



Telecooperation Lab
Prof. Dr. Max Mühlhäuser

TK3: Ubiquitous Computing

Chapter 3: Context-aware Computing
Part 3: Plan Recognition & Prediction
Lecturer: Dr. Immanuel Schweizer

Copyrighted material – for TUD student use only



Example





Example



TECHNISCHE
UNIVERSITÄT
DARMSTADT





Context Aware Systems

- Systems that are aware of their own situation in the *physical*, *virtual*, and *user* environment
- Typically adapt their operation or goal based on contextual cues from the environment or the user's actions
 - Implicit behavior, rather than explicitly directed by the user
 - Lessen the (cognitive) load on the user
 - Requires ability to not only sense environment, but to determine what is relevant to the system's task(s)
 - May require additional processing to convert raw sensor data into relevant information
 - May also need a representation of the relevant knowledge model used to comprehend contextual cues and direct behavior



Humans



TECHNISCHE
UNIVERSITÄT
DARMSTADT

- Humans have a set of intentions I
- Form a set of plans P
- Execute on (parts) of these plans with activities A
- Are able to recognize plans and intentions in other humans
- Are able to predict future actions based on these intentions





Example



TECHNISCHE
UNIVERSITÄT
DARMSTADT





Plan Recognition

- Intention I_1 leads to
Plans $P_1 \dots P_n$ leads to
activities $A_1 \dots A_m$



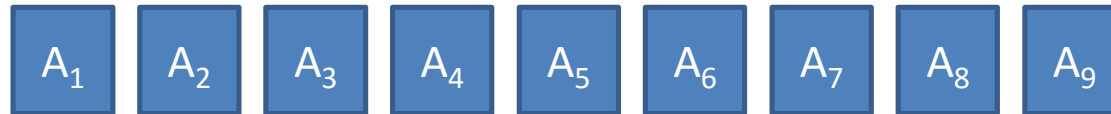
Problem Statement:
Observing $A_1 \dots A_m$ can we
infer P_x and I_1 ?



Partial Chains



TECHNISCHE
UNIVERSITÄT
DARMSTADT

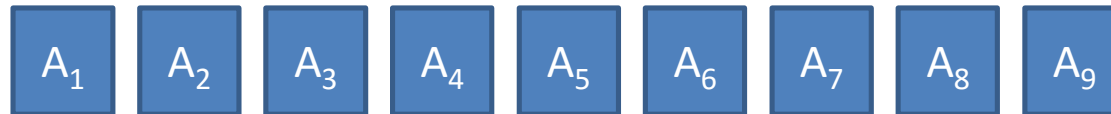




Interleaving



TECHNISCHE
UNIVERSITÄT
DARMSTADT





Conflicting

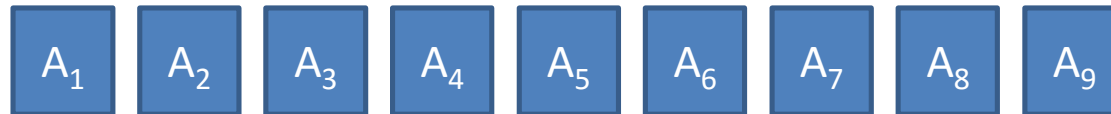




Sharing

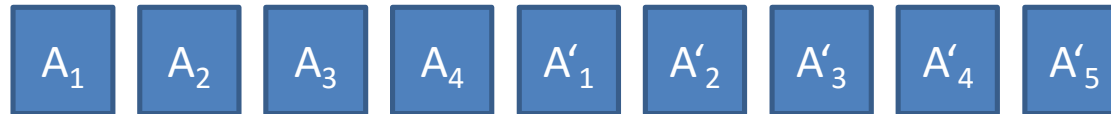


TECHNISCHE
UNIVERSITÄT
DARMSTADT



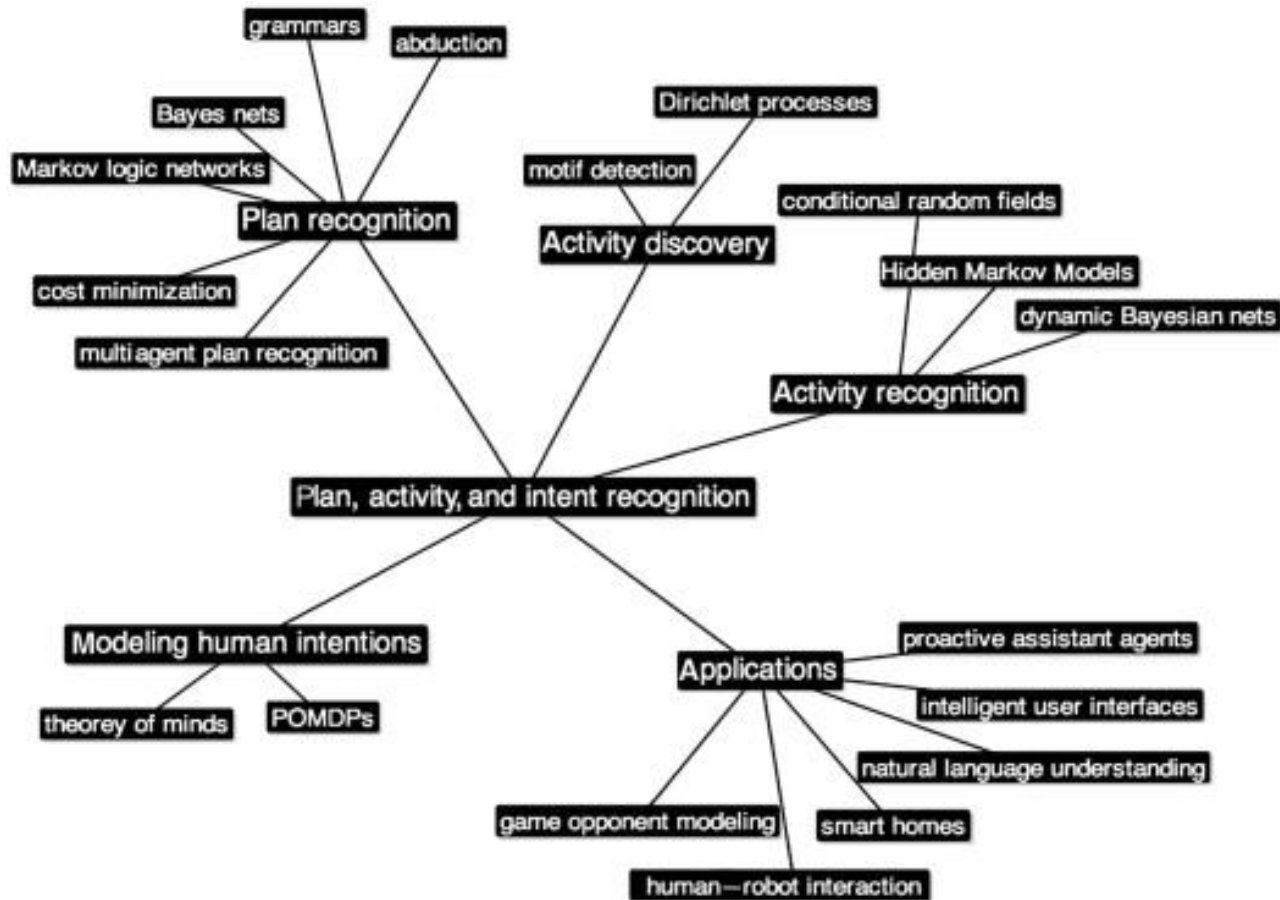


Changes





Research Mindmap



Plan, Activity, and Intent Recognition: Theory and Practice

Edited by: Gita Sukthankar, Christopher Geib, Hung Bui, David Pynadath and Robert P. Goldman

ISBN: 978-0-12-398532-3



Challenges



- Partial Plans
- Recognized Plans

→ Activity Prediction

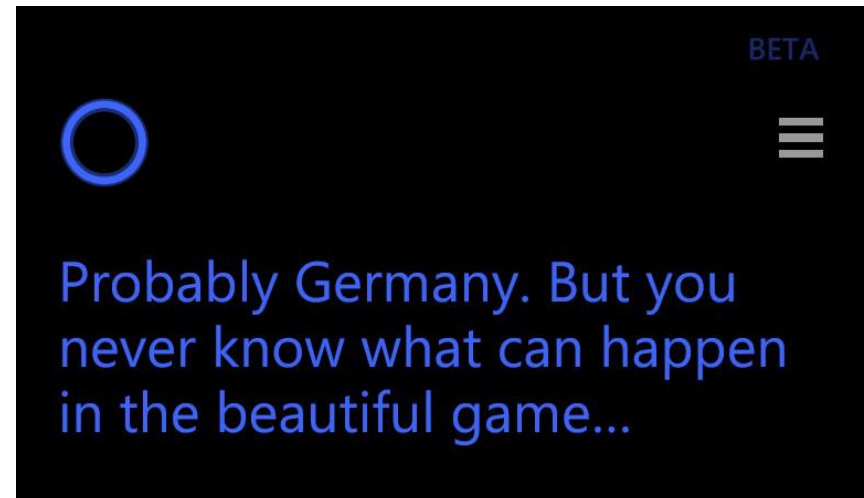
- Provide a chain of activities

→ Activity Detection





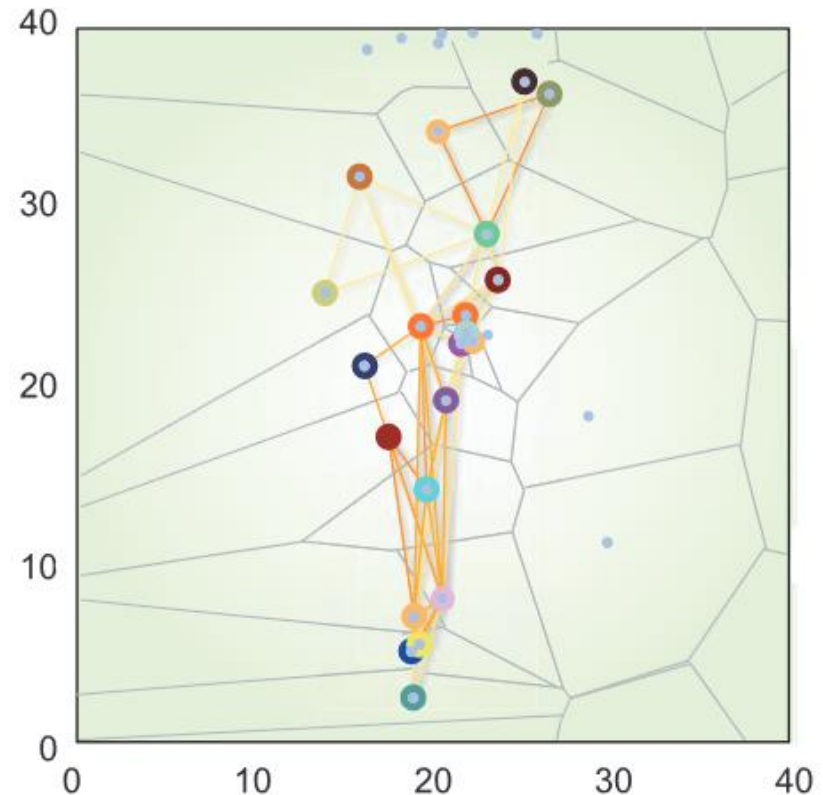
- Prediction attempts to form patterns that permit it to predict the next event(s) given the available input data.
- Deterministic predictions
 - If Bob leaves the bedroom before 7:00 am on a workday, then he will make coffee in the kitchen.
- Probabilistic sequence models
 - If Bob turns on the TV in the evening then he will 80% of the time go to the kitchen to make popcorn.





Location Prediction

- Next-slot Place (NSP)
 - Relevant place for the next time slot
- Next-slot Transition (NST)
 - Transition occurrence
- Next Place (NP)
 - Next place regardless of transition time
- Residence Time (RT)
 - How long will the user stay?





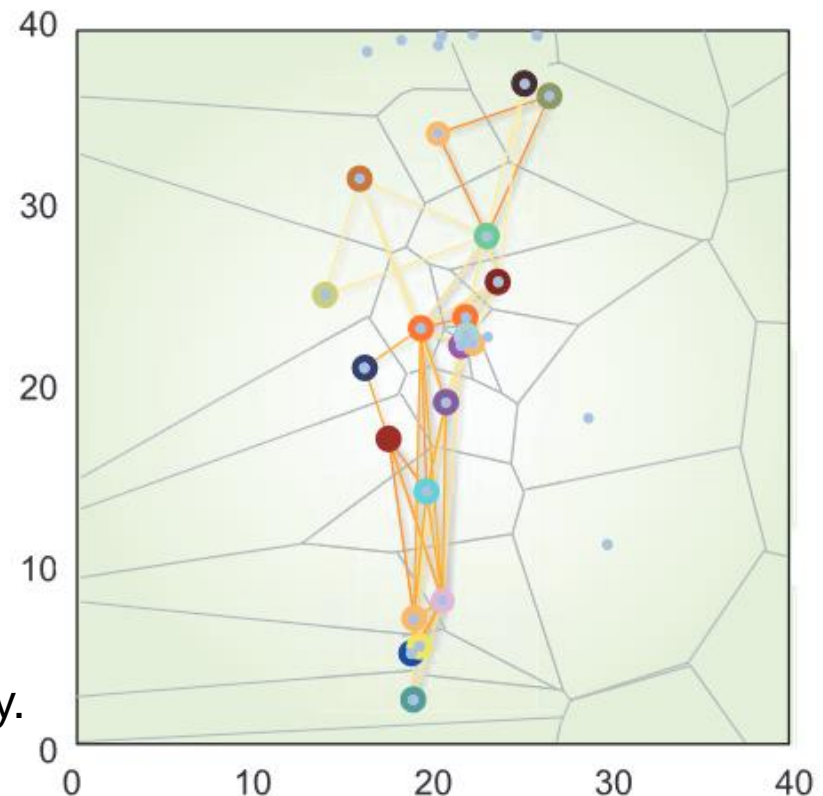
■ Is it even possible?

■ 93% predictability

Limits of Predictability in Human Mobility,
Chaoming Song, Zehui Qu, Nicholas
Blumm, and Albert-László Barabási
Science 19 February 2010: 327 (5968),
1018-1021

■ What features?

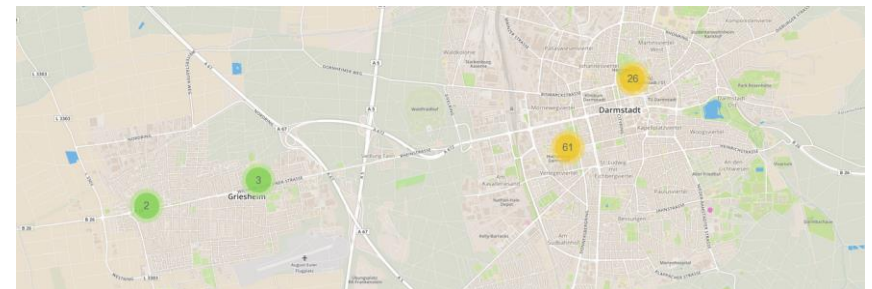
Paul Baumann: Adaptive Sensor
Cooperation for Predicting Human Mobility.
In: *Adjunct Proceedings of the 2014 ACM
International Joint Conference on
Pervasive and Ubiquitous Computing,*
2014.





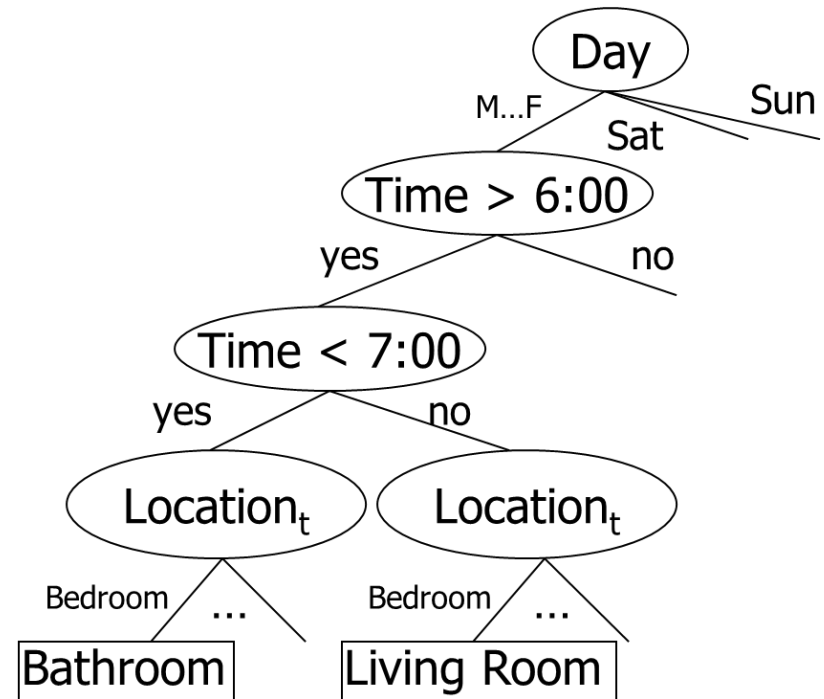
Relevant places

- Places you spend a *significant* amount of time at
- Mobility traces are clustered and filtered
- Cluster center is mapped to symbolic location
- Ask user feedback





- Classification-Based Approaches
 - Nearest Neighbor
 - Neural Networks
 - Bayesian Classifiers
 - Decision Trees
- Sequential Behavior Modeling
 - Hidden Markov Models
 - Temporal Belief Networks





Example: Location Prediction

Time	Date	Day	Location _t	Location _{t+1}
6:30	02/25	Monday	Bedroom	Bathroom
7:00	02/25	Monday	Bathroom	Kitchen
7:30	02/25	Monday	Kitchen	Garage
17:30	02/25	Monday	Garage	Kitchen
18:00	02/25	Monday	Kitchen	Bedroom
18:10	02/25	Monday	Bedroom	Living room
22:00	02/25	Monday	Living room	Bathroom
22:10	02/25	Monday	Bathroom	Bedroom
6:30	02/26	Tuesday	Bedroom	Bathroom



Nearest Neighbor Example: Inhabitant Location

- Training Instances (with concept):

((Bedroom, 6:30), Bathroom), ((Bathroom, 7:00), Kitchen),
((Kitchen, 7:30), Garage), ((Garage, 17:30), Kitchen), ...

- Similarity Metric:

$$d((\text{location}_1, \text{time}_1), (\text{location}_2, \text{time}_2)) = \\ 1000 * (\text{location}_1 \neq \text{location}_2) + | \text{time}_1 - \text{time}_2 |$$

- Query Instance:

$$x_q = (\text{Bedroom}, 6:20)$$

- Nearest Neighbor:

$$x_k = (\text{Bedroom}, 6:30) \quad d(x_k, x_q) = 10$$

- Prediction $f(x_k)$:

Bathroom



Nearest Neighbor

■ Advantages

- Fast training (just store instances)
- Complex target functions
- No loss of information

■ Problems

- Slow at query time (have to evaluate all instances)
- Sensitive to correct choice of similarity metric
- Easily fooled by irrelevant attributes



Sequential Behavior Prediction



■ Problem

- Input: A sequence of states or events
 - States can be represented by their attributes
inhabitant location, device status, etc.
 - Events can be raw observations
Sensor readings, inhabitant input, etc.
- Output: Predicted next event
- Model of behavior has to be built based on past instances and be usable for future predictions.

■ String matching algorithms

- Deterministic best match
- Probabilistic matching

■ Markov Models

- Markov Chains
- Hidden Markov Models

■ Dynamic Belief Networks



- Markov chain models represent the event generating process probabilistically.
 - Markov models can be described by a tuple $\langle S, T \rangle$ representing states and transition probabilities.
 - Markov assumption: The current state contains all information about the past that is necessary to predict the probability of the next state.

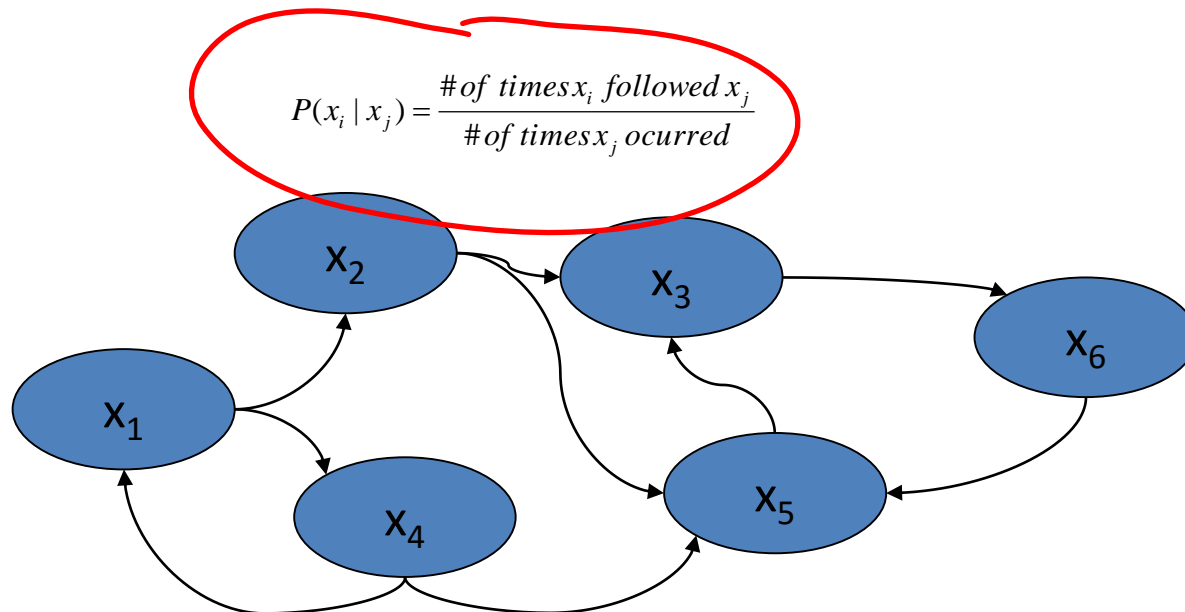
$$P(x_{t+1} | x_t, x_{t-1}, \dots, x_0) = P(x_{t+1} | x_t)$$

- Transitions correspond to events that occurred in the environment (inhabitant actions, etc)
- Prediction of next state (and event)



Markov Chain Example

- Example states:
 - $S = \{(\text{Room, Time, Day, Previous Room})\}$
 - Transition probabilities can be calculated from training data by counting occurrences





■ Advantages

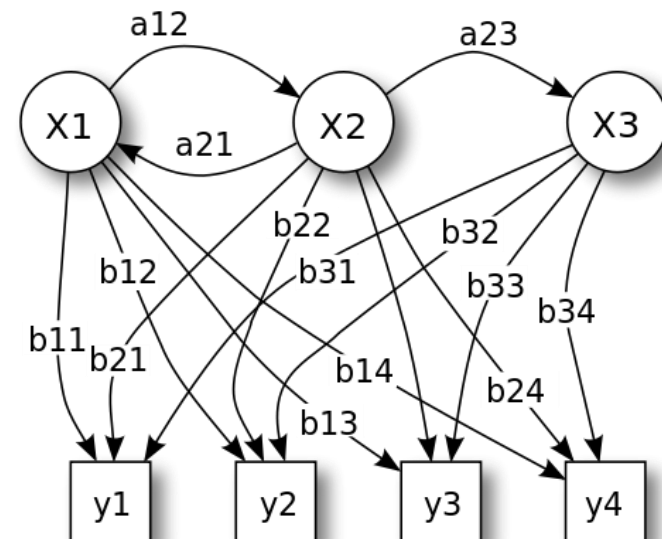
- Permits probabilistic predictions
- Transition probabilities are easy to learn
- Representation is easy to interpret

■ Problems

- State space has to have Markov property
- State space selection is not automatic
- States might have to include previous information
- State attributes might not be observable



- Partially Observable Markov Models extend Markov models by permitting states to be only partially observable.
- Systems can be represented by a tuple $\langle S, T, O, V \rangle$ where $\langle S, T \rangle$ is a Markov model and O, V are mapping observations about the state to probabilities of a given state
 - $O = \{o_i\}$ is the set of observations
 - $V: V(x, o) = P(o \mid x)$
- To determine a prediction the probability of being in any given state is computed



"HiddenMarkovModel" by Tdunningvectorization: Own work - Own work. Licensed under CC BY 3.0 via Wikimedia Commons



Hidden Markov Models

- Hidden Markov Models (HMM) provide mechanisms to learn the Markov Model $\langle S, T \rangle$ underlying a POMM from the sequence of observations.
- Baum-Welch algorithm learns transition and observation probabilities as well as the state space (only the number of states has to be given)
- Model learned is the one that is most likely to explain the observed training sequences



Partially Observable MMs

■ Advantages

- Permits optimal predictions
- HMM provide algorithms to learn the model
- In HMM, Markovian state space description has not to be known

■ Problems

- State space can be enormous
- Learning of HMM is generally very complex
- Computation of belief state is computationally expensive





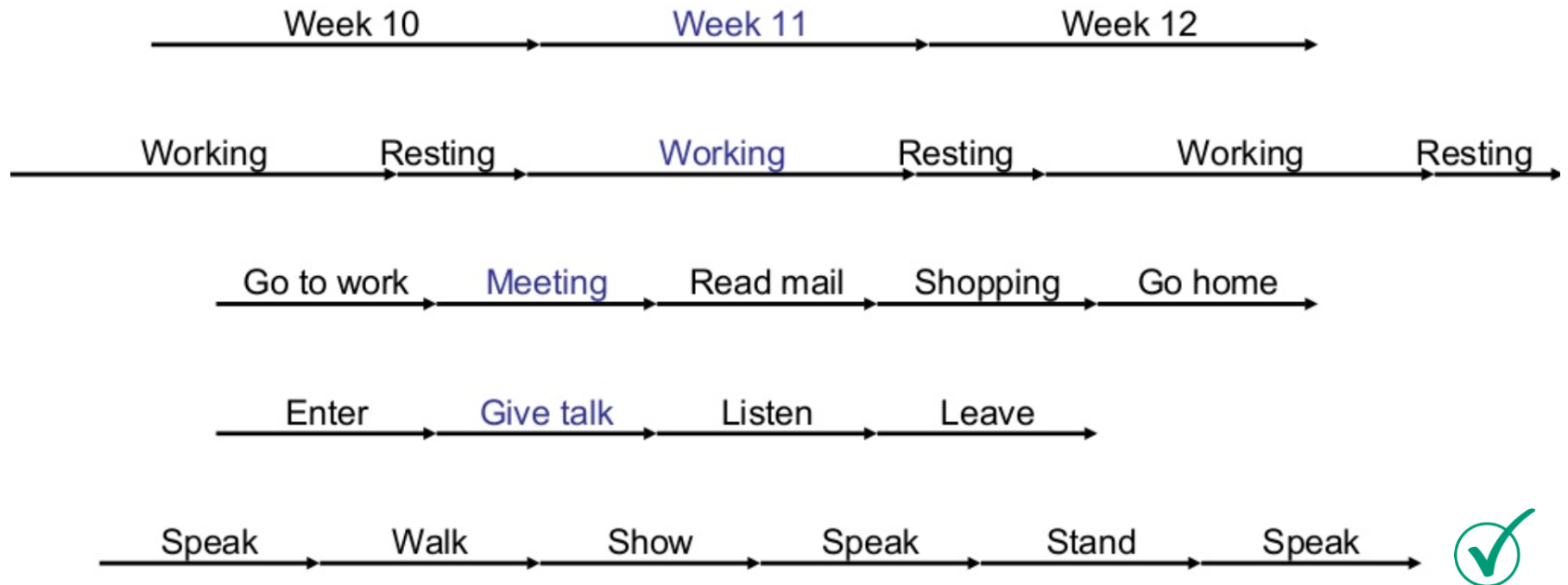
Activity Recognition



- **Activity recognition** aims to recognize the actions and goals of one or more agents from a series of observations on the agents' actions and the environmental conditions. (Wikipedia)
- Sensor-based
 - Single-user activity recognition
 - Multi-user activity recognition
 - Group activity recognition
- Vision-based activity recognition



Activity Hierarchy



<http://de.slideshare.net/danielroggen/wearable-computing-part-iii-the-activity-recognition-chain-arc>



Example 1

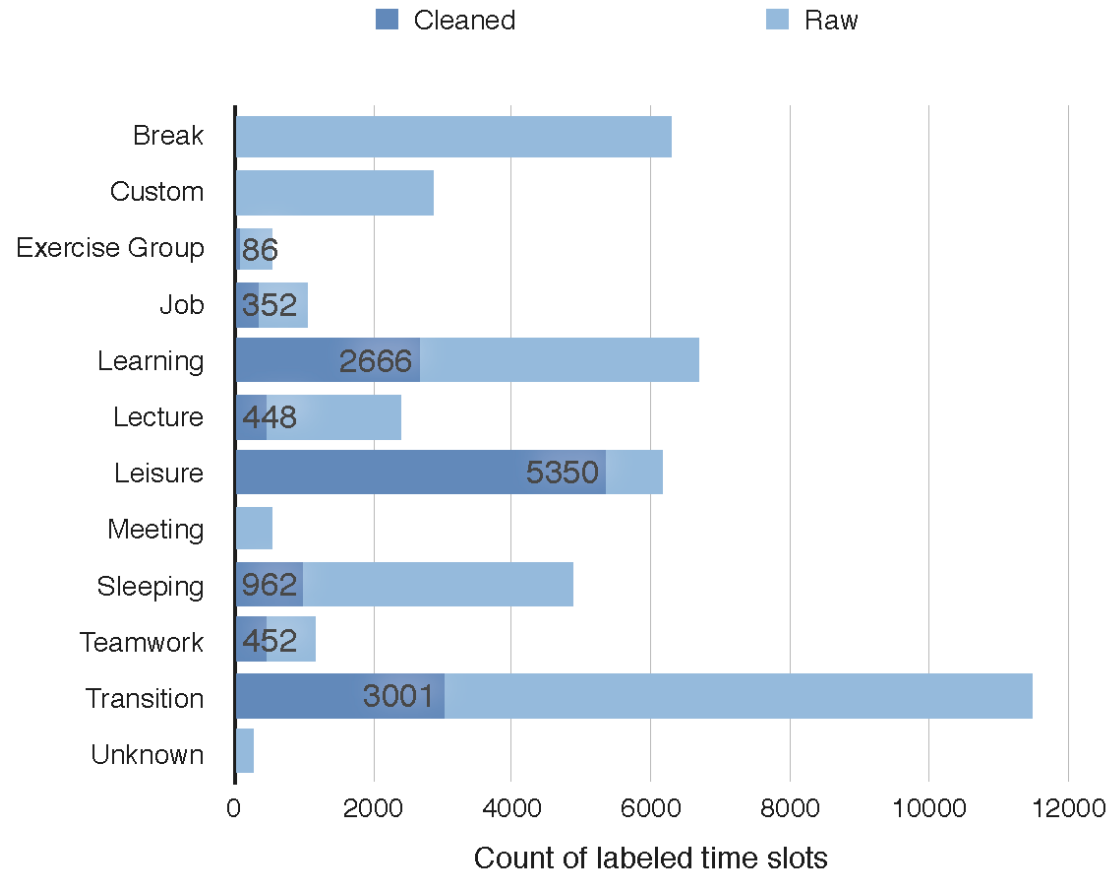
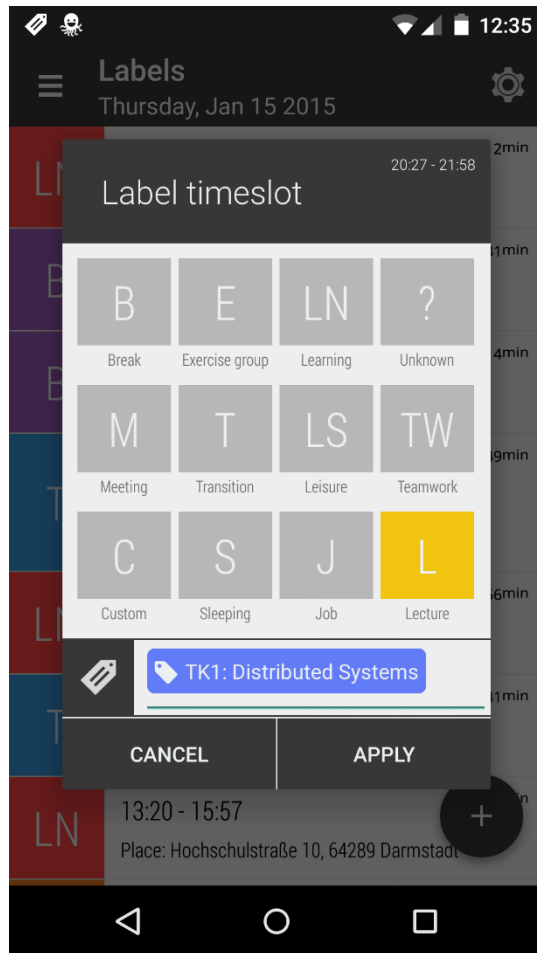


TECHNISCHE
UNIVERSITÄT
DARMSTADT



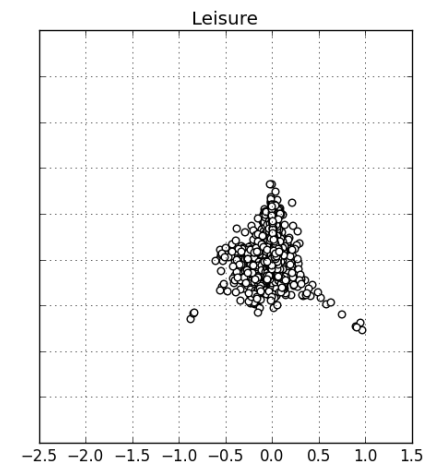
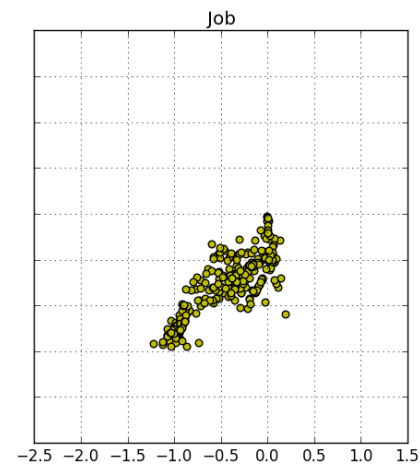
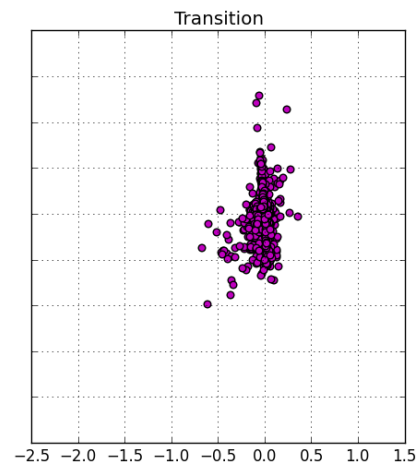
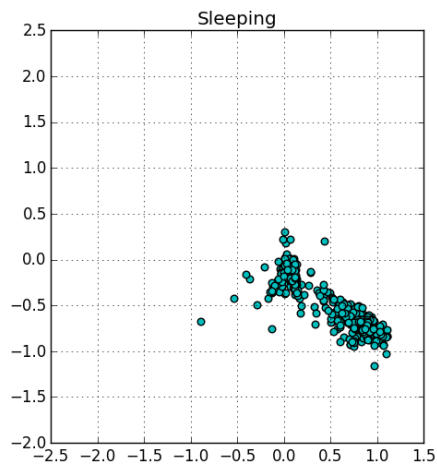
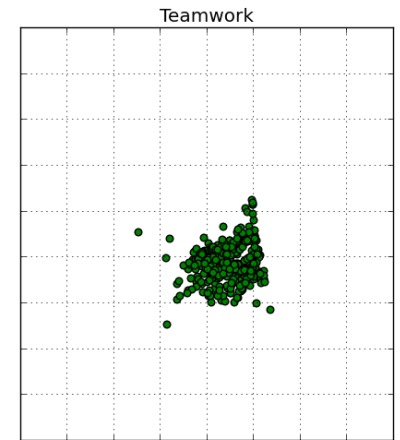
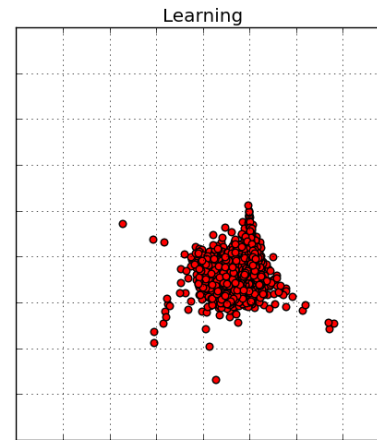
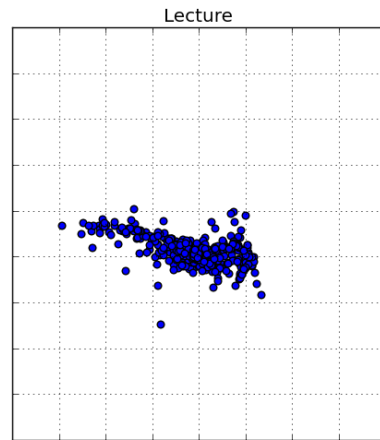
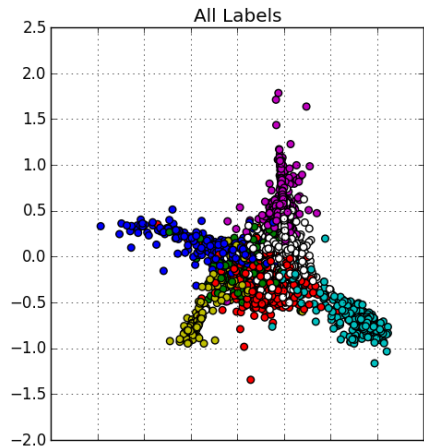


Example 2





Example 2





Summary

- Plan Recognition
 - Challenges and research directions

CHECK

- Prediction
 - Location Prediction

- Activity Recognition
 - Vision-based activity recognition
 - Sensor-based activity recognition

