Telecooperation Lab
Prof. Dr. Max Mühlhäuser

TK3: Ubiquitous Computing

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

Example

Example

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

- 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

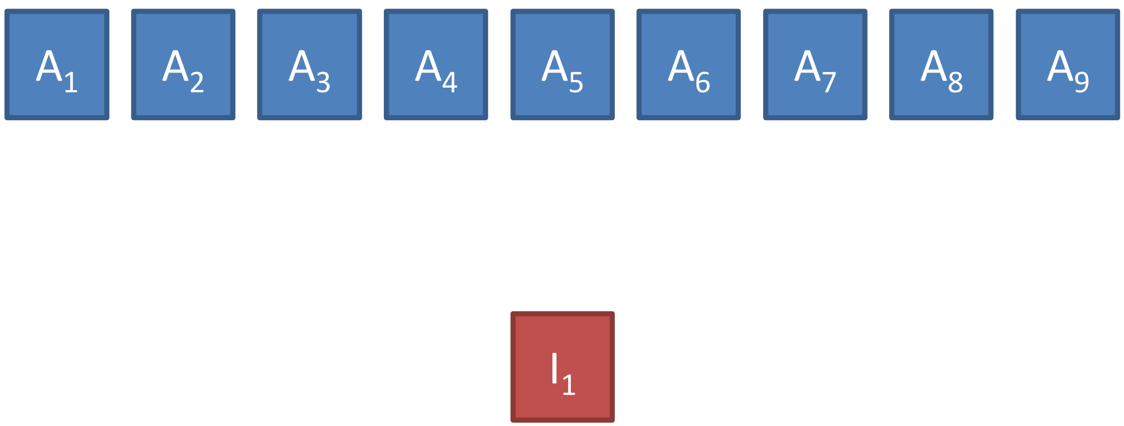
Example

Plan Recognition

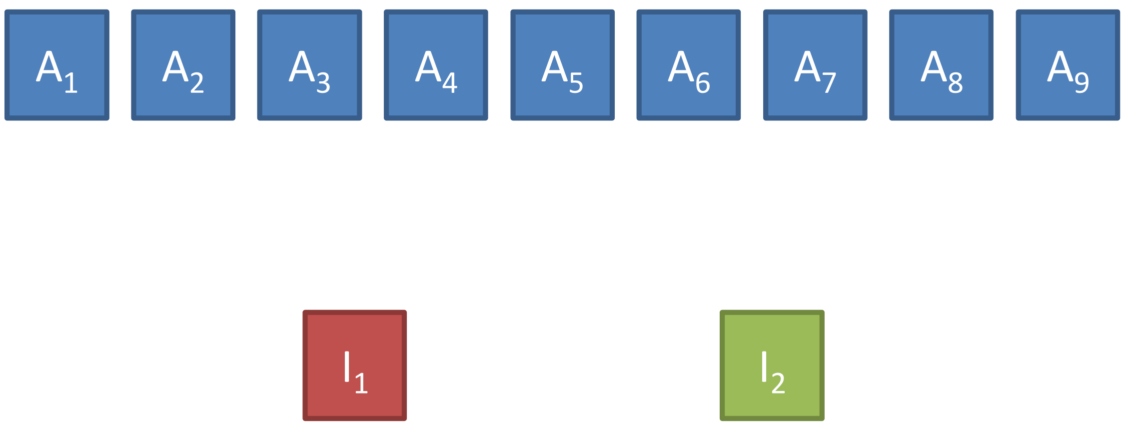
- Intention I_1 leads to Plans $P_1 \ldots P_n$ leads to activities $A_1 \ldots A_m$

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

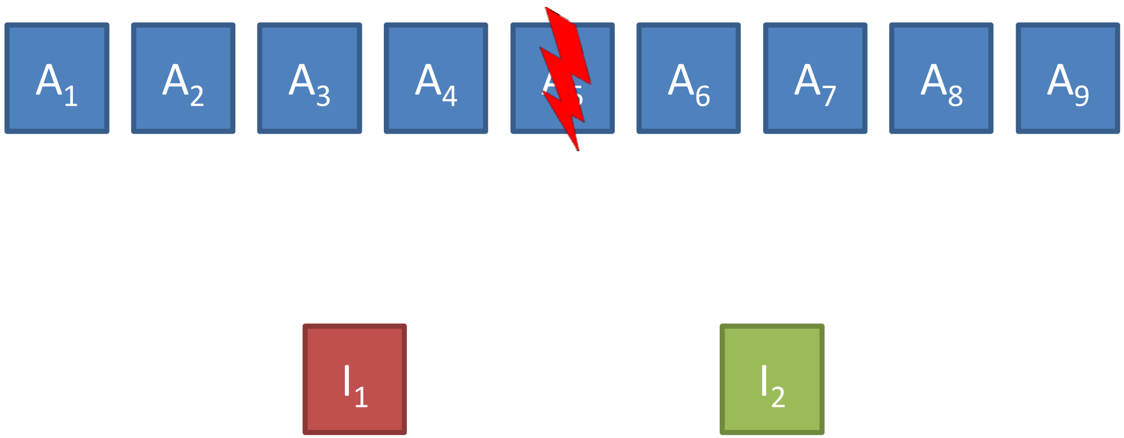
Partial Chains



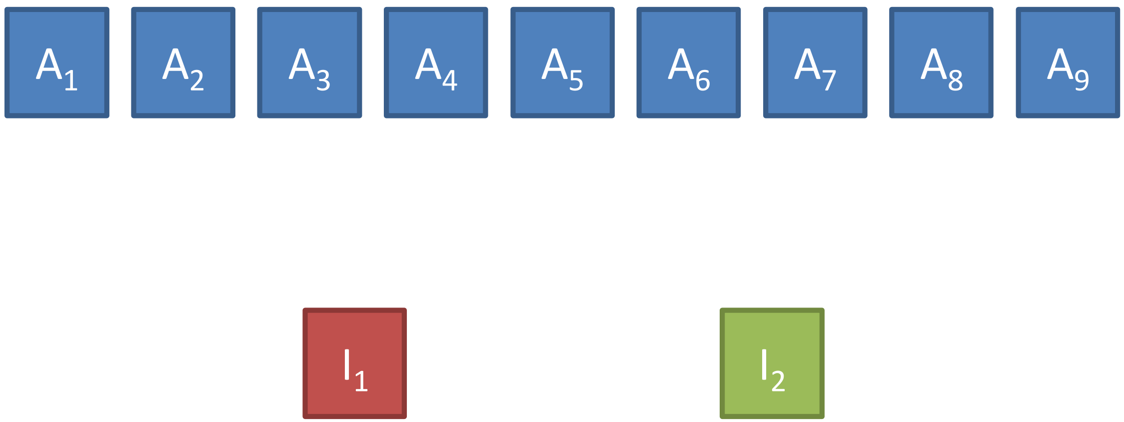
Interleaving



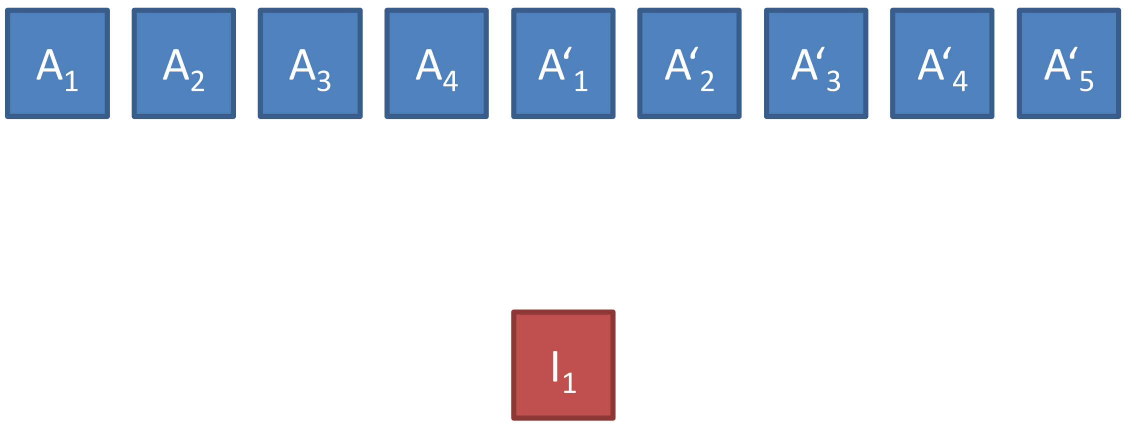
Conflicting



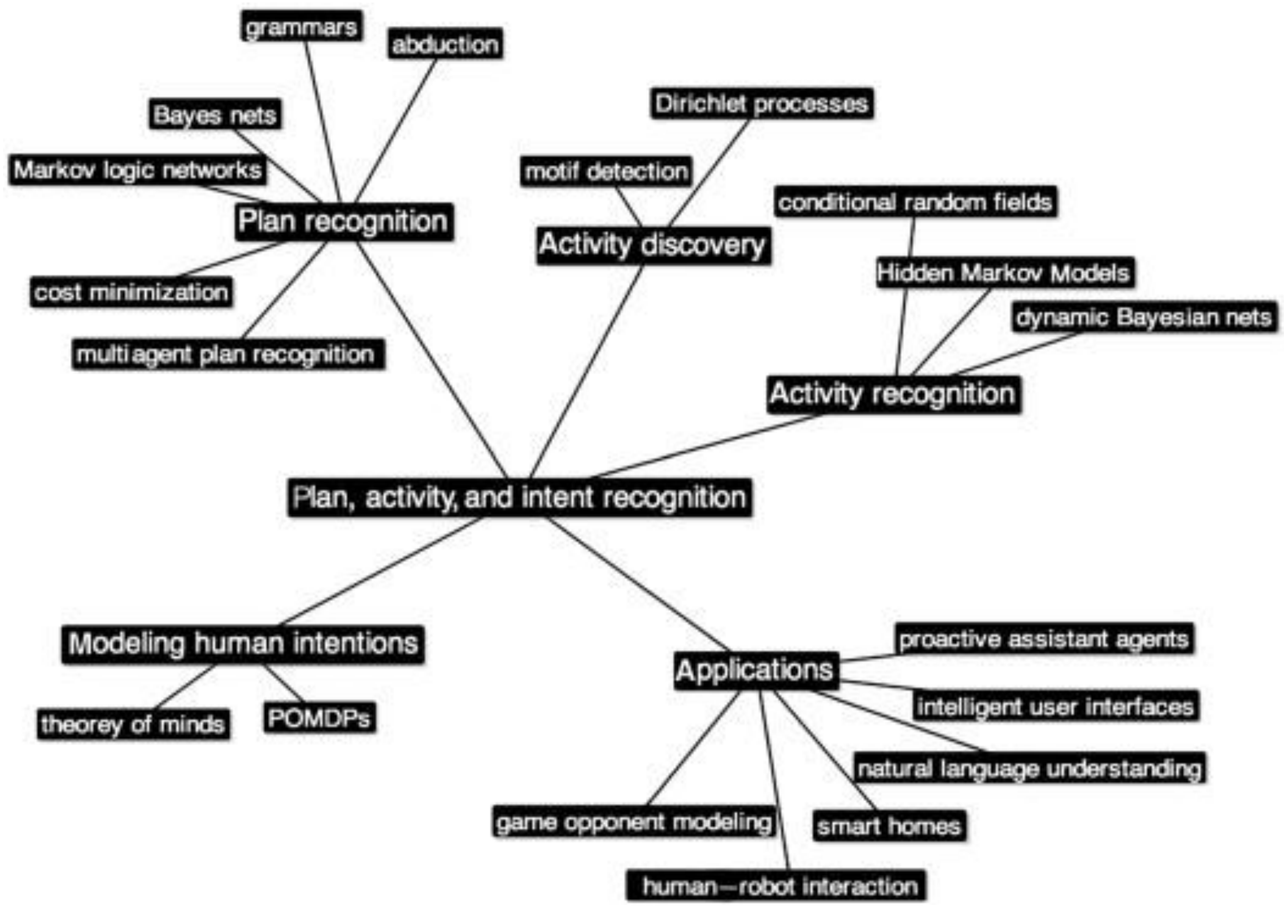
Sharing



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

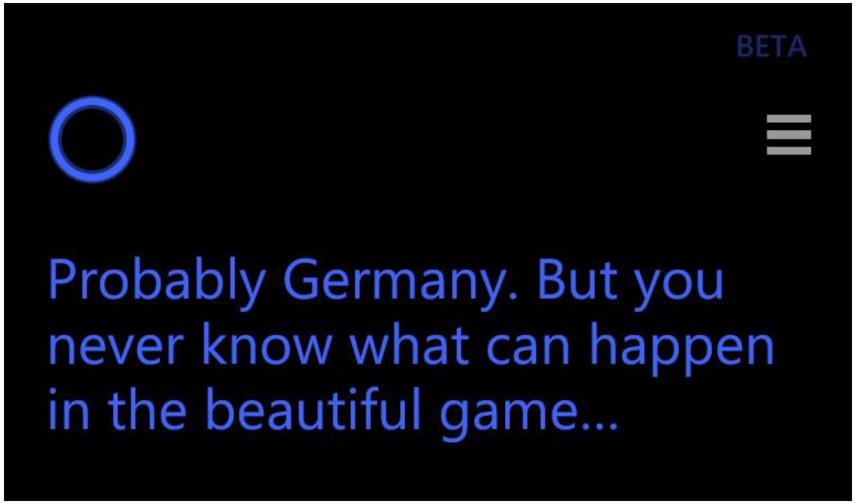
→Activity Prediction

- Provide a chain of activities

→Activity Detection

Data Mining and Prediction

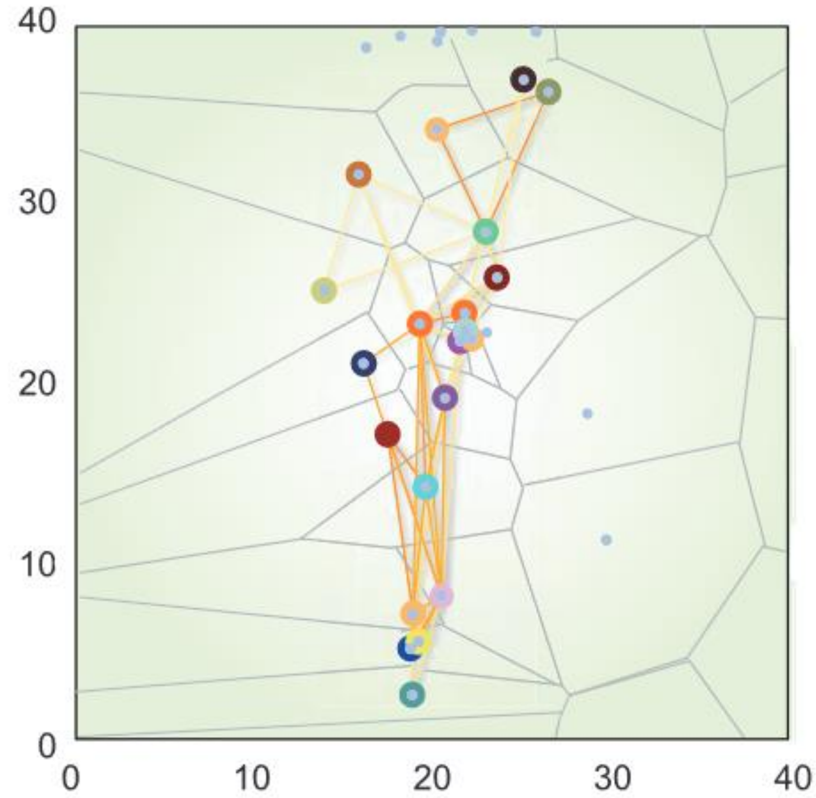
- Prediction attempts to form patterns that permit it to predict the next event(s) given the available input data.
  - Deterministic predictions
    - If Bob leaves the bedroom before 7:00 am on a workday, then he will make coffee in the kitchen.
  - Probabilistic sequence models
    - If Bob turns on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



http://ranger.uta.edu/~huber/cse4392_SmartHome/Lectures/Prediction.ppt

Location Prediction

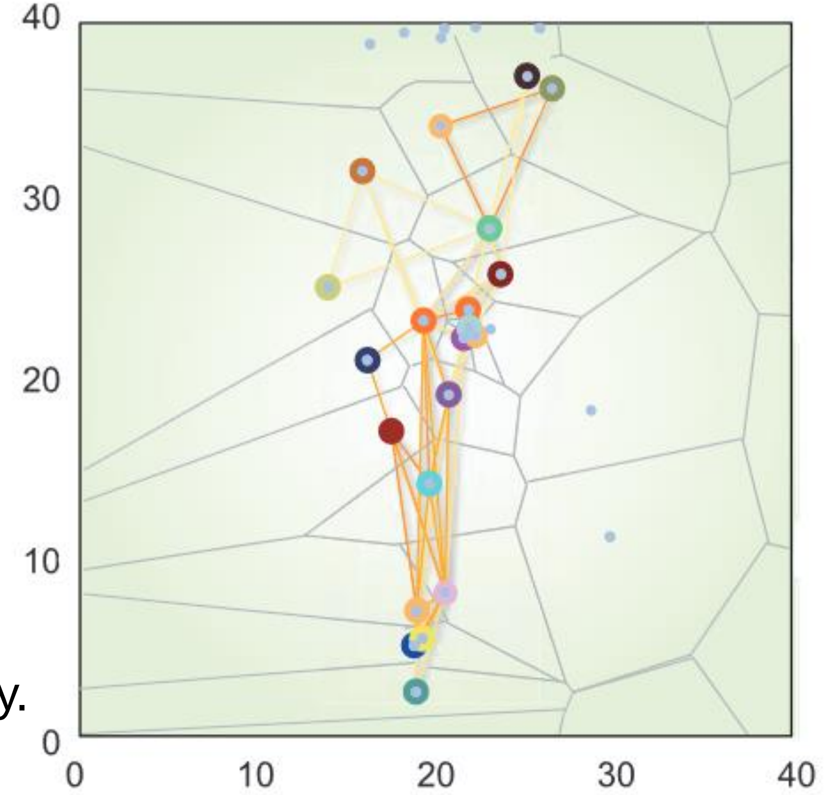
- Next-slot Place (NSP)
  - Relevant place for the next time slot
- Next-slot Transition (NST)
  - Transition occurrence
- Next Place (NP)
  - Next place regardless of transition time
- Residence Time (RT)
  - How long will the user stay?



Location Prediction

- 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.*

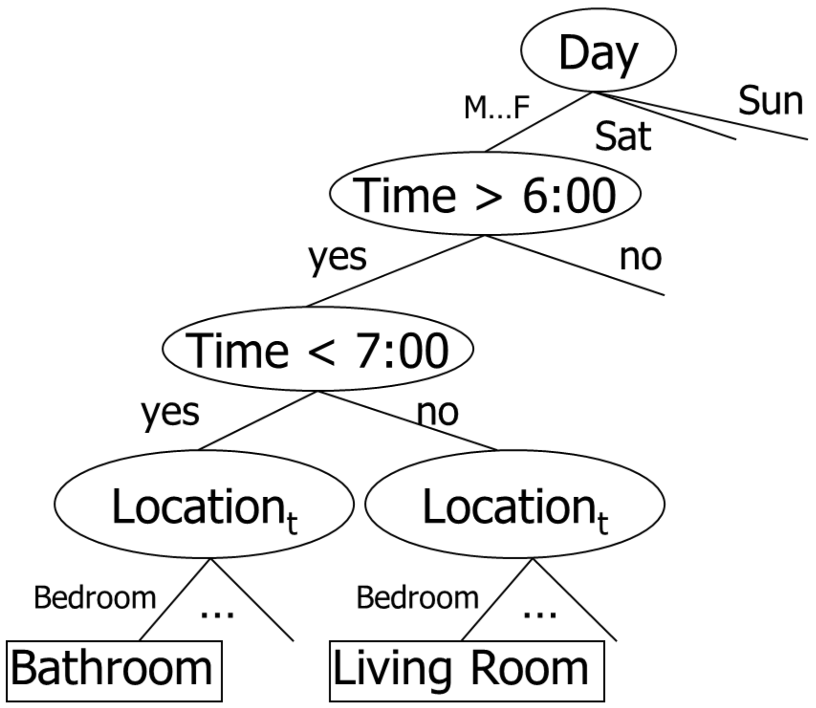
Relevant places

- 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

Prediction Techniques

- 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:

  $d((location_1, time_1), (location_2, time_2)) =$
  $1000*(location_1 \neq location_2) + | time_1 - time_2 |$

- Query Instance:

  x_q = (Bedroom, 6:20)

- Nearest Neighbor:

  x_k = (Bedroom, 6:30) $d(x_k, x_q) = 10$

  - 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

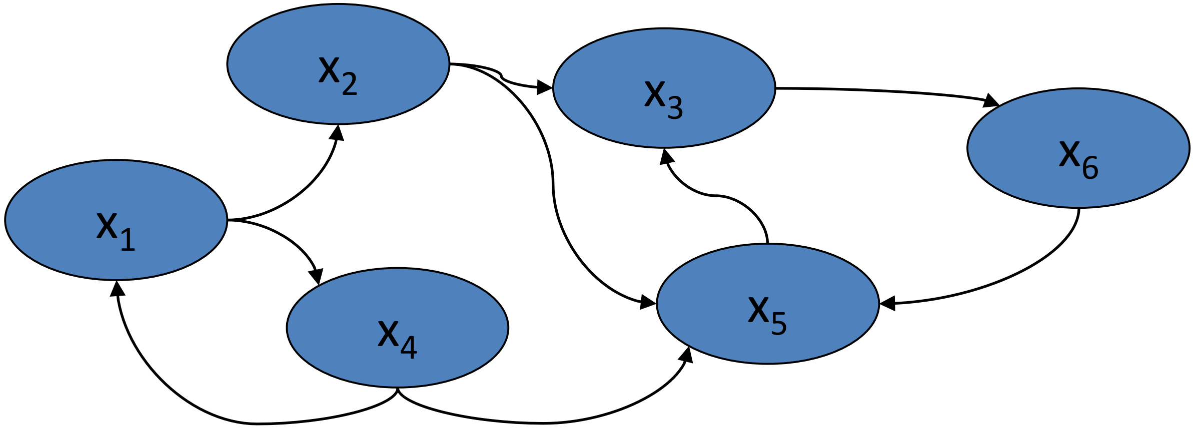
- Markov chain models represent the event generating process probabilistically.
  - Markov models can be described by a tuple *<S, T>* representing states and transition probabilities.
  - Markov assumption: The current state contains all information about the past that is necessary to predict the probability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

    $P(x_{t+1} | x_t, x_{t-1}, \ldots, x_0) = P(x_{t+1} \mid x_t)$
  - Transitions correspond to events that occurred in the environment (inhabitant actions, etc)
- Prediction of next state (and event)

Markov Chain Example

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

$$P(x_i \mid x_j) = \frac{\#of\ times\, x_i\ followed\, x_j}{\#of\ times\, x_j\ ocurred}$$

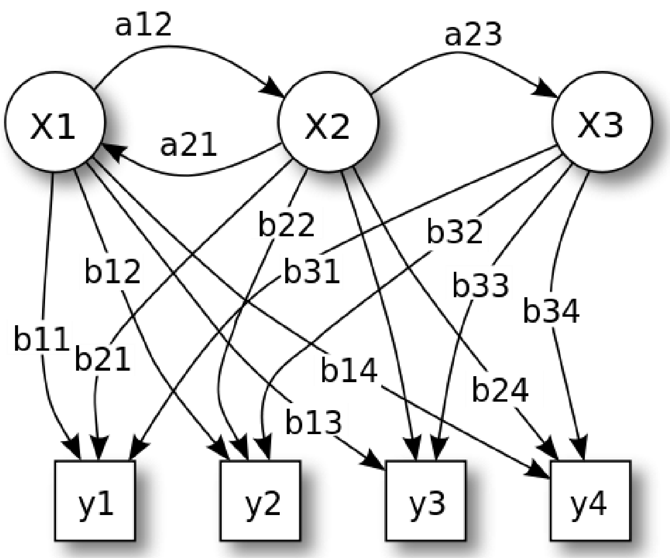


Markov Models

- 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 MMs

- Partially Observable Markov Models extend Markov models by permitting states to be only partially observable.
  - Systems can be represented by a tuple <*S, T, O, V*> where <*S, T*> 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



Hidden Markov Models

- Hidden Markov Models (HMM) provide mechanisms to learn the Markov Model <S, T> 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

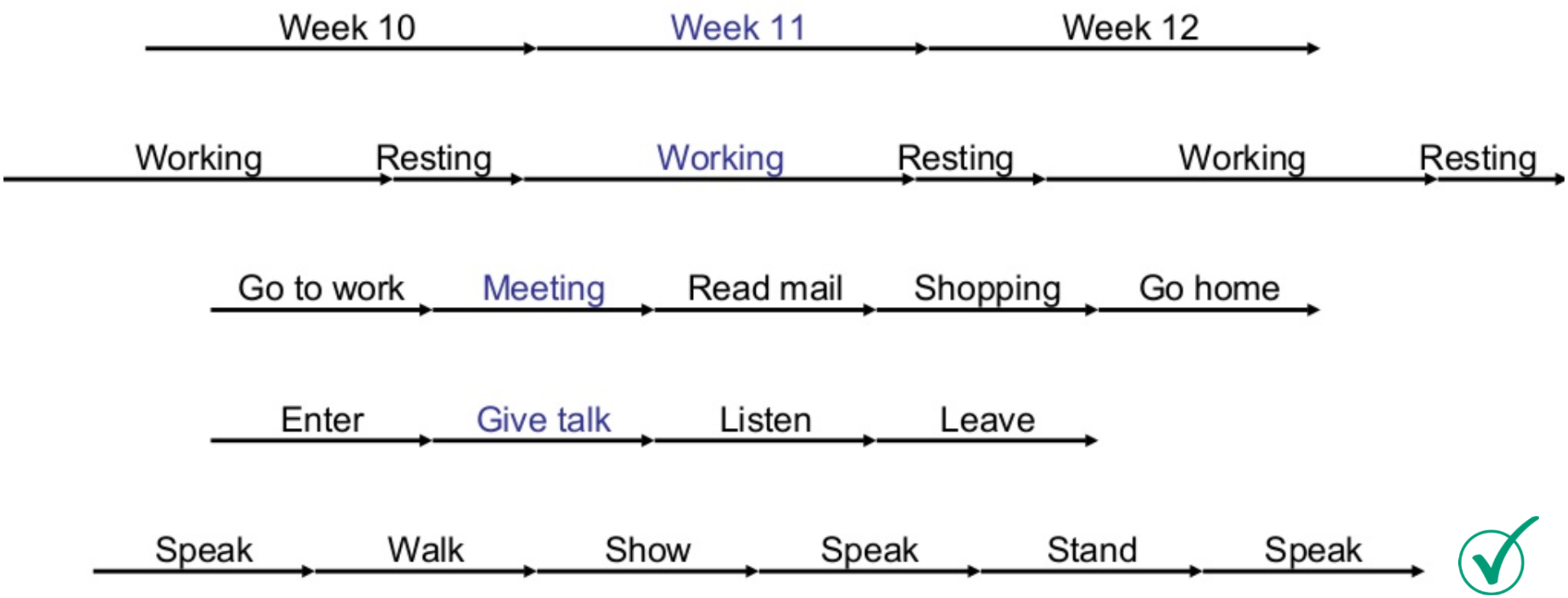
Activity Recognition

- **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

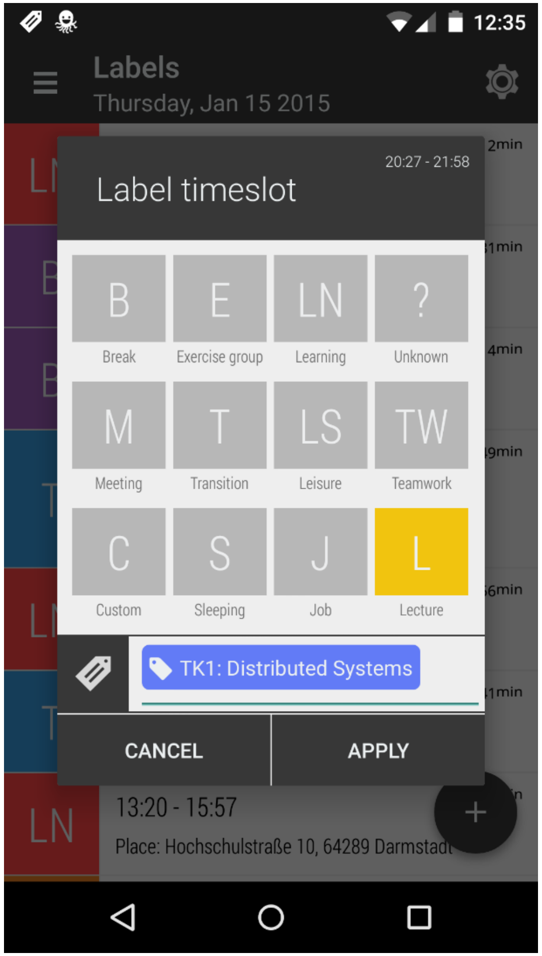
Activity Hierarchy

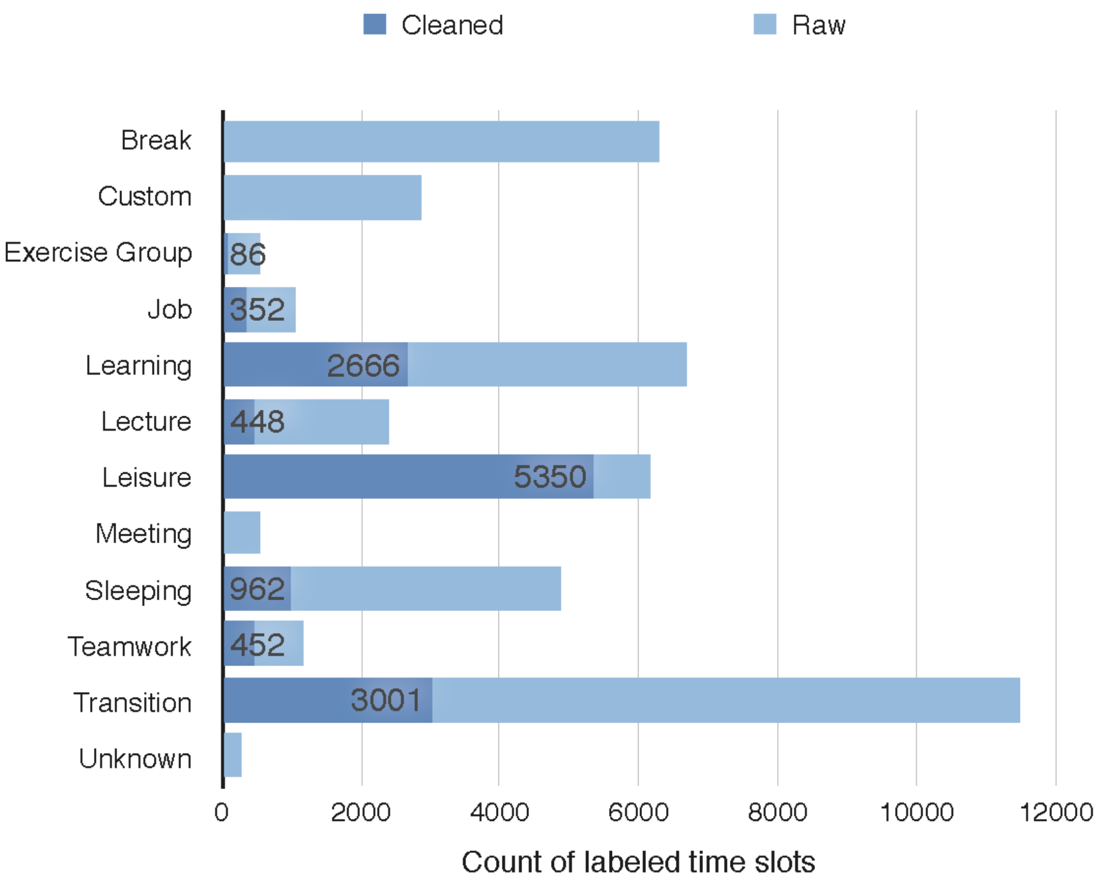


http://de.slideshare.net/danielroggen/wearable-computing-part-iii-the-activity-recognition-chain-arc

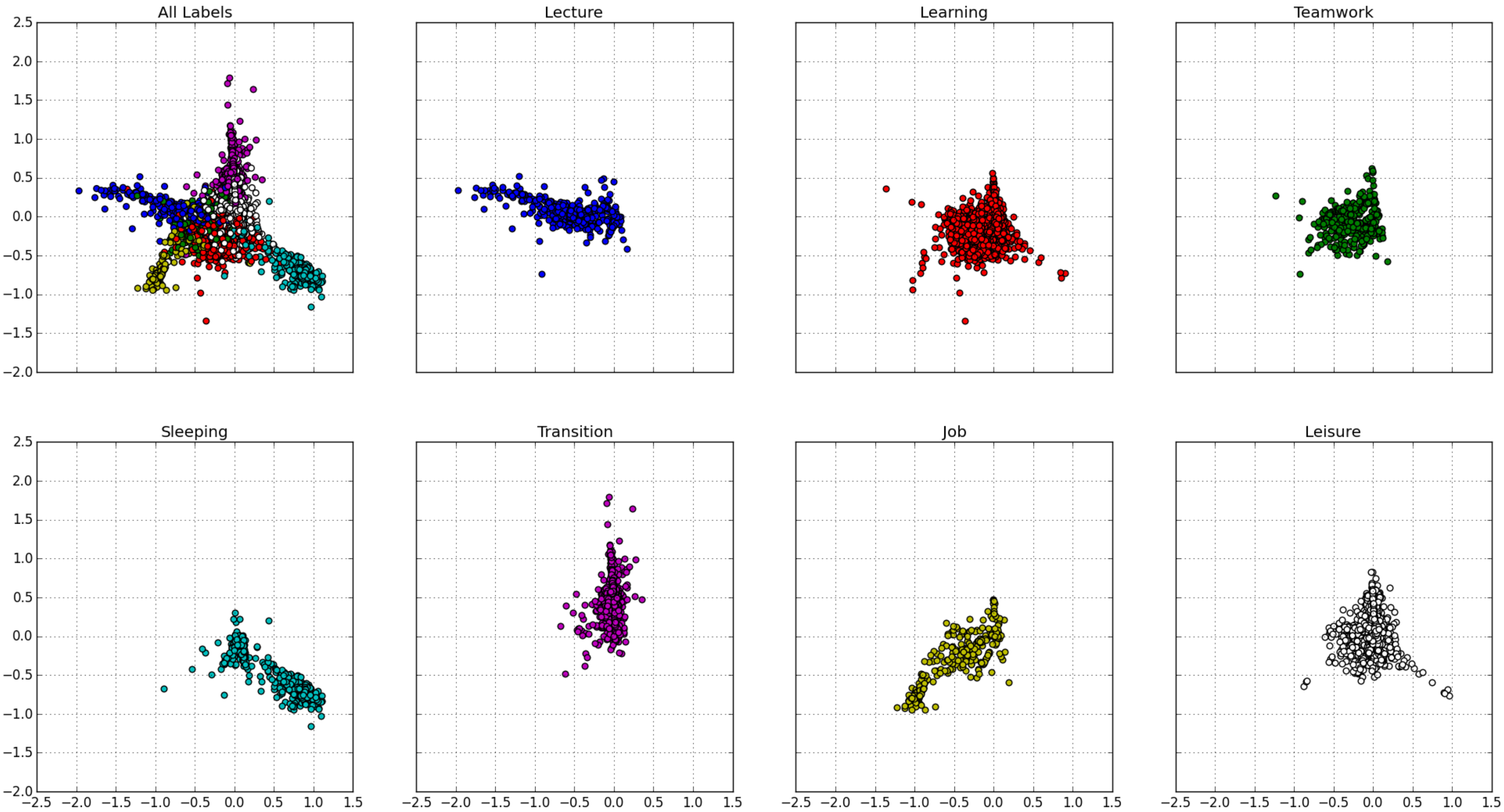
Example 1

Example 2


12:35
Labels
Thursday, Jan 15 2015
Label timeslot
20:27 - 21:58
B
Break
E
Exercise group
LN
Learning
?
Unknown
M
Meeting
T
Transition
LS
Leisure
TW
Teamwork
C
Custom
S
Sleeping
J
Job
L
Lecture
TK1: Distributed Systems
CANCEL
APPLY
13:20 - 15:57
Place: Hochschulstraße 10, 64289 Darmstadt


Cleaned
Raw
Break
Custom
Exercise Group
Job
Learning
Lecture
Leisure
Meeting
Sleeping
Teamwork
Transition
Unknown
86
352
2666
448
5350
962
452
3001
0
2000
4000
6000
8000
10000
12000
Count of labeled time slots

Example 2


All Labels
Lecture
Learning
Teamwork
Sleeping
Transition
Job
Leisure
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

Summary

- Plan Recognition
  - Challenges and research directions
- Prediction
  - Location Prediction
  - Activity Recognition
    - Vision-based activity recognition
    - Sensor-based activity recognition