A large-scale study on predicting and contextualizing building energy usage

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A Large-scale Study on Predicting and Contextualizing Building Energy Usage

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Abstract

In this paper we present a data-driven approach to modeling end user energy consumption in residential and commercial buildings. Our model is based upon a data set of monthly electricity and gas bills, collected by a utility over the course of several years, for approximately 6,500 buildings in Cambridge, MA. In addition, we use publicly available tax assessor records and geographical survey information to determine corresponding features for the buildings. Using both parametric and non-parametric learning methods, we learn models that predict distributions over energy usage based upon these features, and use these models to develop two end-user systems. For utilities or authorized institutions (those who may obtain access to the full data) we provide a system that visualizes energy consumption for each building in the city; this allows companies to quickly identify outliers (buildings which use much more energy than expected even after conditioning on the relevant predictors), for instance allowing them to target homes for potential retrofits or tiered pricing schemes. For other end users, we provide an interface for entering their own electricity and gas usage, along with basic information about their home, to determine how their consumption compares to that of similar buildings as predicted by our model. Merely allowing users to contextualize their consumption in this way, relating it to the consumption in similar buildings, can itself produce behavior changes to significantly reduce consumption.

Introduction

In the effort to build a sustainable society, energy issues play a crucial role. Humans consume an average of more than 16 terrawatts of power and growing, 86% of which comes from (unsustainable) fossil fuels (Multiple 2009). In the United States, 41% of all energy is consumed in residential and commercial buildings, mainly in the forms of electricity and natural gas. Reducing these consumptions in particular will play a large role in reducing our overall energy dependence.

As a whole, however, end users receive relatively little information about their energy usage. Most of the feedback we receive about our energy consumption comes via monthly electricity and gas bills, which provide little information or context to our usage other than a dollar amount. Crucially, energy bills provide no mechanism to determine things such as how a building’s consumption compares to similar buildings, whether retrofits or upgraded appliances are financially reasonable, what portion of the consumption is simply due to location (cold locations will inevitably require more heating, for example) versus personal behavior, etc. Moreover, simply providing people with feedback about their energy use can itself produce behavior changes that significantly reduce energy consumption (Darby 2006; Neenan and Robinson 2009). Recent research has specifically highlighted the value of normative energy feedback, showing users how their usage relates to that of their peers and neighbors (Cialdini and Schultz 2004; Allcott 2010).

In this paper, we present a study of energy consumption in a large number of buildings in Cambridge, Massachusetts, and develop models than can begin to answer such questions. We use a data set consisting of monthly electrical and gas bills, collected by a utility, for approximately 6,500 separate buildings in the city. We integrate this usage information with publicly available tax assessor and geographical survey information to correlate energy usage with features such as living area, building value, building type, etc. We perform a preliminary analysis of the data set, focusing on the value of using logarithmic scaling for energy usage, and we use feature selection methods to determine the most relevant features for predicting consumption. We then apply both parametric and non-parametric learning algorithms to predict distributions over building consumption. Finally, we use these models to develop EnergyView, a system that allows both utilities (at a city-wide scale) and end users (at a single building scale) to view and compare their energy usage to that of similar buildings as predicted by the models.

Related Work

This paper builds upon a number of works, both from the energy sector and the statistics and machine learning communities. Since this is primarily and application and analysis paper, we mainly use existing algorithmic approaches, but with a focus on recently developed methods for regression under non-Gaussian likelihoods (Kotz and Nadarajah 2004; Vanhatalo, Jylanki, and Vehtari 2009).

From the energy community, our work builds most di-
Data Collection and Analysis

The primary data set we build our model upon is a collection of monthly electricity and gas bills, collected over several years from buildings in Cambridge, MA, and obtained from NStar, the electricity and gas utility in Cambridge. The data consists of electricity and gas account numbers, their corresponding street addresses, and monthly electricity and gas meter readings for each account over some period of time, typically two to three years. Electricity usage is given in kilowatt-hours per month, while gas usage is given in therms per month. To convert these to equivalent units, we use the conversion factor (1/3)\(29.3\) therms/kwh, where 29.3 is the standard conversion rate, and 2/3 represents the average conversion loss for electricity generation in the United States; this also corresponds to the relative pricing of gas and electricity, an average of $1.05/therm and $0.11/kwh respectively (Multiple 2009). The primary goal of our algorithms will be to predict this total usage as a function of building features (though we also apply the same techniques to estimating monthly electricity and gas usage separately in order to provide more detailed feedback).

In addition to the energy data, we use publicly available tax assessor records\(^1\) and a Geographic Information System (GIS)\(^2\) database compiled by the city. The tax assessor records contain detailed features about every registered property and building in Cambridge, listing for each address features such as the value of the building, the property class (condominium, single family home, retail store, etc), the square footage, the year a building was built, and other similar features. The GIS database consists of polygonal outlines for parcels and buildings in the city, plus estimated roof heights for buildings (obtained via an aerial lidar scan). We aggregate features at the whole building level, so that, for example, multiple units at a given street address are aggregated into one building; this is a necessity since the utility data does not include unit numbers, but only a street number and street name. After correlating addresses between the energy usage, tax assessor, and GIS databases, and removing any entries for which there are less than a year of full gas and electricity readings, there are a total of 6,499 unique buildings that we include in our data set. This represents slightly more than half of the 12,792 unique addresses in the Cambridge tax assessor records (the main reason for omitting a building is that one or more of the correspond energy accounts don’t span a full uninterrupted year in the utility data we have access to).

Logarithmic Energy Scaling

A preliminary analysis of the data illustrates several interesting features, which we build upon to develop models in the subsequent section. Figure 1 shows a histogram of total energy consumption per year for the different buildings in our data set. The data appears roughly Gaussian (although slightly skewed), but the important fact here is that the \(x\) axis is logarithmic, implying that total energy consumption roughly follows a log-normal distribution. This means that energy consumption varies multiplicatively between different houses: a house in the 80th percentile of energy consumption uses about 3 times as much energy as a house in the 20th percentile. Further, even the log-normal distribution in fact underestimates the spread of the data; the data is heavy-tailed, such that a log Student-t distribution (Cassidy, 2009). We know of no source where the database can be downloaded directly, and instead had to use an automated tool to parse and import the records via this interface.

\(^1\)Tax assessor records for Cambridge are available via a web interface at http://www2.cambridgema.gov/fiscalaffairs/PropertySearch.cfm. We know of no source where the database can be downloaded directly, and instead had to use an automated tool to parse and import the records via this interface.

\(^2\)GIS databases for Cambridge can be ordered at http://www.cambridgema.gov/gis.aspx.
Approximately log-normal distributions of energy usage may initially seem rather surprising, but these are actually quite reasonable given other phenomena in economics and social science. In particular, many observed phenomena naturally follow roughly log-normal distributions (Limpert, Stahel, and Abbt 2001), including factors that would be expected to influence energy consumption, such as income, property sizes, and (in our own data set) building square footage. Furthermore, power-law behaviors, defined as a linear relationships between the logarithms of input and output variables (Newman 2005), are ubiquitous in many empirical domains, including domains related to city consumption and scaling (Kuhnert, Helbing, and West 2006). Since the Gaussian and multivariate T distributions are preserved by linear transformations (Kotz and Nadarajah 2004) (i.e., a linear function of a multivariate Gaussian or multivariate T distribution will also be Gaussian or multivariate T), log-normal or log-T input variables, together with a power-law relationship, would imply the same distribution for the output. Figure 2 illustrates this type of relationship for our data set, plotting building living area as square footage against total energy consumption on a log-log scale. While there is naturally a great deal of noise, there is also a fairly clear linear relationship, indicating an intuitive power-law relationship between square footage and energy consumption. While the relationships are more difficult to display when additional variates are introduced, the chief goal of the next section will be to exploit these types of relationships to derive predictive models of energy consumption based upon known features.

**Data Features and Feature Selection**

Finally, before discussing the modeling methods we use for this data, we discuss the actual features used to predict energy consumption, as well as feature selection procedures that identify the most relevant features for this task. We extract a total of 35 features from the tax assessor and GIS data set, all of which are shown in Table 1. Many of the features are real-valued, in which case we include their logarithm (owing to the discussion above) directly in the final feature vector. For discrete features, we use a standard binary encoding of the feature, i.e., for a $k$-valued discrete value we add the representation

\[
\phi(x_i) \in \{0, 1\}^k = \{1\{x_i = 1\}, \ldots, 1\{x_i = k\}\}
\]

(1)

to the feature vector, where all the entries are zero if a discrete value is previously unseen or if the feature value is unknown. All the features listed in Table 1 are extracted directly from the GIS or tax assessor database with the exception of the “Laplacian Eigenvectors” feature, which

<table>
<thead>
<tr>
<th>Feature</th>
<th>% RMSE Reduction</th>
<th>Individual Correlation</th>
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<tbody>
<tr>
<td>Building Value</td>
<td>24.721 %</td>
<td>0.659</td>
</tr>
<tr>
<td>Num Electric Meters</td>
<td>13.438 %</td>
<td>0.647</td>
</tr>
<tr>
<td>Property Class</td>
<td>12.729 %</td>
<td>0.633</td>
</tr>
<tr>
<td>Living Area</td>
<td>2.760 %</td>
<td>0.611</td>
</tr>
<tr>
<td>Num Gas Meters</td>
<td>2.517 %</td>
<td>0.626</td>
</tr>
<tr>
<td>Heat Fuel</td>
<td>2.241 %</td>
<td>0.480</td>
</tr>
<tr>
<td>Building Style</td>
<td>1.432 %</td>
<td>0.632</td>
</tr>
<tr>
<td>Heat Type</td>
<td>0.826 %</td>
<td>0.431</td>
</tr>
<tr>
<td>Central AC</td>
<td>0.749 %</td>
<td>0.558</td>
</tr>
<tr>
<td>Overall Grade</td>
<td>-0.045 %</td>
<td>0.346</td>
</tr>
<tr>
<td>Roof Material</td>
<td>0.105 %</td>
<td>0.595</td>
</tr>
<tr>
<td>Exterior Wall Type</td>
<td>-0.300 %</td>
<td>0.597</td>
</tr>
<tr>
<td>Occupancy Type</td>
<td>-0.656 %</td>
<td>0.623</td>
</tr>
<tr>
<td>Laplacian Eigenvectors</td>
<td>0.138 %</td>
<td>0.180</td>
</tr>
<tr>
<td>GIS Parcel Area</td>
<td>0.164 %</td>
<td>0.381</td>
</tr>
<tr>
<td>Total Rooms</td>
<td>0.074 %</td>
<td>0.049</td>
</tr>
<tr>
<td>Residential Exemption</td>
<td>0.037 %</td>
<td>0.207</td>
</tr>
<tr>
<td>Fireplaces</td>
<td>0.014 %</td>
<td>0.092</td>
</tr>
<tr>
<td>Overall Condition</td>
<td>-0.068 %</td>
<td>0.234</td>
</tr>
<tr>
<td>Full Baths</td>
<td>0.000 %</td>
<td>0.101</td>
</tr>
<tr>
<td>Roof Type</td>
<td>-0.024 %</td>
<td>0.557</td>
</tr>
<tr>
<td>Assessed Value</td>
<td>-0.010 %</td>
<td>0.615</td>
</tr>
<tr>
<td>GIS Parcel Perimeter</td>
<td>0.001 %</td>
<td>0.371</td>
</tr>
<tr>
<td>Land Area</td>
<td>-0.007 %</td>
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</tr>
<tr>
<td>Land Value</td>
<td>-0.202 %</td>
<td>0.377</td>
</tr>
<tr>
<td>Half Baths</td>
<td>-0.023 %</td>
<td>0.022</td>
</tr>
<tr>
<td>Garage Parking</td>
<td>-0.039 %</td>
<td>0.229</td>
</tr>
<tr>
<td>Year Built</td>
<td>-0.013 %</td>
<td>0.095</td>
</tr>
<tr>
<td>GIS Building Perimeter</td>
<td>-0.014 %</td>
<td>0.104</td>
</tr>
<tr>
<td>GIS Building Area</td>
<td>0.033 %</td>
<td>0.143</td>
</tr>
<tr>
<td>GIS Building Volume</td>
<td>0.016 %</td>
<td>0.112</td>
</tr>
<tr>
<td>Num Stories</td>
<td>-0.041 %</td>
<td>0.064</td>
</tr>
<tr>
<td>Open Parking</td>
<td>-0.011 %</td>
<td>0.069</td>
</tr>
<tr>
<td>Covered Parking</td>
<td>-0.013 %</td>
<td>0.071</td>
</tr>
<tr>
<td>Residential/Commercial</td>
<td>-0.553 %</td>
<td>0.272</td>
</tr>
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</table>

Table 1: All the building features extracted from the tax assessor and GIS data, ranked in the order that they are selected in greedy forward feature selection. The first nine features (above the line) decrease cross-validation RMSE (second column), to a statistically significant degree ($p < 0.01$ in a pairwise t-test). Also shown is the correlation coefficient between total energy and the feature in isolation.

Figure 2: A plot of building square footage versus total yearly energy consumption, both in logarithmic scales. The dotted line shows the least-squares fit.
uses a standard spectral clustering procedure (Chung 1997). Briefly, we construct this feature by building a (symmetric) \( k \)-nn graph on the 2D building locations, then looking at the principle eigenvectors (here corresponding to the lowest eigenvalues) of the discrete normalized Laplacian operator on this graph, defined as

\[
L = I - D^{-1/2} AD^{-1/2}
\]

(2)

where \( D \) is a diagonal matrix of node degrees in the graph and \( A \) is an adjacency matrix. These features provide an optimal orthogonal basis for reconstructing smooth functions on the graph’s manifold, and thus in our setting correspond to smoothly spatially varying functions (in terms of the arrangement of the building locations).

Since we are in a data-rich setting, where we have significantly more features than examples, it is possible to simply pass all these features to our learning algorithms; even the algorithms we consider, which can in theory be sensitive to irrelevant features, do not perform significantly worse when provided with all the features. Nonetheless, for the sake of model simplicity and intuition, it is very useful to determine which of the features we extract are most useful for predicting energy consumption. To this end, we employ a simple greedy forward feature selection procedure that sequentially adds features based on how much they decrease training root mean squared error (RMSE) of a linear regression predictor. Table 1 shows a list of the features in the order they are selected by the greedy procedure. The table also shows how much adding the feature decreases the RMSE as measured by cross validation; thus, while adding a feature by definition will always decrease the training RMSE to some extent, only the first 9 features decrease the RMSE as measured via cross validation to a statistically significant degree (\( p < 0.01 \) in a pairwise t-test). These also correspond to features that we would expect to have a large impact on energy consumption: building value; square footage; number of electric/gas accounts (recall that since we are computing energy usage on a per-building basis, the number of electric and gas accounts serve as a rough proxy for the number of separate units); building class (a discrete feature that designates the building as a condominium, single family home, multi-family home, retail store, office building, etc); heat fuel (oil, gas, or electric); heat type (forced air, hot water, electric radiant, etc), and whether or not the house has central AC.

Equally interesting are the features that do not lead to a significant decrease in RMSE. For example, including the eigenvectors of the graph Laplacian does not significantly improve performance. This suggests that spatially varying attributes are not especially prevalent in this data set: while there is spatial correlation in total energy consumption, once we regress on other features that also are spatially correlated (such as building value), there is little added benefit to including purely spatial features. To illustrate this, we also include in Table 1 the correlation coefficient between each of the different features and the total energy consumption, which captures how correlated each feature is with the total energy independent of any other features. In cases where this correlation is high, yet the feature is ranked low in Table 1, then the feature is also highly correlated with the previously selected features, such that adding the feature to a linear regression model gives little added benefit.

Although the forward selection procedure that we use is well-known to be overly greedy in certain cases (Tibshirani 1996) (this had lead to a variety of alternative procedures such as LASSO-based feature selection (Efron et al. 2004)), the approach is often very effective both in practice and in theory (Zhang 2009). In previous experiments we found virtually no difference in the features selected when considering more complex procedures such as the LASSO. Additionally, since we are performing feature selection based on linear regression, there may be some concern of throwing out features that are potentially of interest to the non-linear regression algorithms we consider later. However, this has not been the case in the experiments we have considered, and we will discuss this further in the next section.

### Modeling and Evaluation

In this section we present learning methods for predicting energy usage given known features of a building. As we don’t expect to predict the energy usage exactly (certainly energy consumption depends on many variables that are not known, including end-user preferences), and since, as we will discuss more in the section, we are concerned with providing users with information about where they lie in the distribution of energy consumption, our focus is on probabilistic methods that return a distribution over possible energy consumption levels. Formally, our predictors will all have the form

\[
y = f(x) + \epsilon
\]

(3)

where \( y \in \mathbb{R}^n \) denotes the predicted energy usage (or rather, the logarithm of the predicted energy usage), \( x \in \mathbb{R}^n \) denotes a vector of inputs describing known features of the house (that we delineate below), and \( \epsilon \) denotes a (possibly input dependent) zero-mean error term. Although we focus in this section on real-valued regression (predicting just the total energy consumption), we apply these same methods to multivariate predictions, for instance to predict the energy consumption in each month as shown later in the paper. We focus on two well-known probabilistic regression techniques: linear models and Gaussian process regression. However, given the above discussion regarding the log \( T \) distribution fitting the data better than log normal distributions, we focus also upon more recent work using non-Gaussian likelihoods.

#### Linear Regression

In the linear regression case,

\[
f(x) = \theta^T x
\]

(4)

for parameters \( \theta \in \mathbb{R}^n \), and the error term is given by some input-independent distribution \( p(\epsilon) \), often referred to as the likelihood function. Based upon the discussion in the previous section, we consider the standard normal error term (leading to ordinary least squares), a Student-\( t \) distributed error term, and a Laplace distributed error term (another heavy-tailed distribution commonly used in robust regression). The densities and notation for the normal, Laplace,
and T distribution are given respectively by
\[
p(\varepsilon ; \sigma) = \frac{1}{\sqrt{2\pi} \sigma} \exp \left( -\frac{\varepsilon^2}{2\sigma^2} \right)
\]
\[
p(\varepsilon ; \nu) = \frac{1}{2\nu} \exp \left( -\frac{\varepsilon}{\nu} \right)
\]
\[
p(\varepsilon ; \nu, \sigma) = \frac{\Gamma((\nu + 1)/2)}{\Gamma(\nu/2)\sqrt{2\pi\sigma^2}} \left(1 + \frac{\varepsilon^2}{\nu\sigma^2}\right)^{-\nu/2 - 1/2}
\]
where \(\sigma\) is a scale parameter and \(\nu\) is a degree of freedom parameter for the T distribution. Given a data set \(\{x_i, y_i\}_{i=1}^n\), we can compute maximum likelihood estimates of \(\hat{\theta}\) and the relevant distribution parameters for each of these models.

Defining the design matrices
\[
X \equiv \begin{bmatrix} x_1^T \cdots x_N^T \end{bmatrix}, \quad y \equiv \begin{bmatrix} y_1 \cdots y_N \end{bmatrix}
\]
then for the normal likelihood the ML estimates are
\[
\hat{\theta} = (X^TX)^{-1}X^Ty
\]
\[
\hat{\sigma}^2 = \frac{1}{n} (y - X\hat{\theta})^T (y - X\hat{\theta}).
\]
For the Laplace likelihood
\[
\hat{\theta} = \arg \min_{\theta} \|y - X\theta\|_1
\]
\[
\hat{\sigma} = \frac{1}{n} \|y - X\hat{\theta}\|_1
\]
where \(\| \cdot \|_1\) denote the \(\ell_1\) norm (the sum of the absolute values of a vector), which makes the optimization over \(\theta\) a convex optimization problem (solved, for example, via linear programming (Boyd and Vandenberghe 2004)). For the T distribution there is no closed form estimate for the parameters, but they can be obtained via the EM algorithm, which amounts to iterating the following updates until convergence
\[
s_i \leftarrow \frac{1}{\sigma^2} (y_i - \hat{\theta}_i^T x_i)^T (y_i - \hat{\theta}_i^T x_i)
\]
\[
w_i \leftarrow \frac{\hat{\nu} + 1}{\hat{\nu} + s_i}
\]
\[
\hat{\theta} \leftarrow (X^T \text{diag}(w) X)^{-1} X^T \text{diag}(w) y
\]
\[
\hat{\sigma}^2 \leftarrow \frac{1}{\hat{\nu} \hat{\nu}^2} (y - X\hat{\theta})^T \text{diag}(w) (y - X\hat{\theta})
\]
\[
\hat{\nu} \leftarrow \arg \min_{\nu} \sum_{i=1}^N \log p(y - \hat{\theta}^T x_i ; 0, \hat{\sigma}, \nu)
\]
where probability in the optimization over \(\nu\) is the density of the T distribution, and this step is performed via numerical optimization. Because the log likelihood is not convex with respect to the parameters, there is no guarantee that this procedure will find the global optimum but in practice if we initialize \(\hat{\theta}\) and \(\hat{\sigma}^2\) to be, for example, the least squares estimates, then this procedure is quite robust.

### Gaussian Process Regression
Gaussian process (GP) regression (Rasmussen and Williams 2006) provides a non-parametric regression method, and allows for much richer representations than in linear regression. In GP regression, the underlying regression function \(f\) is modeled as a Gaussian process, a stochastic process where the distribution of \(f(x_1), f(x_2), \ldots\) for any set of inputs \(x_1, x_2, \ldots\) is jointly Gaussian with some mean (which we will assume to be zero), and covariances
\[
\text{Cov}(f(x_i), f(x_j)) = K(x_i, x_j)
\]
for some positive definite kernel function \(K : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}\). Overloading notation slightly, we write this as
\[
f|X \sim \mathcal{N}(0, K(X, X))
\]
and where in the following we will simply use \(K \in \mathbb{R}^{N \times N}\) to denote \(K(X, X)\) (the kernel matrix formed between all the training examples). As before, we assume that \(y_i = f(x_i) + \epsilon, \) where \(\epsilon\) is a zero-mean error term with one of the three distributions described above. When \(\epsilon\) is Gaussian with variance \(\sigma^2\), the distribution \(p(f(x')|X, y, x')\) (the distribution value of \(f(x')\) for some new input \(x'\)) is also Gaussian, and can be computed in closed form
\[
f(x') \sim \mathcal{N}(K(x', X)(K + \sigma^2 I)^{-1} y, K(x', x') - K(x', X)(K + \sigma^2 I)^{-1} K(X, x')).
\]
When \(\epsilon\) is Laplace or T distributed, there is no longer a closed form expression for the distribution over \(f(x')\), and we must resort to approximate methods such as Expectation Propagation, Variational Bayes, or the Laplace approximation (Rasmussen and Williams 2006; Vanhatalo, Jylanki, and Vehtari 2009). A description of these methods is beyond the scope of this paper, but several freely available software packages exist that implement such approximate methods for GP regression with non-Gaussian likelihood.\(^3\)

For our task we use the squared exponential kernel function, with independent length scales, given by
\[
K(x, x') = s^2 \exp \left( \sum_{i=1}^n \frac{(x_i - x'_i)^2}{2\ell_i^2} \right)
\]
where the the magnitude \(s \in \mathbb{R}_+\) and length scales \(\ell_i \in \mathbb{R}_+\) are free parameters. As is common practice, we estimate these parameters by maximizing the marginal likelihood of the training data, given by
\[
p(y|X) = \int p(y|f, X)p(f|X)df.
\]
As before, when the likelihood is Gaussian this term (and its derivatives with respect to the free parameters) can be computed analytically. When the likelihood is not Gaussian, approximations are again needed, but again the software packages mentioned above provide methods for doing so.\(^4\)

\(^3\)Regression with a T distribution is not often done in this manner (for example, the presentation in (Kotz and Nadarajah 2004) does not describe this procedure), but this a straightforward extension of ML estimation for the T distribution to the regression setting, and seems to be well known.

\(^4\)In this work we use the GPML package (Rasmussen and Hickish 2011) for the Gaussian and Laplace likelihood GP regression, and the GPstuff package (Vanahtalo et al. 2011) for the T likelihood GP regression.
Experimental Setup and Results

We evaluated the performance of the algorithms described above using 5 fold cross validation: we divided the 6,499 data points randomly into 5 approximately equal-sized groups, trained the above regression methods on the union of 4 of these groups, then tested on the held out data; we repeated this for each of the 5 groups, and report the average error and log likelihood over all the held-out examples. To report training errors, we trained and tested on the entire data set. For the GP models, since hyperparameter optimization is quite computationally intensive, we optimized these parameters by maximizing marginal likelihood only on a random subset of 700 of the training examples for each cross validation fold; once we learned these hyperparameters, however, we used the entire training set to predict the held-out data.

Table 2 shows the performance of the different algorithms on this data set. We evaluated the algorithms via three metrics: log likelihood of the data, root mean squared error (RMSE), and RMSE on the data before logarithmic scaling. Items in bold indicate the best performing method, statistically significant in a pairwise t-test with $p < 0.01$.

<table>
<thead>
<tr>
<th>Method</th>
<th>Log Likelihood</th>
<th>RMSE</th>
<th>No Log RMSE ($\times 10^5$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output only, Normal likelihood</td>
<td>-1.484 (-1.482)</td>
<td>1.066 (1.065)</td>
<td>11.106 (11.105)</td>
</tr>
<tr>
<td>Output only, Laplace likelihood</td>
<td>-1.413 (-1.412)</td>
<td>1.079 (1.079)</td>
<td>11.110 (11.110)</td>
</tr>
<tr>
<td>Output only, T likelihood</td>
<td>-1.399 (-1.399)</td>
<td>1.074 (1.074)</td>
<td>11.109 (11.109)</td>
</tr>
<tr>
<td>Linear regression, Normal likelihood</td>
<td>-0.813 (-0.788)</td>
<td>0.545 (0.532)</td>
<td>9.581 (9.231)</td>
</tr>
<tr>
<td>Linear regression, Laplace likelihood</td>
<td>-0.710 (-0.685)</td>
<td>0.549 (0.537)</td>
<td>9.422 (9.397)</td>
</tr>
<tr>
<td>Linear regression, T likelihood</td>
<td>-0.695 (-0.674)</td>
<td>0.547 (0.536)</td>
<td>9.488 (9.402)</td>
</tr>
<tr>
<td>GP regression, Normal likelihood</td>
<td>-0.782 (-0.747)</td>
<td>0.535 (0.495)</td>
<td>9.704 (7.609)</td>
</tr>
<tr>
<td>GP regression, Laplace likelihood</td>
<td>-0.660 (-0.620)</td>
<td>0.535 (0.495)</td>
<td>9.704 (7.609)</td>
</tr>
<tr>
<td>GP regression, T likelihood</td>
<td>-0.629 (-0.557)</td>
<td>0.543 (0.502)</td>
<td>9.746 (5.928)</td>
</tr>
<tr>
<td>GP regression, all features</td>
<td>-0.786 (-0.710)</td>
<td>0.533 (0.485)</td>
<td>9.243 (6.313)</td>
</tr>
<tr>
<td>Linear regression, no log</td>
<td>-15.240 (-14.962)</td>
<td>1.738 (1.732)</td>
<td>9.260 (7.566)</td>
</tr>
<tr>
<td>GP regression, no log</td>
<td>-15.874 (-90.589)</td>
<td>2.775 (0.624)</td>
<td>11.240 (2.889)</td>
</tr>
</tbody>
</table>

Table 2: Cross validation performance (and training set performance in parenthesis) of the different algorithms evaluated by three metrics: log likelihood of the data, root mean squared error (RMSE), and RMSE on the data before logarithmic scaling. Items in bold indicate the best performing method, statistically significant in a pairwise t-test with $p < 0.01$.

EnergyView

Based upon the models from the previous section, we have developed an end-user application, EnergyView, that lets companies or individuals view and compare their energy usage, based upon how their true usage compares to the model’s predictions. The system consists of two parts: for the utilities or authorized organizations (anyone who may obtain access to the individual energy records), we have developed a graphical interface that layers energy consumption over a map of the area. The interface allows users to quickly determine outliers according to the model: building that use significantly more (or less, though presumably little needs to be done in this case) energy than predicted by the model (i.e., even accounting for all the observed features of the building). Thus, these are prime candidates for buildings where energy usage could be reduced by behavior changes, retrofits, etc. Presenting this information to a community organization aimed at energy efficiency, for example, could greatly help such groups decide where to focus resources. A (simulated) screenshot of this system is shown in Figure 3. Due to privacy considerations, such a system is unlikely to become publicly available (though users could opt in to allow public display of their information), but could still be highly valuable for authorized groups.
The second component of the EnergyView system is an end-user tool that lets an owner enter the relevant information about their own home or building, plus gas and electrical consumption, in order to find where they lie in relation to the model’s prediction (we refer to this process as contextualizing energy usage, as it puts it in the context of similar homes). Because such a tool does not disclose identifying information, it can be released publicly and used by building owners or efficiency groups alike. A screenshot of the resulting analysis page is shown in Figure 4, showing a building’s consumption versus expected consumption for each month and displaying where the building lies in the overall distribution. A web version of the tool is available at http://people.csail.mit.edu/kolter/energyview. Although, because our approach is fully data-driving, the validity of the model is specific to the general area of Cambridge, MA, the techniques are quite general, and the same system could be set up for any location given access to similar data.

Conclusion

In this paper we presented a study and analysis of building energy consumption in a large urban environment. To the best of our knowledge, this represents one of the largest academic studies of individual home and building energy consumption using real data for a single city. We have analyzed the distributions of this data, and used these insights to learn models that can predict expected energy usage given features of the home, and which are able to explain roughly 75% of the observed variance in energy consumption according to our logarithmic scaling of the data. Finally, we describe and release EnergyView, a tool that uses these models to visualize both city-level information, and building-level information, allowing end-users to see where their home lies within the expected distribution.

Looking forward, there are numerous possible directions for future work. We are continuing to look for additional sources of data that could be incorporated into the model, such as home survey data or image data. Despite the fact that spatial features did not help the predictions in our current data set, location data seems still to be a promising source of information, and there is a need for algorithms or features that can better capture such relationships. We are working to expand the EnergyView application to allow for opt-in data sharing and incorporation of entered data into the internal models. More broadly speaking, the models and EnergyView tool we present here represents just one facet of the building energy problem; equally important is how we use these models to produce actionable information to the proper groups that can actually lead to energy savings. Understanding how to best achieve these savings using the model’s predictions and determining how the predictions correlate with changeable behaviors in a community, remains a crucial question for further work.

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References


