Energy Prediction for Resident's Activity

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Outline

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- CASAS Smart Environment
- Energy Analysis
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- Discussion
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Introduction

- Based on recent report, buildings are responsible for at least 40% of energy usage in most countries.
- Household consumption of electricity has been growing dramatically.

Related Work:

1. BeAware: Uses an iPhone application to alert users about energy consumption.

2. PowerLine Positioning: Indoor location system capable of localization to subroom level precision.

3. MIT platform: Uses current sensors to monitor changes in electricity flow of different appliances.

Introduction

We envision three applications of smart environment technology for environmental energy efficiency:

1. Analyzing electricity usage to identify trends and anomalies.

2. Predicting the energy that will be used to support specific daily activities.

3. Automating activity support in a more energy efficient manner.

In our current work, ***we validate our hypothesis that energy usage can be predicted from smart home environment sensor data.***

CASAS Smart Environment

Testbed

Two story apartment – Living room, dining area, kitchen on 1st floor and 3 bedrooms and bathroom on the 2nd.

Sensors:
- Motion sensors on the ceiling
- Door sensors on the apartment entry and doors of cabinet, refrigerator and microwave oven
- Temperature sensor in each room
- Power meter
- Analog sensors for burner and water usage
- Sensor to keep track of telephone use.

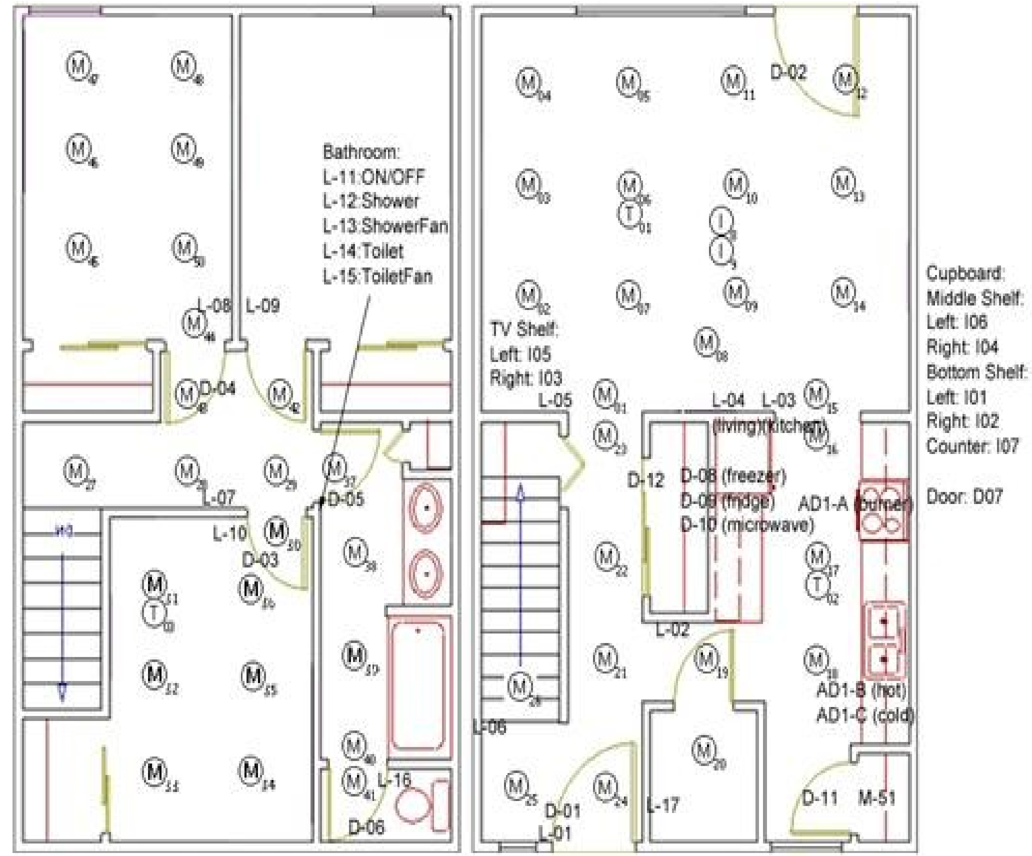

Figure 1. Three-bedroom smart apartment used for data collection (Sensors: motion (M), temperature (T), water (W), burner (B), telephone (P) and item (I)).

CASAS Smart Environment

Annotation

Sample of sensor events:

Date	Time	Sensor ID	Message
2009-02-06	17:17:36	M45	ON
2009-02-06	17:17:40	M45	OFF
2009-02-06	11:13:26	T004	21.5
2009-02-07	11:13:26	P001	0.747kW
2009-02-09	21:15:28	P001	1.929kW

Each of these sensor events are annotated for activities.

CASAS Smart Environment

Data Visualization

Figure 2. PyViz Visualizer

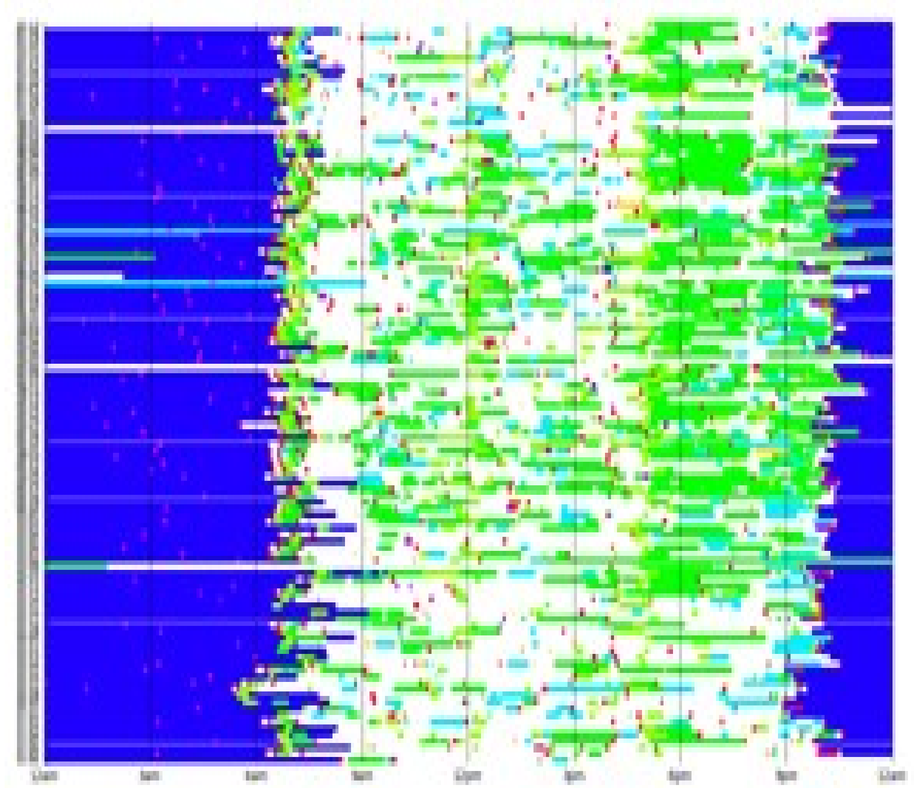

Figure 3. Color coding activities

CASAS Smart Environment

We consider the following activities and the associated appliances for the purpose of our experimentation:

Activity	Appliances Directly Associated	Appliances Indirectly Associated
Work on computer	Computer, printer	Localized lights
Sleep	None	None
Cook	Microwave, oven, stove	Kitchen Lights
Watch TV	TV, DVD player	Localized Lights
Shower	Water heater	Localized Lights
Groom	Blow dryer	Localized Lights

Energy Analysis

Energy fluctuations that occurred during a single day on June 2, 2009.

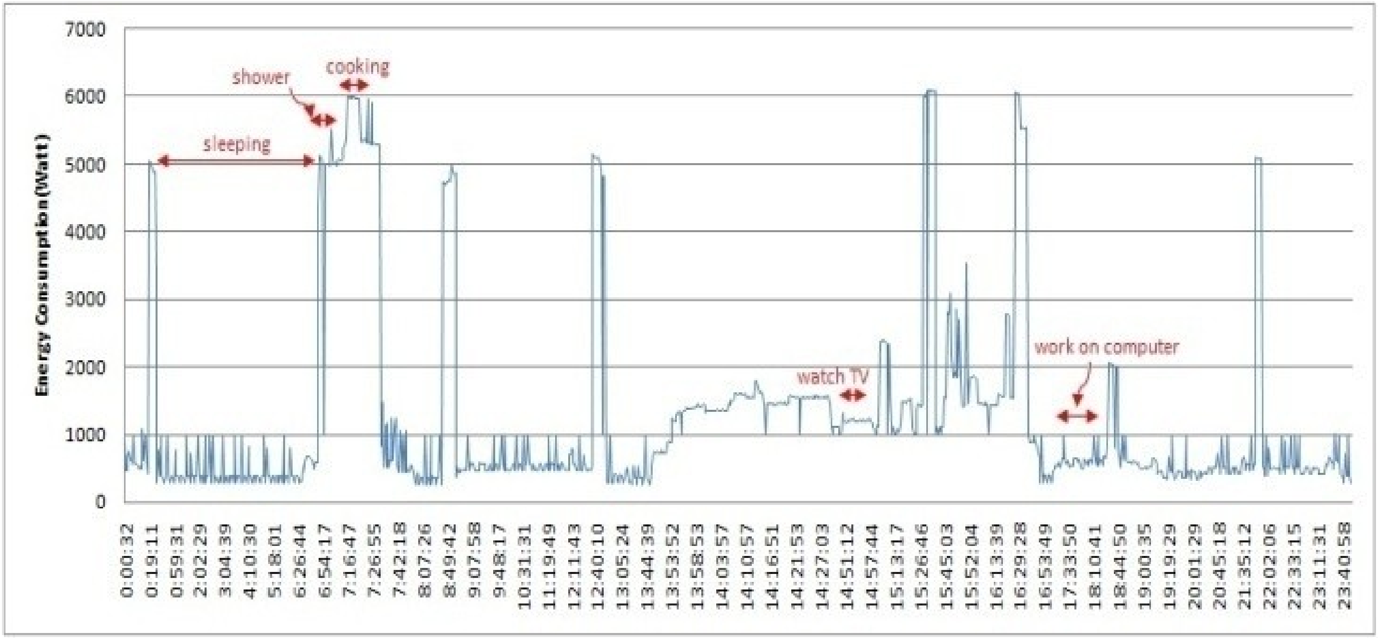

Figure 4. Energy usage for a single day

Energy Analysis

Curve fitting for different activities.

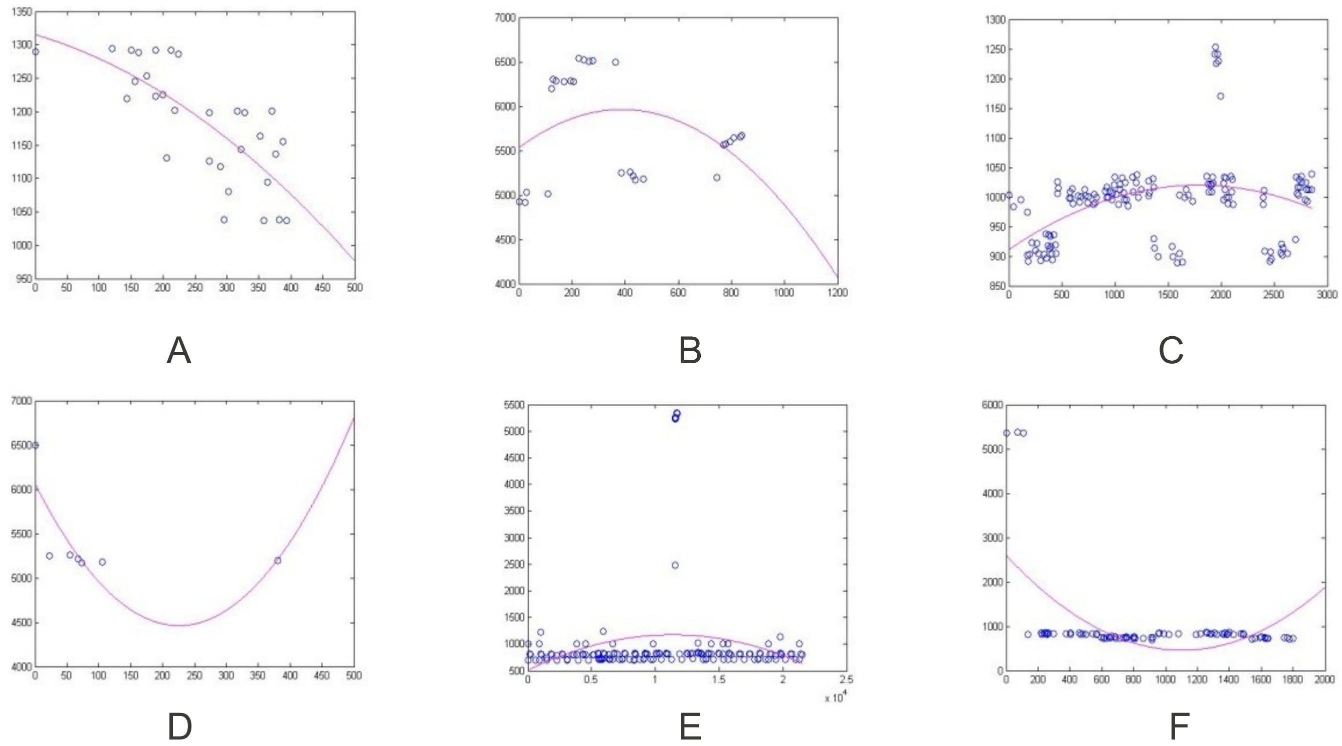

Figure 5. Energy data curve fitting for each activity.
(X-axis: wattage; Y-axis: Time in second; A: Shower; B: Cook;
C: Work on computer; D: Groom; E: Sleep; F: Watch TV)

Energy Analysis

Feature Extraction:

1. Activity Label
2. Activity Length (in seconds)
3. Previous Activity
4. Next Activity
5. Number of types of Motion Sensors involved
6. Total number of times motion sensor events triggered.
7. Motion Sensor M01 … M51 (On/Off)

Target Prediction: Total energy consumption range for an activity (in Watts)

We discretize the target average energy data into several interval classes (2-class, 3-class, 4-class, 5-class and 6-class) with the help of equal length binning.

Feature Selection:

We use information gain to determine the relevant features in our dataset.

Energy Analysis

Energy Prediction:

1. Naïve Bayes Classifier
2. Bayes Net
3. Artificial Neural Network
4. Support Vector Machines

Experimental Results

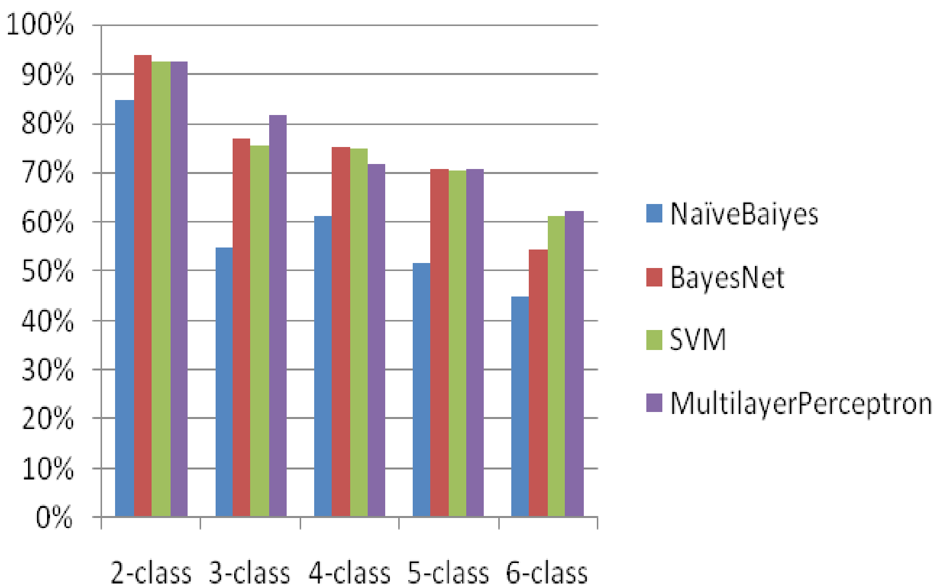

Figure 6. Comparison of the Accuracy for Summer Dataset

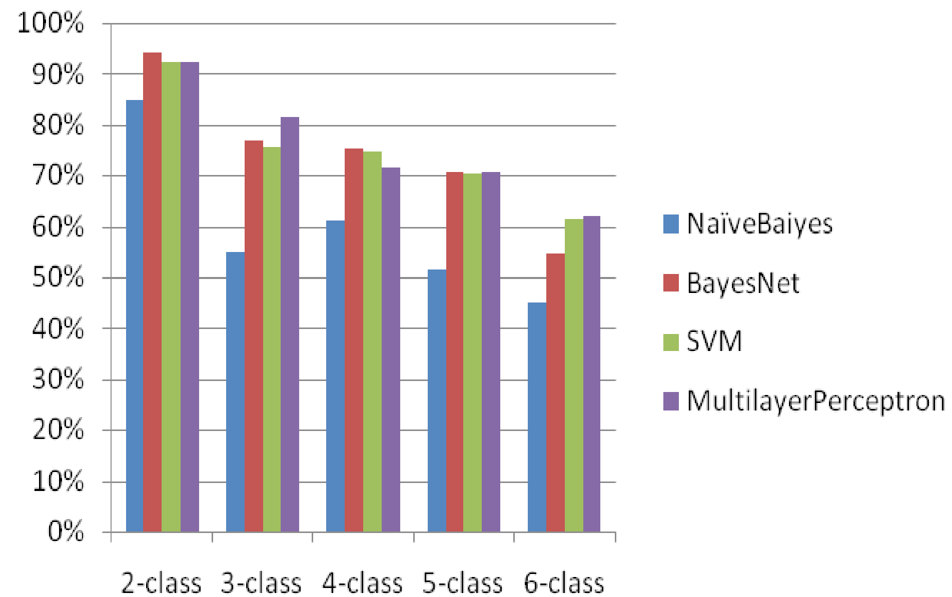

Figure 7. Comparison of the Accuracy for Winter Dataset

Experimental Results

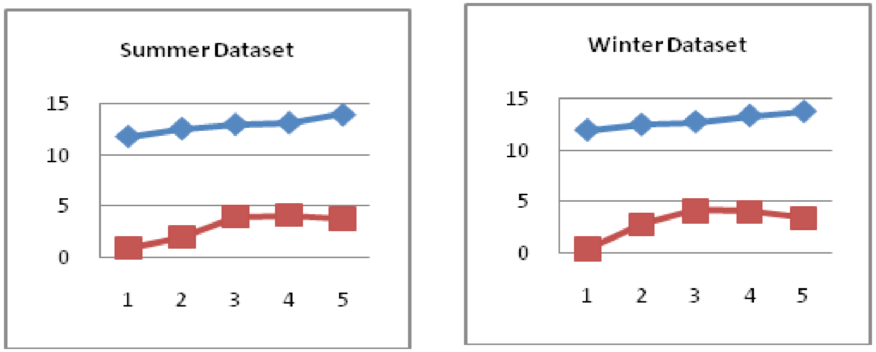

Figure 8. Comparison of time Efficiency.
(X-axis: 1: 2-class; 2: 3-class; 3: 4-class; 4: 5-class; 5: 6-class
Y-axis: Time in seconds; Red: with feature selection; Blue: without feature selection)

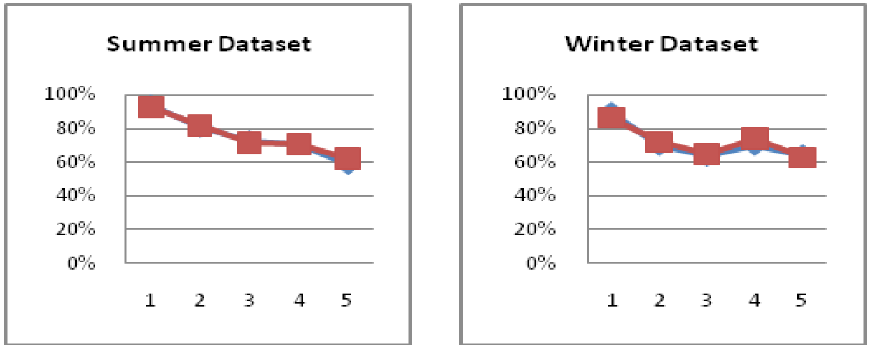

Figure 9. Comparison of Prediction Accuracy.
(X-axis: 1: 2-class; 2: 3-class; 3: 4-class; 4: 5-class; 5: 6-class
Y-axis: Time in seconds; Red: with feature selection; Blue: without feature selection)

Experimental Results

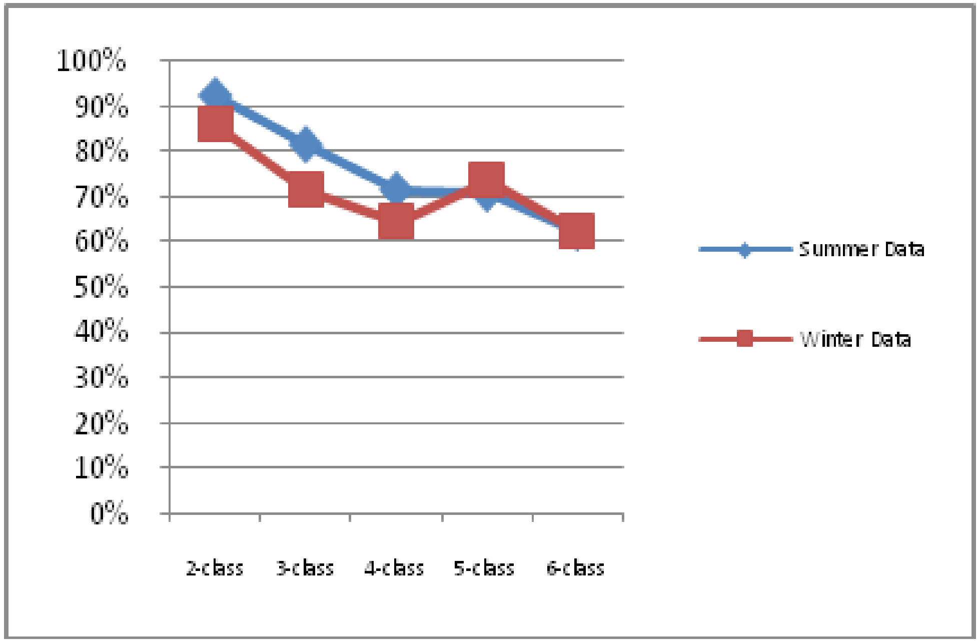

Figure 10. Comparison of accuracy between two datasets

Discussion

The accuracy of these methods is not as high as anticipated when energy data is divided into more than 3 classes.

Reasons:

1. Some of the major devices are difficult to monitor and predict. e.g Floor heater, which also relies on outdoor temperature of the house.

2. No obvious cycle of resident's activities.

3. Noise and perturbation motion when the sensors record data and transfer them into the database.

Conclusion

- Further investigate new and pertinent features to predict the energy more accurately.
- Installing more sensitive sensors.
- Analyze the energy usage data to find the trends and cycles in the data viewed as a time series.

Thank You!