

Learning Situation Models for Context-Aware Services

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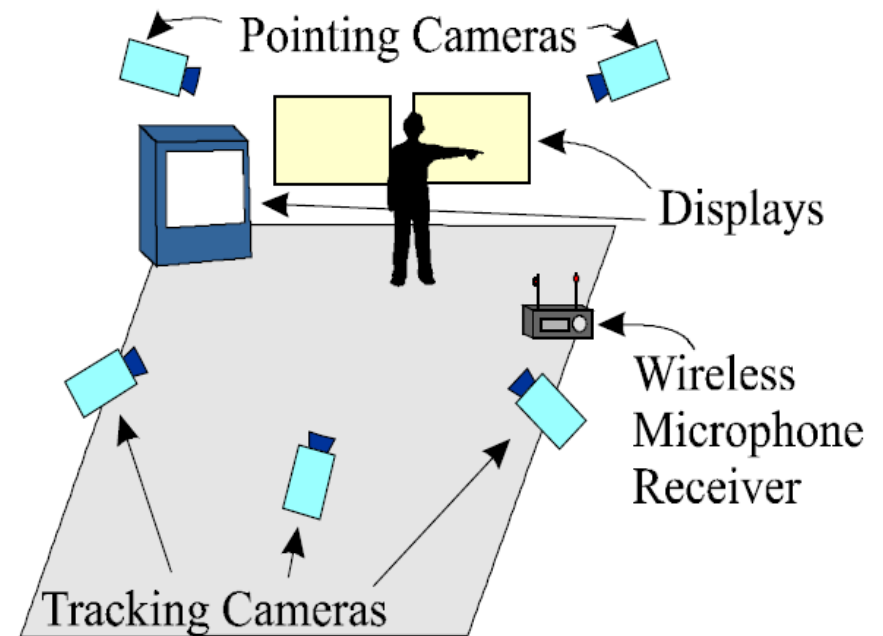
Outline

- 1. Introduction and Problem Definition**
 - **Augmented “Intelligent” Environments**
 - **Context-Aware Services**
 - **Learning Context Models**
2. Situation Model
3. Learning Role Acceptance Tests
4. Unsupervised Situation Discovery
5. Supervised Learning of Situations
6. Adapting to User Preferences
7. Integration and Experimental Evaluation
8. Conclusion and Perspectives

Augmented “Intelligent” Environments

- Augmented “Intelligent” environment or *smart environment*
 - “a **physical world** that is richly and invisibly **interwoven with sensors, actuators**, displays, and computational elements, **embedded seamlessly in the everyday objects of our lives**, and connected through a continuous network“ [Cook2004]

- Smart Home Environments [Mozer1998] [Cook2003]
- Smart Classrooms [Abowd1996] [Xie2001]
- Smart Office Environments [Coen1998] [LeGal2001]



picture from [Coen1998]

Context-Aware Services

- Proactive system behavior

“... the concept proactive refers to two critical features of a system: 1) that the system is working **on behalf of (or pro) the user**, and 2) is **taking initiative autonomously**, without user’s explicit command.”
[Salovaara2004]

- *Context is Key* [Coutaz2005]

“Context informs both recognition and mapping (onto available services) by providing a structured, unified view of the world in which the system operates.” [Coutaz2005]

- Intelligibility [Bellotti2001] → (transparent) context model

“Context-aware systems that seek to act upon what they infer about context must be able to represent to their users what they know, how they know it, and what they are doing about it.” [Bellotti2001]

Context-Aware Services

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Context-Aware Services

Automatic cameraman [Reignier2007]



Learning Context-Models (1/2)

But:

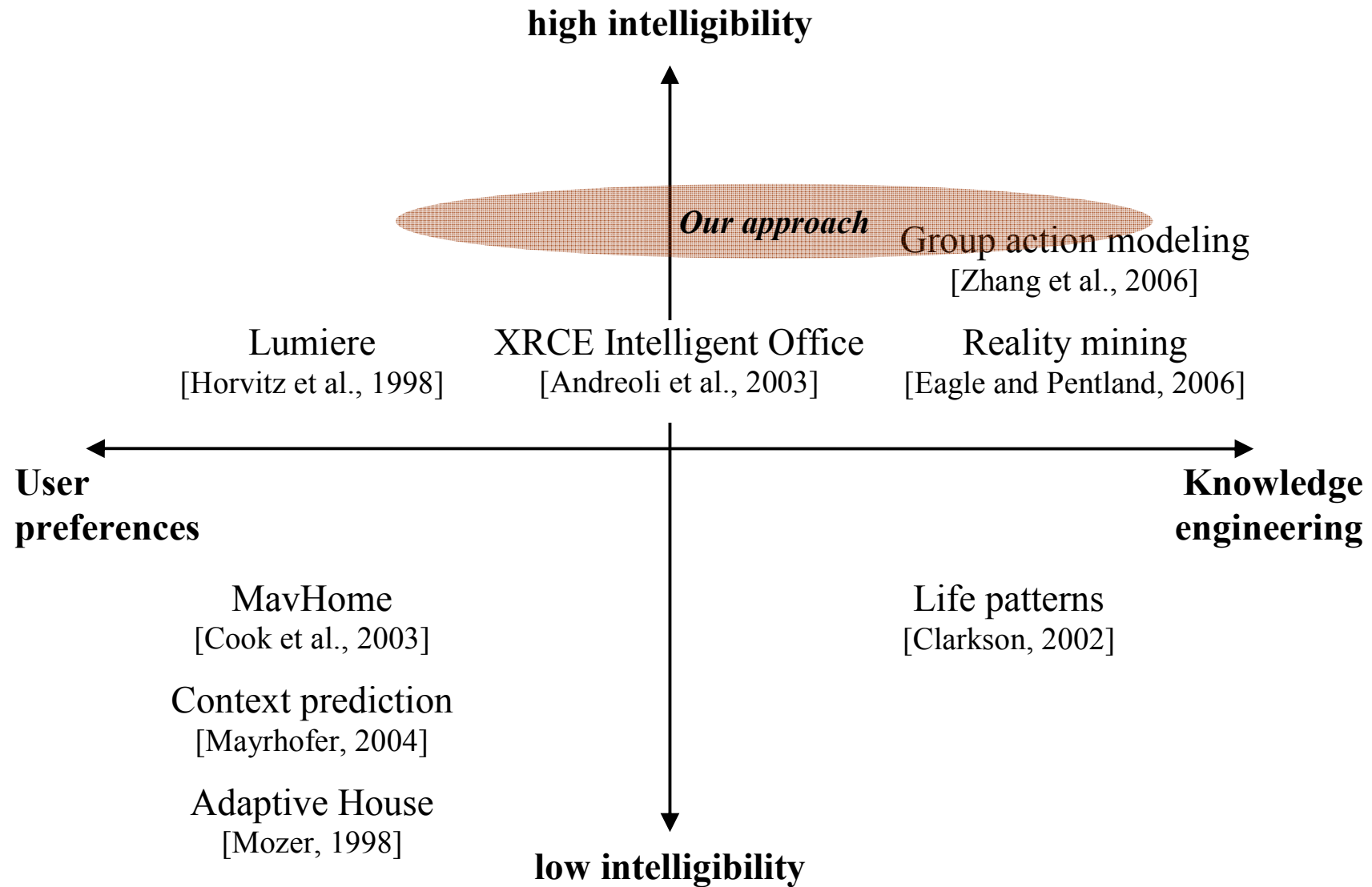
- Human behavior evolves over time
- New services / user preferences emerge, others disappear

⇒ **acquire and adapt context models using machine learning methods**

Two motivations for learning context models:

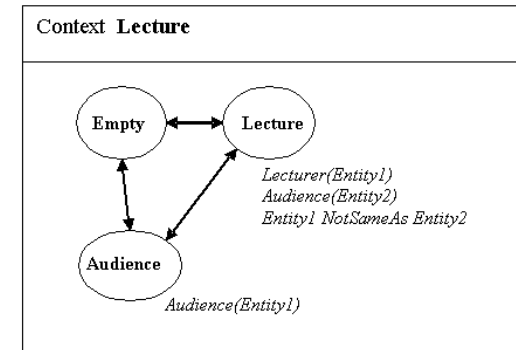
- Knowledge engineering (“offline” acquisition of context model from data)
- User preferences (“online” adaptation / evolving a context model)

Learning Context-Models (2/2)



Outline

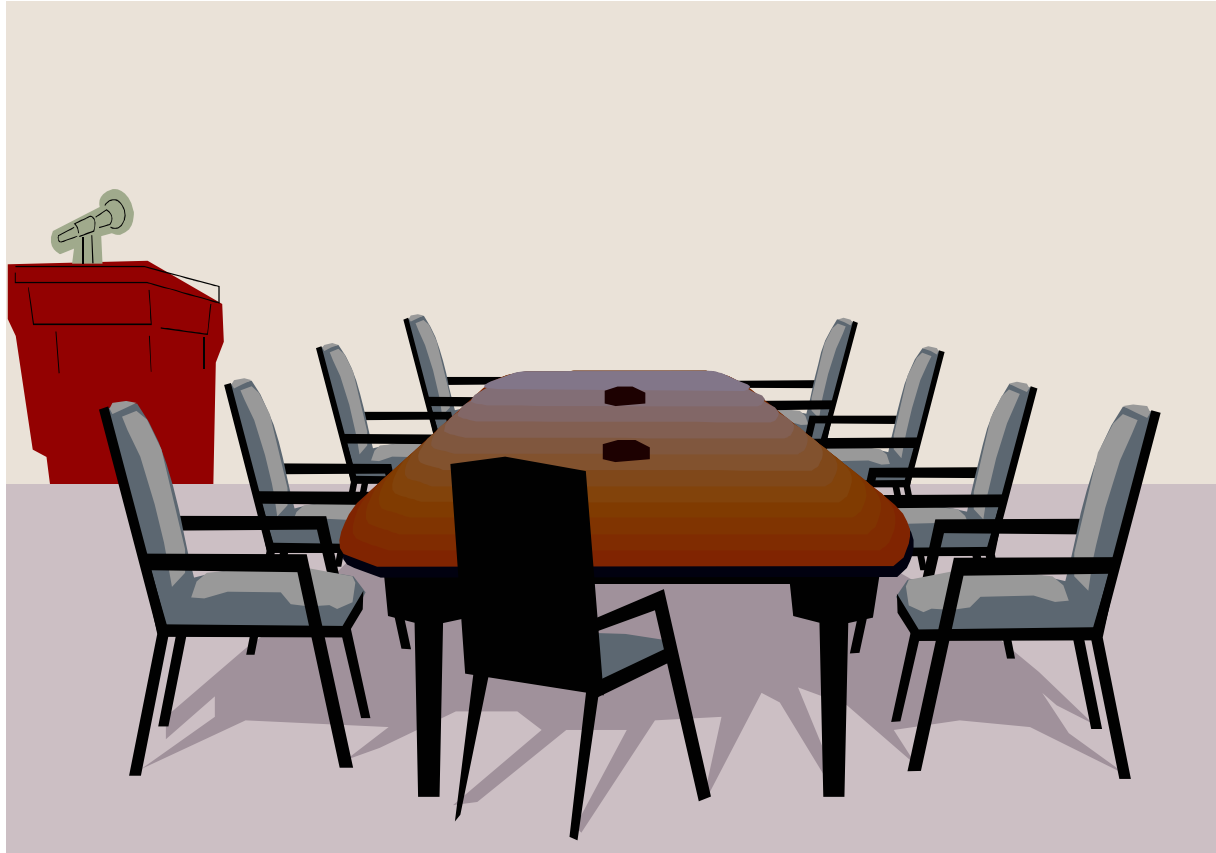
1. Introduction and Problem Definition
- 2. Situation Model**
 - **Defining concepts**
 - **Example: Lecture room**
3. Learning Role Acceptance Tests
4. Unsupervised Situation Discovery
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Defining concepts

- Context is “any information that can be used to characterize the situation of an entity” [Dey2001]
- Situation = temporal state within context, defined by roles and relations [Crowley2002]
- Role is “played” by an entity that passes the role acceptance test
- Relation is applied to several entities that pass the test for the relevant roles
- System service is associated to a situation

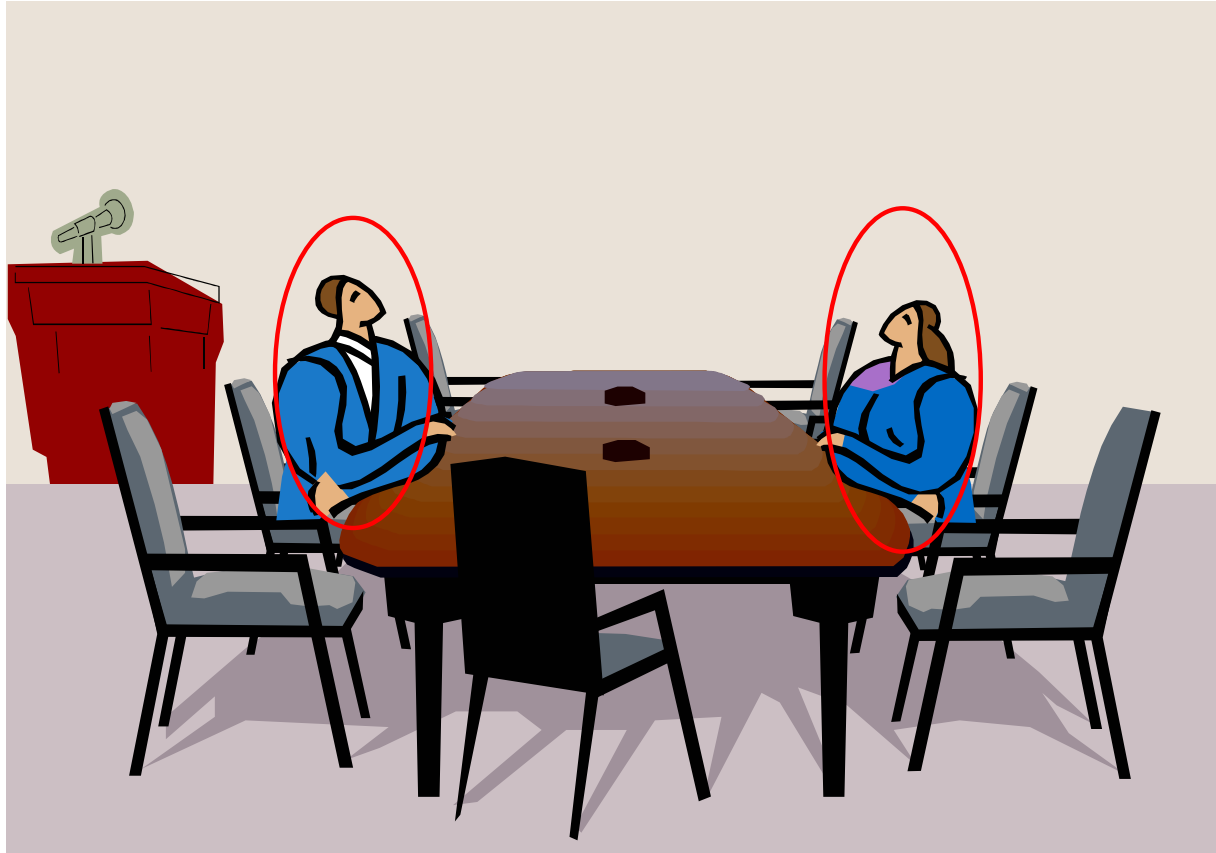
Example: Lecture scenario



Empty

No entity. No role. No relation.

Example: Lecture scenario



Audience

Roles: Participant

Example: Lecture scenario



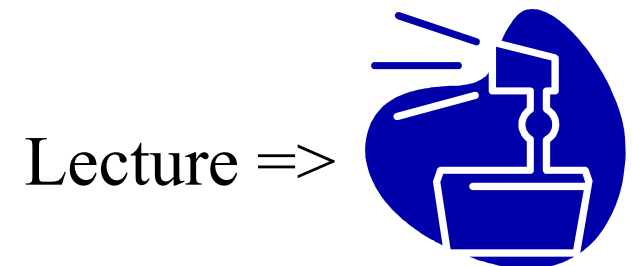
Lecture

Roles: *Participant* , *Lecturer*

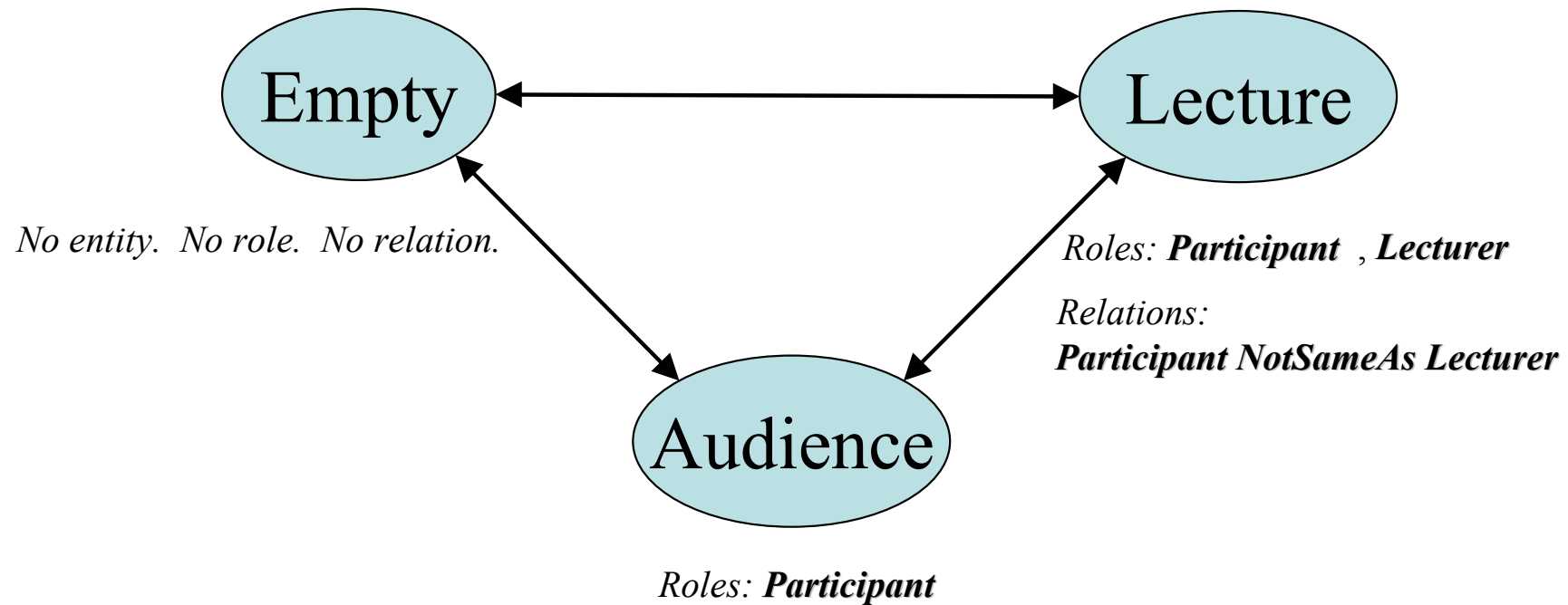
Relations:

Participant NotSameAs Lecturer

Service association:



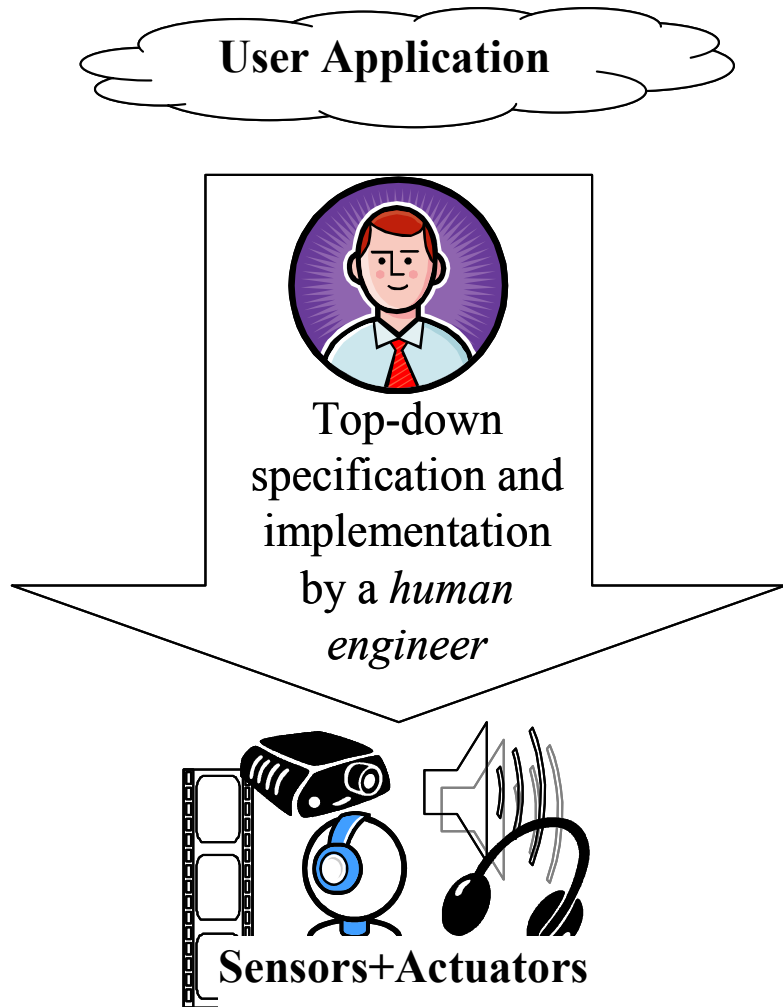
Example: Lecture scenario



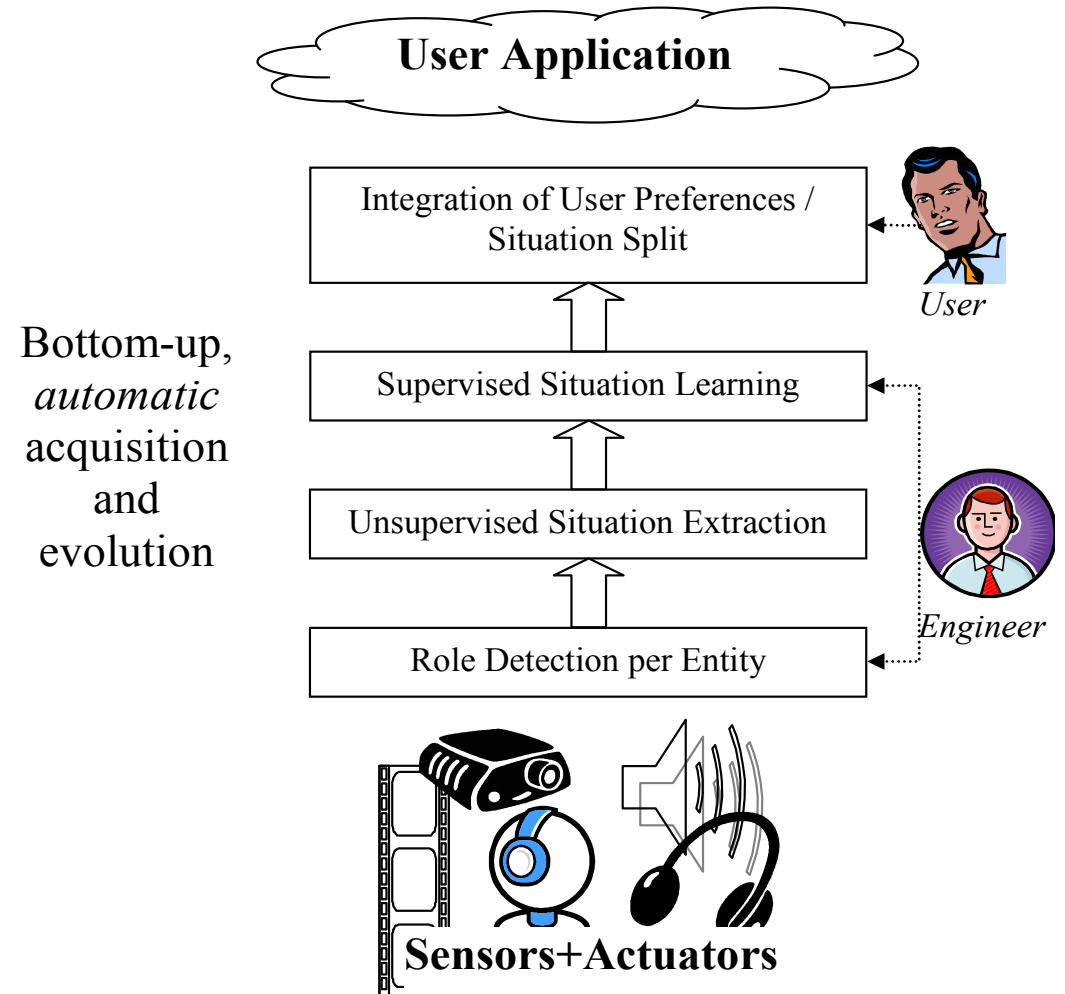
Service associations: Lecture => 

Constructing Situation Models:

Manual Design

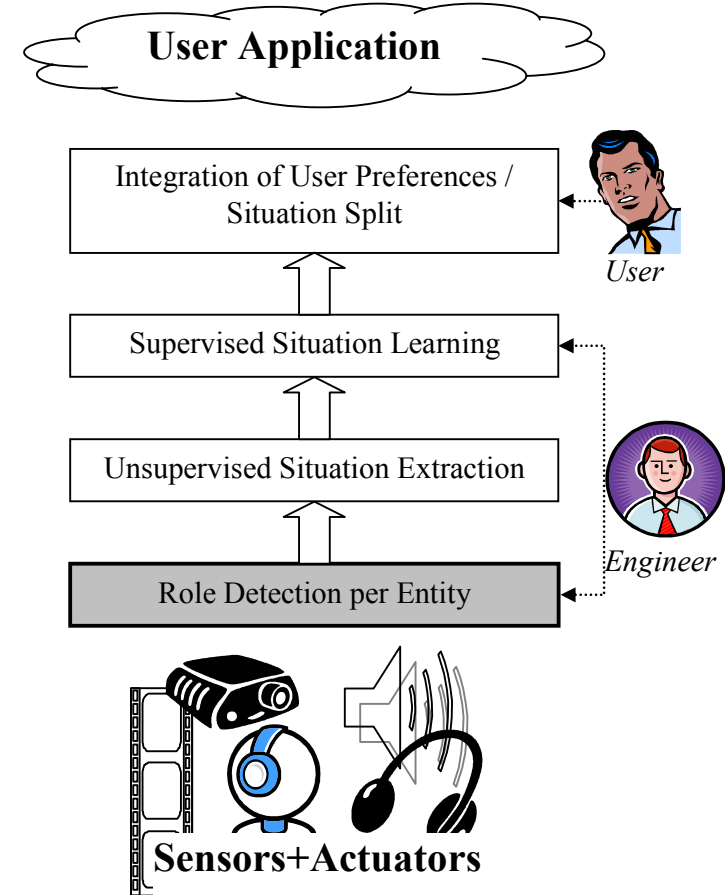


Our Approach



Outline

- I. Introduction and Problem Definition
- II. Situation Model
- III. Learning Role Acceptance Tests**
 - **Role Detection and Learning**
 - **Evaluation and Results**
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Role Detection and Learning (1/4)

- $T = (\text{Entity properties}) \rightarrow \text{role label}$
- Method:
 - Framewise classification of entity properties
 - Classifiers trained on learning data (labeled by a human)

Role Detection and Learning (2/4)

- Bayesian Classifier [Ribeiro2005] [Mühlenbrock2004]

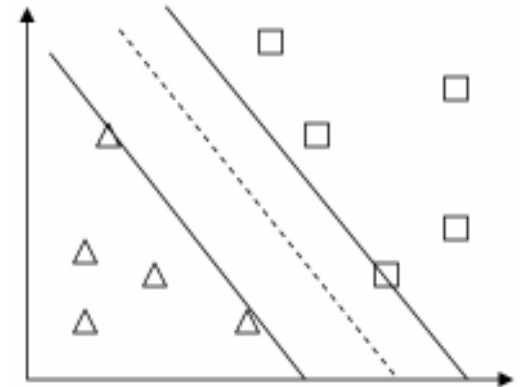
- $r_{MAP} = \arg \max_r P(r | T) = \arg \max_r \frac{P(T | r)P(r)^{P(r) \text{ equiprobable}}}{P(T)} = \arg \max_r P(T | r)$

- $P(T | r)$ - multidimensional Gaussian mixture estimated from learning data using Expectation-Maximization (EM) [Bilmes1998]

+ Creates a model for the learning data sets, permitting to identify wrong detections / unseen classes

Role Detection and Learning (3/4)

- Support Vector Machines (SVMs) [Cortes1995]
 - Discriminative method
 - Estimate a hyperplane in a multidimensional space
 - Radial basis function kernel
 - Multi-class classification

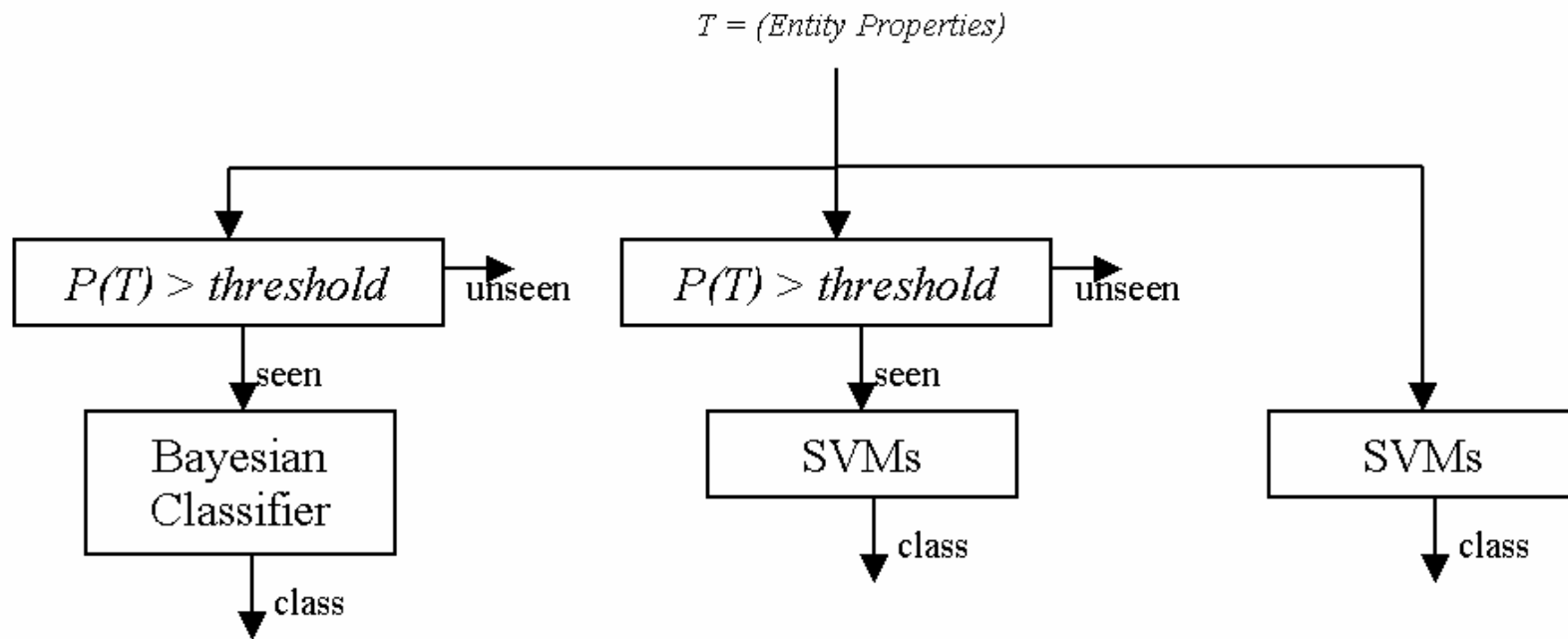


+ High discriminative power

– No model for learning data sets → no identification of wrong detections / unseen classes

Role Detection and Learning (4/4)

- Hybrid Classifier [Brdiczka2007]
 - Combines Bayesian methods + SVMs for detecting unseen role labels



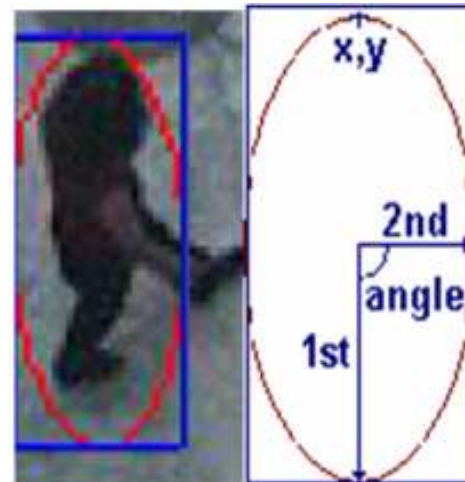
A) Ext. Bayesian Classifier

B) Hybrid Classifier

C) Support Vector M.

Evaluation and Results (1/3)

- Video Tracking System creates entities + properties



- 5 role labels:
 - “walking”, “standing”, “sitting”, “interacting with table” and “lying down”

Evaluation and Results (2/3)

- 8 video sequences (30885 video frames)
- Detection of 5 role labels
 - 8-fold cross-validation: learn from 7 sequences, test 1
 - Bayesian classifier, SVMs (5 classes)

	Bayesian Classifier	SVMs
Mean	0,8150	0,8610
Std. dev.	0,0146	0,0276

Evaluation and Results (3/3)

- Detection of *unseen* role labels
 - Exclusion of each role label once from learning (“unseen” class)
 - 8-fold cross-validation: learn from 7 sequences, test 1
 - 5*8 = 40 test runs

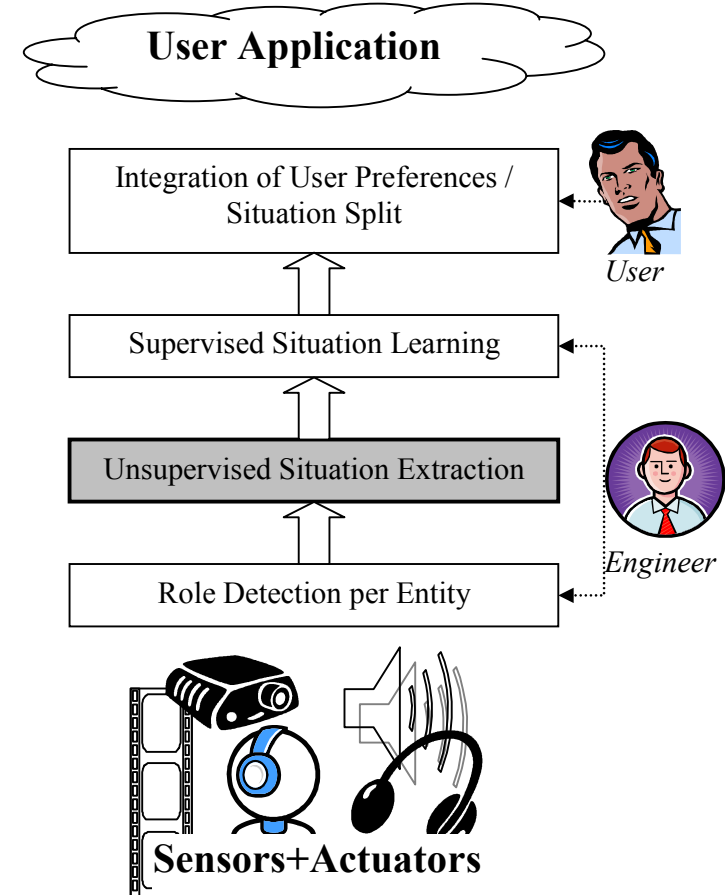
	SVMs	Bayesian Classifier	Hybrid Classifier
Mean	0,7101	0,7523	0,7786
Std. dev.	0,0840	0,0550	0,0639

Class	% in data sets	TP rate	FP rate	Precision	Recall	F-measure
0	18%	0,7374	0,1356	0,6481	0,7374	0,6763
1	9%	0,0108	0,001	0,3938	0,0108	0,0208
2	45%	0,7467	0,2677	0,6576	0,7467	0,6713
3	19%	0,5336	0,1217	0,6845	0,5336	0,5867
4	10%	0,8476	0,0631	0,6557	0,8476	0,723
Total	100%	0,5752	0,1178	0,6079	0,5752	0,5356

“walking”(0), “standing”(1), “sitting”(2), “interacting with table”(3), “lying down”(4)

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 - **Motivation**
 - **Method**
 - **Evaluation and Results**
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Motivation: Small Group Meetings



- *Goal: isolate different Meeting Situations*
 - Based on observation streams
 - Unsupervised, without assigning any labels

Method: Observation Distributions

- *Observations* are generated with a constant sampling rate from multi-sensory input
- *Histograms* represent observation distributions (obs. window)

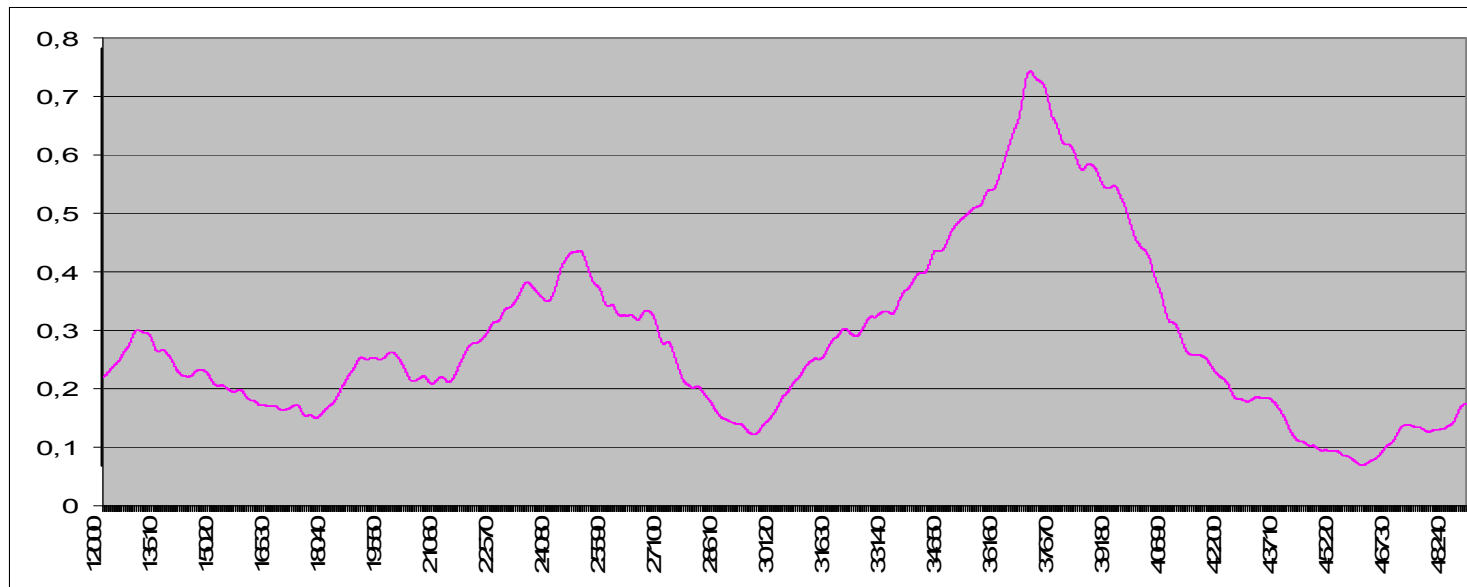
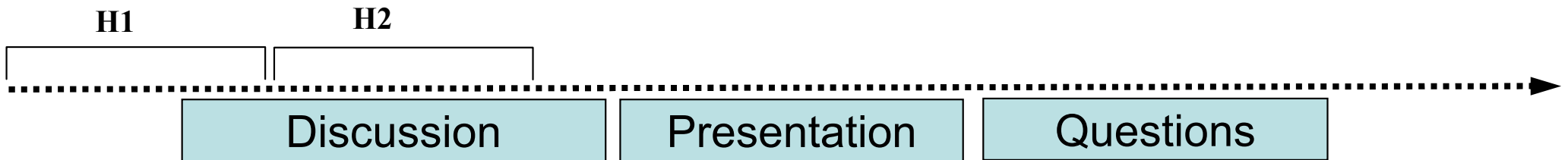


- *Jeffrey divergence* between two histograms p, q

$$J_{p,q} = \sum_{x \in X} p(x) \cdot \log \frac{p(x)}{\frac{p(x) + q(x)}{2}} + q(x) \cdot \log \frac{q(x)}{\frac{p(x) + q(x)}{2}}$$

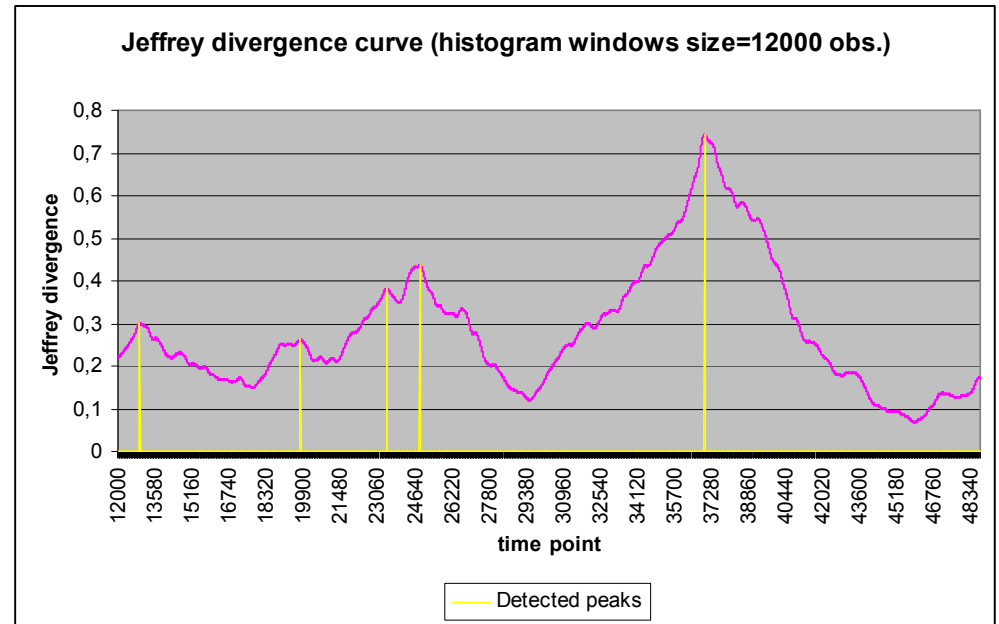
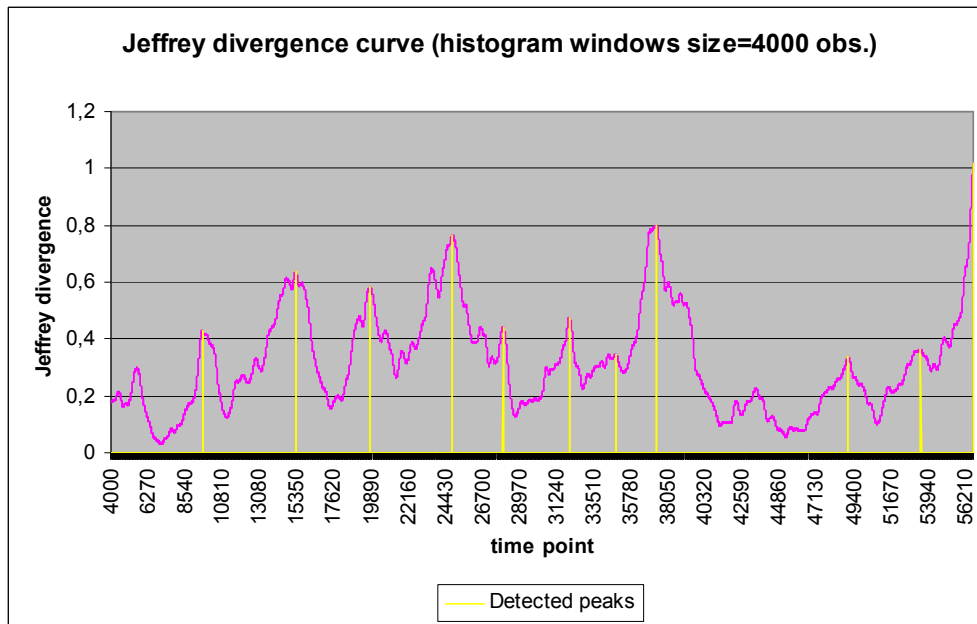
Method: Jeffrey Divergence Curve (1/2)

- Slide two adjacent histograms from the beginning to the end of a recording, while calculating Jeffrey divergence



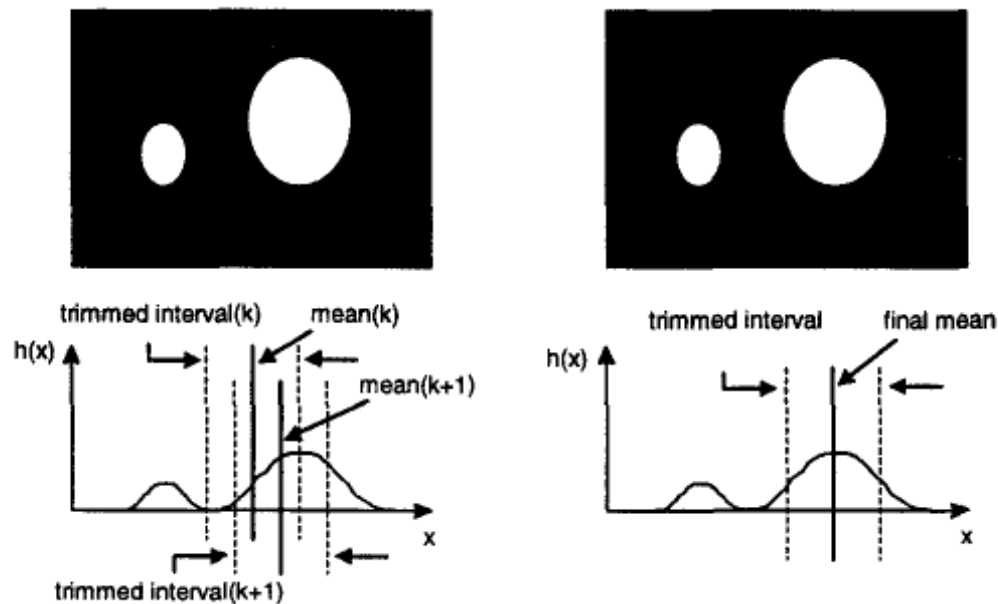
Method: Jeffrey Divergence Curve (2/2)

- *multi-scale analysis*: Jeffrey divergence curves for different window sizes
 - 4000-16000 observations (between 64sec and 4min 16sec)



Method: Peak Detection

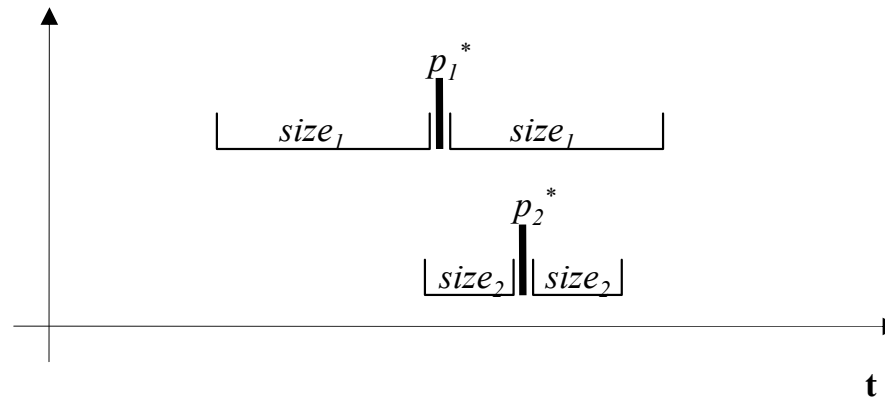
- Robust Mean Estimation [Qian1998]



- *Successive* Robust Mean Estimation [Brdiczka2005]
 - Find successively all local maxima (peaks) of the curve

Method: Merging + Filtering Peaks

- Merge peaks
 - Normalized distance $n_dist < 1.0$



$$n_dist(p_1^*, p_2^*) = \frac{|p_1^* - p_2^*|}{\min(size_1, size_2)}$$

- Filter peaks
 - Relative peak height > 0.5
 - Votes > 2

Method: Model Selection

- Model selection
 - Global search process, combining all detected peaks
 - *Goal*: find best allocation of observation distributions
 - *Criterion*: maximize average Jeffrey divergence between combined peaks

Data size (nb obs) = 34619

Retained Peaks

<u>position</u>	<u>rel. peak value</u>	<u>window size</u>	<u>votes</u>
13340.0	0.74	12000.0	5.0
17430.0	1.0	6000.0	9.0
30610.0	1.0	4000.0	3.0

Model Selection

searching for best model ... 8 combinations:

0	(0.58)	:17430	30610	
1	(0.48)	:13340	17430	30610
2	(0.43)	:13340	30610	
3	(0.27)	:17430		

Evaluation and Results:

Segment Quality Measures [Zhang2004]

$$asp = \frac{1}{N} \sum_{i=1}^{N_s} p_{i\bullet} \times n_{i\bullet} \quad , \quad aap = \frac{1}{N} \sum_{j=1}^{N_a} p_{\bullet j} \times n_{\bullet j} \quad , \quad Q = \sqrt{asp \times aap}$$

with

n_{ij} = total number of observations
in segment i by activity j

$n_{i\bullet}$ = total number of observations
in segment i

$n_{\bullet j}$ = total number of observations

$$p_{i\bullet} = \sum_{j=1}^{N_a} \frac{n_{ij}^2}{n_{i\bullet}}$$

N_a = total number of activities

N_s = total number of segments

N = total number of observations

$$p_{\bullet j} = \sum_{i=1}^{N_s} \frac{n_{ij}^2}{n_{\bullet j}}$$

- asp = average segment purity
 - indicates how well one segment is limited to only one activity
- aap = average activity purity
 - indicates to which extent one activity corresponds to only one segment
- Q : overall criterion

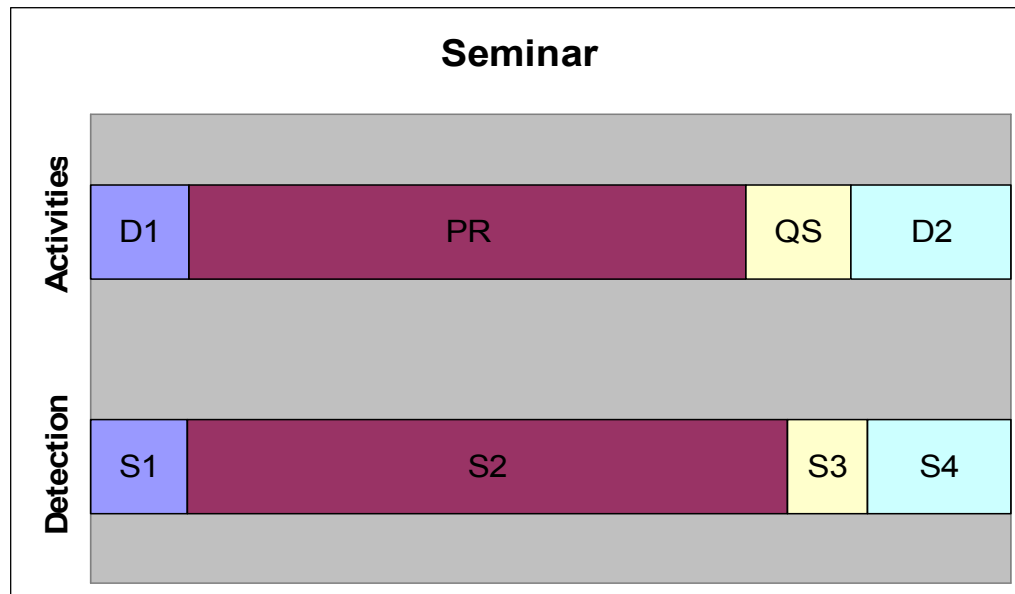
Evaluation and Results: Seminar (1/2)

- Seminar
 - 5 pers; 25 min. 2 sec.
 - lapel microphones + speech activity detection

Observation number	Speech Activity Detection				
	A	B	C	D	E
0	0	0	0	0	0
1	0	0	0	0	1
2	0	0	0	1	0
3	0	0	0	1	1
...

Evaluation and Results: Seminar (2/2)

- Seminar
 - Situations: *discussion in small groups (D1), presentation (PR), questions (QS), discussion in small groups (D2)*



	asp	aap	Q
Seminar	0.88	0.91	0.90

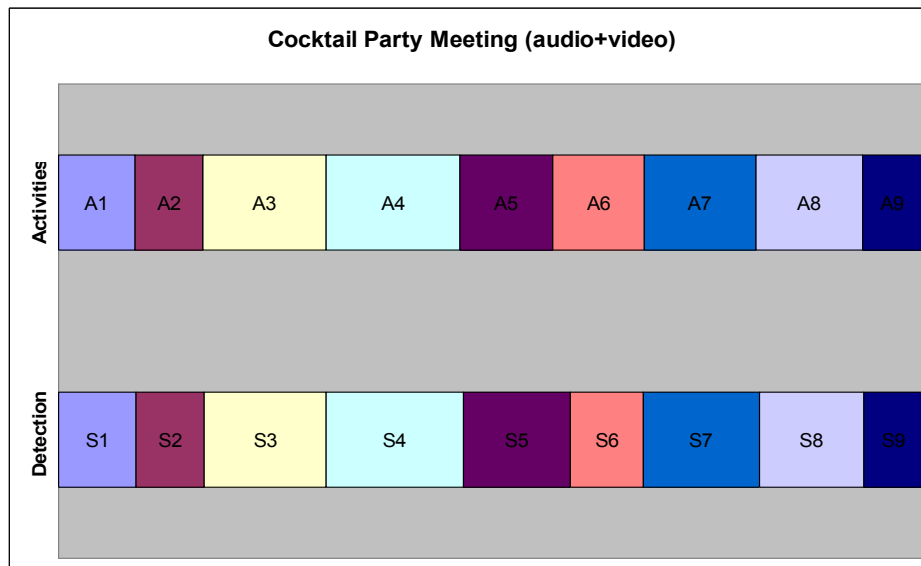
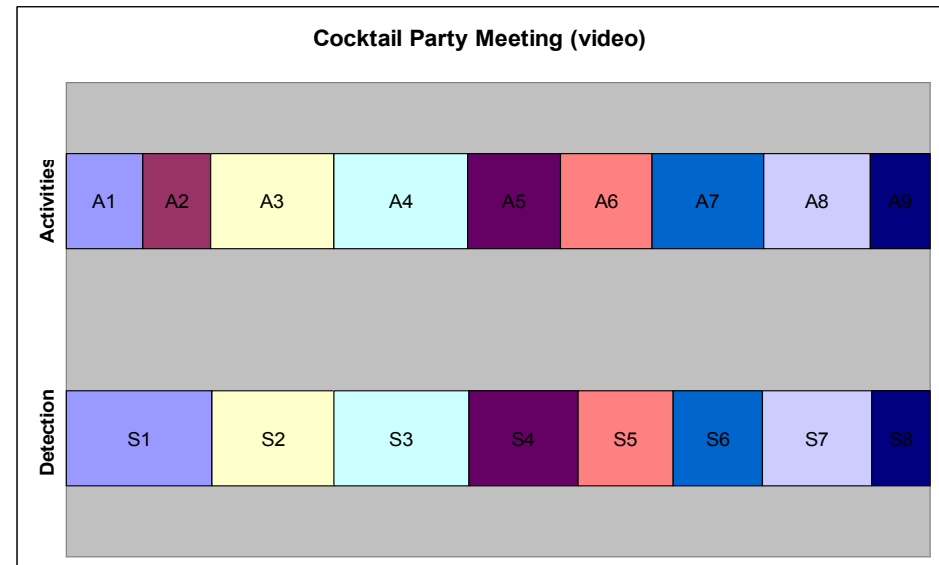
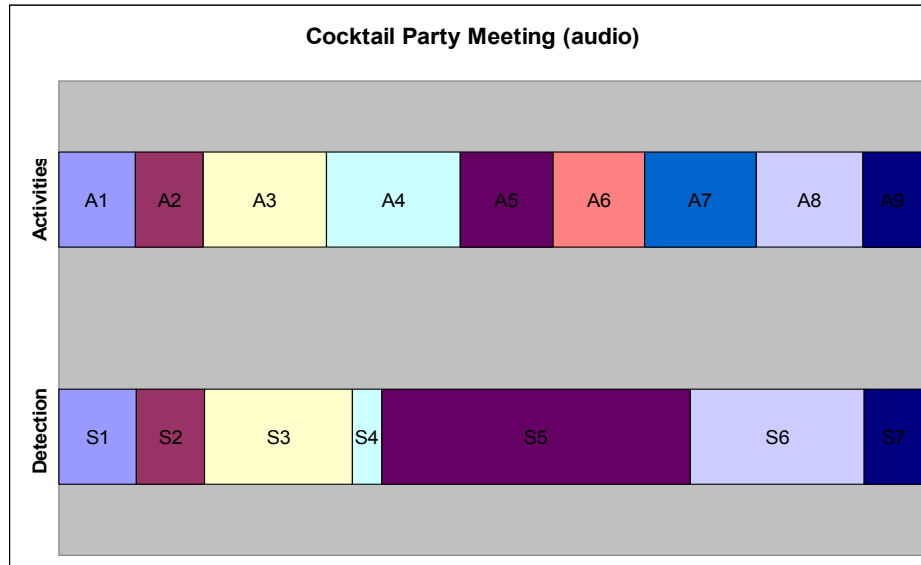
Evaluation and Results: Multimodal Cocktail Party (1/2)



Observation number	Speech Activity Detection				
	A	B	C	D	E
0	0	0	0	0	0
1	0	0	0	0	1
2	0	0	0	1	0
3	0	0	0	1	1
...

- Cocktailparty meeting
 - 5 pers; 30 min. 26 sec.
 - Wide-angle camera + video tracker
 - Lapel microphones + speech activity detection

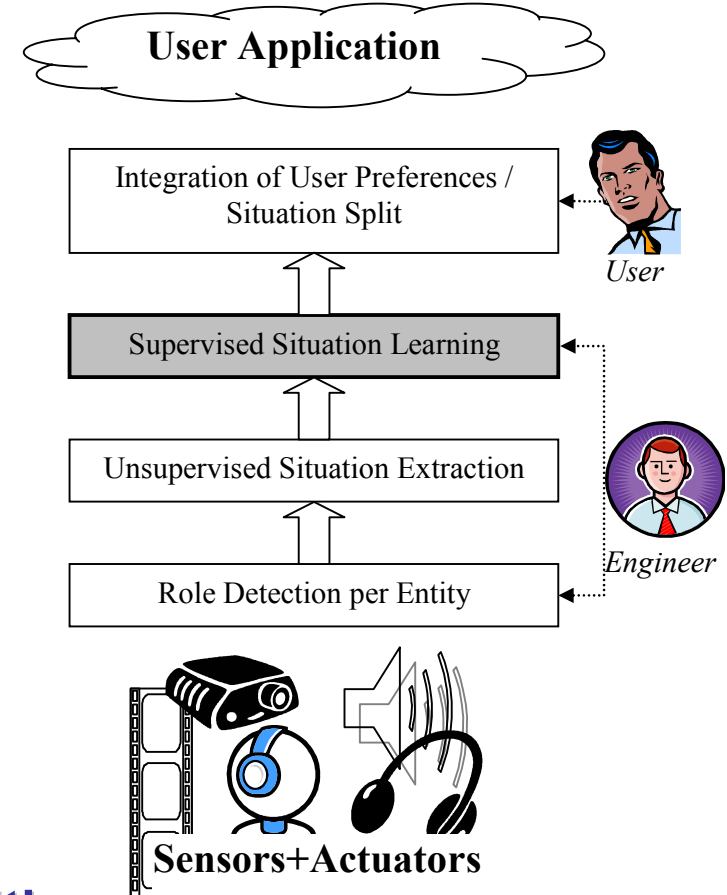
Evaluation and Results: Multimodal Cocktail Party (2/2)



	asp	aap	Q
Audio	0.57	0.83	0.70
Video	0.83	0.92	0.87
Audio+Video	0.94	0.94	0.94

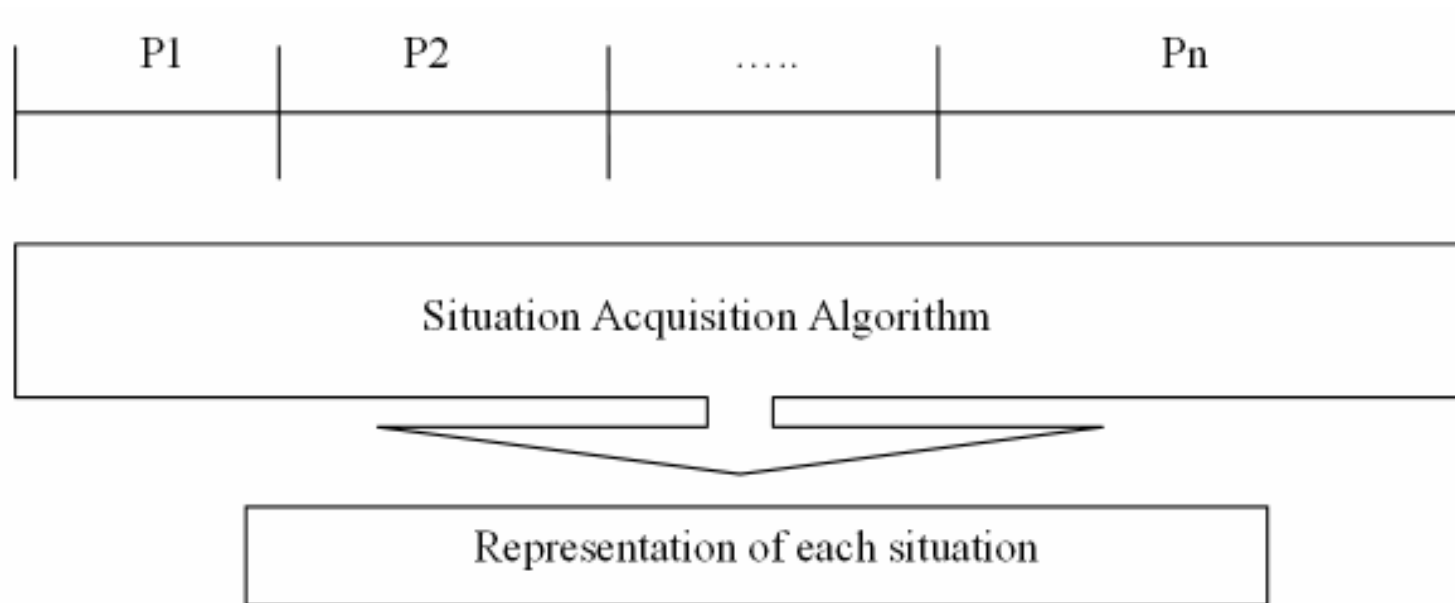
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Supervised Situation Acquisition Algorithm (1/2)

- n observation sequences associated to m situation labels ($m \leq n$)



- Each sequence corresponds to one situation
- Two or more sequences can have the same situation label

Supervised Situation Acquisition Algorithm (2/2)

- learner $L: \{P_1, P_2, \dots, P_k \mid k > 0\} \rightarrow$ situation representation S

```
A. For each learner class do:  
  a. {optimization step}  
    For each situation label do:  
      • Select learner/set of learners  
      • Apply learner to given observations  
  b. {validation step}  
    Calculate quality of obtained situation  
    representations  
  c. Repeat a.-b. until best quality is obtained  
  
B. Choose learner class with best quality of situation  
   representations
```


Supervised Situation Acquisition Algorithm (2/2)

A. For each learner class do:

a. {optimization step}

For each situation label do:

- Select learner/set of learners
- Apply learner to given observations

b. {validation step}



Calculate quality of obtained situation representations

c. Repeat a.-b. until best quality is obtained

B. Choose learner class with best quality of situation representations

-- Iterate over learner classes --

Supervised Situation Acquisition Algorithm (2/2)

- 
- 
- ```
A. For each learner class do:
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 b. {validation step}
 Calculate quality of obtained situation
 representations
 c. Repeat a.-b. until best quality is obtained

B. Choose learner class with best quality of situation
representations
```

-- Iterate over situation labels to be learned --

# Supervised Situation Acquisition Algorithm (2/2)

```
A. For each learner class do:
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 For each situation label do:
 • Select learner/set of learners
 • Apply learner to given observations
 b. {validation step}
 Calculate quality of obtained situation
 representations
 c. Repeat a.-b. until best quality is obtained

B. Choose learner class with best quality of situation
 representations
```

- Quality measure – principle: *maximize the distance between the means of the classes while minimizing the variance within each class [Fisher1938]*

# Evaluation and Results: CAVIAR video clips (1/2)

- 114 sequences extracted from CAVIAR video clips
- 5 situations
  - “walking”, “browsing”, “fighting”, “waiting”, “object left”
- Observations = entity, role and group values from annotated XML files



# Evaluation and Results: CAVIAR video clips (2/2)

- *hidden Markov models* [Rabiner1989] as situation representation
  - EM algorithm is only learner class
  - Set of learners / learner parameters = number of states of the HMM

A. For EM learner class do:

a. *{optimization step}*

For each situation label do:

- Select a number of states for EM training
- Learn HMM parameters with EM

b. *{validation step}*

Calculate quality measure: 
$$\frac{\sum_{i \in SL_j} P(O^{0..l_i} | S_j)}{\sum_{k \neq j} \sum_{i \in SL_j} P(O^{0..l_i} | S_k)}$$

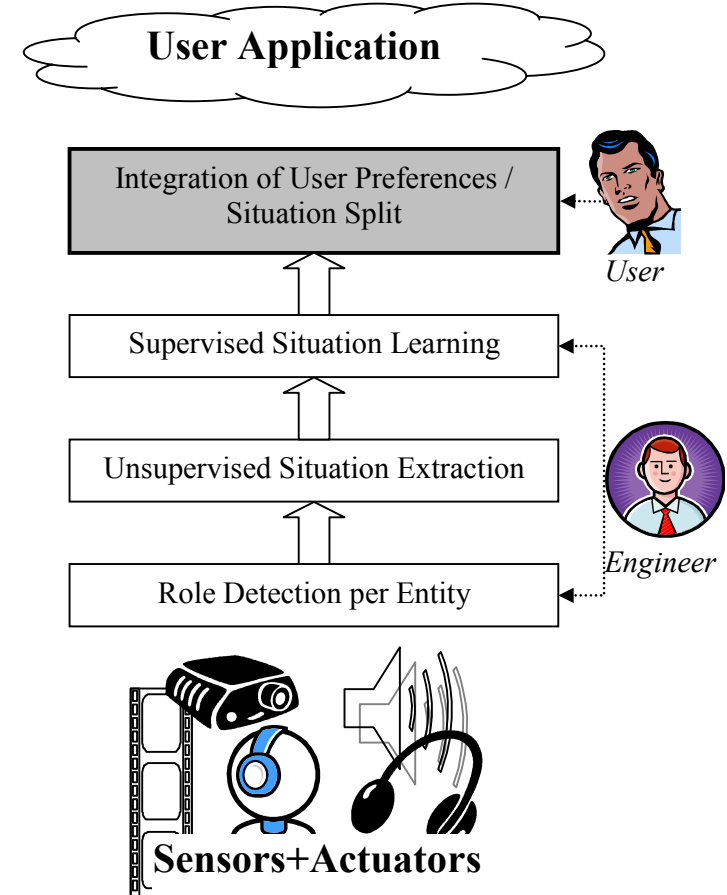
c. Repeat a.-b. until best quality is obtained

} Ratio of observation probability within and outside correct situation

- 3-fold cross-validation: 1/3 for learning, 2/3 for testing
  - Average error: 6.22 %, standard deviation 2.07 %

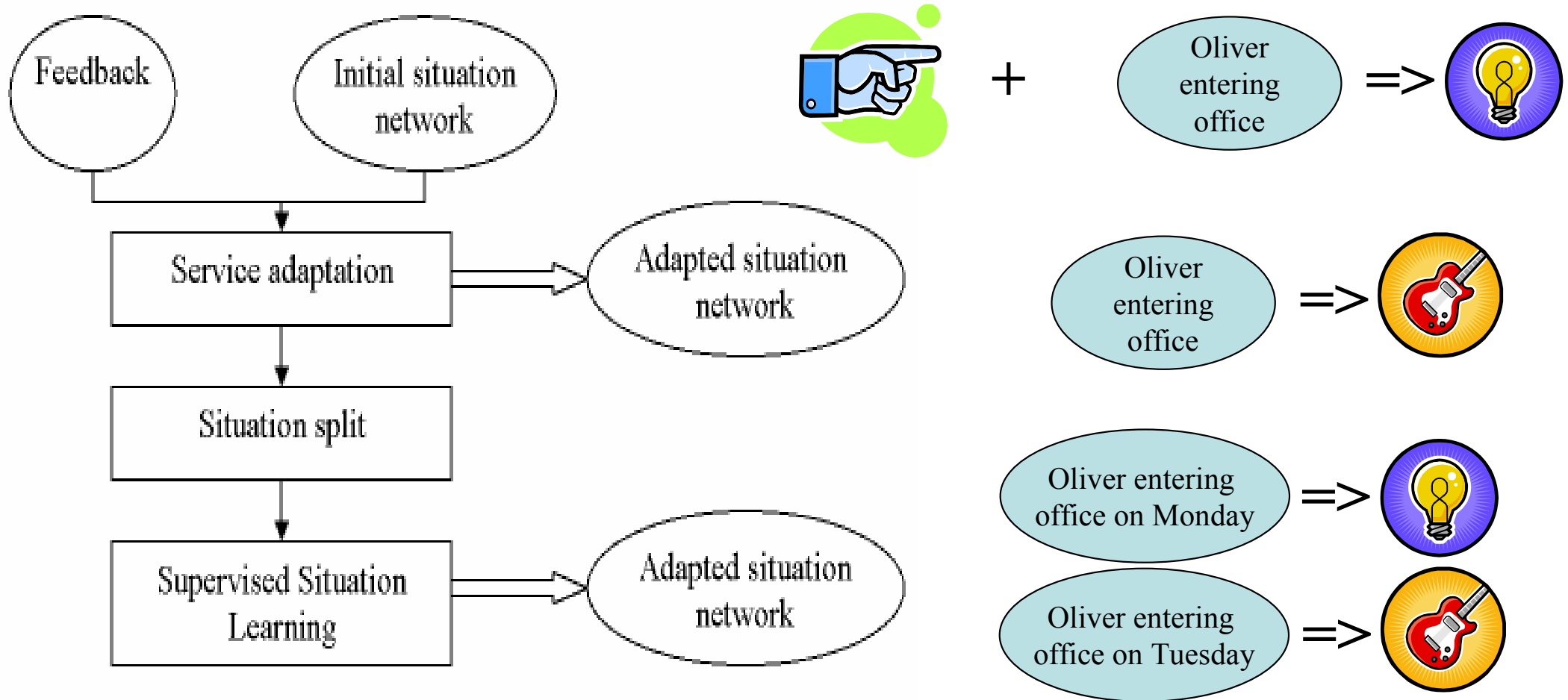
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  - **Situation Split**
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# Situation Split (1/2)

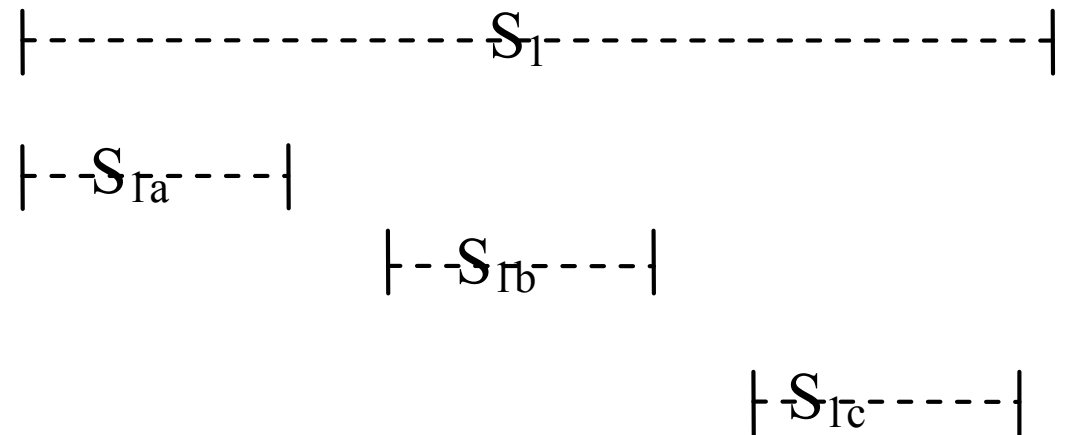
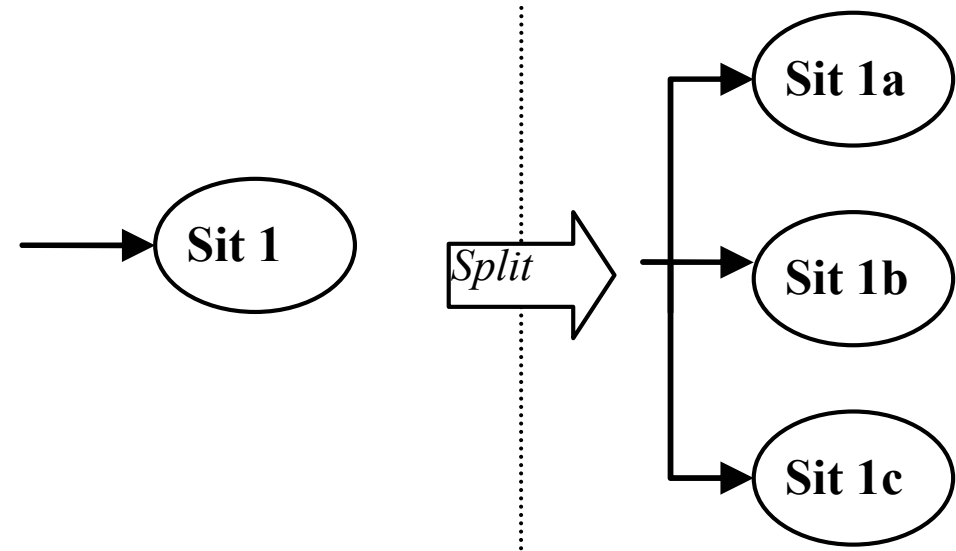
- Feedback: Service correction / deletion / preservation



# Situation Split (2/2)

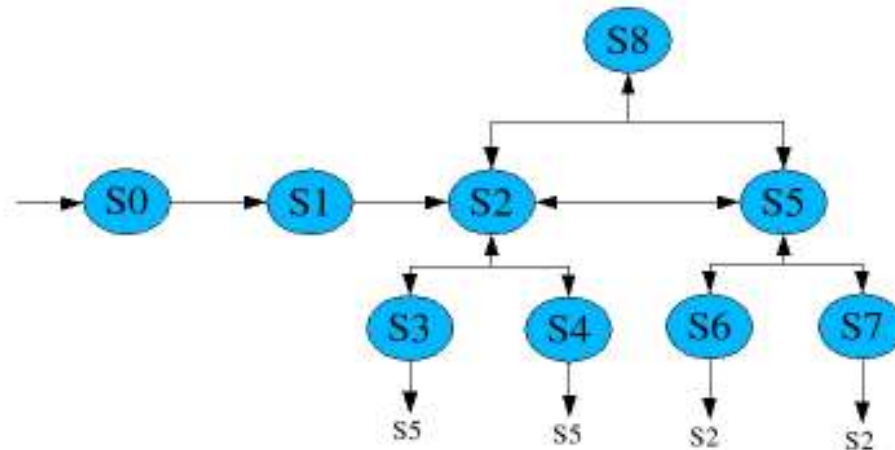
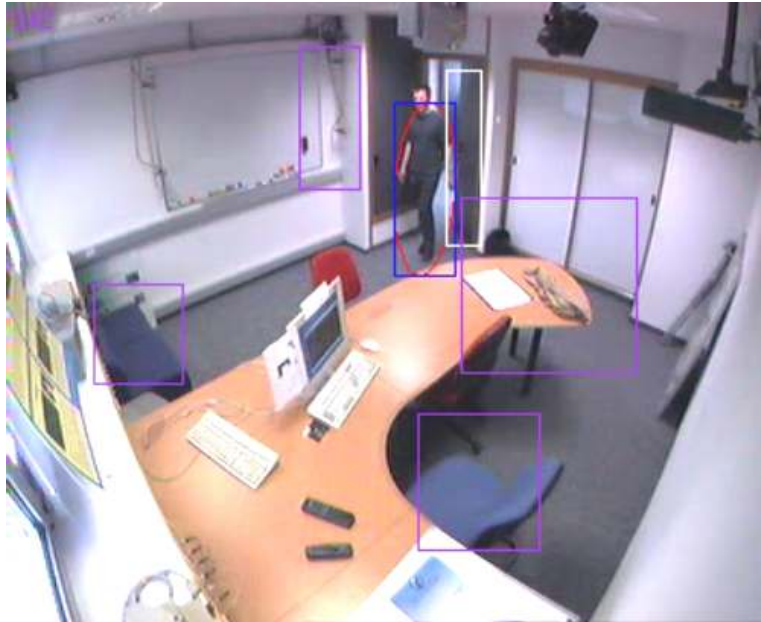
- different disjunctive services for one situation  
→ situation split

- *supervised situation acquisition algorithm* for learning sub-situations





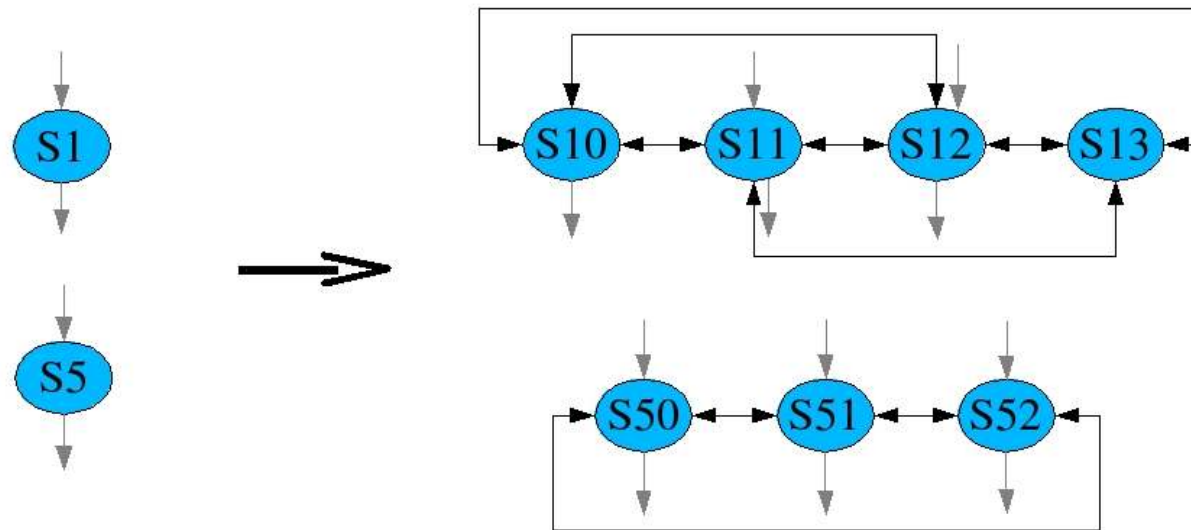
# Evaluation and Results: SmartOffice



- Predefined/learned context model for SmartOffice
- Goal: *integrating the music player service into the model*
- Decision Tree (ID3 [Quinlan1986]) for learning sub-situations

# Evaluation and Results: SmartOffice

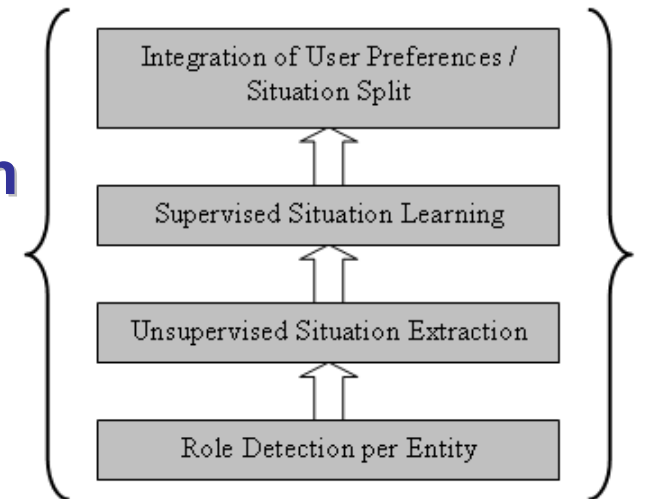
- 2-fold cross-validation: 1 recording for learning, 1 for testing



|              | "do nothing" | music ON | music OFF |
|--------------|--------------|----------|-----------|
| "do nothing" | 0.5985       | 0.1894   | 0.2121    |
| music ON     | 0            | 1        | 0         |
| music OFF    | 0            | 0        | 1         |

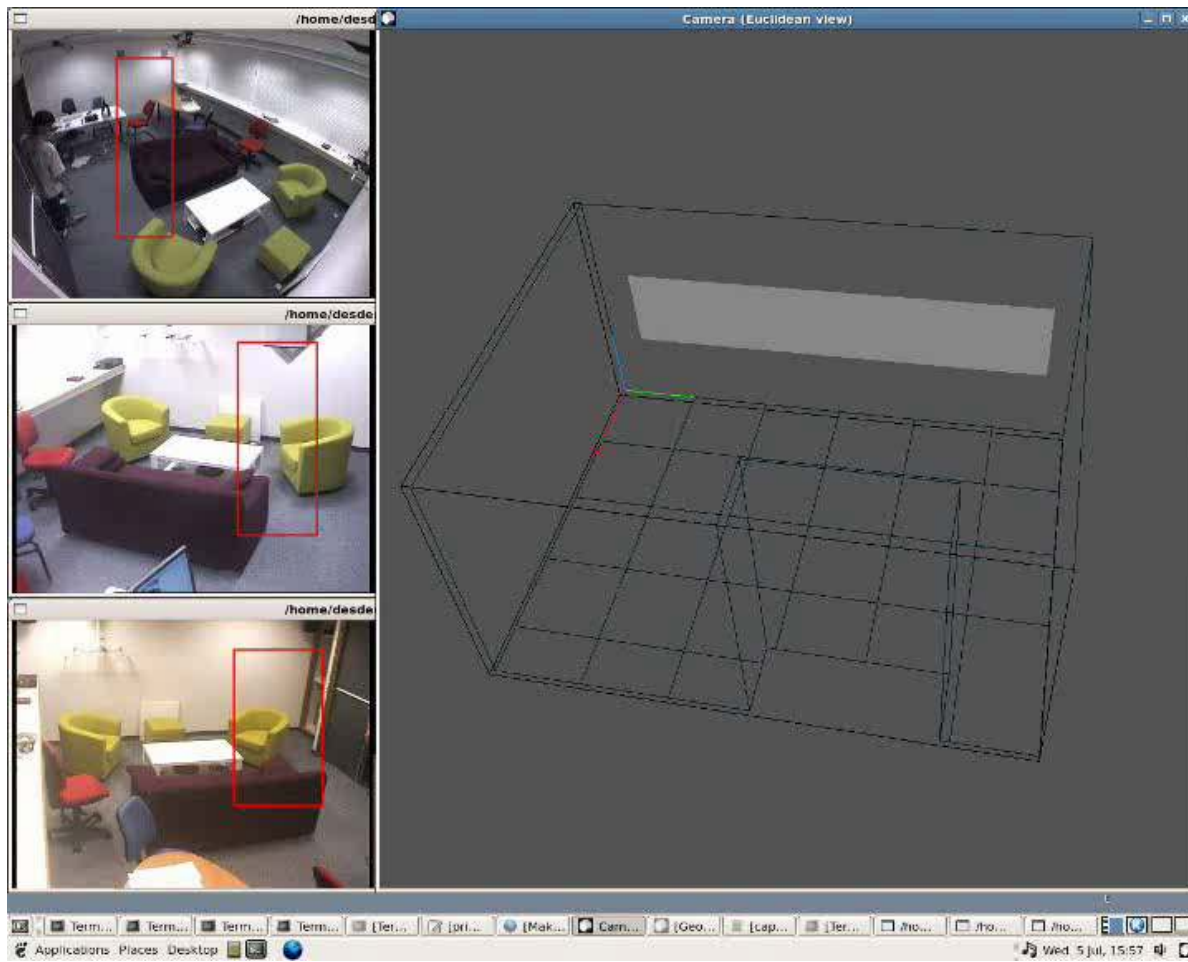
# Outline

- I. Introduction and Problem Definition
- II. Situation Model
- III. Learning Role Acceptance Tests
- IV. Unsupervised Situation Discovery
- V. Supervised Learning of Situations
- VI. Adapting to User Preferences
- VII. Integration and Experimental Evaluation**
  - **Smart Home Environment**
  - **Multimodal Observation of the scene**
  - **Evaluation B**
- VIII. Conclusion and Perspective



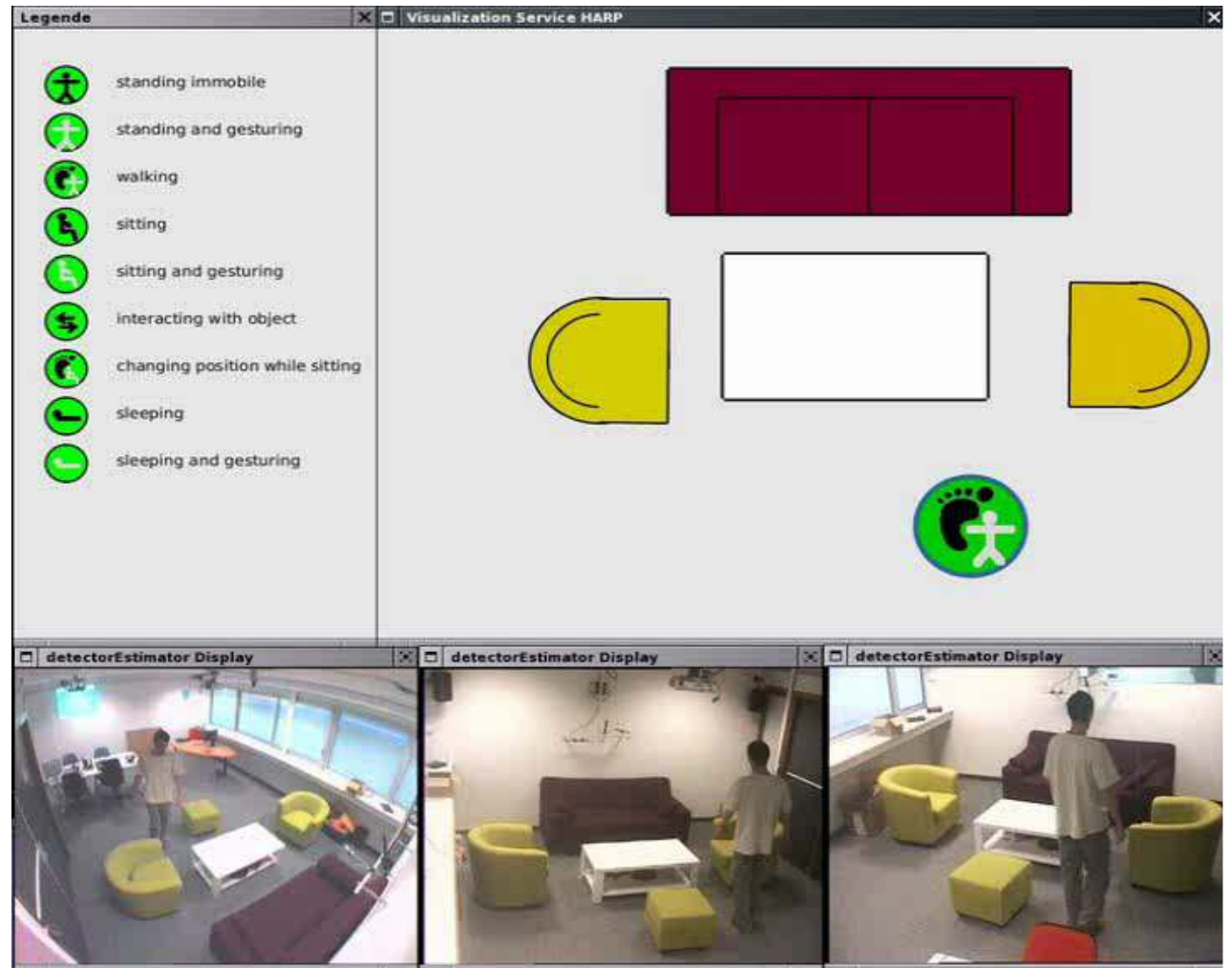
# Smart Home Environment

- 3D tracking system creates and tracks entities



# Multimodal observation of the scene

- role detection per entity
  - using SVMs, target speed and interaction distance



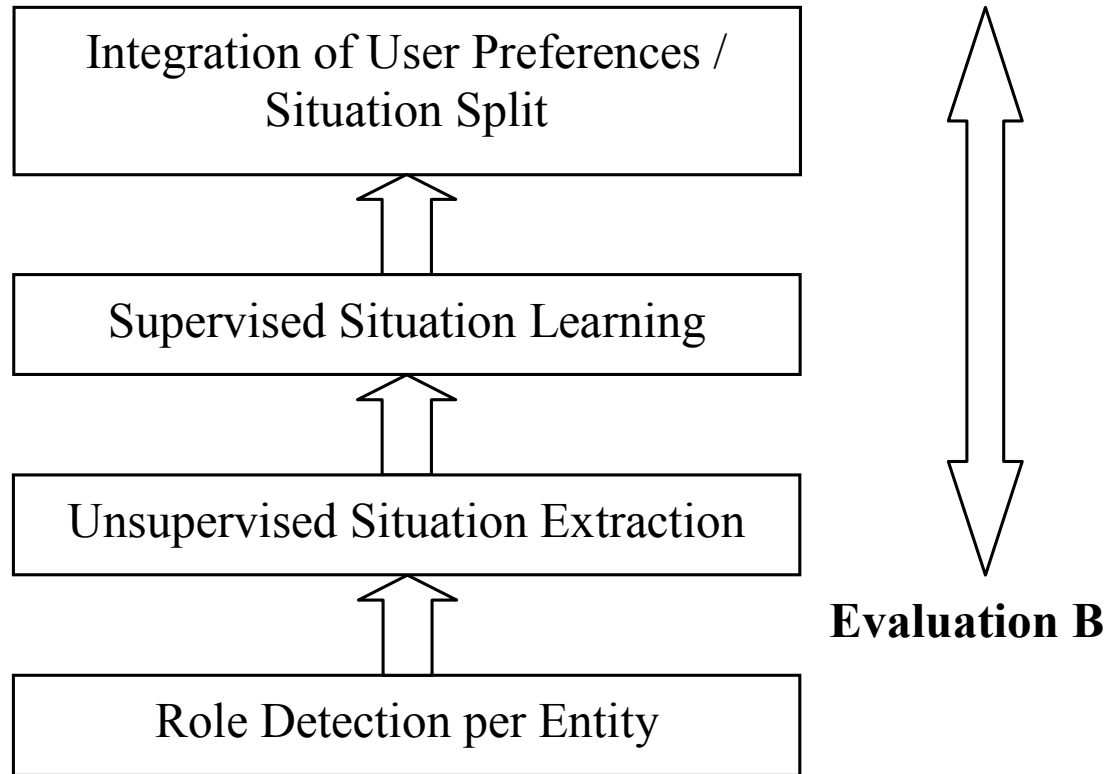
# Multimodal observation of the scene

- head set microphones + speech activity detection
- ambient sound detection
- multimodal entity observation codes:

**0 : entity does not exist**  
**1 : standing immobile**  
**2 : standing and interacting with table**  
**3 : standing and gesturing**  
**4 : standing and interacting with table (in movement)**  
**5 : walking**  
**6 : sitting**  
**7 : sitting and interacting with table**  
**8 : sitting and gesturing**  
**9 : sitting and interacting with table (in movement)**  
**10 : changing position while sitting**  
**11 : lying down**  
**12 : lying down and gesturing**  
**13 : detection error**

**14-26 : entity is speaking**  
**27-39 : there is noise in the environment**  
**40-52 : entity is speaking and there is noise**

# Evaluation B (1/5)



# Evaluation B (2/5)

- 3 scenarios recordings
  - Situations: “introduction”, “aperitif”, “siesta”, “presentation”, “game”



Introduction

Aperitif



Siesta



Presentation

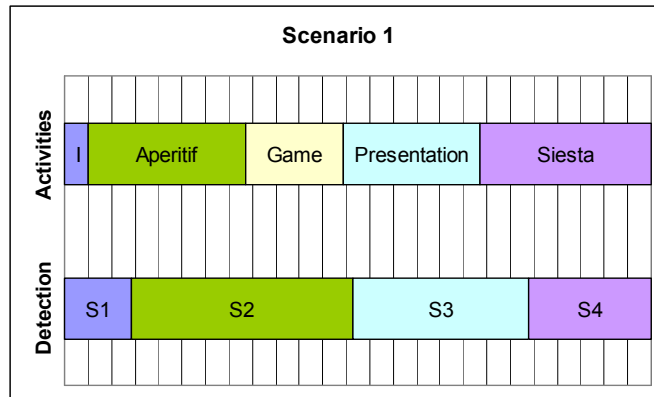
Game

- “online” in-scenario situation recognition

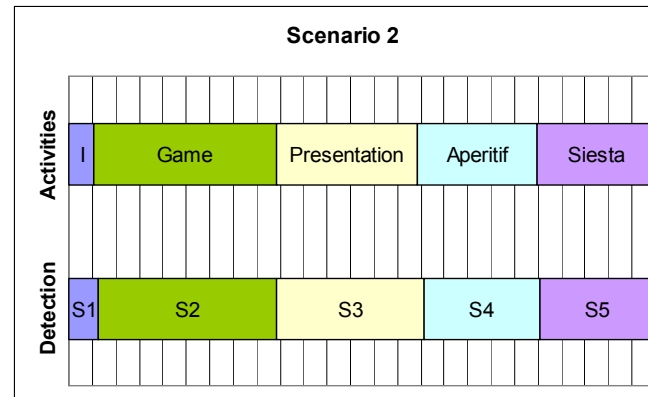


# Evaluation B (3/5)

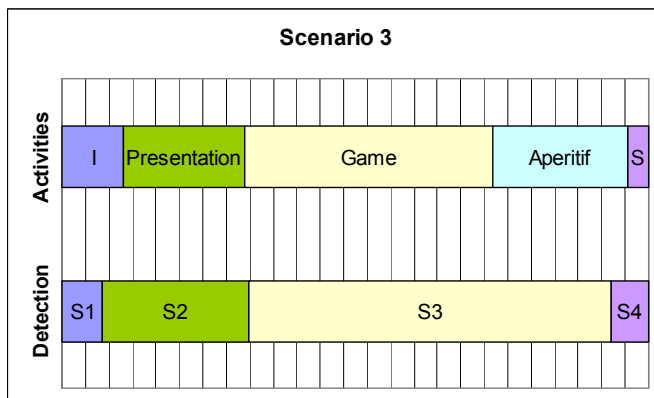
- Unsupervised situation discovery



$Q = 0.68$



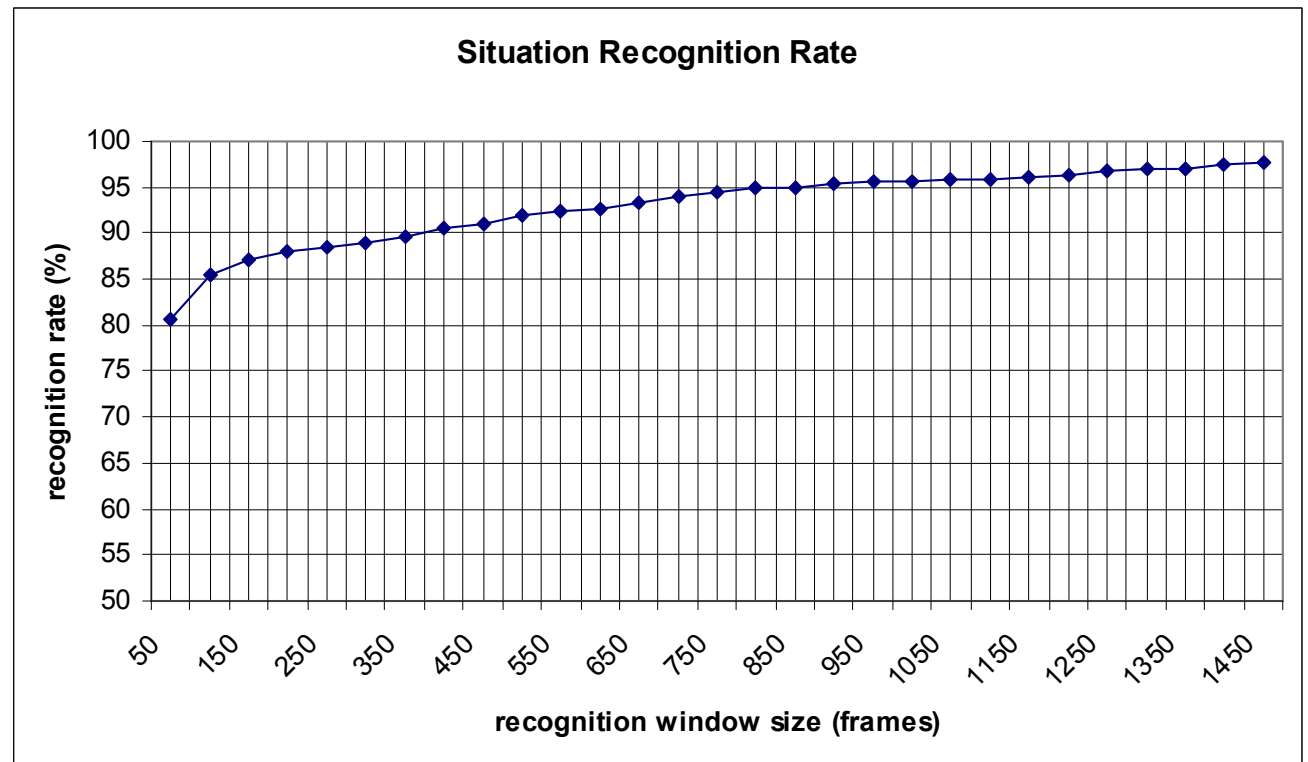
$Q = 0.95$



$Q = 0.74$

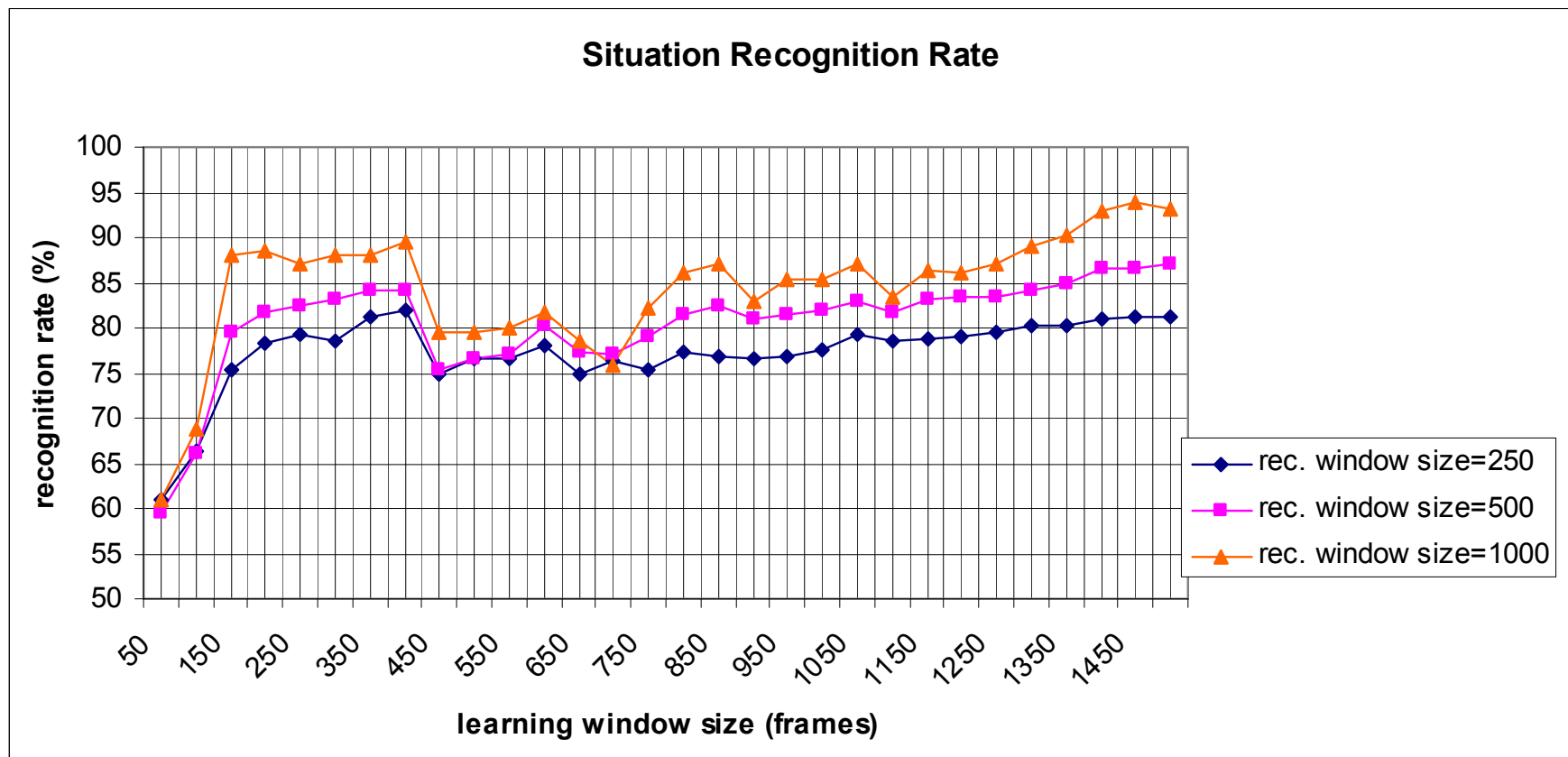
# Evaluation B (4/5)

- Supervised situation learning
  - 4 situations: “introduction”, “presentation”, “siesta” and “*group activity*”
  - 3-fold cross-validation: 2 scenarios for learning, 1 scenario for testing
  - EM as learner class
  - HMMs (8-16 states)



# Evaluation B (5/5)

- Integration of user preferences
  - Split “group activity” and learn new sub-situations “aperitif” and “game”

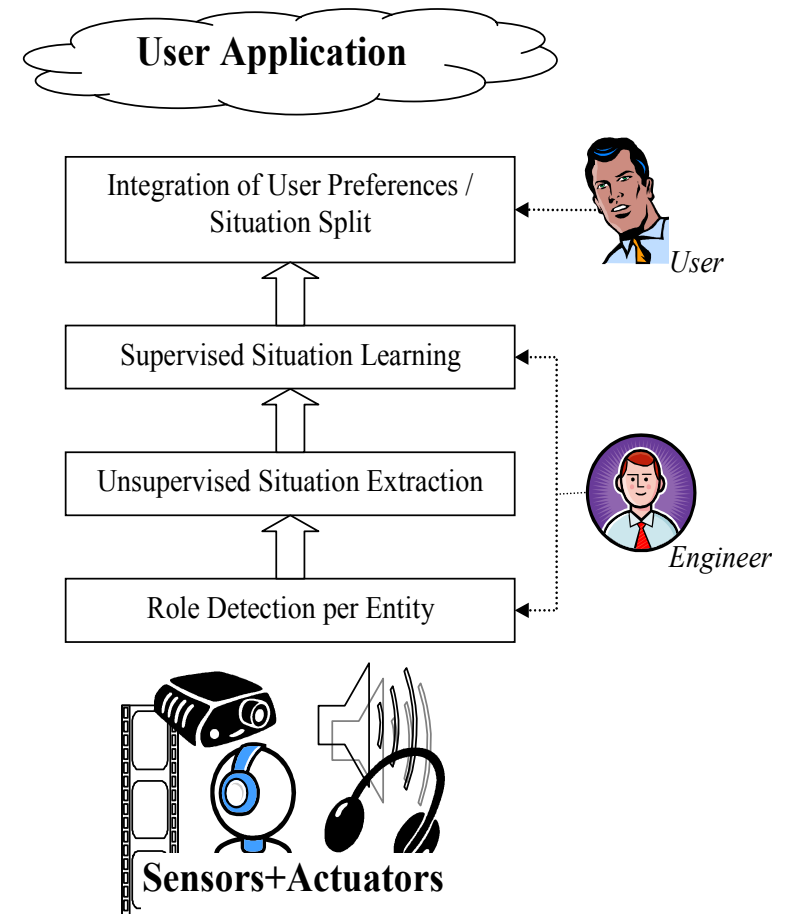


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# Conclusion and Perspectives (1/2)

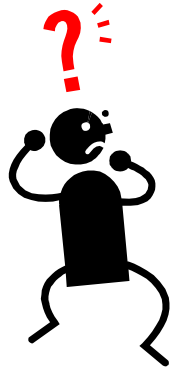
- Contributions of this thesis
  - Implementations of situation model
  - Situation split
  - Supervised situation learning scheme
  - Unsupervised situation discovery
  - Role learning and detection



# Conclusion and Perspectives (2/2)

- Error rates
  - automate uncritical/non-disruptive actions
- Generation of explanations
  - Explain system errors, link with system control
- Controllability and human-computer interaction
  - Keep user in control
  - Visualize contextual information in an intuitive manner
- Interruptability and action cost [Bardram2006]

Thank you for your attention !



Remarks ? Questions ?

# References

- [Abowd1996] G. D. Abowd, C. G. Atkeson, A. Feinstein, C. Hmelo, R. Kooper, S. Long, N. Sawhney, and M. Tani. Teaching and learning as multimedia authoring: the classroom 2000 project. In MULTIMEDIA '96: Proceedings of the fourth ACM international conference on Multimedia, pages 187–198, New York, NY, USA, 1996. ACM Press.
- [Allen1983] Allen, J. (1983). Maintaining Knowledge about Temporal Intervals, In *Communication of ACM* 26(11):832-843.
- [Andreoli2003] J.-M. Andreoli, S. Castellani, A. Grasso, J.-L. Meunier, M. Muehlenbrock, J. O'Neill, F. Ragnet, F. Roulland, and D. Snowdon. Augmenting offices with ubiquitous sensing. In Proceedings of Smart Objects Conference (SOC), Grenoble, France, 2003.
- [Bardram2003] J. E. Bardram, T. R. Hansen, M. Mogensen, and M. Soegaard. Experiences from realworld deployment of context-aware technologies in a hospital environment. In Proceedings of UbiComp, pages 369–386. Springer Berlin / Heidelberg, 2006.
- [Bellotti2001] V. Bellotti and K. Edwards. Intelligibility and accountability: Human considerations in context-aware systems. *Human-Computer Inter.*, 16:193–212, 2001.
- [Bilmes1998] Bilmes, J. A. (1998). A Gentle Tutorial of the EM Algorithm and its Application to Parameter Estimation for Gaussian Mixture and Hidden Markov Models. *Technical Report ICSI-TR-97-021*, University of Berkeley.



# References

- [Brdiczka2005] O. Brdiczka, P. Reignier, and J. Maisonnasse. Unsupervised segmentation of small group meetings using speech activity detection. In ICMI Workshop Proceedings, International Workshop on Multimodal Multiparty Meeting Processing (MMMP), pages 47-52, October 2005.
- [Brdiczka2007] O. Brdiczka, P. Reignier, and J. Crowley. Detecting individual activities from video in a smart home. In 11th International Conference on Knowledge-Based & Intelligent Information & Engineering Systems (KES), 2007. IN PRESS.
- [CAVIAR2001] CAVIAR. Caviar: Context aware vision using image-based active recognition, european commission project ist 2001 37540, 2001.
- [Clarkson2002] B. Clarkson. *Life Patterns: Structure from Wearable Sensors*. PhD thesis, MIT Media Lab, September 2002.
- [Coen1998] M. H. Coen. A prototype intelligent environment. In *CoBuild '98: Proceedings of the First International Workshop on Cooperative Buildings, Integrating Information, Organization, and Architecture*, pages 41–52. Springer Berlin / Heidelberg, 1998.
- [Cook2003] D. Cook, M. Youngblood, I. Heierman, E.O., K. Gopalratnam, S. Rao, A. Litvin, and F. Khawaja. Mavhome: an agent-based smart home. In *Proceedings of the First IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pages 521–524, 23-26 March 2003.
- [Cook2004] D. Cook, S. Das. *Smart Environments: Technology, Protocols and Applications*. Wiley-Interscience. ISBN 0-471-54448-5. 2004.

# References

- [Cortes1995] C. Cortes, and V. Vapnik. Support-vector network. In *Machine Learning* 20:273–297. 1995.
- [Crowley2002] J. L. Crowley, J. Coutaz, G. Rey, and P. Reignier. Perceptual components for context aware computing. In *Proceedings of UbiComp*, pages 117–134. Springer London, 2002.
- [Coutaz2005] J. Coutaz, J. L. Crowley, S. Dobson, and D. Garlan. Context is key. *Commun. ACM* 48, 3 (Mar. 2005), 49-53. 2005.
- [Dey2001] A. K. Dey. Understanding and using context. *Personal and Ubiquitous Computing*, 5(1): 4–7, 2001.
- [Eagle2006] N. Eagle and A. S. Pentland. Reality mining: sensing complex social systems. *Personal and Ubiquitous Computing*, 10(4):255–268, 2006.
- [Fisher1938] R. Fisher. The statistical utilization of multiple measurements. *Annals of Eugenics*, 8: 376–386, 1938.
- [Horvitz1998] E. Horvitz, J. Breese, D. Heckerman, D. Hovel, and K. Rommelse. The lumiere project: Bayesian user modeling for inferring the goals and needs of software users. In *Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence*, pages 256–265, San Francisco, CA, USA, 1998. Morgan Kaufmann Publishers Inc.

# References

- [Kay2003] J. Kay, R. Kummerfeld, and P. Lauder. Managing private user models and shared personas. In *Proceedings of the UM03 Workshop on User Modeling for Ubiquitous Computing*, pages 1–11, Johnstown, PA, 2003.
- [LeGal2001] C. LeGal, J. Martin, A. Lux, and J. L. Crowley. Smart office: Design of an intelligent environment. *IEEE Intelligent Systems*, 16(4):60–66, 2001.
- [Mayrhofer2004] R. Mayrhofer. *An architecture for context prediction*. PhD thesis, Johannes Kepler University of Linz, 2004.
- [Mozer1998] M. C. Mozer. The neural network house: An environment that adapts to its inhabitants. In *Proceedings of the American Association for Artificial Intelligence Spring Symposium on Intelligent Environments*, pages 110–114. Menlo Park, CA, AAAI Press, 1998.
- [Mühlenbrock2004] M. Muehlenbrock, O. Brdiczka, D. Snowdon, and J.-L. Meunier. Learning to detect user activity and availability from a variety of sensor data. In *Proceedings of IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pages 13–23, March 2004.
- [Quian1998] R. Qian, M. Sezan, and K. Mathews. Face tracking using robust statistical estimation. In *Proceedings of Workshop on Perceptual User Interfaces*, San Francisco, 1998.
- [Quinlan1986] J. R. Quinlan. Induction of decision trees. *Machine Learning*, 1(1):81–106, March 1986.

# References

- [Rabiner1989] L. R. Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2):257–286, 1989.
- [Reignier2007] P. Reignier, O. Brdiczka, D. Vaufreydaz, J. Crowley, and J. Maisonnasse. Deterministic and probabilistic implementation of context in smart environments. *Expert Systems: The Journal of Knowledge Engineering*, 2007, Blackwell Publishing. IN PRESS.
- [Ribeiro2005] P. Ribeiro, J. Santos-Victor. Human Activities Recognition from Video: modeling, feature selection and classification architecture. Proc. Workshop on Human Activity Recognition and Modelling (HAREM 2005 - in conjunction with BMVC 2005). pp 61-70, Oxford, Sept 2005.
- [Salovaara2004] A. Salovaara and A. Oulasvirta. Six modes of proactive resource management: a user centric typology for proactive behaviors. In *NordiCHI '04: Proceedings of the third Nordic conference on Human-computer interaction*, pages 57–60, New York, NY, USA, 2004.
- [Schilit1994] B. Schilit and M. Theimer. Disseminating active map information to mobile hosts. *IEEE Network*, 8(5):22–32, Sept.-Oct. 1994.
- [Schmidt2005] A. Schmidt. *Ambient Intelligence*, chapter 9, pages 159–178. IOS Press, 2005.

# References

- [Streitz2005] N. A. Streitz, C. Rucker, T. Prante, D. van Alphen, R. Stenzel, and C. Magerkurth. Designing smart artifacts for smart environments. *Computer*, 38(3):41–49, 2005.
- [Weiser1991] M. Weiser. The computer for the twenty-first century. *Scientific American*, 265(3):94–104, 1991.
- [Xie2001] W. Xie, Y. Shi, G. Xu, and D. Xie. Smart classroom - an intelligent environment for tele-education. In *PCM '01: Proceedings of the Second IEEE Pacific Rim Conference on Multimedia*, pages 662–668. Springer Berlin / Heidelberg, 2001.
- [Zhang2004] D. Zhang, D. Gatica-Perez, S. Bengio, I. McCowan, and G. Lathoud. Multimodal group action clustering in meetings. In *VSSN '04: Proceedings of the ACM 2nd international workshop on Video surveillance & sensor networks*, pages 54–62, New York, NY, USA, 2004. ACM Press.
- [Zhang2006] D. Zhang, D. Gatica-Perez, S. Bengio, and I. McCowan. Modeling individual and group actions in meetings with layered hmms. *IEEE Transactions on Multimedia*, 8(3):509–520, June 2006.