Honeywell

Learning Models of Human Behavior with Sequential Patterns

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i.L.S.A.

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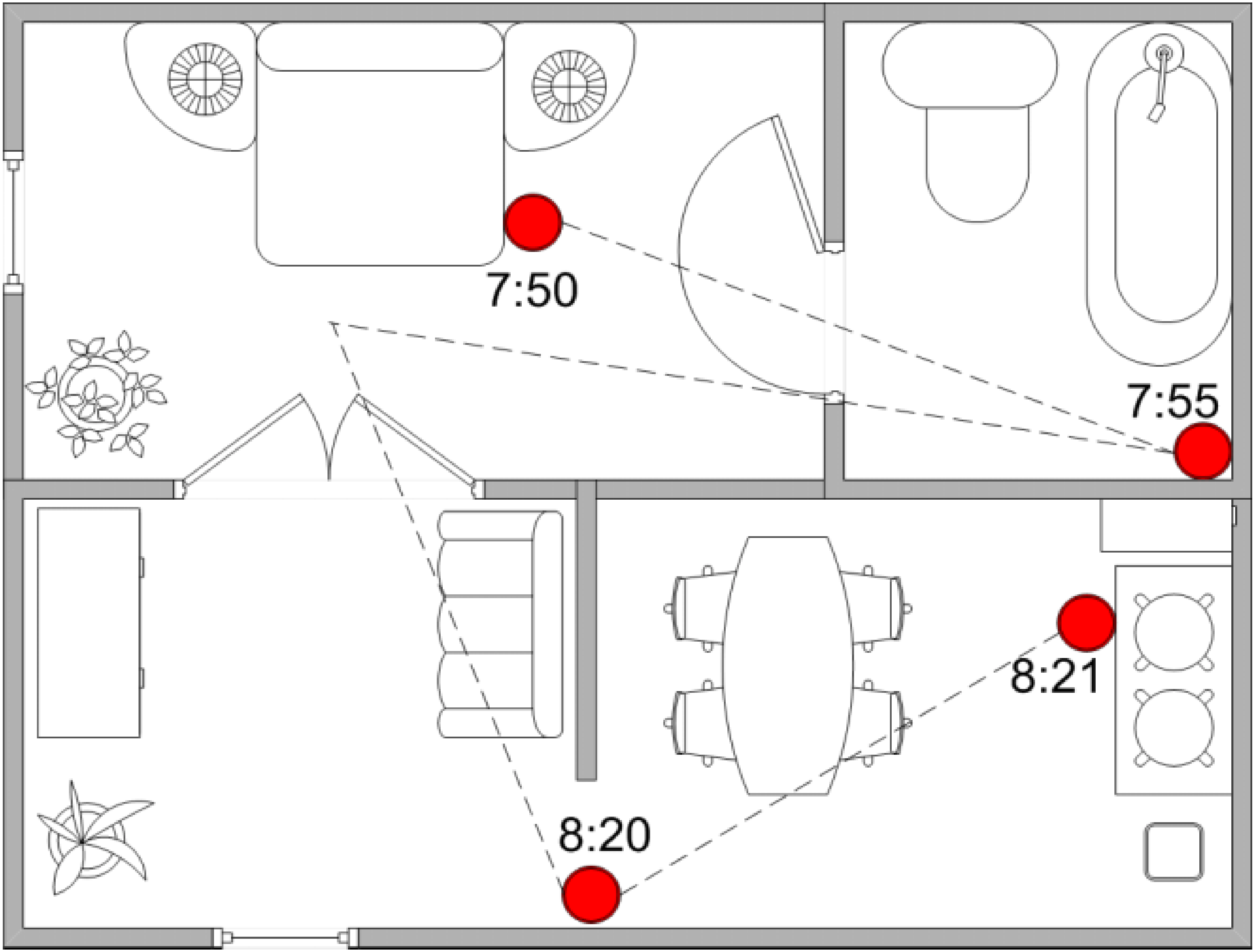
Introduction

I.L.S.A. Needs and Challenges

- be able to automatically configure system to
  - minimize the time and labor involved in set-up and maintenance
  - improve default installation parameters
- adapt to changing conditions
- capture userís preferences

Applied sequential patterns discovery to learn models of elderly regular activities


7:50
7:55
8:21
8:20

Sequential Patterns

Sequential Patterns

- In 75% of days, A → B
- In 75% of days, Bedroom-Motion sensor → Bathroom-Motion Sensor

More Useful Patterns

- In 75% of days, Bedroom-Motion sensor [06:45-07:45] → Bathroom-Motion Sensor [07:00-08:00]

Calculating Time Intervals

NaÔve approach 1: Partition times during sequential patterns discovery phase

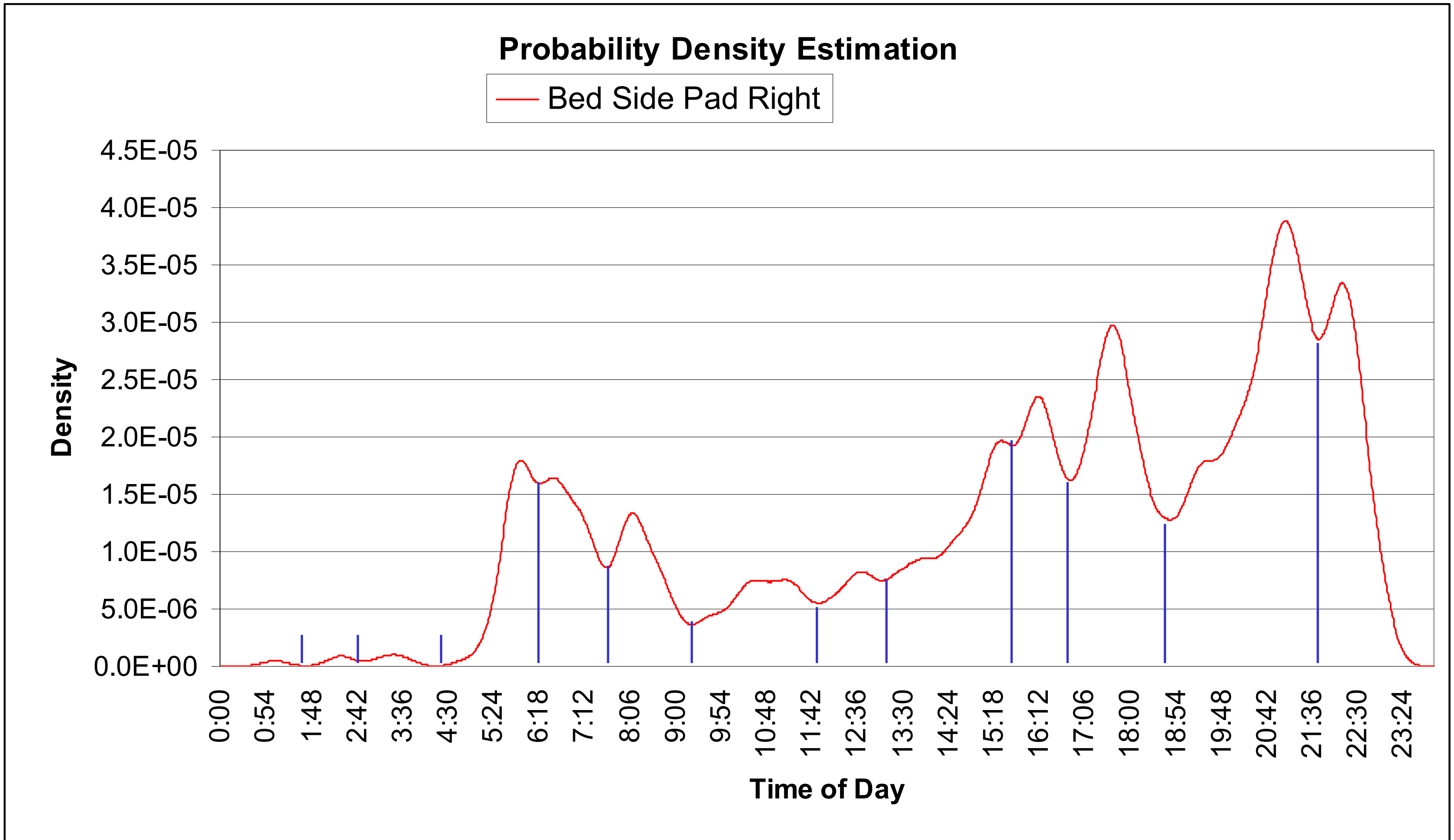
- Intractable

NaÔve approach 2: Partition Time Line of each sensor into equal size bins.

- Drawback: Quality of learning depends on the arbitrary choice of intervals

Better approach: Use Estimate of *probability density function*

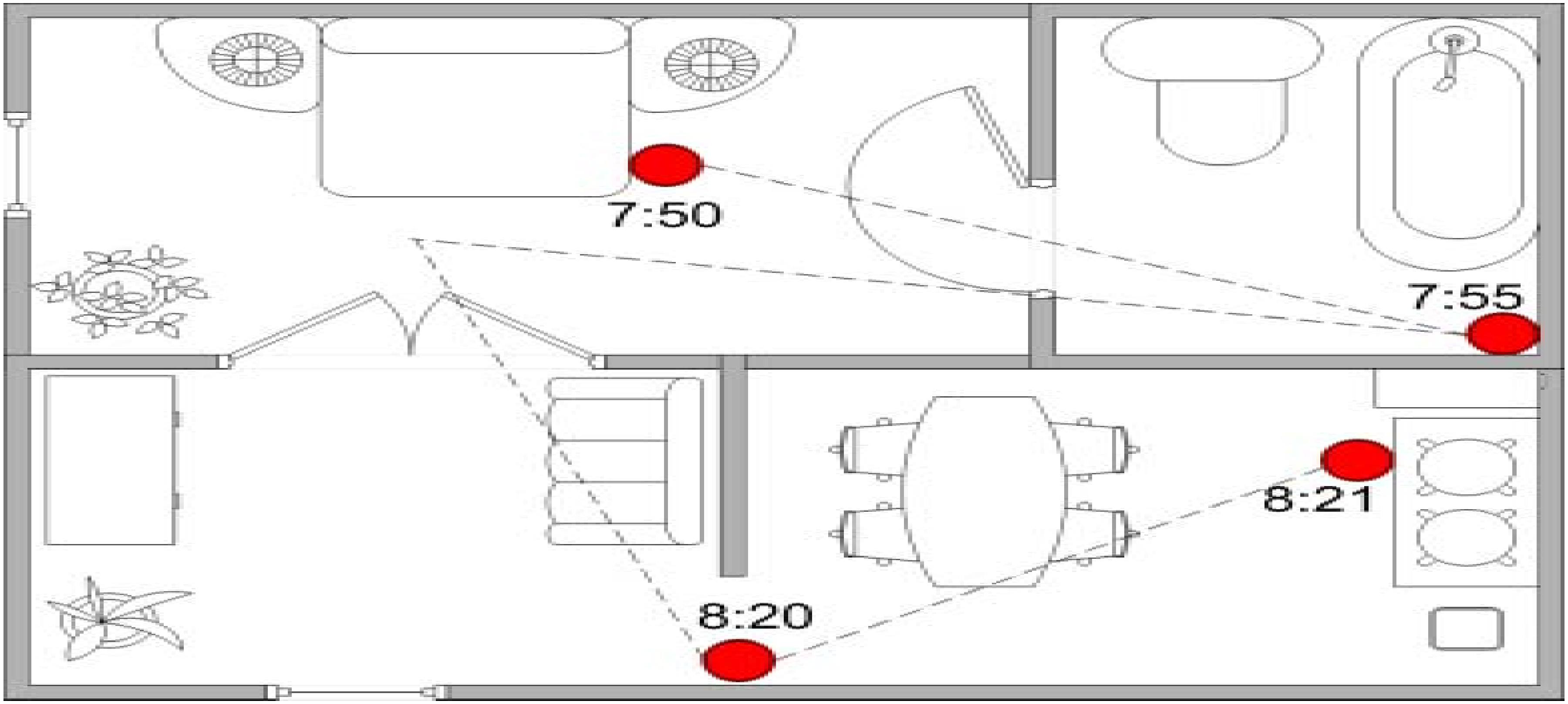
Example of Estimated PDF



Sequential Pattern Learning

Map each sensor reading into a partition

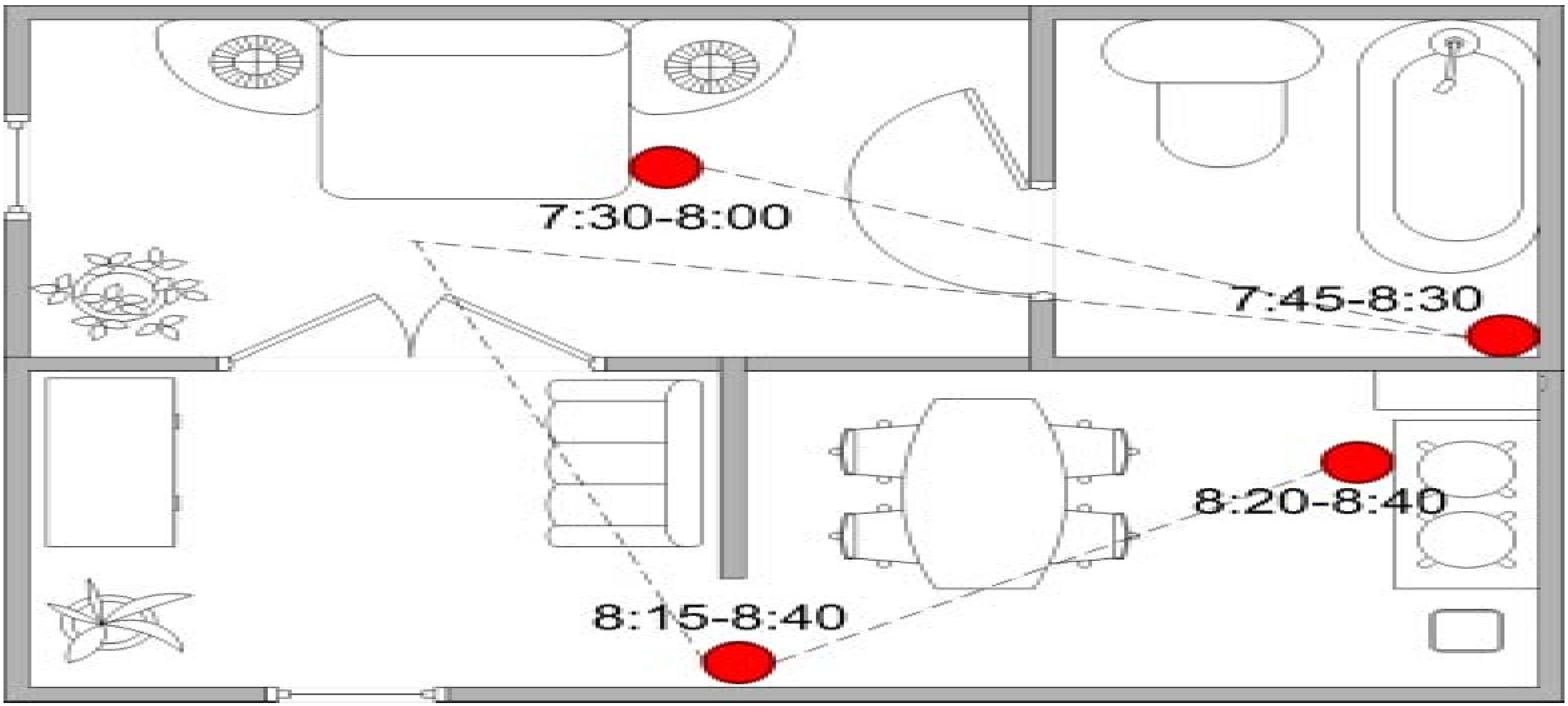
- Bed Side at 7:50 maps to Bed Side between 7:30 and 8:00



Sequential Pattern Learning

Map each sensor reading into a partition

- Bed Side at 7:50 maps to Bed Side between 7:30 and 8:00



Sequential Pattern Learning

- Map each partition into event identifier
  - Bed Side between 7:30 and 8:00 maps into event 1
- Use existing sequential patterns discovery algorithm on event data

Post Processing

Large Number of redundant patterns

Only interested in **interesting** patterns

Defined 3 ìinterestingnessî filters

- ìcloseness in timeî domain filter
- redundancy filter
- ìevent repetitionî domain filter

Post Processing

ìCloseness in Timeî Filter (domain filter)

- Bedroom Motion [6:00-7:00] → Bathroom Motion [6:00-7:00]
- Kitchen Motion [12:00 -13:00] → Dining Room Motion [12:30-13:30] → Kitchen Motion [13:00-14:00]
- Bedroom Motion [6:00-7:00] → Bathroom Motion [6:00-7:00] $\not\rightarrow$ Kitchen Motion [12:00 -13:00] → Dining Room Motion [12:30-13:30] → Kitchen Motion [13:00-14:00]

Post Processing

ìRedundant Patternsî Filter, based on definition of closed sets

ï Bedroom Motion [6:00 - 7:00] → Bathroom Motion [6:00-7:00], support = 3

ï Kitchen Motion [6:30 - 7:30] → Garage Motion [7:15-8:00], support = 4

ï Bedroom Motion [6:00 - 7:00] → Bathroom Motion [6:00-7:00] → Kitchen Motion [6:30 - 7:30] → Garage Motion [7:15-8:00], support = 3

ï First and third patterns are redundant

Post Processing

ìEvent Repetitionî Filter (domain specific)

- Bedroom Motion [6:00 - 7:00] → Bathroom Motion [6:00-7:00]
- Bedroom Motion [6:00 - 7:00] → Bedroom Motion [6:00 - 7:00] → Bathroom Motion [6:00-7:00] → Bathroom Motion [6:00-7:00]
- Second pattern is confusing to human reviewers

Experimental Setup

House Number	*Number of Occupants*	*Number of Sensors*	*Number of Days of Collected Data*	*Number of days of Useful Data*
1	1 adult, 1 80-lb dog	16	80	62
2	2 adults	20	87	40
3	2 adults	10	123	81
4	1 adult	10	63	34

Needed to discard some data due to the following factors

- ï sensors designed and configured for a slightly different task
- ï server went down
- ï occupants left home for vacation

Results: House 1

Number of Occupants	*Number of Sensors*	*Number of Days of Collected Data*	*Number of days of Useful Data*
1 adult, 1 80-lb dog	16	80	62

Pattern	*Support*
UpstairsMotion[06:48-09:58]→LivingRoomMotion[06:48-09:58]→ BathroomSinkPressurePad[7:07-09:58]→LivingRoomMotion[7:07-09:58]	64.5%
BackDoor[16:12-19:07]→LivingRoomMotion[16:53-19:07] → KitchenMotion[16:53-19:07] → LivingRoomMotion[16:53,19:24]	62.9%

Minimum Support Threshold	*Number of Patterns Found*	*Number of Patterns after Filtering*
60%	11411	119

Results: House 2

Number of Occupants	*Number of Sensors*	*Number of Days of Collected Data*	*Number of days of Useful Data*
2 adults	20	87	40

Pattern	*Support*
LivingRoom/DiningRoomMotion[15:19-16:59]→ KitchenMotion[15:19-17:43]	55.0%
BathroomMotion[21:29-23:56]→ LivingRoom/DiningRoomMotion[21:53-23:56]	52.5%

Minimum Support Threshold	*Number of Patterns Found*	*Number of Patterns after Filtering*
50%	5375	50

Results: House 3

Number of Occupants	Number of Sensors	Number of Days of Collected Data	Number of days of Useful Data
2 adults	10	123	81

Pattern	Support
TV/LivingRoomMotion[21:45-23:25] → KitchenMotion[21:45-23:25] → TV/LivingRoomMotion[21:45-23:43] → BedroomMotion[21:45-23:43] → BathroomMotion[21:45-23:43]→BedroomMotion[21:45-23:43]	75.3%
BedroomMotion[03:44-07:28] →Bathroom Motion[04:53-07:28] → BedroomMotion[04:53-07:38]→KitchenMotion[05:25-07:42]	75.3%

Minimum Support Threshold	Number of Patterns Found	Number of Patterns after Filtering
75%	2725	182

Results: House 4

Number of Occupants	*Number of Sensors*	*Number of Days of Collected Data*	*Number of days of Useful Data*
1 adult	10	63	34

Pattern	*Support*
BedroomPreasurePad[04:23-06:12]→ KitchenMotion[06:12-08:23]→ Cupboard[06:45-09:04]→FrontDoor[06:56-08:43]	52.9%

Minimum Support Threshold	*Number of Patterns Found*	*Number of Patterns after Filtering*
50%	340	54

Summary of Results

House Number	*Minimum Support Threshold*	*Number of Patterns Found*	*Number of Patterns after Filtering*	
1	60%	11411	119	1.04%
2	50%	5375	50	0.93%
3	75%	2725	182	6.67%
4	50%	340	54	15.88%

Post Processing: Clusters

In some cases the number of filtered patterns is still large

Can use clustering to present results in batches of similar patterns

- ï each cluster represents different variations of the same activity
- ï vector-space k-means clustering algorithm
  - ñ dimensions are distinct event types
  - ñ patterns are n-dimensional vectors of zeros and ones

Example of Cluster of Patterns

Pattern	Support
UpstairsMotion[06:48-10:30]→BathroomSinkPressurePad[7:07-10:30]	69.3%
BathroomSinkPreasurePad[7:07-10:28]→KitchenMotion[7:07-10:28]	62.9%
LivingRoomMotion[06:19-09:58]→BathroomSinkPressurePad[07:07-10:28]	66.1%
LivingRoomMotion[06:19-09:58]→ BathroomSinkPressurePad[07:07-10:28]→KitchenMotion[07:07-10:28]	61.2%
UpstairsMotion[06:48-09:58]→ LivingRoomMotion[06:48-09:58]→BathroomSinkPressurePad[07:07-09:58] → LivingRoomMotion[07:07-09:58]→BathroomSinkPressurePad[07:07-10:30]	61.2%
UpstairsMotion[06:48-09:58] → LivingRoomMotion[06:19-09:58]→ BathroomSinkPressurePad[07:07-09:58] → LivingRoomMotion[07:07-09:58]	64.5%
LivingRoomMotion[06:19-09:58] → BathroomRoomSinkPressurePad[07:07-19:30] → LivingRoomMotion[06:19-09:58]→BathroomSinkPressurePad[07:07-10:30]	62.9%

Related Work

Other Behavior Models

ï Hidden Markov Models

ï Decision Trees

ï All work in supervised learning setting

Applications to sequential patterns discovery

ï retail customers buying patterns

ï plant failures

ï network alarms

Interestingness filters

ï unexpectedness filter

ï informativeness filter

Conclusions

Results appear promising

Still need a lot of work

- ï Validate approach in the house of elderly people
- ï Be able to use learned patterns in I.L.S.A.
  - ñ recognize patterns
  - ñ adapt and improve I.L.S.A. responsiveness relative to the needs of the elderly
  - ñ automatically configure I.L.S.A.