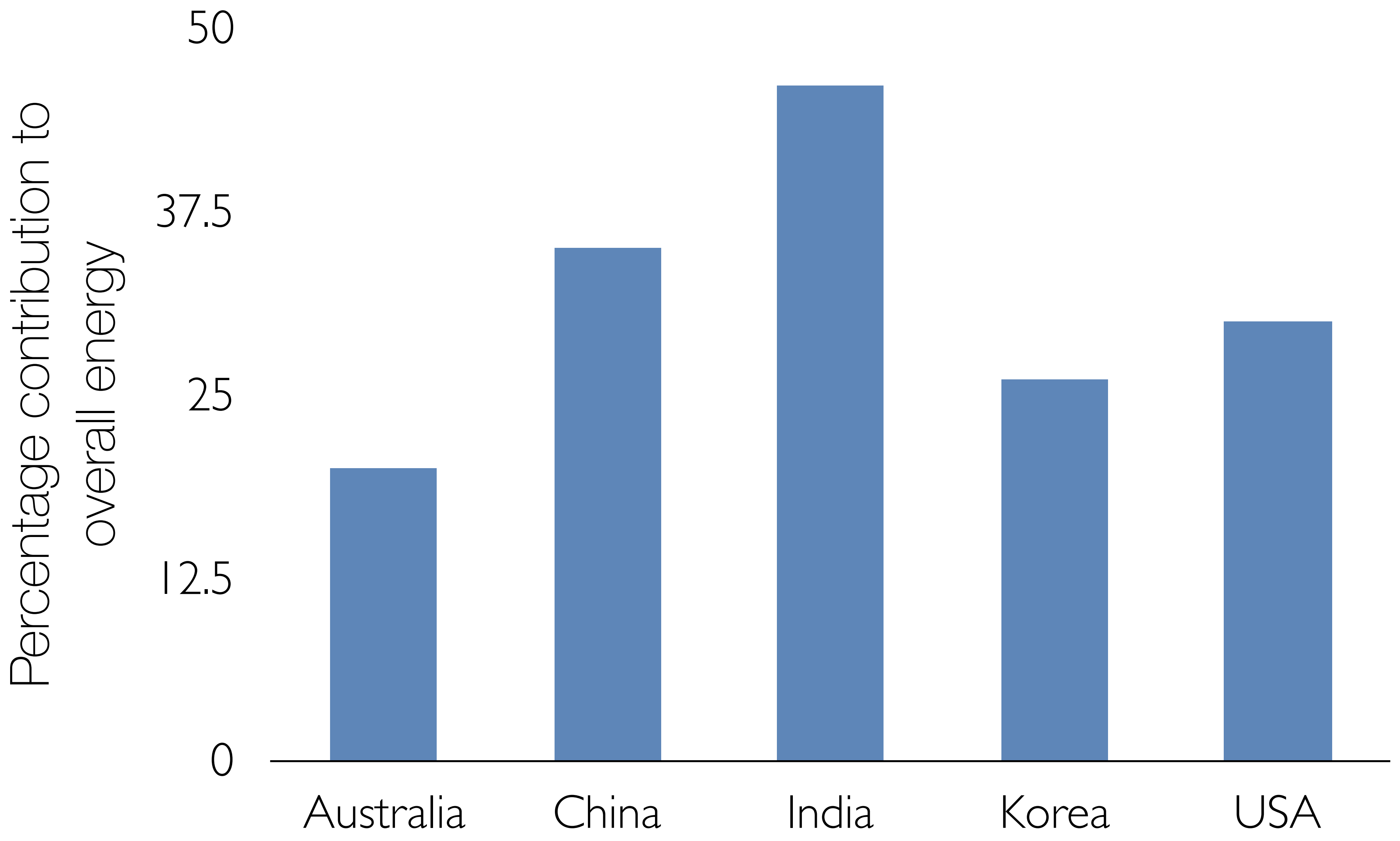
Systems and Analytical Techniques Towards Practical Energy Breakdown for Homes

Nipun Batra
March 7, 2017

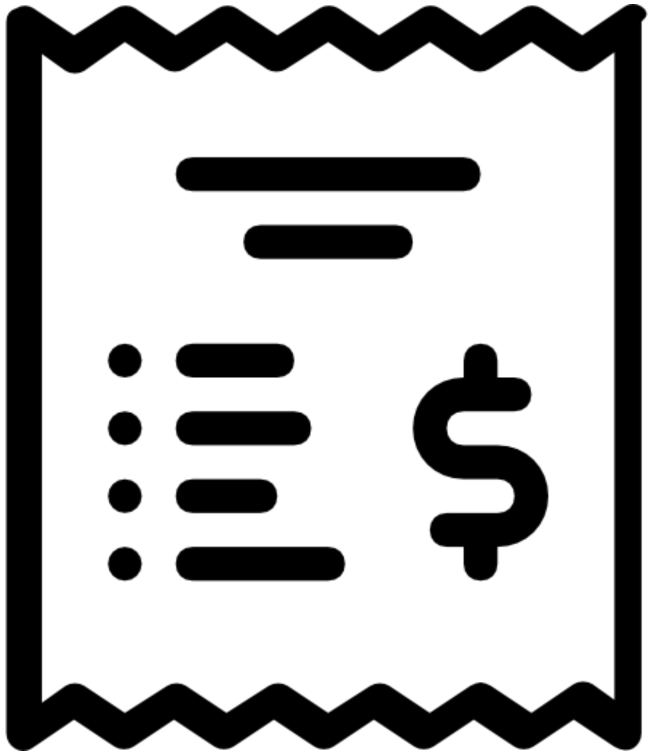
Committee

Dr. Amarjeet Singh
Dr. Kamin Whitehouse
Dr. Krithi Ramamritham
Dr. Prashant Shenoy
Dr. Rahul Mangharam

Building Energy Usage

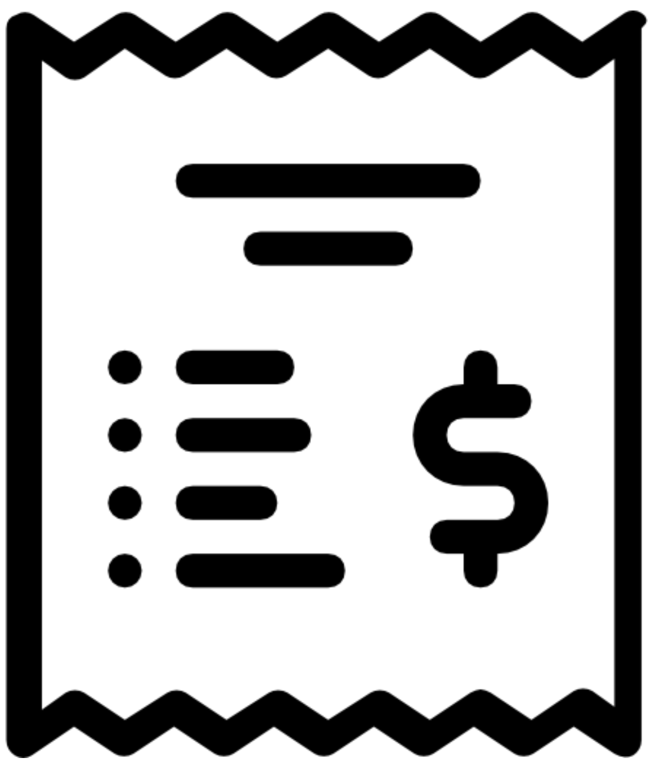


Energy Breakdown

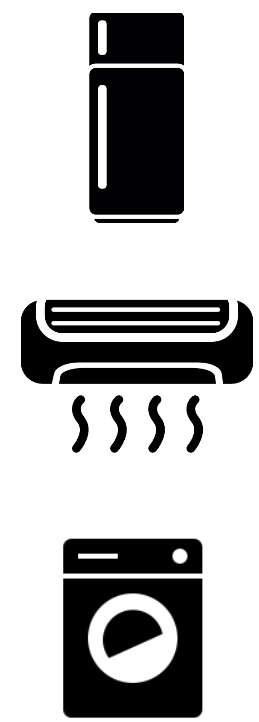


Monthly bill

Energy Breakdown



Monthly bill



20 $

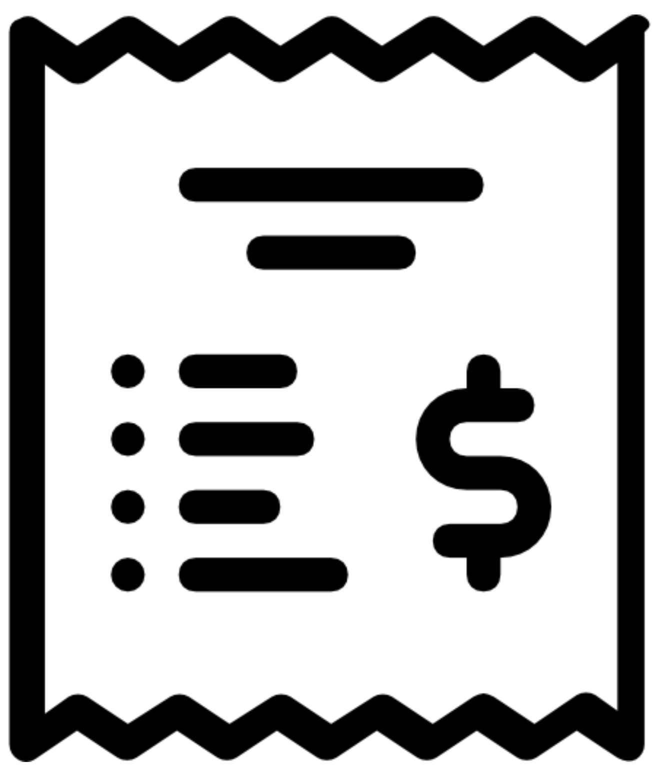
80 $

10 $

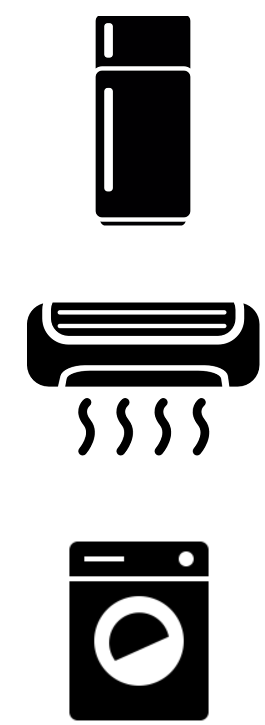
Energy breakdown

Energy Breakdown

Energy breakdown feedback can help save up to 15% energy



Monthly bill



20 $

80 $

10 $

Energy breakdown

Energy Breakdown Matrix

				. . .	
	20$	30$	10$		22$
	90$	85$	35$		25$
	10$	15$	18$		20$

Related Work

Plug load monitors

				...	
	20$	30$	10$		22$
	90$	85$	35$		25$
	10$	15$	18$		20$

Related Work

Non-intrusive load monitoring (NILM)

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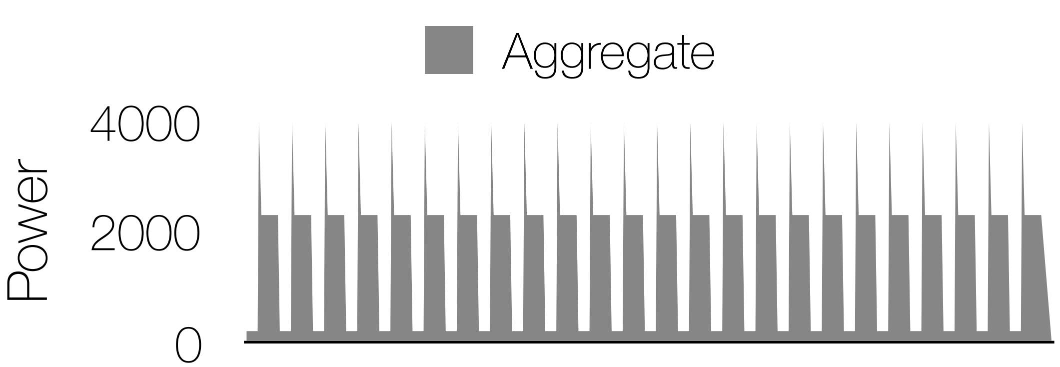
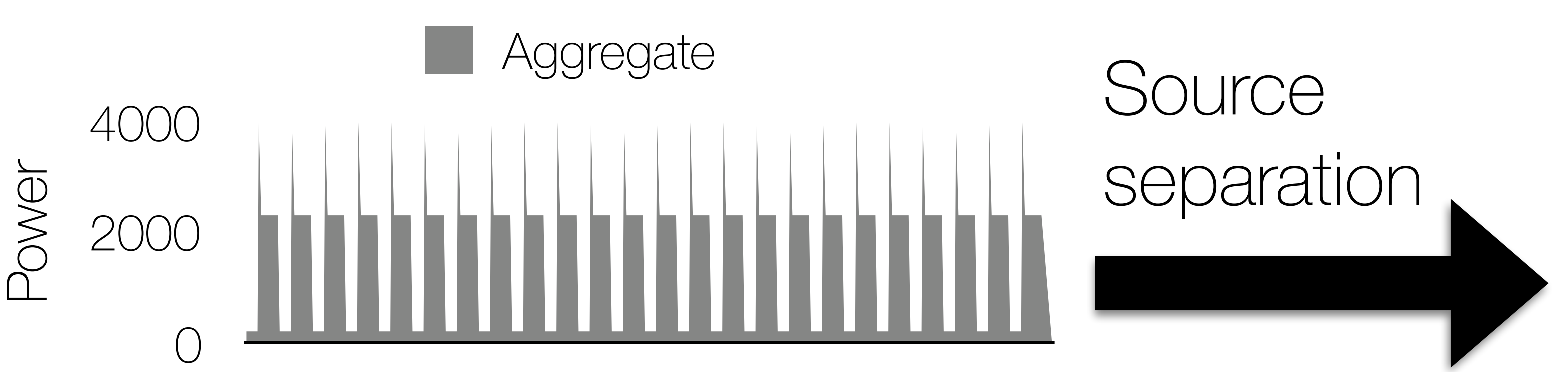


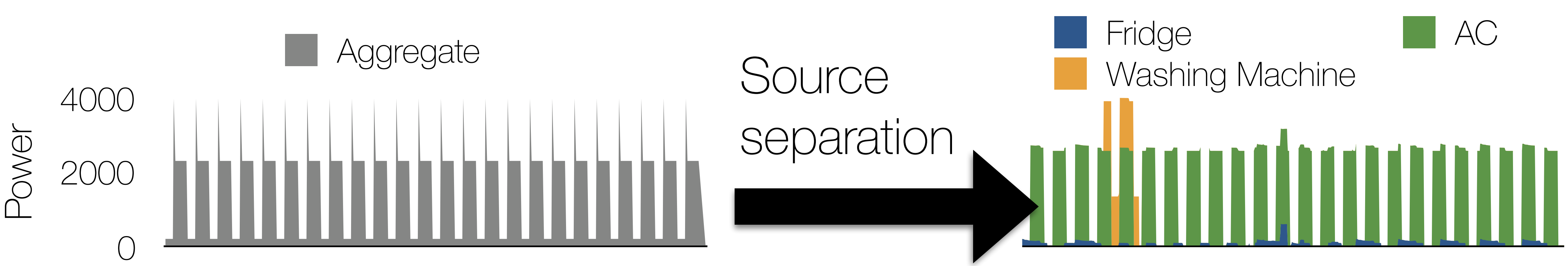
Related Work

Non-intrusive load monitoring (NILM)



Related Work

Non-intrusive load monitoring (NILM)



Related Work

Non-intrusive load monitoring (NILM)

				. . .	
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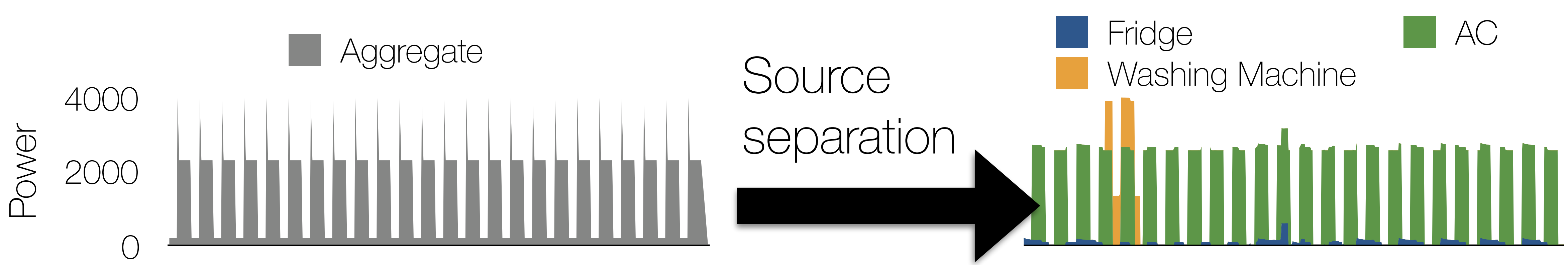
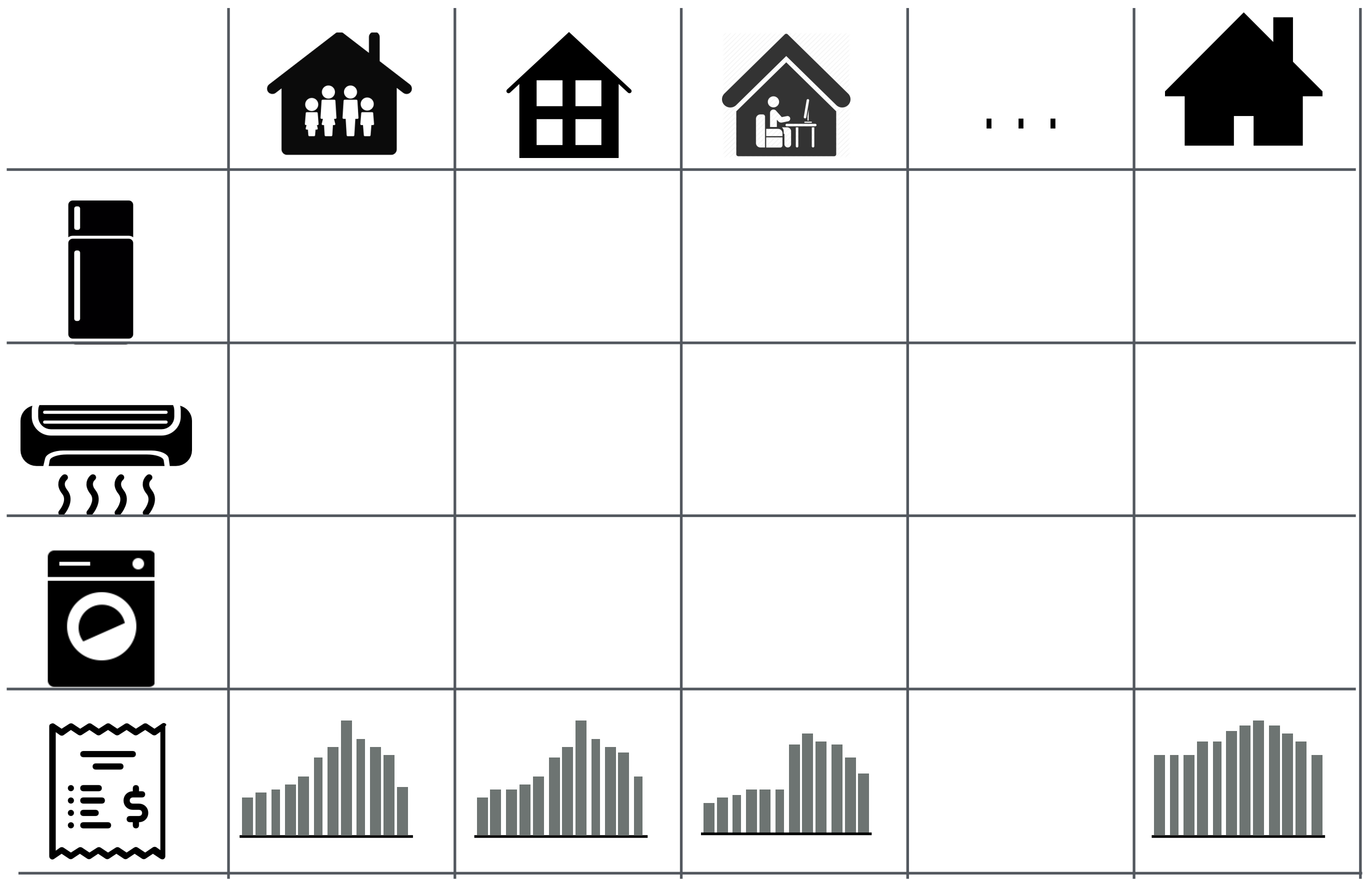


Problem: The Billion Building Challenge

Billion Buildings

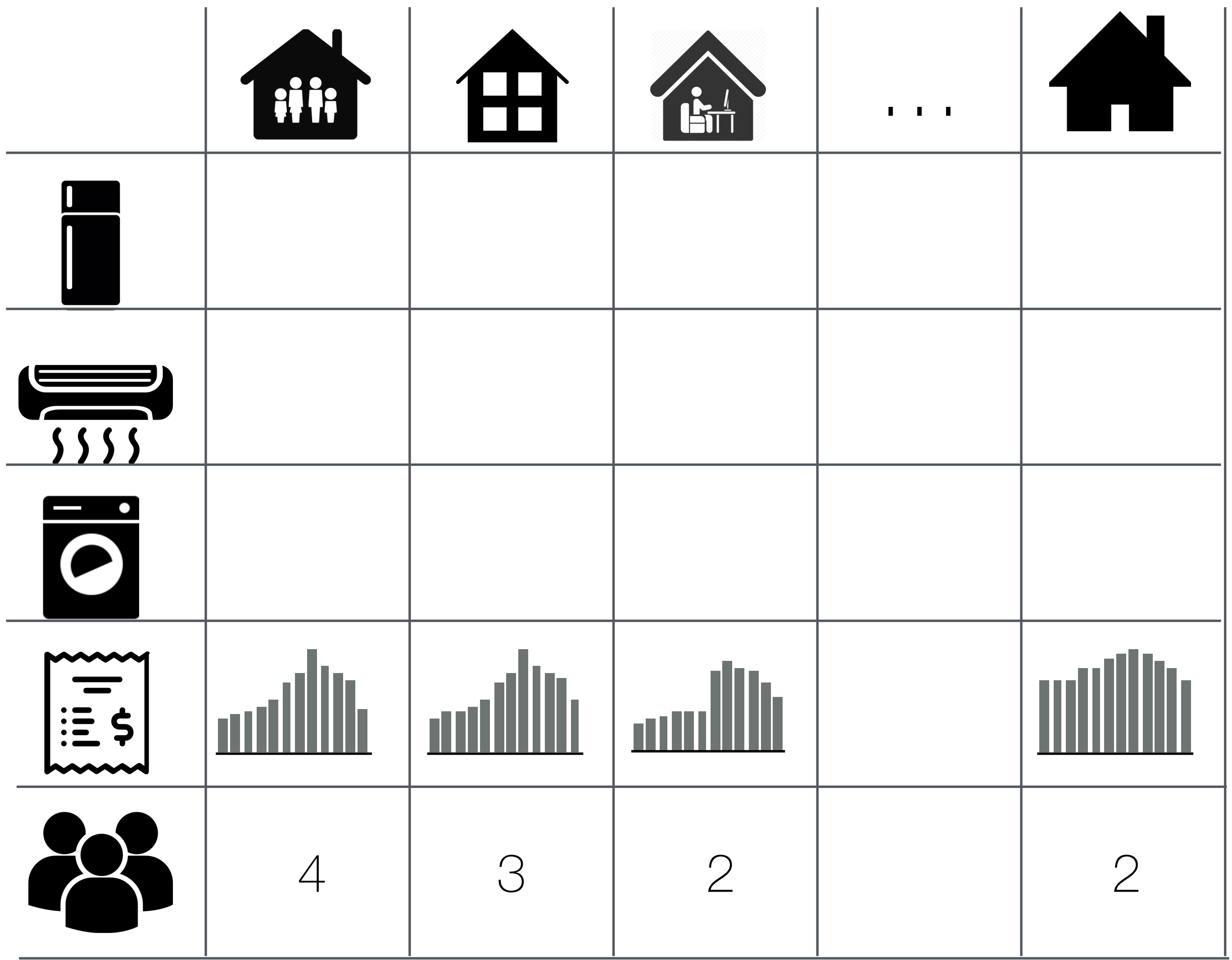
Problem: The Billion Building Challenge

Proposed solution



Problem: The Billion Building Challenge

Proposed solution



Problem: The Billion Building Challenge

Proposed solution

				. . .	
	20$	30$	10$		22$
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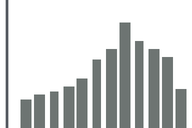
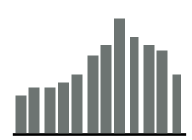
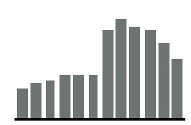
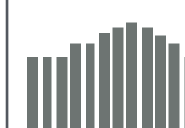
					
	4	3	2		2

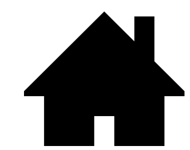
Intuition

Similar homes have similar per-appliance usage

				...	
	20$	30$	10$		22$
	90$	85$	35$		25$
	10$	15$	18$		20$
	4	3	2		2

Intuition

Similar homes have similar per-appliance usage

				. . .	
			18$		20$
			2		2

Intuition

Similar homes have similar per-appliance usage

				. . .	
	20$	30$	10$		22$
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	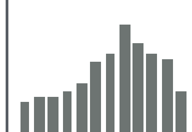	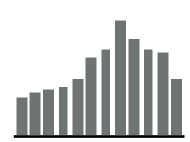	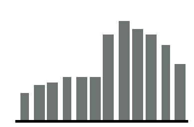		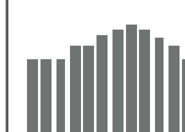
	4	3	2		2

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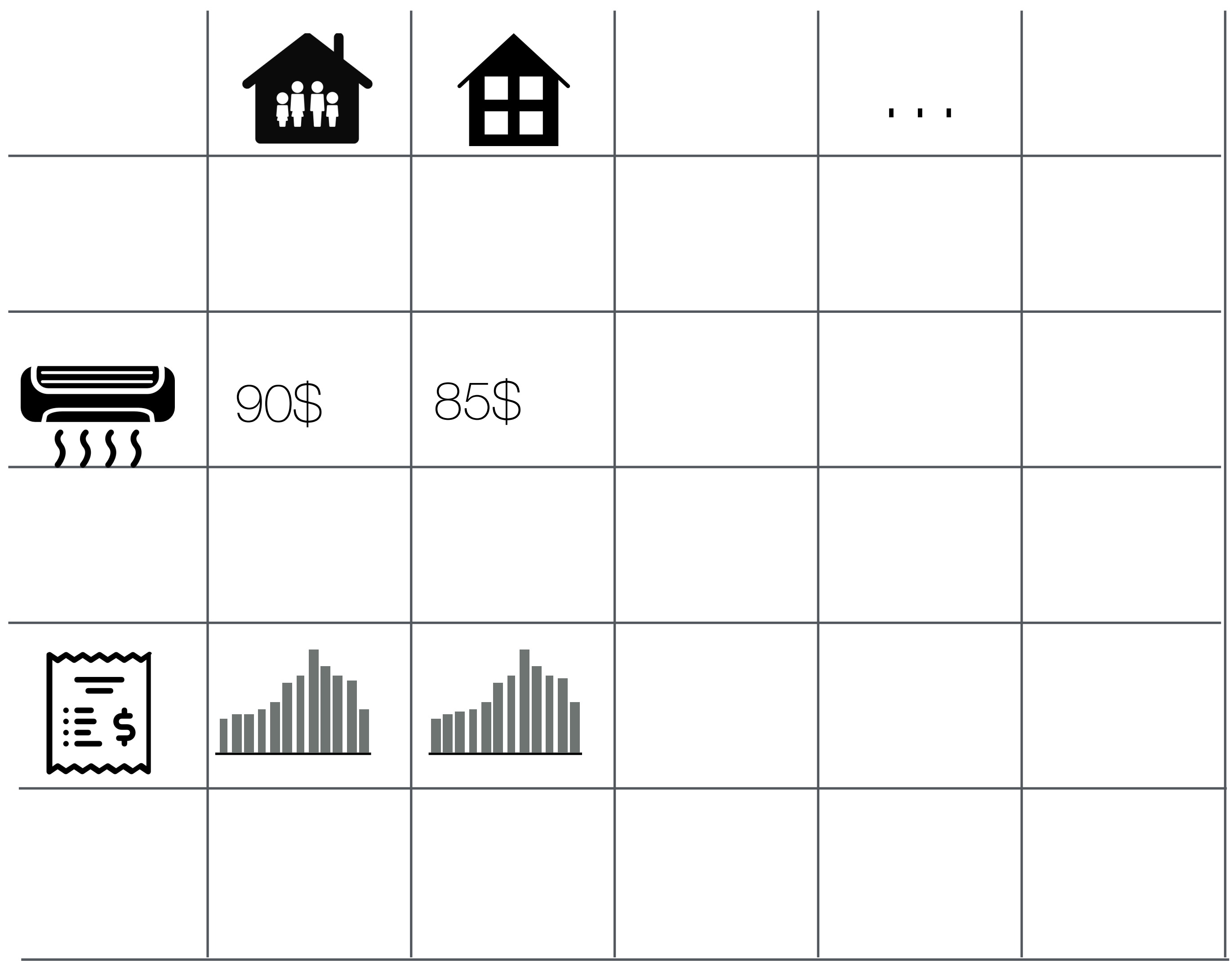
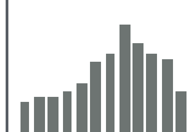
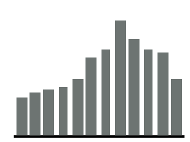
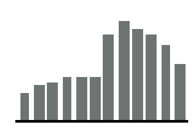
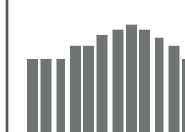


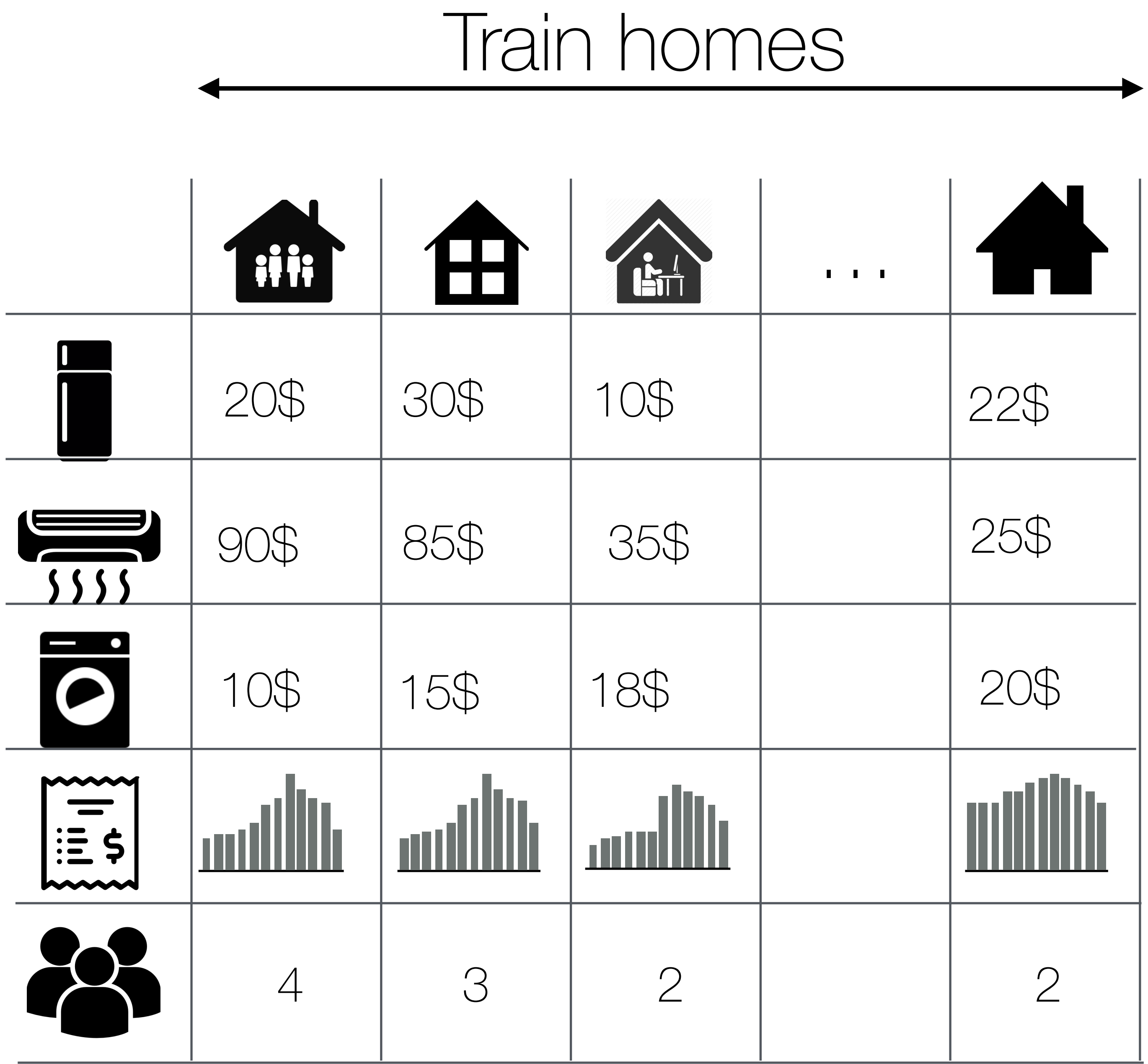
Outline

- Scalable Energy Breakdown
    - **Gemello [KDD 2016]**
    - Matrix Factorisation [AAAI 2017]
- Making NILM better
    - Comparable [Buildsys 2015]
    - Actionable [e-Energy 2014]

Gemello Overview

				...	
	20$	30$	10$		22$
	90$	85$	35$		25$
	10$	15$	18$		20$
					
	4	3	2		2

Gemello Overview



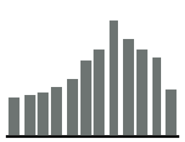
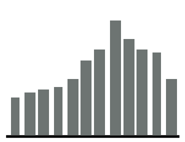
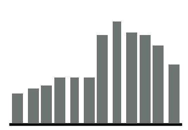
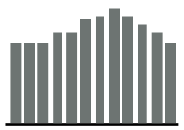
Gemello Overview

Train homes

				. . .	
	20$	30$	10$		22$
	90$	85$	35$		25$
	10$	15$	18$		20$
	4	3	2		2

Gemello Overview

Train homes

				...	
	20$	30$	10$		22$
	90$	85$	35$		25$
	10$	15$	18$		20$
					
	4	3	2		2

Gemello Overview

Train homes

				...	
	20$	30$	10$		22$
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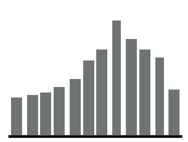
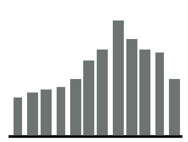
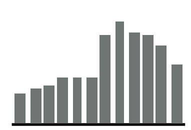
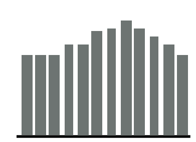
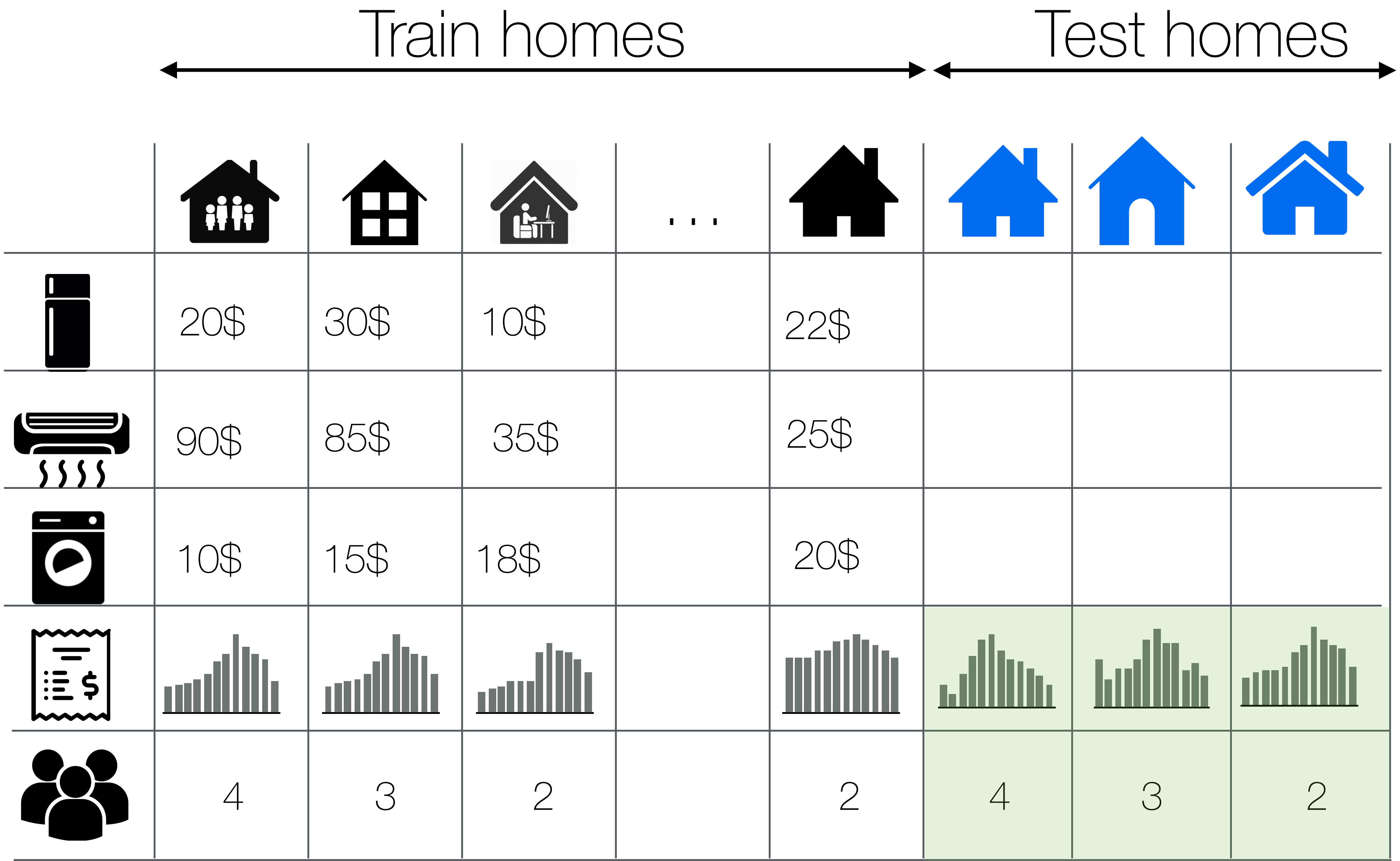
					
	4	3	2		2

Gemello Overview

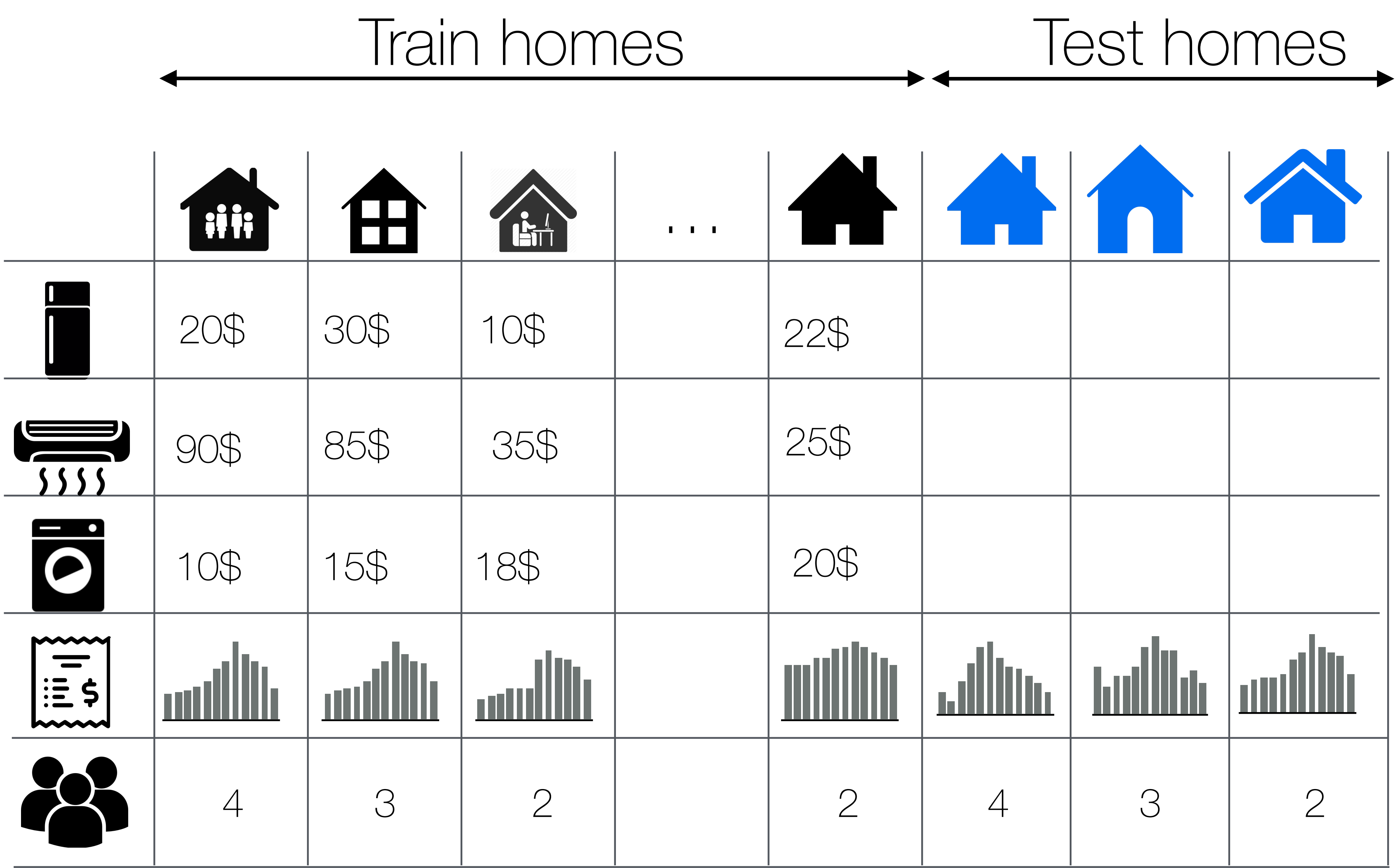
Train homes | Test homes

				. . .				
	20$	30$	10$		22$			
	90$	85$	35$		25$			
	10$	15$	18$		20$			
	4	3	2		2	4	3	2

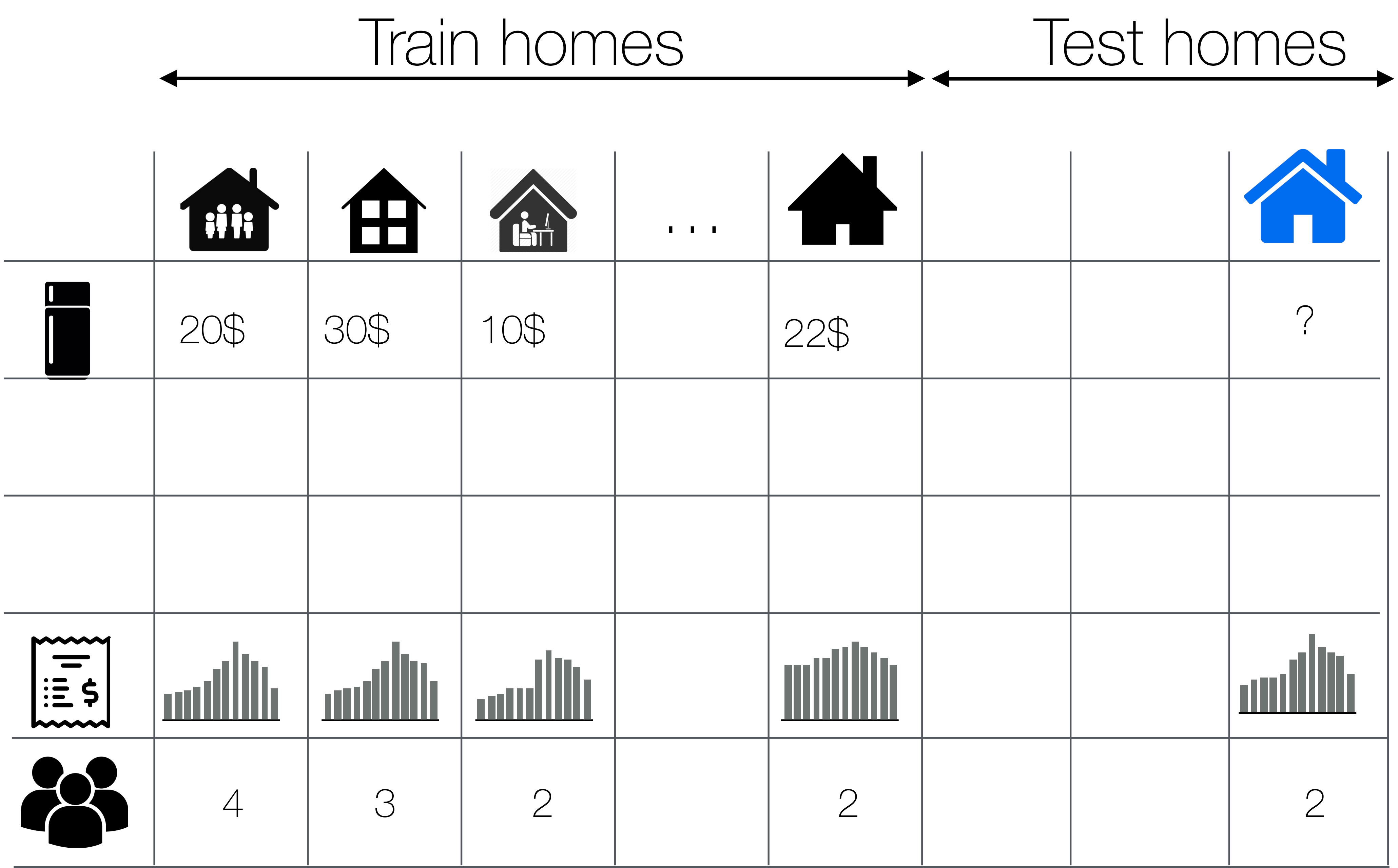
Gemello Overview



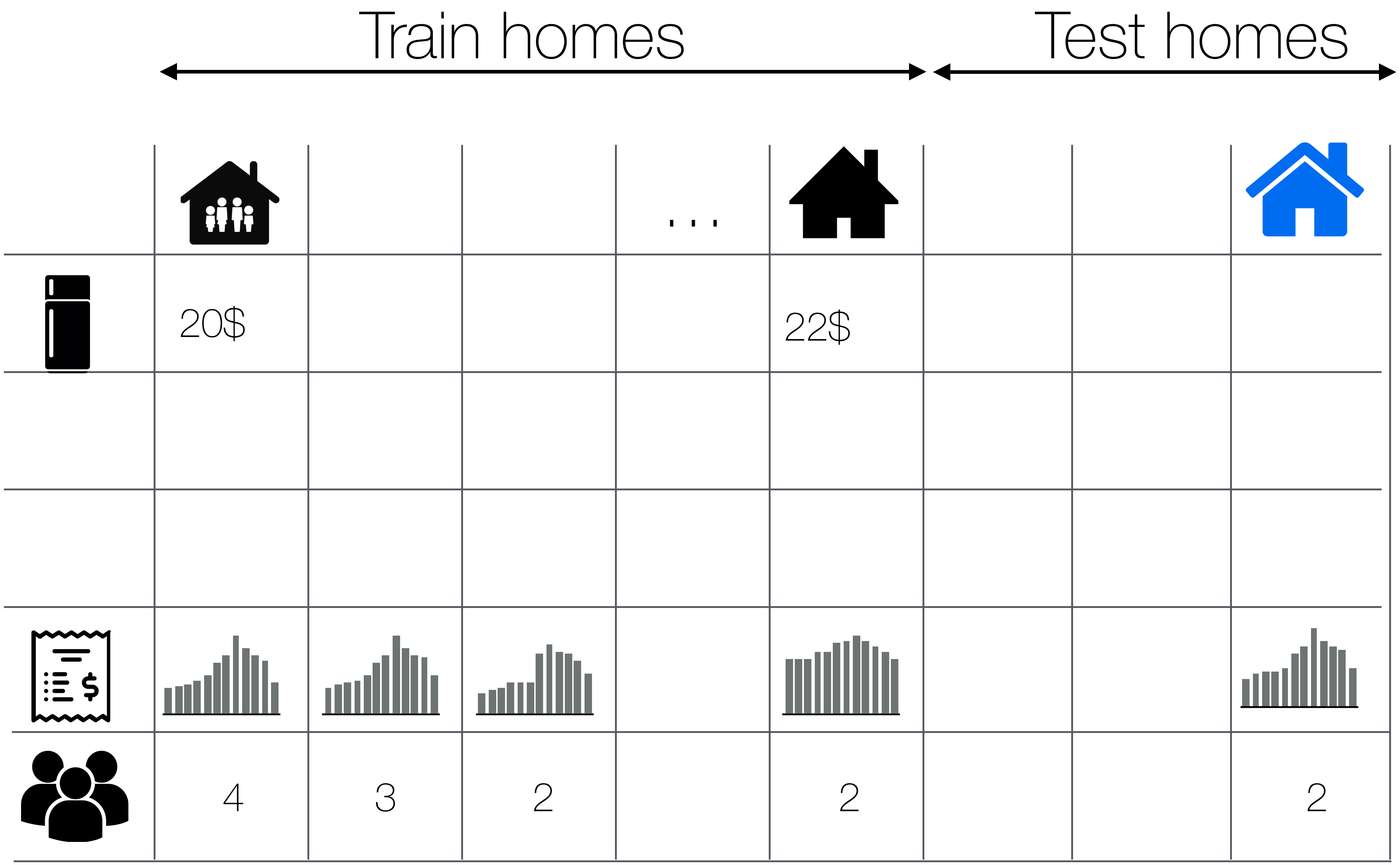
Gemello Overview



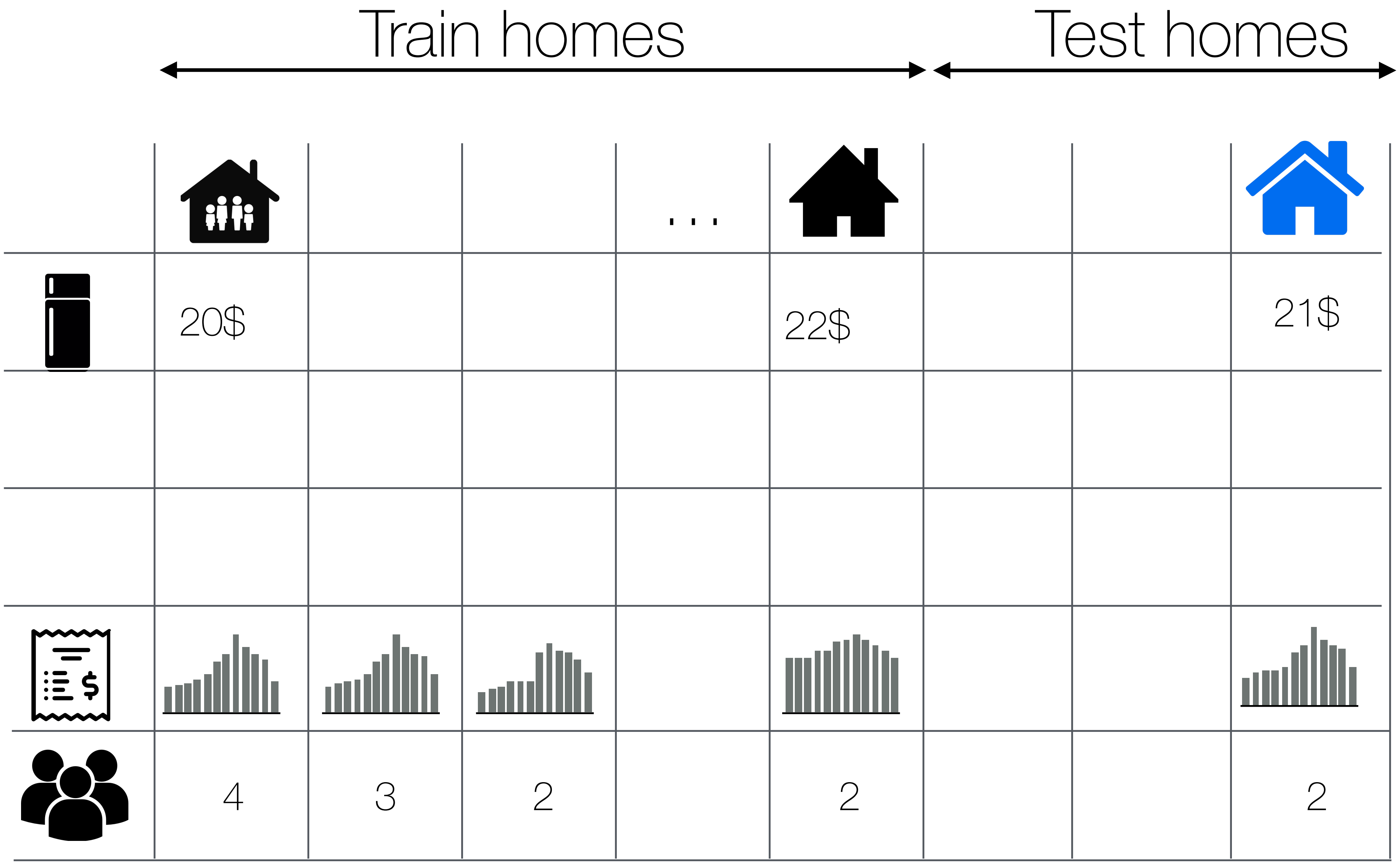
Gemello Overview



Gemello Overview



Gemello Overview



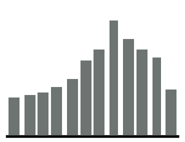
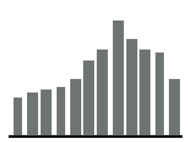
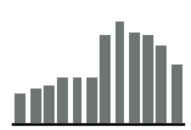
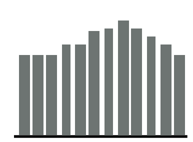
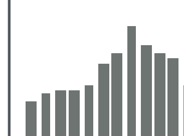
Gemello Overview

Train homes | Test homes

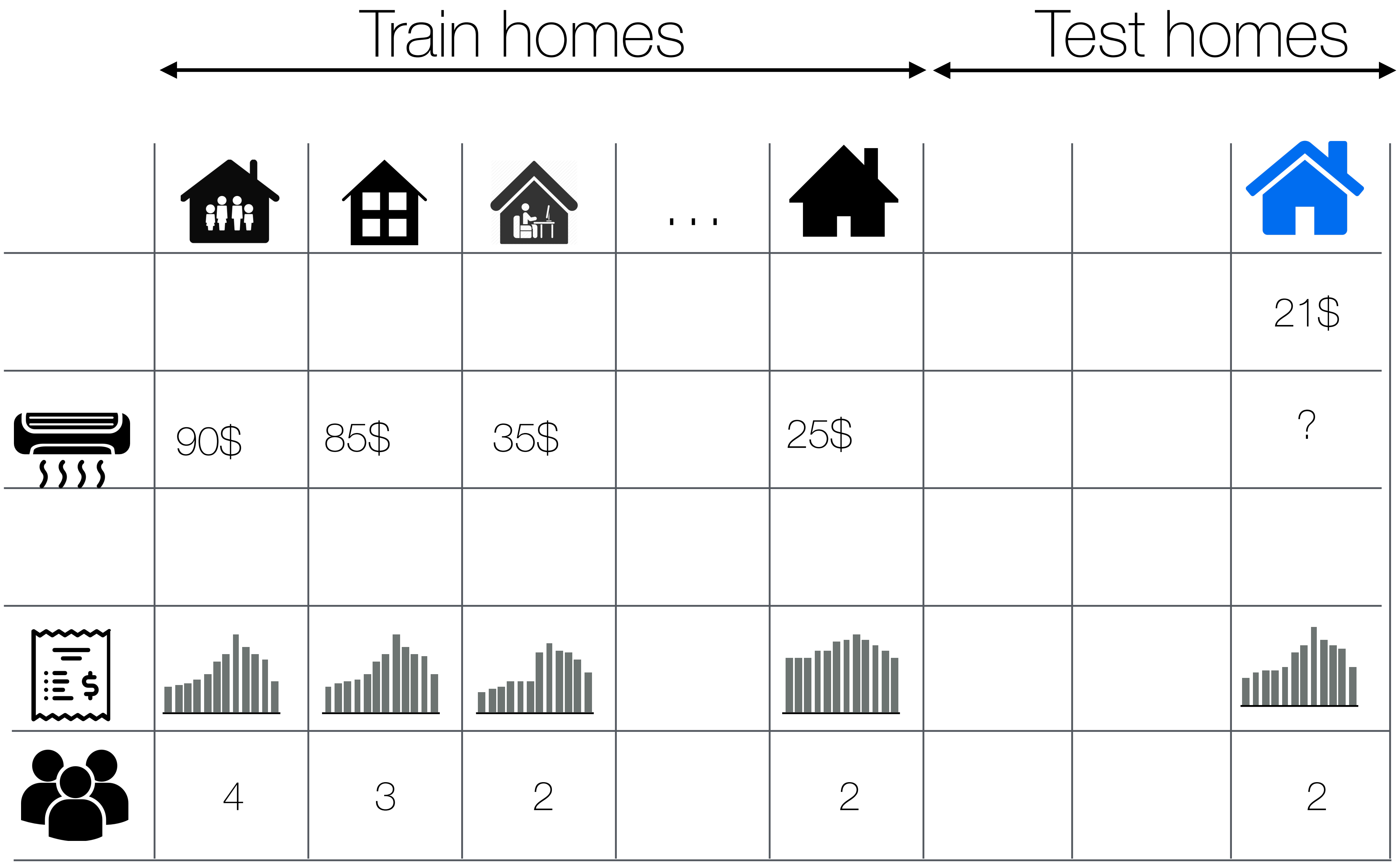
				...				
	20$	30$	10$		22$			21$
	90$	85$	35$		25$			?
	10$	15$	18$		20$			
	4	3	2		2			2

Gemello Overview

Train homes ⟷ Test homes

				. . .				
	20$	30$	10$		22$			21$
	90$	85$	35$		25$			?
	10$	15$	18$		20$			
								
	4	3	2		2			2

Gemello Overview



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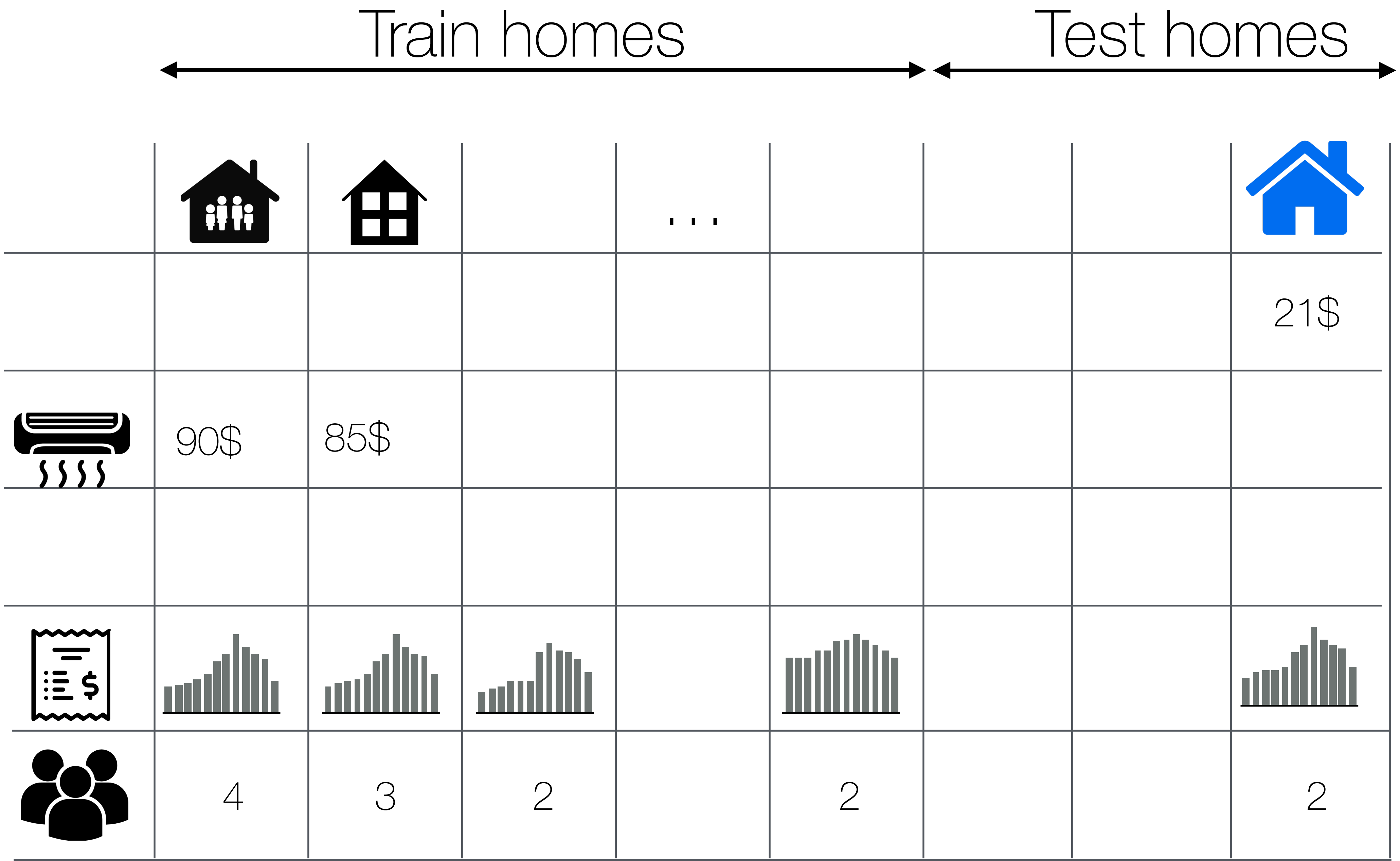

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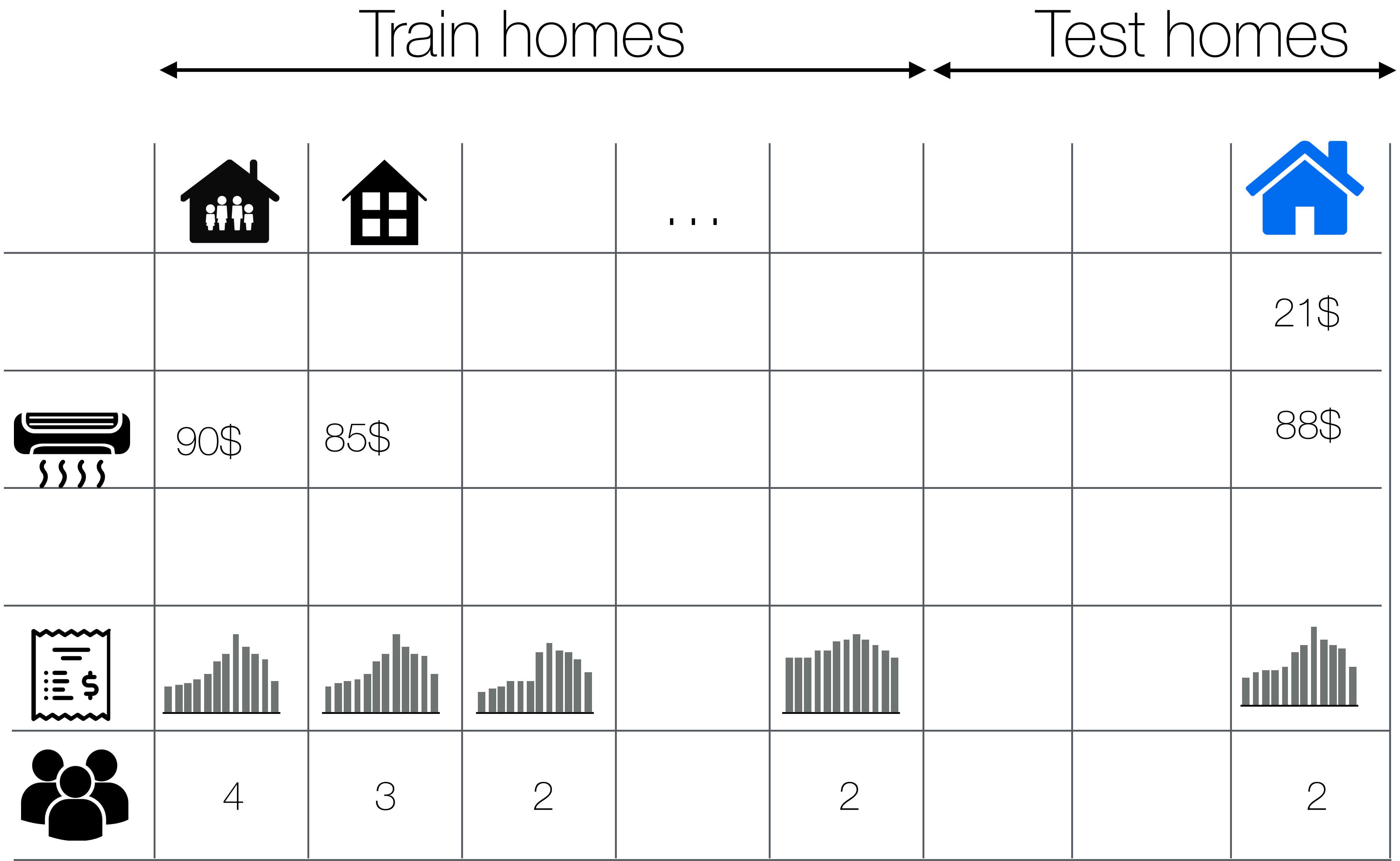


Gemello Overview

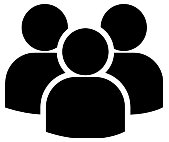
Train homes

Test homes

				. . .				
	20$	30$	10$		22$			21$
	90$	85$	35$		25$			88$
	10$	15$	18$		20$			15$
	4	3	2		2			2

Feature Set

Static features

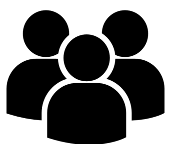


Home Area

Rooms

Feature Set

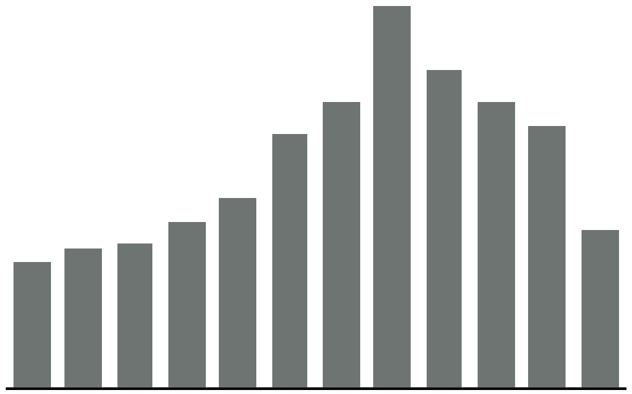
Static features



Home Area

Rooms

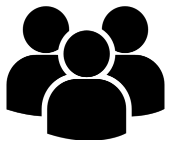
Raw monthly bills features



Month

Feature Set

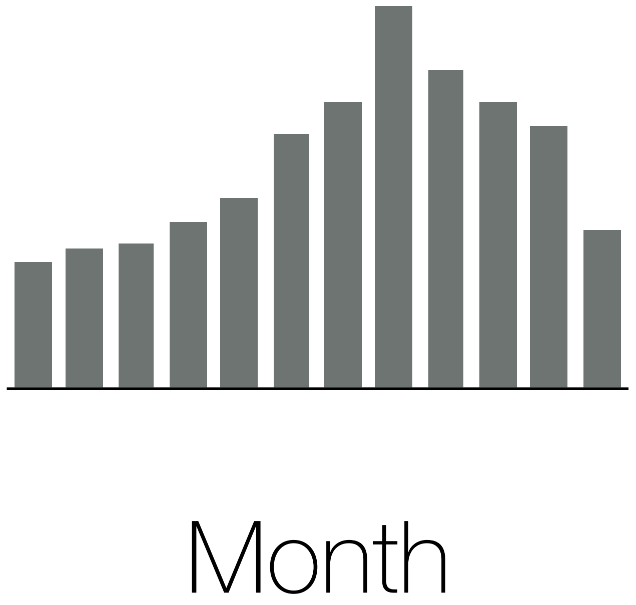
Static features



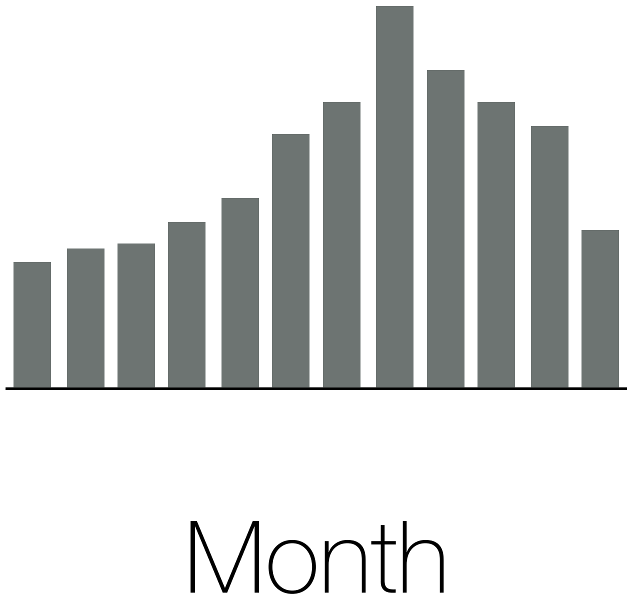
Home Area

Rooms

Raw monthly bills features

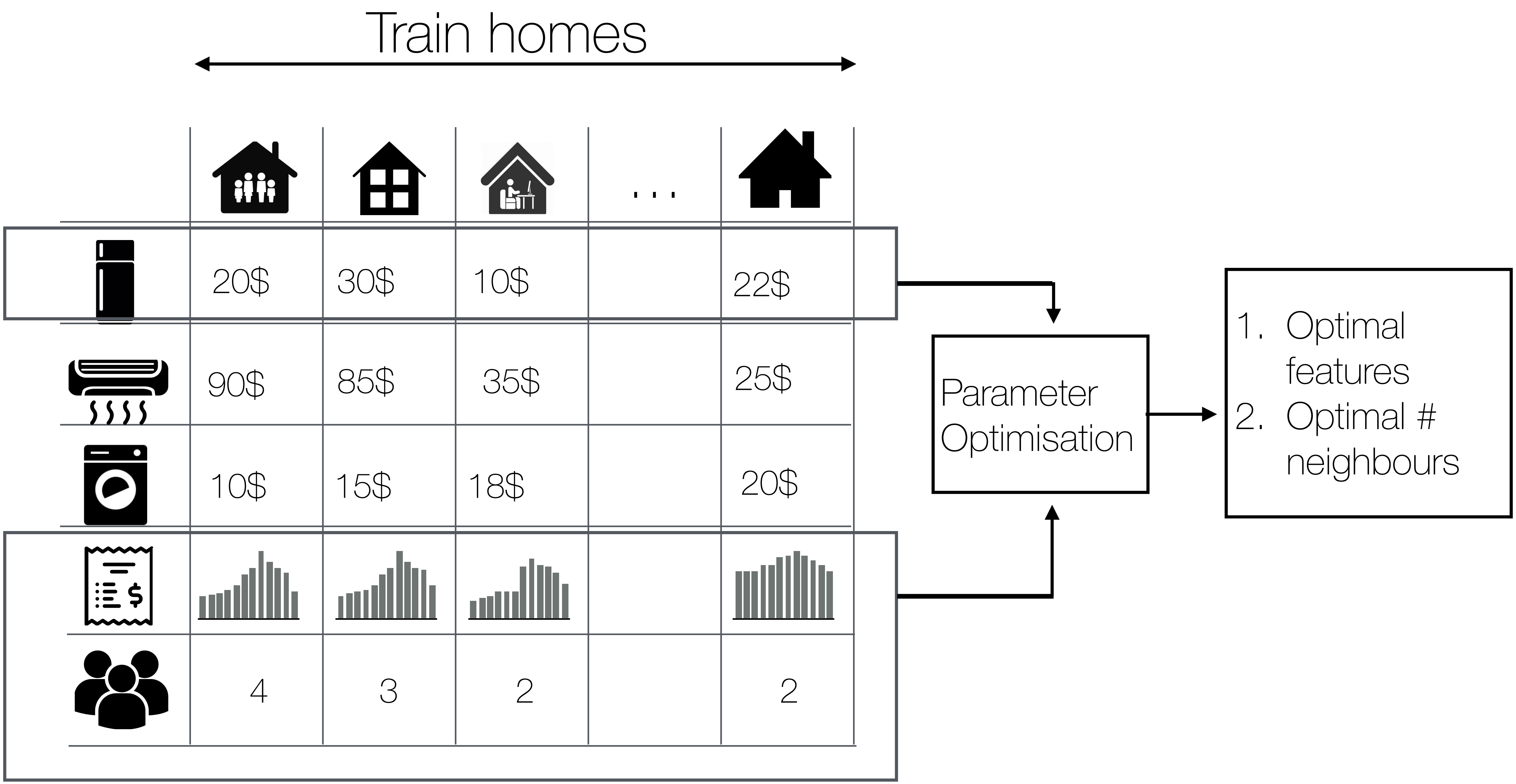


Derived monthly bills features



Mean, Max, Median, Range

Parameter Optimisation



Evaluation

Evaluation

- Dataport dataset

Evaluation

- Dataport dataset
    - 57 homes (Previous evaluations on <15 homes!)

Evaluation

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  - Austin, Texas region

Evaluation

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  - 2 state-of-the-art NILM approaches (15-minute data):

Evaluation

- Dataport dataset
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  - 12 months data in 2013
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    - Factorial Hidden Markov Model (FHMM) [AISTATS 2012]

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    - Latent Bayesian Melding (LBM) [NIPS 2015]

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- Baselines
  - 2 state-of-the-art NILM approaches (15-minute data):
    - Factorial Hidden Markov Model (FHMM) [AISTATS 2012]
    - Latent Bayesian Melding (LBM) [NIPS 2015]
- Leave-one-out cross validation

Evaluation Metric

For each appliance

Evaluation Metric

For each appliance

- Absolute error = |Predicted energy - Actual Energy|

Evaluation Metric

For each appliance

- Absolute error = |Predicted energy - Actual Energy|
- Normalised absolute error = Absolute error/Actual energy

Evaluation Metric

For each appliance

- Absolute error = |Predicted energy - Actual Energy|
- Normalised absolute error = Absolute error/Actual energy
- Normalised percentage error = Normalised absolute error X 100

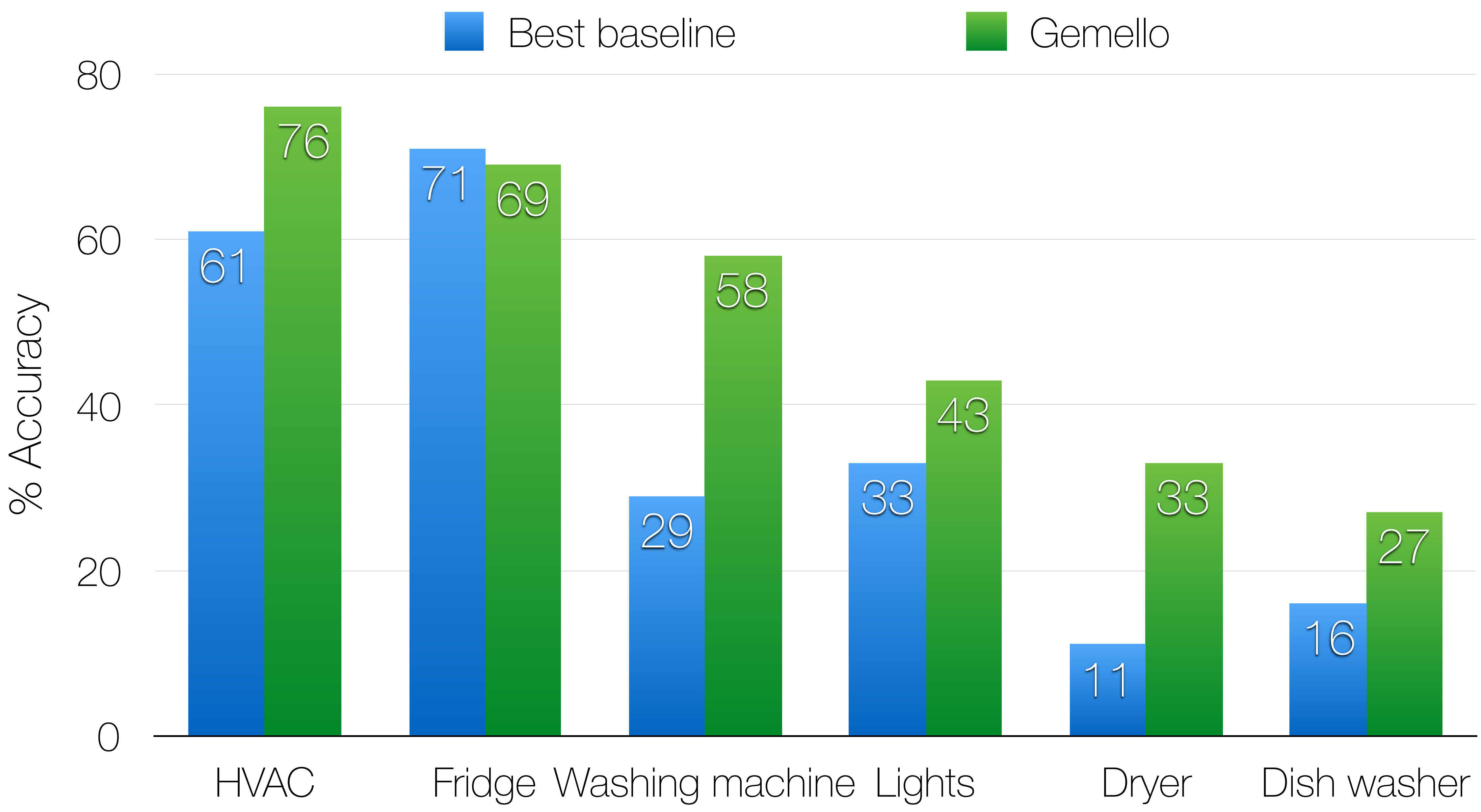
Evaluation Metric

For each appliance

- Absolute error = |Predicted energy - Actual Energy|
- Normalised absolute error = Absolute error/Actual energy
- Normalised percentage error = Normalised absolute error X 100
- Percentage accuracy = 100 - Normalised percentage error

Results

Gemello comparable or better than best NILM baselines



Analysis

Analysis

- Gemello leverages data from other homes whereas NILM only uses data from the individual home.

Analysis

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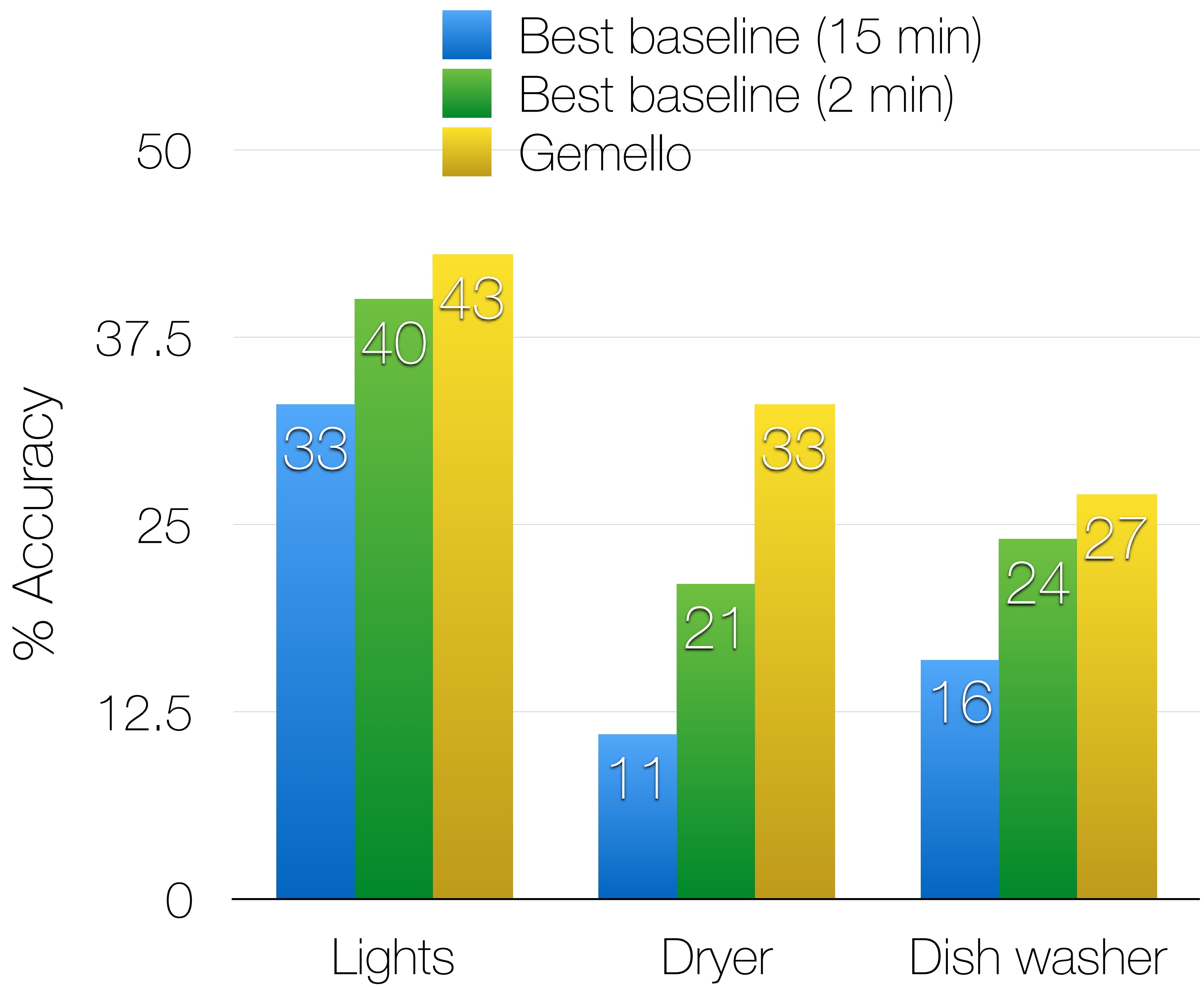
- NILM methods fare poorly for complex loads- washing machine
- KNN is easier to solve than source separation

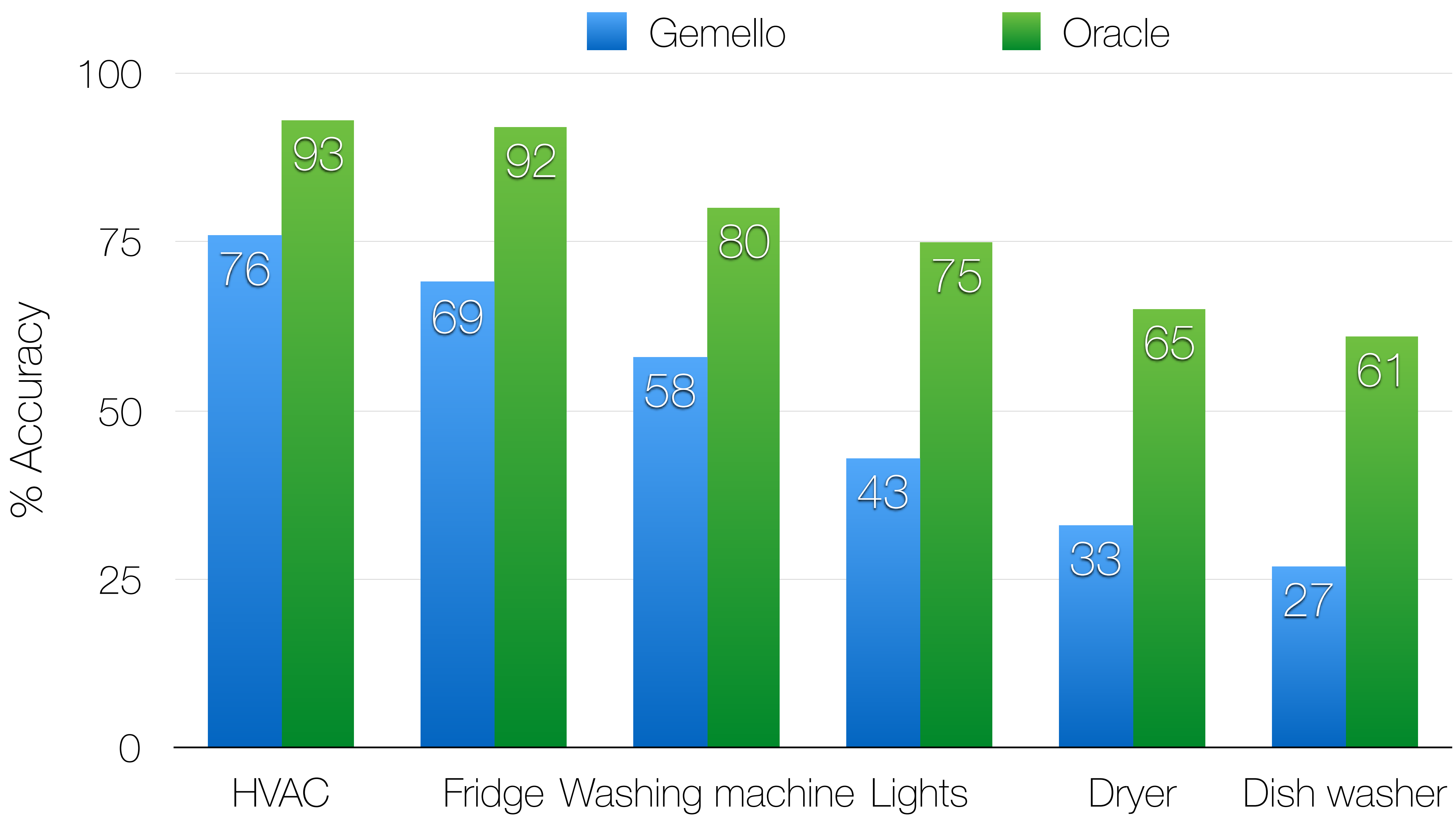
Results

Gemello better even when NILM uses higher freq. data



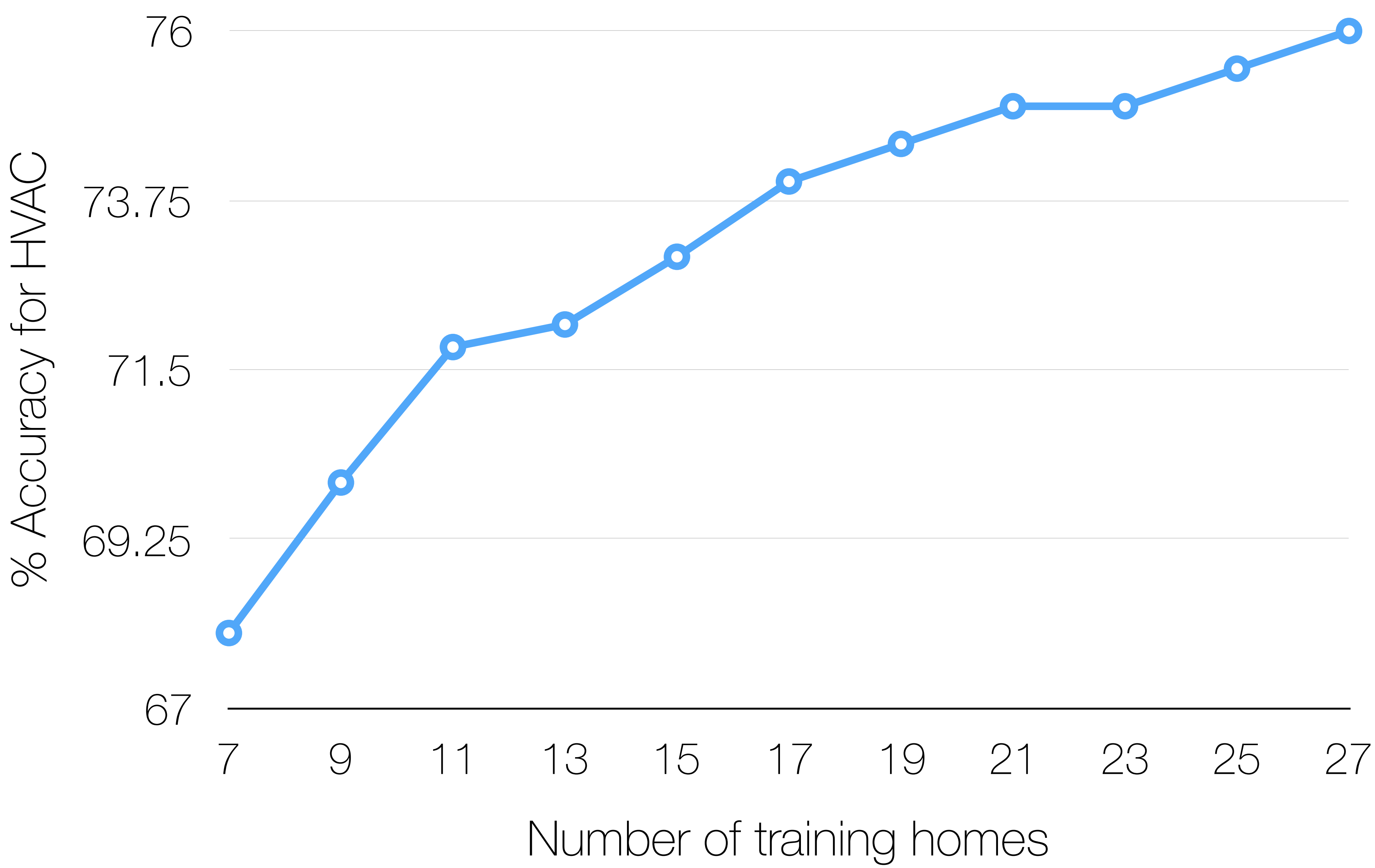
Results

Good scope for improvement



Results

Good accuracy even for small #training homes



Gemello Shortcomings

				. . .				
	20$	30$	10$		22$			
	90$	85$	35$		25$			
	10$	15$	18$		20$			
	4	3	2		2	4	3	2

Gemello Shortcomings

				...				
	20$	30$			22$			
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Gemello Shortcomings

1. Gemello does not work well with “missing” features

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		3	2		2		3	2

Gemello Shortcomings

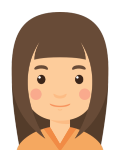
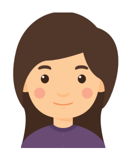
1. Gemello does not work well with “missing” features
2. All features must be manually specified
3. Gemello only uses data from “neighbouring” homes

				. . .				
	20$	30$			22$			
	90$		35$		25$			
	10$	15$	18$		20$			
		3	2		2		3	2

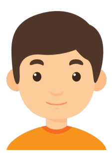
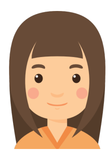
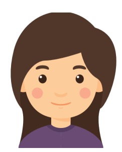
Outline

- Scalable Energy Breakdown
  - Gemello [KDD 2016]
  - **Matrix Factorisation [AAAI 2017]**
- Making NILM better
  - Comparable [Buildsys 2015]
  - Actionable [e-Energy 2014]

Matrix Factorisation

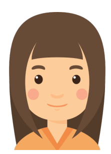
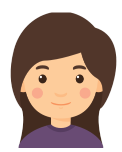
			
Toy Story	—	3	—
Dark Knight	—	—	1
Swades	3	4	—
Mr. Bean	5	—	3
Pursuit of…	5	3	5

Matrix Factorisation

			
Toy Story	—	3	—
Dark Knight	—	—	1
Swades	3	4	—
Mr. Bean	5	—	3
Pursuit of…	5	3	5

Matrix Factorisation

Latent factor
for movies

			
Toy Story	—	3	—
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→

	Action	Length
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Matrix Factorisation

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→

Latent factor for movies

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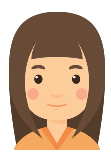
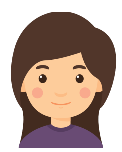
Latent factor for users

Action	.6	.7	.6
Length	.4	.3	.4

Matrix Factorisation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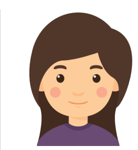
Latent factor for users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Matrix Factorisation

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		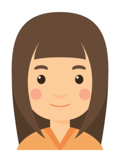	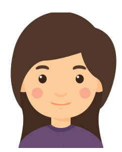
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		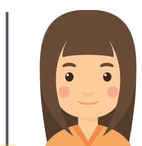	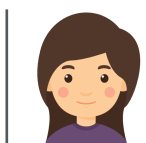
Action	.6	.7	.6
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		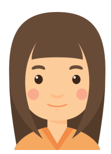	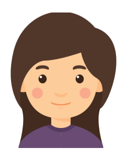
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			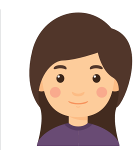
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Matrix Factorisation

Toy Story	2	3	—
Dark Knight	—	—	1
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Latent factor for movies

	Action	Length
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Matrix Factorisation Approach

				. . .				
	20$	30$			22$			
	90$		35$		25$			
	10$	15$	18$		20$			
		3	2		2		3	2

Matrix Factorisation Approach

Data must be homogenous

				...				
	20$	30$			22$			
	90$		35$		25$			
	10$	15$	18$		20$			

Matrix Factorisation Approach

Matrix structure

				...				
Jan	20$	30$	10$		22$			
...	...	...	...		...			
Dec	25$	35$	15$		25$			
Jan	180$	—	250$		310$	200$	250$	210$
...	...	...	...		...	...	...	...
Dec	350$	380$	280$		480$	250$	—	350$

Matrix Factorisation Approach

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Matrix Factorisation Approach

Non-negative matrix factorisation

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Latent factor
for months

	K1	K2
Jan	10	20
…	…	…
Dec	30	40
Jan	130	120
…	…	…
Dec	120	110

…

Matrix Factorisation Approach

Non-negative matrix factorisation

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Latent factor for months

	K1	K2
Jan	10	20
…	…	…
Dec	30	40
Jan	130	120
…	…	…
Dec	120	110

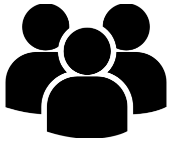
…

Latent factor for homes

		…	
K1	1	…	2
K2	2	…	3

Matrix Factorisation Approach

Static features guide factorisation



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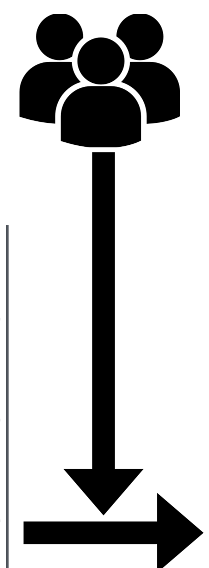

		K1	K2
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…		…	…
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…		…	…
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…

		…	
K1	1	…	2
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Evaluation

Evaluation

- Dataport dataset

Evaluation

- Dataport dataset
    - 516 homes

Evaluation

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  - 516 homes
  - Austin, Texas region

Evaluation

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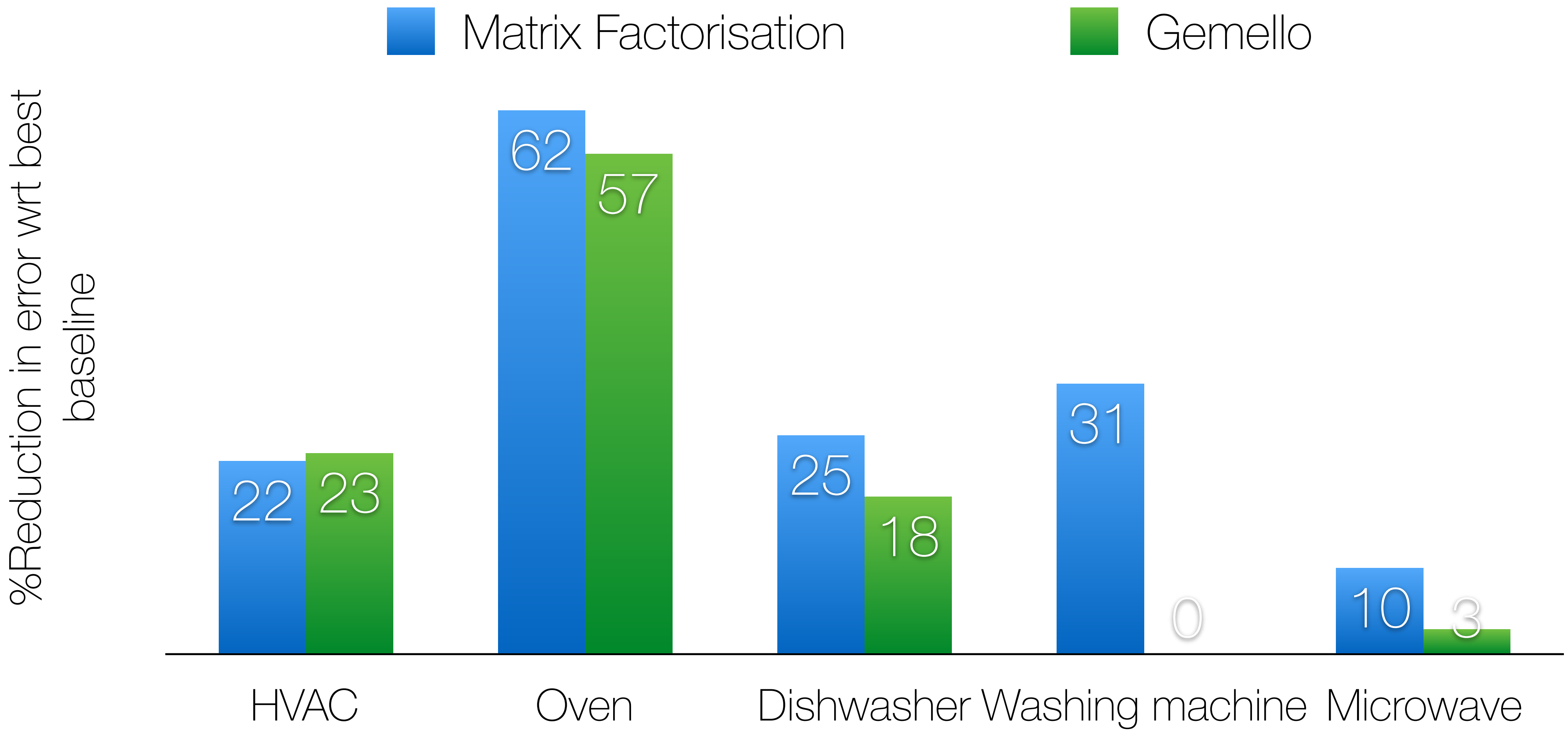
- Leave-one-out cross validation

Evaluation Metric

- GT fraction (Appliance) = Appliance energy/Aggregate energy
- Pred fraction (Appliance) = Appliance energy/Aggregate energy
- RMSE (Appliance) = RMSE(GT fraction, Pred fraction)

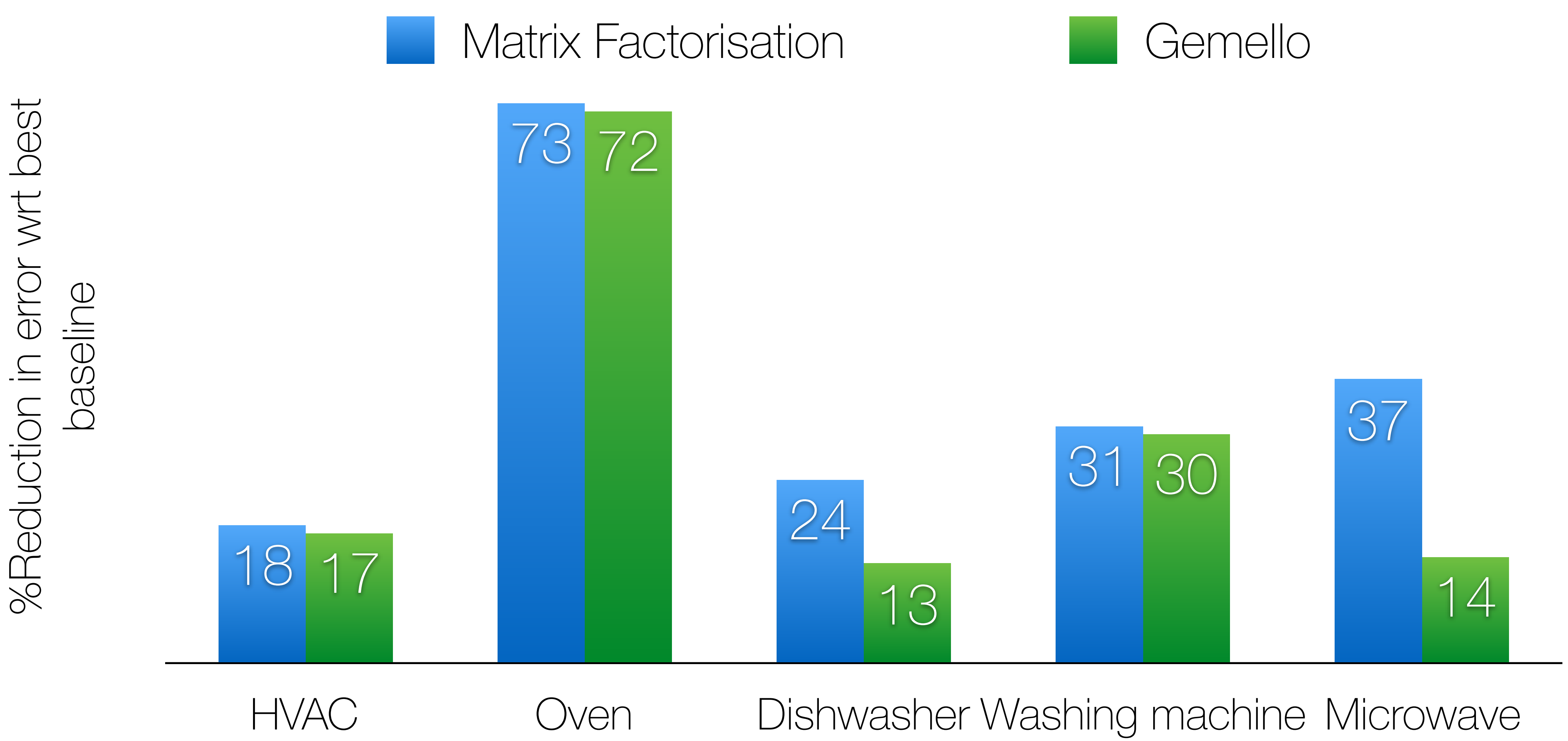
Results

Matrix factorisation better than all baselines



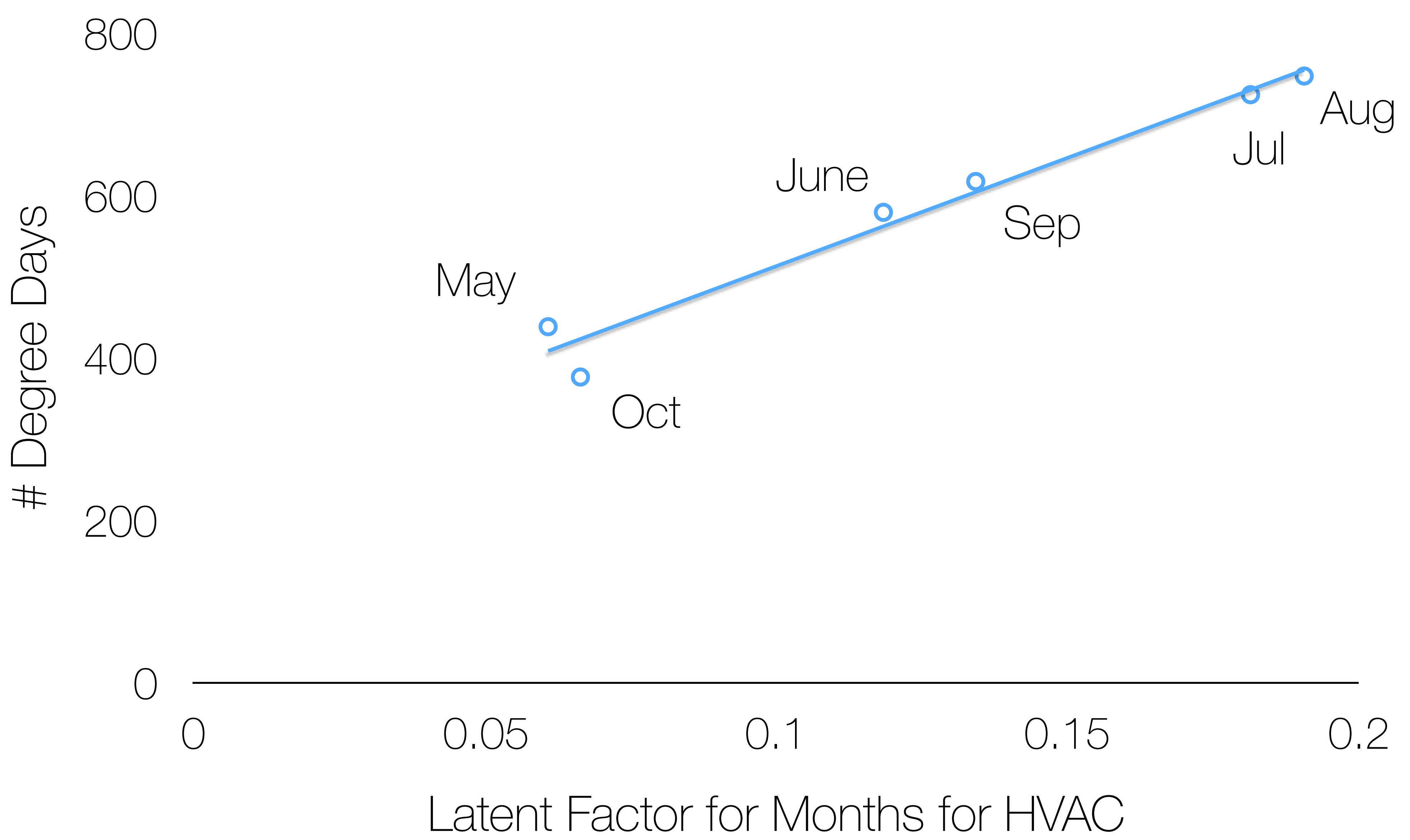
Results

Matrix factorisation better than all baselines on 105 homes with all features



Analysis

Matrix factorisation able to learn latent factors having physical significance



Limitations and Future Work

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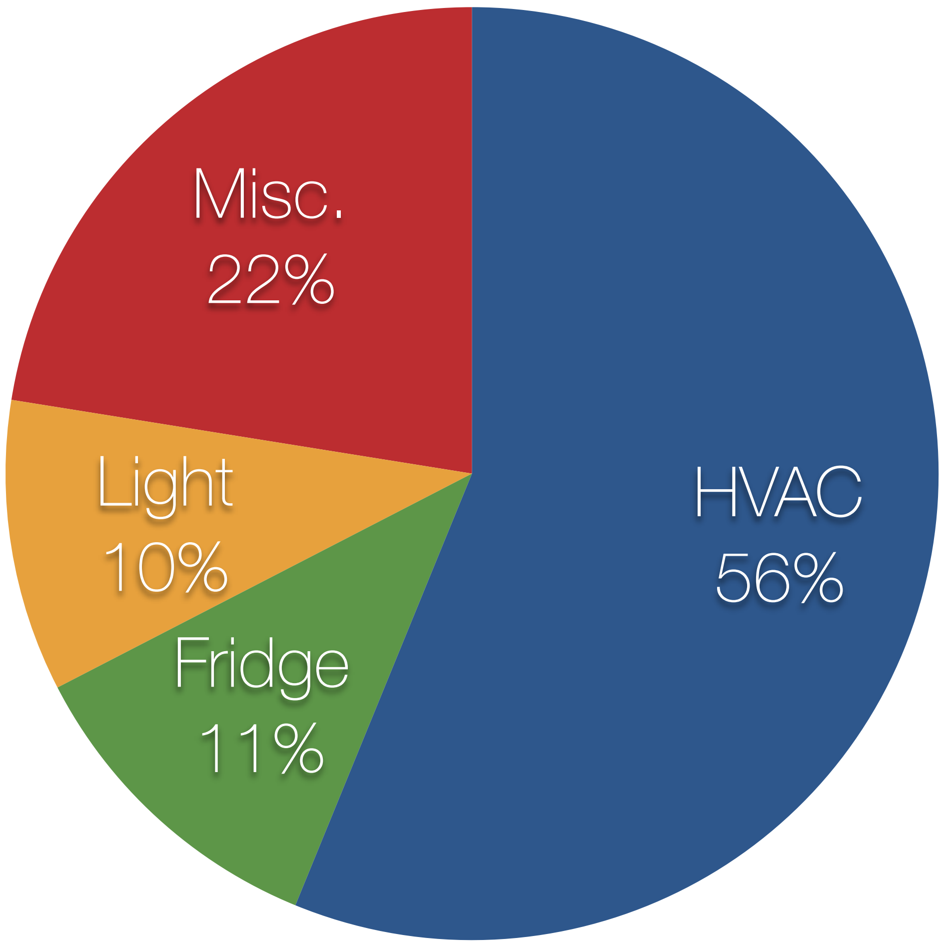
Outline

- Scalable Energy Breakdown
    - Gemello [KDD 2016]
    - Matrix Factorisation [AAAI 2017]
- **Making NILM better (Is it the end of the road for NILM?)**
    - **Actionable [Buildsys 2015]**
    - Comparable [e-Energy 2014]

NILM Beyond Energy Breakdown

General NILM



NILM Beyond Energy Breakdown

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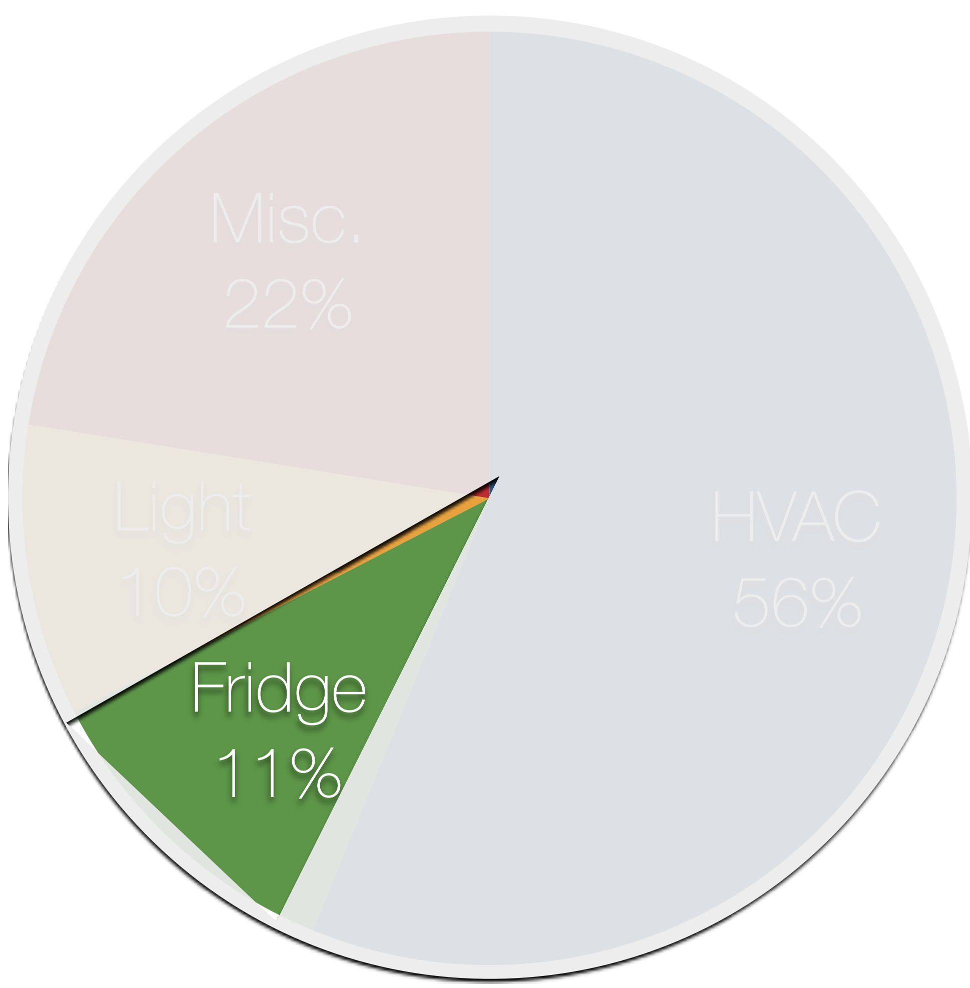
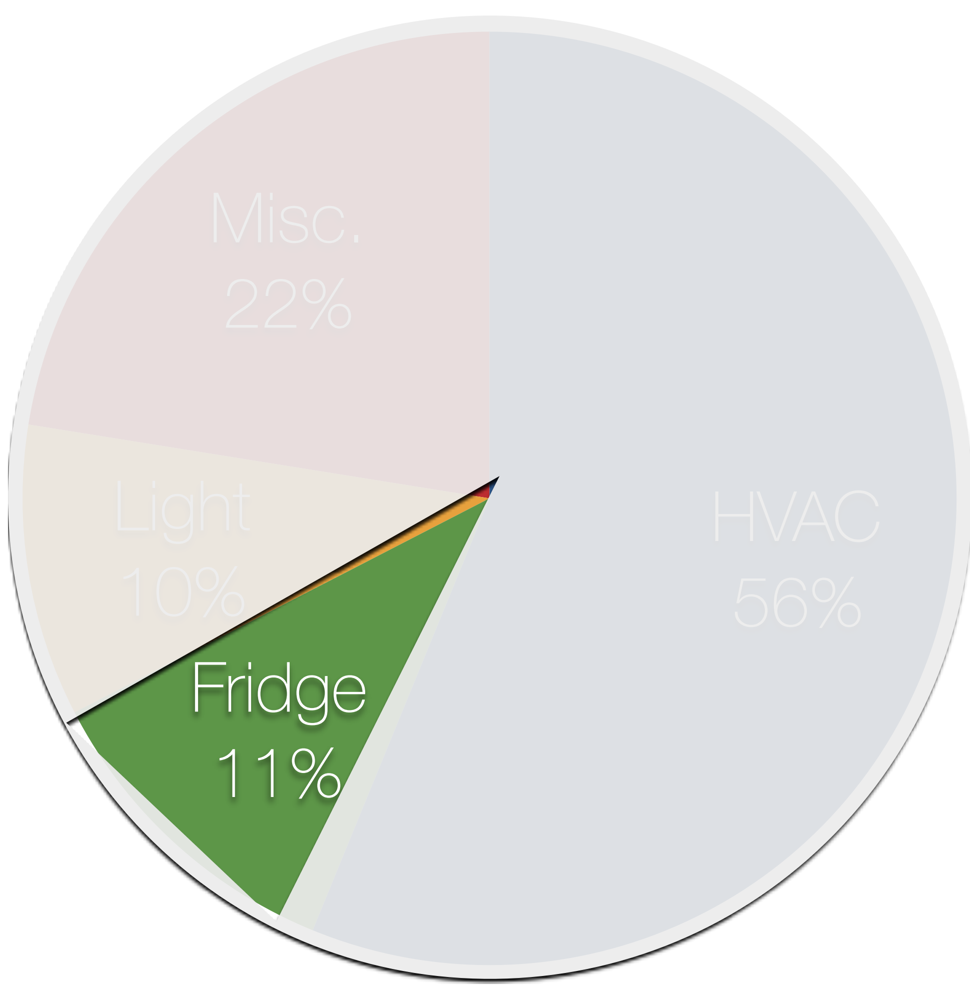


NILM Beyond Energy Breakdown

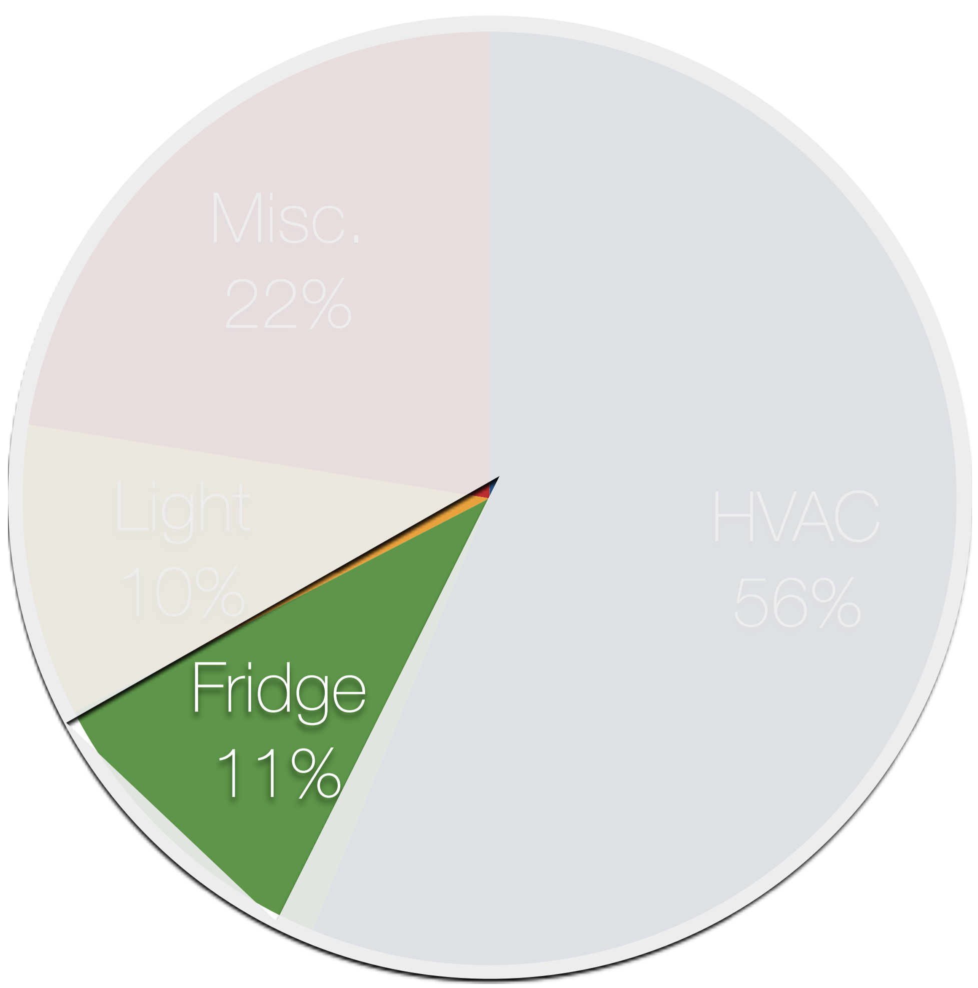
General NILM

Actionable NILM

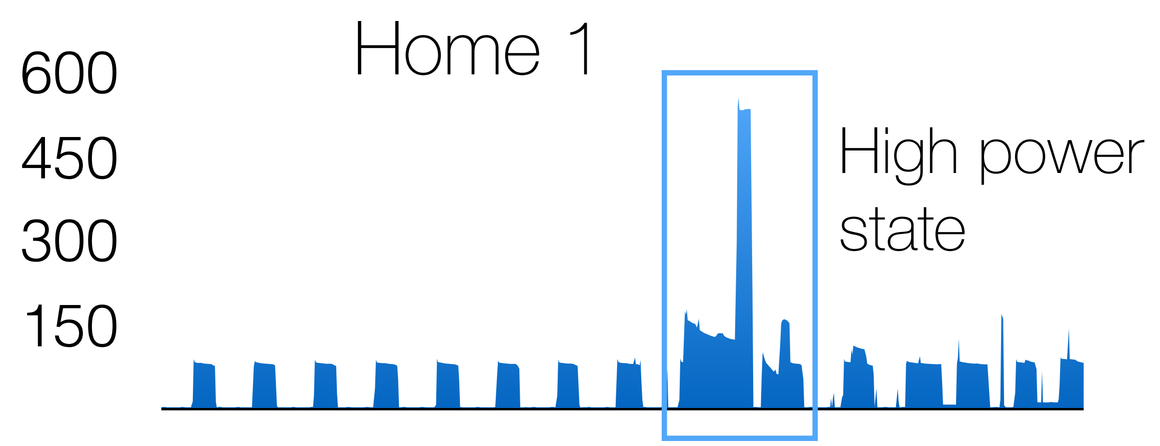


NILM Beyond Energy Breakdown

General NILM



Actionable NILM



NILM Beyond Energy Breakdown

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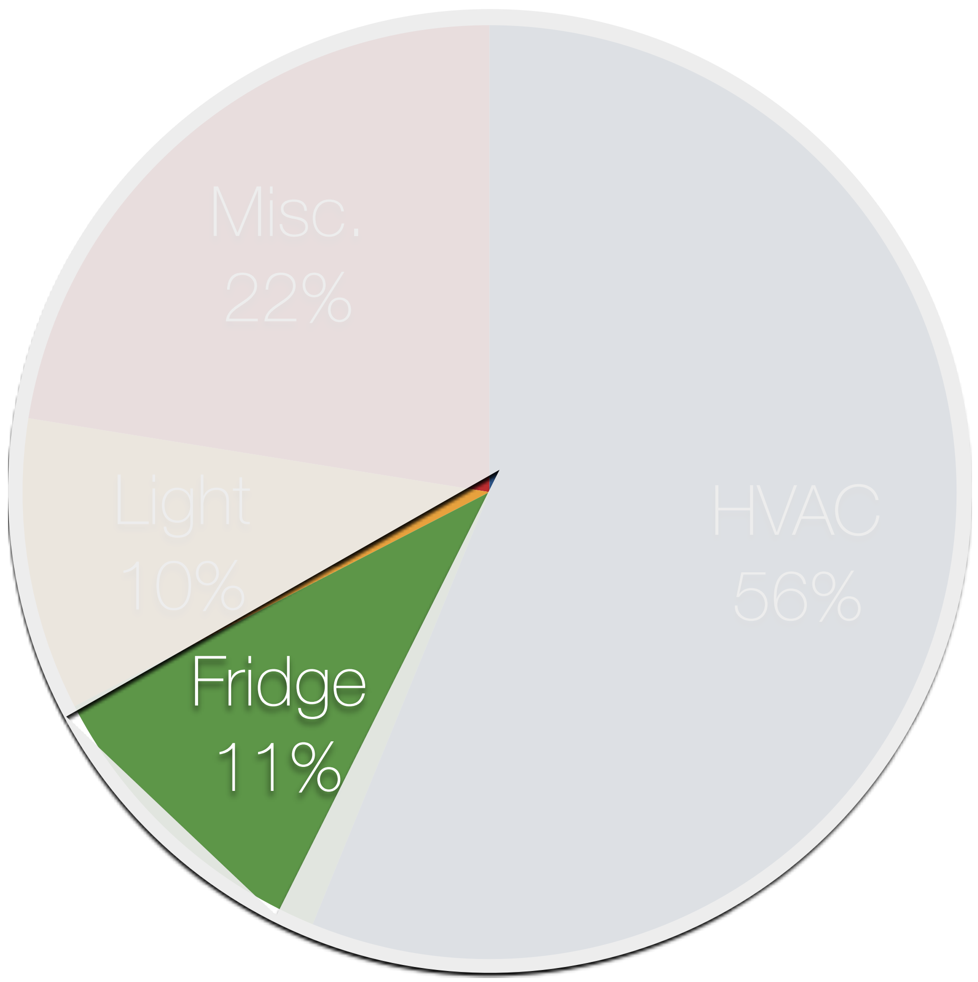

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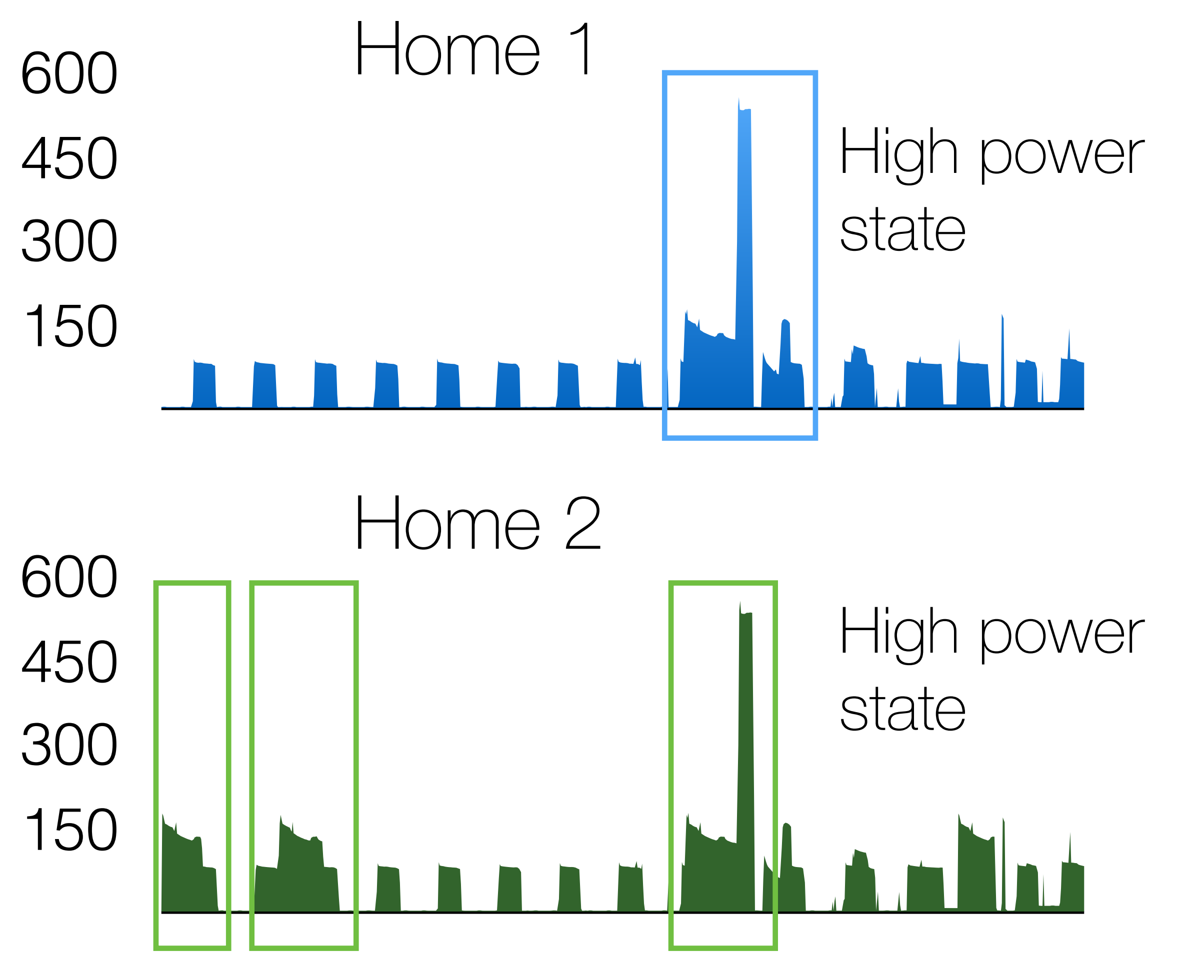

NILM Beyond Energy Breakdown

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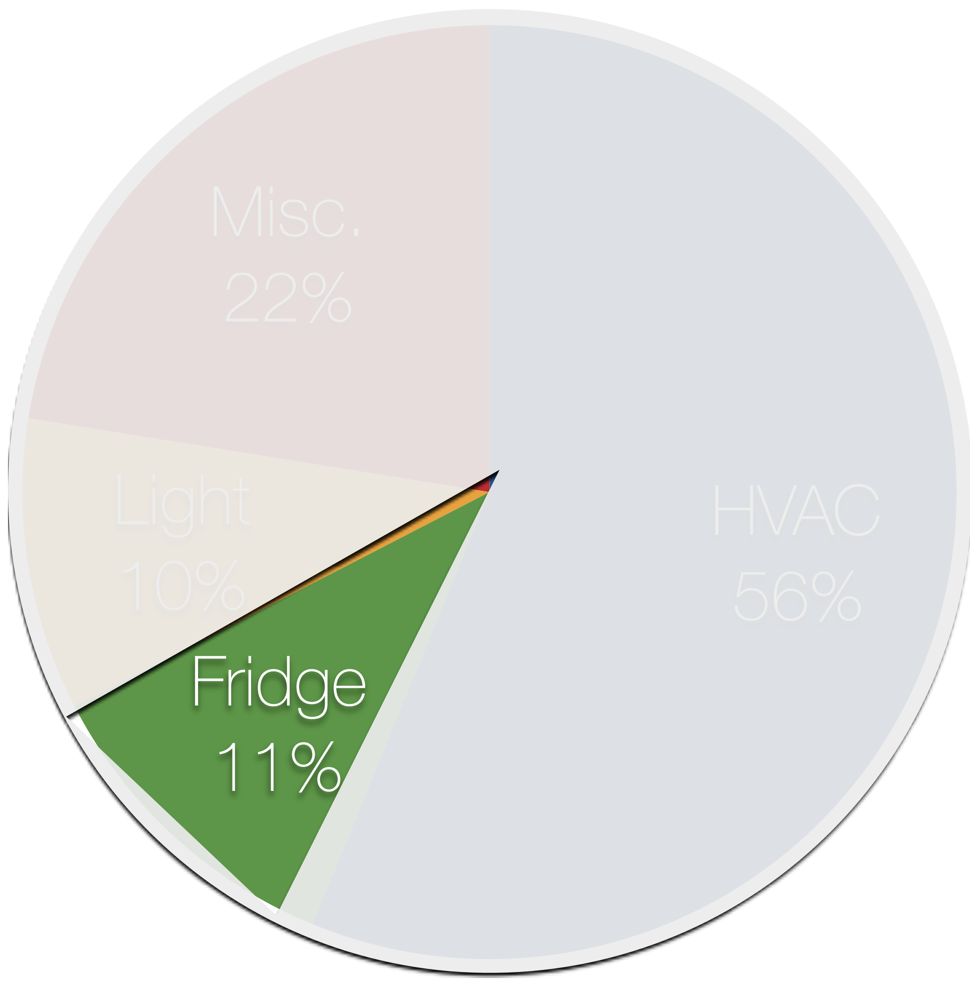
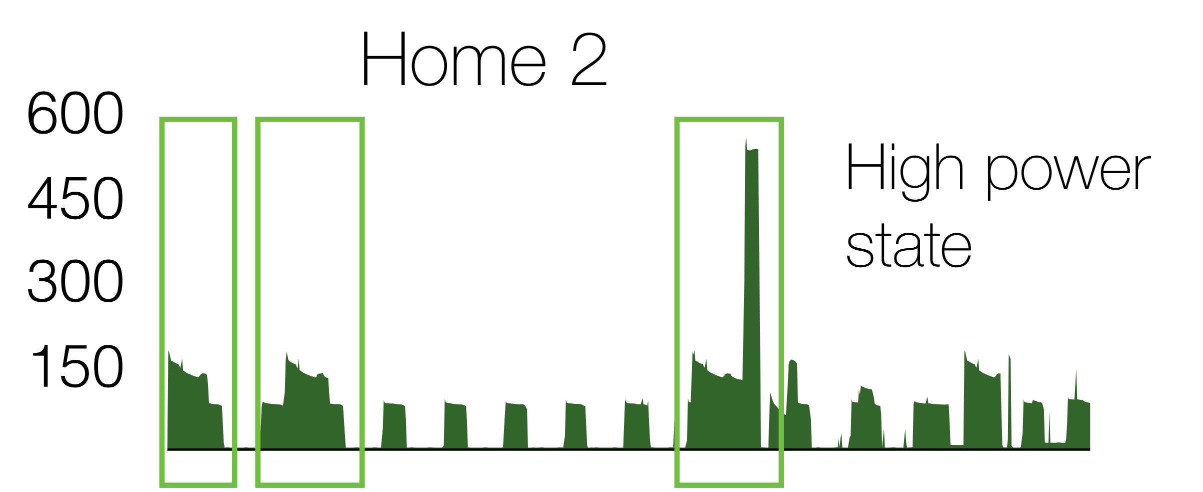


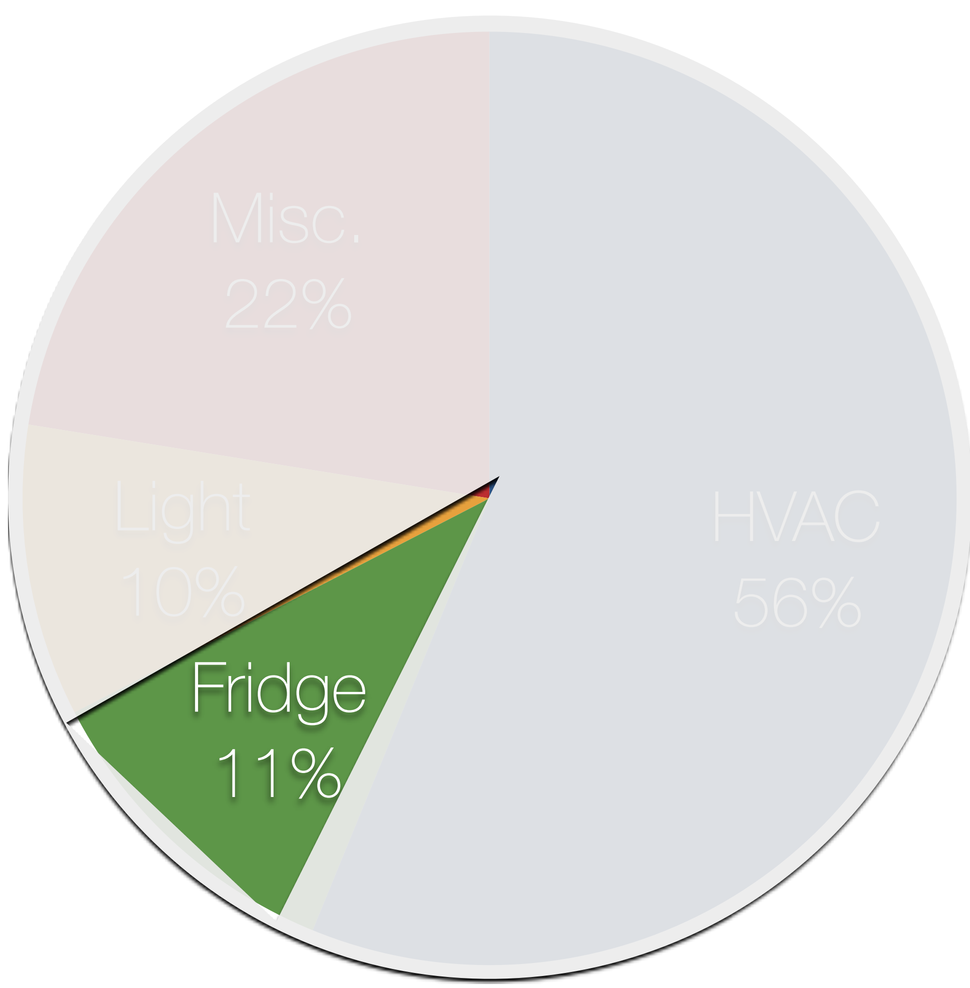
Actionable NILM



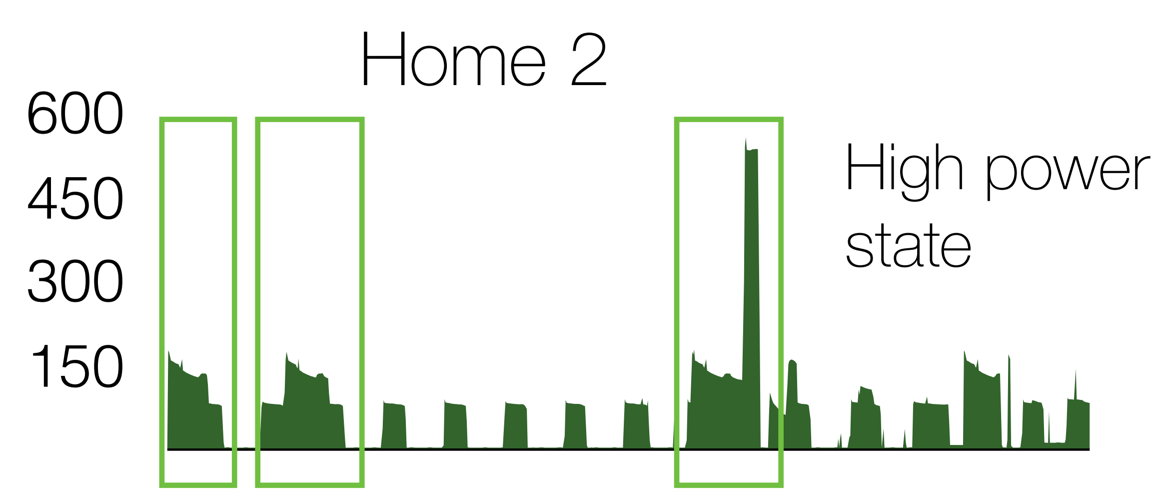
NILM Beyond Energy Breakdown

General NILM

Actionable NILM



Your fridge **defrosts excessively** wasting **30%** energy



Approach Overview- How to Give Feedback

Specific features of trace to infer **why** energy usage is high

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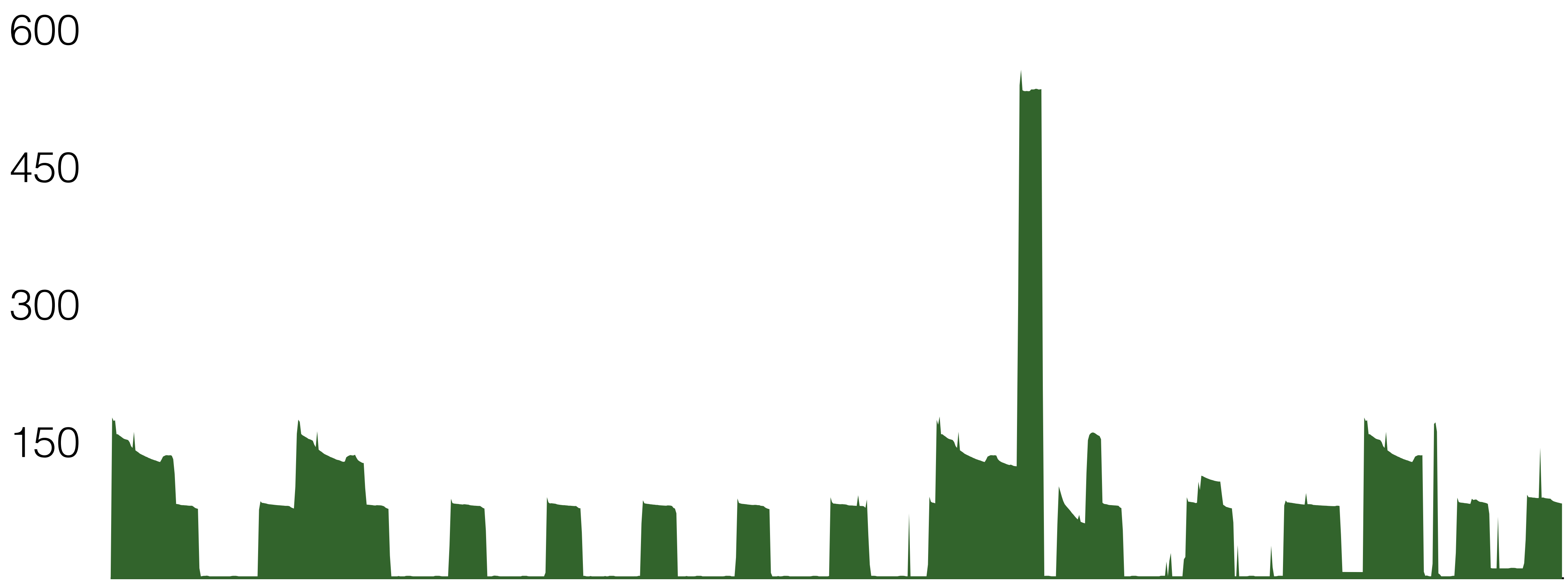

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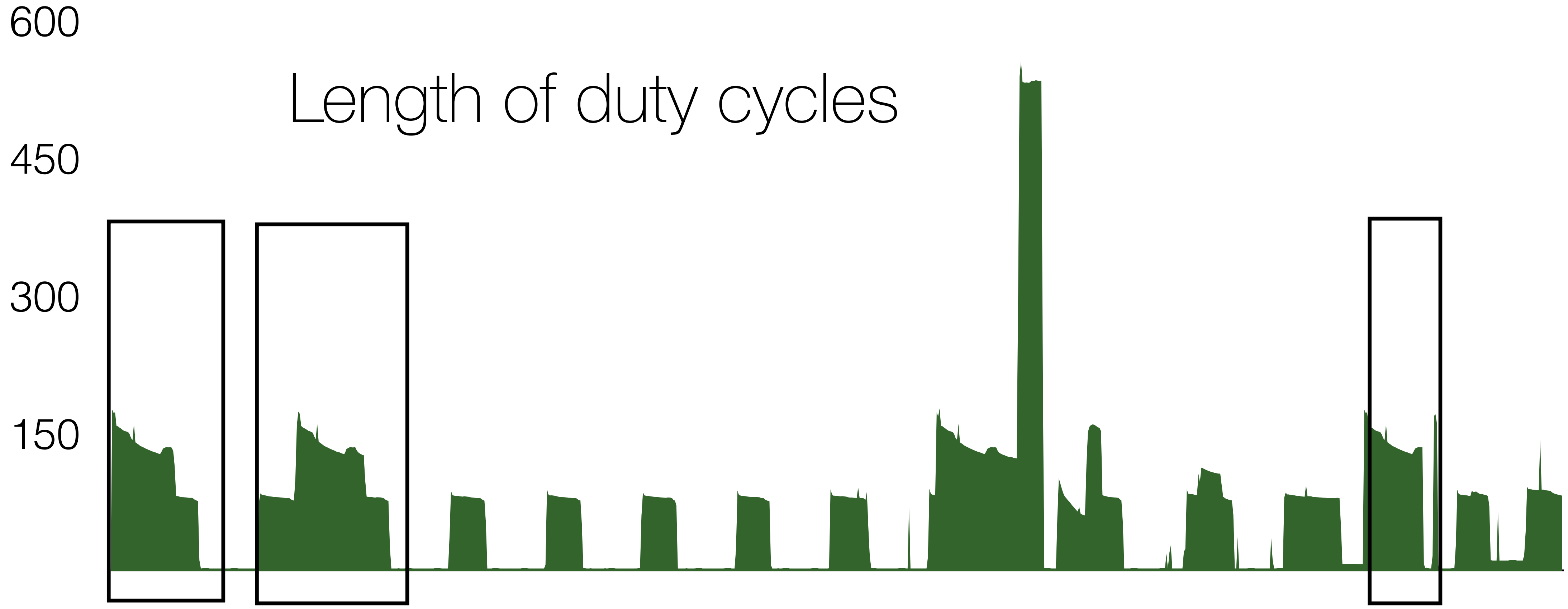

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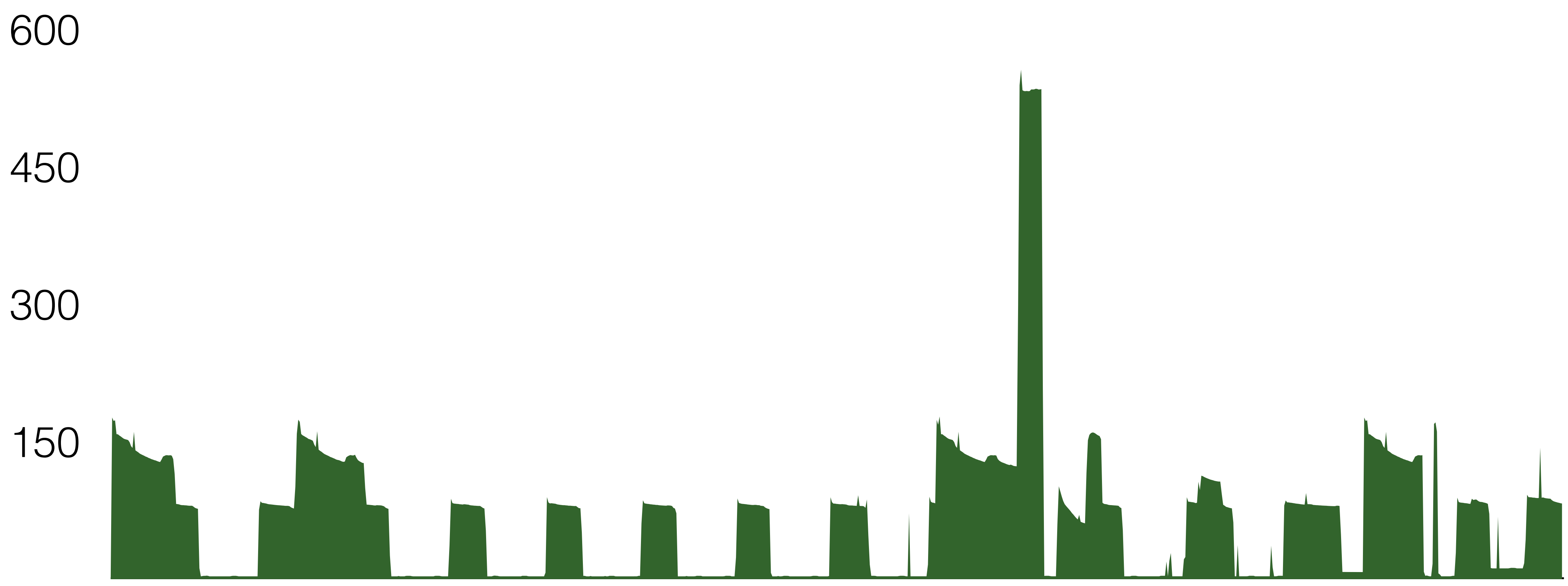

Approach Overview- How to Give Feedback

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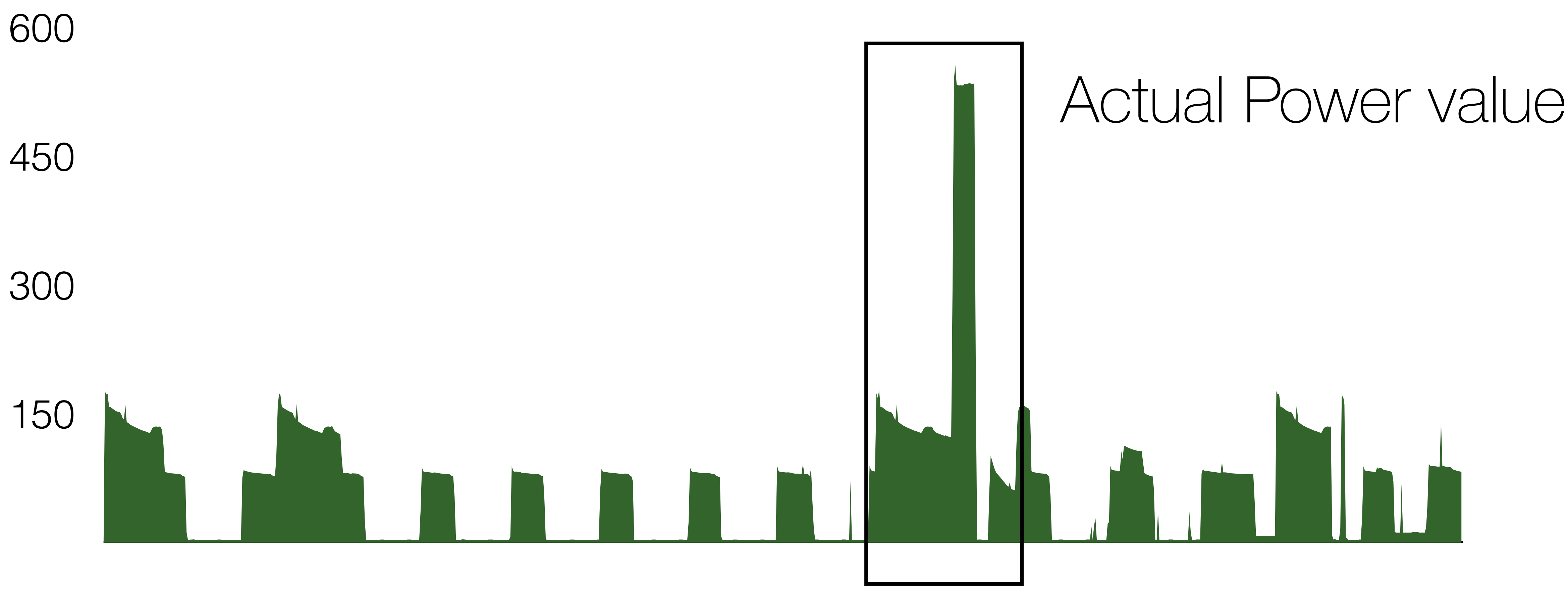
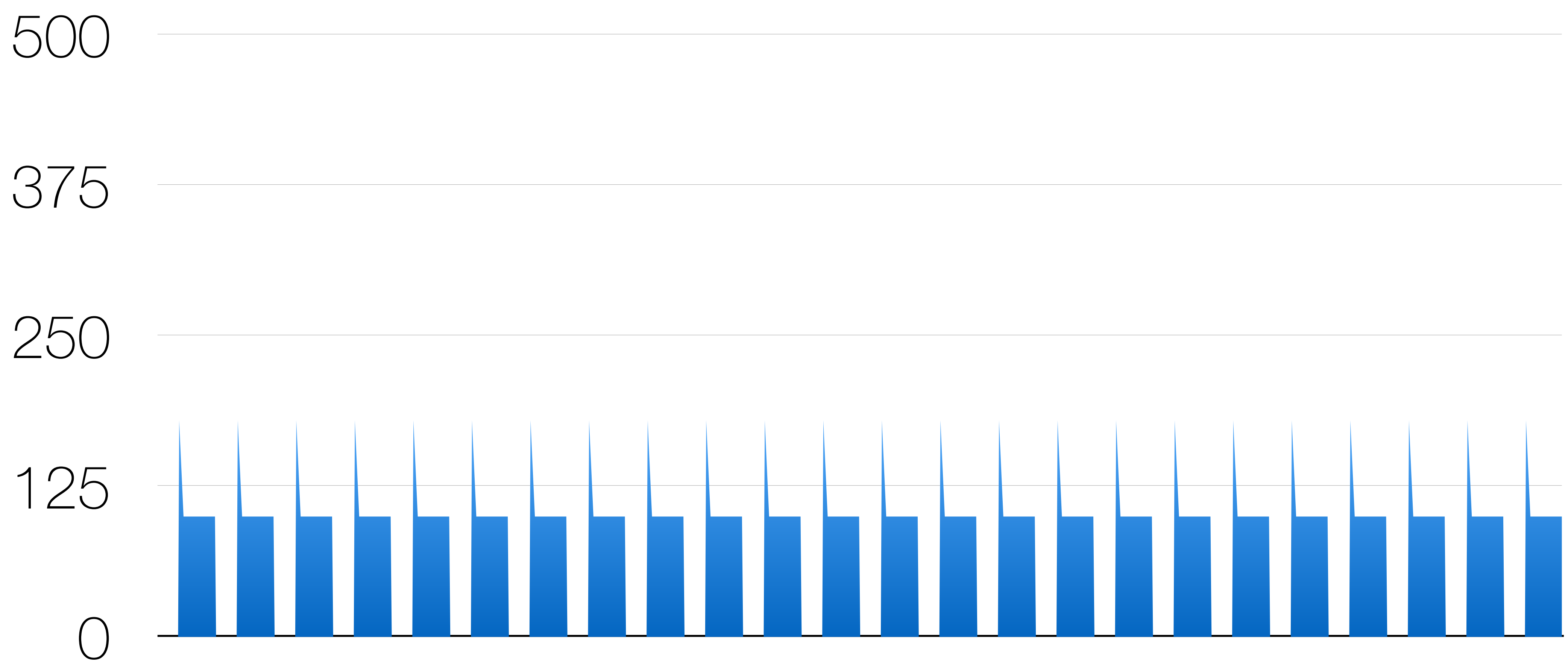


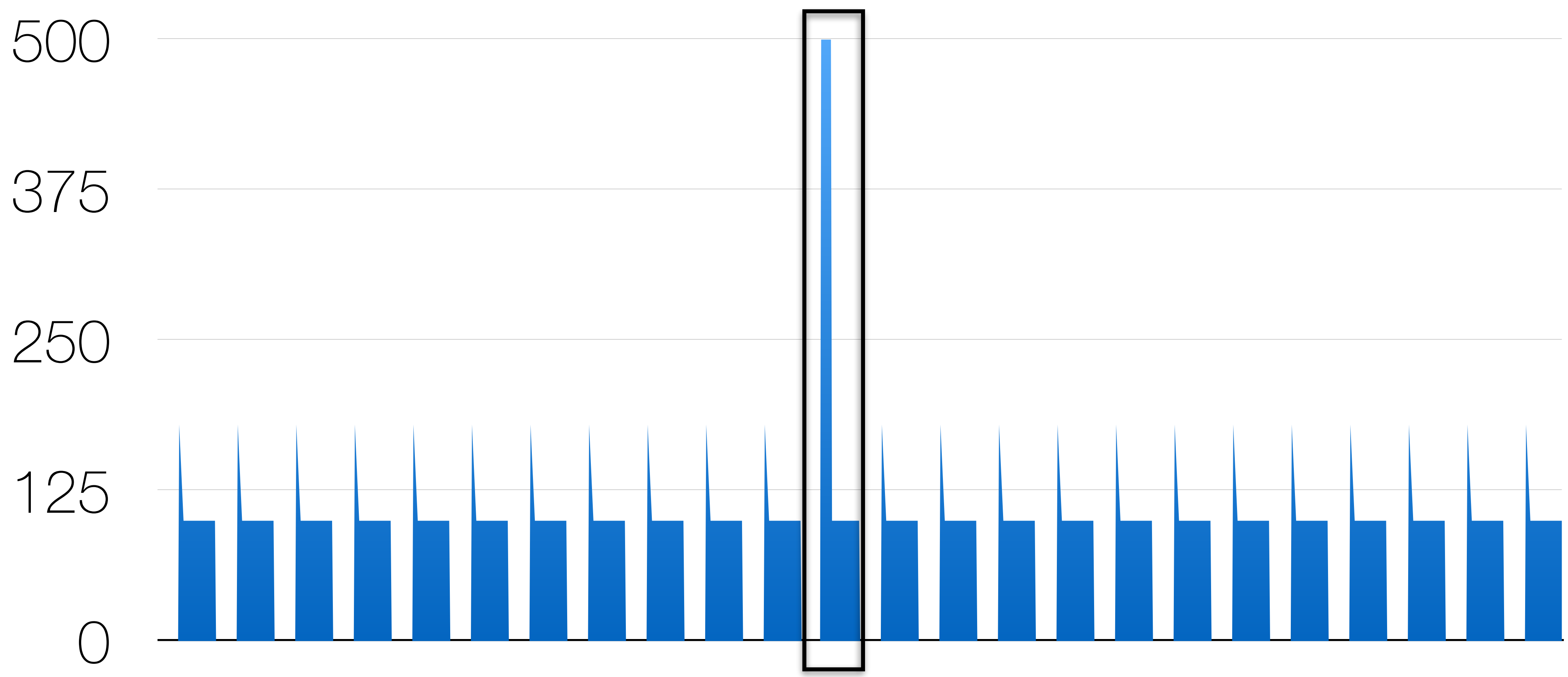
Fridge Model

Fridge is a duty cycle based appliance; compressor turns ON and OFF periodically



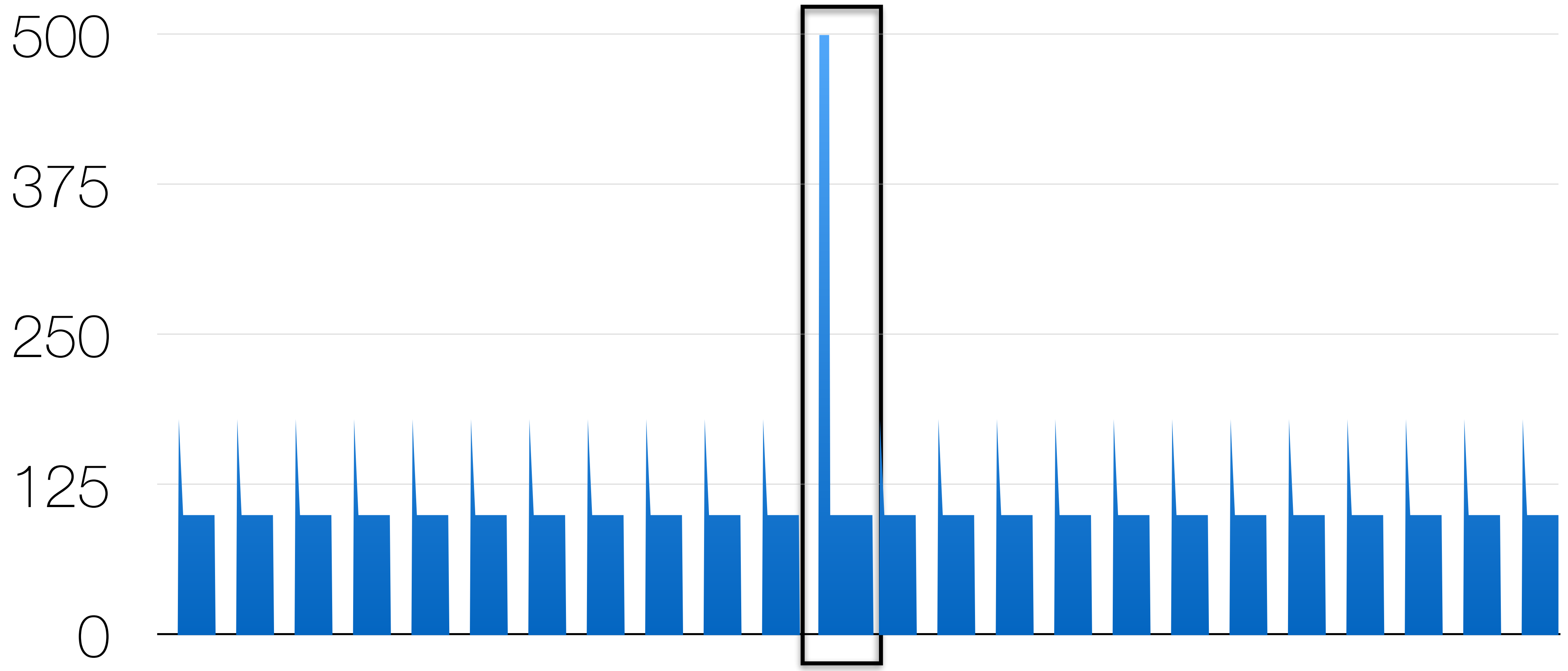
Fridge Model

Defrost cycles occur periodically consuming high power



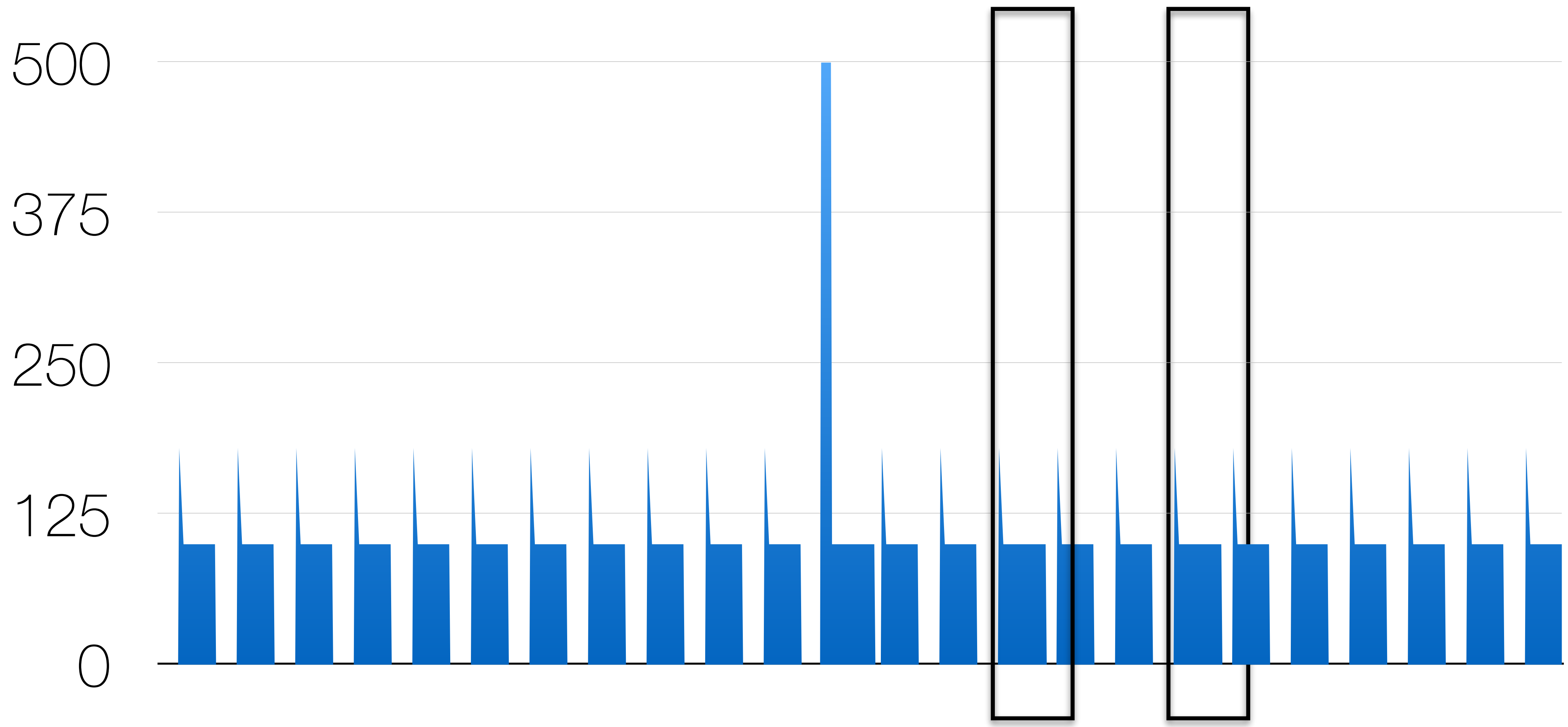
Fridge Model

Defrost introduces heat increasing ON duration of next cycles



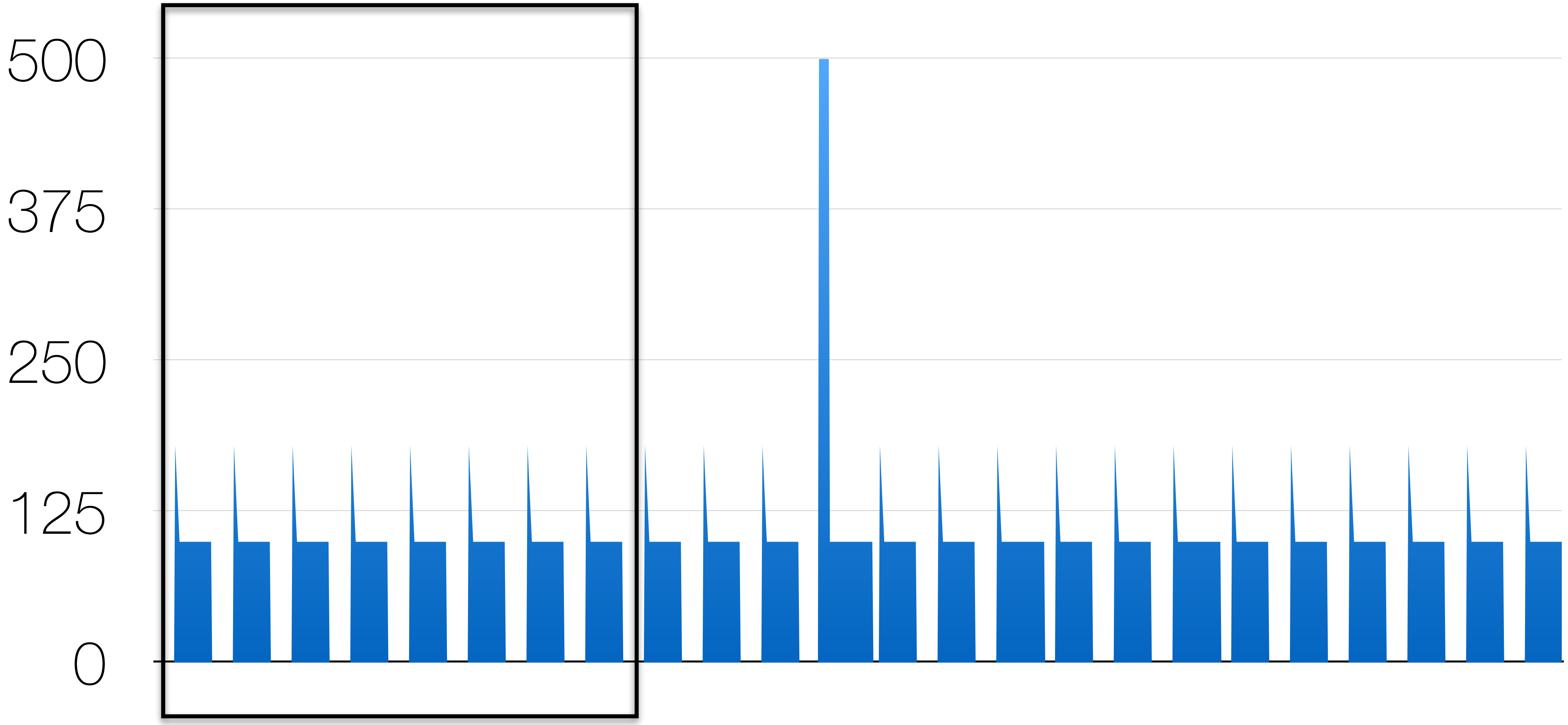
Fridge Model

Fridge usage increases compressor ON durations (and reduce compressor OFF durations)



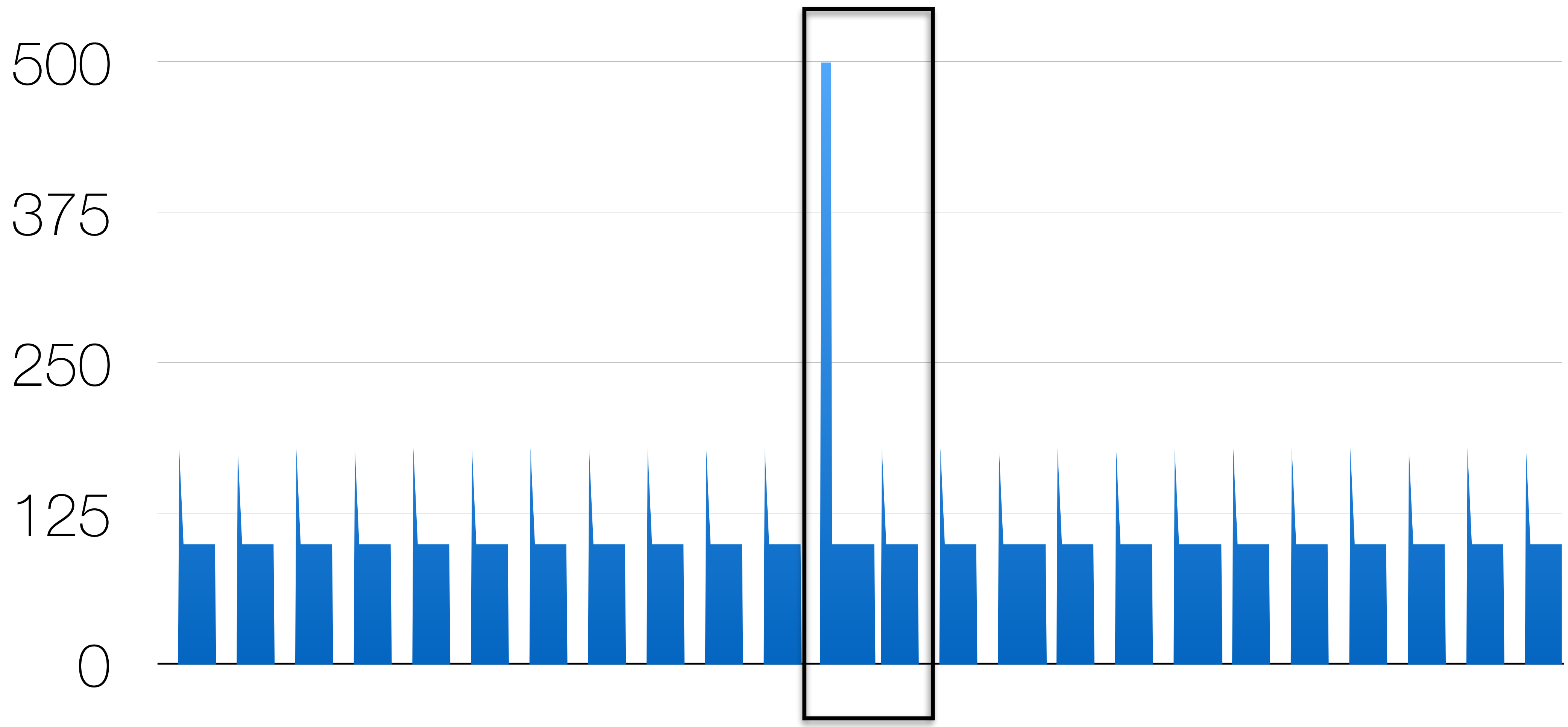
Fridge Model

1. **Baseline duty %** = Median duty % in the night



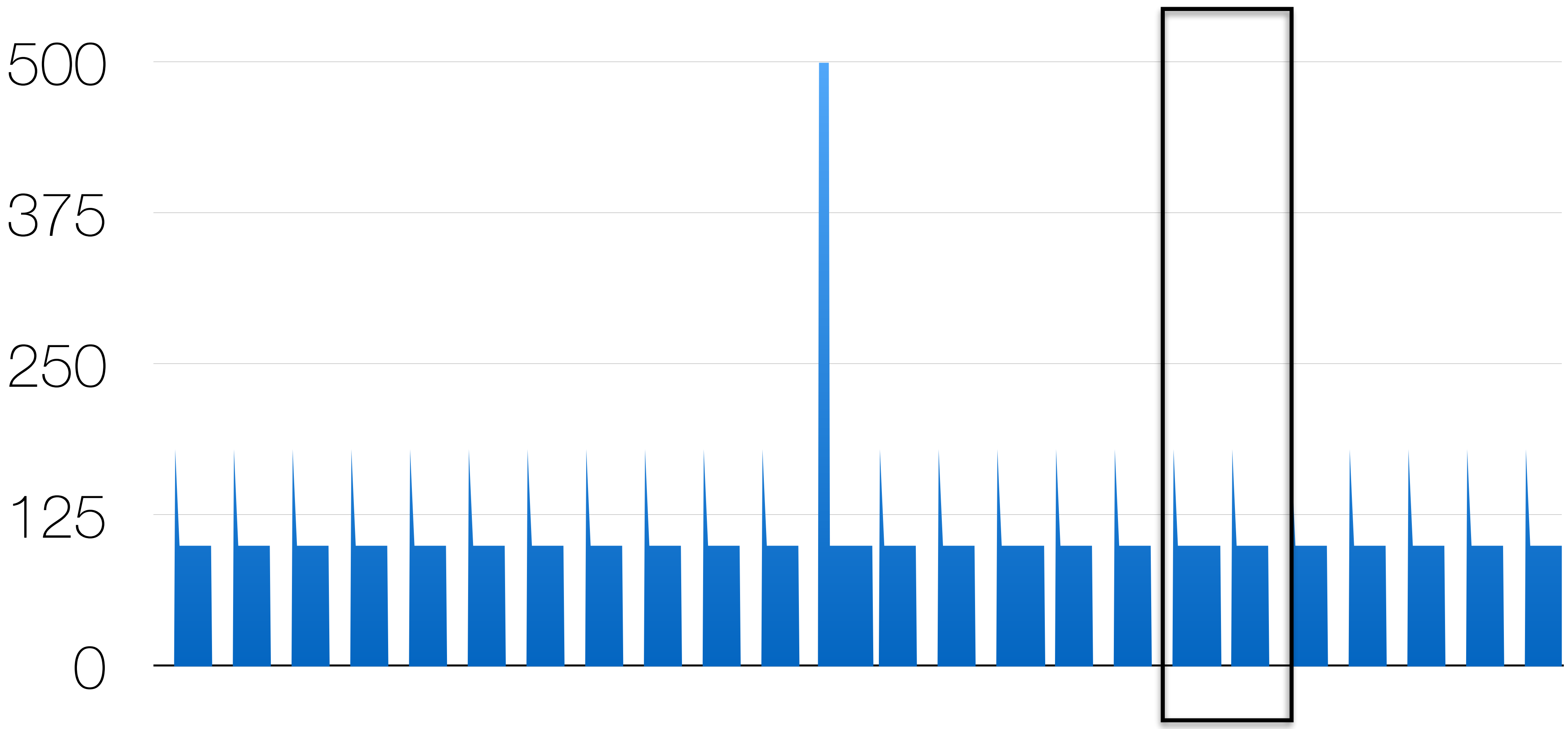
Fridge Model

2. **Defrost Energy** = Energy consumed in defrost state + Extra energy consumed in next few compressor cycles

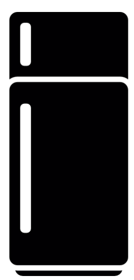


Fridge Model

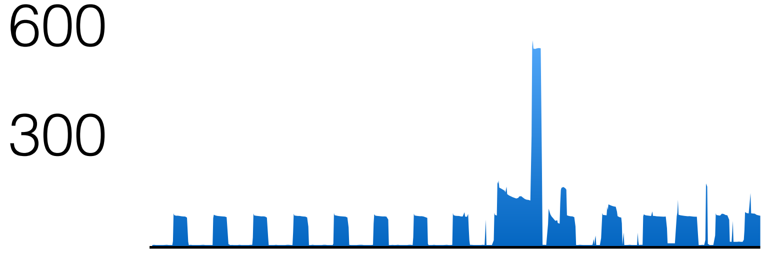
3. **Usage Energy** = Extra energy consumed over baseline



Evaluation Overview



Plug load
monitor



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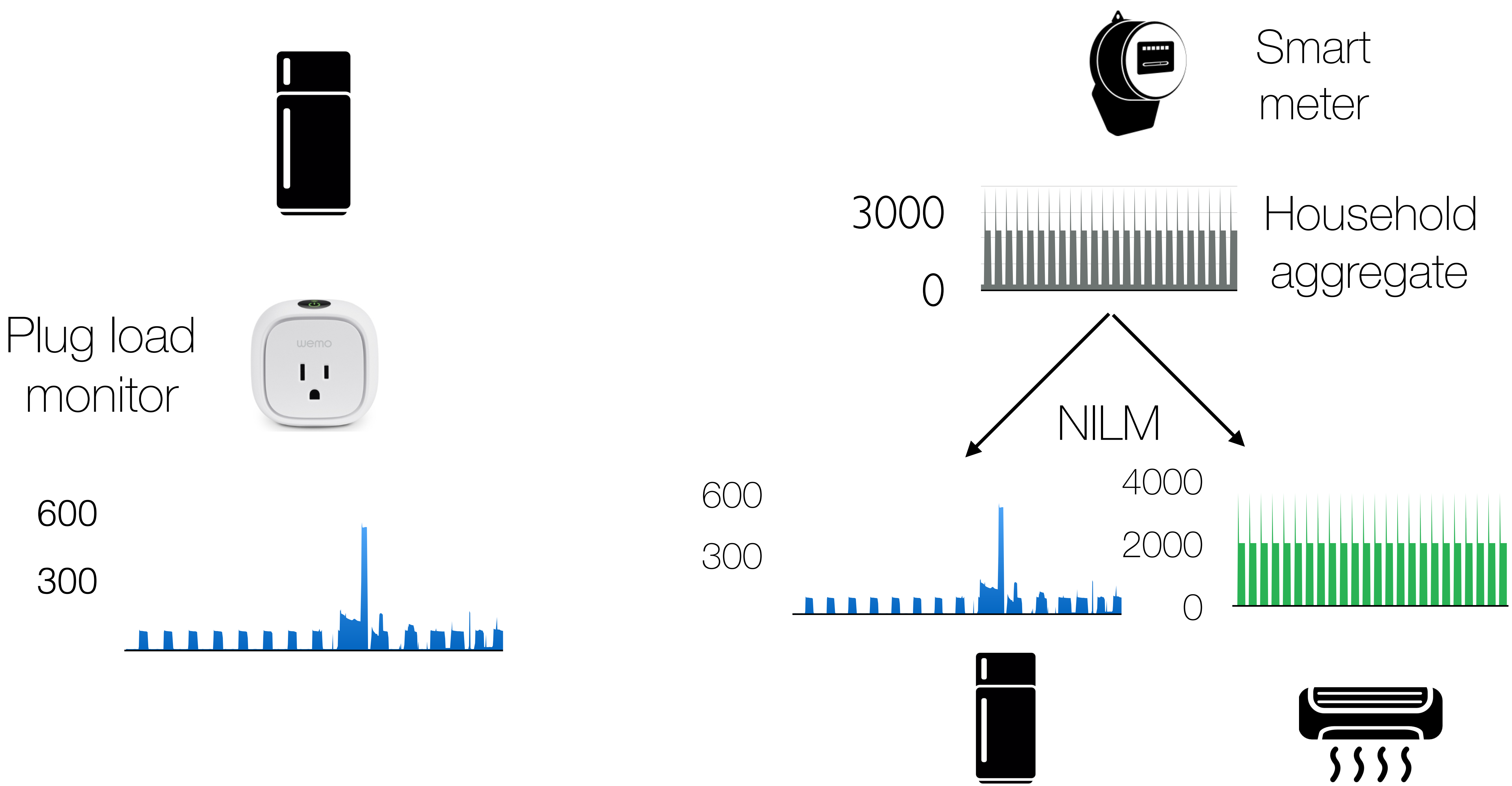
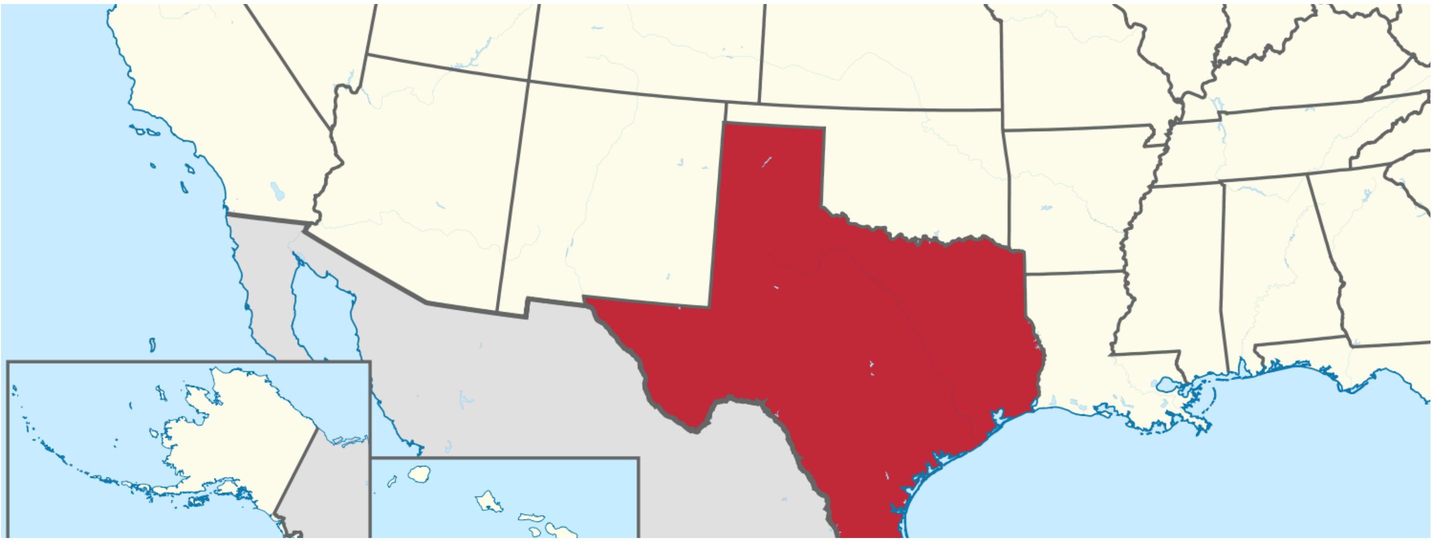


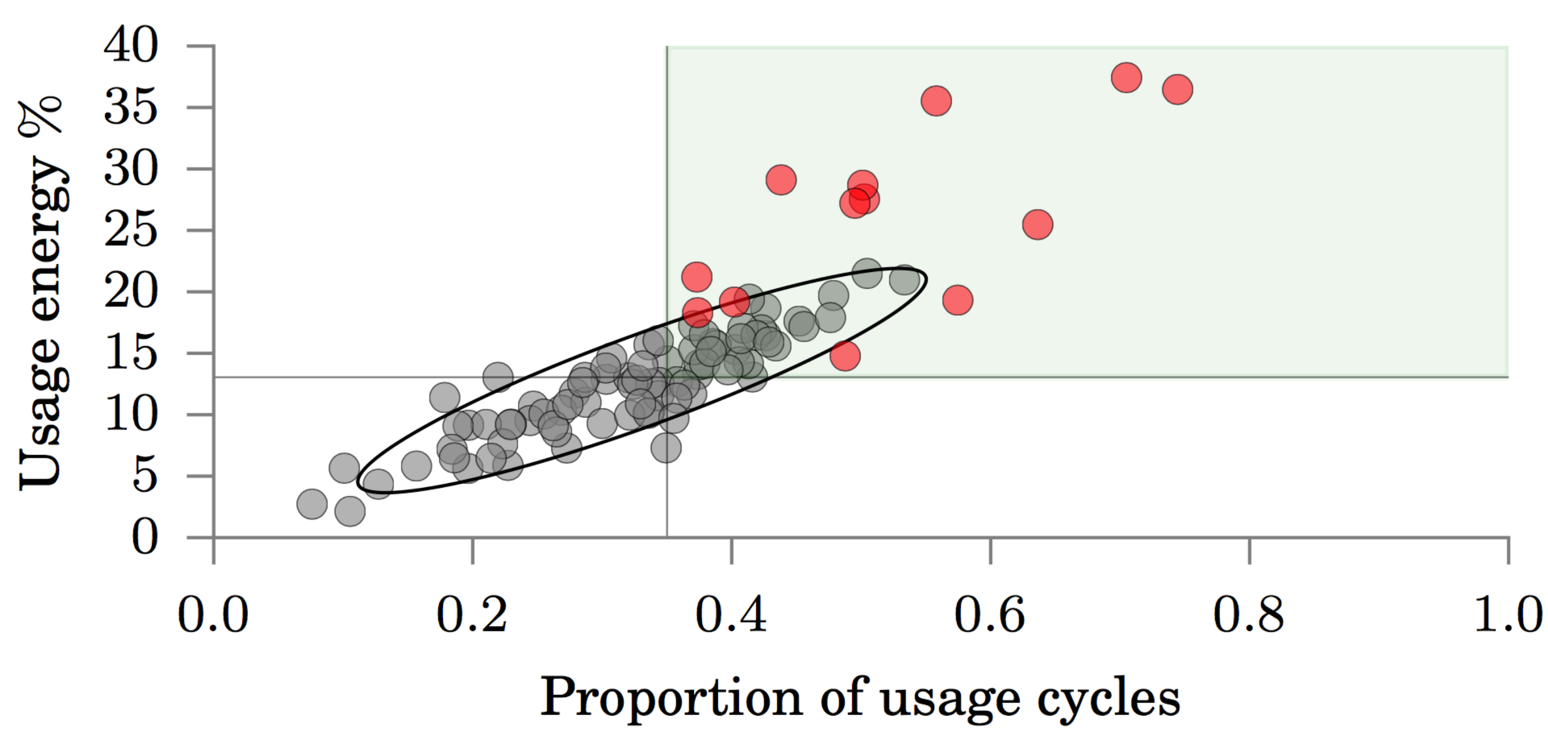
Experimental Setup

- 97 fridges
- 58 HVAC
- Austin region



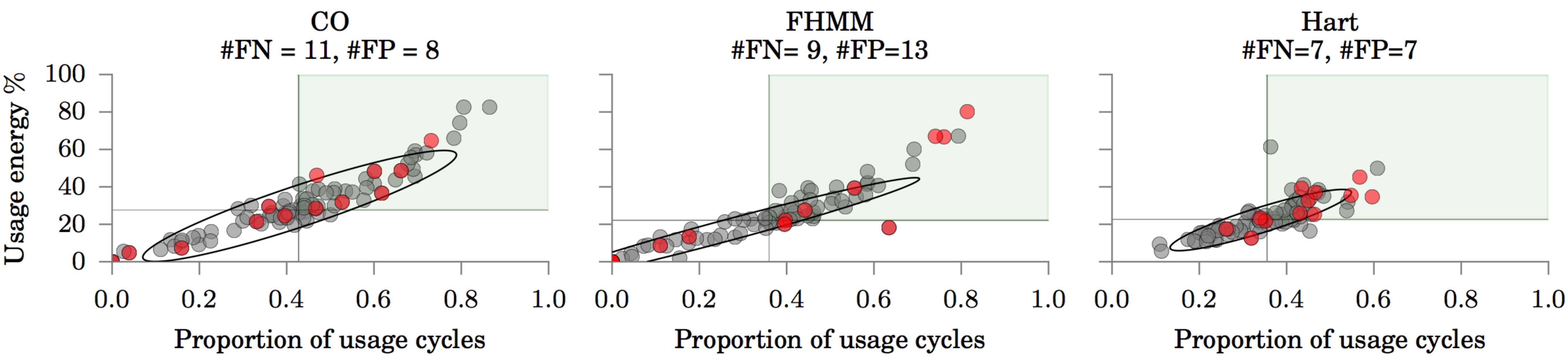
Results

13 out of 95 homes can be given feedback based on **usage energy** saving upto 23% fridge energy



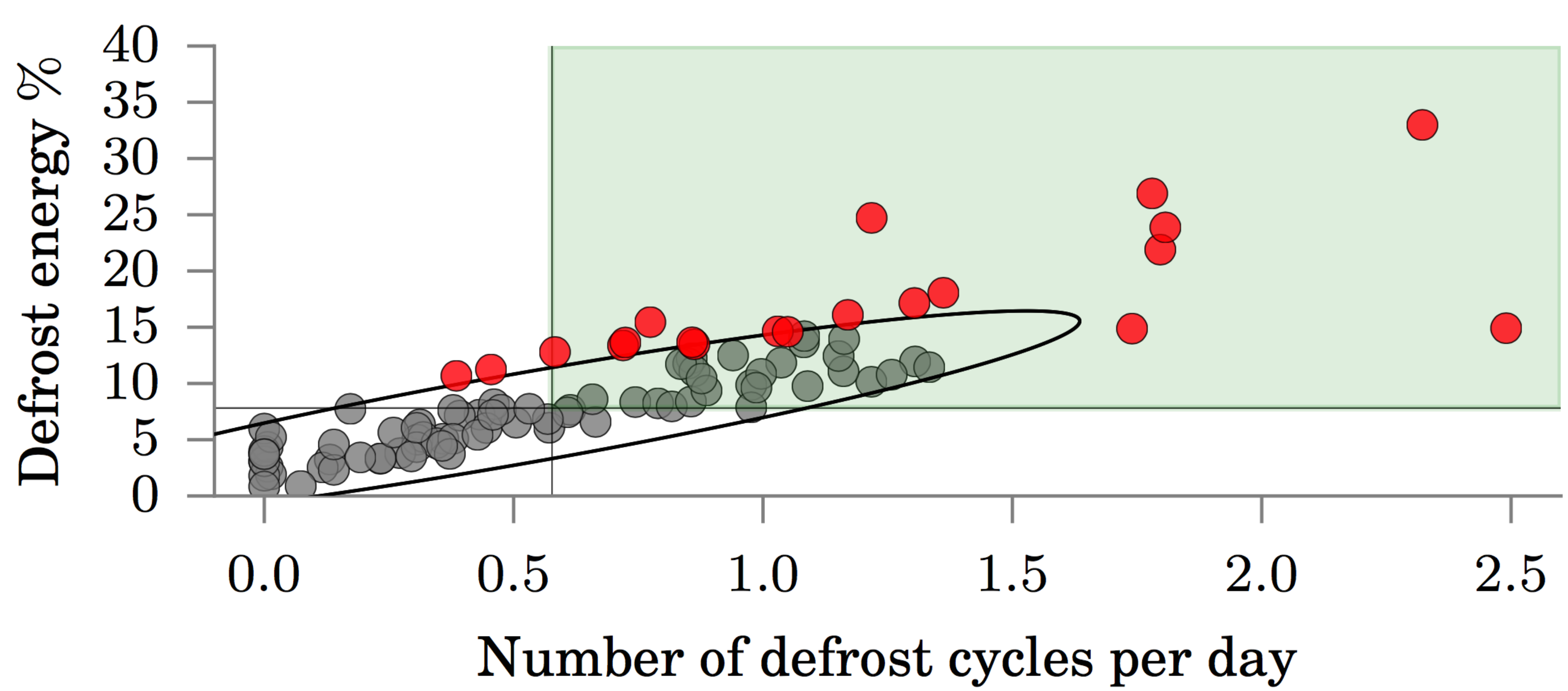
Results

NILM algorithms show poor accuracy in identifying homes which can be given feedback based on **usage energy**



Results

17 out of 95 homes can be given feedback on **excess defrost** saving upto 25% fridge energy

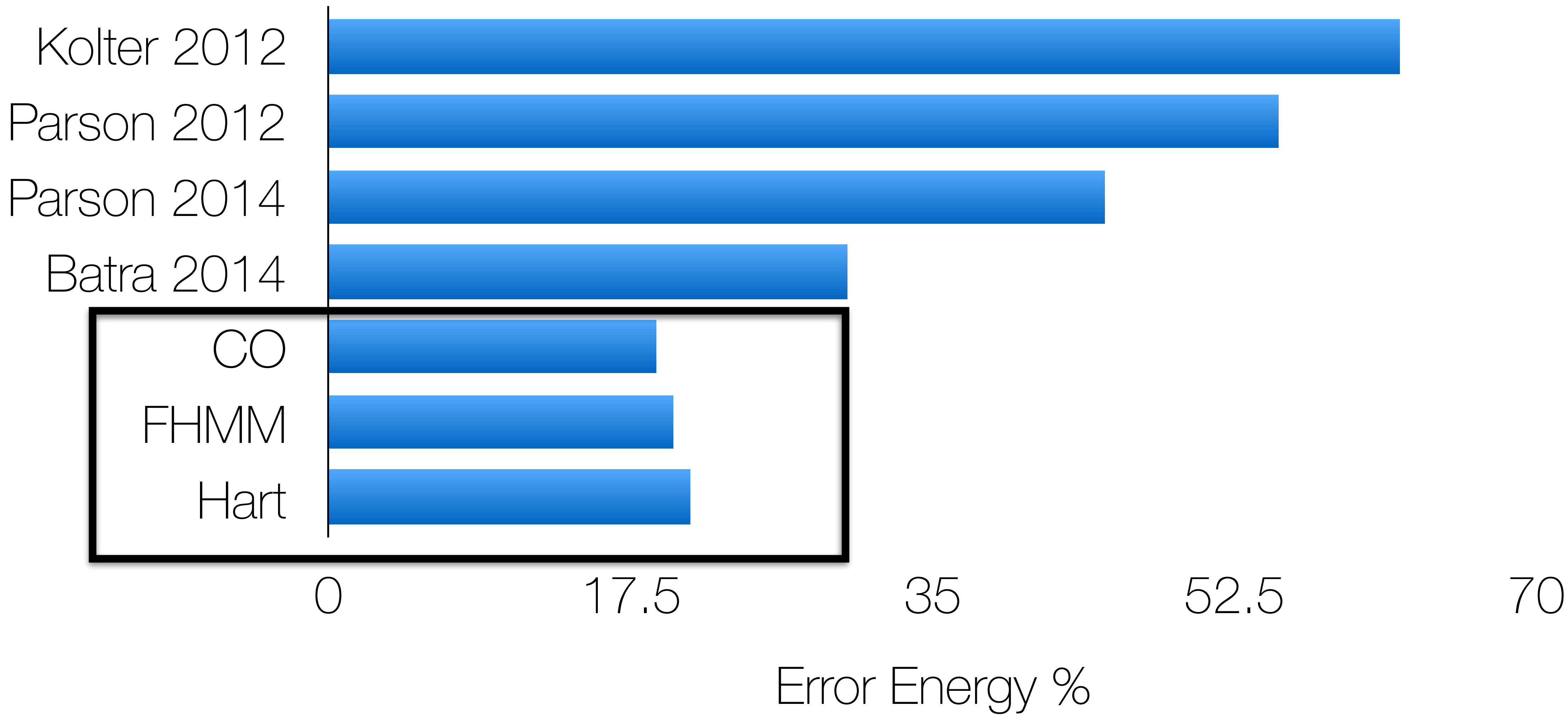


Results

Such feedback can’t be given with NILM traces, since these techniques fare poorly on defrost detection.

Analysis

Benchmark NILM algorithms on our data set give accuracy comparable or better than state-of-the-art



Outline

- Scalable Energy Breakdown
    - Gemello [KDD 2016]
    - Matrix Factorisation [AAAI 2017]
- Making NILM better
    - Actionable [Buildsys 2015]
    - **Comparable [e-Energy 2014]**

NILMTK

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1. Hard to assess generality- 10 datasets in common format

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1. Hard to assess generality- 10 datasets in common format
2. Lack of comparison against the same benchmarks- 3 baseline algorithms
3. Inconsistent metrics - Suite of accuracy metrics

NILMTK Impact

- 100+ citations in <2 years
- 15+ papers using NILMTK
- 3 user contributed NILM algorithms
- 7 user contributed NILM data sets
- Best demonstration award at BuildSys 2014
- Best PhD forum presentation at SenSys 2015

Conclusions

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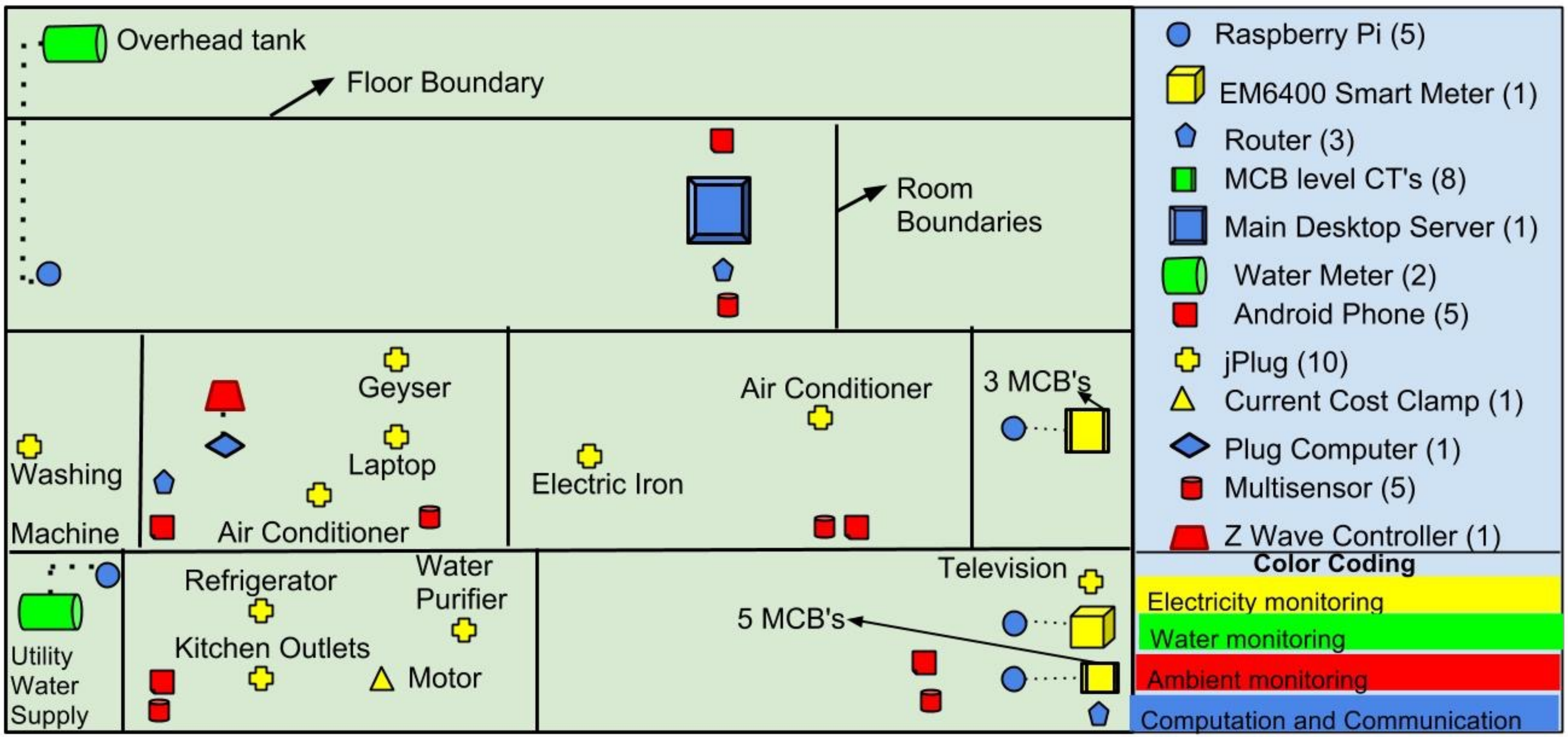
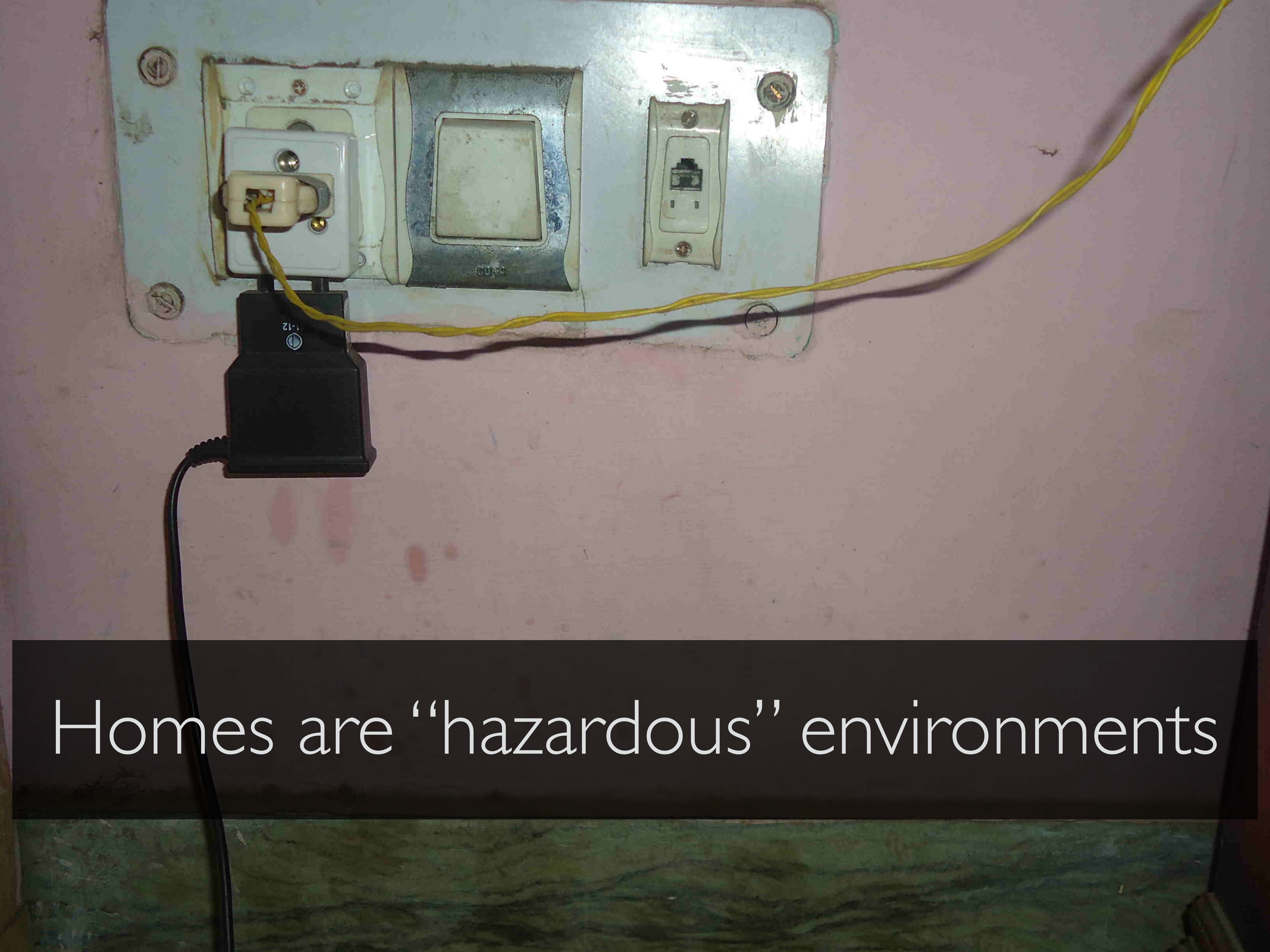
Backup

Residential Deployment





Homes are “hazardous” environments


Aesthetics matter!

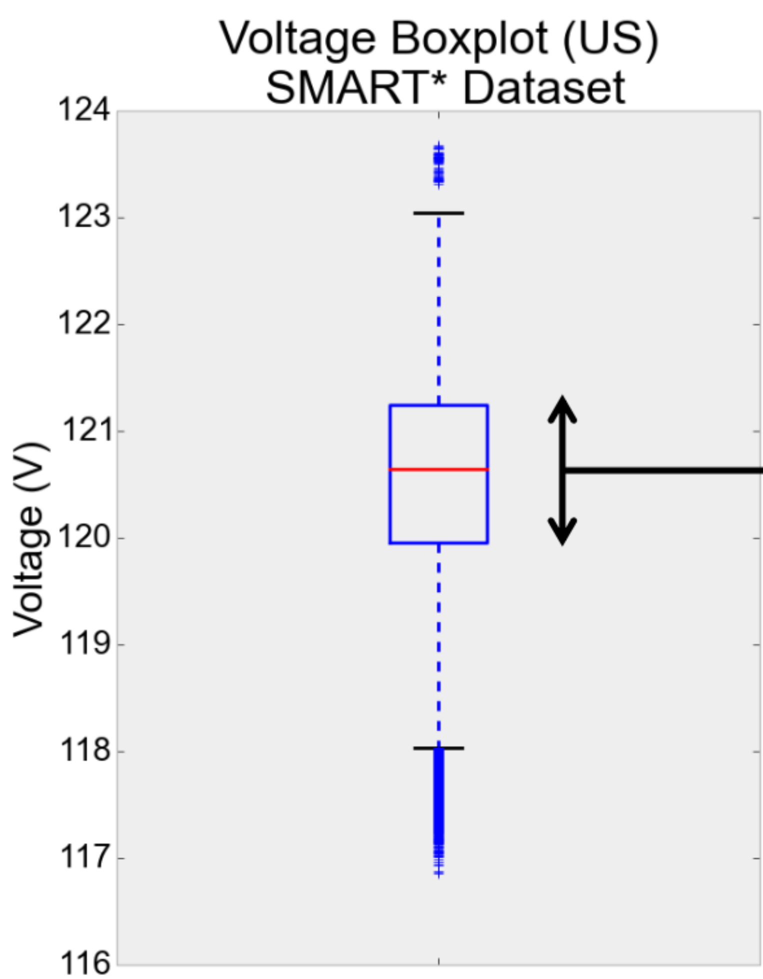
Homes have poor connectivity!

Sensor deployments have several challenges*

1. Homes are not a power panacea
2. Homes have poor connectivity
3. Homes are hazardous
4. Limited user interaction
5. Aesthetics matter

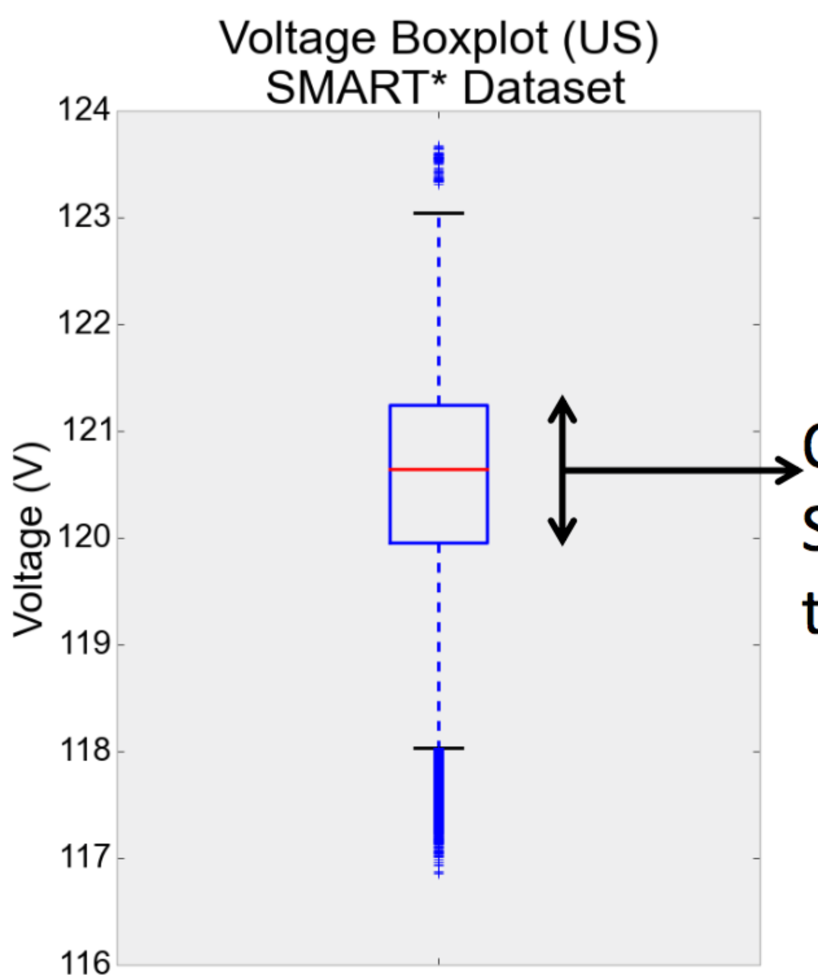
1. Hnat et al. "The hitchhiker's guide to successful residential sensing deployments". Sensys 2010
2. Batra et al. "It's different. Insights into home energy consumption in India". Buildsys 2013

Residential Deployment: Unstable Grid



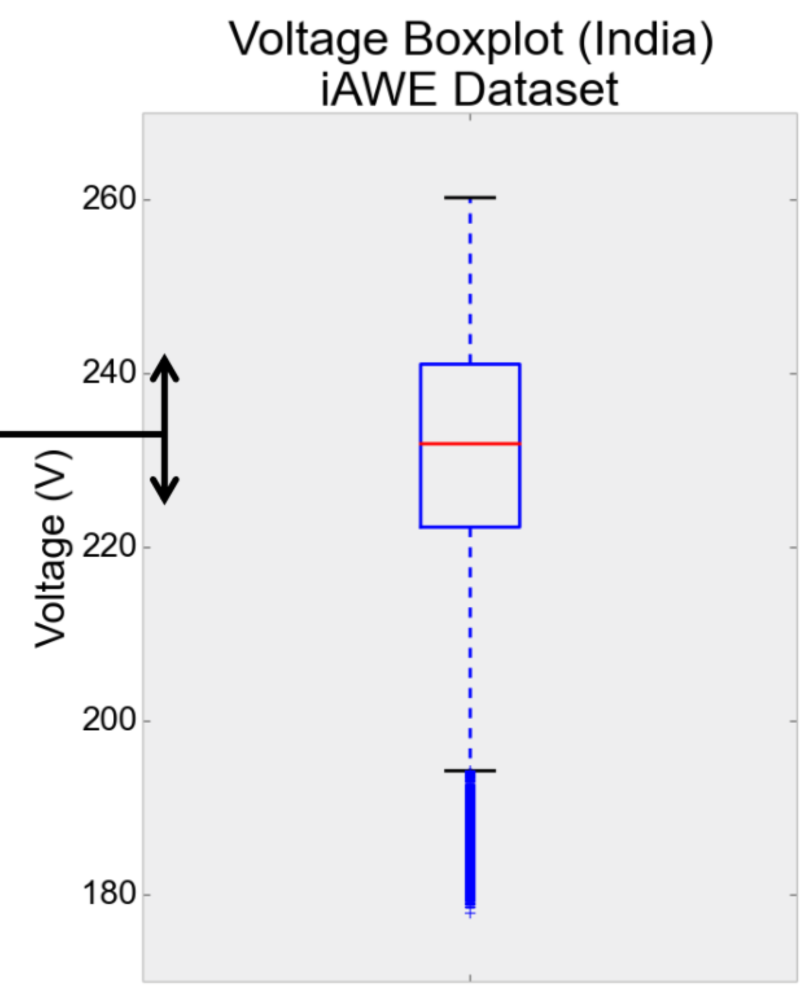
Quartile Spread: Less than 1%

Residential Deployment: Unstable Grid



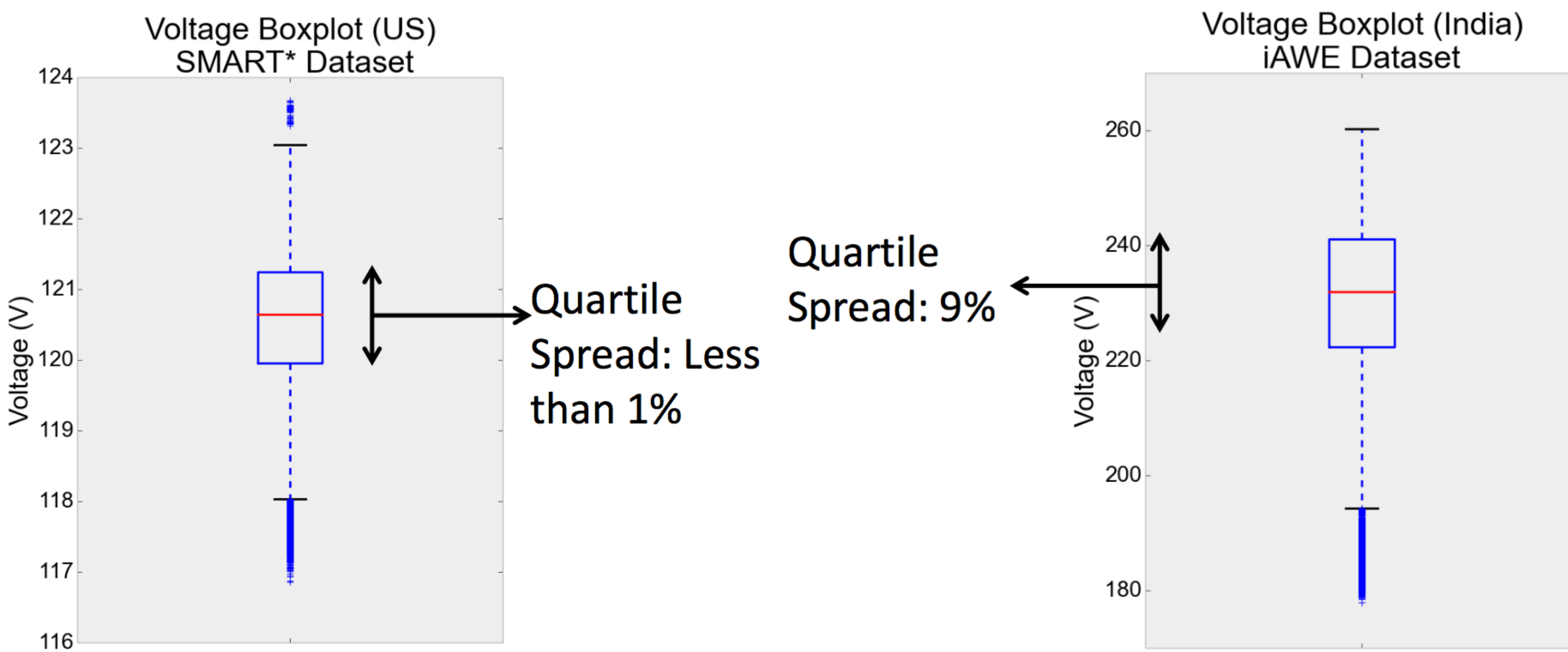
Quartile Spread: Less than 1%

Quartile Spread: 9%

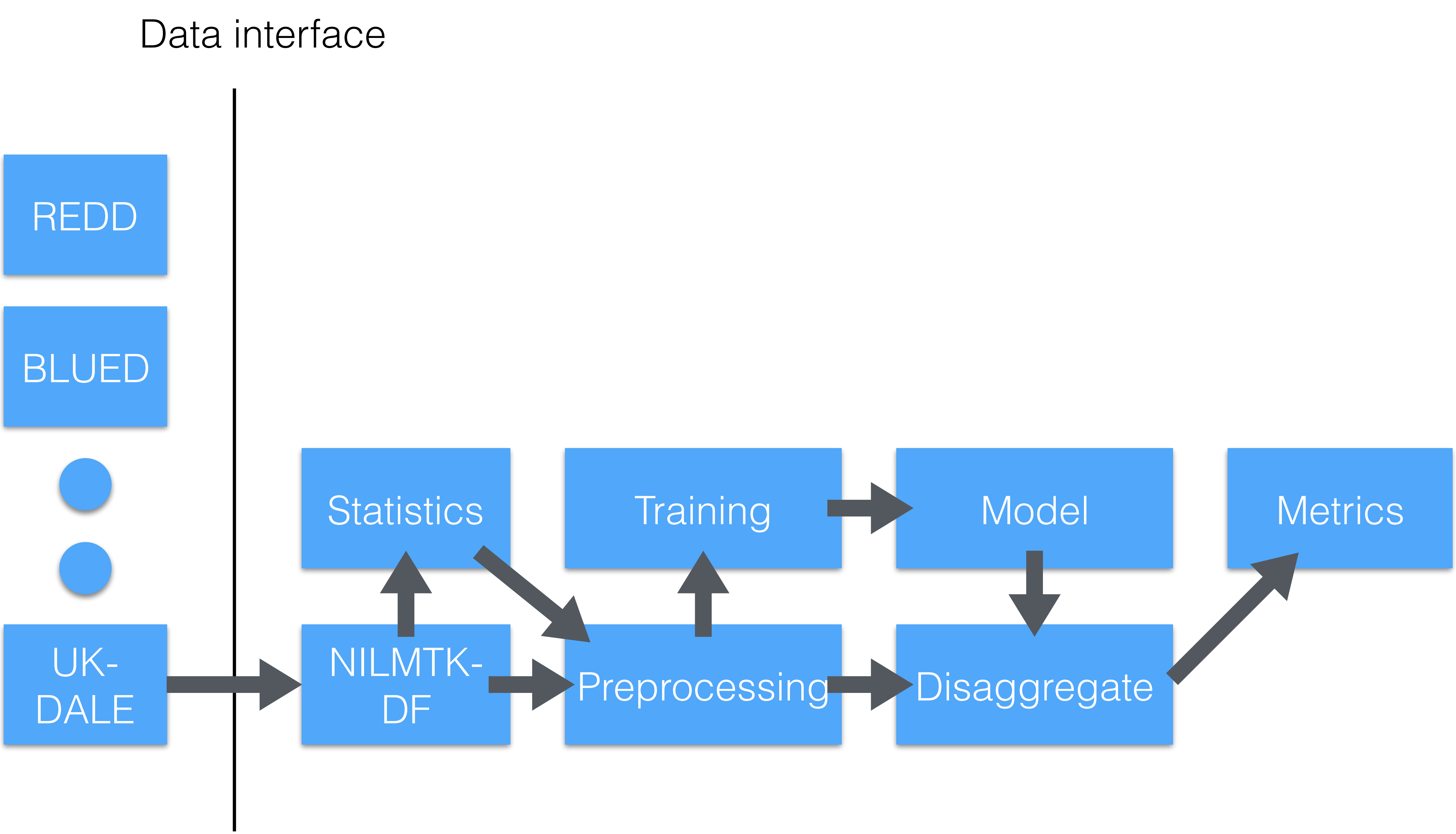


Residential Deployment: Unstable Grid

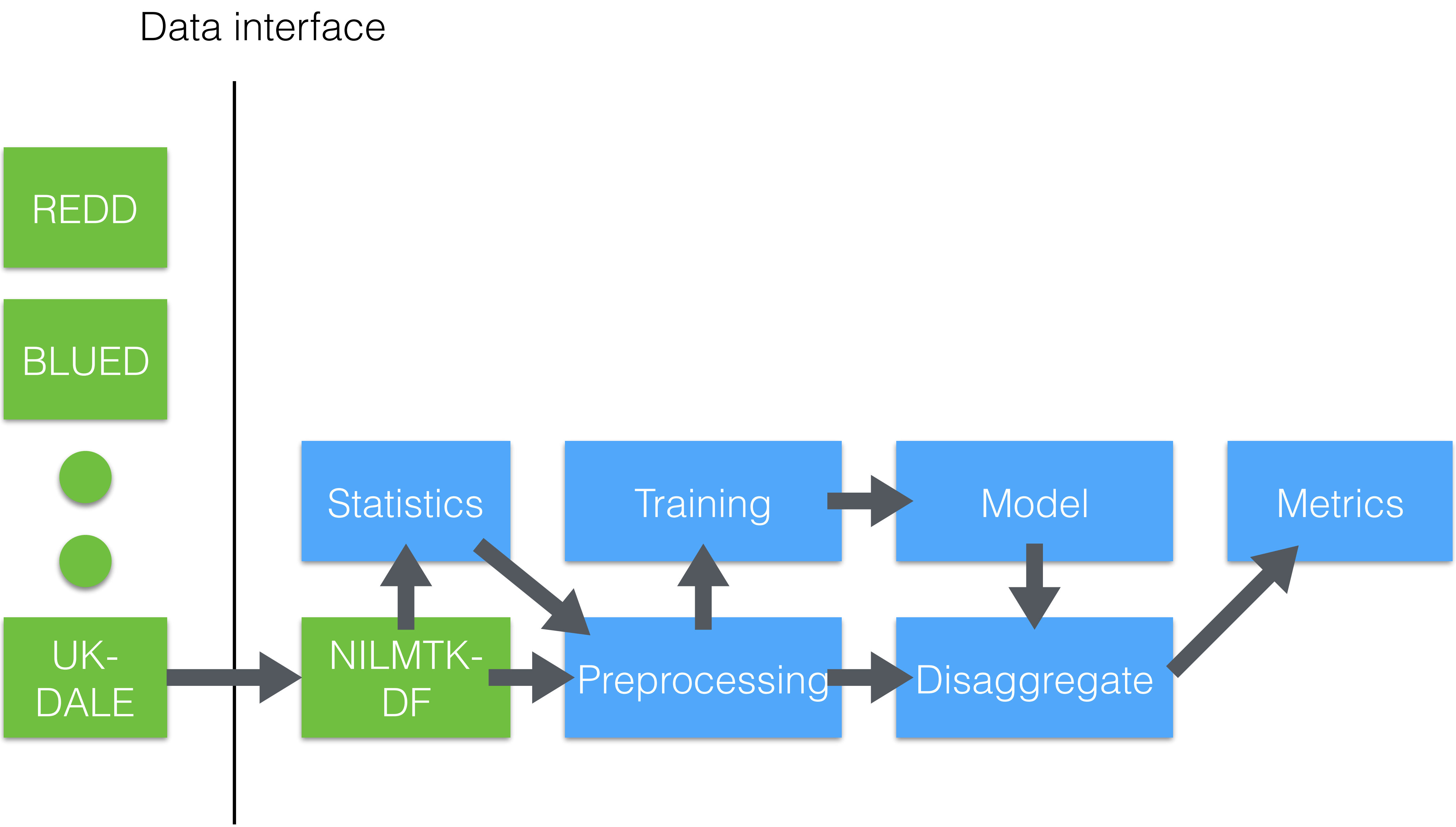
- Need to measure voltage in addition to current
- Dense sensor deployments not scalable



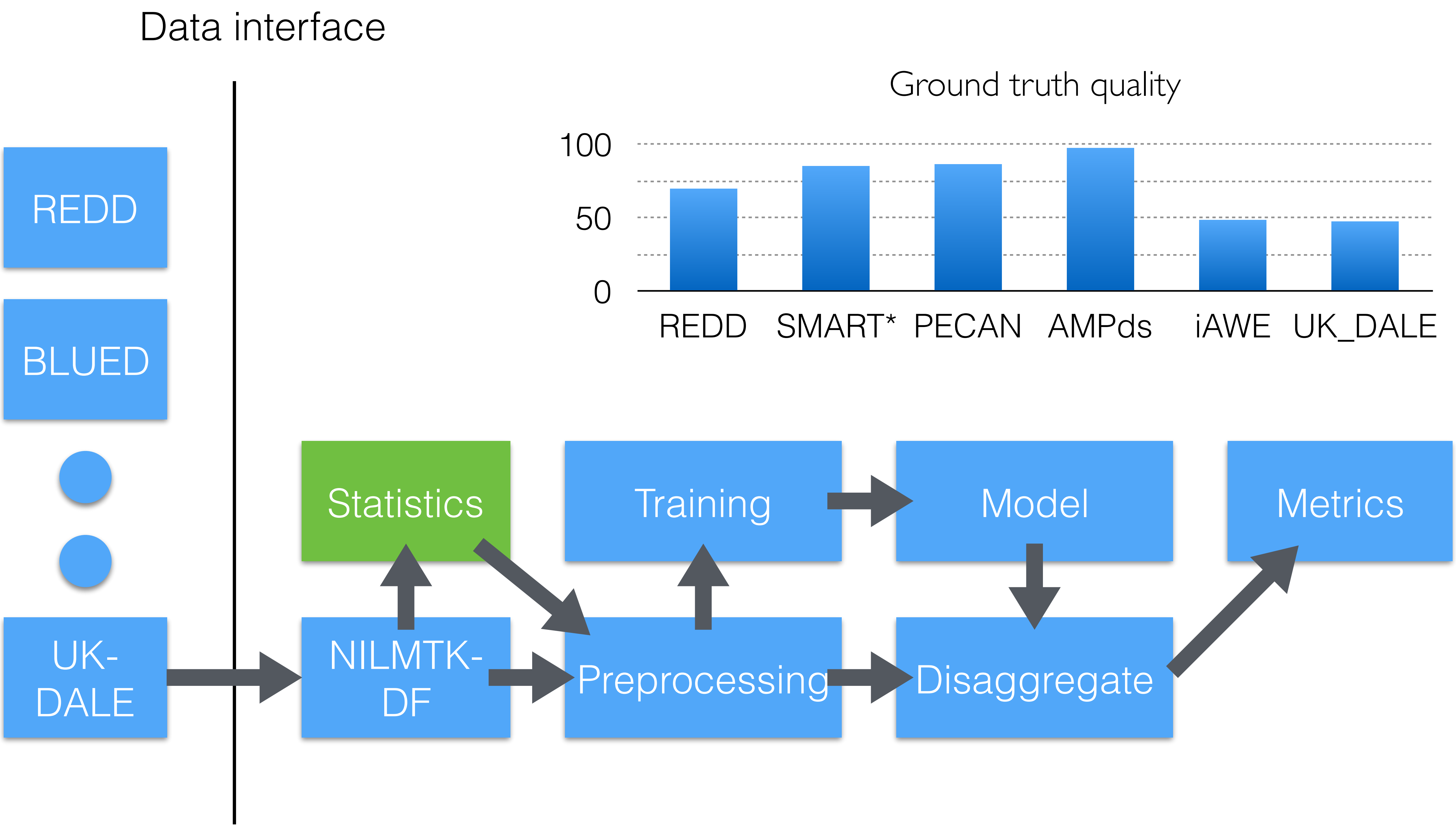
NILMTK Pipeline



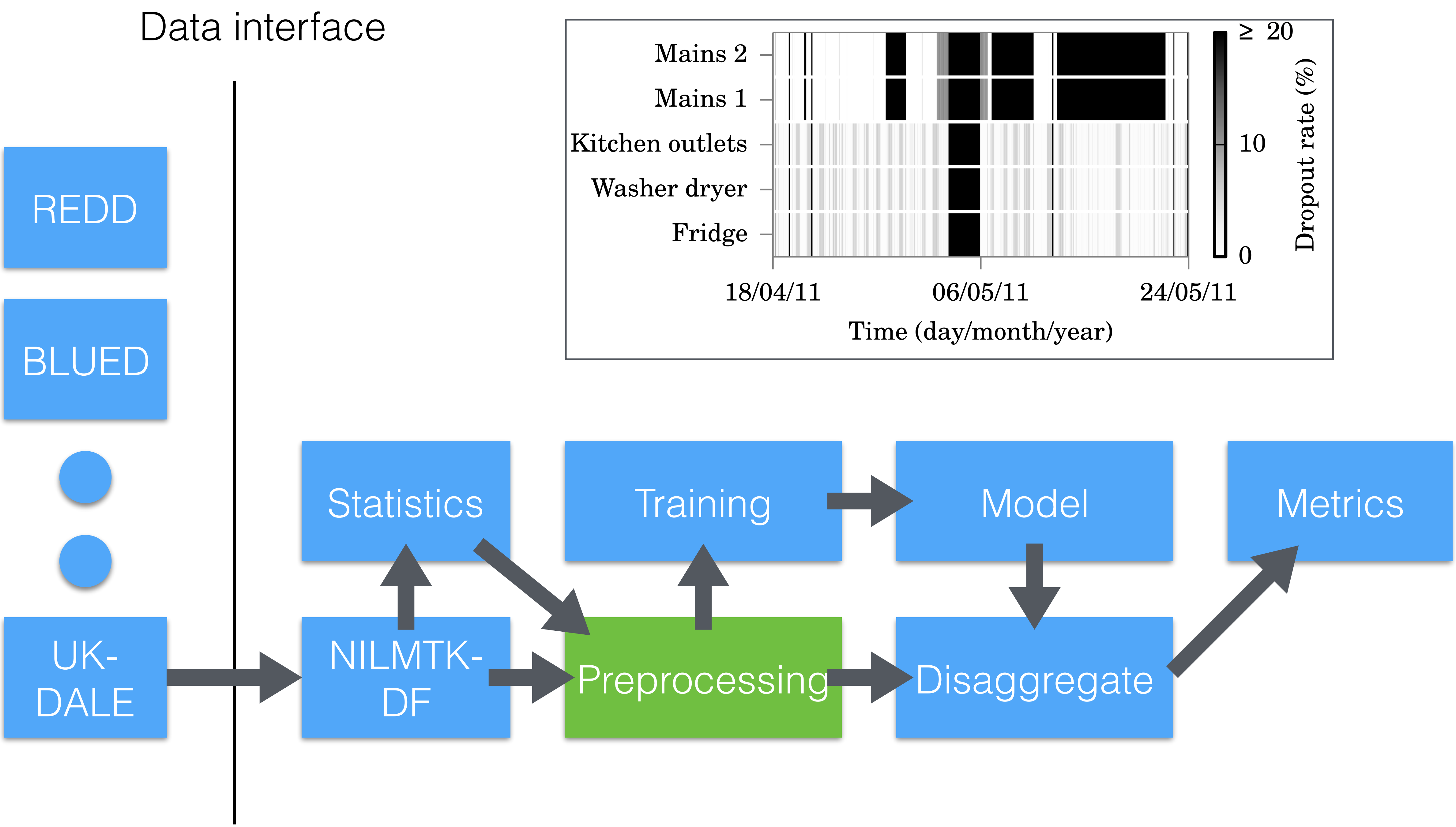
NILMTK Pipeline: Common Data Format



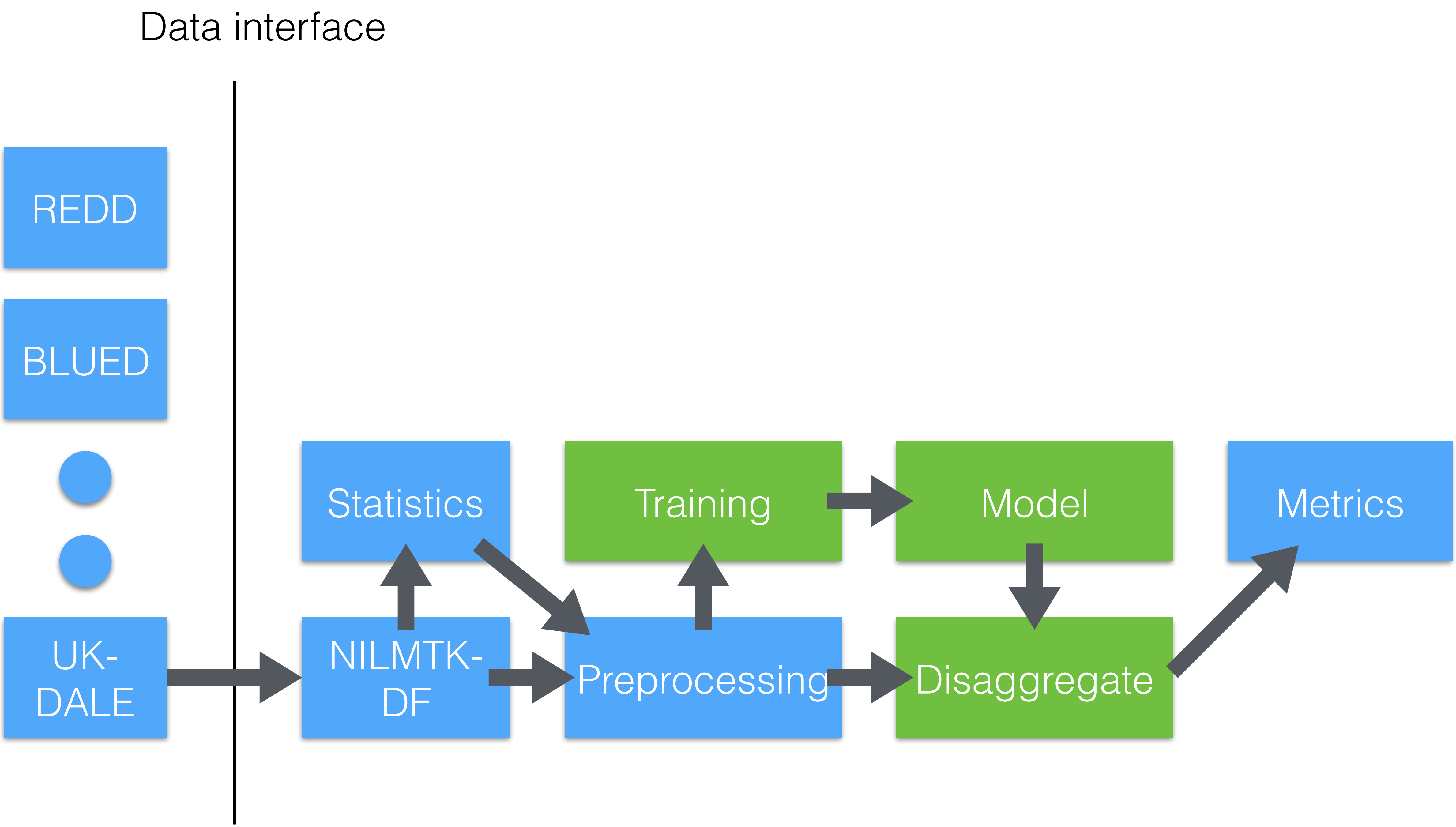
NILMTK Pipeline: Statistical Functions



NILMTK Pipeline: Preprocessing



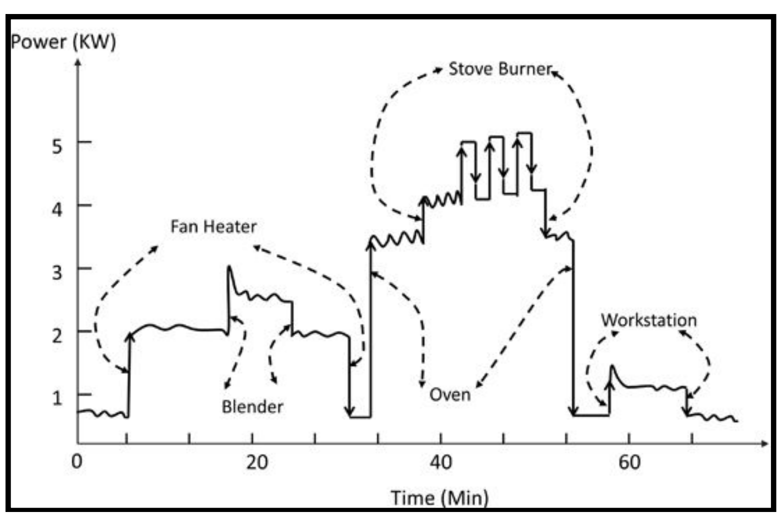
NILMTK Pipeline: Train and Disaggregate



NILMTK Pipeline: Benchmark Algorithms

- 2 Seminal algorithms (CO, Hart's) and 1 state-of-the-art

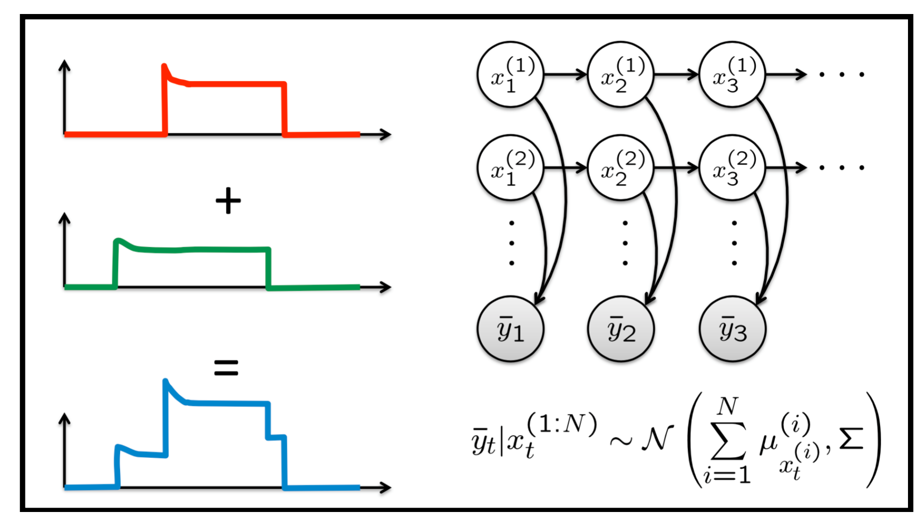
Hart's event detection algorithm



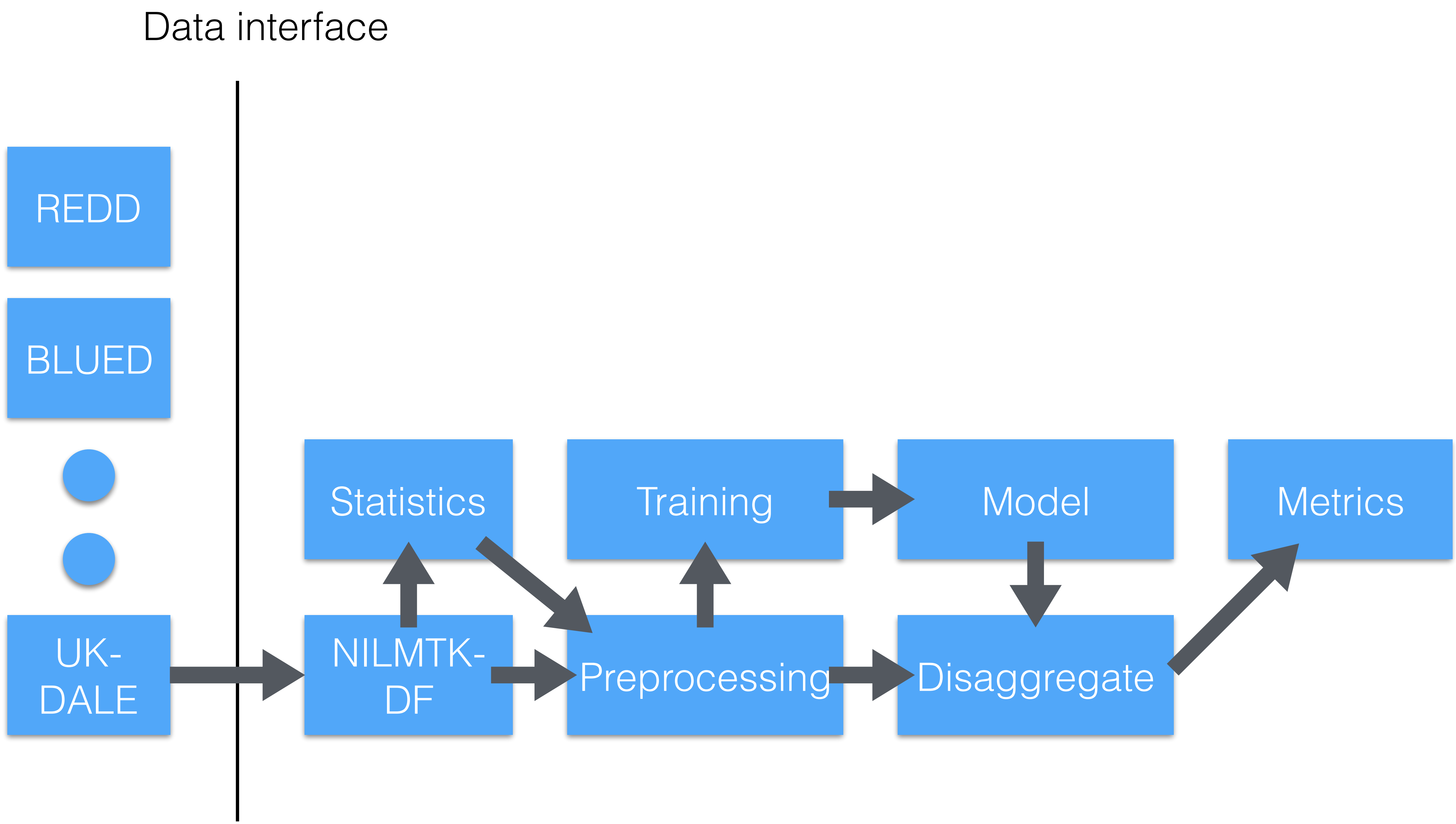
Combinatorial Optimisation (CO)

Appliance	Off power	On power
Light	0	200
Fridge	0	100

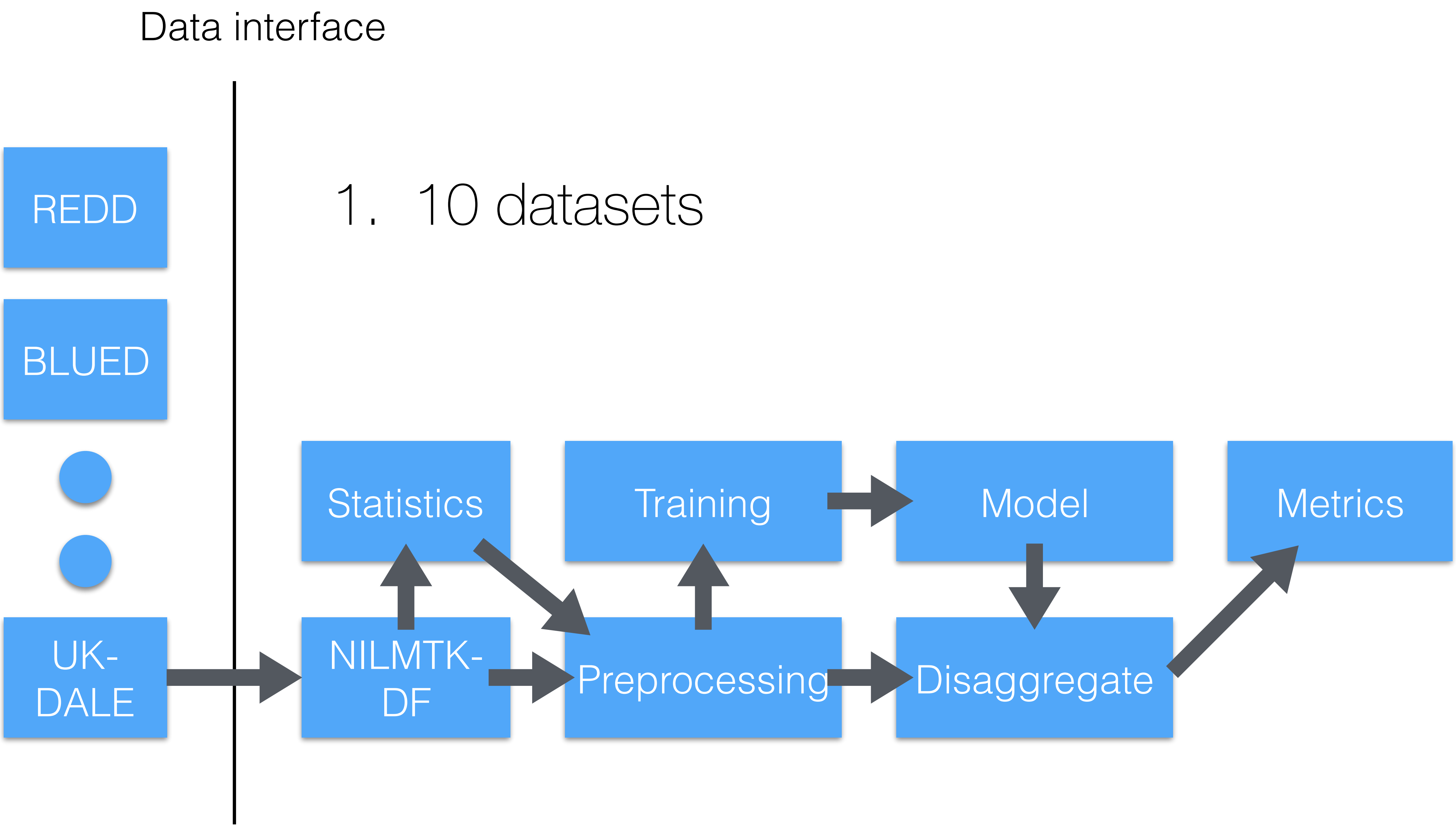
Factorial Hidden Markov Model (FHMM)



NILMTK


Data interface
REDD
BLUED
UK-
DALE
Statistics
NILMTK-
DF
Training
Preprocessing
Model
Disaggregate
Metrics

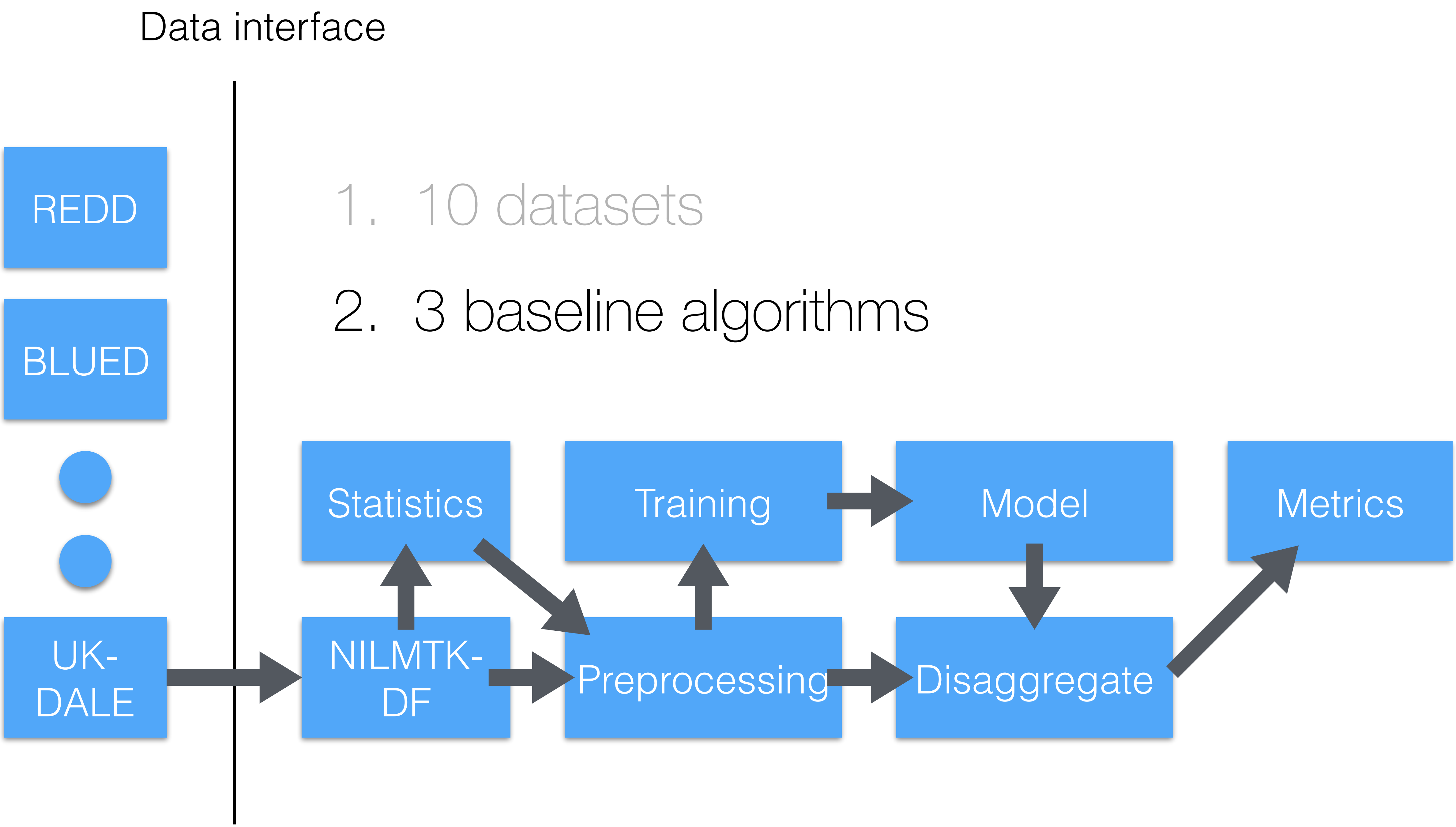
NILMTK



1. 10 datasets

NILMTK

1. 10 datasets
2. 3 baseline algorithms



1993 → 2013

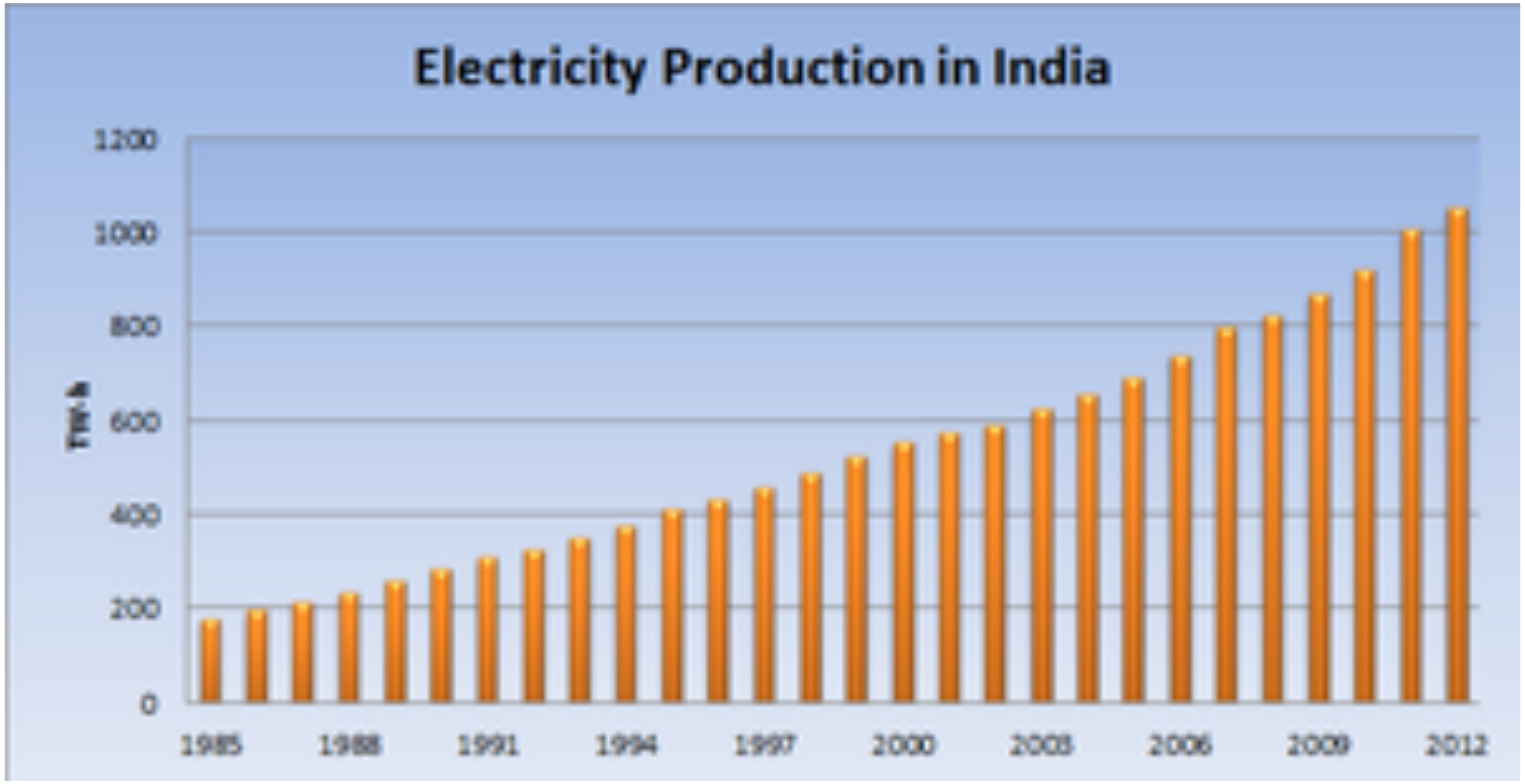
World Population 29% ↑

Electricity Production 83% ↑

Yet!

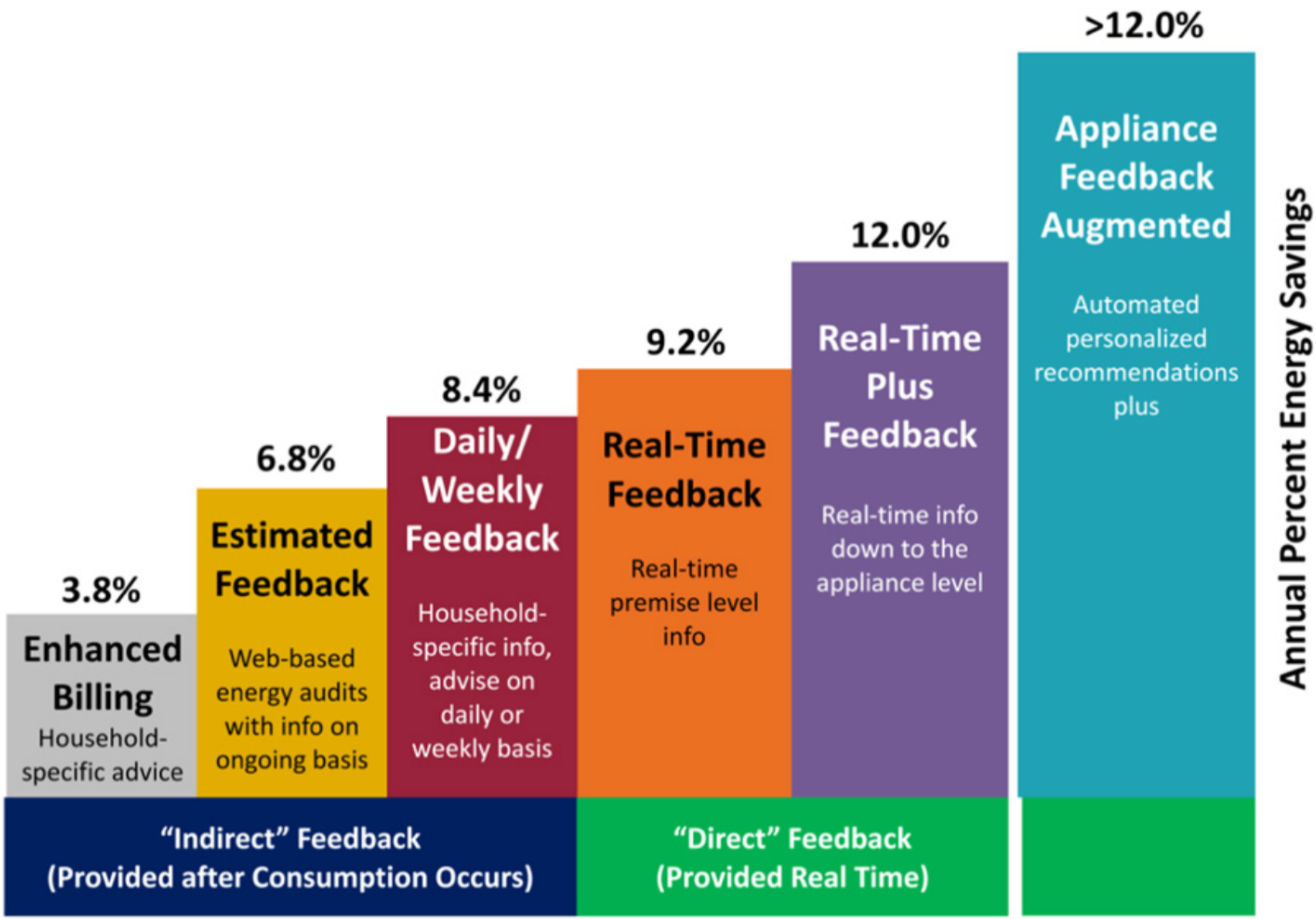

1.5 billion
people worldwide live without electricity
World Bank 2009
Access to electricity
(% of the population)
< 20%
< 50%
< 70%

Energy Efficiency Is The Key



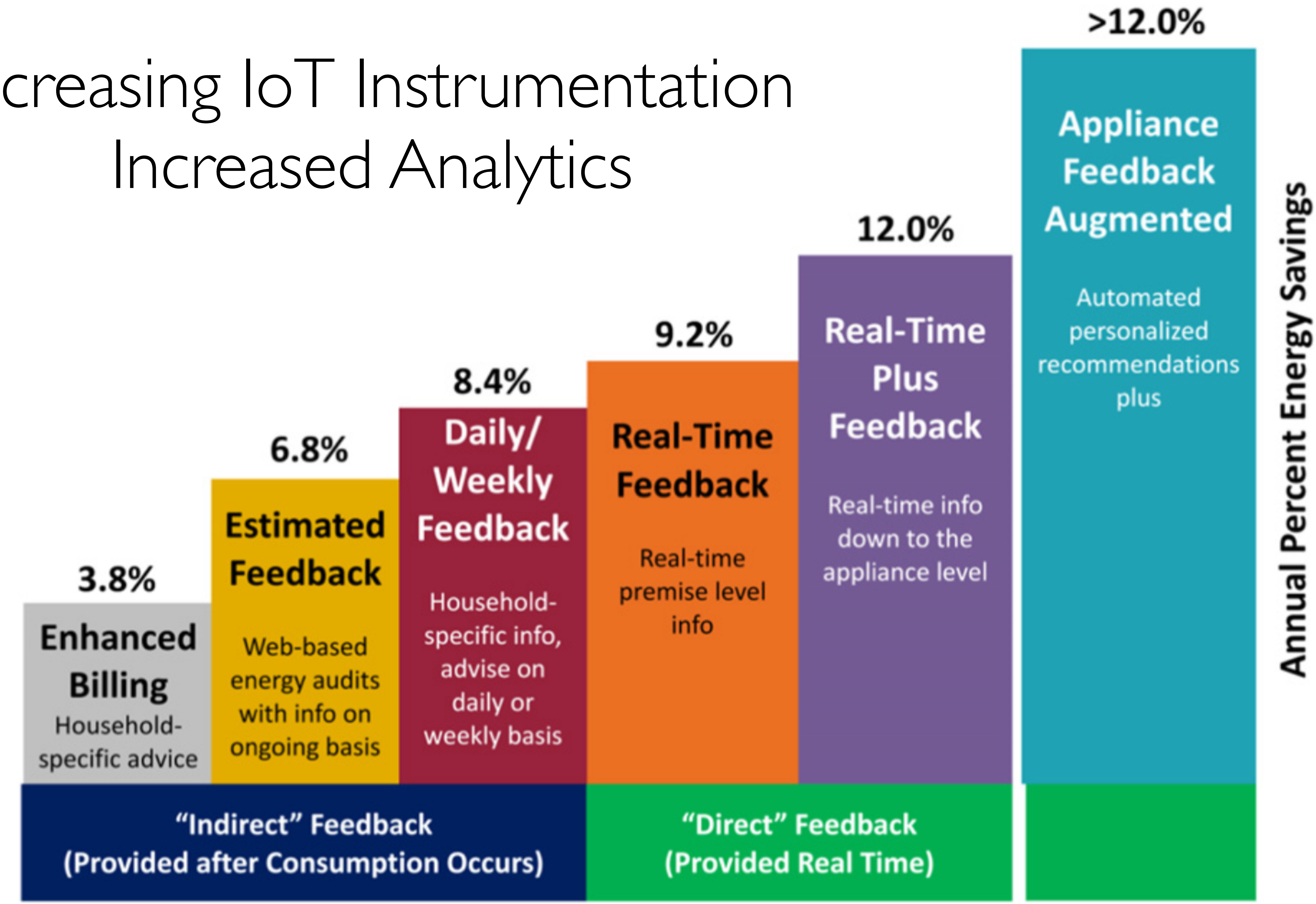
Reduced consumption by eliminating inefficiencies to have large impact

Scope of Energy Feedback



Scope of Energy Feedback

Increasing IoT Instrumentation
Increased Analytics



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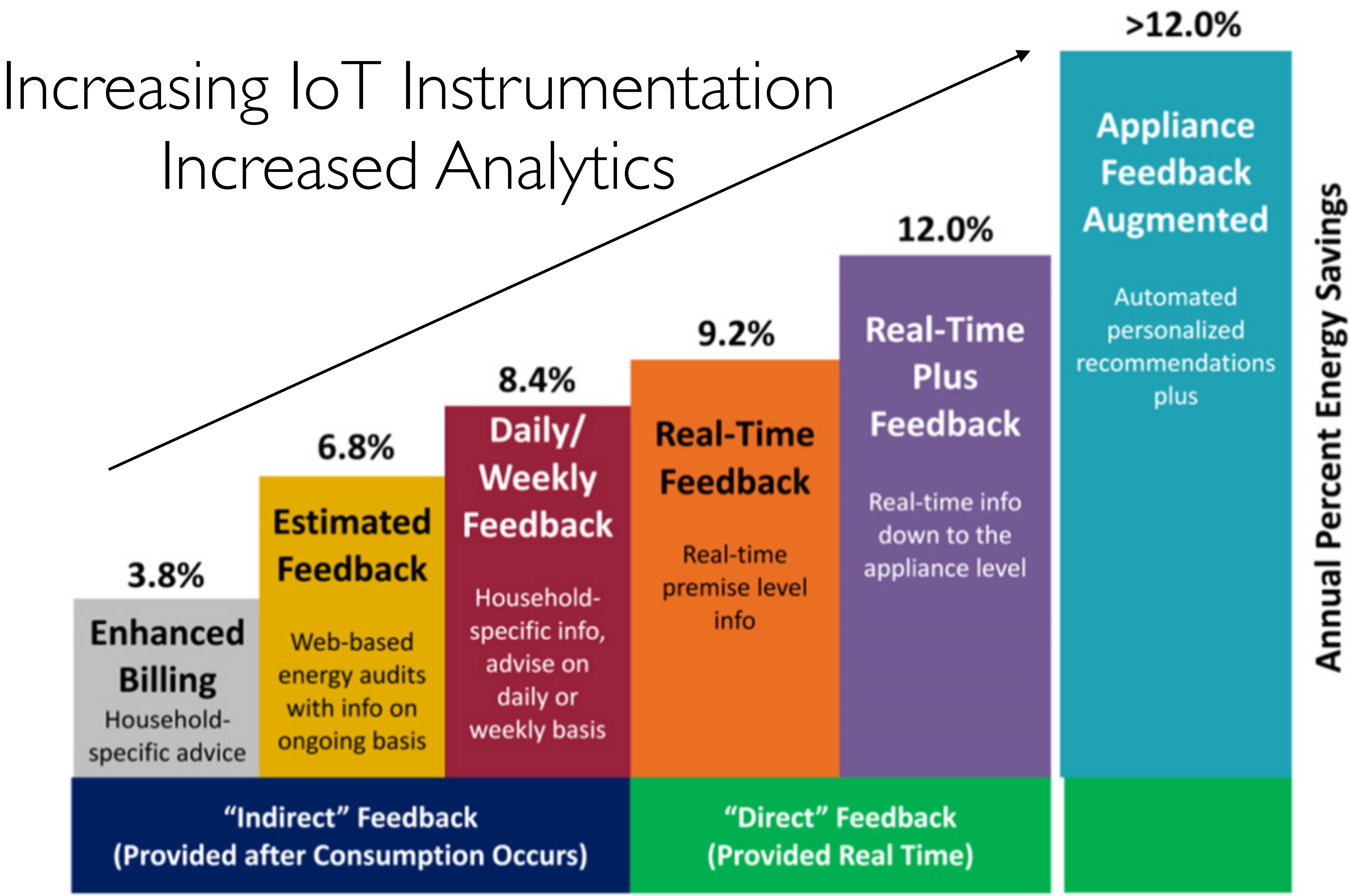
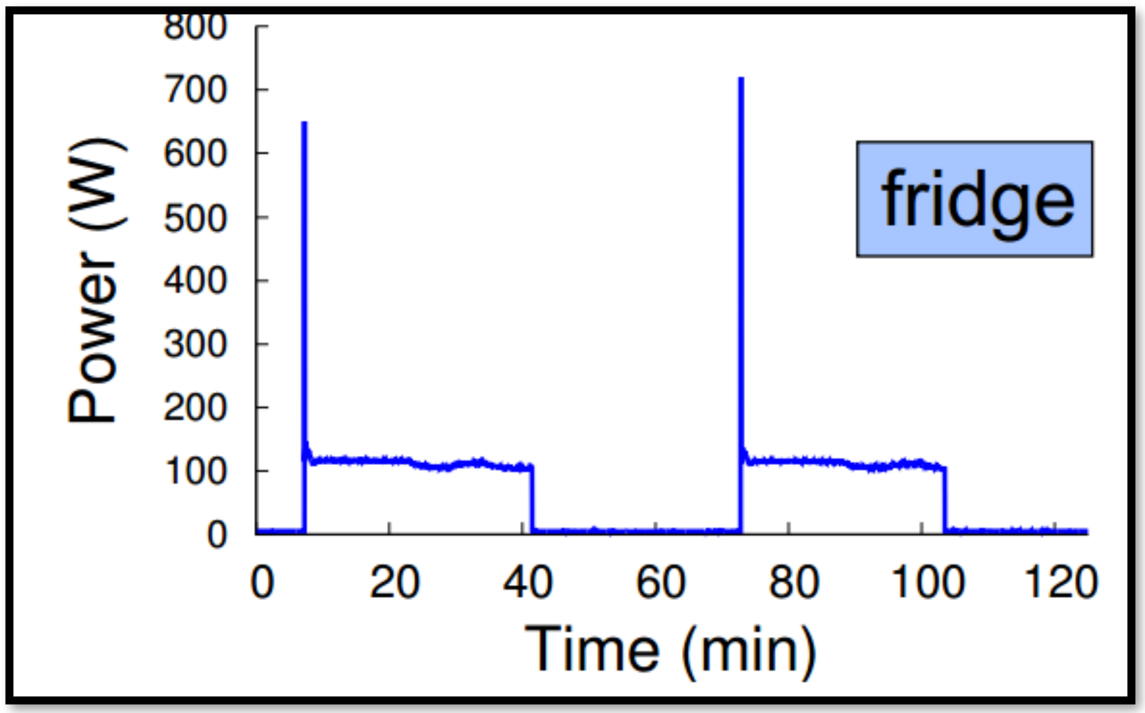
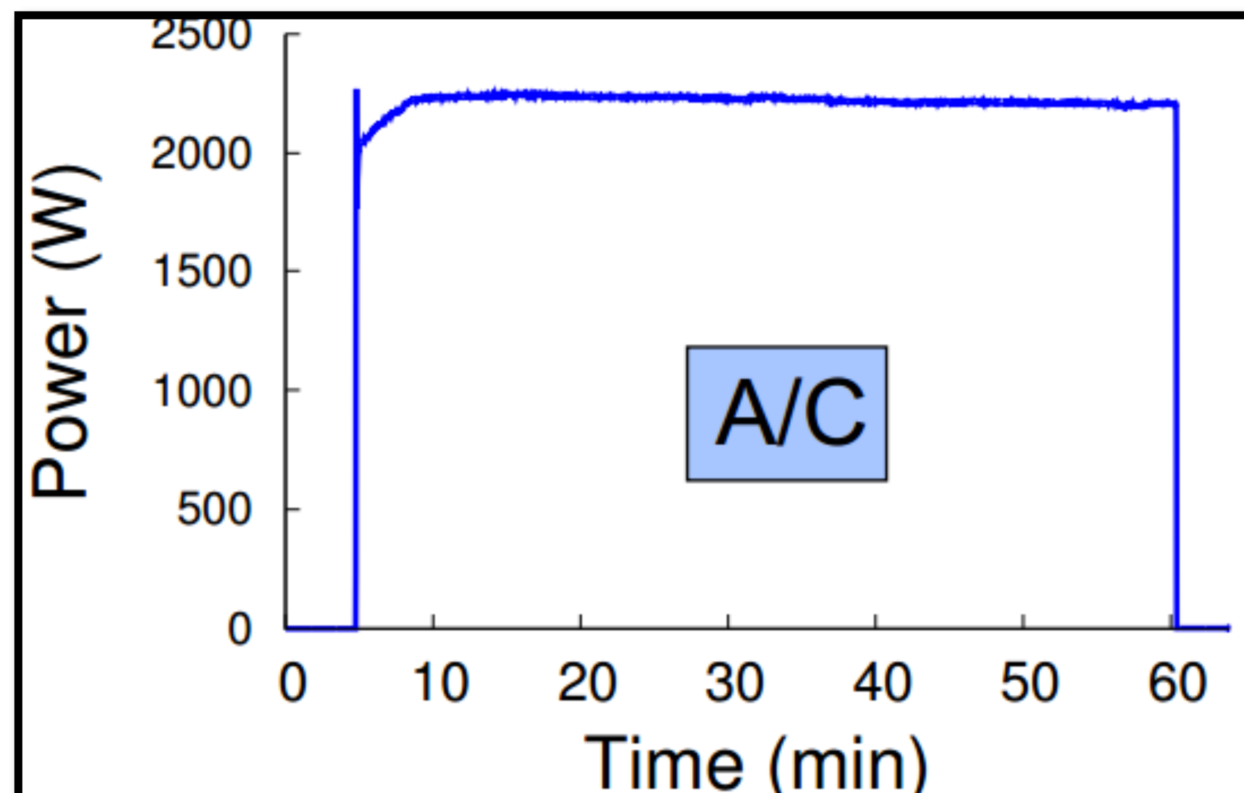


Different Appliances Have Different Signatures





Trivial Combinatorial Optimisation Based NILM Algorithm

Total consumption=200 W

Appliance	Off power	On power
Air conditioner (AC)	0	2000
Refrigerator	0	200

Trivial Combinatorial Optimisation Based NILM Algorithm

Total consumption=2000 W

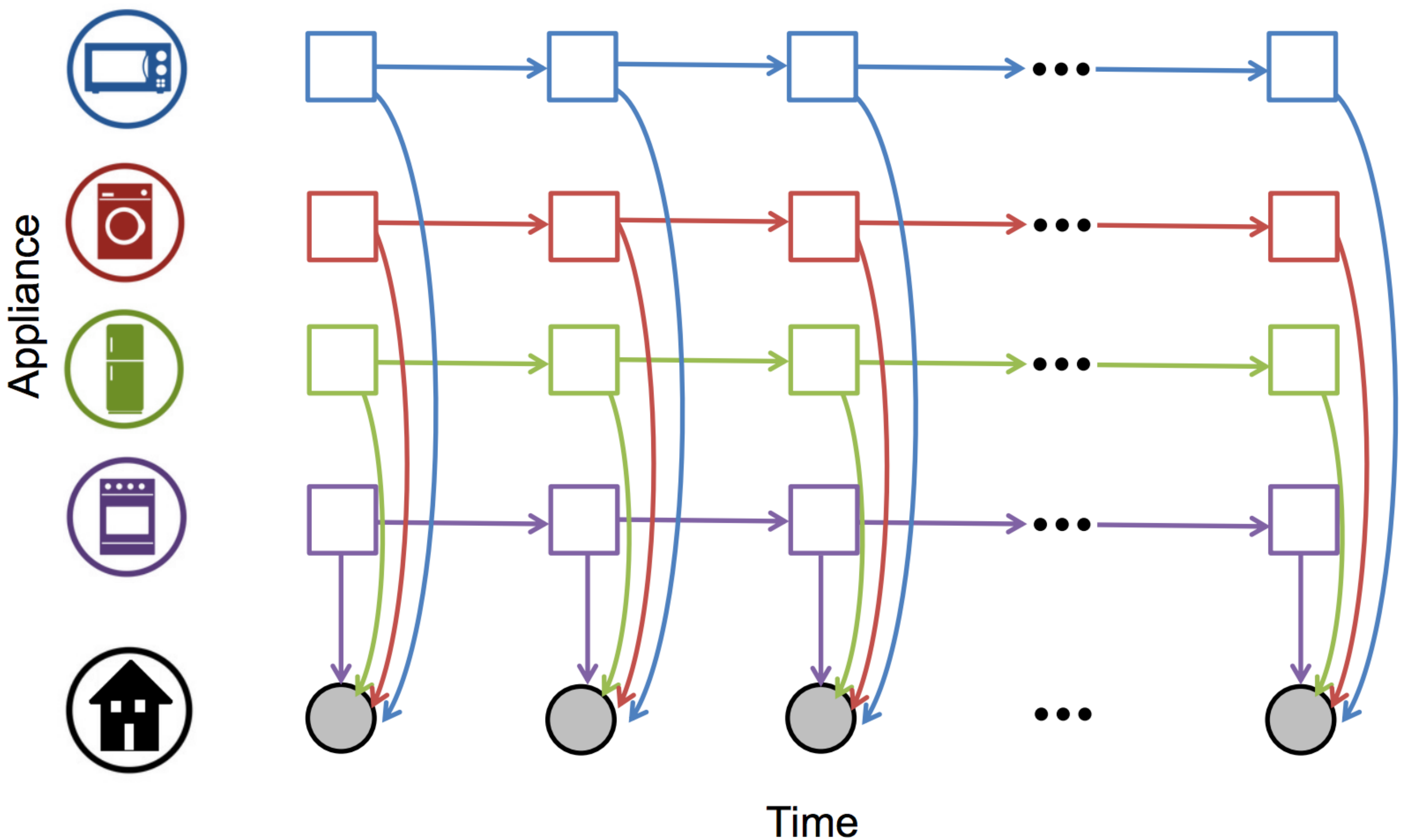
Appliance	Off power	On power
Air conditioner (AC)	0	2000
Refrigerator	0	200

Trivial Combinatorial Optimisation Based NILM Algorithm

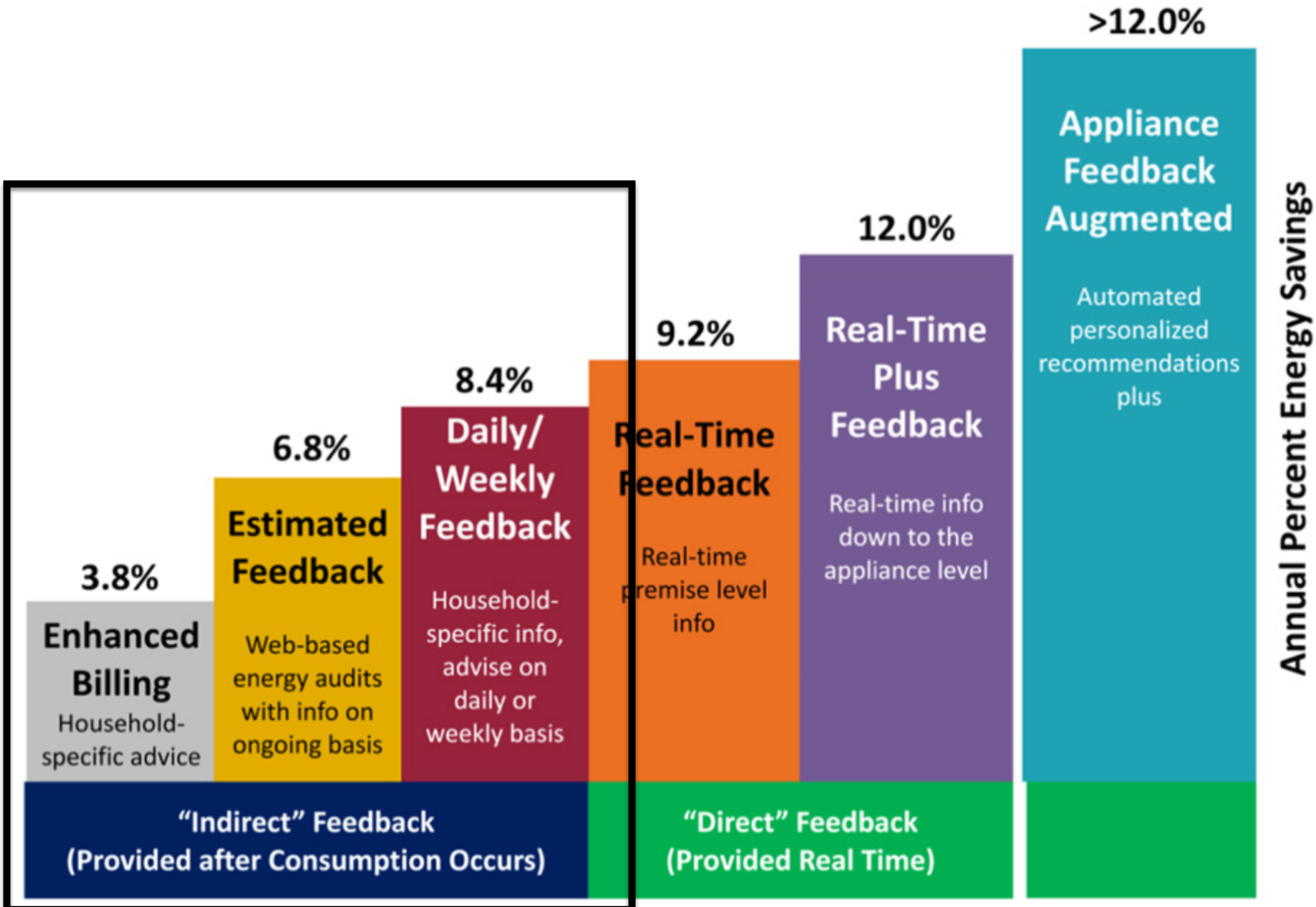
Total consumption=2200 W

Appliance	Off power	On power
Air conditioner (AC)	0	2000
Refrigerator	0	200

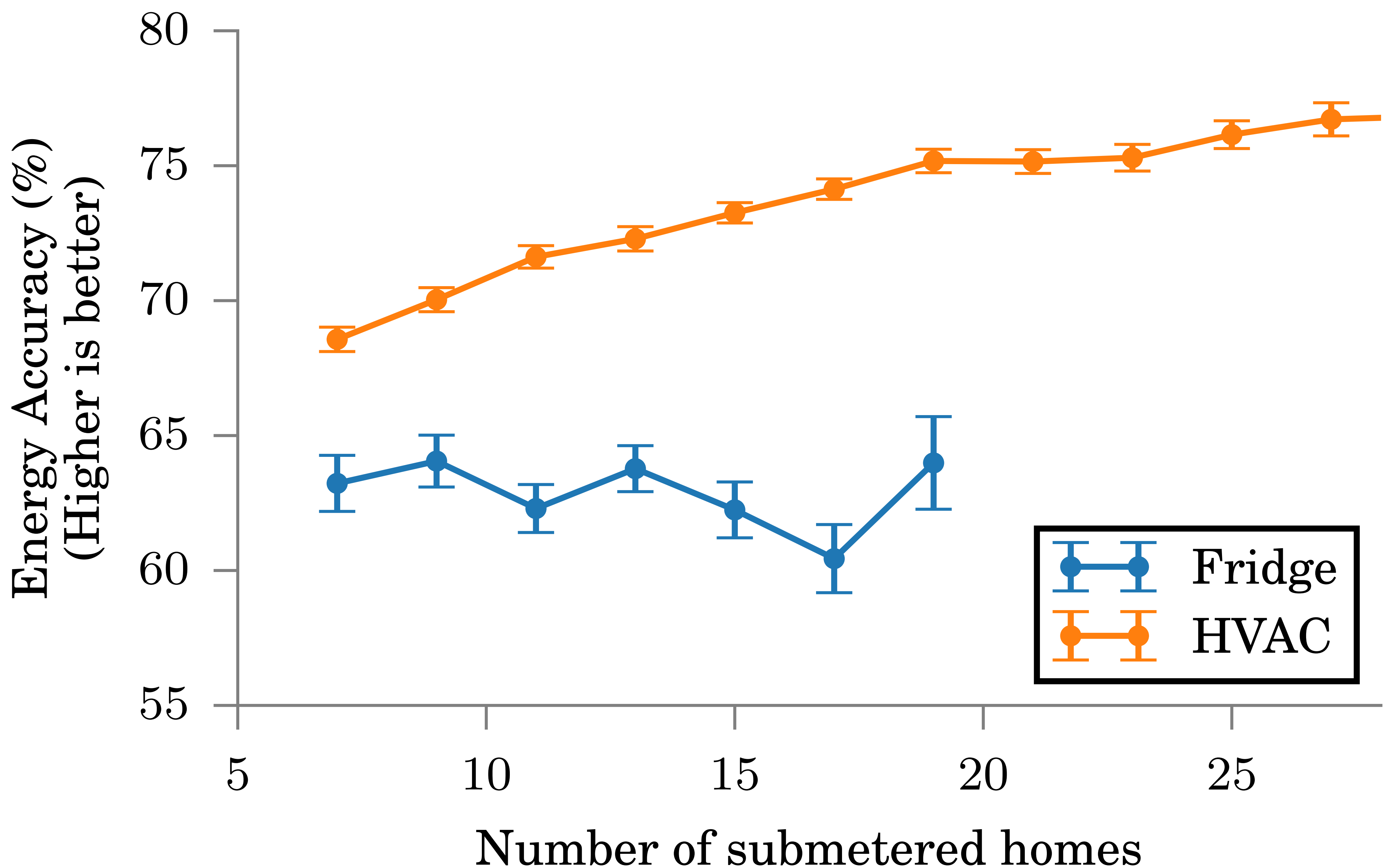
Factorial Hidden Markov Model



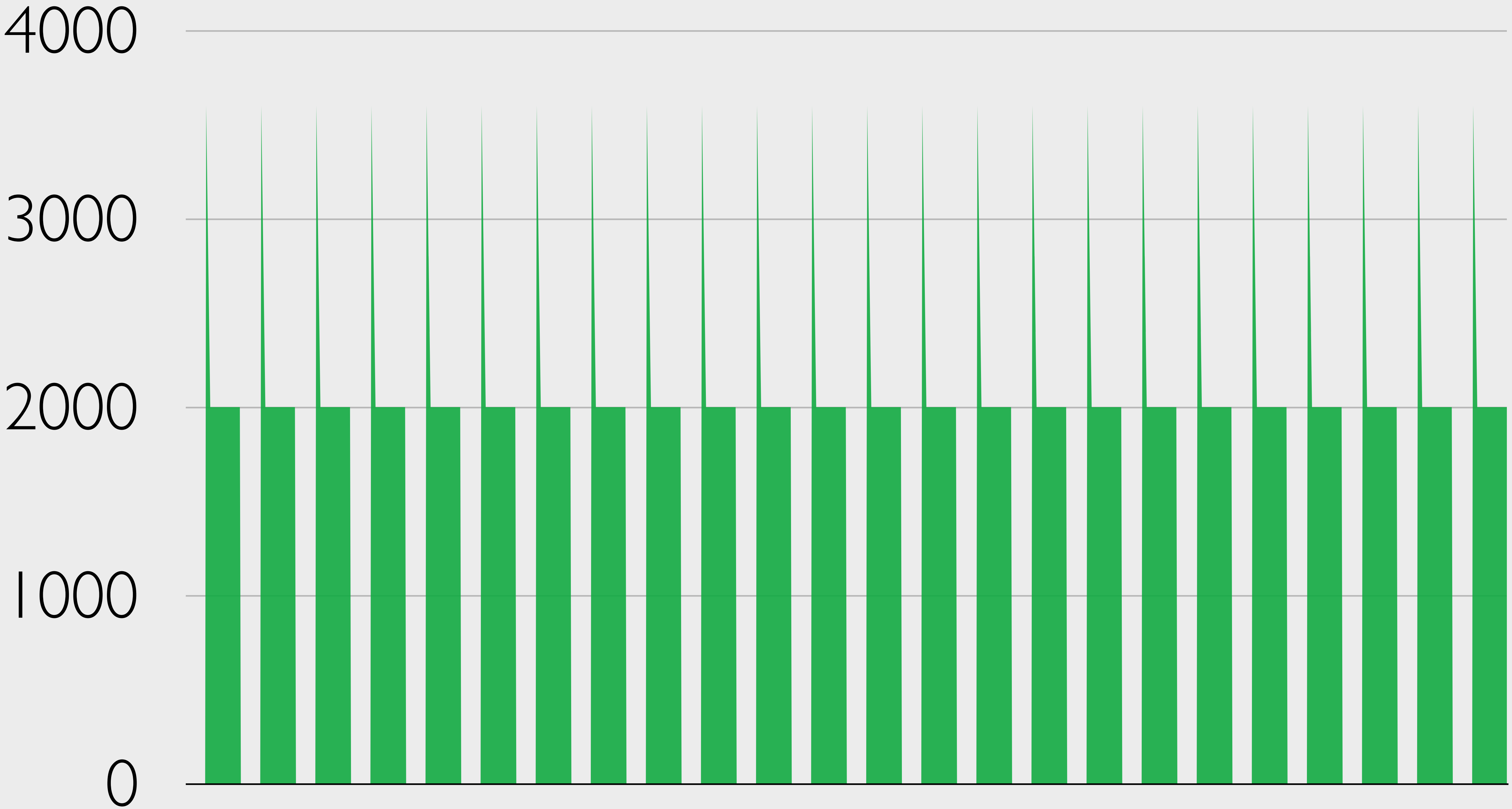
Feedback We Aim For



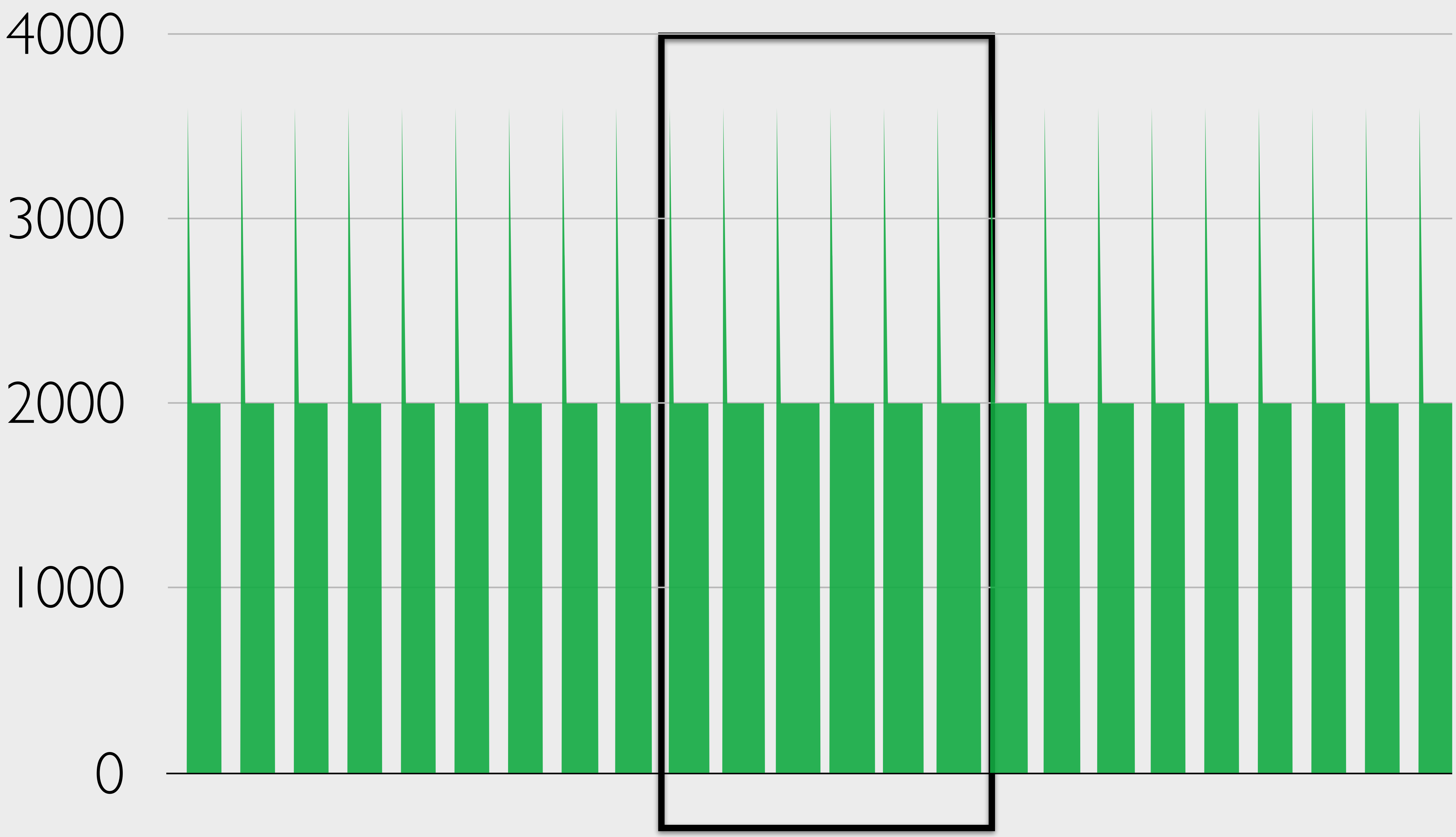
Gemello Sensitivity



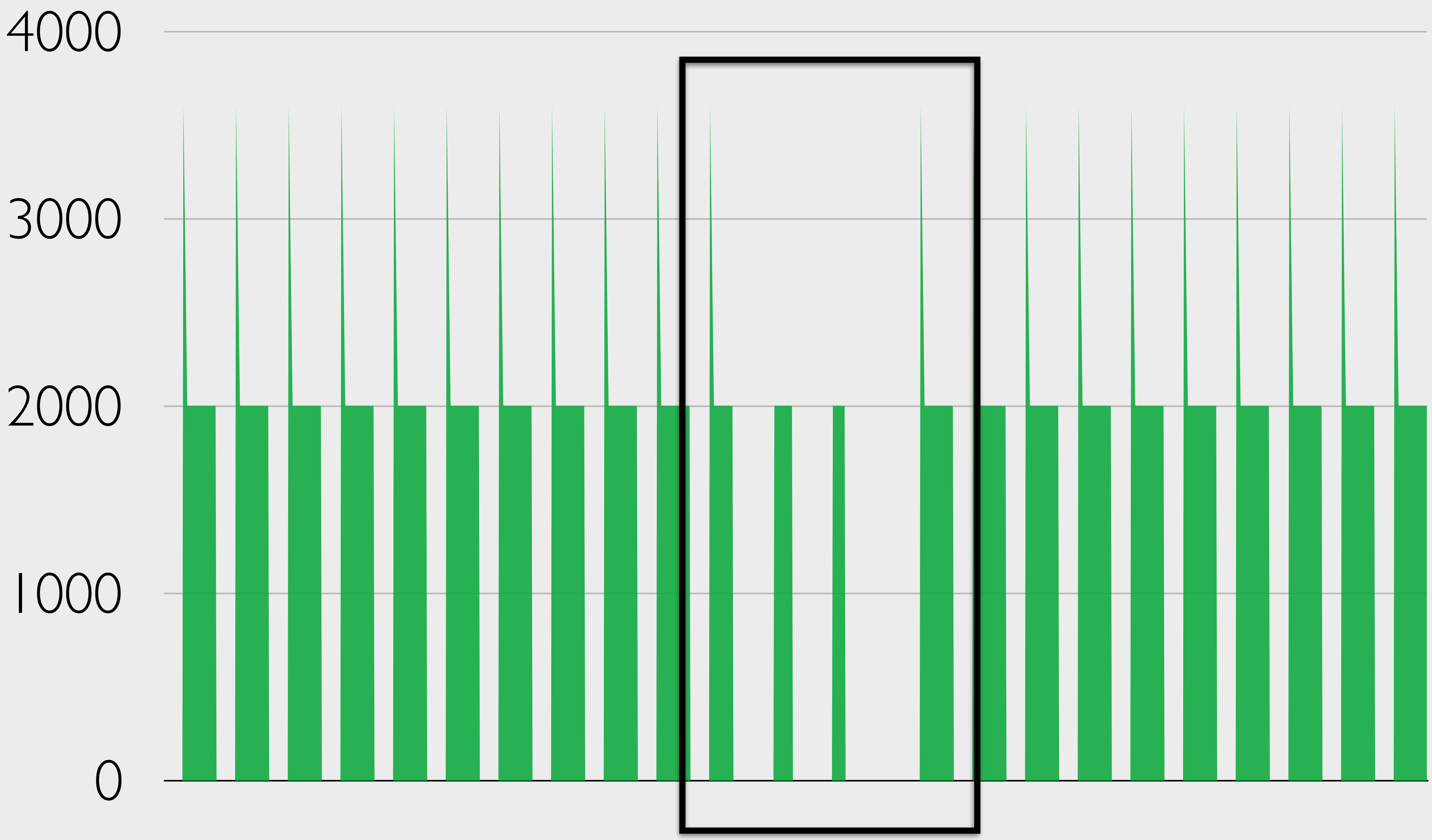
Like fridge, HVAC duty cycles to maintain the set temperature



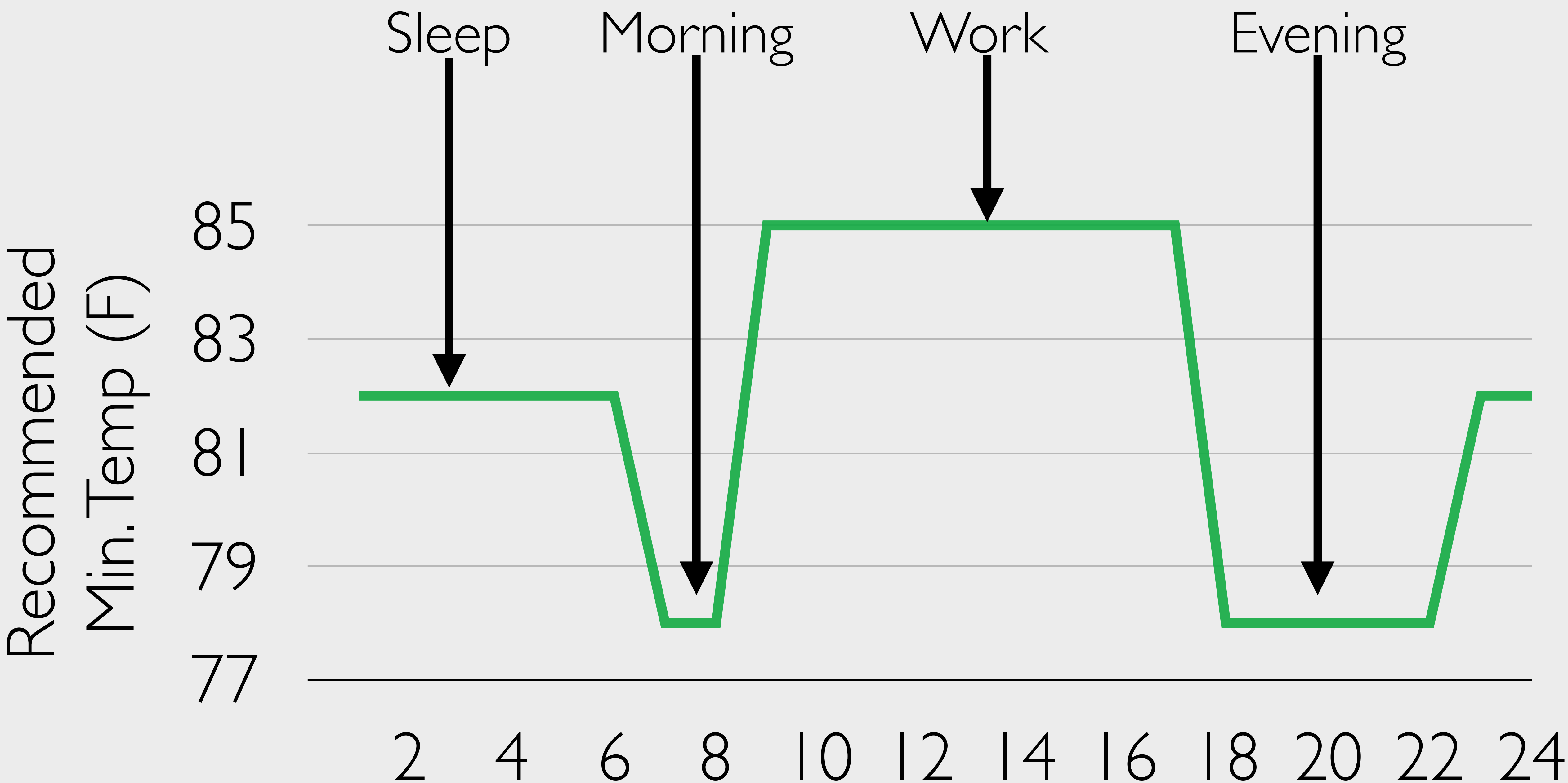
As temperature increases during the day, more energy required to cool the home



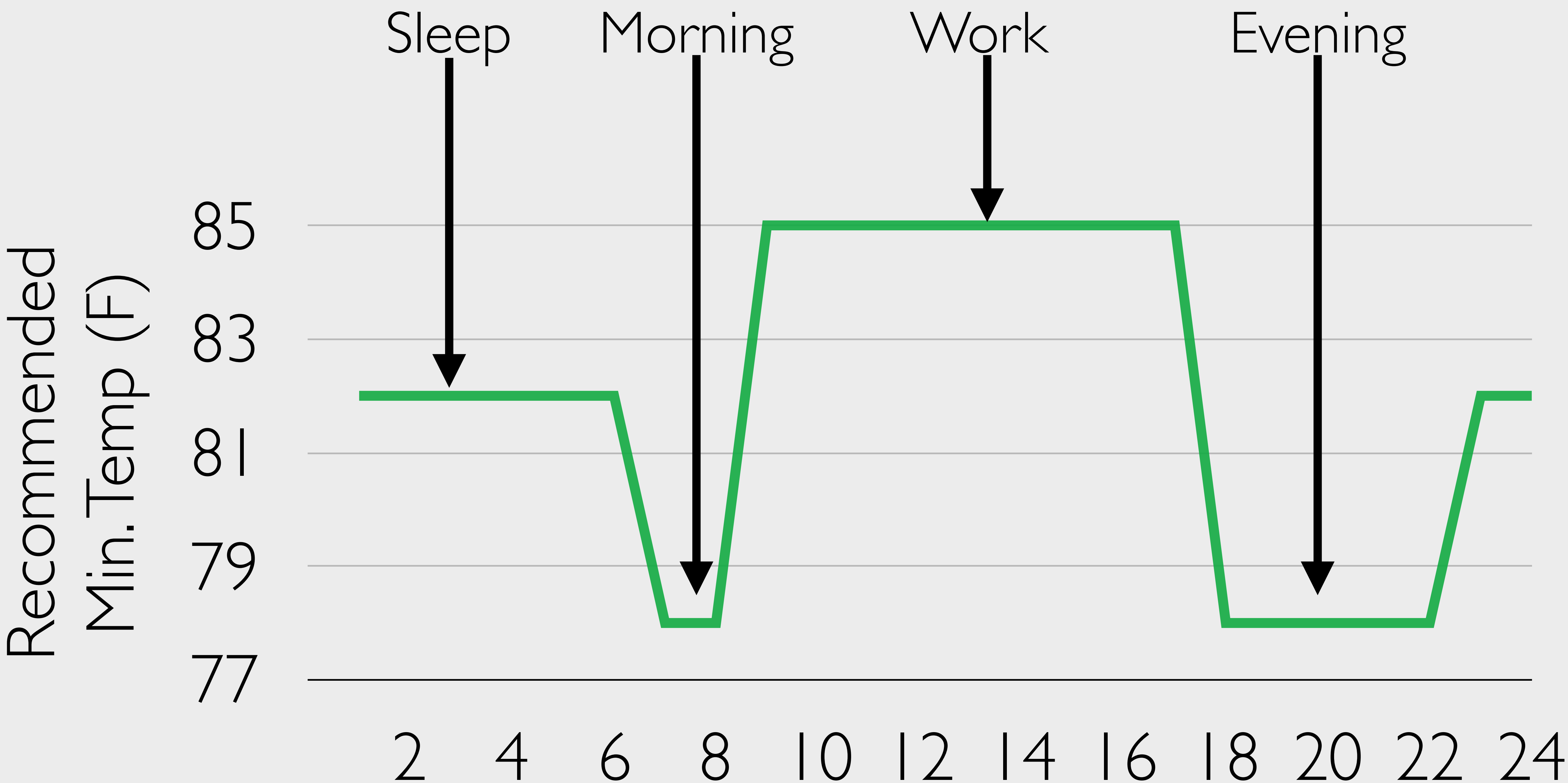
People typically turn up the temperatures when they leave home



EnergyStar.gov recommended HVAC setpoint schedule

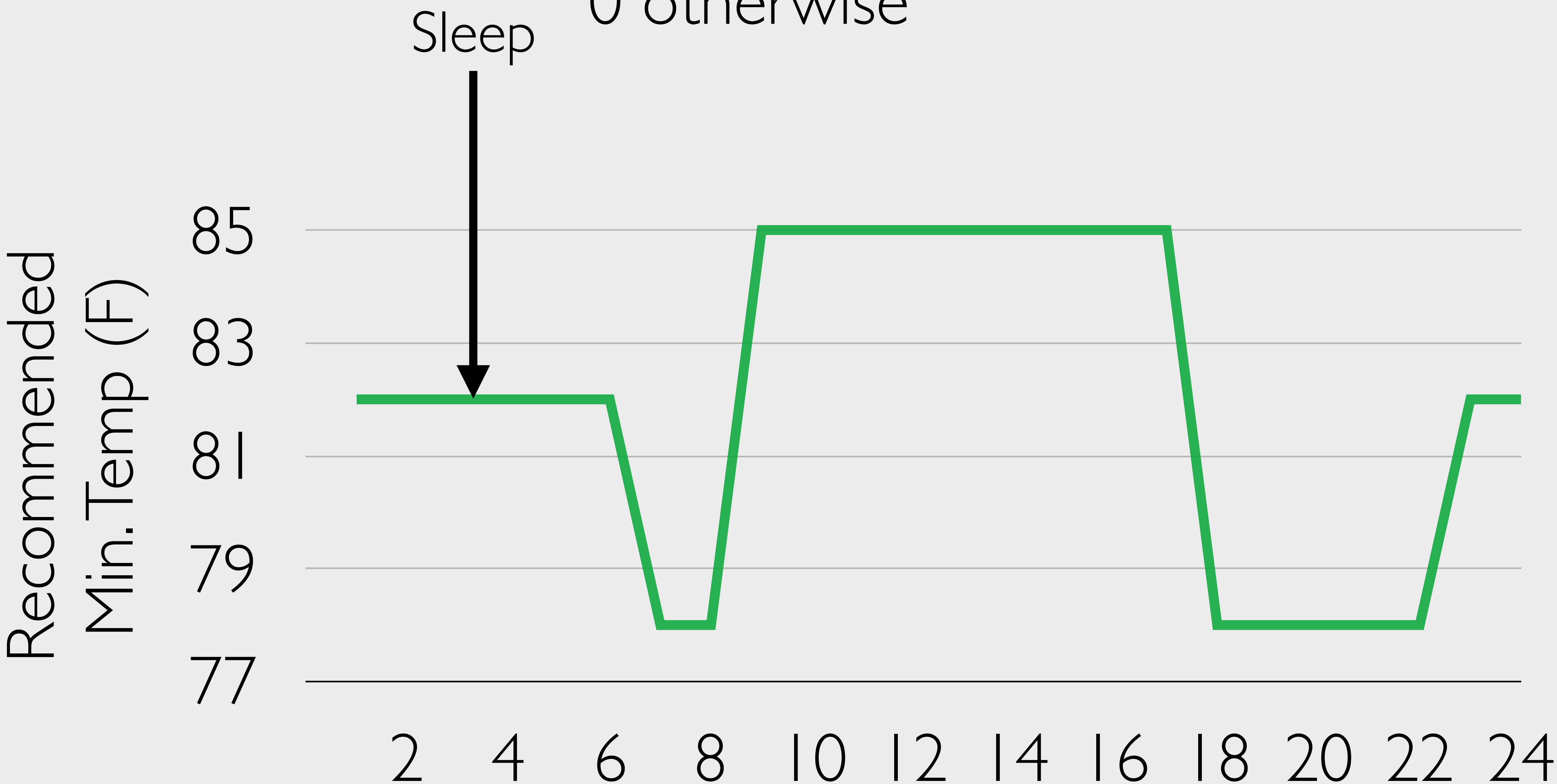


Setpoint schedule score

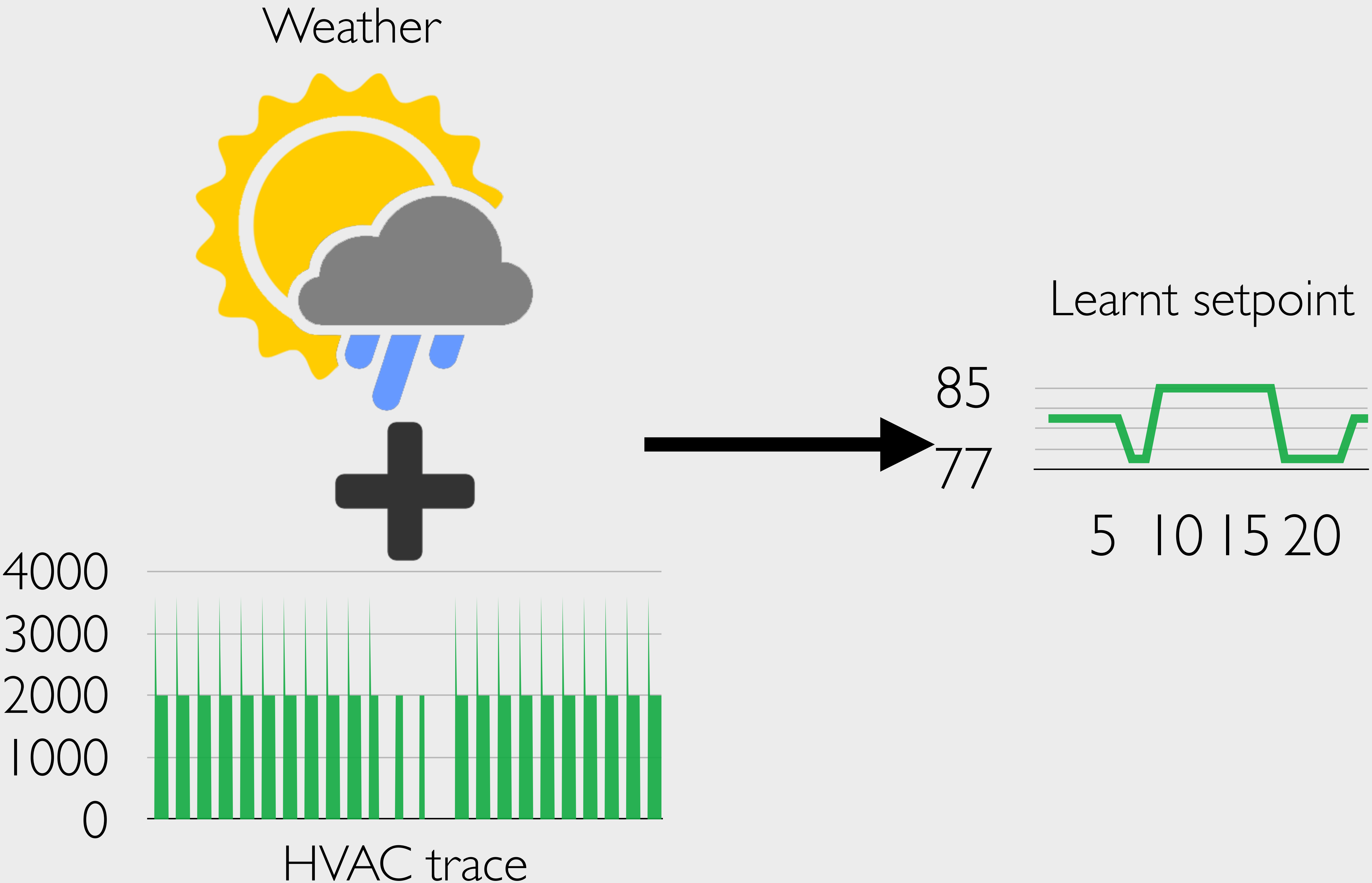


Setpoint schedule score

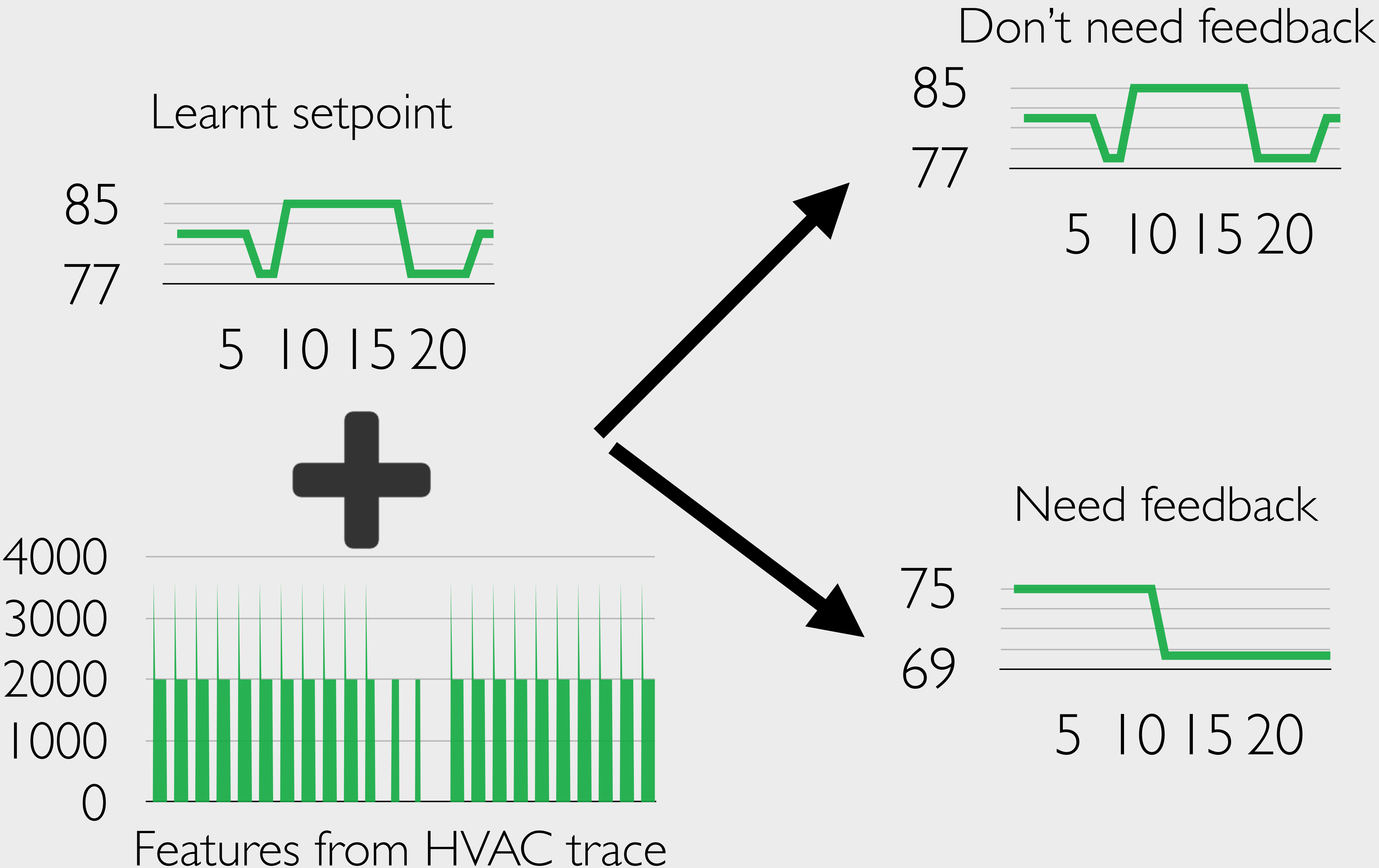
Sleep score = 1 if sleep temp. > 82,
(82-temp.)/4 if 78<sleep temp. <82
0 otherwise



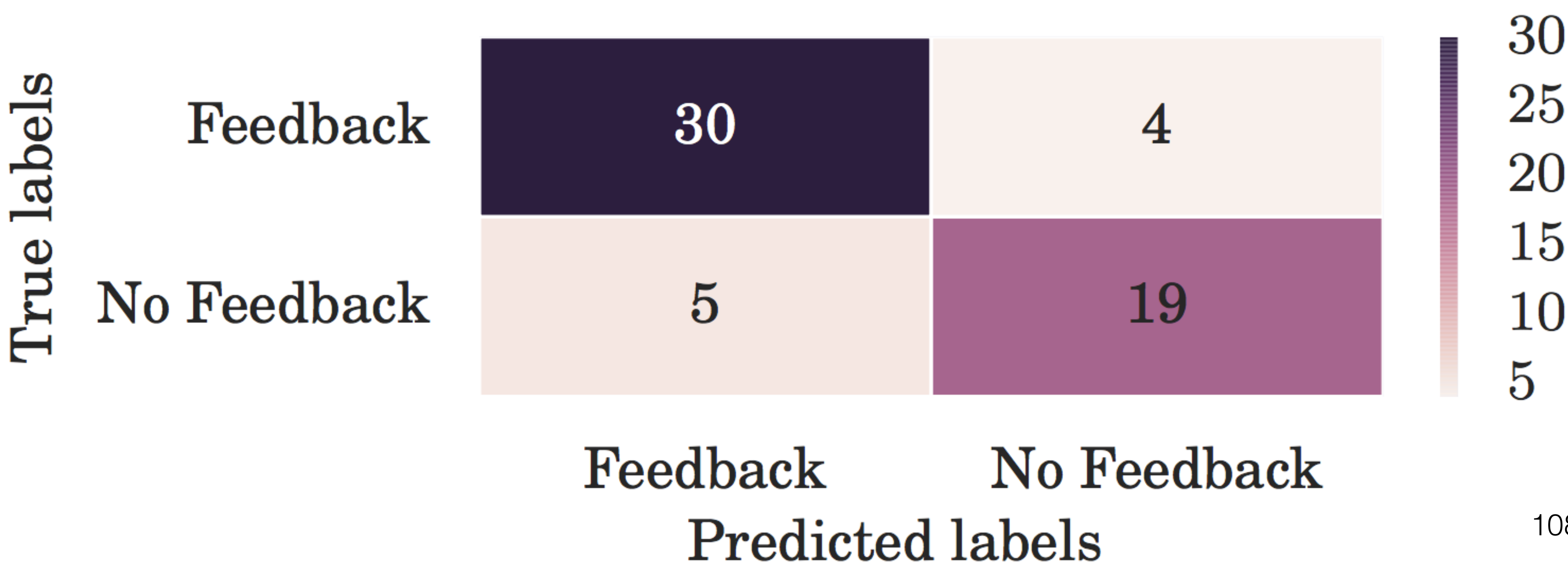
Learning HVAC setpoint

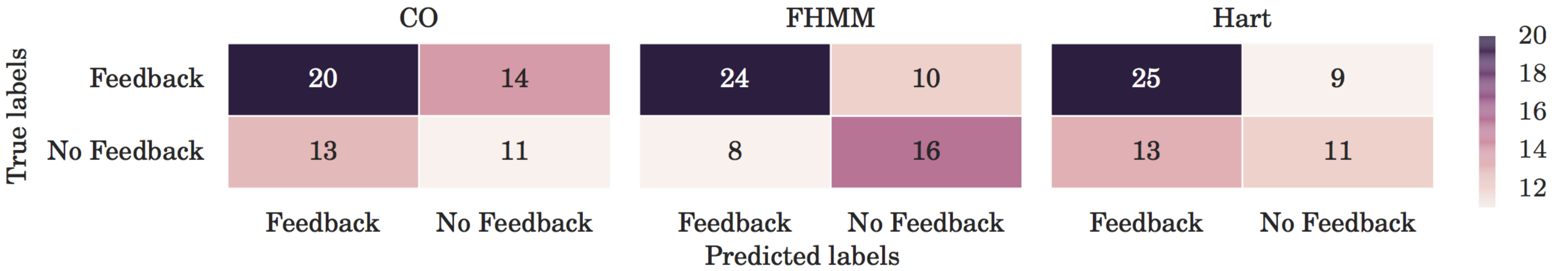


Giving feedback

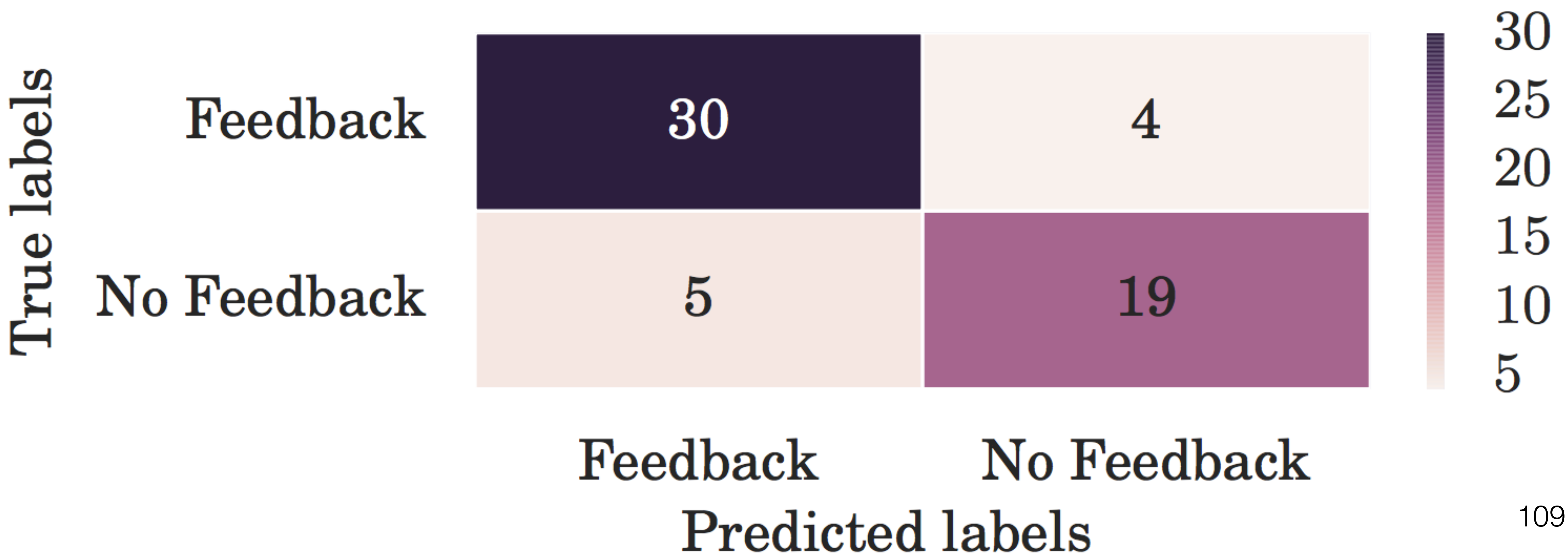


84% accuracy on giving feedback using submetered traces

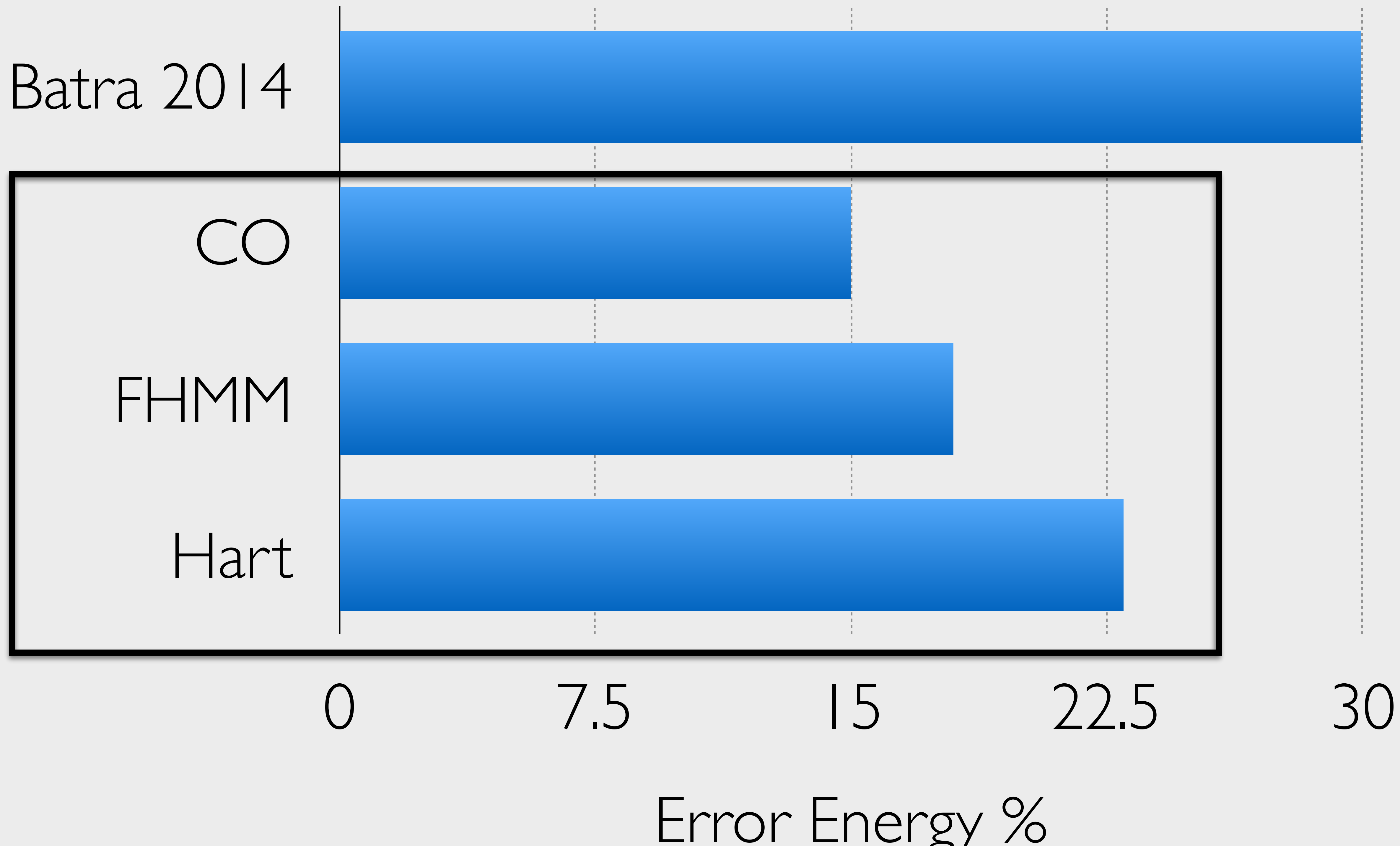




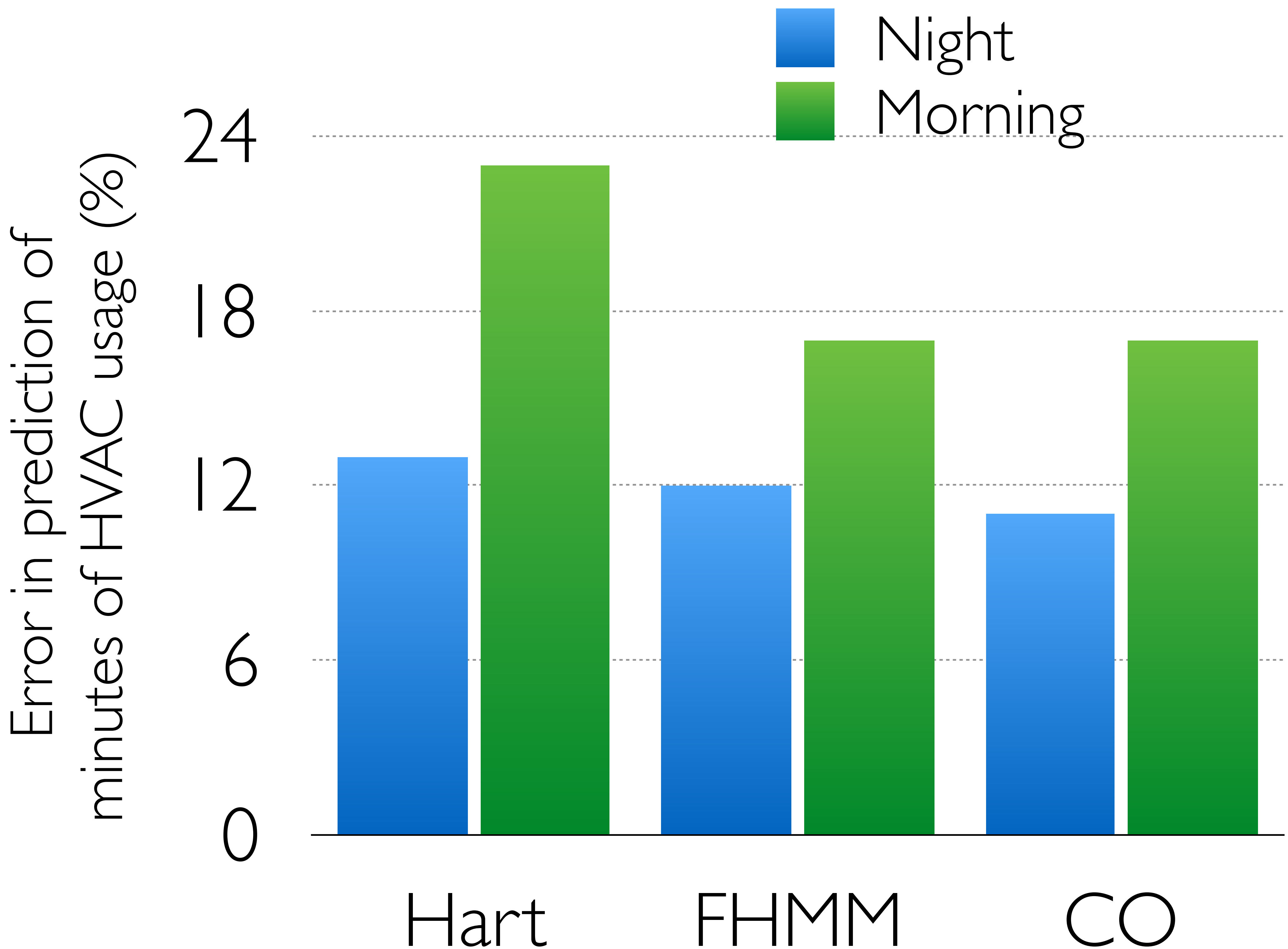
NILM methods give 15-30% worse accuracy for feedback



Benchmark NILM algorithms on our data set give accuracy comparable or better than state-of-the-art



Morning hours which have lesser NILM accuracy are important for HVAC feedback



Related Work

Plug load monitor

Related Work

Plug load monitor

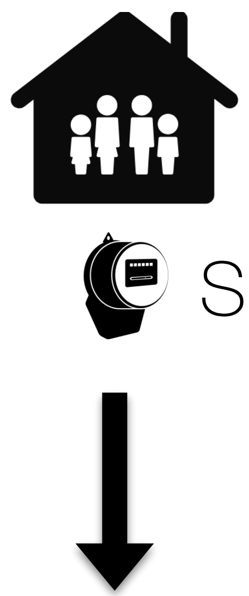
Circuit level monitor

Related Work

Related Work

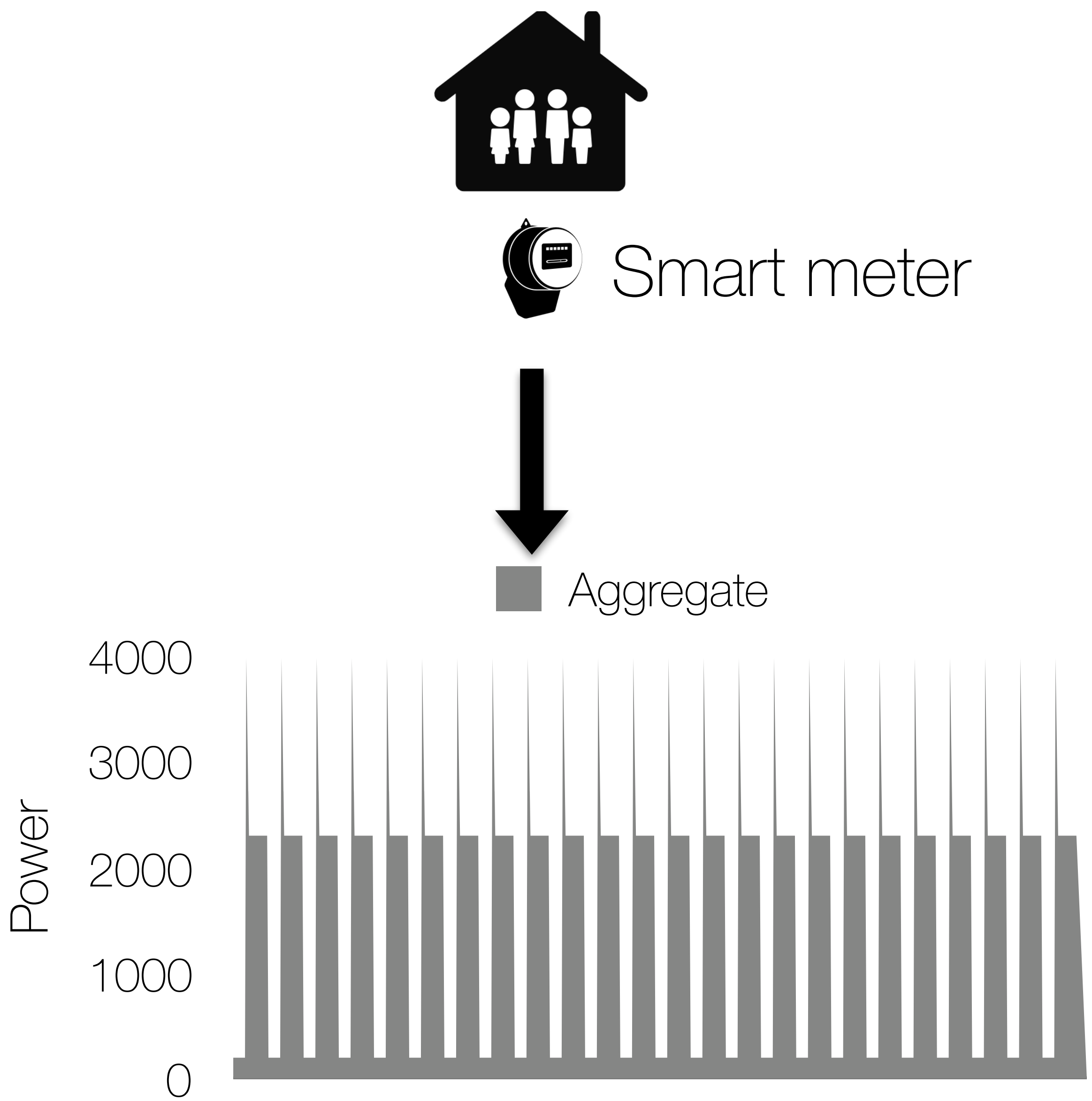
Smart meter

Related Work

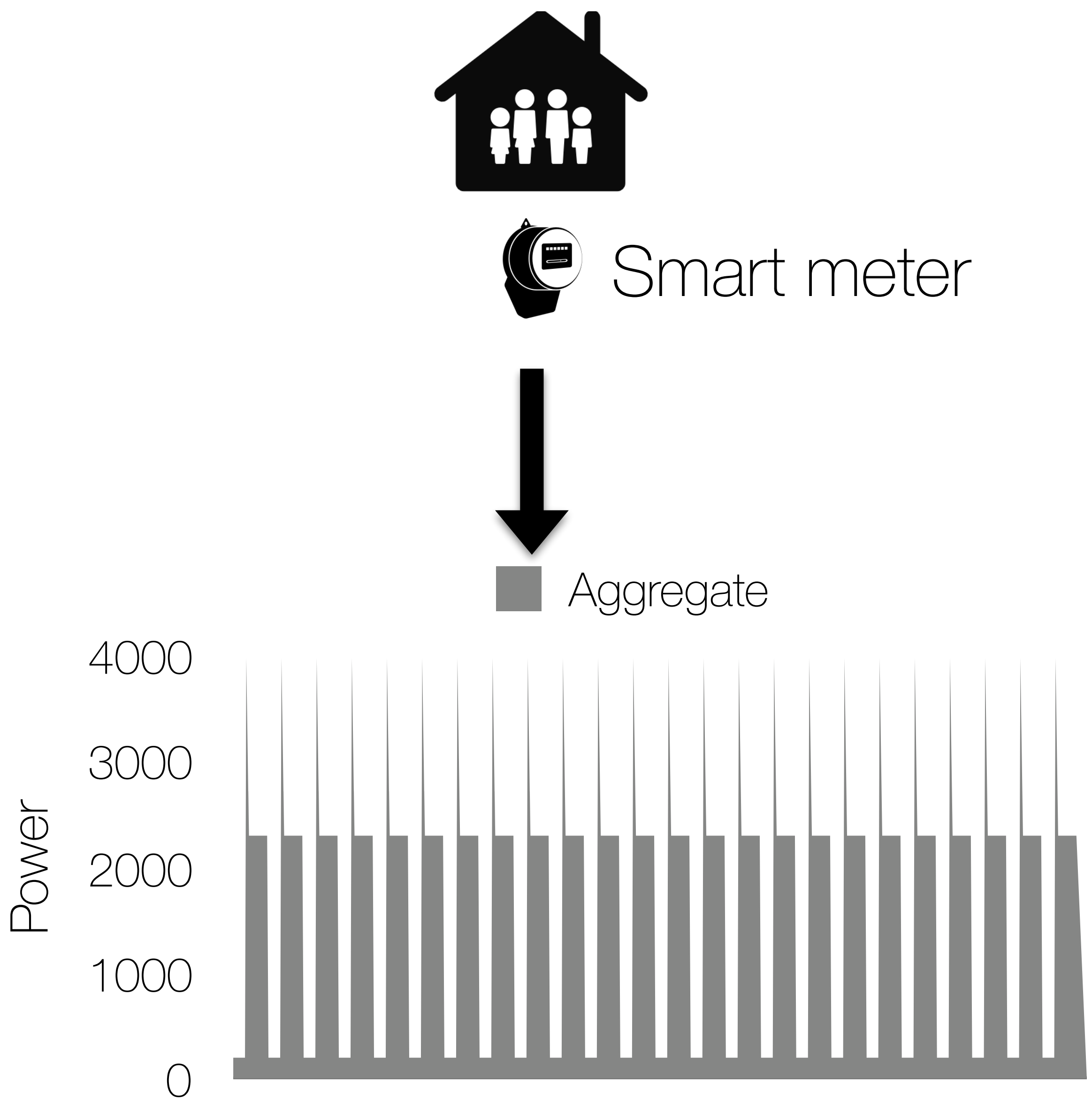


Smart meter

Related Work

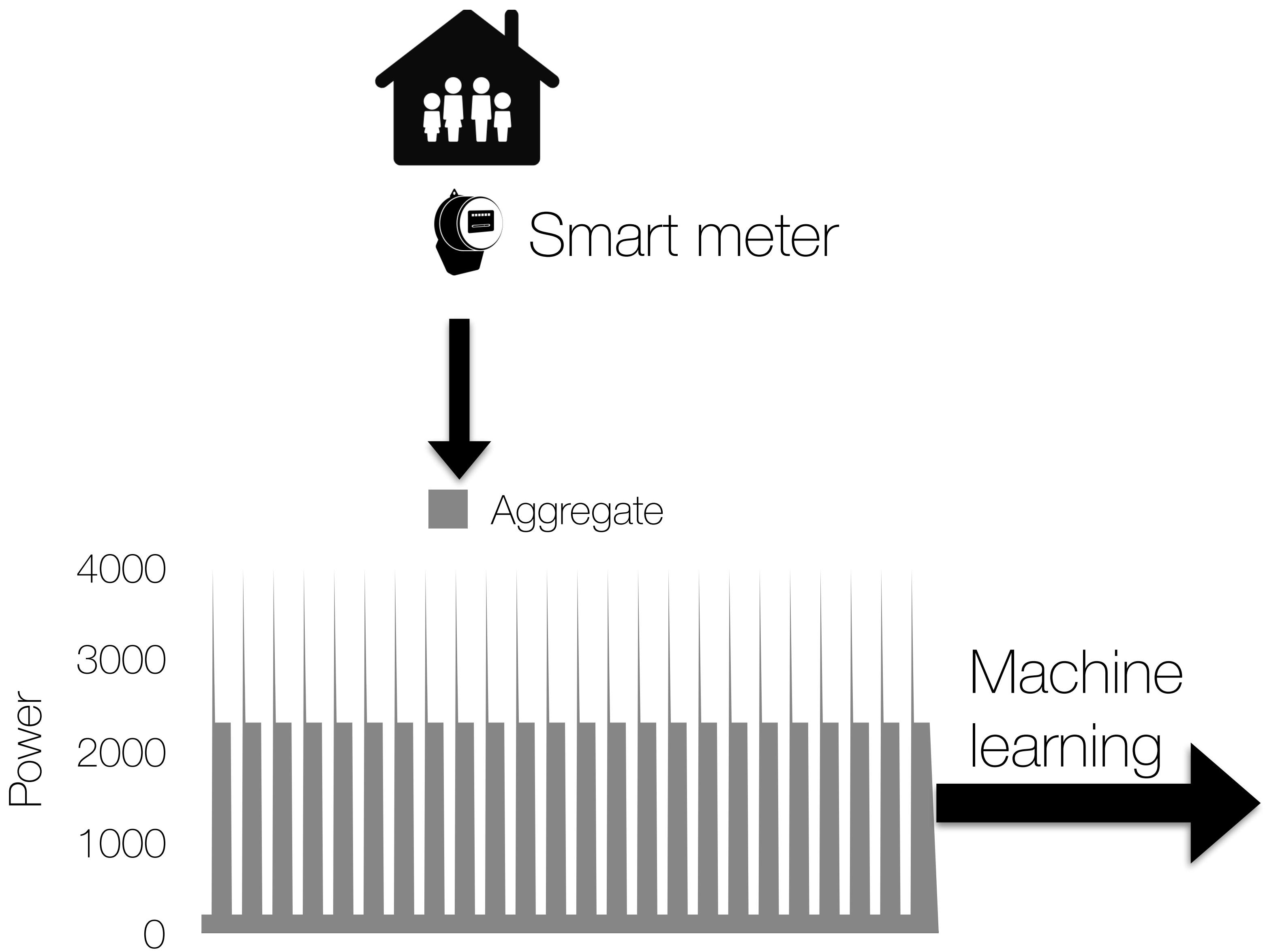


Related Work



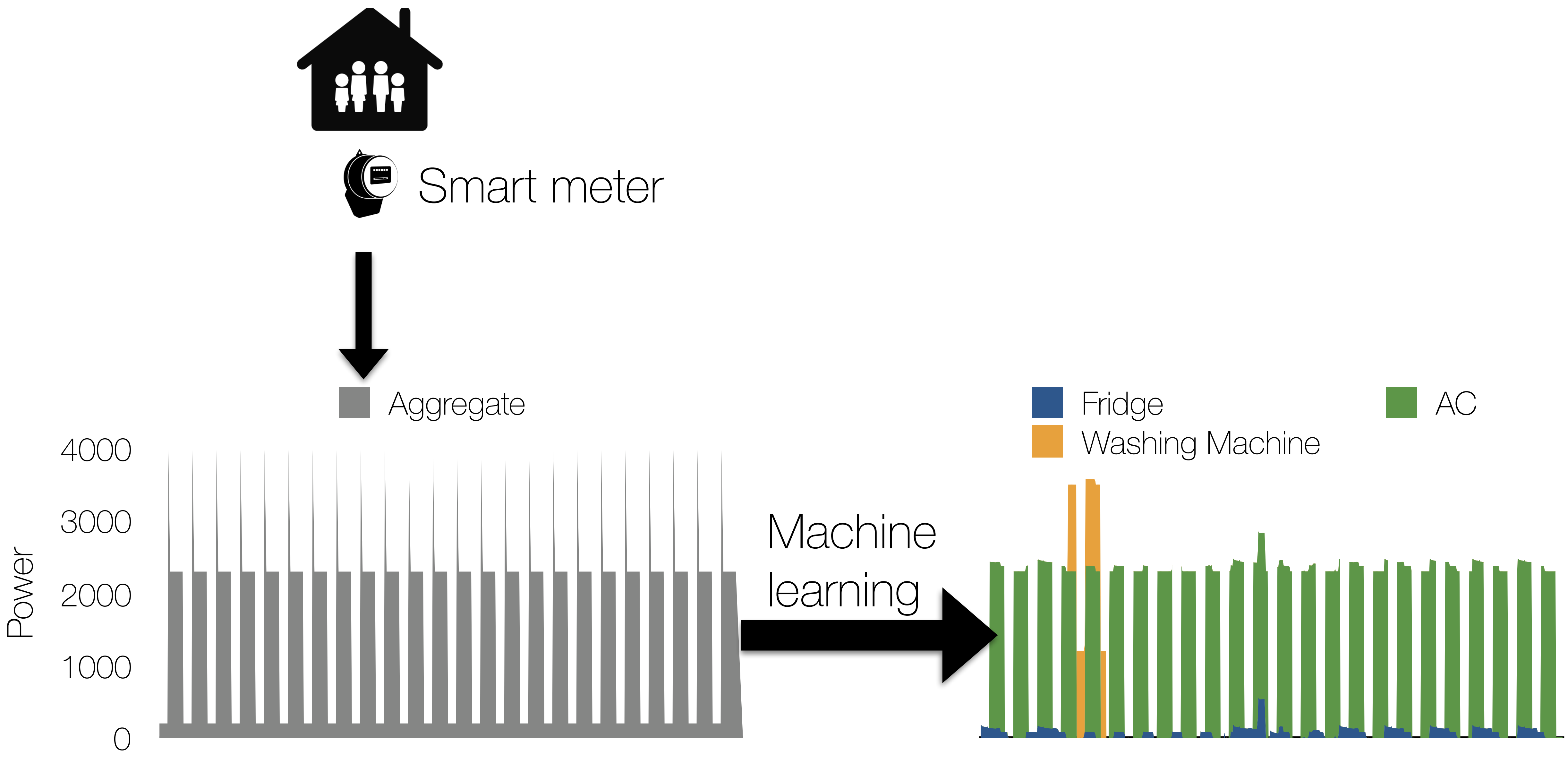
Non-intrusive load monitoring (NILM)

Related Work



Non-intrusive load monitoring (NILM)

Related Work



Non-intrusive load monitoring (NILM)

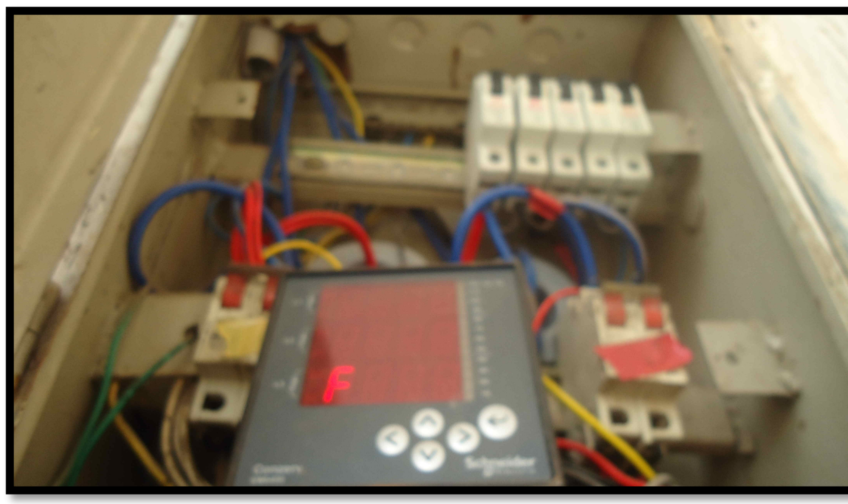
Outline

- Scalable Energy Breakdown
  - Gemello [KDD 2016]
  - Matrix Factorisation [AAAI 2017]
- Making NILM better
  - Comparable [Buildsys 2015]
  - Actionable [e-Energy 2014]

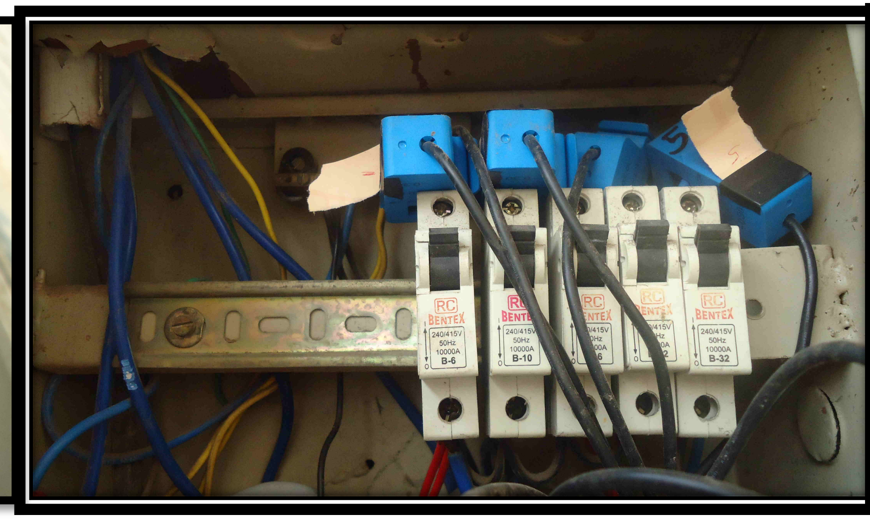
Outline

- **Scalable Energy Breakdown**
    - Gemello [KDD 2016]
    - Matrix Factorisation [AAAI 2017]
- Making NILM better
    - Comparable [Buildsys 2015]
    - Actionable [e-Energy 2014]

Electricity monitoring



Smart Meter

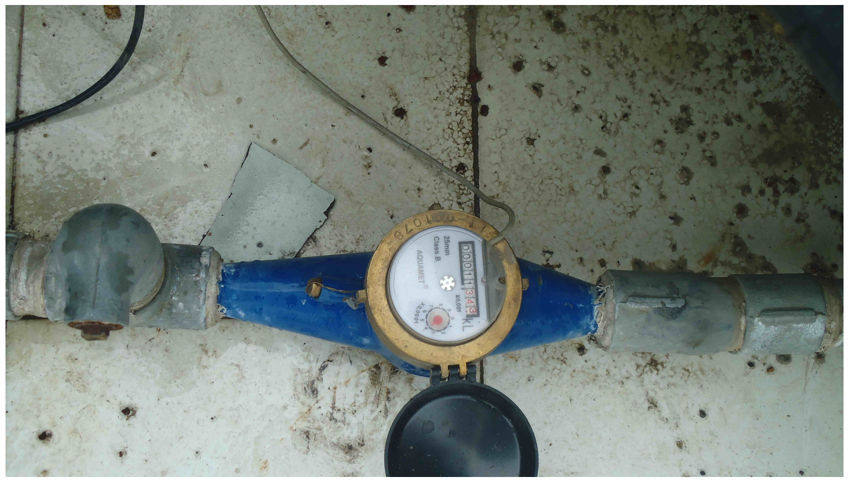


Circuit Breaker

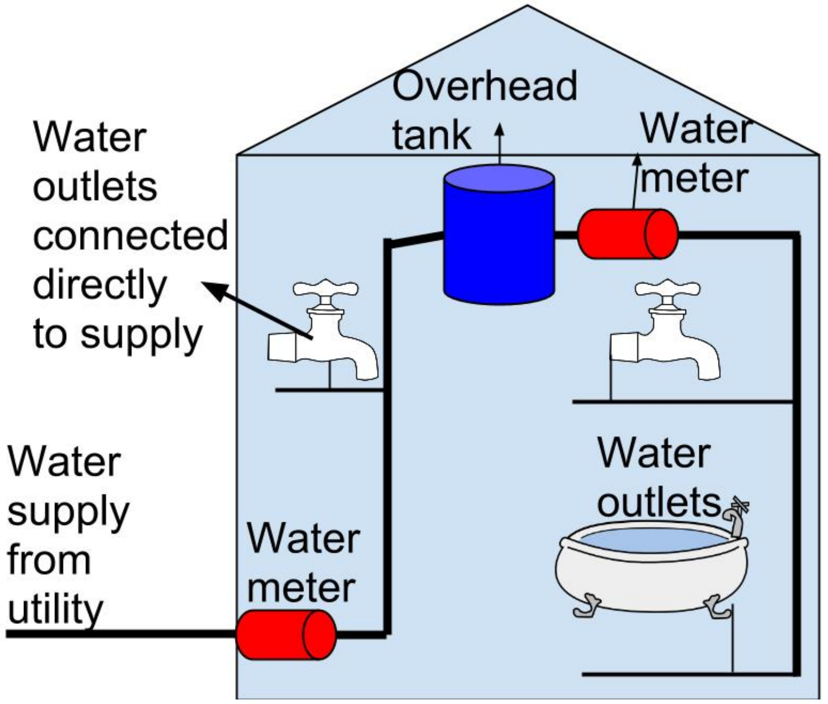
Appliance Level

- Measuring electricity consumption at Supply, MCB, Appliance
- Research questions:
  - Value of additional information (and associated cost)?
  - What level of invasiveness?

Water monitoring



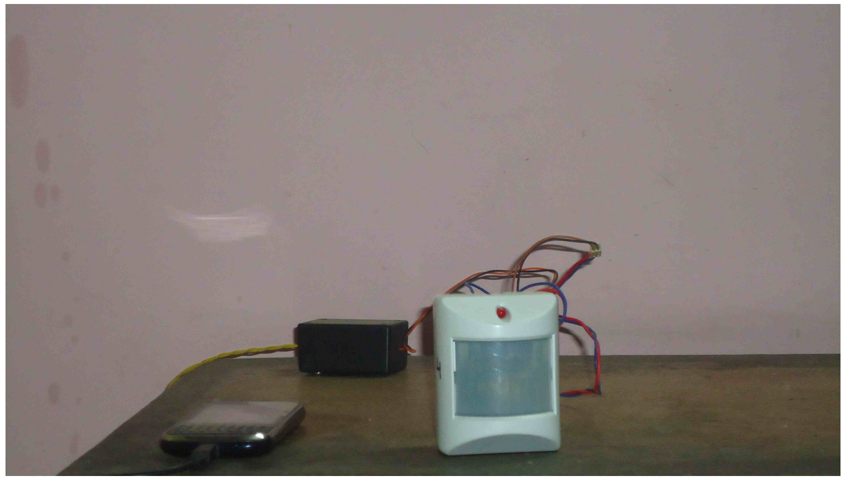
Pulse based water meter



- Water supply available only for 2 hours in a day
  - Pumps used to store water in tanks- Water has EMBEDDED Energy
- Instrument the demand and the supply using Pulse based meters

Ambient sensing

- Energy consumption correlated with ambient settings
- Measure following ambient parameters
  - Light
  - Temperature
  - Motion
  - Sound level
  - Bluetooth, WiFi



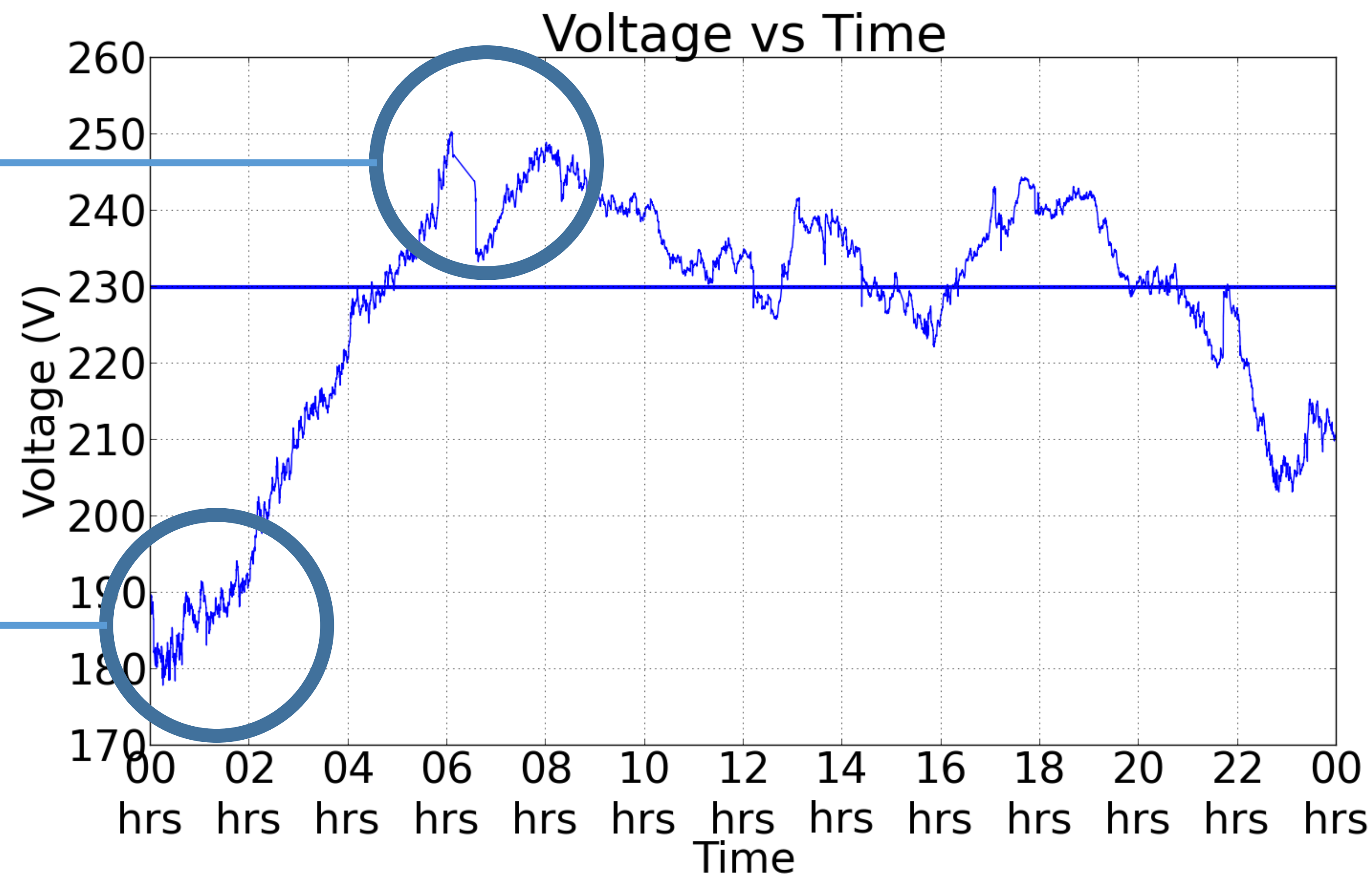
ZWave Multisensor +Android

Unique Features in India
Unreliable Grid

1. Voltage fluctuation

Highest voltage typically seen early morning

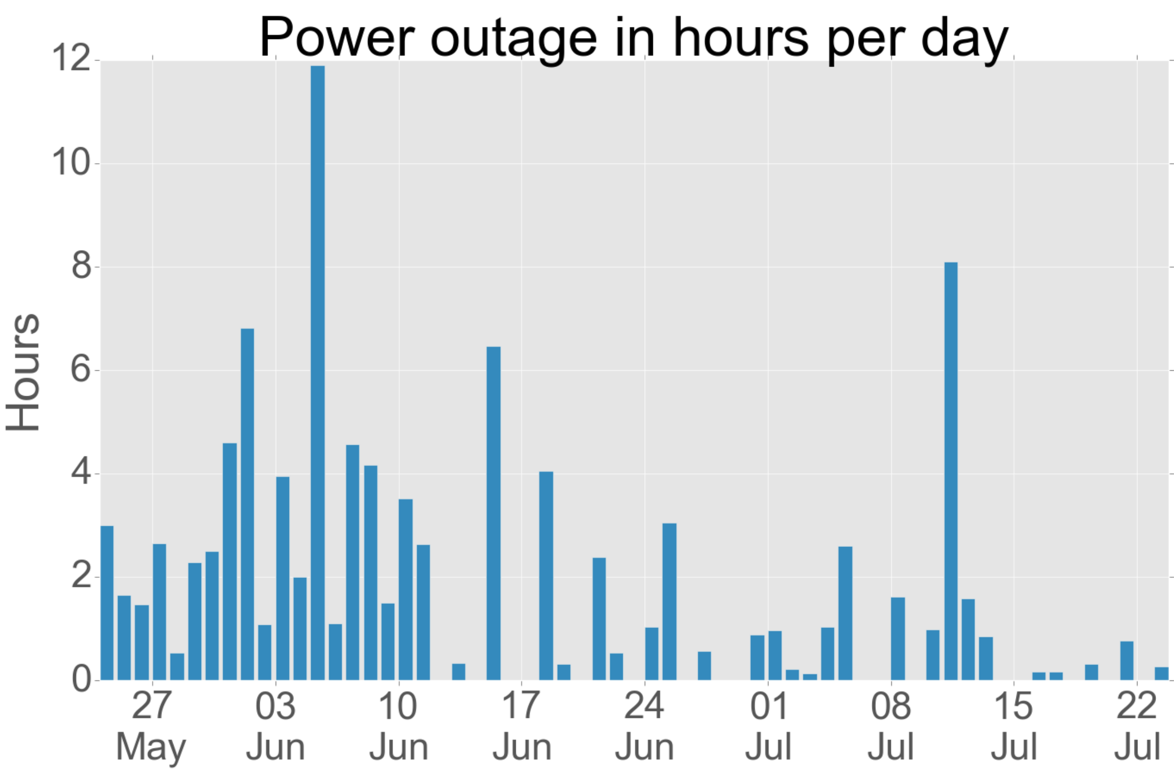
Lowest voltage typically seen around midnight- ACs in most home are ON

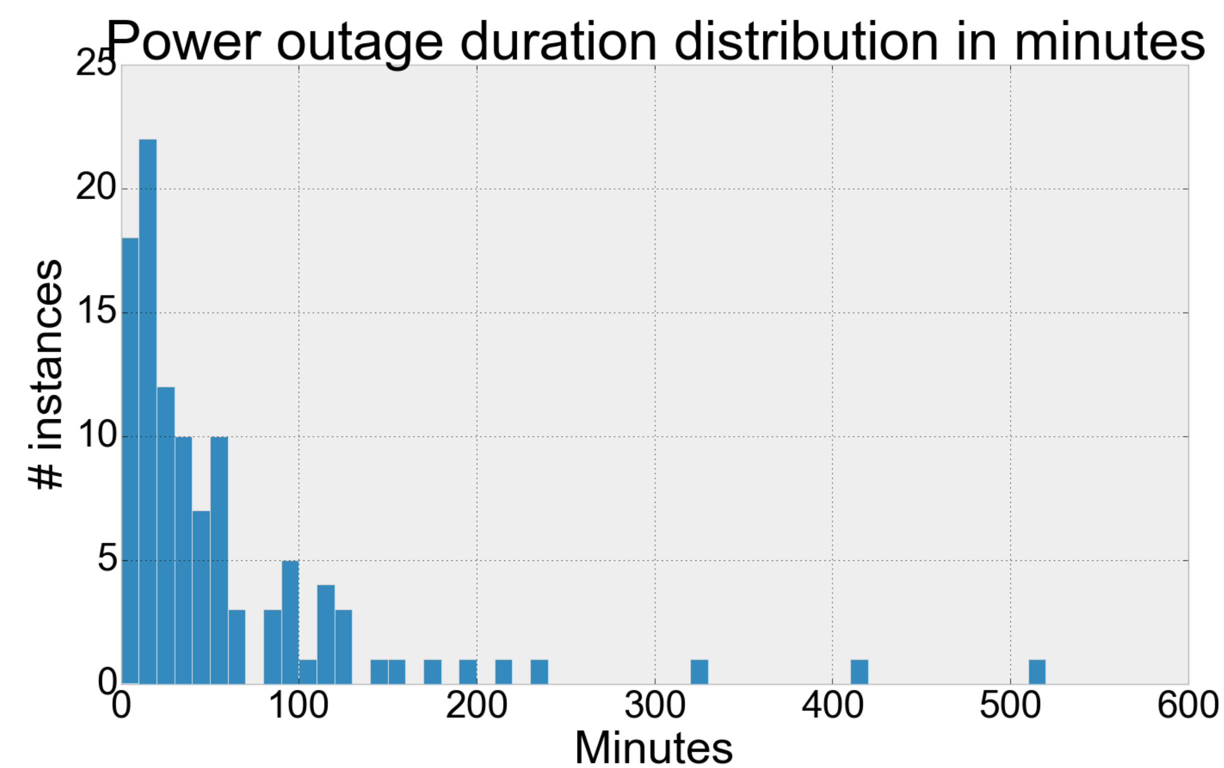


10

Unique Features in India
Unreliable Grid

2. Blackouts





Observed power outages upto 12 hours a day!

Single power outages of upto 9 hrs observed!

11

Unique Features in India
Unreliable Grid

3. Learning

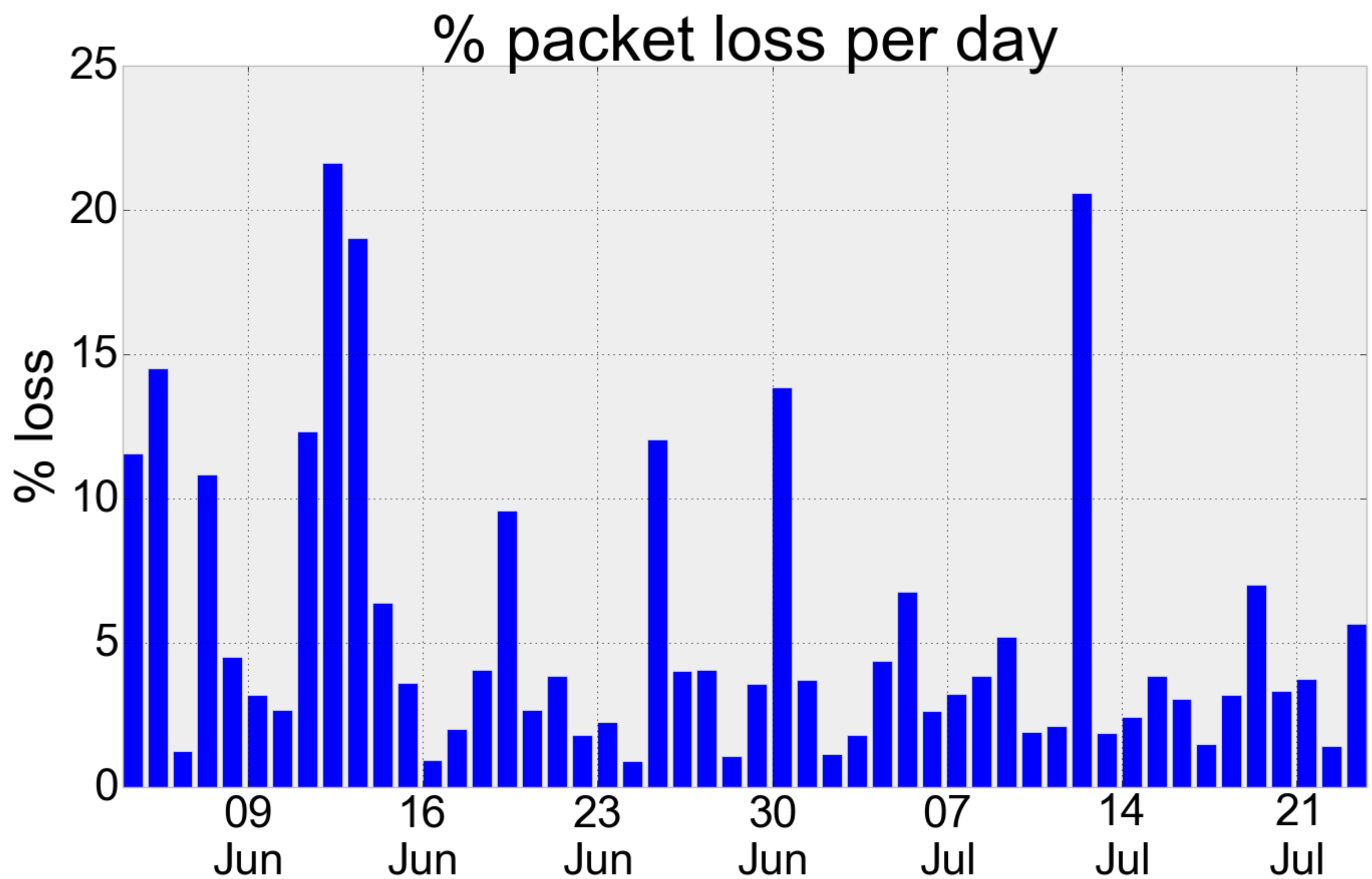
- System Design: System should be capable of resuming in same state as it was before outage (Batteries way too difficult to manage ☹)
- Inferences: Need to measure voltage in addition to current for NILM approaches!

Unique Features in India
Unreliable network- Internet

Observed up to 1/4th packet loss on some days

Learning

- Need to account for unreliable internet
- Need to do local storage of data
- We followed Sense-Local store- Upload



Unique Features in India
Load specifics

- Bathroom level water heating-
  - Runs off electricity as opposed to gas
  - Contributes ~60% of total energy in winters
- Room level air conditioning
  - Used only in summers
  - Control is de-centralized
- These two loads are fairly easy to disaggregate- Easy to act upon to reduce energy footprint

iAWE: Indian Dataset for Ambient, Water and Electricity sensing

- 2+ months of data
  - 1 day fully labeled data
  - Rest semi-labeled
- Electricity, Water, Ambient conditions at different granularities
- Dataset released for public use