KNOWLEDGE-DRIVEN ACTIVITY RECOGNITION AND SEGMENTATION USING CONTEXT CONNECTIONS

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Scope

- Practical ontology-based activity recognition framework.
    - Based on loosely coupled domain activity dependencies rather than on strict contextual constraints.
- RDF dataset of primitive activities (observations).
- **Context connections**, **local contexts**, **context descriptors**.
    - Flexible & reusable framework for recognising complex activities.
    - Simple & reusable ontology pattern for capturing common sense background knowledge.
    - Context-aware activity recognition & segmentation algorithm.

Motivation

- The standard OWL semantics cannot be straightforwardly used for activity recognition
  - Temporal reasoning is not supported (most approaches use predefined time windows for segmentation)
  - The use of strict activity descriptions, either in the form of class axioms or even as rules fail to handle the intrinsically noisy and imperfect information.
- However, ontologies are perfect for:
  - Integrating observations from heterogeneous sources, exploiting the semantics of domain vocabularies (SEM, LODE, etc),
    - activity hierarchies, necessary/sufficient restrictions, etc.
  - Formally sharing and reusing knowledge

Our Approach

- We use ontologies for:
  - Defining the domain vocabulary
    - hierarchies, properties, relations, etc.
  - Describing the context of complex activities through **Context Descriptors**
    - Meta-modelling (punning)
    - *Descriptions and Situations* pattern for annotating domain activity classes with lower level conceptualisations (primitive activities)
- Segmentation and Recognition algorithm based on Context Descriptions
  - Segmentation: identify meaningful contexts from a set of observations
  - Recognition: classify the contexts to higher level activities

Background

- Intelligent, customized user task support across a multitude of domains.
- **Key challenge**: Abstract & fuse captured context in order to elicit a higher level understanding.
- Ontology-based frameworks for modeling & reasoning about context.
  - Map low-level info & activity models onto ontologies.
  - Inference of high-level activities using domain knowledge & reasoning.
  - Deploy rules for representing richer relationships.

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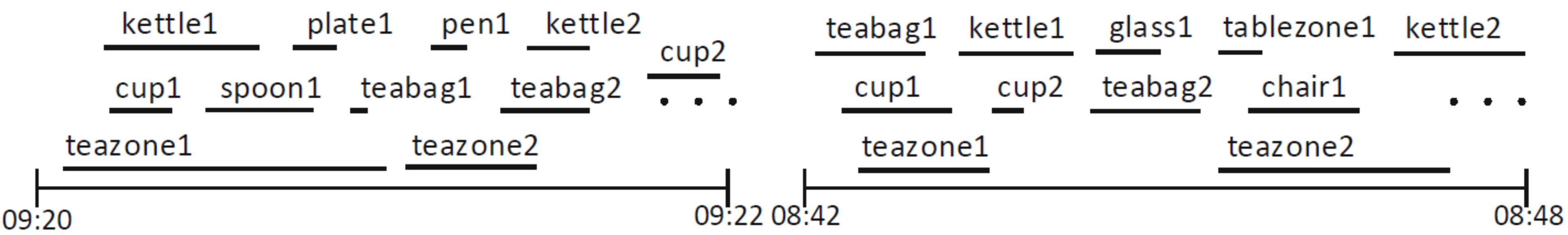
- Ontology-based frameworks for modeling & reasoning about context.
  - Map low-level info & activity models onto ontologies.
  - Inference of high-level activities using domain knowledge & reasoning.
  - Deploy rules for representing richer relationships.
- **How can we identify the context indicating complex activities?**
  - Time windows and slices.
  - Background knowledge about the order or duration of activities.
- Drawbacks:
  - Strict contextual dependencies.
  - Assuming all information is available.
- Fail to capture intrinsic characteristics of pervasive environments!

Challenges

http://http://www.demcare.eu/



- Duration of activities typically varies.
- Activities carried out differently, even by the same person.
- Information integrated from heterogeneous sources is intrinsically noisy, incomplete & with inaccurate temporal correlations.

Domain Context Descriptors

- **Situation** concept [*DnS pattern, DOLCE+DnS Ultralite (DUL)*].

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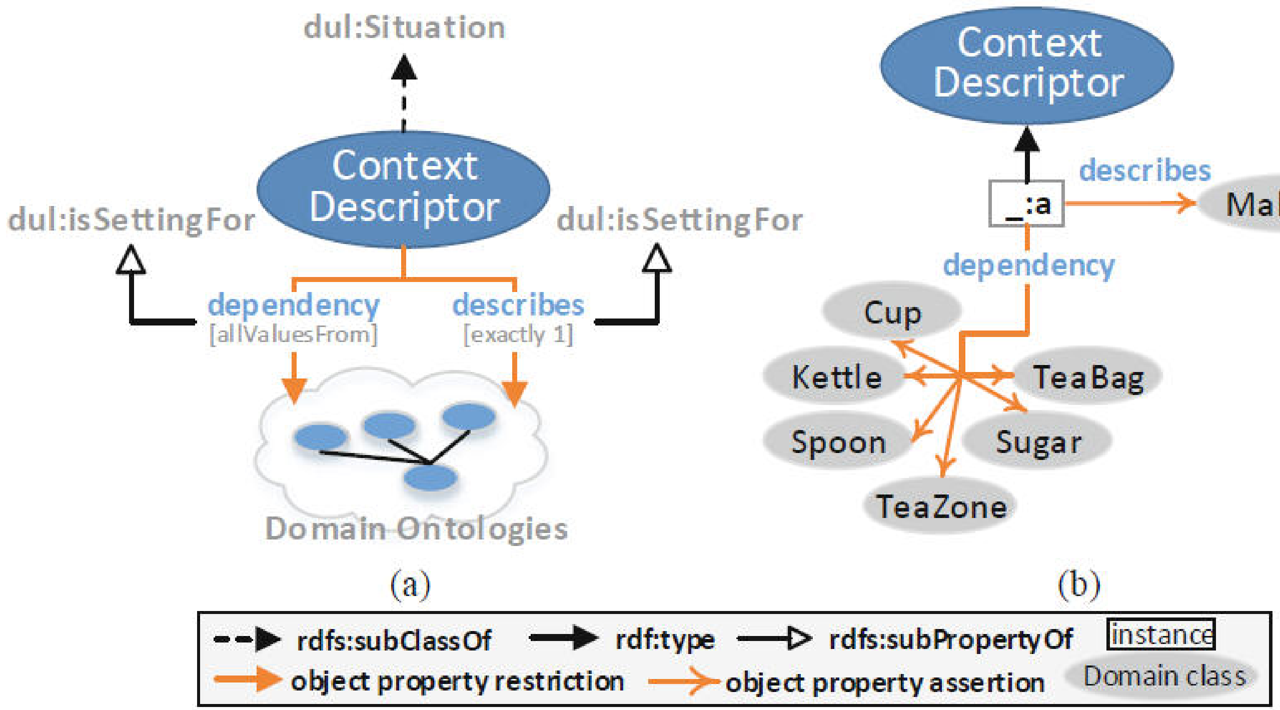

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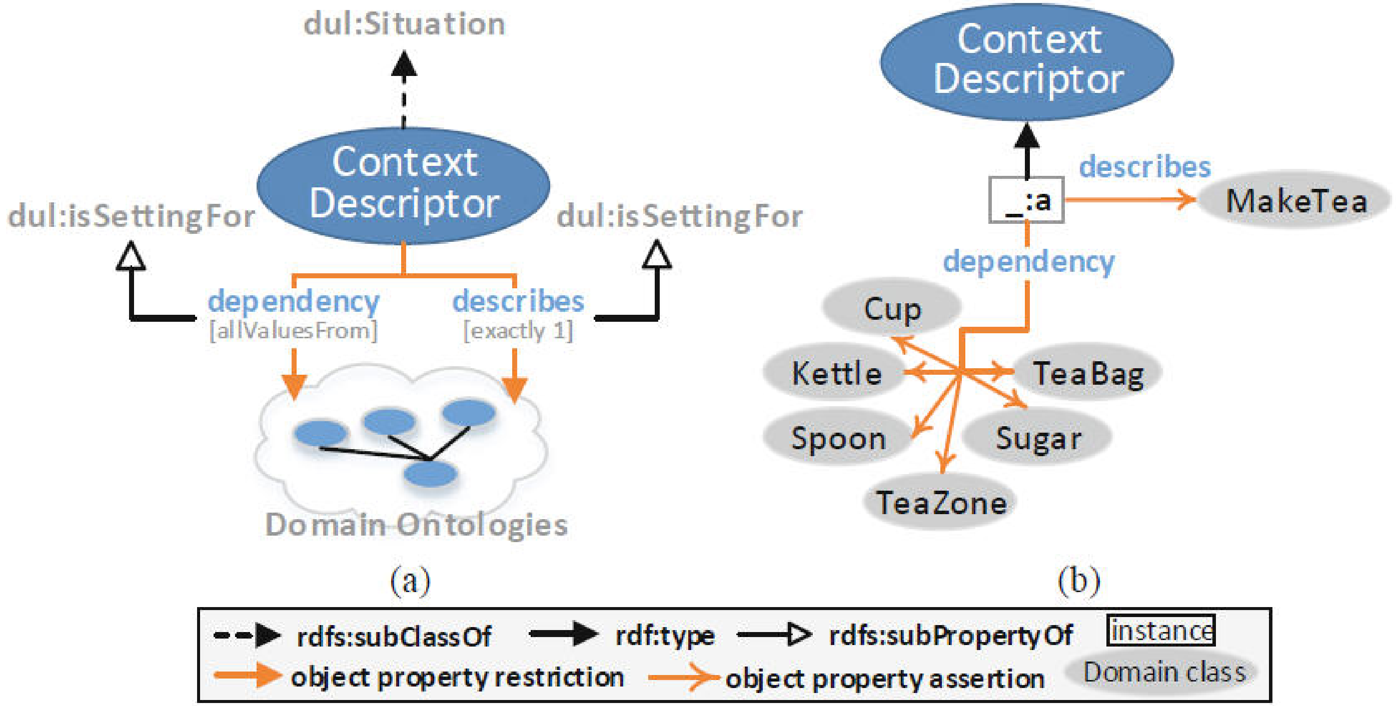

- $d_{MakeTea}$ = { *Cup, Kettle, Spoon, TeaZone, Sugar, TeaBag* }

Segmentation and Activity Recognition

- Low-level observations: $O = \{ o_1, o_2, \ldots, o_n \}$
- Domain context descriptors: $D = \{ d_{C1}, d_{C2}, \ldots, d_{Ck} \}$
- **Segmentation algorithm** for:
  - Identifying meaningful contexts in O;
  - Recognizing higher level activities.

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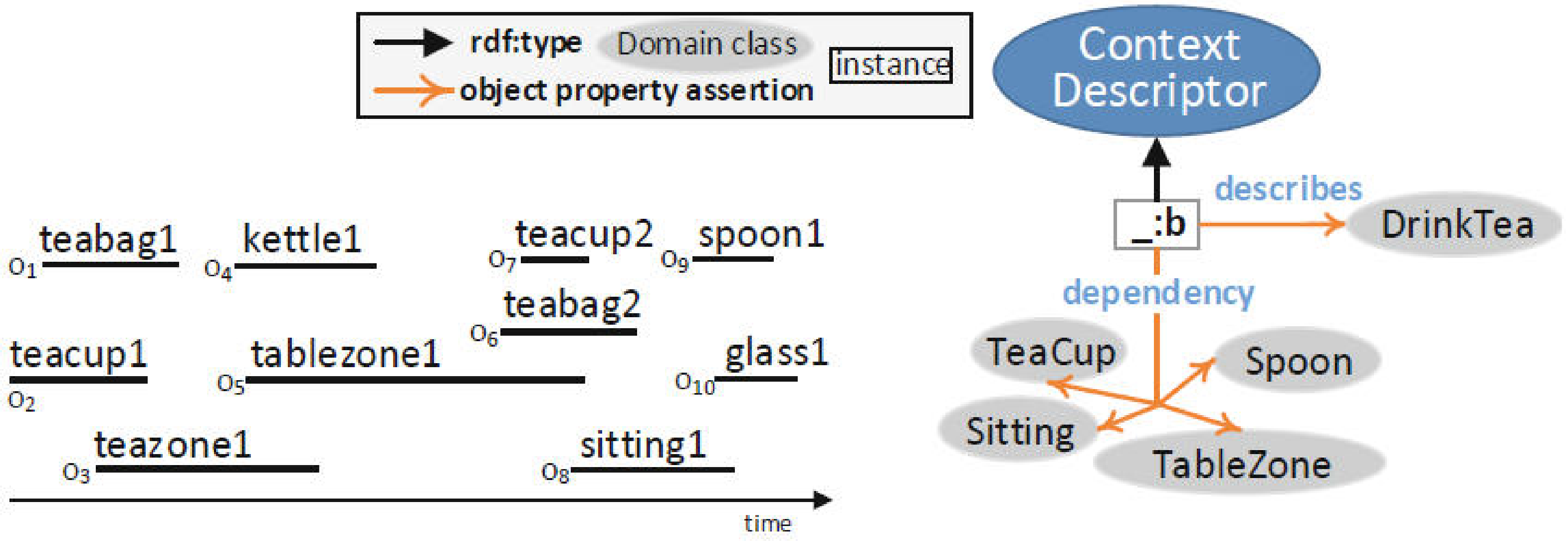


Step #1: Define Local Contexts

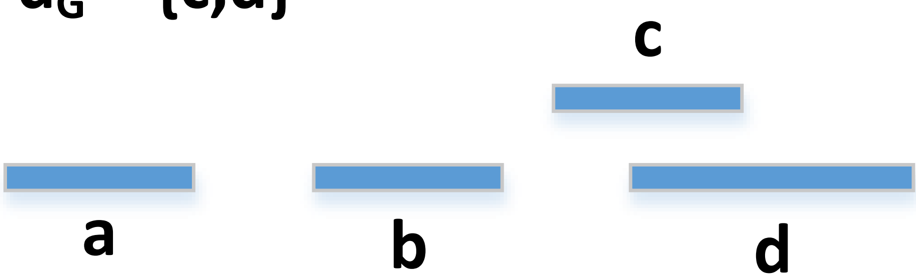
- Assign each observation to a complex activity taking into account the neighbouring observations
- Neighbouring observations
  - Overlapped and *r*-nearest, based on their temporal ordering
- Local context similarity
  - Captures the local plausibility of an observation to be part of a complex activity
    - similarity between the multiset of neighbouring observation types against the Context Descriptor set

Example

Context Descriptors

$d_T = \{a,b\}$

$d_G = \{c,d\}$



Neighbours

$N_a = \{a,b\}$

$N_b = \{a,b,c\}$

$N_c = \{c,b,d\}$

$N_d = \{d,b,c\}$

Local contexts

- $l_a = \langle d_T, 1.0 \rangle$
- $l_b = \langle d_T, 0.66 \rangle, \cancel{\langle d_G, 0.33 \rangle}$
- $l_c = \cancel{\langle d_T, 0.33 \rangle}, \langle d_G, 0.66 \rangle$
- $l_d = \cancel{\langle d_T, 0.33 \rangle}, \langle d_G, 0.66 \rangle$

Step #2: Define Context Connections

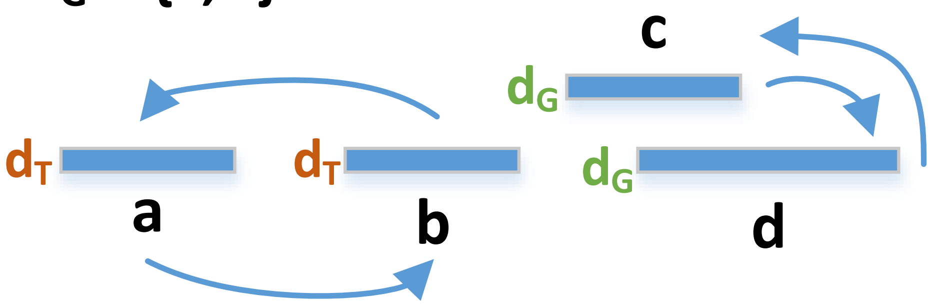
- Links among relevant local contexts.
- Used for creating final segments for activity recognition.
- Capture contextual dependency between 2 neighbouring observations wrt. a common high-level classification activity
- **Context connection rule:**
  - A local context *A* of an observation *a* is linked to a local context *B* of an observation *b*, only if *b* is a neighbour of *a* and both have been classified in the same complex activity

Example

Context Descriptors

d_T = {a,b}

d_G = {c,d}



Neighbours

N_a = {a,b}

N_b = {a,b,c}

N_c = {c,b,d}

N_d = {d,b,c}

Step #3: Create Activity Situations

- The context connections are traversed and the local contexts of the path form an *activity situation*
- The set of observation types of each activity situation is matched against the Context Descriptors in order to derive the *situation similarity*
- Situation similarity
    - Captures the plausibility of the situation to represent a complex activity

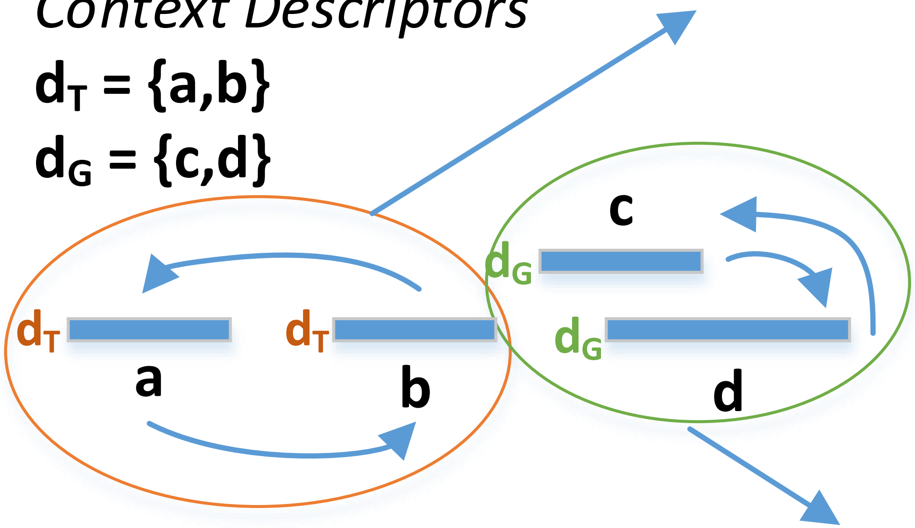
Example

Sim_T = 100%

Context Descriptors

d_T = {a,b}

d_G = {c,d}



Sim_G = 100%

Neighbours

N_a = {a,b}

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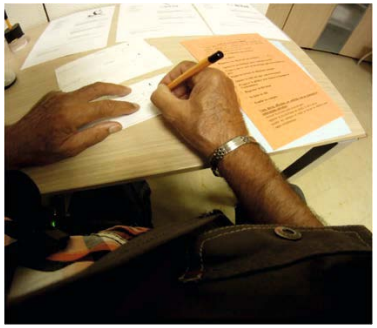
Deployment

- Hospital for monitoring Alzheimer disease patients ***(Dem@Care FP7 EU project)***
- A goal-directed protocol has been defined where participants perform predefined activities
  - e.g. prepare tea, water the plant, etc.
- Based on primitive observations, high-level activities are recognised and clinicians are informed about them
  - Clinicians are not present during the protocol
- The setting involves wearable and ambient video and audio sensors, accelerometers and physiological sensors
  - Primitive observations: postures (e.g. bending), location (e.g. in tea zone), objects used (e.g. cup)

Deployment (1/2)

IADL	Context Descriptor Classes
Establish account balance	Sitting, Accounts, Table, TableZone, Pen
Prepare drug box	Pillbox, Basket, MedicationZone
Prepare hot tea	Kettle, TeaZone, TeaBag, Cup, Sugar, TeaBox
Search for bus line	Map, MapZone, RouteInstructions
Make a phone call	Phone, PhoneZone, PickUpPhone, Talk
Watch TV	Remote, TV, TVZone, Sitting
Water the plant	WateringCan, PlantZone, Bending, Plant
Write a check	Sitting, Pen, Check, TableZone, Table
Read an article	Sitting, TableZone, Newspaper, Table
Enter/Leave the room	DoorOpen, EmptyRoom



Deployment (2/2)

	$r = 0$					$r = 5$	
IADL	**TP**	**FP**	**FN**	**TPR%**	**PPV%**	**TPR%**	**PPV%**
Establish account balance	30	10	4	88.24	75.00	85.71	73.17
Prepare drug box	23	3	2	92.00	88.46	85.19	82.14
Prepare hot tea	23	1	6	79.31	95.83	76.67	88.46
Search for bus line	24	4	1	96.30	86.67	92.86	83.87
Make a phone call	24	1	3	89.29	96.15	86.21	92.59
Watch TV	21	1	4	84.00	95.45	80.77	91.30
Water the plant	20	1	5	80.00	95.24	80.00	86.96
Write a check	28	8	4	87.50	77.78	87.50	75.68
Read an article	23	4	1	95.83	85.19	92.00	85.19
Enter/Leave the room	49	0	1	98.00	100	98.00	98.00

$$TPR = \frac{TP}{TP + FN}, \quad PPV = \frac{TP}{TP + FP}$$

Conclusions & Future Work

- Knowledge-driven framework towards activity recognition and segmentation
  - Ontology models of abstract domain activity dependencies.
  - Context-aware approach for multi-sensor fusion and monitoring.
- Situation conceptualisation of the DnS ontology pattern in DUL.
- Activity segmentation & recognition is reduced in linking and classifying meaningful contextual segments.
- Average TPR and PPV: ~90%
- Cannot handle interleaved activities & resolve conflicts.
- Defeasible reasoning on top of the framework.
- Deploy framework in homes for providing context-aware real-time assistance.
- Patient profiling.

Thank you for your attention!