Predict Energy Consumption with Deep Learning Models using Weather Data

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Abstract

Demand load forecasting is an integral component of optimizing energy consumption. For energy providers, excess demand causes ”brownouts” while excess supply wastes fuel and augments the carbon footprint of the provider. The problem is analogous for building engineeers who everyday face the trade-off between the high cost of energy versus insufficient consumption which could result in uncomfortable building temperatures. Predicting a building's steam demand using weather and building temperature variables is a non-trivial, non-linear problem – the underlying structure of these interactions is not well-known and suggests the need for a complex model. Thus, we turn to neural networks and deep learning algorithms such as Restricted Boltzmann Machines (RBMs) to construct Deep Belief Networks (DBNs) and compare the results to that of other machine learning algorithms and time series modeling methodology.

1 Introduction

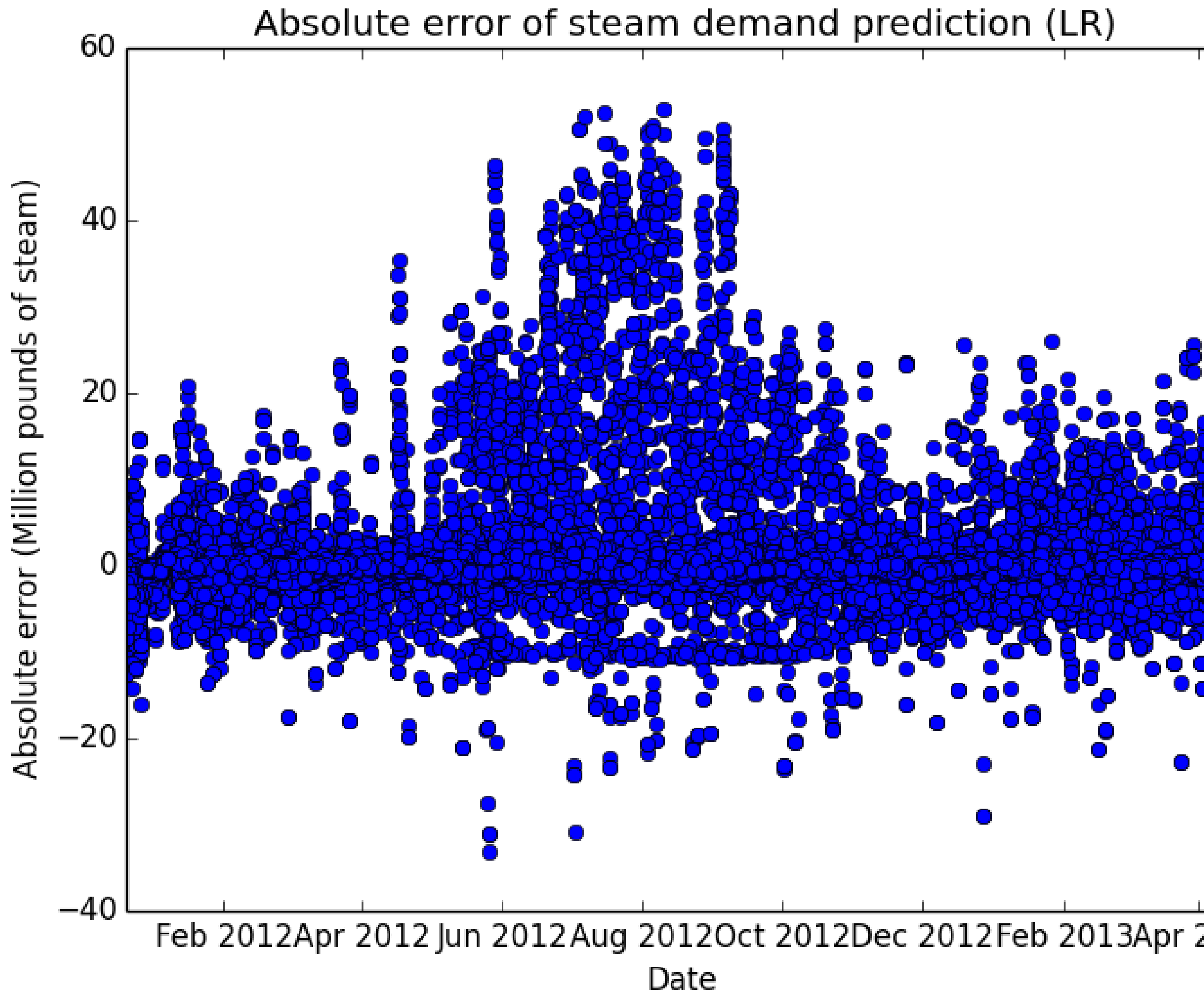
A crucial part of optimizing energy consumption is demand load forecasting, the ability to recognize patterns of consumption. Energy providers are wary of excess demand which causes ”brownouts” and of excess supply which squanders and misuses valuable fuel. Building engineers face an analogous problem in optimizing energy consumption by balancing building comfort and demand with the high cost of usage. Using weather prediction variables and real-time building temperatures by quadrant, we predict building steam consumption throughout the day. The underlying structure behind steam usage is a non-linear, non-trivial problem. Thus, we attempt to model and capture this complex process by training neural networks and implementing deep learning algorithms such as Restricted Boltzmann Machines (RBMs) to construct Deep Belief Networks (DBNs) and compare the results of neural networks to other time series modeling techniques and machine learning algorithms.

The building dat

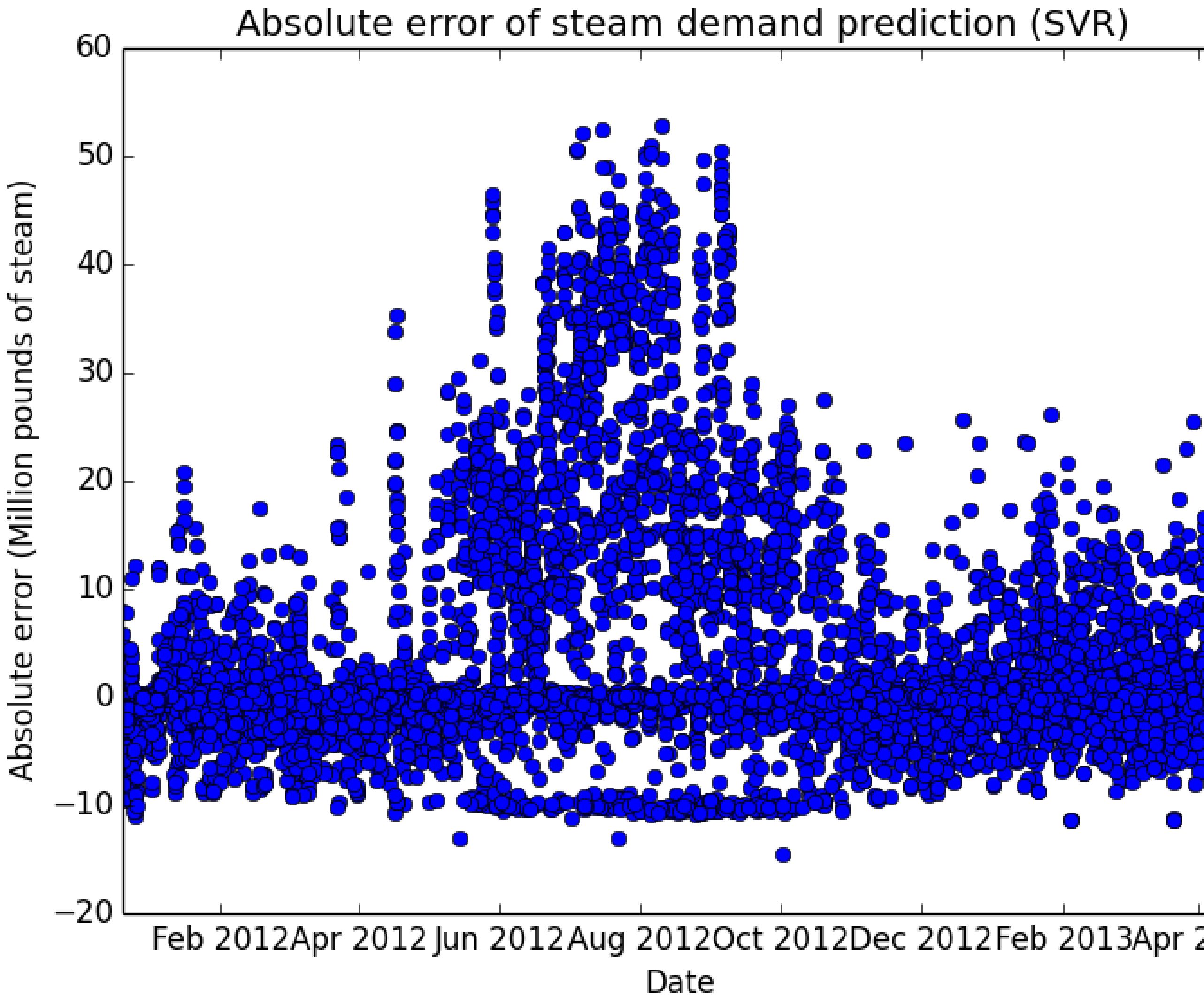
2 Simple Models

The simple models, encompassing linear regressions, support vector machine, random forest, etc, do a poor even miserable job on steam demand prediction. With a relative error from 200% to 300% these models obviously do not fit the underlying structure of weather/energy interactions.
We ran some of the classical regression models on our data to be convinced of this assertion, and our expectation were more than confirmed. Randomly predicted values would have nearly done the same work ! We plotted the absolute errors in thousands of pounds per hour across the whole 2012 year.

Plots:



Absolute error of steam demand prediction (LR)
Absolute error (Million pounds of steam)
60
40
20
0
−20
−40
Feb 2012
Apr 2012
Jun 2012
Aug 2012
Oct 2012
Dec 2012
Feb 2013
Apr 2
Date



3 Implementation of Neural Networks, Restricted Boltzmann's Machine and Deep Belief Networks

3.1 Neural Networks

3.2 Restricted Boltzmann's Machine

3.3 Deep Belief Networks

4 Numerical Results and Plots

5 Conclusion

6 Bibliography

7 Appendix