# BCG Data Science and Analytics Virtual Experience Program

## Task 2: Exploratory Data analysis

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*Here is the background information on your task*

The BCG project team thinks that building a churn model to understand whether price sensitivity is the largest driver of churn has potential. The client has sent over some data and the AD wants you to perform some exploratory data analysis.

The data that was sent over includes:

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

Please submit analysis in a code script, notebook, or PDF format.

Please note, there are multiple ways to approach the task and that the sample answer is just one way to do it.

## Here is your task

*Sub-Task 1:*

Perform some exploratory data analysis. Look into the data types, data statistics, specific parameters, and variable distributions. This first subtask is for you to gain a holistic understanding of the dataset. You should spend around 1 hour on this.

*Sub-Task 2:*

Verify the hypothesis of price sensitivity being to some extent correlated with churn. It is up to you to define price sensitivity and calculate it. You should spend around 30 minutes on this.

*Sub-Task 3:*

Prepare a half-page summary or slide of key findings and add some suggestions for data augmentation – which other sources of data should the client provide you with and which open source datasets might be useful? You should spend 10-15 minutes on this.

For your final deliverable, please submit your analysis (in the form of a jupyter notebook, code script or PDF) as well as your half-page summary document.

Note: Use the 2 datasets within the additional resources for this task and if you're unsure on where to start with visualizing data, use the accompanying links. Be sure to also use the data description document to understand what the columns represent. The task description document outlines the higher-level motivation of the project. Finally, use the eda_starter.ipynb file to get started with some helper functions and methods.

If you are stuck: Think about ways you can define price sensitivity. Make sure to think of all possible ways and investigate them.

```
# import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.preprocessing import StandardScaler
```

```
# Set the working directory
import io
%cd "E:\FORAGE\BCG\Task 2 - Exploratory Data Analysis"
```

```
e:\FORAGE\BCG\Task 2 - Exploratory Data Analysis
```

```
# read the data
client_data = pd.read_csv("client_data.csv")
price_data = pd.read_csv("price_data.csv")
```

```
# check dimensions of our data
print("Client Data:", client_data.shape)
print("Price Data:", price_data.shape)
```

```
Client Data: (14606, 26)
Price Data: (193002, 8)
```

As you can see that there are 14606 observations and 26 features in client data and 193002 observations and 8 features in price data.

```
# Let's look at the first five records from each dataset
print("Client Dataset:")
client_data.head()
```

```
Client Dataset:

                                 id                     channel_sales  
\
0  24011ae4ebbe3035111d65fa7c15bc57  foosdfpfkusacimwkcsosbicdxkicaua   

1  d29c2c54acc38ff3c0614d0a653813dd                           MISSING   

2  764c75f661154dac3a6c254cd082ea7d  foosdfpfkusacimwkcsosbicdxkicaua   

3  bba03439a292a1e166f80264c16191cb  lmkebamcaaclubfxadlmueccxoimlema   

4  149d57cf92fc41cf94415803a877cb4b                           MISSING   
```

```
   cons_12m  cons_gas_12m  cons_last_month  date_activ    date_end  \
0         0         54946                0  2013-06-15  2016-06-15
1      4660             0                0  2009-08-21  2016-08-30
2       544             0                0  2010-04-16  2016-04-16
3      1584             0                0  2010-03-30  2016-03-30
4      4425             0              526  2010-01-13  2016-03-07

  date_modif_prod date_renewal  forecast_cons_12m  ...  has_gas
imp_cons  \
0      2015-11-01   2015-06-23               0.00  ...        t
0.00
1      2009-08-21   2015-08-31             189.95  ...        f
0.00
2      2010-04-16   2015-04-17              47.96  ...        f
0.00
3      2010-03-30   2015-03-31             240.04  ...        f
0.00
4      2010-01-13   2015-03-09             445.75  ...        f
52.32

   margin_gross_pow_ele  margin_net_pow_ele  nb_prod_act
net_margin  \
0                 25.44               25.44            2      678.99

1                 16.38               16.38            1       18.89

2                 28.60               28.60            1        6.60

3                 30.22               30.22            1       25.46

4                 44.91               44.91            1       47.98


  num_years_antig                         origin_up  pow_max  churn
0               3  lxidpiddsbxsbosboudacockeimpuepw   43.648      1
1               6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.800      0
2               6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.856      0
3               6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.200      0
4               6  kamkkxfxxuwbdslkwifmmcsiusiuosws   19.800      0

[5 rows x 26 columns]
```

```python
print("Price Data:")
price_data.head()
```

```
Price Data:

                                 id  price_date  price_off_peak_var  \
0  038af19179925da21a25619c5a24b745  2015-01-01            0.151367
```

```
1  038af19179925da21a25619c5a24b745  2015-02-01           0.151367
2  038af19179925da21a25619c5a24b745  2015-03-01           0.151367
3  038af19179925da21a25619c5a24b745  2015-04-01           0.149626
4  038af19179925da21a25619c5a24b745  2015-05-01           0.149626

   price_peak_var  price_mid_peak_var  price_off_peak_fix
price_peak_fix  \
0             0.0                 0.0           44.266931
0.0
1             0.0                 0.0           44.266931
0.0
2             0.0                 0.0           44.266931
0.0
3             0.0                 0.0           44.266931
0.0
4             0.0                 0.0           44.266931
0.0

   price_mid_peak_fix
0                 0.0
1                 0.0
2                 0.0
3                 0.0
4                 0.0
```

### Data Description:

client_data.csv

● id = client company identifier ● activity_new = category of the company's activity ● 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 consumption of the last month ● date_activ = date of activation of the contract ● date_end = registered date of the end of the contract ● date_modif_prod = date of the last modification of the product ● date_renewal = date of the next contract renewal ● forecast_cons_12m = forecasted electricity consumption for next 12 months ● forecast_cons_year = forecasted electricity consumption for the next calendar year ● forecast_discount_energy = forecasted value of current discount ● forecast_meter_rent_12m = forecasted bill of meter rental for the next 2 months ● forecast_price_energy_off_peak = forecasted energy price for 1st period (off peak) ● forecast_price_energy_peak = forecasted energy price for 2nd period (peak) ● forecast_price_pow_off_peak = forecasted power price for 1st period (off peak) ● 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 ● churn = has the client churned over the next 3 months price_data.csv

● id = client company identifier ● price_date = reference date ● price_off_peak_var = price of energy for the 1st period (off peak) ● price_peak_var = price of energy for the 2nd period (peak) ● price_mid_peak_var = price of energy for the 3rd period (mid peak) ● price_off_peak_fix = price of power for the 1st period (off peak) ● price_peak_fix = price of power for the 2nd period (peak) ● price_mid_peak_fix = price of power for the 3rd period (mid peak)

Note: some fields are hashed text strings. This preserves the privacy of the original data but the commercial meaning is retained and so they may have predictive power

```
# Let's check the datatypes present in both of the dataset
print("Client Dataset:")
client_data.dtypes
```

```
Client Dataset:

id                                 object
channel_sales                      object
cons_12m                            int64
cons_gas_12m                        int64
cons_last_month                     int64
date_activ                         object
date_end                           object
date_modif_prod                    object
date_renewal                       object
forecast_cons_12m                 float64
forecast_cons_year                  int64
forecast_discount_energy          float64
forecast_meter_rent_12m           float64
forecast_price_energy_off_peak    float64
forecast_price_energy_peak        float64
forecast_price_pow_off_peak       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
dtype: object
```

```
print("Price Data:")
price_data.dtypes
```

```
Price Data:
```

```
id                       object
price_date               object
price_off_peak_var      float64
price_peak_var          float64
price_mid_peak_var      float64
price_off_peak_fix      float64
price_peak_fix          float64
price_mid_peak_fix      float64
dtype: object
```

```python
# Descriptive Statistics of each data
print("Client Data:")
client_data.describe()
```

```
Client Data:

           cons_12m  cons_gas_12m  cons_last_month  forecast_cons_12m
\
count  1.460600e+04  1.460600e+04     14606.000000       14606.000000

mean   1.592203e+05  2.809238e+04     16090.269752        1868.614880

std    5.734653e+05  1.629731e+05     64364.196422        2387.571531

min    0.000000e+00  0.000000e+00         0.000000           0.000000

25%    5.674750e+03  0.000000e+00         0.000000         494.995000

50%    1.411550e+04  0.000000e+00       792.500000        1112.875000

75%    4.076375e+04  0.000000e+00      3383.000000        2401.790000

max    6.207104e+06  4.154590e+06    771203.000000       82902.830000


       forecast_cons_year  forecast_discount_energy
forecast_meter_rent_12m  \
count        14606.000000              14606.000000
14606.000000
mean          1399.762906                  0.966726
63.086871
std           3247.786255                  5.108289
66.165783
min              0.000000                  0.000000
0.000000
25%              0.000000                  0.000000
16.180000
50%            314.000000                  0.000000
18.795000
75%           1745.750000                  0.000000
```

```
131.030000
max        175375.000000                  30.000000
599.310000

       forecast_price_energy_off_peak  forecast_price_energy_peak  \
count                    14606.000000                14606.000000
mean                         0.137283                    0.050491
std                          0.024623                    0.049037
min                          0.000000                    0.000000
25%                          0.116340                    0.000000
50%                          0.143166                    0.084138
75%                          0.146348                    0.098837
max                          0.273963                    0.195975

       forecast_price_pow_off_peak      imp_cons  margin_gross_pow_ele
\
count                 14606.000000  14606.000000          14606.000000

mean                     43.130056    152.786896             24.565121

std                       4.485988    341.369366             20.231172

min                       0.000000      0.000000              0.000000

25%                      40.606701      0.000000             14.280000

50%                      44.311378     37.395000             21.640000

75%                      44.311378    193.980000             29.880000

max                      59.266378  15042.790000            374.640000


       margin_net_pow_ele   nb_prod_act    net_margin  num_years_antig
\
count        14606.000000  14606.000000  14606.000000     14606.000000

mean            24.562517      1.292346    189.264522         4.997809

std             20.230280      0.709774    311.798130         1.611749

min              0.000000      1.000000      0.000000         1.000000

25%             14.280000      1.000000     50.712500         4.000000

50%             21.640000      1.000000    112.530000         5.000000

75%             29.880000      1.000000    243.097500         6.000000
```

```
max            374.640000     32.000000  24570.650000        13.000000


            pow_max         churn
count  14606.000000  14606.000000
mean      18.135136      0.097152
std       13.534743      0.296175
min        3.300000      0.000000
25%       12.500000      0.000000
50%       13.856000      0.000000
75%       19.172500      0.000000
max      320.000000      1.000000
```

```
print("Price Data:")
price_data.describe()
```

```
Price Data:

       price_off_peak_var  price_peak_var  price_mid_peak_var  \
count       193002.000000   193002.000000       193002.000000
mean             0.141027        0.054630            0.030496
std              0.025032        0.049924            0.036298
min              0.000000        0.000000            0.000000
25%              0.125976        0.000000            0.000000
50%              0.146033        0.085483            0.000000
75%              0.151635        0.101673            0.072558
max              0.280700        0.229788            0.114102

       price_off_peak_fix  price_peak_fix  price_mid_peak_fix
count       193002.000000   193002.000000       193002.000000
mean            43.334477       10.622875            6.409984
std              5.410297       12.841895            7.773592
min              0.000000        0.000000            0.000000
25%             40.728885        0.000000            0.000000
50%             44.266930        0.000000            0.000000
75%             44.444710       24.339581           16.226389
max             59.444710       36.490692           17.458221
```

```
# Let's check a brief overview of data
print("Client Data:")
client_data.info()
```

```
Client Data:
<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
```

```
print("Price Data:")
price_data.info()
```

```
Price Data:
<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
```

```
# Let's check for null values in our data
print("Missing values in Client Data:")
client_data.isnull().sum()
```

```
Missing values in Client Data:

id                                0
channel_sales                     0
cons_12m                          0
cons_gas_12m                      0
cons_last_month                   0
date_activ                        0
date_end                          0
date_modif_prod                   0
date_renewal                      0
forecast_cons_12m                 0
forecast_cons_year                0
forecast_discount_energy          0
forecast_meter_rent_12m           0
forecast_price_energy_off_peak    0
forecast_price_energy_peak        0
forecast_price_pow_off_peak       0
has_gas                           0
imp_cons                          0
margin_gross_pow_ele              0
margin_net_pow_ele                0
nb_prod_act                       0
net_margin                        0
num_years_antig                   0
origin_up                         0
pow_max                           0
churn                             0
dtype: int64
```

```
print("Missing values in Price Data:")
price_data.isnull().sum()
```

```
Missing values in Price Data:

id                    0
price_date            0
price_off_peak_var    0
price_peak_var        0
price_mid_peak_var    0
price_off_peak_fix    0
price_peak_fix        0
price_mid_peak_fix    0
dtype: int64
```

```
# Check for duplicate records in our data
print("Duplicate records in Client Data:")
client_data.duplicated().sum()
```

```
Duplicate records in Client Data:

0
```

```python
print("Duplicate records in Price Data:")
price_data.duplicated().sum()
```

```
Duplicate records in Price Data:
```

```
0
```

As you can see from above analysis that there are no missing values as well as duplicate records in both of the datasets. Next, we will perform some Exploratory Data Analysis on our datasets to gain more insights.

## Exploratory Data Analysis (EDA):

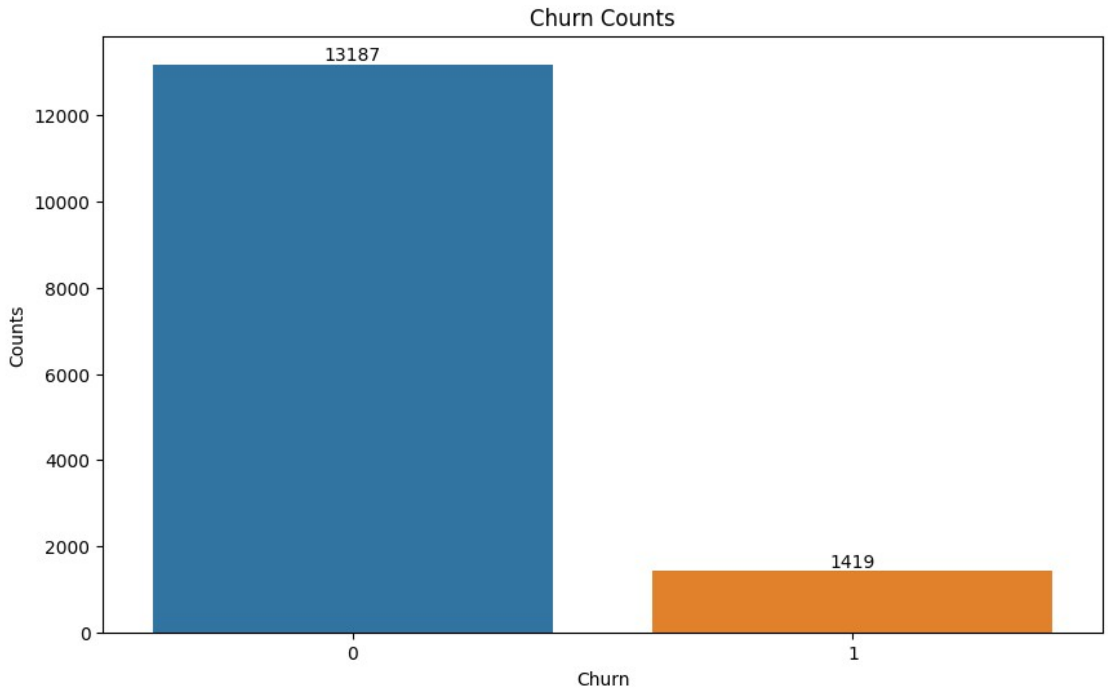
first we will label encode the data of columns channel_sales and origin_up for our better analysis.

Let's see the churn counts of the clients.

```python
client_data['churn'].value_counts()
```

```
0    13187
1     1419
Name: churn, dtype: int64
```

```python
# Let's plot above data
plt.figure(figsize=(10,6))
ax = sns.countplot(x='churn', data=client_data)
abs_val = client_data['churn'].value_counts().values
ax.bar_label(container=ax.containers[0], labels=abs_val)
plt.xlabel("Churn")
plt.ylabel("Counts")
plt.title("Churn Counts")
plt.show()
```




As you can see from above countplot the the number of clients that has been churned are 1419.

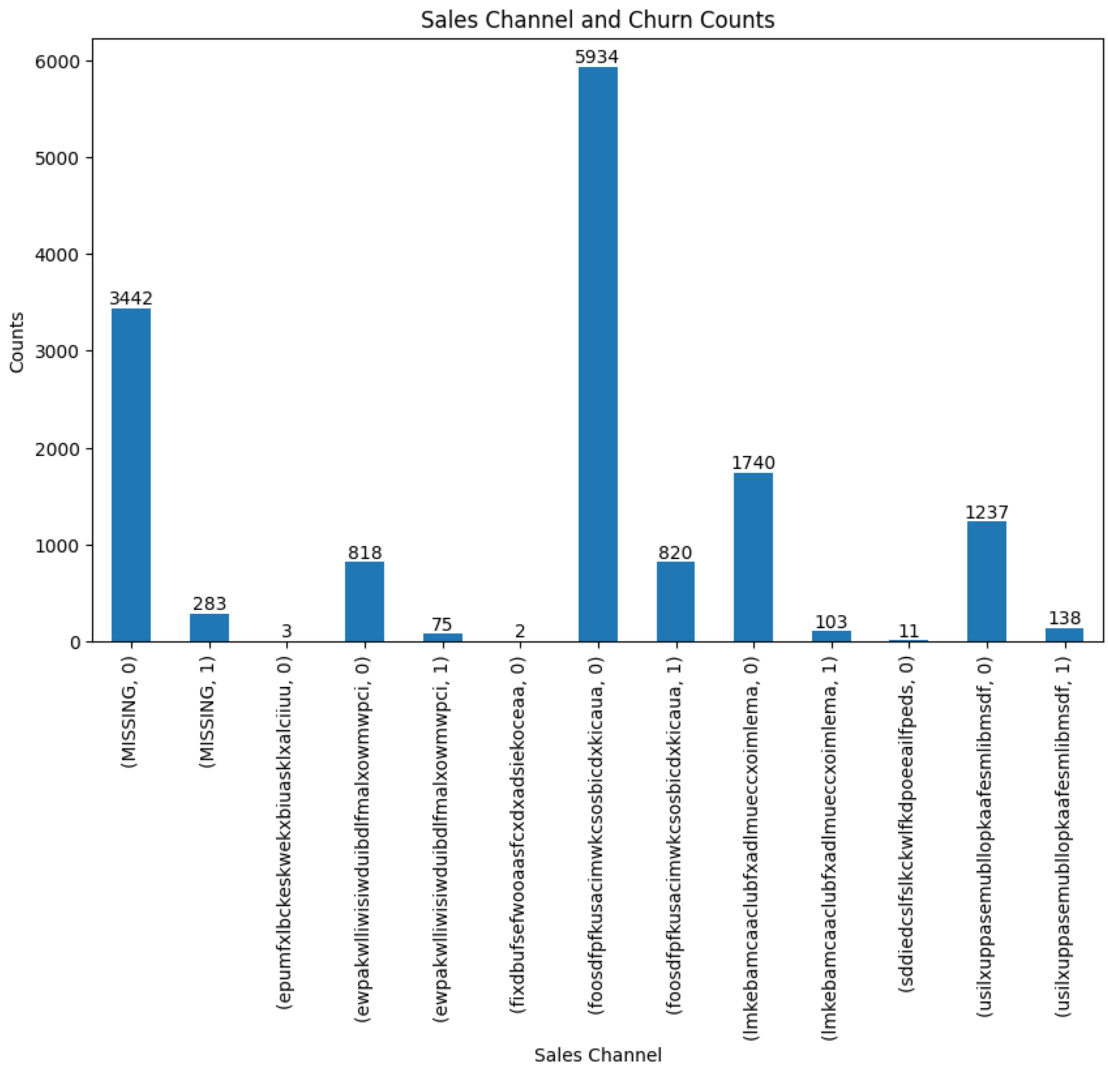
Let's visualize the code of the sales channel.

```
client_data.groupby(['channel_sales', 'churn'])
['churn'].count().sort_values(ascending=False)
```

```
channel_sales                      churn
foosdfpfkusacimwkcsosbicdxkicaua  0        5934
MISSING                           0        3442
lmkebamcaaclubfxadlmueccxoimlema  0        1740
usilxuppasemubllopkaafesmlibmsdf  0        1237
foosdfpfkusacimwkcsosbicdxkicaua  1         820
ewpakwlliwisiwduibdlfmalxowmwpci  0         818
MISSING                           1         283
usilxuppasemubllopkaafesmlibmsdf  1         138
lmkebamcaaclubfxadlmueccxoimlema  1         103
ewpakwlliwisiwduibdlfmalxowmwpci  1          75
sddiedcslfslkckwlfkdpoeeailfpeds  0          11
epumfxlbckeskwekxbiuasklxalciiuu  0           3
fixdbufsefwooaasfcxdxadsiekoceaa  0           2
Name: churn, dtype: int64
```

```
# Let's visualize above data using the countplot
plt.figure(figsize=(10,6))
ax = client_data.groupby(['channel_sales', 'churn'])
['churn'].count().plot(kind='bar')
abs_val = client_data.groupby(['channel_sales', 'churn'])
```

```
['churn'].count().values
ax.bar_label(container=ax.containers[0], labels=abs_val)
plt.xlabel("Sales Channel")
plt.ylabel("Counts")
plt.title("Sales Channel and Churn Counts")
plt.show()
```



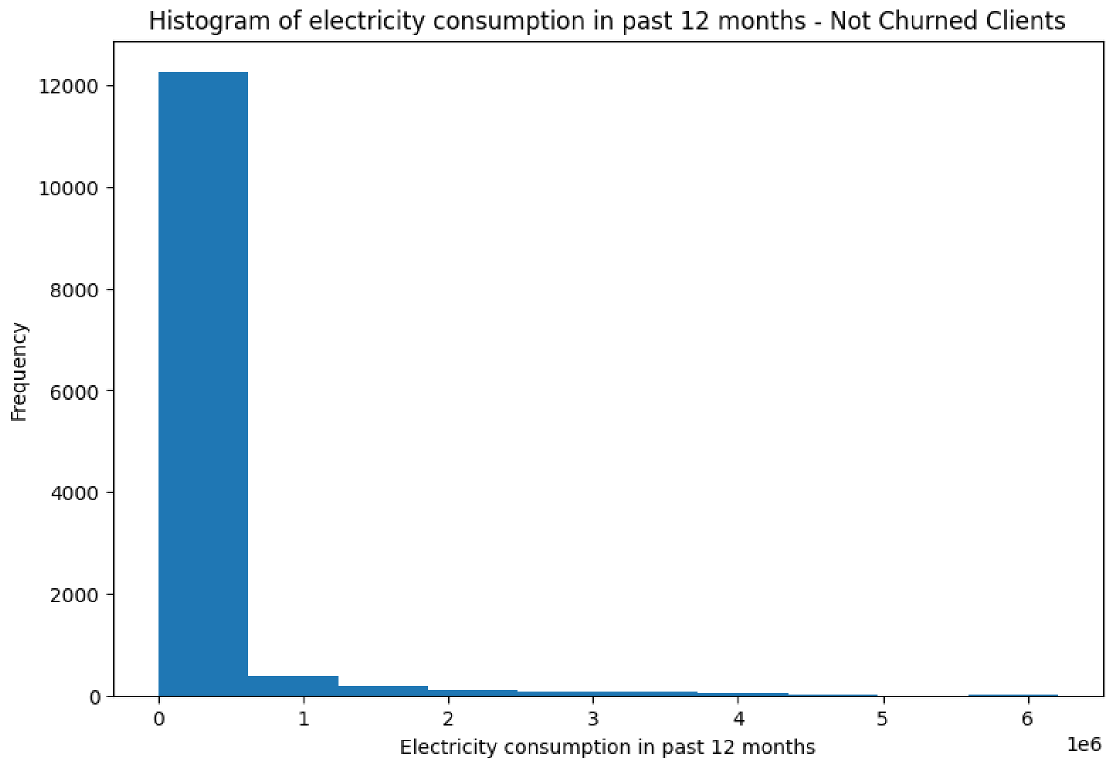

Let's see the electricity consumption of the past 12 months of the clients which did not churned.

```
not_churned = client_data[client_data['churn']==0]
not_churned['churn'].value_counts()
```

```
0    13187
Name: churn, dtype: int64
```

```
plt.figure(figsize=(9,6))
not_churned['cons_12m'].plot(kind='hist')
plt.xlabel('Electricity consumption in past 12 months')
```

```
plt.ylabel('Frequency')
plt.title("Histogram of electricity consumption in past 12 months - Not Churned Clients")
plt.show()
```

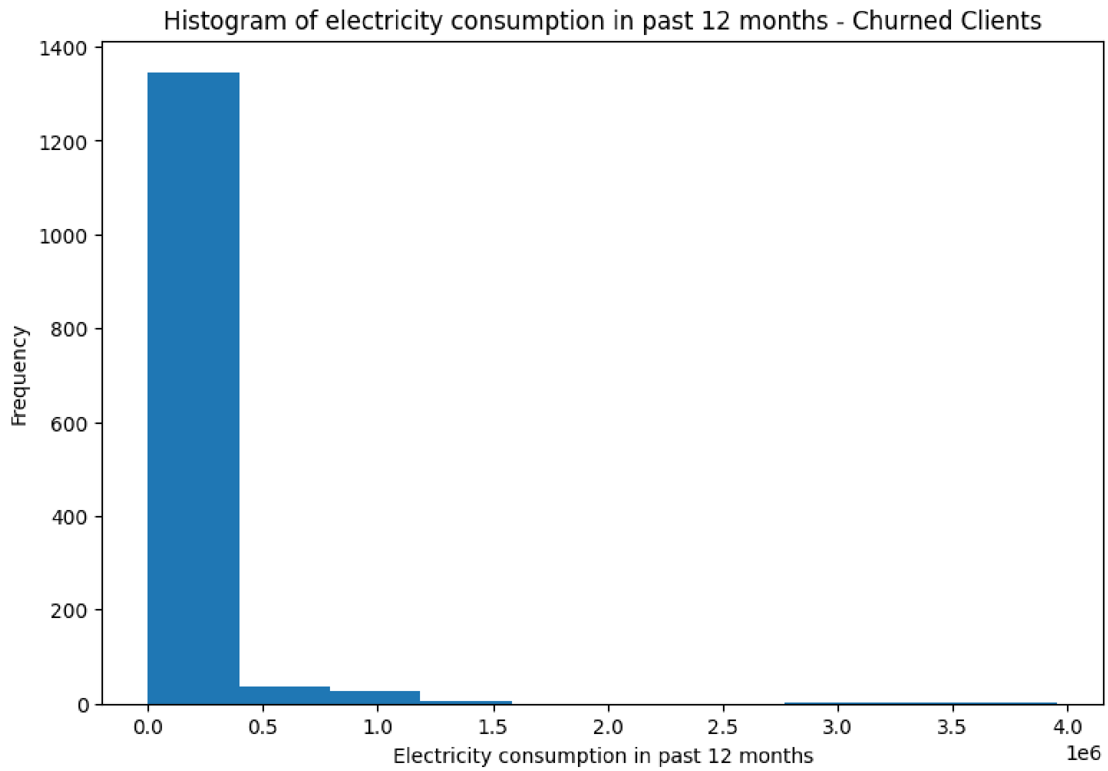



Let's see the electricity consumption of the past 12 months of the clients which are churned.

```
churned = client_data[client_data['churn']==1]
churned['churn'].value_counts()
```

```
1    1419
Name: churn, dtype: int64
```

```
plt.figure(figsize=(9,6))
churned['cons_12m'].plot(kind='hist')
plt.xlabel('Electricity consumption in past 12 months')
plt.ylabel('Frequency')
plt.title("Histogram of electricity consumption in past 12 months - Churned Clients")
plt.show()
```



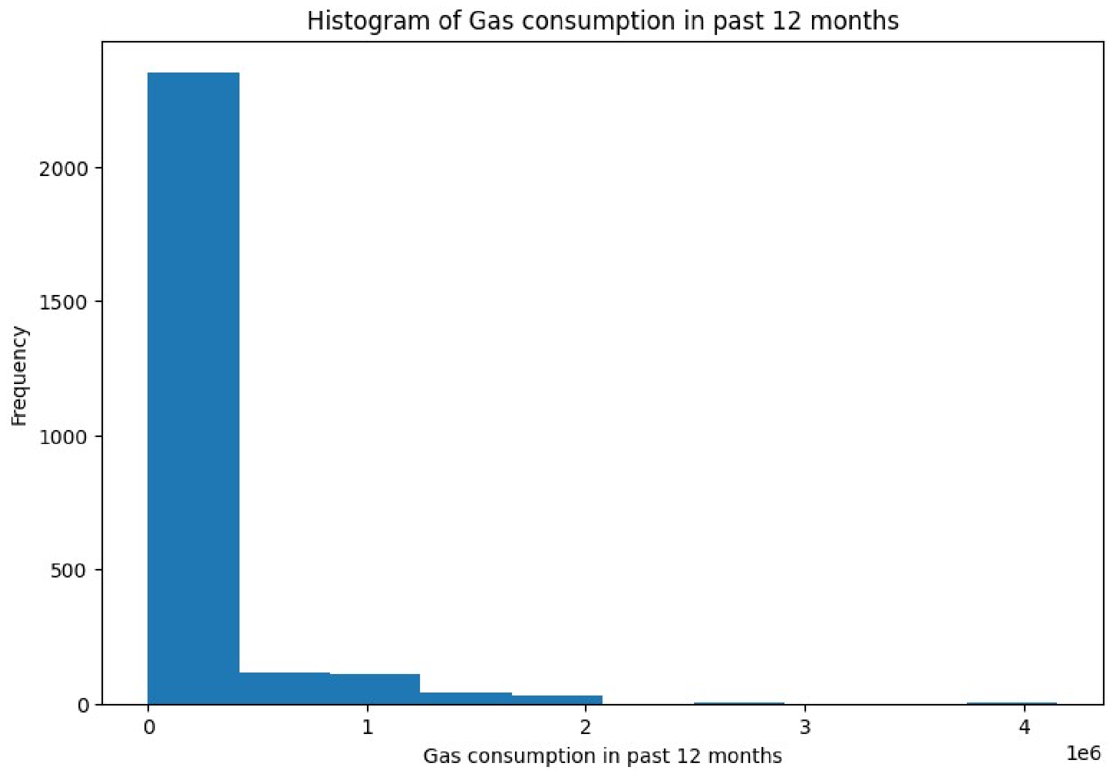

As you can see from above 2 histograms the we got a positively skewed distribution in each cases.

Now we will see the distribution for clients who also used gas.

```
gas_clients = client_data[client_data['has_gas']=='t']
gas_clients['has_gas'].value_counts()
```

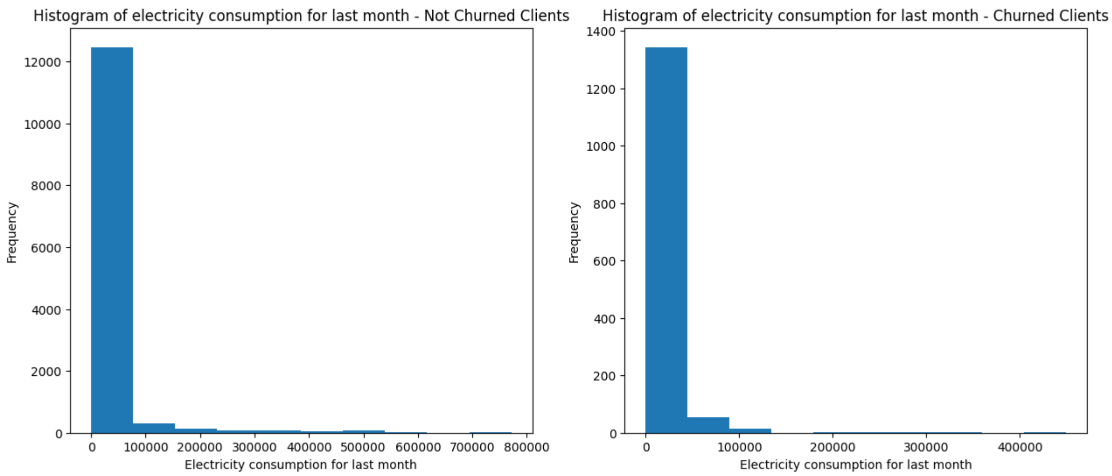
```
t    2651
Name: has_gas, dtype: int64
```

```
plt.figure(figsize=(9,6))
gas_clients['cons_gas_12m'].plot(kind='hist')
plt.xlabel('Gas consumption in past 12 months')
plt.ylabel('Frequency')
plt.title("Histogram of Gas consumption in past 12 months")
plt.show()
```



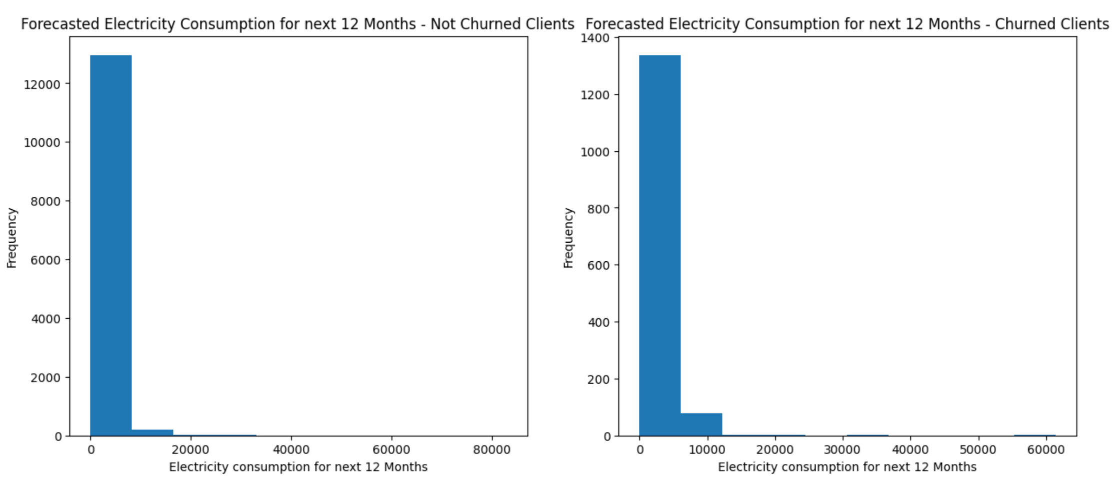

Now we will see the distribution of consumption of electricity in last month for churned as well as non-churned clients.

```
plt.figure(figsize=(15,6))

plt.subplot(121)
not_churned['cons_last_month'].plot(kind='hist')
plt.xlabel('Electricity consumption for last month')
plt.ylabel('Frequency')
plt.title("Histogram of electricity consumption for last month - Not Churned Clients")

plt.subplot(122)
churned['cons_last_month'].plot(kind='hist')
plt.xlabel('Electricity consumption for last month')
plt.ylabel('Frequency')
plt.title("Histogram of electricity consumption for last month - Churned Clients")

plt.show()
```



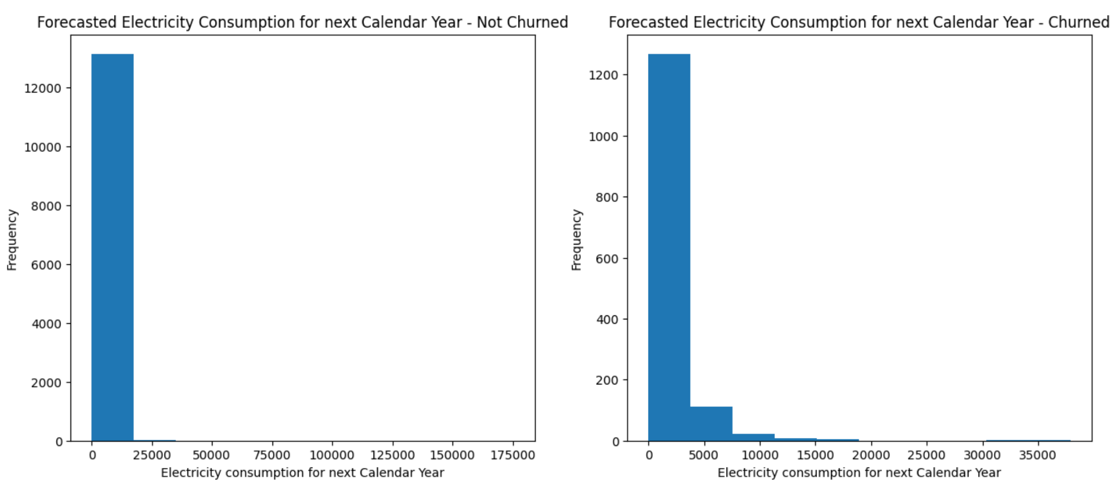

Forecasted Electricity Consumption for next 12 Months - Churned and Non-Churned Clients.

```
plt.figure(figsize=(15,6))

plt.subplot(121)
not_churned['forecast_cons_12m'].plot(kind='hist')
plt.xlabel('Electricity consumption for next 12 Months')
plt.ylabel('Frequency')
plt.title("Forecasted Electricity Consumption for next 12 Months - Not Churned Clients")

plt.subplot(122)
churned['forecast_cons_12m'].plot(kind='hist')
plt.xlabel('Electricity consumption for next 12 Months')
plt.ylabel('Frequency')
plt.title("Forecasted Electricity Consumption for next 12 Months - Churned Clients")

plt.show()
```



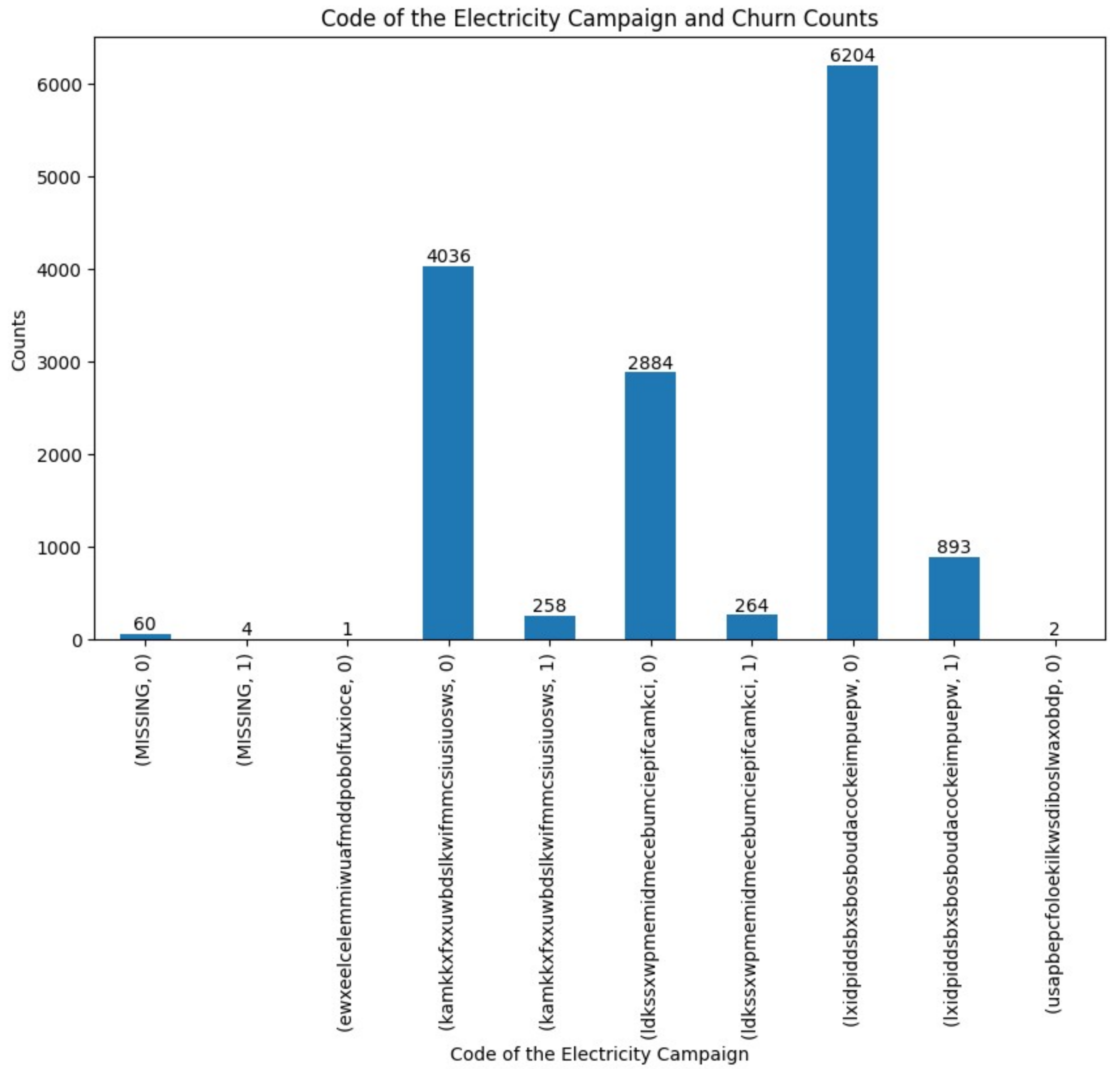
Forecasted Electricity Consumption for next Calendar Year - Churned and Non-Churned Clients.

```
plt.figure(figsize=(15,6))

plt.subplot(121)
not_churned['forecast_cons_year'].plot(kind='hist')
plt.xlabel('Electricity consumption for next Calendar Year')
plt.ylabel('Frequency')
plt.title("Forecasted Electricity Consumption for next Calendar Year - Not Churned")

plt.subplot(122)
churned['forecast_cons_year'].plot(kind='hist')
plt.xlabel('Electricity consumption for next Calendar Year')
plt.ylabel('Frequency')
plt.title("Forecasted Electricity Consumption for next Calendar Year - Churned")

plt.show()
```



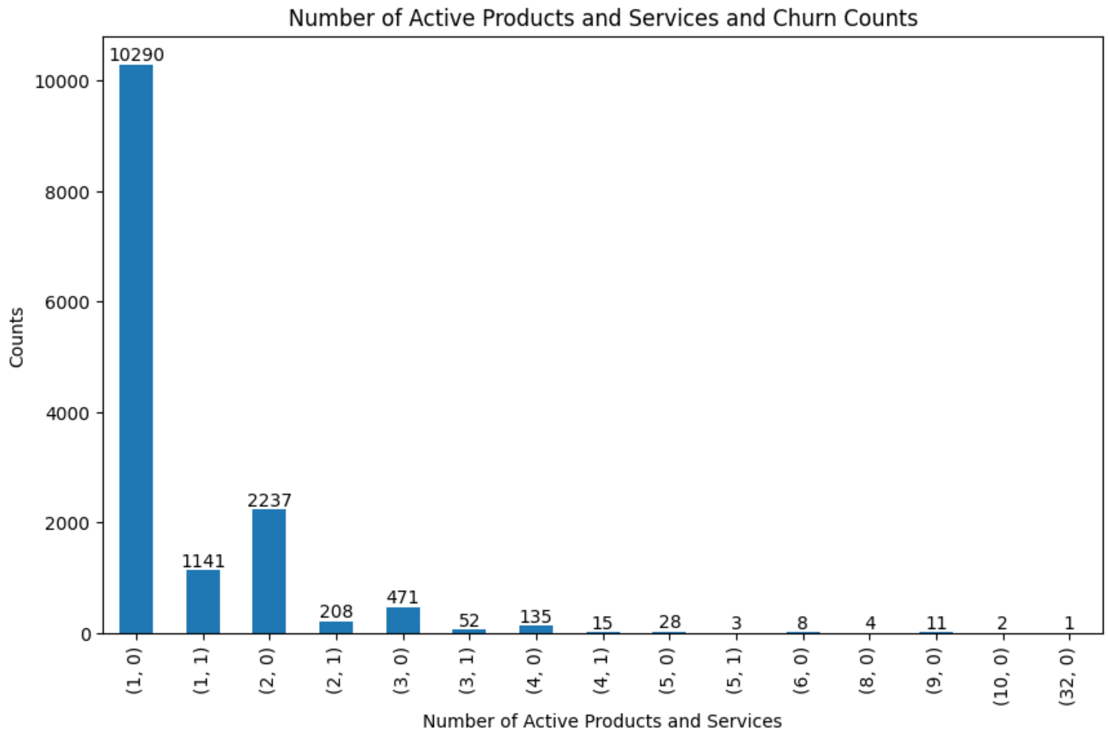

Code of the Electricity Campaign the Customer First Subscribed To Analysis

```
plt.figure(figsize=(10,6))
ax = client_data.groupby(['origin_up', 'churn'])
['churn'].count().plot(kind='bar')
abs_val = client_data.groupby(['origin_up', 'churn'])
['churn'].count().values
ax.bar_label(container=ax.containers[0], labels=abs_val)
plt.xlabel("Code of the Electricity Campaign")
plt.ylabel("Counts")
plt.title("Code of the Electricity Campaign and Churn Counts")
plt.show()
```



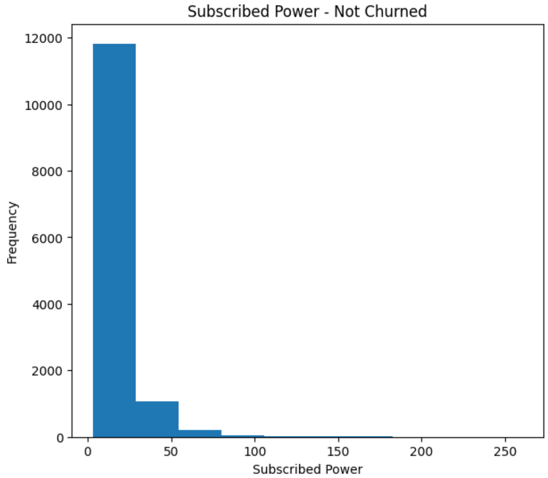

Number of Active Products and Services.

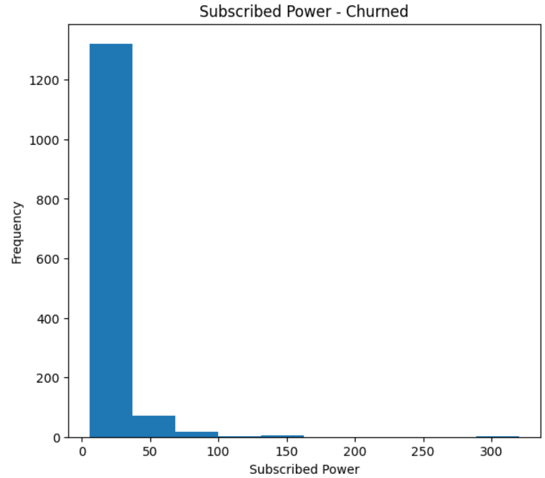
```
plt.figure(figsize=(10,6))
ax = client_data.groupby(['nb_prod_act', 'churn'])
['churn'].count().plot(kind='bar')
abs_val = client_data.groupby(['nb_prod_act', 'churn'])
['churn'].count().values
ax.bar_label(container=ax.containers[0], labels=abs_val)
plt.xlabel("Number of Active Products and Services")
plt.ylabel("Counts")
plt.title("Number of Active Products and Services and Churn Counts")
plt.show()
```




Subscribed Power

```
plt.figure(figsize=(15,6))

plt.subplot(121)
not_churned['pow_max'].plot(kind='hist')
plt.xlabel('Subscribed Power')
plt.ylabel('Frequency')
plt.title("Subscribed Power - Not Churned")

plt.subplot(122)
churned['pow_max'].plot(kind='hist')
plt.xlabel('Subscribed Power')
plt.ylabel('Frequency')
plt.title("Subscribed Power - Churned")

plt.show()
```



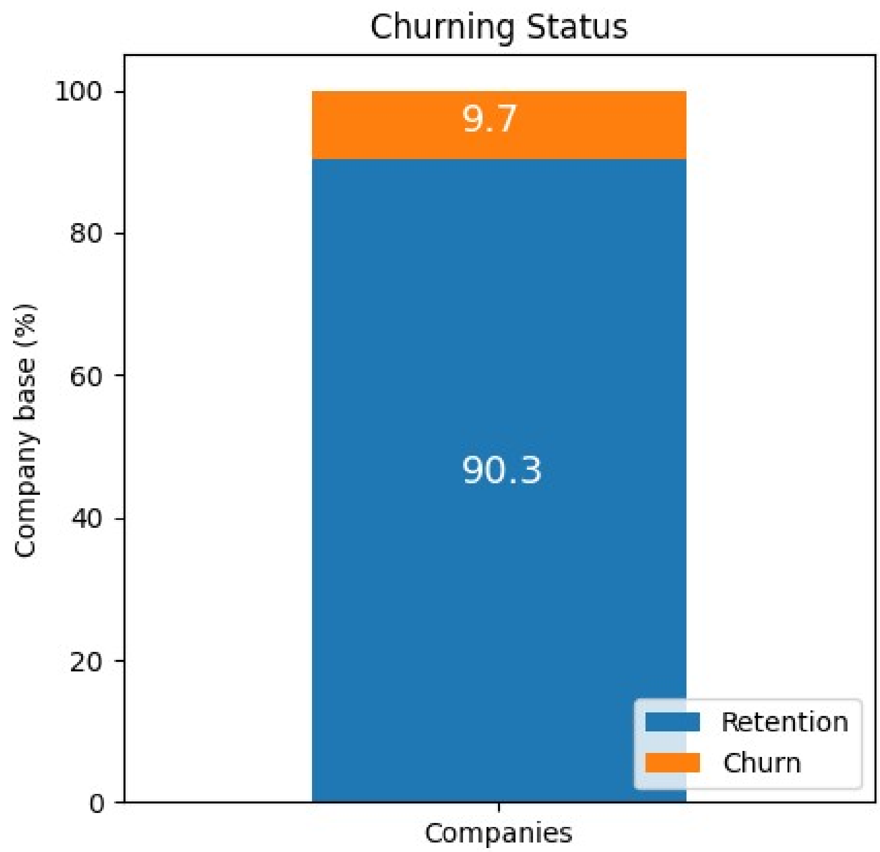



```
def plot_stacked_bars(dataframe, title_, size_=(18, 10), rot_=0,
legend_="upper right"):
    """
    Plot stacked bars with annotations
    """
    ax = dataframe.plot(
        kind="bar",
        stacked=True,
        figsize=size_,
        rot=rot_,
        title=title_
    )

    # 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 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
        )
```

*Churn*

```
churn = client_data[['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")
```



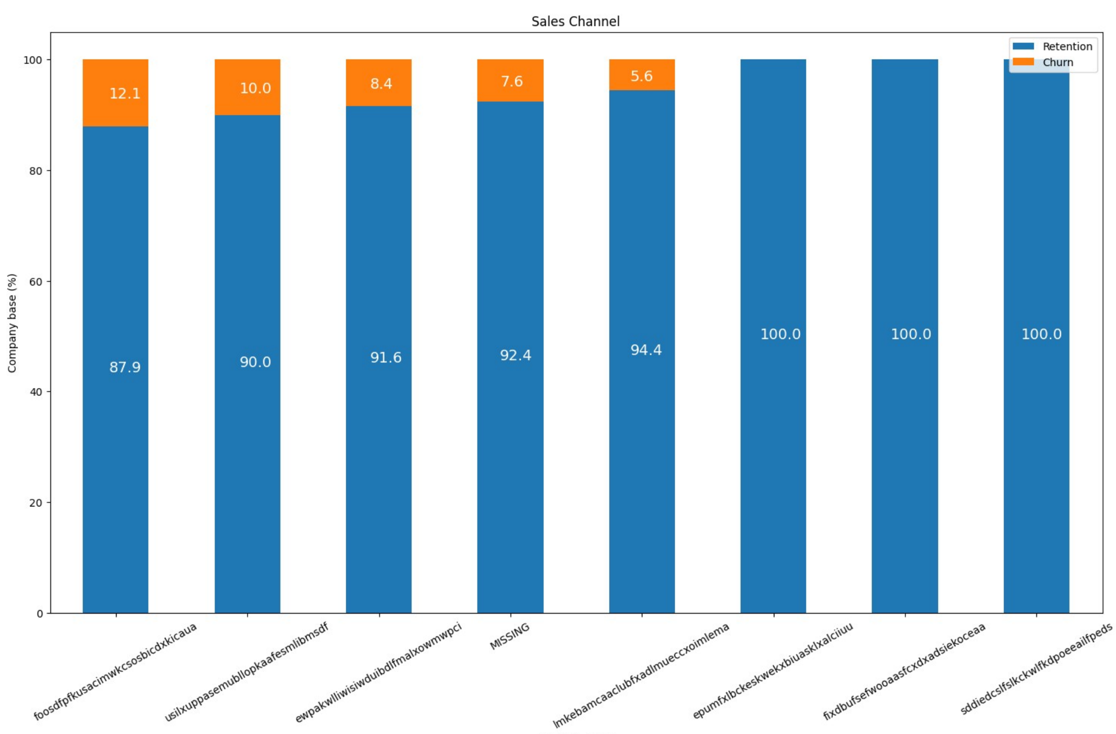

About 10% of the total customers have churned.

*Sales Channel*

```
channel = client_data[['id', 'channel_sales', 'churn']]
channel = channel.groupby(['channel_sales', '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                                     0      1
channel_sales
MISSING                              3442.0  283.0
epumfxlbckeskwekxbiuasklxalciiuu        3.0    0.0
ewpakwlliwisiwduibdlfmalxowmwpci      818.0   75.0
fixdbufsefwooaasfcxdxadsiekoceaa        2.0    0.0
foosdfpfkusacimwkcsosbicdxkicaua     5934.0  820.0
lmkebamcaaclubfxadlmueccxoimlema     1740.0  103.0
sddiedcslfslkckwlfkdpoeeailfpeds       11.0    0.0
usilxuppasemubllopkaafesmlibmsdf     1237.0  138.0

channel_churn

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
```

```
plot_stacked_bars(channel_churn, 'Sales Channel', rot_=30)
```

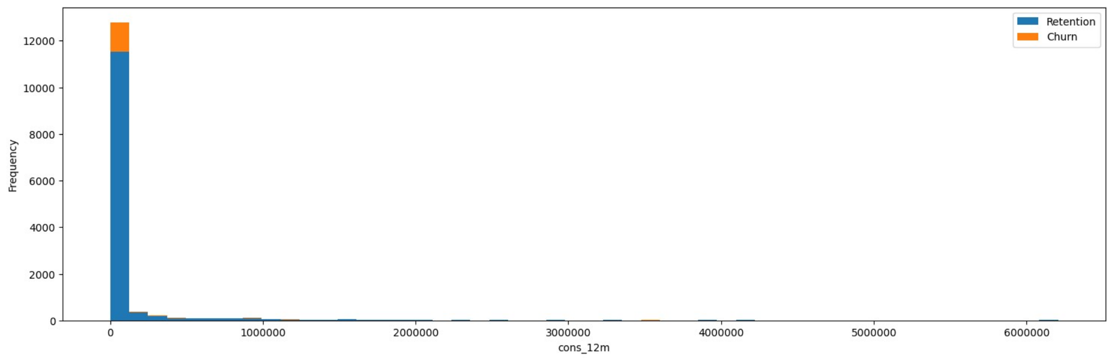


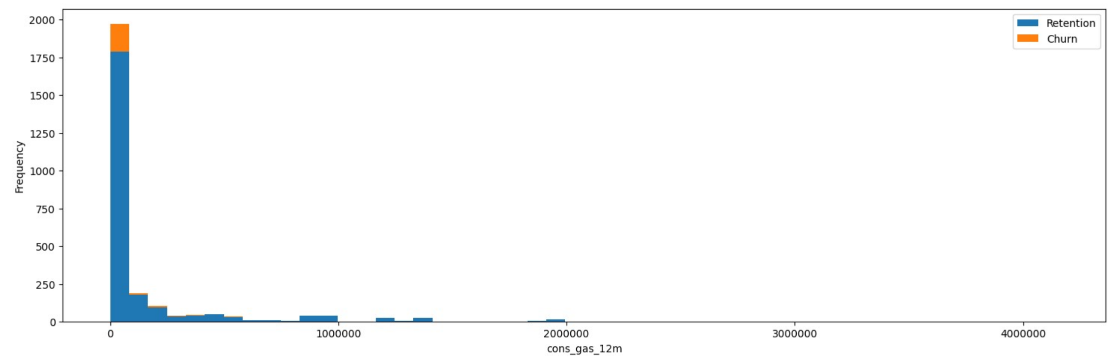
Interestingly, the churning customers are distributed over 5 different values for channel_sales. As well as this, the value of MISSING has a churn rate of 7.6%. MISSING indicates a missing value and was added by the team when they were cleaning the dataset. This feature could be an important feature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

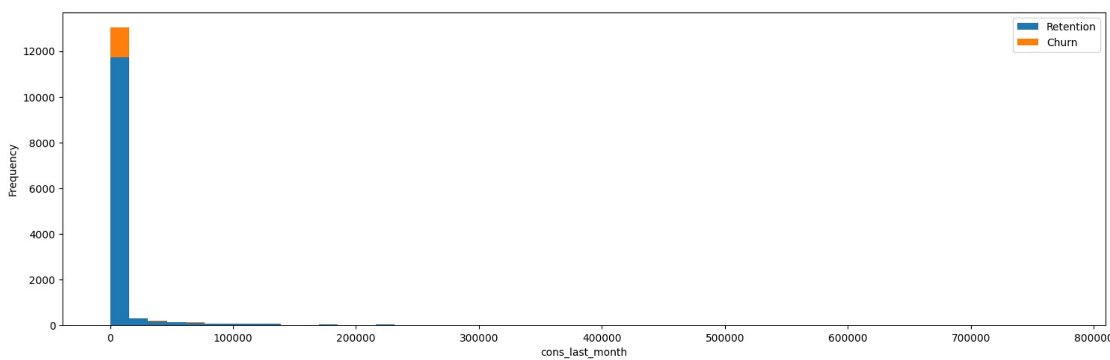
*Consumption:*

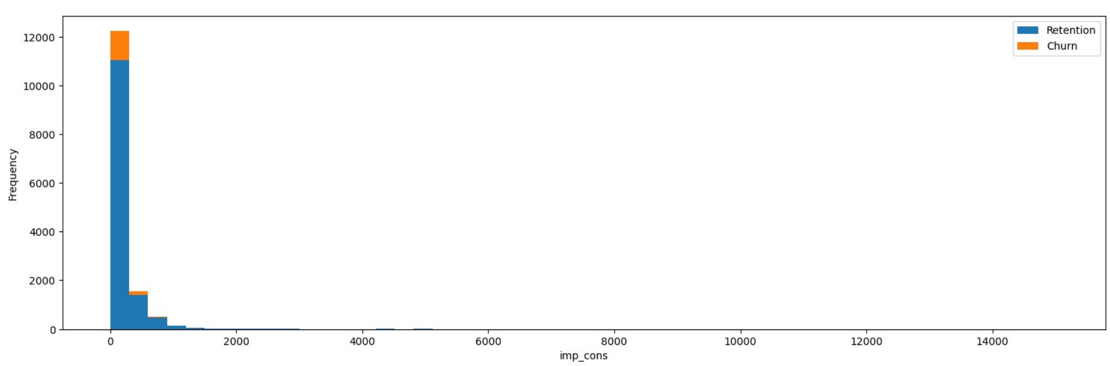
Let's see the distribution of the consumption in the last year and month. Since the consumption data is univariate, let's use histograms to visualize their distribution.

```
consumption = client_data[['id', 'cons_12m', 'cons_gas_12m',
'cons_last_month', 'imp_cons', 'has_gas', 'churn']]

def plot_distribution(dataframe, column, ax, bins_=50):
    """Plot Variable Distribution in a stacked histogram of churned or
retained company """
    # Create a temporary dataframe with 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 x-axis to plainstyle
    ax.ticklabel_format(style='plain', axis='x')

fig, axs = plt.subplots(nrows=4, figsize=(18,25))

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])
```




Clearly, the consumption data is highly positively skewed, presenting a very long right-tail towards the higher values of the distribution. The values on the higher and lower end 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 based on a five number summary: - Minimum, - First quartile (Q1) - Median - Third quartile (Q3) -

Maximum. It can reveal outliers and what their values are. It can also tell us if our data is symmetrical, how tightly our data is grouped and if/how our data is skewed.

```
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()
```

```
d:\anaconda\envs\machinelearning\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
d:\anaconda\envs\machinelearning\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
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_decorators.py:36: FutureWarning: Pass the following variable as a
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will be `data`, and passing other arguments without an explicit
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d:\anaconda\envs\machinelearning\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
```
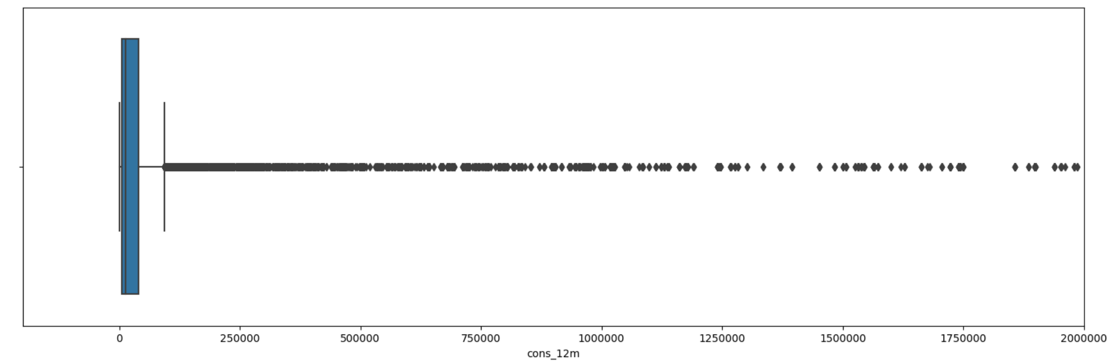
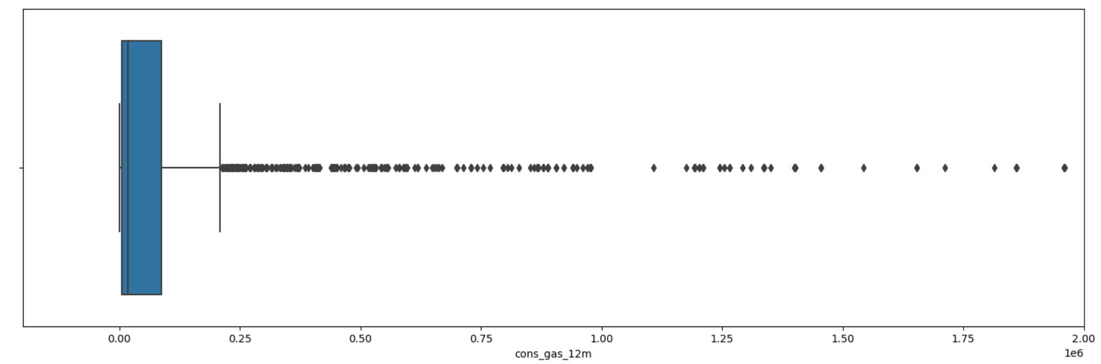
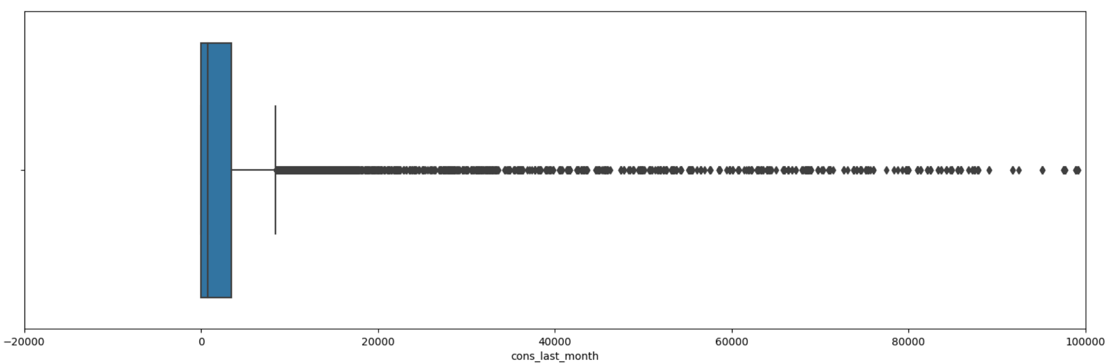
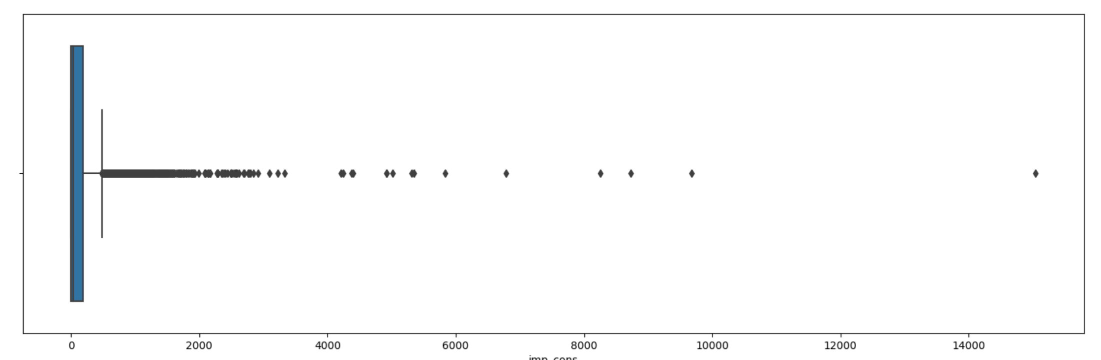



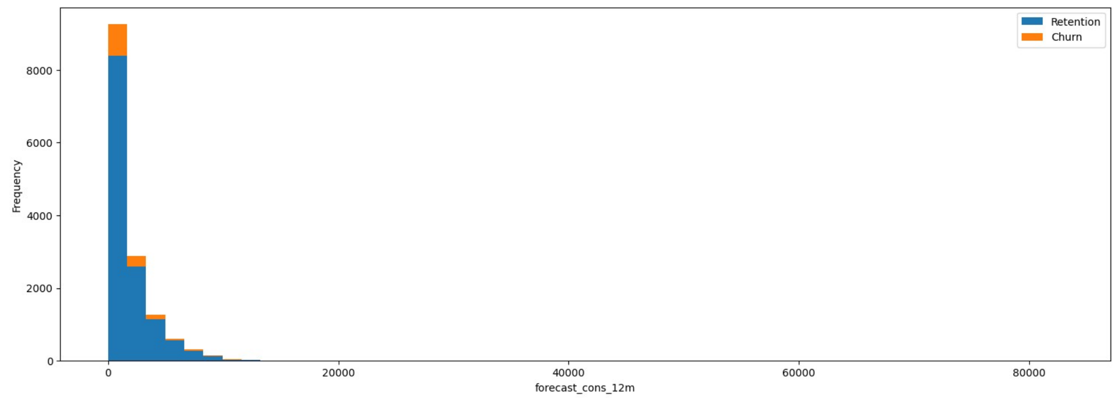



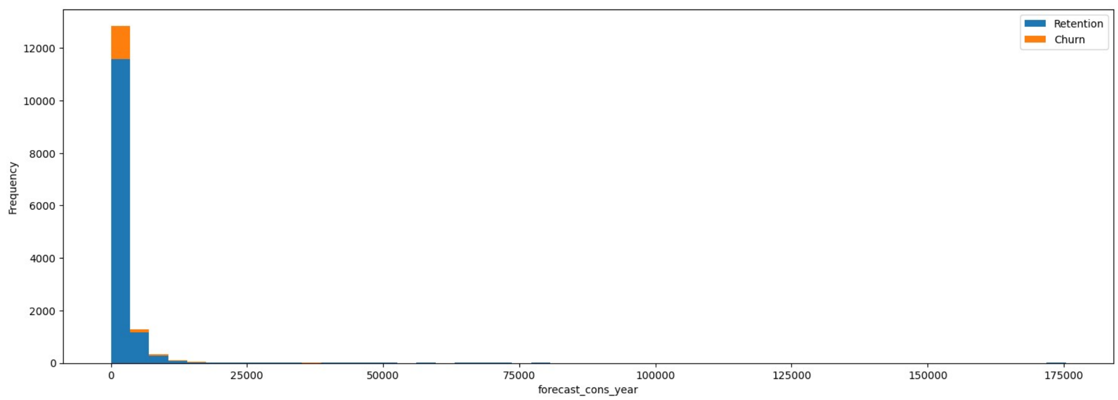



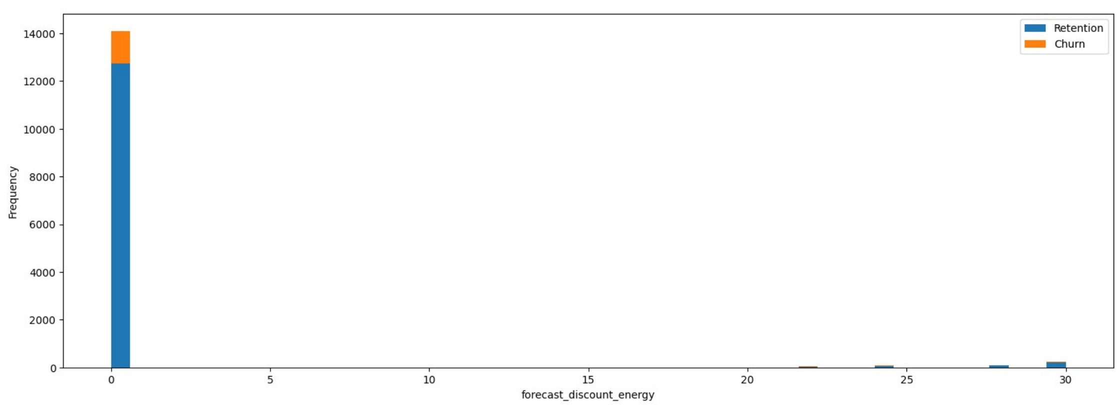

*Forecast*

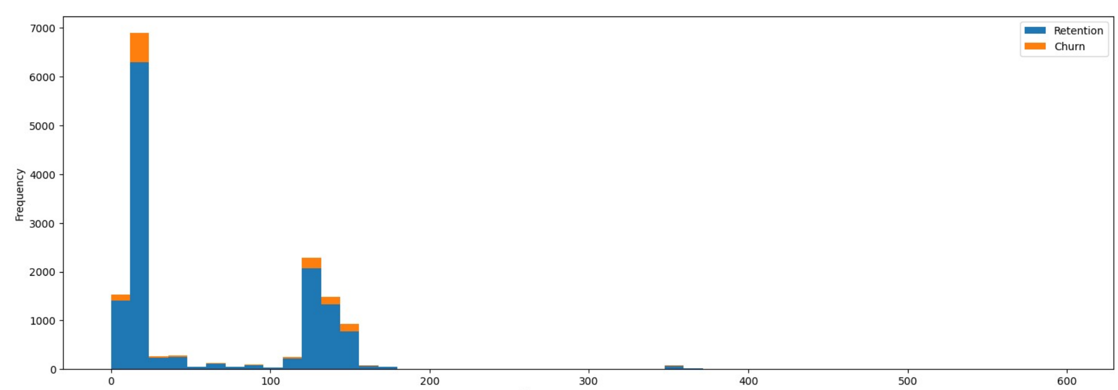
```
forecast = client_data[["id",
"forecast_cons_12m","forecast_cons_year","forecast_discount_energy","f
orecast_meter_rent_12m",
```

```
"forecast_price_energy_off_peak","forecast_price_energy_peak","forecas
t_price_pow_off_peak","churn"]]

fig, axs = plt.subplots(nrows=7, figsize=(18,50))
# Plot histogram
plot_distribution(client_data, "forecast_cons_12m", axs[0])
plot_distribution(client_data, "forecast_cons_year", axs[1])
plot_distribution(client_data, "forecast_discount_energy", axs[2])
plot_distribution(client_data, "forecast_meter_rent_12m", axs[3])
plot_distribution(client_data, "forecast_price_energy_off_peak",
axs[4])
plot_distribution(client_data, "forecast_price_energy_peak", axs[5])
plot_distribution(client_data, "forecast_price_pow_off_peak", axs[6])
```


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


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


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

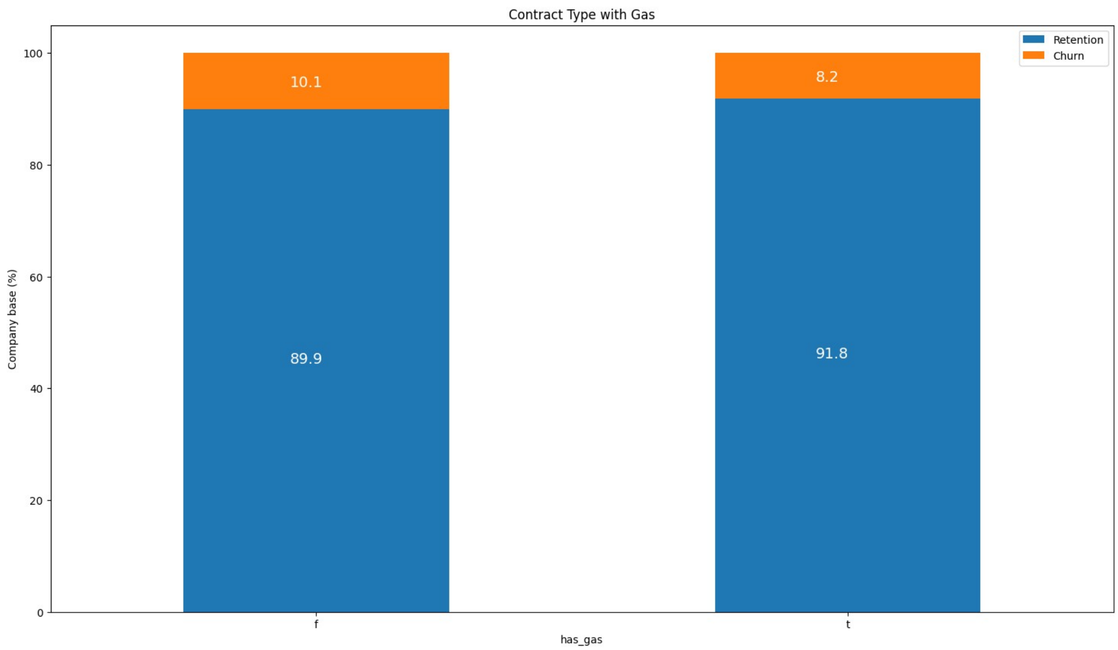

Retention
Churn
Frequency
0
1000
2000
3000
4000
5000
6000
7000
0
100
200
300
400
500
600
forecast_meter_rent_12m


Retention

Similarly to the consumption plots, we can observe that a lot of the variables are highly positively skewed, creating a very long tail for the higher values.

*Contract Type*

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

plot_stacked_bars(contract_percentage, "Contract Type with Gas")
```

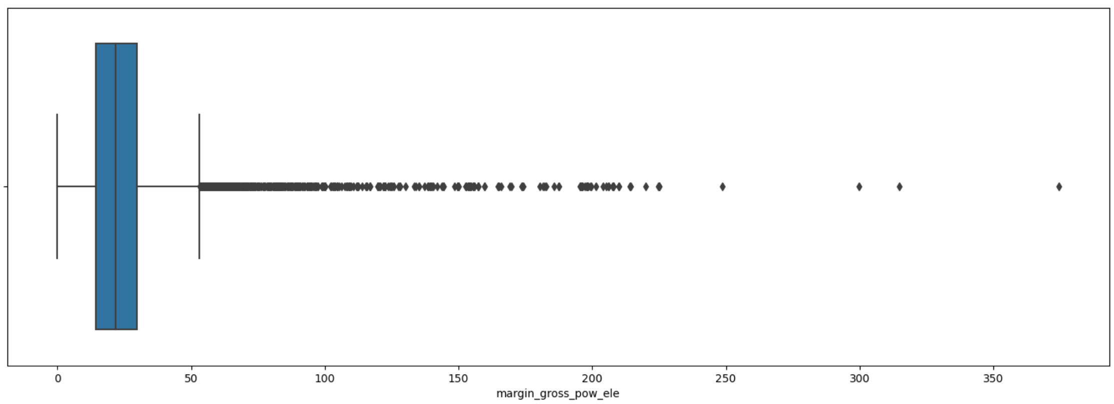


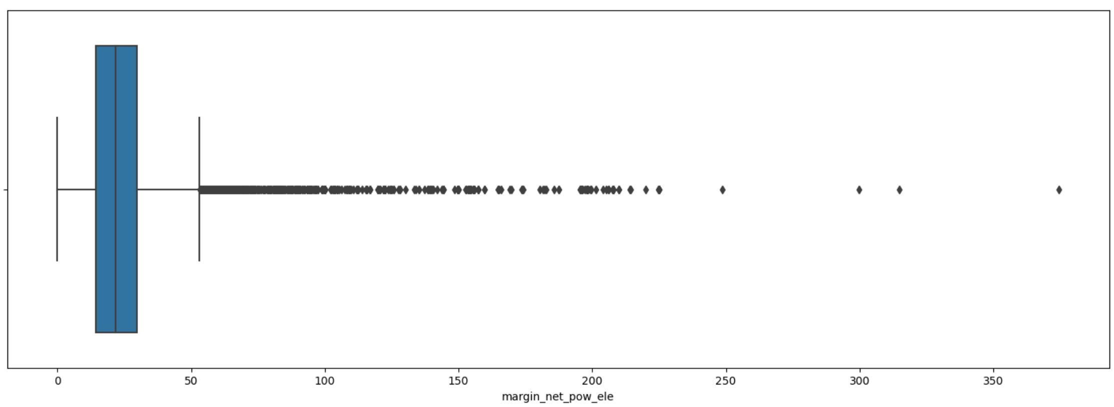

*Margin*

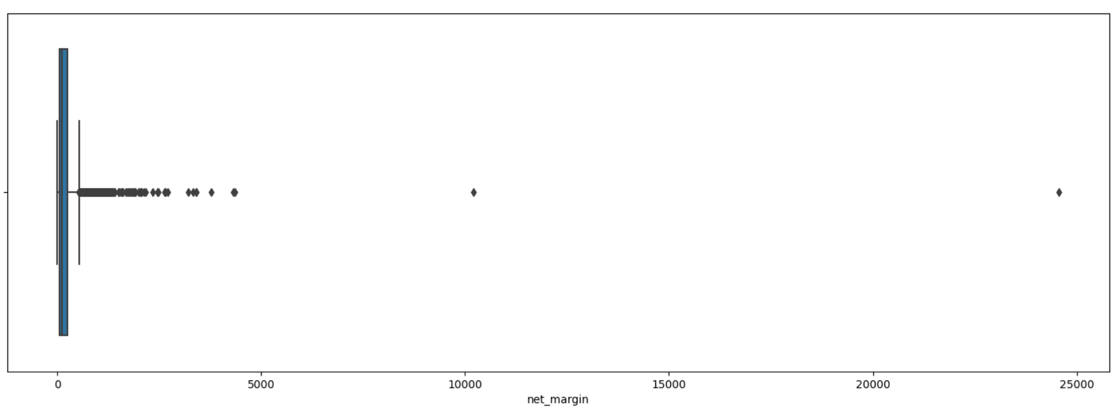
```
margin = client_data[['id', 'margin_gross_pow_ele',
'margin_net_pow_ele', 'net_margin']]

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()
```

```
d:\anaconda\envs\machinelearning\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
```

```
keyword will result in an error or misinterpretation.
  warnings.warn(
d:\anaconda\envs\machinelearning\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
d:\anaconda\envs\machinelearning\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
```

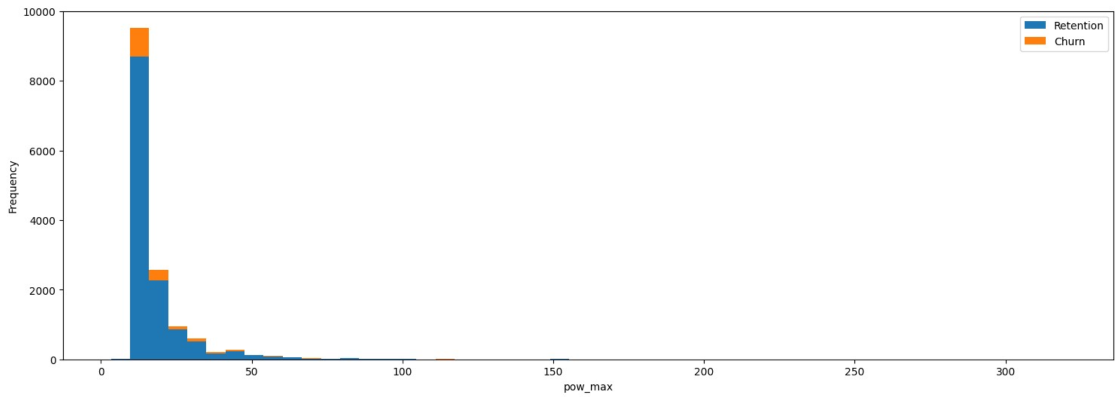


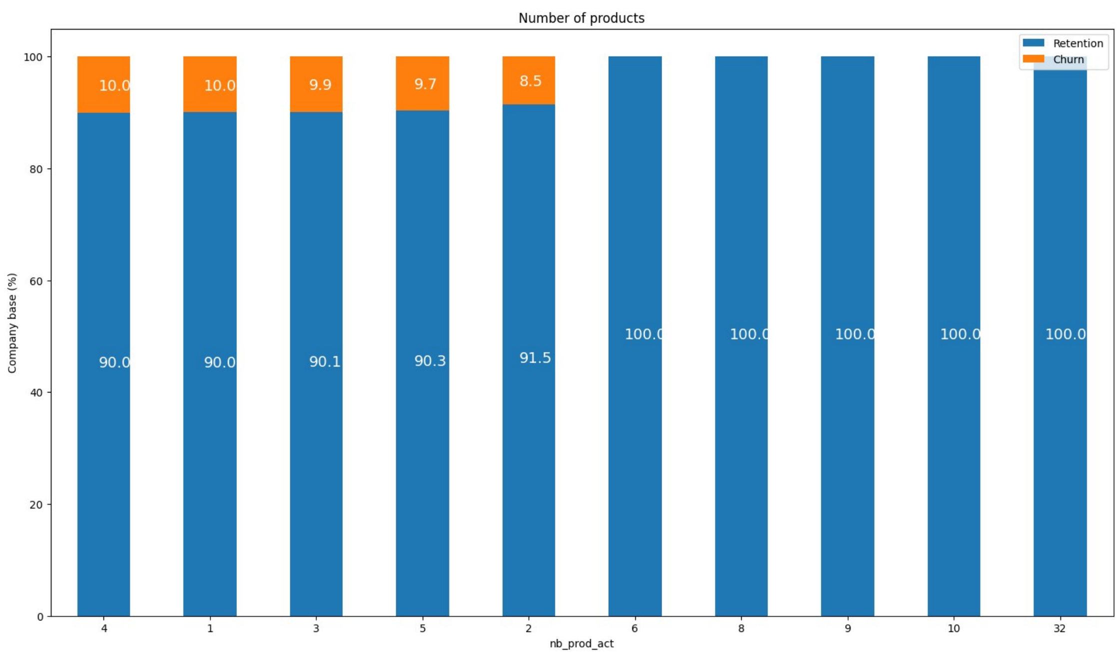

### *Subscribed Power*

```
power = client_data[['id', 'pow_max', 'churn']]

fig, axs = plt.subplots(nrows=1, figsize=(18, 6))
plot_distribution(power, 'pow_max', axs)
```

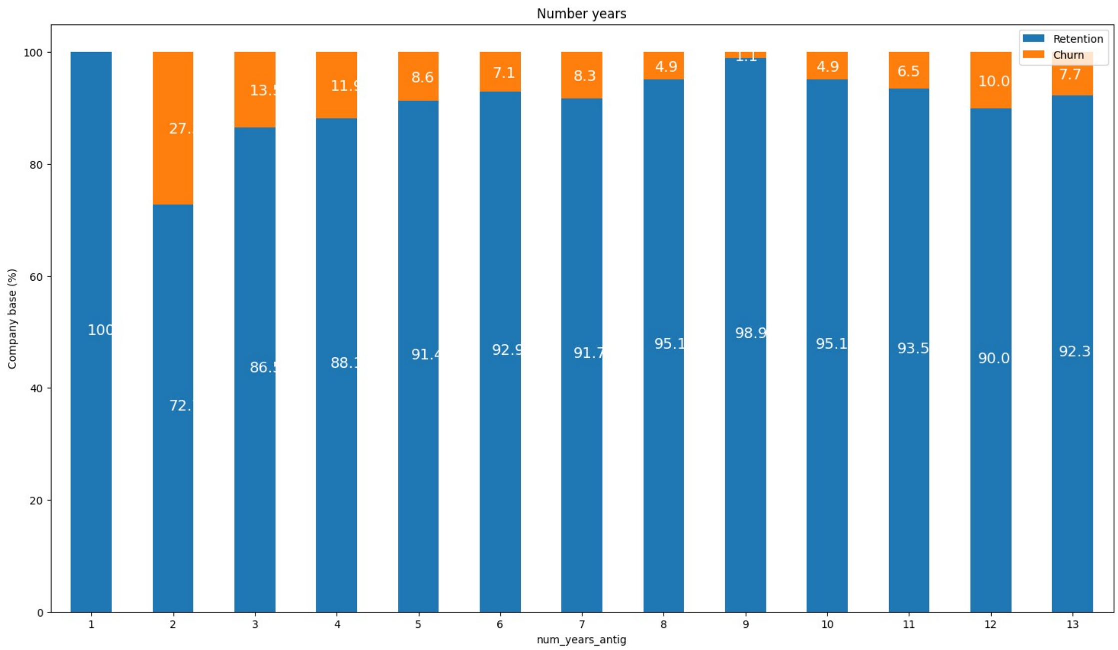



*Other Columns*

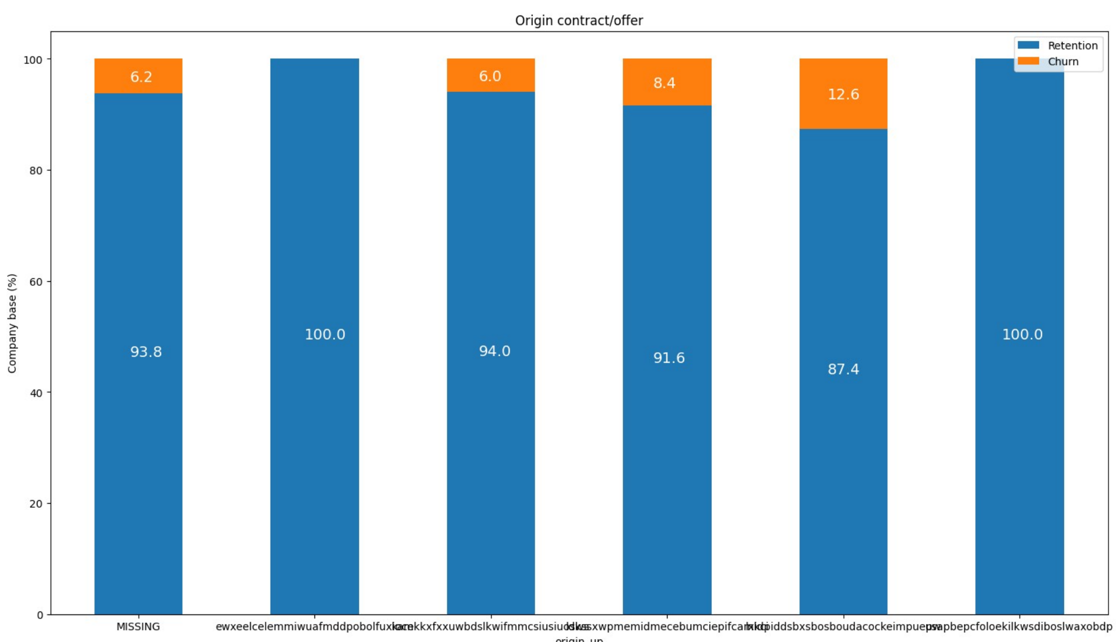
```
others = client_data[['id', 'nb_prod_act', 'num_years_antig',
'origin_up','churn']]
products = others.groupby([others["nb_prod_act"],others["churn"]])
["id"].count().unstack(level=1)
products_percentage = (products.div(products.sum(axis=1),
axis=0)*100).sort_values(by=[1], ascending=False)

plot_stacked_bars(products_percentage, "Number of products")
```




```
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")
```




```
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")
```




*Hypothesis Investigation*

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

```
client_data["date_modif_prod"] =
pd.to_datetime(client_data["date_modif_prod"],format='%Y-%m-%d')
client_data["date_renewal"] =
pd.to_datetime(client_data["date_renewal"],format='%Y-%m-%d')
price_data['price_date'] =
pd.to_datetime(price_data['price_date'],format='%Y-%m-%d')

# Create yearly sensitivity features
var_year = price_data.groupby(['id',
'price_date']).mean().groupby(['id']).var().reset_index()
var_year
```

```
                                     id  price_off_peak_var
price_peak_var  \
0      0002203ffbb812588b632b9e628cc38d            0.000016
0.000004
1      0004351ebdd665e6ee664792efc4fd13            0.000005
0.000000
2      0010bcc39e42b3c2131ed2ce55246e3c            0.000676
0.000000
3      0010ee3855fdea87602a5b7aba8e42de            0.000025
0.000007
4      00114d74e963e47177db89bc70108537            0.000005
0.000000
...                                 ...                 ...
...
16091  ffef185810e44254c3a4c6395e6b4d8a            0.000688
0.000422
16092  fffac626da707b1b5ab11e8431a4d0a2            0.000004
0.000000
16093  fffc0cacd305dd51f316424bbb08d1bd            0.000009
0.000006
16094  fffe4f5646aa39c7f97f95ae2679ce64            0.000021
0.000006
16095  ffff7fa066f1fb305ae285bb03bf325a            0.000023
0.000006

       price_mid_peak_var  price_off_peak_fix  price_peak_fix  \
0            1.871602e-06        4.021438e-03        0.001448
1            0.000000e+00        7.661891e-03        0.000000
2            0.000000e+00        5.965909e-01        0.000000
3            1.627620e-07        7.238536e-03        0.002606
4            0.000000e+00        3.490909e-13        0.000000
...                   ...                 ...             ...
16091        1.563148e-04        3.062232e-02        0.043691
16092        0.000000e+00        6.464760e-03        0.000000
16093        1.857770e-05        7.211360e-03        0.002638
16094        2.220744e-07        5.428835e-03        0.001954
16095        4.345784e-07        7.238536e-03        0.002606
```

```
       price_mid_peak_fix
0                0.000643
1                0.000000
2                0.000000
3                0.001158
4                0.000000
...                   ...
16091            0.051094
16092            0.000000
16093            0.001196
16094            0.000869
16095            0.001158

[16096 rows x 7 columns]
```

```
# Create last 6 months sensitivity features
var_6m = price_data[price_data['price_date'] > '2015-06-
01'].groupby(['id',
'price_date']).mean().groupby(['id']).var().reset_index()
var_6m
```

```
                                     id  price_off_peak_var
price_peak_var  \
0      0002203ffbb812588b632b9e628cc38d            0.000011
0.000003
1      0004351ebdd665e6ee664792efc4fd13            0.000003
0.000000
2      0010bcc39e42b3c2131ed2ce55246e3c            0.000003
0.000000
3      0010ee3855fdea87602a5b7aba8e42de            0.000011
0.000003
4      00114d74e963e47177db89bc70108537            0.000003
0.000000
...                                 ...                 ...
...
16091  ffef185810e44254c3a4c6395e6b4d8a            0.000011
0.000003
16092  fffac626da707b1b5ab11e8431a4d0a2            0.000003
0.000000
16093  fffc0cacd305dd51f316424bbb08d1bd            0.000011
0.000003
16094  fffe4f5646aa39c7f97f95ae2679ce64            0.000014
0.000004
16095  ffff7fa066f1fb305ae285bb03bf325a            0.000011
0.000003

       price_mid_peak_var  price_off_peak_fix  price_peak_fix  \
0            4.860000e-10            0.000000        0.000000
1            0.000000e+00            0.000000        0.000000
2            0.000000e+00            0.000000        0.000000
```

```
3            4.860000e-10            0.000000        0.000000
4            0.000000e+00            0.000000        0.000000
...                   ...                 ...             ...
16091        4.860000e-10            0.000000        0.000000
16092        0.000000e+00            0.009482        0.000000
16093        4.860000e-10            0.000000        0.000000
16094        3.406563e-07            0.007962        0.002867
16095        4.860000e-10            0.000000        0.000000

       price_mid_peak_fix
0                0.000000
1                0.000000
2                0.000000
3                0.000000
4                0.000000
...                   ...
16091            0.000000
16092            0.000000
16093            0.000000
16094            0.001274
16095            0.000000

[16096 rows x 7 columns]
```

```
# Rename columns
var_year = var_year.rename(columns={
"price_off_peak_var": "var_year_price_p1_var",
"price_peak_var": "var_year_price_p2_var",
"price_mid_peak_var": "var_year_price_p3_var",
"price_off_peak_fix": "var_year_price_p1_fix",
"price_peak_fix": "var_year_price_p2_fix",
"price_mid_peak_fix": "var_year_price_p3_fix"})

var_6m = var_6m.rename(columns={
"price_off_peak_var": "var_6m_price_p1_var",
"price_peak_var": "var_6m_price_p2_var",
"price_mid_peak_var": "var_6m_price_p3_var",
"price_off_peak_fix": "var_6m_price_p1_fix",
"price_peak_fix": "var_6m_price_p2_fix",
"price_mid_peak_fix": "var_6m_price_p3_fix"})

var_year["var_year_price_p1"] = var_year["var_year_price_p1_var"] +
var_year["var_year_price_p1_fix"]
var_year["var_year_price_p2"] = var_year["var_year_price_p2_var"] +
var_year["var_year_price_p2_fix"]
var_year["var_year_price_p3"] = var_year["var_year_price_p3_var"] +
var_year["var_year_price_p3_fix"]

var_6m["var_6m_price_p1"] = var_6m["var_6m_price_p1_var"] +
var_6m["var_6m_price_p1_fix"]
var_6m["var_6m_price_p2"] = var_6m["var_6m_price_p2_var"] +
```

```
var_6m["var_6m_price_p2_fix"]
var_6m["var_6m_price_p3"] = var_6m["var_6m_price_p3_var"] +
var_6m["var_6m_price_p3_fix"]

var_year

                                      id  var_year_price_p1_var  \
0      0002203ffbb812588b632b9e628cc38d               0.000016
1      0004351ebdd665e6ee664792efc4fd13               0.000005
2      0010bcc39e42b3c2131ed2ce55246e3c               0.000676
3      0010ee3855fdea87602a5b7aba8e42de               0.000025
4      00114d74e963e47177db89bc70108537               0.000005
...                                  ...                    ...
16091  ffef185810e44254c3a4c6395e6b4d8a               0.000688
16092  fffac626da707b1b5ab11e8431a4d0a2               0.000004
16093  fffc0cacd305dd51f316424bbb08d1bd               0.000009
16094  fffe4f5646aa39c7f97f95ae2679ce64               0.000021
16095  ffff7fa066f1fb305ae285bb03bf325a               0.000023

       var_year_price_p2_var  var_year_price_p3_var
var_year_price_p1_fix  \
0                   0.000004           1.871602e-06
4.021438e-03
1                   0.000000           0.000000e+00
7.661891e-03
2                   0.000000           0.000000e+00
5.965909e-01
3                   0.000007           1.627620e-07
7.238536e-03
4                   0.000000           0.000000e+00
3.490909e-13
...                      ...                    ...
...
16091               0.000422           1.563148e-04
3.062232e-02
16092               0.000000           0.000000e+00
6.464760e-03
16093               0.000006           1.857770e-05
7.211360e-03
16094               0.000006           2.220744e-07
5.428835e-03
16095               0.000006           4.345784e-07
7.238536e-03

       var_year_price_p2_fix  var_year_price_p3_fix  var_year_price_p1
\
0                   0.001448               0.000643           0.004037

1                   0.000000               0.000000           0.007667
```

```
2                      0.000000                  0.000000             0.597267

3                      0.002606                  0.001158             0.007264

4                      0.000000                  0.000000             0.000005

...                         ...                       ...                  ...

16091                  0.043691                  0.051094             0.031311

16092                  0.000000                  0.000000             0.006469

16093                  0.002638                  0.001196             0.007221

16094                  0.001954                  0.000869             0.005450

16095                  0.002606                  0.001158             0.007262


       var_year_price_p2  var_year_price_p3
0               0.001452           0.000645
1               0.000000           0.000000
2               0.000000           0.000000
3               0.002613           0.001158
4               0.000000           0.000000
...                  ...                ...
16091           0.044114           0.051251
16092           0.000000           0.000000
16093           0.002644           0.001215
16094           0.001960           0.000869
16095           0.002611           0.001159

[16096 rows x 10 columns]

var_6m

                                     id  var_6m_price_p1_var  \
0      0002203ffbb812588b632b9e628cc38d             0.000011
1      0004351ebdd665e6ee664792efc4fd13             0.000003
2      0010bcc39e42b3c2131ed2ce55246e3c             0.000003
3      0010ee3855fdea87602a5b7aba8e42de             0.000011
4      00114d74e963e47177db89bc70108537             0.000003
...                                 ...                  ...
16091  ffef185810e44254c3a4c6395e6b4d8a             0.000011
16092  fffac626da707b1b5ab11e8431a4d0a2             0.000003
16093  fffc0cacd305dd51f316424bbb08d1bd             0.000011
16094  fffe4f5646aa39c7f97f95ae2679ce64             0.000014
16095  ffff7fa066f1fb305ae285bb03bf325a             0.000011
```

```
       var_6m_price_p2_var  var_6m_price_p3_var
var_6m_price_p1_fix  \
0                 0.000003         4.860000e-10             0.000000

1                 0.000000         0.000000e+00             0.000000

2                 0.000000         0.000000e+00             0.000000

3                 0.000003         4.860000e-10             0.000000

4                 0.000000         0.000000e+00             0.000000

...                    ...                  ...                  ...

16091             0.000003         4.860000e-10             0.000000

16092             0.000000         0.000000e+00             0.009482

16093             0.000003         4.860000e-10             0.000000

16094             0.000004         3.406563e-07             0.007962

16095             0.000003         4.860000e-10             0.000000


       var_6m_price_p2_fix  var_6m_price_p3_fix  var_6m_price_p1  \
0                 0.000000             0.000000         0.000011
1                 0.000000             0.000000         0.000003
2                 0.000000             0.000000         0.000003
3                 0.000000             0.000000         0.000011
4                 0.000000             0.000000         0.000003
...                    ...                  ...              ...
16091             0.000000             0.000000         0.000011
16092             0.000000             0.000000         0.009485
16093             0.000000             0.000000         0.000011
16094             0.002867             0.001274         0.007976
16095             0.000000             0.000000         0.000011

       var_6m_price_p2  var_6m_price_p3
0             0.000003     4.860000e-10
1             0.000000     0.000000e+00
2             0.000000     0.000000e+00
3             0.000003     4.860000e-10
4             0.000000     0.000000e+00
...                ...              ...
16091         0.000003     4.860000e-10
16092         0.000000     0.000000e+00
16093         0.000003     4.860000e-10
16094         0.002870     1.274558e-03
```

```
16095         0.000003     4.860000e-10

[16096 rows x 10 columns]
```

```python
# Merge into 1 dataframe
price_features = pd.merge(var_year, var_6m, on='id')

price_features.head()
```

```
                                 id  var_year_price_p1_var  \
0  0002203ffbb812588b632b9e628cc38d               0.000016
1  0004351ebdd665e6ee664792efc4fd13               0.000005
2  0010bcc39e42b3c2131ed2ce55246e3c               0.000676
3  0010ee3855fdea87602a5b7aba8e42de               0.000025
4  00114d74e963e47177db89bc70108537               0.000005

   var_year_price_p2_var  var_year_price_p3_var  var_year_price_p1_fix
\
0               0.000004           1.871602e-06           4.021438e-03

1               0.000000           0.000000e+00           7.661891e-03

2               0.000000           0.000000e+00           5.965909e-01

3               0.000007           1.627620e-07           7.238536e-03

4               0.000000           0.000000e+00           3.490909e-13


   var_year_price_p2_fix  var_year_price_p3_fix  var_year_price_p1  \
0               0.001448               0.000643           0.004037
1               0.000000               0.000000           0.007667
2               0.000000               0.000000           0.597267
3               0.002606               0.001158           0.007264
4               0.000000               0.000000           0.000005

   var_year_price_p2  var_year_price_p3  var_6m_price_p1_var  \
0           0.001452           0.000645             0.000011
1           0.000000           0.000000             0.000003
2           0.000000           0.000000             0.000003
3           0.002613           0.001158             0.000011
4           0.000000           0.000000             0.000003

   var_6m_price_p2_var  var_6m_price_p3_var  var_6m_price_p1_fix  \
0             0.000003         4.860000e-10                  0.0
1             0.000000         0.000000e+00                  0.0
2             0.000000         0.000000e+00                  0.0
3             0.000003         4.860000e-10                  0.0
4             0.000000         0.000000e+00                  0.0
```

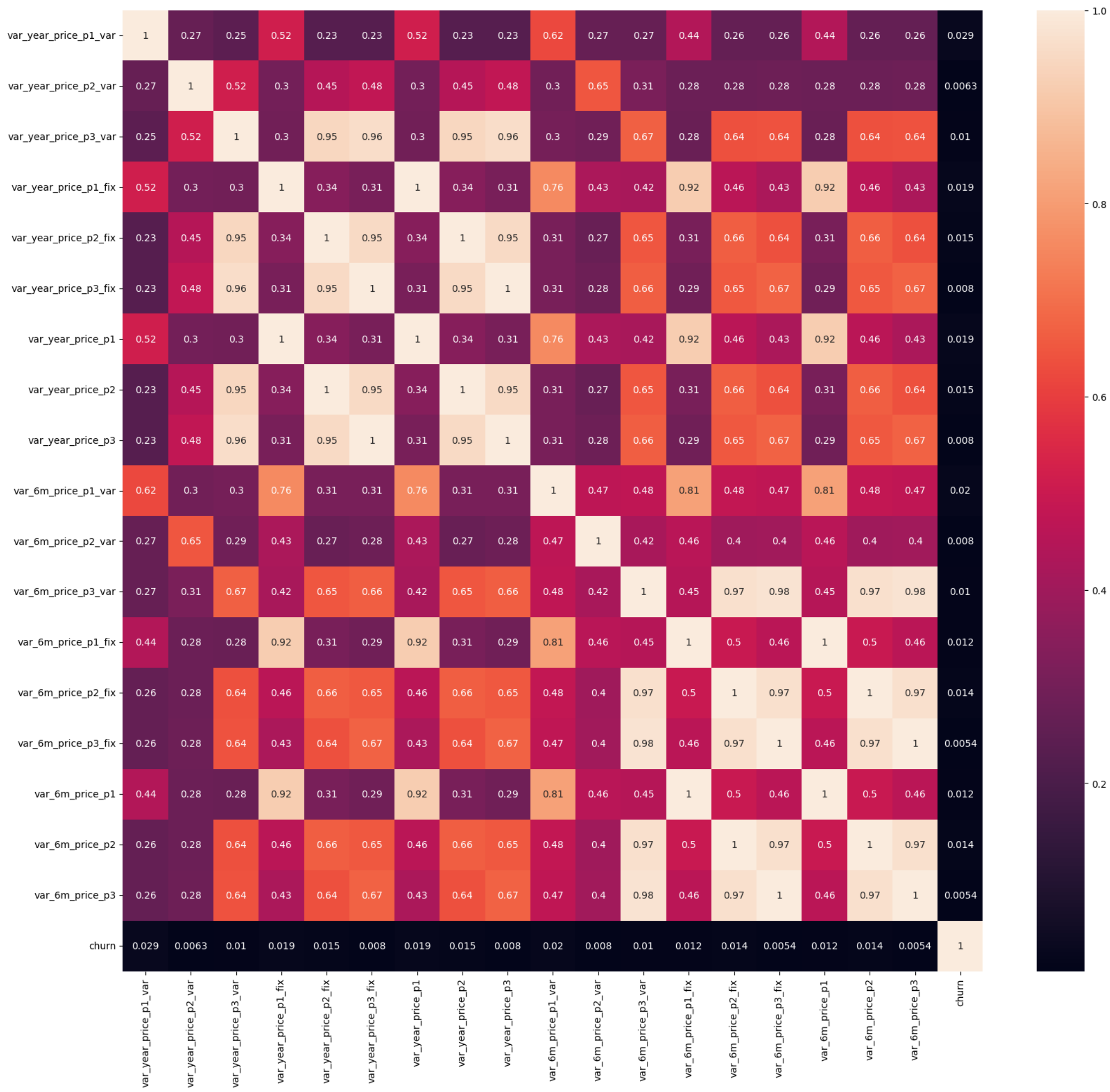
```
   var_6m_price_p2_fix  var_6m_price_p3_fix  var_6m_price_p1  
var_6m_price_p2  \
0                  0.0                  0.0         0.000011  
0.000003   
1                  0.0                  0.0         0.000003  
0.000000   
2                  0.0                  0.0         0.000003  
0.000000   
3                  0.0                  0.0         0.000011  
0.000003   
4                  0.0                  0.0         0.000003  
0.000000   

   var_6m_price_p3  
0     4.860000e-10  
1     0.000000e+00  
2     0.000000e+00  
3     4.860000e-10  
4     0.000000e+00  
```

Now lets merge in the churn data and see whether price sensitivity has any correlation with churn

```
price_analysis = pd.merge(price_features, client_data[['id', 
'churn']], on='id')
price_analysis.head()
```

```
                                 id  var_year_price_p1_var  \
0  0002203ffbb812588b632b9e628cc38d               0.000016   
1  0004351ebdd665e6ee664792efc4fd13               0.000005   
2  0010bcc39e42b3c2131ed2ce55246e3c               0.000676   
3  00114d74e963e47177db89bc70108537               0.000005   
4  0013f326a839a2f6ad87a1859952d227               0.000016   

   var_year_price_p2_var  var_year_price_p3_var  var_year_price_p1_fix  
\
0               0.000004               0.000002           4.021438e-03   

1               0.000000               0.000000           7.661891e-03   

2               0.000000               0.000000           5.965909e-01   

3               0.000000               0.000000           3.490909e-13   

4               0.000004               0.000002           0.000000e+00   


   var_year_price_p2_fix  var_year_price_p3_fix  var_year_price_p1  \
0               0.001448               0.000643           0.004037   
1               0.000000               0.000000           0.007667   
```

```
2               0.000000               0.000000          0.597267
3               0.000000               0.000000          0.000005
4               0.000000               0.000000          0.000016

   var_year_price_p2  var_year_price_p3  var_6m_price_p1_var  \
0           0.001452           0.000645             0.000011
1           0.000000           0.000000             0.000003
2           0.000000           0.000000             0.000003
3           0.000000           0.000000             0.000003
4           0.000004           0.000002             0.000011

   var_6m_price_p2_var  var_6m_price_p3_var  var_6m_price_p1_fix  \
0             0.000003         4.860000e-10                  0.0
1             0.000000         0.000000e+00                  0.0
2             0.000000         0.000000e+00                  0.0
3             0.000000         0.000000e+00                  0.0
4             0.000003         4.860000e-10                  0.0

   var_6m_price_p2_fix  var_6m_price_p3_fix  var_6m_price_p1
var_6m_price_p2  \
0                  0.0                  0.0         0.000011
0.000003
1                  0.0                  0.0         0.000003
0.000000
2                  0.0                  0.0         0.000003
0.000000
3                  0.0                  0.0         0.000003
0.000000
4                  0.0                  0.0         0.000011
0.000003

   var_6m_price_p3  churn
0     4.860000e-10      0
1     0.000000e+00      0
2     0.000000e+00      0
3     0.000000e+00      0
4     4.860000e-10      0

corr = price_analysis.corr()
# Plot correlation
plt.figure(figsize=(20,18))
sns.heatmap(corr, xticklabels=corr.columns.values,
yticklabels=corr.columns.values, annot = True, annot_kws={'size':10})
# Axis ticks size
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.show()
```




From the correlation plot, it shows that the price sensitivity features a high inter-correlation with each other, but overall the correlation with churn is very low. This indicates that there is a weak linear relationship between price sensitity and churn. This suggests that for price sensivity to be a major driver for predicting churn, we may need to engineer the features differently.

```
merged_data = pd.merge(client_data.drop(columns=['churn']),
price_analysis,on='id')
```

```
merged_data.head()
```

```
                                 id                     channel_sales
\
0  24011ae4ebbe3035111d65fa7c15bc57  foosdfpfkusacimwkcsosbicdxkicaua

1  d29c2c54acc38ff3c0614d0a653813dd                           MISSING
```

```
2  764c75f661154dac3a6c254cd082ea7d  foosdfpfkusacimwkcsosbicdxkicaua

3  bba03439a292a1e166f80264c16191cb  lmkebamcaaclubfxadlmueccxoimlema

4  149d57cf92fc41cf94415803a877cb4b                           MISSING


   cons_12m  cons_gas_12m  cons_last_month date_activ   date_end  \
0         0         54946                0 2013-06-15 2016-06-15
1      4660             0                0 2009-08-21 2016-08-30
2       544             0                0 2010-04-16 2016-04-16
3      1584             0                0 2010-03-30 2016-03-30
4      4425             0              526 2010-01-13 2016-03-07

  date_modif_prod date_renewal  forecast_cons_12m  ...
var_6m_price_p1_var  \
0      2015-11-01   2015-06-23               0.00  ...
0.000131
1      2009-08-21   2015-08-31             189.95  ...
0.000003
2      2010-04-16   2015-04-17              47.96  ...
0.000004
3      2010-03-30   2015-03-31             240.04  ...
0.000003
4      2010-01-13   2015-03-09             445.75  ...
0.000011

   var_6m_price_p2_var  var_6m_price_p3_var  var_6m_price_p1_fix  \
0         4.100838e-05         9.084737e-04             2.086294
1         1.217891e-03         0.000000e+00             0.009482
2         9.450150e-08         0.000000e+00             0.000000
3         0.000000e+00         0.000000e+00             0.000000
4         2.896760e-06         4.860000e-10             0.000000

   var_6m_price_p2_fix  var_6m_price_p3_fix var_6m_price_p1
var_6m_price_p2  \
0            99.530517            44.235794        2.086425
9.953056e+01
1             0.000000             0.000000        0.009485
1.217891e-03
2             0.000000             0.000000        0.000004
9.450150e-08
3             0.000000             0.000000        0.000003
0.000000e+00
4             0.000000             0.000000        0.000011
2.896760e-06

   var_6m_price_p3  churn
0     4.423670e+01      1
```

```
1     0.000000e+00      0
2     0.000000e+00      0
3     0.000000e+00      0
4     4.860000e-10      0

[5 rows x 44 columns]
```

```
merged_data.to_csv('clean_data_after_eda.csv')
```