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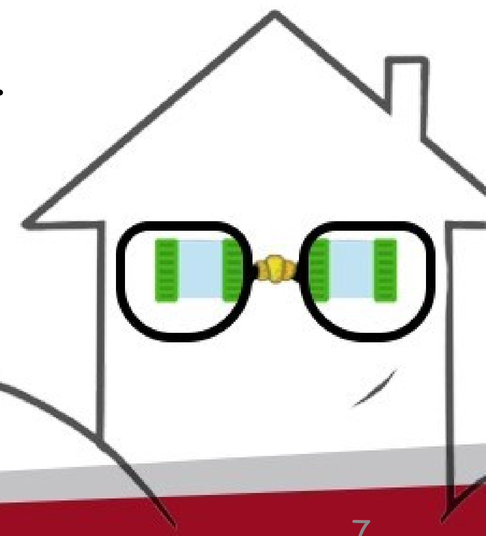
# Introduction to Smart Spaces: State of the Art (SotA) and Open Challenges

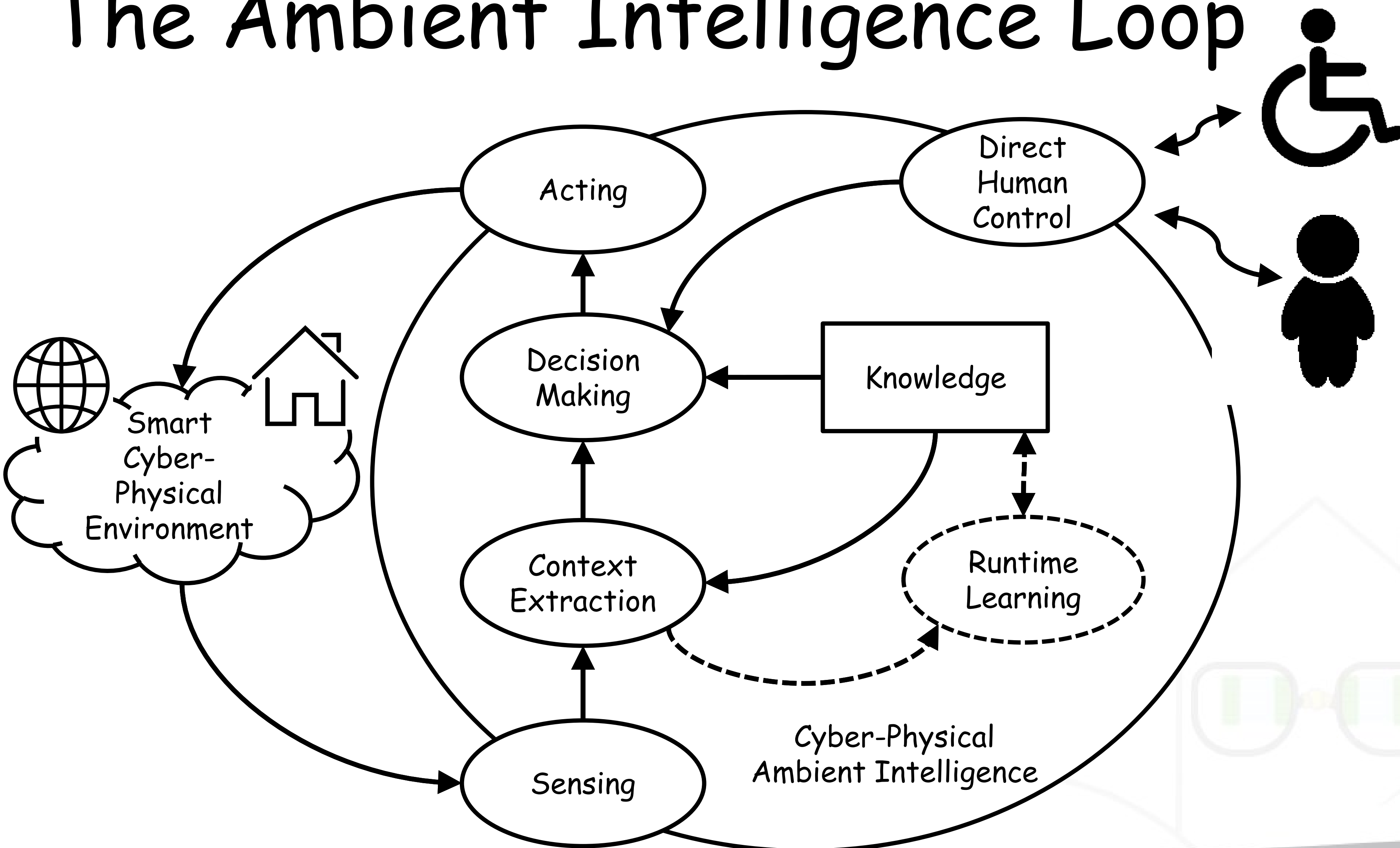
Leotta F., Mecella M., Sora D., Catarci T.
"Surveying Human Habit Modeling and Mining Techniques in Smart Spaces."
MDPI – Future Internet, 2019.



# Smart Spaces

- "an environment centered on its human users in which a set of embedded networked artefacts, both hardware and software, collectively realize the paradigm of ambient intelligence (AmI)" [UniversAAL Specification]
  - E.g., smart homes, factories, offices, public spaces, business activities
- AmI is Artificial Intelligence applied to Human Computer (Space) Interaction. Main features are:
  - Sensitivity → Sense the environment
  - Responsiveness → Reactively respond to environment changes
  - Adaptivity → Long-term adapt to user preferences

# The Ambient Intelligence Loop



# Sensors

- Significant progress on designing sensors
  - Smaller size, lighter weight, lower cost, and longer battery life
  - Embedded in an environment and integrated into everyday objects and onto human bodies
- Large availability of different sensors
  - Traditionally employed for home and building automation
    - e.g. presence detectors, smoke detectors, contact switches for doors and windows, network-attached and close circuit cameras
  - More modern units growingly available as off-the-shelf products.
    - e.g. IMUs - Inertial Measurements Units such as accelerometer and gyroscopes, WSN nodes

# Actuators

- Most common actuators in building automation are switches and dimmers
  - usually employed to control lights, and motors, which control blind/roller shutters, doors, windows and ventilation flaps
- As an AmI system is supposed to assist users in the widest range possible of daily routines, more complex devices need to be controlled
  - Software services on the Internet can be considered as an additional form of (virtual) actuators

# Interfaces

- Amazon Alexa, Google Home
  - Integrate wireless devices (via Zigbee protocol for example)
  - Integrate online data


# Knowledge: Models for What? (1)

- **Context:** the state of the environment including the human inhabitants with their actions/activities/habits
- **Action:** atomic interaction of the human with the environment or a part of it (e.g., a device)
  - Some techniques in literature focuses only on actions
  - Other techniques skip actions while recognizing activities
- **Human Preferences:** a specific set of rules over contextual variables. The goal here is user satisfaction.
  - Controllable and Uncontrollable variables

# Knowledge: Models for What? (2)

- **Activity:** a sequence of actions (one in the extreme case) or sensor measurements/events with a final goal
  - Activities can be collaborative
- **Habit:** a set of interleaving of activities that happen in specific contextual conditions
  - E.g., what a user does each morning between 08:00 and 10:00am
  - E.g., what a user does between very specific actions (e.g., leaving the bed and leaving the house)

# Classification of Modeling Methods (1)

- Specification-based methods
  - Knowledge expressed in terms of some kind of logic language
  - Pros ☺: Human readable → easy to validate
  - Cons ☹: Hand made by experts → feasible only with a limited number of sensors

# Classification of Modeling Methods (2)

- **Learning-based** methods
  - Techniques from both machine learning and data mining
    - Supervised, Unsupervised, Semi-Supervised methods
  - Pros ☺: No need for hand-made models
    - Supervised methods still require a lot of labeled data
  - Cons ☹: Usually not human readable
    - E.g., statistical formalisms as HMM

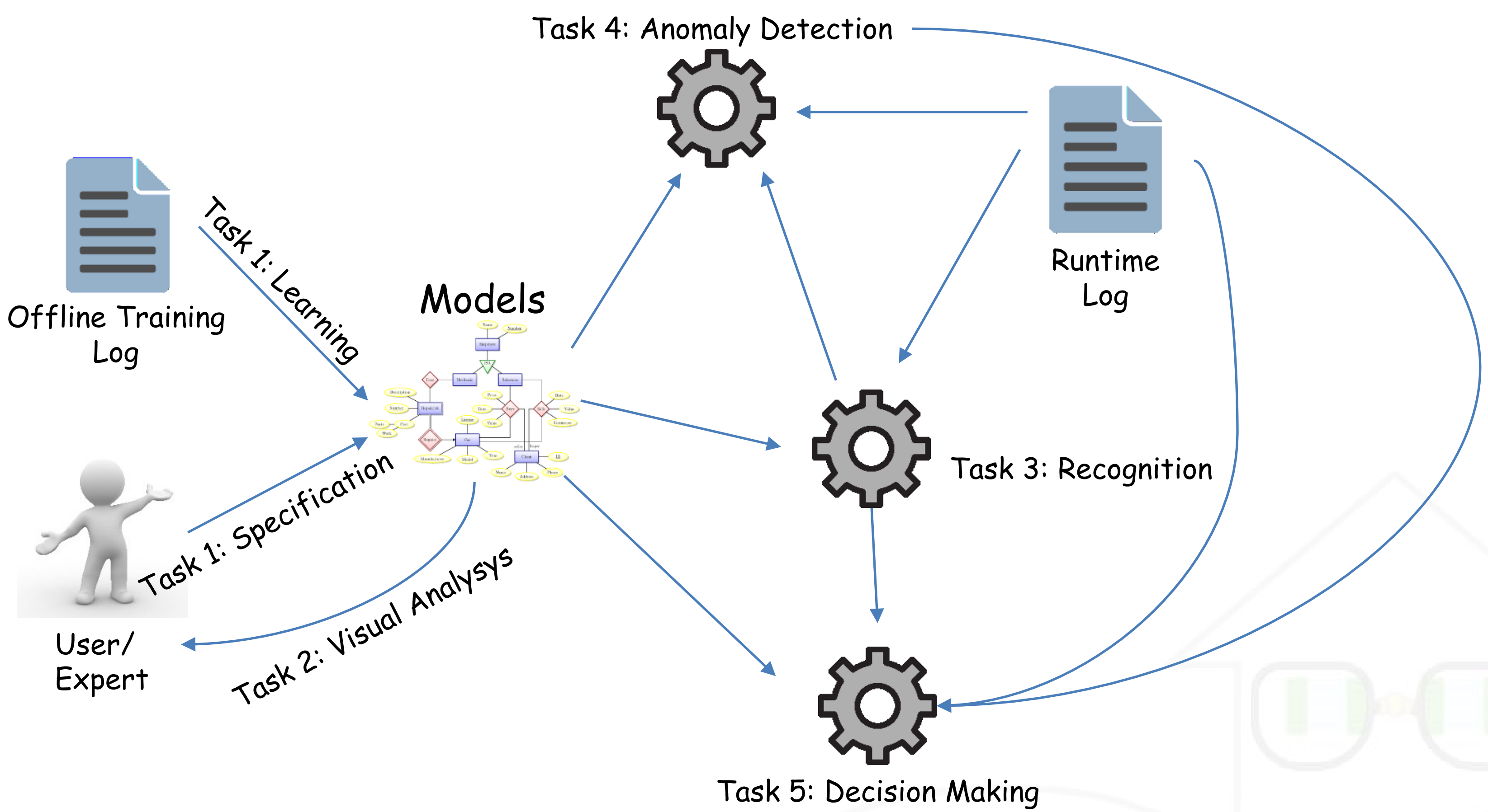
# Model Lifecycle (1)

1. Specification/Learning
   - The task of manually defining or learning a model from data
   - **The specific learning technique has a huge impact on the following tasks**
2. Visual Analysis
   - The task of inspecting models to understand main characteristics of human life
   - **It requires an high level of details of the model**
   - Helpful to:
     - understand problems (e.g., for elderly)
     - better design the environment

# Model Lifecycle (2)

3. Recognition
   - The task of understanding at run-time what is going on by using real-time data
   - **Not all modeling formalisms allow to perform this task**
4. Anomaly Detection
   - The task of detecting if anything strange is happening with respect to the model
   - Produce Alarms
   - **Triggers Model Enhancement**
     - Manual
     - Runtime Learning
5. Decision Making
   - **Help human users and or soft bots to act according to their activities/habits/preferences**

# Lifecycle Pipeline



# LEARNING BASED METHODS

# Bayes Theorem based (1/2)

- Bayes Rule $P(H|X) = \frac{P(X|H)P(H)}{P(X)}$
  - H is our hypotheses
    - i.e., the user is performing a specific activity/habit
  - X is our evidence
    - i.e., the variables representing the current context
  - Inpractical to compute P(X|H)
- **Bayesian derivatives usually allows for learning and recognition**
- Naive Bayes (method) supposes variables in X to be independent given H
  - Widely used in Ambient Intelligence
  - Supervised method

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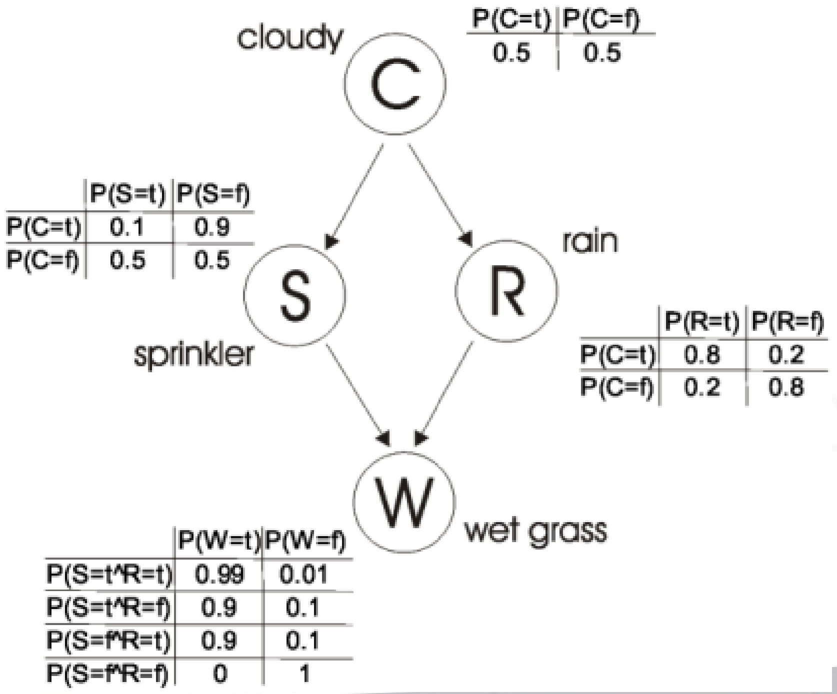
# Bayes Theorem based (2/2)

- Dependencies between variables are sometimes known → Bayesian Network
  - Difficult to compute
  - An interesting version is Dynamic Bayesian Network (DBN)
    - Introduce the notion of temporal evolution

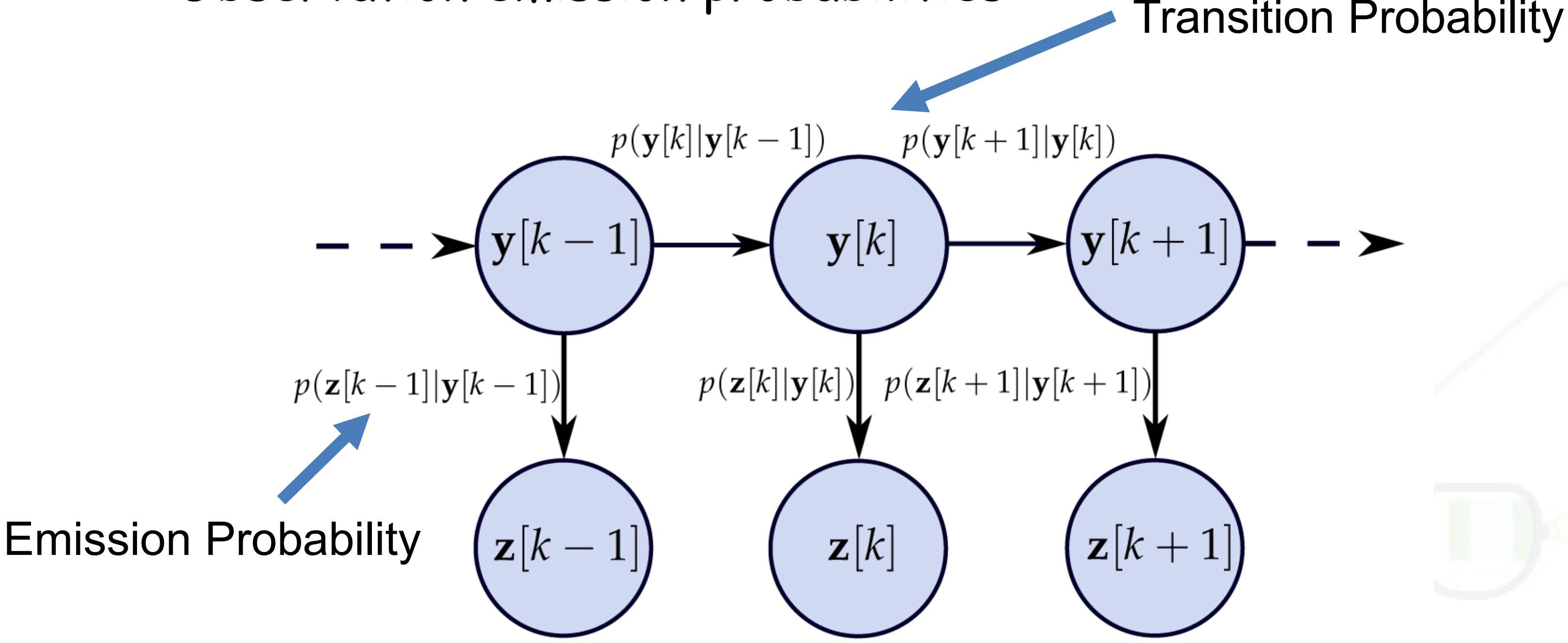


# Hidden Markov Models (1)

- Frequently employed for learning and recognition
- Hidden Markov Models (HMMs) are DBNs where the system being modeled is assumed to be a Markov chain that is a sequence of events
- *A* HMM is composed of a finite set of hidden states (e.g., s(t−1), s(t), and s(t+1)) and observations (e.g., o(t−1), o(t), and o(t+1)) that are generated from states

# Hidden Markov Models (2)

- Three types of probability distributions
  - Prior probabilities over initial state
  - State transition probabilities
  - Observation emission probabilities



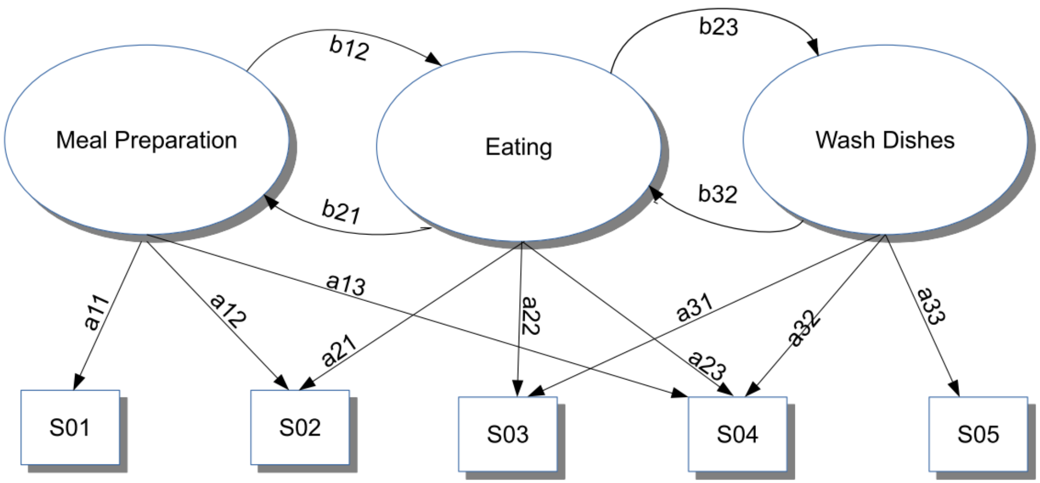

Hidden Markov Model

# Hidden Markov Models (3)

- HMM is built on three assumptions:
  - Each state depends only on its immediate predecessor
  - Each observation variable only depends on the current state
  - Observations are independent each other
- Supervised Learning
- Unsupervised Learning through Baum-Welch or Viterbi Algorithm

!!! Discovered hidden states are meaningless without manual labeling !!!

# Hidden Markov Models (4)



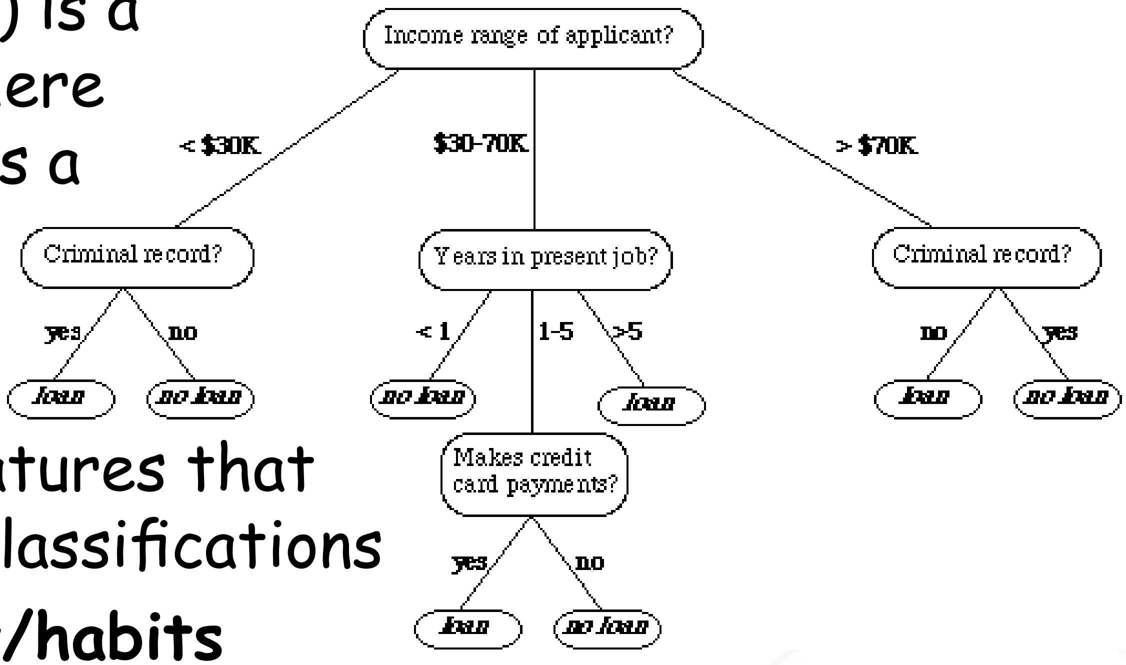

- States are activities/habits
- Observations are considered independent given the state
- Possibility for hierarchical models
  - **Also allowing for visual analysis**

# Conditional Random Fields

- Used to recognize frequent observation sequences
- Can be considered a generalization of HMM
  - Probabilities of emissions and transitions are not constant
  - Probabilities depend on the current subsequence of hidden states given previous emissions

# Decision Trees

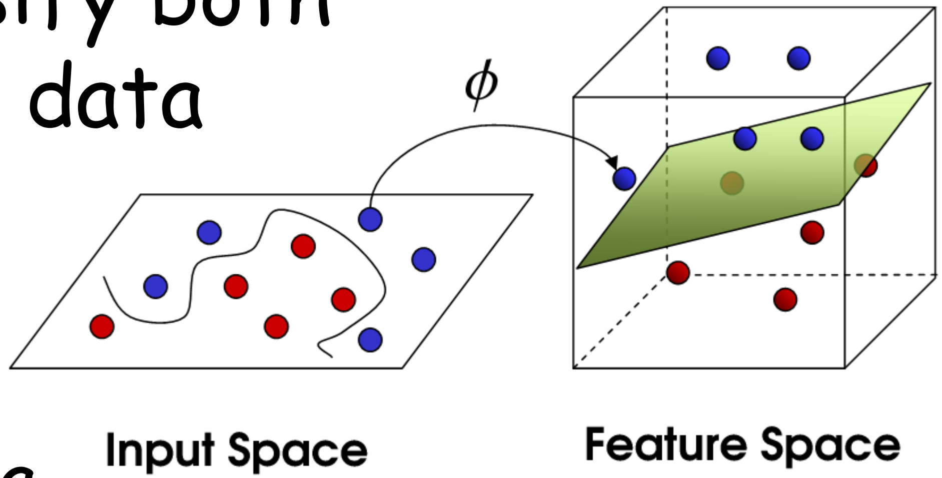
- A decision tree (DT) is a predictive model where each leaf represents a classification and each branch represents a conjunction of features that lead to the target classifications




- **Leaves are activity/habits**
- Supervised Learning methods
- **Not taking into account temporal evolution**
- Useful for modeling and recognition in static conditions

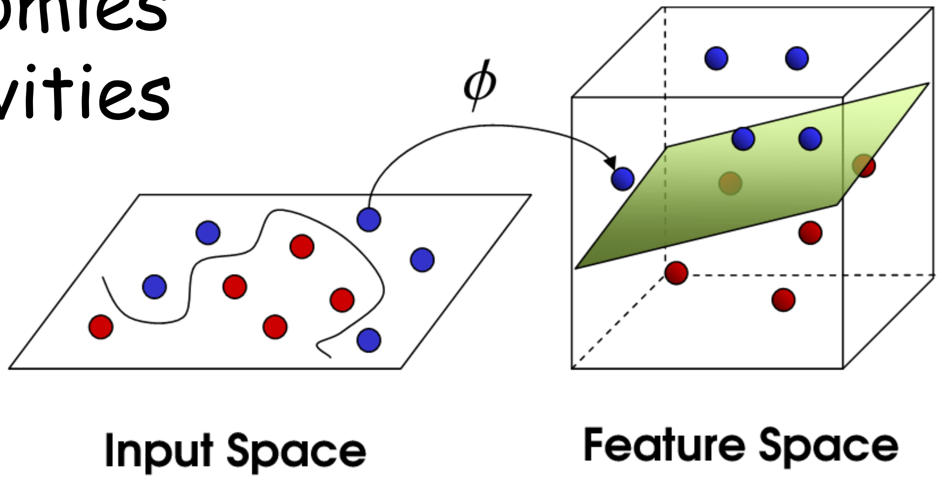
# Support Vector Machines (1)

- SVMs allow to classify both linear and nonlinear data
  - A SVM uses a nonlinear mapping to transform the original training data into a higher dimension
  - Within this new dimension, it searches for the linear optimal separating hyperplane that separates the training data of one class the other one



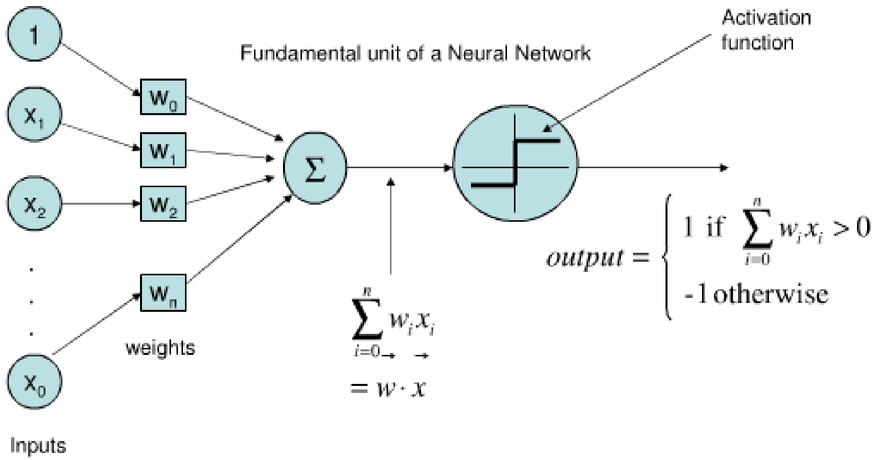
# Support Vector Machines (2)

- Supervised binary classification
  - This activity or another
- Combined with other learning techniques
  - E.g., Learning taxonomies (e.g., these two activities are not compatible)



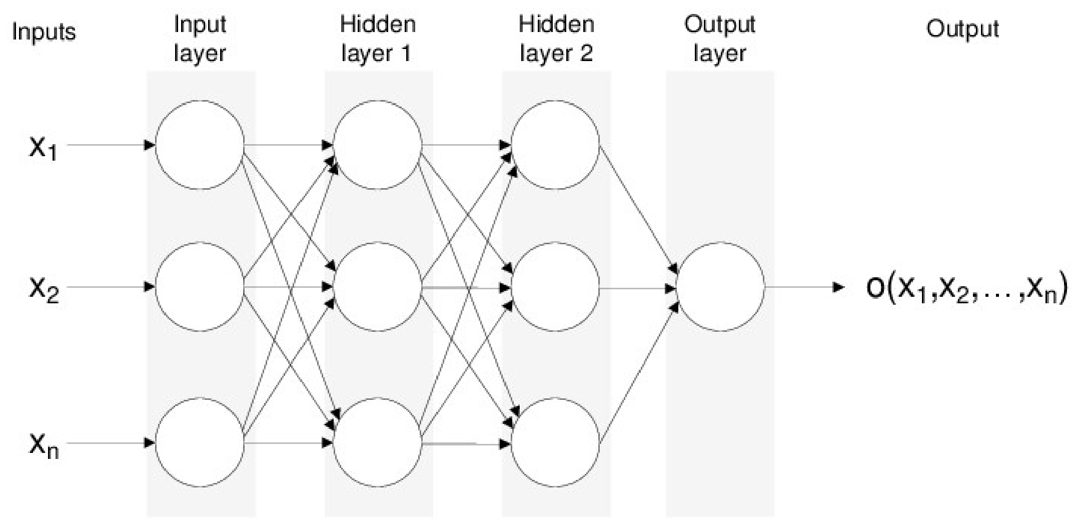
# ANN – Artificial Neural Networks (1)

- In an ANN, simple artificial nodes, known as "neurons", "processing elements" or "units", are connected together
  - Originally inspired by biological neuron networks
  - They can automatically learn complex mappings and extract a non-linear combination of features



# ANN – Artificial Neural Networks (2)

- When to use them
  - Input is high-dimensional discrete or real-valued (e.g. raw sensor input)
  - Output is discrete or real valued
  - Output is a vector of values
  - Possibly noisy data
  - Form of target function is unknown
  - Human readability of result is unimportant
  - **A lot of training data required**
  - **Curse of overfitting (i.e., models do not easily generalize)**
  - **Potentially useful to extract feature vectors for other learning methos**



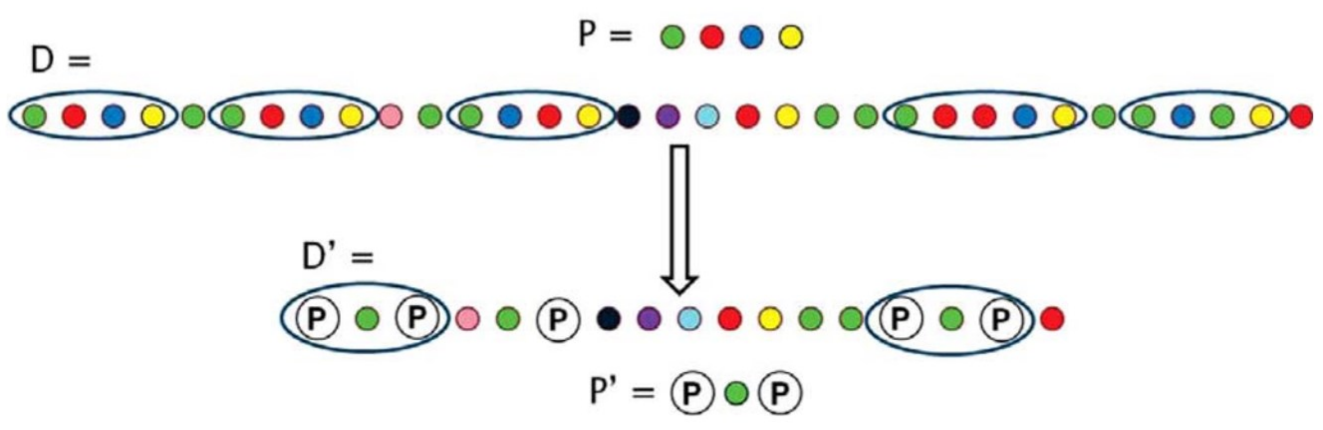
# Pattern Mining

- Approaches related to pattern analysis in data mining take as input an event log and extract patterns of events obtained by windowing
- e.g., CASAS project employs a pattern mining technique to discover human activity patterns
  Allows to discover discontinuous patterns and variations
  - **Unsupervised learning**
  - **Used for labeling unlabeled activities…**
  - **…then HMM, CRF, SVM can be used**

# CASAS Pattern Mining Approach

- Based on a compression mechanism
  - A sequence pattern (P) is identified and used to compress the data set
  - A new best pattern (pattern P) is found in the next iteration of the algorithm

$$Compression = \frac{DL(D)}{DL(P) + DL(D|P)}$$



# Emerging Patterns - EPs

- Are patterns of events that strongly characterize an activity or habit
- Given two databases of transactions T1 and T2
  - A transaction is a combination of variable assignments where all the variables are assigned
  - T1 is a set of transactions valid for a specific activity
  - T2 is a set of transactions from contrasting classes
- An itemset is an EP if its support in T1 wrt its support in T2 is high
  - The ratio is referred to as *growth rate*
- Usually supervised learning

# Event Condition Action - ECA Rules

- Initially a specification-based method
- Can be compared to decision making in AI agents
  - Reflex agents with state take as input the current state of the world and a set of Condition-Action rules to choose the action to be performed
- An Event Condition Action - ECA rule basically has the form "ON event IF condition THEN action", where conditions can take into account time
  - E.g.,

```
ON occurs ( Shower , Off , t0 )
IF context (BathroomHumidityLevel (>, 75))
THEN do (On, BathroomFan , t) when t = t0 + 10s
```

- **Unsupervised learning**
- **Mainly useful for decision making and analysis**

# SPECIFICATION BASED METHODS

# Prolog Based

Prolog is a logic based programming language mainly used in AI

- The "in-situation" operator captures a common form of reasoning in context-aware applications
  - *To ask if an entity E is in a given situation S (denoted as S*>E)*
- Recognizing the in_meeting_now situation

```
if in_meeting_now(E) then
    with_someone_now(E) ,
    has_entry_for_meeting_in_diary(E) .
if with_someone_now(E) then
    location*(E, L) , people_in_room*(L, N) , N > 1.
if has_entry_for_meeting_in_diary(E) then
    current_time*(T1) ,
    diary*(E, 'meeting', entry(StartTime, Duration)) ,
    within_interval(T1, StartTime, Duration) .
```

- **Reasoning about situations is decoupled from the acquisition procedure of sensor readings**

# Ontology-Based

- Recognizing situations according to an ontology
  - A semantically rich conceptualization of a domai
  - e.g., daily life and activities/habits
- As in PROLOG based, the engineering effort is mainly in constructing the knowledge base (the ontology)
- Recognizing the «sleeping» situation

```
(?user rdf:type socam:Person),
(?user, socam:locatedIn, socam:Bedroom),
(?user, socam:hasPosture, 'LIEDOWN'),
(socam:Bedroom, socam:lightLevel, 'LOW'),
(socam:Bedroom, socam:doorStatus, 'CLOSED')
-> (?user socam:status 'SLEEPING')
```

- **Few approaches try to learn ontologies**
- Ontologies are used either to
  - infer a situation or
  - to assess the validity of the results obtained by statistical techniques (learning based)

# Temporal and Spatial Logics

- Several initiatives employ temporal and spatial logics such as:
  - Allen's Temporal Logic
  - Spatial Calculi
  - Linear Temporal Logic (LTL)
- Helpful to reason about multiple users

# SOTA CONCLUDING REMARKS

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# Wrapping-up SotA

| References | RQ-B1.1 | RQ-B1.2 | RQ-B1.3 |
|---|---|---|---|
| AUG-ECA [9]<br>AUG-APUBS [10] | ECA | H | Action<br>Action |
| CASAS-HMMNBCRF [16] | NB | L | Activity |
| CASAS-DISCOREC [11–13]<br>CASAS-HMM [14]<br>CASAS-HMMNBCRF [16]<br>KROS-CRF [24]<br>REIG-SITUATION [25]<br>LES-PHI [31]<br>BUE-WISPS [32] | HMM | M | Activity<br>Activity<br>Activity<br>Activity<br>Situation<br>Activity<br>Activity |
| CASAS-HAM [15] | MC | M | Event |
| CASAS-HMMNBCRF [16]<br>KROS-CRF [24] | CRF | L | Activity<br>Activity |
| REIG-SITUATION [25]<br>STIK-MISVM [27]<br>FLEURY-MCSVM [28] | SVM | L | Situation<br>Activity<br>Activity |
| CHEN-ONT [18]<br>RIB-PROB [20,21]<br>NUG-EVFUS [22] | ONTO | H | Activity<br>Action/Activity<br>Action |
| WANG-EP [19] | EP | L | Action/Activity |
| YANG-NN [26] | ANN | L | Activity |
| PALMES-OBJREL [29] | Other | H | Activity |

For references see the paper Leotta et al. @ MDPI Future Internet 2019 on the USB stick

# Current Limitations/Opportunities (1)

- Several methods require an extensive labeling
  - **Feasible in the lab but more difficult in real settings**
  - **Human in the loop approach must be followed (e.g., NEST Thermostat)**
  - **Merge Specification and Learning based approaches**
  - If not labeling, at least segmentation
- ***In several cases, the recognition is performed, but it is coarse-grained***
  - To help the user throughout the pipeline (cf. step 5 in slide 19) is very challenging
  - Hierarchical models can be helpful

**Labeling**: *full annotation* of activity/habit instances

**Segmentation**: *surrogate* in which *only separation* is performed

# Current Limitations/Opportunities (2)

- The problem of multiple users is usually addressed only if labeling the dataset is possible
  - Not all devices/sensors can be equipped with tags
  - Tags are usually considered invasive by users
  - **Few papers so far addressing non-invasive sensors and/or without prelabeling**
- Visual analysis of human habits and activity is usually difficult
  - It may help to design better smart spaces

# An Idea: BPM?

- Business Process Management - BPM can be helpful at modeling human habits and activities
  - **Due to the different application contexts, challenges must be addressed**
- Few approaches using workflows already proposed but they do not leverage the strong and recent research in process mining
  - **BPM in IoT is now a hot trend**
- Great benefits from the point of view of visual analysis
- Grounded in logics, potentially a trade-off between specification-based and learning-based approaches

Aztiria, A.; Izaguirre, A.; Basagoiti, R.; Augusto, J.C.; Cook, D. Automatic modeling of frequent user behaviours in intelligent environments. In Proc. Intelligent Environments 2010.