# Sensor-based Human Activity Recognition: Overcoming Issues in a Real World Setting

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# MOTIVATION

# Motivation (Why?)



Insufficient physical activities but also the absence of needed help can lead to difficult-to-treat long-term effects.

The consequences are ...

- ... loss of self-confidence
- ... change in behavior to prevent issues
- ... physical but also a psychological decline in health
- ... premature death

# Motivation (How?)

Human Activity Recognition has been deeply investigated in the last decade.

- sensor miniaturization and wireless communications have paved the way
- knowledge about the performed activities is a fundamental requirement

➡ many pervasive health care systems have been proposed

- effective in controlled environments
- effectiveness out of the lab is still limited

**Our goal is to overcome this shortcomings and limitations!**

# Activity Recognition



Interpreting sensor data or signals to determine the activity which initially triggered them

**<u>Sensor types</u>**

- motion, proximity, environmental, video, and physiological

**<u>External sensors</u>**

- intelligent- or smart-homes are typical examples of external sensing and recognize fairly complex activities like taking medicine

**<u>Wearable sensors</u>**

- carried by the user and are mostly used to recognize simpler activities like motions or postures

# Activity Recognition

## Physical Activities

- refers to walking, standing, sitting, running, …
- usually recognized by sensors that are attached to certain body parts (wearable sensors)

## Activities of Daily Living (ADL)

- refers to people's daily self-care activities
- usually recognized by sensors that are attached to preselected objects or locations (external sensors)

➡ As this suggests, the HAR research area is fragmented …

# Activity Recognition

Recognizing activities enables …

… to recognize the daily routine

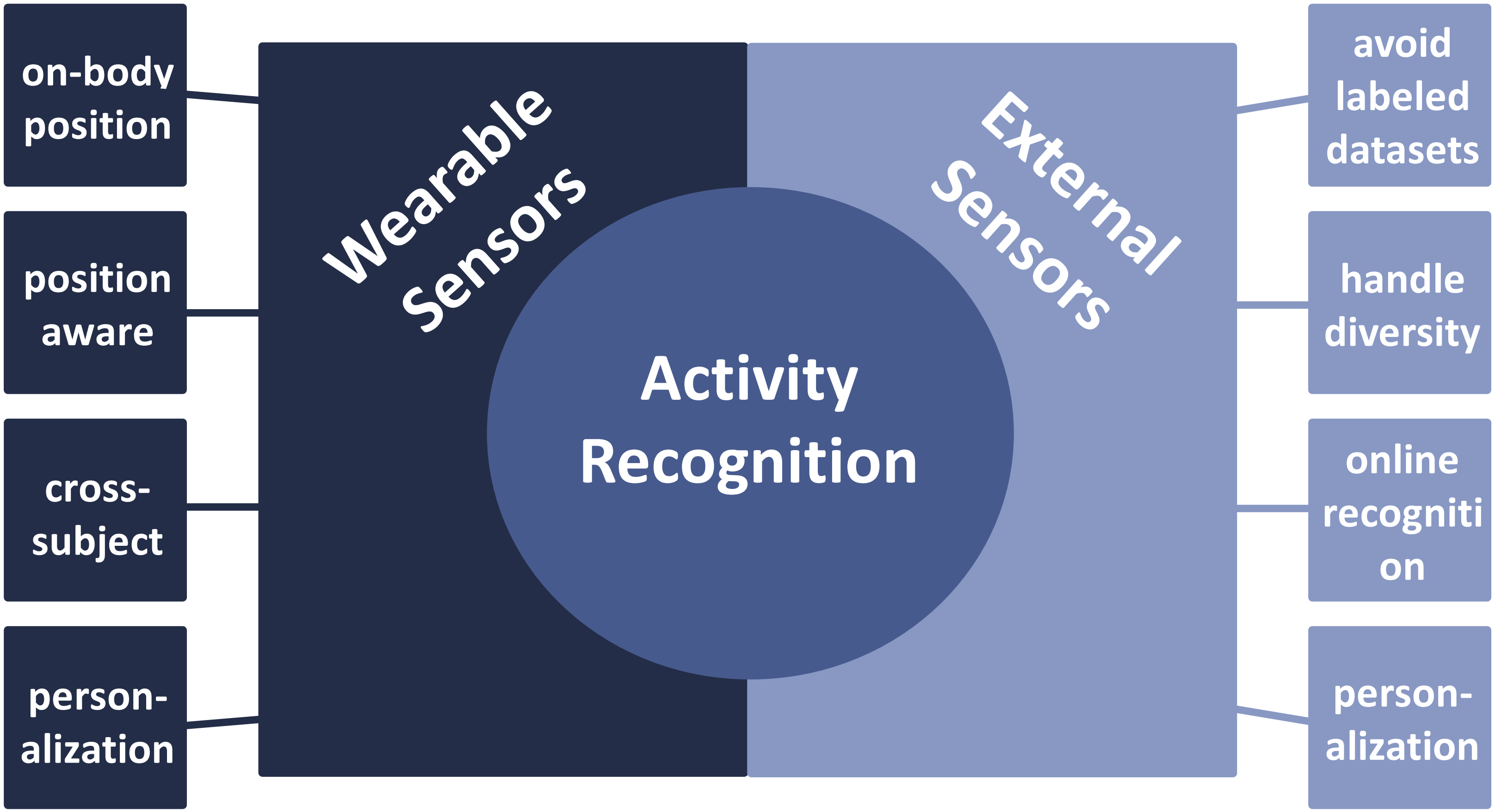
… to learn the user's behavior

… to optimize the course of the day

… to verify predefined patterns like medical instructions

State-of-the-art human activity recognition systems are far from being able to achieve this

# Activity Recognition



# ACTIVITY RECOGNITION WITH WEARABLE DEVICES

# Activity Recognition with Wearable Devices



Especially accelerometers were investigated for recognizing physical activities (mainly under laboratory conditions)

The step out of the lab leads to new unaddressed problems:

- the user decides where to carry a wearable device
- elderly or patients might not be able to collect data
- movement patterns of a person could change

→ We aim to develop robust activity recognition methods that generate high quality results in a real world setting.

# Research Questions



**RQ1.1** Is it possible to recognize automatically the on-body position of a wearable device by the device itself?

**RQ1.2** How does the information about the wearable device on-body position influence the physical activity recognition performance?

**RQ1.3** Which technique can be used to build cross-subjects based activity recognition systems?

**RQ1.4** Given a cross-subjects based activity recognition model, how can we adapt the model efficiently to the movement patterns of the user?

# Research Questions (Catchwords)

**RQ1.1 … recognizing the on-body position …**

**RQ1.2 … position-aware physical activity recognition …**

# Data Collection

To address the mentioned problem it was necessary to create a new data set

- 15 subjects (8 males / 7 females)
- seven wearable devices / body positions
- **chest, forearm, head, shin, thigh, upper arm, waist**
- acceleration, GPS, gyroscope, light, magnetic field, and sound level
- **climbing stairs up/down, jumping, lying, standing, sitting, running, walking**
- each subject performed each activity ≈10 minutes

# Data Collection

We focused on realistic conditions

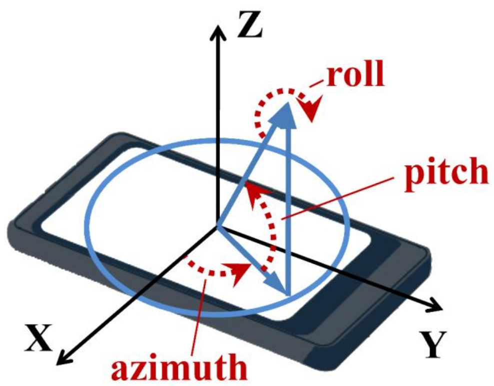
- common objects and clothes to attach the devices
- subjects walked through downtown or jogged in a forest.
- each movement was recorded by a video camera
- We recorded for each position and axes 1065 minutes

→ complete, realistic, and transparent data set

# Feature Extraction

So far, there is no agreed set of features …

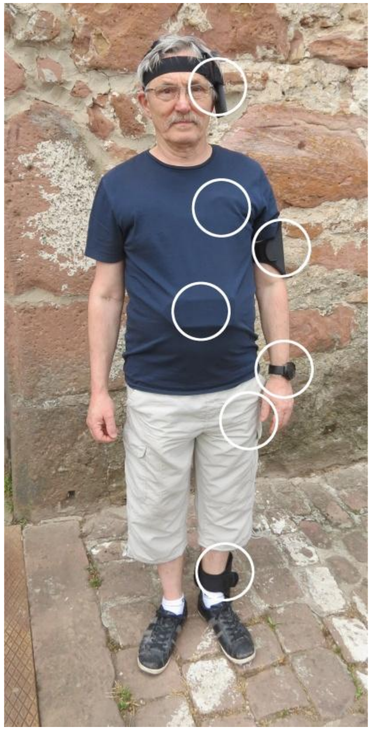
- time and frequency-based features
- gravity-based features (low-pass filter)
  - derive device orientation (roll, pitch)




… but splitting the recorded data into small overlapping segments has been shown to be the best setting.

| | Methods |
|---|---|
| **Time** | Correlation coefficient (Pearson), entropy (Shannon), gravity (roll, pitch), mean, mean absolute deviation, interquartile range (type R-5), kurtosis, median, standard deviation, variance |
| **Frequency** | Energy (Fourier, Parseval), entropy (Fourier, Shannon), DC mean (Fourier) |

# Position Detection



### Setting

- Scenario: Single User
- Stratified sampling and 10-fold cross validation
- Broad set of classifiers

### Insights

- lying, standing, and sitting lead to misclassification

➡ static vs. dynamic activities

- gravity provides useful information but …

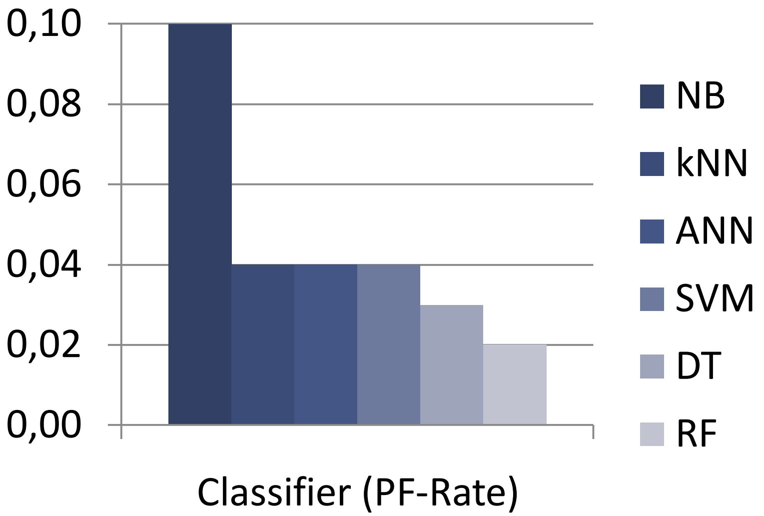
➡ … it is no indicator of the device position

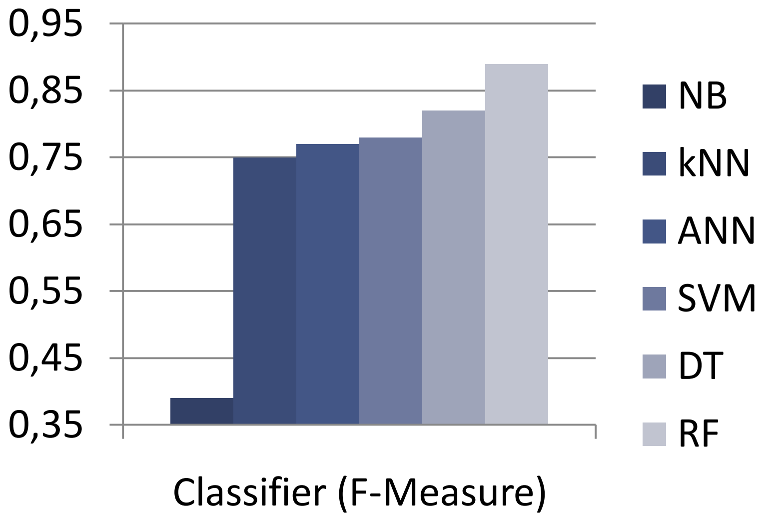
# Position Detection



To compare the results we also evaluated further classifiers

- RF outperforms the other classifier (89%)
- The training phase of RF was one of the fastest
- k-NN (75%), ANN (77%), and SVM (78%) achieved reasonable results
  (parameter optimization was performed)



# Physical Activity Recognition

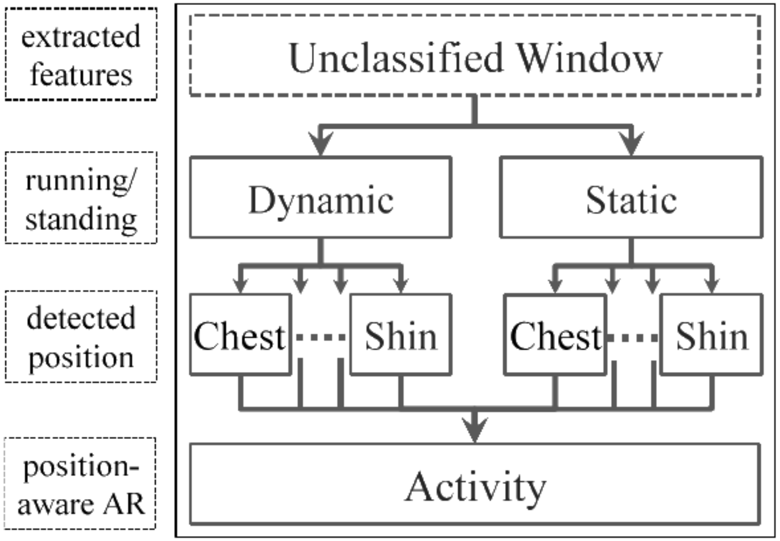
*Feasibility*: Used the results of the previous experiment (including all mistakes)

Again, we evaluated two approaches …

- position-independent activity recognition
- position-aware activity recognition

➡ Set of individual classifiers for each position and subject

1) First decide if static or dynamic
2) Apply activity-level depended classifier (different feature sets)
3) Apply position-depended classifier

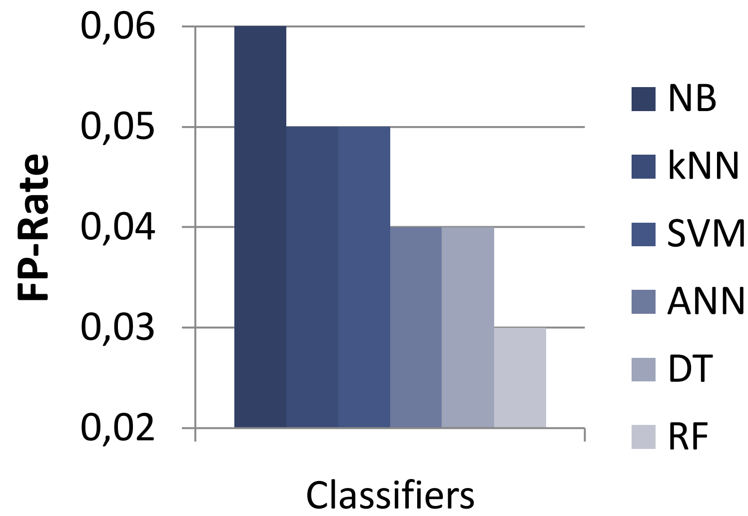


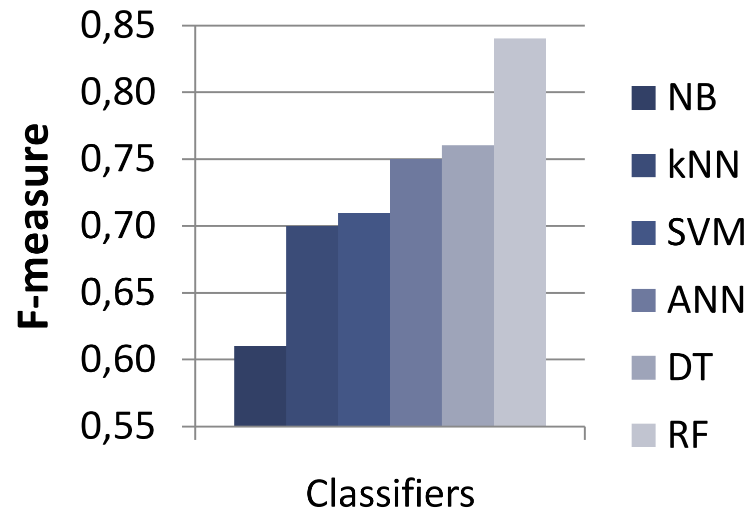
# Physical Activity Recognition

To compare the results we also evaluated further classifiers

- RF achieved the highest recognition rate (84%)
- k-NN (70%) and SVM (71%) performed almost equal but worse than ANN (75%) and DT (76%)
- **All classifier performed worse in a position-independent scenario**

➔ RF performed the best in all settings.



# Research Questions (catchwords)

**RQ1.3 … cross-subjects based activity recognition …**

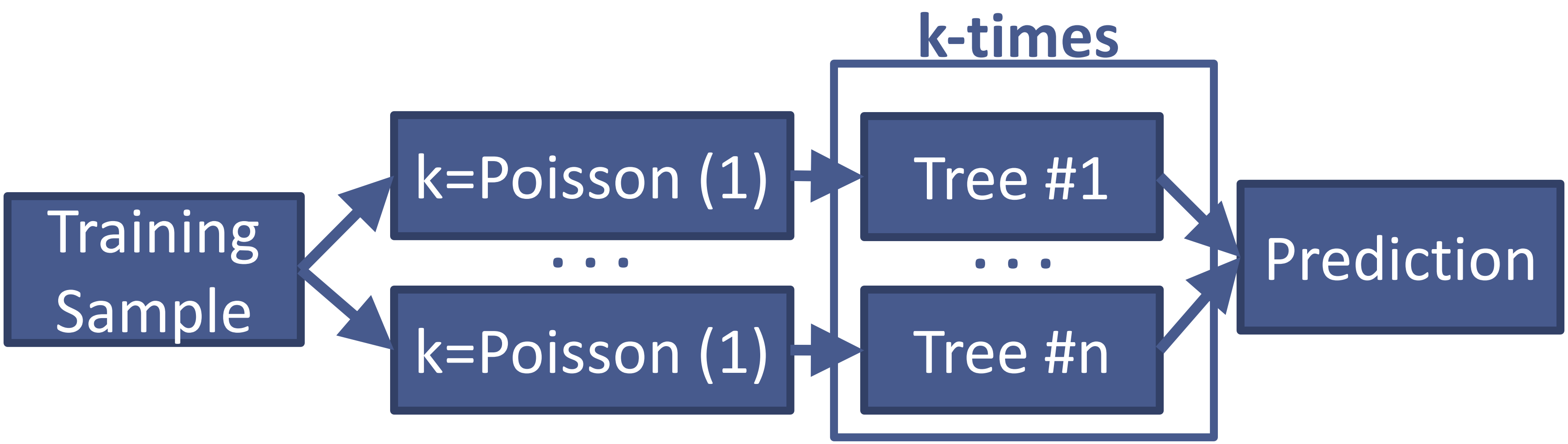
**RQ1.4 … personalization of activity recognition models…**

# Online Random Forest



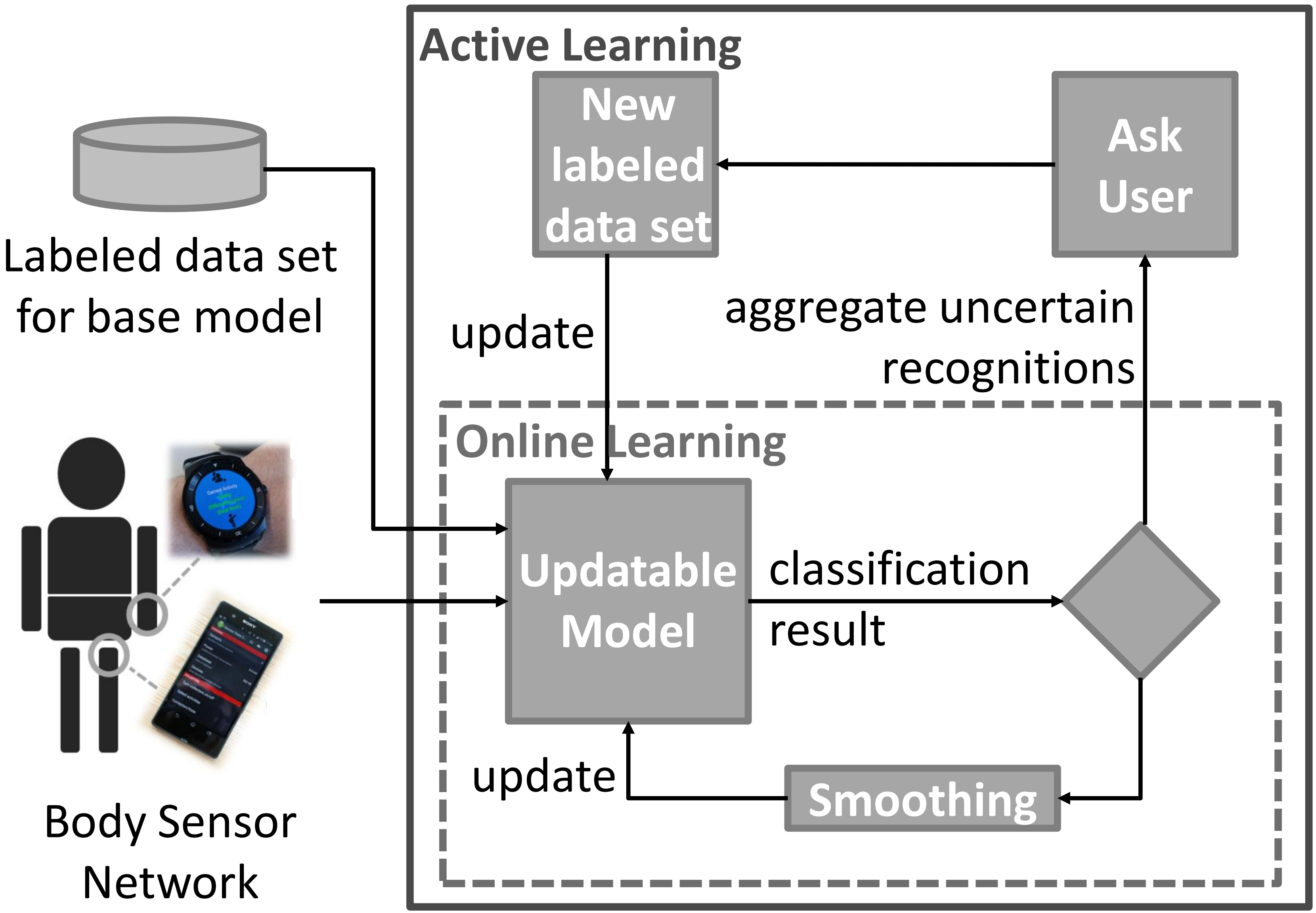
Considering online mode, the main differences are …

- bagging (generation of subsamples)
  - replace *sample with replacement* with *Poisson(1)*
- growing of the individual trees
  - Select thresholds and features randomly *(Extreme Randomized Forest)*



# Personalization: Online and Active Learning





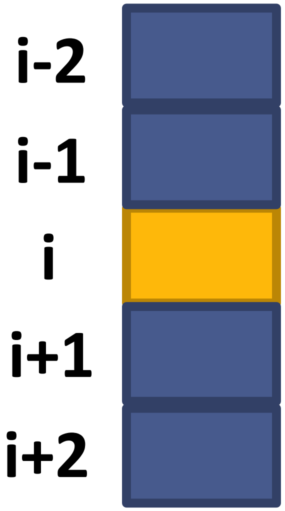
# Personalization: Online and Active Learning

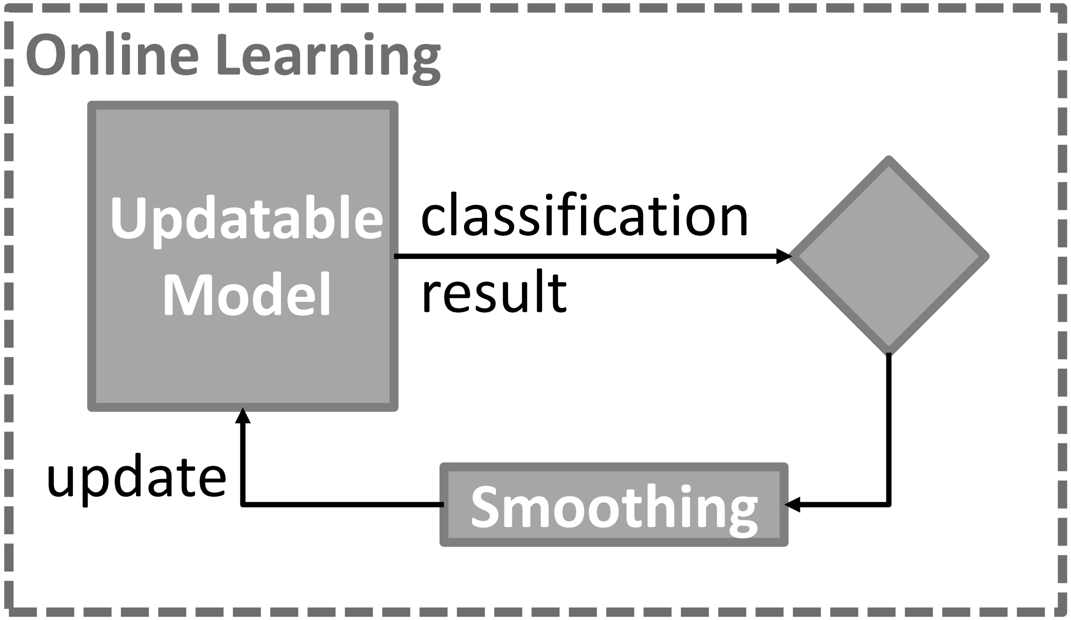


*Smoothing* adjusts the classification result of a single window if it is surrounded by another activity

➡ adjusted window is used to update the model

➡ focuses on minor classification errors



# Personalization: Online and Active Learning

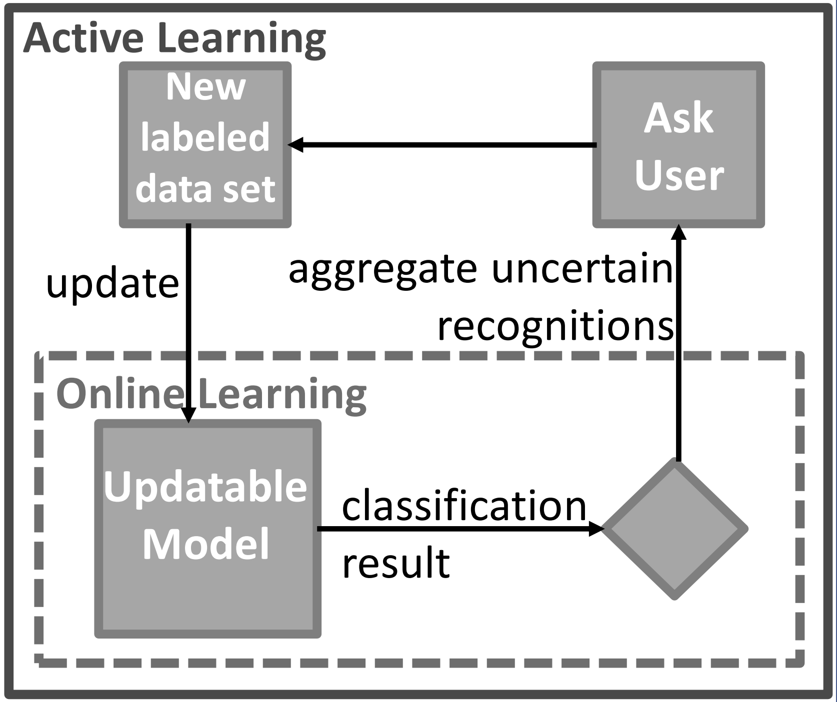


*User-Feedback* queries the user regarding uncertain classification results

➡ infeasible to ask for a specific window (1 sec)

- specified a duration of uncertainty
- query result is a new data set

➡ focuses on major classification errors



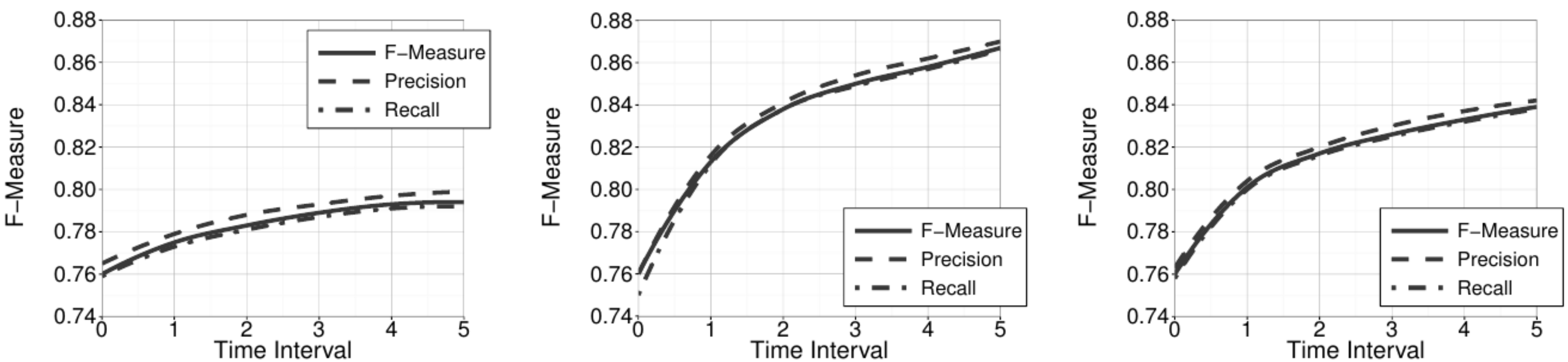
# Personalization (Results)

*Personalization is a continuous process …*

- especially dynamic activities improve significantly
- most improvement in the first two time intervals

➡ first iteration +4%, five iterations +8%

➡ number of windows with a low confidence value decrease with each iteration

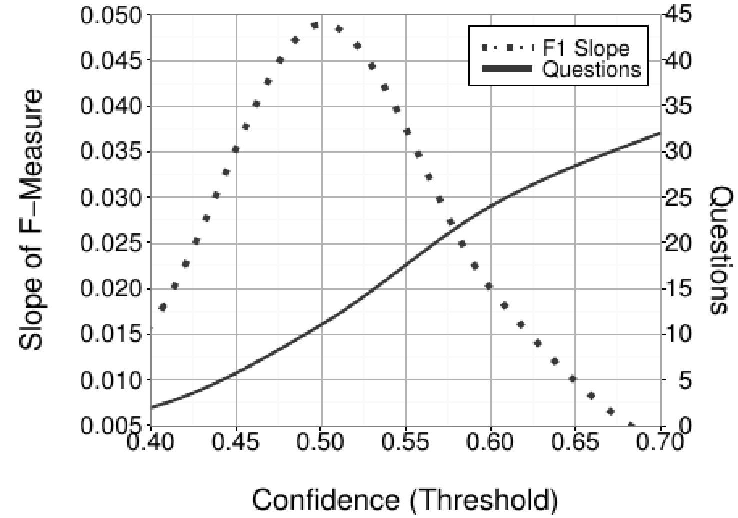



(a) Static activities (b) Dynamic activities (c) All activities

# Parameter

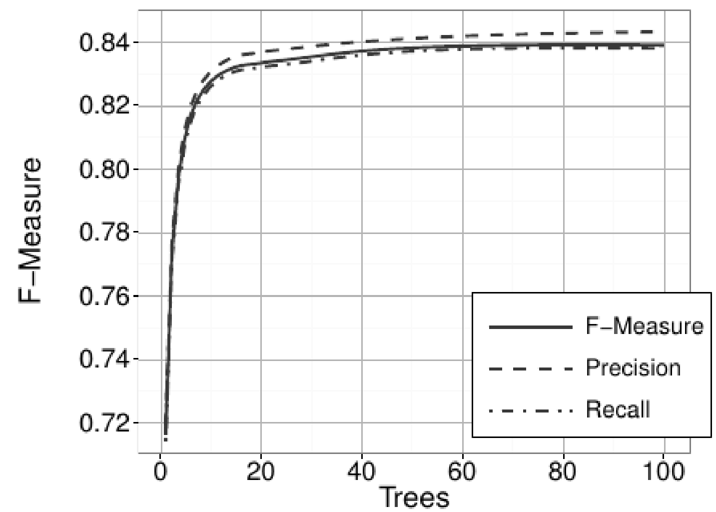
*Considering different confidence thresholds …*

- *turning point → t=0.5*
- *10 questions → +8%*




*Considering a different number of trees…*

- *10 trees vs. 100 trees*
- *a smaller forest is more feasible concerning wearable devices*



# Main Contributions

- A **new real world dataset** for on-body position detection and position-aware physical activity recognition
- We show that our **on-body position recognition method** consistently improves the recognition of physical activities in a real world setting.
- We show that using labeled data of different people of the same gender and with a similar level of fitness and statue is feasible for **cross-subjects activity recognition** for people that are unable to collect required data.
- We present a physical activity recognition approach that **personalize cross-subjects based recognition models** by querying the user with a reasonable number of questions.

# ACTIVITY RECOGNITION WITHIN SMART ENVIRONMENTS

# Activity Recognition within Smart Environments



While the physical activity is a valuable information …

… it says nothing about the actual situation

➡ Critical activities (*Activities of Daily Living*) are not recognized

- Sensors that are attached to items, furniture, or walls should overcome this problem.
- An ADLs is more diverse than a physical activity.

# State of the Art and Open Issues



Most ADL recognition systems rely on …

… supervised-based approaches:

- acquire expensive labeled data set
- often user/environment-specific

… knowledge-based approaches:

- enumerating all possible actions of an ADL

➡ not flexible

➡ questionable if such models could cover different environments and modes of execution

# Research Questions



**RQ2.1** Which method can be used to overcome the requirement of a large expensive labeled dataset of Activities of Daily Living?

**RQ2.2** Which type of recognition method is suitable for handling the diversity and complexity of Activities of Daily Living?

**RQ2.3** How can external sensor events be exploited to recognize Activities of Daily Living in almost real-time?

**RQ2.4** Given a generic model of a smart environment, how can it be adapted to a certain environment and user at run-time?

# Research Questions (catchwords)

**RQ2.1 … avoid large expensive labeled dataset …**

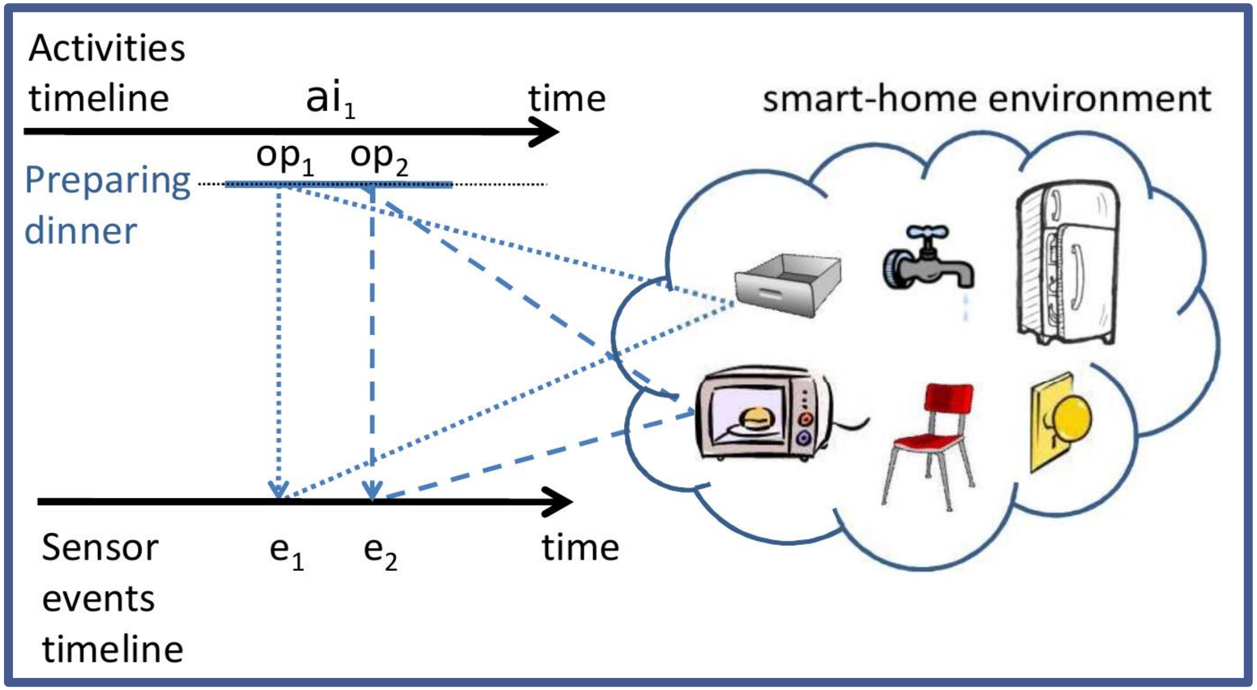
**RQ2.2 … method for handling the diversity of ADLs …**

# Scenario

Recognizing activities of daily living in a smart-home

➡ to support healthcare, home automation, a more independent life, …

We rely on unobtrusive sensors …



# Our approach …

… overcomes drawbacks of supervised-based approaches

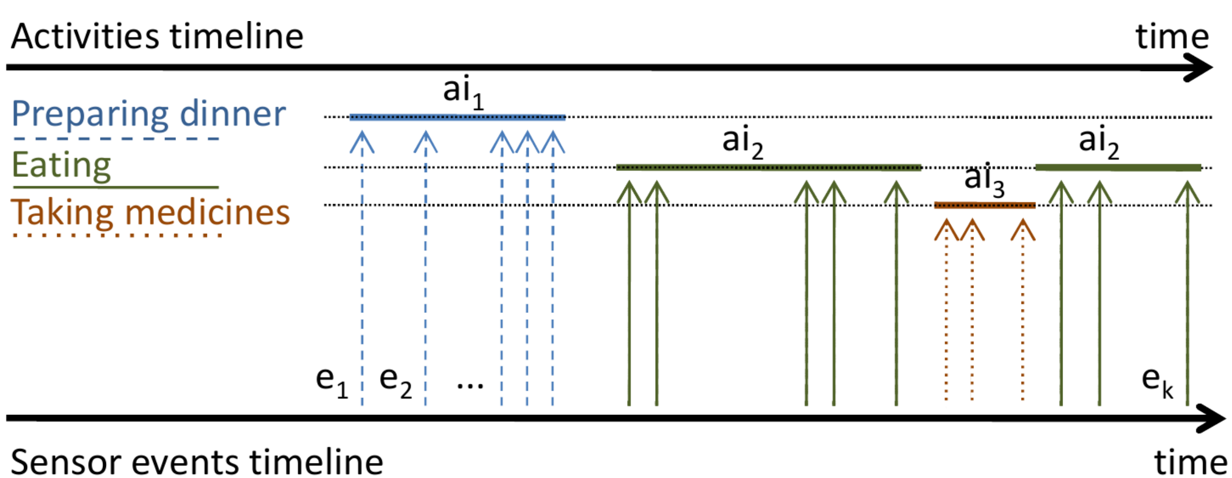
➡ not user/environment-specific, no expensive data set, …

… relies on semantic relations (activities↔ events)

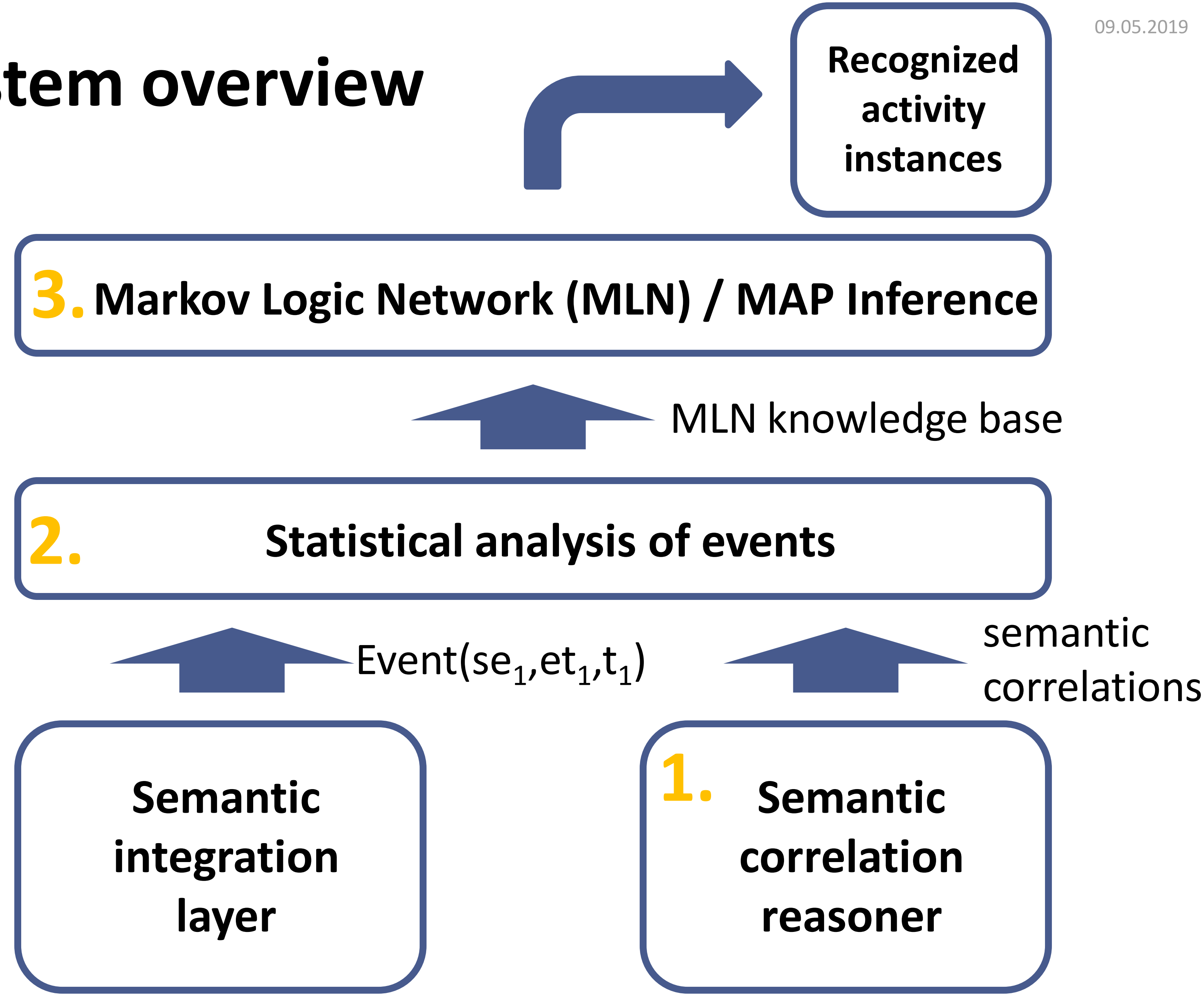
➡ derived from ontological reasoning

… recognizes interleaved activities

➡ inferred by a probabilistic model



# System overview

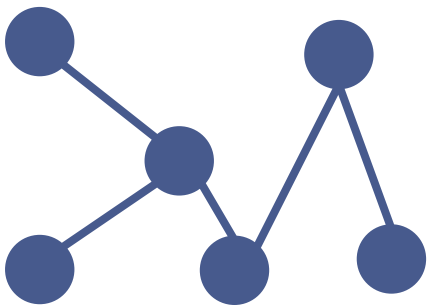


# 1. Semantic Correlation Reasoner

Why do we use Ontology (OWL2)?

→ to derive semantic correlations (event type ↔ activity class)

**Ontology**



**OWL2 Reasoner infers**

*{turn on stove} is a predictive sensor event type for {Prepare hot meal} and {Prepare tea}*

**interact**

**prepare**

| PPM Matrix | stove | silverware_drawer | freezer |
|---|---|---|---|
| Hot meal | 0.5 | 0.33 | 0.5 |
| Cold meal | 0.0 | 0.33 | 0.5 |
| Tea | 0.5 | 0.33 | 0.0 |

# Issues of this approach



Semantic correlations are computed based on an ontology written by knowledge engineers (humans)

→ it is very likely that the ontology is incomplete

→ it is hence questionable if it can cover different environments/mode of execution

**Our goal is to refine and improve semantic correlations thanks to collaborative active learning!**

# 2. Statistical Analysis of Events

**Input**: PPM matrix and temporally ordered events

- infers most probable activity class for each event
- allows to define activity boundaries (activity instance candidate)

**activity instance candidate**

+

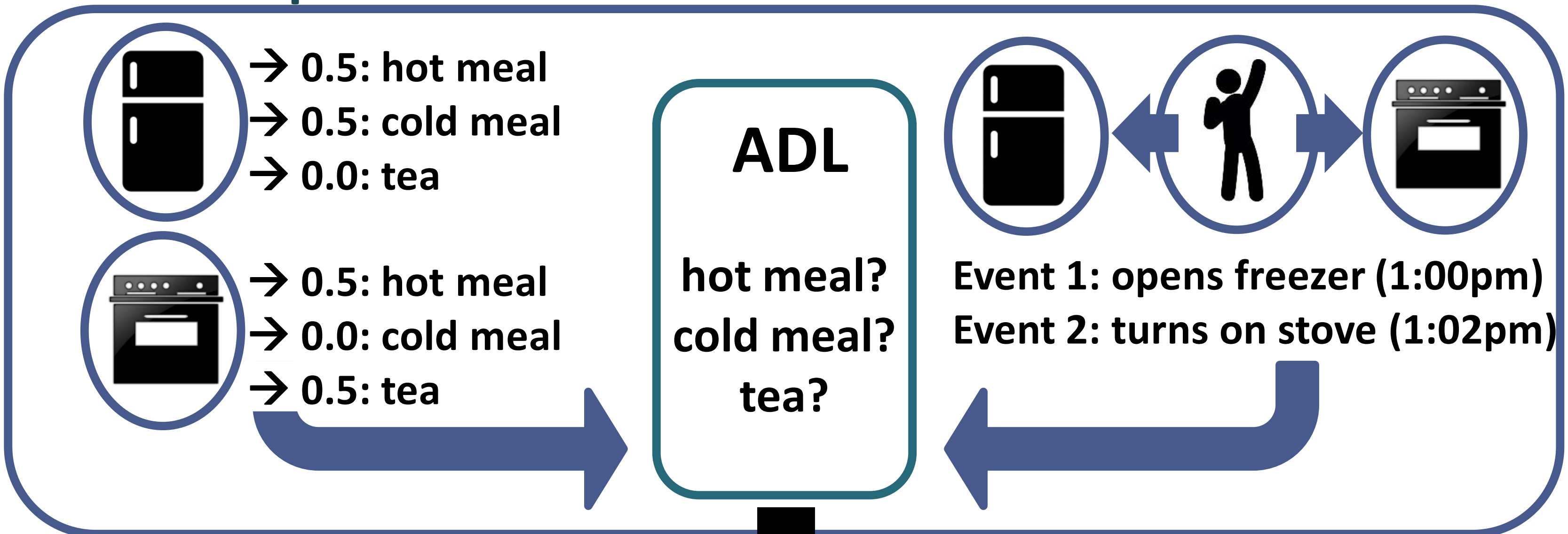
**Events**

**Temporal extension of MLN ($MLN_{NC}$ ) Knowledge Base**

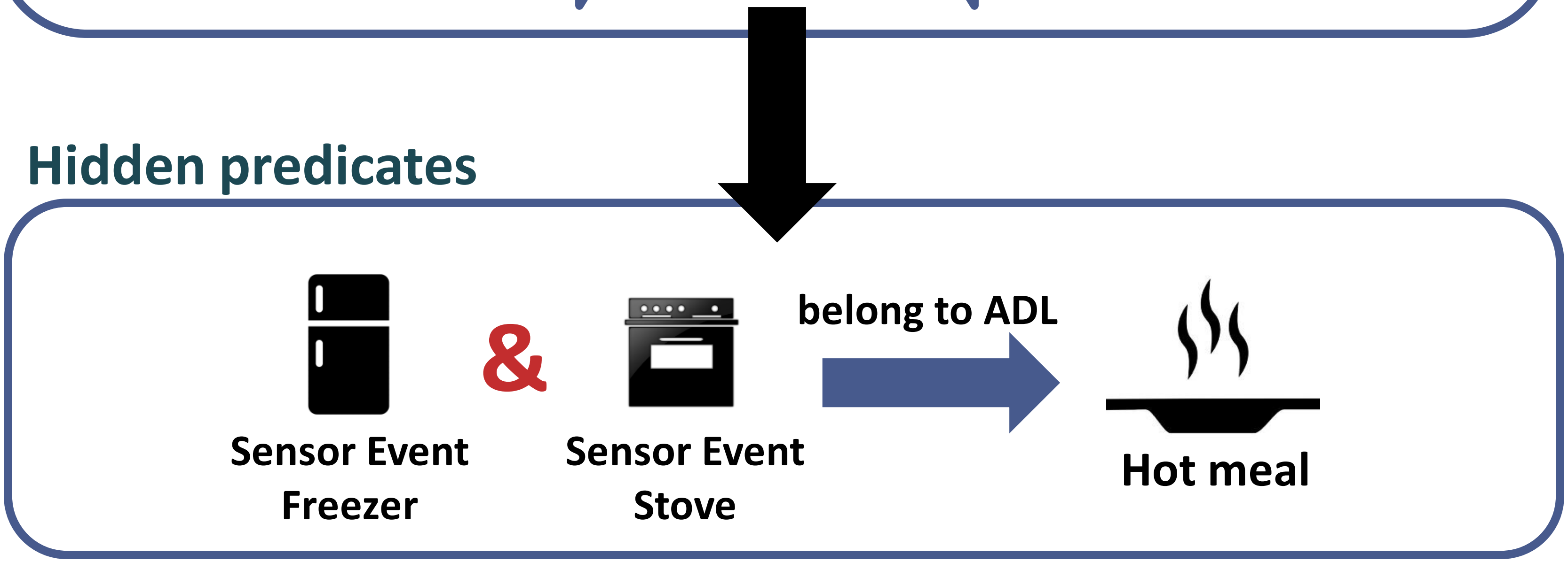
*Our ontology is translated into the $MLN_{NC}$ model*

# 3. MLN / MAP Inference

## Observed predicates




## Hidden predicates



# Data Sets

We consider two well-known data sets …

1. **CASAS (controlled environment)**
   - Interleaved ADLs of twenty-one subjects
   - Sensors: movement, water, interaction, door, phone
   - Activities: fill medications dispenser, watch DVD, water plants, answer the phone, clean, choose outfit, …

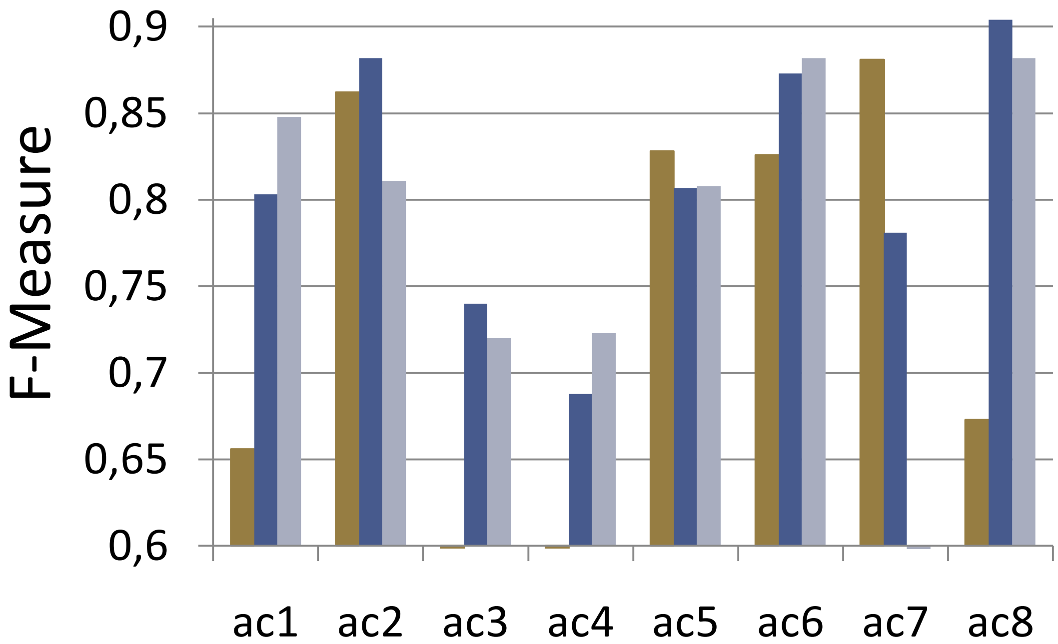
2. **SmartFABER (uncontrolled environment)**
   - An elderly woman diagnosed with Mild Cognitive Impairment
   - Sensors: magnetic, motion, presence, temperature
   - Activities: taking medicines, cooking, …

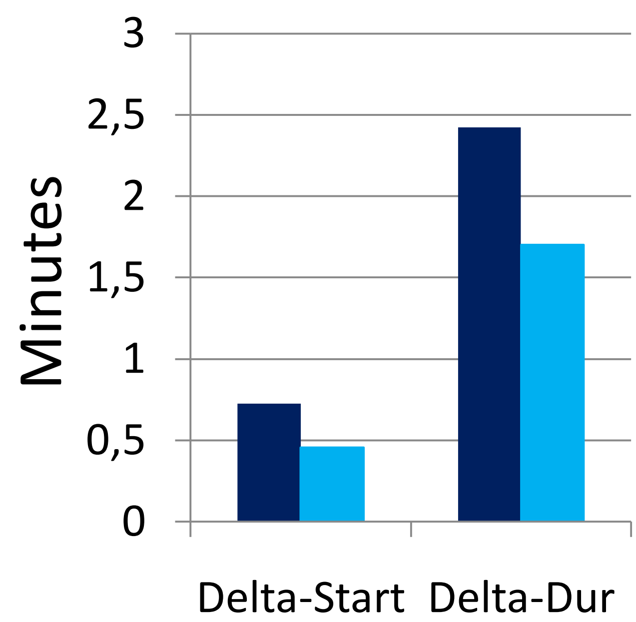
# CASAS (1/2)

- Our approach outperforms HMM
  - ➡ ontological reasoning is effective
- Refinement improves boundary precision

- $MLN_{NC}$ (Ontology)
- $MLN_{NC}$ (Dataset)
- HMM (related work)

- Candidate
- Refined



# SmartFABER (2/2)

- unsupervised and supervised-based results are comparable
- results were penalized by a poor choice of sensors

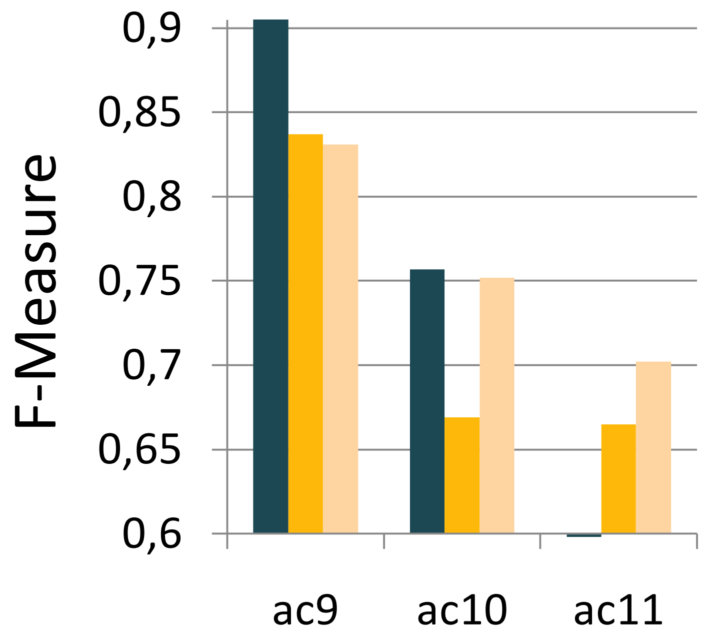
**$MLN_{NC}$ (Ontology)**

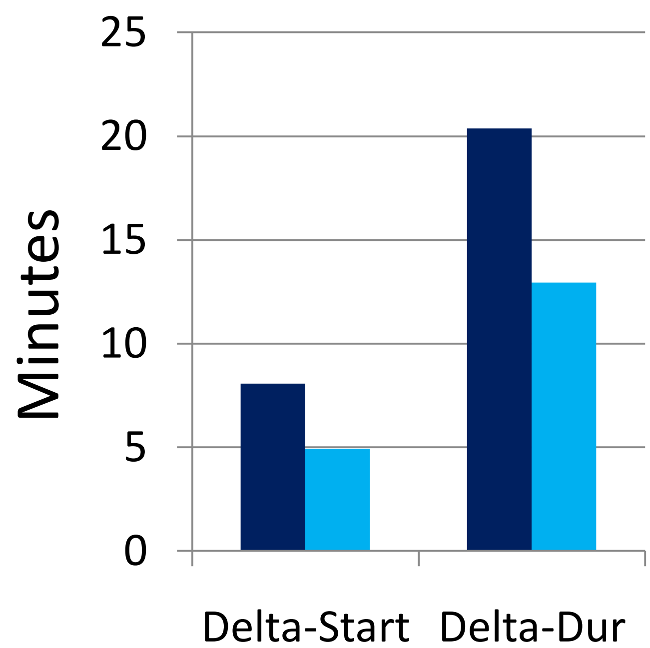
**$MLN_{NC}$ (Dataset)**

**Supervised / SmartFarber**

**Candidate**

**Refined**



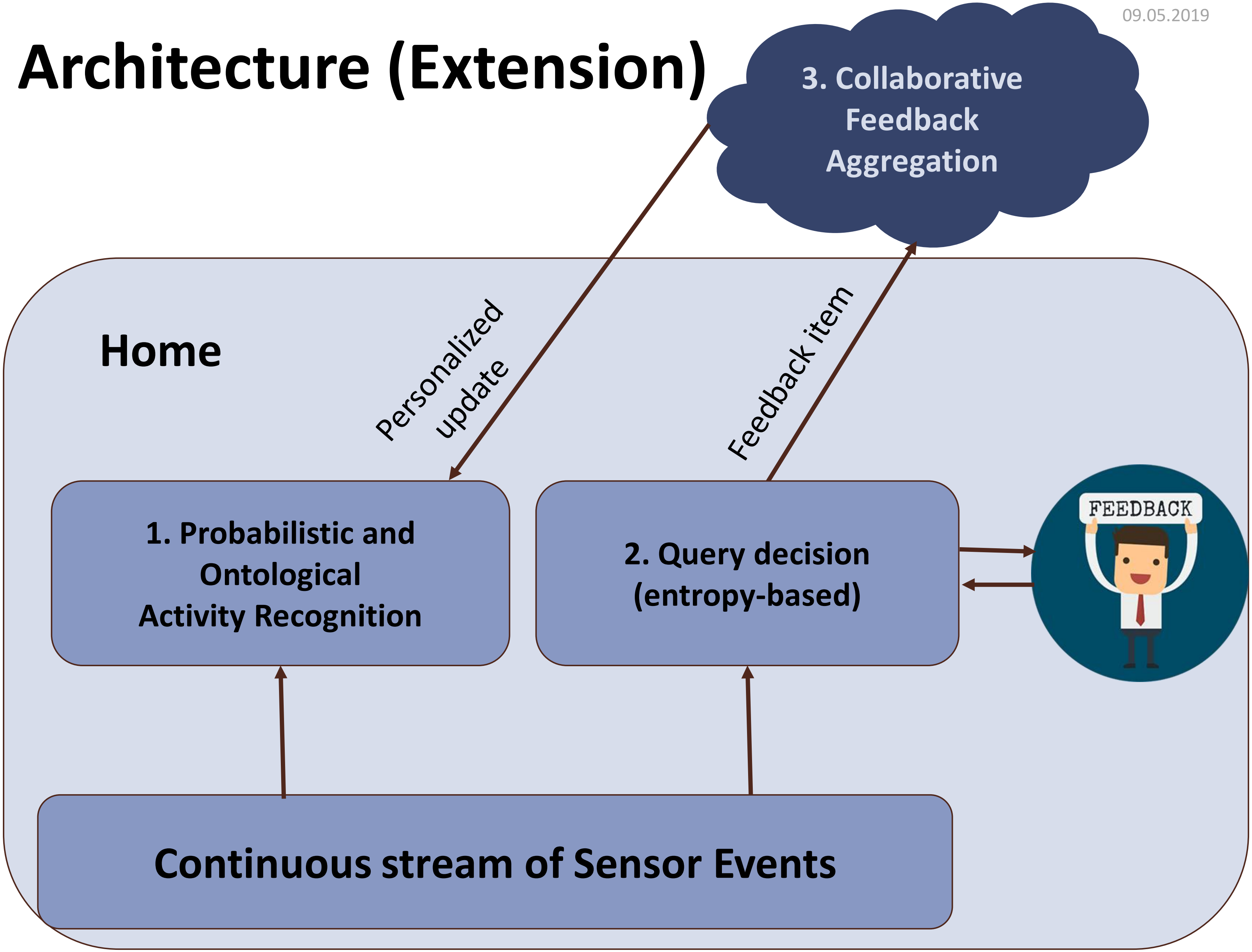



# Research Questions (catchwords)

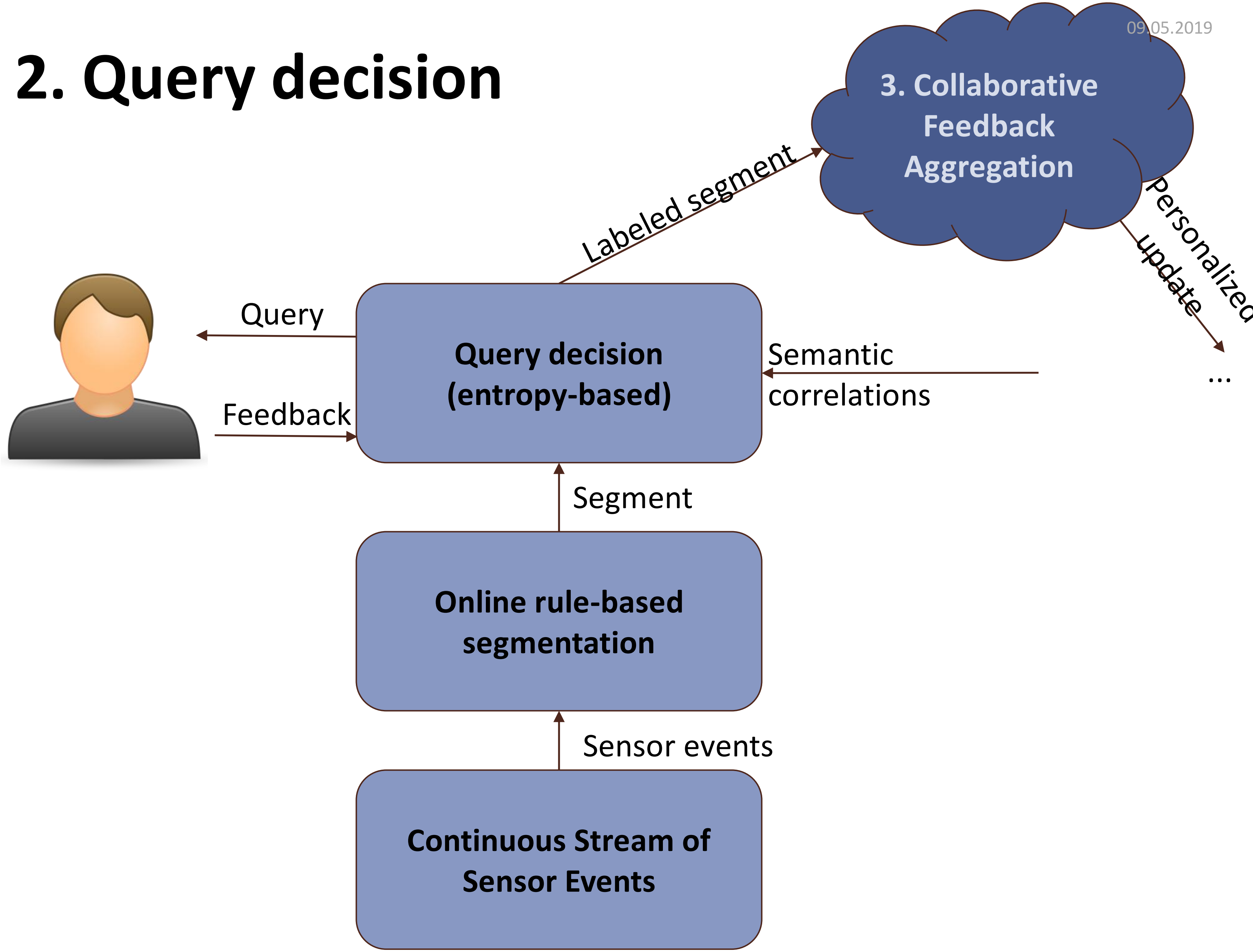
**RQ2.3 … recognizing ADLs in almost real-time …**

**RQ2.4 … personalize model to a user and environment …**

# Architecture (Extension)



# 2. Query decision



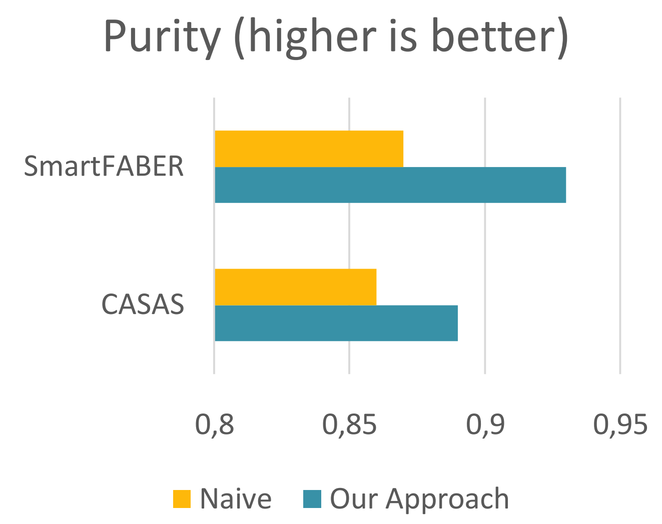
# Online rule-based segmentation

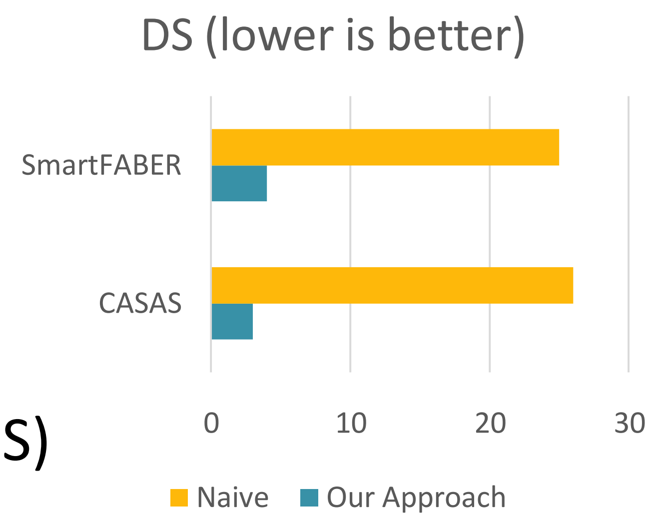
We consider five aspects …

- Object interaction
- Change of context
- Consistency likelihood
- Time leap
- Change of location

We introduced two metrics …

- Purity of a segment
- Number of generated segments (DS)



# 3. Collaborative Feedback Aggregation



Labeled segments are transmitted to a ***cloud service*** by the participating homes

➡ it stores **feedback items**: correspondence between sensor event types and activities

Periodically, a **personalized update** is transmitted to each home

➡ it contains **reliable** *feedback items* provided by similar environments

# Semantic Correlation Updater

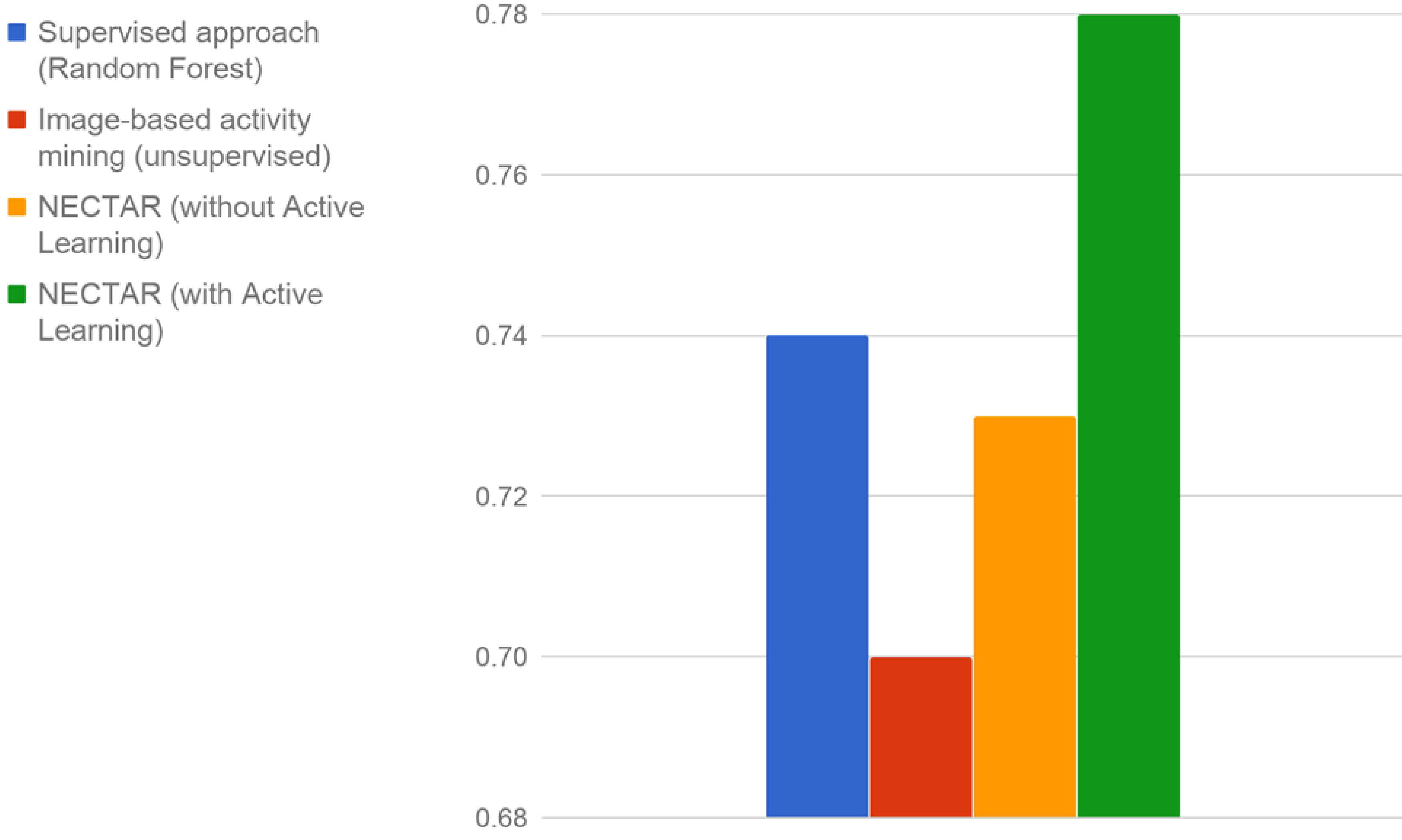


Each home receives periodically a set of **personalized feedback items**

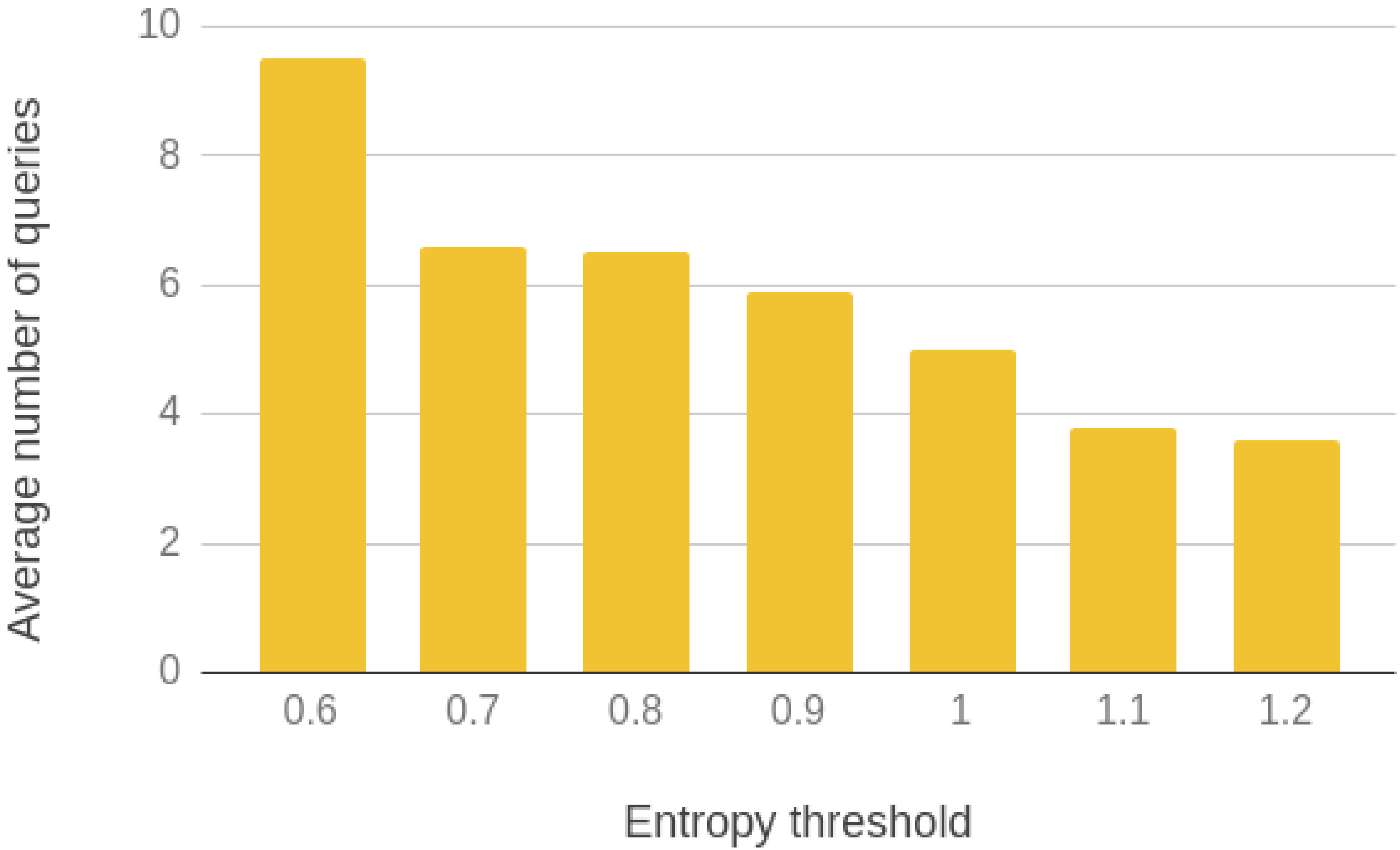
- *predictiveness* is used to provide a semantic correlation to those event types for which the original ontology did not provide a starting correlation

- *estimated similarity* is used to scale semantic correlations of an event type which were originally computed by the ontology

# Recognition results (F1 score)



# Entropy threshold vs. number of queries

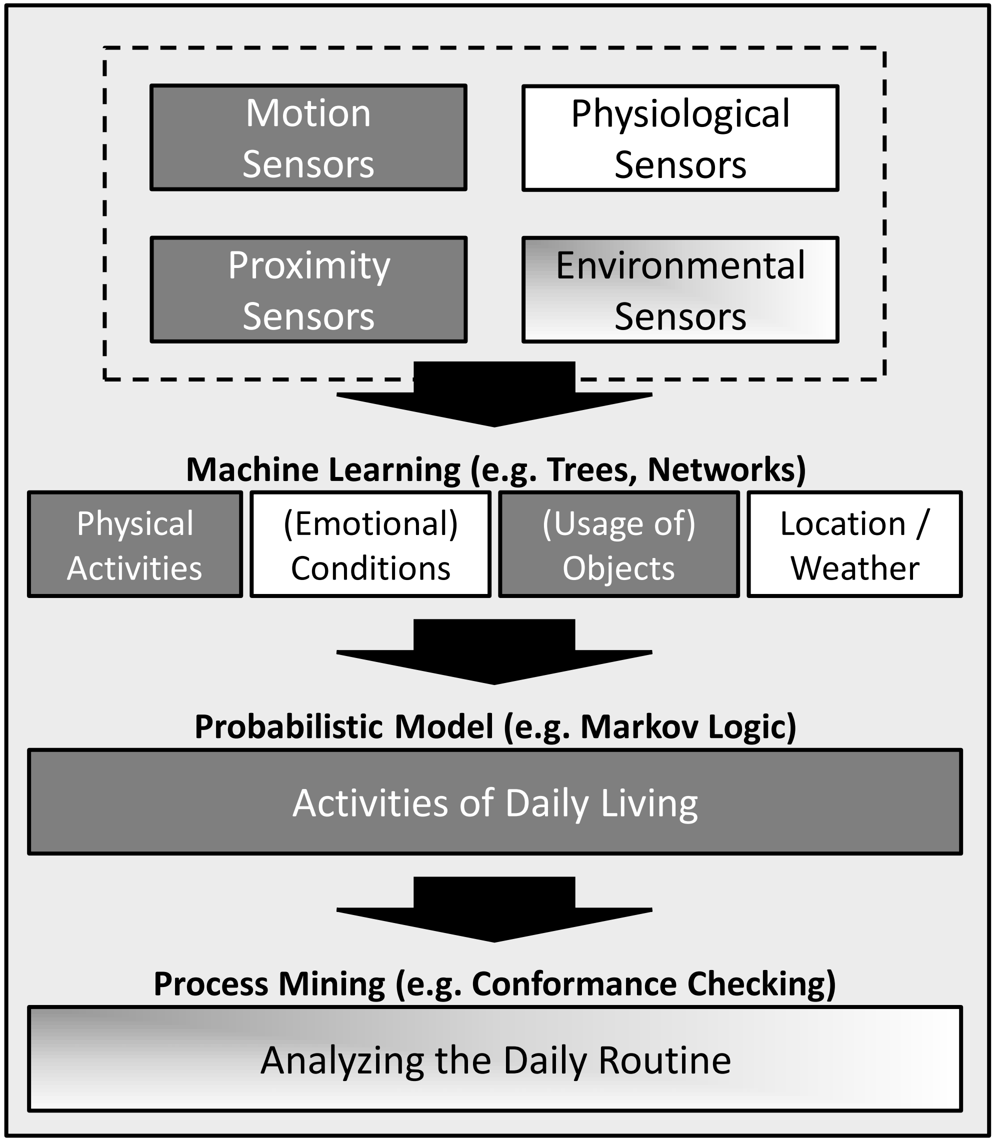


# Main Contributions



- An unsupervised ADL recognition method that **overcomes the main drawbacks** of supervised- and specification-based approaches.
- A **novel online segmentation algorithm** that combines probabilistic and symbolic reasoning to divide on the fly a continuous stream of sensor events into high quality segments.
- A **new active learning approach** to Activity of Daily Living recognition that addresses the main problems of current statistical and knowledge-based methods
- …

# Summary - Activity Recognition



# Publications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- D. Riboni, T. Sztyler, G. Civitarese, and H. Stuckenschmidt, "Unsupervised recognition of interleaved activities of daily living through ontological and probabilistic reasoning," in Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, 2016, pp. 1–12, doi: 10.1145/2971648.2971691.
- T. Sztyler, H. Stuckenschmidt, and W. Petrich, "Position-aware activity recognition with wearable devices," Pervasive and Mobile Computing, vol. 38, no. Part 2, pp. 281–295, 2017, doi: 10.1016/j.pmcj.2017.01.008.
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# Publications




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# Publications




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- T. Sztyler, J. Völker, J. Carmona, O. Meier, and H. Stuckenschmidt, "Discovery of personal processes from labeled sensor data - An application of process mining to personalized health care, " in Proceedings of the International Workshop on Algorithms & Theories for the Analysis of Event Data, ATAED. CEUR-WS.org, 2015, pp. 31–46. ISSN 1613-0073
- C. Civitarese, G. Bettini, T. Sztyler, D. Riboni, and H. Stuckenschmidt, "newNECTAR: Collaborative active learning for knowledge-based probabilistic activity recognition", Pervasive and Mobile Computing (2019), vol. 56, pp. 88–105, doi: j.pmcj.2019.04.006


- **and more ….**

# Thank you for your attention :)

# …and especially "thank you" to all my friends and co-authors!