Feature_Engineering

April 19, 2021

[58]:
```
import datetime
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import os
import seaborn as sns
import pickle
import missingno as msno

%matplotlib inline

sns.set(color_codes = True)
pd.set_option('display.max_columns', 100)
```

0.1 Context

- Section ??
- Section ??
- Section ??
- Section ??
- Section ??

Loading Data

Data Directory Explicitly show how opaths are indicated

[59]:
```
pickle_train_dir = os.path.join('..', 'processed_data', 'client_low_missing.
 ↪pkl')
pickle_history_dir = os.path.join('..', 'processed_data', 'history_price.pkl')
```

0.1.1 Load data into dataframes

Data file are in csv format, hence we can use the built in functions in pandas

[60]:
```
history_data = pd.read_pickle(pickle_history_dir)
train = pd.read_pickle(pickle_train_dir)
```

[61]:
```
history_data.head()
```

[61]:
```
                                 id price_date  price_p1_var  price_p2_var  \
0  038af19179925da21a25619c5a24b745 2015-01-01      0.151367           0.0
1  038af19179925da21a25619c5a24b745 2015-02-01      0.151367           0.0
2  038af19179925da21a25619c5a24b745 2015-03-01      0.151367           0.0
3  038af19179925da21a25619c5a24b745 2015-04-01      0.149626           0.0
4  038af19179925da21a25619c5a24b745 2015-05-01      0.149626           0.0

   price_p3_var  price_p1_fix  price_p2_fix  price_p3_fix
0           0.0     44.266931           0.0           0.0
1           0.0     44.266931           0.0           0.0
2           0.0     44.266931           0.0           0.0
3           0.0     44.266931           0.0           0.0
4           0.0     44.266931           0.0           0.0
```

[62]:
```python
train.head()
```

[62]:
```
                                 id                      activity_new  \
0  48ada52261e7cf58715202705a0451c9  esoiiifxdlbkcsluxmfuacbdckommixw
1  24011ae4ebbe3035111d65fa7c15bc57                               NaN
2  d29c2c54acc38ff3c0614d0a653813dd                               NaN
3  764c75f661154dac3a6c254cd082ea7d                               NaN
4  bba03439a292a1e166f80264c16191cb                               NaN

                      channel_sales  cons_12m  cons_gas_12m  cons_last_month  \
0  lmkebamcaaclubfxadlmueccxoimlema    309275             0            10025
1  foosdfpfkusacimwkcsosbicdxkicaua         0         54946                0
2                               NaN      4660             0                0
3  foosdfpfkusacimwkcsosbicdxkicaua       544             0                0
4  lmkebamcaaclubfxadlmueccxoimlema      1584             0                0

  date_activ   date_end date_modif_prod date_renewal  forecast_cons_12m  \
0 2012-11-07 2016-11-06      2012-11-07   2015-11-09           26520.30
1 2013-06-15 2016-06-15      2015-11-01   2015-06-23               0.00
2 2009-08-21 2016-08-30      2009-08-21   2015-08-31             189.95
3 2010-04-16 2016-04-16      2010-04-16   2015-04-17              47.96
4 2010-03-30 2016-03-30      2010-03-30   2015-03-31             240.04

   forecast_cons_year  forecast_discount_energy  forecast_meter_rent_12m  \
0               10025                       0.0                   359.29
1                   0                       0.0                     1.78
2                   0                       0.0                    16.27
3                   0                       0.0                    38.72
4                   0                       0.0                    19.83

   forecast_price_energy_p1  forecast_price_energy_p2  forecast_price_pow_p1  \
0                  0.095919                  0.088347              58.995952
1                  0.114481                  0.098142              40.606701
```

```
2              0.145711              0.000000          44.311378
3              0.165794              0.087899          44.311378
4              0.146694              0.000000          44.311378

  has_gas  imp_cons  margin_gross_pow_ele  margin_net_pow_ele  nb_prod_act  \
0       f     831.8                -41.76              -41.76            1
1       t       0.0                 25.44               25.44            2
2       f       0.0                 16.38               16.38            1
3       f       0.0                 28.60               28.60            1
4       f       0.0                 30.22               30.22            1

   net_margin  num_years_antig                       origin_up  pow_max  \
0     1732.36                3  ldkssxwpmemidmecebumciepifcamkci  180.000
1      678.99                3  lxidpiddsbxsbosboudacockeimpuepw   43.648
2       18.89                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.800
3        6.60                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.856
4       25.46                6  kamkkxfxxuwbdslkwifmmcsiusiuosws   13.200

   churn
0      0
1      1
2      0
3      0
4      0
```

Feature Engineering Since we have the consumption data for each of the companies for the year 2015, we will create new features using the `average` of the year, the last six months, and the three months to our model

[63]:
```
mean_year = history_data.groupby(['id']).mean().reset_index()
mean_6m = history_data[history_data['price_date'] > '2015-06-01'].
 ↪groupby(['id']).mean().reset_index()
mean_3m = history_data[history_data['price_date'] > '2015-10-01'].
 ↪groupby(['id']).mean().reset_index()
```

[64]:
```
mean_year = mean_year.rename(index=str, columns={"price_p1_var":␣
 ↪"mean_year_price_p1_var",
 "price_p2_var": "mean_year_price_p2_var",
"price_p3_var": "mean_year_price_p3_var",
"price_p1_fix": "mean_year_price_p1_fix",
"price_p2_fix": "mean_year_price_p2_fix",
"price_p3_fix": "mean_year_price_p3_fix",})
mean_year["mean_year_price_p1"] = mean_year["mean_year_price_p1_var"] +␣
 ↪mean_year["mean_year_price_p1_fix"]
mean_year["mean_year_price_p2"] = mean_year["mean_year_price_p2_var"] +␣
 ↪mean_year["mean_year_price_p2_fix"]
```

```
mean_year["mean_year_price_p3"] = mean_year["mean_year_price_p3_var"] +␣
↪mean_year["mean_year_price_p3_fix"]
```

[65]:
```
mean_6m = mean_6m.rename(index=str, columns={"price_p1_var":␣
↪"mean_6m_price_p1_var",
 "price_p2_var": "mean_6m_price_p2_var",
"price_p3_var": "mean_6m_price_p3_var",
"price_p1_fix": "mean_6m_price_p1_fix",
"price_p2_fix": "mean_6m_price_p2_fix",
"price_p3_fix": "mean_6m_price_p3_fix",})
mean_6m["mean_6m_price_p1"] = mean_6m["mean_6m_price_p1_var"] +␣
↪mean_6m["mean_6m_price_p1_fix"]
mean_6m["mean_6m_price_p2"] = mean_6m["mean_6m_price_p2_var"] +␣
↪mean_6m["mean_6m_price_p2_fix"]
mean_6m["mean_6m_price_p3"] = mean_6m["mean_6m_price_p3_var"] +␣
↪mean_6m["mean_6m_price_p3_fix"]
```

[66]:
```
mean_3m = mean_3m.rename(index=str, columns={"price_p1_var":␣
↪"mean_3m_price_p1_var",
 "price_p2_var": "mean_3m_price_p2_var",
"price_p3_var": "mean_3m_price_p3_var",
"price_p1_fix": "mean_3m_price_p1_fix",
"price_p2_fix": "mean_3m_price_p2_fix",
"price_p3_fix": "mean_3m_price_p3_fix",})
mean_3m["mean_3m_price_p1"] = mean_3m["mean_3m_price_p1_var"] +␣
↪mean_3m["mean_3m_price_p1_fix"]
mean_3m["mean_3m_price_p2"] = mean_3m["mean_3m_price_p2_var"] +␣
↪mean_3m["mean_3m_price_p2_fix"]
mean_3m["mean_3m_price_p3"] = mean_3m["mean_3m_price_p3_var"] +␣
↪mean_3m["mean_3m_price_p3_fix"]
```

[67]:
```
features = mean_year
```

0.1.2 Feature Engineering

In the previous nootebook, we explore the data and made a deep dive into the churn by dates. Nonetheless, that exploration was quite shallow and did not provide us with any relevant insight.

What if we could create a new variable that could provide us more relevant insights? > We will define a variable tenure = date_end - date_activ

[68]:
```
train.head(2)
```

[68]:
```
                                 id                    activity_new  \
0  48ada52261e7cf58715202705a0451c9  esoiiifxdlbkcsluxmfuacbdckommixw
1  24011ae4ebbe3035111d65fa7c15bc57                             NaN
```

```
                      channel_sales  cons_12m  cons_gas_12m  cons_last_month  \
0  lmkebamcaaclubfxadlmueccxoimlema    309275             0            10025
1  foosdfpfkusacimwkcsosbicdxkicaua         0         54946                0

  date_activ   date_end date_modif_prod date_renewal  forecast_cons_12m  \
0 2012-11-07 2016-11-06      2012-11-07   2015-11-09            26520.3
1 2013-06-15 2016-06-15      2015-11-01   2015-06-23                0.0

   forecast_cons_year  forecast_discount_energy  forecast_meter_rent_12m  \
0               10025                       0.0                   359.29
1                   0                       0.0                     1.78

   forecast_price_energy_p1  forecast_price_energy_p2  forecast_price_pow_p1  \
0                  0.095919                  0.088347              58.995952
1                  0.114481                  0.098142              40.606701

  has_gas  imp_cons  margin_gross_pow_ele  margin_net_pow_ele  nb_prod_act  \
0       f     831.8                -41.76              -41.76            1
1       t       0.0                 25.44               25.44            2

   net_margin  num_years_antig                      origin_up  pow_max  \
0     1732.36                3  ldkssxwpmemidmecebumciepifcamkci  180.000
1      678.99                3  lxidpiddsbxsbosboudacockeimpuepw   43.648

   churn
0      0
1      1
```

[69]:

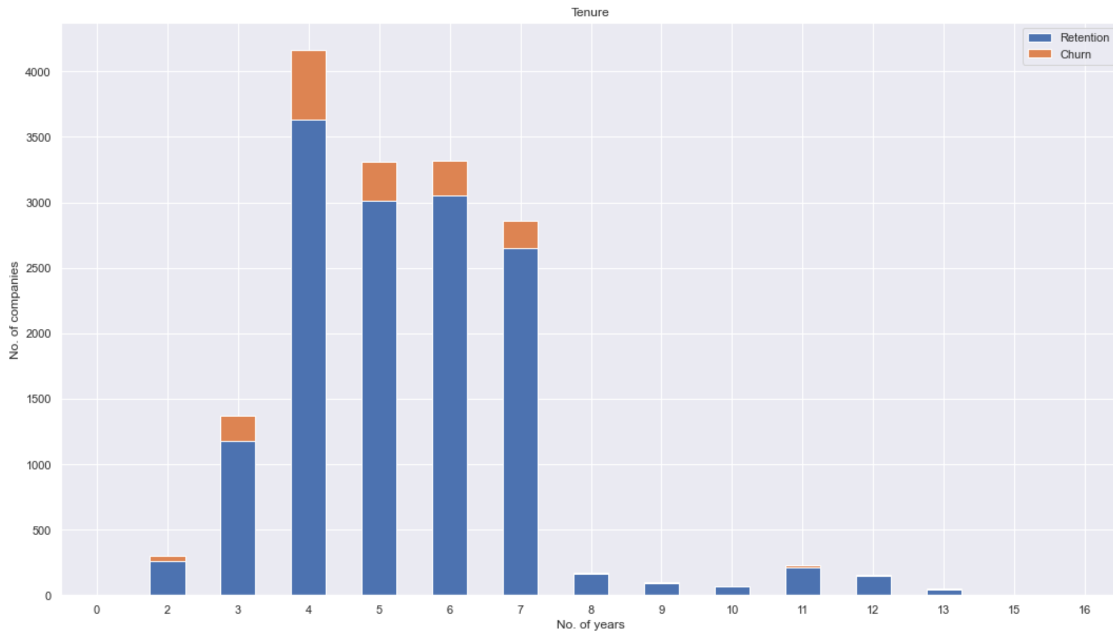
```
train['tenure'] = ((train['date_end'] - train['date_activ'])/np.timedelta64(1,␣
↪'Y')).astype(int)
```

[70]:

```
tenure = train[['id', 'tenure', 'churn']].groupby(['tenure', 'churn'])['id'].
↪count().unstack(level = 1).fillna(0)
tenure_percentage = (tenure.div(tenure.sum(axis = 1), axis = 0)* 100)
```

[71]:

```
tenure.plot(kind = 'bar',
            figsize = (18, 10),
            stacked = True,
            rot = 0,
            title = 'Tenure');
plt.legend(['Retention', 'Churn'], loc = 'upper right')
plt.ylabel('No. of companies')
plt.xlabel('No. of years')
plt.show();
```



We can clearly that churn is very low foor companies which jooined recently or that have made the contract a long time ago. With the higher number of churners within the 3-7 years of tenure. We will also transform the dates provided insuch a way that we can make more sense out of those. > `months_activ`: Number of months active until reference date (Jan 2016)

> `months_to_end`: Number of months of the contact left at reference date (Jan 2016)
>
> `months_modif_prod`: Number of months since last modification at reference date (Jan 2016)
>
> `months_renewal`: Number of months since last renewal at reference date (Jan 2016)

To create the month column we will follow a simple process: 1. Substract the reference date and the column date 2. Convert the timedelta in months 3. Convert to interger (we are not interested in having decimal months)

[72]:
```
def convert_months(reference_date, dataframe, column):
    '''
    Input a column with timedeltas and return months
    '''
    time_delta = REFERENCE_DATE - dataframe[column]
    months = (time_delta/np.timedelta64(1, 'M')).astype(int)
    return months
```

[73]:
```
REFERENCE_DATE = datetime.datetime(2016, 1, 1)
```

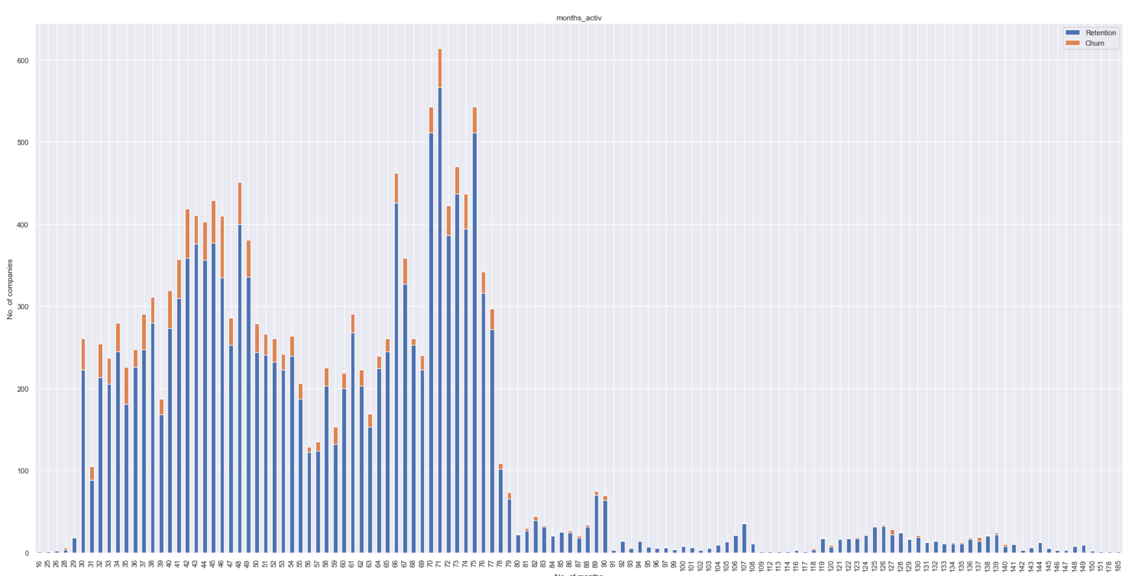
[74]:
```
train["months_activ"] = convert_months(REFERENCE_DATE, train, "date_activ")
train["months_to_end"] = -convert_months(REFERENCE_DATE, train, "date_end")
```

```
train["months_modif_prod"] = convert_months(REFERENCE_DATE, train,␣
↪"date_modif_prod")
train["months_renewal"] = convert_months(REFERENCE_DATE, train, "date_renewal")
```

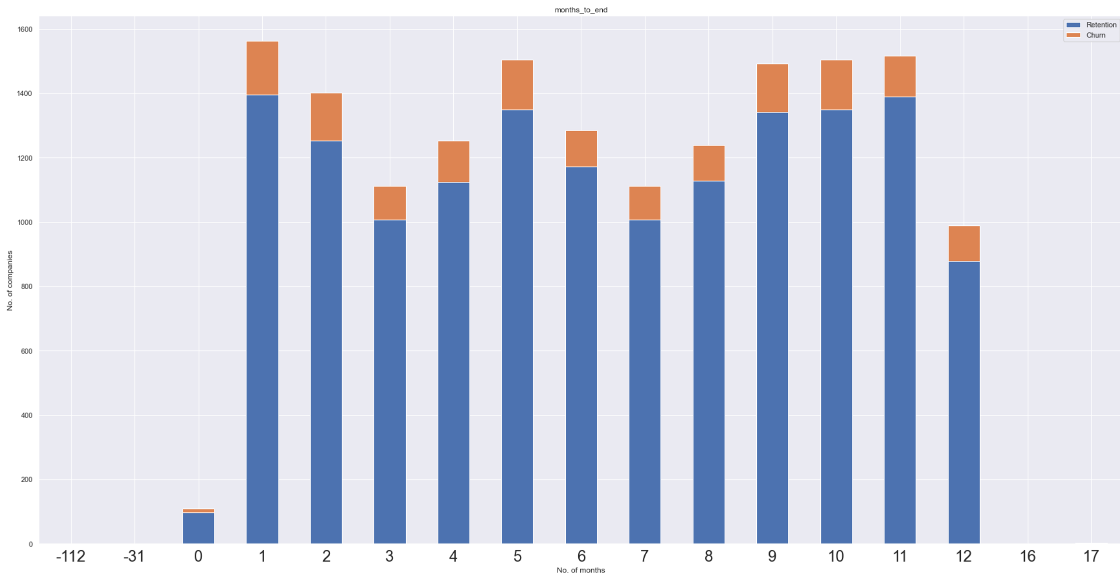
Let's see if we can get any insights

[75]:
```
def plot_churn_by_month(dataframe, column, fontsize_ = 11, rot_ = 0):
    '''
    Plot churn distribution by monthly variable
    '''
    temp = dataframe[[column, 'churn', 'id']].groupby([column, 'churn'])['id'].
↪count().unstack(level = 1)
    temp.plot(kind = 'bar',
              figsize = (30, 15),
              stacked = True,
              rot = rot_,
              title = column);
    # rename legend
    plt.legend(['Retention', 'Churn'], loc = 'upper right')
    # Labels
    plt.ylabel('No. of companies')
    plt.xlabel('No. of months')
    plt.xticks(fontsize = fontsize_)
    plt.show();
```

[76]:
```
plot_churn_by_month(train, 'months_activ', rot_ = 90)
```

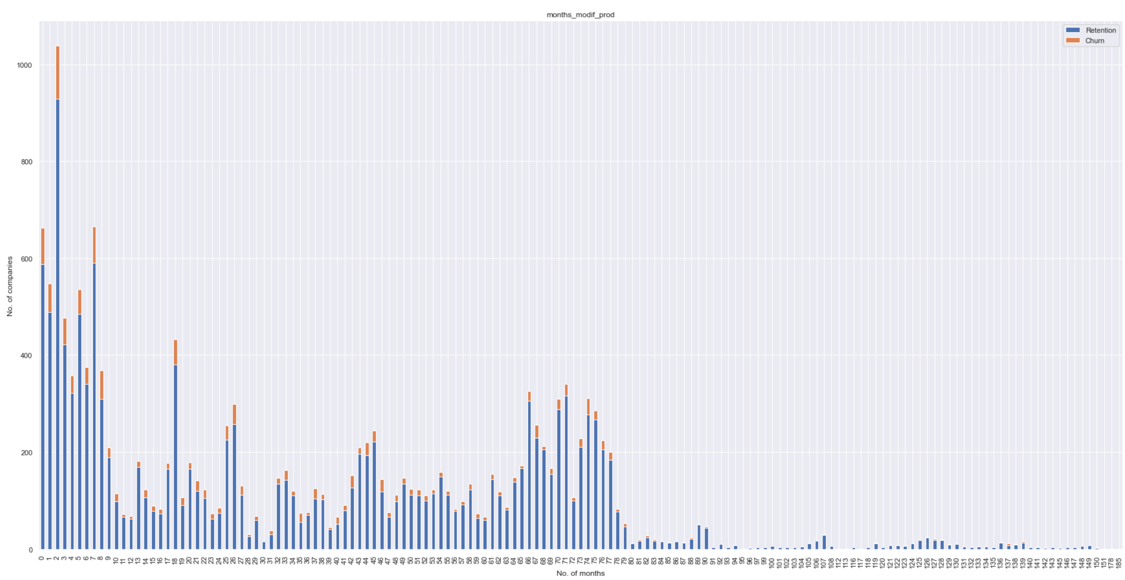


[77]:
```
plot_churn_by_month(train, 'months_to_end', 24)
```



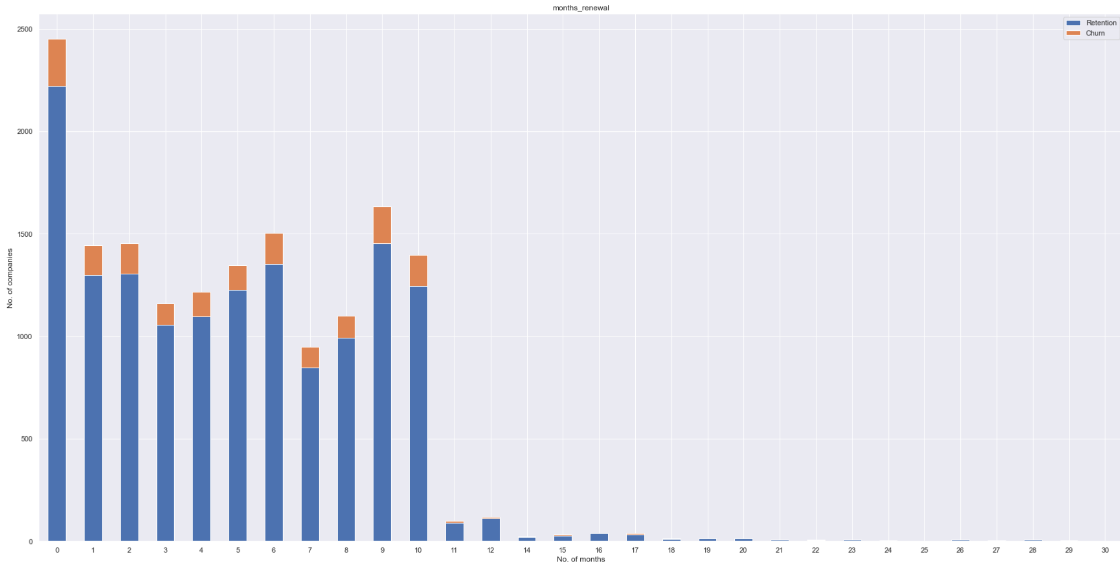
[78]:

```
plot_churn_by_month(train, 'months_modif_prod', rot_ = 90)
```



[79]:

```
plot_churn_by_month(train, 'months_renewal')
```



Remove the date columns

[80]:
```
train = train.drop(columns = ['date_activ', 'date_end', 'date_modif_prod', 'date_renewal'])
```

0.1.3 Transforming boolean data

For the column has_gas, we will replace t for True or 1, and f for False or 0. This process is usually referred as `onehot` encoding

[81]:
```
train['has_gas'] = train['has_gas'].replace(['t', 'f'], [1, 0])
```

0.1.4 Categorical data and dummy variables

When training our model we cannot use `string` data as such, so we will need to encode it into numerical data. The easiest method is mapping each category to an integer (label encoding) but this will not work because the model will misunderstand the data to be in some kind of order or hierarchy. For that reason we will use a method with `dummy` variables or `onehot` encoder

- activity_new
- channel_sales
- origin_up

Categorical data `channel_sales` What we are doing here relatively simple, we want to convert each category into a new dummy `variable` which will have 0s and 1s depending wheather than entry belongs to that particular category or not.

First of all let's replace the `Nan` values with a string called `null_values_channel`

[82]:
```python
train['channel_sales'] = train['channel_sales'].fillna('null_channel_sales').
    ↪astype('category')
pd.DataFrame({'samples_in_category': train['channel_sales'].value_counts()})
```

[82]:

	samples_in_category
foosdfpfkusacimwkcsosbicdxkicaua	7377
null_channel_sales	4218
lmkebamcaaclubfxadlmueccxoimlema	2073
usilxuppasemubllopkaafesmlibmsdf	1444
ewpakwlliwisiwduibdlfmalxowmwpci	966
sddiedcslfslkckwlfkdpoeeailfpeds	12
epumfxlbckeskwekxbiuasklxalciiuu	4
fixdbufsefwooaasfcxdxadsiekoceaa	2

[83]:
```python
# create dummy variables
categories_channel = pd.get_dummies(train['channel_sales'], prefix = 'channel')
```

[84]:
```python
# rename column name for simplicity
categories_channel.columns = [col_name[: 11] for col_name in categories_channel.
    ↪columns]
```

We will explain the concept of `multicollinearity` in the next section. Simply put, multicollinearity is when two or more independent variables in a regression are highly related to one another, such that they do not provide unique or independent information to the regression.

`Multicollinearity` can affect our models so we will remove one of columns.

[85]:
```python
categories_channel = categories_channel.drop(columns = ['channel_nul'])
```

Categorical data `origin_up` First of all let's replace the `Nan` values with a string called `null_values_origin` Then transform the `origin_up` to categorical data type.

[86]:
```python
train['origin_up'] = train['origin_up'].fillna('null_values_origin').
    ↪astype('category')
pd.DataFrame({'sample_in_origin_up': train['origin_up'].value_counts()})
```

[86]:

	sample_in_origin_up
lxidpiddsbxsbosboudacockeimpuepw	7825
kamkkxfxxuwbdslkwifmmcsiusiuosws	4517
ldkssxwpmemidmecebumciepifcamkci	3664
null_values_origin	87
usapbepcfoloekilkwsdiboslwaxobdp	2
ewxeelcelemmiwuafmddpobolfuxioce	1

[87]:
```python
# create dummy variables
categories_origin = pd.get_dummies(train['origin_up'], prefix = 'origin')
```

[88]:
```
# rename column name for simplicity
categories_origin.columns = [col_name[:10] for col_name in categories_origin.
 ↪columns]
```

[89]:
```
# remove one column to avoid dummy variable
categories_origin = categories_origin.drop(columns = ['origin_nul'])
```

Categorical Data `activity_new` First of all let's replace the `Nan` values with a string called `null_values_activity`. We want to see how many categories we will end up with

As we could see below there are too many categories with very few number of samples. So we will replace any category with less than 75 samples as `null_values_categories`.

[90]:
```
train['activity_new'] = train['activity_new'].fillna('null_activity_new')
categories_activity = pd.DataFrame({'sample_in_activity': train['activity_new'].
 ↪value_counts()})
```

[91]:
```
# get the categories with less than 75 samples
to_replace = list(categories_activity[categories_activity['sample_in_activity']␣
 ↪<= 75].index)
# replace them with `null_activity_new`
train['activity_new'] = train['activity_new'].replace(to_replace,␣
 ↪'null_activity_new')
```

[92]:
```
# create dummy variables
categories_activity = pd.get_dummies(train['activity_new'], prefix = 'activity')
categories_activity.columns = [col_name[:12] for col_name in␣
 ↪categories_activity.columns]
```

[93]:
```
categories_activity = categories_activity.drop(columns = ['activity_nul'])
categories_activity.head()
```

[93]:
```
   activity_apd  activity_ckf  activity_clu  activity_cwo  activity_fmw  \
0             0             0             0             0             0
1             0             0             0             0             0
2             0             0             0             0             0
3             0             0             0             0             0
4             0             0             0             0             0

   activity_kkk  activity_kwu  activity_sfi  activity_wxe
0             0             0             0             0
1             0             0             0             0
2             0             0             0             0
3             0             0             0             0
4             0             0             0             0
```

Merge dummy variables to main dataframe We wil merge all the new categories into our main dataframe and remove the old categorical columns

[94]:
```
train = pd.merge(train, categories_channel, left_index = True, right_index =␣
 ↪True)
train = pd.merge(train, categories_origin, left_index = True, right_index =␣
 ↪True)
train = pd.merge(train, categories_activity, left_index = True, right_index =␣
 ↪True)
```

[95]:
```
# finally remove the columns to avoid the dummy variable trap
train.drop(columns = ['channel_sales', 'activity_new', 'origin_up'], inplace =␣
 ↪True)
```

0.1.5 Log Transformation

Remember from the previous exercise that a lot of the variables we are dealing with are highly skewed to the right **Why is skewness relevant?** Skewness is not bad per se. Nonetheless, some predictive models make fundamental assumptions related to variables being 'normallyu distributed'. Hence, the model will perform poorly if the data is highly skewed There are several methods in which we can reduce skewness such as `square root`, `cube root`, and `log`. In this case, we will use a `log transformation` which is usually recommended for right skewed data.

[96]:
```
train.describe()
```

[96]:
```
            cons_12m  cons_gas_12m  cons_last_month  forecast_cons_12m  \
count  1.609600e+04  1.609600e+04     1.609600e+04       16096.000000
mean   1.948044e+05  3.191164e+04     1.946154e+04        2370.555949
std    6.795151e+05  1.775885e+05     8.235676e+04        4035.085664
min   -1.252760e+05 -3.037000e+03    -9.138600e+04      -16689.260000
25%    5.906250e+03  0.000000e+00     0.000000e+00         513.230000
50%    1.533250e+04  0.000000e+00     9.010000e+02        1179.160000
75%    5.022150e+04  0.000000e+00     4.127000e+03        2692.077500
max    1.609711e+07  4.188440e+06     4.538720e+06      103801.930000

       forecast_cons_year  forecast_discount_energy  forecast_meter_rent_12m  \
count        16096.000000              15970.000000             16096.000000
mean          1907.347229                  0.991547                70.309945
std           5257.364759                  5.160969                79.023251
min         -85627.000000                  0.000000              -242.960000
25%              0.000000                  0.000000                16.230000
50%            378.000000                  0.000000                19.440000
75%           1994.250000                  0.000000               131.470000
max         175375.000000                 50.000000              2411.690000

       forecast_price_energy_p1  forecast_price_energy_p2  \
count              15970.000000              15970.000000
mean                   0.135901                  0.052951
std                    0.026252                  0.048617
min                    0.000000                  0.000000
```

25%	0.115237	0.000000
50%	0.142881	0.086163
75%	0.146348	0.098837
max	0.273963	0.195975

	forecast_price_pow_p1	has_gas	imp_cons \
count	15970.000000	16096.000000	16096.000000
mean	43.533496	0.184145	196.123447
std	5.212252	0.387615	494.366979
min	-0.122184	0.000000	-9038.210000
25%	40.606701	0.000000	0.000000
50%	44.311378	0.000000	44.465000
75%	44.311378	0.000000	218.090000
max	59.444710	1.000000	15042.790000

	margin_gross_pow_ele	margin_net_pow_ele	nb_prod_act	net_margin \
count	16083.000000	16083.000000	16096.000000	16081.000000
mean	22.462276	21.460318	1.347788	217.987028
std	23.700883	27.917349	1.459808	366.742030
min	-525.540000	-615.660000	1.000000	-4148.990000
25%	11.960000	11.950000	1.000000	51.970000
50%	21.090000	20.970000	1.000000	119.680000
75%	29.640000	29.640000	1.000000	275.810000
max	374.640000	374.640000	32.000000	24570.650000

	num_years_antig	pow_max	churn	tenure \
count	16096.000000	16093.000000	16096.000000	16096.000000
mean	5.030629	20.604131	0.099093	5.329958
std	1.676101	21.772421	0.298796	1.749248
min	1.000000	1.000000	0.000000	0.000000
25%	4.000000	12.500000	0.000000	4.000000
50%	5.000000	13.856000	0.000000	5.000000
75%	6.000000	19.800000	0.000000	6.000000
max	16.000000	500.000000	1.000000	16.000000

	months_activ	months_to_end	months_modif_prod	months_renewal \
count	16096.000000	16096.000000	16096.000000	16096.000000
mean	58.929858	6.376615	35.741240	4.924640
std	20.125024	3.633479	30.609746	3.812127
min	16.000000	-112.000000	0.000000	0.000000
25%	44.000000	3.000000	7.000000	2.000000
50%	57.000000	6.000000	29.000000	5.000000
75%	71.000000	9.000000	64.000000	8.000000
max	185.000000	17.000000	185.000000	30.000000

	channel_epu	channel_ewp	channel_fix	channel_foo	channel_lmk \
count	16096.000000	16096.000000	16096.000000	16096.000000	16096.000000

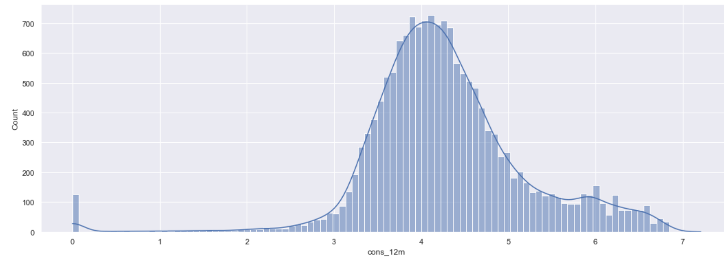
```
mean      0.000249     0.060015     0.000124     0.458313     0.128790
std       0.015763     0.237522     0.011147     0.498275     0.334978
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     1.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

        channel_sdd   channel_usi    origin_ewx    origin_kam    origin_ldk  \
count  16096.000000  16096.000000  16096.000000  16096.000000  16096.000000
mean       0.000746      0.089712      0.000062      0.280629      0.227634
std        0.027295      0.285777      0.007882      0.449320      0.419318
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      1.000000      0.000000
max        1.000000      1.000000      1.000000      1.000000      1.000000

         origin_lxi    origin_usa  activity_apd  activity_ckf  activity_clu  \
count  16096.000000  16096.000000  16096.000000  16096.000000  16096.000000
mean       0.486146      0.000124      0.097975      0.011742      0.007393
std        0.499824      0.011147      0.297290      0.107726      0.085668
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        1.000000      0.000000      0.000000      0.000000      0.000000
max        1.000000      1.000000      1.000000      1.000000      1.000000

       activity_cwo  activity_fmw  activity_kkk  activity_kwu  activity_sfi  \
count  16096.000000  16096.000000  16096.000000  16096.000000  16096.000000
mean       0.007580      0.013606      0.026218      0.014289      0.005157
std        0.086733      0.115852      0.159787      0.118684      0.071626
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max        1.000000      1.000000      1.000000      1.000000      1.000000

       activity_wxe
count  16096.000000
mean       0.007393
std        0.085668
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000
```

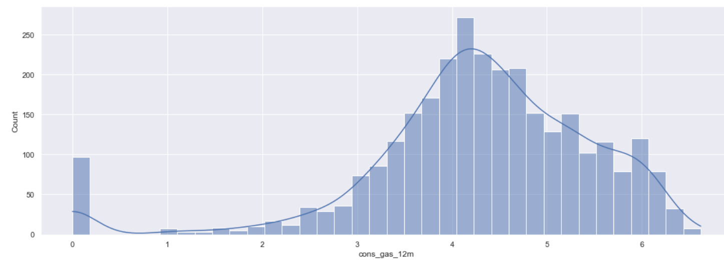
Particularly relevant to look at the standard devviation `std` which is bery very high for some variables. Log transformation does not work with negative data, so we will convert the negative values to `NaN` Also we cannot apply a log transformation to 0 valued entires, so we will add a constant 1

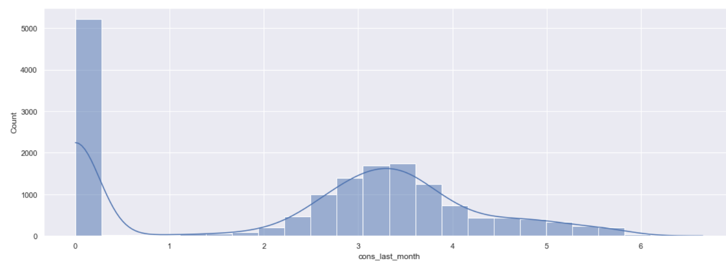
[97]:
```
# remove negative values
train.loc[train.cons_12m < 0, 'cons_12m'] = np.nan
train.loc[train.cons_gas_12m < 0, 'cons_gas_12m'] = np.nan
train.loc[train.cons_last_month < 0, 'cons_last_month'] = np.nan
train.loc[train.forecast_cons_12m < 0, 'forecast_cons_12m'] = np.nan
train.loc[train.forecast_cons_year < 0, 'forecast_cons_year'] = np.nan
train.loc[train.forecast_meter_rent_12m < 0, 'forecast_meter_rent_12m'] = np.nan
train.loc[train.imp_cons < 0, 'imp_cons'] = np.nan
```

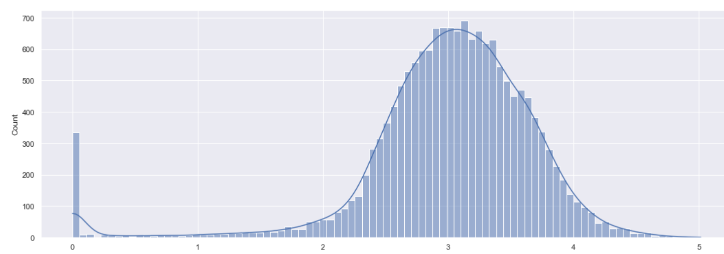
[98]:
```
# apply log10 transformation
train['cons_12m'] = np.log10(train['cons_12m'] + 1)
train['cons_gas_12m'] = np.log10(train['cons_gas_12m'] + 1)
train['cons_last_month'] = np.log10(train['cons_last_month'] + 1)
train['forecast_cons_12m'] = np.log10(train['forecast_cons_12m'] + 1)
train['forecast_cons_year'] = np.log10(train['forecast_cons_year'] + 1)
train['forecast_meter_rent_12m'] = np.log10(train['forecast_meter_rent_12m'] +␣
↪1)
train['imp_cons'] = np.log10(train['imp_cons'] + 1)
```

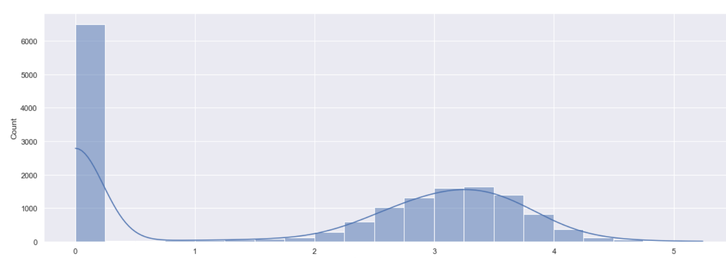
[99]:
```
fig, axs = plt.subplots(nrows = 7, figsize = (18, 50));
# Plot Histogram
sns.histplot(train['cons_12m'].dropna(), ax = axs[0], kde=True);
sns.histplot(train[train['has_gas'] == 1]['cons_gas_12m'].dropna(), ax =␣
↪axs[1], kde=True);
sns.histplot(train['cons_last_month'].dropna(), ax = axs[2], kde=True);
sns.histplot(train['forecast_cons_12m'].dropna(), ax = axs[3], kde=True);
sns.histplot(train['forecast_cons_year'].dropna(), ax = axs[4], kde=True);
sns.histplot(train['forecast_meter_rent_12m'].dropna(), ax = axs[5], kde=True);
sns.histplot(train['imp_cons'].dropna(), ax = axs[6], kde=True);
plt.show()
```

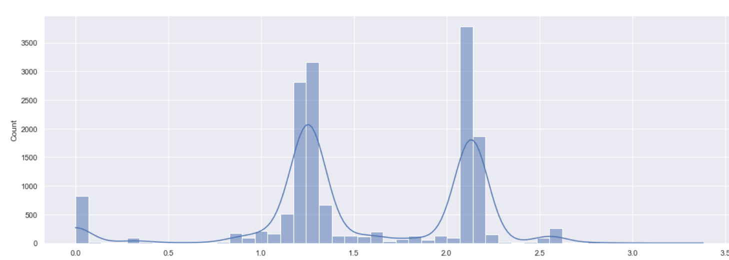

Count
cons_12m

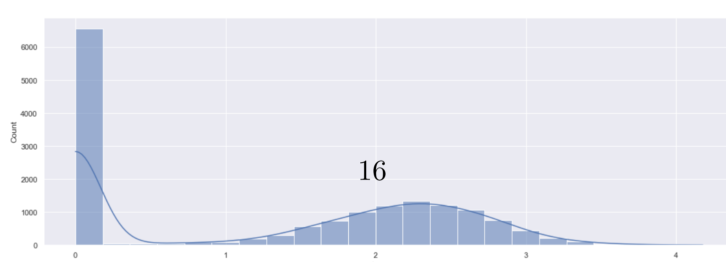

Count
cons_gas_12m


Count
cons_last_month

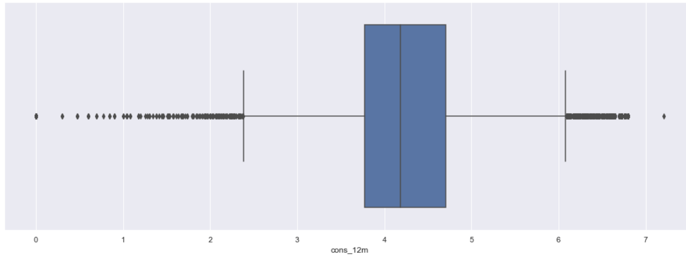

Count
forecast_cons_12m

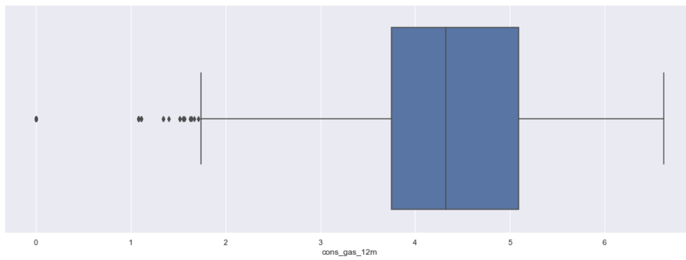

Count
forecast_cons_year

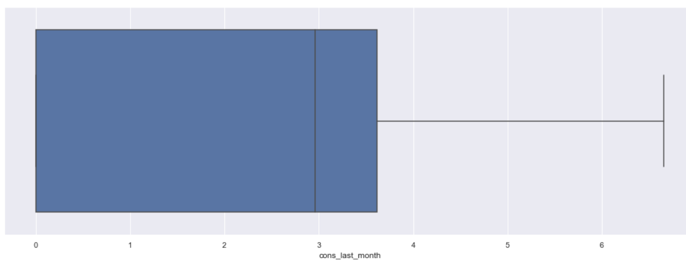

Count
forecast_meter_rent_12m

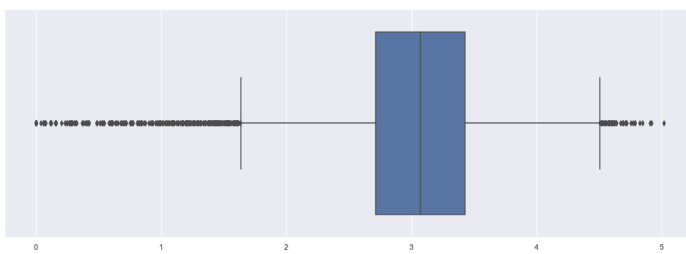

Count
imp_cons

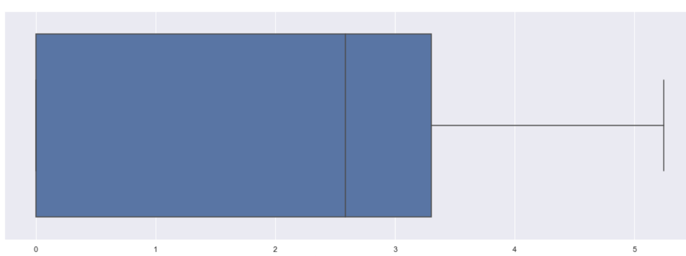
[100]:
```
fig, axs = plt.subplots(nrows = 7, figsize = (18, 50));
# Plot Boxplot
sns.boxplot(x = train['cons_12m'].dropna(), ax = axs[0]);
sns.boxplot(x = train[train['has_gas'] == 1]['cons_gas_12m'].dropna(), ax =␣
 ↪axs[1]);
sns.boxplot(x = train['cons_last_month'].dropna(), ax = axs[2]);
sns.boxplot(x = train['forecast_cons_12m'].dropna(), ax = axs[3]);
sns.boxplot(x = train['forecast_cons_year'].dropna(), ax = axs[4]);
sns.boxplot(x = train['forecast_meter_rent_12m'].dropna(), ax = axs[5]);
sns.boxplot(x = train['imp_cons'].dropna(), ax = axs[6]);
plt.show()
```

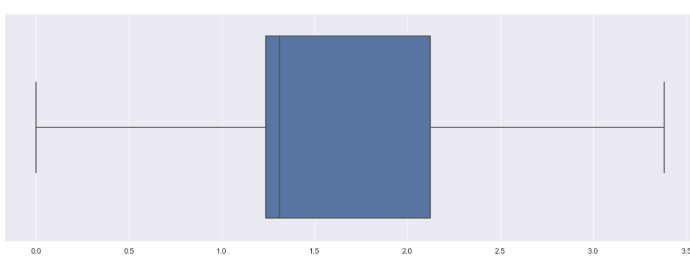

0 1 2 3 4 5 6 7
cons_12m

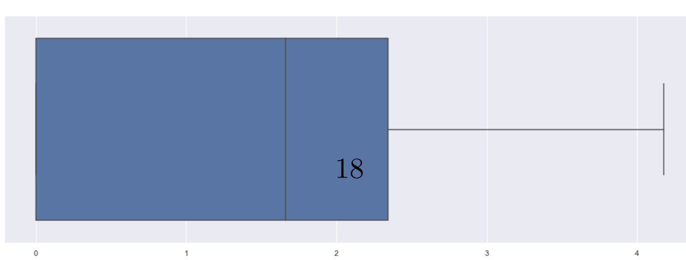

0 1 2 3 4 5 6
cons_gas_12m


0 1 2 3 4 5 6
cons_last_month


0 1 2 3 4 5
forecast_cons_12m


0 1 2 3 4 5
forecast_cons_year


0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5
forecast_meter_rent_12m


0 1 2 3 4
imp_cons

The distribution looks much closer to normal distributions now Notice how the standard deviation `std` has changed From the boxplots we can still see move values are quite far from the range (outliers). We will deal with them later.

0.2 High Correlation Variables

Calculate the correlation of the variables

We can remove highly correlated variables. Multicollinearity happens when one predictor variable in a multiple regression model can be linearly predicteed from the others with a high degree of accuracy. This can lead to skewed or misleading results. Luckily, decision trees and boosted tree algorithms are immune to multicollinearity by nature, When they decide to split, the tree will choose only one of the perfectly correlated features. However, other algorithms like Logistic Regression or linear Regression are not immune to that problem and should be fixed before training the model.

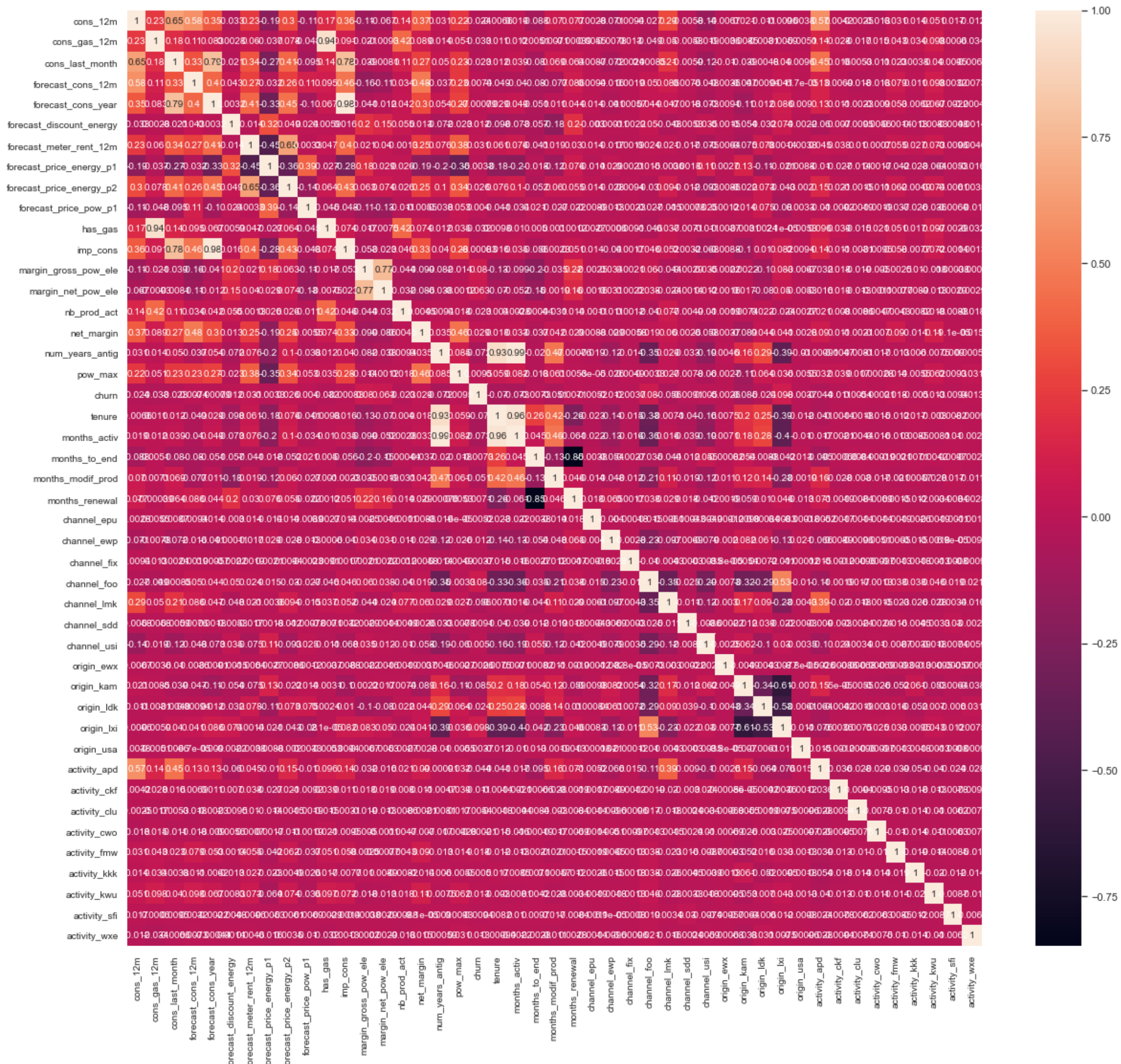
As expected, `num_years_antig` has a high correlation with `months_activ`

[101]:
```
# calculate correlation of variables
correlation = features.corr()
```

[102]:
```
# Plot correlation
plt.figure(figsize = (19, 15))
sns.heatmap(correlation,
            xticklabels = correlation.columns.values,
           yticklabels = correlation.columns.values,
           annot = True,
           annot_kws = {'size': 10})
# Axis ticks size
plt.xticks(fontsize = 10)
plt.yticks(fontsize = 10)
plt.show()
```

[103]:
```
# calculate correlation of variables
correlation = train.corr()
```

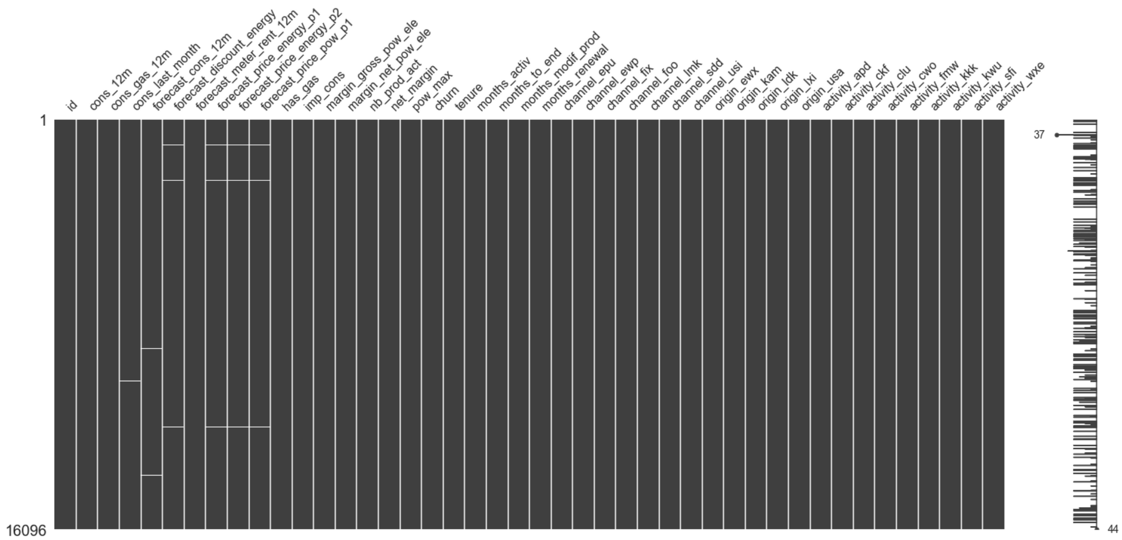
[104]:
```
# Plot correlation
plt.figure(figsize = (20, 18))
sns.heatmap(correlation,
            xticklabels = correlation.columns.values,
           yticklabels = correlation.columns.values,
           annot = True,
           annot_kws = {'size': 10})
# Axis ticks size
plt.xticks(fontsize = 10)
plt.yticks(fontsize = 10)
plt.show()
```



[105]:
```
train.drop(columns = ['num_years_antig', 'forecast_cons_year'], inplace = True)
```

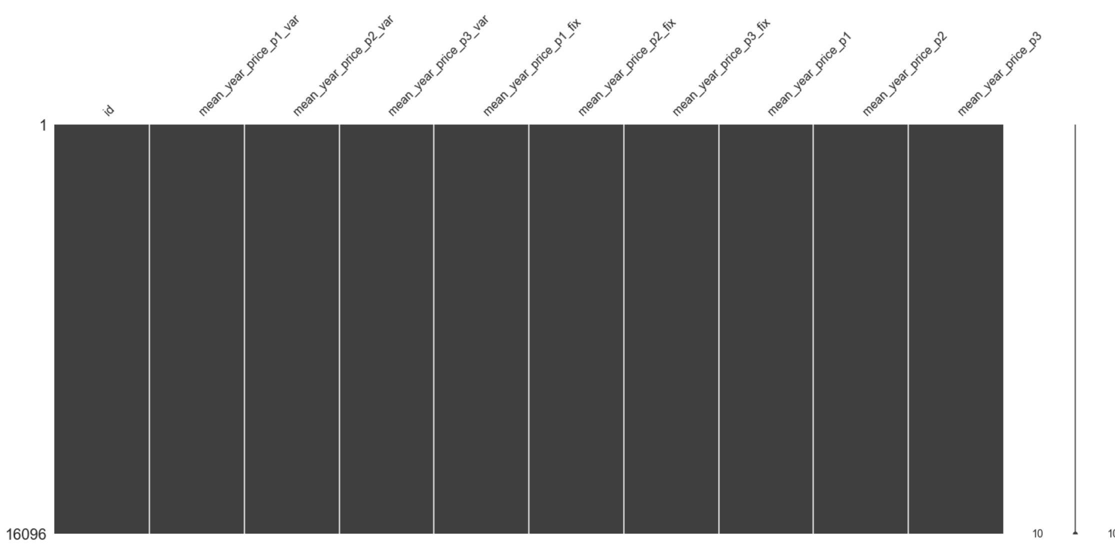
[106]:
```
msno.matrix(train)
```

[106]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc2e85fc0d0>



[107]:
```
msno.matrix(features)
```

[107]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fc2e7ecdb10>`



0.3 Removing Outliers

as we identified during the exploratory phase, the consumption data has several outliers. We are going to remove those outliers.

What are the criteria to identify an outlier

The most common way to identify an outlier are: > 1. Data point that falls outside of 1.5 times of an iterquartile range above the 3rd quartile and below the 1st quartile > 2. Data point that falls outside of 3 standard deviations

Once, we have identified the outlier, **What do we do with the outliers?** There are several ways to handle with those outliers such as removing them (this works well for massive datasets) or replacing them with sensible data (works better when the dataset is not that big) We will replace the outliers with mean (average of the values excluding outliers).

As we identified during the exploratory phase, and when carrying out the `log transformation`, the dataset has several outliers.

[114]:
```
def replace_outliers_z_score(dataframe, column, Z = 3):
    '''
    Replace outliers with the mean values using the Z score.
    Nan values are also replaced with the mean values

    Parameters
    ----------
    dataframe: pandas dataframe
        Contains the data where the outliers are to be found
    column: str
        Usually a string with the name of the column

    Returns
    -------
    Dataframe
        With ouotliers under the lower the above the upper bound removed
    '''
    from scipy.stats import zscore
    df = dataframe.copy(deep = True)
    df.dropna(inplace = True, subset = [column])

    # Calculate mean withuot outliers
    df['zscore'] = zscore(df[column])
    df.dropna(inplace = True, subset = [column])

    # Calculate mean without outliers
    df['zscore'] = zscore(df[column])
    mean_ = df[(df['zscore'] > -Z)&(df['zscore'] < Z)][column].mean()
    # Replace with mean values
    dataframe[column] = dataframe[column].fillna(mean_)
    dataframe['zscore'] = zscore(dataframe[column])
    no_outliers = dataframe[(dataframe['zscore'] < -Z)&(dataframe['zscore'] >␣
↪Z)].shape[0]
    dataframe.loc[(dataframe['zscore'] < -Z)|(dataframe['zscore'] > Z), column]␣
↪= mean_

    # print message
```

```
    print('Replaced:', no_outliers, 'outliers in ', column)
    return dataframe.drop(columns = 'zscore')
```

[115]:
```
for c in features.columns:
    if c != 'id':
        features = replace_outliers_z_score(features, c)
```

```
Replaced: 0 outliers in  mean_year_price_p1_var
Replaced: 0 outliers in  mean_year_price_p2_var
Replaced: 0 outliers in  mean_year_price_p3_var
Replaced: 0 outliers in  mean_year_price_p1_fix
Replaced: 0 outliers in  mean_year_price_p2_fix
Replaced: 0 outliers in  mean_year_price_p3_fix
Replaced: 0 outliers in  mean_year_price_p1
Replaced: 0 outliers in  mean_year_price_p2
Replaced: 0 outliers in  mean_year_price_p3
```

[116]:
```
features.reset_index(drop = True, inplace = True)
```

[118]:
```
def _find_outliers_iqr(datarame, column):
    '''
    Find outliers using the 1.5*IQR rule

    Parameters
    ----------
    dataframe: pandas dataframe
        Contains the data where the outliers are to be found
    column: str
        Usually a string with the name of the column

    Returns
    -------
    Dict
        With the values of the IQR, lower_bound and upper_bound
    '''
    col = sorted(dataframe[column])
    q1, q3 = np.percentile(col, [25, 75])
    iqr = q3 - q1
    lower_bound = q1 - (1.5*iqr)
    upper_bound = q3 + (1.5*iqr)

    results = {'iqr': iqr,
               'lower_bound': lower_bound,
               'upper_bound': upper_bound}
    return results

def remove_outliers_iqr(dataframe, column):
```

```python
    '''
    Remove outliers using the 1.5*IQR rule.

    Parameters
    ----------
    dataframe: pandas dataframe
        Contains the data where the outliers are to be found
    column: str
        Usually a string with the name of the column

    Returns
    -------
    DataFrame
        With outliers under the lower and above the upper bound removed
    '''
    outliers = _find_outliers_iqr(dataframe, column)
    removed = dataframe[(dataframe[column] < outliers['lower_bound'])|(dataframe[column] > outliers['upper_bound'])]\
    .shape
    dataframe = dataframe[(dataframe[column] > outliers['lower_bound'])&(dataframe[column] < outliers['upper_bound'])]
    print('Removed:', removed[0], 'outliers')
    return dataframe

def remove_outliers_z_score(dataframe, column, Z = 3):
    '''
    Remove outliers using the Z score. Values with more than 3 are removed.

    Parameters
    ----------
    dataframe: pandas dataframe
        Contains the data where the outliers are to be found
    column: str
        Usually a string with the name of the column

    Returns
    -------
    Dataframe
        With outliers under the lowerr and above the upper bound removed
    '''
    from scipy.stats import zscore

    dataframe['zscore'] = zscore(dataframe[column])

    removed = dataframe[(dataframe['zscore'] < -Z)|(dataframe['zscore'] > Z)]\
    .shape
```

```
    dataframe = dataframe[(dataframe['zscore'] > -Z)&(dataframe['zscore'] < Z)]
    print('Removed:', removed[0], 'outliers of ', column)
    return dataframe.drop(columns = 'zscore')

def replace_outliers_z_score(dataframe, column, Z = 3):
    '''
    Replace outliers with the mean values using the Z score.
    Nan values are also replaced with mean values.

    Parameters
    ----------
    dataframe: pandas dataframe
        Contains the data where the outliers are to be found
    column: str
        Usually a string with name of the column

    Returns
    -------
    Dataframe
        With outliers under the lower and above the upper bound removed
    '''
    from scipy.stats import zscore

    df = dataframe.copy(deep = True)
    df.dropna(inplace = True, subset = [column])
    # Calculate mean without uotliers
    df['zscore'] = zscore(df[column])
    mean_ = df[(df['zscore'] > -Z)&(df['zscore'] < Z)][column].mean()
    # Replace with mean values
    no_outliers = dataframe[column].isnull().sum()
    dataframe[column] = dataframe[column].fillna(mean_)
    dataframe['zscore'] = zscore(dataframe[column])
    dataframe.loc[(dataframe['zscore'] < -Z)|(dataframe['zscore'] > Z), column]␣
 ↪= mean_
    # print message
    print('Replaced:', no_outliers, ' outliers in ', column)
    return dataframe.drop(columns = 'zscore')
```

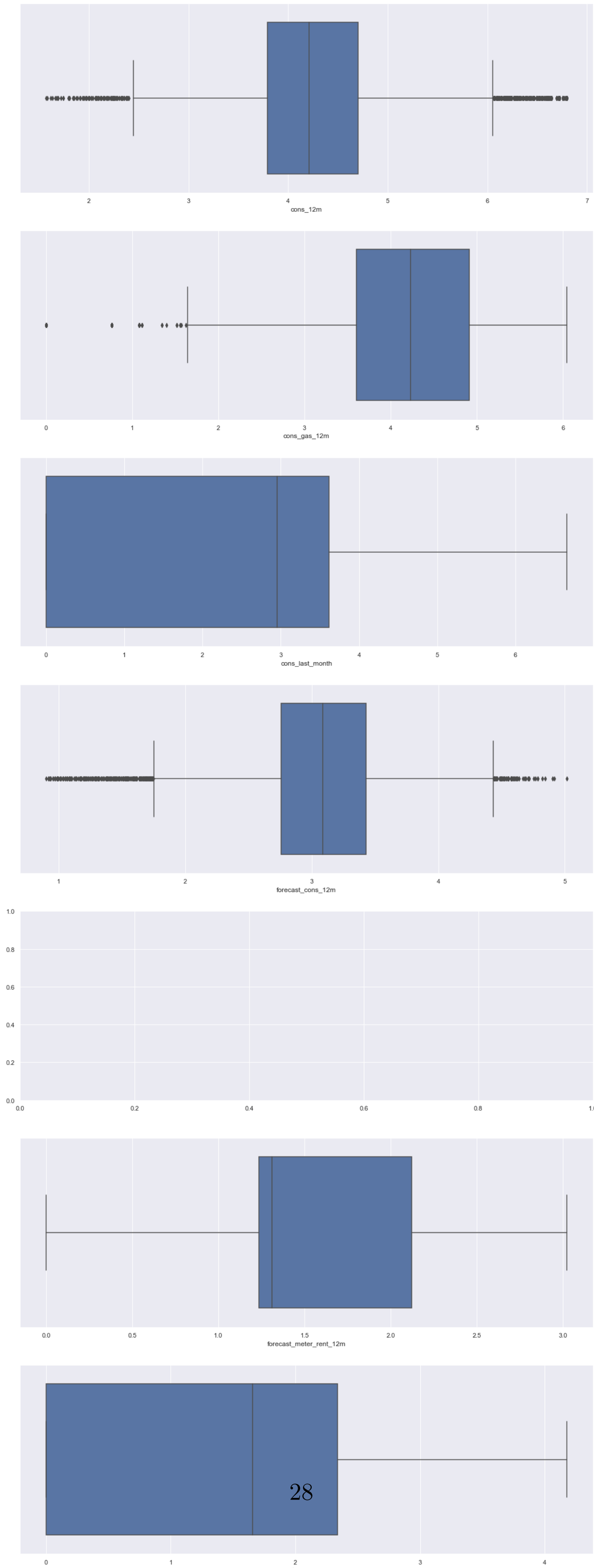
[119]:
```
dummy_col = ['id', 'has_gas', 'nb_prod_act', 'churn', 'tenure', 'channel_epu',
       'channel_ewp', 'channel_fix', 'channel_foo', 'channel_lmk',
       'channel_sdd', 'channel_usi', 'origin_ewx', 'origin_kam', 'origin_ldk',
       'origin_lxi', 'origin_usa', 'activity_apd', 'activity_ckf',
       'activity_clu', 'activity_cwo', 'activity_fmw', 'activity_kkk',
       'activity_kwu', 'activity_sfi', 'activity_wxe']


for c in train.columns:
    if c not in dummy_col:
```

```
        train = replace_outliers_z_score(train, c)
```

```
Replaced: 27  outliers in  cons_12m
Replaced: 6  outliers in  cons_gas_12m
Replaced: 46  outliers in  cons_last_month
Replaced: 41  outliers in  forecast_cons_12m
Replaced: 126  outliers in  forecast_discount_energy
Replaced: 4  outliers in  forecast_meter_rent_12m
Replaced: 126  outliers in  forecast_price_energy_p1
Replaced: 126  outliers in  forecast_price_energy_p2
Replaced: 126  outliers in  forecast_price_pow_p1
Replaced: 27  outliers in  imp_cons
Replaced: 13  outliers in  margin_gross_pow_ele
Replaced: 13  outliers in  margin_net_pow_ele
Replaced: 15  outliers in  net_margin
Replaced: 3  outliers in  pow_max
Replaced: 0  outliers in  months_activ
Replaced: 0  outliers in  months_to_end
Replaced: 0  outliers in  months_modif_prod
Replaced: 0  outliers in  months_renewal
```

[121]:
```
train.reset_index(drop = True, inplace = True)
```

[123]:
```
fig, axs = plt.subplots(nrows = 7, figsize = (18, 50));
# Plot Boxplot
sns.boxplot(x = train['cons_12m'].dropna(), ax = axs[0]);
sns.boxplot(x = train[train['has_gas'] == 1]['cons_gas_12m'].dropna(), ax =␣
 ↪axs[1]);
sns.boxplot(x = train['cons_last_month'].dropna(), ax = axs[2]);
sns.boxplot(x = train['forecast_cons_12m'].dropna(), ax = axs[3]);
#sns.boxplot(x = train['forecast_cons_year'].dropna(), ax = axs[4]);
sns.boxplot(x = train['forecast_meter_rent_12m'].dropna(), ax = axs[5]);
sns.boxplot(x = train['imp_cons'].dropna(), ax = axs[6]);
plt.show()
```


cons_12m
cons_gas_12m
cons_last_month
forecast_cons_12m
forecast_meter_rent_12m
imp_cons

0.4 4 Pickling

we will pickle the data so that we can easily retrieve it in for the next exercise

[127]:
```
PICKLE_TRAIN_DIR = os.path.join('..', 'BCG', 'processed_data', 'train_data.pkl')
PICKLE_HISTORY_DIR = os.path.join('..', 'BCG', 'processed_data', 'history_data.
 ↪pkl')
```

[128]:
```
pd.to_pickle(train, PICKLE_TRAIN_DIR)
pd.to_pickle(history_data, PICKLE_HISTORY_DIR)
```

[ ]:
```
```