Sensing and Feedback to Promote Environmentally Sustainable Behaviors

@jonfroehlich

Virginia Tech Seminar Series
Friday, February 17, 2012

dub design: use: build: UNIVERSITY of WASHINGTON
UNIVERSITY OF MARYLAND HCIL

346

million gallons/day

2x Japan, China, Canada, Russia, Germany Combined

[Foreign Policy Magazine, Aug 2007]

[Weber & Matthews, Ecological Economics, 2008]

growing demand

in 2010, water consumption rose to 938 billion gallons in beijing

water supply = 576 billion gallons

[Guardian, Dec 2010]


"china melting snow to meet
freshwater demand"
[Guardian, Dec 2010]

[Bloomberg News, Feb 2009]


economic
political
behavioral
technological
WALL ST
1-9
PRIUS

toyota prius

toyota prius

The Washington Post

washingtonpost.com > Nation > Green

More news on: Environment | Climate | Science

For Hybrid Drivers, Every Trip Is a Race for Fuel Efficiency

By Michael S. Rosenwald
Washington Post Staff Writer
Monday, May 26, 2008

Evan Hirsche averages 43 mpg with his Prius, while Katie Sebastian, shown with her son, Cole, averages 41 mpg. The drivers have friendly rivalry over their mpg scores, fueled by the Prius hybrid's real-time mileage readings. (By Kevin Clark -- The Washington Post)

Buy Photo

Katie Sebastian accuses her friend Evan Hirsche of getting better mileage than she does because he lives in Bethesda and has flatter everyday trips than she encounters in hilly Takoma Park. She suspects the Hirsche family of taking frequent long drives out of town, which also helps them.

"They claim they haven't been out of town in a while," she said, "but I know they have."

Hirsche retorts: "It is well known that Katie is a lead-footer."

Their friendly rivalry stems from the Prius effect. Both drive a Prius, the Toyota hybrid with an elaborate dashboard monitor that constantly informs drivers how many miles per gallon they are getting and whether the engine is running on battery or gasoline power. That can change driving in startling ways, making drivers

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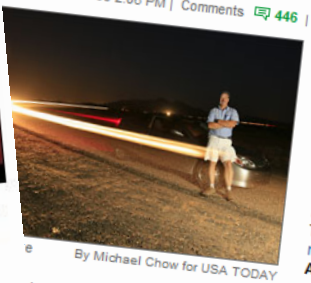
100 mpg? For 'hypermilers,' that sounds about right

Updated 6/27/2008 2:06 PM | Comments 446 | Recommend 103 E-mail | Save | Print | Reprints & Permissions | RSS



By Michael Chow for USA TODAY

in of Gilbert, Ariz., squeezes as much an get from his 2000 Honda Insight.

By Chris Woodyard, USA TODAY

GILBERT, Ariz. — After a 29-mile jaunt from his Phoenix office to his home here, Louis Hudgin proclaimed his gas mileage "pitiful."

He averaged just 88.3 miles per gallon.

MAXIMIZING MPG: What experts think of hypermiler techniques
TELL US: How do you squeeze the most miles out of every gallon?
ACROSS THE USA: Drivers slow down as costs accelerate

Most drivers would take a victory lap if they managed to squeeze that kind of mileage out of increasingly precious gasoline. Even on this, a bad day, Hudgin coaxed 28 mpg more out of his 2000 Honda Insight hybrid than its federal highway mpg rating.

Hudgin's disappointment — he usually averages about 100 mpg this time of year — stems from his pride in being no ordinary driver.

He's a hypermiler, part of a loose-knit legion of commuters who've made racking up seemingly unattainable mpg an art. And a sport.

Hypermilers practice such unorthodox techniques as coasting for blocks with their car's engine turned off, driving far below speed limits on the freeway, pumping up tire pressure far beyond car and tire makers' recommendations, manipulating the

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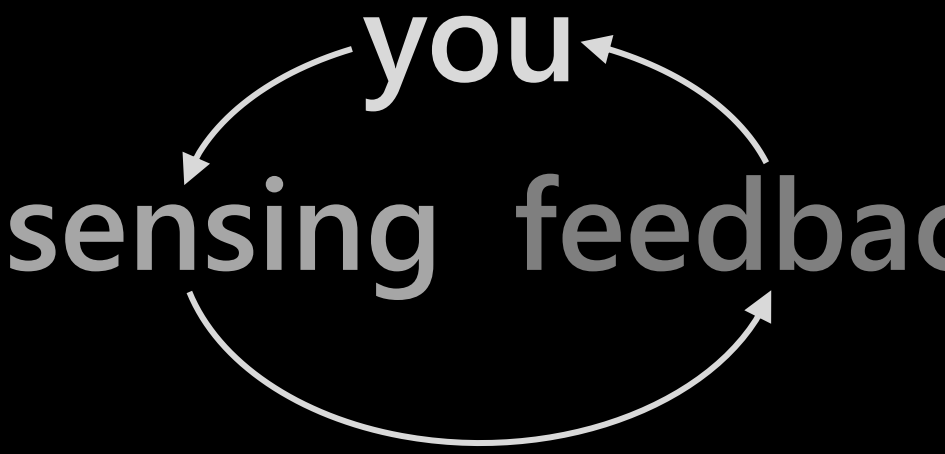
THE DISCUSSION

price of a
ar gasoline
low has
ted you?
sion at
Fuel
stories
g tips
rs.

GAS AT A PREMIUM

eco-feedback

sensing and visualizing behavior to reduce environmental impact




what about
sensing and
feedback in the
home?


KILOWATTHOURS
240V 3W
DE435

traditional bill:

Florida Power & Light Company
PO Box 025576
Miami, FL 33102

/ 27

Please request changes on the back.
Notes on the front will not be detected.

The amount enclosed includes the following donation:
FPL Care To Share $ _____

B 2,3,4,7,8 4118 6

#BWNDJNQ *** AUTO **C0 4501
#0148843BQ485818# 116049 Z

DELRAY BEACH FL 33445-3504

Make check payable to FPL in U.S. funds and mail along with this coupon to:

FPL
GENERAL MAIL FACILITY
MIAMI FL 33188-0001

Account number	Total amount you owe	New charges due by	Amount enclosed
	$295.43	Jul 16 2008	$

Your electric statement

For: May 27 2008 to Jun 25 2008 (29 days)
Customer name:
Service address:

Account number:

Statement date: Jun 25 2008
Next meter reading: Jul 25 2008

Amount of your last bill	Payments (-)	Additional activity (+ or -)	Balance before new charges (=)	New charges (+)	Total amount you owe (=)	New charges due by
328.10	328.10 CR	0.00	0.00	295.43	$295.43	Jul 16 2008

Meter reading - Meter 7C18171

Current reading	52489
Previous reading	- 50153
kWh used	2336

Energy usage

	Last Year	This Year
kWh this month	3375	2336
Service days	32	29
kWh per day	105	81

****The electric service amount includes the following charges:**

Customer charge:	$5.34
Fuel:	$135.46
(First 1000 kWh at $0.052270)	
(Over 1000 kWh at $0.062270)	
Non-fuel:	$110.35
(First 1000 kWh at $0.041340)	
(Over 1000 kWh at $0.051660)	

Amount of your last bill		328.10
Payment received - Thank you		328.10 CR
Balance before new charges		$0.00
New charges (Rate: RS-1 RESIDENTIAL SERVICE)		
Electric service amount	251.15**	
Storm charge	2.59	
Gross receipts tax	6.51	
Franchise charge	15.75	
Utility tax	14.51	
Late payment charge	4.92	
Total new charges		$295.43
Total amount you owe		**$295.43**

- A late payment charge of 1.50% will apply if not paid by July 16, 2008, and your account may be subject to being billed an additional deposit.
- Would you like one less bill to think about & help the environment too? Enroll in FPL Automatic Bill Pay & your bill is always paid on time. Save time, postage, check writing & paper. Plus, cut fuel consumption of cars & trucks that transport checks. Enroll at FPL.com or see authorization form in this bill.

opower bill:

ComEd
An Exelon Company

Home electricity report

Account number: 1234567890
Report period: 04/10/09 - 05/08/09

JOHN DOE

We are pleased to provide this personalized report to you as part of a pilot program. The purpose of the report is to:

Provide information This report is an educational tool to help you understand your home's electricity use in the context of other homes.

Track progress We will help you learn about how your home's usage changes over time and where you likely have opportunities to save.

Share energy efficiency tips On the back of the report, we provide ideas for saving energy and money. You can find more tips at **www.ComEd.com/energyreport**

Last Month Neighbor Comparison

You used **48% more** than your efficient neighbors.

HOW YOU'RE DOING:
GREAT
GOOD
MORE THAN AVERAGE

* kWh: A 100-Watt bulb burning for 10 hours uses 1 kilowatt-hour.

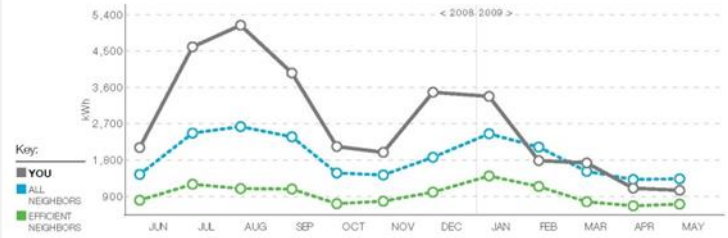
WHO ARE YOUR "NEIGHBORS"?

ALL NEIGHBORS
Approximately 60 occupied, nearby homes that are similar in size to yours (avg 5,379 sq ft)

EFFICIENT NEIGHBORS
The most efficient 20 percent from the "All Neighbors" group

Last 12 Months Neighbor Comparison

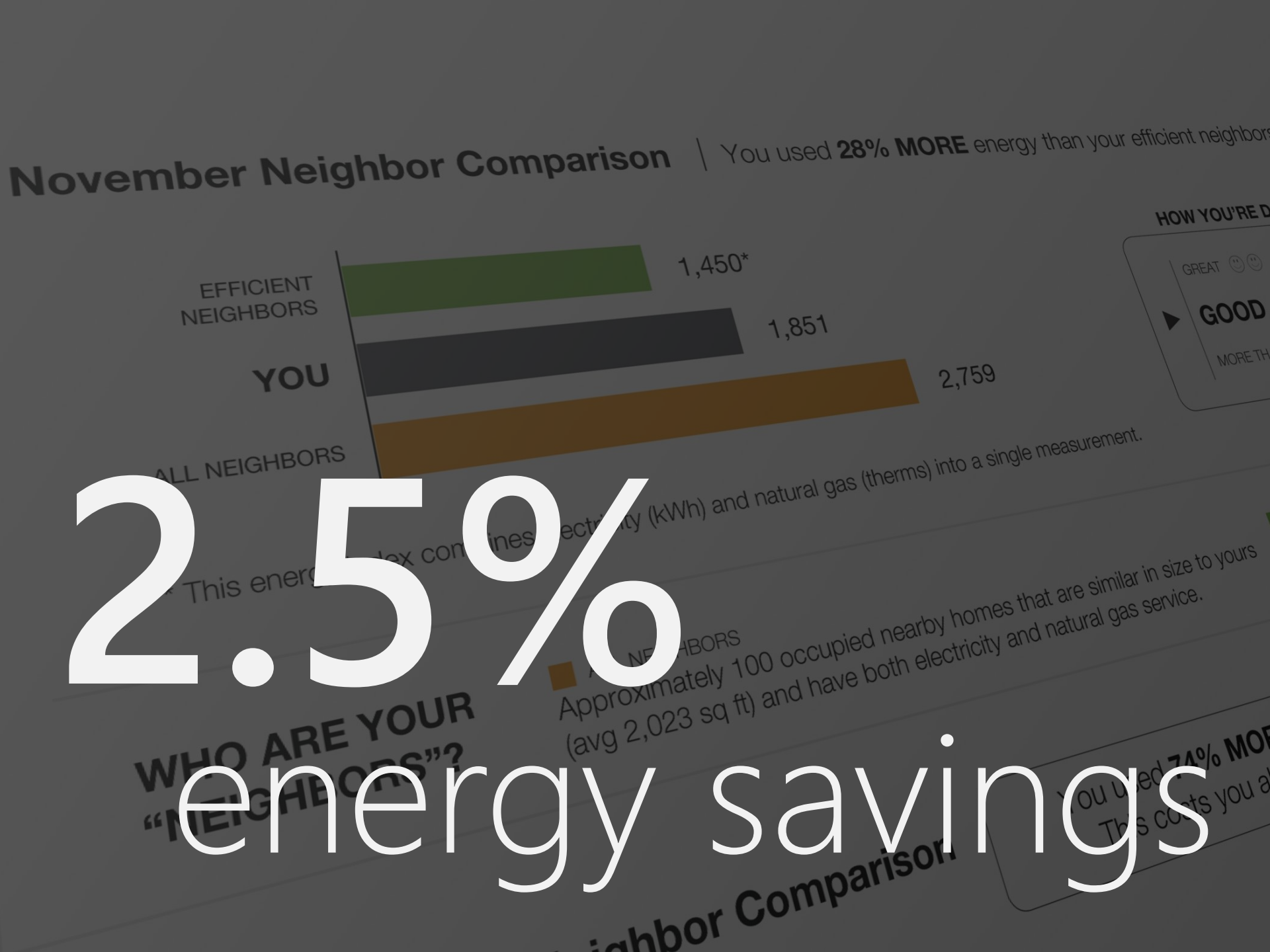
You used **45% more** electricity than your neighbors.
This costs you about **$1,029 extra** per year.



Personalized Action Steps

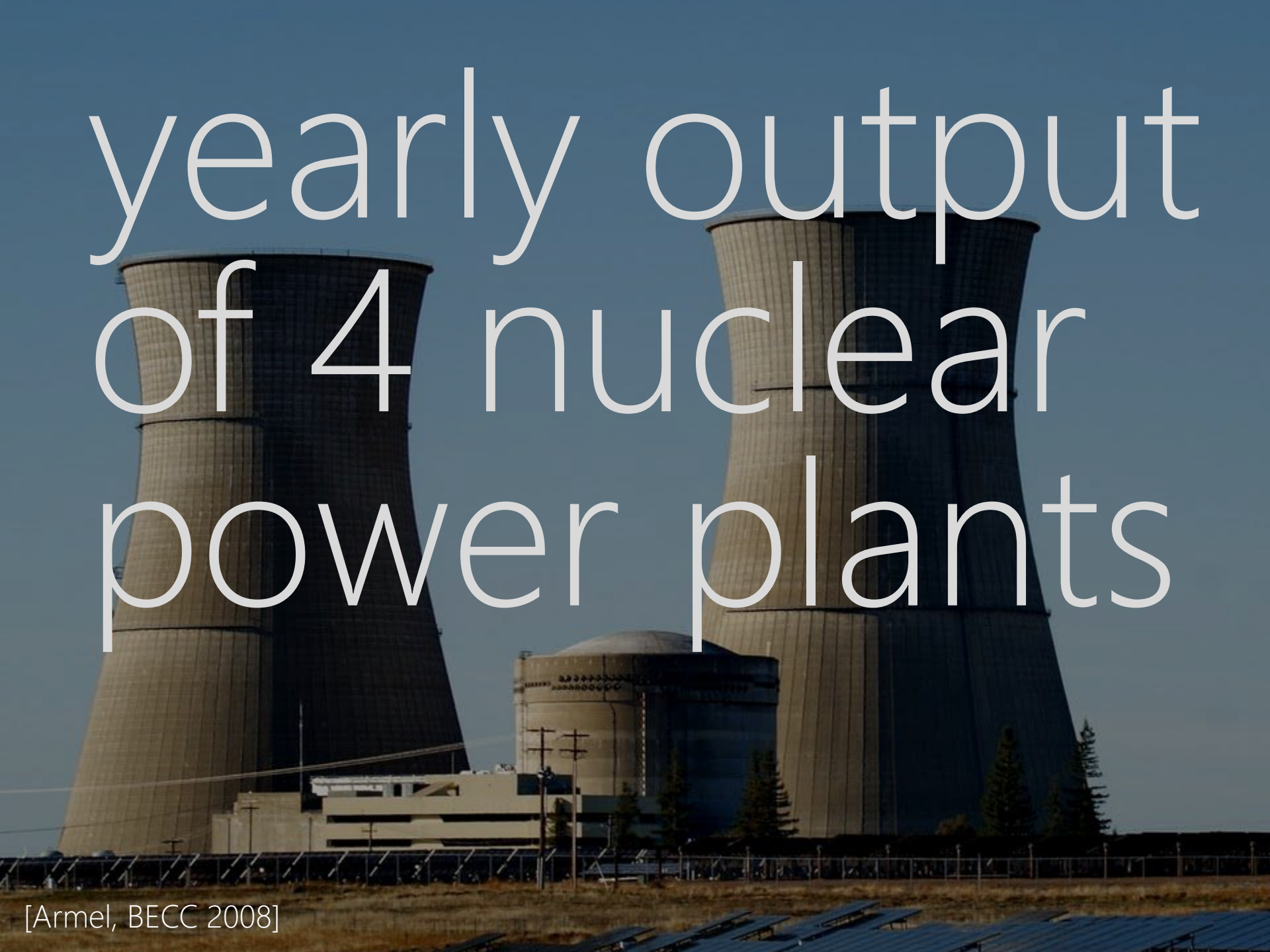
- ☐ Set your thermostat for comfort and savings
- ☐ Choose efficient light bulbs
- ☐ Look for the ENERGY STAR® label

TURN OVER TO LEARN MORE



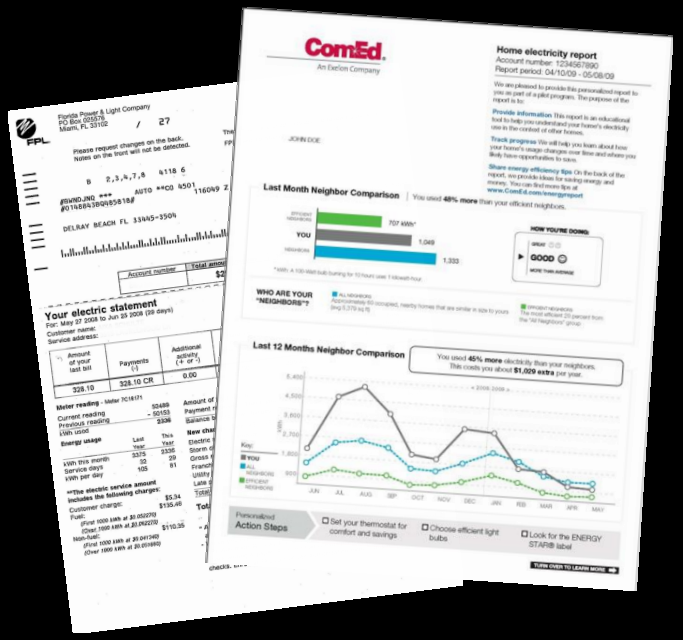
2.5% energy savings


20 million
tons of coal



[Armel, BECC 2008]

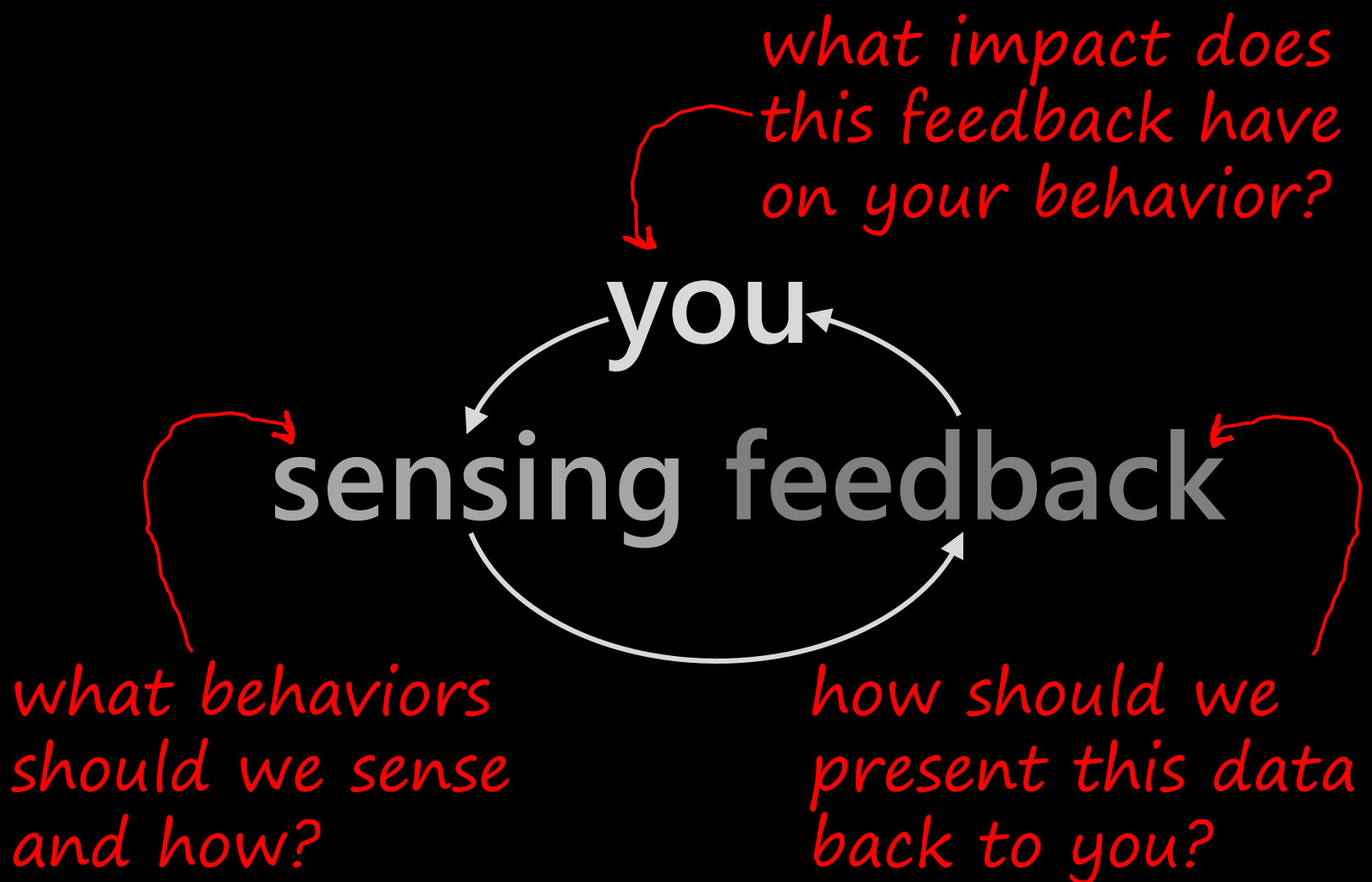
can we do better than paper?



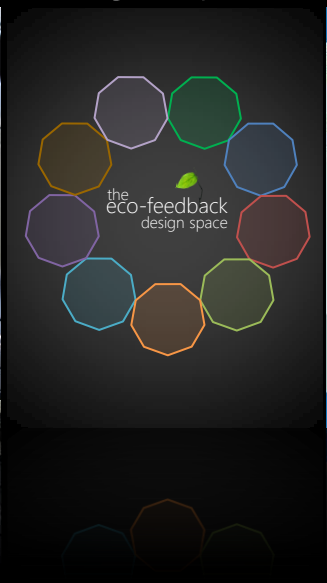
plethora of **display mediums**

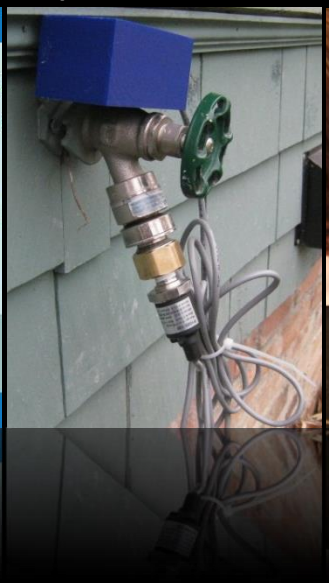
advances in **sensing** and **machine learning**

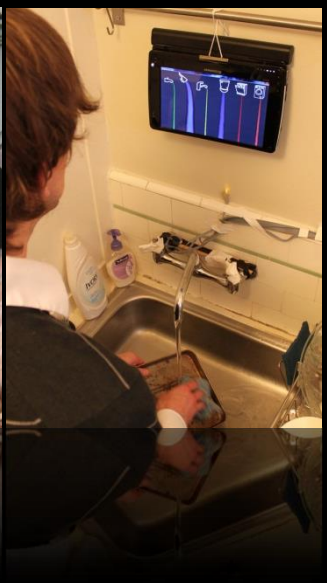
philips directlife
activity sensor

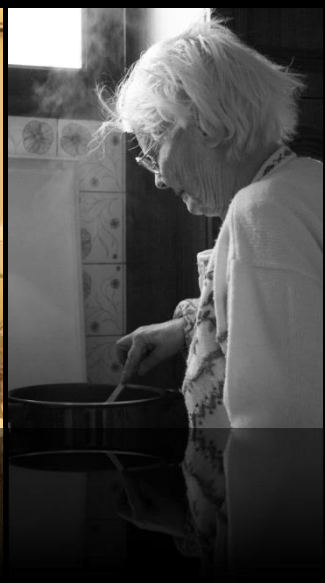

what impact does this feedback have on your behavior?
you
sensing feedback
what behaviors should we sense and how?
how should we present this data back to you?

intro design space ubigreen hydrosense reflect future work

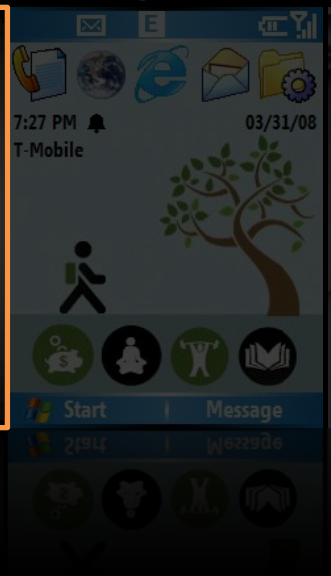


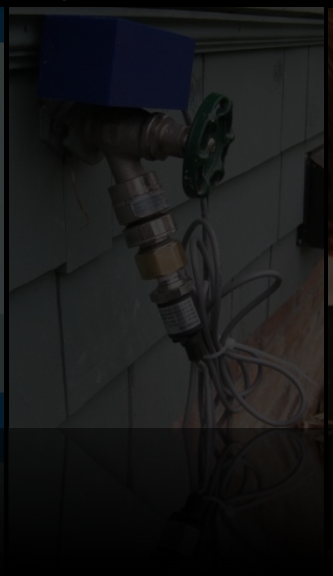


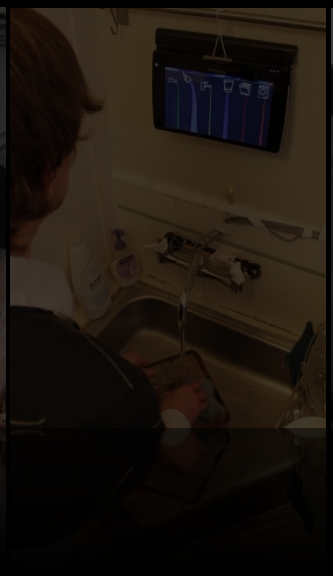


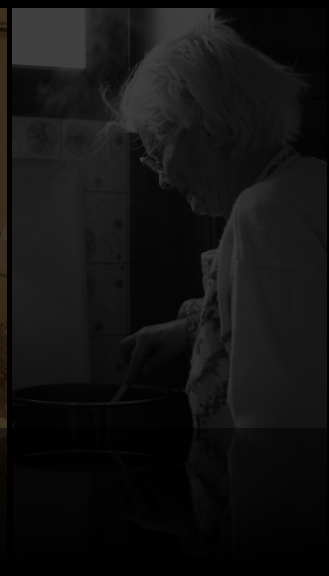


intro | design space | ubigreen | hydrosense | reflect | future work





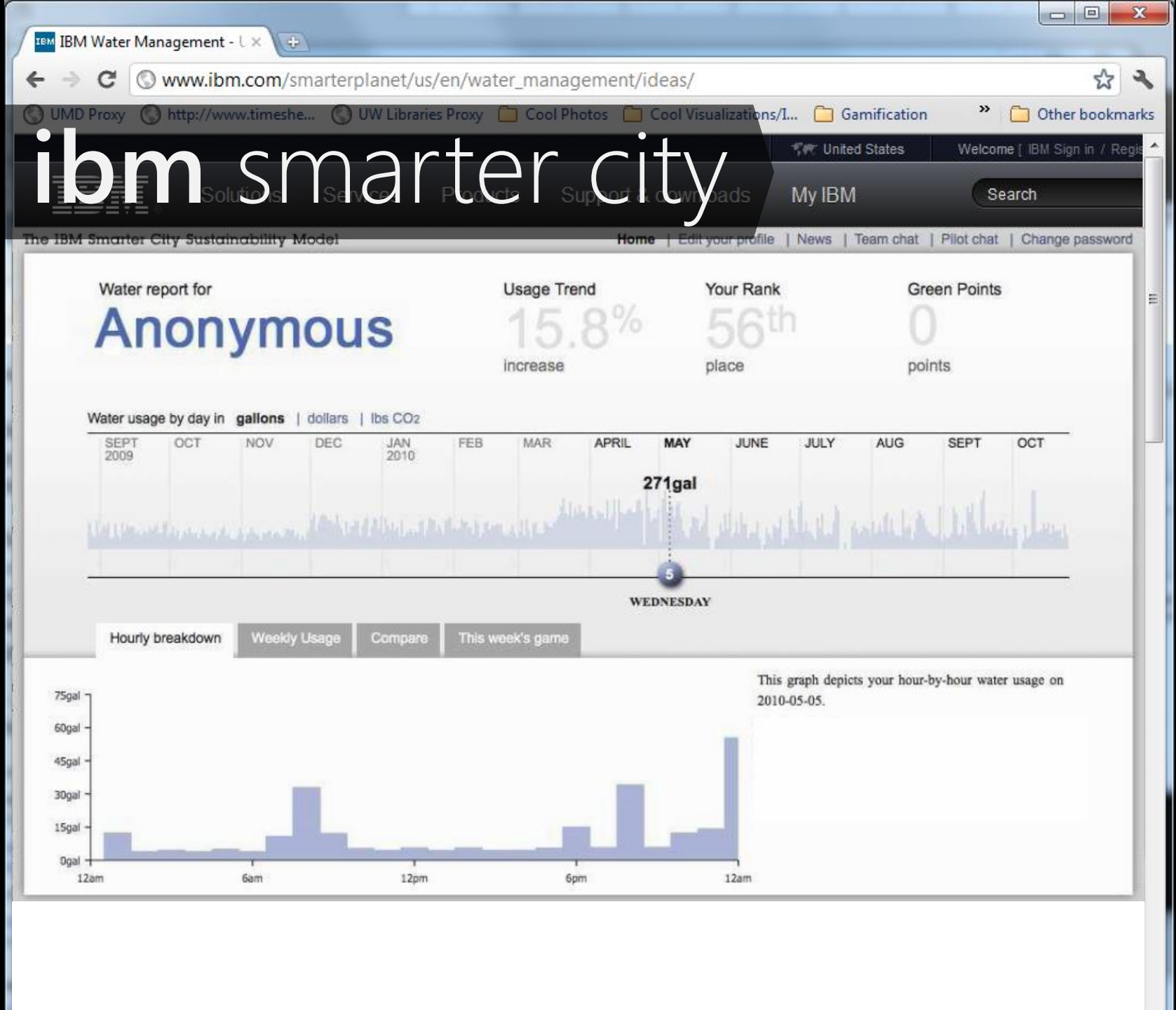




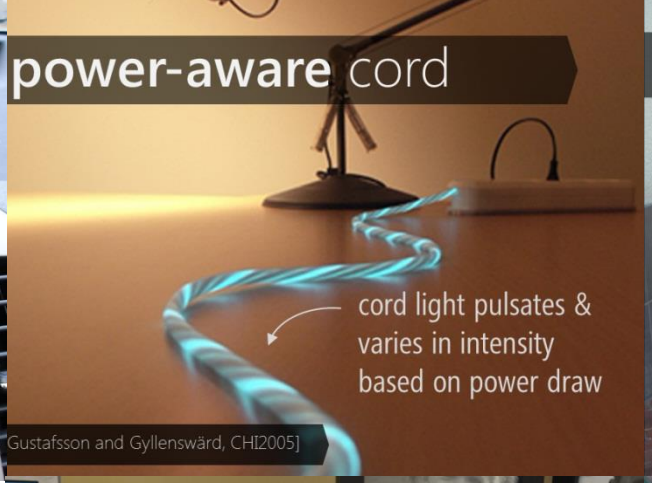

power-aware cord
cord light pulsates &
varies in intensity
based on power draw
[Gustafsson and Gyllenswärd, CHI2005]

the energy detective

ibm smarter city




toyota prius
Consumption
MPG
Current
Energy
60.5 MPG
204 miles
Reset


power-aware cord
cord light pulsates & varies in intensity based on power draw
Gustafsson and Gyllenswärd, CHI2005]


jetsam
visualization allows pedestrians to view amount and type of garbage at-a-glance
[Paulos and Jenkins, CHI2005]


microsoft hohm
Energy Charts
Electricity Usage


the energy detective
Real-Time Use
$ 0.40 per Hour
2,480 kilowatts
TED

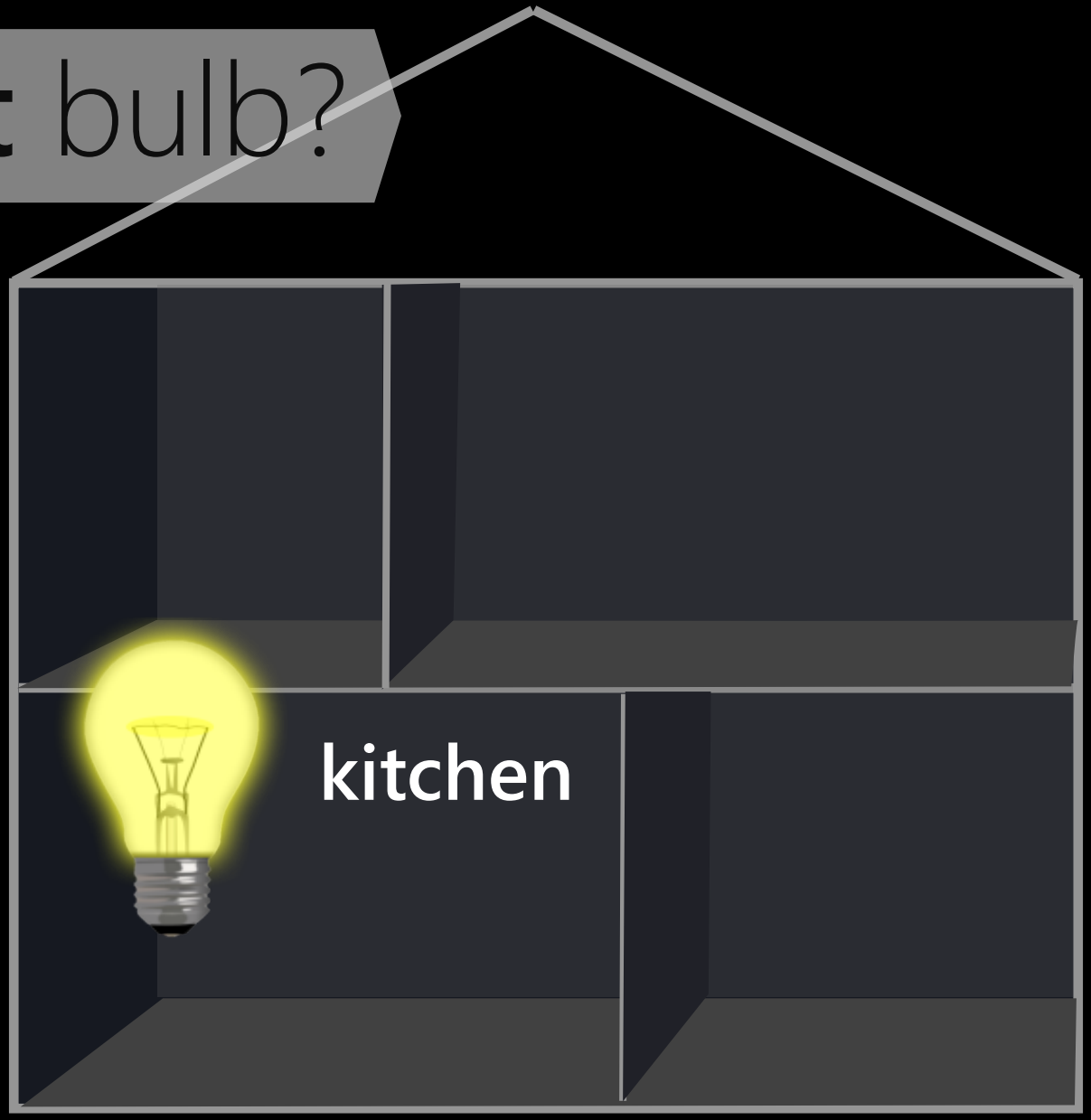

wattson


control4 dashboard
Menu
Thursday, January 6
My Home Now
Price Per kWh
$0.00
5:30 pm
0.1 kW
78°
My Cost Per Hour
$0.01
62°
So Far Today 0.6 kWh
Control4

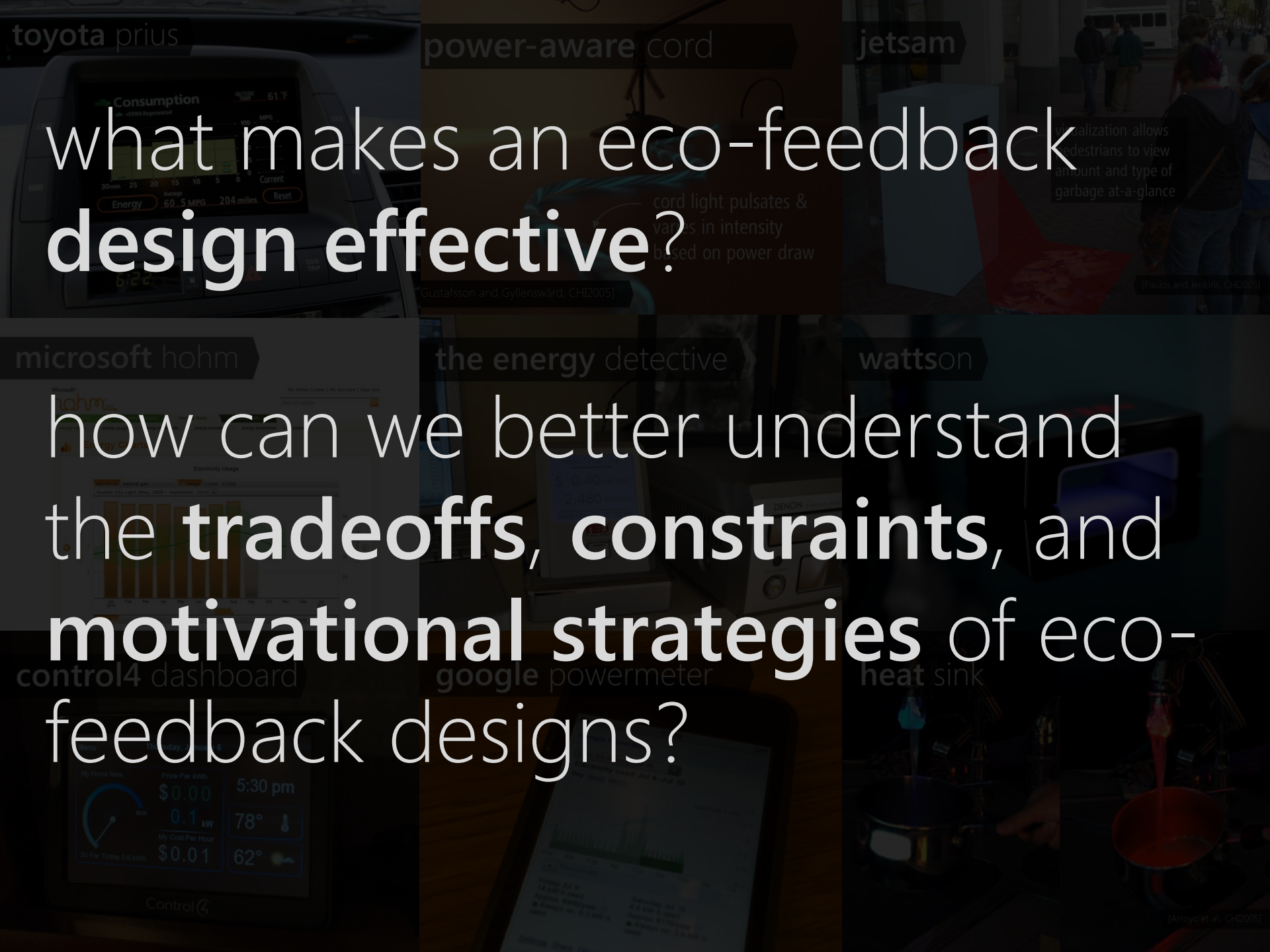

google powermeter
Google PowerMeter
Electricity used Jul 9–Jul 10


heat sink
[Arroyo et al., CHI2005]

light bulb?



[Kohlenberg et al., J. of Applied Behavior Analysis, 1976]



what makes an eco-feedback **design effective**?

how can we better understand the **tradeoffs**, **constraints**, and **motivational strategies** of eco-feedback designs?

literature survey
eco-feedback

150 papers in environmental HCI
82 papers in environmental psychology

also literature in: persuasive technology, ambient displays, information visualization, behavioral economics, health behavior change, visual design

[Froehlich et al., HCIC2009; CHI2010; PhDThesis2011]


data representation
information access
display medium
comparison
actionability
motivational strategies
social
behavioral models
inputs
the
eco-feedback
design space


data representation
information access
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comparison
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motivational strategies
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comparison
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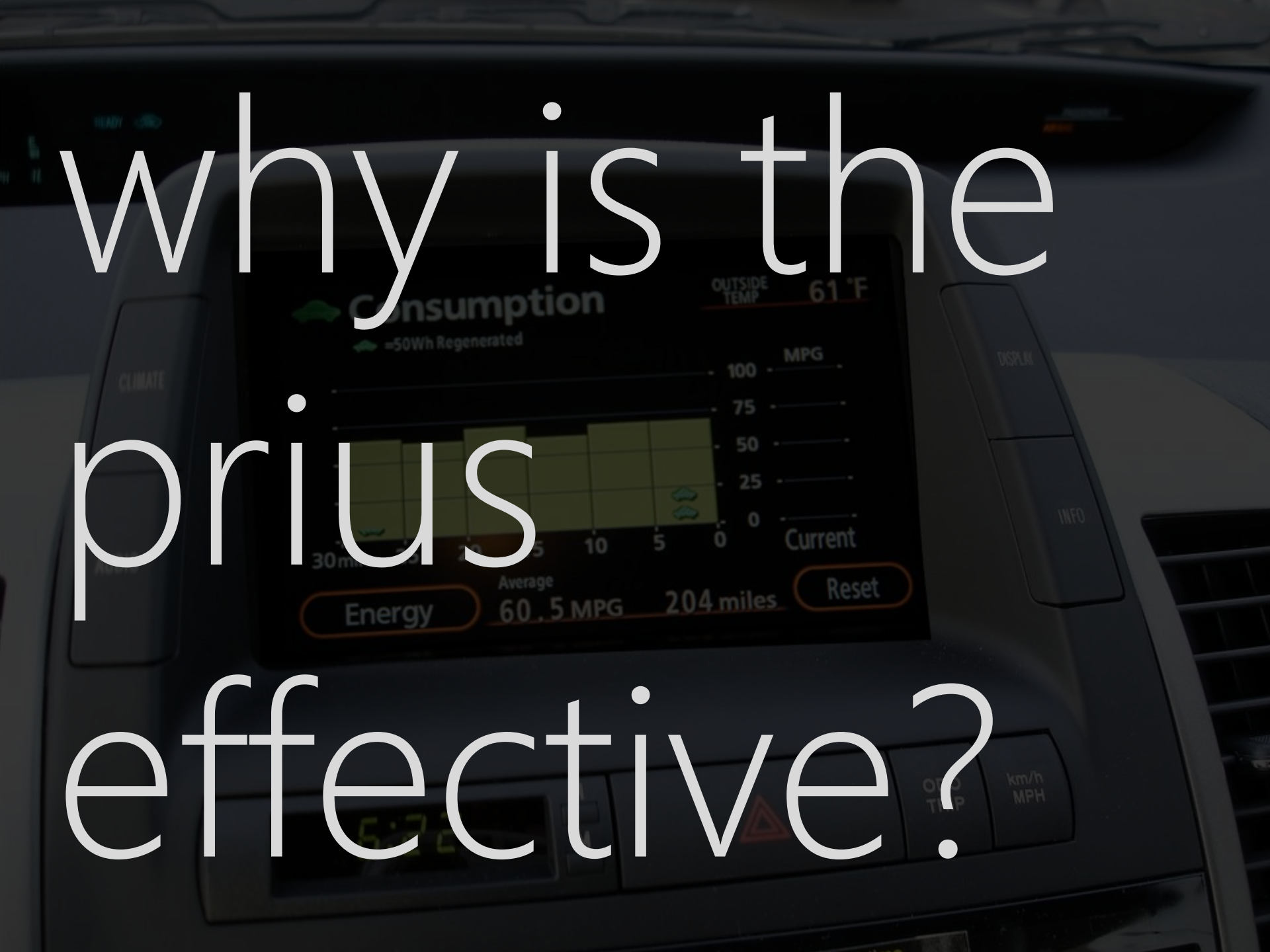
actionability
motivational strategies



why is the prius effective?

- Graphical
- Textual
- Temporal

data representation

- Real-time
- Spatially co-located
- Constrained environment

information access

- Real-time mpg

inputs

- In-car display

display medium

behavioral models

comparison

- Educates
- Reason to care

social

- To self

actionability

motivational strategies

- Informs only one action

data representation

information access

inputs

display medium

behavioral models

comparison

social

actionability

motivational strategies

data representation

information access

inputs

display medium

behavioral models

comparison

social

actionability

motivational strategies

comparison

historic average last 30 mins

to self past projected

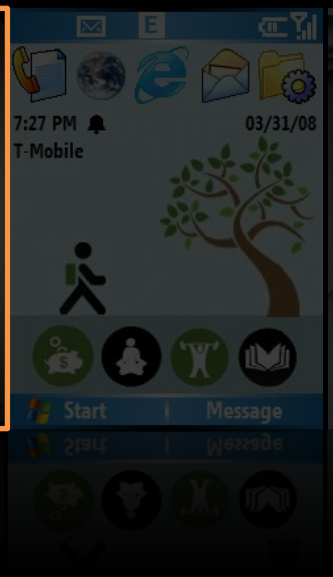
to others past projected

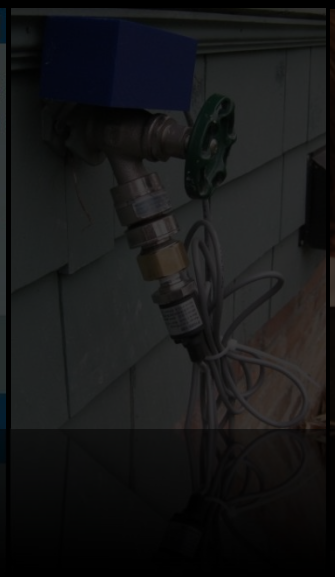
to a goal easy challenging

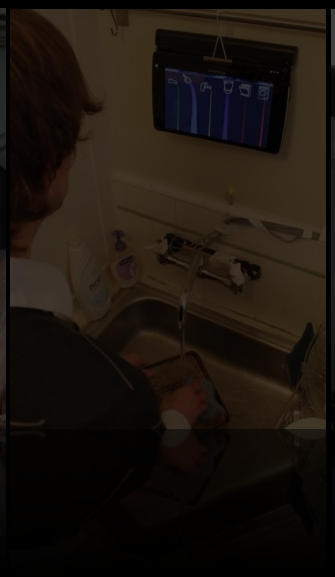
[Effectiveness of Feedback on Performance: Becker, J. of Applied Psychology, 1978]

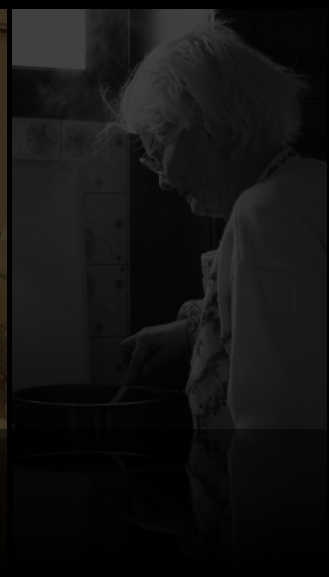

Consumption
61 °F
Energy
60.5 MPG
204 miles
Reset
Current


the
eco-feedback
design space


7:27 PM
03/31/08
T-Mobile
Start
Message







ubigreen

eco-feedback

goals

increase awareness of transit habits

attempt to motivate green transit

ubifit

- fitness monitoring application
- automatically senses activity
- at-a-glance goal information


strength


cardio


flexibility

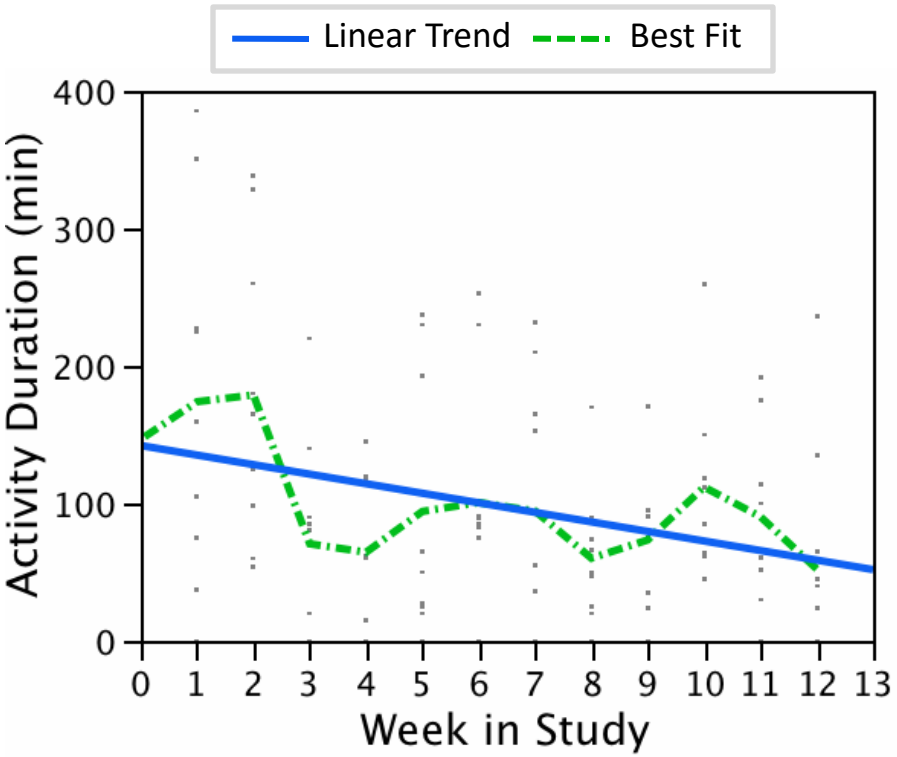

walk


week's goal met

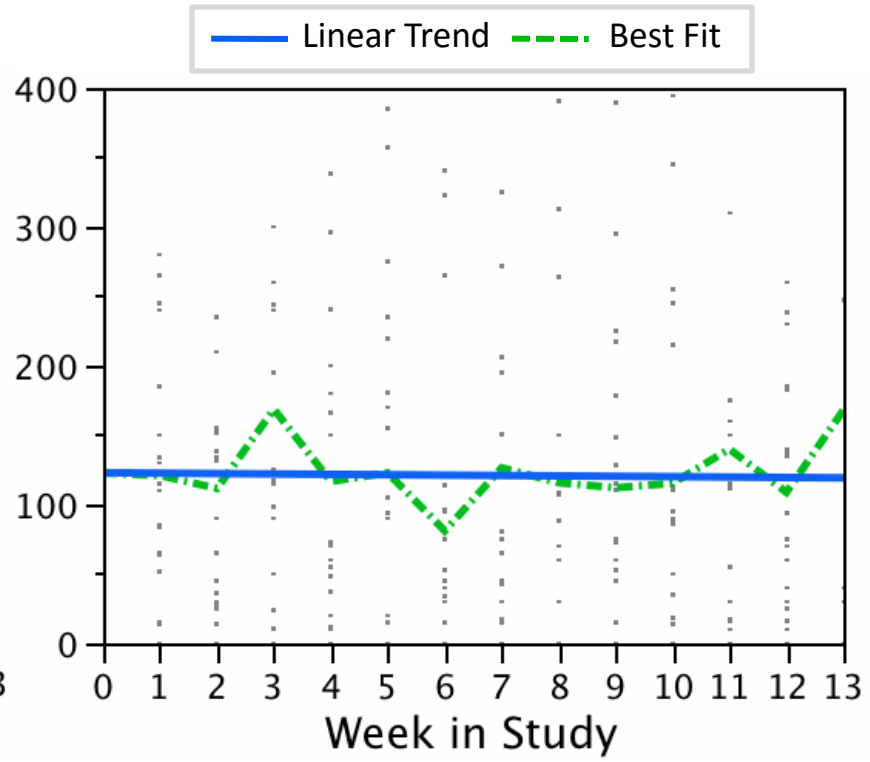

recent goal met

[Consolvo et al., CHI2008; Consolvo et al., UbiComp2008;

effectiveness of the ubifit glanceable display



no glanceable display



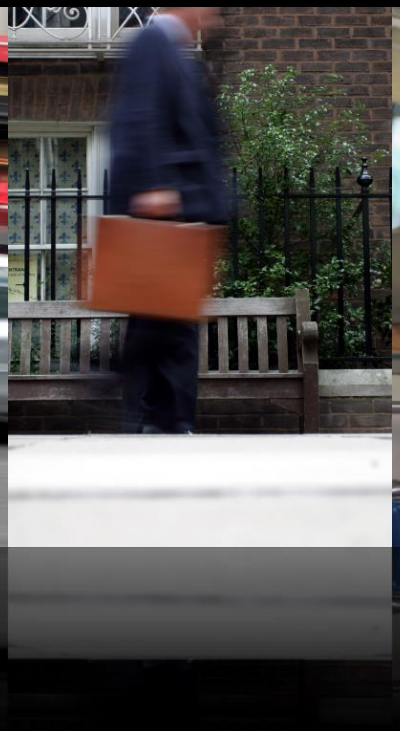
glanceable display

[Consolvo et al., CHI2008; Consolvo et al., UbiComp2008;

we want to **sense**

biking

walking



taking the bus

riding the train

driving

ubigreen

transit sensing infrastructure

mobile sensing platform

how should we visualize this data in an eco-feedback display?

Visualizations Informed By:

- Our eco-feedback design space
- Our experiences designing and evaluating UbiFit
- We conducted two formative studies of transit usage
- Past work on feedback systems

ubigreen

personal ambient display

current activity

phone background (wallpaper)

value icon bar

evolving image

ubigreen

personal ambient display

tree design:

wed thu fri

everything resets on sunday

tree

polar bear

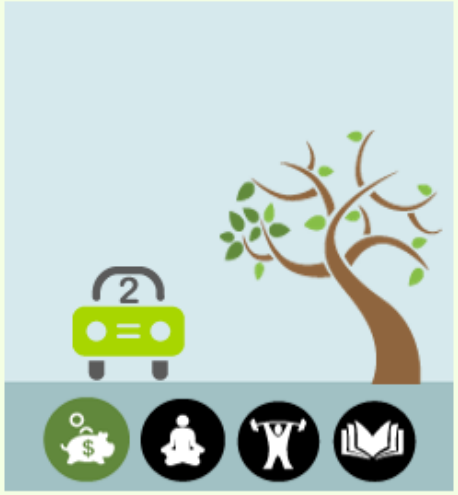

3wk field study
43
VIA
U DISTR
ubigreen eco-feedback
mobile sensing platform

current ubigreen phone images

march 2008 field study

Sunday

RESEARCH PARTICIPANTS

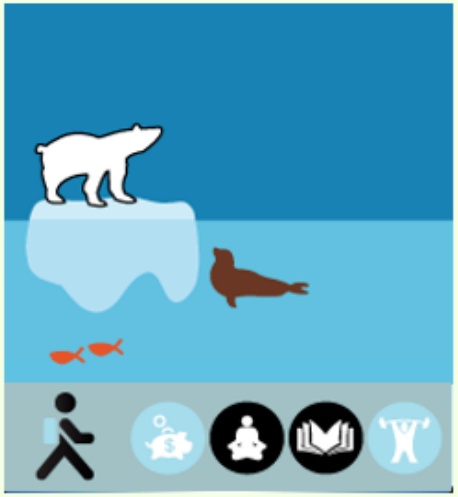


ubiqreen1

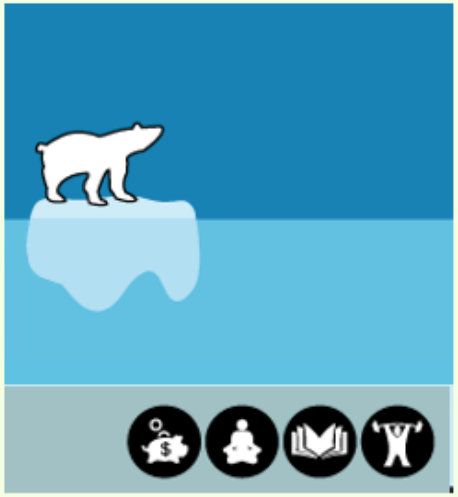
ubiqreen2

ubiqreen3

ubiqreen4

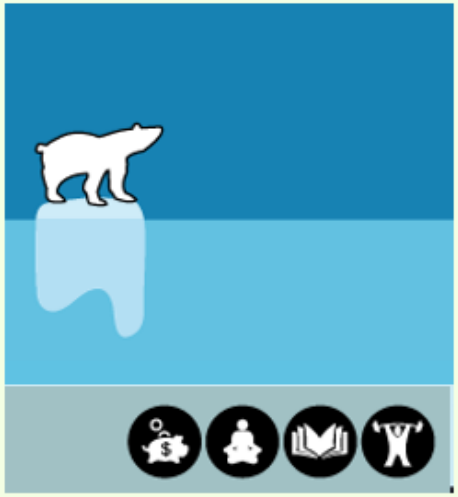


ubiqreen5



ubiqreen6

ubiqreen7



ubiqreen8

ubigreen
study results

"i liked the tree because it was, to my mind, a pretty progress bar. i could tell the difference at a glance" [p11]

"i liked how stories were used" [p8]

"i want different stories every week" [p8]

"i would like to see some graph or raw data—a breakdown of transit activity by type for the week" [p13]

"it would be nice to see your carbon footprint" [p15]

ubigreen
study results

"i liked that we didn't know what the background was going to do" [p15]

"negative feedback would also be good; maybe my polar bear should drown if i don't take green transit" [p14]

"i wanted to see the final stage i could get to" [p7]

"i don't like incentives for getting points artificially by taking unnecessary green trips" [p11]

"if i didn't get a leaf or a flower after, i felt like I was getting cheated out of my points" [p15]

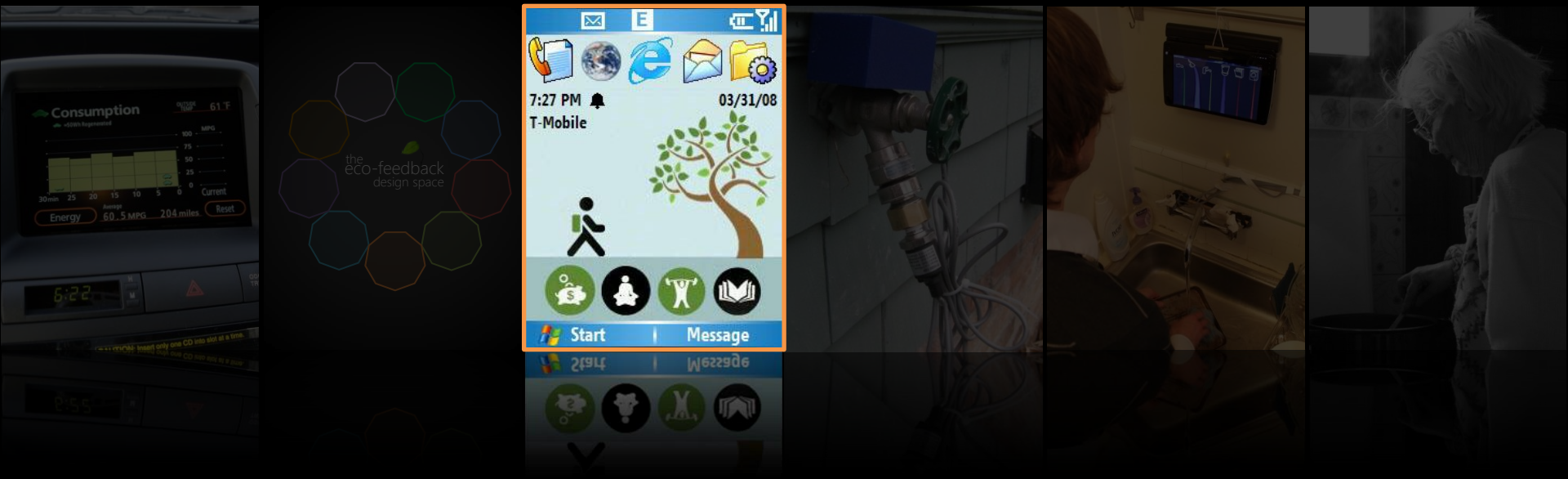
ubigreen

contributions

first system to semi-automatically track and feedback personal transit information

empirical findings from field deployment have implications for other eco-feedback systems:

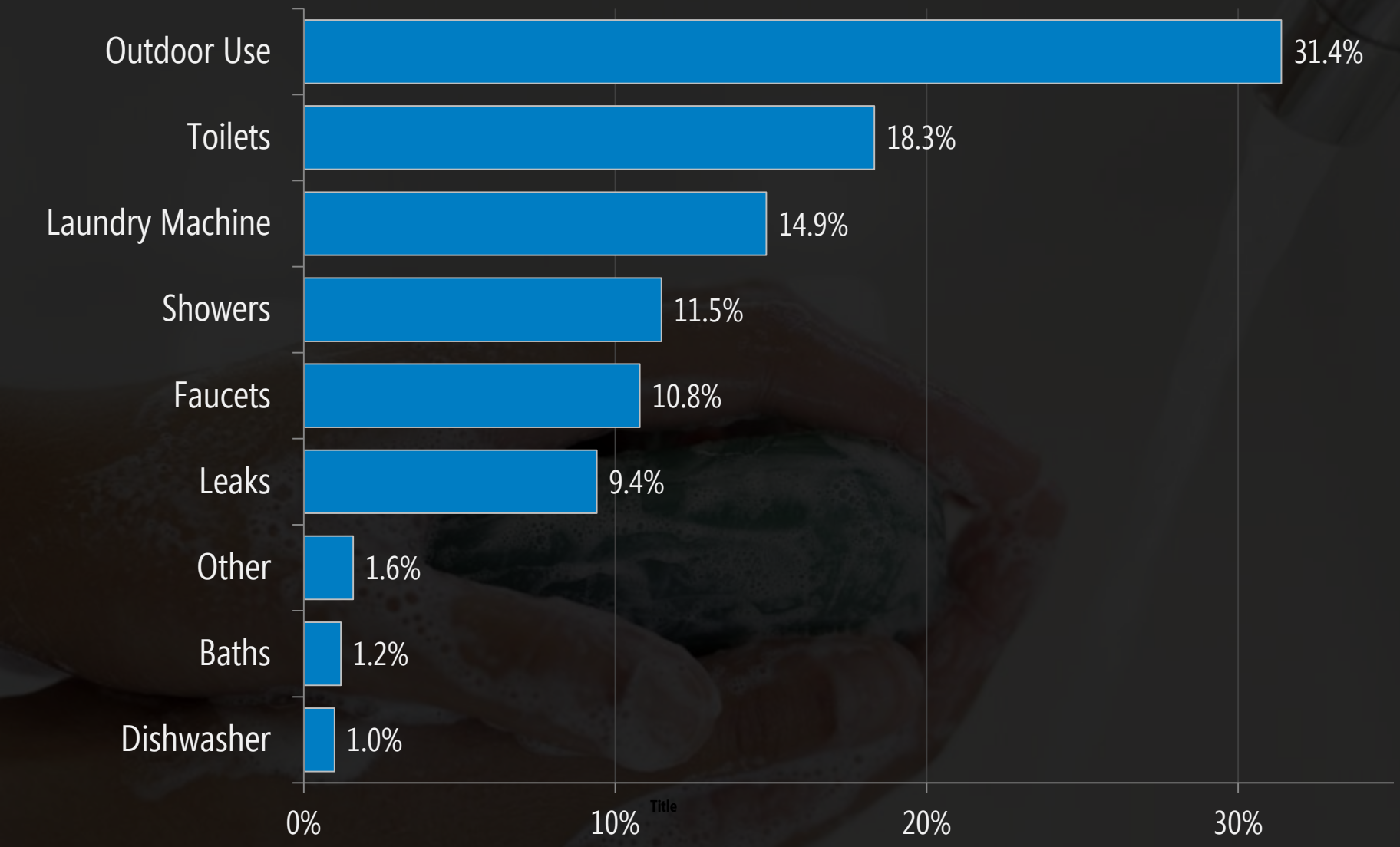
- abstraction can make comparisons difficult
- users desire actionable feedback
- reward systems need to be carefully constructed


Consumption
61 °F
MPG
100
75
50
25
0
30min 25 20 15 10 5 0
Current
Energy
60.5 MPG
204 miles
Reset
6:22
the
eco-feedback
design space
7:27 PM
03/31/08
T-Mobile
Start
Message

what

are the most water consuming activities in the average North American home?

top water usage activities

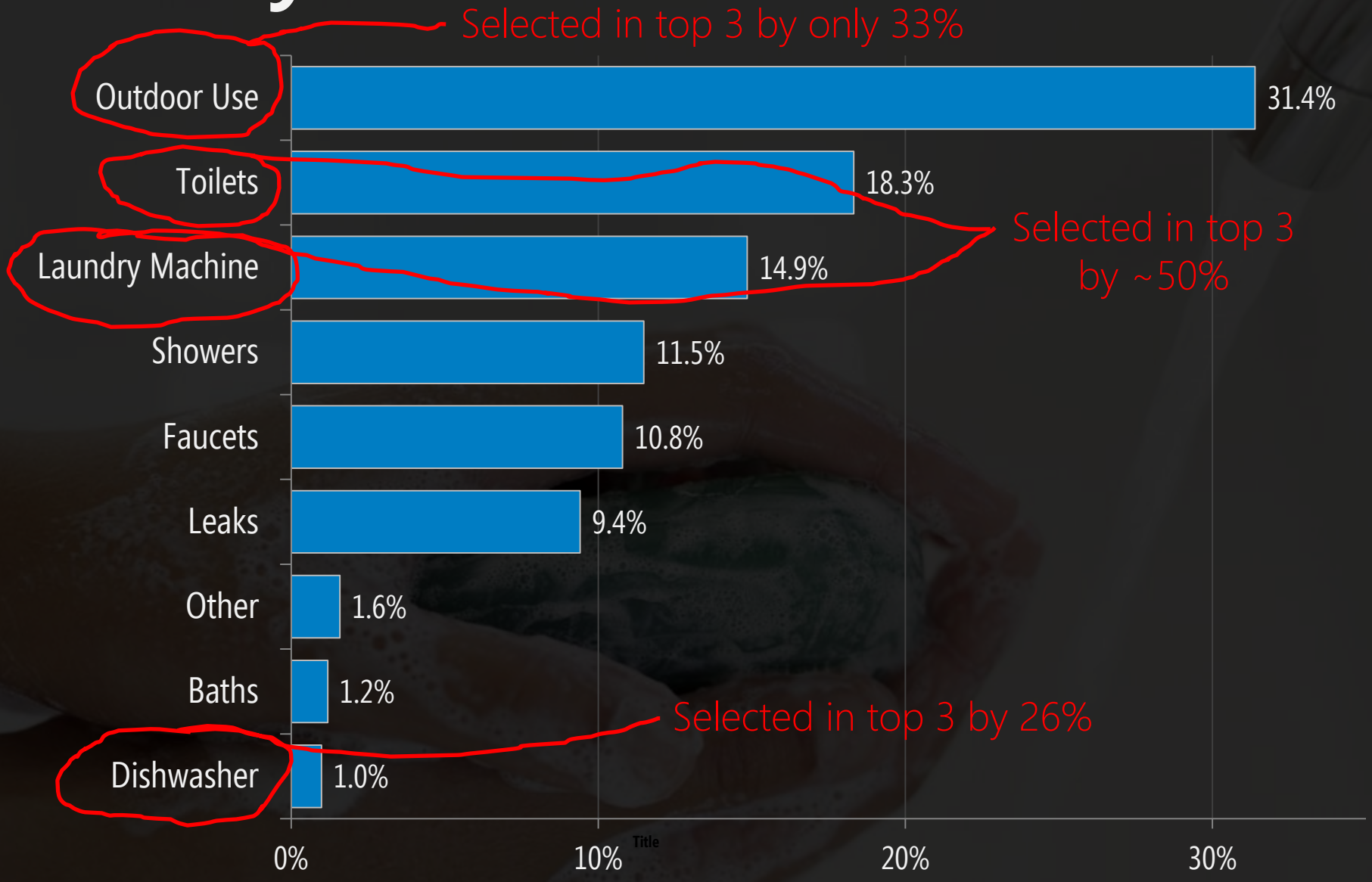


[Vickers, Handbook of Water Use and Conservation, 2001]

we asked **656 people** the same thing

select the top 3 most water consuming activities in an average home

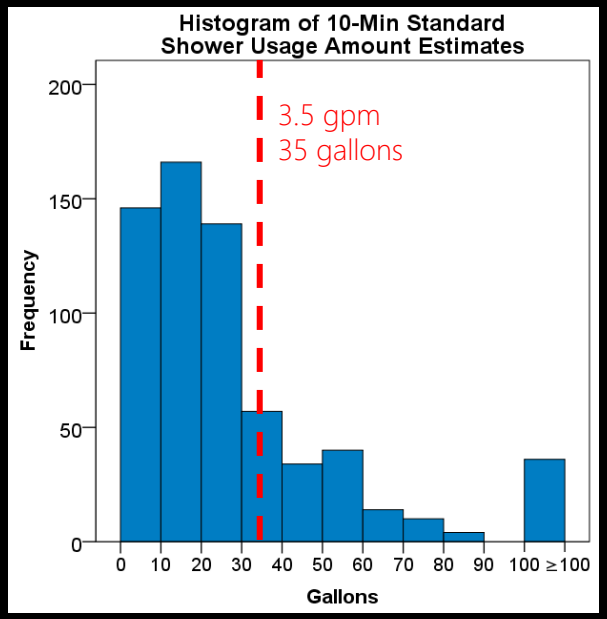
survey results

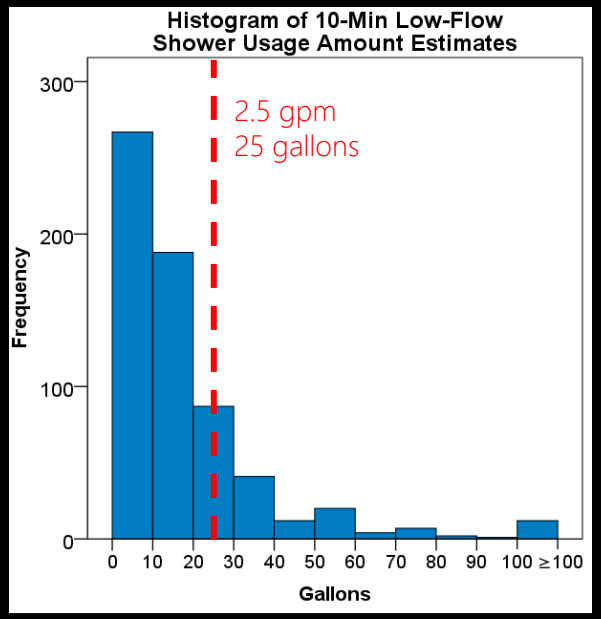


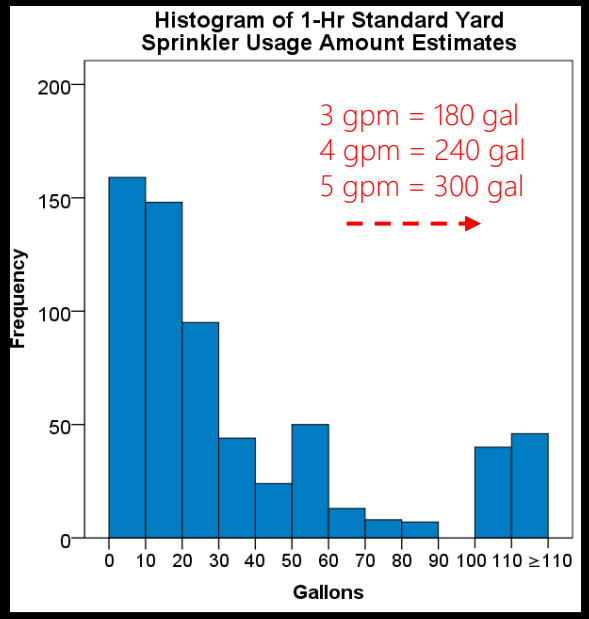
[Vickers, Handbook of Water Use and Conservation, 2001]

how much water do people think common activities actually use?

water usage estimates (N=656)







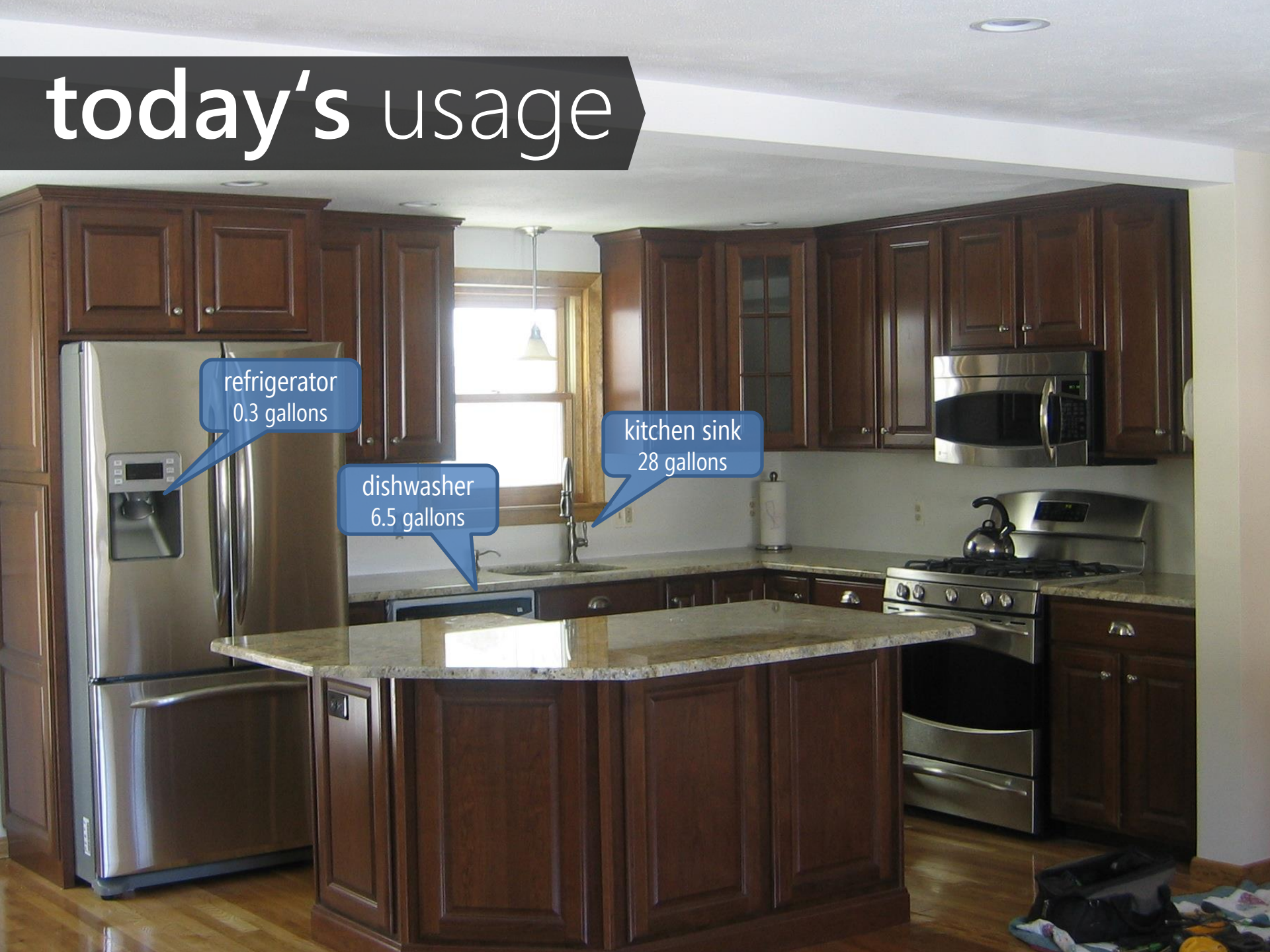
These were individuals greatly interested in water conservation!

- **88%** interested in conserving water at home
- **84%** try to limit their water usage


SAFEWAY
SAVE MORE AT SAFEWAY
GROCERY
SFWY PRTZLE STICK
RegPrice 1.79
CardSav .29
1.50 B
BLKBERY PRES
SFY CANOLA OIL
CEREAL PNT BUTTER
CHILI SAUCE SWT
CHF-B PIZZA
LK GRLC SCE
REFRIG/FROZEN
LUC CHEESE
RegPrice 6.79
SPINACH ARTICHOKE
RegPrice 3.79
3S CRWN VEG RSTD
RegPrice 3.79
2@2.50 SFWY SEL MEDALL FC
RegPrice 7.58
MARGARINE
GEN MERCHANDIS
#SFY BENEHIST TAB
BAKED GOODS
LD COSMIC BROWNIES
1.29 B
OROWEAT RYE
3.14 B
CUSTARD PIE 9IN
4.99 B
RegPrice 5.99
CardSav 1.00
CHOC CREAM PIE
4.99 B
RegPrice 5.99
CardSav 1.00
**** TAX
6.76 BAL
144.25
VF MC XXXXXXXXX
144.25
.00
CHANGE
TOTAL SAVINGS 16.97
NUMBER OF ITEMS = 35
SAFEWAY
SAVE MORE AT SAFEWAY
Month: April 2006
Total Food Units: 1527
Total Price:
$642

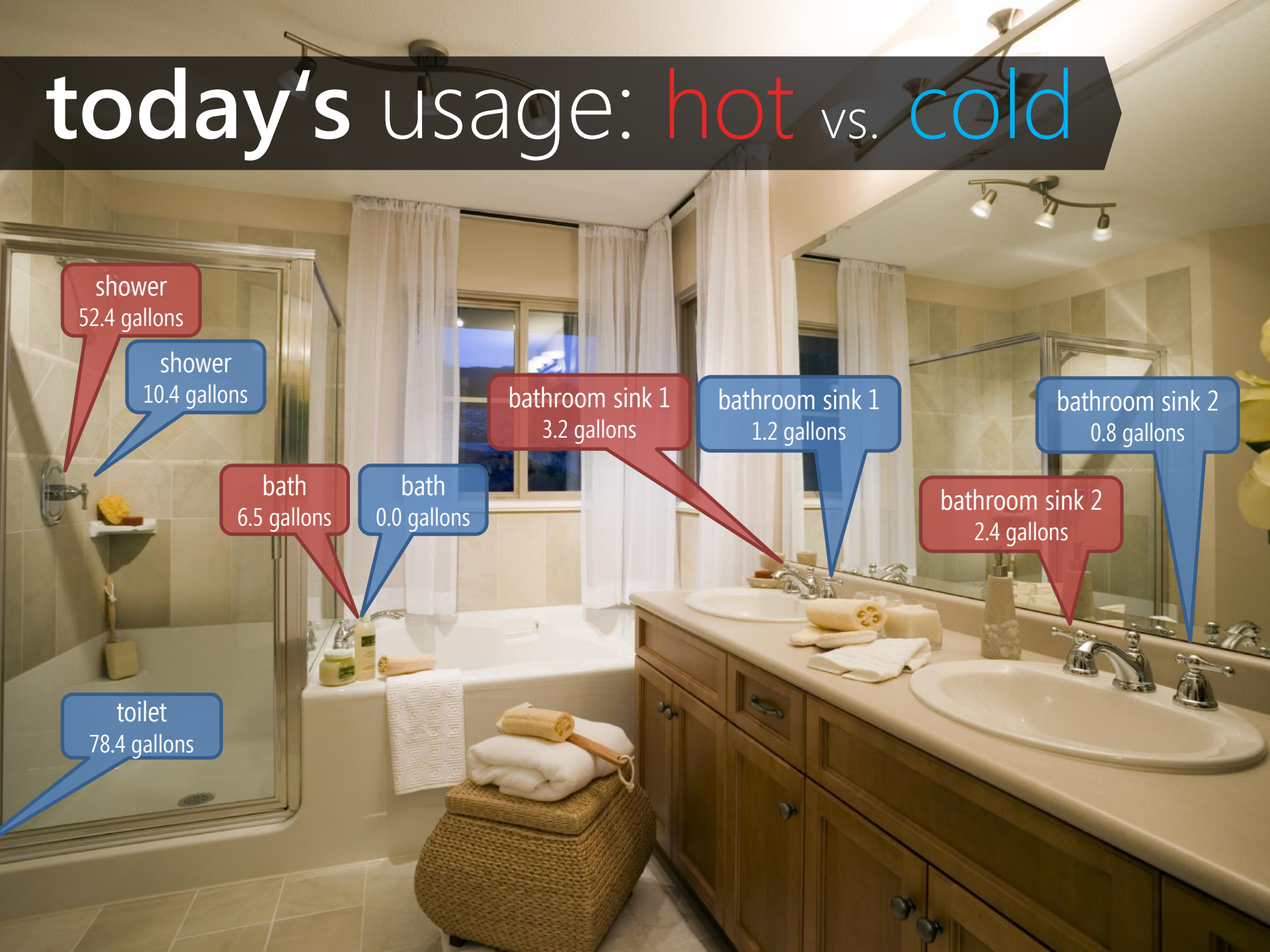
what if you could get the same level of feedback in the home?

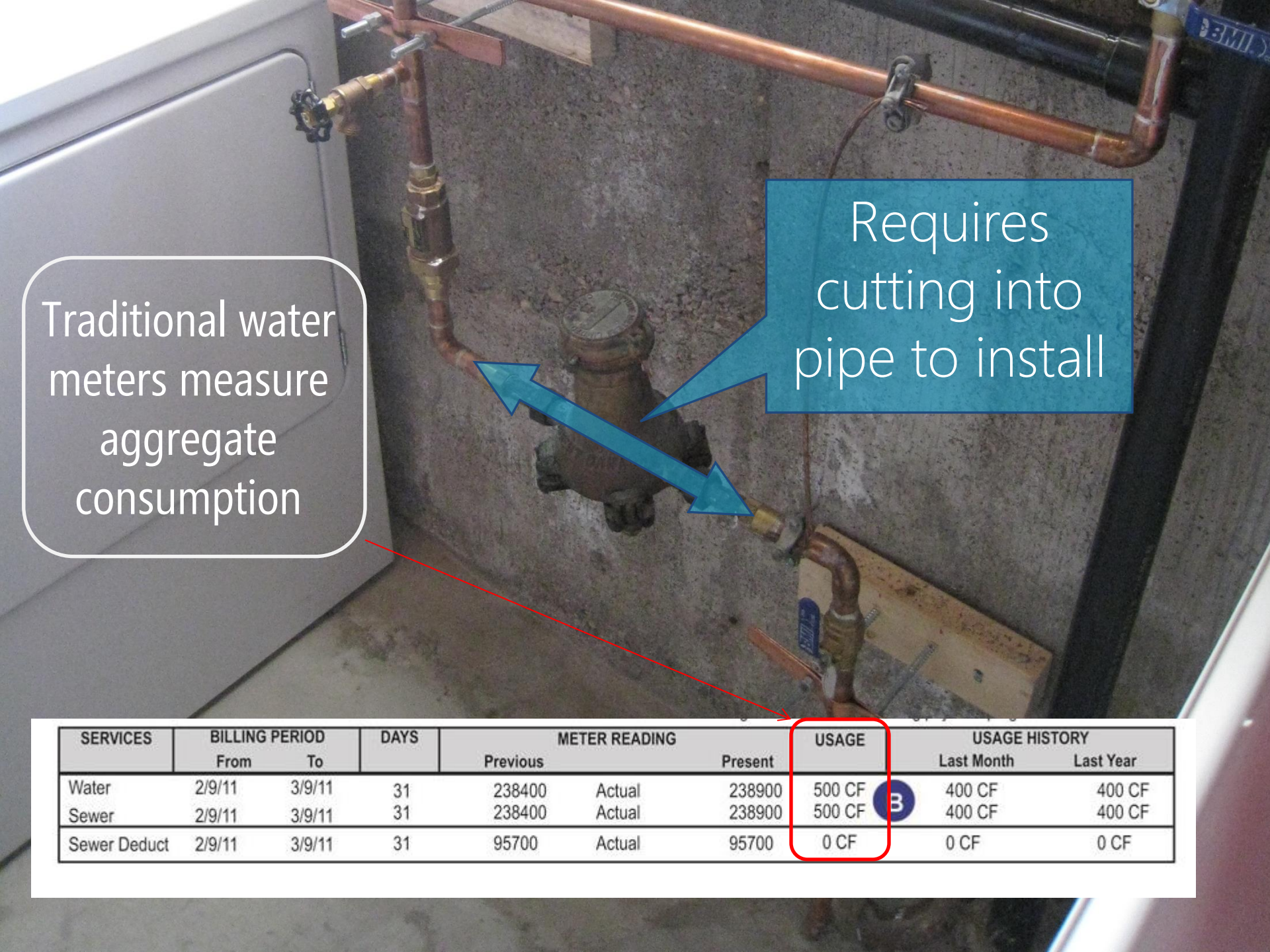
today's usage



today's usage

today's usage: hot vs. cold





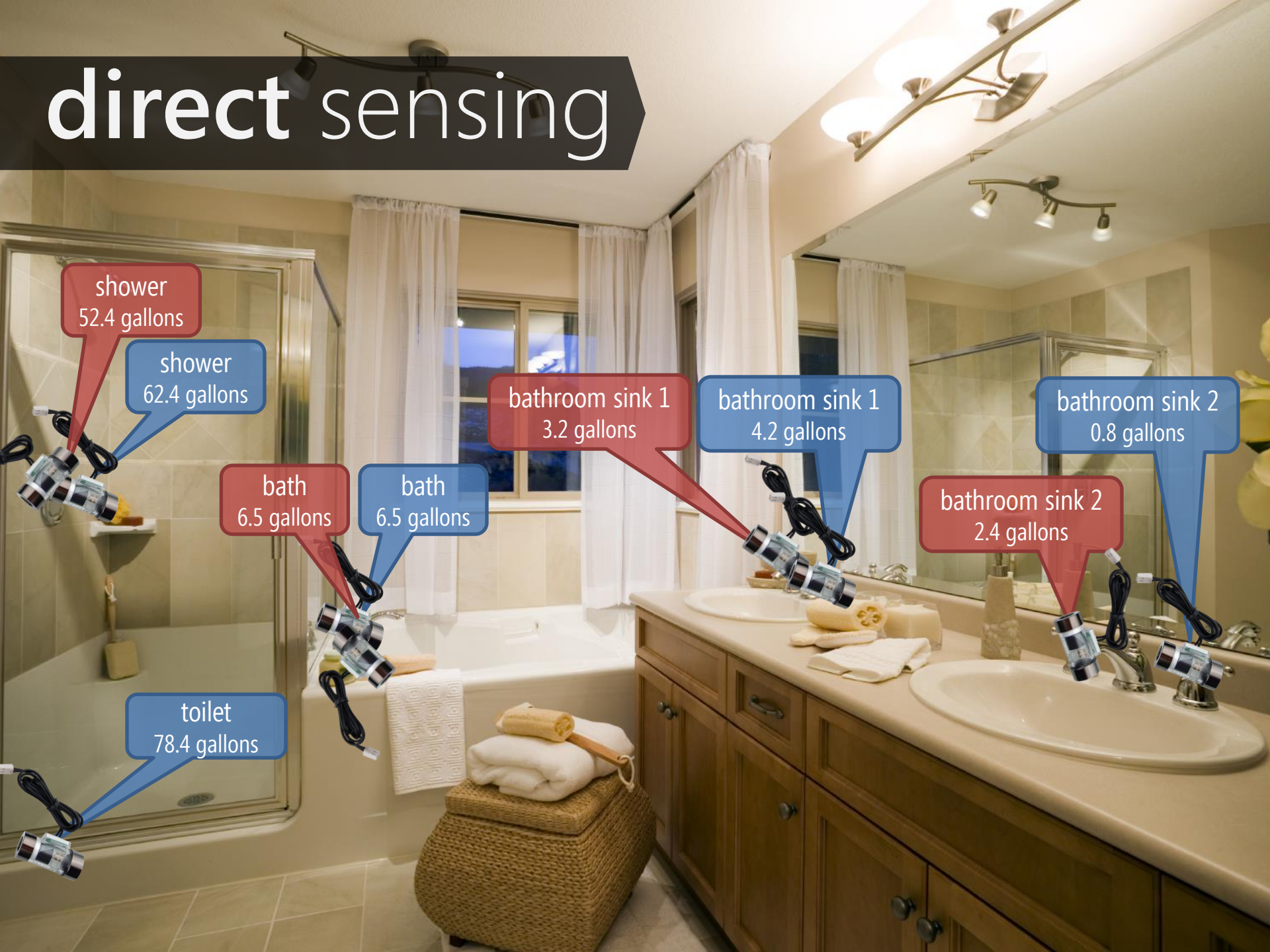
SERVICES	BILLING PERIOD From	To	DAYS	METER READING Previous		Present	USAGE	USAGE HISTORY Last Month	Last Year
Water	2/9/11	3/9/11	31	238400	Actual	238900	500 CF	400 CF	400 CF
Sewer	2/9/11	3/9/11	31	238400	Actual	238900	500 CF	400 CF	400 CF
Sewer Deduct	2/9/11	3/9/11	31	95700	Actual	95700	0 CF	0 CF	0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

direct sensing

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

direct sensing

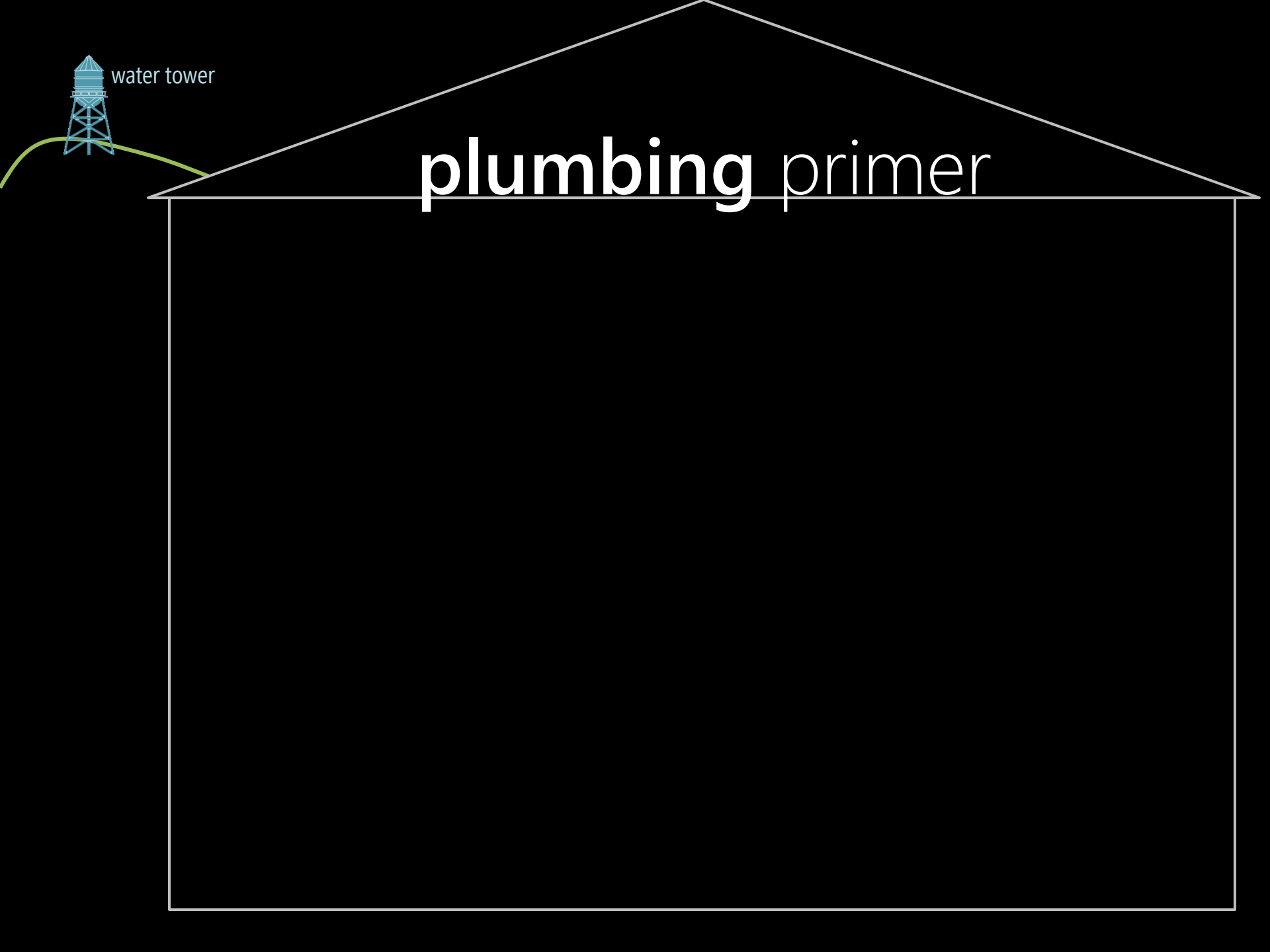
direct sensing



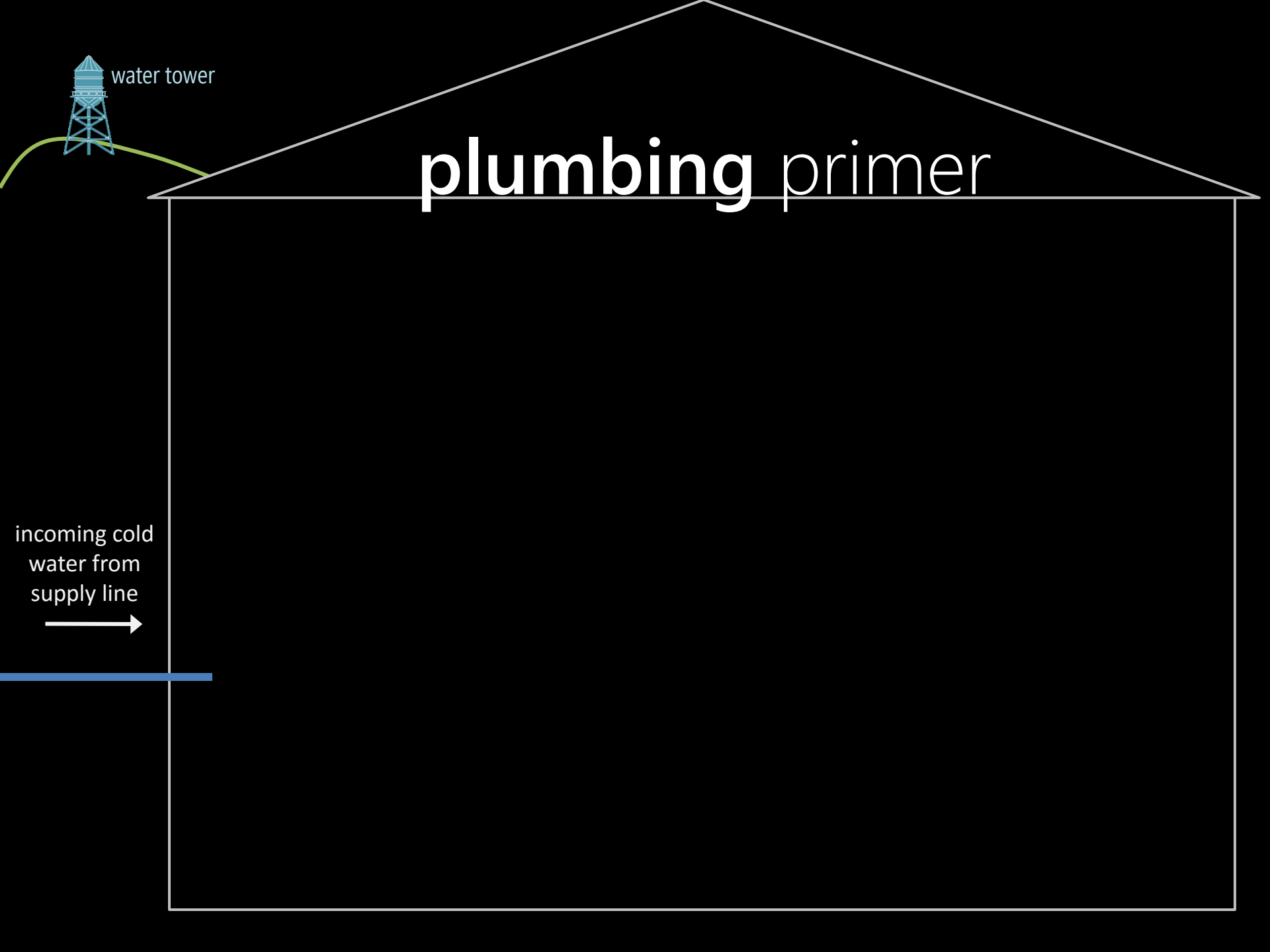
scalable
fixture-level sensing
easy-to-install
easy-to-maintain
low-cost

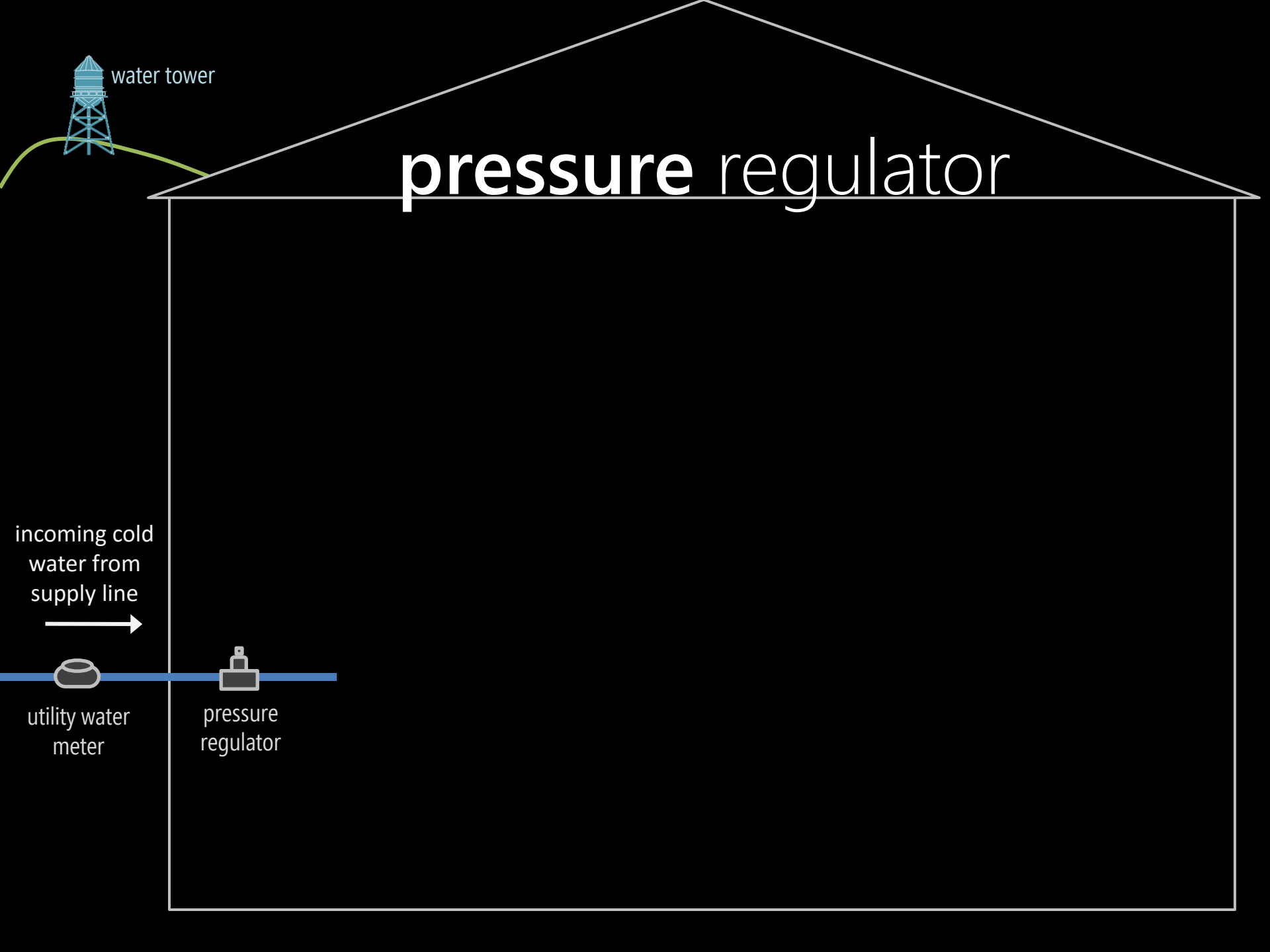

hydrosense
single, screw-on sensor
identifies fixture usage
estimates flow
Froehlich et al., UbiComp2009; Larson et al., PMC2010; Froehlich et al., Pervasive2011

brief plumbing primer

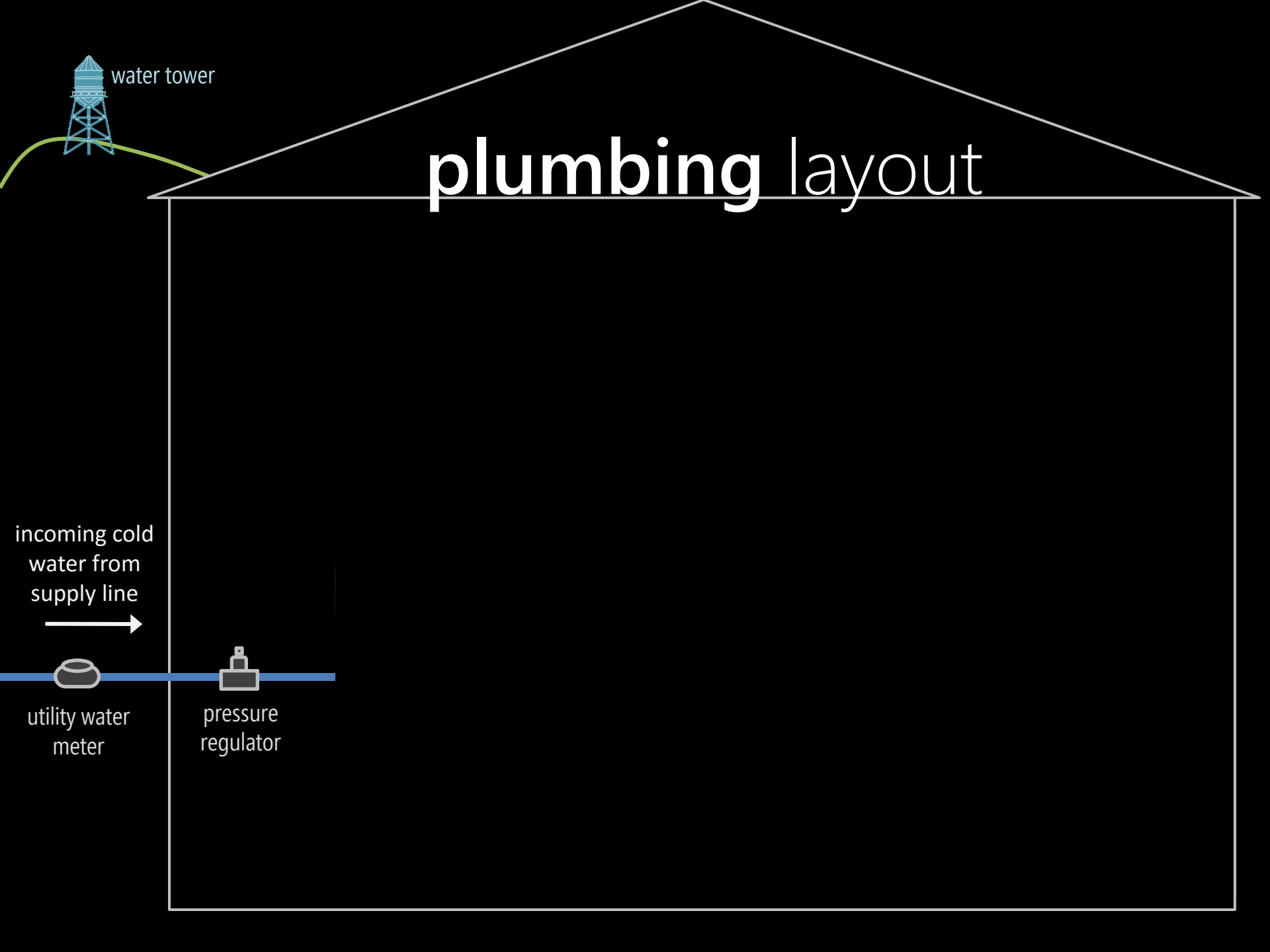


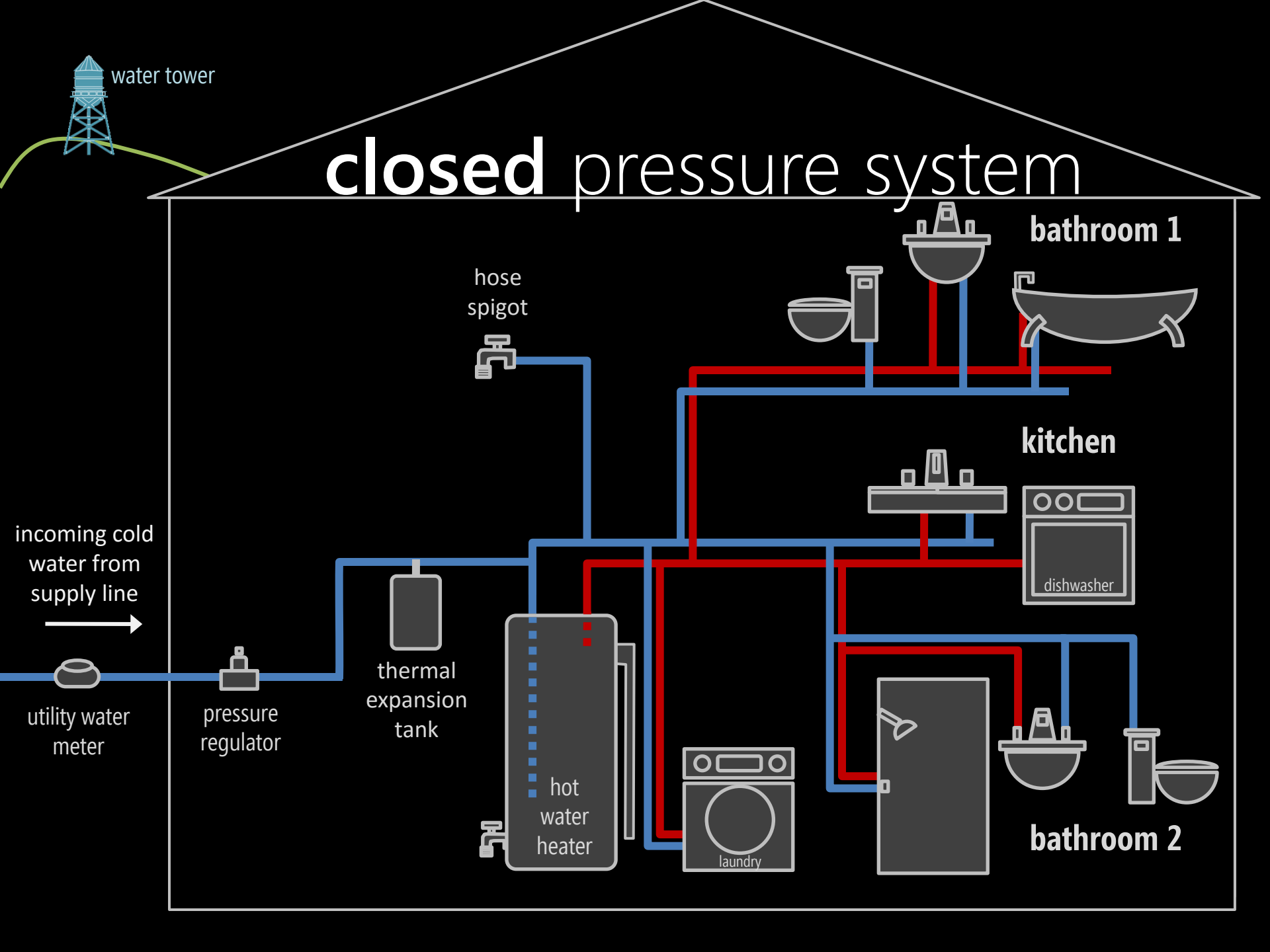
plumbing primer

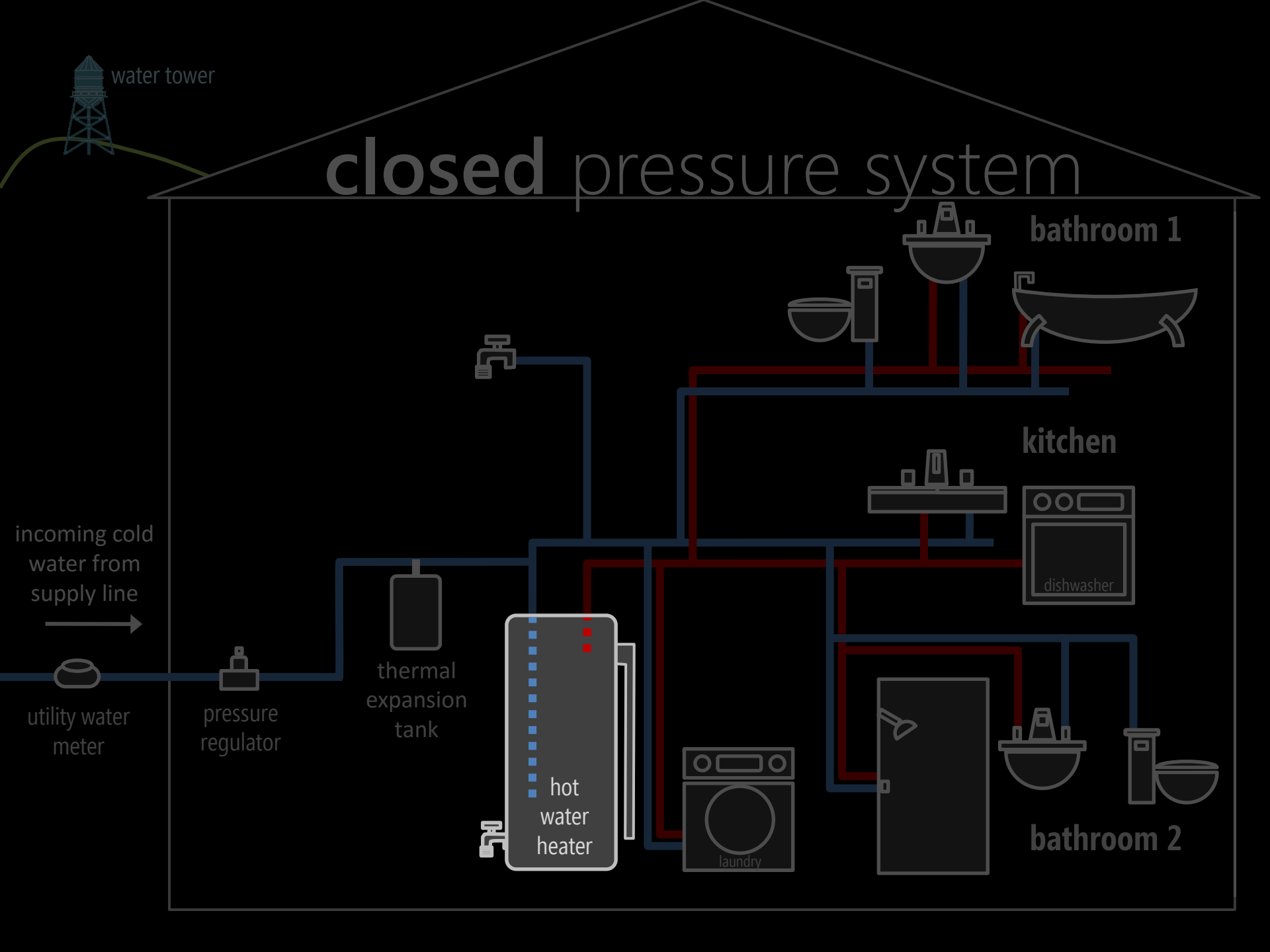

water tower
plumbing primer
incoming cold water from supply line

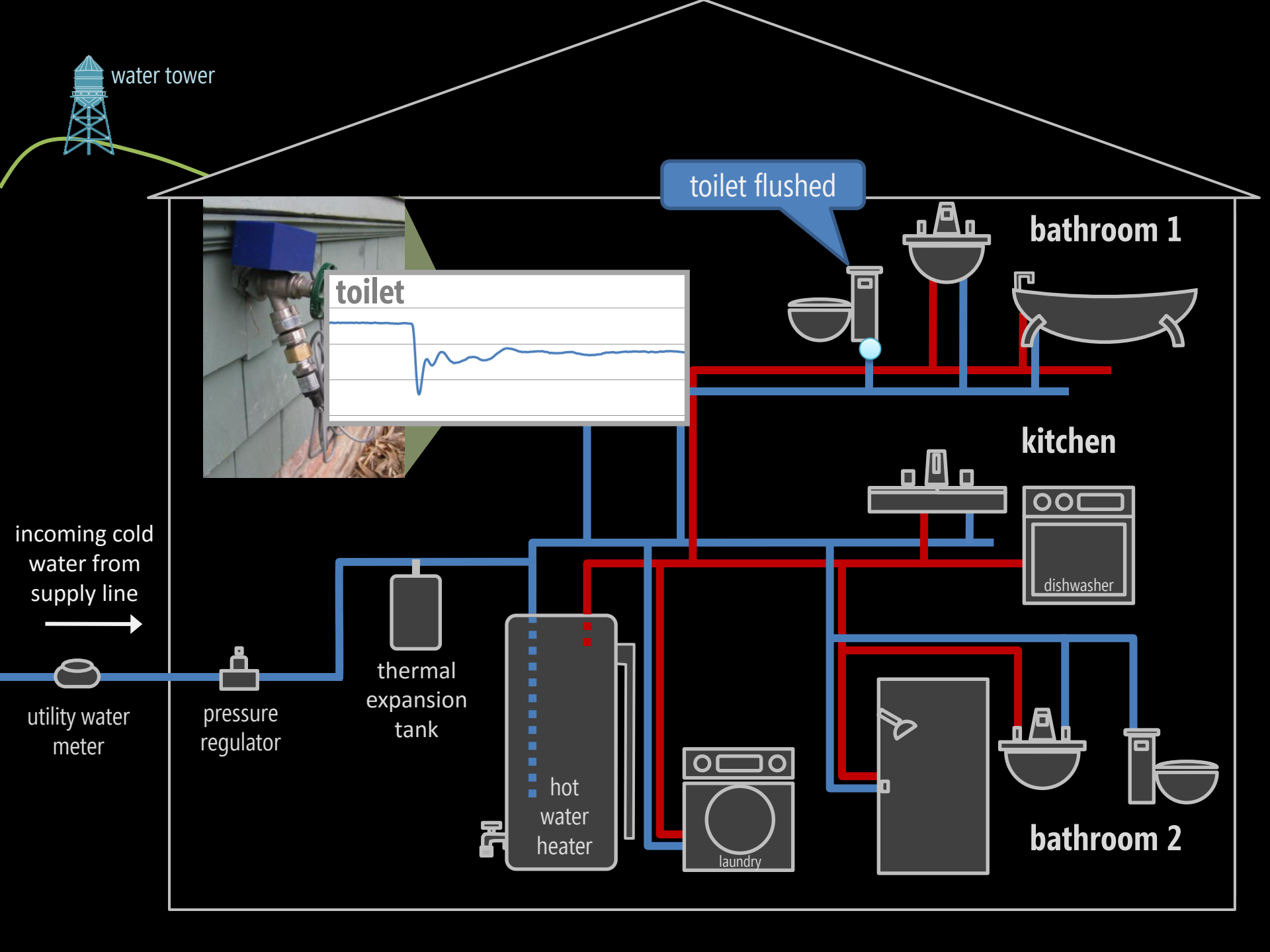

water tower
pressure regulator
incoming cold water from supply line
utility water meter
pressure regulator

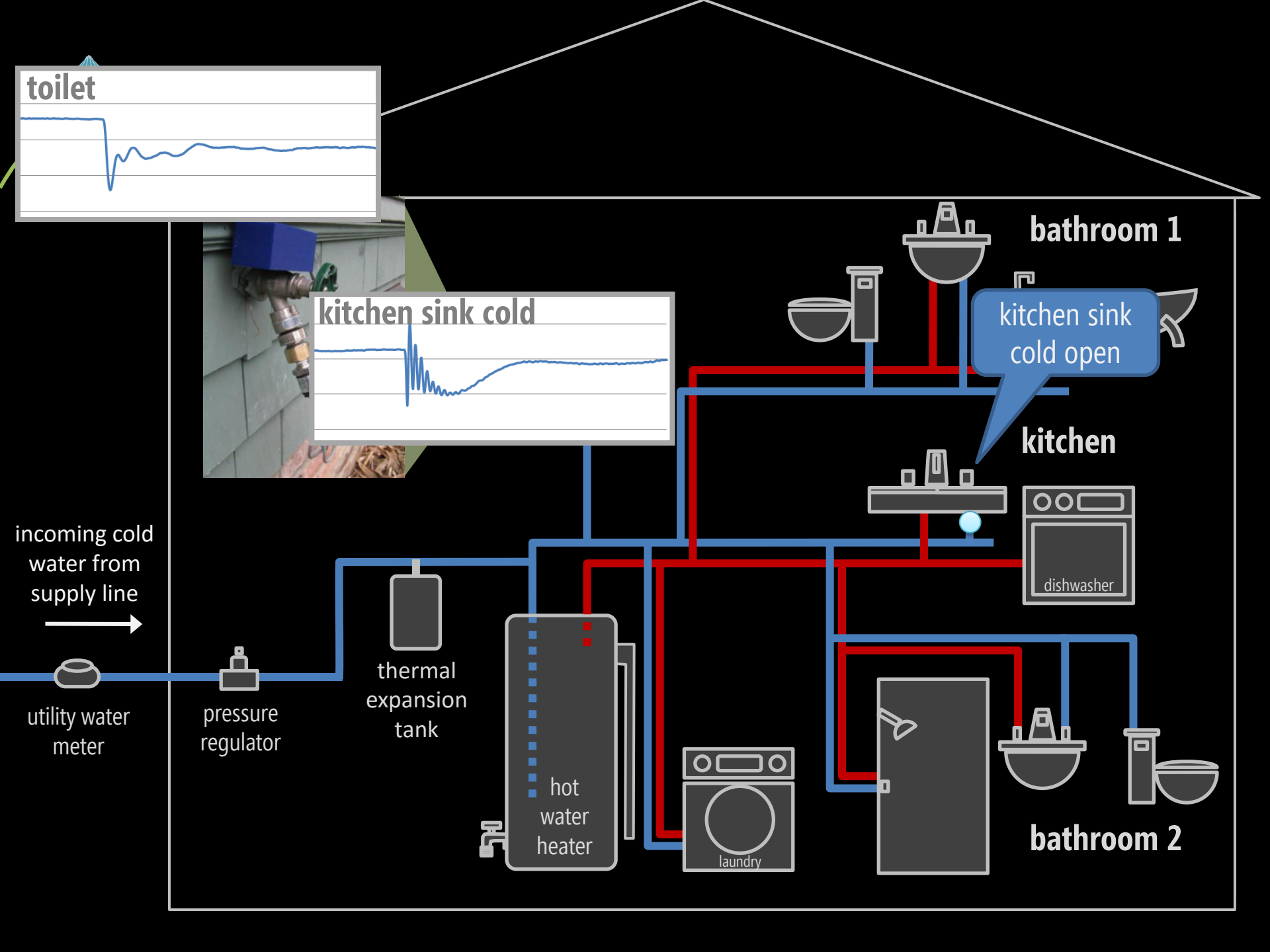
plumbing layout

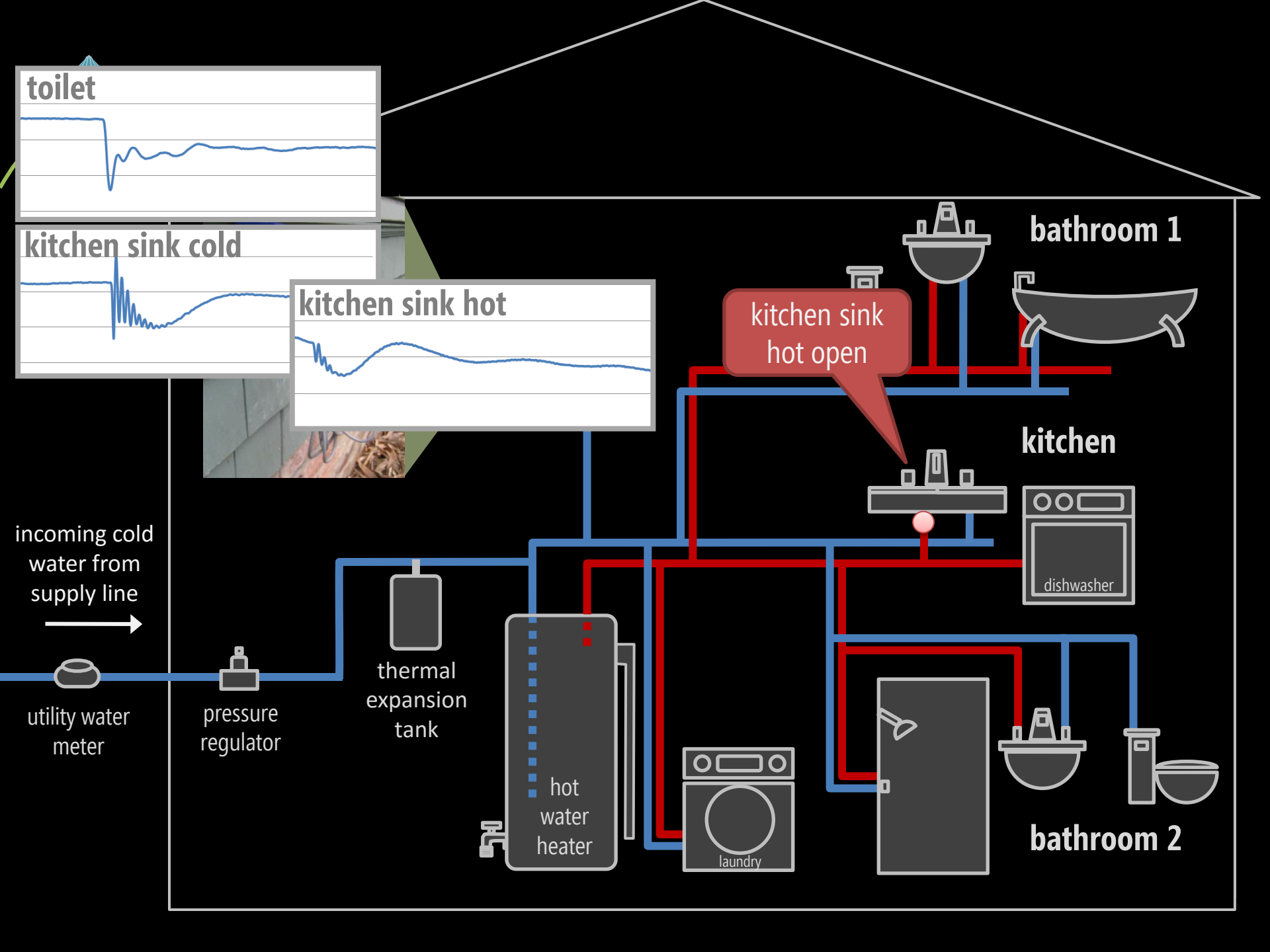


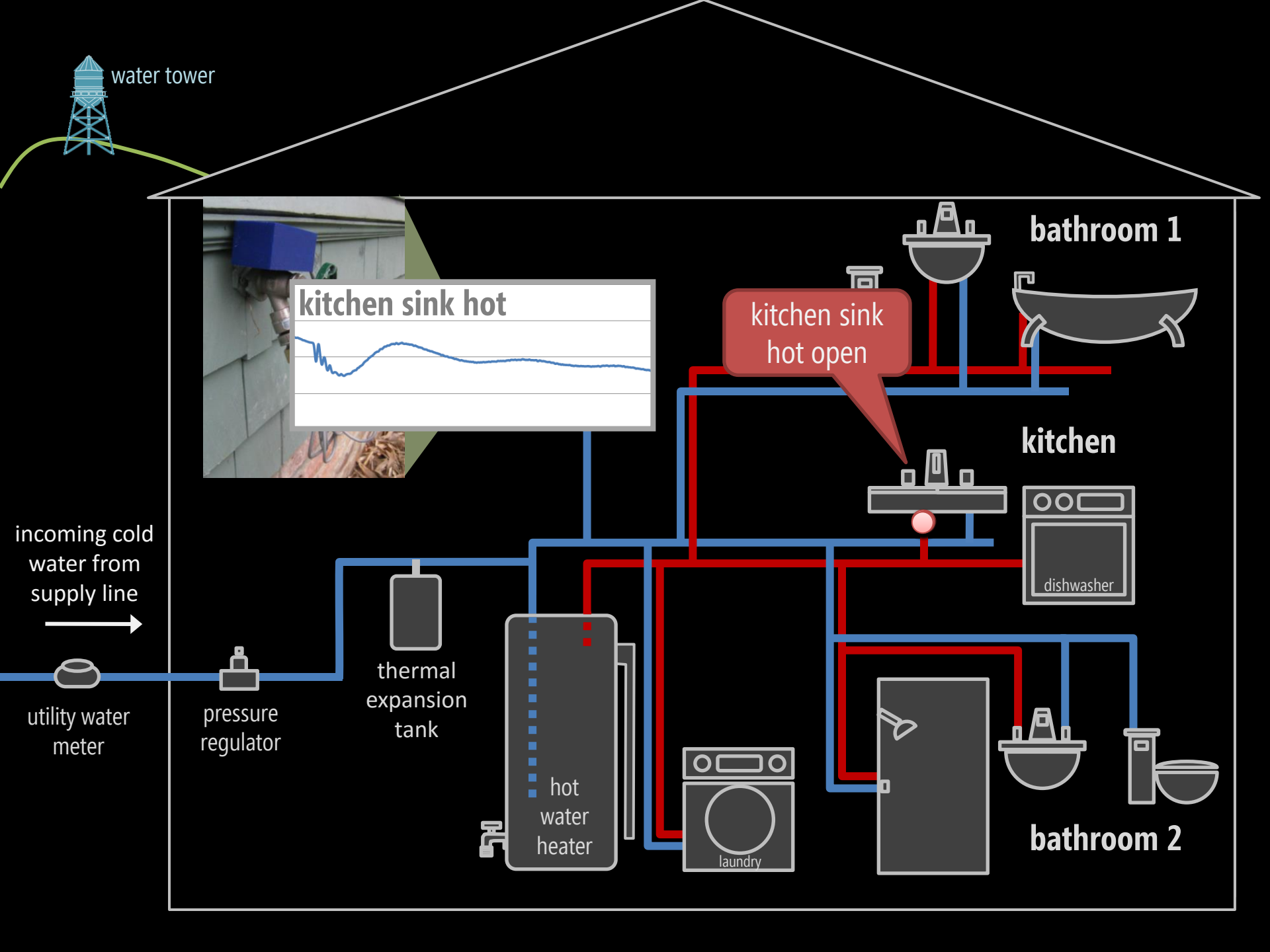

water tower
closed pressure system
bathroom 1
hose spigot
kitchen
dishwasher
incoming cold water from supply line
utility water meter
pressure regulator
thermal expansion tank
hot water heater
laundry
bathroom 2

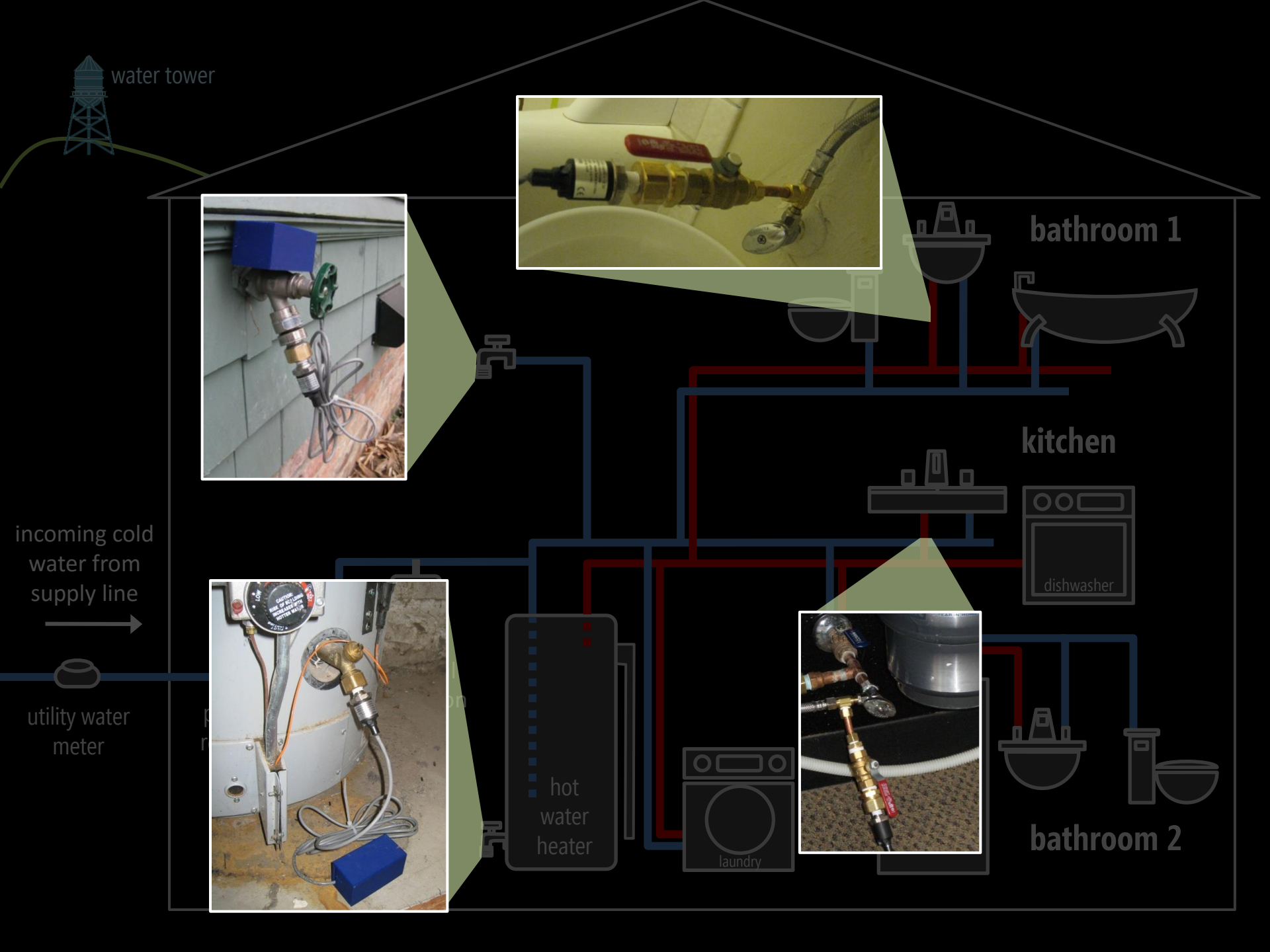

water tower
closed pressure system
bathroom 1
kitchen
dishwasher
incoming cold water from supply line
utility water meter
pressure regulator
thermal expansion tank
hot water heater
laundry
bathroom 2


water tower
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

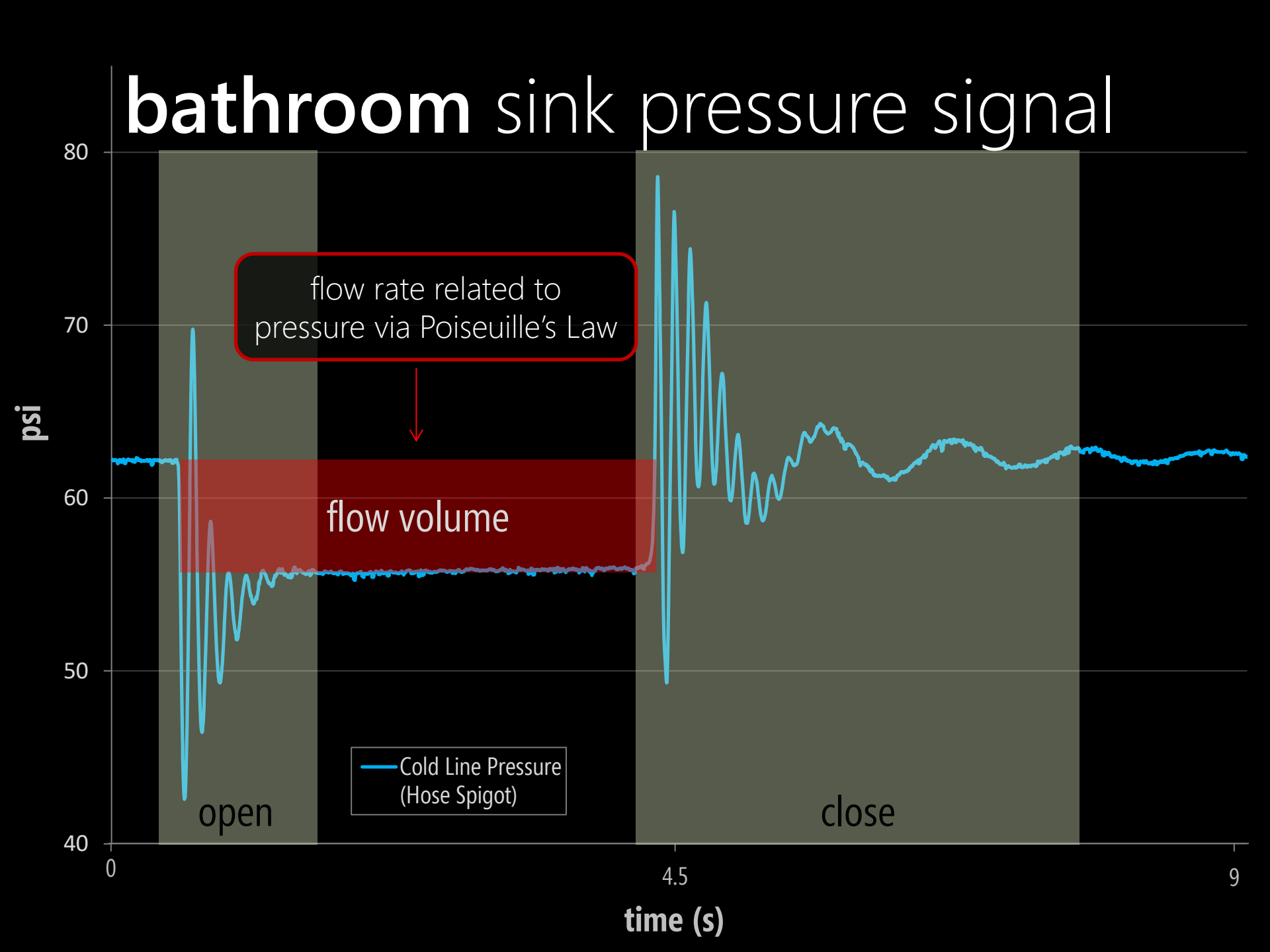

toilet
kitchen sink cold
bathroom 1
kitchen sink cold open
kitchen
dishwasher
incoming cold water from supply line
utility water meter
pressure regulator
thermal expansion tank
hot water heater
laundry
bathroom 2

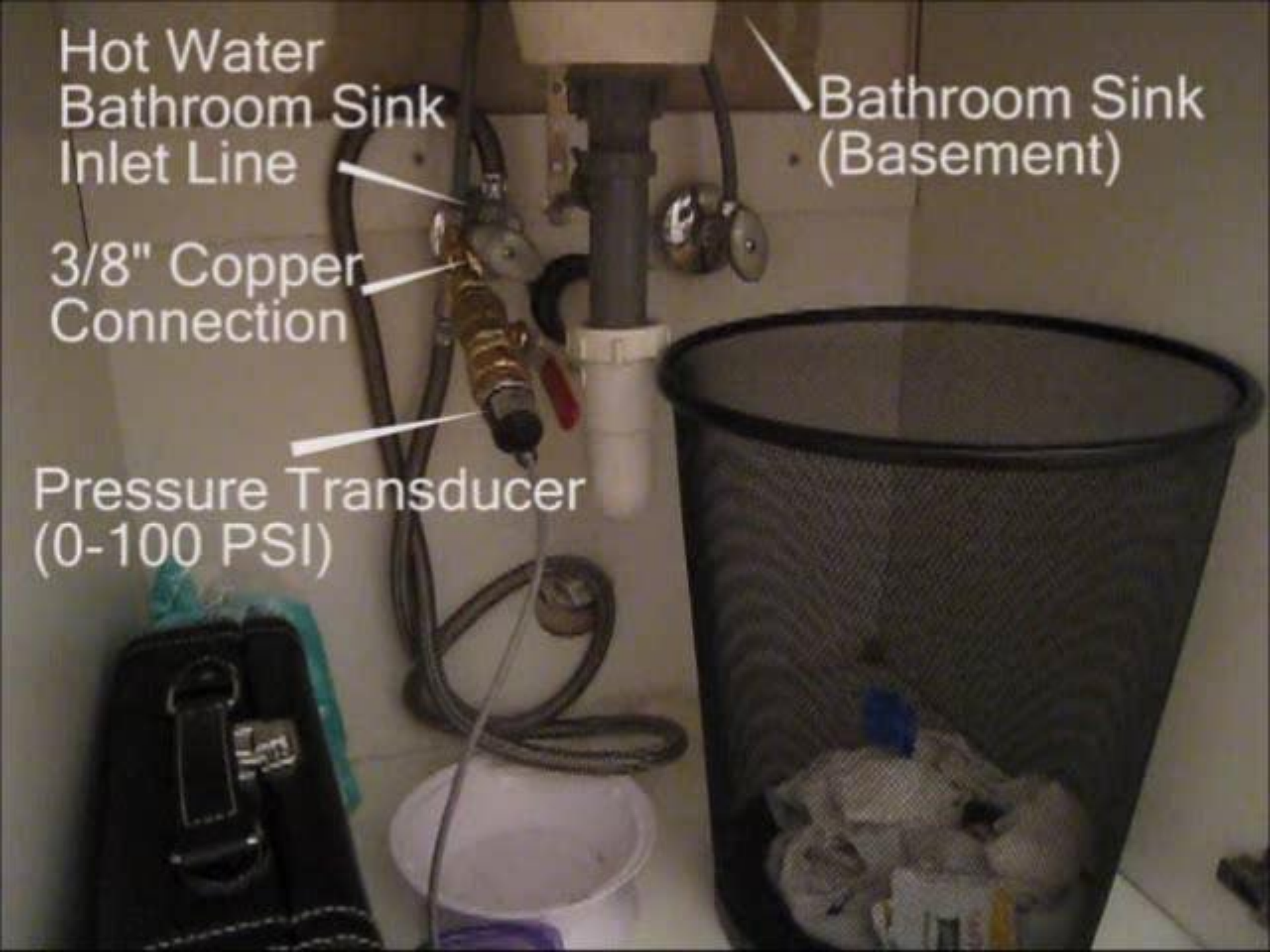

toilet
kitchen sink cold
kitchen sink hot
bathroom 1
kitchen sink hot open
kitchen
dishwasher
incoming cold water from supply line
utility water meter
pressure regulator
thermal expansion tank
hot water heater
laundry
bathroom 2


water tower
kitchen sink hot
kitchen sink hot open
bathroom 1
kitchen
dishwasher
incoming cold water from supply line
utility water meter
pressure regulator
thermal expansion tank
hot water heater
laundry
bathroom 2

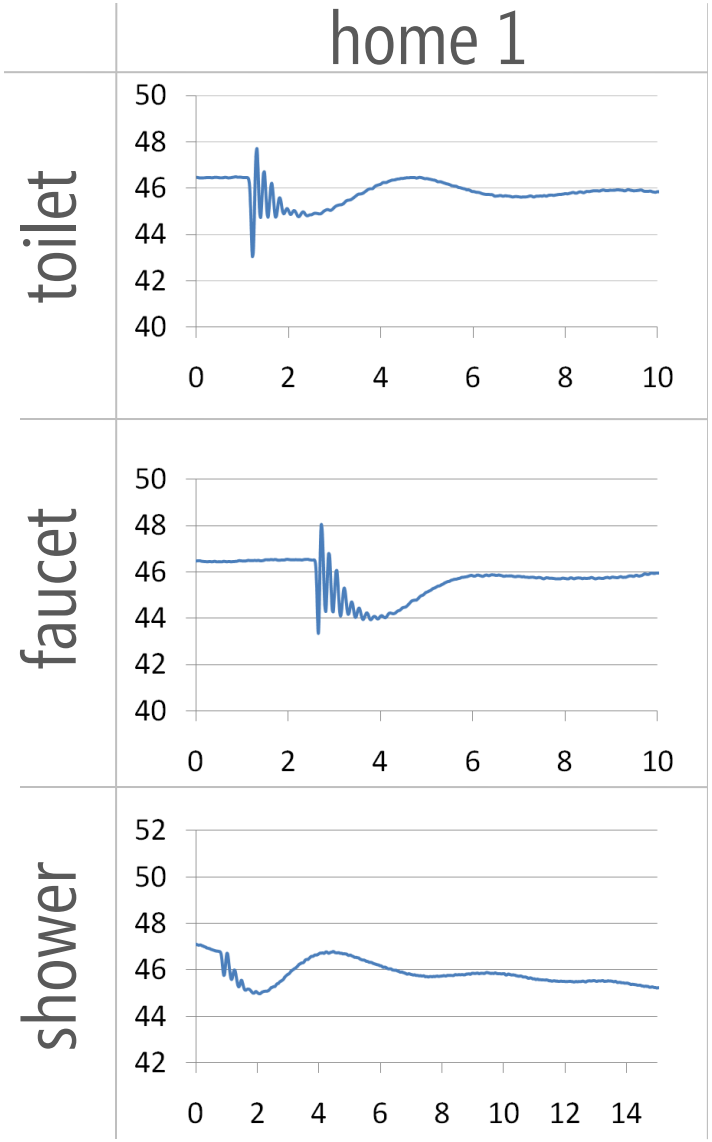

water tower
bathroom 1
kitchen
dishwasher
incoming cold water from supply line
utility water meter
hot water heater
laundry
bathroom 2


bathroom sink pressure signal
80
70
60
50
40
psi
0
4.5
9
time (s)


bathroom sink pressure signal
80
70
60
50
40
psi
flow rate related to
pressure via Poiseuille's Law
flow volume
Cold Line Pressure
(Hose Spigot)
open
close
0
4.5
9
time (s)

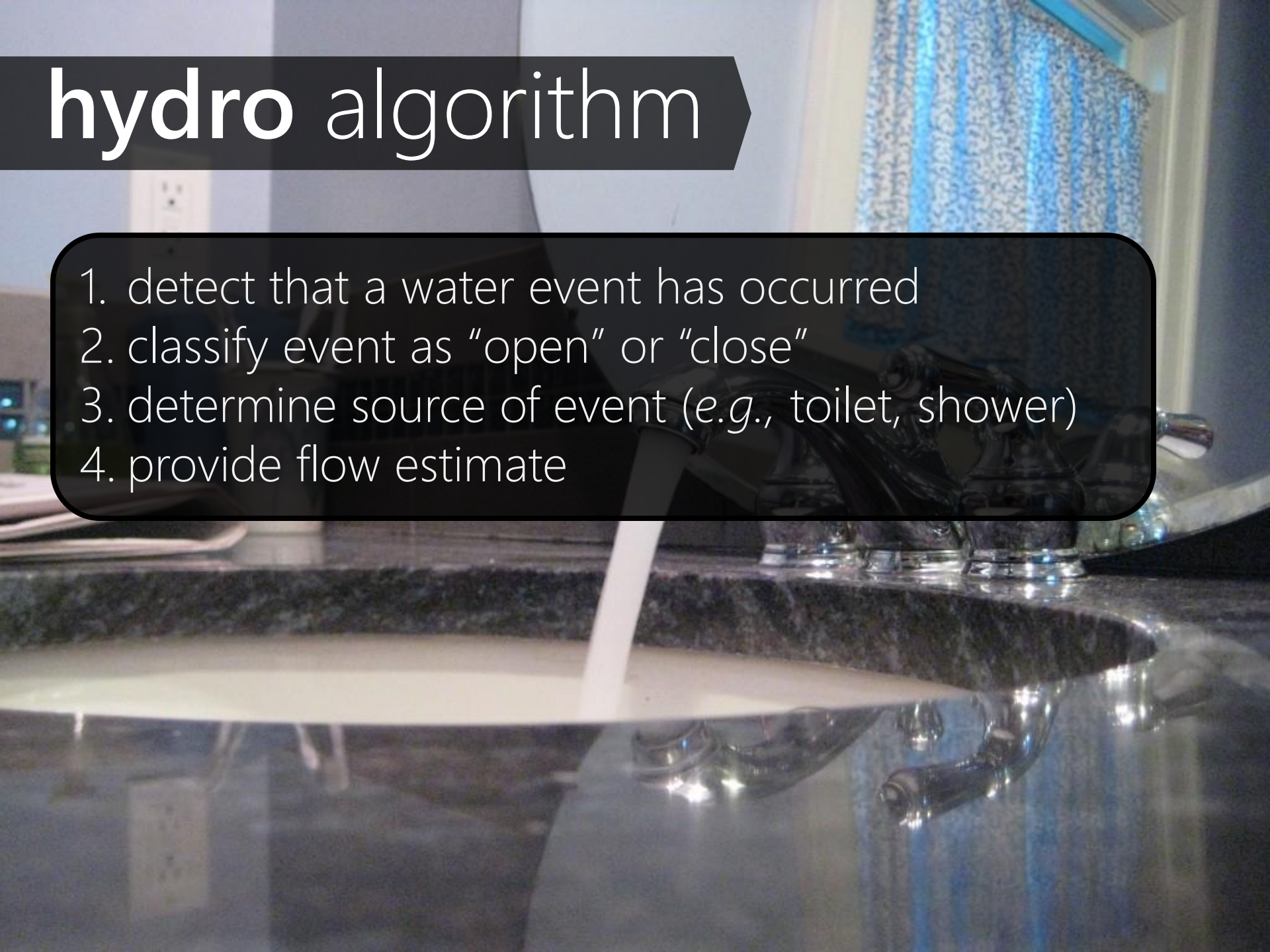

Hot Water
Bathroom Sink
Inlet Line
Bathroom Sink
(Basement)
3/8" Copper
Connection
Pressure Transducer
(0-100 PSI)

example open events



signature dependent on:

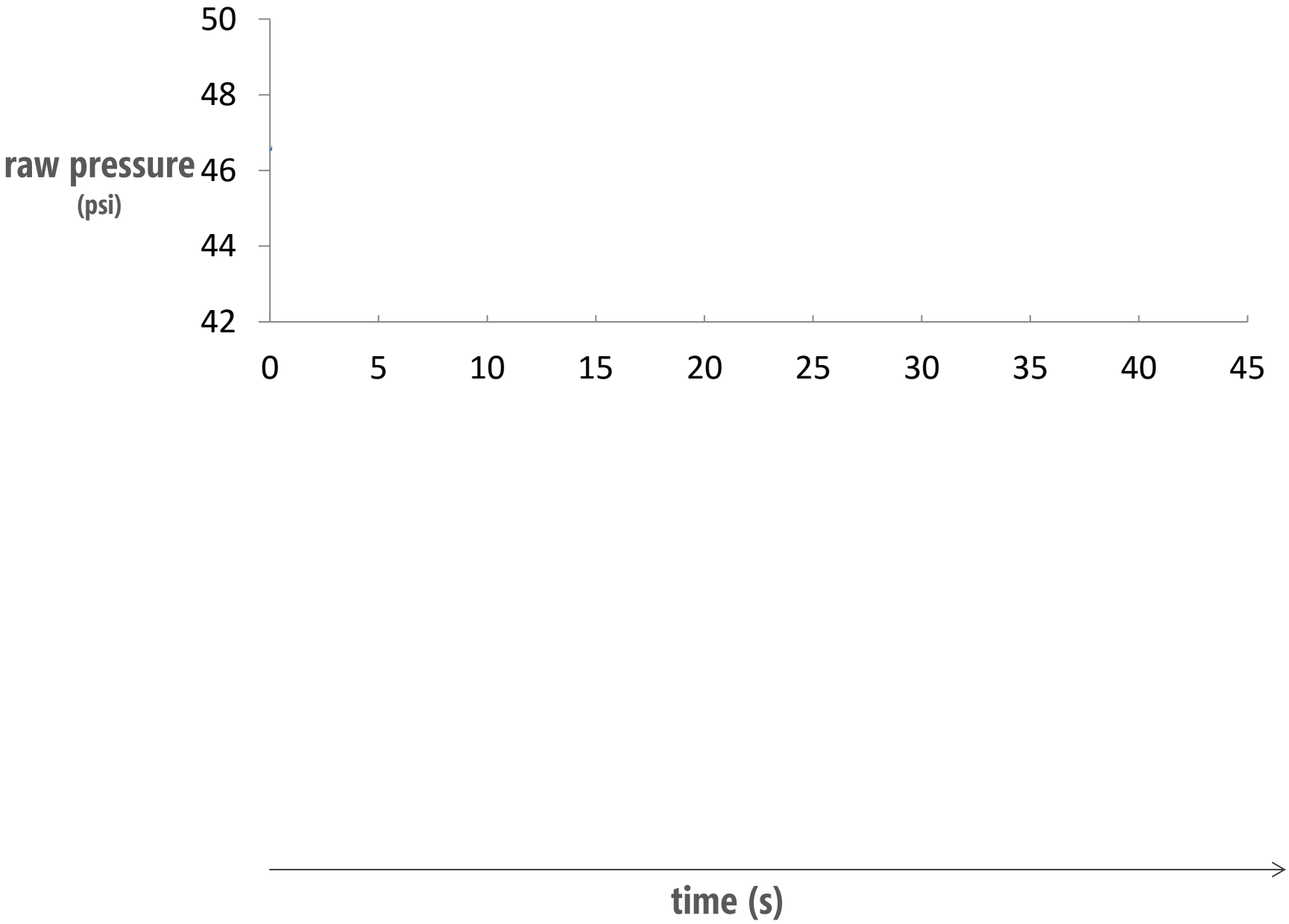
- fixture type
- valve type
- valve location in home



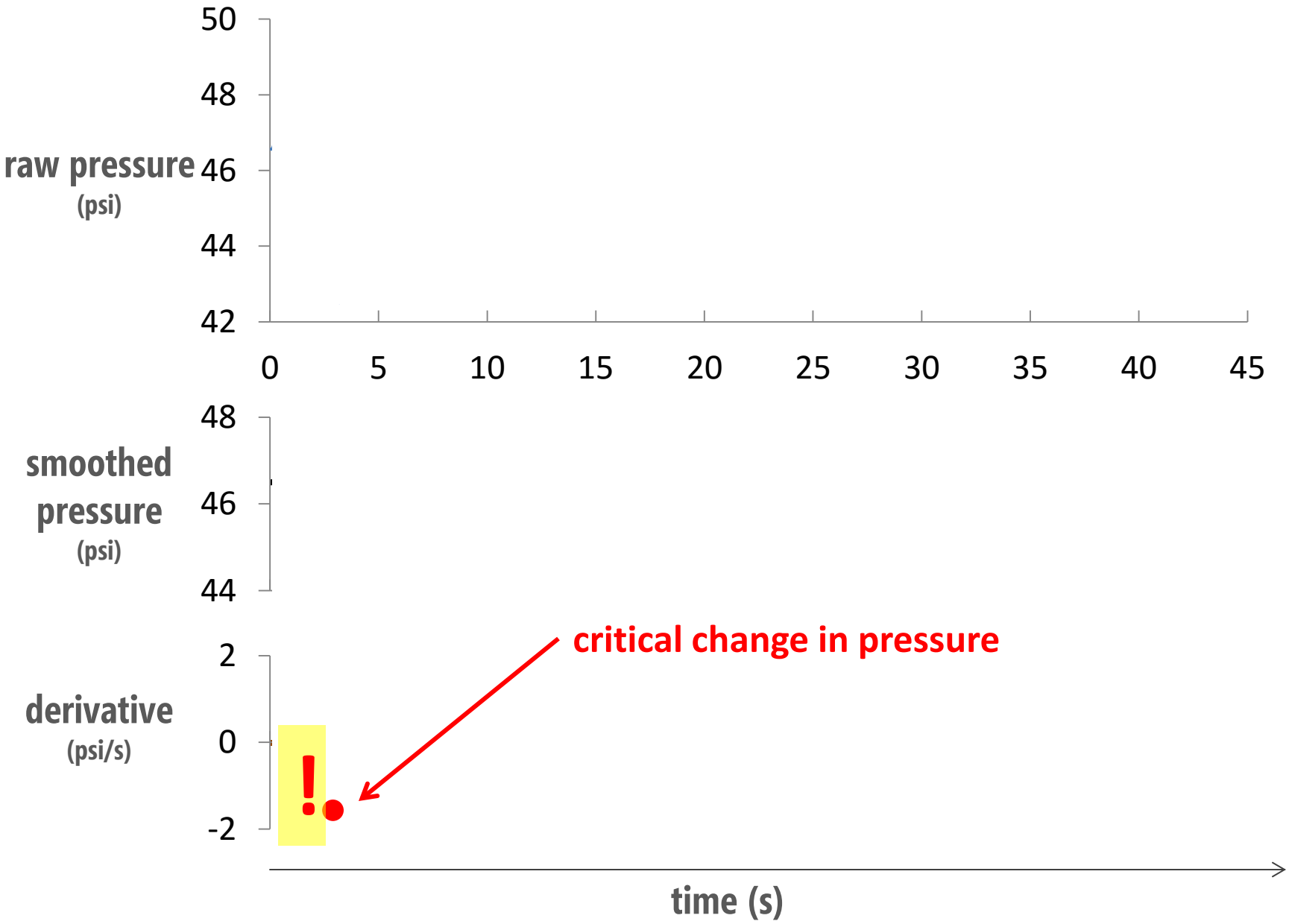
hydro algorithm

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

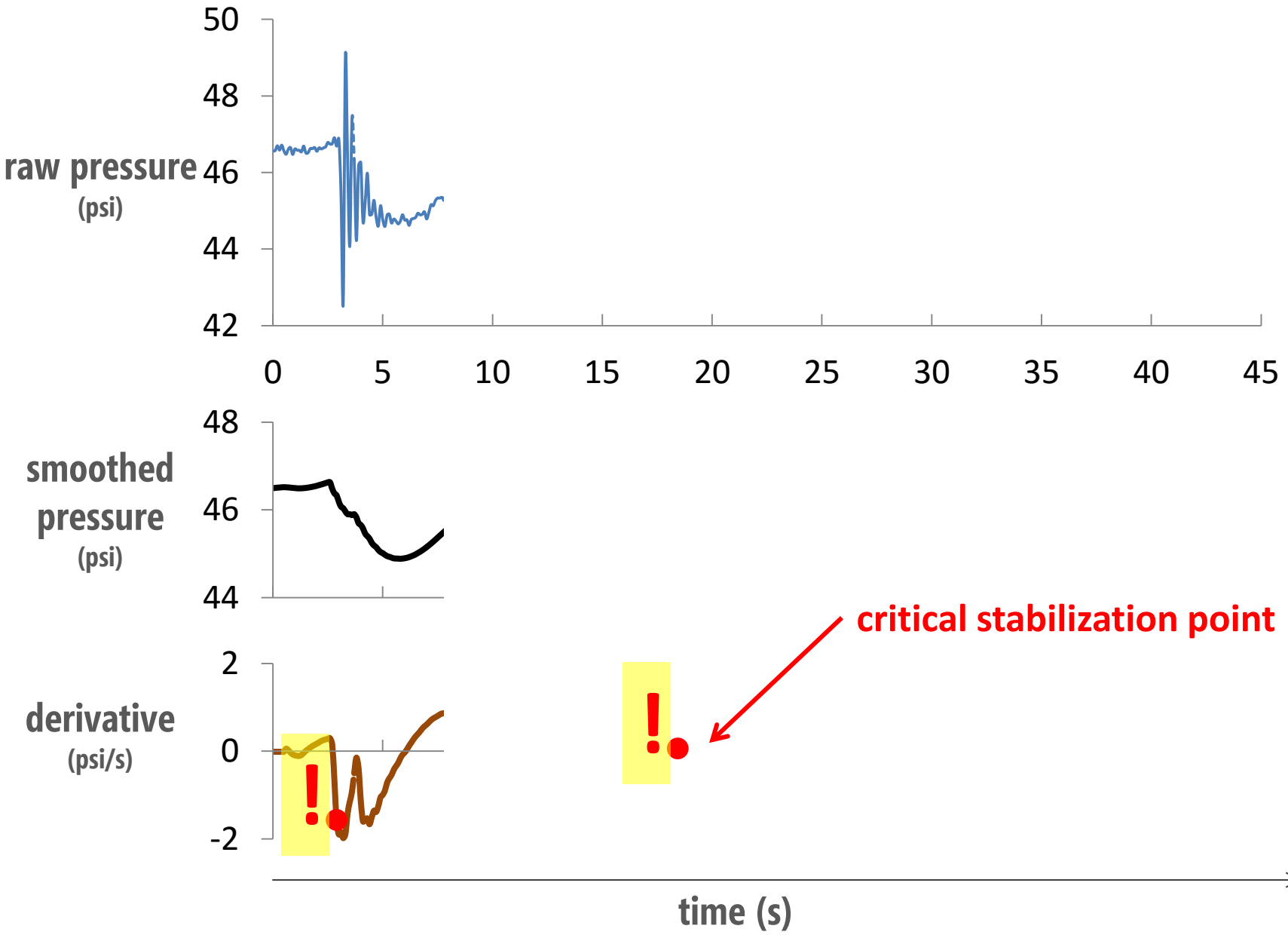
event detection/segmentation



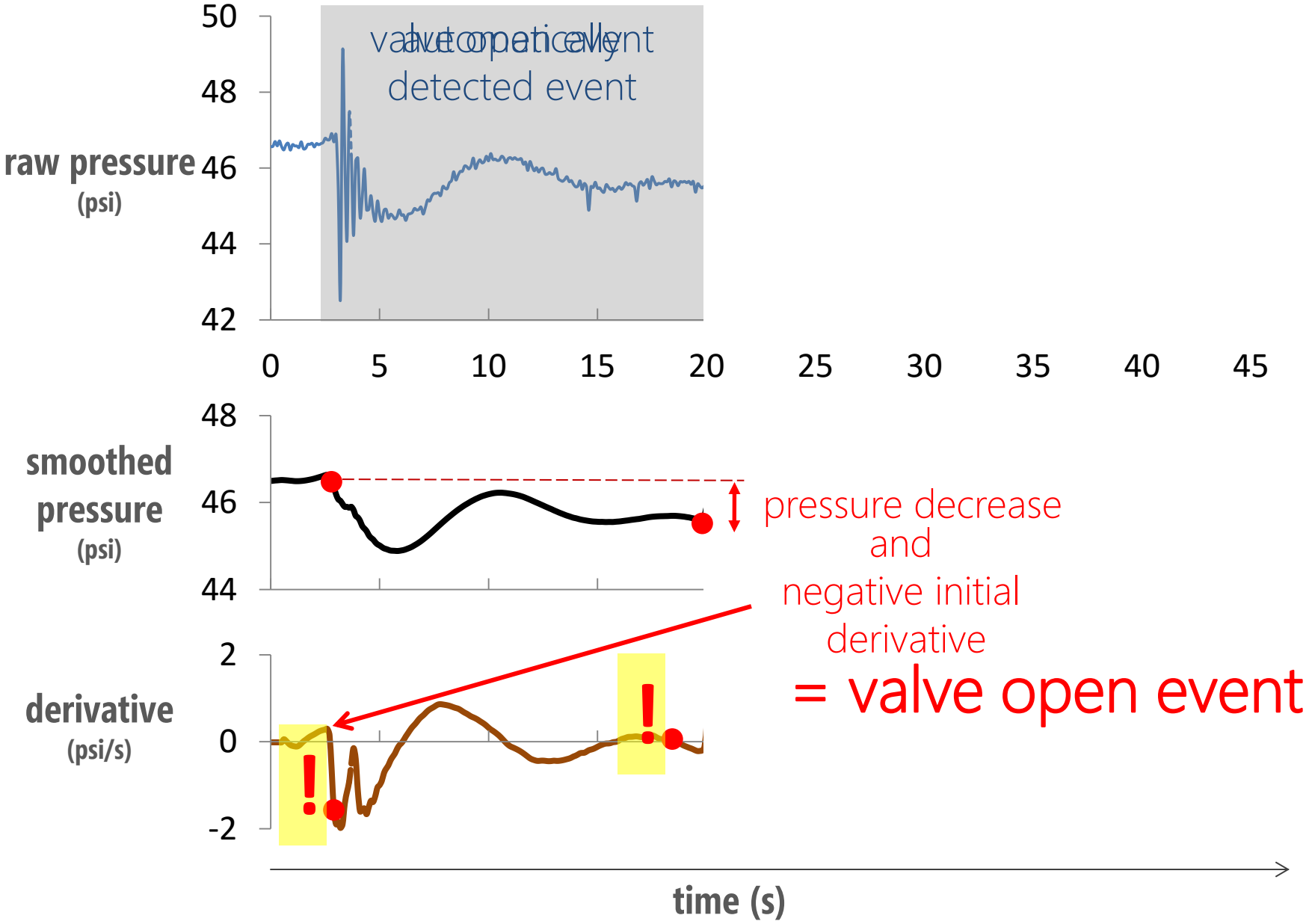
event detection/segmentation



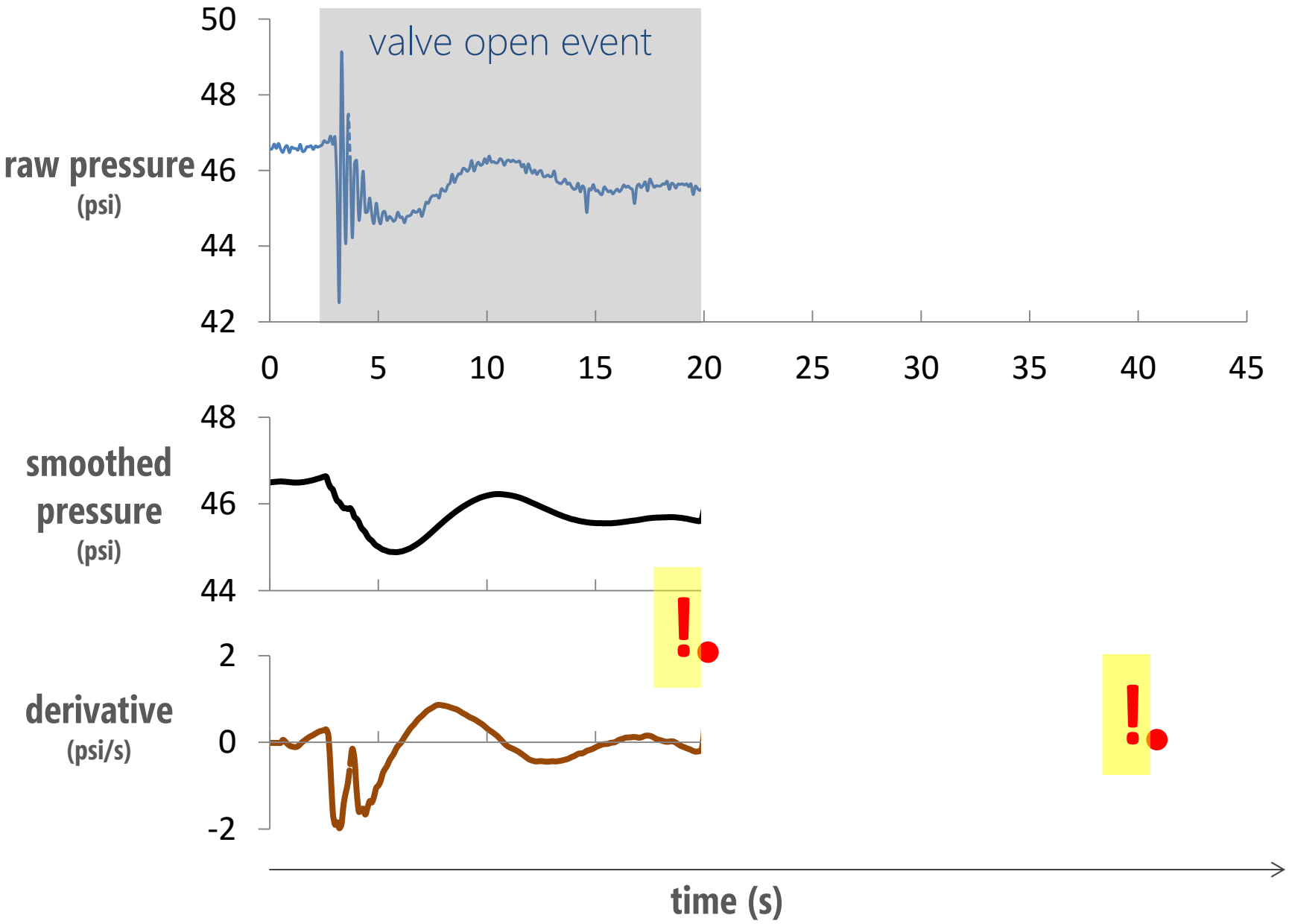
event detection/segmentation



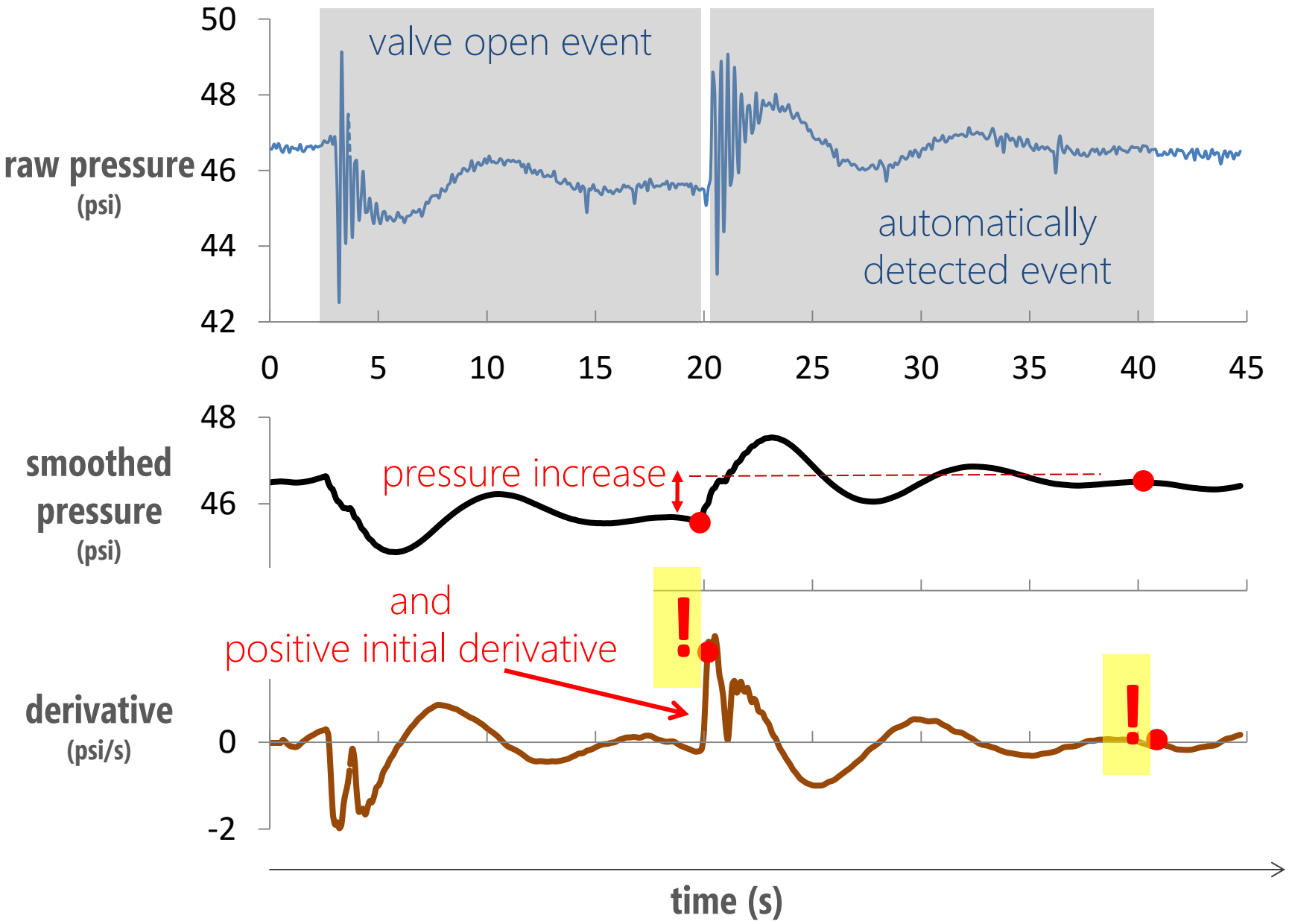
event detection/segmentation



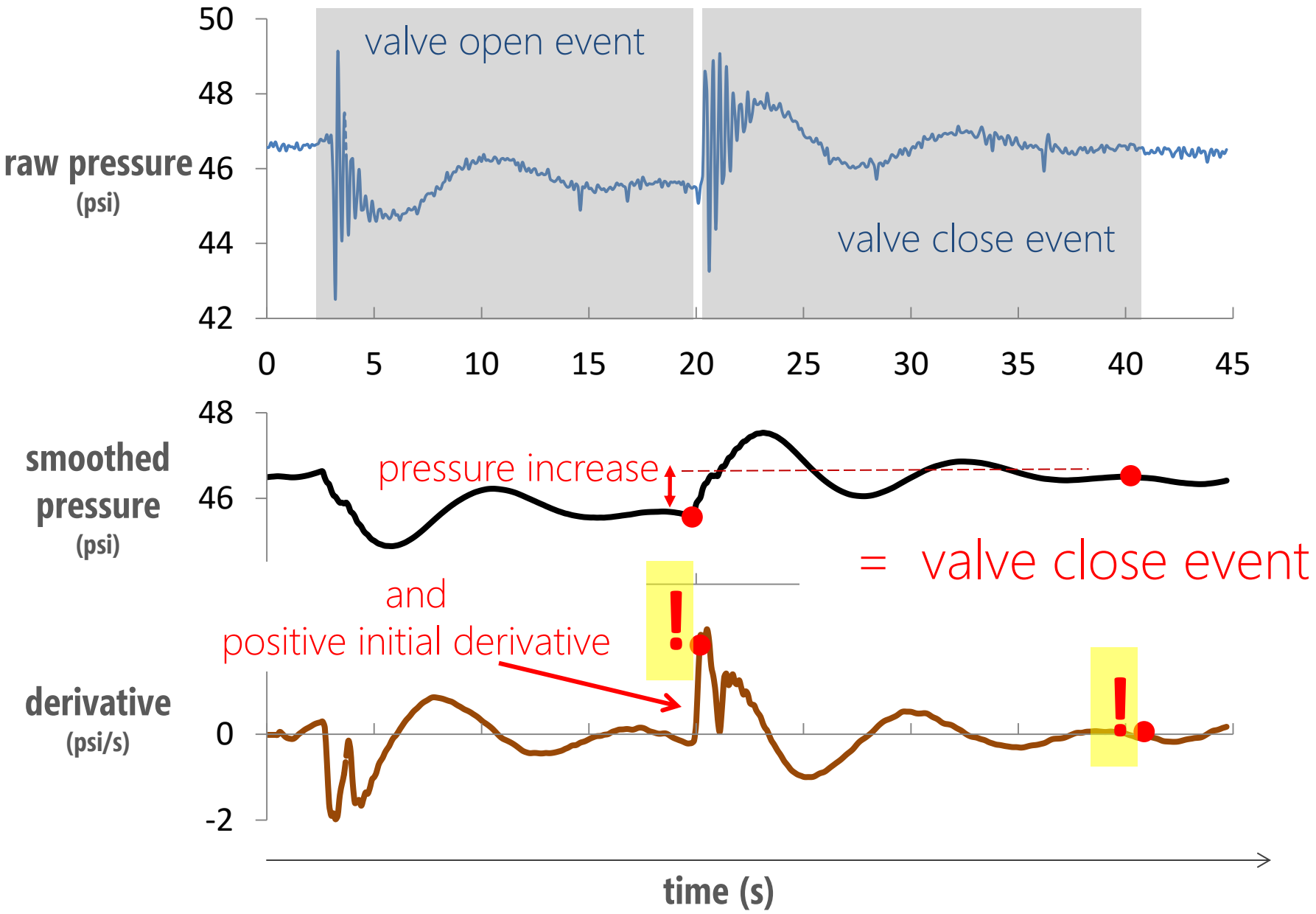
event detection/segmentation



event detection/segmentation

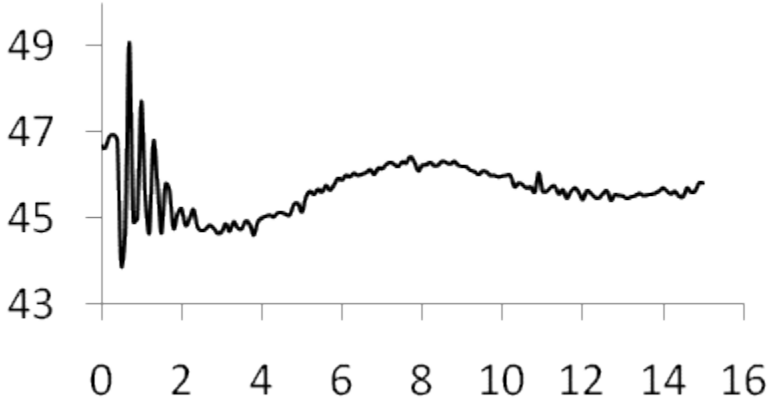


event detection/segmentation

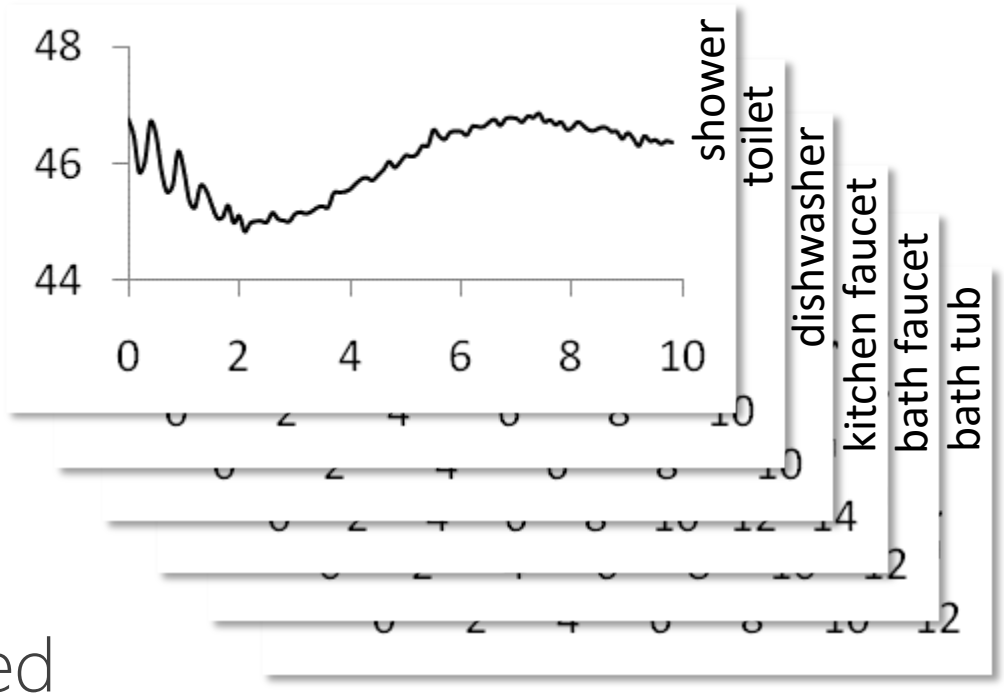


fixture classification

unclassified open event

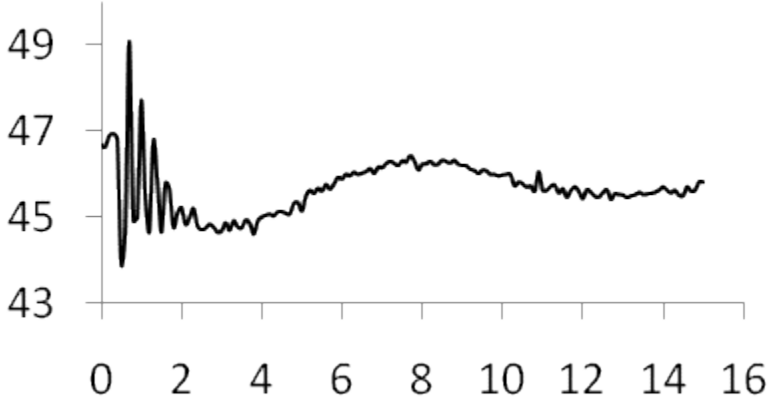


open event library

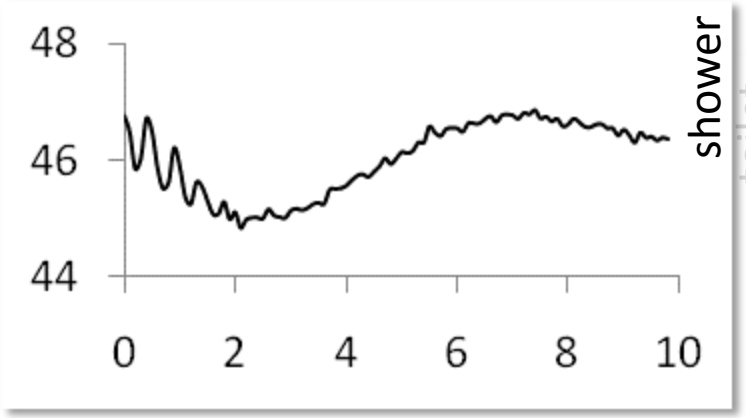


compare via matched filtering across multiple signal transformations

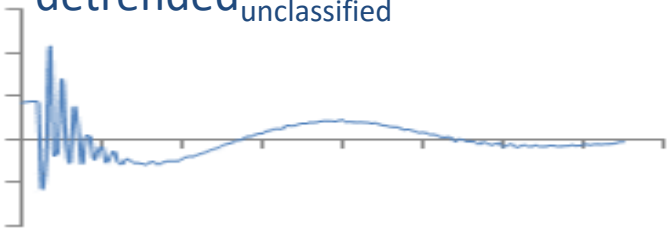
unclassified open event



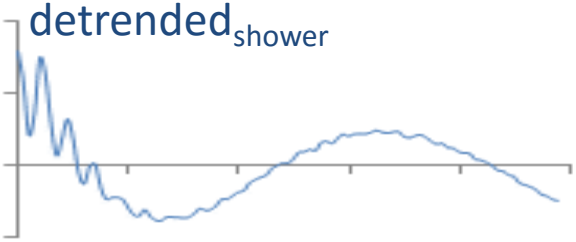
open event library



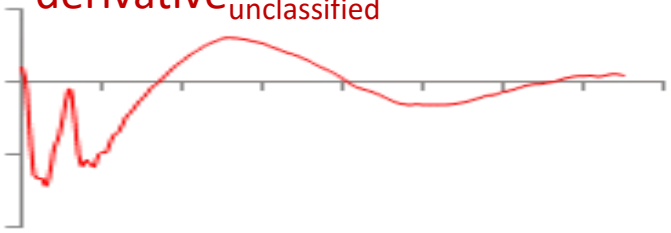
detrended$_{unclassified}$



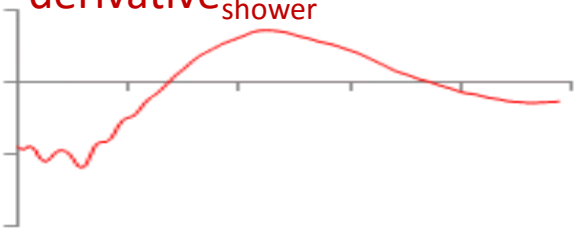
detrended$_{shower}$



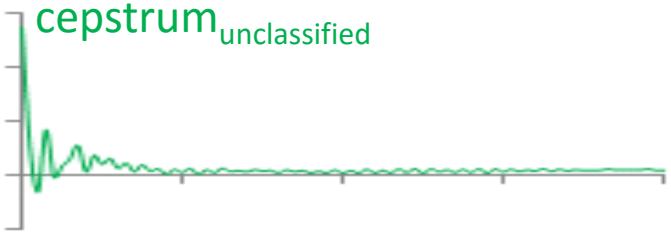
derivative$_{unclassified}$



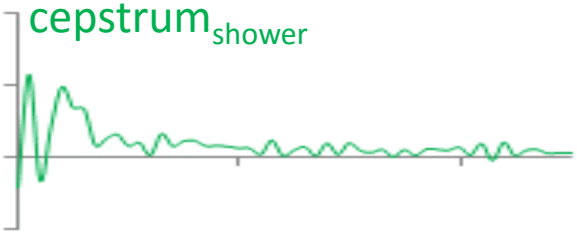
derivative$_{shower}$

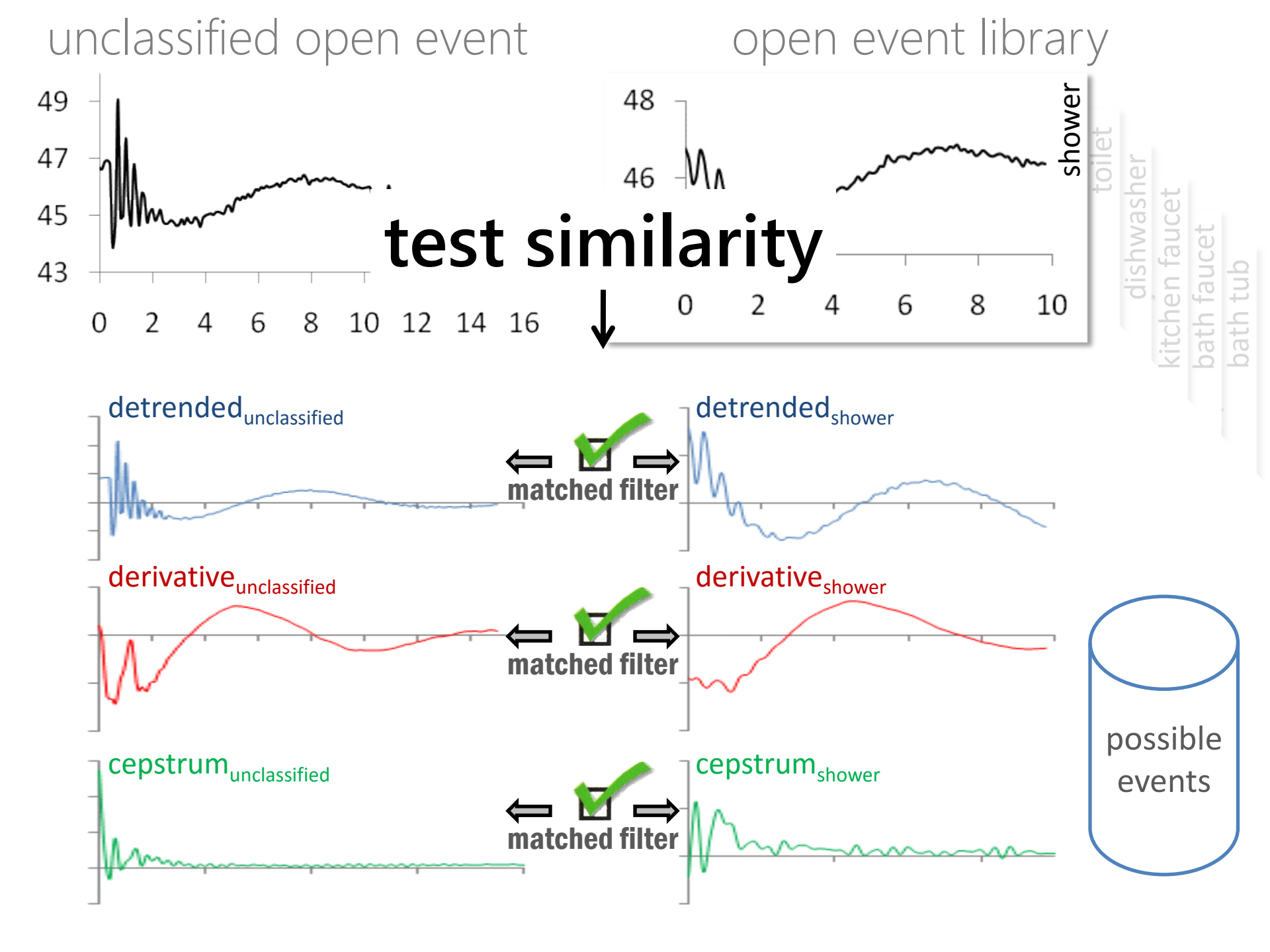


cepstrum$_{unclassified}$

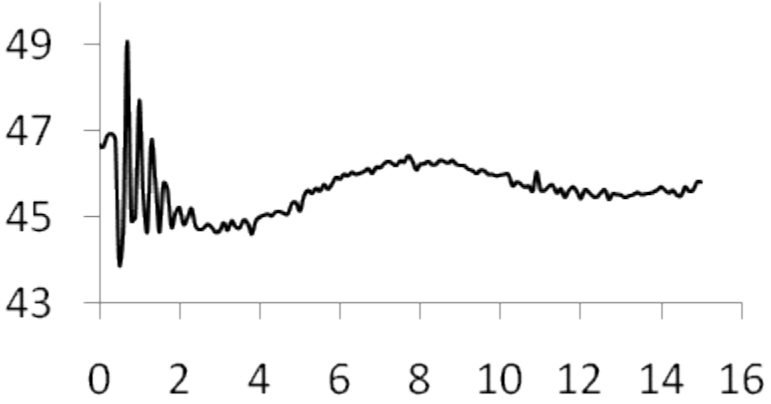


cepstrum$_{shower}$

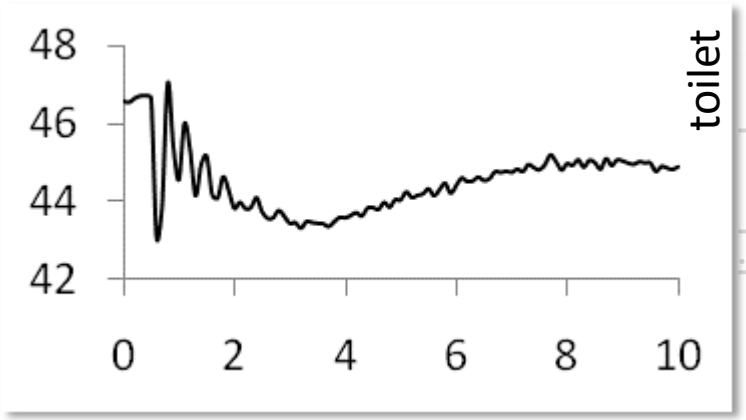


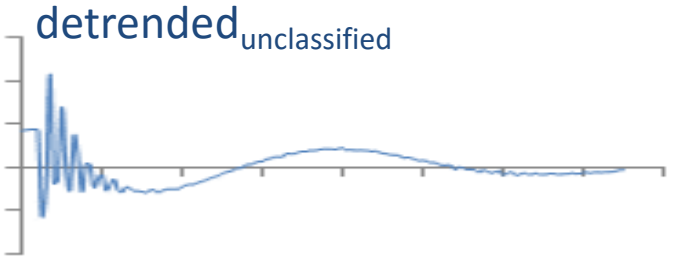

unclassified open event
open event library
49
47
45
43
0 2 4 6 8 10 12 14 16
48
46
shower
toilet
dishwasher
kitchen faucet
bath faucet
bath tub
0 2 4 6 8 10
test similarity
detrended unclassified
detrended shower
matched filter
derivative unclassified
derivative shower
matched filter
cepstrum unclassified
cepstrum shower
matched filter
possible events

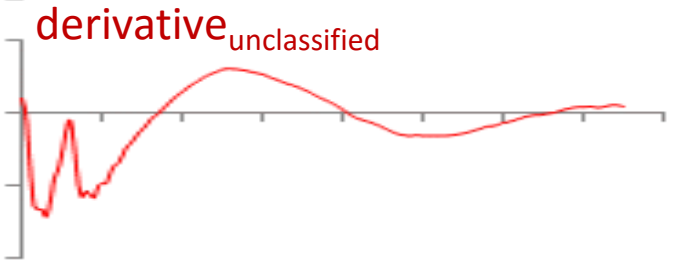
unclassified open event

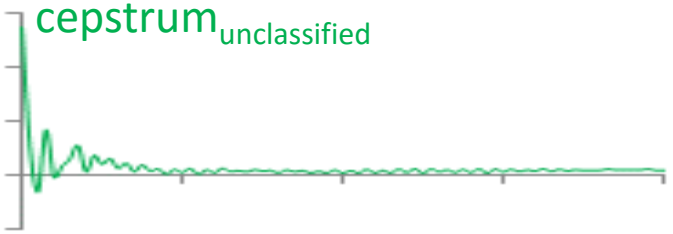


open event library

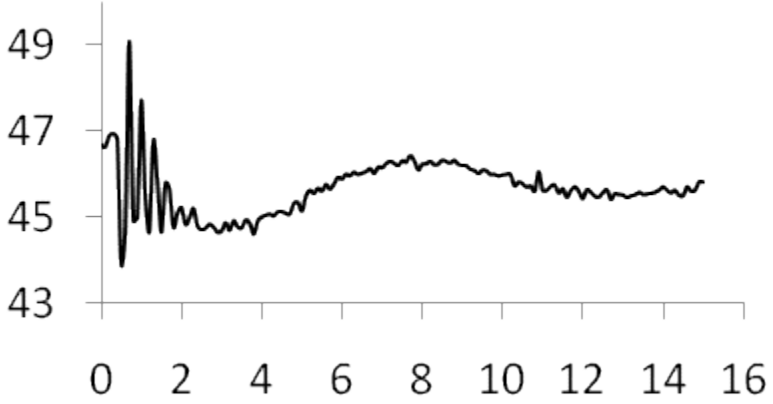




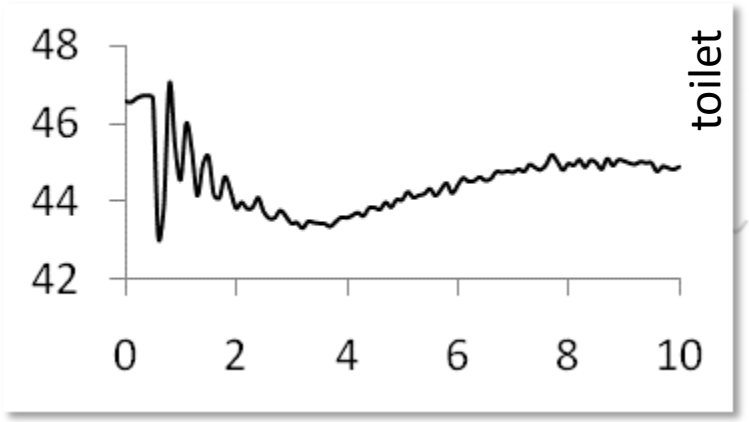




unclassified open event

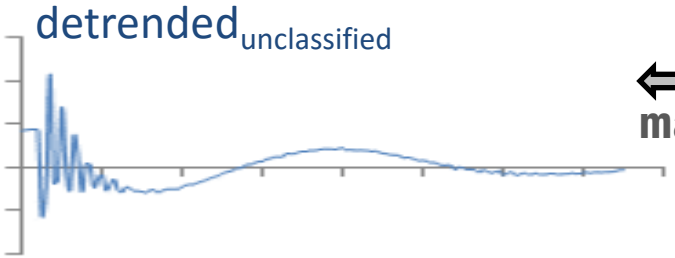


open event library



dishwasher
kitchen faucet
bath faucet
bath tub

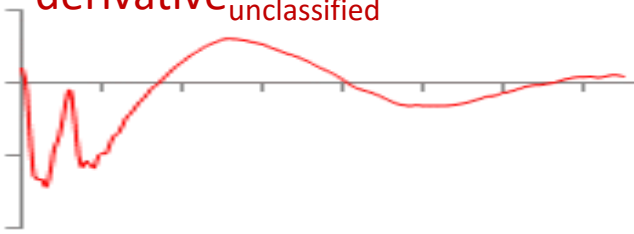
detrended$_{unclassified}$



matched filter

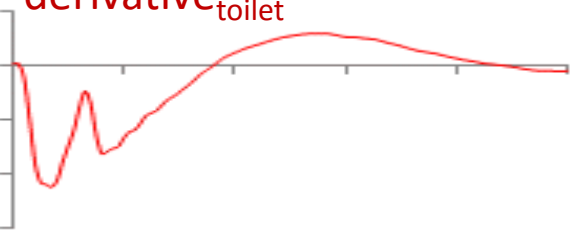
detrended$_{toilet}$

derivative$_{unclassified}$

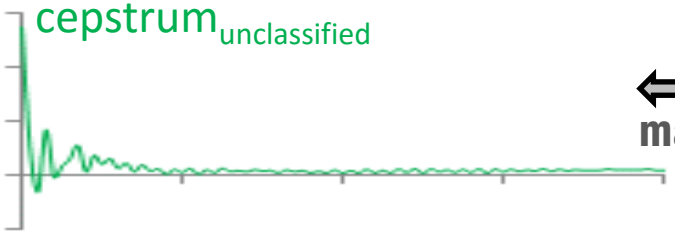


matched filter

derivative$_{toilet}$



cepstrum$_{unclassified}$

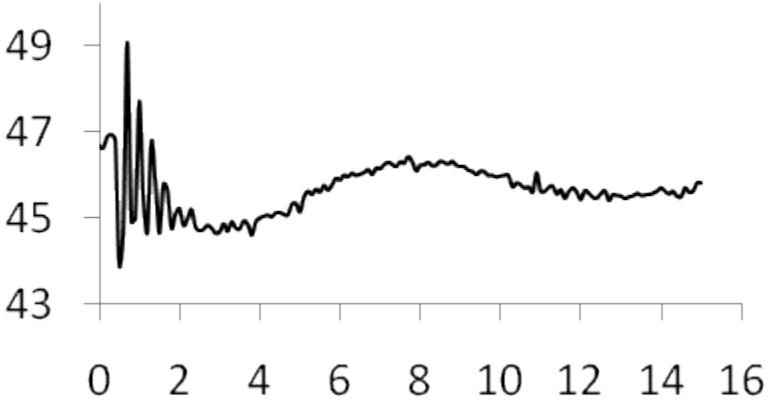


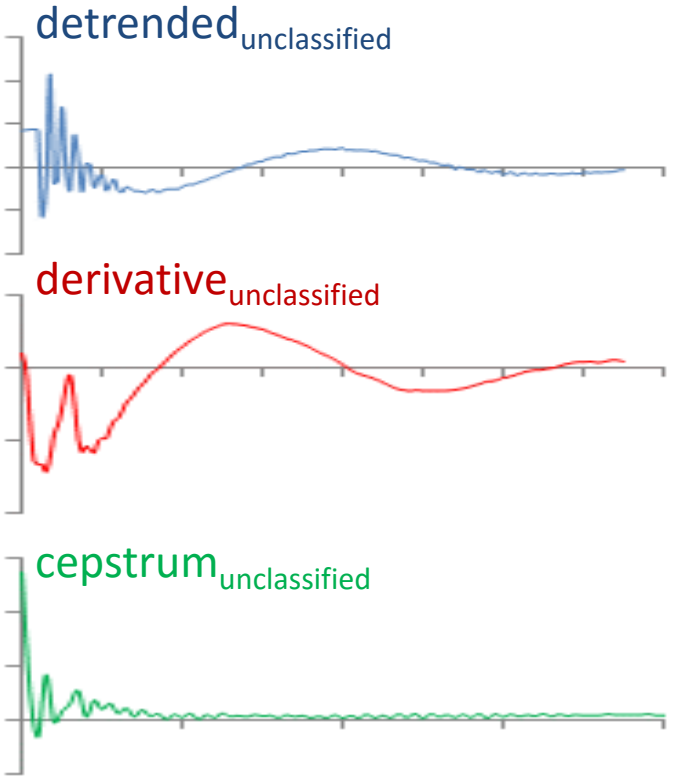
matched filter

cepstrum$_{toilet}$

possible events

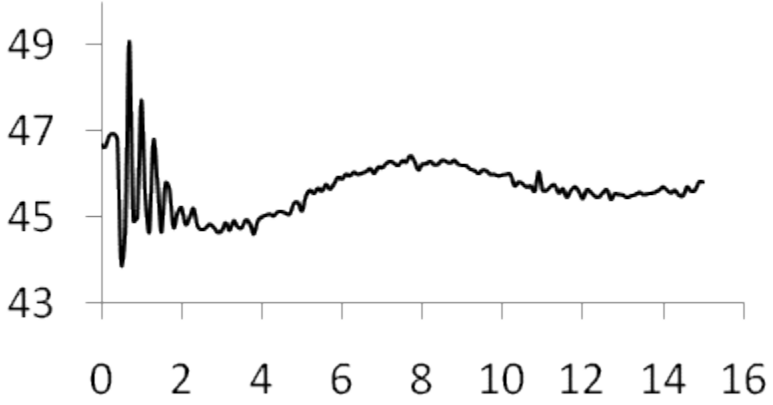
unclassified open event

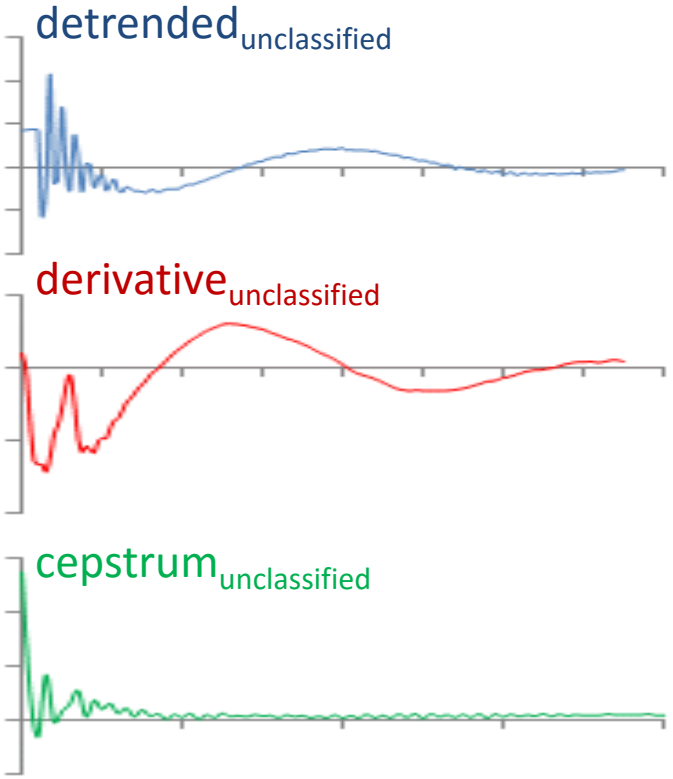




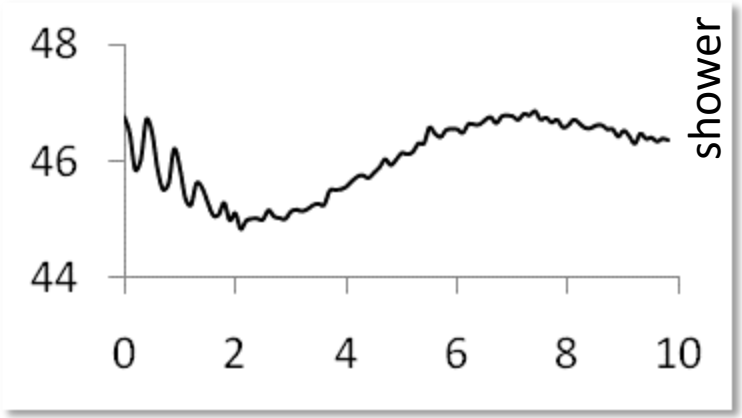
open event library

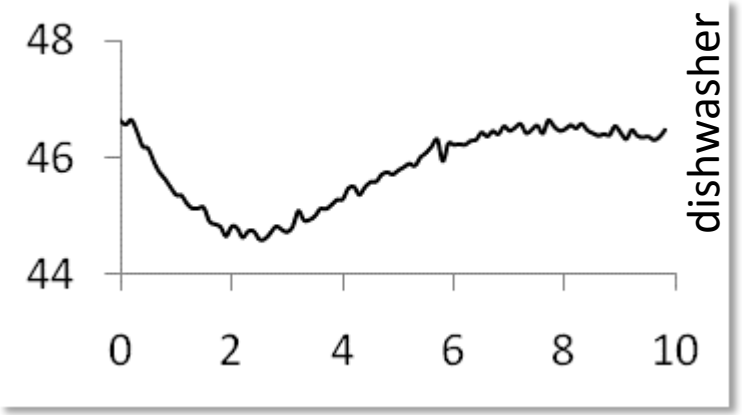
unclassified open event

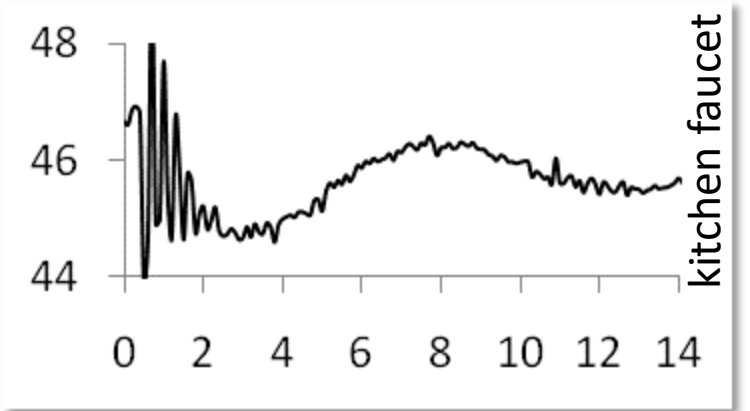




open event library

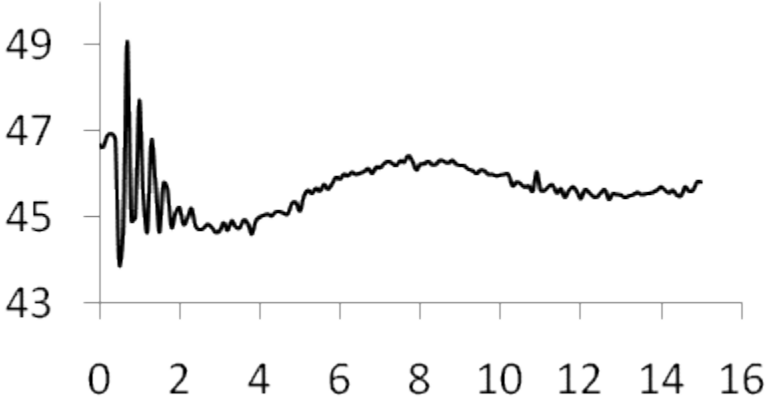


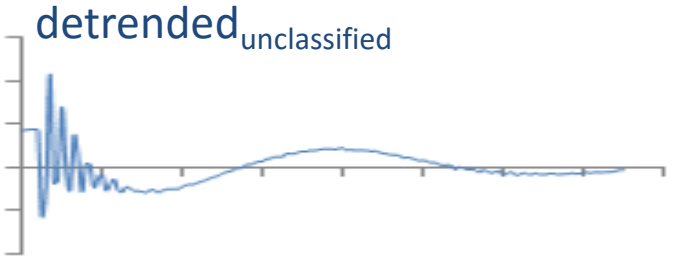


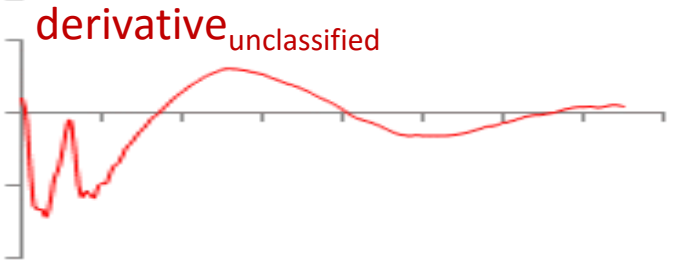


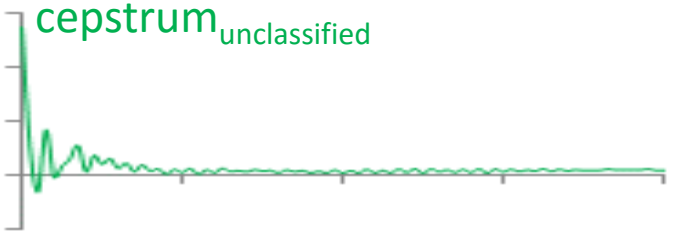
possible events

unclassified open event

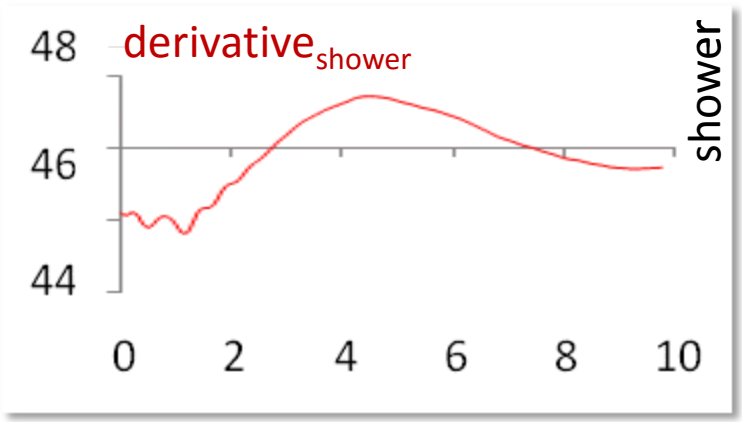


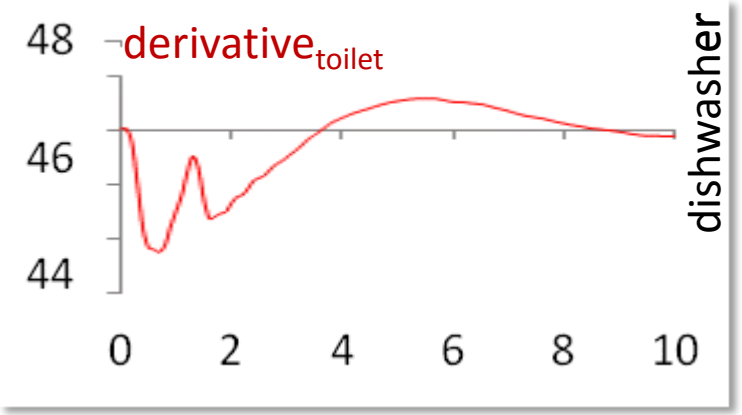


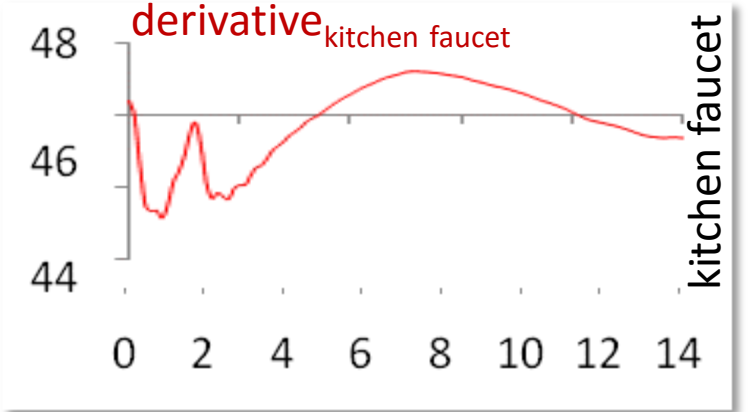




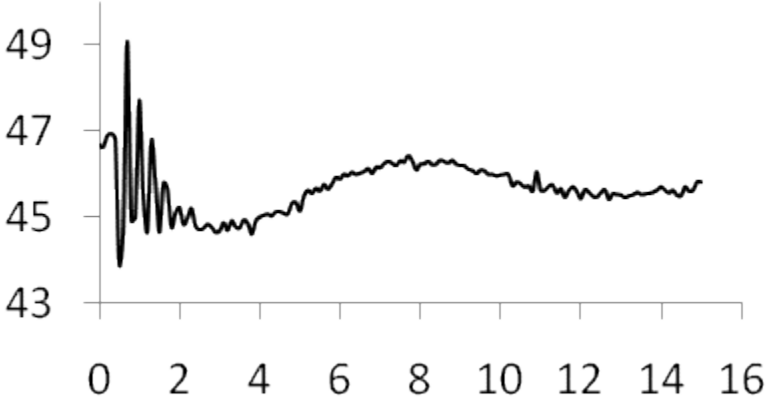
open event library



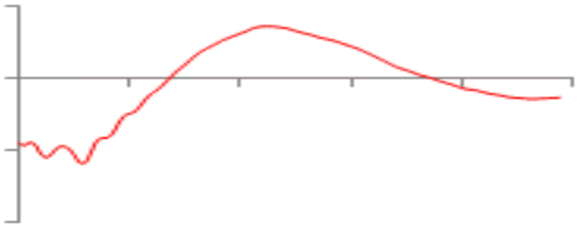




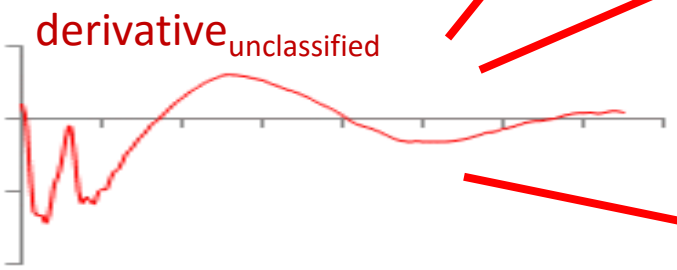
unclassified open event

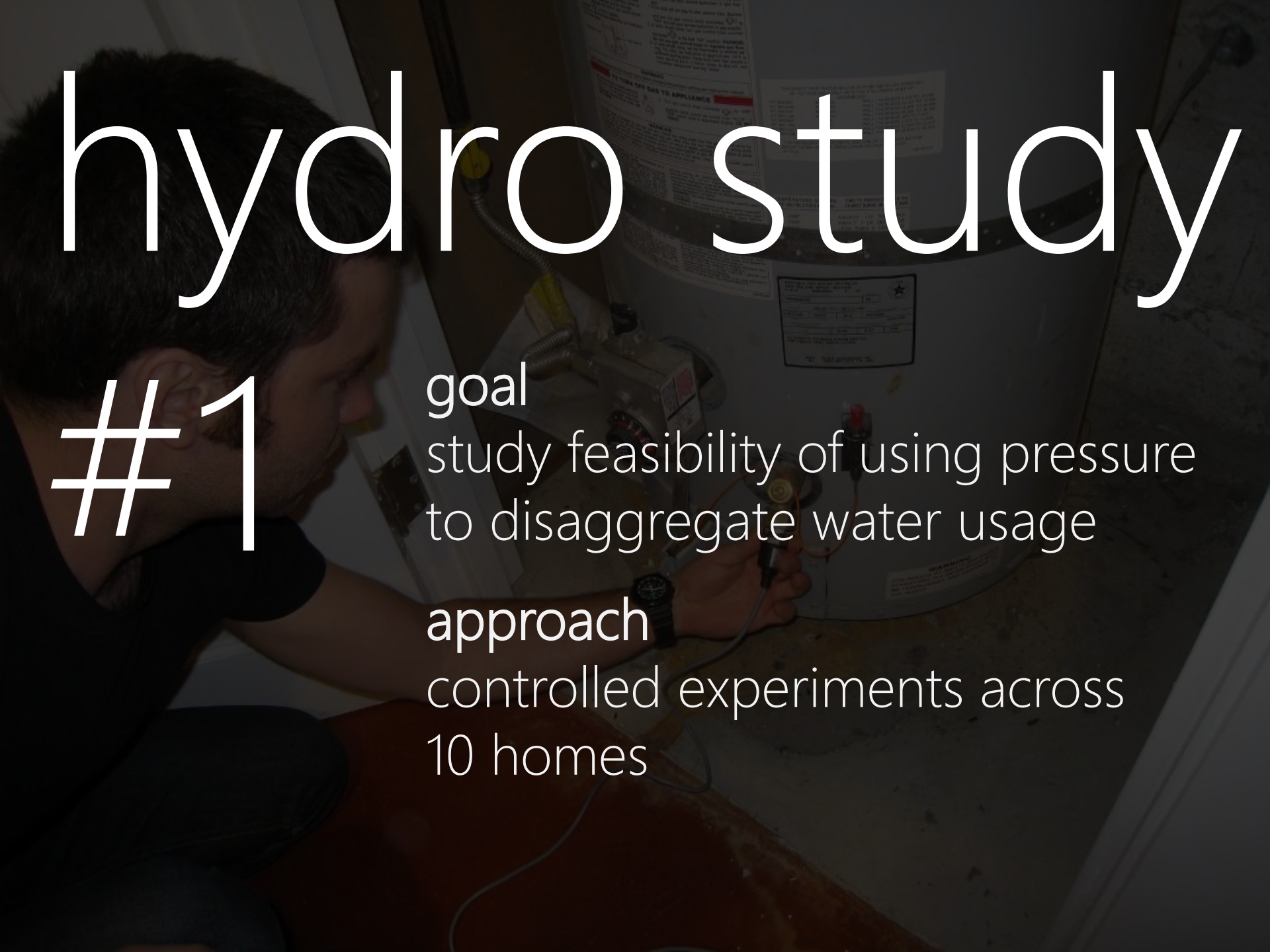


open event library



nearest neighbor match



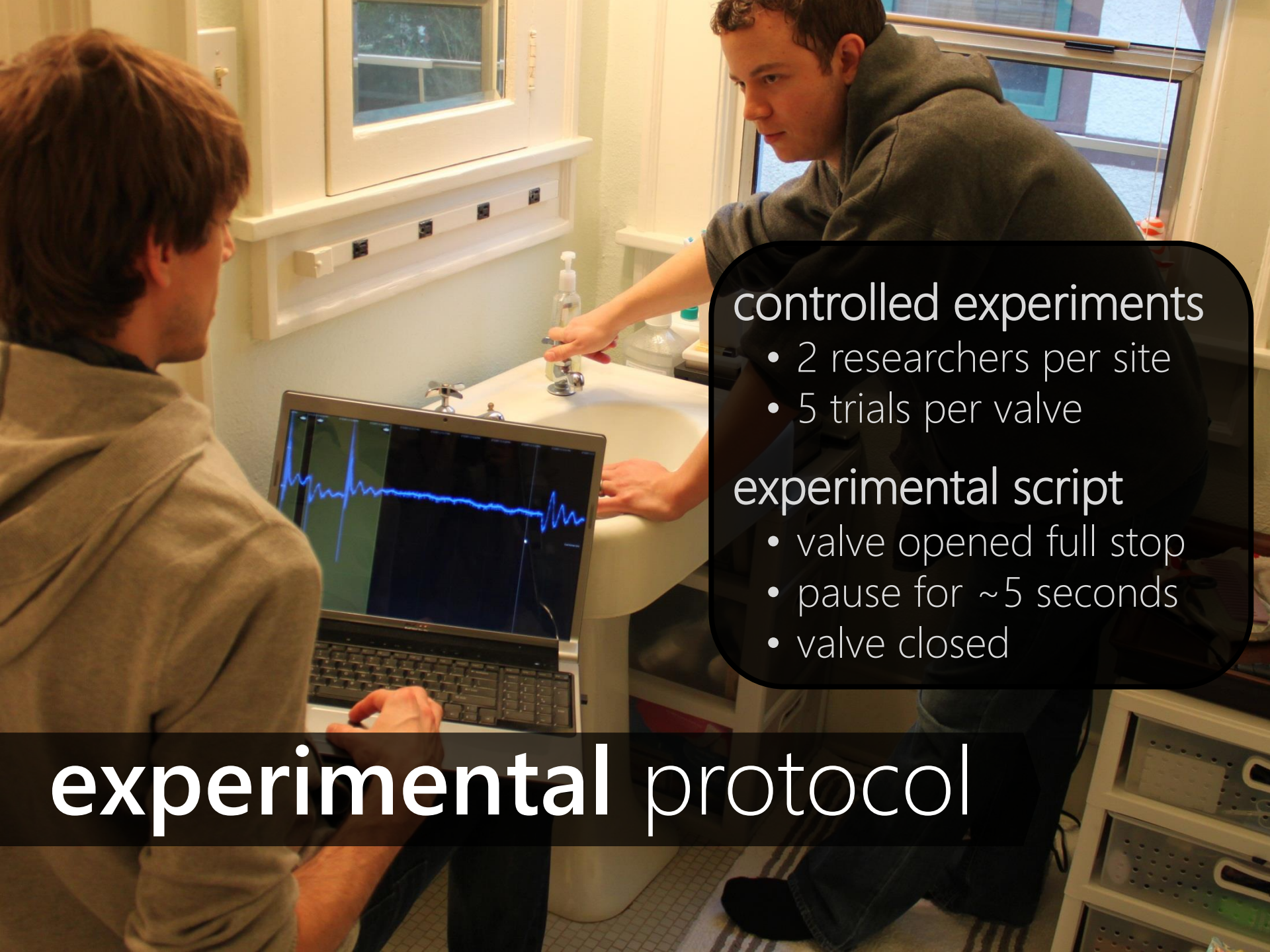


hydro study

#1

goal
study feasibility of using pressure to disaggregate water usage

approach
controlled experiments across 10 homes



controlled experiments

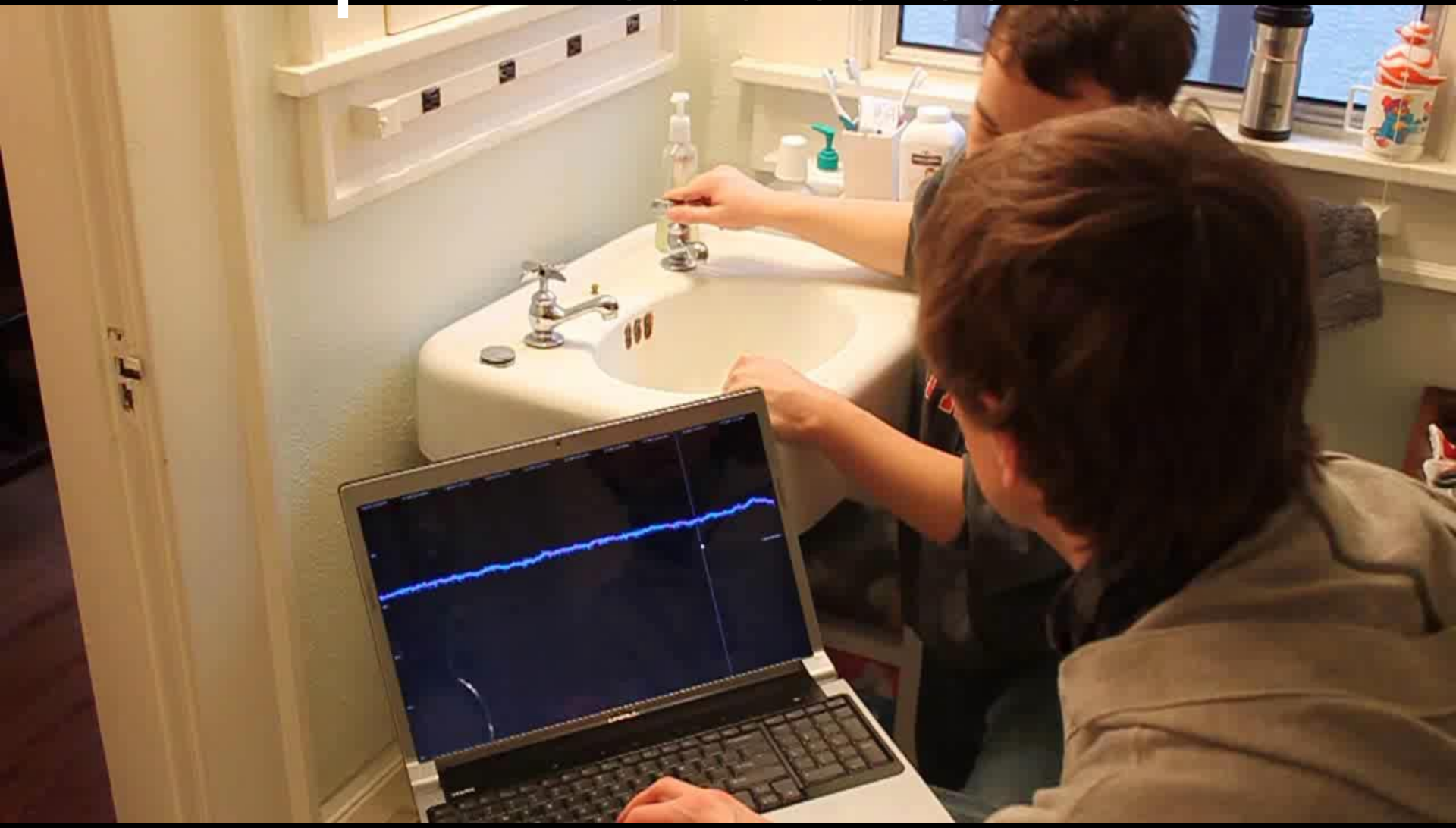
- 2 researchers per site
- 5 trials per valve

experimental script

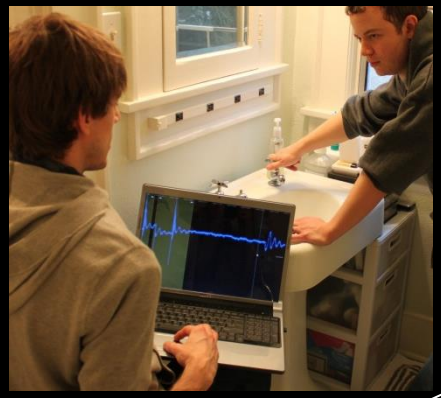
- valve opened full stop
- pause for ~5 seconds
- valve closed

experimental protocol

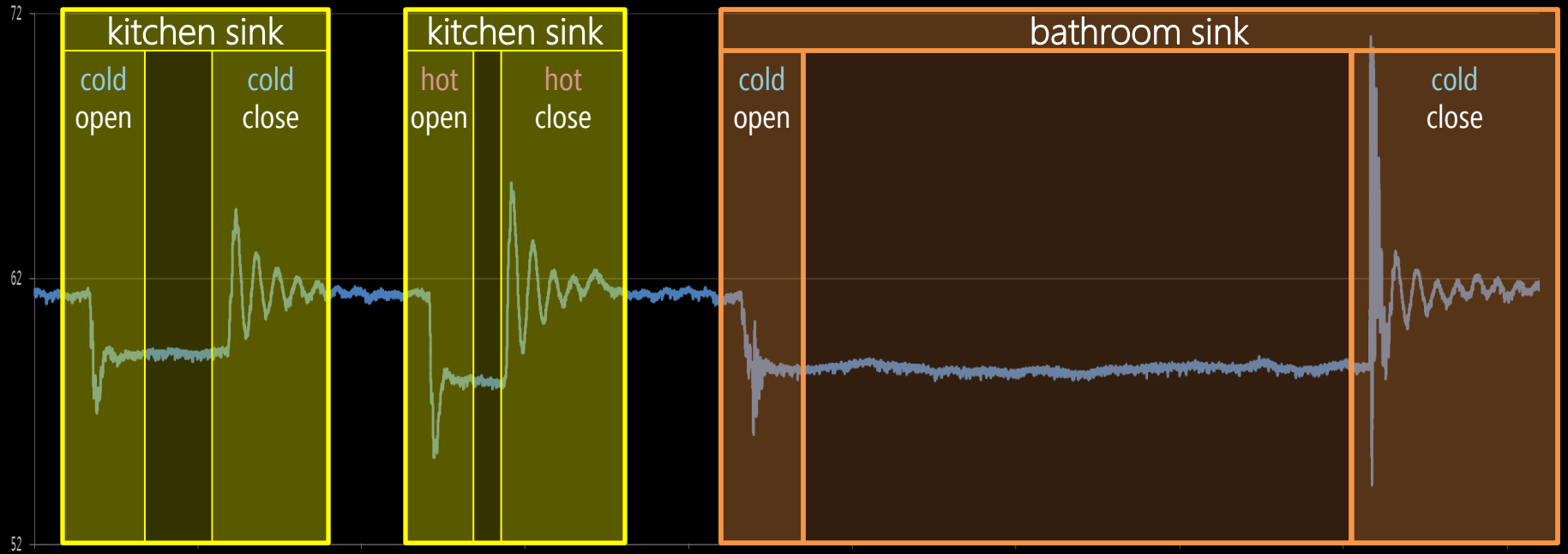
ubicomp2009 data collection



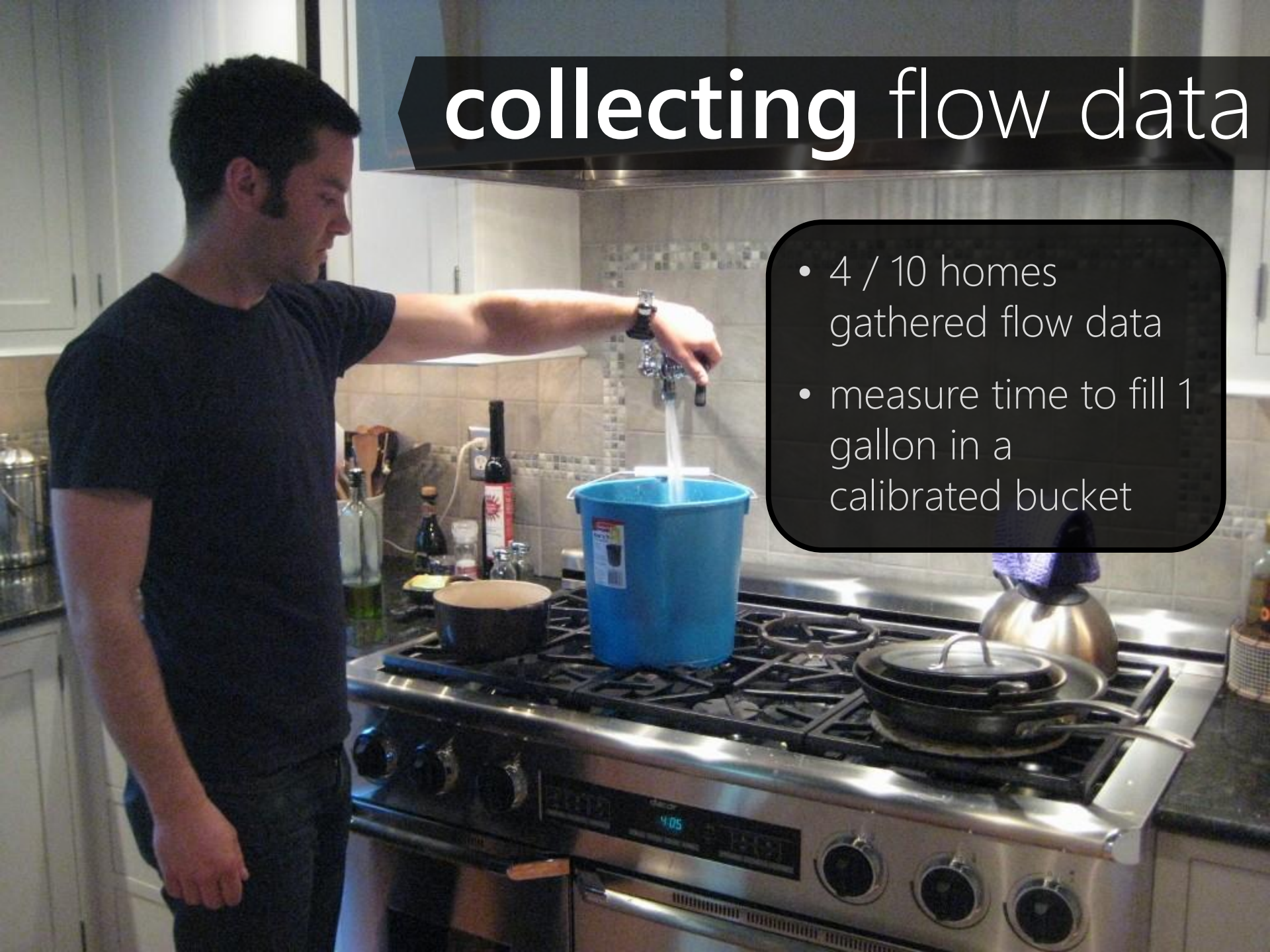
ground truth labels



These labels are going to help train and validate our algorithm



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

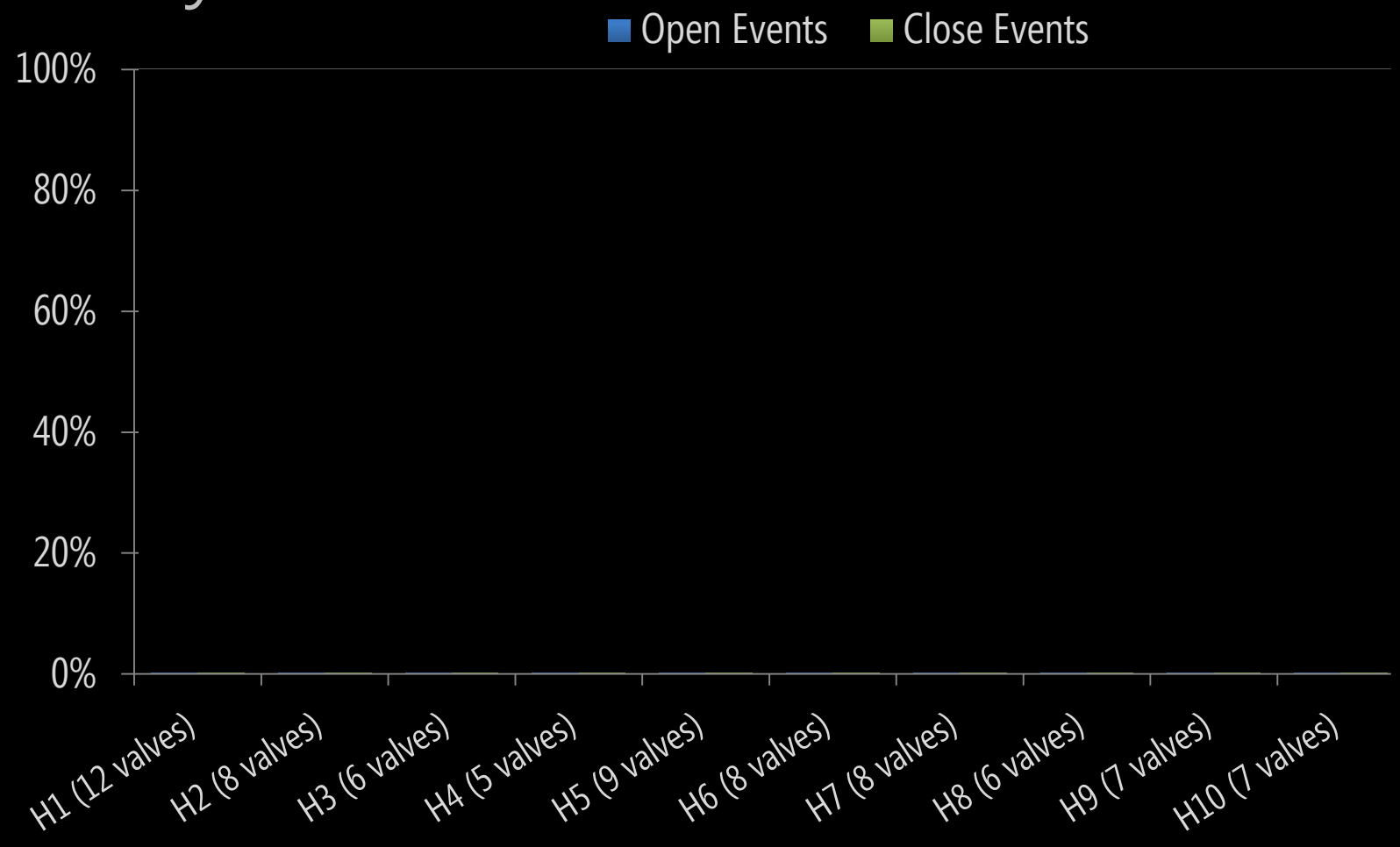
classification experiments

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

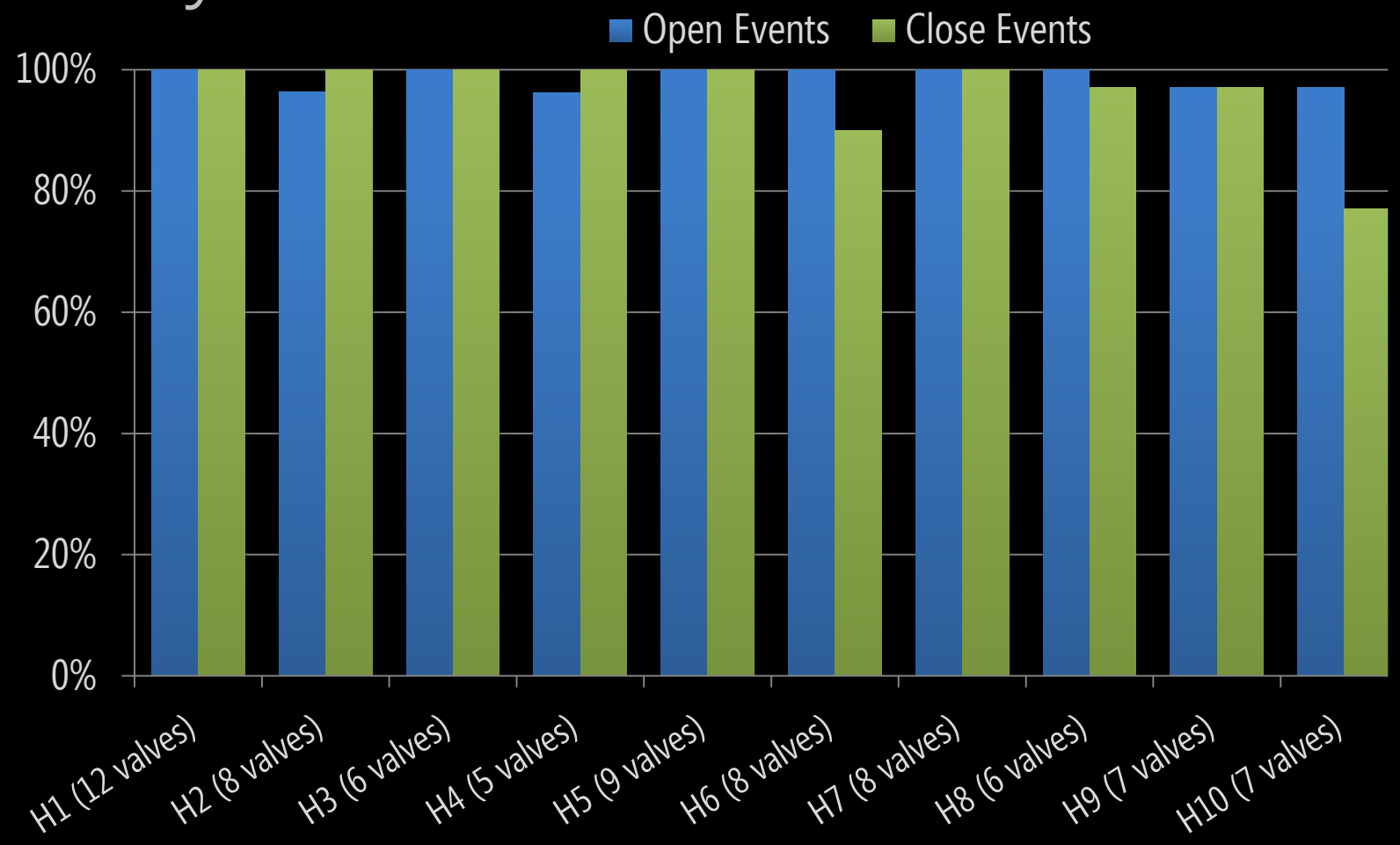
by home



10-fold cross validation

fixture classification results

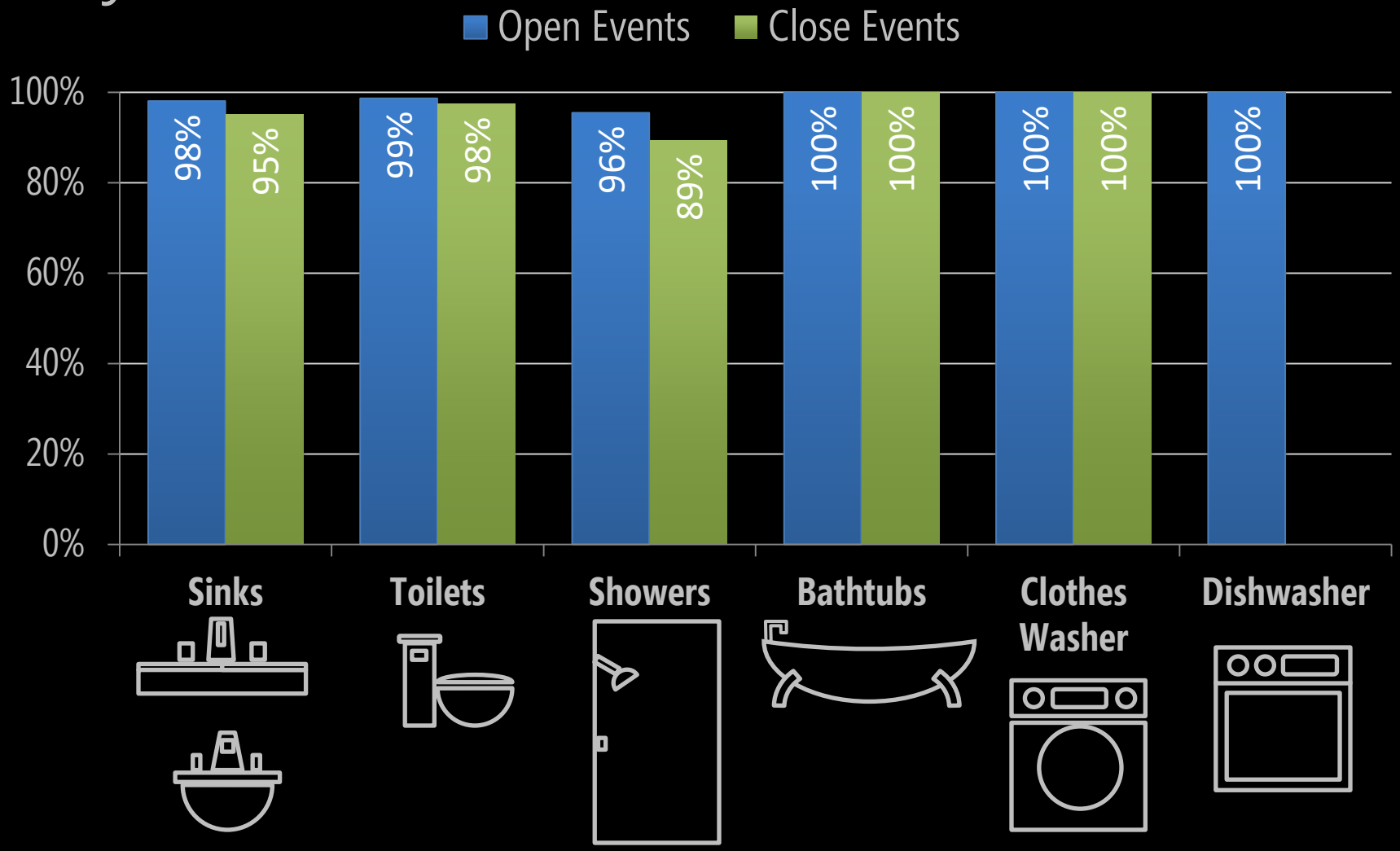
by home



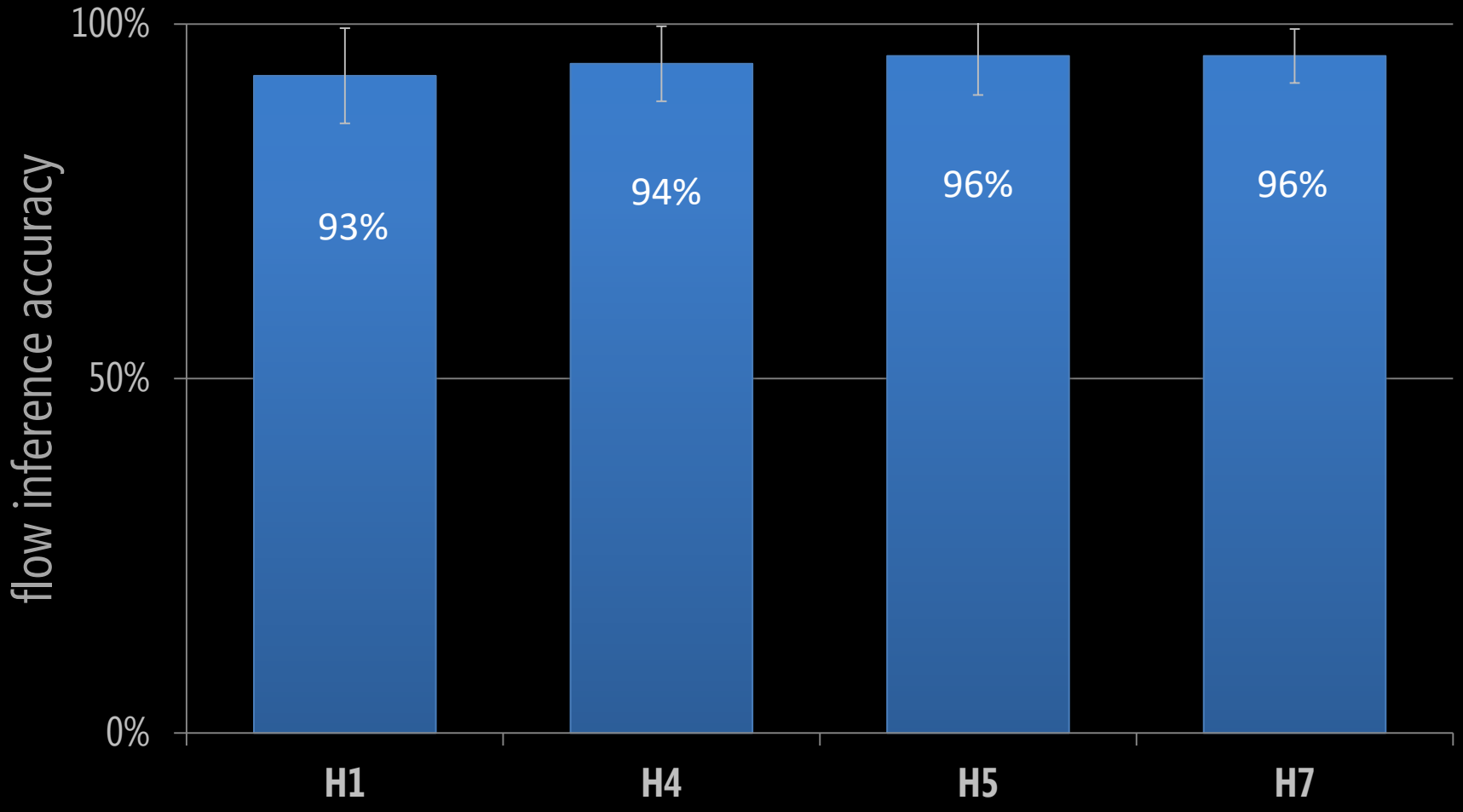
10-fold cross validation

fixture classification results

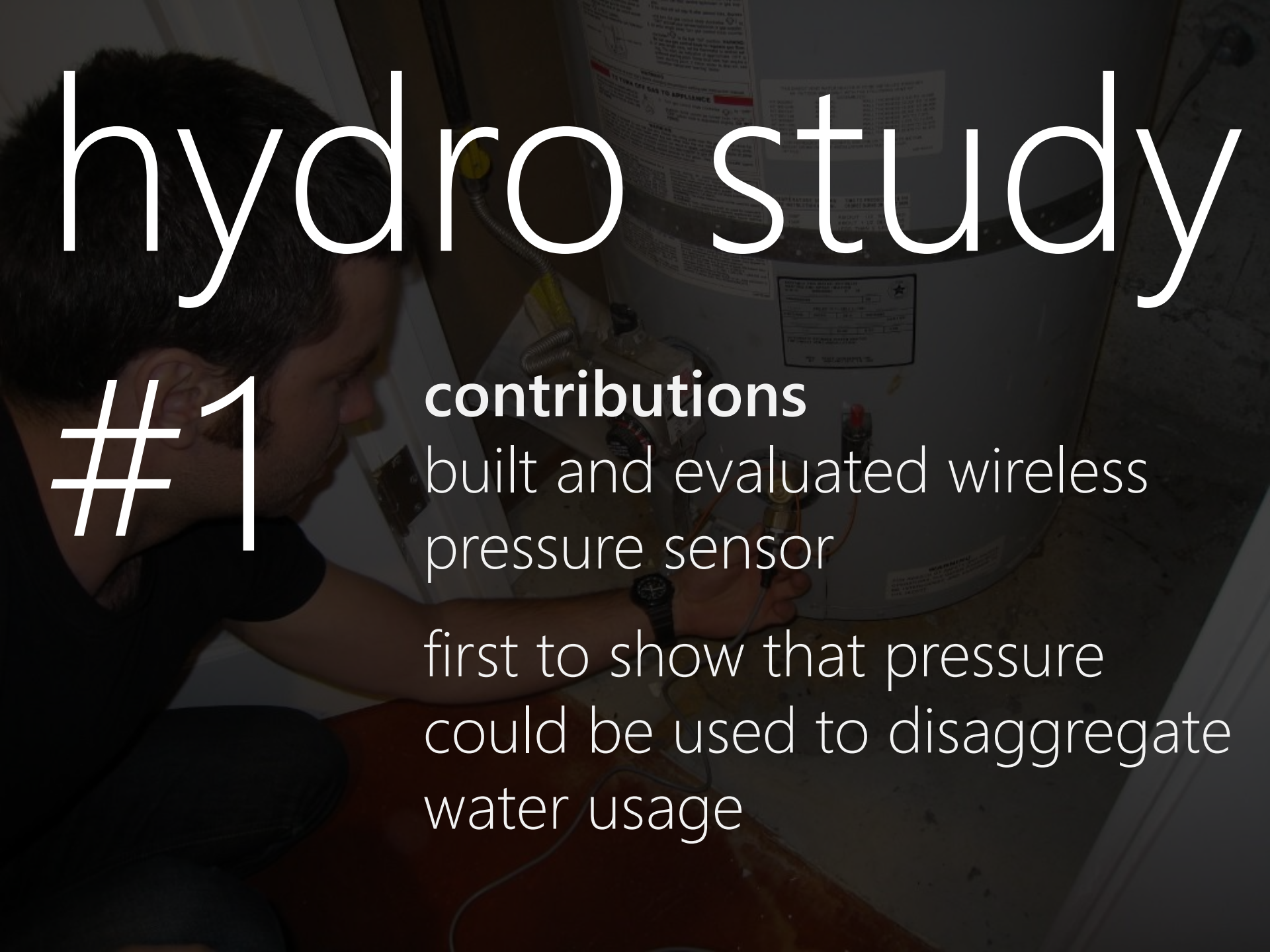
by fixture



flow inference results
by home



[Arregui, Evaluation of Domestic Water Meter Accuracy, 2003]



hydro study

#1

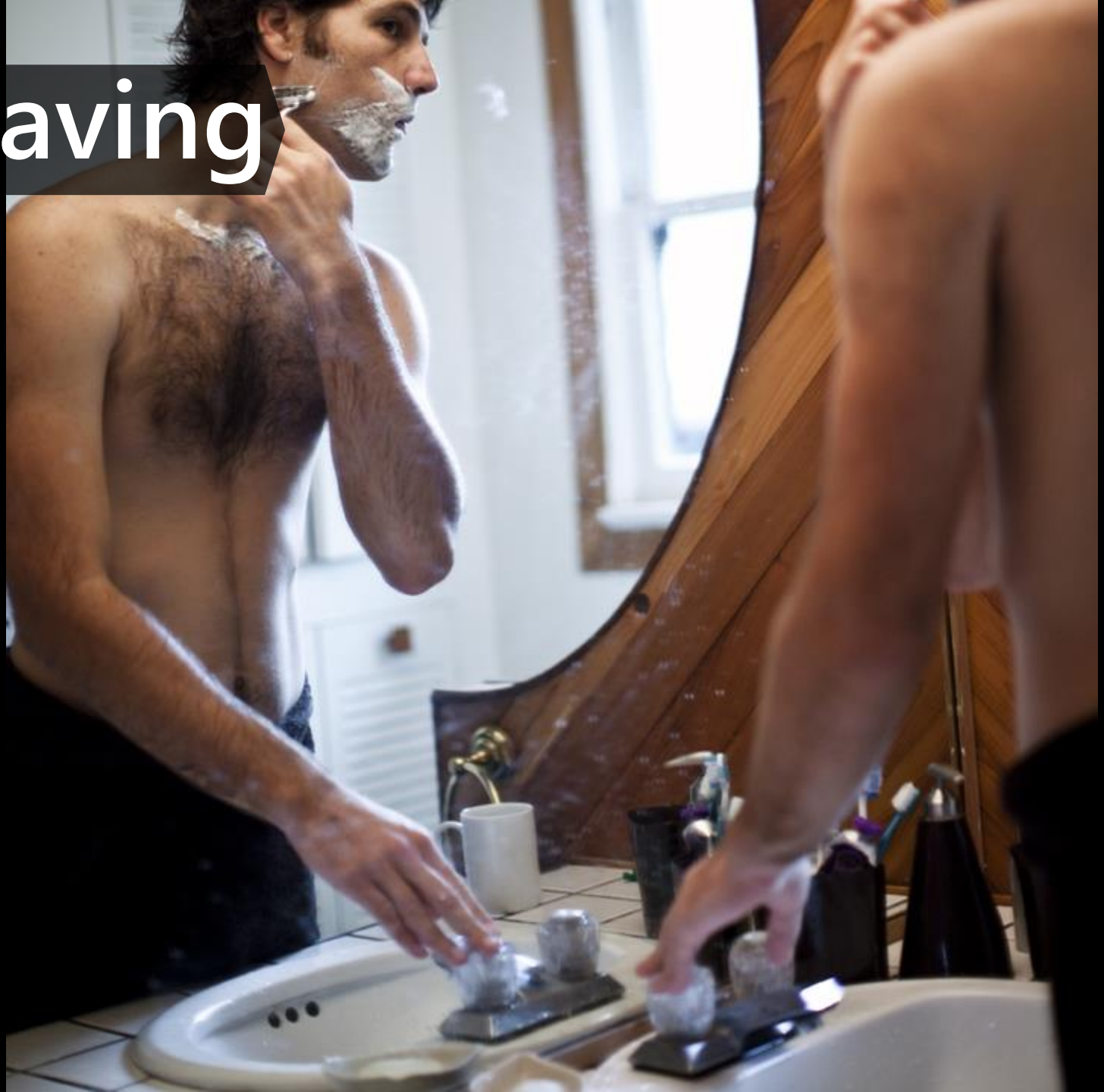
contributions

built and evaluated wireless pressure sensor

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

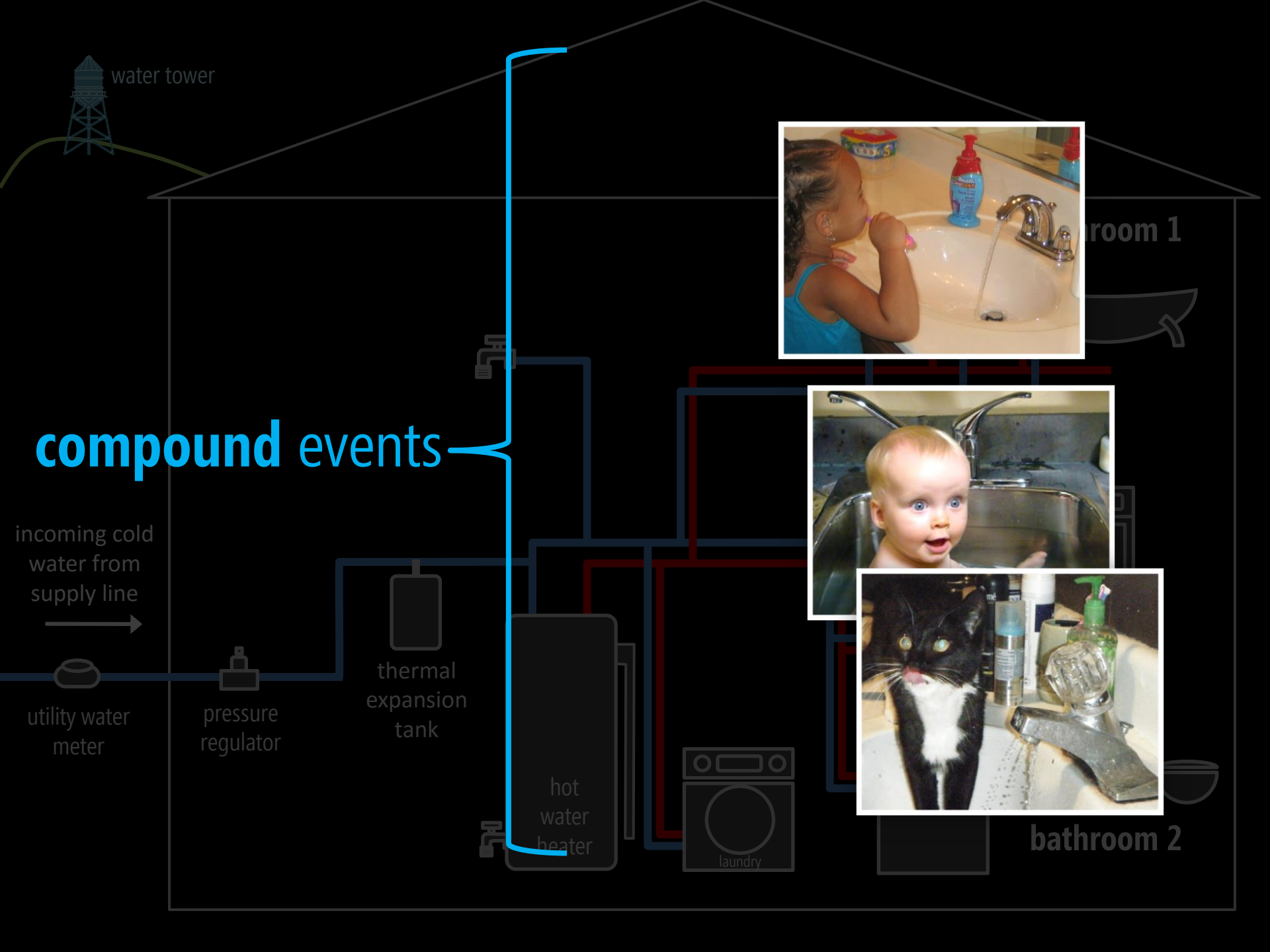

brushing teeth
Huggies
Clean & Fresh
hand soap
savon à mains

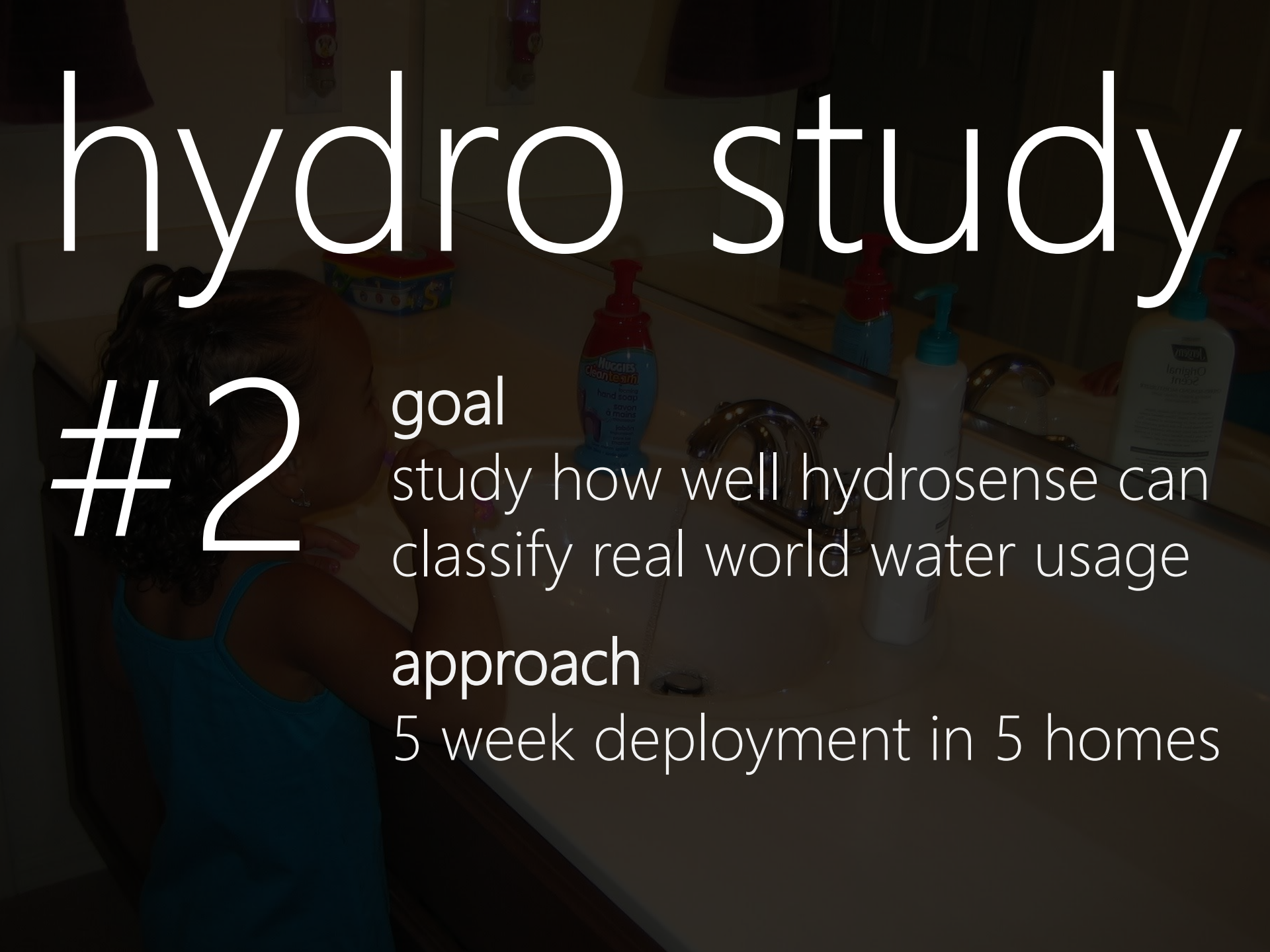
shaving




bathing

paw washing


water tower
compound events
incoming cold water from supply line
utility water meter
pressure regulator
thermal expansion tank
hot water heater
laundry
bathroom 2



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

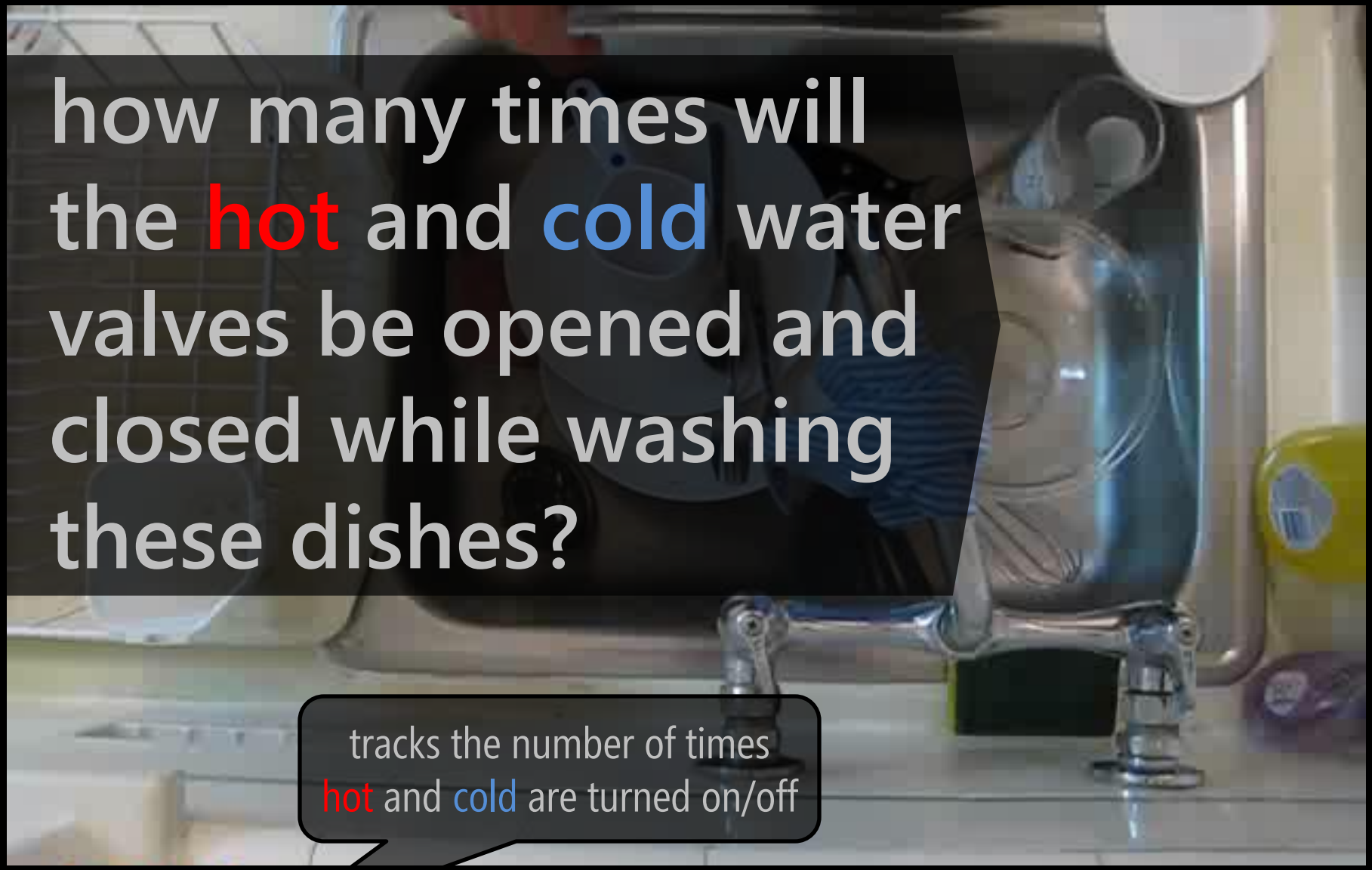

I’m about to flush the toilet!
Awesome. Got it. Thanks Mr. Johnson

how

collect ground truth labels of

can we record **real-world** water usage?

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


hot: 20
cold: 1

after many failed attempts

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

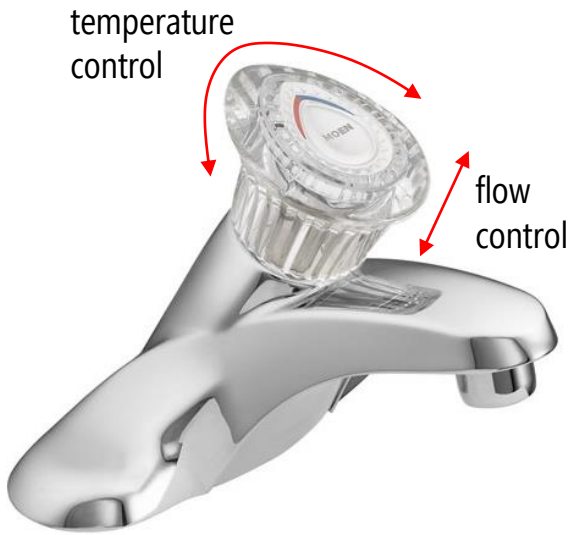
toilet

laundry basin

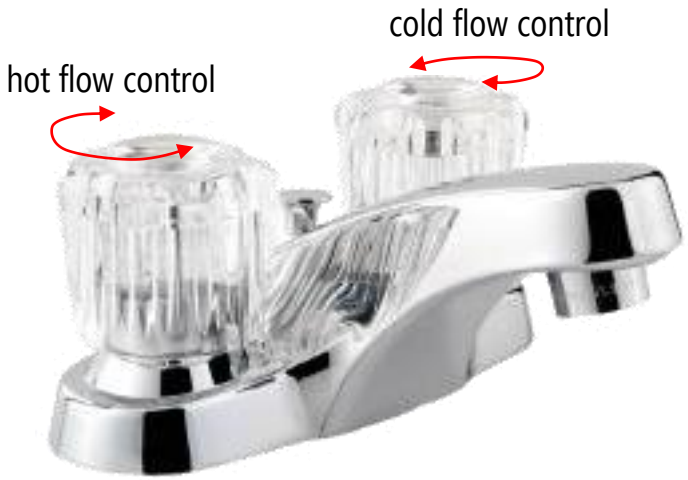
washing machine

dishwasher

challenge: fixture diversity



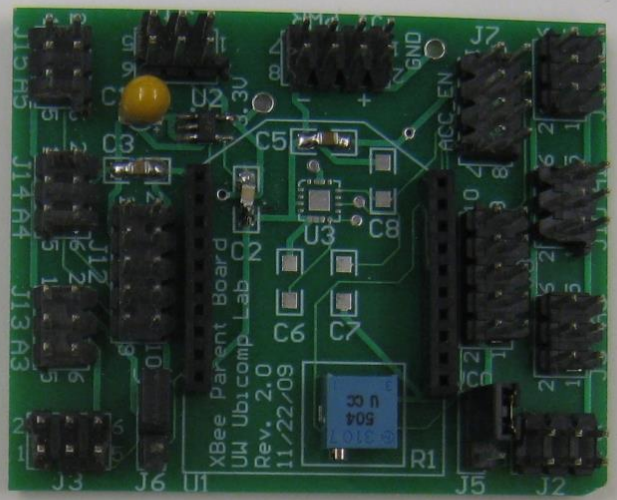
single handle faucet



dual handle faucet

custom ground truth data collection system

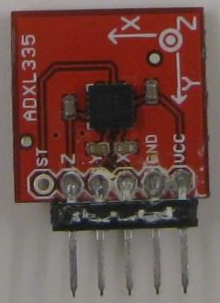
xbee wireless modem



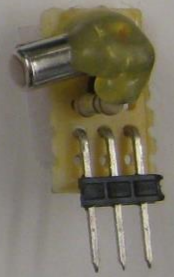
fixture usage sensor board

hall effect

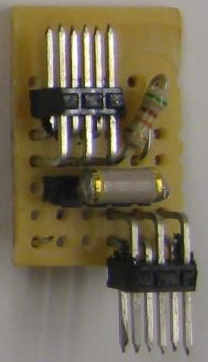
reed switch



3-axis accelerometer



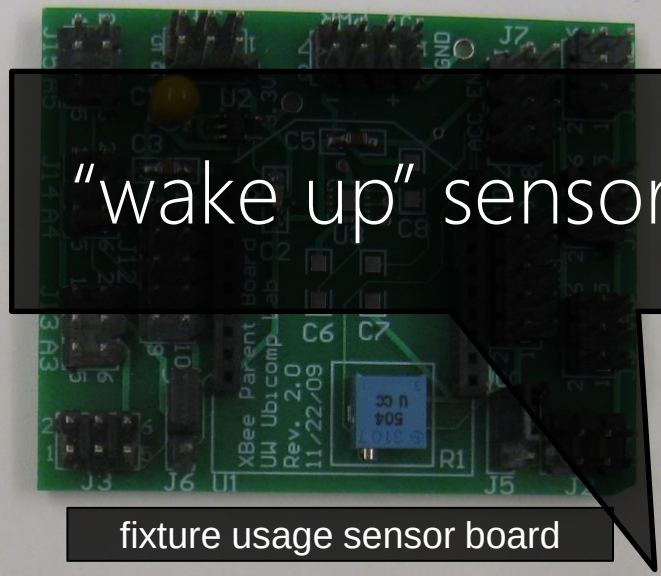
unidirectional ball switch



omnidirectional ball switch

custom ground truth data collection system

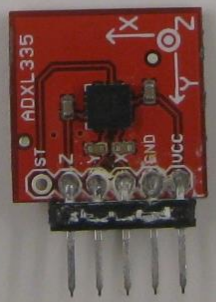
xbee wireless modem



fixture usage sensor board

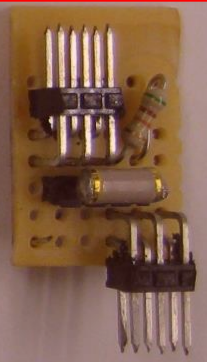
hall effect

reed switch



3-axis accelerometer

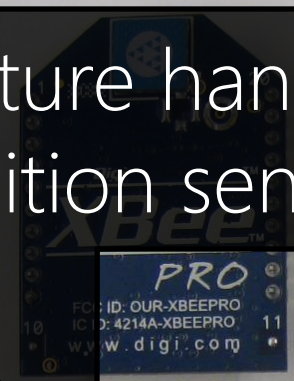
unidirectional ball switch



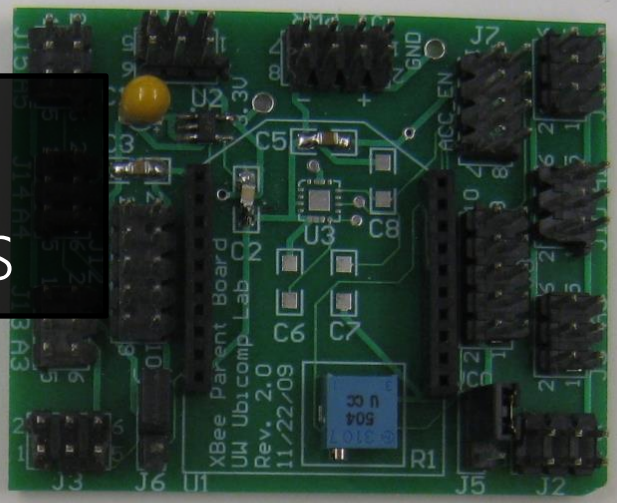
omnidirectional ball switch

custom ground truth data collection system

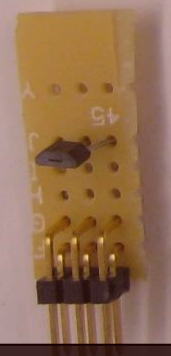
fixture handle position sensors



xbee wireless modem

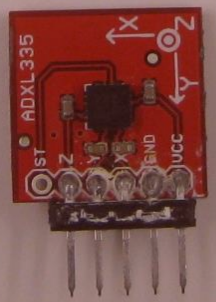


fixture usage sensor board



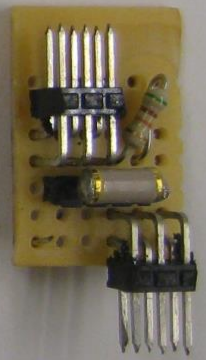
hall effect

reed switch



3-axis accelerometer

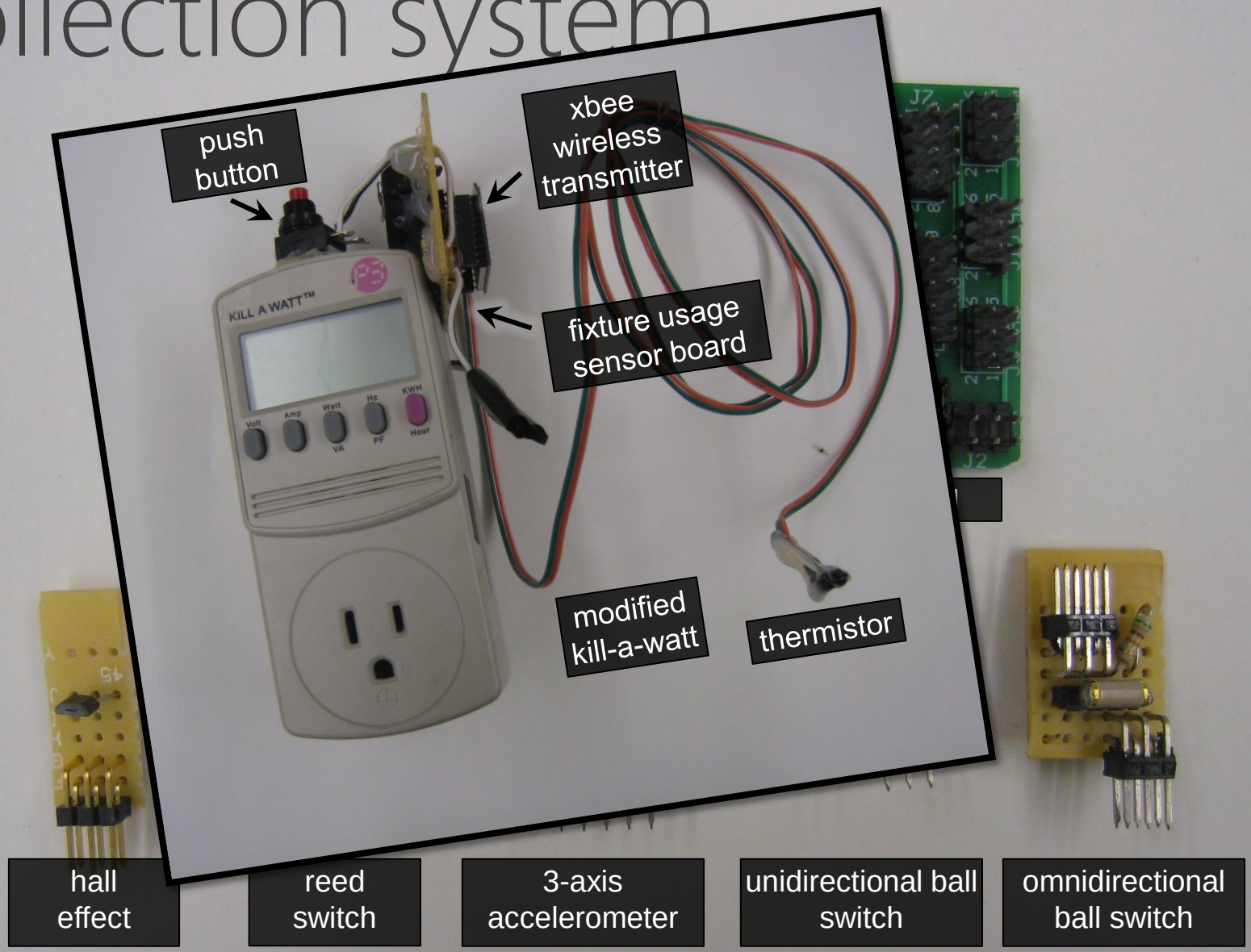
unidirectional ball switch



omnidirectional ball switch


accelerometer
Accelerometer
& Ball Switch
Taped on

custom ground truth data collection system

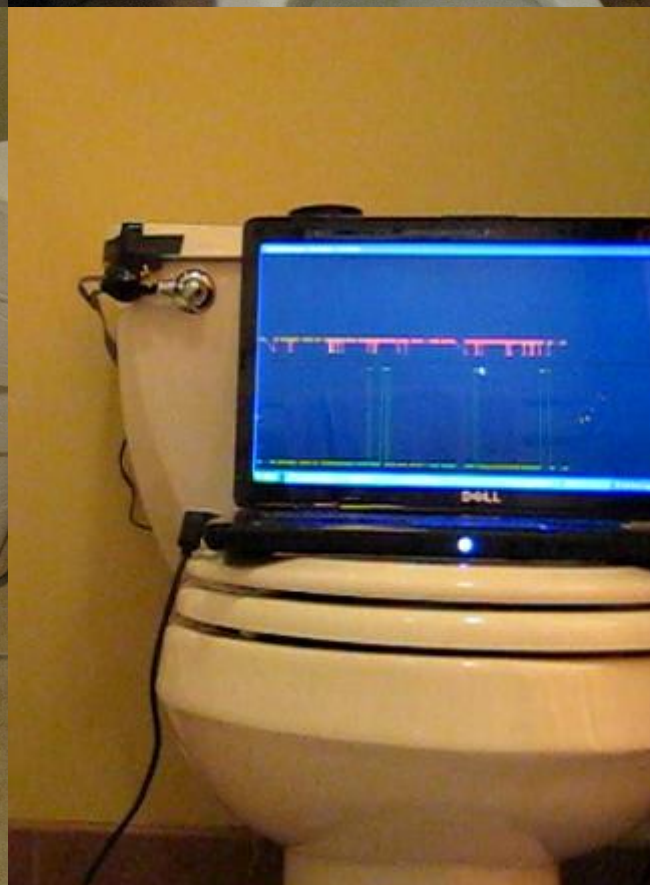


deployment sites

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







DELL



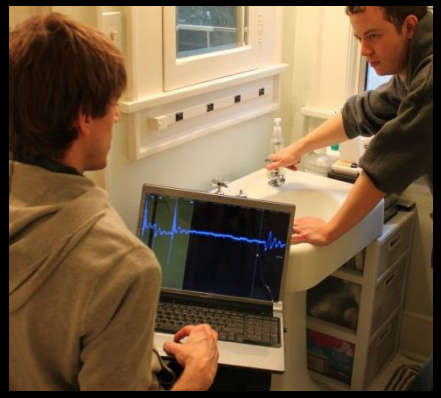




HOT
COLD

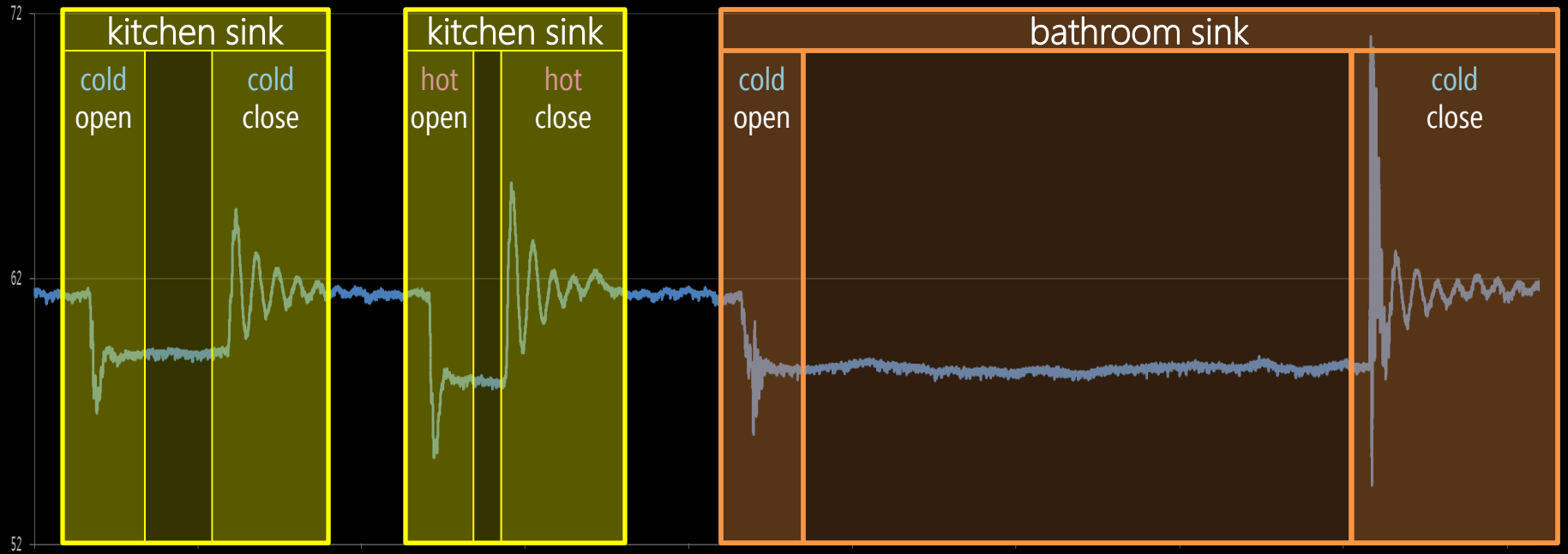

PB32
XBee
PULL KNOB TO START-PUSH TO STOP
XTRA RINSE
SET
COTTONS REGULAR
PERMANENT PRESS KNITS
PERMANENT PRESS
DELICATES
LIGHT SOIL
MEDIUM
HEAVY
POWER WASH
30 MIN AUTO SOAK
vy Duty Super Capacity
= RINSE
= EXTRA RINSE
= SPIN

ground truth labels

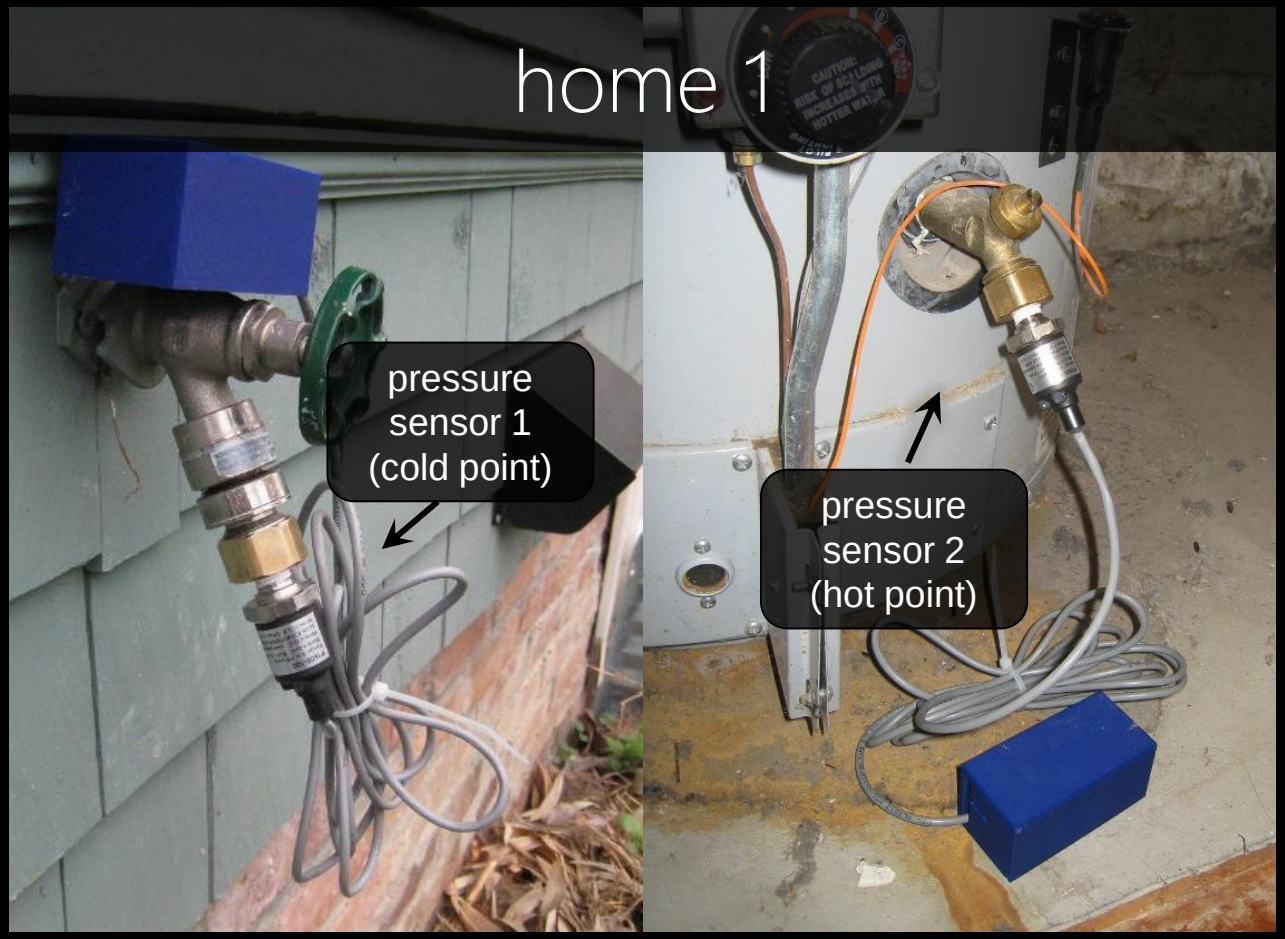


manual

automatic

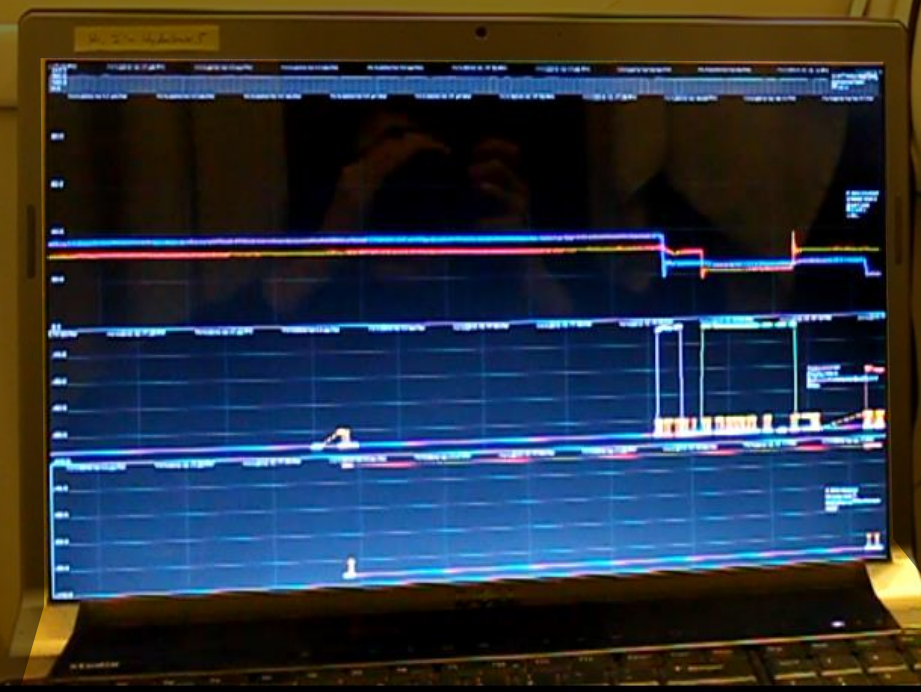


two pressure sensors per home



hydrosense data logger

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

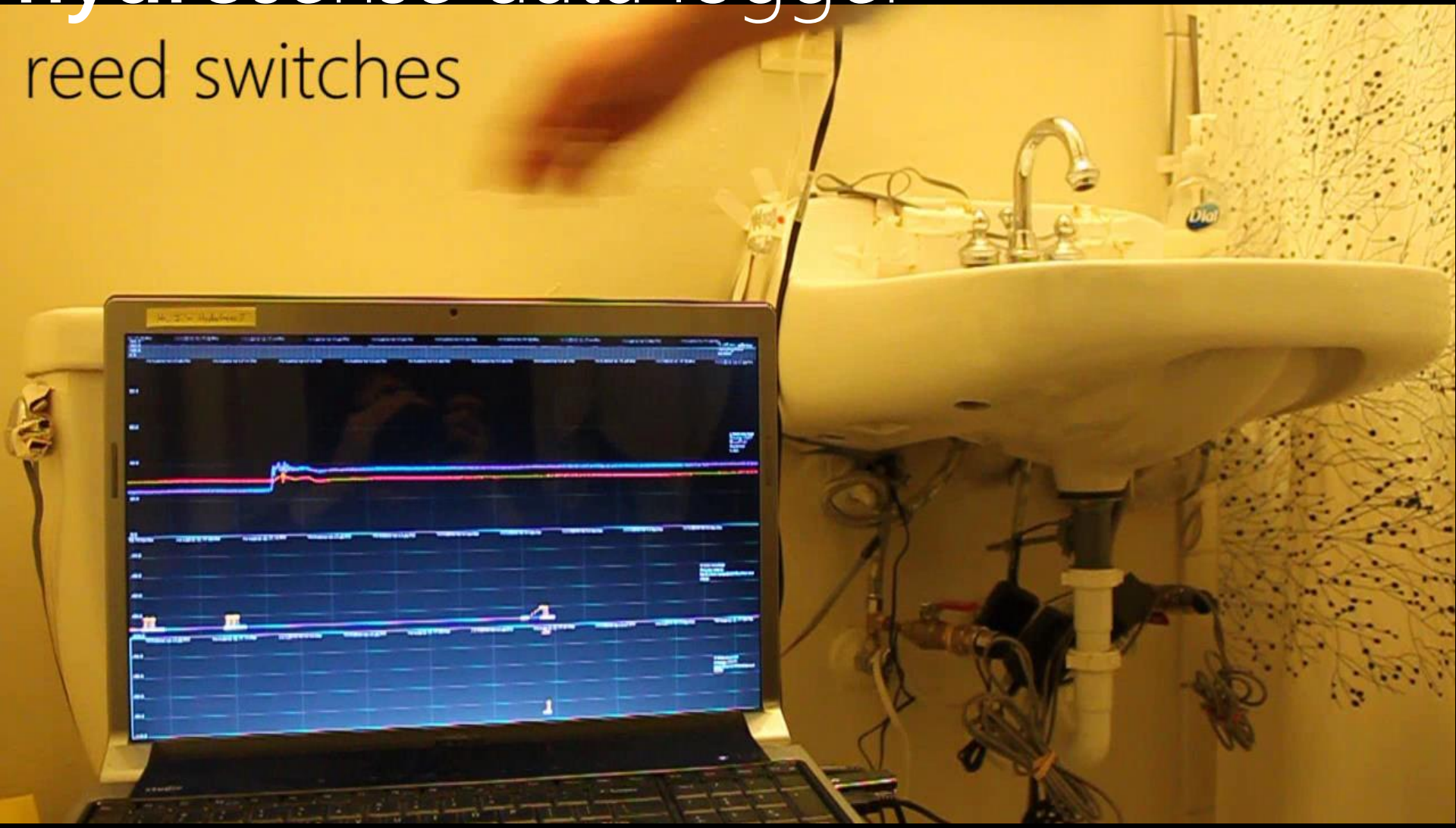


pressure stream
red = hot line
blue = cold line

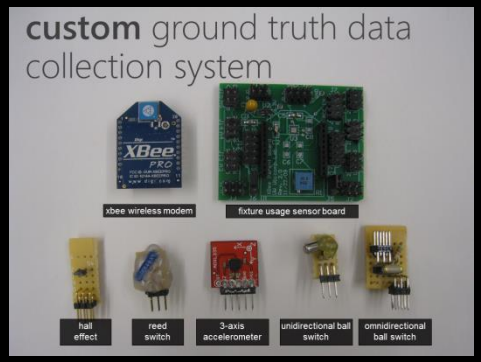
reed switches
high = active
low = inactive

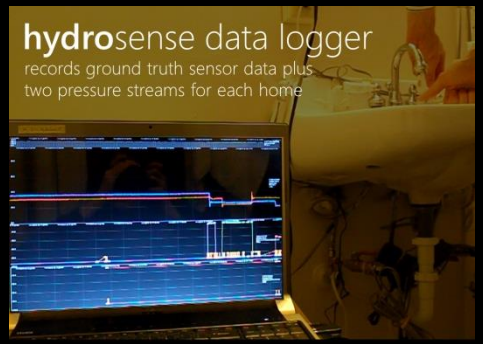
hydrosense data logger

reed switches

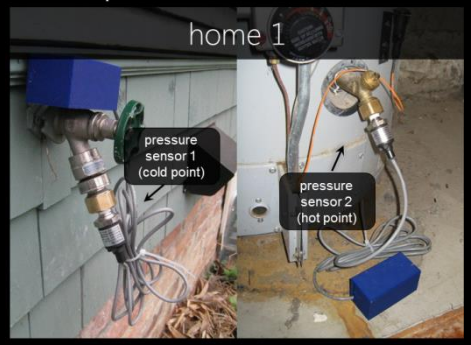


hydro deployment infrastructure

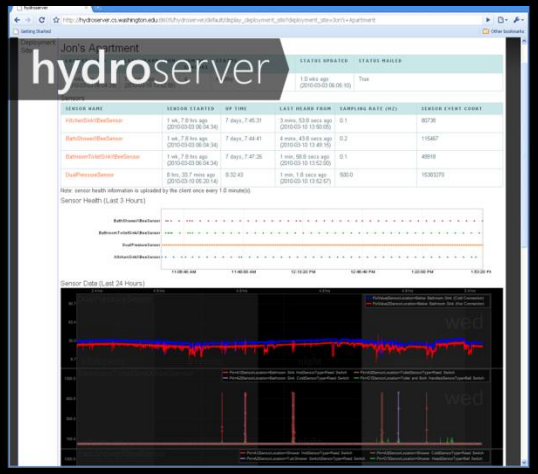




two pressure sensors

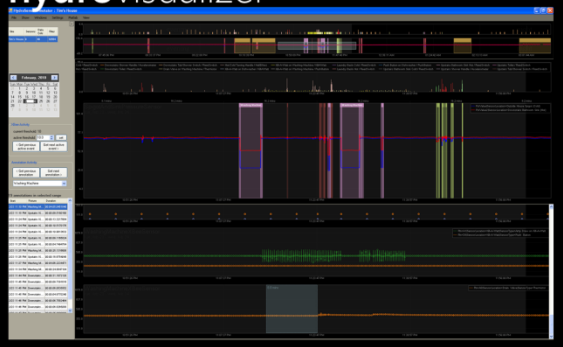


on-site sensing infrastructure

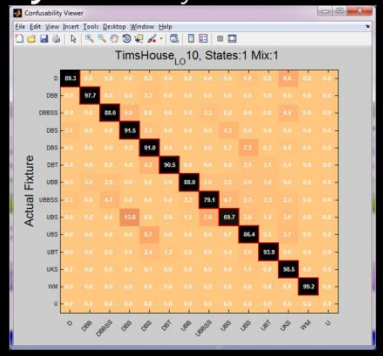


python web backend

hydrovisualizer



hydroanalyzer

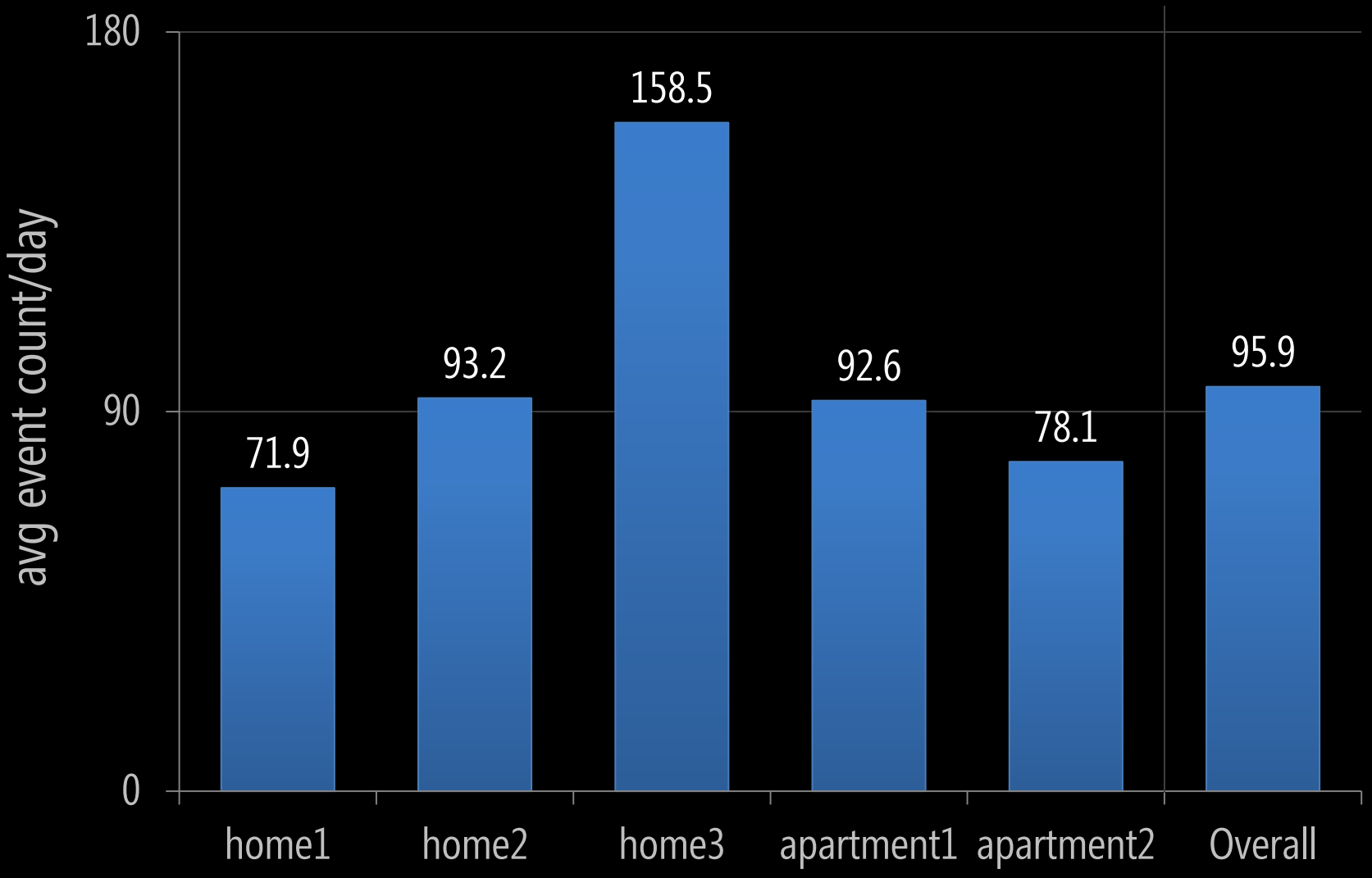


c# and matlab analysis tools

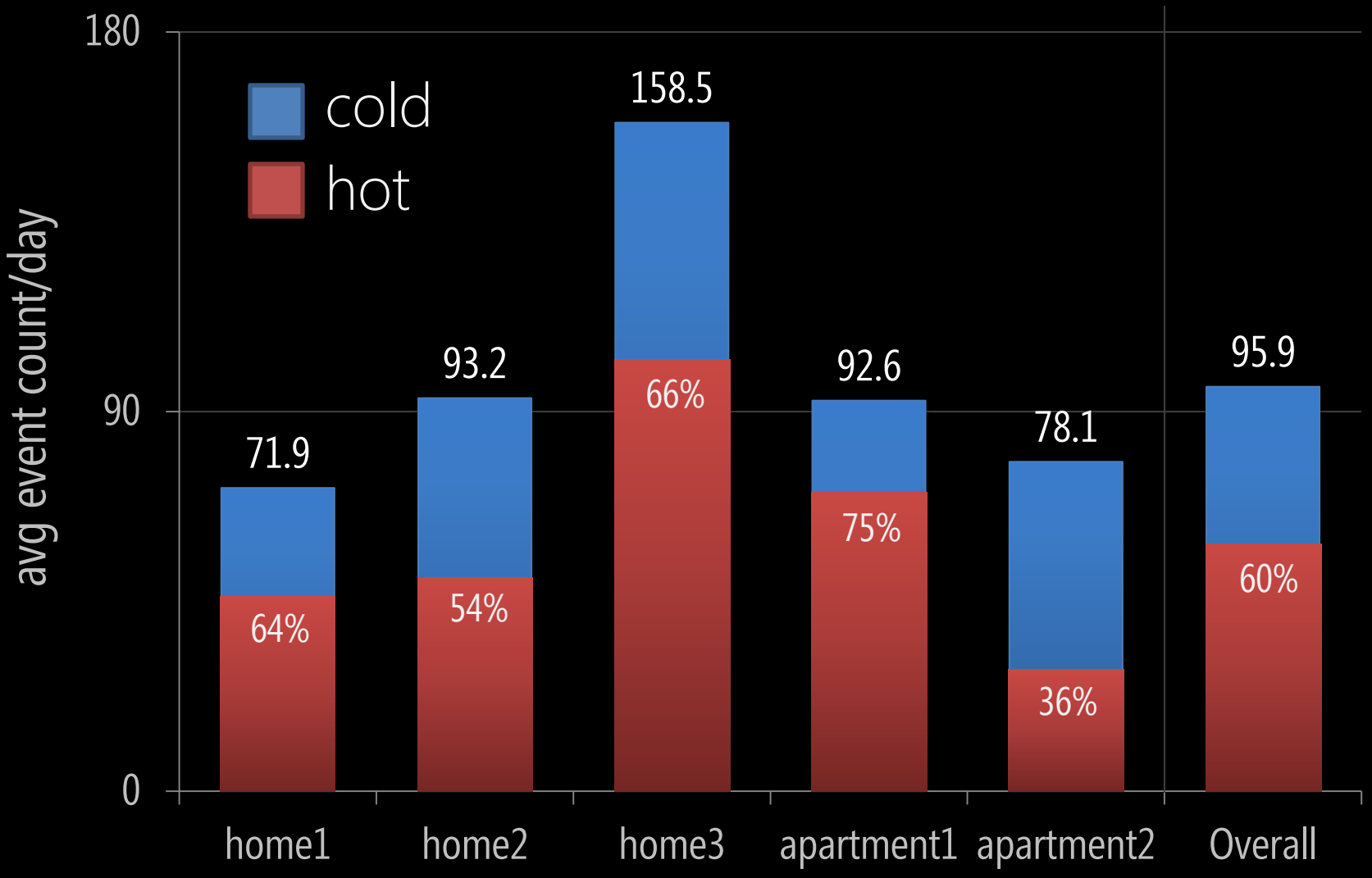
5-week dataset

						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

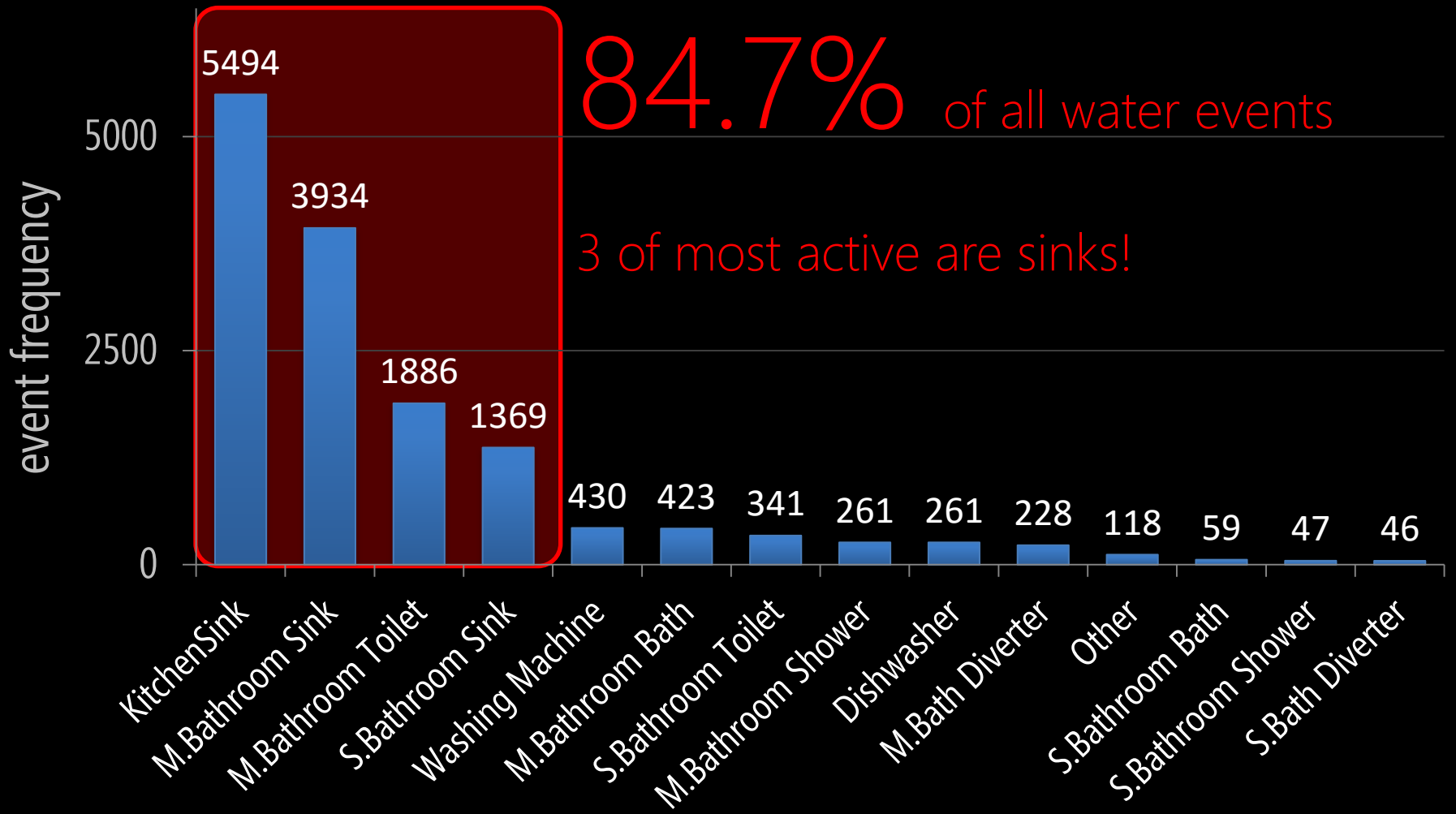
avg num water events/day

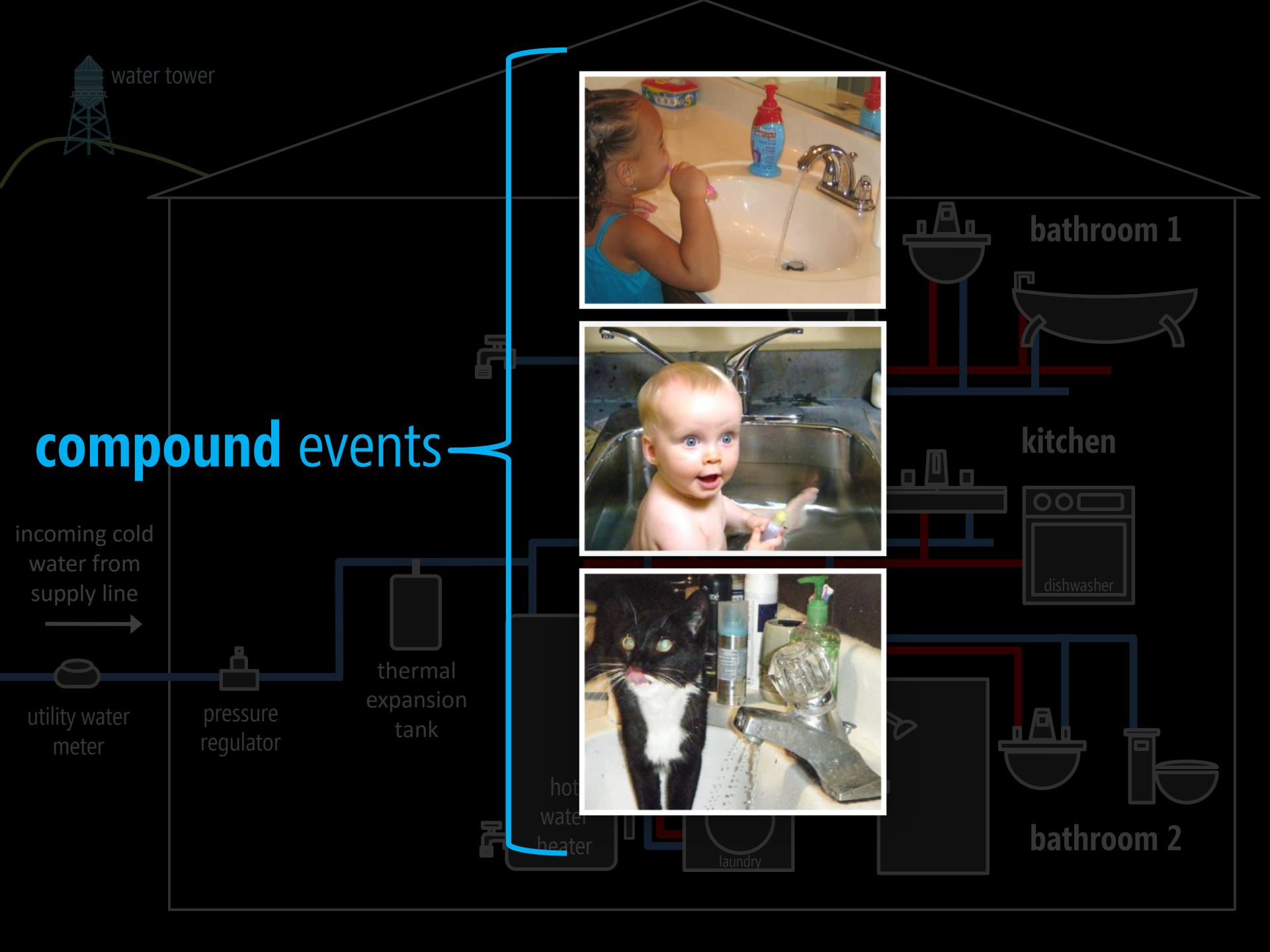


avg num water events/day



fixture activity frequency




water tower
compound events
incoming cold water from supply line
utility water meter
pressure regulator
thermal expansion tank
hot water heater
laundry
bathroom 1
kitchen
dishwasher
bathroom 2

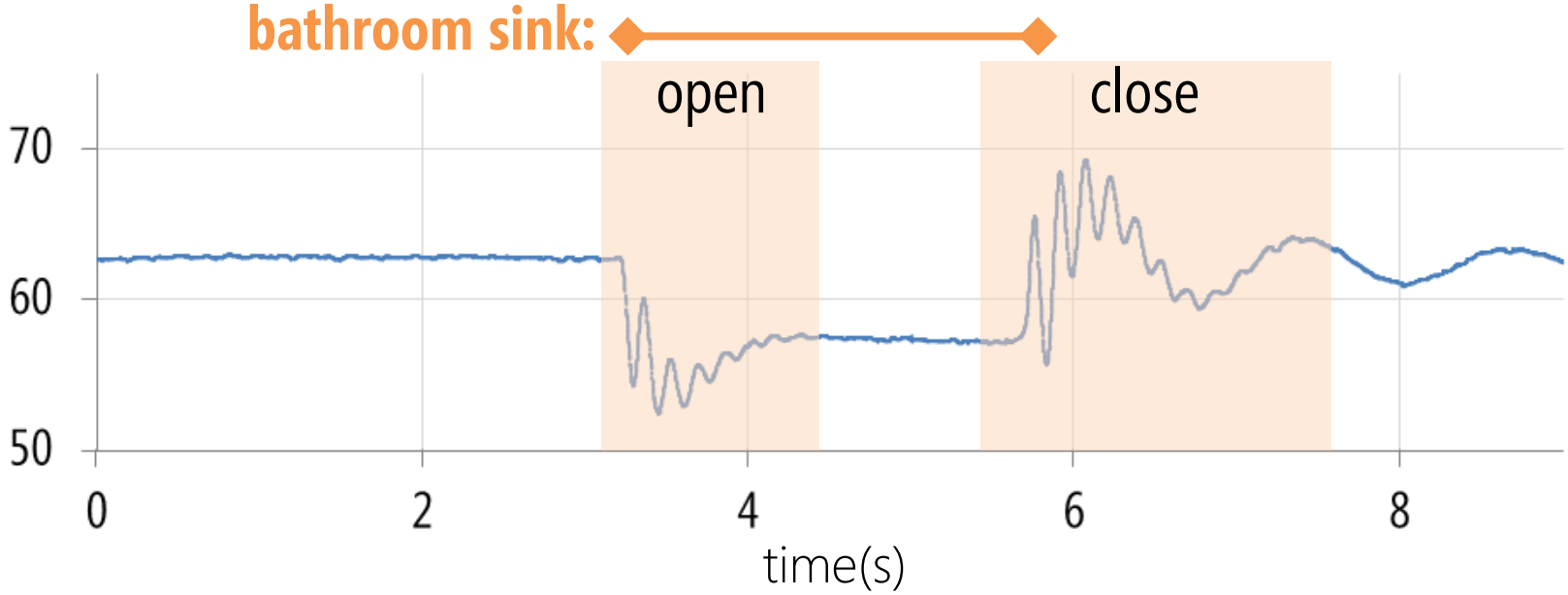
22%

of all water events were compound

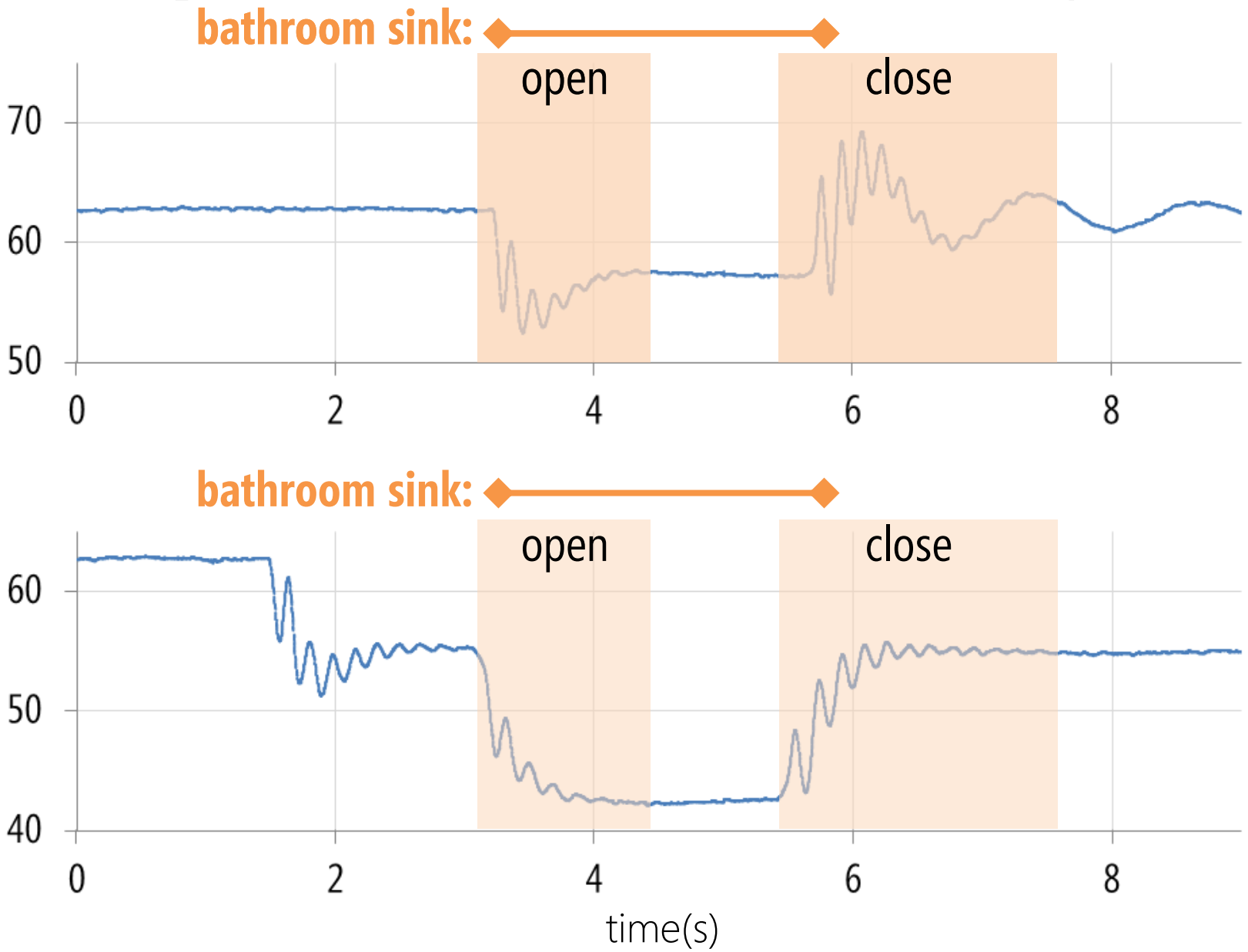
41.8%

of all bathroom sink events were compound

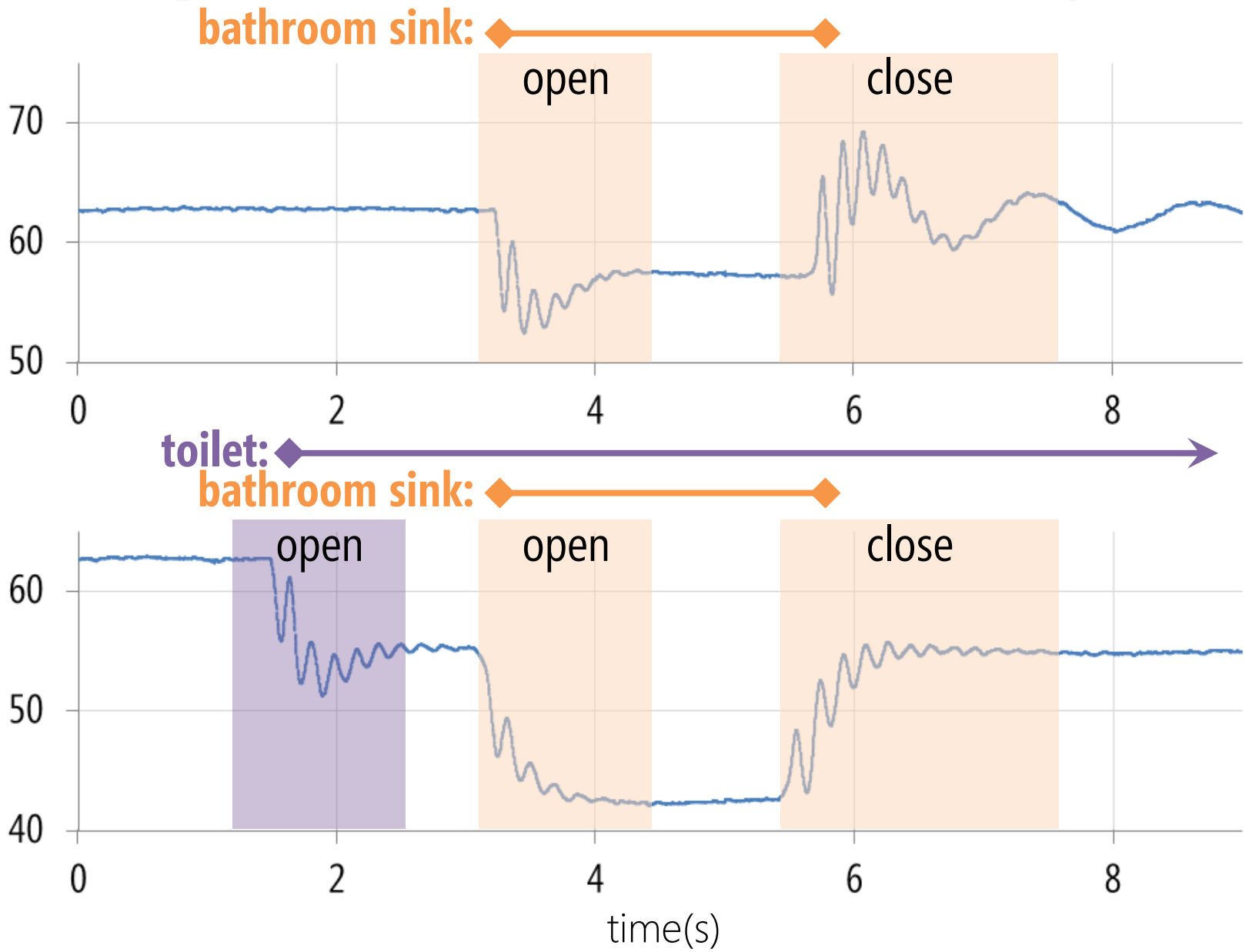
compound event example



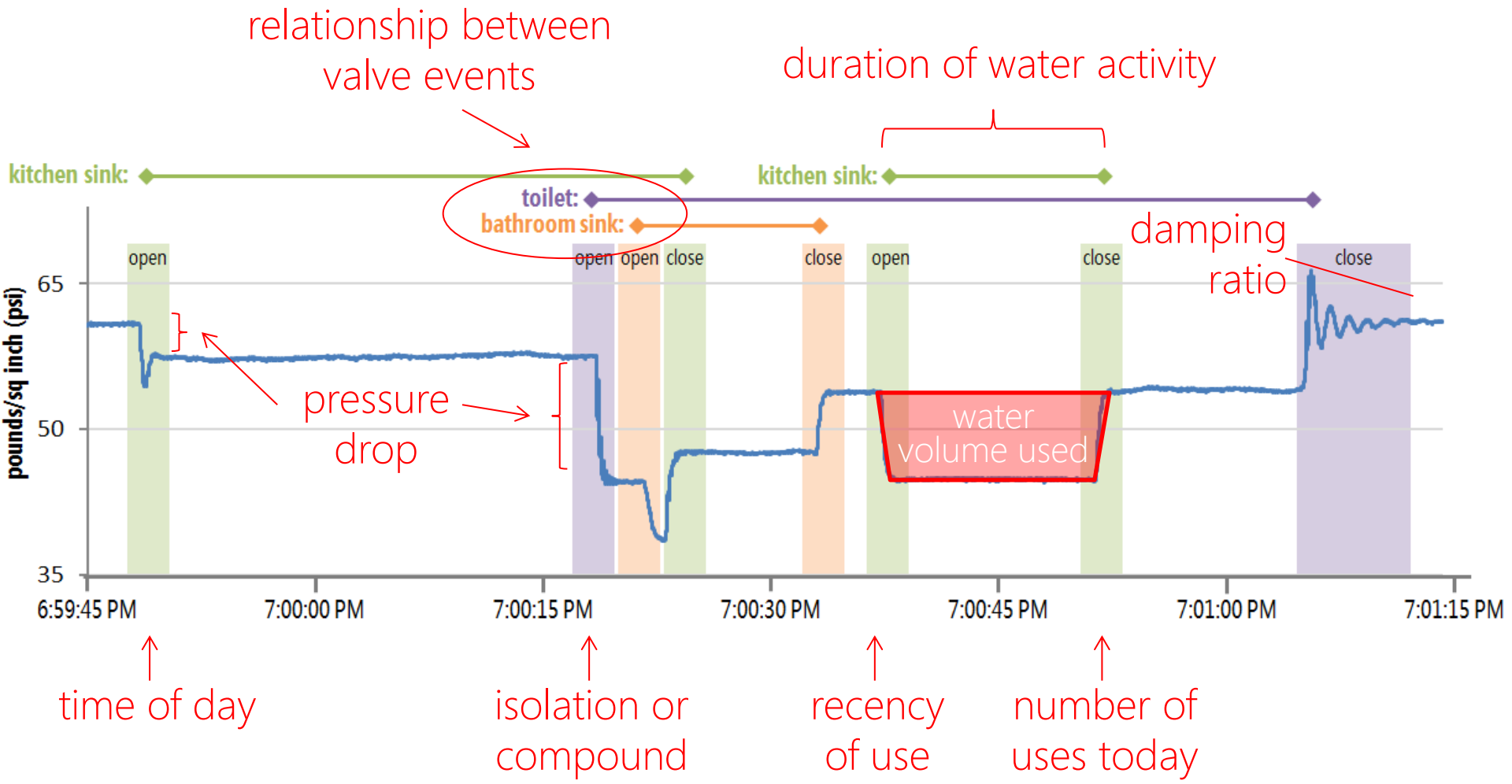
compound event example



compound event example



beyond **template matching**



bayesian approach

V = pressure signature library

S = sequence of unknown pressure transients

most likely valve sequence

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

bayesian approach

V = pressure signature library

S = sequence of unknown pressure transients

conditional probability term

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

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

(i) templates and signal features

e.g., matched filtering and stabilized pressure drop

bayesian approach

V = pressure signature library

S = sequence of unknown pressure transients

prior probability term

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

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

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

bayesian approach

V = pressure signature library

S = sequence of unknown pressure transients

prior probability term

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

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

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

bayesian approach

V = pressure signature library

S = sequence of unknown pressure transients

prior probability term

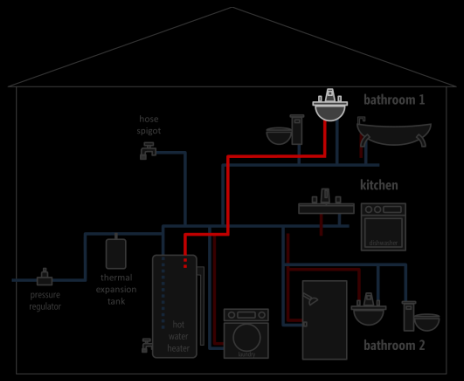
$$\hat{V} = \arg\max P(\mathbf{V} \mid \mathbf{S}) = \arg\max \frac{P(\mathbf{S} \mid \mathbf{V}) P(\mathbf{V})}{P(\mathbf{S})}$$

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

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

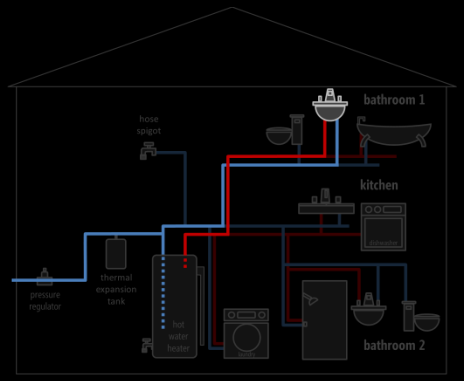
e.g., water usage duration

three levels of granularity



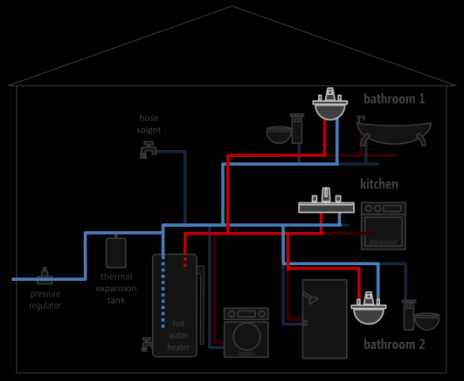
① valve level

e.g., upstairs bathroom faucet hot water activated



② fixture level

e.g., upstairs bathroom faucet activated

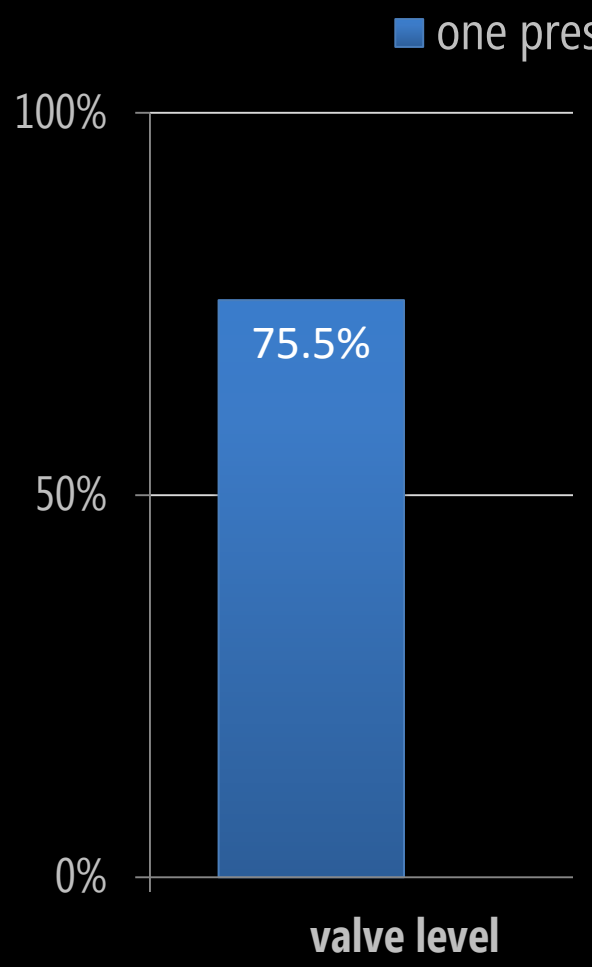


③ fixture category level

e.g., faucet activated

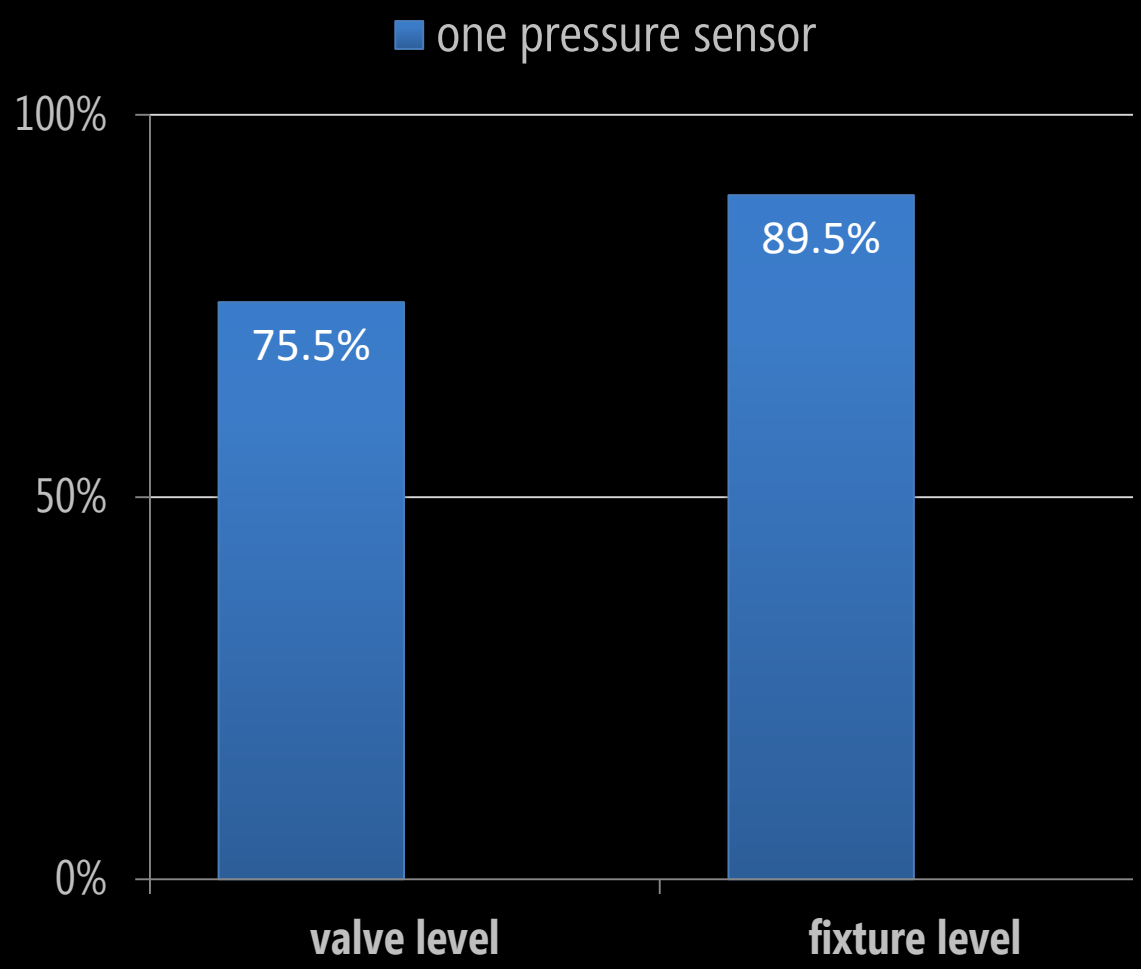
hydrosense classification results

real-world water usage data



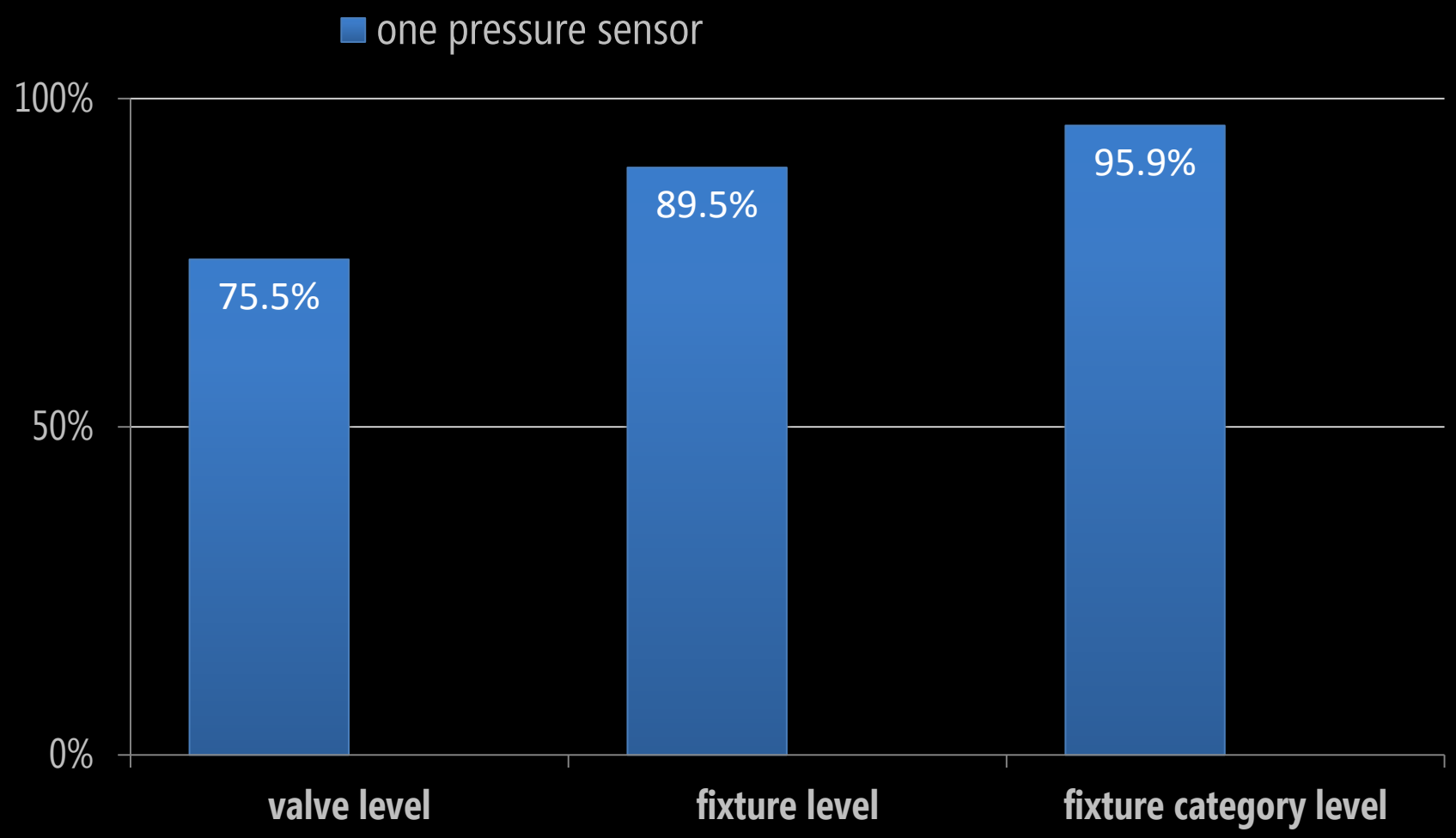
hydrosense classification results

real-world water usage data



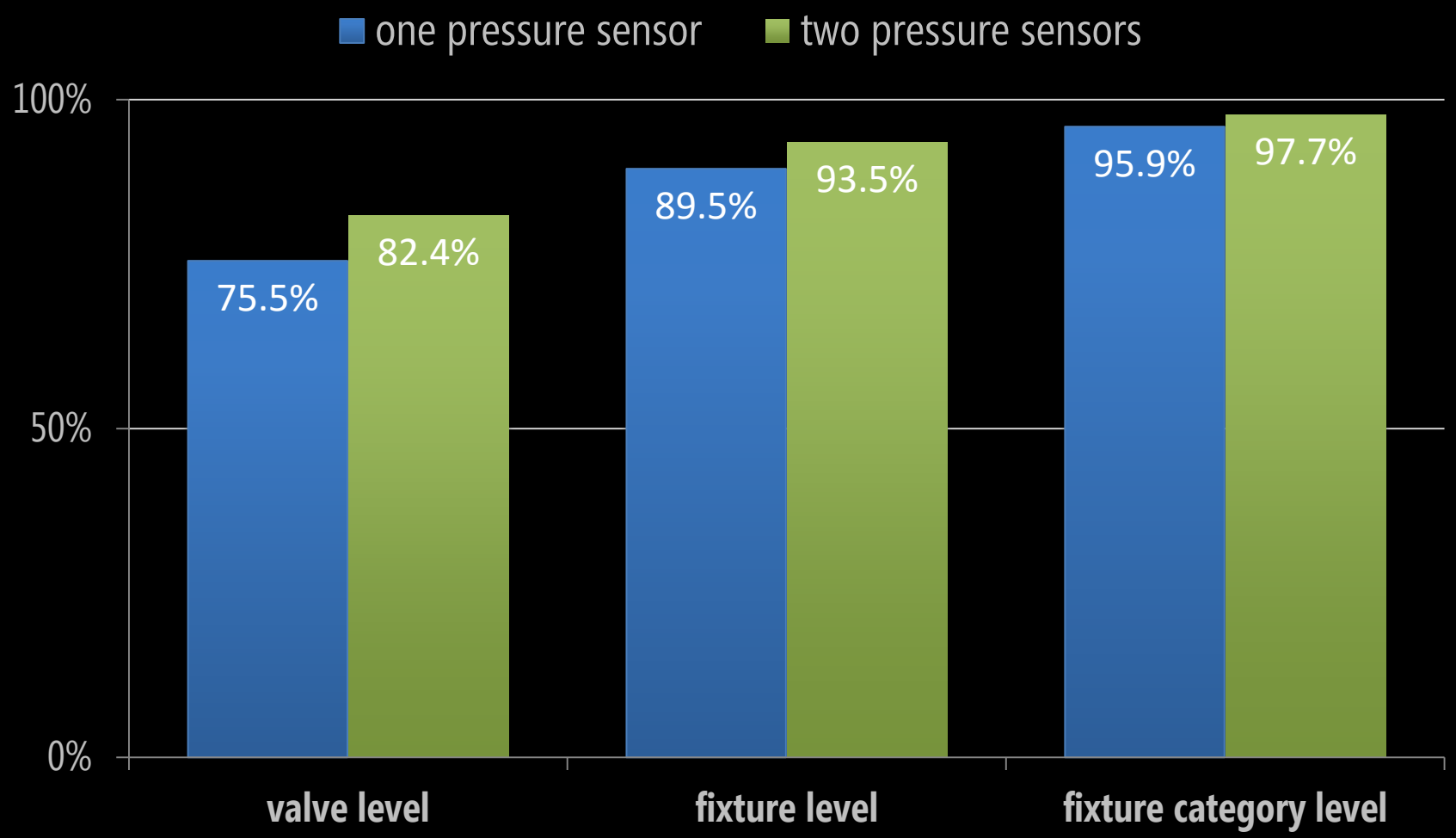
hydrosense classification results

real-world water usage data



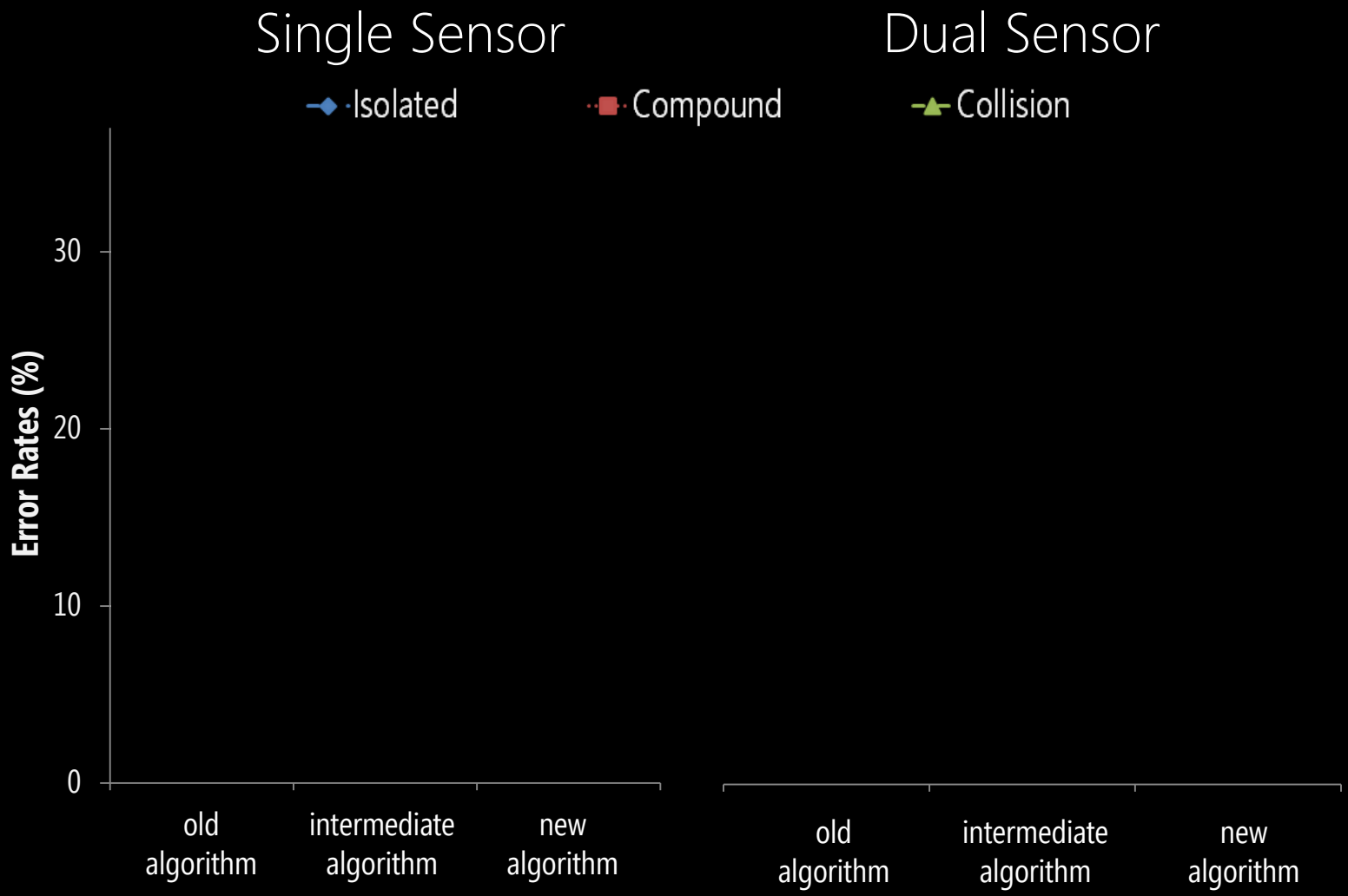
hydrosense classification results

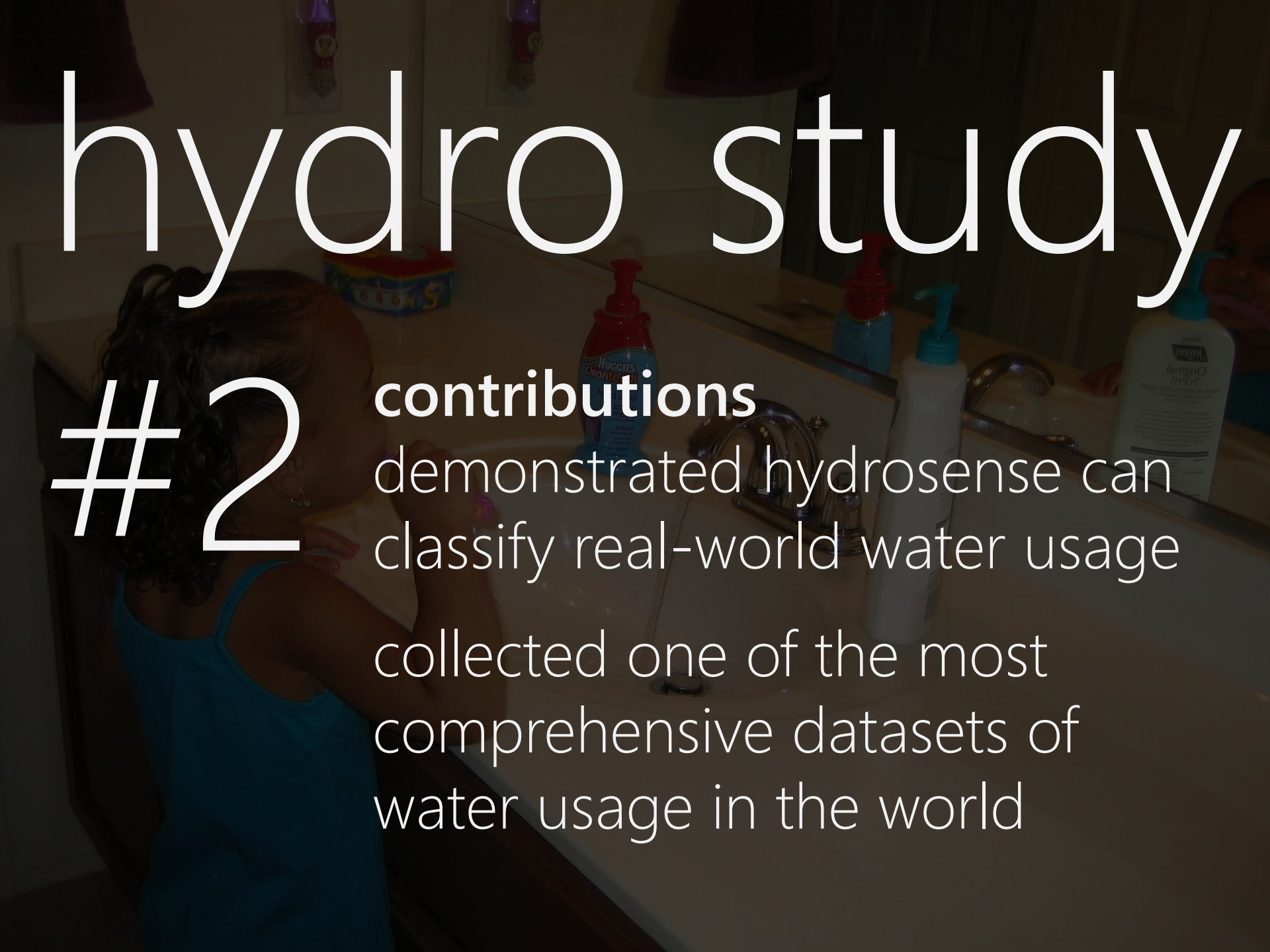
real-world water usage data



compound events results

real-world water usage data





hydro study #2

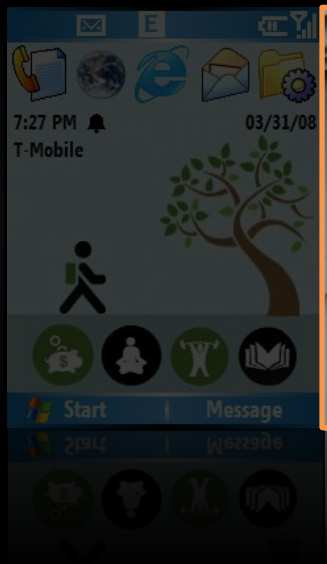
contributions

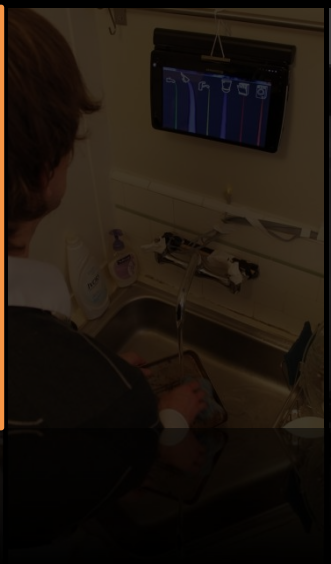
demonstrated hydrosense can classify real-world water usage

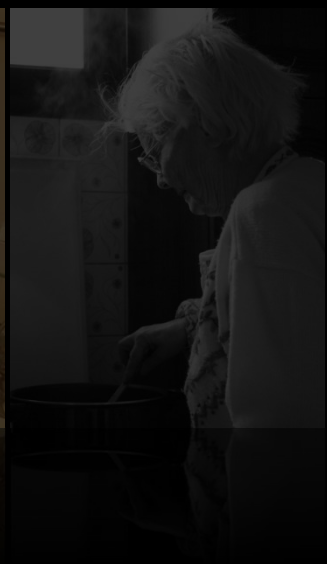
collected one of the most comprehensive datasets of water usage in the world


Consumption
61 °F
MPG
100
75
50
25
0
30min 25 20 15 10 5 0
Current
Energy
Average
60.5 MPG
204 miles
Reset
6:22


the
eco-feedback
design space


7:27 PM
03/31/08
T-Mobile
Start
Message



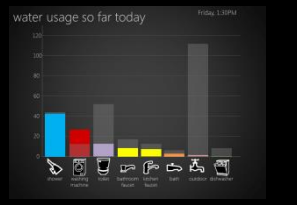


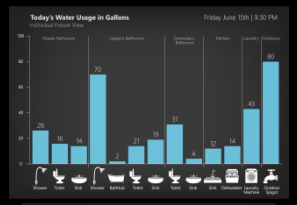
reflect water eco-feedback display

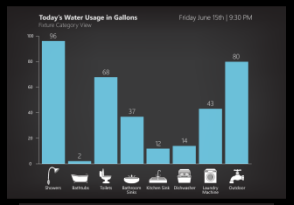
goals

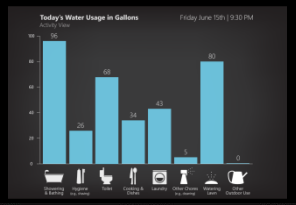
explore large design space for water feedback interfaces

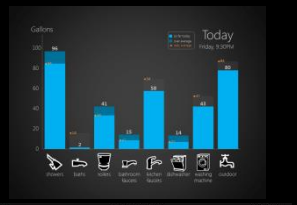
evaluate designs both qualitatively and quantitatively

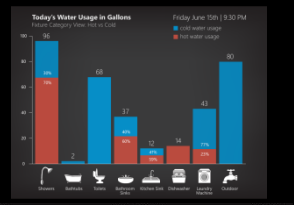

water usage so far today
Friday 1:39PM

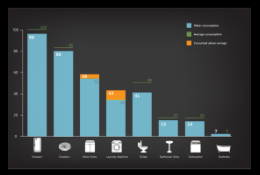

Today's Water Usage in Gallons
Individual Fixture View
Friday June 15th | 9:30 PM

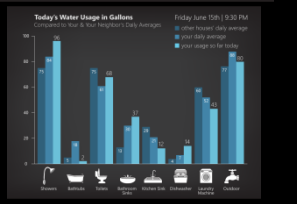

Today's Water Usage in Gallons
Fixture Category View
Friday June 15th | 9:30 PM

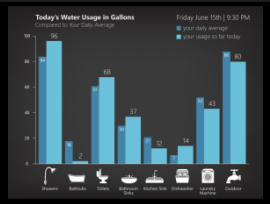

Today's Water Usage in Gallons
Activity View
Friday June 15th | 9:30 PM

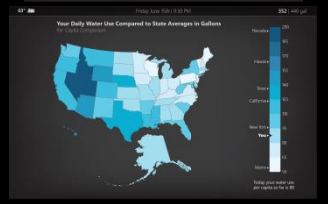

Gallons
Today
Friday 9:30PM


Today's Water Usage in Gallons
Future Category View: Hot & Cold
Friday June 15th | 9:30 PM



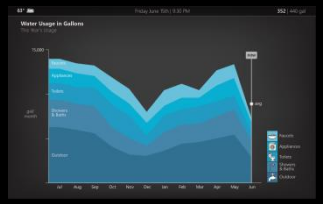

Today's Water Usage in Gallons
Compared to Your & Your Neighbor's Daily Averages
Friday June 15th | 9:30 PM

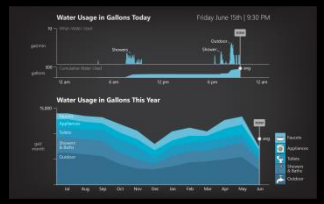

Today's Water Usage in Gallons
Compared to Your Daily Average
Friday June 15th | 9:30 PM

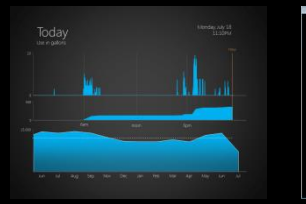

Your Daily Water Use Compared to State Averages in Gallons
Per Capita Comparison

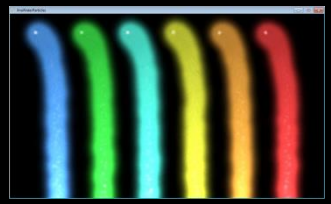

Your Daily Water Use Compared to National Averages in Gallons
Per Capita Comparison


Water Usage in Gallons
Today's Usage
Friday June 15th | 9:30 PM

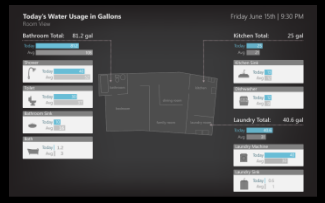

Water Usage in Gallons
This Year's Usage

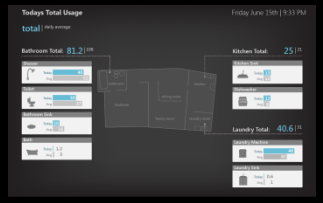

Water Usage in Gallons Today
Water Usage in Gallons This Year
Friday June 15th | 9:30 PM


Today
Use in gallons
Monday, July 18
11:10PM




January
Sunday
30
04:39PM

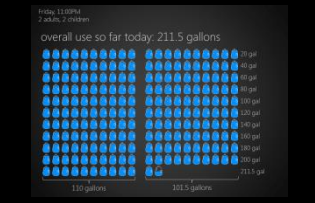

Today's Water Usage in Gallons
Fixture View
Friday June 15th | 9:30 PM
Bathroom Total: 81.2 gal
Kitchen Total: 25 gal
Laundry Total: 40.6 gal

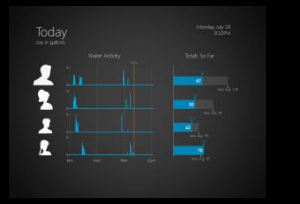

Todays Total Usage
total | daily average
Friday June 15th | 9:33 PM
Bathroom Total: 81.2
Kitchen Total: 25
Laundry Total: 40.6


toilet
bathroom sink
kitchen sink
bath
shower
laundry machine
dishwasher
58 gals
8 gals
4.9 gals


Monday, 9:30AM
2 adults, 2 children
master bathroom
upstairs bathroom
downstairs bathroom
kitchen
laundry room
by room
by fixture category


January
Sunday
30
04:39PM

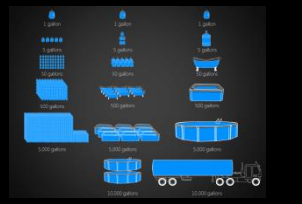

Friday, 11:09PM
2 adults, 2 children
overall use so far today: 211.5 gallons
110 gallons
101.5 gallons

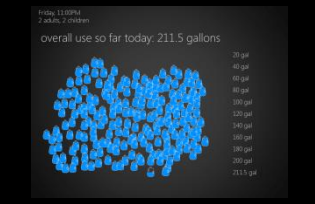

Today
Use in gallons
Monday, July 18
8:10PM

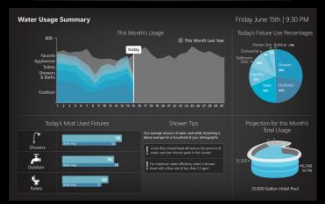

Today
Use in gallons
Monday, July 18
7:28PM

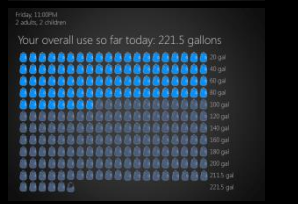

Personal Usage Totals
Friday June 15th | 9:30 PM

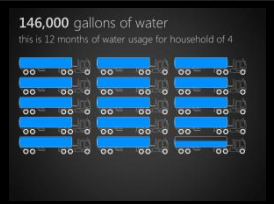

Personal Usage Totals
Friday June 15th | 9:30 PM

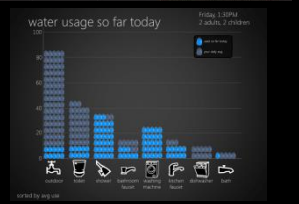


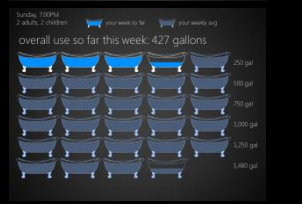

Friday, 11:09PM
2 adults, 2 children
overall use so far today: 211.5 gallons


Water Usage Summary
Friday June 15th | 9:30 PM
This Month's Usage
Today's Most Used Fixtures
Shower Tips
Projection for this Months Total Usage

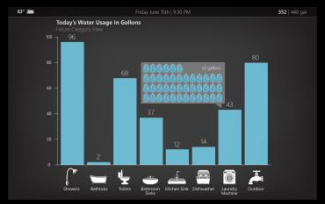

Friday, 11:09PM
2 adults, 2 children
Your overall use so far today: 221.5 gallons

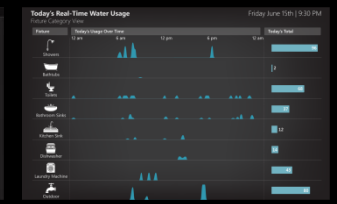

146,000 gallons of water
this is 12 months of water usage for household of 4

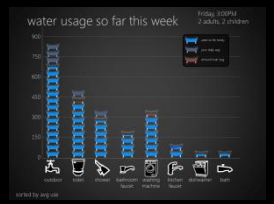

water usage so far today
Friday, 1:39PM
2 adults, 2 children

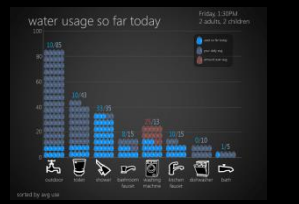

Sunday, 7:00PM
2 adults, 2 children
overall use so far this week: 427 gallons


Friday, 11:09PM
2 adults, 2 children
overall use so far this week: 1,305 gallons
1,000 gallons
305 gallons


Today's Water Usage in Gallons
Future Category View
Friday June 15th | 9:30 PM


Today's Real-Time Water Usage
Future Category View
Friday June 15th | 9:30 PM


water usage so far this week
Friday, 3:00PM
2 adults, 2 children


water usage so far today
Friday, 1:39PM
2 adults, 2 children

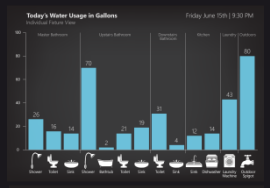
Water Usage Summary
One Day
440 Gallons
One Week
3,080 Gallons
One Month
13,200 Gallons
One Year
160,710 Gallons

Water Usage Summary
One Day
440 Gallons
One Week
3,080 Gallons
One Month
13,200 Gallons
One Year
160,710 Gallons

Two sets of designs:

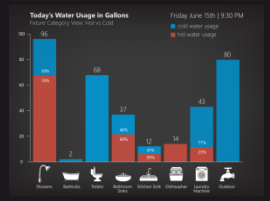
1 **Design Dimensions**
Isolate eco-feedback design dimensions in the context of water usage

2 **Design Probes**
Meant to elicit reactions about how displays would fit within a household and potentially affect family dynamics



By fixture

By fixture category



By activity

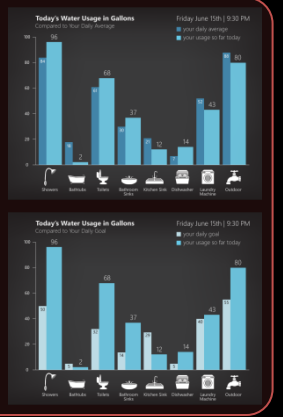
With temperature information

To past performance

To a goal

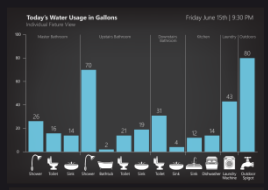
To nearby neighbors

To demographically similar neighbors



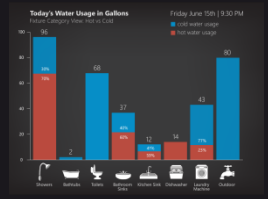
design dimensions

design dimensions



By fixture

By fixture category

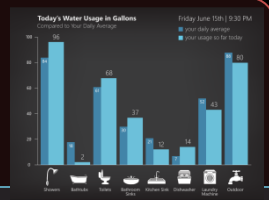


By activity

With temperature information

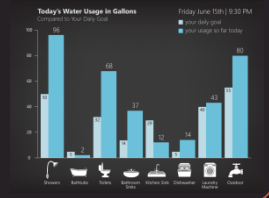
To past performance

To a goal



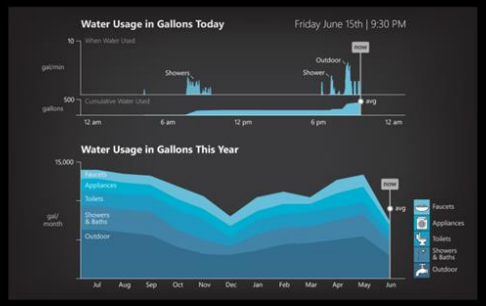
To nearby neighbors

To demographically similar neighbors



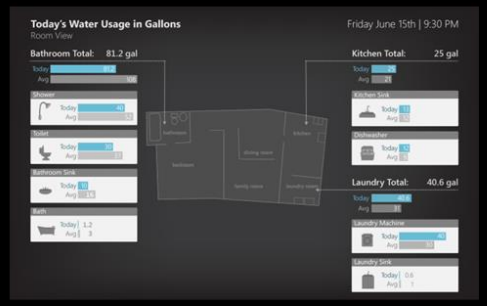
design probes

Time-Series



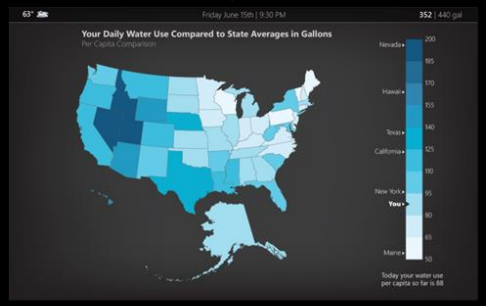
Per-Occupant

Spatial

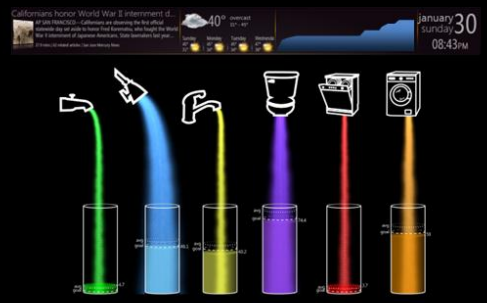


Location Preferences

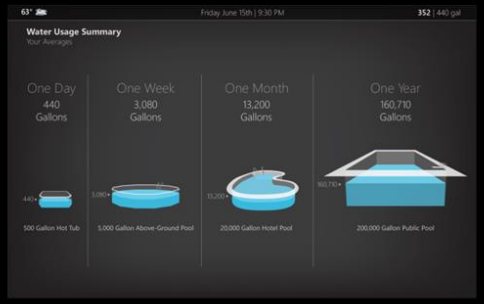
Comparison



Rainflow

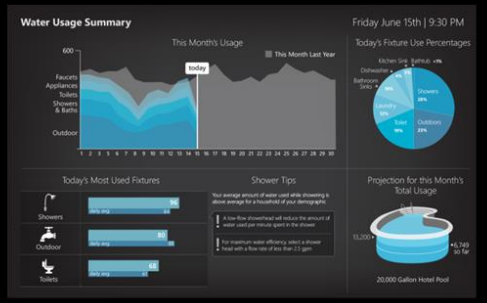


Measurement

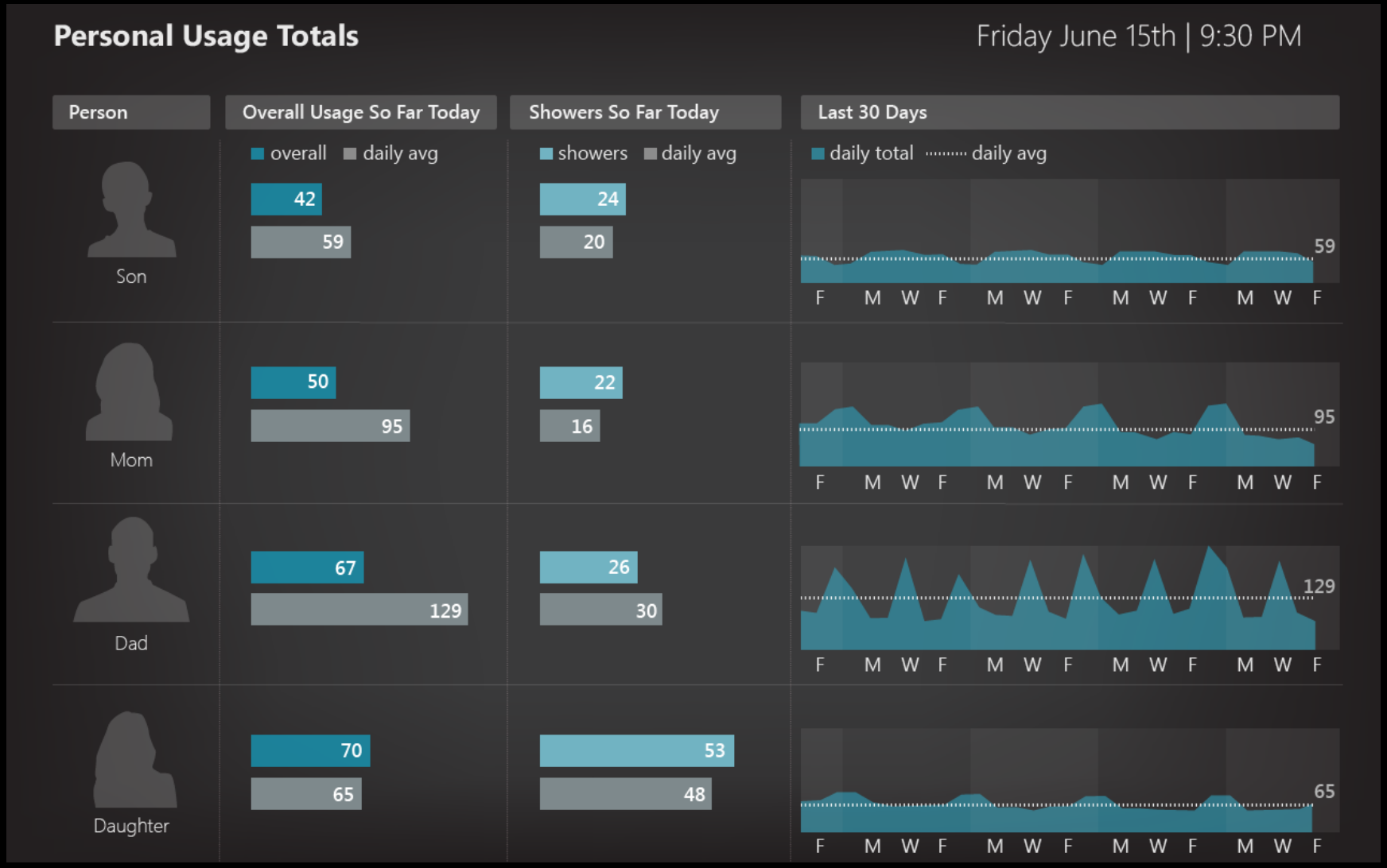


Aquatic Eco-System

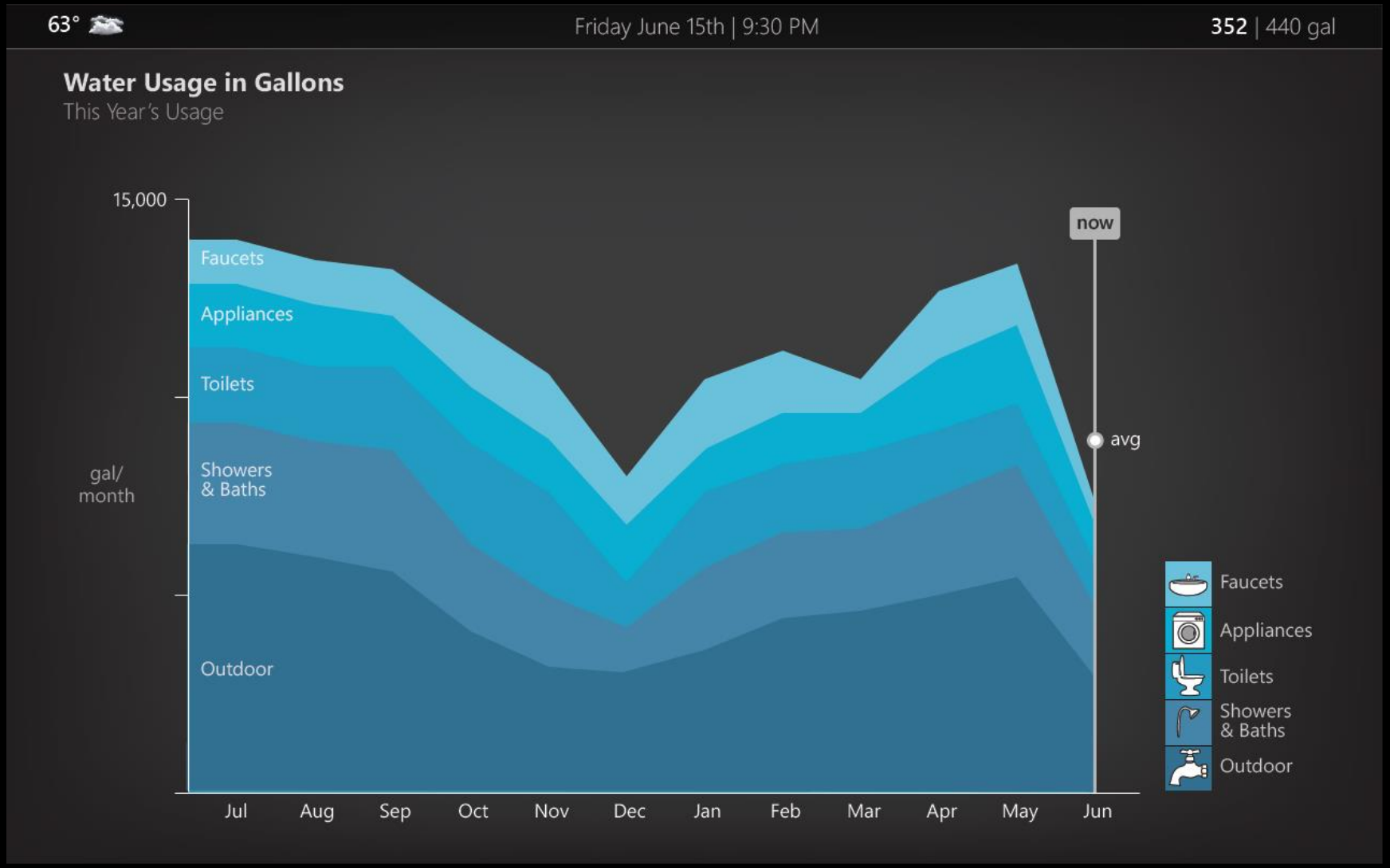
Action Recommendations



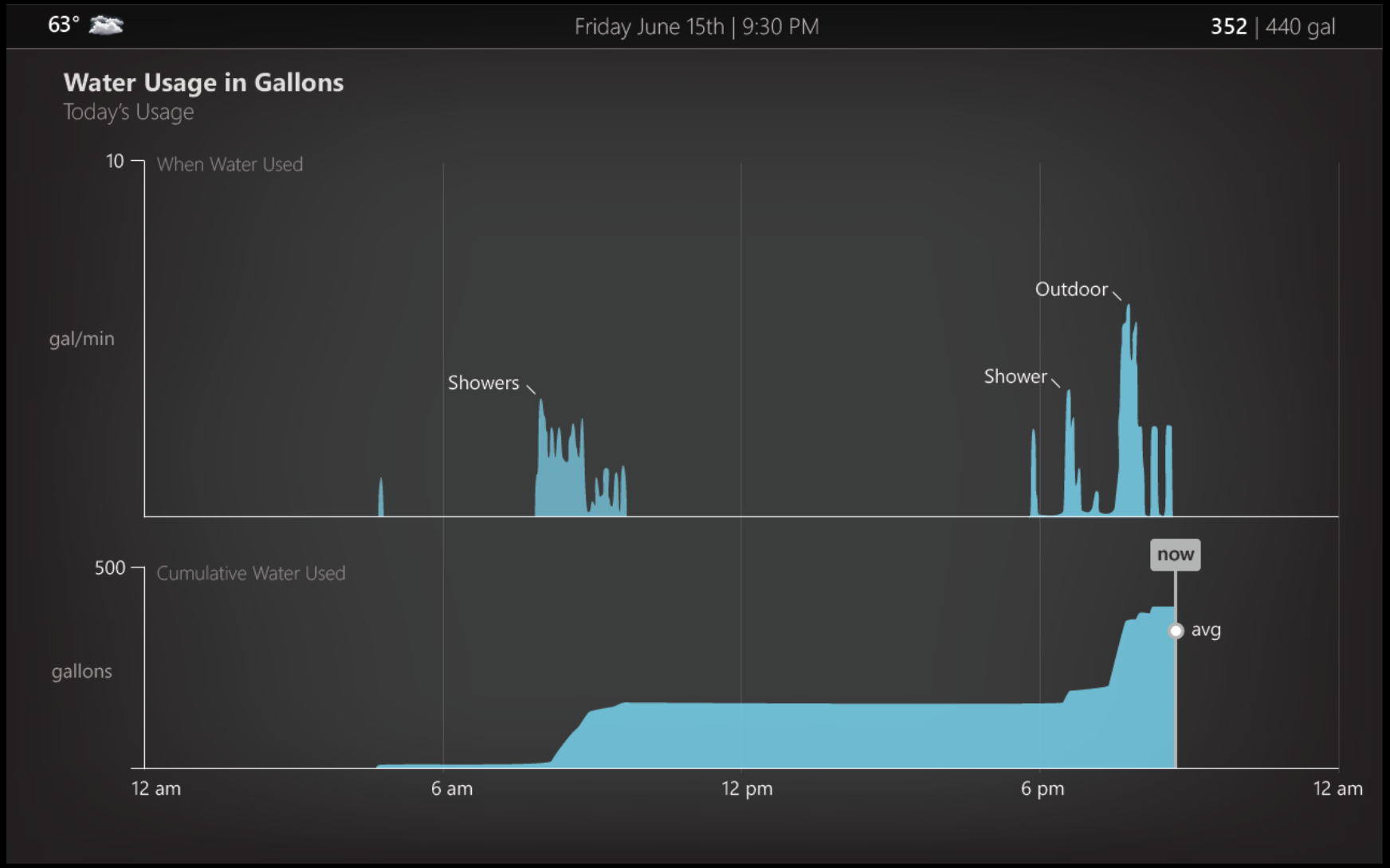
per-occupant view



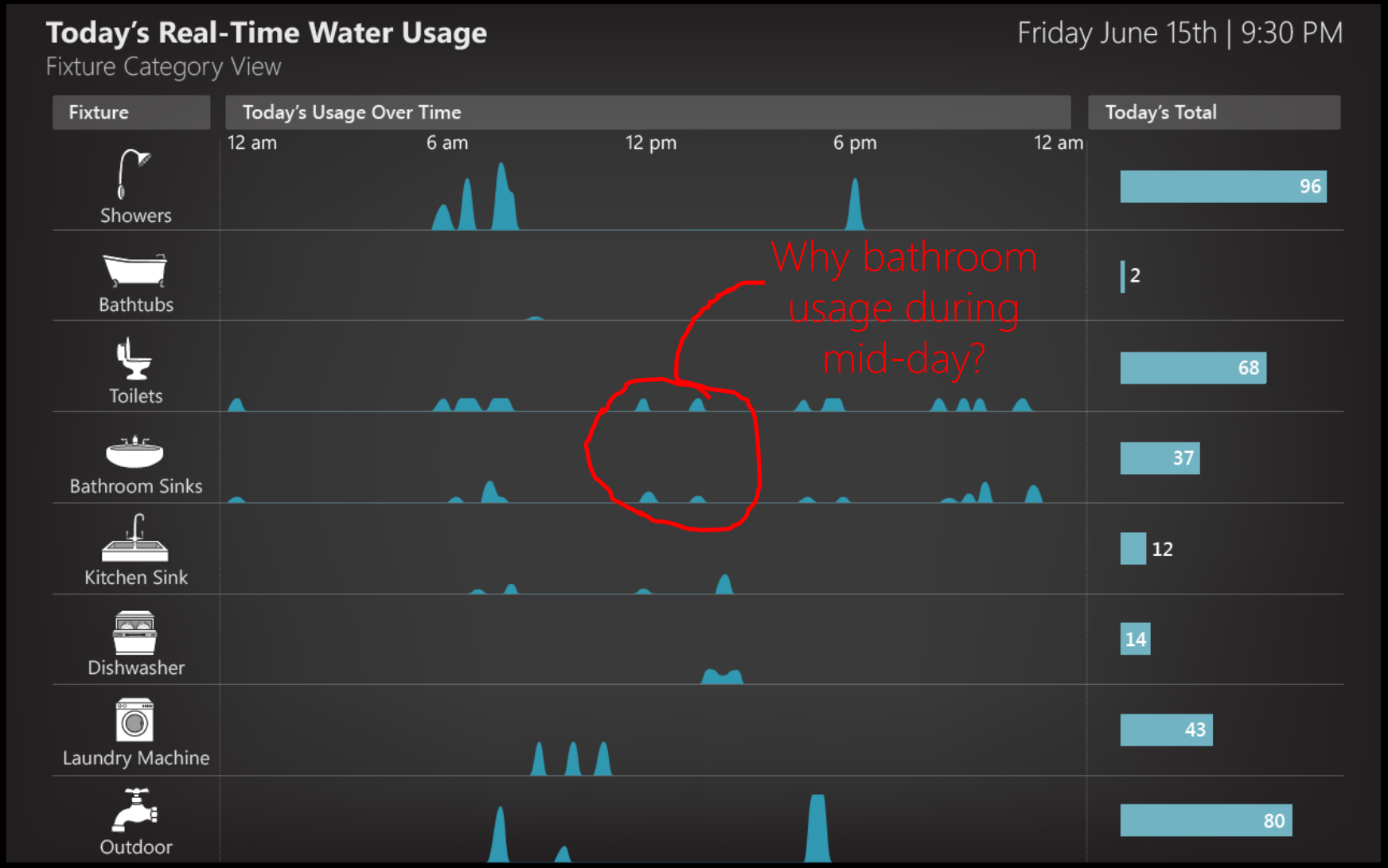
time-series year view



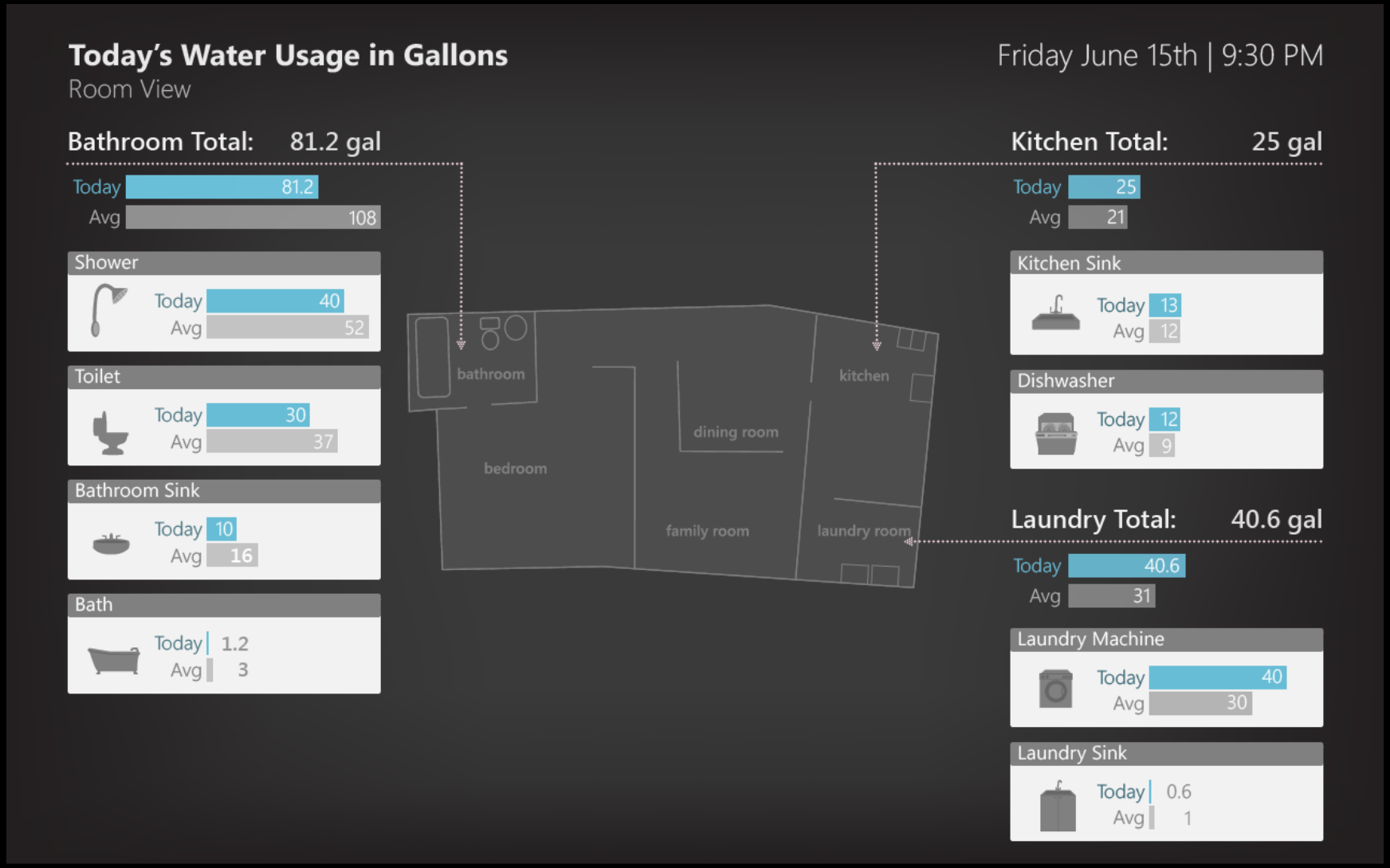
time-series day view



time-series day view



spatial view

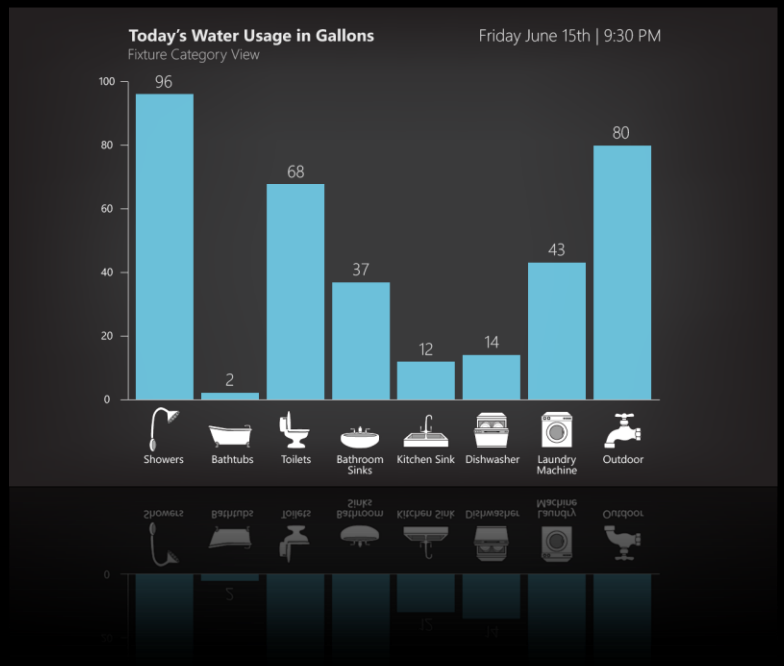


we also explored more *ambient* displays that were less "data-centric" and **more fun and playful**

aquatic eco-system

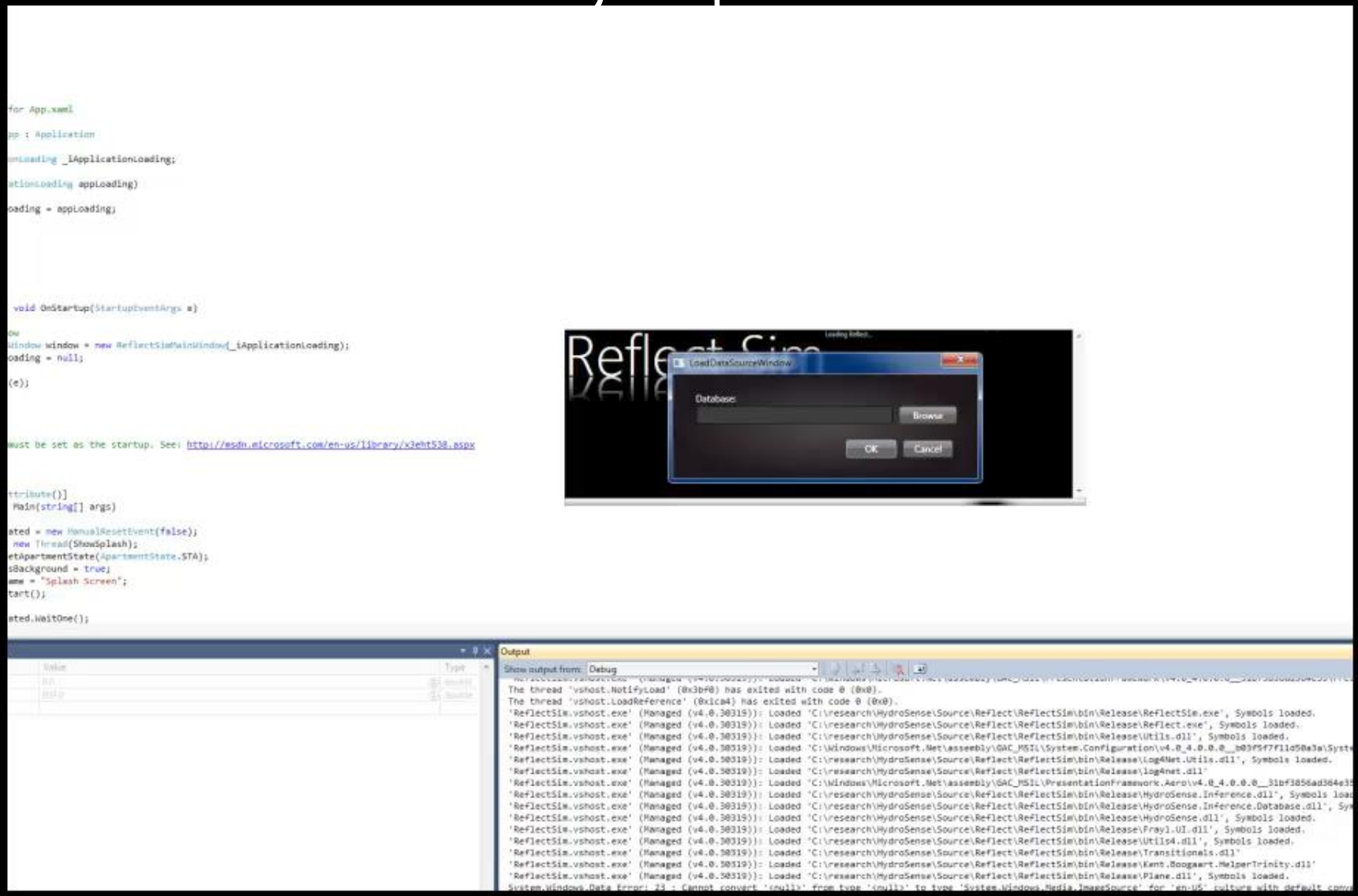
functional vs. stylized

Bar Graph



Rainflow Bar Graph

rainflow bar graph



study method

① Online survey of 656 respondents exploring water usage attitudes, beliefs, knowledge

② Online survey of 651 respondents evaluating design dimensions and design probes

③ Interviews with 10 households examining a greater set of designs and exploring social dynamics within household

study findings

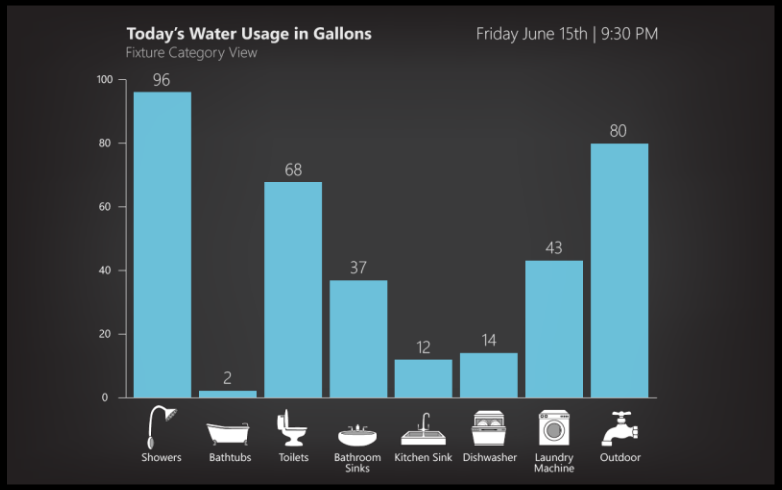
Overall preference

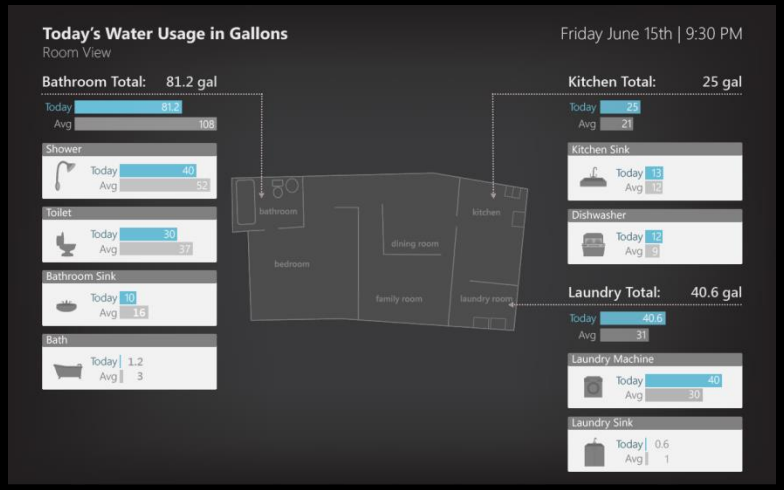
Privacy concerns

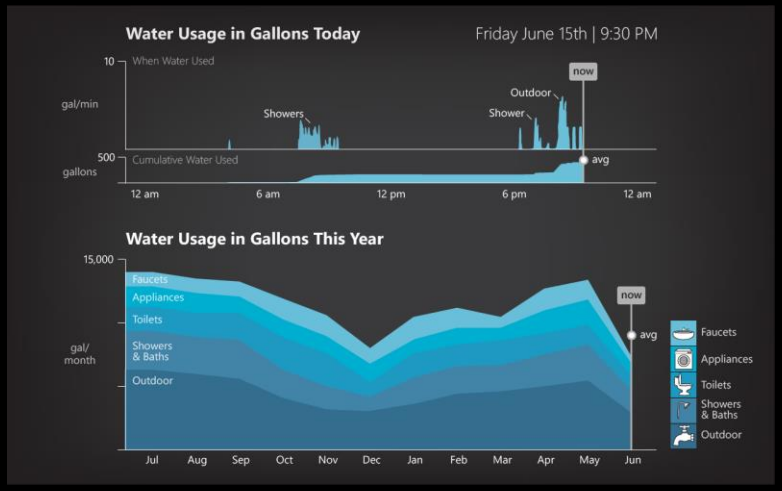
Comparison/competition

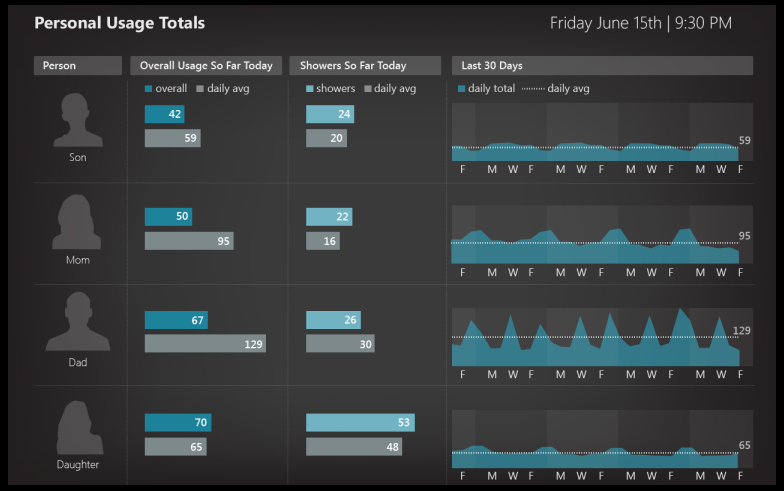
Location of display

overall preference

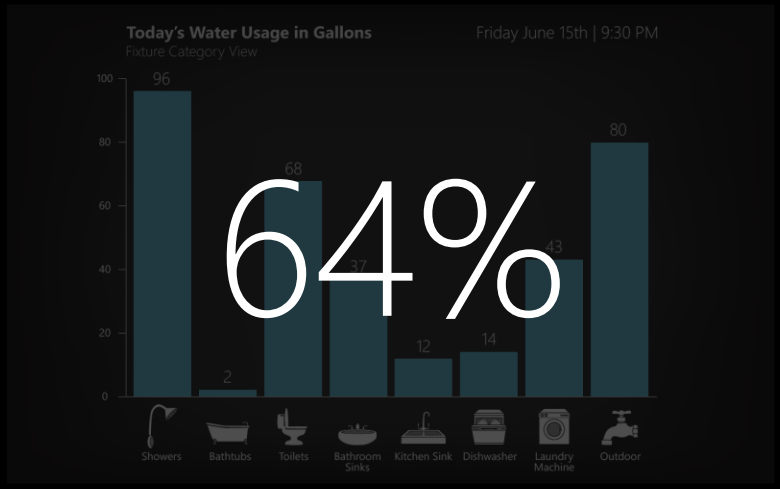


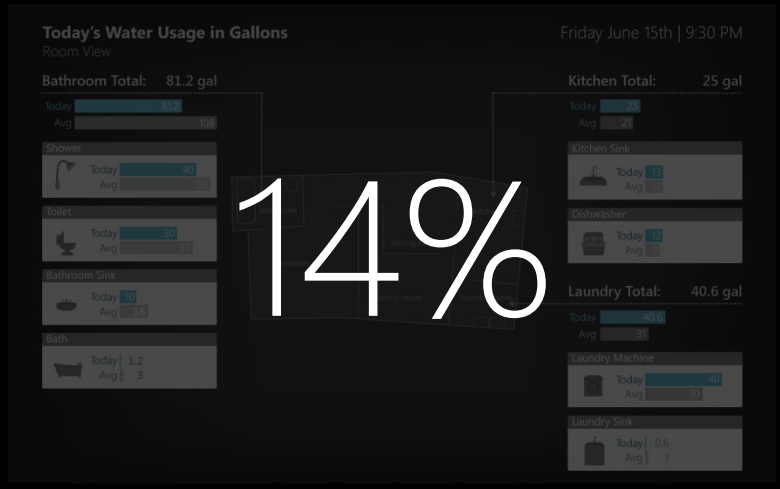


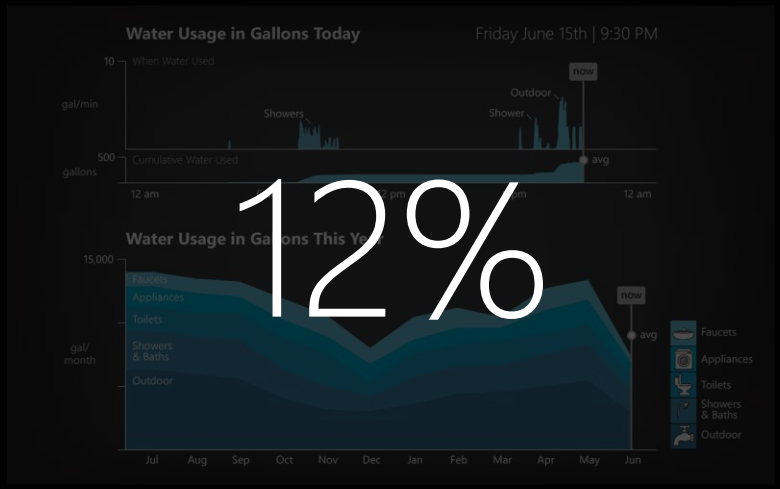


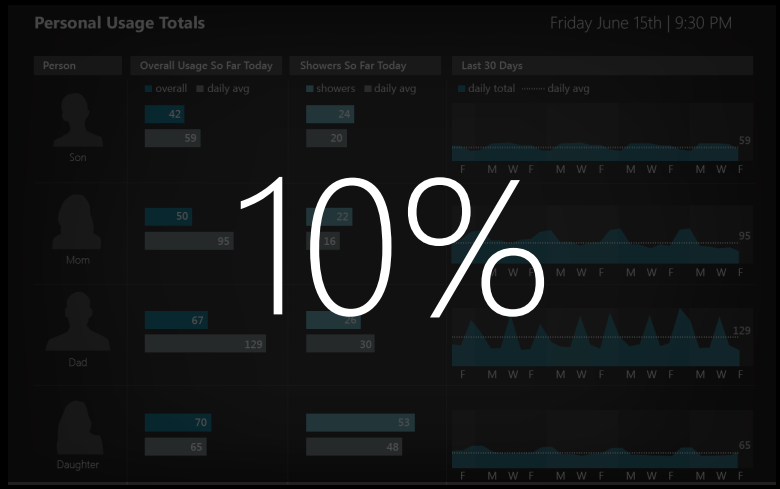


overall preference

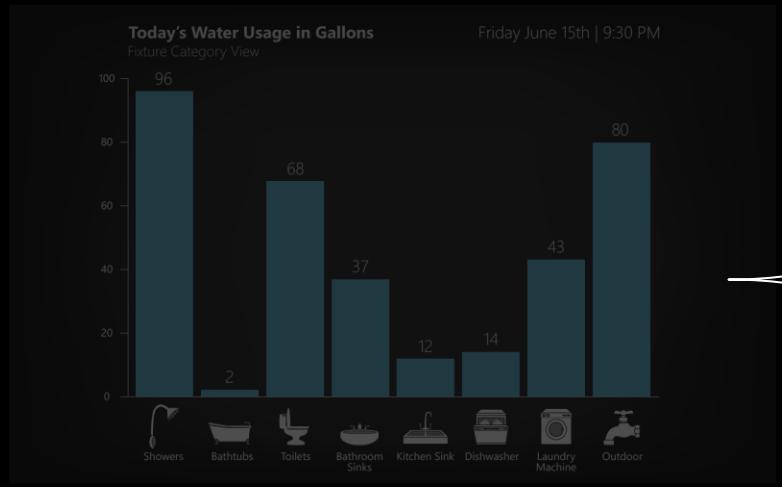


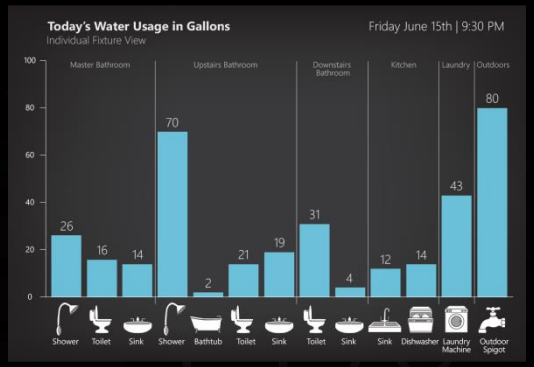






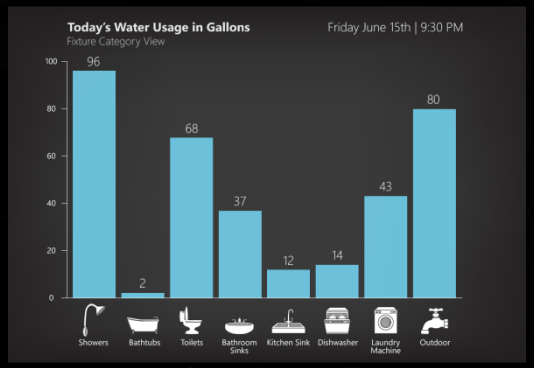
data granularity preference





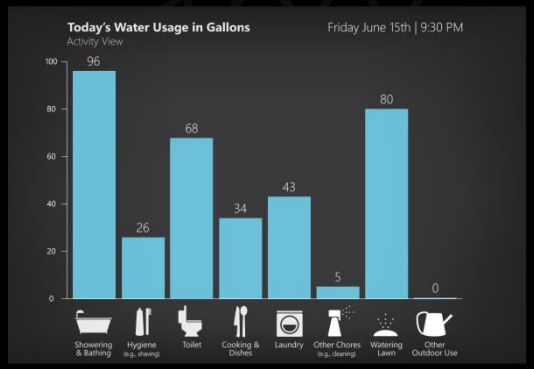
54%

Individual Fixture View



27%

Fixture Category View



19%

Activity View

activity preference

"It's more action oriented than plumbing oriented"

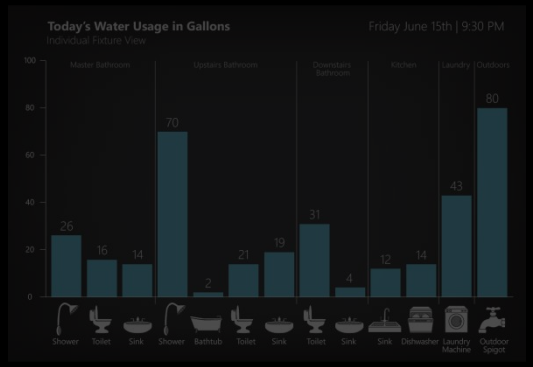
-R824

"It makes it so much easier to visualize what actions I need to take in order to reduce water usage"

-R48

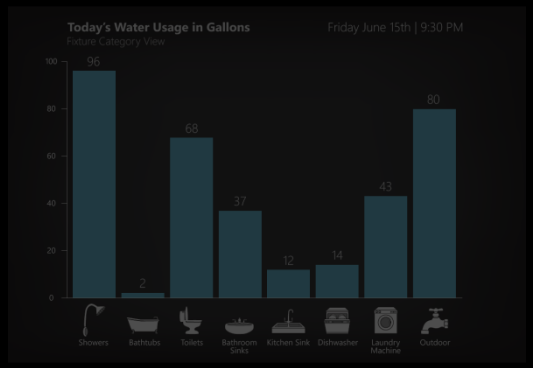
"I wouldn't trust the activity view. How do you know if I am showering or cleaning the shower?"

-R80



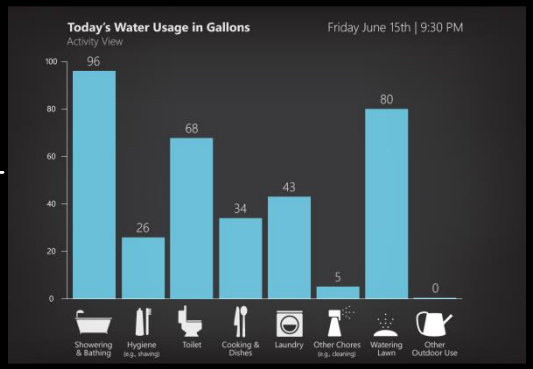
54%

Individual Fixture View



27%

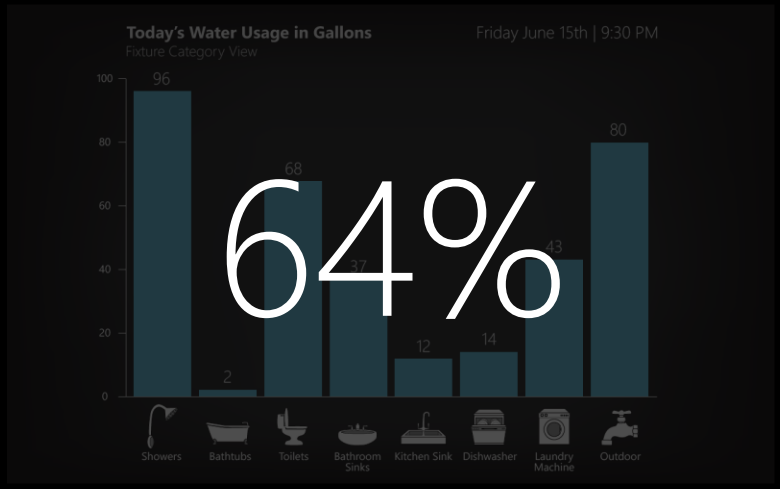
Fixture Category View



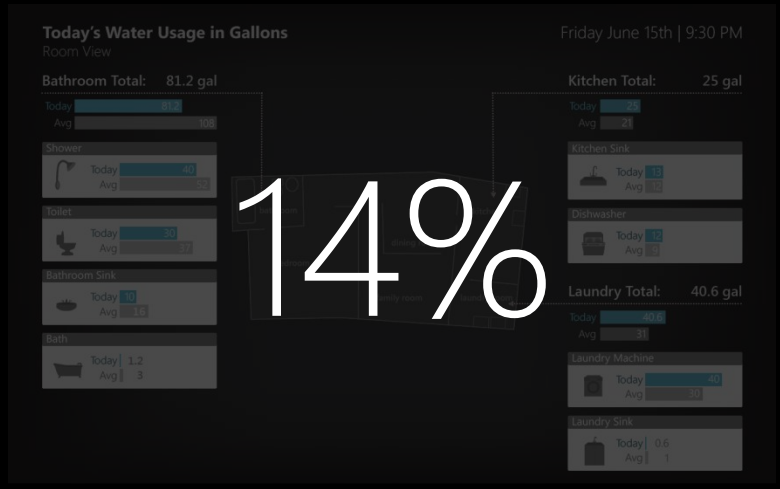
19%

Activity View

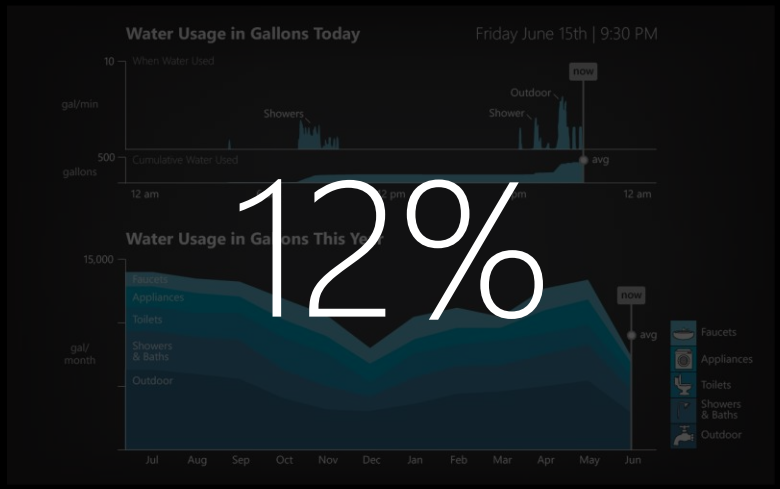
spatial preference



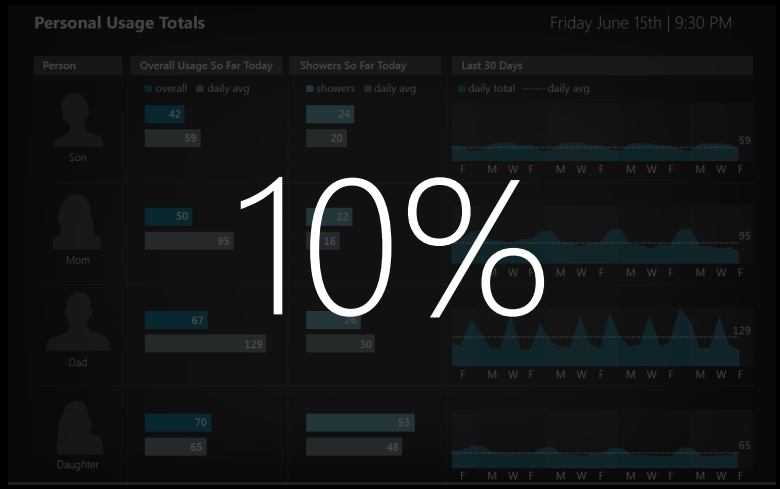
64%



14%



12%



10%

spatial preference

"The breakdown between rooms and appliances is clear and gives an intuitive sense of where water is being used"

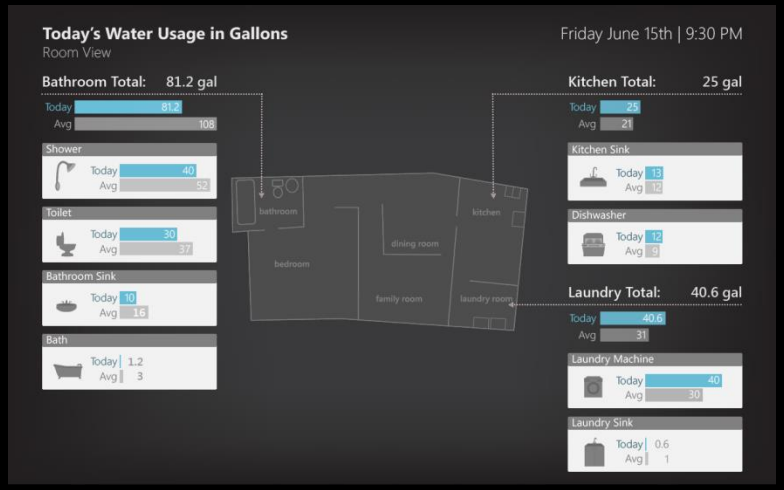
-R182

"Not sure why I'd want a map of my house here"

-R125

"We know the house layout... we don't need to see it"

-R342



privacy concerns

It feels “creepy” (R5) or like “Big Brother” (R826)

“This display comes across more ‘big brotherish’ to me”

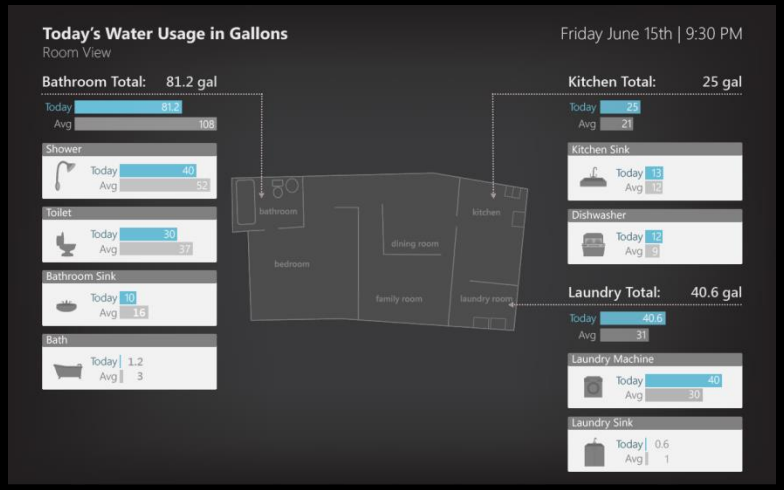
-R84

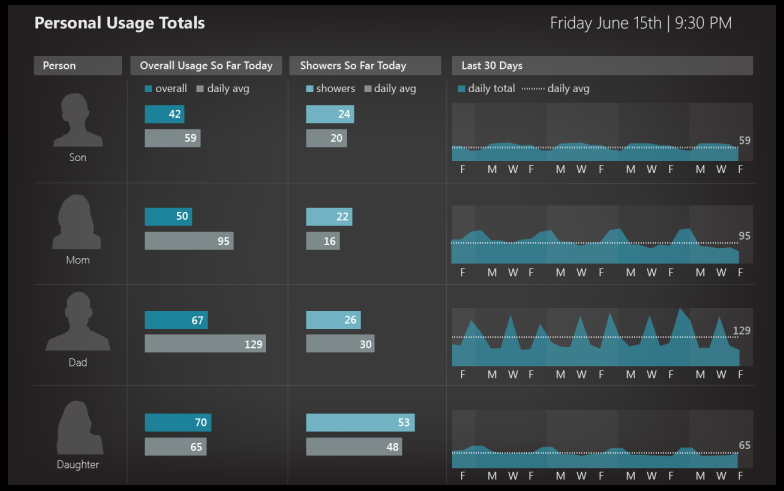
“It's incredibly invasive. And other people's water consumption is not my business”

-R25

“I feel this is an invasion of privacy within my household. I wouldn't want them to know how long I was in the shower or how many trips to the restroom I took.”

-R68



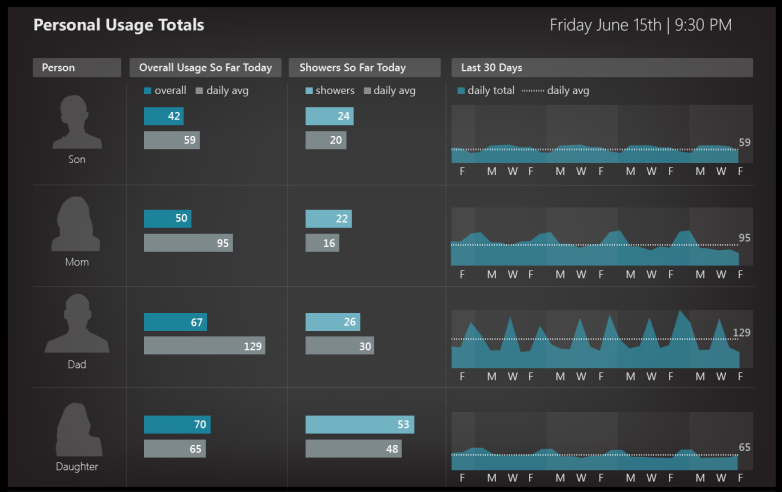


broad interest in comparison

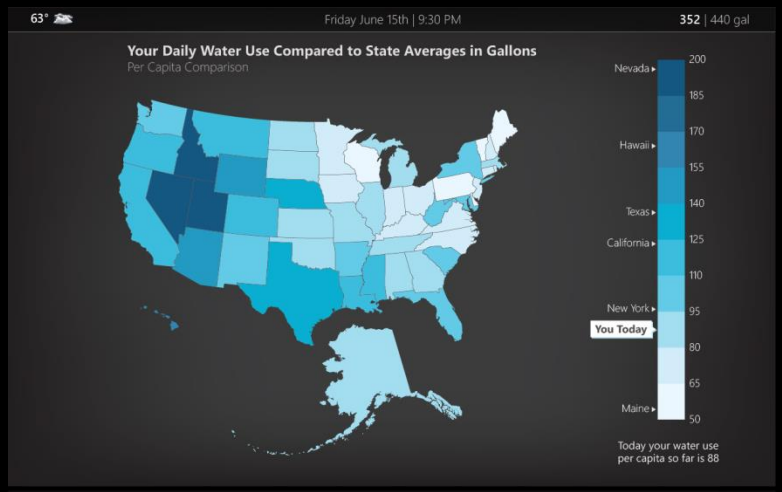
91% : self-comparison
68% : goal-comparison
68% : social-comparison

competition vs. cooperation

Comparing Within Home



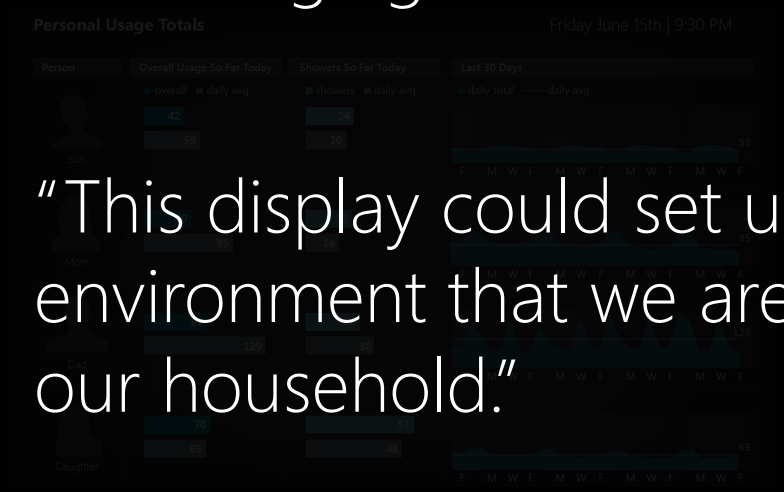
Comparing Outside Home



competition vs. cooperation

"It pits the family members together rather than encouraging collaboration."

-R485



"This display could set up a 'competitive' environment that we are trying not to create in our household."

-R493

"You can compare usage to others, and create friendly competition"

-R220

display location preferences

display location preferences

kitchen

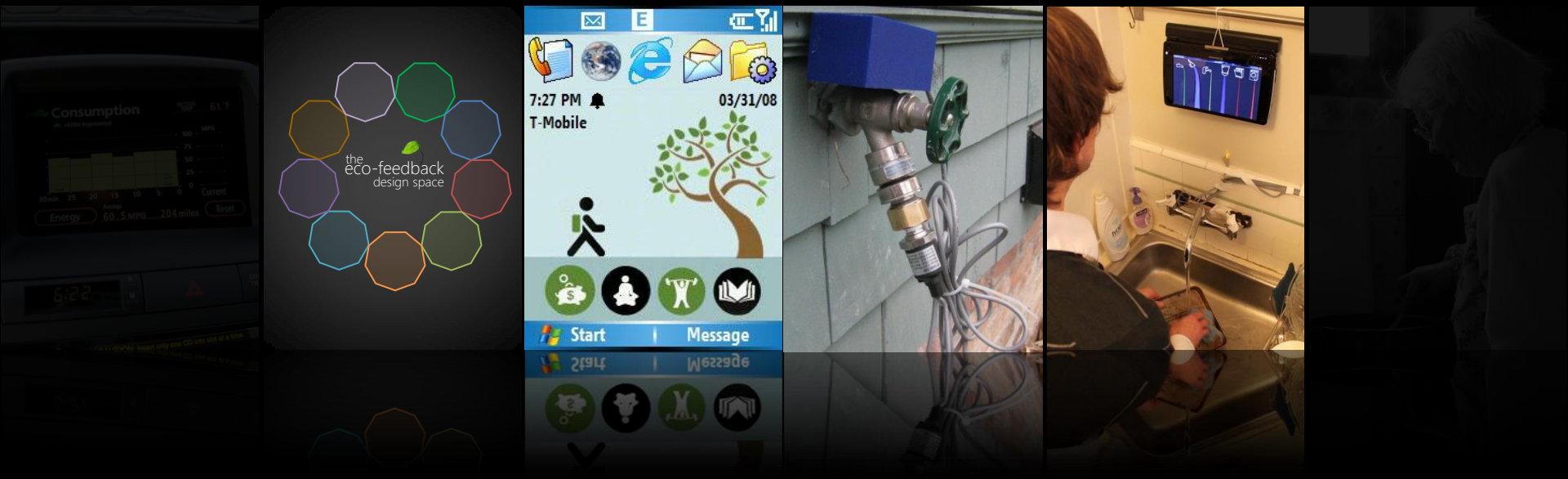
near thermostat

high traffic areas

accessible when needed

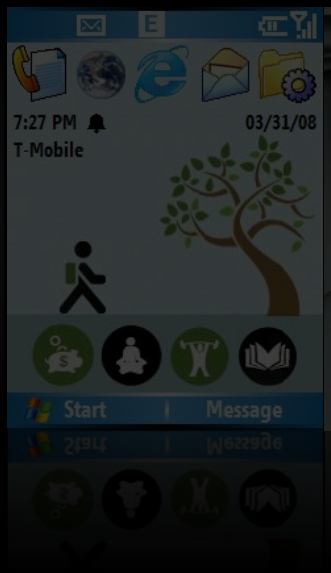
summary of water vis findings

1. Information should be simple, glanceable, easy-to-understand, actionable
2. Comparison is important but may upset family / household dynamics
3. Balance between information transparency and privacy of future eco-feedback displays is likely going to affect adoption
4. Multiple representations of information may be necessary to satisfy different individuals in household


Consumption
Energy
Reset
the
eco-feedback
design space
7:27 PM
03/31/08
T-Mobile
Start
Message


Consumption
61 °F
MPG
100
75
50
25
0
30min 25 20 15 10 5 0
Current
Energy
Average
60.5 MPG
204 miles
Reset
6:22


the
eco-feedback
design space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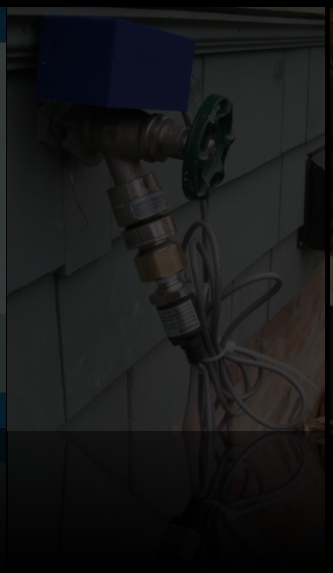
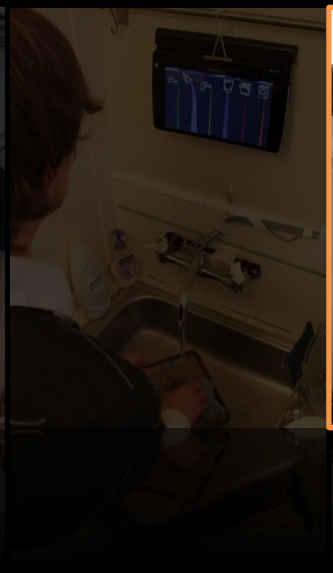
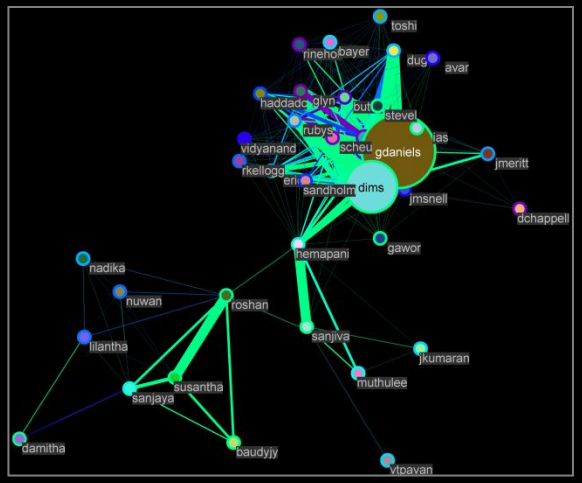
Message

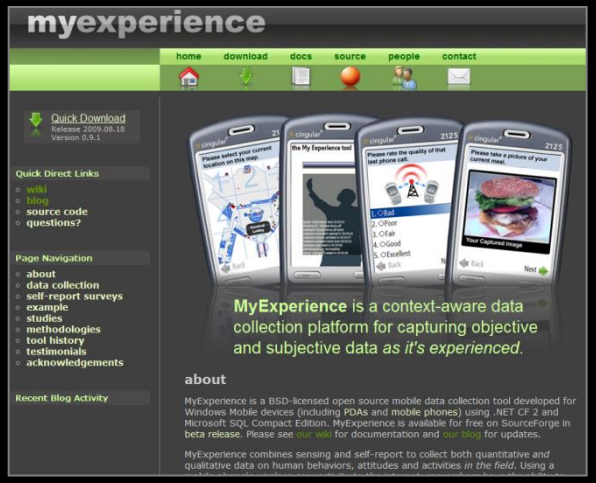






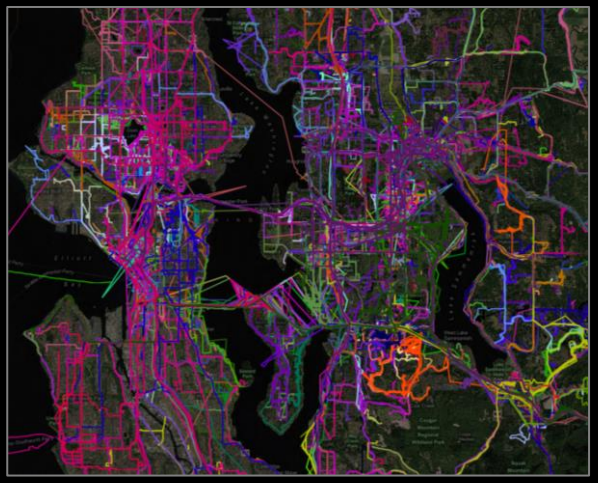
visualization and analysis tools of open source software teams

[ICSE2004; GROUP2005]



mobile tools to support field studies human behavior

[MobiSys2007]

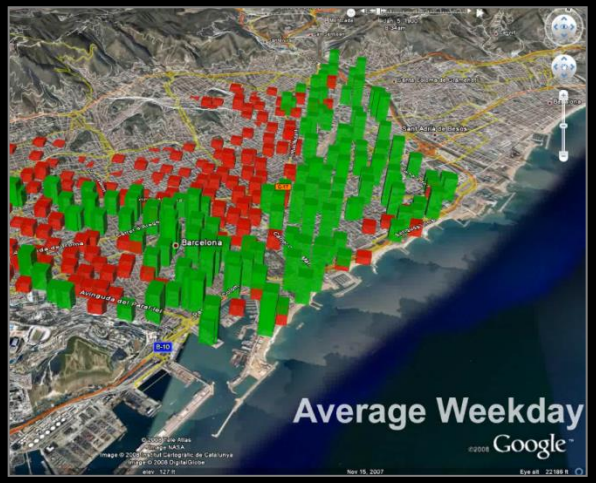


analyzing and predicting individual travel patterns

[UbiComp2006; SAE2008]

mobile device (touch screen) accessibility for impaired users

[ASSETS2007; TACCESS2011]



urban informatics – sensing, analyzing & visualizing cities

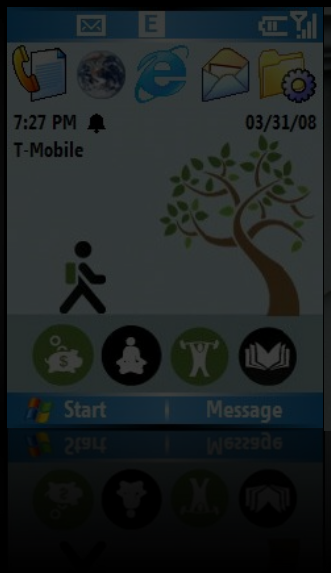
[UrbanSense2008; IJCAI2008; ICDM2011]

sensing and feedback of health and wellness behaviors

[CHI2008; UbiComp2008]


Consumption
61 °F
MPG
100
75
50
25
0
30min 25 20 15 10 5 0
Current
Energy
Average
60.5 MPG
204 miles
Reset
6:22


the
eco-feedback
design space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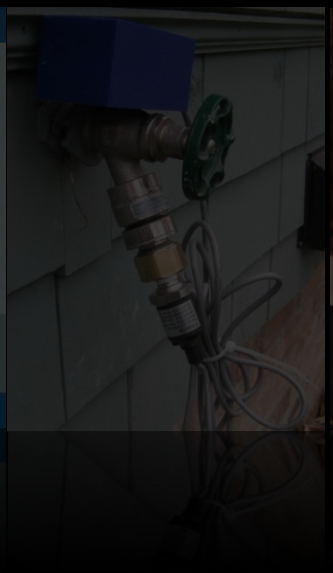
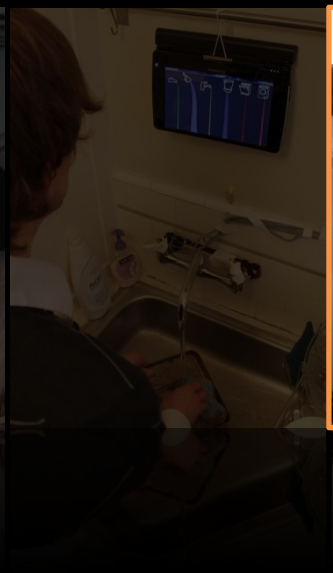
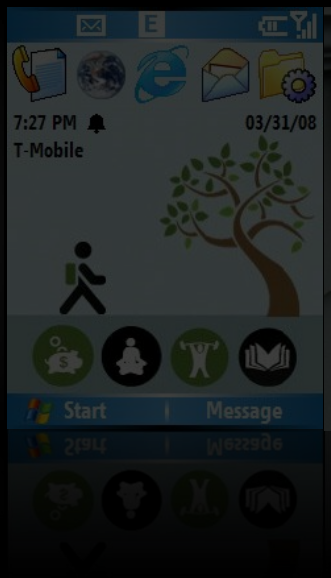
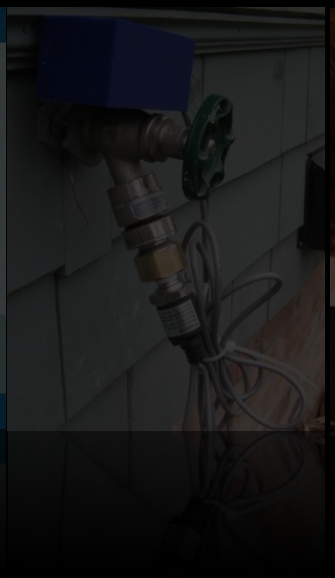
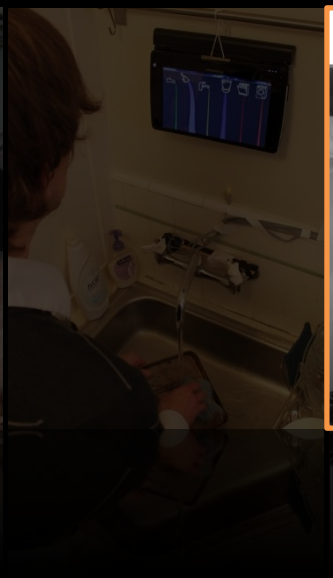






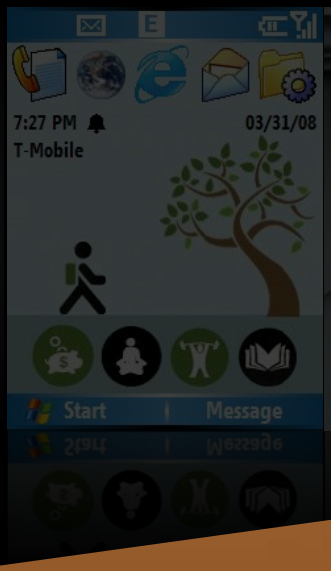


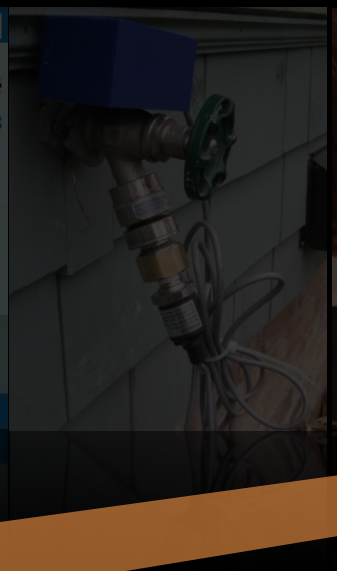


eco-feedback

urban informatics

new hydrosense applications





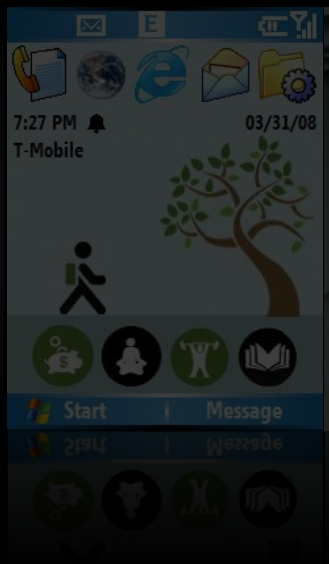
eco-feedback

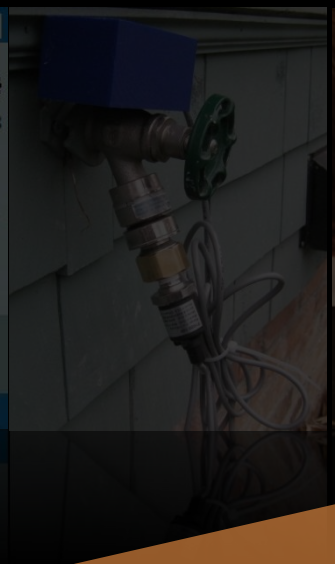
urban informatics

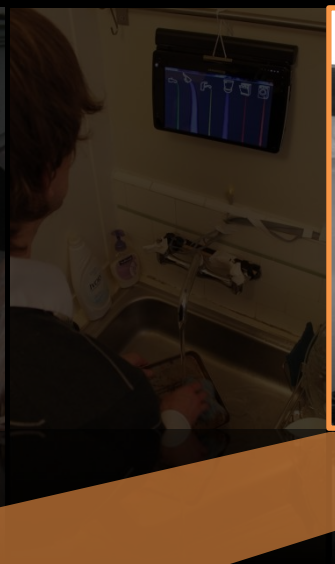
new hydrosense applications

eco-feedback future work

1. exploring lightweight field deployment study designs
2. longitudinal behavioral intervention study of water visualizations
3. applications of eco-feedback to health behaviors



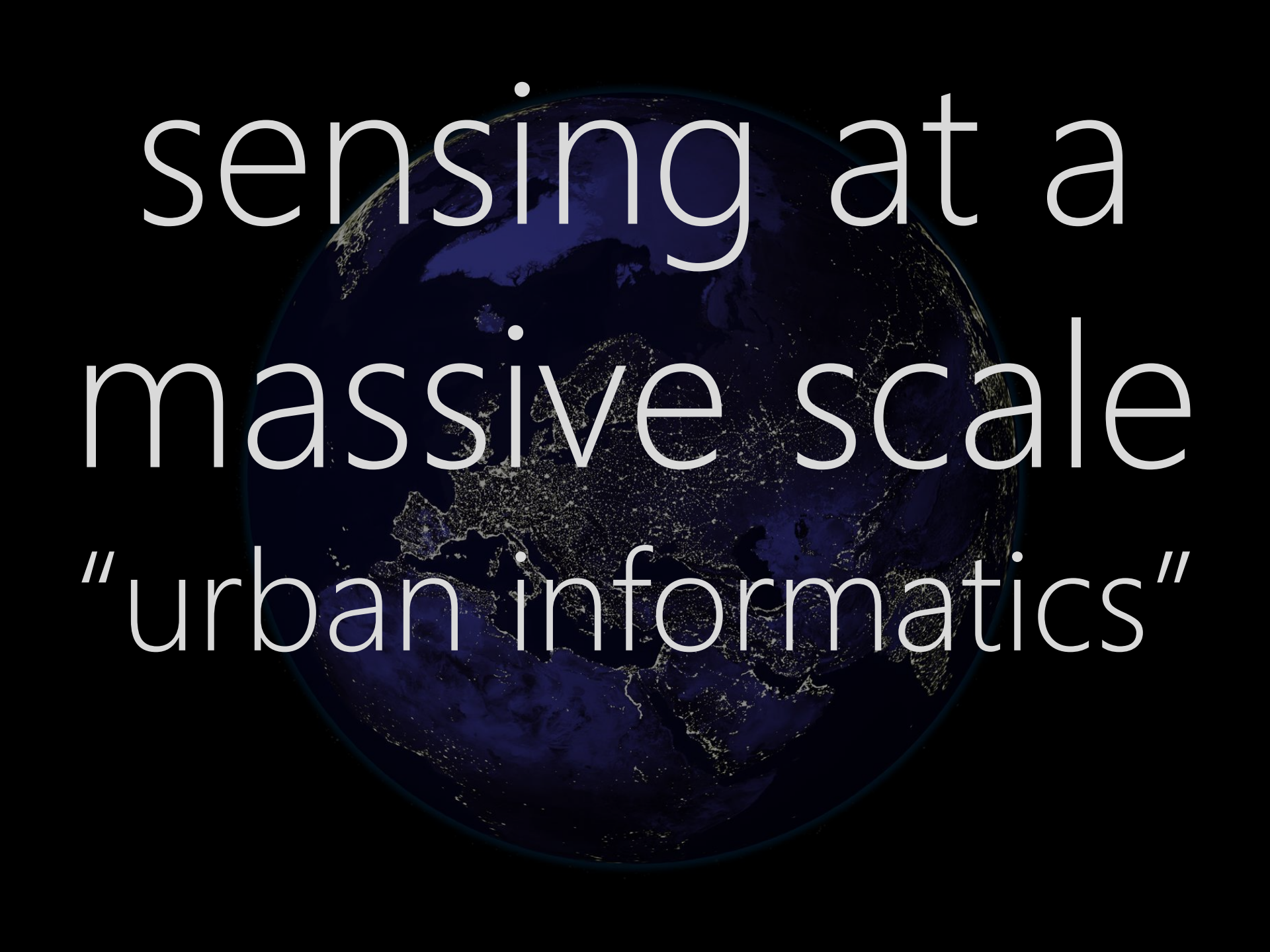




eco-feedback

urban informatics

new hydrosense applications


sensing at a
massive scale
“urban informatics”

sensing and predicting the movement of a city via shared bicycling

[Froehlich et al., UrbanSense2008; IJCAI2009]

bicing

barcelona, spain

Summer 2008:
- 373 stations
- 6,000 bicycles
- 150,000 subscribers


bicing
105
estacions
bicing
2178

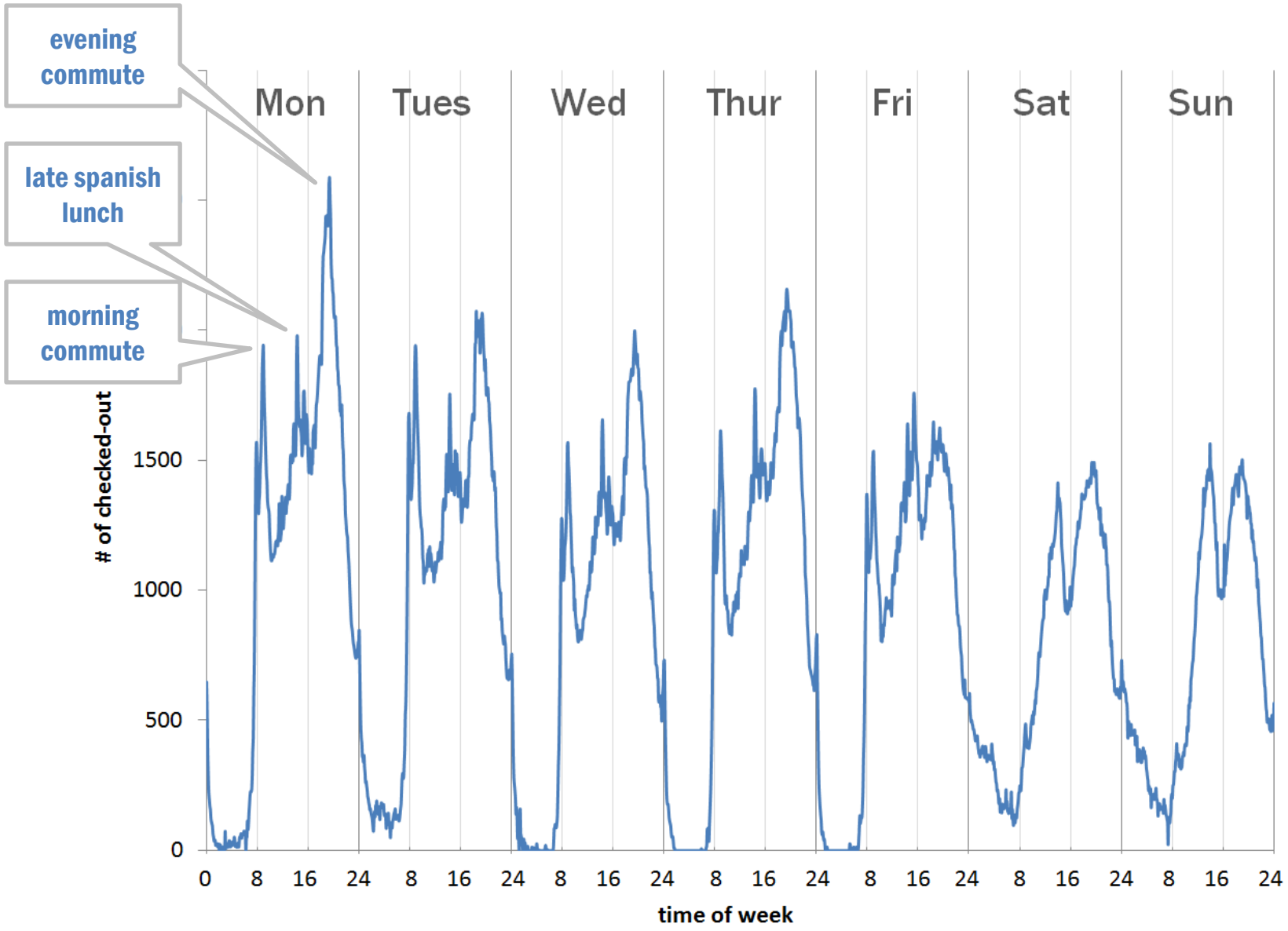

bicing
217
estacions
bicing


10
bicing
Assegura't de tornar la bicicleta correctament!
10

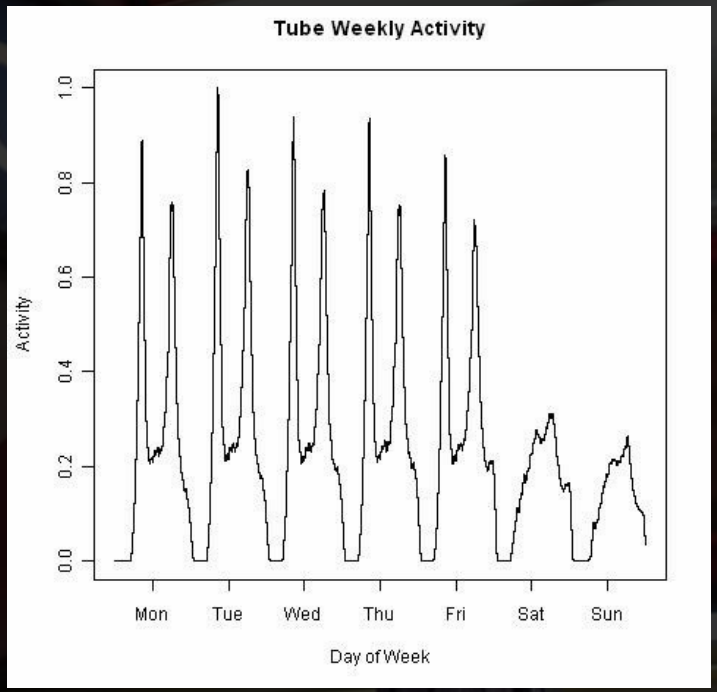

4
4


Jul 16, 2009
3:59am
2724 m
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image © 2009 Institut Cartogràfic de Catalunya
Image © 2009 TerraMetrics
©2008 Google

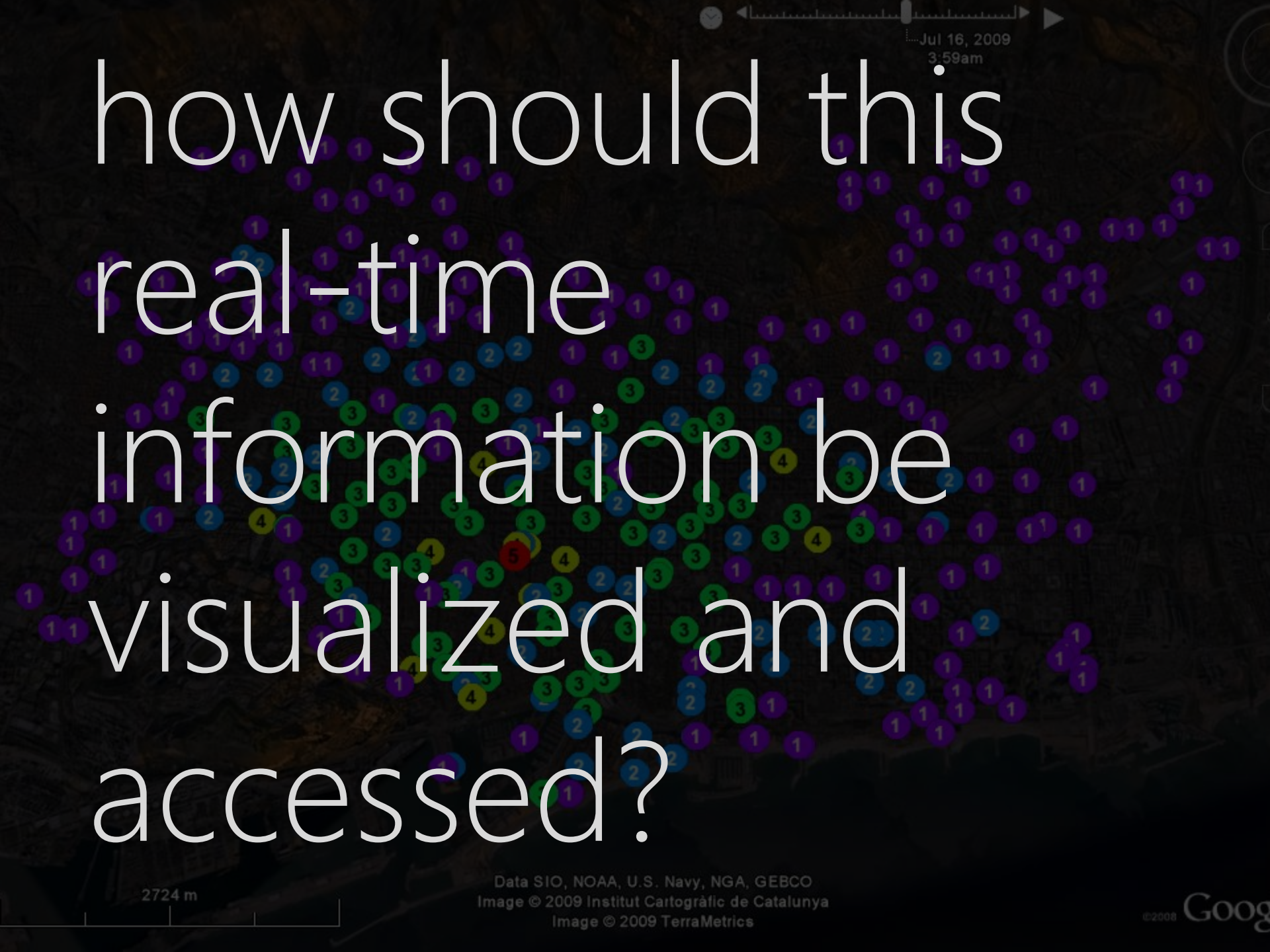
num checked-out bicycles across all stations



what can we learn if we combine data from other sources?

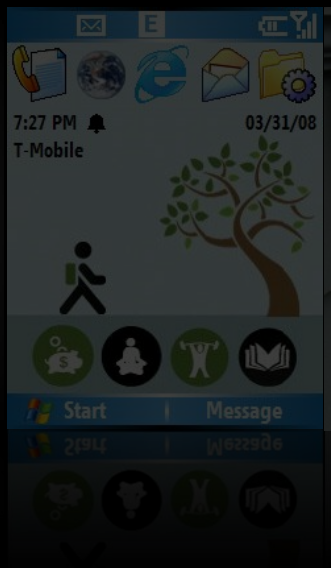


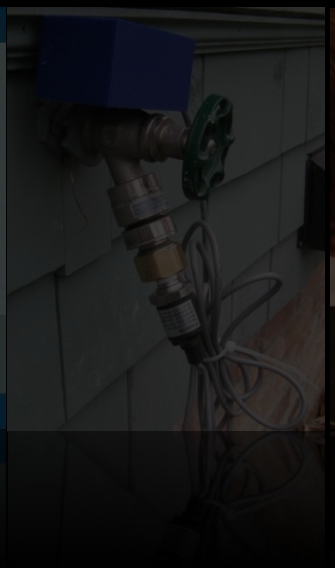
[Lathia, Froehlich & Capra, ICDM2010]

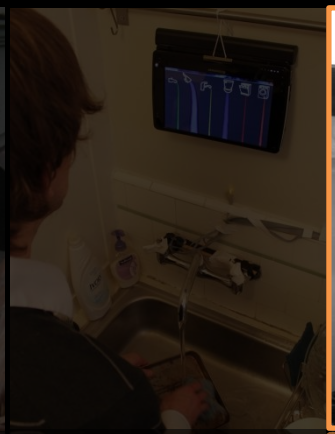


how should this real-time information be visualized and accessed?

can we use this data to automatically detect events in the city?







eco-feedback

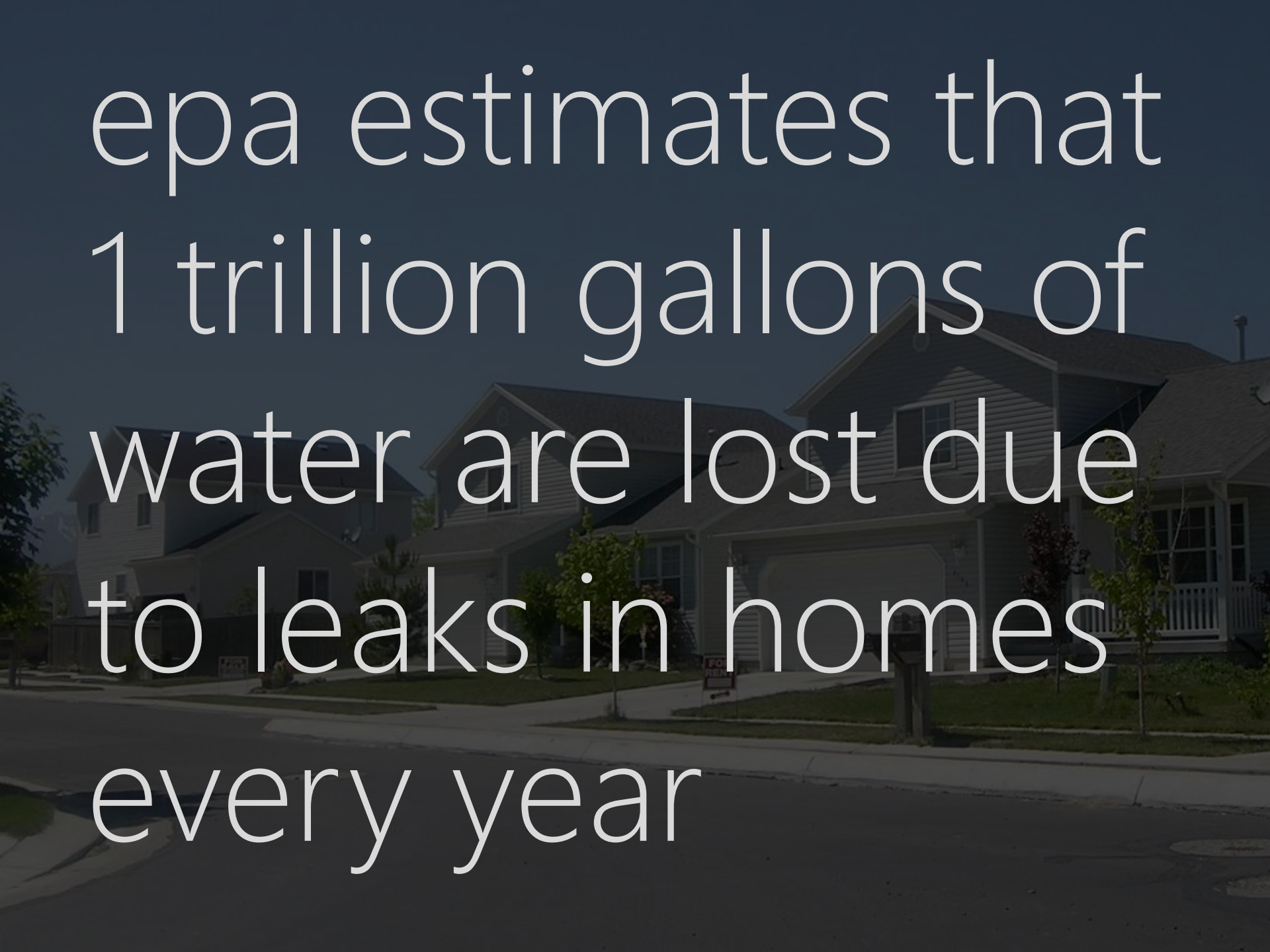
urban informatics

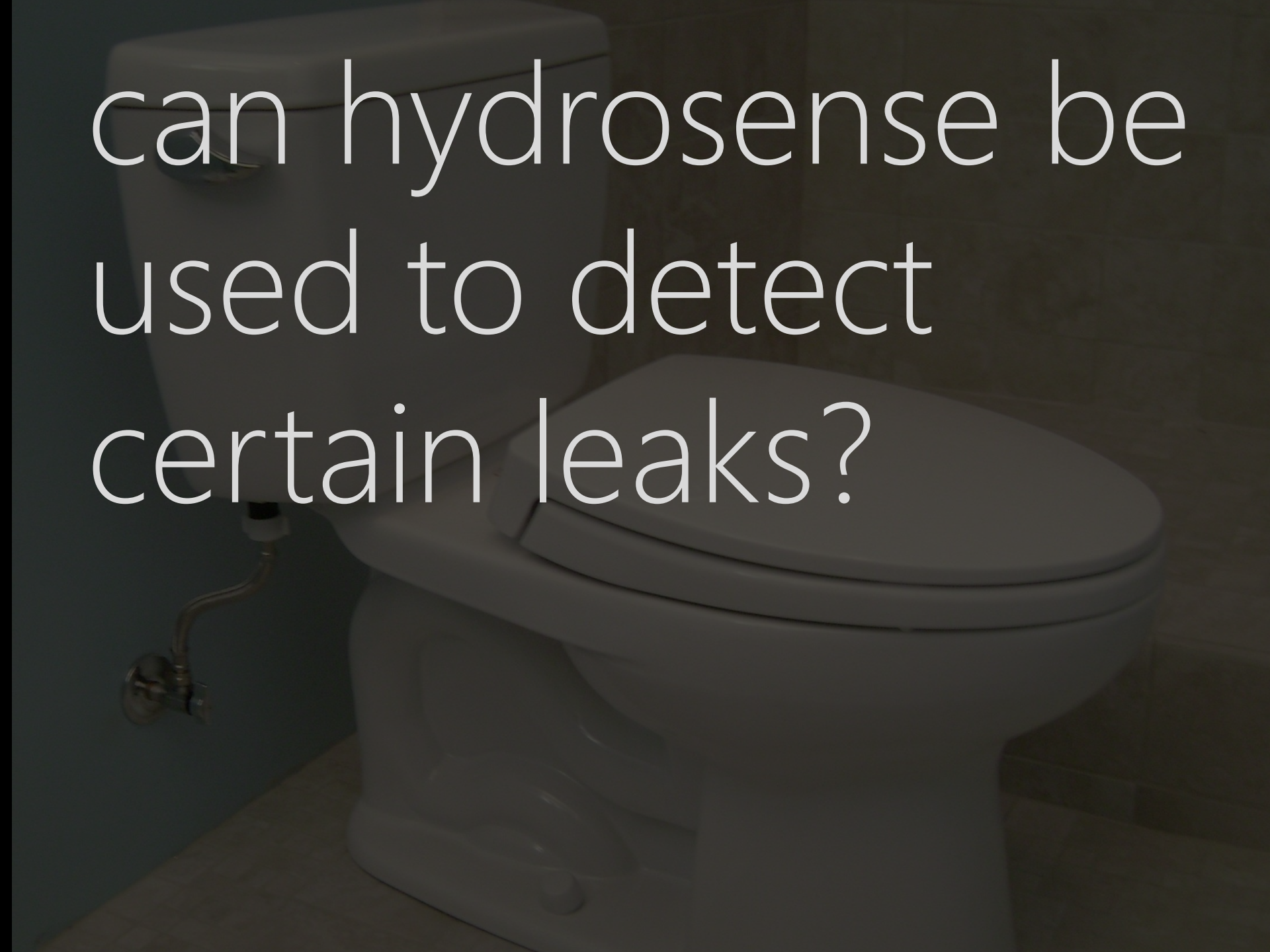
new hydrosense applications

63° | Friday June 15th | 9:30 PM | **30,222** | 28,970 gal

Today's Water Usage in Gallons

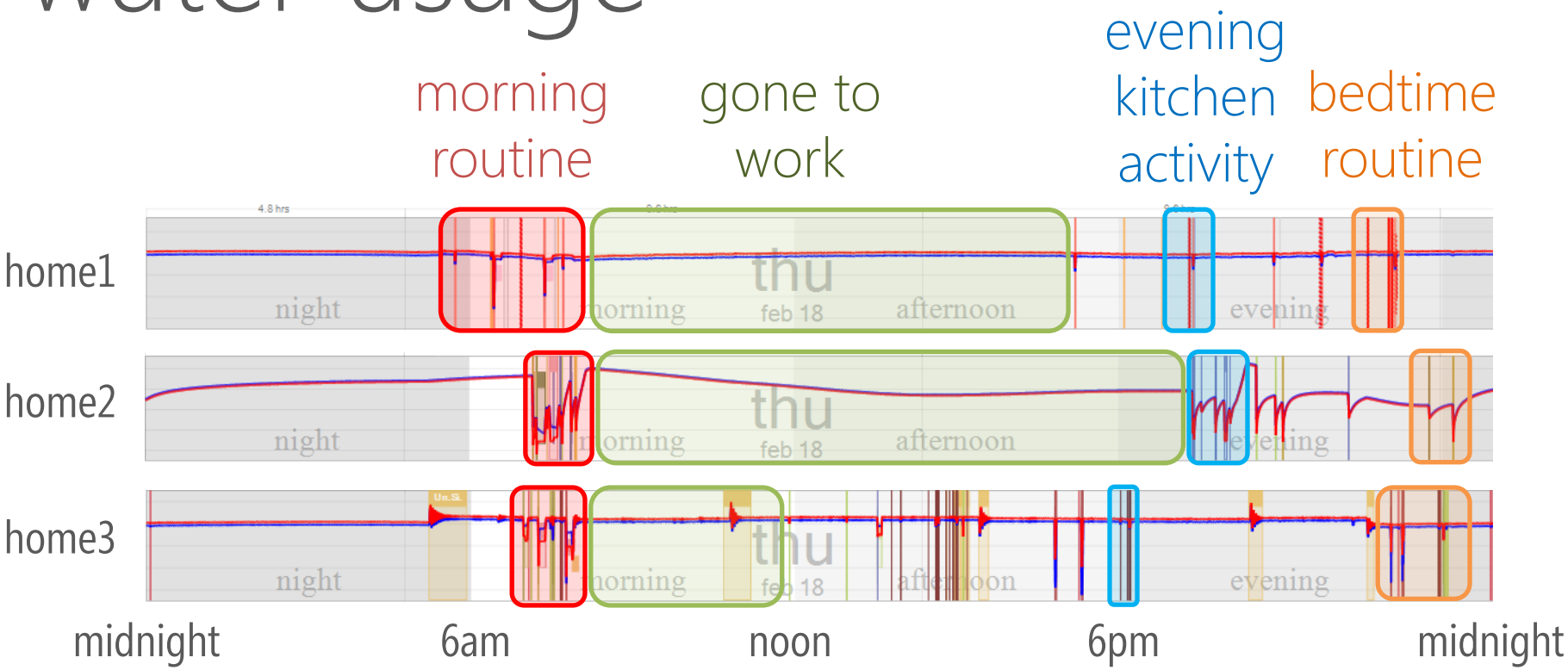
Individual Fixture View


epa estimates that
1 trillion gallons of
water are lost due
to leaks in homes
every year


can hydrosense be used to detect certain leaks?


hydrosense algorithms
1. minimal training set
2. cross-home training
3. unsupervised learning

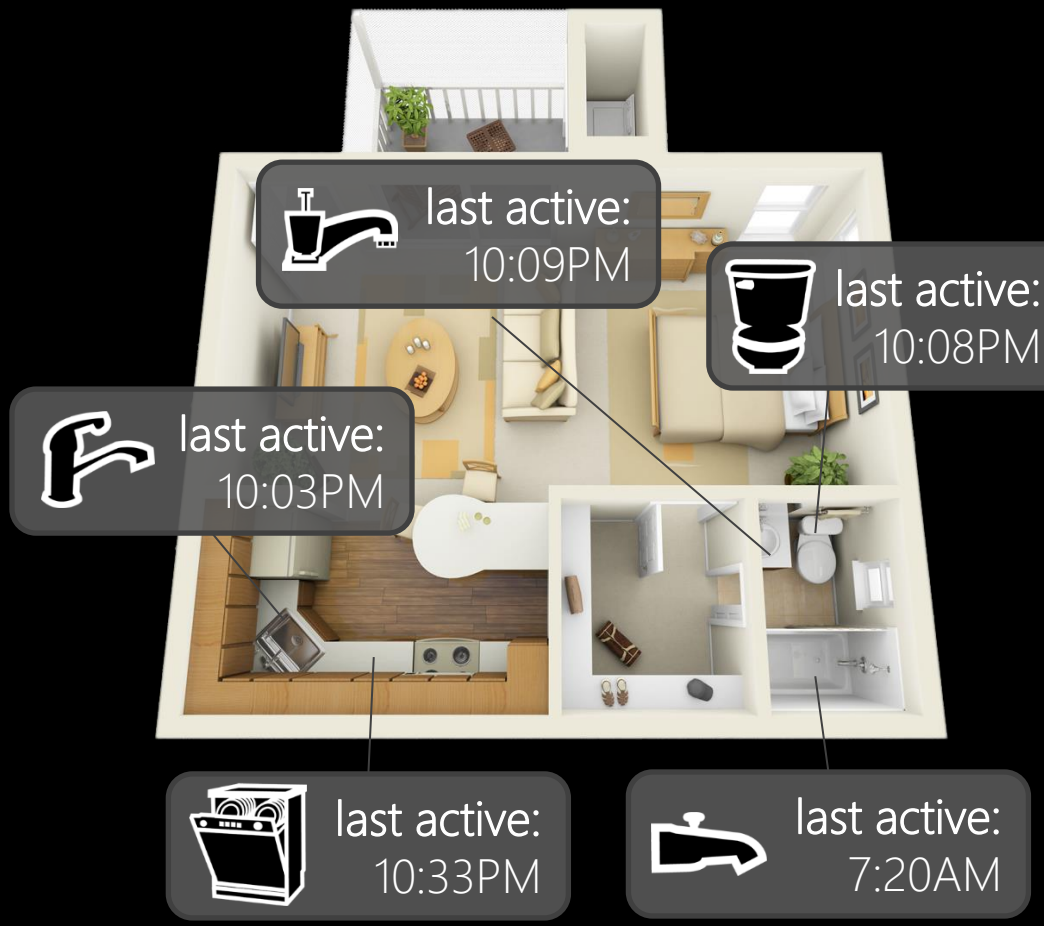
behavioral patterns of water usage



how predictable are home water usage patterns?


how can
hydrosense be
used to support
aging in place
applications?

assisted living applications




you
sensing
feedback

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external collaborators

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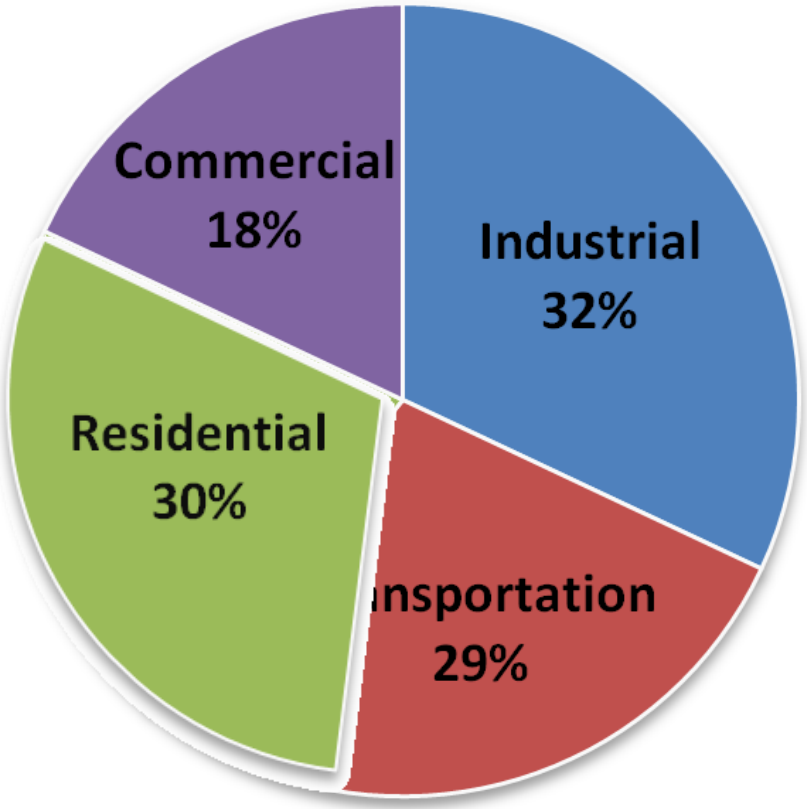
Nuria Oliver, Telefonica Research
Joachim Neumann, Telefonica Research
Sunny Consolvo, Intel Labs
Beverly Harrison, Intel Labs
Carrie Armel, Stanford University

thank you!

@jonfroehlich

US Energy Consumption by Sector



US Public Water Use by Sector