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

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**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

$$
\max_{\theta} \sum \left[ y \log f(x; \theta) + (1 - y) \log(1 - f(x; \theta)) \right] - \lambda \| \theta \|^2
$$

II. Random forest classifier

$$
\min \sum \left[ \log f(x; \theta) + \frac{1}{m} \log \Omega f(x) \right]
$$

with \( y^2 - \frac{1}{k} \sum f(x) \)

and \( \Omega f(x) \) is complexity of true \( f \)

III. Gradient boosting classifier

$$
\sum \left[ y \log f(x; \theta) + \frac{1}{m} \log \Omega f(x) \right] + \alpha f(x)
$$

with \( y = \delta_{\text{spike}}(y_i, t_i) \) and \( \alpha = \delta_{\text{spike}}(y_i, t_i) \)

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

**FEATURES AND TARGET**

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

II. Day Ahead Market
   - Load forecast and electricity price

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

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

**RESULTS**

<table>
<thead>
<tr>
<th>Model</th>
<th>Training (m=26,640)</th>
<th>Test (m=30,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic Regression</td>
<td>88.90% (97.2%/0.777)</td>
<td>93.2% (97.2%/0.777)</td>
</tr>
<tr>
<td>Random Forest Classifier</td>
<td>99.99% (97.2%/0.777)</td>
<td>94.6% (97.2%/0.777)</td>
</tr>
<tr>
<td>Gradient Boosted Classifier</td>
<td>100% (97.2%/0.777)</td>
<td>95.1% (97.2%/0.777)</td>
</tr>
</tbody>
</table>

**DISCUSSION**

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

**OBSERVATIONS**

- 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)

**SAMPLE MODEL OUTPUT**

- Figure 1. Distribution of hourly electricity prices from ISO-NE service territory
- Figure 2. Model performance (positive recall) as the threshold definition of a “spike” increases
- Figure 3. Timeseries of hourly electricity prices, price spike threshold, and corresponding model predictions for dates of 7/27/2011 to 8/9/2011