DeepNilm: A deep learning approach to non-intrusive load monitoring

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DISCOVERGY

Discovergy in a Nutshell

- Founded in **2009** by **Ralf Esser** and **Nikolaus Starzacher**
- Located in **Heidelberg** and **Aachen**

- **Smart Metering** for consumers and businesses
- Communication **Gateway** developed in-house
- Compatible with **any meter** for **any medium**
- **Scaleable backend** infrastructure for
  Storage, **Visualisation**, **Alerting**, **Engagement**, **Disaggregation** and **Value Added Services**

- Independent metering operator for **Electricity** and **Gas**
- Nationwide network of **installers**

- Discovergy offers **full-stack** metering operations in Germany

Discovergy in a Nutshell

measure up

Power consumption and device or asset creation are captured in real-time and sent to Discovergy's server.

Evaluate

The raw data is securely stored, processed and evaluated by Discovergy using highly specialized algorithms.

Discover

Users see their data live via web or mobile app and receive smart notifications for unusual values.

The problem

- Buildings account for 20-40% of primary energy consumption.
- About 20% of this can be saved through energy efficiency improvements.
- It is believed that these reductions have not been achieved due to behavioural barriers

Energy consumption is a black-box for most people

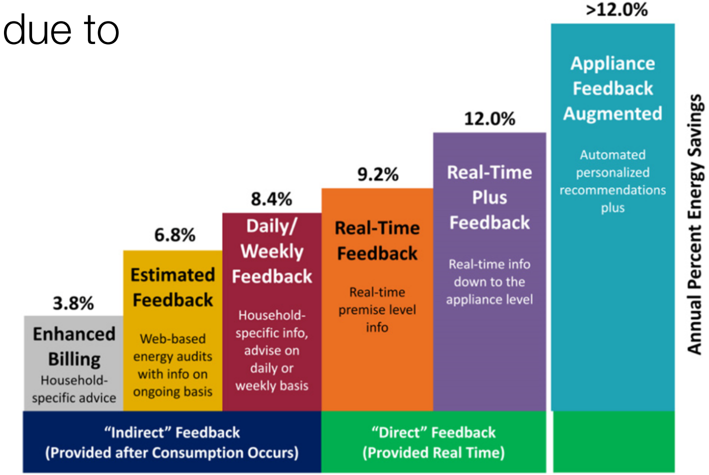

Image source: Armel, K. Carrie, et al. "Is disaggregation the holy grail of energy efficiency? The case of electricity." Energy Policy 52 (2013): 213-234.

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How can we open up the black box?

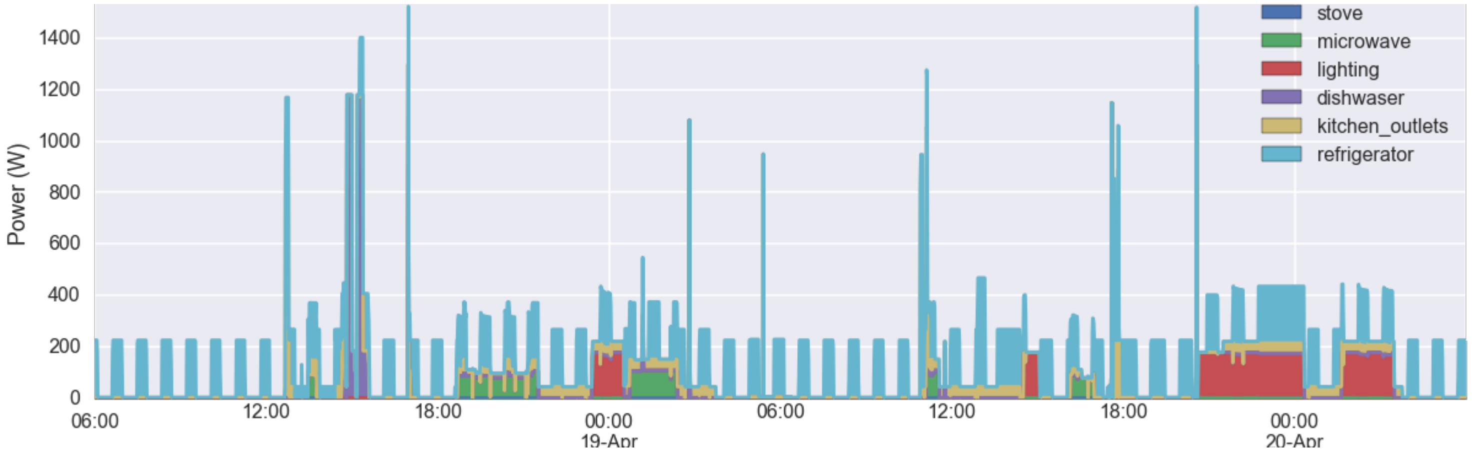
Direct monitoring of each appliance

- Connect each relevant appliance to a smart plug.
- Typical smart plug costs €30. For a typical household the total cost could go upwards of €300.
- High accuracy but can get super expensive

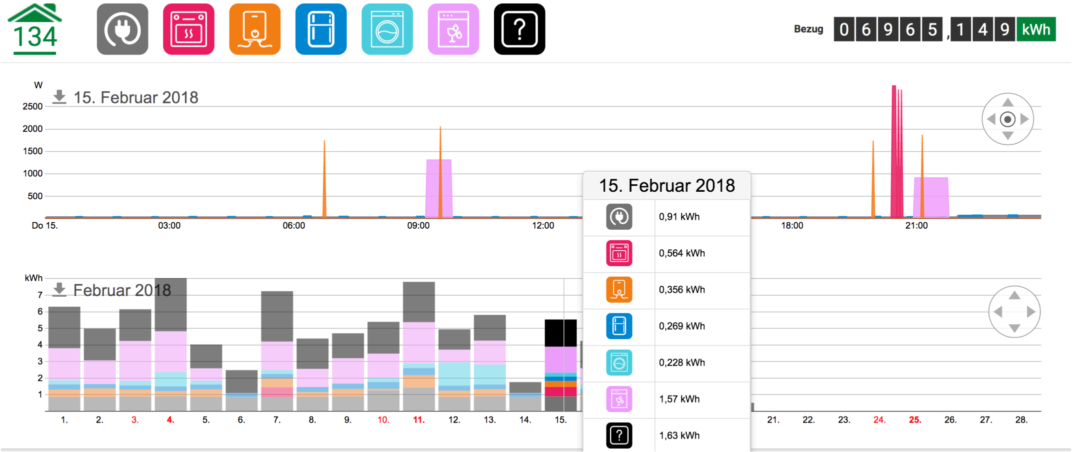
How can we open up the black box?

Non intrusive load monitoring (NILM)

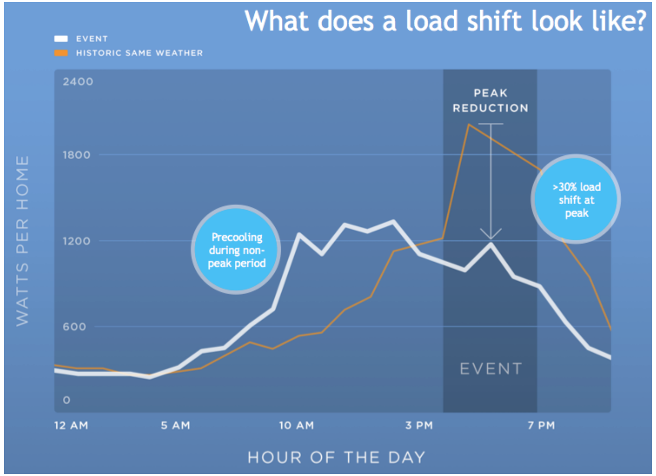
- Statistical/Machine learning techniques can be used to infer the appliance level energy consumption from the aggregate
- Growth in the installation of smart meters which report data at 15 min intervals and faster.



Benefits of Non-intrusive load monitoring



Better understanding of electricity consumption



Demand response

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Benefits of Non-intrusive load monitoring

Effizienz der Mikrowelle

Wenn Sie wasser- bzw. fettreiches Essen erhitzen, ist es bedeutend effizienter, dies in der Mikrowelle statt auf dem Herd zu tun.

Investition: 0.0 Euro
Ersparnis: 65.00 %
Amortisationsdauer: sofort

☑ Erledigt
du und 37 Leute haben das gemacht

Essen erhitzen

Befeuchten Sie Ihr Essen, bevor Sie es in die Mikrowelle stellen.
Warum?

Investition: 0.0 Euro
Ersparnis: 0.00 %
Amortisationsdauer: sofort

☑ Erledigt
du und 29 Leute haben das gemacht

Restwärme des Bügeleisens nutzen

Nutzen Sie die Restwäre des Bügeleisens und schalten Sie es 5 Minuten, bevor Sie fertig sind, ab.
Warum?

Investition: 0.0 Euro
Ersparnis: 20.00 %
Amortisationsdauer: sofort

☐ Erledigt
25 Leute haben das gemacht

Automatisches abschalten

Benutzen Sie ein Bügeleisen, das sich automatisch ausschalten kann.
Warum?

Investition: 0.0 Euro
Ersparnis: 30.00 %
Amortisationsdauer: sofort

☐ Erledigt
23 Leute haben das gemacht

Personalised energy savings tips & notifications

Predictive maintenance & faulty appliance detection

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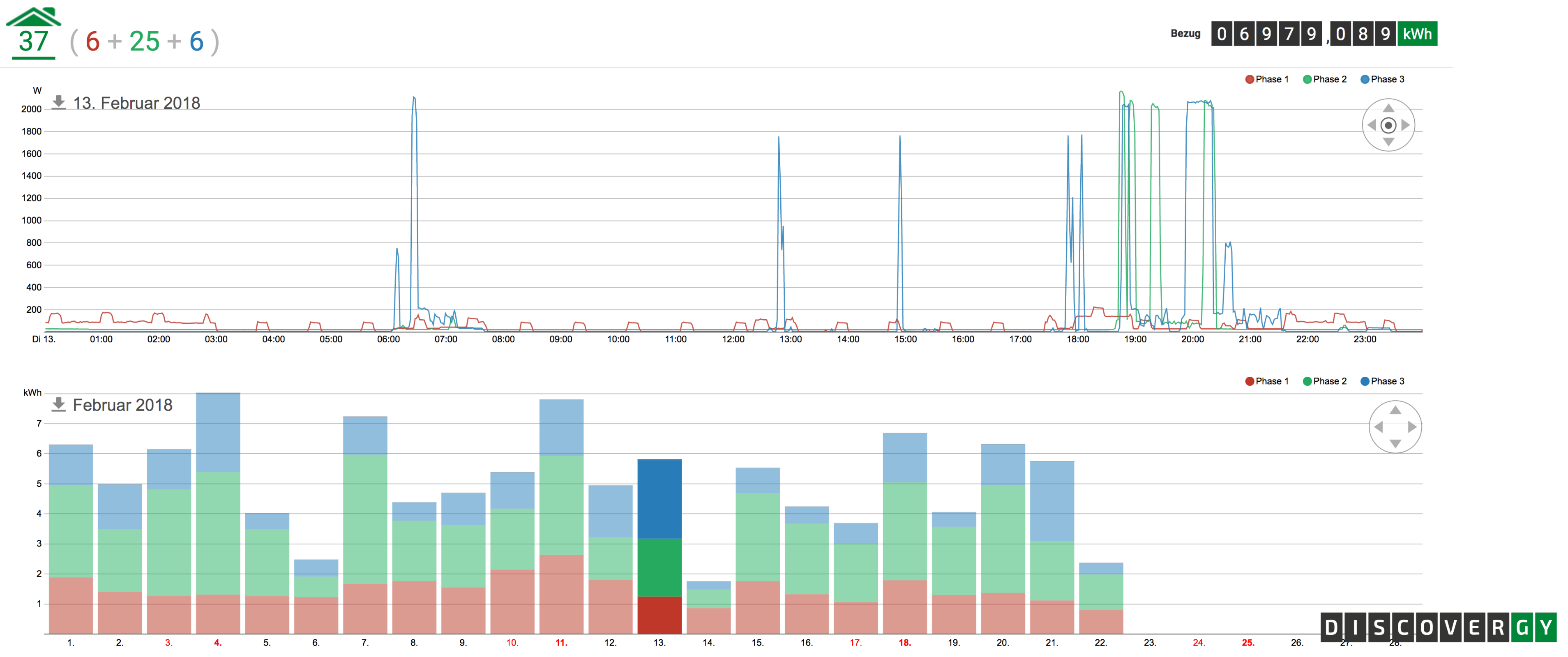
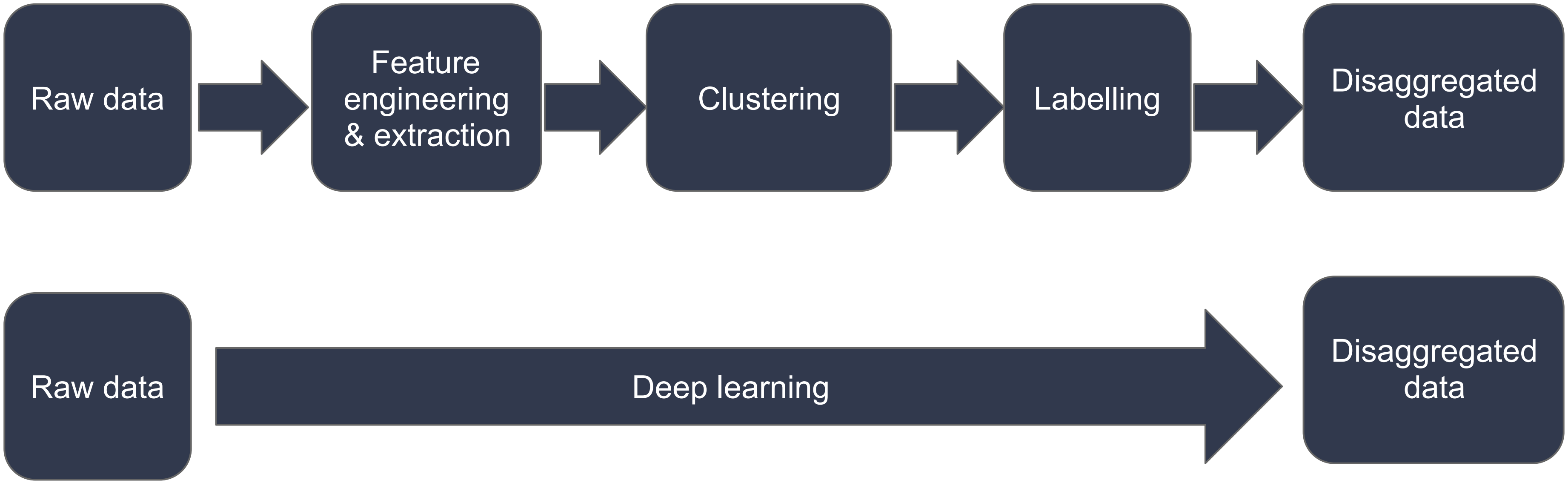
Requirements for NILM Algorithm

- Works well with data resolutions around 1 Hz
- Generalises well to buildings and homes not seen in the training data
- Modular and flexible: Easy to add models for new appliances
- Computationally scalable during inference
- High accuracy in appliance detection
- Works like magic !

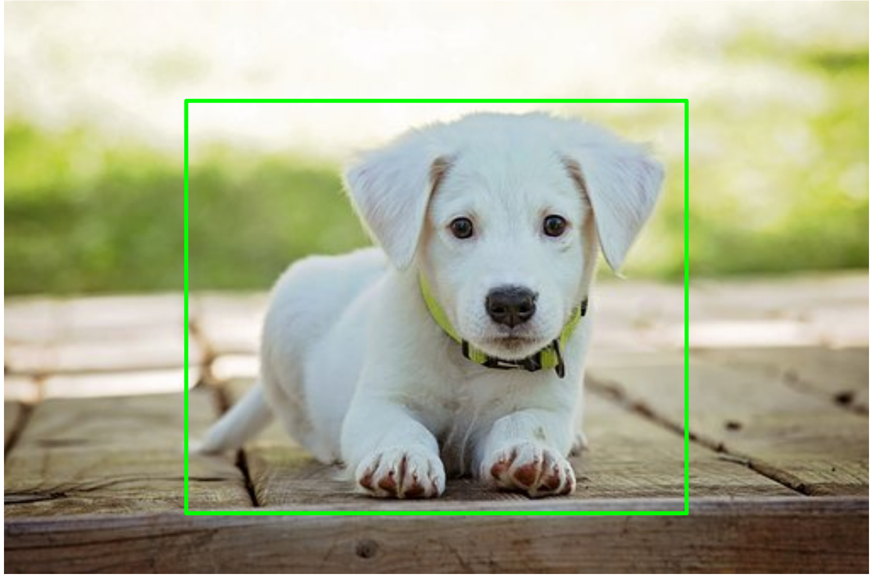
Typical 3-phase smart meter data

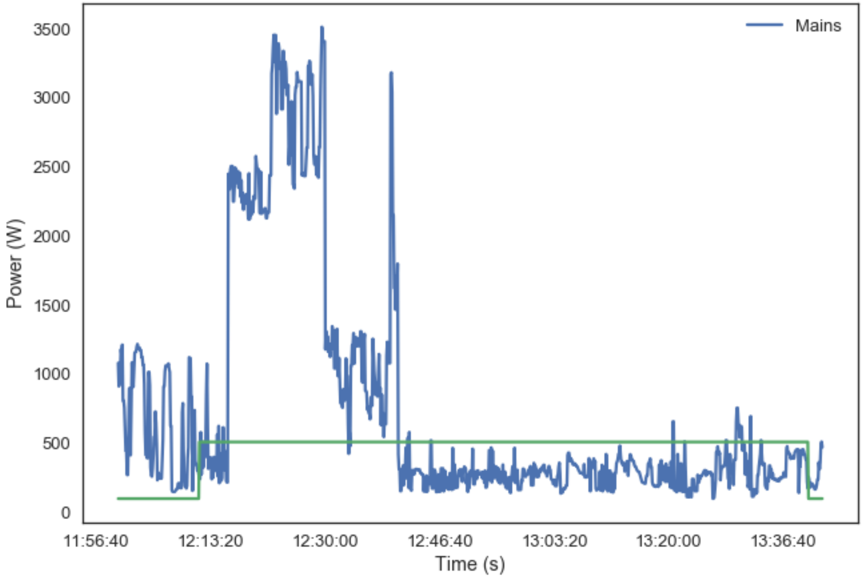


Approach


Raw data
Feature engineering & extraction
Clustering
Labelling
Disaggregated data
Raw data
Deep learning
Disaggregated data

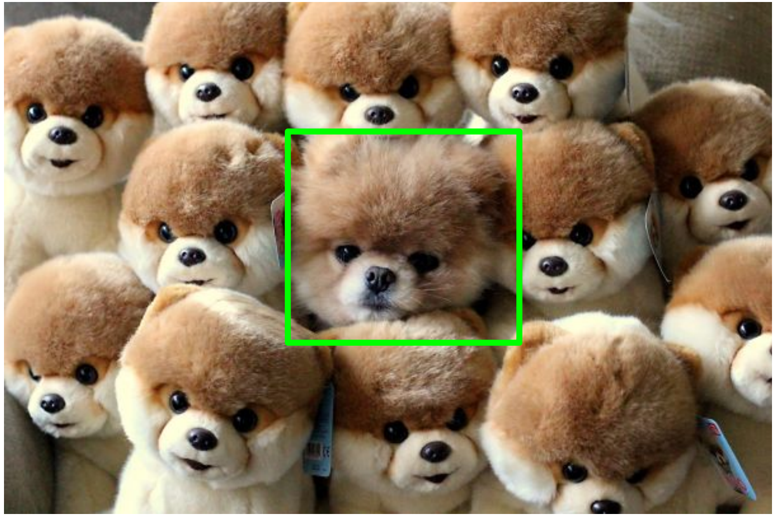
Inspiration - Image Detection & Localisation

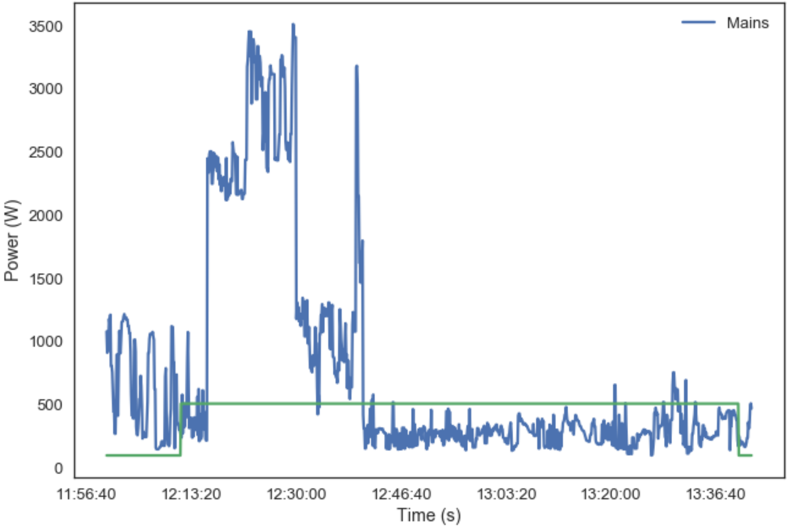




DISCOVERGY

Inspiration - Image Detection & Localisation





Background Clutter

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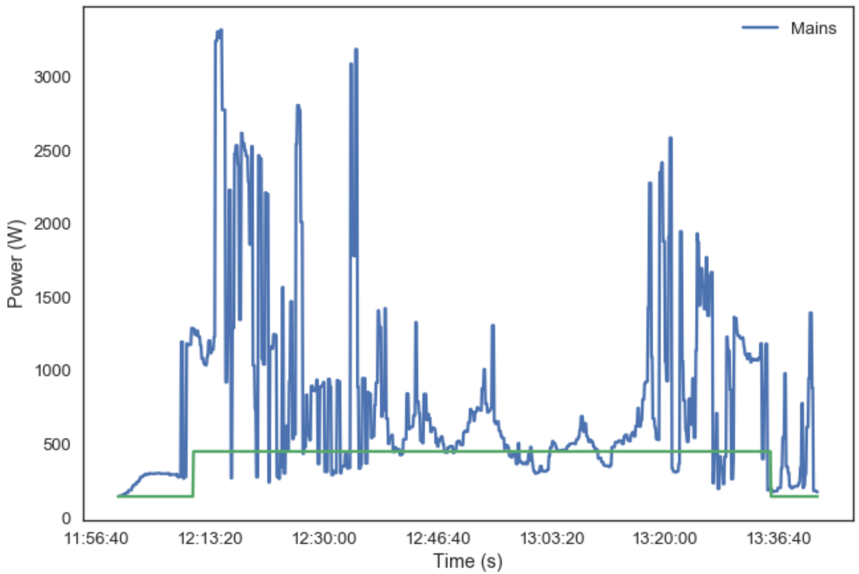
Inspiration - Image Detection & Localisation



Occlusion

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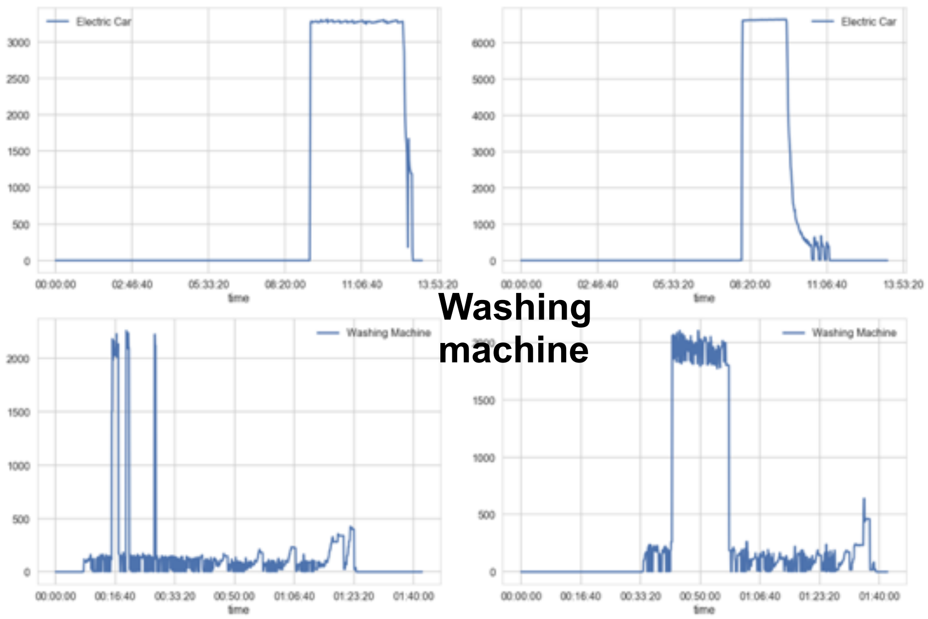
Inspiration - Image Detection & Localisation

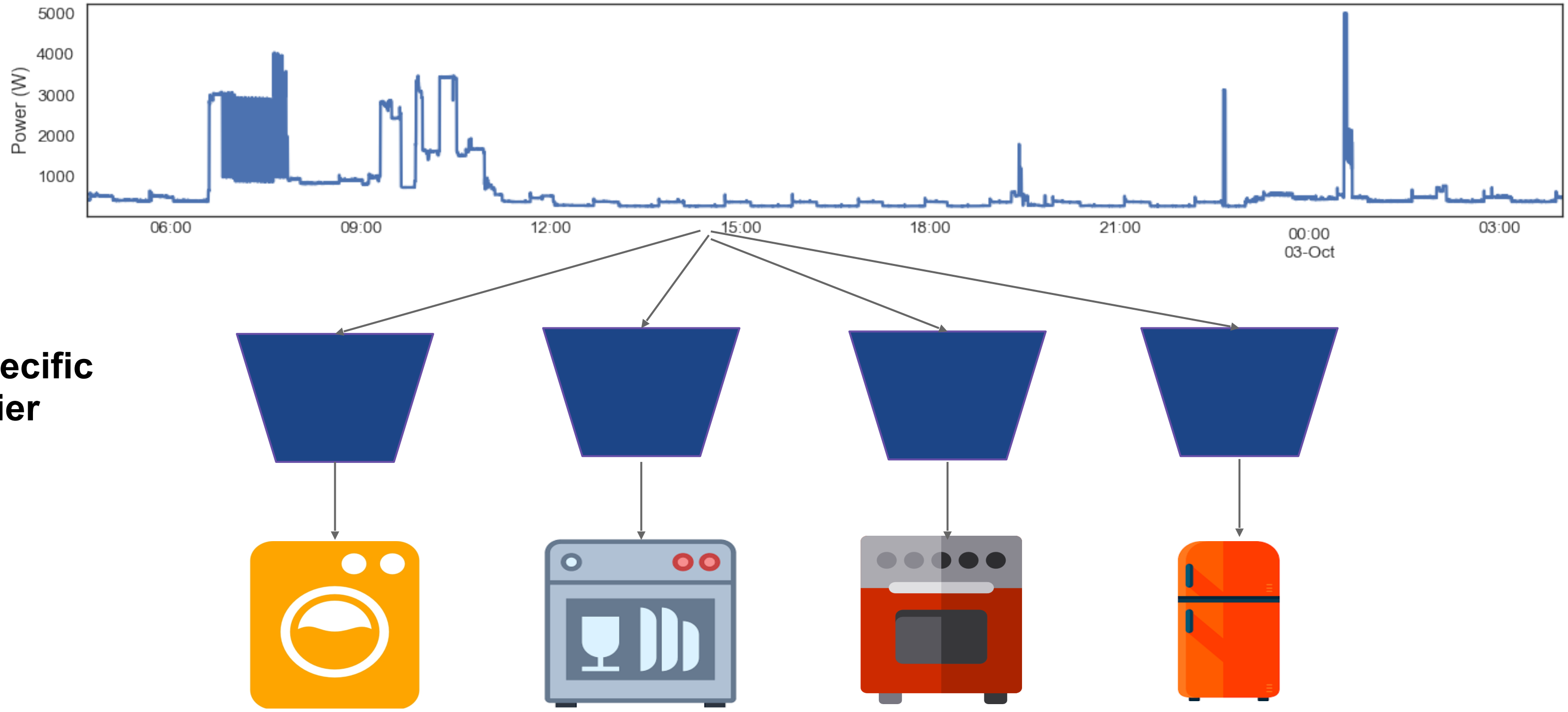
Electric Car



Washing machine

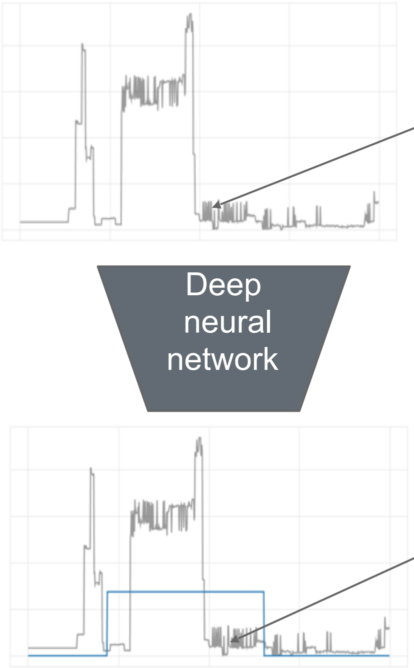
Intra-class variation

Scheme



Device specific classifier

Deep Learning



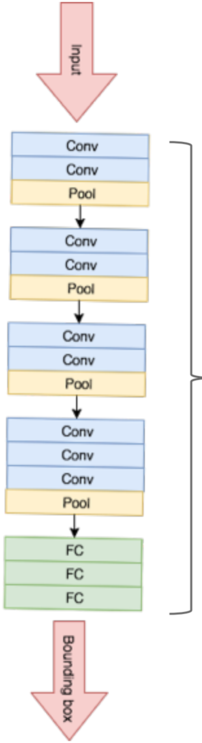
Input window

Prediction box[1]:

- Start time
- End time
- Mean power

We can answer

- How many times a device was operated and at what time ?
- How much energy it consumed during each of those runs ?



~15 -20 Layers

1) Kelly, J., & Knottenbelt, W. (2015, November). Neural nilm: Deep neural networks applied to energy disaggregation. In *Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments* (pp. 55-64). ACM.

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Generalisation Performance to Unseen Houses

	Washing Machine		
Metrics	**Train**	**Validation**	**Test**
Mean Absolute Error (W)	38.86	42.64	10.11
Relative Error	0.1091	0.1082	0.2535
F1 Score	0.9704	0.9595	0.9163
Precision	0.9680	0.9513	0.9107
Recall	0.9727	0.9678	0.9219

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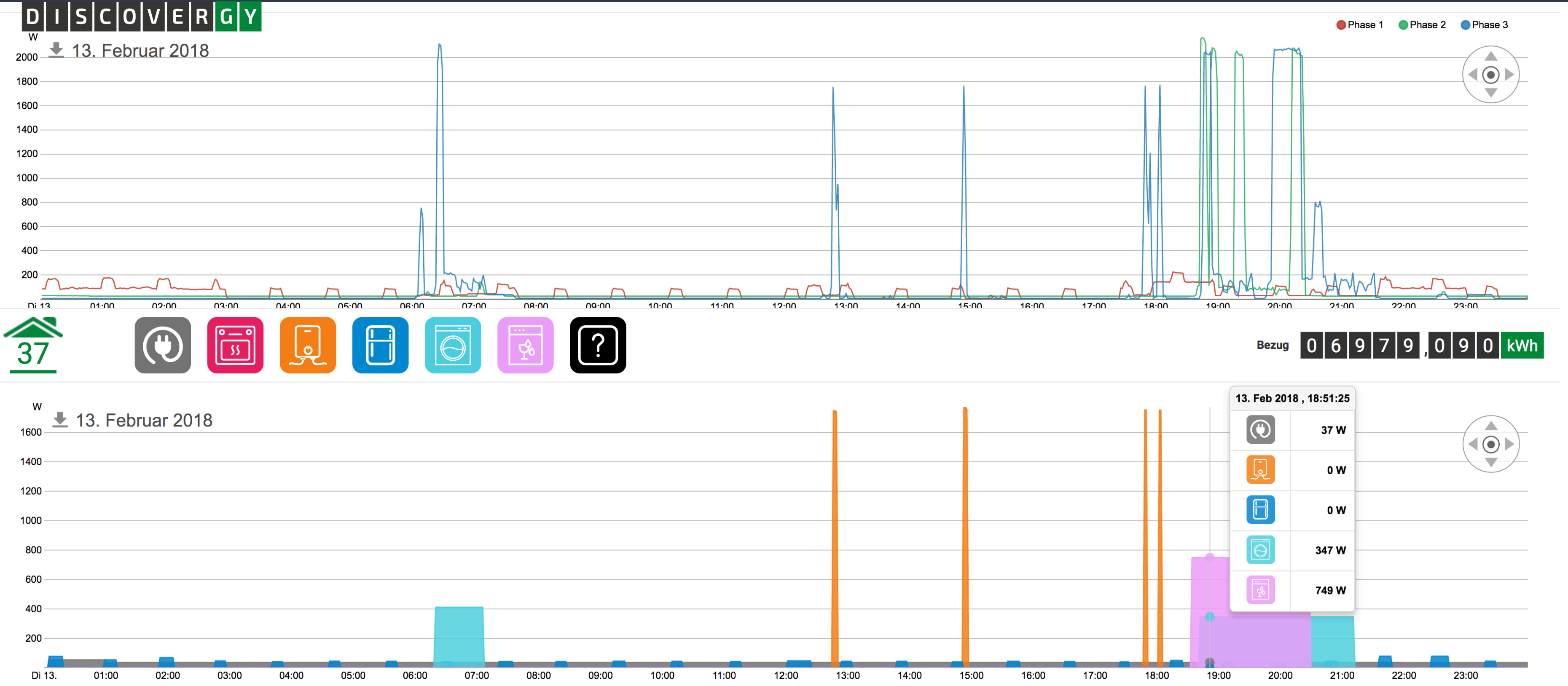
Disaggregation in action



Peeking under the hood

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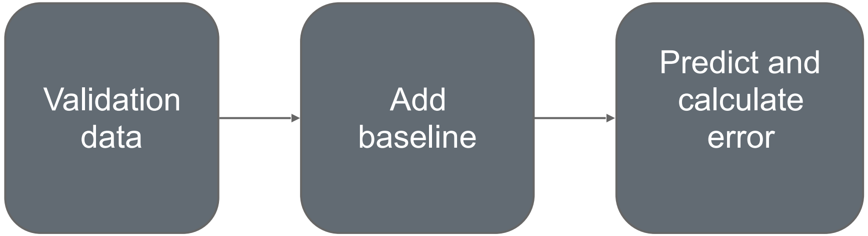
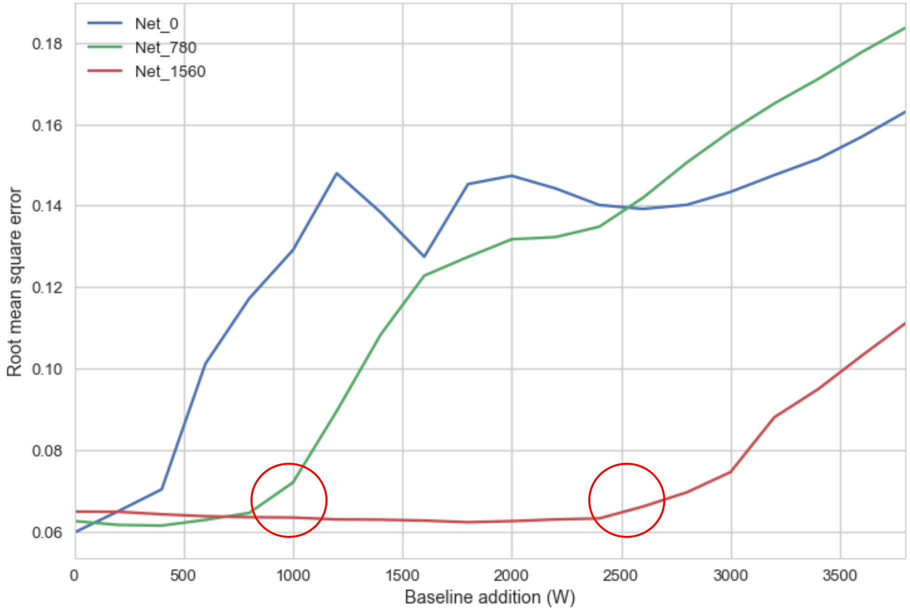
Baseline Invariant

Predicted appliance energy should be invariant to the baseline



Data augmentation helps



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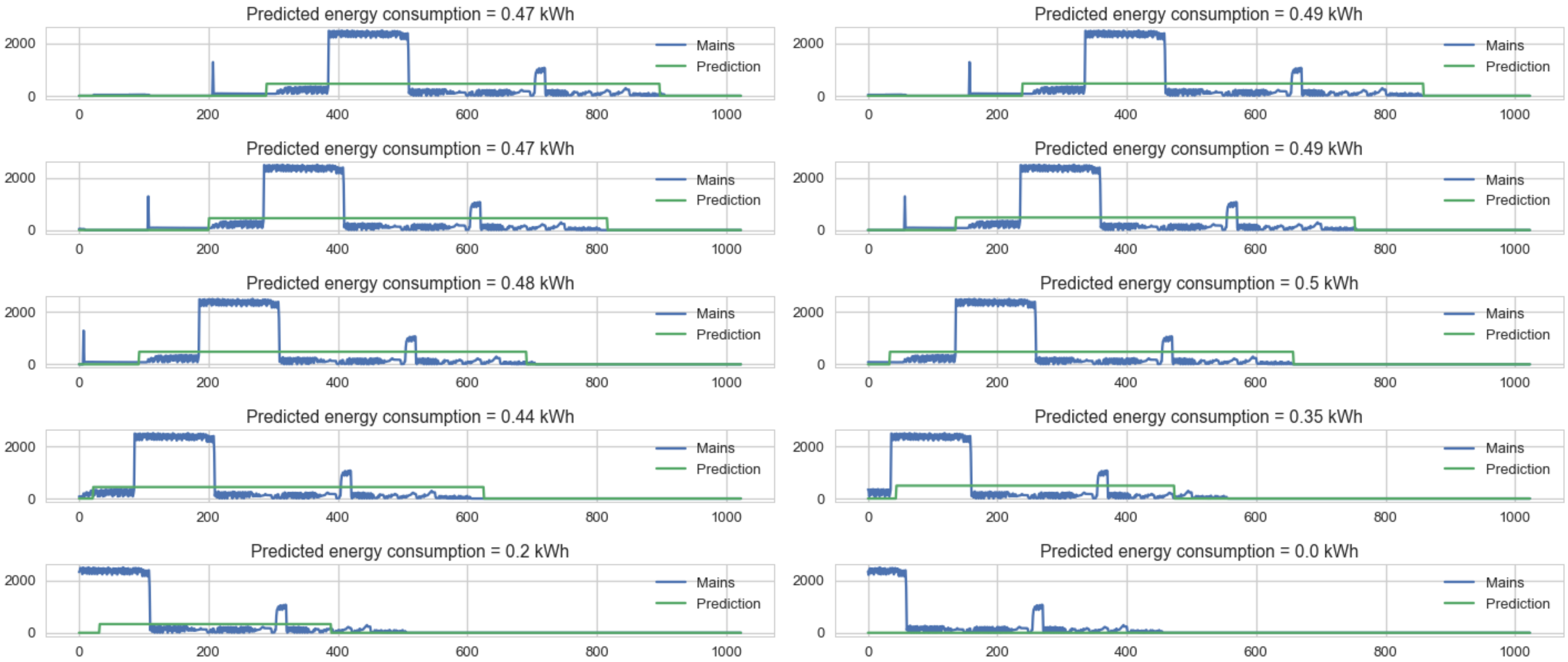
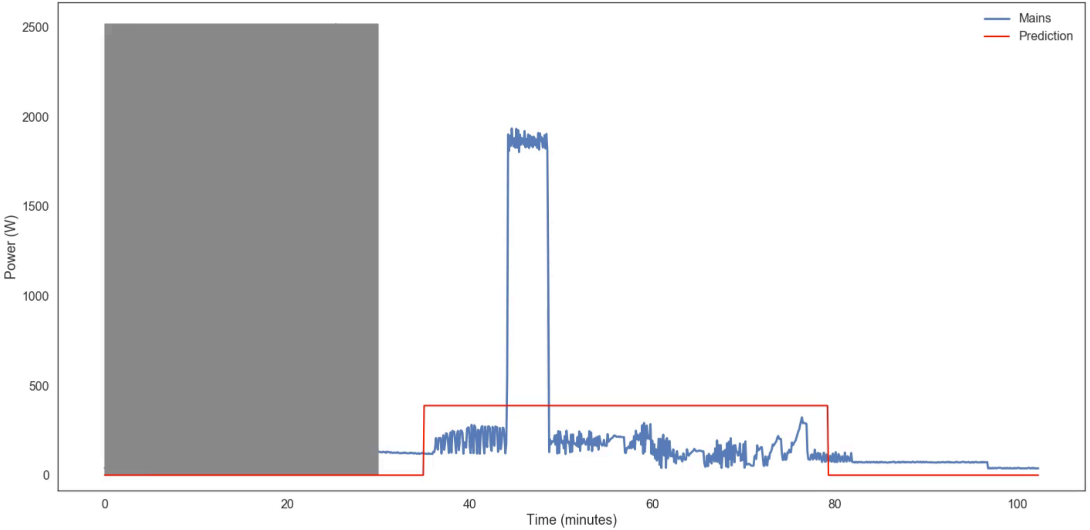
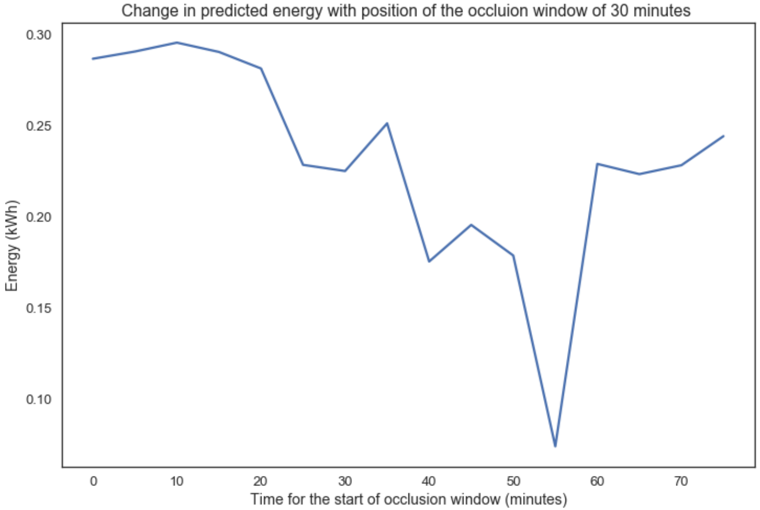
Translation Invariant



What Features are Important ?





You can view the video here: [link]

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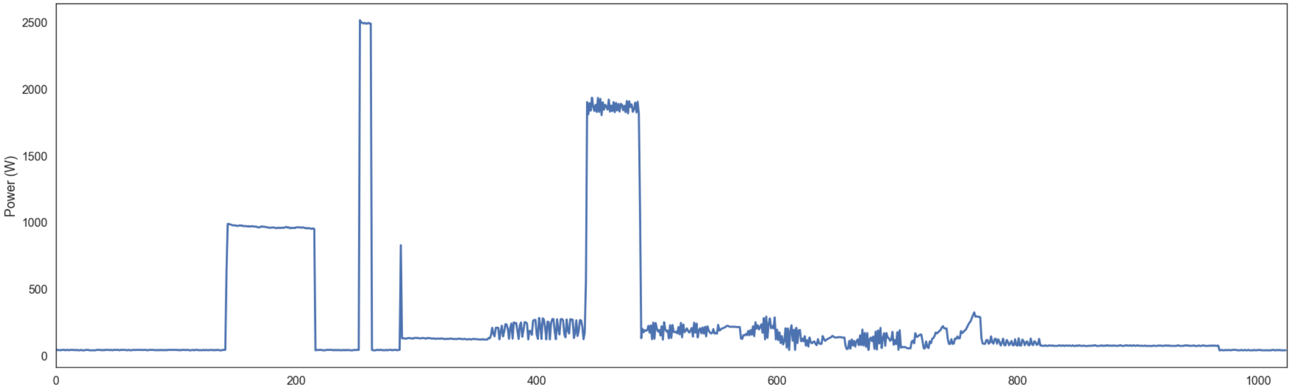
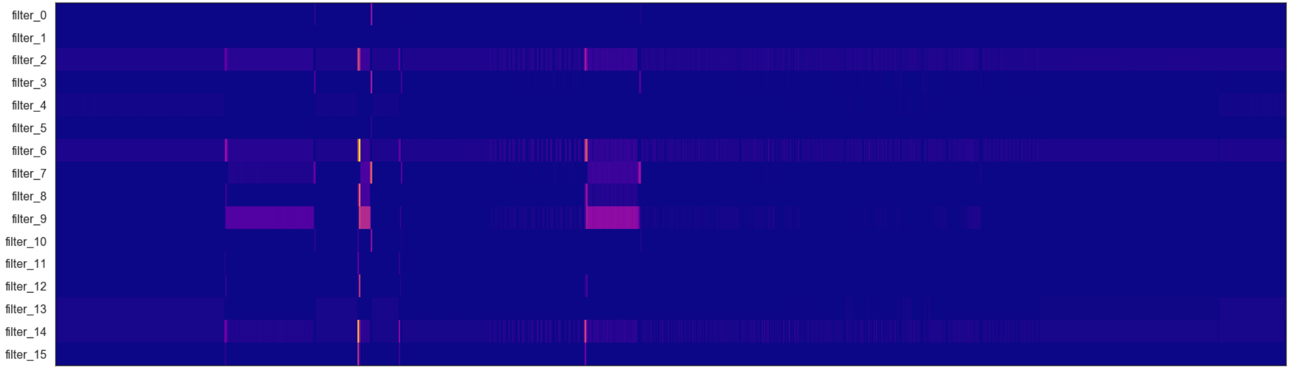
Features Learnt - First Convolutional Layer





Filter 2 behaves like a rectified difference series
Filter 3 is detecting negative edges

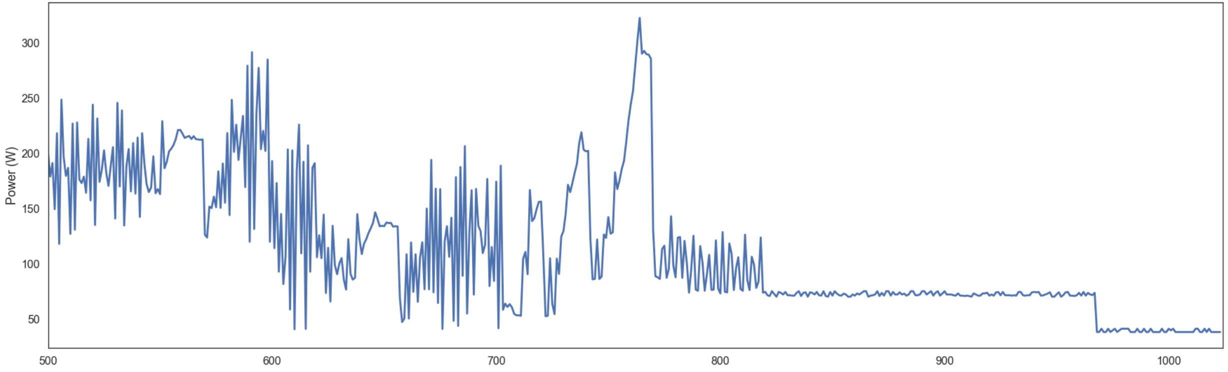
Filter 7 is detecting large negative edges

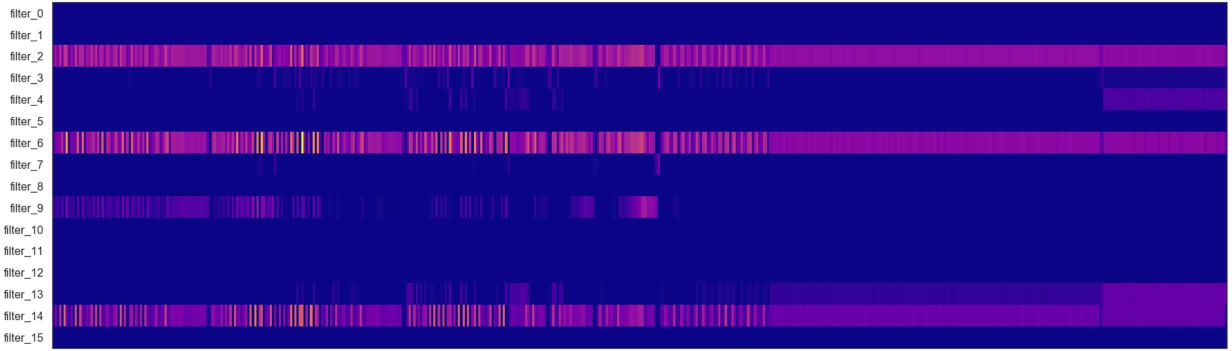
Filter 8 is detecting large positive edges

Filter 9 is tracking high magnitudes

Activations from the conv1 layer

Zoomed in View



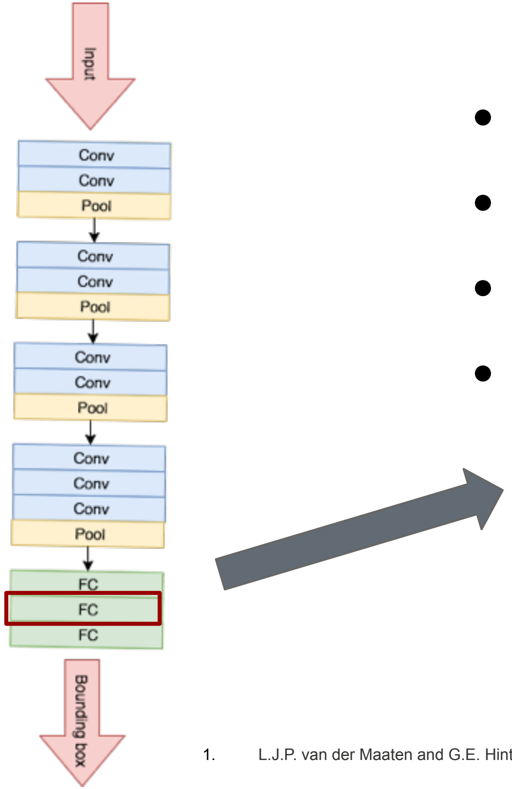


Filter 2 behaves like a rectified difference series

Filter 8 is detecting large positive edges

Filter 13 is detecting sort of minimum in the input

t-SNE Visualization[1]



- t-distributed Stochastic Neighbour Embedding
- Dimensionality reduction technique
- Preserves pairwise distances approximately
- Take the activations from the last layer before the prediction layer and reduce them to 2-dimensions using t-SNE

1. L.J.P. van der Maaten and G.E. Hinton. **Visualizing High-Dimensional Data Using t-SNE**. *Journal of Machine Learning Research* 9(Nov):2579-2605, 2008.

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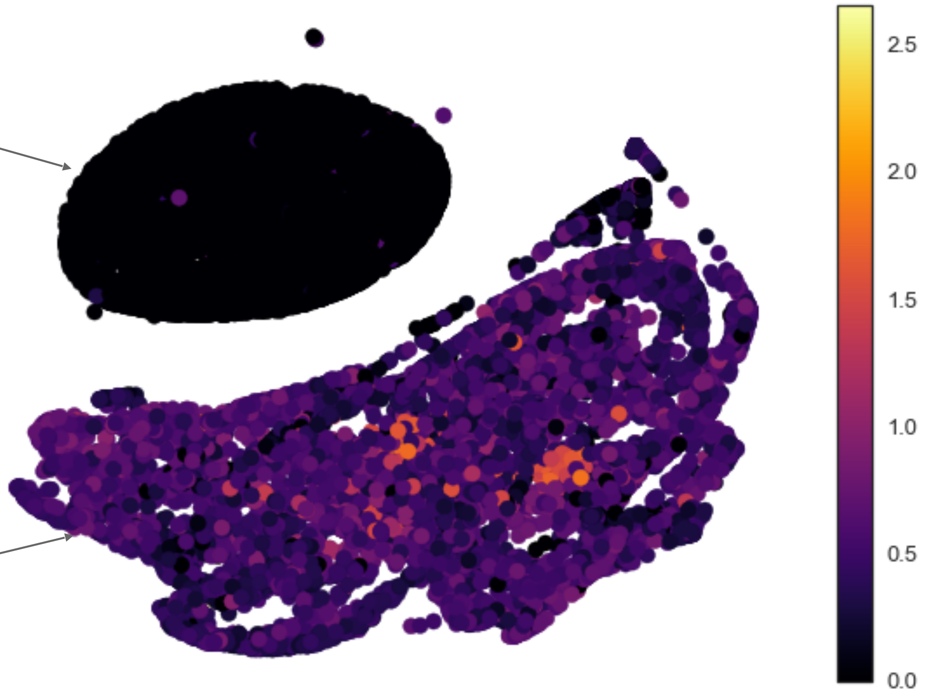
t-SNE Visualization

Input windows without washing machine activation

Input windows with washing machine activation



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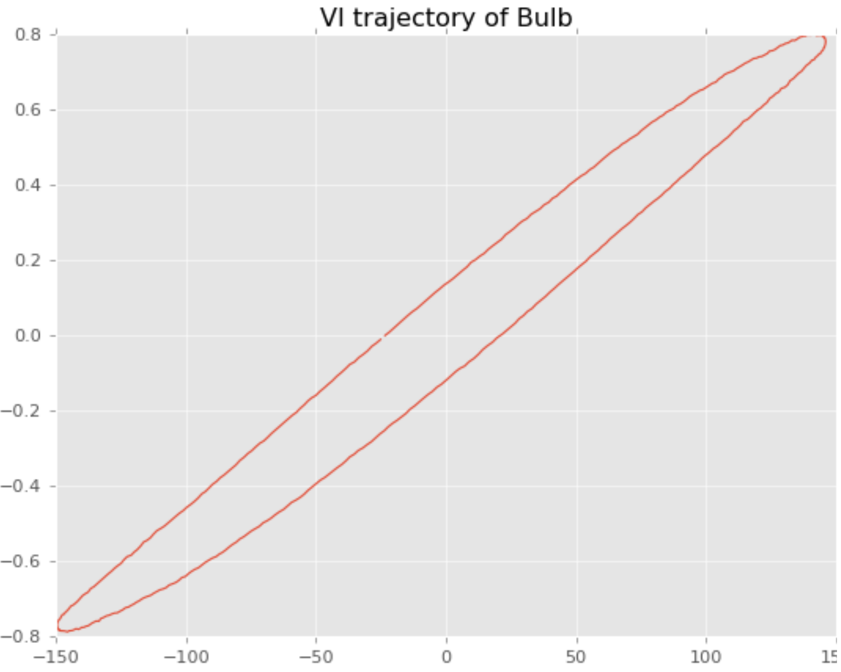
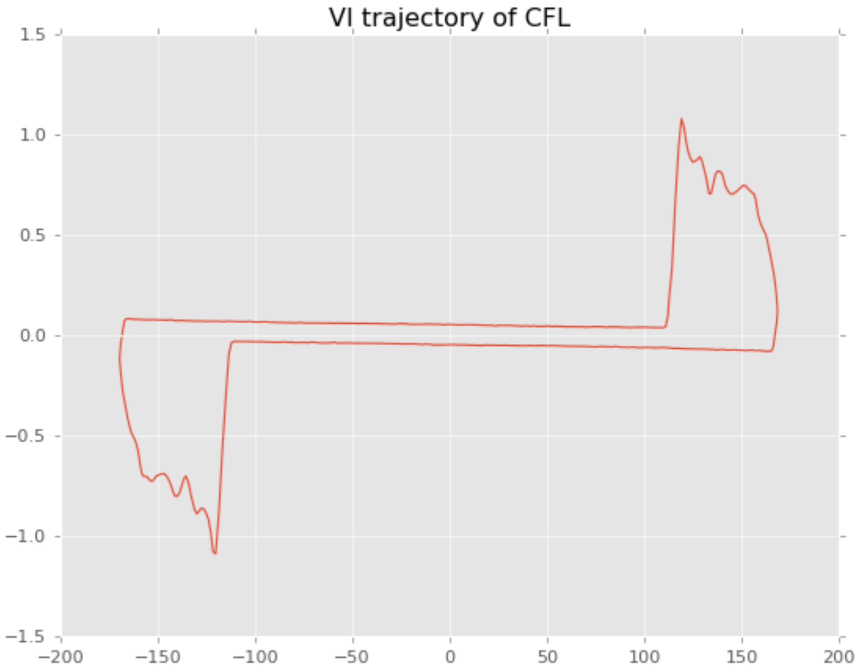
Challenges that we want to tackle

- Take an unsupervised approach for machine learning. Tons and tons of unlabelled data
- Personalise and tweak the appliance models for each user
- Incorporate user feedback into improving the models

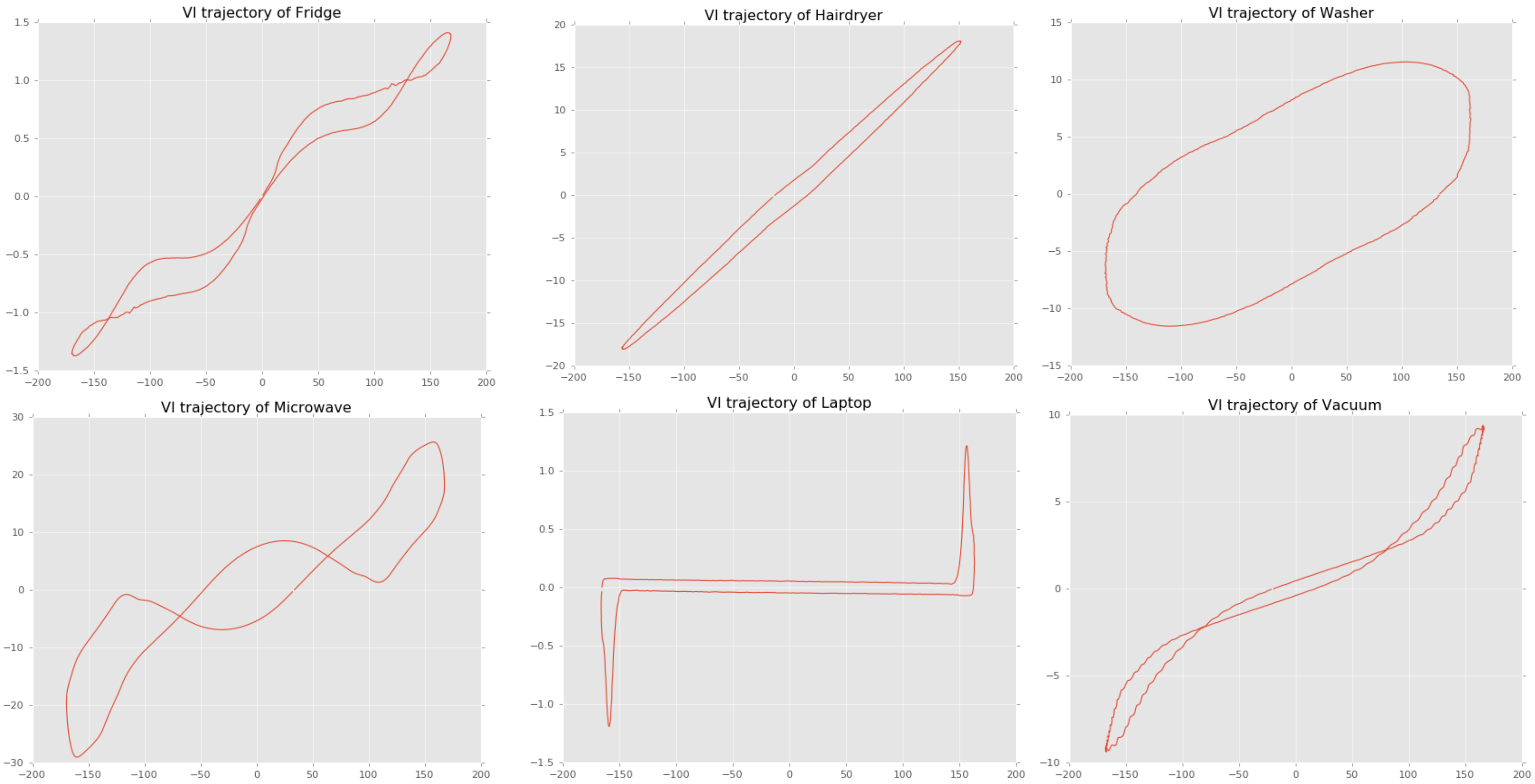
High frequency data - Rich Fingerprints

NILM: 8kHz - VI Trajectories





High frequency data - Rich Fingerprints



Thank you

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Say hi to me at sb@discovergy.com