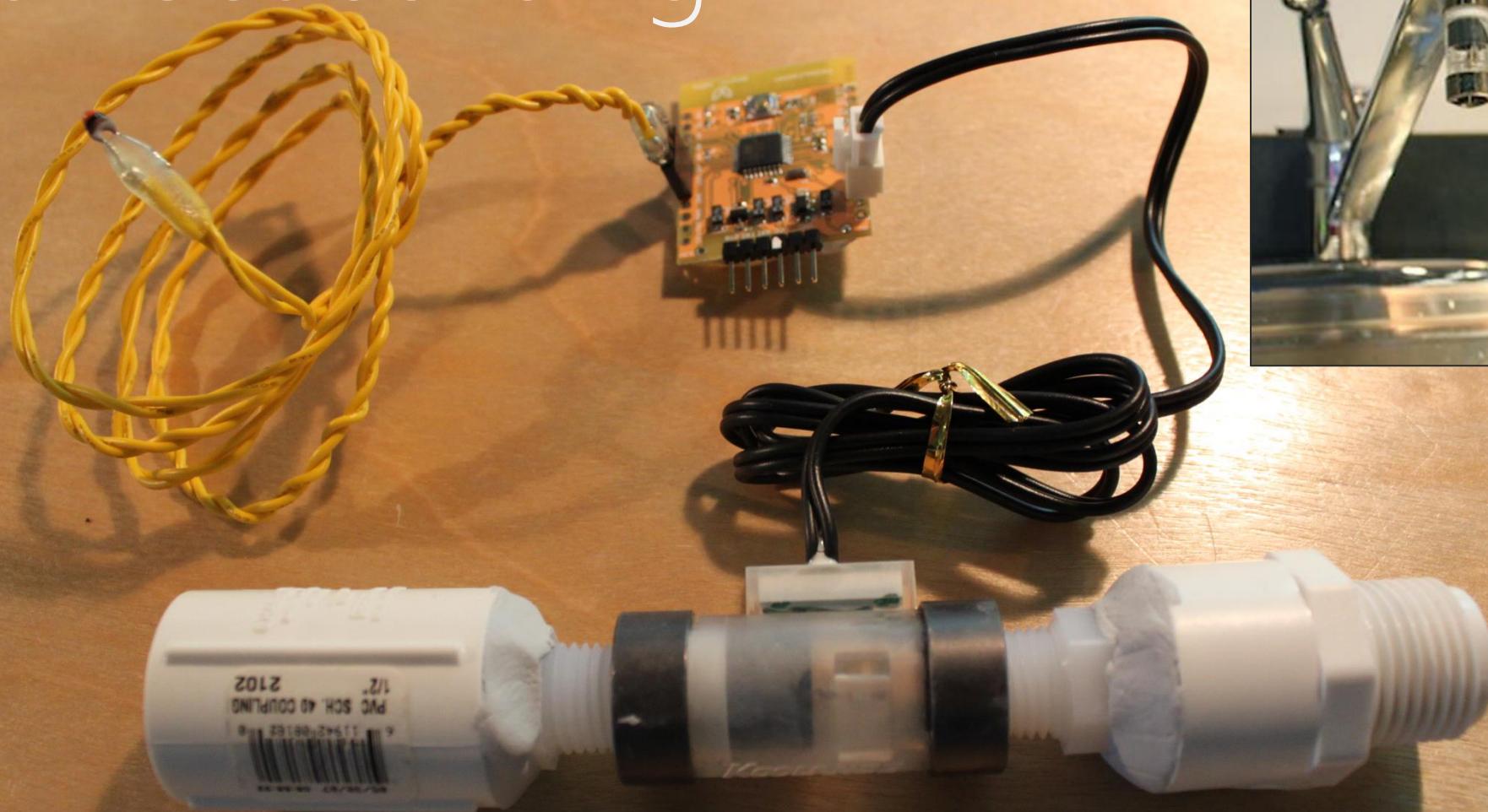


direct sensing

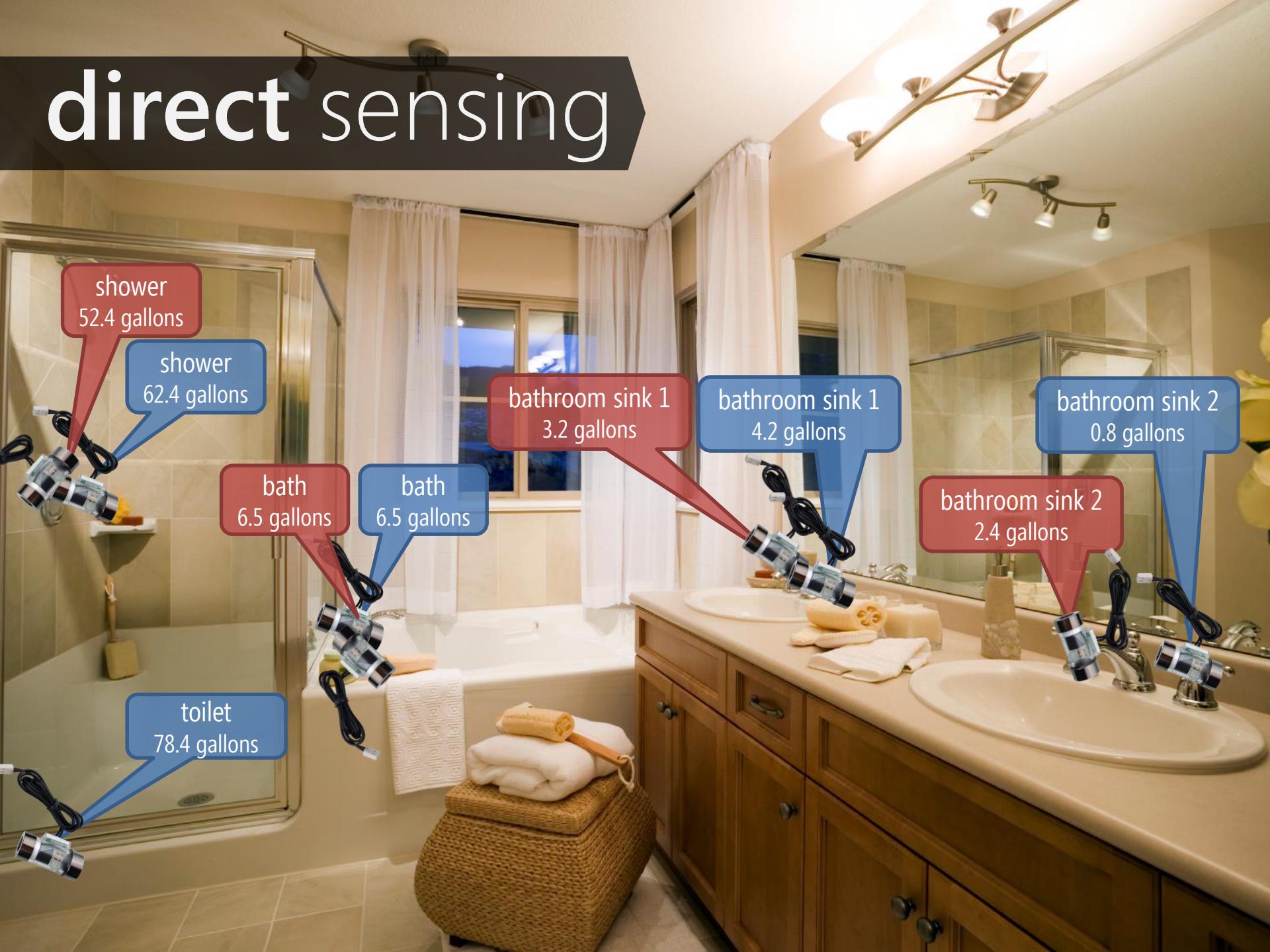


[Teague Labs, Arduino Water Meter, <http://labs.teague.com/?p=722>]

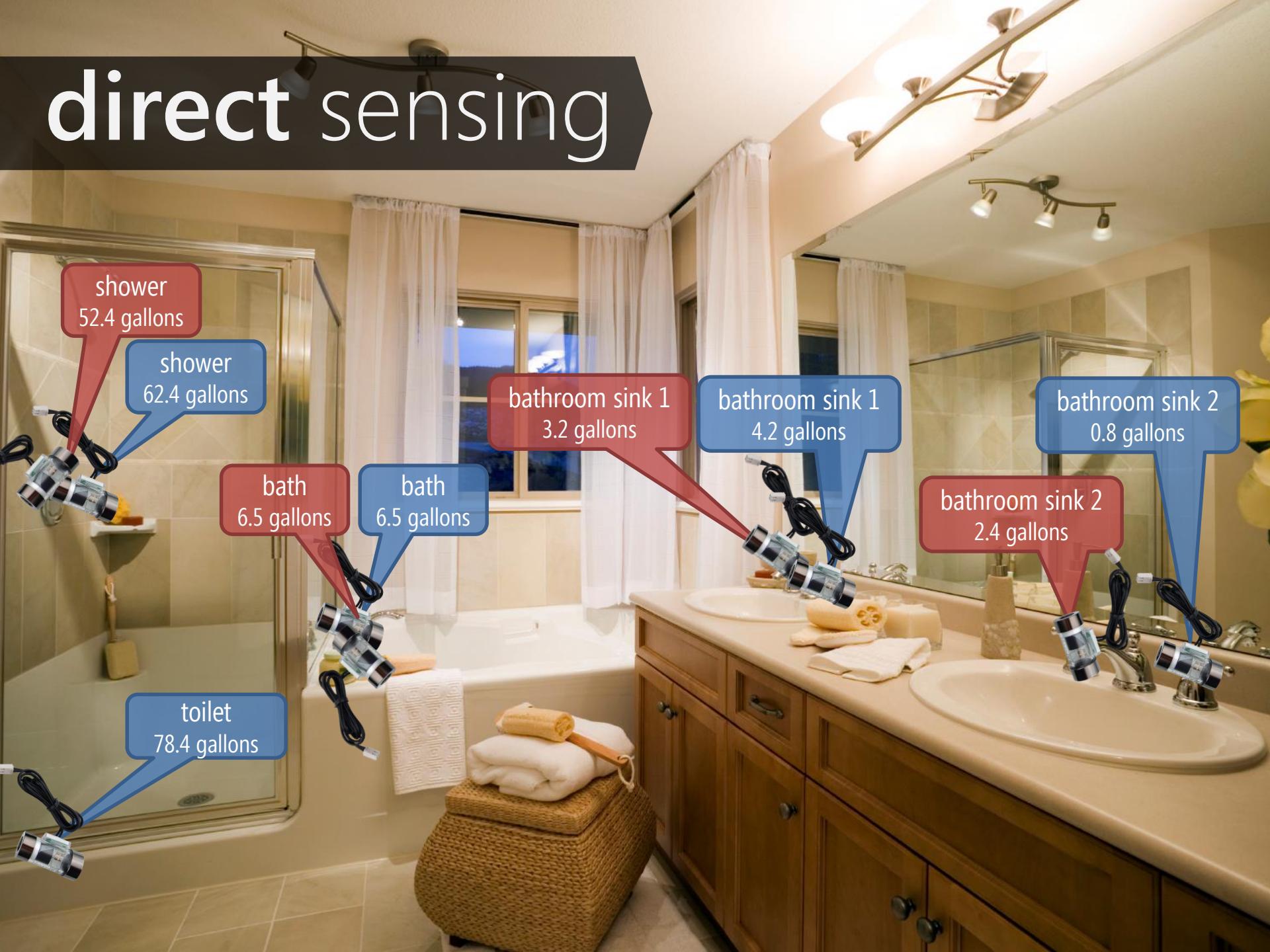
direct sensing



direct sensing



direct sensing



indirect sensing

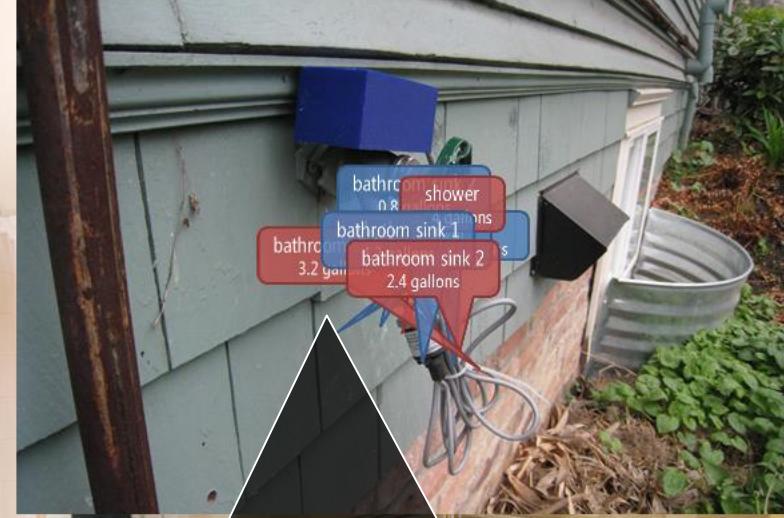


[HydroSense, UbiComp 2009]

indirect sensing



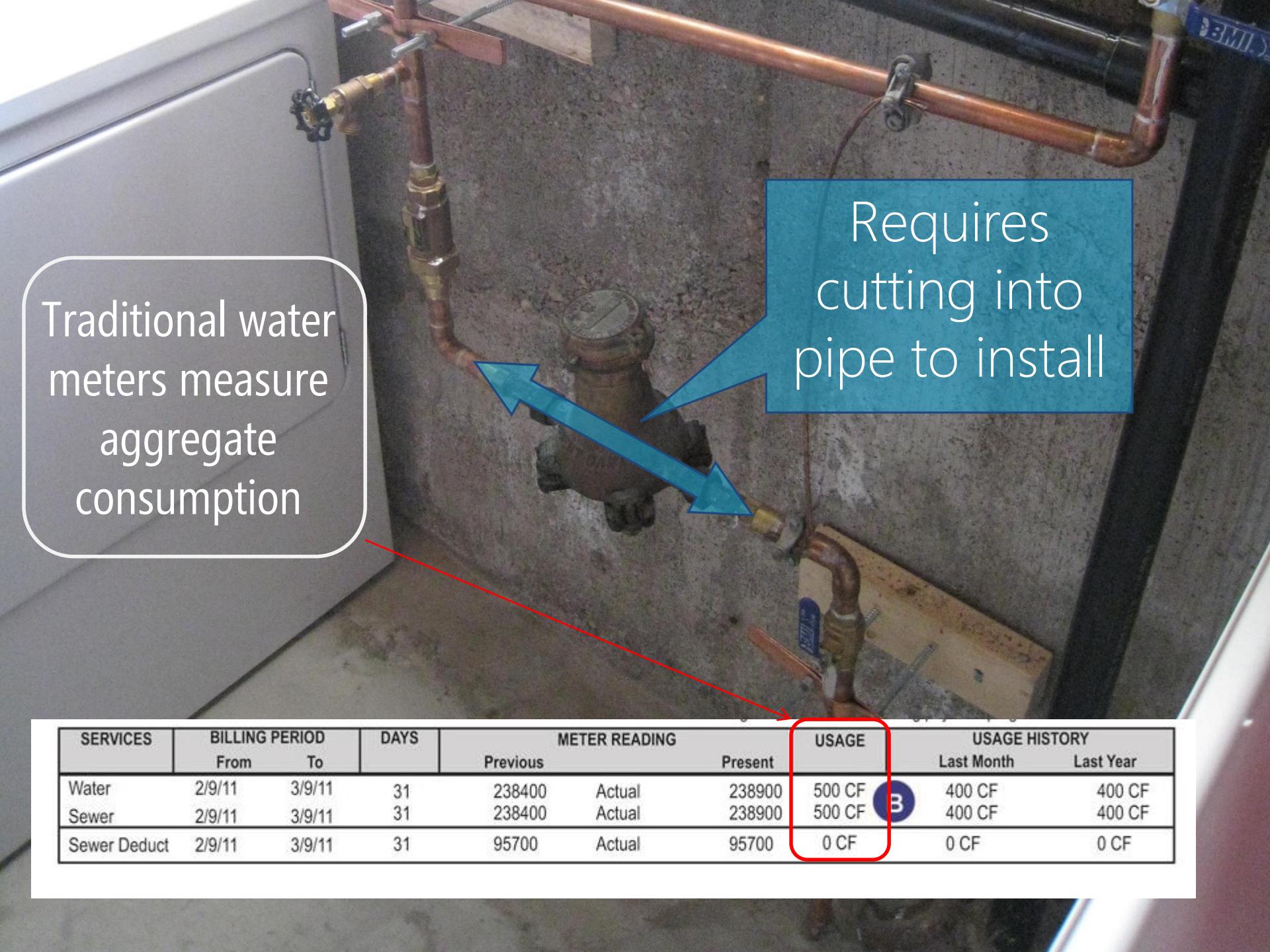
HydroSense attempts to infer fixture-level usage for the entire home from a **single** point.



[HydroSense, UbiComp 2009]

hydrosense

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

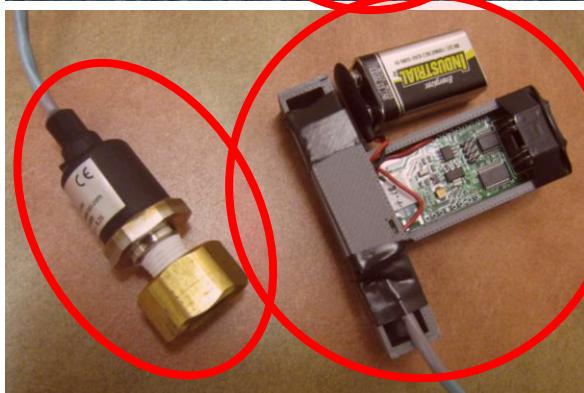
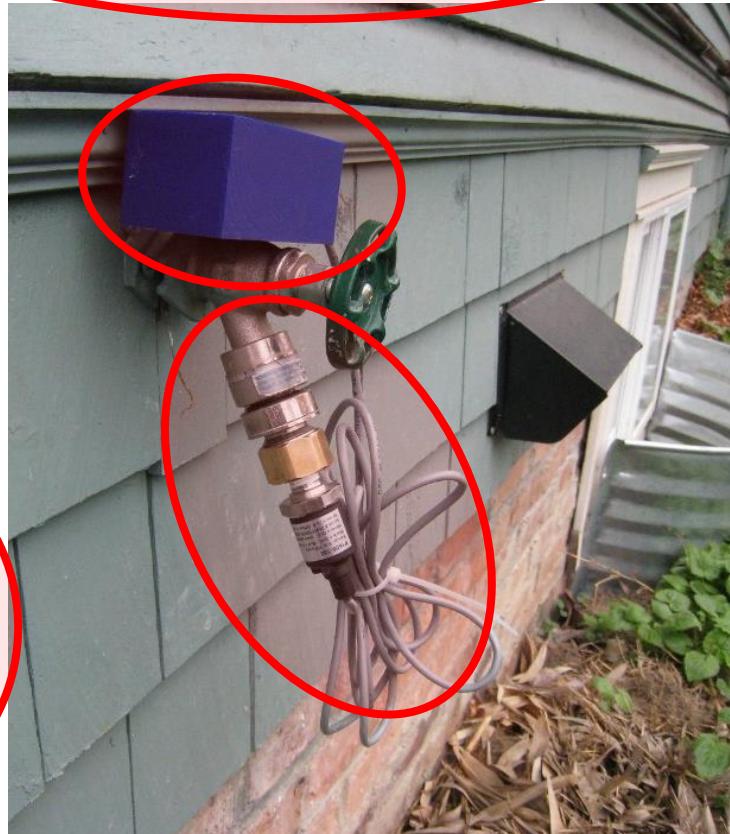
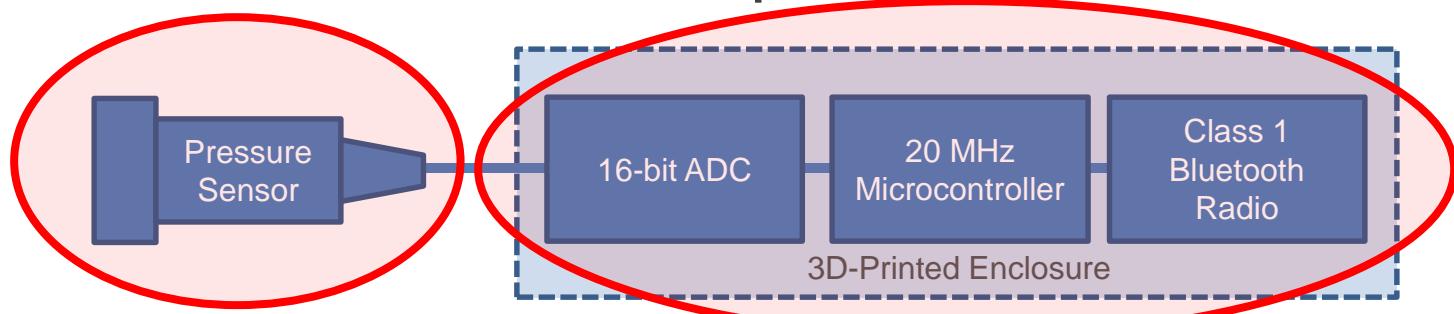


Traditional water meters measure aggregate consumption

Requires cutting into pipe to install

SERVICES	BILLING PERIOD		DAYS	METER READING		USAGE	USAGE HISTORY	
	From	To		Previous	Present		Last Month	Last Year
Water	2/9/11	3/9/11	31	238400	Actual	238900	500 CF	400 CF
Sewer	2/9/11	3/9/11	31	238400	Actual	238900	500 CF	400 CF
Sewer Deduct	2/9/11	3/9/11	31	95700	Actual	95700	0 CF	0 CF

hydrosense implementation



brief plumbing primer



brief plumbing primer





water tower

plumbing primer

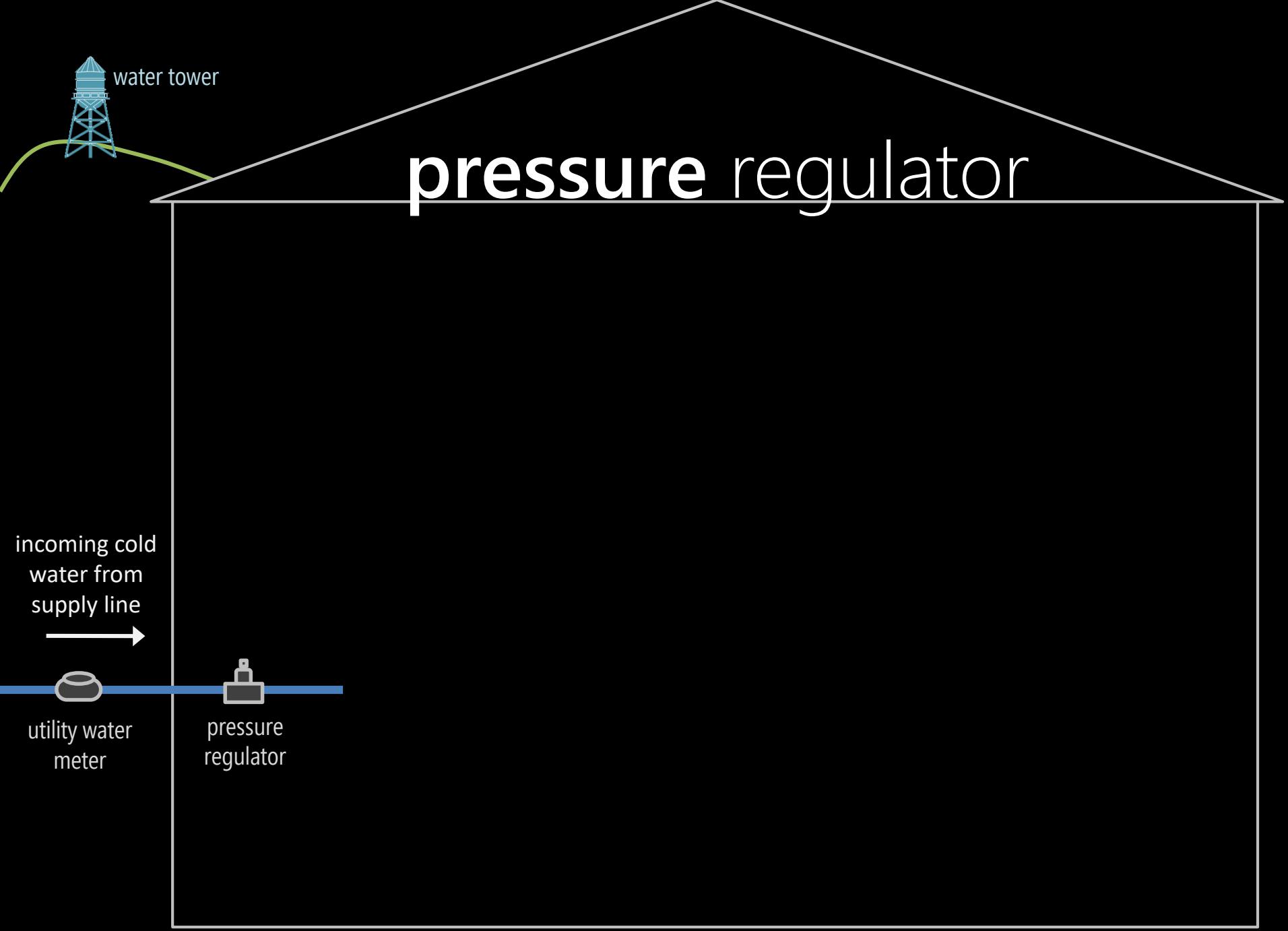


water tower

plumbing primer

incoming cold
water from
supply line







water tower

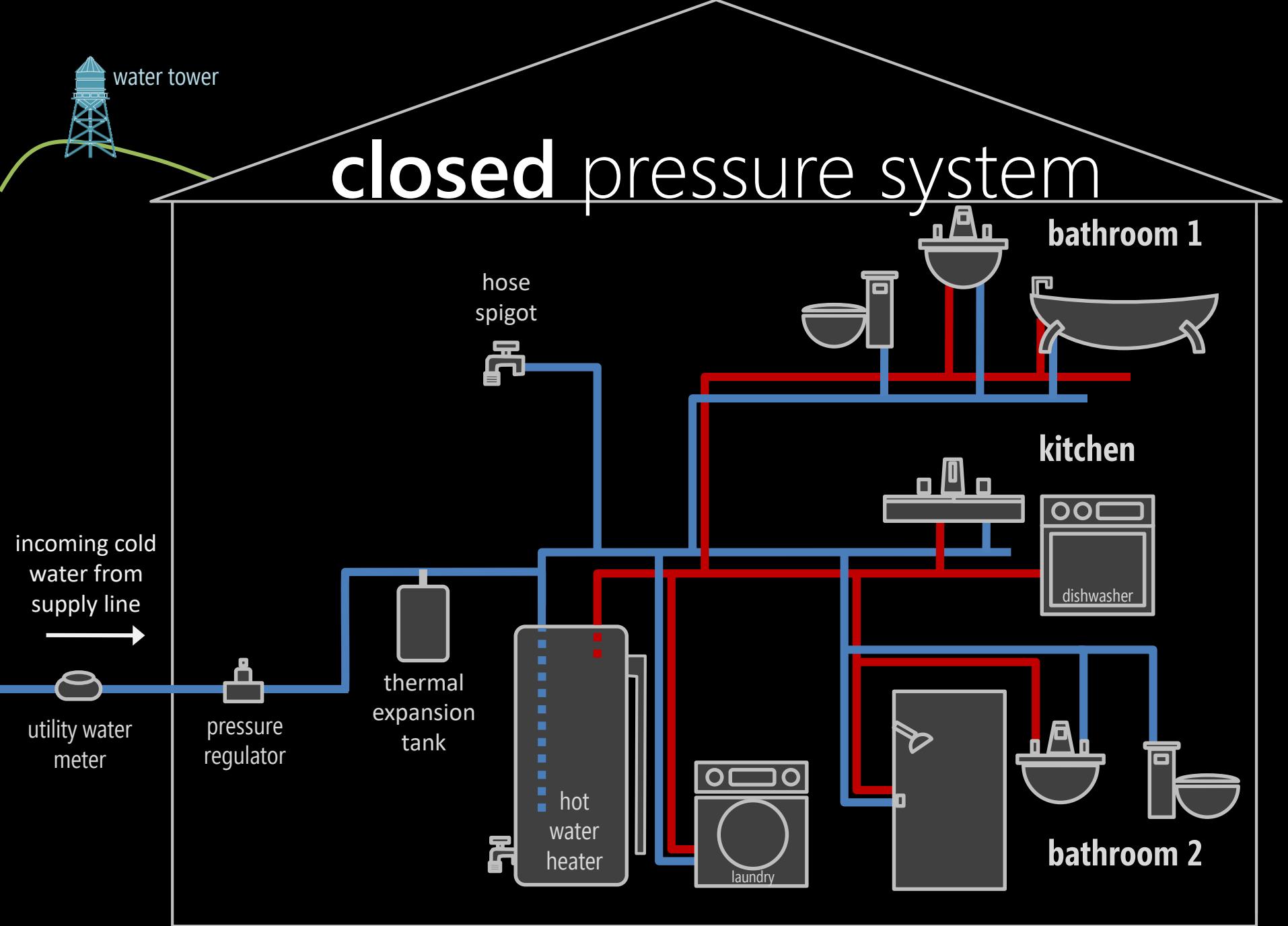
plumbing layout

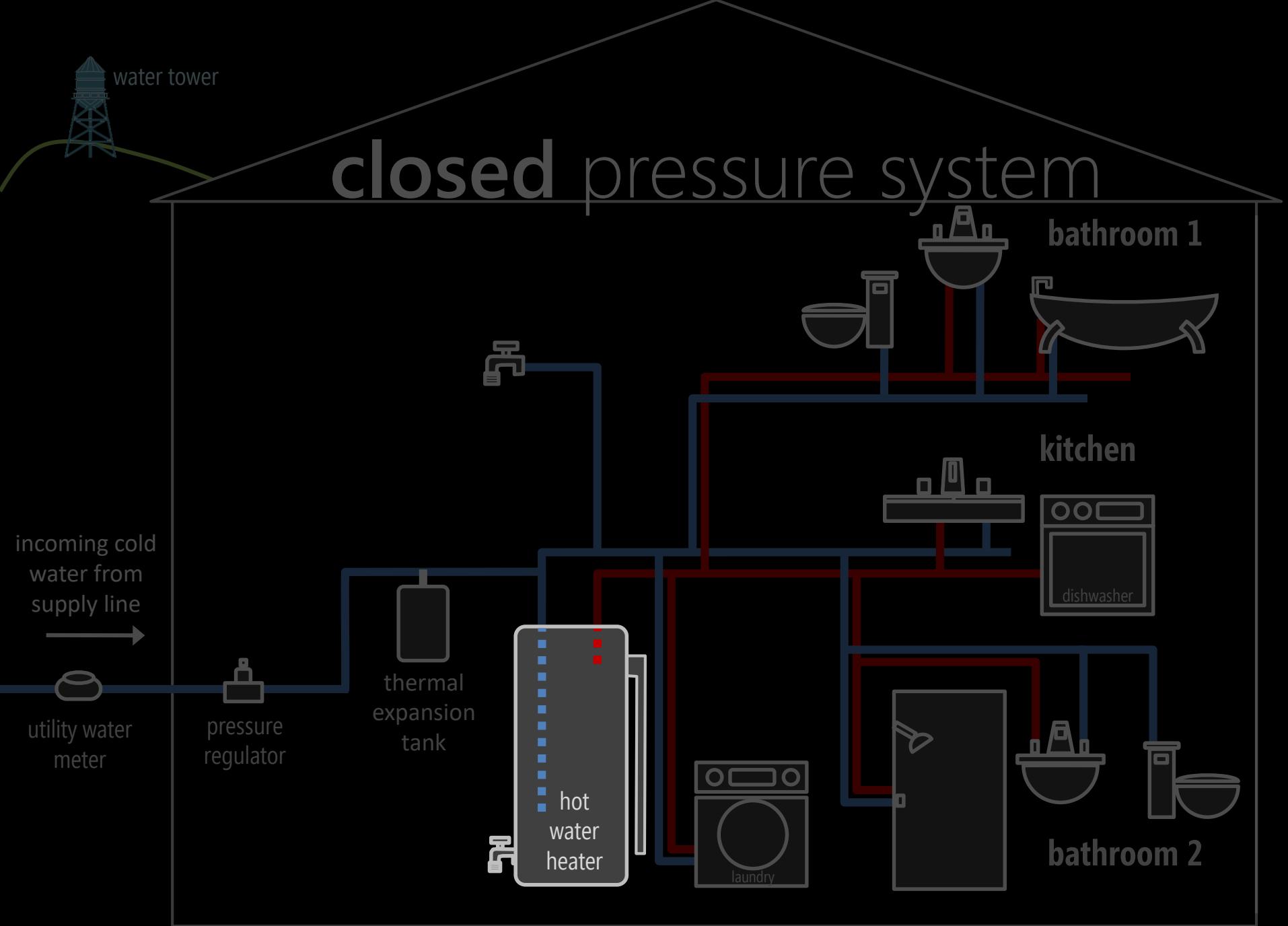
incoming cold
water from
supply line

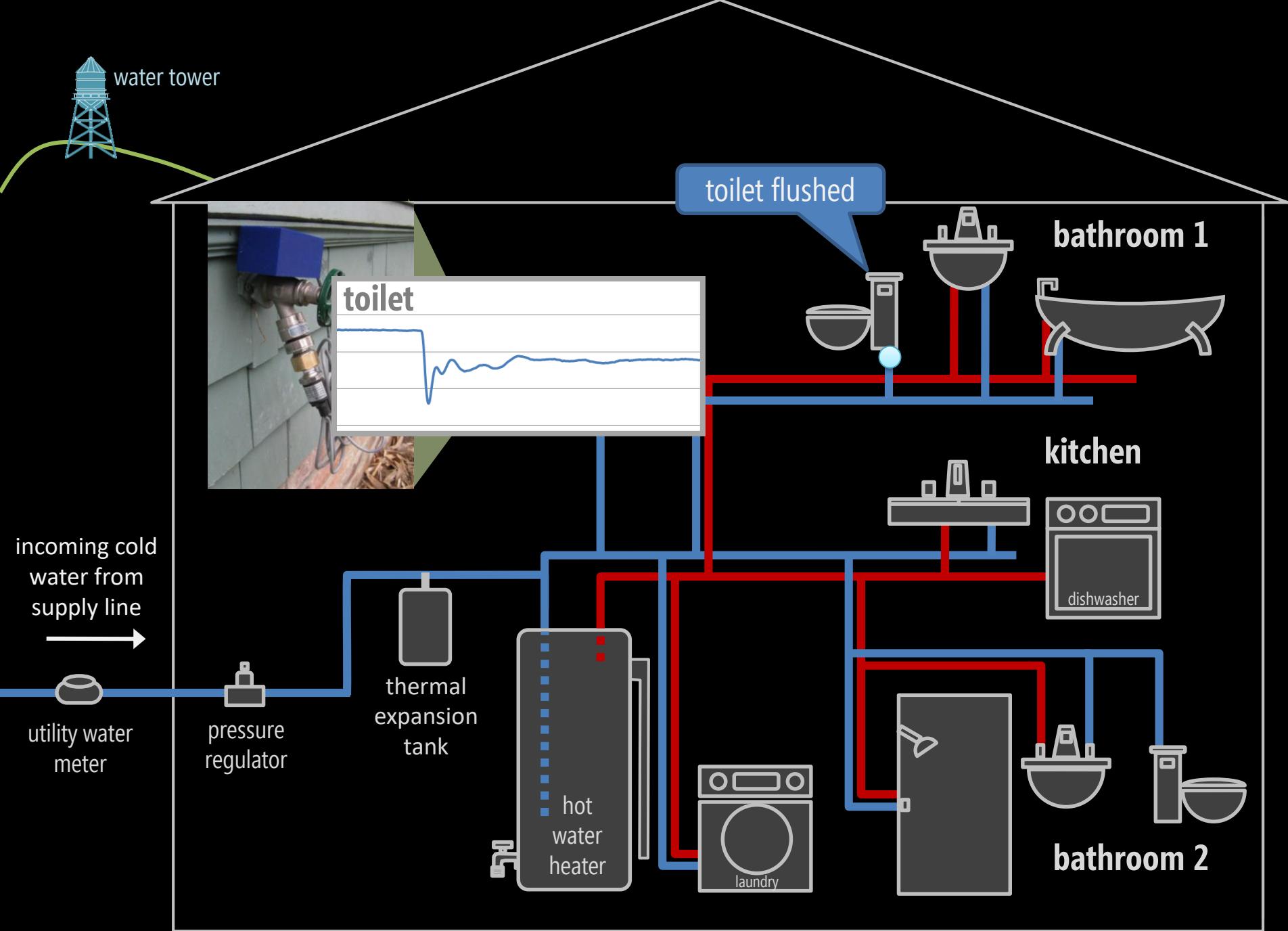


utility water
meter

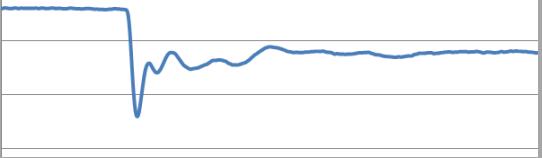
pressure
regulator



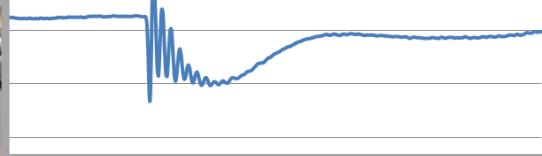




toilet



kitchen sink cold



bathroom 1

kitchen sink
cold open

kitchen

bathroom 2

incoming cold
water from
supply line



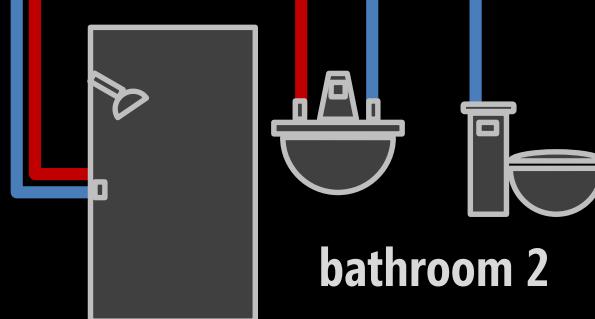
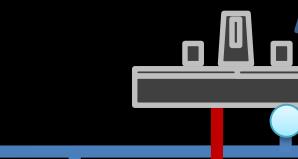
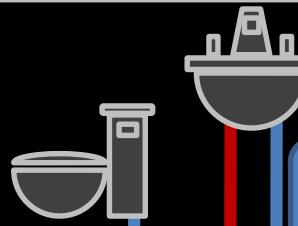
utility water
meter

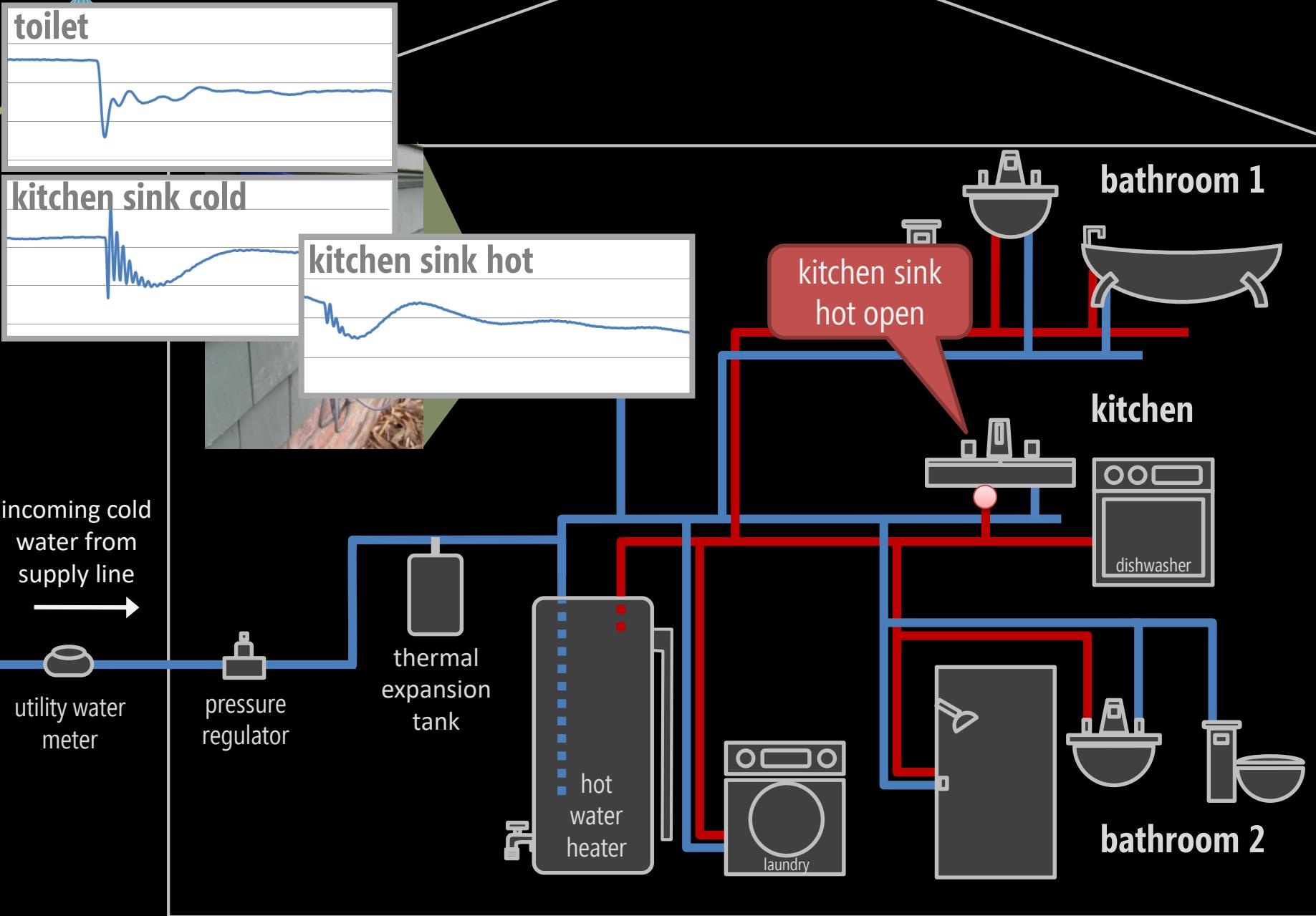
pressure
regulator

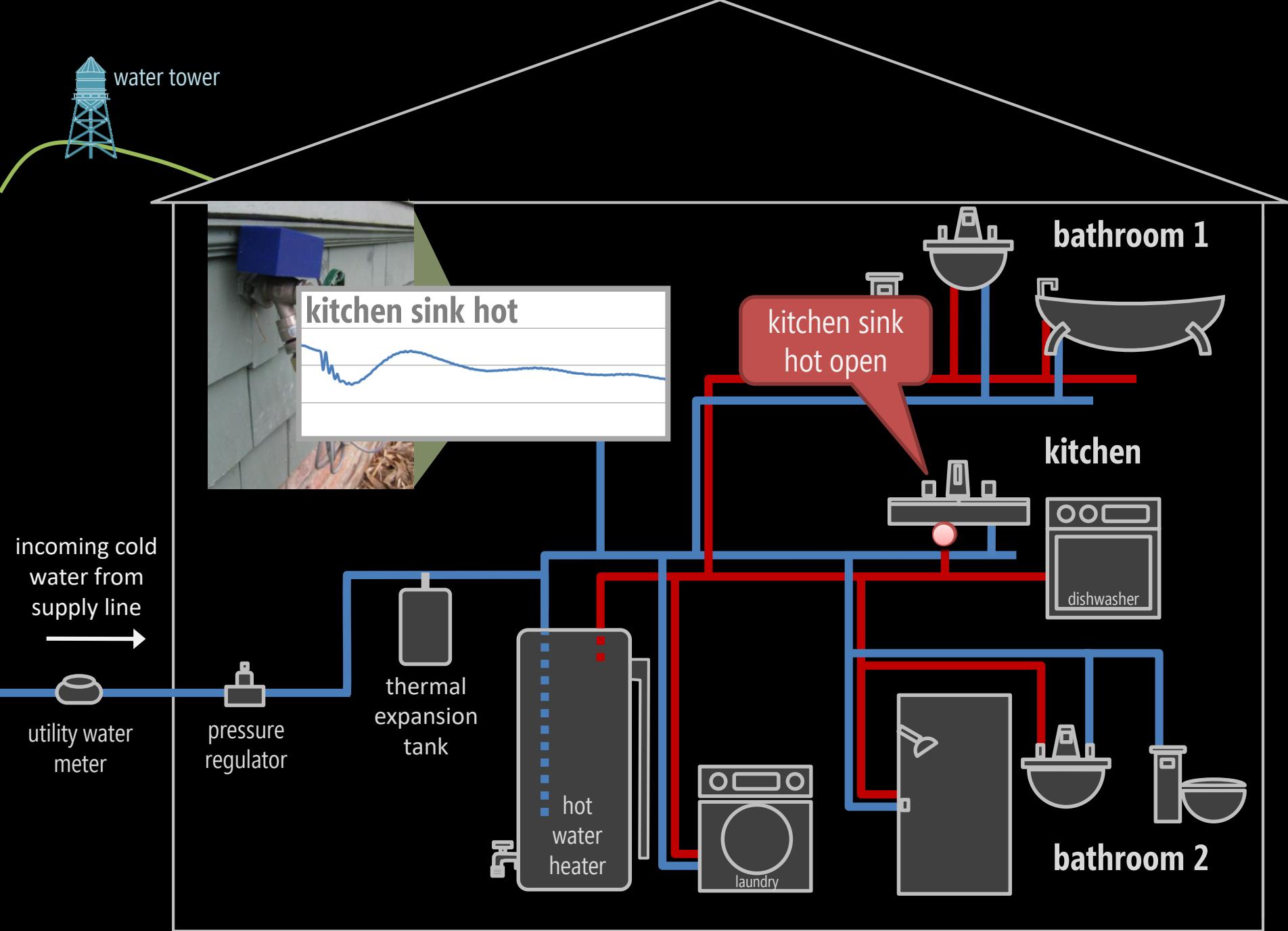
thermal
expansion
tank

hot
water
heater

laundry







bathroom sink pressure signal

psi

80

70

60

50

40

0

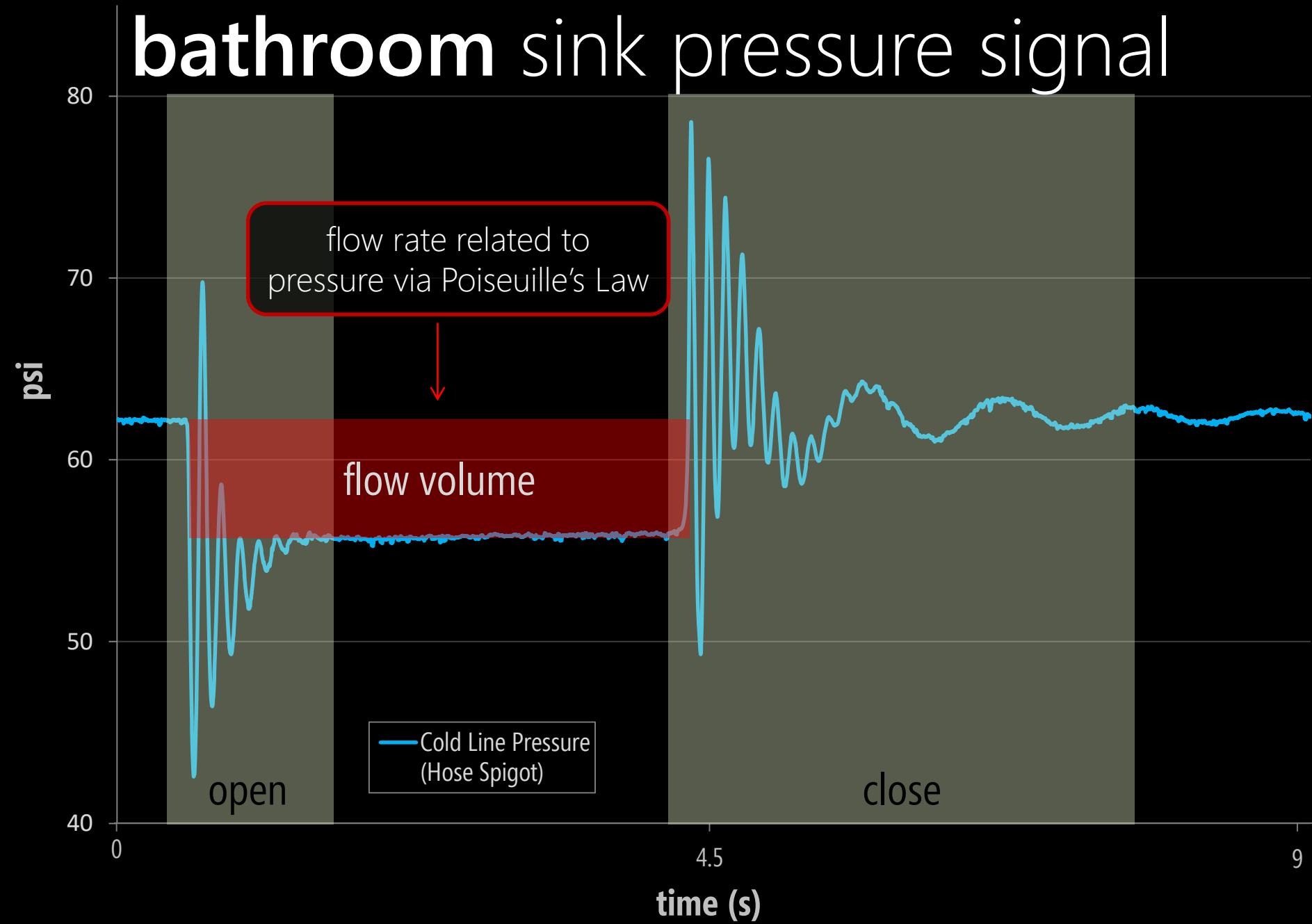
4.5

9

time (s)



bathroom sink pressure signal

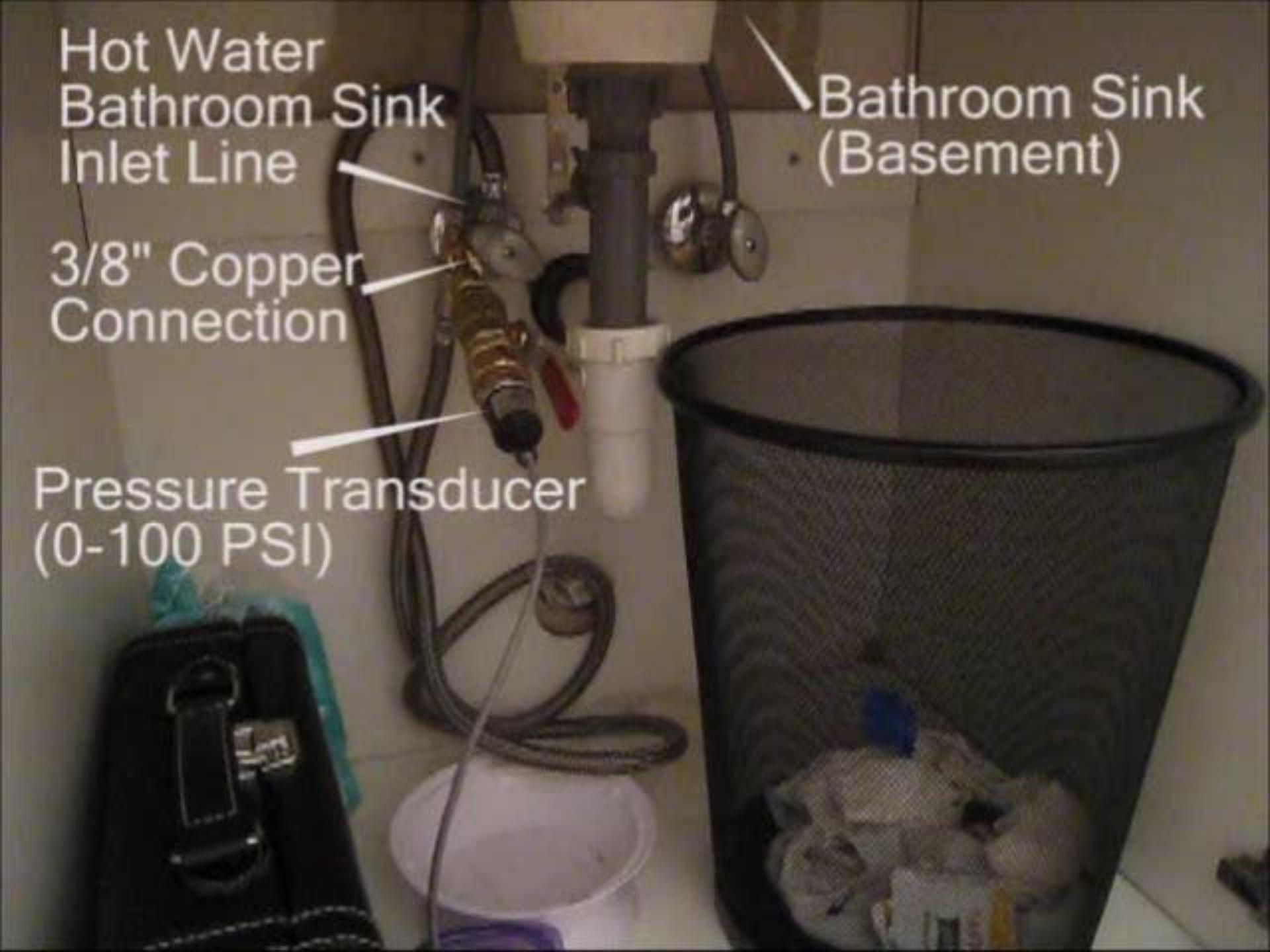


Hot Water
Bathroom Sink
Inlet Line

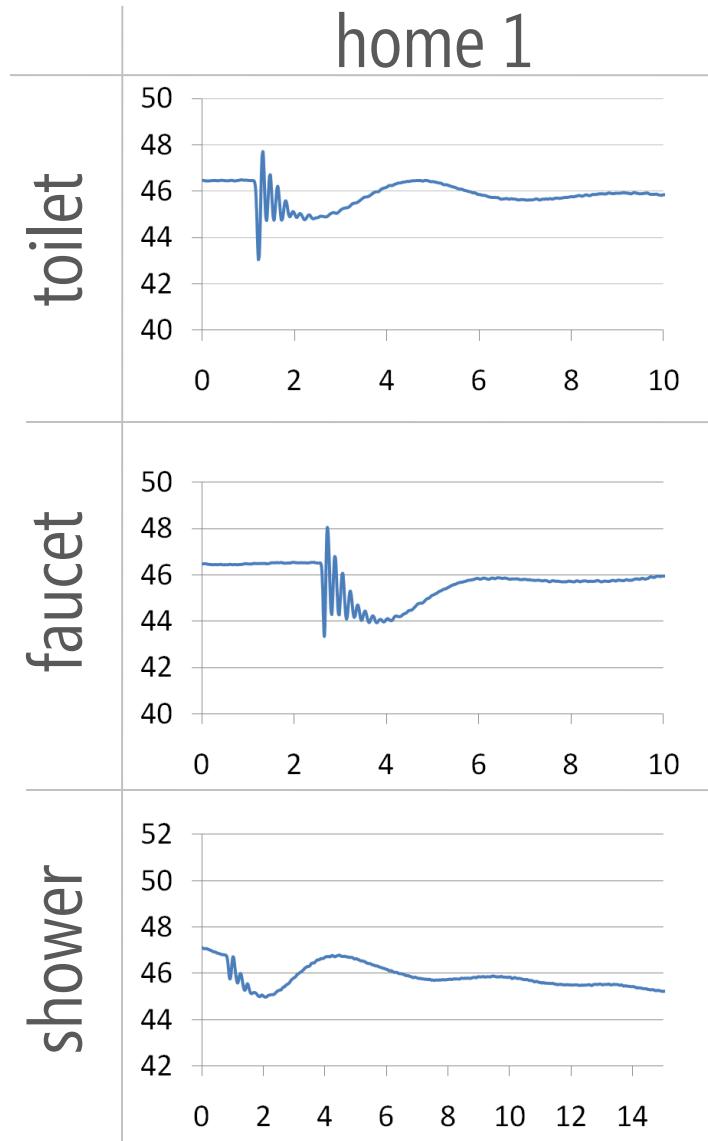
3/8" Copper
Connection

Pressure Transducer
(0-100 PSI)

Bathroom Sink
(Basement)



example open events



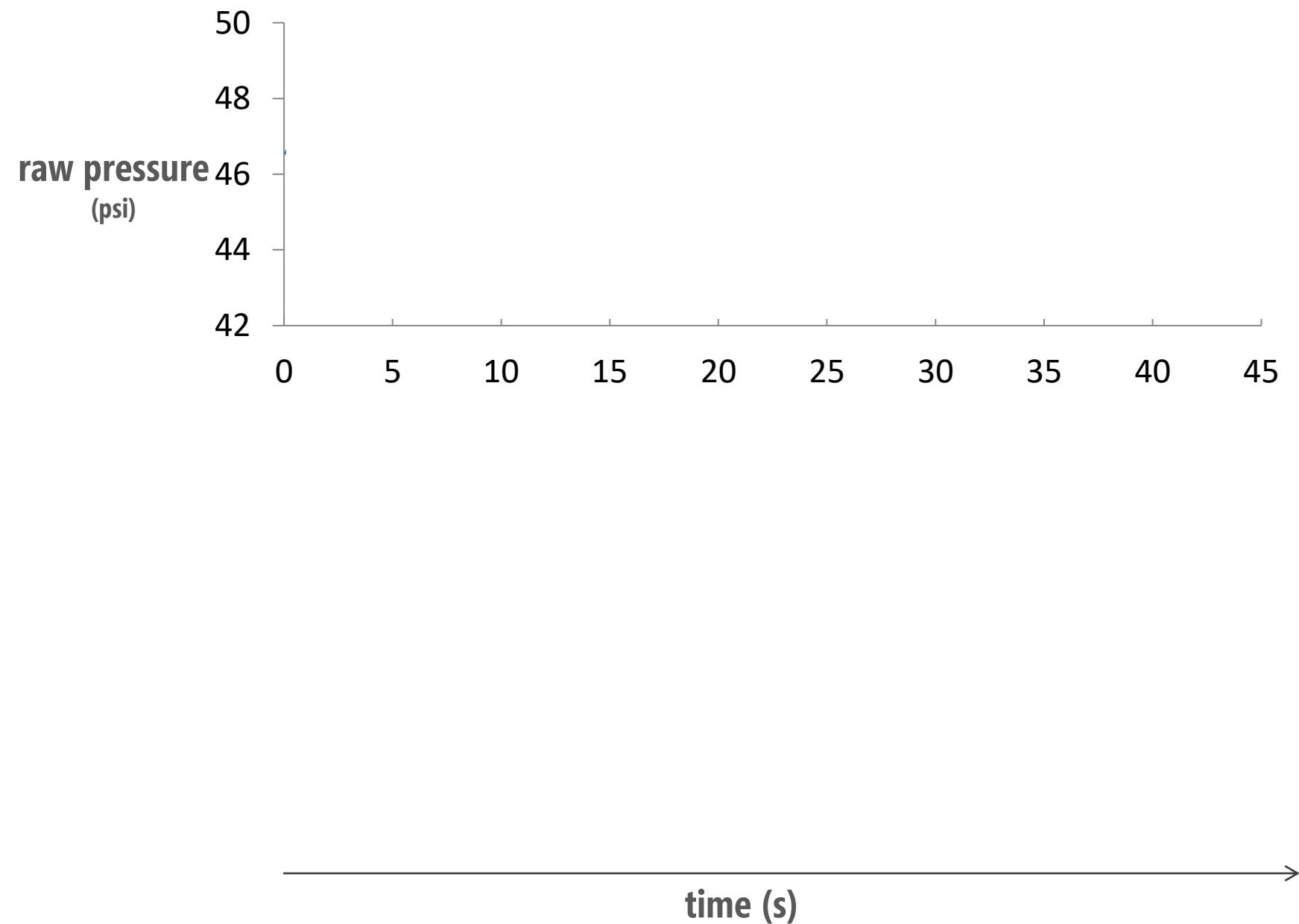
signature dependent on:

- fixture type
- valve type
- valve location in home

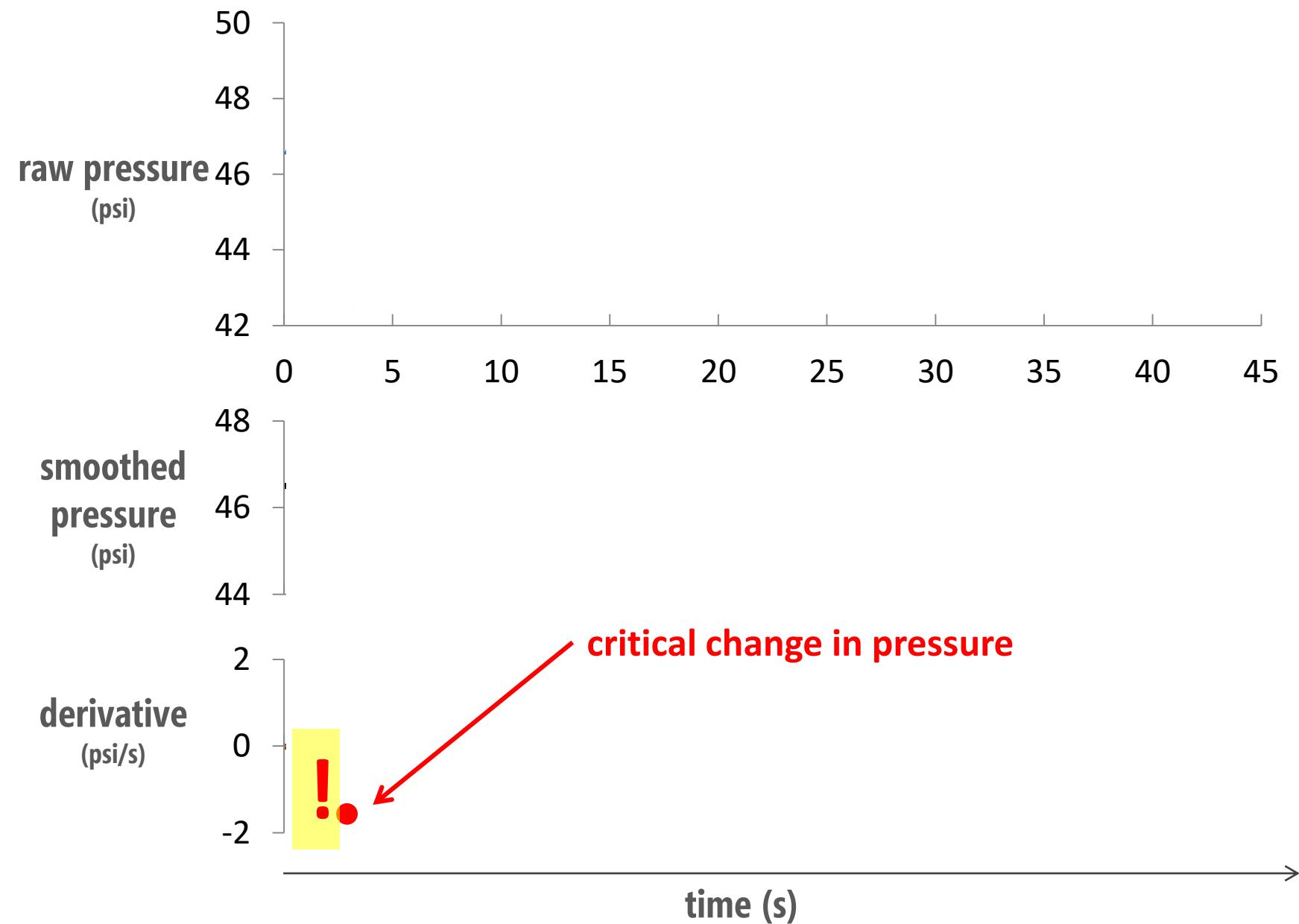
hydro algorithm

1. detect that a water event has occurred
2. classify event as "open" or "close"
3. determine source of event (e.g., toilet, shower)
4. provide flow estimate

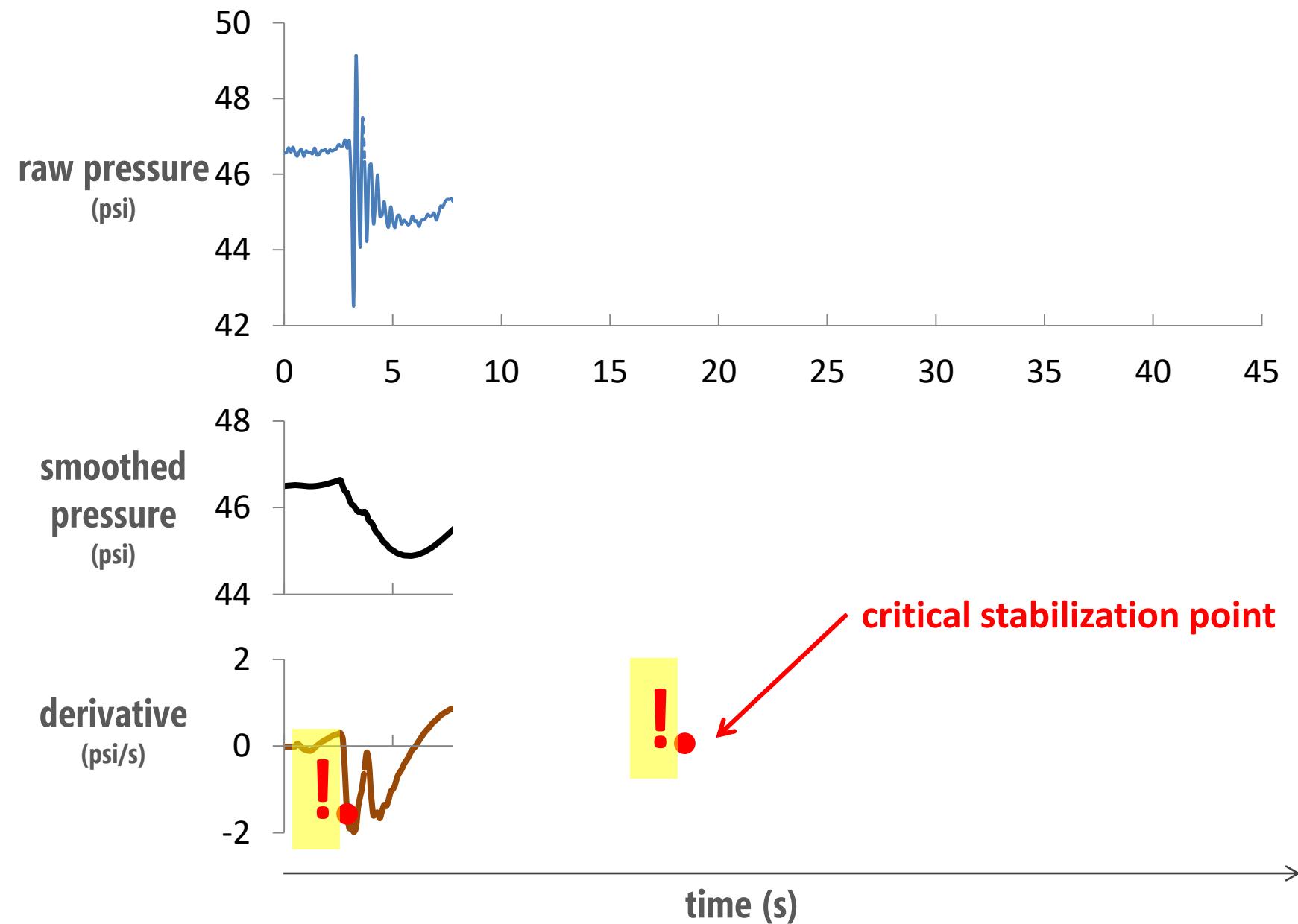
event detection/segmentation



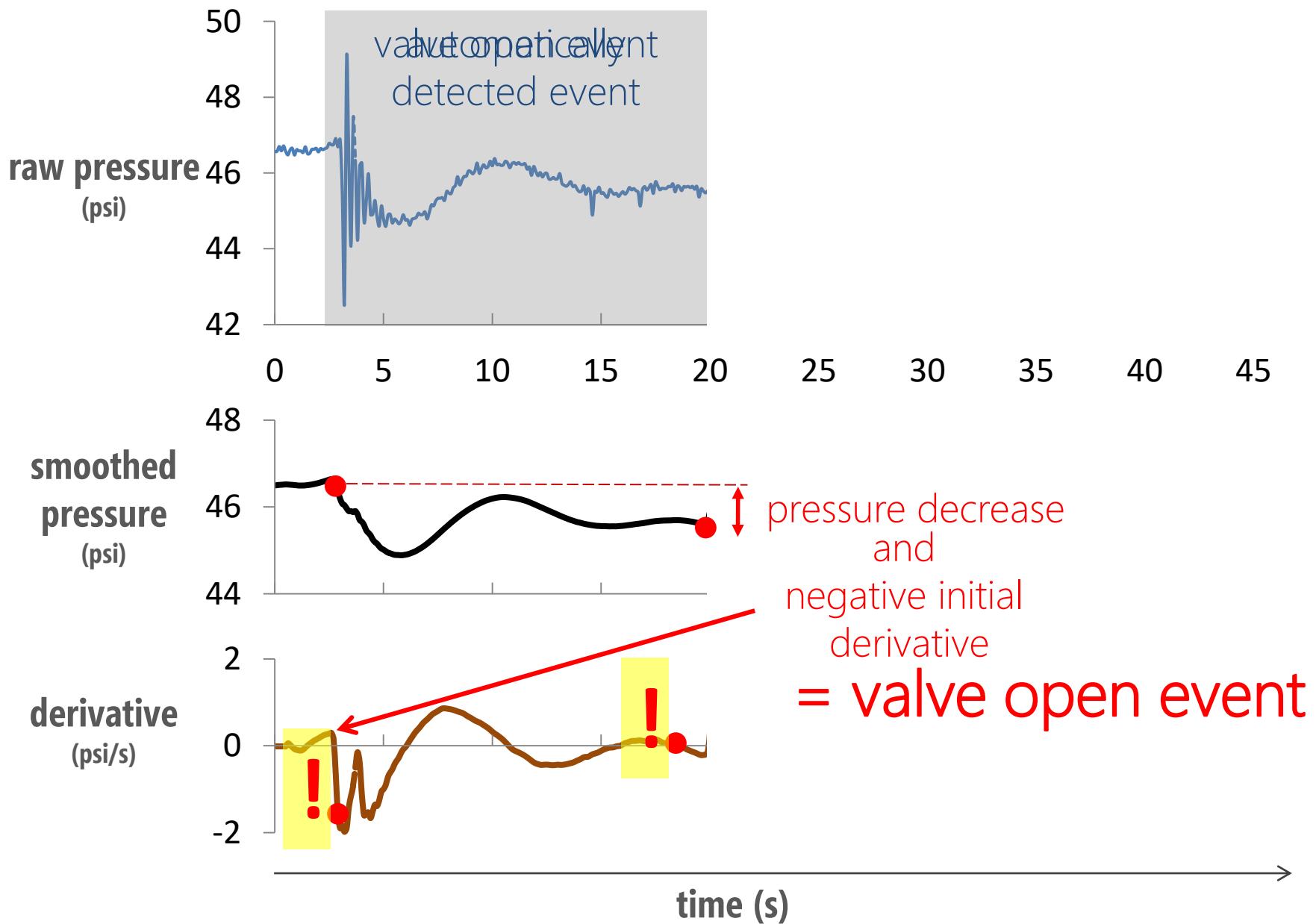
event detection/segmentation



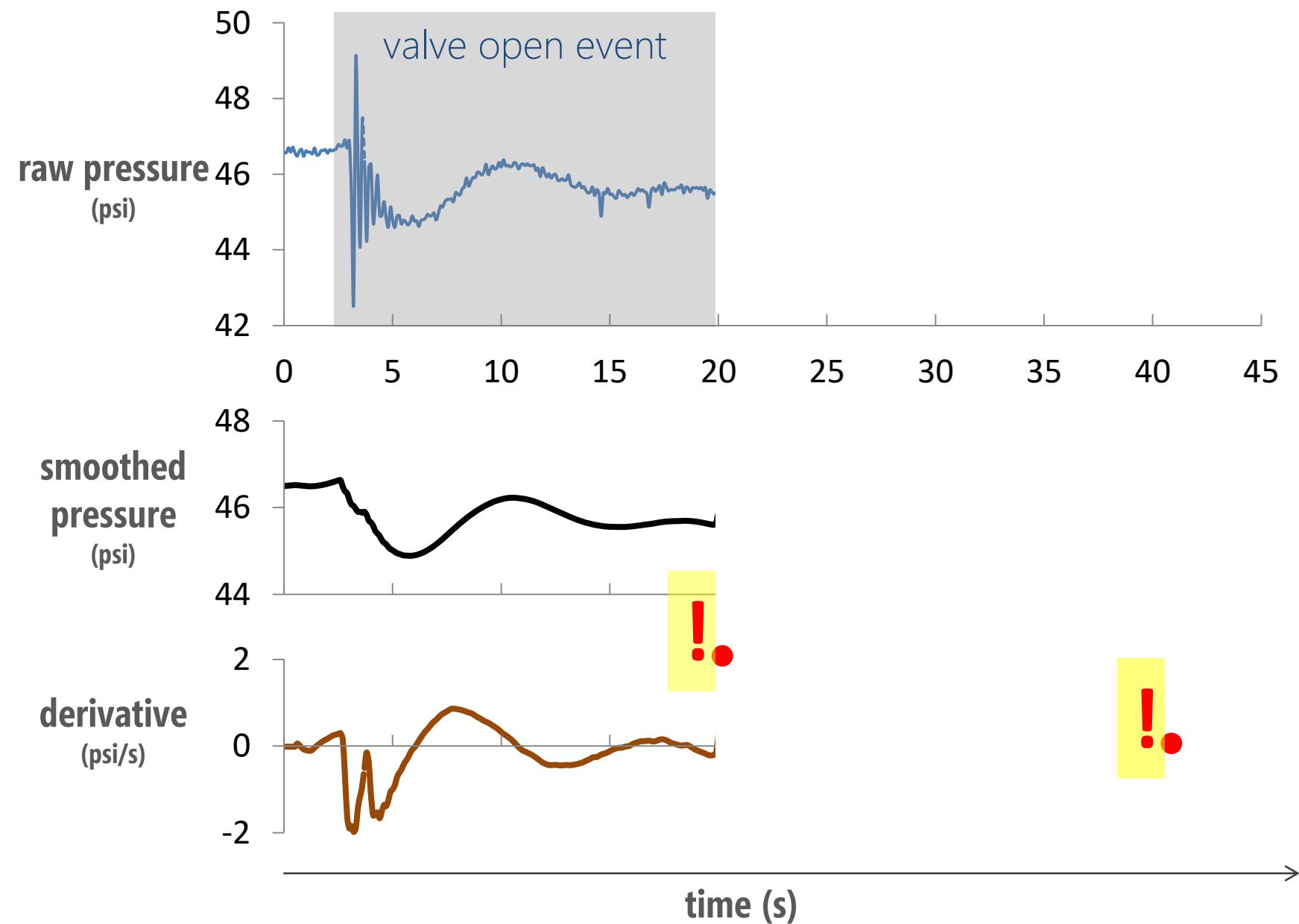
event detection/segmentation



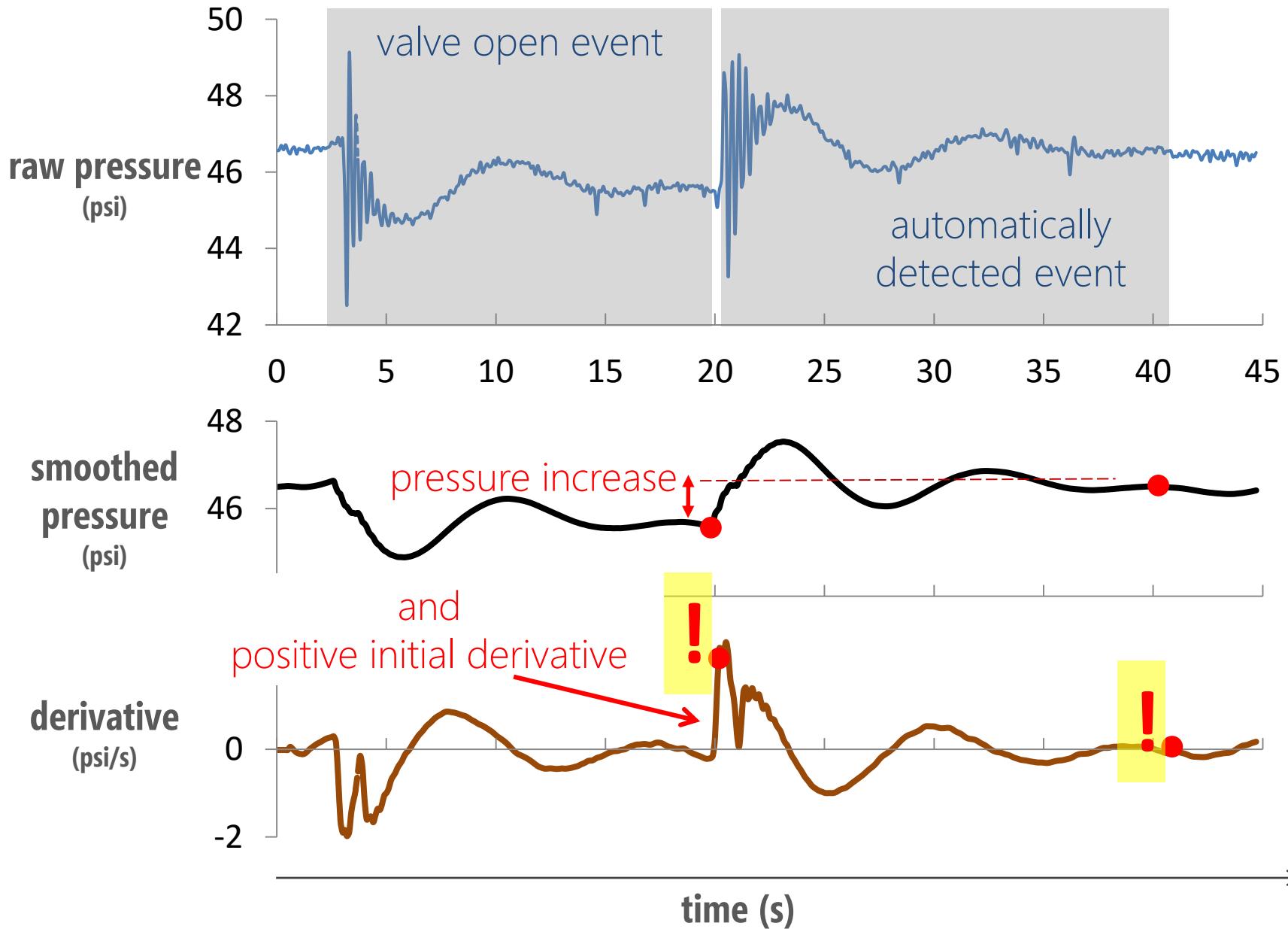
event detection/segmentation



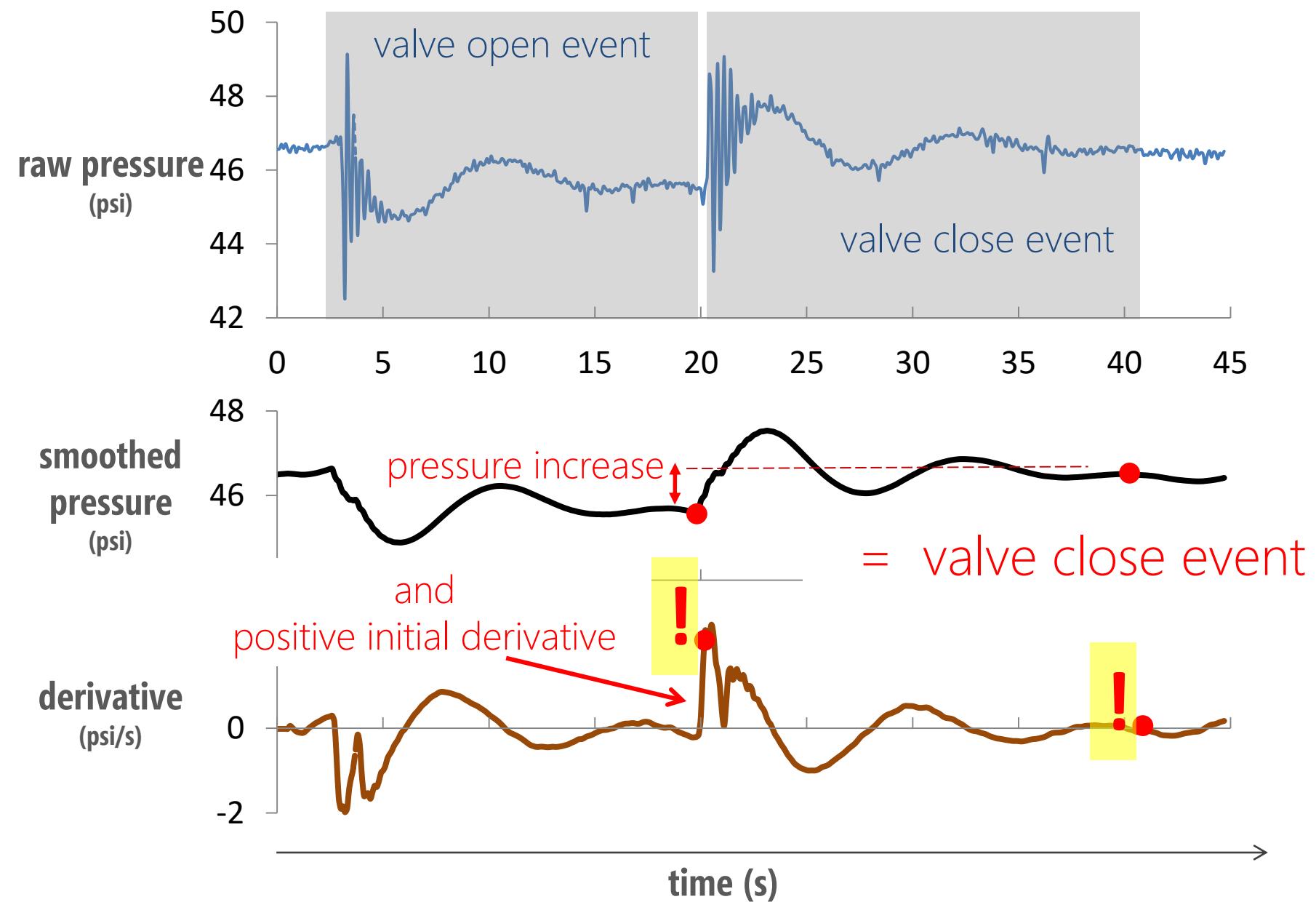
event detection/segmentation



event detection/segmentation

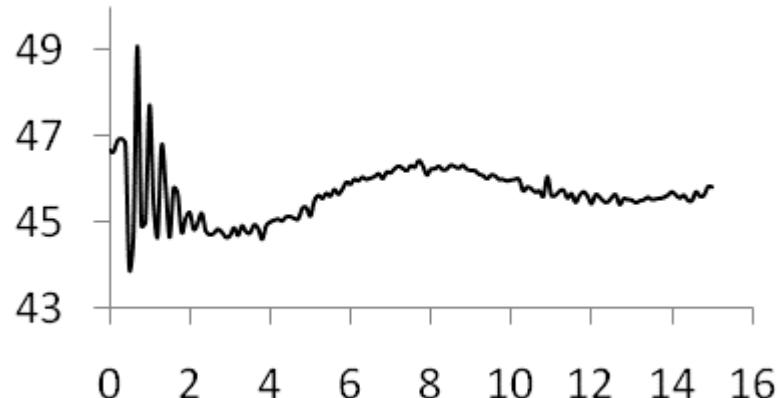


event detection/segmentation

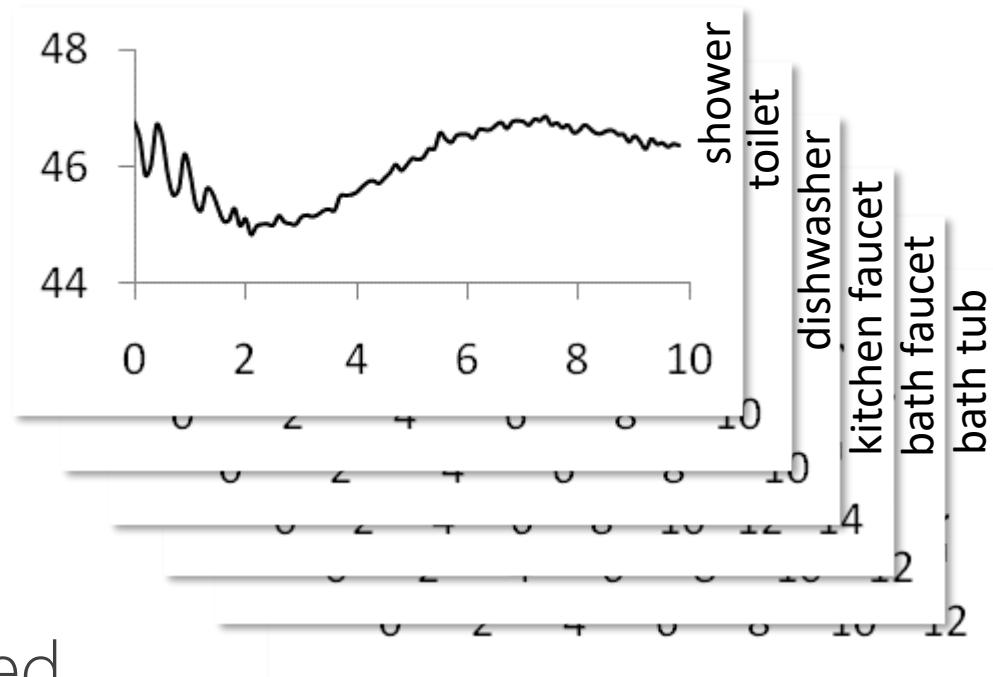


fixture classification

unclassified open event

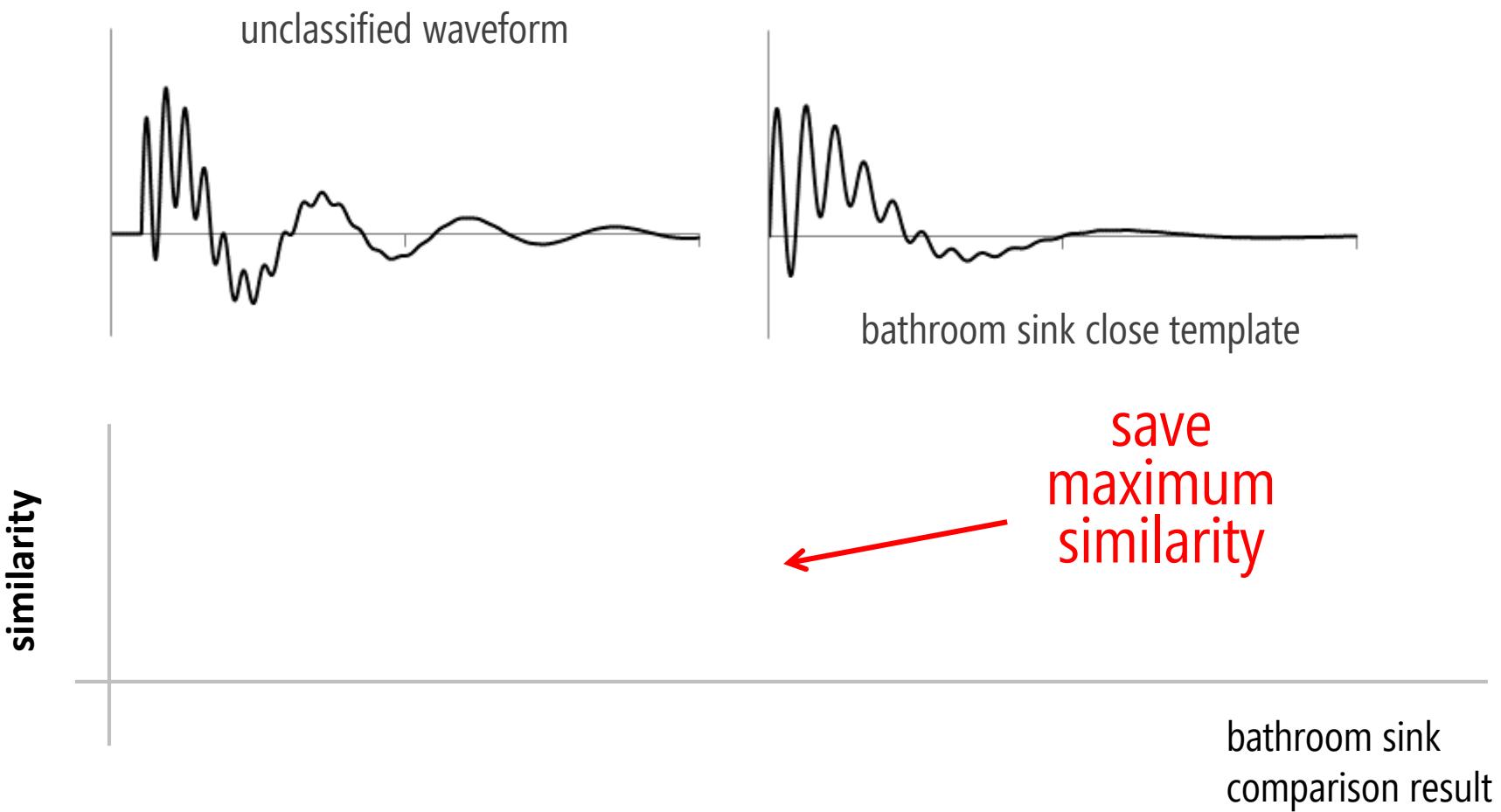


open event library

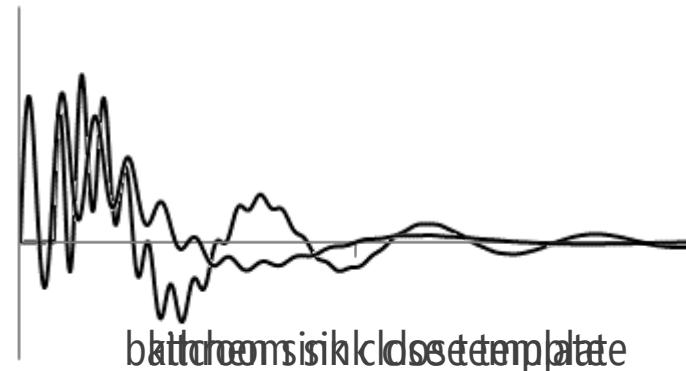


compare via matched
filtering across multiple signal
transformations

matched filtering



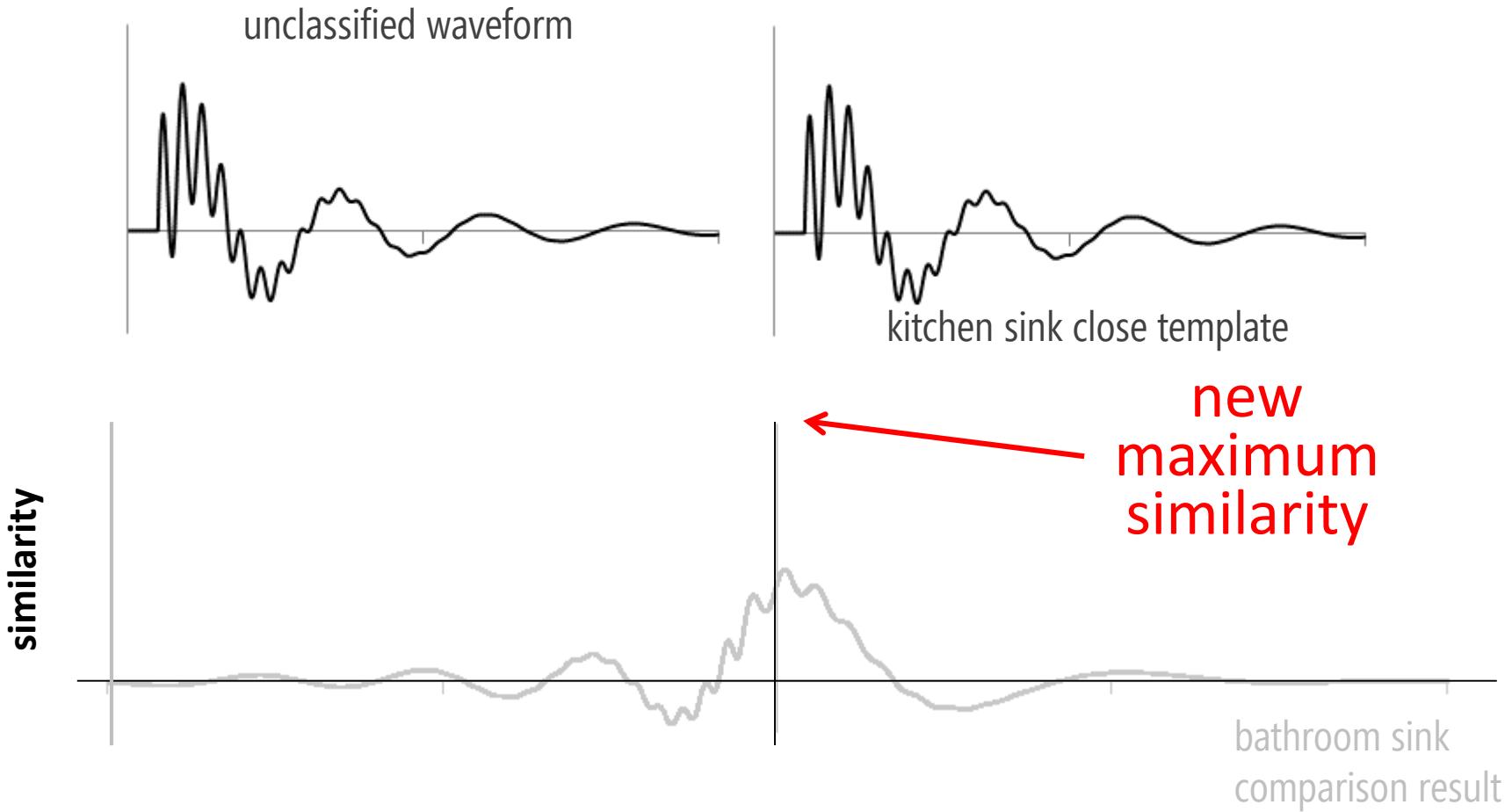
matched filtering



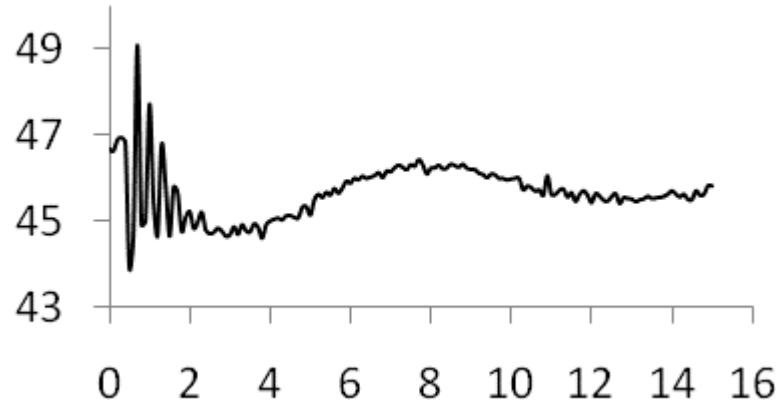
similarity

bathroom sink
comparison result

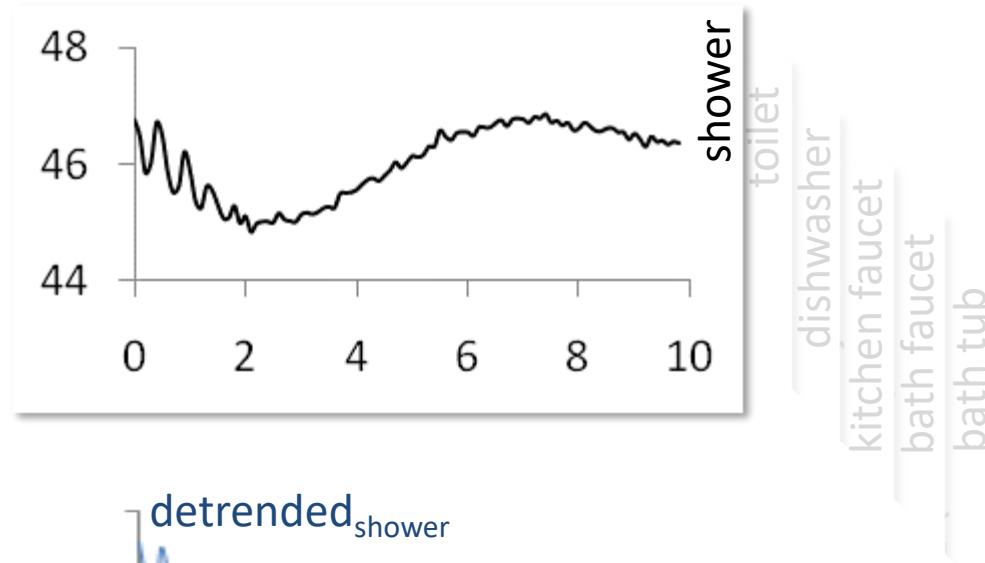
matched filtering



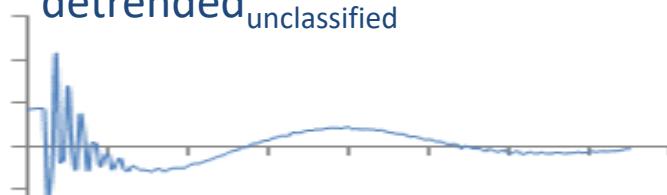
unclassified open event



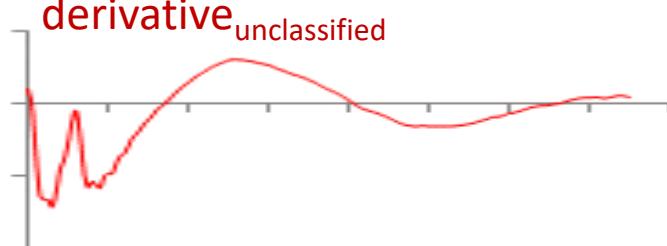
open event library



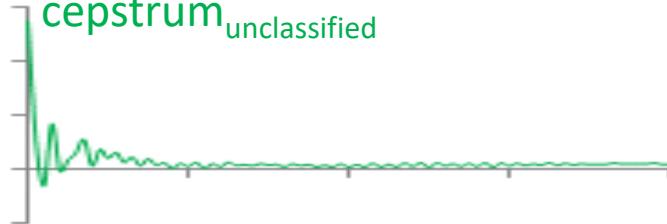
detrended_{unclassified}



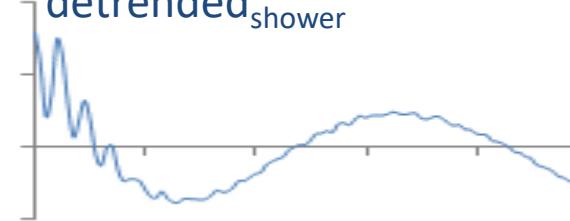
derivative_{unclassified}



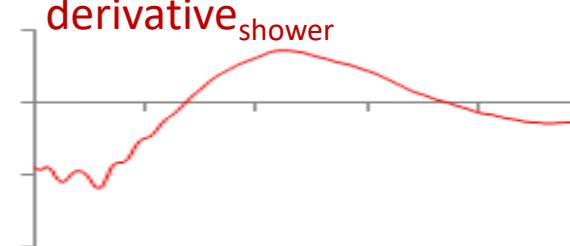
cepstrum_{unclassified}



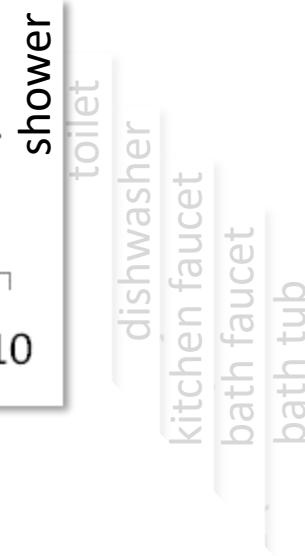
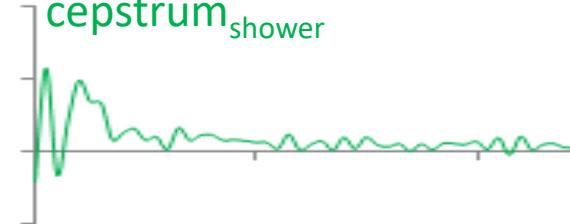
detrended_{shower}



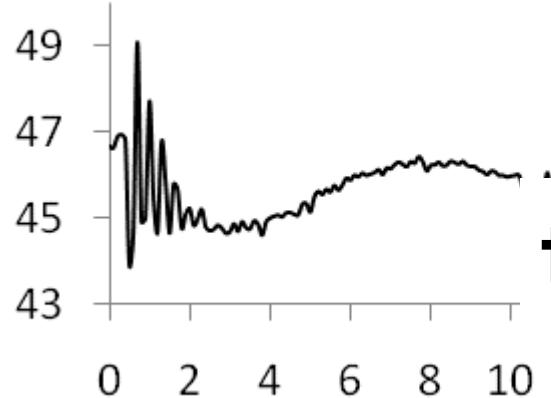
derivative_{shower}



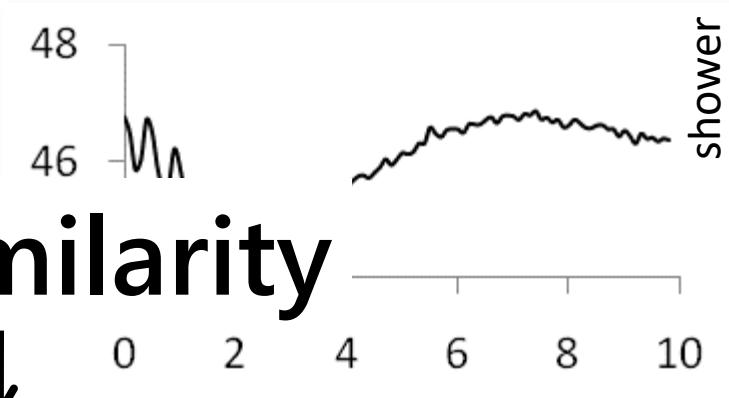
cepstrum_{shower}



unclassified open event



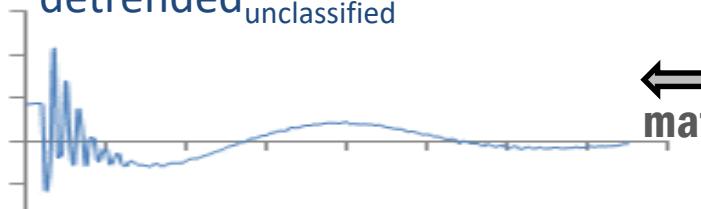
open event library



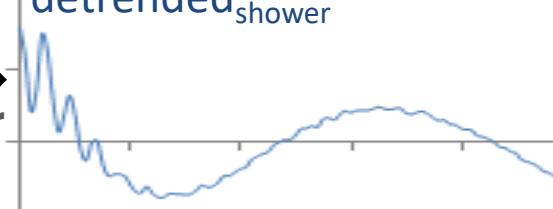
test similarity



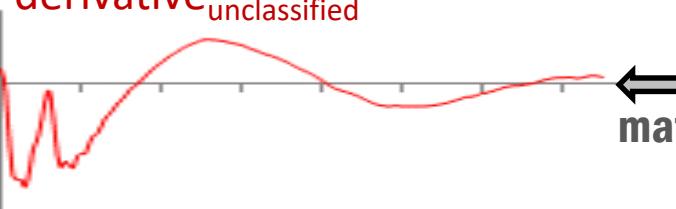
detrended_{unclassified}



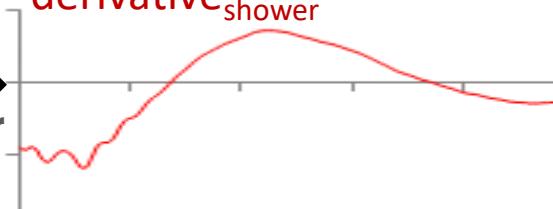
detrended_{shower}



derivative_{unclassified}



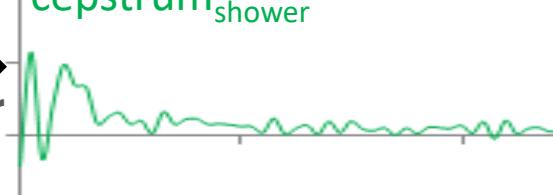
derivative_{shower}



cepstrum_{unclassified}



cepstrum_{shower}



↔ ↔
matched filter

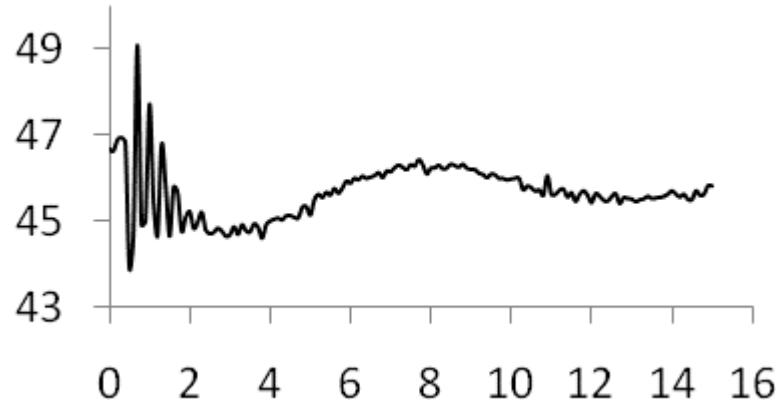
↔ ↔
matched filter

↔ ↔
matched filter

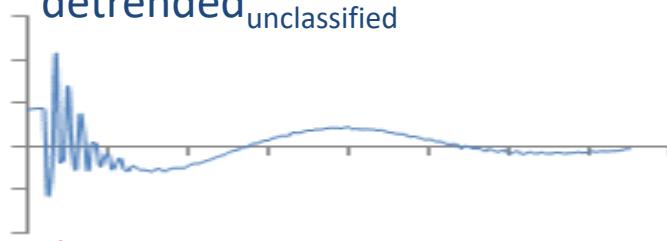


possible
events

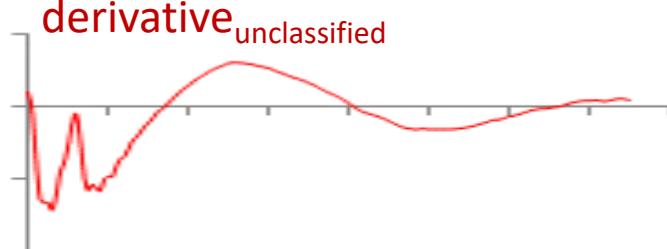
unclassified open event



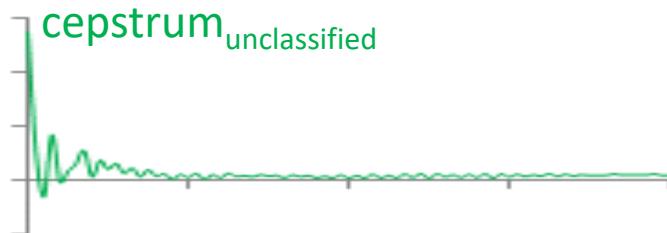
detrended_{unclassified}



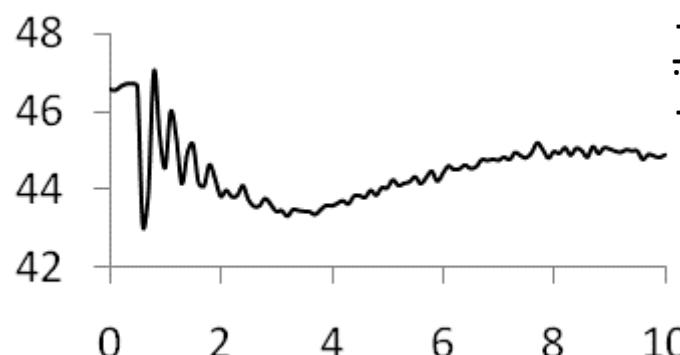
derivative_{unclassified}



cepstrum_{unclassified}



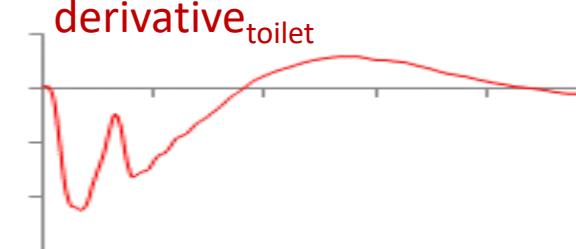
open event library



detrended_{toilet}



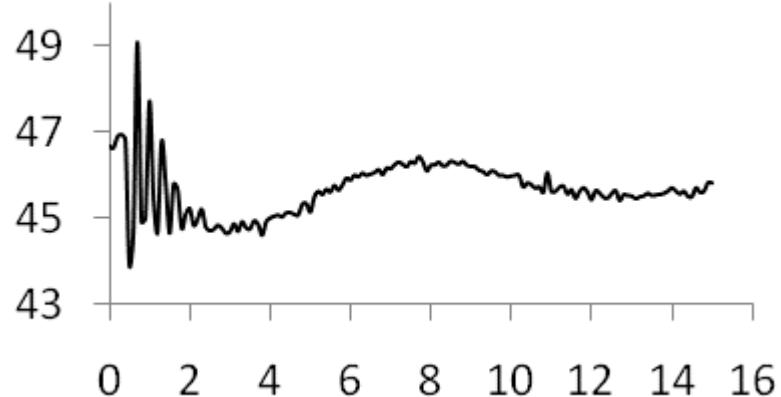
derivative_{toilet}



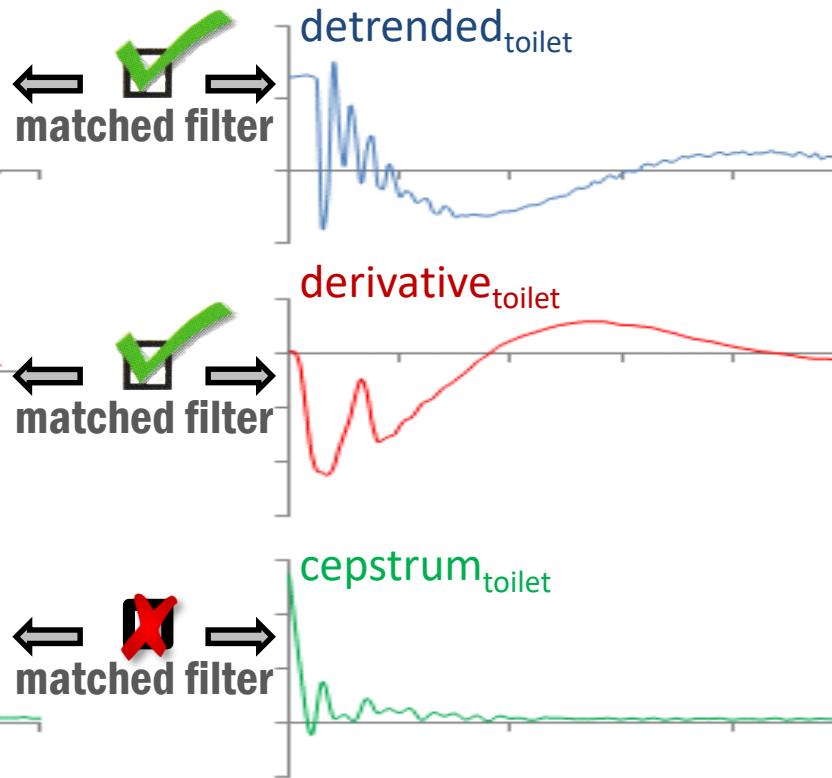
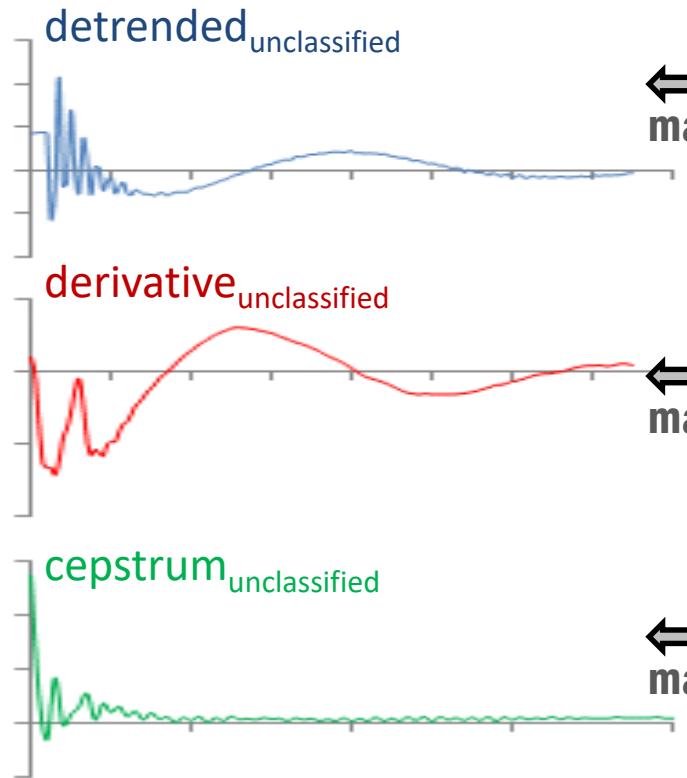
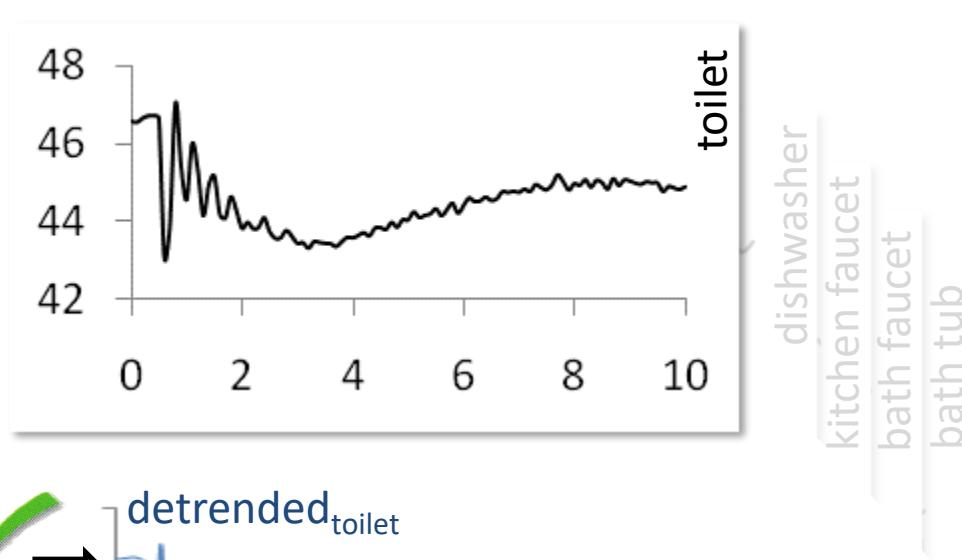
cepstrum_{toilet}



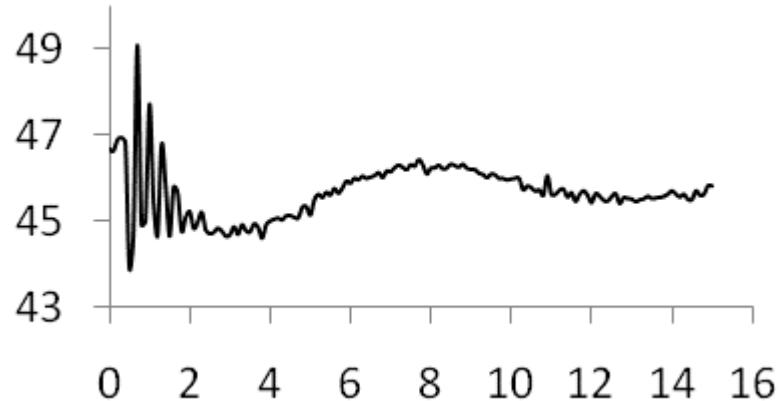
unclassified open event



open event library



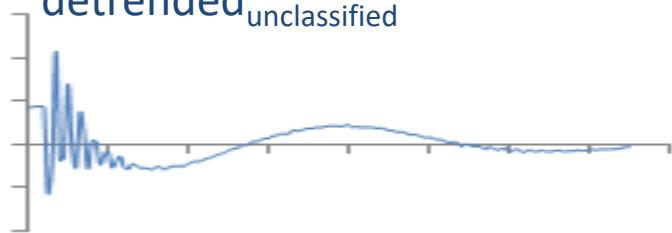
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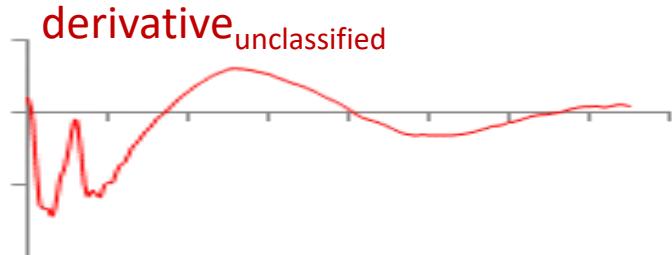
open event library



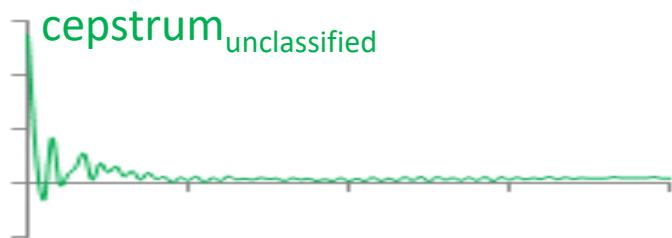
detrended_{unclassified}



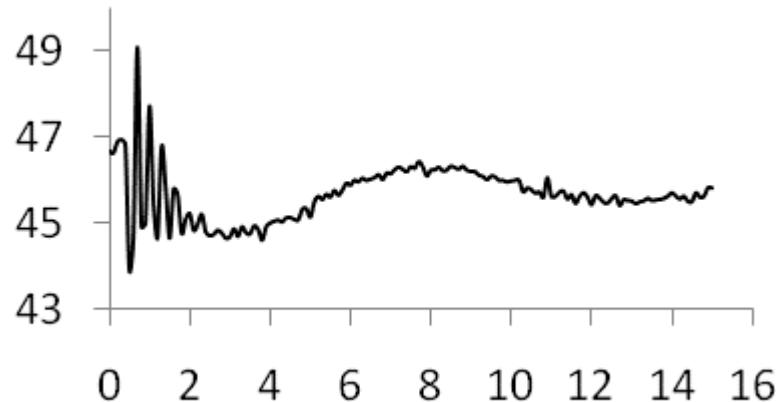
derivative_{unclassified}



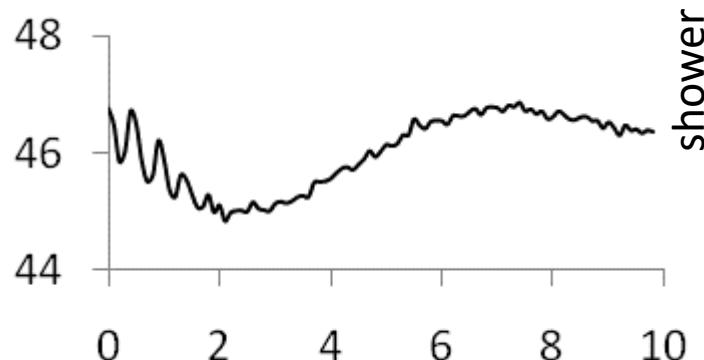
cepstrum_{unclassified}



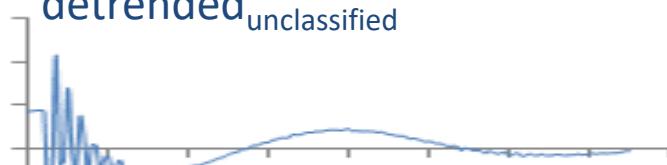
unclassified open event



open event library



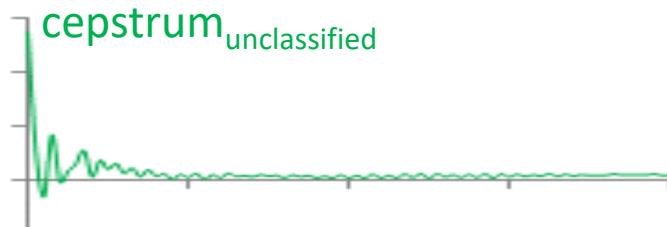
detrended_{unclassified}



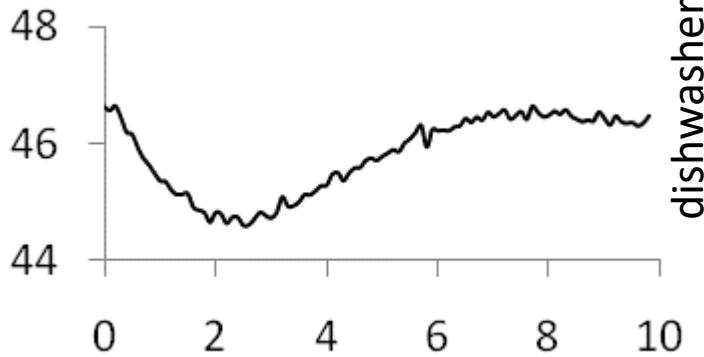
derivative_{unclassified}



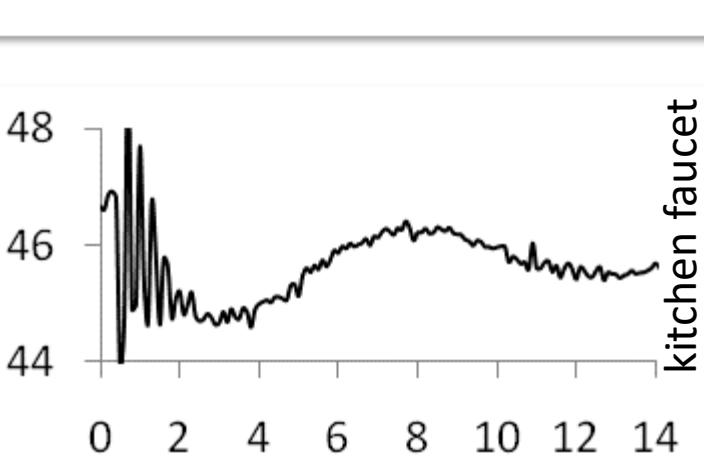
cepstrum_{unclassified}



shower



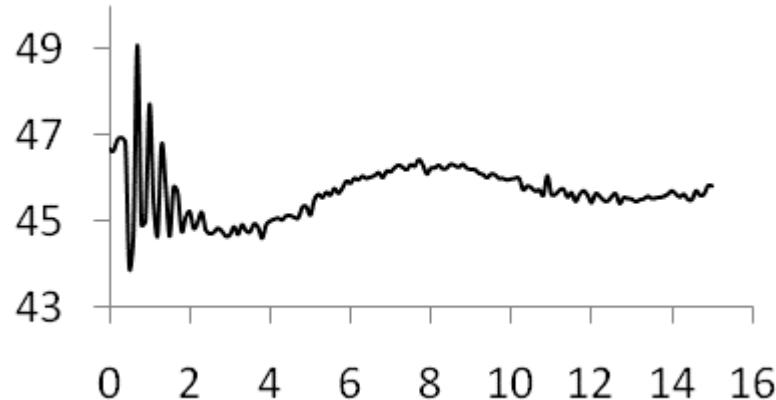
dishwasher



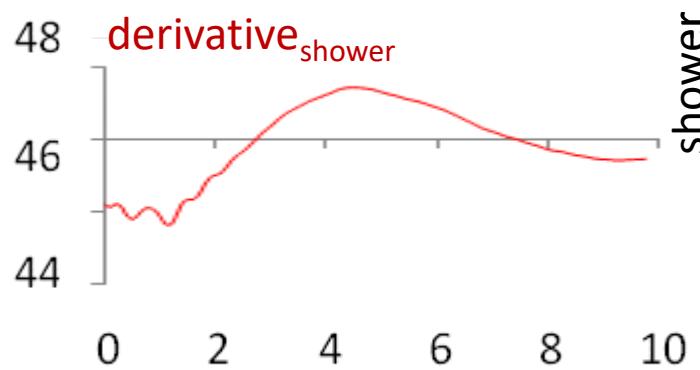
kitchen faucet



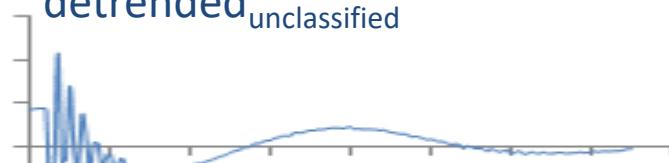
unclassified open event



open event library



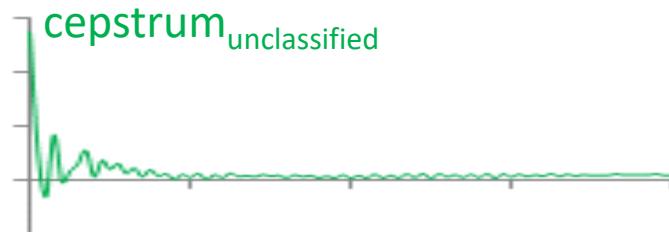
detrended_{unclassified}



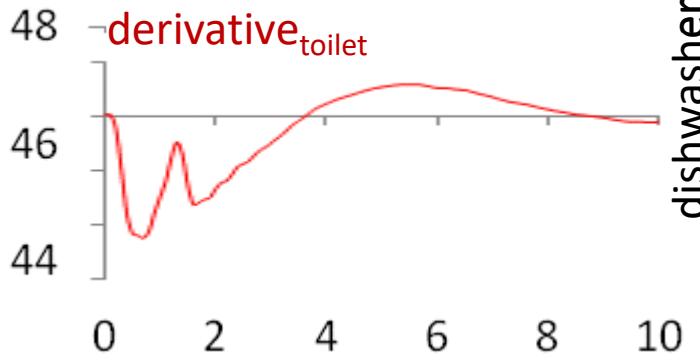
derivative_{unclassified}



cepstrum_{unclassified}



derivative_{toilet}



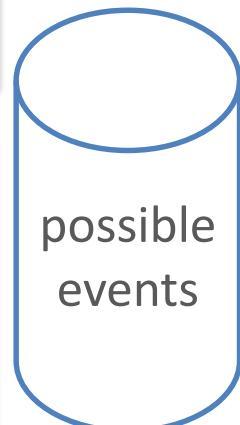
derivative_{kitchen faucet}



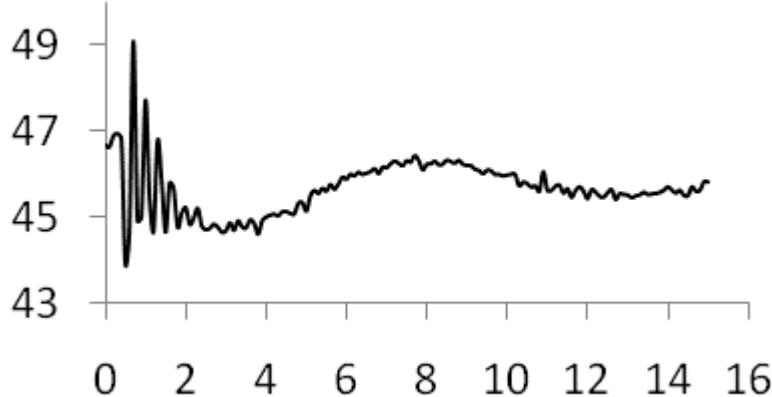
shower

dishwasher

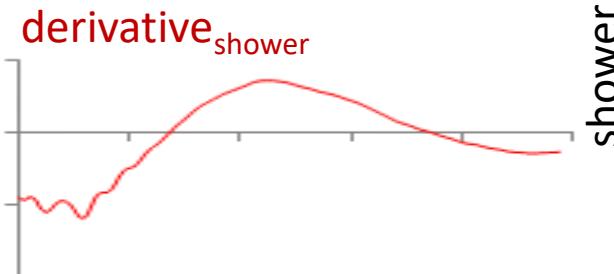
kitchen faucet



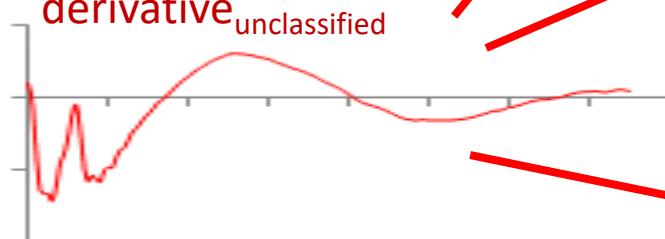
unclassified open event



open event library



nearest neighbor
match



shower

dishwasher

kitchen faucet



hydro study

#1

goal

study feasibility of using pressure
to disaggregate water usage

approach

controlled experiments across
10 homes

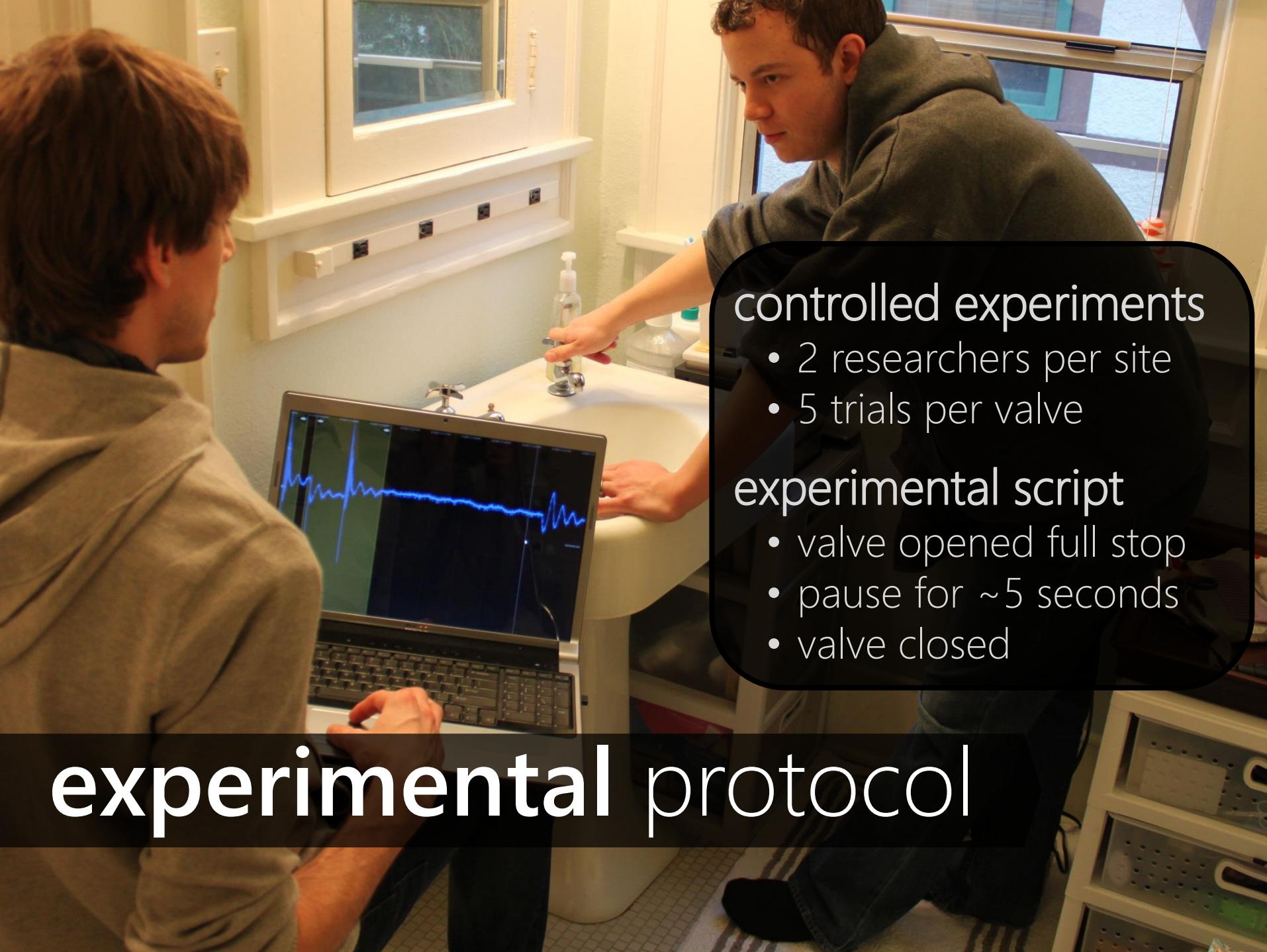
experimental protocol

controlled experiments

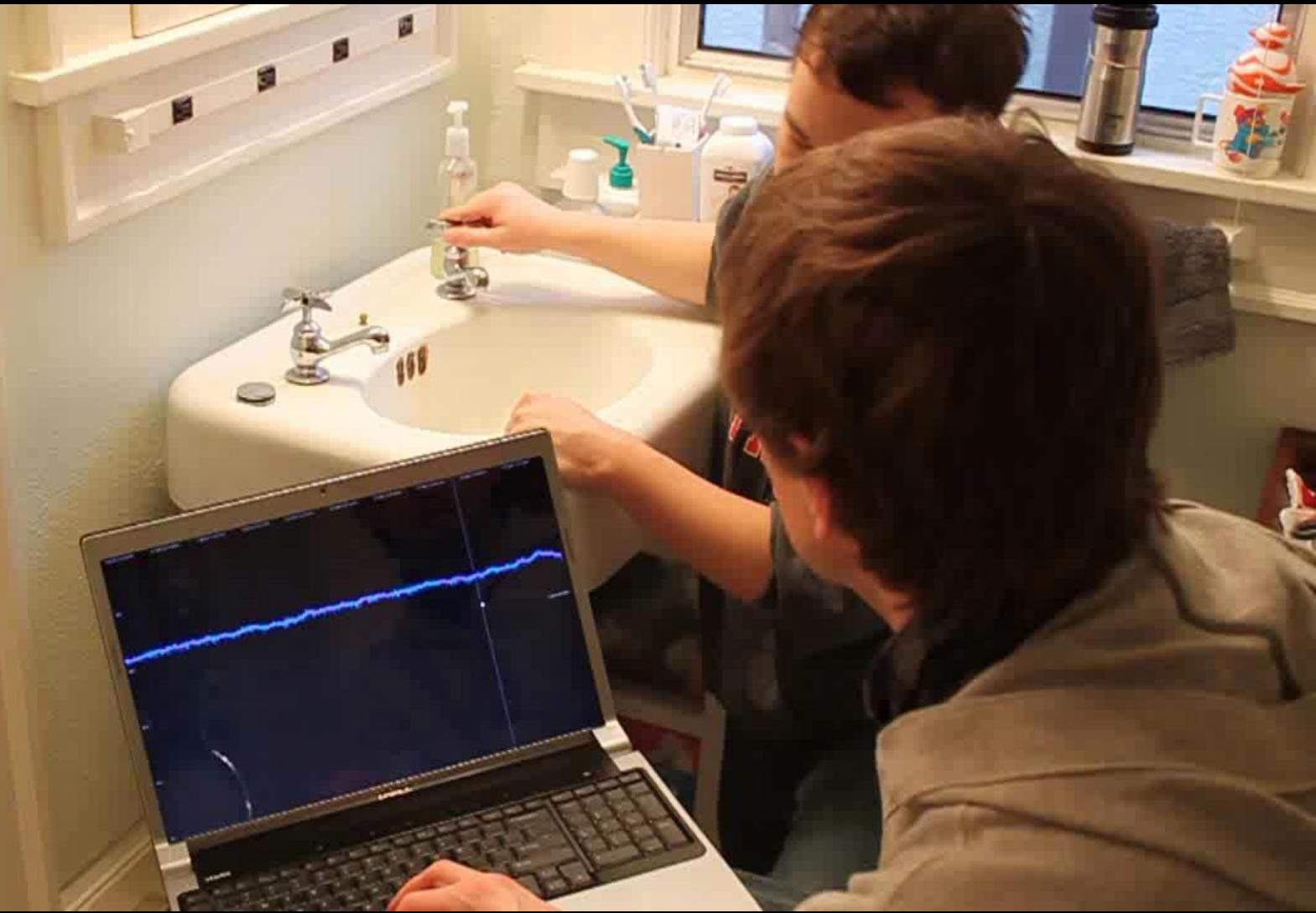
- 2 researchers per site
- 5 trials per valve

experimental script

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



controlled data collection



collecting flow data

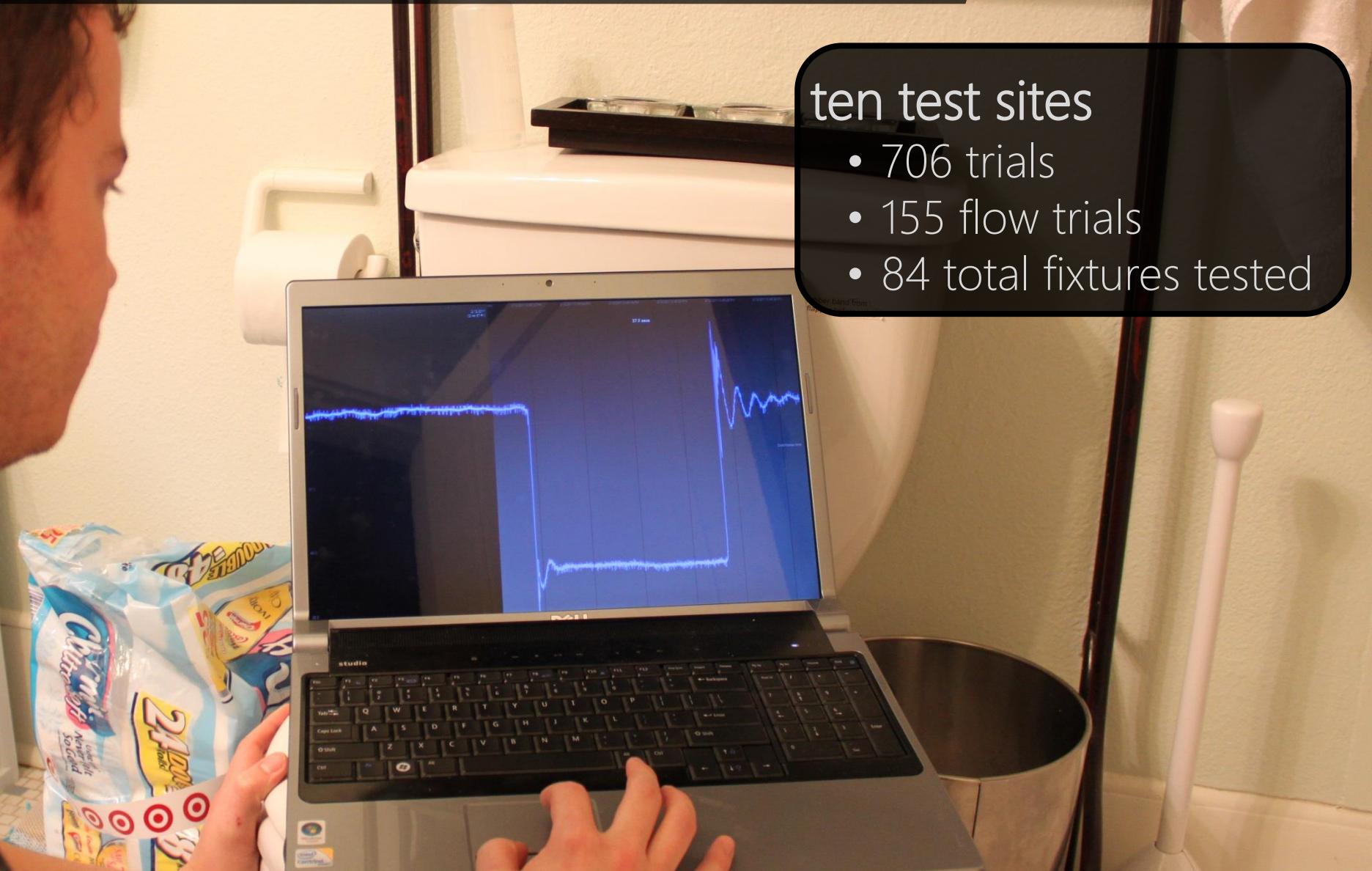


- 4 / 10 homes gathered flow data
- measure time to fill 1 gallon in a calibrated bucket

data collection stats

ten test sites

- 706 trials
- 155 flow trials
- 84 total fixtures tested

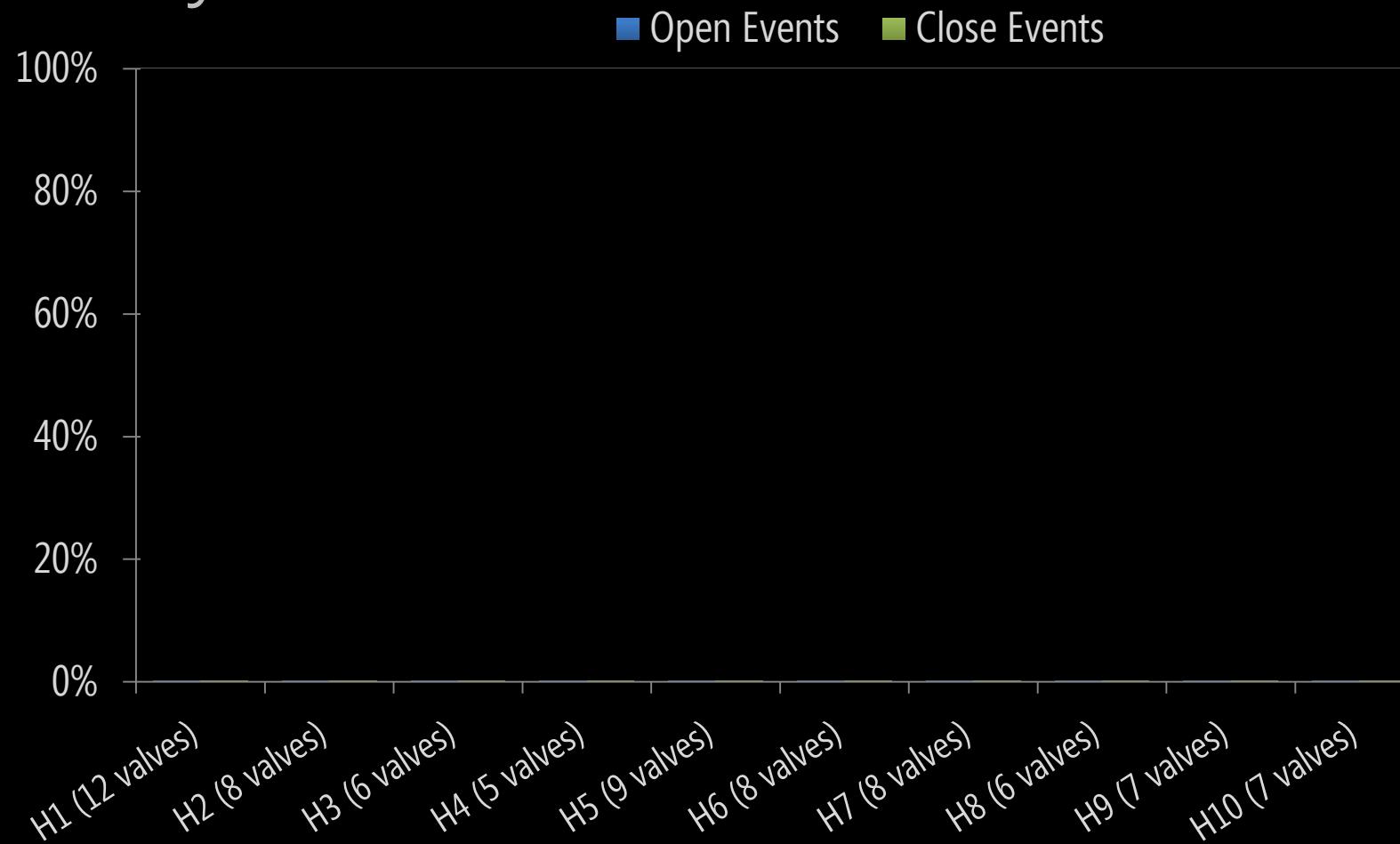


classification experiments

10-fold cross validation

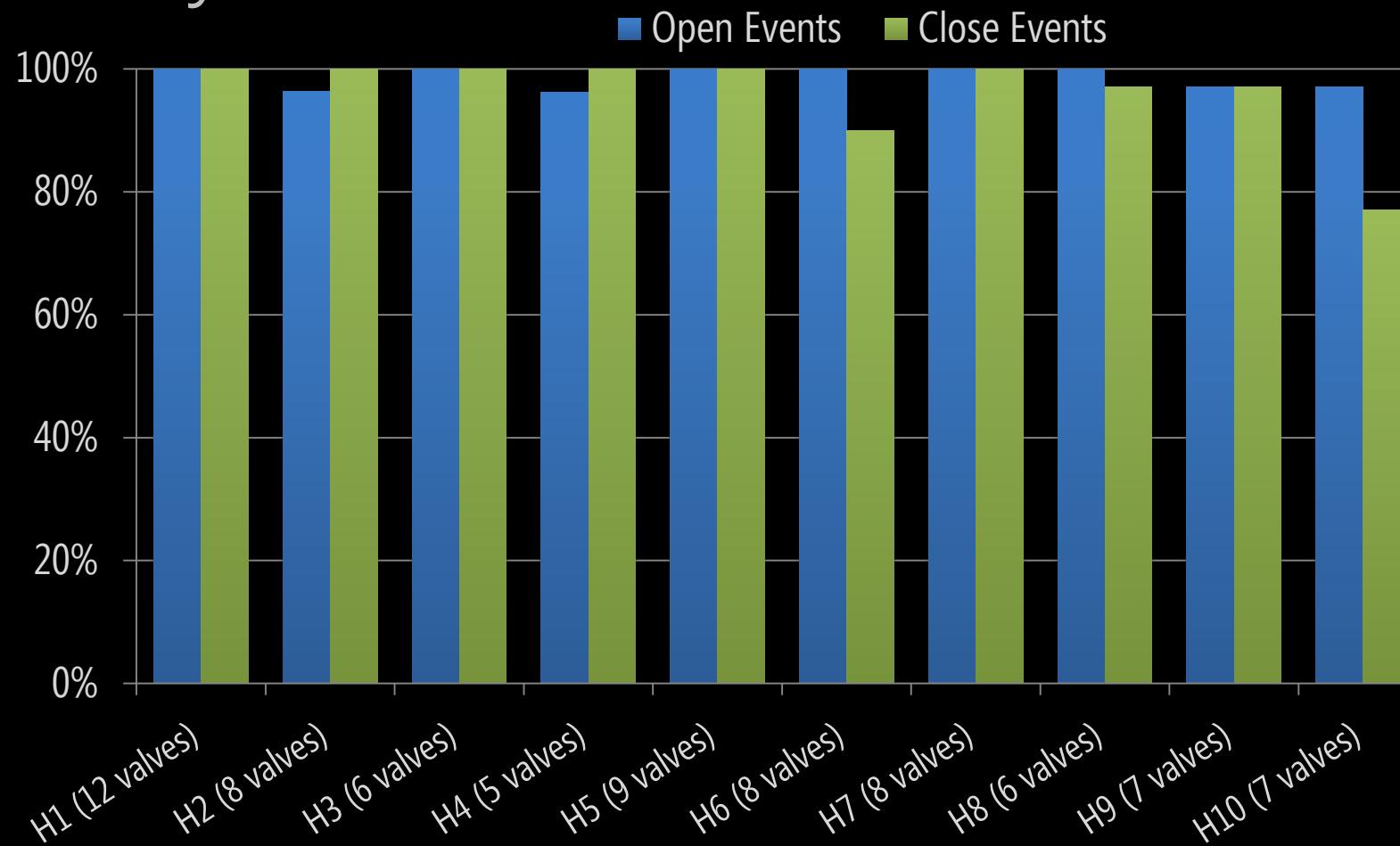
1. break data into 10 sets of size $n/10$
2. train on 9 datasets and test on 1
3. repeat for each combination of datasets
4. take mean accuracy

fixture classification results by home



10-fold cross validation

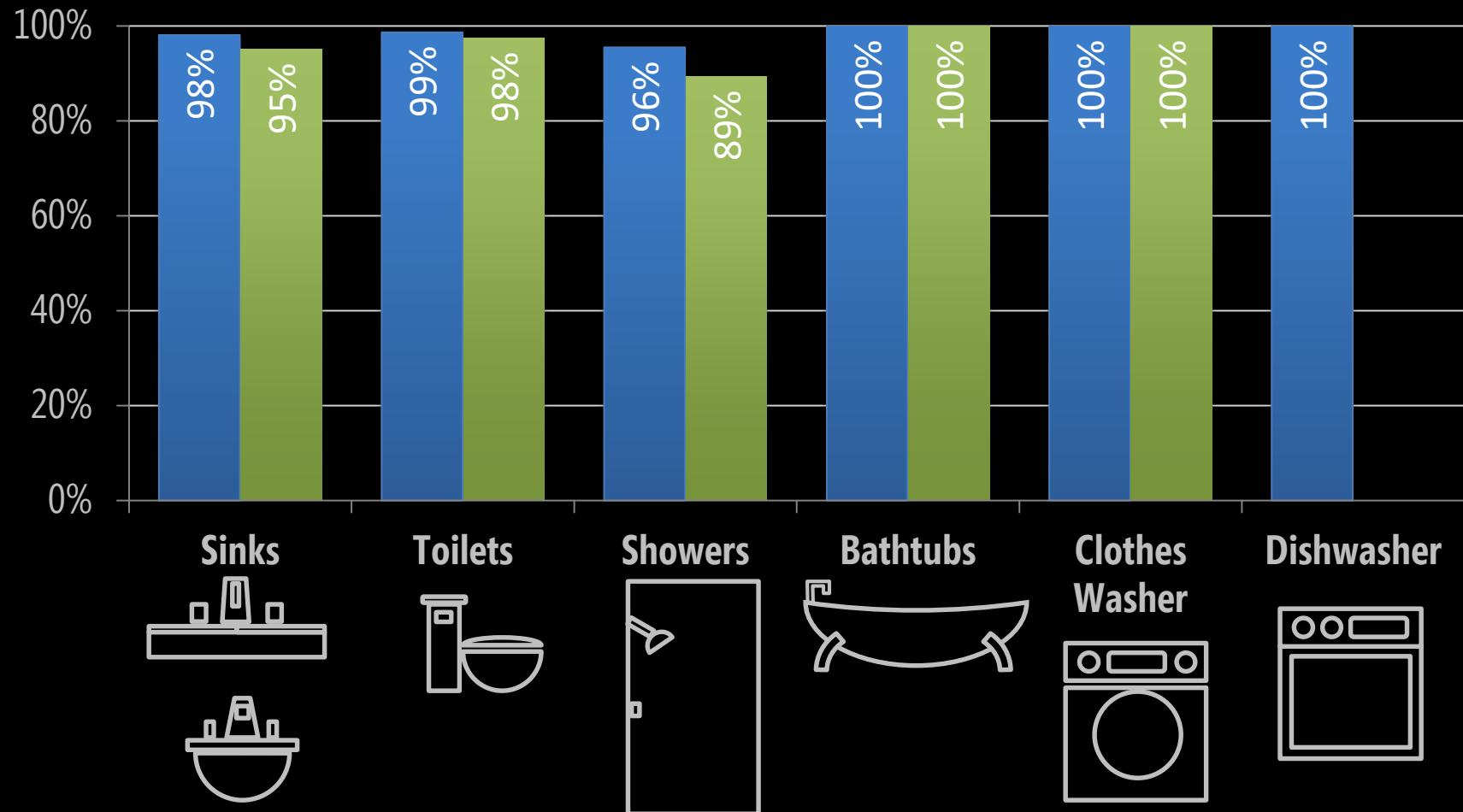
fixture classification results by home



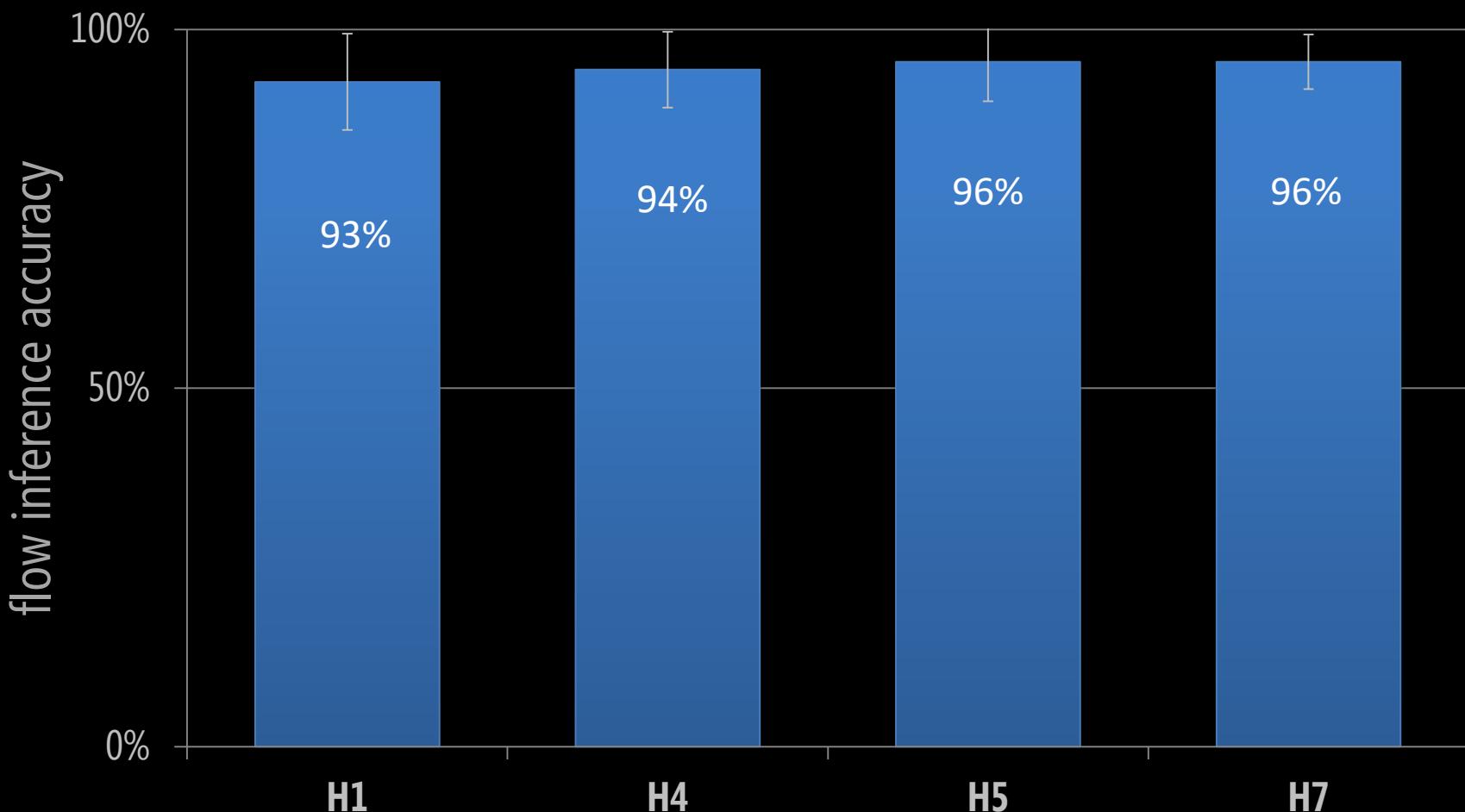
10-fold cross validation

fixture classification results by fixture

■ Open Events ■ Close Events



flow inference results by home



Within tolerances of domestic water meter accuracy; see [Arregui, 2003]

hydro study

#1

contributions

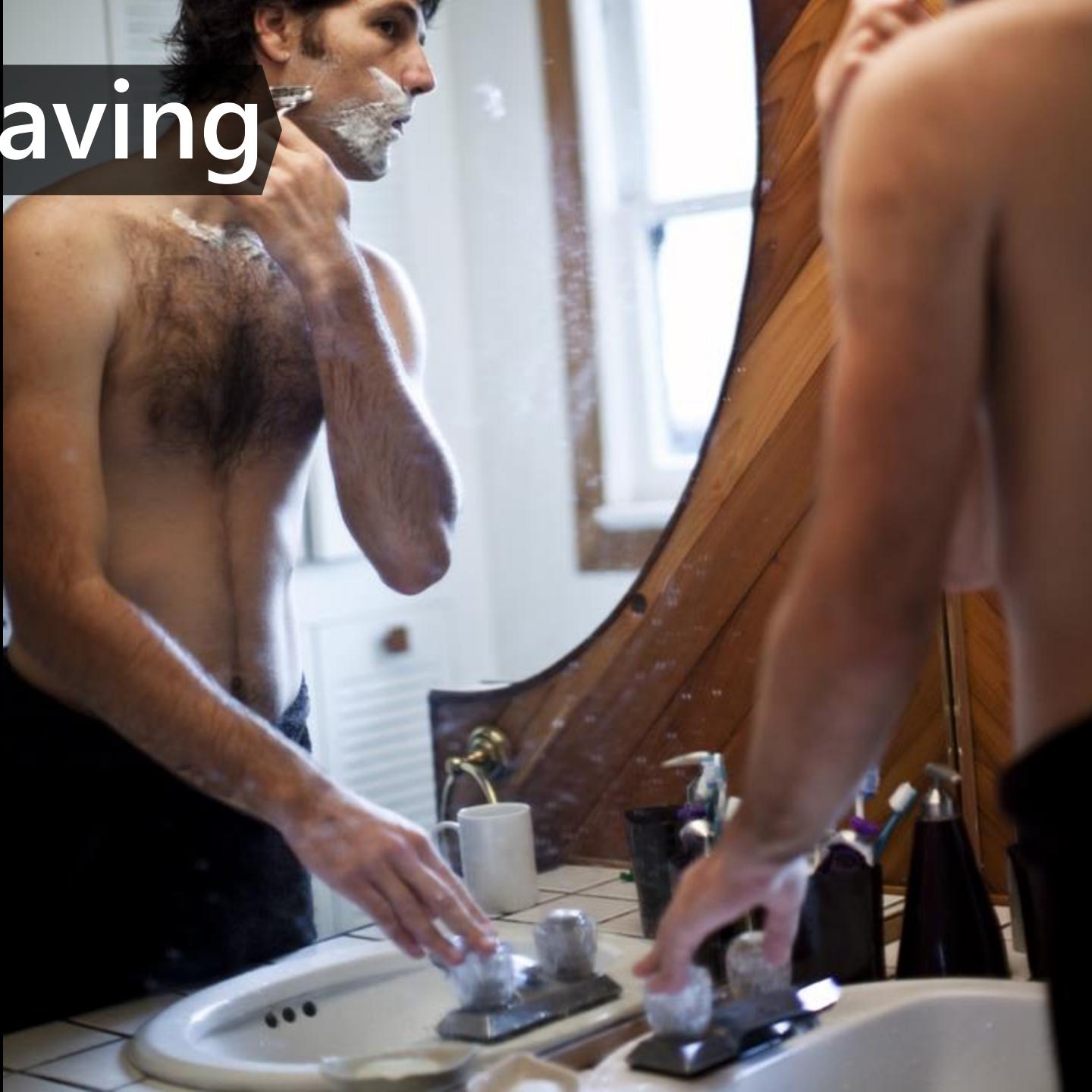
built and evaluated wireless
pressure sensor

first to show that pressure
could be used to disaggregate
water usage

brushing teeth



shaving

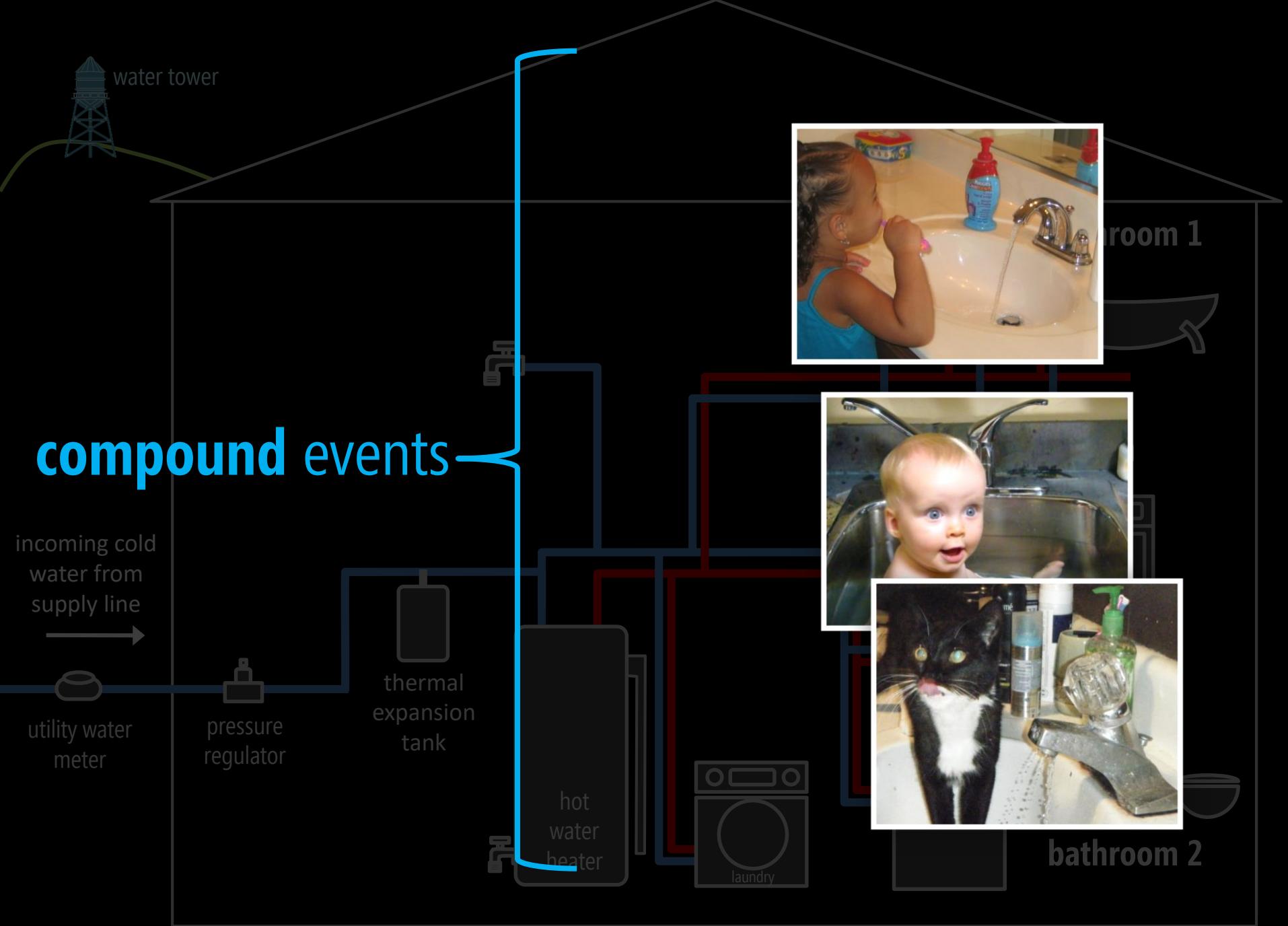


bathing



paw washing





hydro study

#2

goal

study how well hydrosense can
classify real world water usage

approach

5 week deployment in 5 homes



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

- the fixture used
- the water temperature

A photograph of a man from the side, wearing a brown button-down shirt. He is looking towards a computer monitor which displays a blue waveform. A large green speech bubble originates from the monitor and contains the text "Awesome! Marked it. Thanks Mr. Johnson". A blue speech bubble originates from the top right corner of the image and contains the text "I'm about to flush the toilet!"

I'm about to
flush the
toilet!

Awesome!
Marked it. Thanks
Mr. Johnson

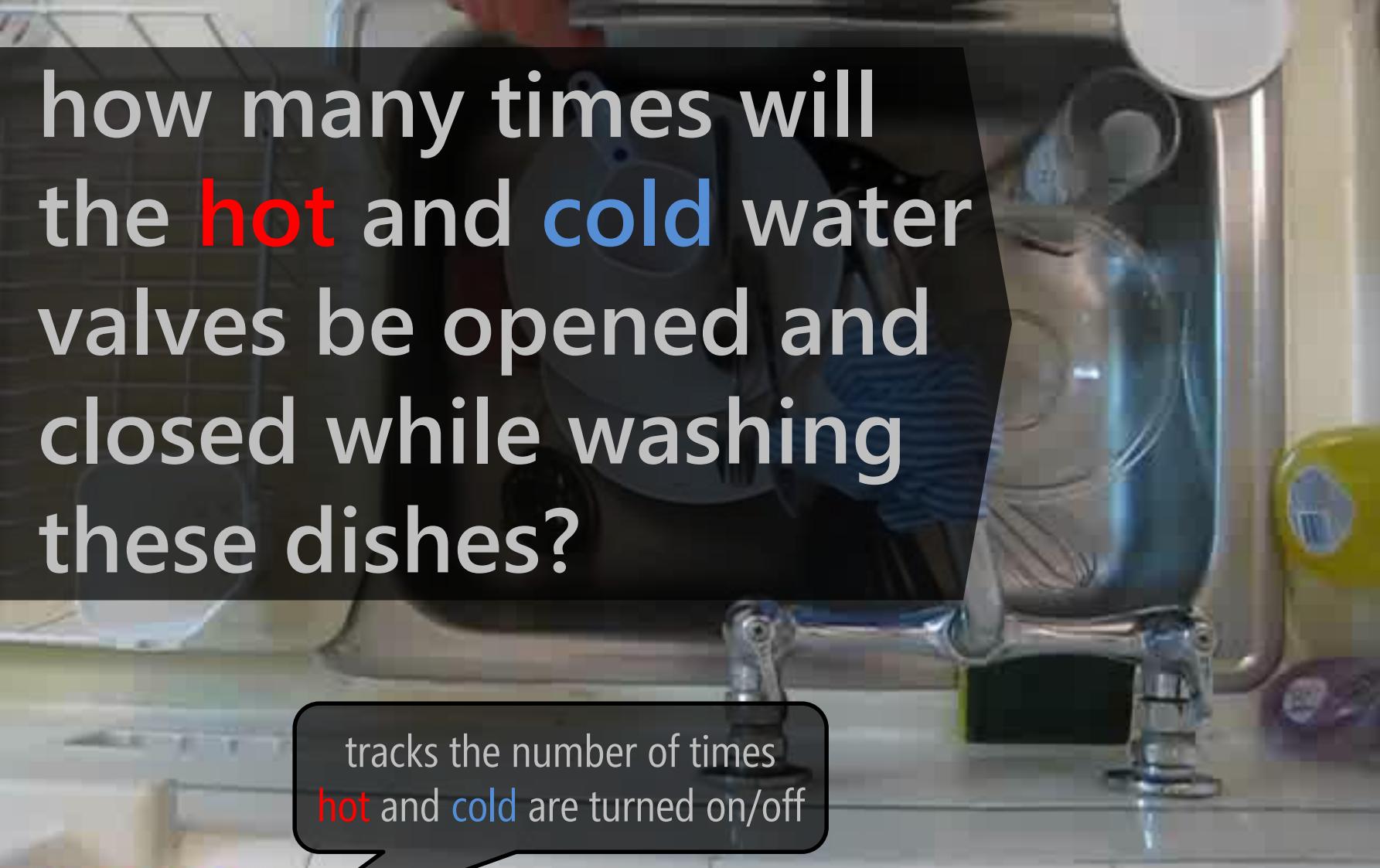
h O W

can we record real-
world water usage?

*collect ground
truth labels of*

wireless buttons





how many times will
the **hot** and **cold** water
valves be opened and
closed while washing
these dishes?

tracks the number of times
hot and **cold** are turned on/off



hot: 0
cold: 0

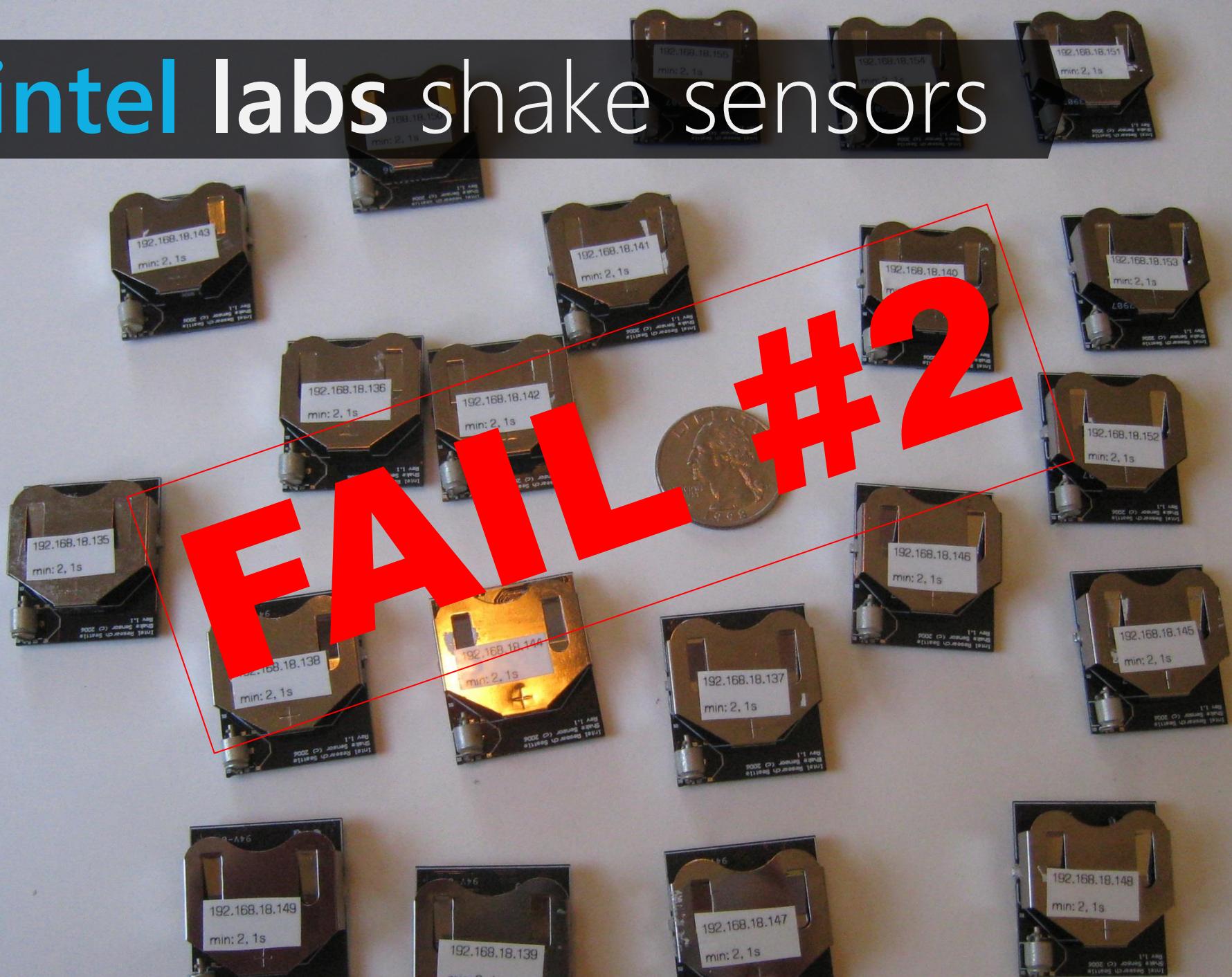
wireless buttons



other failed solutions



intel labs shake sensors



thermistors

FAIL #3

nike+ piezo sensor





Can the Nike+iPod Detect Water Facuet Handle Movement

jonfroehlich

Subscribe

6 videos ▾



0:11 / 1:06



Like



Share



Download



4,244



0 likes, 16 dislikes

Uploaded by [jonfroehlich](#) on Aug 7, 2009

The HydroSense team conducted a set of short, simple experiments investigating whether the Nike+iPod piezoelectric sensor could be used to detect faucet open/close handle movements.

Show more



Ad

**Insane Home Chest Workout**

by sixpackshortcuts

1,011,603 views

Ad

**Do it yourself DIY Nike+iPod pouch**

by iamjames2

217,165 FEATURED VIDEO

**How to split open a Nike+ iPod sensor**

by cadnyc

75,883 views

**tDL Product Review: Nike Plus Sport Kit**

our solution...



custom
direct
sensors



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

function across fixtures



kitchen sink



bathroom sink



bath



shower



toilet



laundry basin

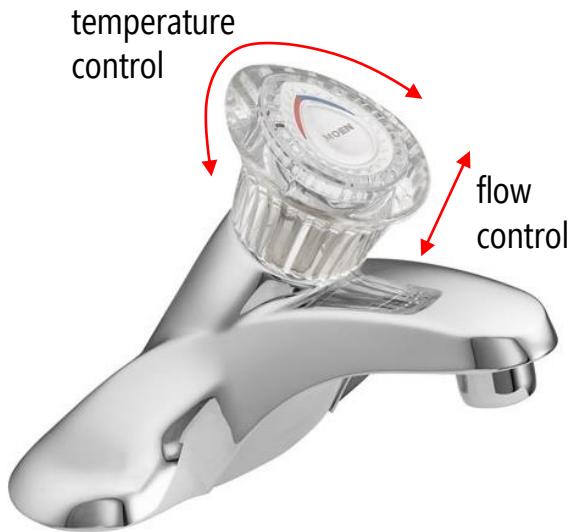


washing machine

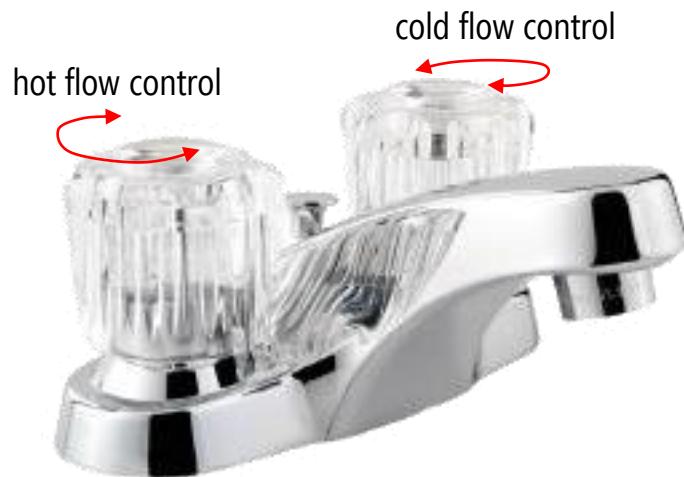


dishwasher

challenge: fixture diversity



single handle faucet

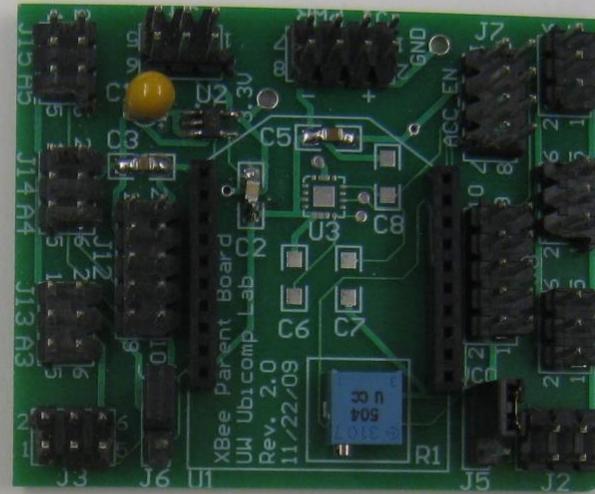


dual handle faucet

custom ground truth data collection system



xbee wireless modem



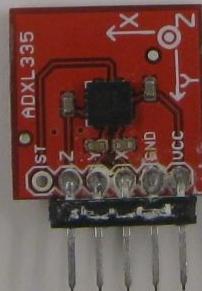
fixture usage sensor board



hall effect



reed switch



3-axis accelerometer



unidirectional ball switch

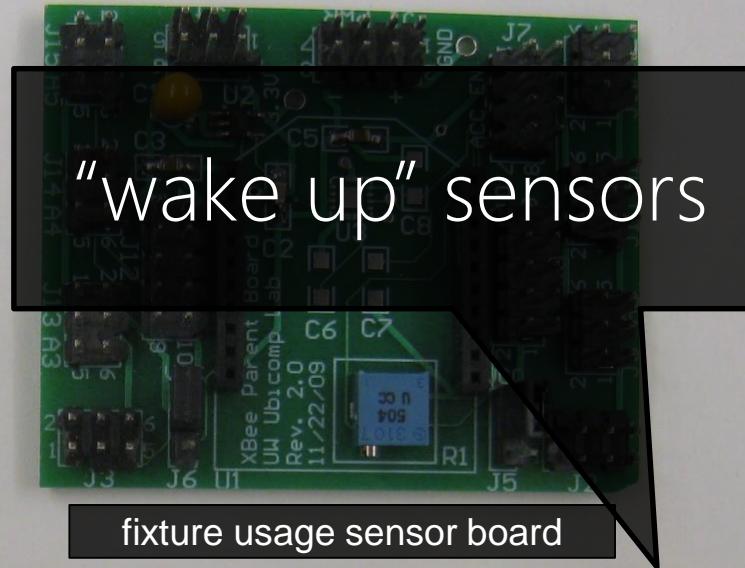


omnidirectional ball switch

custom ground truth data collection system



xbee wireless modem



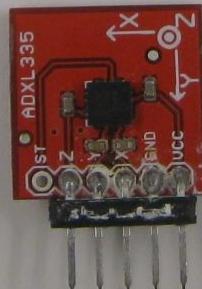
fixture usage sensor board



hall effect



reed switch



3-axis accelerometer



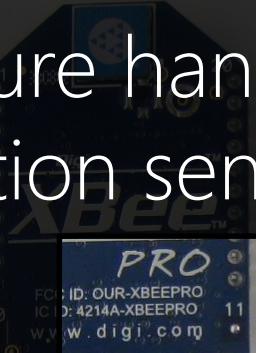
unidirectional ball switch



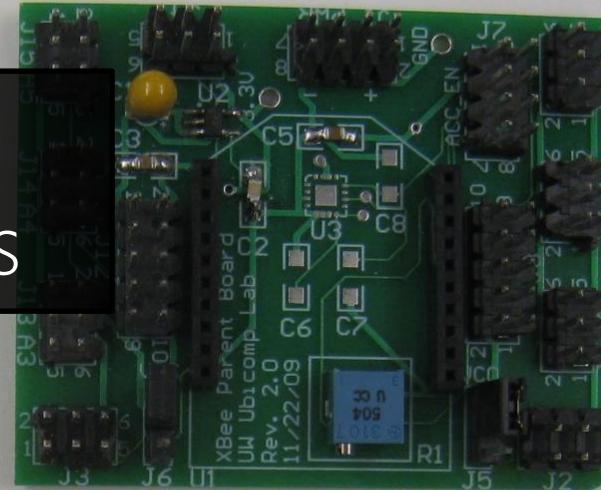
omnidirectional ball switch

custom ground truth data collection system

fixture handle
position sensors



xbee wireless modem



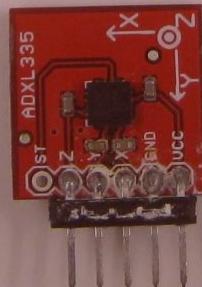
fixture usage sensor board



hall
effect



reed
switch



3-axis
accelerometer



unidirectional ball
switch



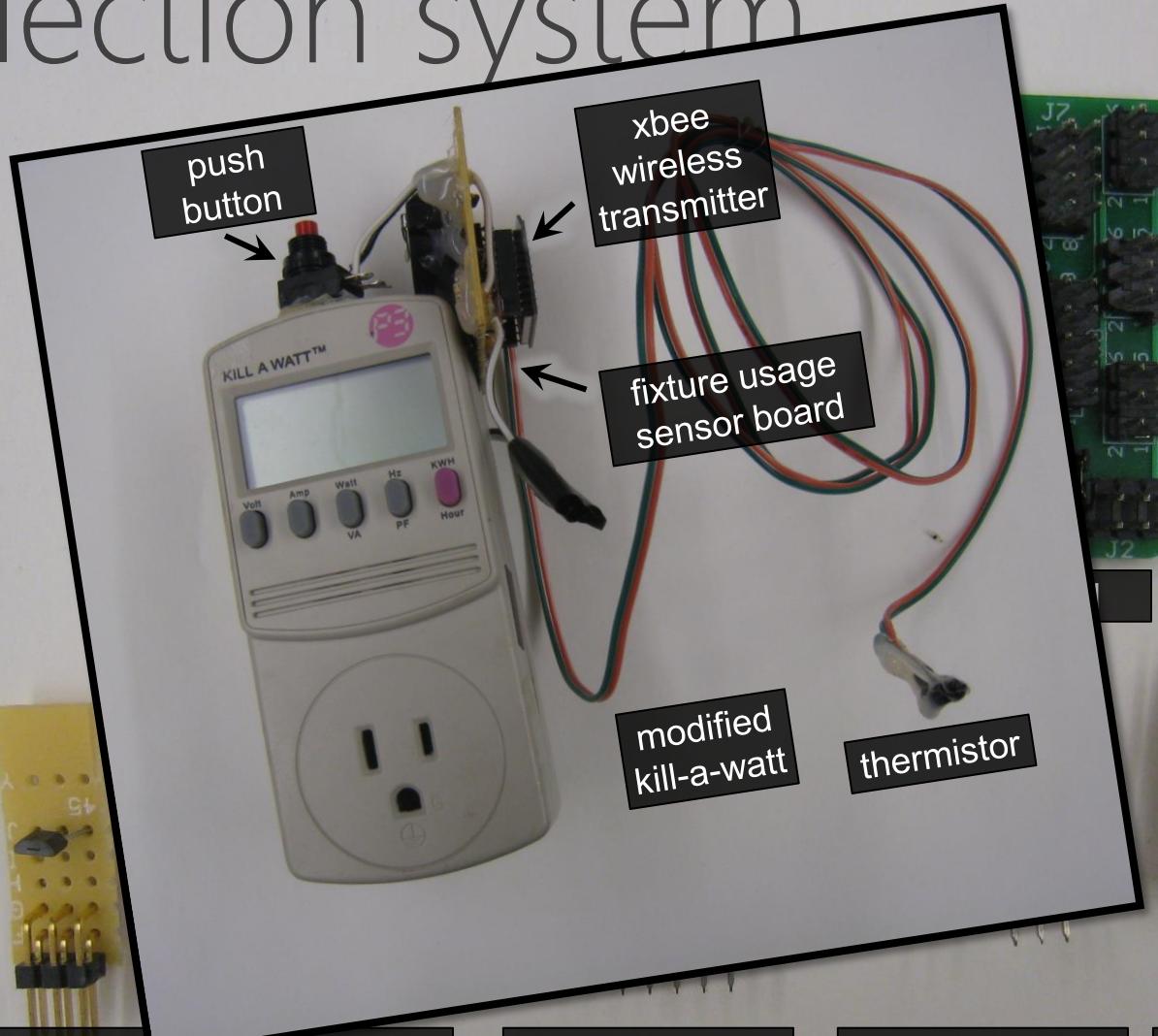
omnidirectional
ball switch



accelerometer



custom ground truth data collection system



hall effect

reed switch

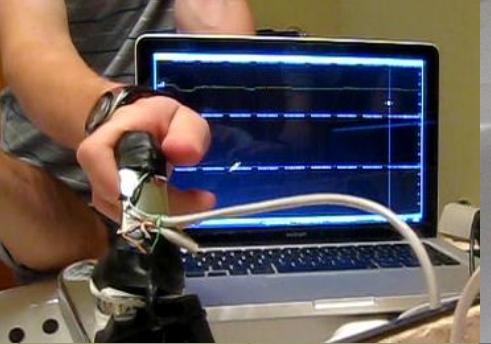
3-axis accelerometer

unidirectional ball switch

omnidirectional ball switch

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





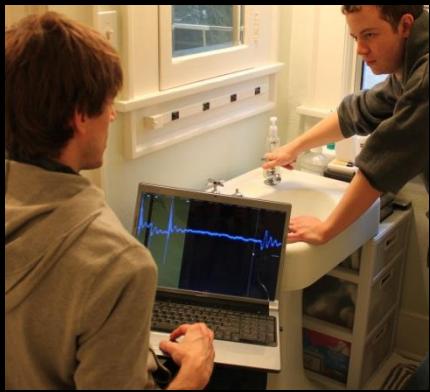




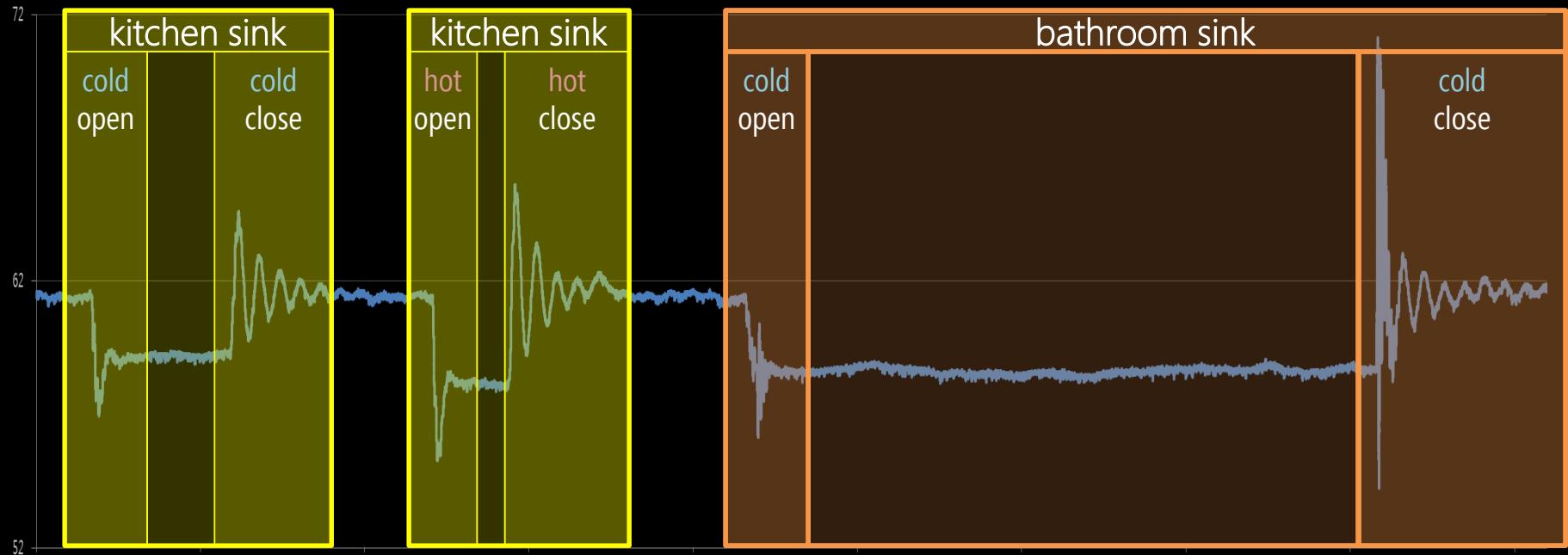




ground truth labels

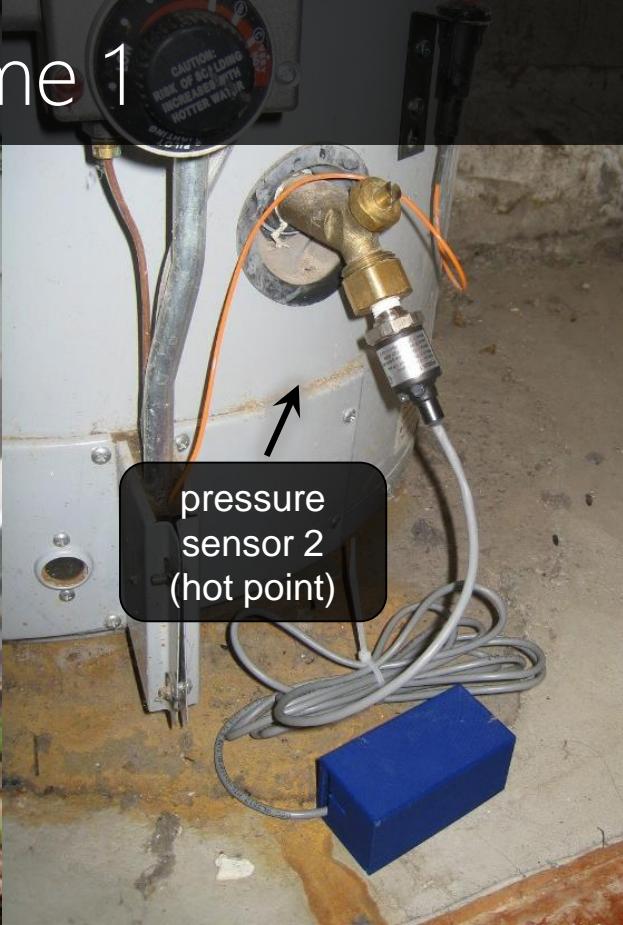


manual → automatic



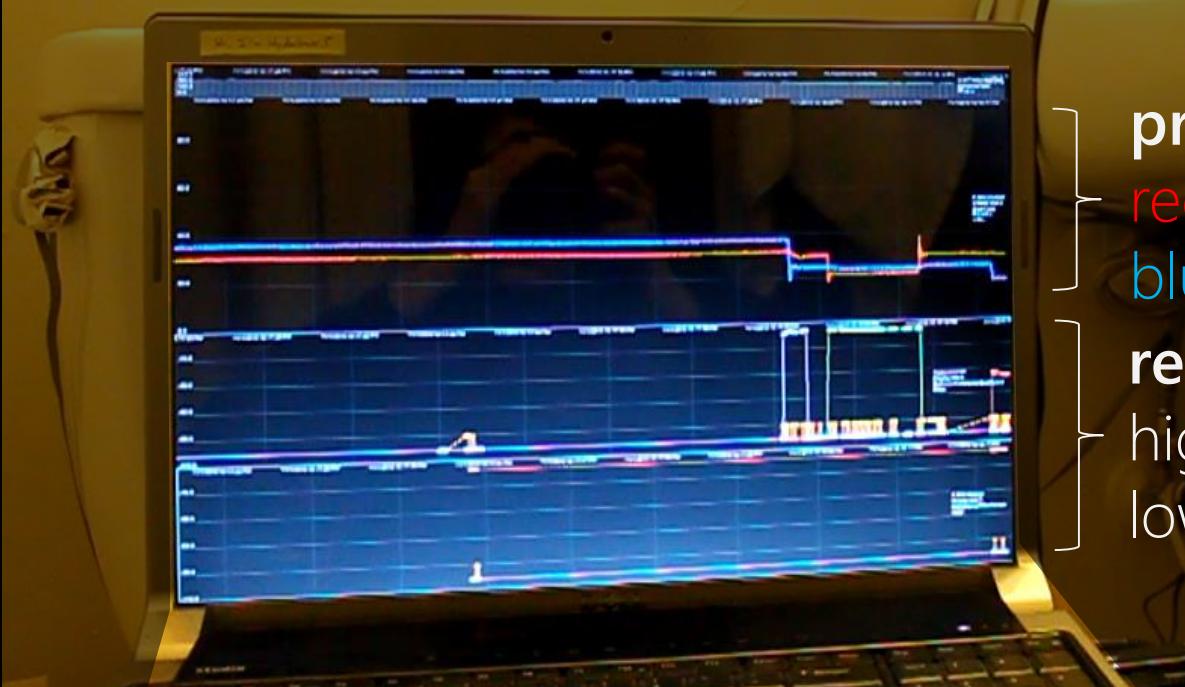
two pressure sensors per home

home 1



hydrosense data logger

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



pressure stream

red = hot line

blue = cold line

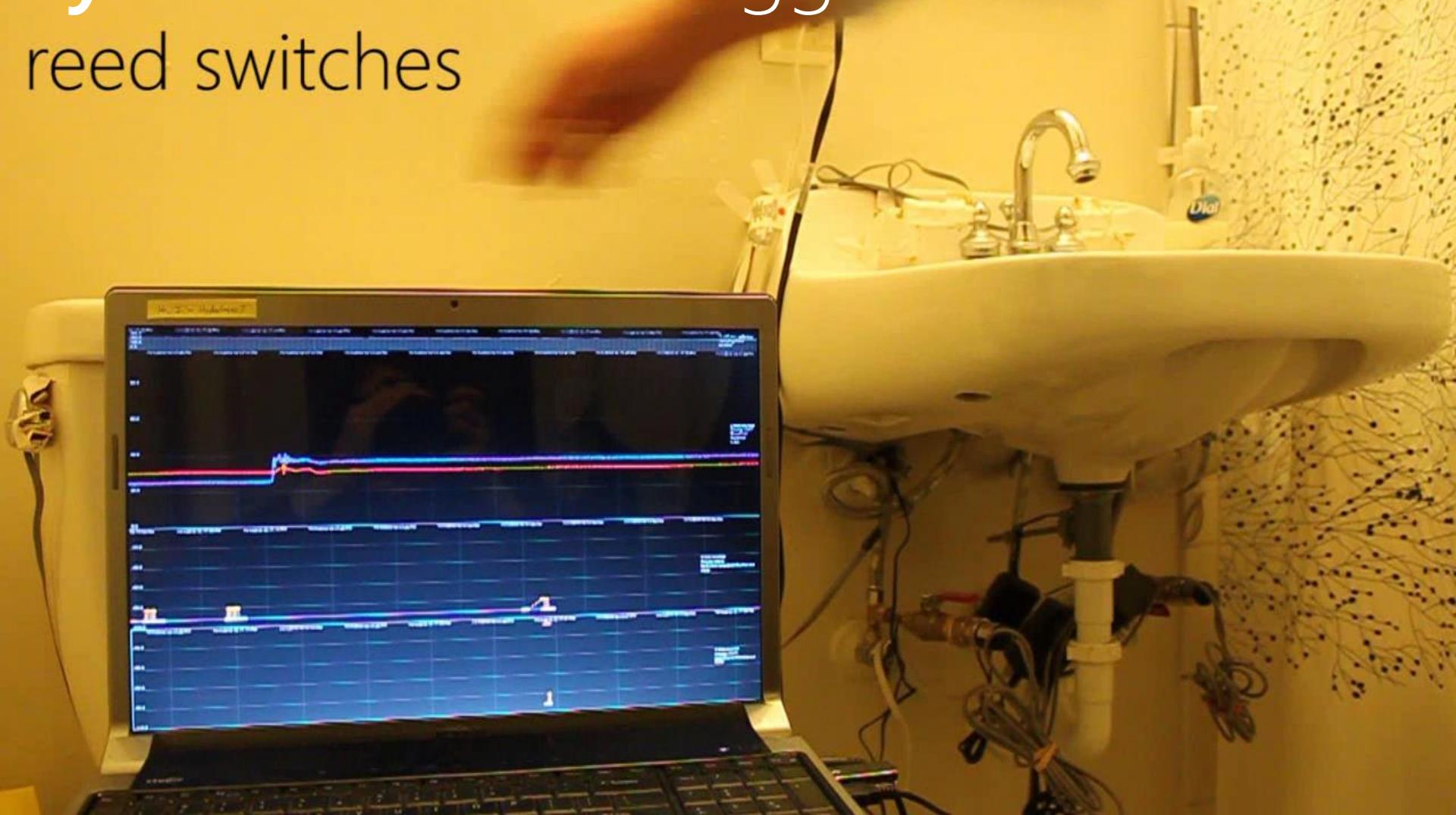
reed switches

high = active

low = inactive

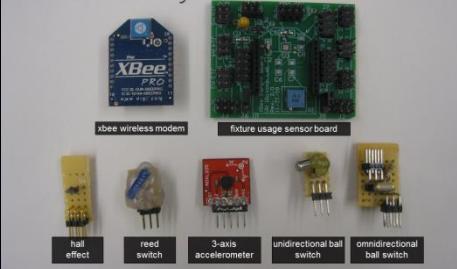
hydroSense data logger

reed switches



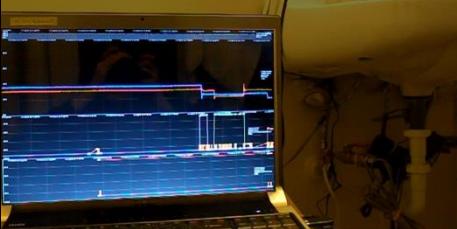
hydro deployment infrastructure

custom ground truth data collection system



hydrosense data logger

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



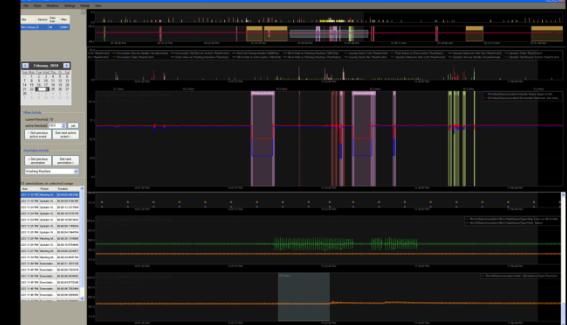
two pressure sensors



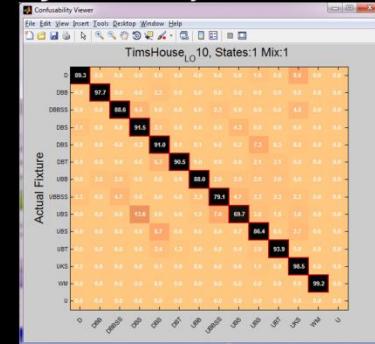
on-site sensing infrastructure

python web backend

hydrovisualizer



hydroanalyzer



c# and matlab analysis tools

hydroSense annotations

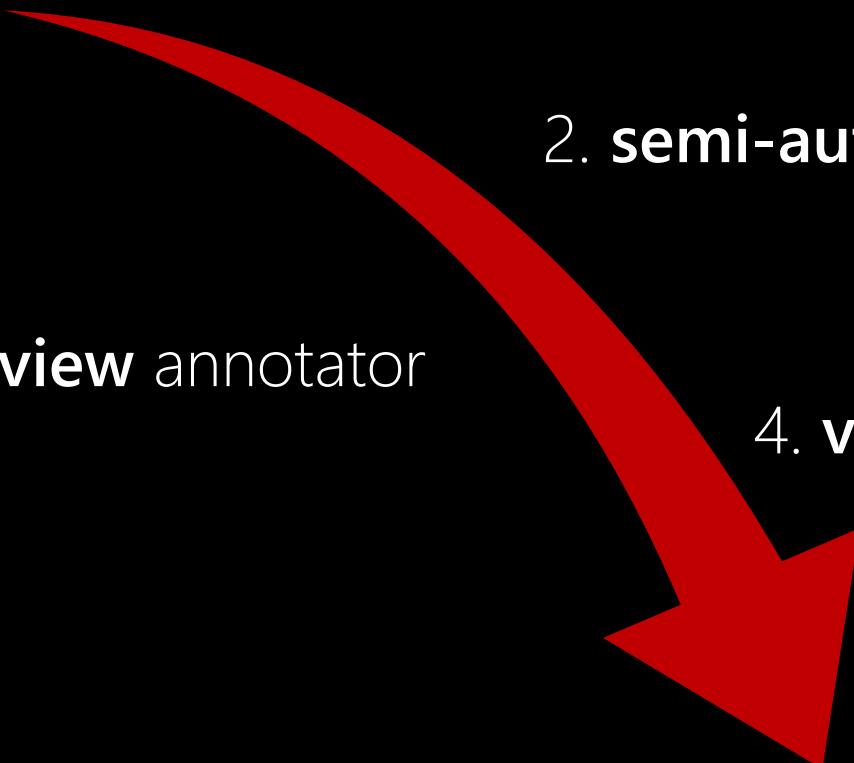
1. **ground truth** sensor

2. **semi-automated** label

3. **review** annotator

4. **verification**

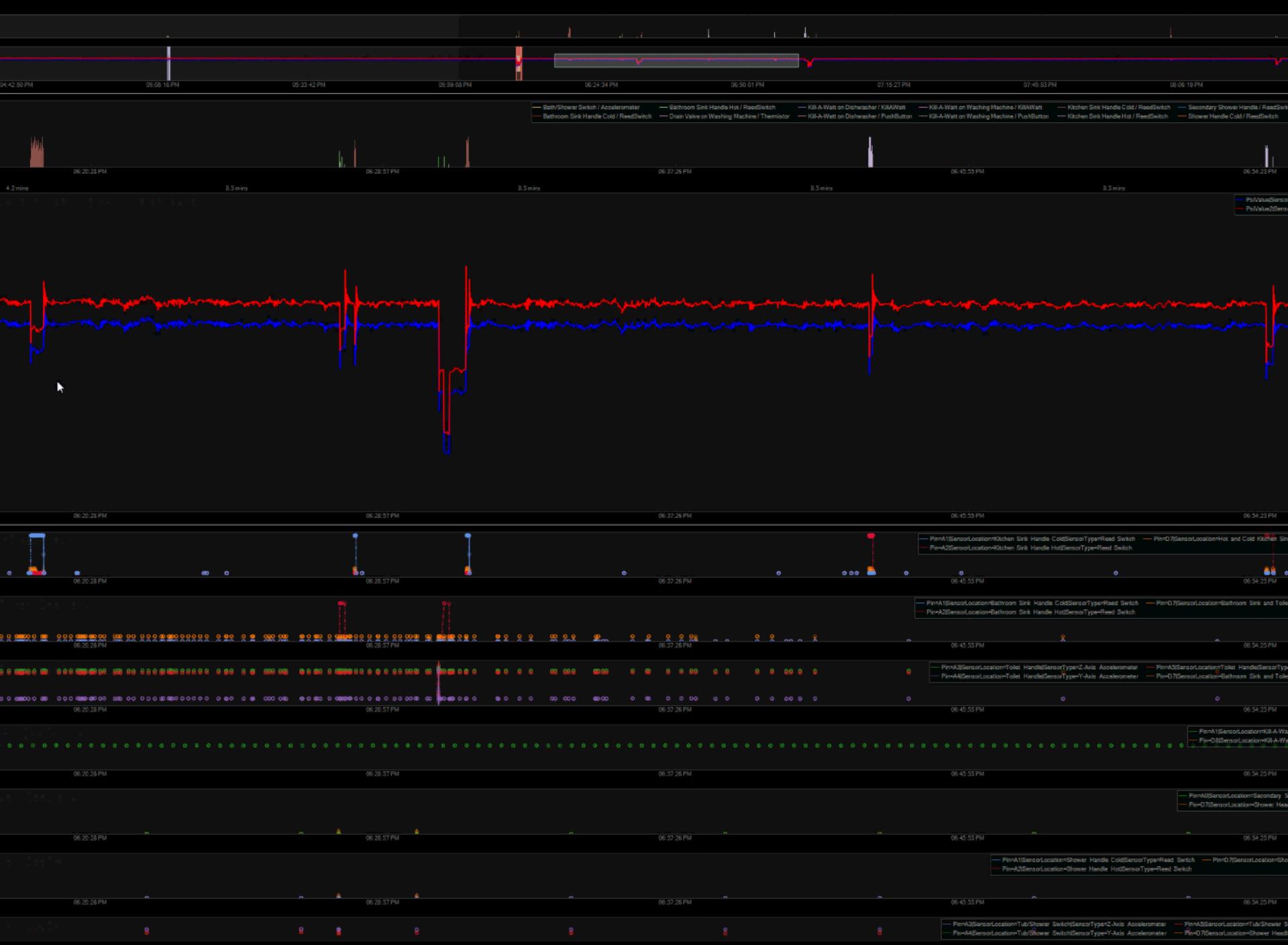
5. **final** label







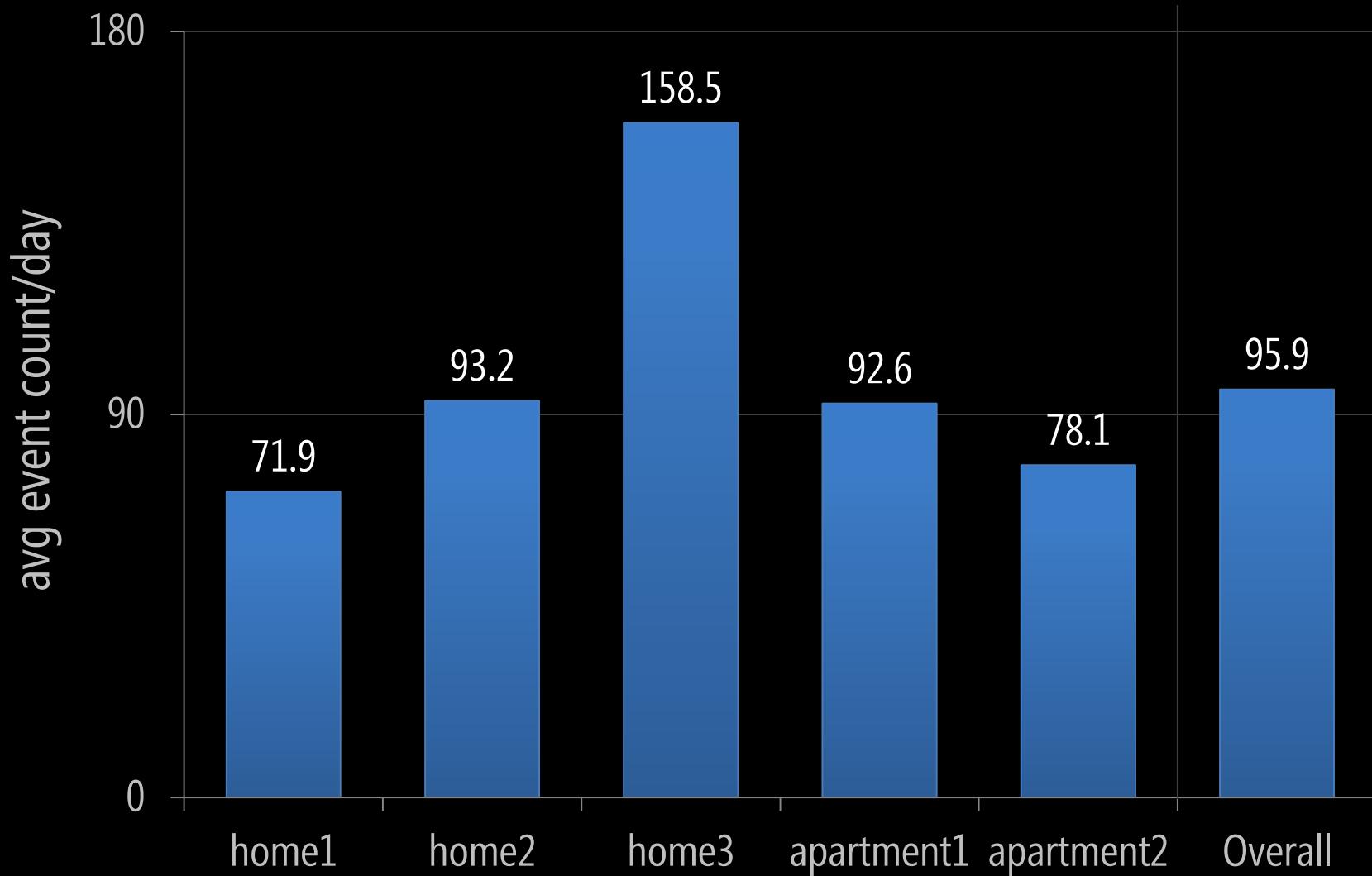




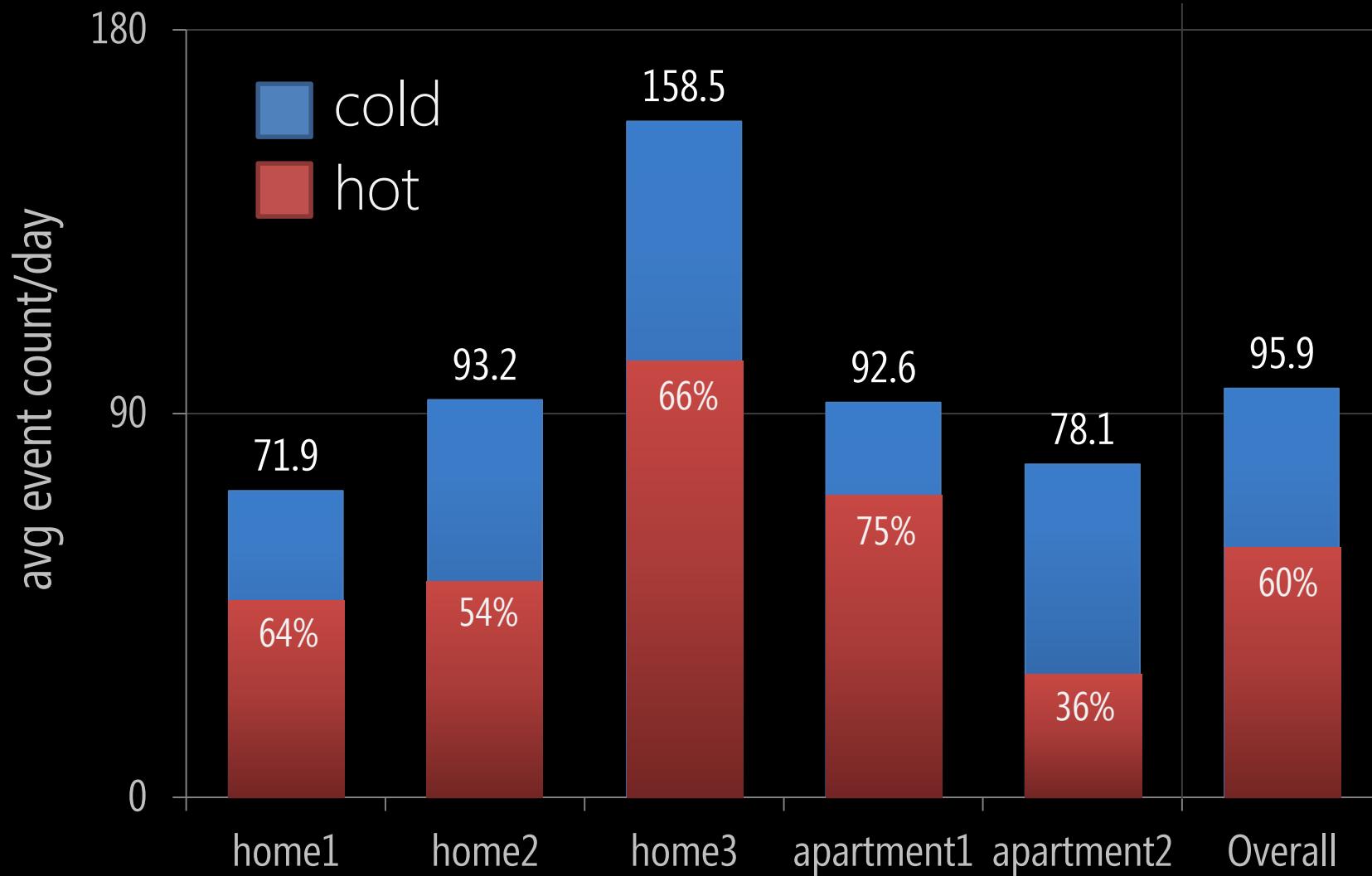
5-week dataset

						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

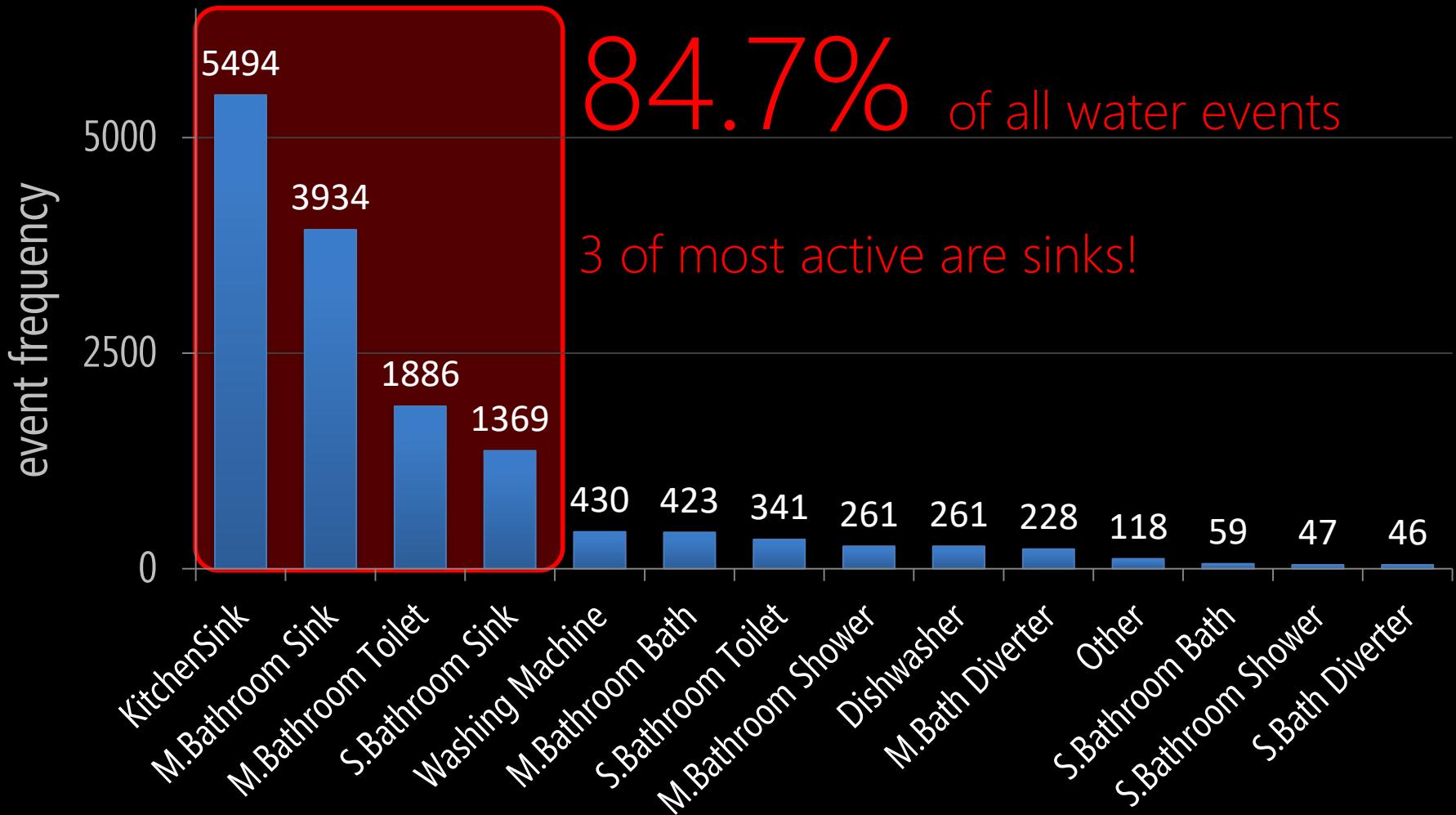
avg num water events/day

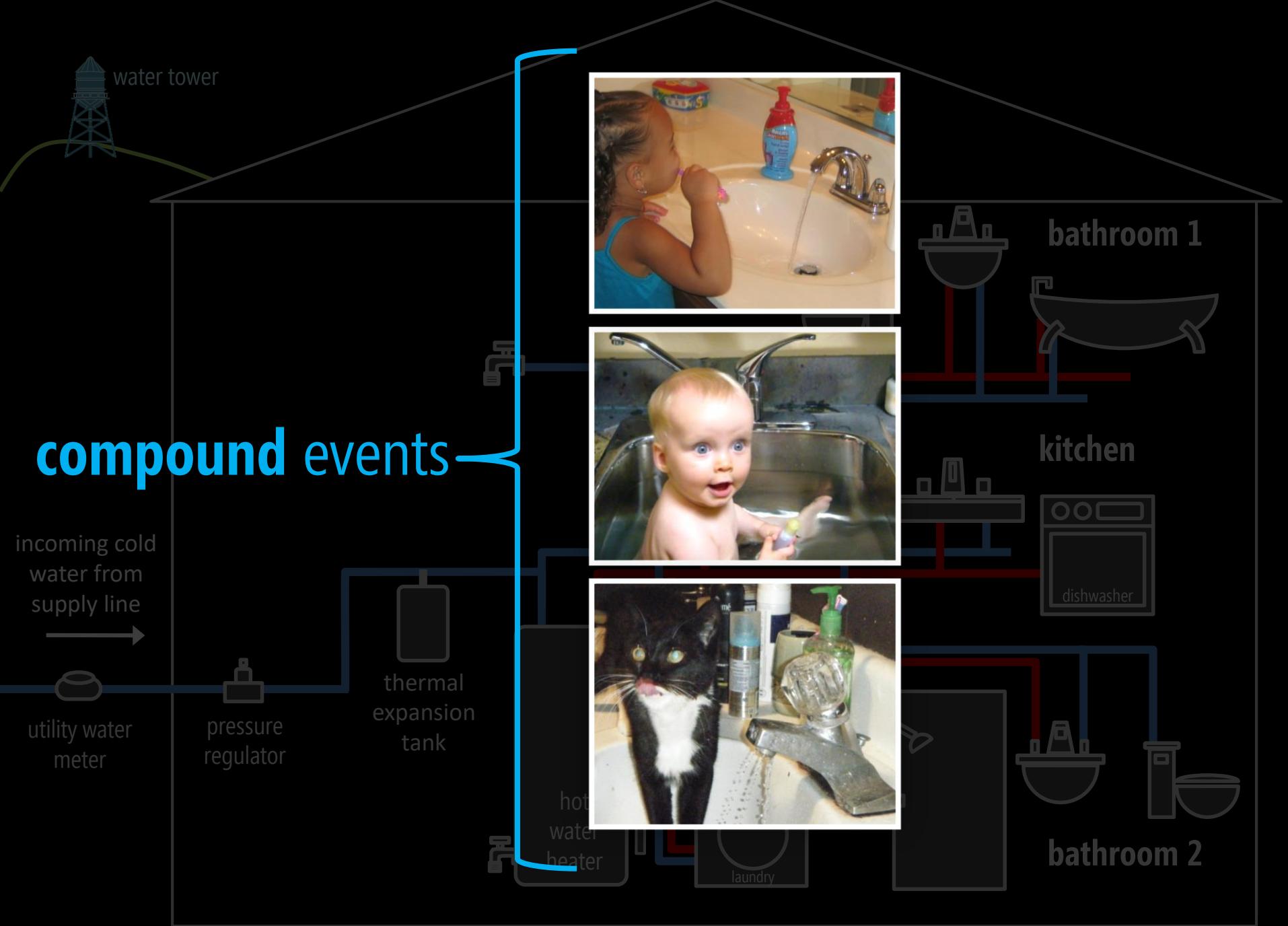


avg num water events/day



fixture activity frequency





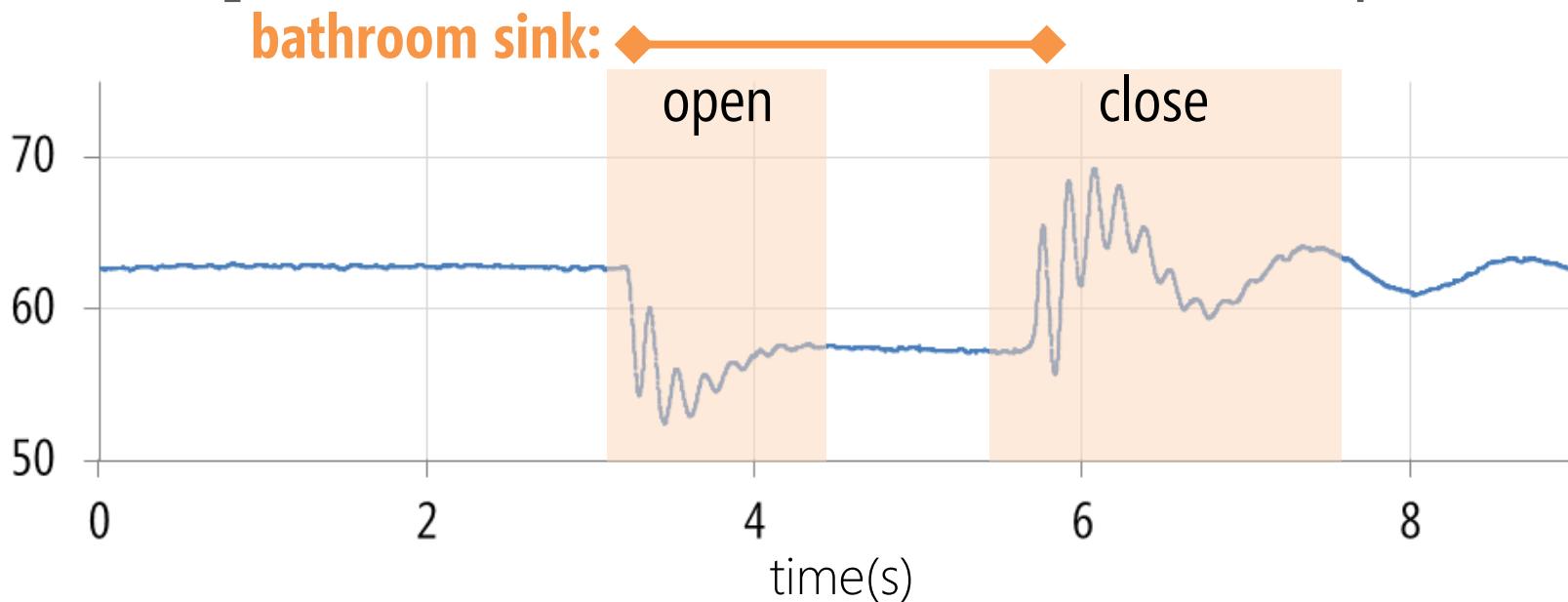
22%

of all water events were compound

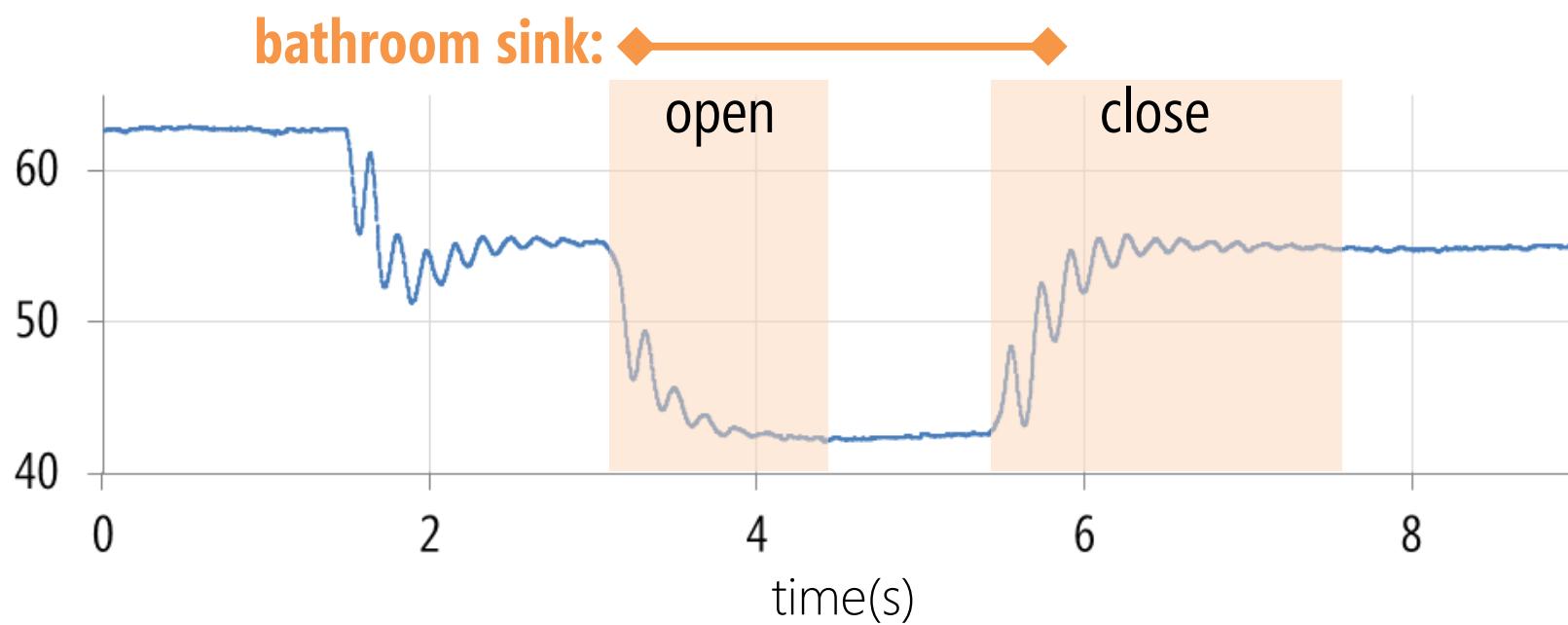
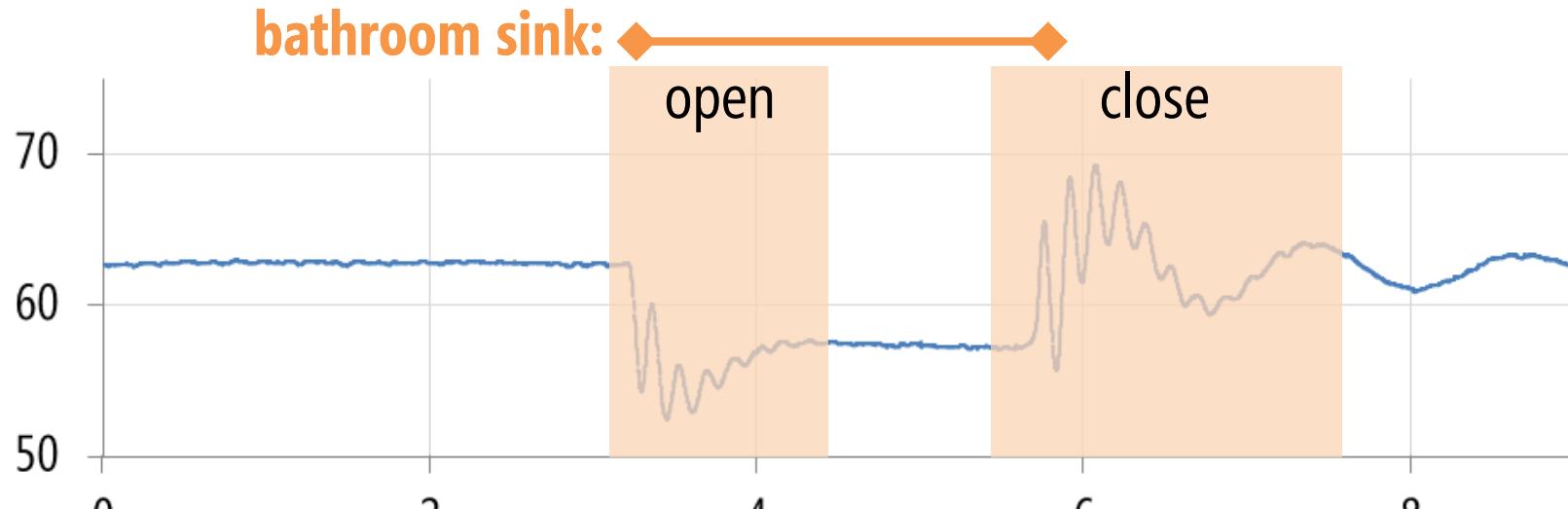
41.8%

of all bathroom sink events were compound

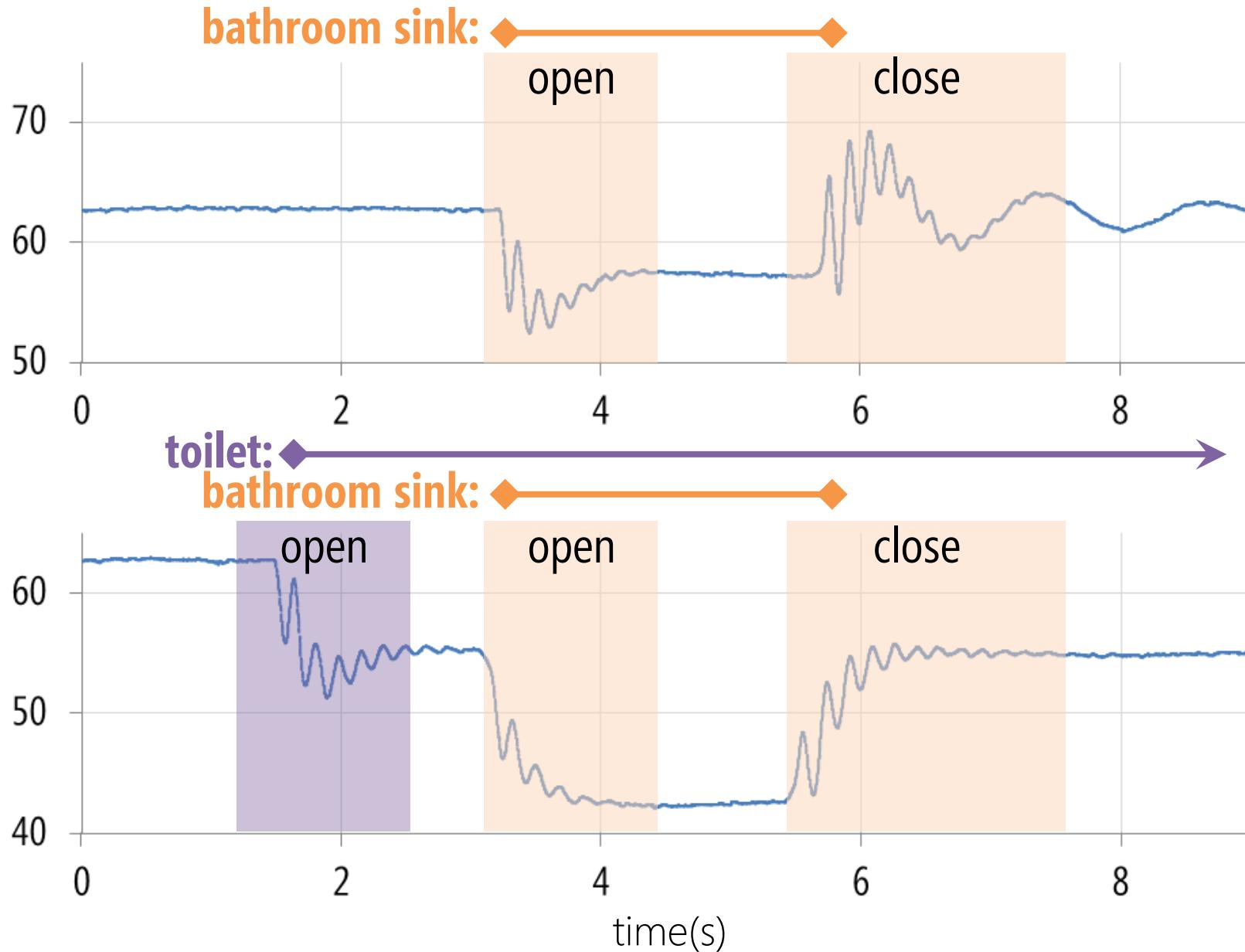
compound event example



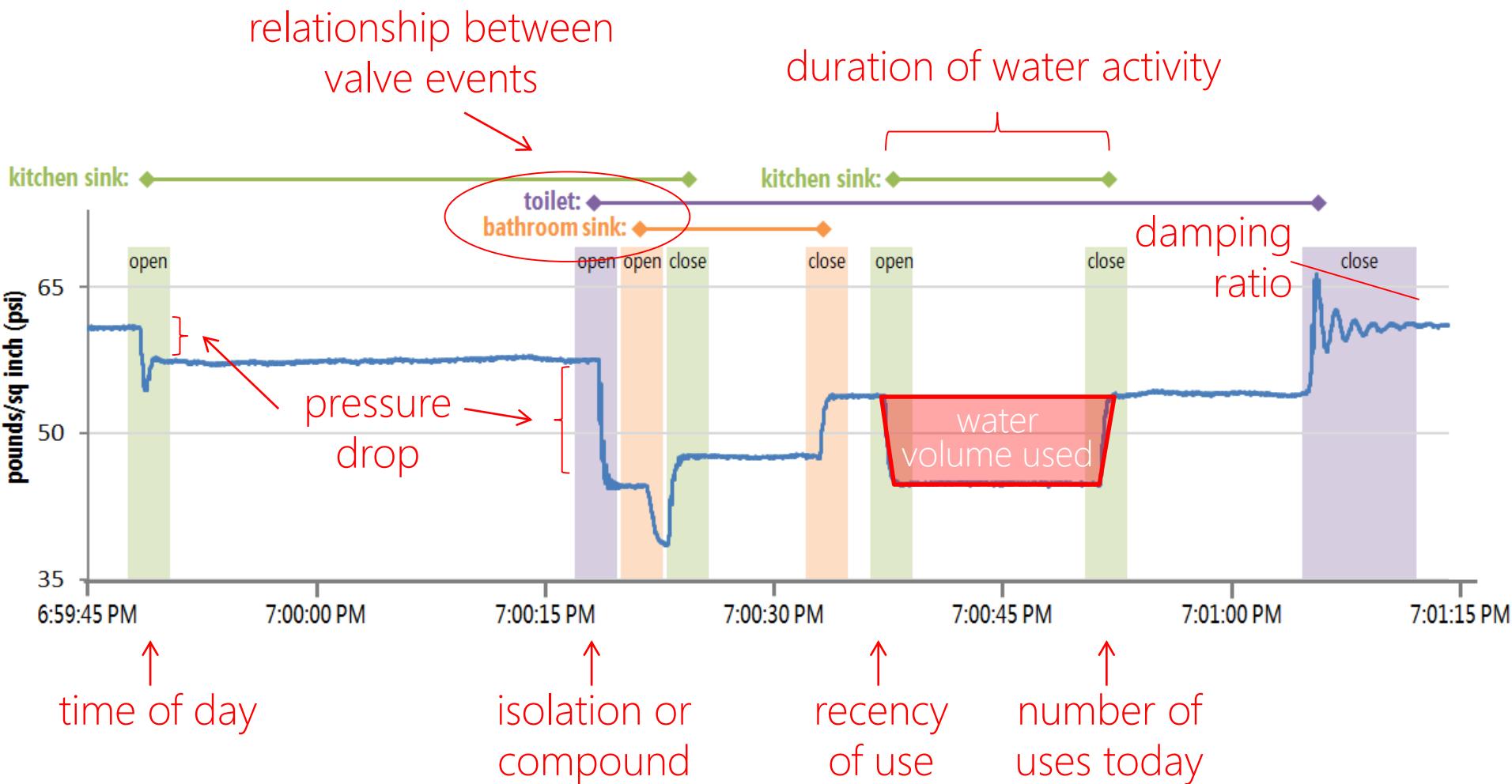
compound event example



compound event example



beyond template matching



bayesian approach

New algorithm borrows from Bayesian inference in speech recognition

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

bayesian approach

\mathbf{V} = pressure signature library

\mathbf{S} = sequence of unknown pressure transients

most likely valve sequence



$$\hat{\mathbf{V}} = \arg \max P(\mathbf{V} | \mathbf{S}) = \arg \max \frac{P(\mathbf{S} | \mathbf{V})P(\mathbf{V})}{P(\mathbf{S})}$$

bayesian approach

\mathbf{V} = pressure signature library

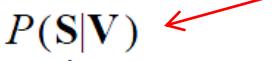
\mathbf{S} = sequence of unknown pressure transients

$$\hat{\mathbf{V}} = \arg \max P(\mathbf{V} | \mathbf{S}) = \arg \max \frac{P(\mathbf{S} | \mathbf{V})P(\mathbf{V})}{P(\mathbf{S})}$$

conditional probability term

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

$P(\mathbf{S} | \mathbf{V})$



e.g., matched filtering and stabilized pressure drop

bayesian approach

\mathbf{V} = pressure signature library

\mathbf{S} = sequence of unknown pressure transients

$$\hat{\mathbf{V}} = \arg \max P(\mathbf{V} | \mathbf{S}) = \arg \max \frac{P(\mathbf{S} | \mathbf{V}) P(\mathbf{V})}{P(\mathbf{S})}$$

prior probability term

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

e.g., transition probability for toilet
open->bathroom sink open

bayesian approach

\mathbf{V} = pressure signature library

\mathbf{S} = sequence of unknown pressure transients

$$\hat{\mathbf{V}} = \arg \max P(\mathbf{V} | \mathbf{S}) = \arg \max \frac{P(\mathbf{S} | \mathbf{V}) P(\mathbf{V})}{P(\mathbf{S})}$$

prior probability term

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

e.g., opening of valve v_x must be followed by closing of v_x

bayesian approach

\mathbf{V} = pressure signature library

\mathbf{S} = sequence of unknown pressure transients

$$\hat{\mathbf{V}} = \arg \max P(\mathbf{V} | \mathbf{S}) = \arg \max \frac{P(\mathbf{S} | \mathbf{V}) P(\mathbf{V})}{P(\mathbf{S})}$$

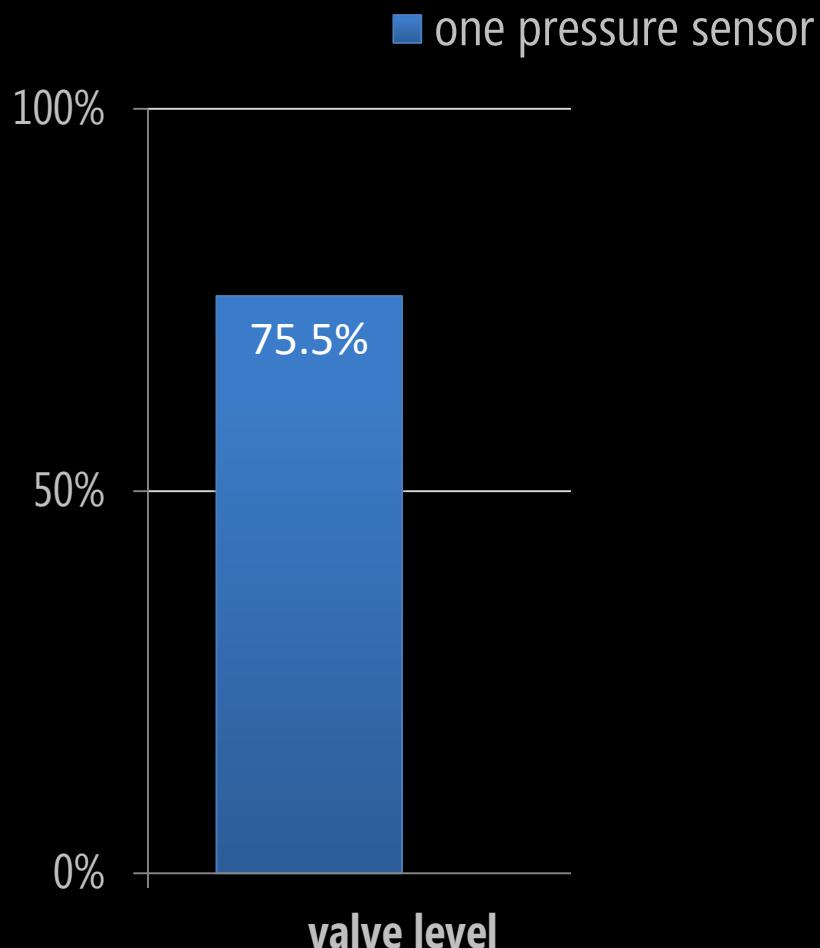
prior probability term

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

e.g., water usage duration

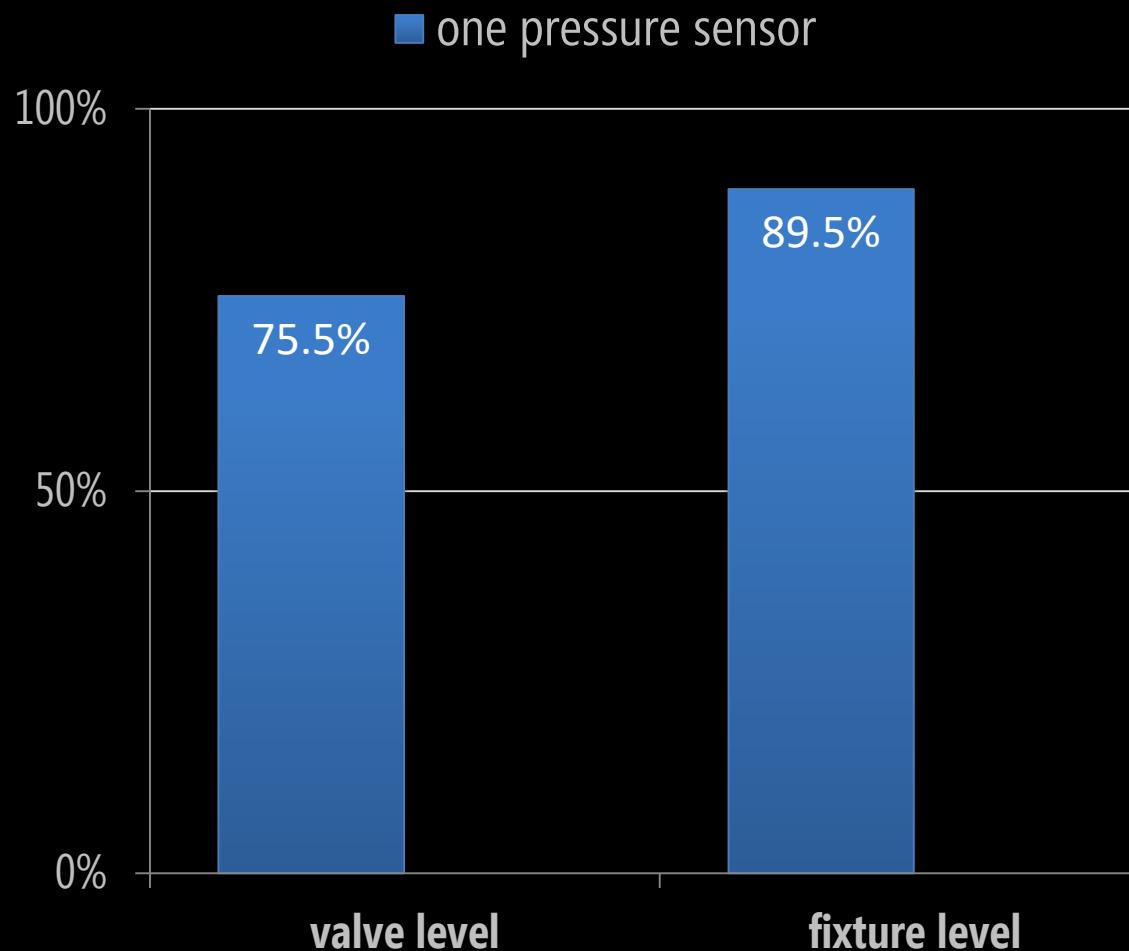
hydrosense classification results

real-world water usage data



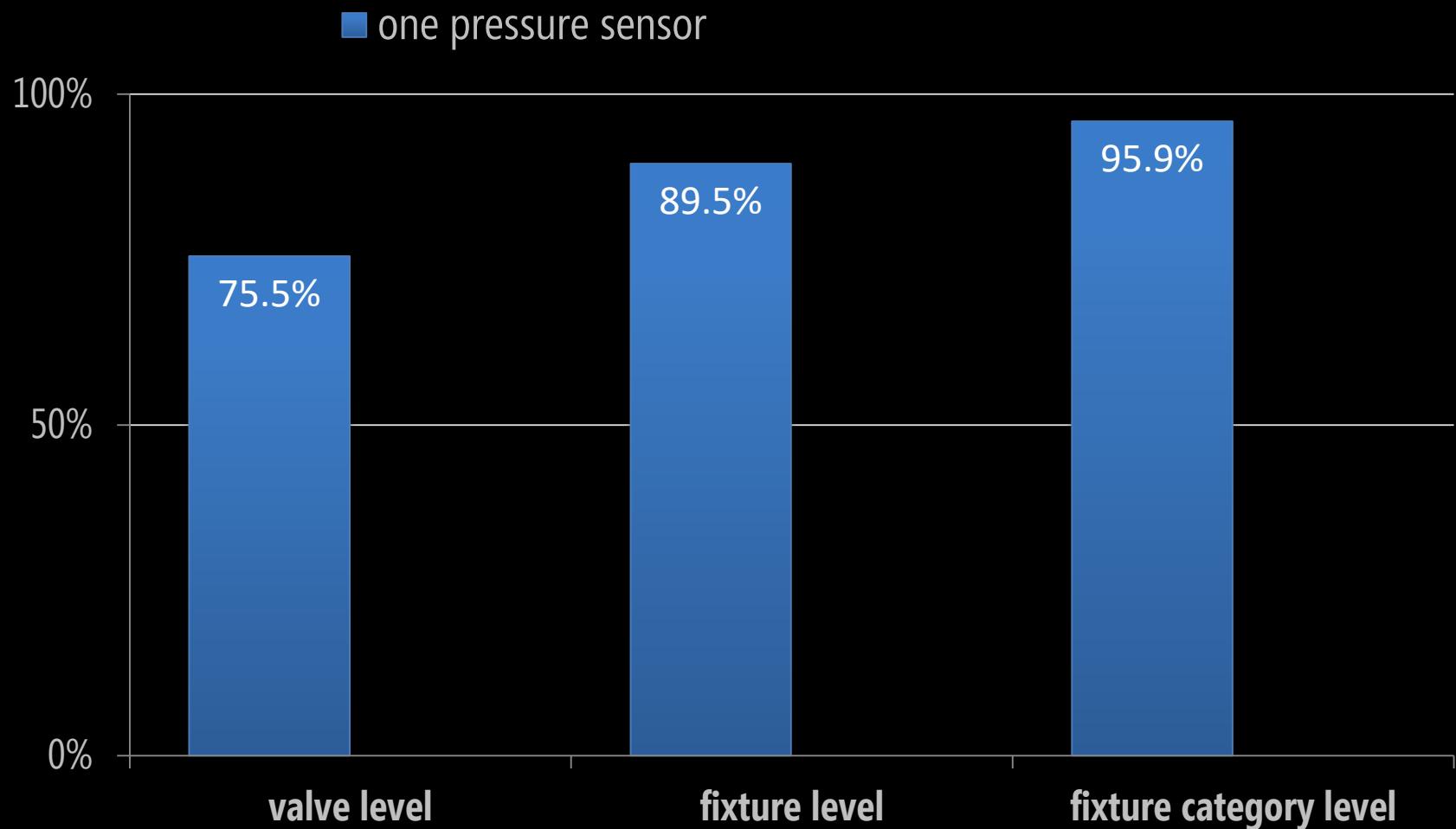
hydrosense classification results

real-world water usage data



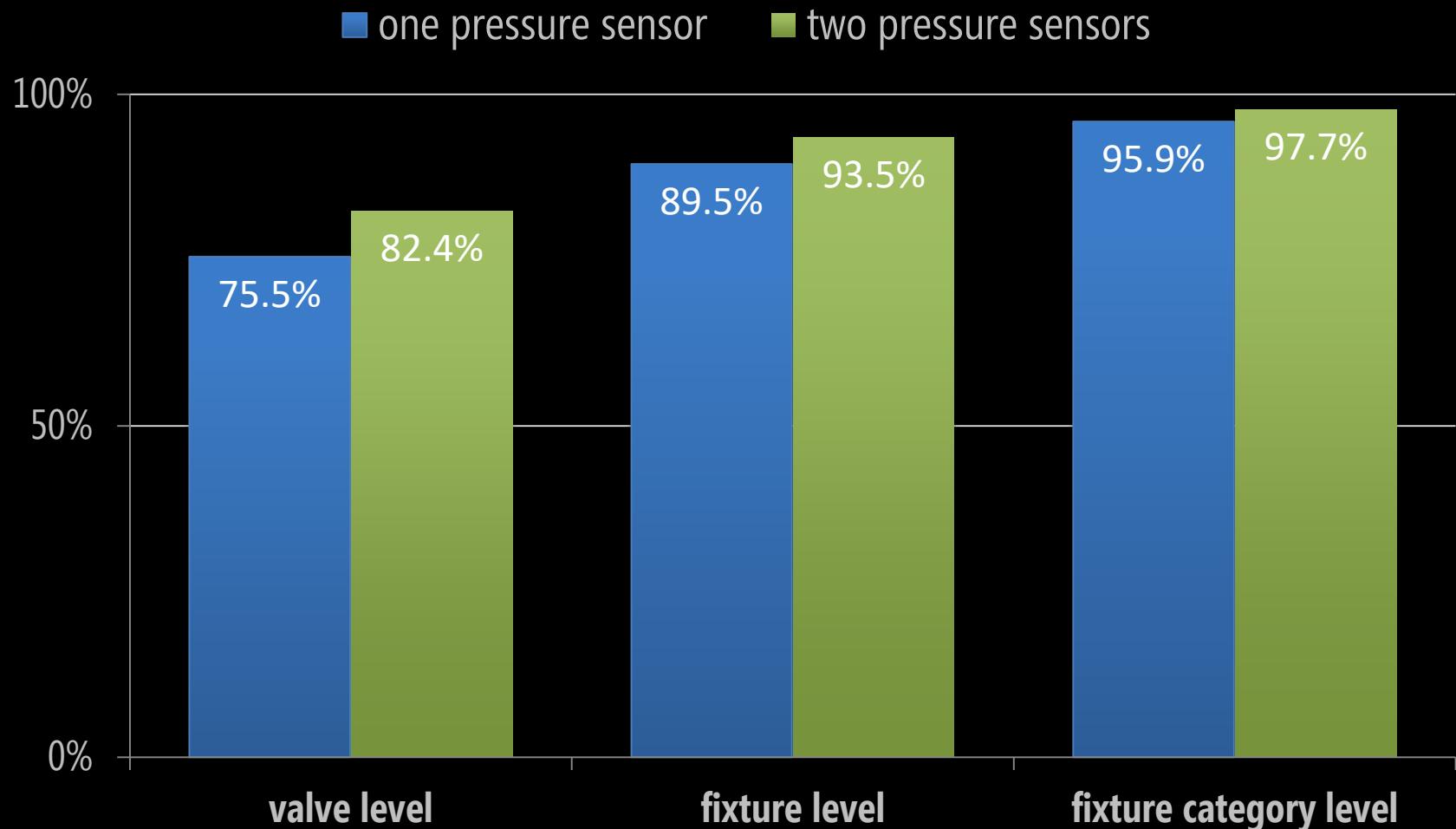
hydrosense classification results

real-world water usage data



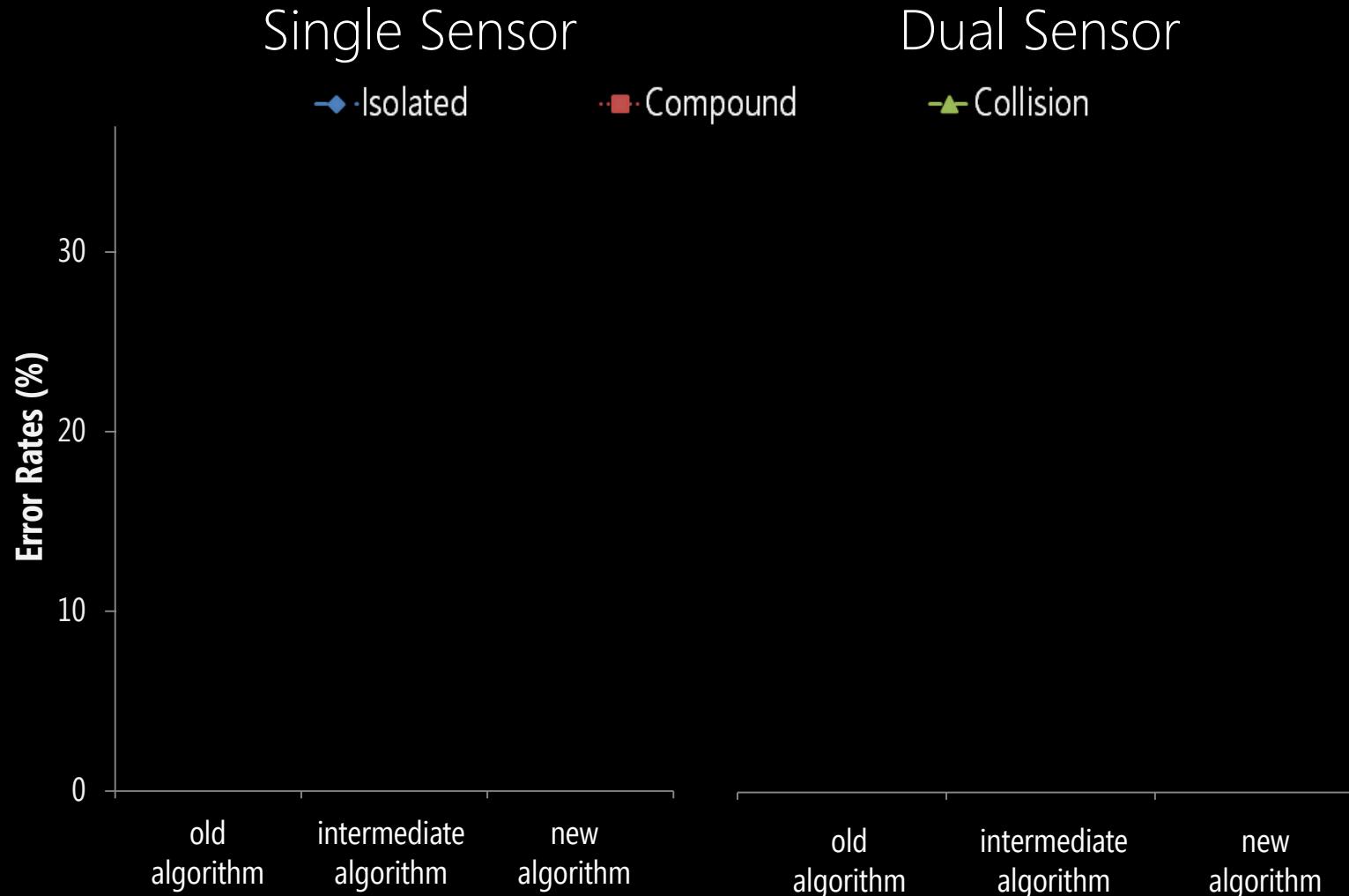
hydrosense classification results

real-world water usage data



compound events results

real-world water usage data



hydrosense training results

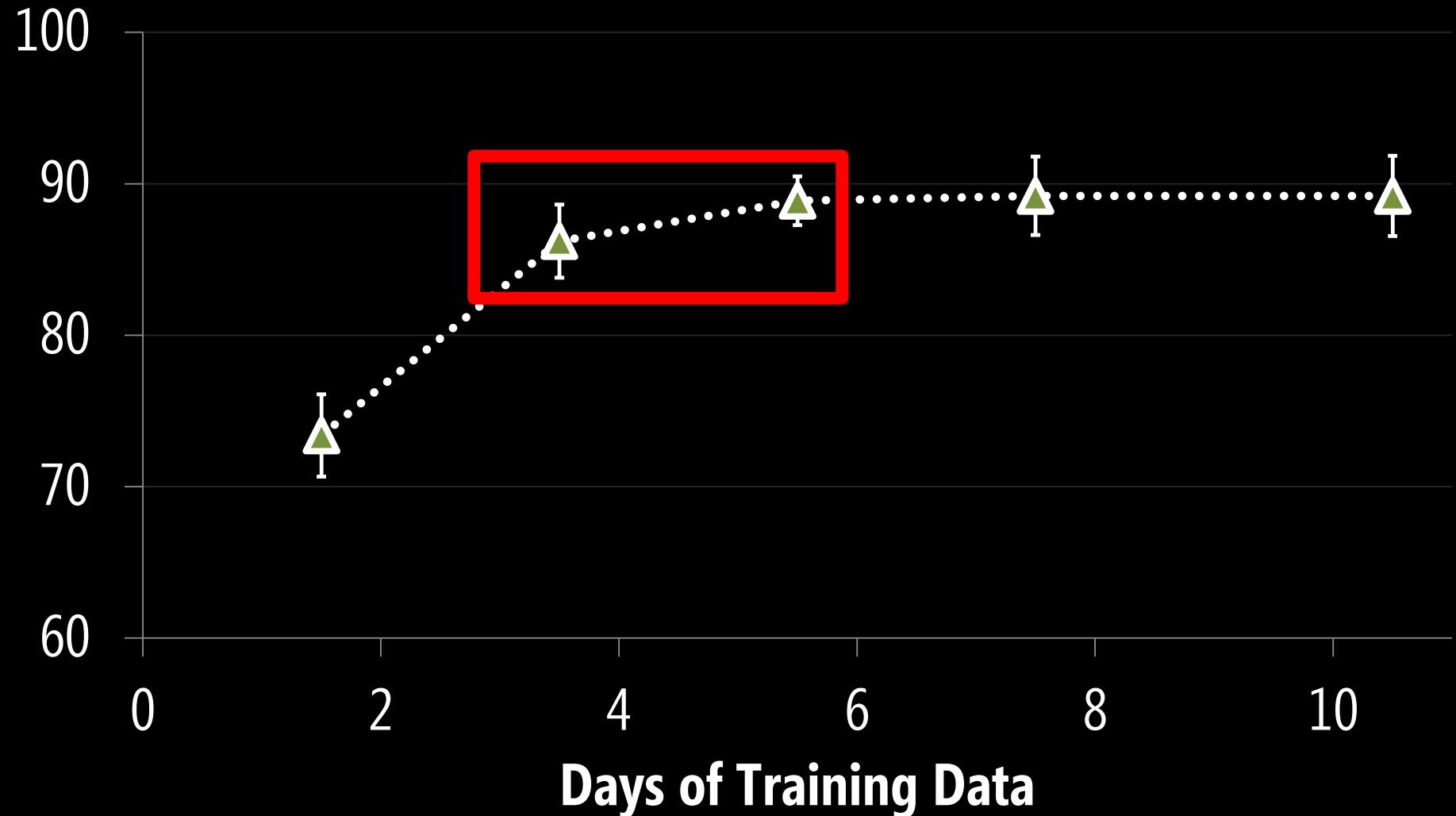
real-world water usage data



*error bars = std error

hydrosense training results

real-world water usage data



*error bars = std error

hydro study

#2

contributions

demonstrated hydrosense can
classify real-world water usage

collected one of the most
comprehensive datasets of
water usage in the world