Introduction

This is the ***fourth*** of a series where I look at big datasets, and in each case I'm using a different tool to carry out the same analysis on the same dataset.

This time I'm using **Talend Open Studio**, an open source ETL tool. You can find each notebook in the series in my Github repo, including:

1. Pandas chunksize
2. Dask library
3. PySpark
4. Talend Open Studio

There is a little more explanation in the first notebook (Pandas chunksize) on the overall approach to the analysis. In the other notebooks I focus more on the elements specific to the tool being used.

Dataset description

Throughout the series we'll use the SmartMeter Energy Consumption Data in London Households dataset, which according to the website contains:

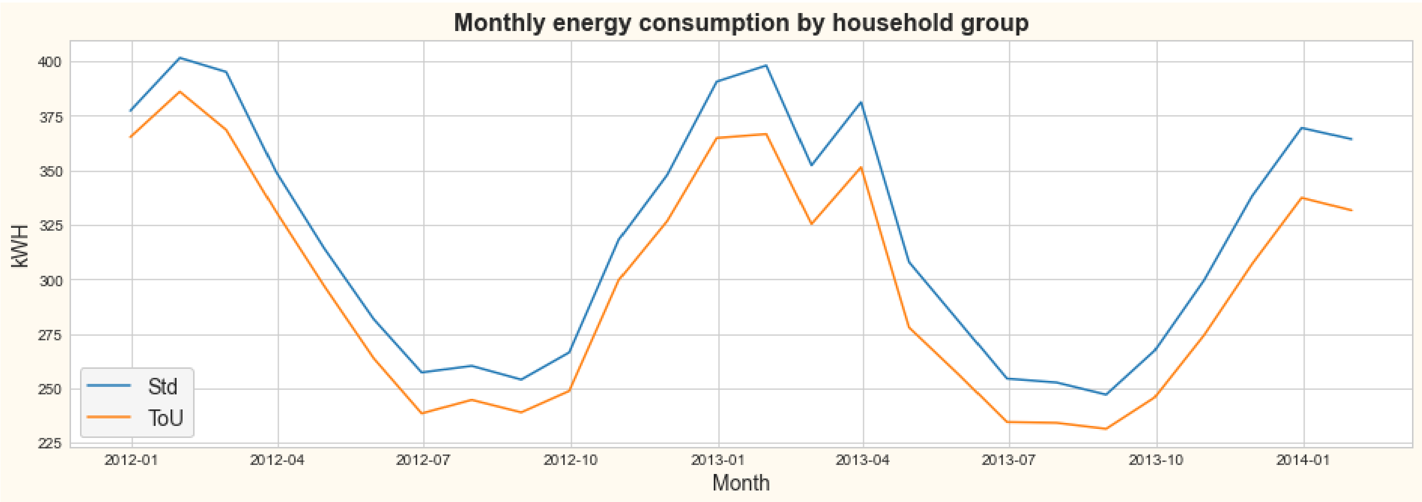
> Energy consumption readings for a sample of 5,567 London Households that took part in the UK Power Networks led Low Carbon London project between November 2011 and February 2014.

The households were divided into two groups:

- Those who were sent Dynamic Time of Use (dToU) energy prices (labelled "High", "Medium", or "Low") a day in advance of the price being applied.
- Those who were subject to the Standard tariff.

One aim of the study was to see if pricing knowledge would affect energy consumption behaviour.

Results



The results show the expected seasonal variation with a clear difference between the two groups, suggesting that energy price knowledge does indeed help reduce energy consumption.

The rest of the notebook shows how this chart was produced from the raw data.

Introduction to Talend Open Studio

Talend Open Studio is a free ETL (Extract-Transform-Load) program. Here's how Talend describe it:

> With Talend Open Studio, you can begin building basic data pipelines in no time. Execute simple ETL and data integration tasks, get graphical profiles of your data, and manage files — from a locally installed, open-source environment that you control.

Although we'll be carrying out largely the same operations as in the other notebooks, this time we'll be using the Talend GUI to create those operations, and where we need to use code it will be Java, not Python, as Open Studio runs on Java.

I will assume a basic knowledge of how to use Talend Open Studio, so this will not be a detailed how-to guide.

NB Please note also that this is just a training exercise for me - Talend may not be the best tool for some of the tasks presented here.

Installation

The program is downloadable here. I am using an old version 7.01 (because during my data science course our trainer used it saying it is reliable). Note you will also need Java installed - v11 is required for the latest version of Open Studio, while v8 works for older versions.

Talend files

All the job files that I use are available in this Github repository in a zip file in the folder `Talend`. You should be able to import them as an archive into a Talend project and use them yourself with the data.

However, throughout this exercise you will see I use absolute filepaths. That's because a relative filepath for Talend is relative to its installation folder and that is not where I want to store data. That means you will need to adjust the filepaths for the jobs to work on your computer.

Accessing the data

The data is downloadable as a single zip file which contains a csv file of 167 million rows. If the `curl` command doesn't work (and it will take a while as it's a file of 800MB), you can download the file here and put it in the folder `data` which is in the folder where this notebook is saved.

In [ ]:
```
!curl "https://data.london.gov.uk/download/smartmeter-energy-use-data-in-london-households/3527bf39-d93e-4071-8451-df2ade1ea4f2/LCL-FullData.zip" --location --create-dirs -o "data/LCL-FullData.zip"
```

First we unzip the data. This may take a while! Alternatively you can unzip it manually using whatever unzip utility you have. Just make sure the extracted file is in a folder called `data` within the folder where your notebook is saved.

In [1]:
```
!unzip "data/LCL-FullData.zip" -d "data"
```

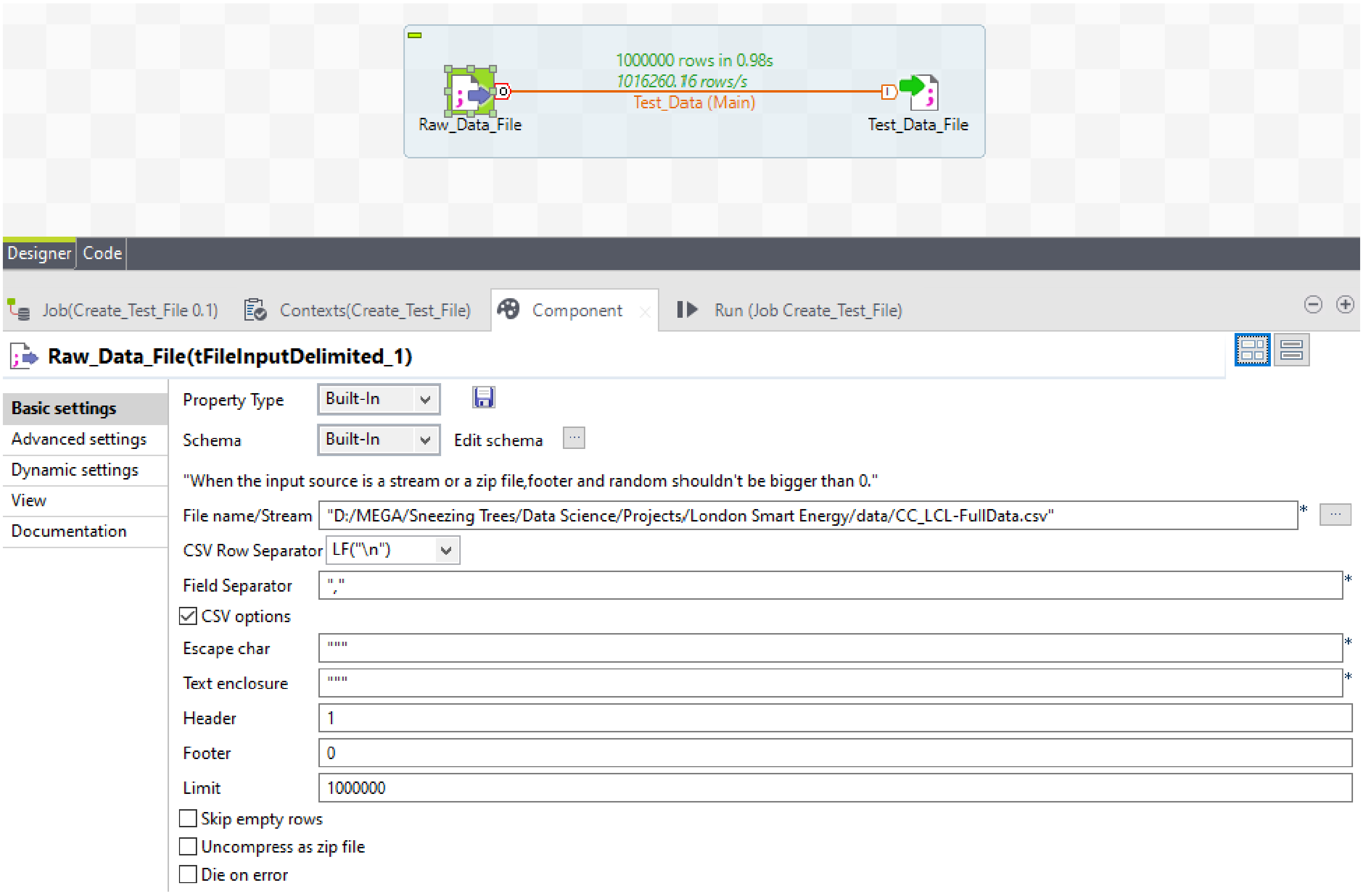
```
Archive:  data/LCL-FullData.zip
  inflating: data/CC_LCL-FullData.csv
```

Examining the data

First we'll create a test file - a file containing a small subset of the data. For this job "Job_Create_Test_File" we use a tFileInputDelimited component and a tFileOutputDelimited component. The important setting is shown near the bottom of the screenshot for the tFileInputDelimited component - the Limit is set to 1,000,000 rows.

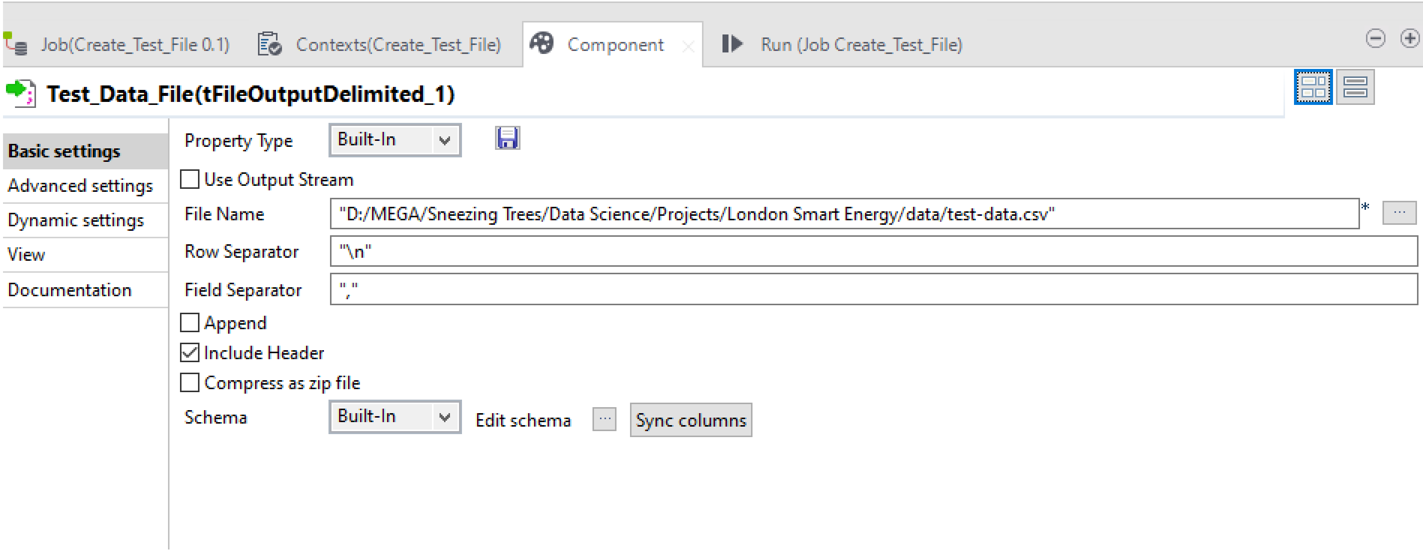
Job_Create_Test_File

tFileInputDelimited - Raw_Data_File



tFile_Output_Delimited - Test_Data_File

We save our output file of 1,000,000 rows as "test-data.csv".



And now we can view the file using Pandas.

In [2]:
```python
import pandas as pd
```

In [3]:
```python
test_data = pd.read_csv("data/test-data.csv")
```

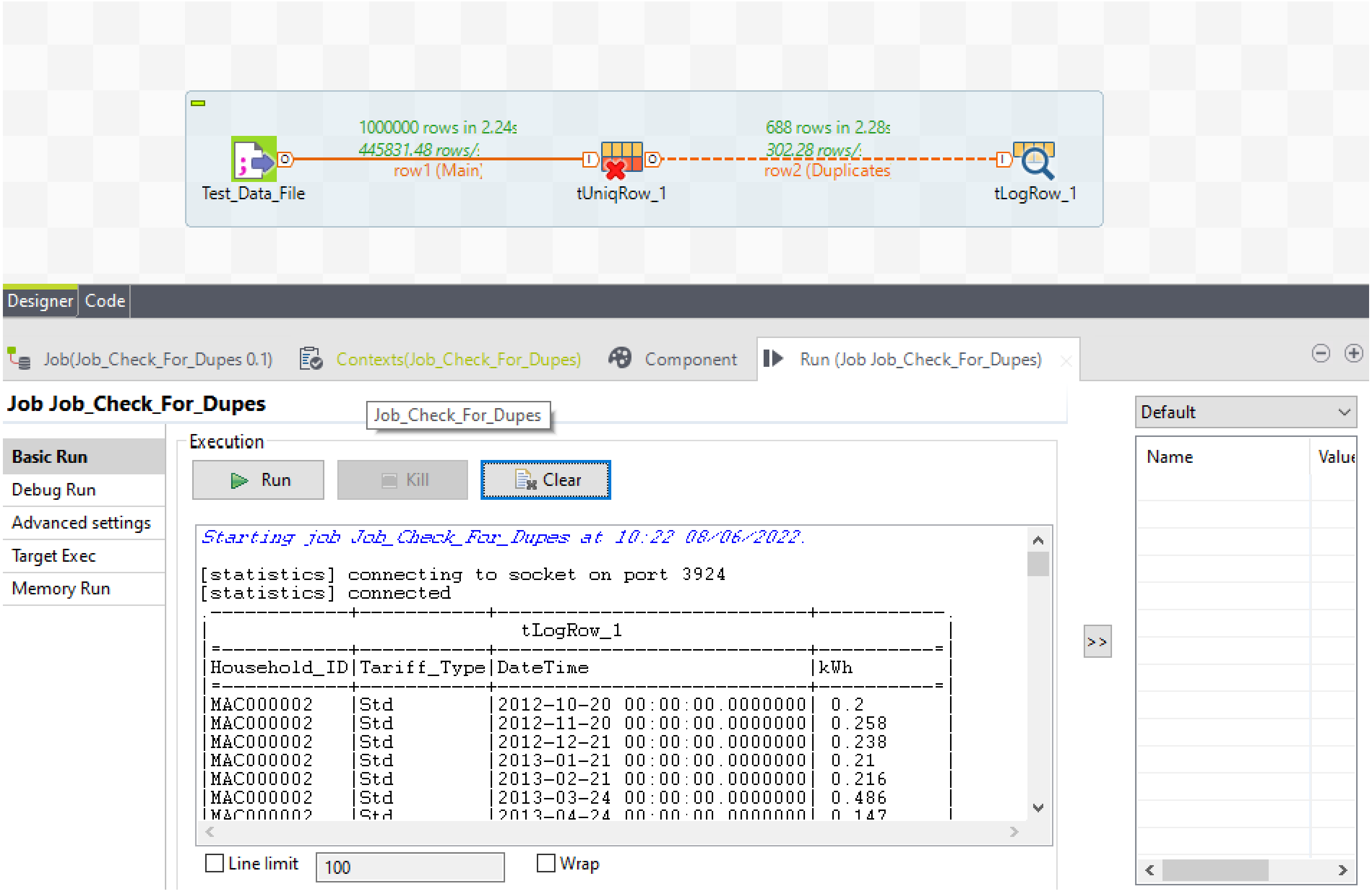
In [4]:
```python
test_data
```

Out[4]:

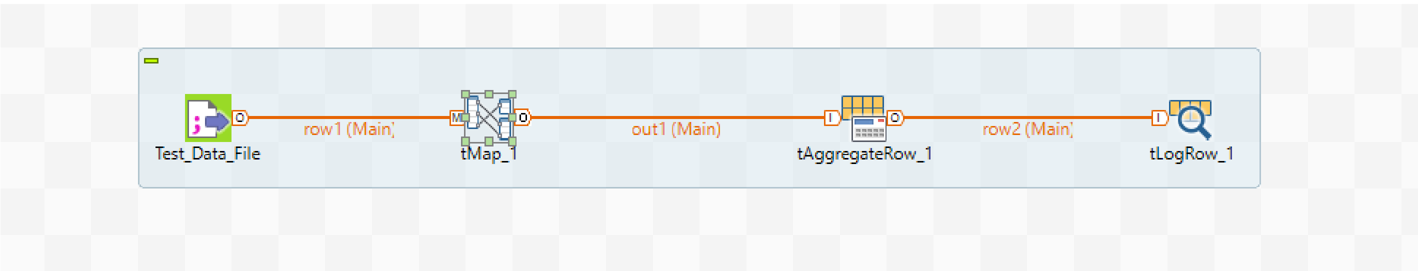
	LCLid	stdorToU	DateTime	KWH_hh__per_half_hour_
0	MAC000002	Std	2012-10-12 00:30:00.0000000	0
1	MAC000002	Std	2012-10-12 01:00:00.0000000	0
2	MAC000002	Std	2012-10-12 01:30:00.0000000	0
3	MAC000002	Std	2012-10-12 02:00:00.0000000	0
4	MAC000002	Std	2012-10-12 02:30:00.0000000	0
...	...	...	...	...
999995	MAC000036	Std	2012-11-08 08:00:00.0000000	0.228
999996	MAC000036	Std	2012-11-08 08:30:00.0000000	0.042
999997	MAC000036	Std	2012-11-08 09:00:00.0000000	0.076
999998	MAC000036	Std	2012-11-08 09:30:00.0000000	0.07
999999	MAC000036	Std	2012-11-08 10:00:00.0000000	0.005

1000000 rows × 4 columns

Now we check for duplicates in our test data using a tUniqRow component and a tLogRow component. The results show we have duplicates that will need to be removed.



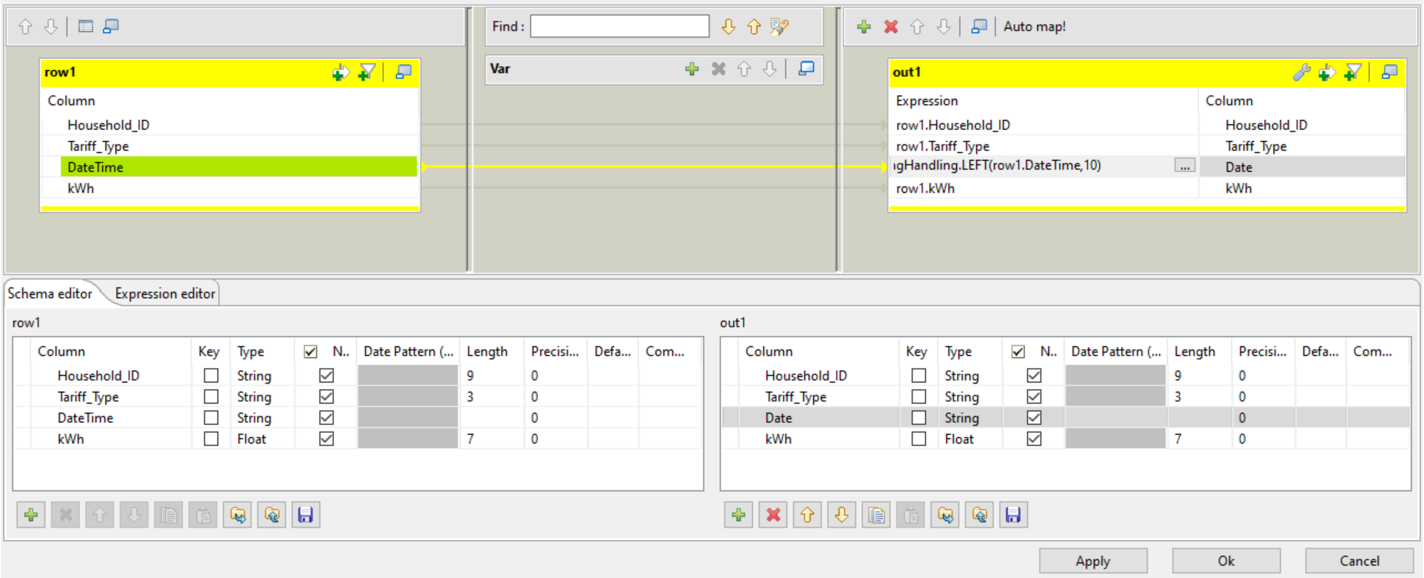
Let's also check the aggregation. We're going to aggregate the half-hourly data into daily data, so for that we'll use a tMap and a tAggregateRow.



tMap Settings

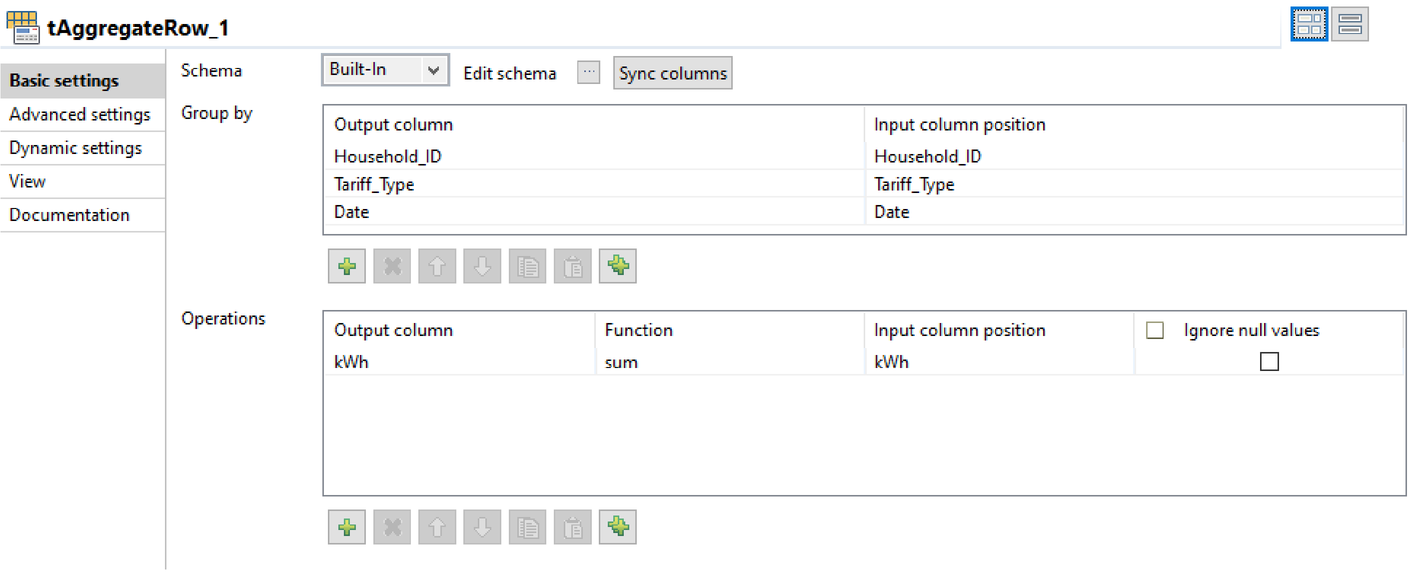
Note:

- I changed the Type of kWh in the Test_Data_File tFileInputDelimited component from `String` to `Float` as we expect them to be decimal numbers.
- I have used an expression to convert the DateTime values to Date values, but for simplicity we are keeping them as type `String`.

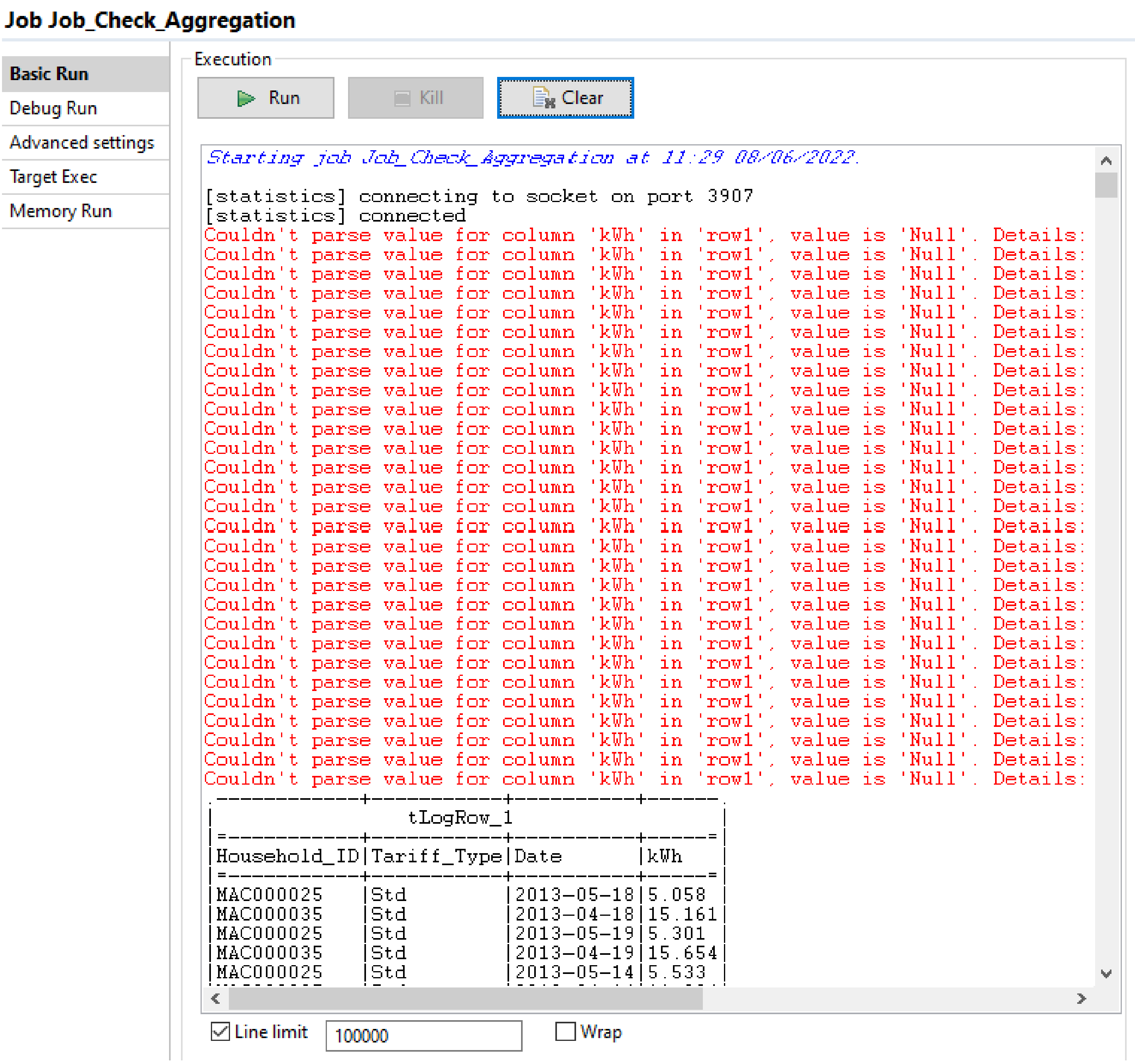


tAggregateRow settings

We group by `Household_ID`, `Tariff_Type`, and `Date` and sum the kWh data.

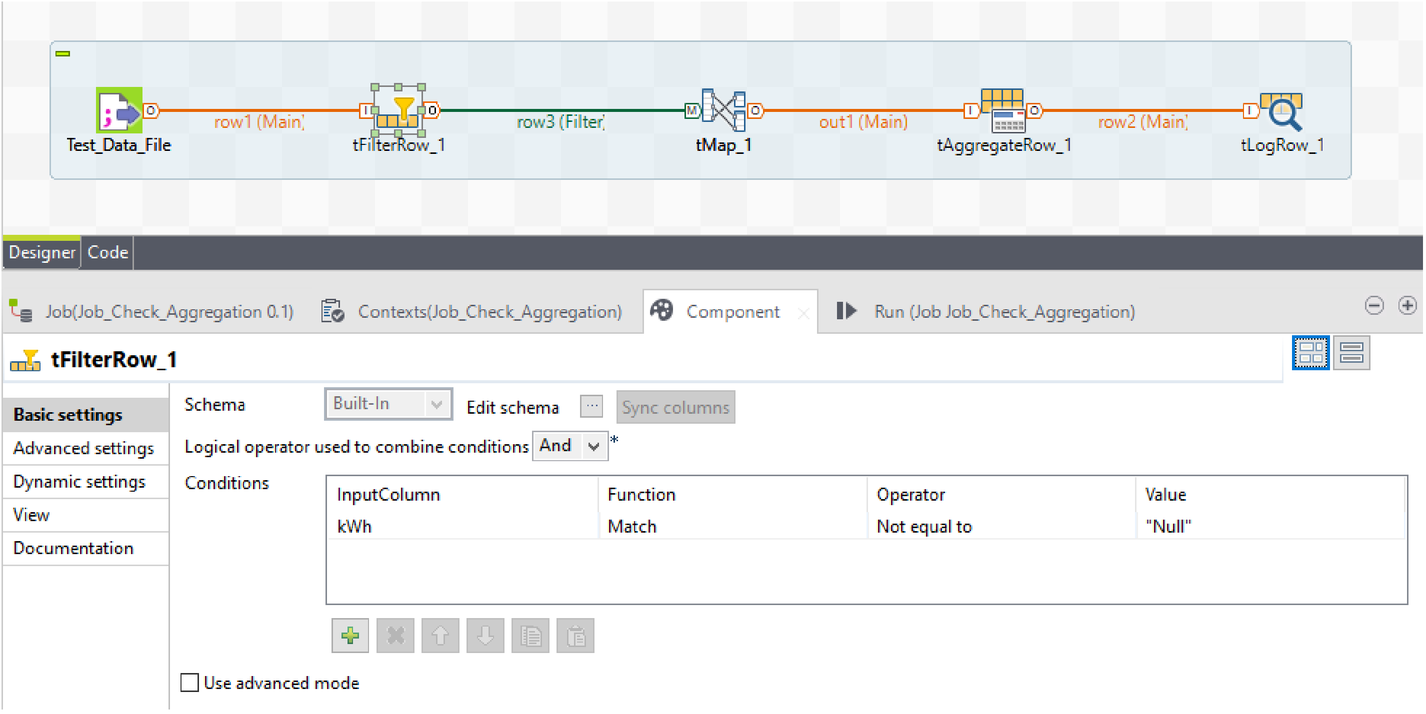


When we execute however, the tLogRow shows us some errors as well as some successful aggregation.

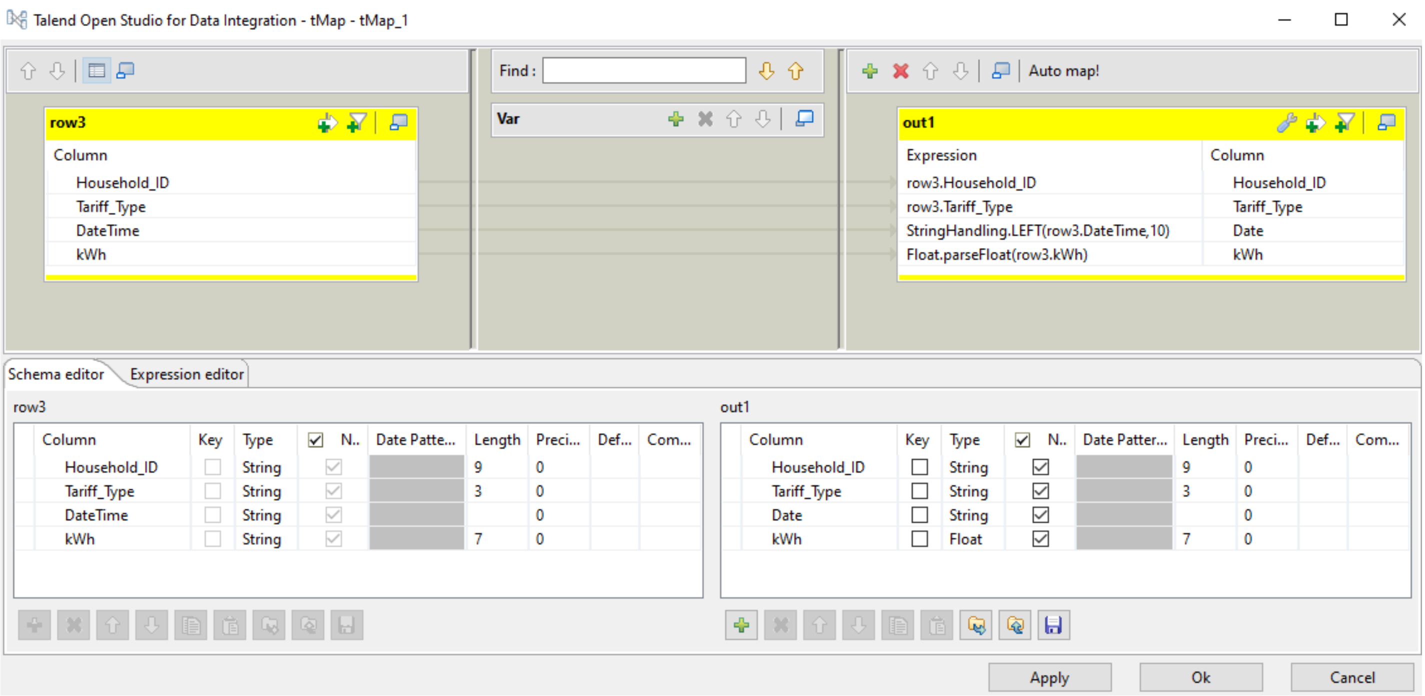


The error message tells us we have some `"Null"` values which we will have to remove.

We remove them using a tFilterRow component. Note however that I have reset the `kWh` data type back to `String` for the Test_Data_File tFileInputDelimited component and for the tFilterRow component. Then we can set the tFilterRow to pass on all kWh values that are not equal to `"Null"`.



The tMap is unchanged except for the transformation of kWh from type `String` to type `Float` using the functions `Float.parseFloat()`.

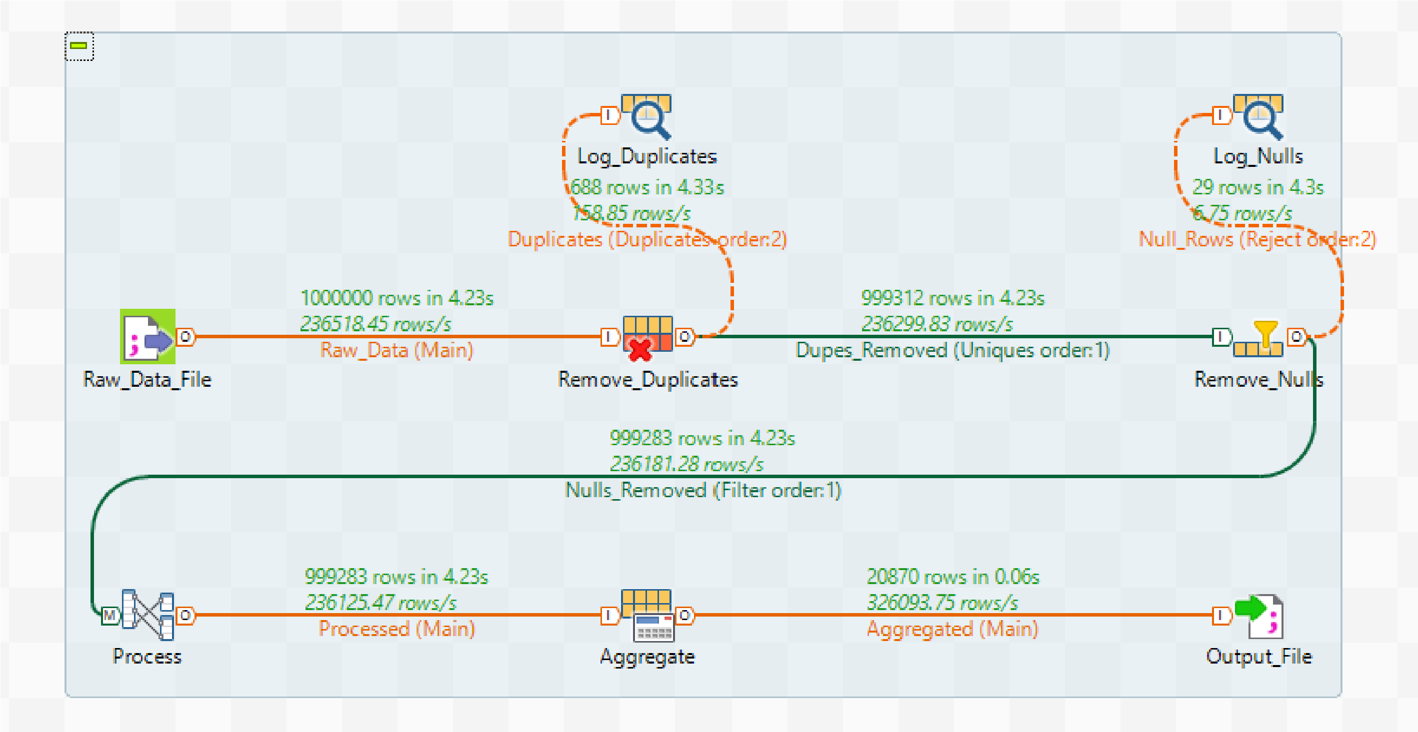


Now when we run we get no errors.

Aggregating the test data

The overall process for the test data is then as shown below:

- Remove duplicates using a tUniqRow.
- Remove nulls using a tFilterRow.
- Convert timestamp to date and kWh from `String` to `Float` using a tMap.
- Aggregate using a tAggregate row.
- Output to a csv (test-out.csv).



We can read the results into pandas.

In [5]:
```
test_summary_data = pd.read_csv("data/test-out.csv")
```

In [6]:
```
test_summary_data.sort_values(['Household_ID', 'Tariff_Type', 'Date'])
```

Out[6]:

	Household_ID	Tariff_Type	Date	kWh
14463	MAC000002	Std	2012-10-12	7.098
14464	MAC000002	Std	2012-10-13	11.087
14440	MAC000002	Std	2012-10-14	13.223
14443	MAC000002	Std	2012-10-15	10.257
14446	MAC000002	Std	2012-10-16	9.769
...	...	...	...	...
19879	MAC000036	Std	2012-11-04	2.401
19870	MAC000036	Std	2012-11-05	2.379
19873	MAC000036	Std	2012-11-06	2.352
19885	MAC000036	Std	2012-11-07	2.599
19888	MAC000036	Std	2012-11-08	0.689

20870 rows × 4 columns

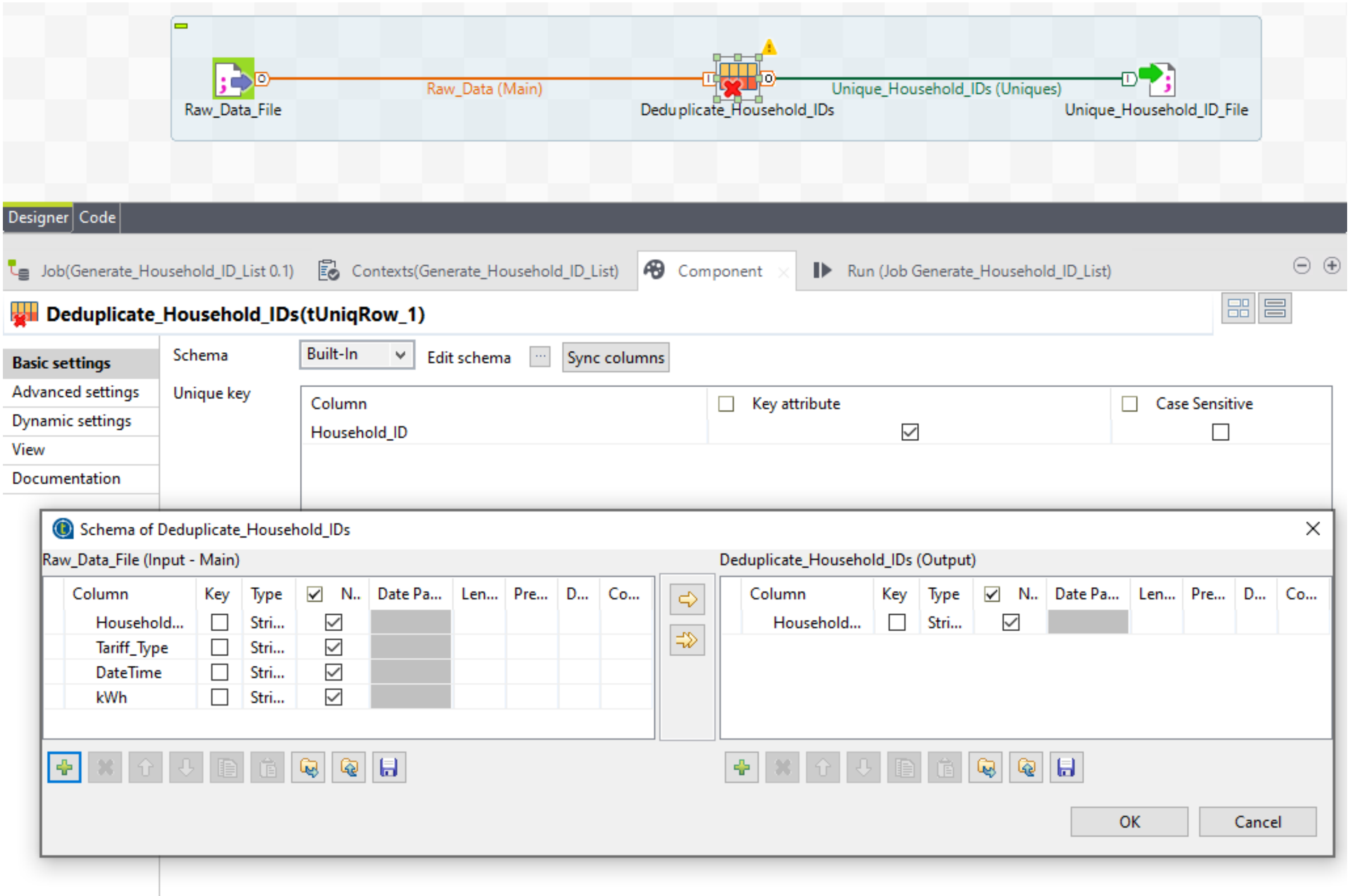
This works fine on the test data. But when we run it on the full data we quickly encounter memory errors. After testing various approaches, my conclusions were:

1. The deduplication is the most memory-intensive operation.
2. Even when using techniques like increasing the maximum available memory for the job (see here) and using the Use of disk setting for the tUniqRow component (see in the Advanced Settings here), the task still failed for lack of memory.

3. The solution I found - (there may be well better) - was to split the initial file into several files. However for deduplication to work the splits have to be located so that there cannot be duplicates between files, only within each file. For that we'll look at splitting by household ID or by year-month. Either approach guarantees no duplicates between files.

Unique Household IDs

Below is the process used to generate a list of unique household IDs.



Note the schema of the tUniqRow component has only Household_ID as its output.

We can view the list as a Pandas dataframe.

In [7]:
```
household_ids = pd.read_csv("data/unique-household-ids.csv", header=None, names=['Household IDs'])
```

In [8]:
```
household_ids.sort_values(['Household IDs']).reset_index(drop=True)
```

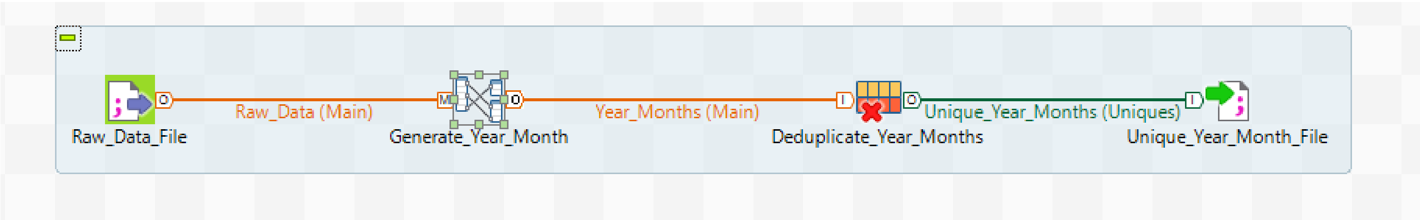
Out[8]:

	Household IDs
0	MAC000002
1	MAC000003
2	MAC000004
3	MAC000005
4	MAC000006
...	...
5561	MAC005563
5562	MAC005564
5563	MAC005565
5564	MAC005566
5565	MAC005567

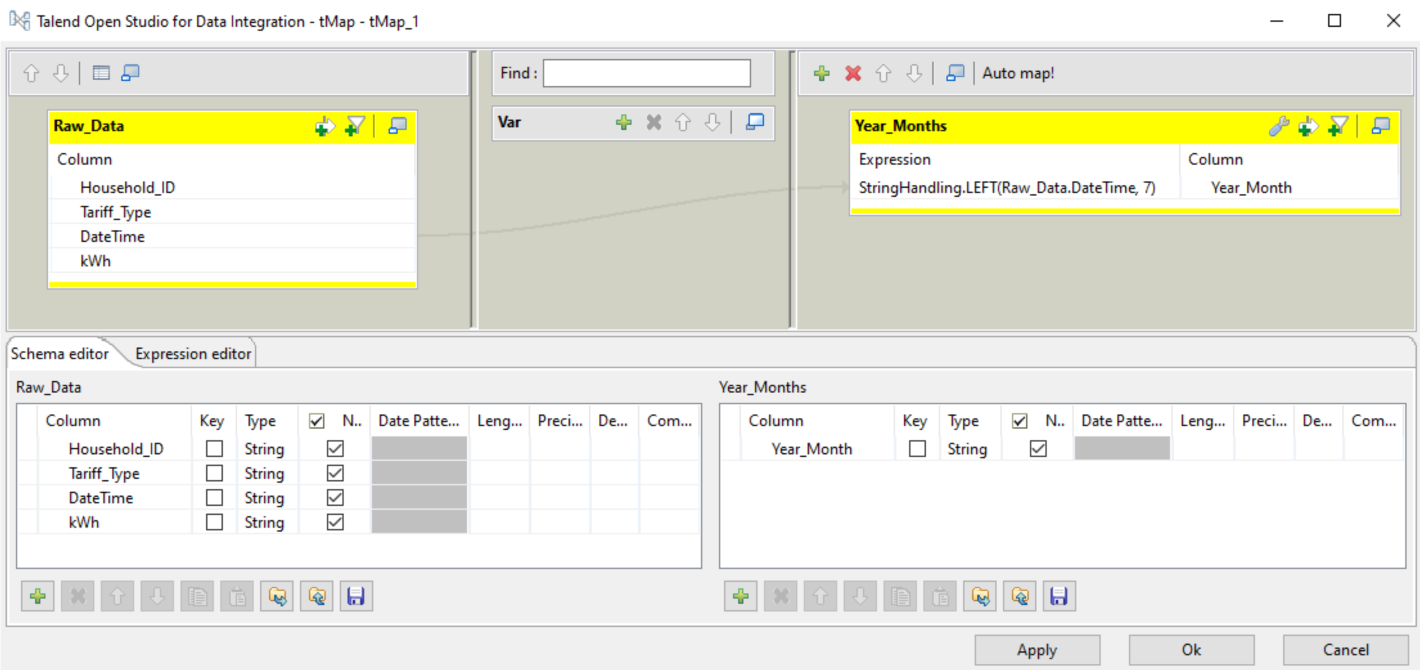
5566 rows × 1 columns

Unique year months

Below is the process to generate the year months.



In the tMap we use a StringHandling function to convert the timestamp to a year-month format.



The output shows that we have 28 unique months.

In [9]:
```
year_months = pd.read_csv("data/unique-year-month.csv", header=None, names=['Year-Month'])
```

In [10]:
```
year_months.sort_values(['Year-Month']).reset_index(drop=True)
```

Out[10]:

	Year-Month
0	2011-11
1	2011-12
2	2012-01
3	2012-02
4	2012-03
5	2012-04
6	2012-05
7	2012-06
8	2012-07
9	2012-08
10	2012-09
11	2012-10
12	2012-11
13	2012-12
14	2013-01
15	2013-02
16	2013-03
17	2013-04
18	2013-05
19	2013-06
20	2013-07
21	2013-08
22	2013-09
23	2013-10
24	2013-11
25	2013-12
26	2014-01
27	2014-02

Splitting by year-month seems a sensible approach - easy to do and divides into a reasonable number of files.

Processing the full data

These are the steps used to process the full data:

1. Generate list of unique year-months (as above).

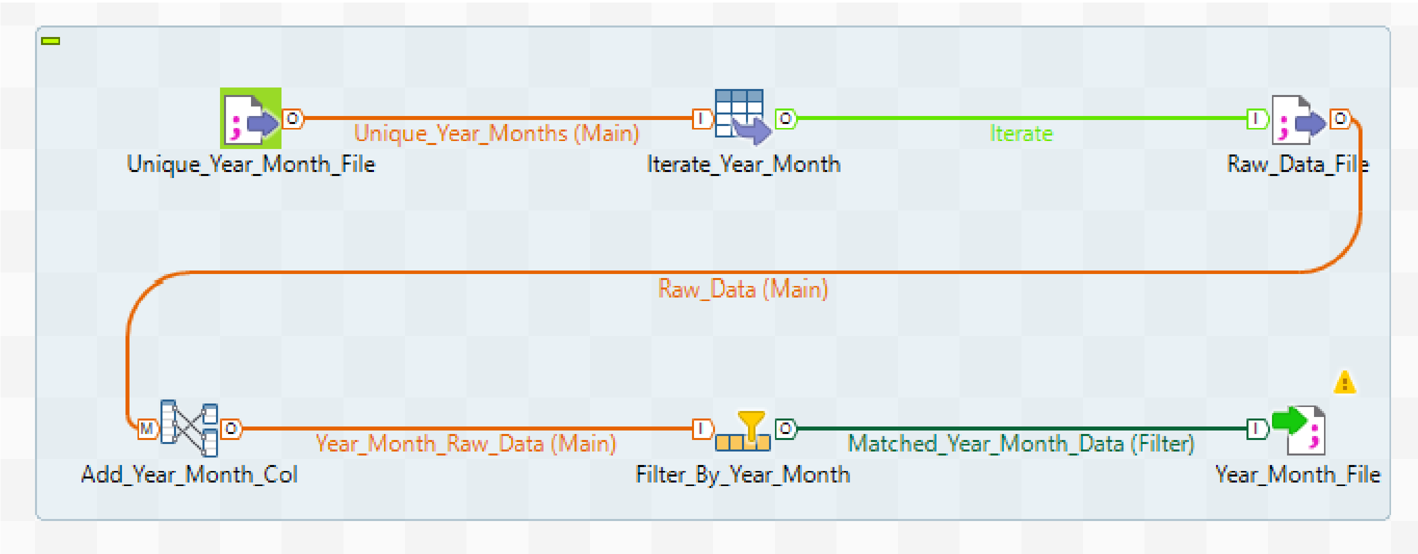
2. Use the list of unique year-months to iterate through the full data generating an individual file for each month of data (28 in all).
3. Deduplicate in each of the 28 year-month files.
4. For each of the 28 year-month files: Remove nulls; Group by `Household_ID`, `Tariff_Type` and `Date` and sum `kWh`; Save the aggregated results a new file.
5. Merge the 28 aggregated files into one.

The overall process is slow, particularly the splitting of the original file, as we iterate through the whole dataset 28 times. There are almost certainly better ways of doing this! The entire process from beginning to end takes about an hour and a half to run on my laptop.

1. Generate list of unique year-months

Done above.

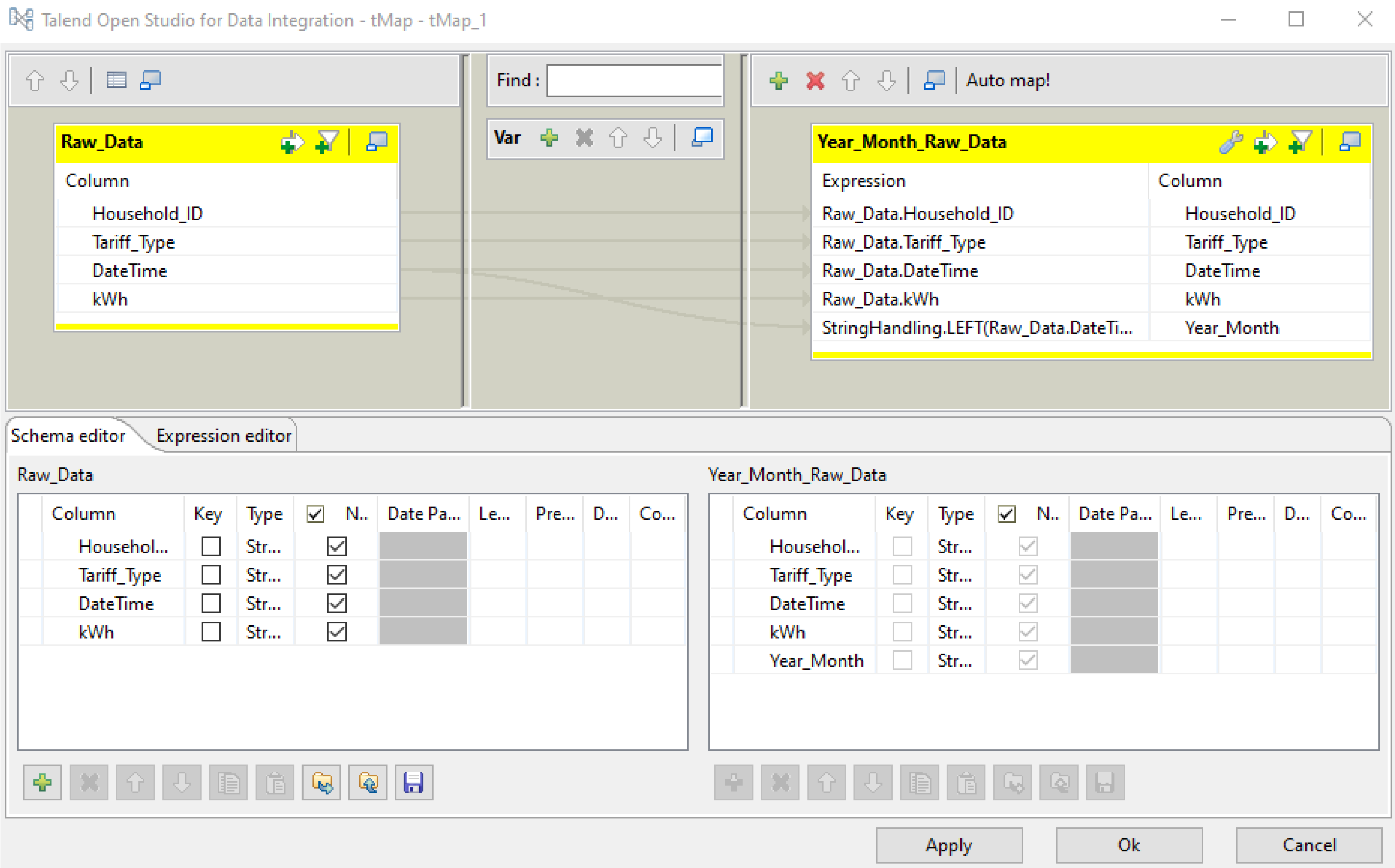
2. Split original file into year-month files



We use a tFlowToIterate component to iterate over the full data 28 times, each time filtering the raw data by the year month.

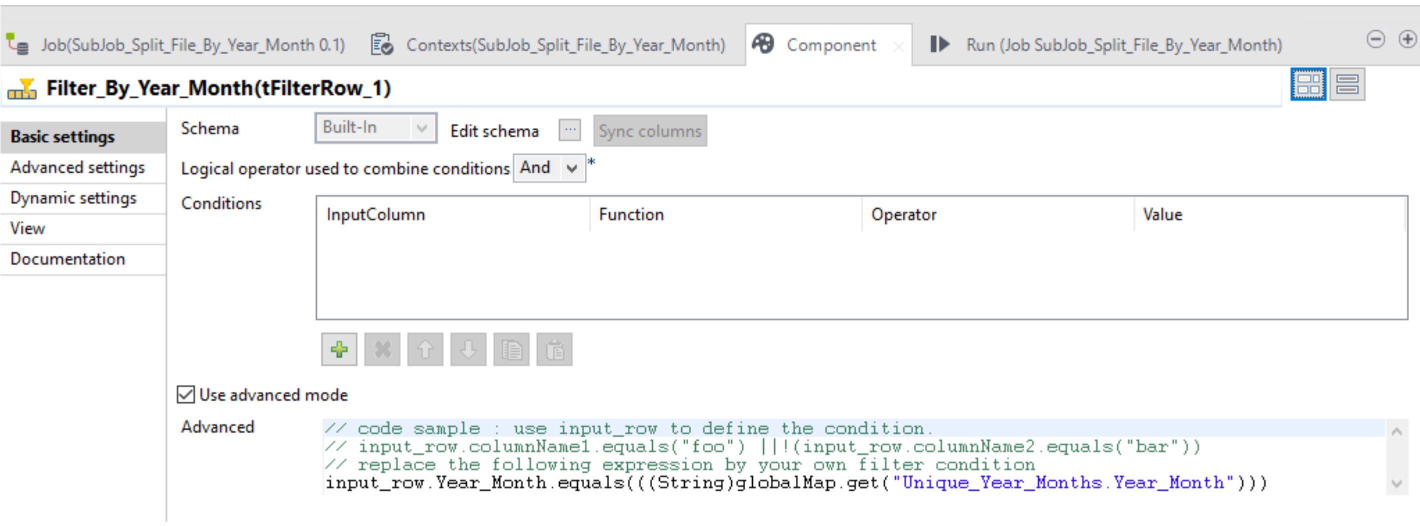
tMap - Add_Year_Month_Col Settings

We use the tMap to add in the `Year_Month` column using the StringHandling function.



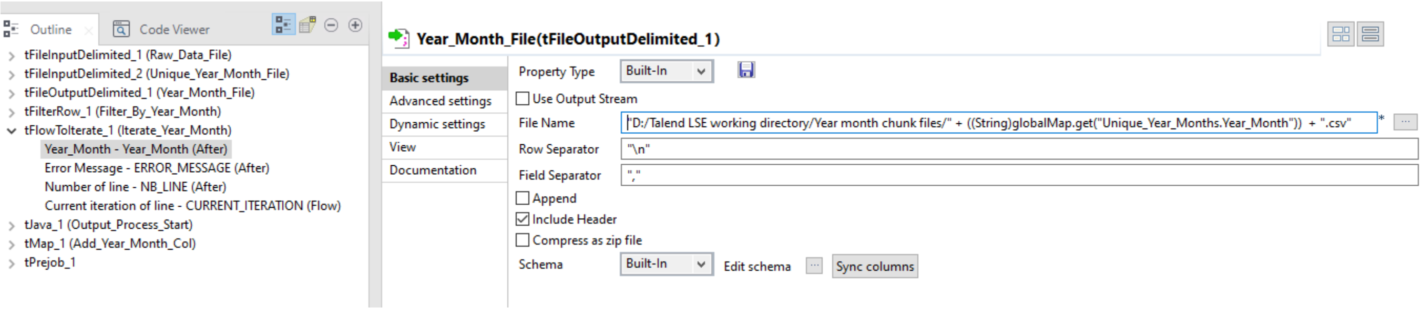
tFilterRow - Filter_By_Year_Month Settings

We use the advanced mode of the tFilterRow component to filter by the `Year_Month` value that has been set by the tFlowToIterate component.



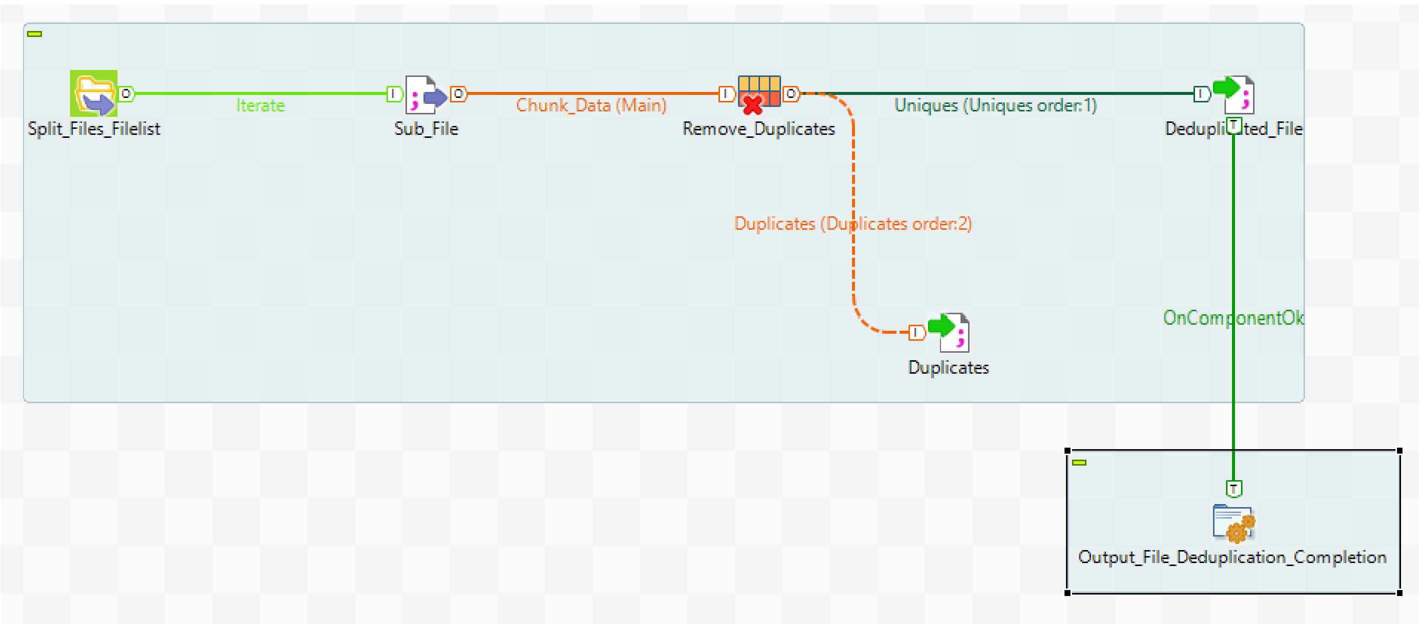
tFileOutputDelimited - Year_Month_File Settings

We also use the stored `Year_Month` value to set the filename of each of the 28 files produced. Note that the code `((String)globalMap.get("Unique_Year_Months.Year_Month"))` can be generated automatically by dragging and dropping the `Year_Month - Year_Month (After)` element of the tFlowIterate component from the left-hand window into the File Name field in the right-hand window.



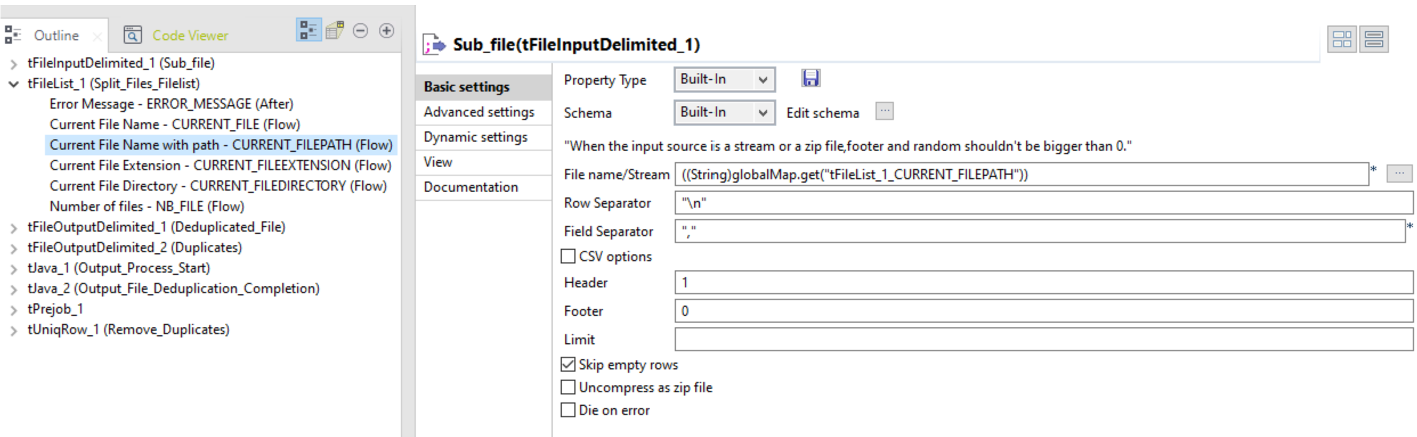
3. Deduplicate in each of the year-month files

We use a tFileList component to iterate over the 28 year-month files and remove duplicates from each one, saving to a new file.

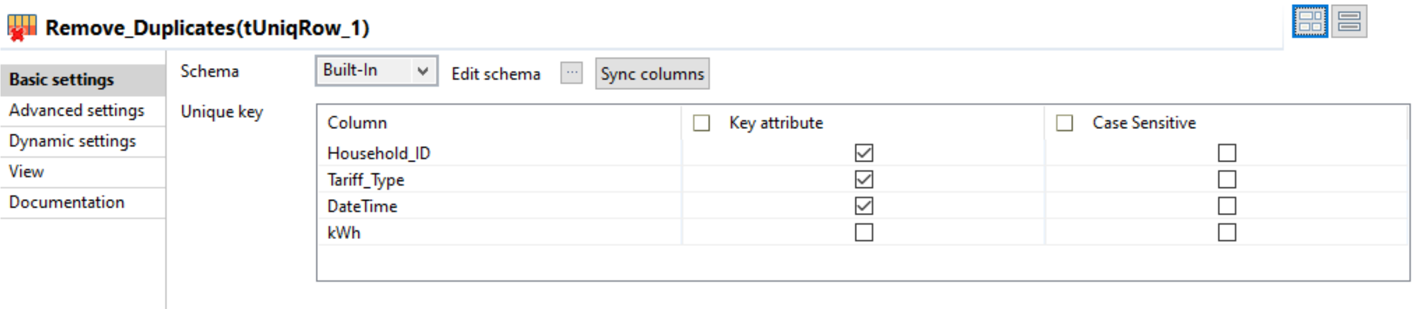


tFileInputDelimited - Sub_File Settings

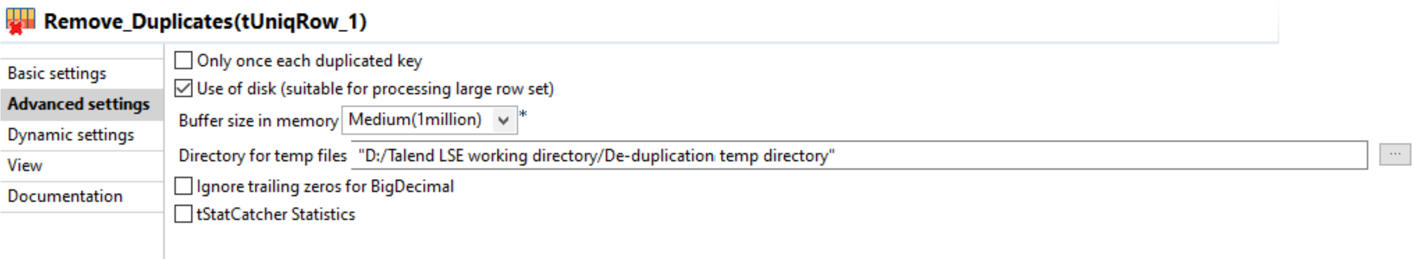
We can drag the `Current File Name with path - CURRENT_FILEPATH (Flow)` from the left-hand window into the File name/Stream field in the right hand window to generate the code in that field.



tUniqRow - Remove_Duplicates Settings (Basic and Advanced)

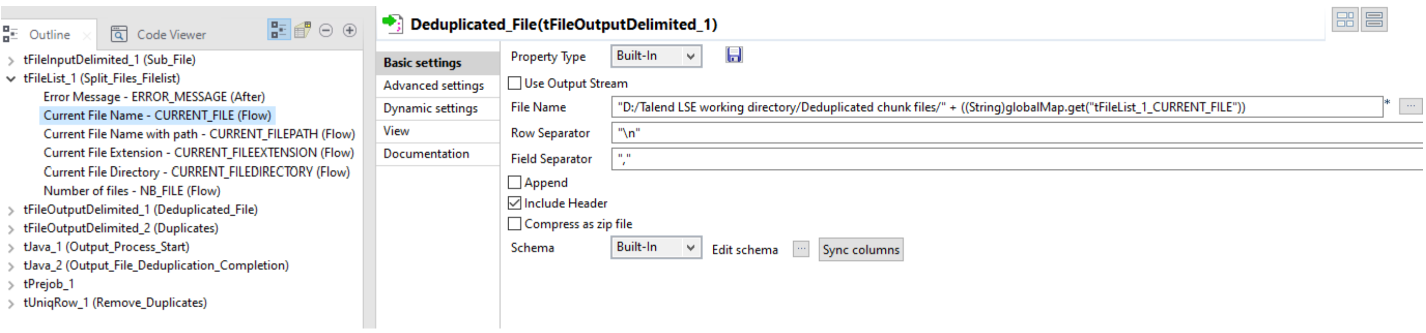


Note that we use the Use of disk setting in Advanced settings to reduce the memory requirements.



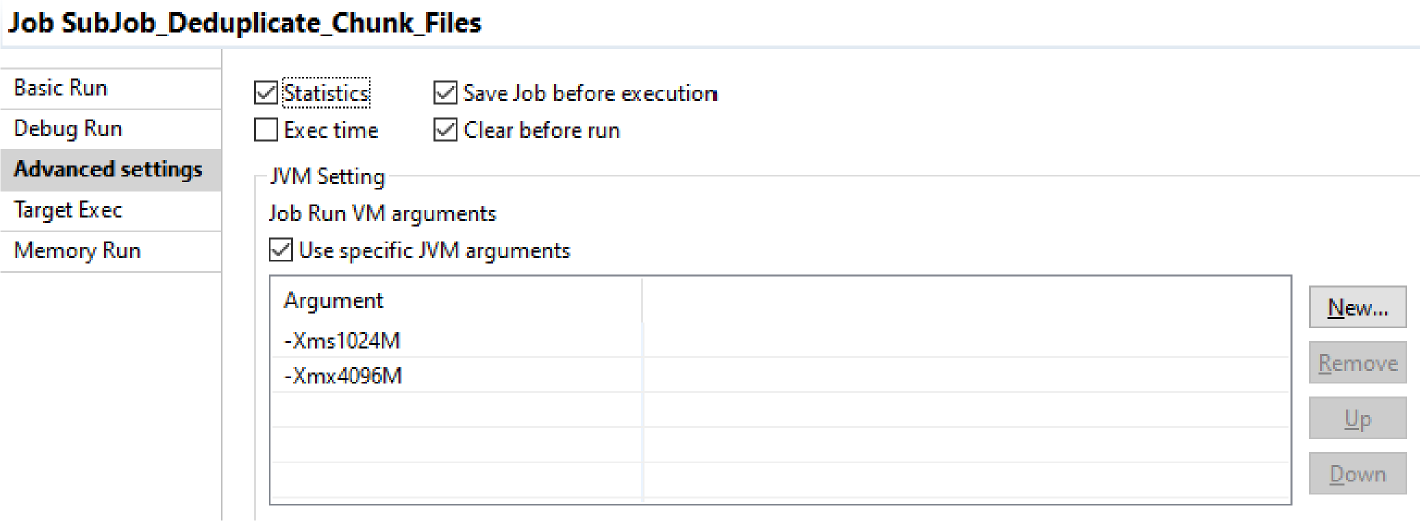
tFileOutputDelimited - Deduplicated_File Settings

We use a similar drag-drop to generate the filename for the deduplicated file.

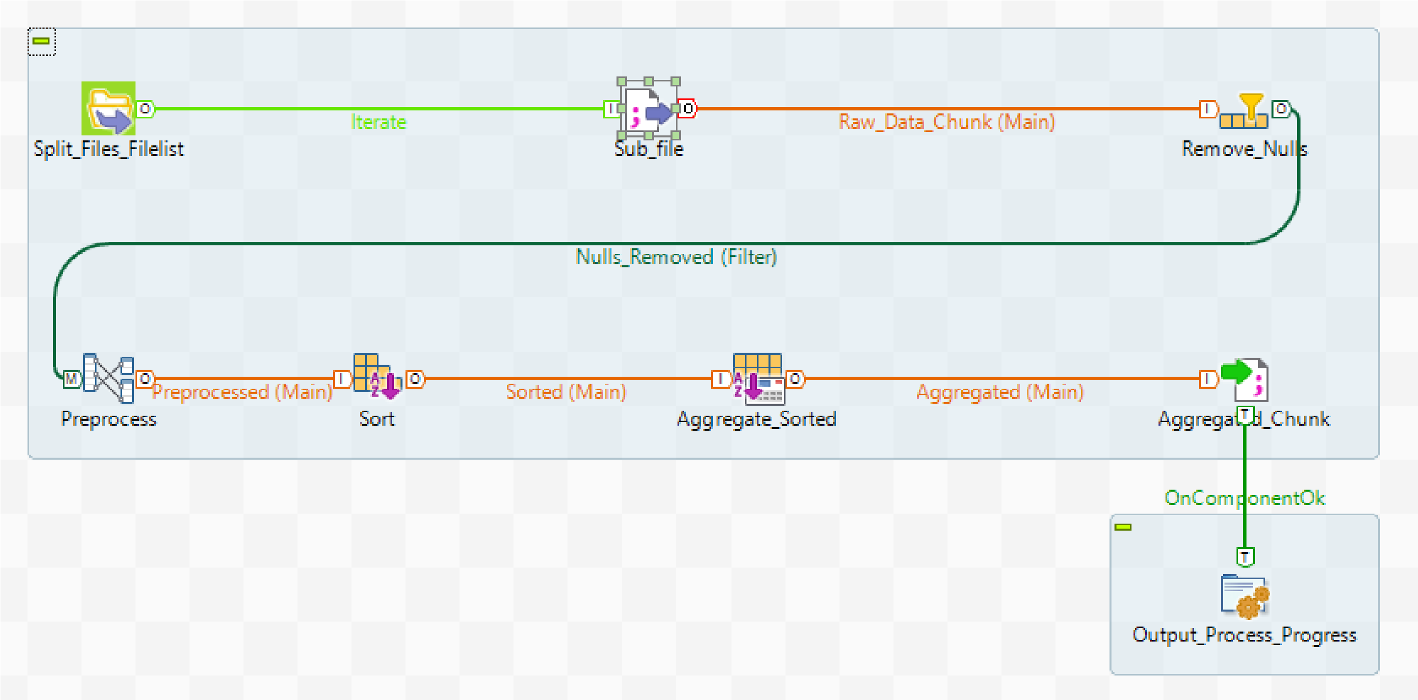


Job execution settings

For this job I changed the execution settings to increase the Java Virtual Machine memory allocation - raising the initial memory allocation from the default of 256MB `-Xms256M` to 1GB `-Xms1024M` and the maximum allocation from the default of 1GB `-Xmx1024M` to 4GB `-Xmx4096M`. It may have been possible to avoid this by reducing the buffer size of the "Use of disk" tUniqRow setting.

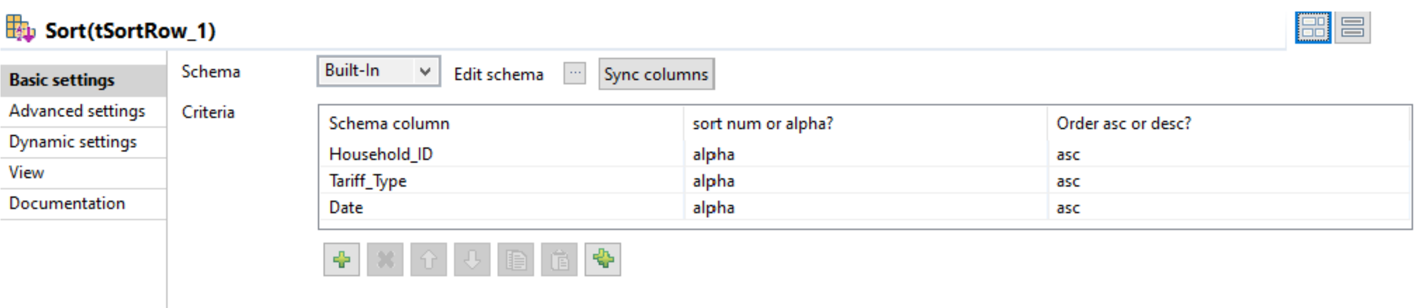


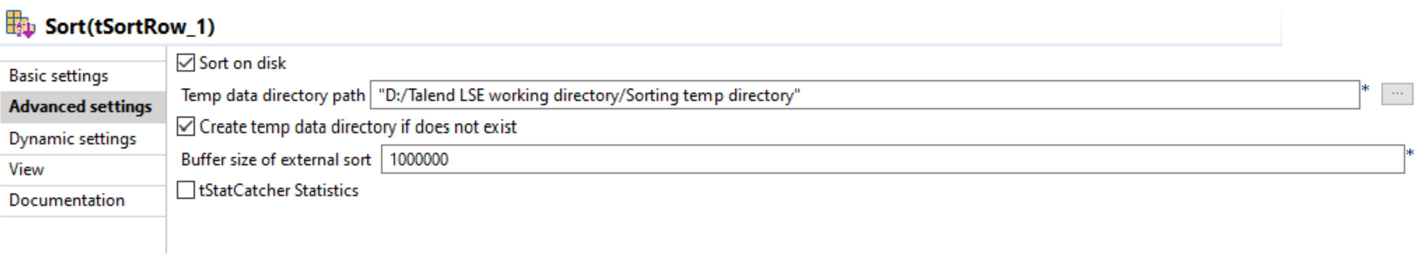
4. Remove nulls and aggregate by year-month



The Remove_Nulls tFilterRow component and the Preprocess tMap component have the same settings as their equivalents in the test data aggregation process. However the aggregation had to be handled differently because a single tAggregateRow component would cause Out of memory errors. The answer was to use a tSortRow component and then a tAggregateSortedRow component as this reduced memory requirements. It was also necessary to use the Sort on disk option for the tSortRow component to further reduce memory load.

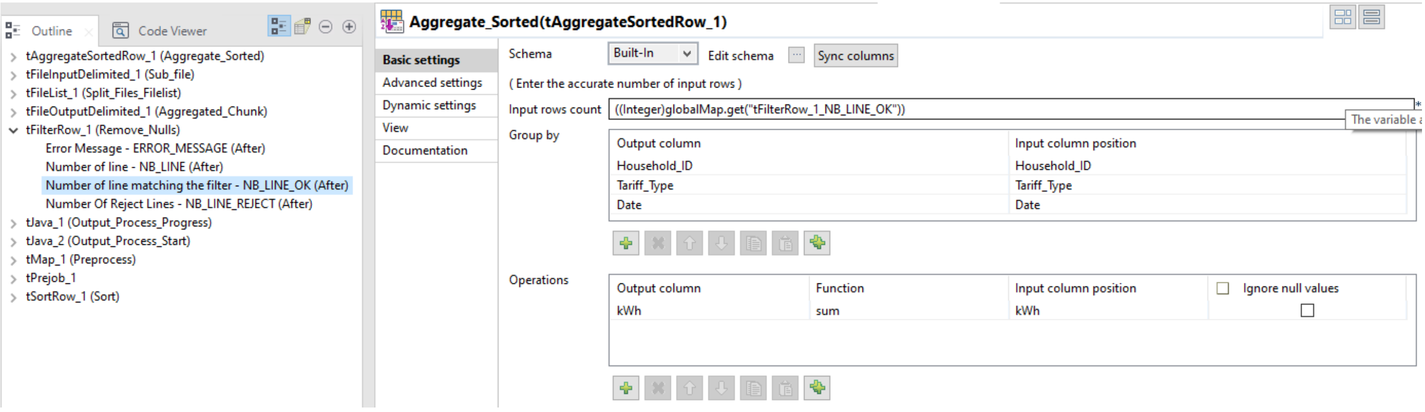
tSortRow - Sort Settings (Basic and Advanced)



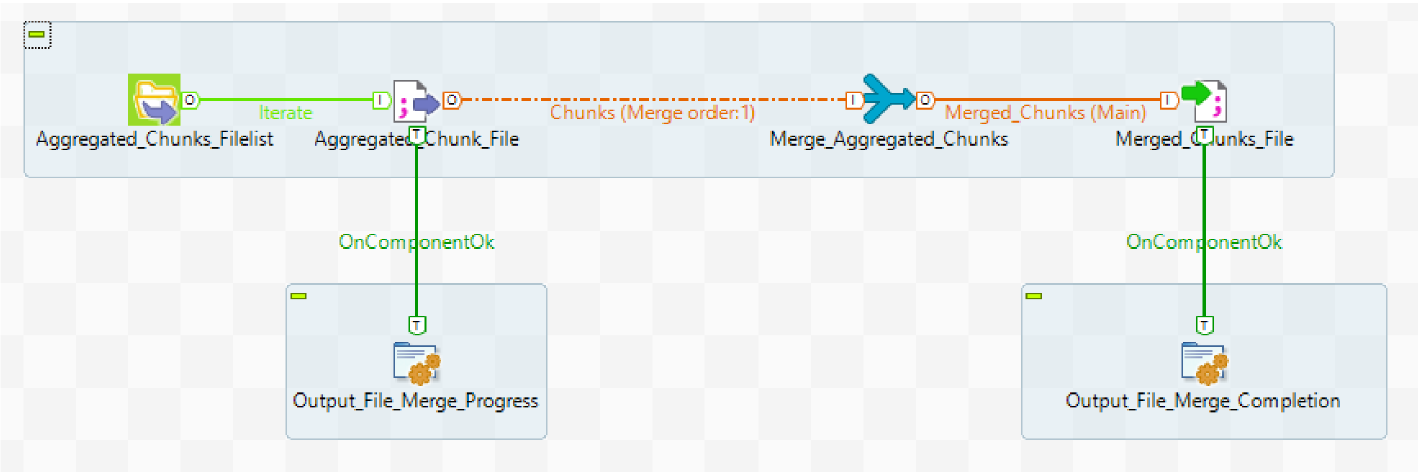


tAggregateSortedRow - Aggregate_Sorted Settings

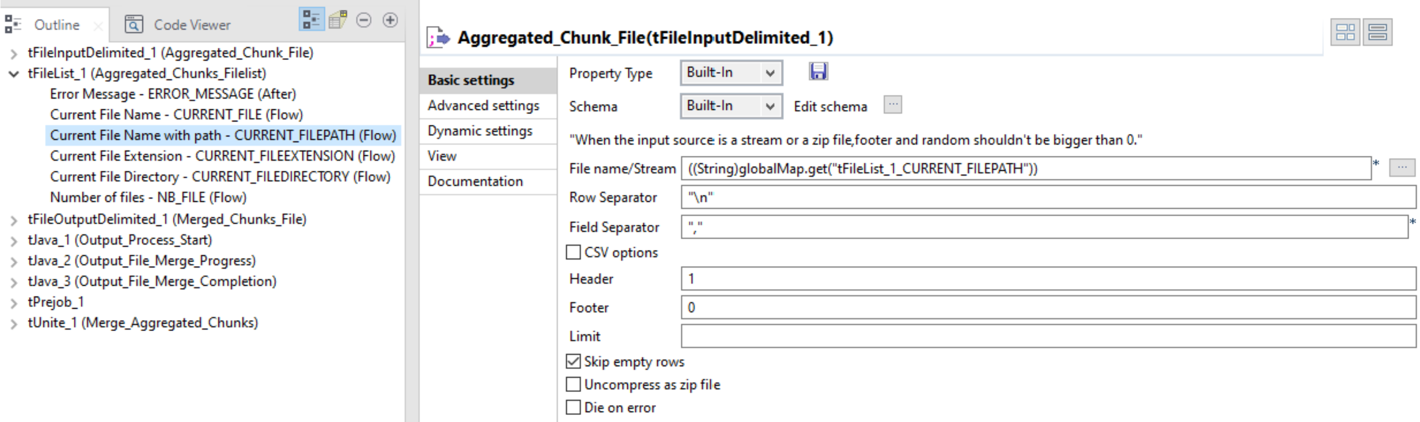
The tAggregateSortedRow component needs to know the number of input rows. We can get that by dragging the `Number of line matching the filter - NB_LINE_OK (After)` element of the tFilterRow component in the left-hand window into the Input rows count field in the right-hand window.



5. Merge the processed year-month files into a single file



tFileInputDelimited - Aggrgated_Chunk_File Settings



Viewing the results

We can access the resulting data in a Pandas dataframe.

In [11]:
```
daily_summary = (
    pd.read_csv("data/merged-processed-chunks.csv").sort_values(
        ['Household_ID', 'Tariff_Type', 'Date']
    )
    .reset_index(drop=True)
    .rename(columns = {
        'Household_ID' : 'Household ID',
        'Tariff_Type' : 'Tariff Type'
```

```
    })
)
```

In [12]:
```
daily_summary
```

Out[12]:

	Household ID	Tariff Type	Date	kWh
0	MAC000002	Std	2012-10-12	7.098
1	MAC000002	Std	2012-10-13	11.087
2	MAC000002	Std	2012-10-14	13.223
3	MAC000002	Std	2012-10-15	10.257
4	MAC000002	Std	2012-10-16	9.769
...	...	...	...	...
3510398	MAC005567	Std	2014-02-24	4.107
3510399	MAC005567	Std	2014-02-25	5.762
3510400	MAC005567	Std	2014-02-26	5.066
3510401	MAC005567	Std	2014-02-27	3.217
3510402	MAC005567	Std	2014-02-28	0.183

3510403 rows × 4 columns

Saving aggregated data

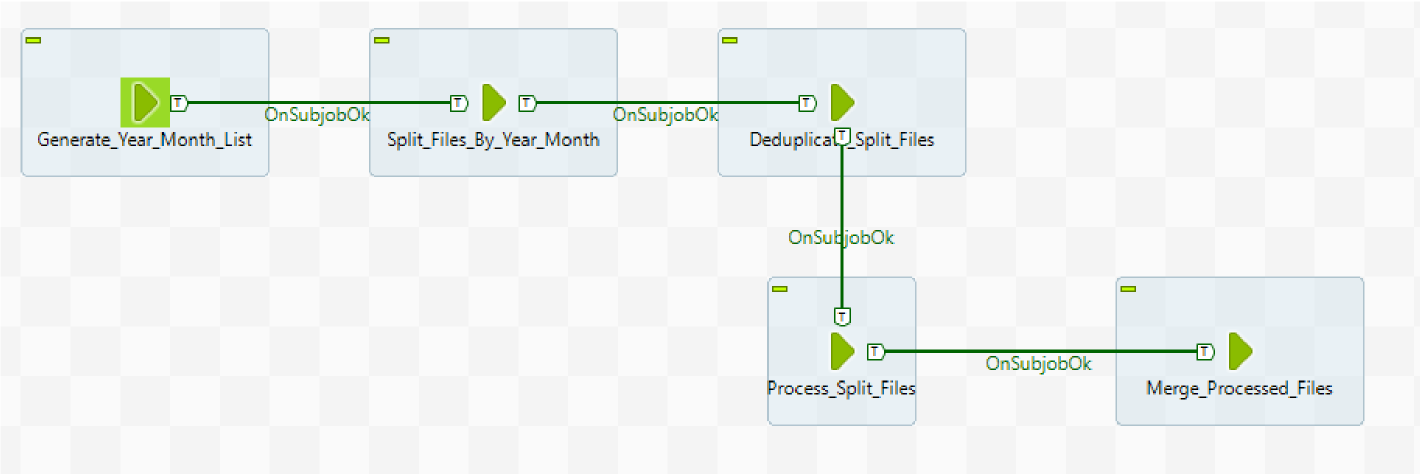
Now that we have reduced the data down to about 3 million rows it should be managable in a single dataframe. It's useful to save the data so that we don't have to re-run the aggregation every time we want to work on the aggregated data.

We'll save it in a compressed gz format - pandas automatically recognizes the filetype we specify.

In [13]:
```
daily_summary.to_csv("data/daily-summary-data.gz", index=False)
```

Overall process coordination

To run all the jobs in a single go we have a Process_Coordinator job which executes the jobs in sequence. There are also various tJava elements in the subjobs which output progress information to the console while jobs are being executed.



The rest of this notebook is now essentially the same processing as applied in all the other notebooks in the series.

Analysing the data

In [14]:
```
saved_daily_summary = pd.read_csv("data/daily-summary-data.gz")
```

In [15]:
```
saved_daily_summary
```

Out[15]:

	Household ID	Tariff Type	Date	kWh
0	MAC000002	Std	2012-10-12	7.098
1	MAC000002	Std	2012-10-13	11.087
2	MAC000002	Std	2012-10-14	13.223
3	MAC000002	Std	2012-10-15	10.257
4	MAC000002	Std	2012-10-16	9.769
...	...	...	...	...
3510398	MAC005567	Std	2014-02-24	4.107
3510399	MAC005567	Std	2014-02-25	5.762
3510400	MAC005567	Std	2014-02-26	5.066
3510401	MAC005567	Std	2014-02-27	3.217
3510402	MAC005567	Std	2014-02-28	0.183

3510403 rows × 4 columns

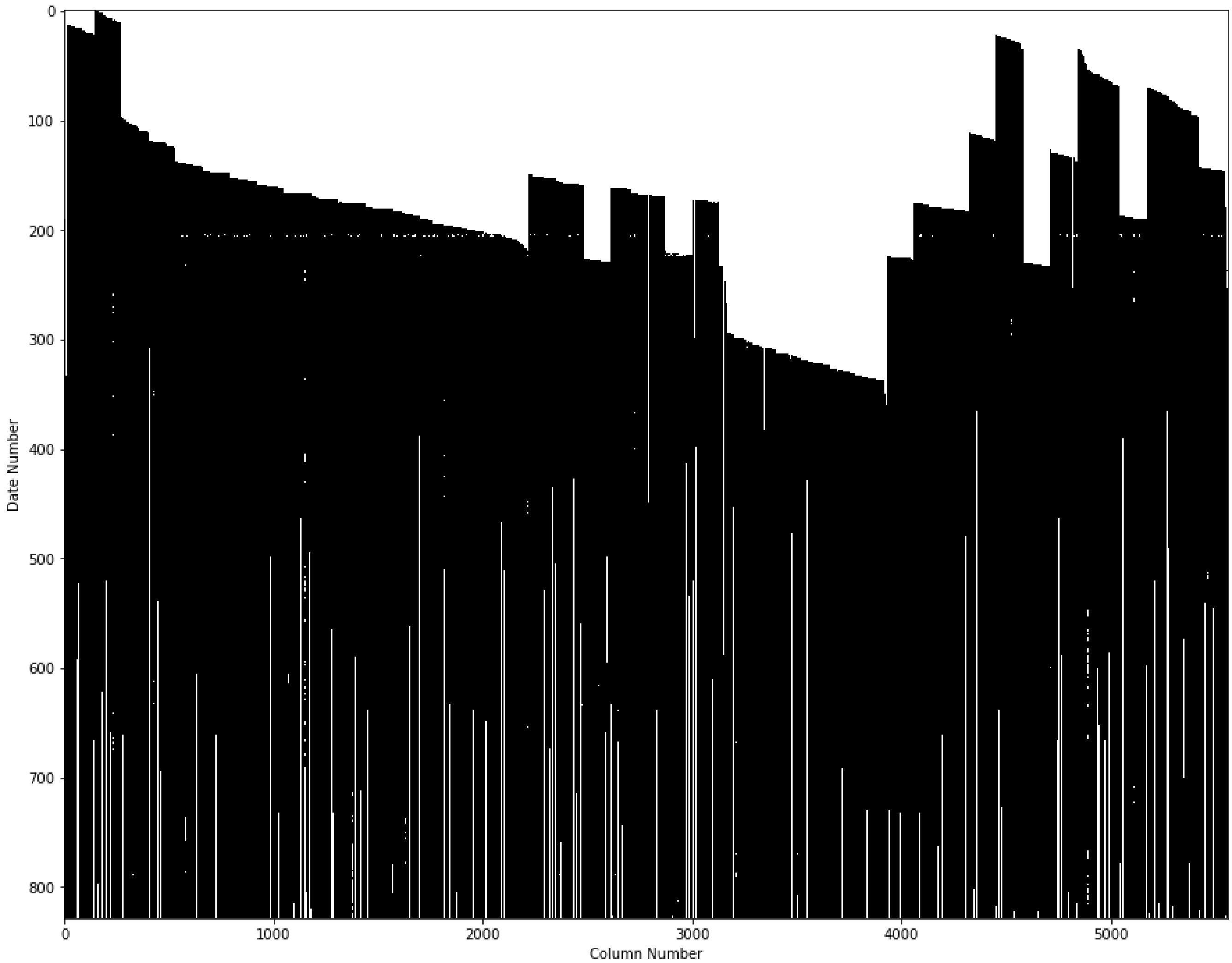
Out of interest let's see what sort of data coverage we have. First we re-organize so that we have households as columns and dates as rows.

In [16]:
```
summary_table = saved_daily_summary.pivot_table(
    'kWh',
    index='Date',
    columns='Household ID',
    aggfunc='sum'
)
```

Then we can plot where we have data (black) and where we don't (white).

In [17]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(15, 12))
plt.imshow(summary_table.isna(), aspect="auto", interpolation="nearest", cmap="gray")
plt.xlabel("Column Number")
plt.ylabel("Date Number");
```



Despite a slightly patchy data coverage, averaging by tariff type across all households for each day should give us a useful comparison.

In [18]:
```
daily_mean_by_tariff_type = saved_daily_summary.pivot_table(
    'kWh',
    index='Date',
    columns='Tariff Type',
    aggfunc='mean'
)
daily_mean_by_tariff_type
```

Out[18]:

Tariff Type	Std	ToU
Date		
2011-11-23	7.430000	4.327500
2011-11-24	8.998333	6.111750
2011-11-25	10.102885	6.886333
2011-11-26	10.706257	7.709500
2011-11-27	11.371486	7.813500
...	...	...
2014-02-24	10.580187	9.759439
2014-02-25	10.453365	9.683862
2014-02-26	10.329026	9.716652
2014-02-27	10.506416	9.776561
2014-02-28	0.218075	0.173949

829 rows × 2 columns

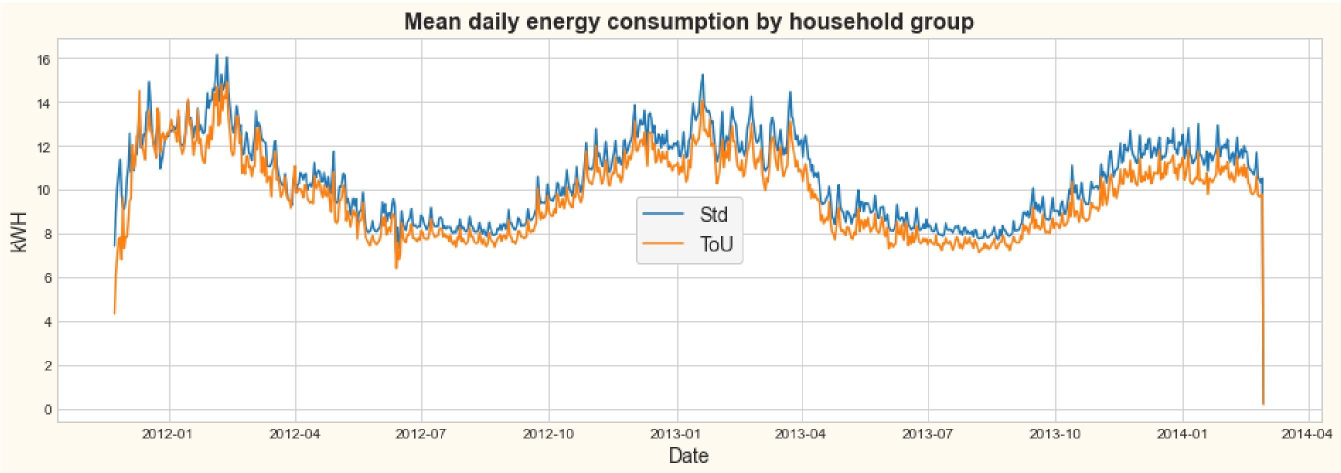
Finally we can plot the two sets of data. The plotting works better if we convert the date from type `string` to type `datetime`.

In [19]:
```
daily_mean_by_tariff_type.index = pd.to_datetime(daily_mean_by_tariff_type.index)
```

In [20]:
```
plt.style.use('seaborn-whitegrid')

plt.figure(figsize=(16, 5), facecolor='floralwhite')
for tariff in daily_mean_by_tariff_type.columns.to_list():
    plt.plot(
        daily_mean_by_tariff_type.index.values,
        daily_mean_by_tariff_type[tariff],
        label = tariff
    )

plt.legend(loc='center', frameon=True, facecolor='whitesmoke', framealpha=1, fontsize=14)
plt.title(
    'Mean daily energy consumption by household group',
    fontdict = {'fontsize' : 16, 'fontweight' : 'bold'}
)
plt.xlabel('Date', fontsize = 14)
plt.ylabel('kWH', fontsize = 14)
plt.show()
```



The pattern looks seasonal which makes sense given heating energy demand.

It also looks like there's a difference between the two groups with the ToU group tending to consume less, but the display is too granular. Let's aggregate again into months.

In [21]:
```
daily_mean_by_tariff_type
```

Out[21]:

Tariff Type	Std	ToU
Date		
2011-11-23	7.430000	4.327500
2011-11-24	8.998333	6.111750
2011-11-25	10.102885	6.886333
2011-11-26	10.706257	7.709500
2011-11-27	11.371486	7.813500
...	...	...
2014-02-24	10.580187	9.759439
2014-02-25	10.453365	9.683862
2014-02-26	10.329026	9.716652
2014-02-27	10.506416	9.776561
2014-02-28	0.218075	0.173949

829 rows × 2 columns

We can see that the data starts partway through November 2011, so we'll start from 1 December. It looks like the data finishes perfectly at the end of February, but the last value looks suspiciously low compared to the others. It seems likely the data finished part way through the last day. This may be a problem elsewhere in the data too, but it shouldn't have an enormous effect as at worst it will reduce the month's energy consumption for that household by two days (one at the beginning and one at the end).

In [22]:
```
monthly_mean_by_tariff_type = daily_mean_by_tariff_type['2011-12-01' : '2014-01-31'].resample('M').sum()
monthly_mean_by_tariff_type
```

Out[22]:

Tariff Type	Std	ToU
Date		
2011-12-31	377.218580	365.145947
2012-01-31	401.511261	386.016403
2012-02-29	395.065321	368.475150
2012-03-31	349.153085	330.900633
2012-04-30	314.173857	296.903425
2012-05-31	281.666428	263.694338
2012-06-30	257.204029	238.417505
2012-07-31	260.231952	244.641359
2012-08-31	253.939017	238.904097
2012-09-30	266.392973	248.707929
2012-10-31	318.214026	299.714701
2012-11-30	347.818025	326.651435
2012-12-31	390.616106	364.754528
2013-01-31	398.004581	366.548143
2013-02-28	352.189818	325.298845
2013-03-31	381.191994	351.371278
2013-04-30	307.857771	277.856327
2013-05-31	280.762752	256.292247
2013-06-30	254.399013	234.481016
2013-07-31	252.609890	234.104814
2013-08-31	247.046087	231.347310
2013-09-30	267.024791	245.597424
2013-10-31	299.533302	274.332936
2013-11-30	338.082197	306.942424
2013-12-31	369.381371	337.331504
2014-01-31	364.225311	331.578243

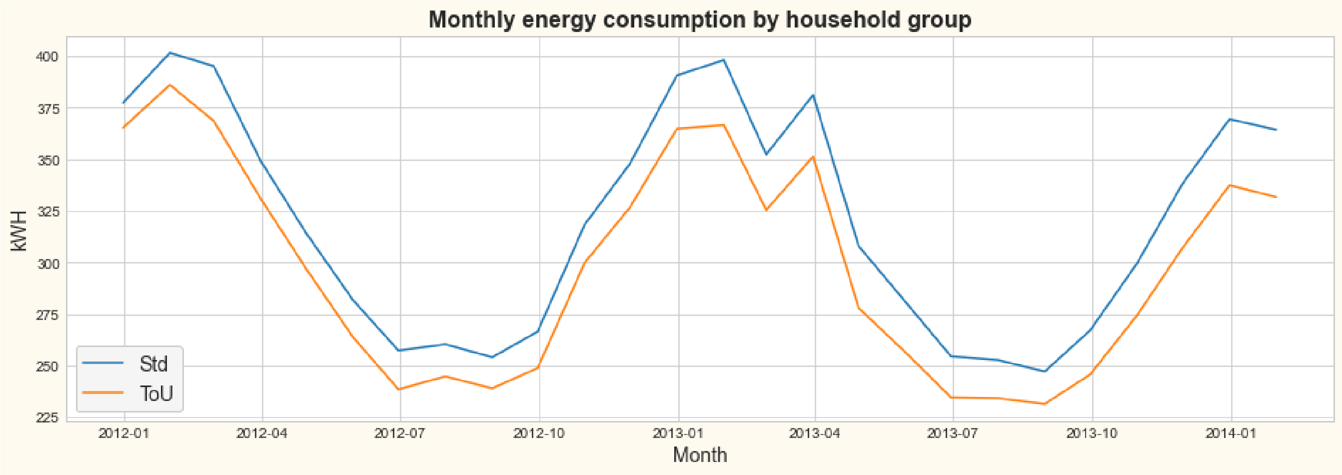
In [23]:

```
plt.figure(figsize=(16, 5), facecolor='floralwhite')
for tariff in daily_mean_by_tariff_type.columns.to_list():
    plt.plot(
        monthly_mean_by_tariff_type.index.values,
        monthly_mean_by_tariff_type[tariff],
        label = tariff
    )

plt.legend(loc='lower left', frameon=True, facecolor='whitesmoke', framealpha=1, fontsize=14)
plt.title(
    'Monthly energy consumption by household group',
    fontdict = {'fontsize' : 16, 'fontweight' : 'bold'}
)
plt.xlabel('Month', fontsize = 14)
plt.ylabel('kWH', fontsize = 14)
```

```python
# Uncomment for a copy to display in results
# plt.savefig(fname='images/result1-no-dupes.png', bbox_inches='tight')

plt.show()
```



The pattern is much clearer and there is an obvious difference between the two groups of consumers.

Note that the chart does not show mean monthly energy consumption, but the sum over each month of the daily means. To calculate true monthly means we would need to drop the daily data for each household where the data was incomplete for a month. Our method should give a reasonable approximation.