Hourly Energy Consumption End-to-End Analysis

See Kaggle Dataset for details.

See GitHub for full codebase of this and other days.

Import project libraries

01 - Data Modeling and Preprocessing

0035

On this day we load the provided separate time series files, build a file reader and processor, and use this to ingress and combine the data into a single dataframe for the next few steps.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45443 entries, 0 to 45442
Data columns (total 26 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   site       45443 non-null  object
 1   read_date  45443 non-null  datetime64[ns]
 2   hour00     45424 non-null  float64
 3   hour01     45431 non-null  float64
 4   hour02     45349 non-null  float64
 5   hour03     45305 non-null  float64
 6   hour04     45430 non-null  float64
 7   hour05     45431 non-null  float64
 8   hour06     45431 non-null  float64
 9   hour07     45431 non-null  float64
 10  hour08     45431 non-null  float64
 11  hour09     45431 non-null  float64
 12  hour10     45431 non-null  float64
 13  hour11     45431 non-null  float64
 14  hour12     45431 non-null  float64
 15  hour13     45431 non-null  float64
 16  hour14     45430 non-null  float64
 17  hour15     45431 non-null  float64
 18  hour16     45431 non-null  float64
 19  hour17     45431 non-null  float64
 20  hour18     45431 non-null  float64
 21  hour19     45431 non-null  float64
 22  hour20     45431 non-null  float64
 23  hour21     45431 non-null  float64
 24  hour22     45431 non-null  float64
 25  hour23     45431 non-null  float64
dtypes: datetime64[ns](1), float64(24), object(1)
memory usage: 9.0+ MB
None
```

02 - Data Exploration and Visualization

0036

For this day, we want to explore the data visually. Having a background in energy consumption analyics, these are a couple of my go-to approaches to understand usage trends. While this data is at the system level for Duke Energy instead of individual households, the techniques are useful to understand. More on this below.

Processing

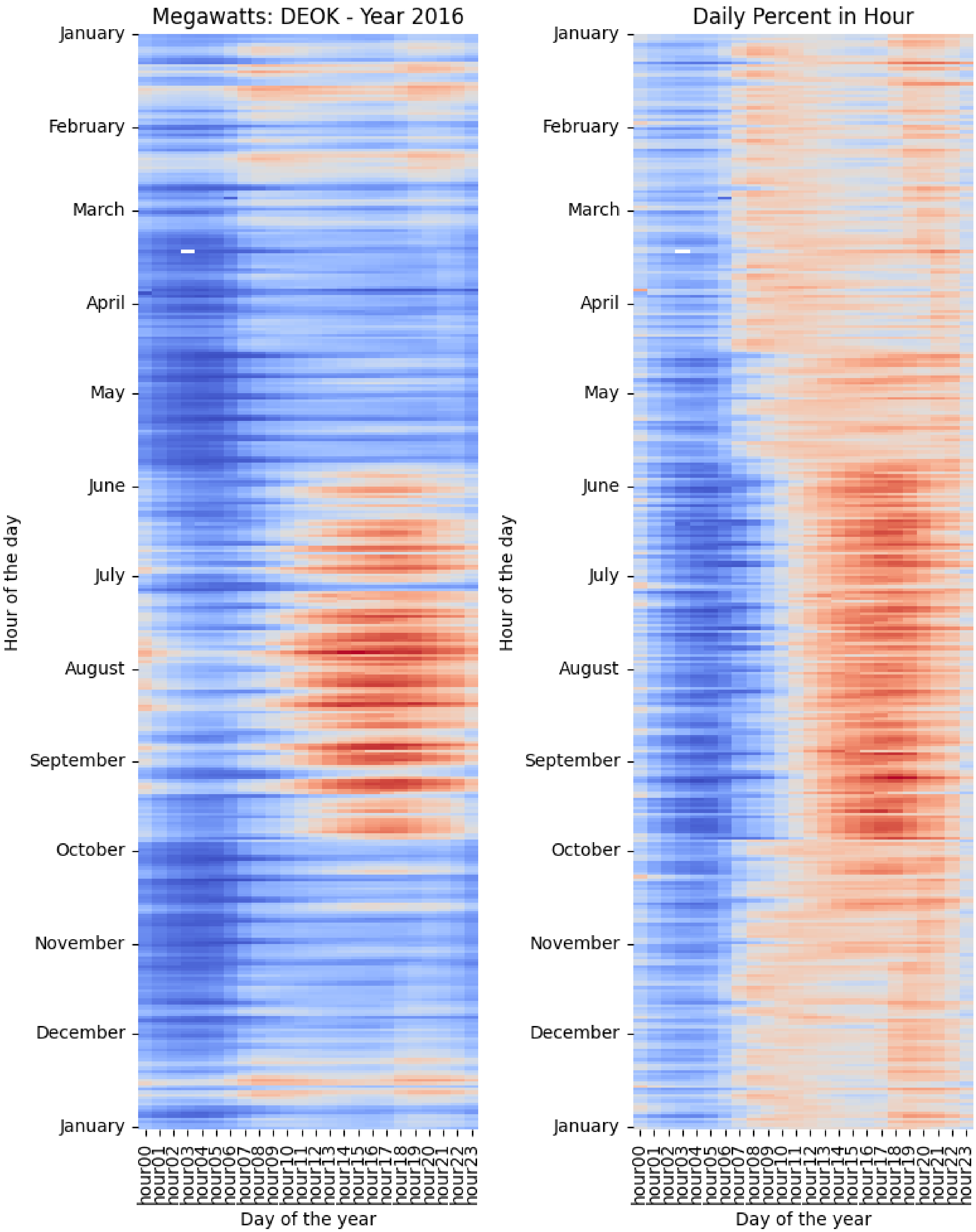
Here we take the data in wide format and filter for the given site and year. Then I pull the attributes out as indexes so the values are nothing but the 24 hourly columns. But when comparing across days, we need to normalize for apples-to-apples comparisons. One way to achieve this is to convert each hourly value to the percent consumed in that day.

The benefit of this approach is you can look at daily variations via the daily totals, but any given day has a certain energy budget consumed. By looking at how much energy was "spent" in any given hour as a percentage, we can determine the timing of consumption events, which are important to utilities for various reasons I won't get into detail here.

Heat Maps

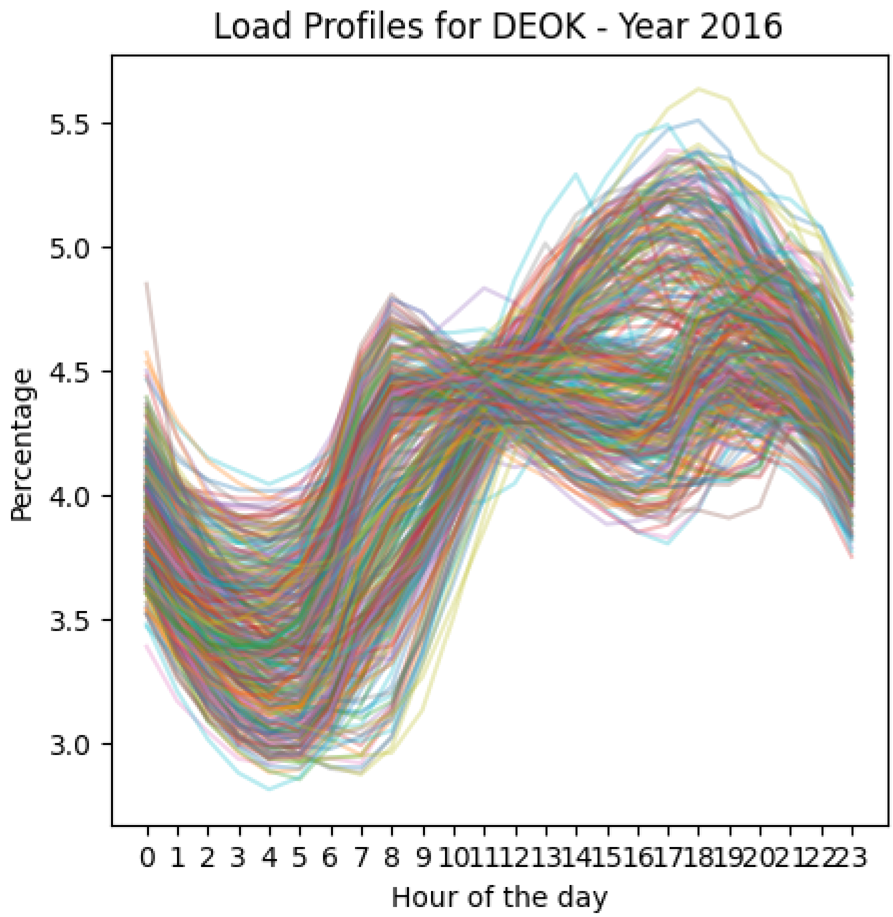
First we plot the nominal values and see throughout 2016 when Duke Energy electricity was consumed. As is expected, it's highest in summer, but we do see some peak consumption during winter times. This is typically due to electric heating during cold seasons.

Next, we're looking at the timing of consumption across days, and we see a clear pattern between summer and non-summer days. This is typical for most utilities. While the timing shifts slightly between winter and shoulder months, there is a 2 timing peak, but summer is driven by pure heating loads in the afternoon.



Percentage Load Profiles or Load Shapes

If we think of the heat map being laid on its side and each row being a line graph, we get the plot below. Essentially we're overlaying each daily loade shape. While not done here, because it didn't turn out as nice, in R I would plot each line as a transparent grey stroke so that where there is significant overlap we can see darkening thickening lines. We would most likely see 2 or 3 patterns we would expect from the trends in the heat map above, and we kind of do see that.



Machine Learning and Modeling

0037

The next step is to see if we can automate, off a subset of the data, some dictionary of load shapes via unsupervised learning or clustering. In the past I've used versions of K-Means for identify centroids that are themselves "typical" load shapes we can then map to any daily load in the past or in the future. By doing this, we can have a catalog of load shapes that have embedded meaning, based on the timing of their consumption events.

Working with a researcher at Stanford, he came up with a 200 shape dictionary for this purpose.

Here, and because I'm just looking at one utility instead of a variety of 100,000s of households, we'll just look for a few prototypical shapes!

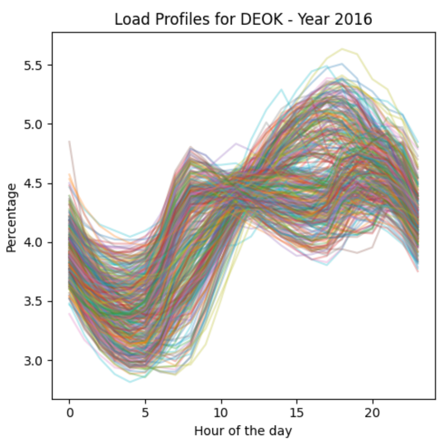
Processing

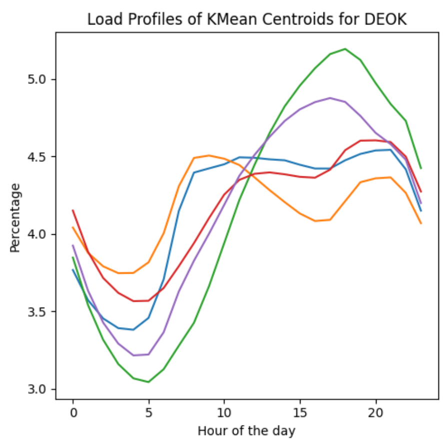
We access the original source dataframe and process out the given site across years, but take a random sample of daily instances and compute the daily percentages as before. Then we fit both a K-Means and DBSCAN model. Since DBSCAN does not return centroids we can use to represent the model, I take the cluster means as representatives for this purpose.

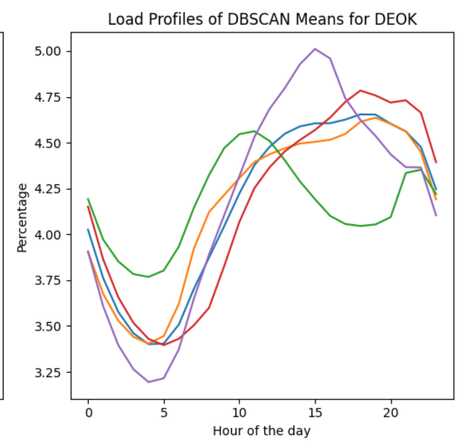
```
/home/codespace/.local/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

Visualizations

I plot the overlay graph from before, and the cluster representatives for comparison. There is a lot more that can be done here, to investigate goodness-of-fit, use out-of-sample test data, and evaluate the outliers in DBSCAN, which I've never used in practice, myself. But nevertheless, we do see a consistent picture of Duke Energy!







Statistical Modeling and Day Ahead Forecasting

0039

Taking a different turn on this day, we want to explore statistical modeling, and specifically something utilies have to do for purchasing energy is day ahead forecasting. This was an exercise I did years ago when I worked as a data scientist--I'm a data engineer now. Again we look at Duke Energy and this time for the summer of 2012. Instead of the wide-format dataset (hours in columns), we keep things as a simple time series (datetime and megawatts).

	read_dt	read_mw
0	2012-05-01 00:00:00	2671.0
1	2012-05-01 01:00:00	2456.0
2	2012-05-01 02:00:00	2324.0
3	2012-05-01 03:00:00	2254.0
4	2012-05-01 04:00:00	2187.0

	ds	y
0	2012-05-01 00:00:00	2671.0
1	2012-05-01 01:00:00	2456.0
2	2012-05-01 02:00:00	2324.0
3	2012-05-01 03:00:00	2254.0
4	2012-05-01 04:00:00	2187.0

Statistical Models

I use the ARIMA function, specifying the 24 hour seasonality. There is a lot more that goes into this analysis, and other seasonality periods to consider. For getting something out quick and dirty, the visuals show it turns out pretty good!

```
/home/codespace/.python/current/lib/python3.10/site-packages/statsmodels/tsa/base/tsa
_model.py:473: ValueWarning: No frequency information was provided, so inferred frequ
ency H will be used.
  self._init_dates(dates, freq)
/home/codespace/.python/current/lib/python3.10/site-packages/statsmodels/tsa/base/tsa
_model.py:473: ValueWarning: No frequency information was provided, so inferred frequ
ency H will be used.
  self._init_dates(dates, freq)
/home/codespace/.python/current/lib/python3.10/site-packages/statsmodels/tsa/base/tsa
_model.py:473: ValueWarning: No frequency information was provided, so inferred frequ
ency H will be used.
  self._init_dates(dates, freq)
```

```
2012-08-31 00:00:00    3303.470112
2012-08-31 01:00:00    3067.738536
2012-08-31 02:00:00    2893.161136
2012-08-31 03:00:00    2772.409085
2012-08-31 04:00:00    2715.242754
Freq: H, Name: predicted_mean, dtype: float64
```

Prophet Model

I asked Chappy (Chat-GPT) to give me ideas for this exercise, and he introduced me to Prophet. It was created at Facebook, and I really like how simple it is to feed it a time series (just name your columns ds and y, respectively), and it does the rest. Not only did it come up with an accurate model, it provides you a clean dataframe with the daily and weekly trends, plus confidence intervals. With a little code, it's easy to visualize them to your liking (or just plot the whole dataframe!)

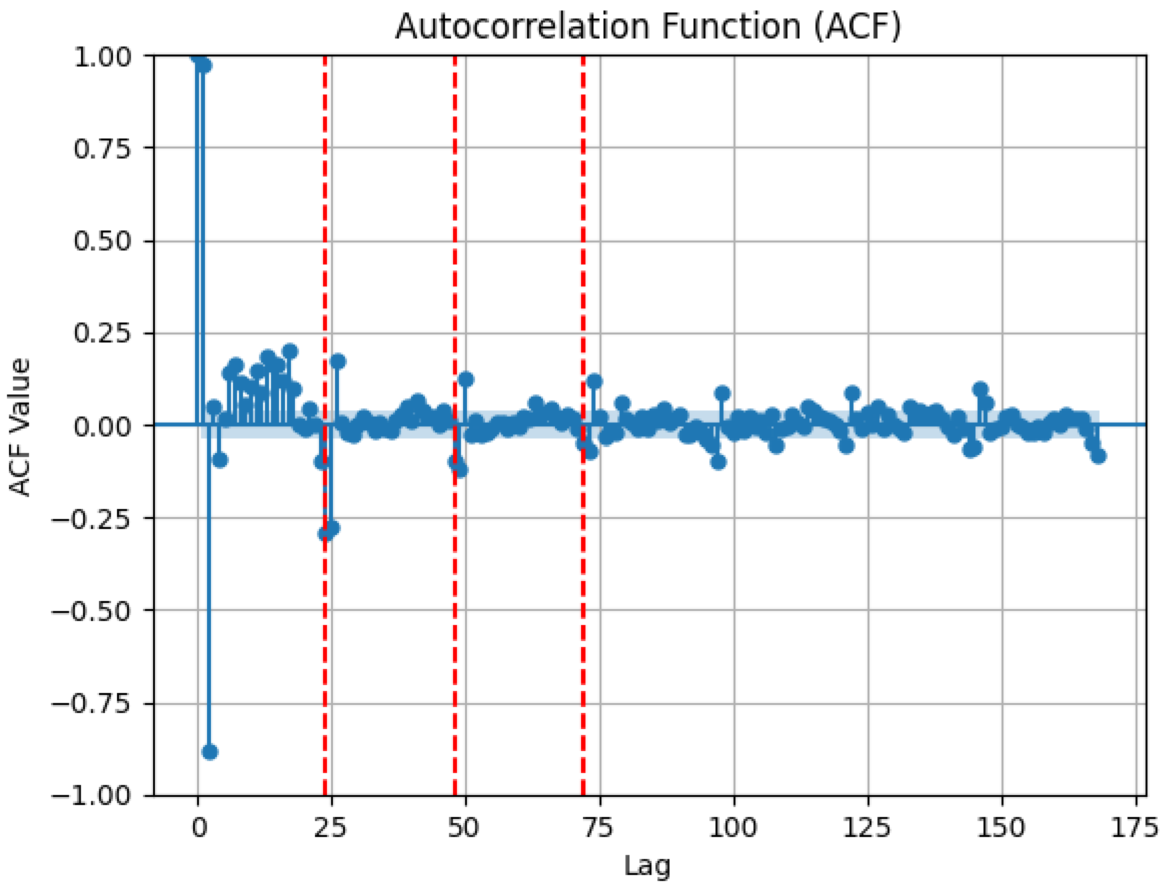
```
20:44:38 - cmdstanpy - INFO - Chain [1] start processing
20:44:38 - cmdstanpy - INFO - Chain [1] done processing
```

	ds	trend	daily	weekly	yhat
0	2012-05-01 00:00:00	3098.695050	-153.769740	140.509463	3085.434772
1	2012-05-01 01:00:00	3097.454209	-425.104049	138.371404	2810.721565
2	2012-05-01 02:00:00	3096.213369	-655.322827	135.572561	2576.463102
3	2012-05-01 03:00:00	3094.972528	-802.724572	132.170413	2424.418370
4	2012-05-01 04:00:00	3093.731688	-859.969972	128.226298	2361.988014

Exploration

While I didn't go into the deep analyses of identifying lags, nonstationarity, and seasonality frequencies (ugh), I did at least want to show how easy it is to look at the ACF or PACF (the one plottd here) graphs. There are models for these you can use to look at the data directly, but again, quick and dirty. I add the 24 hour lags for the last 3 days which nearly align to the 24 hour frequency I would expect and used in the ARIMA model.

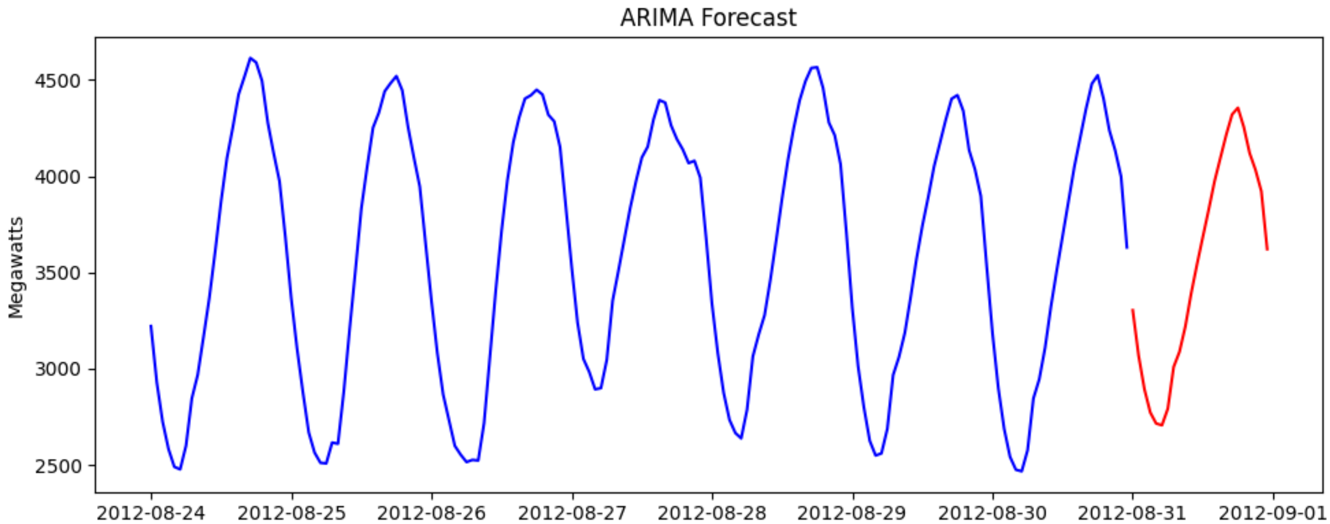
```
<Figure size 1200x600 with 0 Axes>
```

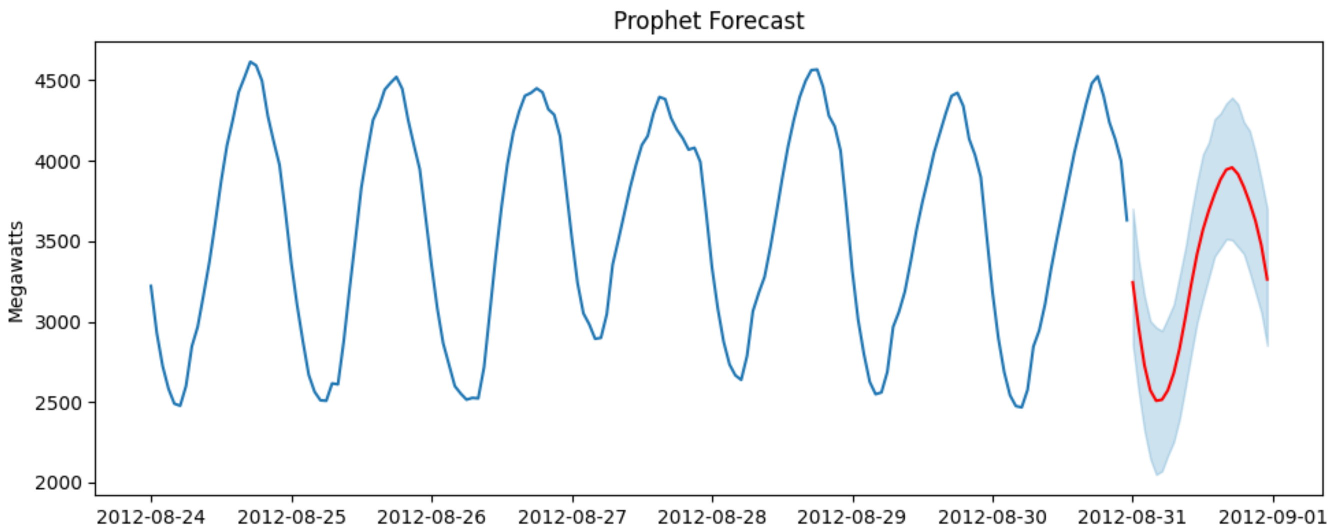


Forecasts

As we see below, I look at the last week of days to give some context. Using the whole summer would make this one day lookahead hard to see. It's very easy to plot either model results, and I simply split between plotting the last several days of the original time series and the day ahead foreast. Both tell a similar story, but the ARIMA model looks more like the confidence bounds of the Prophet model, which gives you a much nicer trend prediction.

I didn't explore it today, but you can also dig into the component decomposition of those different seasonality trends it has.





FIN

Let me know what you think! Follow me at GitHub (https://www.github.com/bryangoodrich) or Threads (@bryangoodrich.xyz).