Forecasting New England Energy Consumption

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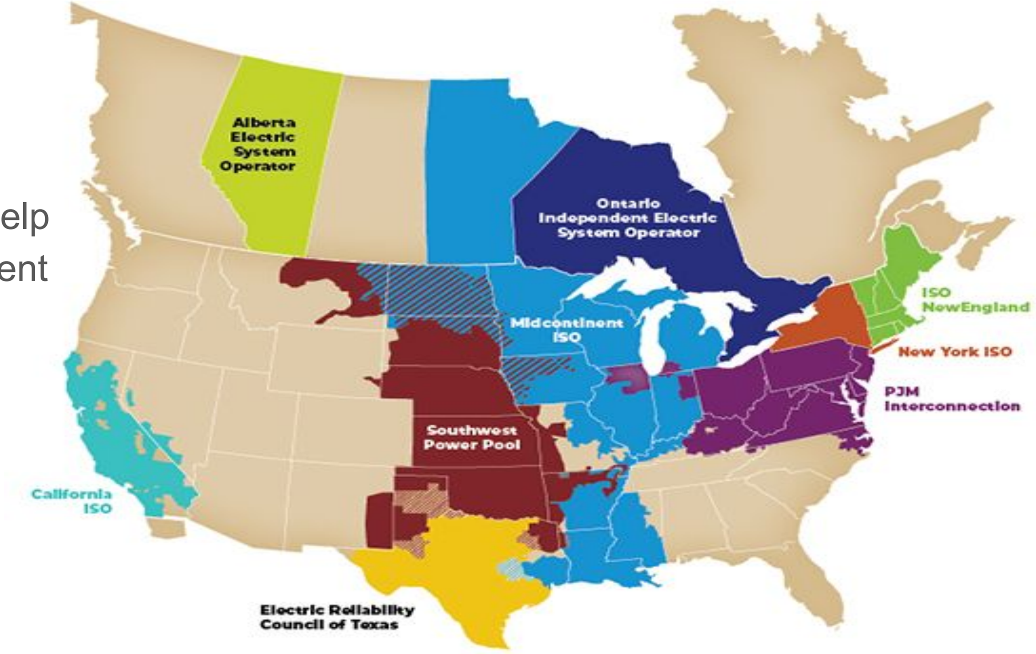
Project Motivation

Energy consumption forecasting is vitally important for energy companies and government agencies to properly hedge their assets and control prices.

An accurate prediction of rise and fall in the amount of power consumption for a region will help in maintaining the required workforce and augment the facilities ahead of time if a huge surge is expected in near future.



Project description and motivation

- Aim: Develop a methodology to forecast energy usage in the ISO New England (Nepool) region on an hourly basis for a period of 1 to 3 months
- Incorporate various parameters in the model which affect and influence energy consumption
  - Temperature
  - time of the day
  - day of the week
  - etc.
- Present a statistical comparison between two different model predictions.

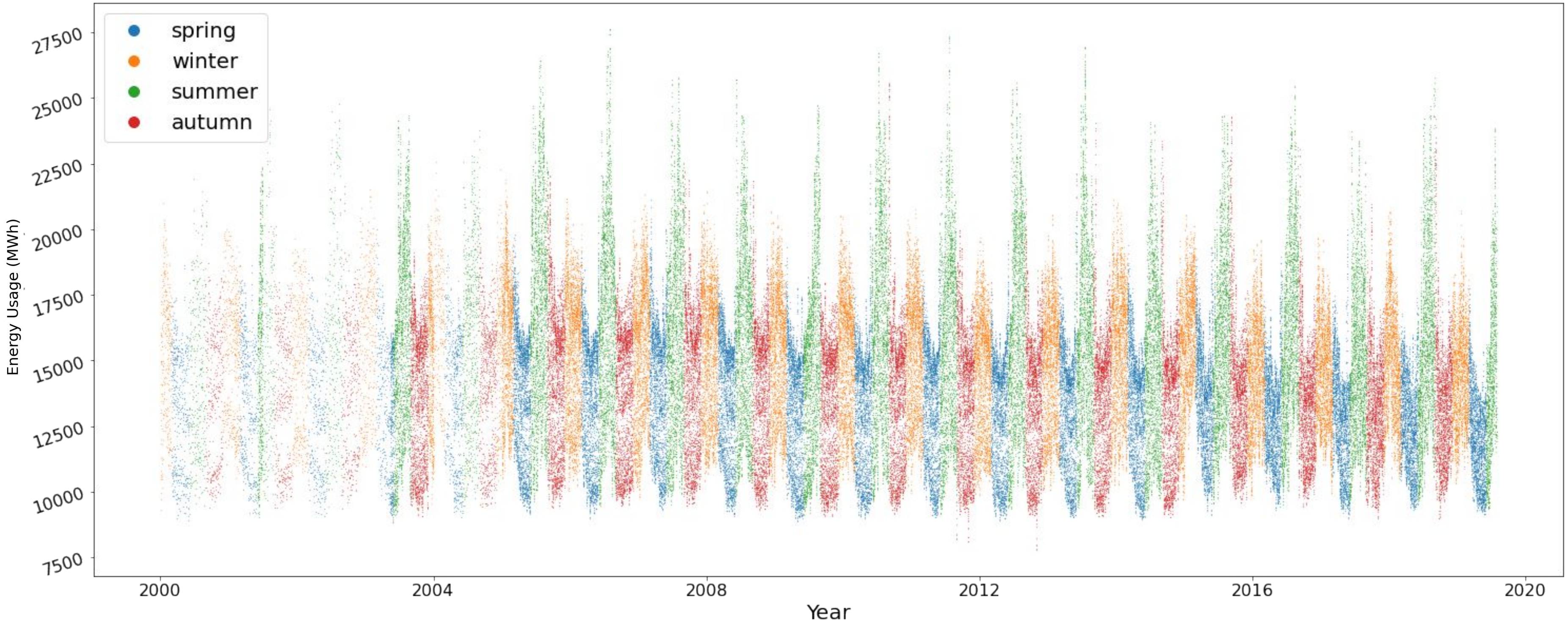
Data sources

- ISO New England
    - Net Energy peak and load data is released monthly
    - Dataset covers hourly energy load from January 1st, 2000 to July 29th, 2019
    - Features:
        - Energy Load (MW-hr)
        - Humidity Index (C)
- Climate Data Online (CDO)
    - Historical Boston weather data (hourly)
    - Potential weather features
        - Altimeter Setting (inches)
        - Temperature features (°F)
        - Precipitation (inches)
        - Relative Humidity (%)
        - Sea Level Pressure (inches)
        - Wind Speed (mph)

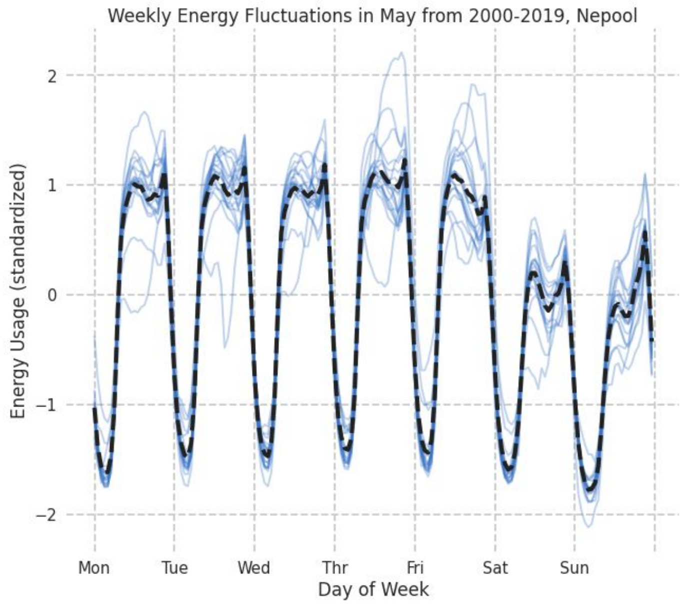
Structure of the final dataset

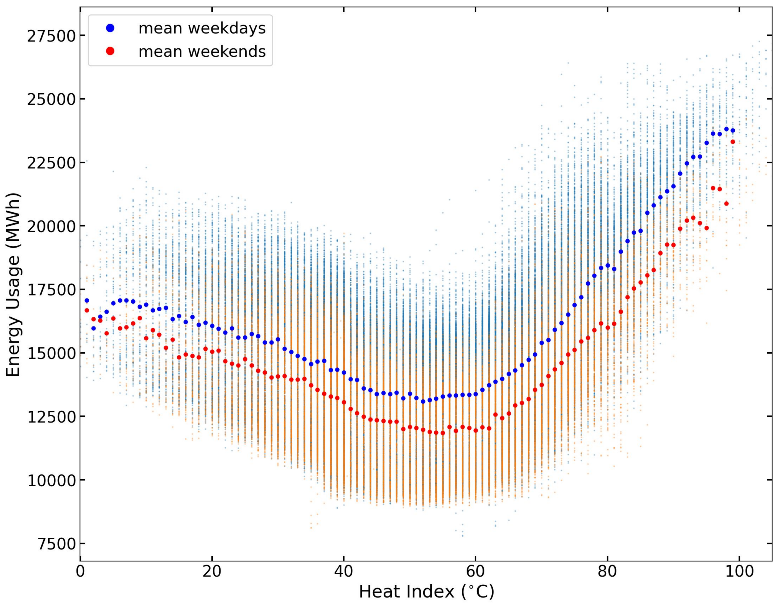
Date	Energy Load	Dew Point Temp	...	Humidity
2000-01-01 00:00:00	12849	30.18	...	66
2000-01-01 01:00:00	12513	30.18	...	69
2000-01-01 02:00:00	12531	30.18	...	66

Data Exploration - Yearly seasonality

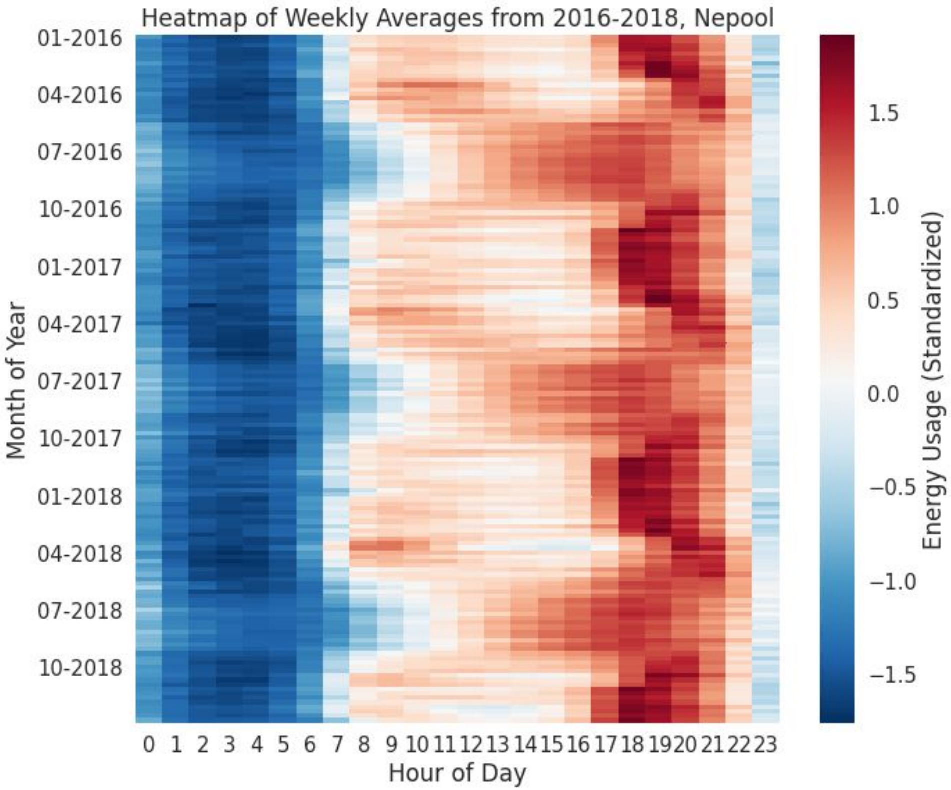


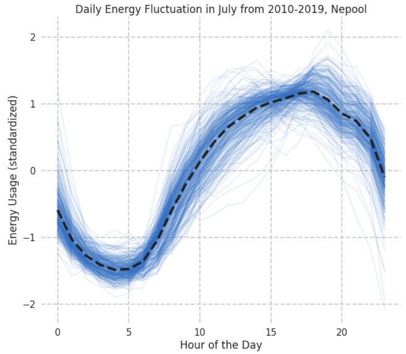
Data Exploration - Weekdays vs. Weekends

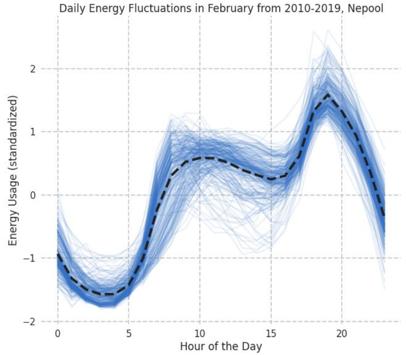




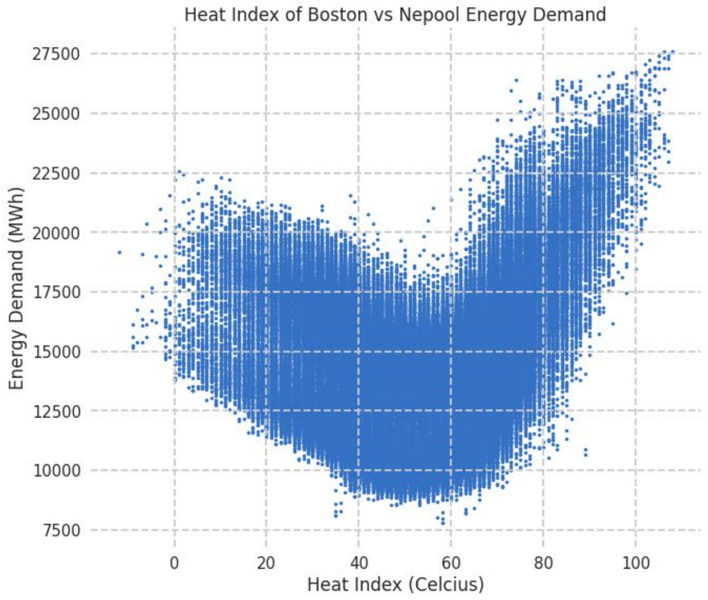
Data Exploration - Winter vs. Summer (daily)

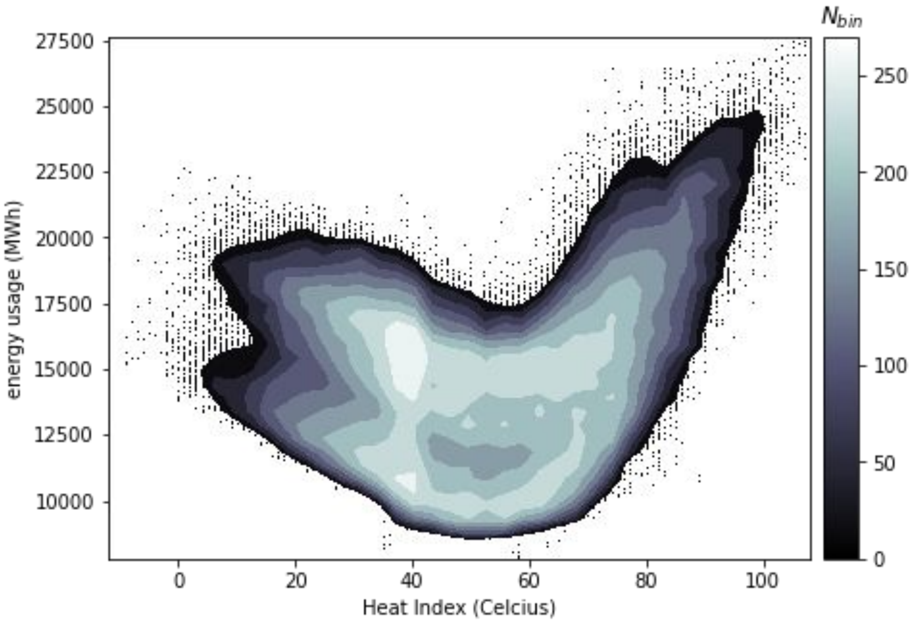






Data Exploration - Heat Index

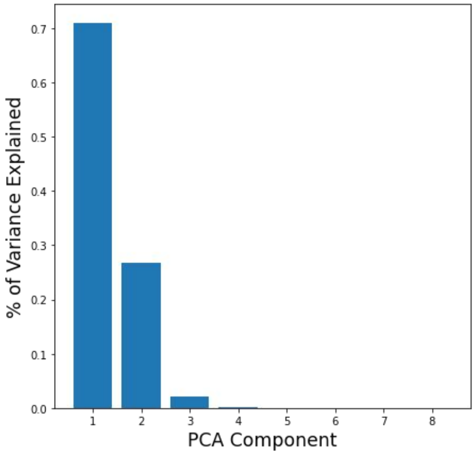


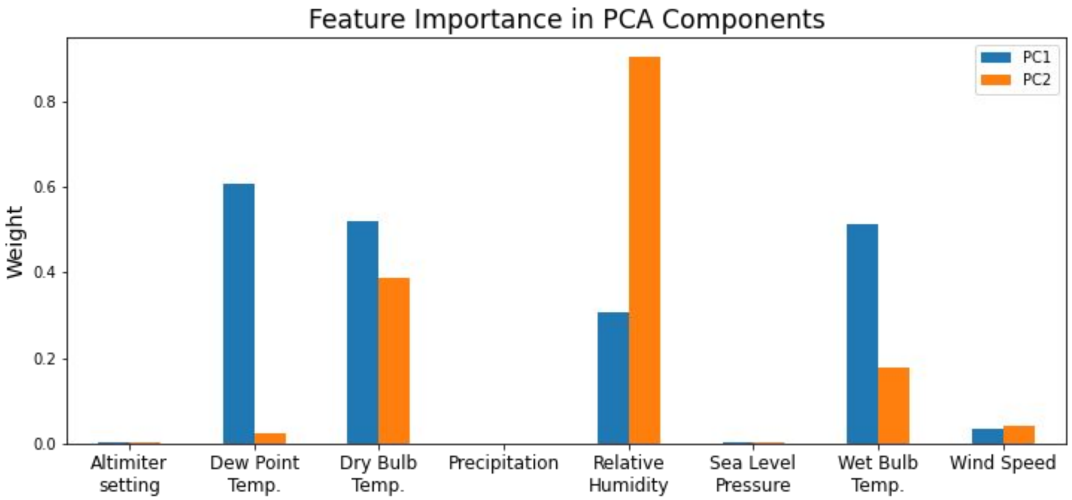


Relationship between energy consumption and Heat Index of Boston
for the period between 2001 and 2019

Principal Component Analysis (PCA)

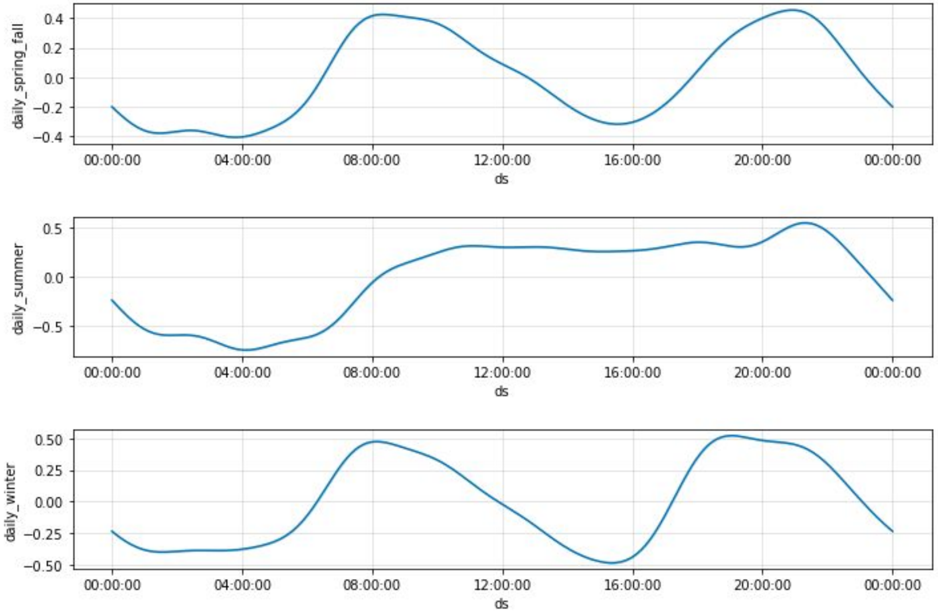
- The weather features were aggregated into fewer principal components.
  - The first 2 components explained 97.65% of the variance in the original dataset
  - Components dominated by humidity and temperature





Additive Regression with Facebook Prophet

- Model components
  - Daily seasonality
    - separate for winter, summer, and fall/spring
  - Weekly seasonality
  - Quarterly seasonality
  - Yearly seasonality
  - 2 weather principal component regressors
  - Holidays



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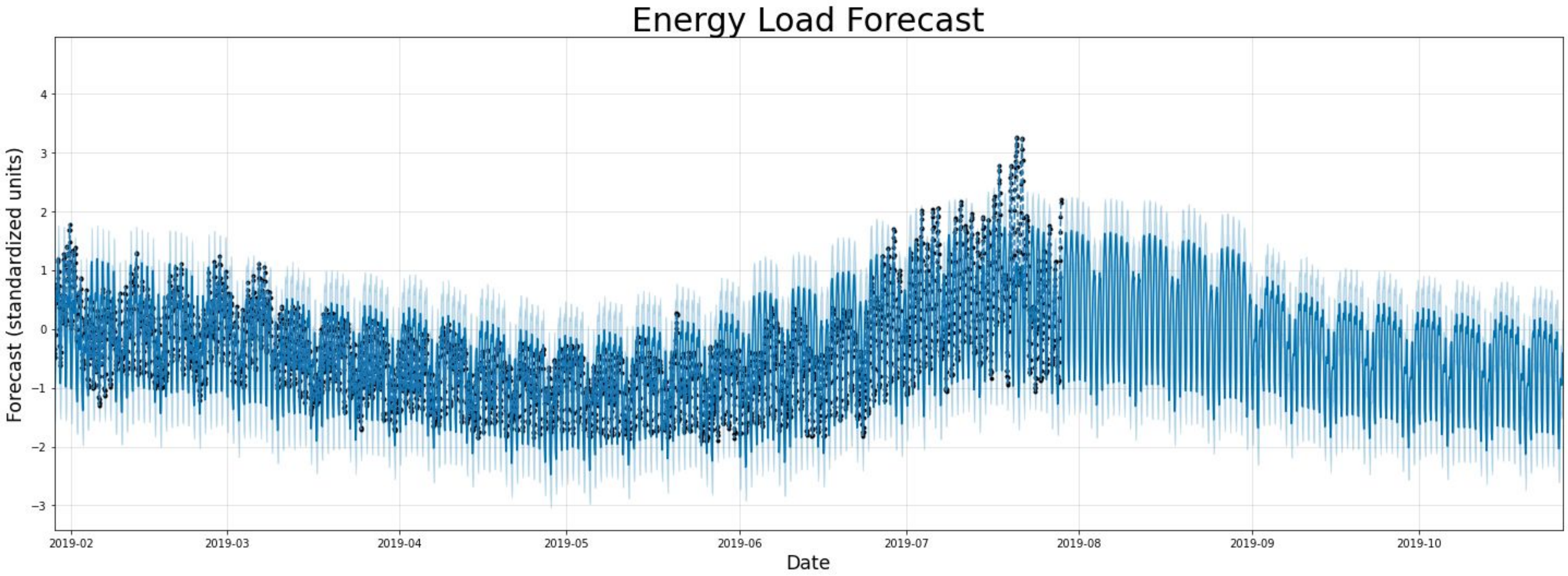
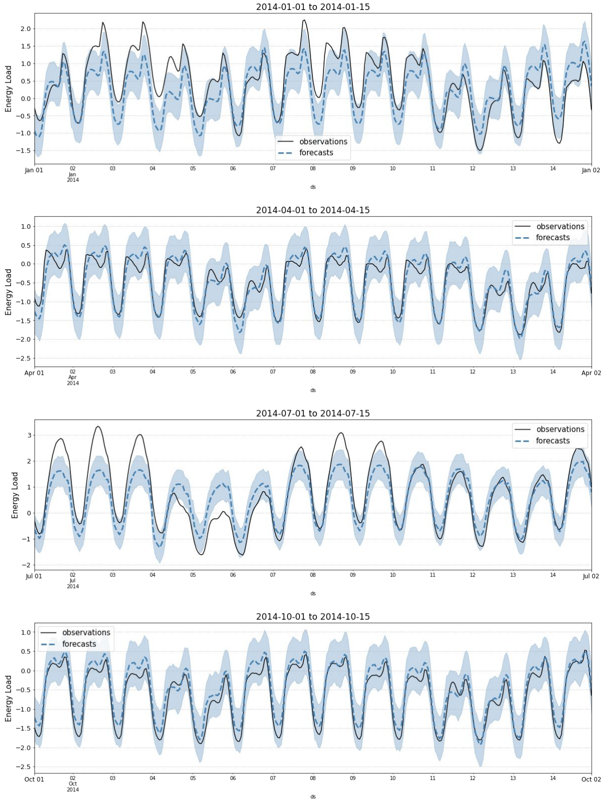
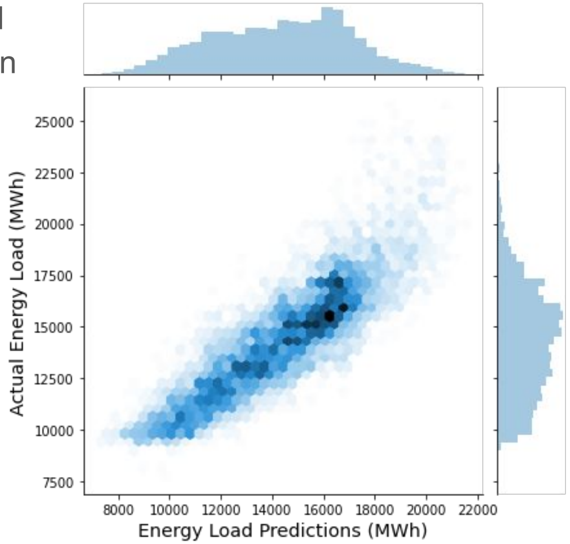


At a high level, we can see that the model was able to capture the general trend of the energy consumption and can predict 90 days into the future at the hourly level without blowing up.

Additive Regression with Facebook Prophet

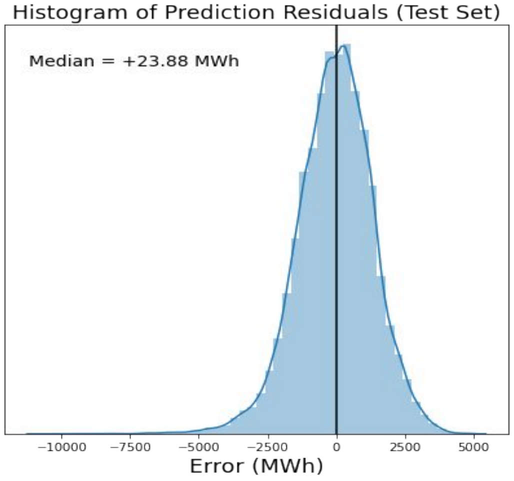


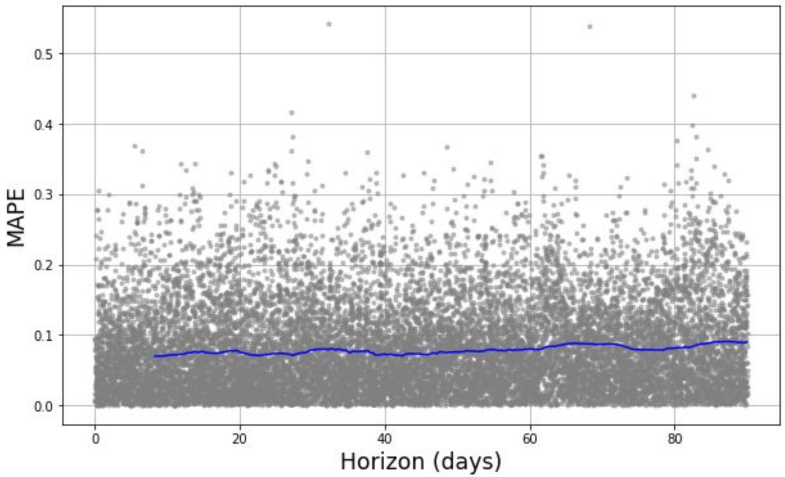
- The model was the best at predicting the spring and fall months
- The model was less accurate at predicting summer energy load
- The error was consistent across most of the energy load range
    - However, he model produced conservative predictions when there were actually large demand for energy consumption



Additive Regression with Facebook Prophet

- The errors were well behaved
  - Hourly mean absolute percent error (MAPE) of 7.45% for a 3-month forecast
  - Cumulative energy load MAPE of 2.35% for a 3-month forecast
- The error was consistent throughout the entire prediction period
  - Roughly the same error 10 days out and 80 days out





Additive Regression with Facebook Prophet

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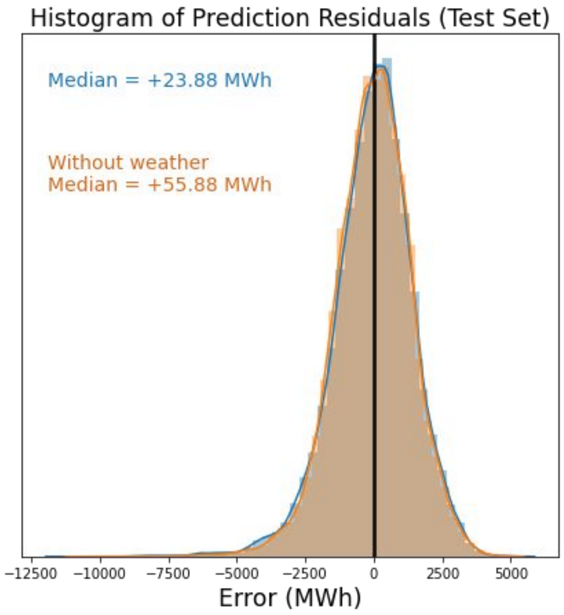
- The error was very similar in models that did not include weather

	Median Error (MWh)	Hourly MAPE	3-Month MAPE
With weather	23.88	7.45%	2.35%
Without weather	55.88	7.78%	2.32%

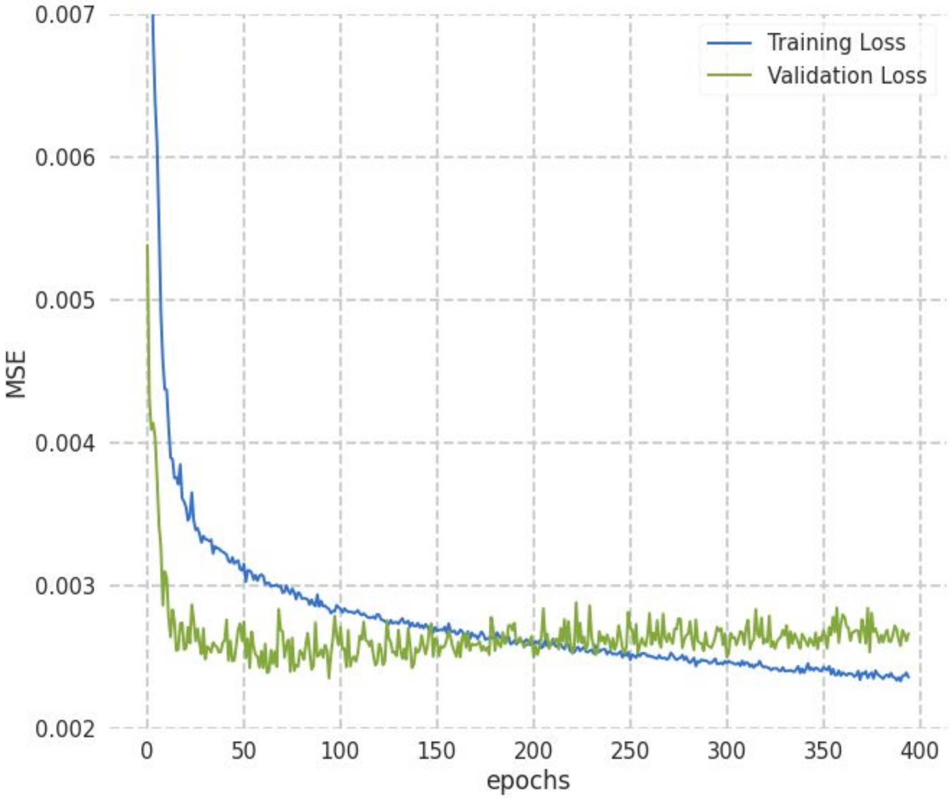


Feedforward Neural Networks - Structure

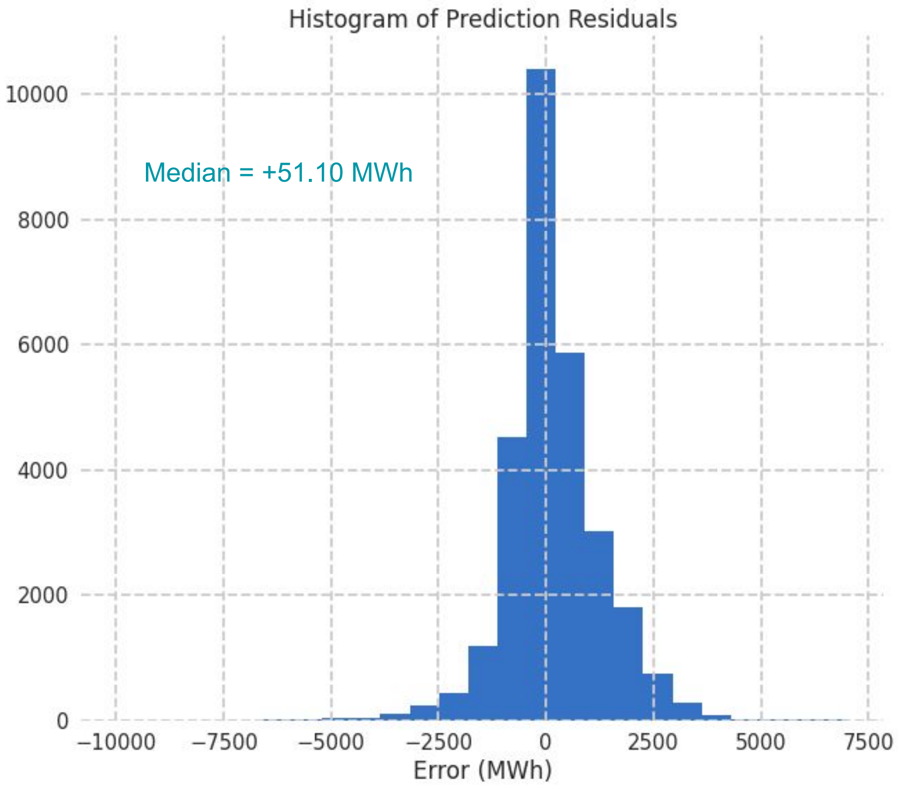
- Create dummy variables for each month, each hour, and holidays
- No PCA necessary
  - NNs approximate nonlinear mappings through learning
- 8 dense layers , with 4 dropout layers
  - Activation function: tanh
- Mean-squared error loss function
  - Suitable for a regression problem
- Training: Previous 5 years before validation
- Validation: Previous 2 months
- Testing: Upcoming 3 months
- NOTE: Cross validation was done on only 3 years of data

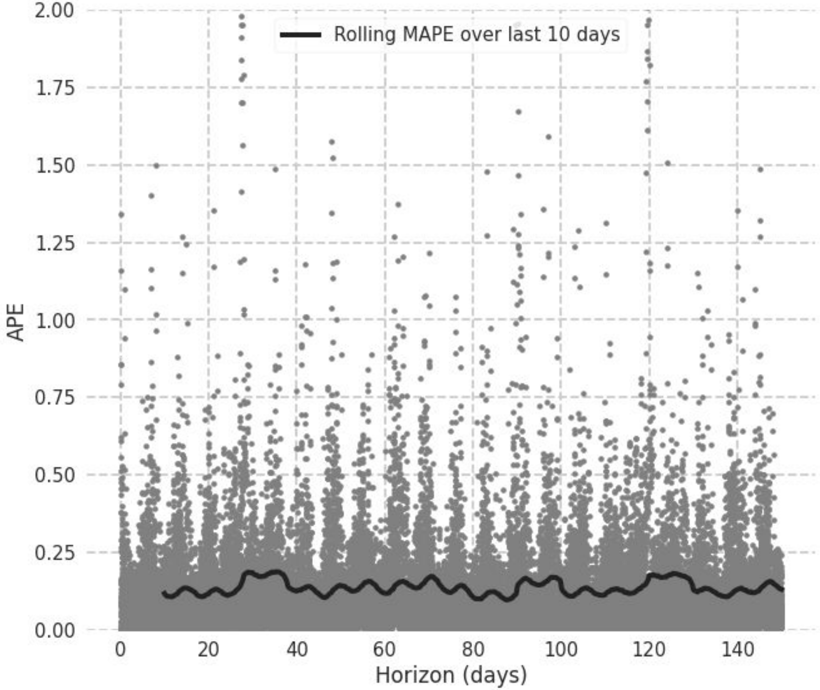
Feedforward Neural Networks - Training

- Training error will always decrease due to overfitting
- Goal: minimize model on validation data and restore weights calculated at that minimization



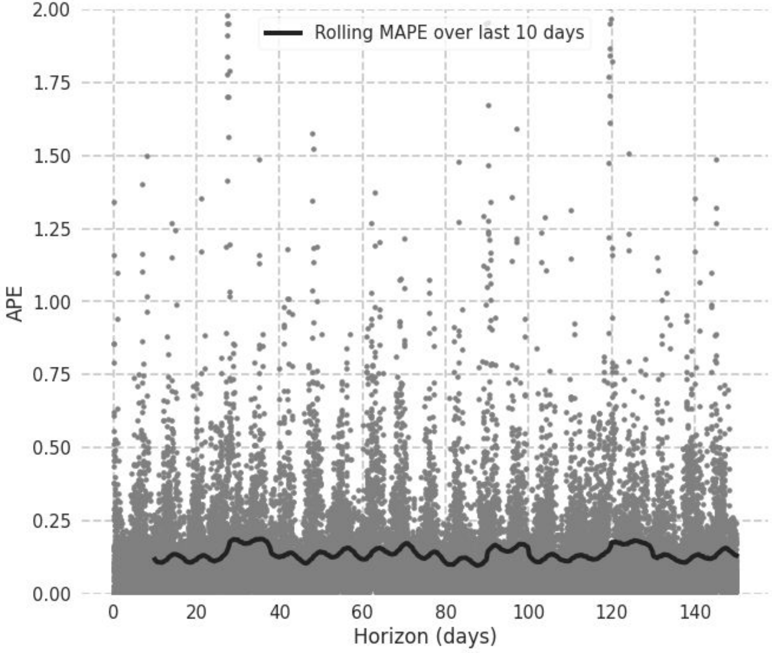
Feedforward Neural Networks - Results



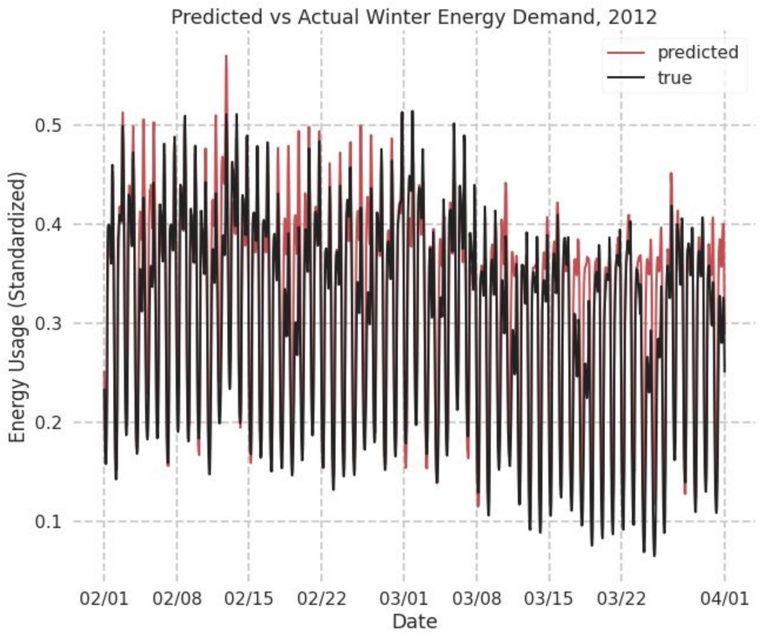


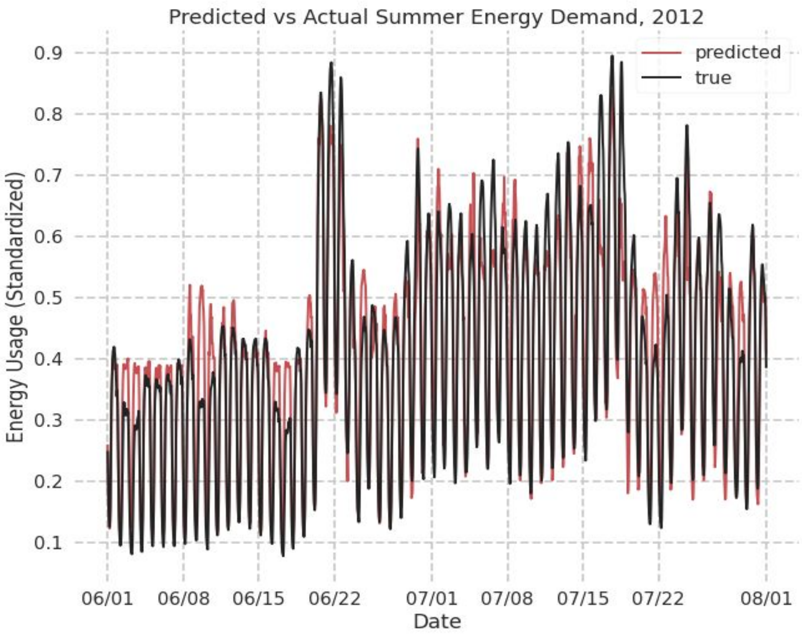
Feedforward Neural Networks - Results

- The errors were not as successful overall
  - Hourly MAPE of 13.5% for a 3-month forecast
    - Prophet achieved 7.45%
- The NN performed worse in the summer
  - Summer MAPE: 15.8%
  - Winter MAPE: 12.2%
- The error itself had an oscillatory behavior with visible bands.



Feedforward Neural Networks - Results





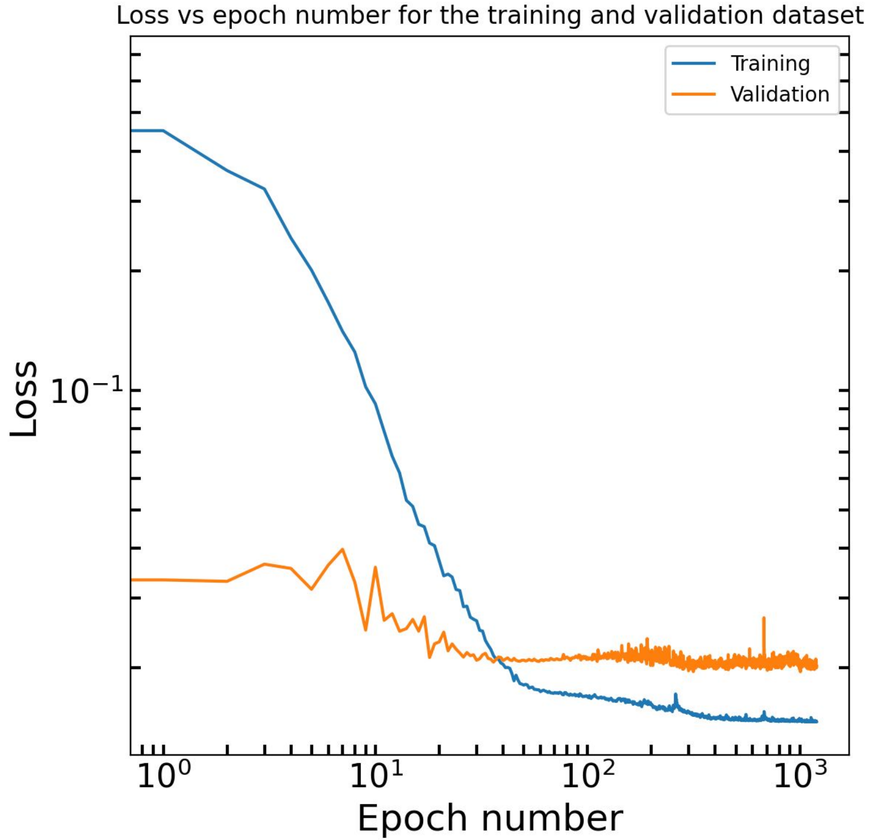
There is a high propensity for all fitted models to overpredict peaks

Feedforward Neural Networks - Issues

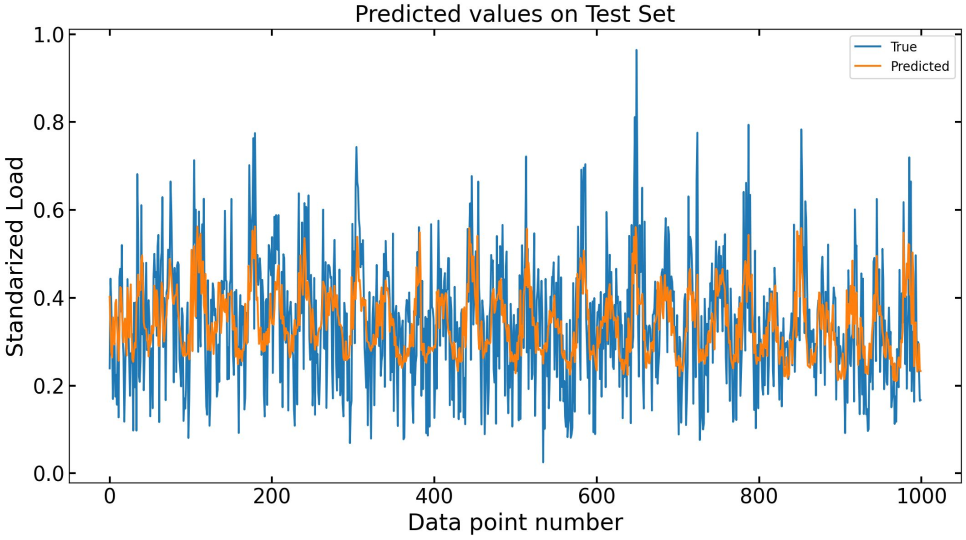
- Memory leak in the creation of the model prevented proper cross validation for more than 3 years
- Size of training and validation set
- Embargo Cross validation - prevent overfitting by leaving gap between training/validation
- Hyperparameter tuning:
  - Activation functions
  - Number of layers
  - Number of weights between layers

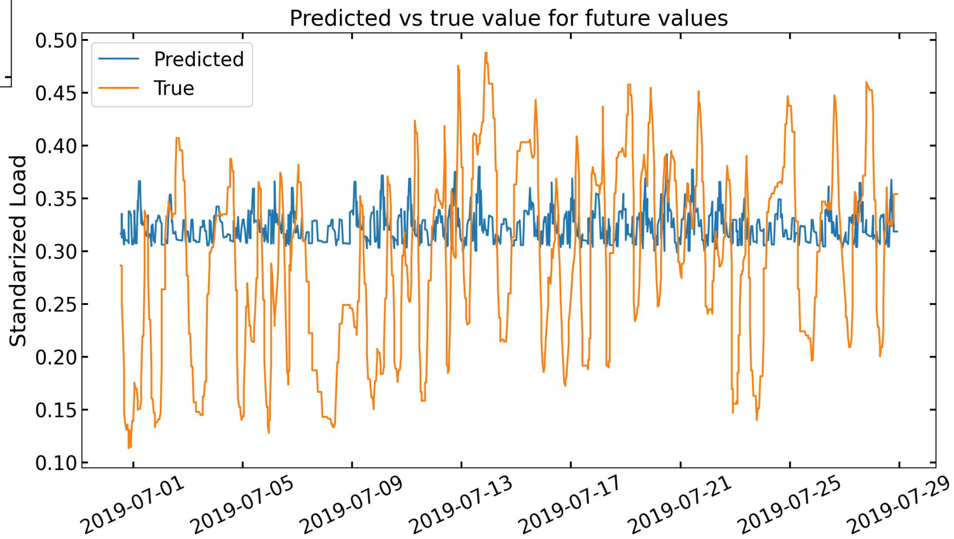
Recurrent Neural Network

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_6 (LSTM)                (None, 163, 128)          88576
_________________________________________________________________
dropout_8 (Dropout)          (None, 163, 128)          0
_________________________________________________________________
batch_normalization_6 (Batch (None, 163, 128)          512
_________________________________________________________________
lstm_7 (LSTM)                (None, 163, 128)          131584
_________________________________________________________________
dropout_9 (Dropout)          (None, 163, 128)          0
_________________________________________________________________
batch_normalization_7 (Batch (None, 163, 128)          512
_________________________________________________________________
lstm_8 (LSTM)                (None, 128)               131584
_________________________________________________________________
dropout_10 (Dropout)         (None, 128)               0
_________________________________________________________________
batch_normalization_8 (Batch (None, 128)               512
_________________________________________________________________
dense_4 (Dense)              (None, 32)                4128
_________________________________________________________________
dropout_11 (Dropout)         (None, 32)                0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 33
=================================================================
Total params: 357,441
Trainable params: 356,673
Non-trainable params: 768
_________________________________________________________________
None
```



Recurrent Neural Network





Conclusion: Probably not the best Neural Network method for this purpose

Moving Forward

- Improve cross-validation
  - Validate on more forecasting periods to confirm the robustness of the models
  - This is computationally very expensive, and thus limited in these results
- Expand forecasting
  - Obtain forecasted weather data as test data
  - Obtain uncertainty bounds for forecasted data to precisely evaluate test error ([1] [2])
- Larger sampling
  - Nepool is a large area
  - Room for improvement in both models by sampling weather data from different cities in Nepool besides Boston
- Transferability
  - Ultimate goal is to show our models can be transferred to different load series of different spatial scales

[1]: https://journals.sagepub.com/doi/abs/10.1260/0958-305X.21.8.969?journalCode=eaea
[2]: https://www.jstor.org/stable/520501?seq=1

Project roles

Data Manager	Jon Clifford
Methodology Manager	Desi Pilla
Communication Manager	Ramiz Qudsi
Visualization Manager	Ramiz Qudsi
Literature Manager	Jon Clifford