APPLIANCE-SPECIFIC POWER USAGE CLASSIFICATION & DISAGGREGATION

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Introduction

- Appliance-specific energy usage feedback provides consumers with a better understanding of the impact of their consumption behavior, and may lead to behavioral changes that improve energy efficiency
- Energy disaggregation (also referred to as non-intrusive load monitoring) is the task of inferring individual loads of the system from an aggregated signal
- Once a signal is disaggregated, the signals need to be classified according to the appropriate appliance
- With the increasing interest in energy efficiency and recent relevance of machine learning, there is a lot of potential for both predicting and classifying appliance-specific load signals using a wide range of machine learning algorithms

Dataset

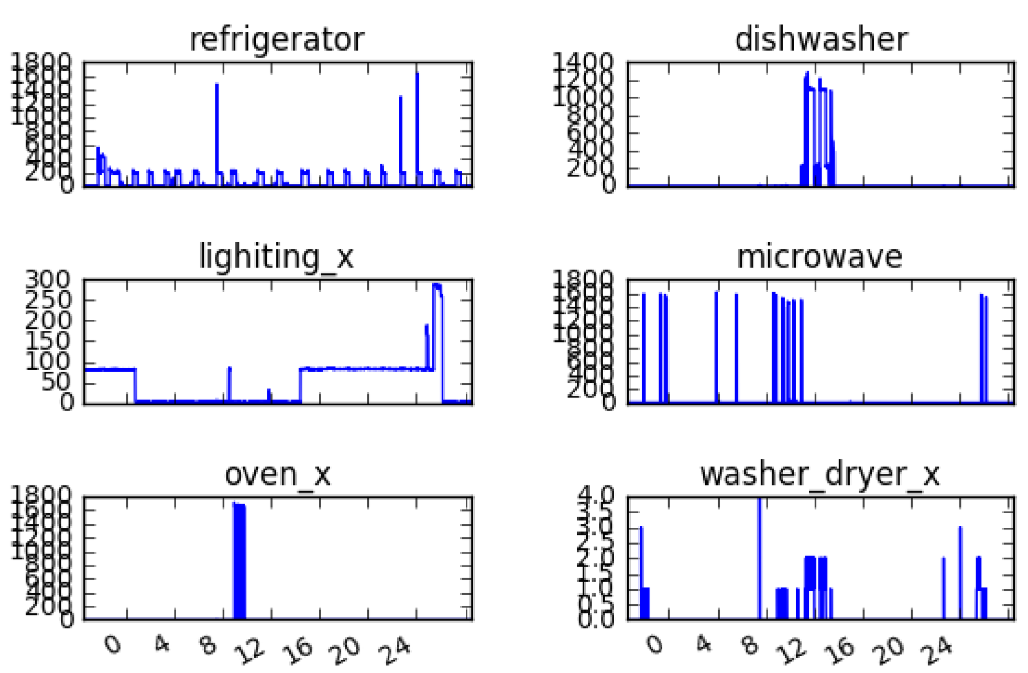

Figure 1. House 1 appliance loads over one day

- Used Reference Energy Disaggregation Data Set (REDD) dataset
- Appliance specific consumption data from six households
- Data collected every 3 seconds over the course of 6-10 days

Feature Extraction

In order to capture the behavior of signals including random high peaks of energy use, we extracted the following as the features of the dataset:

- The maximum and minimum power consumption of the day
- The mean and variance of the power consumption of the appliance over the course of an hour
- The baseline value of the appliance by day
- The weekday, hour, minute & second that the appliance is operating.

Method

Disaggregation

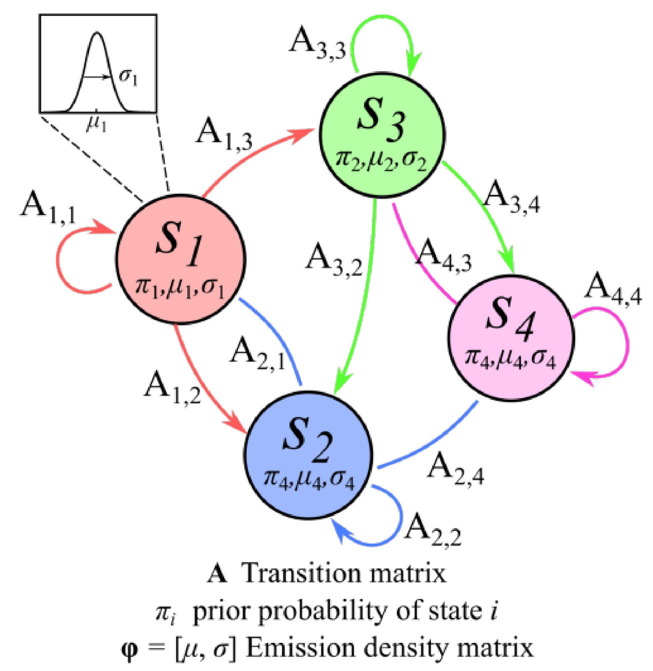

Figure 2. Appliance HMM

- Individual appliance models were built to model the power consumption of each appliance as a series of hidden states as a mixture of Gaussian HMM
- A custom HMM with hidden states as the Kronecker product of the parameters of the individual appliance model was developed to represent the aggregated load
- Final model fit parameters from the individual appliance models (π ,A, μ, σ) are used as initialization parameters for the aggregated HMM

Results: Classification

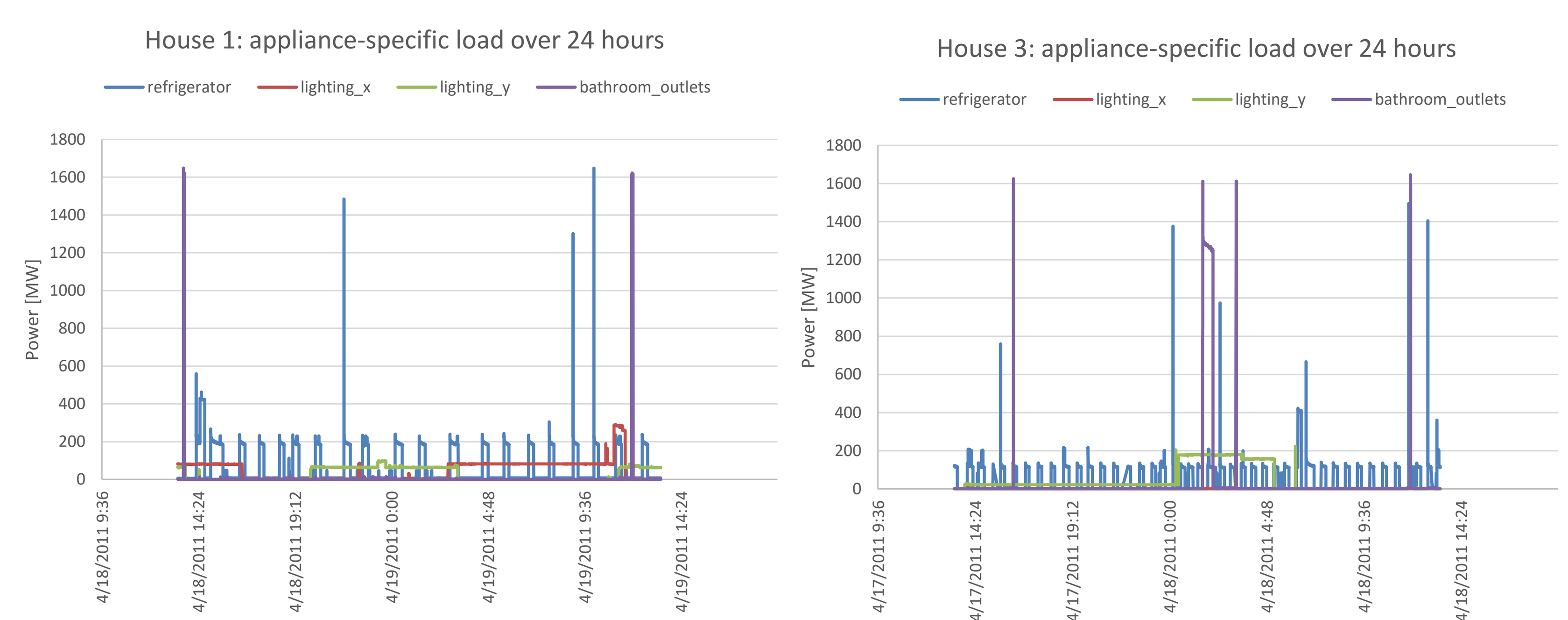

Figure 3. House 1 and 3 appliance loads over one day

3 Different Types of Classification
- Type 1: Train and test on House 1 data
- Type 2: Train and test on aggregated House 1 and House 3 data
- Type 3: Train on House 1 and test on House 3 data

	Type 1	Type 2	Type 3
Training Set Accuracy	0.811	0.566	0.810
Test Set Accuracy	0.810	0.565	0.211

Results: Disaggregation

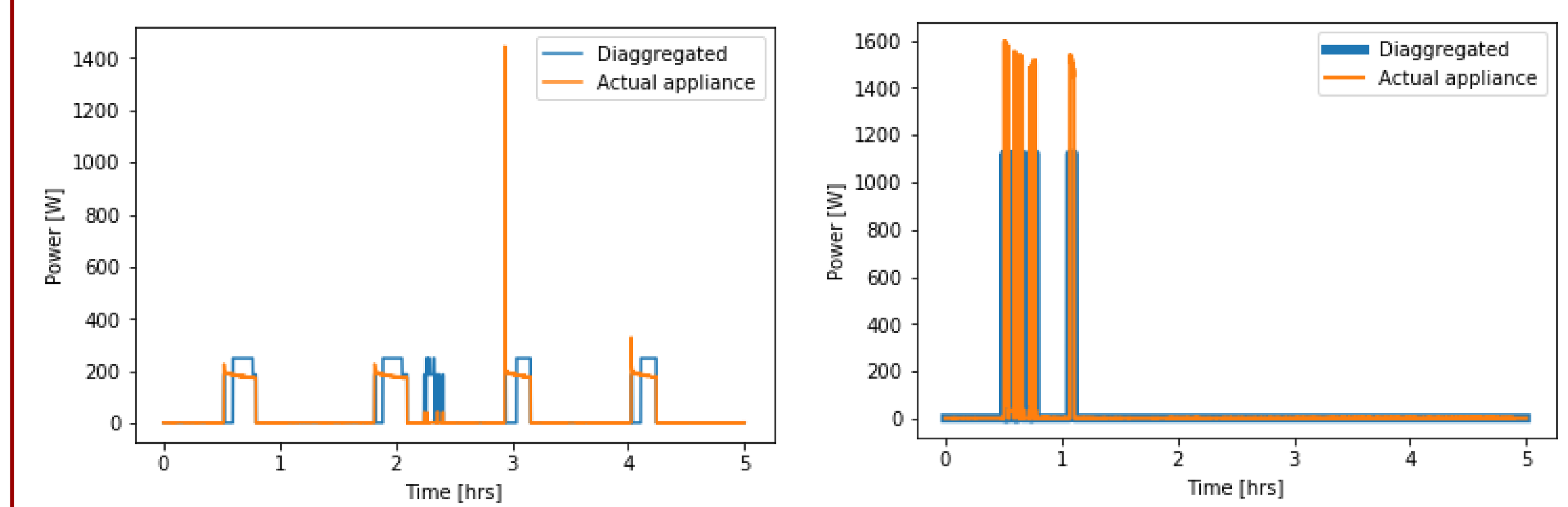

Figure 4. Refrigerator and microwave disaggregation

Appliance	Actual Energy (%)	Estimated Energy (%)
Refrigerator	77.95	78.37
Microwave	22.05	16.57

Conclusions

- Significant variations in household consumption profiles implies that classification algorithms trained on one house perform poorly on others
- Disaggregation using a two-step modeling approach outperforms simple HMMs trained on individual appliances
- Correlations between appliances are esoteric and modelling approaches need account for these differences

Future Work

- Customize the emission probabilities in Hidden Markov Model to include constraints to prevent overestimation of energy consumption
- Efficient modelling of aggregated states to include more than two appliances

References

Kolter, J Zico, and Matthew J Johnson. "A Public Data Set for Energy Disaggregation Research." *SustKDD*, Aug. 2011, doi:1 ACM 978-1-4503-0840-3

Faustine, Anthony, et al. "A Survey on Non-Intrusive Load Monitoring Methodies and Techniques for Energy Disaggregation Problem." arXiv preprint arXiv:1703.00785 (2017)

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