Introduction

This is the ***second*** 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 the **Dask library** for parallel computing to manage a large file size. You can find each notebook in the series in my Github repo, including:

1. Pandas chunksize
2. Dask library

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:

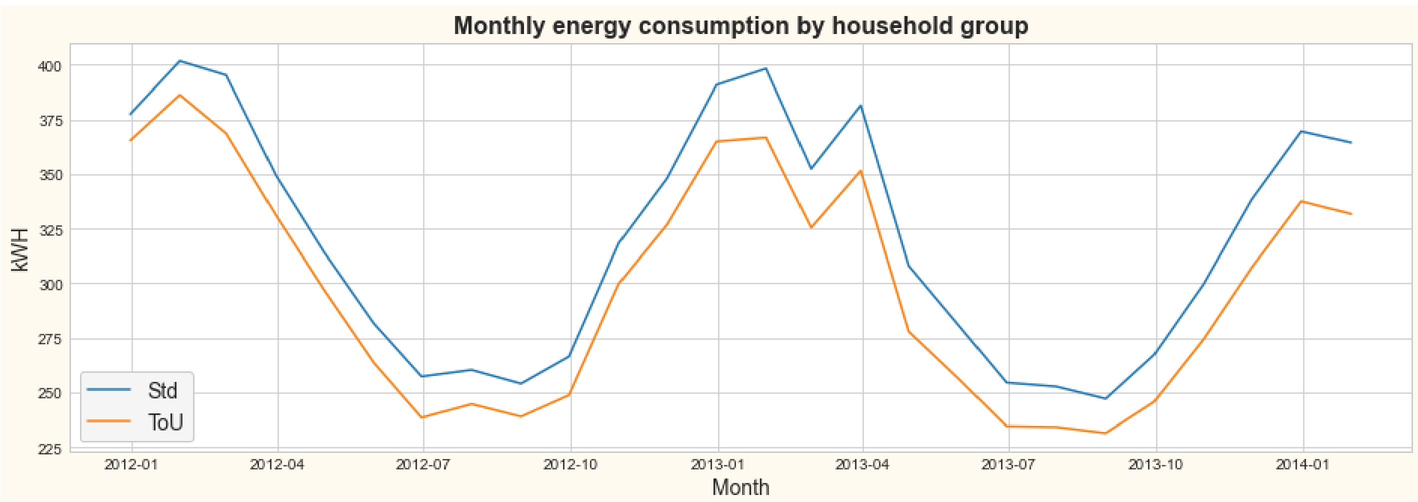
> Energy consumption readings for a sample of 5,567 London Households that took part in the UK Power Networks led Low Carbon London project between November 2011 and February 2014.

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 Dask

According to the docs:

> *Dask is a flexible library for parallel computing in Python*
>
> Dask is composed of two parts:
>
> - Dynamic task scheduling optimized for computation. This is similar to Airflow, Luigi, Celery, or Make, but optimized for interactive computational workloads.
> - "Big Data" collections like parallel arrays, dataframes, and lists that extend common interfaces like NumPy, Pandas, or Python iterators to larger-than-memory or distributed environments. These parallel collections run on top of dynamic task schedulers.

This means that not only can we process larger-than-memory files, but unlike the pandas chunksize approach, we can also make use of clusters - or multiple CPU cores when working on a single machine.

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

In [2]:
```
import pandas as pd
from dask import dataframe as dd
```

Now let's load the data into a Dask dataframe.

In [3]:
```
raw_data_ddf = dd.read_csv('data/CC_LCL-FullData.csv')
raw_data_ddf
```

Out[3]: **Dask DataFrame Structure:**

	LCLid	stdorToU	DateTime	KWH/hh (per half hour)
npartitions=133				
	object	object	object	int64
	...	...	...	...
...	...	...	...	...
	...	...	...	...
	...	...	...	...

Dask Name: read-csv, 133 tasks

Viewing the dataframe shows that Dask has divided our data into 133 partitions. Dask has also "guessed" the data types by taking a sample of data. Leaving the dataframe as it is will eventually cause errors, because the kWh data is a mix of numbers and 'Null' string values.

As a first step we can specify the kWh data type, using `object` to handle strings.

In [4]:
```
raw_data_ddf = dd.read_csv(
    'data/CC_LCL-FullData.csv',
    dtype={'KWH/hh (per half hour) ': 'object'}
)
raw_data_ddf
```

Out[4]: **Dask DataFrame Structure:**

	LCLid	stdorToU	DateTime	KWH/hh (per half hour)
npartitions=133				
	object	object	object	object
	...	...	...	...
...	...	...	...	...
	...	...	...	...
	...	...	...	...

Dask Name: read-csv, 133 tasks

We rename the columns to make them more readable.

In [5]:
```
col_renaming = {
    'LCLid' : 'Household ID',
    'stdorToU' : 'Tariff Type',
    'KWH/hh (per half hour) ' : 'kWh'
}
full_data_ddf = raw_data_ddf.rename(columns=col_renaming)
```

Let's work on a small subset of the data (10,000 rows) to develop each processing step.

In [6]:
```
test_data = full_data_ddf.head(10000)
test_data
```

Out[6]:

	Household ID	Tariff Type	DateTime	kWh
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
...	...	...	...	...
9995	MAC000002	Std	2013-05-09 03:30:00.0000000	0.09
9996	MAC000002	Std	2013-05-09 04:00:00.0000000	0.114
9997	MAC000002	Std	2013-05-09 04:30:00.0000000	0.105
9998	MAC000002	Std	2013-05-09 05:00:00.0000000	0.099
9999	MAC000002	Std	2013-05-09 05:30:00.0000000	0.117

10000 rows × 4 columns

We need to convert this data back into a Dask dataframe. We'll split it into 2 partitions so we know we are testing across partitions.

In [7]:
```
test_data_ddf = dd.from_pandas(test_data, npartitions=2)
test_data_ddf
```

Out[7]: **Dask DataFrame Structure:**

	Household ID	Tariff Type	DateTime	kWh
npartitions=2				
0	object	object	object	object
5000	...	...	...	...
9999	...	...	...	...

Dask Name: from_pandas, 2 tasks

Cleaning the data

We can see there is at least one string `"Null"` value in the kWH data as there is one example in our test dataset.

In [8]:
```
test_nulls = test_data[test_data['kWh'] == 'Null']
test_nulls
```

Out[8]:

	Household ID	Tariff Type	DateTime	kWh
3240	MAC000002	Std	2012-12-19 12:37:27.0000000	Null

Let's remove those `"Null"` values.

In [9]:
```
def remove_nulls(df):
    output = df.copy()
```

```
    output.loc[:, 'kWh'] = pd.to_numeric(output['kWh'], errors='coerce')
    return output.dropna(subset=['kWh'])
```

In [10]:
```
test_data_no_nulls_ddf = test_data_ddf.map_partitions(remove_nulls)
```

Notice that nothing has happened yet. Dask methods are generally "lazy" in that they only run when needed. To execute we need to call `compute`. This means we can chain together lots of methods, and then run them all at once.

In [11]:
```
test_data_no_nulls = test_data_no_nulls_ddf.compute()
test_data_no_nulls
```

Out[11]:

	Household ID	Tariff Type	DateTime	kWh
0	MAC000002	Std	2012-10-12 00:30:00.0000000	0.000
1	MAC000002	Std	2012-10-12 01:00:00.0000000	0.000
2	MAC000002	Std	2012-10-12 01:30:00.0000000	0.000
3	MAC000002	Std	2012-10-12 02:00:00.0000000	0.000
4	MAC000002	Std	2012-10-12 02:30:00.0000000	0.000
...	...	...	...	...
9995	MAC000002	Std	2013-05-09 03:30:00.0000000	0.090
9996	MAC000002	Std	2013-05-09 04:00:00.0000000	0.114
9997	MAC000002	Std	2013-05-09 04:30:00.0000000	0.105
9998	MAC000002	Std	2013-05-09 05:00:00.0000000	0.099
9999	MAC000002	Std	2013-05-09 05:30:00.0000000	0.117

9999 rows × 4 columns

That's worked as we now have one less row in our test data (9,999).

Aggregating the data

The goal here is to ***reduce*** the data by aggregating it in some way. Since we know that we have data in half-hour intervals, we'll aggregate it to daily data by summing over each 24-hour period. That should reduce the number of rows by a factor of about 48.

Aggregation is simple when using Dask, as the `groupby` function works across the partitions. However first we need to convert the timestamp data into date format so that we can group by date. To do this we use the Dask `map_partitions` method, which is similar to Pandas `map` but is applied across all partitions. One important difference though is that we need to specify the output types using the `meta` parameter.

In [12]:
```
def timestamp_to_date(df):
    df.loc[:, 'DateTime'] = pd.to_datetime(df['DateTime']).dt.date
    return df
```

In [13]:
```
meta = {
    'Household ID' : object,
    'Tariff Type' : object,
    'DateTime' : object,
```

```
    'kWh' : float
}
```

In [14]:
```
test_data_by_date_ddf = (
    test_data_no_nulls_ddf.map_partitions(timestamp_to_date, meta=meta)
    .rename(columns={'DateTime' : 'Date'})
)
```

In [15]:
```
test_data_by_date = test_data_by_date_ddf.compute()
test_data_by_date
```

Out[15]:

	Household ID	Tariff Type	Date	kWh
0	MAC000002	Std	2012-10-12	0.000
1	MAC000002	Std	2012-10-12	0.000
2	MAC000002	Std	2012-10-12	0.000
3	MAC000002	Std	2012-10-12	0.000
4	MAC000002	Std	2012-10-12	0.000
...	...	...	...	...
9995	MAC000002	Std	2013-05-09	0.090
9996	MAC000002	Std	2013-05-09	0.114
9997	MAC000002	Std	2013-05-09	0.105
9998	MAC000002	Std	2013-05-09	0.099
9999	MAC000002	Std	2013-05-09	0.117

9999 rows × 4 columns

Now we can aggregate by day.

In [16]:
```
test_summary_daily_ddf = test_data_by_date_ddf.groupby(['Household ID', 'Tariff Type',
'Date']).sum()
```

In [17]:
```
test_summary_daily = test_summary_daily_ddf.compute()
test_summary_daily
```

Out[17]:

			kWh
Household ID	**Tariff Type**	**Date**	
MAC000002	**Std**	**2012-10-12**	7.098
		2012-10-13	11.087
		2012-10-14	13.223
		2012-10-15	10.257
		2012-10-16	9.769
		...	...
		2013-05-05	8.826
		2013-05-06	7.418
		2013-05-07	7.607
		2013-05-08	8.576
		2013-05-09	1.567

210 rows × 1 columns

Operating on the full data

Now we can apply the same methods to the full data. Note that nothing will happen until we call `compute`.

In [18]:
```
full_data_no_nulls_ddf = full_data_ddf.map_partitions(remove_nulls)
```

In [19]:
```
full_data_by_date_ddf = (
    full_data_no_nulls_ddf.map_partitions(timestamp_to_date, meta=meta)
    .rename(columns={'DateTime' : 'Date'})
)
```

In [20]:
```
full_summary_daily_ddf = full_data_by_date_ddf.groupby(['Household ID', 'Tariff Type',
'Date']).sum()
```

We'll start a Dask Client which is generally used for interacting with a cluster, but it's also useful on a single machine as it shows progress during an operation.

In [21]:
```
from dask.distributed import Client
client = Client()
client
```

Out[21]:

Client

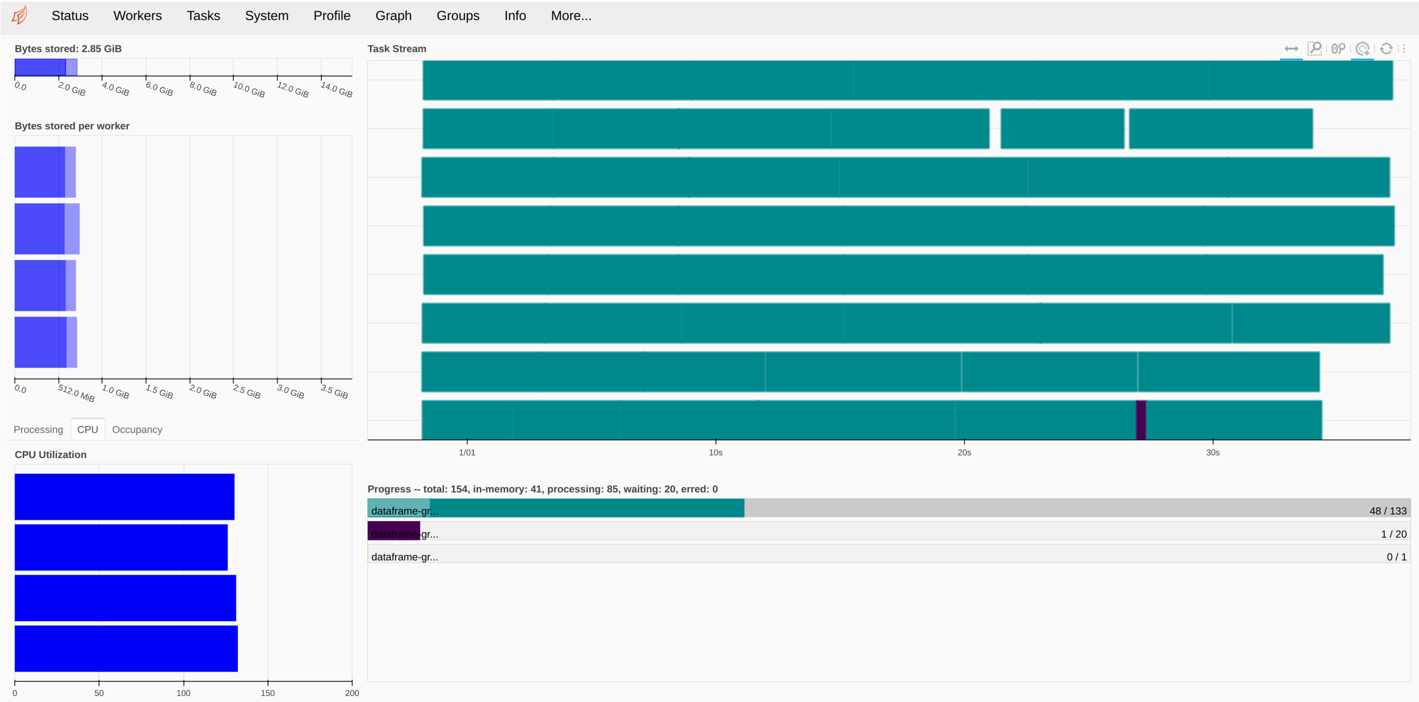
Client-ebbe2596-e0d9-11ec-aa24-e45e37a84c64

Connection method: Cluster object	**Cluster type:** distributed.LocalCluster
Dashboard: http://127.0.0.1:8787/status	

▸ Cluster Info

We can click on the dashboard link above and open as a new window. Then we run `compute` and we can watch the progress on the dashboard in the client window.

```
In [22]: daily_summary = full_summary_daily_ddf.compute()
```



At the bottom right we can see the progress bar - very handy! We can also see at the bottom left that all 4 of my CPUs are in use, and the 8 task streams (upper right) represent the 8 logical CPUs (2 per physical CPU).

Obviously the tasks complete much more quickly than when using a non-distributed approach (like Pandas chunksize for example).

```
In [23]: daily_summary
```

Out[23]:

Household ID	Tariff Type	Date	kWh
MAC000002	**Std**	**2012-10-12**	7.098
		2012-10-13	11.087
		2012-10-14	13.223
		2012-10-15	10.257
		2012-10-16	9.769
...	**...**	**...**	...
MAC005564	**ToU**	**2014-02-26**	3.431
		2014-02-27	4.235
		2014-02-28	0.122
MAC005565	**ToU**	**2012-06-20**	3.896
		2012-06-21	1.894

3510403 rows × 1 columns

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

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 [24]:
```
daily_summary.to_csv("data/daily-summary-data.gz")
```

Analysing the data

In [25]:
```
saved_daily_summary = pd.read_csv("data/daily-summary-data.gz")
```

In [26]:
```
saved_daily_summary
```

Out[26]:

	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	MAC005564	ToU	2014-02-26	3.431
3510399	MAC005564	ToU	2014-02-27	4.235
3510400	MAC005564	ToU	2014-02-28	0.122
3510401	MAC005565	ToU	2012-06-20	3.896
3510402	MAC005565	ToU	2012-06-21	1.894

3510403 rows × 4 columns

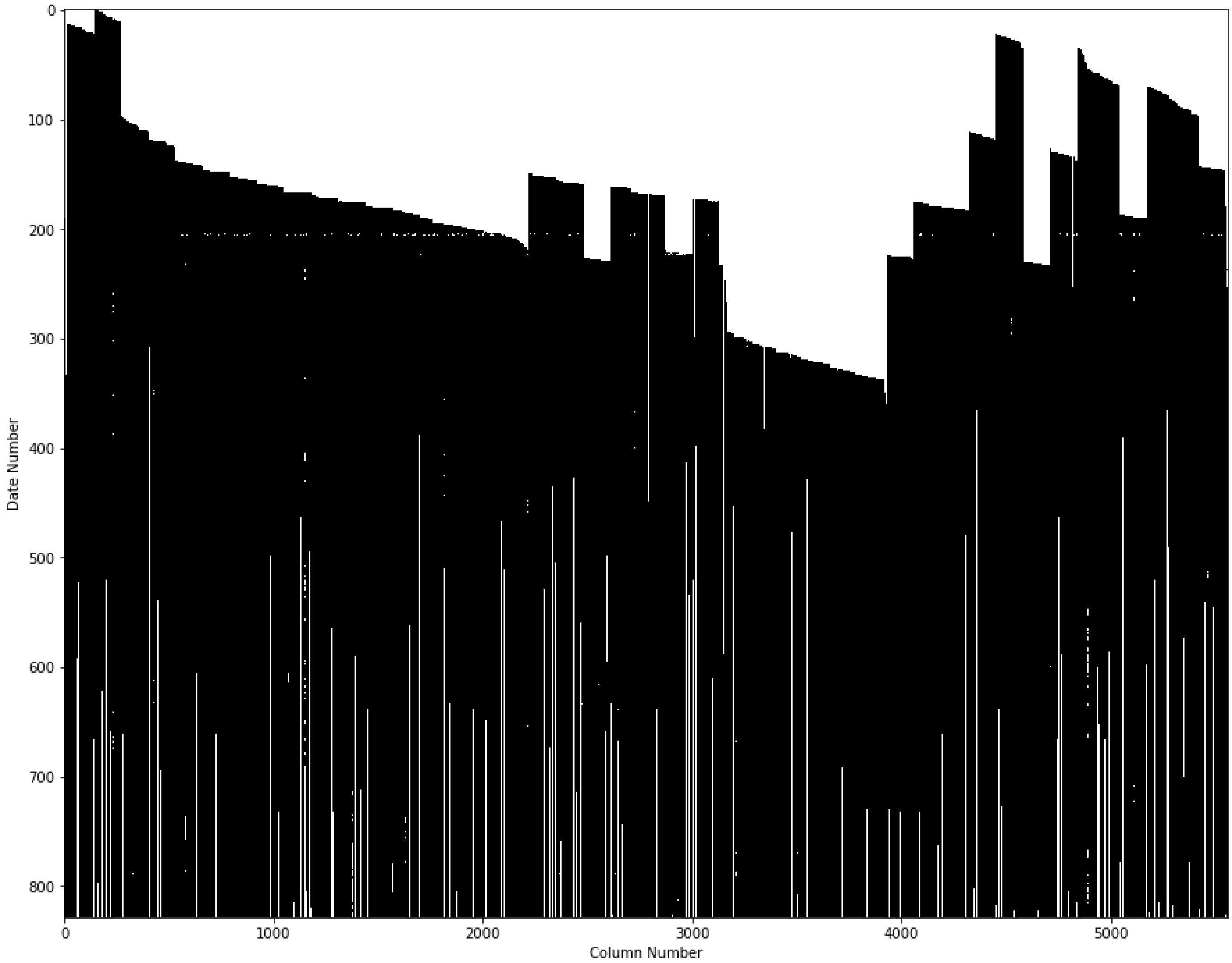
Out of interest let's see what sort of data coverage we have. First we re-organize so that we have households as columns and dates as rows.

In [27]:
```
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 [28]:
```
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 [29]:
```
daily_mean_by_tariff_type = saved_daily_summary.pivot_table(
    'kWh',
    index='Date',
    columns='Tariff Type',
    aggfunc='mean'
)
daily_mean_by_tariff_type
```

Out[29]:

Tariff Type Date	Std	ToU
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	0.436149	0.347899

829 rows × 2 columns

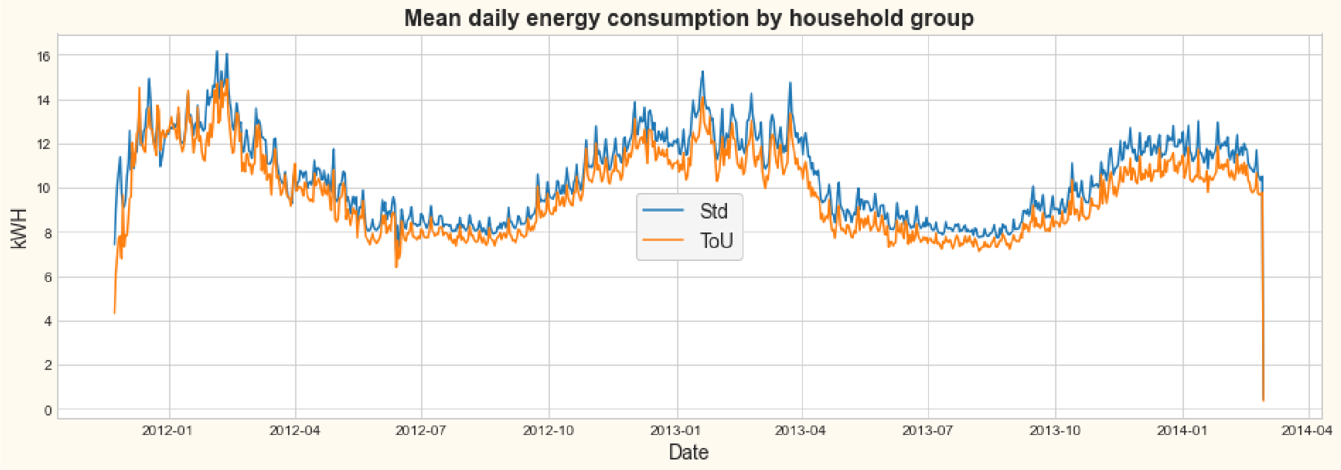
Finally we can plot the two sets of data. The plotting works better if we convert the date from type `string` to type `datetime`.

In [30]:
```
daily_mean_by_tariff_type.index = pd.to_datetime(daily_mean_by_tariff_type.index)
```

In [31]:
```
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 [32]:
```
daily_mean_by_tariff_type
```

Out[32]:

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	0.436149	0.347899

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 [33]:
```
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[33]:

Tariff Type	Std	ToU
Date		
2011-12-31	377.443042	365.391597
2012-01-31	401.744672	386.253703
2012-02-29	395.294296	368.663764
2012-03-31	349.367317	331.095386
2012-04-30	314.323216	297.032370
2012-05-31	281.796440	263.812879
2012-06-30	257.333248	238.532452
2012-07-31	260.359313	244.757999
2012-08-31	254.085724	239.041805
2012-09-30	266.515247	248.820055
2012-10-31	318.361735	299.849633
2012-11-30	348.007365	326.831890
2012-12-31	390.864676	364.969958
2013-01-31	398.275908	366.779573
2013-02-28	352.440444	325.489548
2013-03-31	381.472409	351.591760
2013-04-30	308.005098	277.976132
2013-05-31	280.934227	256.428977
2013-06-30	254.542531	234.591000
2013-07-31	252.761147	234.224724
2013-08-31	247.190593	231.464453
2013-09-30	267.165424	245.707678
2013-10-31	299.703934	274.464114
2013-11-30	338.317167	307.131828
2013-12-31	369.630558	337.524715
2014-01-31	364.460042	331.767440

In [34]:

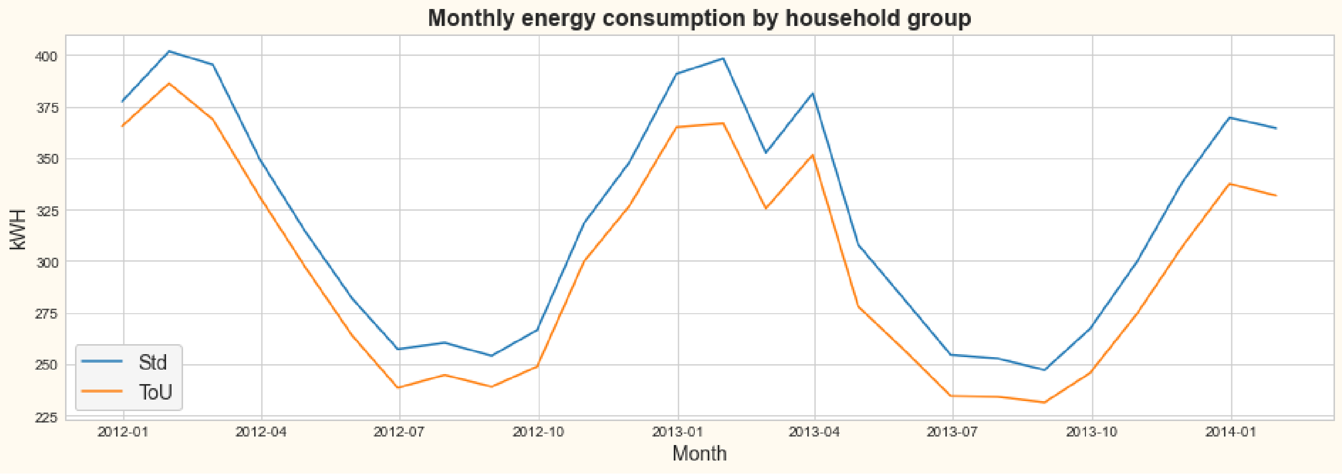
```
plt.figure(figsize=(16, 5), facecolor='floralwhite')
for tariff in daily_mean_by_tariff_type.columns.to_list():
    plt.plot(
        monthly_mean_by_tariff_type.index.values,
        monthly_mean_by_tariff_type[tariff],
        label = tariff
    )

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)

# Uncomment for a copy to display in results
plt.savefig(fname='images/result1.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.

Lastly we close the Dask client although it will automatically close when our Python session ends.

In [35]:
```
client.close()
```