# Ambient Assisted Living: Fuzzy Logic & Stochastic Modelling

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- Ambient Assisted Living
- Activity Recognition
  - A Fuzzy Logic approach
  - A Stochastic Model approach
- A joint proposal

# Overview

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- A Fuzzy Logic approach
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- A Stochastic Modelling approach
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# Ambient Assisted Living

# Ambient Assisted Living

**Ambient Assisted Living** is a research area that aims to help those people living within *smart environments* (i.e., provided with sensors and actuators) exploiting sensors and data processing technology.

# Objectives

A *smart environment* is a **partially observable** system:

- the actual state of the system is hidden;
- only events are observables (*observations*) as they are emitted by the system (e.g. the activation of a sensor).

Main analyses of interest:

- **Diagnosis**: (a.k.a. Activity Recognition, AR) esteem the actual present state of the system from the events observed.
- **Prediction**: esteem what's going to be the actual system's state after a certain amount of time or the probability density function that a certain event happens.
- **Action scheduling**: chose the best action and when to execute it in order to avoid critical situations.

Online analysis:

- analyse the system *while* it is evolving.

# Activity Recognition

Activity Recognition techniques can be divided into two classes:

- **Knowledge-Driven Approaches** (KDA)
  - domain-specific expert knowledge is used in order to build the AR model.
- **Data-Driven Approaches** (DDA)
  - a training dataset is used in order to automatically build the AR model, in a supervised fashion.

Comparative survey between AR researches:

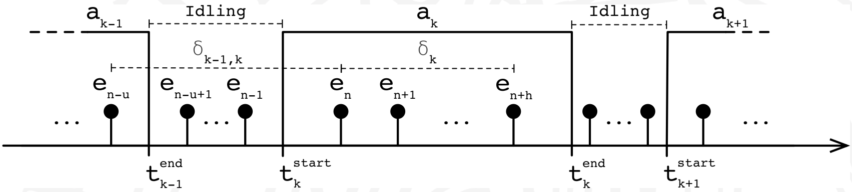
- *STLab* research group[1]
  - stochastic modelling techniques.
- *Sinbad*[2] research group[2]
  - fuzzy logic techniques and temporal window-based classification

[1] https://stlab.dinfo.unifi.it/
[2] http://sinbad2.ujaen.es/

# Annotated datasets

An *annotated dataset* of a partially observable system is a dataset with:

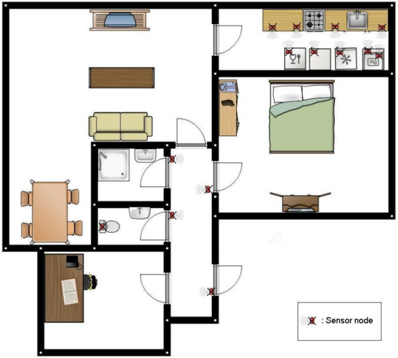
- recorded events and when each happened (timestamp);
- manual annotations of the evolution of the actual state of the system (with time intervals for each state).



# Annotated datasets

## van Kasteren

A classic example is the *van Kasteren*[3][4] annotated dataset for AAL




[3] https://sites.google.com/site/tim0306/datasets

[4] Van Kasteren, T., Noulas, A., Englebienne, G. and Kröse, B., 2008, September. Accurate activity recognition in a home setting. In Proceedings of the 10th international conference on Ubiquitous computing (pp. 1-9). ACM.

# Annotated datasets

## van Kasteren

- 7+1 types of activities (Activities of Daily Living, ADL[5]):
  - {Leaving house, Preparing a beverage, Preparing breakfast, Preparing dinner, Sleeping, Taking shower, Toileting} ∪ {Idling}.
- 28 types of events (on/off of 14 sensors):
  - toilet door open/closed, fridge open/closed, . . . .
- 28 of events and annotated activities:
  - 245 activities, annotated through a Bluetooth device with voice recognition;
  - 219 *Idling* intervals;
  - 2638 observed events.

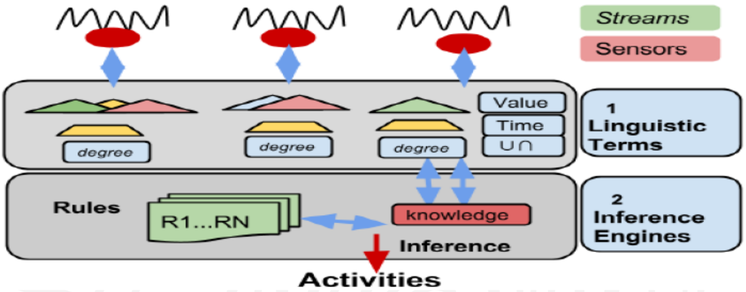
[5]Katz, S., Downs, T.D., Cash, H.R. and Grotz, R.C., 1970. Progress in development of the index of ADL. The gerontologist, 10(1 Part 1), pp.20-30.

# A Fuzzy Logic approach

# A Fuzzy Logic approach

A Knowledge-Driven Approach for Activity Recognition:[6]

- expert knowledge to define **time** and **sensor-specific fuzzy sets**;
- expert knowledge to define **classification fuzzy rules**.




[6]Medina, J., Espinilla, M., Moya, F., and Nugent, C. Activity recognition by means of rule-based inference engine based on fuzzy linguistic approach. In 13th Scandinavian Conference on Artificial Intelligence Halmstad (November 2015 2015).

# Definitions

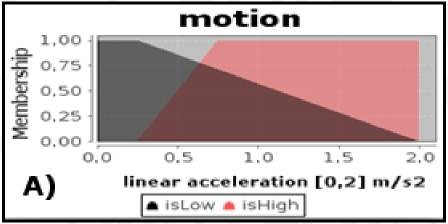
- Each sensor $j$ has an associated sensor stream $s^j$;
- sensor stream $s^j = \{m_i^j\}$ set of measures;
- measure $m_i^j = \langle v_i^j, t_i^j \rangle$;
  - measure value $v_i^j$;
  - measure timestamp $t_i^j$.

# Linguistic terms & membership functions

## Sensors

For each sensor $s^j$, we define:

- a fuzzy linguistic variable (e.g. *Motion*);
- the linguistic terms (e.g. *High* and *Low*);
- their membership functions $\mu V(v_i^j)$
  - degree of membership of the measure value $v_i^j$ in the fuzzy set $V$.

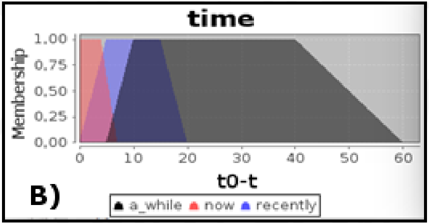


# Linguistic terms & membership functions

## Time

For the time dimension (only once), we define:

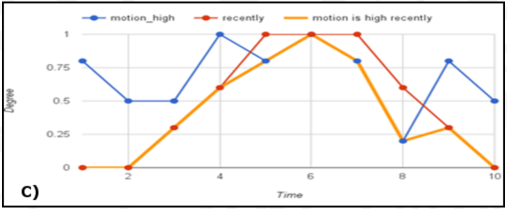
- the fuzzy linguistic variable *Time*;
- three linguistic terms *Now*, *Recently* and *aWhile*;
- their membership functions $\mu T(t_i^j)$
  - degree of membership of the measure timestamp $t_i^j$ in the fuzzy set $T$.



# Intersection membership functions

For each sensor and time linguistic term, we define the intersection membership function:

- $V \cap T(m_i^j) = V(v_i^j) \cap T(t_i^j)$
  - t-norm $\cap = MIN$;
- e.g. *High_motion Recently*.




The degree of membership of all measures $\{m_i^j\}$ of a sensor $s^j$ to $V \cap T$ is given by aggregation through union:

- $V \cap T(s^j) = \bigcup_{m_i^j \in s^j} V \cap T(m_i^j)$

# Rule-based inference engine

A domain expert gives temporal fuzzy rules, through which linguistic terms from multiple sensors can be processed.

Fuzzy temporal logic rules have the form:

*IF v is V WHEN t is T THEN m IS M*

For example:

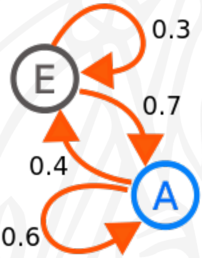
*IF (movement IS significant AND inhabitant IS close to living room ) WHEN now AND (inhabitant IS cooking) WHEN a while THEN inhabitant IS eating*

# A Stochastic Modelling approach

## Stochastic Models

*Stochastic Models* represent an approximation of systems where are modelled:

- the evolution of the system's state;
- the stochastic parameters that characterize how the system passes from a state to another.



# Process mining

## From annotated datasets to stochastic models

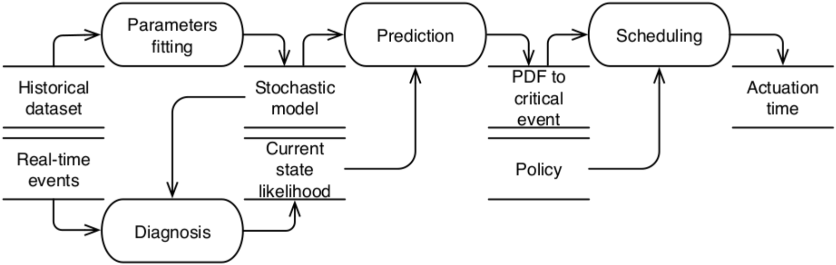
The term **process mining** indicates a set of techniques for building a stochastic model of a partially observable system from an annotated dataset of that same system.

Process mining is composed of two main techniques:

- **Process elicitation**: builds the discrete model (i.e., with no information about the sojourn times in different system's state) from events and annotated activities in the dataset.
- **Process enhancement**: adds a continuous time vision to the discrete model introducing stochastic parameters that describe how the system evolves during time, using statistical measures calculated from the dataset.

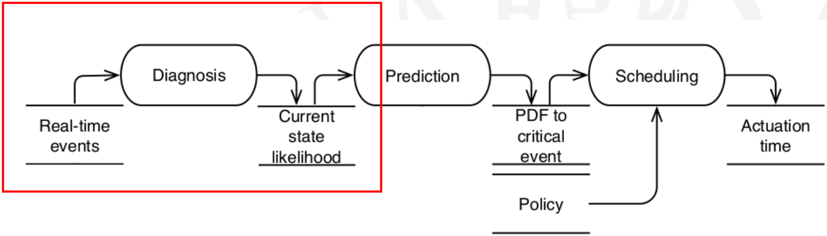
# Smart environments analyses

## General schema




- **Process mining**: from annotated datasets to stochastic model.
- **Diagnosis**: from actual events to likelihood of the current state (on a specific stochastic model).
- **Prediction**: from likelihood of the current state to probability that a critical event occurs.
- **Scheduling**: from probability that a critical event occurs to time when to schedule the response action (with a specific reaction policy).

# Diagnosis




**Diagnosis** computes the most likely actual state of the model at present time, given all the events observed up until the present time.

# H-MRGP-M

The **Hidden-Markov Regenerative Process-Model** (H-MRGP-M) has been developed by STLab at University of Florence.[7]

- Models the continuous sojourn time in the system's states and the events inter-times.
- The model's state evolves as a *Markov Regenerative Process* (MRP).

[7] Carnevali, L., Nugent, C., Patara, F. and Vicario, E., 2015, September. A continuous-time model-based approach to activity recognition for ambient assisted living. In International Conference on Quantitative Evaluation of Systems (pp. 38-53). Springer International Publishing.

# H-MRGP-M

## Statistical measures

- Experiments on the van Kasteren dataset.
- Starting from timestamps in the dataset, statistical measures are computed:
  - on the sojourn time in each activity;
  - of the inter-time between events in each activity.

| | **Sojourn time** | | **Inter-time between events** | |
|---|---|---|---|---|
| | $\mu$ (s) | **CV** | $\mu$ (s) | **CV** |
| **Leaving house** | 40 261.455 | 1.042 | 9 354.190 | 2.810 |
| **Preparing a beverage** | 35.667 | 1.361 | 7.643 | 2.613 |
| **Preparing breakfast** | 108.684 | 0.713 | 9.928 | 1.844 |
| **Preparing dinner** | 1 801.889 | 0.640 | 77.966 | 2.589 |
| **Sleeping** | 26 116.571 | 0.442 | 1 871.836 | 3.090 |
| **Taking shower** | 485.910 | 0.298 | 102.788 | 1.969 |
| **Toileting** | 88.742 | 1.175 | 14.814 | 2.449 |

# H-MRGP-M

## Stochastic model @runtime

- The model is created with *process mining* techniques:
  - *process elicitation* in order to define the model topology;
  - *process enhancement* in order to add stochastic parameters from the statistical measures calculated (Whitt technique[8] and software PhFit[9]).
- Model **@runtime**: the model is updated each time a new event is observed.[10]
- The model formalism used is that of **stochastic Timed Petri Net** (sTPN).[11][12]

[8] Whitt, W., 1982. Approximating a point process by a renewal process, I: Two basic methods. Operations Research, 30(1), pp.125-147.

[9] Horváth, A. and Telek, M., 2002, April. Phfit: A general phase-type fitting tool. In International Conference on Modelling Techniques and Tools for Computer Performance Evaluation (pp. 82-91). Springer Berlin Heidelberg.

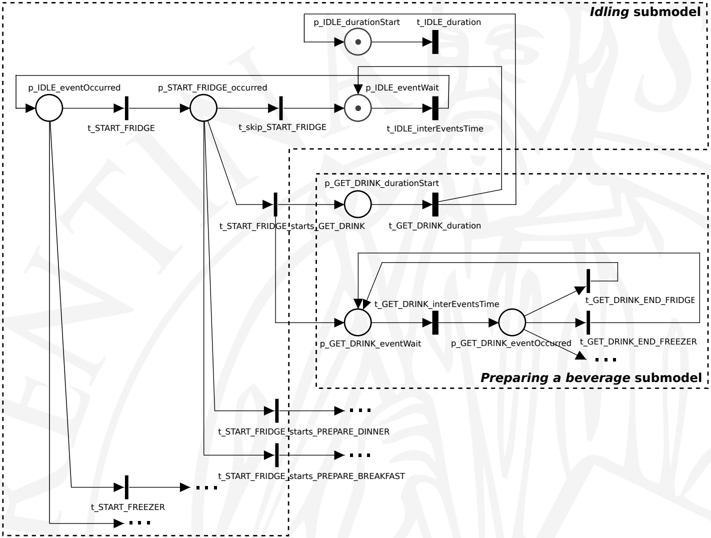
[10] Blair, G., Bencomo, N. and France, R.B., 2009. Models@ run. time. Computer, 42(10).

[11] Horváth, A. and Vicario, E., 2009, September. Aggregated stochastic state classes in quantitative evaluation of non-markovian stochastic Petri nets. In Quantitative Evaluation of Systems, 2009. QEST'09. Sixth International Conference on the (pp. 155-164). IEEE.

[12] Vicario, E., 2001. Static analysis and dynamic steering of time-dependent systems. IEEE transactions on software engineering, 27(8), pp.728-748.

# H-MRGP-M

## sTPN

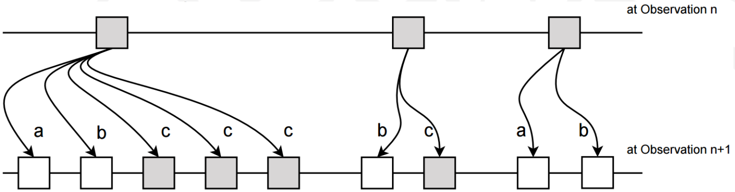

Idling submodel
p_IDLE_durationStart
t_IDLE_duration
p_IDLE_eventOccurred
p_START_FRIDGE_occurred
p_IDLE_eventWait
t_START_FRIDGE
t_skip_START_FRIDGE
t_IDLE_interEventsTime
p_GET_DRINK_durationStart
t_START_FRIDGE_starts_GET_DRINK
t_GET_DRINK_duration
t_GET_DRINK_interEventsTime
t_GET_DRINK_END_FRIDGE
p_GET_DRINK_eventWait
p_GET_DRINK_eventOccurred
t_GET_DRINK_END_FREEZER
Preparing a beverage submodel
t_START_FRIDGE_starts_PREPARE_DINNER
t_START_FRIDGE_starts_PREPARE_BREAKFAST
t_START_FREEZER

# H-MRGP-M

## Transient analysis

After each observation, likelihoods of being in different system's states can be computed up until the next observation.

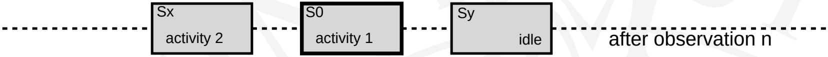
- The transient analysis technique for MRP based on stochastic state classes is exploited.[13]




The state with highest likelihood is the diagnosed current activity.

[13] Horváth, A., Paolieri, M., Ridi, L. and Vicario, E., 2012. Transient analysis of non-Markovian models using stochastic state classes. Performance Evaluation, 69(7), pp.315-335.

# H-MRGP-M
## Transient analysis

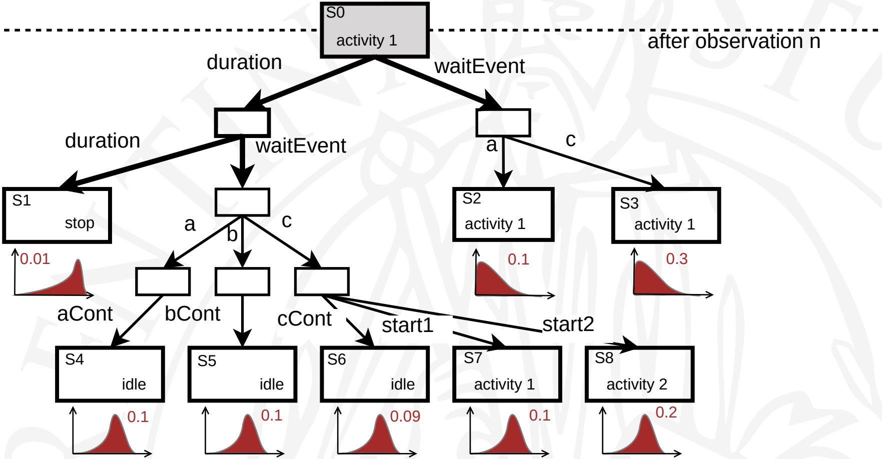



After having observed the event *n*, for each (possible) current activity

- a classes tree is built until the next observation (event $n + 1$) is met;
- leaves corresponding to the new observed event are selected;
- the PDF of the selected leaves is computed in the delay *d* (inter-time between events *n* and $n + 1$) in each tree and summing them with weight the root likelihood;
- the highest is given as most likely current activity.

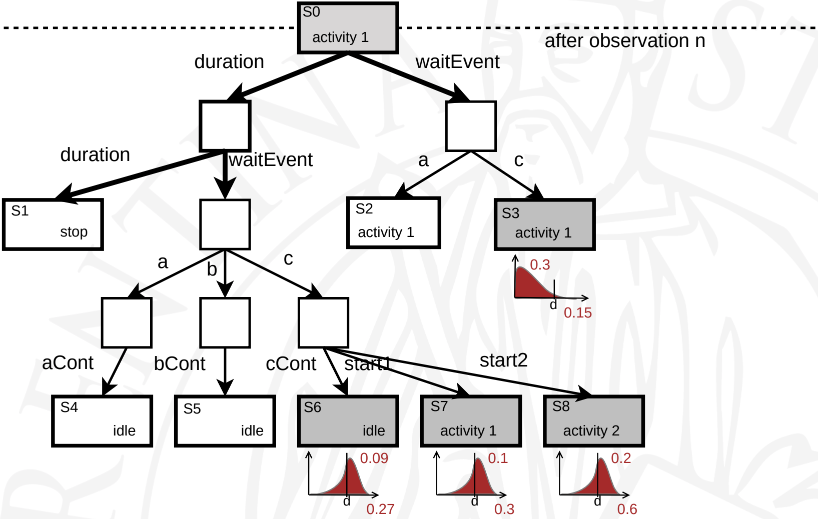
# H-MRGP-M

## Transient analysis



# H-MRGP-M

## Transient analysis



# A joint proposal

# Pros & cons

The H-MRGP-M model has several pros and cons.

Pros:

- DDA;
- accurate description of system evolution through stochastic modellization.

Cons:

- no support for continuous sensors;
- only last event taken into consideration.

Exploiting linguistic terms and temporal fuzzy rules, support for continuous sensors can be added to the H-MRGP-M model!

# Proposal

## $\alpha$-cuts

- Use linguistic variables as before:
  - provided by an expert;
  - one for the time dimension and one for each continuous sensor.
- Define state-changes for each continuous sensor:
  - for each continuous sensor, define one or more $\alpha$-cuts;
  - each resulting interval is seen as a different state-change for a specific sensor.
- The new state-changes of the continuous sensor are added to the model.

When a new continuous event is observed:

- compute the degree of membership of the data stream for that sensor to the intersection fuzzy set $v \cap T$;
- defuzzify on the intersection fuzzy set $V \cap T$;
- the state-change corresponding to the defuzzification output is fired in the H-MRGP-M model.

# Proposal

## State-change fuzzy temporal rules

- Use linguistic variables as before:
  - provided by an expert;
  - one for the time dimension and one for each continuous sensor.
- Define state-changes for each continuous sensor:
  - define state-change fuzzy temporal rules (by an expert);
  - each rule is applied to the whole sensor data stream;
  - e.g. *IF (movement IS high) WHEN now AND (movement IS low) WHEN a while THEN inhabitant IS started moving*.
- The new state-changes of the continuous sensor are added to the model.

When a new continuous event is observed:

- infer the state-change using the fuzzy temporal rule engine and the sensor data stream;
- the inferred state-change is fired in the H-MRGP-M model.

# Future proposals

- Full DDA:
  - extended belief rule-based inference;[14]
  - ANFIS.
- Sensor-specific time linguistic terms:
  - each sensor might have different variation distributions in time.
  - e.g. a sensor motion might have very rapid and very high variations, while a temperature sensor is usually smoother

[14] Espinilla, M., Medina, J., Calzada, A., Liu, J., Martínez, L. and Nugent, C., 2016. Optimizing the configuration of an heterogeneous architecture of sensors for activity recognition, using the extended belief rule-based inference methodology. Microprocessors and Microsystems.

*The end.*

*Questions? Thanks!*