Activity Profiles of Independent Older Adults in Smart Homes

Proposal Defense

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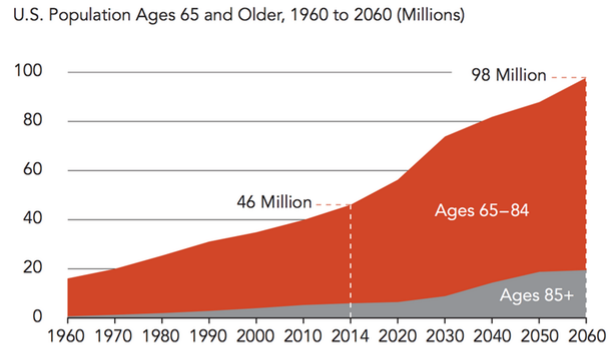
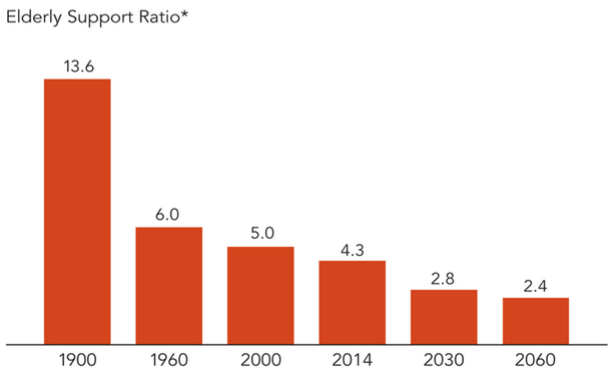
Introduction

Aging Population Demographics

- Baby boomers born 1946—1964 are driving significant demographic trends
- Number of Americans 65+ to **double** from 46M (2014) to 98M (2060)
- More older adults are divorced
- More older adults live alone
- 2/3 have multiple chronic conditions
- Increase in elder care needs, in nursing homes and for home health and informal caregivers
- Decrease in available traditional family care givers



Source: PRB analysis of data from the U.S. Census Bureau.



*Number of persons ages 18 to 64 for every person age 65 or older.

Source: PRB analysis of data from the U.S. Census Bureau.

Mather et al. (2015). Aging in the United States. pbr.org

Aging in Place

The ability to live in a residence of their choice without moving as needs for health care services change.[1]

- Older adults prefer to retain their indepencence and remain in community based settings
- Half of older adults require help[2]
  - 75% of those receiving help live in houses or apartments
  - 70% receive informal help
  - 95% of informal care outside of nursing homes is from family members
- Number of 75+ without...
  - a *spouse* to double from 2010 to 2030 to 1.8M
  - an *adult child* within 10 miles to increase by factor of **six**[3]

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1. Marek & Rantz (2000). pmid:10986927
2. Scommegna (2016). Today's Research on Aging: Family Caregiving
3. Ryan et al. (2012). doi:10.1093/geront/gnr142

Technology and Aging

Simple unobtrusive sensors and computing systems

Monitor older adults to support aging in place and bring piece of mind to caregivers

Acceptance by older adults and their families:

- 8 of 10 say using these devices would help them feel safer
- 46% would be interested in a system that monitors daily routine
- But only 1 of 10 currently use personal health technology devices[1]

1. Barrett (2011). Healthy@ Home 2.0 https://assets.aarp.org/rgcenter/health/healthy-home-11.pdf

Technology in the Home

IoT, Home Security, and Home Automation

Smart devices for the home:

- Google Home
- Amazon Alexa
- Apple HomeKit
- Samsung SmartThings
- Nest, Wink, WeMo, Lutron, Hue

Enable things like:

- Open the shades when you wake up
- Turn off the lights before bed by voice
- Lock the front door when you leave home
- Turn on the A/C when you're headed home

Summary

Driving Challenge

> Provide care for aging adults in face of demographic and cultural shifts

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Driving Challenge

> Provide care for aging adults in face of demographic and cultural shifts

Goals

- Build on cost-effective home monitoring technology
- Connect older adults with health care systems and family
- **Lifestyle reassurance**
  - raise awareness of health status and changes
  - support effective, early intervention

Challenges

Sensors in the home

- Real occupants in unscripted situations performing unknown actions
- Remote sensing in low-visibility locations
- Balance between high density of sensors and cost-efficiency and acceptance

Challenges

Sensors in the home

Reliability issues

- Low-power wireless network — communication issues
- Battery powered sensors
- Human interaction with sensors[1]
- Various devices, device types and manufacturers
- Non-failure related messiness

1. Hnat et al. (2011). doi:10.1145/2070942.2070966.

Challenges

Sensors in the home

Reliability issues

Spatio-temporal interactions

- Inherent heirarchy of sensor data as function of floor plan
- Overlapping regions of detection
- Various degrees of temporal resolution
- Data stored out of context as discrete events

Other Smart Home Projects for Older Adults

- TigerPlace[1]
  - Pioneer of *age-in-place* and AAL
  - 17 apartments in assisted living facility
- CASAS (ORCATECH)[2]
  - Over 400 homes in Portland area
  - Real-world settings with older adults, long-term
  - Limited number of sensors
- PlaceLab[3]
  - Live-in apartment-scale laboratory
  - MIT - Cambridge, MA
  - 100s of sensors

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1. Skubic et al. (2009). doi:10.3233/THC-2009-0551
2. Cook et al. (2013). doi:10.1109/MC.2012.328
3. Intilleet al. (2005)

Proposal

Context

Maximize acceptance and cost efficiency, minimize reliability issues

- Simple set of low-cost sensors
- Prefer most reliable sensors
- Sparsely installed within the home of older adults

Proposal

Context

Research Questions

Can we make meaningful and timely observations of older adult's activities

- without needing labels
- without knowing floor plan or layout
- without an annotated training set
- and that works "out of the box"?

to create/enable

- Activity profiles
- Detection of changes in routine
- Early warning notification systems

Proposal

Context

Research Questions

Outline

1. *Health BOOST in The Villages*
2. Our sensor system
3. Software layers
4. Activity Profiles
5. Dissertation Proposal

Health BOOST

Sensor Based Response Oriented Technology for In-Home Monitoring of Senior Health and Well-Being

Health BOOST in The Villages

Better **O**utcomes for **O**lder Adults Using **S**ensor **T**echnology

Overview

- Interdisciplinary effort involving faculty and students from College of Engineering and Public Health at USF
- Explore the use of passive wireless sensor technology in the homes of older adults
- Test a comprehensive system of sensors in real-world settings

Participants

- 55+ resident of The Villages
- Living alone in pet-free home with internet access
- Do not exhibit signs of cognitive impairment

The Villages, FL

- The largest retirement community in the US: 115,000+ residents
- 30 minutes south of Ocala, 75 miles north of USF Tampa Campus
- ~50k homes, 80% occupied by at least one person 55+
- Average age of a Villager is 62 (male) and 60 (female)
- 32 square miles, 3 town squares, 10 commercial areas, 63 rec centers
- A Villager could play 30 straight days of golf, 18 holes/day

Overview of Study Participation

- 14 total participants (7 ongoing) with 5,230 total days of observation
- 12 have completed at least 6 months, 1 exited prior, 1 recently joined

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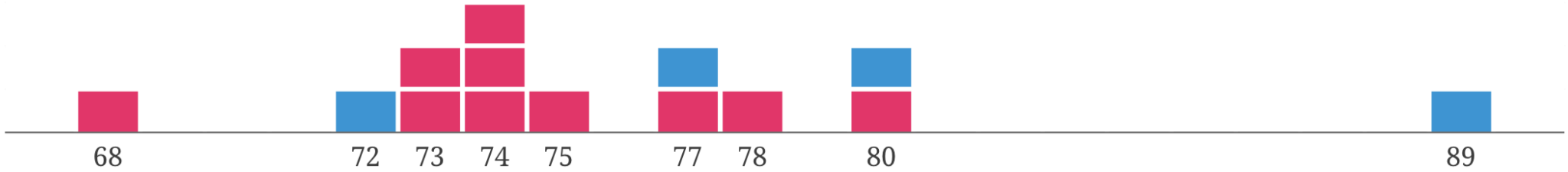

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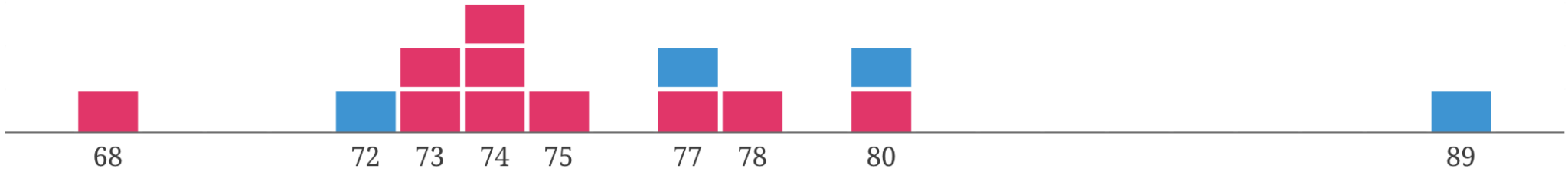
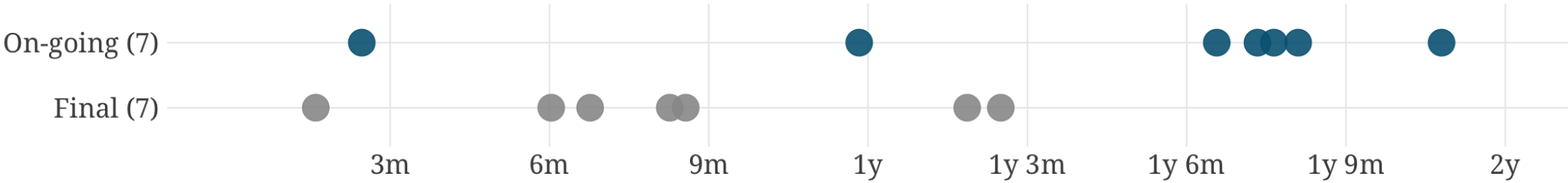
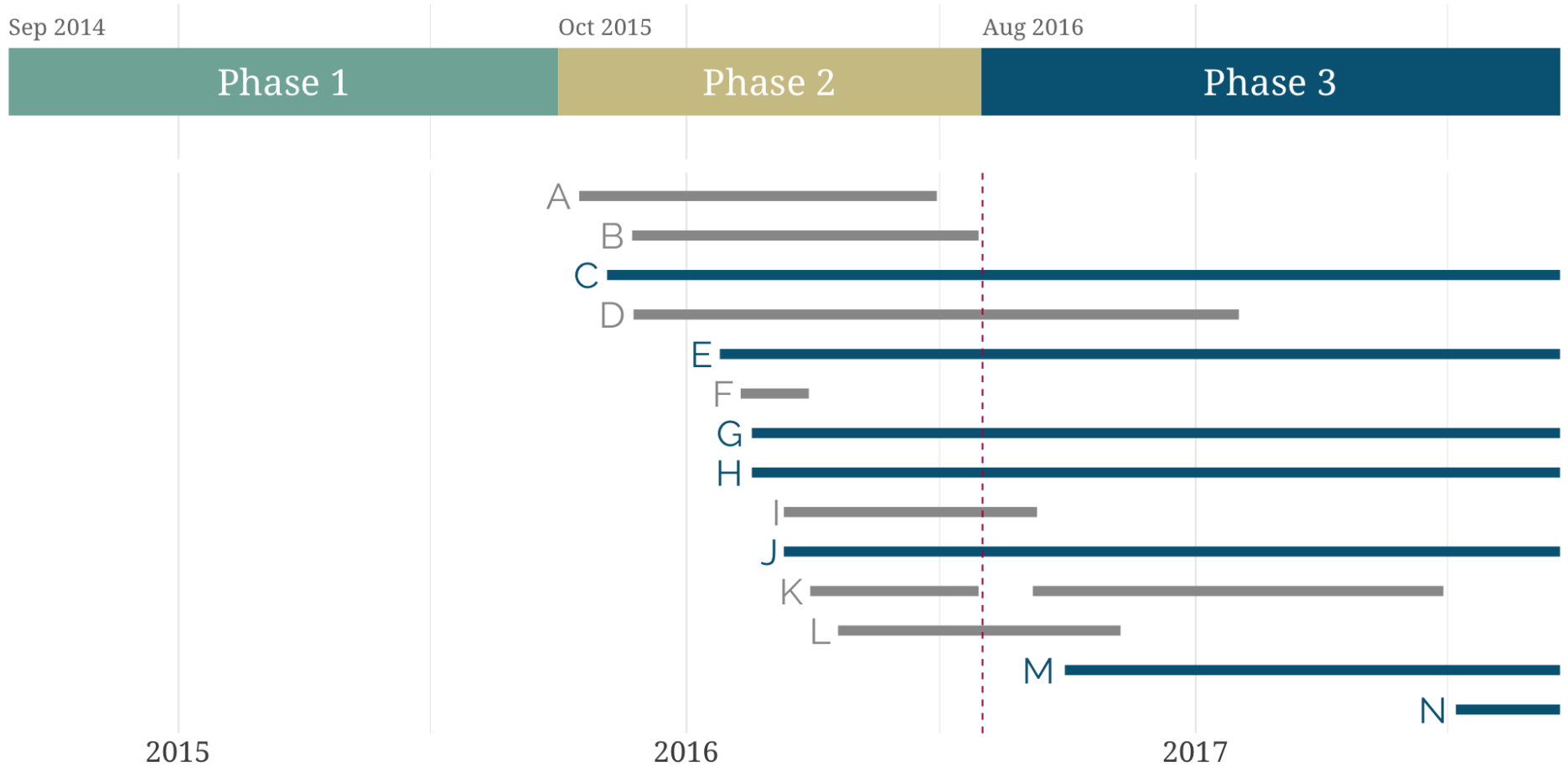


- Days of participation in study



Timeline


Sep 2014
Oct 2015
Aug 2016
Phase 1
Phase 2
Phase 3
A
B
C
D
E
F
G
H
I
J
K
L
M
N
2015
2016
2017

Our system

Sensors

Motion



Sensors

Motion

Contact

Sensors

Motion

Contact

Power

Sensors

Motion

Contact

Power

Water

Sensors

Motion

Contact

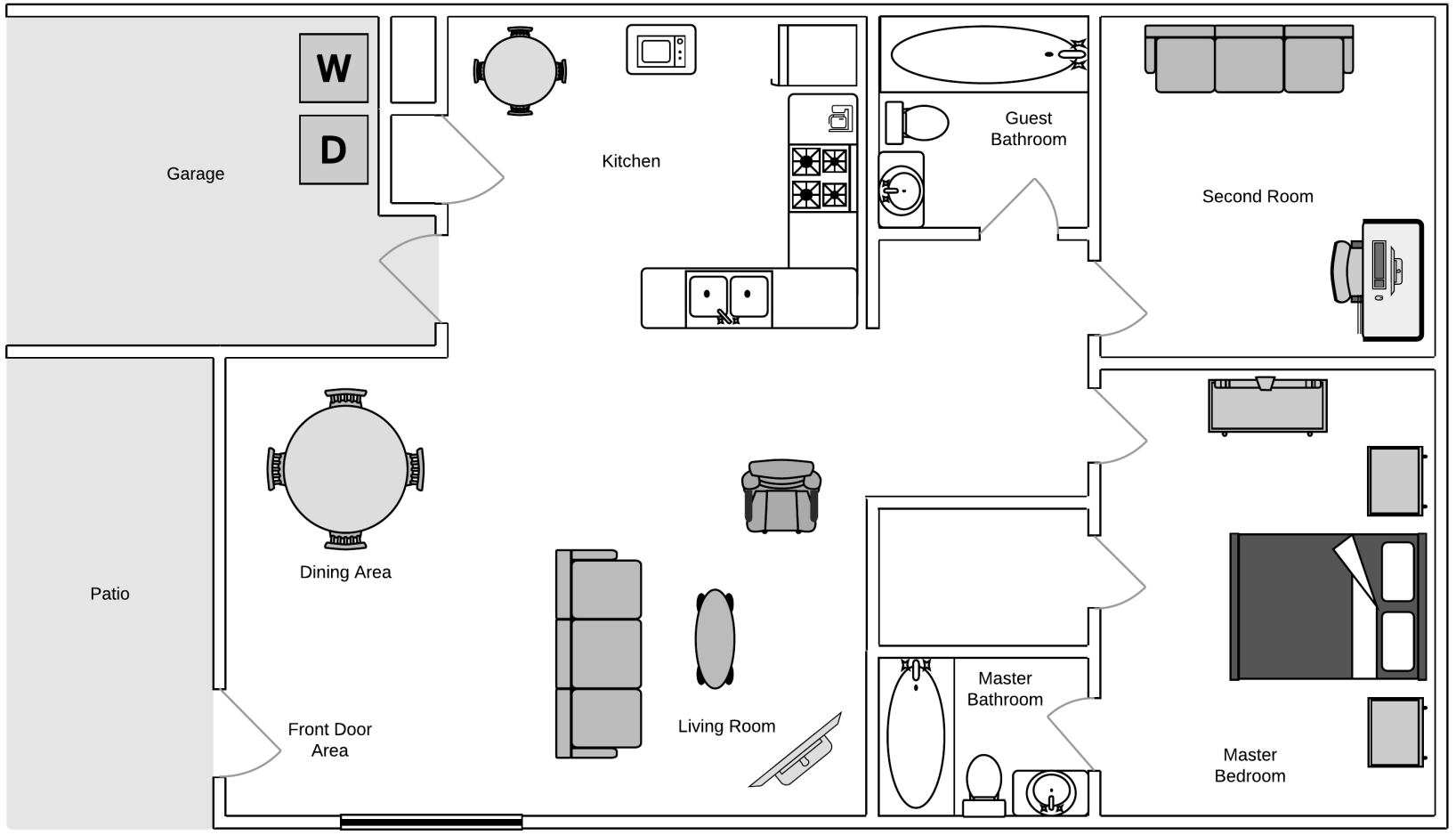
Power

Water

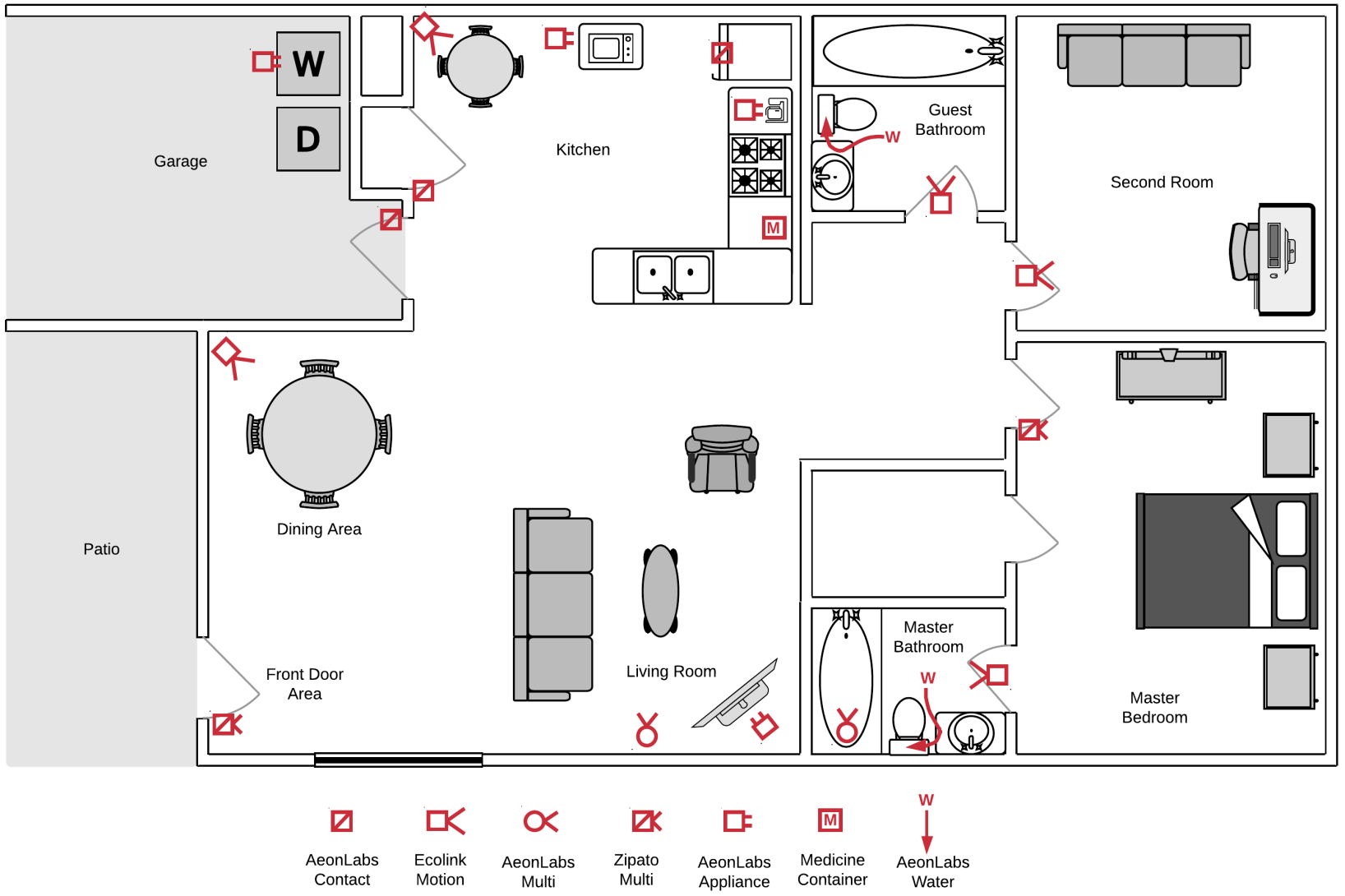
System

Bed/Seat Mats

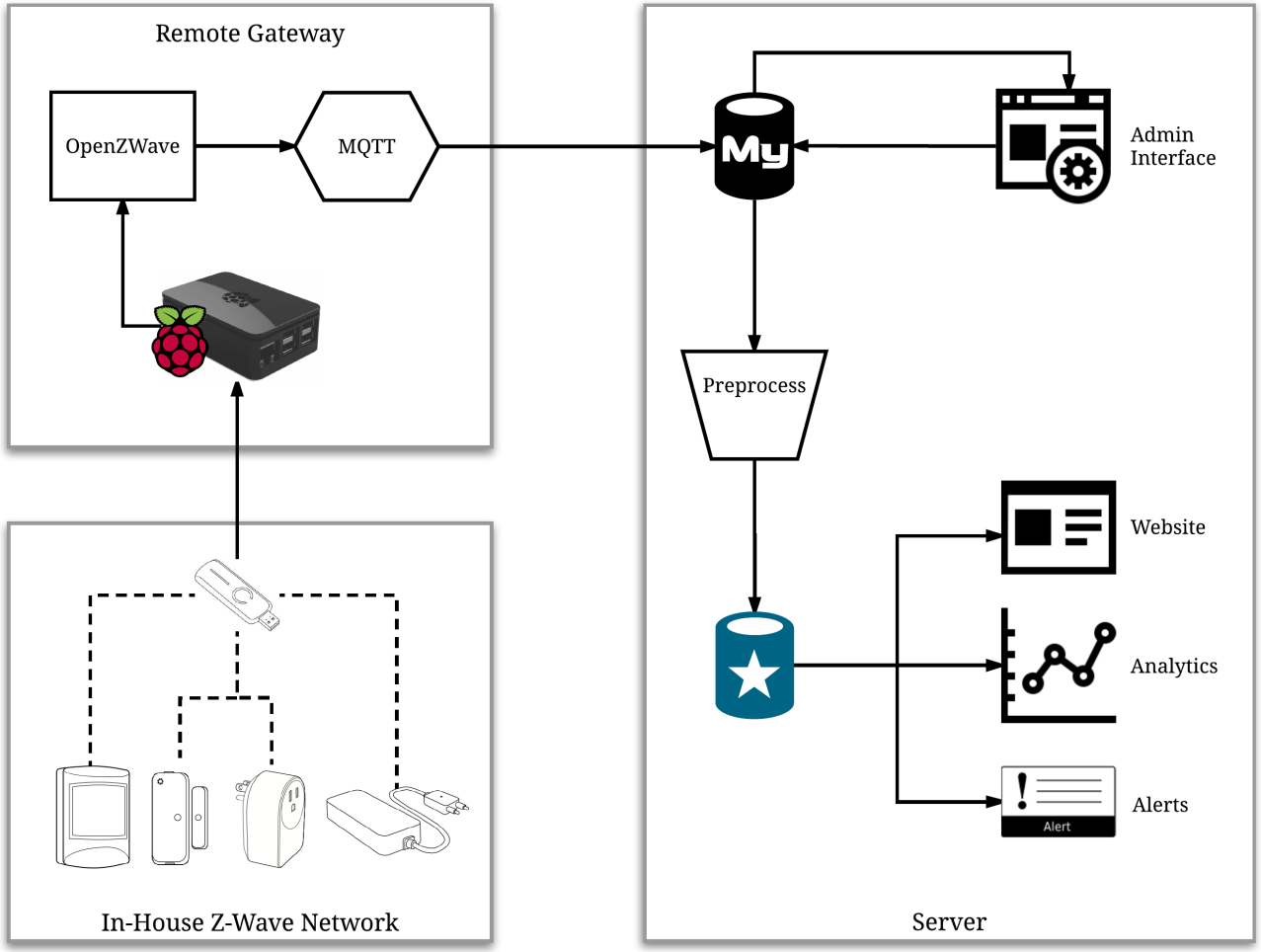
Home Layout


W
D
Garage
Kitchen
Guest
Bathroom
Second Room
Patio
Dining Area
Front Door
Area
Living Room
Master
Bathroom
Master
Bedroom

Home Layout


W
D
Garage
Kitchen
M
Guest
Bathroom
W
Second Room
Patio
Dining Area
Front Door
Area
Living Room
Master
Bathroom
W
Master
Bedroom
AeonLabs
Contact
Ecolink
Motion
AeonLabs
Multi
Zipato
Multi
AeonLabs
Appliance
M
Medicine
Container
W
AeonLabs
Water

System architecture



Software layers

Data Collection

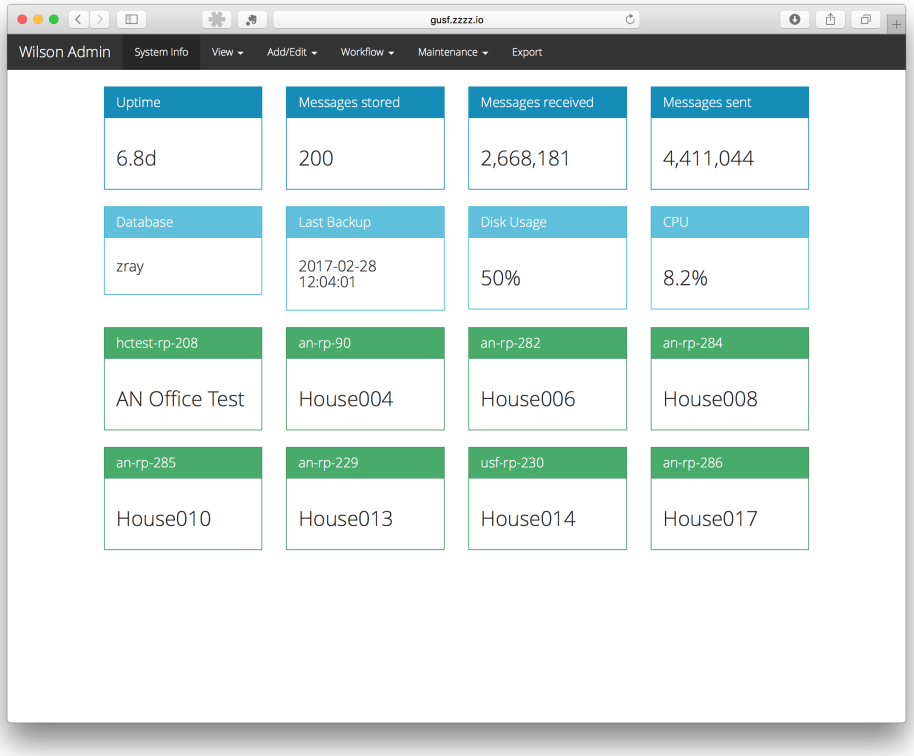
- `zrayd` — An OpenZWave client in C++, collects sensor data
- **`zmonitor`** — Monitor daemons, services, system state, OTA updates
- `mqtt` — Lightweight message passing service for real-time transfer of sensor events
- **`zcollector`** — Python script on server processes messages and associates with physical sensors
- **`zproc`** — Micro-batch preprocessing of sensor data (R scripts)
- **`notiproc`** — Framework and daemon for near real-time alert processing (R scripts)

Databases

- **`zray`** — Raw data warehouse, **53 million** sensor events from 5,516 sensor streams
- **`zproc`** — Preprocessed data, batch updated and recomputed on config changes, reduced to **6 - 17M** events

Admin Interface (System configuration)

- Inventory Management
- Installation Preparation
- System Configuration
- Planning and Review
- Maintenance Visits
- Data Export



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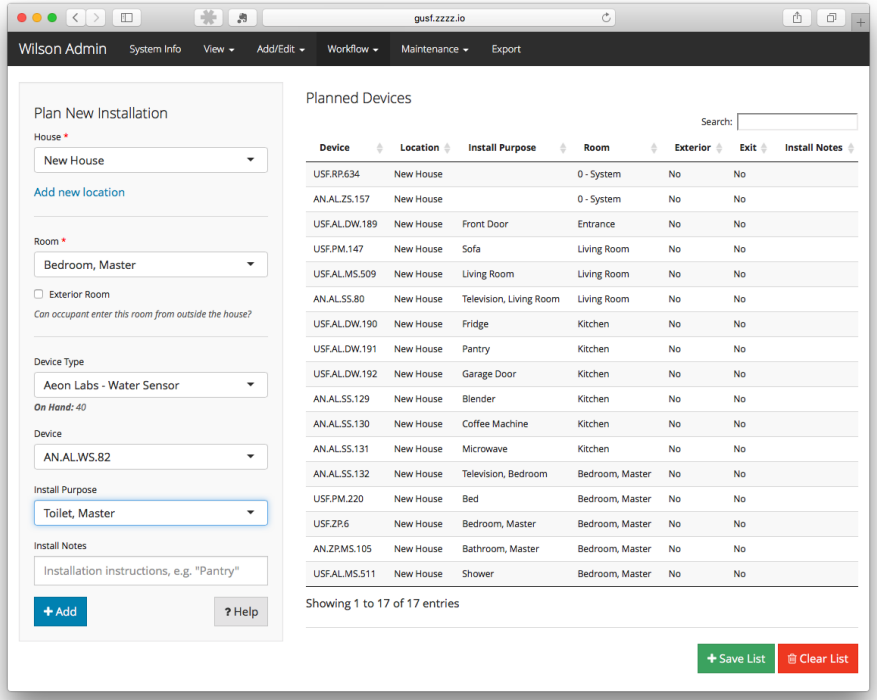

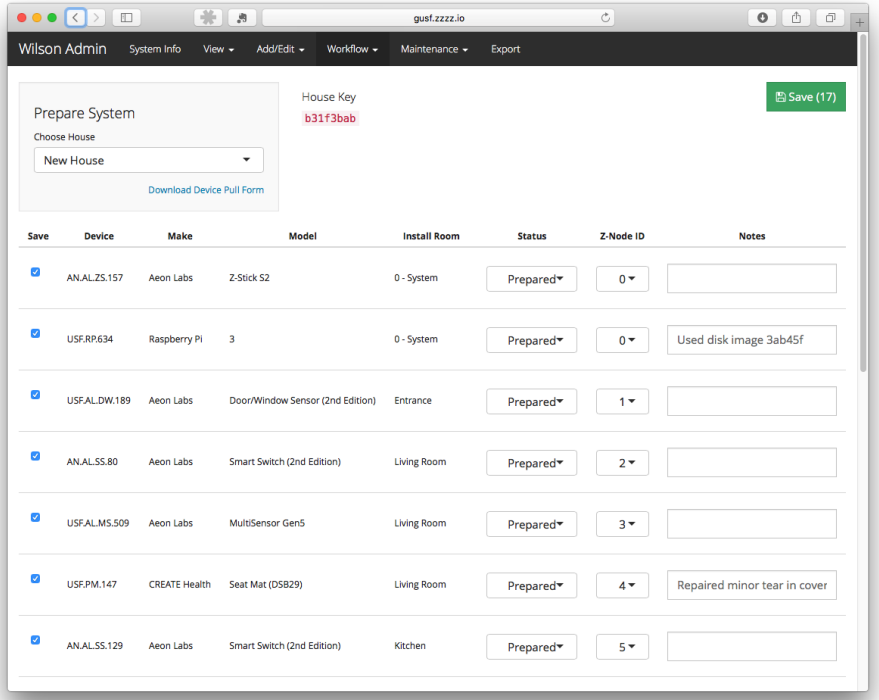

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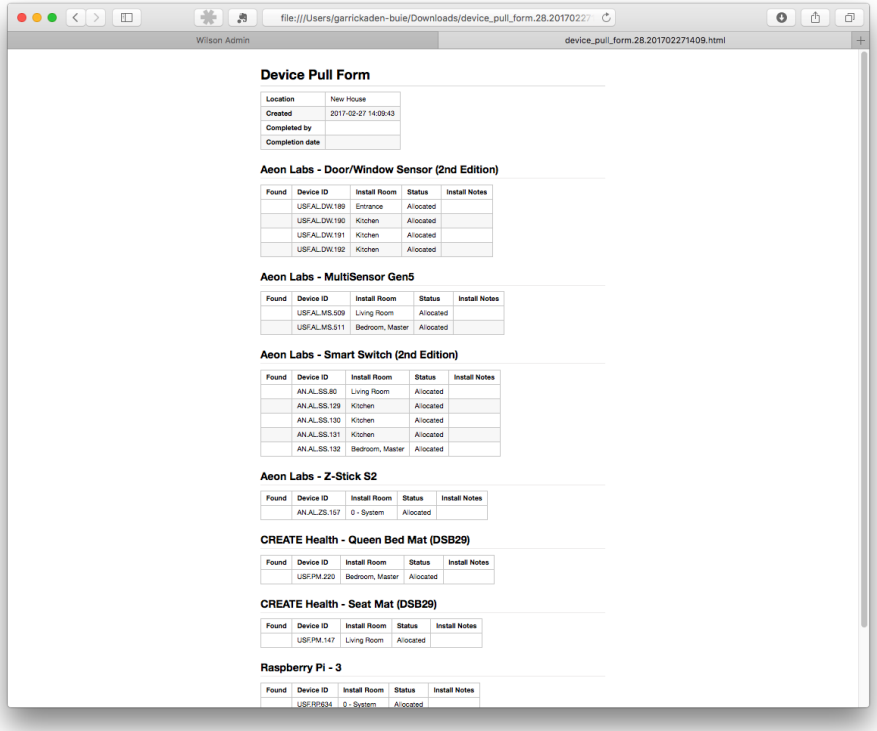

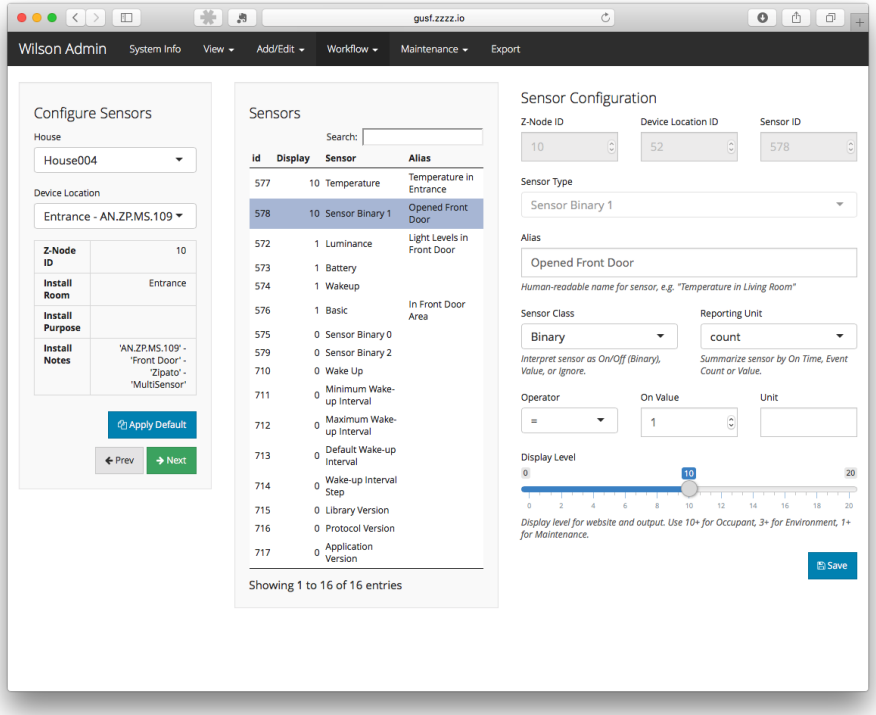

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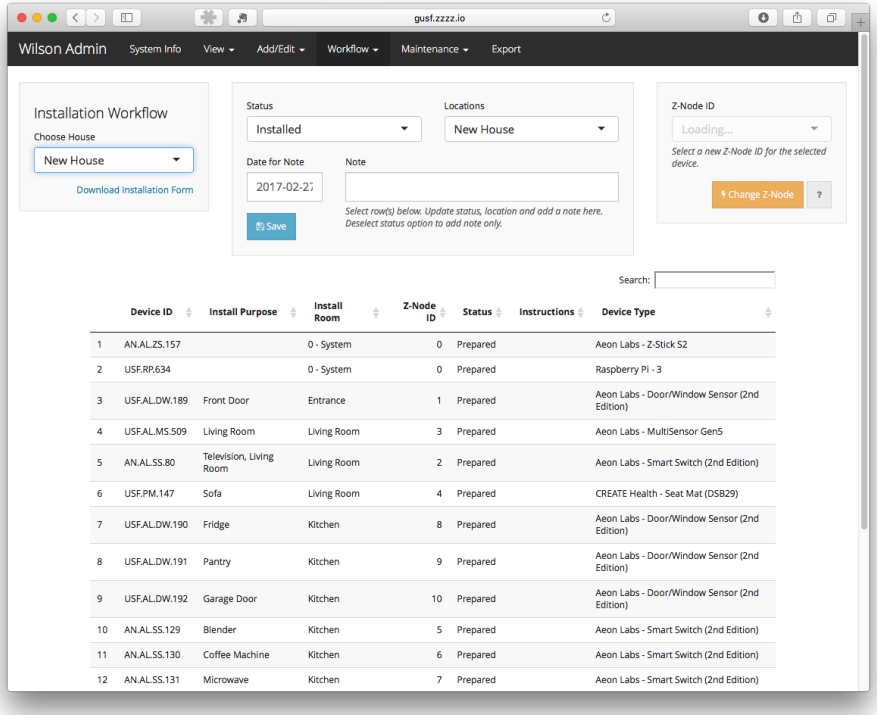
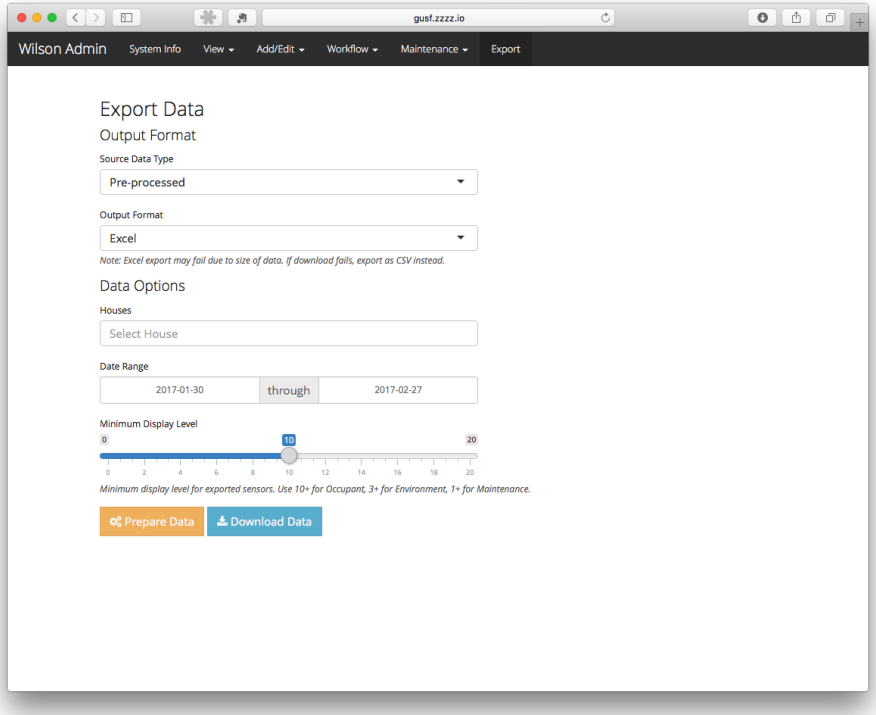




Data Preprocessing

Raw

sensor_id	event_time	value
618	2017-07-11 20:22:22	0.000
618	2017-07-11 20:22:33	1.000
612	2017-07-11 20:23:19	2.233
612	2017-07-11 20:23:22	28.806
612	2017-07-11 20:23:25	50.397
612	2017-07-11 20:32:43	26.411
612	2017-07-11 20:32:46	28.425
612	2017-07-11 20:32:49	30.159
612	2017-07-11 20:32:55	32.124
618	2017-07-11 20:32:56	0.000

Preprocessed

sensor_id	start_time	end_time	value	duration
618	20:22:33	20:26:18	1	223
612	20:23:22	20:29:07	1	345
618	20:26:18	20:28:58	0	160
618	20:28:58	20:32:56	1	238
612	20:29:07	20:29:10	0	2
612	20:29:10	20:37:16	1	486
618	20:32:56	20:38:23	0	326

Data Preprocessing

Metadata

id	alias	install_room	devid	model	manufacturer	type
612	Using Television	Living Room	AN.AL.SS.133	Smart Switch (2nd Edition)	Aeon Labs	Power
618	In Living Room	Living Room	USF.EL.MS.216	Motion Sensor	Ecolink	Sensor Binary 0

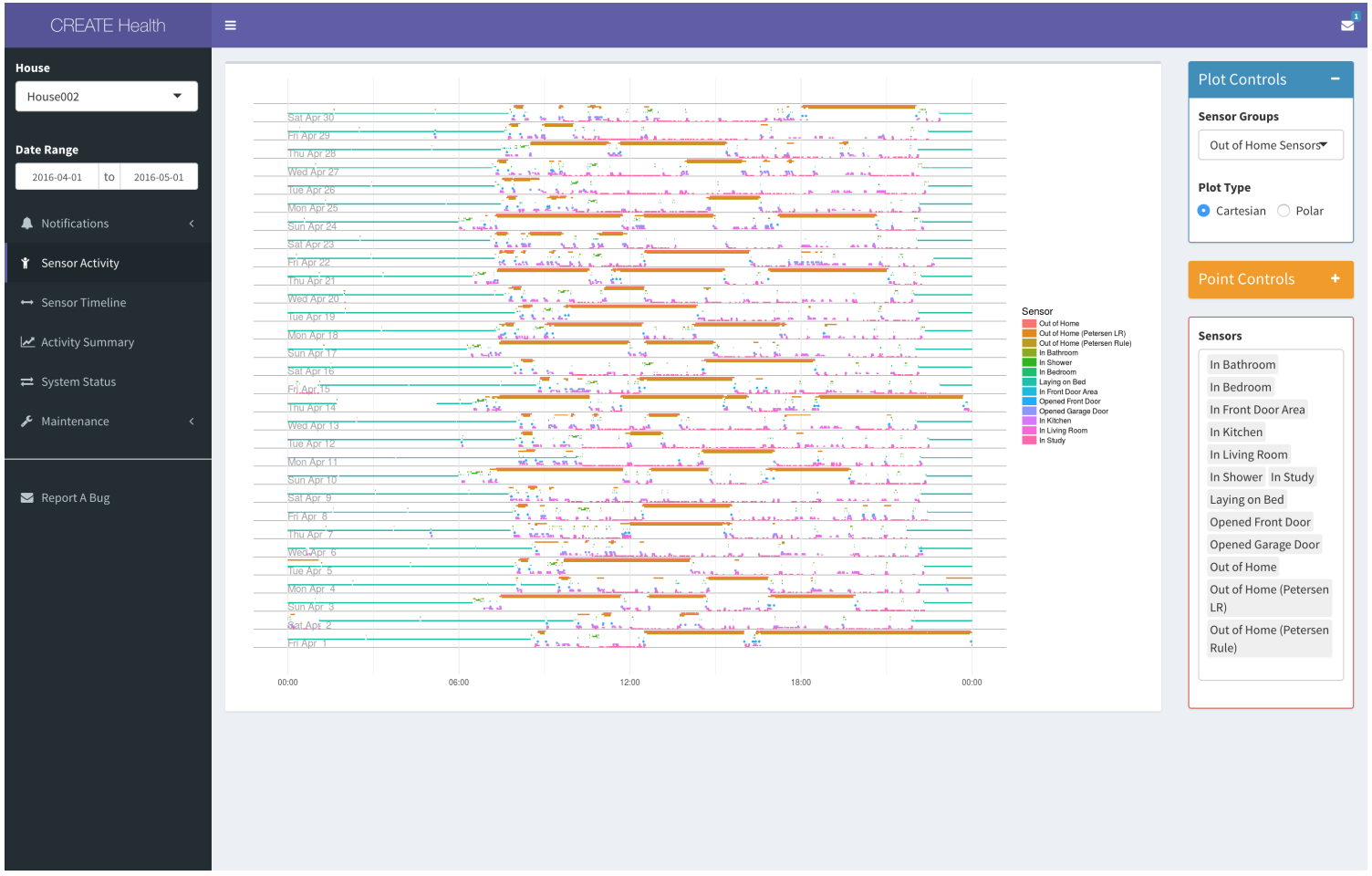
Data Preprocessing

- Enforce ordering of events by timestamp
- Remove duplicate and non-state-change events
- **Binary**: Convert values to state and reduce again
- **Value**: Compress old values
- Monitor run state and current position in event data stream

Modes

- **Micro-batch:** Process only new events since last run
- **Full rebuild:** Rebuild entire preprocessed database
- **Add/rebuild/remove individual:** Update preprocessed data on config change

Data Visualization and Exploration



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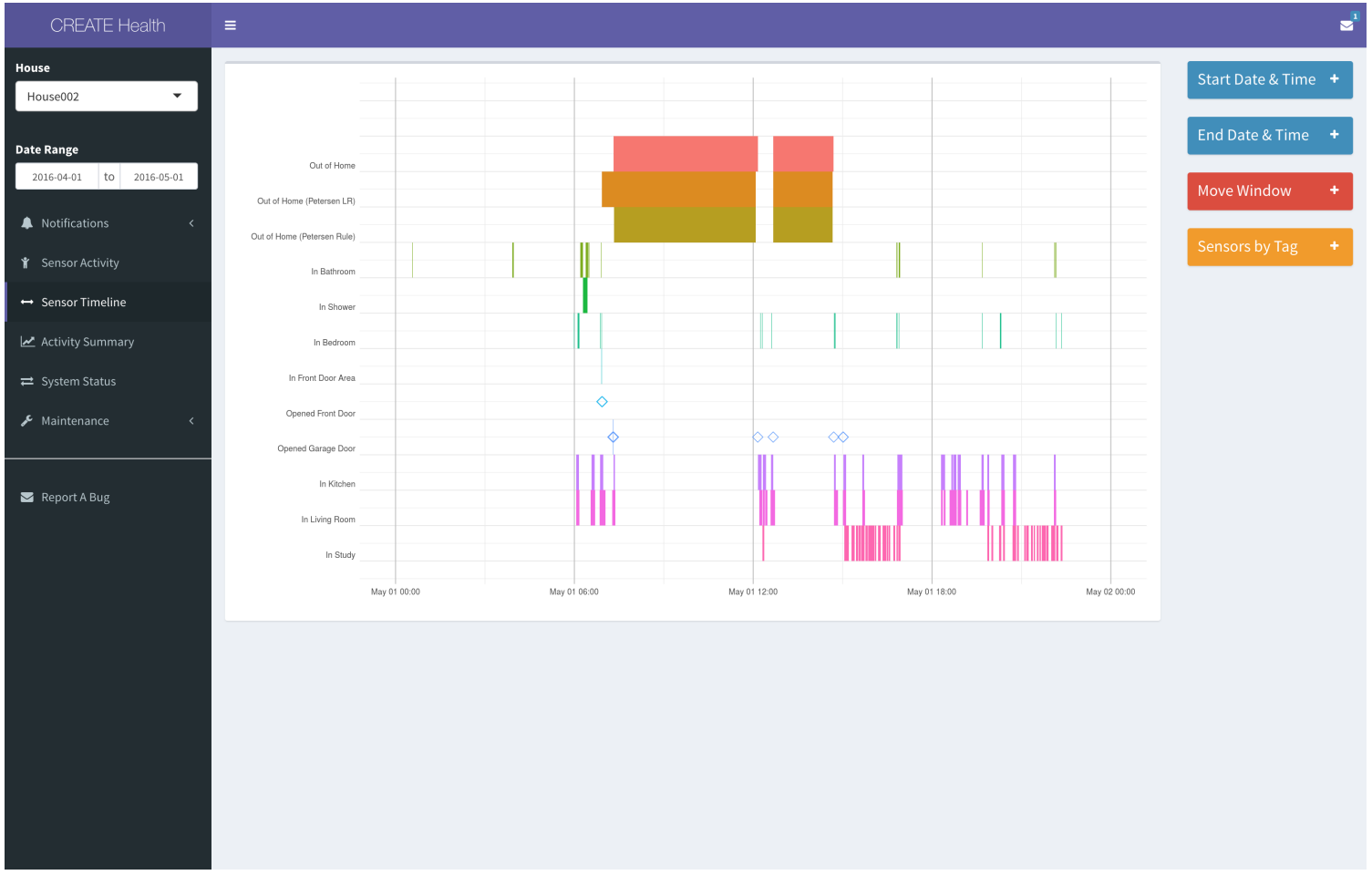

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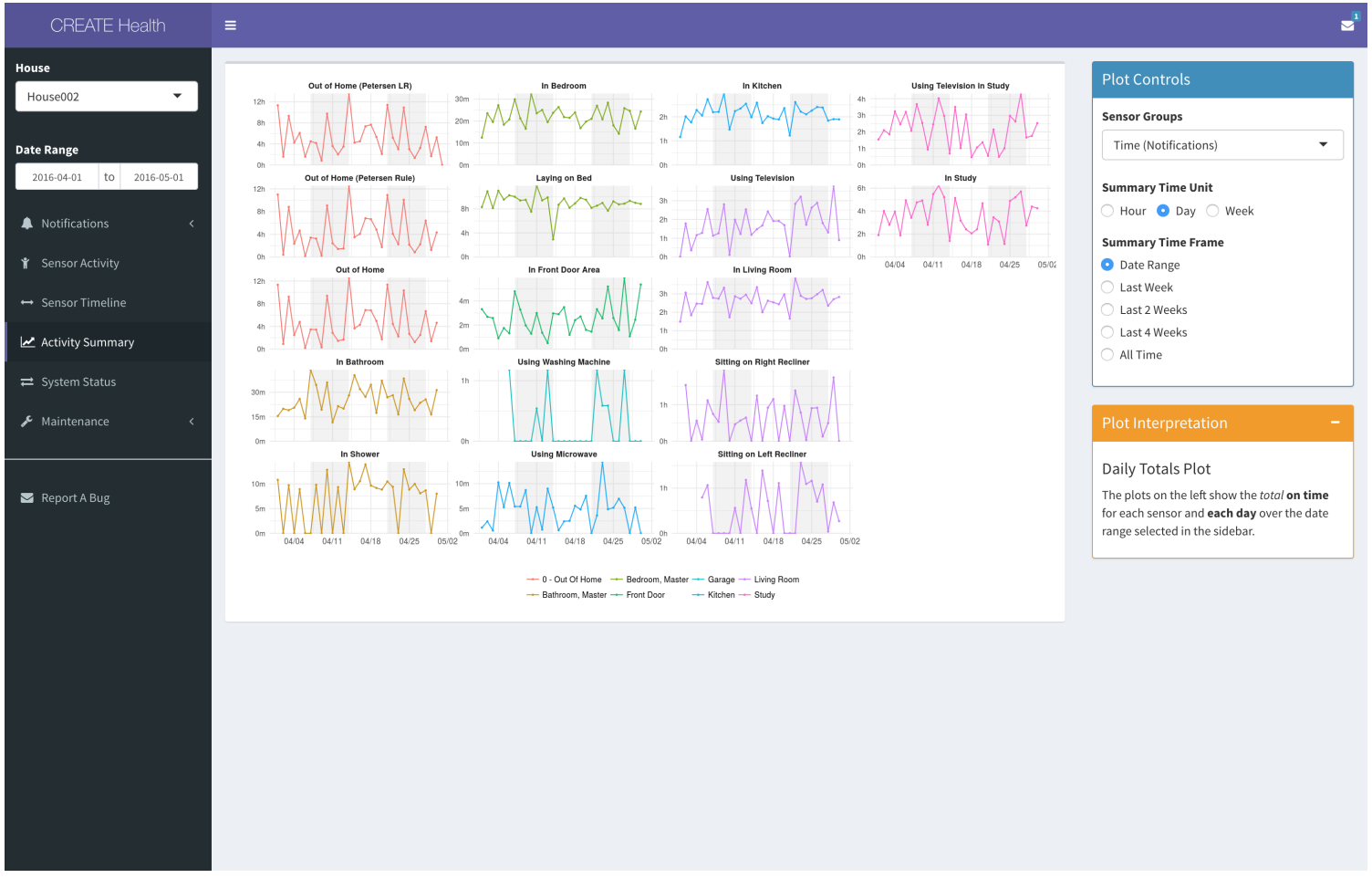
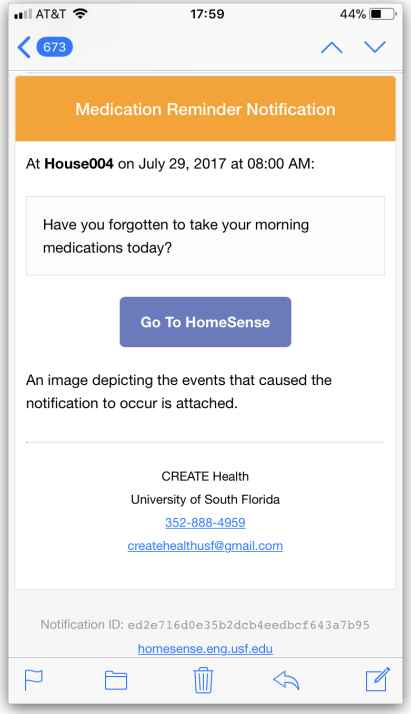


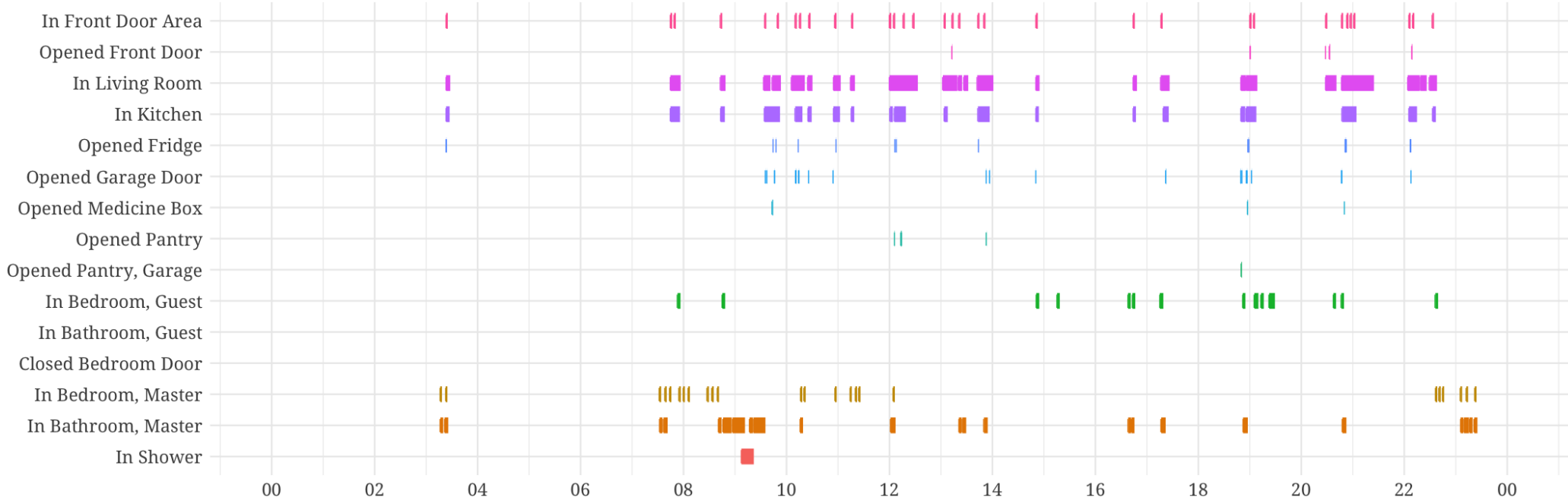
Notification System



- Real-time alert processing to deliver timely notifications
- Both a processing script and a framework
- As a framework it provides
  - Ability to run **arbitrarily complex alert** state evaluation
  - A comprehensive design pattern for deciding **when, how and for whom**
  - Easy access to alert **actions** (email, text message, etc.)
  - A **simulation mode** for post-hoc analysis of models and methods

Activity Profiles

Example Day of Sensor Activity



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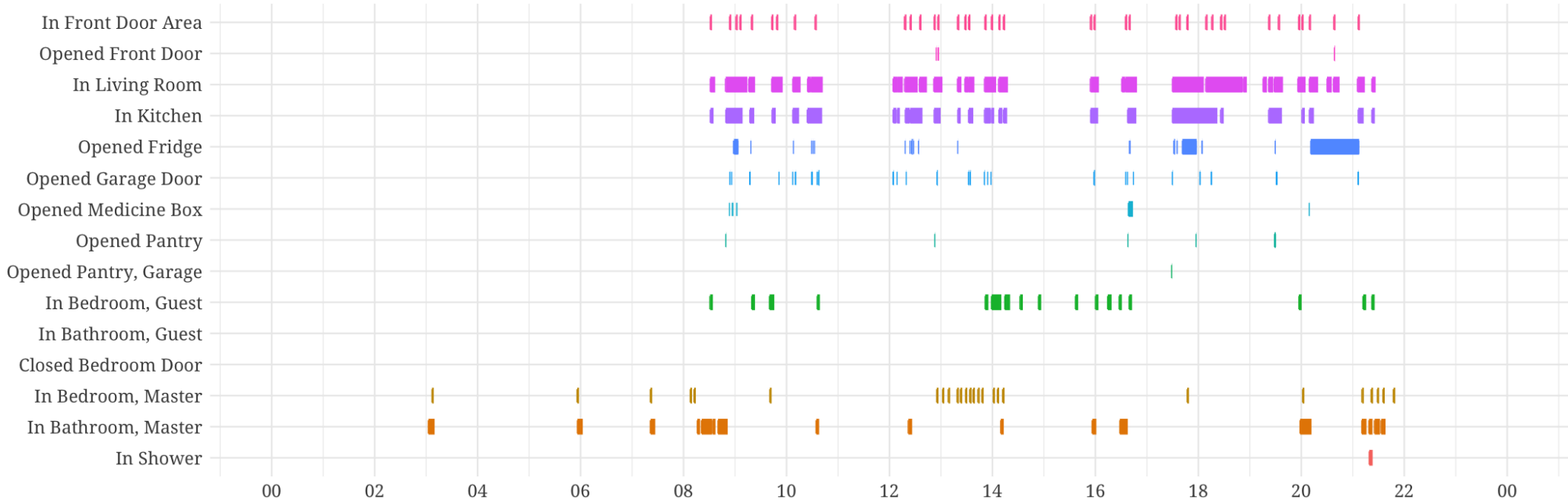

Activity Profiles Background

n-grams

- Bag-of-words document summarization model — Zhang et al. (2010)
- Text categorization and "language profiles" — Cavnar and Trenkle (1994)
- Text prediction systems — Garay-Vitoria and Abascal (2006)
- Automatic generation of summaries — Lin and Hovy (2003)
- Word-embedding method (word2vec) — Goldber and Levy (2014)

Pattern and Motif learning

- Sequential Aggregate Approximation (SAX) — Lin et al. (2007)
- Periodic outlier detection in time-serier sequences — Rasheed and Alhajj (2014)

Anamolous Activity Detection

- Detect and explain anamolous activities — Hamid et al. (2005)

Routine Discovery in Smart Homes

- Unsupervised routine detection of older adults using SAX — Yin et al. (2015)

n-grams

corpus

n-grams

corpus

n-grams

corpus

n-grams

corpus

n-grams

corpus

n-grams

_	c	o	r	p	u	s	_
_c	co	or	rp	pu	us	s_	
_co	cor	orp	rpu	pus	us_		
_cor	corp	orpu	rpus	pus_			
_corp	corpu	orpus	rpus_				
_corpu	corpus	corpus_					
_corpus	corpus_						
corpus							

n-grams

_	c	o	r	p	u	s	_
_c	co	or	rp	pu	us	s_	
_co	cor	orp	rpu	pus	us_		
_cor	corp	orpu	rpus	pus_			
_corp	corpu	orpus	rpus_				
_corpu	corpus	corpus_					
_corpus	corpus_						
corpus							

Hornik et al. (2013). doi:10.18637/jss.v052.i06.

n-grams

1. `o` `r` `p` `u`
2. `_c` `or` `rp` `pu` `s_`
3. `_co` `orp` `rpu` `us_`
4. `_cor` `orpu` `pus_`
5. `_corp` `rpus_`
6. `_corpu` `orpus_`
7.
8. `_corpus_`

Sensor Events as Event-Strings

Sensor Inclusion

Keep only *active* events that indicate interaction or movement within the environment

Motion: Keep only ON activation events

Contact: Keep both ON and OFF events

In Front Door Area	In Study	Opened Medicine Drawer
In Living Room	In Bedroom, Guest	Opened Medicine Cabinet
In Kitchen	In Bedroom, Guest 2	Opened Medicine Closet
In Dining Area	In Bathroom, Guest	Opened Medicine Box
In Bedroom, Master	In Bath, Guest	Opened Garage Door
In Bathroom, Master	In Sewing Room	Opened Front Door
In Shower	Opened Pantry, Garage	Opened Fridge
In Office	Opened Pantry	Closed Bedroom Door

Sensor Events as Event-Strings

Sensor Inclusion

sensor_id	alias	start_time	value
3807	In Bathroom, Master	2017-07-19 03:21:28	1
3772	In Bedroom, Master	2017-07-19 03:22:44	1
3910	In Living Room	2017-07-19 03:23:09	1
3613	In Front Door Area	2017-07-19 03:23:12	1
3721	In Kitchen	2017-07-19 03:23:13	1
5255	Opened Fridge	2017-07-19 03:23:22	1
5255	Opened Fridge	2017-07-19 03:23:29	0
5255	Opened Fridge	2017-07-19 03:23:53	1
5255	Opened Fridge	2017-07-19 03:23:59	0
3772	In Bedroom, Master	2017-07-19 03:24:44	0
3613	In Front Door Area	2017-07-19 03:25:12	0

Sensor Events as Event-Strings

Sensor Inclusion

Standardizing Names

Global

- `In Living Room` → `InLivingRoom`
- `Opened`*`FrontDoor`* → `Opened`*`FrontDoor`* and `!Opened`*`FrontDoor`*
- `Opened`*`MedicineCont`* for medicine *box*, *cabinet*, *drawer*, etc.

Specific adjustments

- `InShower` for primary bathing location
- Activity rooms and guest bedrooms: `InSecondRoom` and `InBedroomGuest`

Sensor Events as Event-Strings

Sensor Inclusion

Pauses are inserted when no activity is observed

Timestamp of **15 minutes** after last event before pause

Standardizing Names

Pauses

Pause Type	Time Between Events
Short	$15 \leq x < 60$ *minutes*
Medium	$1 \leq x < 3$ *hours*
Long	$3 \leq x$ *hours*

Sensor Events as Event-Strings

Sensor Inclusion

Standardizing Names

Pauses

Dictionary

Motion	Vowel	Active	Letter	Pause	Separator
InFrontDoorArea	a	ClosedBedroomDoor	B	PauseLong	3
InLivingRoom	A	!ClosedBedroomDoor	b	PauseMedium	2
InDiningArea	e	OpenedFridge	D	PauseShort	1
InKitchen	E	!OpenedFridge	d		
InBathroomMaster	i	OpenedFrontDoor	F	PauseLong	⏎
InBedroomMaster	I	!OpenedFrontDoor	f	PauseMedium	._
InSecondRoom	o	OpenedGarageDoor	G	PauseShort	_
InShower	O	!OpenedGarageDoor	g		
InBedroomGuest	u	OpenedMedicineCont	M		
InBathroomGuest	U	!OpenedMedicineCont	m		
		OpenedPantry	P		
		!OpenedPantry	p		

Sensor Events as Event-Strings

Sensor Inclusion

Standardizing Names

Pauses

Dictionary

Original

`InBedroomMaster` `InBathroomMaster` `InBathroomMaster` `InBedroomMaster` `InLivingRoom` `InFrontDoorArea` `InKitchen` `OpenedFridge` `!OpenedFridge` `OpenedFridge` `!OpenedFridge` `PauseLong` `InBedroomMaster` `InBathroomMaster` `InBathroomMaster` `InBedroomMaster` `InBedroomMaster` `InLivingRoom` `InFrontDoorArea` `InKitchen`

Encoded

`I` `i` `i` `I` `A` `a` `E` `D` `d` `D` `d` `3` `I` `i` `i` `I` `I` `A` `a` `E`

Event-String Example

```
_IiiIAaEDdDd3IiiIIAaEaoIII1IIIiAaEoiiOiiAEaGgGgAMmDdGgGgDd
a1AaEGgGgGgDdGgGgaiIIAEaGg1GEAgaIDd1IAEaII1AaEiIaEPpDdDdPp
Ppaa1AaEaFfAaiiA1AaEDaiGgPpGg1GEAgao1o1oiioAaE1oAaiEGg1GAE
gPGgoiAEGgGgMmdDdDdaFfFfGgaooo1AaFfFfooAaGgGEgiMmDdDdDdDda
aa1AaEDdDdDGgFfaAAaEoIII1IiiIiiI3_
```

`A` = Living Room, `E` = Kitchen, `I` = Bedroom, `i` = Bathroom (M), `U` = Bathroom (G), `a` = Near Front Door, `o` = 2nd Room

`Dd` = Fridge, `Ff` = Front Door, `Gg` = Garage Door, `Pp` = Pantry, `Mm` = Med Container

Event-String Example

```
_IiiIAaEDdDd3IiiIIAaEaoIII1IIIiAaEoiiOiiAEaGgGgAMmDdGgGgDd
a1AaEGgGgGgDdGgGgaiIIAEaGg1GEAgaIDd1IAEaII1AaEiIaEPpDdDdPp
Ppaa1AaEaFfAaiiA1AaEDaiGgPpGg1GEAgao1o1oiioAaE1oAaiEGg1GAE
gPGgoiAEGgGgMmdDdDdaFfFfGgaooo1AaFfFfooAaGgGEgiMmDdDdDdDda
aa1AaEDdDdDGgFfaAAaEoIII1IiiIiiI3_
```

`A` = Living Room, `E` = Kitchen, `I` = Bedroom, `i` = Bathroom (M), `U` = Bathroom (G), `a` = Near Front Door, `o` = 2nd Room

`Dd` = Fridge, `Ff` = Front Door, `Gg` = Garage Door, `Pp` = Pantry, `Mm` = Med Container

Event-String Example

```
_IiiIAaEDdDd.
>IiiIIAaEaoIII IIIiAaEoiiOiiAEaGgGgAMmDdGgGgDda
AaEGgGgGgDdGgGgaiIIAEaGg GEAgaIDd IAEaII
AaEiIaEPpDdDdPpPpaa AaEaFfAaiiA AaEDaiGgPpGg GEAgao o
oiioAaE oAaiEGg GAEgPGgoiAEGgGgMmdDdDdaFfFfGgaooo
AaFfFfooAaGgGEgiMmDdDdDdDdaaa AaEDdDdDGgFfaAAaEoIII
IiiIiiI.
>_
```

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```
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AaEGgGgGgDdGgGgaiIIAEaGg GEAgaIDd IAEaII
AaEiIaEPpDdDdPpPpaa AaEaFfAaiiA AaEDaiGgPpGg GEAgao o
oiioAaE oAaiEGg GAEgPGgoiAEGgGgMmdDdDdaFfFfGgaooo
AaFfFfooAaGgGEgiMmDdDdDdDdaaa AaEDdDdDGgFfaAAaEoIII
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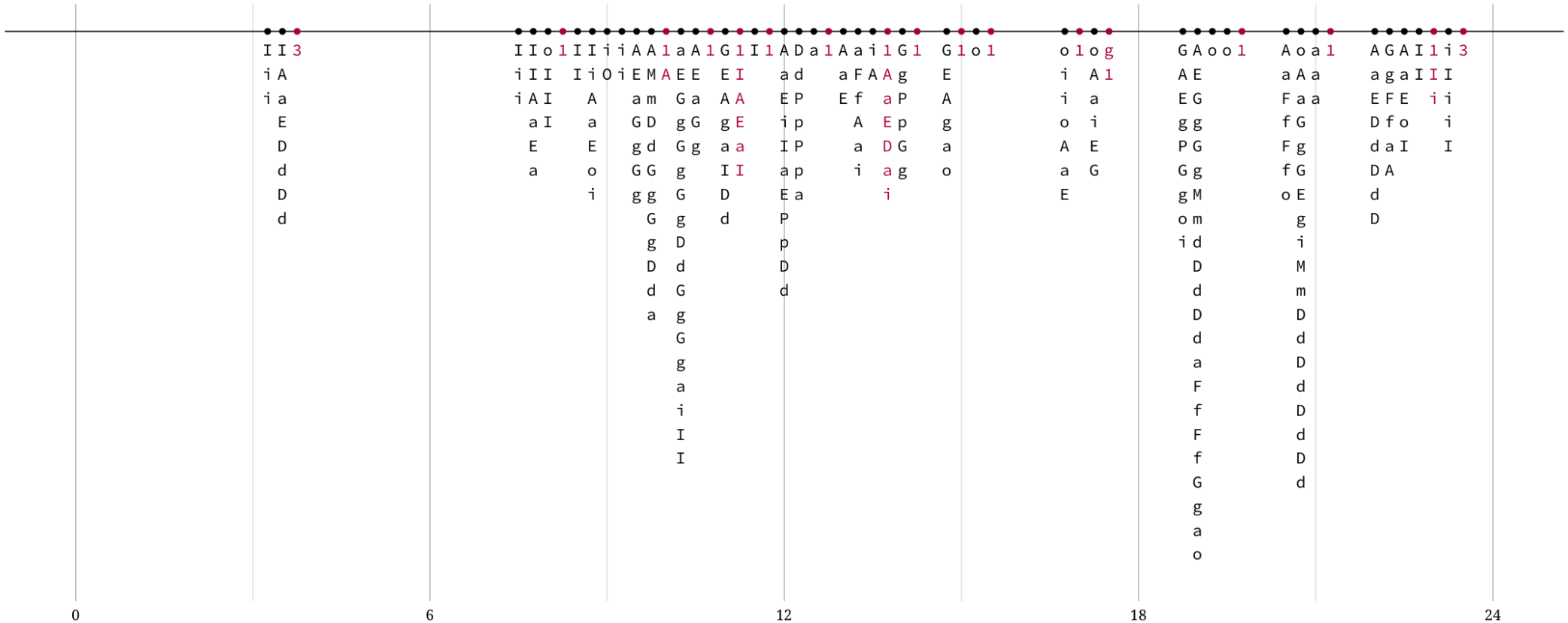
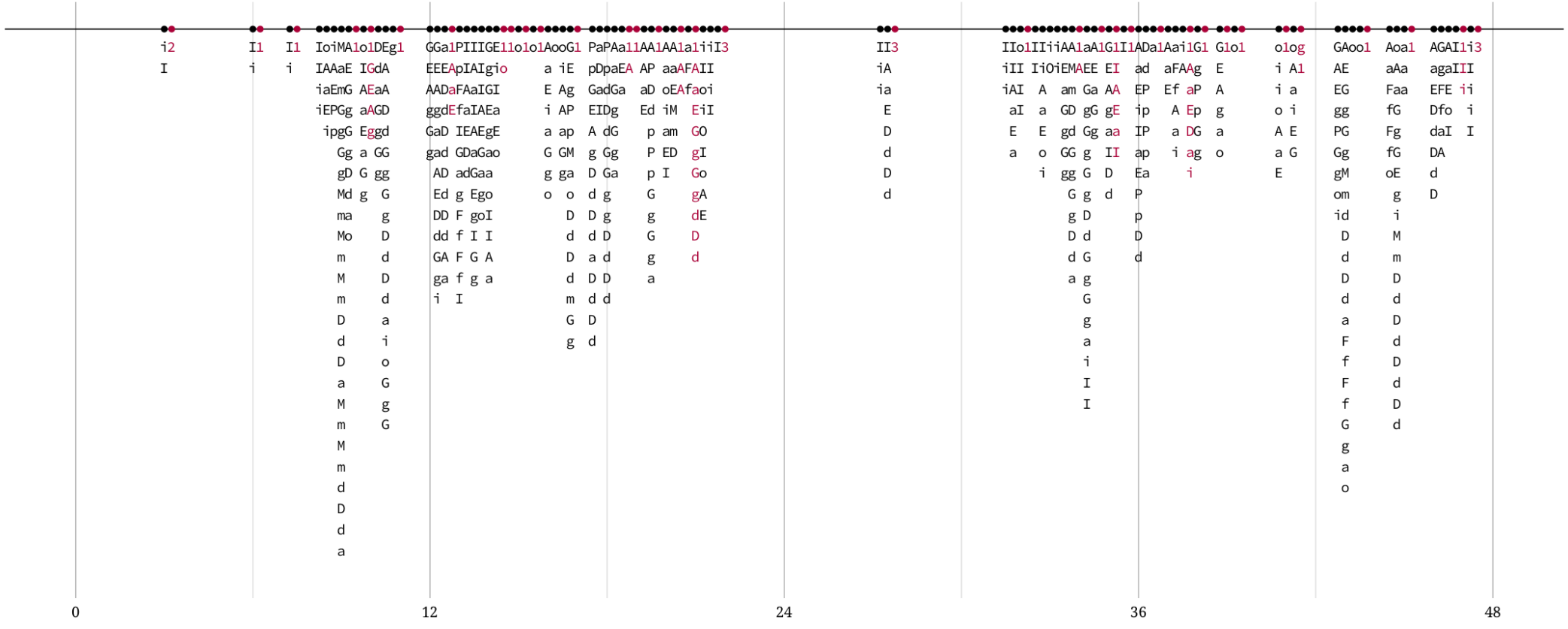
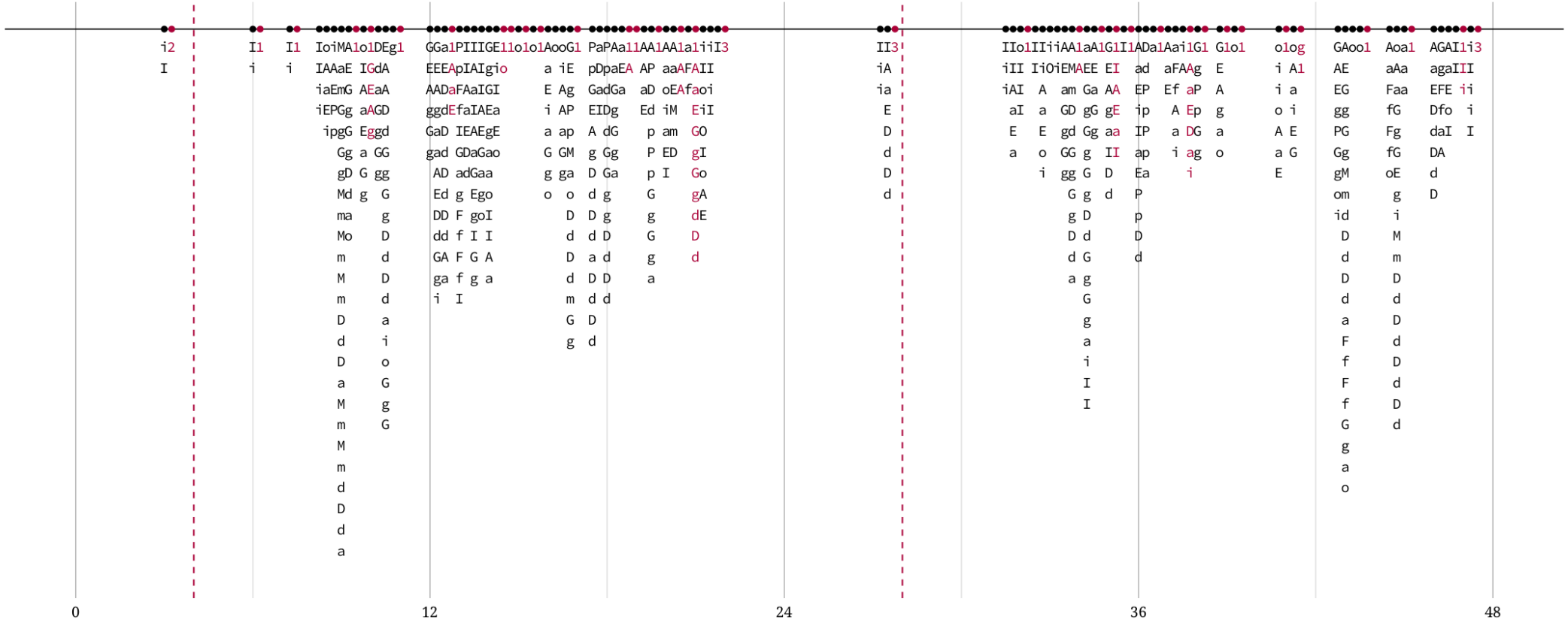
Event-String Timeline



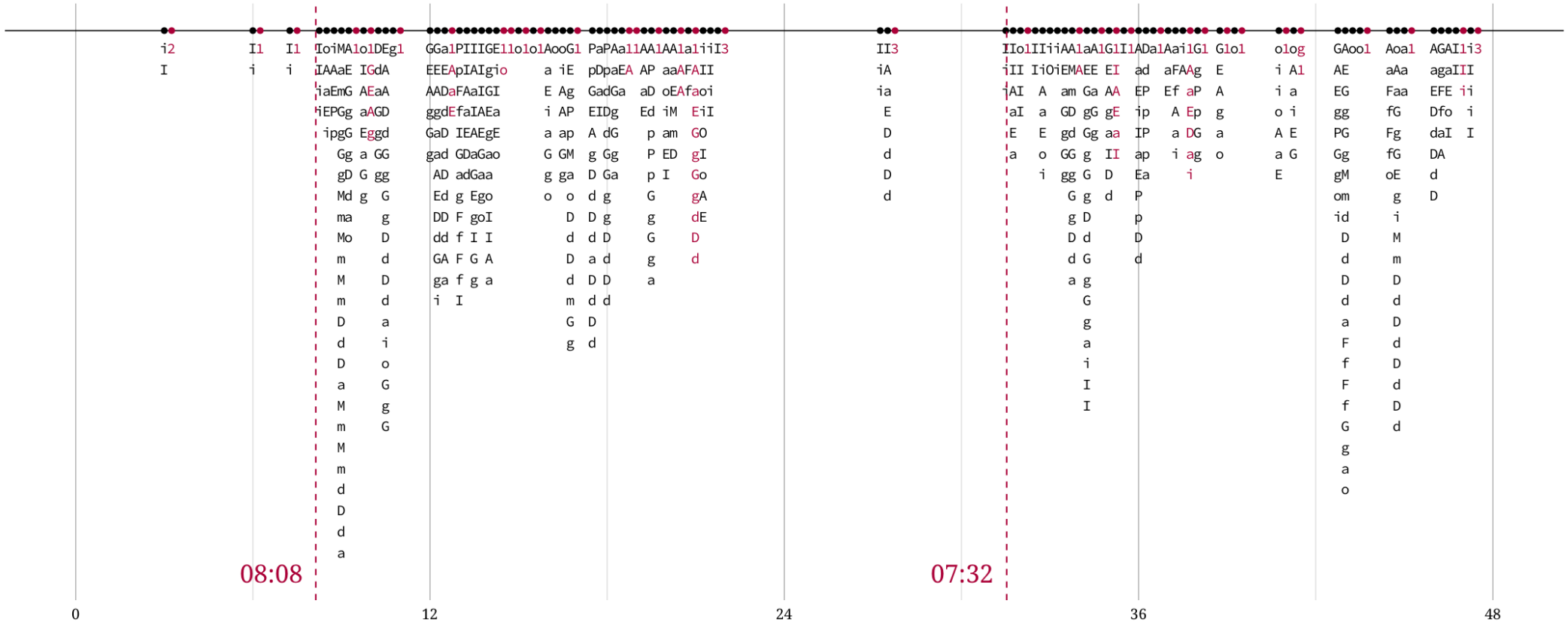
Day-Event Strings



Day-Event Strings



Day-Event Strings



Day-Event Strings

Day 1

```
_IIiioAaEiiAEPpMamGgGgMmMmMmDdDaMmMmdDdaAEGgGgDdao1...
```

Day 2

```
_IiiIIAaEaoIII1IIIiAaEoiiOiiAEaGgGgAMmDdGgGgDda1AaE...
```

Bags of *n*-grams from day-event-strings

Bigram

`_I` `ii` `iI` `II` `IA` `Aa` `aE` `Ea` `ao` `oI` `II` `II` `I1` `1I` `II` `II` `Ii` `iA` `Aa` `aE`

Trigram

`_Ii` `iiI` `iII` `IIA` `IAa` `AaE` `aEa` `Eao` `aoI` `oII` `III` `II1` `I1I` `1II` `III` `IIi` `IiA` `iAa` `AaE` `aEo`

4-gram

`_Iii` `iiII` `iIIA` `IIAa` `IAaE` `AaEa` `aEao` `EaoI` `aoII` `oIII` `III1` `II1I` `I1II` `1III` `IIIi` `IIiA` `IiAa` `iAaE` `AaEo` `aEoi`

5-gram

`_IiiI` `iiIIA` `iIIAa` `IIAaE` `IAaEa` `AaEao` `aEaoI` `EaoII` `aoIII` `oIII1` `III1I` `II1II` `I1III` `1IIIi` `IIIiA` `IIiAa` `IiAaE` `iAaEo` `AaEoi` `aEoii`

6-gram

`_IiiII` `iiIIAa` `iIIAaE` `IIAaEa` `IAaEao` `AaEaoI` `aEaoII` `EaoIII` `aoIII1` `oIII1I` `III1II` `II1III` `I1IIIi` `1IIIiA` `IIIiAa` `IIiAaE` `IiAaEo` `iAaEoi` `AaEoii` `aEoii0`

Activity Profiles

Day 1 - Top *n*-grams

ngram	count	rank	freq
Dd	26	1	0.0152941
Gg	25	2	0.0147059
Aa	17	3	0.0100000
aE	14	4	0.0082353
dD	13	5	0.0076471
dDd	12	6	0.0070588
gG	12	7	0.0070588
GgG	11	8	0.0064706
AaE	10	9	0.0058824
DdD	10	10	0.0058824

Day 2 - Top *n*-grams

ngram	count	rank	freq
Gg	19	1	0.0152610
Dd	14	2	0.0112450
Aa	13	3	0.0104418
aE	10	4	0.0080321
AaE	9	5	0.0072289
II	9	6	0.0072289
dD	8	7	0.0064257
dDd	7	8	0.0056225
DdD	7	9	0.0056225
gG	7	10	0.0056225

Activity Profiles

Day 1 - Bottom *n*-grams

ngram	count	rank	freq
PpGggG	1	1211	0.0005882
PpGggGg	1	1212	0.0005882
PpMam	1	1213	0.0005882
PpMamG	1	1214	0.0005882
PpMao	1	1215	0.0005882
PpMaoD	1	1216	0.0005882
pPp	1	1217	0.0005882
pPpG	1	1218	0.0005882
pPpGg	1	1219	0.0005882
pPpGggG	1	1220	0.0005882

Day 2 - Bottom *n*-grams

ngram	count	rank	freq
PpGg1	1	903	0.0008032
PpGg1G	1	904	0.0008032
pPp	1	905	0.0008032
PpP	1	906	0.0008032
pPpa	1	907	0.0008032
pPpaa	1	908	0.0008032
pPpaa1	1	909	0.0008032
PpPp	1	910	0.0008032
PpPpa	1	911	0.0008032
PpPpaa	1	912	0.0008032

Activity Profiles

1. Transform sensor data into day-event-strings

2. Overall Activity Profiles

    - Bag, count and rank *n*-grams from collated observed day-event-strings
    - Compare activity profile (rank, freq) with unseen days

3. Daily or activity-level Activity Profiles

    - Bag, count and rank *n*-grams from individual day-event-strings
    - Compare activity profile across days

Similarity Measures

- Out of Place Ranking (Cavnar & Trenkle)

$$OOP = \sum_{s \in D} |r_P(s) - r_D(s)|$$

- Kullback-Leibler J-divergence

$$J(p, q) = \sum_i (p_i - q_i) \log(p_i / q_i)$$

- Distance measures directly on n-gram vectors

Cavnar and Trenkle (1994). doi:10.1.1.53.9367

Hornik et al. (2013). doi:10.18637/jss.v052.i06.

Sonnenburg et al. (2007). doi:10.1.1.84.6387.

Activity Profile Demonstration

Given a collection of profiles for occupants and a day-event-string for a new day
can we correctly identify the occupant from their activity string?

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Setup

- 10 Houses
- 180 days
- Standardize sensor names

Activity Profile Demonstration

Given a collection of profiles for occupants and a day-event-string for a new day
can we correctly identify the occupant from their activity string?

Setup

- 10 Houses
- 180 days
- Standardize sensor names

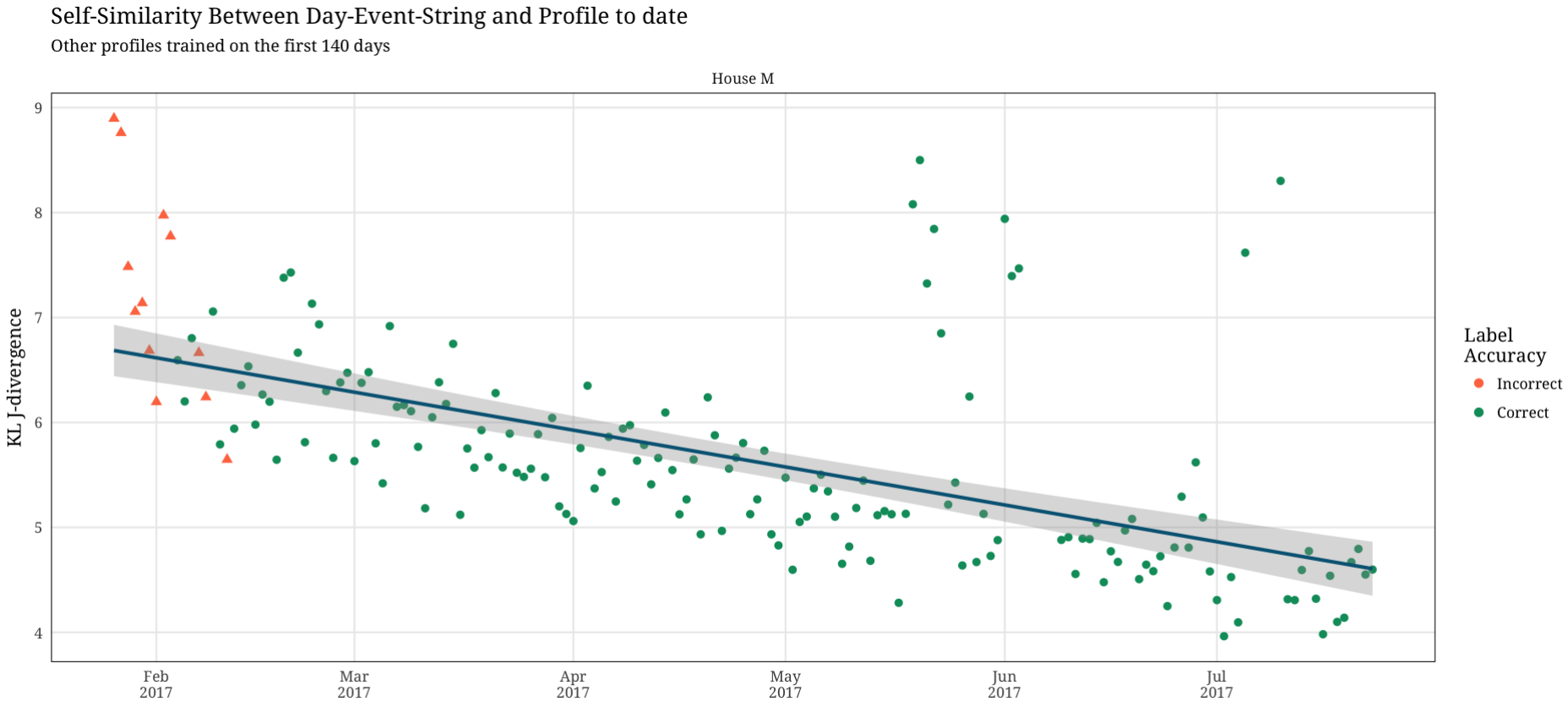
Scenarios

- Add new house to "immature" group
- Add new house to "mature" group
- All houses evolve together

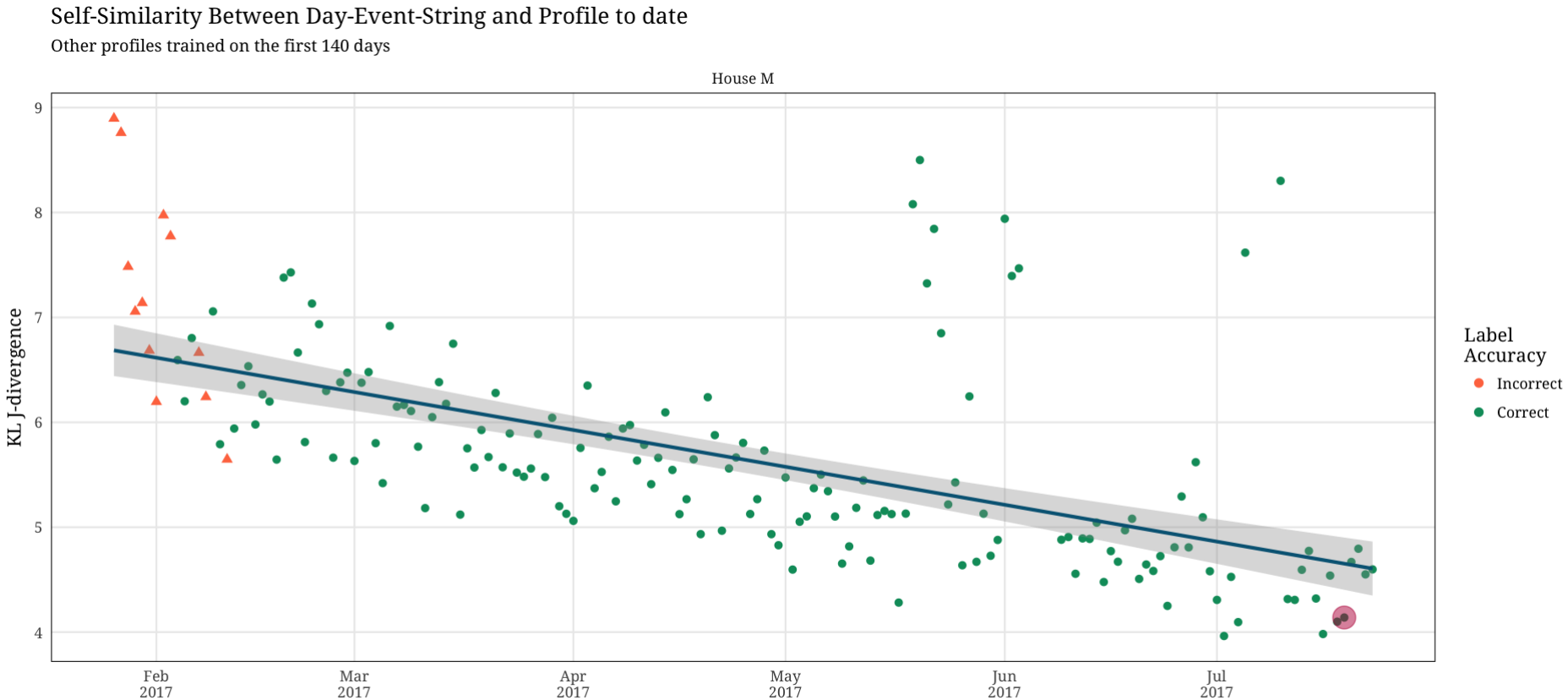
Results

House	30 days	140 days	Full Evolve
Average	**98.45**	**96.09**	**99.02**
B	100	99.42	100
C	98.32	95.53	100
D	98.88	97.21	100
E	100	100	100
G	98.29	96	98.29
H	96.65	91.62	100
I	97.69	95.95	95.95
J	99.44	97.75	100
L	98.08	94.23	95.51
M	97.06	92.94	100

Results


Self-Similarity Between Day-Event-String and Profile to date
Other profiles trained on the first 140 days
House M
KL J-divergence
9
8
7
6
5
4
Feb 2017
Mar 2017
Apr 2017
May 2017
Jun 2017
Jul 2017
Label Accuracy
Incorrect
Correct

Results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Correct

Dissertation

Dissertation

Research Questions

Can we make meaningful and timely observations of older adult's activities

- without needing labels
- without knowing floor plan or layout
- without an annotated training set
- and that works "out of the box"?

to create/enable

- Activity profiles
- Detection of changes in routine
- Early warning notification systems

Dissertation

Research Questions

Dissertation Outline

Create framework based on *n*-grams to naturally resolve the above problems, and demonstrate effectiveness with the following

1. **Demonstrating day-event strings**:
    - Build individual profiles of each home
    - How well can these profiles identify the originator of new activity data?
    - Explore use of activity profiles to track occupant behavior change
2. **Extending day-event strings**:
    - Use cluster analysis with the *n*-grams approach to identify and provide insight into anomalous days and events

Publications and Presentations

- **Ambient Intelligence Applications in Healthcare**.
  Garrick Aden-Buie, A. Yalcin, C. VandeWeerd, A. Ngozichukwuka, J. Hammet, E. Yetisener, C. Radwan. *IIE Industrial and Systems Engineering Research Conferencee*. 2015
- **Comparison of Final Examination Formats in a Numerical Methods Course.**
  Garrick Aden-Buie, A. Kaw, A. Yalcin. *International Journal of Engineering Education*. 2015
- **Rough Set Theory Based Prognostic Classification Models for Hospice Referral.**
  E. Gil-Herrera and Garrick Aden-Buie, A. Yalcin, A. Tsalatsanis, L.E. Barnes, B. Djulbegovic. *BMC Medical Informatics and Decision Making*. 2015
- **Introduction to Engineering Design: Piloting design projects for the first year engineering experience**.
  J. Gaines, B. Joseph, Garrick Aden-Buie. *Sixth Annual First Year Engineering Experience Conference*. 2014
- **Are multiple-choice questions suitable for a final examination in a STEM course?**
  Garrick Aden-Buie, A. Kaw, A. Yalcin, R. Pendyala. *American Society for Engineering Education*, 2014.
- **Boosted Tree Ensembles for Predicting Postsurgical ICU Mortality.**
  Garrick Aden-Buie, Y. Chen, R. Kayal, G. Romero, H. Yang. *INFORMS Annual Meeting*. 2013.

Thank you

Questions & Comments?