

```
In [1]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import datetime as dt
import numpy as np
from functools import reduce

sns.set_theme()
pd.set_option('display.max_rows', 157)
```

```
In [2]: df = pd.read_csv('dataport-export_gas_oct2015-mar2016.csv', index_col='localminute',
df
```

Out[2]:

	dataid	meter_value
localminute		
2015-10-01 05:00:10+00:00	739	88858
2015-10-01 05:00:13+00:00	8890	197164
2015-10-01 05:00:20+00:00	6910	179118
2015-10-01 05:00:22+00:00	3635	151318
2015-10-01 05:00:22+00:00	1507	390354
...	...	...
2016-04-01 04:59:14.336743+00:00	2129	201726
2016-04-01 04:59:17.427165+00:00	2945	161232
2016-04-01 04:59:35.370782+00:00	9729	138146
2016-04-01 04:59:47.816286+00:00	5129	166488
2016-04-01 04:59:58.923080+00:00	484	114174

1584823 rows × 2 columns

## Question 1.1

### Part A: How many houses are included in the measurement study?

The attribute, dataid is unique for each meter. As such, to count the total number of houses, we just need to count the number of unique dataid numbers.

```
In [3]: unique_households = df['dataid'].unique()
```

```
In [4]: unique_households.sort()
unique_households
```

```
Out[4]: array([ 35,   44,   77,   94,  114,  187,  222,  252,  370,  483,  484,
```

```
661, 739, 744, 871, 1042, 1086, 1103, 1185, 1283, 1403, 1415,
1507, 1556, 1589, 1619, 1697, 1714, 1718, 1790, 1791, 1792, 1800,
1801, 2018, 2034, 2072, 2094, 2129, 2233, 2335, 2378, 2449, 2461,
2470, 2575, 2638, 2645, 2755, 2814, 2818, 2945, 2946, 2965, 2980,
3036, 3039, 3134, 3310, 3367, 3527, 3544, 3577, 3635, 3723, 3778,
3849, 3893, 3918, 4029, 4031, 4193, 4228, 4296, 4352, 4356, 4373,
4421, 4447, 4514, 4671, 4732, 4767, 4874, 4998, 5129, 5131, 5193,
5275, 5317, 5395, 5403, 5439, 5484, 5545, 5636, 5658, 5785, 5810,
5814, 5892, 5972, 6101, 6412, 6505, 6578, 6673, 6685, 6830, 6836,
6863, 6910, 7016, 7017, 7030, 7117, 7287, 7429, 7460, 7566, 7674,
7682, 7739, 7741, 7794, 7900, 7919, 7965, 7989, 8059, 8084, 8086,
8155, 8156, 8244, 8386, 8467, 8703, 8829, 8890, 8967, 9052, 9121,
9134, 9160, 9278, 9295, 9474, 9600, 9620, 9631, 9639, 9729, 9766,
9849, 9956, 9982], dtype=int64)
```

In [5]:

```
print(f'Number of unique households: {len(unique_households)}')
```

Number of unique households: 157

## Part B: Are there any malfunctioning meters? If so, identify them and the time periods where they were malfunctioning.

We know that the meter readings are all supposed to be cumulative. With this in mind, lets first check whether are there any meter readings that have a lower value at a later timestamp, i.e are not cumulative.

In [6]:

```
uncumulative_vals = {}
uncumulative_vals_length = {}

# group by its unique id, then sort by timestamp
grouped_df = df.groupby(['dataid'], sort=['localminute'])

# obtain meters with uncumulative values
for meter_id, item in grouped_df:
    group = grouped_df.get_group(meter_id)['meter_value']

    # to Look at the groupby result
    # print(grouped_df.get_group(meter_id), "\n\n")

    # initialize with 0 as minimum meter value cannot be below 0
    prev_meter_value = 0

    for index, curr_meter_value in group.iteritems():
        # check whether is it uncumulative
        if curr_meter_value < prev_meter_value:
            # if meter_id already present, append current uncumulative value and prev
            if meter_id in uncumulative_vals:
                uncumulative_vals[meter_id].append([prev_meter_value, curr_meter_val
                uncumulative_vals_length[meter_id] += 1
            else: # meter_id not present, so create new
                uncumulative_vals[meter_id] = []
                uncumulative_vals_length[meter_id] = 1
                uncumulative_vals[meter_id].append([prev_meter_value, curr_meter_val
            prev_meter_value = curr_meter_value

temp_df = pd.DataFrame.from_dict(uncumulative_vals_length, orient="index")
temp_df.reset_index(inplace=True)
temp_df.rename(columns={0: "No of uncumulative readings", "index": "dataid"}, inplace=True)
```

Out[6]:

	dataid	No of uncumulative readings
0	35	1
1	77	1
2	94	6
3	483	1
4	484	9
5	1042	1
6	1086	1
7	1185	135
8	1507	2
9	1556	12
10	1718	4
11	1790	1
12	1801	1
13	2129	3
14	2335	5
15	2449	93
16	3134	18
17	3527	1
18	3544	18
19	3893	2
20	4031	16
21	4193	1
22	4514	141
23	4998	1
24	5129	76
25	5131	1
26	5193	4
27	5403	156
28	5810	10
29	5814	1
30	5892	1
31	6836	51
32	7017	1
33	7030	90
34	7117	123
35	7739	1

	dataid	No of uncumulative readings
36	7794	1
37	7989	2
38	8156	151
39	8890	44
40	9134	115
41	9639	2
42	9982	2

As can be seen above, there are 43 meters that have uncumulative values, at times. The total number of uncumulative readings obtained for each meter is also reflected above. Now, for each meter, lets find out the ratio of uncumulative readings to the total readings sent out by the respective meter. Also, for each meter, lets calculate the average drop in meter readings.

In [7]:

```
def analysis(row):
    meter_id = row["dataid"]
    values = row["No of uncumulative readings"]
    values_list = uncumulative_vals[meter_id]

    new_row = row
    new_row["Average decrease across uncumulative readings"] = reduce(lambda x, y: x - y, values) / len(values)
    new_row["Percentage of uncumulative readings"] = (values / grouped_df.get_group(meter_id).size).sum()

    new_row["dataid"] = new_row["dataid"].astype(np.int64)

    return new_row
```

In [8]:

```
temp_df2 = temp_df.apply(lambda x:analysis(x), axis=1)
temp_df2
```

Out[8]:

	dataid	No of uncumulative readings	Average decrease across uncumulative readings	Percentage of uncumulative readings
0	35.0	1.0	2.000000	0.008423
1	77.0	1.0	2.000000	0.009361
2	94.0	6.0	9.000000	0.016513
3	483.0	1.0	14.000000	0.003620
4	484.0	9.0	2.444444	0.020439
5	1042.0	1.0	2.000000	0.026110
6	1086.0	1.0	2.000000	0.003330
7	1185.0	135.0	16267.674074	0.731469
8	1507.0	2.0	2.000000	0.006134
9	1556.0	12.0	13574.000000	0.325203
10	1718.0	4.0	5.000000	0.016347
11	1790.0	1.0	2.000000	0.007494
12	1801.0	1.0	2.000000	0.006292

<b>dataid</b>	<b>No of uncumulative readings</b>	<b>Average decrease across uncumulative readings</b>	<b>Percentage of uncumulative readings</b>
<b>13</b>	2129.0	3.0	0.021760
<b>14</b>	2335.0	5.0	0.056117
<b>15</b>	2449.0	93.0	1.706735
<b>16</b>	3134.0	18.0	0.448096
<b>17</b>	3527.0	1.0	0.009214
<b>18</b>	3544.0	18.0	0.810446
<b>19</b>	3893.0	2.0	0.007450
<b>20</b>	4031.0	16.0	0.127653
<b>21</b>	4193.0	1.0	0.098135
<b>22</b>	4514.0	141.0	0.739226
<b>23</b>	4998.0	1.0	0.007156
<b>24</b>	5129.0	76.0	1.694160
<b>25</b>	5131.0	1.0	0.006585
<b>26</b>	5193.0	4.0	0.020551
<b>27</b>	5403.0	156.0	0.610353
<b>28</b>	5810.0	10.0	0.023678
<b>29</b>	5814.0	1.0	0.002357
<b>30</b>	5892.0	1.0	0.007073
<b>31</b>	6836.0	51.0	1.128319
<b>32</b>	7017.0	1.0	0.003956
<b>33</b>	7030.0	90.0	0.502372
<b>34</b>	7117.0	123.0	0.600205
<b>35</b>	7739.0	1.0	0.022558
<b>36</b>	7794.0	1.0	0.011725
<b>37</b>	7989.0	2.0	0.005035
<b>38</b>	8156.0	151.0	0.596932
<b>39</b>	8890.0	44.0	0.265476
<b>40</b>	9134.0	115.0	0.817691
<b>41</b>	9639.0	2.0	0.014497
<b>42</b>	9982.0	2.0	0.129870

As shown above, all the meters' percentage of uncumulative readings are below 2%. Hence, our group has decided to use the average decrease across uncumulative readings as a benchmark to decide which meters might be faulty.

After doing a manual inspection, we have decided to define our threshold to be above 1000 because firstly, a drop of 1000 cubic feet is indeed a big drop and cannot be easily ignored. Second, the readings above 1000 are sufficient to indicate an anomaly.

In [54]:

```
# filter average readings that are above 1000
temp_df2[temp_df2["Average decrease across uncumulative readings"] > 1000]
```

Out[54]:

	dataid	No of uncumulative readings	Average decrease across uncumulative readings	Percentage of uncumulative readings
7	1185.0	135.0	16267.674074	0.731469
9	1556.0	12.0	13574.000000	0.325203
14	2335.0	5.0	22942.000000	0.056117
15	2449.0	93.0	15472.860215	1.706735
16	3134.0	18.0	12877.222222	0.448096
18	3544.0	18.0	8488.222222	0.810446
22	4514.0	141.0	23971.815603	0.739226
24	5129.0	76.0	11116.815789	1.694160
27	5403.0	156.0	10897.371795	0.610353
31	6836.0	51.0	11397.176471	1.128319
33	7030.0	90.0	17217.155556	0.502372
34	7117.0	123.0	16809.414634	0.600205
38	8156.0	151.0	16260.622517	0.596932
40	9134.0	115.0	32439.008696	0.817691
41	9639.0	2.0	29376.000000	0.014497
42	9982.0	2.0	14036.000000	0.129870

We now have established the criteria for deciding what constitutes a malfunctioning meter. The meters that have readings that fail our criteria are shown above. We will now demonstrate that we can consolidate faulty readings into time periods.

In [9]:

```
# obtain and parse data
df2 = pd.read_csv('dataport-export_gas_oct2015-mar2016.csv', parse_dates=['localminu
grouped = df2.groupby(['dataid'], sort=['localminute'])
```

In [10]:

```
def get_faulty_readings(meter_readings):
    """
    Responsible for obtaining a list of times when the meter reading was uncumulative
    """
    total_readings = meter_readings.shape[0]
    faulty_times = []
    for i in range(1, total_readings):
        if meter_readings.iloc[i].meter_value < (meter_readings.iloc[i-1].meter_valu
            faulty_times.append(meter_readings.iloc[i])

    return faulty_times
```

In [11]:

```
# obtain list of faulty meters according to our criteria
faulty_ids = temp_df2[temp_df2["Average decrease across uncumulative readings"] > 10

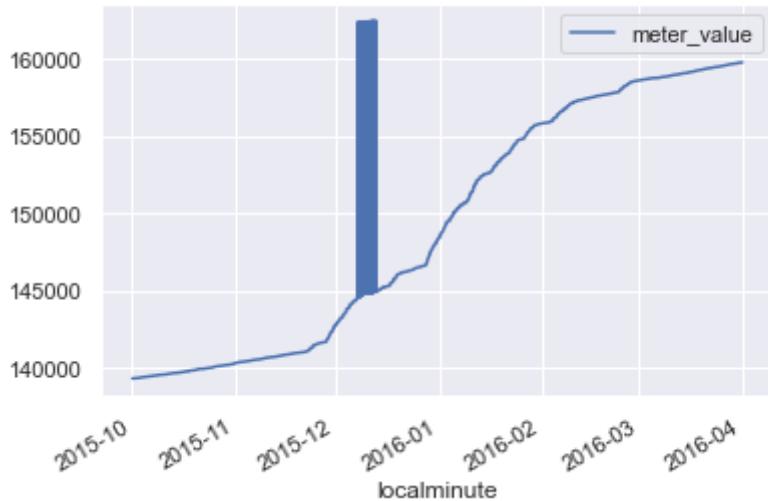
# print faulty time period and plot to verify.
```

```

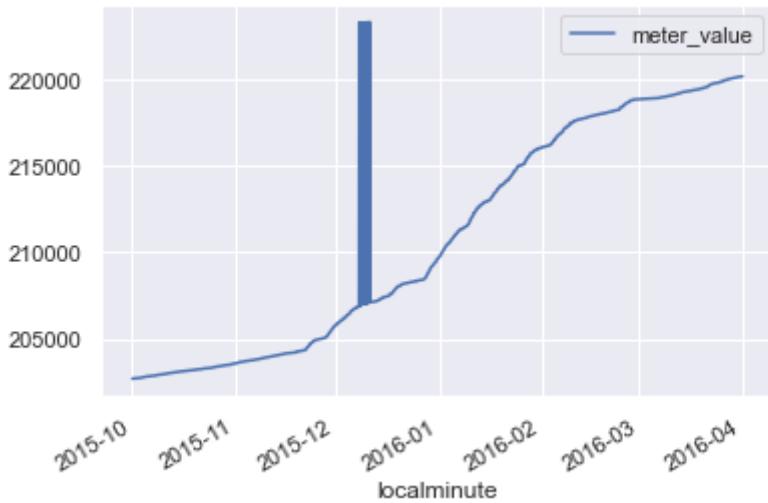
for id in faulty_ids:
    most_faulty_meter = grouped.get_group(id)
    faulty_time_periods = get_faulty_readings(most_faulty_meter)
    meter_title = f'Meter {id} faulty from {faulty_time_periods[0].localminute} to {faulty_time_periods[-1].localminute}'
    most_faulty_meter.plot(x='localminute', y='meter_value', title=meter_title)

```

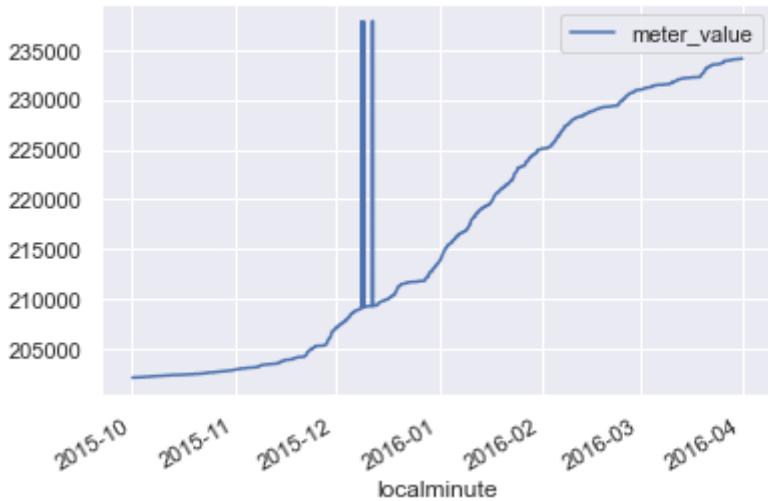
Meter 1185.0 faulty from 2015-12-07 17:19:59-06:00 to 2015-12-13 01:27:54-06:00



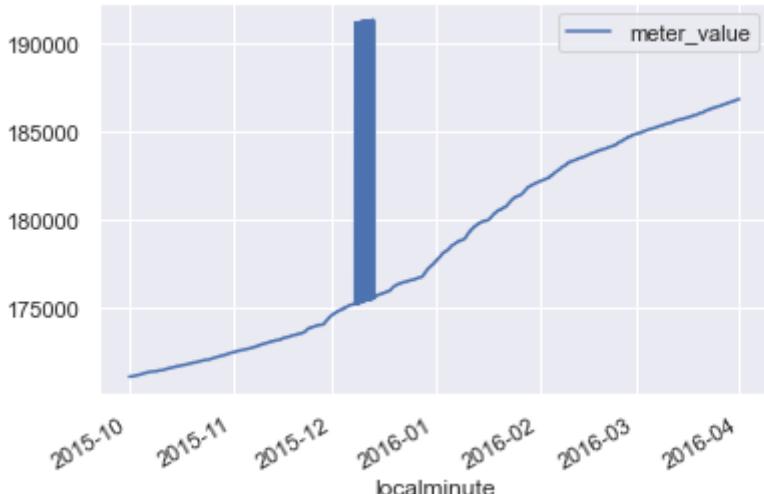
Meter 1556.0 faulty from 2015-12-08 02:36:42-06:00 to 2015-12-11 02:14:36-06:00



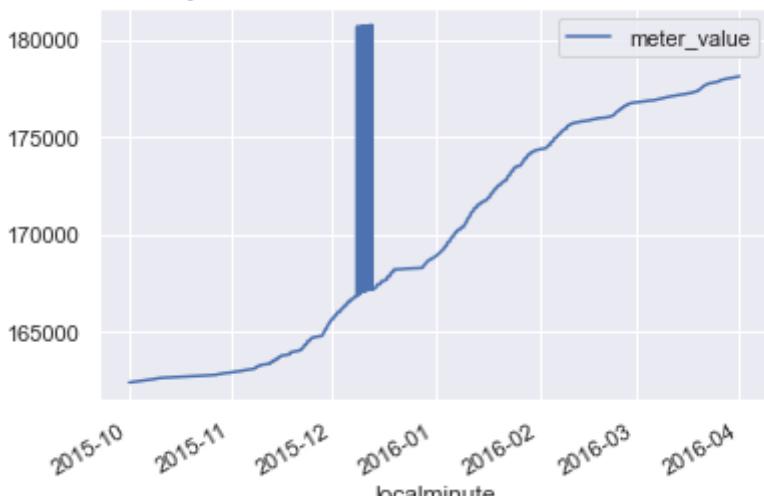
Meter 2335.0 faulty from 2015-12-08 16:33:26-06:00 to 2015-12-11 23:52:27-06:00



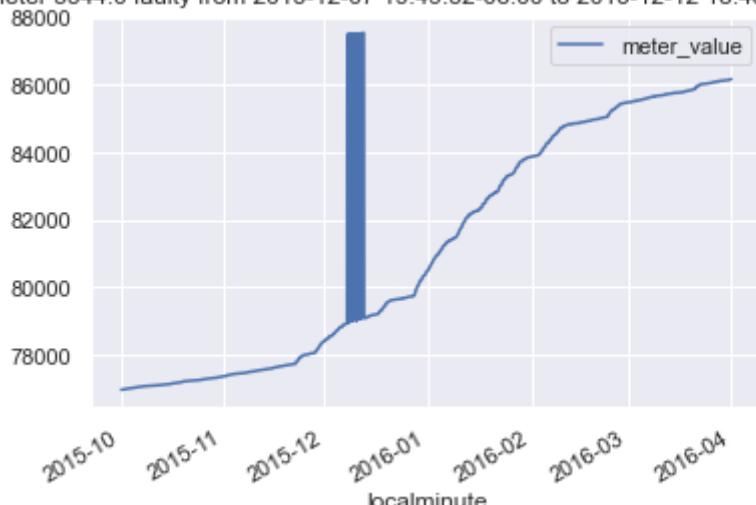
Meter 2449.0 faulty from 2015-12-07 17:07:19-06:00 to 2015-12-13 01:34:19-06:00



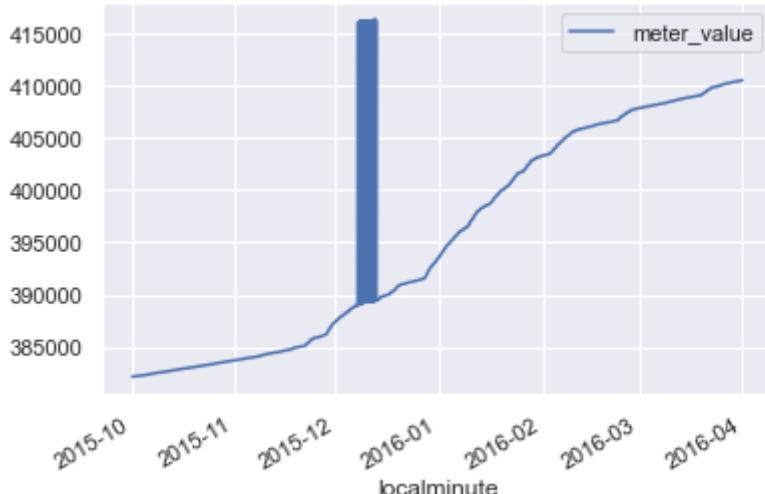
Meter 3134.0 faulty from 2015-12-08 06:56:40-06:00 to 2015-12-12 17:10:28-06:00



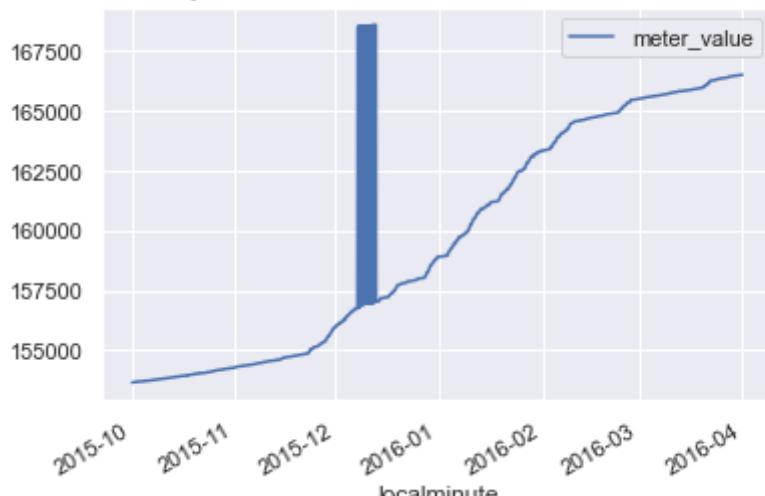
Meter 3544.0 faulty from 2015-12-07 19:49:52-06:00 to 2015-12-12 18:48:35-06:00



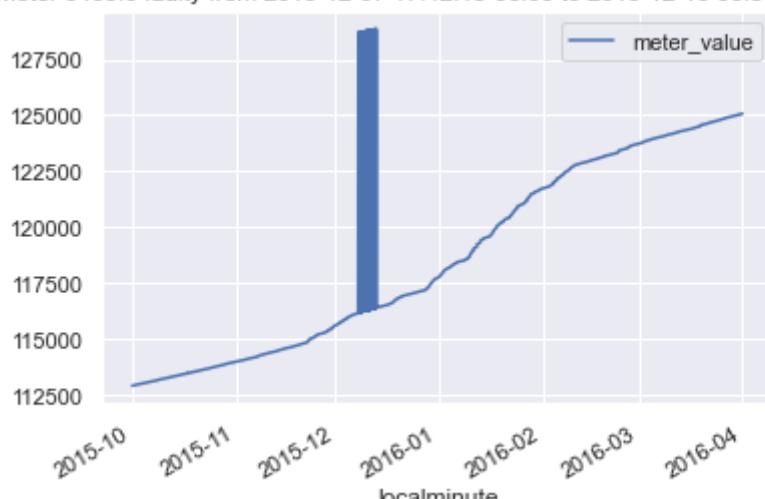
Meter 4514.0 faulty from 2015-12-07 16:41:04-06:00 to 2015-12-13 01:19:59-06:00



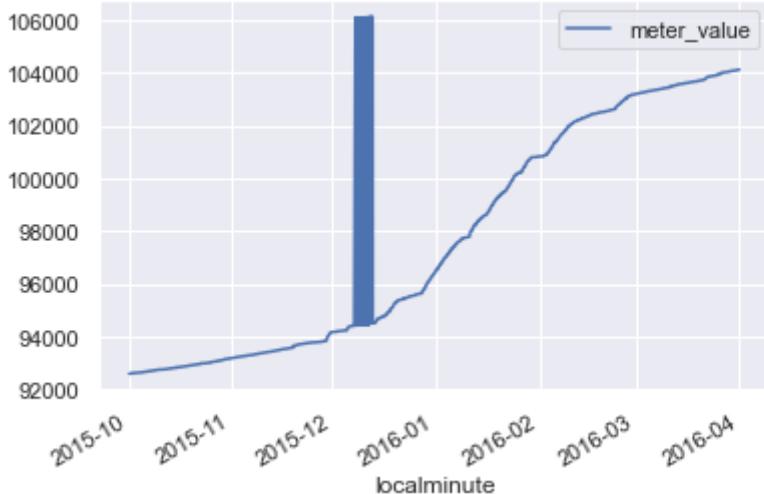
Meter 5129.0 faulty from 2015-12-07 17:10:13-06:00 to 2015-12-13 02:02:14-06:00



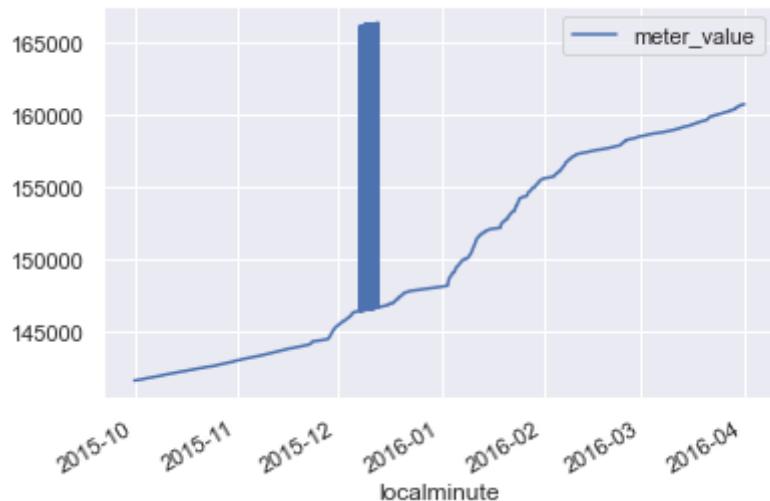
Meter 5403.0 faulty from 2015-12-07 17:42:18-06:00 to 2015-12-13 00:38:00-06:00



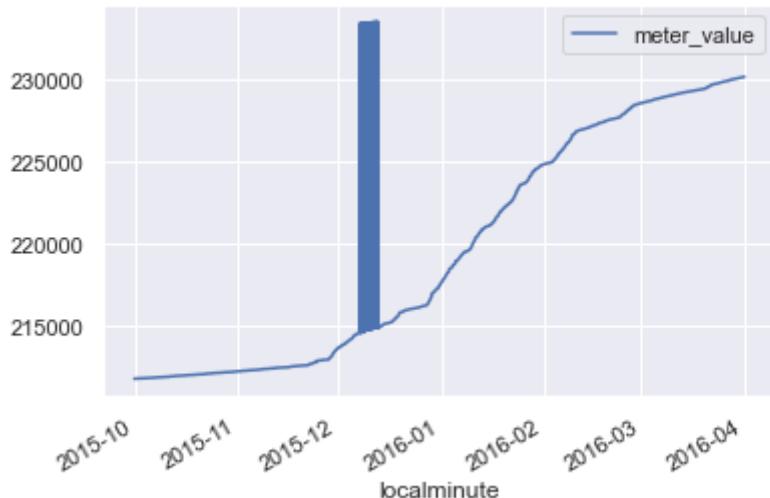
Meter 6836.0 faulty from 2015-12-07 20:07:34-06:00 to 2015-12-12 23:56:47-06:00



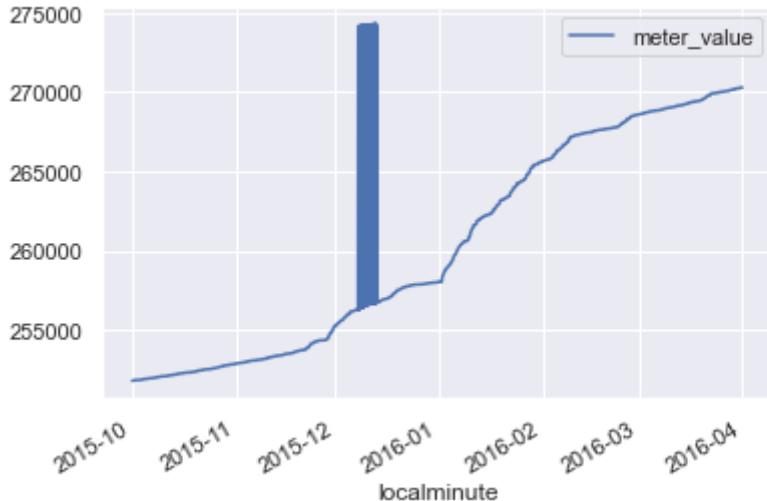
Meter 7030.0 faulty from 2015-12-07 17:54:21-06:00 to 2015-12-13 01:20:11-06:00



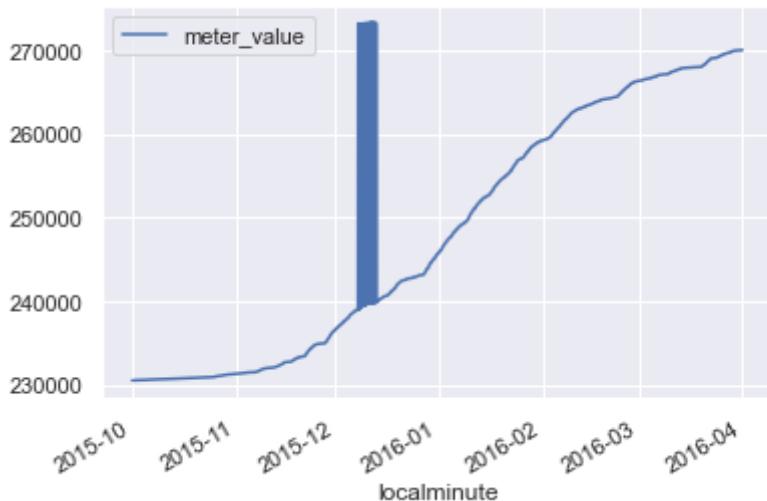
Meter 7117.0 faulty from 2015-12-07 17:15:09-06:00 to 2015-12-13 01:12:02-06:00



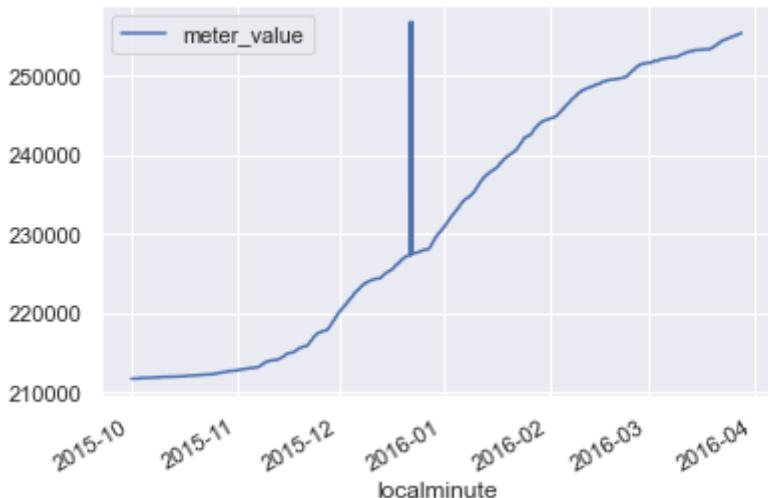
Meter 8156.0 faulty from 2015-12-07 16:47:45-06:00 to 2015-12-13 00:53:41-06:00



Meter 9134.0 faulty from 2015-12-07 17:16:58-06:00 to 2015-12-13 02:01:12-06:00



Meter 9639.0 faulty from 2015-12-22 00:27:07.912441-06:00 to 2015-12-22 11:54:52-06:00





## Insights

As can be seen from our graphs above, almost all the faulty readings (except for those belonging to dataid 9639) occurred around the same time period, between 7th December 2015 and 13th December 2015. This is an interesting find because this possibly indicates a malfunction in the system rather than the individual meters themselves. Hence, instead of labeling these meters as faulty, the gas provider might want to debug and check what exactly happened during the specified time period to determine the exact cause for the malfunctionings.

## Additional Note

Initially, we had also wanted to consider readings where the marginal consumption was lesser than 2 cubic feet. However, when we analysed them, there were a lot of meters with such readings (155 meters to be exact). We assumed that these readings were a way for the gas company to know whether the meter was still working properly. As such, we decided to not include this in our criteria.

## Q1.2

### Hourly Data Collection and Plotting the Data

#### Approach

For a particular meter, we are going to have maximum 4 readings every minute (if the cumulative gas consumption measured every 15 seconds by the meter is "reported" to the MDMS as it is at least 2 cubic foot higher than the previous reading).

As such, for every hour, we are going to have maximum 240 readings ( $60 \text{ mins} * 4 = 240$ ).

Out of all the readings that we obtain for a particular hour, our approach is to pick the last reading of that hour. This reading will be subsequently be used as an estimate of that hour's cumulative gas consumption data. This is because, in our case, this reading would be the most suitable in approximating the consumption amount during the hour.

However, with this approach, there are two considerations to be made, which are reflected below:

## Additional Considerations

### Missing Data

The first consideration is when we have absolutely no data for a particular hour. In such a scenario, we can simply assume that there has not been any significant gas consumption during the time period. As such, for that particular hour, we will use the most recent hourly data obtained.

### Uncumulative Data

The second consideration is when the reading is uncumulative, or in other words, has a lower value than the previous hourly data obtained. In this case, we are probably more interested in obtaining and visualizing the general hourly consumption level rather than looking for faulty meters or any decrease in gas consumption, which we discussed in the previous question. As such, we will not consider this case for this question.

For this question, we have chosen to plot the hourly readings for the month of December, 2015 (i.e from 2015-12-01 00:00:00+00:00 to 2015-12-31 23:59:59+00:00)

We have chosen this month for closer observation as we felt that we might obtain some interesting insights about the data, considering that this is a holiday month in the US. For instance, it is common for people to stay at home during work hours or go for a vacation during the entire holidays. As such, we would like to explore this data more.

```
In [12]: def plot_hourly_df(df, dataid):
    """
    Plot hourly readings against cumulative data
    """
    x = pd.to_datetime(df.index).array.to_numpy()
    y = df.array.to_numpy()
    plt.figure(figsize=(16, 5), dpi=100)
    plt.title('dataid ' + str(dataid))
    plt.plot(x, y)
```

Since the meter readings are cumulative, it would be more suitable to interpolate them rather than forward filling them. This will ensure that the data is more apt for linear regression analysis, which we will do in question 2. Forward filling would be better for the analysis of non-cumulative hourly usage.

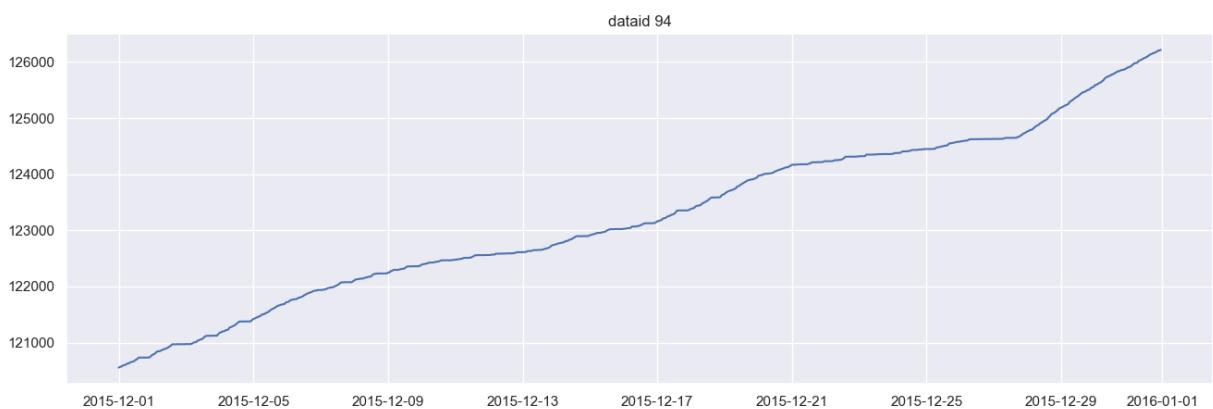
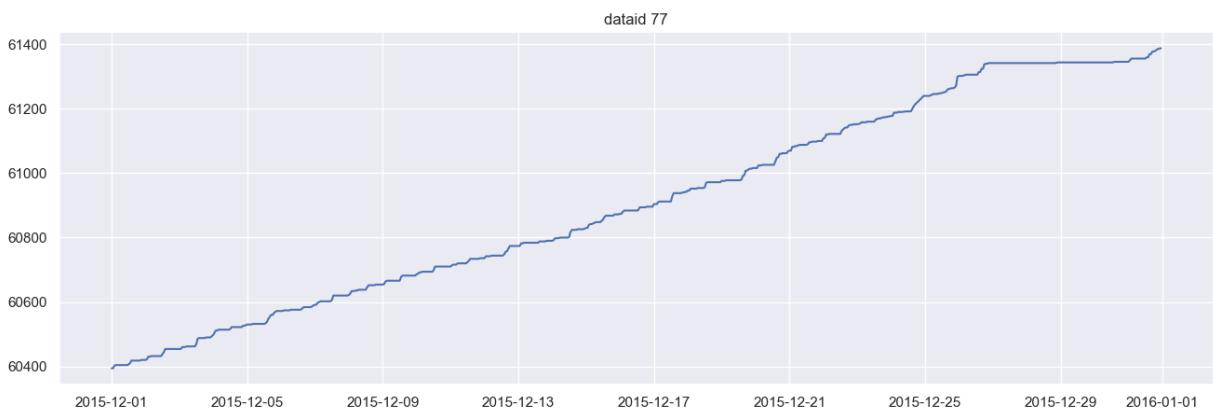
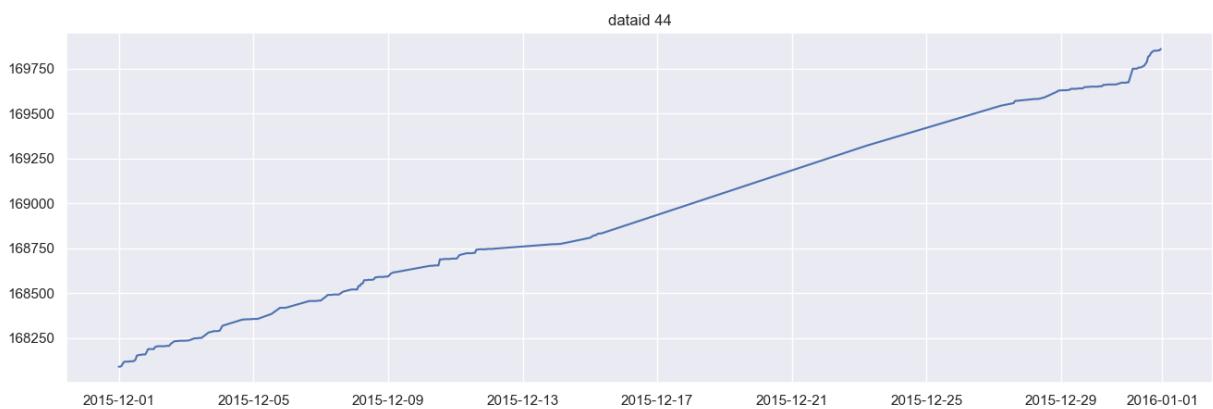
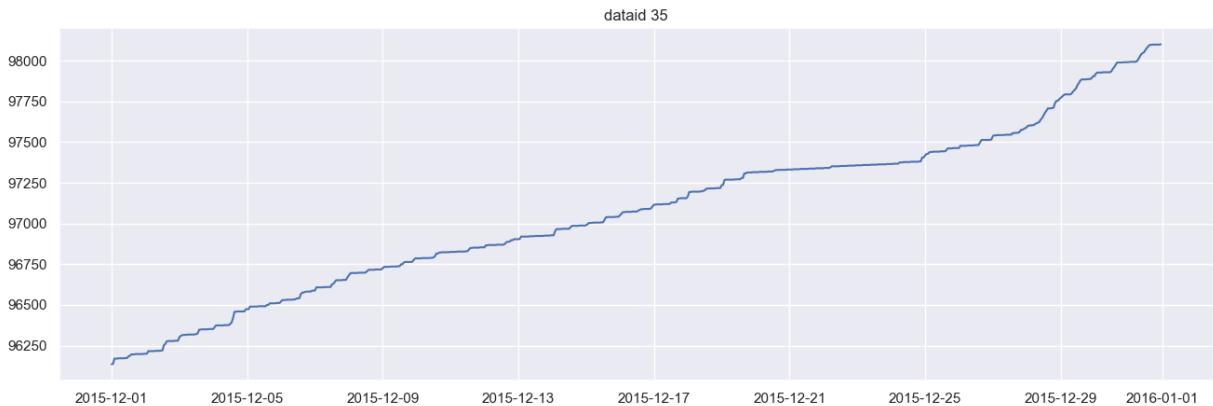
```
In [13]: hourlydfs = []
for house in unique_households:
    house_df = df.loc[df['dataid'] == house]

    # we simply interpolate the hours with no data since meter_value is the cumulative
    house_dec_df = house_df.resample('1H').last().interpolate()
    hourlydf = house_dec_df['meter_value']
    hourlydf = hourlydf["2015-12-01": "2015-12-31"]
    hourlydf = hourlydf.reindex(pd.date_range("2015-12-01 00:00:00+00:00", "2015-12-31 23:59:59+00:00"))
    hourlydf = hourlydf.rename(house)
```

```
hourly_dfs.append(hourly_df)
plot_hourly_df(hourly_df, house)
```

<ipython-input-12-193811361870>:7: RuntimeWarning: More than 20 figures have been opened. Figures created through the pyplot interface (`matplotlib.pyplot.figure`) are retained until explicitly closed and may consume too much memory. (To control this warning, see the rcParam `figure.max\_open\_warning`).

```
plt.figure(figsize=(16, 5), dpi=100)
```



## Group9\_Q1

dataid 114



dataid 187



dataid 222



dataid 252



## Group9\_Q1

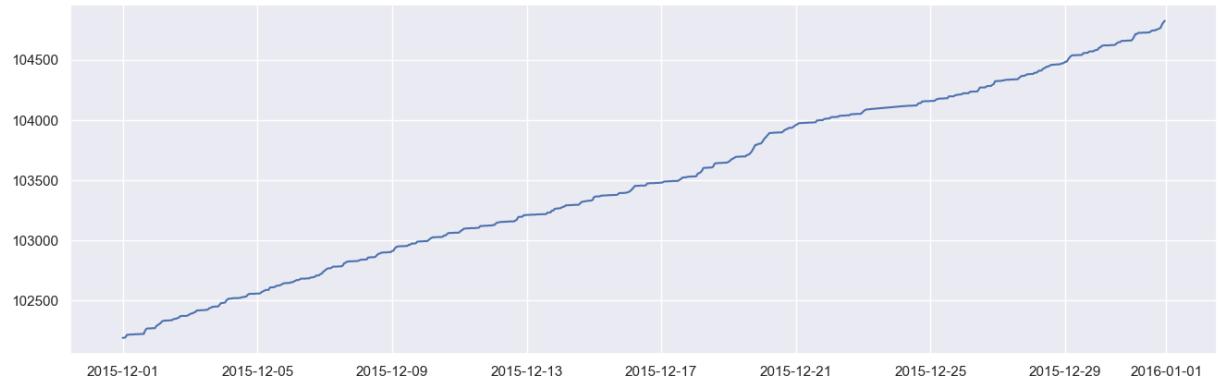
dataid 370



dataid 483



dataid 484



dataid 661



## Group9\_Q1

dataid 739



dataid 744



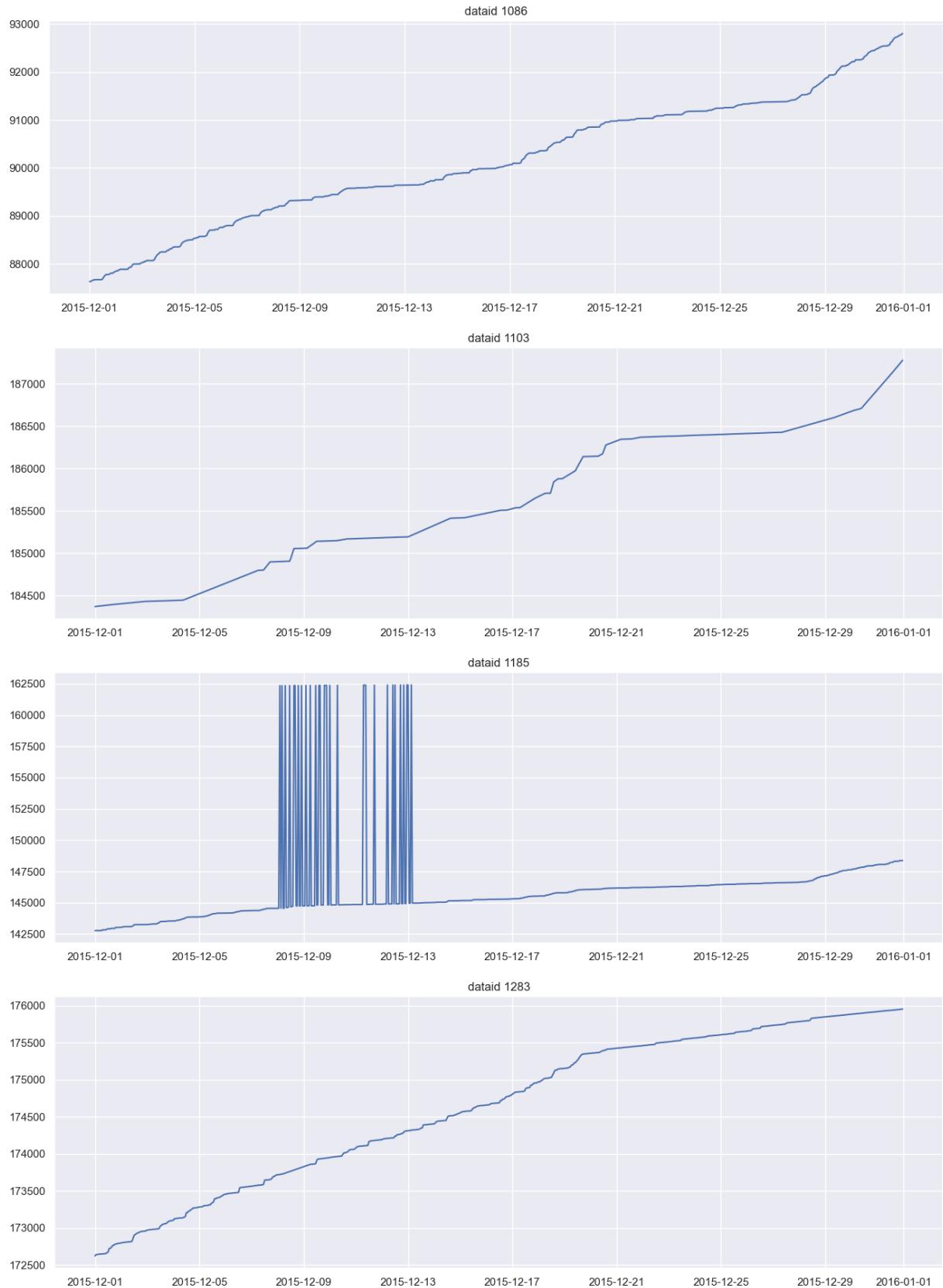
dataid 871



dataid 1042

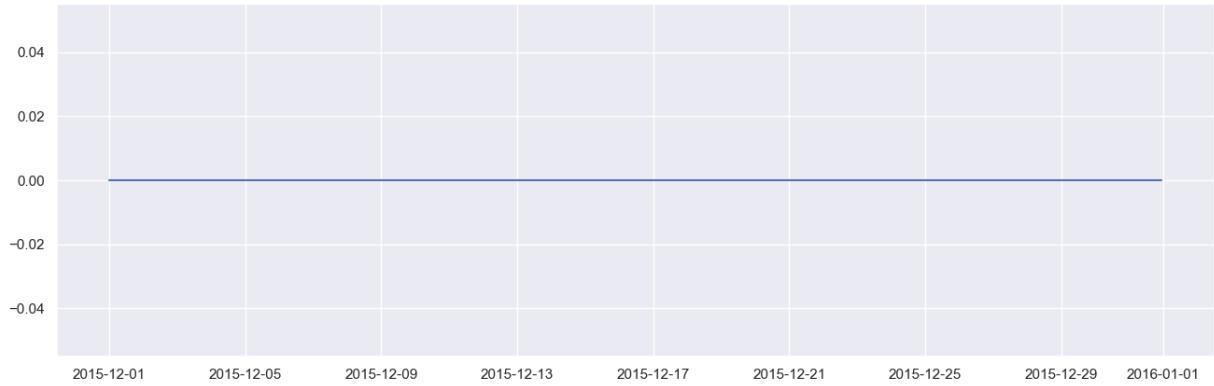


## Group9\_Q1

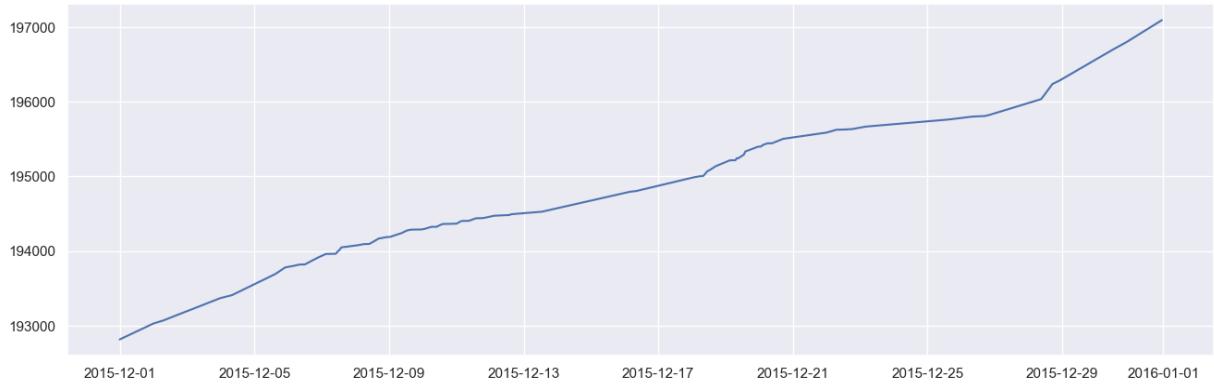


## Group9\_Q1

dataid 1403



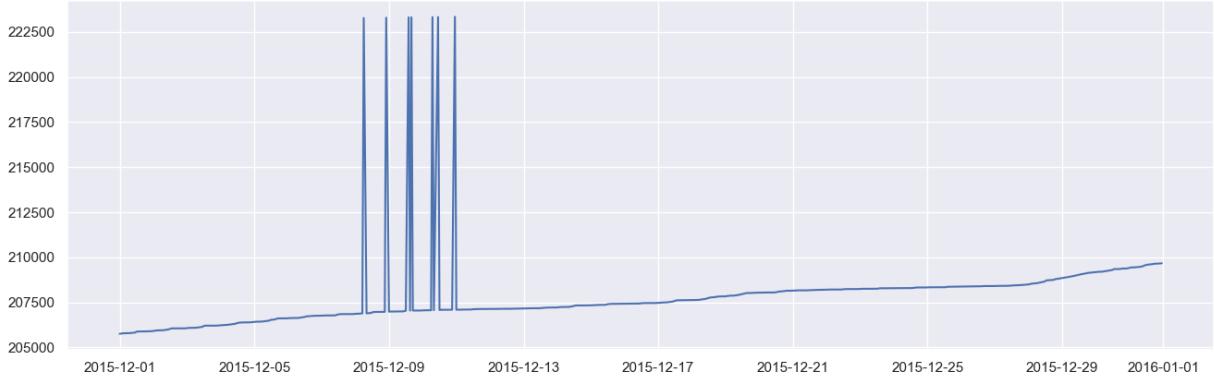
dataid 1415



dataid 1507



dataid 1556



## Group9\_Q1

dataid 1589



dataid 1619



dataid 1697

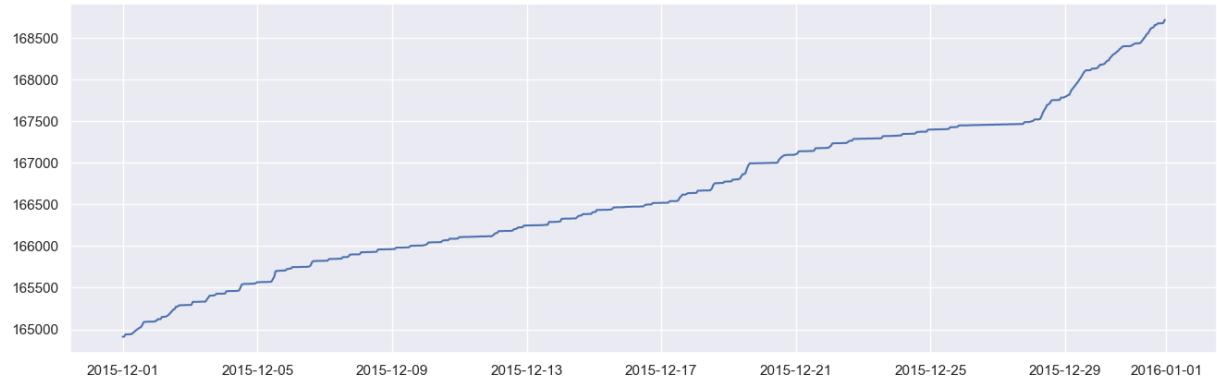


dataid 1714



## Group9\_Q1

dataid 1718



dataid 1790



dataid 1791



dataid 1792



## Group9\_Q1

dataid 1800



dataid 1801



dataid 2018



dataid 2034



## Group9\_Q1

dataid 2072



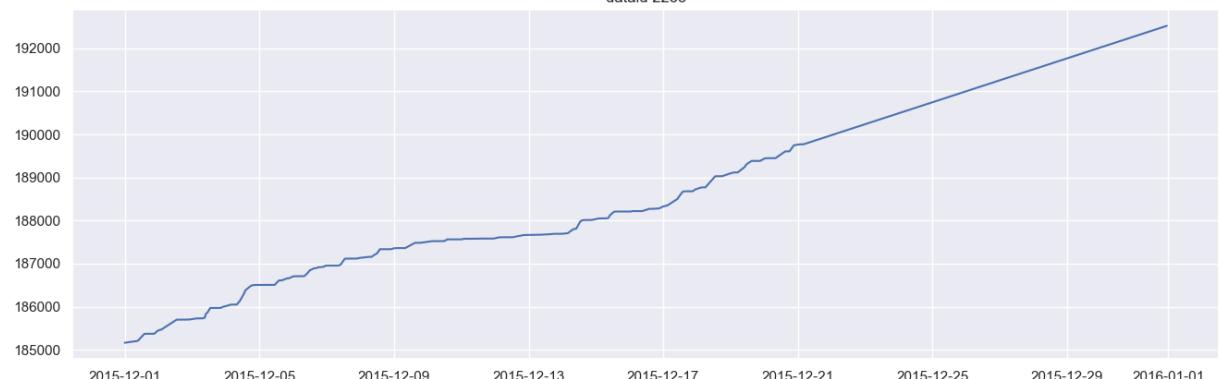
dataid 2094



dataid 2129



dataid 2233



## Group9\_Q1

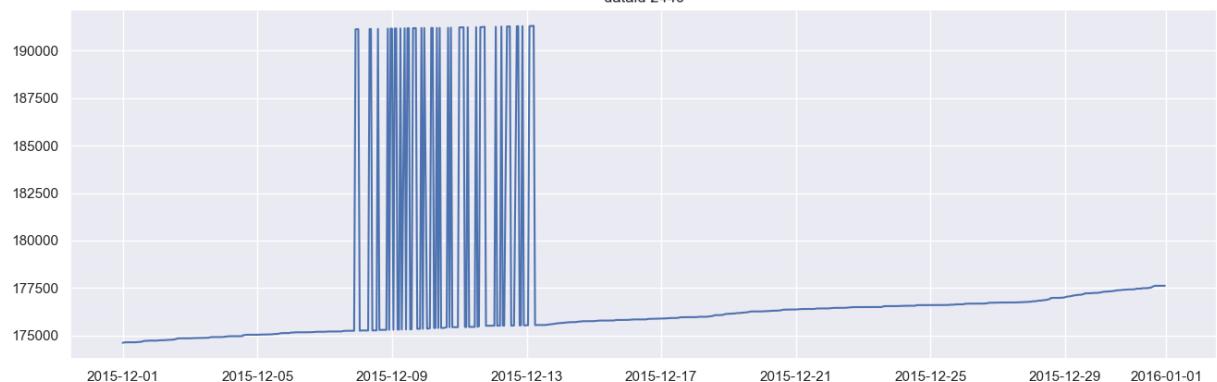
dataid 2335



dataid 2378



dataid 2449



dataid 2461



## Group9\_Q1

dataid 2470



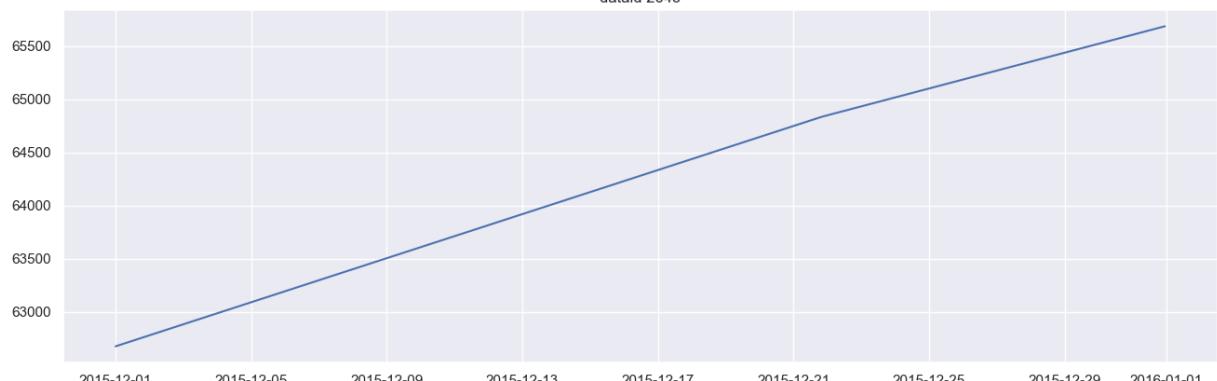
dataid 2575



dataid 2638

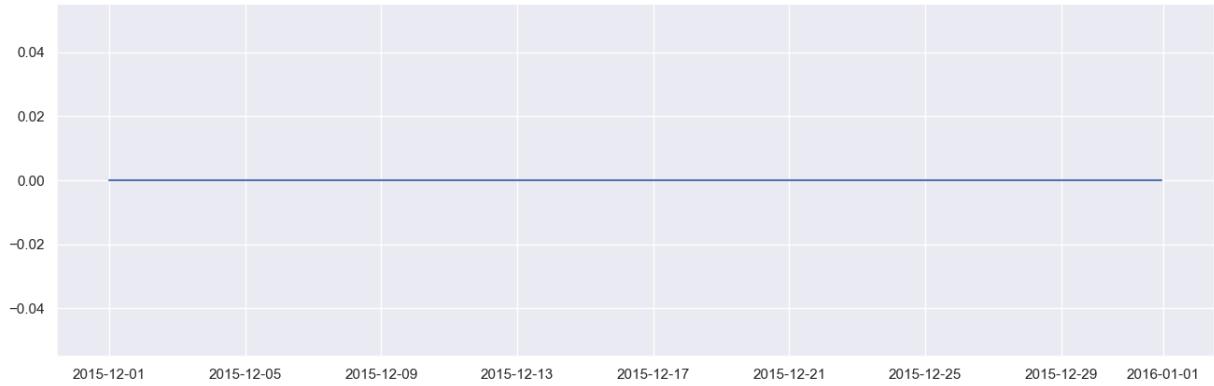


dataid 2645

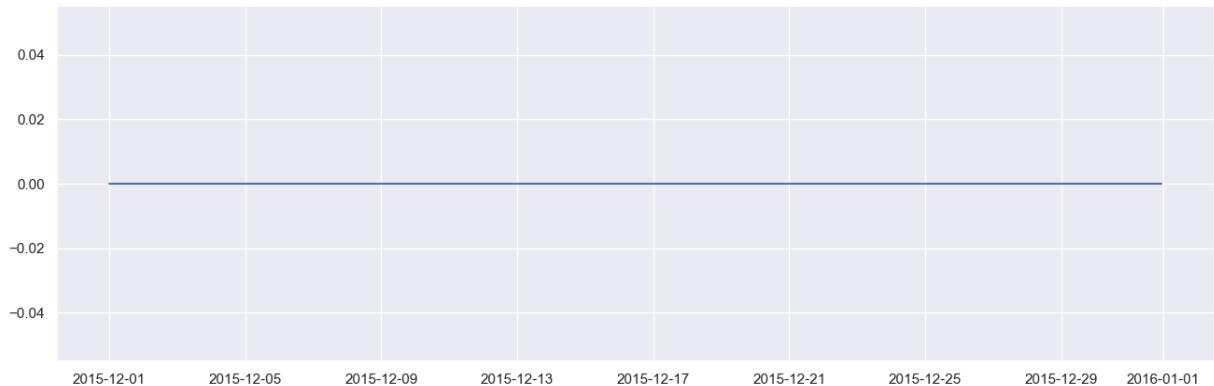


## Group9\_Q1

dataid 2755



dataid 2814



dataid 2818

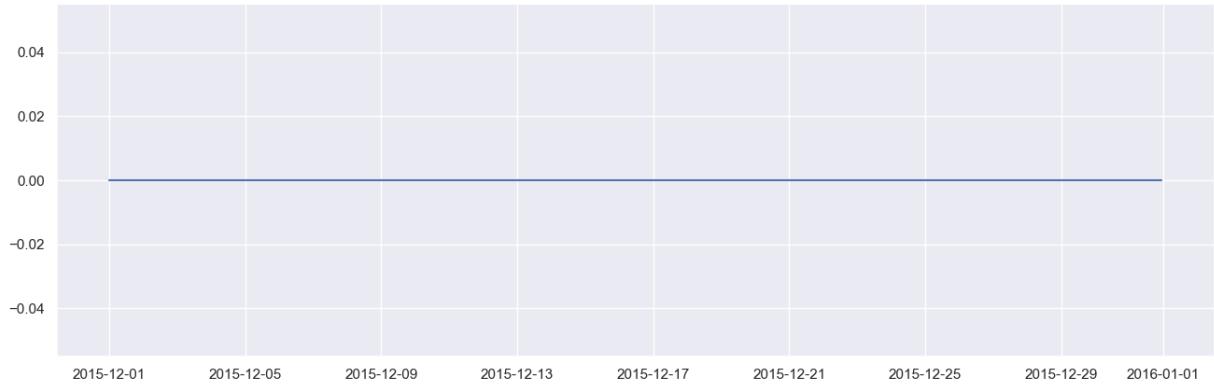


dataid 2945



## Group9\_Q1

dataid 2946



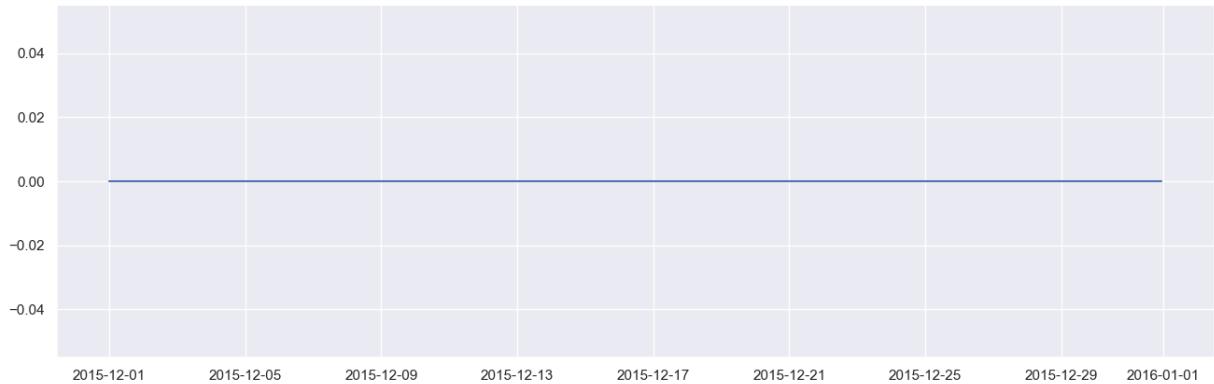
dataid 2965



dataid 2980



dataid 3036

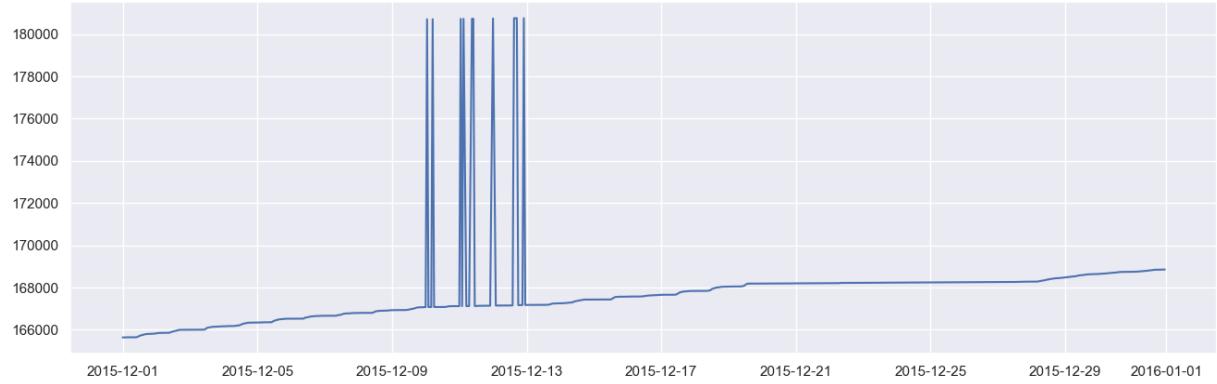


## Group9\_Q1

dataid 3039



dataid 3134



dataid 3310



dataid 3367

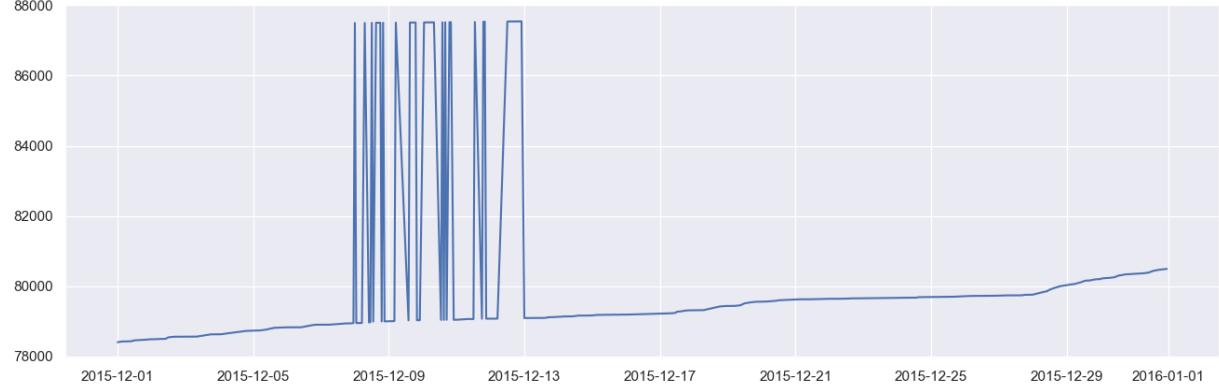


## Group9\_Q1

dataid 3527



dataid 3544



dataid 3577

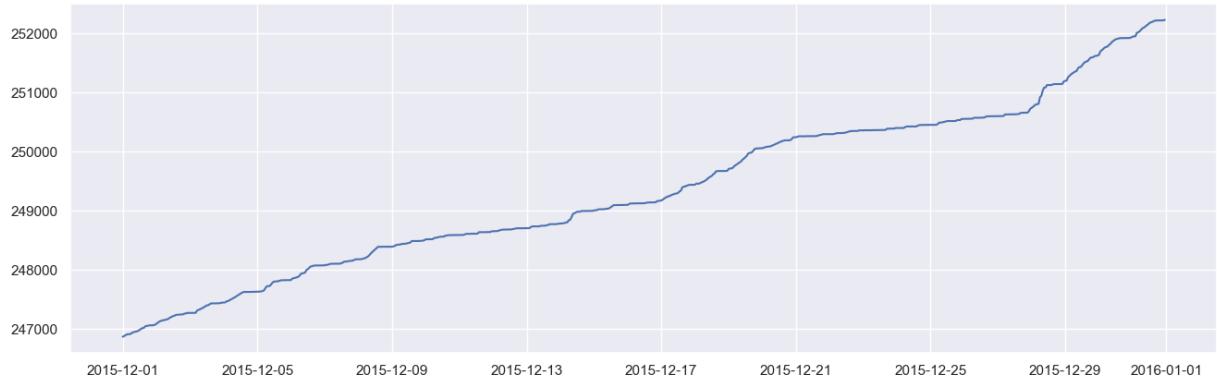


dataid 3635



## Group9\_Q1

dataid 3723



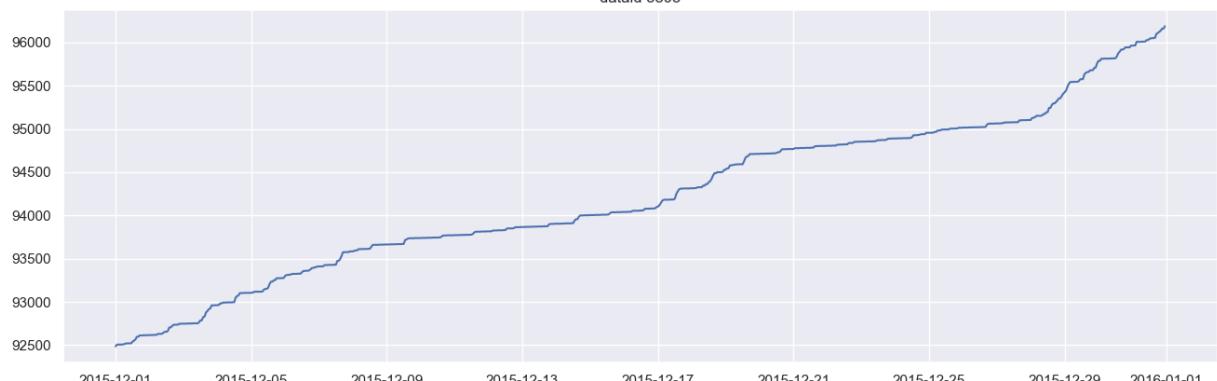
dataid 3778



dataid 3849



dataid 3893



## Group9\_Q1

dataid 3918



dataid 4029



dataid 4031



dataid 4193



dataid 4228



dataid 4296



dataid 4352



dataid 4356



## Group9\_Q1

dataid 4373



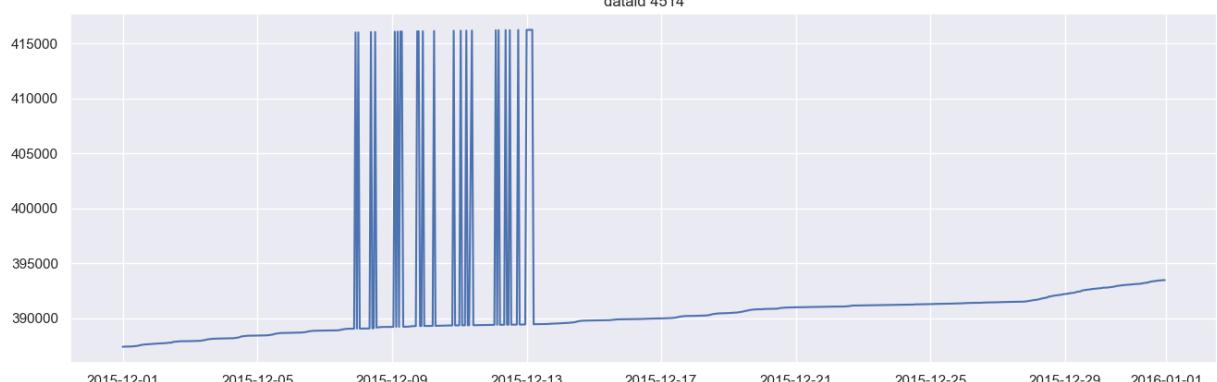
dataid 4421



dataid 4447

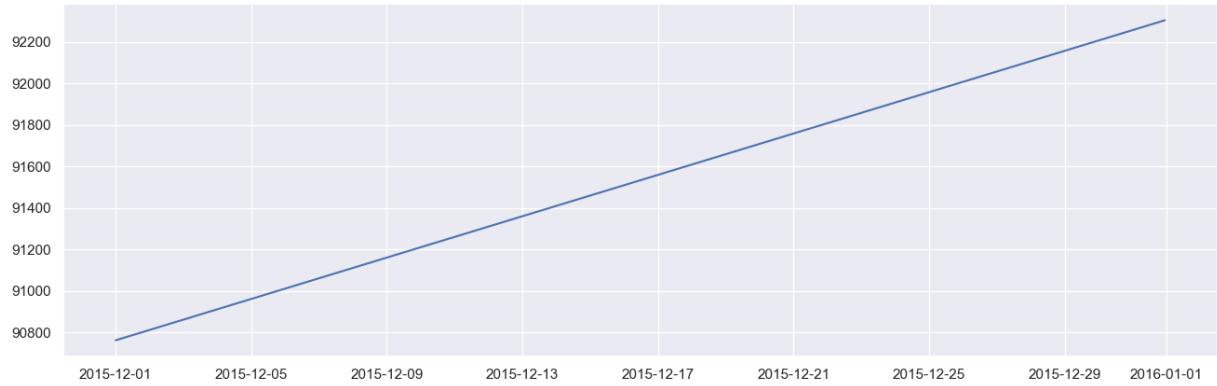


dataid 4514



## Group9\_Q1

dataid 4671



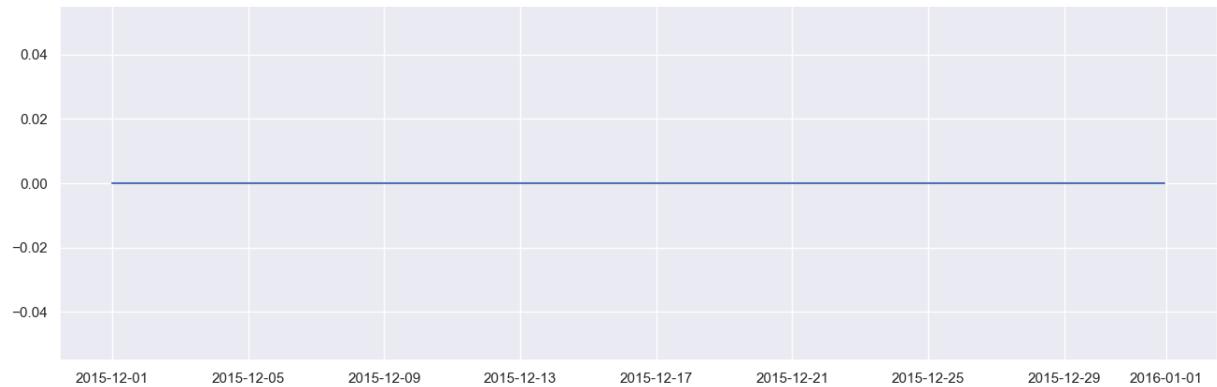
dataid 4732



dataid 4767



dataid 4874

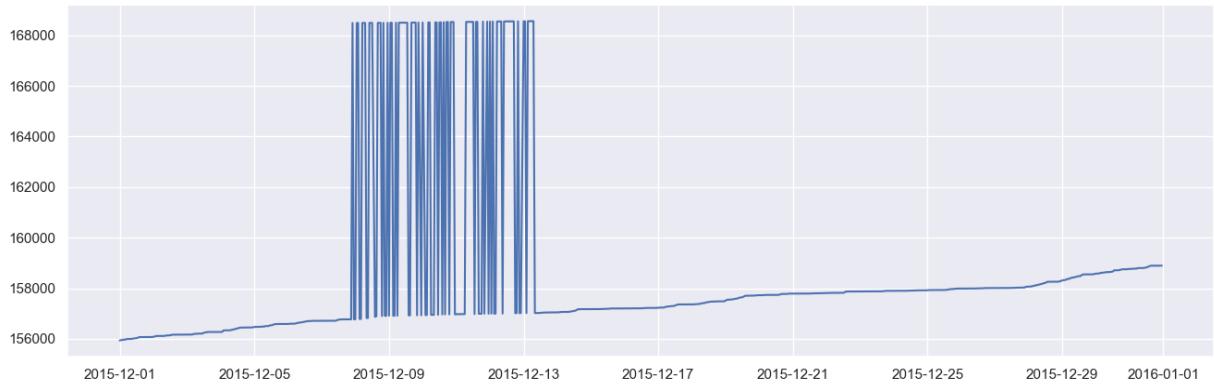


## Group9\_Q1

dataid 4998



dataid 5129



dataid 5131



dataid 5193



## Group9\_Q1

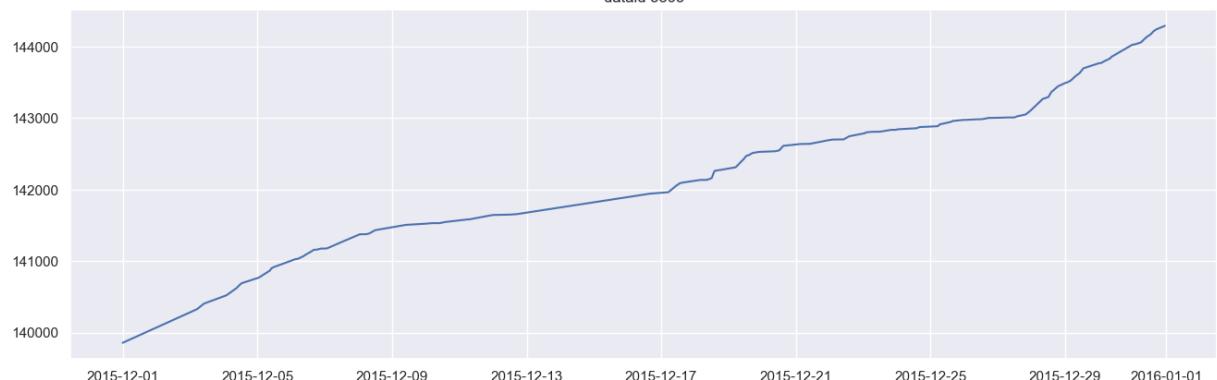
dataid 5275



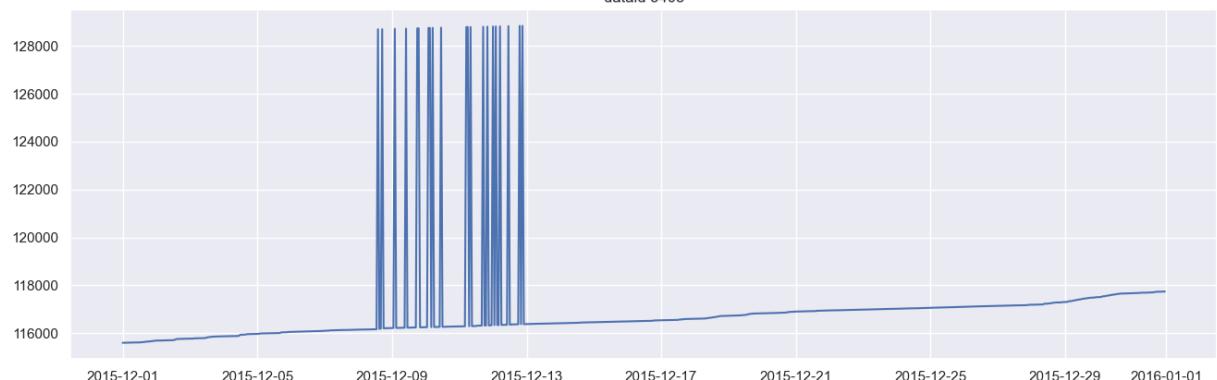
dataid 5317



dataid 5395



dataid 5403

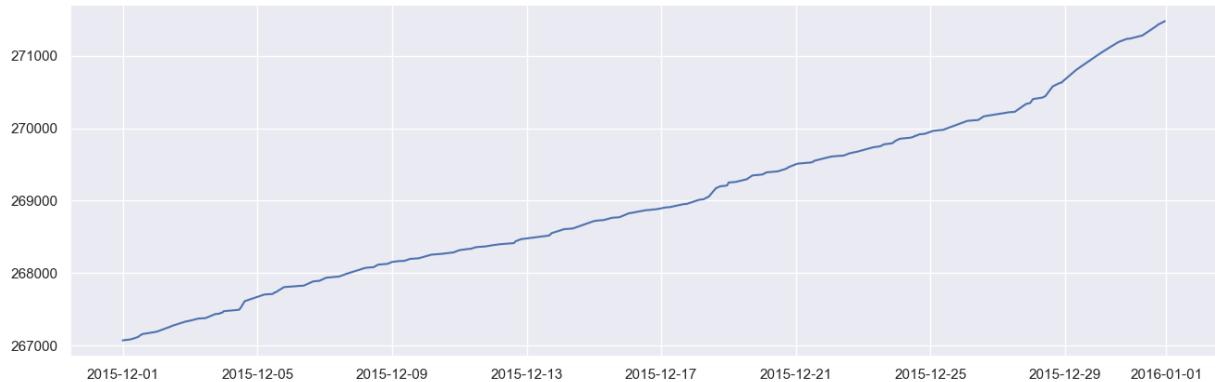


## Group9\_Q1

dataid 5439



dataid 5484



dataid 5545



dataid 5636



## Group9\_Q1

dataid 5658



dataid 5785



dataid 5810



dataid 5814



## Group9\_Q1

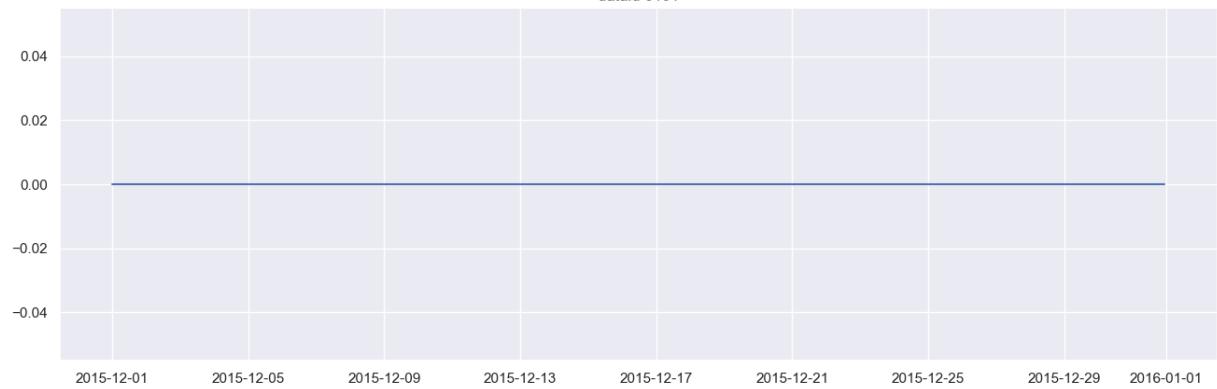
dataid 5892



dataid 5972



dataid 6101



dataid 6412



## Group9\_Q1

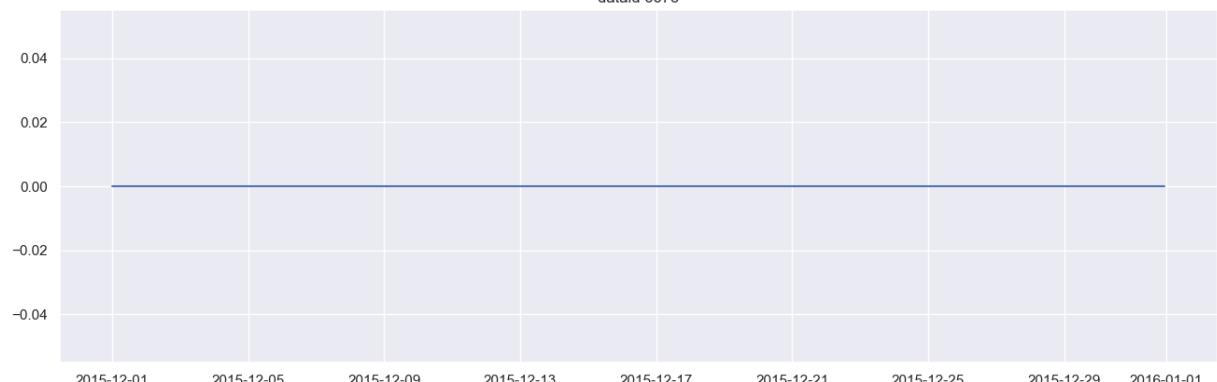
dataid 6505



dataid 6578



dataid 6673



dataid 6685

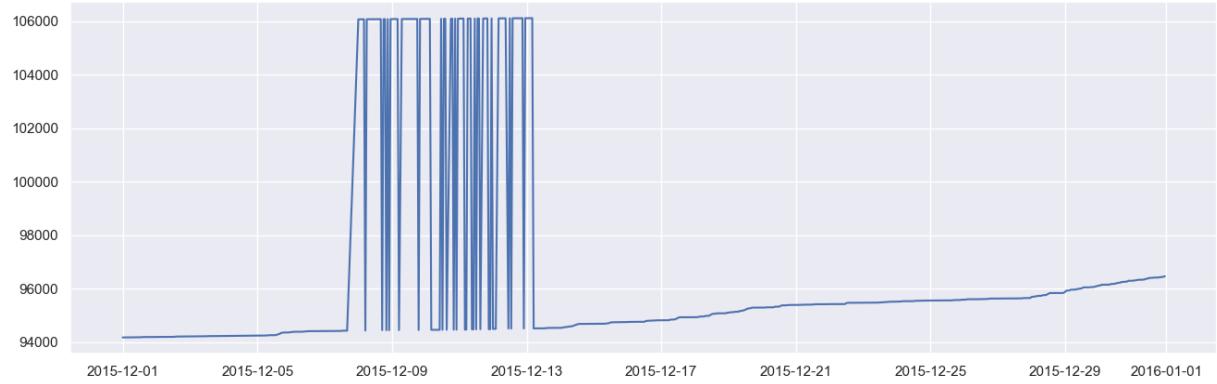


## Group9\_Q1

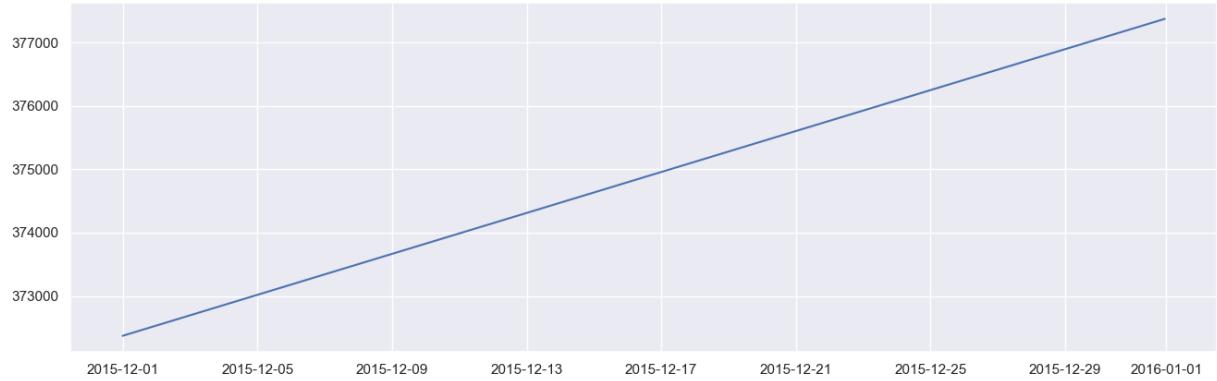
dataid 6830



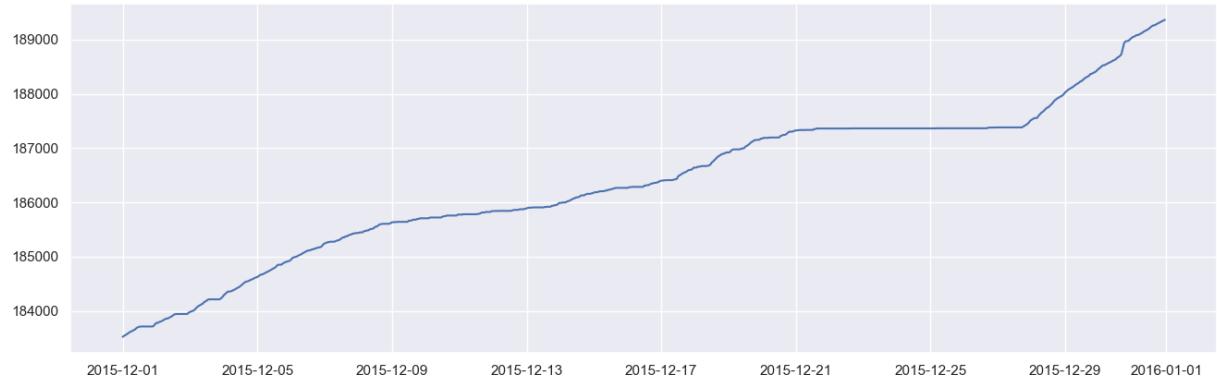
dataid 6836



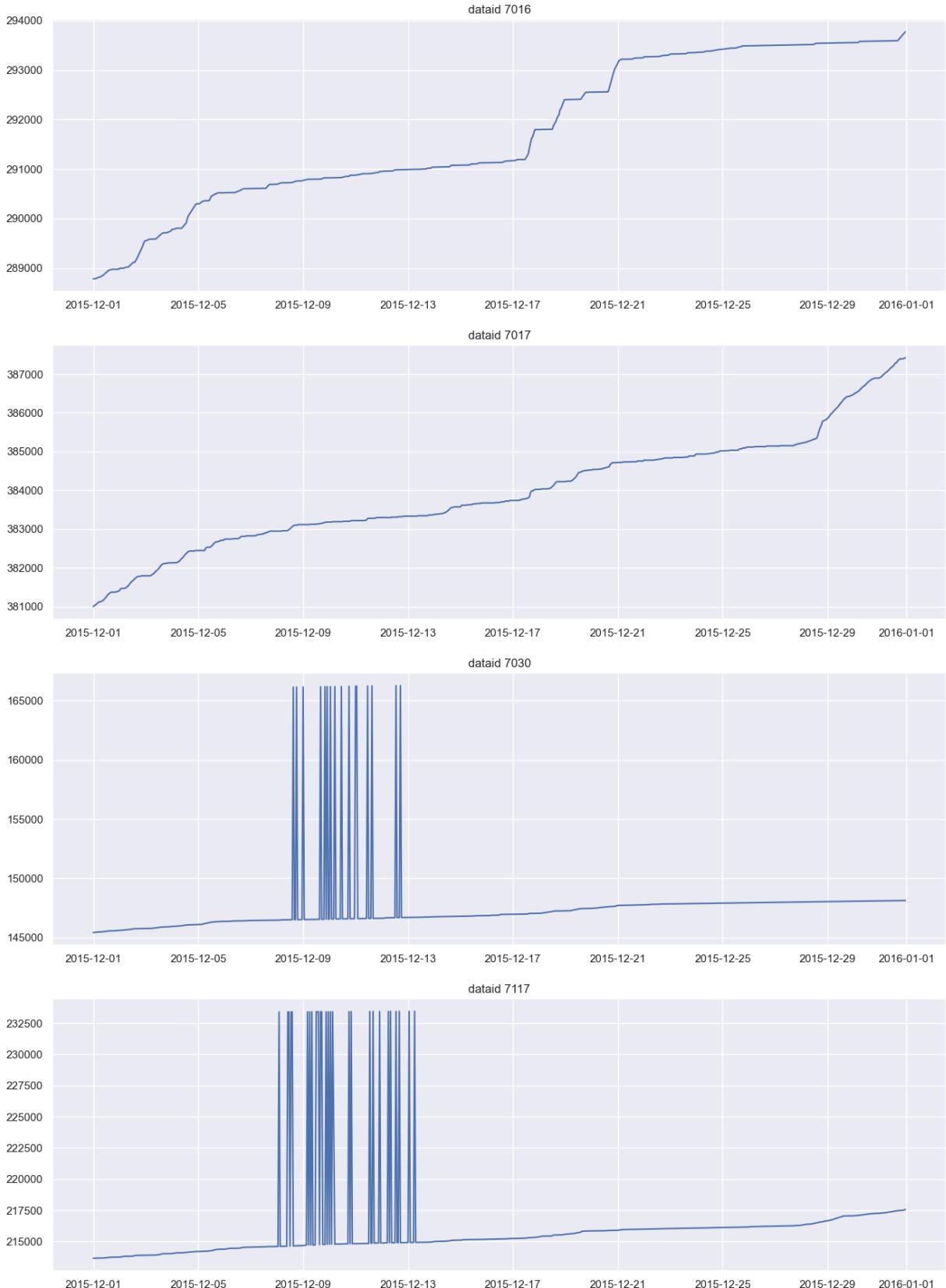
dataid 6863



dataid 6910



## Group9\_Q1

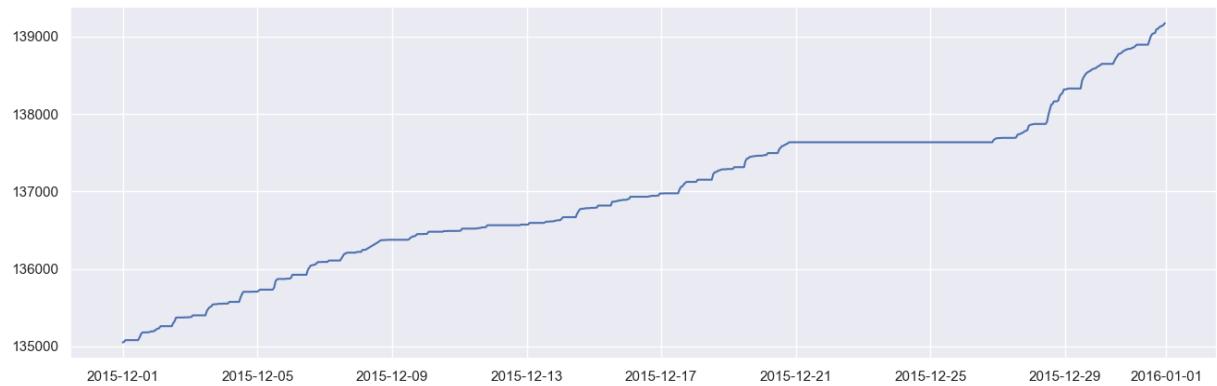


## Group9\_Q1

dataid 7287



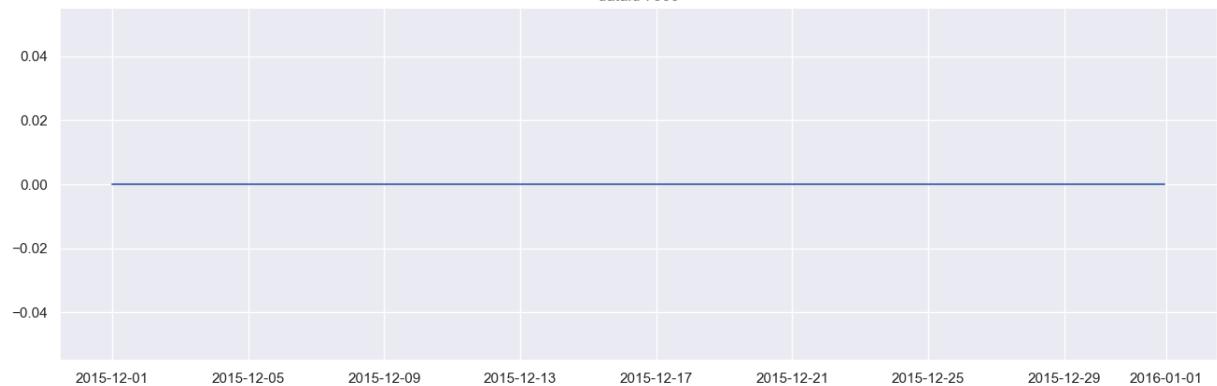
dataid 7429



dataid 7460



dataid 7566



## Group9\_Q1

dataid 7674



dataid 7682



dataid 7739



dataid 7741



## Group9\_Q1

dataid 7794



dataid 7900



dataid 7919



dataid 7965

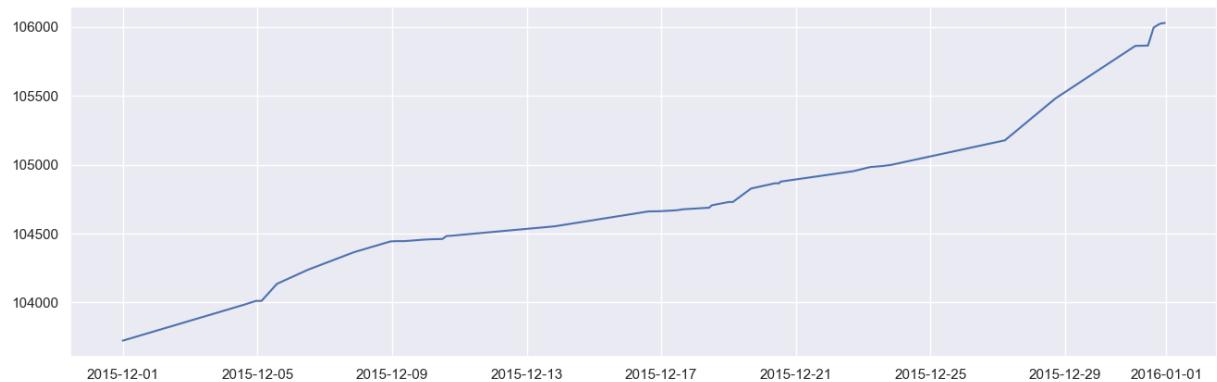


## Group9\_Q1

dataid 7989



dataid 8059



dataid 8084



dataid 8086

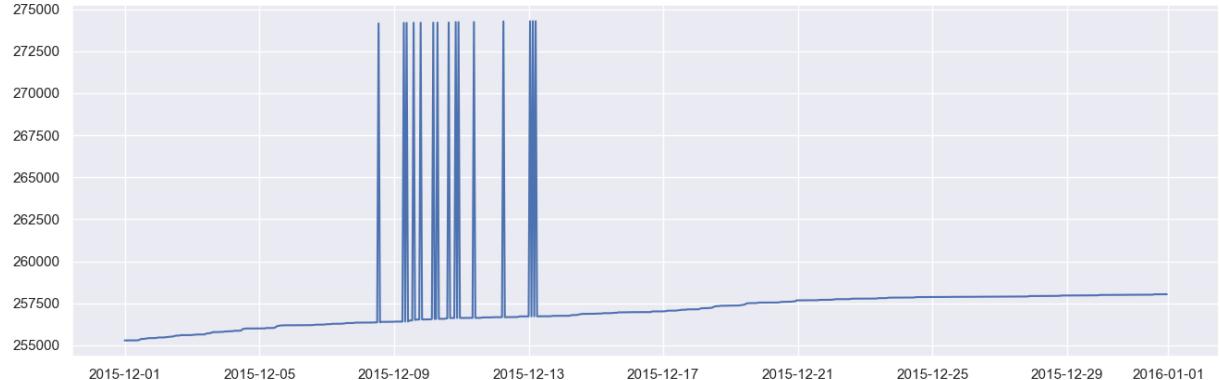


## Group9\_Q1

dataid 8155



dataid 8156



dataid 8244



dataid 8386

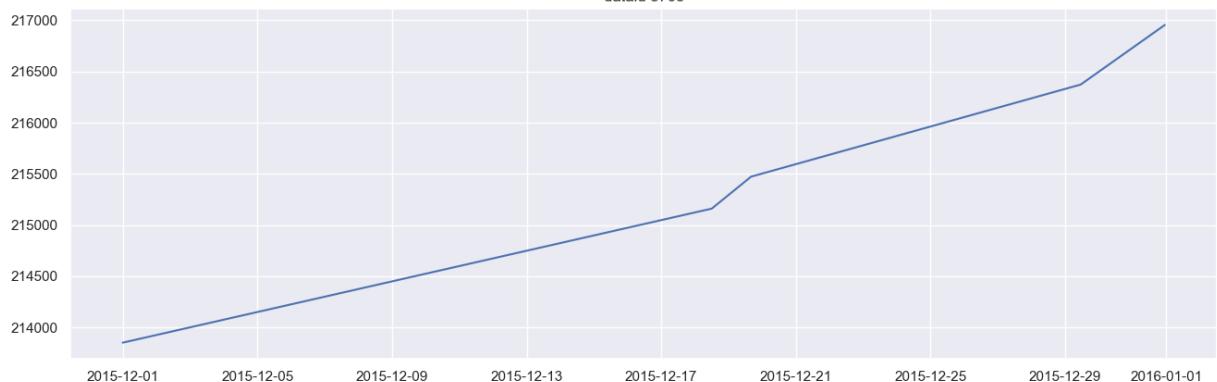


## Group9\_Q1

dataid 8467



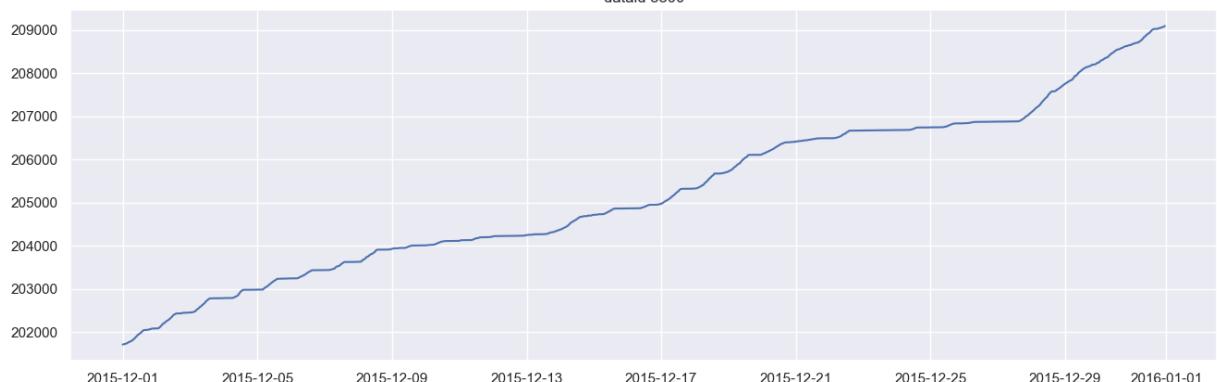
dataid 8703



dataid 8829



dataid 8890



## Group9\_Q1

dataid 8967



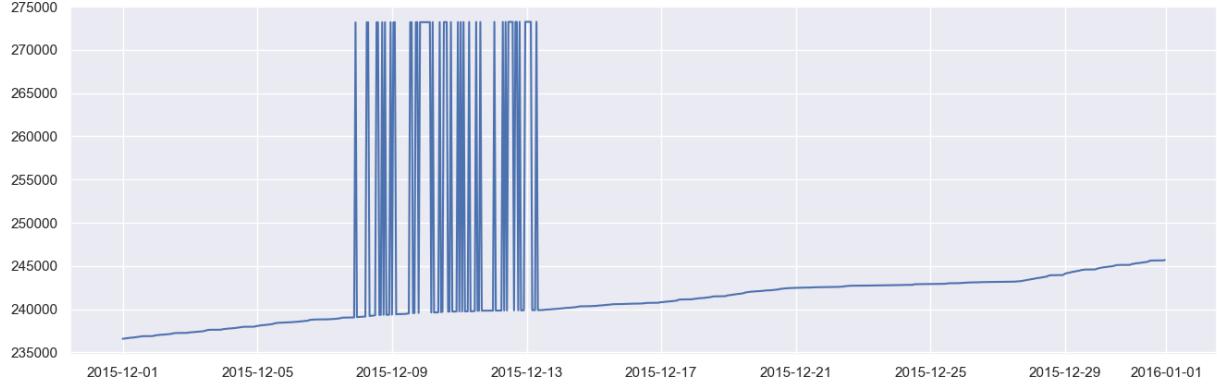
dataid 9052



dataid 9121

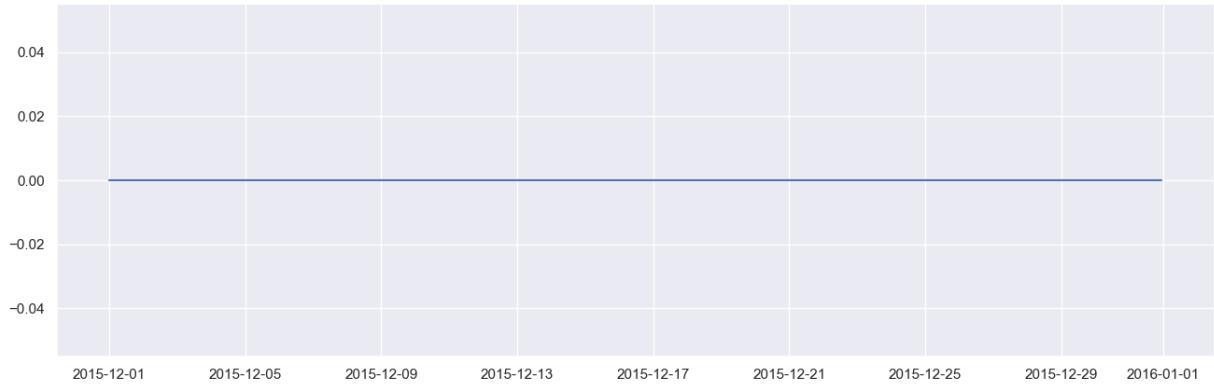


dataid 9134



## Group9\_Q1

dataid 9160



dataid 9278



dataid 9295

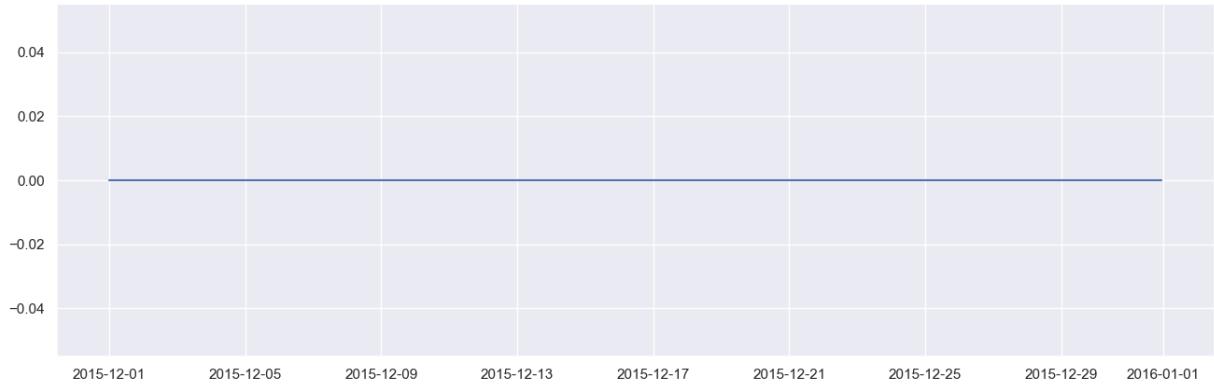


dataid 9474

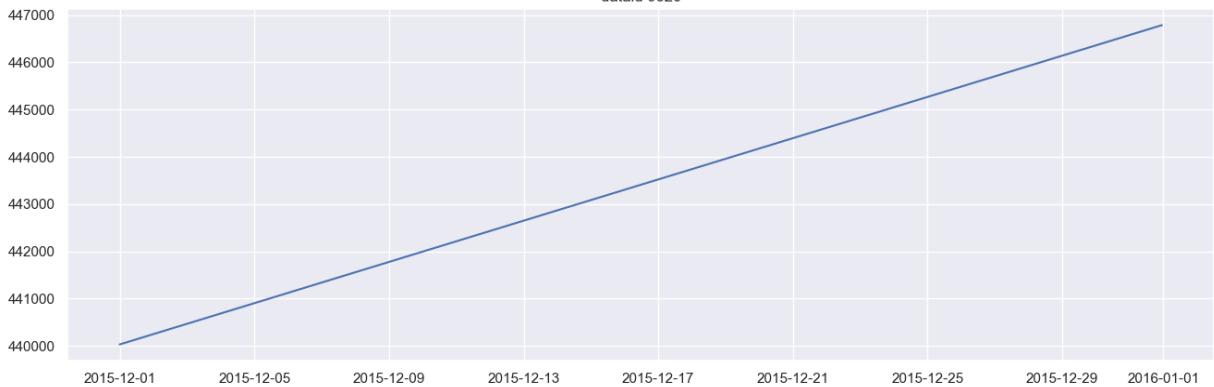


## Group9\_Q1

dataid 9600



dataid 9620



dataid 9631

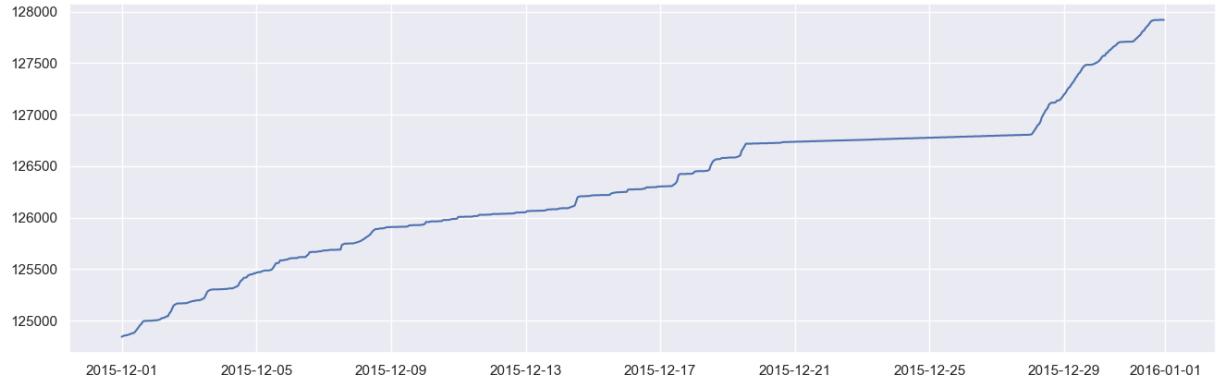


dataid 9639



## Group9\_Q1

dataid 9729



dataid 9766



dataid 9849



dataid 9956





As can be seen above, for certain households (e.g: 2814), the total gas consumption was 0. This possibly indicates that the particular household might have went for a vacation during the holidays and hence was not occupied during the month. We will be considering this insight when answering question 2.

## Q1.3

**For each home, find the top five homes with which it shows the highest correlation**

### Approach

First, we concatnate the hourly dataframes. Then, for every meter, we calculate the correlation between it and the other meters. Next, we set the correlation of that particular meter with itself as 0. And lastly, for every meter, we sorted the correlation list to obtain the top five meters with which it shows the highest correlation.

In [14]:

```
def get_top_five_corr(row):
    """
    For each home, to find the top five homes with which it shows the highest correlation
    """
    new_row = row
    key_val_pair_list = [(value, key) for key, value in row.items()]
    key_val_pair_list = sorted(key_val_pair_list, reverse=True)
    result = key_val_pair_list[:5]
    for index, (value, key) in enumerate(result):
        new_row[f'Top {index + 1} value'] = value
        new_row[f'Top {index + 1} dataid'] = key

    return new_row
```

In [15]:

```
# create correlation matrix, filling diagonals and NaN with 0
merged = pd.concat(hourly_dfs, axis=1)
corr_df = merged.corr().fillna(0)
corr_df.values[[np.arange(corr_df.shape[0])]*2] = 0
new_corr_df = corr_df.apply(lambda x: get_top_five_corr(x), axis=1)
columns = []
for index in range(5):
    columns.append(f'Top {index+1} dataid')
    columns.append(f'Top {index+1} value')

new_corr_df = new_corr_df[columns]
```

```
<ipython-input-15-8689a979ca8c>:4: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.
```

```
corr_df.values[[np.arange(corr_df.shape[0])] * 2] = 0
```

In [16]:

new\_corr\_df

Out[16]:

	<b>Top 1 dataid</b>	<b>Top 1 value</b>	<b>Top 2 dataid</b>	<b>Top 2 value</b>	<b>Top 3 dataid</b>	<b>Top 3 value</b>	<b>Top 4 dataid</b>	<b>Top 4 value</b>	<b>Top 5 dataid</b>	<b>Top 5 value</b>	
	<b>35</b>	1790.0	0.997973	9766.0	0.997802	7794.0	0.997340	1415.0	0.997289	7682.0	0.997278
	<b>44</b>	5658.0	0.998230	9620.0	0.997971	4671.0	0.997971	6863.0	0.997971	484.0	0.997940
	<b>77</b>	44.0	0.996479	9620.0	0.996237	4671.0	0.996237	6863.0	0.996237	2645.0	0.995397
	<b>94</b>	661.0	0.999683	2129.0	0.999401	5892.0	0.999342	1415.0	0.999193	1086.0	0.999127
	<b>114</b>	1801.0	0.998541	3527.0	0.998399	5814.0	0.998331	5636.0	0.998299	8829.0	0.998250
	<b>187</b>	3577.0	0.999341	5814.0	0.998972	3918.0	0.998848	5636.0	0.998805	5131.0	0.998710
	<b>222</b>	8467.0	0.990999	2378.0	0.981276	739.0	0.980332	1042.0	0.978934	5785.0	0.978355
	<b>252</b>	3918.0	0.998840	3577.0	0.998667	5636.0	0.998491	5439.0	0.998473	5131.0	0.998395
	<b>370</b>	6578.0	0.998936	5484.0	0.998256	7900.0	0.998061	2980.0	0.997194	1718.0	0.997184
	<b>483</b>	2072.0	0.999341	3527.0	0.999135	1714.0	0.998966	4998.0	0.998842	4228.0	0.998566
	<b>484</b>	8967.0	0.998710	9620.0	0.998567	4671.0	0.998567	6863.0	0.998567	5658.0	0.998447
	<b>661</b>	94.0	0.999683	2129.0	0.999477	4356.0	0.999138	5892.0	0.999121	9121.0	0.999073
	<b>739</b>	9295.0	0.998697	1042.0	0.997758	2965.0	0.997633	7287.0	0.997479	9639.0	0.997409
	<b>744</b>	9121.0	0.999112	2945.0	0.998363	5484.0	0.998277	4228.0	0.998256	1801.0	0.998208
	<b>871</b>	5439.0	0.998752	4031.0	0.998701	5814.0	0.998446	2034.0	0.998157	9729.0	0.997819
	<b>1042</b>	5193.0	0.998075	739.0	0.997758	9295.0	0.996685	2965.0	0.996562	8155.0	0.996553
	<b>1086</b>	1507.0	0.999633	2129.0	0.999507	1415.0	0.999409	4732.0	0.999329	9639.0	0.999275
	<b>1103</b>	4373.0	0.993722	6505.0	0.993067	4296.0	0.992734	9052.0	0.992588	484.0	0.992370
	<b>1185</b>	6836.0	0.406719	5129.0	0.359864	9134.0	0.312297	3849.0	0.282571	3544.0	0.280734
	<b>1283</b>	8155.0	0.995247	2378.0	0.995001	1042.0	0.992776	2645.0	0.992056	739.0	0.990124
	<b>1403</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>1415</b>	2094.0	0.999534	1086.0	0.999409	4732.0	0.999289	94.0	0.999193	1507.0	0.999048
	<b>1507</b>	1086.0	0.999633	2129.0	0.999431	9639.0	0.999301	9295.0	0.999259	3778.0	0.999059
	<b>1556</b>	3849.0	0.438792	2461.0	0.435690	871.0	0.434578	2018.0	0.434244	3367.0	0.434046
	<b>1589</b>	5636.0	0.999564	3577.0	0.999398	3723.0	0.999153	5131.0	0.999143	4356.0	0.999138
	<b>1619</b>	5814.0	0.999239	5636.0	0.998969	8086.0	0.998963	3527.0	0.998876	3918.0	0.998761
	<b>1697</b>	7287.0	0.998826	5892.0	0.998616	4373.0	0.998093	9052.0	0.998006	661.0	0.997771
	<b>1714</b>	8829.0	0.999296	3527.0	0.999134	483.0	0.998966	2072.0	0.998874	4228.0	0.998651
	<b>1718</b>	4228.0	0.998809	7989.0	0.998785	9121.0	0.998740	5636.0	0.998671	8829.0	0.998559
	<b>1790</b>	35.0	0.997973	9639.0	0.997579	1415.0	0.997496	7794.0	0.997438	9766.0	0.997281

	<b>Top 1 dataid</b>	<b>Top 1 value</b>	<b>Top 2 dataid</b>	<b>Top 2 value</b>	<b>Top 3 dataid</b>	<b>Top 3 value</b>	<b>Top 4 dataid</b>	<b>Top 4 value</b>	<b>Top 5 dataid</b>	<b>Top 5 value</b>	
	<b>1791</b>	9121.0	0.998385	3723.0	0.997868	661.0	0.997839	94.0	0.997834	2575.0	0.997813
	<b>1792</b>	4193.0	0.998206	7900.0	0.997611	4228.0	0.997418	2072.0	0.997376	3310.0	0.997256
	<b>1800</b>	8386.0	0.994875	7682.0	0.993952	2945.0	0.992978	114.0	0.992586	8059.0	0.992342
	<b>1801</b>	5636.0	0.999299	7989.0	0.999115	1589.0	0.999009	8829.0	0.998959	3577.0	0.998948
	<b>2018</b>	9729.0	0.997085	6910.0	0.995106	7429.0	0.994911	871.0	0.993924	9766.0	0.993309
	<b>2034</b>	5439.0	0.998578	3893.0	0.998559	4031.0	0.998166	871.0	0.998157	1507.0	0.998138
	<b>2072</b>	483.0	0.999341	1714.0	0.998874	3527.0	0.998817	4998.0	0.998562	7017.0	0.998482
	<b>2094</b>	1415.0	0.999534	1086.0	0.999101	9639.0	0.999017	4732.0	0.998831	1507.0	0.998553
	<b>2129</b>	1086.0	0.999507	661.0	0.999477	1507.0	0.999431	3778.0	0.999415	94.0	0.999401
	<b>2233</b>	7460.0	0.998758	7919.0	0.998627	4421.0	0.998424	2818.0	0.997153	44.0	0.996375
	<b>2335</b>	9052.0	0.845110	1507.0	0.844958	2129.0	0.844915	3778.0	0.844802	2470.0	0.844757
	<b>2378</b>	1283.0	0.995001	8155.0	0.994040	8467.0	0.990143	1042.0	0.988805	739.0	0.988246
	<b>2449</b>	6836.0	0.502700	3544.0	0.367652	9134.0	0.353476	5129.0	0.342206	4514.0	0.303415
	<b>2461</b>	3367.0	0.998929	1714.0	0.998469	3310.0	0.998264	2072.0	0.998028	3527.0	0.997870
	<b>2470</b>	5275.0	0.998360	114.0	0.998198	5439.0	0.998015	3367.0	0.997701	2034.0	0.997613
	<b>2575</b>	5892.0	0.998418	661.0	0.998336	94.0	0.998252	7965.0	0.998158	9956.0	0.998144
	<b>2638</b>	4352.0	0.999637	4421.0	0.998676	9474.0	0.998259	7460.0	0.998053	3039.0	0.996694
	<b>2645</b>	9620.0	0.999160	4671.0	0.999160	6863.0	0.999160	8967.0	0.998467	484.0	0.998027
	<b>2755</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>2814</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>2818</b>	1791.0	0.997348	9121.0	0.997275	2233.0	0.997153	7919.0	0.996973	744.0	0.996922
	<b>2945</b>	4228.0	0.998537	3527.0	0.998363	744.0	0.998363	5484.0	0.998321	9121.0	0.998238
	<b>2946</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>2965</b>	7287.0	0.998773	5810.0	0.998682	9639.0	0.998226	9295.0	0.998200	5892.0	0.998005
	<b>2980</b>	7900.0	0.997424	370.0	0.997194	7674.0	0.996690	1792.0	0.996233	9631.0	0.996213
	<b>3036</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>3039</b>	9474.0	0.999108	4352.0	0.997042	2638.0	0.996694	4421.0	0.995466	9849.0	0.995445
	<b>3134</b>	8467.0	0.420003	222.0	0.413216	2018.0	0.409037	3849.0	0.407027	2378.0	0.406498
	<b>3310</b>	3367.0	0.998787	3527.0	0.998721	5814.0	0.998714	8829.0	0.998637	1714.0	0.998380
	<b>3367</b>	2461.0	0.998929	3310.0	0.998787	7017.0	0.998334	1714.0	0.998156	2072.0	0.998114
	<b>3527</b>	4228.0	0.999423	8829.0	0.999334	483.0	0.999135	1714.0	0.999134	5636.0	0.998986
	<b>3544</b>	6836.0	0.500550	5129.0	0.487876	2449.0	0.367652	9134.0	0.364752	5403.0	0.318298
	<b>3577</b>	5636.0	0.999681	5439.0	0.999530	3918.0	0.999490	1589.0	0.999398	187.0	0.999341
	<b>3635</b>	744.0	0.997996	9121.0	0.996541	35.0	0.996422	5484.0	0.996293	94.0	0.996187
	<b>3723</b>	8890.0	0.999357	9121.0	0.999206	1589.0	0.999153	5972.0	0.999141	5131.0	0.999116

## Group9\_Q1

	<b>Top 1 dataid</b>	<b>Top 1 value</b>	<b>Top 2 dataid</b>	<b>Top 2 value</b>	<b>Top 3 dataid</b>	<b>Top 3 value</b>	<b>Top 4 dataid</b>	<b>Top 4 value</b>	<b>Top 5 dataid</b>	<b>Top 5 value</b>	
	<b>3778</b>	2129.0	0.999415	1086.0	0.999114	94.0	0.999074	1507.0	0.999059	5892.0	0.999044
	<b>3849</b>	5395.0	0.991215	7682.0	0.990239	8059.0	0.990048	9766.0	0.989843	5785.0	0.988710
	<b>3893</b>	1589.0	0.999102	3577.0	0.998908	1801.0	0.998861	1086.0	0.998820	5439.0	0.998810
	<b>3918</b>	3577.0	0.999490	5636.0	0.999433	5131.0	0.999349	5439.0	0.999242	8829.0	0.999194
	<b>4029</b>	7016.0	0.994179	8155.0	0.990987	5193.0	0.990573	1042.0	0.986966	4296.0	0.986605
	<b>4031</b>	5439.0	0.999537	3577.0	0.999264	5814.0	0.999081	3918.0	0.998800	5636.0	0.998720
	<b>4193</b>	4228.0	0.999102	3527.0	0.998935	7900.0	0.998848	483.0	0.998506	1792.0	0.998206
	<b>4228</b>	3527.0	0.999423	8829.0	0.999240	4193.0	0.999102	5636.0	0.998902	1718.0	0.998809
	<b>4296</b>	4373.0	0.996946	3778.0	0.996749	5810.0	0.996720	739.0	0.996281	7287.0	0.996096
	<b>4352</b>	2638.0	0.999637	9474.0	0.998463	4421.0	0.997827	3039.0	0.997042	7460.0	0.996737
	<b>4356</b>	5131.0	0.999503	5972.0	0.999390	5636.0	0.999210	8890.0	0.999185	661.0	0.999138
	<b>4373</b>	7287.0	0.999121	5892.0	0.999096	5810.0	0.998822	3778.0	0.998622	2129.0	0.998548
	<b>4421</b>	7460.0	0.999284	2638.0	0.998676	2233.0	0.998424	7919.0	0.998173	9474.0	0.997882
	<b>4447</b>	5545.0	0.943983	4421.0	0.927708	9474.0	0.925997	3039.0	0.924912	2233.0	0.923704
	<b>4514</b>	6836.0	0.329191	8156.0	0.305019	2449.0	0.303415	5129.0	0.280266	9134.0	0.271397
	<b>4671</b>	9620.0	1.000000	6863.0	1.000000	8967.0	0.999508	2645.0	0.999160	5658.0	0.998999
	<b>4732</b>	1086.0	0.999329	1415.0	0.999289	3778.0	0.999033	94.0	0.999006	2129.0	0.998966
	<b>4767</b>	7674.0	0.993220	8084.0	0.993216	7017.0	0.992716	2072.0	0.991004	1792.0	0.990684
	<b>4874</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>4998</b>	3527.0	0.998847	483.0	0.998842	2072.0	0.998562	7900.0	0.998496	4228.0	0.998393
	<b>5129</b>	6836.0	0.520670	3544.0	0.487876	9134.0	0.479967	7117.0	0.370820	1185.0	0.359864
	<b>5131</b>	4356.0	0.999503	5972.0	0.999437	5636.0	0.999396	3918.0	0.999349	3577.0	0.999324
	<b>5193</b>	1042.0	0.998075	1697.0	0.996506	739.0	0.996057	484.0	0.995856	7287.0	0.995854
	<b>5275</b>	4031.0	0.998622	5439.0	0.998530	1714.0	0.998462	2470.0	0.998360	5814.0	0.998287
	<b>5317</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>5395</b>	1415.0	0.998350	3893.0	0.998177	5814.0	0.998144	114.0	0.998061	9766.0	0.998021
	<b>5403</b>	3544.0	0.318298	9134.0	0.250308	6836.0	0.246224	4514.0	0.224097	5129.0	0.222840
	<b>5439</b>	4031.0	0.999537	3577.0	0.999530	5814.0	0.999250	3918.0	0.999242	5636.0	0.999222
	<b>5484</b>	6578.0	0.998996	2945.0	0.998321	744.0	0.998277	370.0	0.998256	9121.0	0.997638
	<b>5545</b>	4447.0	0.943983	3039.0	0.875780	9474.0	0.871656	4352.0	0.866422	2638.0	0.862727
	<b>5636</b>	3577.0	0.999681	7989.0	0.999607	1589.0	0.999564	3918.0	0.999433	8829.0	0.999423
	<b>5658</b>	8967.0	0.999081	9620.0	0.998999	4671.0	0.998999	6863.0	0.998999	484.0	0.998447
	<b>5785</b>	9639.0	0.997184	5395.0	0.997139	6910.0	0.996879	7429.0	0.996819	7794.0	0.996601
	<b>5810</b>	7287.0	0.999315	5892.0	0.999240	1086.0	0.998999	1415.0	0.998823	4373.0	0.998822
	<b>5814</b>	5439.0	0.999250	3577.0	0.999241	1619.0	0.999239	4031.0	0.999081	5636.0	0.999004

## Group9\_Q1

	<b>Top 1 dataid</b>	<b>Top 1 value</b>	<b>Top 2 dataid</b>	<b>Top 2 value</b>	<b>Top 3 dataid</b>	<b>Top 3 value</b>	<b>Top 4 dataid</b>	<b>Top 4 value</b>	<b>Top 5 dataid</b>	<b>Top 5 value</b>	
	<b>5892</b>	7287.0	0.999522	94.0	0.999342	5810.0	0.999240	661.0	0.999121	4373.0	0.999096
	<b>5972</b>	5131.0	0.999437	4356.0	0.999390	8890.0	0.999199	3723.0	0.999141	1589.0	0.998938
	<b>6101</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>6412</b>	5972.0	0.998115	1714.0	0.997475	1718.0	0.997463	5131.0	0.997380	4356.0	0.997321
	<b>6505</b>	2129.0	0.998598	5892.0	0.998571	3778.0	0.998396	7287.0	0.998072	94.0	0.998057
	<b>6578</b>	5484.0	0.998996	370.0	0.998936	1718.0	0.997589	6685.0	0.997479	7900.0	0.997474
	<b>6673</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>6685</b>	6578.0	0.997479	5484.0	0.997069	6412.0	0.996997	8703.0	0.996846	2818.0	0.996529
	<b>6830</b>	2072.0	0.995922	1714.0	0.995815	1792.0	0.995771	3310.0	0.995629	4228.0	0.995559
	<b>6836</b>	5129.0	0.520670	9134.0	0.515677	2449.0	0.502700	3544.0	0.500550	1185.0	0.406719
	<b>6863</b>	9620.0	1.000000	4671.0	1.000000	8967.0	0.999508	2645.0	0.999160	5658.0	0.998999
	<b>6910</b>	7429.0	0.997838	871.0	0.997738	2034.0	0.997287	7794.0	0.997117	9729.0	0.996881
	<b>7016</b>	4029.0	0.994179	8155.0	0.984460	5193.0	0.983353	4296.0	0.979531	739.0	0.978381
	<b>7017</b>	2072.0	0.998482	3367.0	0.998334	3527.0	0.998219	3310.0	0.998183	1619.0	0.997688
	<b>7030</b>	3134.0	0.317051	9134.0	0.297001	6836.0	0.276328	3544.0	0.268095	2449.0	0.247233
	<b>7117</b>	6836.0	0.384287	5129.0	0.370820	9134.0	0.311216	3544.0	0.292894	8156.0	0.262069
	<b>7287</b>	5892.0	0.999522	5810.0	0.999315	4373.0	0.999121	1507.0	0.998967	1697.0	0.998826
	<b>7429</b>	7794.0	0.998906	9729.0	0.998246	3577.0	0.997946	6910.0	0.997838	187.0	0.997827
	<b>7460</b>	4421.0	0.999284	2233.0	0.998758	7919.0	0.998706	2638.0	0.998053	2818.0	0.996891
	<b>7566</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>7674</b>	7900.0	0.997000	1792.0	0.996696	2980.0	0.996690	2072.0	0.996441	4193.0	0.995659
	<b>7682</b>	9766.0	0.998368	35.0	0.997278	8086.0	0.997179	1790.0	0.996513	744.0	0.995800
	<b>7739</b>	9631.0	0.984316	2980.0	0.977384	370.0	0.976283	6578.0	0.973846	7900.0	0.973746
	<b>7741</b>	114.0	0.997998	5395.0	0.997932	3893.0	0.997443	1415.0	0.997214	1589.0	0.997107
	<b>7794</b>	1415.0	0.998936	7429.0	0.998906	3577.0	0.998866	5439.0	0.998619	5636.0	0.998534
	<b>7900</b>	4193.0	0.998848	4228.0	0.998721	4998.0	0.998496	3527.0	0.998317	483.0	0.998230
	<b>7919</b>	7460.0	0.998706	2233.0	0.998627	4421.0	0.998173	8703.0	0.997377	2818.0	0.996973
	<b>7965</b>	8967.0	0.998570	2575.0	0.998158	484.0	0.998153	6863.0	0.997914	9620.0	0.997914
	<b>7989</b>	5636.0	0.999607	3577.0	0.999252	5131.0	0.999228	1589.0	0.999116	1801.0	0.999115
	<b>8059</b>	8386.0	0.996291	1792.0	0.995824	7682.0	0.994155	4193.0	0.994125	3310.0	0.993903
	<b>8084</b>	4767.0	0.993216	7674.0	0.991751	8059.0	0.988961	1792.0	0.985117	7017.0	0.985077
	<b>8086</b>	1619.0	0.998963	1801.0	0.998303	5636.0	0.998198	5814.0	0.998126	3527.0	0.997969
	<b>8155</b>	1042.0	0.996553	739.0	0.996468	5193.0	0.995269	1283.0	0.995247	2378.0	0.994040
	<b>8156</b>	5129.0	0.331922	4514.0	0.305019	1556.0	0.274218	8467.0	0.263311	7117.0	0.262069
	<b>8244</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000

	<b>Top 1 dataid</b>	<b>Top 1 value</b>	<b>Top 2 dataid</b>	<b>Top 2 value</b>	<b>Top 3 dataid</b>	<b>Top 3 value</b>	<b>Top 4 dataid</b>	<b>Top 4 value</b>	<b>Top 5 dataid</b>	<b>Top 5 value</b>	
	<b>8386</b>	2945.0	0.997288	4193.0	0.996623	8059.0	0.996291	5484.0	0.996079	744.0	0.995974
	<b>8467</b>	222.0	0.990999	2378.0	0.990143	1042.0	0.986174	1283.0	0.985783	9278.0	0.985490
	<b>8703</b>	7919.0	0.997377	6685.0	0.996846	1791.0	0.996234	5484.0	0.995932	6578.0	0.995916
	<b>8829</b>	5636.0	0.999423	3527.0	0.999334	3577.0	0.999298	1714.0	0.999296	4228.0	0.999240
	<b>8890</b>	3723.0	0.999357	5972.0	0.999199	4356.0	0.999185	5131.0	0.999125	661.0	0.998895
	<b>8967</b>	9620.0	0.999508	6863.0	0.999508	4671.0	0.999508	5658.0	0.999081	484.0	0.998710
	<b>9052</b>	661.0	0.998617	2129.0	0.998497	94.0	0.998241	4373.0	0.998237	5892.0	0.998189
	<b>9121</b>	3723.0	0.999206	744.0	0.999112	661.0	0.999073	94.0	0.999015	1801.0	0.998920
	<b>9134</b>	6836.0	0.515677	5129.0	0.479967	3544.0	0.364752	2449.0	0.353476	1185.0	0.312297
	<b>9160</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>9278</b>	2965.0	0.993538	9639.0	0.992491	2094.0	0.991658	35.0	0.991505	1042.0	0.990951
	<b>9295</b>	9639.0	0.999304	1507.0	0.999259	1086.0	0.999136	739.0	0.998697	2129.0	0.998676
	<b>9474</b>	3039.0	0.999108	4352.0	0.998463	2638.0	0.998259	4421.0	0.997882	7460.0	0.996455
	<b>9600</b>	9982.0	0.000000	9956.0	0.000000	9849.0	0.000000	9766.0	0.000000	9729.0	0.000000
	<b>9620</b>	6863.0	1.000000	4671.0	1.000000	8967.0	0.999508	2645.0	0.999160	5658.0	0.998999
	<b>9631</b>	2980.0	0.996213	370.0	0.995539	6578.0	0.994746	7900.0	0.994662	4998.0	0.993703
	<b>9639</b>	9295.0	0.999304	1507.0	0.999301	1086.0	0.999275	1415.0	0.999040	2094.0	0.999017
	<b>9729</b>	7429.0	0.998246	871.0	0.997819	2018.0	0.997085	187.0	0.996940	6910.0	0.996881
	<b>9766</b>	7682.0	0.998368	2094.0	0.998090	5395.0	0.998021	1415.0	0.997935	35.0	0.997802
	<b>9849</b>	9474.0	0.996227	7919.0	0.995720	3039.0	0.995445	4421.0	0.994915	7460.0	0.994493
	<b>9956</b>	5892.0	0.998335	94.0	0.998313	2575.0	0.998144	3723.0	0.998041	4732.0	0.997906
	<b>9982</b>	8467.0	0.506414	6910.0	0.505673	222.0	0.504239	871.0	0.504162	2034.0	0.503763

The above dataframe shows each meter (dataid) and the top five homes with which it shows the highest correlation, together with the respective correlation value.