Predicting Energy Usage to Better Estimate and Market Efficiency Upgrades to Customers

Brian Cain, Brendan Gillenwater, William Ho, Shiv Patel, Xiaoping Zhu, Matthew A. Lanham
Purdue University Krannert School of Management
cain43@purdue.edu; gillenwa@purdue.edu; ho114@purdue.edu; patel596@purdue.edu; zhu546@purdue.edu; lanhamm@purdue.edu

Abstract

The motivation of this study is that being able to accurately predict energy usage would allow companies to better estimate the value of energy efficient upgrades and market those savings to customers. These energy efficient improvements would lead to cost savings to customers, as well as positive environmental impacts. While research has been performed in this area, we focus on developing models that lead to the most accurate predictions which allow companies more precise estimates of efficiency gains.

Introduction

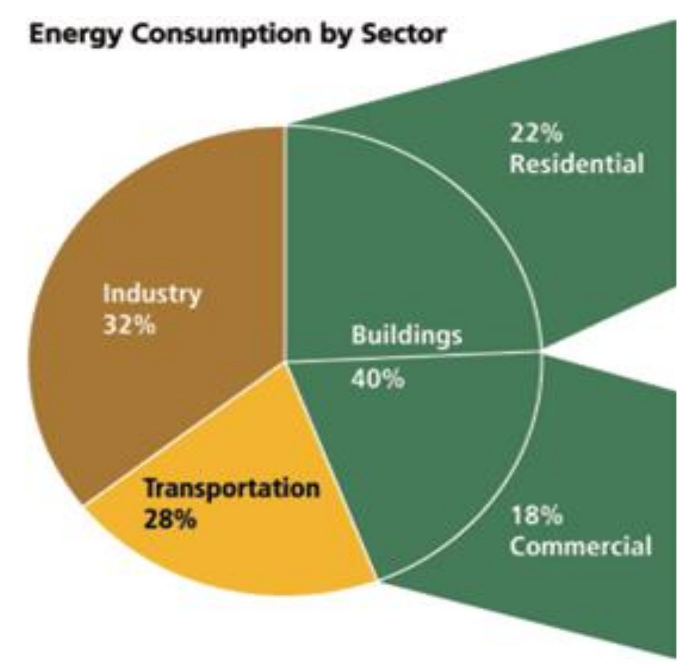


Figure 1. Energy usage separated by sector

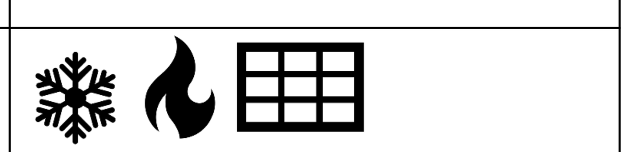
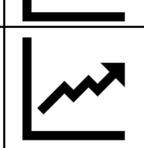
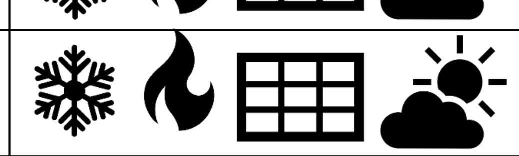
A 2018 study done by the United States Energy Information Administration on energy usage in US buildings concluded that energy consumption from buildings alone account for around 40% of the total energy consumption in the United States. A clear model to measure energy usage is necessary to serve as a baseline to compare potential energy savings.

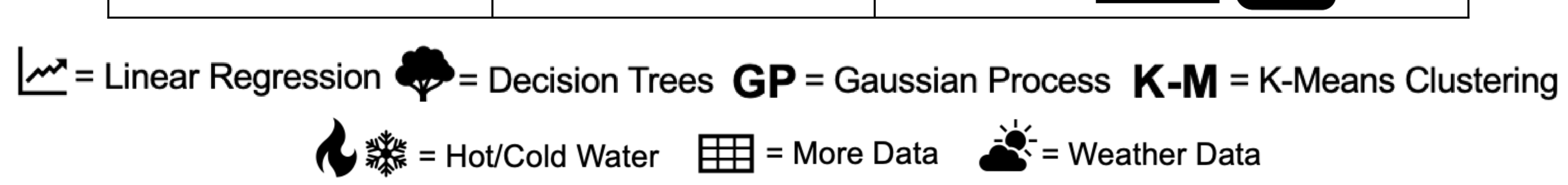
Our model is driven by past data on 4 energy types, basic building information, and past weather data. With predictions on building usage, we can then better predict energy savings for various efficiency upgrades.

Research Question:
Given information on building characteristics, area weather data, and energy use types, what is the predicted energy consumption for a building?

Literature Review

Other similar studies exist; however, our study incorporates multiple energy input types, considerably more data, and many weather inputs.

Study	Methods	Differences in our study
Williams, 2016		
Kolter, 2011	 GP	
Deb & Lee, 2017	K-M	



Methodology

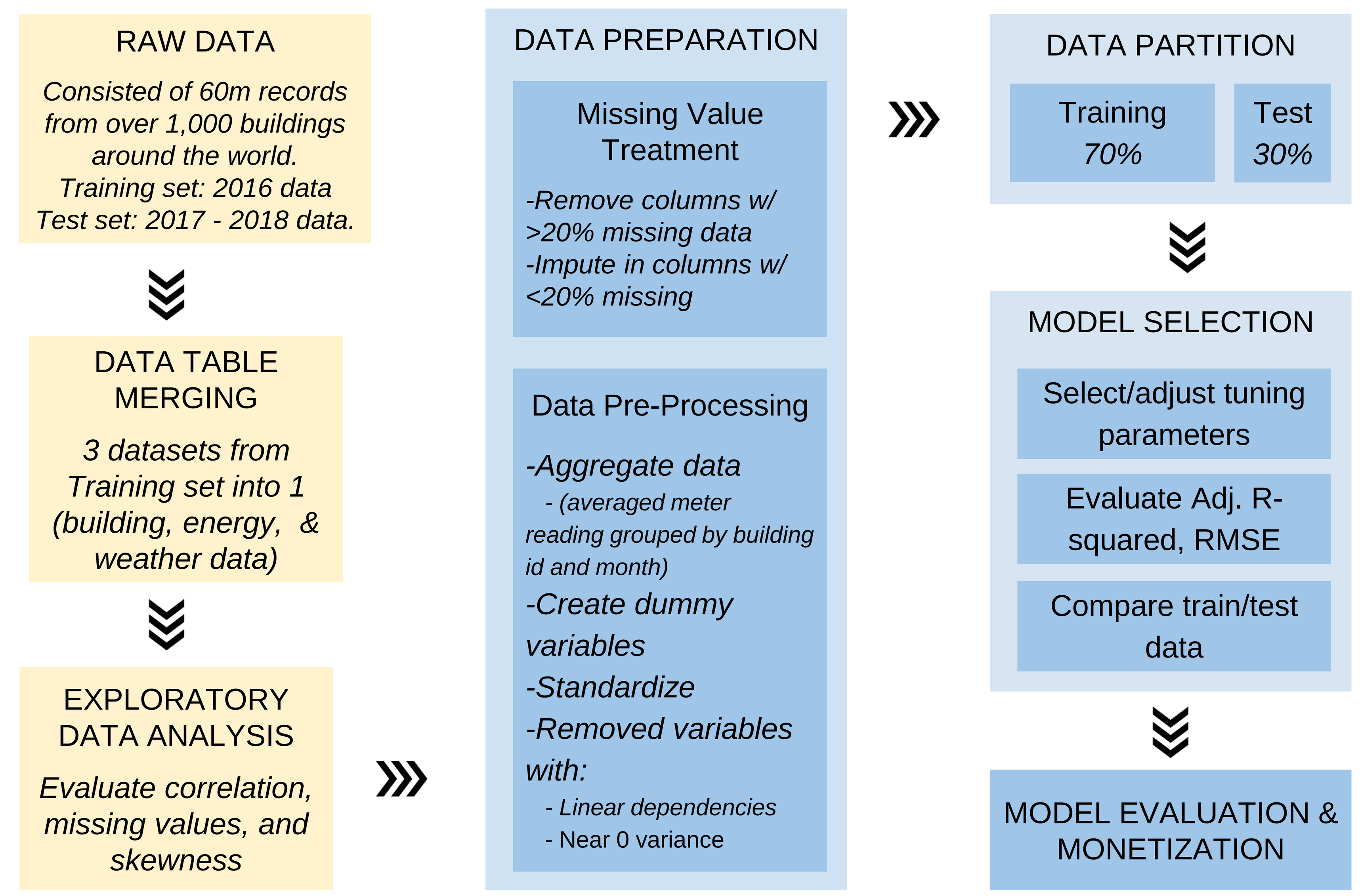


Figure 2. Study Design

Data

- Collected from January 2016 – December 2018 (raw test data set included data in 2016, raw training data set included data from 2017 - 2018).
- Basic building characteristics, hourly weather data, 4 energy meter types.
- Data provided by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) organization.

Methodology

Gradient Boosting Machines (GBM), the selected model, is a machine learning model similar to a Decision Tree. The model makes sequential decision trees and corrects the error from the tree before. Each iteration attempts to better the error from the one before.

A simple Linear Regression and K-Nearest Neighbors were also evaluated. Models were evaluated on Root Mean Squared Error (RMSE) independently and comparing the test set to the train set.

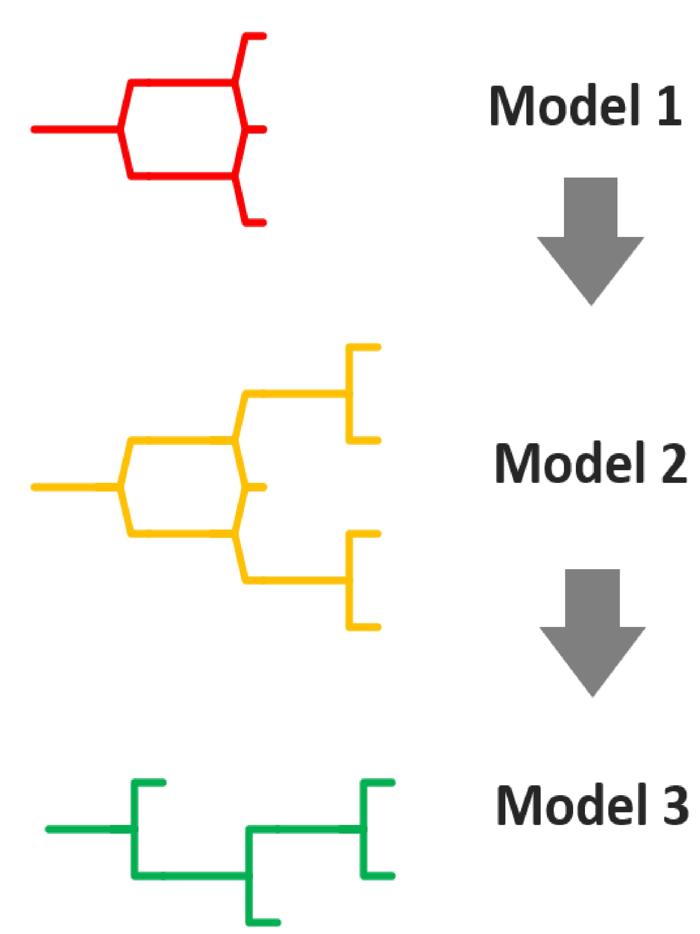


Figure 3. Gradient Boosting Process

Results

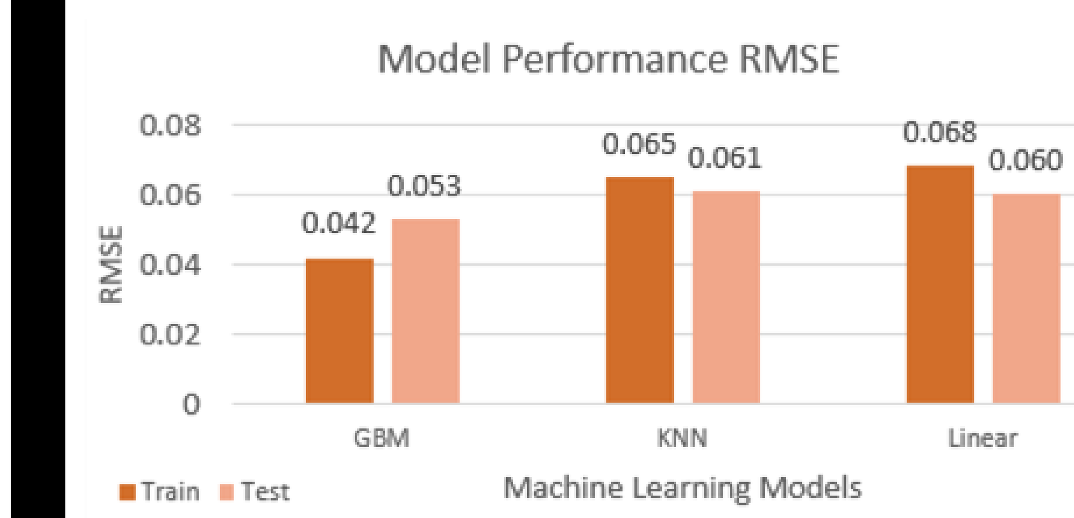


Figure 4. Model Performance Comparison Based on RMSE

Out of the three models, the gradient boosting model (GBM) is the best performing model based on root mean squared error (RMSE). Although the test set from the GBM had a higher RMSE compared to the training set, it provided more accuracy, which was the goal of our research question.

Model Error Explained

$$Z = \frac{Energy\ Prediction - Mean\ Monthly\ Energy\ Usage}{Monthly\ Energy\ Standard\ Deviation}$$

$$Z = \frac{Energy\ Prediction - 1663.67}{80686.95}$$

$$RSME(Z - Score) = .053 = \frac{Energy\ Prediction - 1663.67}{80686.95}$$

$$RMSE\ in\ KwH\ of\ 2612.74\ Per\ Month$$

$$2612.74 * Local\ Energy\ Cost$$

$$Price = \$\ Value\ of\ Error$$

$$\$275\ /\ month\ in\ Indiana$$

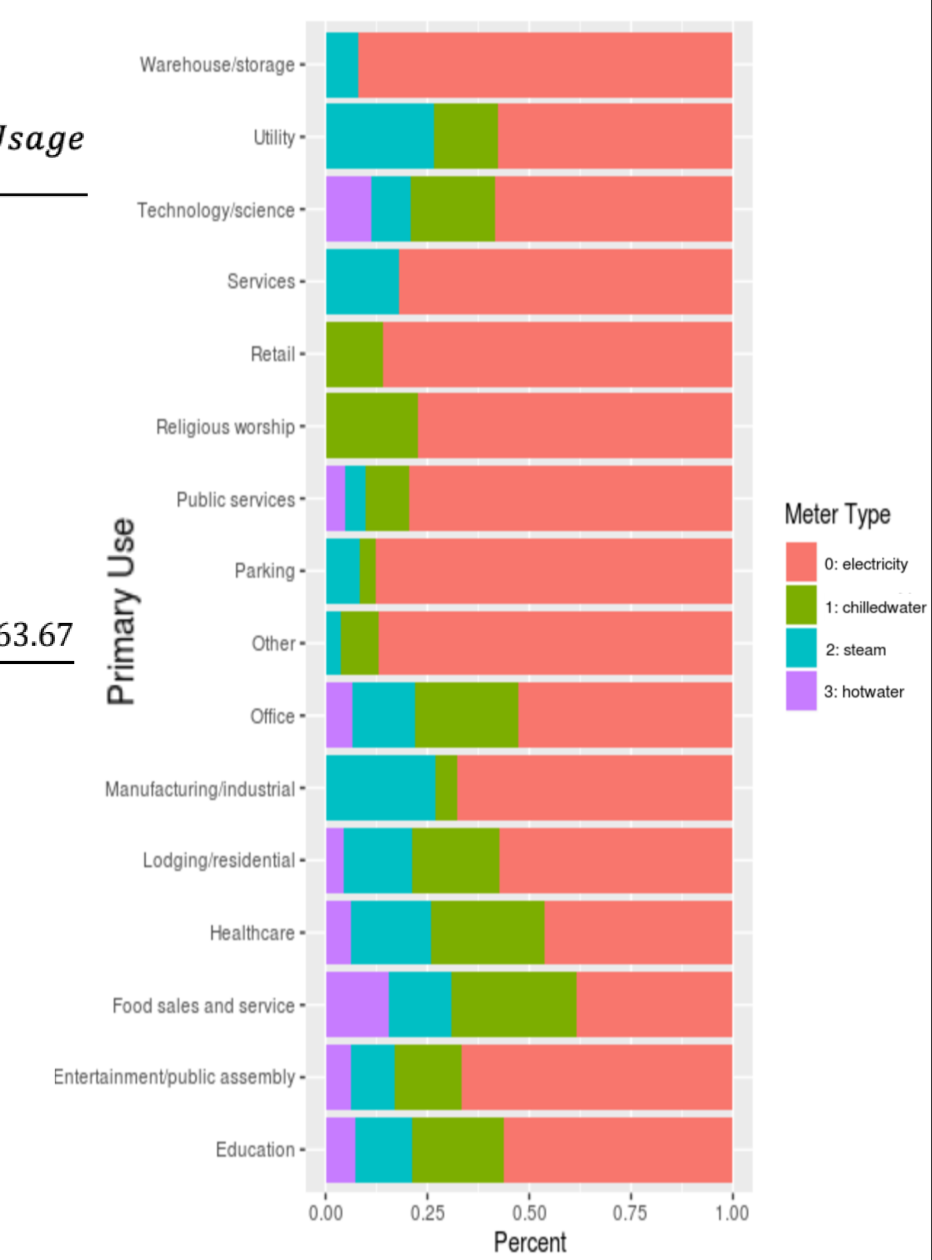


Figure 6. Percent of Meter Type by Primary Use

Conclusions

With our analysis, a company can predict their building energy consumption values to within ± 2,600 KwH/month (~$275/month with Indiana energy rates), which is comparable to approximately 5% of the average energy consumption of a public high school. In addition to square footage, static building data and dynamic climate conditions have importance on energy consumption. From these factors, companies can use these values to help predict their future spending on energy or help in evaluating cost savings (loss) from energy efficiency upgrades.

Acknowledgements

We thank Professor Matthew Lanham for constant guidance on this project.