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# Automatic Recognition of Major End-Uses in Disaggregation of Home Energy Display Data

International Conference on Consumer Electronics, Las Vegas 2013

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*Michael Zeifman*

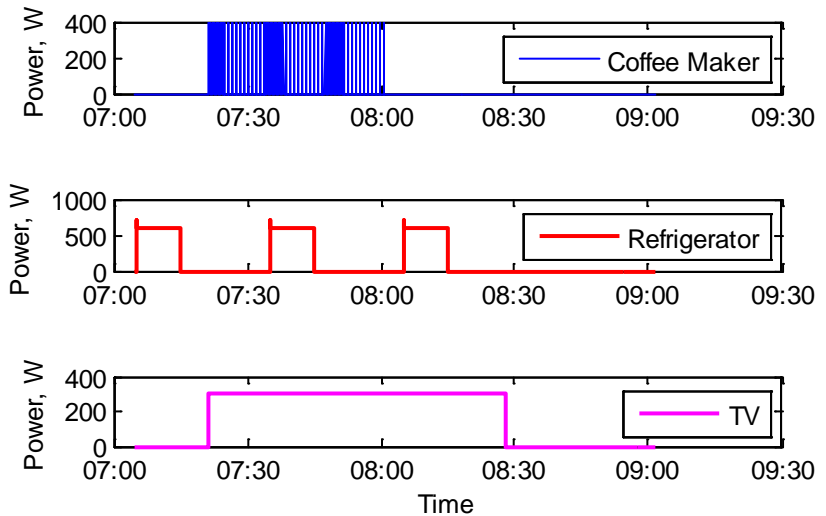
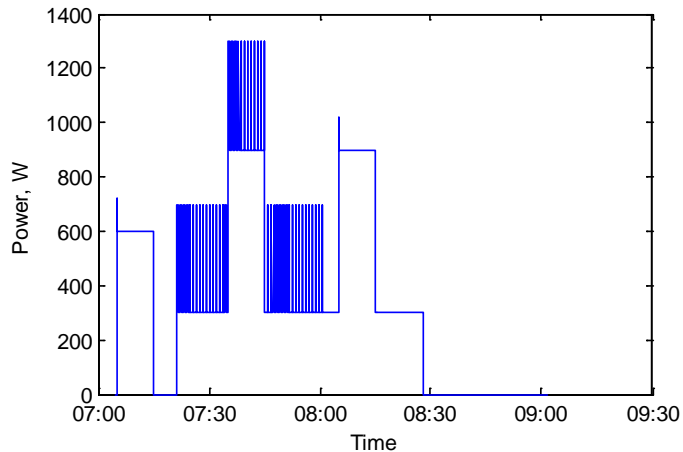
*Kurt Roth*

*Johannes Stefan*

# What Is Disaggregation/NIALM?

■ NIALM = Non-Intrusive Appliance Load Monitoring

■ A.k.a. Non-Intrusive Load Monitoring



■ Main breaker/circuit level

■ Data acquisition (hardware) and disaggregation algorithms (software)

# Low-frequency Disaggregation: the Opportunity

■ “The Smart-Meter-to-Home Retail Sales Channel Goes Live in SoCal. Will hefty rebates from Southern California Edison drive sales into the nascent HAN market?”

Jeff St. John: November 13, 2012

<https://www.greentechmedia.com/articles/read/the-smart-meter-to-home-retail-sales-channel-goes-live-in-socal>



Rainforest

Automation products



Real-time smart meter  
data on your PC

■ “SoCal Edison plans to contact about **100,000** of its customers via email... \$10 for a device you can take home, plug in, and, after a short setup process with the utility, start getting **eight-second** updates on your household energy usage.”

■ “**Southern California Edison and ADT Pulse offer customers real-time smart meter data.**” Jeff St. John: November 28, 2012

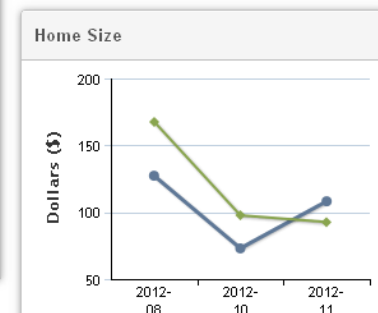
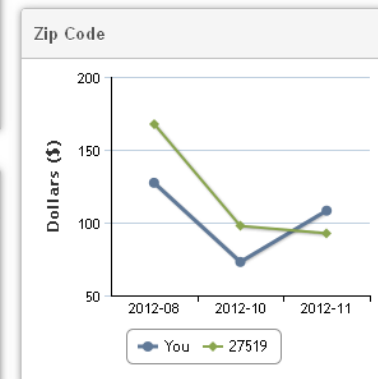
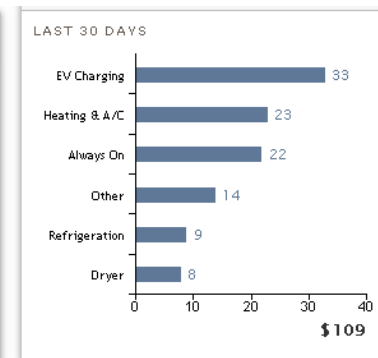
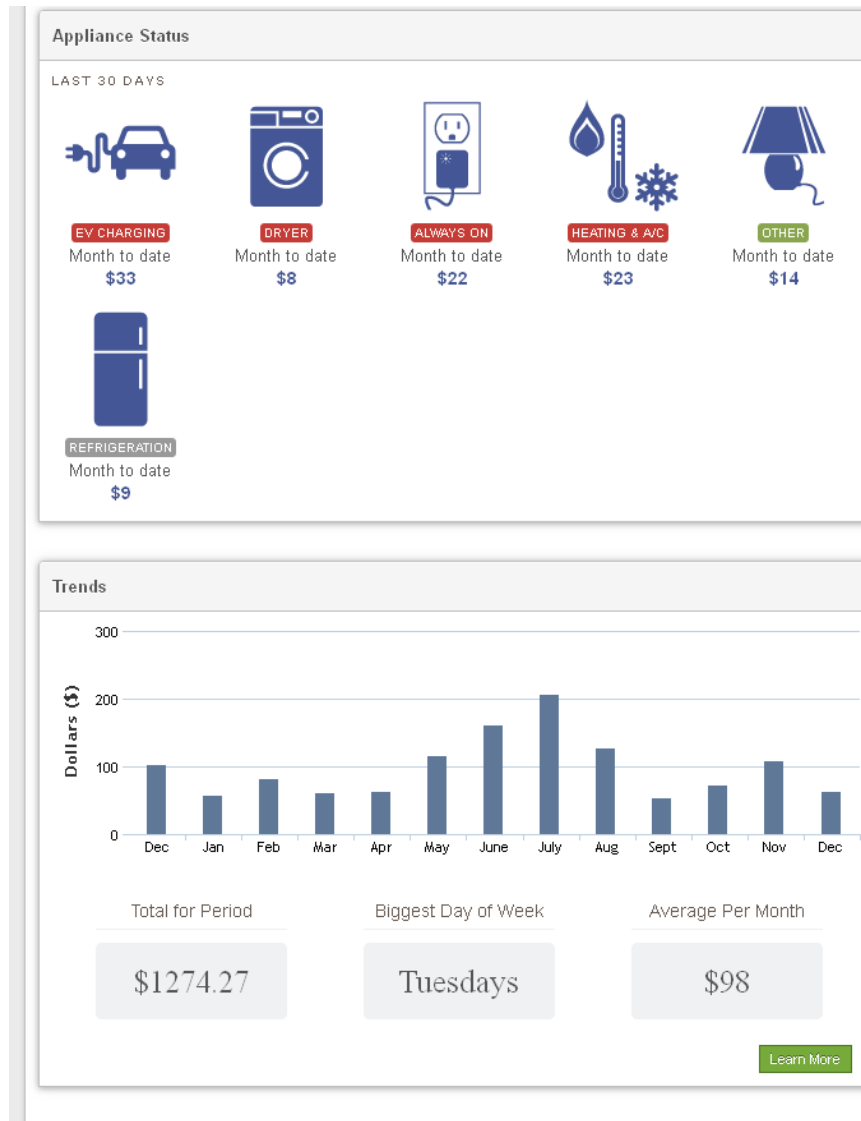
“Utilities in California and across the country are awaiting the release of the next version of the standard, SEP 2.0, which will include Wi-Fi and the powerline carrier HomePlug standard as well, some time next year.”

# Estimated Potential Customer Requirements for Commercialization of NIALM

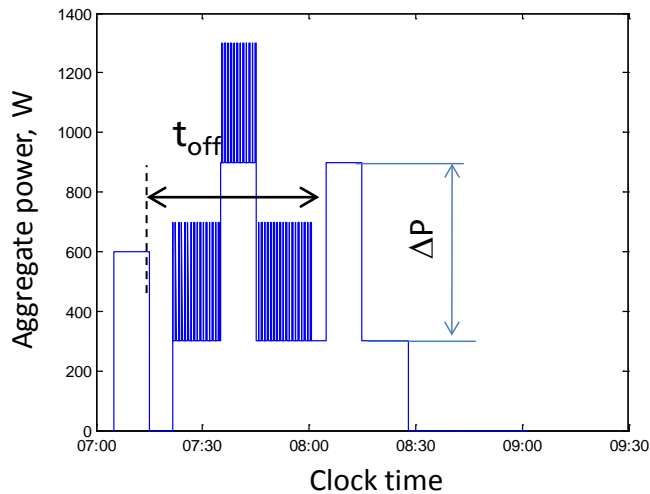
- Automatic identification of major end-uses (e.g., >80% of household electricity)
- Accurate detection of the found end-uses (e.g., >85% though no clear measure)
  - Historical electricity consumption, operating hours data (day, week, month, year)
  - Near-real time (within 1-5 min)
- Self-contained system – no data leaving house (privacy concerns, computational concerns)
- Field performance validated – in-home validation at main electric panel
- Specific recommendations for
  - Saving energy
  - Demand response

# NIALM State of the Art: PlotWatt

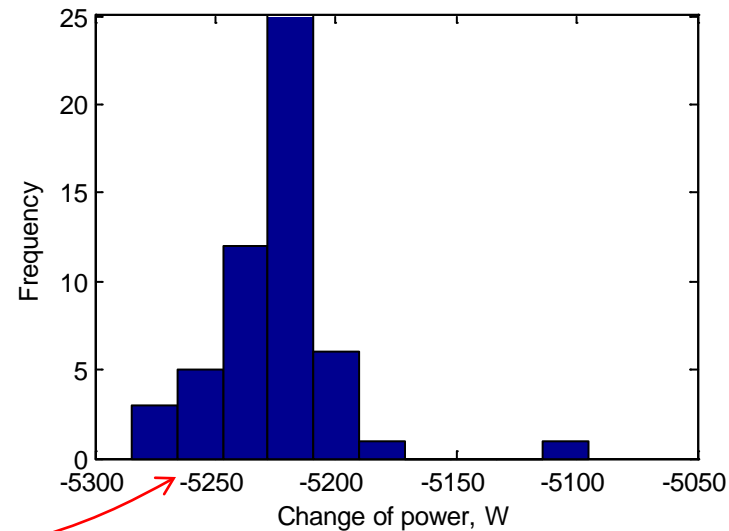
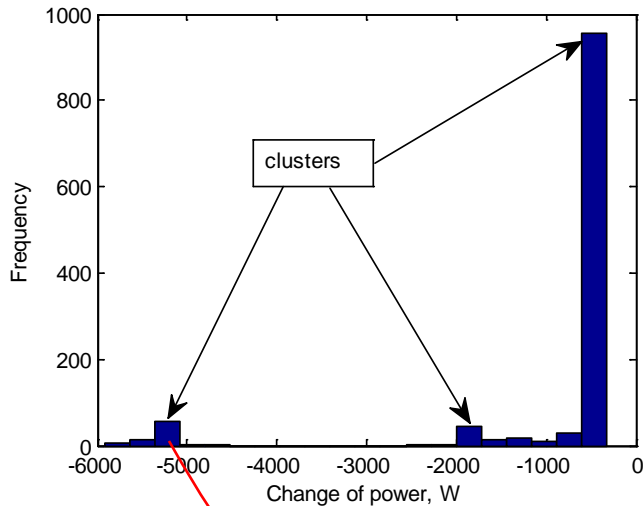
- Customers need to surrender data
- No real time
- No accuracy
- 3 end uses



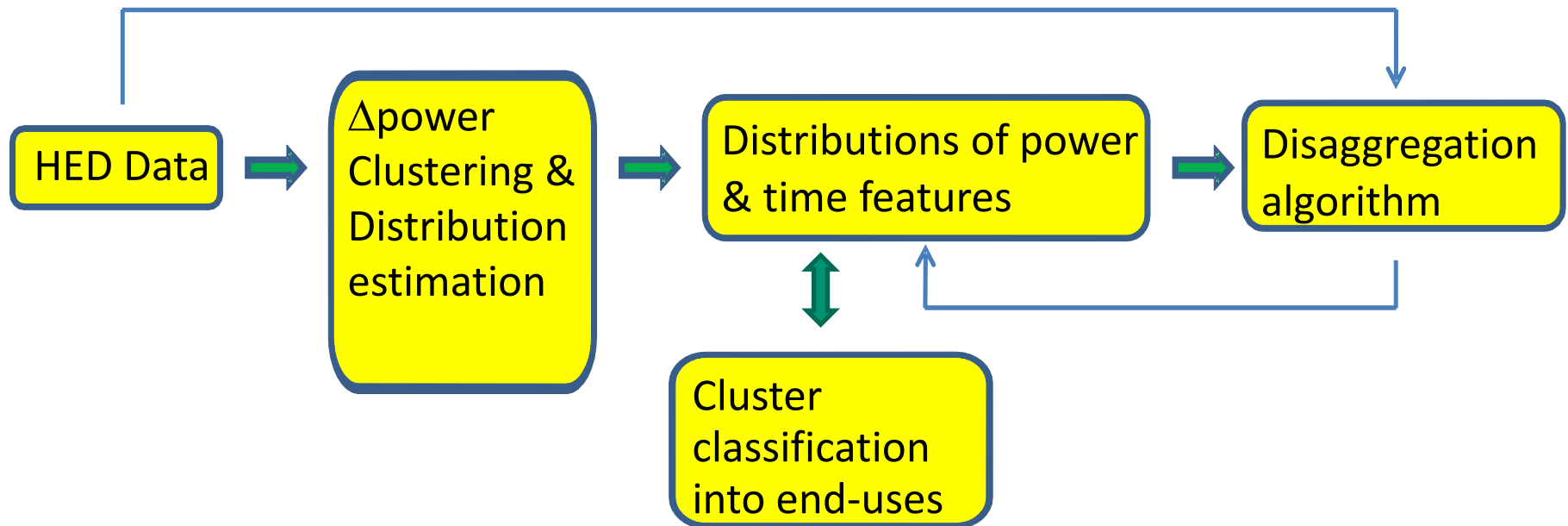
# Our NIALM: Features Clustering and Distribution Estimation



- ❑ Power-related:  $\Delta P$ , Surge amplitude
- ❑ Time-related: time on duration, time off duration
- ❑ Clusters of  $\Delta P$  by distance metrics
- ❑ Distributions of  $\Delta P$ , Surge,  $t_{on}$  and  $t_{off}$  for each cluster, by non-parametric or parametric method



# Our NIALM: High-Level Block Scheme



# Cluster Classification into End-uses

- Major end-uses (>80% of household energy consumption on average):
  - space cooling systems
  - space heating systems
  - domestic hot water
  - lighting
  - refrigerators
  - electric clothes dryers
  - consumer electronics
- Approach: probabilistic pattern recognition (naïve Bayes Classifier)
  - Estimate distributions of  $\Delta P$ , surge,  $t_{on}$ ,  $t_{off}$  from first principles/literature
  - Update distributions and use new features by experimental data
- Testing by end-use data and aggregated data



# Statistical Distributions of Major End-uses

- Typical distributions:
  - $\Delta P$ , Surge,  $t_{on}$  and  $t_{off}$  mutually independent
  - Known range and mean value - beta distribution using the maxim entropy concept
  - Applicable to clothes dryers, domestic hot water systems, refrigerators
- Mixture distributions
  - Two or more sub-populations
  - Model each separately and use known ratios to get mixture distributions
  - Air-conditioners: window or central units
- Complex distributions
  - Consumer electronics: desktop computers (sum of processor and monitor, some discrete distribution data available)
  - Lighting: separate distributions for different room types, discrete wattage, fixtures, bulb type

## Some data sources:

Ashe, M., et al., "2010 U.S. Lighting Market Characterization," Report to U.S. Department of Energy, 2012.

"Water Heating in U.S. Homes in Northeast Region, Divisions, and States," Residential Energy Consumption Survey (RECS) 2009

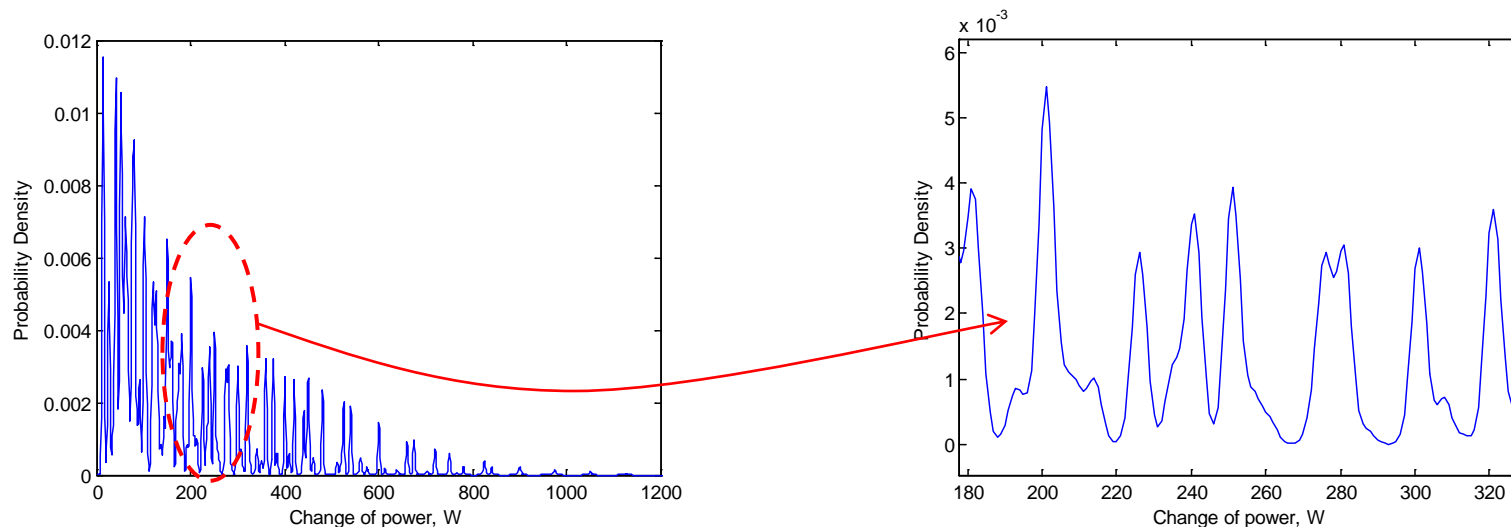
Similar RECS data for other end-uses

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# Example: Lighting Distributions

## ■ Methodology

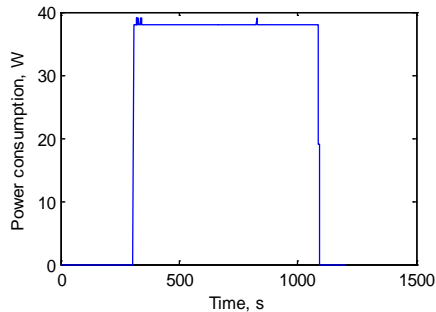
- Single detached home, 7 types of rooms (living, dining, kitchen, utility, bedroom, hall, bathroom), average switch number per room
- 3 types of bulbs (incandescent, halogen, CFL), average fractions for each
- Fixtures of up to 15 bulbs
- Average and mode for change of power to get Beta distributions, incandescent – 120 or 130 V with correction
- For each room type – separate distribution of  $t_{\text{on}}/t_{\text{off}}$  (3-dimensional mixtures for total)



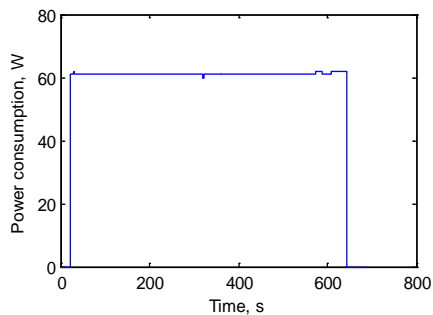
Marginal Distribution of  $\Delta P$  for lighting

# Fine Features: CE vs. Lighting

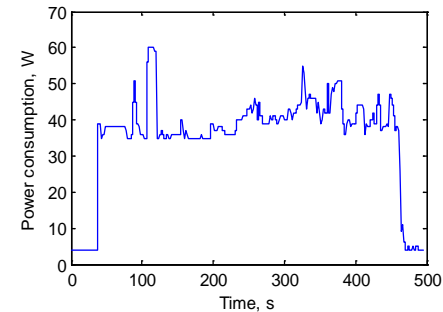
- Variability
  - Lighting: very stable, small fluctuations (need to normalize by voltage)
  - Major CE devices (desktop computers, TV-s): highly variable
  - Parametric distributions of  $\text{std}_{\text{fluctuations}}$



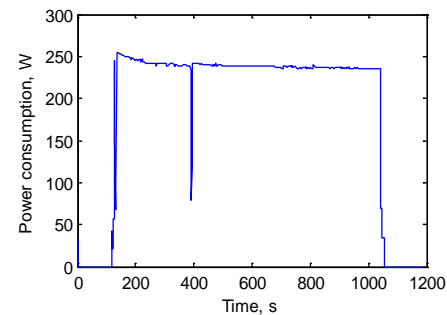
Incandescent bulb, 40W



Incandescent bulb, 60W



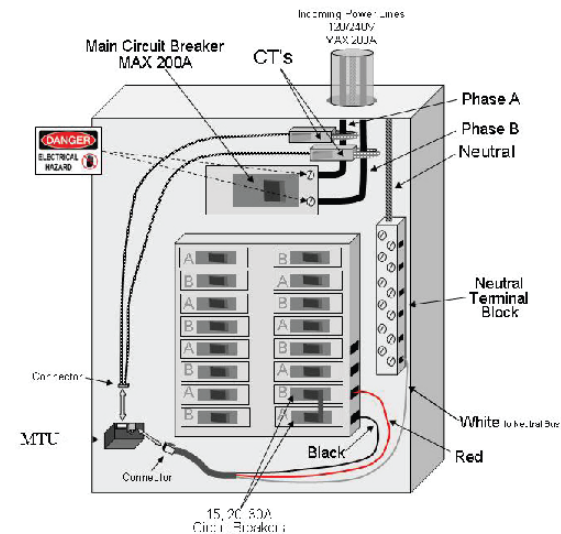
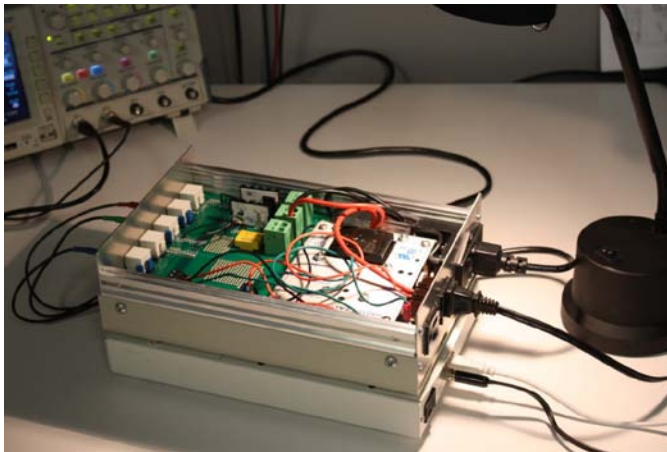
TV, CRT



TV, LCD

# Testing: Submetering (1/2)

- Our Own Data:
  - Plug loads (CE, refrigerators, some lighting): custom-build DAQ based on TED-5000 (The Energy Detective)
  - Large loads: TED-5000 connected to circuits
  - Real power at 1 Hz, used in 10+ households
- Open Data (only circuits):
  - REDD database – 4 households in North-East USA, apparent power at 1/3 Hz  
<http://redd.csail.mit.edu/>
  - Smart\* data sets – Massachusetts, 1 home, both real and apparent power at 1 Hz  
<http://traces.cs.umass.edu/index.php/Smart/Smart>



# Testing: Submetering (2/2)

## ■ Results

- Separate submetered sets
- Our and public data, cooling season
- Accuracy metrics: F-measure

$$F = 2 \frac{\frac{TP}{TP + FP} \cdot \frac{TP}{TP + FN}}{\frac{TP}{TP + FP} + \frac{TP}{TP + FN}}$$

## Cluster Classification Accuracy

End-use	Accuracy, our data	Accuracy, public data
Air conditioner	0.9	0.85
Clothes dryer	0.9	0.9
Domestic hot water	0.99	n/a
Refrigerator	0.9	0.91
Lighting	0.65 (0.92 with fine features)	0.54 (0.95)
Consumer electronics	0.70 (0.90 with fine features)	0.62 (0.83)

# Testing: Aggregate Data

- Results
  - Our data: submetered data combined together, no “else” end-uses
  - Public data, aggregated data used, “else” end-uses: cooking, washing machine, dishwasher, small CE, unknown appliances
  - About 3 weeks of data clustered and classified

## Cluster Classification Accuracy

End-use	Accuracy, our data	Accuracy, public data
Air conditioner	0.82	0.80
Clothes dryer	0.86	0.89
Domestic hot water	0.99	n/a
Refrigerator	0.85	0.82
Lighting	0.55 (0.83 with fine features)	0.51 (0.85)
Consumer electronics	0.60 (0.84 with fine features)	0.52 (0.80)
Else	n/a	0.76

# Conclusions

- Statistical classification scheme developed
- Preliminary results encouraging
  - Uses generic prior knowledge
  - Can be customized for targeted households (multifamily, single detached, CFL lightings, gas-based water heating)
- Need further work
  - Heating season
  - Testing, distribution updating (Bayesian)
  - More end-uses (washing machines, kitchen appliances, pool pumps)
  - Class “else”