NECTAR: Knowledge-based Collaborative Active Learning for Activity Recognition

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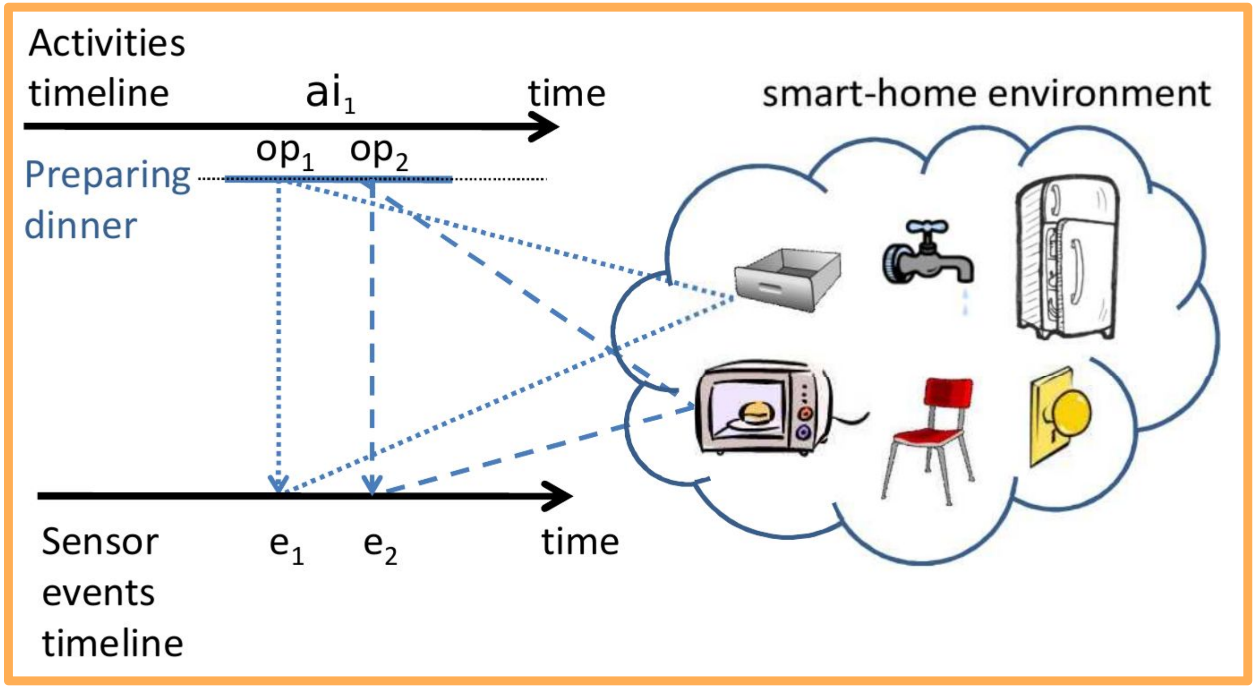
MOTIVATION

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:

- require a significant effort in knowledge engineering
- not flexible
- questionable if such models could cover different environments and modes of execution

Our solution: NECTAR

kNowledge-basEd Collaborative acTive learning for Activity Recognition

It overcomes drawbacks of supervised-based approach

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

It relies on semantic correlations

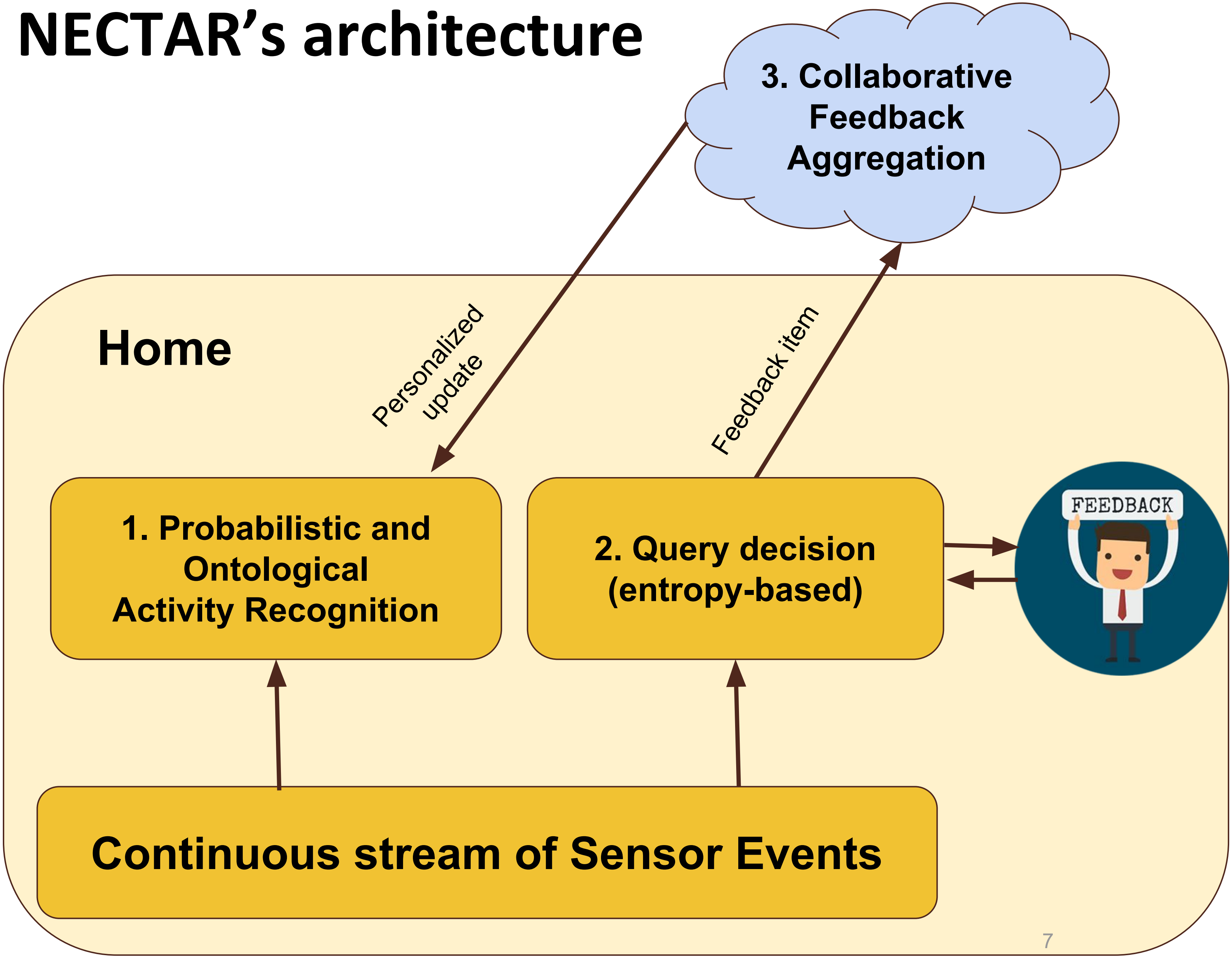
- probabilistic dependencies (activities↔ events)
- derived from a possibly incomplete ontology

It exploits collaborative active learning

- ...to refine rough correlations inferred by the ontology

MODEL AND SYSTEM

NECTAR's architecture

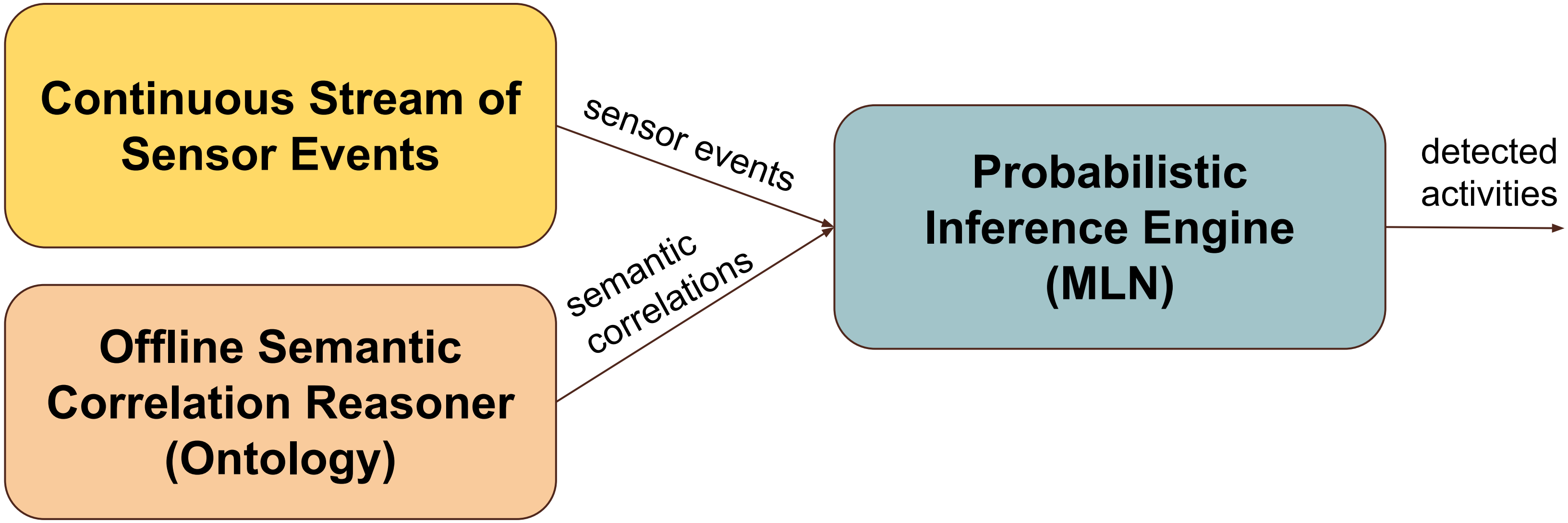


1. Probabilistic/ontological activity recognition

We rely on ontological reasoning to pre-compute in an *offline phase* **semantic correlations**

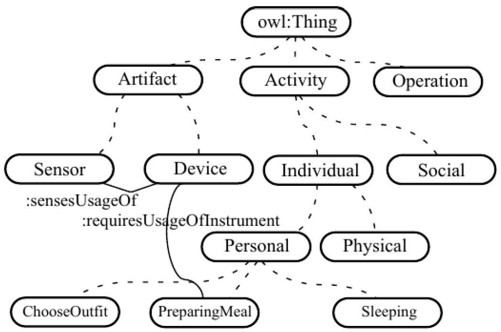
➡ they define probabilistic dependencies between home infrastructure and sensor events

A MLN combines those semantic correlations and sensor events to infer the most likely executed activities



Semantic Correlation Reasoner

Ontology / Axioms



OWL2 Reasoner infers

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

interact

prepare

SC 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

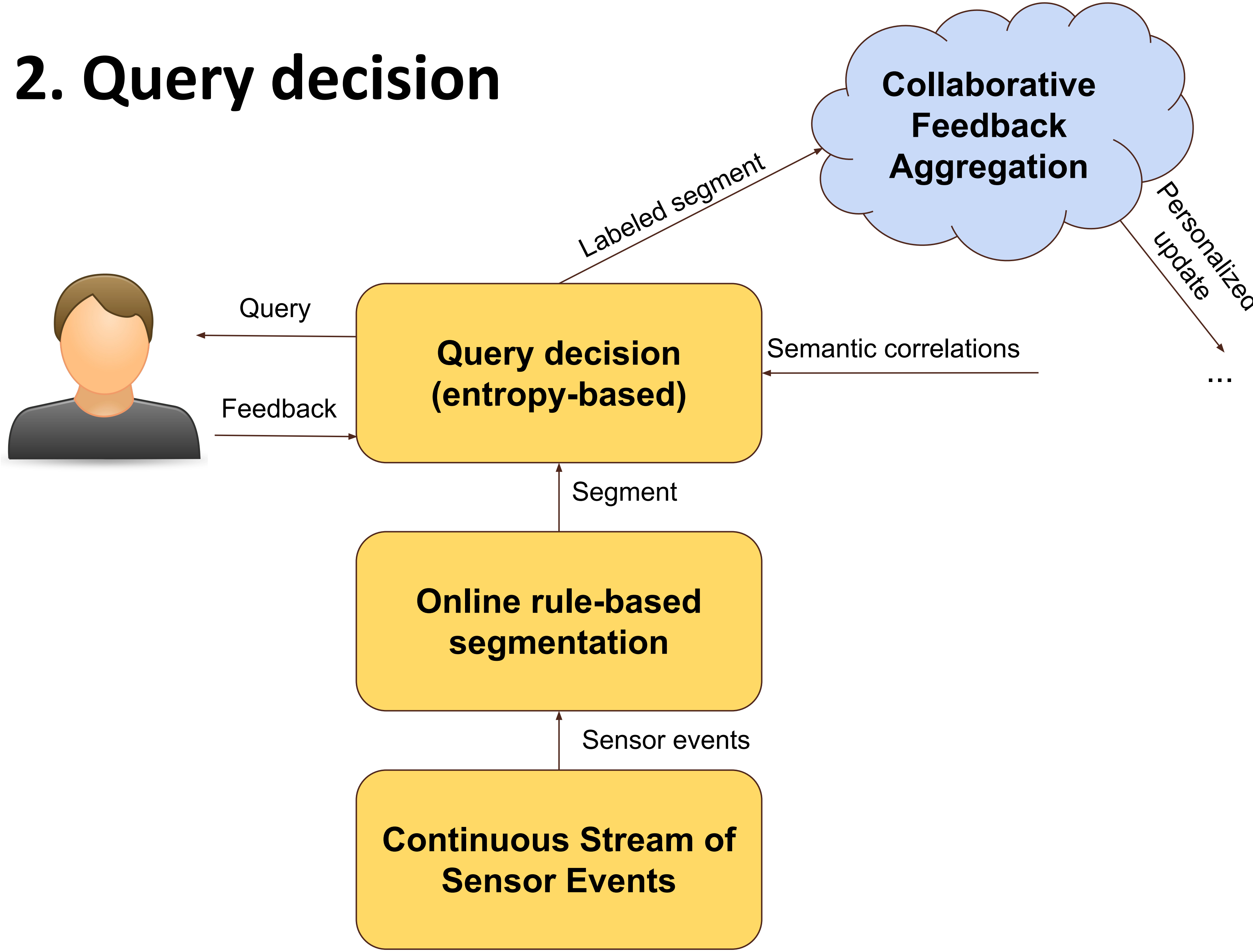
Issues of this approach

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. Query decision



Online rule-based segmentation

We continuously segment the stream of sensor events

- based on knowledge-base conditions (e.g., interaction with objects, time gaps, changes of room)
- those conditions aim to generate segments which cover **at most** one activity instance

Query decision

For each segment we derive a probability distribution over activities by **mining semantic correlations**

→ segments with high entropy values are queried to the inhabitant

$$H(S) = \sum_{ac \in A} P(X = ac \mid S) \cdot log(\frac{1}{P(X = ac \mid S)})$$

When *H(S)* is over a certain threshold we ask to the inhabitant the actual label of the segment *S*

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

Personalized update

To include only reliable feedback items in an update, we consider only whose *support* is larger than a threshold

- *support* is a value which indicates how many times the feedback was provided from different similar homes

We associate to each feedback item in an update:

- its **predictiveness:** computed as the normalization of support values
- its **estimated similarity:** the median value of similarity between origin/target 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

EXPERIMENTS

Data Set

We consider a well-known data set …

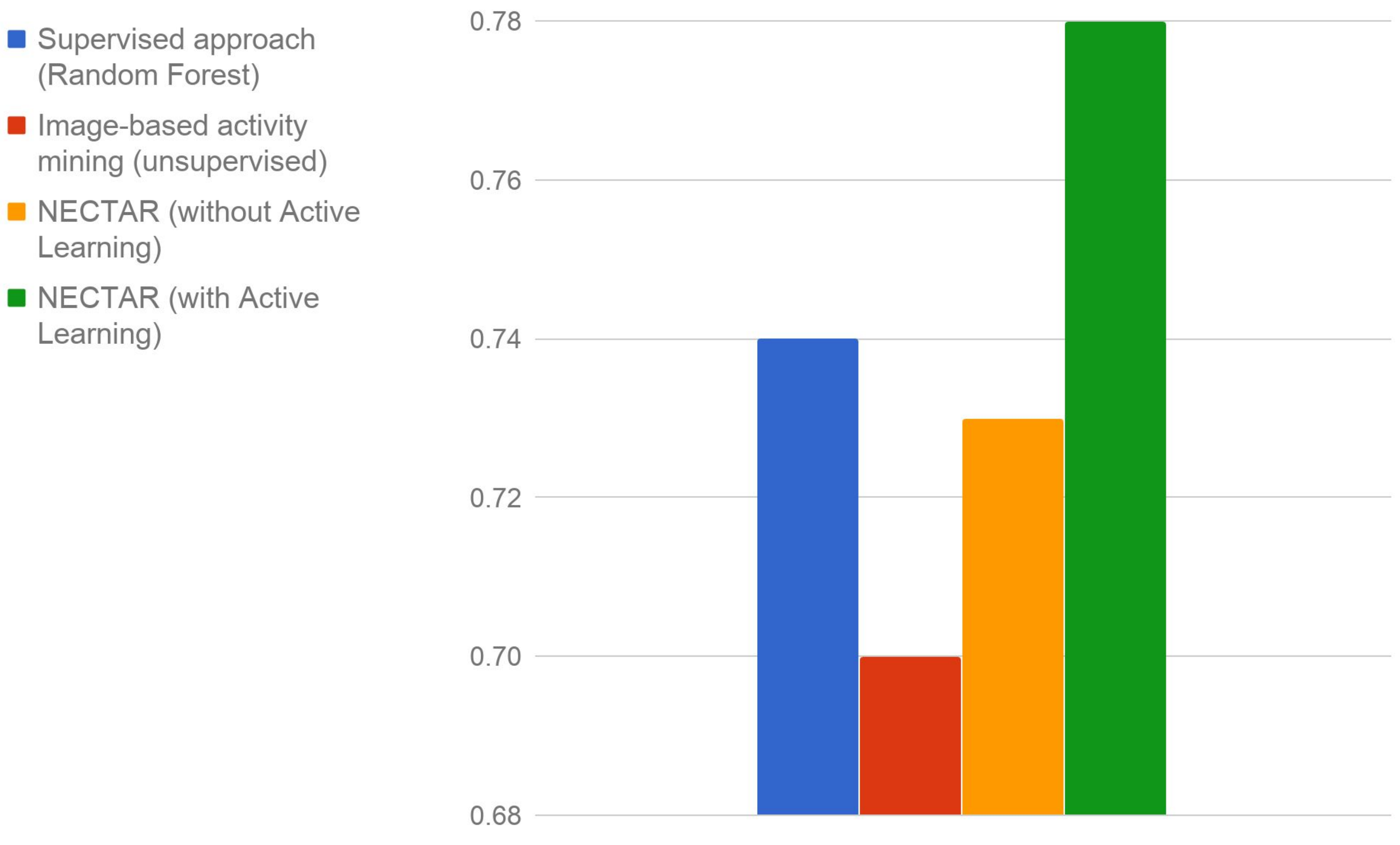
CASAS

- 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, …

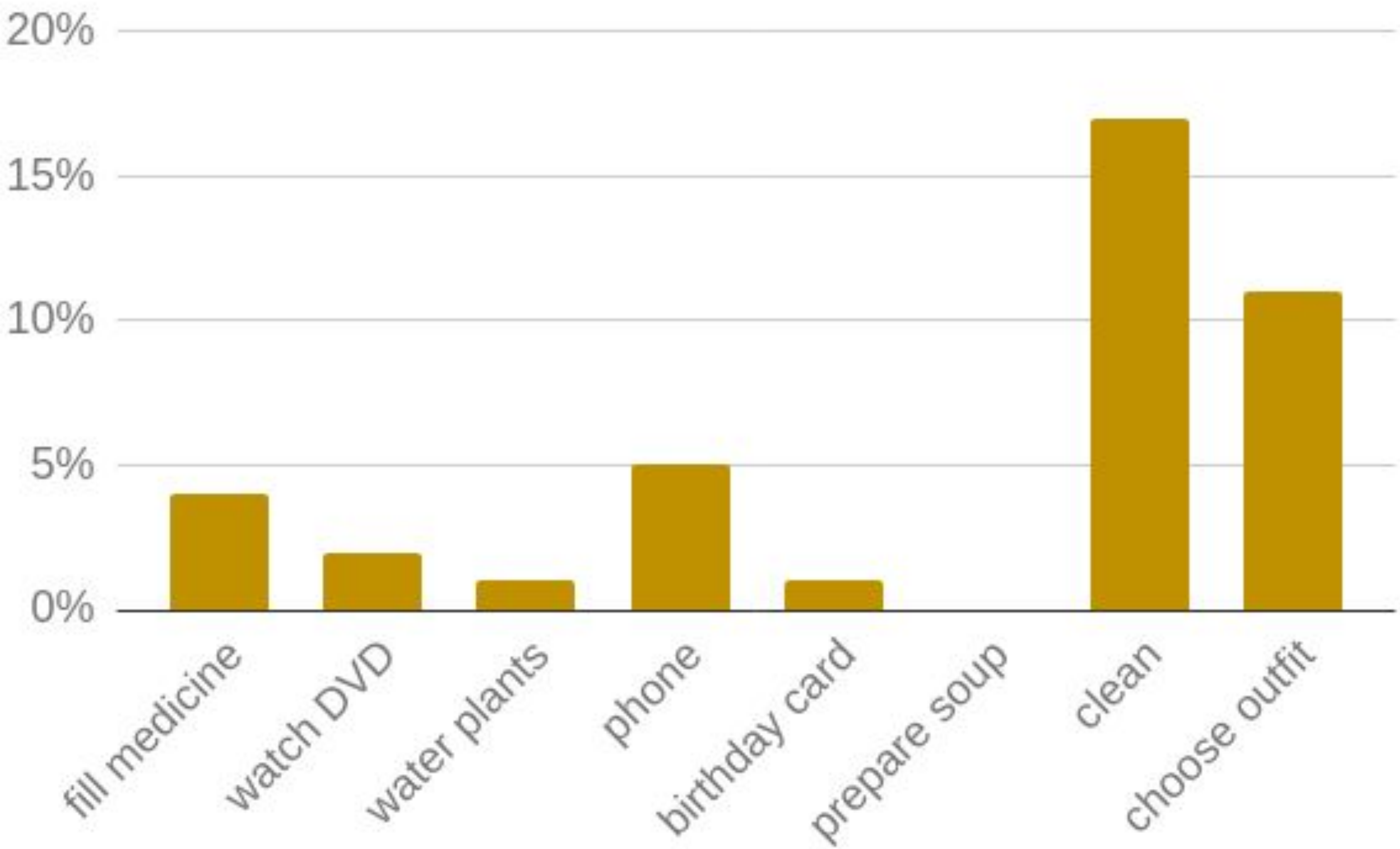
We apply *leave-one-subject-out* cross validation:

➡ in each fold we collect feedback from 20 subjects to update semantic correlations for the remaining one

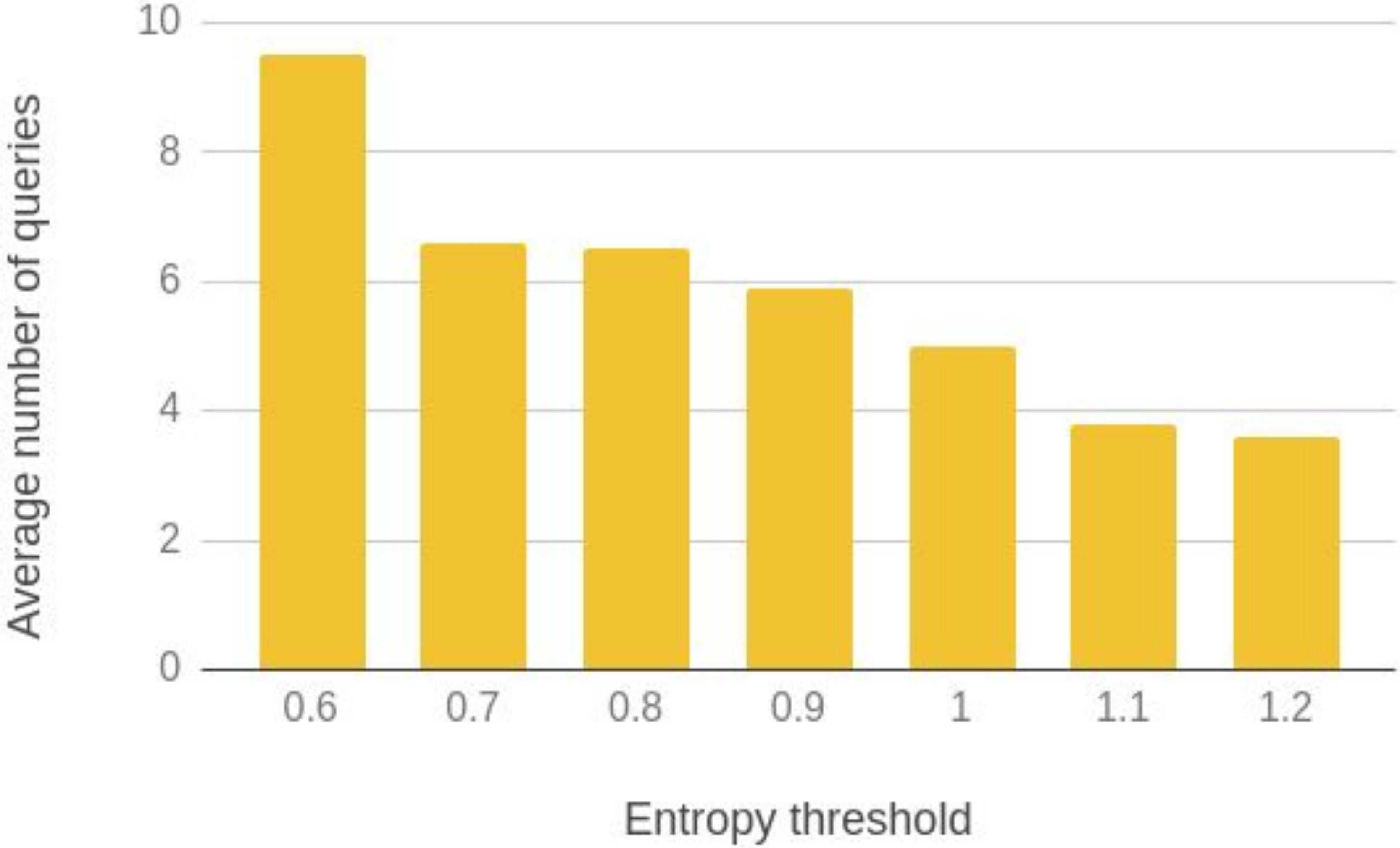
Recognition results (F1 score)



Improvement of collaborative active learning



Entropy threshold VS number of queries



DISCUSSION / FUTURE WORK

Discussion

Results with a well-known dataset were positive, but...

- … contextual aspects should be taken in account to evaluate whether to ask a feedback

➡ e.g., number of queries already been asked, current mood, availability

- ...user interfaces need to be designed

➡ e.g., vocal interfaces

- … knowledge engineering is still required (build starting ontology)

➡ existing smart-home ontologies can be reused

Future Work

Data outsourced to the cloud service is sensitive …

… we will investigate solutions based on homomorphic encryption or secure multi-party computation

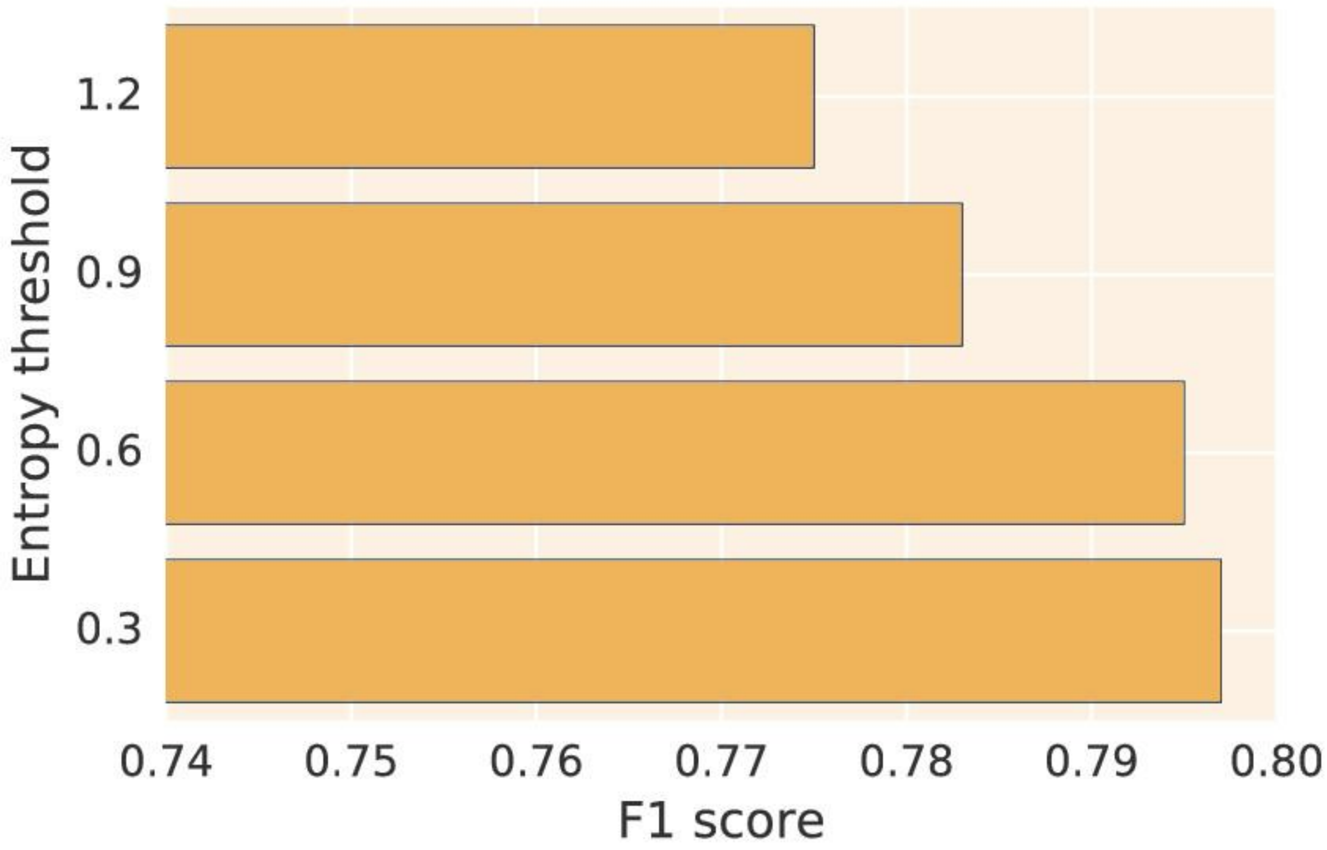
We also aim to extend our system …

… learning semantic correlations also for *temporal patterns*

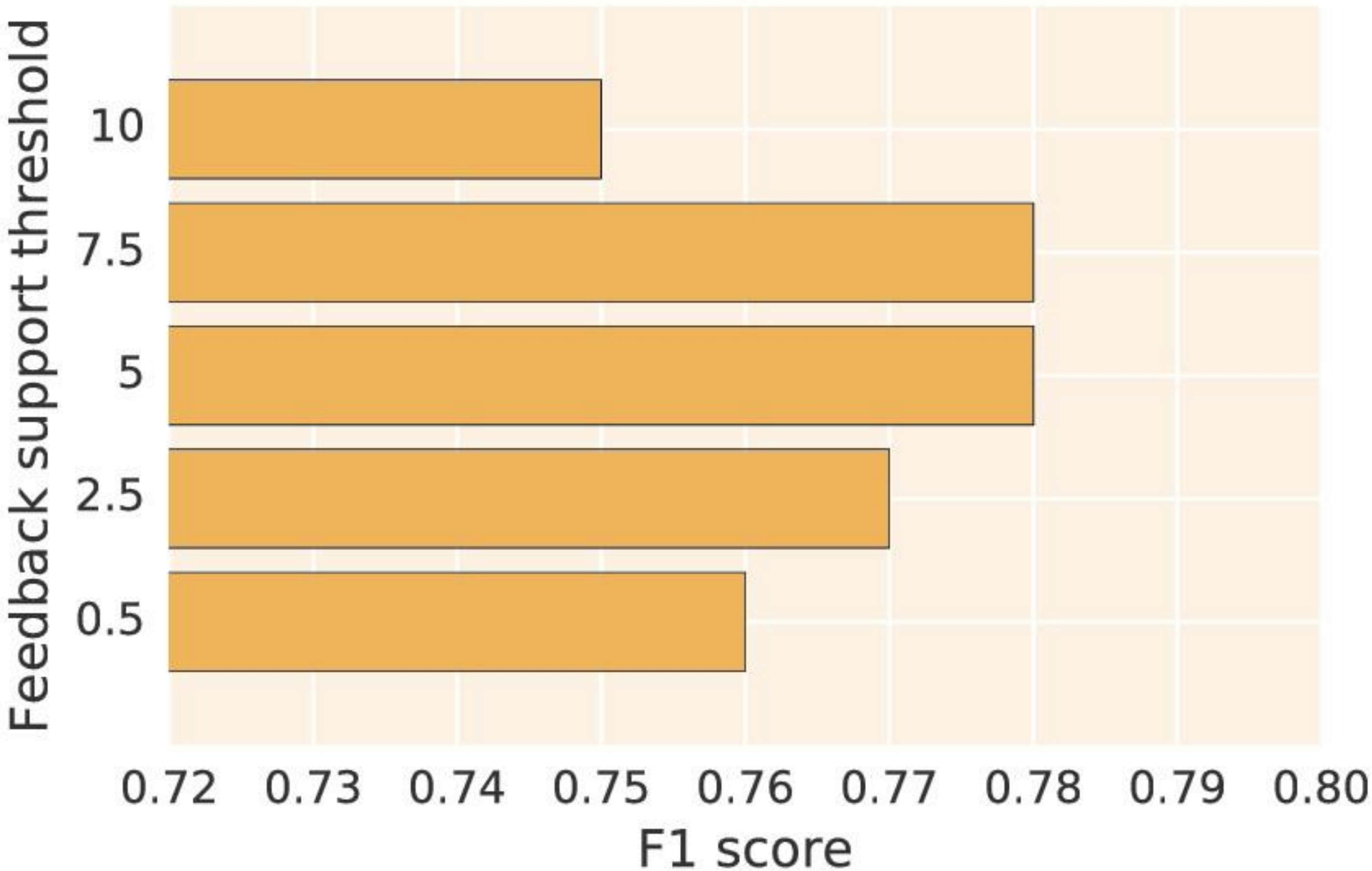
THANKS FOR YOUR ATTENTION!

BACKUP SLIDES

Entropy threshold VS F1 score



Feedback support threshold vs F1 score



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

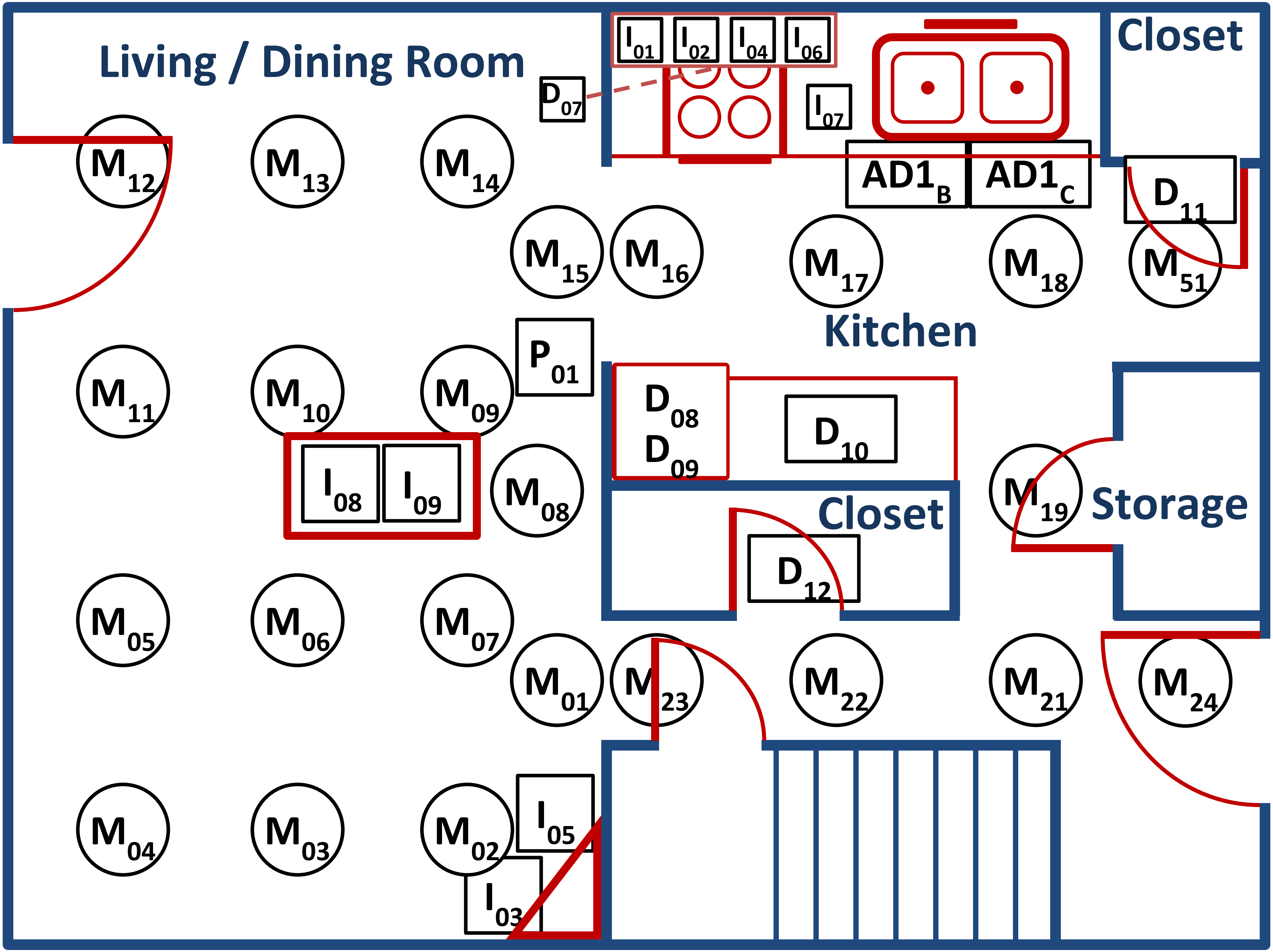
ADL

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



Living / Dining Room
I01
I02
I04
I06
D07
I07
Closet
AD1B
AD1C
D11
M12
M13
M14
M15
M16
M17
M18
M51
Kitchen
P01
M11
M10
M09
D08
D09
D10
I08
I09
M08
Closet
M19
Storage
D12
M05
M06
M07
M01
M23
M22
M21
M24
M04
M03
M02
I05
I03

MLN Model (detailed)

PPM Matrix

➡ *SemanticCorrelation

Statistical analysis of events

➡ *InstanceCandidate / *Event

Ontological constraints

time-aware inference
temporal
knowledge-based

Observed predicates

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

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

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

Hidden predicates

OccursIn (SenEvent, ADL)

InstanceClass (ActivClass, ADL)

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”

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

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