NoFaRe
Non-Intrusive Facility and Resource Monitoring

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4. D-A-CH Konferenz Energieinformatik
12.-13. November Karlsruhe

Department of Computer Science
Chair for Application and Middleware Systems (I13)

Motivation

What is the problem?

No information available about appliances and the electricity grid without intrusive measurements (e.g. smart plugs).

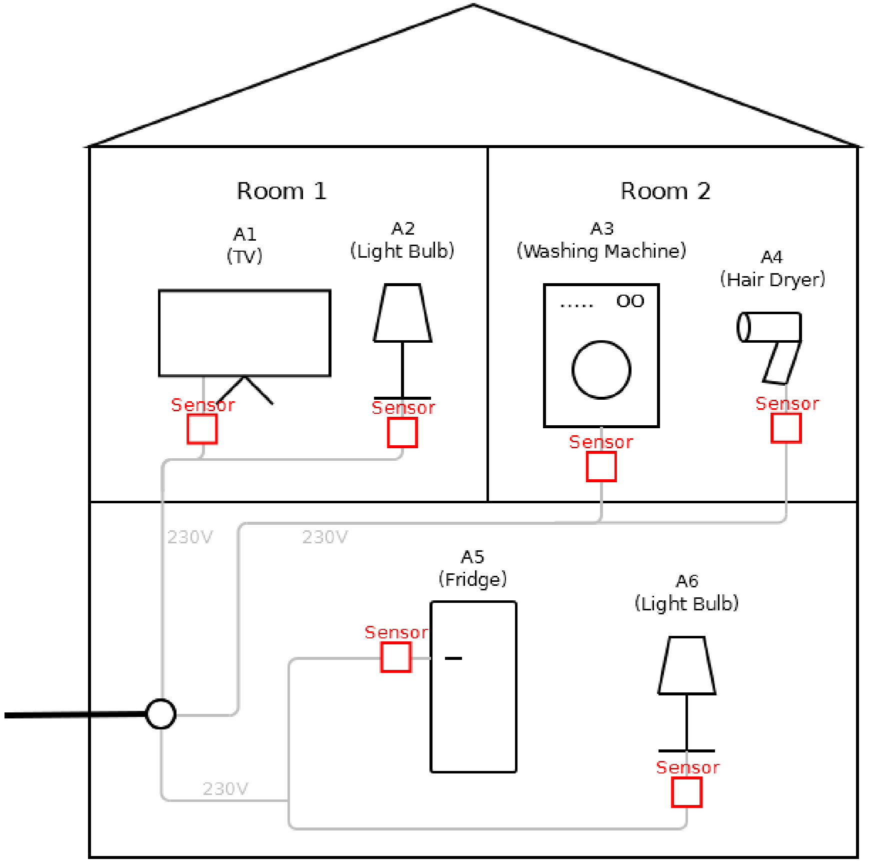
What is the goal?

A smart meter that enables appliance and electricity information retrieval with machine learning techniques.

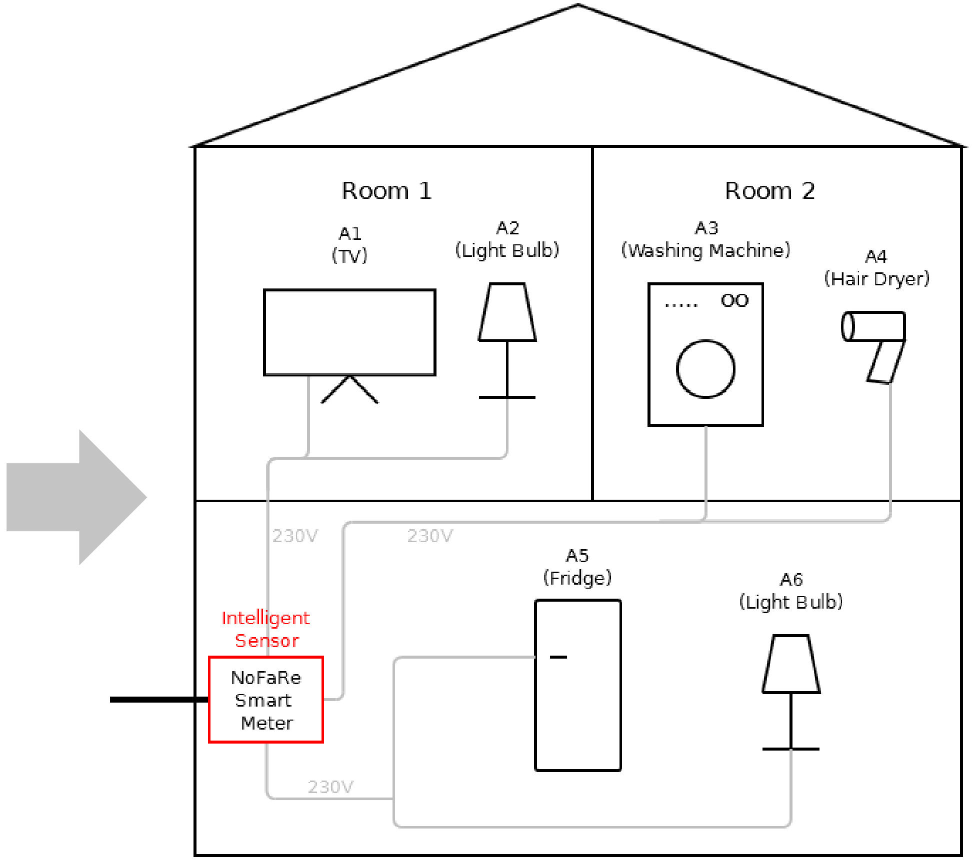
What is the task?

Classification of appliances and power disaggregation.

What we would like to have



intrusive measurement



non-intrusive measurement

Use Cases

- Identification of currently running appliances
  - Is this a toaster, TV or a hair dryer?
- Information retrieval from currently running appliances
  - Power, on-duration, state patterns
- Detection of energy waste
  - Out-of-behavior pattern
- Maintenance support
  - Localizing and predicting of appliance faults
- Building safety
  - Detection of unauthorized appliances usage

State-of-the-Art Overview

- Reinhardt et al. [1]: up to **98%** accuracy **(laboratory environment)**
  - **3,400** high frequency samples
  - 16 appliances
  - 10 spectral features
- Jiang et al. [2]: around 90% accuracy **(real and laboratory environment)**
  - **low amount** of high frequency samples
  - 11 appliances with an
  - edge based startup transient recognition
- Yang et al. [3]: around 95% accuracy **(laboratory environment)**
  - 341 high frequency samples
  - 5 appliances
  - industrial loads
- Patel et al. [4]: around 85-90% accuracy **(real environment)**
  - ~3000 high frequency samples
  - ~19 appliances
  - household loads, up to 100kHz observations, **only voltage transients**

State-of-the-Art Discussion

- Too few data samples
- Too few appliances
- Often laboratory environment
- Mostly only household
- Non-public data sets
- Missing ground truth
- Low appliance type diversity

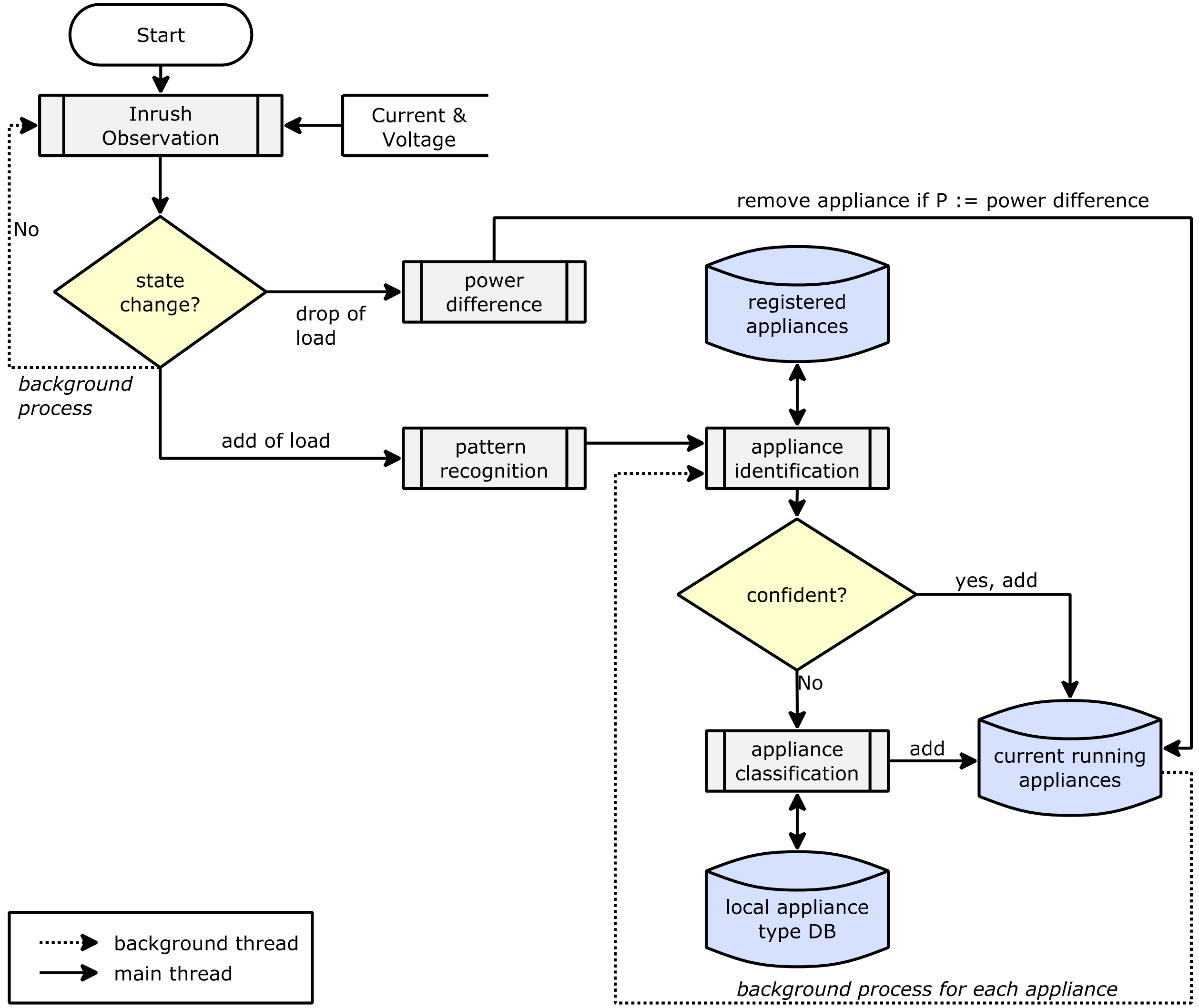
http://www.begincollege.com

http://www.geappliances.com

Our Contribution

- Online and real-time electricity and appliance information retrieval system
- Comprehensive approach to appliance identification, recognition and classification
- Preliminary evaluation on existing data sets

Classification Flow Chart



Appliance Classification & Identification

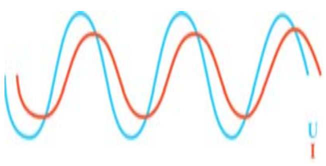
Data Acquisition → Preprocessing → Feature Extraction → training mode: Training / runtime mode: Classification

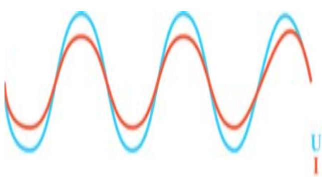
non-intrusive
3-phases
measurements

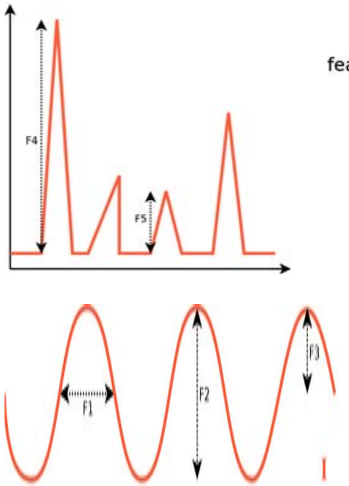
compensation
calibration
filtering

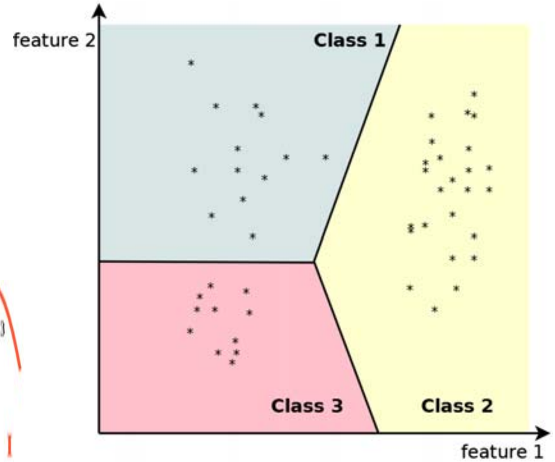
power
harmonics
cos-phi

SVM, ANN









Existing and Forthcoming Data Sets

Household	Office	Industrial
UK-DALE BLUED REDD PLAID	NoFaRe Office *(to be collected)* NoFaRe Lab *(to be collected)*	NoFaRe Industrial *(to be collected)*

- ☑ High sampling frequency (>10kHz)
- ☑ High sampling resolution (>12bit)
- ☑ Appliance event ground truth

Preprocessing

- Compensating phase shift

  Induced by measurement system

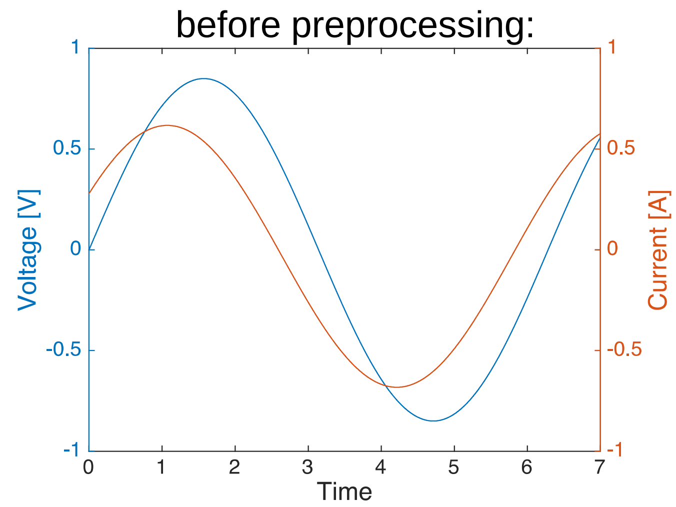
- Scaling of voltage & current

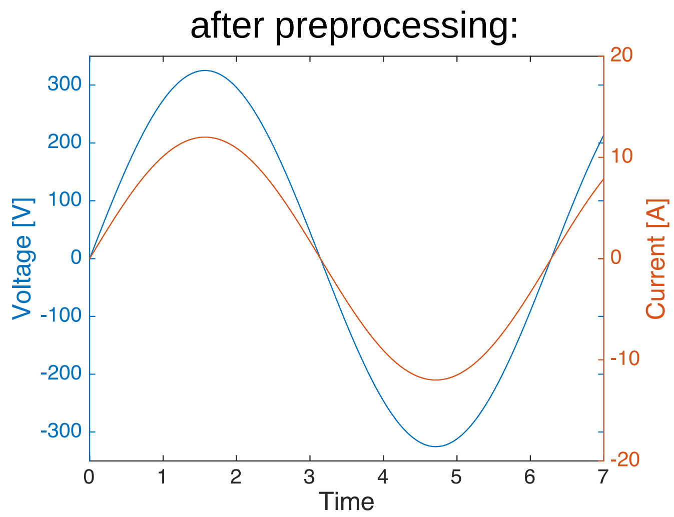
  current

$$I = I' \cdot \frac{N_{turns}}{R_{burden}}$$

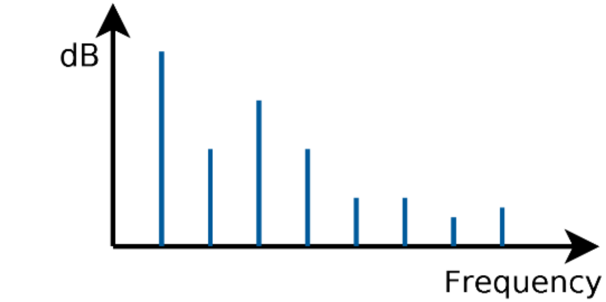
  voltage

$$V = V' \cdot \frac{V_{primary}}{V_{secundary}} \cdot \frac{R_1 + R_2}{R_2}$$

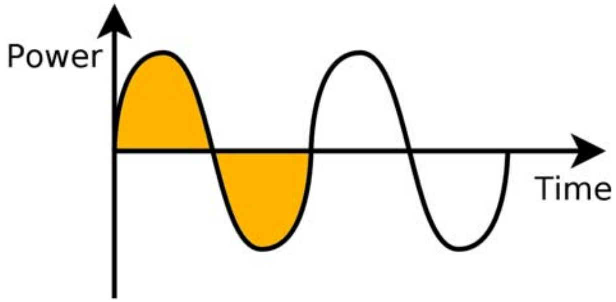




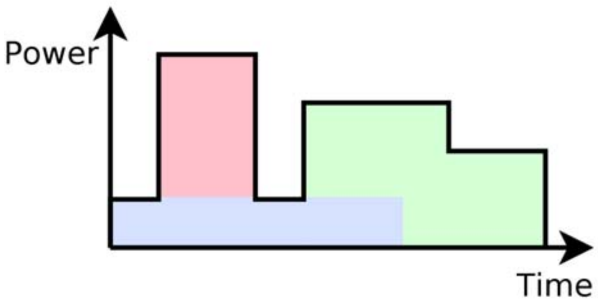
Feature Extraction



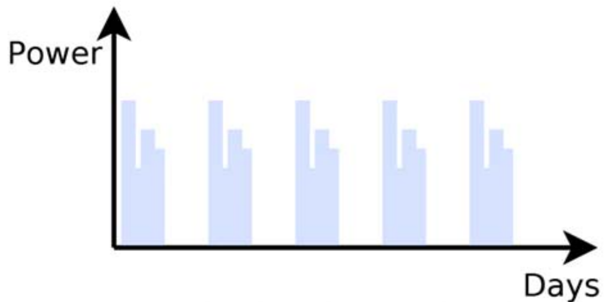
short-time features



computed mid-time features



long-time features



statistical analysis

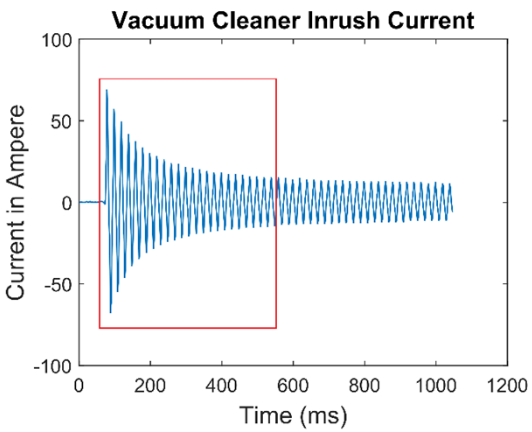
Learning & Classification

- Learning of feature states in *training mode*
- Use of machine learning (k-NN, SVM, ANN …)
- Classification of unknown appliance in *runtime mode*

		Features		
	Class	**F1**	**F2**	**F3**
Training	Kettle1	0.13	0.86	0.34
	Kettle2	0.12	0.91	0.35
	Toaster1	0.33	0.31	0.75
	Toaster2	0.34	0.28	0.68
Classification	?	0.14	0.88	0.33

Experimental Setup

- Extracting start-up transients
- Feature extraction on start-up transients
- Classification of start-up transients



Features		
F1	F2	F3
0.13	0.86	0.34
0.12	0.91	0.35
0.33	0.31	0.75
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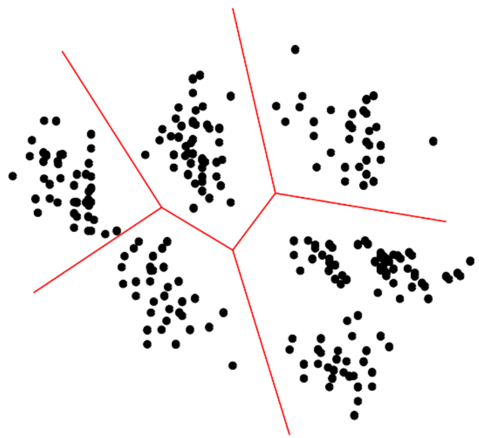
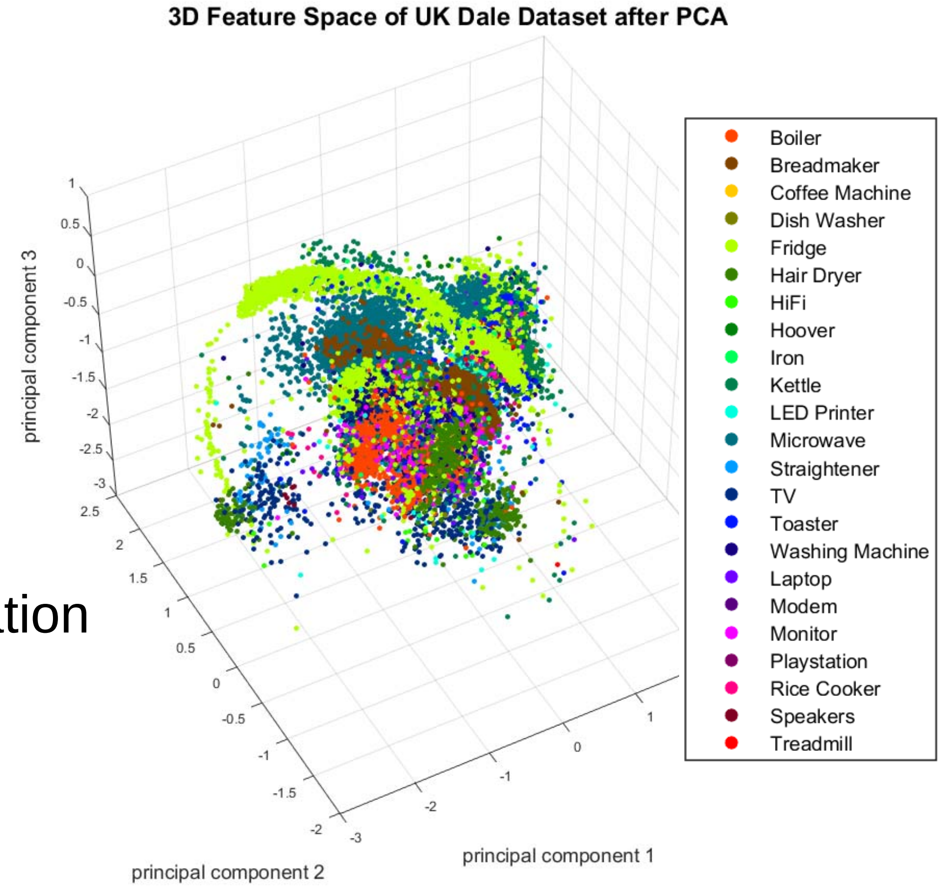
.	.	.



UK-DALE Data Set Results

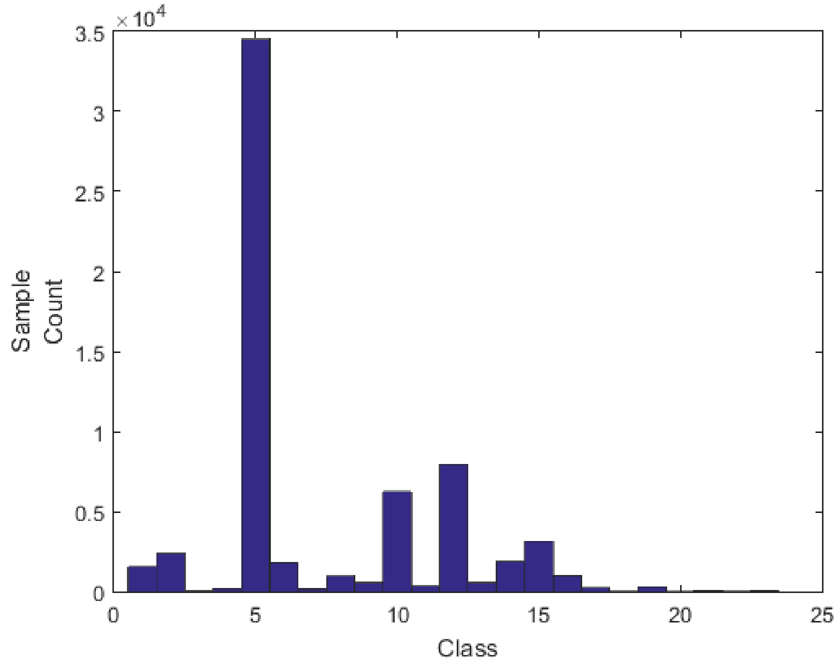
- **37299** samples from
- **2** households
- **23** classes
- 7 discriminating features
- **low** diversity per class
- **High** amount of samples
- Accuracy with Cross Validation
  - with SVM: **93**%
  - with k-NN: **89**%



UK-DALE Data Set Discussion

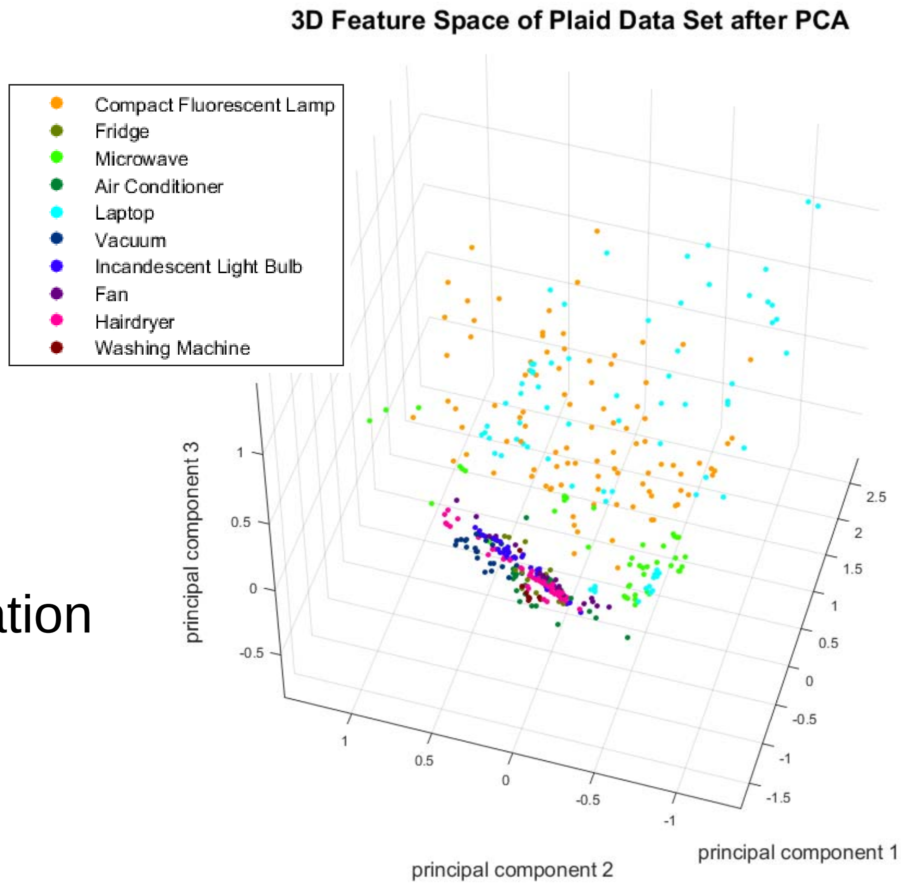
- Indirect startup ground truth
- Real-world scenario
- Sample counts vary highly across classes
- Low diversity per class

High accuracy because of low inner-class diversity and uneven class distributions



Plaid Plug Data Set Results

- **408** samples
- **11** classes
- **55** households
- 7 discriminating features
- **High** diversity per class
- **Low** amount of samples
- Accuracy with Cross Validation
  - with SVM: **92**%
  - with k-NN: **88**%



Plaid Plug Data Set Discussion

- Data inconsistently labeled
- Not a real-world scenario but isolated samples
- High amount of data unusable because of missing calibration information

High accuracy because of laboratory quality

Future Work & Discussion

- More datasets (REDD, …)
- Features and feature combinations
- Influence of different sampling rates on accuracy
- Different classifier (SVM, K-NN, ANN, HMM,…)
- Feature space transformation (PCA, LDA)

References

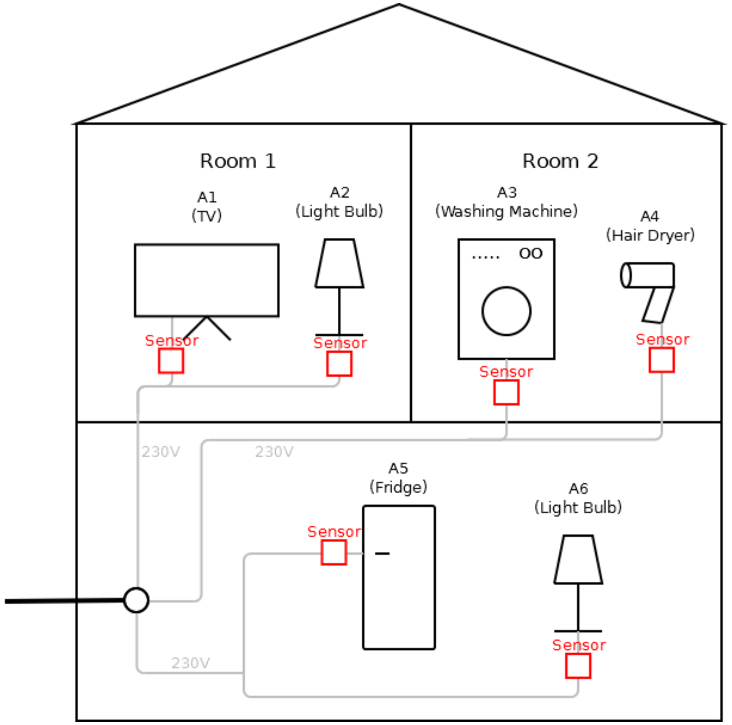
[1] Reinhardt, Andreas, et al. *"Electric appliance classification based on distributed high resolution current sensing.“7th IEEE International Workshop on Practical Issues in Building Sensor Network Applications, 2012.*

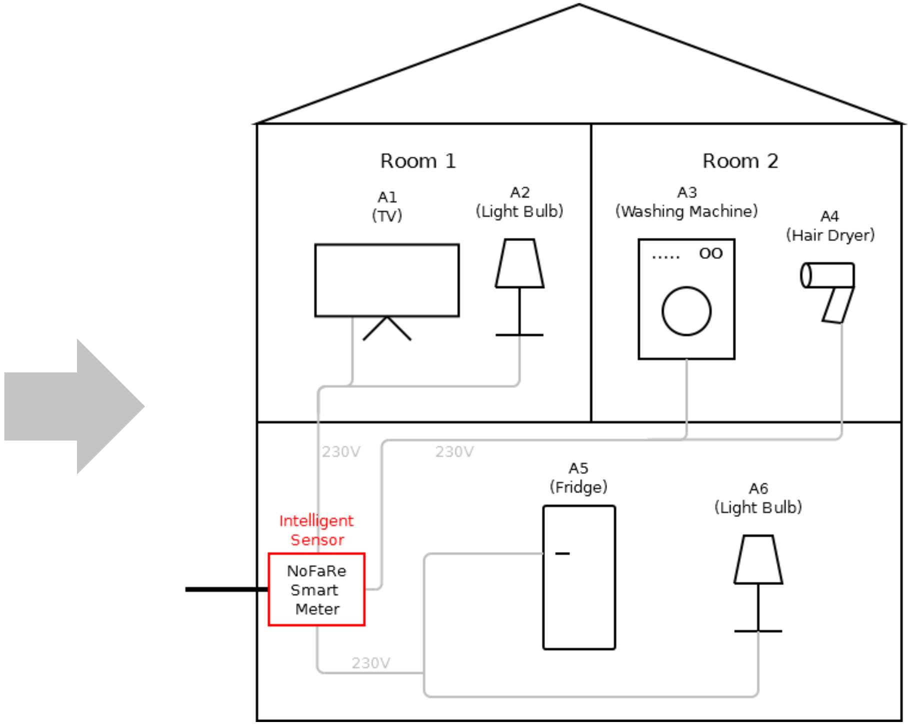
[2] Jiang, Lei, Suhuai Luo, and Jiaming Li. *"Automatic power load event detection and appliance classification based on power harmonic features in nonintrusive appliance load monitoring." 8th IEEE Conference on Industrial and Applications. IEEE, 2013.*

[3] Yang, Hong-Tzer, Hsueh-Hsien Chang, and Ching-Lung Lin. *"Design a neural network for features selection in non-intrusive monitoring of industrial electrical loads." 11th International Conference on Computer Supported Cooperative Work in Design., 2007.*

[4] Patel, Shwetak N., et al. *"At the flick of a switch: Detecting and classifying unique electrical events on the residential power line." Lecture Notes in Computer Science 4717 (2007): 271-288.*

What we would like to have





- Many intrusive sensors for each appliance
- Simple measuring device
- High hardware effort
- Low Software effort

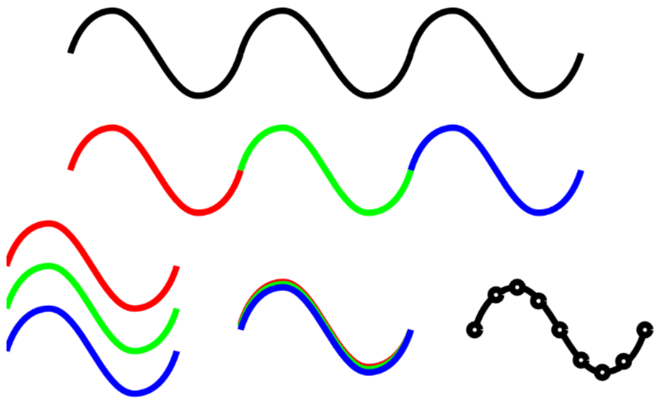
- One non-intrusive Sensors for all appliances
- Intelligent Measuring device
- Low Hardware effort
- High Software effort

Features

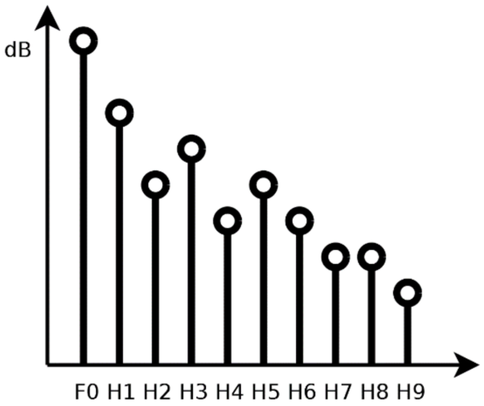
- Mean Power: $P = RMS(I) \cdot RMS(V) - P_{pre}$
- Signal to Signal-Mean Ratio: $mags = abs(fft(I))$ $\quad SSMR = \frac{max(mags)}{mean(mags)}$
- Inrush Current Ratio: $ICR = \frac{I_{startup}}{I_{stationary}}$
- Phase Shift: $PS = angle(mags_{current}(50Hz)) - angle(mags_{volt}(50Hz))$

Features (2)

- Curve Shape Approximation:



- Harmonics:



- V-I Trajectory:

Outline

- Motivation
- State-of-the-Art
- Algorithmic approach
- Pattern recognition in NILM

- Experiments
- Results
- Future Work & Discussion

Feature Extraction

- Ultra short-time features
- Acquired short-time features
- Long-time features
- Statistical analysis