Harnessing Machine Learning for Predicting Consumption

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Incentive Program Evaluation

- Incentive programs are big business – averaging $24/customer in 2016 (EIA 2018)
- Verification of these program results is of major importance
- Current best practice requires a full year of consumption data both pre- and post-installation
- This practice necessitates a large gap in time before analysis can be performed
- Data requirements also exclude meters without a full year of data pre-installation
- Quicker verification would allow more timely adjustment of incentive amounts

Consumption Forecasting

- Physics-based models usually require detailed information
  - Typically unavailable
- Ideal is a model based only on past consumption data
- Machine learning models do not require knowledge of the statistical distribution of the data
- ML models use past observational patterns to implicitly handle trends, causality, etc.
- Tested two types of ML models: Random Forest and Long Short-term Memory Recurrent Neural Network

Consumption Data

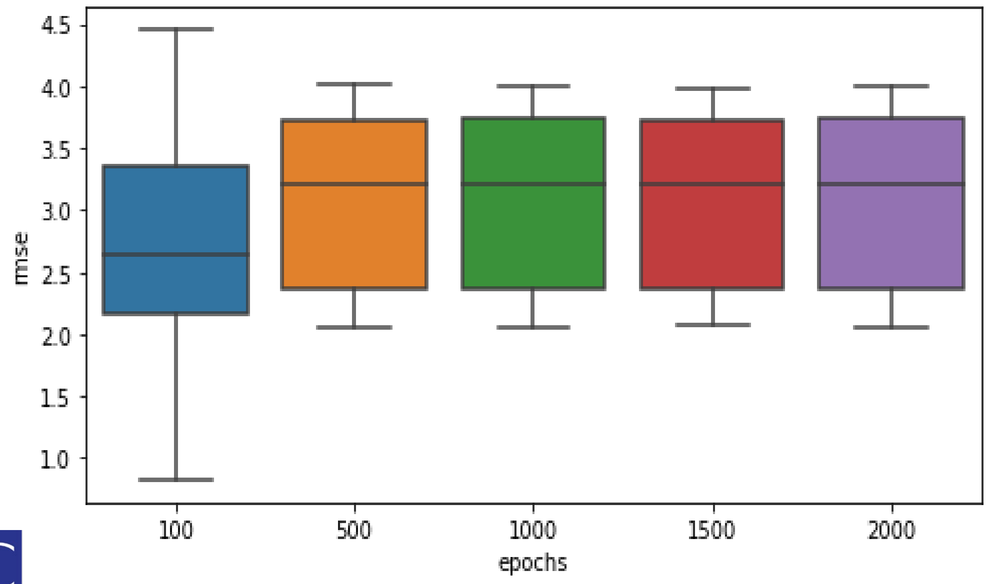
- Monthly data
  - Monthly billing records are still the most commonly available
  - Two years of available residential data
  - Test both as monthly and disaggregated to daily values
- Smart meter data (AMI)
  - Smart meter data are increasingly available
  - Almost two years of available residential data
  - 15-minute interval consumption data

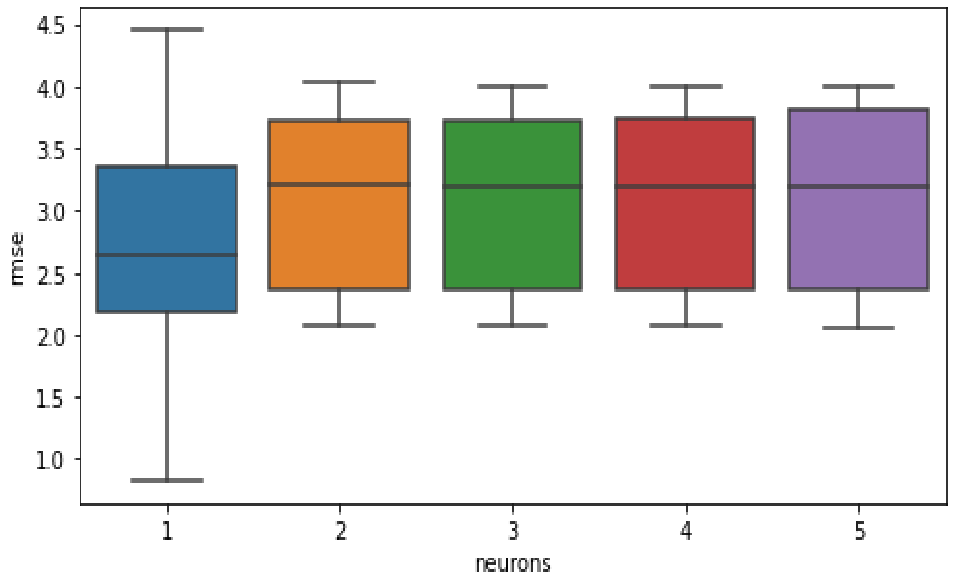
Weather Normalization

- Weather-normalized both data sets
  - Used hourly temperature data from nearest ASOS station
  - Calculated kWh per degree day
    - Heating: 65 degrees
    - Cooling: 75 degrees
- Because we won't have temperature data for forecast, most logical to predict weather-normalized values

Long Short-Term Memory (LTSM) Model

* Use two lagged values, 100 epochs, and 1 neuron





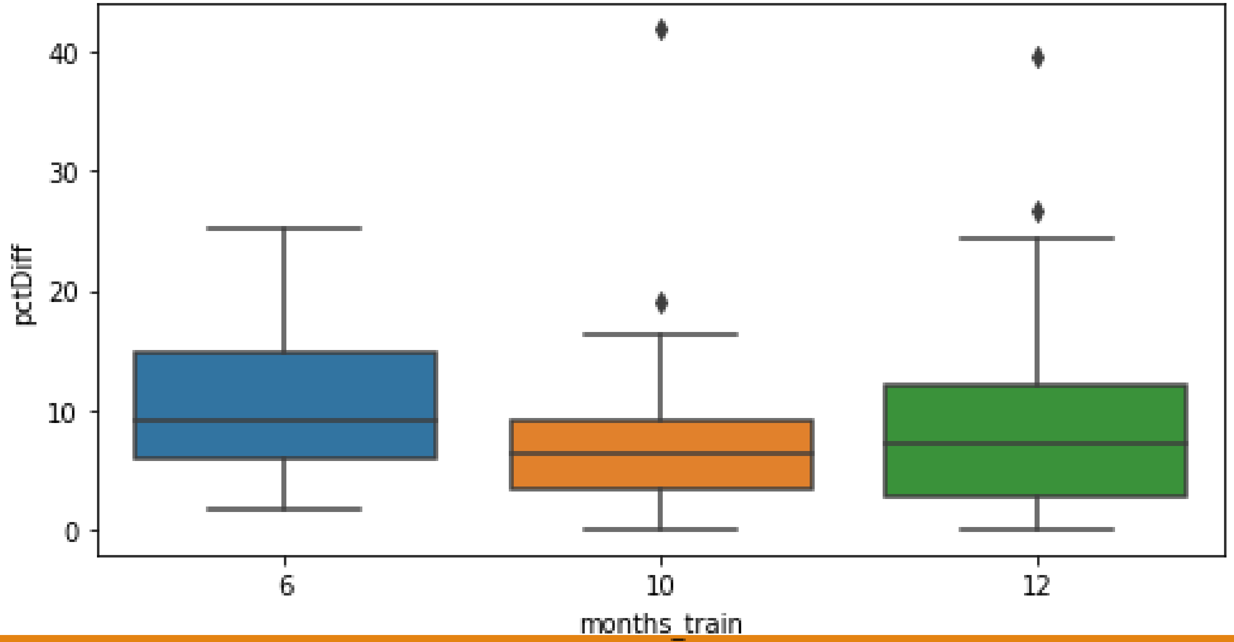
LSTM Model Results

- Monthly data disaggregated to daily has the worst model fit
- Interval data has the best fit, but it is not great on a per measurement basis

Months Training	Monthly RMSE	Monthly R^2	Monthly disagg RMSE	Monthly disagg R^2	Hourly RMSE	Hourly R^2
6	2.0	0.39	2.9	0.38	1.8	0.66
10	1.9	0.54	3.0	0.39	1.7	0.68
12	2.0	0.52	2.9	0.44	1.6	0.68

LSTM Model Results (2)

- Goal: forecast accurately enough to capture the total consumption over the given period
- Percent difference in modeled interval test data has a mean of <10%



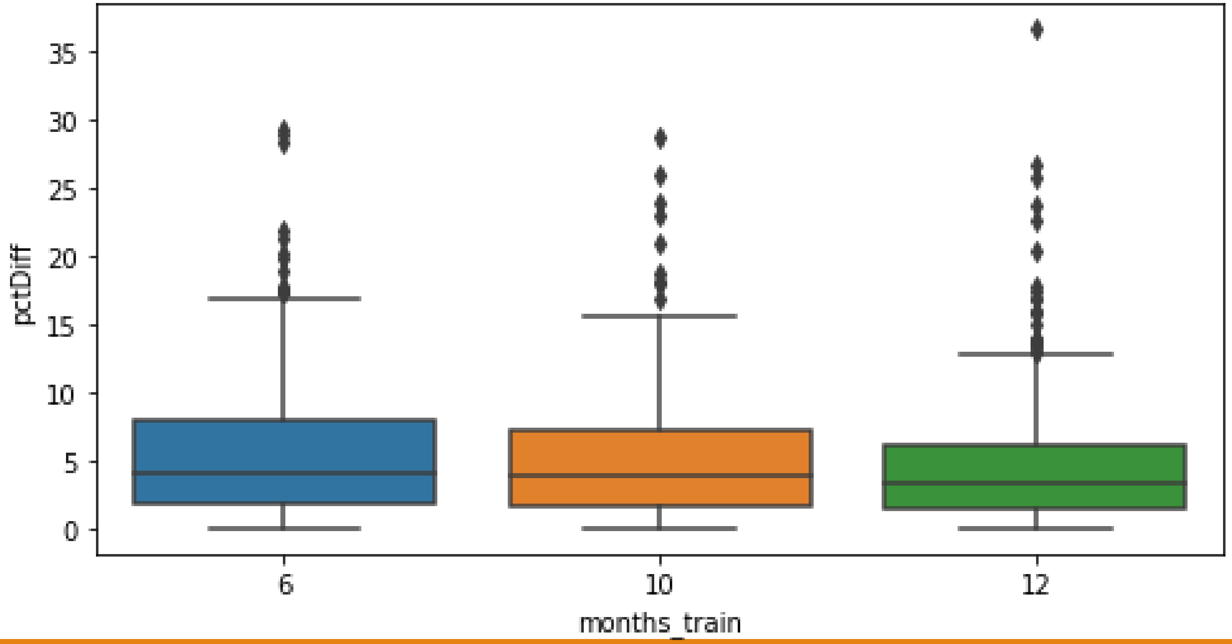
Random Forest Model

- Monthly data disaggregated to daily has the worst model fit
- Interval data has the best fit, but it is not great on a per measurement basis

Months Training	Monthly RMSE	Monthly R^2	Monthly disagg RMSE	Monthly disagg R^2	Hourly RMSE	Hourly R^2
6	2.3	0.02	3.2	0.27	1.8	0.63
10	2.0	0.45	3.2	0.34	1.6	0.67
12	1.9	0.59	3.2	0.39	1.6	0.67

Random Forest Model Results

- Goal: forecast accurately enough to capture the total consumption over the given period
- Percent difference in modeled interval test data has a mean of <5%



Conclusions

- Monthly data are not useful for accureatly forecasting consumption
- Disaggregation of monthly data did not improve, and sometimes worsened consumption forecasts
- Smart meter data showed promise for forecasting consumption data based on 6-months of values
- What level of error is acceptable?
- What percent change is generally expected for these incentive programs? Is it enough to be distinguishable outside of forecast error?

Future Exploration

- Investigate commonalities between residences with particularly large errors in forecast
- Try adding other features to the models
  - Past measurement distribution characteristics (e.g. mean, median)
  - Residence features (geolocation, house size, etc.)
- Run forecast using original 15-minute cadence rather than aggregating to hourly