Electric Power Load Forecasting

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1 Introduction

Accurate models for electric power load forecasting are very important for the electric industry. Load forecasts are used by energy suppliers, independent system operators (ISOs), financial institutions, and other participants in electric energy generation, transmission, and distribution. Many methods have been proposed for load forecasting, including time series models, regression, neural networks, support vector machines, etc. [1, 2, 3, 4, 5].

Power demand pattern is usually very complex, particularly because of the deregulation of the energy industries. Thus finding an appropriate forecasting model for a specific electricity network is not an easy task. In this project we apply and compare several machine learning algorithms for developing forecasting models for the energy grid of the state of New York. We perform most of our data wrangling and statistical analysis in Python.

2 Data

We use the real-time actual load data for the energy grid of the state of New York (http://mis.nyiso.com/public/) for the years 2008-2014. (The data for 2015 was not used because of the large number of missing values).

Weather is an important factor that influences the load. Some important predictors in power load forecasting include the air temperature and the dew point. We accordingly also use the relevant weather data from the weather stations in the state of New York. This weather data is provided by the National Climatic Data Center: https://www.ncdc.noaa.gov. We aggregate multiple files containing the load data and multiple files containing the weather data. We then clean and reformat the data and merge the electric load data and weather data together.

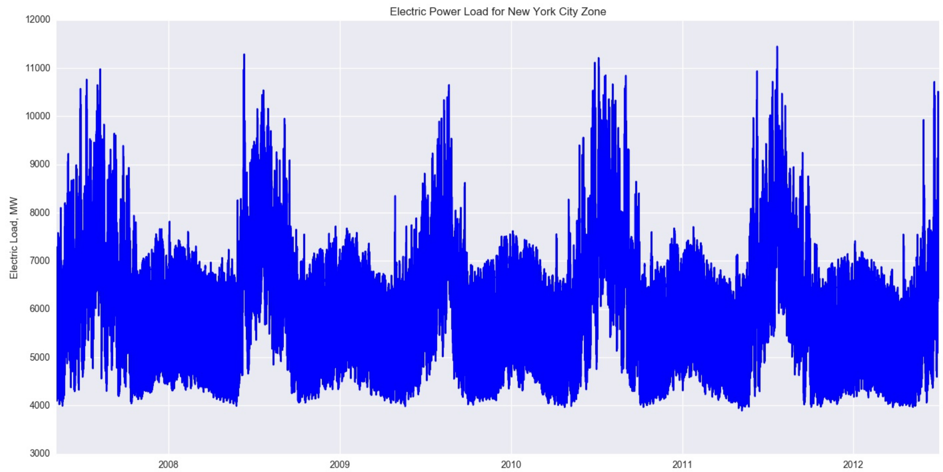

Figure 1: Electric power load for the New York City zone showing a complex almost periodic pattern

3 Models

We focus on medium-term forecasting models that aim to give accurate predictions over the period from one week to one year.

We break the date into separate parts to create the following temporal predictors: hour, day of the week, month, year, and an indicator variable corresponding to weekends. Since we expect the load data to be strongly autocorrelated, we also use the following predictors: load from the same hour on the previous day (prior day load), and load from the same hour and same day from the previous week. In addition, we use two weather-related predictors: air temperature and dew point (which is a measure of atmospheric moisture).

We split the data into training and testing sets based on the date. The observations before 31 December 2012 constitute the training set, and those after 31 December 2012 constitute the testing set. (A more sophisticated alternative to that is cross validation).

For the sake of illustration we will evaluate our models on the New York City zone. The weather station at Laguardia airport covers most of the zone. Fig. 1 shows the fluctuations of the actual electric power load for the New York City zone. Fig. 2 shows scatter plots of the actual load versus the following predictors: month, hour, air temperature, and prior day load. The scatter plot of the load versus the month predictor displays seasonal variations of the load: the power demand is higher during the hotter time of the year (air-conditioning generally requires more power than heating). The plot of the load versus the hour predictor displays daily variations of the load: the power demand

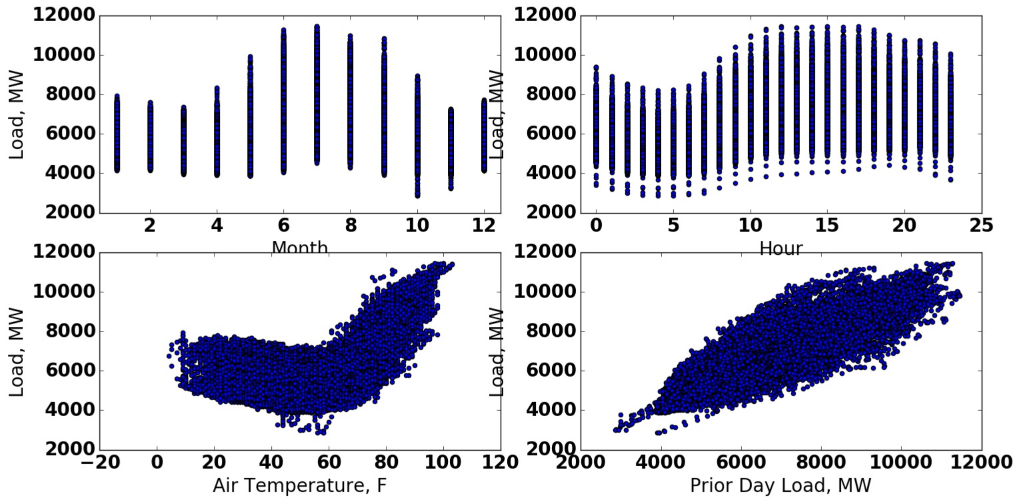

Figure 2: Scatter plots of the load versus the following predictors: month, hour, air temperature, prior day load

is generally smallest in the early morning between 2 a.m. and 5 a.m. and highest during the day between 12 noon and 6 p.m. The plot of the load versus air temperature displays a strong positive relationship for temperatures above 60 F as more power is required for air-conditioning when the temperature is higher. When the temperature is below 40 F the relationship appears to be negative as more power is required for heating when the temperatures are lower. The lack of symmetry in this scatter plot can be related to the fact that air cooling generally requires more power than heating. Finally the plot of the load versus the prior day load displays a strong positive relationship, which reflects the fact that the load data is autocorrelated.

Linear regression model. The linear regression model performs reasonably well. The (adjusted) R-Squared is 0.88. Fig. 3 shows a plot of the residuals versus the fitted values and a histogram of the residuals for our model. The histogram implies that the assumption that the residuals are normally distributed is not unreasonable. The plot of the residuals versus the fitted values displays no distinct pattern, implying that the other assumptions of the linear regression model (homoscedasticity, independence of errors, mean zero of errors) are not unreasonable.

Tree bagging. We train a bagged regression tree model that involves building an ensemble of trees, each trained on a resampled subset of the training set. Each tree creates a forecast and the average of all forecasts is taken.

Gradient Boosting. We fit a gradient boosting model based on decision trees with maximum tree depth equal to 3. The number of

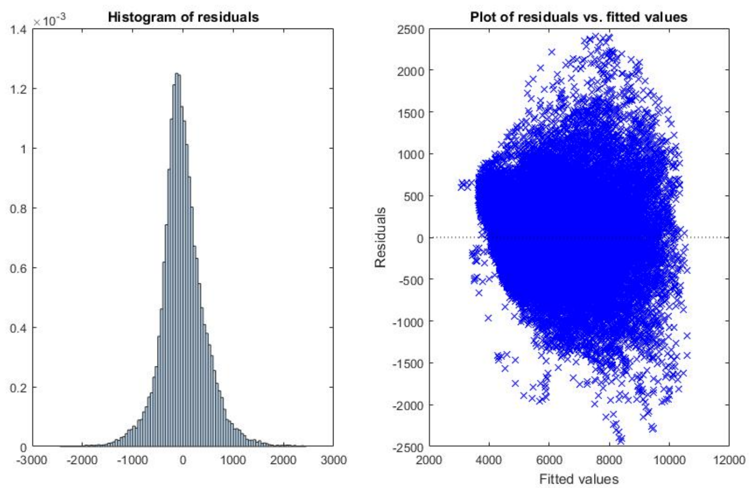

Figure 3: Linear Regression Model: Plot of Residuals vs. Fitted Values, and Histogram of the Residuals

boosting stages is set equal to 100, and the learning rate (which shrinks the contribution of each tree) is 0.1. Fig. 4 shows the relative importance of the features (based on their average contribution to reducing the residual sum of squares).

4 Comparison of Model Performances

Fig. 5 compares the mean squared errors (MSEs) for our models on the training and testing sets. The linear regression model has the largest MSEs both on the training set and testing set. The tree bagging model has by far the lowest MSE on the training set; however, its MSE on the testing set is slightly higher than that of the gradient boosting model. This is likely due to the fact that the tree bagging model has overfit on the training set (gradient boosting models are generally more robust to overfitting).

Fig. 6 shows the measured (actual) load and the load predicted by the gradient boosting model as well as the error between the actual and predicted loads. Fig. 5 shows that on average our model gives reasonably accurate predictions. However, there are several problematic time periods. First it is easy to see that many of the points where the error magnitude is particularly large correspond to holidays: Fourth of July, Labor Day, Thanksgiving, Christmas, New Year's. Our model could be accordingly improved simply by incorporating these holidays into the model as appropriate indicator variables. However, there remains a problematic period at the end of October 2012. It is likely that the poor performance of our model during that timeframe is related to ab-

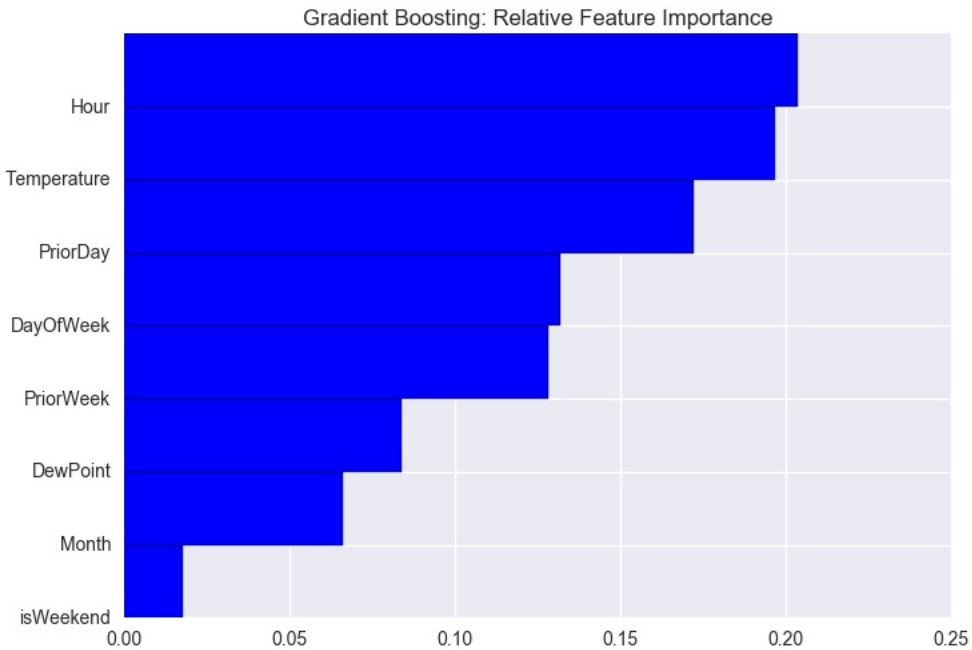

Figure 4: Gradient Boosting: Relative Feature Importance

normal weather conditions. In fact on 27 October, 2012 New York City (along with other parts of the East Coast) was hit by the hurricane Sandy (the second-costliest hurricane in United States history). It is thus not surprising that our model prediction is not accurate during that period since the actual power demand was unusually low during such a severe storm.

The performance of our models can be further improved by adding more useful predictors. For example, we could add a predictor corresponding to holidays and additional predictors related to weather factors. Moreover, other important factors could be incorporated, such as the number of customers in different categories, the appliances in the area, the economic and demographic data, and the appliance sales data. A more significant improvement in the performance could be achieved by using multiple weather forecasts as multiple inputs for load forecasts. Averaging this ensemble of forecasts may lead to a more accurate prediction.

References

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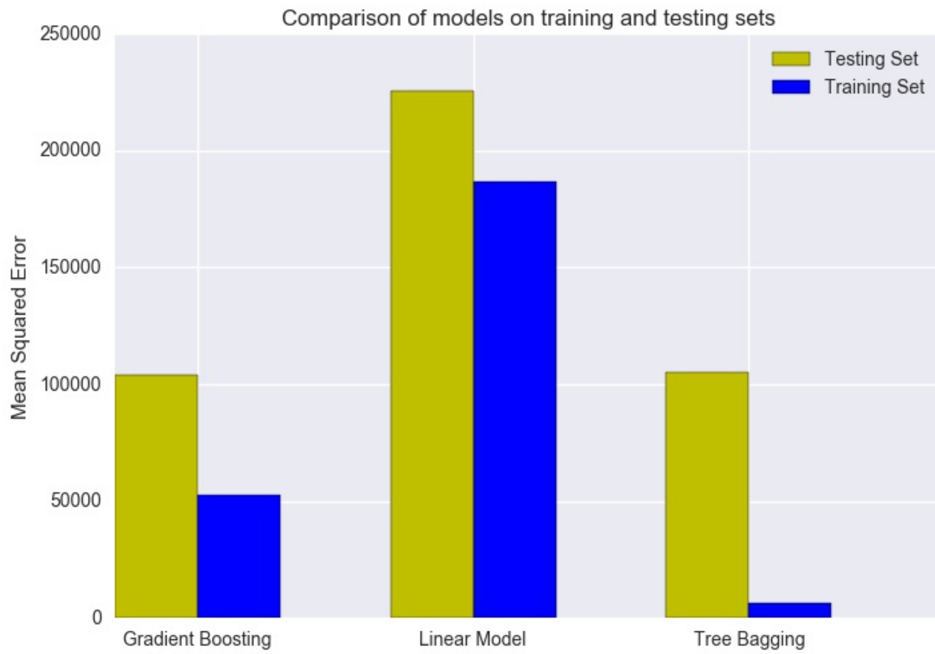

Figure 5: Performance comparison: mean squared errors for various models.

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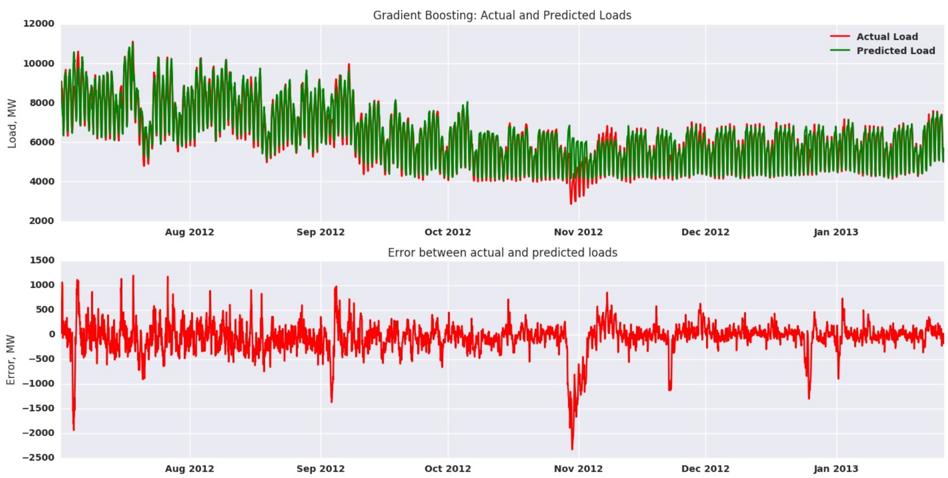

Figure 6: Above: Measured (actual) load and load predicted by the gradient boosting model. Below: Error between the actual and predicted loads.