Forecasting Energy Demand

Analysis and Predictive Modeling

Ryan Blauwaert

About Me

- Originally from Bloomfield Hills, Michigan
- Studied Evolutionary Anthropology and Economics
- Fields of interest include wildlife conservation, energy & resource economics
- Hobbies include:
  - Hiking
  - Soccer
  - Live Music
- Fun Fact: I lived in Southeast Asia for a year

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Motivation

Accurately forecasting electricity demand allows companies to:

- Make informed long-term business decisions such as building new power plants in response to increasing demand
- Better allocate resources such as labor from plant to plant
- Start and stop generators in response to anticipated demand
- Adjust load transmission in response to short-term demand fluctuations

Storing electricity for future use is extremely costly and inefficient. Therefore, it is important for electricity producers to generate only as much as is demanded by consumers.

The Data

The U.S. Energy Information Administration provides hourly energy demand data, measured hourly, from across the United States

These records span from July 1, 2015 to the retrieval date: March 21, 2021

An example of these data can be seen to the right

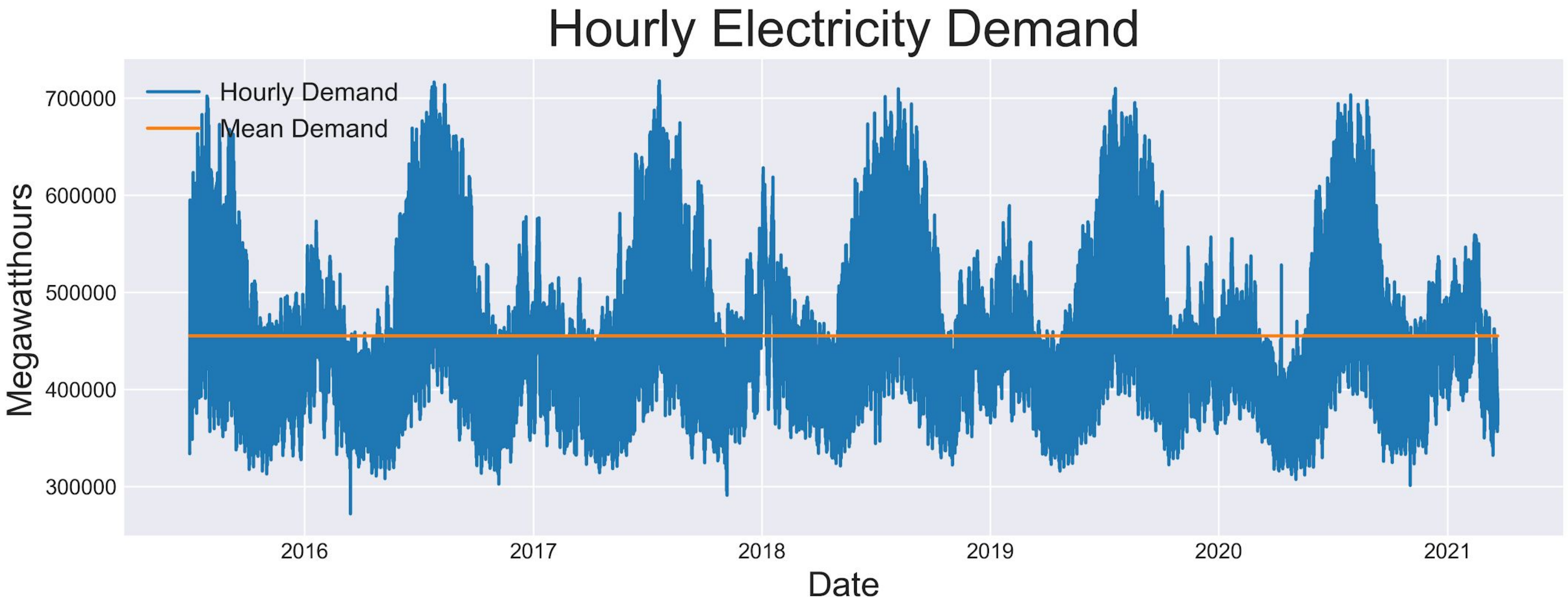
Time	Megawatthours
2015-07-01 02:00:00	335153
2015-07-01 03:00:00	333837
2015-07-01 04:00:00	398386
2015-07-01 05:00:00	388954
2015-07-01 06:00:00	392487

Featurizing the Data

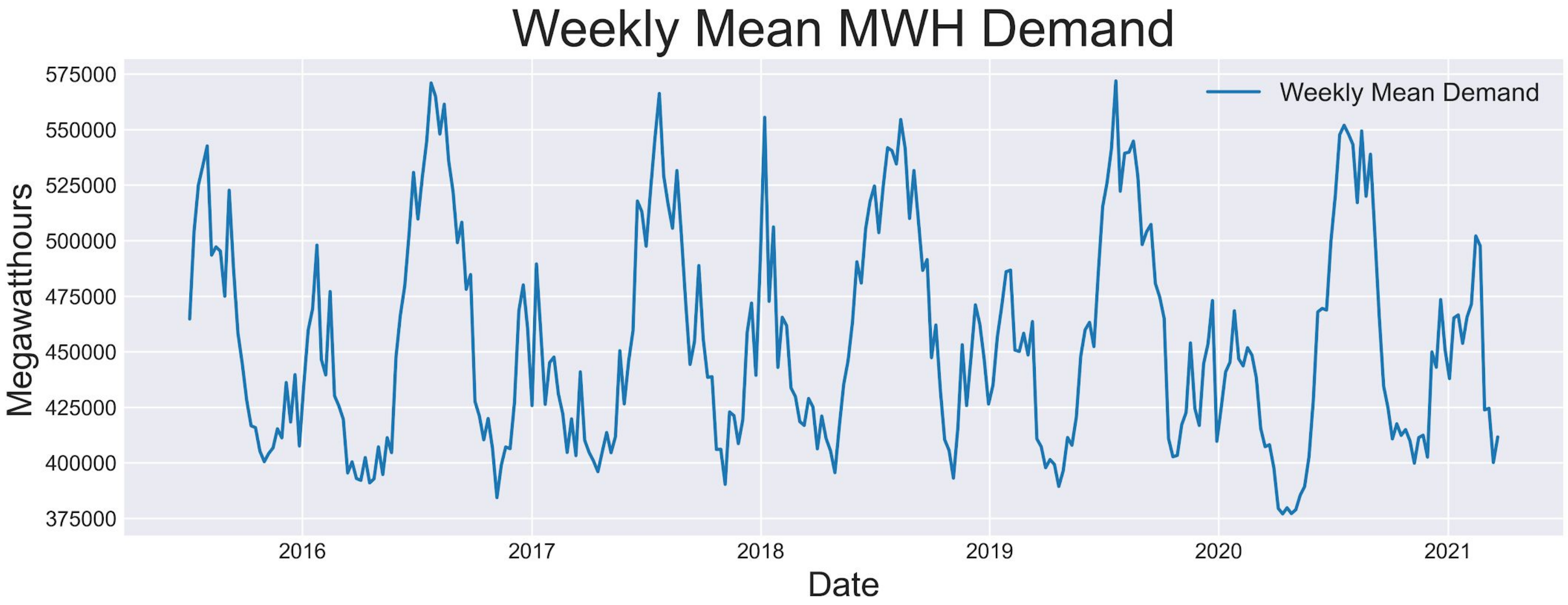
In order to better utilize these data, I created a number of time features as seen below:

Time	Megawatthours	Year	Month	Hour	Day of Week	Day of Month	Day of Year
2015-07-01 02:00:00	335153	2015	7	2	2	1	182
2015-07-01 03:00:00	333837	2015	7	3	2	1	182
2015-07-01 04:00:00	398386	2015	7	4	2	1	182

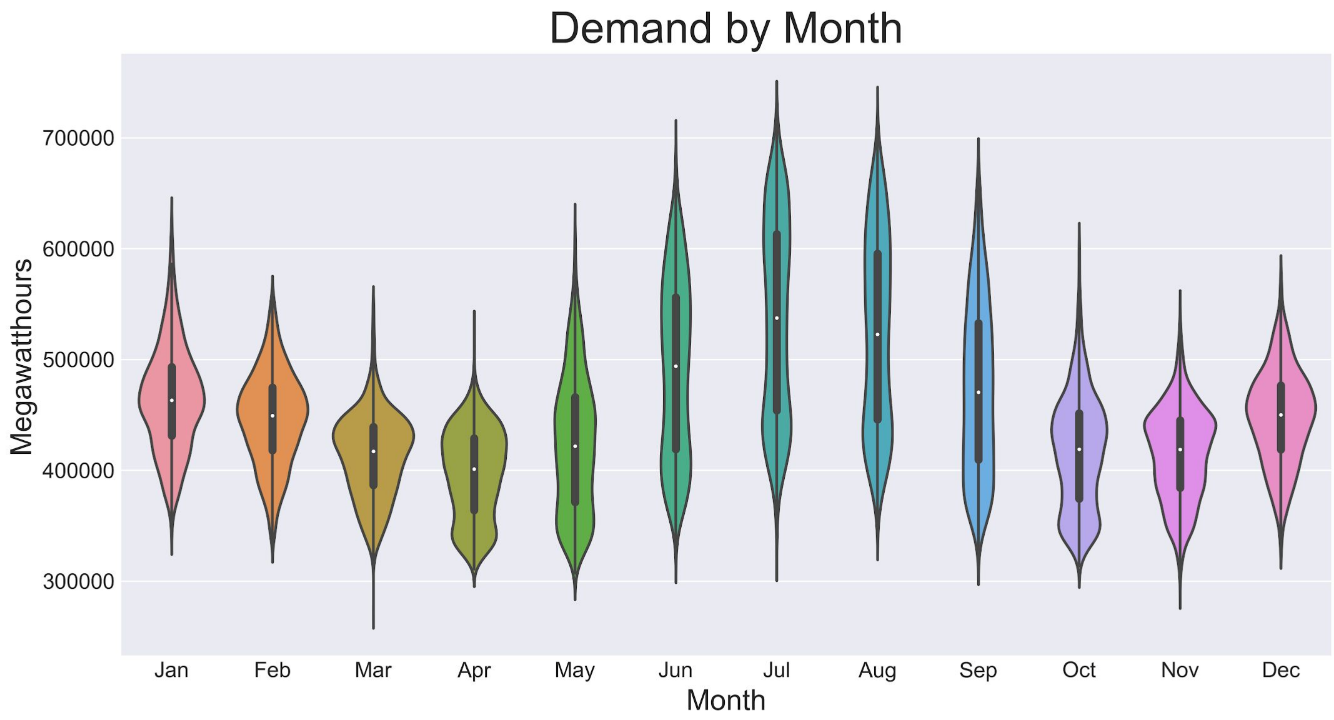
Visualizing the Data



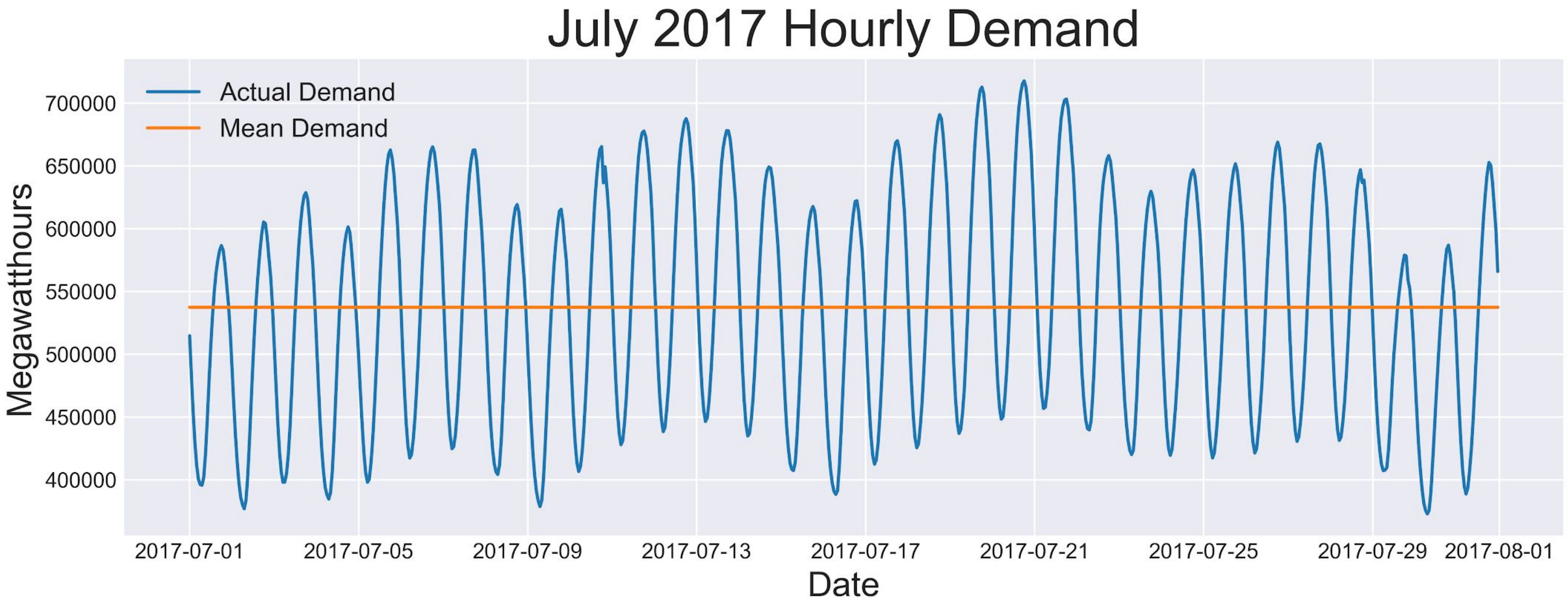
Visualizing the Data



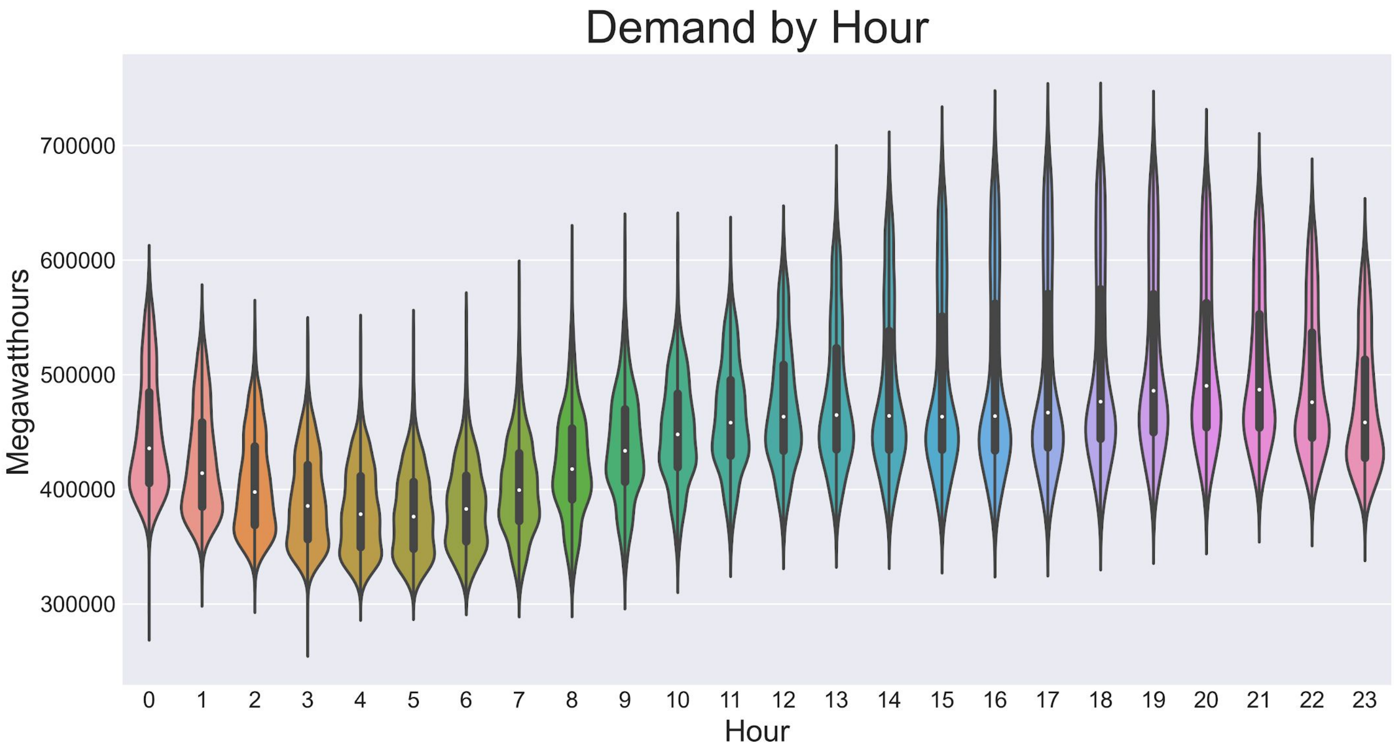
Visualizing the Data



Visualizing the Data



Visualizing the Data



Modeling

Models used:

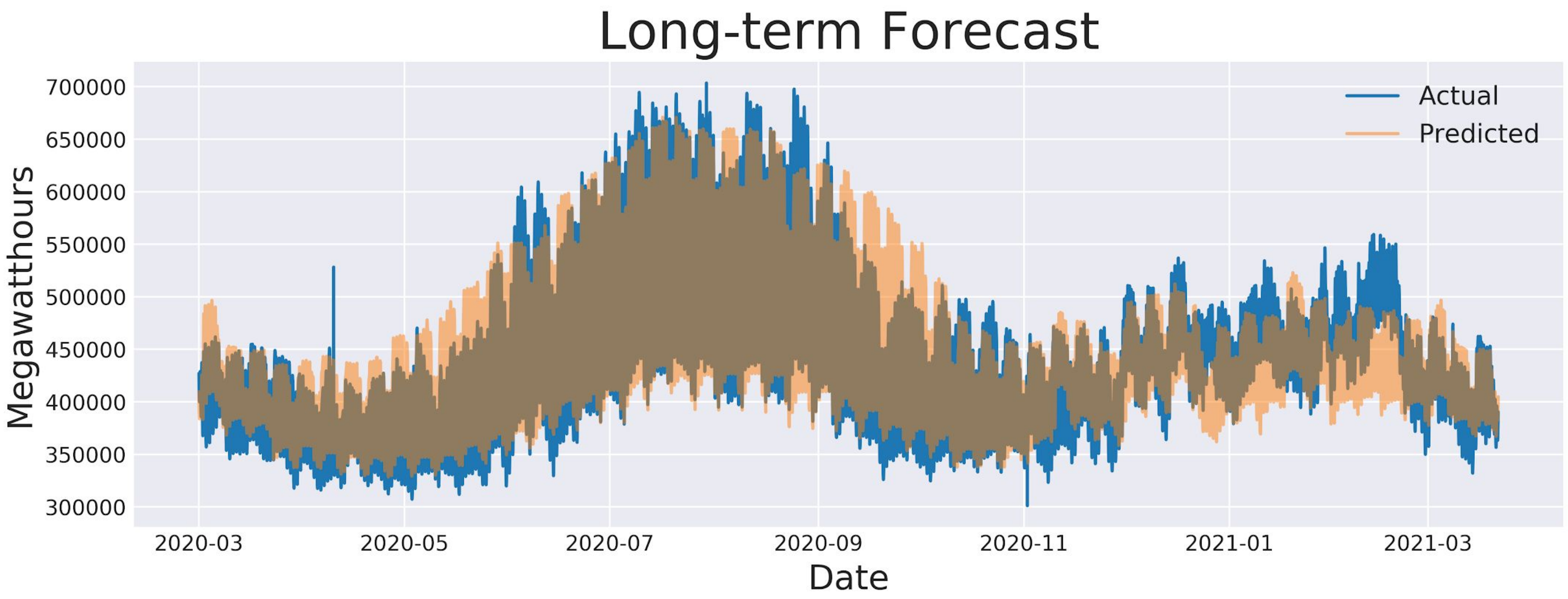
- XGBoost - Gradient Boosting Regressor
- Recurrent Neural Network using various lag metrics

It is important to make note of the error metric used to evaluate the prediction made by the following supervised learning models.

Mean Absolute Percent Error (MAPE) allows us to evaluate error from both over and under-estimation. It is also easily interpretable when working with large numbers.

As a point of comparison, the MAPE when predicting using mean electricity demand is 19.3%

XGBoost Model



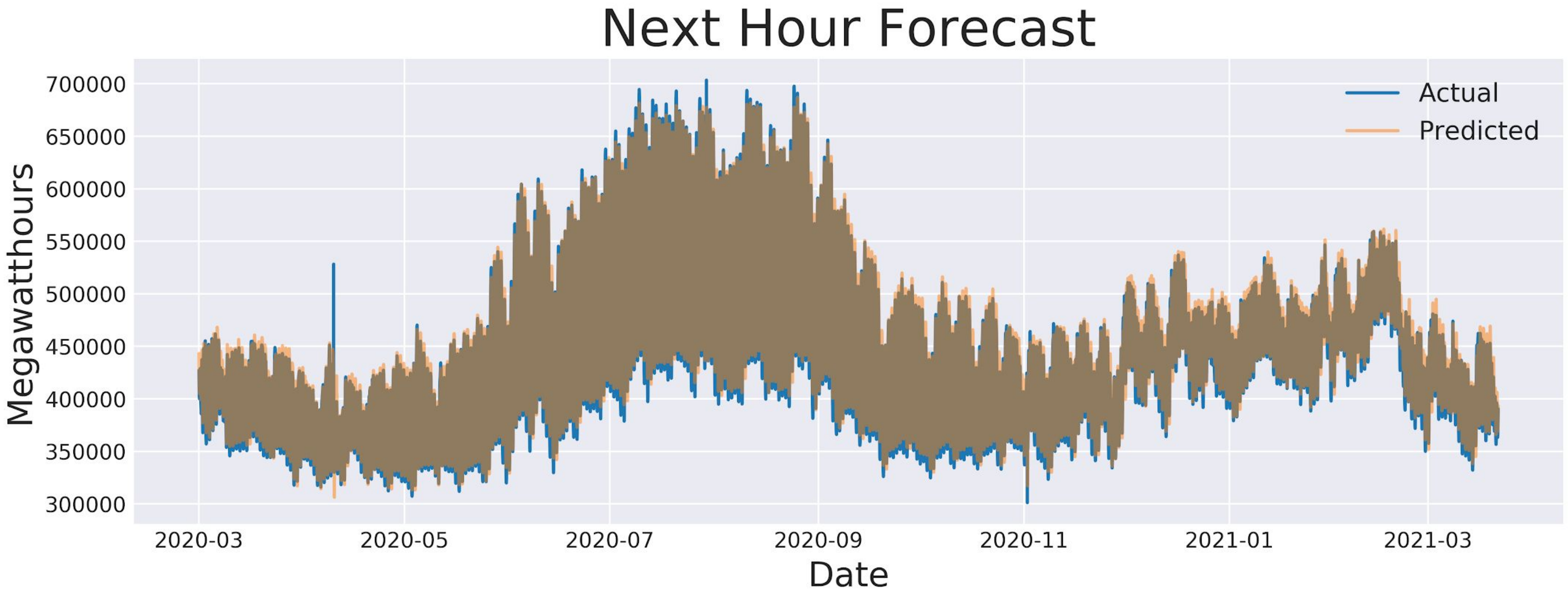
MAPE: 5.0%

Featurizing the Data for RNN

For use in the RNN, I created autoregressive features:

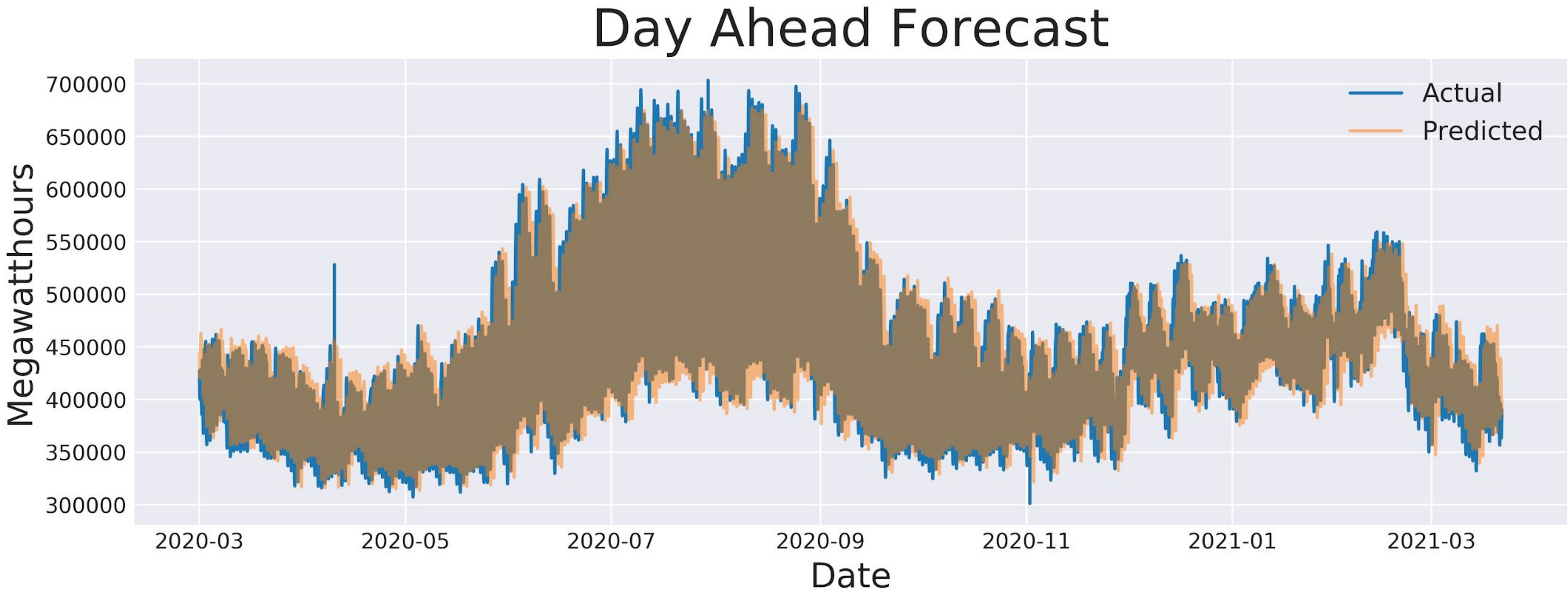
Time	**n-24**	**n-23**	**...**	**n-2**	**n-1**	**Megawatthours**
2015-07-01 02:00:00	335153	333837	...	48572	45284	429199
2015-07-01 03:00:00	333837	398386	...	453284	429199	407007
2015-07-01 04:00:00	398386	388954	...	429199	407007	395194

RNN Model - Next Hour



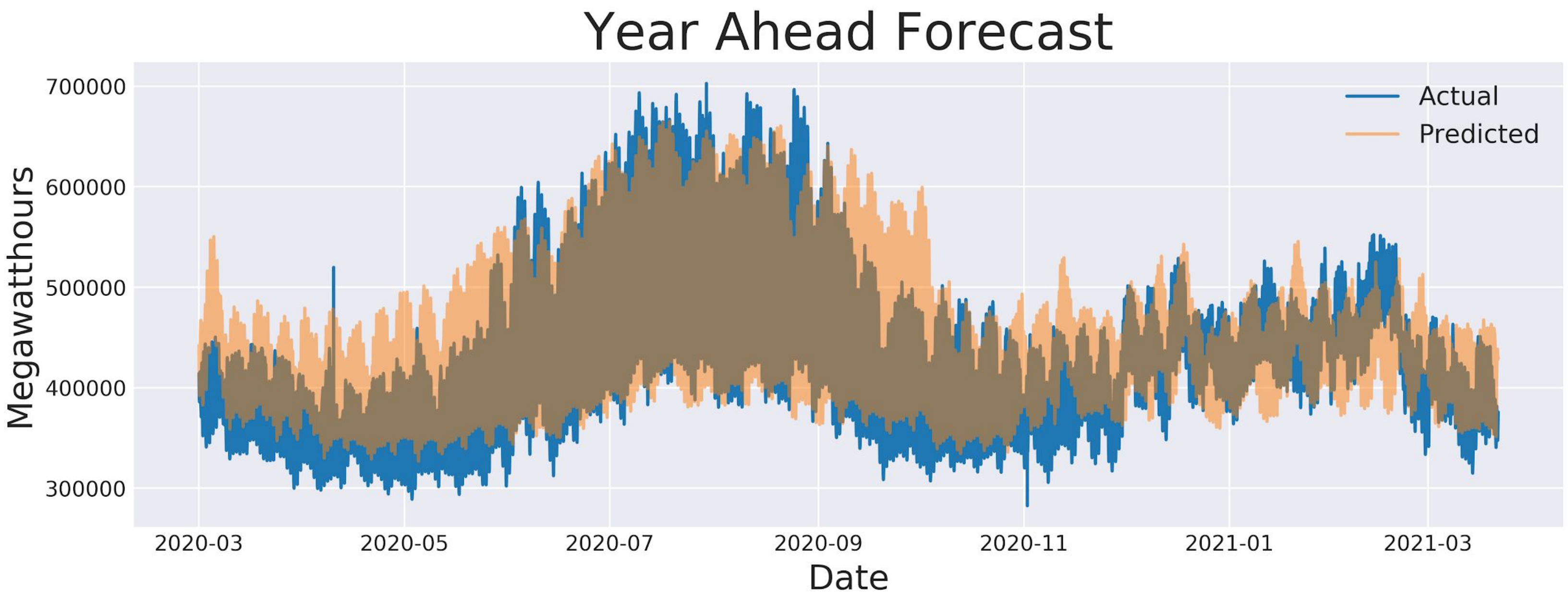
MAPE: 1.9%

RNN Model - 24 Hours Ahead



MAPE: 3.9%

RNN Model - 1 Year Ahead



MAPE: 8.9%

Conclusions

- All tested models outperformed our baseline predictions
- Autoregressive RNN performs best for short-term forecasting
- XGBoost performs best for long-term forecasting

Model	Error
5 Year Mean Prediction	19.3%
Time Feature XGBoost	5.0%
Next Hour RNN 24 Lag Features	1.9%
Day Ahead RNN 24 Lag Features	3.9%
Year Ahead RNN 24 Lag Features	8.9%

Directions for Further Analysis

- Incorporation of weather data to capture short-term fluctuations in demand
- Incorporation of additional historical data to assess long-term electricity demand trends
- Similar analysis and modeling of regional energy production and demand
- Incorporation of real-time electricity demand updates from the EIA website

Stay Tuned:

- github.com/ryan-blauwaert
- linkedin.com/in/ryanblauwaert