Supero:
A Sensor System for Unsupervised Residential Power Usage Monitoring

Dennis E. Phillips[1], Rui Tan[2]; Mohammad-Mahdi Moazzami[1]; Guoliang Xing[1]; Jinzhu Chen[1]; David K. Y. Yau[2,3]

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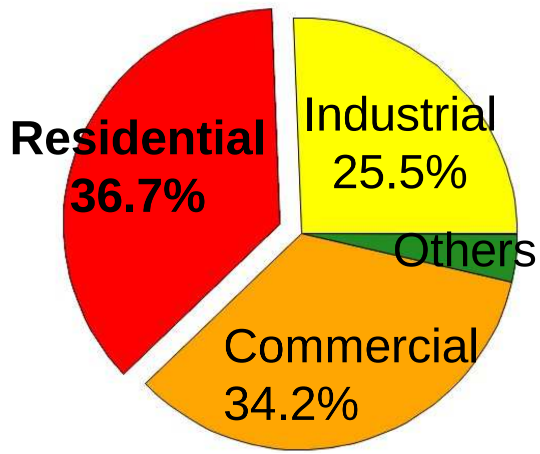
Outline

- **Motivation & Approach**
- Light Sensing
- Acoustic Sensing
- Implementation & Experiments

Residential Electricity in U.S.

- Residential electricity
  - Largest sector
- Rising cost
  - Increase by 75% in 10 years
- Understanding usage
  - Real-time power readings
  - Fine-grained usage info



Electricity retail sales in U.S. 2011

[US EIA-861, EIA-923]

Appl.	Joul %	When?
Bed light	5%	7pm-11pm
Fridge	8%	Every 1h
Space heater	30%	Jan 1 …
….	….	….

Related Work

- Direct sensing
  - **ACme** [IPSN'09]
    Per-appliance inline meter, intrusive


[Jiang IPSN'09]

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    High-rate ADC, in-situ training

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- Indirect sensing
  - **At-the-flick** [UbiComp'07]
    High-rate ADC, in-situ training
  - **ViridiScope** [UbiComp'09]
    Labor-intensive sensor installation

[Kim UbiComp'09]

Objective & Challenge

- Fine-grained usage monitoring
  - Accurate energy disaggregation
  - Inexpensive and easy-to-install sensors
  - Training-free, ad hoc system deployment (“place sensor on shelf facing light to be monitored”)

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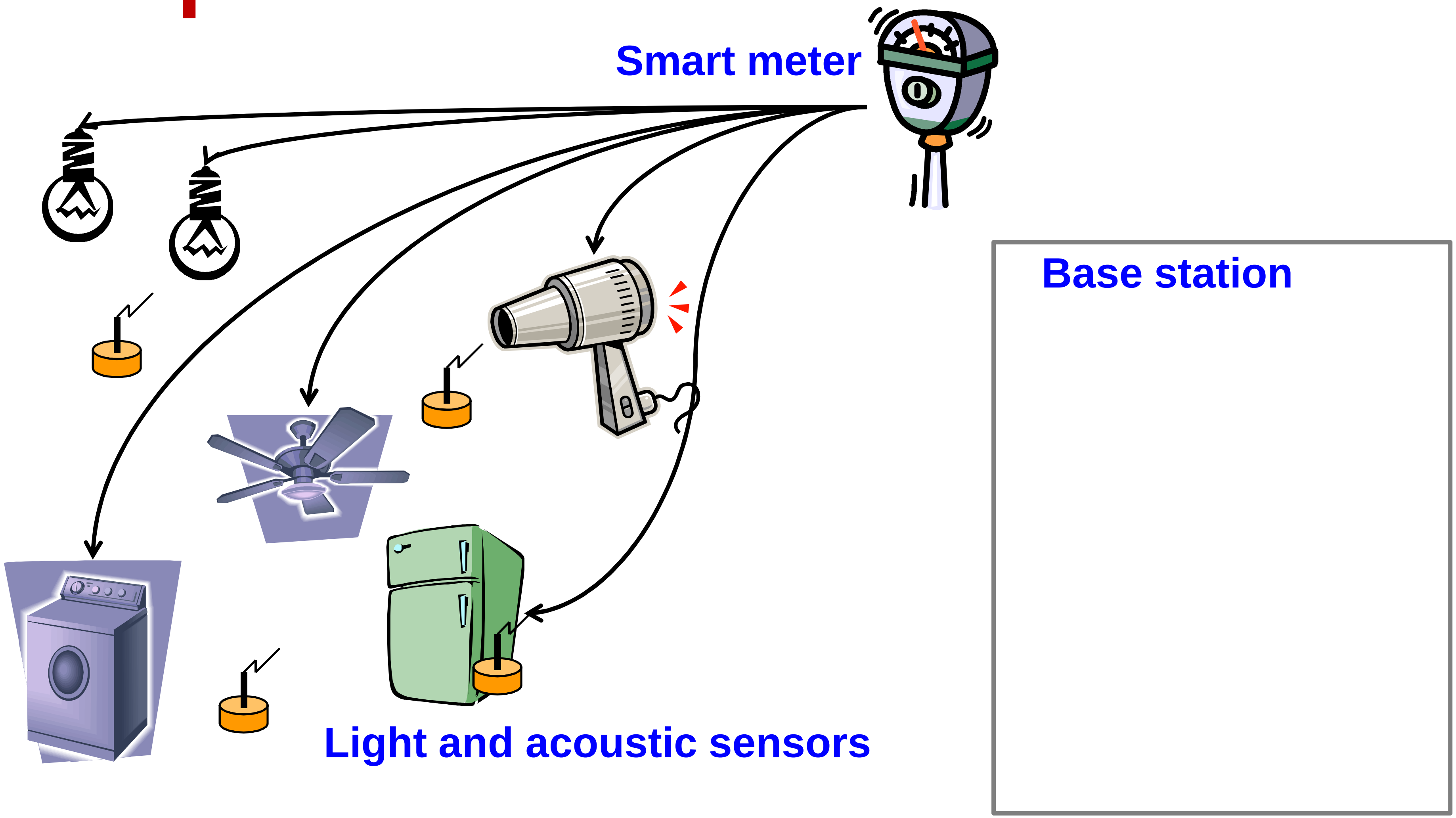
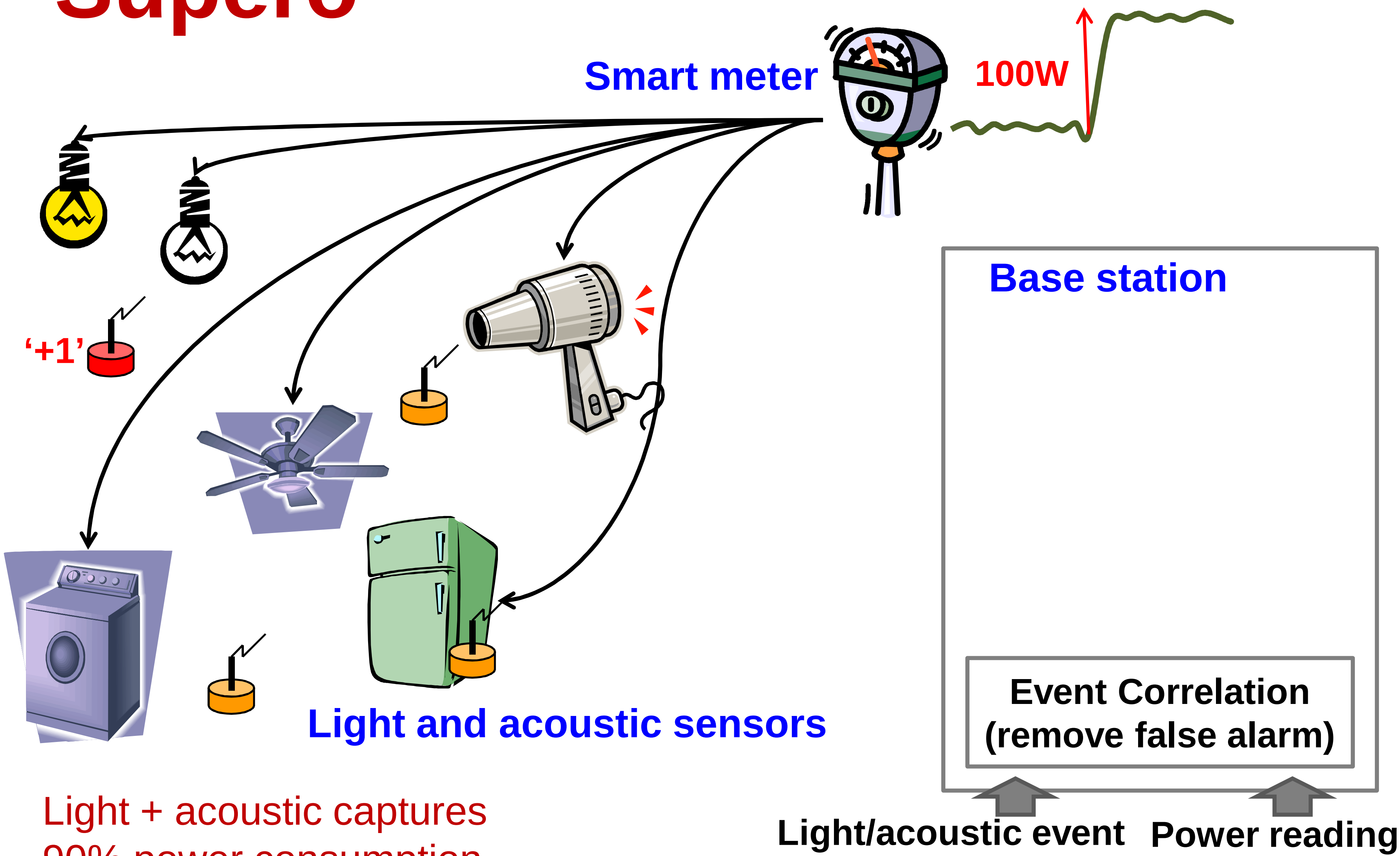
- High-degree sensing uncertainty
  - Noises from environment and human activities
  - Source appliance identification
    - A sensor can sense multiple appliances
    - An appliance can be sensed by multiple sensors

Supero



Light + acoustic captures
90% power consumption

Supero



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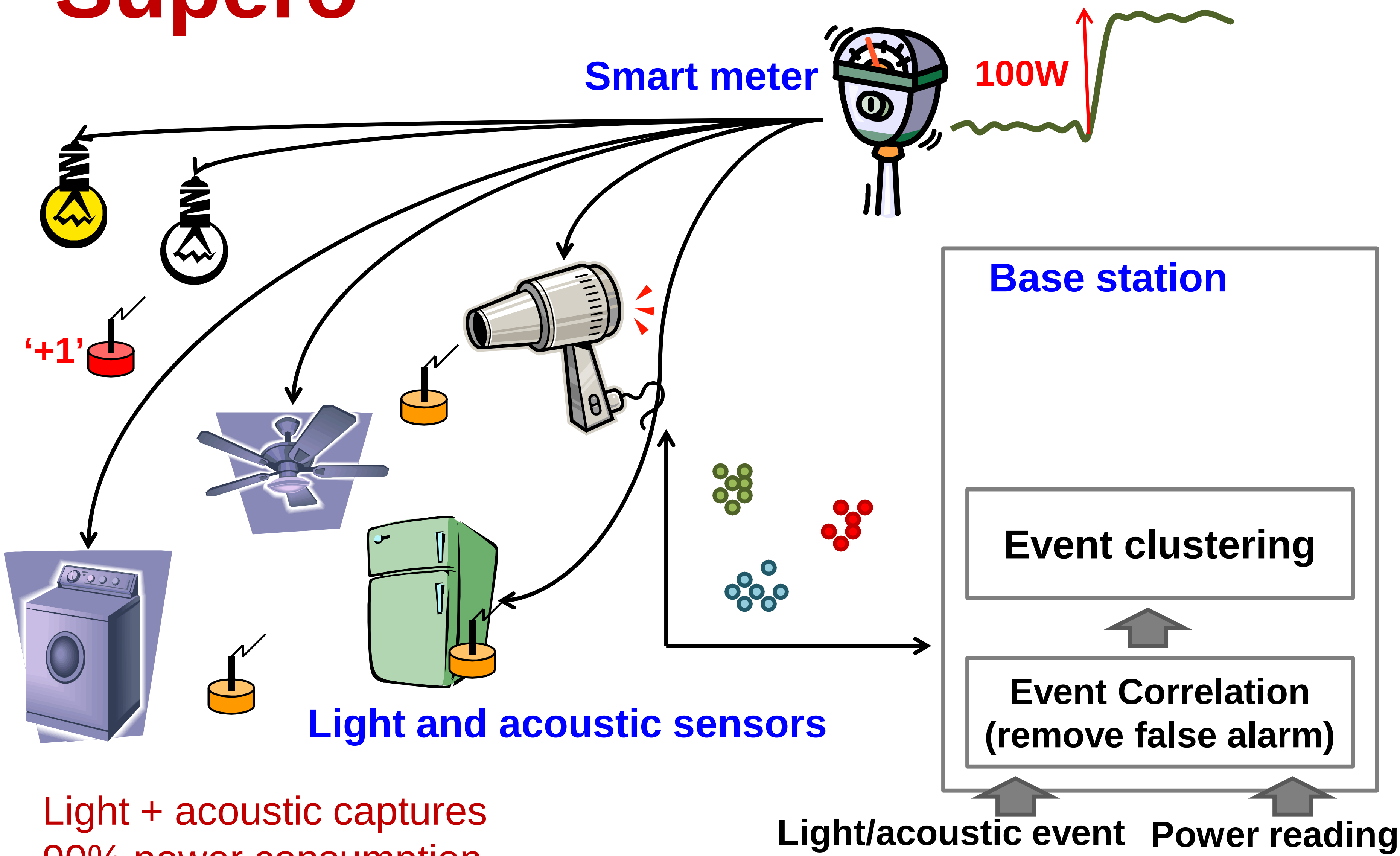

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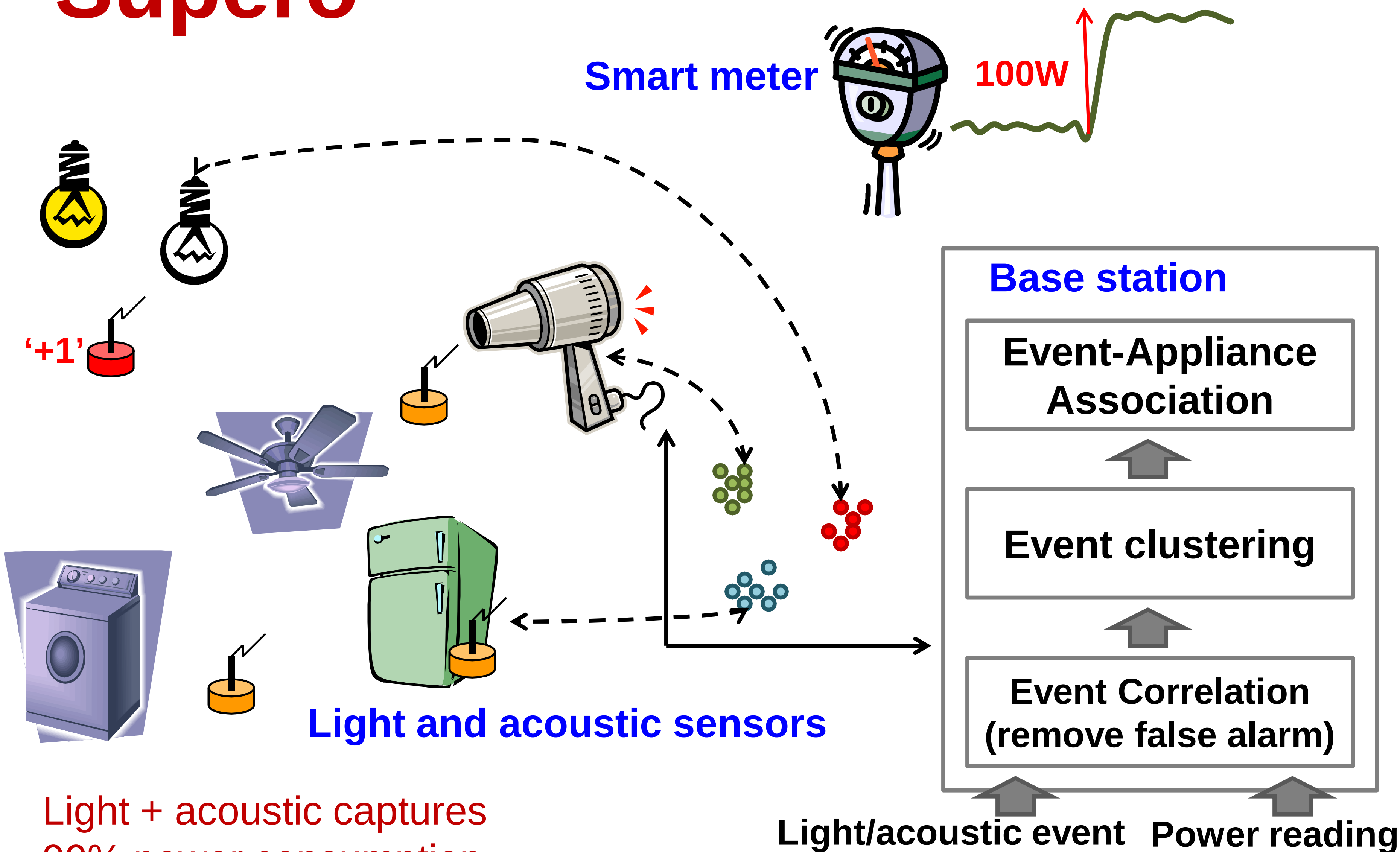

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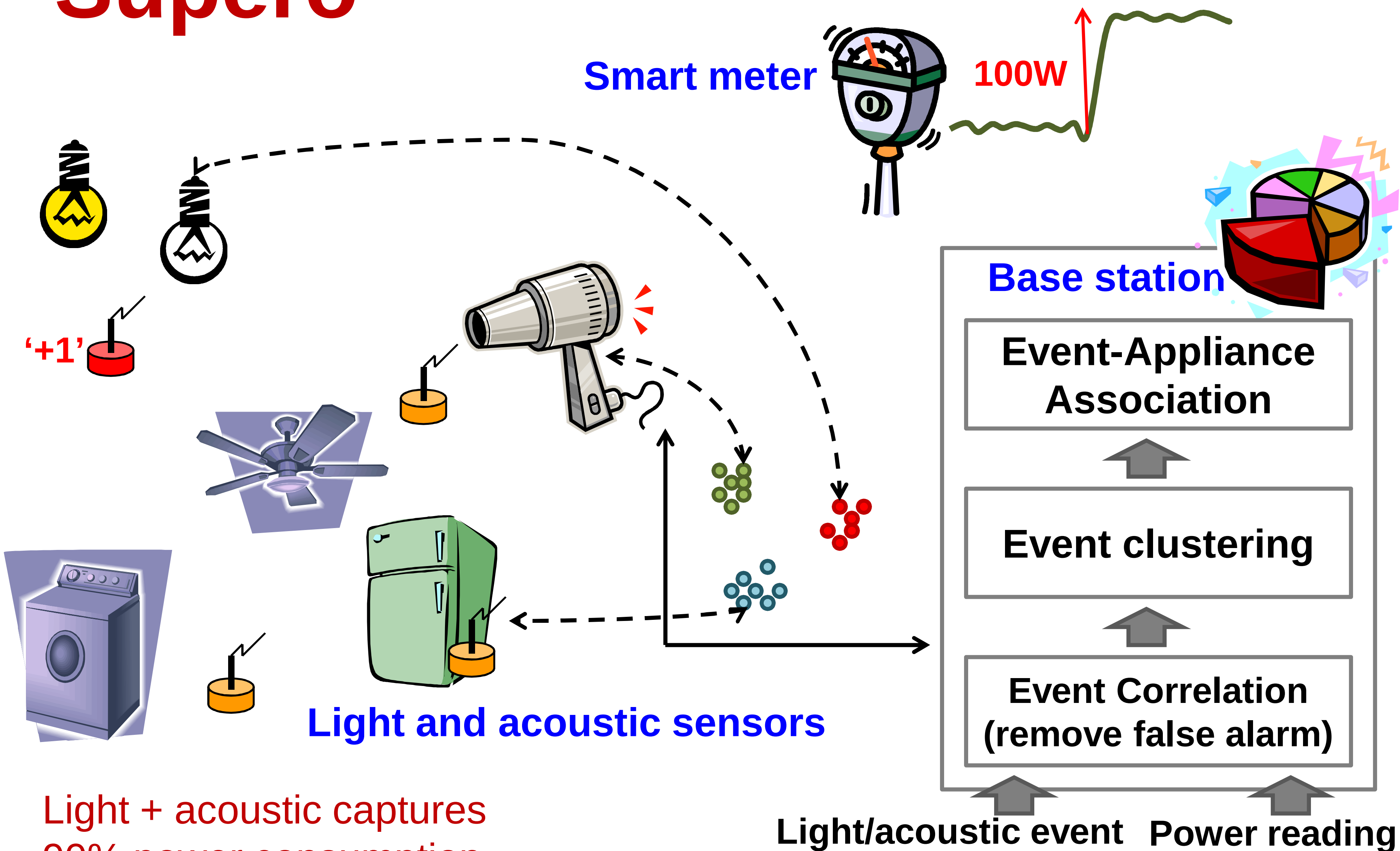

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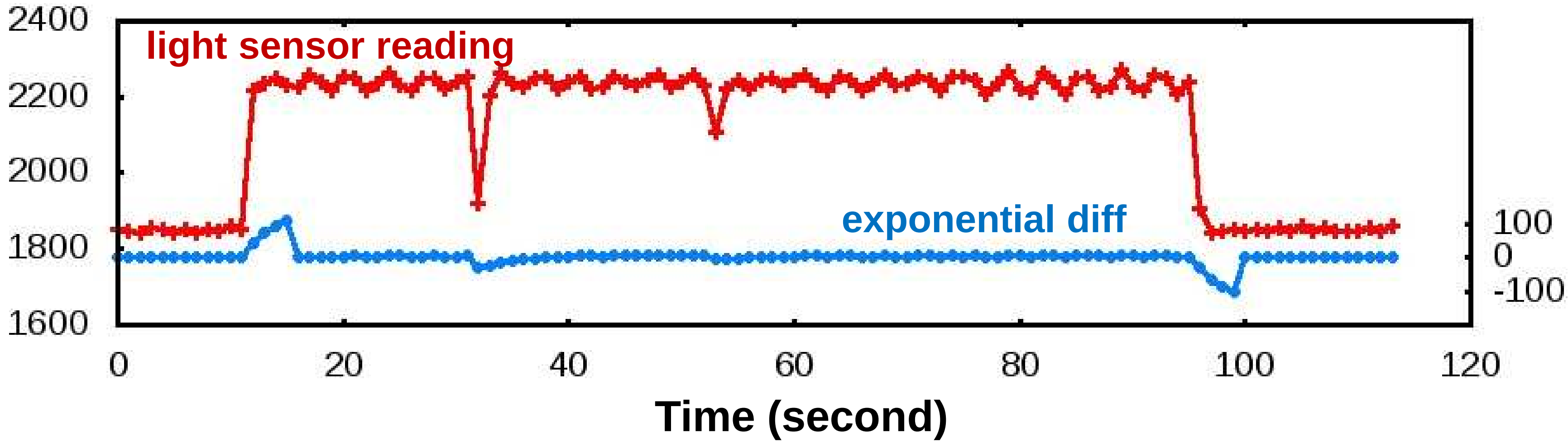
Event Detection & Correlation



- Exponential difference filter
  - Diff between long-/short-term moving averages

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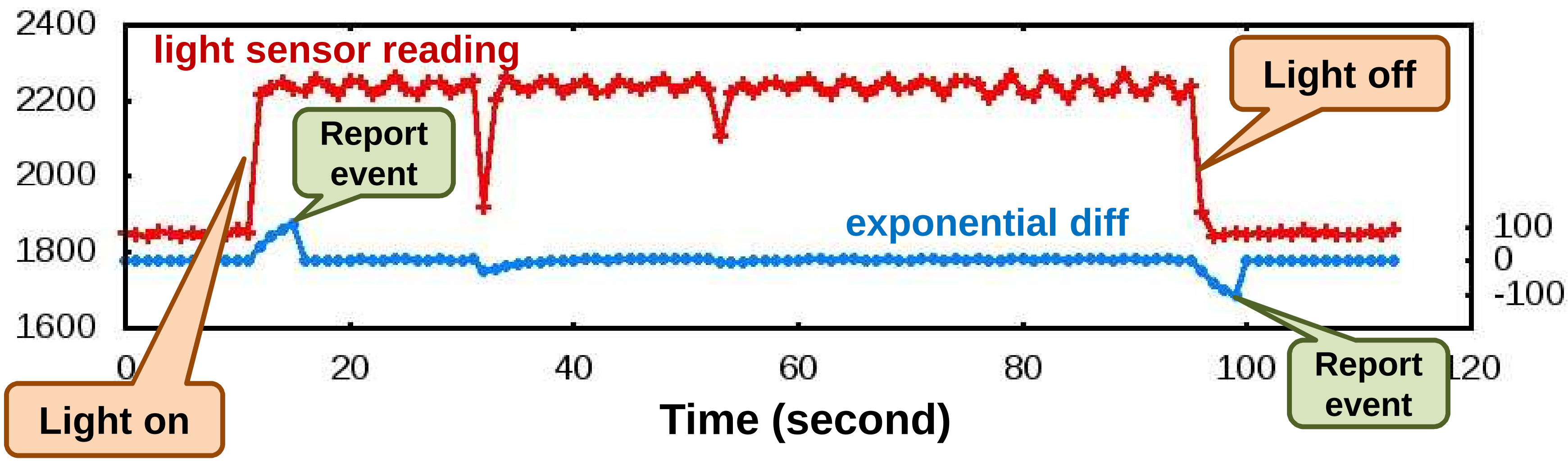

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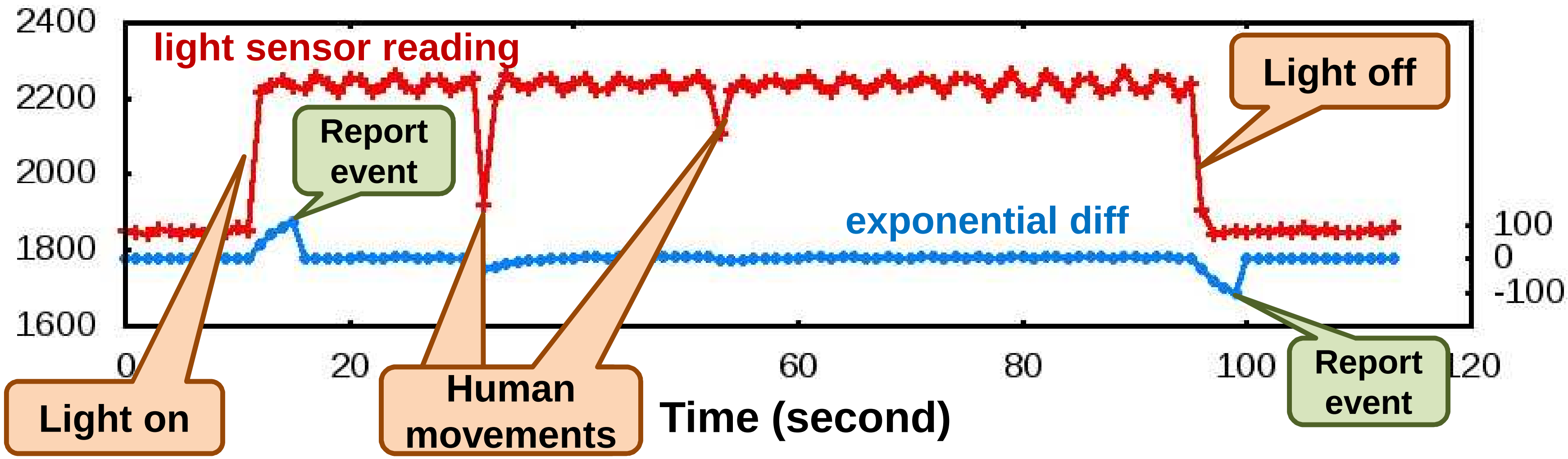

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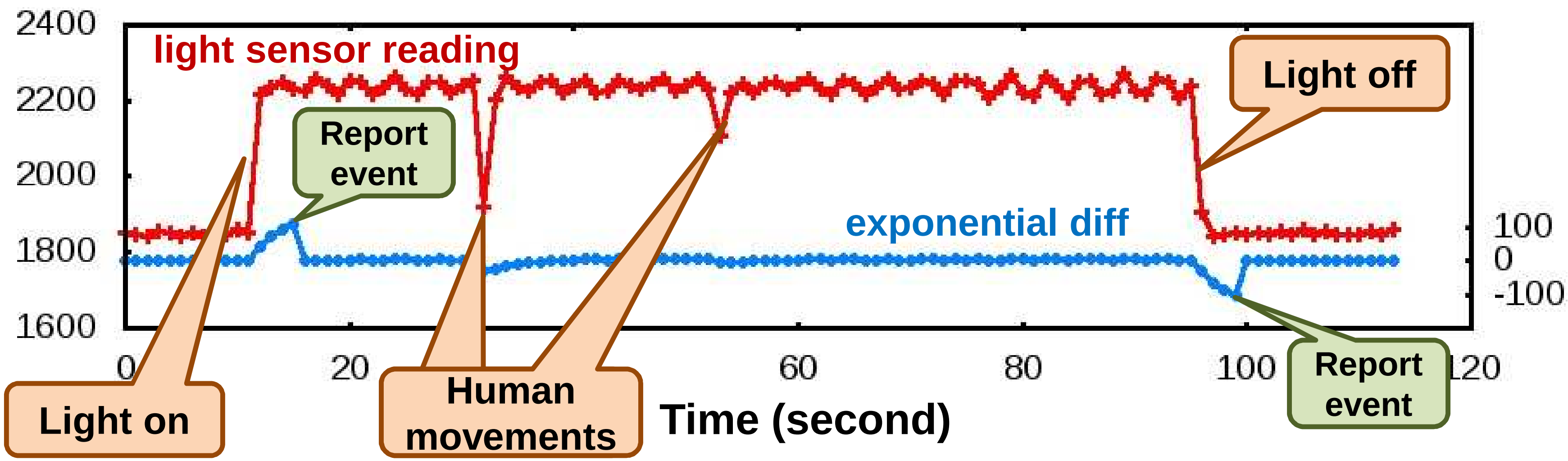
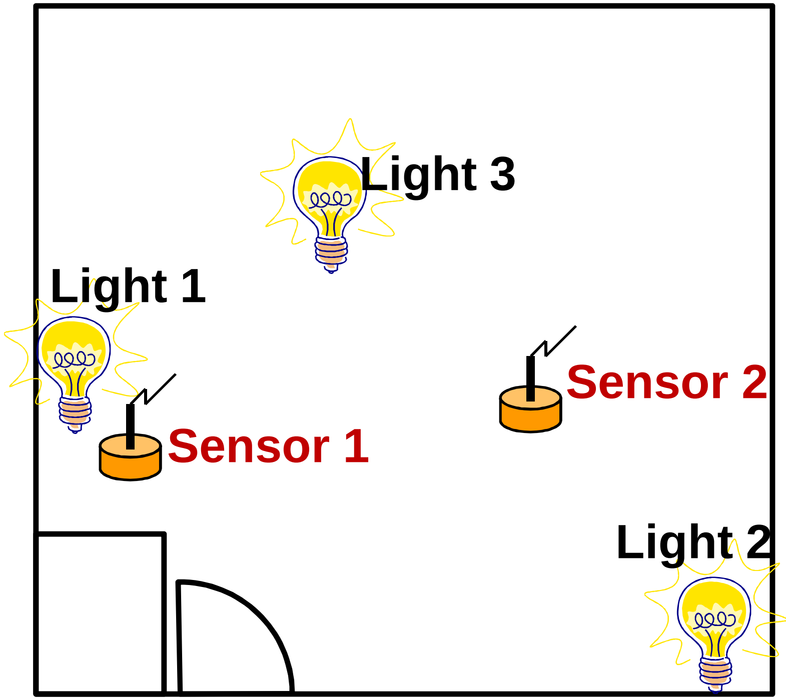
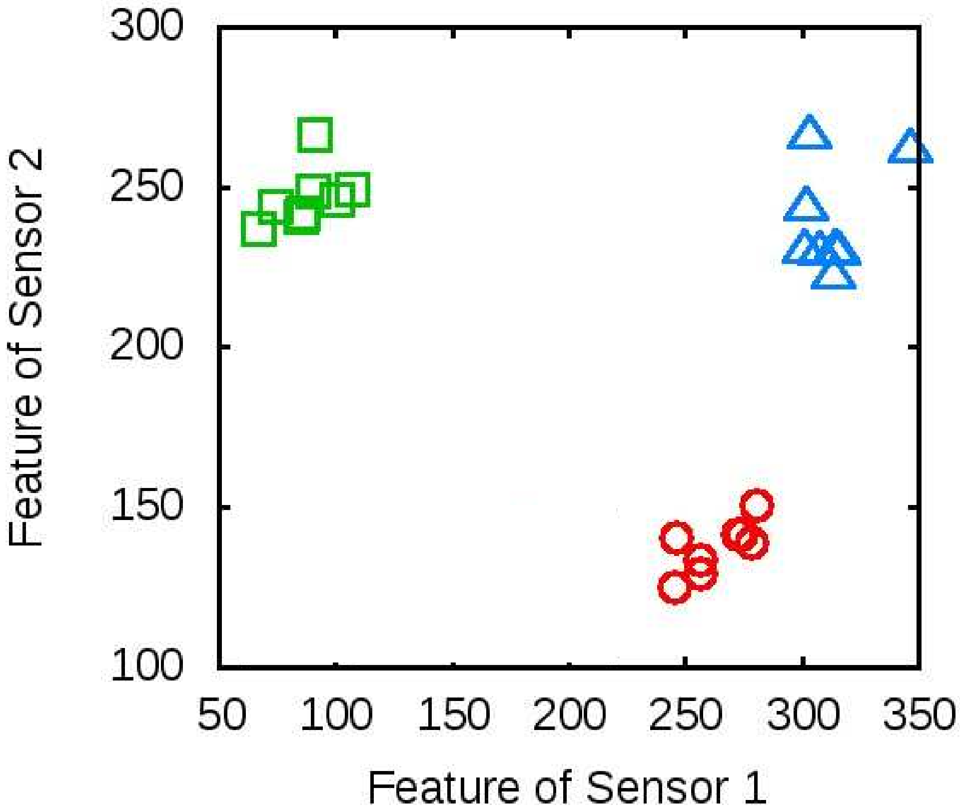


- Exponential difference filter
  - Diff between long-/short-term moving averages
- Event correlation
  - Simultaneous events have same source
  - False alarm if no power reading change

Light Event Clustering



Floor plan



Clustering on intensity changes

- Feature: change of light intensity

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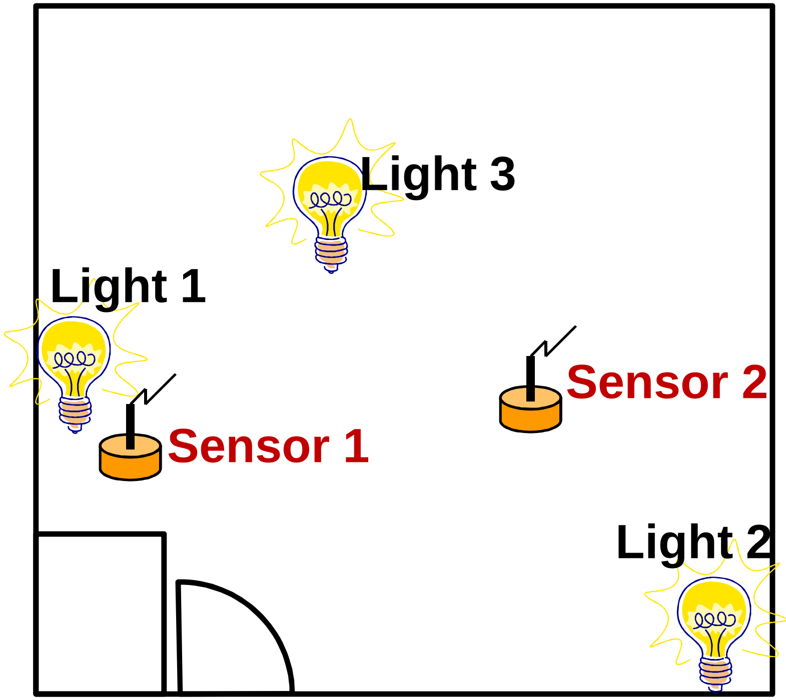

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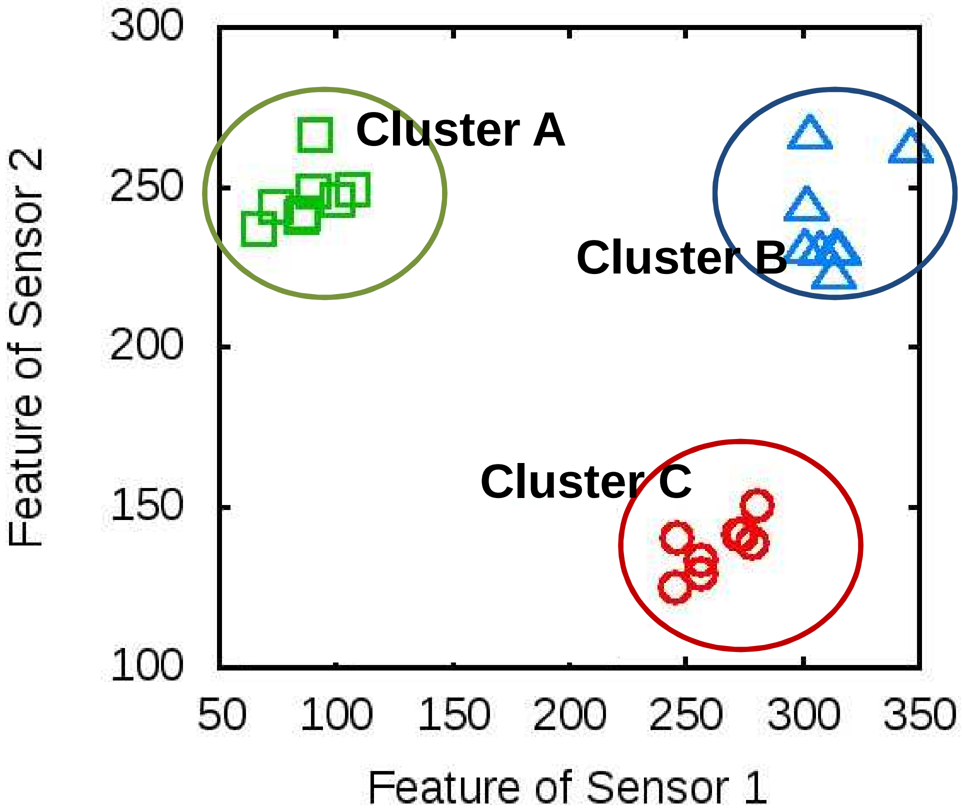

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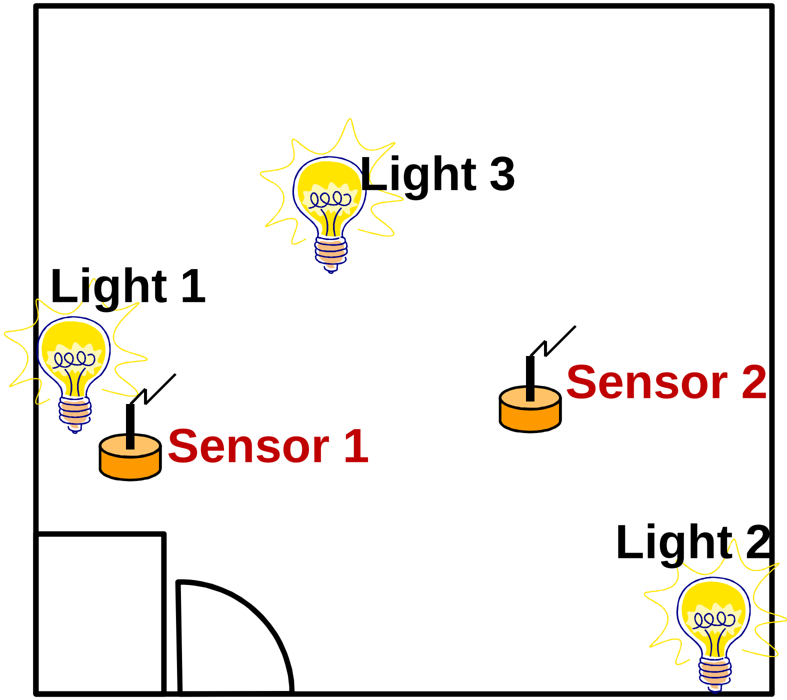

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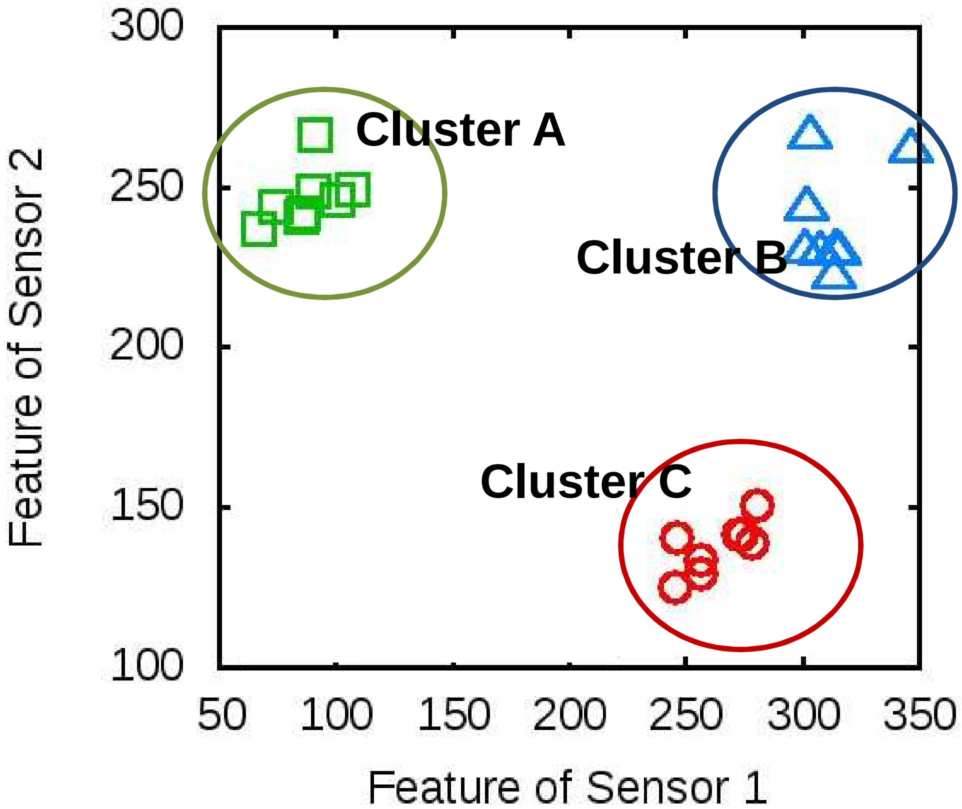
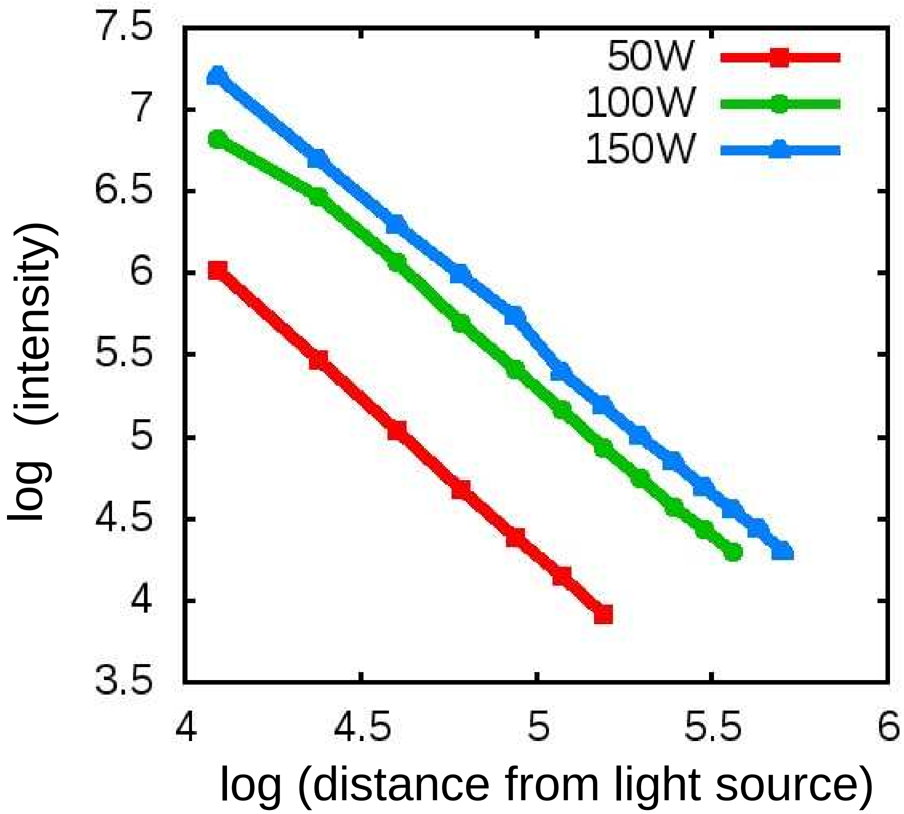


Clustering on intensity changes

- Feature: change of light intensity
- {Cluster A, B, C} ↔ {Light 1, 2, 3}?

Power Law Decay of Light



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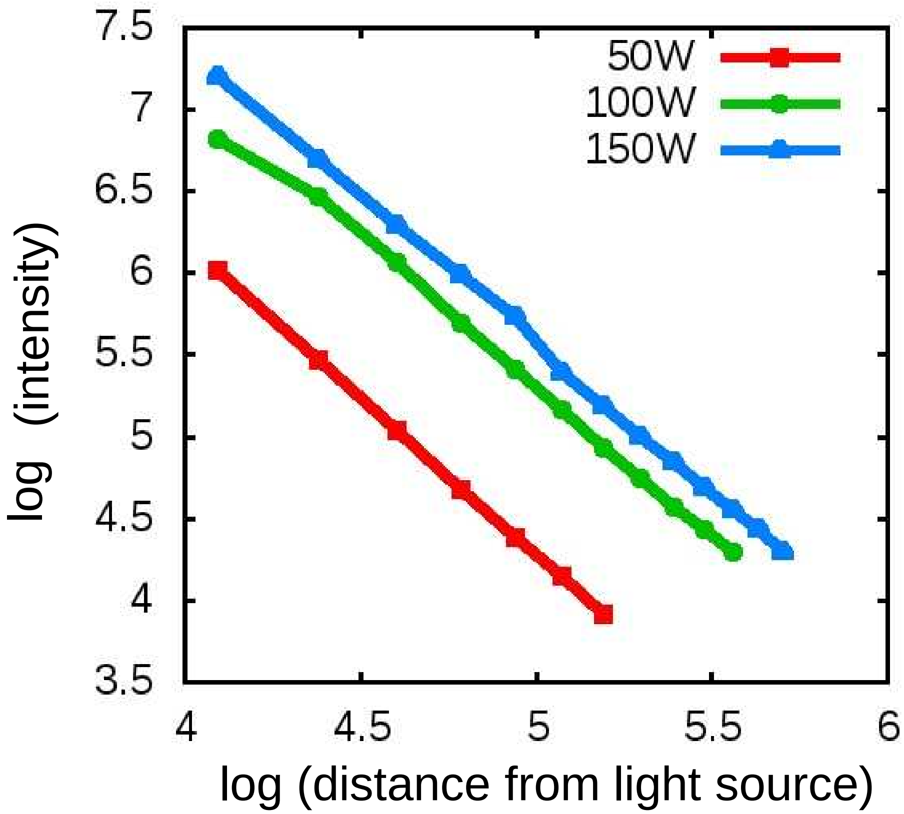

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distance from light source

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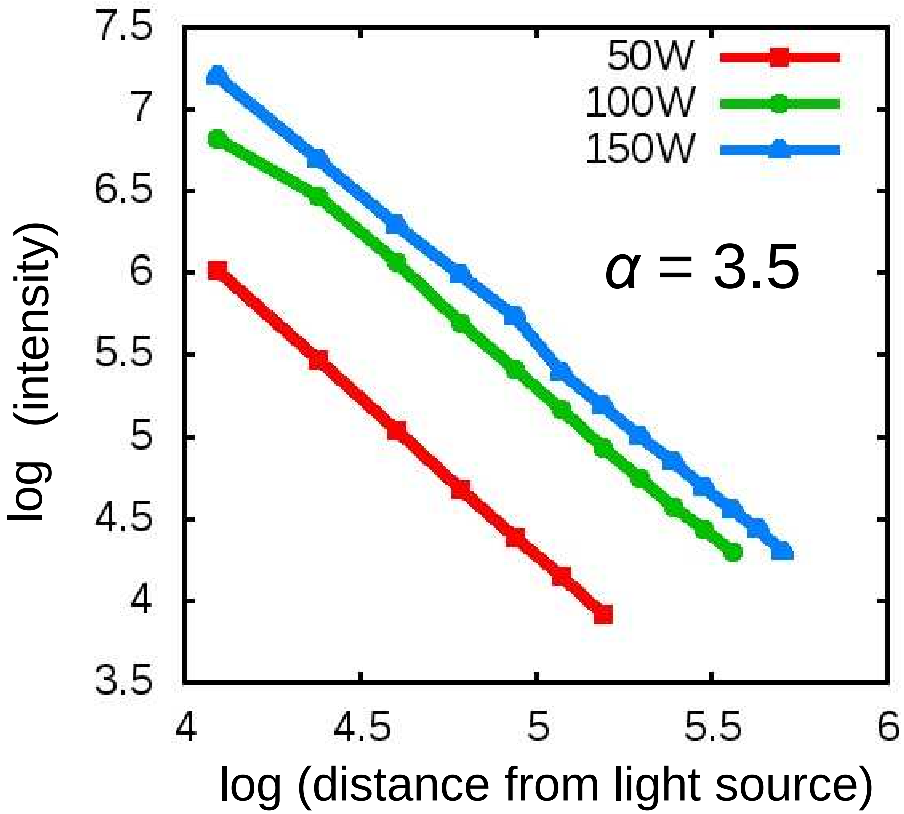

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Path loss exponent
$\alpha \in [2, 5]$

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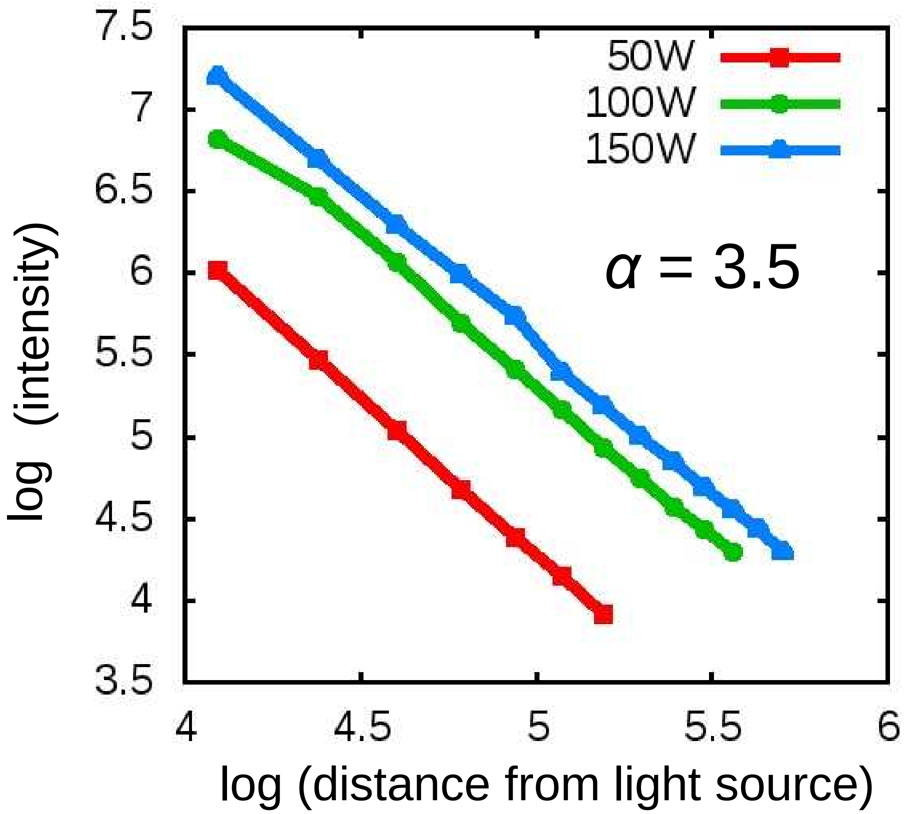

Path loss exponent
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Scaling factor

distance from light source

Cluster-Light Association

- Error of associating cluster *m* and light *j*

$$e_{m,j} = \sum_{i \in R_m} \left| \beta \cdot P_m \cdot d_{i,j}^{-\alpha} - \mu_{i,m} \right|$$

Discrepancy between model prediction and observation for sensor *i*

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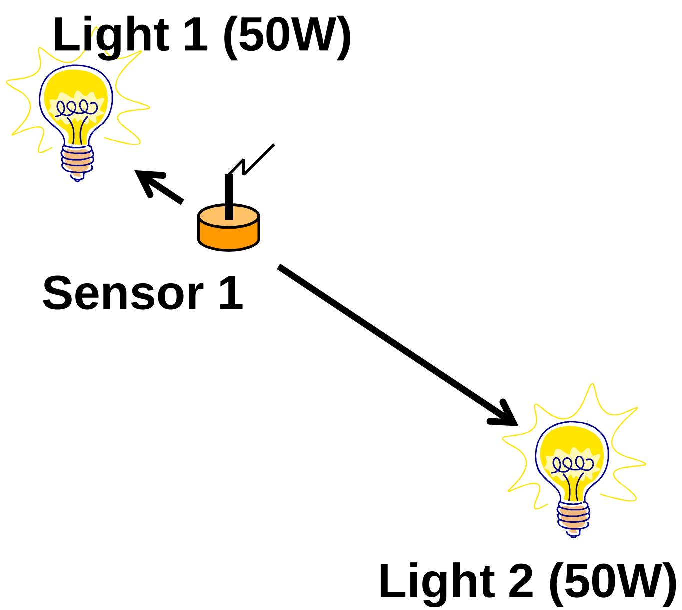

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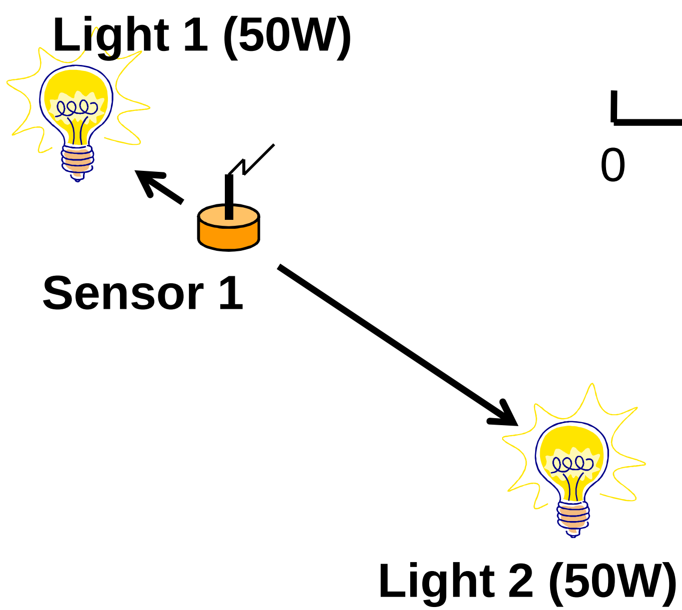

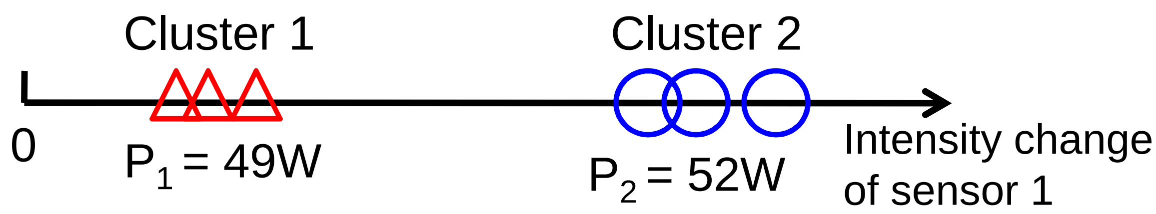

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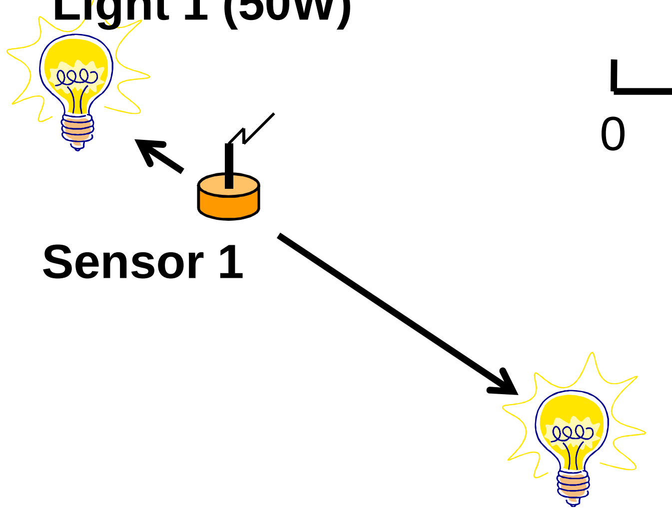

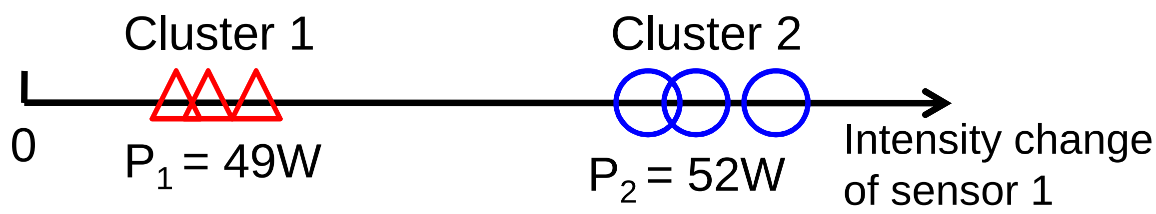

$e_{m,j}$	Light 1	Light 2
Cluster 1	3000	100
Cluster 2	110	4000

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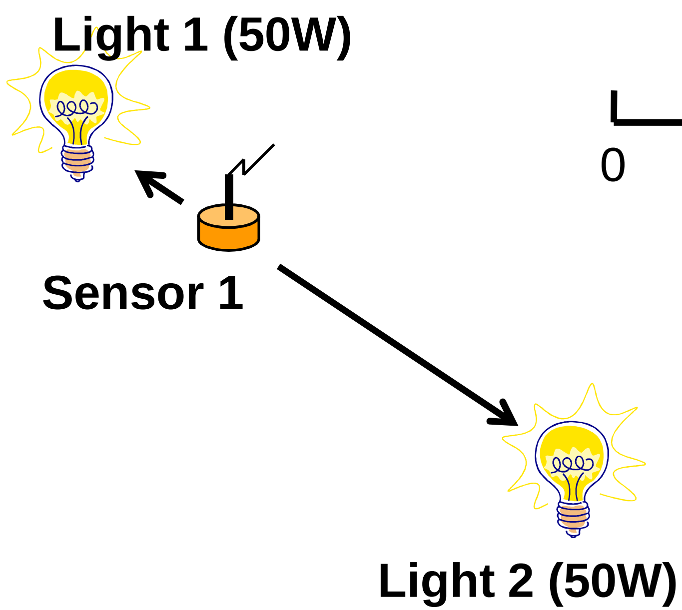

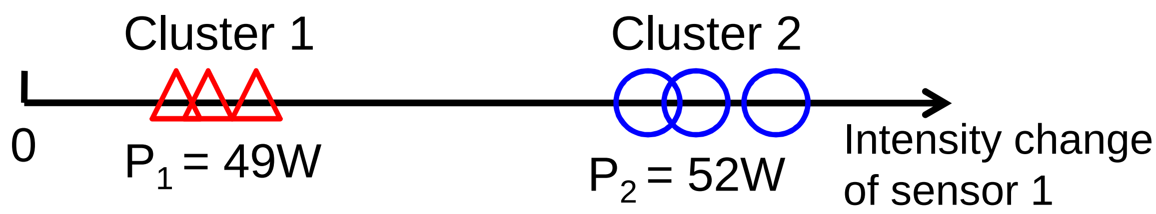

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Cluster-Light Association (cont'd)

- For given light decay model, find a binary matrix [$a_{m,j}$]

  $a_{m,j}$=1: cluster *m* is associated with light *j*

$$\min \quad E(\alpha,\beta) = \sum_{\forall m,\forall j} a_{m,j} \cdot e_{m,j}$$

$$\text{s.t.} \quad \sum_{\forall m} a_{m,j} = 1, \quad \sum_{\forall j} a_{m,j} = 1$$

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One-to-one mapping

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- Iterate *α* and *β* to further minimize *E*(*α*, *β*)
  – Adaptively calibrate environment-dependent *α* and *β*

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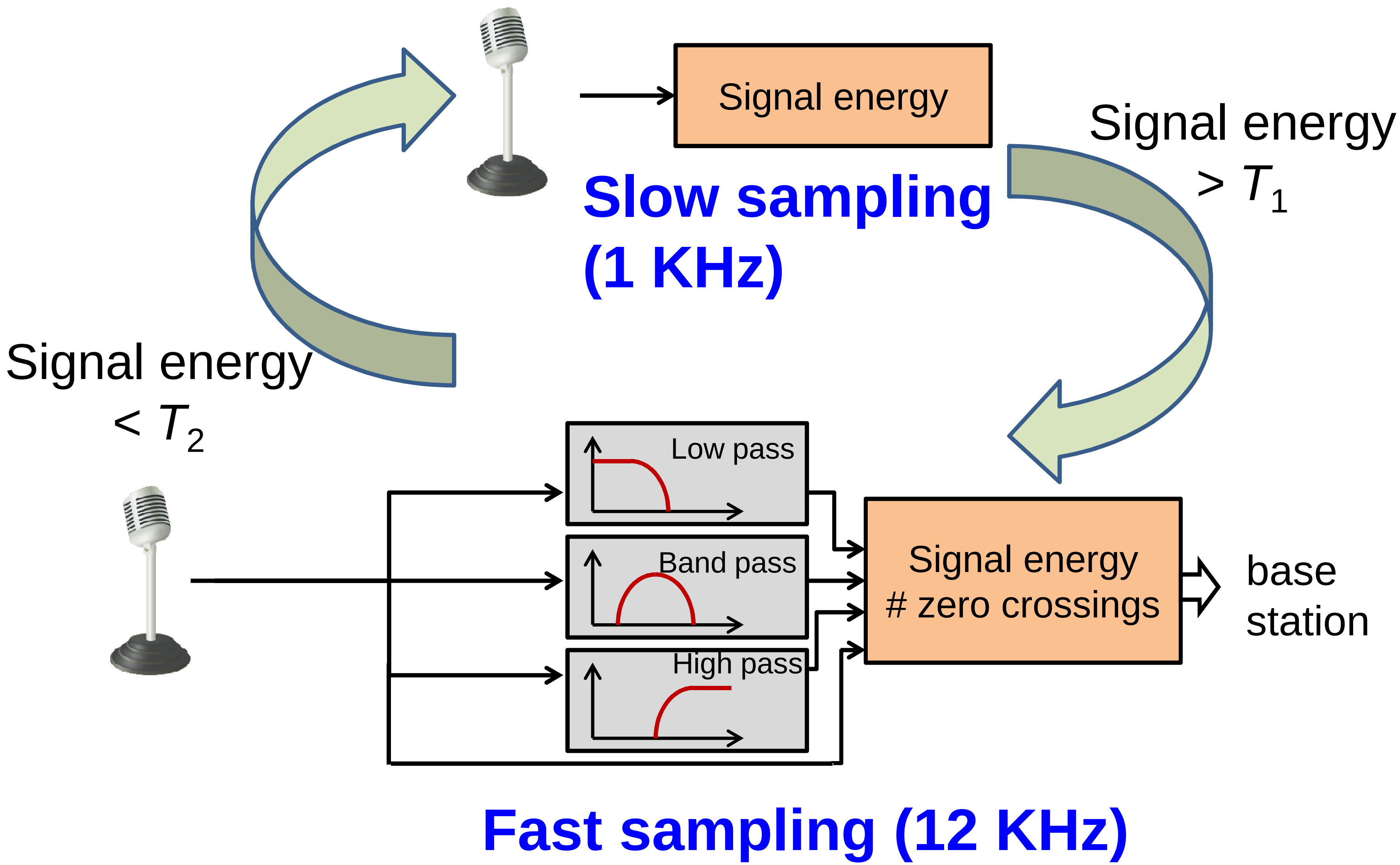
Adaptive Acoustic Sampling



Clustering-based Event Detection

- Multiple phases (fan, microwave)
  - Unknown and unpredictable
- *K*-means clustering
  - Automatically identify *K*

$$\max \frac{\text{between cluster scatter}}{\text{within cluster scatter}}$$

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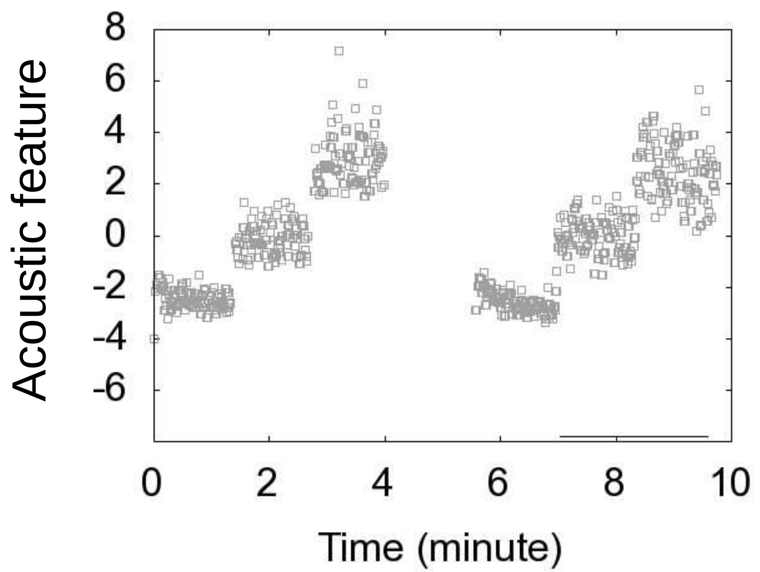
Detect the phase changes of 3-speed fan



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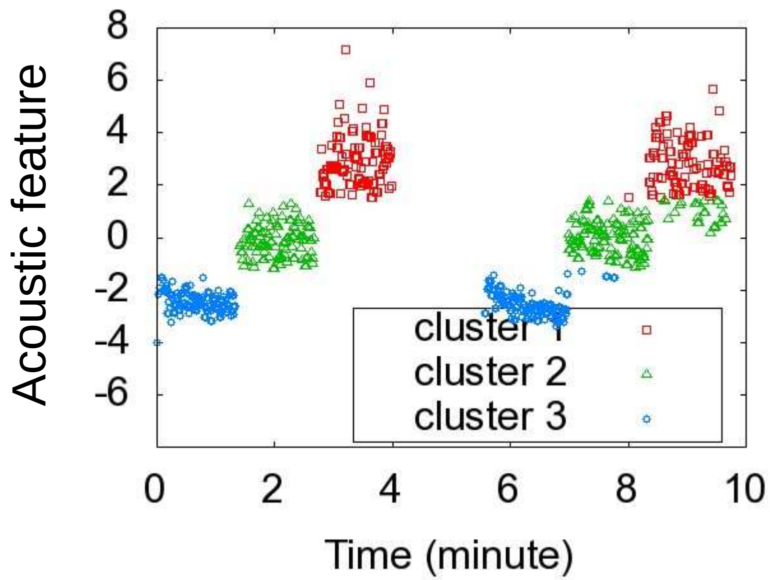

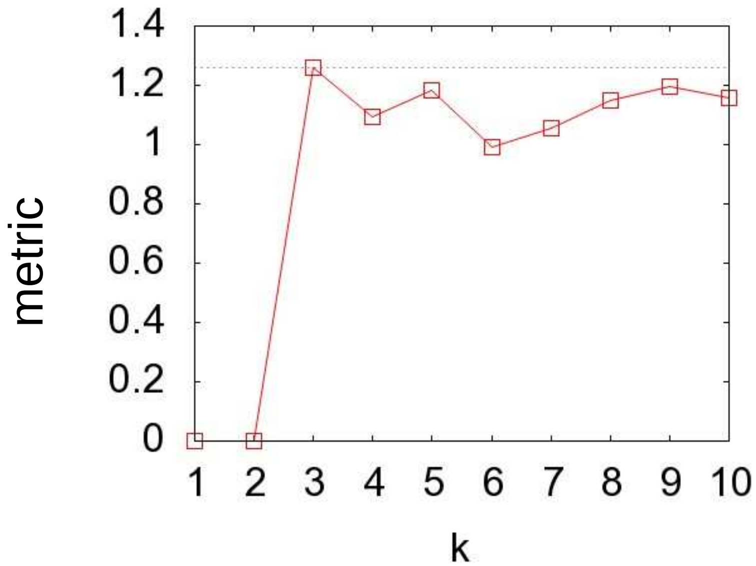

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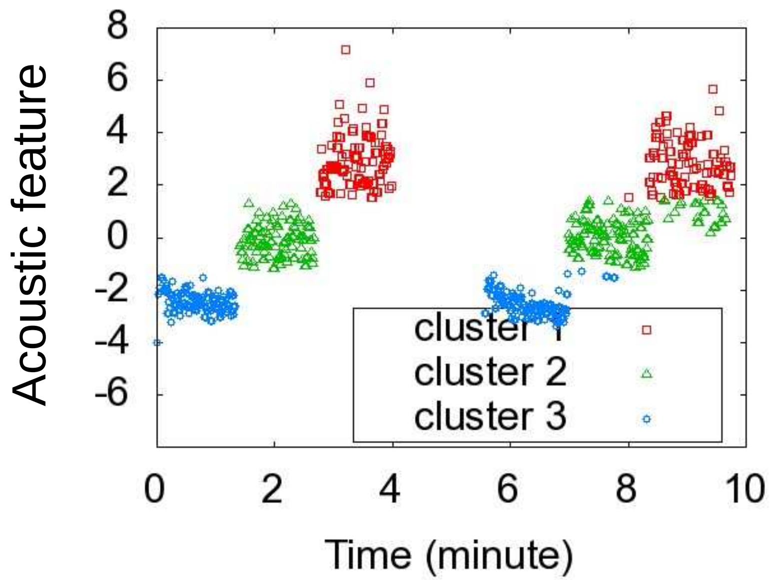

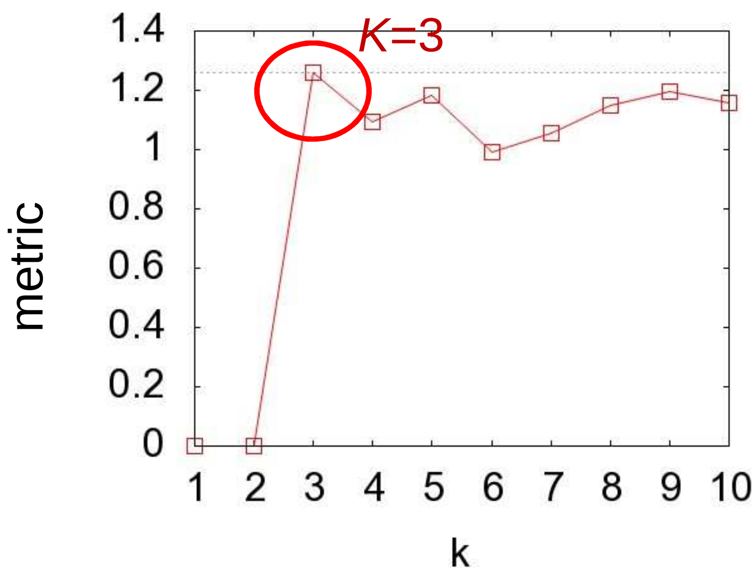

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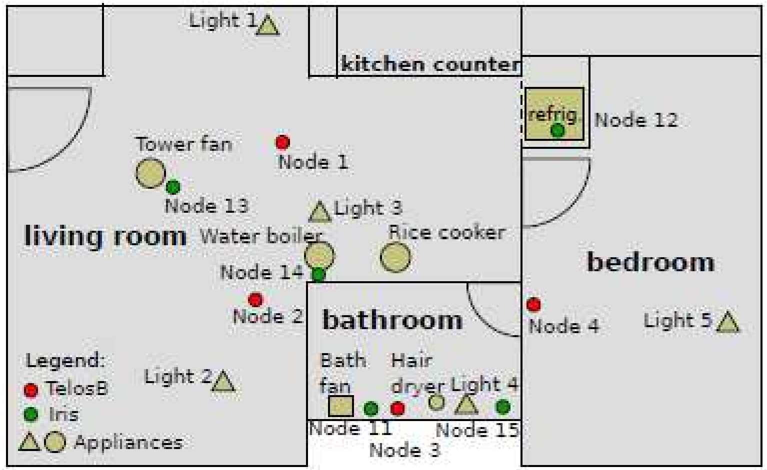
Implementation & Deployments

TelosB (light)
Iris (acoustic)

Kill-A-Watt



Apartment-1 deployment

- System
  - TelosB/Iris + TED5000 + KAW ground truth meters
- Five deployments
  - Three apartments (40~150 m^2), two houses
  - 9 ~ 22 sensors

Supero in Action

- Video demonstrating installation and setup

Evaluation

- 10 days experiment in Apartment-1
- Impact of sensor deployment in Apartment-2
- Compare with ViridiScope [UbiComp'09] (Regression on appliance states + power readings)
  - **Oracle:** ground truth appliance states
  - **Baseline:** closest appliance is source

10-day Results

Appliance	Supero		Oracle		Baseline	
	kWh	Error (%)	kWh	Error (%)	kWh	Error (%)
Light 1	4.17	0.5	4.11	0.9	4.11	0.9
Light 2	4.96	0.1	4.92	0.8	4.92	0.8
Light 3	6.24	1.4	6.25	1.7	6.25	1.7
Light 4	1.45	0.1	1.45	0.1	1.48	1.7
Light 5	0.39	0.2	0.39	0.7	0.41	5.5
Water boiler	0.48	0.5	0.48	0.5	0	100
Tower fan	0.21	50	0.17	17.9	0.24	66.2
Rice cooker	0.98	2.2	1.01	1.2	1.01	0.8
Hair dryer	0.07	19.2	0.09	0.4	0.02	73.2
Fridge	11.8	3.7	11.8	3.2	11.8	3.2
Bath fan	0.12	N/A	0.17	N/A	0	N/A
Router	2.03	4.3	3.04	43.3	3.04	43.3
Average error		7.5		6.5		27.0

- **Supero**
  - All 146 light events detected, no false alarm, no miss

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Rice cooker	0.98	2.2	1.01	1.2	1.01	0.8
Hair dryer	0.07	19.2	0.09	0.4	0.02	73.2
Fridge	11.8	3.7	11.8	3.2	11.8	3.2
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  - Comparable to **Oracle**

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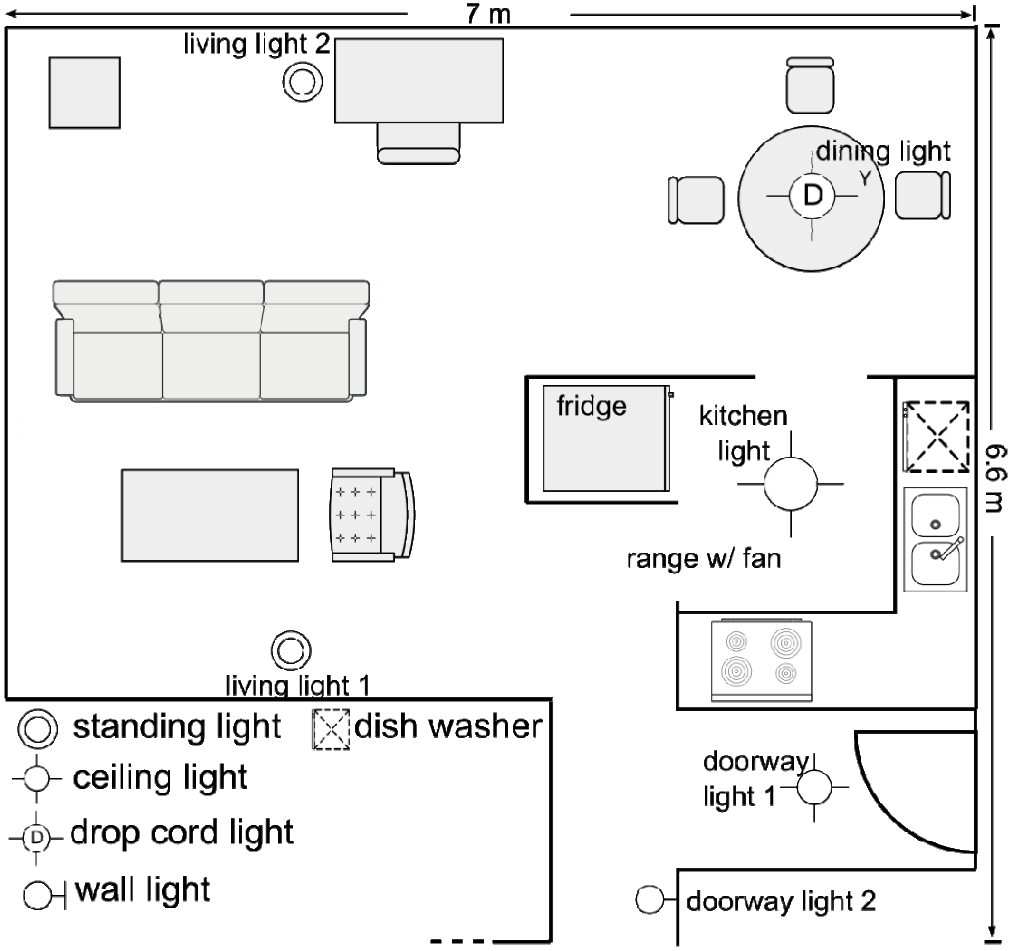
Light 5	0.39	0.2	0.39	0.7	0.41	5.5
Water boiler	0.48	0.5	0.48	0.5	0	100
Tower fan	0.21	50	0.17	17.9	0.24	66.2
Rice cooker	0.98	2.2	1.01	1.2	1.01	0.8
Hair dryer	0.07	19.2	0.09	0.4	0.02	73.2
Fridge	11.8	3.7	11.8	3.2	11.8	3.2
Bath fan	0.12	N/A	0.17	N/A	0	N/A
Router	2.03	4.3	3.04	43.3	3.04	43.3
Average error		7.5		6.5		27.0

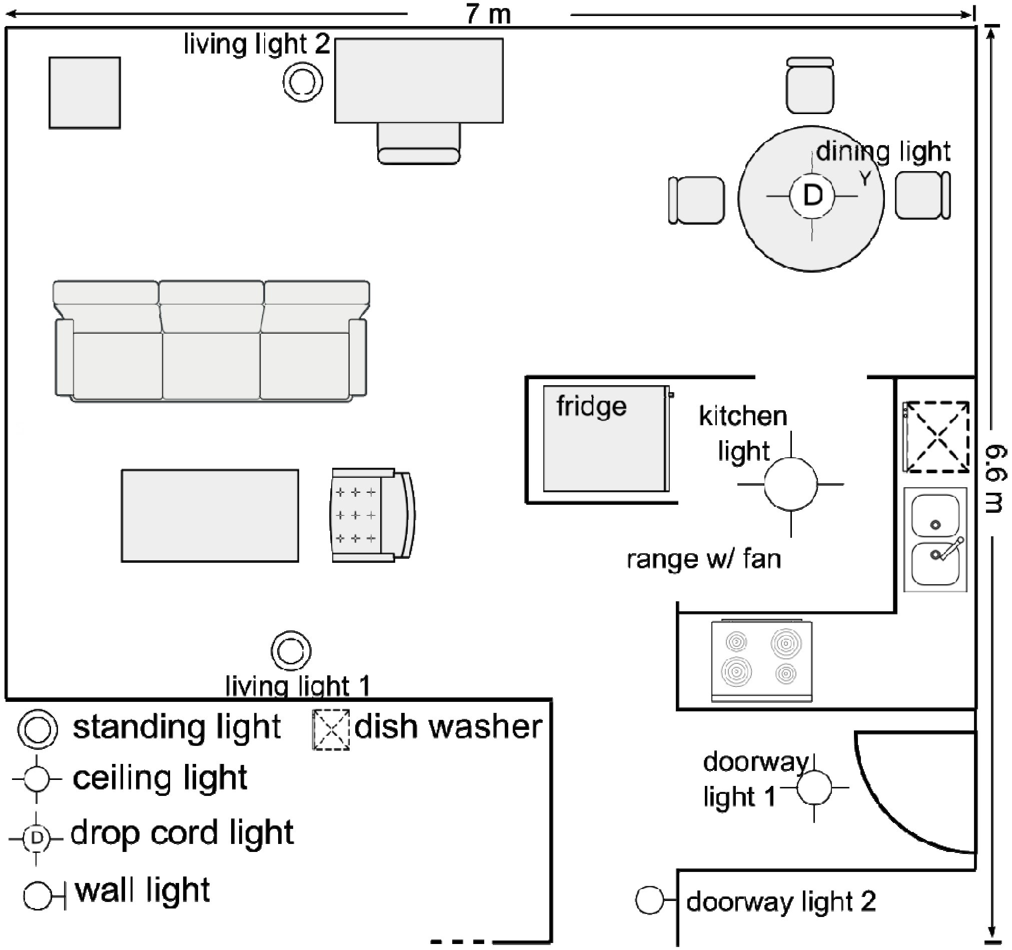
- **Supero**
  - All 146 light events detected, no false alarm, no miss
  - Comparable to **Oracle**
- **Baseline:** False alarms caused by hair dryer and bath fan

Impact of Sensor Placement



6 lights, exhaust fan, waste disposer
dish washer, vacuum cleaner
6 TelosB, 11 Iris

Impact of Sensor Placement



Light sensing

Deployment	Sensor #	result
Red	6	✓
Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	×

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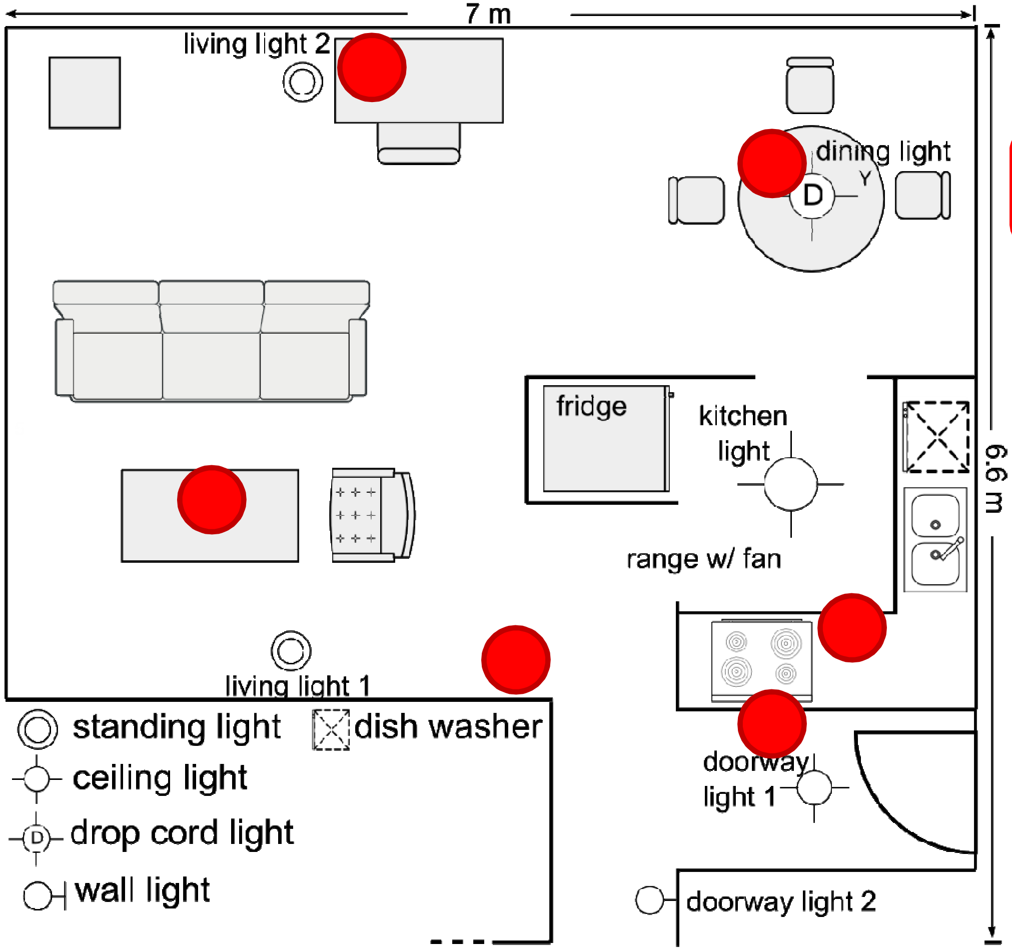
Impact of Sensor Placement



Light sensing

Deployment	Sensor #	result
Red	6	✓
Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	×

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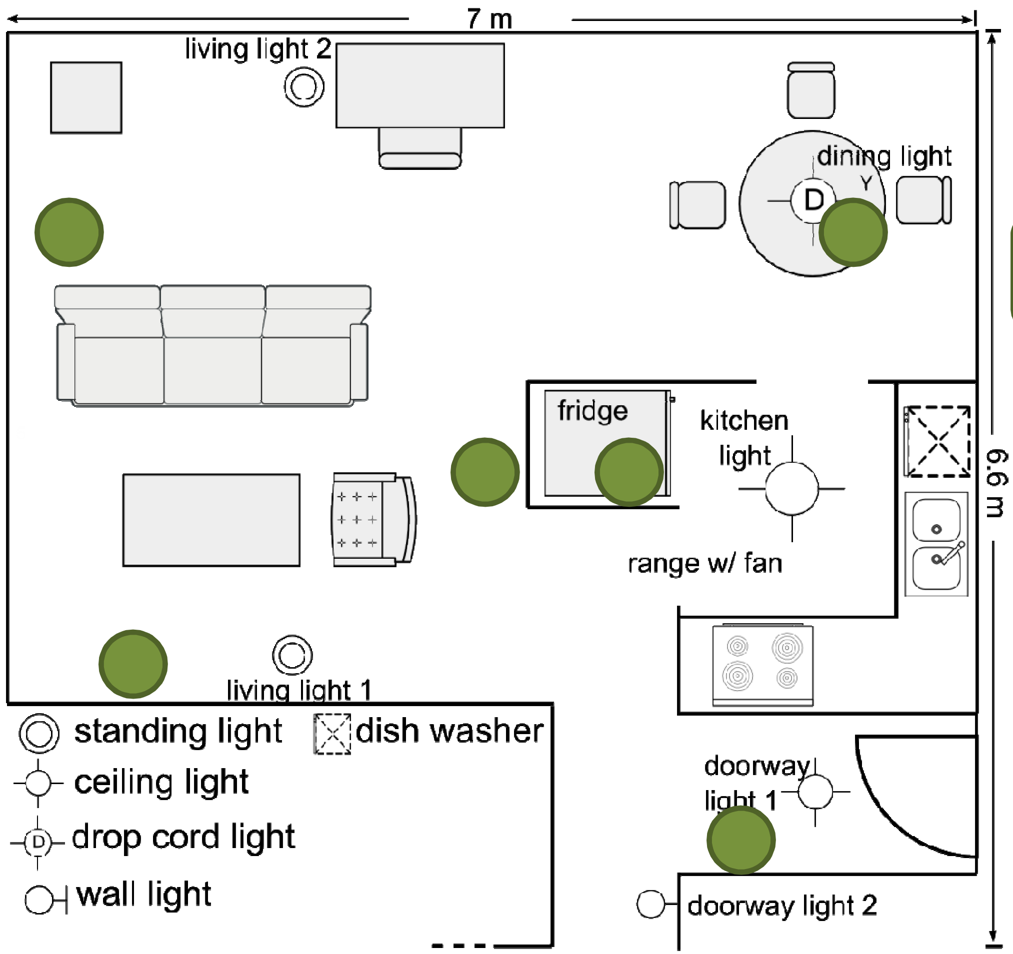
Impact of Sensor Placement



Light sensing

Deployment	Sensor #	result
Red	6	✓
Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	×

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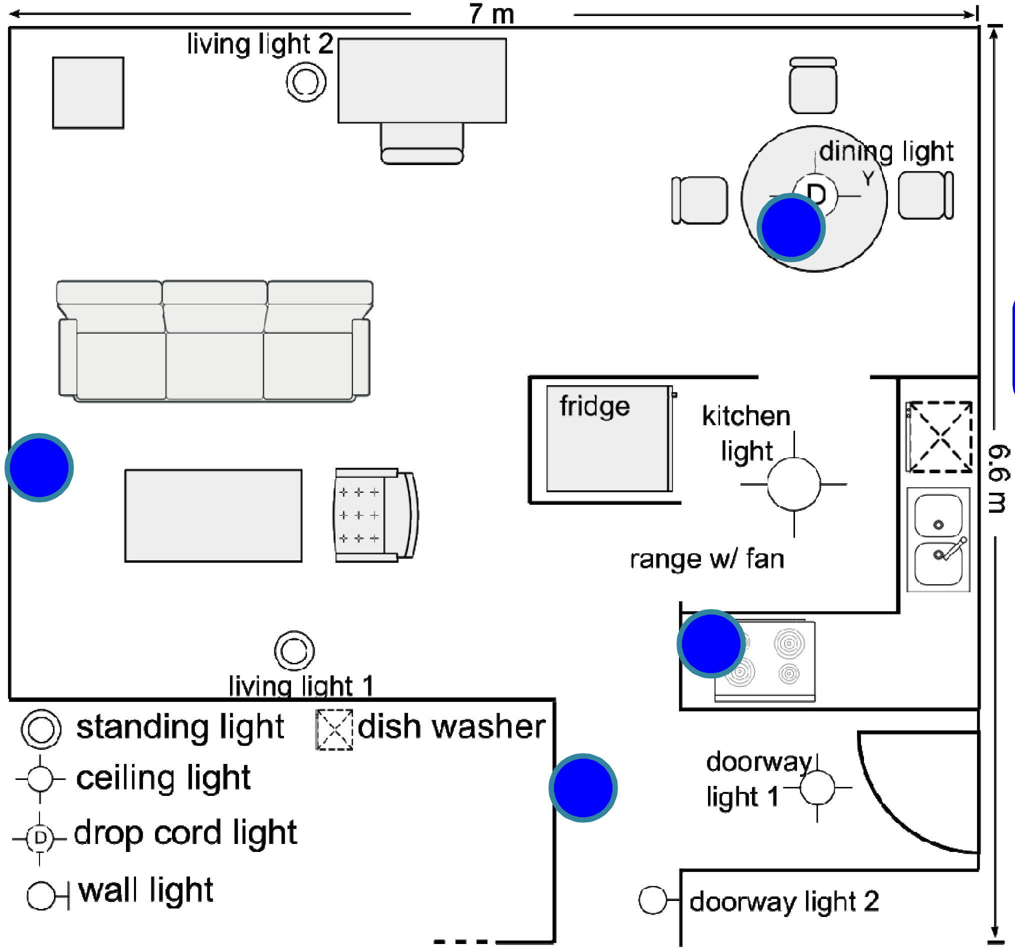
Impact of Sensor Placement



Light sensing

Deployment	Sensor #	result
Red	6	✓
Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	✗

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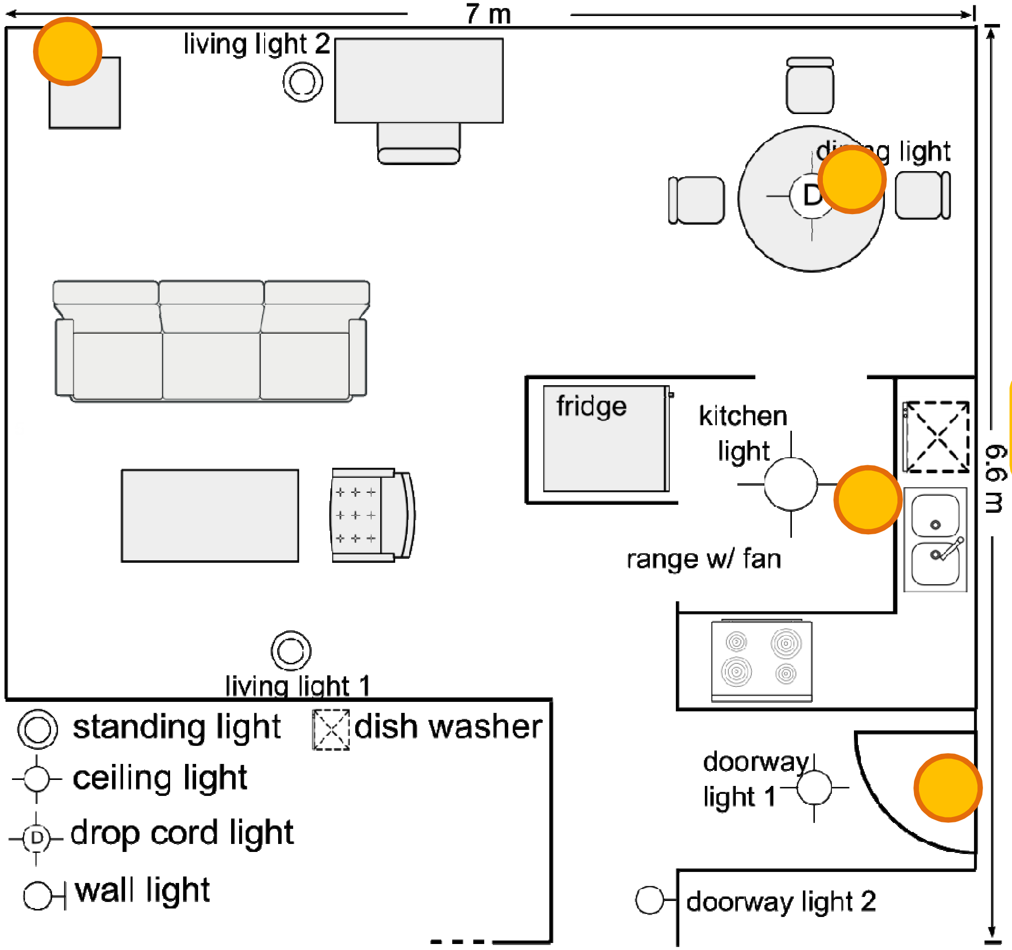
Impact of Sensor Placement



Light sensing

Deployment	Sensor #	result
Red	6	✓
Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	✗

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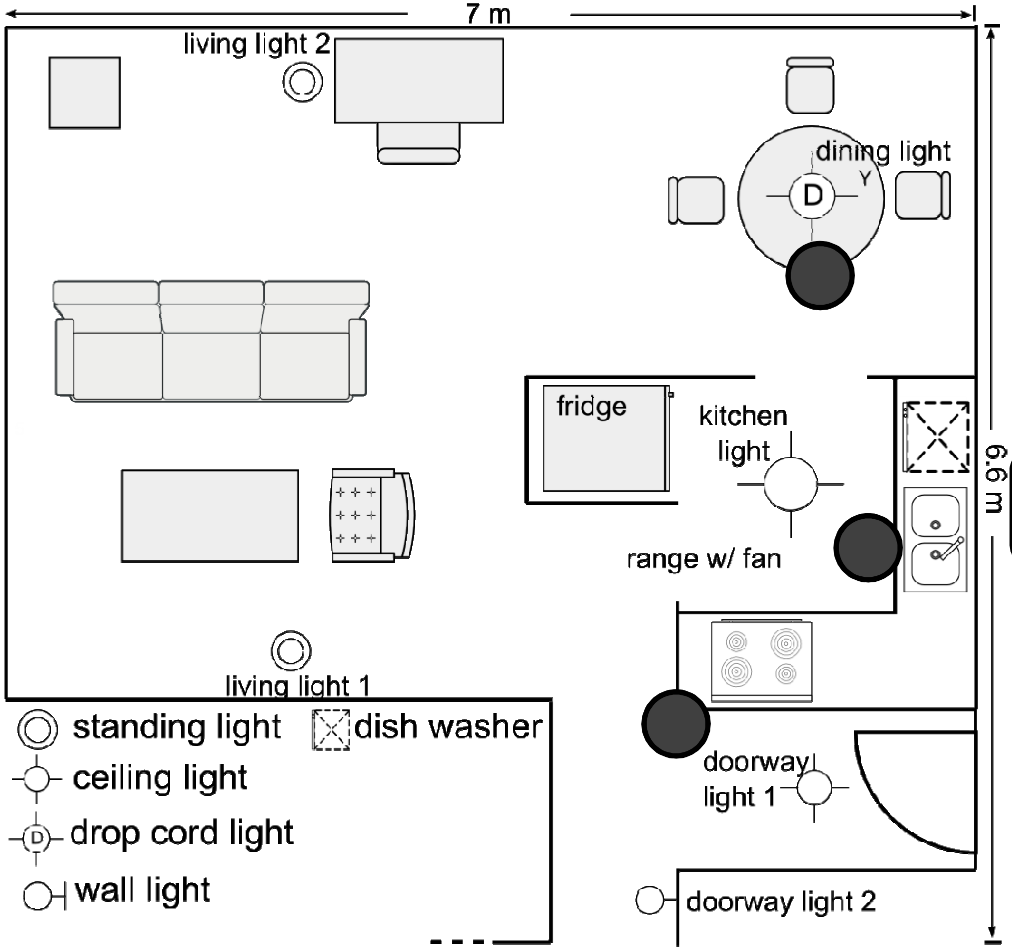
Impact of Sensor Placement



Light sensing

Deployment	Sensor #	result
Red	6	✓
Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	×

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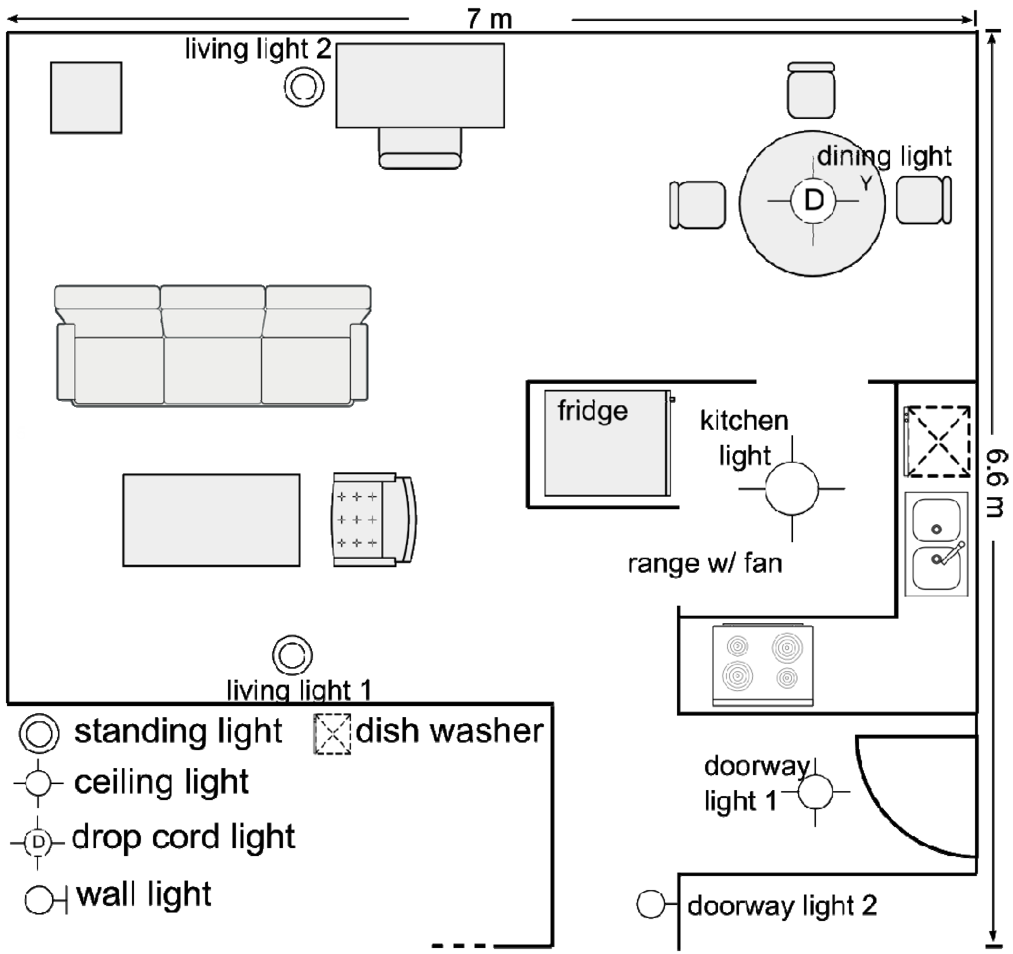
Impact of Sensor Placement



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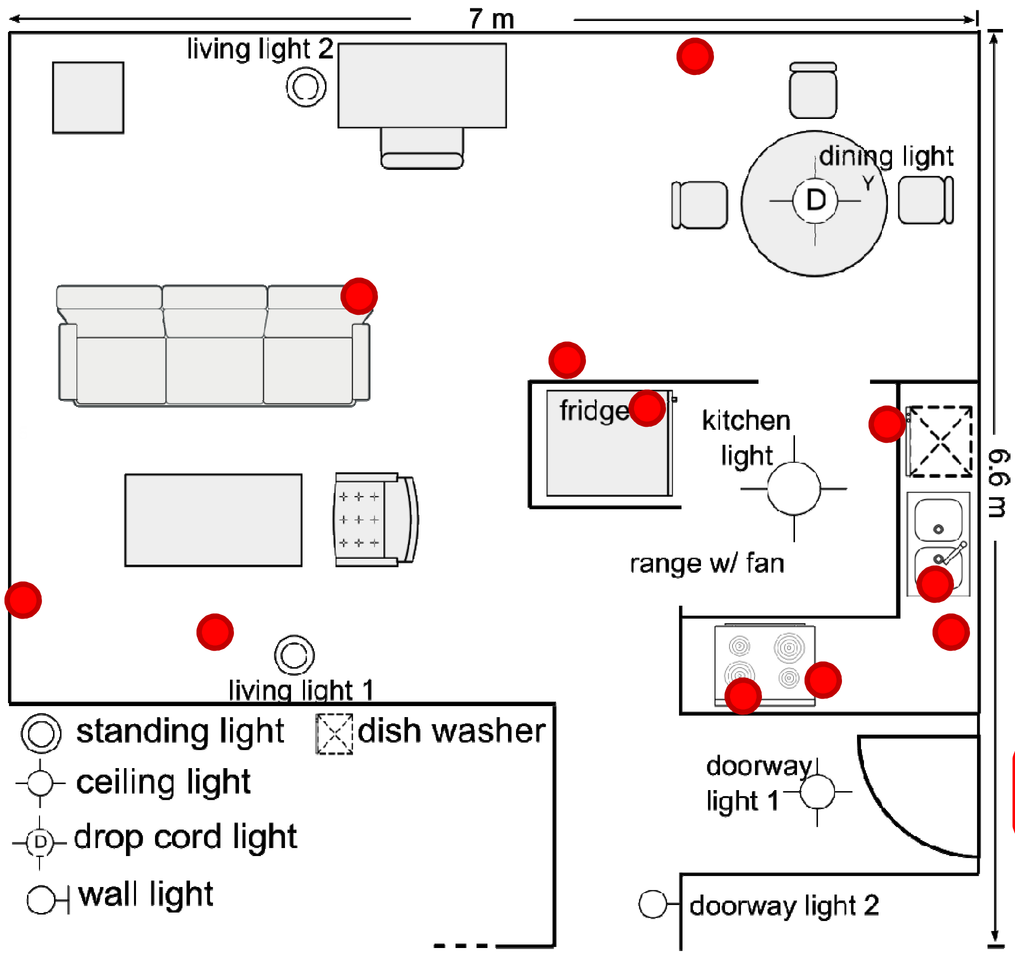
Light sensing

Deployment	Sensor #	result
Red	6	✓
Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	×

Acoustic sensing

Deployment	Sensor #	result
Red	11	✓
Green	7	✓
Blue	4	✓
Black	2	×

Impact of Sensor Placement



6 lights, exhaust fan, waste disposer dish washer, vacuum cleaner
6 TelosB, 11 Iris

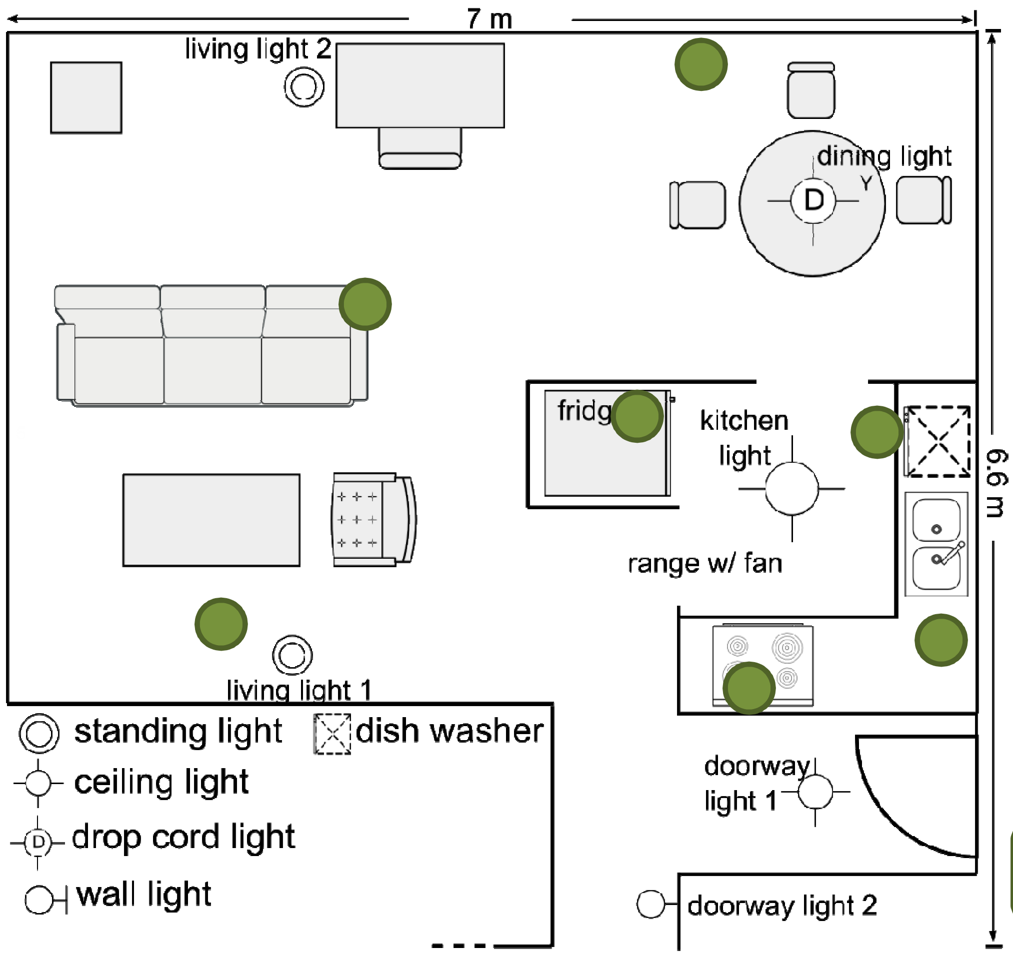
Light sensing

Deployment	Sensor #	result
Red	6	✓
Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	✗

Acoustic sensing

Deployment	Sensor #	result
Red	11	✓
Green	7	✓
Blue	4	✓
Black	2	✗

Impact of Sensor Placement



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Light sensing

Deployment	Sensor #	result
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Green	6	✓
Blue	4	✓
Yellow	4	✓
Black	3	✗

Acoustic sensing

Deployment	Sensor #	result
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Green	7	✓
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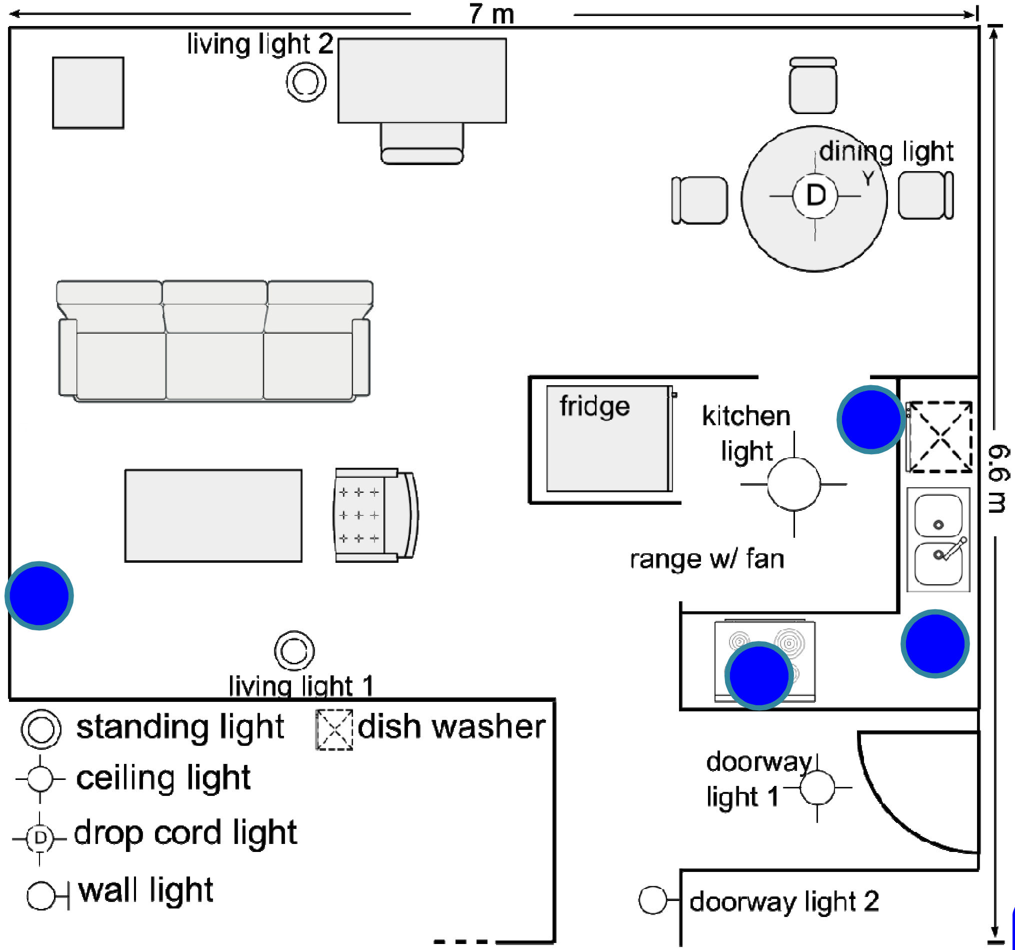
Black	2	✗

Impact of Sensor Placement



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Acoustic sensing

Deployment	Sensor #	result
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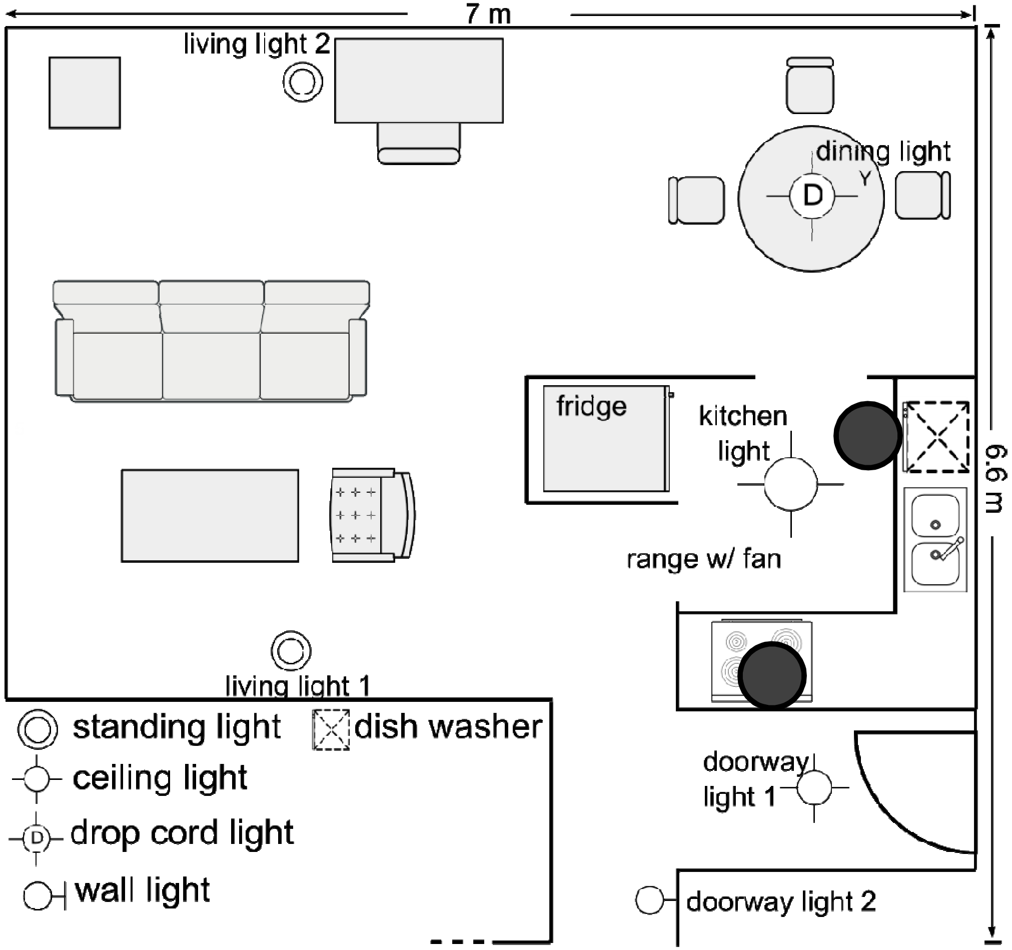
Impact of Sensor Placement



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Light sensing

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Black	3	✗

Acoustic sensing

Deployment	Sensor #	result
Red	11	✓
Green	7	✓
Blue	4	✓
Black	2	✗

Conclusion

- Supero
  - Multi-sensor fusion
  - Unsupervised event clustering
  - Autonomous appliance association
- Easy to install
  - Considerable flexibility in sensor placement
- Real Implementation/Evaluation
  - 5 environments (3 apartments, 2 houses)
  - Accurate, 7.5% average error

Q & A