Activity Recognition in the Home Setting Using Simple and Ubiquitous Sensors

Emmanuel Munguia Tapia
Stephen Intille, Kent Larson
MIT House_*n*
Massachusetts Institute of Technology

Take away message

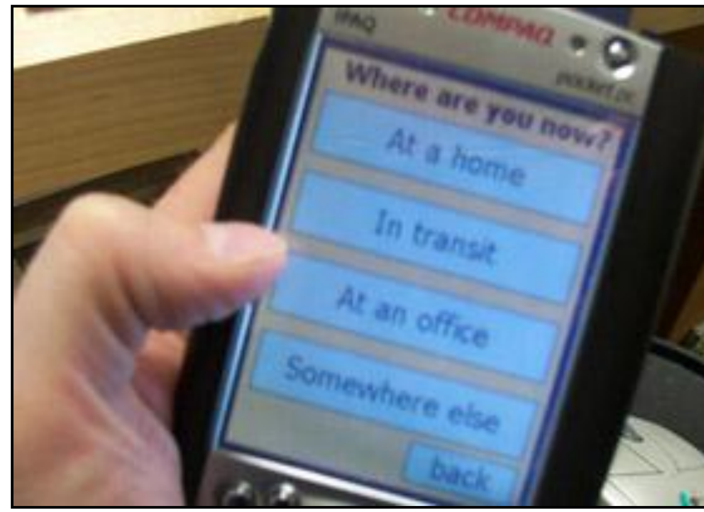
- Contribution
  - Ubiquitous but simple sensors may permit automatic activity recognition
  - System deployed in multiple homes
  - Goal: recognition of ADLs
  - Results:
    - Accuracies ranging from 25%-89%
    - Preliminary, but promising

Motivation

- Activity recognition in the home to enable new home-based preventive healthcare systems
- Possible uses:
  - Monitoring patient care (ADLs, IADLs, EADLs)
  - Judging independence of elderly people
  - Detecting changes in behavior over time
  - Human-computer interfaces to motivate healthy behavior

Prior approaches to activity detection

- Just ask!
- E.g.
  – Experience sampling (mobile computer prompts)
- Drawbacks:
  – Interruption burden
  – Repetition burden
  – Requires user input



(Intille et al., 2003)

Prior approaches to activity detection

- Detection using audio, visual, electromagnetic or other sensors placed in the environment

- Drawbacks
  - Signal interpretation extremely difficult
  - Difficulty of signal interpretation depends on sensor placement (increasing installation difficulty)
  - Sensors may be perceived as invasive

Prior approaches to activity detection

- Attach sensors to the person
- Can get good recognition of activities with repetitive body motion
(e.g. Bao & Intille, Pervasive 2004)
- Drawbacks
  - Signal interpretation difficult for activities where limb motion highly variable (e.g. cooking)
  - People must remember to wear sensors (potentially a problem for the elderly)

Prior approaches to activity detection

- Attach sensors to the person *and* many objects in the environment
- E.g. Philipose, Fishkin, et al, 2003
  - Recognition of activities RFID reader glove when objects tagged
  - Automatic text and web mining & Monte-Carlo based inference engine

- Drawbacks
  - All items must be tagged
  - Currently requires a glove

Prior approaches to activity detection

- Attach many simple sensors to objects in the environment (but not on the person)

- E.g.
  - MARC Smart home (primarily kitchen)
    - Barger, Alwan, et al. 2002
    - Unsupervised clustering
  - Neural network house
    - Mozer, 1998
    - Neural networks for lighting/HVAC optimization

Our approach to activity detection

- Many simple switch sensors
- Stick on and forget

- First study to our knowledge with:
  - Multiple homes
  - Of non-researchers
  - With 77+ sensors per home
  - For 2 week deployments

Our pilot study goals

- Recognize activities of daily living using a set of small and simple sensors

- Explore which patterns/activities can be detected

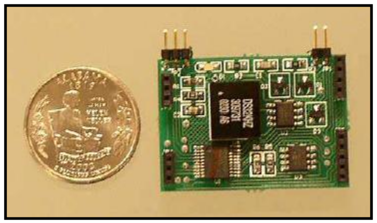
- Learn how to deploy hundreds of sensors in homes for research studies

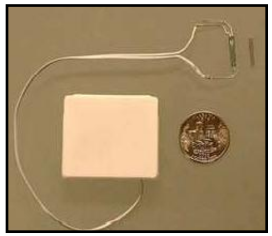
Experiment

- Designed state-change data recorder sensors
- Installed in 2 homes, 2 weeks each
- Collected activity labels with experience sampling
- Collected sensors
- Hand-annotated additional data
- Trained/tested recognition algorithms

System overview

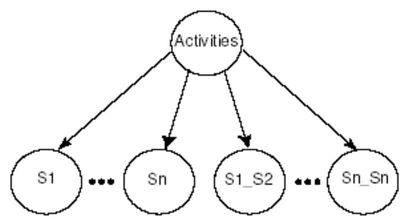
Sensor firings



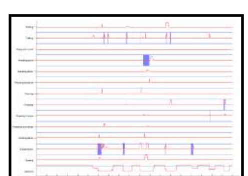


Activity labels

Classifier training

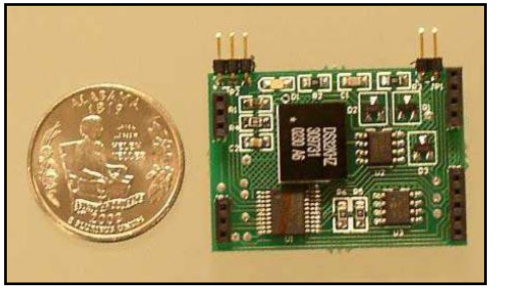


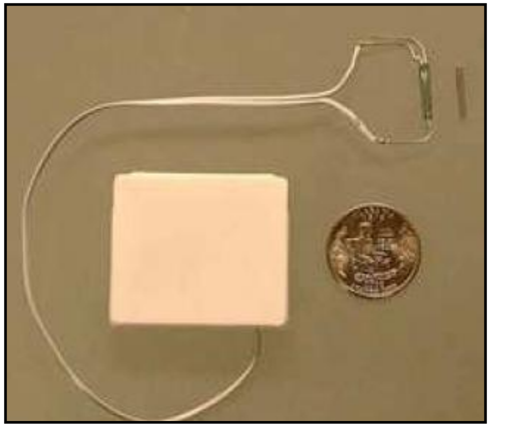
Activity likelihoods



State-change sensors

- Requirements
  - Relatively inexpensive
  - Low power consumption
  - Small size
  - High reliability





- How they work
  - Reed magnet switch
  - Record a time stamp
  - Store data in local EEPROM memory
  - Accurate real-time clock to keep synchronization among sensors

Installation

- 3 hours with small team
- Install: stick-on

Examples

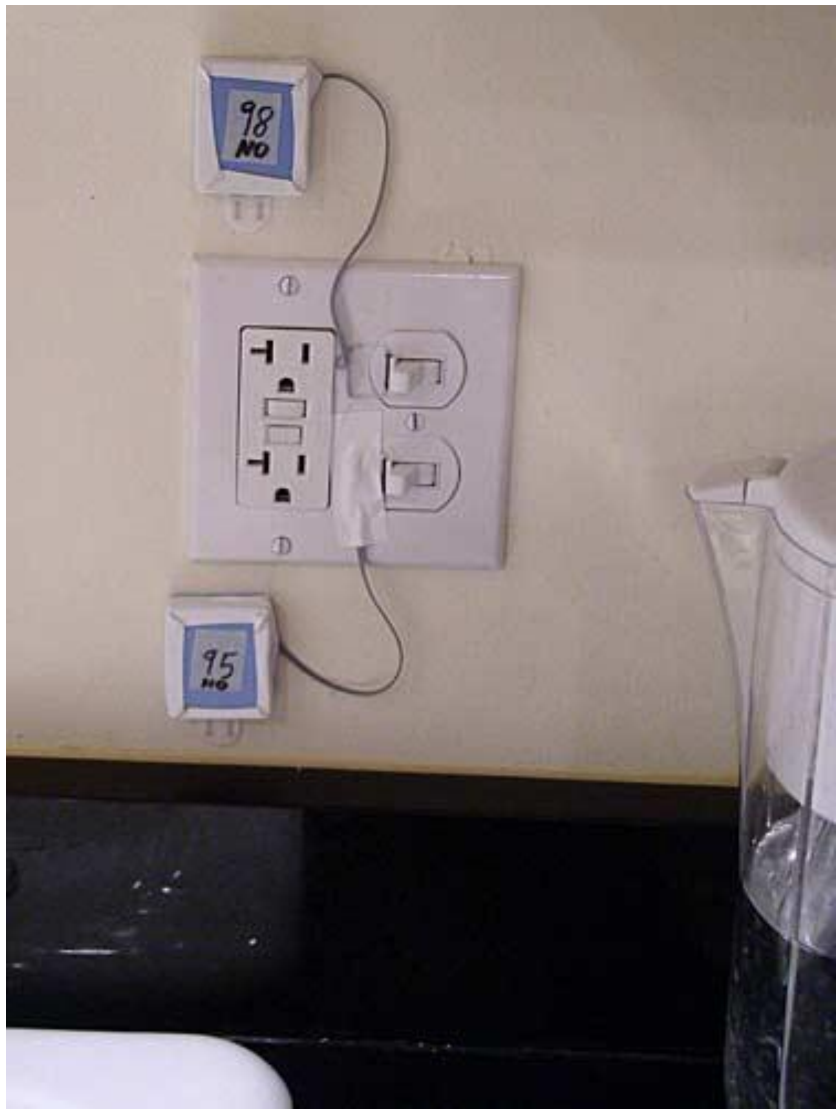

79
NC

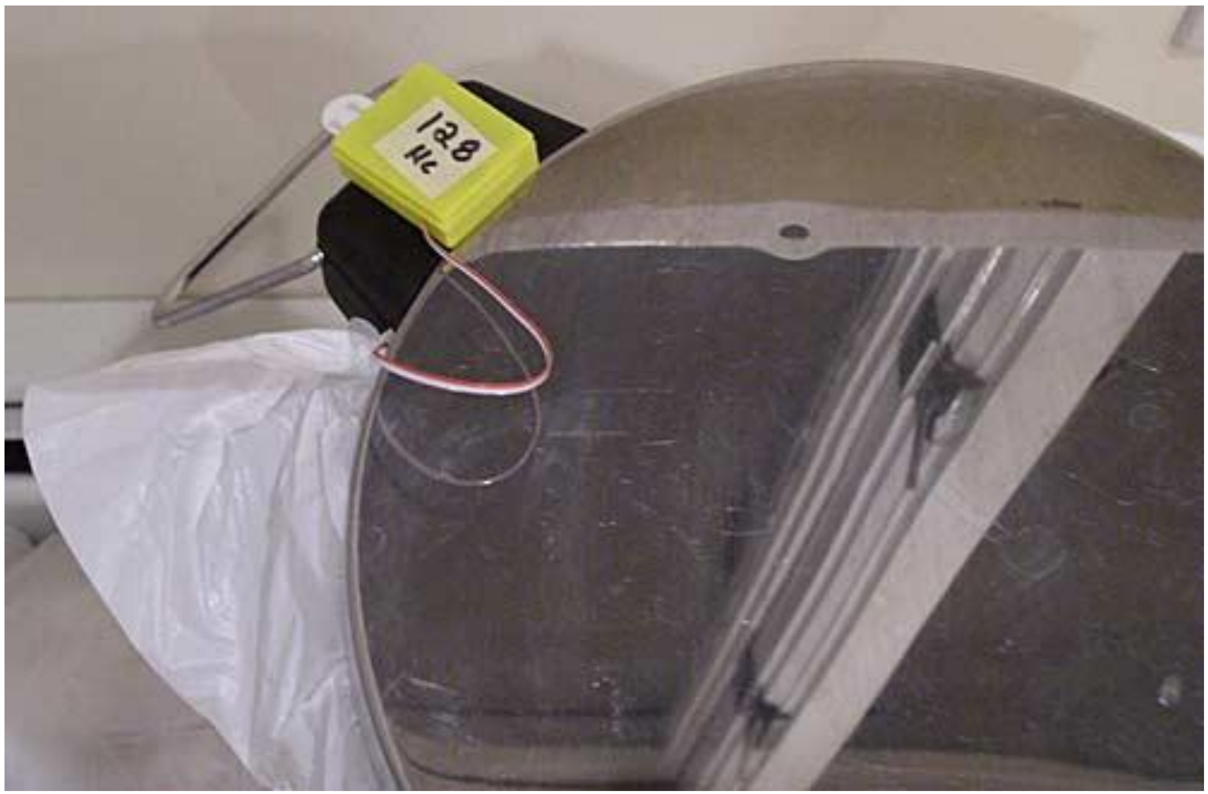

69
NC


OFF


90


REAR
OFF
FRONT
OFF
LITE
LO
HI
99
NO
hb
ON
PRECISE


98
NO
95
NO


128


142
MC

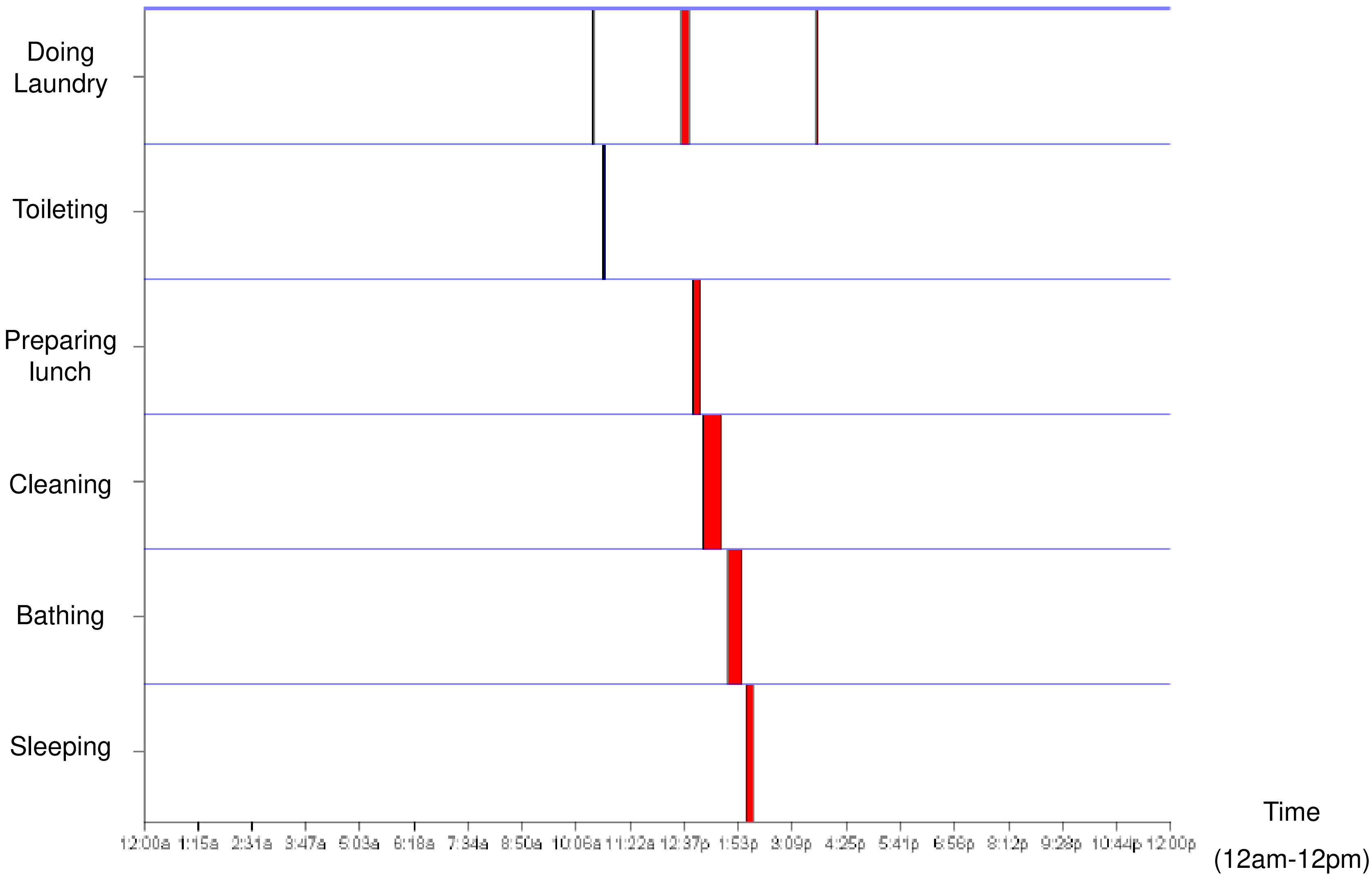

GLAD
Palmolive

Subject used experience sampling

- Attempt to collect training data
  - Samples each 15 minutes
- Questions
  - What were you doing at the beep (Choose from list of 35 activities)
  - For how long were you doing this activity? (<2min, <5min, <10min, >10min)
  - Were you doing another activity before the beep? (Choose from list of 35 activities)

ESM Data Example

Sunday, 3/30/2003



Two pilot studies

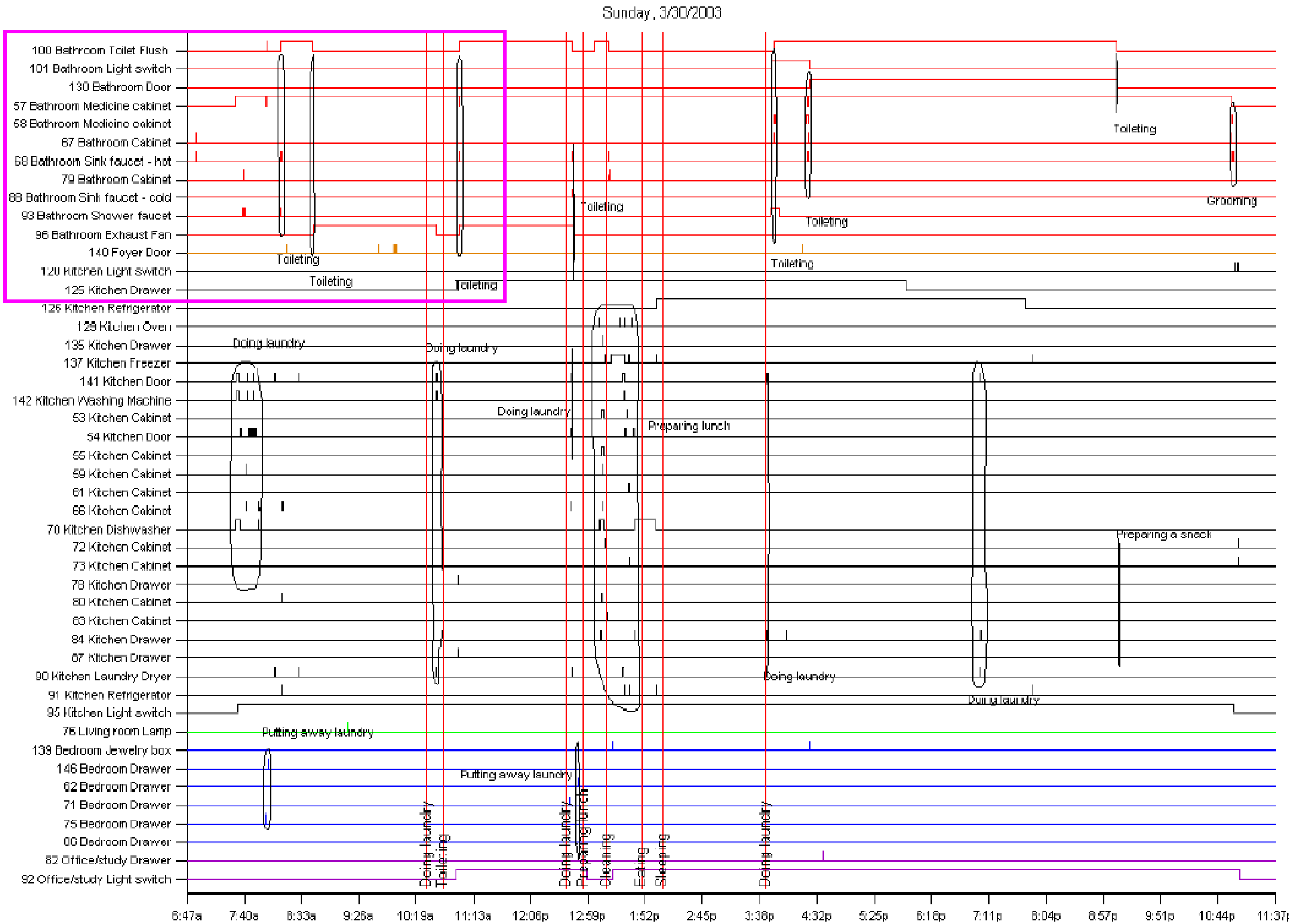
- State-change sensors + ESM
- Two weeks
- Subjects not affiliated with researchers

- Subjects:
  - Professional 30-year-old woman
  - 80-year-old woman

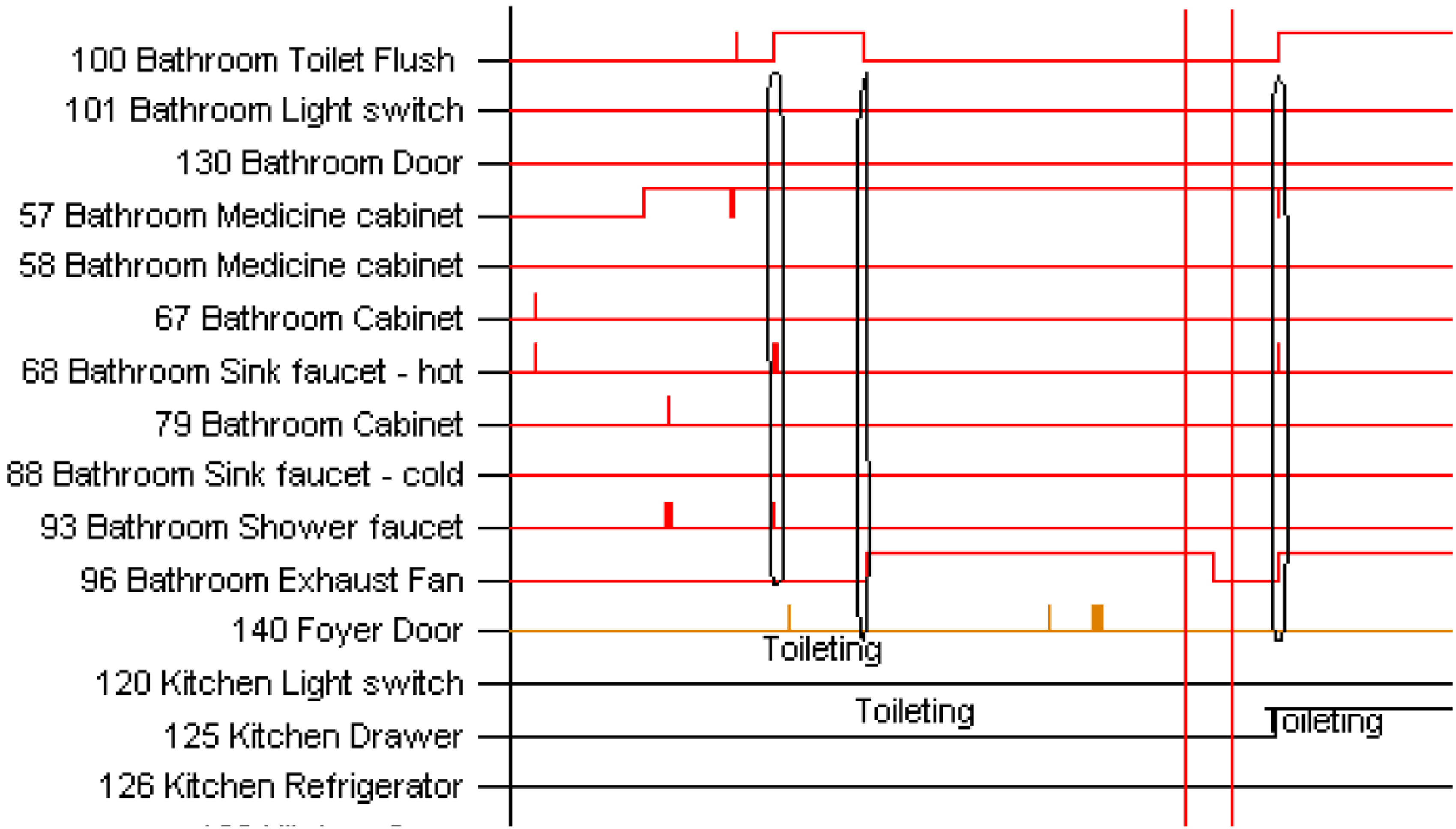
Sensor installation locations

- 77 in home 1
- 84 in home 2

Sensor Data Example



Zoom in



100 Bathroom Toilet Flush
101 Bathroom Light switch
130 Bathroom Door
57 Bathroom Medicine cabinet
58 Bathroom Medicine cabinet
67 Bathroom Cabinet
68 Bathroom Sink faucet - hot
79 Bathroom Cabinet
88 Bathroom Sink faucet - cold
93 Bathroom Shower faucet
96 Bathroom Exhaust Fan
140 Foyer Door
120 Kitchen Light switch
125 Kitchen Drawer
126 Kitchen Refrigerator
Toileting
Toileting
Toileting

Problems with ESM

- Human error
- False starts
- Activities with no sensor activations
- Multitasking
- Short duration activities not captured
- Delays
- Only limited number of labels collected

For these reasons, it was necessary to add labels using indirect observation of the sensor activations(subject+researcher).

(ESM is being improved in current work)

Simplifying assumptions

- When hand labeling activities, we made simplifying assumptions
(which are frequently violated in real life)

  - No multi-tasking except for “Listening to music” and “Watching TV”
  - Only the primary activity is labeled while a person is multitasking
  - Only activities for which sensors could fire were labeled

Activity recognition algorithm desired properties

- Robust to noise
- Allows some variation in sensor firing
- Learned from data, not hand-coded
- Online learning possible
- Model based learning
- Capable of real-time recognition performance
- **Ideal: room location and object type does not need to be recorded during installation**

Recognition algorithm

Naïve Bayesian classifier

- Assumptions
  - Attributes are independent given class
- Hypothesis space
  - Linear decision boundaries
- Advantages
  - Combines advantages of parametric and non-parametric methods.
  - Doesn’t suffer from curse of dimensionality (features/examples)
  - Fast training and classification
- Disadvantages
  - Features cannot interact in interesting ways

Feature extraction

Set of binary features

- Sensor fired
- Temporal information
  - Before, after
  - Duration

Feature description	Example
exist($sensorA$, $start$, end)	Sensor A fires within time interval
before($sensorA$, $sensorB$, $start$, end)	Sensor A fires before sensor B within time interval
before($sensorTypeA$, $sensorTypeB$, $start$, end)	Sensor in a drawer fires before a sensor in the fridge within time interval
before($sensorLocationA$, $sensorLocationB$, $start$, end)	Sensor in kitchen fires before sensor in bathroom within time interval

Feature extraction

- Sensor fired
- Temporal information
  - Before, after
  - Duration

Sensor 68 → Sensor 50

Feature description	Example
exist($sensorA$, $start$, end)	Sensor A fires within time interval
$\boxed{\text{before}(sensorA, sensorB, start, end)}$	Sensor A fires before sensor B within time interval
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Feature extraction

- Sensor fired
- Temporal information
  – Before, after
  – Duration

Sensor at drawer → Sensor at fridge

Feature description	Example
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before($sensorLocationA$, $sensorLocationB$, $start$, end)	Sensor in kitchen fires before sensor in bathroom within time interval

Feature extraction

- Sensor fired
- Temporal information
  - Before, after
  - Duration

Sensor in kitchen → Sensor in Bathroom

Feature description	Example
exist($sensorA$, $start$, end)	Sensor A fires within time interval
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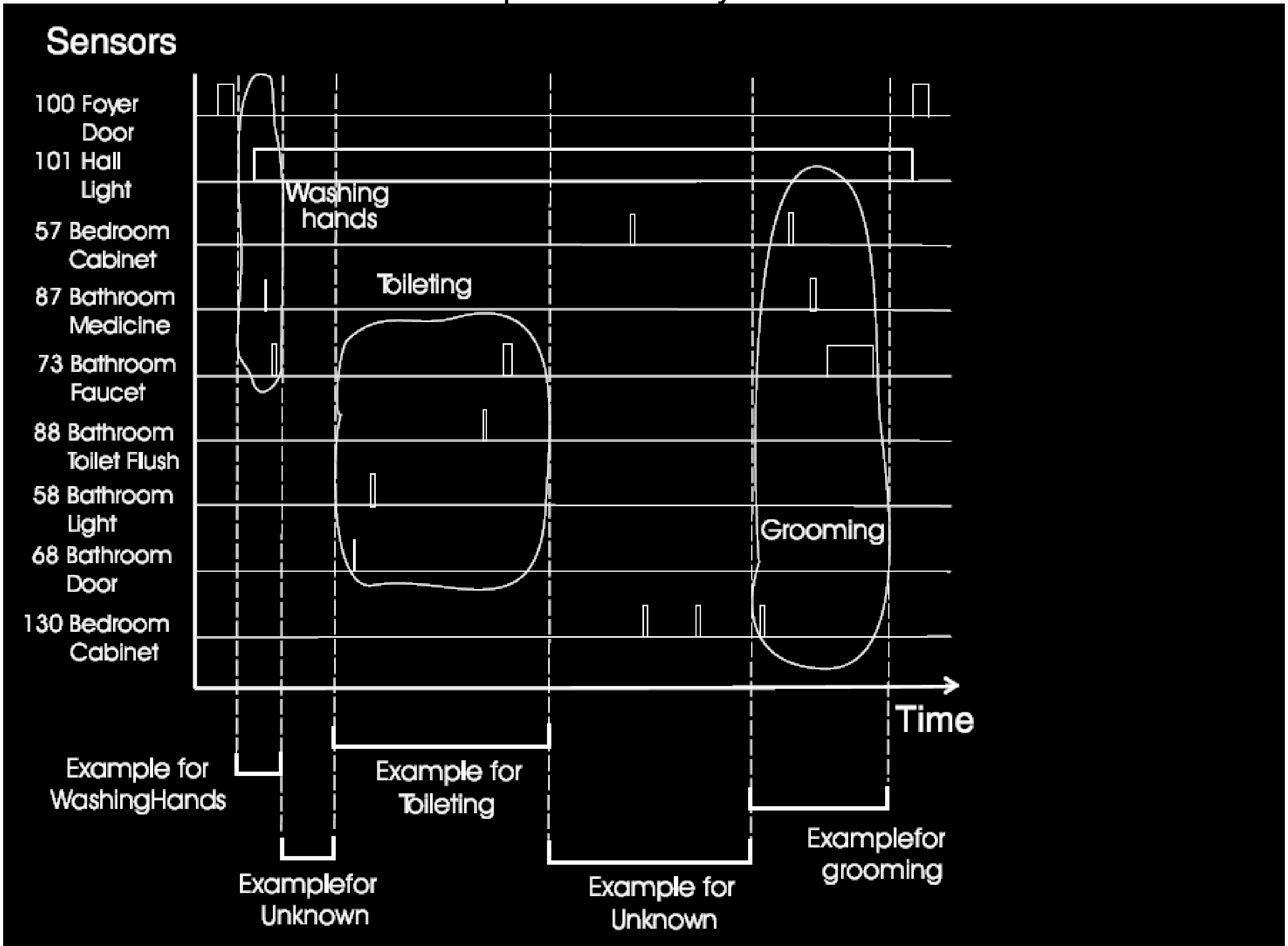
Feature extraction

-Incorporate temporal information
-Incorporate activity duration



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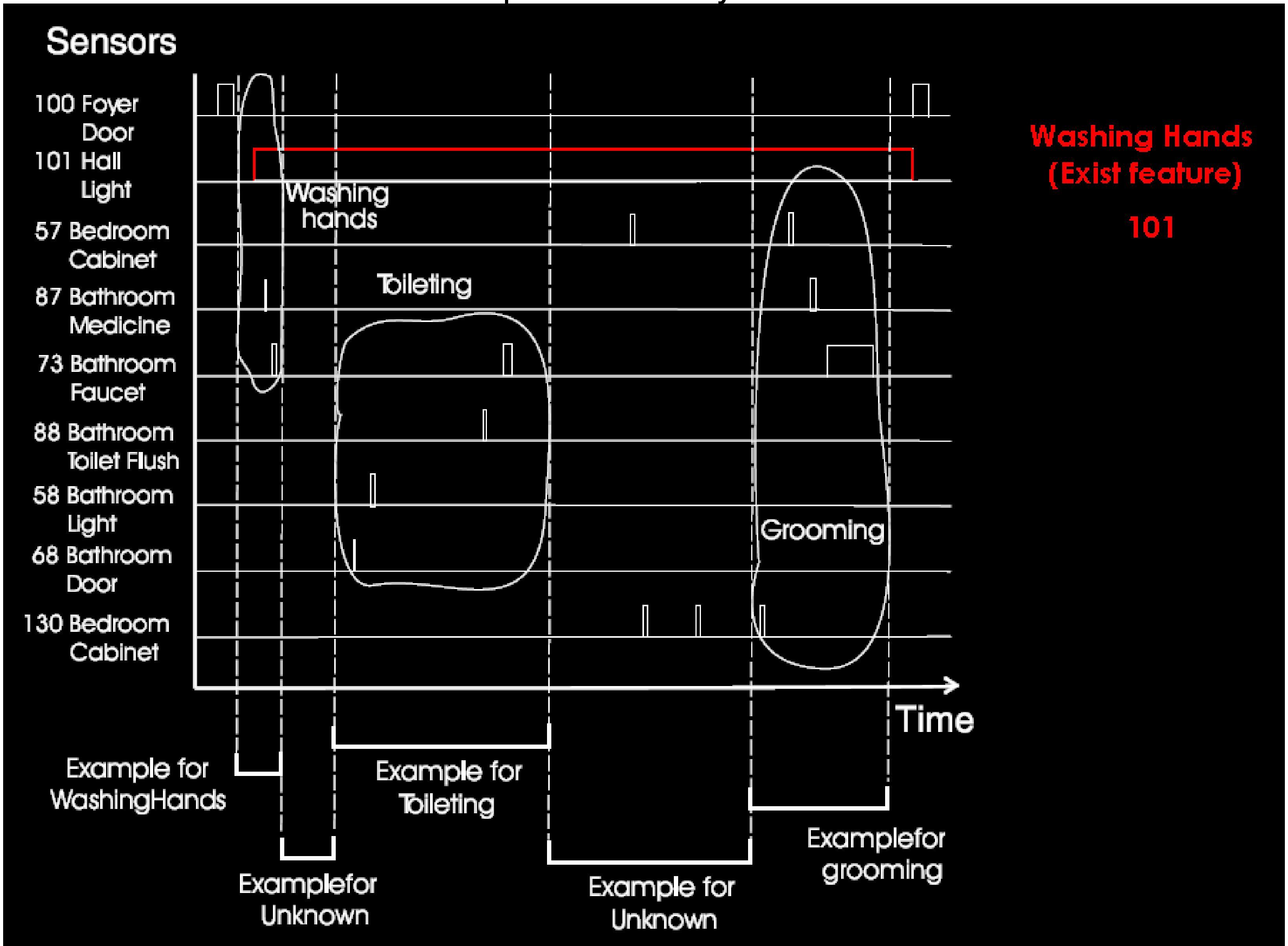

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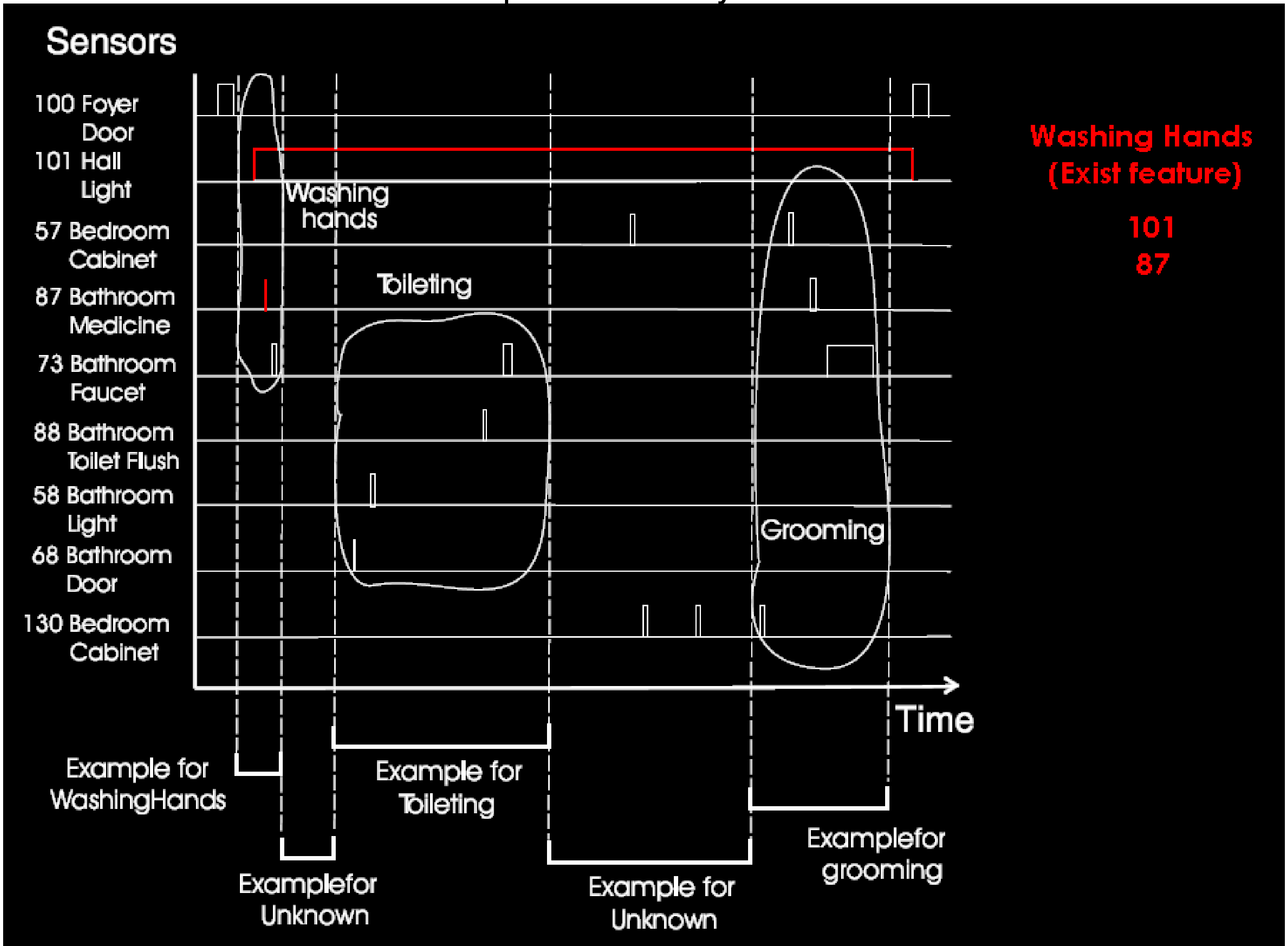

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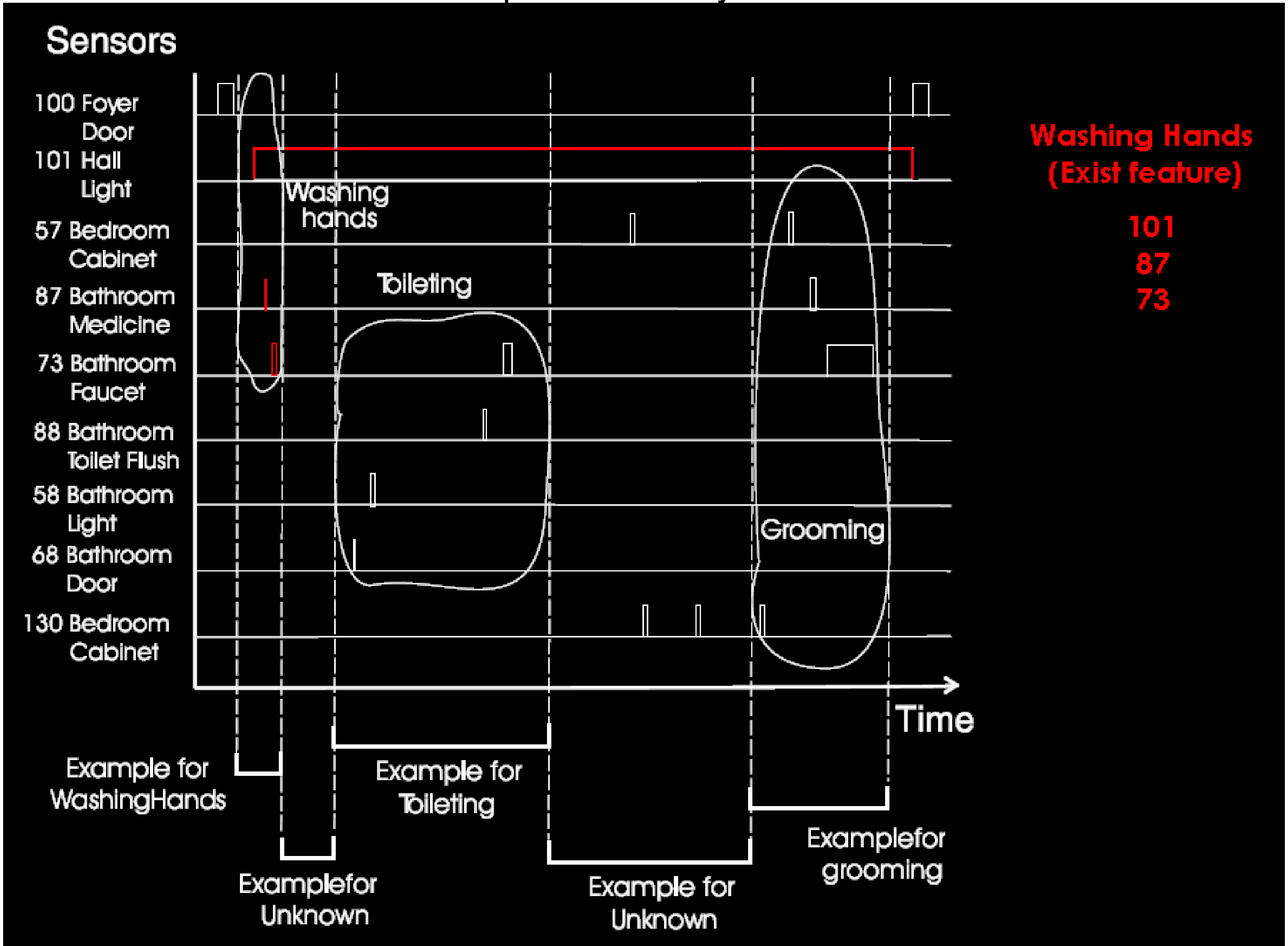

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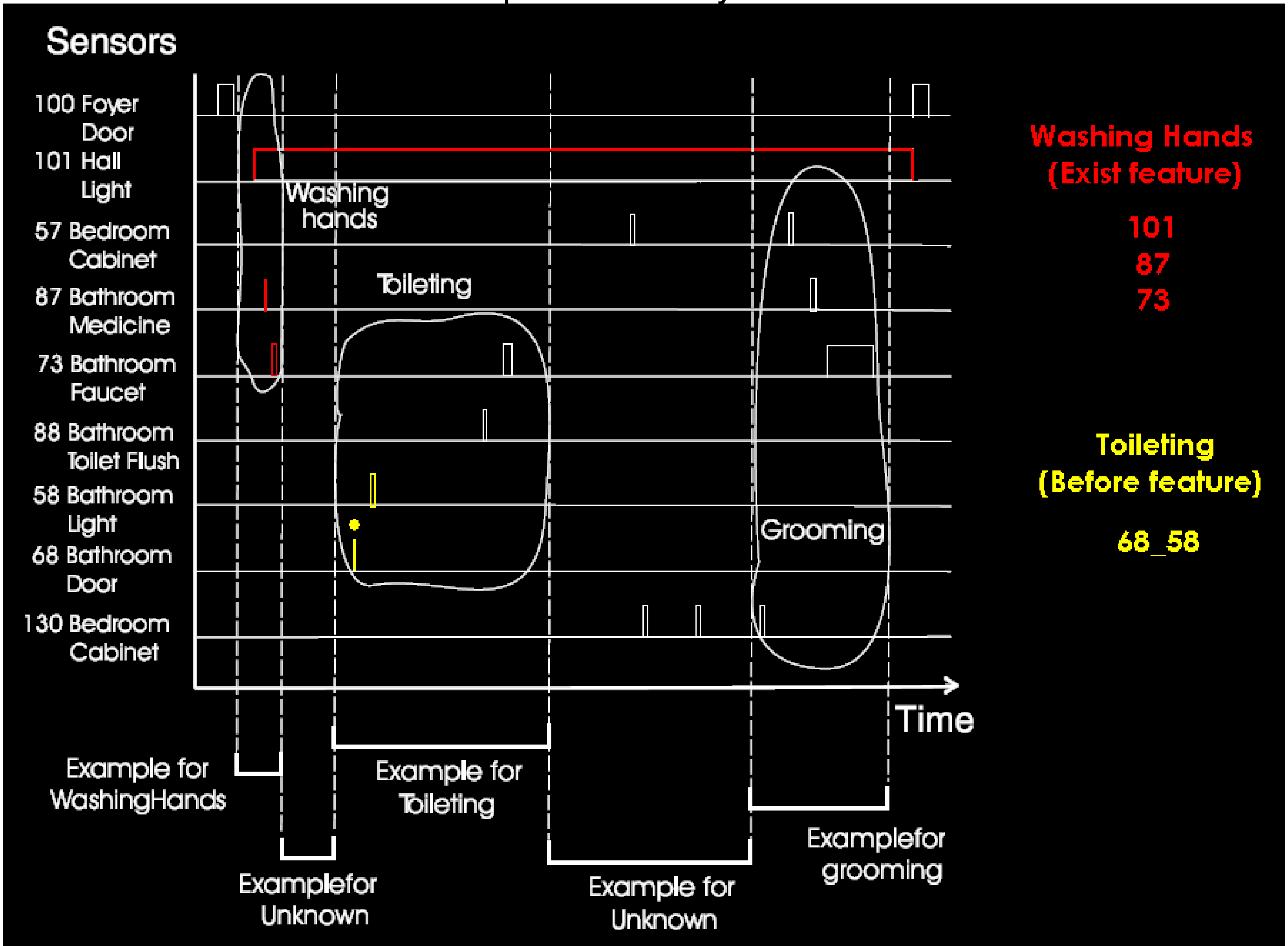

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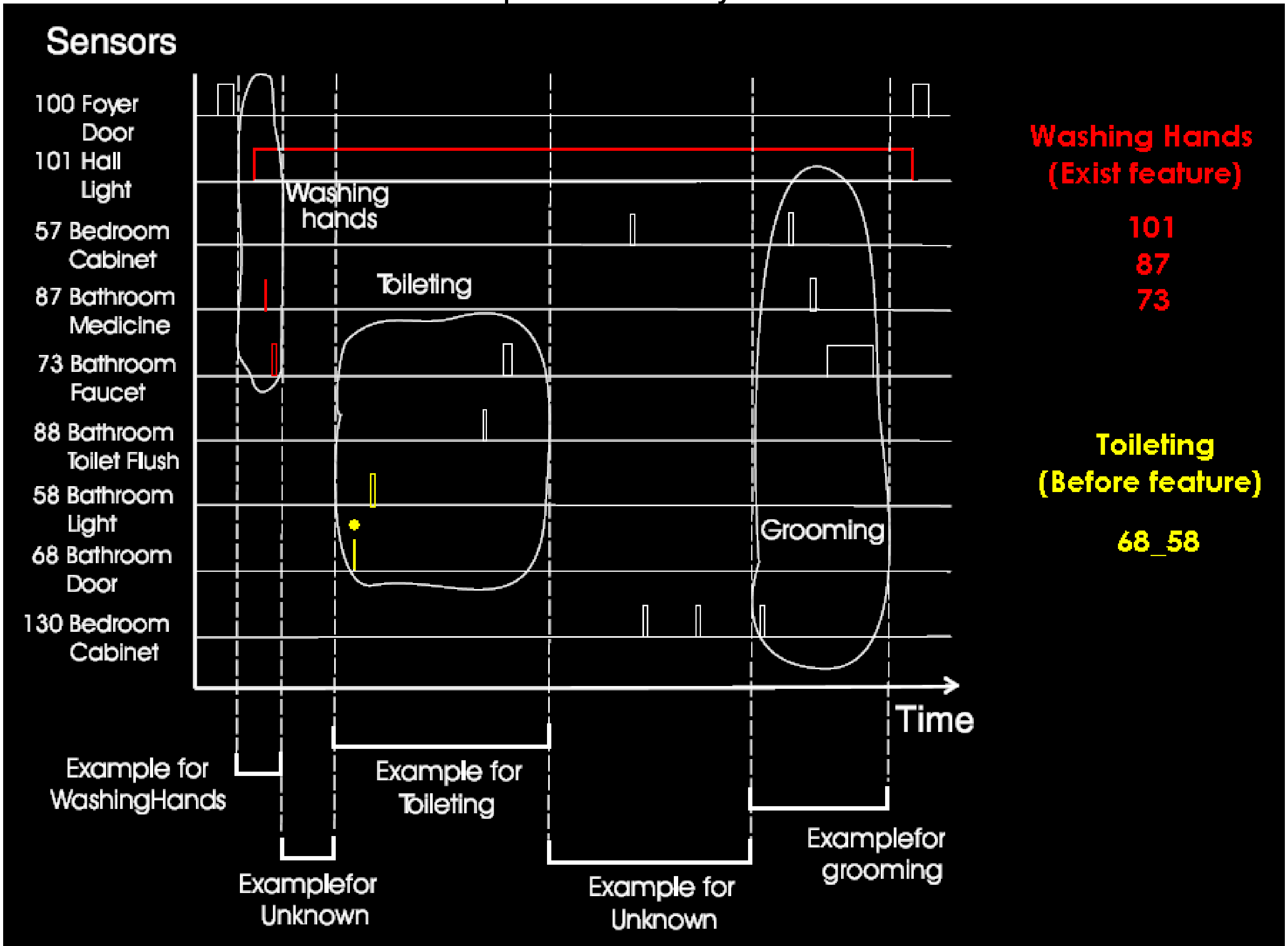

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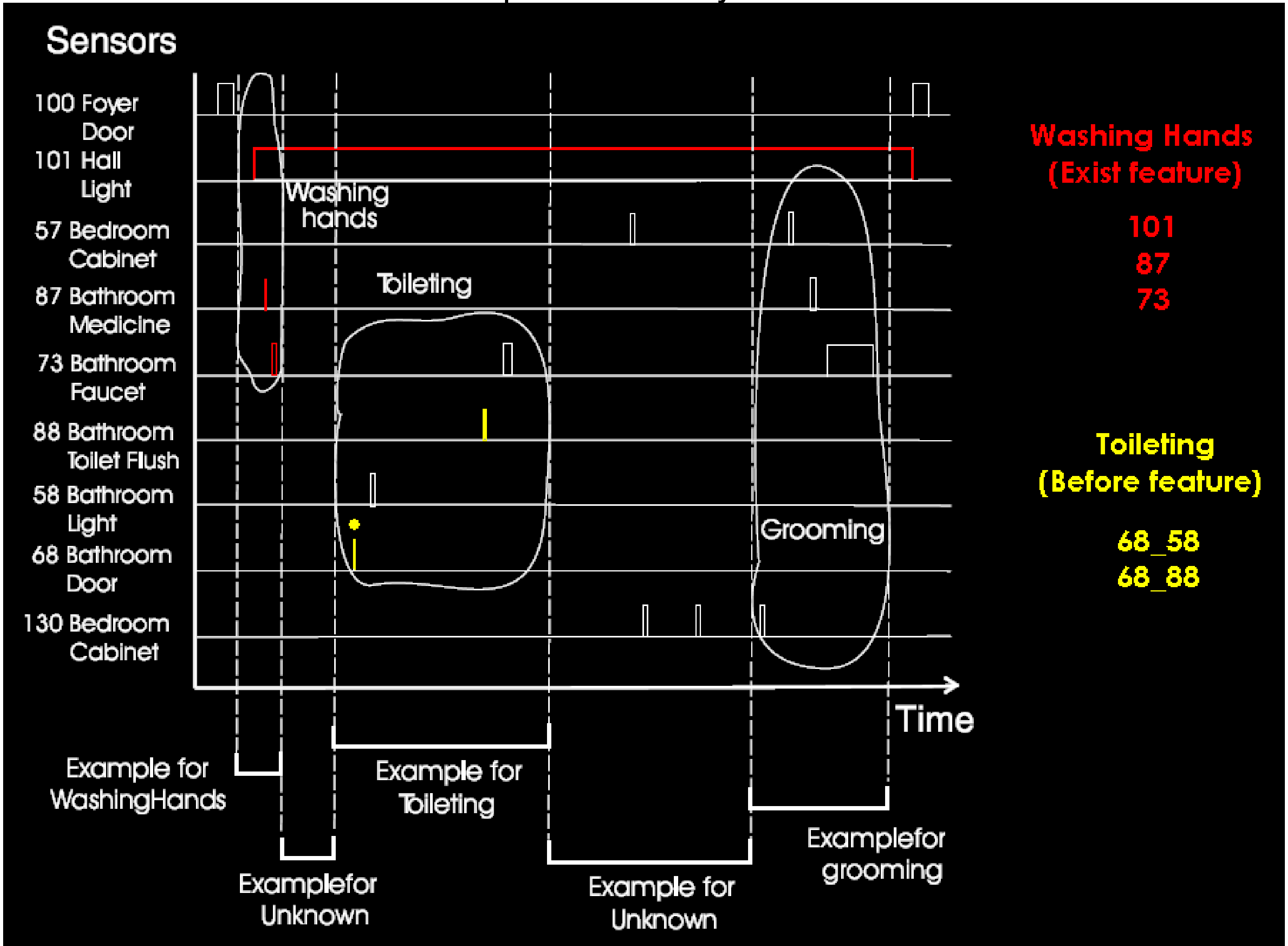

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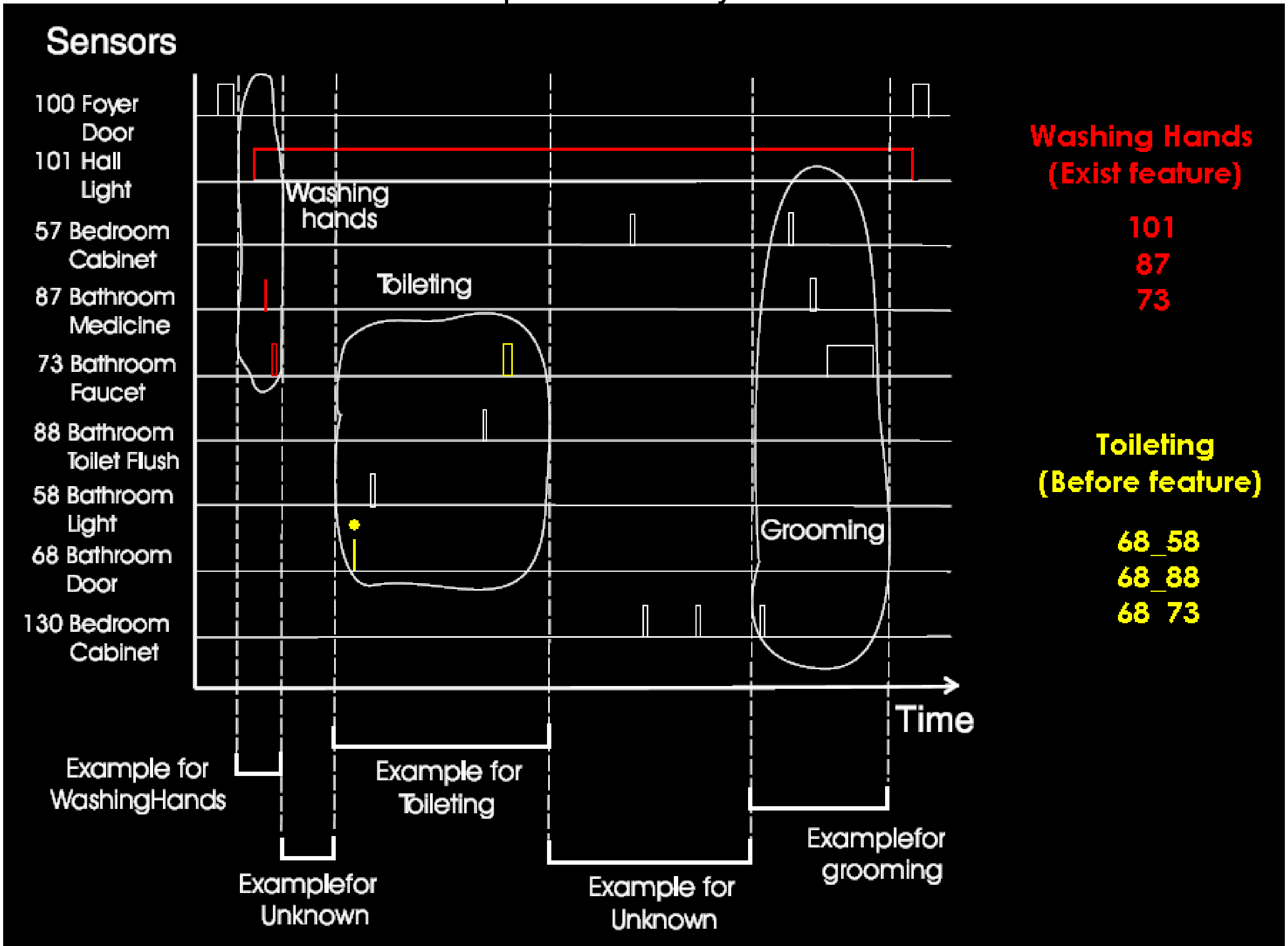

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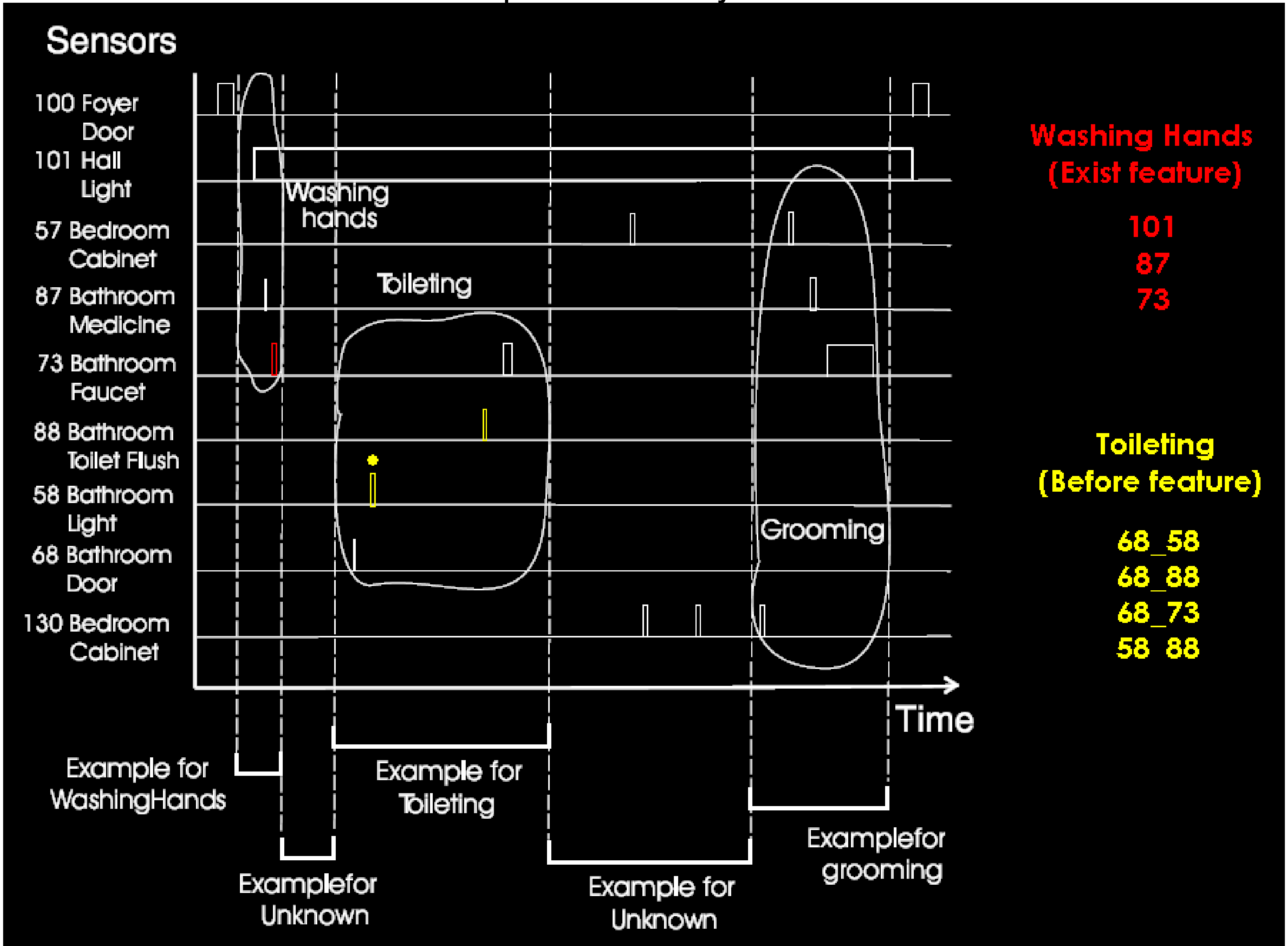
-Incorporate activity duration



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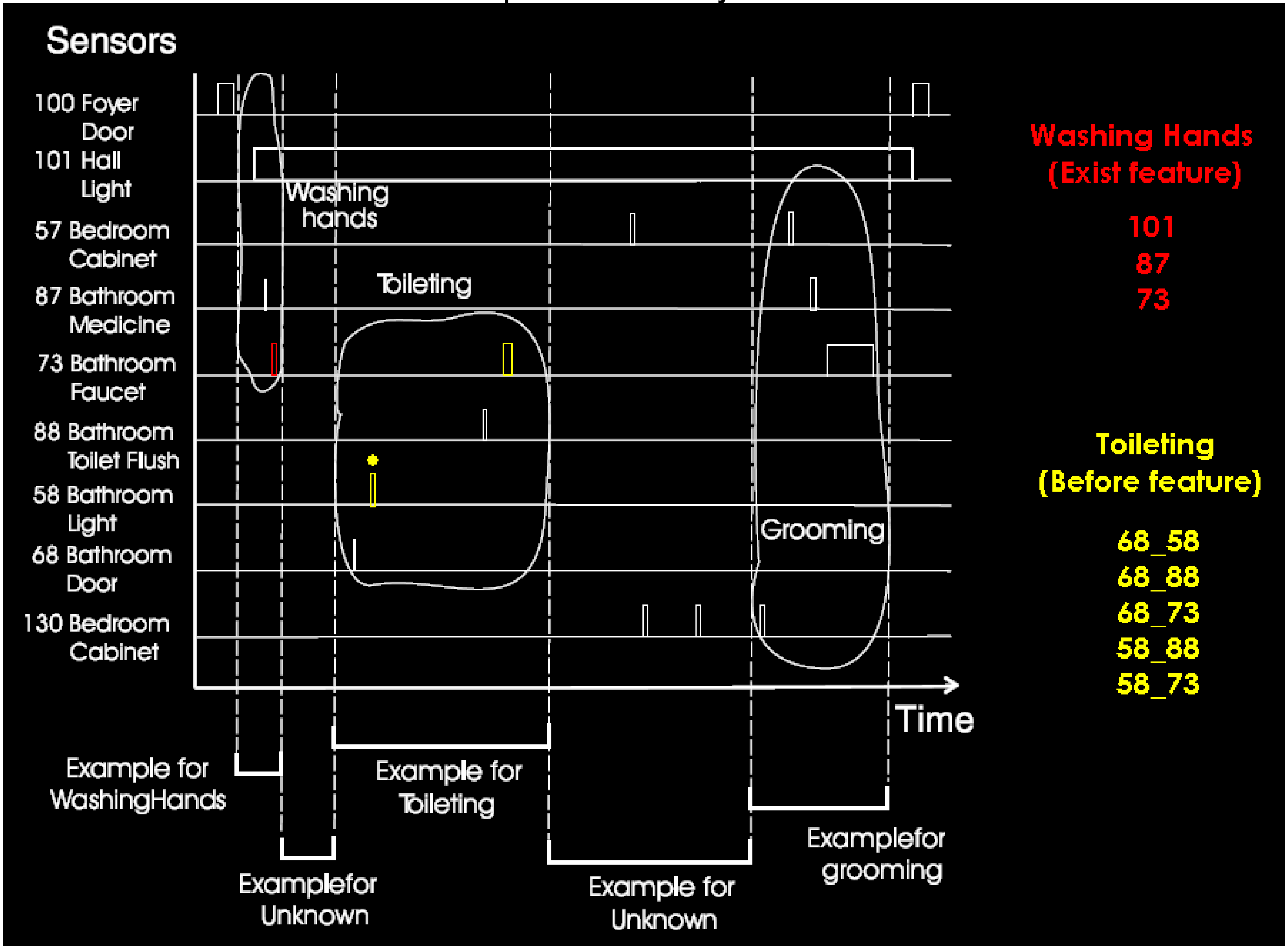

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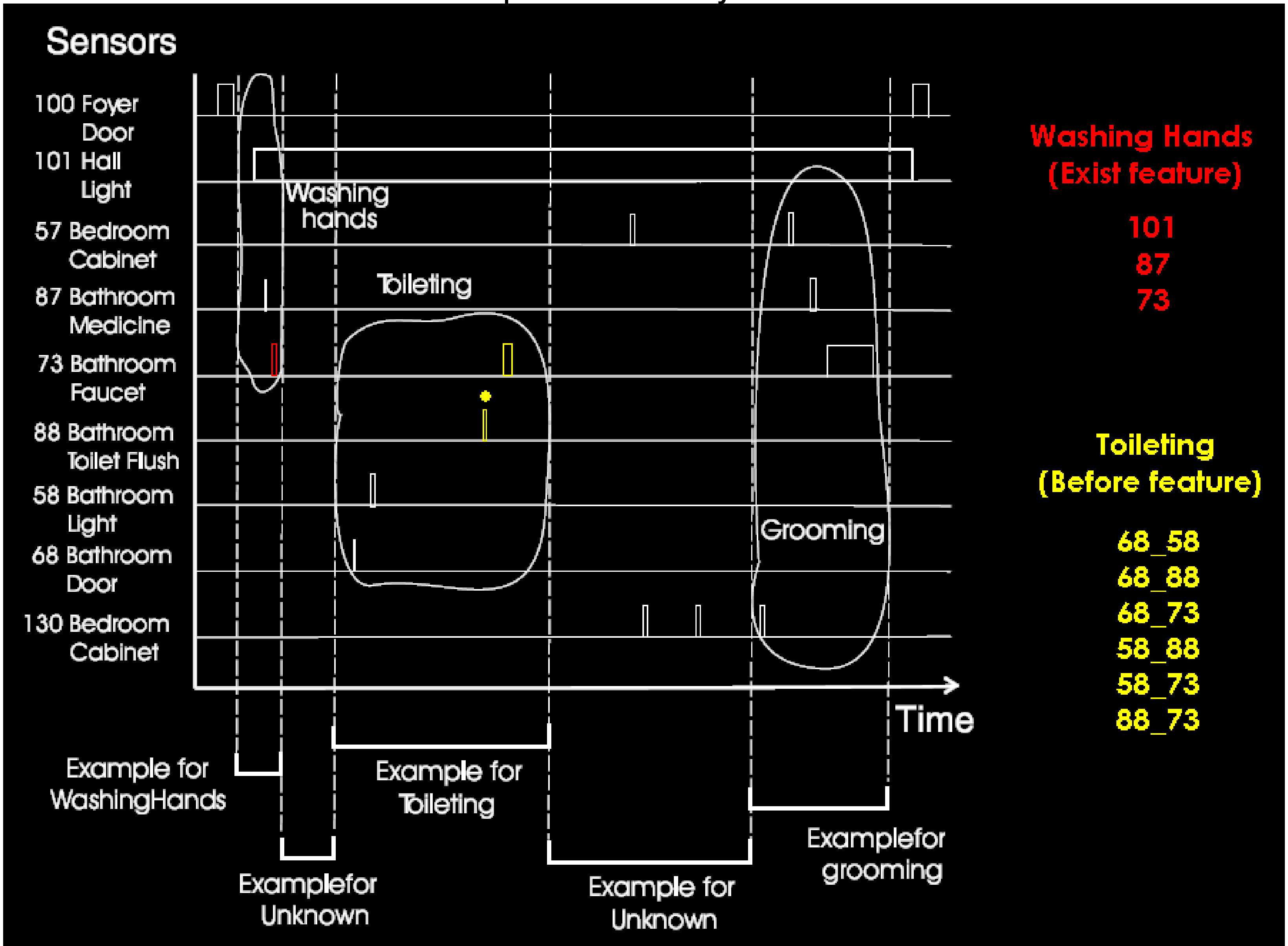
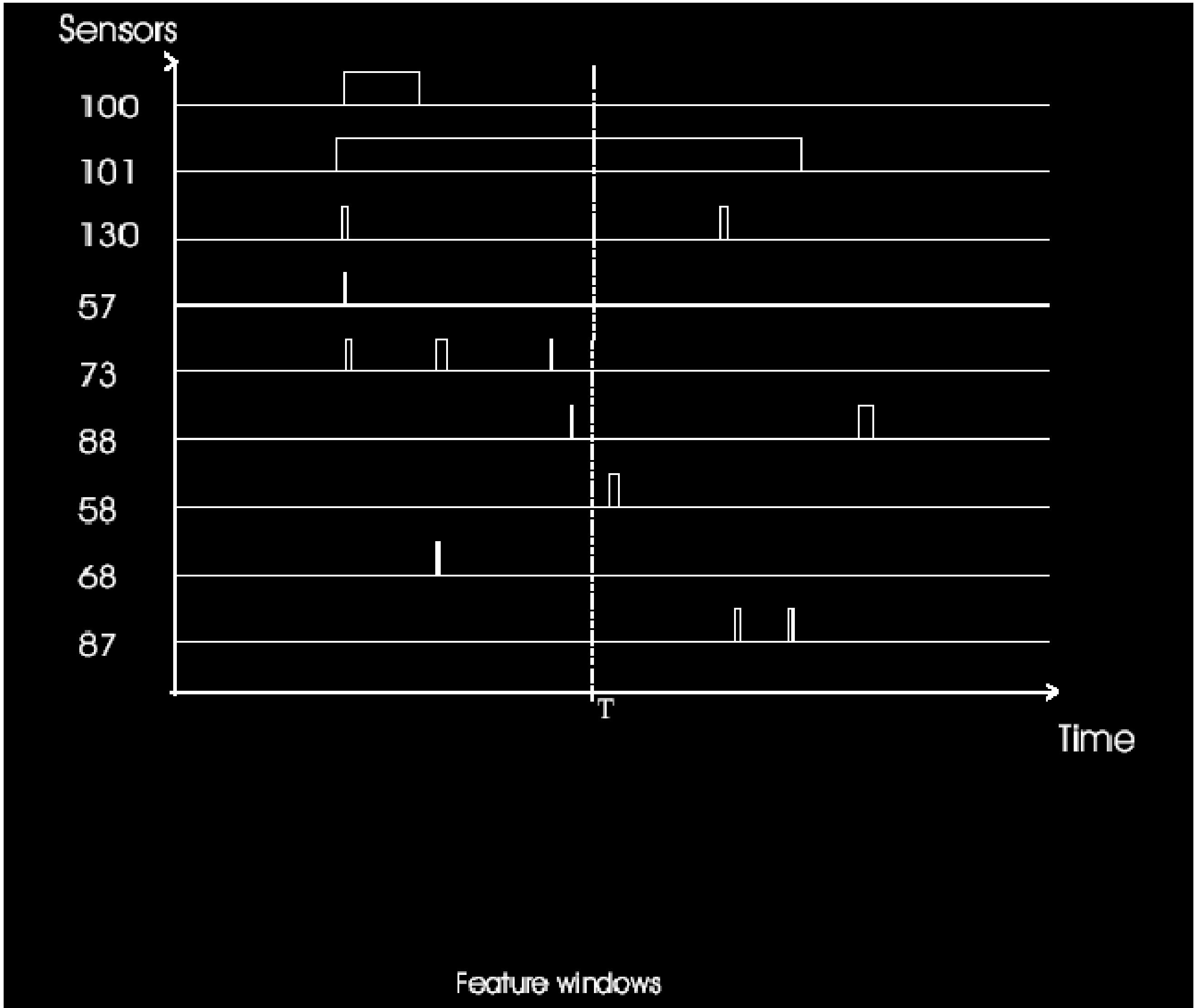
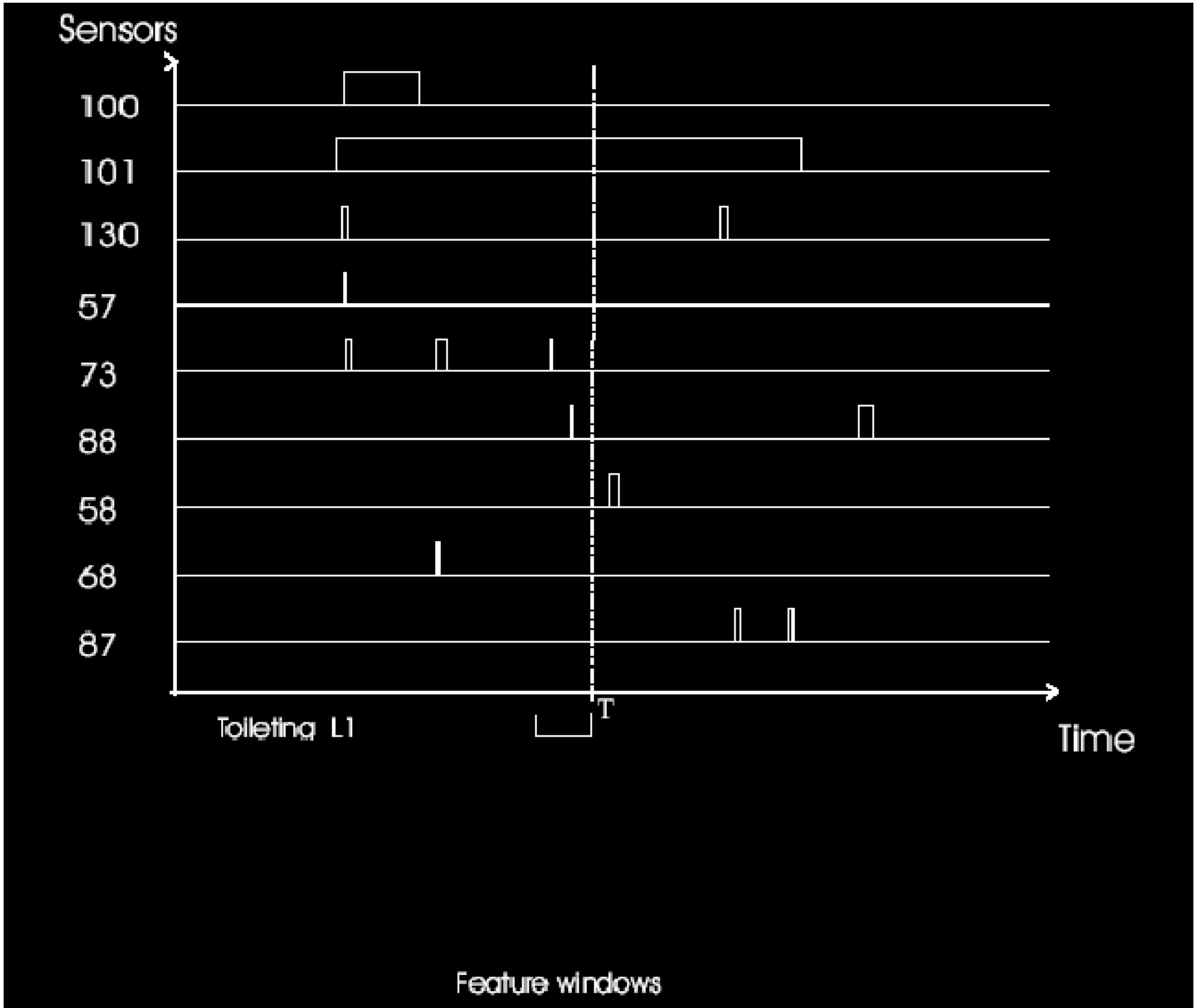


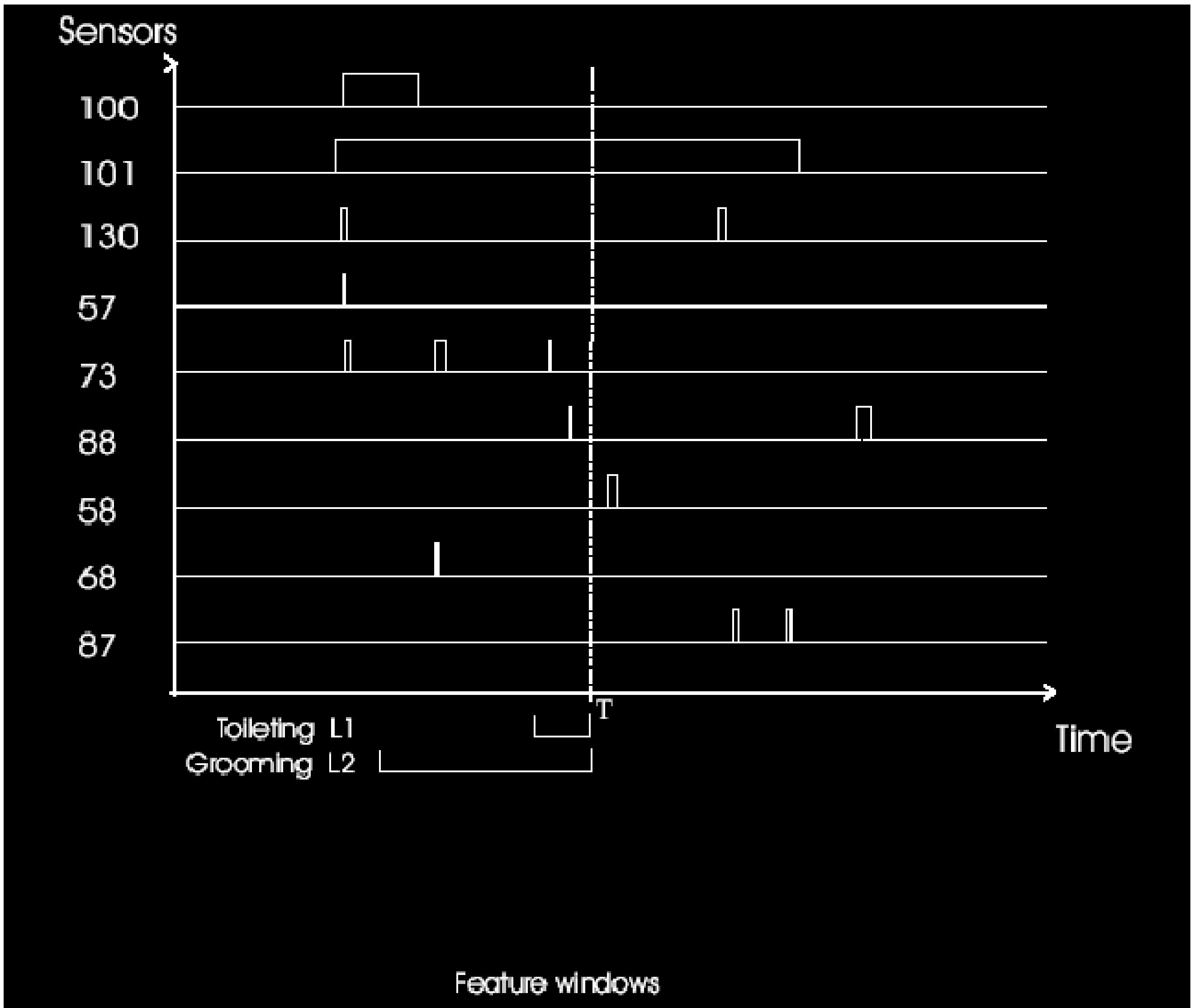
Activity duration & feature calculation



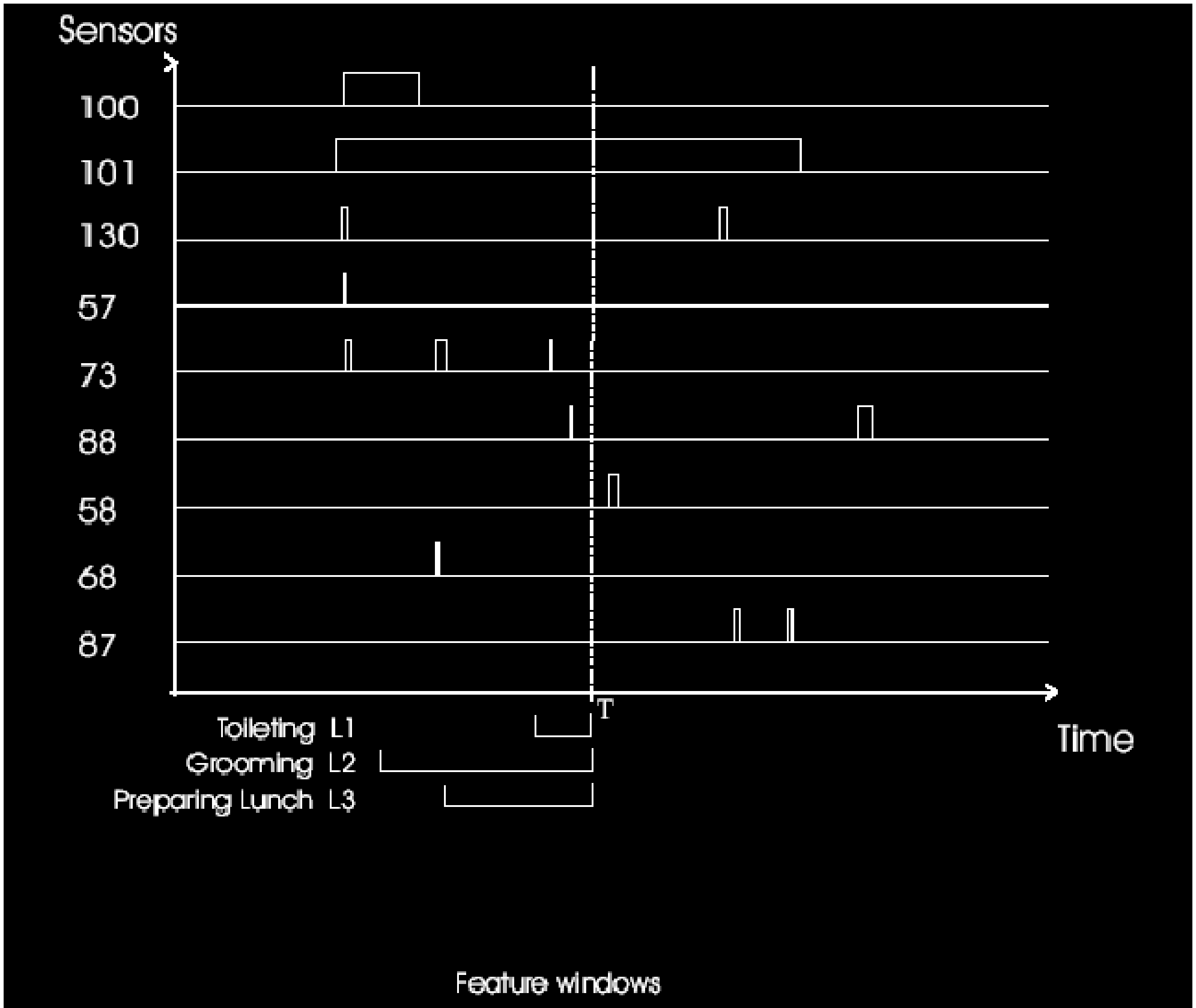
Activity duration & feature calculation



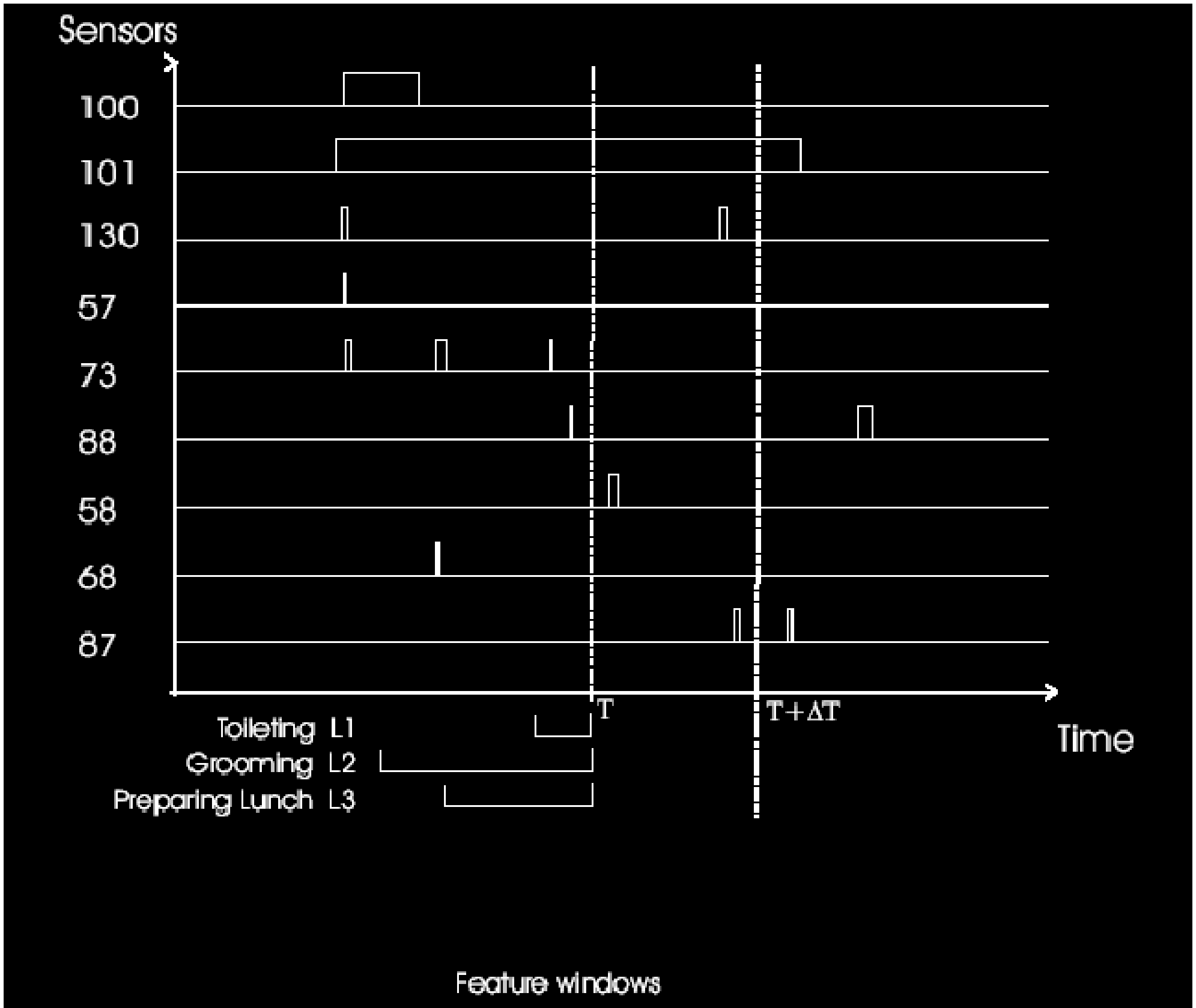
Activity duration & feature calculation



Activity duration & feature calculation



Activity duration & feature calculation



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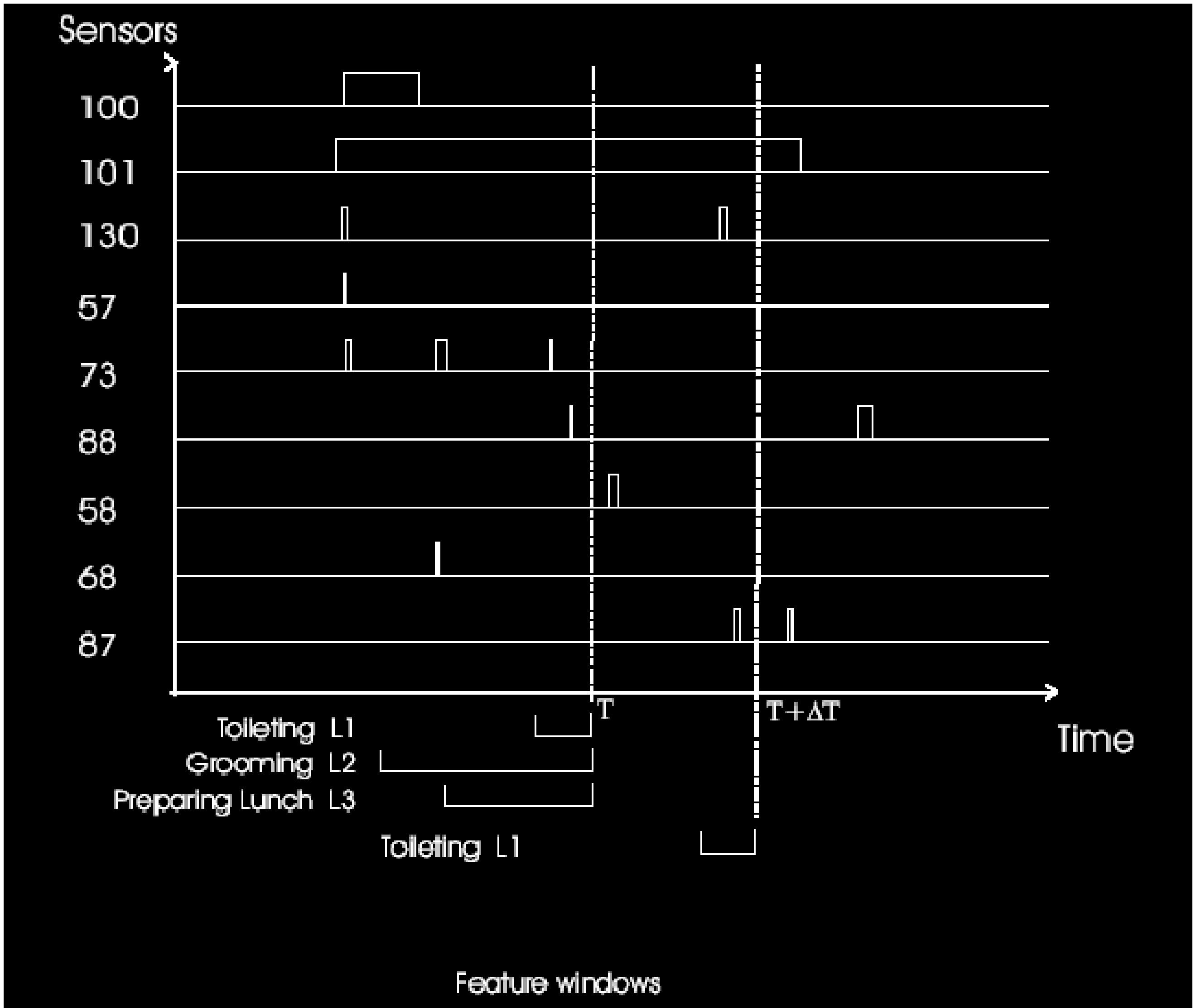
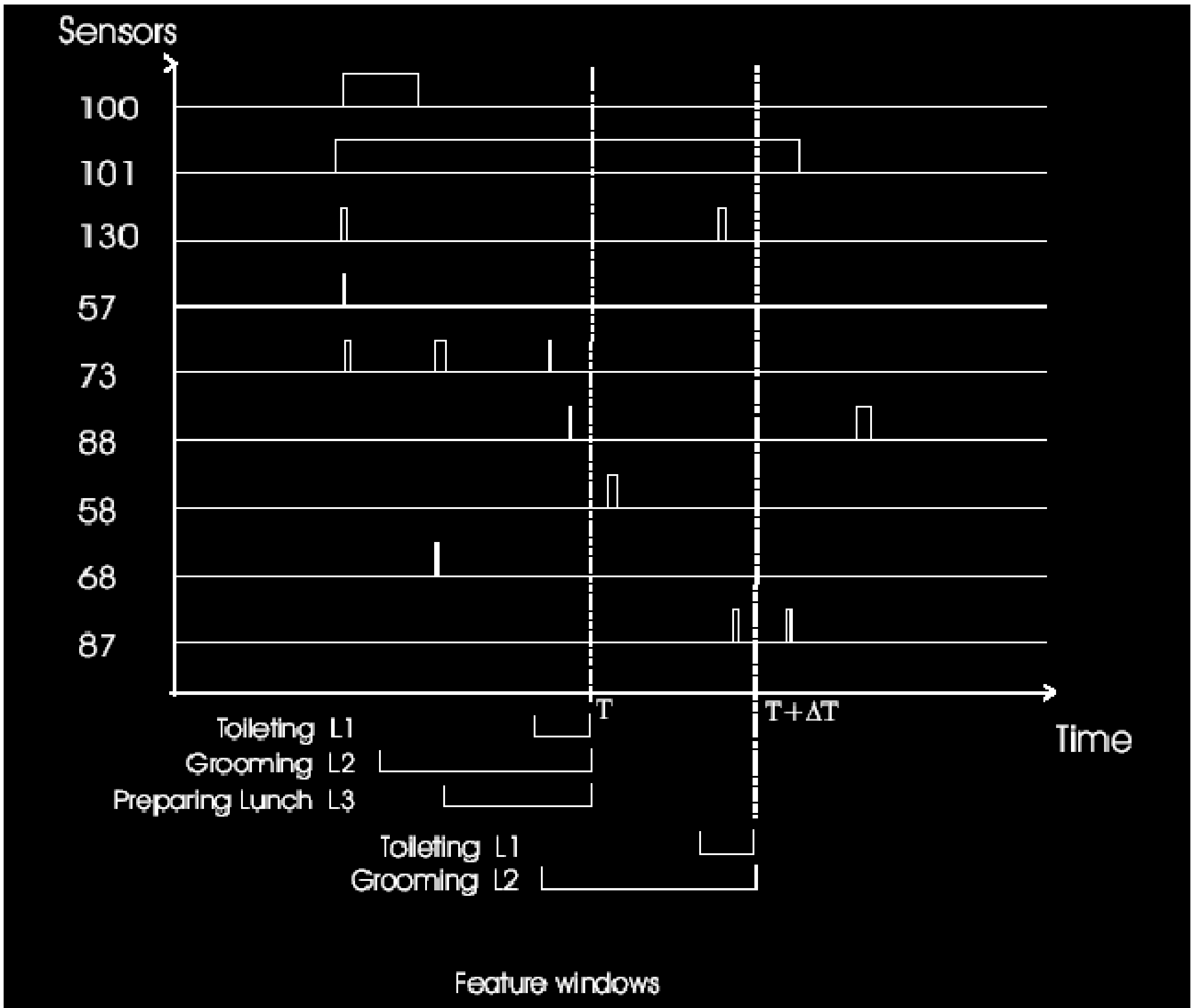


Activity duration & feature calculation



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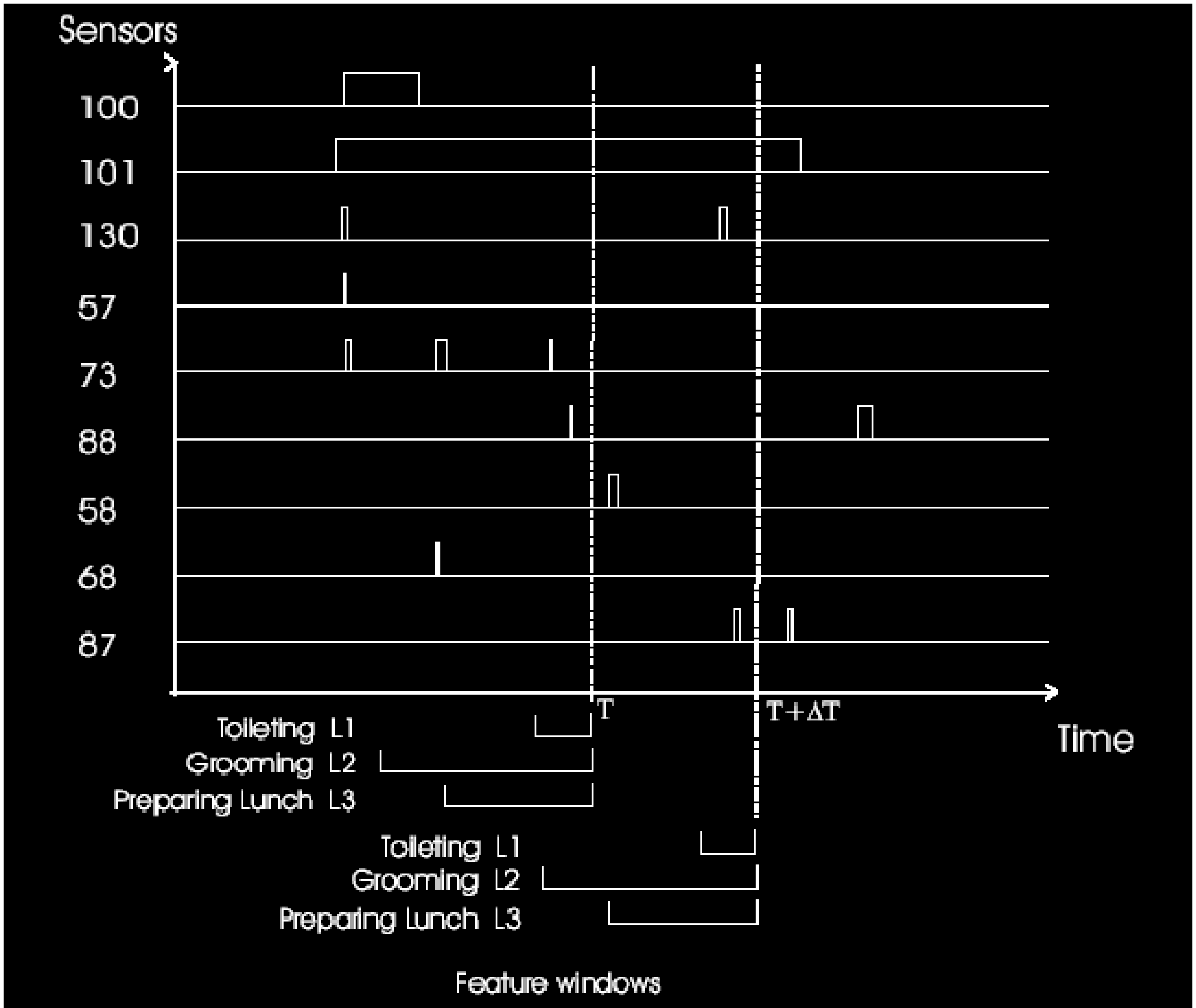
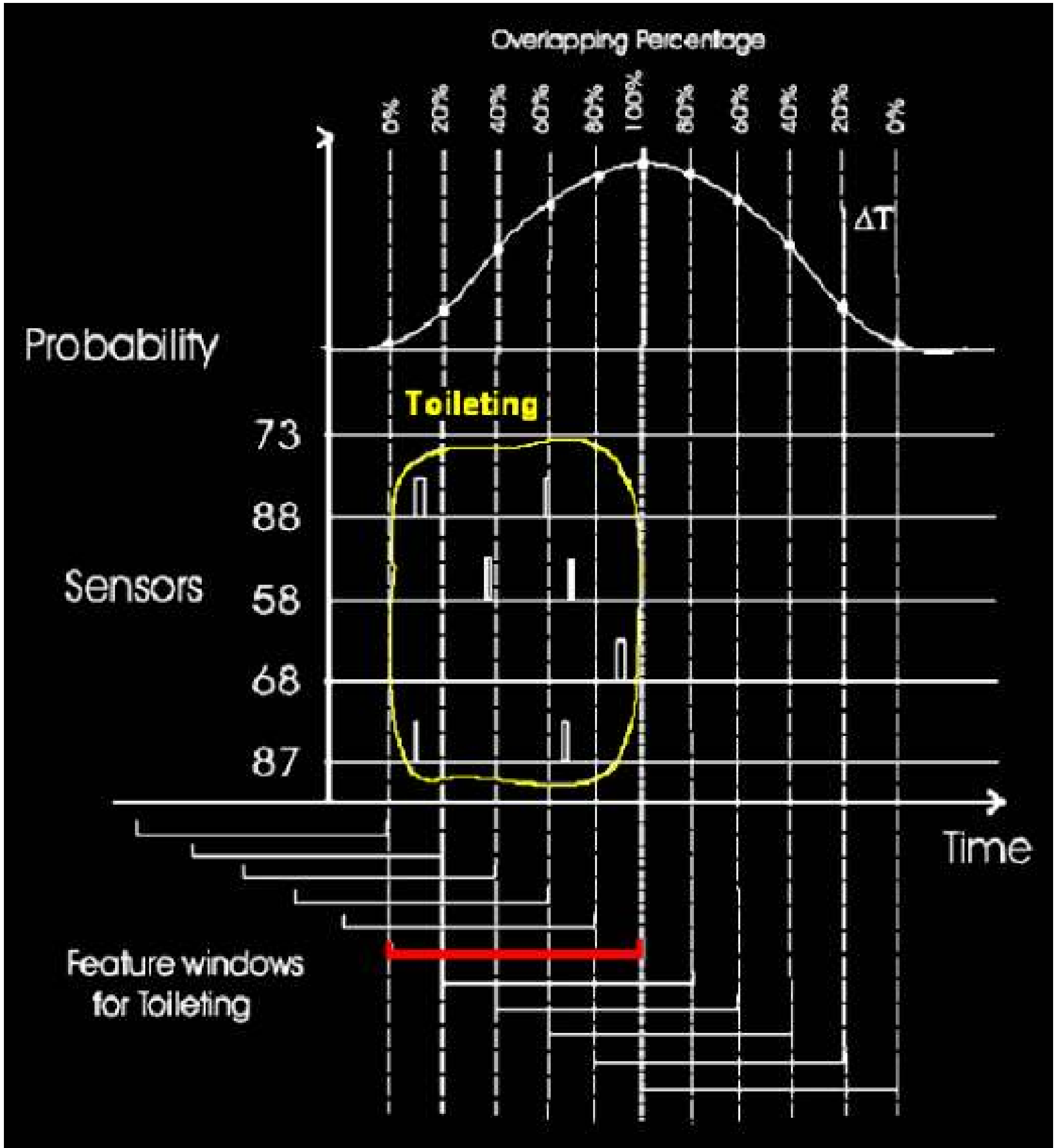


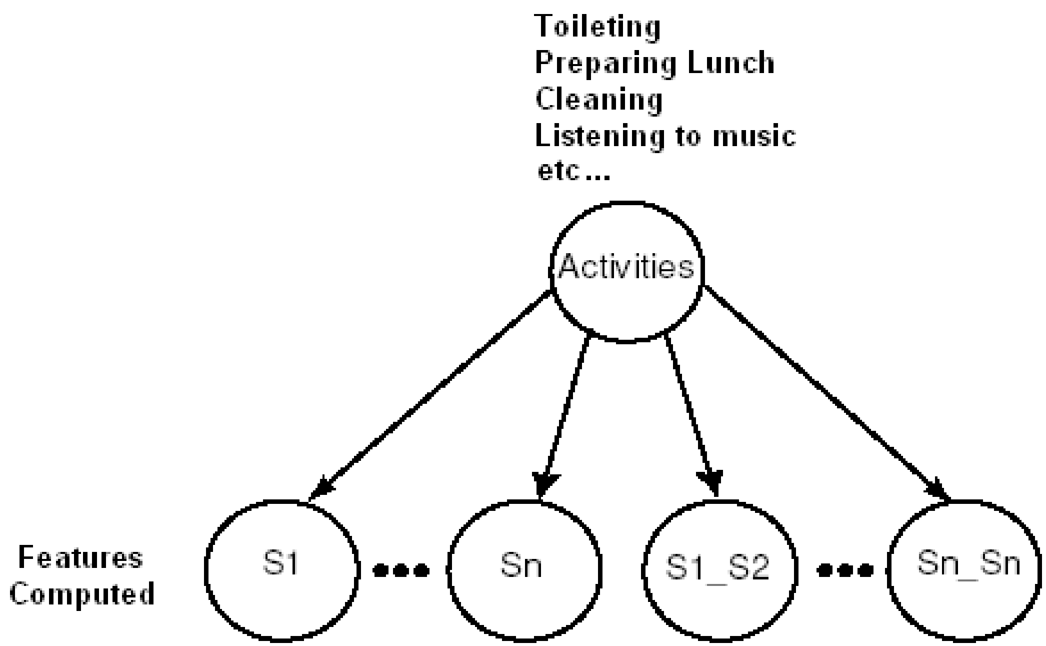
Probability generation



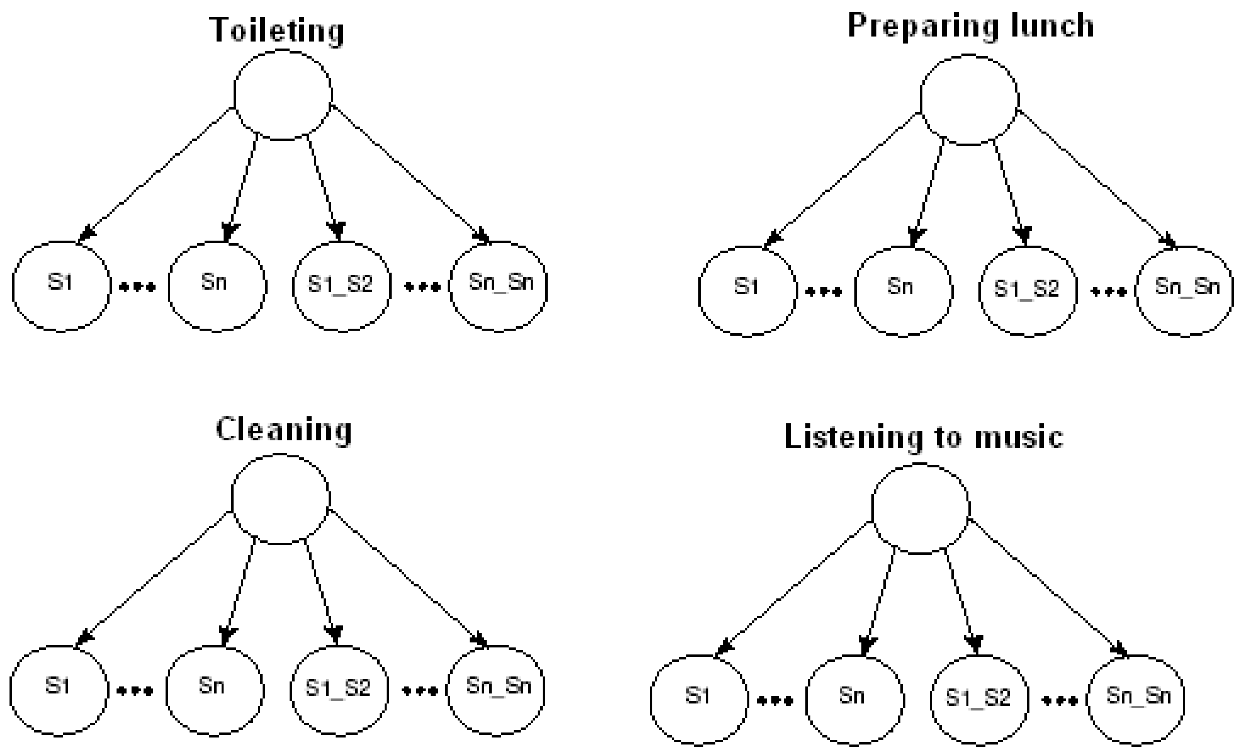
Activity classifiers

- Two versions
- One Multiclass Naïve Bayes Classifier
  - The parent node represent all the activities to classify
- Multiple Binary Naïve Bayes Classifiers
  - Multiple networks in which each parent node represents an activity “happening” or not happening

Multiclass naïve Bayesian classifier



Multiple binary naïve Bayesian classifiers



Evaluation of the algorithms

Diffucult:

- People label activities differently

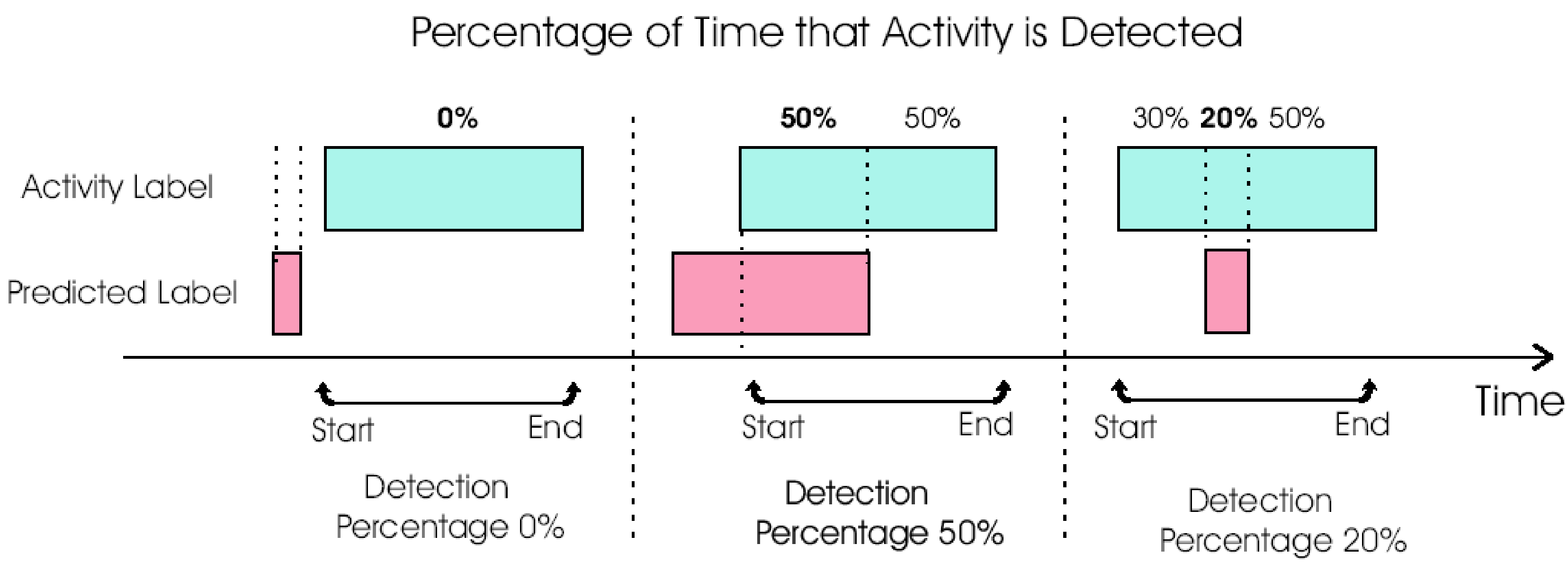
Three methods

Best evaluation method depends upon the application that needs the data

- Activity detected $\rightarrow$ Monitoring
- Percentage time $\rightarrow$ Judging independence

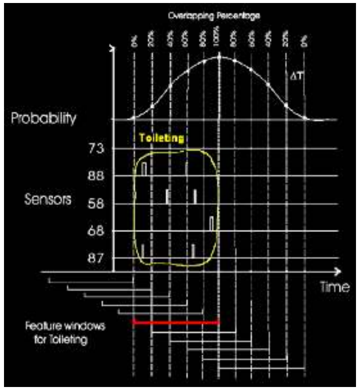
Methods of evaluation

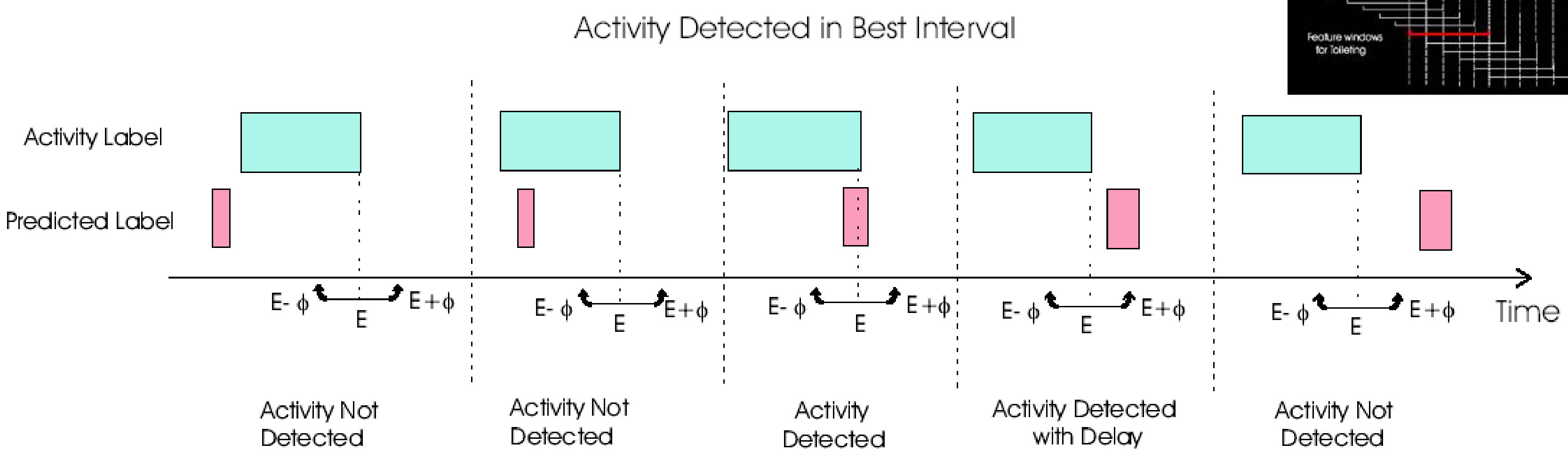
1. Percentage of time activity is detected



Methods of evaluation

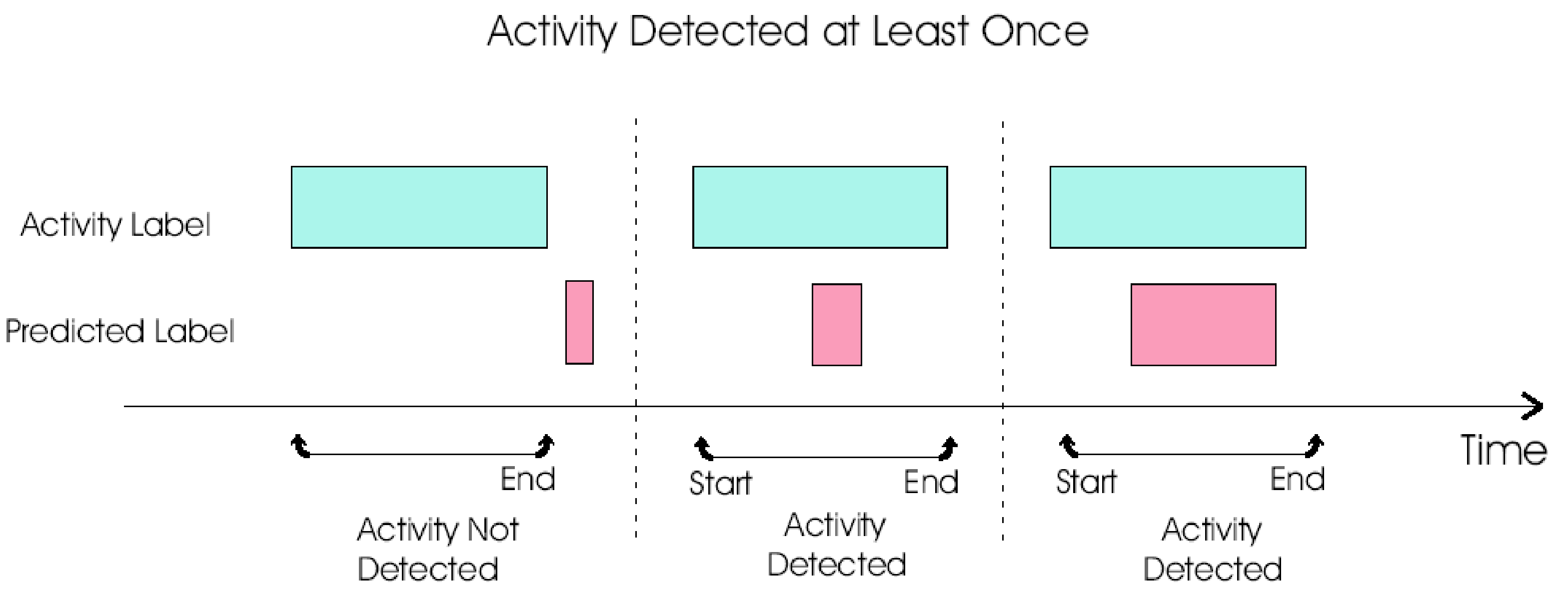
2. Activity detected in best interval



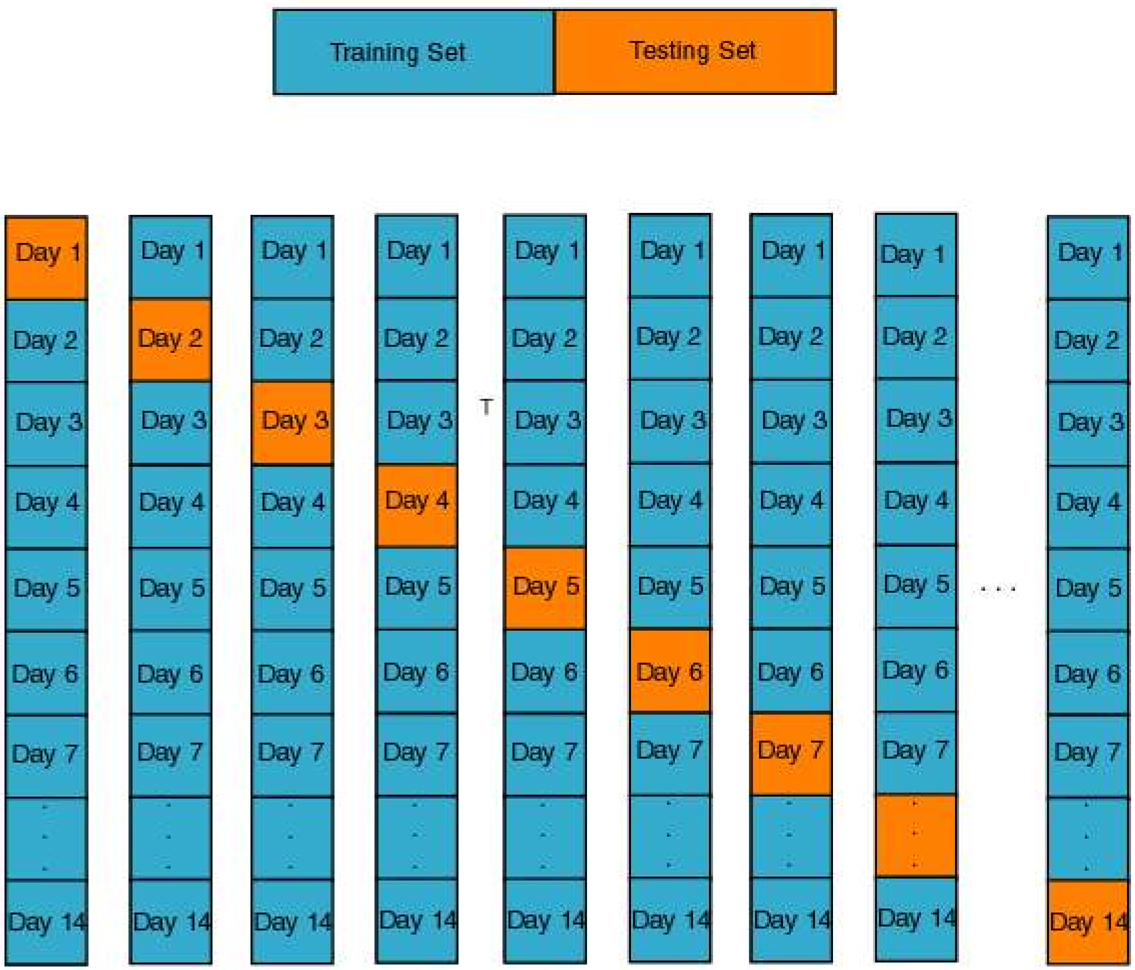


Methods of evaluation

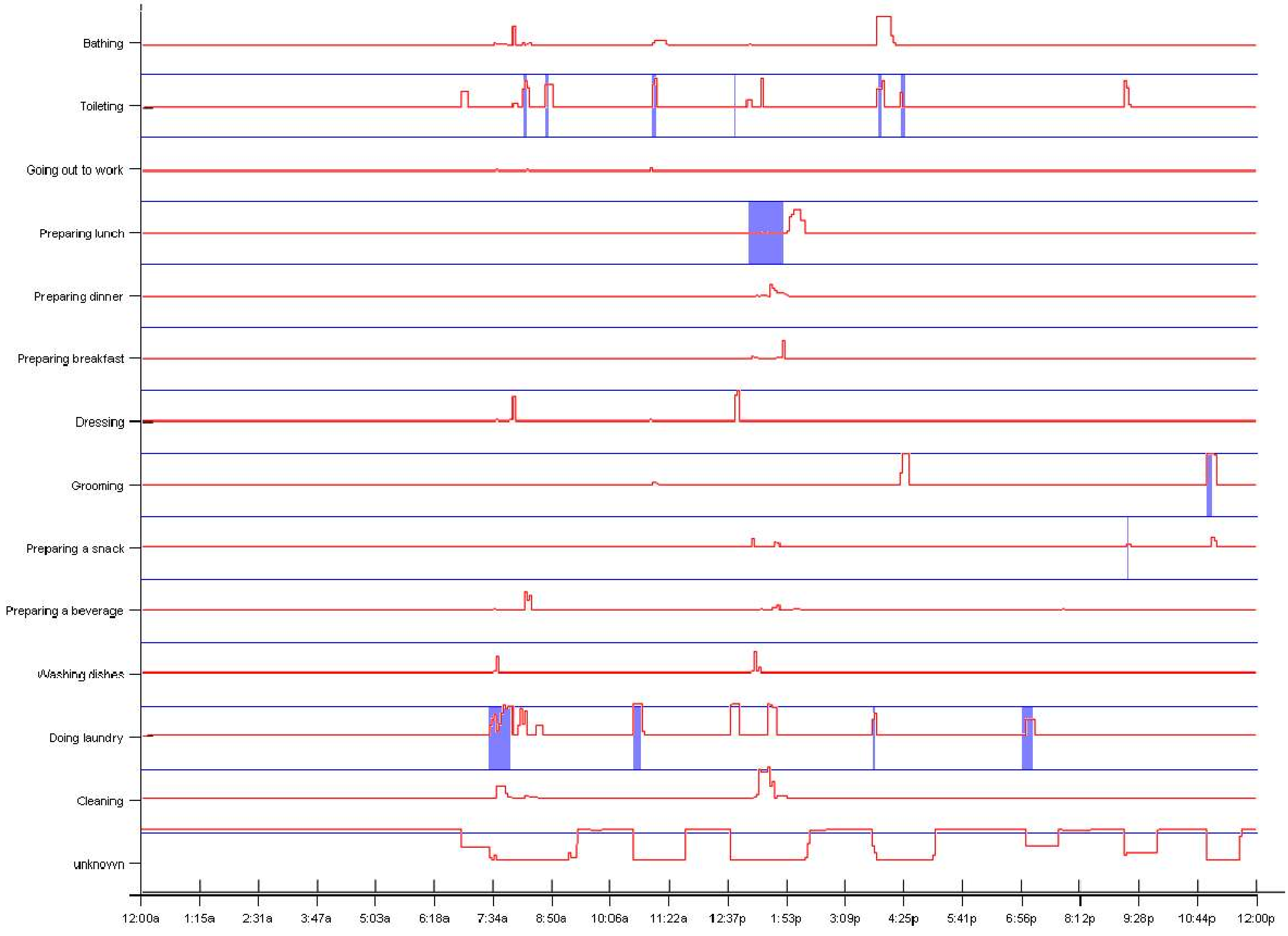
3. Activity detected at least once



Leave-one-day-out cross-validation



Example output multiclass classifier



Results Multiclass classifier (Subject 1)

Multiclass Naive Bayes Classifier for Subject One					
Activity	**No. Examples**	**E**	**E+BT**	**Random Guess**	**Evaluation**
Preparing lunch	17	0.25	0.29	0.07	Percentage of Time Activity is Detected
Toileting	85	0.27	0.31	0.07	
Preparing breakfast	14	0.08	0.06	0.07	
Bathing	18	0.25	0.29	0.07	
Dressing	24	0.07	0.03	0.07	
Grooming	37	0.26	0.26	0.07	
Preparing a beverage	15	0.07	0.13	0.07	
Doing laundry	19	0.09	0.07	0.07	
Preparing lunch	17	0.59	0.78	0.30	Activity Detected in Best Interval
Toileting	85	0.71	0.71	0.30	
Preparing breakfast	14	0.45	0.45	0.30	
Bathing	18	0.87	0.79	0.30	
Dressing	24	0.64	0.41	0.30	
Grooming	37	0.89	0.86	0.30	
Preparing a beverage	15	0.36	0.36	0.30	
Doing laundry	19	0.86	0.78	0.30	
Preparing lunch	17	0.50	0.68	0.17	Activity Detected at Least Once
Toileting	85	0.42	0.43	0.03	
Preparing breakfast	14	0.20	0.12	0.07	
Preparing a snack	14	0.08	0.05	0.03	
Bathing	18	0.70	0.75	0.11	
Going out to work	12	0.12	0.00	0.02	
Dressing	24	0.21	0.07	0.02	
Grooming	37	0.68	0.71	0.05	
Preparing a beverage	15	0.22	0.31	0.04	
Doing laundry	19	0.27	0.23	0.05	
Activities with Less than Six Examples					
Work at home(0), Eating(0), Washing hands(1), Sleeping(0), Taking medication(0), Sleeping(0), Talking on telephone(0), Resting(0), Putting away dishes(2), Putting away groceries(2), Putting away laundry(2), Taking out the trash(0), Lawnwork(1), Pet care(0), Home education(0) Going out to school(0), Going out for entertainment(1), Working at computer(0), Going out to exercise(0), Going out for shopping(2), Listening to music(0), and Watching TV(3).					
Activities Not Recognized Better than Random Guess)					
Preparing dinner(8), Washing dishes(7), Preparing a snack(14), Going out to work(12), and cleaning(8)					

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Preparing a beverage	15	0.36	0.36	0.30	
Doing laundry	19	0.86	0.78	0.30	
Preparing lunch	17	0.50	0.68	0.17	Activity Detected at Least Once
Toileting	85	0.42	0.43	0.03	
Preparing breakfast	14	0.20	0.12	0.07	
Preparing a snack	14	0.08	0.05	0.03	
Bathing	18	0.70	0.75	0.11	
Going out to work	12	0.12	0.00	0.02	
Dressing	24	0.21	0.07	0.02	
Grooming	37	0.68	0.71	0.05	
Preparing a beverage	15	0.22	0.31	0.04	
Doing laundry	19	0.27	0.23	0.05	
Activities with Less than Six Examples					
Work at home(0), Eating(0), Washing hands(1), Sleeping(0), Taking medication(0), Sleeping(0), Talking on telephone(0), Resting(0), Putting away dishes(2), Putting away groceries(2), Putting away laundry(2), Taking out the trash(0), Lawnwork(1), Pet care(0), Home education(0) Going out to school(0), Going out for entertainment(1), Working at computer(0), Going out to exercise(0), Going out for shopping(2), Listening to music(0), and Watching TV(3).					
Activities Not Recognized Better than Random Guess)					
Preparing dinner(8), Washing dishes(7), Preparing a snack(14), Going out to work(12), and cleaning(8)					

Results Multiclass classifier (Subject 1)

Multiclass Naive Bayes Classifier for Subject One					
Activity	**No. Examples**	**E**	**E+BT**	**Random Guess**	**Evaluation**
Preparing lunch	17	0.25	0.29	0.07	Percentage of Time Activity is Detected
Toileting	85	0.27	0.31	0.07	
Preparing breakfast	14	0.08	0.06	0.07	
Bathing	18	0.25	0.29	0.07	
Dressing	24	0.07	0.03	0.07	
Grooming	37	0.26	0.26	0.07	
Preparing a beverage	15	0.07	0.13	0.07	
Doing laundry	19	0.09	0.07	0.07	
Preparing lunch	17	0.59	0.78	0.30	Activity Detected in Best Interval
Toileting	85	0.71	0.71	0.30	
Preparing breakfast	14	0.45	0.45	0.30	
Bathing	18	0.87	0.79	0.30	
Dressing	24	0.64	0.41	0.30	
Grooming	37	0.89	0.86	0.30	
Preparing a beverage	15	0.36	0.36	0.30	
Doing laundry	19	0.86	0.78	0.30	
Preparing lunch	17	0.50	0.68	0.17	Activity Detected at Least Once
Toileting	85	0.42	0.43	0.03	
Preparing breakfast	14	0.20	0.12	0.07	
Preparing a snack	14	0.08	0.05	0.03	
Bathing	18	0.70	0.75	0.11	
Going out to work	12	0.12	0.00	0.02	
Dressing	24	0.21	0.07	0.02	
Grooming	37	0.68	0.71	0.05	
Preparing a beverage	15	0.22	0.31	0.04	
Doing laundry	19	0.27	0.23	0.05	

Activities with Less than Six Examples

Work at home(0), Eating(0), Washing hands(1), Sleeping(0), Taking medication(0), Sleeping(0), Talking on telephone(0), Resting(0), Putting away dishes(2), Putting away groceries(2), Putting away laundry(2), Taking out the trash(0), Lawnwork(1), Pet care(0), Home education(0) Going out to school(0), Going out for entertainment(1), Working at computer(0), Going out to exercise(0), Going out for shopping(2), Listening to music(0), and Watching TV(3).

Activities Not Recognized Better than Random Guess)

Preparing dinner(8), Washing dishes(7), Preparing a snack(14), Going out to work(12), and cleaning(8)

Results Multiclass classifier (Subject 1)

Multiclass Naive Bayes Classifier for Subject One					
Activity	**No. Examples**	**E**	**E+BT**	**Random Guess**	**Evaluation**
Preparing lunch	17	0.25	0.29	0.07	Percentage of Time Activity is Detected
Toileting	85	0.27	0.31	0.07	
Preparing breakfast	14	0.08	0.06	0.07	
Bathing	18	0.25	0.29	0.07	
Dressing	24	0.07	0.03	0.07	
Grooming	37	0.26	0.26	0.07	
Preparing a beverage	15	0.07	0.13	0.07	
Doing laundry	19	0.09	0.07	0.07	
Preparing lunch	17	0.59	0.78	0.30	Activity Detected in Best Interval
Toileting	85	0.71	0.71	0.30	
Preparing breakfast	14	0.45	0.45	0.30	
Bathing	18	0.87	0.79	0.30	
Dressing	24	0.64	0.41	0.30	
Grooming	37	0.89	0.86	0.30	
Preparing a beverage	15	0.36	0.36	0.30	
Doing laundry	19	0.86	0.78	0.30	
Preparing lunch	17	0.50	0.68	0.17	Activity Detected at Least Once
Toileting	85	0.42	0.43	0.03	
Preparing breakfast	14	0.20	0.12	0.07	
Preparing a snack	14	0.08	0.05	0.03	
Bathing	18	0.70	0.75	0.11	
Going out to work	12	0.12	0.00	0.02	
Dressing	24	0.21	0.07	0.02	
Grooming	37	0.68	0.71	0.05	
Preparing a beverage	15	0.22	0.31	0.04	
Doing laundry	19	0.27	0.23	0.05	

Activities with Less than Six Examples

Work at home(0), Eating(0), Washing hands(1), Sleeping(0), Taking medication(0), Sleeping(0), Talking on telephone(0), Resting(0), Putting away dishes(2), Putting away groceries(2), Putting away laundry(2), Taking out the trash(0), Lawnwork(1), Pet care(0), Home education(0) Going out to school(0), Going out for entertainment(1), Working at computer(0), Going out to exercise(0), Going out for shopping(2), Listening to music(0), and Watching TV(3).

Activities Not Recognized Better than Random Guess)

Preparing dinner(8), Washing dishes(7), Preparing a snack(14), Going out to work(12), and cleaning(8)

Results Multiclass classifier (Subject 2)

Multiclass Naive Bayes Classifier for Subject Two					
Activity	No. Examples	E	E+BT	Random Guess	Evaluation
Preparing lunch	20	0.22	0.22	0.10	Percentage of Time Activity is Detected
Listening to music	18	0.20	0.09	0.10	
Toileting	40	0.20	0.23	0.10	
Preparing breakfast	18	0.30	0.24	0.10	
Washing dishes	21	0.05	0.11	0.10	
Watching TV	15	0.04	0.16	0.10	
Preparing lunch	20	0.51	0.48	0.40	Activity Detected in Best Interval
Listening to music	18	0.61	0.44	0.40	
Toileting	40	0.52	0.48	0.40	
Preparing breakfast	18	0.68	0.59	0.40	
Washing dishes	21	0.51	0.54	0.40	
Watching TV	15	0.25	0.52	0.40	
Preparing dinner	14	0.38	0.30	0.24	Activity Detected at Least Once
Preparing lunch	20	0.48	0.61	0.26	
Listening to music	18	0.66	0.45	0.38	
Toileting	40	0.46	0.43	0.10	
Preparing breakfast	18	0.75	0.65	0.16	
Washing dishes	21	0.15	0.28	0.09	
Watching TV	15	0.08	0.45	0.30	
Activities with Less than Six Examples					
Work at home(0), Going out to work(0), Eating(0), Bathing(3), Grooming(3), Dressing(5), Washing hands(0), Sleeping(0), Talking on telephone(4), Resting(0), Preparing a beverage(1), Putting away dishes(3), Putting away groceries(1), Cleaning(3), Doing laundry(0), Putting away laundry(1), Taking out the trash(0), Lawnwork(1), Pet care(0), Home education(2), Going out to school(0), Going out for entertainment(1), Working at computer(5), Going out to exercise(0), and Going out for shopping(3).					
Activities Not Recognized Better than Random Guess					
Preparing dinner(14), Taking medication(14), and Preparing a snack(16).					

Number of examples collected in two weeks

Number of Examples per Class		
Activity	**Subject 1**	**Subject 2**
Preparing dinner	8	14
Preparing lunch	17	20
Listening to music	-	18
Taking medication	-	14
Toileting	85	40
Preparing breakfast	14	18
Washing dishes	7	21
Preparing a snack	14	16
Watching TV	-	15
Bathing	18	-
Going out to work	12	-
Dressing	24	-
Grooming	37	-
Preparing a beverage	15	-
Doing laundry	19	-
cleaning	8	-

Discriminant power of features

1. Exist (best performance)
2. Before ID
3. Before Type (best performance)
4. Before Location
5. Exist + Before ID
6. Exist + Before Type
7. Exist + Before Location

Analysis of results

- More examples $\rightarrow$ better recognition accuracy
- More sensors $\rightarrow$ better recognition accuracy
- Multiclass accuracy $\approx$ multiple classifier accuracy
- Accuracy for Subject 1 $>$ Accuracy for Subject 2
- **Adding the “type” and “location” attributes did not improve recognition considerable**
- Sensor did not cover all important locations
- Considerable improvement over random guess baseline for some activities

Remaining challenges (many!)

- Multitasking
- Periodic variations (daily,weekly, monthly, yearly and seasonal)
- Differences in activity length
- False starts
- Importance of knowing location
- Cultural differences

Take away message

- Contribution
  - Ubiquitous but simple sensors may permit automatic activity recognition
  - System deployed in multiple homes
  - Goal: recognition of ADLs
  - Results:
    - Accuracies ranging from 25%-89%
    - Preliminary, but promising

Thank you!

- For more information on the House_n portable sensor toolkit, contact
  - Emmanuel Munguia Tapia
    emunguia@media.mit.edu
  - Stephen Intille
    intille@mit.edu