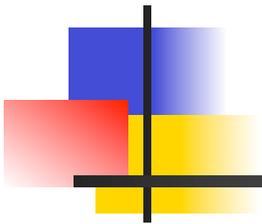


Activity Recognition in Smart Homes



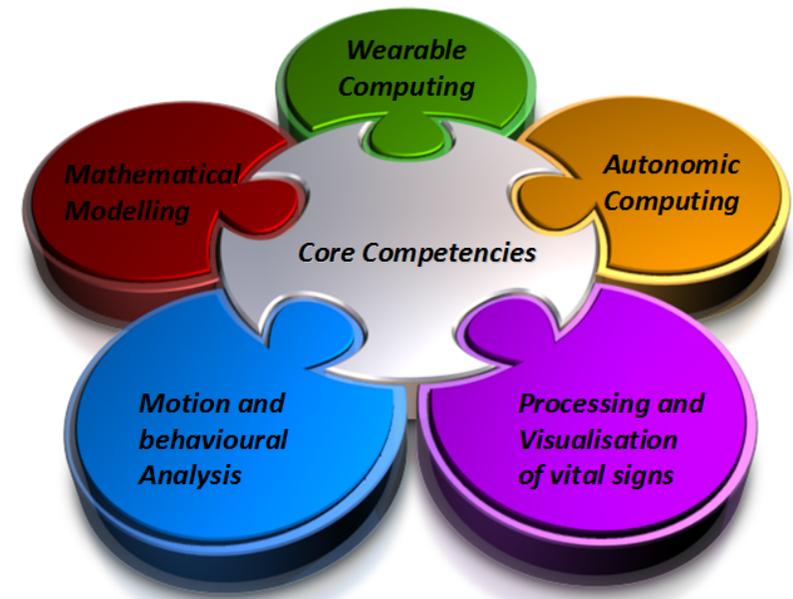
The 11th International Conference on Information Integration and
Web-based Applications & Services

The 7th International Conference on Advances in Mobile Computing &
Multimedia

14th-16th, Dec. 2009, Kuala Lumpur, Malaysia

Dr. Luke L. Chen

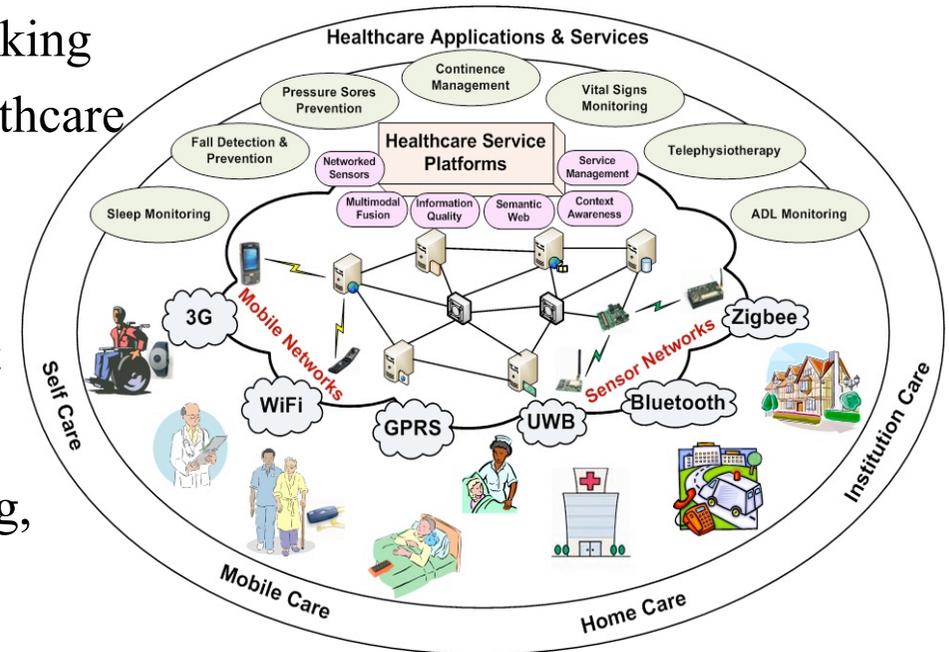
- Research Institute of Computer Science, University of Ulster
 - ❖ One of two Universities in Northern Ireland
 - ❖ Ranked 15th for research power out of 81 UK Universities in 2008 RAE
- Intelligent Environment Research Group
 - ❖ Multiple research themes
 - ❖ Both theoretical and applied
 - ❖ Focus on AAL, assistive technologies
- Research expertise
 - ❖ AI, esp. intelligent agent
 - ❖ Knowledge and semantic technologies
 - ❖ Their applications, e.g., semantic services, Grid, data integration, etc.

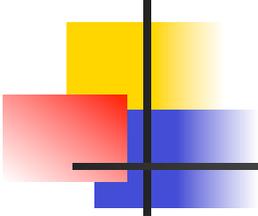


Dr. Jit Biswas, I²R



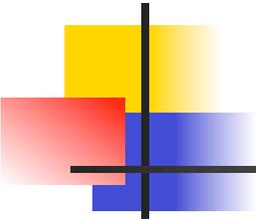
- Institute for Infocomm Research (I²R), A*STAR, Singapore
 - ❖ Research Institute under Agency for Science, Technology and Research
 - ❖ Leading in Information Communications and Media, in South East Asia
- Role in Matrix: Networking Protocols Dept. & Healthcare Program
 - ❖ Core strength in Wireless Sensor Networking
 - ❖ Strong collaborative applications in Healthcare
- Research expertise
 - ❖ Wireless Sensor Networking
 - ❖ Information Quality based Resource Mgt
 - ❖ Healthcare application and services involving pattern recognition, data mining, integrated systems approach





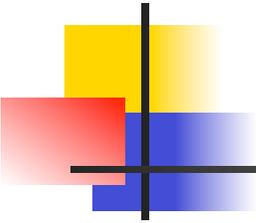
The Program

- Introduction to the Tutorial
 - ❖ The context
 - ❖ The schedule
- Data-driven activity recognition
- Knowledge-driven activity recognition
- Discussion



An Emerging Ageing Society

- A worldwide demographic change
 - ❖ Ageing population is increasing in an unprecedented rate
 - ❖ 80+ is the fastest growing age group.
- Social and healthcare crisis
 - ❖ Prevalence of physical, sensory deficiency and cognitive decline
 - ❖ Already overstretched social and healthcare resources
 - ❖ Increased resource needs outpace resource investment
- Demand on new models for social and healthcare delivery with affordable costs



Converging Trends

- Pervasive sensing infrastructure
 - ❖ Low cost, low power, high performance sensors, e.g., RFID, wireless motes, etc.
 - ❖ Communication protocols, standards
- Advances in core computer science
 - ❖ Artificial intelligence techniques – ambient intelligence
 - e.g., algorithms for probabilistic reasoning and machine learning, such as Bayesian networks, Stochastic sampling, etc
 - ❖ Knowledge technologies
 - ❖ Semantic technologies
- Ambient Assisted Living (AAL)
 - ❖ Support independent living for the elderly and disabled
 - ❖ Improve health care – Ageing in place, intervention and prevention

Smart Homes (SH)

- A specific realisation of AAL

Smart homes are augmented residential environments equipped with sensors, actuators and devices, inhabited by the elderly or disables, operated by professionals and health services

- The purpose and aspirations

To enhance and improve quality of life, prolong stay at home with technology-enabled assistance



Sensors



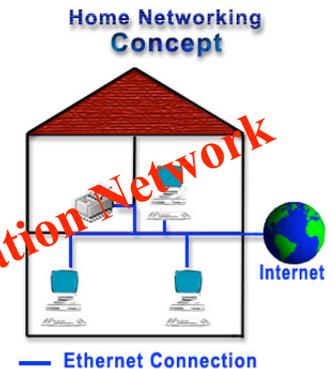
Actuator

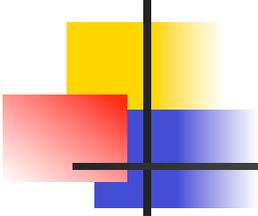


Control Interfaces



Communication Network

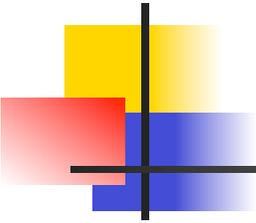




The Challenge

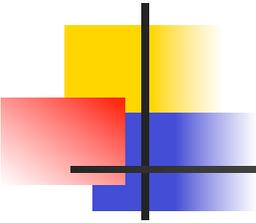
Given the real-time data streams from multiple sensors in multiple formats

- Infer an inhabitant's location, action and activities
- Predict what the inhabitant's will do
 - ❖ Provide just-in-time context-aware activity assistance
- Detect behavior patterns and/or behavior anomaly
 - ❖ Support intervention and prevention before serious health problems happen
 - ❖ Opportunities for learning
- Activity recognition is key



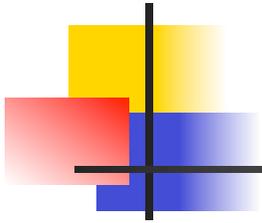
Activity Recognition

- Based on the types of sensor data
 - ❖ Vision-based
 - ❖ Non-vision-based
 - Wearable sensors
 - Object-attached sensors
- Based on the way data are analysed
 - ❖ Data-driven approaches
 - Probabilistic reasoning and machine learning, e.g., Bayesian networks, Stochastic sampling, etc.
 - ❖ Knowledge-driven approaches
 - Formal knowledge modelling, representation and reasoning, e.g., logics, ontologies, etc.



The Central Issues

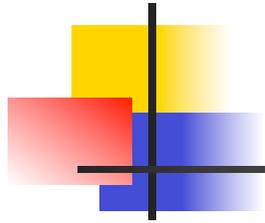
- Modeling Activities of Daily Living (ADLs)
 - ❖ From sensor data
 - Data-driven approaches
 - ❖ By engineering commonsense domain knowledge
 - Knowledge-driven approaches
 - ❖ By mining textual descriptions
 - Information
- Tracking and predicting a user's activities
- Recognizing user errors and needs
 - ❖ Toward proactive assistive technology



Activity Recognition

The Data-driven Approach

By Dr. Jit Biswas

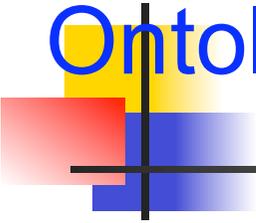


Activity Recognition

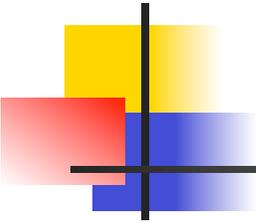
The Knowledge-driven Approach

By Dr. Liming Chen

Ontology-based Activity Recognition (O-BAR)

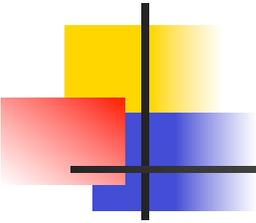


- Generic knowledge-driven approaches
- Ontologies and their use for activity recognition
- Ontology-based activity recognition
- A case study walk-through
- Implementation and demo



Knowledge-driven Approach

- Capture and engineer domain knowledge
- Create formal ADL models
- Represent both ADL models and sensor data using a formal knowledge representation formalism
- Map activity recognition, prediction and assistance to inference and reasoning, e.g., induction, deduction and abduction



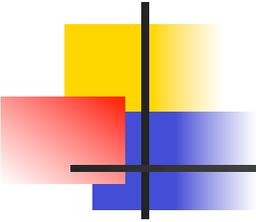
Existing Methods

■ Process based activity modelling

- ❖ Using logical knowledge representation formalisms
 - Situation theory, key-hole planning (Kauz, 1991; Wobke, 2002)
 - Event calculus (IJARM, Chen et al. 2008)
 - Description Logic + lattice theory (Bouchard et al. 2006)
 - Temporal reasoning and action theory (Augusto, 2004; Chua, 2009)

■ State based activity modelling

- ❖ Mining textual descriptions (Tapia, 2006)
- ❖ Ontological modelling and reasoning (Akdemir et al. 2008; Yamada et al. 2007; Chen & Nugent 2009)



Ontologies

■ Definition

- ❖ An explicit specification of various conceptualisations in a problem domain
- ❖ A vocabulary for the specifications and representation of the generic concepts, attributes, relations and axioms of a domain

■ In essence, an approach to knowledge modelling

- ❖ Provide a homogeneous view over heterogeneous data sources, thus enabling seamless integration, interoperability and sharing
- ❖ Enable a higher level of automation based on the machine understandable content
- ❖ Facilitate reasoning and inference for knowledge (pattern) discovery and advanced intelligent applications.

Ontology Languages

- Define and represent ontologies

- ❖ A set of modelling primitives for describing classes, properties and individuals
- ❖ A set of axioms and entailment rules for inferring relationships and supporting reasoning

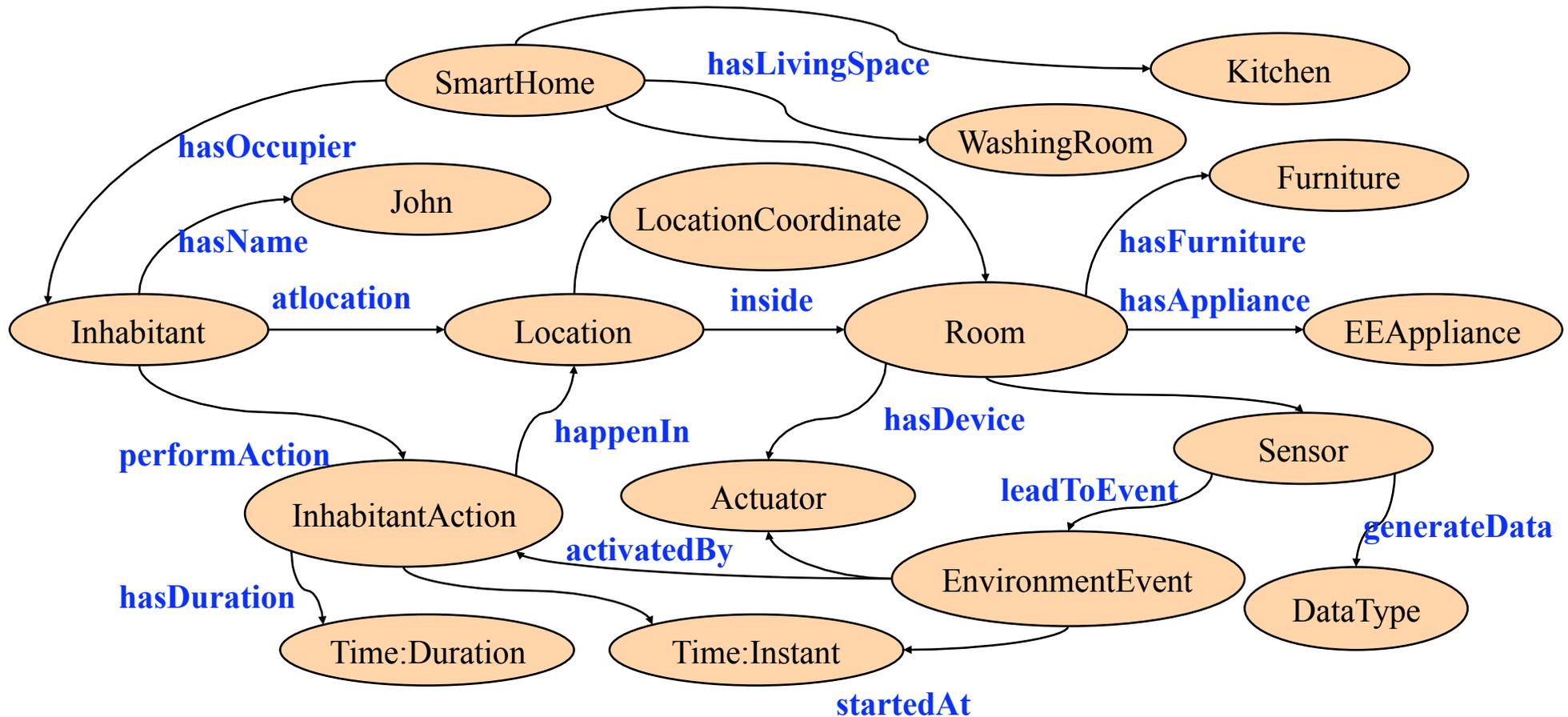
- RDFS and OWL

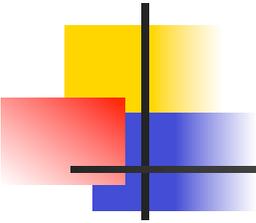
- ❖ RDFS - A graphical data model



- ❖ OWL – extended RDFS with three species compliant with DL

Example: Ontological Context Representation

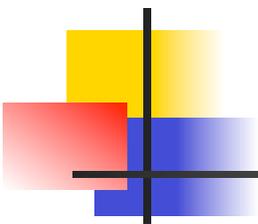




Current Use of Ontologies

For vision based activity recognition

- Specifying common terms for activity definition (a set of rules)
 - ❖ An ontology for analyzing social interaction in nursing homes (Chen, 2004)
 - ❖ Ontologies for the classification of meeting videos (Hakeem, 2004)
 - ❖ Monitor activities in a bank setting (Georis, 2004)
 - ❖ An initiative to define ontologies for six domains of video surveillance
 - ❖ A video event ontology and representation language (Hobbs, 2004)
- Activity recognition is performed using individually preferred algorithms
 - ❖ such as rule-based systems (Hakeem, 2004) and finite-state machines (Akdemir, 2008)

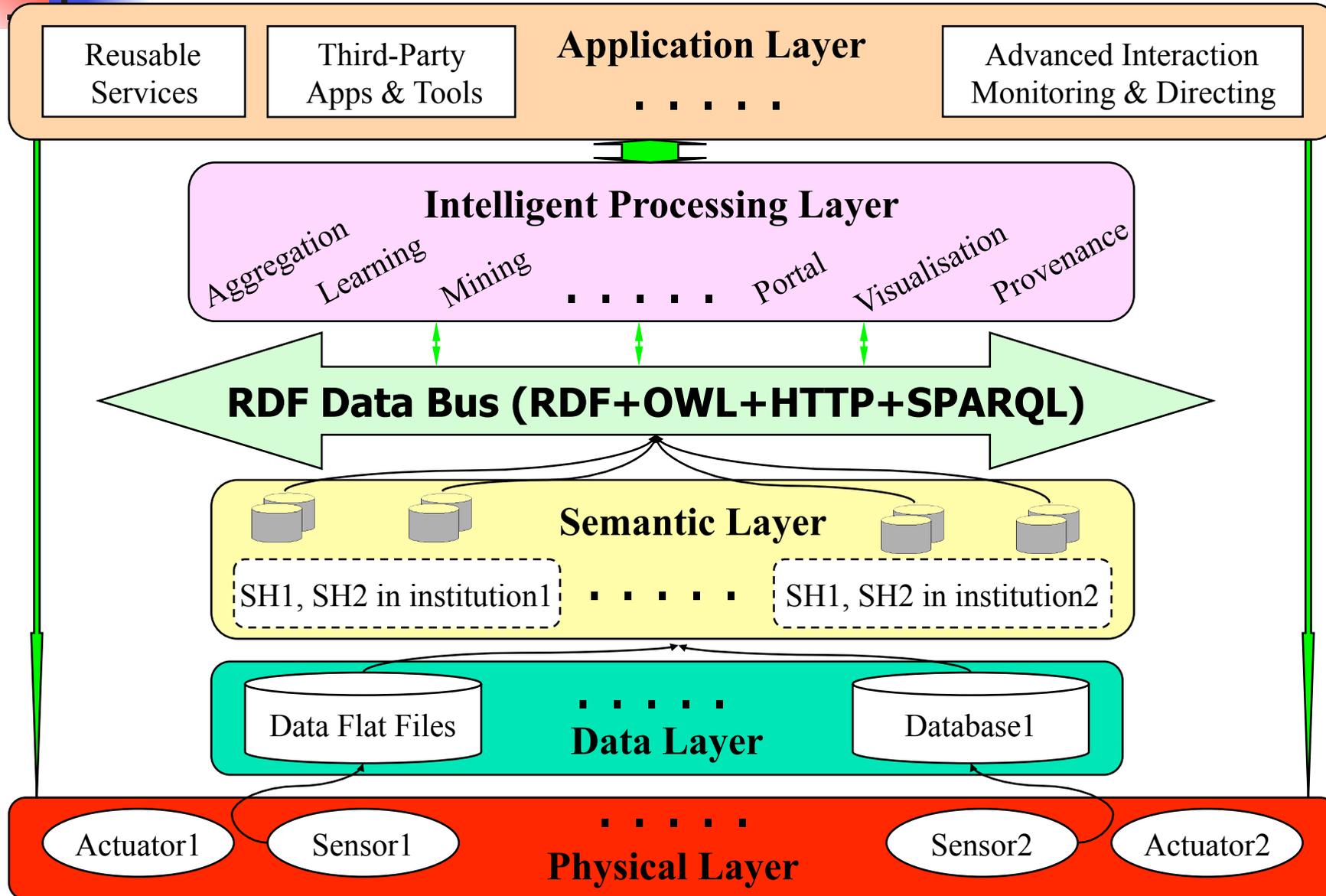


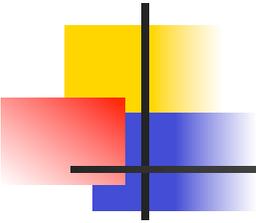
Current Use of Ontologies

For sensor based activity recognition

- Modelling incompleteness and multiple representations of terms
 - ❖ E.g., object ontologies from WordNet (Tapia, 2006); Ontologies of things (Yamada et al. 2007)
- Activity recognition is performed using probabilistic and/or statistical algorithms
- Ontology-centric design for middleware and system – addressing interoperability, e.g., (Latfi, 2007; Michael, 2007)
- The Semantic Smart Home concept (Chen 2009)
 - ❖ leverage the full potentials of semantic technologies in the whole lifecycle of assistive living

Semantic Smart Home



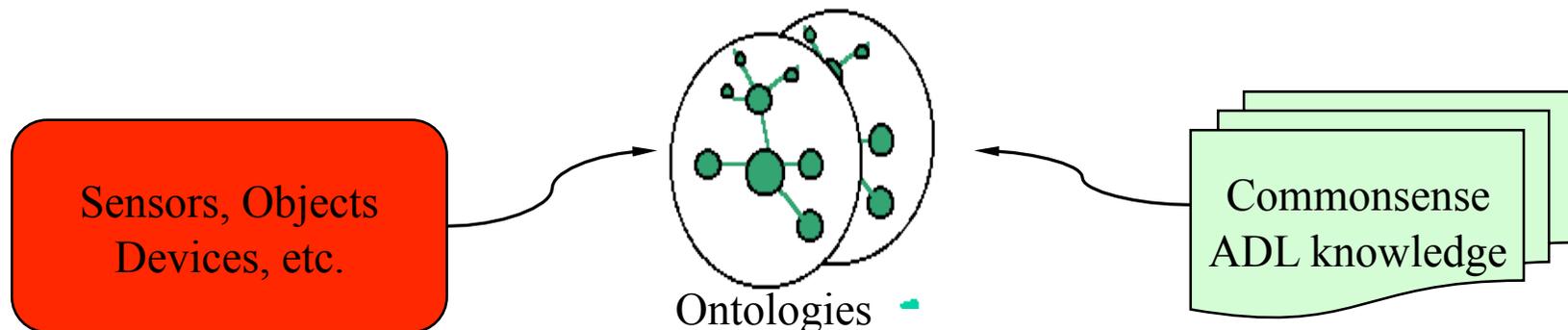


O-BAR Rationale

- **Ontological context modelling**
 - ❖ Ontologies - sensors, objects, time, environment states, etc.
 - ❖ Data fusion
- **Ontological activity modelling**
 - ❖ Not only describing activities using common terms
 - ❖ But also describing interrelationships between activities as well as activities and objects
- **Semantic reasoning**
 - ❖ Activity recognition
 - ❖ Activity learning
 - ❖ Activity assistance

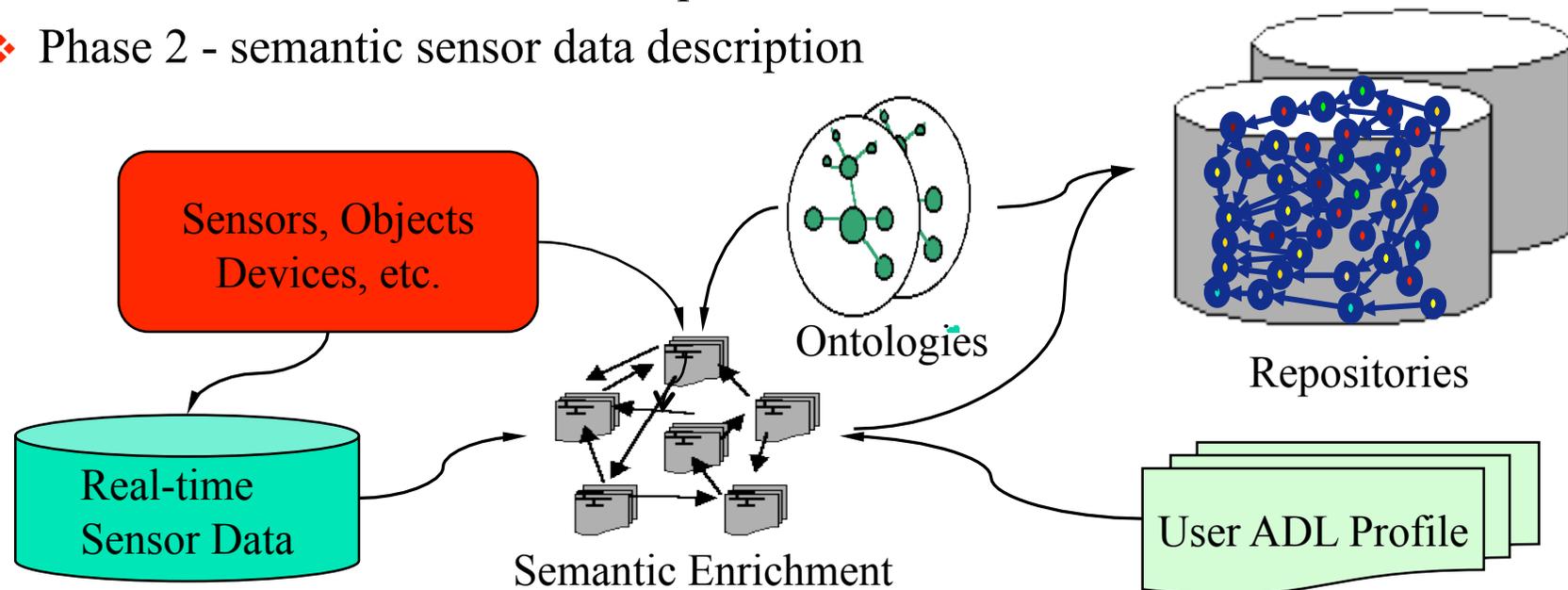
O-BAR Methodology: Ontological Modelling

- Domain analysis and knowledge acquisition
 - ❖ Entity identification, e.g., sensors, objects, devices, ...
 - ❖ Activity characterisation
- Ontology construction
 - ❖ Context ontologies, inc. time ontologies, ..
 - ❖ Activity ontologies



O-BAR Methodology: Semantic Repository

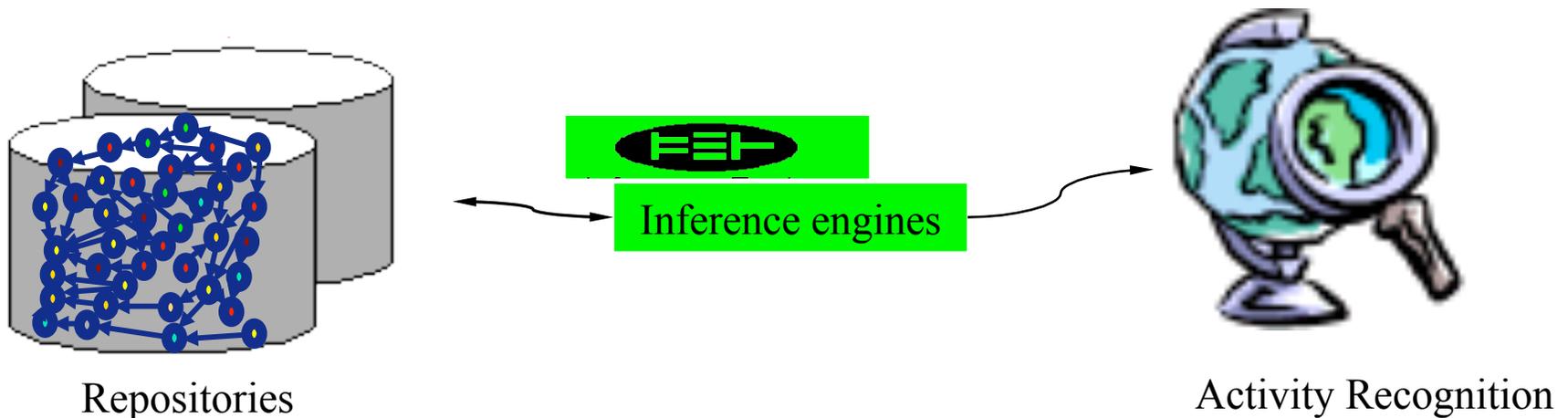
- User activity (ADL) profiles
 - ❖ Customised semantic activity descriptions for individuals
- Two phase semantic metadata generation
 - ❖ Phase 1 – semantic sensor description
 - ❖ Phase 2 - semantic sensor data description

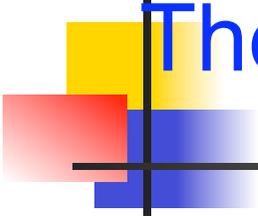


O-BAR Methodology: Activity Recognition

■ Equivalent to concept classification

- ❖ Given a SH semantic repository $KR(T, A)$, with a set of terminological axioms T and a set of assertional axioms A
- ❖ Given a context at a specific time with a set of sensor readings linking to objects that form part of an activity description
- ❖ Performed by DL subsumption reasoning

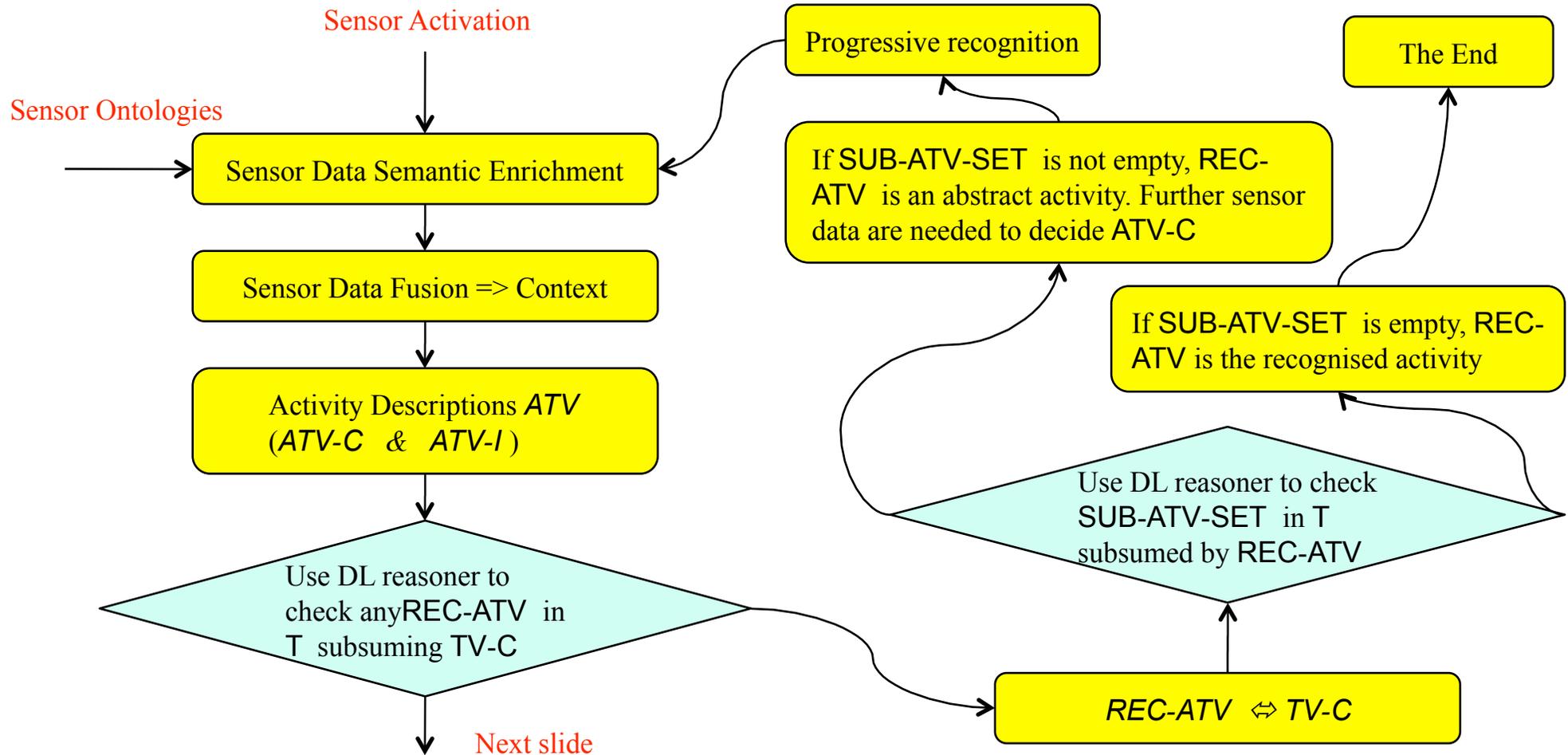




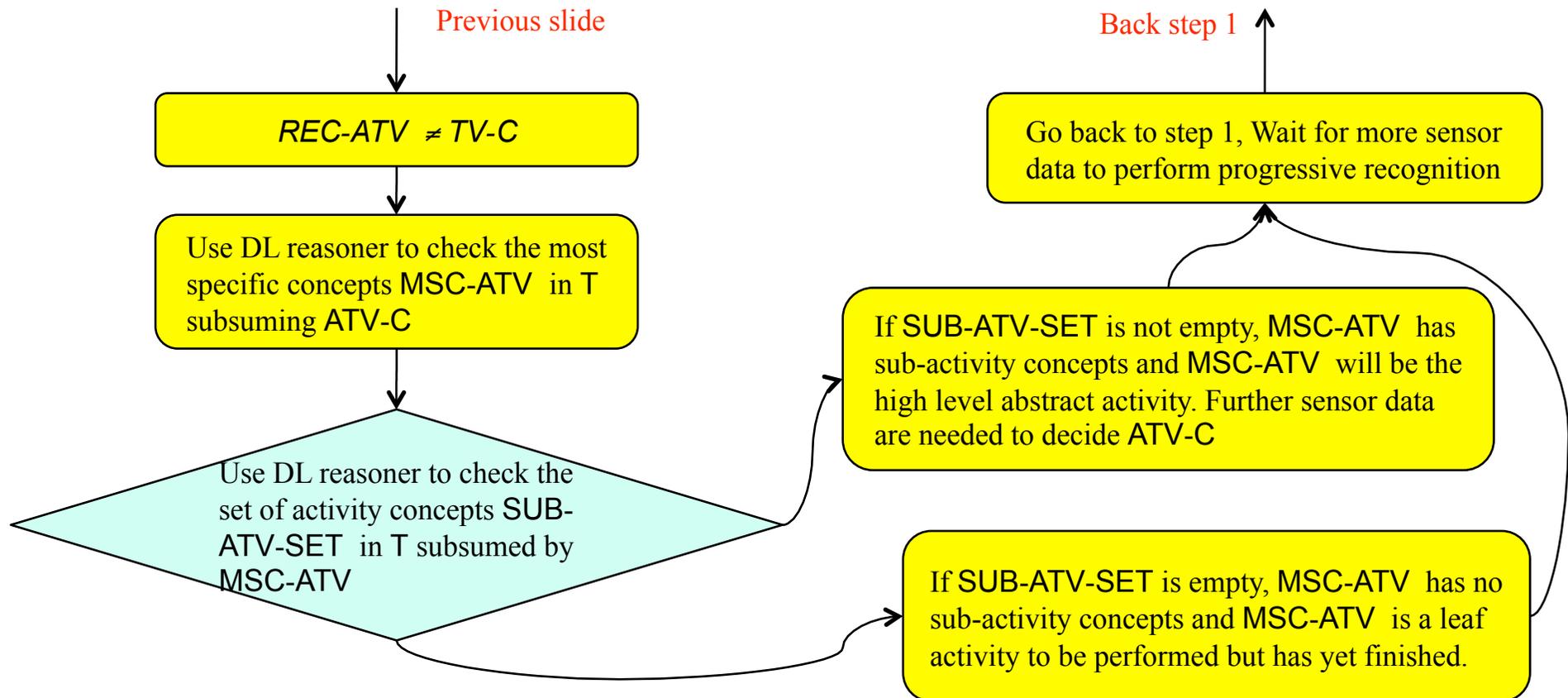
Theoretical Subsumption Algorithm in DL

- Structured subsumption algorithm
 - ❖ $A_1 \sqcup \dots \sqcup A_m \sqcup \exists R_1. C_1 \sqcup \dots \sqcup \exists R_n. C_n$
 - ❖ $B_1 \sqcup \dots \sqcup B_k \sqcup \exists S_1. D_1 \sqcup \dots \sqcup \exists S_l. D_l$
 - ❖ A & B classes, S & R properties, C & D descriptions
- $C \sqcup D$ (C subsume D)
 - ❖ For all i , $1 \leq i \leq k$, there exists j , $1 \leq j \leq m$ such that $B_i = A_j$
 - ❖ For all i , $1 \leq i \leq l$, there exists j , $1 \leq j \leq n$ such that $S_i = R_j$ and $C_j \sqcup D_i$
- More complex one based on tableau algorithm

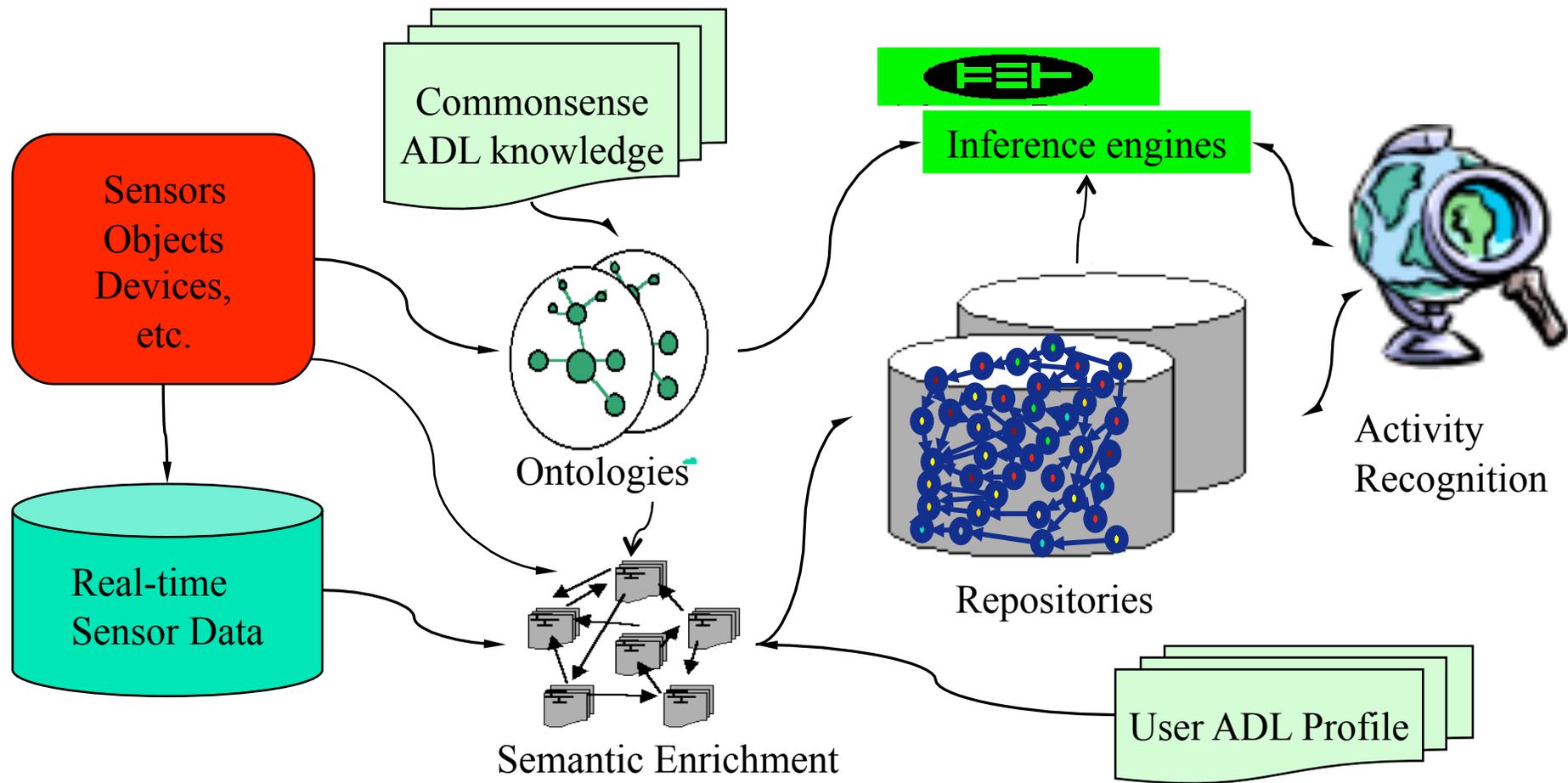
Algorithm Mapped to Activity Recognition



Algorithm Mapped to Activity Recognition

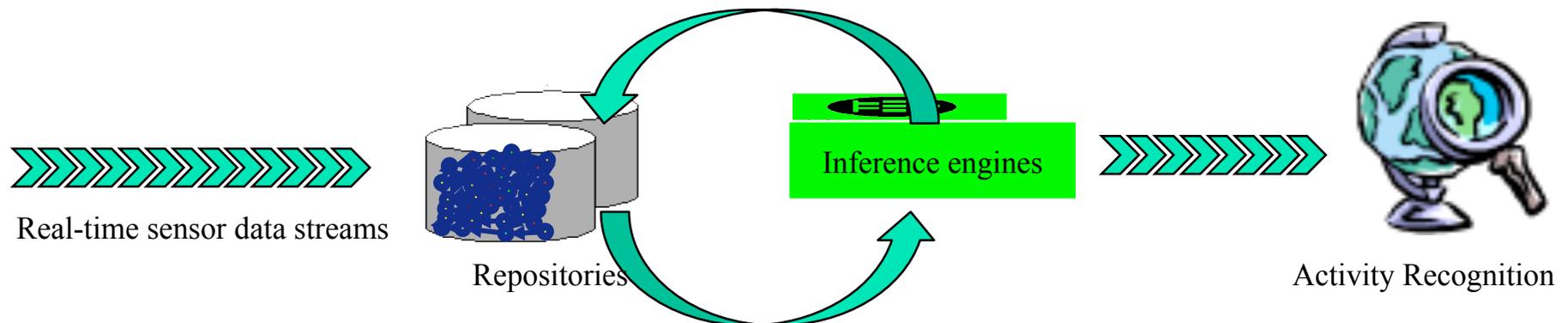


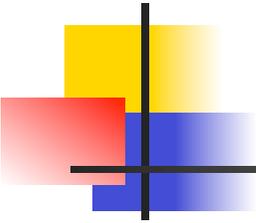
O-BAR Lifecycle



O-BAR Features

- No requirements for large dataset to learn and test activity models
- Support incremental progressive activity recognition
 - ❖ An activity unfolds in a timeline
 - ❖ Each time new sensor data become available (or every 20 seconds)
 - ❖ New context will be used to perform recognition





O-BAR Features

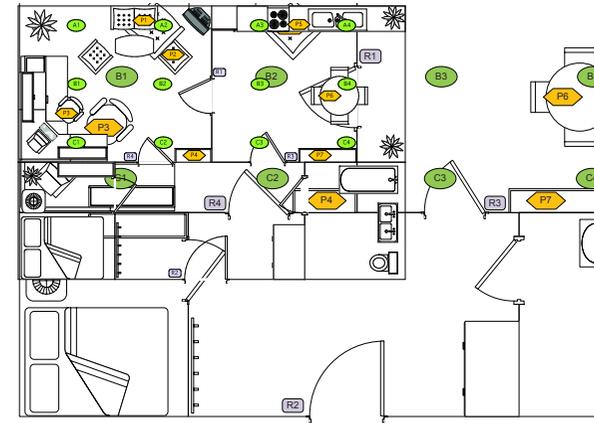
- Organic activity model evolution
 - ❖ Ontological activity modelling creates the “seed” ADL models
 - ❖ Using learning to extract new patterns and improve the models
- Activity priority / importance modelling
 - ❖ Discriminating parallel activities
- Enable activity assistance at two levels of abstraction
 - ❖ Course-grained activity assistance
 - Perform reasoning against conceptual activity models (Tbox)
 - ❖ Fine-grained activity assistance
 - Perform reasoning against activity instances (Abox)
- Activity specific sliding window
 - ❖ Dynamically change the sliding window to adapt to the activities

O-BAR Case Study

- Activity monitoring, activity recognition and assistance at SERG in University of Ulster



Sensor based interaction tracking and recognition

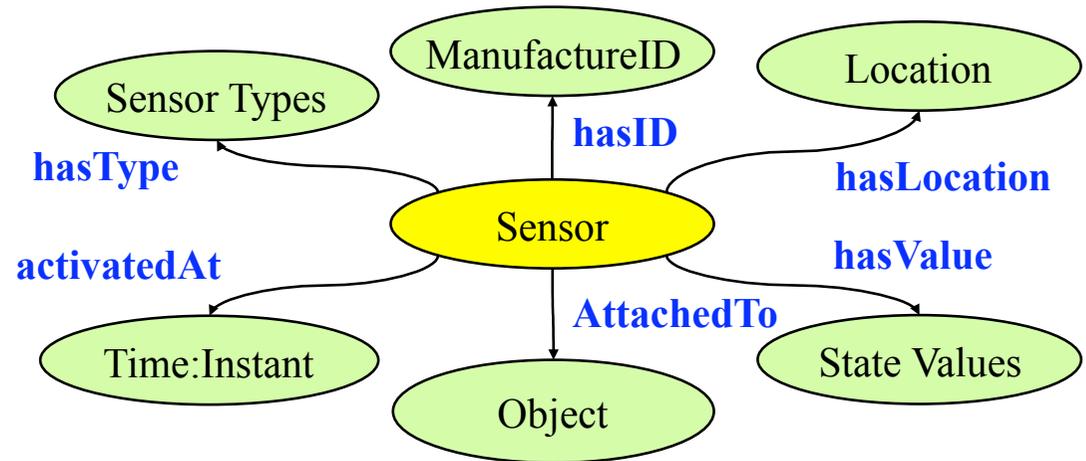


Wearable Devices and activity monitoring

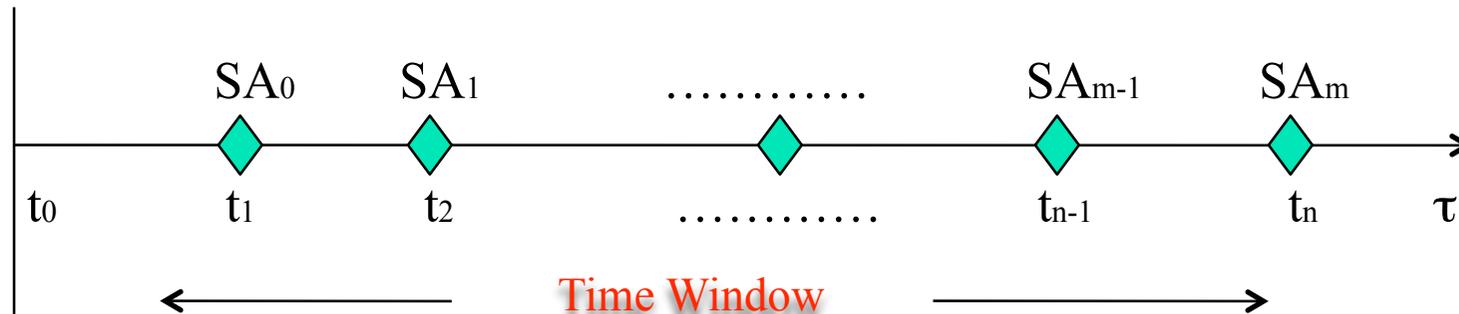


Semantic Context Modelling

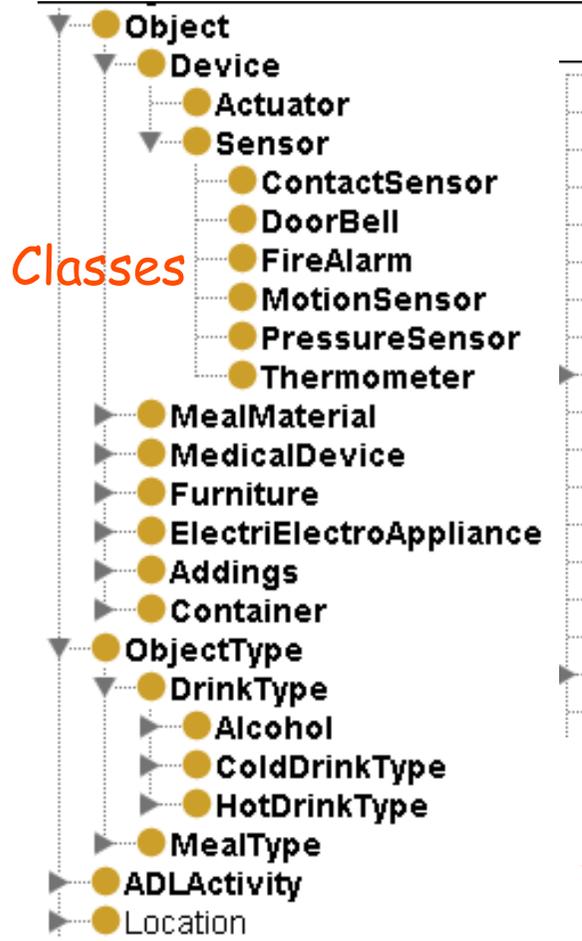
- Object (Equipment/Device/Appliance)
- Location (Environment/space)
- Temporal information



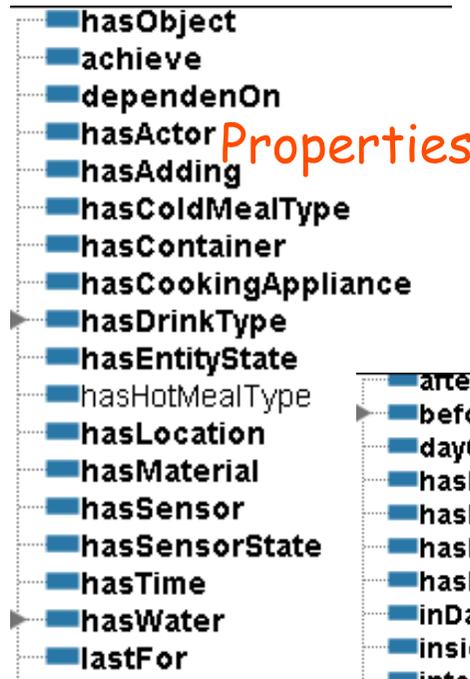
Context at $\tau \Rightarrow SSD_0 \cup SSD_1 \cup \dots \cup SSD_{m-1} \cup SSD_m$



Sensor Ontologies

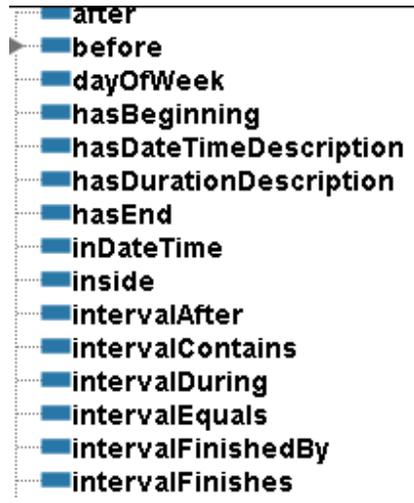


Classes



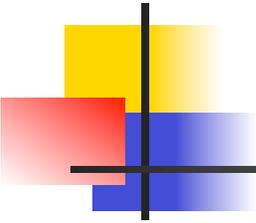
Properties

Time classes



Time Properties

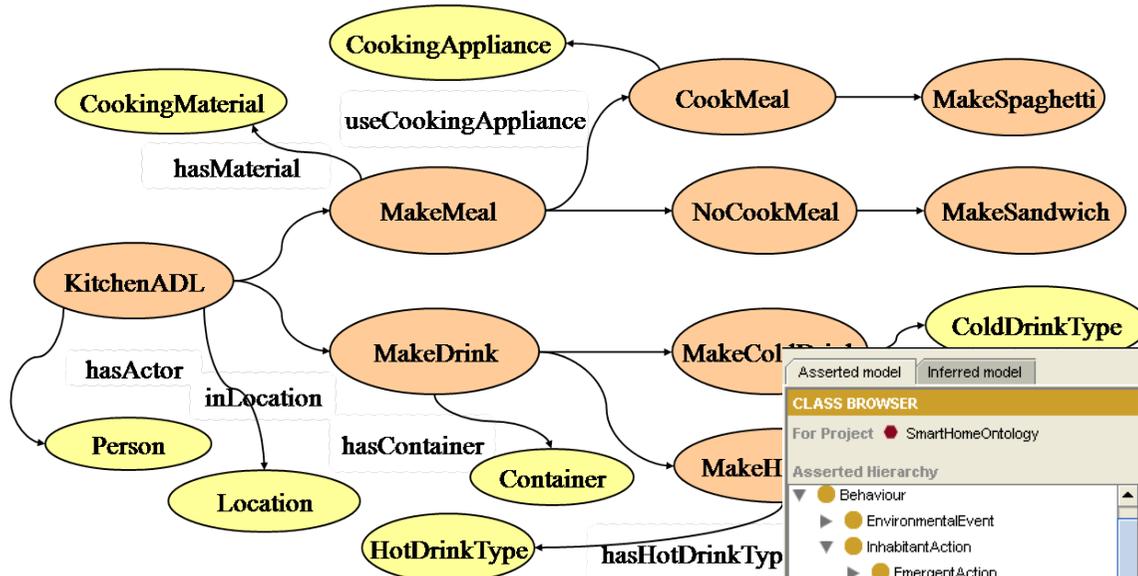
- Protégé ontology editor
- Import W3C Time ontology
- Potential for using current medical data ontologies



Activity Modelling

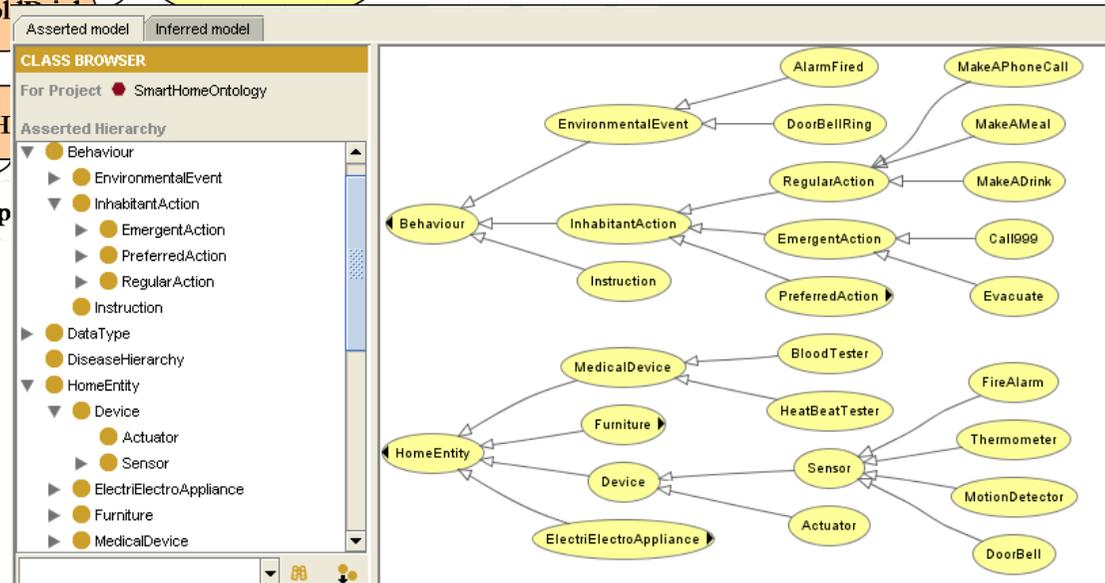
- A process model
 - ❖ A sequence of situations
 - ❖ Emphasis on sequential order
- A descriptive model
 - ❖ Characterised by a number of properties
 - ❖ Emphasis on states
- Ontological activity modelling
 - ❖ Explicitly specify relationships between objects and activities
 - ❖ Build a hierarchical structure to encode the interrelations between activities
 - ❖ There are usually a “is a” and “part of” relationships

Informal and Formal ADL Models



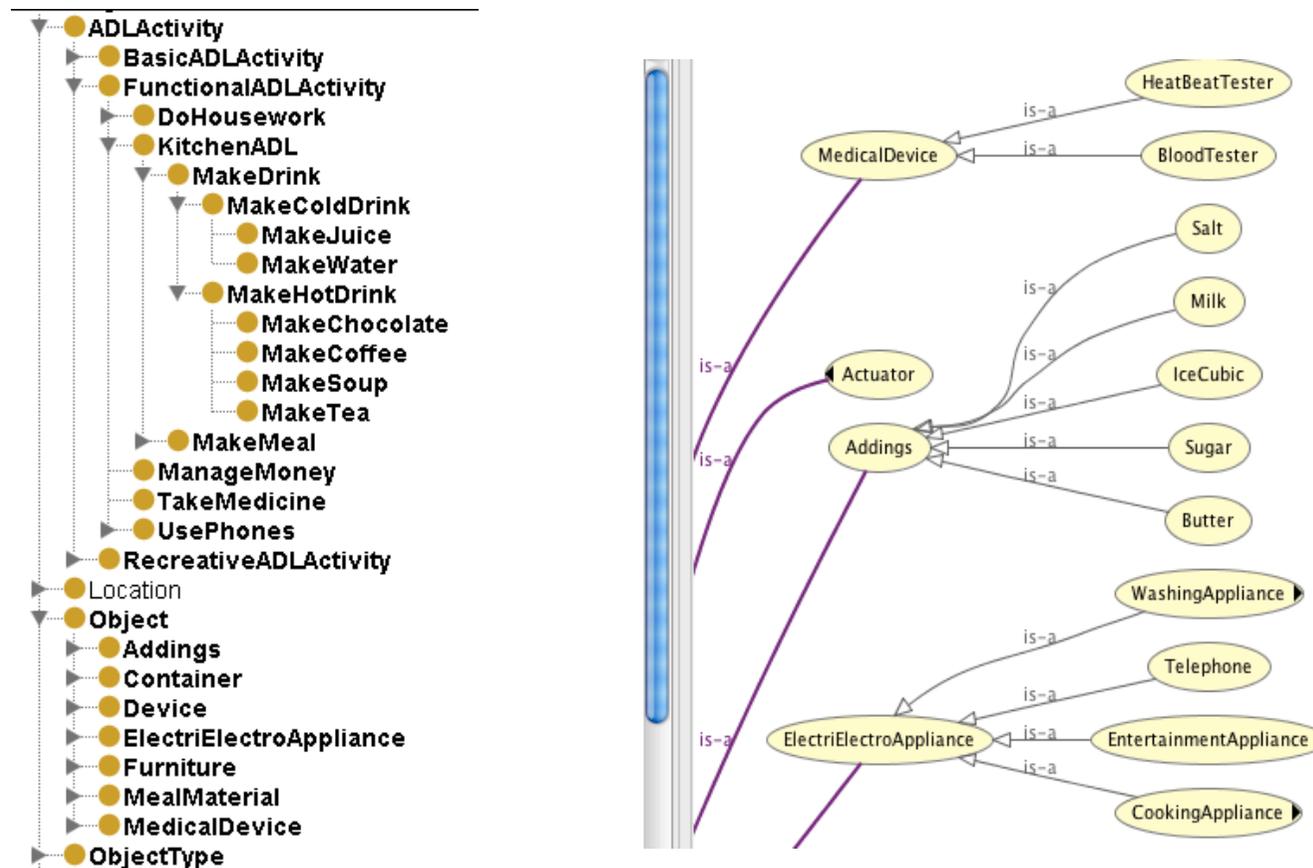
ADL ontologies

Graphical ADL representation



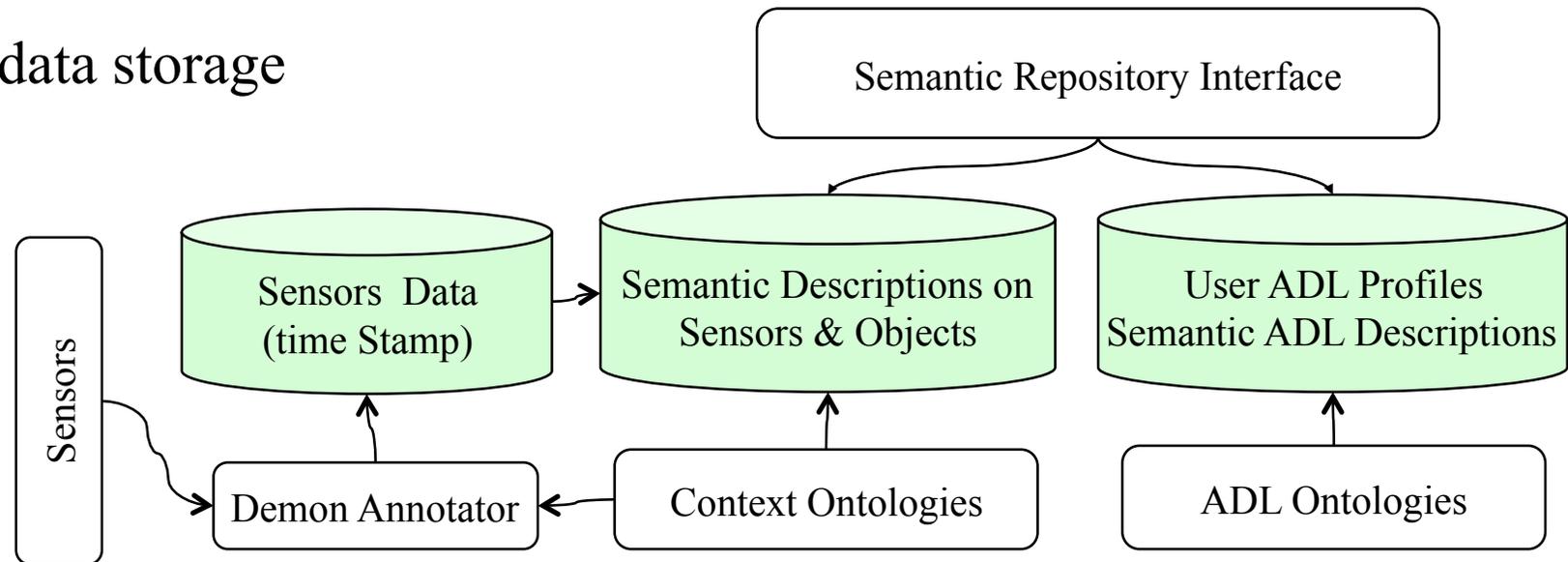
An Example: MakeDrink ADL Class

- Linking context ontologies to ADL ontologies



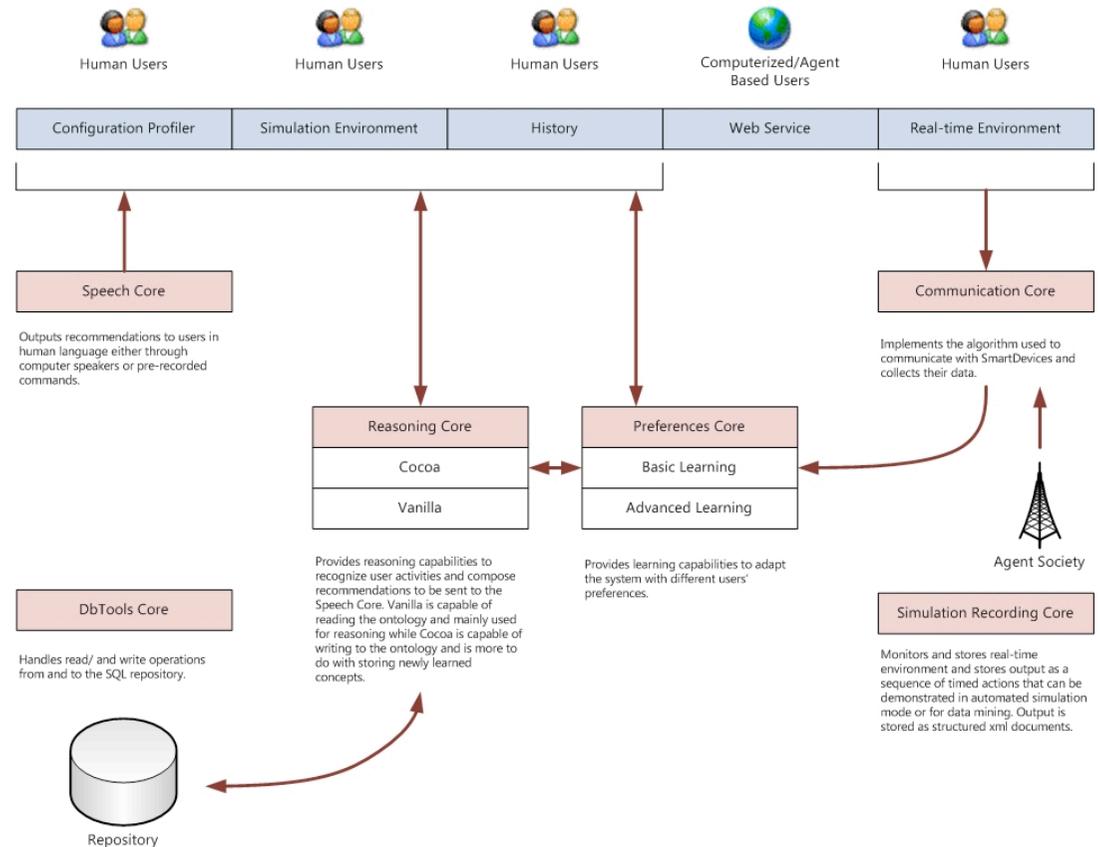
Semantic Data Creation and Storage

- Two-phase approach for creating semantic data
 - ❖ Manual annotation for sensors, devices, objects and user ADL profiles
 - ❖ Light-weight demon-style annotator for real-time sensor data
- Two mechanisms for data storage



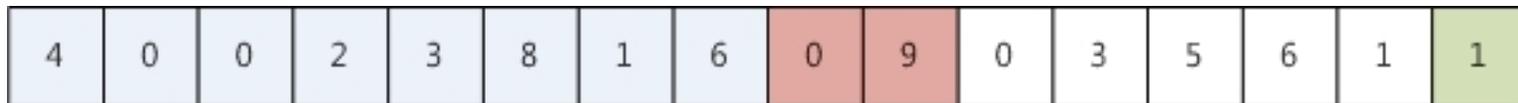
Implementation Architecture

- Reasoning core
- Preferences (adaptive learning) core
- DB Tools
- Communication core
- Speech core
- User Interface tools



Communication Core

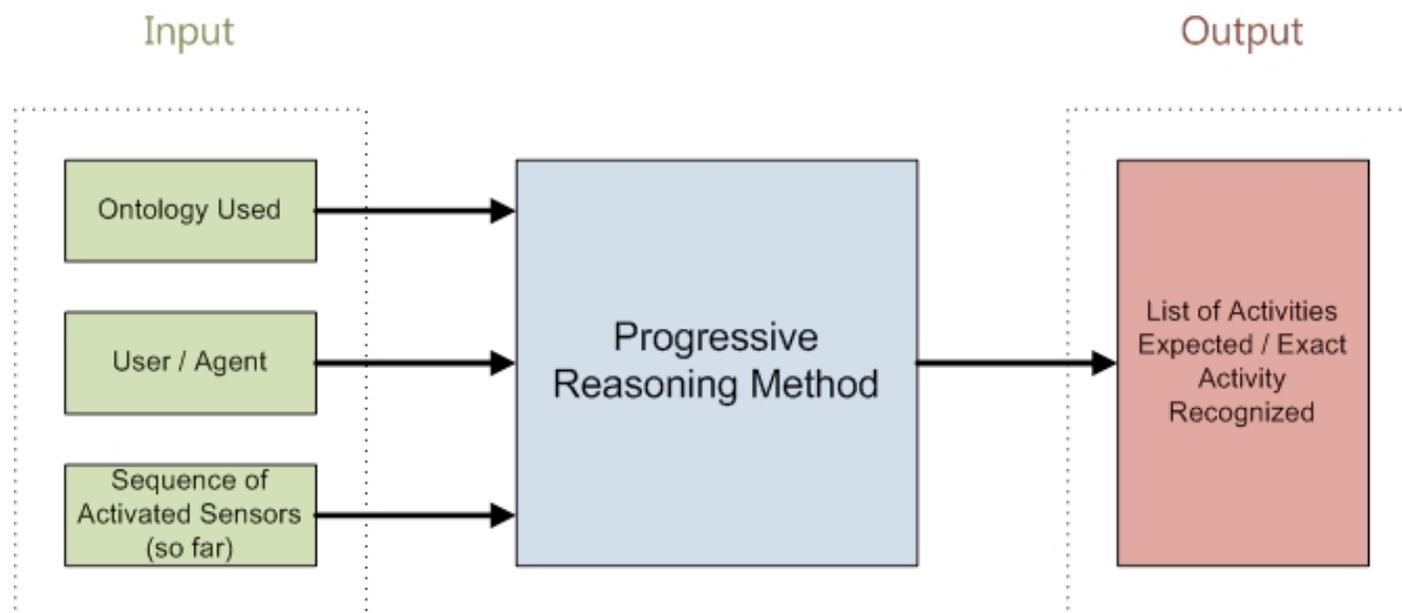
- Provide a physical-digital interface gateway
 - ❖ Sensor data collection
 - ❖ Sensor data transformation
- Sensor data semantic enrichment
 - ❖ Using sensor ontologies
- Archive the semantic sensor data



 Sensor ID  Sensor Type  Message

Reasoning Core - Vanilla

- Perform progressive activity recognition by implementing the recursive subsumption reasoning



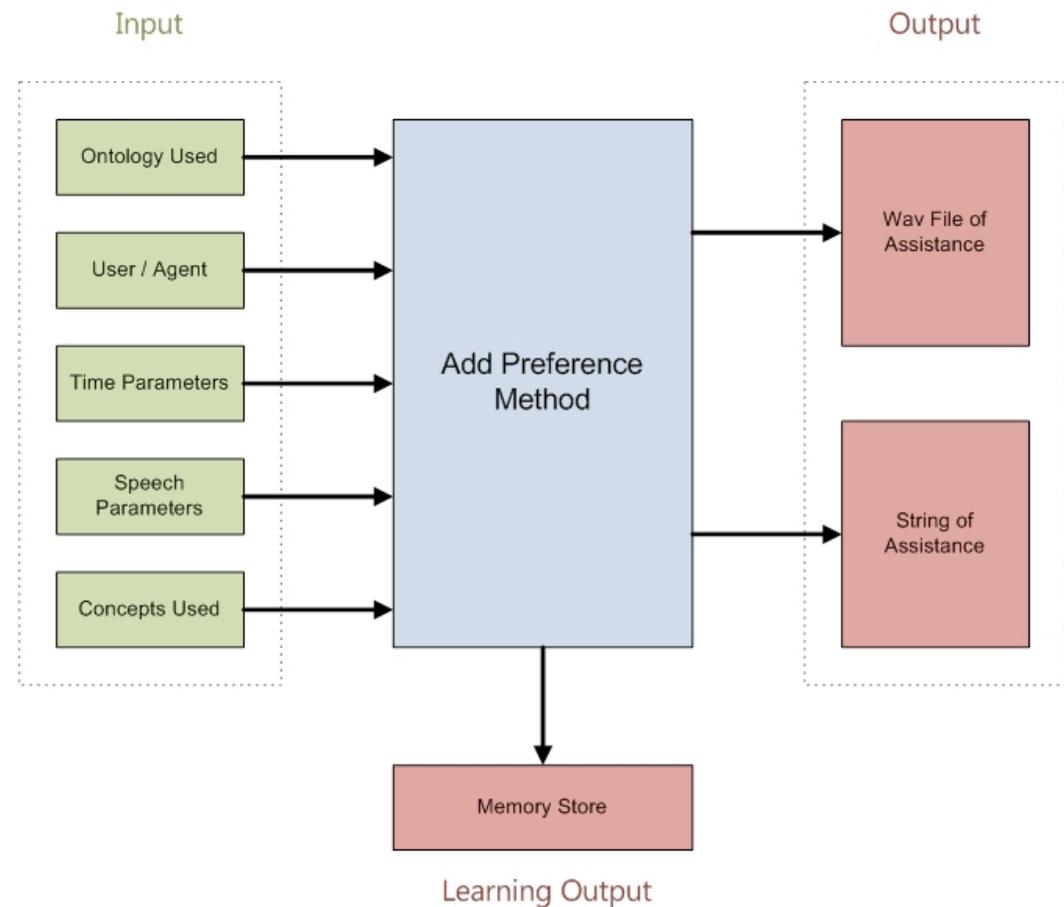
Reasoning Core - Cocoa

■ Activity assistance

- ❖ Setting up activity duration & urgency
- ❖ Visual and vocal
- ❖ Synthetic or pre-recorded

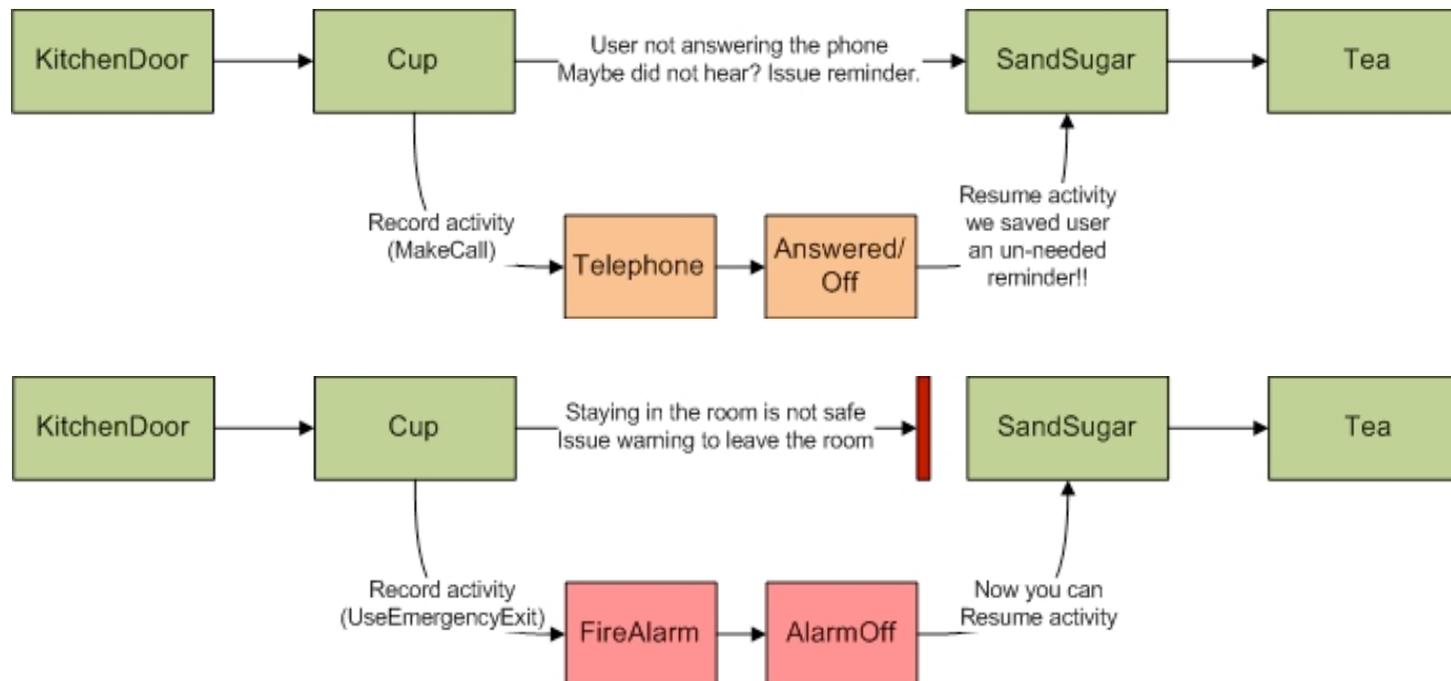
■ Learning preferences

- ❖ Basic learning
 - User's specific ADL profiles
- ❖ Advanced learning
 - New activity classes
- ❖ Manual specification



Parallel Activity Recognition & Assistance

- Specify a hierarchy of importance for activities
- Provide assistance in terms of urgency



User Interface Tools: System Configuration

ACTIVE ONTOLOGY

You can modify the ontology in-use using this form ..

Current Ontology: SmartHomeOntologyRDF.xml Add [?]

Upload New Ontology: Browse... Upload [?]

Click on 'Upload' to start ..

REAL-TIME ENVIRONMENT PARAMETERS

This configures the port used for communication with signal receiver ..

Communication Port: [?]

Refresh Rate (seconds): [?]

RECORD A NEW COMMAND

Please use the table below to create your custom commands that suites your needs. We hope that the quick list will help you to find your way around ..

Quick List

Activ. Iden.	Activ. Expec.
Flag Type	Note
MakeTea	MakeCoffee
WholeMilk	HotWater

Record Your Commands

Command Name: File was stored

SPEECH PARAMETERS

This configures how the system should speak

Speech Mode:

Options for Computer Voice

Voice Speed: 1 2 3 4 5

Voice Selection:

Voice Volume: 1 2 3 4 5

Expreience the future with the 'Smart' project.

[Click here for pre-recorded speech options ..](#)

USER PREFERENCES

[Click here to manage existing preferences ..](#)

Learning Parameters

- Add to activity to preference if it appears in more than
- Remove activity from preference if not used for

Preferences Preview

```

abashrawi_Preferred_Tea
type: MakeTea
hasContainer: ChinaCup
hasHotDrinkType: ChineseTea
hasPlace: KitchenDoor
hasHotDrinkType: KitchenHotWater
hasAddings: SandSugar
hasAddings: WholeMilk
hasTime: 03:00
lastFor: 57
    
```

Sensors in the Ontology:

- #SandSugar
- #BrownCubicSugar
- #WholeMilk
- #SkimmedMilk
- #GreenTea
- #ChineseTea
- #BritishTea
- #KitchenDoor
- #KitchenHotWater
- #PlasticCup
- #ChinaCup
- #AmericanCoffee
- #KitchenBoiler
- #MyTea

Sensor Name:

Sensor Type: Add

Sensor (MyTea) has been added ..

Assign ID to Sensor: Go

Sensor (MyTea) is now having the ID (4003490) ..

SENSOR ID's

Use the list below to delete/update sensors used currently in the real-time environment.

Tools	Sensor ID	Sensor Name
	4003490	MyTea

Click on 'Delete' or 'Update' button next to the sensor to be deleted ..

User Interface Tools: Presentation

RECOGNIZED ACTIVITIES

- + #KitchenDoor
- #KitchenDoor -> #ChinaCup
 - #MakeSoup
 - + #MakeDrink

LEARNING OUTPUT

```

-----
User {abashrawi}
-----
Loading Ontology
-----
01:18:49: Graph parsed
successfully with {0} errors
..
01:18:49: Ontology imported
successfully ..
-----
01:18:49: Ontology contains
{16} sensors ..
01:18:49: System is now ready
to monitor sensors ..
-----
01:18:51: Getting current
state for sensor
{#KitchenDoor} ..
01:18:51: Current state for
sensor {#KitchenDoor} is
{#SensorOff} ..
-----
01:18:56: Sensor
{#KitchenDoor} has been
activated ..
            
```

SENSOR STATE AND ACTIVATION SEQUENCE

Sensor Status	Set/Reset	Sensor/Activity Preview
#SensorOn <input type="radio"/> #SensorOff <input checked="" type="radio"/>	Go	
Urgency: Low		

Activation Sequence

Activation sequence of this sensor: 0

◀

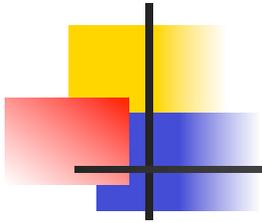


▶

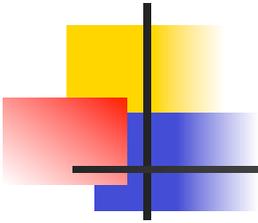
RECORDING STATUS

Recording Status - ●

New

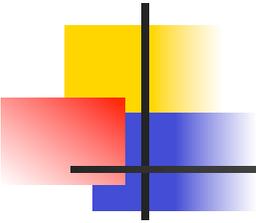


System Demonstration



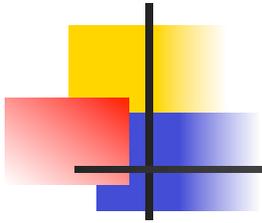
Conclusions

- With abundant domain knowledge on ADL, knowledge-driven approach, in particular, O-BAR, provides a number of advantages:
 - ❖ Easy to get started – everyone knows how they perform an activity
 - ❖ State based modelling and reasoning is more robust - there is no fixed sequences for an activity, esp. for ADLs
 - ❖ Support incremental progressive activity recognition
 - ❖ Able to discriminate importance and urgency of activities through semantic descriptions
 - ❖ Support course-grained and fine-grained activity assistance
- O-BAR is still in its infancy
 - ❖ Large-scale experimenting - more use scenarios and sensor types
 - ❖ Real world use case study
 - ❖ A number of open issues – the future work



Future Research Directions

- A hybrid activity modelling approach
 - ❖ Create a “seed” activity model from knowledge-driven approach
 - ❖ Evolve activity models through data-driven approach
- Enhance O-BAR with process knowledge
 - ❖ Incorporate procedural activity knowledge, e.g. order, sequence
 - ❖ Use rule-based constraints
- Combine subsumption classification with temporal reasoning
 - ❖ Enable explicit temporal processing supporting just-in-time assistance
- Handle data uncertainty and incompleteness
 - ❖ Extend description logic with fuzzy logics or possibility theories



Thank you!

Questions?

Contact: l.chen@ulster.ac.uk