Feature engineering

0. Package Import and Data Loading
1. Feature engineering
2. Variable correlation
3. Removing outliers
4. Pickling

---

0. Import packages

Load the necessary packages for this exercise

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

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

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

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

---

0. Loading data

Data directory

Explicitly show how paths are indicated

In [5]:
```
PICKLE_TRAIN_DIR = os.path.join("..", "processed_data", "train_data.pkl")
PICKLE_HISTORY_DIR = os.path.join("..", "processed_data", "history_data.pkl")
```

Load data into dataframes

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

In [6]:
```
history_data = pd.read_pickle(PICKLE_HISTORY_DIR)
train = pd.read_pickle(PICKLE_TRAIN_DIR)
```

---

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.

In [7]:
```
mean_year = history_data.groupby(["id"]).mean().reset_index()
```

In [8]:
```
mean_6m = history_data[history_data["price_date"] > "2015-06-01"].groupby(["id"]).mean().reset_index()
```

In [9]:
```
mean_3m = history_data[history_data["price_date"] > "2015-10-01"].groupby(["id"]).mean().reset_index()
```

In [10]:
```
### Combine them in a single dataframe
```

In [11]:
```
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"]
```

In [12]:
```
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"]
```

In [13]:
```
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"]
```

Now we will merge them into a single dataframe

Note: I am not confident the `mean_6m` and `mean_3m` could help the prediction model. We will see below the variables are also highly correlated to actually using only the `mean_year` is OK

In [14]:
```
#features = pd.merge(mean_year,mean_6m, on="id")
#features = pd.merge(features,mean_3m, on="id")
features = mean_year
```

Feature engineering

In the previous notebook we explored 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?

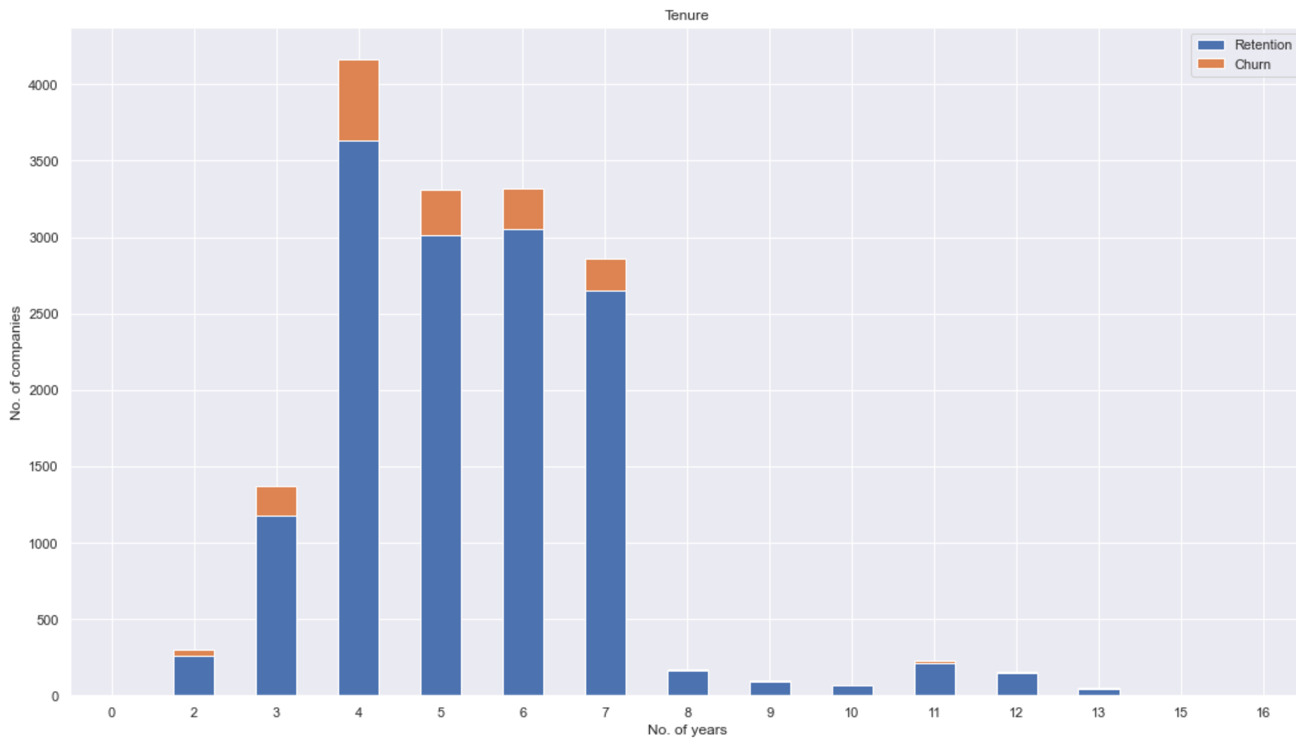
> We will define a variable `tenure = date_end - date_activ`

In [15]:
```
train["tenure"] = ((train["date_end"]-train["date_activ"])/ np.timedelta64(1, "Y")).astype(int)
```

In [16]:
```
tenure = train[["tenure", "churn", "id"]].groupby(["tenure", "churn"])["id"].count().unstack(level=1)
tenure_percentage = (tenure.div(tenure.sum(axis=1), axis=0)*100)
```

In [17]:
```
tenure.plot(kind="bar",
                        figsize=(18,10),
                        stacked=True,
                        rot=0,
                       title= "Tenure")

# Rename legend
plt.legend(["Retention", "Churn"], loc="upper right")
# Labels
plt.ylabel("No. of companies")
plt.xlabel("No. of years")
plt.show()
```



We can clearly that churn is very low for companies which joined 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 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)
```

In [18]:
```python
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
```

In [19]:
```python
# Create reference date as provided on the exercise statement
REFERENCE_DATE = datetime.datetime(2016,1,1)
```

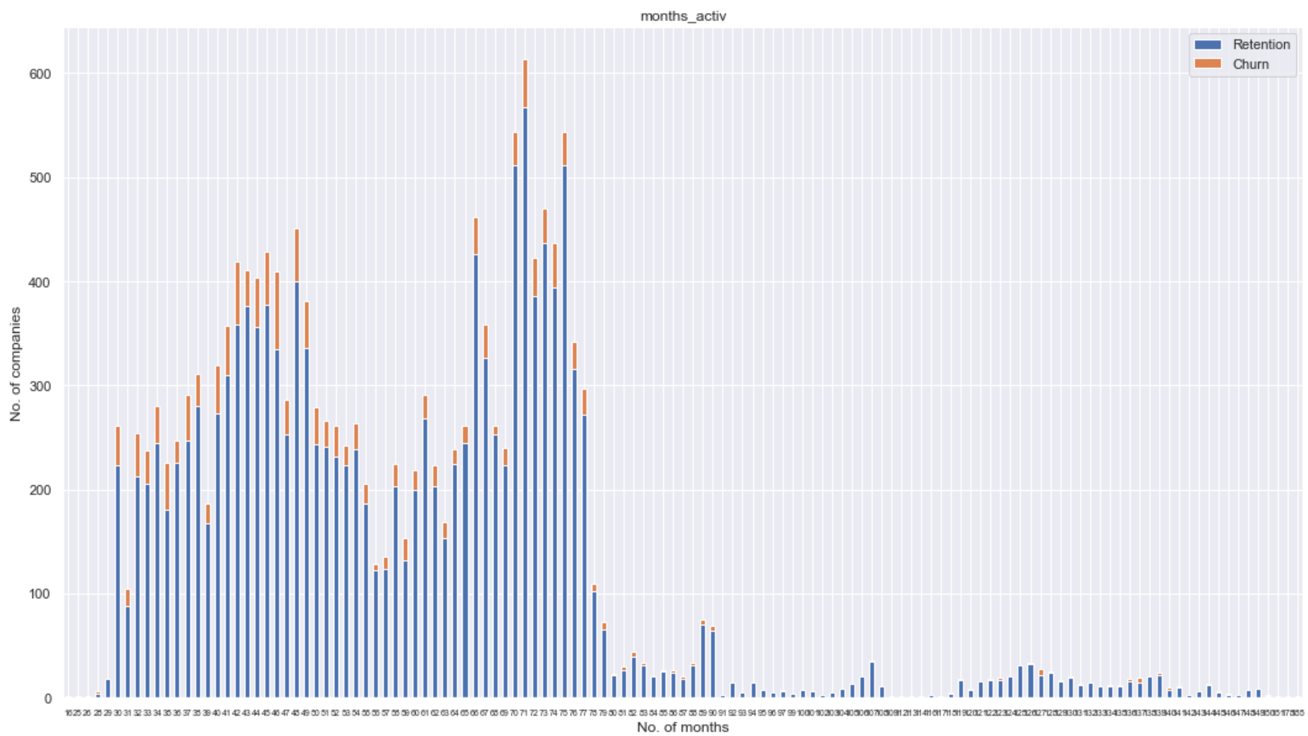
In [20]:
```python
train["months_activ"] = convert_months(REFERENCE_DATE, train, "date_activ")
train["months_to_end"] = -convert_months(REFERENCE_DATE, train, "date_end")
train["months_modif_prod"] = convert_months(REFERENCE_DATE, train, "date_modif_prod")
train["months_renewal"] = convert_months(REFERENCE_DATE, train, "date_renewal")
```

Let's see if we can get any insights

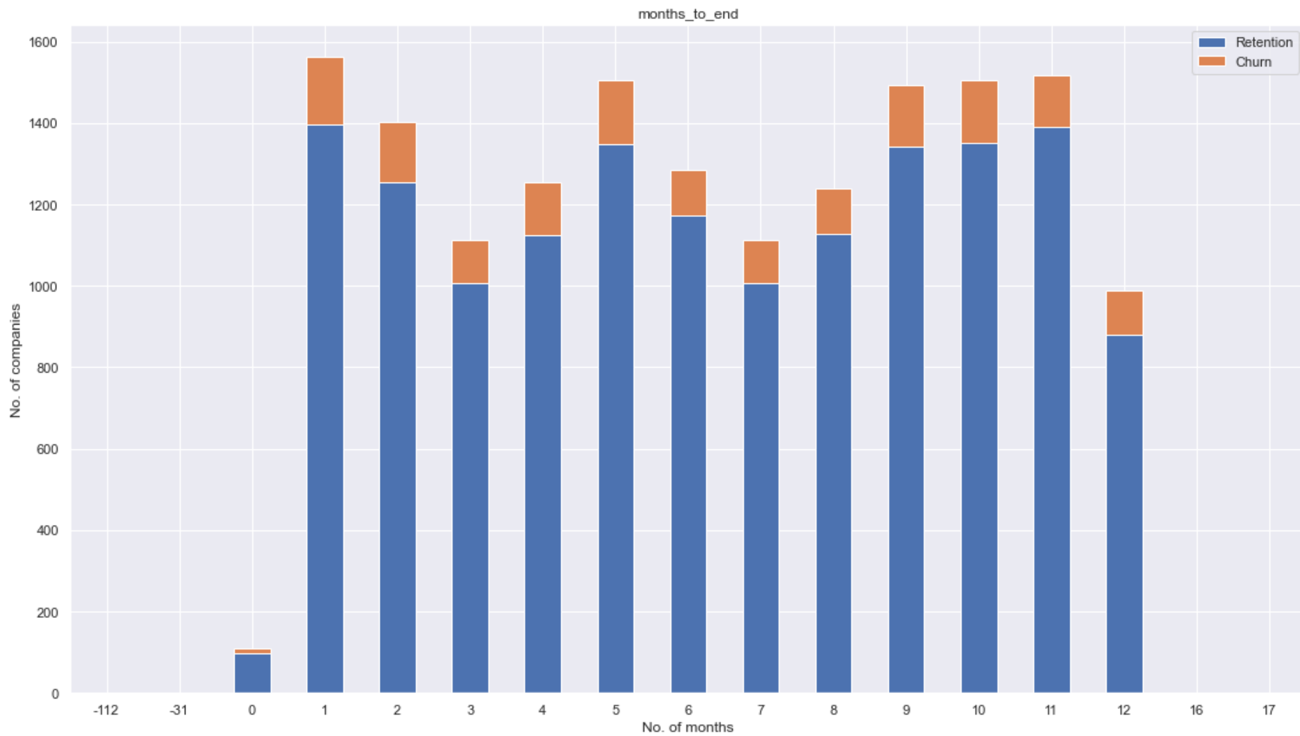
In [21]:
```python
def plot_churn_by_month(dataframe, column, fontsize_=11):
    """
    Plot churn distribution by monthly variable
    """
    temp = dataframe[[column, "churn", "id"]].groupby([column, "churn"])["id"].count().unstack(level=1)
    temp.plot(kind="bar",
              figsize=(18,10),
              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()
```

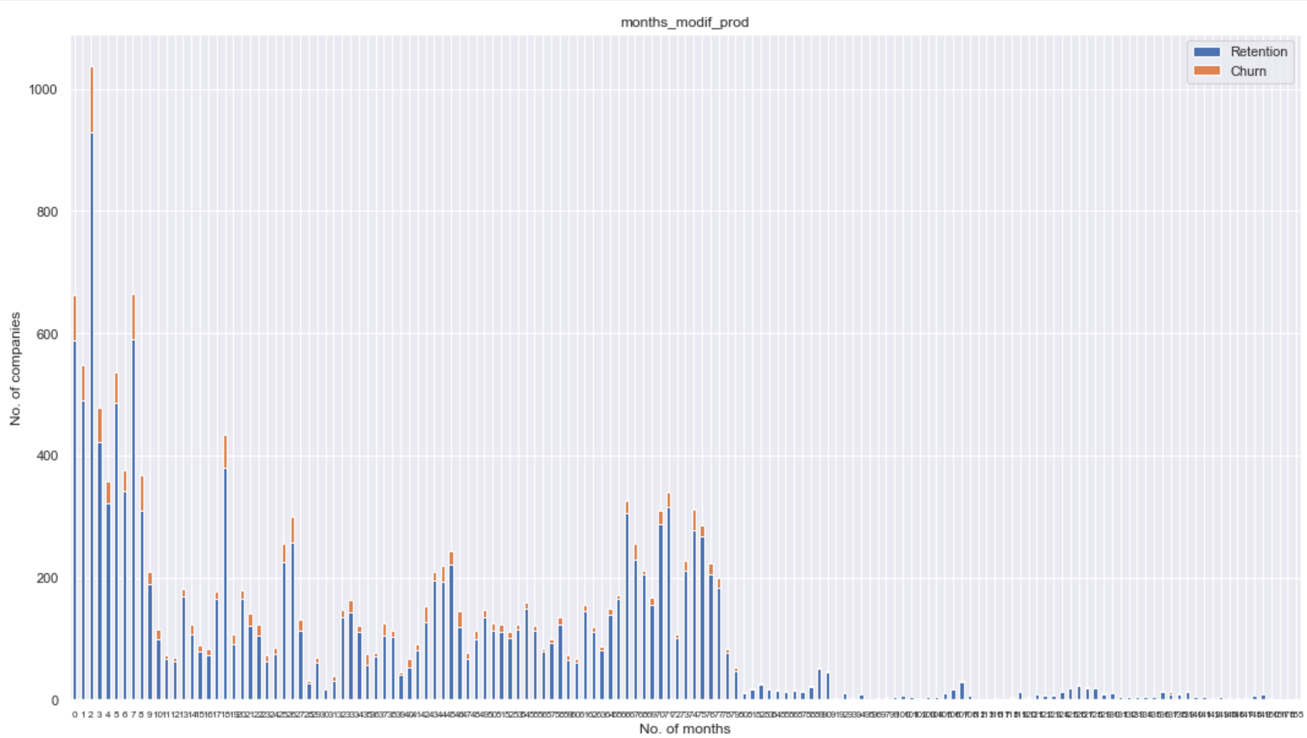
In [22]:
```python
plot_churn_by_month(train, "months_activ", 7)
```



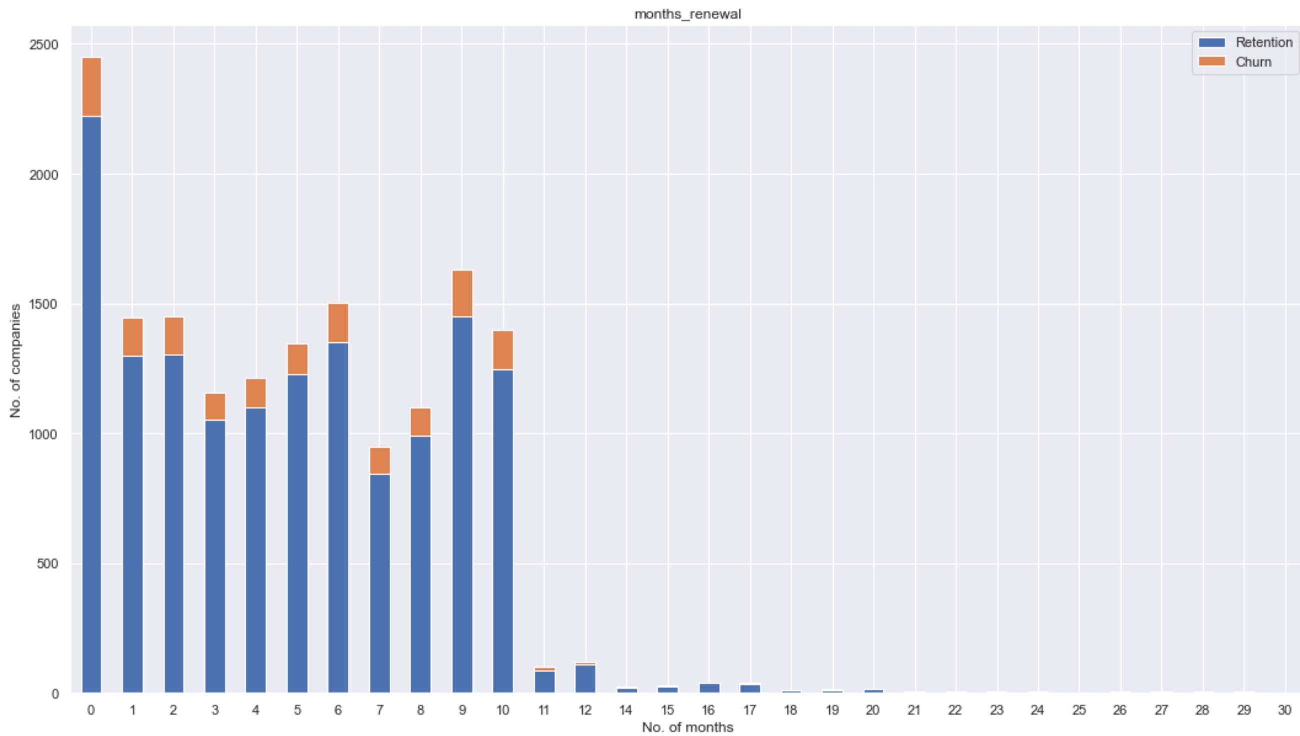
In [23]:
```
plot_churn_by_month(train, "months_to_end")
```



In [24]:
```
plot_churn_by_month(train, "months_modif_prod", 8)
```



In [25]:
```
plot_churn_by_month(train, "months_renewal")
```



Remove the date columns

In [26]:
```
train.drop(columns=["date_activ", "date_end", "date_modif_prod", "date_renewal"],inplace=True)
```

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

In [27]:
```
train["has_gas"]=train["has_gas"].replace(["t", "f"],[1,0])
```

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, `0 < 1 < 2 < 3 ...`

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

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`

In [28]:
```
train["channel_sales"] = train["channel_sales"].fillna("null_values_channel")
```

Now transform the `channel_sales` column into categorical data type

In [29]:
```python
# Transform to categorical data type
train["channel_sales"] = train["channel_sales"].astype("category")
```

We want to see how many categories we will end up with

In [30]:
```python
pd.DataFrame({"Samples in category": train["channel_sales"].value_counts()})
```

Out[30]:

	Samples in category
foosdfpfkusacimwkcsosbicdxkicaua	7377
null_values_channel	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.

In [31]:
```python
# Create dummy variables
categories_channel = pd.get_dummies(train["channel_sales"], prefix = "channel")
```

In [32]:
```python
# Rename columns for simplicity
categories_channel.columns = [col_name[:11] for col_name in categories_channel.columns]
```

In [33]:
```python
categories_channel.head(5)
```

Out[33]:

	channel_epu	channel_ewp	channel_fix	channel_foo	channel_lmk	channel_nul	channel_sdd	channel_usi
0	0	0	0	0	1	0	0	0
1	0	0	0	1	0	0	0	0
2	0	0	0	0	0	1	0	0
3	0	0	0	1	0	0	0	0
4	0	0	0	0	1	0	0	0

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 the columns.

In [34]:
```python
categories_channel.drop(columns=["channel_nul"],inplace=True)
```

Categorical data `origin_up`

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

In [35]:
```python
train["origin_up"] = train["origin_up"].fillna("null_values_origin")
```

Now transform the `origin_up` column into categorical data type

In [36]:
```python
train["origin_up"] = train["origin_up"].astype("category")
```

We want to see how many categories we will end up with

In [37]:
```python
pd.DataFrame({"Samples in category": train["origin_up"].value_counts()})
```

Out[37]:

	Samples in category
lxidpiddsbxsbosboudacockeimpuepw	7825
kamkkxfxxuwbdslkwifmmcsiusiuosws	4517
ldkssxwpmemidmecebumciepifcamkci	3664
null_values_origin	87
usapbepcfoloekilkwsdiboslwaxobdp	2
ewxeelcelemmiwuafmddpobolfuxioce	1

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

In [38]:
```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]
```

In [39]:
```python
categories_origin.head(5)
```

Out[39]:

	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`

In [40]:
```python
categories_origin.drop(columns=["origin_nul"],inplace=True)
```

Categorical data - Feature engineering

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

In [41]:
```python
train["activity_new"] = train["activity_new"].fillna("null_values_activity")
```

We want to see how many categories we will end up with

In [42]:
```python
categories_activity = pd.DataFrame({"Activity samples":train["activity_new"].value_counts()})
categories_activity
```

Out[42]:

	Activity samples
null_values_activity	9545
apdekpcbwosbxepsfxclislboipuxpop	1577
kkklcdamwfafdcfwofuscwfwadblfmce	422
kwuslieomapmswolewpobpplkaooaaew	230
fmwdwsxillemwbbwelxsampiuwwpcdcb	219
...	...
xpwokbdseslumlsislulloalddkioslw	1
eddebmodfooxxwfaslcswiepfmaoxxss	1
axicmuscucbmiecbxaiuudxiacufcpcx	1
dwdflbsopucwoxdmccmulwiiefiiabel	1
wceaopxmdpccxfmcdpopulcaubcxibuw	1

420 rows × 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`

In [43]:
```
# 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")
```

In [44]:
```
# 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]
```

In [45]:
```
categories_activity.head(5)
```

Out[45]:

	activity_apd	activity_ckf	activity_clu	activity_cwo	activity_fmw	activity_kkk	activity_kwu	activity_nul	activity_sfi	activity_wxe
0	0	0	0	0	0	0	0	1	0	0
1	0	0	0	0	0	0	0	1	0	0
2	0	0	0	0	0	0	0	1	0	0
3	0	0	0	0	0	0	0	1	0	0
4	0	0	0	0	0	0	0	1	0	0

Finally remove one column to avoid the `dummy variable trap`

In [46]:
```
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

In [47]:
```
# 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)
```

In [48]:
```
train.drop(columns=["channel_sales", "origin_up", "activity_new"],inplace=True)
```

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 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.

In [49]:
```
train.describe()
```

Out[49]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_year	forecast_discount_energy	forecast_meter_rent_12m	fore
count	1.609600e+04	1.609600e+04	1.609600e+04	16096.000000	16096.000000	15970.000000	16096.000000	
mean	1.948044e+05	3.191164e+04	1.946154e+04	2370.555949	1907.347229	0.991547	70.309945	
std	6.795151e+05	1.775885e+05	8.235676e+04	4035.085664	5257.364759	5.160969	79.023251	
min	-1.252760e+05	-3.037000e+03	-9.138600e+04	-16689.260000	-85627.000000	0.000000	-242.960000	
25%	5.906250e+03	0.000000e+00	0.000000e+00	513.230000	0.000000	0.000000	16.230000	
50%	1.533250e+04	0.000000e+00	9.010000e+02	1179.160000	378.000000	0.000000	19.440000	
75%	5.022150e+04	0.000000e+00	4.127000e+03	2692.077500	1994.250000	0.000000	131.470000	
max	1.609711e+07	4.188440e+06	4.538720e+06	103801.930000	175375.000000	50.000000	2411.690000	

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`.

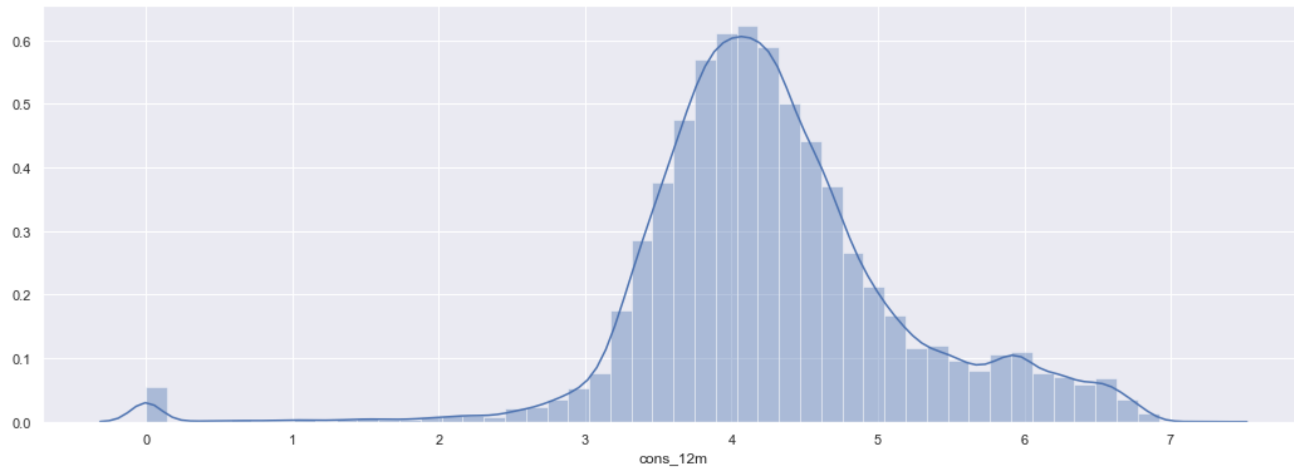
Also we cannot apply a log transformation to `0` valued entries, so we will add a constant `1`

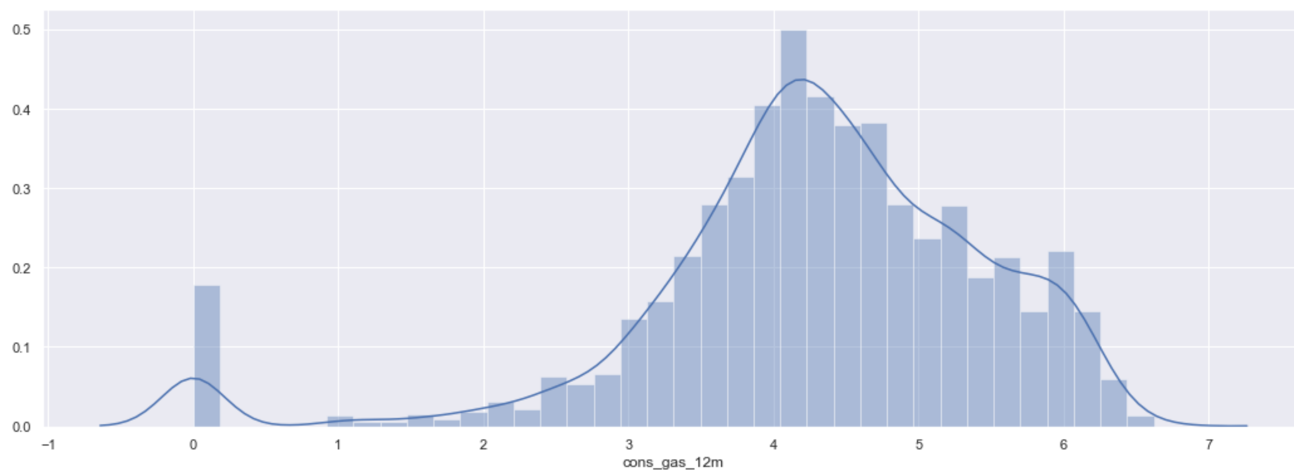
In [50]:
```
# Remove negative values
train.loc[train.cons_12m < 0,"cons_12m"] = np.nan
train.loc[train.cons_gas_12m < 0,"cons_gas_12m"] = np.nan
train.loc[train.cons_last_month < 0,"cons_last_month"] = np.nan
train.loc[train.forecast_cons_12m < 0,"forecast_cons_12m"] = np.nan
train.loc[train.forecast_cons_year < 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
```

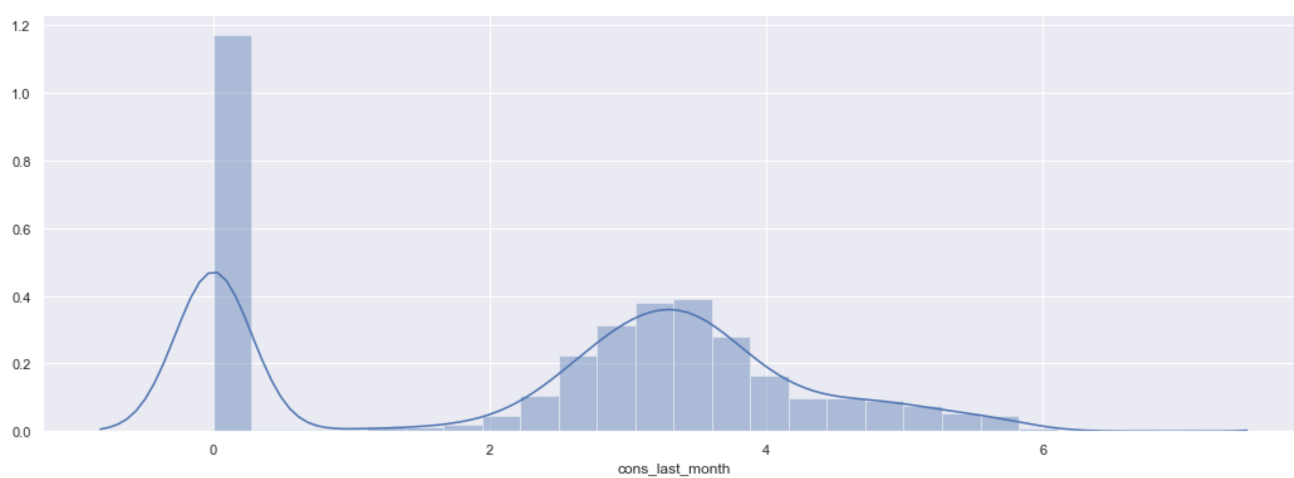
In [51]:
```
# Apply log10 transformation
train["cons_12m"] = np.log10(train["cons_12m"]+1)
train["cons_gas_12m"] = np.log10(train["cons_gas_12m"]+1)
train["cons_last_month"] = np.log10(train["cons_last_month"]+1)
train["forecast_cons_12m"] = np.log10(train["forecast_cons_12m"]+1)
train["forecast_cons_year"] = 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)
```

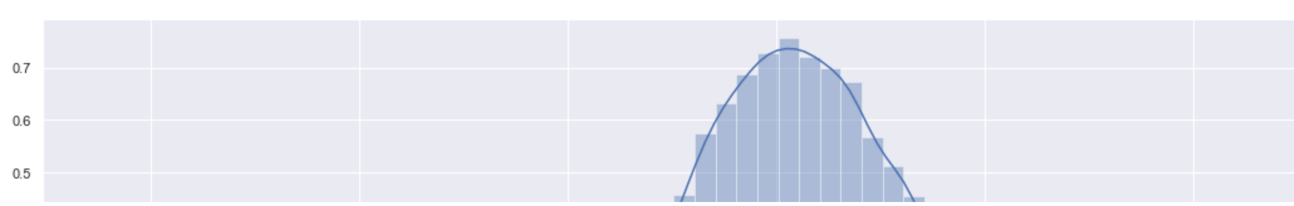
Now let's see how the distribution looks like.

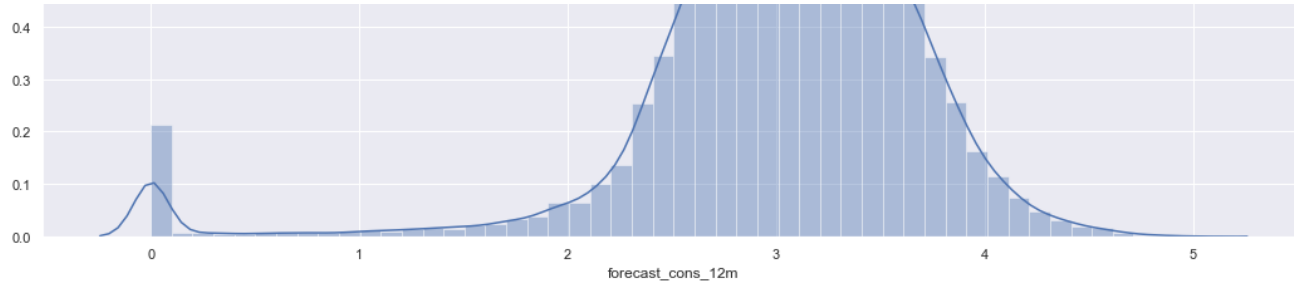
In [52]:
```
fig, axs = plt.subplots(nrows=7, figsize=(18,50))
# Plot histograms
sns.distplot((train["cons_12m"].dropna()), ax=axs[0])
sns.distplot((train[train["has_gas"]==1]["cons_gas_12m"].dropna()), ax=axs[1])
sns.distplot((train["cons_last_month"].dropna()), ax=axs[2])
sns.distplot((train["forecast_cons_12m"].dropna()), 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()
```

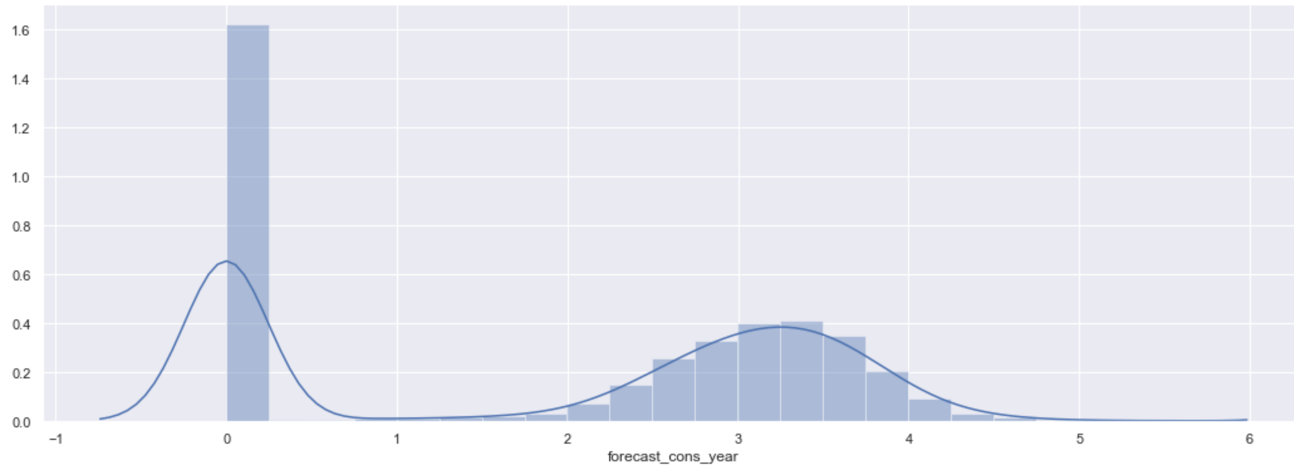


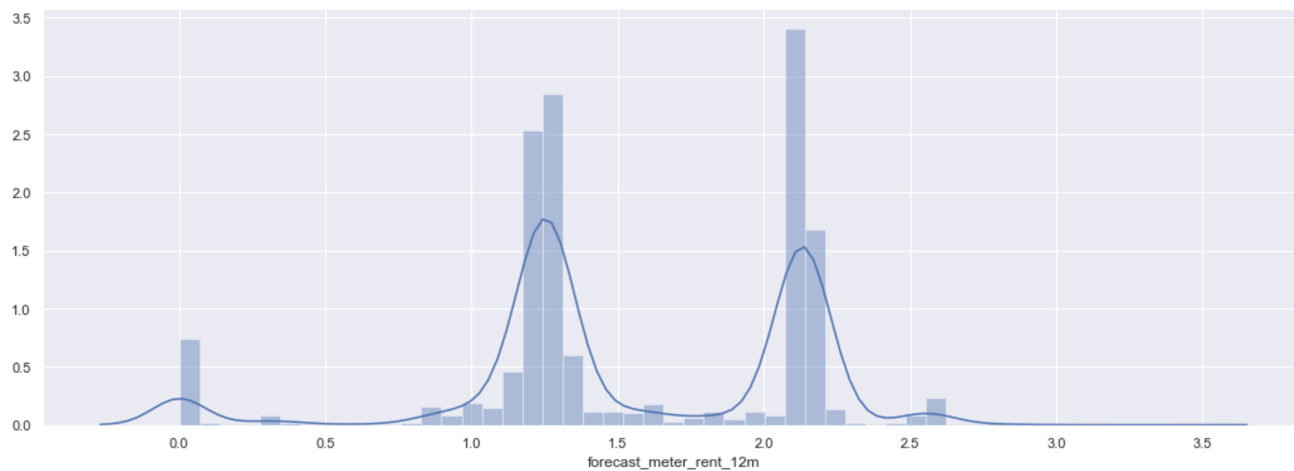


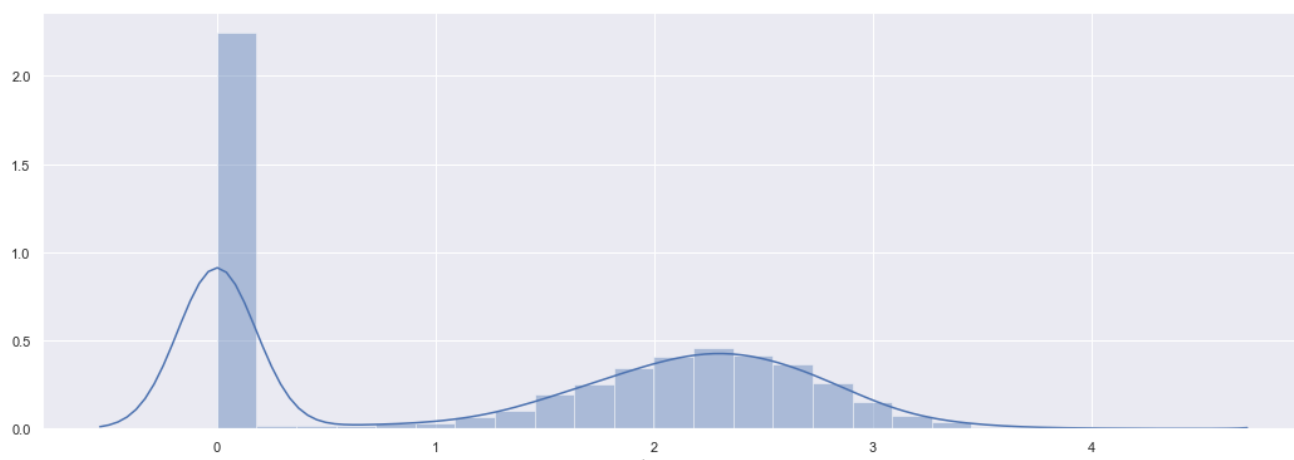




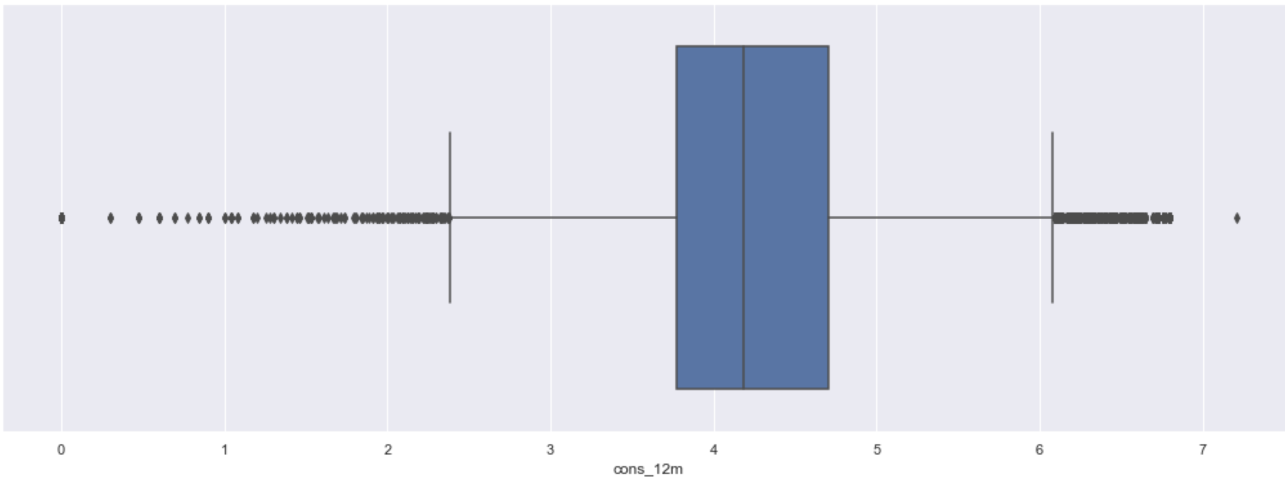

0.4
0.3
0.2
0.1
0.0
0
1
2
3
4
5
forecast_cons_12m

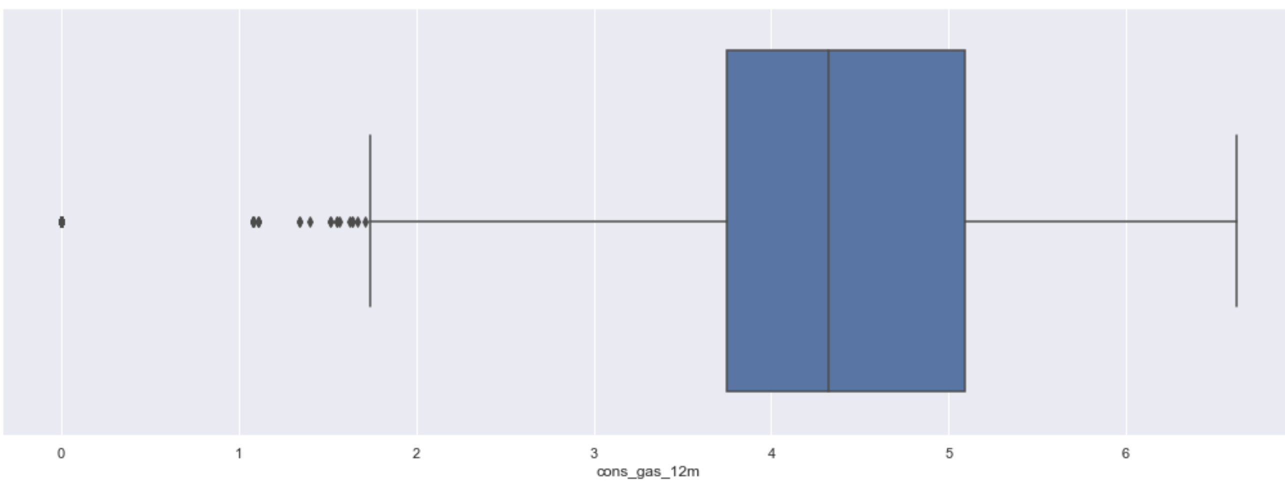

1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
−1
0
1
2
3
4
5
6
forecast_cons_year

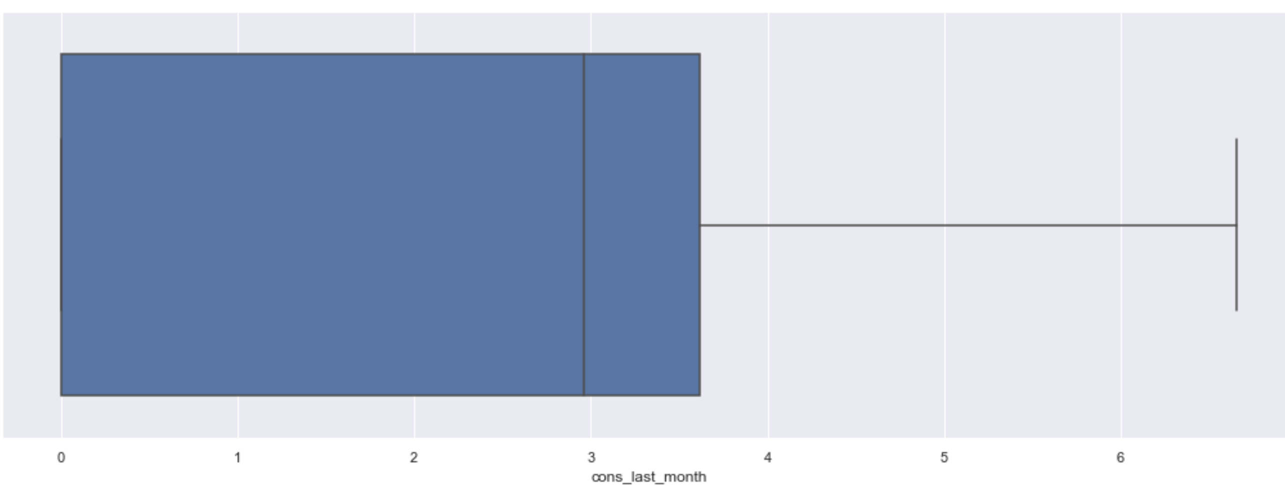

3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
forecast_meter_rent_12m

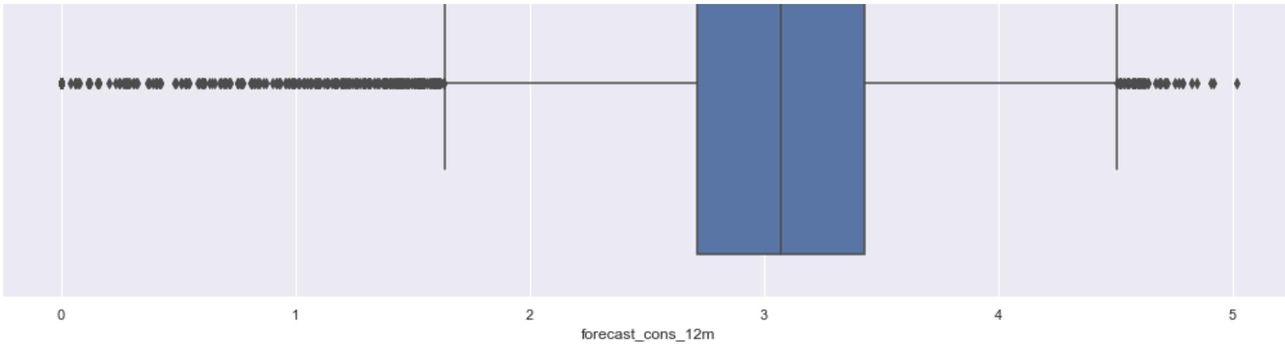

2.0
1.5
1.0
0.5
0.0
0
1
2
3
4
imp_cons

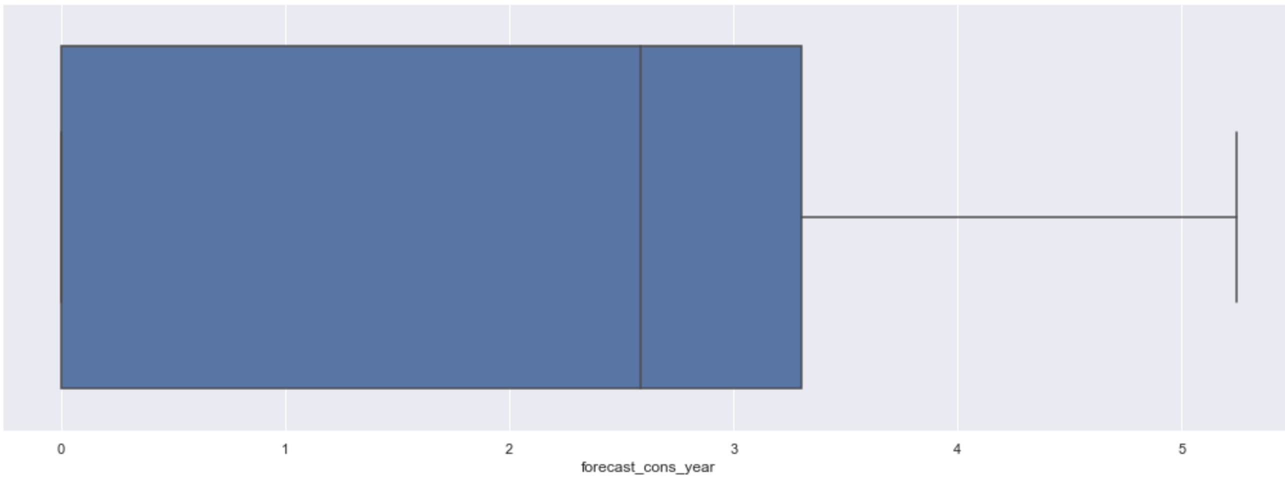
In [53]:
```
fig, axs = plt.subplots(nrows=7, figsize=(18,50))
# Plot boxplots
sns.boxplot((train["cons_12m"].dropna()), ax=axs[0])
sns.boxplot((train[train["has_gas"]==1]["cons_gas_12m"].dropna()), ax=axs[1])
sns.boxplot((train["cons_last_month"].dropna()), ax=axs[2])
sns.boxplot((train["forecast_cons_12m"].dropna()), 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()
```

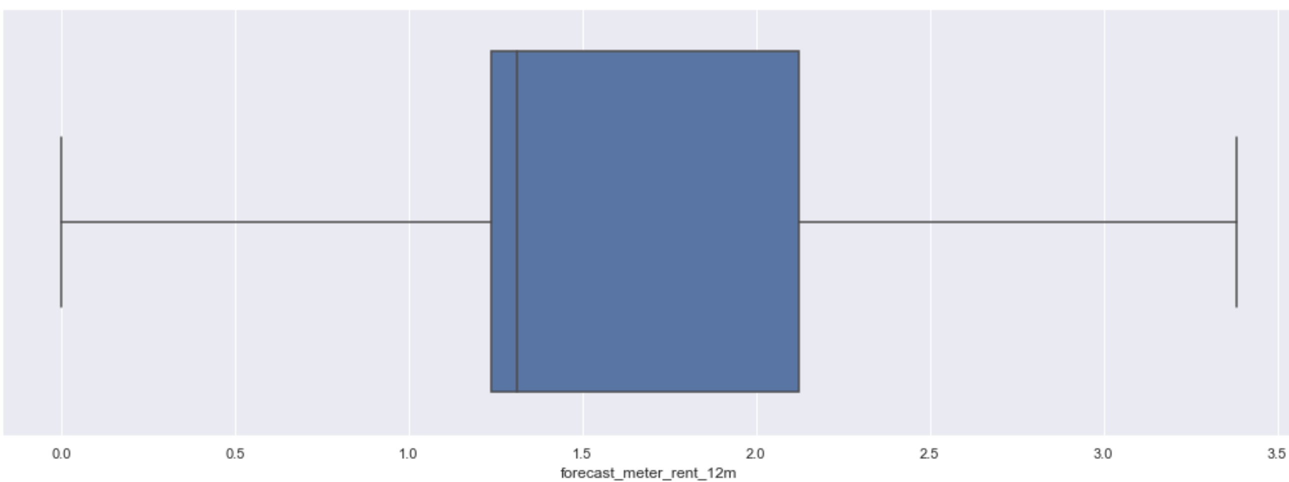


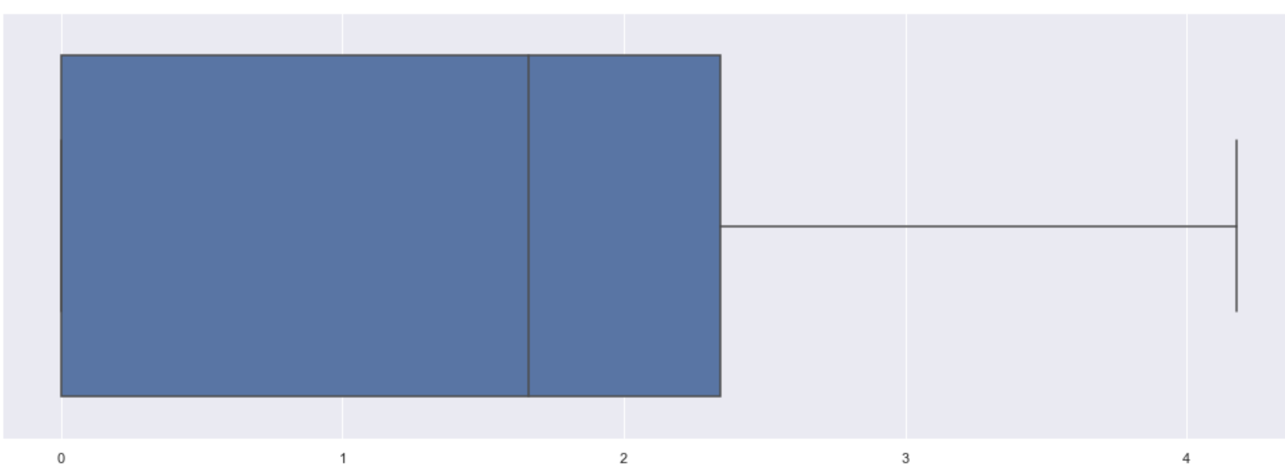





0
1
2
3
4
5
forecast_cons_12m


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

In [54]:
```
train.describe()
```

Out[54]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_year	forecast_discount_energy	forecast_meter_rent_12m	fo
count	16069.000000	16090.000000	16050.000000	16055.000000	16071.000000	15970.000000	16092.000000	
mean	4.283812	0.800300	2.359281	3.006826	1.869956	0.991547	1.549610	
std	0.915265	1.748833	1.789067	0.709778	1.612963	5.160969	0.589394	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	3.773786	0.000000	0.000000	2.713952	0.000000	0.000000	1.236285	
50%	4.187408	0.000000	2.959041	3.073579	2.583199	0.000000	1.310481	
75%	4.701508	0.000000	3.617000	3.430950	3.301030	0.000000	2.122126	
max	7.206748	6.622052	6.656933	5.016210	5.243970	50.000000	3.382502	

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.

---

2. High correlation variables

Calculate the correlation of the variables

In [55]:
```
# Calculate correlation of variables
correlation = features.corr()
```

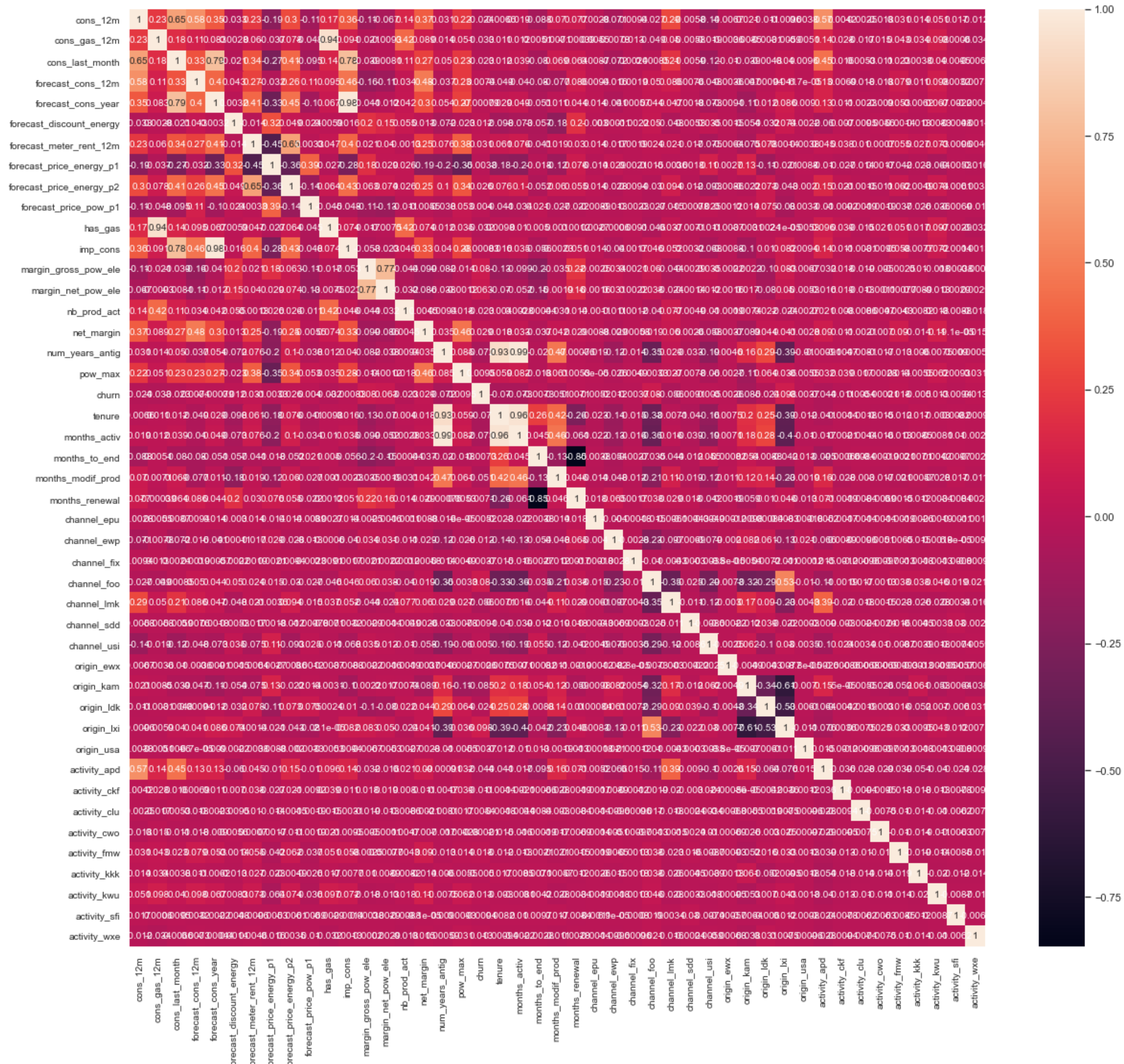
In [56]:
```
# Plot correlation
plt.figure(figsize=(19,15))
sns.heatmap(correlation, xticklabels=correlation.columns.values,
            yticklabels=correlation.columns.values, annot = True, annot_kws={'size':10})
# Axis ticks size
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.show()
```

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.

In [57]:
```
# Calculate correlation of variables
correlation = train.corr()
```

In [58]:
```
# 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.

In [59]:
```
train.drop(columns=["num_years_antig", "forecast_cons_year"],inplace=True)
```

---

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 interquartile range above the 3rd quartile and below the 1st quartile

OR

> 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).

In [60]:
```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")
```

In [61]:
```python
for c in features.columns:
    if c != "id":
        features = replace_outliers_z_score(features,c)
```

```
Replaced: 276  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: 120  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
```

In [62]:
```python
features.reset_index(drop=True, inplace=True)
```

As we identified during the exploratory phase, and when carrying out the `log transformation`, the dataset has several 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 and below the 1st quartile

OR

> 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).

In [63]:
```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")
```

```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
    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")
```

In [64]:
```python
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,"months_activ")
train = replace_outliers_z_score(train,"months_to_end")
train = replace_outliers_z_score(train,"months_modif_prod")
train = replace_outliers_z_score(train,"months_renewal")
```

```
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
```

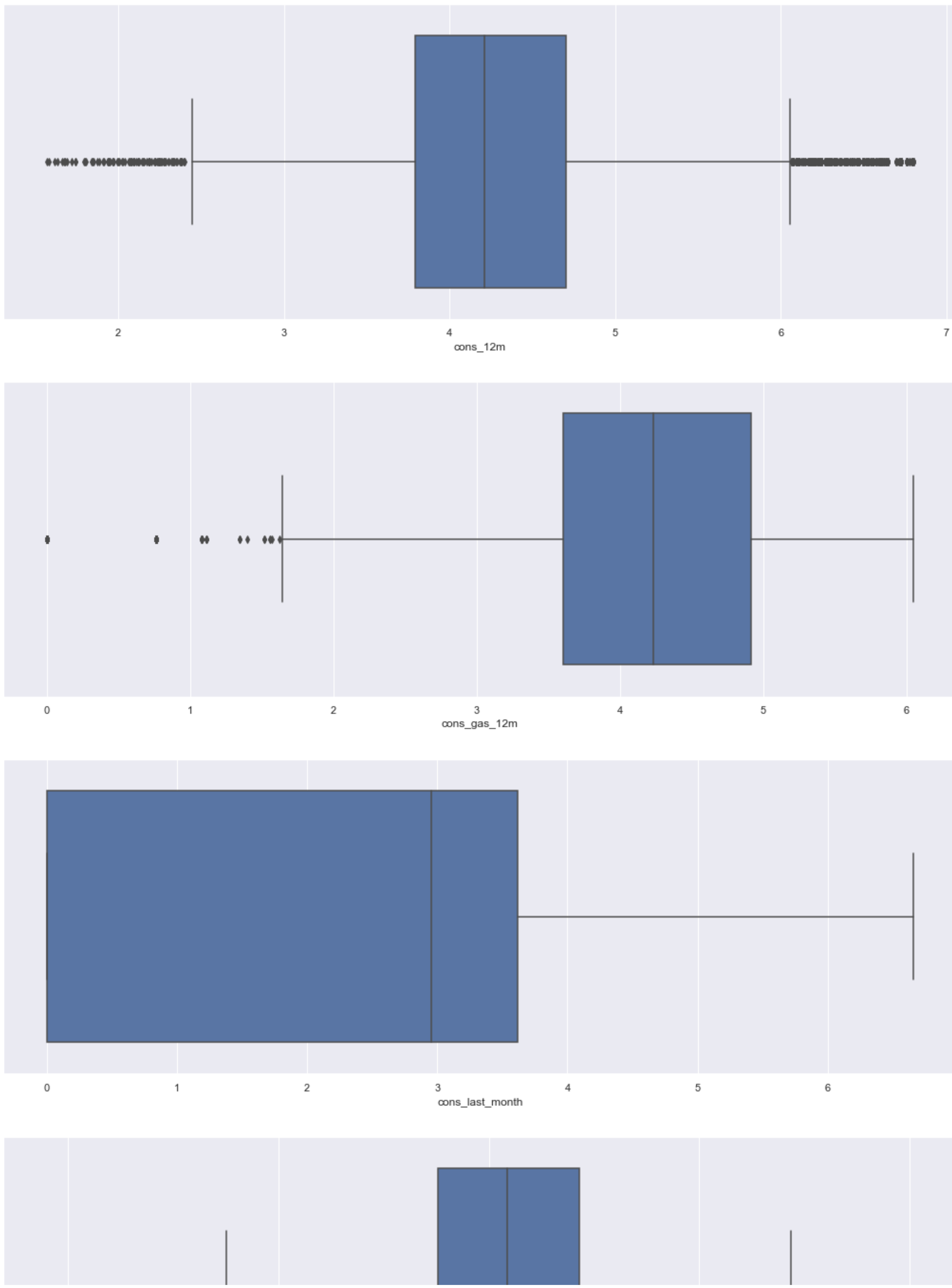
In [65]:
```python
train.reset_index(drop=True, inplace=True)
```

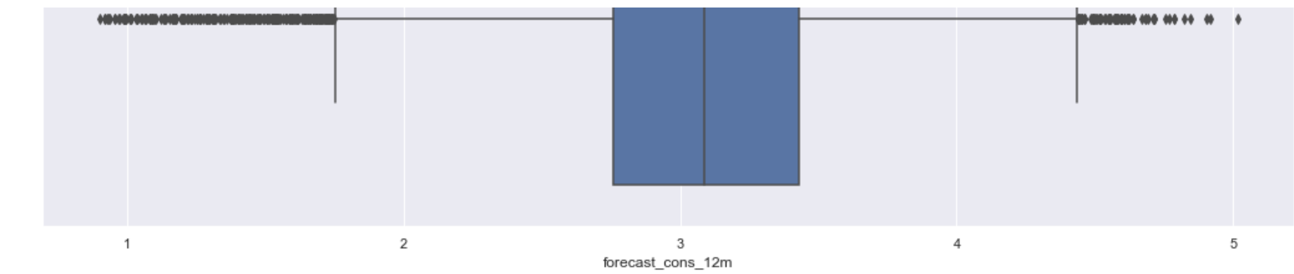
Let's see how the boxplots changed!

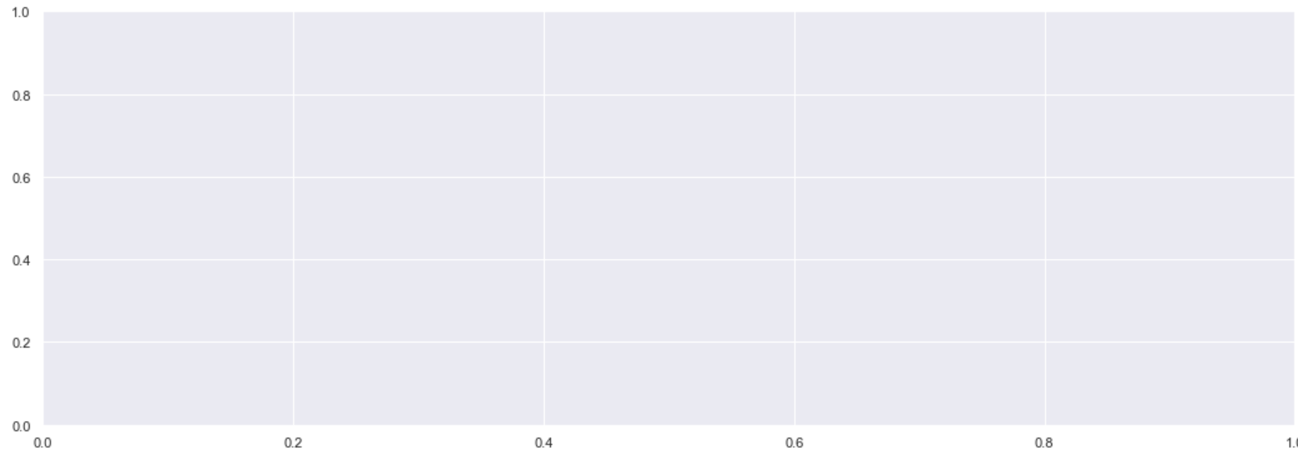
Note: I do like applying a light Z-score of 3, although IQR is usually heavier on the data.

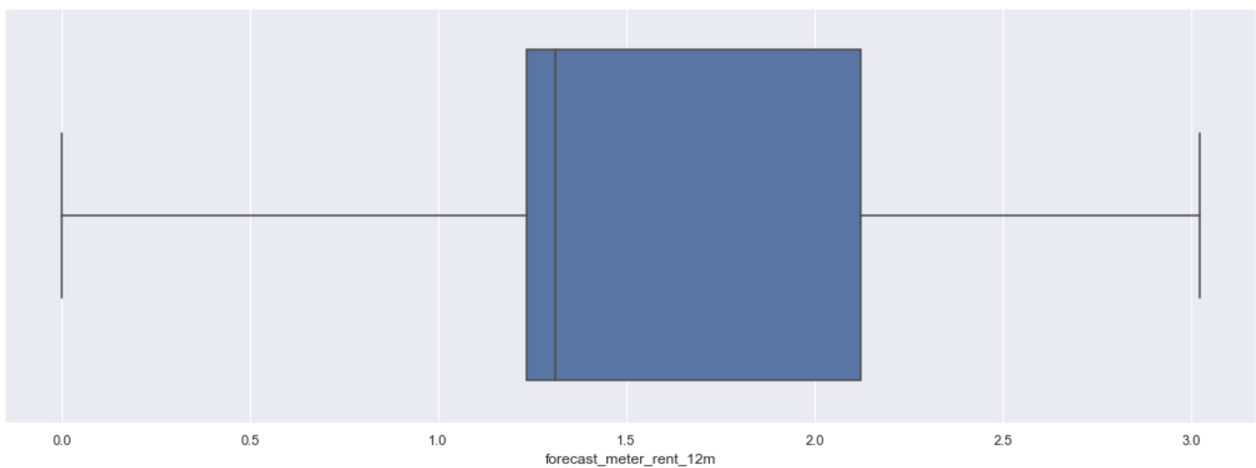
In [66]:

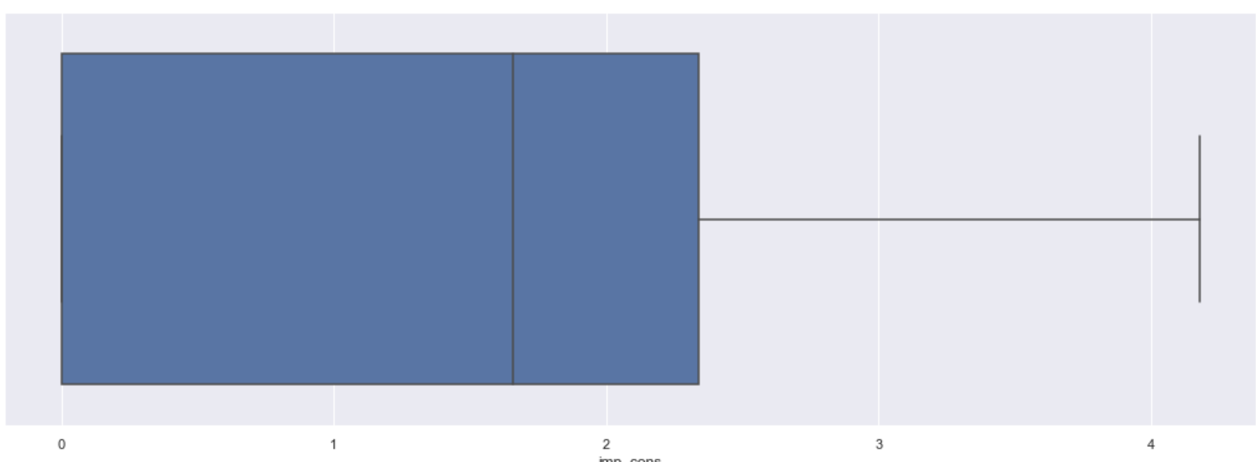
```
fig, axs = plt.subplots(nrows=7, figsize=(18,50))
# Plot boxplots
sns.boxplot((train["cons_12m"].dropna()), ax=axs[0])
sns.boxplot((train[train["has_gas"]==1]["cons_gas_12m"].dropna()), ax=axs[1])
sns.boxplot((train["cons_last_month"].dropna()), ax=axs[2])
sns.boxplot((train["forecast_cons_12m"].dropna()),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











4. Pickling

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

In [67]:
```
PICKLE_TRAIN_DIR = os.path.join("..", "processed_data", "train_data.pkl")
PICKLE_HISTORY_DIR = os.path.join("..", "processed_data", "history_data.pkl")
```

In [68]:
```
pd.to_pickle(train, PICKLE_TRAIN_DIR)
pd.to_pickle(history_data, PICKLE_HISTORY_DIR)
```