Explaining and Predicting Price-Spikes in Real-Time Electricity Markets

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PREDICTING

MOTIVATION AND OBJECTIVE

- The electricity market is designed to ensure optimal generation and delivery of power. When the grid is under stress, price spikes may occur, yielding up to a 100-fold increase in the electricity price.
- This study utilizes a suite of supervised classification algorithms to predict the likelihood of a real-time price spike occurrence based on the weather, day-ahead market information, and temporal characteristics.

MODELS & FEATURES

3 BINARY CLASSIFICATION MODELS

I. Logistic regression

$$max \sum_{i=1}^{m} \hat{y}^i log y^i + (1-y^i)\log(1-\hat{y}^i) - \lambda\|\theta\|^2{}_2$$

II. Random forest classifier

$$min \sum_{i=1}^{m} l(y^i, \hat{y}^i) + \sum_{k=1}^{K} \Omega(f_k)$$

$$with\ \hat{y}^i = \frac{1}{K}\sum_{k=1}^{K} f_k(x^i)$$

$$and\ \Omega(f_k)\ is\ complexity\ of\ tree\ k$$

III. Gradient boosting classifier

$$\sum_{i=1}^{m}\left[g_i f_t(x_i) + \frac{1}{2} h_i f_t{}^2(x_i)\right] + \Omega(f_t)$$

$$with\ g_i = \partial_{\hat{y}^{t+1}} l(y_i, \hat{y}_i{}^{t-1}), h_i = \partial^2_{\hat{y}^{t+1}} l(y_i, \hat{y}_i{}^{t-1})$$

Optimized hyperparameters for each model to maximize overall accuracy, positive recall, and precision.

FEATURES AND TARGET

I. Weather
   i. Temperature, wind speed, relative humidity, dewpoint

II. Day Ahead Market
   ii. Load forecast and electricity price

III. Time *(cyclic and binary values)*
   iii. Hour of day, day of week, peak/off-peak, weekend/weekday, holiday

IV. Target - Price Spikes
   III. Defined arbitrary threshold and assigned binary tag to each sample

DATA

- 10 years of zonal hourly prices for ISO-NE
- NOAA weather data mapped to each ISO-NE zone
- Balanced dataset for training models
- Imbalanced datasets for predictions and scoring

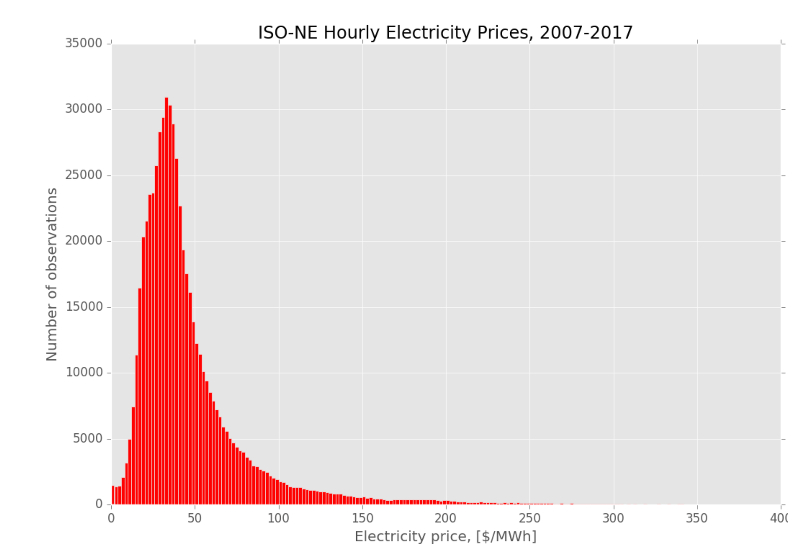

Figure 1. Distribution of hourly electricity prices from ISO-NE service territory.

RESULTS

Model	Training (m=26,640)	Test (m=30,000)
	Accuracy	Accuracy *(recall/score)*
Logistic Regression	88.90%	93.2% *(88.2%/.711)*
Random Forest Classifier	99.99%	94.46% *(97.0%/.764)*
Gradient Boosted Classifier	100%	95.1% *(97.2%/.777)*

MODEL PERFORMANCE:

- Gradient Boosted Classifier performed the best overall

Table 1. Performance of all three models as measured by accuracy, positive recall, and a composite score (arithmetic mean of the previous metrics and precision)

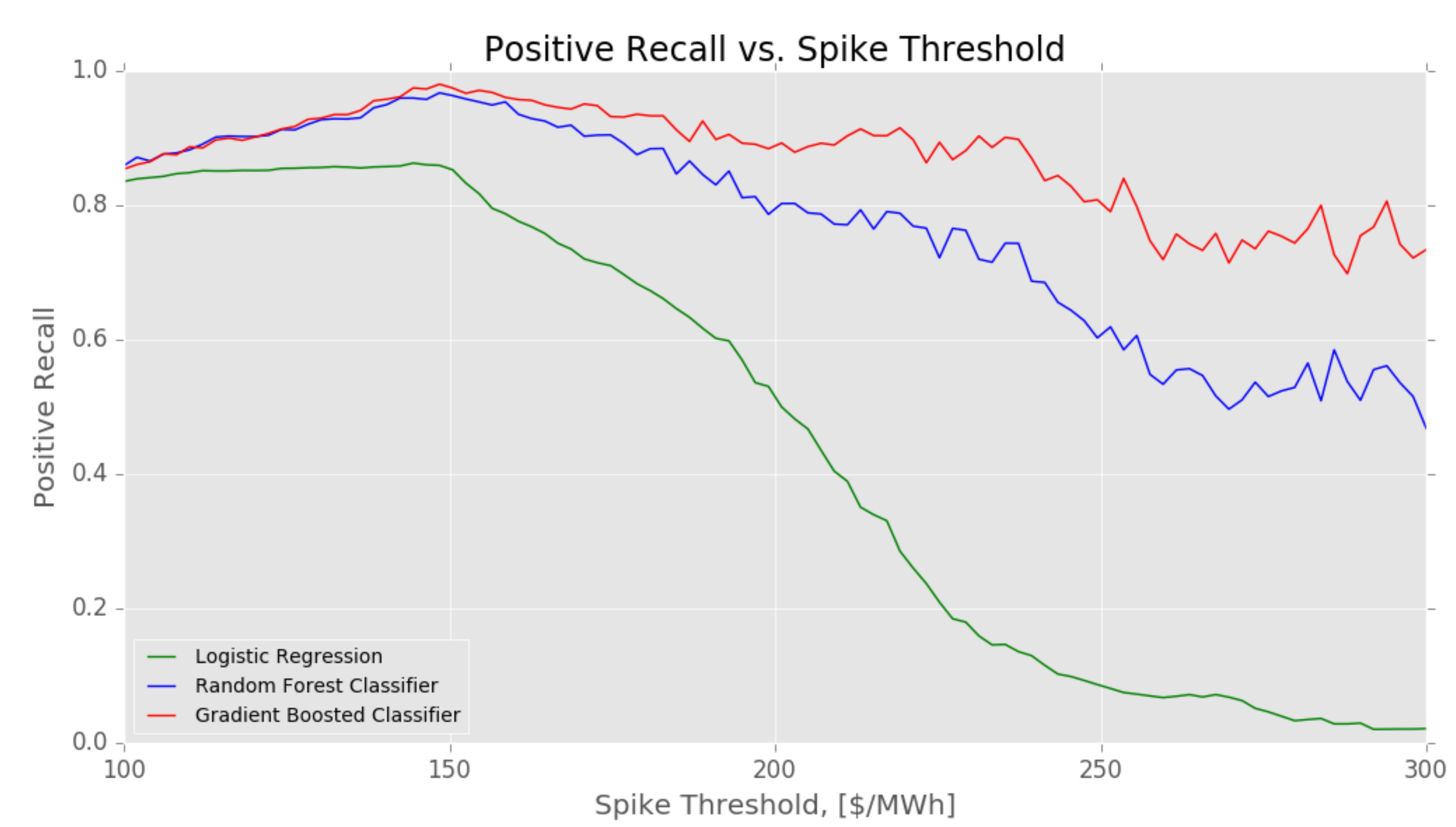

Figure 2. Model performance (positive recall) as the threshold definition of a "spike" increases.

DISCUSSION

OBSERVATIONS

I. Logistic Regression performs more poorly than decision tree based methods
II. Gradient boosted classifier slightly outperforms random forest classifier
III. Decision tree models displayed best performance with high variance hyperparameters
IV. Averaging model outputs does not improve accuracy

SAMPLE MODEL OUTPUT:

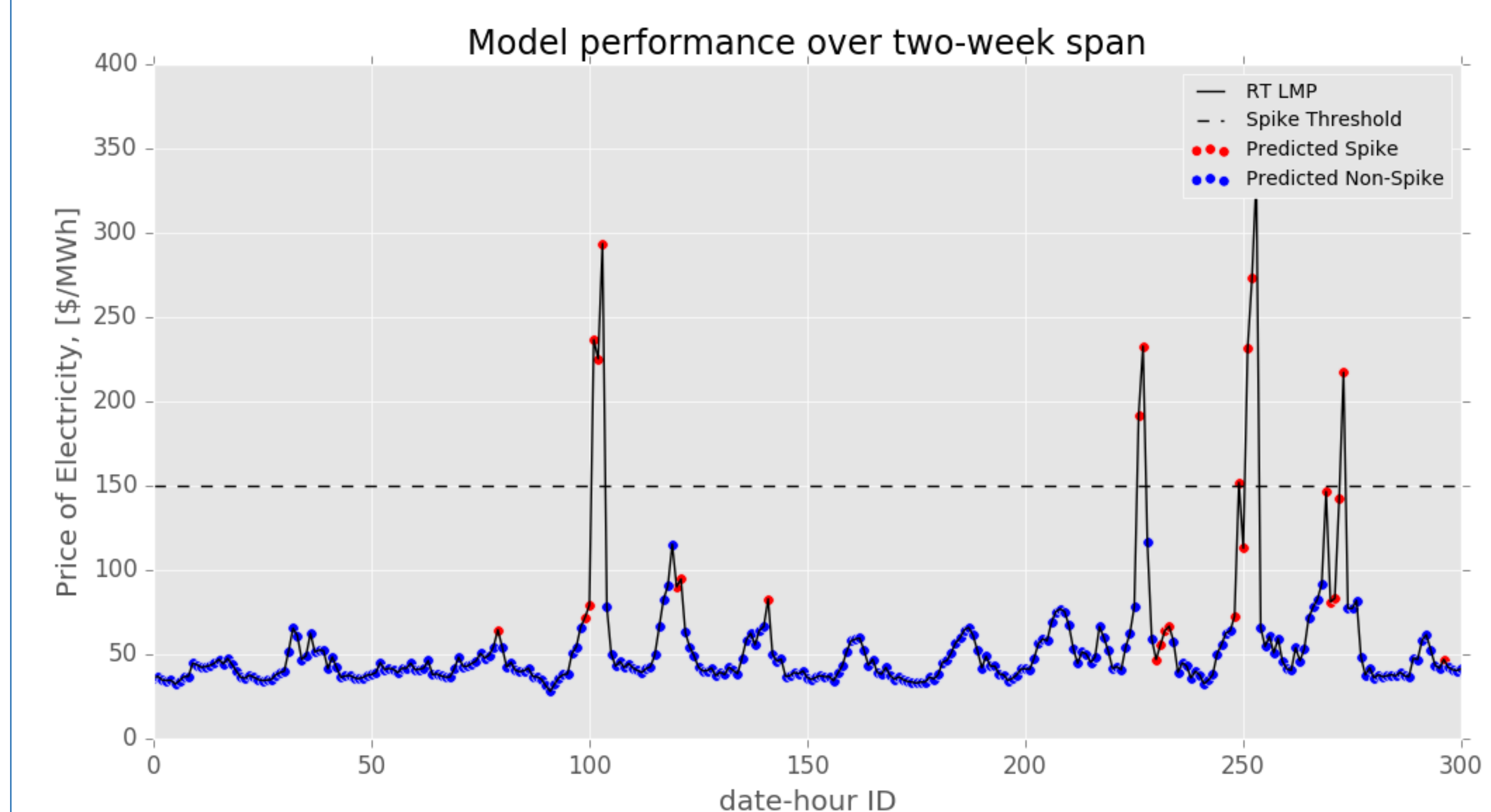

Figure 3. Timeseries of hourly electricity prices, price-spike threshold, and corresponding model predictions for dates of 7/27/2011 to 8/9/2011.

- High positive recall rate indicates that the model can be used as a tool for hedging in the power markets
- Type II errors are the primary source of inaccuracy

FUTURE

- Limit feature set to data that is available 24 hours in advance (i.e. use weather forecasts)
- Future works include feature selection and model reduction, implementation of a deep learning model
- Incorporate a more flexible definition of spike (i.e. a large price increase relative to the previous hour)