Towards a Low-Cost, Non-Invasive System for Occupancy Detection using a Thermal Detector Array

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Introduction

Background

- Aging population [ABS2012, CCE09]
  – Need to lower human burden
- Rising energy prices [Swo15]
  – Affects both businesses and the elderly
- Internet of Things
  – Cheaper embedded systems
  – Better sensors
  – Occupancy detection

Occupancy Detection

- Detecting people
- Good for home/office automation
- Occupancy detection can save up to 25% on these costs [BEC13]
- Climate control accounts for
  - up to 40% of household energy usage [ABS11]
  - 43% of office building usage [CAG12]

An ideal system would be…

- Low-Cost
  - – Prototype stage < $300
- Non-Invasive
  - – Minimal information gathered by system
- Reliable
  - – >75% occupancy detection accuracy
- Energy Efficient
  - – Prototype can last at least a week

Can we create this system?

Necessary steps

1. Design Choices
2. Prototype Design
   a) Hardware
   b) Software
3. Criteria Evaluation
4. Did we meet our goals?

Design Choices

How do we evaluate sensors?

- We want to
  - See individual people
- We don’t want to
  - Know who they are
  - Know what they’re doing

Thermal Sensors

- Cost is coming down fast
- Exciting new area for research
- Interesting applications
- “ThermoSense” [BEC13]
  - Can see human “blobs” in thermal data
  - Very low resolution (8x8 pixels)
  - 0.346 Root Mean Squared Error

Research Gap

- Sensor space is changing fast
- Contribution of system elements
- Does their approach translate
- ThermoSense sensor not in Australia

Prototype Design

HW Architecture – Current

- Direct data collection

Sensing

- Raw data to processed data

Pre-Processing

- Processed data to insights

Analysis

HW Architecture – Current

Melexis MLX90620
- Collects thermal data
- Narrower FOV (16°x60° vs 60°x60°)
- Rectangular (16x4 vs 8x8)
- Communicates bi-directionally

Sensing | **Pre-Processing** | **Analysis**

HW Architecture – Current

Passive Infrared Sensor (PIR)

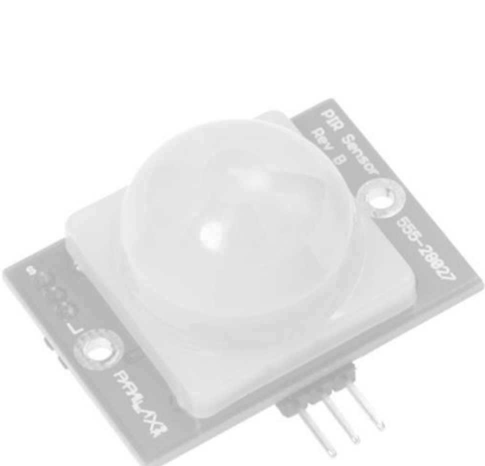
- Collections motion data
- Provides rising signal on motion

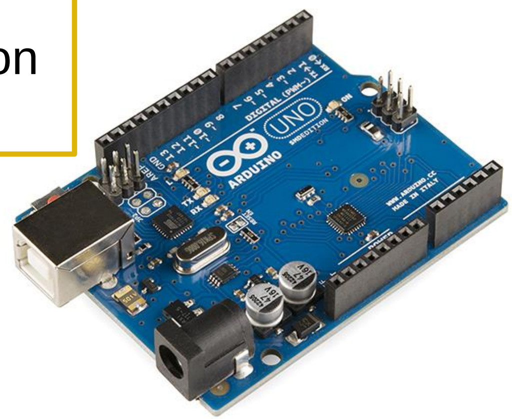
Sensing | **Pre-Processing** | **Analysis**

HW Architecture – Current

Arduino Uno R3

- Embedded controller with broad library support
- Converts raw sensing data into degrees Celsius / motion each frame



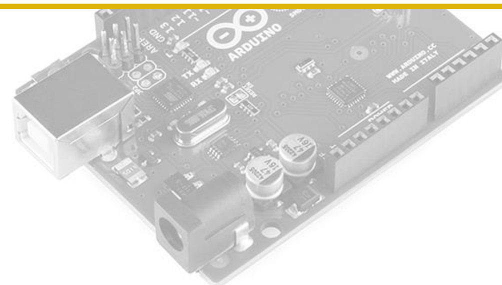


Sensing | **Pre-Processing** | **Analysis**

HW Architecture – Current

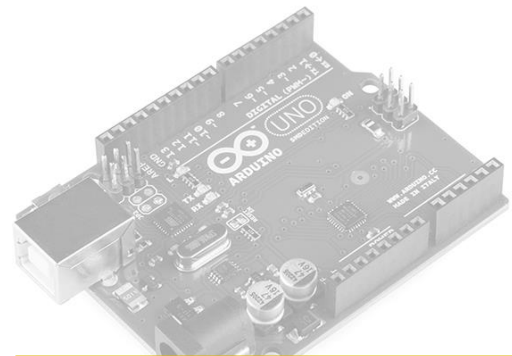
Raspberry Pi B+

- Cheap and powerful Linux platform
- Performs advanced analysis on processed data
- Generates occupancy predictions



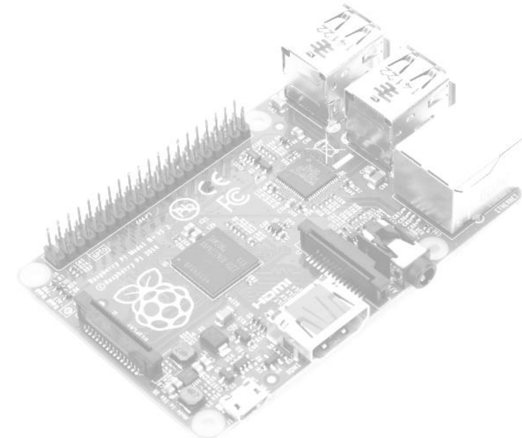
Sensing **Pre-Processing** **Analysis**

HW Architecture – Current



RPi Camera

- 1080p resolution
- Ground truth collection in prototype stage



Sensing | **Pre-Processing** | **Analysis**

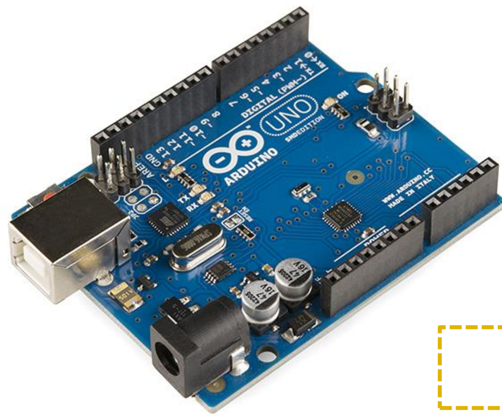
HW Architecture – Current

MLX90620 (MLX)

Passive Infrared Sensor (PIR)

Wired

Wired



Arduino Uno R3

Wired

Raspberry Pi B+

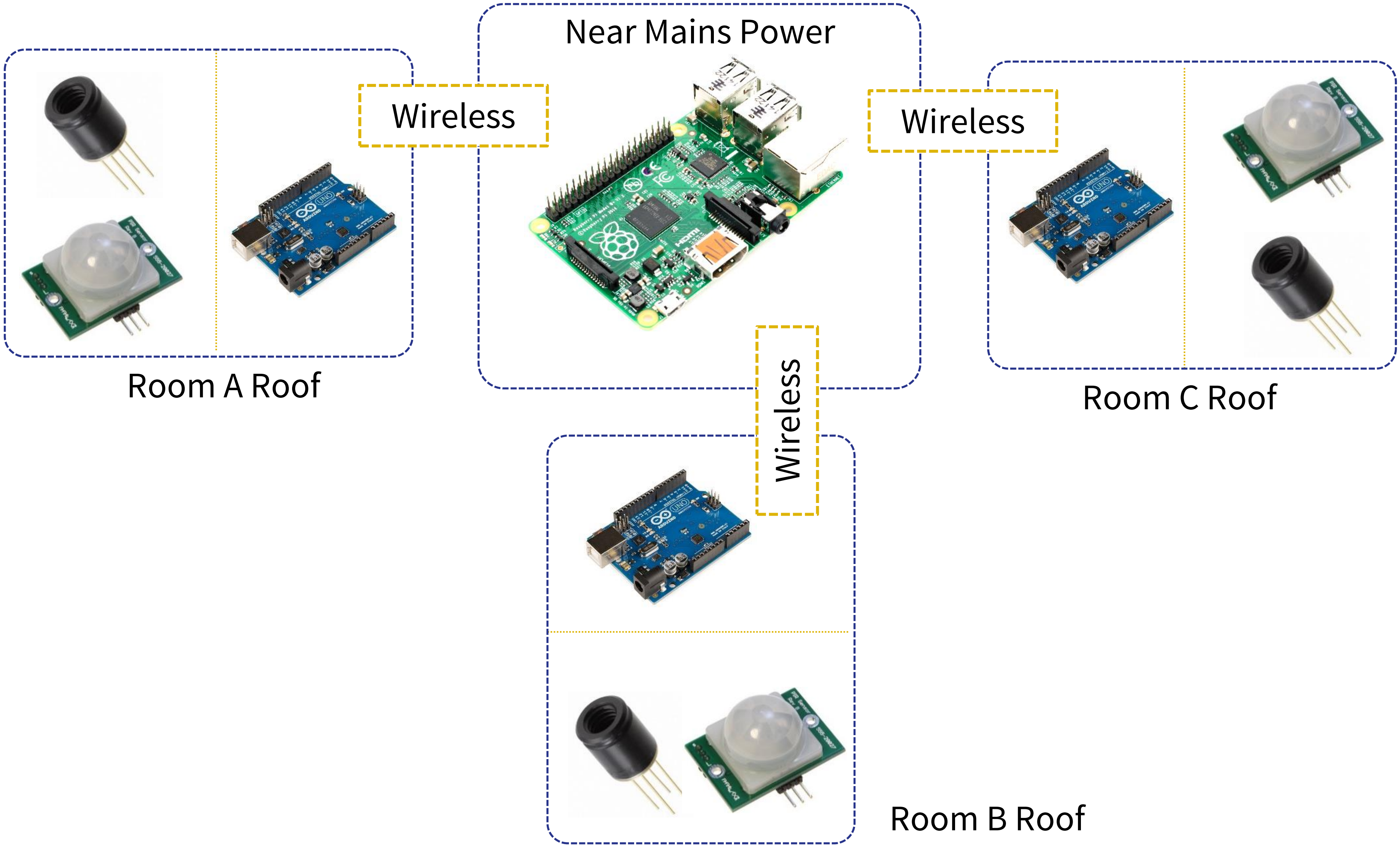
RPi Camera (ground truth)

Sensing

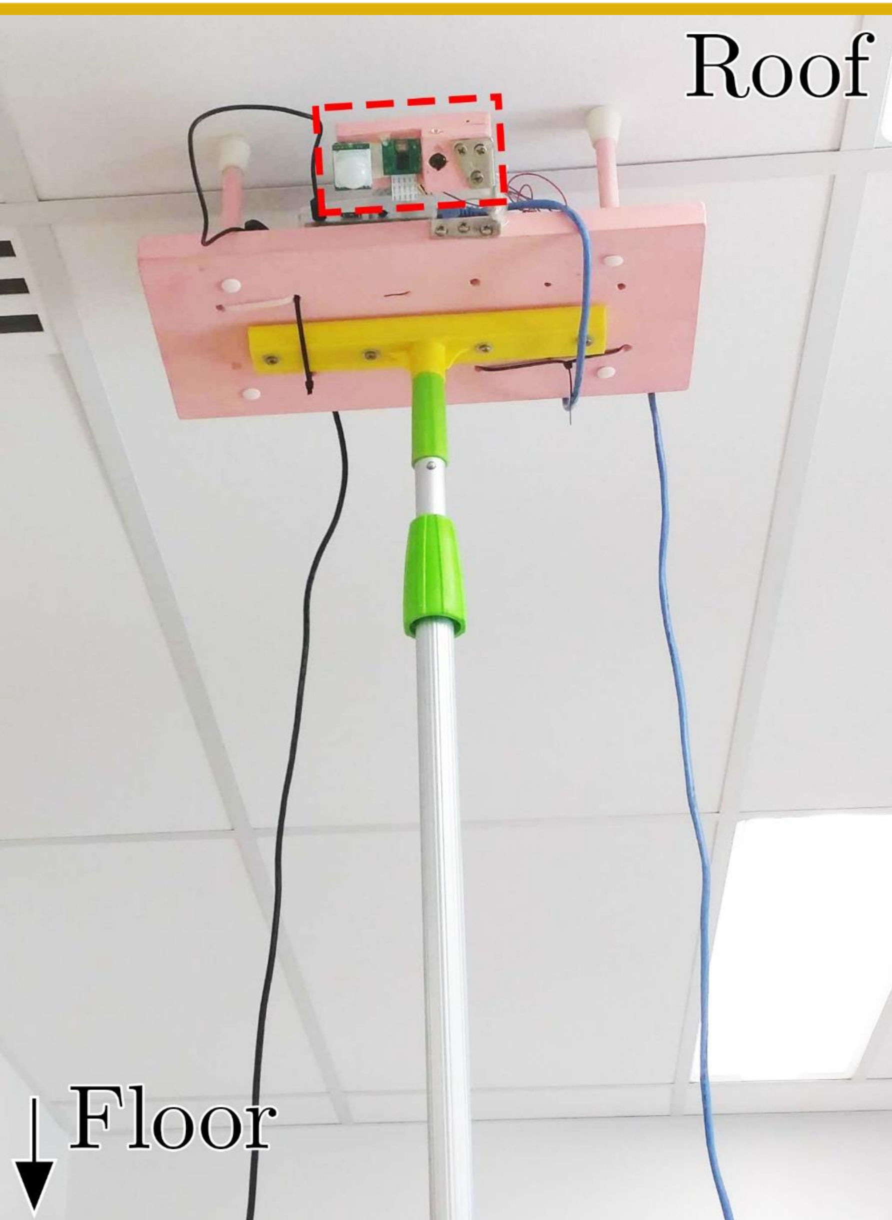
Pre-Processing

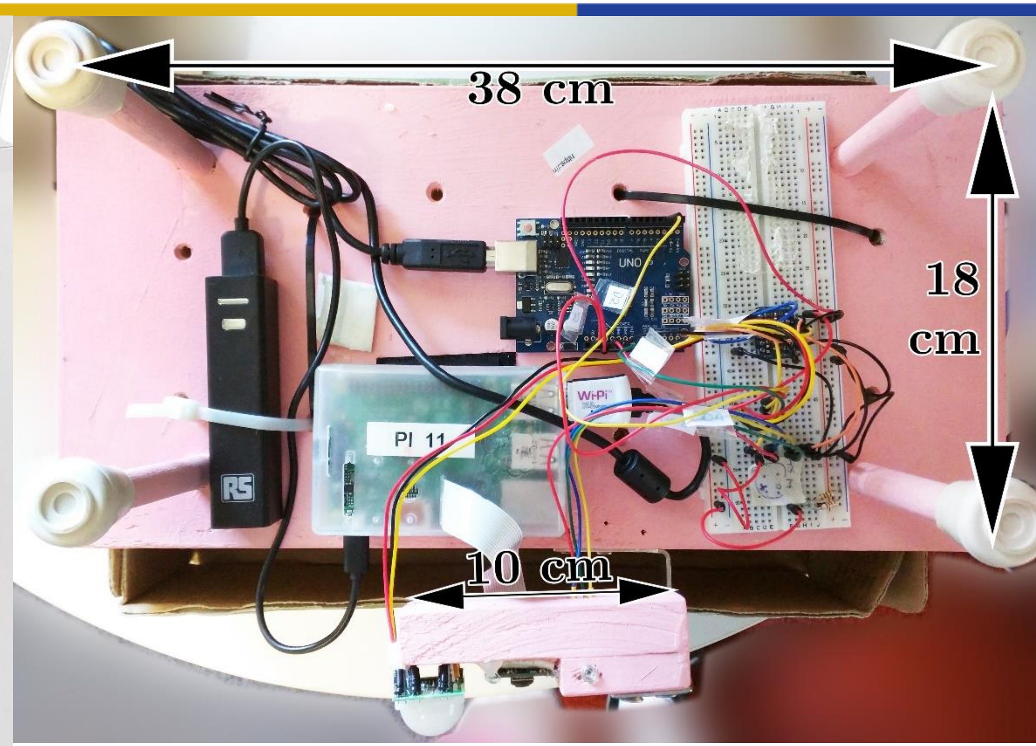
Analysis

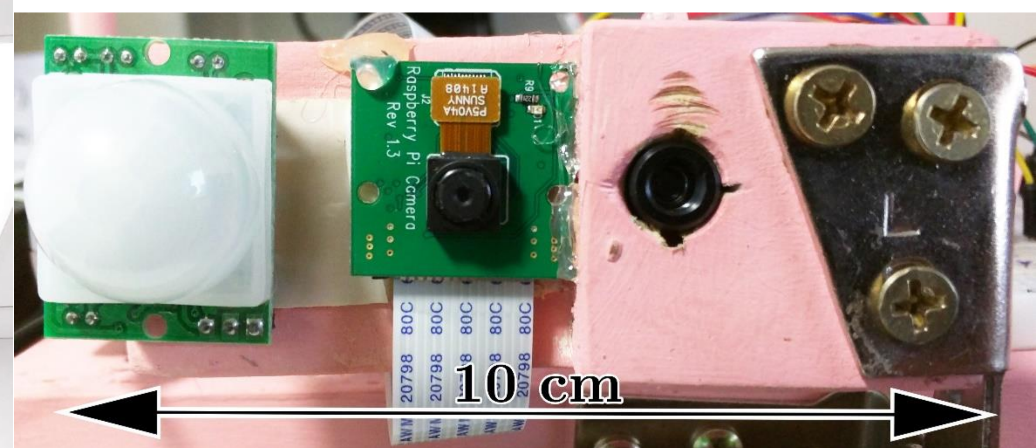
HW Architecture – Ideal M:1



Physical Prototype







Software

- 1,600 SLOC
  - Approx. 500 lines on Arduino (C++)
  - Remaining 1,000 on Raspberry Pi (Python)
- Code allows capture, visualization and analysis of thermal images

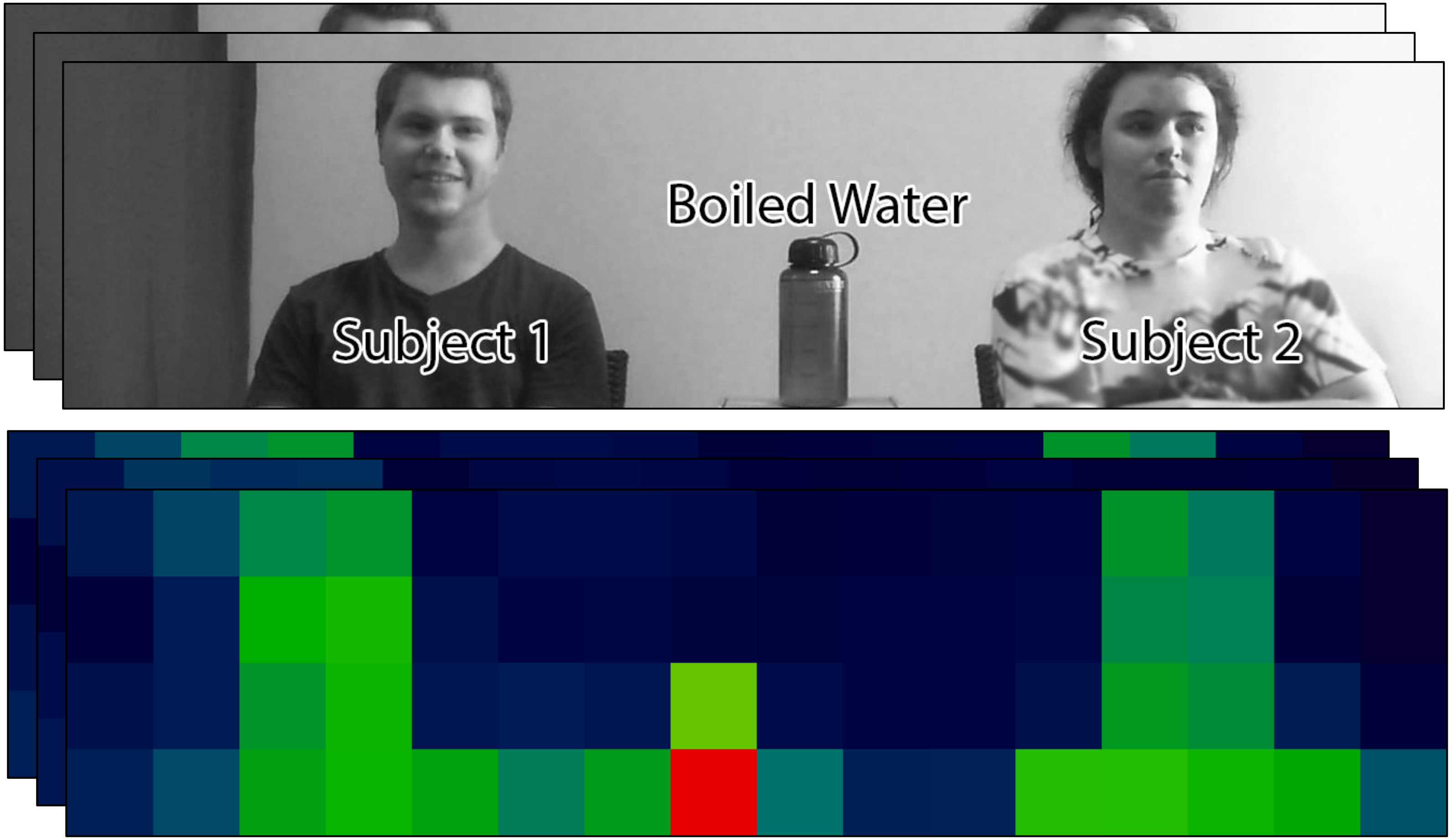
Technique

Technique

- Overview
  1. Motion detection
  2. Image subtraction
  3. Machine learning
     - Distilling good examples (feature extraction)
     - Providing examples with correct answer (training)
     - Get out a model that can predict attributes

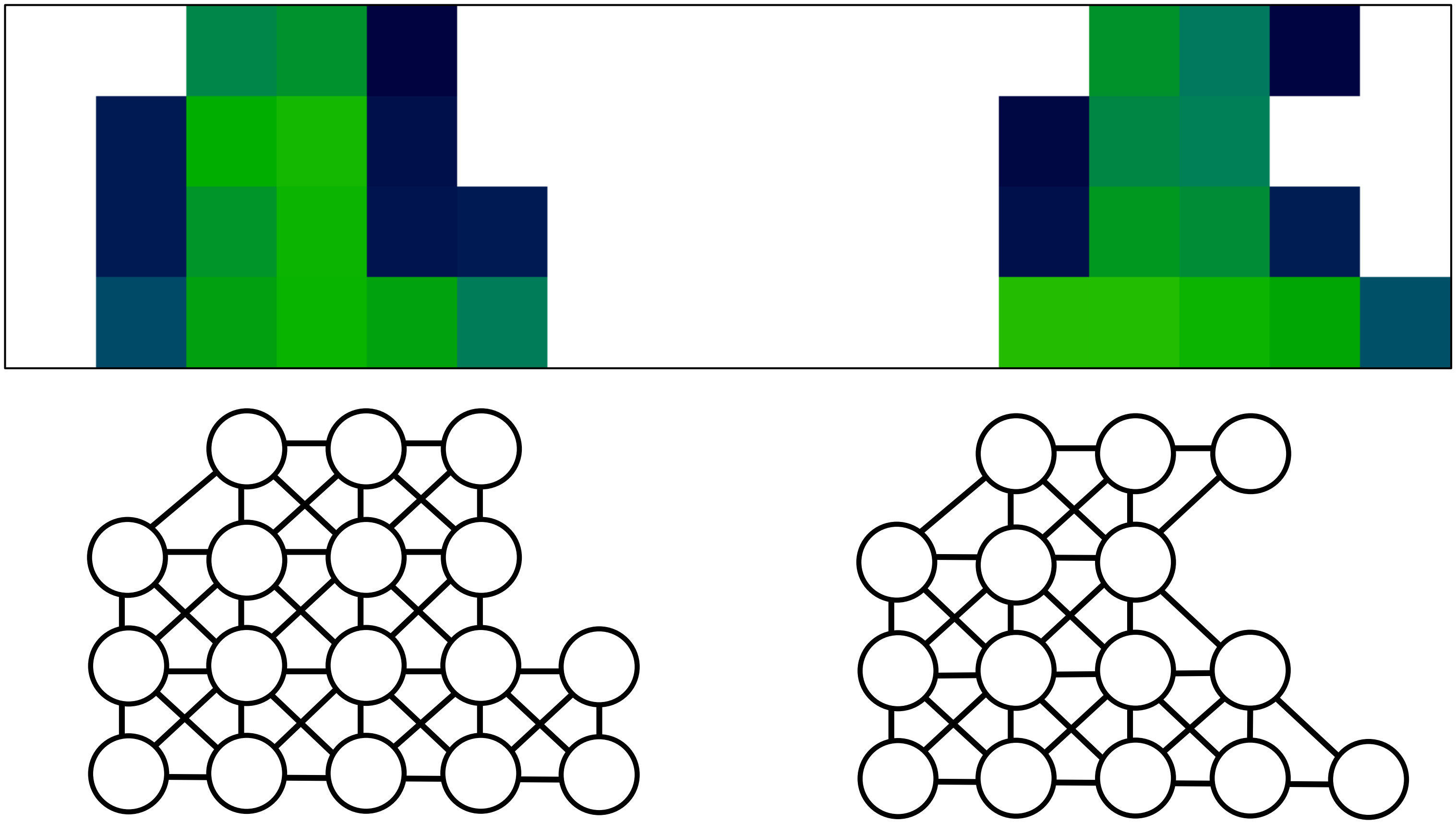
Technique

1. Capture thermal image sequence



Technique

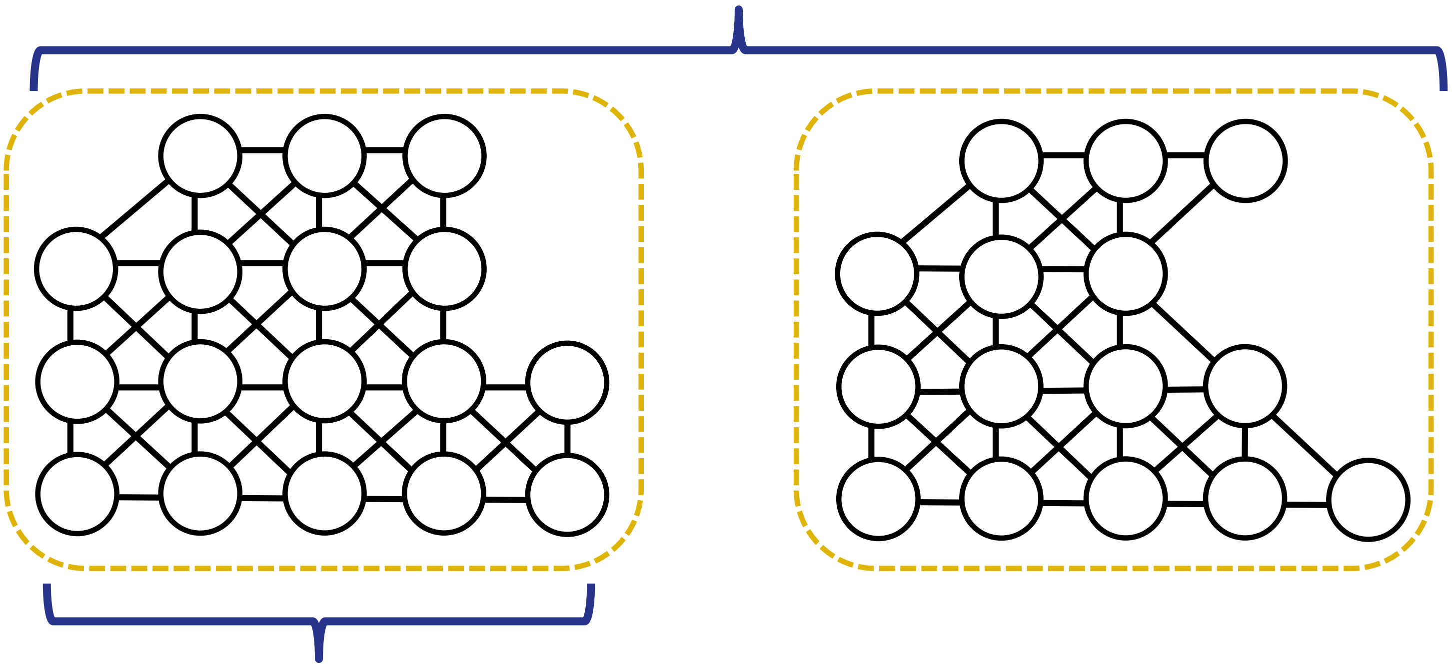
2. Generate graph from “active” pixels, which deviate significantly from mean



Technique

3. Extract features from graph for classification purposes

Number of connected components = **2**



Size of largest connected component = **17**

Number of total active pixels = **32**

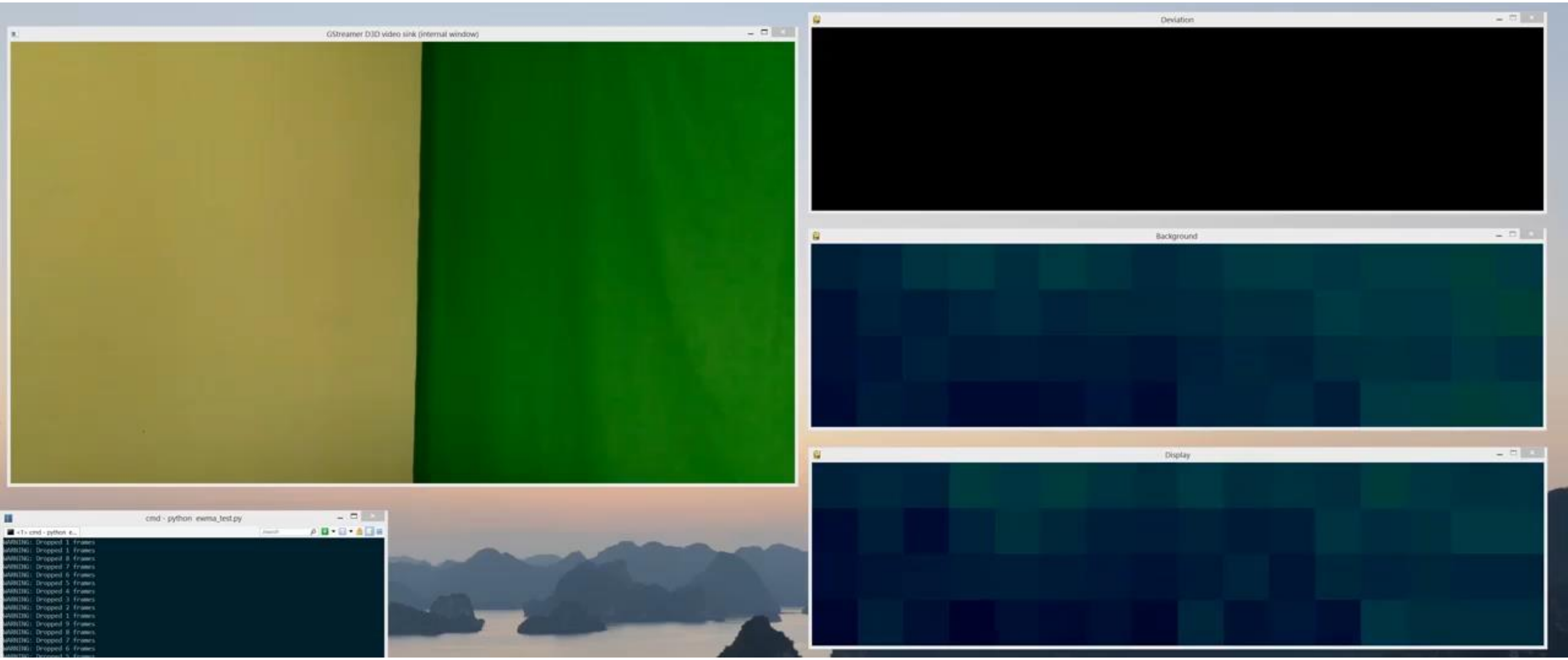
Technique

4. Perform machine learning

    1. Train on examples with true value (features and ground truth)

    2. Make predictions with your generated model

Video Demonstration



Evaluation

Non-Invasiveness

- Fulfilled through sensor choice
- Low resolution masks person and action identification

Cost

- Prototype < $300 target
- On par with ThermoSense cost

Part	Cost
MLX90620	$80
Raspberry Pi B+	$50
Arduino Uno R3	$40
Passive Infrared Sensor	$10
I^2C level shifter	$5
TOTAL	**$185**

(a) Our project

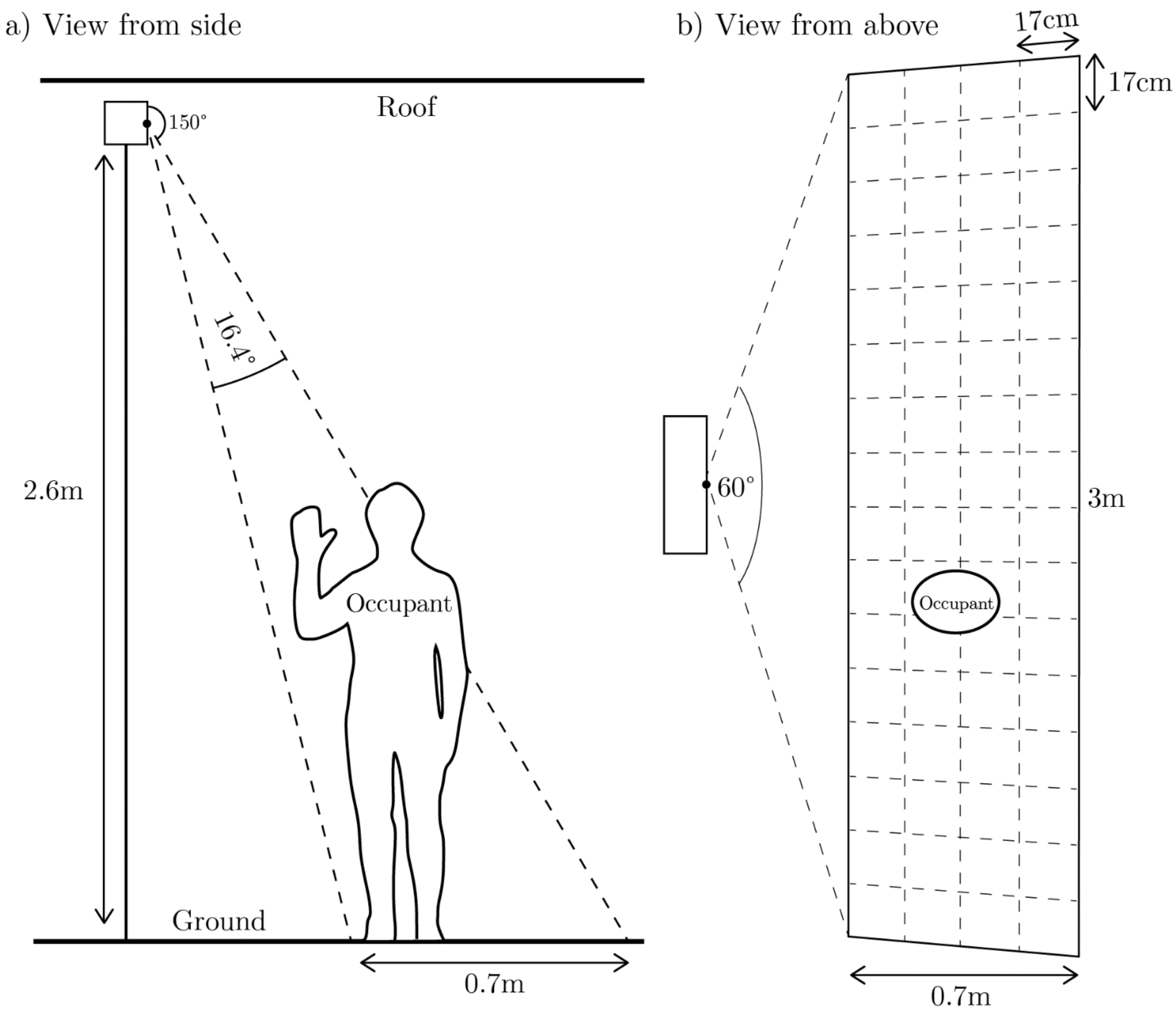
Part	Cost
TMote Sky	$110
Grid-EYE	$50
Passive Infrared Sensor	$10
TOTAL	**$170**

(b) ThermoSense (estimated)

Cost comparison

Experimental Setup

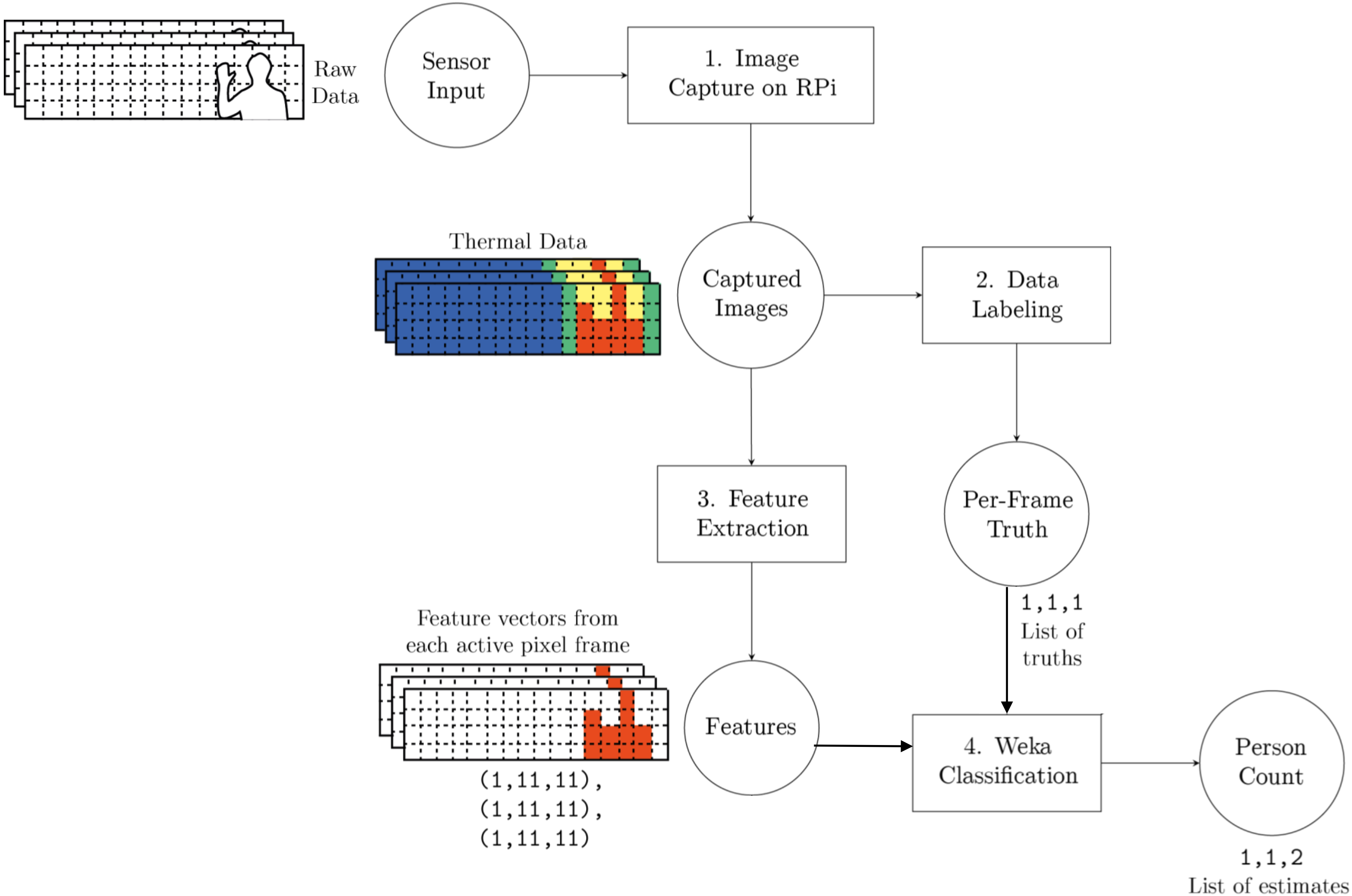
- Testing reliability and energy efficiency



Reliability – Aim

- Replicating ThermoSense's classification algorithms:
  - K Nearest Neighbours (numeric / nominal)
  - Linear Regression (numeric)
  - Multi-Layer Perceptron (numeric)
- Trying our own
  - Multi-Layer Perceptron (nominal)
  - K*
  - C4.5
  - Support Vector Machine
  - Naïve Bayes
  - 0-R

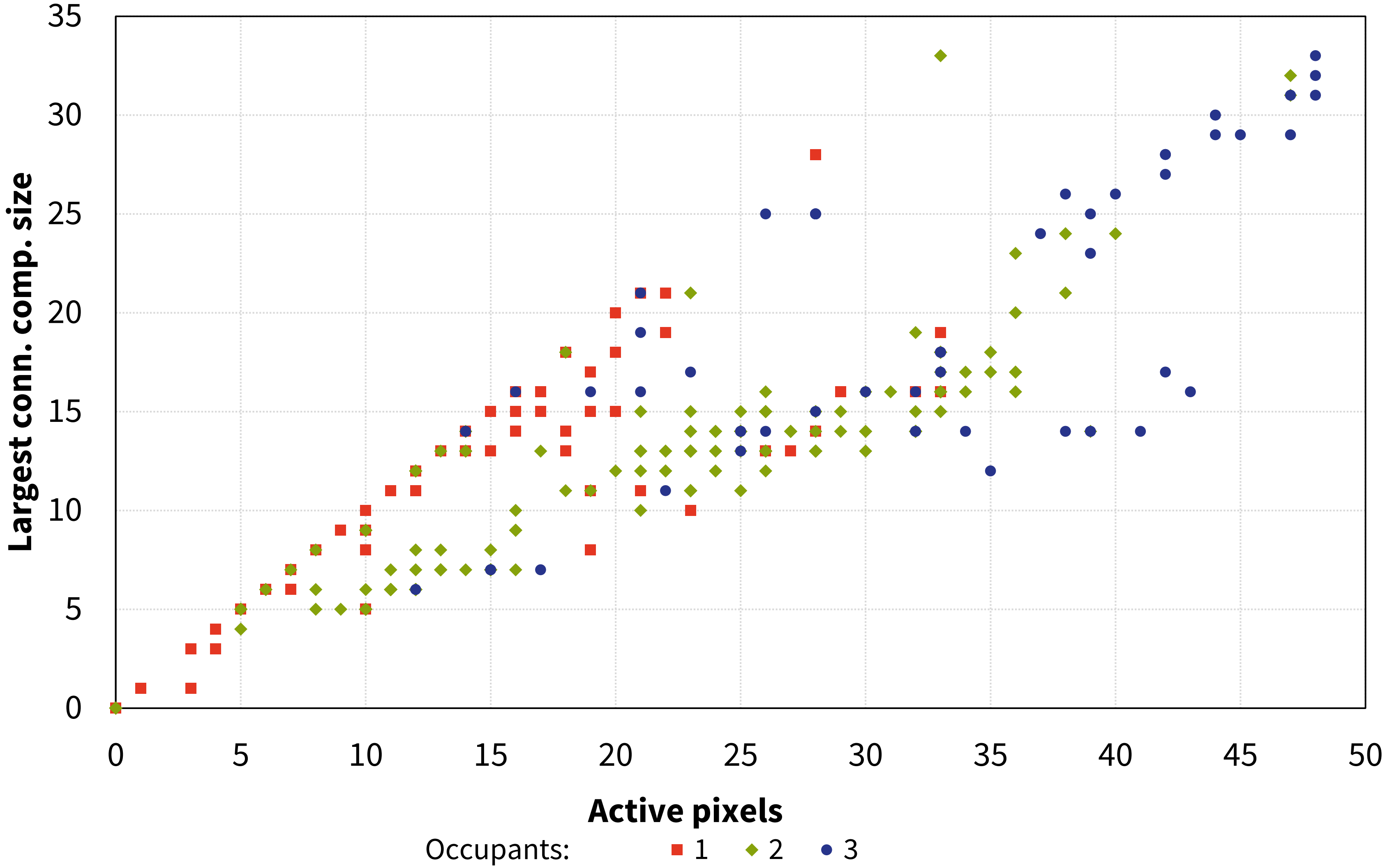
Reliability – Processing Pipeline



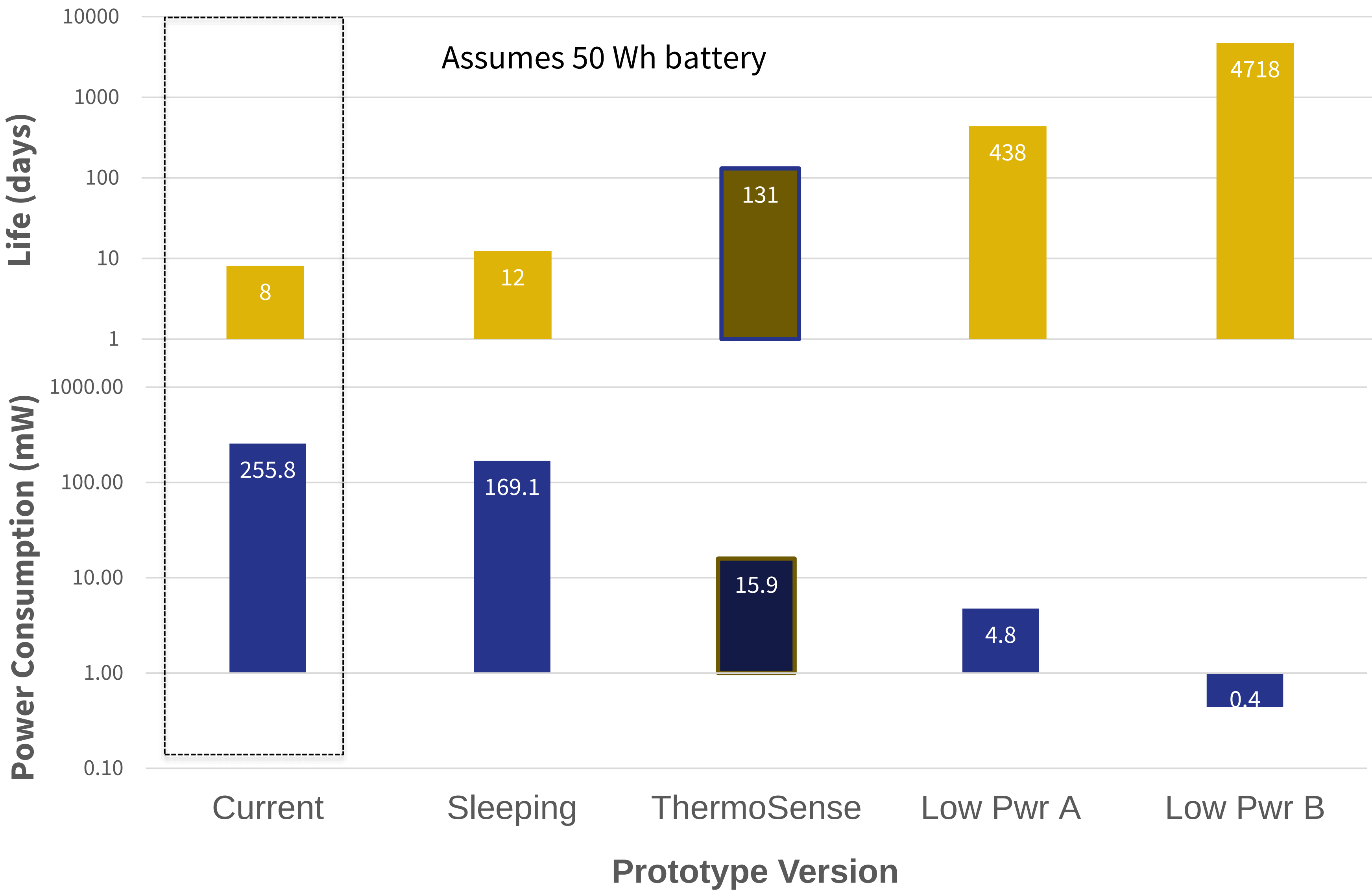
Reliability – Summary

- Best results
  - K*, C4.5 (both ~82%)
  - MLP also passable (~77%)
- ThermoSense paper's choices not sufficiently reliable with our dataset
  - Why?
  - So many unknowns
- Why are K* and C4.5 so much better?
  - Entropy?

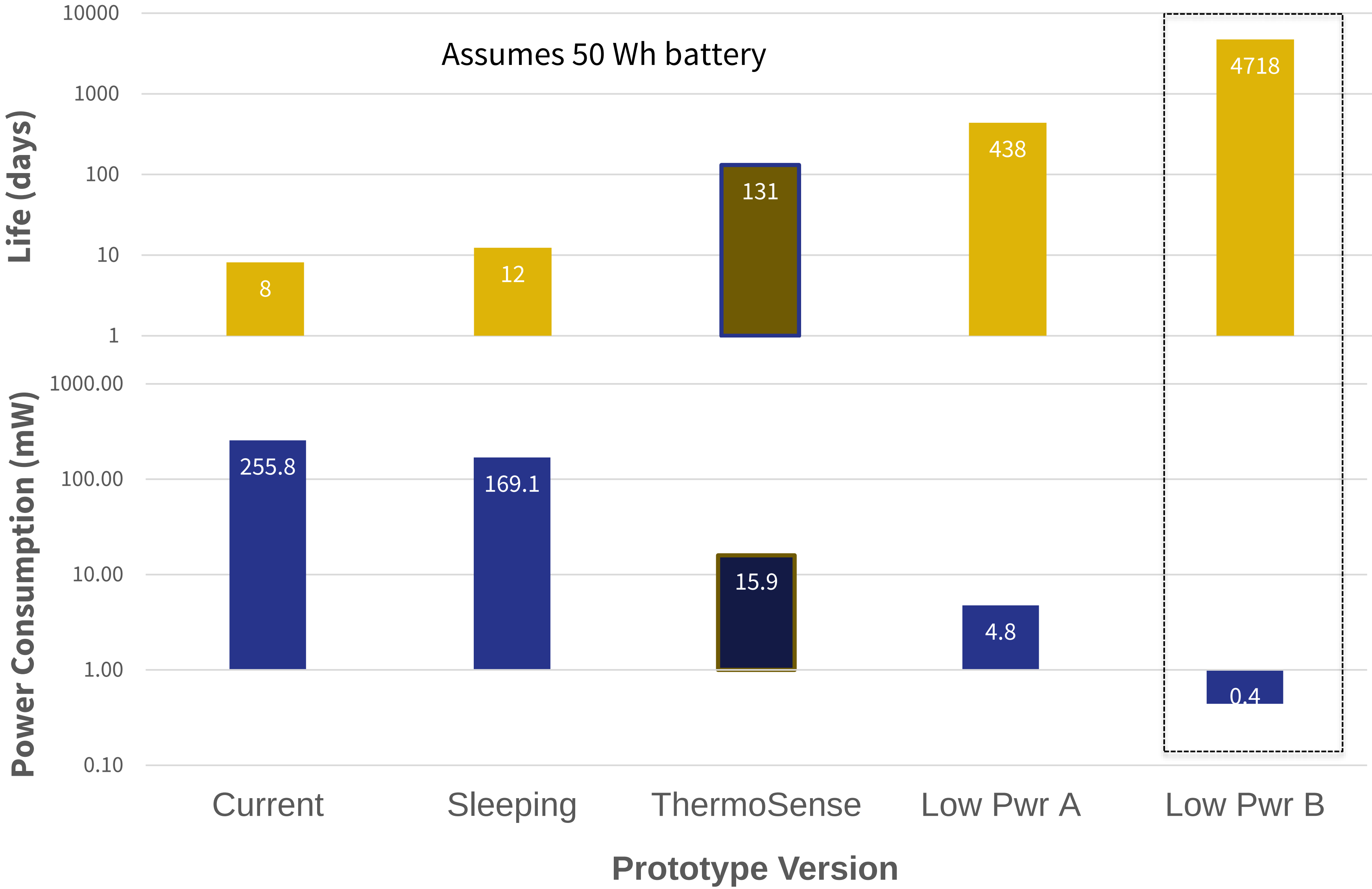
Feature Plot – No Clear Cut



Energy Efficiency (log scales)



Energy Efficiency (log scales)



Conclusions

Conclusions

- Low Cost
  - $185, and will only get cheaper
- Non-Invasive
  - Thermal sensing is a good technique
- Reliable
  - 82% classification accuracy
- Energy Efficient
  - Prototype: 8 days. Minor changes: years

Recommended Future Work

- IoT integration
  - How would this talk to other systems?
- Field-of-View modifications
  - Undistorting captured images
- New Sensors
  - MLX90621 (wider FOV)
  - FliR Lepton (80x60 pixel)

References & Questions?

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[ABS12] Australian Bureau of Statistics. Disability, ageing and carers, Australia: Summary of findings: Carers - key findings. Tech. Rep. 4430.0, 2012. Retrieved April 10, 2015 from http://abs.gov.au/ausstats/abs@.nsf/Lookup/D9BD84DBA2528FC9CA257C21000E4FC5.

[ABS11] Australian Bureau of Statistics. Household water and energy use, Victoria: Heating and cooling. Tech. Rep. 4602.2, 2011. Retrieved October 6, 2014 from http://abs.gov.au/ausstats/abs@.nsf/0/ 85424ADCCF6E5AE9CA257A670013AF89.

[BEC13] Beltran, A., Erickson, V. L., and Cerpa, A. E. ThermoSense: Occupancy thermal based sensing for HVAC control. In *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings* (2013), ACM, pp. 1–8.

[CCE09] Chan, M., Campo, E., Esteve, D., and Fourniols, J.-Y. Smart homes - current features and future perspectives. *Maturitas 64*, 2 (2009), 90–97.

[CAG12] Council of Australian Governments. Baseline Energy Consumption and Greenhouse Gas Emissions: In Commercial Buildings in Australia: Part 1 – Report. 2012. Retrieved April 10, 2015 from http://industry.gov.au/Energy/EnergyEfficiency/Non-residentialBuildings/Documents/CBBS-Part-1.pdf.

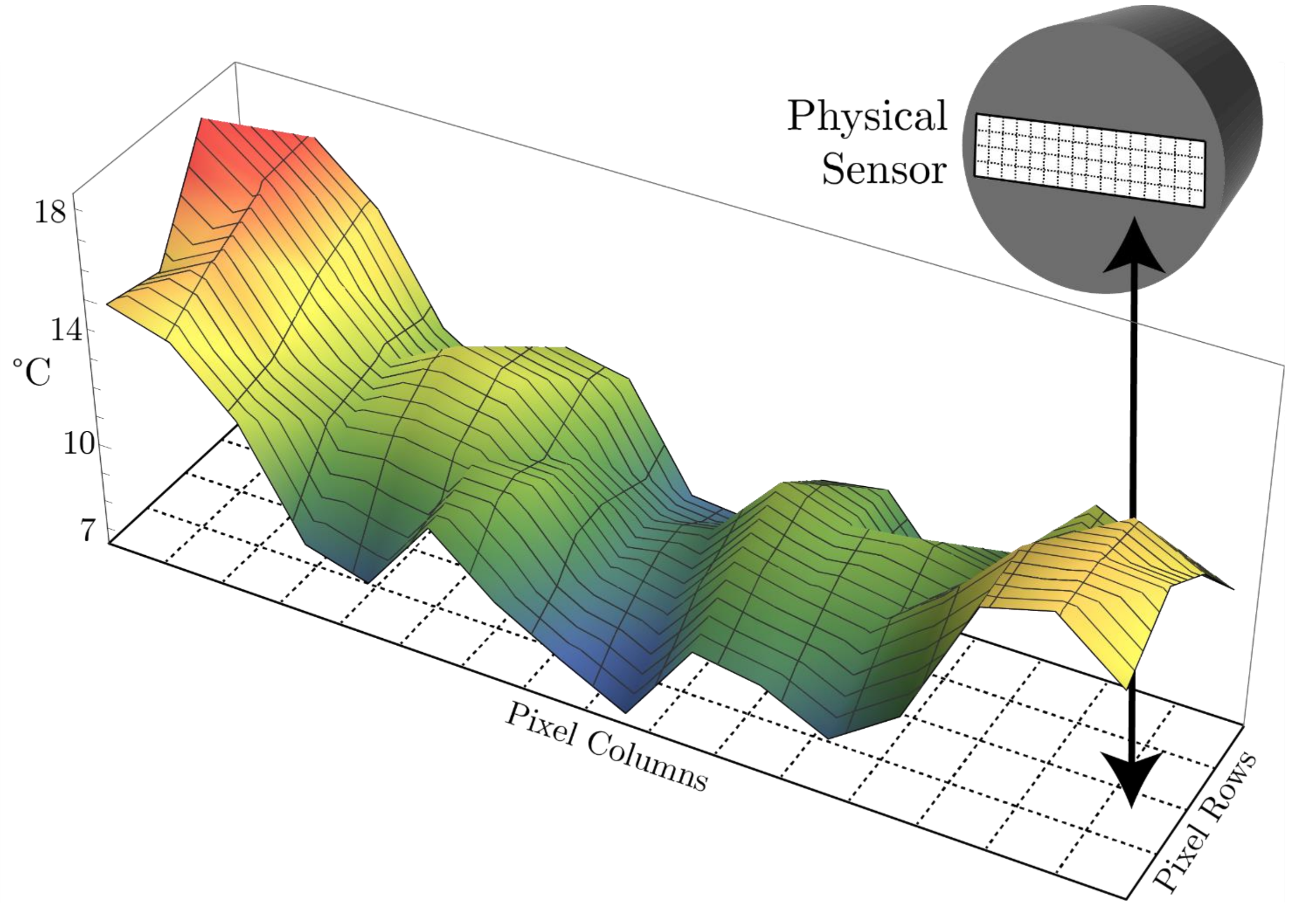
[Swo15] Swoboda, K. Energy prices–the story behind rising costs. In Parliamentary Library Briefing Book - 44th Parliament. Australian Parliament House Parliamentary Library, 2013. Retrieved February 3, 2015 from http://aph.gov.au/About_Parliament/Parliamentary_Departments/Parliamentary_Library/pubs/BriefingBook44p/EnergyPrices.

Questions?

Additional Content

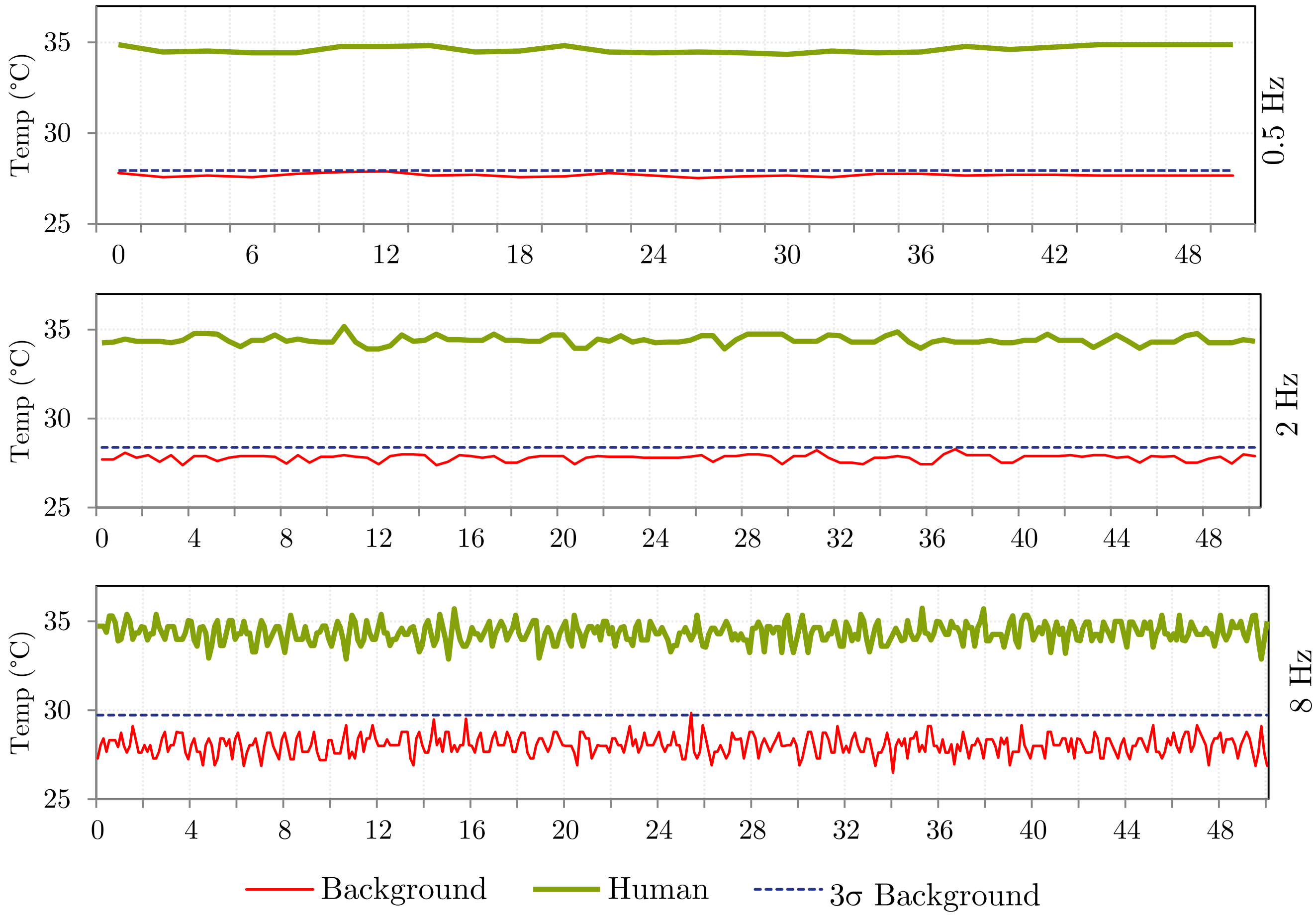
Sensor Properties

Sensor Properties – Bias



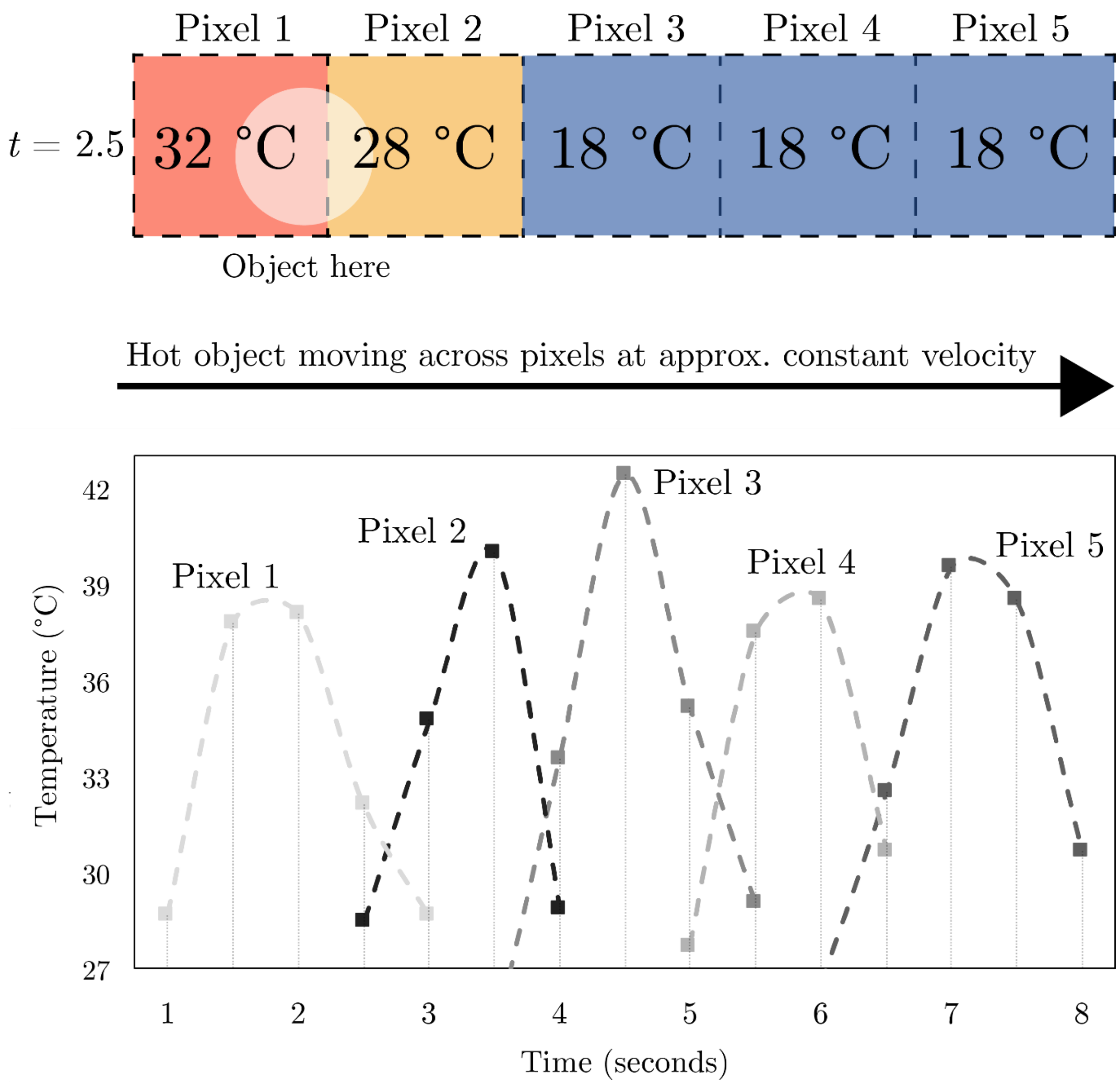
Average mean values over capture window

Sensor Properties – Noise



Graphs of noise of human pixel and background pixel

Sensor Properties – Sensitivity



Hot object moving across row of five pixels

Evaluating Sensors

How do we evaluate sensors?

1. Presence
   – Is there any occupant present in the sensed area?

[TDS14]

How do we evaluate sensors?

2. Count
   - How many occupants are there in the sensed area?

[TDS14]

How do we evaluate sensors?

3. Location
   - Where are the occupants in the sensed area?

[TDS14]

How do we evaluate sensors?

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4. Track
   - Where do the occupants move in the sensed area? (local identification)

[TDS14]

How do we evaluate sensors?

5. Identity
   – Who are the occupants in the sensed area? (global identification)

[TDS14]

How do we evaluate sensors?

	Requires		Excludes	Irrelevant	
	Presence	Count	Identity	Location	Track
Intrinsic					
Static					
Thermal	✓	✓	✓	✓	
CO_2	✓	✓	✓		
Video	✓	✓	✗	✓	✓
Dynamic					
Ultrasonic	✓	✓	✗		✓
PIR	✓	✗	✓		
Extrinsic					
Instrumented					
RFID	✓[1]	✓	✓	✓	
WiFi assoc.[2]	✓[1]	✓	✗	✓	
WiFi triang.[2]	✓[1]	✓	✗		
GPS[2]	✓[1]	✗	✓	✓	
Correlative					
Electricity	✓[1]	✗	✓		

[1] Doesn't provide data at required level of accuracy for residential use.
[2] Uses smartphone as detector.

Evaluating sensors against our criteria

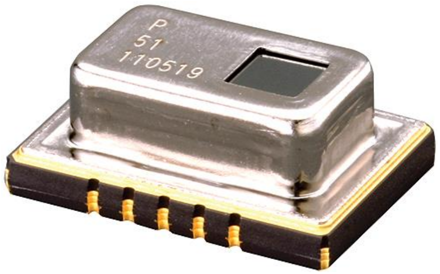
How do we evaluate sensors?

- We want
  - Presence
  - Count
- We don’t want
  - Identity
- We don’t care about
  - Location
  - Track

References

[TDS14] Teixeira, T., Dublon, G., and Savvides, A. A survey of human-sensing: Methods for detecting presence, count, location, track, and identity. Tech. rep., Embedded Networks and Applications Lab (ENALAB), Yale University, 2010. Retrieved October 6, 2014 from http://www.eng.yale.edu/enalab/publications/human_sensing_enalabWIP.pdf.

Thermosense Technique



Panasonic Grid-EYE
8x8 Thermal Array

Passive Infrared Sensor (PIR)

T-Mote Sky

PC?

Sensing

Pre-Processing

Analysis

Technique

- Overview
  1. Motion detection
  2. Image subtraction
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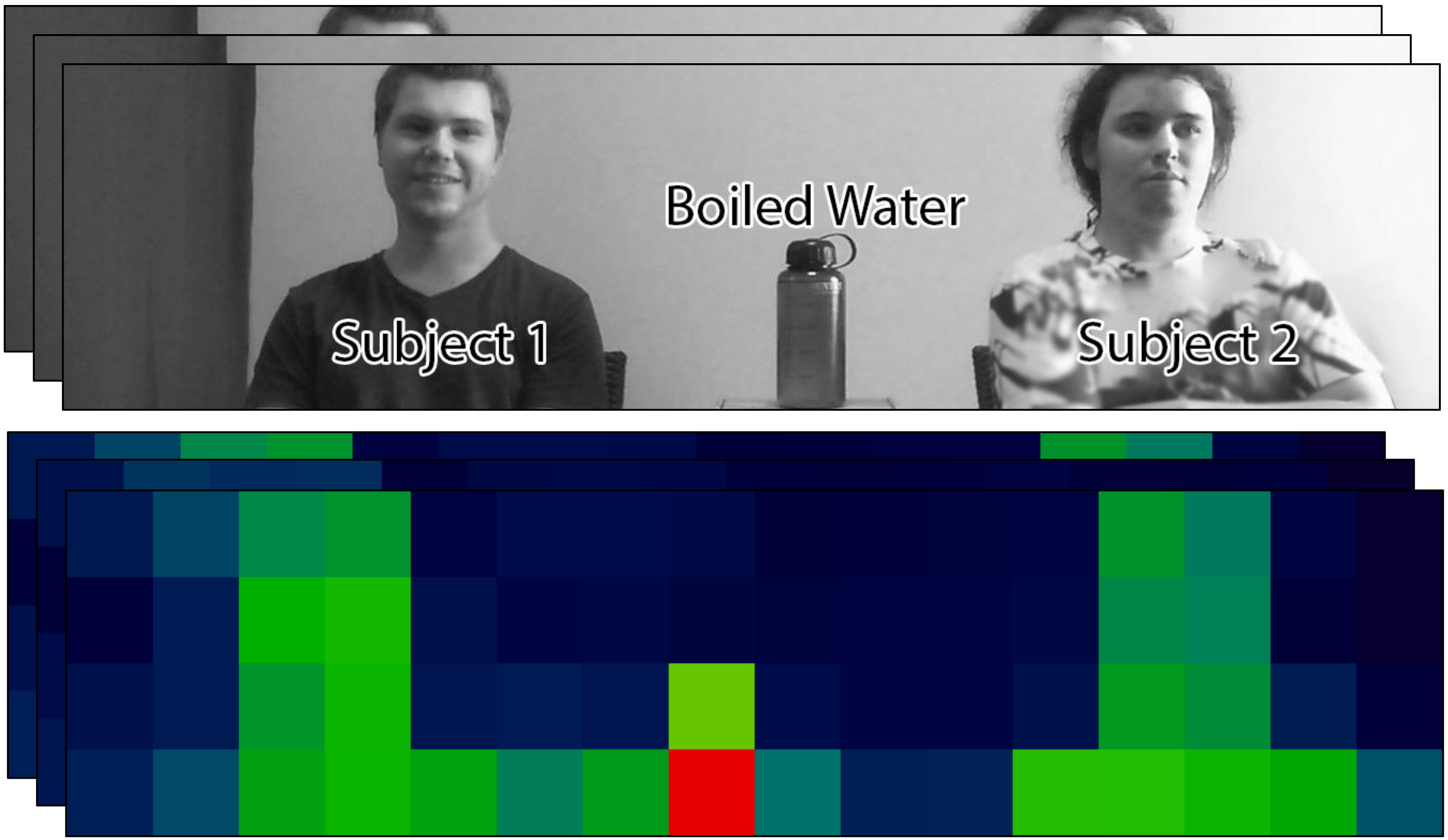
     - Distilling good examples (feature extraction)
     - Providing examples with correct answer (training)
     - Get out a model that can predict attributes

Technique

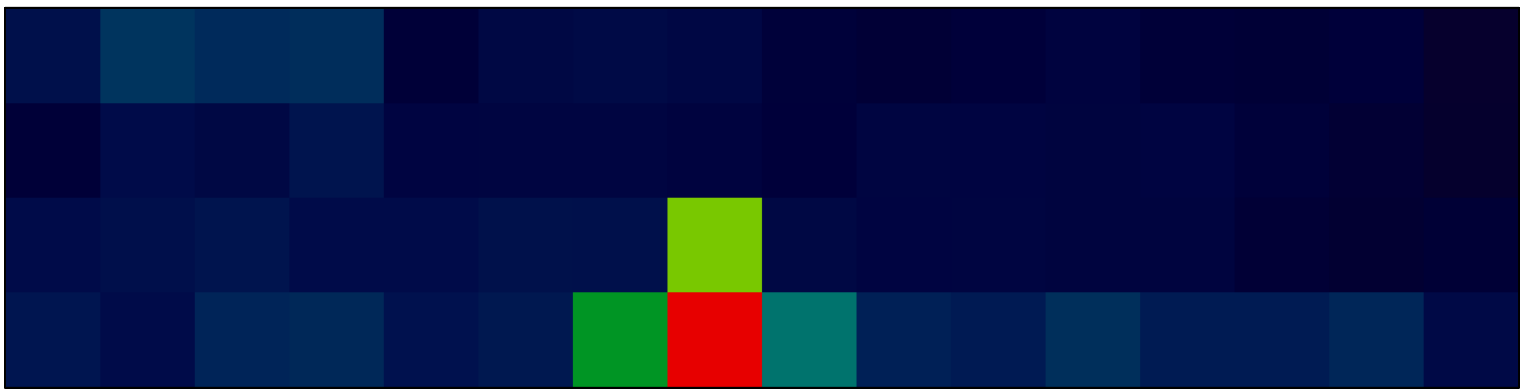
1. Capture thermal image sequence



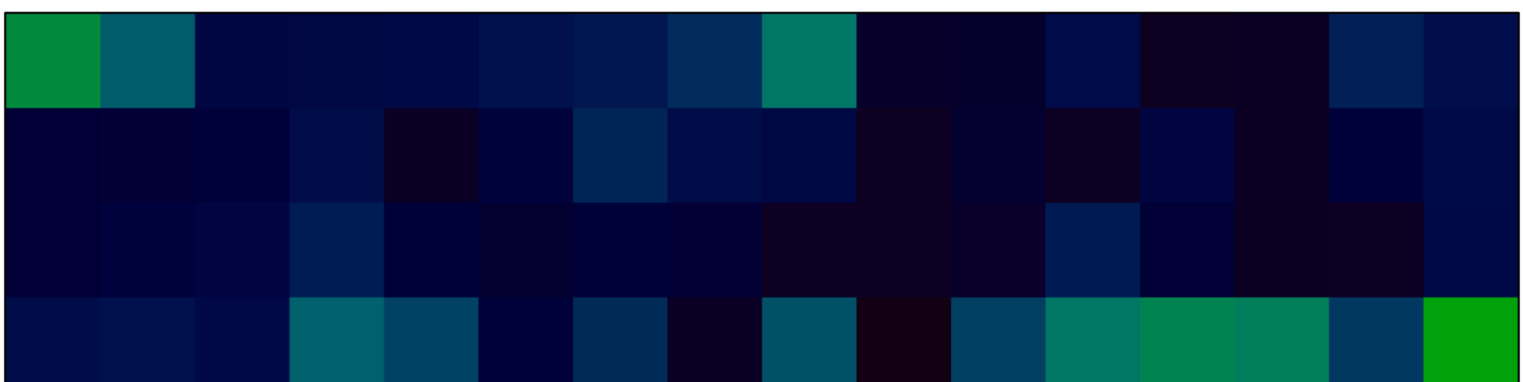
Technique

2. When no motion (use PIR), update a background map (*b*), standard deviation (σ) and means using an Exponential Weighted Moving Average

$b =$

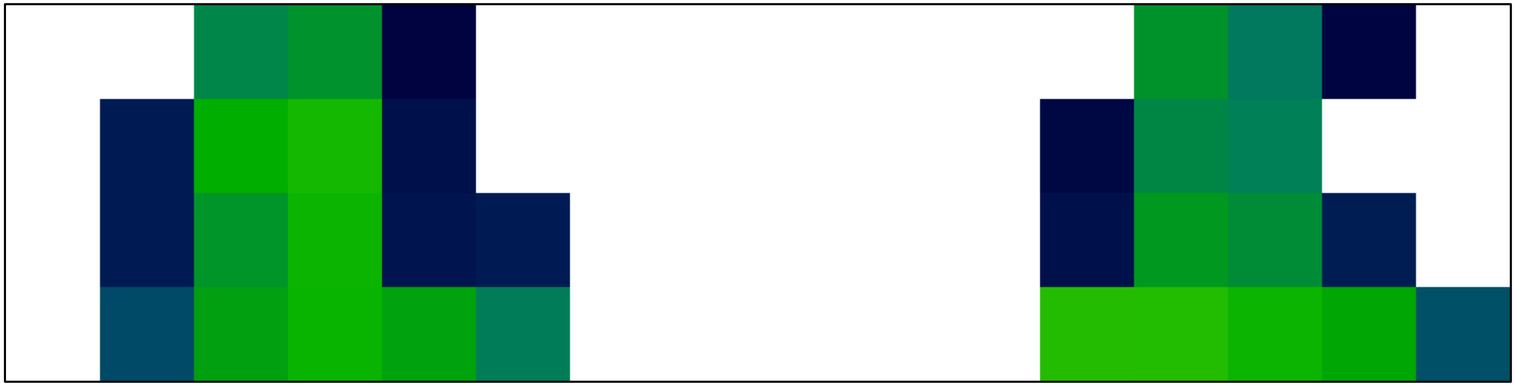


$\sigma =$



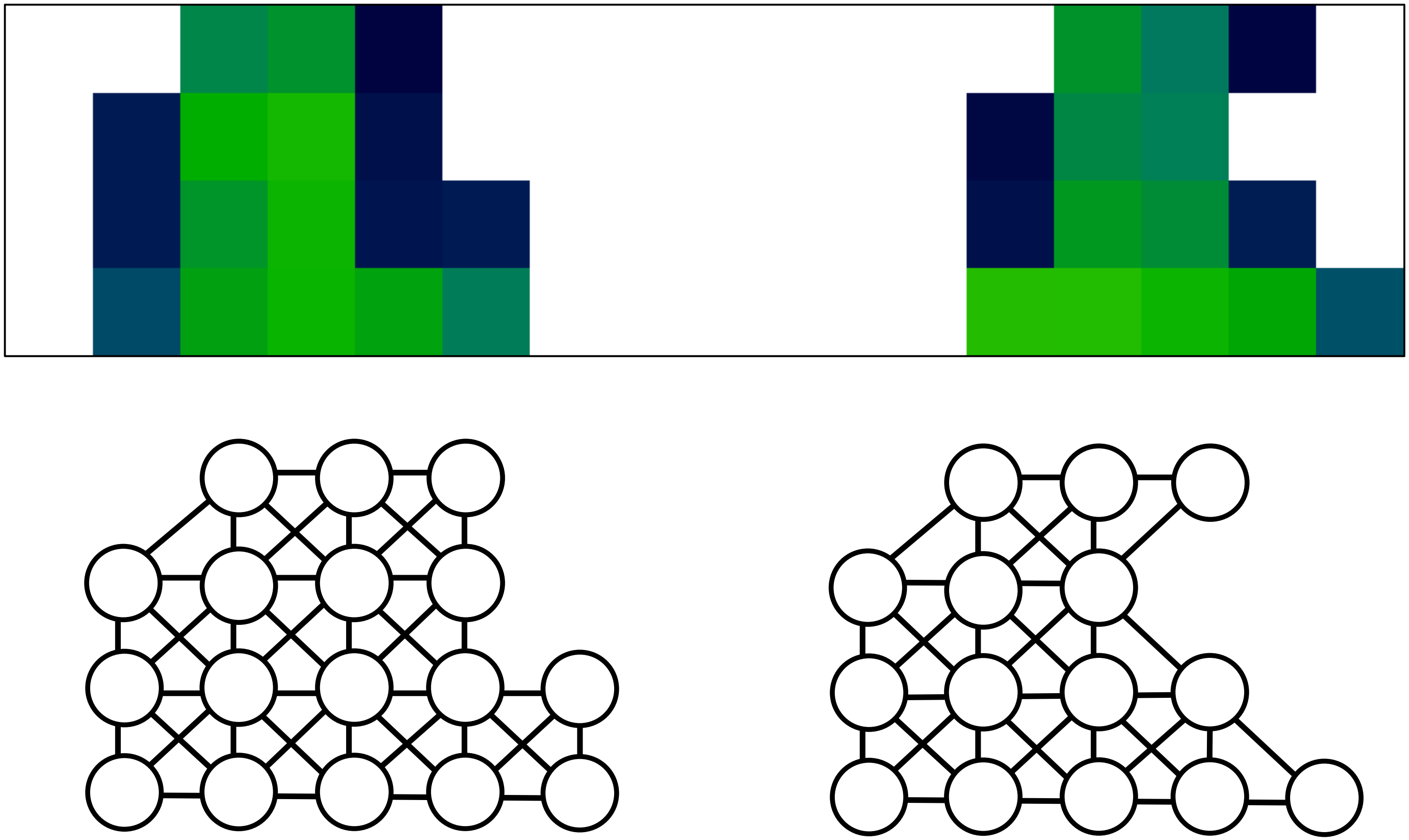
Technique

3. When motion, consider pixels > 3σ to be "active"



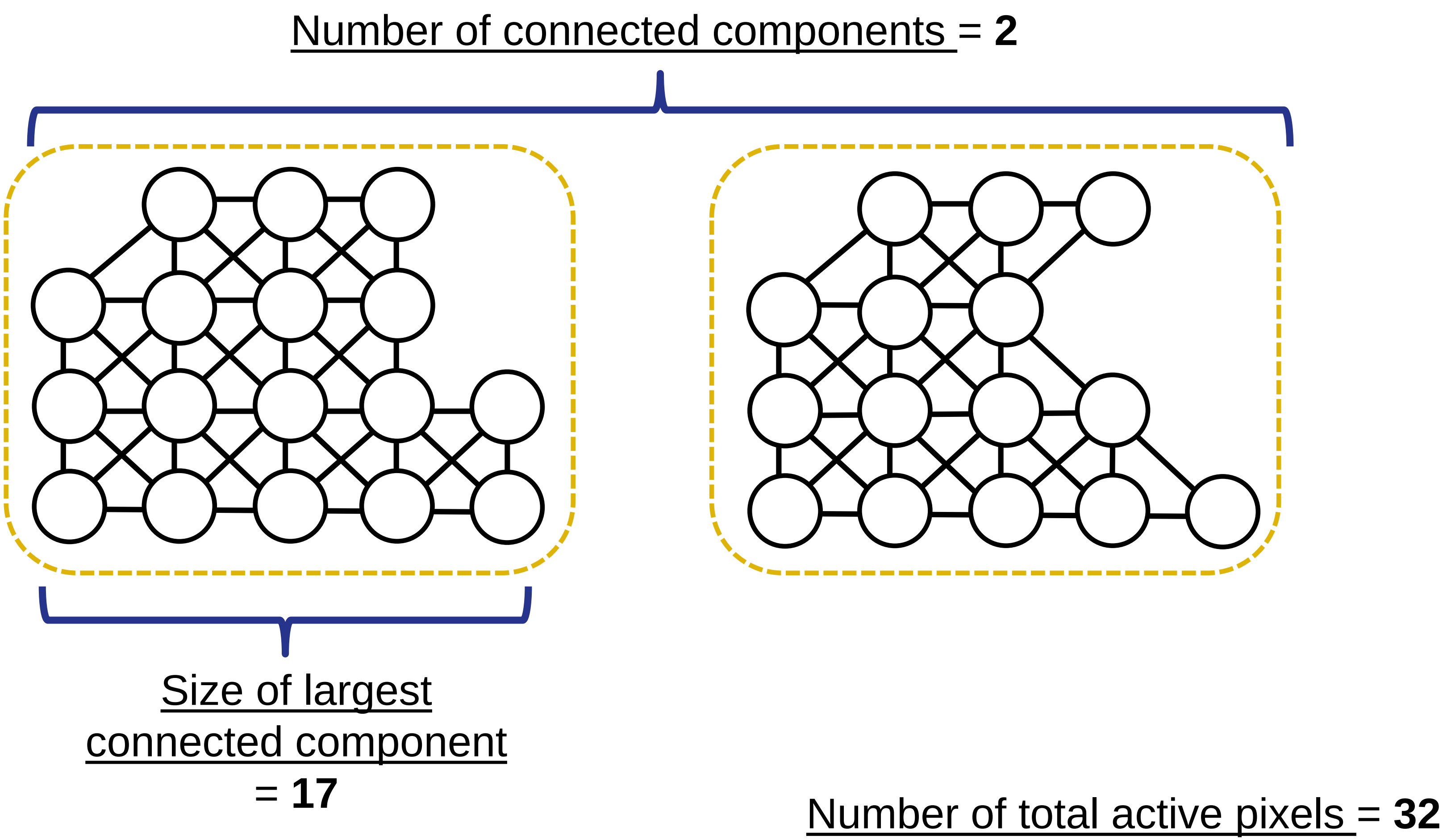
Technique

4. Generate graph from active pixels



Technique

5. Extract features from graph for classification purposes



Technique

6. Perform machine learning

    1. Train on examples with true value (features and ground truth)

    2. Make predictions with your generated model

Evaluation – Accuracy

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Worst – Best

- Thermosense
  - RMSE: 0.409 – 0.346
  - Correlation: 0.926 – 0.946

- **K* Numeric**
  - RMSE: 0.423 (**-0.077**)
  - Correlation: 0.760 (**-0.166**)

Evaluation – Accuracy

Classifier	RMSE	Precision (%)	Correlation (r)
ThermoSense Actual			
KNN[1]	0.346		
Lin Reg[2]	0.385		0.926
MLP	0.409		0.945
ThermoSense Replication			
KNN (Nom)[1]	0.364	65.65	
MLP	0.592		0.687
Lin Reg[2]	0.525		0.589
KNN (Num)[1]	1.123		0.377
Numeric			
K*	0.423		0.760
0-R	0.651		-0.118
Nominal			
K*	0.304	82.56	
C4.5	0.314	82.39	
MLP	0.362	77.14	
SVM	0.398	67.18	
N. Bayes	0.405	63.59	
0-R	0.442	49.74	

[1]: Includes zero occupant cases in training data

[2]: Excludes number of connected components feature

%: Precision, measuring a nominal test result

r: Correlation coefficient, measuring a numeric test result

Results

Evaluation – Accuracy

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	Worst – Best
• Thermosense	
– RMSE:	0.409 – 0.346
– Correlation:	0.926 – 0.946

- Three Test Suites
  - Replication of their algorithms
  - Our numeric algorithm, K* (measured with r)
  - Our nominal algorithms (measured with %)

Evaluation – Accuracy

	Worst – Best
• Thermosense	
– RMSE:	0.409 – 0.346
– Correlation:	0.926 – 0.946
• Our Replication	
– RMSE:	1.123 – 0.364 (**-0.018**)
– Correlation:	0.377 – 0.687 (**-0.239**)

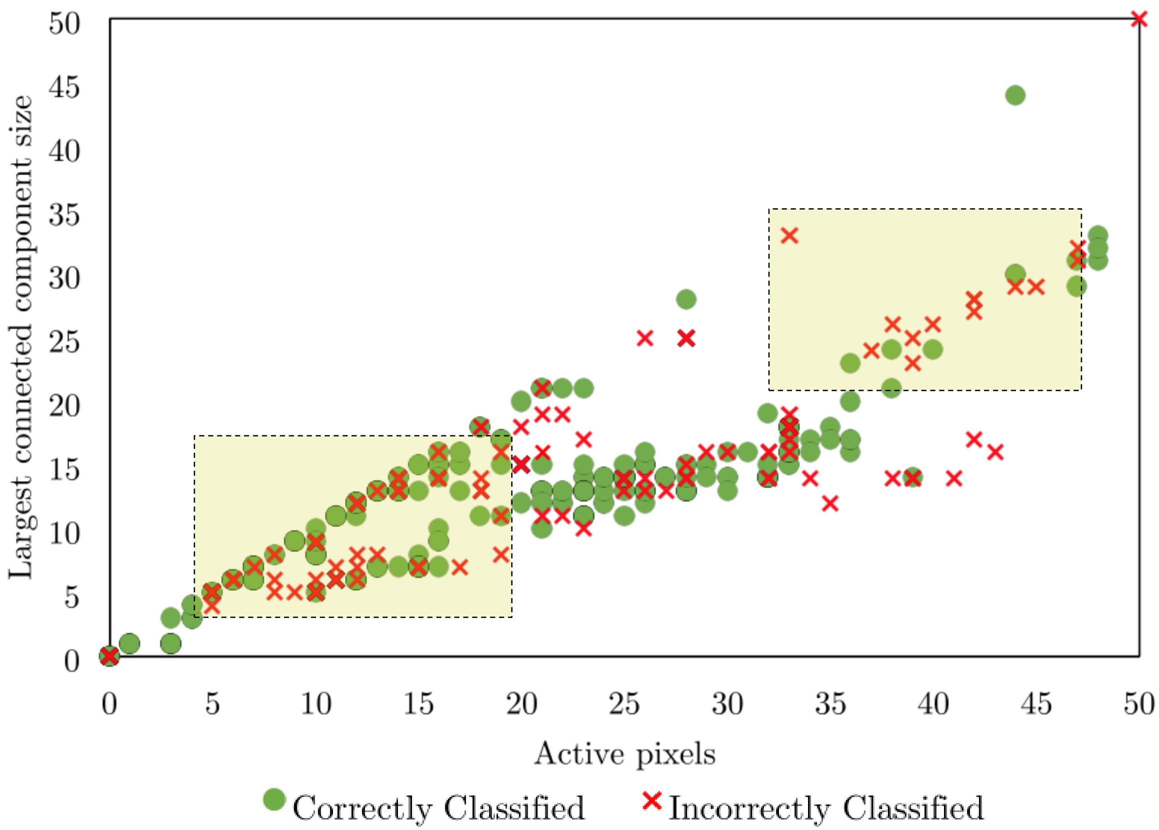
– Insufficient accuracy

Evaluation – Accuracy

Worst – Best

- Thermosense
  - RMSE: 0.409 – 0.346
- **Nominal Suite**
  - RMSE: 0.304 – 0.405 (**+0.042**)
  - Accuracy: 63.59 – 82.56
  - Higher end does have sufficient accuracy

Evaluation – Accuracy



SVM Predictions

67% accuracy

Energy Efficiency

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Different Prototype Designs

Model	Radio	Sleep (mA)	Wake (mA)	Volts (V)	Wake (ms)	Sample (Hz)	Avg (mW)	Life (days)
Existing	✗	34	52	4.9	∞	0.20	255.84	8
Sleep	✗	34	52	4.9	100	0.20	169.05	12
ThermoS.	✓	?	?	3.3	?	0.20	15.91	131
LowPwr A	✓	0.065	23	3.3	300	0.20	4.76	438
LowPwr B	✓	0.065	23	3.3	300	0.01	0.44	4718

Radio: Does the model use radio transmission?
Sleep (mA): Milliamp current consumption in sleep state
Wake (mA): Milliamp current consumption in wake state
Volts (V): Voltage requirement of model
Wake (ms): Min. millisecond time model must be awake to sample & transmit once (∞ = never sleeps)
Sample (Hz): Freq. that model wakes and performs sample & transmit
Avg (mW): Avg. milliwatt power given sleep/wake current, voltage, sample and wake time
Life (days): Est. life of model assuming a perfect 50 watt-hour (Wh) battery