Team Fortum

Disaggregation of household electricity consumption

Final Presentation

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Outline of the presentation

- What is electricity disaggregation?
- Project objectives
- Electricity disaggregation methods
- Hidden Markov model theory
- Model implementation
- Results
- Discussion
- Conclusion

What is electricity disaggregation?

- Separating the total electricity load of a household into appliance specific loads
- Intrusive device specific monitoring is avoided
- Smart meter data
- Opens possibilities to gain insights on customer electricity usage behavior

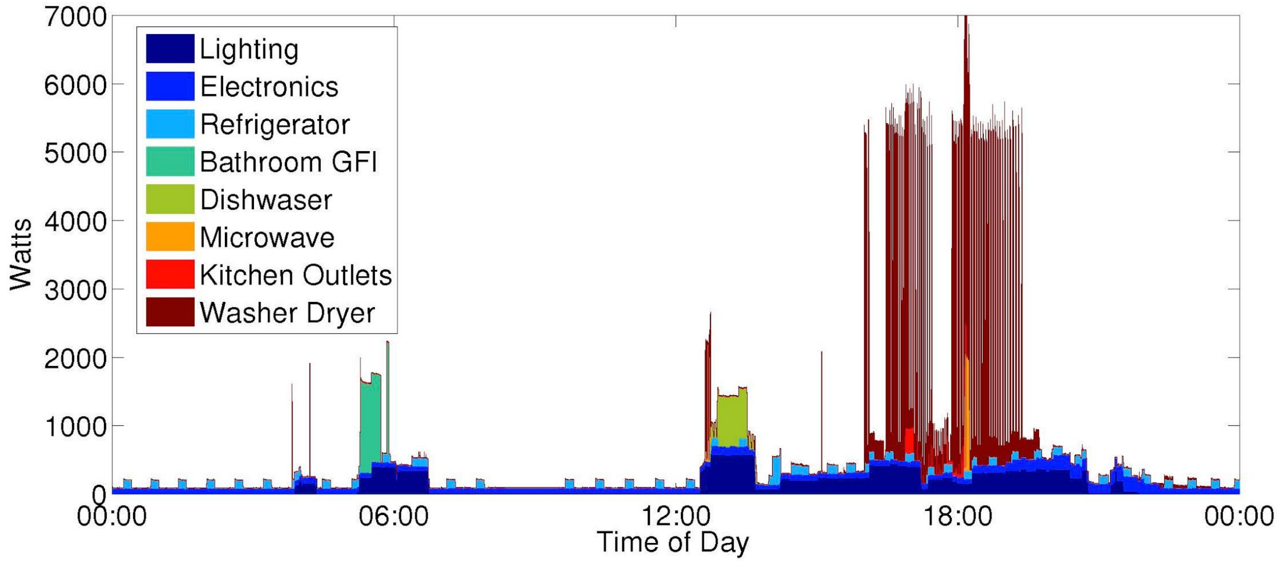

 Image source: MIT LIDS

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Project objectives

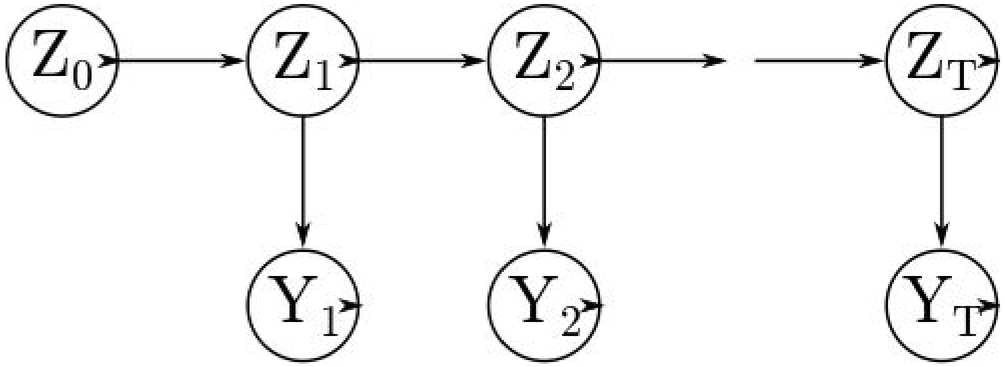
- Provide a study of current electricity disaggregation methods
- Understand the possibilities and limitations
- Compare different methods
- Implement a proof of concept unsupervised electricity disaggregation model
- Test model with Fortum’s own data

Electricity disaggregation methods

- Supervised disaggregation algorithms
  - Require labelled appliance-level training data
    - Training data from each household → Fully supervised
    - Training data from some households → Semi-supervised
  - Different approaches
    - Optimization based methods, e.g. Combinatorial Optimization (CO)
    - Pattern recognition based methods, e.g. Artificial Neural Networks, Support Vector Machines
- Unsupervised disaggregation algorithms
  - Training data not needed
  - Different approaches
    - Hidden Markov Model based approaches most common
    - Graphical Signal Processing, Dynamic Time Warping, Deep Learning etc.

Theory
Hidden Markov Models (HMM)

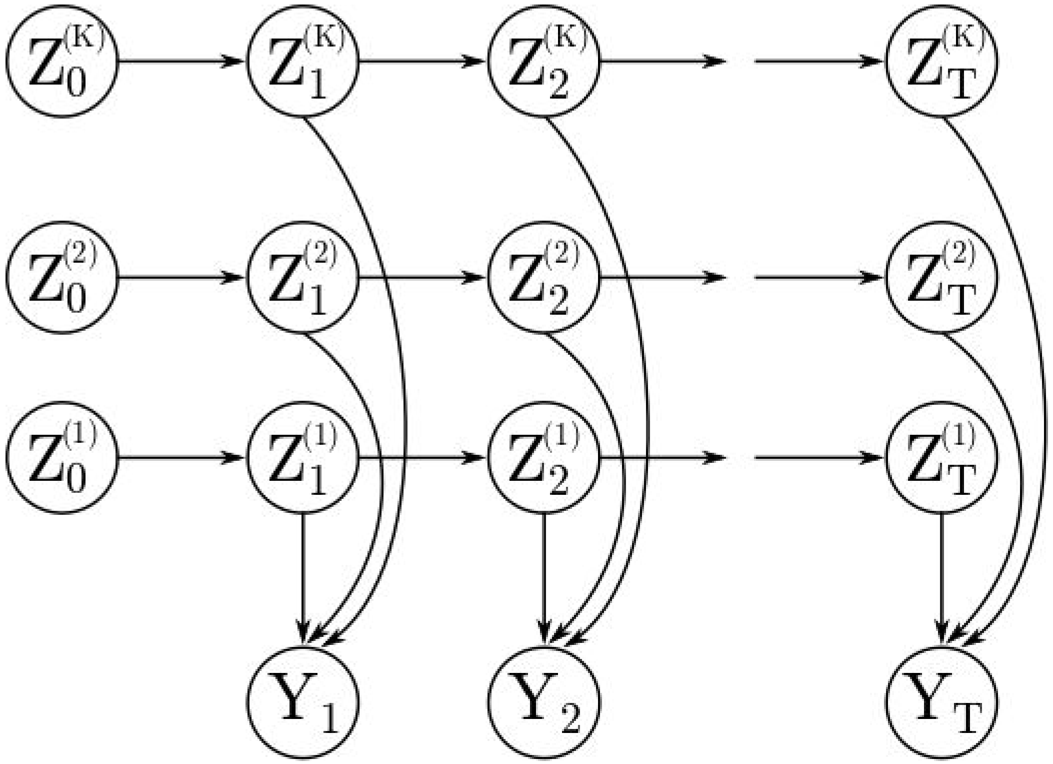
- Widely used in modeling discrete time series
- System state is modeled as a hidden Markov chain Z_t
- Observations Y_t are emitted by the hidden variable Z_t
- Simple and efficient parameter estimation
- Many extensions exist



Theory

Factorial Hidden Markov Models (FHMM)

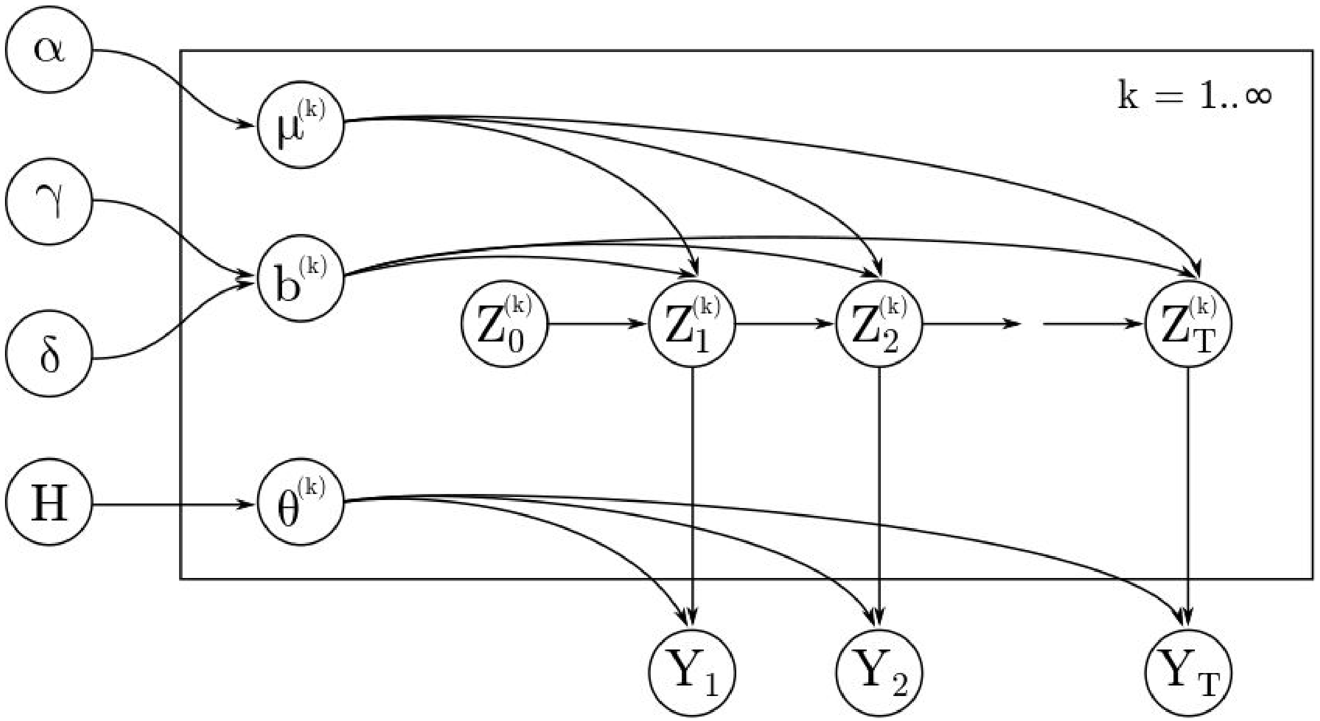
- An extension of the classical HMM
- The hidden state is factored into separate components
- Each component evolves with independent Markov dynamics
- Observation Y_t is a function of component outputs
- The number of components is known beforehand



Theory

Nonparametric Factorial Hidden Markov Model (NFHMM)

- Bayesian nonparametric extension of the FHMM
- The number of components is unbounded
- The Markov Indian Buffet Process is used as a prior over binary matrices with infinite columns
- Stick-breaking representation possible



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Implementation

Inference algorithm

Input

Y: Aggregate electricity consumption data

Initialization

$\mathbf{Z}, \mu, b, \theta$

Iteration number `IterNum`.

Iteration loop

while `IterNum` > 0 **do**

1. Sample slice variable s
2. Expand representation of $\mathbf{Z}, \mu, b, \theta$.
3. Sample $\mathbf{Z}$ using blocked Gibbs sampling and Forward Filtering Backward Sampling (FFBS).
4. Sample θ, μ, b
5. Sample hyperparameters $\alpha, \delta, \gamma, \mu_\theta, \sigma^2_\theta, \sigma^2_\epsilon$ from their conjugate posterior distributions.
6. `IterNum` $\leftarrow$ `IterNum` - 1.

Output

Z: Binary state matrix

θ: Device power levels.

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Implementation

Non-Intrusive Load Monitoring Toolkit (NILMTK)

- Toolkit to facilitate electricity disaggregation research
- Published in 2014 in the 5th International Conference on Future Energy Systems
- Convert and import public datasets
- Statistics, preprocessing and disaggregation metrics
- Benchmark disaggregation algorithms

NILMTK: An Open Source Toolkit for Non-intrusive Load Monitoring

[Extended Abstract]

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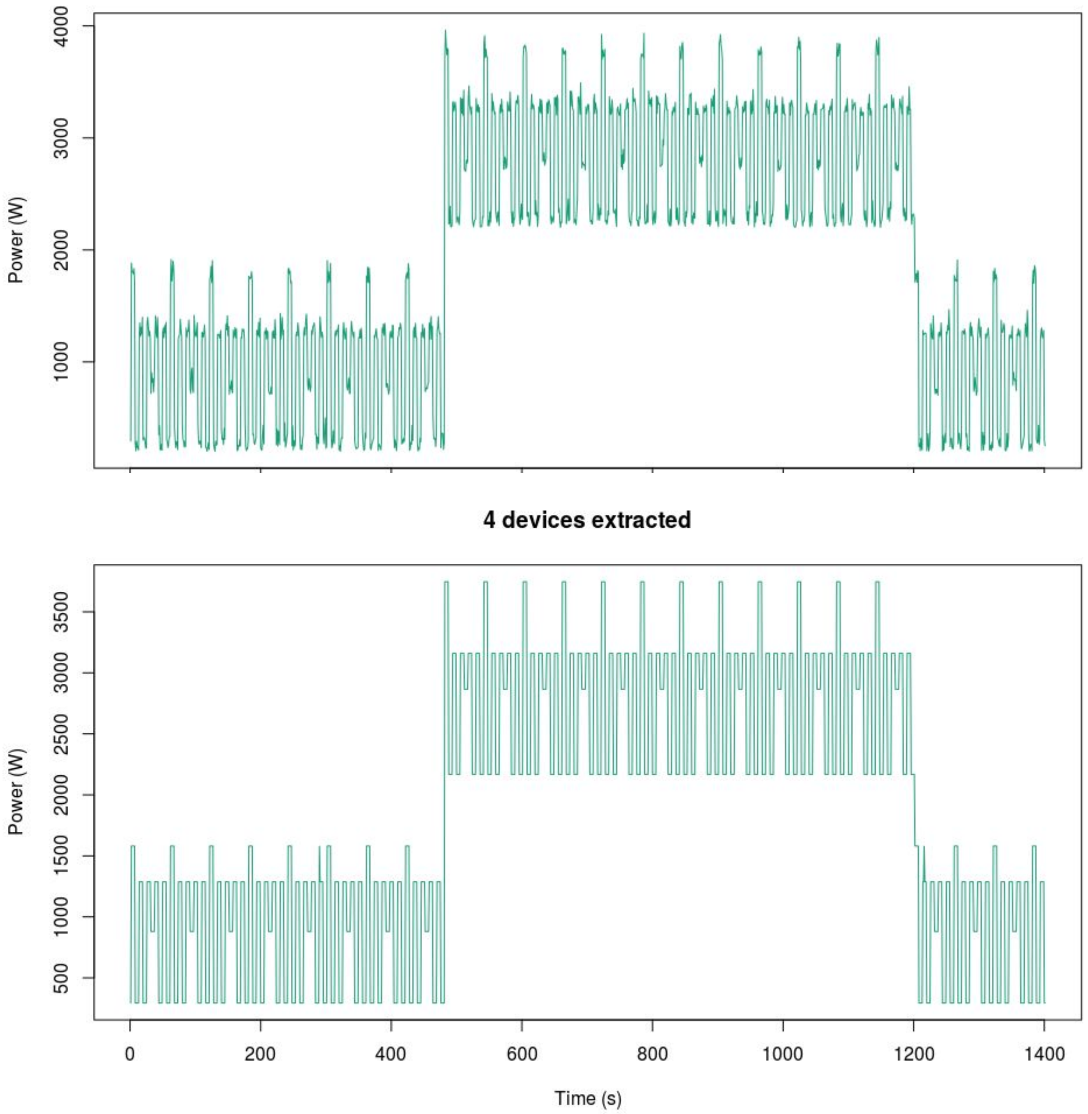
http://nilmtk.github.io/

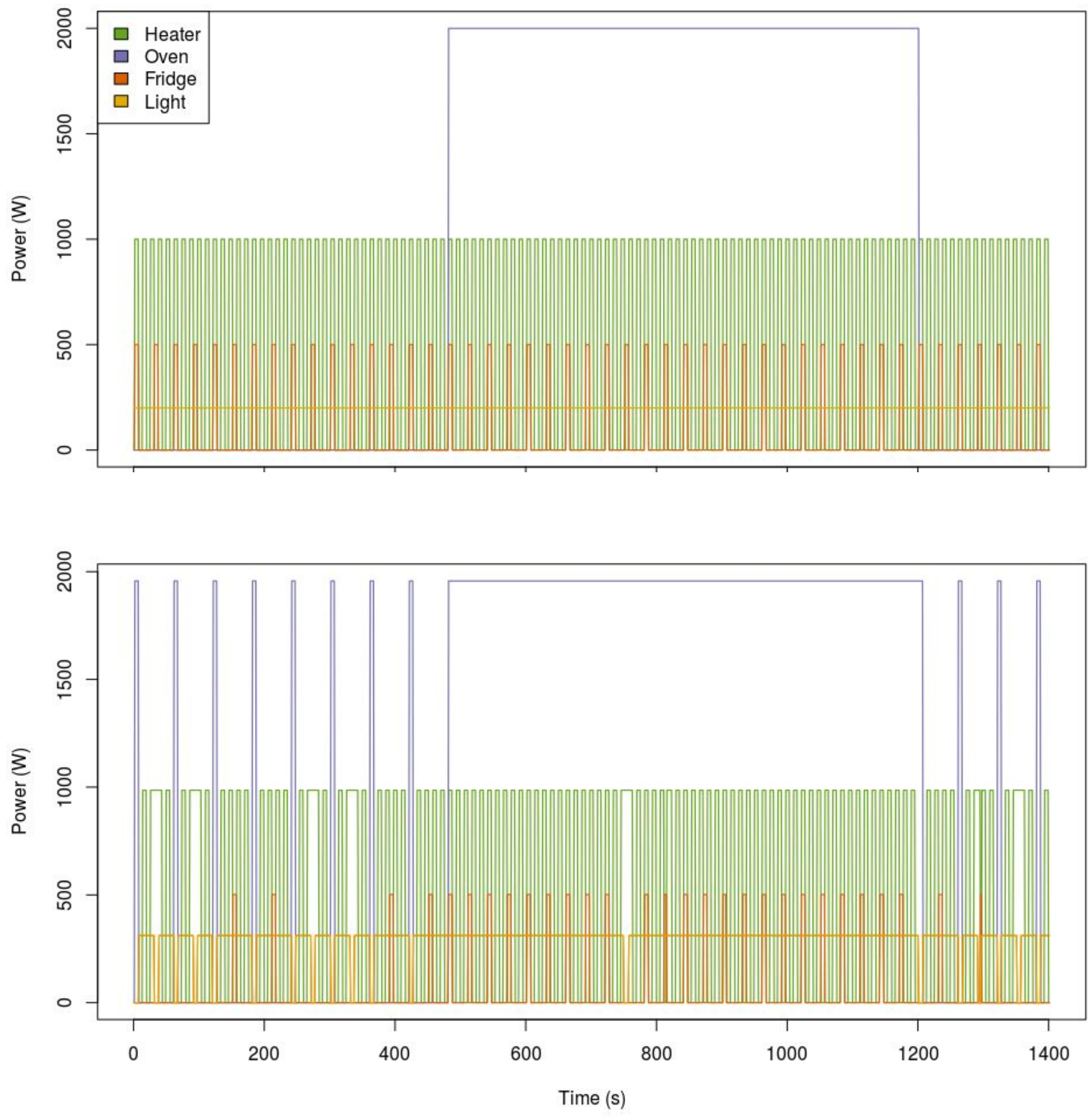
Results
Synthetic dataset

- A simple synthetic dataset was created to test the disaggregation
- The dataset is comprised by a heater, an oven, a fridge and a light
- 4 devices are extracted by the algorithm
- Observation matches sum of disaggregates
- Noise in signal is quite well estimated



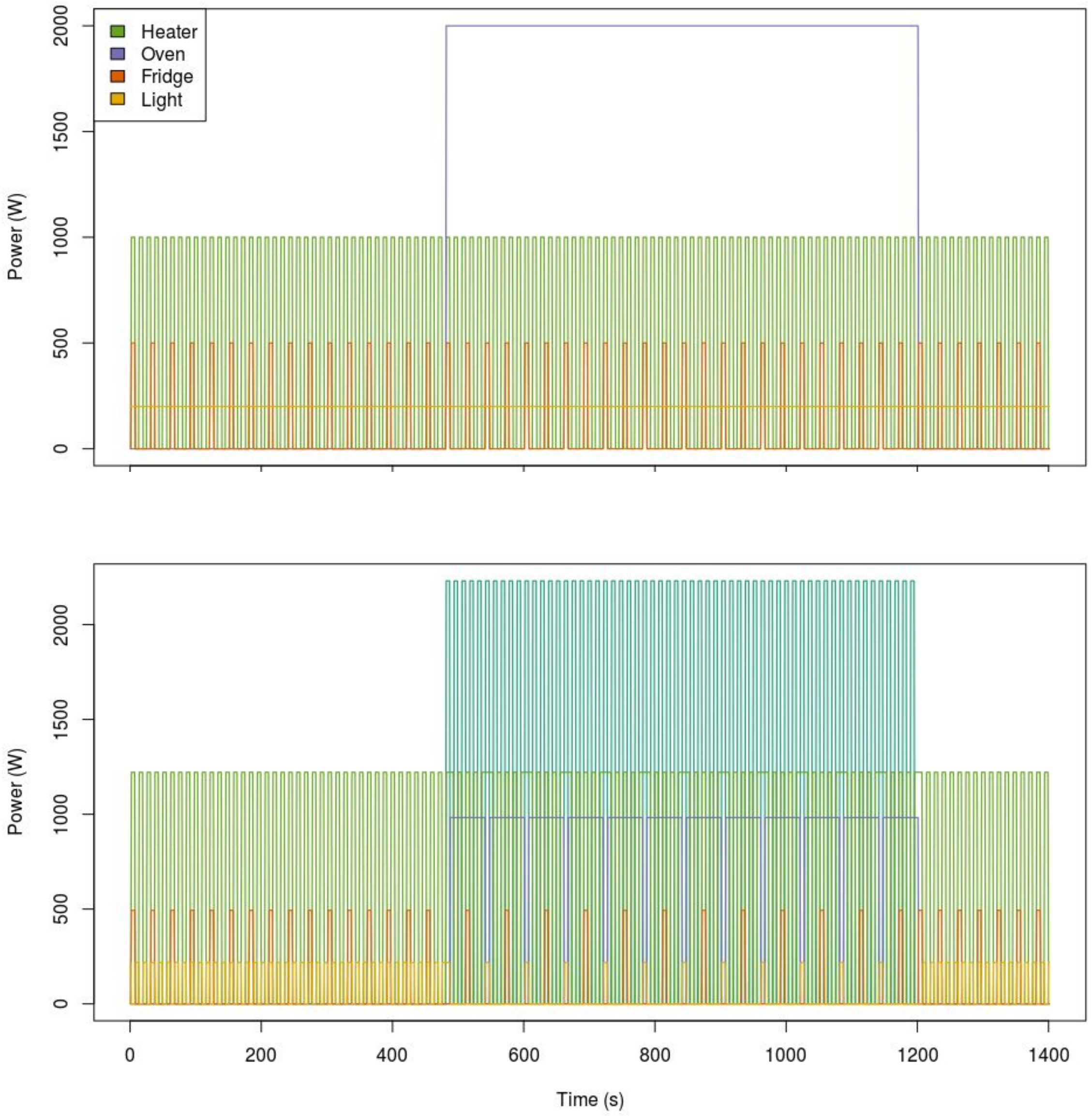
Results
Synthetic dataset

- Disaggregation results seem quite reasonable
- Correct number of appliances
- Power levels are correct
- Some usage durations are not realistic
- Semi-Markov property would be helpful



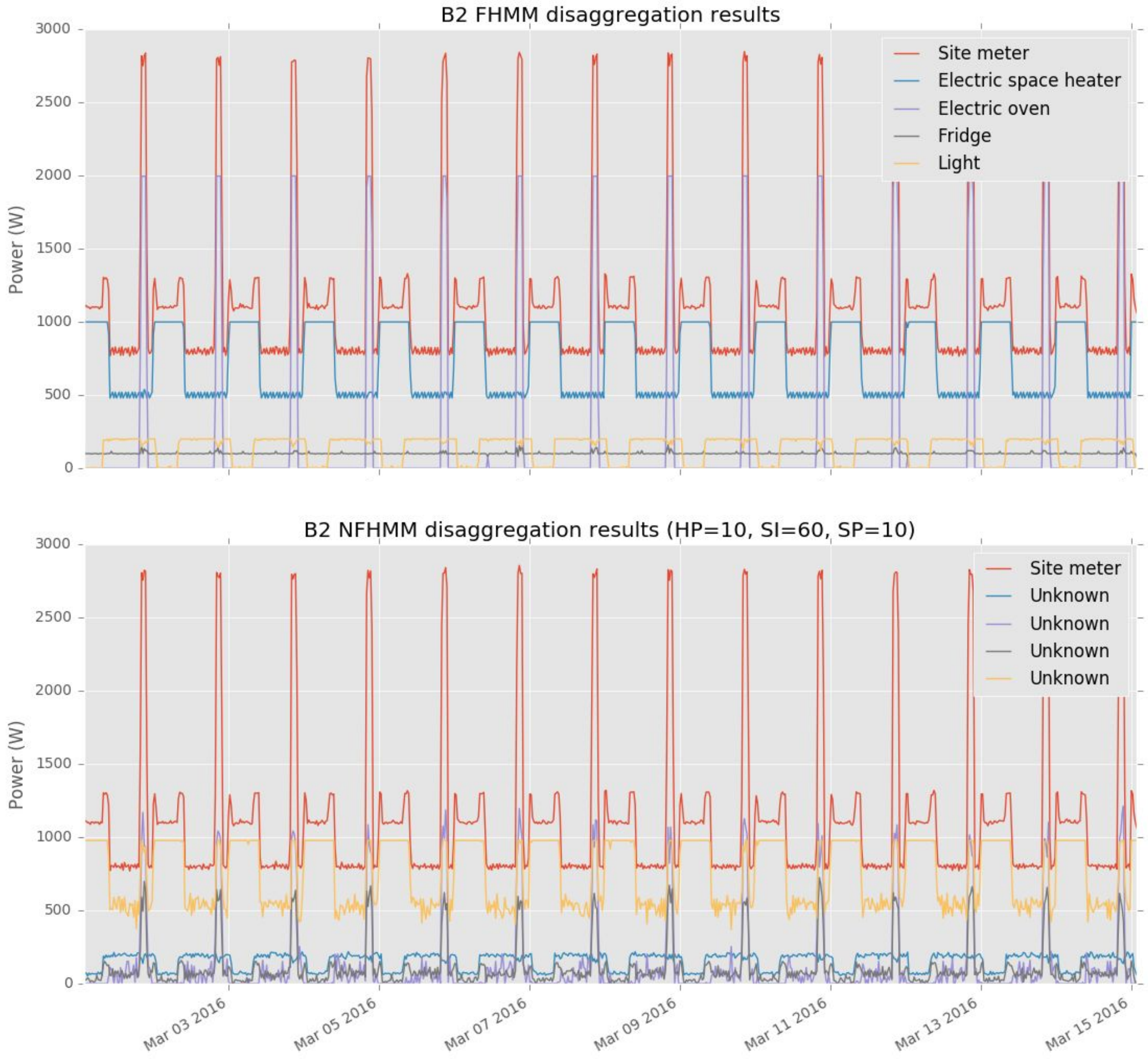
Results
Synthetic dataset

- The probabilistic nature of the model can cause variation in the number of extracted appliances
- Results again seem reasonable, however one extra appliance is present
- Difficult to know correctness, without any knowledge of ground truth



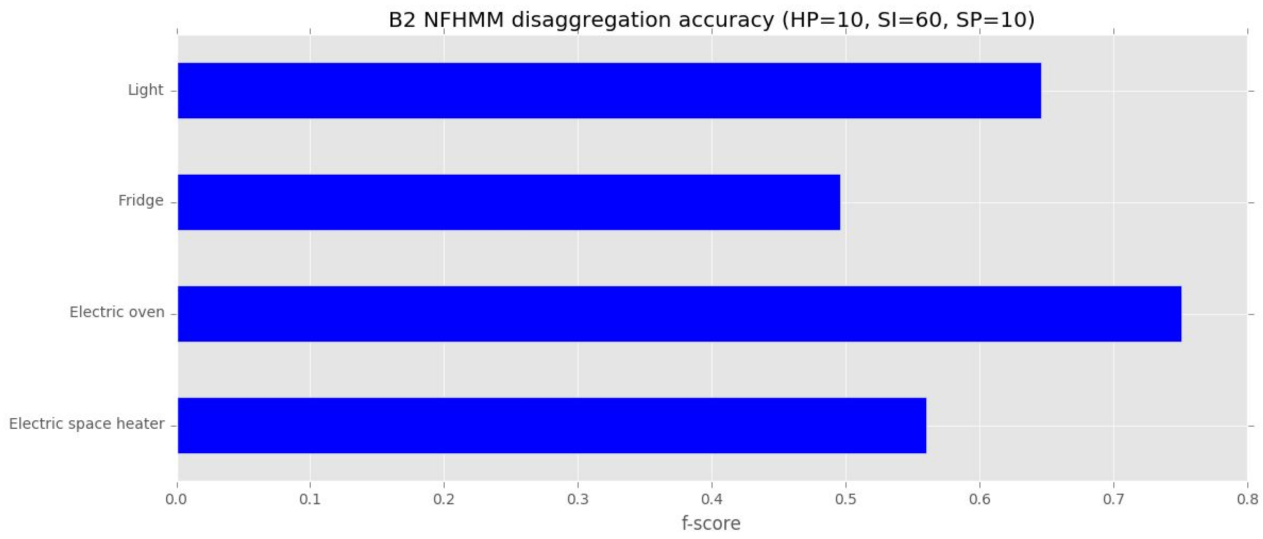
Results
Supervised vs Unsupervised

- Supervised FHMM and CO was compared to the unsupervised NFHMM
- Supervised FHMM outperforms NFHMM with an almost perfect score
- Comparison between the supervised and unsupervised methods is nontrivial
- Used comparison scheme problematic
- NILMTK designed for supervised methods



Results
Supervised vs Unsupervised

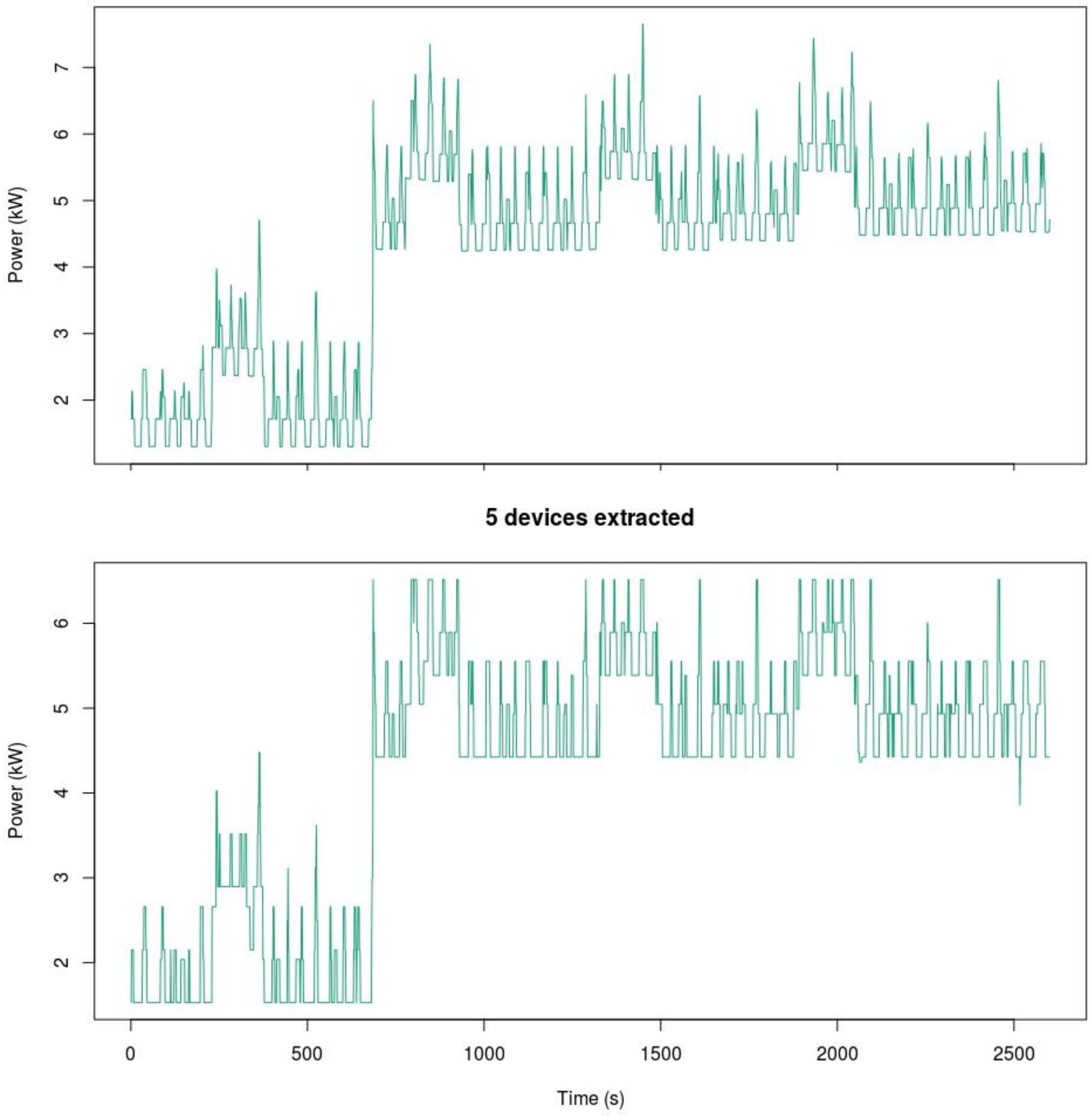
- F-scores were computed with NILMTK
- NFHMM: Appliance F-scores vary from 0.5 to 0.8
- Supervised FHMM: Almost perfect F-scores (>0.95)
- However, the supervised FHMM was trained with perfect data
  - no real difference between training and testing datasets
- F-score metric makes sense with supervised data



$$\mathrm{F-score} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

Results
Fortum boiler data

- Fortum customer household data containing water heater boilers
- Disaggregation was performed with NFHMM
- Algorithm extracted 5 distinct appliances
- Observation and sum of disaggregated components match reasonably well



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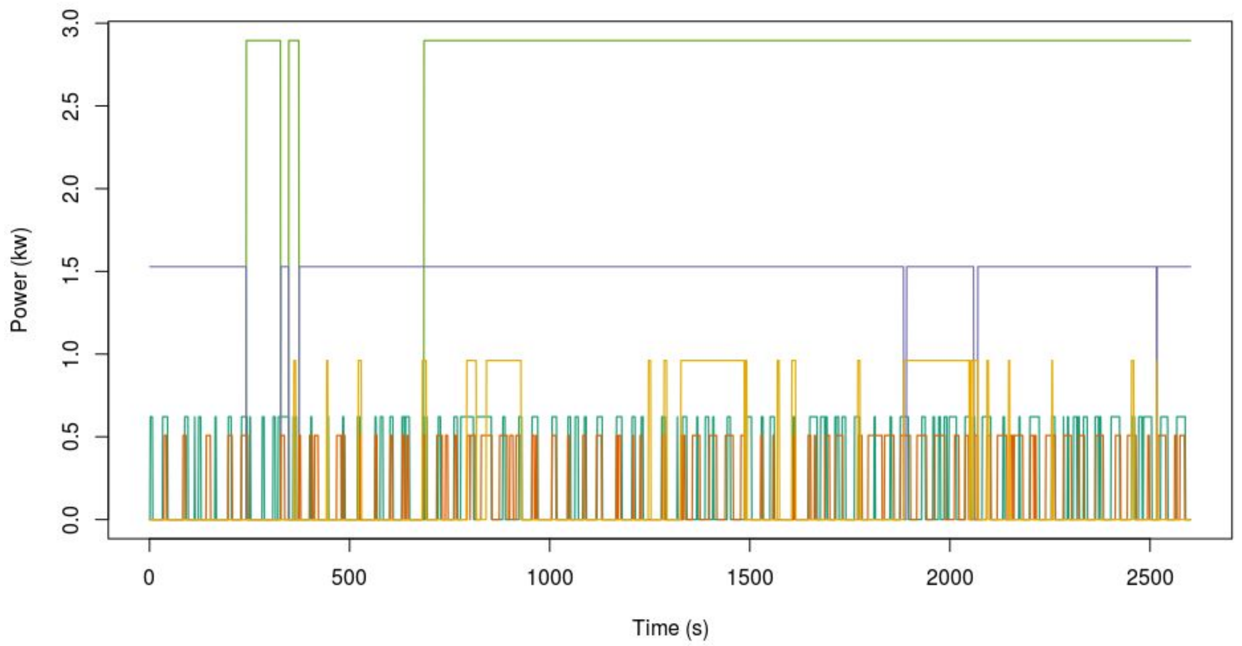
Results

Fortum boiler data

- Boiler dataset disaggregates shown
- Boiler event of ~3 kW detected
- Duration of boiler usage is not properly considered
- A few one second on/off events
- Semi-Markov property would help suppress the false switch events



Discussion

- Implementation
  - Multi-state designation could be added
  - Negative power levels possible
- Model
  - Markov property does not consider state durations (recall the oven and boiler)
  - NFHMM algorithm seems to converge sometimes to local optima
  - No additional features considered (e.g. time of day)
- Comparison of supervised and unsupervised methods difficult

Conclusion

- Recent advances in electricity disaggregation methods
  - Supervised
  - Unsupervised
- Reference for the development of the client’s vision on electricity disaggregation services
- Disaggregation problem not trivial
- Results of unsupervised methods are promising
- Results of implemented NFHMM not quite comparable to supervised methods

Questions