Contextually Supervised Source Separation with Application to Energy Disaggregation

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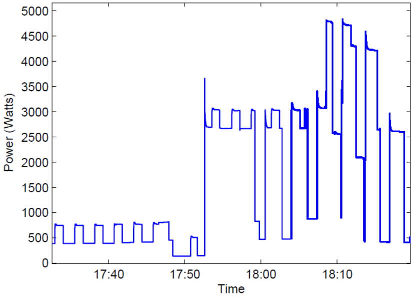
Energy disaggregation

Goal: separate whole-home power signal into different energy uses

Total Power



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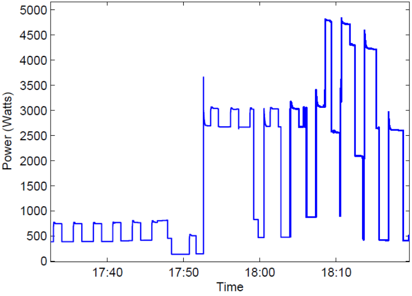
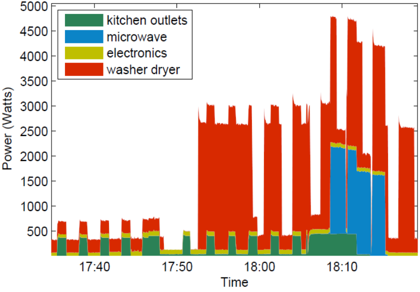


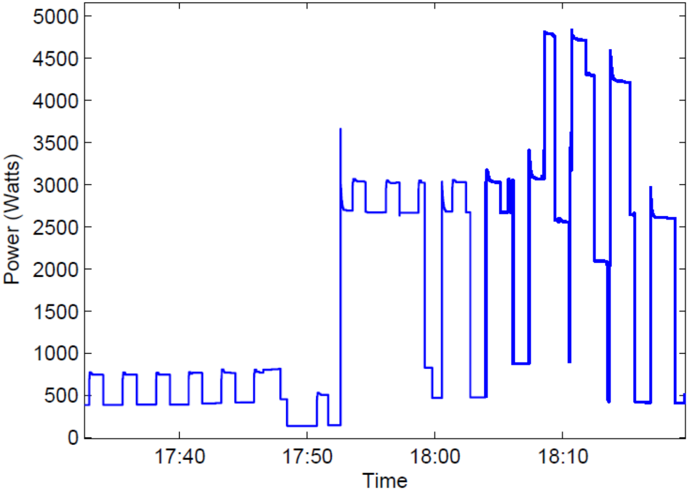
Disaggregated Power



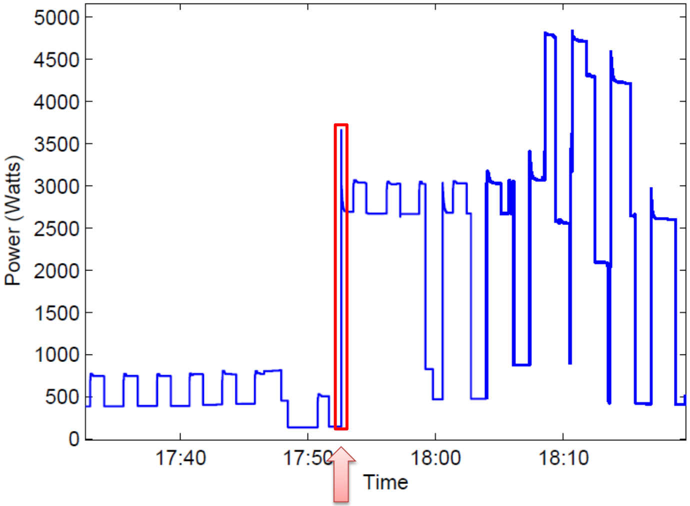
Motivation

- Consumer perspective: Studies have shown that itemized electricity bills lead to increased efficiency by giving actionable information
- Utility perspective: Understanding appliance level usage allows for targeting consumer incentives, improved demand response programs, etc.

Energy disaggregation



Energy disaggregation



Existing approaches

- Large amount of work going back more than 20 years

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- Now, utilities collecting data from millions of homes
- But...
  - Readings are very low resolution (hourly)
  - No labeled appliance data
- Existing approaches not very practical
- What can we do?

Contextual supervision

- We propose a framework of contextual supervision: use easily observable context to disambiguate energy usage
- Examples
  - A/C correlates with hot weather
  - Heating correlates with cold weather
  - Lights correlate with darkness
  - etc.

Mathematical formulation

- Consider the energy disaggregation task for a single home
- Let $y_i \in \mathbb{R}^T$ denote the amount of energy used by appliance i over the entire time series
- We actually observe $\bar{y} = \sum_{i=1}^k y_i$, total energy usage
- However, suppose for each appliance we can provide features believed to be correlated with that usage $X_i \in \mathbb{R}^{T \times n_i}$

$$y_i \approx X_i \theta_i$$

Optimization problem

- Given $\bar{y}$ and X_i for each appliance (which we design), we solve the optimization problem

$$\begin{array}{ll} \underset{y_1,\ldots,y_k,\theta_1,\ldots,\theta_k}{\text{minimize}} & \sum_{i=1}^{k} \ell_i(y_i, X_i\theta_i) + g_i(y_i) \\ \text{subject to} & \sum_{i=1}^{k} y_i = \bar{y} \end{array}$$

- ℓ_i and g_i are functions that we choose to encode the likely nature of energy usage for appliance i

- y_i (disaggregated energy use) and θ_i are outputs of optimization

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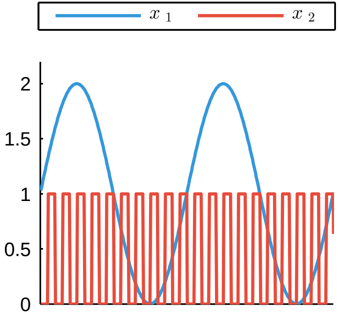
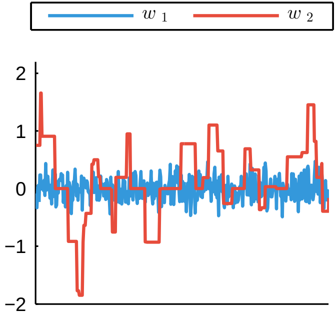
Synthetic problem





Simple example containing two signals with different noise models

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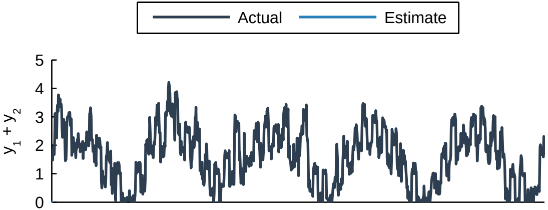

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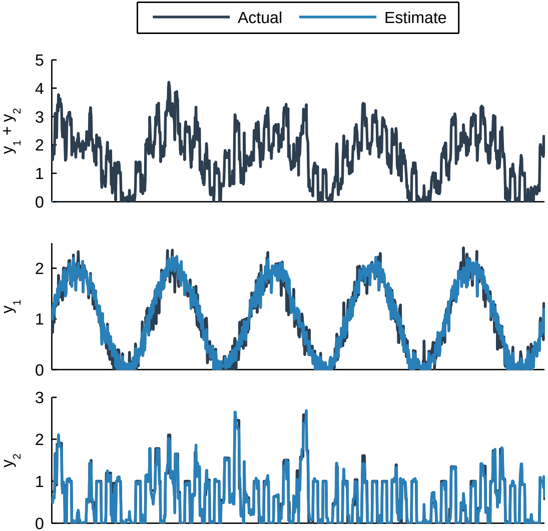


Model for energy disaggregation

- Recall optimization objective

$$\underset{y_1,\ldots,y_k,\theta_1,\ldots,\theta_k}{\text{minimize}} \sum_{i=1}^{k} \ell_i(y_i, X_i\theta_i) + g_i(y_i)$$

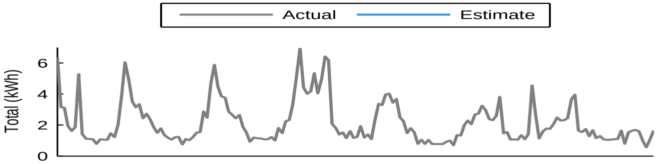
- Simple model with four sources

Category	**Features**	ℓ_i	g_i
Base	Hour of day	$\alpha_1\|y_1 - X_1\theta_1\|_1$	$\beta_1\|Dy_1\|_2^2$
A/C	RBFs $> 70°\mathrm{F}$	$\alpha_2\|S_2(y_2 - X_2\theta_2)\|_1$	$\beta_2\|Dy_2\|_1$
Heating	RBFs $< 50°\mathrm{F}$	$\alpha_3\|S_2(y_3 - X_3\theta_3)\|_1$	$\beta_3\|Dy_3\|_1$
Appliance	None	$\alpha_4\|y_4\|_1$	$\beta_4\|Dy_4\|_1$

- Validate model with small amount of labeled data from Pecan Street project (84 homes)

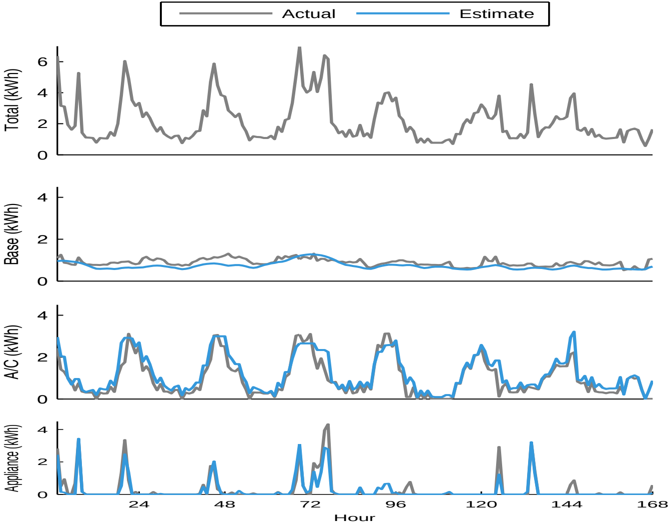
- Apply to large-scale dataset with 10,000+ homes (PG&E)

Energy disaggregation results



One week of energy usage from a single home

Energy disaggregation results

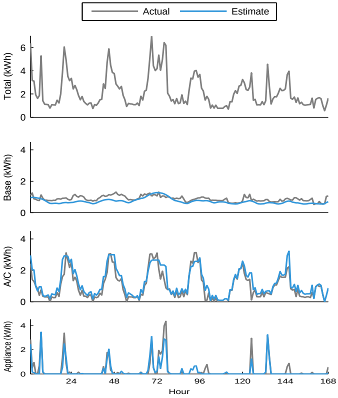


Performance comparison

Category	Mean	NNSC	Contextual
Base	0.2534	0.2793	0.1849
A/C	0.2849	0.2894	0.1919
Appliance	0.2262	0.2416	0.1900
Average	0.2548	0.2701	**0.1889**

Contextual supervision improves 26% over baselines in mean absolute error (MAE)

Summary and conclusions



- Propose *contextual supervision* which lies between the fully supervised and unsupervised setting

- Motivating application is energy disaggregation of hourly smart meter data

- Can provide itemized energy usage for millions of homes