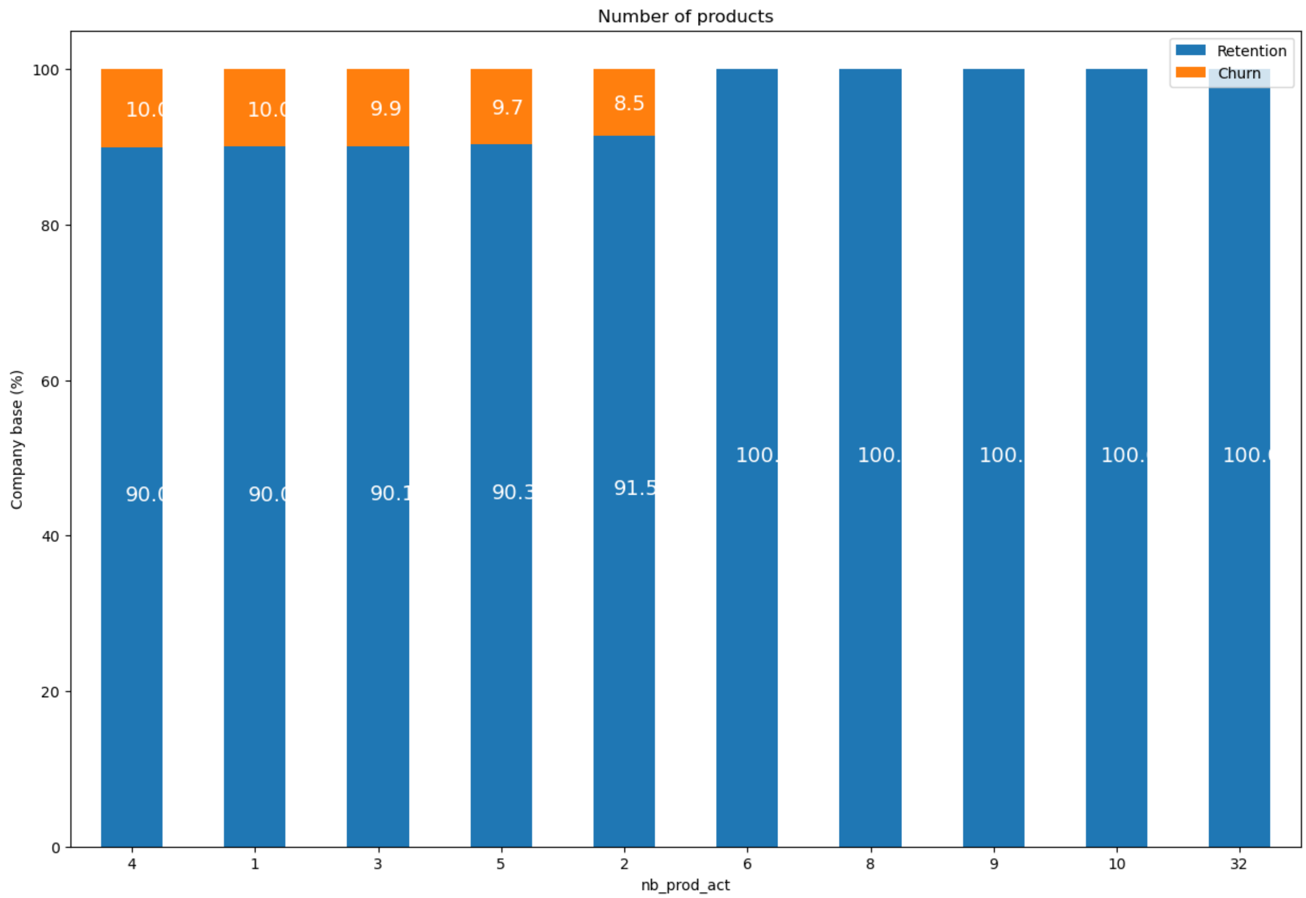
In [203]:
```
fig, axs=plt.subplots(nrows=1,figsize=(18,10))
plot_distribution(power,'pow_max',axs)
```



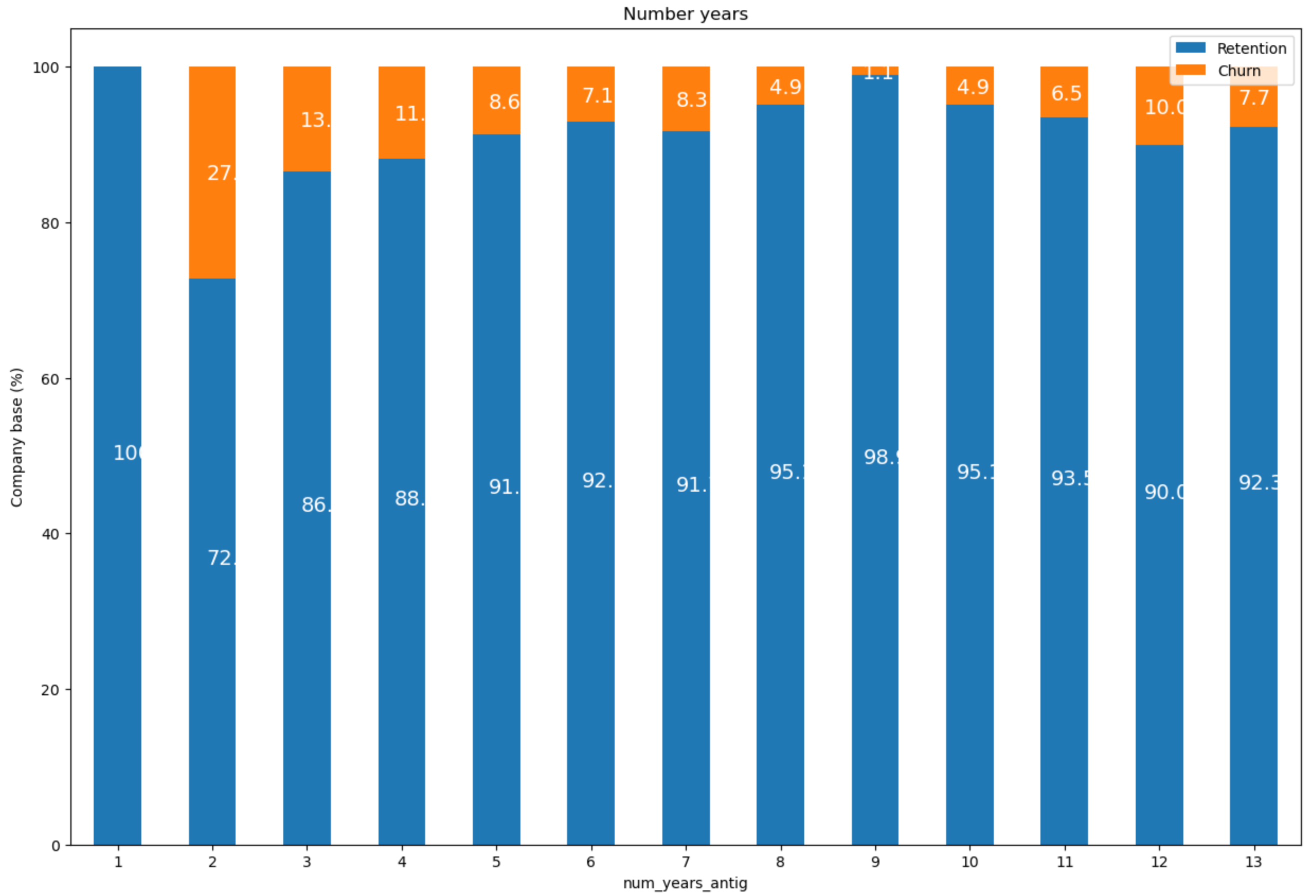
Other Columns

In [204]:
```
others=client_df[['id','nb_prod_act','num_years_antig','origin_up','churn']]
products=others.groupby([others['nb_prod_act'],others['churn']])['id'].count().unstack(level=1)
product_percentage=(products.div(products.sum(axis=1),axis=0)*100).sort_values(by=[1],ascending=False)
```

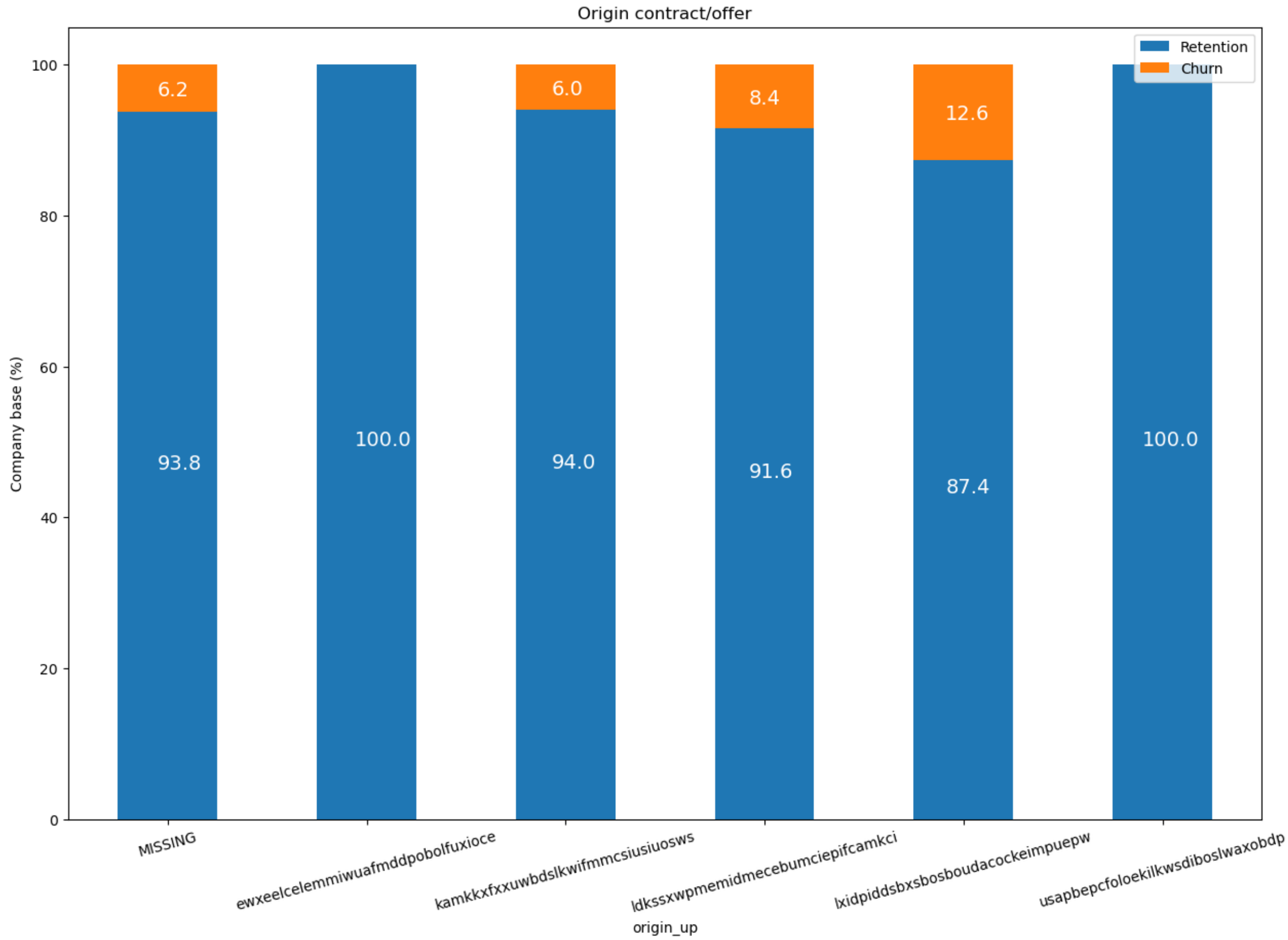
In [205]:
```
plot_stacked_bars(product_percentage,'Number of products')
```



In [206]:
```
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 [208]:
```
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",rot_=15)
```



Hypothesis Testing

```
Now, after exploring the data, its time to investigate whether price sensitivity has some influence on the churning. First we
need to define price sensitivity.
Since, we have consumption data for each companies for the year 2015, we will create new features to measure price sensitivity
using the average of the year, the last 6 months and the last 3 months.
```

In [265]:
```
#Transform the columns to datetime type

client_df['date_activ']=pd.to_datetime(client_df['date_activ'],format='%Y-%m-%d')
client_df["date_end"] = pd.to_datetime(client_df["date_end"], format='%Y-%m-%d')
client_df["date_modif_prod"] = pd.to_datetime(client_df["date_modif_prod"], format='%Y-%m-%d')
client_df["date_renewal"] = pd.to_datetime(client_df["date_renewal"], format='%Y-%m-%d')
price_df['price_date'] = pd.to_datetime(price_df['price_date'], format='%Y-%m-%d')
```

In [266]:
```
price_df['price_date'].describe()
```

```
C:\Users\sudee\AppData\Local\Temp\ipykernel_30232\3024386980.py:1: FutureWarning: Treating datetime data as categorical rather
than numeric in `.describe` is deprecated and will be removed in a future version of pandas. Specify `datetime_is_numeric=True`
to silence this warning and adopt the future behavior now.
  price_df['price_date'].describe()
```

Out[266]:
```
count                  193002
unique                     12
top       2015-08-01 00:00:00
freq                    16094
first     2015-01-01 00:00:00
last      2015-12-01 00:00:00
Name: price_date, dtype: object
```

In [268]:
```
price_df.head(1)
```

Out[268]:

	id	price_date	price_off_peak_var	price_peak_var	price_mid_peak_var	price_off_peak_fix	price_peak_fix	price_mid_peak_fix
0	038af19179925da21a25619c5a24b745	2015-01-01	0.151367	0.0	0.0	44.266931	0.0	0.0

In [303]:
```
#Create mean average
mean_year = price_df.groupby(['id']).mean().reset_index()
mean_6m = price_df[price_df['price_date'] > '2015-06-01'].groupby(['id']).mean().reset_index()
mean_3m = price_df[price_df['price_date'] > '2015-10-01'].groupby(['id']).mean().reset_index()
```

In [304]:
```
mean_year.head(1)
```

Out[304]:

	id	price_off_peak_var	price_peak_var	price_mid_peak_var	price_off_peak_fix	price_peak_fix	price_mid_peak_fix
0	0002203ffbb812588b632b9e628cc38d	0.124338	0.103794	0.07316	40.701732	24.421038	16.280694

In [305]:
```
#Combining into single dataframe

mean_year = mean_year.rename(
    index=str,
    columns={
        'price_off_peak_var':'mean_year_price_off_peak_var',
        'price_peak_var':'mean_year_price_peak_var',
        'price_mid_peak_var':'mean_year_price_mid_peak_var',
        'price_off_peak_fix':'mean_year_price_off_peak_fix',
        'price_peak_fix':'mean_year_price_peak_fix',
        'price_mid_peak_fix':'mean_year_price_mid_peak_fix'
    })

mean_6m = mean_6m.rename(
    index=str,
    columns={
        'price_off_peak_var':'mean_6m_price_off_peak_var',
        'price_peak_var':'mean_6m_price_peak_var',
        'price_mid_peak_var':'mean_6m_price_mid_peak_var',
        'price_off_peak_fix':'mean_6m_price_off_peak_fix',
        'price_peak_fix':'mean_6m_price_peak_fix',
        'price_mid_peak_fix':'mean_6m_price_mid_peak_fix'
    })


mean_3m = mean_3m.rename(
    index=str,
    columns={
        'price_off_peak_var':'mean_3m_price_off_peak_var',
        'price_peak_var':'mean_3m_price_peak_var',
        'price_mid_peak_var':'mean_3m_price_mid_peak_var',
        'price_off_peak_fix':'mean_3m_price_off_peak_fix',
        'price_peak_fix':'mean_3m_price_peak_fix',
        'price_mid_peak_fix':'mean_3m_price_mid_peak_fix'
    })
```

In [306]:
```
mean_6m.head(1)
```

Out[306]:

	id	mean_6m_price_off_peak_var	mean_6m_price_peak_var	mean_6m_price_mid_peak_var	mean_6m_price_off_peak_fix	mean_
0	0002203ffbb812588b632b9e628cc38d	0.121266	0.102368	0.073728	40.728885	

In [309]:
```
mean_3m.head(1)
```

Out[309]:

	id	mean_3m_price_off_peak_var	mean_3m_price_peak_var	mean_3m_price_mid_peak_var	mean_3m_price_off_peak_fix	mean_
0	0002203ffbb812588b632b9e628cc38d	0.119906	0.101673	0.073719	40.728885	

In [311]:
```
mean_year['mean_year_price_off_peak']=mean_year['mean_year_price_off_peak_var']+mean_year['mean_year_price_off_peak_fix']
mean_year['mean_year_price_peak']=mean_year['mean_year_price_peak_var']+mean_year['mean_year_price_peak_fix']
mean_year['mean_year_price_mid_peak']=mean_year['mean_year_price_mid_peak_var']+mean_year['mean_year_price_mid_peak_fix']

mean_6m['mean_6m_price_off_peak']=mean_6m['mean_6m_price_off_peak_var']+mean_6m['mean_6m_price_off_peak_fix']
mean_6m['mean_6m_price_peak']=mean_6m['mean_6m_price_peak_var']+mean_6m['mean_6m_price_peak_fix']
mean_6m['mean_6m_price_mid_peak']=mean_6m['mean_6m_price_mid_peak_var']+mean_6m['mean_6m_price_mid_peak_fix']

mean_3m['mean_3m_price_off_peak']=mean_3m['mean_3m_price_off_peak_var']+mean_3m['mean_3m_price_off_peak_fix']
mean_3m['mean_3m_price_peak']=mean_3m['mean_3m_price_peak_var']+mean_3m['mean_3m_price_peak_fix']
mean_3m['mean_3m_price_mid_peak']=mean_3m['mean_3m_price_mid_peak_var']+mean_3m['mean_3m_price_mid_peak_fix']
```

In [312]:
```
#Merge into 1 DataFrame

price_features=pd.merge(mean_year,mean_6m,on='id')
price_features=pd.merge(price_features,mean_3m,on='id')
```

In [313]:
```
price_features.head()
```

Out[313]:

ır	mean_3m_price_off_peak_fix	mean_3m_price_peak_fix	mean_3m_price_mid_peak_fix	mean_3m_price_off_peak	mean_3m_price_peak	mean_3m_price_mid_peak
9	40.728885	24.43733	16.291555	40.848791	24.539003	16.365274
0	44.444710	0.00000	0.000000	44.588653	0.000000	0.000000
0	45.944710	0.00000	0.000000	46.145990	0.000000	0.000000
9	40.728885	24.43733	16.291555	40.841953	24.532715	16.360964
0	44.266930	0.00000	0.000000	44.412370	0.000000	0.000000

Now, lets merge the churn data and see whether price sensitivity has any corelation with churn

In [317]:
```
price_analysis=pd.merge(price_features,client_df[['id','churn']], on='id')
price_analysis.head(10)
```

Out[317]:

	id	mean_year_price_off_peak_var	mean_year_price_peak_var	mean_year_price_mid_peak_var	mean_year_price_off_peak_fix
0	0002203ffbb812588b632b9e628cc38d	0.124338	0.103794	0.073160	40.701732
1	0004351ebdd665e6ee664792efc4fd13	0.146426	0.000000	0.000000	44.385450
2	0010bcc39e42b3c2131ed2ce55246e3c	0.181558	0.000000	0.000000	45.319710
3	00114d74e963e47177db89bc70108537	0.147926	0.000000	0.000000	44.266930
4	0013f326a839a2f6ad87a1859952d227	0.126076	0.105542	0.074921	40.728885
5	00184e957277eeef733a7b563fdabd06	0.147637	0.000000	0.000000	44.266930
6	001987ed9dbdab4efa274a9c7233e1f4	0.122756	0.102290	0.073030	40.647427
7	0019baf3ed1242cd99b3cb592030446f	0.267449	0.000000	0.000000	57.961930
8	001cb880d847a0b63b404a48e50aec17	0.145099	0.000000	0.000000	44.370635
9	001cd16732dc7d5bdf46b0d49996c271	0.172369	0.000000	0.000000	45.189154

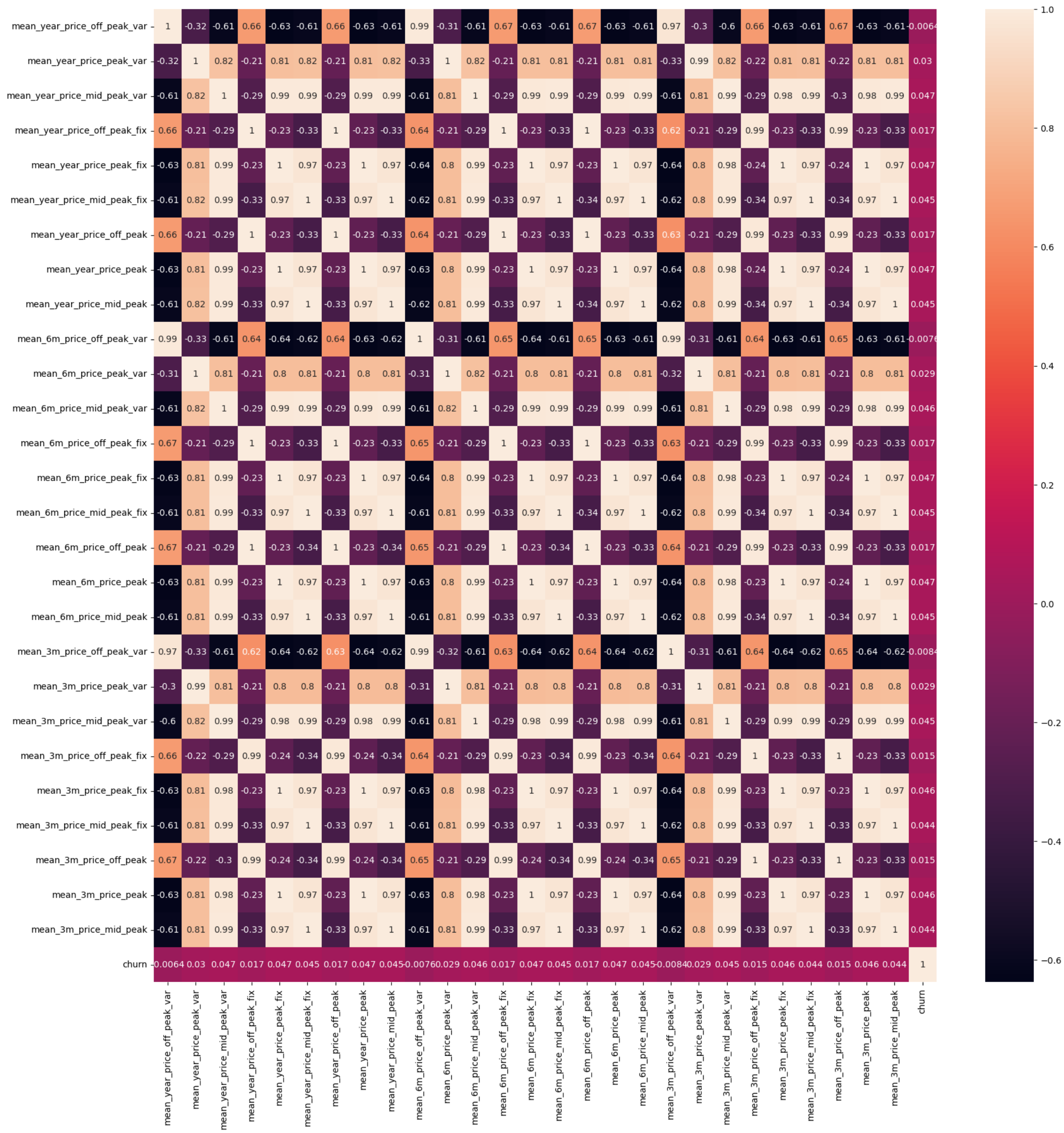
10 rows × 29 columns

In [319]:
```
rice_off_peak','mean_year_price_peak','mean_6m_price_off_peak','mean_6m_price_peak','mean_3m_price_off_peak','mean_3m_price_peak'
n].head(10)
```

Out[319]:

	mean_year_price_off_peak	mean_year_price_peak	mean_6m_price_off_peak	mean_6m_price_peak	mean_3m_price_off_peak	mean_3m_price_peak	churn
0	40.826071	24.524832	40.850151	24.539698	40.848791	24.539003	0
1	44.531877	0.000000	44.589397	0.000000	44.588653	0.000000	0
2	45.501268	0.000000	46.146734	0.000000	46.145990	0.000000	0
3	44.414856	0.000000	44.413114	0.000000	44.412370	0.000000	0
4	40.854961	24.542872	40.851892	24.541438	40.850532	24.540743	0
5	44.414568	0.000000	44.412767	0.000000	44.412023	0.000000	0
6	40.770183	24.490746	40.848420	24.538516	40.847060	24.537821	0
7	58.229380	0.000000	59.482798	0.000000	59.482054	0.000000	1
8	44.515734	0.000000	44.585626	0.000000	44.584882	0.000000	1
9	45.361523	0.000000	46.303670	0.000000	46.644852	0.000000	0

In [324]:
```
corr=price_analysis.corr()

#Ploting Correlation

plt.figure(figsize=(20,20))
sns.heatmap(corr, xticklabels=corr.columns.values, yticklabels=corr.columns.values,annot=True,annot_kws={'size':10})

#Axis tick size

plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.show()
```



This corelation plot shows higher magnitude of corelation between other price sensitivity variables, however overall the corelation
with churn is very low. This indicates that there is a weak linear relationship between price sensitivity and churn. This suggests that for
price sensitivity ti be a major driver for pretending churn, we may need to engineer the feature differently.

In [326]:
```
merged_data=pd.merge(client_df.drop(columns=['churn']),price_analysis, on ='id')
merged_data.head(3)
```

Out[326]:

n_3m_price_off_peak_fix	mean_3m_price_peak_fix	mean_3m_price_mid_peak_fix	mean_3m_price_off_peak	mean_3m_price_peak	mean_3m_price_mid_peak	churn
42.497907	12.218665	8.145777	42.629663	12.311304	8.182687	1
44.444710	0.000000	0.000000	44.592310	0.000000	0.000000	0
44.444710	0.000000	0.000000	44.612508	0.088409	0.000000	0

In [327]:
```
merged_data.to_csv('clean_data_after_eda.csv')
```

In [ ]: