

# From Space to Smart Homes: Constraint-Based Planning for Domestic Assistance

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# Outline

- 1 Motivation: Contextualized Proactive Services for Human Assistance in Smart Environments
- 2 A Solution Based on Constraint Reasoning
  - Background: the OMPS Framework
  - SAM is an Activity Manager
  - Sensors and Actuators as Constraint Reasoners
  - Example Run in the PEIS-Home
- 3 Summary and Conclusions
- 4 Appendix: Open Questions and On-Going Work
- 5 Appendix: Related Work



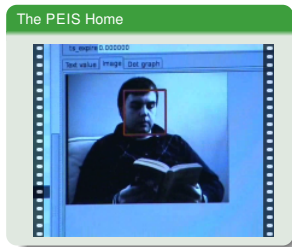
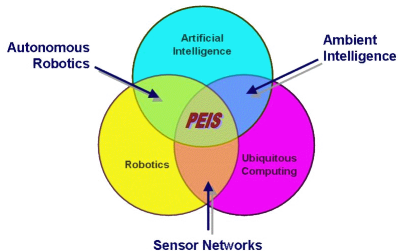
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## Ecologies of PEIS

- The PEIS-Ecology approach combines insights from several fields
- Grounded on an “ecological” vision of robotics [Saffiotti et al., 2008]
- Each individual in the ecology is a Physically Embedded Intelligent System



- The PEIS-Home is a prototypical smart home environment developed at AASS
- A number of PEIS have been realized: refrigerator, vision sensors, mobile robots, artificial noses, RFID-tagged floor and objects, ...

## Synthesizing Intelligent Services in the PEIS-Home

- **Activity recognition:** the ability of the intelligent system to deduce temporally contextualized knowledge regarding the state of the user
  - based on heterogeneous sensor readings and previously inferred knowledge
- **Planning and Execution:** the ability to proactively plan and execute services that provide contextualized assistance
  - based on the results of activity recognition
- This requires a way to model the temporal and causal dependencies that exist between sensor readings, tasks to be planned/executed and the state of the human user



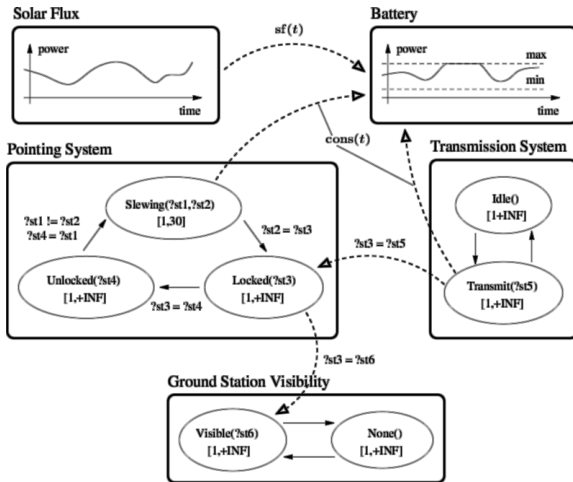
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# Constraint Reasoning for Domestic Plan Management

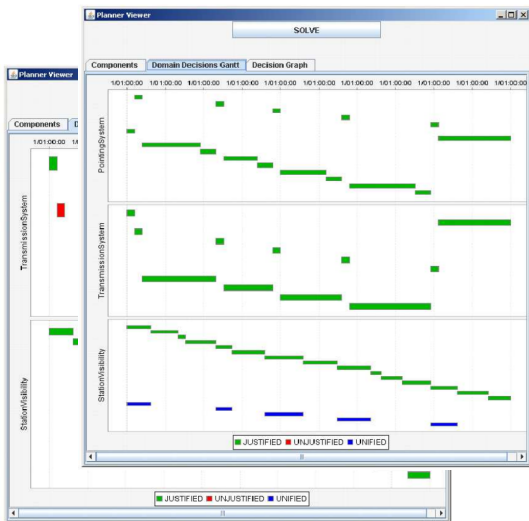
- The **SAM Activity Management architecture**: a constraint-based approach for activity recognition, planning and execution in PEIS Ecologies
- Based on the **OMPS framework for constraint-based temporal reasoning** [Fratini et al., 2008]
  - developed for ESA to improve the cost-effectiveness and flexibility of mission planning support tool development
  - used for Science Operations planning in the Mars Express mission [Cesta et al., 2008] and other domains [Cesta and Fratini, 2008]
- Grounded on the notions of **component**, **decision**, and **constraint**

# Space Mission Planning in OMPS





# Space Mission Planning in OMPS

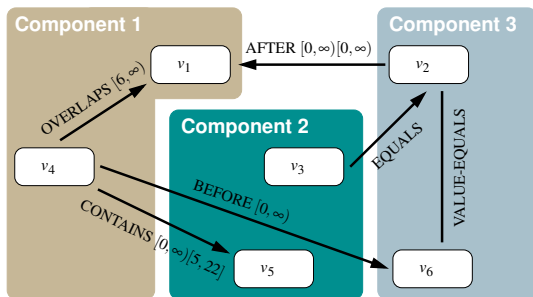


# Constraint Reasoning in OMPS

- **Components** are logical or physical entities whose behavior evolves in time
  - functions of **values** in time, values can be numeric, symbolic, . . .
  - e.g., **RoboticArm** : {**grasp**, **free**, **drop**}
- **Decisions** are assertions on the value of a component in a flexible time interval
  - $d = \langle v, [I_s, I_e] \rangle$ , where  $I_s, I_e$  are intervals of admissibility of start and end times of the decision
  - e.g.,  $\langle \mathbf{grasp}, [[5, 5], [23, \infty]] \rangle$  ,  $\langle \mathbf{grasp} \vee \mathbf{free}, [[2, 7], [13, 45]] \rangle$
- **Constraints** among the values or time intervals of decisions
  - temporal constraints extend the relations in Allen's interval algebra [Allen, 1984] and can involve decisions across components
  - e.g.,  $\langle \mathbf{drop}, [I_s, I_e] \rangle$  **DURING**  $[0, \infty][5, 8]$   $\langle \mathbf{docked}, [I_s, I_e] \rangle$

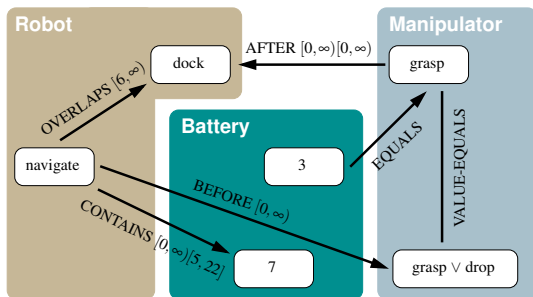
# Constraint Reasoning in OMPS

- Decisions and constraints are maintained in a **Decision Network**
- Values of decisions **depend on component type**:  
consumable/renewable resources, state variables, ...



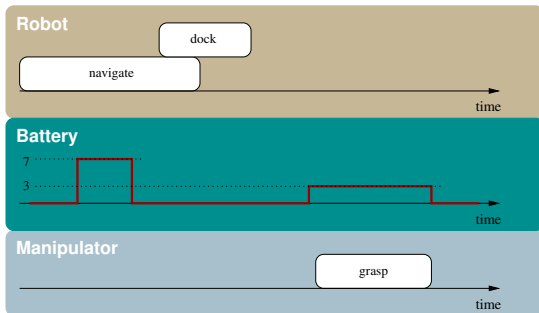
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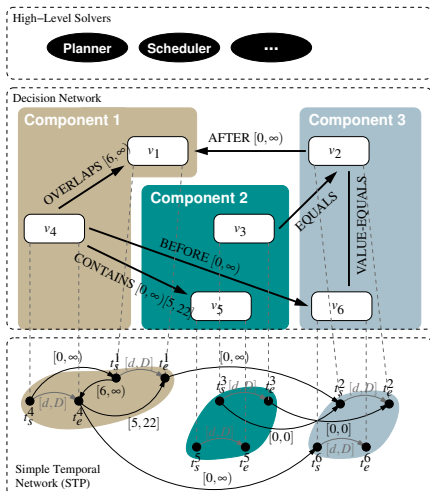


## Constraint Reasoning in OMPS

- **Timeline:** the evolution in time of a component given the decision network
- Given the flexible nature of the decisions' temporal intervals, many timelines can be extracted (e.g., earliest start time)

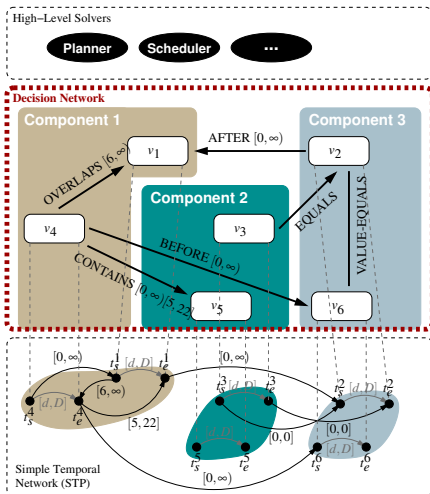


# Constraint Reasoning in OMPS



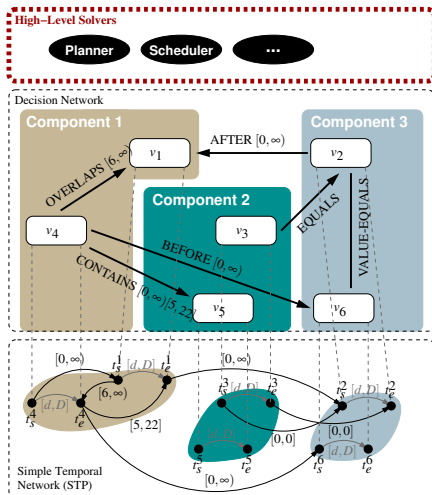
- OMPS is a **three-tiered architecture** in which the **Decision Network** allows to share **information between tiers**
- DN represents the current **state of computation**
- High-level solvers add/remove decisions and constraints to the DN
- OMPS provides a framework to implement new high-level reasoning modules

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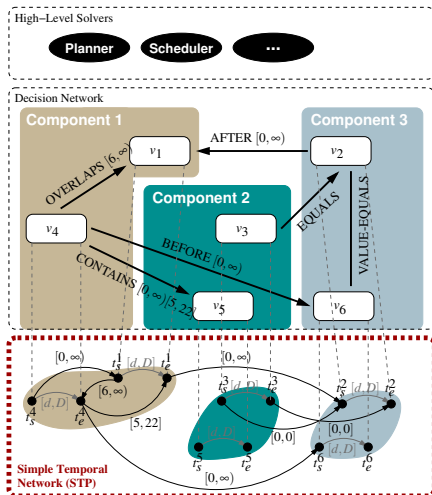


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# Constraint Reasoning in OMPS



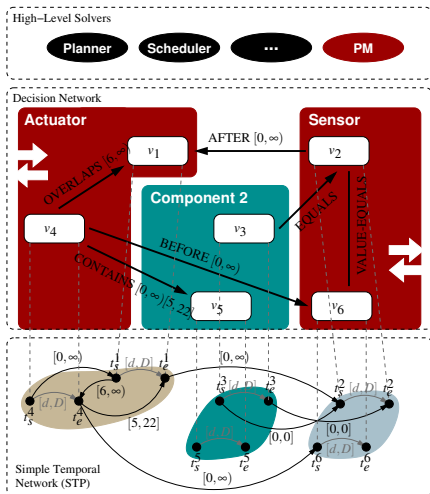
- Decisions' flexible time intervals represented as pairs of time points in a **Simple Temporal Problem (STP)** [Dechter et al., 1991]
- Each decision represented by **start** and **end time points in the STP**
- High-level temporal constraints translated to **simple distance constraints** between decisions' time points
  - propagation is  $O(n^3)$ ,  $n$  = number of time points ( $O(n^2)$  if incremental)

# Constraint Reasoning in OMPS

- OMPS provides a number of built-in functionalities
  - ① propagation of **temporal/value constraints**
  - ② suite of **profile-based scheduling algorithms**  
[Cesta et al., 2002, Policella et al., 2009]
  - ③ can deal with **Disjunctive Temporal Problems** at the lower layer  
[Oddi and Cesta, 2000]
  - ④ **planning capabilities** [Fratini et al., 2008]
  - ⑤ **state variable** and other component types
  - ⑥ ability to **extend/create component types**
- SAM leverages (4–6) to achieve an on-line activity monitoring system which is **fully integrated with the PEIS-Home**



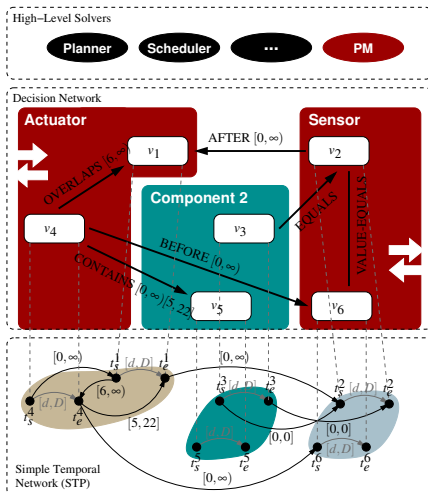
# SAM is an Activity Manager



- SAM is an Activity Manager = **Plan Monitor + Sensors + Actuators**
- The **Plan Monitor** is a **solver** that deduces possible activities in which the human is engaged in
- **Sensors** are **components** that represent the reality as it is observed in the real world in the DN
- **Actuators** are **components** that receive commands and maintain the execution status of real actuators



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## The Plan Monitor

- The Plan Monitor **continuously** attempts to support all un-supported decisions in the DN
- This is done by a combination of **unification** and **domain theory expansion** steps [Fratini et al., 2008]

### Unification

Assert that a decision occurs **simultaneously** with and has the **same value** as another decision

### Domain Theory Expansion

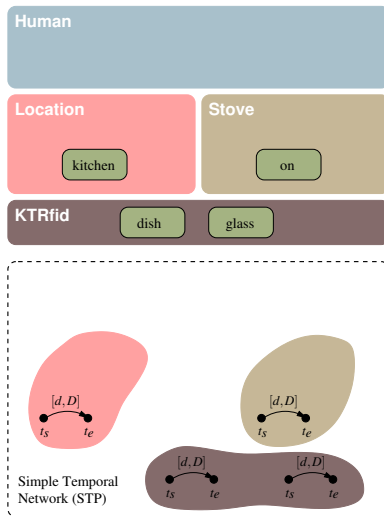
Assert the **consequences** of a decision on **other components**

## The Plan Monitor – Unification

- Supporting a decision by unification ~ “confirming” that a component is already due to take on that value in a given time frame
- Support by unification does not impose new decisions, **only constraints ensuring that support is present** in the DN

### Querying sensors

If the DN represents real world sensor readings, then **unification is a way to “query” the sensors**

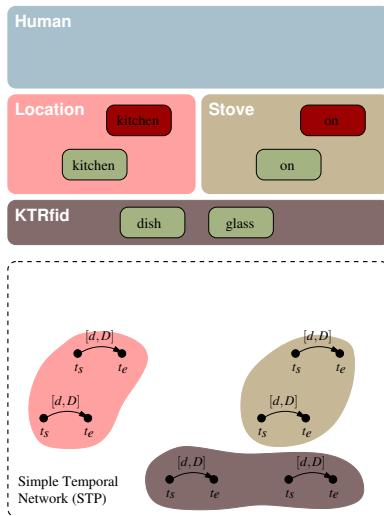


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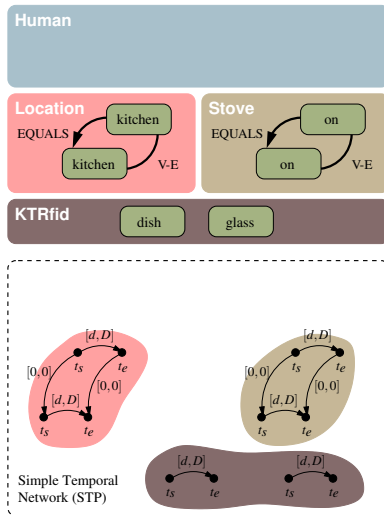


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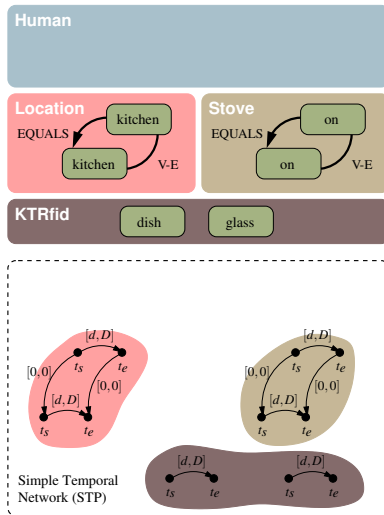


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## The Plan Monitor – Domain Theory Expansion

- **Domain Theory:** a collection of **synchronizations**
- **Synchronization:** a collection of **requirements** on other components
- **Requirements:** sub-network of decisions to be added to other components **in support of this decision**

Human : **Cooking**

EQUALS Stove : **on**

DURING  $[0, \infty)[0, \infty)$  Location : **kitchen**

Human : **Eating**

EQUALS KTRfid : **dish**

DURING  $[0, \infty)[0, \infty)$  Location : **kitchenTable**

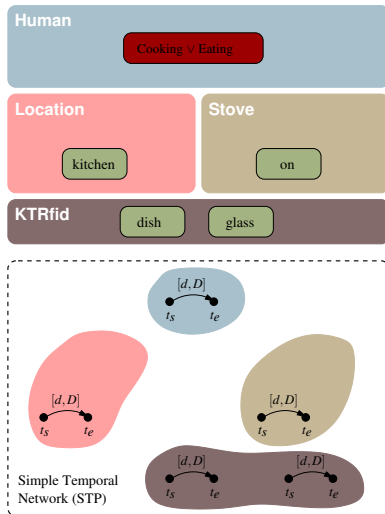


## The Plan Monitor – Domain Theory Expansion

- Supporting a decision by domain theory expansion ~ finding “indirect” support for the decision through other components
- Support by expansion imposes **new decisions and constraints ensuring that support is present** in the DN

### Activity recognition

If the DN represents real world sensor readings, then **expansion is a way to “hypothesize” a case for support for a given decision**

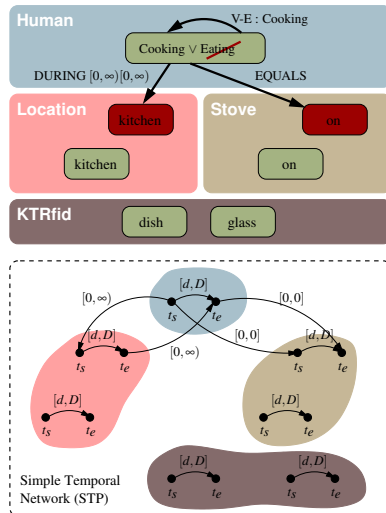


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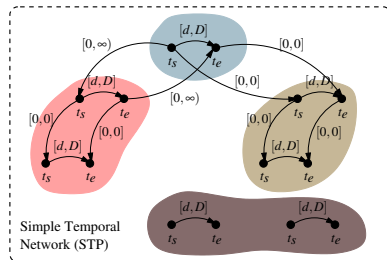
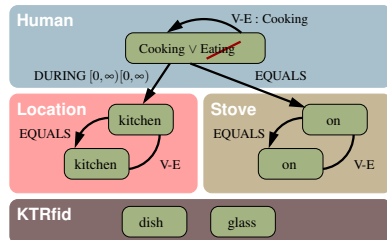


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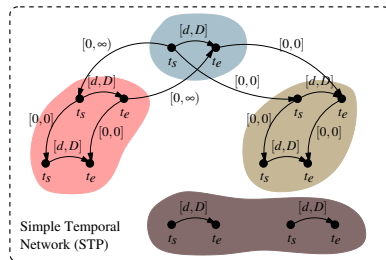
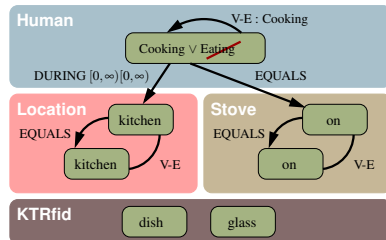


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## The Plan Monitor: Details

- The Plan Monitor continuously executes the following

---

Procedure `Replan (DN)`

---

**foreach** *component c* **do**

**if** *c* is controllable **then**

$\mathbf{v} = \bigvee_{v_i \in \text{possibleValues}(c)} v_i$

$\text{DN} \leftarrow d = \langle \mathbf{v}, [I_s, I_e] \rangle$

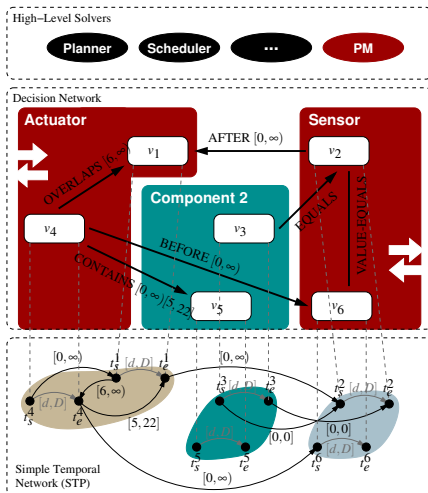
    mark *d* as not supported

**foreach** *d'* on component *c* **do**  $\text{DN} \leftarrow d$  AFTER  $[0, \infty) d'$

  SupportDecisions (*DN*)

---

# SAM is an Activity Manager



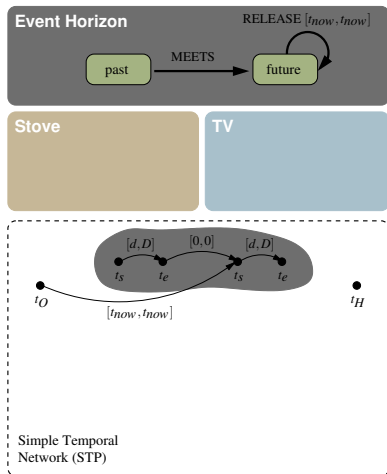
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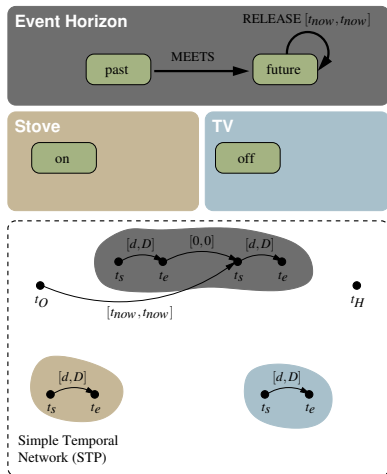
## Sensor Components

- A special component represents **the current clock time** in the DN (“Event Horizon”)
  - modifies the **release time constraint with current  $t_{now}$**
- When a real-world sensor signals a new sensor reading, the SAM sensor
  - adds a new decision
  - constrains it to start at  $t_{now}$
  - constrains it to end in the future



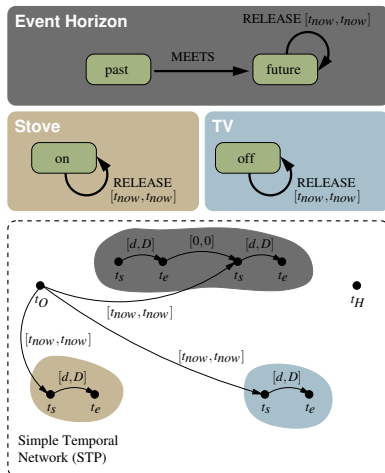
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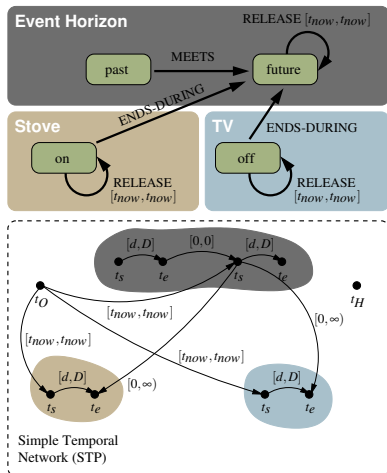
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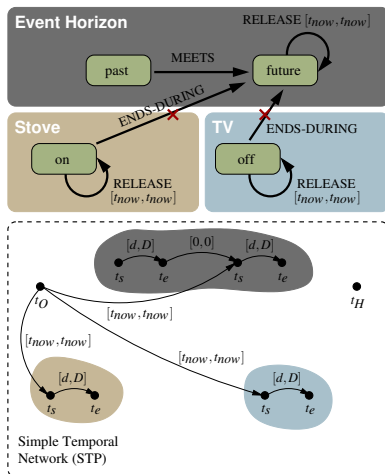
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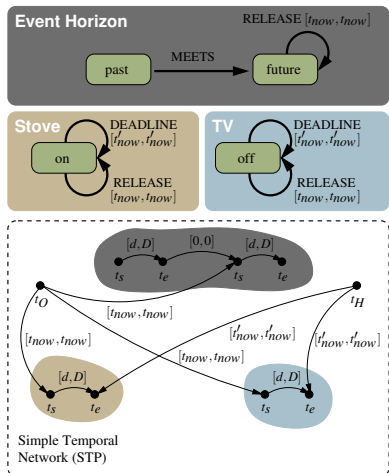
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- Periodic updates to the release time of the “future” decision entails the **update of end times of current sensor readings**
- Propagation of sensor-related constraints entails the **update of the end times of recognized activities**



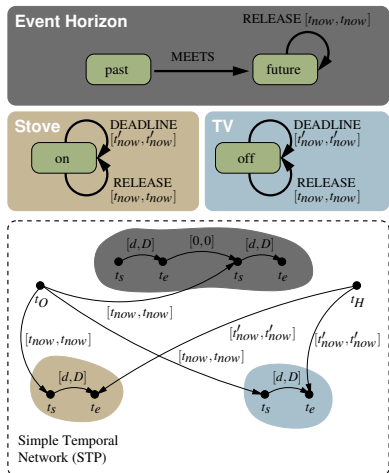
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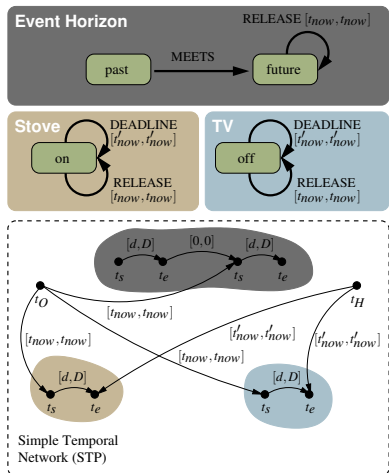
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## Sensor Components: Details

- Each sensor continuously executes the following

---

Procedure UpdateSensorValues (DN,  $t_{\text{now}}$ )

---

$d = \langle \mathbf{v}, [[l_s, u_s], [l_e, u_e]] \rangle \in \text{DN}$  s.t.  $u_e = \infty$

$\mathbf{v}_s \leftarrow \text{ReadSensor}()$

**if**  $d = \text{null} \wedge \mathbf{v}_s \neq \text{null}$  **then**

DN  $\leftarrow d' = \langle \mathbf{v}_s, [[0, \infty), [0, \infty)] \rangle$   
 DN  $\leftarrow d'$  RELEASE  $[t_{\text{now}}, t_{\text{now}}]$   
 DN  $\leftarrow d'$  DEADLINE  $[t_{\text{now}} + 1, \infty]$

**else if**  $d \neq \text{null} \wedge \mathbf{v}_s = \text{null}$  **then** DN  $\leftarrow d$  DEADLINE  $[t_{\text{now}}, t_{\text{now}}]$

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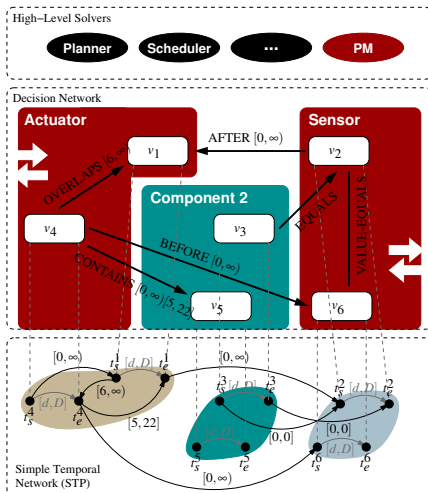
**if**  $\mathbf{v}_s = \mathbf{v}$  **then** DN  $\leftarrow d$  DEADLINE  $[t_{\text{now}}, \infty]$

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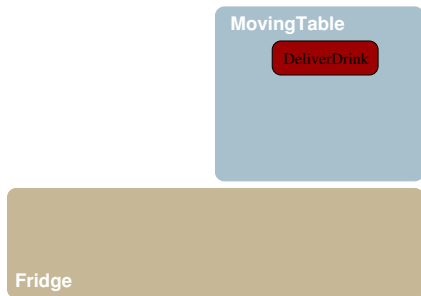
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## Actuator Components

- **Actuators** trigger commands that are planned (i.e., that appear in the DN) on their physical counterparts
- Like sensors, **actuators maintain the status of execution** of planned decisions in the DN
  - “sense” whether a command has begun, is continuing, or has ended
  - add decisions, impose and retract constraints reflecting the perceived status
- An approach similar to [Jonsson et al., 2000]
- Details in forthcoming papers and [Cirillo et al., 2009]



## Actuator Components: Example



MovingTable : **DockFridge**  
 MET-BY Fridge : **Open**

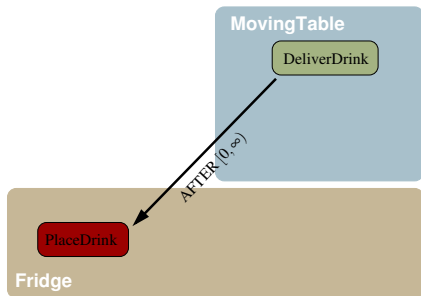
MovingTable : **UndockFridge**  
 BEFORE  $[0, \infty)$  Fridge : **Close**

MovingTable : **DeliverDrink**  
 AFTER  $[0, \infty)$  Fridge : **PlaceDrink**

Fridge : **PlaceDrink**  
 MET-BY MovingTable : **DockFridge**  
 MEETS MovingTable : **UndockFridge**

Fridge : **Open**  
 MET-BY Fridge : **GraspDrink**

## Actuator Components: Example



MovingTable : **DockFridge**

MET-BY Fridge : **Open**

MovingTable : **UndockFridge**

BEFORE  $[0, \infty)$  Fridge : **Close**

MovingTable : **DeliverDrink**

AFTER  $[0, \infty)$  Fridge : **PlaceDrink**

Fridge : **PlaceDrink**

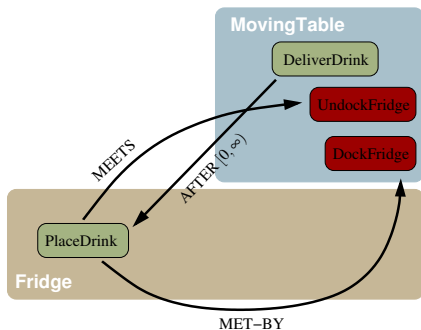
MET-BY MovingTable : **DockFridge**

MEETS MovingTable : **UndockFridge**

Fridge : **Open**

MET-BY Fridge : **GraspDrink**

## Actuator Components: Example



MovingTable : **DockFridge**

MET-BY Fridge : **Open**

MovingTable : **UndockFridge**

BEFORE [0, ∞) Fridge : **Close**

MovingTable : **DeliverDrink**

AFTER [0, ∞) Fridge : **PlaceDrink**

Fridge : **PlaceDrink**

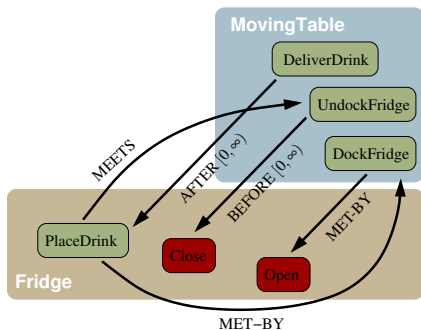
MET-BY MovingTable : **DockFridge**

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Fridge : **Open**

MET-BY Fridge : **GraspDrink**

## Actuator Components: Example



MovingTable : **DockFridge**

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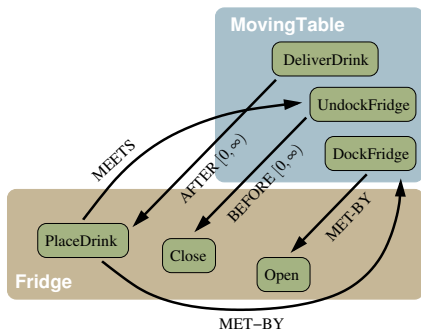
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## Actuator Components: Details

- Each actuator continuously executes the following

---

```
Procedure UpdateExecutionState (DN,  $t_{\text{now}}$ )
```

---

```
 $D = \{ \langle \mathbf{v}, [[l_s, u_s], [l_e, u_e]] \rangle \in \text{DN} \text{ s.t. } u_e = \infty \}$ 
```

```
foreach  $d \in D$  do
```

```
  if IsExecuting ( $\mathbf{v}$ ) then DN  $\leftarrow$   $d$  DEADLINE [ $t_{\text{now}} + 1, \infty$ ]
```

```
  else if  $l_s = l_e$  then StartExecuting ( $\mathbf{v}$ )
```

```
  DN  $\leftarrow$   $d$  RELEASE [ $t_{\text{now}}, t_{\text{now}}$ ]
```

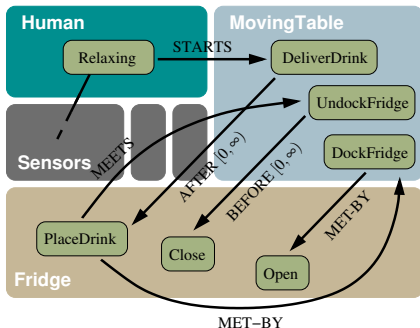
```
  else DN  $\leftarrow$   $d$  DEADLINE [ $t_{\text{now}}, t_{\text{now}}$ ]
```

---

### Recognition and Actuation in one Formalism

Both **activity recognition** and **actuation requirements** are modeled as **temporal relations among decisions**

# Uniform Representation of Recognition and Actuation



## Human : **Relaxing**

*<requirements for recognition>*

STARTS MovingTable : **DeliverDrink**

## MovingTable : **DockFridge**

MET-BY Fridge : **Open**

## MovingTable : **UndockFridge**

BEFORE  $[0, \infty)$  Fridge : **Close**

## MovingTable : **DeliverDrink**

AFTER  $[0, \infty)$  Fridge : **PlaceDrink**

## Fridge : **PlaceDrink**

MET-BY MovingTable : **DockFridge**

MEETS MovingTable : **UndockFridge**

## Fridge : **Open**

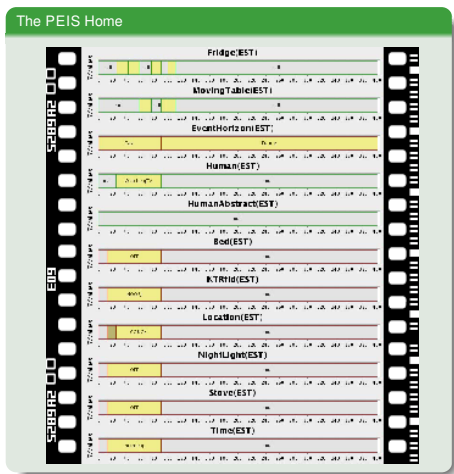
MET-BY Fridge : **GraspDrink**

## Example Run

- SAM is interfaced with **five sensors** in the PEIS-Home
  - stereo camera for **person localization**
  - **pressure sensor** under the bed
  - **RFID tag reader in the kitchen table** and a number of tagged kitchen utensils
  - **stove state sensor**
  - **luminosity sensor** next to the bed
- **Two actuators** are also present
  - **autonomous mobile table** that can dock the fridge
  - **actuated fridge** that can grasp a drink and place it on the docked table
- A **human subject** carries out a number of actions in the PEIS-Home involving the use of the sensors



# Example Run



## SAM: Performance

- SAM heavily leverages temporal constraint propagation
  - complexity of adding/removing decisions and constraints to the DN is cubic in the number of decisions
- However, the bulk of computation is performed by the planner
  - still polynomial in the number of decisions (with a bounded horizon)
  - notice that number of decisions depends on how “active” the sensors are
- In a run like the previous, all processes can sample at a rate of about 1 Hz
  - we can recognize activities so long as their requirements persist within the sampling rate
- The performance of the plan monitor deteriorates for horizons of more than 20 minutes



# Outline

- 1 Motivation: Contextualized Proactive Services for Human Assistance in Smart Environments
- 2 A Solution Based on Constraint Reasoning
  - Background: the OMPS Framework
  - SAM is an Activity Manager
  - Sensors and Actuators as Constraint Reasoners
  - Example Run in the PEIS-Home
- 3 **Summary and Conclusions**
- 4 Appendix: Open Questions and On-Going Work
- 5 Appendix: Related Work

## Summary

- SAM leverages **temporal constraint reasoning** to perform **concurrent activity recognition, planning and execution** in a sensor/actuator-rich environments
- Deductive, sensory and actuation processes **share information and reason on a dynamic constraint network**
  - sensors represent the **real world** as it is observed
  - actuators **trigger commands** and **monitor execution**
  - a plan monitor adds **deduced information on the context** of one or more monitored entities (e.g., a human user)
- Both context and actuation requirements are modeled as **temporal relations among decisions**
  - **single formalism** for recognition and actuation
- SAM is **fully integrated** into the PEIS-Home

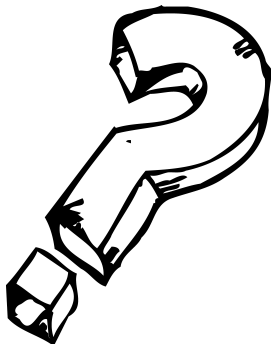
## SAM: Open Questions and On-Going Work

- How to increase **computational efficiency** of the system?
- How to ensure **robustness of recognition process**?
- How to include **plan forecasting** capability?
- How to model **preferences/soft requirements**?

*See Appendix: "Open Questions and On-Going Work"*



# Questions



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## Computational Efficiency

- How to increase **computational efficiency** of the system?  
(*J. Ullberg*)
  - application domain is such that entire parts of the DN become useless with time
  - recognition of activities in the evening probably does not depend on sensor readings obtained in the morning or afternoon
  - restricting planning and temporal propagation to decisions within a sliding window
- Motivation: **sleep disorder diagnosis domain**, in which **weeks** of daily and nightly activities need to be monitored

## Robustness in Activity Recognition

- How to ensure **robustness of recognition process?**  
(*F. Dell'Osa, J. Ullberg*)

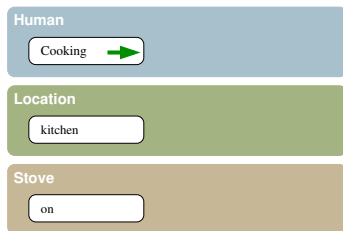


Human : **Cooking**  
 EQUALS Stove : **on**  
 DURING  $[0, \infty)[0, \infty)$  Location : **kitchen**

- Maintaining a different DN for each candidate outcome
- Late commitment based on analysis of constraint network

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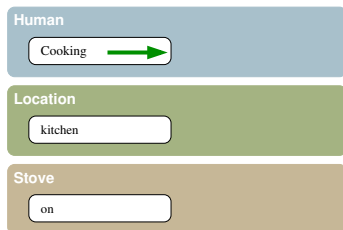


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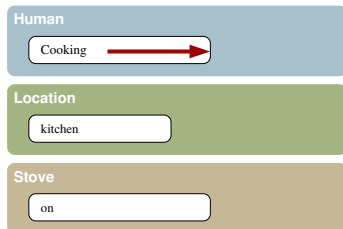


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## Plan Forecasting and Soft Requirements

- How to include **plan forecasting** capability?  
(*M. Cirillo*)
  - ability to forecast human plans can increase proactiveness of the system
  - instrumental for **human-aware robot planning** [Cirillo et al., 2008]
- How to model **preferences/soft requirements**?  
(*F. Venturini*)
  - adding the capability to reason about **fuzzy temporal constraints**
  - fuzzy extension of **Allen's interval algebra** [Badaloni and Giacomini, 2000], fuzzy extension of the **Simple Temporal Problem** [Marín et al., 1997]



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## Synergy with Other Approaches to Recognition

- **Data-driven approaches**: e.g., Hidden Markov Models (HMMs) for learning sequences of sensor observations with given transition probabilities (e.g., [Wu et al., 2007])
- **Knowledge-driven approaches**: patterns of observations are modeled from first principles rather than learned
- The two strategies seem **complementary in scope**
  - data-driven approaches provide an effective way to recognize **elementary activities from large amounts of continuous data**
  - knowledge-driven approaches are useful when the criteria for recognizing human activities are given by complex but **general rules that are clearly identifiable**
- Data-driven approaches have been **more extensively validated** within real scenarios
  - important to **assess our approach in a real application domain**

## Related Work in Constraint Reasoning for Recognition and Execution

- Schedule execution monitoring techniques for domestic activity monitoring [Cesta et al., 2007, Pollack et al., 2003]
  - pre-compiled (albeit highly flexible) schedules as models for human behavior
  - SAM employs a planning process to actually instantiate such candidate schedules on-line
- Other timeline-based approaches to planning, e.g., [Jonsson et al., 2000]
  - address concurrent planning and execution, not specifically geared towards activity recognition
  - provides only state variable component type, lack of extensible component types (e.g., “active” components like sensors and actuators)

## References



Allen, J. (1984).

Towards a general theory of action and time.  
*Artificial Intelligence*, 23(2):123–154.



Badaloni, S. and Giacomini, M. (2000).

A fuzzy extension of Allen's interval algebra.  
In Verlag, S., editor, *LNAI*, volume 1792, pages 1555–165.



Cesta, A., Cortellesa, G., Giuliani, M., Pecora, F., Scopelliti, M., and Tiberio, L. (2007).

Caring About the User's View: The Joys and Sorrows of Experiments with People.  
In *ICAPS07 Workshop on Moving Planning and Scheduling Systems into the Real World*.



Cesta, A. and Fratini, S. (2008).

The Timeline Representation Framework as a Planning and Scheduling Software Development Environment.  
In *Proc. of 27th Workshop of the UK Planning and Scheduling SIG*.



Cesta, A., Fratini, S., Oddi, A., and Pecora, F. (2008).

APSI Case#1: Pre-planning Science Operations in Mars Express.  
In *Proc. of iSAIRAS-08*.



Cesta, A., Oddi, A., and Smith, S. F. (2002).

A constraint-based method for project scheduling with time windows.  
*Journal of Heuristics*, 8(1):109–136.



Cirillo, M., Karlsson, L., and Saffiotti, A. (2008).

A framework for human-aware robot planning.

In *Proc. of the Scandinavian Conf. on Artificial Intelligence (SCAI)*, Stockholm, SE.



Online at <http://www.aass.oru.se/~asaffio/>.



Cirillo, M., Lanzello, F., Pecora, F., and Saffiotti, A. (2009).

Monitoring domestic activities with temporal constraints and components.  
In *5th International Conference on Intelligent Environments (IE'09)*.  
(to appear).



Dechter, R., Meiri, I., and Pearl, J. (1991).

Temporal constraint networks.  
*Artif. Intell.*, 49(1-3):61–95.



Fratini, S., Pecora, F., and Cesta, A. (2008).

Unifying Planning and Scheduling as Timelines in a Component-Based Perspective.  
*Archives of Control Sciences*, 18(2):231–271.



Jonsson, A., Morris, P., Muscettola, N., Rajan, K., and Smith, B. (2000).

Planning in Interplanetary Space: Theory and Practice.  
In *Proc. Int. Conf. on AI Planning and Scheduling (AIPS-00)*.



Marín, R., Cárdenas, M., Balsa, M., and Sánchez, J. L. (1997).

Obtaining solutions in fuzzy constraint networks.  
*International Journal of Approximate Reasoning*, 16:261–288.



Oddi, A. and Cesta, A. (2000).

Incremental forward checking for the disjunctive temporal problem.  
In *Proceedings of ECAI*.



Policella, N., Cesta, A., Oddi, A., and Smith, S. (2009).

Solve-and-Robustify. Synthesizing Partial Order Schedules by Chaining.  
*Journal of Scheduling*, 12(3):299–314.



Pollack, M., Brown, L., Colbry, D., McCarthy, C., Orosz, C., Peintner, B., Ramakrishnan, S., and Tsamardinos, I. (2003).



Autominder: an intelligent cognitive orthotic system for people with memory impairment.

*Robotics and Autonomous Systems*, 44(3-4):273–282.



Saffiotti, A., Broxvall, M., Gritti, M., LeBlanc, K., Lundh, R., J., R., Seo, B., and Cho, Y. (2008).

The PEIS-ecology project: vision and results.

*In Proc of the IEEE/RSJ Int Conf on Intelligent Robots and Systems (IROS)*, Nice, France.



Wu, J., Osuntogun, A., Choudhury, T., Philipose, M., and Rehg, J. (2007).

A Scalable Approach to Activity Recognition Based on Object Use.

*In Proceedings of ICCV 2007. Rio de Janeiro, Brazil.*