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## Unsupervised Recognition of Interleaved Activities of Daily Living through Ontological and Probabilistic Reasoning


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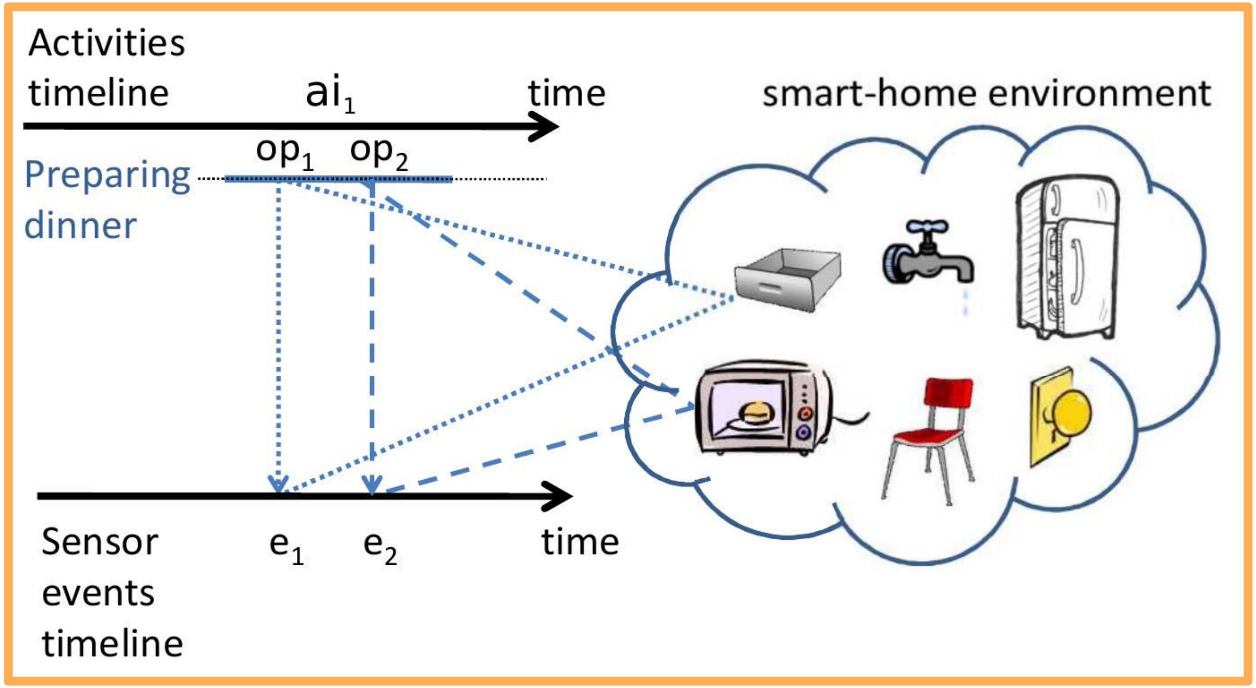
# MOTIVATION

# Scenario

Recognizing activities of daily living in a smart-home

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

We rely on unobtrusive sensors …



# State of the Art and Open Issues

Most activity recognition systems rely on …

… supervised-based approaches:

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

… knowledge-based approaches:

- unfeasible to enumerate all activity patterns

**We propose an unsupervised method to recognize complex/interleaved ADLs**

**Based on hybrid ontological – probabilistic reasoning**

# Our approach …

… overcomes drawbacks of supervised-based approach

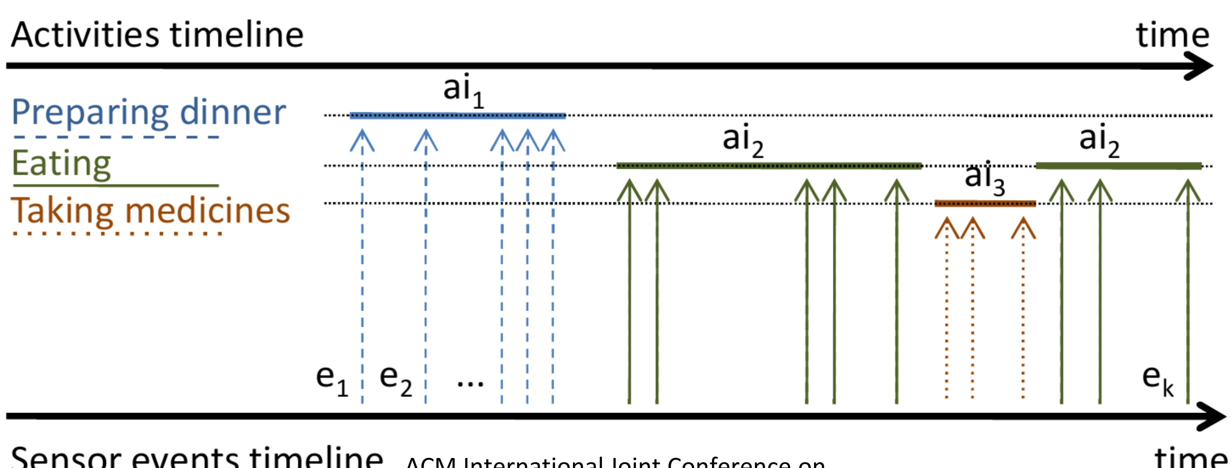
- not user/environment-specific, no expensive data set, …

… relies on semantic relations (activities↔ events)

- derived from ontological reasoning

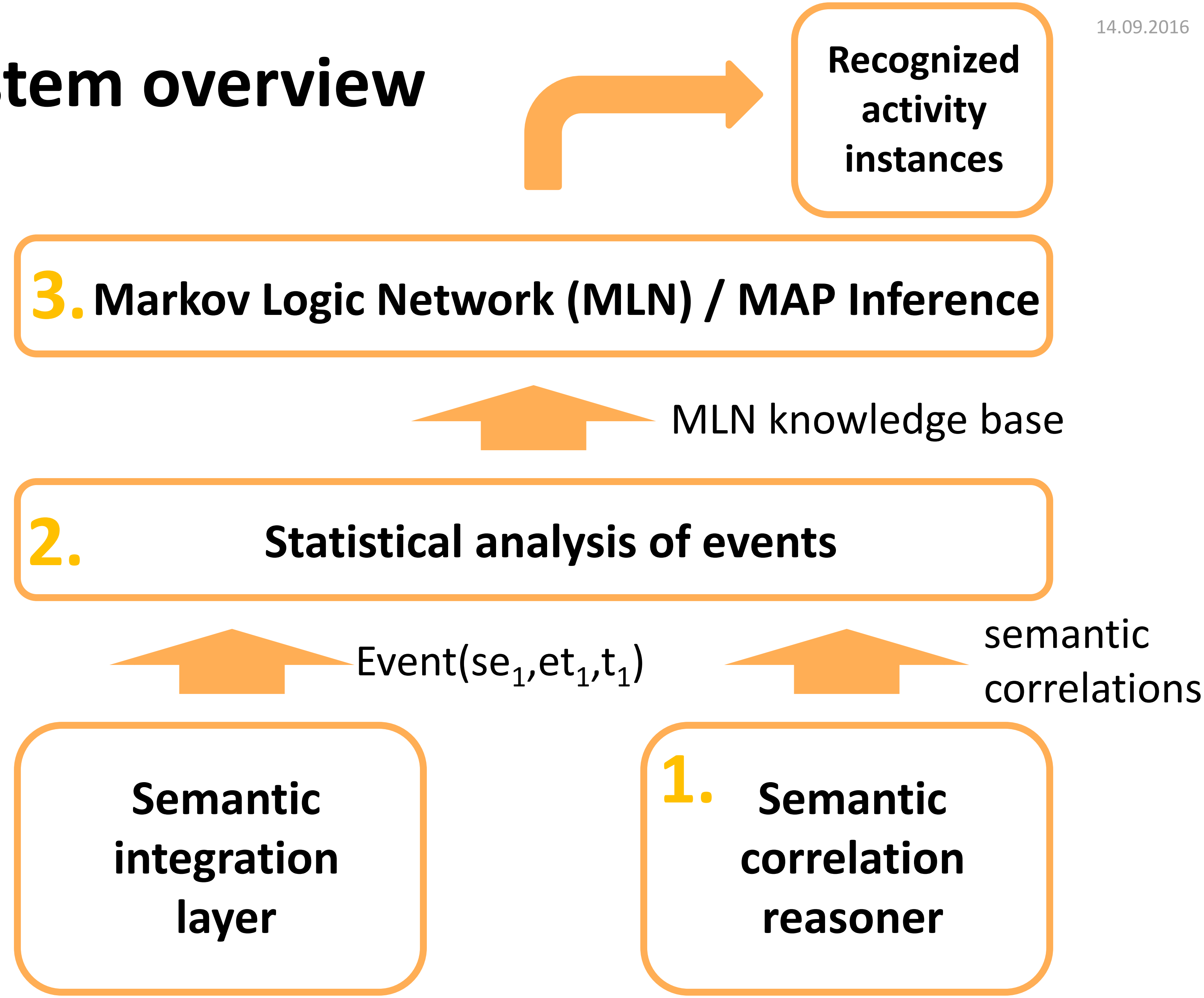
… recognizes interleaved activities

- inferred by a probabilistic model



# MODEL AND SYSTEM

# System overview

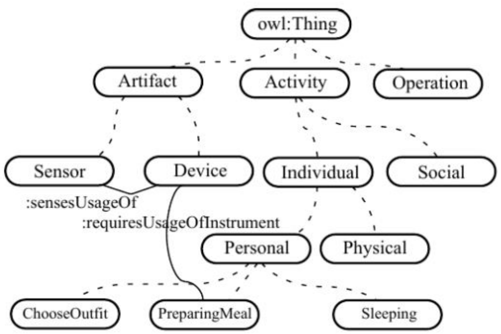


# 1. Semantic Correlation Reasoner

Why do we use Ontology (OWL2)?

to derive semantic correlations (event type ↔ activity class)

**Ontology / Axioms**




**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 |

# 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

→ 0.5: hot meal
→ 0.5: cold meal
→ 0.0: tea

→ 0.5: hot meal
→ 0.0: cold meal
→ 0.5: tea

**ADL**

hot meal?
cold meal?
tea?

Event 1: opens freezer (1:00pm)
Event 2: turns on stove (1:02pm)

## Hidden predicates

Sensor Event Freezer & Sensor Event Stove — belong to ADL → Hot meal

# EXPERIMENTS

# Data Sets

We consider two well-known data sets …

## 1. CASAS (controlled environment)

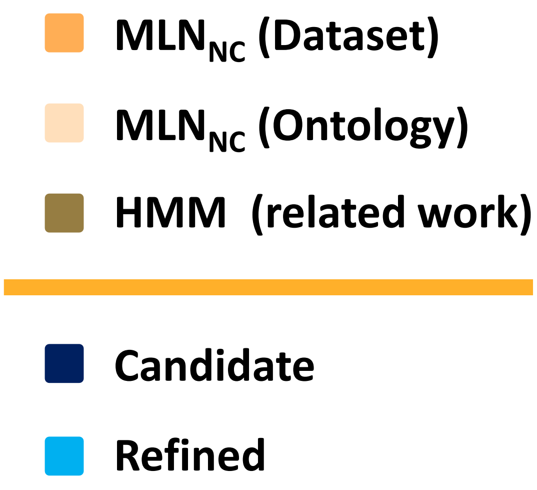
- Interleaved ADLs of twenty-one subjects
- Sensors: movement, water, interaction, door, phone
- Activities: fill medications dispenser, watch DVD, water plants, answer the phone, clean, choose outfit, …

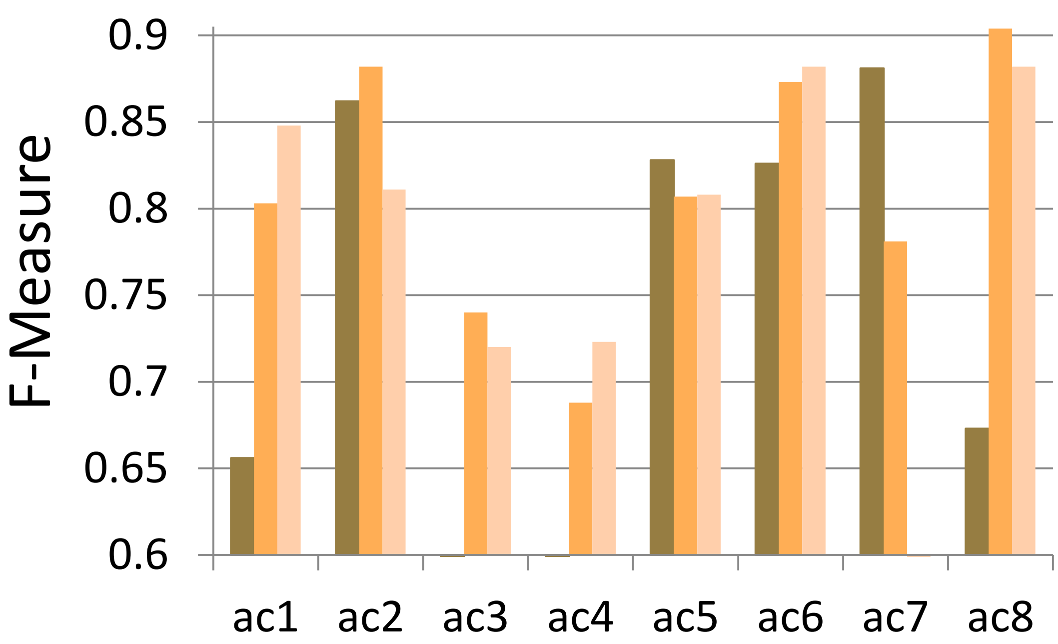
## 2. SmartFaber (uncontrolled environment)

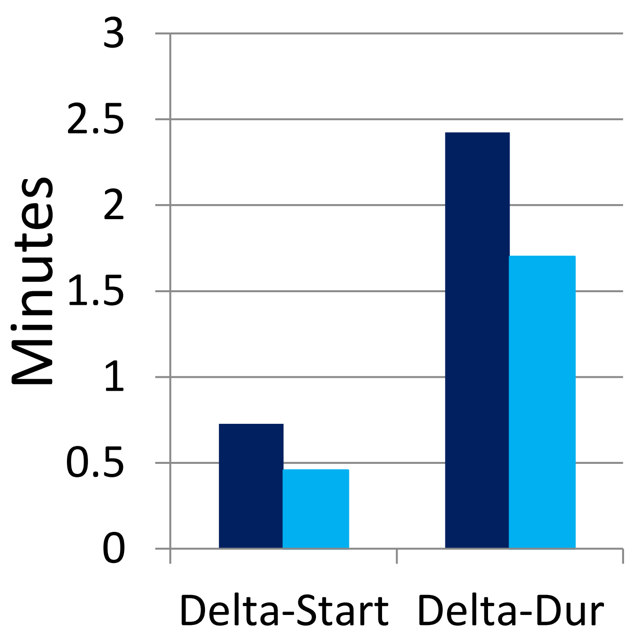
- An elderly woman diagnosed with Mild Cognitive Impairment
- Sensors: magnetic, motion, presence, temperature
- Activities: taking medicines, cooking, …

# CASAS (1/2)

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



# SmartFaber (2/2)

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

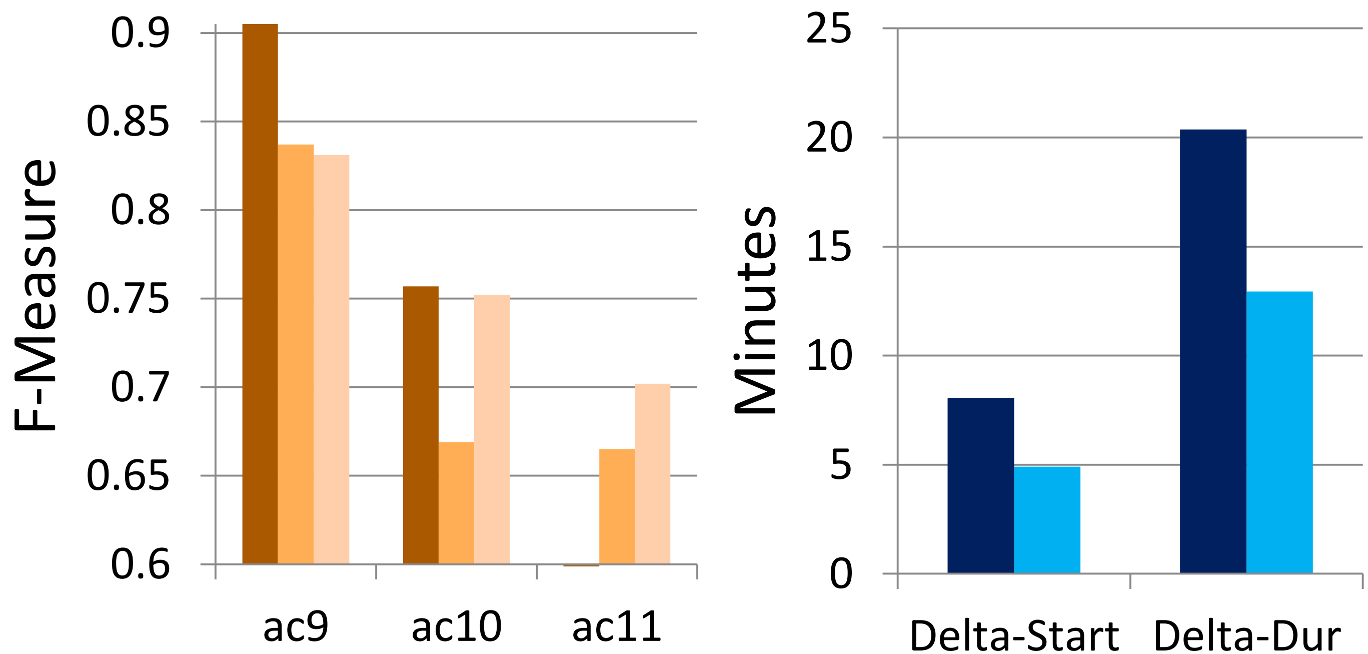
**$MLN_{NC}$ (Dataset)**

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

**Supervised / SmartFarber**

**Candidate**

**Refined**



# DISCUSSION / FUTURE WORK

# Discussion

Results with two large datasets of interleaved ADLs were positive, but...

- … knowledge engineering is required (build ontology)

➡ existing smart-home ontologies can be reused

- … it is questionable if one ontology can cover every home

➡ adaptation/extension should be performed (semi-) automatically

# Future Work

Extensive real-world experiments should show …

… if and how the ontology has to be adapted

… what happens in a multi-user environment

Can active learning allow to …

… fine-tune existing models? (user’s environment/habits)

… evolve the ontology according to the current context?

**THANK YOU FOR YOUR ATTENTION**

# BACKUP SLIDES

# Semantic Integration Layer

- collects events data from a sensor network
- applies preprocessing rules to detect operations

**Example**

fridge door sensor signaled “1”

→

the operation is “opening the fridge”

$$<Event(se_1, et_1, t_1), \dots, Event(se_k,et_k,t_k)>$$

# MLN Model (detailed)

**PPM Matrix**

→ *PriorProbability

**Statistical analysis of events**

→ *InstanceCandidate / *Event

## Ontological constraints

time-aware inference
temporal
knowledge-based

## Observed predicates

***PriorProbability**
**(SenEvent, ADL, ActivClass, p)**

***Event**
**(SenEvent, EventType, Time)**

***InstanceCandidate**
**(ADL, Start, Stop)**

## Hidden predicates

**OccursIn**
**(SenEvent, ADL)**

**InstanceClass**
**(ActivClass, ADL)**