Task 3 - feature_engineering

July 18, 2024

1 Feature Engineering

---

1. Import packages
2. Load data
3. Feature engineering

1.1 1. Import packages

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

1.2 2. Load data

[ ]:
```
df = pd.read_csv('./clean_data_after_eda.csv')
df["date_activ"] = pd.to_datetime(df["date_activ"], format='%Y-%m-%d')
df["date_end"] = pd.to_datetime(df["date_end"], format='%Y-%m-%d')
df["date_modif_prod"] = pd.to_datetime(df["date_modif_prod"], format='%Y-%m-%d')
df["date_renewal"] = pd.to_datetime(df["date_renewal"], format='%Y-%m-%d')
```

[ ]:
```
df.head(3)
```

[ ]:
```
                                 id                     channel_sales  \
0  24011ae4ebbe3035111d65fa7c15bc57  foosdfpfkusacimwkcsosbicdxkicaua
1  d29c2c54acc38ff3c0614d0a653813dd                           MISSING
2  764c75f661154dac3a6c254cd082ea7d  foosdfpfkusacimwkcsosbicdxkicaua

   cons_12m  cons_gas_12m  cons_last_month date_activ   date_end  \
0         0         54946                0 2013-06-15 2016-06-15
1      4660             0                0 2009-08-21 2016-08-30
2       544             0                0 2010-04-16 2016-04-16
```

```
  date_modif_prod date_renewal  forecast_cons_12m  …  \
0      2015-11-01   2015-06-23               0.00  …
1      2009-08-21   2015-08-31             189.95  …
2      2010-04-16   2015-04-17              47.96  …

   var_6m_price_off_peak_var  var_6m_price_peak_var  \
0                   0.000131           4.100838e-05
1                   0.000003           1.217891e-03
2                   0.000004           9.450150e-08

   var_6m_price_mid_peak_var  var_6m_price_off_peak_fix  \
0                   0.000908                   2.086294
1                   0.000000                   0.009482
2                   0.000000                   0.000000

   var_6m_price_peak_fix  var_6m_price_mid_peak_fix var_6m_price_off_peak  \
0              99.530517                  44.235794              2.086425
1               0.000000                   0.000000              0.009485
2               0.000000                   0.000000              0.000004

   var_6m_price_peak  var_6m_price_mid_peak  churn
0       9.953056e+01              44.236702      1
1       1.217891e-03               0.000000      0
2       9.450150e-08               0.000000      0

[3 rows x 44 columns]
```

1.3 3. Feature engineering

Difference between off-peak prices in December and preceding January

Below is the code created by your colleague to calculate the feature described above. Use this code to re-create this feature and then think about ways to build on this feature to create features with a higher predictive power.

[ ]:
```
price_df = pd.read_csv('price_data.csv')
price_df["price_date"] = pd.to_datetime(price_df["price_date"],␣
↪format='%Y-%m-%d')
price_df.head()
```

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

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

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

[ ]:
```
# Group off-peak prices by companies and month
monthly_price_by_id = price_df.groupby(['id', 'price_date']).
 ↪agg({'price_off_peak_var': 'mean', 'price_off_peak_fix': 'mean'}).
 ↪reset_index()

# Get january and december prices
jan_prices = monthly_price_by_id.groupby('id').first().reset_index()
dec_prices = monthly_price_by_id.groupby('id').last().reset_index()

# Calculate the difference
diff = pd.merge(dec_prices.rename(columns={'price_off_peak_var': 'dec_1',␣
 ↪'price_off_peak_fix': 'dec_2'}), jan_prices.drop(columns='price_date'),␣
 ↪on='id')
diff['offpeak_diff_dec_january_energy'] = diff['dec_1'] -␣
 ↪diff['price_off_peak_var']
diff['offpeak_diff_dec_january_power'] = diff['dec_2'] -␣
 ↪diff['price_off_peak_fix']
diff = diff[['id',␣
 ↪'offpeak_diff_dec_january_energy','offpeak_diff_dec_january_power']]
diff.head()
```

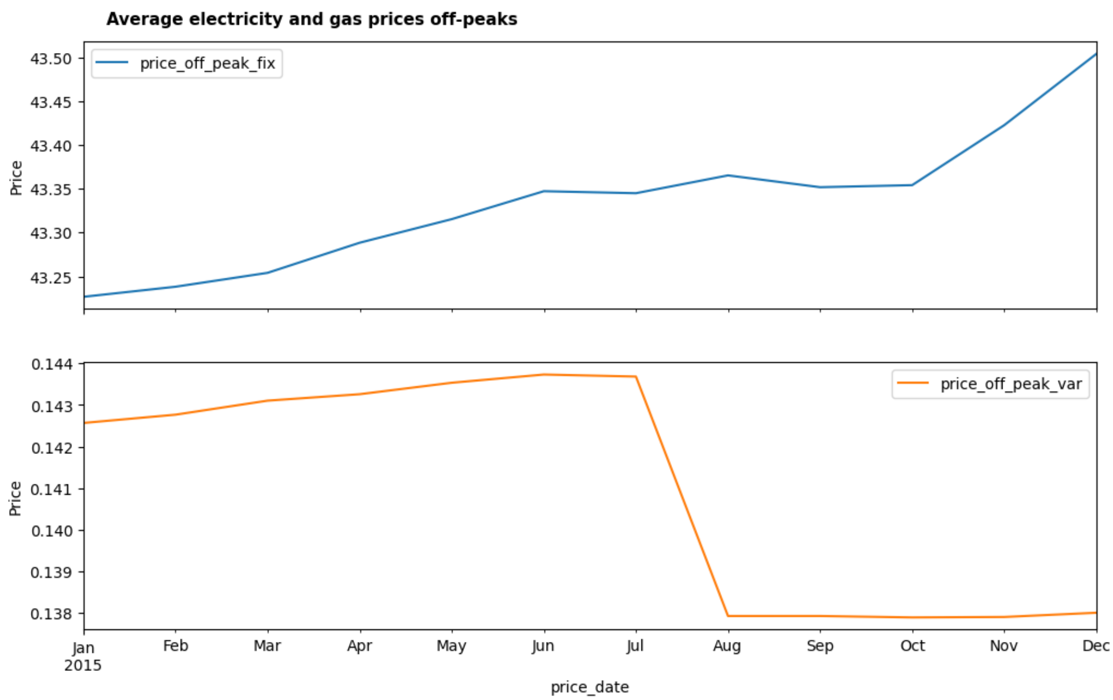
[ ]:
```
                                 id  offpeak_diff_dec_january_energy  \
0  0002203ffbb812588b632b9e628cc38d                        -0.006192
1  0004351ebdd665e6ee664792efc4fd13                        -0.004104
2  0010bcc39e42b3c2131ed2ce55246e3c                         0.050443
3  0010ee3855fdea87602a5b7aba8e42de                        -0.010018
4  00114d74e963e47177db89bc70108537                        -0.003994

   offpeak_diff_dec_january_power
0                        0.162916
1                        0.177779
2                        1.500000
```

```
3                          0.162916
4                         -0.000001
```

Now it is time to get creative and to conduct some of your own feature engineering! Have fun with it, explore different ideas and try to create as many as yo can!

```
[ ]: price_df.resample('MS', on='price_date')[['price_off_peak_fix',␣
     ↪'price_off_peak_var']].mean().plot(
         subplots=True, figsize=(12,7), ylabel='Price')
     plt.suptitle('Average electricity and gas prices off-peaks', x=0.3, y=0.92,␣
     ↪fontsize=11, fontweight='bold')
     plt.show()
```



We will create

- The average electricity and gas prices of each client over the 12-month period
- The difference in price between the last 5-month and the 5-months preceding it
- The number of days from contract modification to the next renewal of the contract
- The number of days from contract modification to start and end of contract
- Duration of signed contract
- Total electricity consumption
- Difference between off-peak prices and peak/mid-peak prices prices and difference between peak and mid-peak prices
- A binary variable that indicates if a customer subscribed to electricity billing
- A binary variable to indicate if a customer has a current paid consumption (imp_cos)

Average electricity and gas prices over the 12-month period

```
[ ]: # average gas and electricity prices off peak, during peak and on mid-peak␣
      ↪periods
     mean_prices = (
         price_df.drop('price_date', axis=1).groupby('id').mean()
         .rename({i:'mean_'+i for i in price_df.columns if 'fix' in i or 'var' in␣
      ↪i}, axis=1)
         .merge(df, on='id', how='right')
         .filter(regex='mean|^id$')
     )
```

```
[ ]: mean_prices.columns
```

```
[ ]: Index(['id', 'mean_price_off_peak_var', 'mean_price_peak_var',
            'mean_price_mid_peak_var', 'mean_price_off_peak_fix',
            'mean_price_peak_fix', 'mean_price_mid_peak_fix'],
           dtype='object')
```

```
[ ]: # Calculate the mean difference between consecutive periods
     mean_prices['off_peak_peak_var_mean_diff'] =␣
      ↪mean_prices['mean_price_off_peak_var'] - mean_prices['mean_price_peak_var']
     mean_prices['peak_mid_peak_var_mean_diff'] = mean_prices['mean_price_peak_var']␣
      ↪- mean_prices['mean_price_mid_peak_var']
     mean_prices['off_peak_mid_peak_var_mean_diff'] =␣
      ↪mean_prices['mean_price_off_peak_var'] -␣
      ↪mean_prices['mean_price_mid_peak_var']
     mean_prices['off_peak_peak_fix_mean_diff'] =␣
      ↪mean_prices['mean_price_off_peak_fix'] - mean_prices['mean_price_peak_fix']
     mean_prices['peak_mid_peak_fix_mean_diff'] = mean_prices['mean_price_peak_fix']␣
      ↪- mean_prices['mean_price_mid_peak_fix']
     mean_prices['off_peak_mid_peak_fix_mean_diff'] =␣
      ↪mean_prices['mean_price_off_peak_fix'] -␣
      ↪mean_prices['mean_price_mid_peak_fix']
```

```
[ ]: columns = [
         'id',
         'off_peak_peak_var_mean_diff',
         'peak_mid_peak_var_mean_diff',
         'off_peak_mid_peak_var_mean_diff',
         'off_peak_peak_fix_mean_diff',
         'peak_mid_peak_fix_mean_diff',
         'off_peak_mid_peak_fix_mean_diff'
     ]

     mean_prices = mean_prices[columns]
```

Maximum change in price per moonth

[ ]:
```python
# Aggregate average prices per period by company
mean_prices_by_month = price_df.groupby(['id', 'price_date']).agg({
    'price_off_peak_var': 'mean',
    'price_peak_var': 'mean',
    'price_mid_peak_var': 'mean',
    'price_off_peak_fix': 'mean',
    'price_peak_fix': 'mean',
    'price_mid_peak_fix': 'mean'
}).reset_index()
```

[ ]:
```python
# Calculate the mean difference between consecutive periods
mean_prices_by_month['off_peak_peak_var_mean_diff'] = ␣
 ↪mean_prices_by_month['price_off_peak_var'] - ␣
 ↪mean_prices_by_month['price_peak_var']
mean_prices_by_month['peak_mid_peak_var_mean_diff'] = ␣
 ↪mean_prices_by_month['price_peak_var'] - ␣
 ↪mean_prices_by_month['price_mid_peak_var']
mean_prices_by_month['off_peak_mid_peak_var_mean_diff'] = ␣
 ↪mean_prices_by_month['price_off_peak_var'] - ␣
 ↪mean_prices_by_month['price_mid_peak_var']
mean_prices_by_month['off_peak_peak_fix_mean_diff'] = ␣
 ↪mean_prices_by_month['price_off_peak_fix'] - ␣
 ↪mean_prices_by_month['price_peak_fix']
mean_prices_by_month['peak_mid_peak_fix_mean_diff'] = ␣
 ↪mean_prices_by_month['price_peak_fix'] - ␣
 ↪mean_prices_by_month['price_mid_peak_fix']
mean_prices_by_month['off_peak_mid_peak_fix_mean_diff'] = ␣
 ↪mean_prices_by_month['price_off_peak_fix'] - ␣
 ↪mean_prices_by_month['price_mid_peak_fix']
```

[ ]:
```python
# Calculate the maximum monthly difference across time periods
max_diff_across_periods_months = mean_prices_by_month.groupby(['id']).agg({
    'off_peak_peak_var_mean_diff': 'max',
    'peak_mid_peak_var_mean_diff': 'max',
    'off_peak_mid_peak_var_mean_diff': 'max',
    'off_peak_peak_fix_mean_diff': 'max',
    'peak_mid_peak_fix_mean_diff': 'max',
    'off_peak_mid_peak_fix_mean_diff': 'max'
}).reset_index().rename(
    columns={
        'off_peak_peak_var_mean_diff': 'off_peak_peak_var_max_monthly_diff',
        'peak_mid_peak_var_mean_diff': 'peak_mid_peak_var_max_monthly_diff',
        'off_peak_mid_peak_var_mean_diff':␣
 ↪'off_peak_mid_peak_var_max_monthly_diff',
        'off_peak_peak_fix_mean_diff': 'off_peak_peak_fix_max_monthly_diff',
        'peak_mid_peak_fix_mean_diff': 'peak_mid_peak_fix_max_monthly_diff',
```

```
        'off_peak_mid_peak_fix_mean_diff':␣
↪'off_peak_mid_peak_fix_max_monthly_diff'
    }
)
```

[ ]:
```
columns = [
    'id',
    'off_peak_peak_var_max_monthly_diff',
    'peak_mid_peak_var_max_monthly_diff',
    'off_peak_mid_peak_var_max_monthly_diff',
    'off_peak_peak_fix_max_monthly_diff',
    'peak_mid_peak_fix_max_monthly_diff',
    'off_peak_mid_peak_fix_max_monthly_diff'
]

max_diff_across_periods_months = max_diff_across_periods_months[columns]
```

Electricity and gas price change the past n-months and the months preceding it

[ ]:
```
def price_change(df, n_months=6):
    """
    Calculates the average gas and electricity bill last n months and checks␣
↪their difference
    """
    last_n_month = df.set_index('price_date').groupby('id').
↪nth(range(-n_months,0)).groupby('id').mean()
    prev_n_month = df.set_index('price_date').groupby('id').
↪nth(range(-n_months*2,-n_months)).groupby('id').mean()
    price_diff = (last_n_month - prev_n_month)
    price_diff.columns = [i+f'_{n_months}m_diff' for i in price_diff.columns]
    return price_diff
```

[ ]:
```
# energy and power price last 6 months
price_diff = price_change(price_df, 6)
```

Price fluctuation

Average monthly change in energy and power prices

[ ]:
```
# get the average price difference over the year
price_fluctuation = price_df.set_index('price_date').groupby('id').apply(lambda␣
↪x: x.diff().mean())
price_fluctuation.columns = [i+'_avg_price_chg' for i in price_fluctuation.
↪columns]
```

Date features extraction

- Number of months from start of contract to contract modification
- Number of months from contract modification to end of contract

- Number of months from contract modification to next contract renewal
- Contract duration (in months)

[ ]:
```
df = df.assign(
    cont_mod_activ_month = (df.date_modif_prod - df.date_activ).dt.days / 30,
    cont_mod_end_num = (df.date_end - df.date_modif_prod).dt.days / 30,
    cont_mod_renew_num = (df.date_renewal - df.date_modif_prod).dt.days / 30,
    cont_duration = (df.date_end - df.date_activ).dt.days / 30
)
```

Total electricity consumed

[ ]:
```
df['total_cons_elec'] = df[['cons_12m', 'cons_last_month']].sum(1)
```

is not Electricity subscriber and has current paid consumption

[ ]:
```
df['no_elec'] = np.where(df['total_cons_elec'] > 0, 'f', 't')
df['has_paid_cons'] = np.where(df.imp_cons > 0, 't', 'f')
```

Merging data to main dataset

[ ]:
```
df = (
    df
    .merge(diff, on='id')
    .merge(mean_prices, on='id', how='left')
    .merge(max_diff_across_periods_months, on='id', how='left')
    .merge(price_diff, on='id', how='left')
    .merge(price_fluctuation, on='id', how='left')
    .set_index('id'))
```

Handling categorical variables

- We will one hot encode categorical variables with more than 2 categories and convert to binary variables categorical variables with 2 categories

[ ]:
```
binary_map = {'f':0, 't':1}
```

[ ]:
```
df[['has_gas', 'has_paid_cons', 'no_elec']] = df[['has_gas', 'has_paid_cons',␣
 ↪'no_elec']].apply(
    lambda x: [binary_map.get(i) for i in x]
)
```

Recoding channel and origin up variables

[ ]:
```
df.channel_sales.value_counts()
```

[ ]:
```
channel_sales
foosdfpfkusacimwkcsosbicdxkicaua    6754
MISSING                             3725
lmkebamcaaclubfxadlmueccxoimlema    1843
usilxuppasemubllopkaafesmlibmsdf    1375
```

```
ewpakwlliwisiwduibdlfmalxowmwpci     893
sddiedcslfslkckwlfkdpoeeailfpeds      11
epumfxlbckeskwekxbiuasklxalciiuu       3
fixdbufsefwooaasfcxdxadsiekoceaa       2
Name: count, dtype: int64
```

[ ]:
```
df.origin_up.value_counts()
```

[ ]:
```
origin_up
lxidpiddsbxsbosboudacockeimpuepw    7097
kamkkxfxxuwbdslkwifmmcsiusiuosws    4294
ldkssxwpmemidmecebumciepifcamkci    3148
MISSING                               64
usapbepcfoloekilkwsdiboslwaxobdp       2
ewxeelcelemmiwuafmddpobolfuxioce       1
Name: count, dtype: int64
```

[ ]:
```
# recoding the sales channel and electricity campaign type of customer
channel_map = {j:f'cs{i}' for i, j in enumerate(np.sort(df.channel_sales.
 ↪unique()), start=1)}
origin_up_map = {j:f'ct{i}' for i, j in enumerate(np.sort(df.origin_up.
 ↪unique()), start=1)}
```

[ ]:
```
channel_map
```

[ ]:
```
{'MISSING': 'cs1',
 'epumfxlbckeskwekxbiuasklxalciiuu': 'cs2',
 'ewpakwlliwisiwduibdlfmalxowmwpci': 'cs3',
 'fixdbufsefwooaasfcxdxadsiekoceaa': 'cs4',
 'foosdfpfkusacimwkcsosbicdxkicaua': 'cs5',
 'lmkebamcaaclubfxadlmueccxoimlema': 'cs6',
 'sddiedcslfslkckwlfkdpoeeailfpeds': 'cs7',
 'usilxuppasemubllopkaafesmlibmsdf': 'cs8'}
```

[ ]:
```
origin_up_map
```

[ ]:
```
{'MISSING': 'ct1',
 'ewxeelcelemmiwuafmddpobolfuxioce': 'ct2',
 'kamkkxfxxuwbdslkwifmmcsiusiuosws': 'ct3',
 'ldkssxwpmemidmecebumciepifcamkci': 'ct4',
 'lxidpiddsbxsbosboudacockeimpuepw': 'ct5',
 'usapbepcfoloekilkwsdiboslwaxobdp': 'ct6'}
```

[ ]:
```
# recoding the categorical variables
df = df.assign(channel_sales = df.channel_sales.map(channel_map),
               origin_up = df.origin_up.map(origin_up_map))
```

[ ]:
```
df = pd.get_dummies(df, dtype='int')
```

```
[ ]: # dropping less frequent categories
     df = df.drop(columns=['origin_up_ct1', 'origin_up_ct6', 'origin_up_ct2',␣
      ↪'channel_sales_cs7', 'channel_sales_cs2', 'channel_sales_cs4'])
```

Selecting relevant features

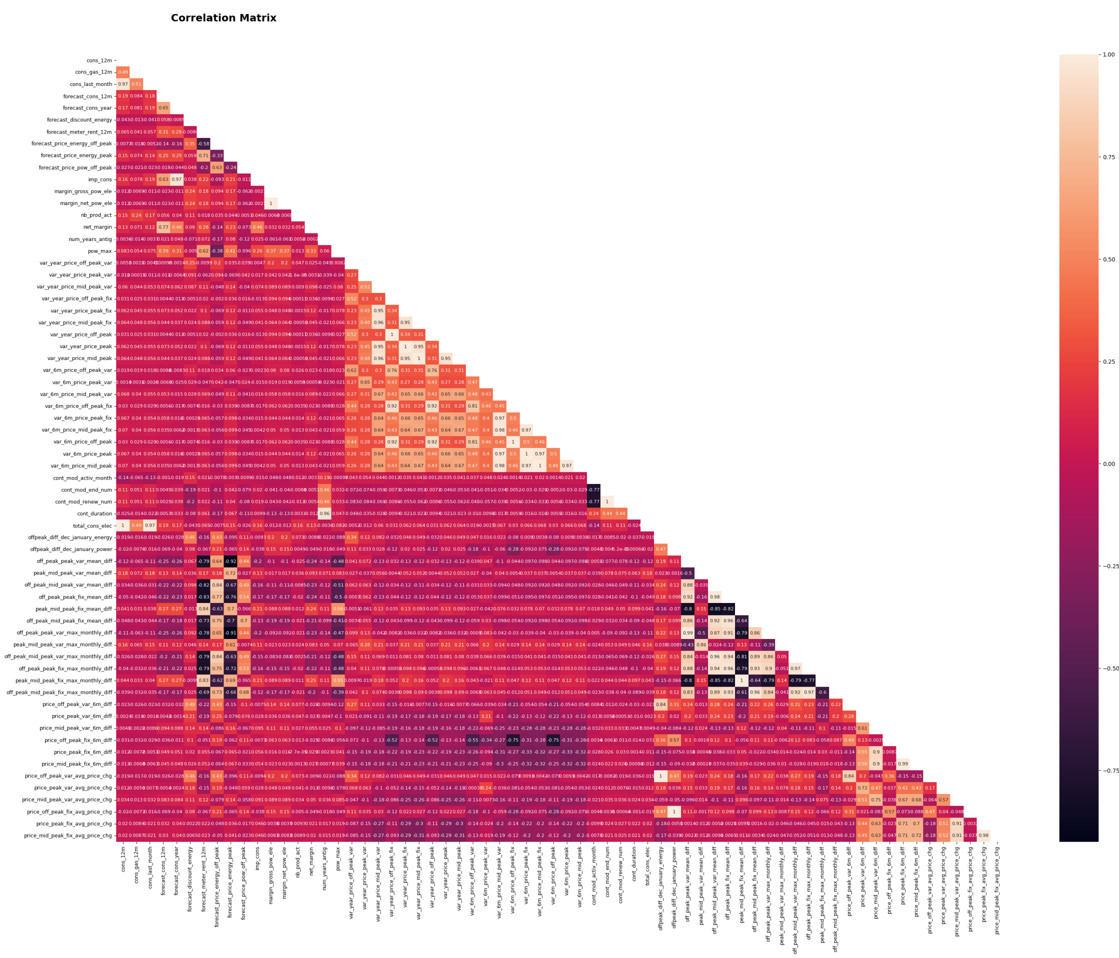
- We will be dropping the date features

```
[ ]: # select relevant variables
     df = df.drop(columns=[col for col in df.columns if 'date' in col])
```

Checking for multicolinearity

```
[ ]: corr = df.loc[:, (df.nunique() != 2)].corr()
```

```
[ ]: fig, ax = plt.subplots(1, figsize=(35,25))
     sns.heatmap(corr, mask=np.triu(corr), ax=ax, annot=True, annot_kws={'size':8})
     plt.xticks(fontsize=9)
     plt.yticks(fontsize=9)
     fig.suptitle('Correlation Matrix', x=0.2, fontsize=18, fontweight='bold', y=0.
      ↪92)
     plt.show()
```



- We will drop the cons_12m and cons_last_month variables since they were combined to obtain the total electricity used by a customer. We will create a binary variable to indicate if the customer paid for electricity consumption last month

[ ]:
```
df = df.assign(has_elec_last_month = np.where(df.cons_last_month > 0, 1, 0))
```

[ ]:
```
# drop multicolinear features
df = df.drop(columns=['cons_12m', 'cons_last_month', 'margin_net_pow_ele'])
```

Numerical Feature Transformation

Because the model that will be used is a random forest model which doesn't have any assumptions on the distribution of the numerical features, feature transformation will not be done.

[ ]:
```
df.head()
```

[ ]:
```
                                  cons_gas_12m  forecast_cons_12m  \
id
24011ae4ebbe3035111d65fa7c15bc57         54946               0.00
d29c2c54acc38ff3c0614d0a653813dd             0             189.95
764c75f661154dac3a6c254cd082ea7d             0              47.96
bba03439a292a1e166f80264c16191cb             0             240.04
149d57cf92fc41cf94415803a877cb4b             0             445.75

                                  forecast_cons_year  \
id
24011ae4ebbe3035111d65fa7c15bc57                   0
d29c2c54acc38ff3c0614d0a653813dd                   0
764c75f661154dac3a6c254cd082ea7d                   0
bba03439a292a1e166f80264c16191cb                   0
149d57cf92fc41cf94415803a877cb4b                 526

                                  forecast_discount_energy  \
id
24011ae4ebbe3035111d65fa7c15bc57                       0.0
d29c2c54acc38ff3c0614d0a653813dd                       0.0
764c75f661154dac3a6c254cd082ea7d                       0.0
bba03439a292a1e166f80264c16191cb                       0.0
149d57cf92fc41cf94415803a877cb4b                       0.0

                                  forecast_meter_rent_12m  \
id
24011ae4ebbe3035111d65fa7c15bc57                     1.78
d29c2c54acc38ff3c0614d0a653813dd                    16.27
764c75f661154dac3a6c254cd082ea7d                    38.72
bba03439a292a1e166f80264c16191cb                    19.83
```

```
149d57cf92fc41cf94415803a877cb4b                   131.73

                                  forecast_price_energy_off_peak  \
id
24011ae4ebbe3035111d65fa7c15bc57                        0.114481
d29c2c54acc38ff3c0614d0a653813dd                        0.145711
764c75f661154dac3a6c254cd082ea7d                        0.165794
bba03439a292a1e166f80264c16191cb                        0.146694
149d57cf92fc41cf94415803a877cb4b                        0.116900

                                  forecast_price_energy_peak  \
id
24011ae4ebbe3035111d65fa7c15bc57                    0.098142
d29c2c54acc38ff3c0614d0a653813dd                    0.000000
764c75f661154dac3a6c254cd082ea7d                    0.087899
bba03439a292a1e166f80264c16191cb                    0.000000
149d57cf92fc41cf94415803a877cb4b                    0.100015

                                  forecast_price_pow_off_peak  has_gas  \
id
24011ae4ebbe3035111d65fa7c15bc57                    40.606701        1
d29c2c54acc38ff3c0614d0a653813dd                    44.311378        0
764c75f661154dac3a6c254cd082ea7d                    44.311378        0
bba03439a292a1e166f80264c16191cb                    44.311378        0
149d57cf92fc41cf94415803a877cb4b                    40.606701        0

                                  imp_cons  …  \
id                                          …
24011ae4ebbe3035111d65fa7c15bc57      0.00  …
d29c2c54acc38ff3c0614d0a653813dd      0.00  …
764c75f661154dac3a6c254cd082ea7d      0.00  …
bba03439a292a1e166f80264c16191cb      0.00  …
149d57cf92fc41cf94415803a877cb4b     52.32  …

                                  price_mid_peak_fix_avg_price_chg  \
id
24011ae4ebbe3035111d65fa7c15bc57                         -1.475126
d29c2c54acc38ff3c0614d0a653813dd                          0.000000
764c75f661154dac3a6c254cd082ea7d                          0.000000
bba03439a292a1e166f80264c16191cb                          0.000000
149d57cf92fc41cf94415803a877cb4b                          0.005924

                                  channel_sales_cs1  channel_sales_cs3  \
id
24011ae4ebbe3035111d65fa7c15bc57                  0                  0
d29c2c54acc38ff3c0614d0a653813dd                  1                  0
764c75f661154dac3a6c254cd082ea7d                  0                  0
```

```
bba03439a292a1e166f80264c16191cb                 0                 0
149d57cf92fc41cf94415803a877cb4b                 1                 0

                                  channel_sales_cs5  channel_sales_cs6  \
id
24011ae4ebbe3035111d65fa7c15bc57                 1                 0
d29c2c54acc38ff3c0614d0a653813dd                 0                 0
764c75f661154dac3a6c254cd082ea7d                 1                 0
bba03439a292a1e166f80264c16191cb                 0                 1
149d57cf92fc41cf94415803a877cb4b                 0                 0

                                  channel_sales_cs8  origin_up_ct3  \
id
24011ae4ebbe3035111d65fa7c15bc57                 0              0
d29c2c54acc38ff3c0614d0a653813dd                 0              1
764c75f661154dac3a6c254cd082ea7d                 0              1
bba03439a292a1e166f80264c16191cb                 0              1
149d57cf92fc41cf94415803a877cb4b                 0              1

                                  origin_up_ct4  origin_up_ct5  \
id
24011ae4ebbe3035111d65fa7c15bc57              0              1
d29c2c54acc38ff3c0614d0a653813dd              0              0
764c75f661154dac3a6c254cd082ea7d              0              0
bba03439a292a1e166f80264c16191cb              0              0
149d57cf92fc41cf94415803a877cb4b              0              0

                                  has_elec_last_month
id
24011ae4ebbe3035111d65fa7c15bc57                    0
d29c2c54acc38ff3c0614d0a653813dd                    0
764c75f661154dac3a6c254cd082ea7d                    0
bba03439a292a1e166f80264c16191cb                    0
149d57cf92fc41cf94415803a877cb4b                    1

[5 rows x 76 columns]
```