

A Longitudinal Study of Pressure Sensing to Infer Real-World Water Usage Events in the Home

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today's usage

refrigerator
0.3 gallons

dishwasher
6.5 gallons

kitchen sink
28 gallons



today's usage

shower
62.4 gallons

bath
6.5 gallons

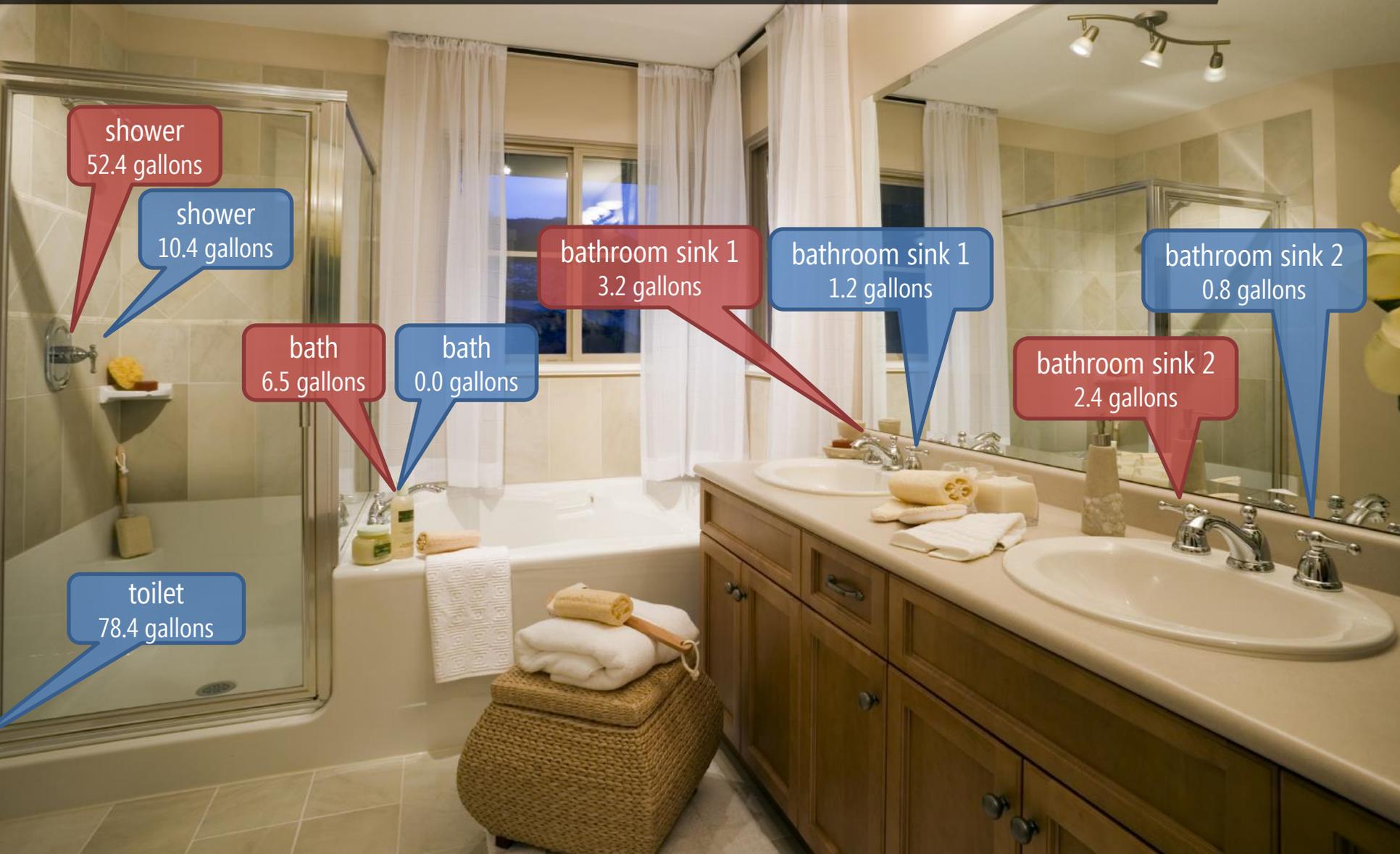
toilet
78.4 gallons

bathroom sink 1
4.2 gallons

bathroom sink 2
0.8 gallons



today's usage: hot vs. cold



shower
52.4 gallons

shower
10.4 gallons

bath
6.5 gallons

bath
0.0 gallons

toilet
78.4 gallons

bathroom sink 1
3.2 gallons

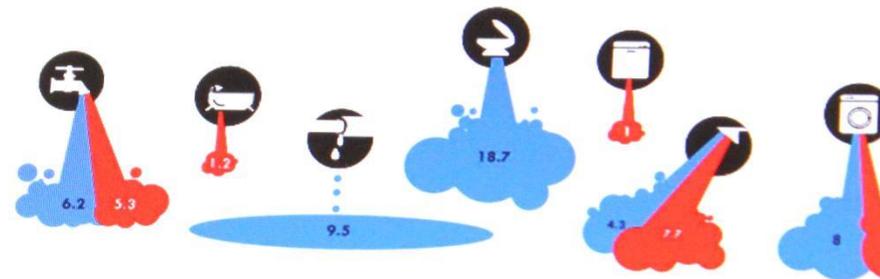
bathroom sink 1
1.2 gallons

bathroom sink 2
2.4 gallons

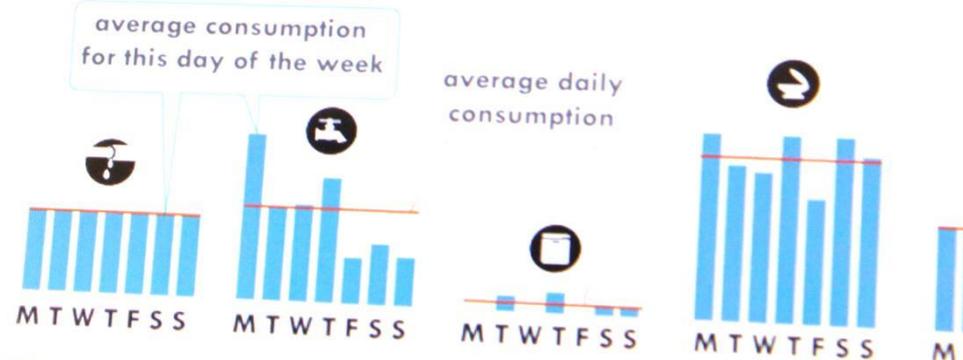
bathroom sink 2
0.8 gallons

sustainability applications

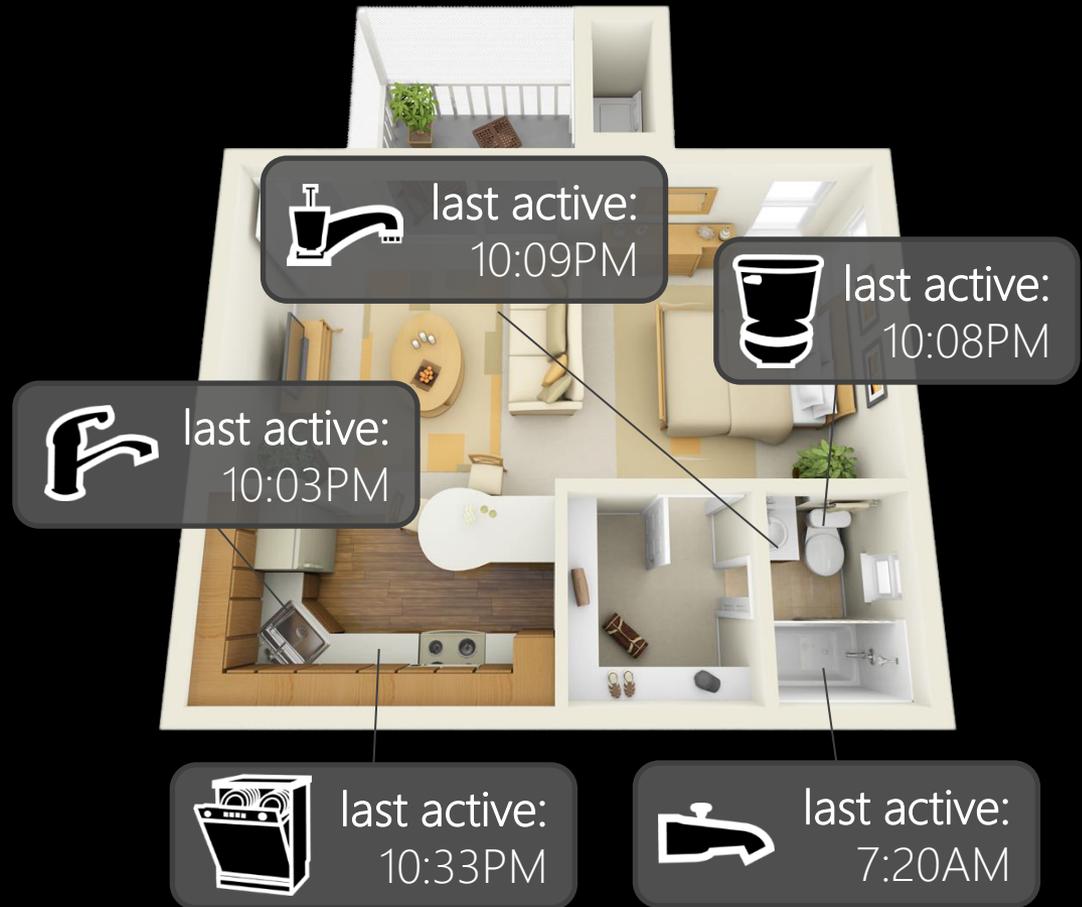
Daily average consumption by fixture for the month of



Weekly consumption pattern for the month of



assisted living applications



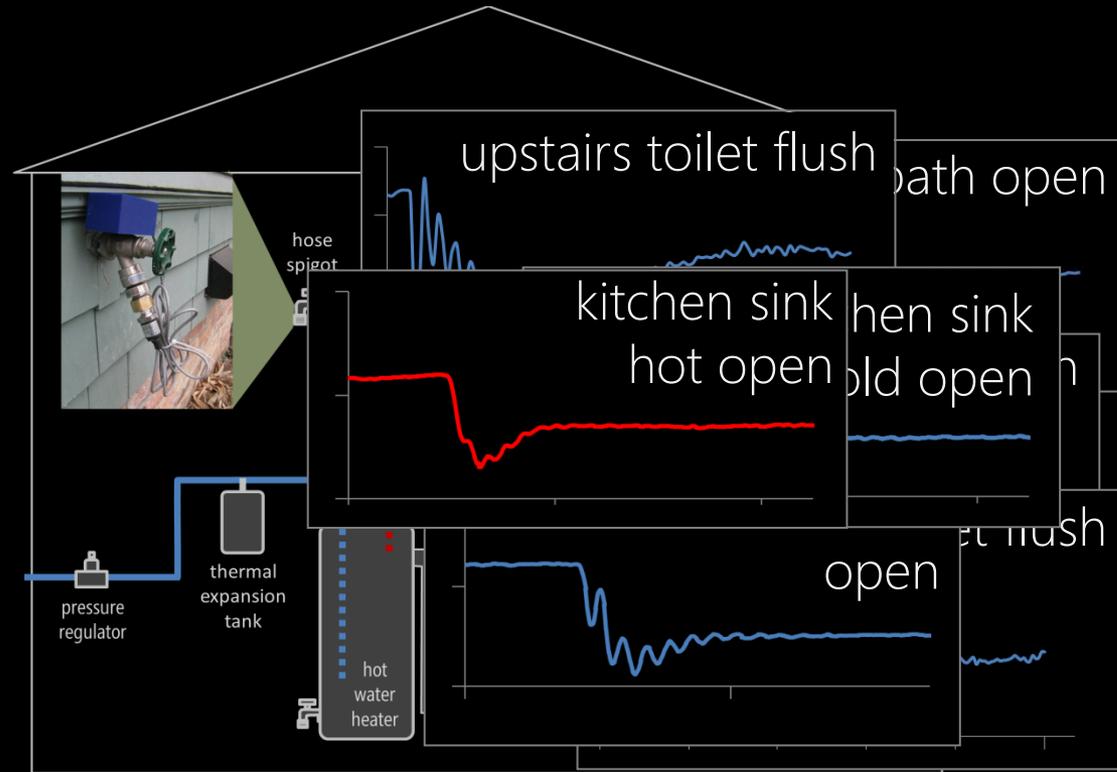
at ubicomp09, we introduced **hydrosense**

hydrosense

- single, screw-on sensor
- identifies fixture usage
- estimates flow

hydrosense

uses pressure waves to identify usage



ubicomp2009

feasibility study

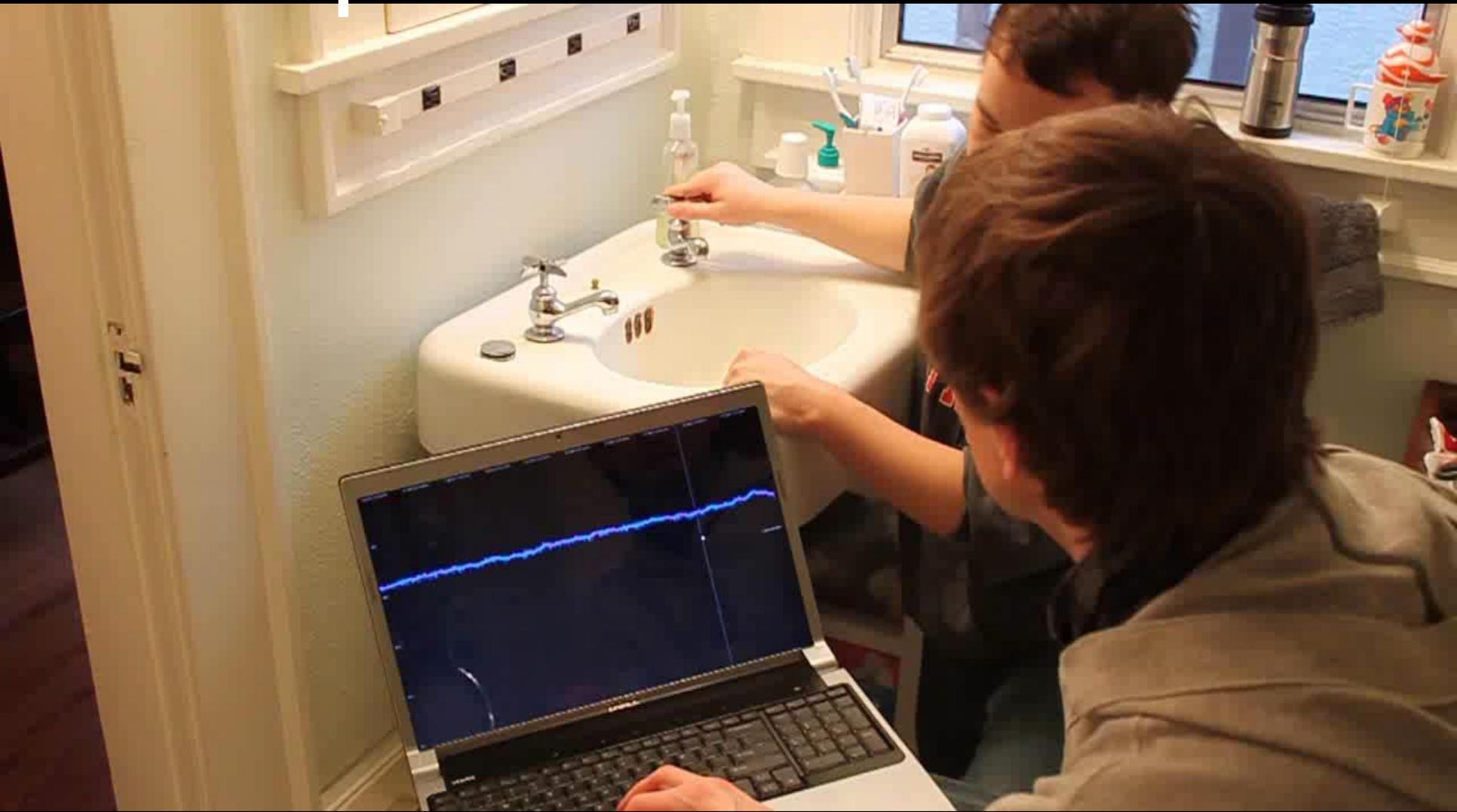
controlled experiments

- 2 researchers per site
- 5 trials per valve

experimental script

- valve opened full stop
- pause for ~5 seconds
- valve closed

ubicomp2009 data collection



ubicomp2009 paper



successfully demonstrated the potential of using pressure waves to identify fixture usage



evaluation method

staged experiments

all faucet handles were operated at approximately the same flow rates

all fixtures were tested in isolation

algorithm

each pressure wave treated independently

did not consider context of usage

was not probabilistic

what we're really interested in...

how well will **hydrosense**
perform on **real-world**
water usage data?

brushing teeth



shaving



bathing



paw washing





compound events



room 1



bathroom 2

incoming cold water from supply line



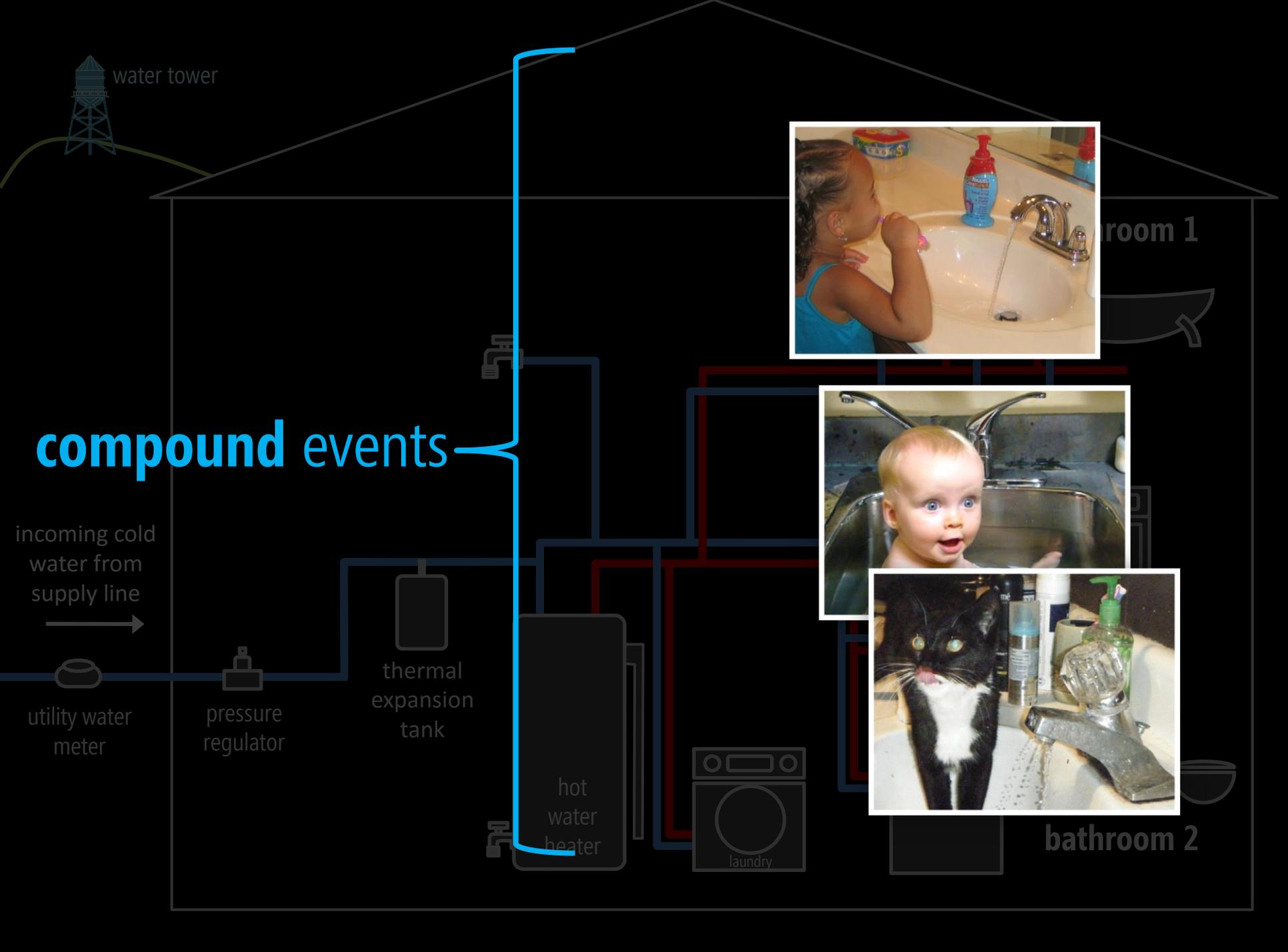
utility water meter

pressure regulator

thermal expansion tank

hot water heater

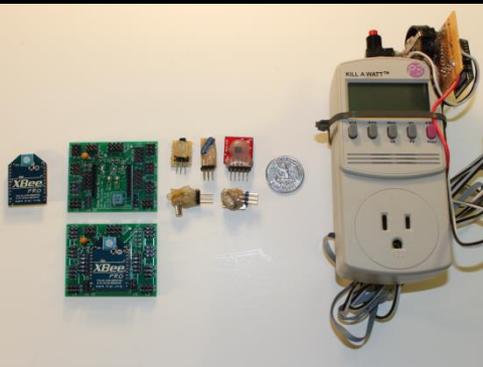
laundry



pervasive 2011 contributions

- ① longitudinal study of real-world water usage and the resulting dataset
- ② a new probabilistic approach to water usage classification
- ③ demonstrate that this new approach can accurately classify real world data

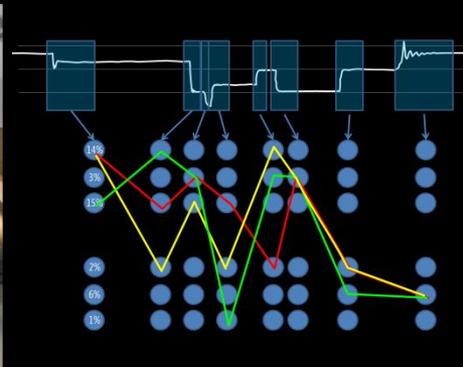
ground truth
sensors



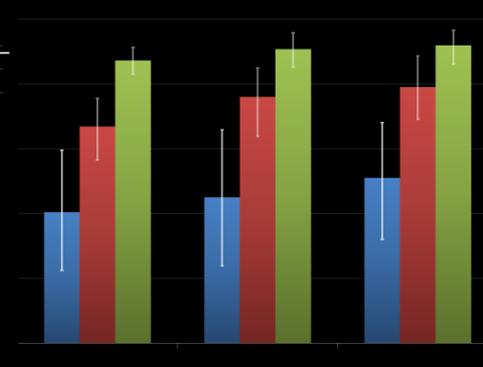
5-week
deployment



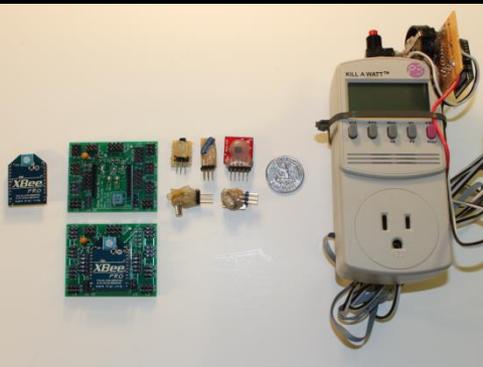
classification
algorithm



classification
results



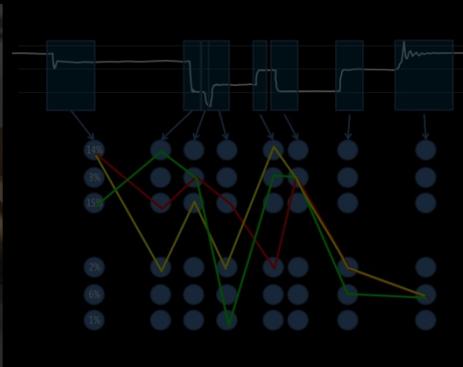
ground truth
sensors



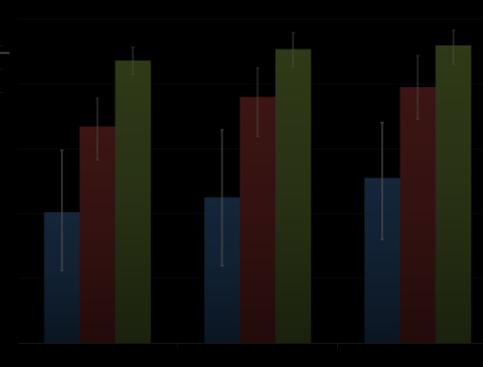
5-week
deployment



classification
algorithm



classification
results



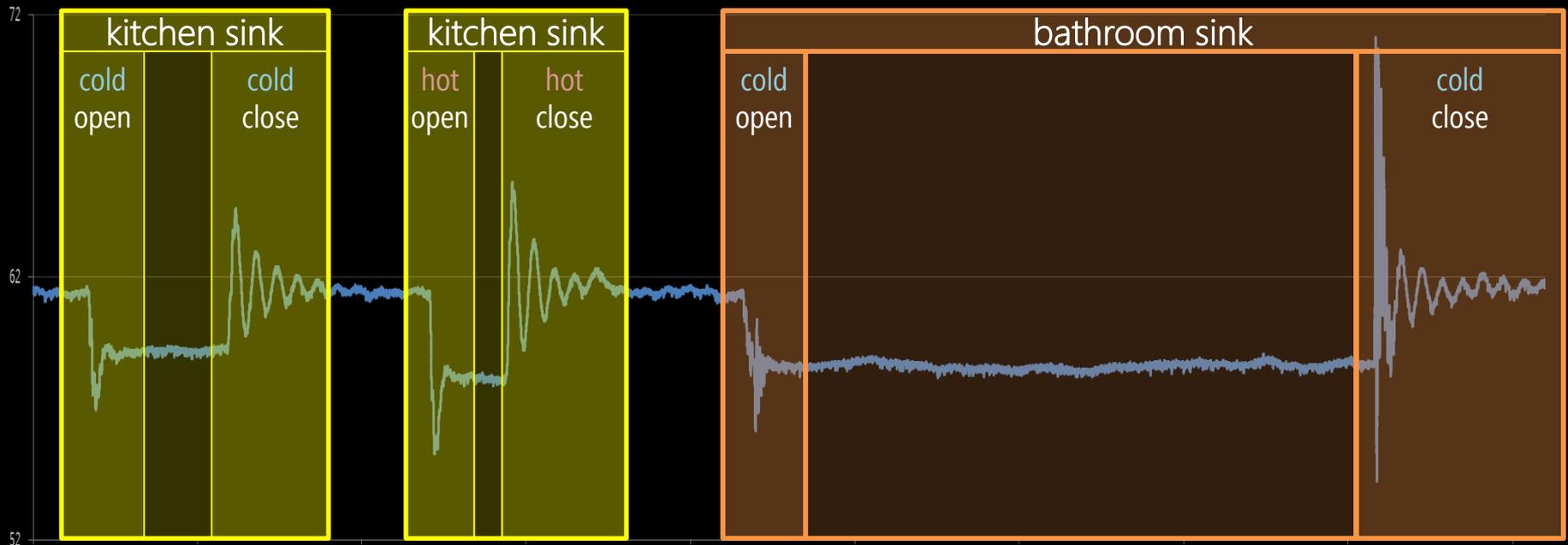
ground truth labels

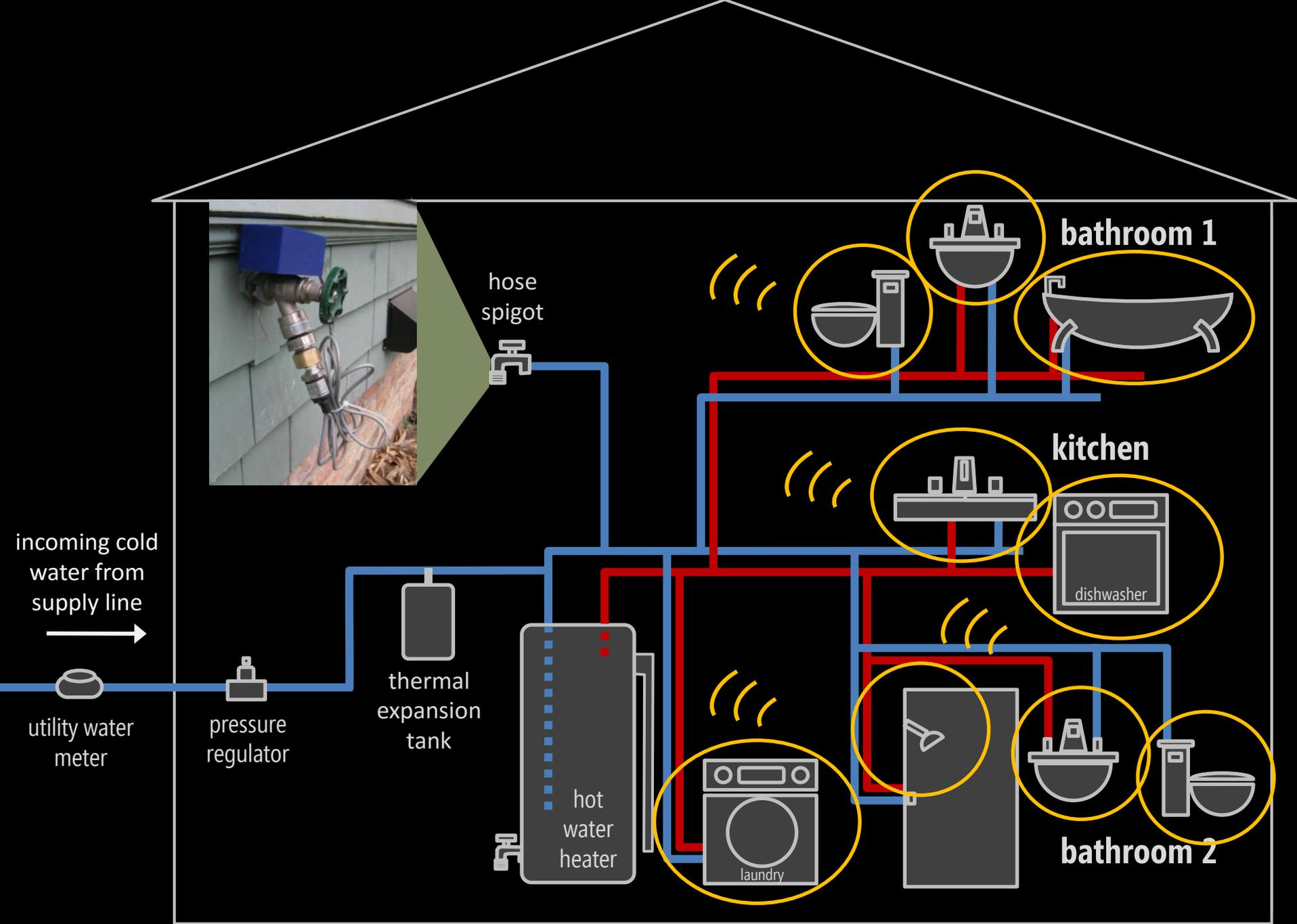


manual



automatic





how can we obtain water usage
labels at the **valve-level**?

this is actually a challenging question...

function across fixtures



kitchen sink



bathroom sink



bath



shower



toilet



laundry basin



washing machine



dishwasher

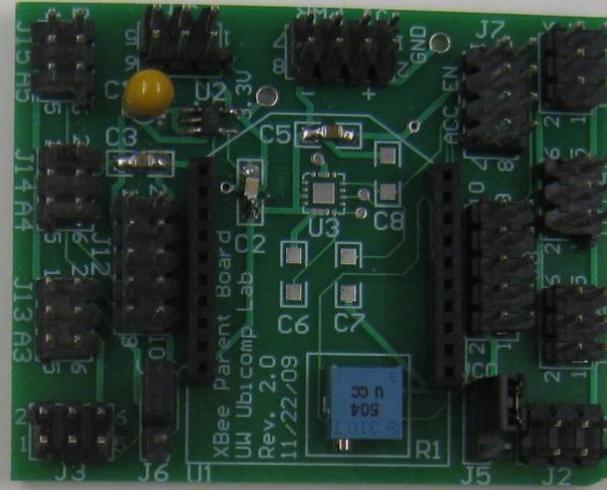
after many failed attempts



custom ground truth data collection system



xbee wireless modem



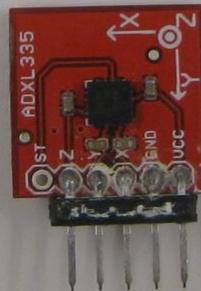
fixture usage sensor board



hall effect



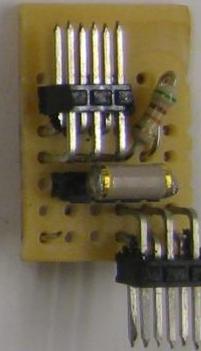
reed switch



3-axis accelerometer



unidirectional ball switch

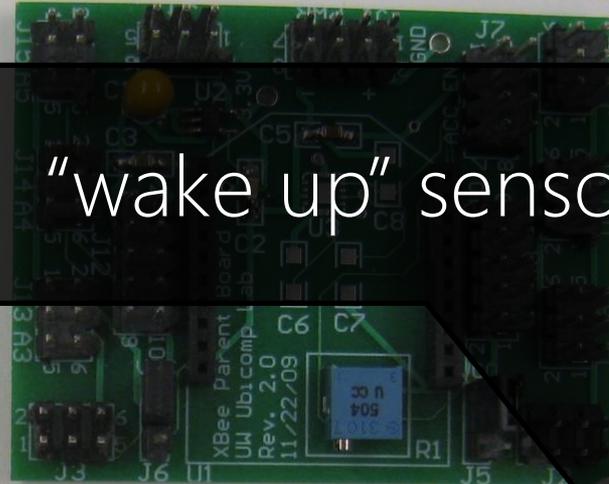


omnidirectional ball switch

custom ground truth data collection system



xbee wireless modem



"wake up" sensors

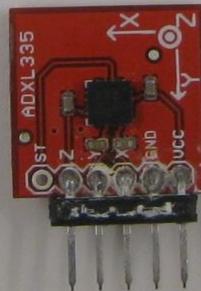
fixture usage sensor board



hall effect



reed switch



3-axis accelerometer



unidirectional ball switch



omnidirectional ball switch

custom ground truth data collection system

fixture handle
position sensors

xbee wireless modem

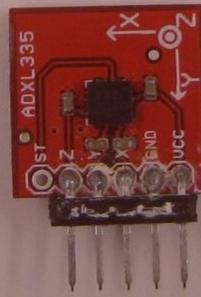
fixture usage sensor board



hall effect



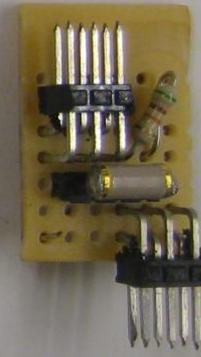
reed switch



3-axis accelerometer



unidirectional ball switch

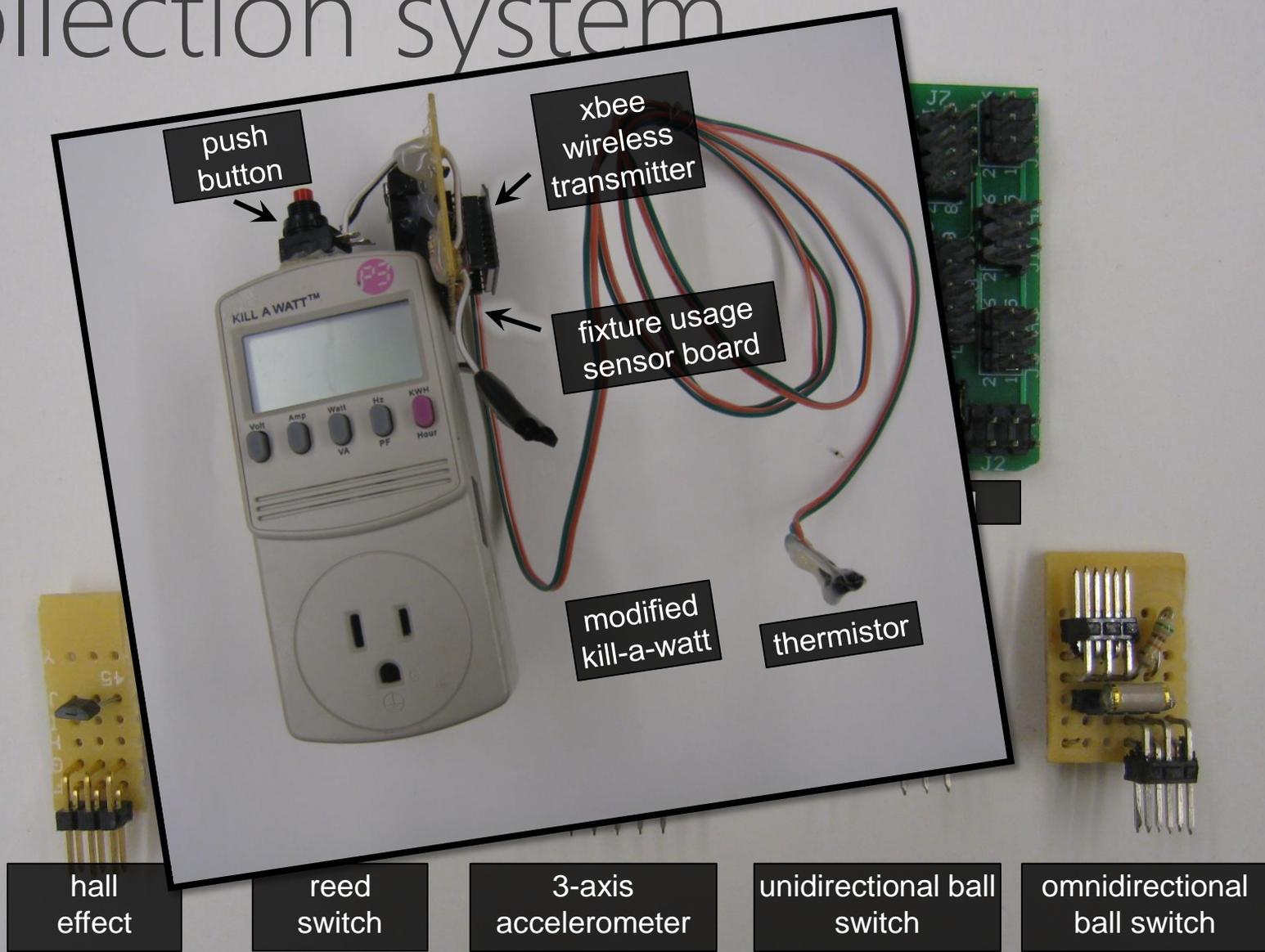


omnidirectional ball switch

accelerometer



custom ground truth data collection system



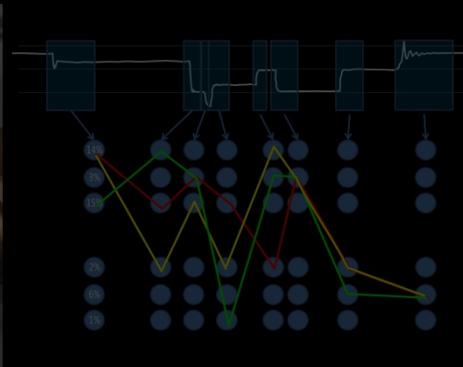
ground truth
sensors



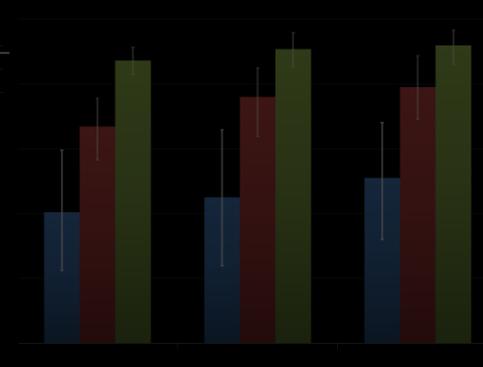
5-week
deployment



classification
algorithm



classification
results



deployment sites

					
residents	2	2	4	2	2
size	3000 sqft	750 sqft	1200 sqft	700 sqft	750 sqft
floors	3	2	2	3 rd flr	6 th flr
fixtures	17	8	13	8	8
valves	28	13	21	13	13

deployment infrastructure

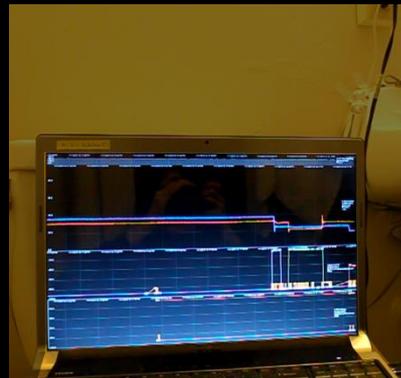
ground truth sensor
on every valve



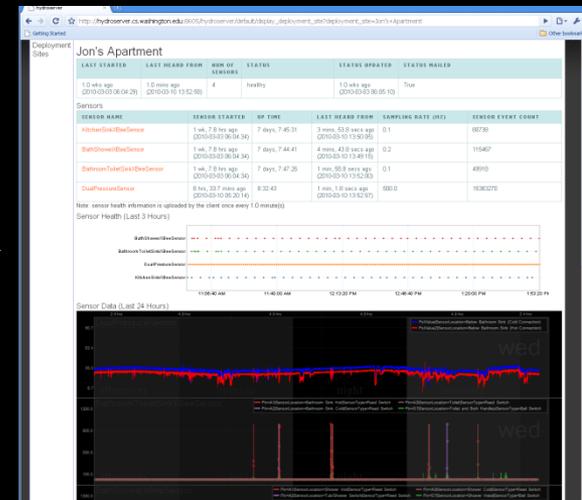
pressure sensor



a laptop running
hydrologger



backend python
hydroserver



two pressure sensors per home

home 1



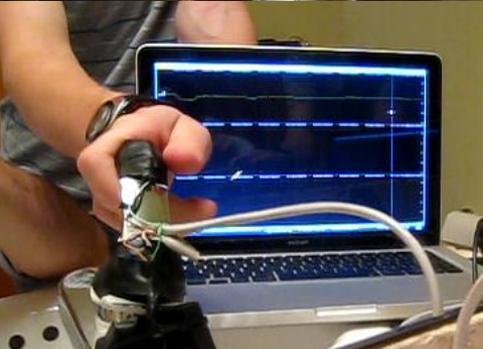
pressure sensor 1 (cold point)

The image shows a close-up of a pressure sensor installed on a water valve. The sensor is a small, cylindrical device with a brass fitting and a grey cable. It is mounted on a pipe with a green handle. A blue rectangular box is visible in the background, partially obscured by the sensor. The sensor is connected to a grey cable that is bundled together.



pressure sensor 2 (hot point)

The image shows a close-up of a pressure sensor installed on a water valve. The sensor is a small, cylindrical device with a brass fitting and a grey cable. It is mounted on a pipe with a brass fitting. A blue rectangular box is visible in the background, partially obscured by the sensor. The sensor is connected to a grey cable that is bundled together.









PB32
XBee

EXTRA RINSE

SET

COTTONS
REGULAR

LIGHT SOIL
MEDIUM
HEAVY
POWER WASH

PULL KNOB TO START. PUSH TO STOP

• RINSE • EXTRA RINSE • SPIN

PERMANENT PRESS
KNITS

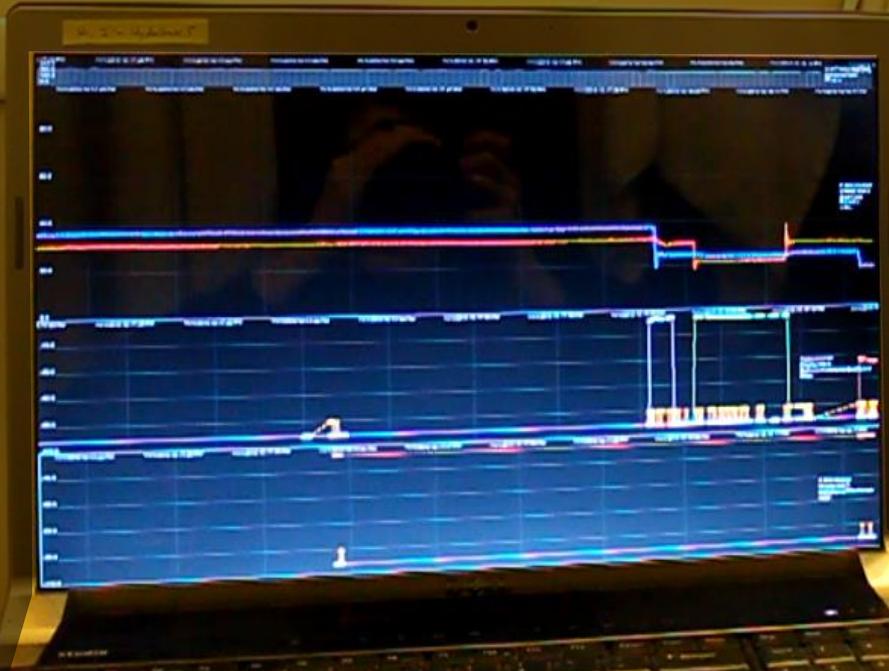
PERMANENT
PRESS

DELICATES

Heavy Duty Super Capacity







pressure stream

red = hot line

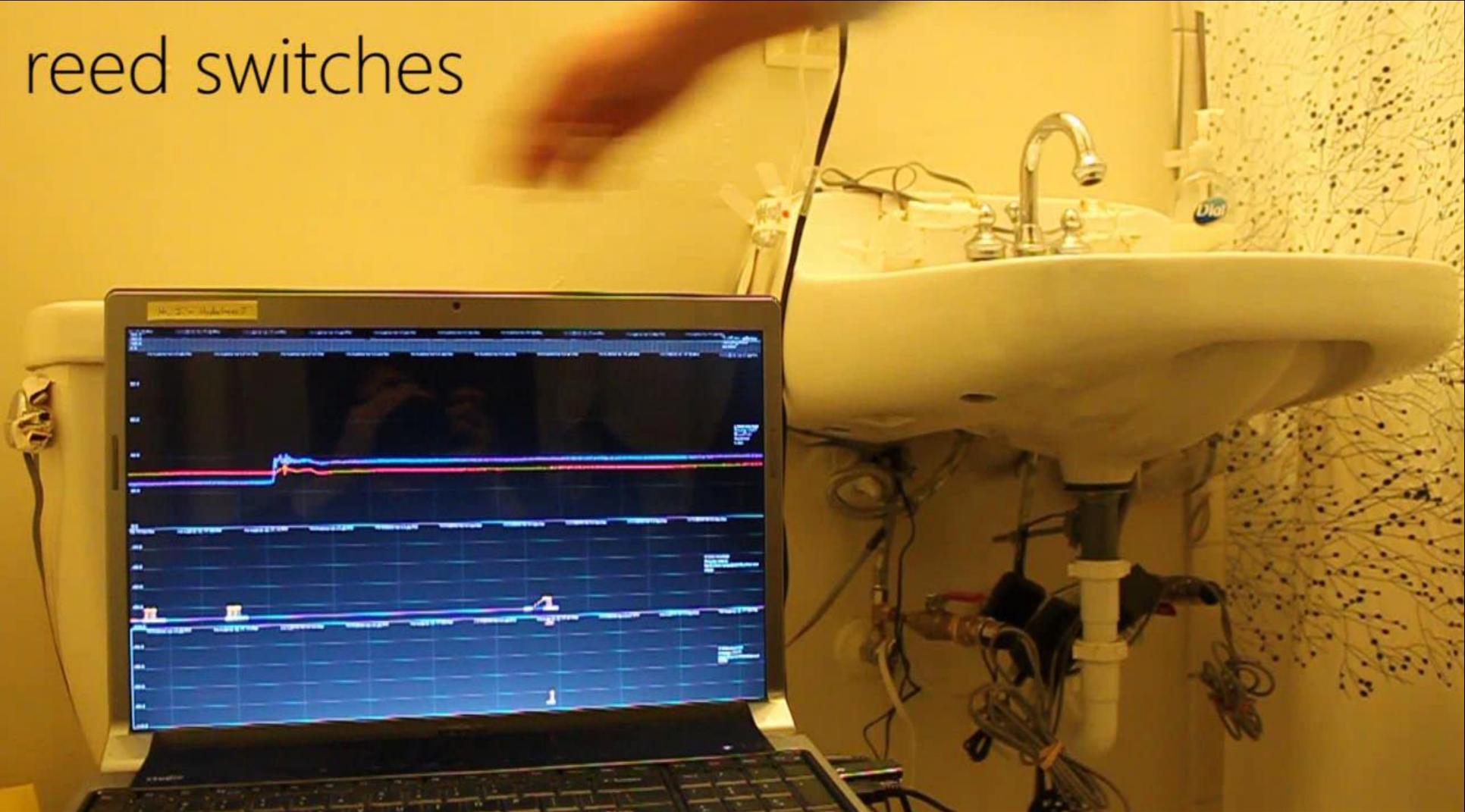
blue = cold line

reed switches

high = active

low = inactive

reed switches



hydrosense annotations

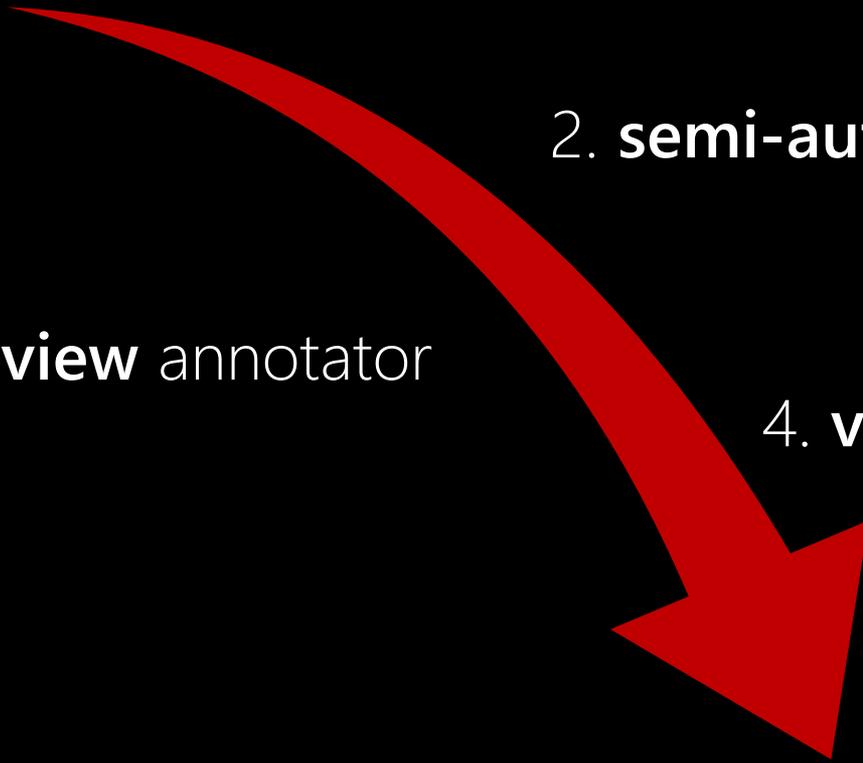
1. **ground truth** sensor

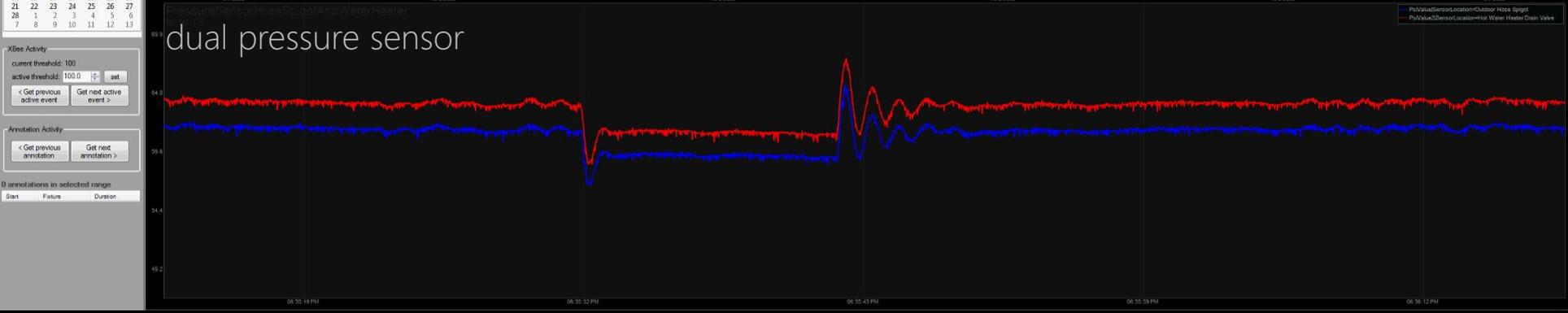
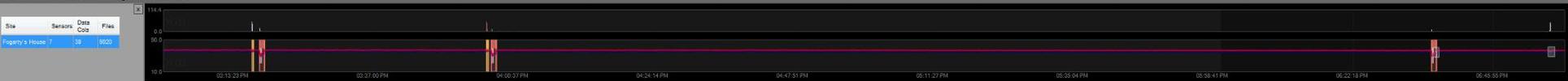
2. **semi-automated** label

3. **review** annotator

4. **verification**

5. **final** label





XBox Activity

current threshold: 100
active threshold: 100.0

< Get previous active event Get next active event >

Annotation Activity

< Get previous annotation Get next annotation >

0 annotations in selected range

Start	Fixture	Duration
-------	---------	----------

Site	Sensors	Data Size	Files
Fogarty's House 7	38	1600	

February, 2010

Sun	Mon	Tue	Wed	Thu	Fri	Sat
31	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	1	2	3	4	5	6
7	8	9	10	11	12	13

XBee Activity

current threshold: 100
active threshold: 100.0

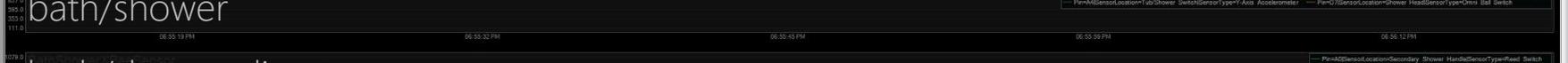
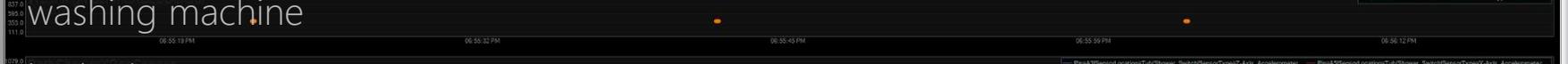
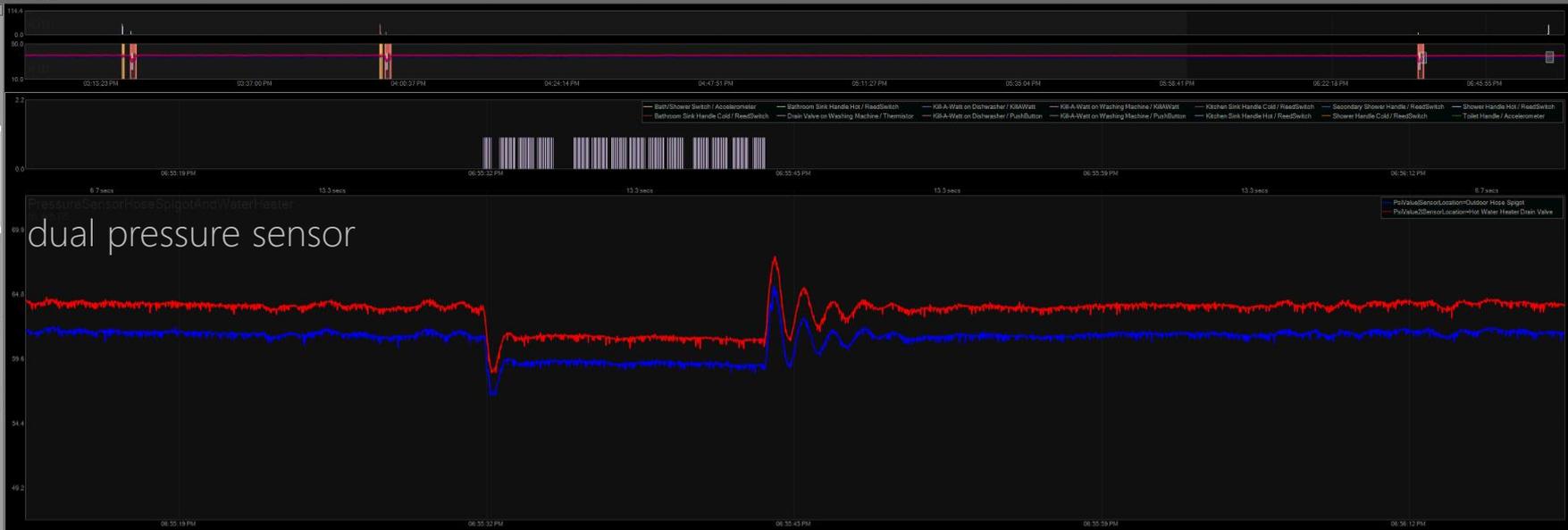
< Get previous active event Get next active event >

Annotation Activity

< Get previous annotation Get next annotation >

0 annotations in selected range

Start	Fixture	Duration
-------	---------	----------





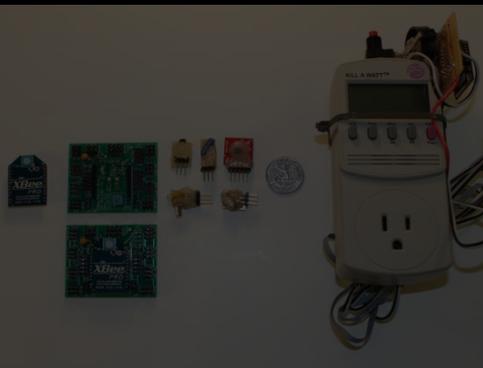


5-week dataset

						totals
days	33	33	30	27	33	156
events	2374	3075	4754	2499	2578	14,960
events/day	71.9	93.2	158.5	92.6	78.1	95.9
compound	22.2%	21.8%	16.6%	32%	21.3%	21.9%

22% of all events were compound

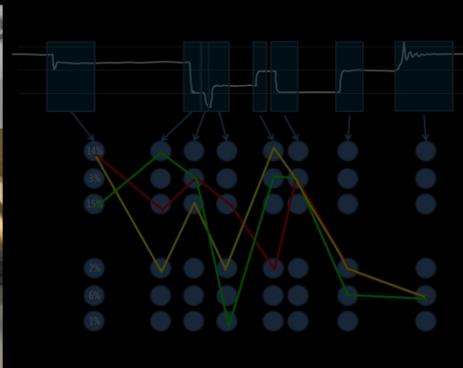
ground truth
sensors



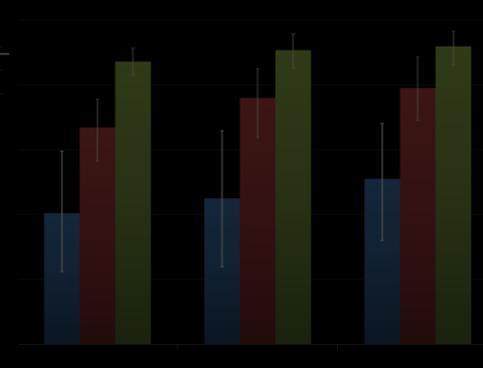
5-week
deployment



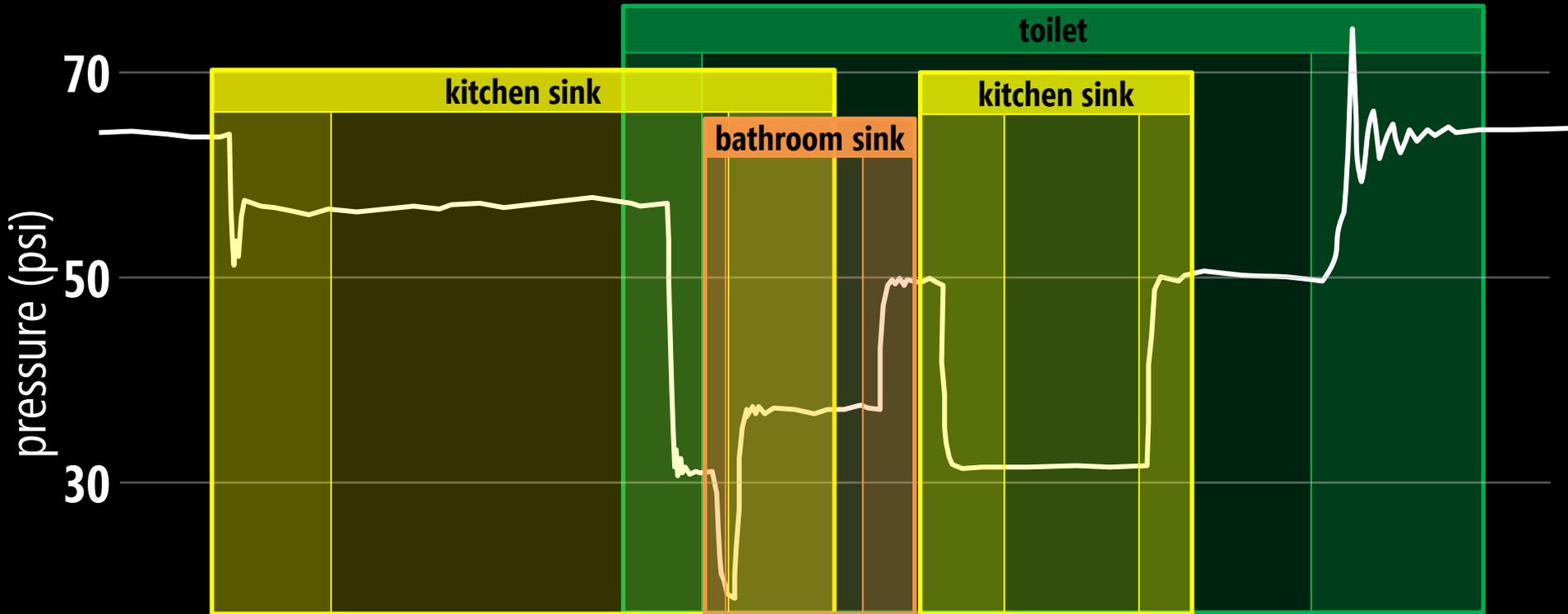
classification
algorithm



classification
results



natural water use



bayesian inference

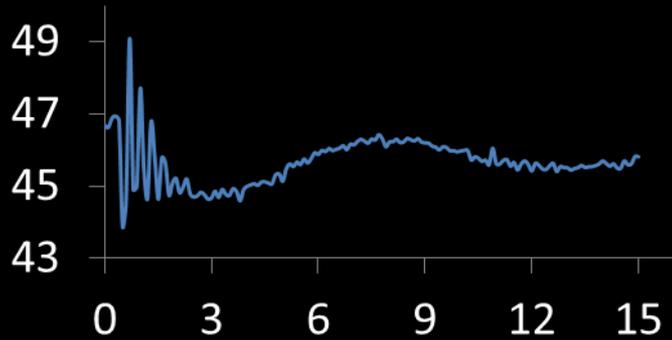
signal

behavior

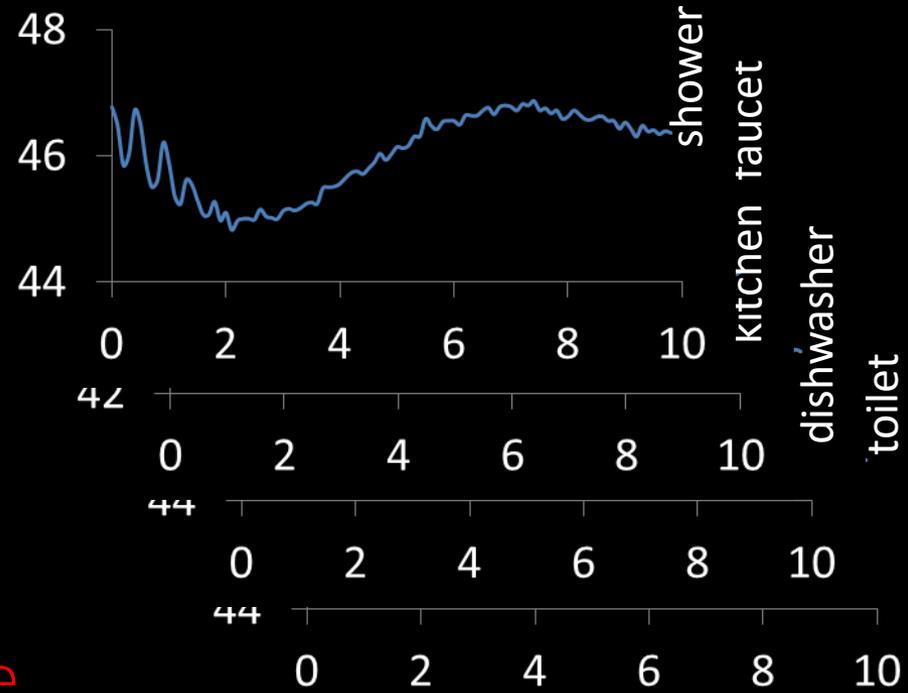
$$\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r | \hat{\mathbf{V}}_r) \prod_{n=0}^{N-1} P(v_n | v_{n-1}) \prod_{i \notin \beta} f_p(v_i) \prod_{k=0}^{K-1} \prod_{\langle a, b \rangle \in \beta} f_k(\langle v_a, v_b \rangle)$$

term(i) template matching

unclassified event

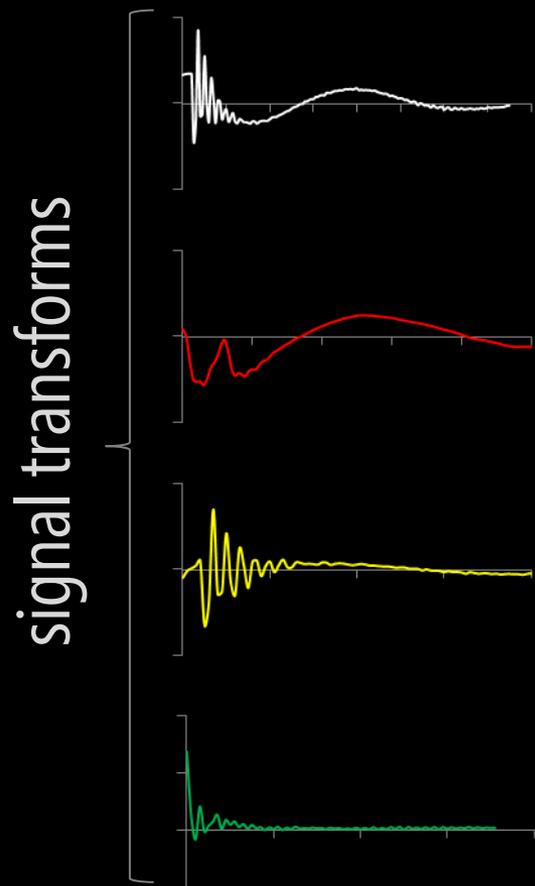
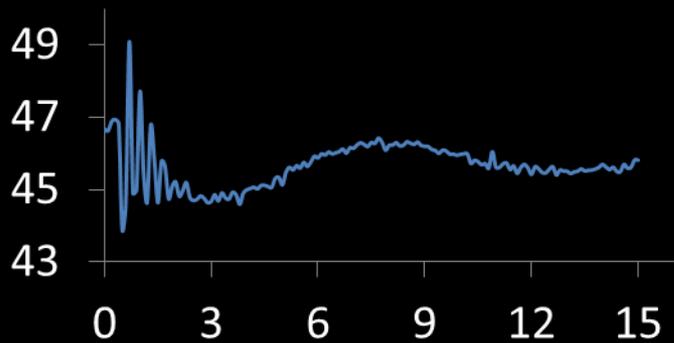


event library

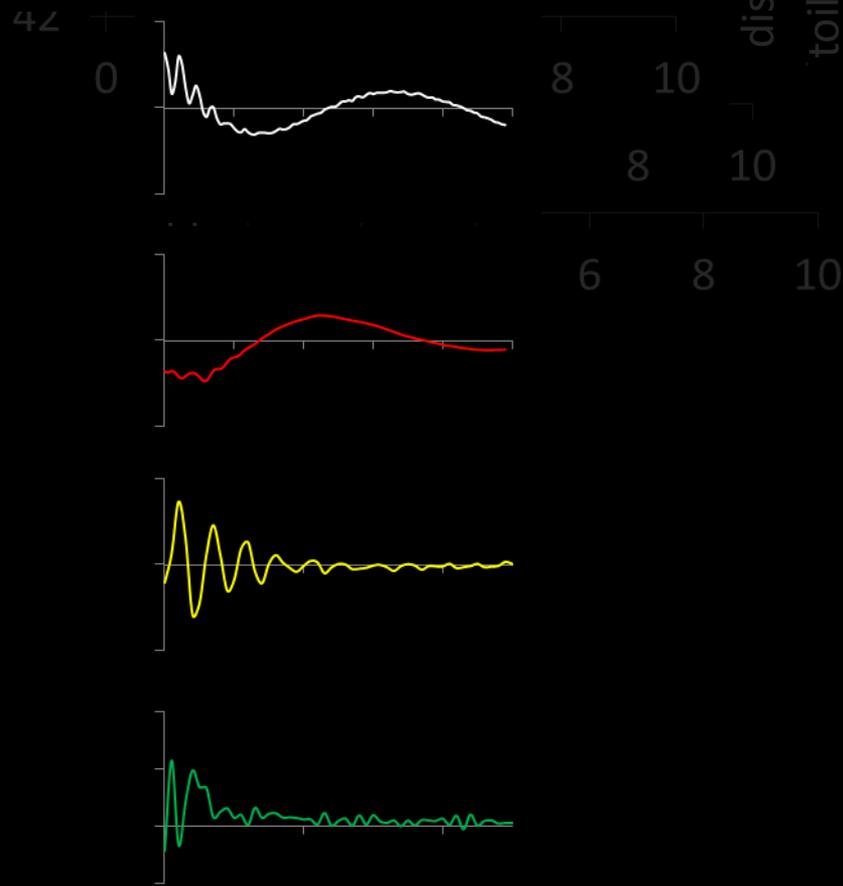
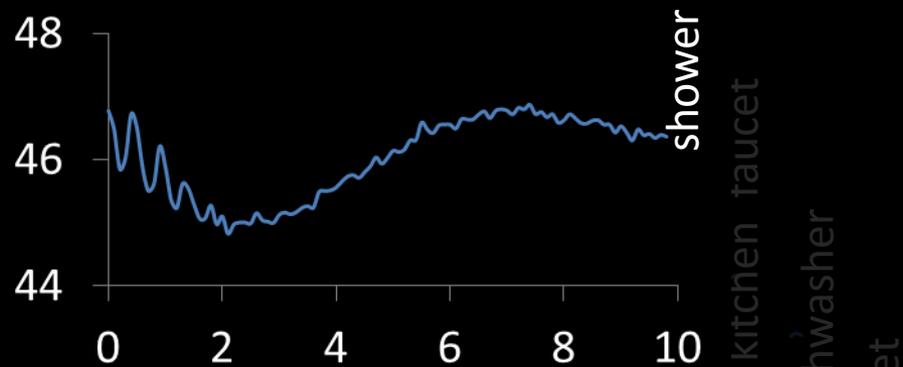


compare across multiple
signal transformations

unclassified event



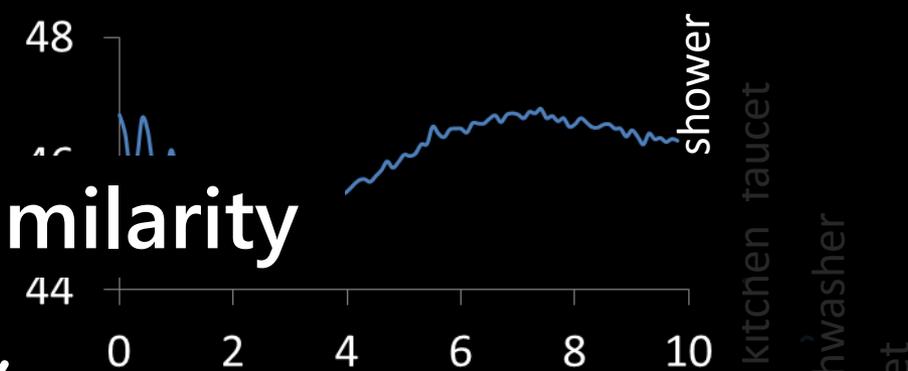
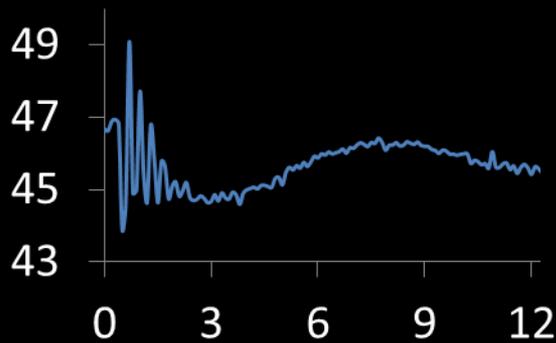
event library



kitchen faucet
dishwasher
toilet

unclassified event

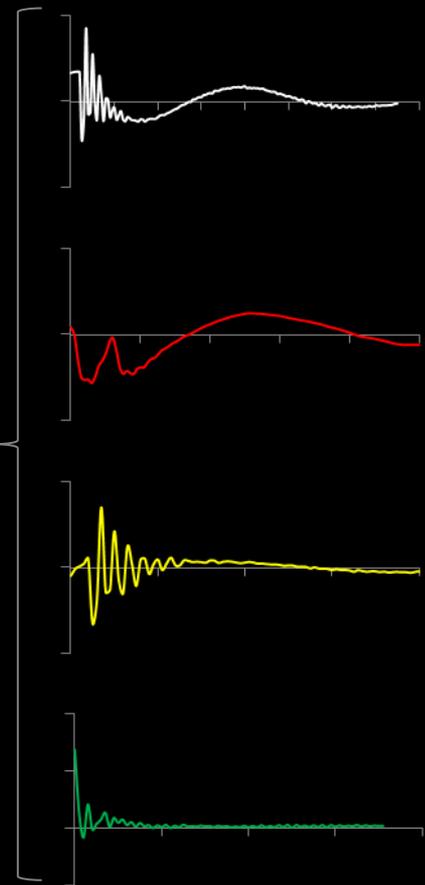
event library



assess similarity



signal transforms

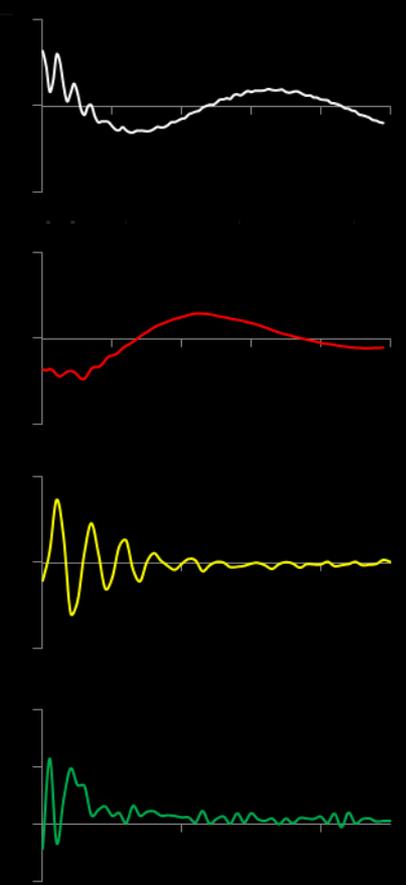


← 15% →

← 55% →

← 18% →

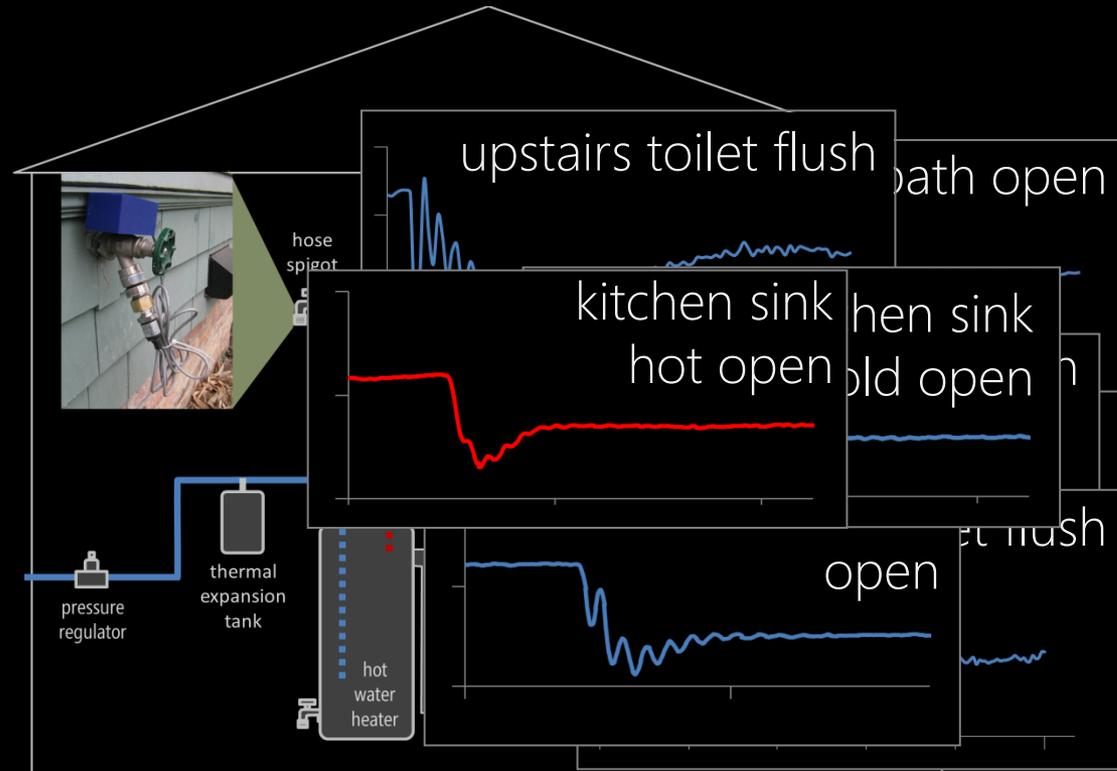
← 9% →



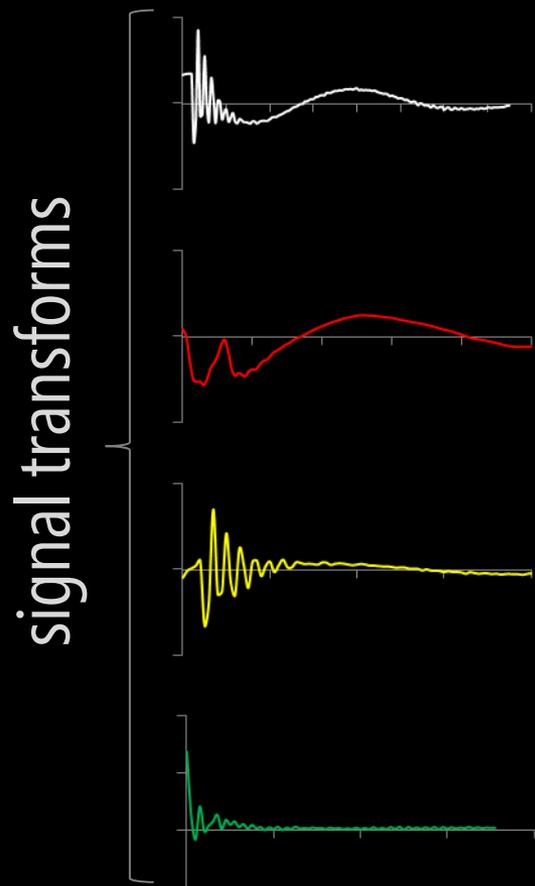
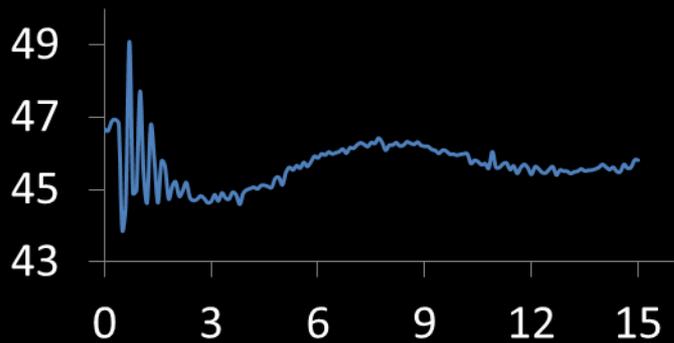
shower
kitchen faucet
dishwasher
toilet

hydrosense

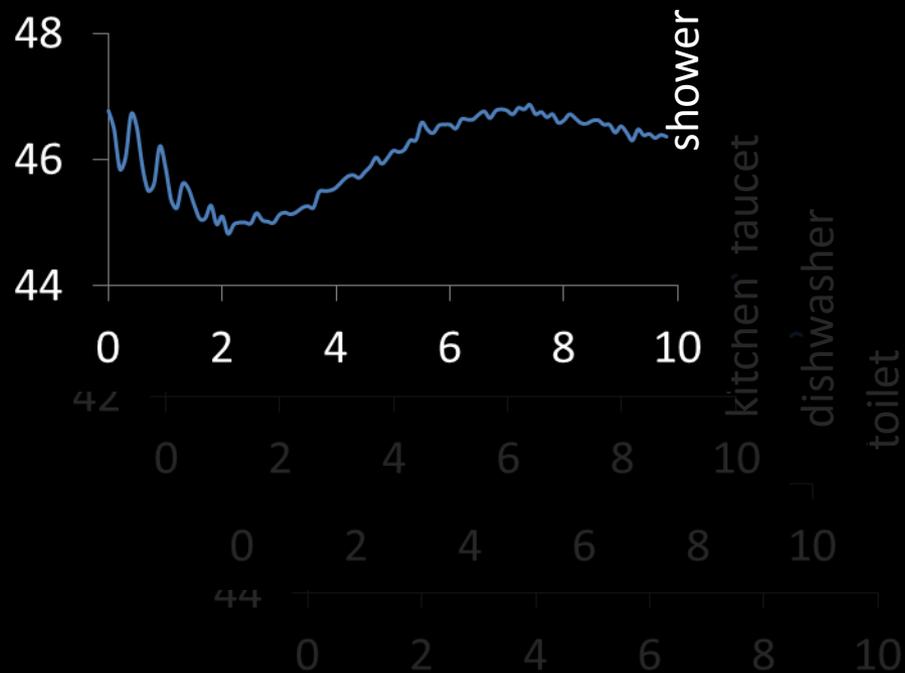
example pressure waves



unclassified event

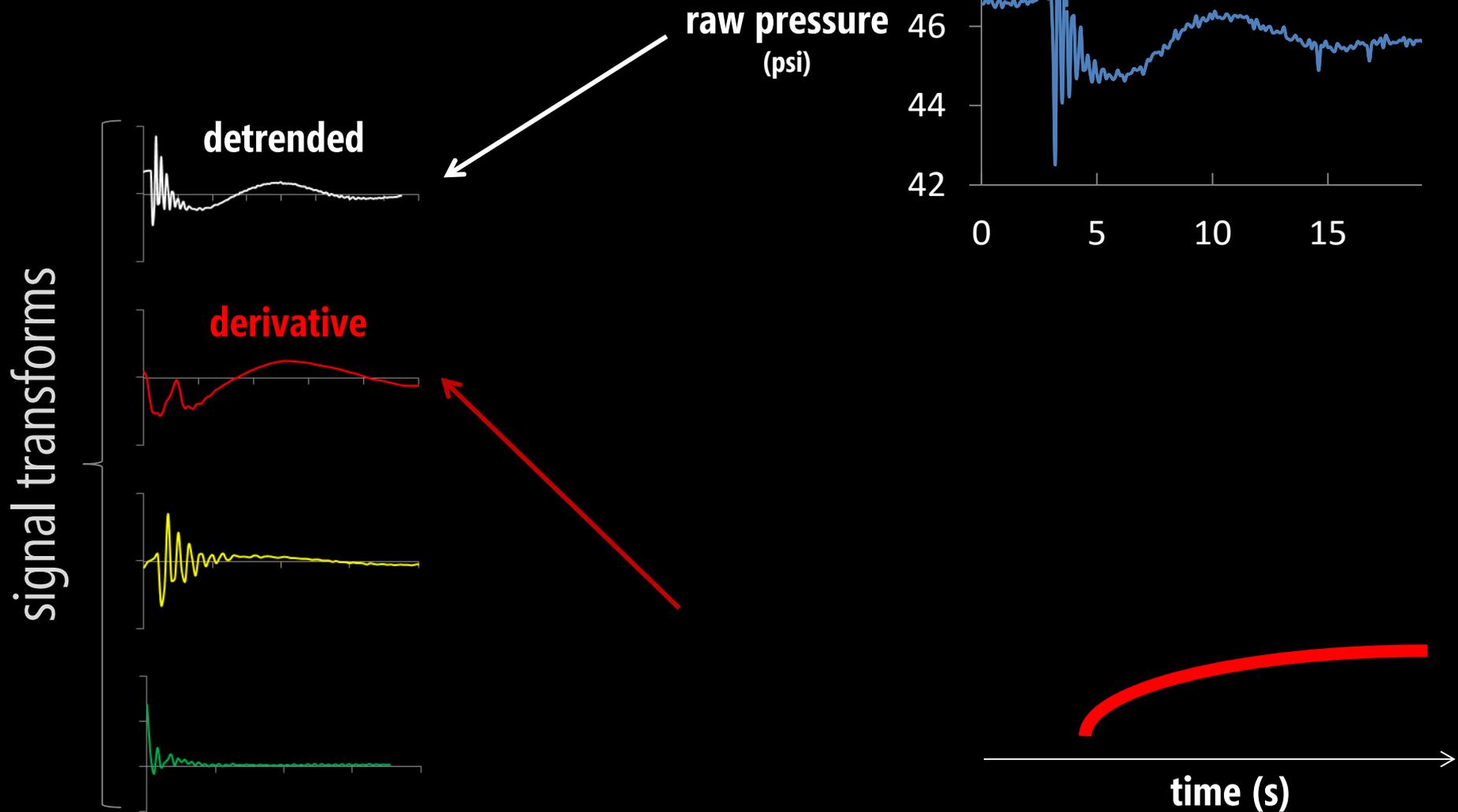


event library



term(i) template matching

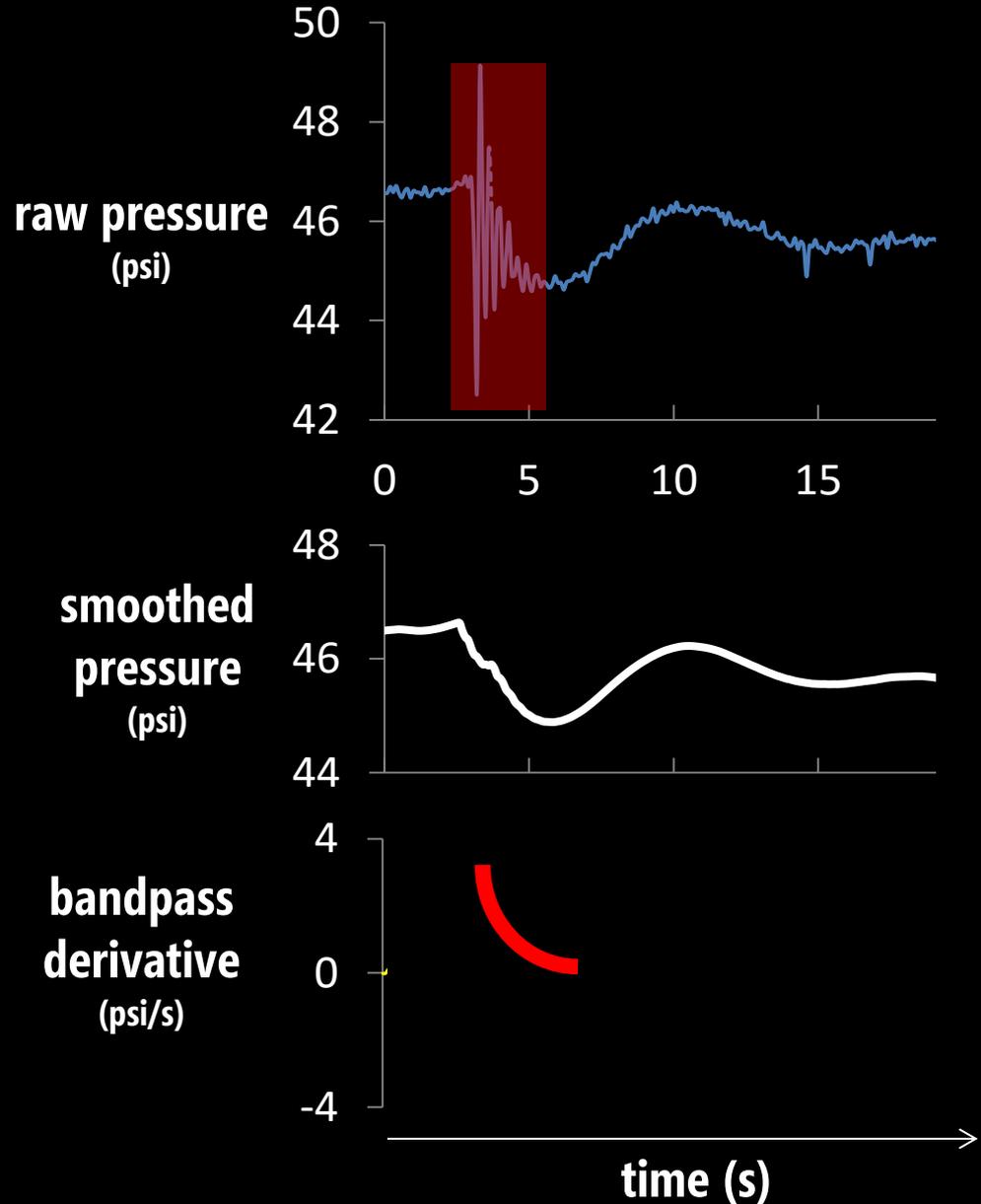
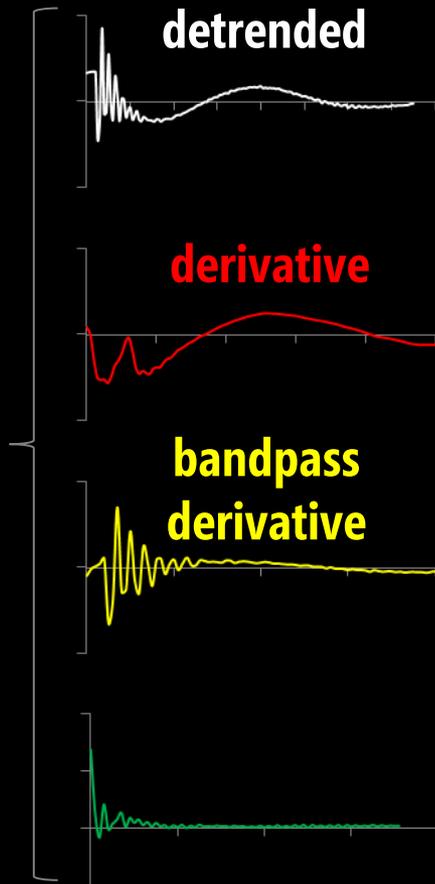
filter transforms



term(i) template matching

filter transforms

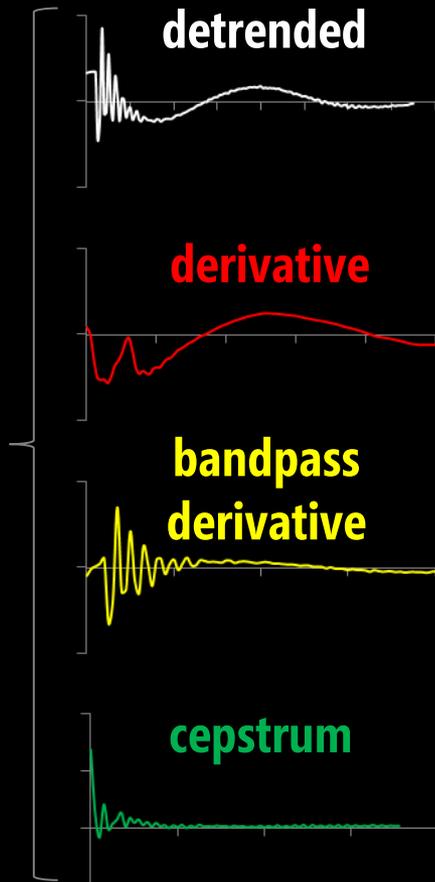
signal transforms



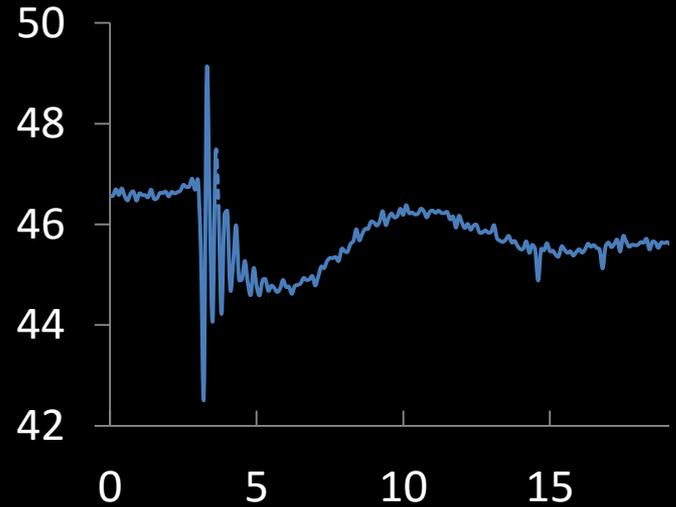
term(i) template matching

filter transforms

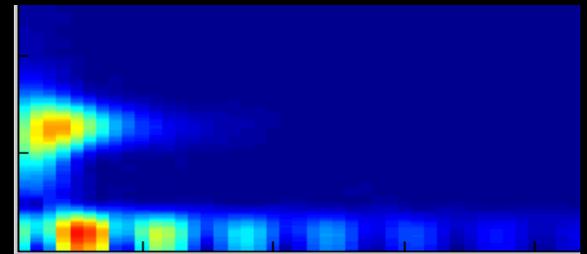
signal transforms



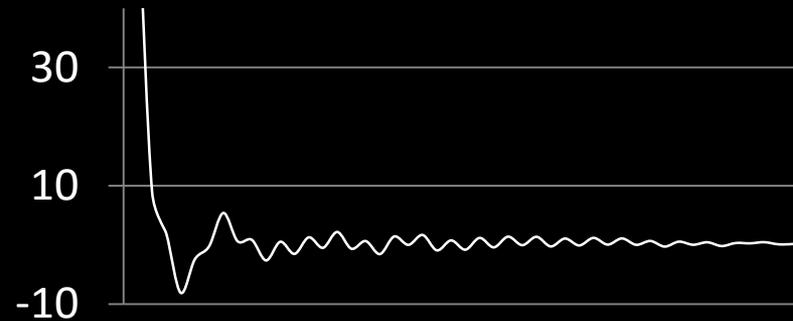
raw pressure (psi)



frequency

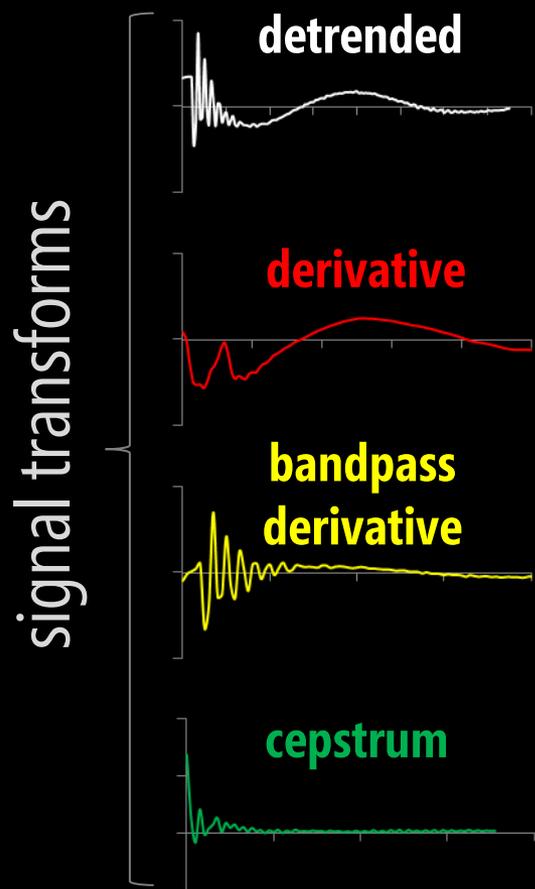
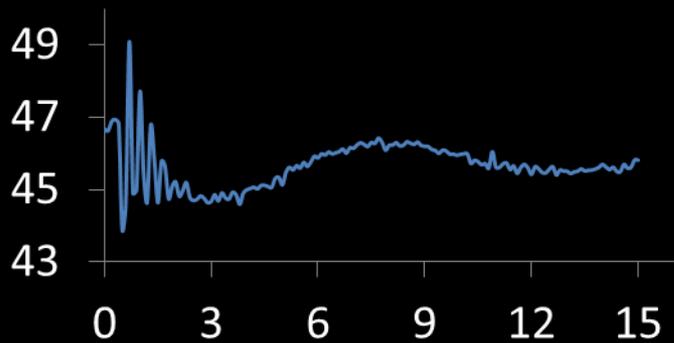


cepstral amplitude

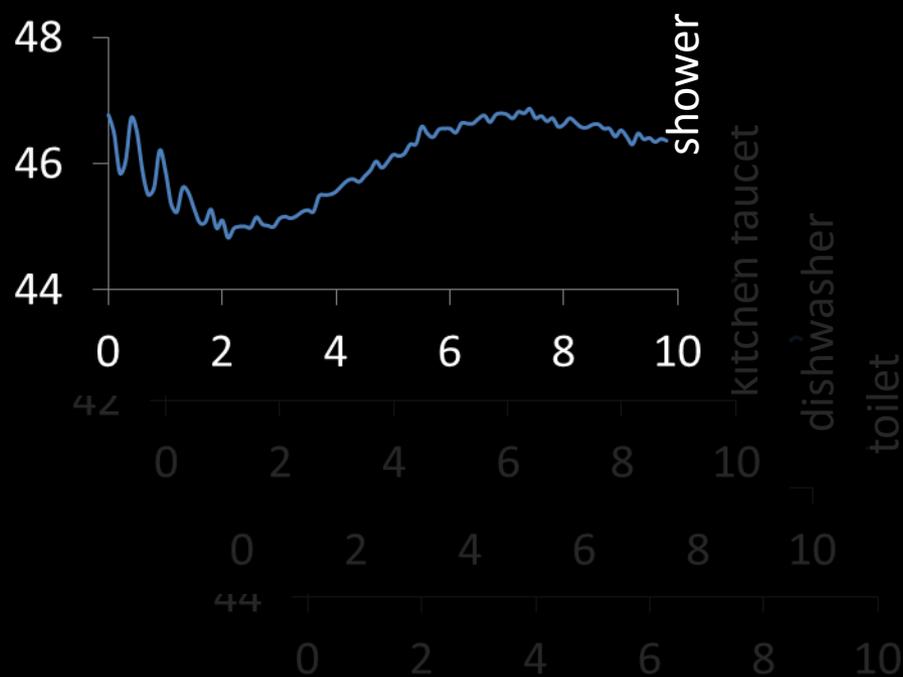


index →

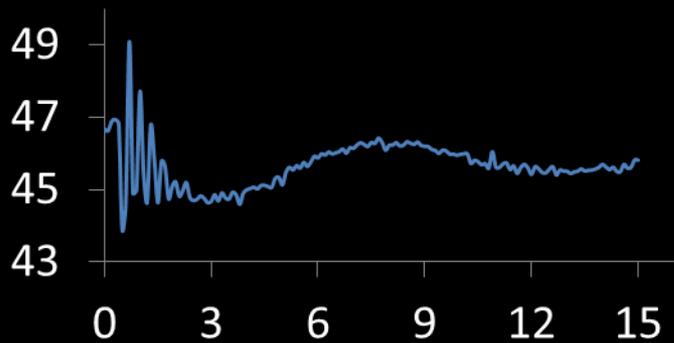
unclassified event



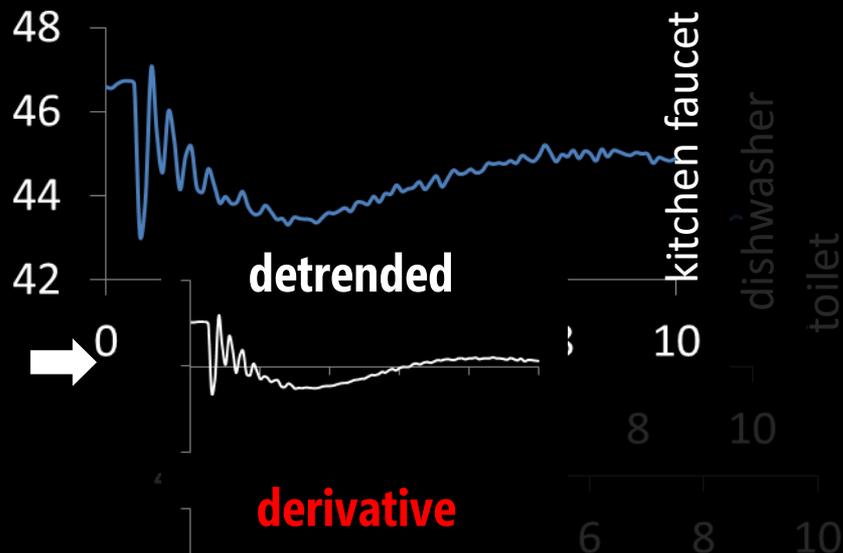
event library



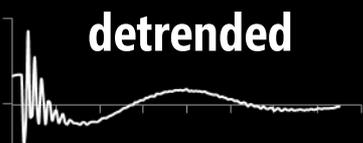
unclassified event



event library



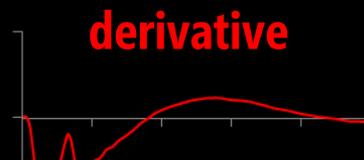
signal transforms



← 55% →



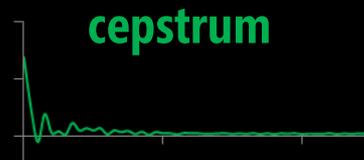
← 85% →



← 65% →

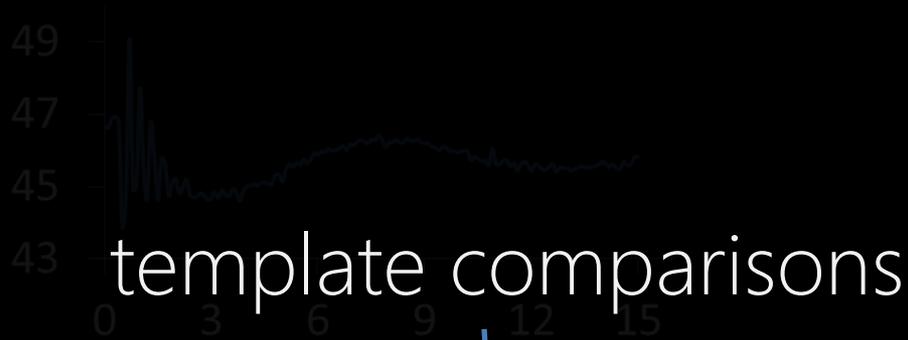


← 90% →

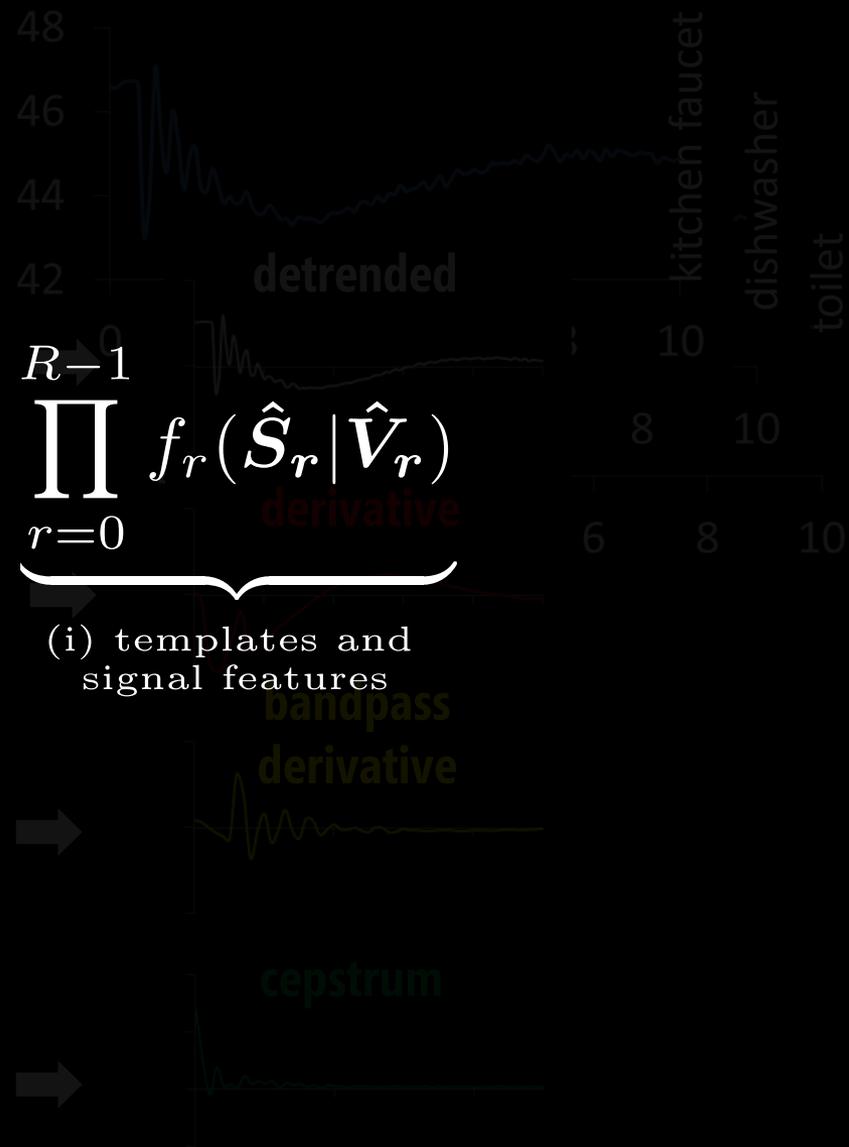
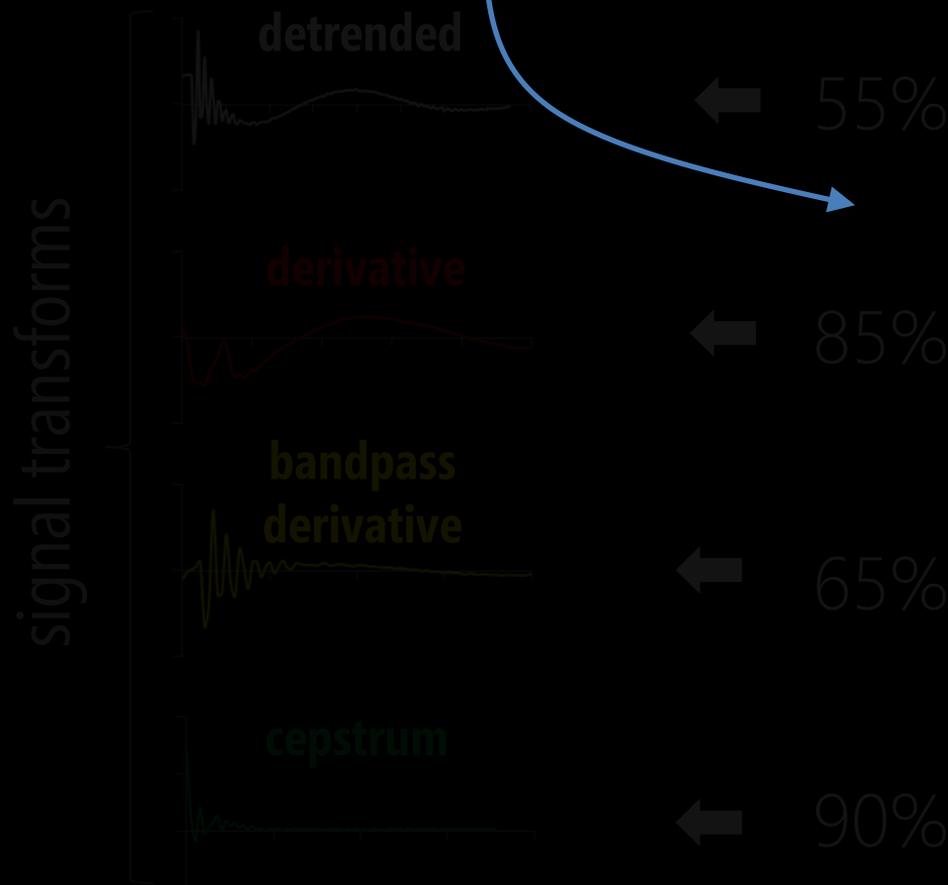


unclassified event

event library



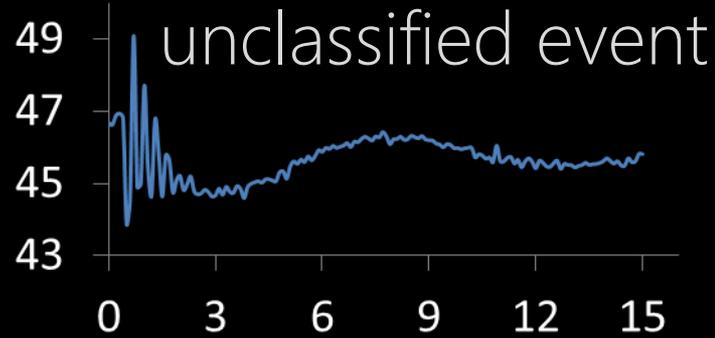
template comparisons



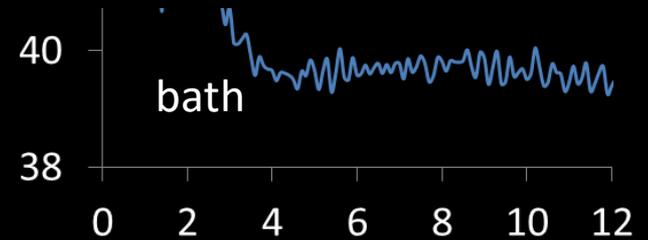
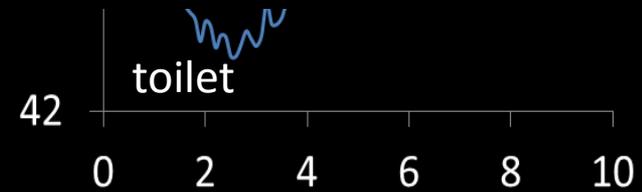
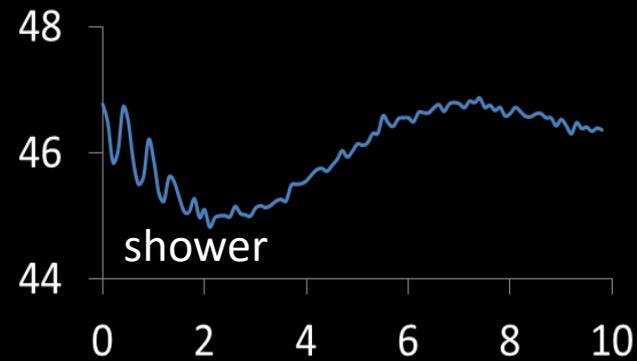
$$\prod_{r=0}^{R-1} f_r(\hat{S}_r | \hat{V}_r)$$

(i) templates and signal features

term(i) signal features

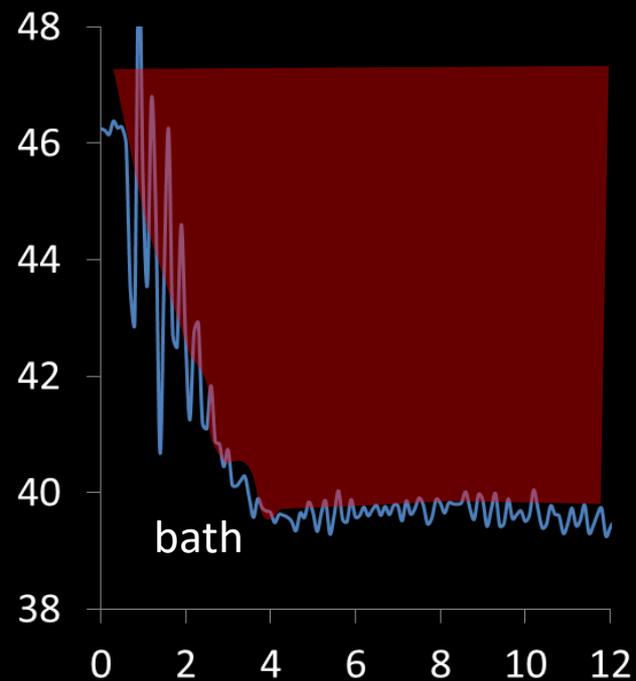
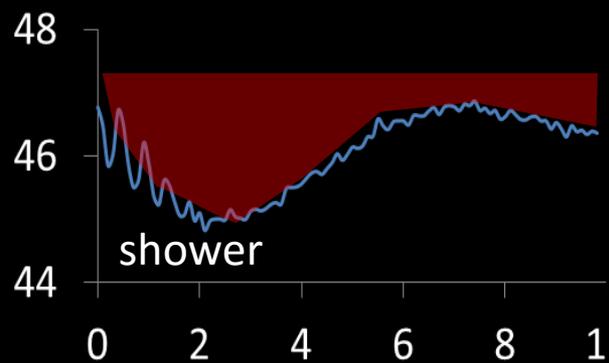
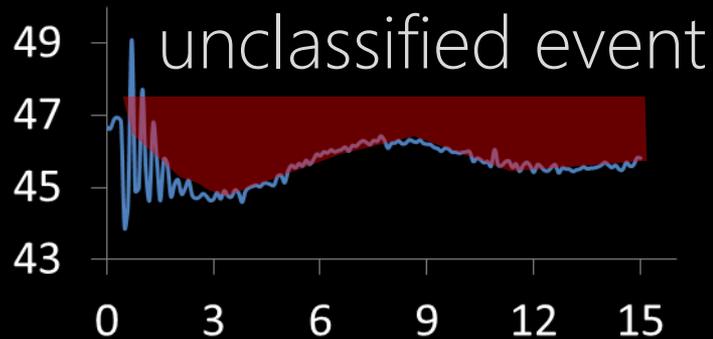


event library



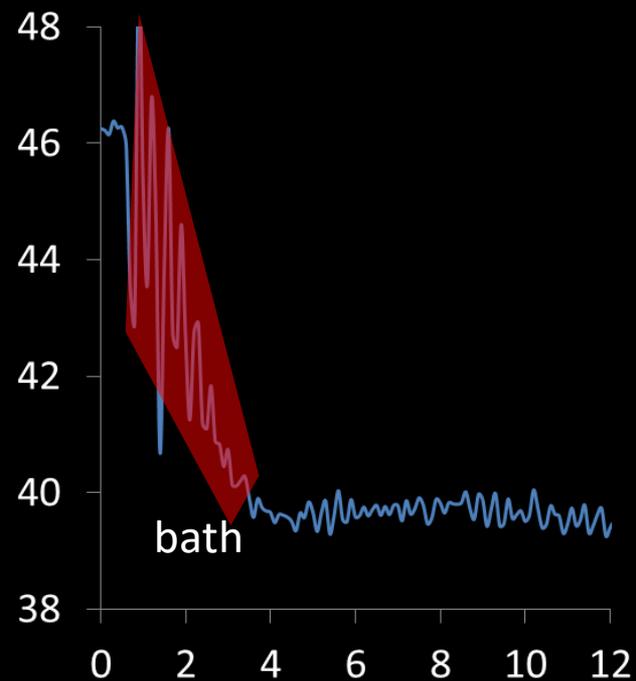
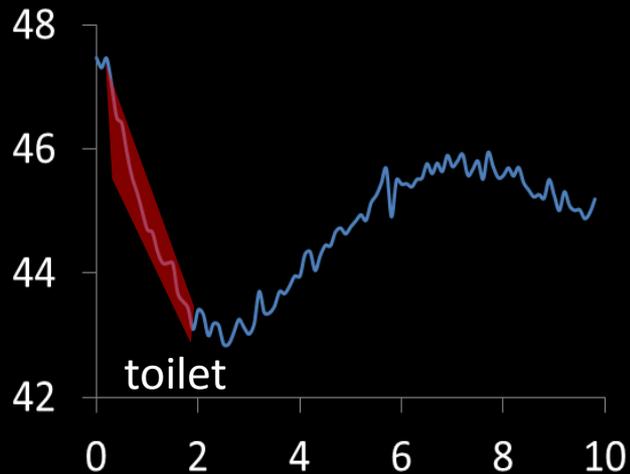
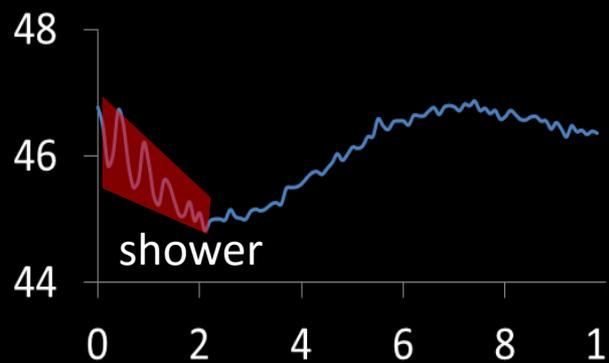
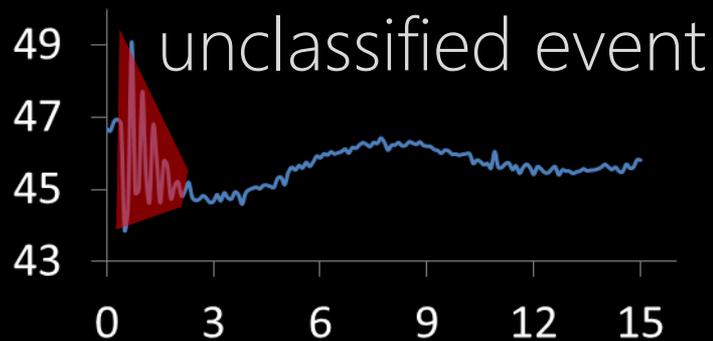
term(i) signal features

pressure drop



term(i) signal features

resonance tracking



term(i) signal features

resonance tracking

template comparisons

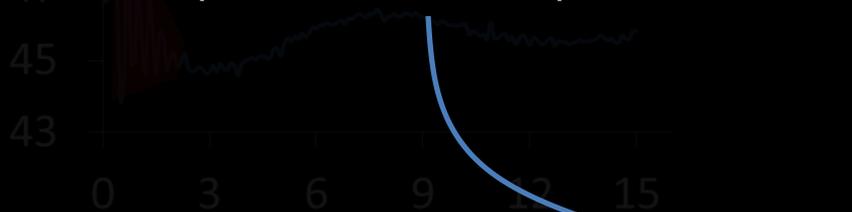
$$\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r | \hat{\mathbf{V}}_r)$$

(i) templates and signal features

signal feature comparisons

unclassified event

template comparisons



template comparisons

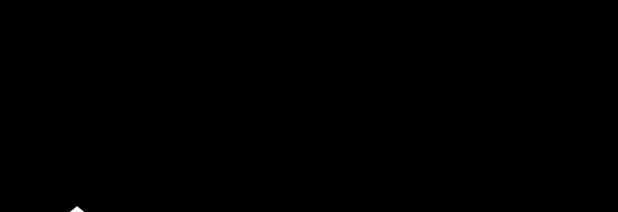


signal feature comparisons

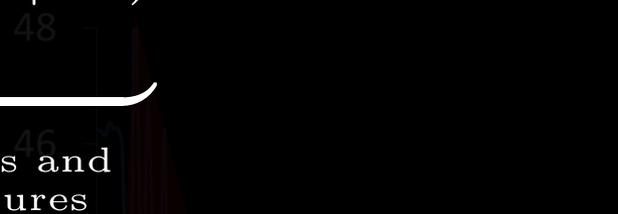


unclassified event

template comparisons



template comparisons

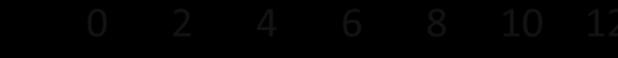


signal feature comparisons



bath

signal feature comparisons



term (i): templates and signal features



P(kitchen sink hot open) 14%

P(kitchen sink cold open) 3%

P(toilet open) 15%



P(kitchen hot/cold close) 2%

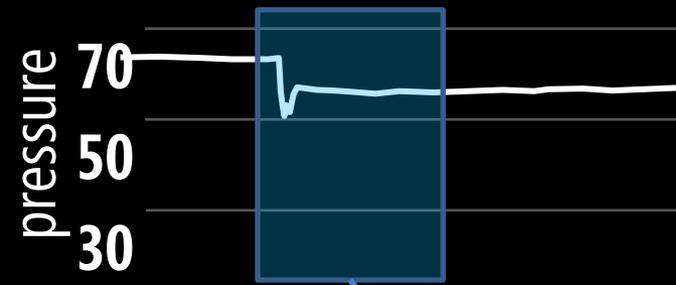
P(kitchen hot close) 6%

P(toilet close) 1%

$$\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r | \hat{\mathbf{V}}_r)$$

(i) templates and
signal features

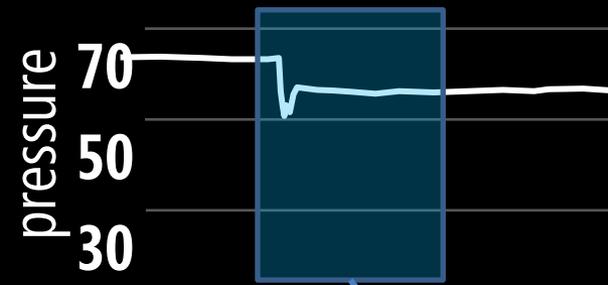
term (i): templates and signal features



- P(kitchen sink hot open)** 14%
- P(kitchen sink cold open)** 3%
- P(toilet open)** 15%
-
-
-
- P(kitchen hot/cold close)** 2%
- P(kitchen hot close)** 6%
- P(toilet close)** 1%

$$\underbrace{\prod_{r=0}^{R-1} f_r(\hat{S}_r | \hat{V}_r)}_{\text{(i) templates and signal features}}$$

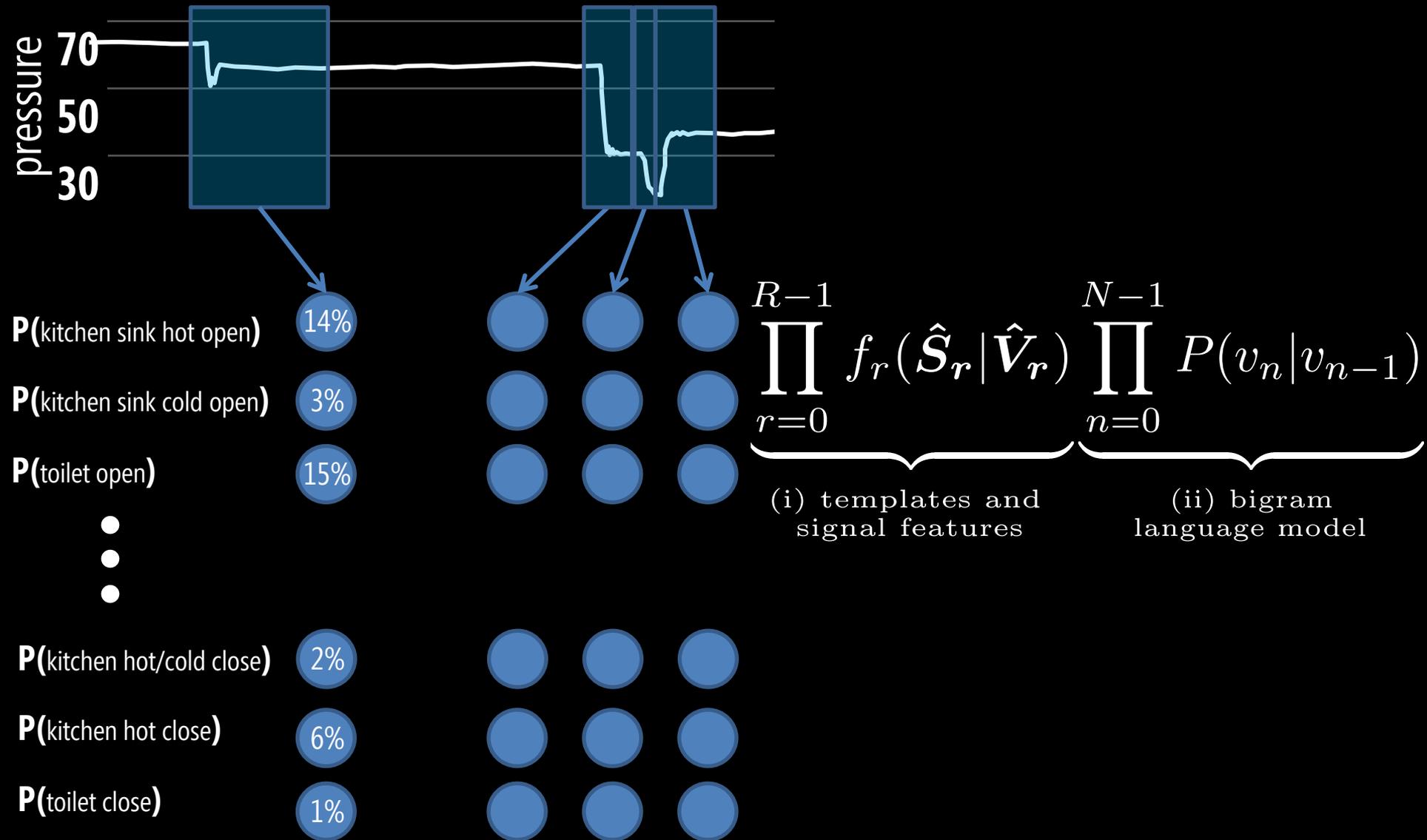
term (ii): bigram language model



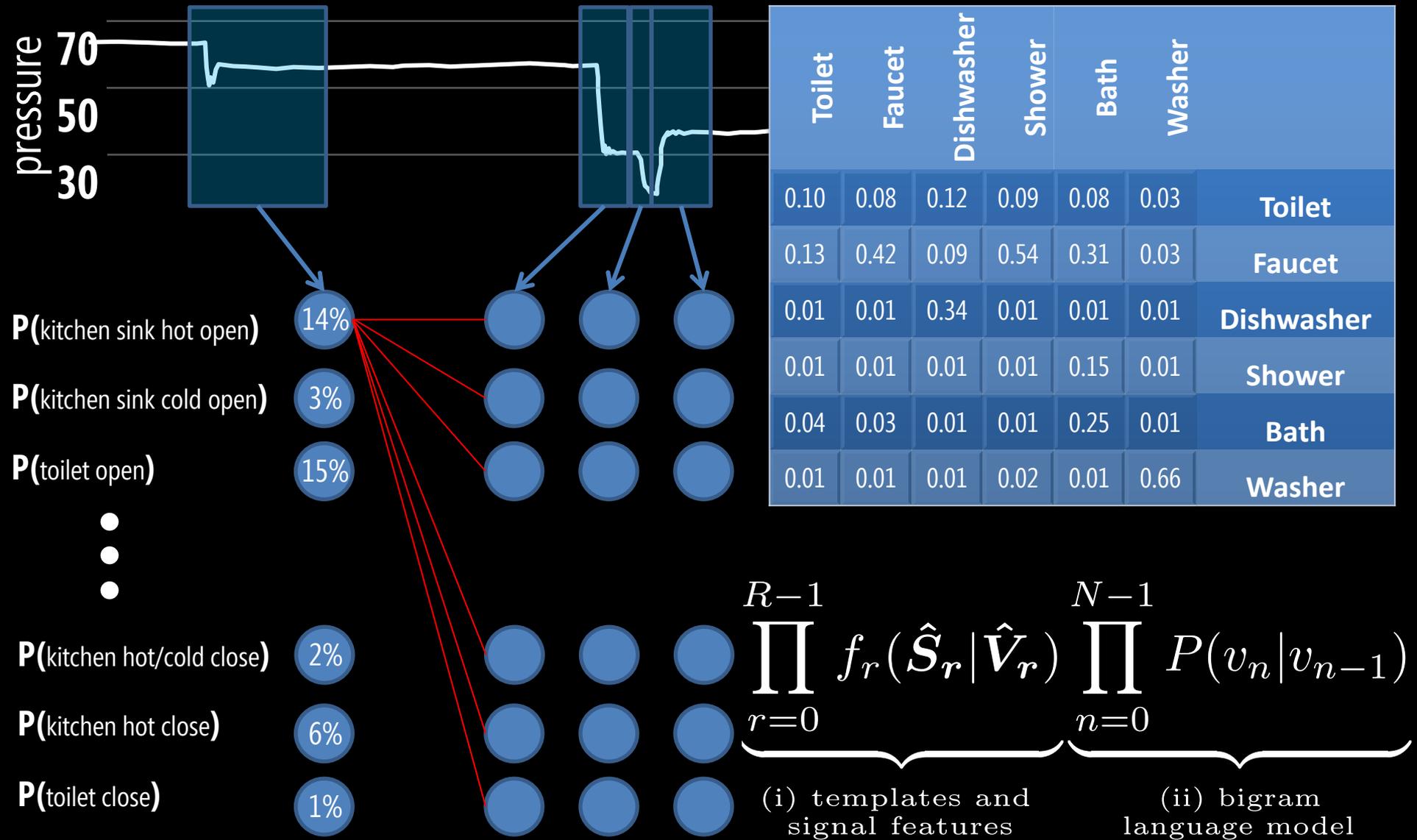
- $P(\text{kitchen sink hot open})$ 14%
- $P(\text{kitchen sink cold open})$ 3%
- $P(\text{toilet open})$ 15%
-
-
-
- $P(\text{kitchen hot/cold close})$ 2%
- $P(\text{kitchen hot close})$ 6%
- $P(\text{toilet close})$ 1%

$$\underbrace{\prod_{r=0}^{R-1} f_r(\hat{S}_r | \hat{V}_r)}_{\text{(i) templates and signal features}} \underbrace{\prod_{n=0}^{N-1} P(v_n | v_{n-1})}_{\text{(ii) bigram language model}}$$

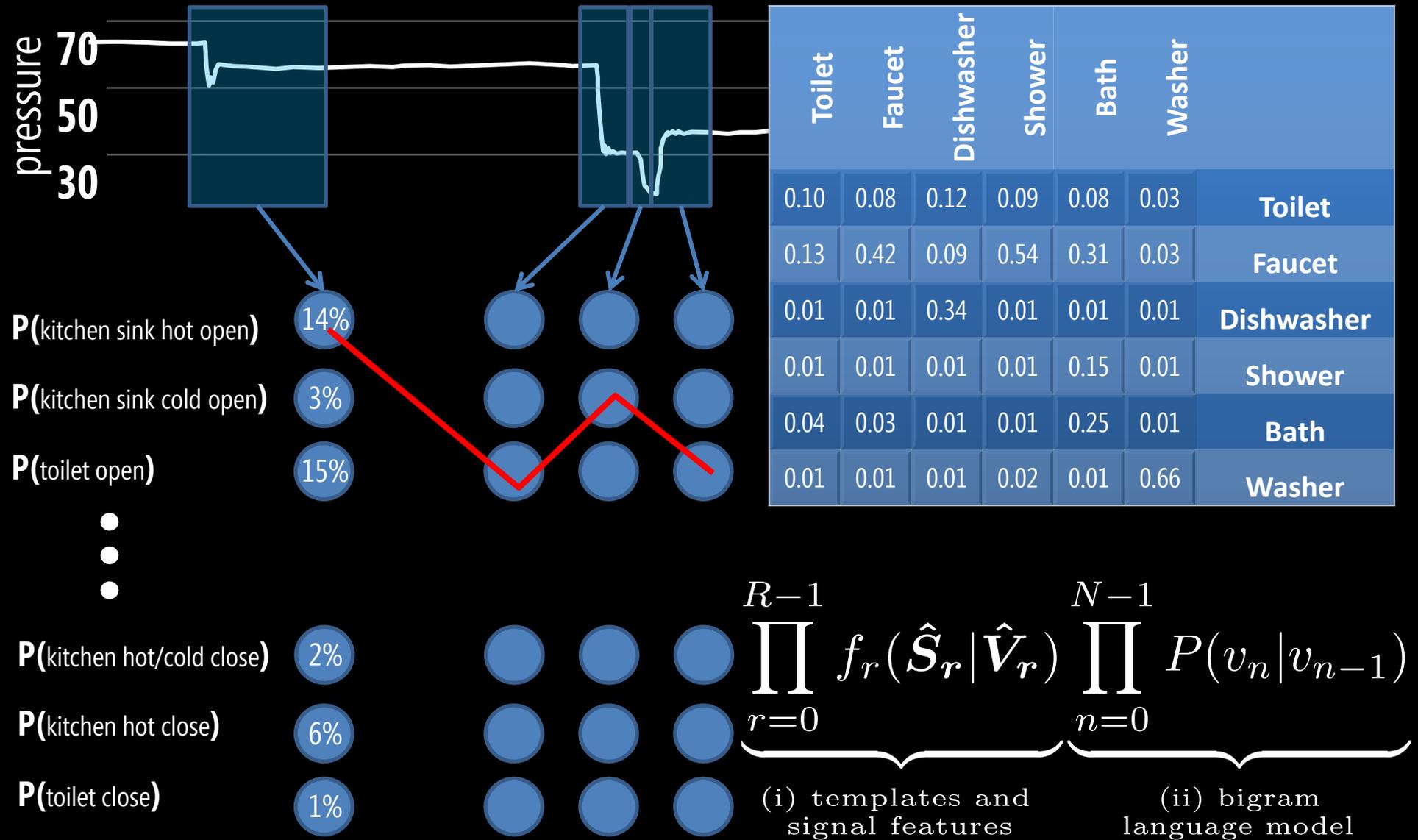
term (ii): bigram language model



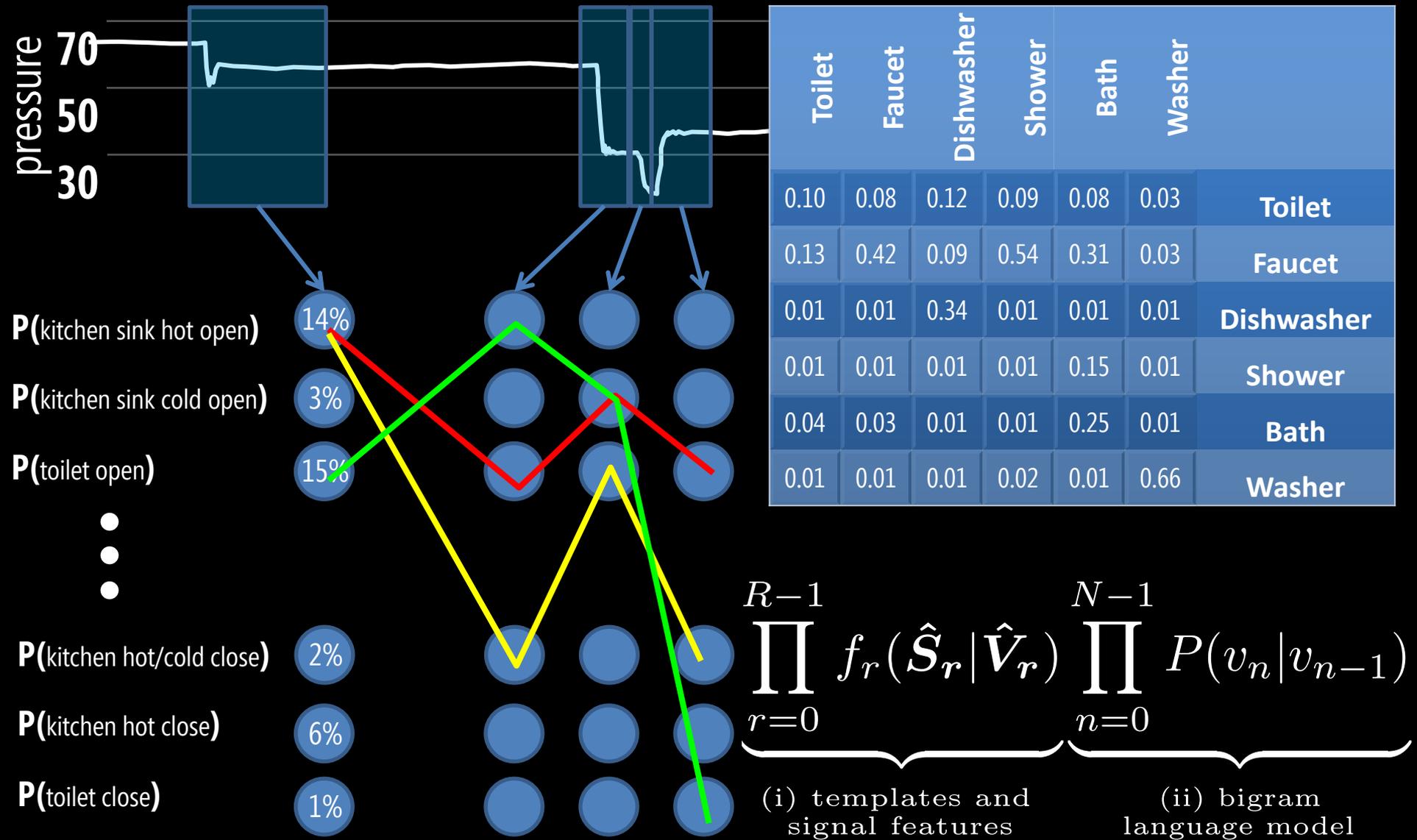
term (ii): bigram language model



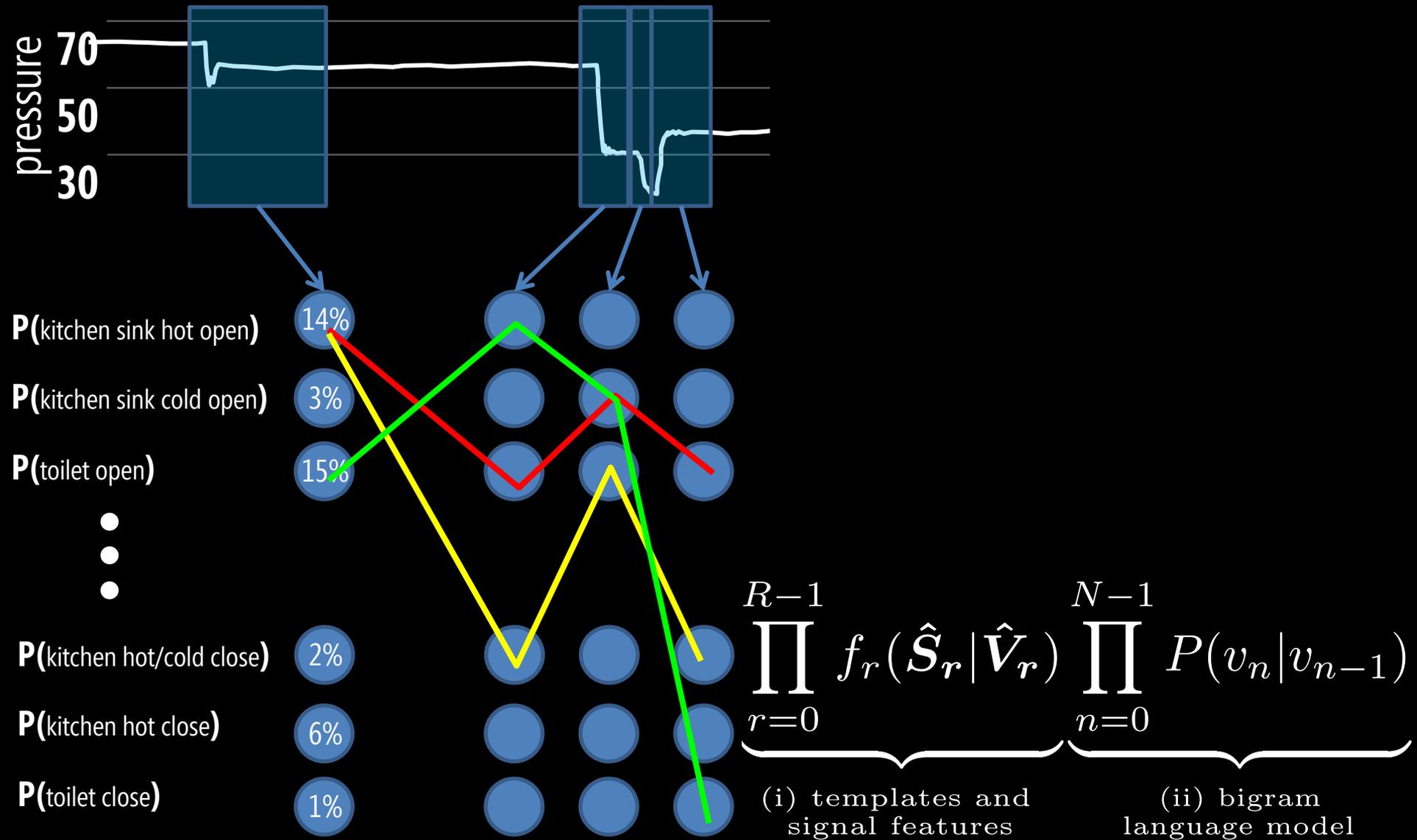
term (ii): bigram language model



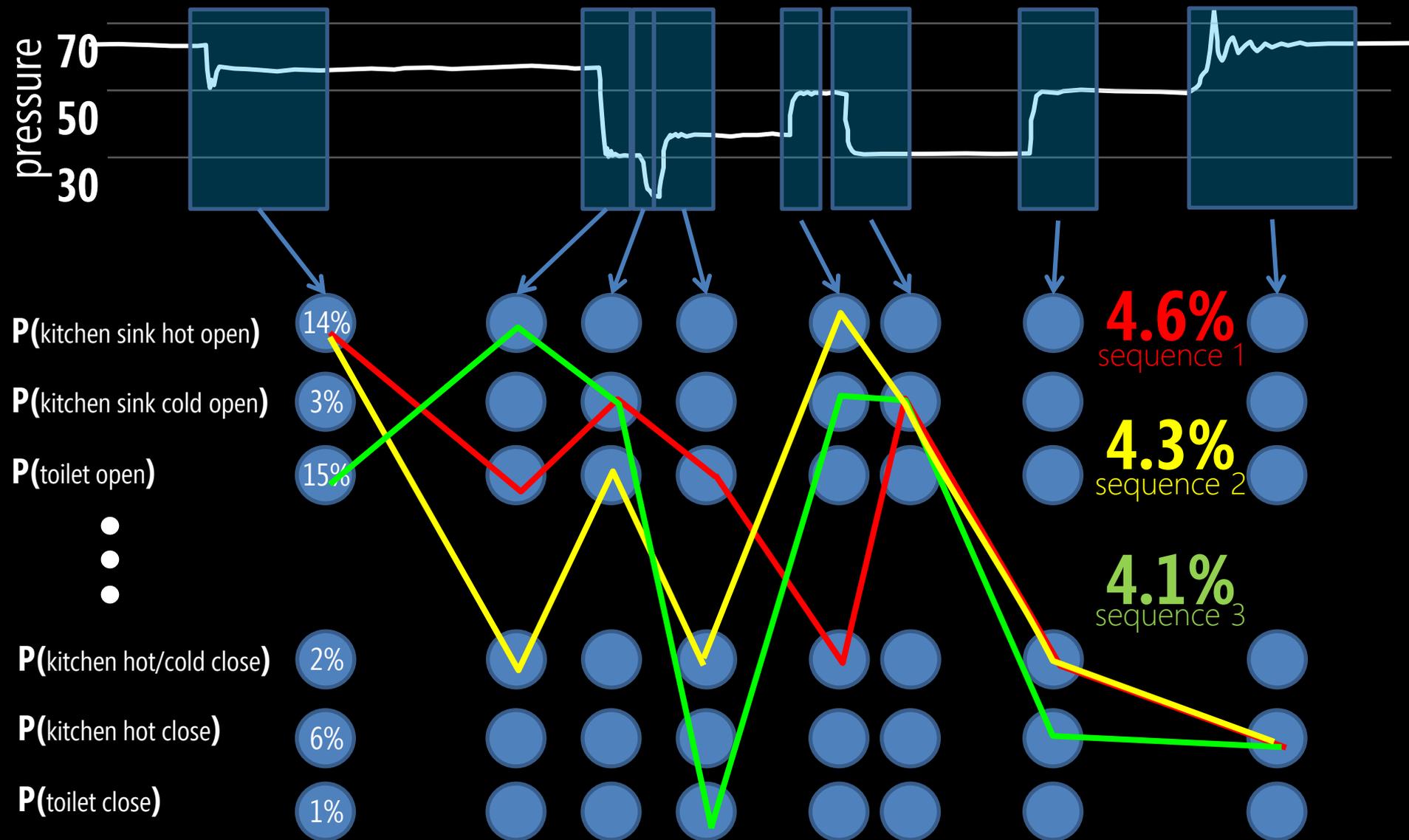
term (ii): bigram language model



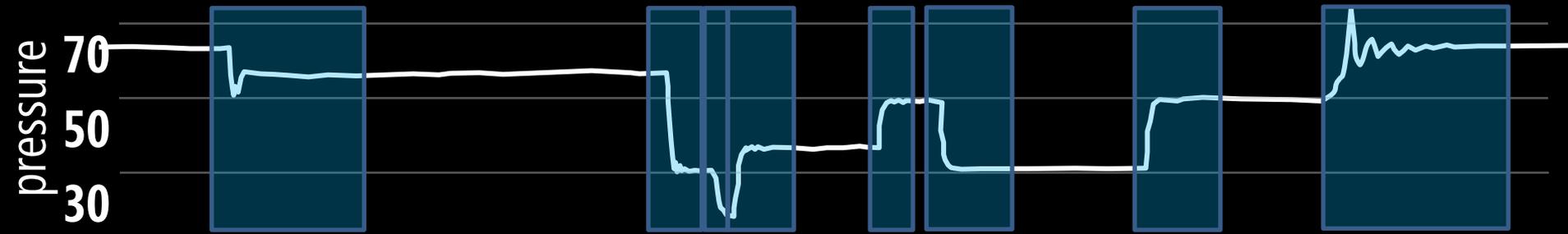
term (ii): bigram language model



term (ii): bigram language model



term (ii): bigram language model



sequence 1

kitchen sink hot open → kitchen sink cold open → dishwasher open → bathroom sink hot close → kitchen sink hot close → toilet open → toilet close → kitchen sink hot close

sequence 2

kitchen sink hot open → shower cold open → toilet open → bathroom sink hot close → kitchen sink hot close → kitchen sink hot open → kitchen sink hot close → kitchen sink hot close

sequence 3

kitchen sink hot open → toilet open → bathroom sink hot open → bathroom sink hot close → kitchen sink hot close → kitchen sink hot open → kitchen sink hot close → toilet close

⋮

$$\underbrace{\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r | \hat{\mathbf{V}}_r)}_{\text{(i) templates and signal features}} \underbrace{\prod_{n=0}^{N-1} P(v_n | v_{n-1})}_{\text{(ii) bigram language model}} \underbrace{\prod_{i \notin \beta} f_p(v_i)}_{\text{(iii) grammar}}$$

(i) templates and signal features

(ii) bigram language model

(iii) grammar

term(iii): grammar

① opened \Rightarrow closed

② opened \Leftarrow closed

③ temperature consistency

soft penalty



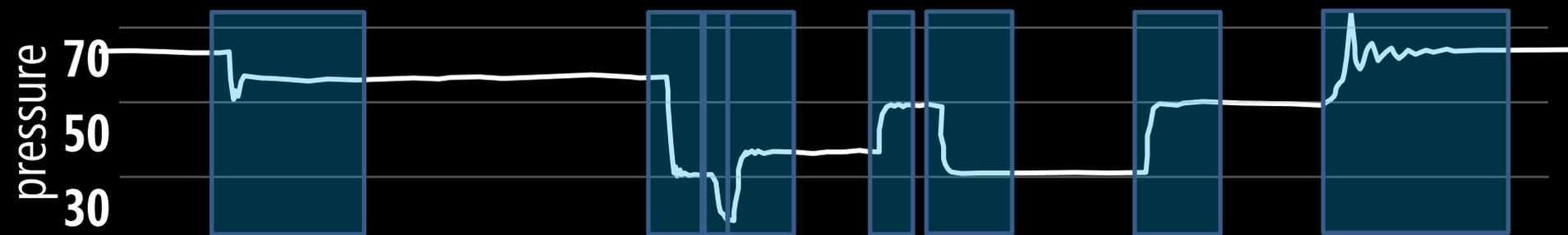
$$\underbrace{\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r | \hat{\mathbf{V}}_r)}_{\text{(i) templates and signal features}} \underbrace{\prod_{n=0}^{N-1} P(v_n | v_{n-1})}_{\text{(ii) bigram language model}} \underbrace{\prod_{i \notin \beta} f_p(v_i)}_{\text{(iii) grammar}}$$

(i) templates and
signal features

(ii) bigram
language model

(iii) grammar

term(iii): grammar



sequence 1

kitchen sink hot open → kitchen sink cold open → dishwasher open → bathroom sink hot close → kitchen sink hot close → toilet open → toilet close → kitchen sink hot close

sequence 2

bathroom sink hot open → shower cold open → toilet open → bathroom sink hot close → shower cold close → kitchen sink hot open → toilet close → kitchen sink hot close

sequence 3

kitchen sink hot open → toilet open → bathroom sink hot open → bathroom sink hot close → kitchen sink hot close → kitchen sink hot open → kitchen sink hot close → toilet close

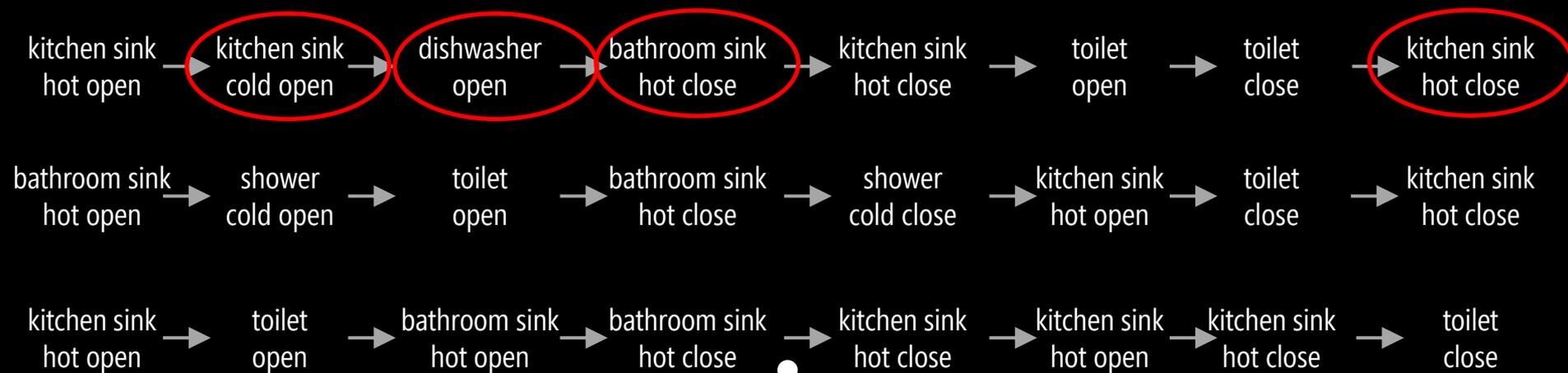
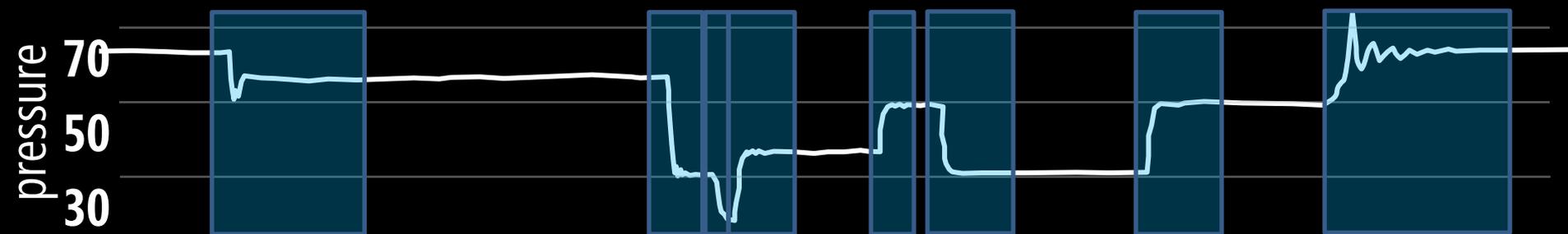
$$\prod_{r=0}^{R-1} f_r(\hat{S}_r | \hat{V}_r) \prod_{n=0}^{N-1} P(v_n | v_{n-1}) \prod_{i \notin \beta} f_p(v_i)$$

(i) templates and signal features

(ii) bigram language model

(iii) grammar

term(iii): grammar



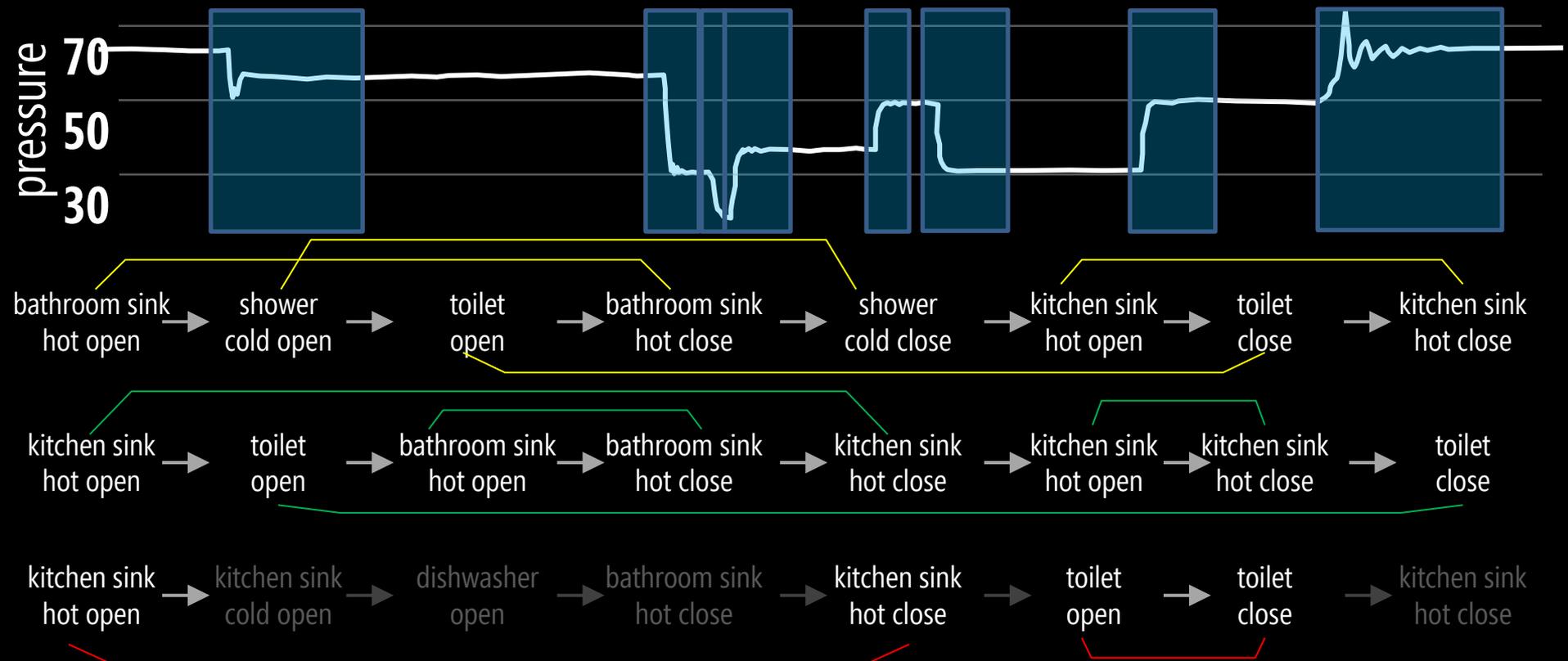
$$\underbrace{\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r | \hat{\mathbf{V}}_r)}_{\text{(i) templates and signal features}} \underbrace{\prod_{n=0}^{N-1} P(v_n | v_{n-1})}_{\text{(ii) bigram language model}} \underbrace{\prod_{i \notin \beta} f_p(v_i)}_{\text{(iii) grammar}}$$

(i) templates and signal features

(ii) bigram language model

(iii) grammar

term(iii): grammar



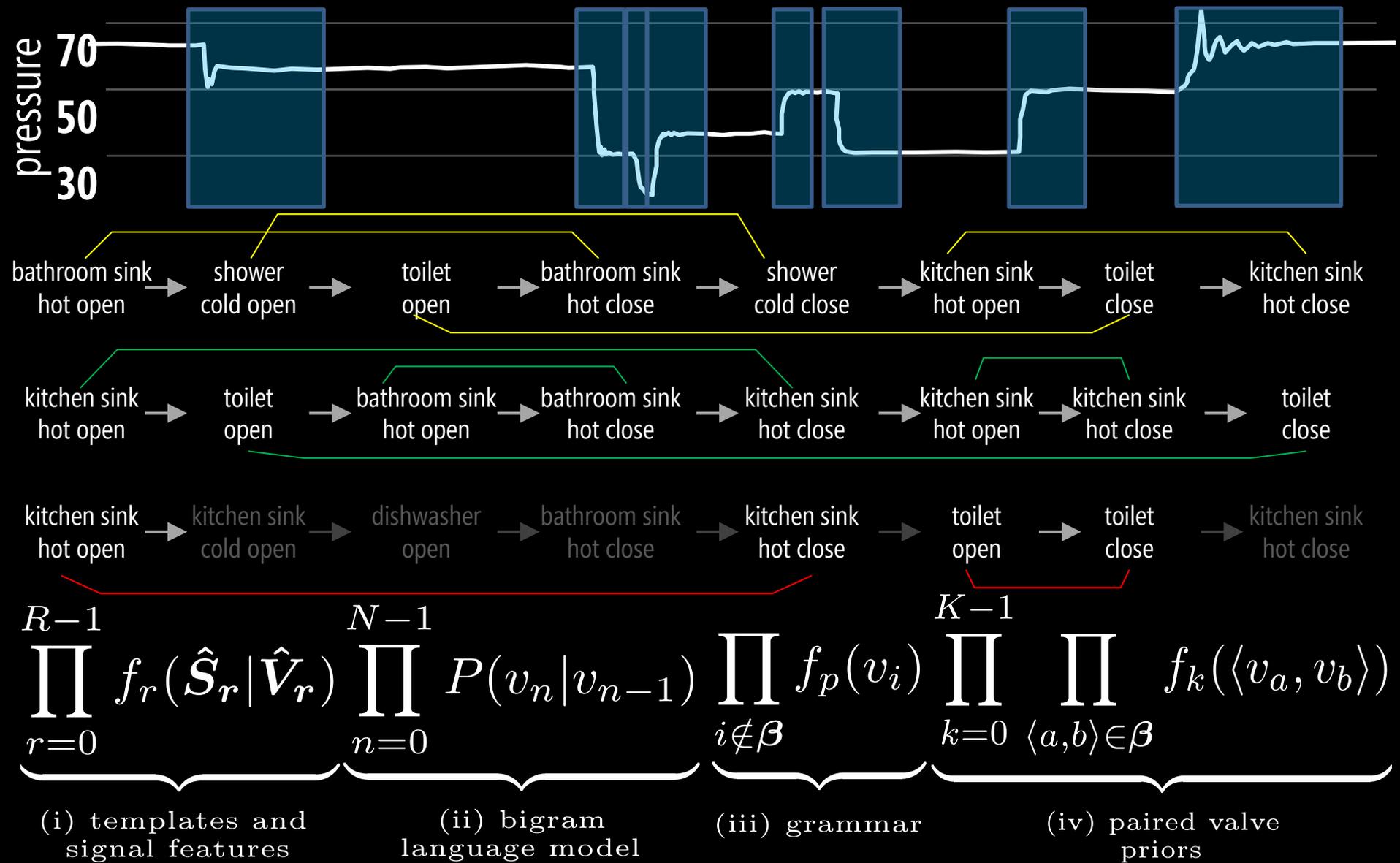
$$\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r | \hat{\mathbf{V}}_r) \prod_{n=0}^{N-1} P(v_n | v_{n-1}) \prod_{i \notin \beta} f_p(v_i)$$

(i) templates and signal features

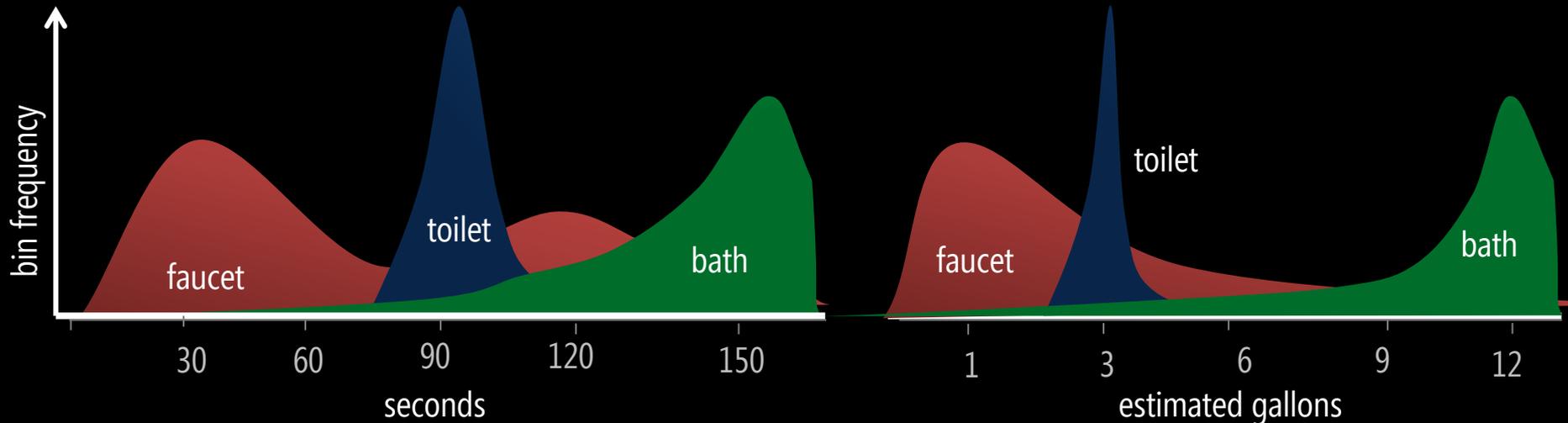
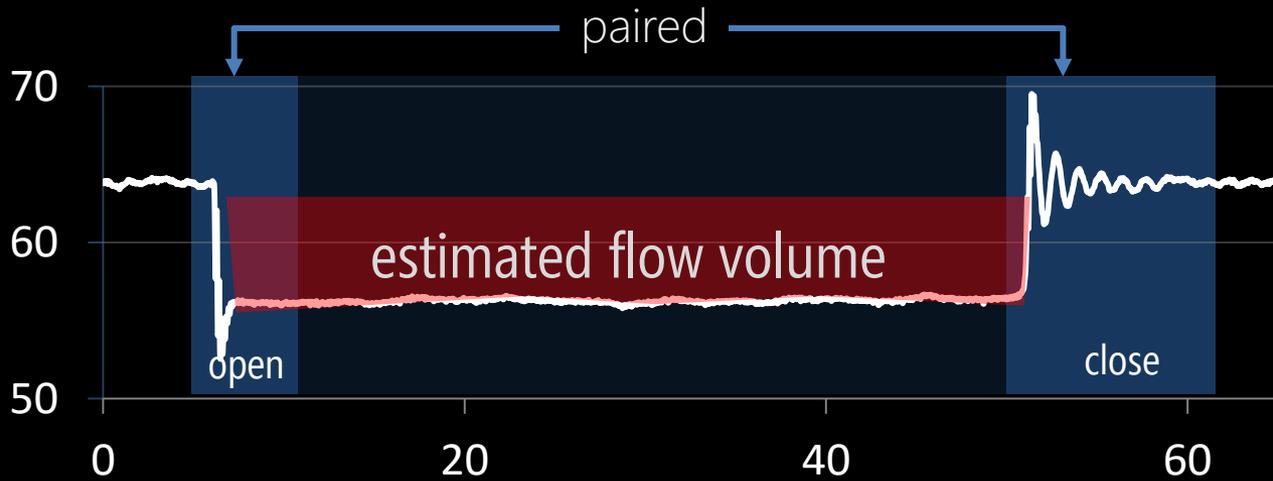
(ii) bigram language model

(iii) grammar

term(iii): grammar



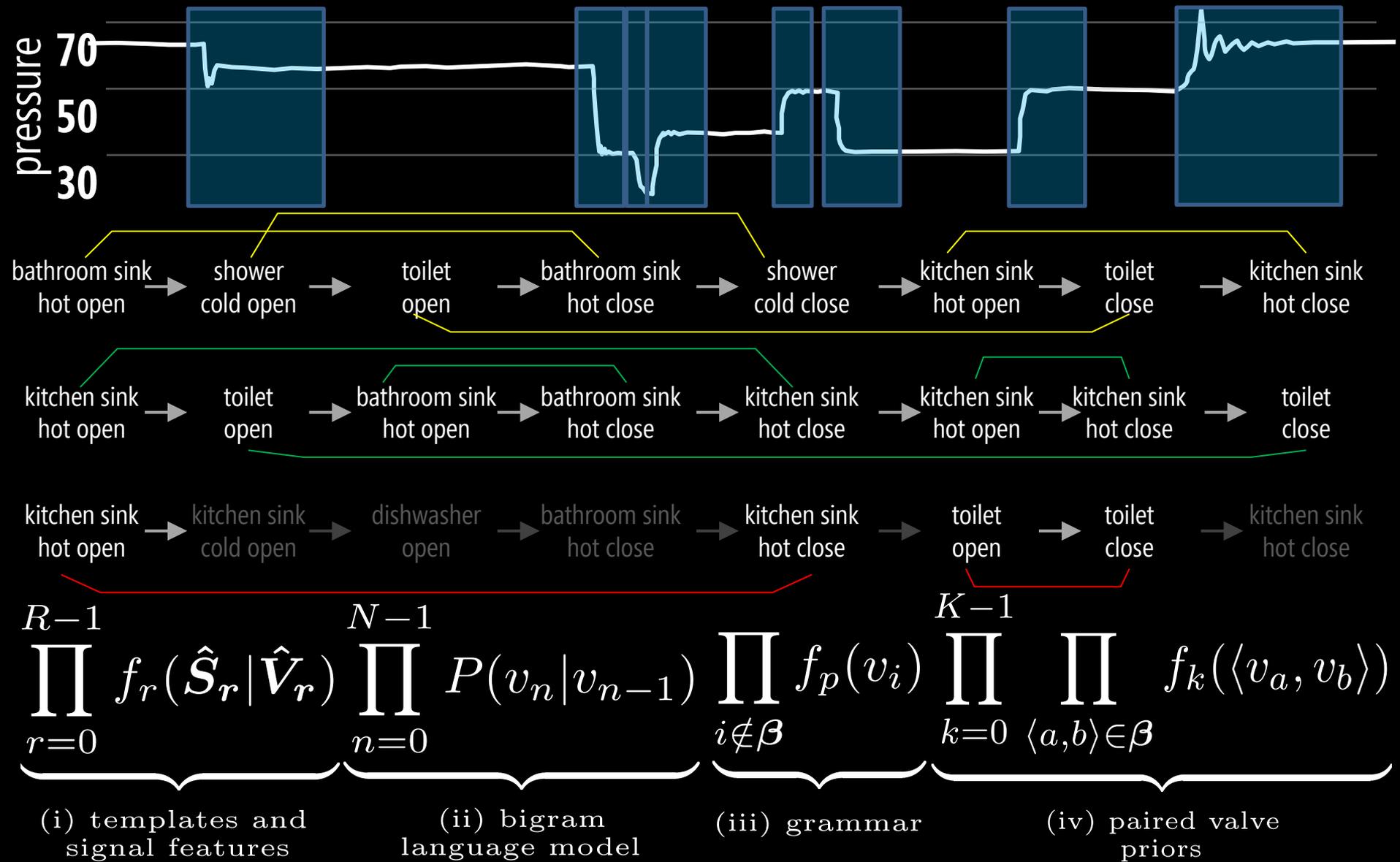
term(iv): paired valve priors



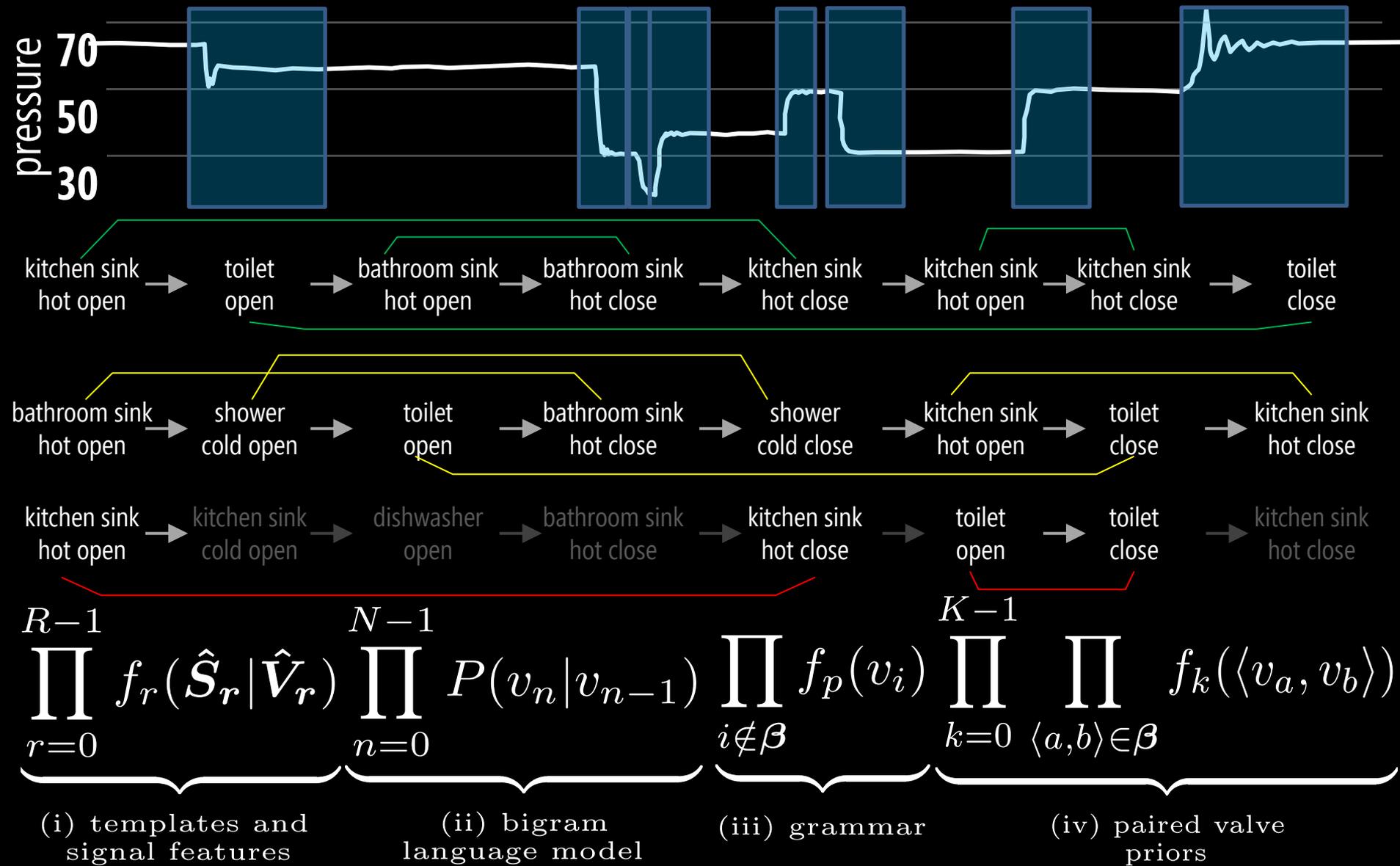
fixture usage duration

flow volume

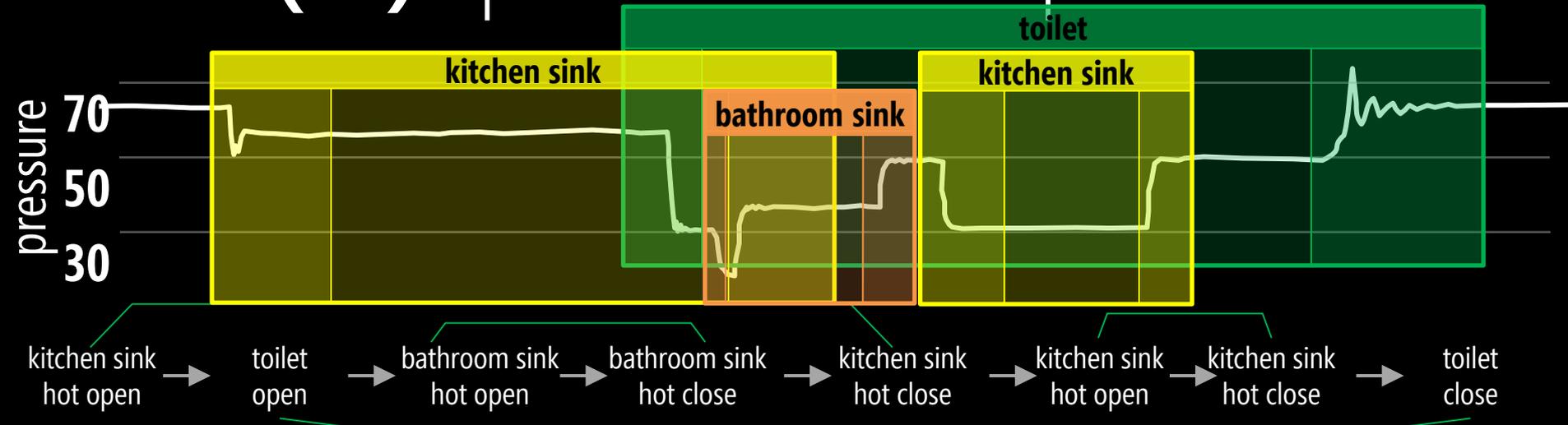
term(iv): paired valve priors



term(iv): paired valve priors

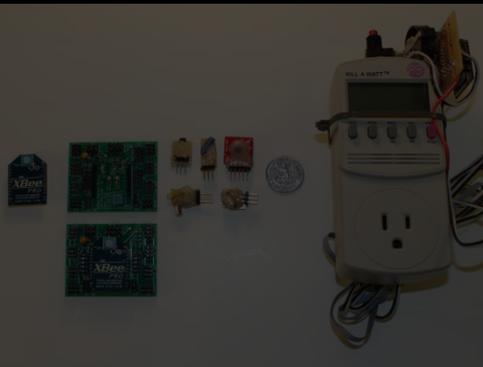


term(iv): paired valve priors



$$\underbrace{\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r | \hat{\mathbf{V}}_r)}_{\text{(i) templates and signal features}} \underbrace{\prod_{n=0}^{N-1} P(v_n | v_{n-1})}_{\text{(ii) bigram language model}} \underbrace{\prod_{i \notin \beta} f_p(v_i)}_{\text{(iii) grammar}} \underbrace{\prod_{k=0}^{K-1} \prod_{\langle a, b \rangle \in \beta} f_k(\langle v_a, v_b \rangle)}_{\text{(iv) paired valve priors}}$$

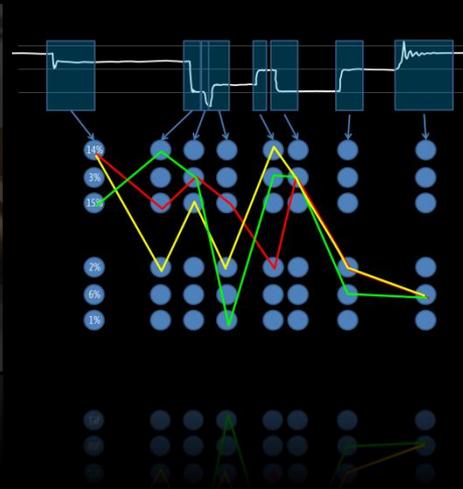
ground truth
sensors



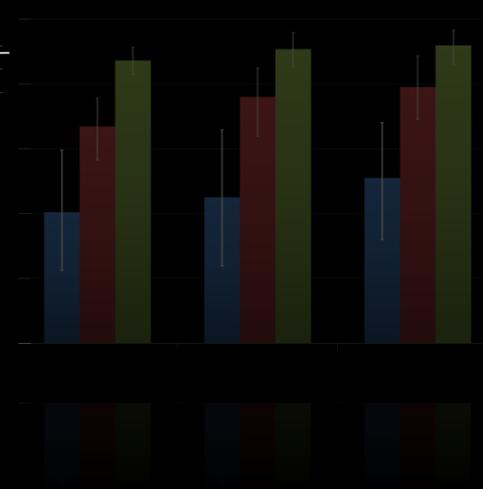
5-week
deployment



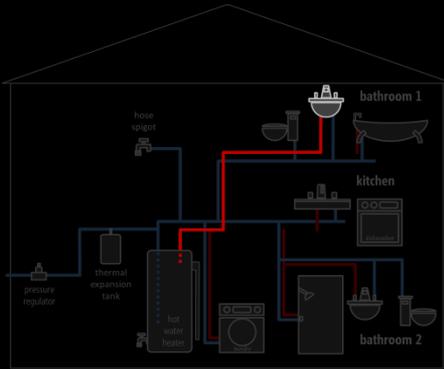
classification
algorithm



classification
results

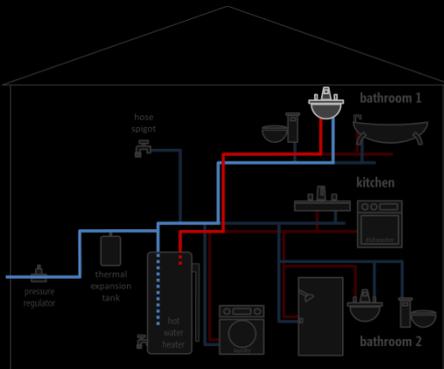


three levels of granularity



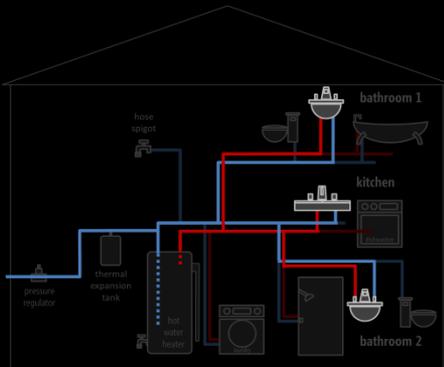
① valve level

e.g., upstairs bathroom faucet hot water activated



② fixture level

e.g., upstairs bathroom faucet activated

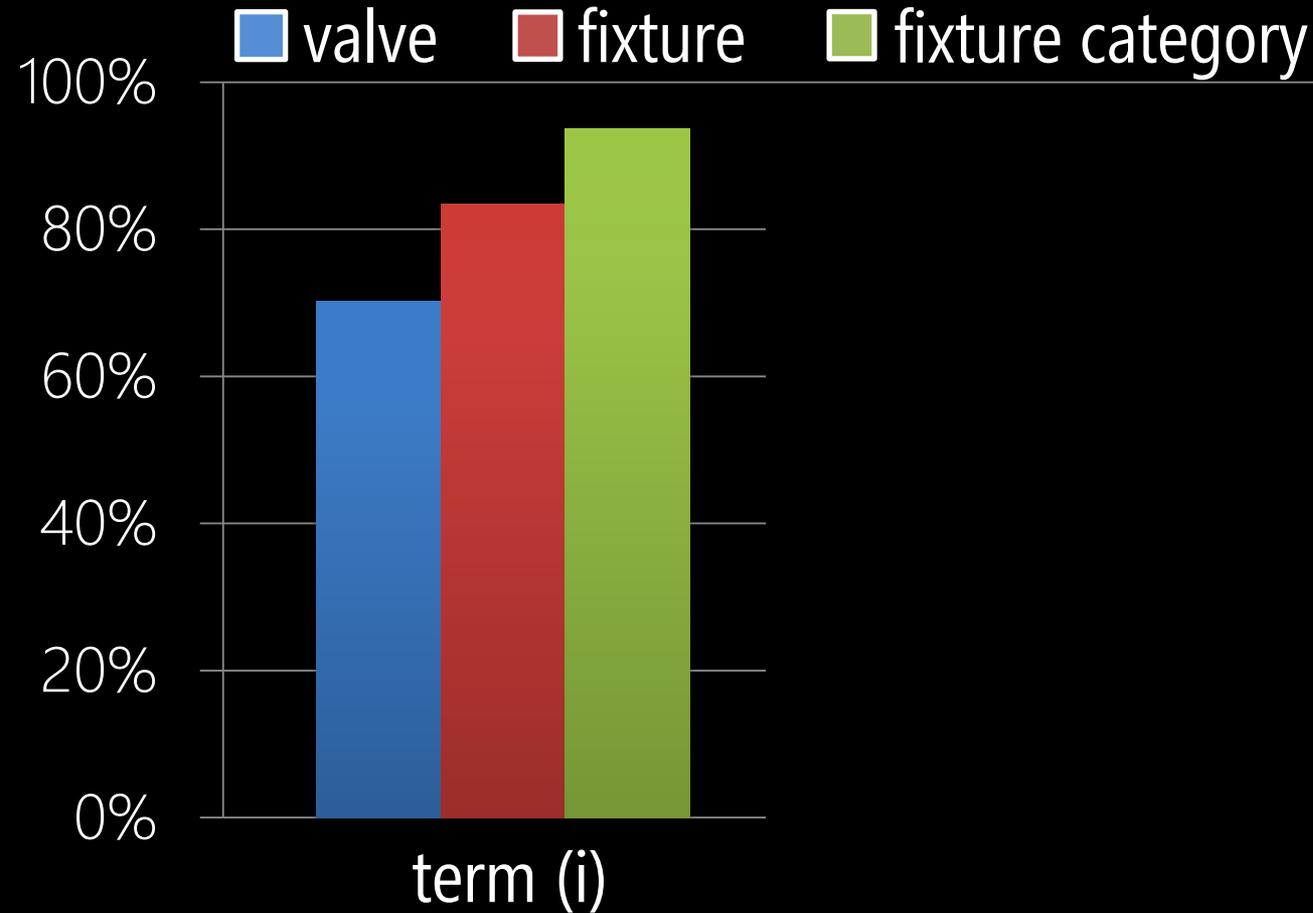


③ fixture category level

e.g., faucet activated

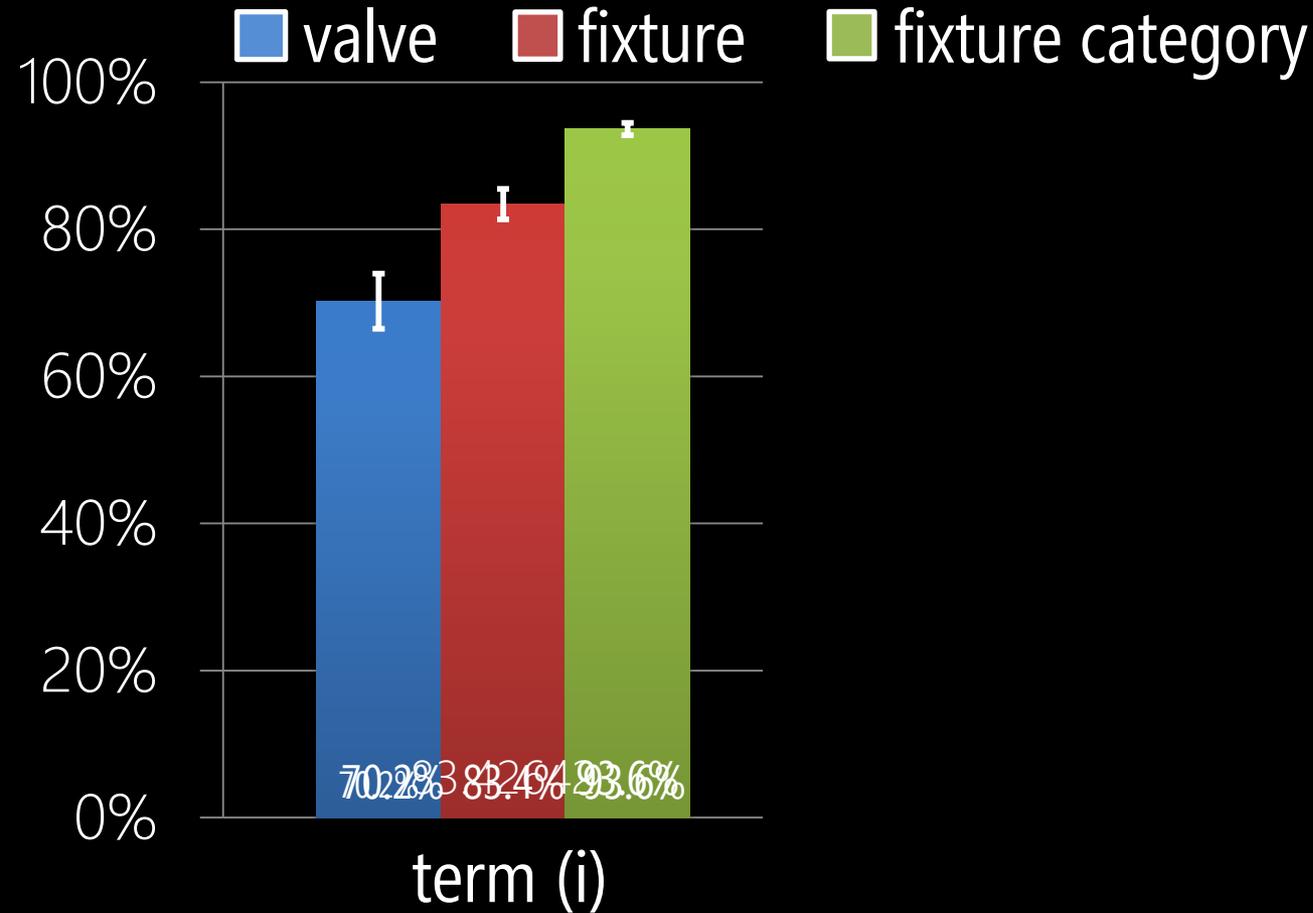
hydrosense classification results

real-world water usage data



hydrosense classification results

real-world water usage data

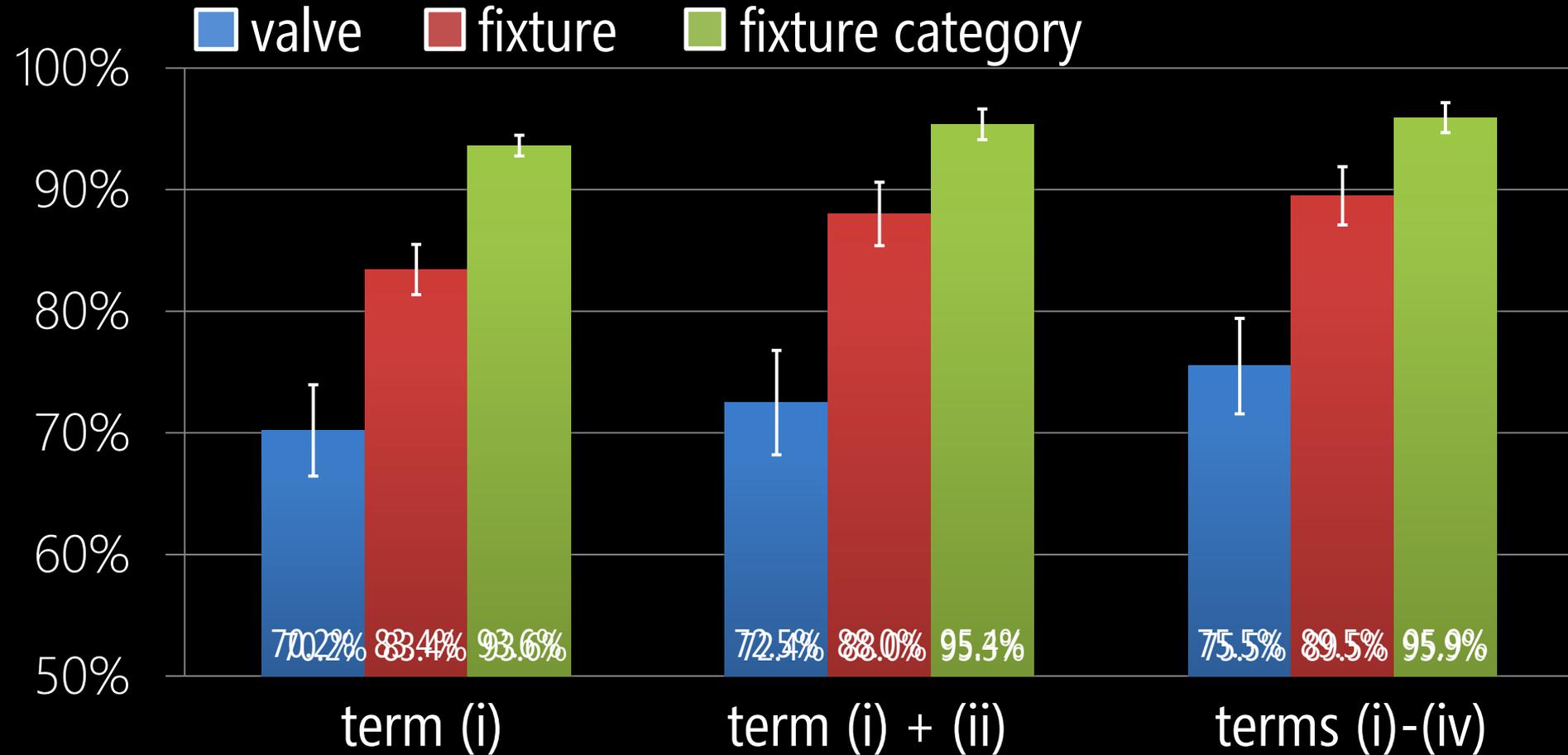


*error bars = std error

*10-fold cross validation

hydrosense classification results

real-world water usage data

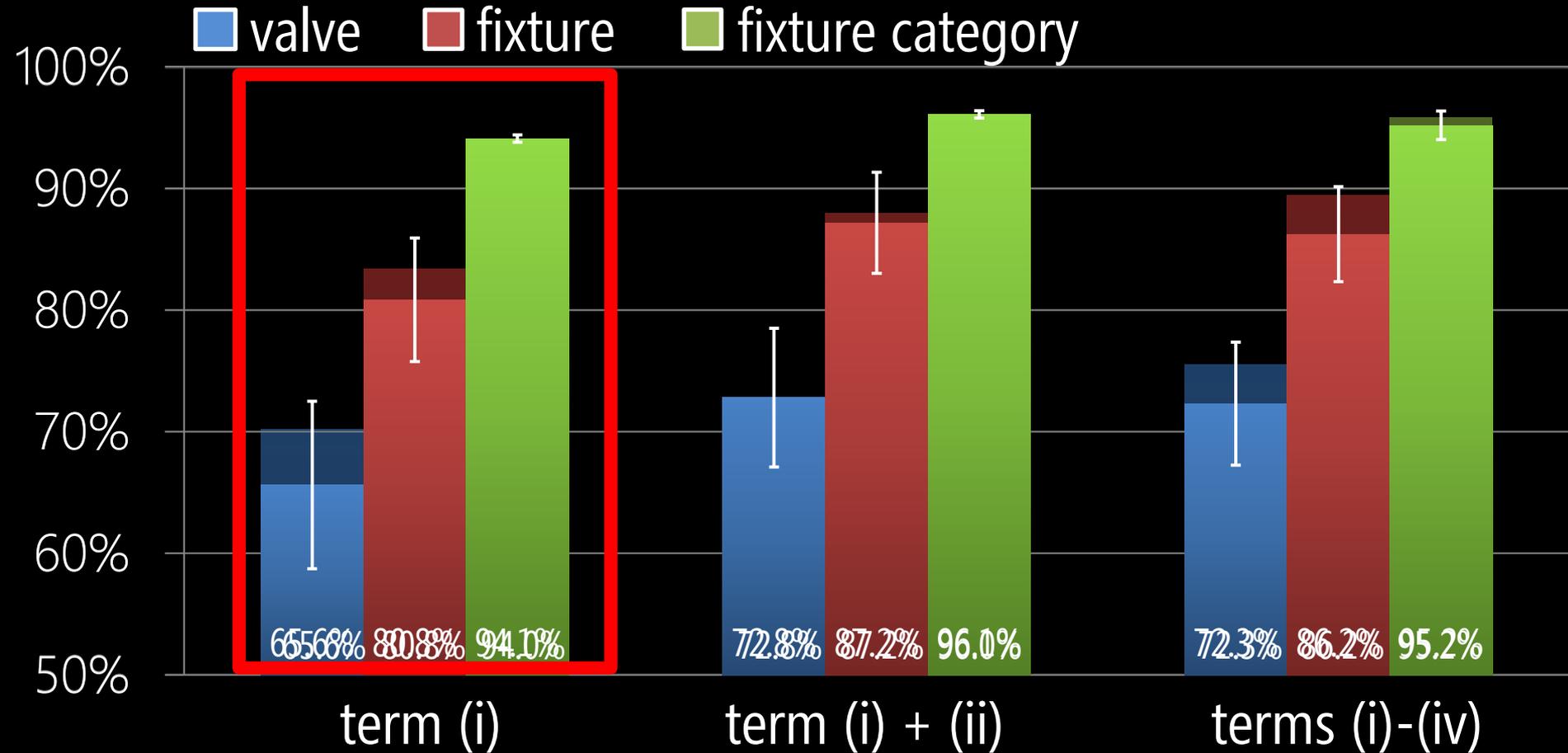


*error bars = std error

*10-fold cross validation

compound events

real-world water usage data



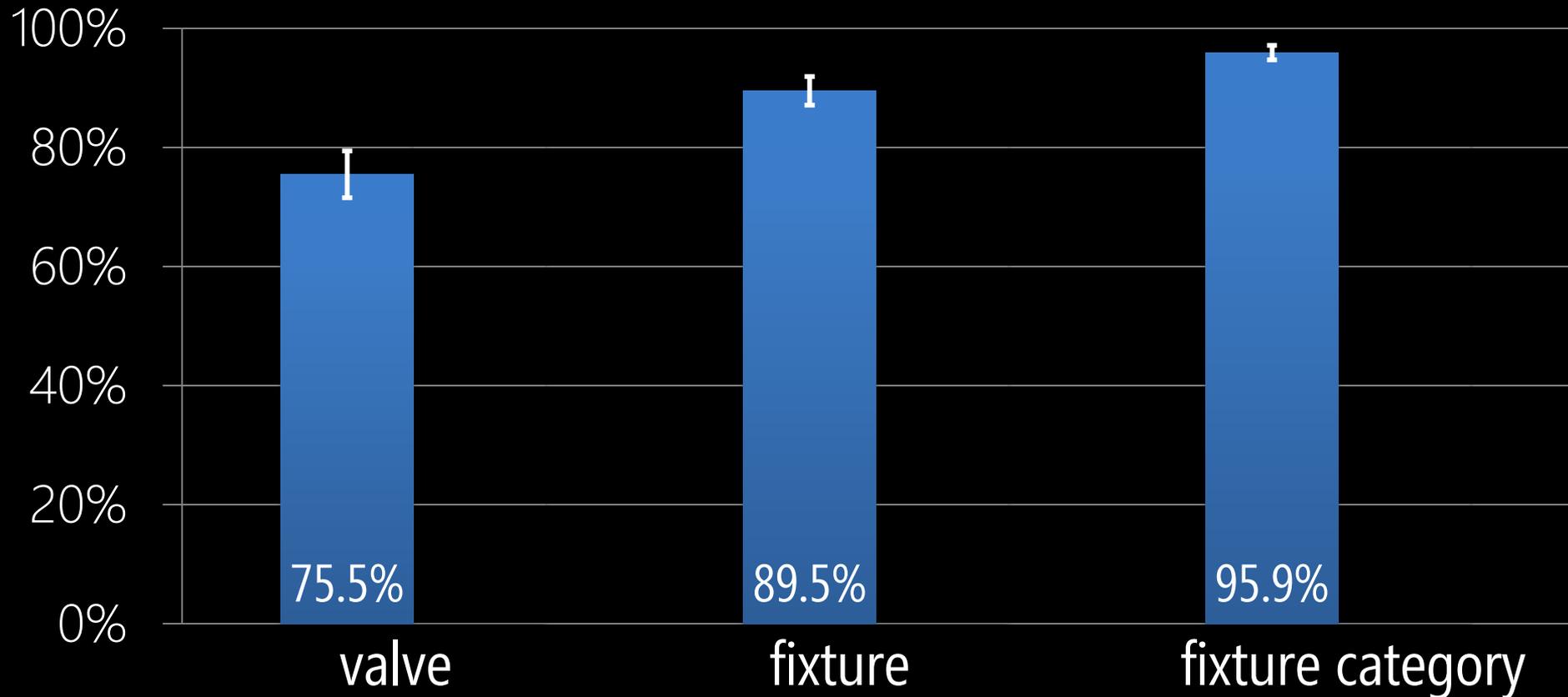
*error bars = std error

*10-fold cross validation

hydrosense classification results

real-world water usage data

■ one sensor, terms(i)-(iv)



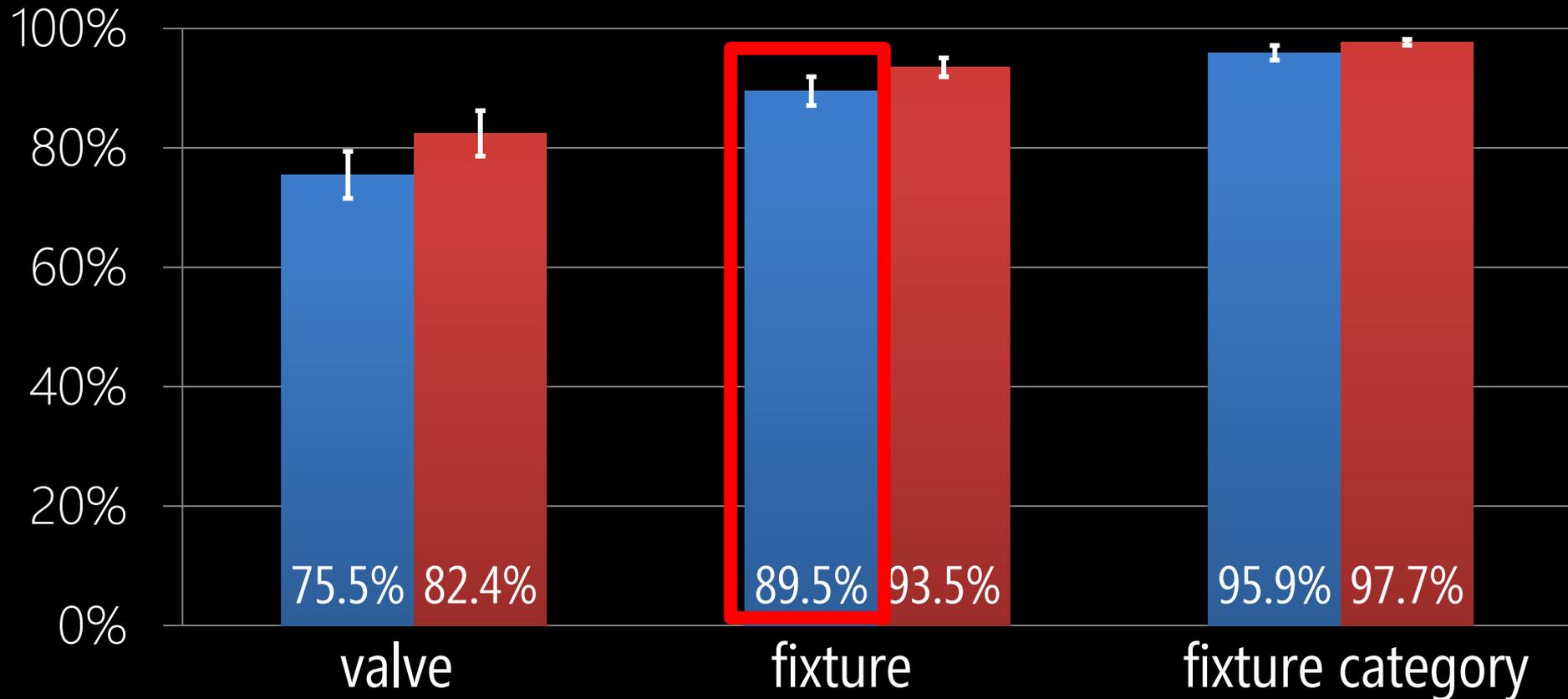
*error bars = std error

*10-fold cross validation

hydrosense classification results

real-world water usage data

one sensor, terms(i)-(iv) two sensors, terms(i)-(iv)



*error bars = std error

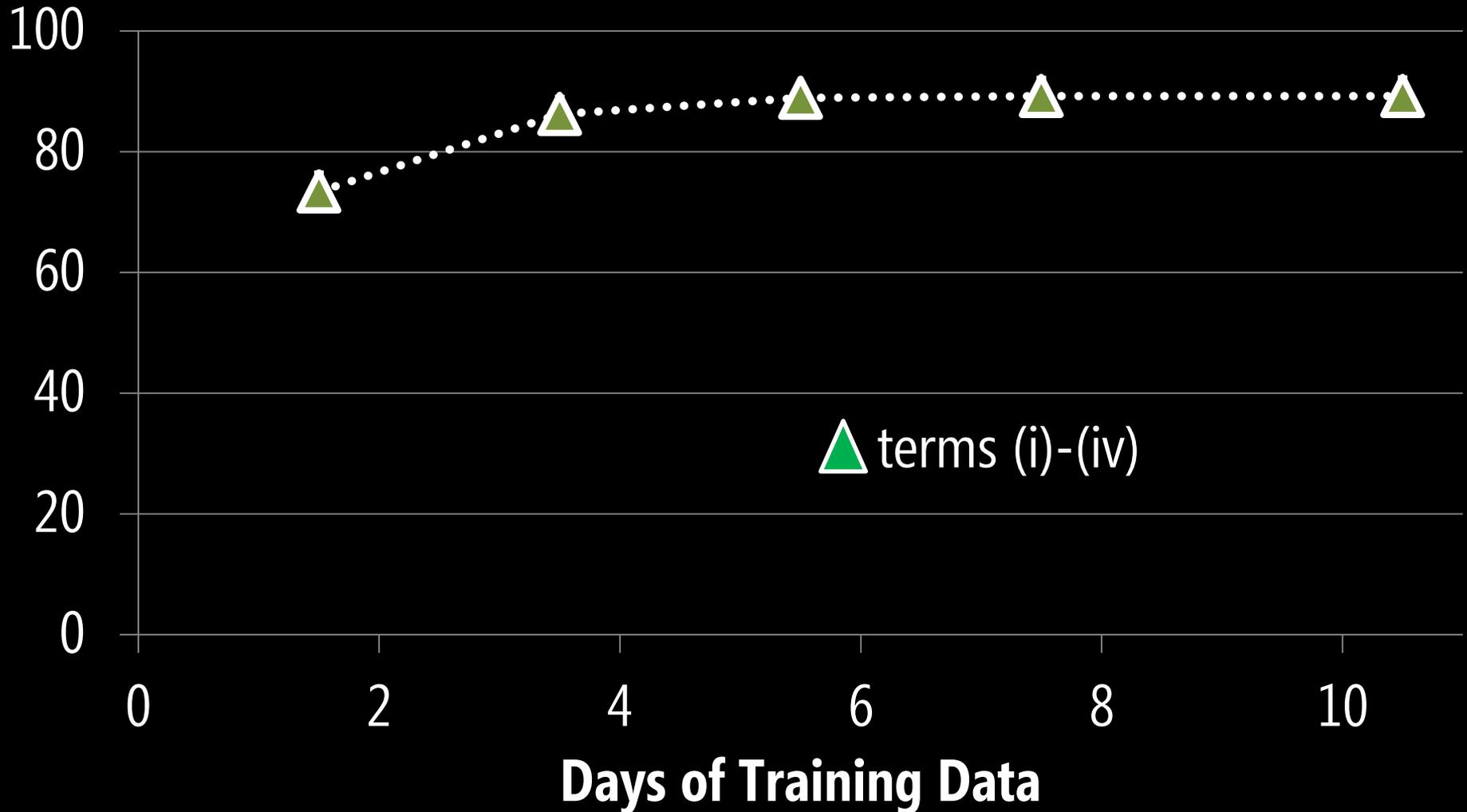
*10-fold cross validation

*terms (i)-(iv)

...what about **training**?

hydrosense training results

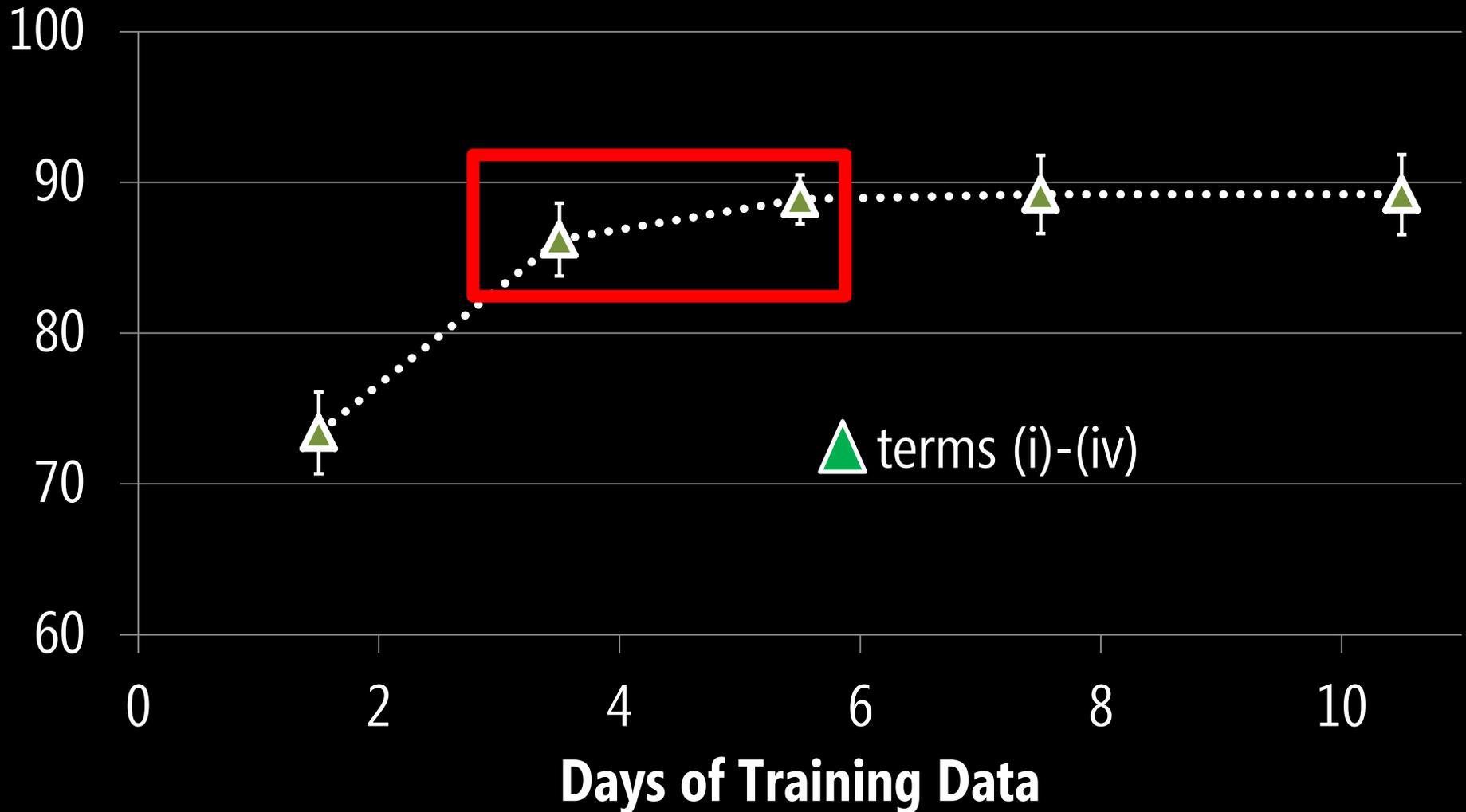
real-world water usage data



*error bars = std error

hydrosense training results

real-world water usage data



*error bars = std error

pervasive 2011 contributions

- ① longitudinal study of real-world water usage and the resulting dataset
- ② a new probabilistic approach to water usage classification
- ③ demonstrate that this new approach can accurately classify real world data

future work

① additional features

② segmentation

③ ease of training



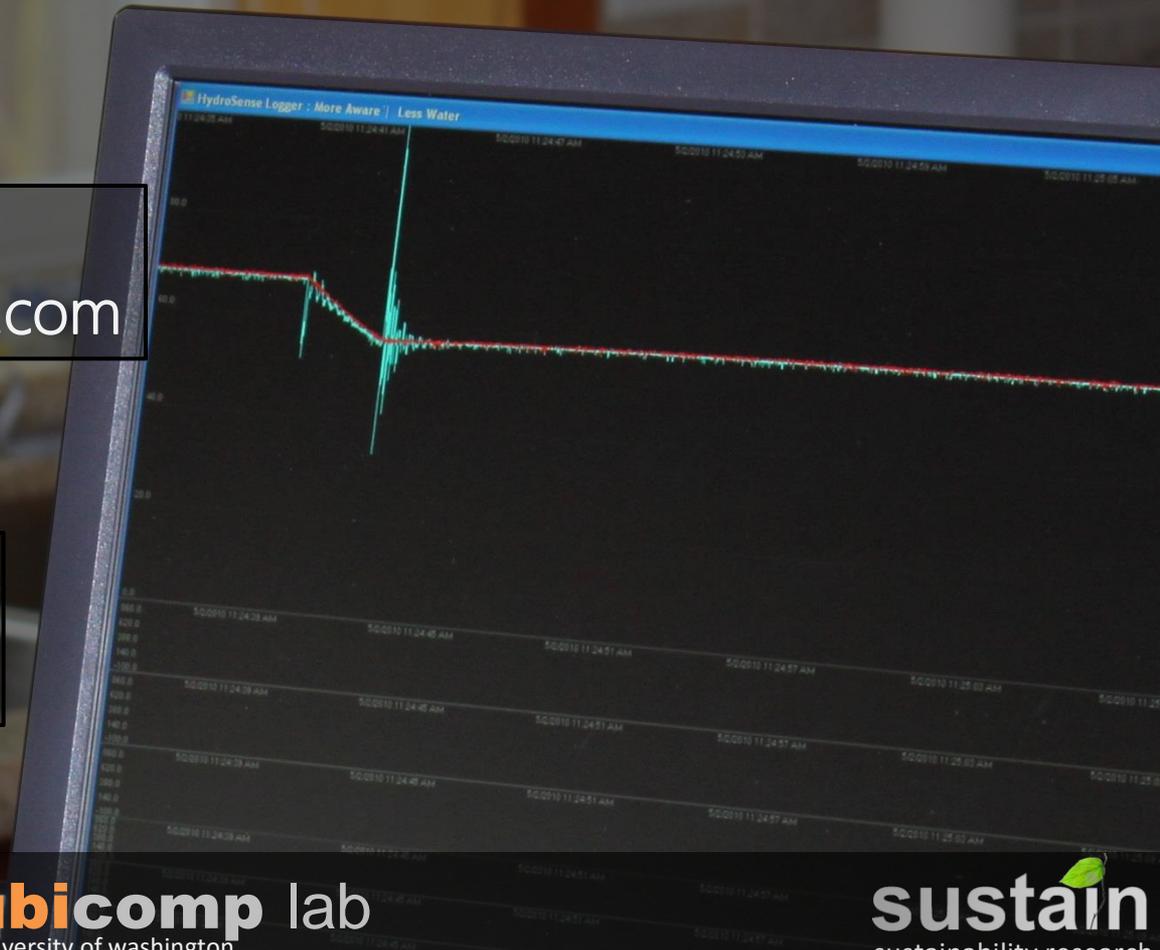


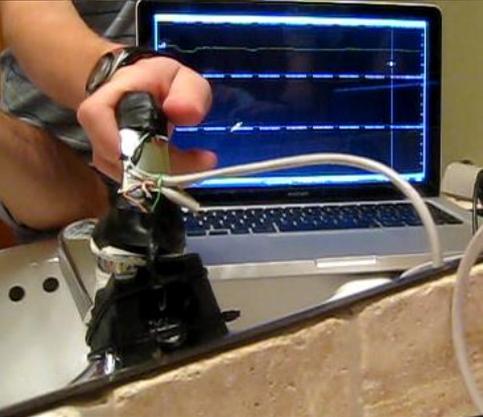
A Longitudinal Study of Pressure Sensing to Infer Real-World Water Usage Events in the Home

Eric Larson

eric.cooper.larson@gmail.com

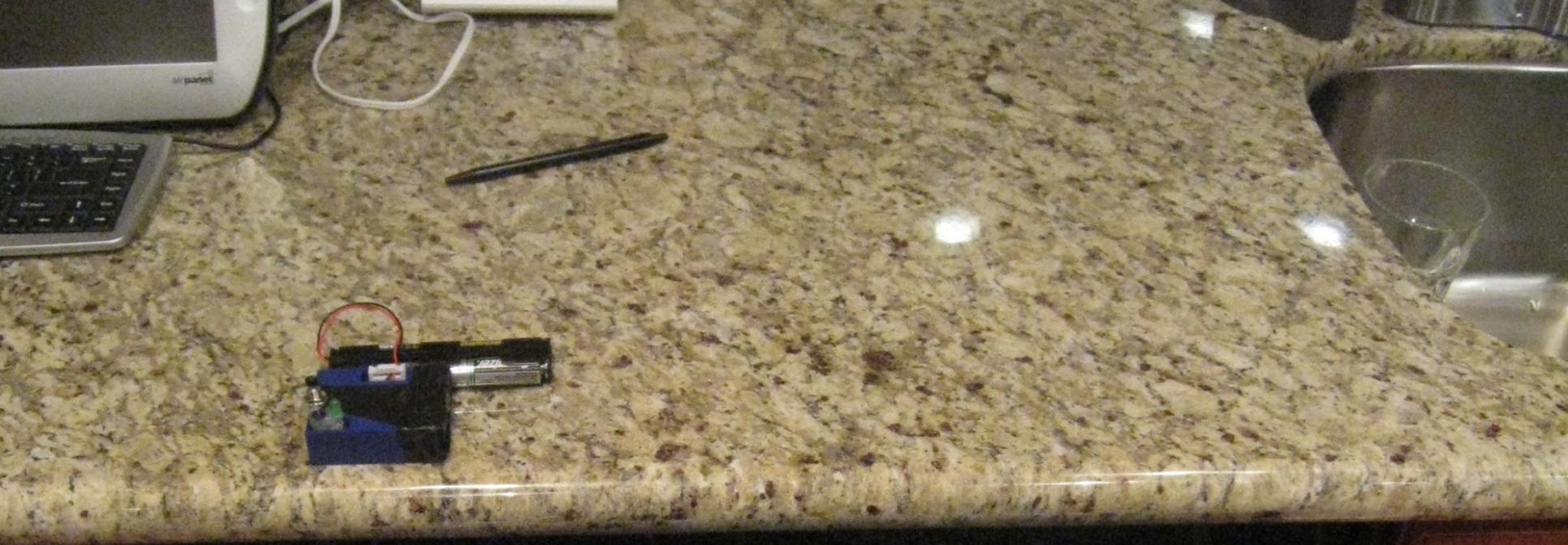
Jon Froehlich, Elliot Saba, Tim Campbell,
Les Atlas, James Fogarty and
Shwetak Patel

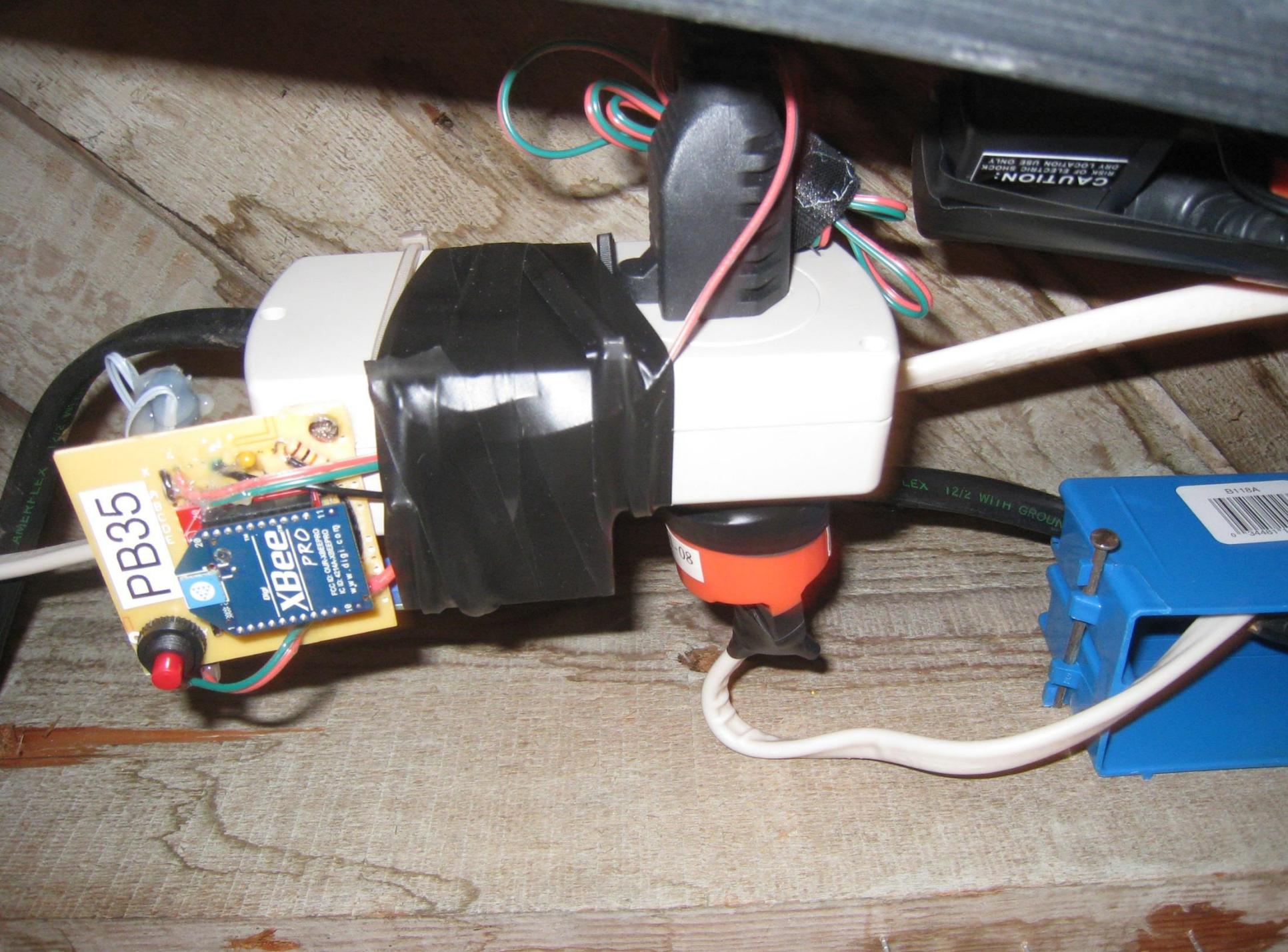












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PB35

XBee PRO
FCC ID: C9A-11111
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www.digi.com

B118A
0 34451

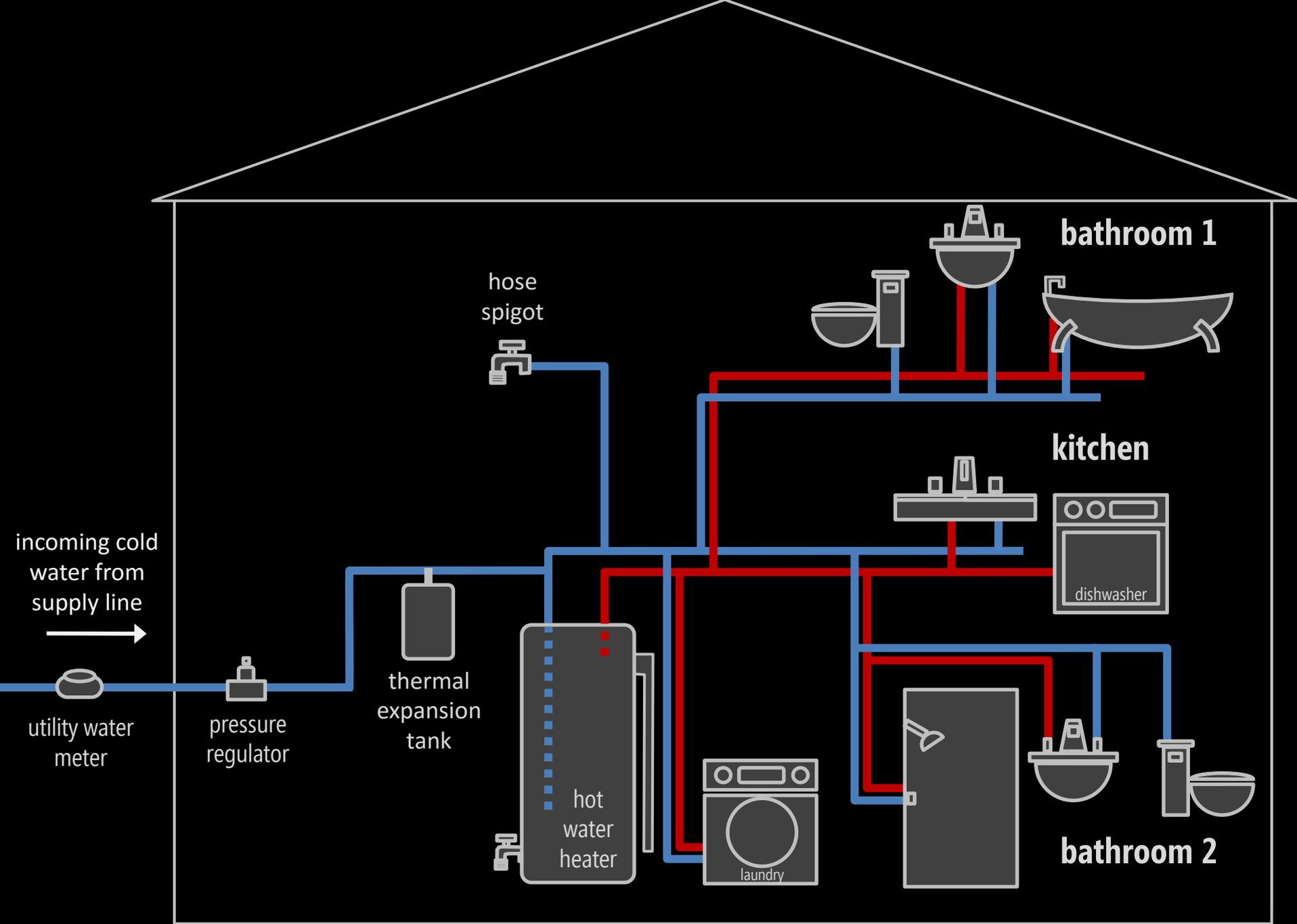
LEX 12/2 WITH GROUND

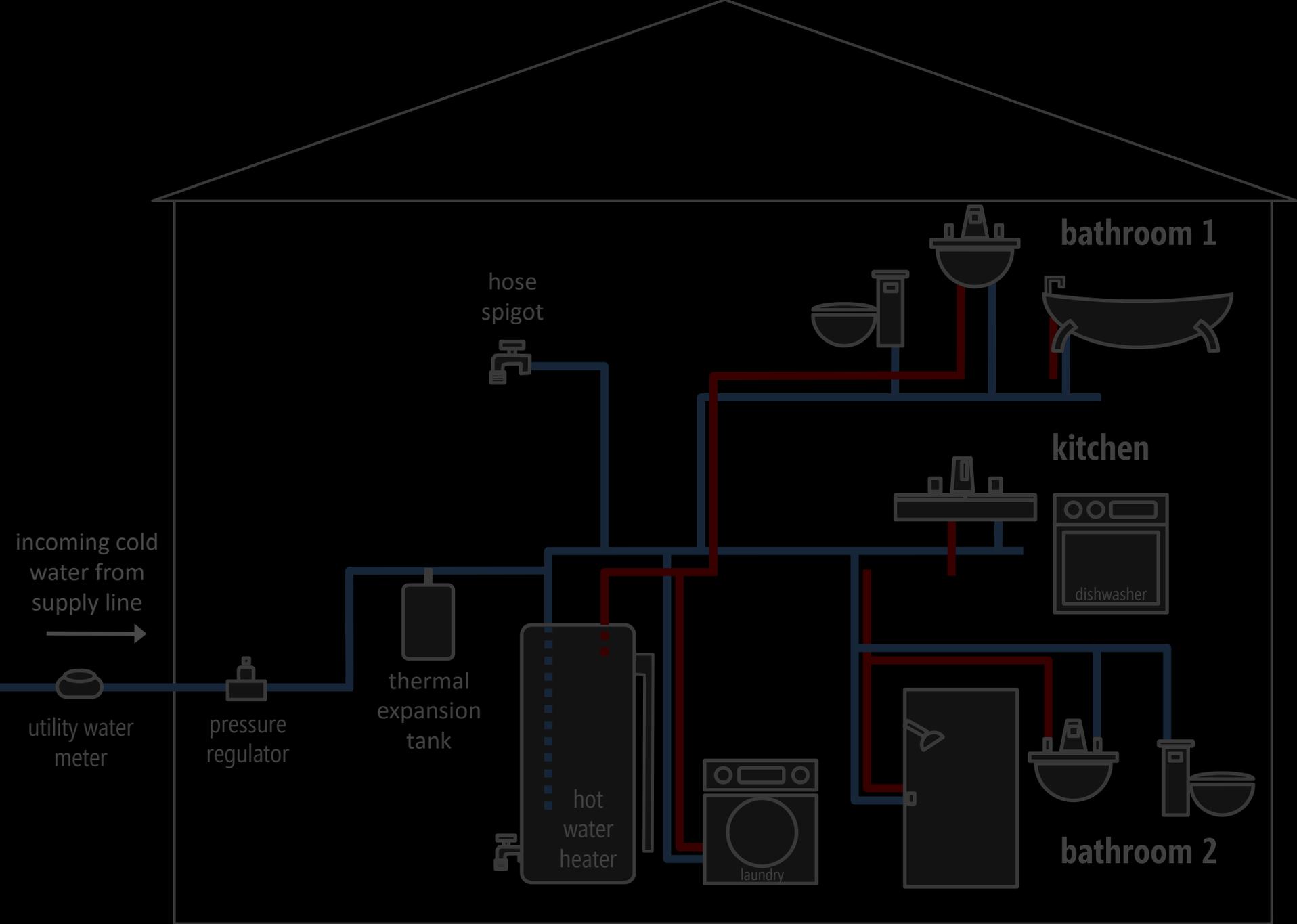
08











incoming cold water from supply line



utility water meter

pressure regulator

thermal expansion tank

hose spigot

hot water heater

laundry

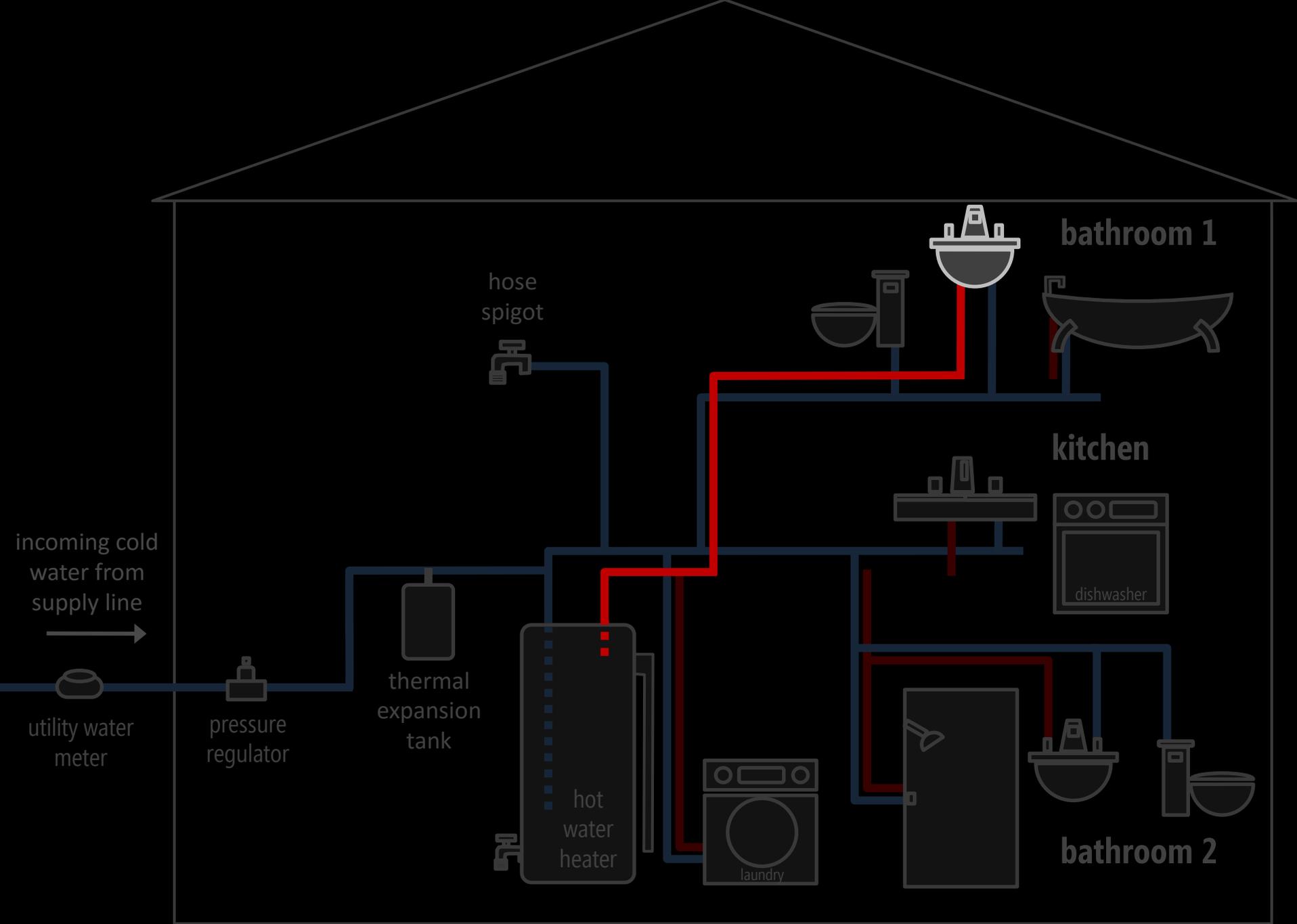


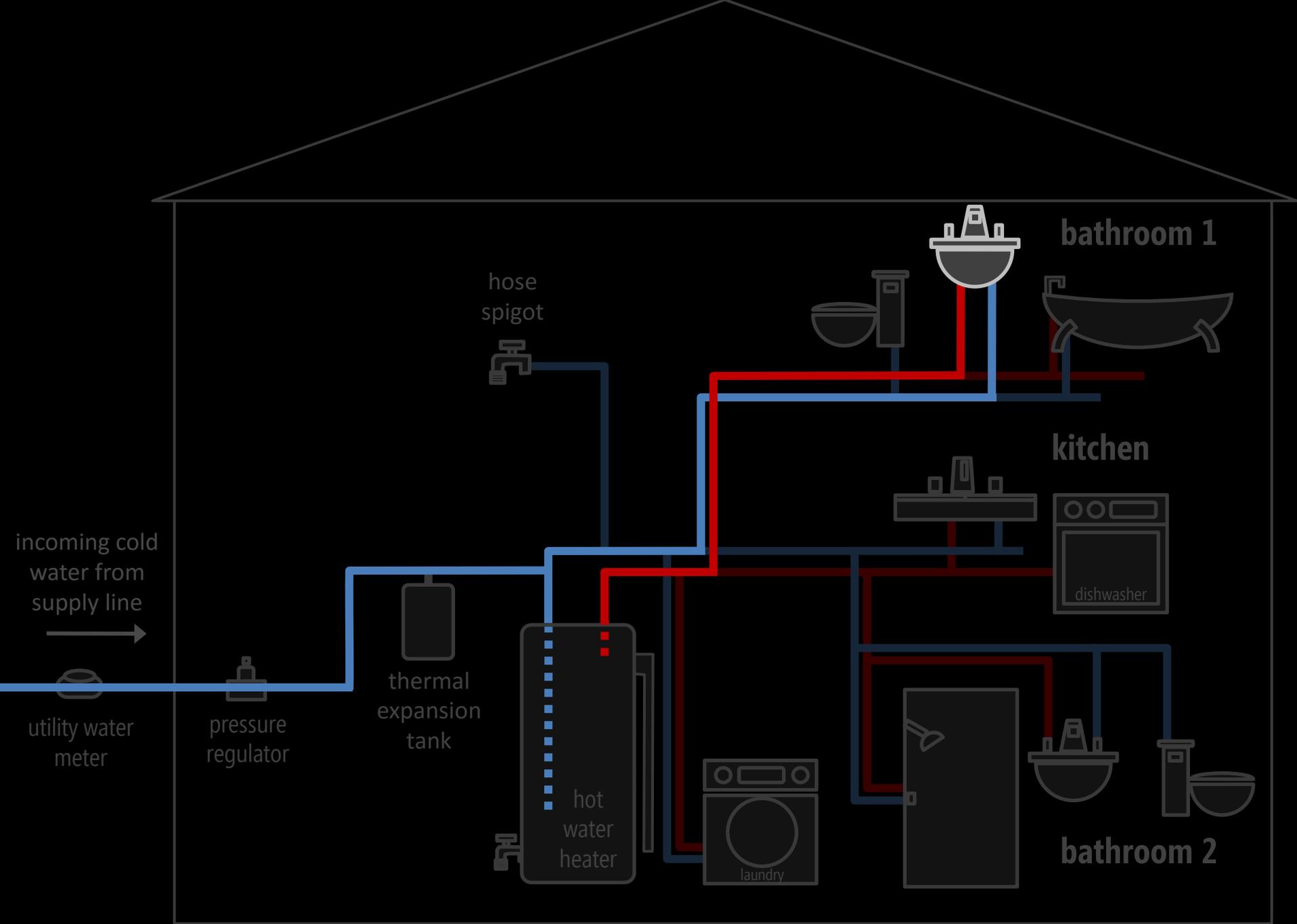
bathroom 1

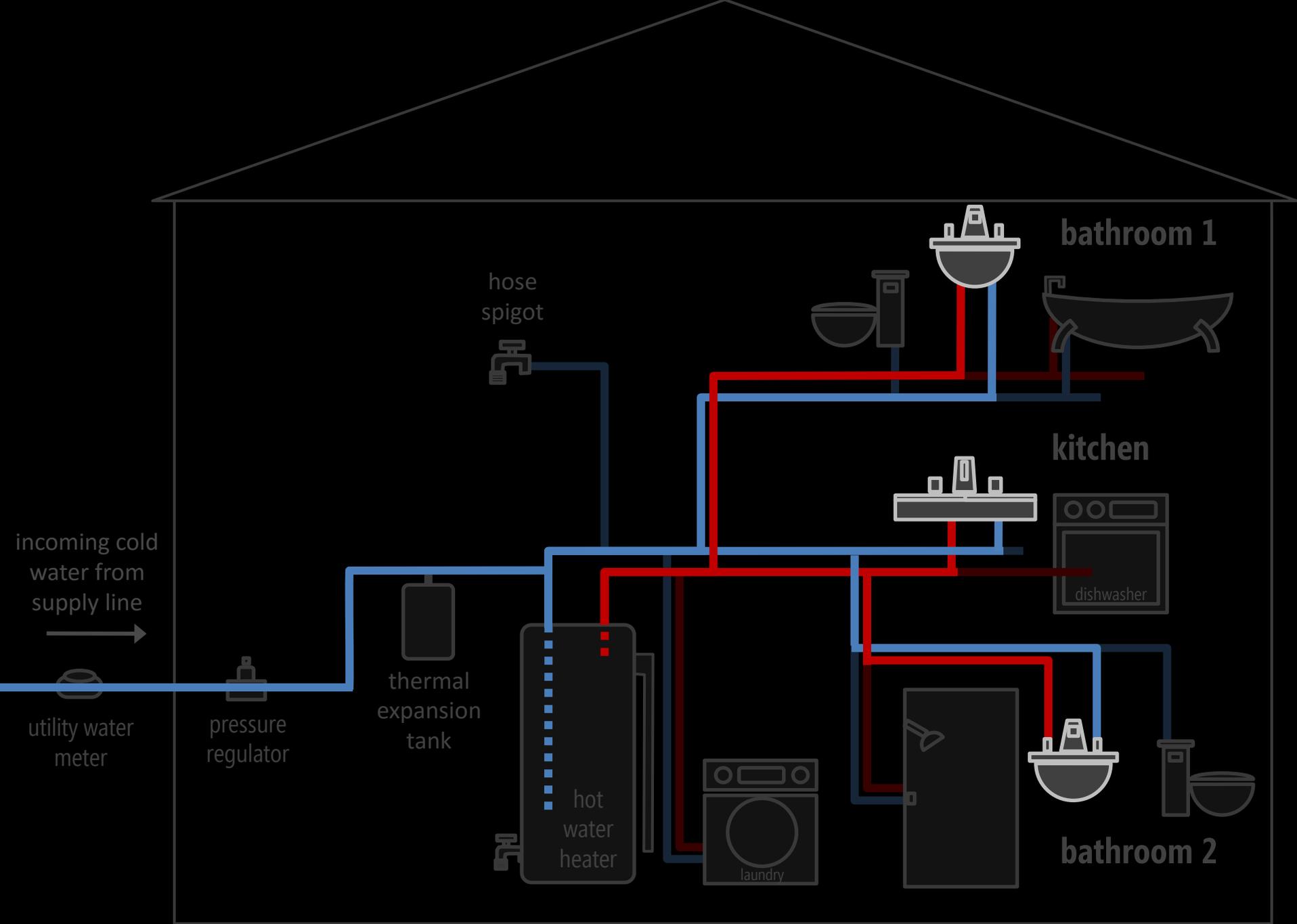
kitchen

dishwasher

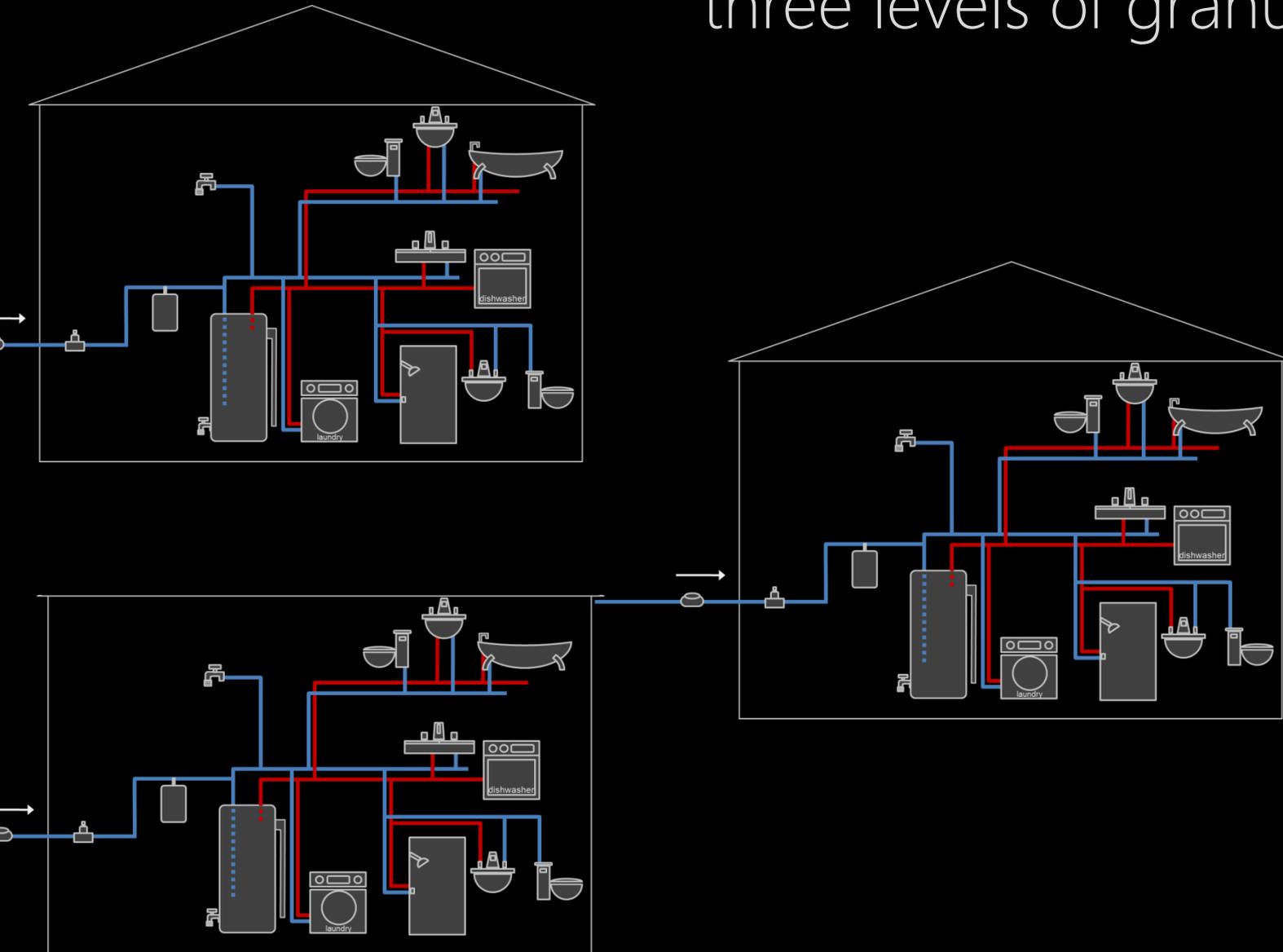
bathroom 2







three levels of granularity



On the Ground

Detailed Water-Use Data Without Customer Involvement

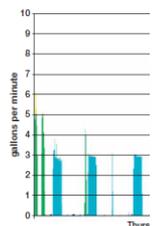
William R. DeOro - Aquacraft Inc. and **Fiona Sanchez** - Irvine Ranch Water District
 Accurate information about customers' water-use patterns and efficiency levels is essential for planning or evaluating any water conservation program—but obtaining high-quality data can be difficult. One approach uses mailed surveys in which the customer reports the types of water-using fixtures and appliances in the home. Another attempts to select random samples of volunteer homes for site visits and audits. What is needed is a truly random and anonymous procedure for collecting detailed end-use data from single-family homes that allows water use to be fully characterized. The results from a properly selected sample can be applied to the entire population to determine the remaining conservation potential.

Quality Data, Minimal Interference
 An example of such an approach is the California Single Family Home Water Use Efficiency Study funded by the California Department of Water Resources. Data collection and analysis were conducted from 2006 through 2008 on 700 homes statewide. While final results are pending, its methodology can be shared, including procedures for sampling and obtaining data and the information this type of study can provide.

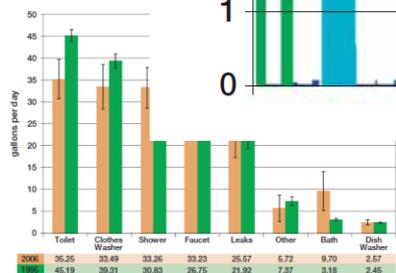
Three main data sources are available, including the single-family billing database, flow-trace files collected from customers' water meters, and aerial photography of lots from GIS sources. None require customer involvement, so the entire study is conducted in a unbiased and controlled manner. Samples are chosen at random from the population of single-family accounts, and data are collected from sources that are either publicly available or owned by water agencies. All results are kept anonymous, thus maintaining customer confidentiality.

Flow Trace Tells All
 The basic of this methodology is the flow-trace analysis using the

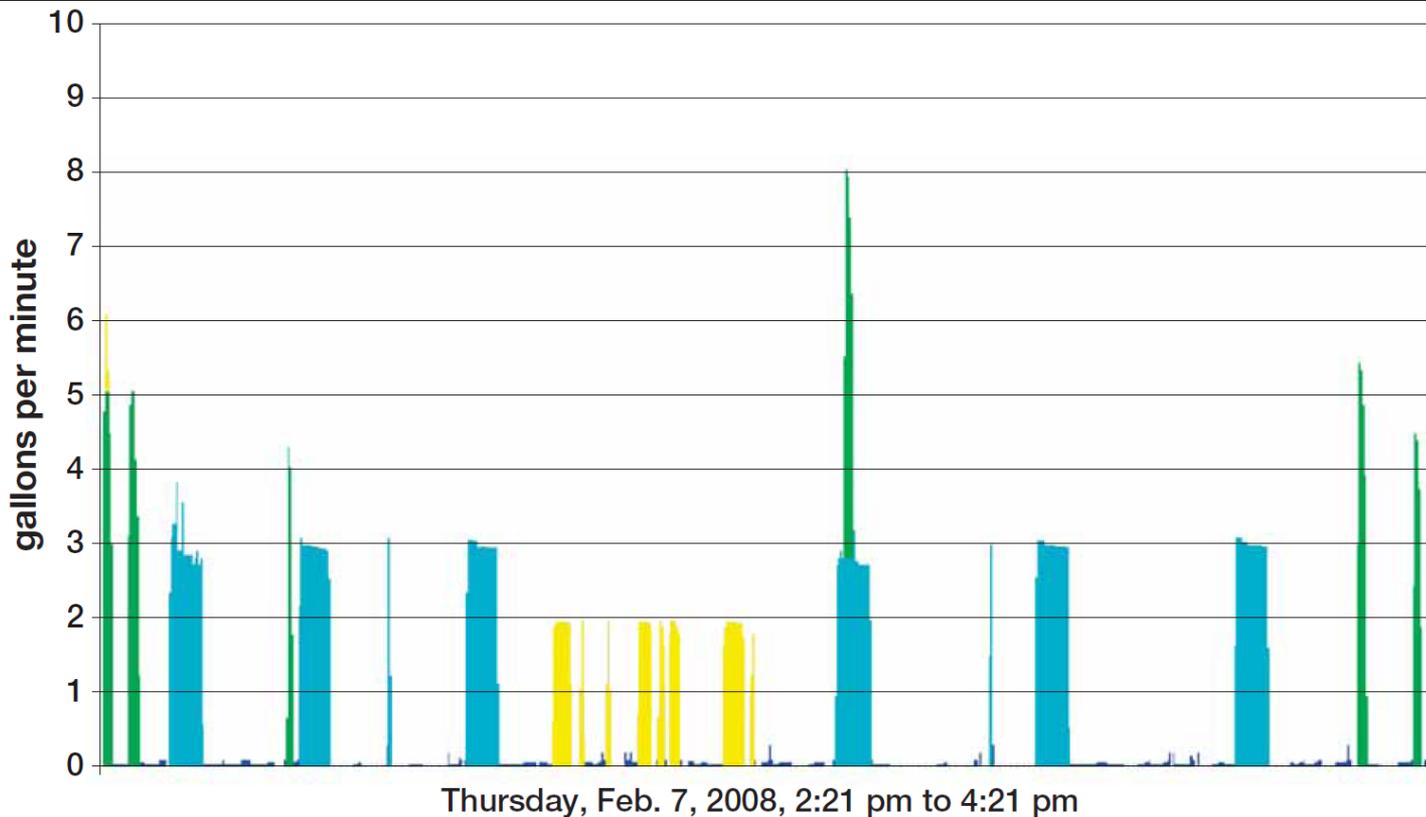
Trace Wizard program developed by Aquacraft Inc. Most residential meters have internal magnets that between 60 and 100 pulses per gallon of flow. The data loggers used for this study collect these pulses at 10-s intervals, providing a very accurate record of the flow versus time—flow trace. Experience has shown water-use events in flow traces categorized into individual end uses such as baths, showers, toilet flush



This typical flow-trace segment shows i (green), faucets (yellow), and leaks (da



A breakdown of end uses for two study groups, one in 1995 (green) and one in 2006 (orange). Note that the 2006 set had lower water use for toilets and clothes washers, but higher use for most other categories.

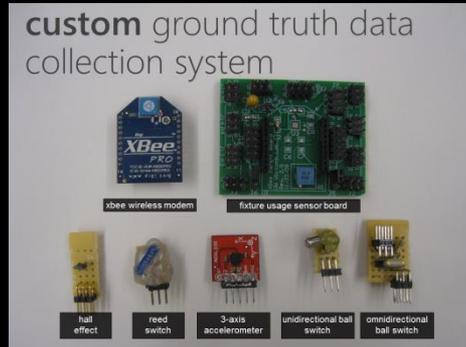


The flow-trace analysis using the Trace Wizard program developed by Aquacraft Inc. Most residential meters have internal magnets that between 60 and 100 pulses per gallon of flow. The data loggers used for this study collect these pulses at 10-s intervals, providing a very accurate record of the flow versus time—flow trace. Experience has shown water-use events in flow traces categorized into individual end uses such as baths, showers, toilet flush



hydro deployment infrastructure

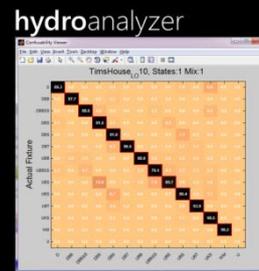
on-site
infrastructure



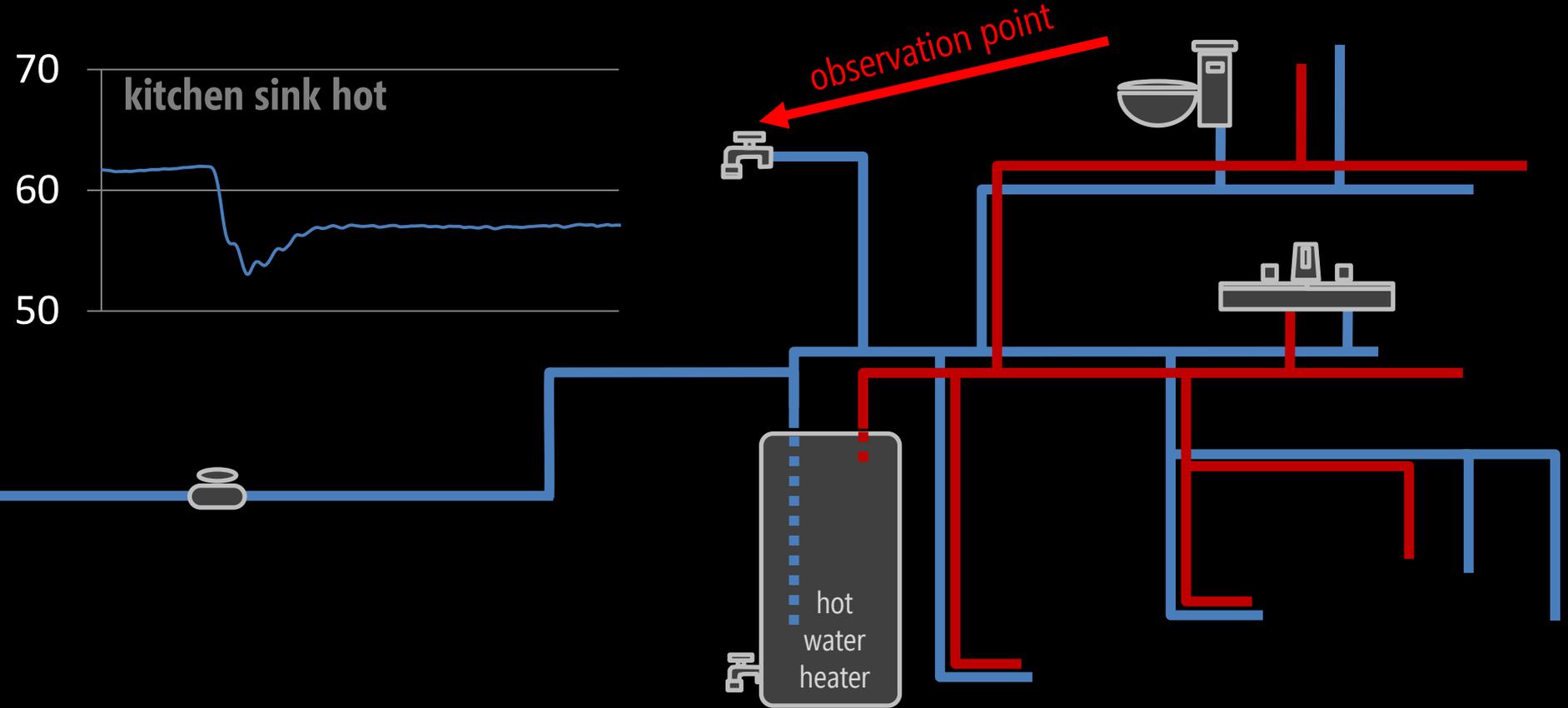
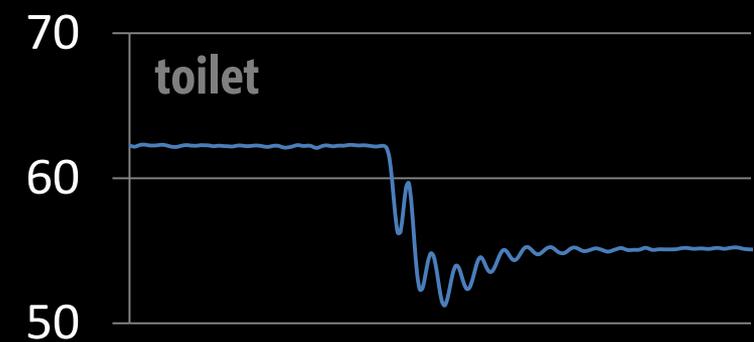
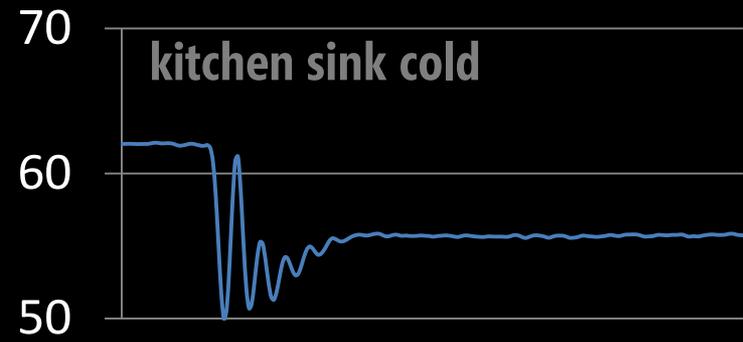
python web
backend



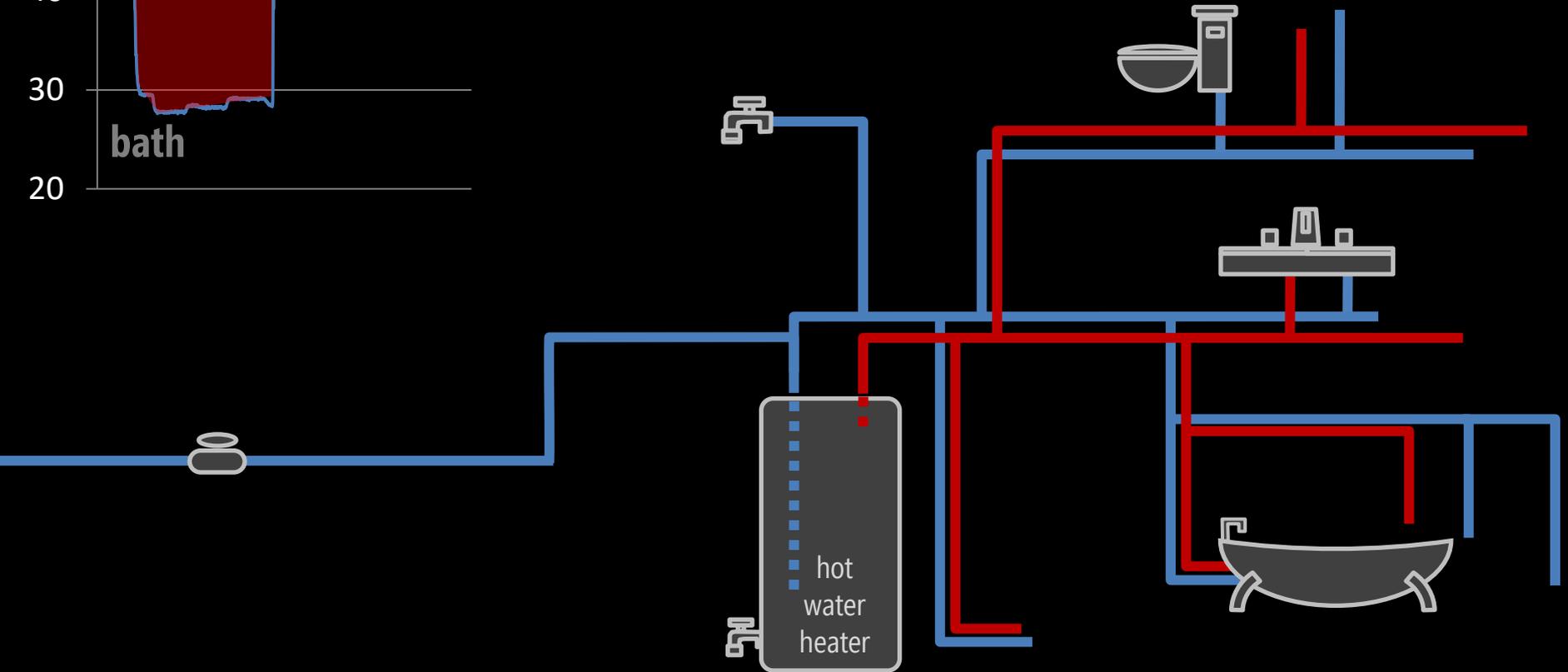
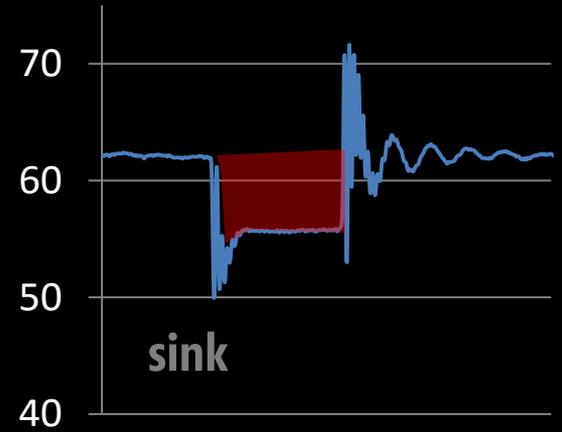
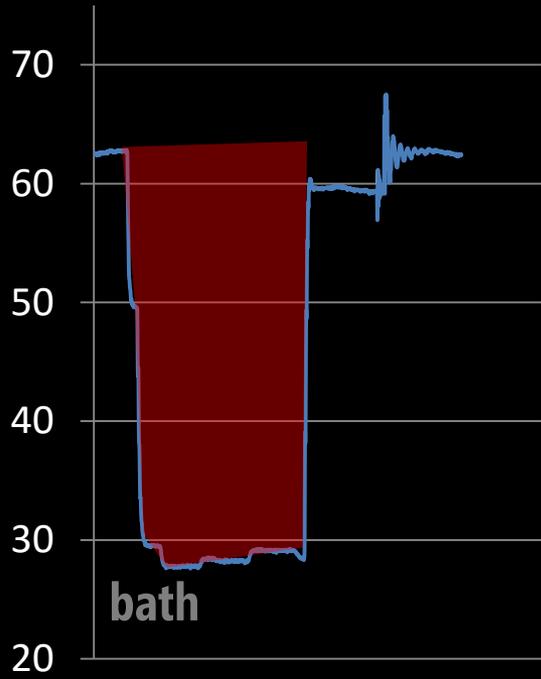
analysis tools
& algorithms

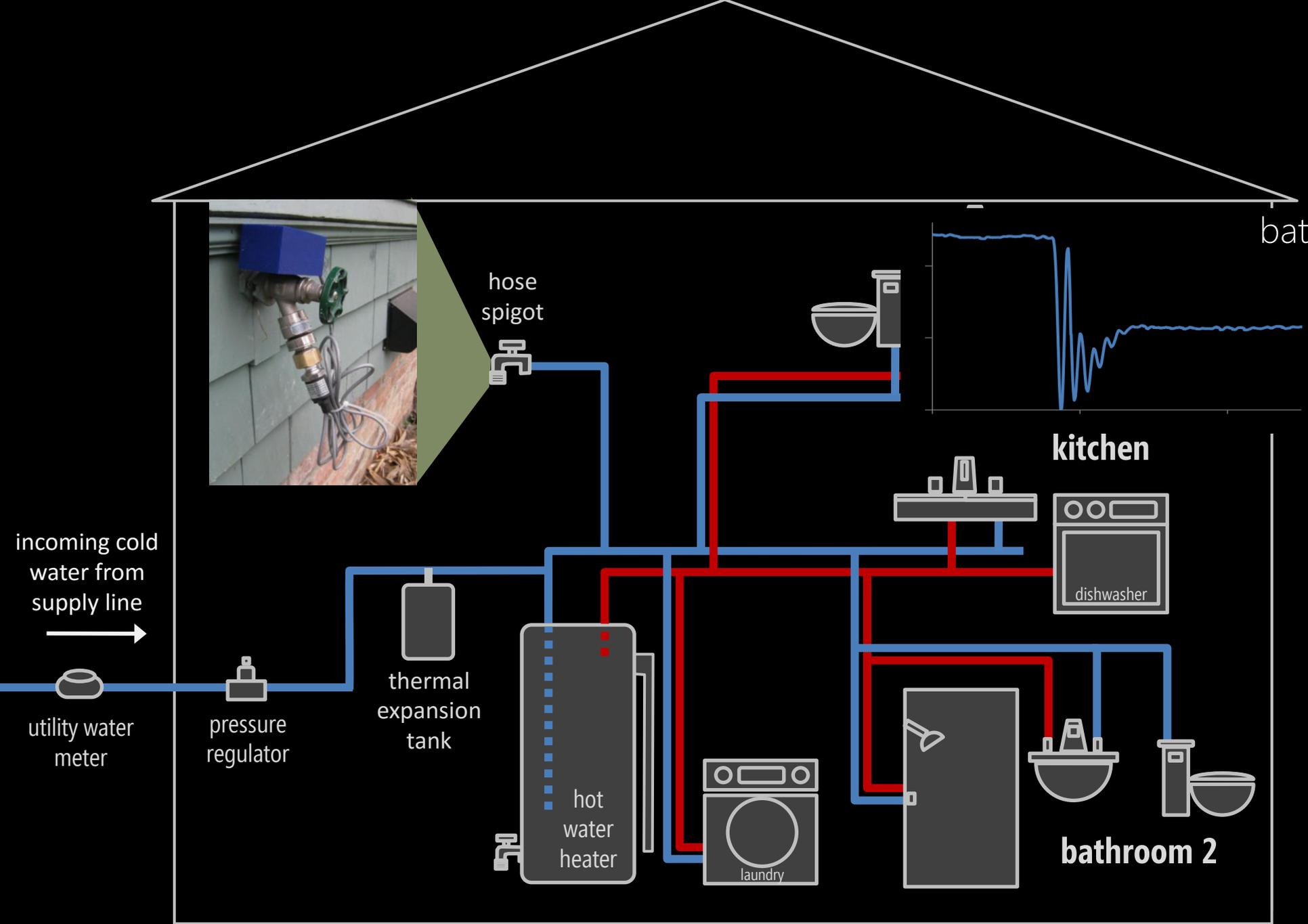


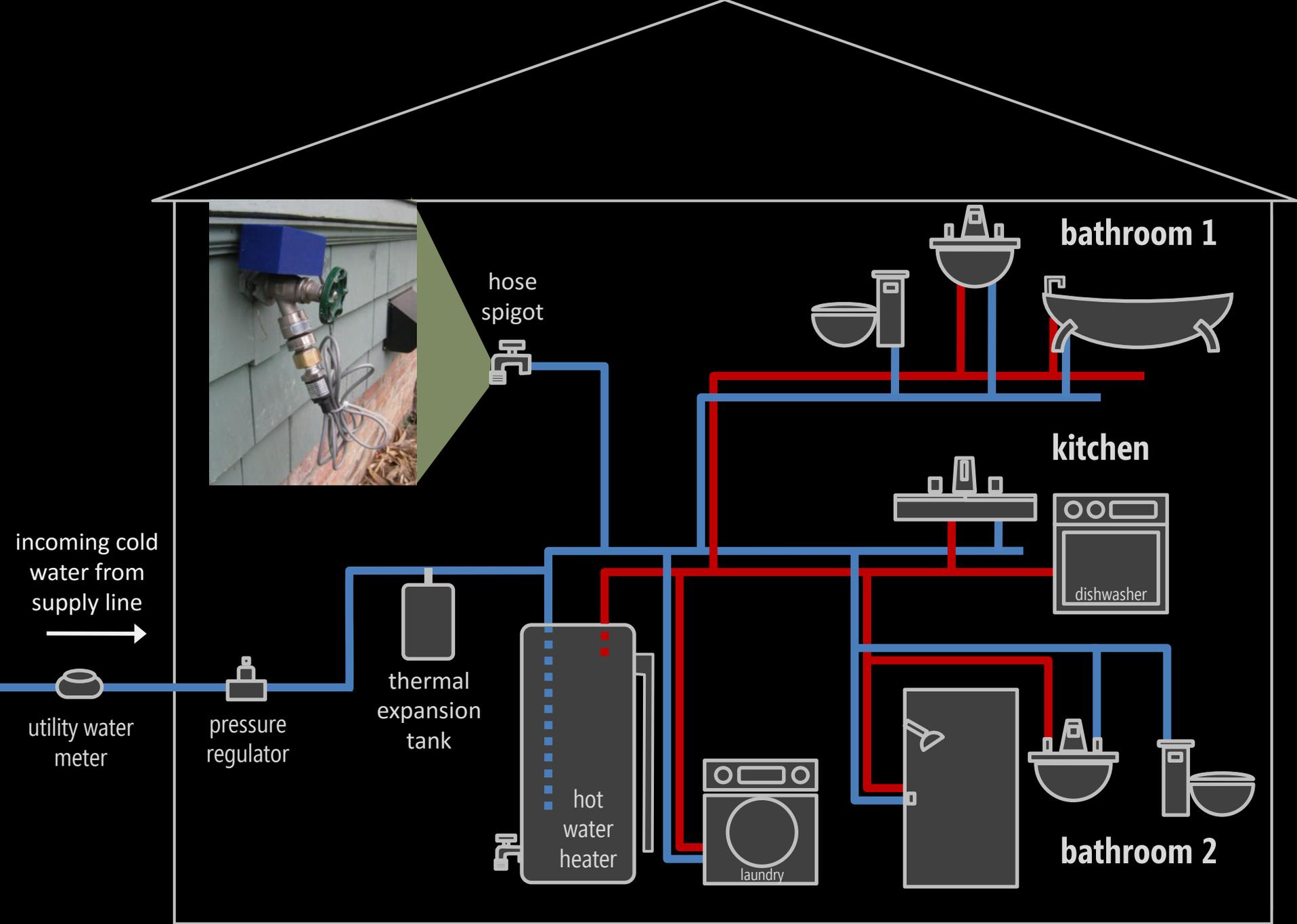
valve mechanics: water tank dampening

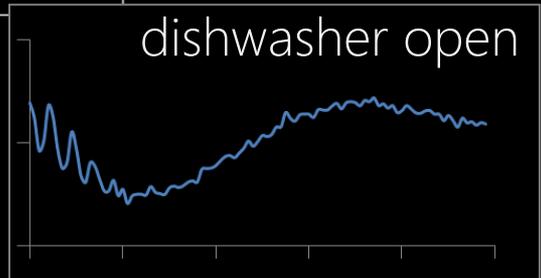
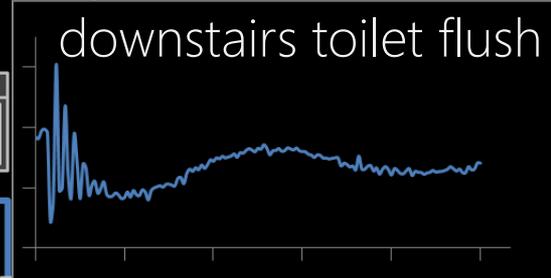
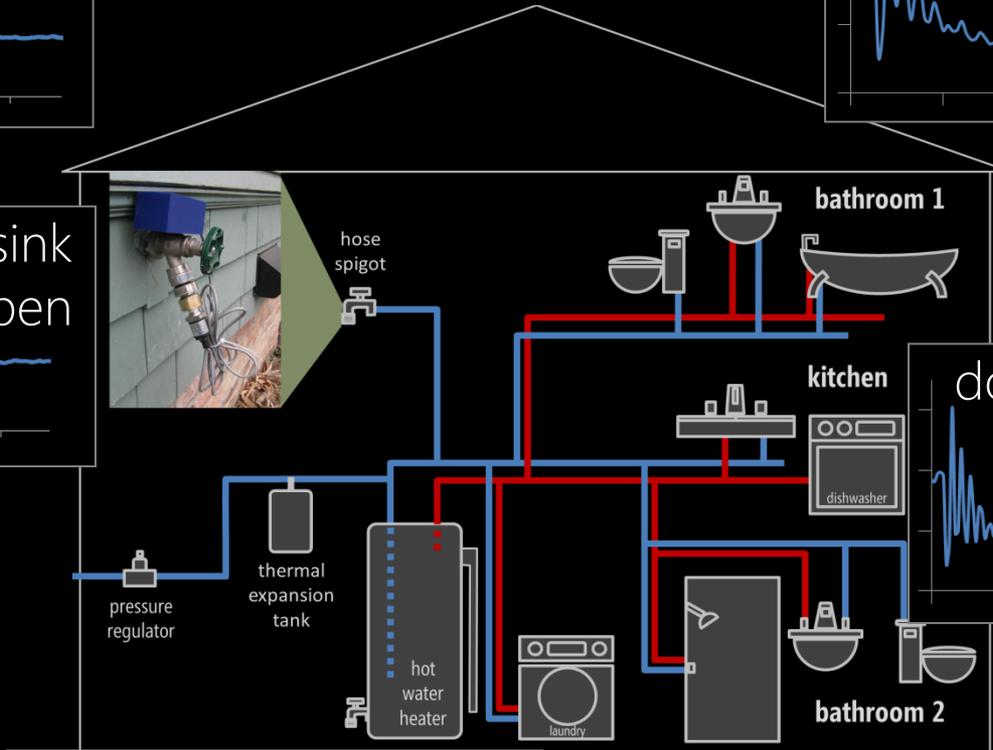
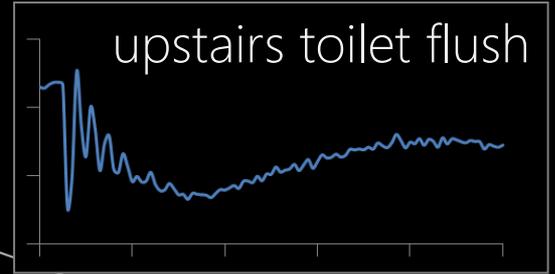
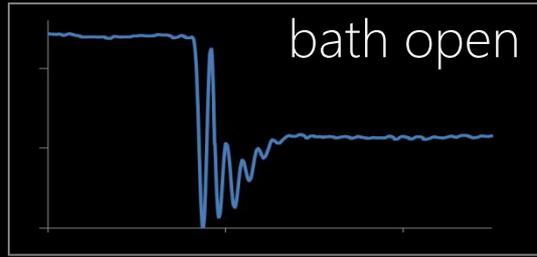


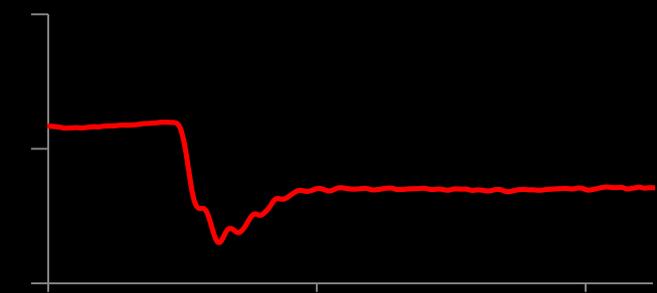
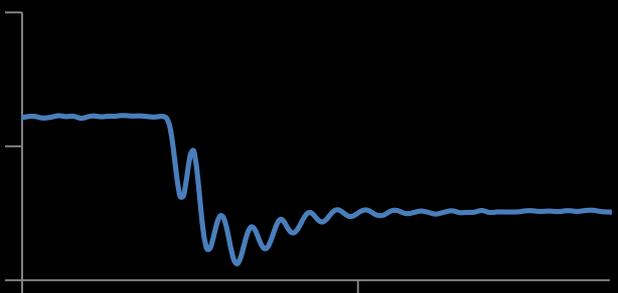
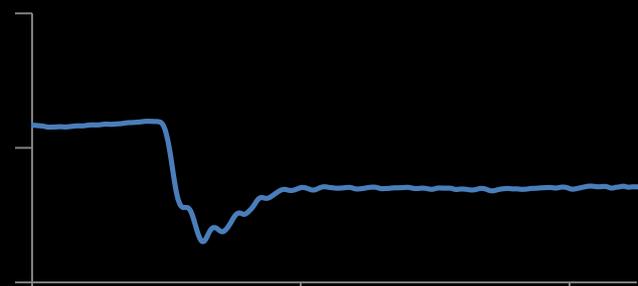
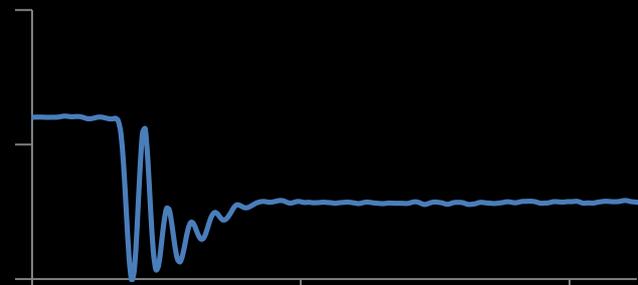
valve mechanics: flow rate

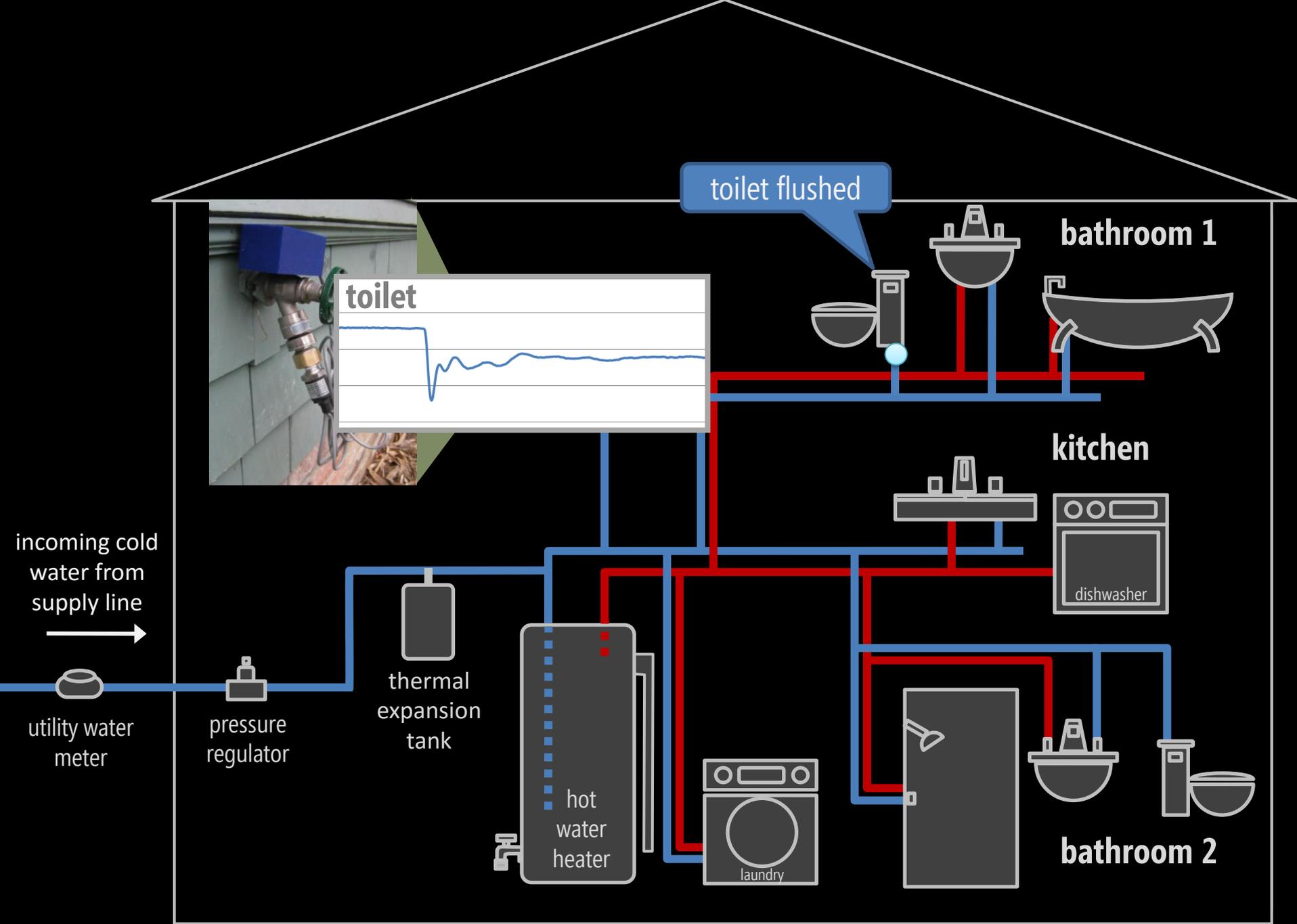












toilet flushed

bathroom 1

toilet

kitchen

dishwasher

incoming cold water from supply line

utility water meter

pressure regulator

thermal expansion tank

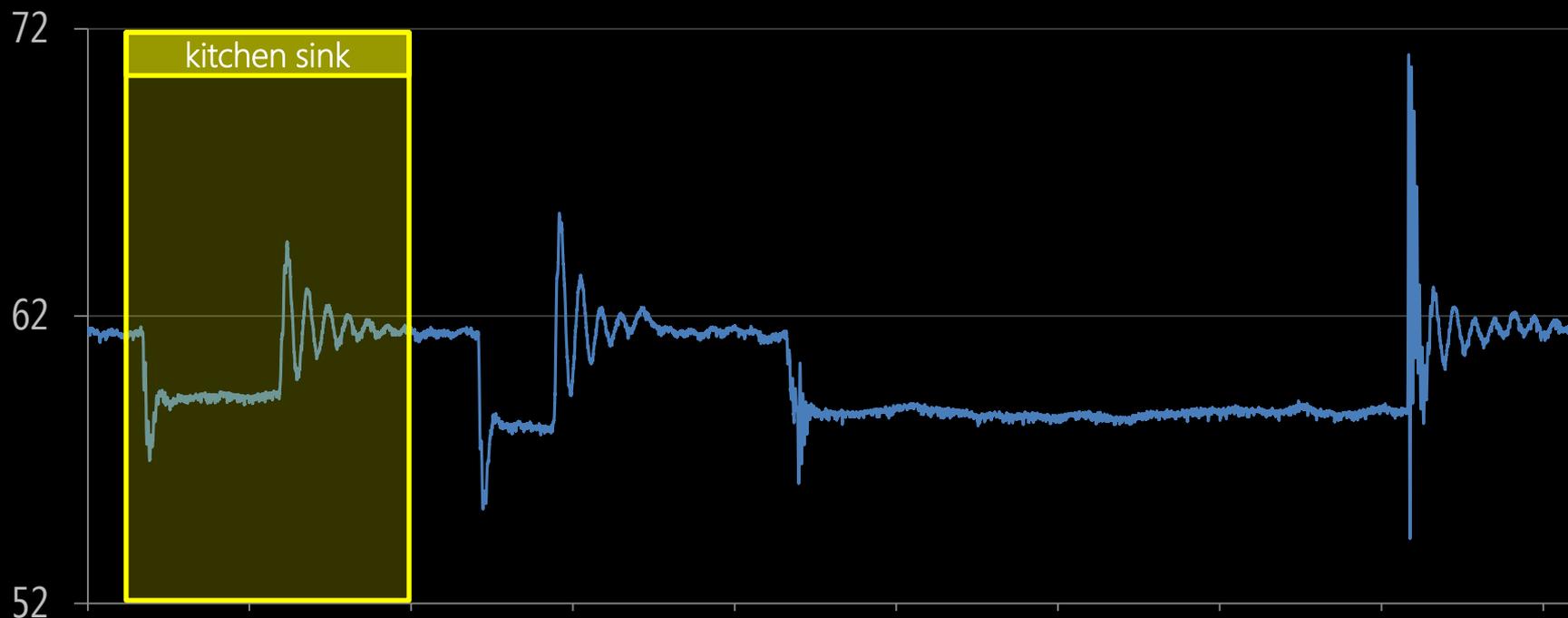
hot water heater

laundry

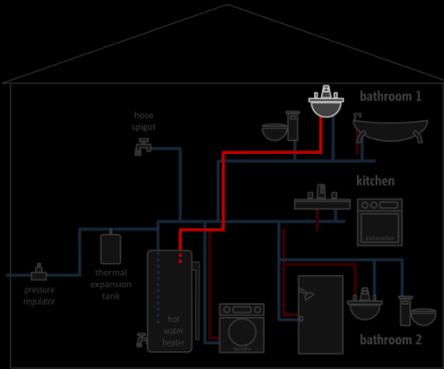
bathroom 2

ground truth labels

for the ubicomp2009 study, we manually provided ground truth labels for the pressure stream during the experiment

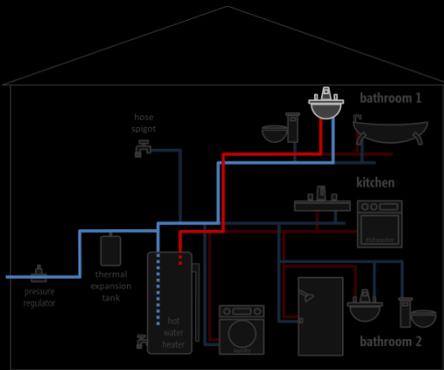


three levels of granularity



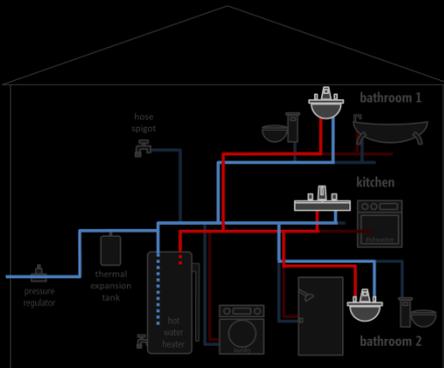
① valve level

e.g., upstairs bathroom faucet hot water activated



② fixture level

e.g., upstairs bathroom faucet activated

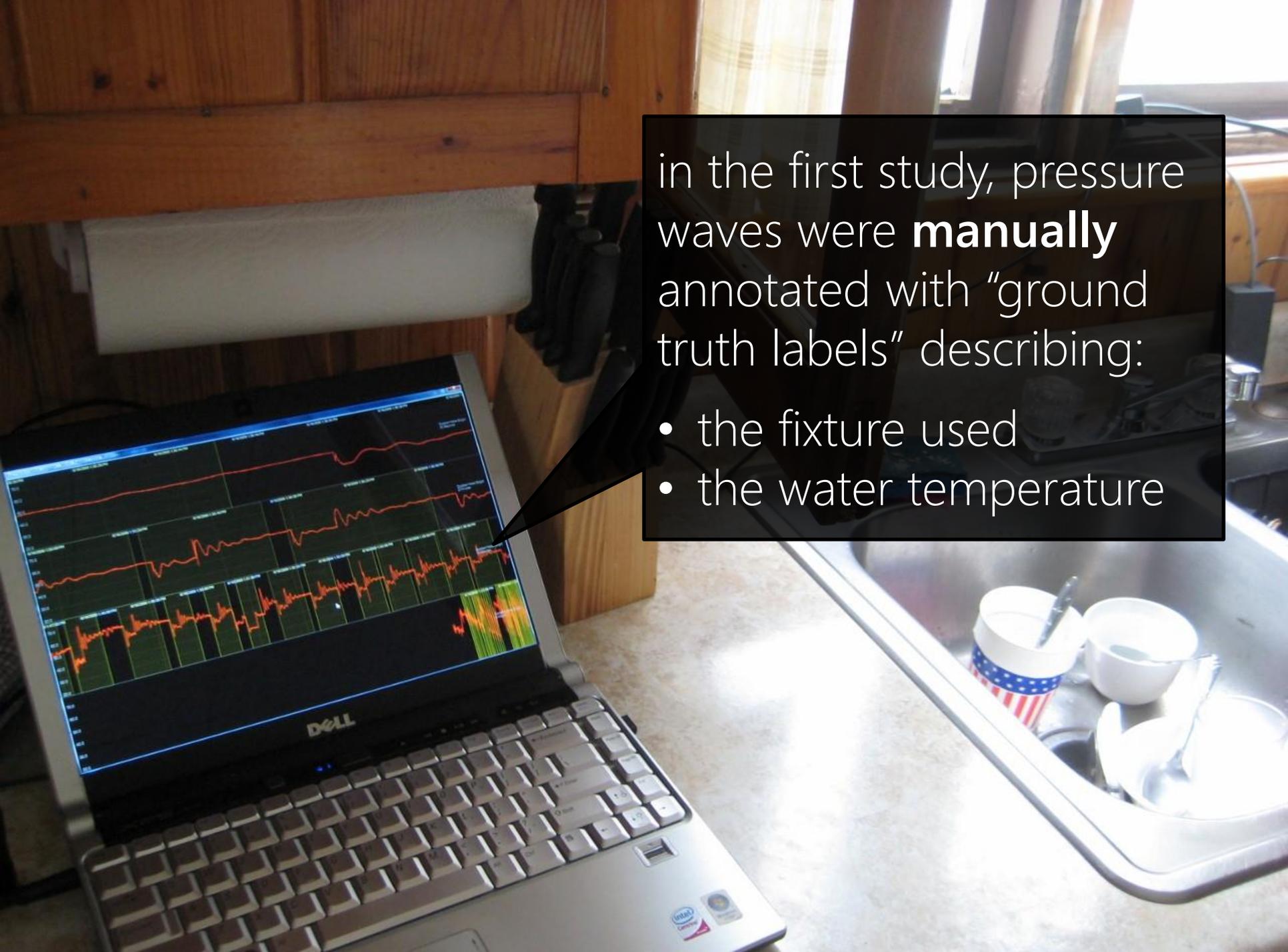


③ fixture category level

e.g., faucet activated

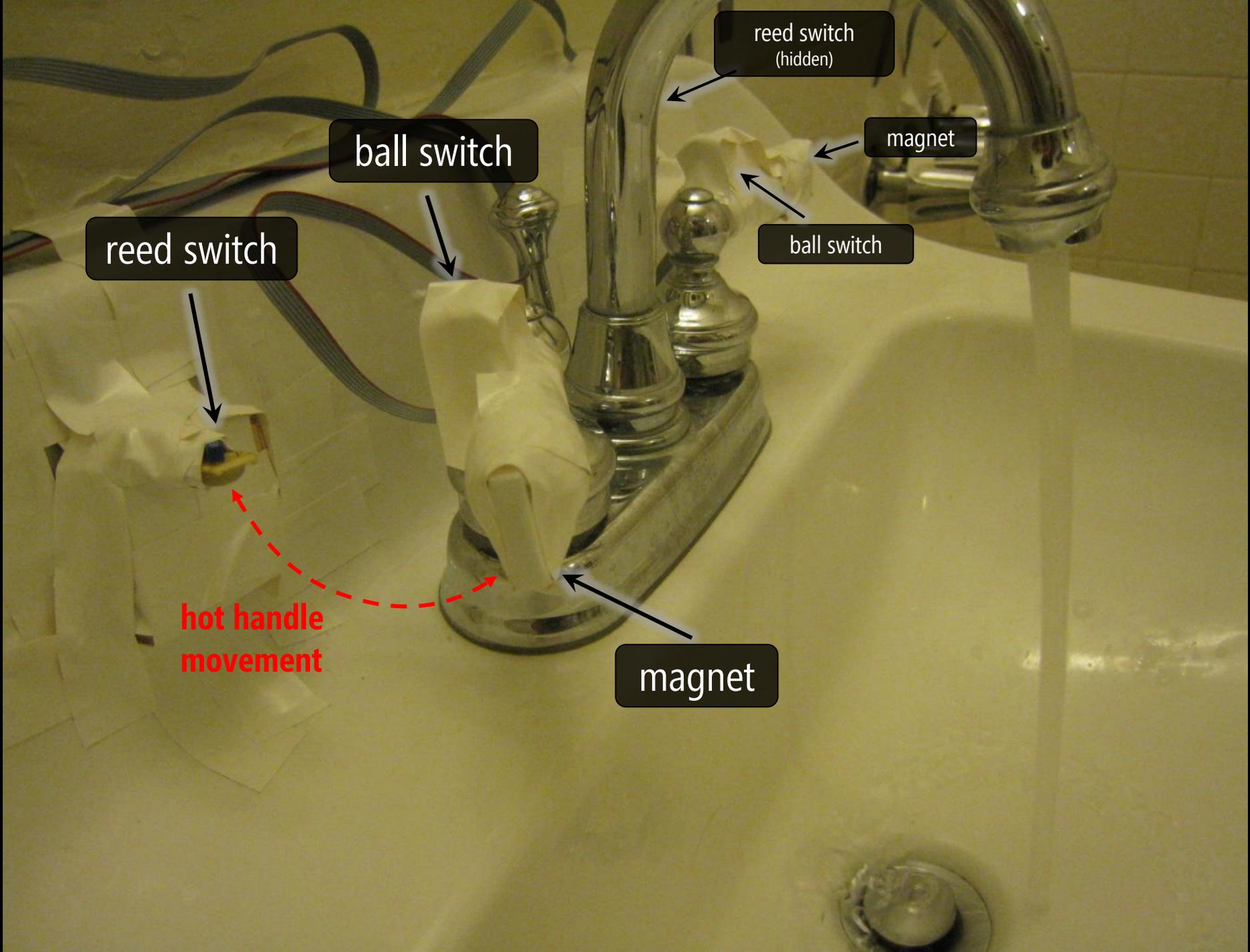




A photograph of a kitchen counter. On the left, a silver Dell laptop is open, displaying a software interface with multiple panels of data graphs. The graphs show various waveforms and a spectrogram. The laptop is on a light-colored countertop. To the right, a stainless steel sink contains a white cup with a red, white, and blue American flag pattern, a white bowl, and a white plate with a spoon. In the background, there is a wooden cabinet and a window with yellow curtains. A black callout box with white text and a list is overlaid on the right side of the image, pointing towards the laptop screen.

in the first study, pressure waves were **manually** annotated with "ground truth labels" describing:

- the fixture used
- the water temperature



reed switch
(hidden)

magnet

ball switch

ball switch

reed switch

magnet

hot handle
movement



parent sensor board



accelerometer & ball switch





magnet & ball switch

reed switch
(cold handle)

reed switch
(hot handle)

magnet & ball switch



magnet

reed
switch

omni-directional
ball switch

omni-directional
ball switch



accelerometer



parent
sensor
board

xbee
wireless
transmitter

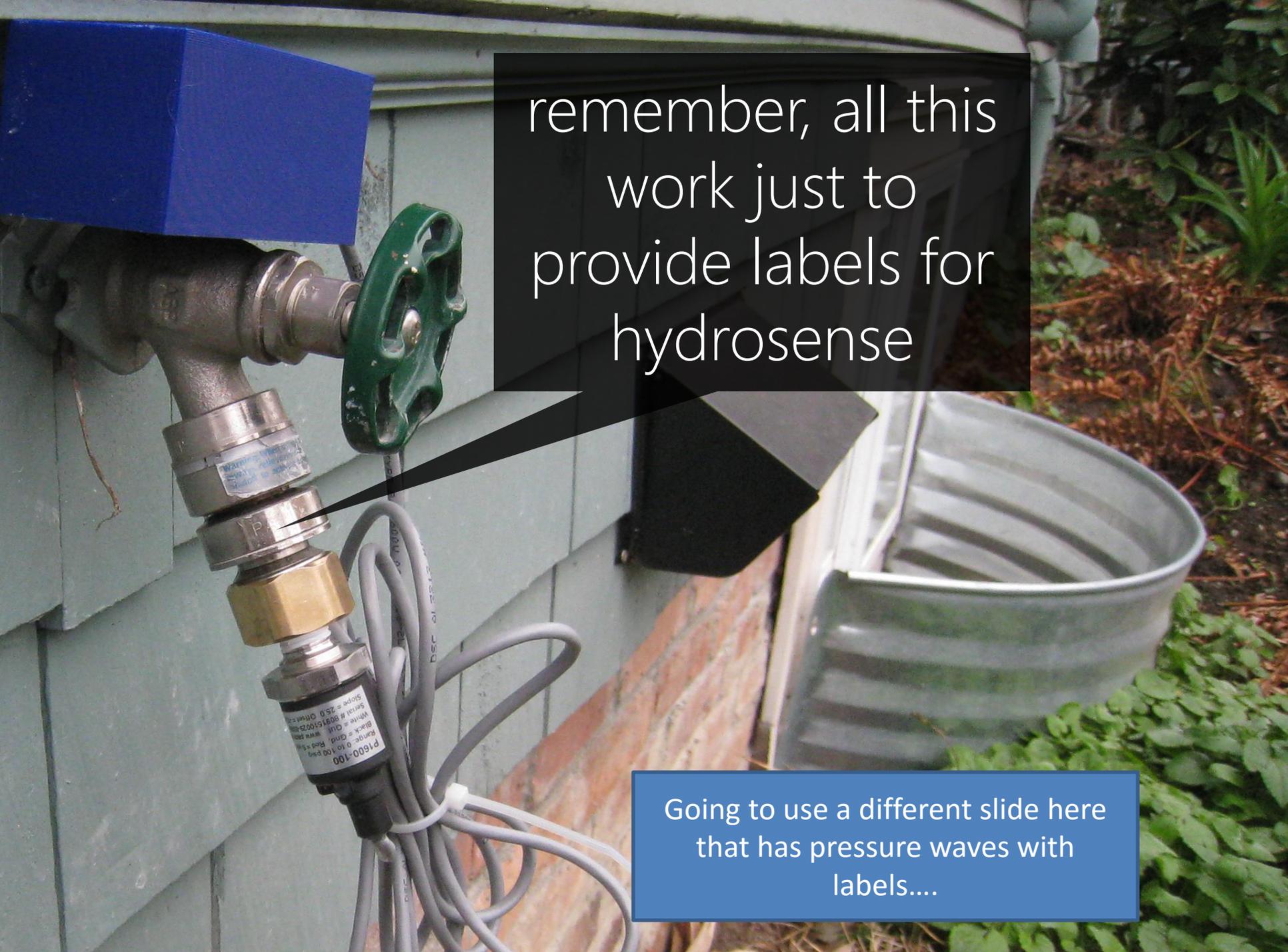
modified
kill-a-watt



thermistor
cable for
drain pipe
(in red)

washing
machine plug
(connects to
kill-a-watt outlet)



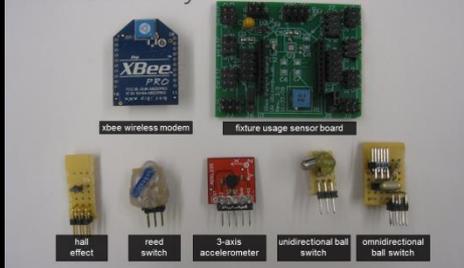


remember, all this
work just to
provide labels for
hydrosense

Going to use a different slide here
that has pressure waves with
labels....

on-site sensing & logging

custom ground truth data collection system



two pressure sensors

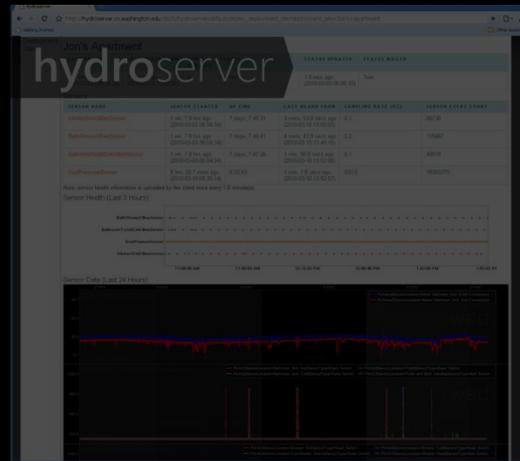


hydrosense data logger

records ground truth sensor data plus two pressure streams for each home



web backend

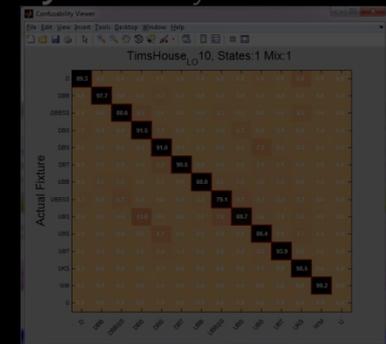


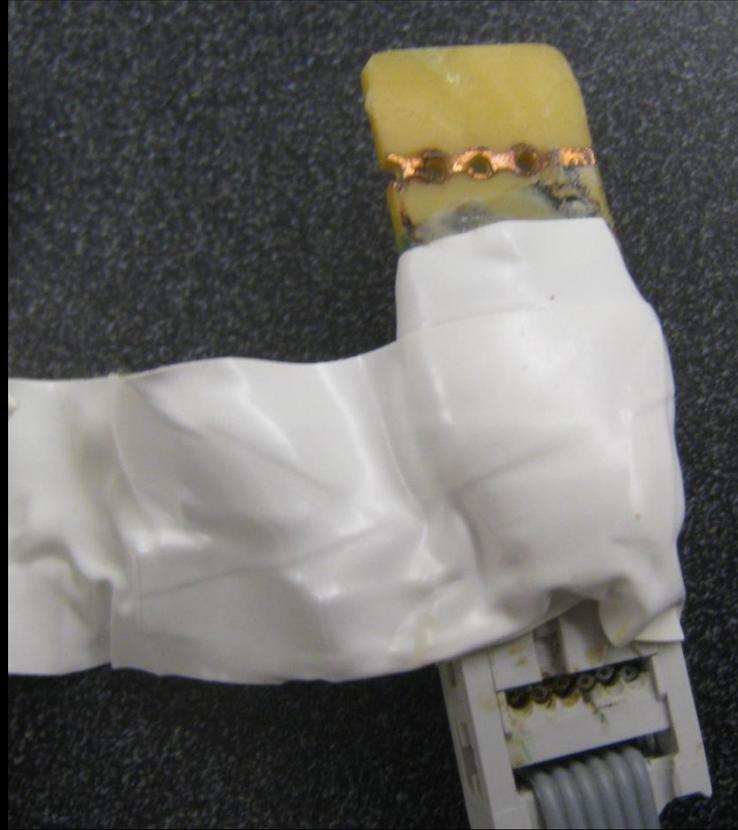
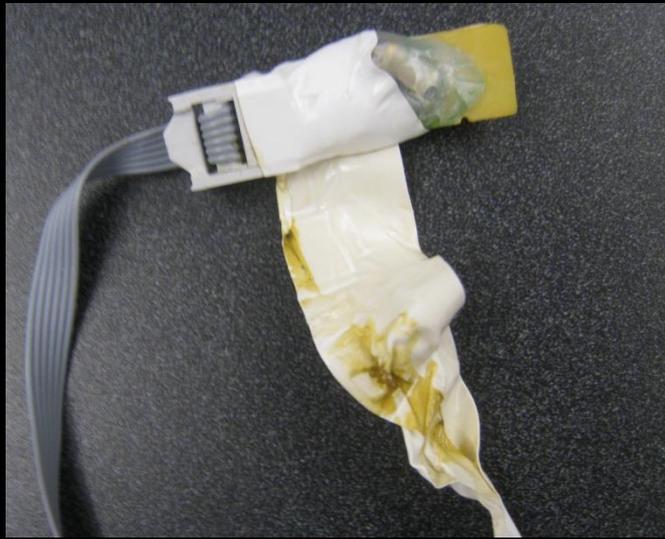
analysis tools & algorithms

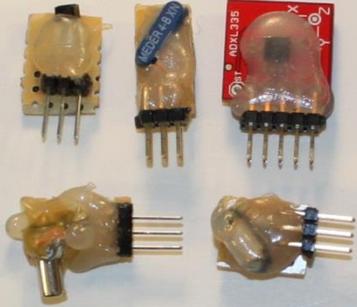
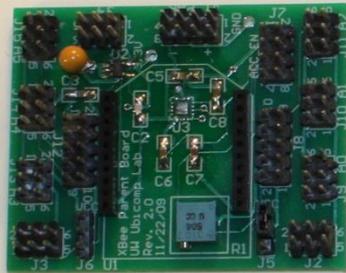
hydrovisualizer

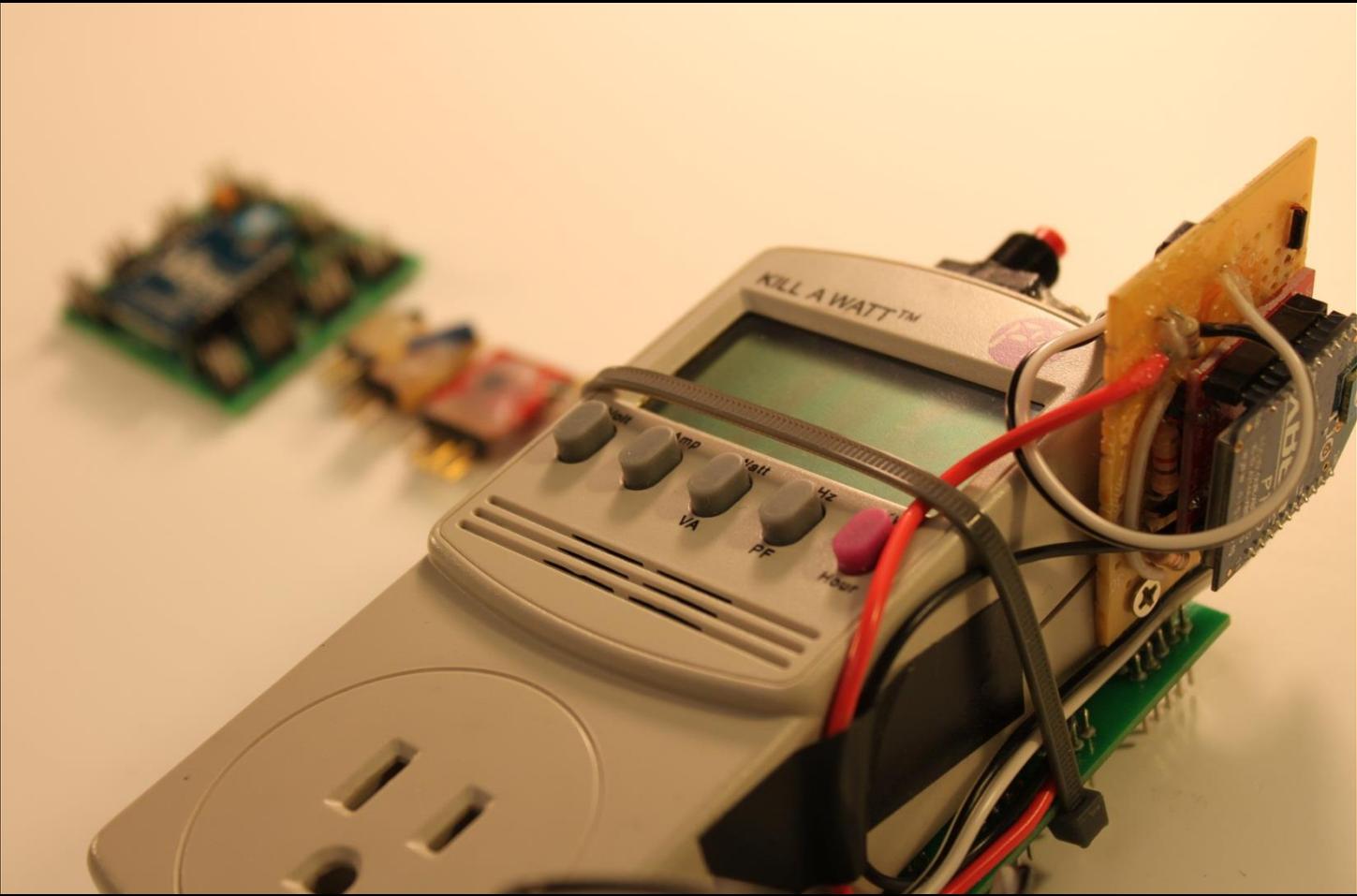


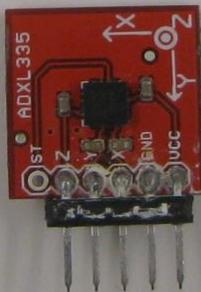
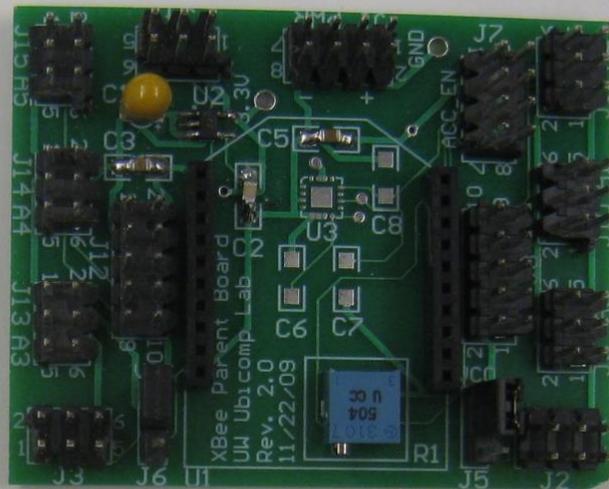
hydroanalyzer

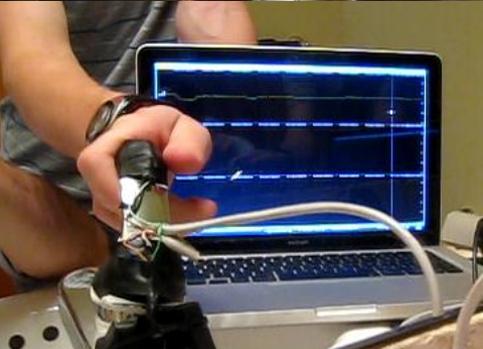


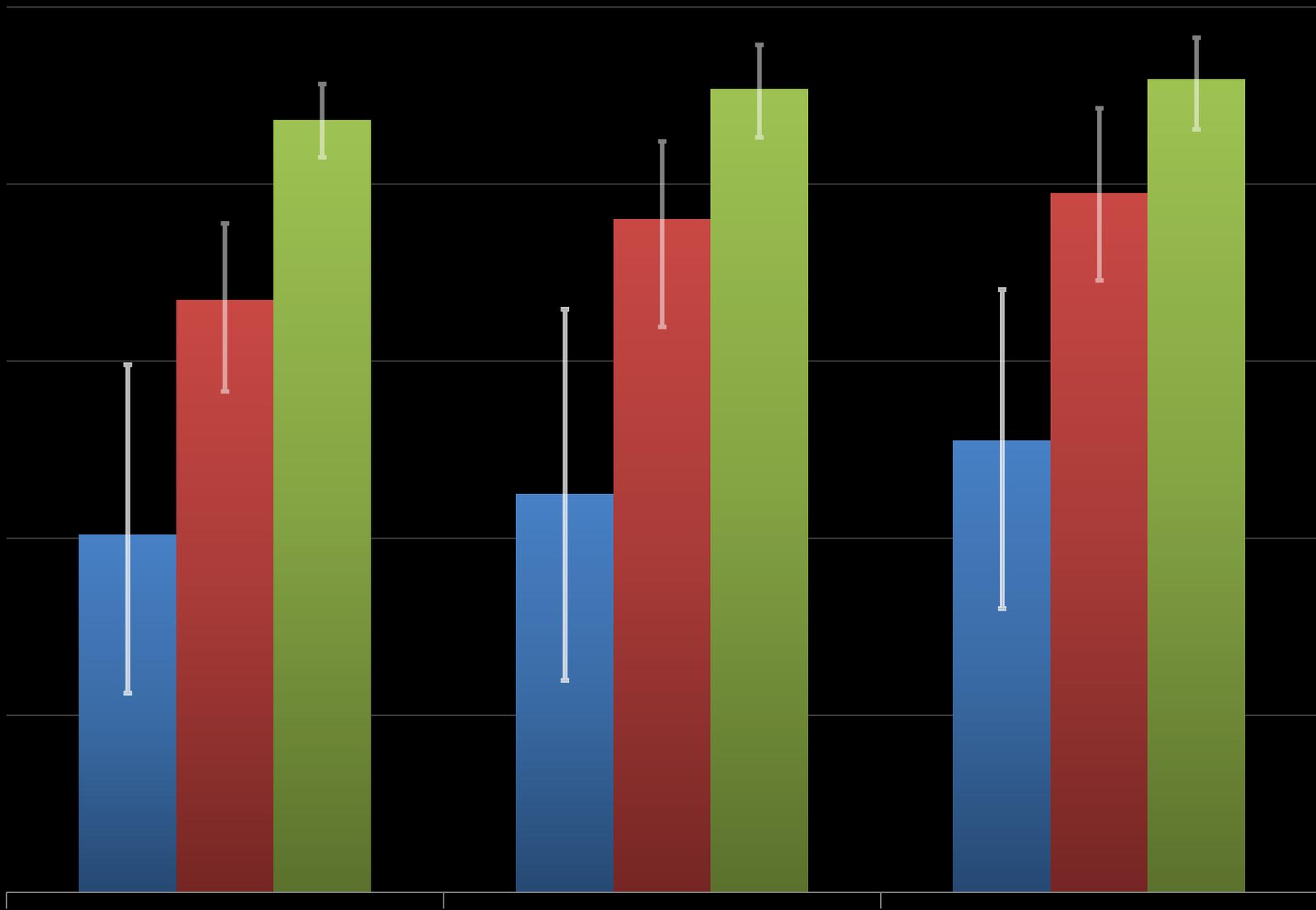








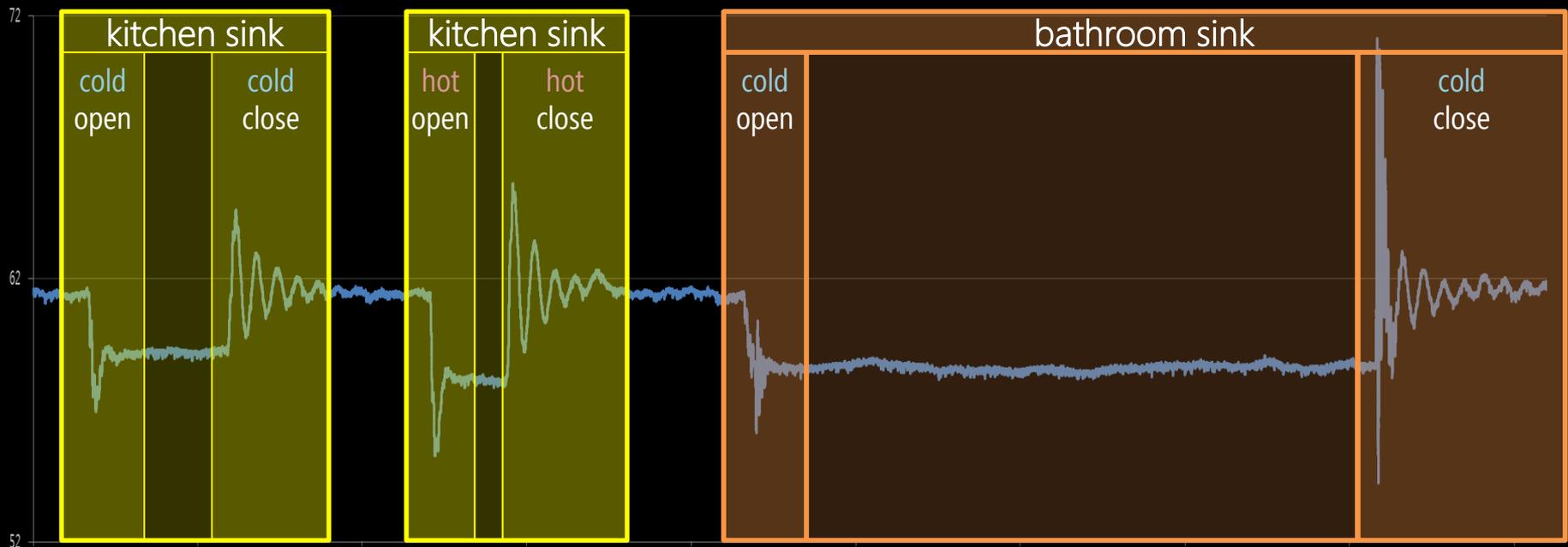




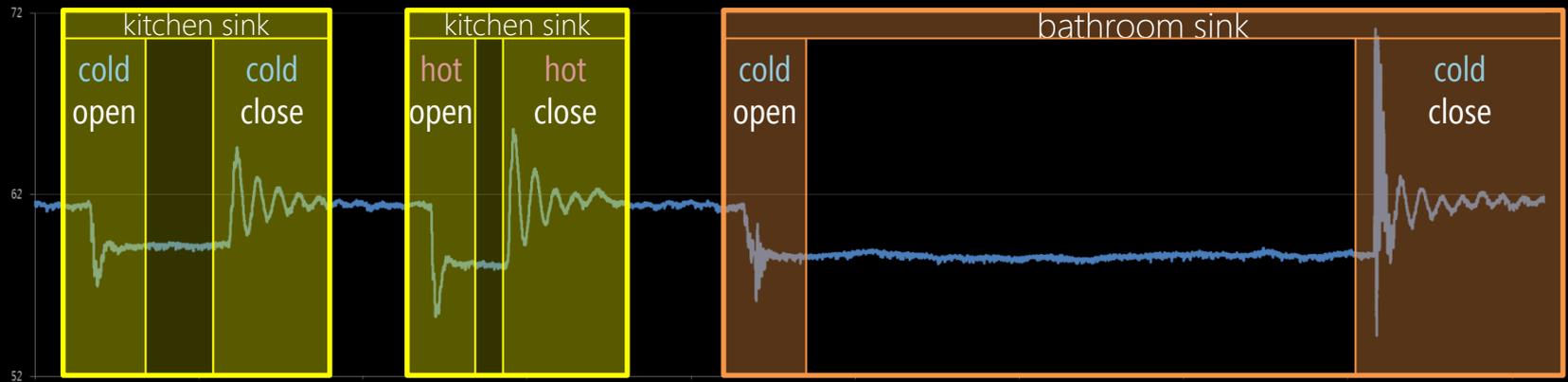
ground truth labels



for the ubicomp2009 study, we manually provided ground truth labels for the pressure stream



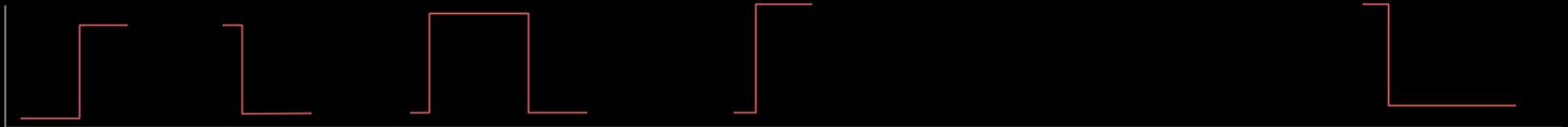
ground truth labels



ball switch



reed switch



hall effect



accelerometer



automated ground truth labeling method

design goals

hardware capabilities

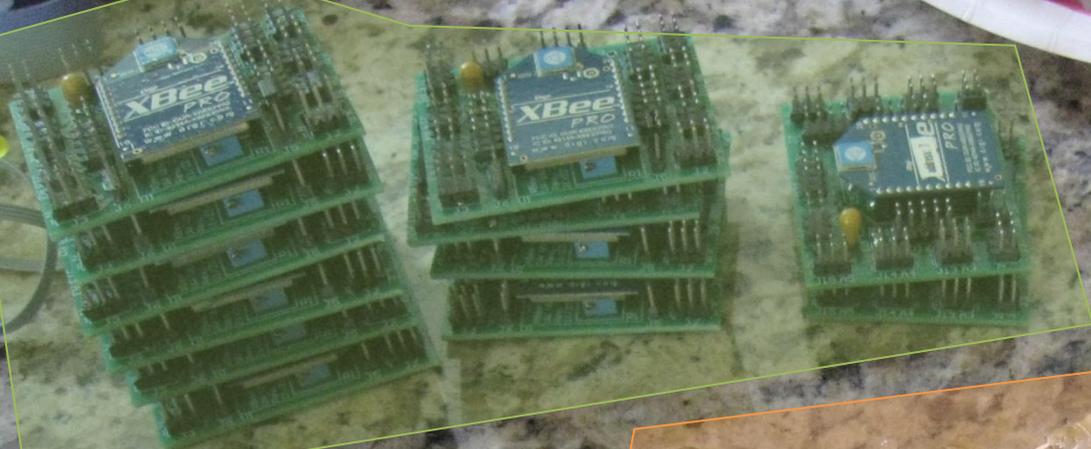
1. wireless communication
2. low-power
3. water resistant

sensing capabilities

1. work across fixtures/appliances
2. detect opens/closes
3. discriminate hot/cold/mixed

*Lots of
tape*





12
pcbs

*lots of
tape*



14 ball
switches



9 reed
switches



8 acceler-
ometers

challenge: fixture diversity



single handle faucet



dual handle faucet







