

Summary of Polson and Sokolov 2018

Deep Learning for Energy Markets

David Prentiss

OR750-004

November 12, 2018

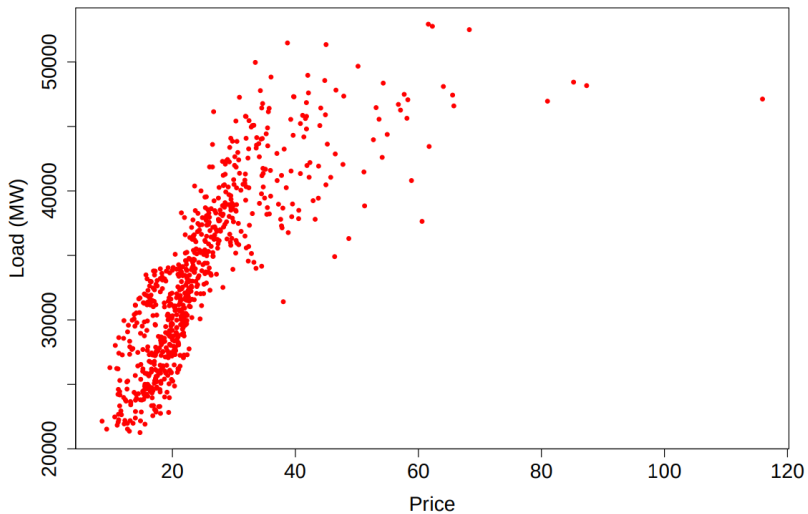
The PJM Interconnection

- ▶ The Pennsylvania–New Jersey–Maryland Interconnection (PTO) is a regional transmission organization (RTO).
- ▶ It implements a wholesale electricity market for a network of producers and consumers in the Mid-Atlantic.
- ▶ It's primary purpose is to prevent outages or otherwise un-met demand.
- ▶ Obligations are exchanged in bilateral contracts, the day-ahead market, and the real-time market.

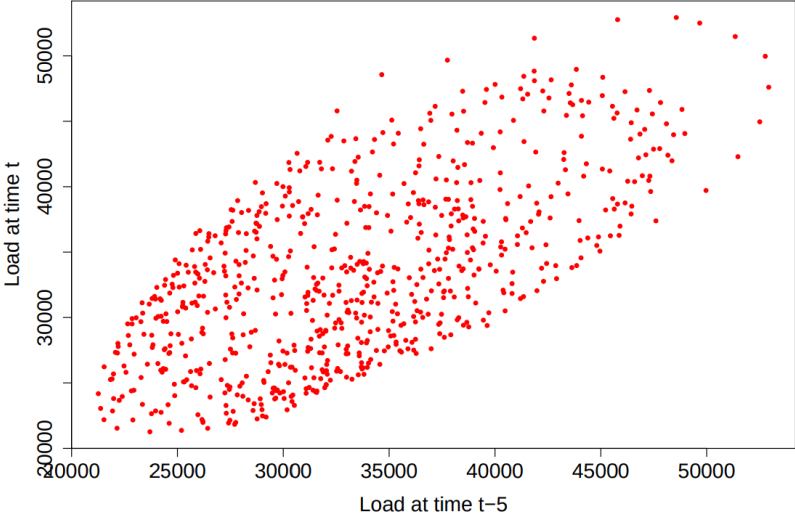
Local marginal price data

- ▶ Local Marginal Prices (LMP) are price data aggregated for prices in various locations and interconnection services in the network.
- ▶ They reflect the cost of producing and transmitting electricity in the network.
- ▶ Prices are non-linear because of electricity.
- ▶ This paper proposes a NN to model price extremes.

Load vs. price



Load vs. previous load



RNN vs. long short-term memory

Vanilla RNN

$$h_t = \tanh \left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)$$

LSTM

$$\begin{pmatrix} i \\ f \\ o \\ k \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} \circ W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot k$$

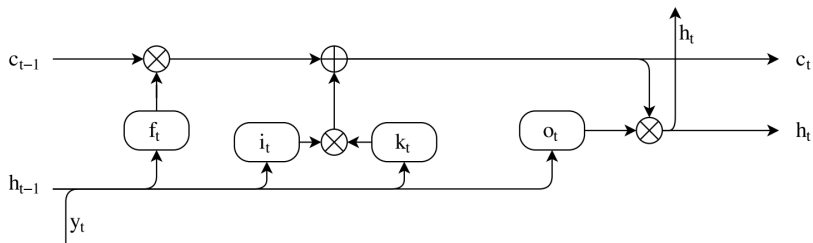
$$h_t = o \odot \tanh(c_t)$$

LTSM model

$$\begin{pmatrix} i \\ f \\ o \\ k \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} \circ W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot k$$

$$h_t = o \odot \tanh(c_t)$$



Extreme value theory

- ▶ Extreme value analysis begins by filtering the data to select “extreme” values.
- ▶ Extreme values are selected by one of two methods.
 - ▶ Block maxima: Select the peak values after dividing the series into periods.
 - ▶ Peak over threshold: Select values larger than some threshold.
- ▶ Peak over threshold used in this paper.

Peak over threshold

- ▶ Pickands–Balkema–de Hann (1974 and 1975) theorem characterizes the asymptotic tail distribution of an unknown distribution.
- ▶ Distribution of events that exceed a threshold are approximated with the generalized Pareto distribution.
- ▶ Low threshold increases bias.
- ▶ High threshold increases variance.

Generalized Pareto distribution

► CDF

$$H(y | \sigma, \xi) = 1 - \left(1 + \xi \frac{y - u}{\sigma}\right)_+^{\frac{-1}{\xi}}$$

► PDF

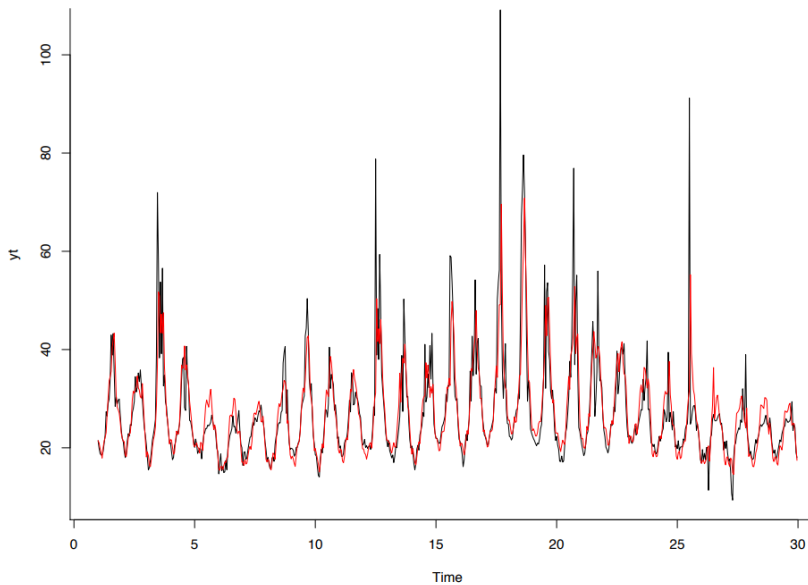
$$h(y | \sigma, \xi) = \frac{1}{\sigma} \left(1 + \xi \frac{y - u}{\sigma}\right)_+^{\frac{-1}{\xi} - 1}$$

Parameters

$$h(y | \sigma, \xi) = 1 - \frac{1}{\sigma} \left(1 + \xi \frac{y - u}{\sigma} \right)^{\frac{-1}{\xi} - 1}$$

- ▶ Location, u , is the threshold
- ▶ Scale, σ , is our learned parameter
- ▶ Shape, $\xi = f(u, \sigma)$? $EX[y] = \sigma + u \implies \xi = 0$?

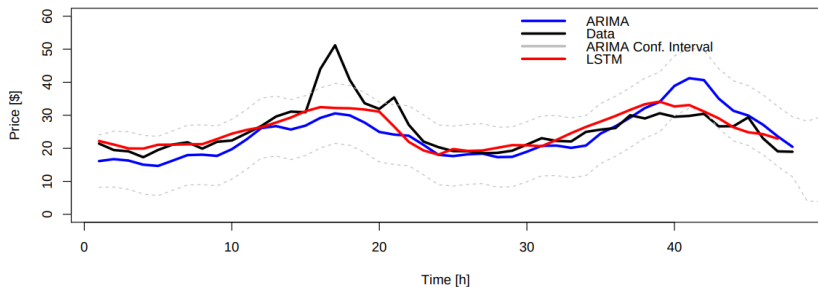
Fourier (ARIMA) model



Fourier (ARIMA) model vs DL

| | mse | mrse | mae | mape |
|---------|------|------|-----|------|
| Fourier | 26.6 | 5.1 | 4 | 0.19 |
| LSTM | 16.8 | 4.1 | 2.4 | 0.09 |

Table 2: Out-of-sample performance of DL and Fourier models



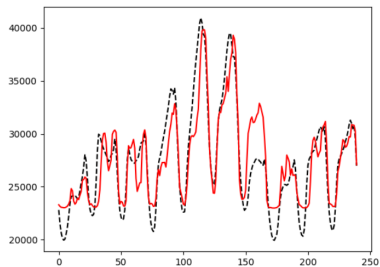
Demand forecasting DL-EVT

- ▶ DL-EVT Architecture

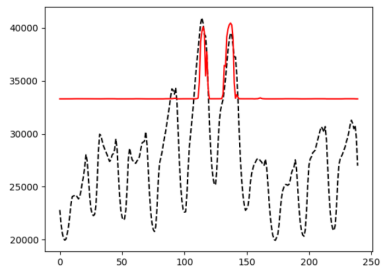
$$X \rightarrow \tanh \left(W^{(1)}X + b^{(1)} \right) \rightarrow Z^{(1)} \rightarrow \exp \left(\tanh \left(Z^{(1)} \right) \right) \rightarrow \sigma(X)$$

- ▶ $W^{(1)} \in \mathbb{R}^{p \times 3}$, $x \in \mathbb{R}^p$, $p = 24$ (one day)
- ▶ Threshold, $u = 31,000$

Vanilla DL vs. DL-EVT



(a) DL (MSE Loss)



(b) DL-EVT (GP Loss)