BCG_Feature_Engineering_V2

June 18, 2021

[52]:
```
import datetime
import matplotlib.pyplot as plt
import numpy as np
import os
import seaborn as sns
import pandas as pd
# import pickle
```

[143]:
```
train = pd.read_pickle('Processed_train_data.pkl')
history_data = pd.read_pickle('Processed_history_data.pkl')
```

1 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 last three months** to our model.

[144]:
```
history_data[history_data['id'] == "0002203ffbb812588b632b9e628cc38d"]
```

[144]:
```
                                     id price_date  price_p1_var  \
72163  0002203ffbb812588b632b9e628cc38d 2015-01-01      0.126098
72164  0002203ffbb812588b632b9e628cc38d 2015-02-01      0.126098
72165  0002203ffbb812588b632b9e628cc38d 2015-03-01      0.128067
72166  0002203ffbb812588b632b9e628cc38d 2015-04-01      0.128067
72167  0002203ffbb812588b632b9e628cc38d 2015-05-01      0.128067
72168  0002203ffbb812588b632b9e628cc38d 2015-06-01      0.128067
72169  0002203ffbb812588b632b9e628cc38d 2015-07-01      0.128067
72170  0002203ffbb812588b632b9e628cc38d 2015-08-01      0.119906
72171  0002203ffbb812588b632b9e628cc38d 2015-09-01      0.119906
72172  0002203ffbb812588b632b9e628cc38d 2015-10-01      0.119906
72173  0002203ffbb812588b632b9e628cc38d 2015-11-01      0.119906
72174  0002203ffbb812588b632b9e628cc38d 2015-12-01      0.119906

       price_p2_var  price_p3_var  price_p1_fix  price_p2_fix  price_p3_fix
72163      0.103975      0.070232     40.565969     24.339581     16.226389
72164      0.103975      0.070232     40.565969     24.339581     16.226389
72165      0.105842      0.073773     40.728885     24.437330     16.291555
```

```
72166       0.105842     0.073773     40.728885     24.437330     16.291555
72167       0.105842     0.073773     40.728885     24.437330     16.291555
72168       0.105842     0.073773     40.728885     24.437330     16.291555
72169       0.105842     0.073773     40.728885     24.437330     16.291555
72170       0.101673     0.073719     40.728885     24.437330     16.291555
72171       0.101673     0.073719     40.728885     24.437330     16.291555
72172       0.101673     0.073719     40.728885     24.437330     16.291555
72173       0.101673     0.073719     40.728885     24.437330     16.291555
72174       0.101673     0.073719     40.728885     24.437330     16.291555
```

[145]:
```
mean_year = history_data.groupby(['id']).mean().reset_index() # calculate the average price of each period
```

[146]:
```
mean_6m = history_data[history_data['price_date']>"2015-06-01"].groupby(['id']).mean().reset_index()
```

[147]:
```
mean_3m = history_data[history_data['price_date']>"2015-09-01"].groupby(['id']).mean().reset_index()
```

[148]:
```
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"]
```

[149]:
```
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"]
```

[150]:
```
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"]
```

KEY: By now, doing these feature engineer cannot assure there will be a valid effect. So Idea is to find as many potential attribute to be better.

[151]:
```
feature = mean_year.merge(mean_6m, on = 'id')
feature = feature.merge(mean_3m, on = 'id')
# features = mean_year
```

1.1 Such average is shallow, how to find valuable insight (KEY, domain in each industries is important)

Find tenure = date_end - date_start

[152]:
```
(pd.to_datetime(train['date_end']) - pd.to_datetime(train['date_activ']))
```

[152]:
```
0       1460 days
1       1096 days
2       2566 days
```

```
3        2192 days
4        2192 days
            …
16091    1445 days
16092    1461 days
16093    1460 days
16094    1461 days
16095    2556 days
Length: 16096, dtype: timedelta64[ns]
```

[153]:
```
train['tenure'] = ((train['date_end'] - train['date_activ'])/np.timedelta64(1,␣
↪'Y')).astype(int)
```

[154]:
```
tenure = train[['tenure', 'churn','id']].groupby(['tenure','churn'])['id'].
↪count().unstack(level = 1)
```

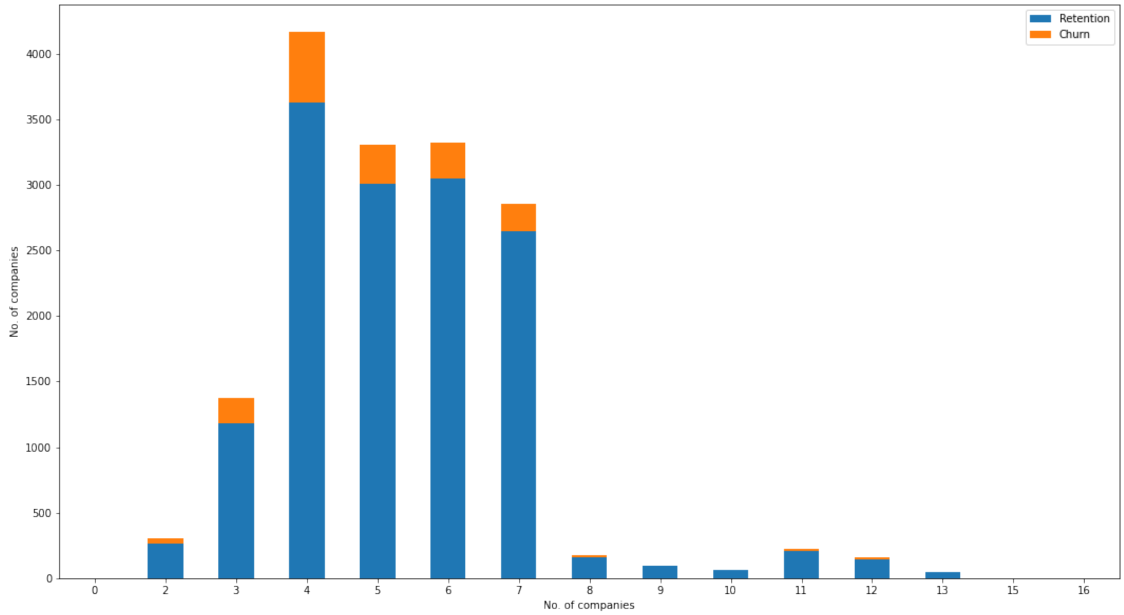
[155]:
```
tenure_percetage = (tenure.div(tenure.sum(axis =1), axis = 0) * 100)
```

[156]:
```
tenure_percetage
```

[156]:
```
churn            0          1
tenure
0       100.000000        NaN
2        86.754967  13.245033
3        85.922684  14.077316
4        87.161027  12.838973
5        91.019050   8.980950
6        91.900030   8.099970
7        92.654774   7.345226
8        93.641618   6.358382
9        97.916667   2.083333
10       96.969697   3.030303
11       92.035398   7.964602
12       91.139241   8.860759
13       91.489362   8.510638
15      100.000000        NaN
16      100.000000        NaN
```

[157]:
```
tenure.plot(kind='bar',
            figsize=(18,10),
            stacked = True,
            rot = 0)
# legend
plt.legend(['Retention','Churn'],loc = 'upper right')
# label
plt.ylabel('No. of companies')
plt.xlabel('No. of companies')
```

```
plt.show()
```



1.2 Transforming Datetime variable

We can cleary see that churn is **very low for companies which joied recently or that have made the contract a long time ago**. With the high numerber of churn within 3-7 years of tenures

We will also transform the dates provided in such 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 contract 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 integer (we are not interested in having decimal months)
```

[158]:
```
REFERENCE_DATE = datetime.datetime(2016,1,1)
```

[159]:
```
def convert_months(ref_date, df, col):
    time_delta = ref_date - df[col]
    months = (time_delta / np.timedelta64(1,'M')).astype(int)
    return months
```

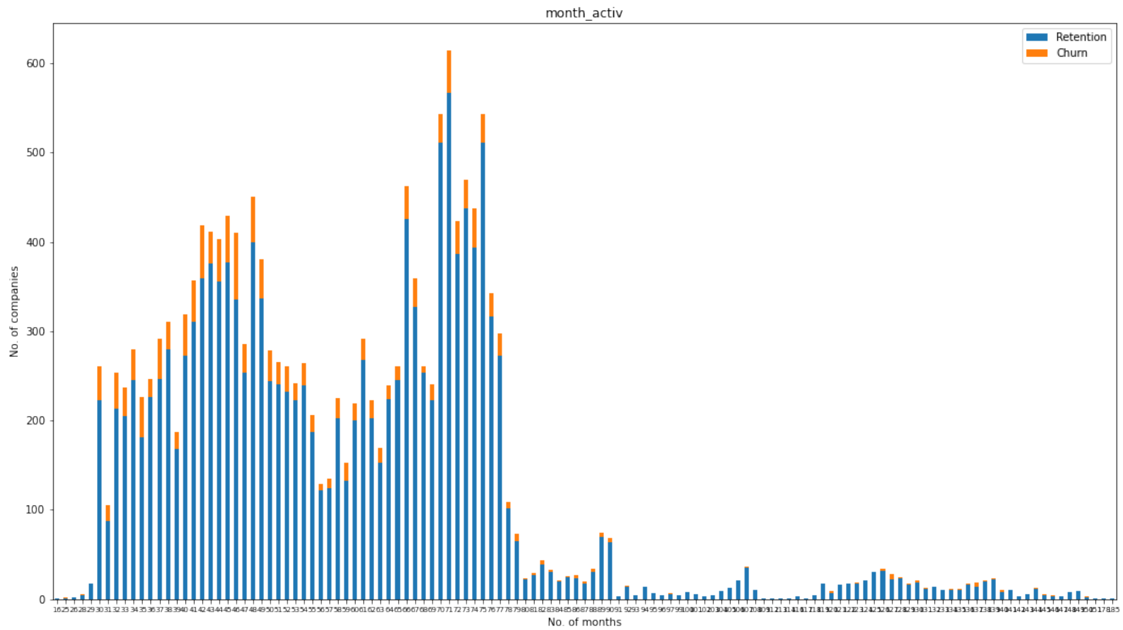
[160]:
```
train['month_activ'] = convert_months(REFERENCE_DATE, train, 'date_activ')
train['month_to_end'] = -convert_months(REFERENCE_DATE, train, 'date_end')
train['month_modif_prod'] = convert_months(REFERENCE_DATE, train,␣
↪'date_modif_prod')
train['month_renewal'] = convert_months(REFERENCE_DATE, train, 'date_renewal')
```

[161]:
```
# train[['date_activ', 'month_activ']]
train[['date_end','month_to_end']].sort_values(by = 'date_end')
```

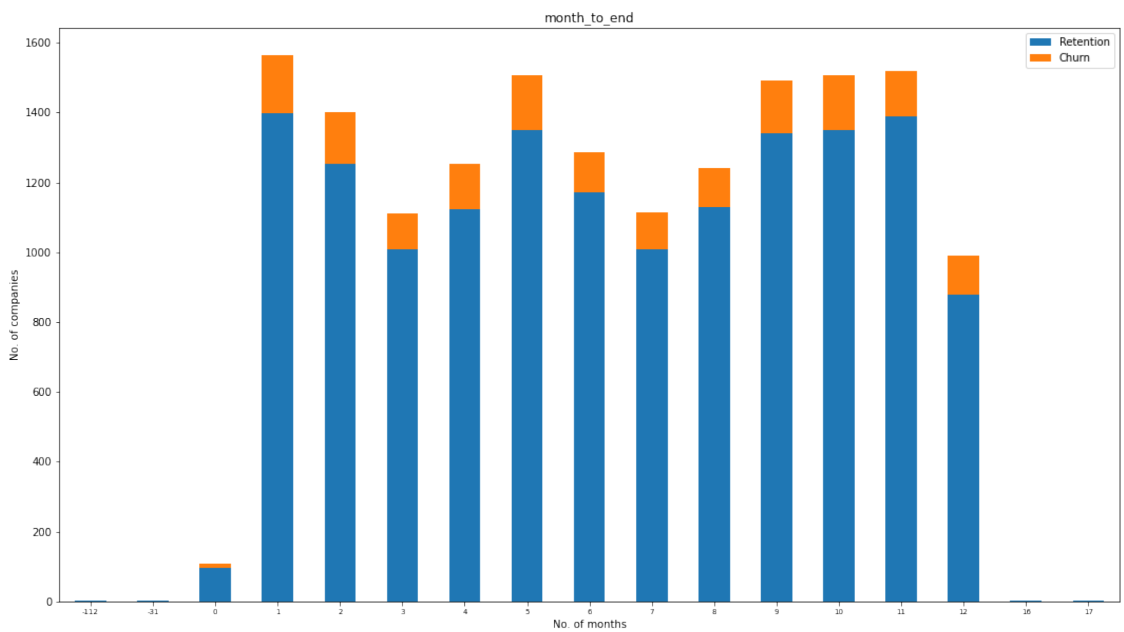
[161]:
```
         date_end  month_to_end
5910   2006-08-26          -112
15373  2013-05-06           -31
14490  2016-01-28             0
6936   2016-01-28             0
1553   2016-01-28             0
…             …           …
9221   2017-01-28            12
2130   2017-01-29            12
8688   2017-06-01            16
15742  2017-06-11            17
14929  2017-06-13            17

[16096 rows x 2 columns]
```

[162]:
```
def plot_churn_by_month(dataframe, column, fontsize_=11):
    """
    Plot churn distribution by monthly variable
    """
    temp = dataframe[[column, "churn", "id"]].groupby([column, "churn"])["id"].
↪count().unstack(level=1)
    temp.plot(kind="bar",
            figsize=(18,10),
            stacked=True,
            rot=0,
            title= column)
    # Rename legend
    plt.legend(["Retention", "Churn"], loc="upper right")
    # Labels
    plt.ylabel("No. of companies")
    plt.xlabel("No. of months")
    # Set xlabel fontsize
    plt.xticks(fontsize=fontsize_)
    plt.show()
```

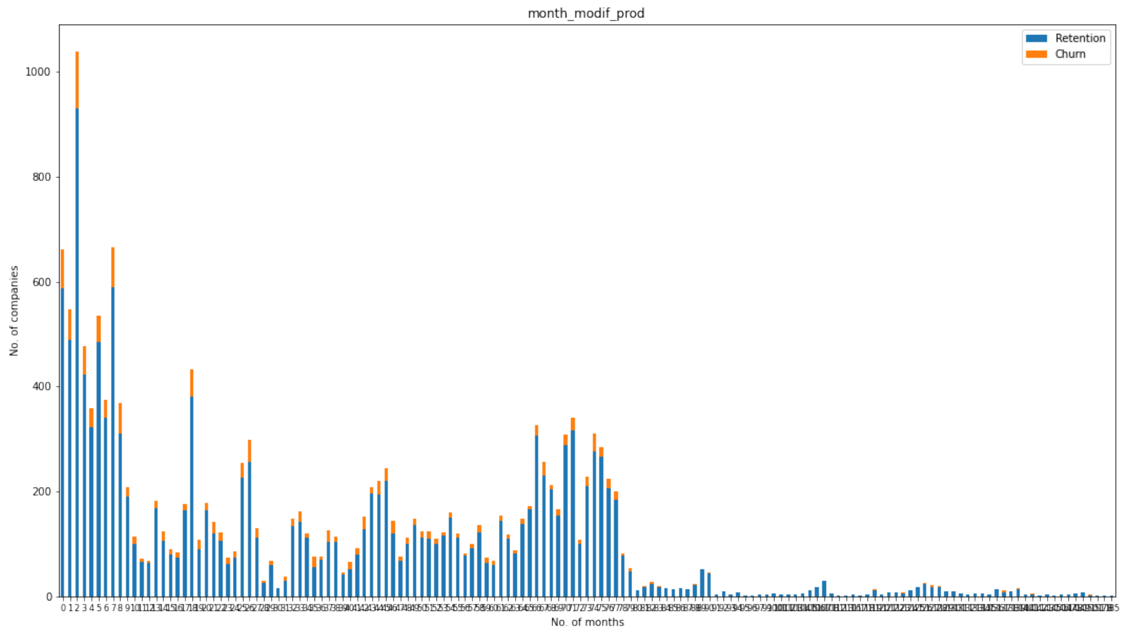
[163]:
```
plot_churn_by_month(train, "month_activ", 7)
```



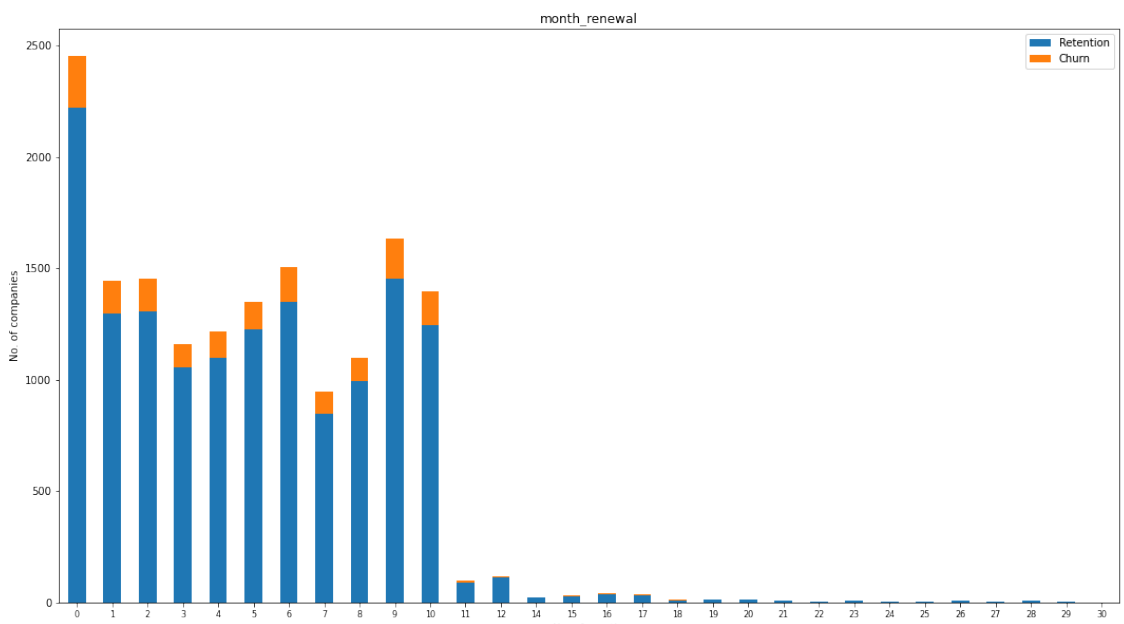
[164]:
```
plot_churn_by_month(train, "month_to_end", 7)
```



[165]:
```
plot_churn_by_month(train, "month_modif_prod", 8)
```



[166]:
```
plot_churn_by_month(train, "month_renewal", 8)
```



1.3 Transforming boolean data

Perform **label encoding** for Bool data

[167]:
```
train['has_gas'] = train['has_gas'].replace(['t','f'],[1,0])
```

[168]:
```
train['has_gas']
```

[168]:
```
0        0
1        1
2        0
3        0
4        0
        ..
16091    1
16092    0
16093    0
16094    0
16095    0
Name: has_gas, Length: 16096, dtype: int64
```

1.4 Transform categorical data and dumm variable

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, 0 < 1 < 2 < 3 ...**

For that reason we will use a method with dummy variables or onehot encoder

1.4.1 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 0 s and 1 s depending whether 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

[172]:
```
train['channel_sales'].value_counts()
```

[172]:
```
foosdfpfkusacimwkcsosbicdxkicaua    7377
null_value                          4218
lmkebamcaaclubfxadlmueccxoimlema    2073
usilxuppasemubllopkaafesmlibmsdf    1444
ewpakwlliwisiwduibdlfmalxowmwpci     966
sddiedcslfslkckwlfkdpoeeailfpeds      12
epumfxlbckeskwekxbiuasklxalciiuu       4
fixdbufsefwooaasfcxdxadsiekoceaa       2
Name: channel_sales, dtype: int64
```

[173]:
```
# Transform to categorical data type
train["channel_sales"] = train["channel_sales"].astype("category") # KEY, can␣
↪direct transform to category data type
```

[174]:
```
pd.DataFrame({'Sample in category':train['channel_sales'].value_counts() })
```

[174]:
```
                                  Sample in category
foosdfpfkusacimwkcsosbicdxkicaua                7377
null_value                                      4218
lmkebamcaaclubfxadlmueccxoimlema                2073
usilxuppasemubllopkaafesmlibmsdf                1444
ewpakwlliwisiwduibdlfmalxowmwpci                 966
sddiedcslfslkckwlfkdpoeeailfpeds                  12
epumfxlbckeskwekxbiuasklxalciiuu                   4
fixdbufsefwooaasfcxdxadsiekoceaa                   2
```

So that means we will create 8 different dummy variables . Each variable will become a different column.

[175]:
```
# Create dummy variables
categories_channel = pd.get_dummies(train["channel_sales"], prefix = "channel")
```

[177]:
```
# Rename for simplicity
categories_channel.columns = [col_name[:11] for col_name in categories_channel.
 ↪columns]
```

[179]:
```
categories_channel.head()
```

[179]:
```
   channel_epu  channel_ewp  channel_fix  channel_foo  channel_lmk  \
0            0            0            0            0            1
1            0            0            0            1            0
2            0            0            0            0            0
3            0            0            0            1            0
4            0            0            0            0            1

   channel_nul  channel_sdd  channel_usi
0            0            0            0
1            0            0            0
2            1            0            0
3            0            0            0
4            0            0            0
```

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 the columns.
How to know which to discard?

[183]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor


X = categories_channel
```

```python
# VIF dataframe
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]

print(vif_data)
```

```
       feature       VIF
0  channel_epu  1.000000
1  channel_ewp  0.204969
2  channel_fix  1.000000
3  channel_foo  0.028331
4  channel_lmk  0.012060
5  channel_nul  0.028924
6  channel_sdd  1.000000
7  channel_usi  0.113573
```

1.4.2 Categorical data origin_up

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

[186]:
```python
train['origin_up'].value_counts()
```

[186]:
```
lxidpiddsbxsbosboudacockeimpuepw    7825
kamkkxfxxuwbdslkwifmmcsiusiuosws    4517
ldkssxwpmemidmecebumciepifcamkci    3664
null_value                            87
usapbepcfoloekilkwsdiboslwaxobdp       2
ewxeelcelemmiwuafmddpobolfuxioce       1
Name: origin_up, dtype: int64
```

[187]:
```python
pd.DataFrame({"Samples in category": train["origin_up"].value_counts()})
```

[187]:
```
                                  Samples in category
lxidpiddsbxsbosboudacockeimpuepw                 7825
kamkkxfxxuwbdslkwifmmcsiusiuosws                 4517
ldkssxwpmemidmecebumciepifcamkci                 3664
null_value                                         87
usapbepcfoloekilkwsdiboslwaxobdp                    2
ewxeelcelemmiwuafmddpobolfuxioce                    1
```

[188]:
```python
# Create dummy variables
categories_origin = pd.get_dummies(train["origin_up"], prefix = "origin")
# Rename columns for simplicity
```

```
categories_origin.columns = [col_name[:10] for col_name in categories_origin.
    ↪columns]
```

[189]:
```
categories_origin.head(5)
```

[189]:

	origin_ewx	origin_kam	origin_ldk	origin_lxi	origin_nul	origin_usa
0	0	0	1	0	0	0
1	0	0	0	1	0	0
2	0	1	0	0	0	0
3	0	1	0	0	0	0
4	0	1	0	0	0	0

Finally remove one column to avoid the **dummy variable trap** dummy variable trap explanation

[190]:
```
categories_origin.drop(columns=["origin_nul"],inplace=True)
```

1.4.3 Categorical data - Featre engineering

[194]:
```
categories_activity = pd.DataFrame({"Activity samples":train["activity_new"].
    ↪value_counts()})
categories_activity
```

[194]:

	Activity samples
null_value	9545
apdekpcbwosbxepsfxclislboipuxpop	1577
kkklcdamwfafdcfwofuscwfwadblfmce	422
kwuslieomapmswolewpobpplkaooaaew	230
fmwdwsxillemwbbwelxsampiuwwpcdcb	219
…	…
xbwipkcuemuidpumuiomukkicculdmsb	1
xumuokeiidieboawuxkidxufcexecbbl	1
cswwlpkkduufdbfwfpflussouxbmbxbe	1
iilxdefdkwudppkiekwlcexkdupeucla	1
kllldxcildwkssbmoabmsdffmawsafsf	1

[420 rows x 1 columns]

As we can 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_category**

[195]:
```
# Get the categories with less than 75 samples
to_replace = list(categories_activity[categories_activity["Activity samples"]␣
    ↪<= 75].index)
# Replace them with `null_values_categories`
train["activity_new"]=train["activity_new"].
    ↪replace(to_replace,"null_values_activity")
```

[196]:
```python
# Create dummy variables
categories_activity = pd.get_dummies(train["activity_new"], prefix = "activity")
# Rename columns for simplicity
categories_activity.columns = [col_name[:12] for col_name in␣
↪categories_activity.columns]
```

[197]:
```python
categories_activity.drop(columns=["activity_nul"],inplace=True)
```

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

[198]:
```python
# Use common index to merge
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)
```

[199]:
```python
train.drop(columns=["channel_sales", "origin_up", "activity_new"],inplace=True)
```

2 Log transformation (KEY)

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 predective models make fundamental assumptions related to variables being **"normally 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.**

[200]:
```python
train.describe()
```

[200]:
```
          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              16096.000000             16096.000000
mean          1907.347229                  0.983785                70.309945
```

```
std       5257.364759                  5.141470               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              16096.000000              16096.000000
mean                   0.135955                  0.053211
std                    0.026157                  0.048515
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  …    origin_usa  activity_apd  activity_ckf  \
count           16096.000000  …  16096.000000  16096.000000  16096.000000
mean               43.539585  …      0.000124      0.097975      0.011742
std                 5.192262  …      0.011147      0.297290      0.107726
min                -0.122184  …      0.000000      0.000000      0.000000
25%                40.606701  …      0.000000      0.000000      0.000000
50%                44.311378  …      0.000000      0.000000      0.000000
75%                44.311378  …      0.000000      0.000000      0.000000
max                59.444710  …      1.000000      1.000000      1.000000

       activity_clu  activity_cwo  activity_fmw  activity_kkk  activity_kwu  \
count  16096.000000  16096.000000  16096.000000  16096.000000  16096.000000
mean       0.007393      0.007580      0.013606      0.026218      0.014289
std        0.085668      0.086733      0.115852      0.159787      0.118684
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_sfi  activity_wxe
count  16096.000000  16096.000000
mean       0.005157      0.007393
std        0.071626      0.085668
min        0.000000      0.000000
25%        0.000000      0.000000
50%        0.000000      0.000000
75%        0.000000      0.000000
max        1.000000      1.000000
```

```
[8 rows x 46 columns]
```

Particularly relevant to look at the **standard deviation std which is very very high for some variables.**

Log transformation does not work with negative data, so we will convert the negative values to **NaN.**

[201]:
```python
# 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
```

[202]:
```python
# 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)
```

[204]:
```python
fig, axs = plt.subplots(nrows=7, figsize=(18,50))
# Plot histograms
sns.distplot((train["cons_12m"].dropna()), ax=axs[0])
sns.distplot((train[train["has_gas"]==1]["cons_gas_12m"].dropna()), ax=axs[1])
sns.distplot((train["cons_last_month"].dropna()), ax=axs[2])
sns.distplot((train["forecast_cons_12m"].dropna()), ax=axs[3])
sns.distplot((train["forecast_cons_year"].dropna()), ax=axs[4])
sns.distplot((train["forecast_meter_rent_12m"].dropna()), ax=axs[5])
sns.distplot((train["imp_cons"].dropna()), ax=axs[6])
plt.show()
```

```
/home/brian/miniconda3/lib/python3.8/site-
packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/home/brian/miniconda3/lib/python3.8/site-
packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
```

```
  warnings.warn(msg, FutureWarning)
/home/brian/miniconda3/lib/python3.8/site-
packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/home/brian/miniconda3/lib/python3.8/site-
packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
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packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a
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/home/brian/miniconda3/lib/python3.8/site-
packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```
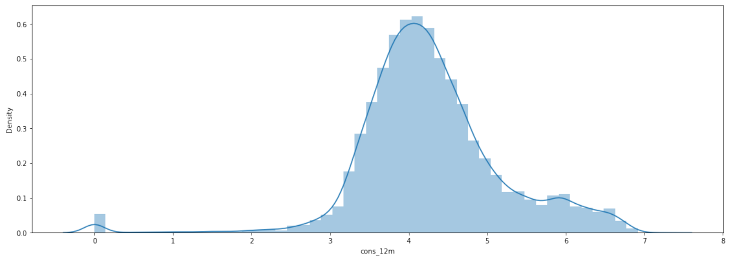
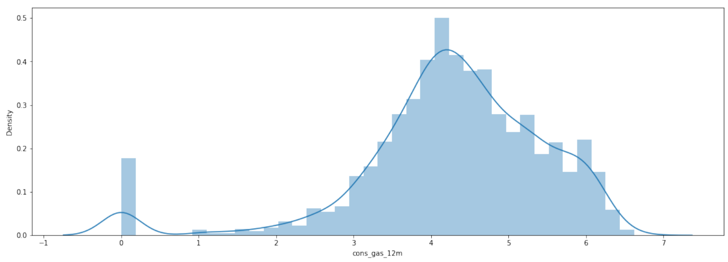
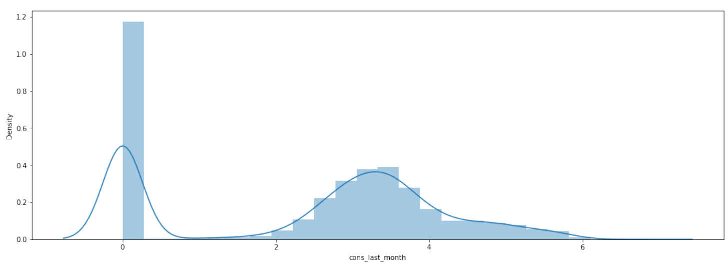
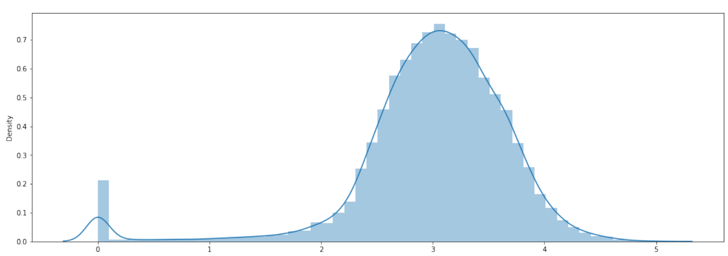
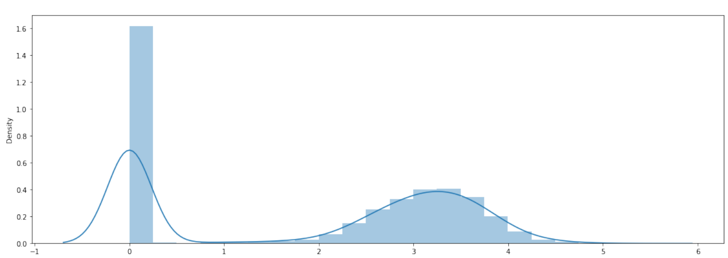
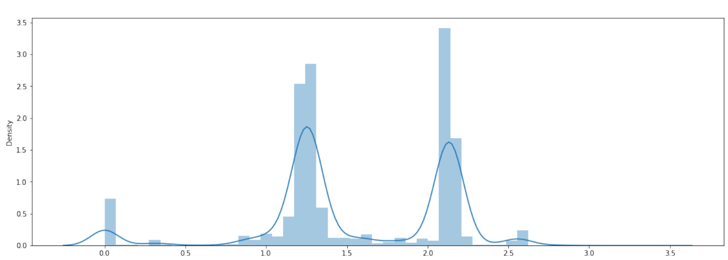


Density
cons_12m

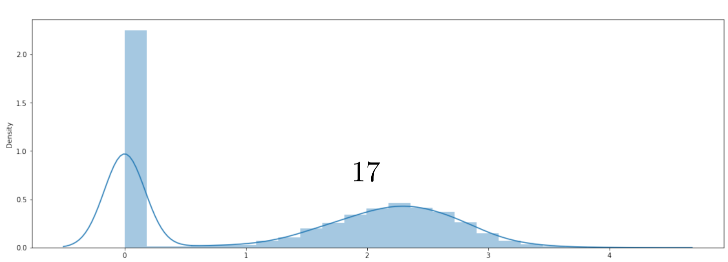

Density
cons_gas_12m


Density
cons_last_month


Density
forecast_cons_12m


Density
forecast_cons_year


Density
forecast_meter_rent_12m


Density
imp_cons

[205]:
```python
fig, axs = plt.subplots(nrows=7, figsize=(18,50))
# Plot boxplots
sns.boxplot((train["cons_12m"].dropna()), ax=axs[0])
sns.boxplot((train[train["has_gas"]==1]["cons_gas_12m"].dropna()), ax=axs[1])
sns.boxplot((train["cons_last_month"].dropna()), ax=axs[2])
sns.boxplot((train["forecast_cons_12m"].dropna()), ax=axs[3])
sns.boxplot((train["forecast_cons_year"].dropna()), ax=axs[4])
sns.boxplot((train["forecast_meter_rent_12m"].dropna()), ax=axs[5])
sns.boxplot((train["imp_cons"].dropna()), ax=axs[6])
plt.show()
```

```
/home/brian/miniconda3/lib/python3.8/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(
/home/brian/miniconda3/lib/python3.8/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
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/home/brian/miniconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
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/home/brian/miniconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
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FutureWarning: Pass the following variable as a keyword arg: x. From version
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arguments without an explicit keyword will result in an error or
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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
```
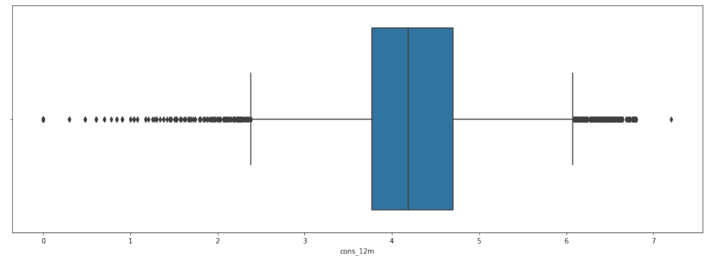
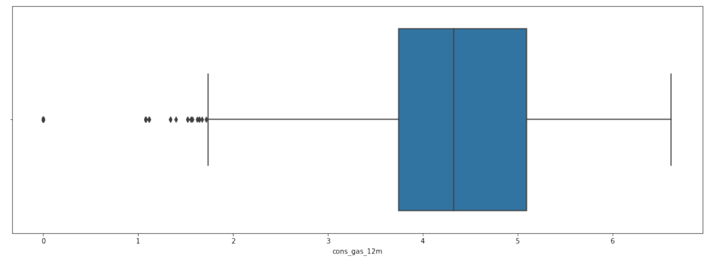
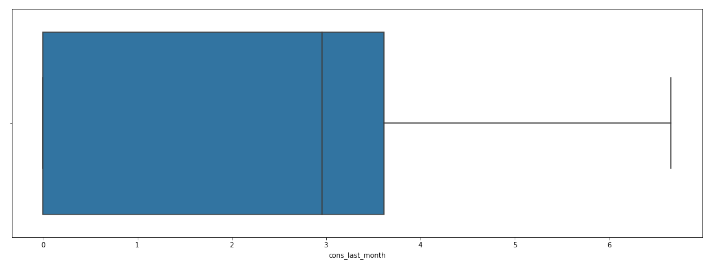
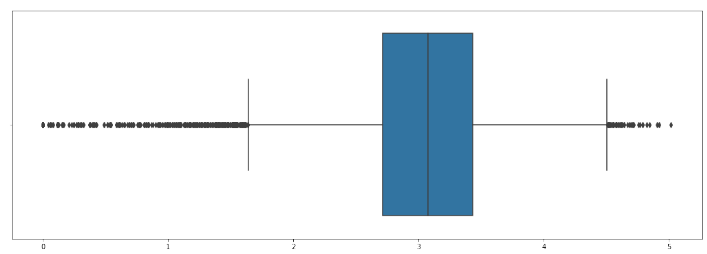
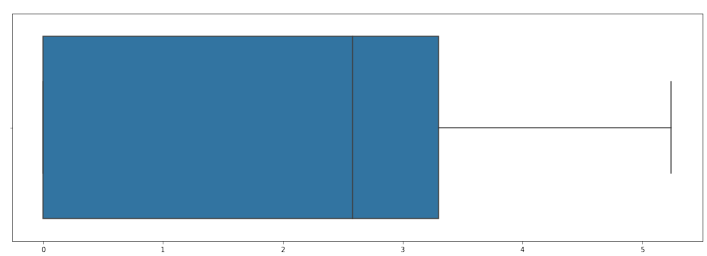

```
misinterpretation.
  warnings.warn(
/home/brian/miniconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

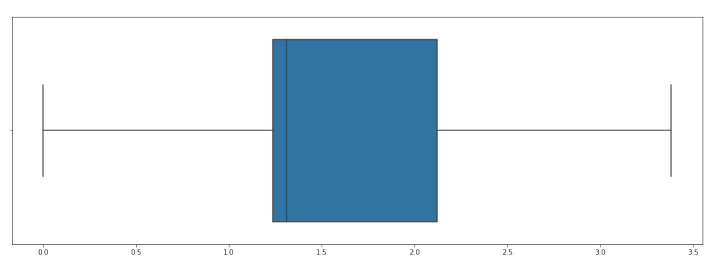

0 1 2 3 4 5 6 7
cons_12m

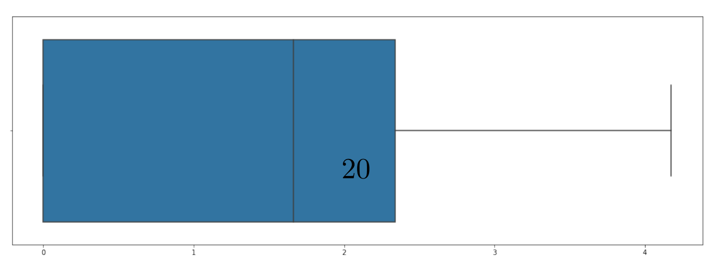

0 1 2 3 4 5 6
cons_gas_12m


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

[203]:

```
train.describe()
```

[203]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	\
count	16069.000000	16090.000000	16050.000000	16055.000000	
mean	4.283812	0.800300	2.359281	3.006826	
std	0.915265	1.748833	1.789067	0.709778	
min	0.000000	0.000000	0.000000	0.000000	
25%	3.773786	0.000000	0.000000	2.713952	
50%	4.187408	0.000000	2.959041	3.073579	
75%	4.701508	0.000000	3.617000	3.430950	
max	7.206748	6.622052	6.656933	5.016210	

	forecast_cons_year	forecast_discount_energy	forecast_meter_rent_12m	\
count	16071.000000	16096.000000	16092.000000	
mean	1.869956	0.983785	1.549610	
std	1.612963	5.141470	0.589394	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	1.236285	
50%	2.583199	0.000000	1.310481	
75%	3.301030	0.000000	2.122126	
max	5.243970	50.000000	3.382502	

	forecast_price_energy_p1	forecast_price_energy_p2	\
count	16096.000000	16096.000000	
mean	0.135955	0.053211	
std	0.026157	0.048515	
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	…	origin_usa	activity_apd	activity_ckf	\
count	16096.000000	…	16096.000000	16096.000000	16096.000000	
mean	43.539585	…	0.000124	0.097975	0.011742	
std	5.192262	…	0.011147	0.297290	0.107726	
min	-0.122184	…	0.000000	0.000000	0.000000	
25%	40.606701	…	0.000000	0.000000	0.000000	
50%	44.311378	…	0.000000	0.000000	0.000000	
75%	44.311378	…	0.000000	0.000000	0.000000	
max	59.444710	…	1.000000	1.000000	1.000000	

	activity_clu	activity_cwo	activity_fmw	activity_kkk	activity_kwu	\
count	16096.000000	16096.000000	16096.000000	16096.000000	16096.000000	
mean	0.007393	0.007580	0.013606	0.026218	0.014289	

```
std        0.085668       0.086733       0.115852       0.159787       0.118684
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_sfi  activity_wxe
count  16096.000000  16096.000000
mean       0.005157      0.007393
std        0.071626      0.085668
min        0.000000      0.000000
25%        0.000000      0.000000
50%        0.000000      0.000000
75%        0.000000      0.000000
max        1.000000      1.000000

[8 rows x 46 columns]
```

The distributions look much closer to normal distributions now!
Notice how the **standard deviation std has changed.**

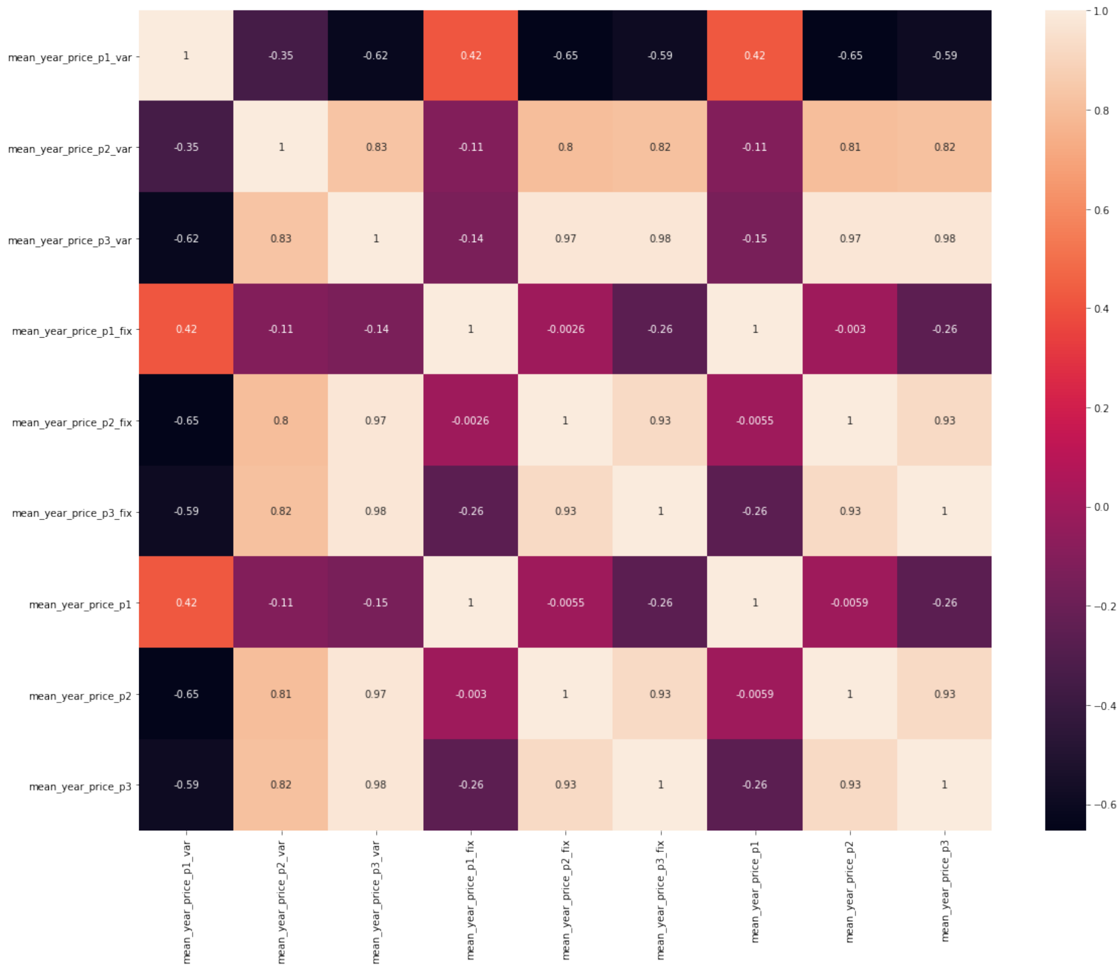
From the boxplots we can still see some values are quite far from the range (**outliers**). **We will deal with them later.**

3 High correlation variables(history data set)

[210]:
```
feature = mean_year
```

[211]:
```
# Calculate correlation of variables
correlation = feature.corr()
```

[212]:
```
# 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()
```



We can remove **highly correlated variables.**

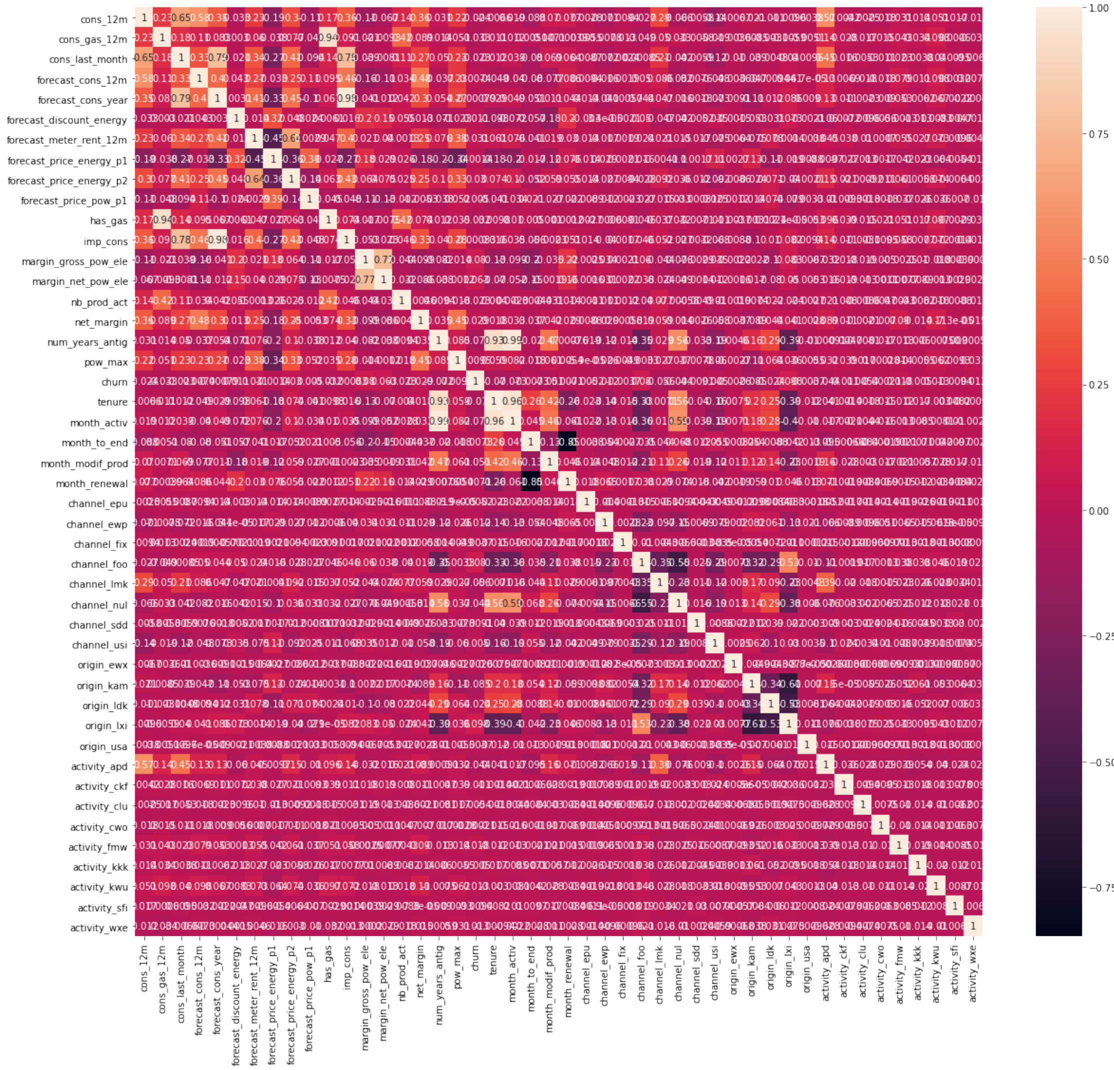
Multicollinearity happens when one predictor variable in a multiple regression model can be linearly predicted from the others with a high degree of accuracy.

This can lead to skewed or misleading results. Luckily, **decision trees and boosted trees 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.

[214]:
```python
correlation = train.corr()
# 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()
```



As expected, num_years_antig has a high correlation with months_activ (it provides us the same information). We can remove variables with very high correlation

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

4 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 interquartile range above the 3rd 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 the mean (average of the values excluding outliers).

[216]:
```python
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 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 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")
```

[220]:
```python
for c in feature.columns:
    if c != "id":
        feature = replace_outliers_z_score(feature,c)
```

```
Replaced: 277  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: 121  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: 122  outliers in  mean_year_price_p1
Replaced: 0  outliers in  mean_year_price_p2
Replaced: 0  outliers in  mean_year_price_p3
```

[221]:

```
feature
```

[221]:

```
                                     id  mean_year_price_p1_var  \
0      0002203ffbb812588b632b9e628cc38d                0.124338
1      0004351ebdd665e6ee664792efc4fd13                0.146426
2      0010bcc39e42b3c2131ed2ce55246e3c                0.181558
3      0010ee3855fdea87602a5b7aba8e42de                0.118757
4      00114d74e963e47177db89bc70108537                0.147926
…                                   …                     …
16091  ffef185810e44254c3a4c6395e6b4d8a                0.138863
16092  fffac626da707b1b5ab11e8431a4d0a2                0.147137
16093  fffc0cacd305dd51f316424bbb08d1bd                0.153879
16094  fffe4f5646aa39c7f97f95ae2679ce64                0.123858
16095  ffff7fa066f1fb305ae285bb03bf325a                0.125360

       mean_year_price_p2_var  mean_year_price_p3_var  mean_year_price_p1_fix  \
0                    0.103794                0.073160               40.701732
1                    0.000000                0.000000               44.385450
2                    0.000000                0.000000               45.319710
3                    0.098292                0.069032               40.647427
4                    0.000000                0.000000               44.266930
…                         …                       …                       …
16091                0.115125                0.080780               40.896427
16092                0.000000                0.000000               44.311375
16093                0.129497                0.094842               41.160171
16094                0.103499                0.073735               40.606699
16095                0.104895                0.075635               40.647427

       mean_year_price_p2_fix  mean_year_price_p3_fix  mean_year_price_p1  \
0                   24.421038               16.280694           40.826071
1                    0.000000                0.000000           44.531877
2                    0.000000                0.000000           45.501268
3                   24.388455               16.258971           40.766185
4                    0.000000                0.000000           44.414856
…                         …                       …                  …
16091               24.637456               16.507972           41.035291
16092                0.000000                0.000000           44.458512
16093               24.895768               16.763569           41.314049
```

```
16094                24.364017                16.242678               40.730558
16095                24.388455                16.258971               40.772788

       mean_year_price_p2  mean_year_price_p3
0               24.524832           16.353854
1                0.000000            0.000000
2                0.000000            0.000000
3               24.486748           16.328003
4                0.000000            0.000000
…                     …                   …
16091           24.752581           16.588752
16092            0.000000            0.000000
16093           25.025265           16.858411
16094           24.467516           16.316414
16095           24.493350           16.334606

[16096 rows x 10 columns]
```

[222]:

```python
def _find_outliers_iqr(dataframe, 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):
    """
    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 lower 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 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 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 outliers
    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")
```

[226]:
```
train = replace_outliers_z_score(train,"cons_12m")
train = replace_outliers_z_score(train,"cons_gas_12m")
train = replace_outliers_z_score(train,"cons_last_month")
train = replace_outliers_z_score(train,"forecast_cons_12m")
#train = replace_outliers_z_score(train,"forecast_cons_year")
train = replace_outliers_z_score(train,"forecast_discount_energy")
train = replace_outliers_z_score(train,"forecast_meter_rent_12m")
train = replace_outliers_z_score(train,"forecast_price_energy_p1")
train = replace_outliers_z_score(train,"forecast_price_energy_p2")
train = replace_outliers_z_score(train,"forecast_price_pow_p1")
train = replace_outliers_z_score(train,"imp_cons")
train = replace_outliers_z_score(train,"margin_gross_pow_ele")
train = replace_outliers_z_score(train,"margin_net_pow_ele")
train = replace_outliers_z_score(train,"net_margin")
train = replace_outliers_z_score(train,"pow_max")
train = replace_outliers_z_score(train,"month_activ")
train = replace_outliers_z_score(train,"month_to_end")
train = replace_outliers_z_score(train,"month_modif_prod")
train = replace_outliers_z_score(train,"month_renewal")
```

```
Replaced: 0  outliers in  cons_12m
Replaced: 0  outliers in  cons_gas_12m
Replaced: 0  outliers in  cons_last_month
Replaced: 0  outliers in  forecast_cons_12m
Replaced: 0  outliers in  forecast_discount_energy
```

```
Replaced: 0  outliers in  forecast_meter_rent_12m
Replaced: 0  outliers in  forecast_price_energy_p1
Replaced: 0  outliers in  forecast_price_energy_p2
Replaced: 0  outliers in  forecast_price_pow_p1
Replaced: 0  outliers in  imp_cons
Replaced: 0  outliers in  margin_gross_pow_ele
Replaced: 0  outliers in  margin_net_pow_ele
Replaced: 0  outliers in  net_margin
Replaced: 0  outliers in  pow_max
Replaced: 0  outliers in  month_activ
Replaced: 0  outliers in  month_to_end
Replaced: 0  outliers in  month_modif_prod
Replaced: 0  outliers in  month_renewal
```

[227]:

```
train.reset_index(drop=True, inplace=True)
```

Let's see how the boxplots changed!

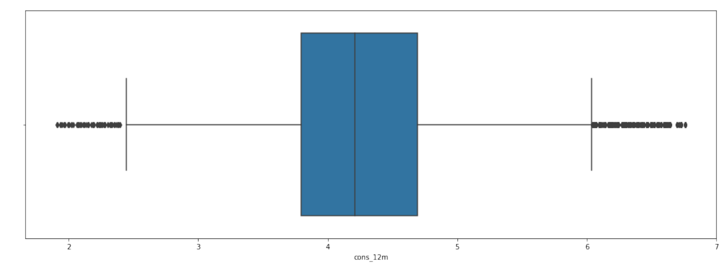
Note: I do like applying a light Z-score of 3, although IQR is usually heavier on the data.

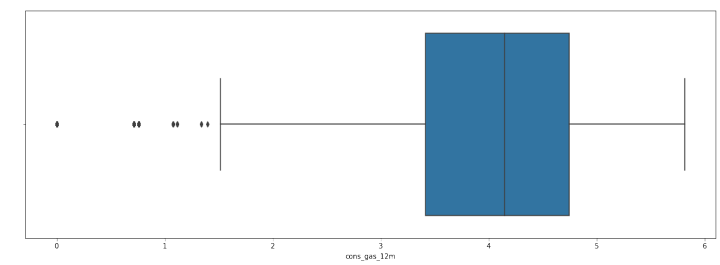
[228]:

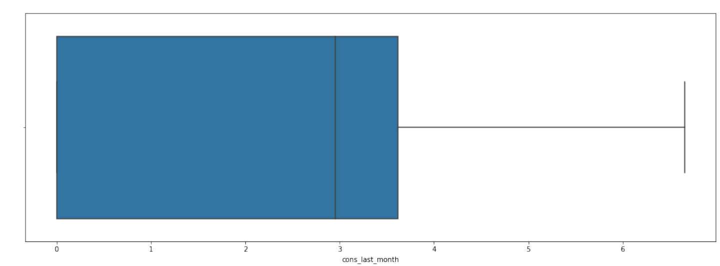
```
fig, axs = plt.subplots(nrows=7, figsize=(18,50))
# Plot boxplots
sns.boxplot((train["cons_12m"].dropna()), ax=axs[0])
sns.boxplot((train[train["has_gas"]==1]["cons_gas_12m"].dropna()), ax=axs[1])
sns.boxplot((train["cons_last_month"].dropna()), ax=axs[2])
sns.boxplot((train["forecast_cons_12m"].dropna()),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

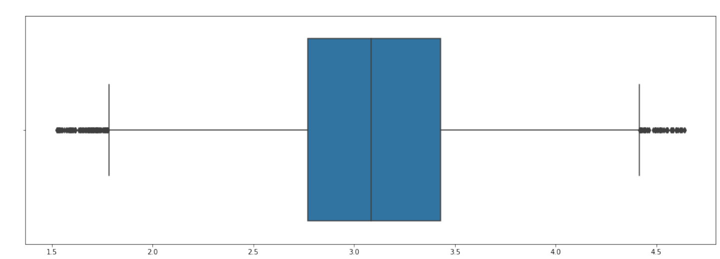
```
/home/brian/miniconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
/home/brian/miniconda3/lib/python3.8/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(
/home/brian/miniconda3/lib/python3.8/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(
```

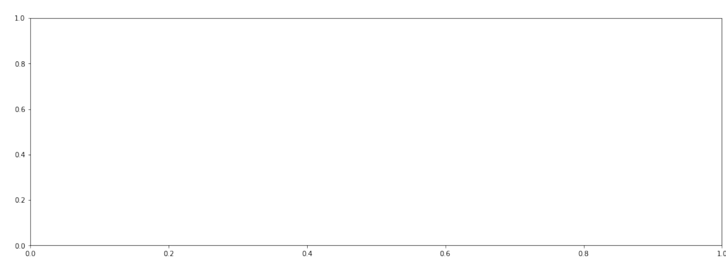
```
/home/brian/miniconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
/home/brian/miniconda3/lib/python3.8/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(
/home/brian/miniconda3/lib/python3.8/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(
```

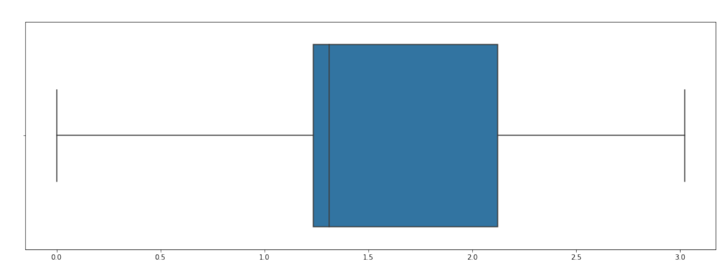

2 3 4 5 6 7
cons_12m

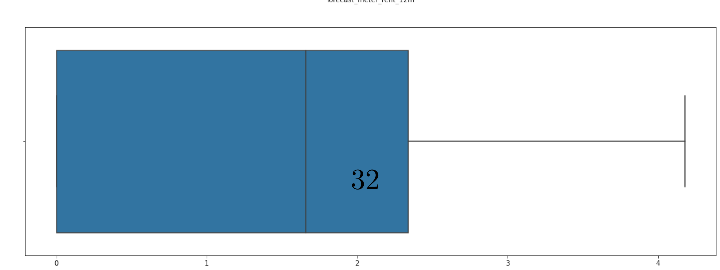

0 1 2 3 4 5 6
cons_gas_12m


0 1 2 3 4 5 6
cons_last_month


1.5 2.0 2.5 3.0 3.5 4.0 4.5
forecast_cons_12m


0.0 0.2 0.4 0.6 0.8 1.0
0.0 0.2 0.4 0.6 0.8 1.0


0.0 0.5 1.0 1.5 2.0 2.5 3.0
forecast_meter_rent_12m


0 1 2 3 4
imp_cons

5 Pickling

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

[229]:
```
pd.to_pickle(train, 'feature_engineered_train_data.pkl')
pd.to_pickle(history_data, 'feature_engineered_history_data.pkl')
```

[ ]:
```
```