SAPIENZA
UNIVERSITÀ DI ROMA

Ambient Intelligence (Part 1)

PhD Course on Smart Environments: Technologies, state of the art and research challenges

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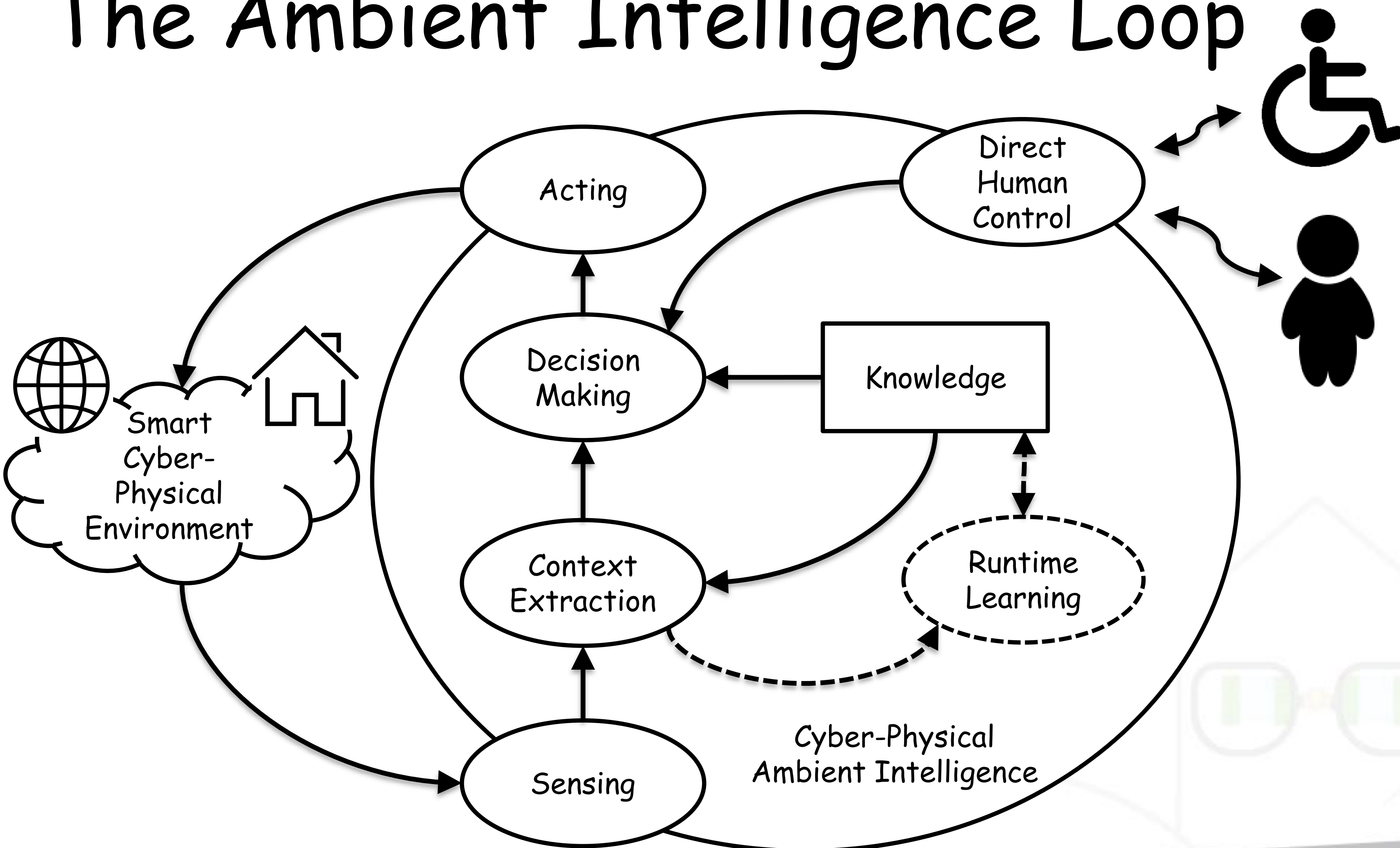
Smart Spaces

- "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

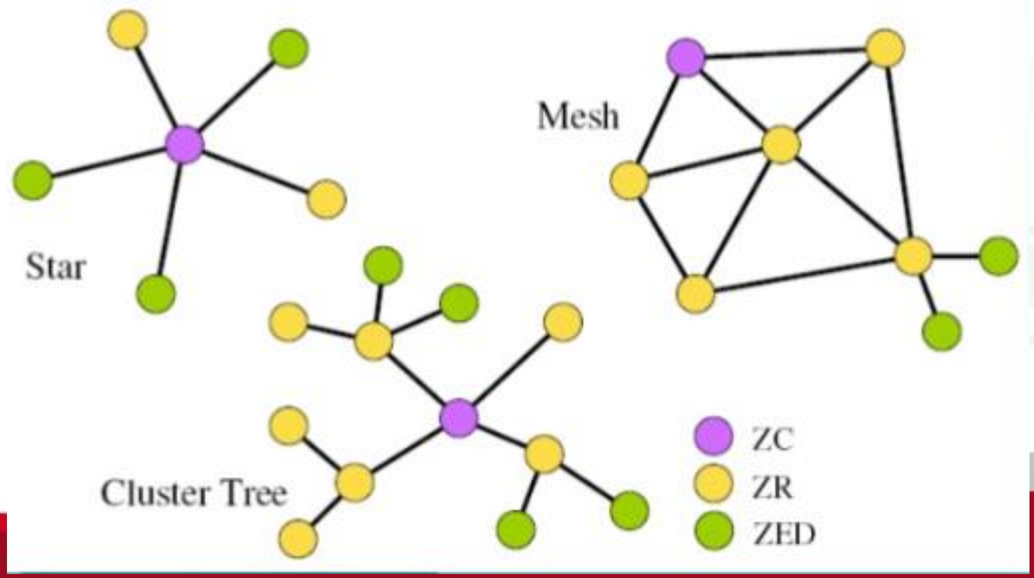
Communication Technologies

- Power Line Communication (PLC)
  - Home power network employed to carry data together with power by modulation
  - X10 is the oldest protocol in this category
  - Technique employed in commercial solution (e.g., BTicino MyHome)
- Reserved wired solutions
- **Wi-Fi**, Bluetooth, **Zigbee**, Zwave

ZigBee Technology

- A suite of communication protocol intended to be cheaper than BlueTooth
  - ZigBee code is 10% of BlueTooth code
  - Low energy → Ideal for battery powered devices
  - IEEE 802.15.4
  - Different topologies supported
  - Max data rate (@2.4GHz) 256kbps

ZC – ZigBee Coordinator
ZR – ZigBee Router
ZEE – ZigBee End Device



Examples of Zigbee enabled sensors and actuators

Smart Plugs

LED Lights

Wall Switches

Temperature/Humidity Sensors

Contact Sensors

Presence Sensors

Current/Voltage Meters

Thermostatic Valve

ZigBee vs Z-Wave

- Both cheaper than BlueTooth
- ZigBee is an open protocol, Z-Wave is proprietary of Silicon Labs
- ZigBee covers up to 15 meters (2.4GHz band), Z-Wave covers up to 30 meters (900MHz)
  - Less hub nodes required
- ZigBee supports energy harvesting

WiFi Devices

- Bigger households (e.g., oven, fridges) do not need to save energy → Wifi can be used
- Home Connect is nowadays the standard interface for intelligent households
  – Replaced DPWS – Device Profile for Web Services, which is still used in routers

Hubs and Interfaces

- Philips Hue Bridge, SmartThings Hub
- Amazon Alexa, Google Home, Apple Home
  - Integrate wireless devices
    - via Zigbee protocol, if the device is a Zigbee hub (usually a ZC)
      - E.g., Amazon Echo Plus but not Amazon Echo Dot
    - via Wifi
  - Integrate online data
  - Provide Natural User Interface (e.g., voice)
- Few hubs allows to access low level data ☹

Rule Definition Frameworks

- IFTTT – If-This-Then-That
  - A web service allowing to define simple condition chains called **applets**
  - Chains can be defined using the web interface, ore graphical languages like blocky
  - Born to combine digital services (e.g., send an email when something happen)
  - Integrated with Alexa, Google and Apple HomeKit
  - Also integrated with Home Connect and SmartThings
- Stringify
  - Allow more complex conditions than IFTTT ☺
  - Much less supported then IFTTT ☹
- Yonomi
  - Allow more complex conditions than IFTTT ☺
  - Many devices supported
  - Integrated with Alexa
- Apple Home Hub
  - Proprietary solution from Apple

AmI vs Building Automation

- Building Automation is a sector born back in the 70s
- Different evolutions throughout years
- Rule definition frameworks represent their latest evolution
- **AmI intelligence results from the application of artificial intelligence and machine learning to building automation**
  - Models can support complex reasoning
  - Models can be automatically learnt and updated
  - Human-in-the-loop approaches possible

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

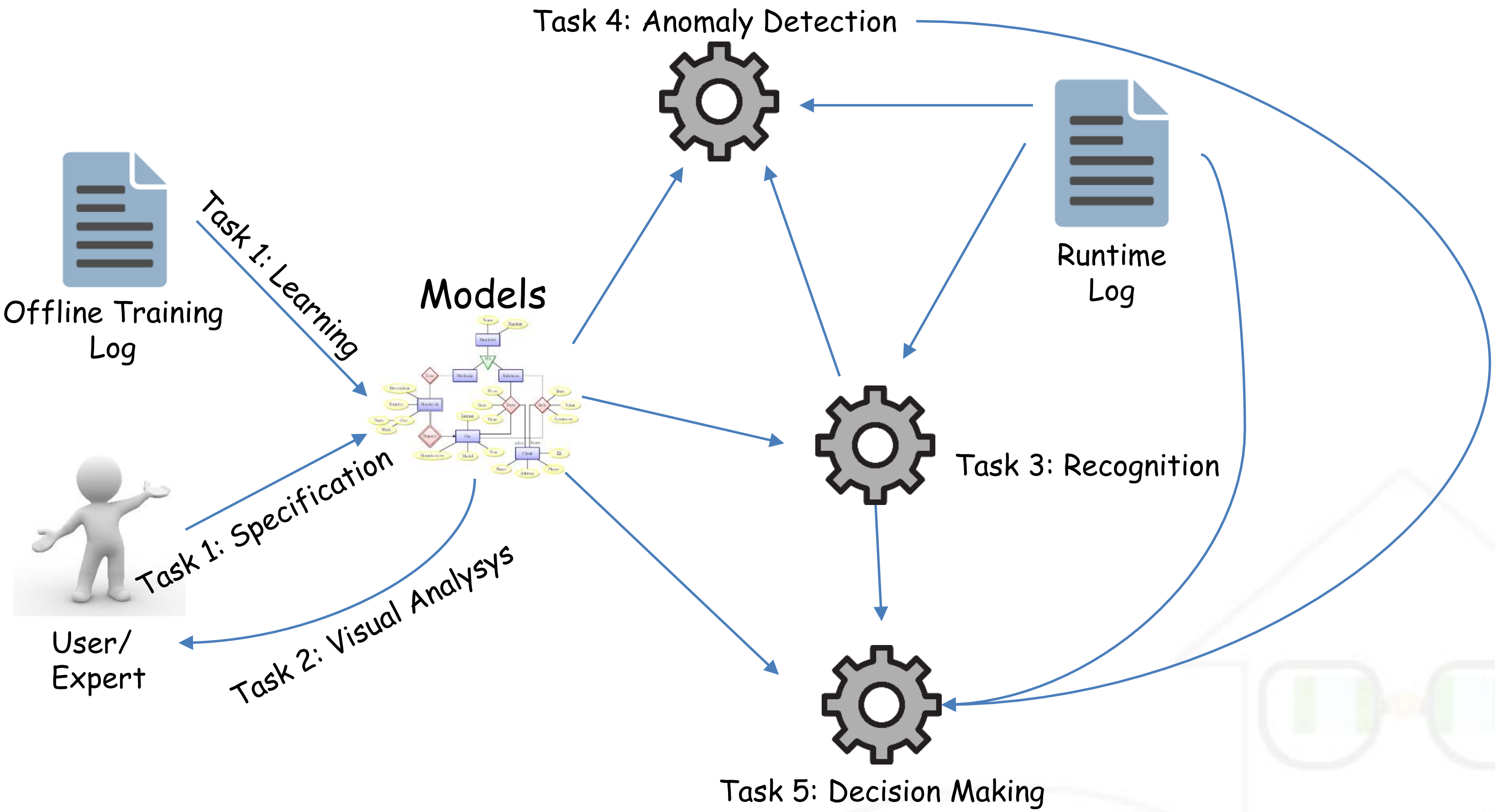
Model Lifecycle (1)

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 and Forecasting
   - The task of understanding at run-time what is going on by using real-time data, and what is going to happen
   - **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



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**

Loke. Logic programming for context-aware pervasive computing: Language support, characterizing situations, and integration with the web. In Proc. of IEEE/WIC/ACM International Conference on Web Intelligence, 2004

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)

Riboni, Sztyler, Civitarese, Stuckenschmidt. Unsupervised recognition of interleaved activities of daily living through ontological and probabilistic reasoning. In Proc. of the ACM International Joint Conference on Pervasive and Ubiquitous Computing, 2016

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

Magherini, Fantechi, Nugent, Vicario. Using temporal logic and model checking in automated recognition of human activities for ambient-assisted living. IEEE Trans. Hum.-Mach. Syst. 2013

LEARNING BASED METHODS

Wrapping-up SotA

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

Leotta, Mecella, Sora, Catarci. Surveying Human Habit Modeling and Mining Techniques in Smart Spaces, Future Internet 2019

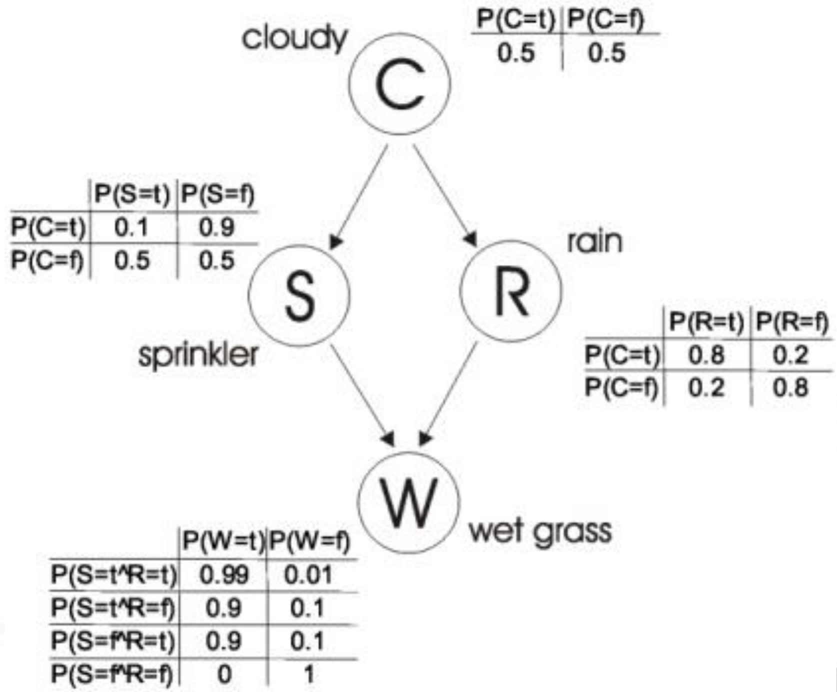
Bayes Theorem based (1/2)

- 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

Cook, D.J. Learning setting-generalized activity models for smart spaces. IEEE Intell. Syst. 2012

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



P(C=t)	P(C=f)
0.5	0.5

	P(S=t)	P(S=f)
P(C=t)	0.1	0.9
P(C=f)	0.5	0.5

	P(R=t)	P(R=f)
P(C=t)	0.8	0.2
P(C=f)	0.2	0.8

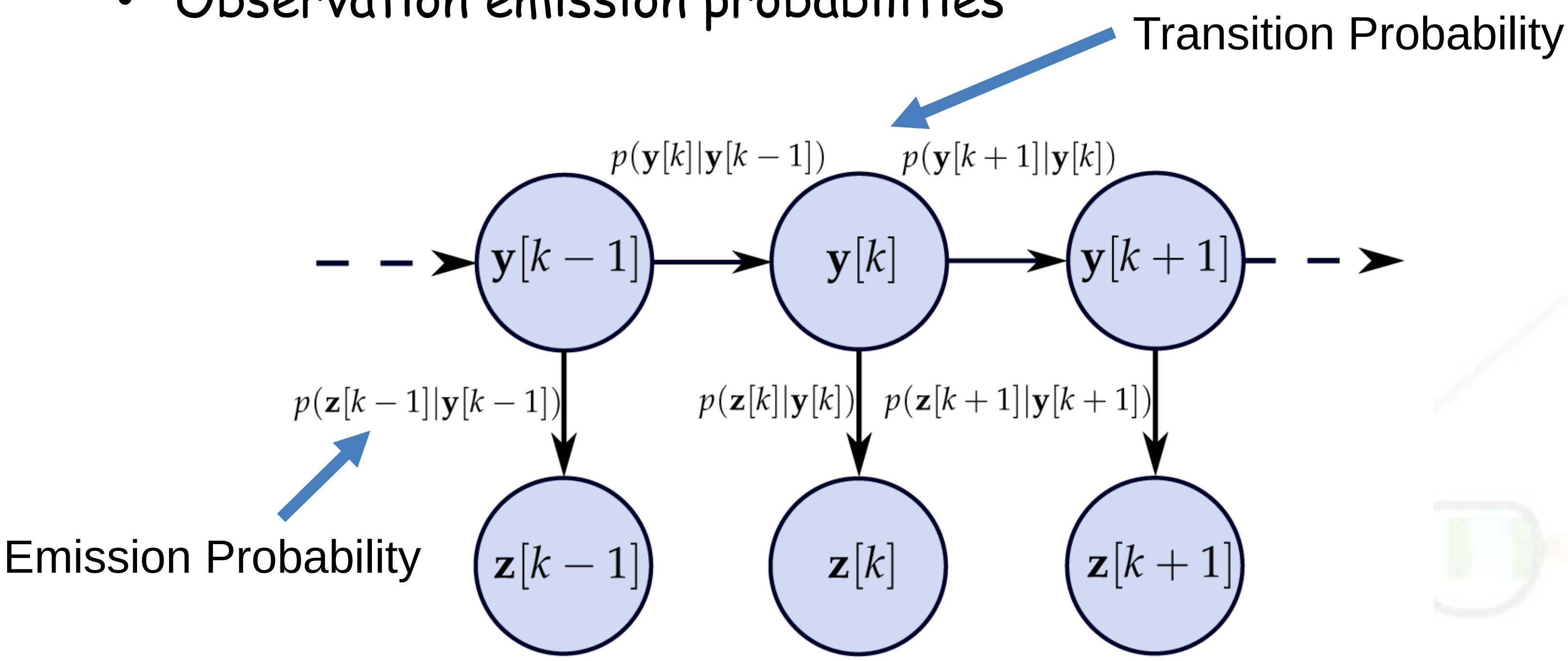
	P(W=t)	P(W=f)
P(S=t^R=t)	0.99	0.01
P(S=t^R=f)	0.9	0.1
P(S=f^R=t)	0.9	0.1
P(S=f^R=f)	0	1

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

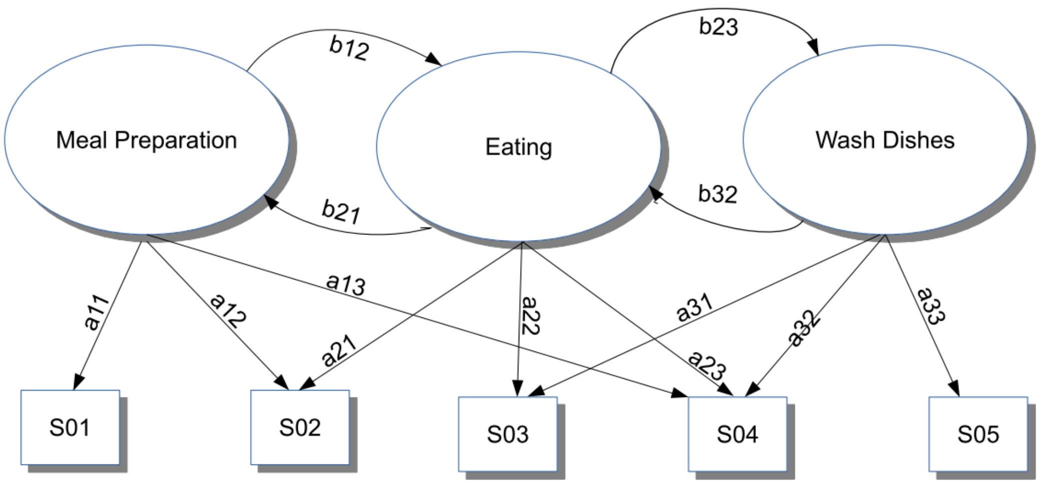
Hidden Markov Models (3)

- 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 !!!

Singla, Cook, Schmitter-Edgecombe. Recognizing independent and joint activities among multiple residents in smart environments. J. Ambient Intell. Human. Comput. 2010
Cook, D.J. Learning setting-generalized activity models for smart spaces. IEEE Intell. Syst. 2012

Hidden Markov Models (4)



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

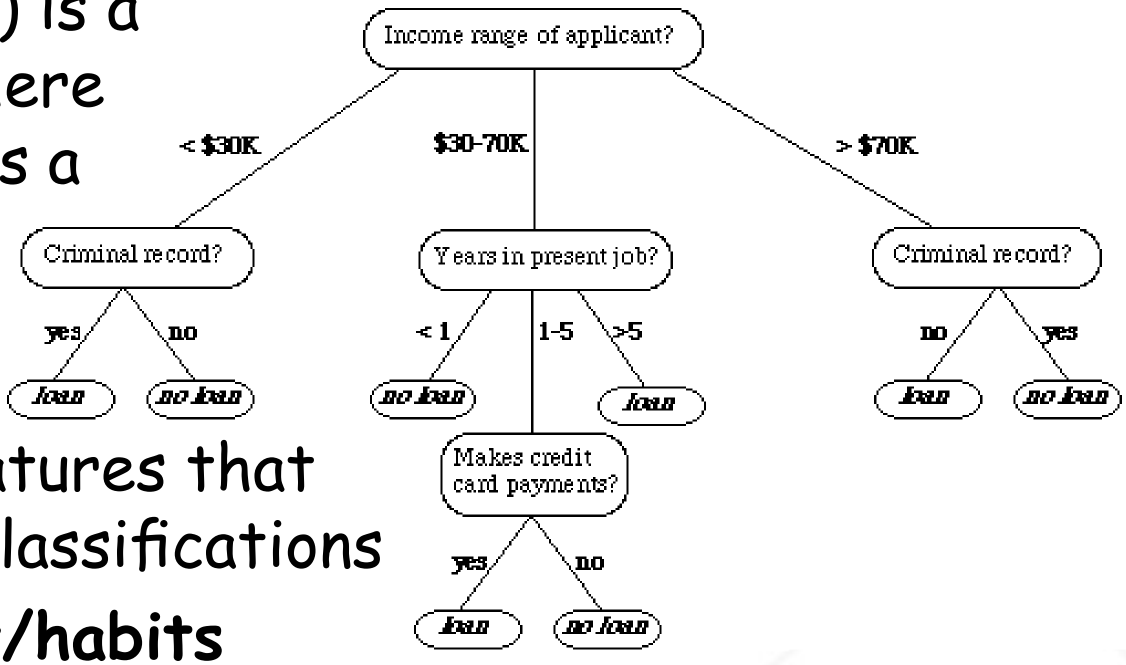
Conditional Random Fields

- 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

Van Kasteren, Noulas, Englebienne, Kröse. Accurate activity recognition in a home setting. In Proc. of the 10th Int. Conference on Ubiquitous computing, 2008
Cook, D.J. Learning setting-generalized activity models for smart spaces. IEEE Intell. Syst. 2012

Decision Trees

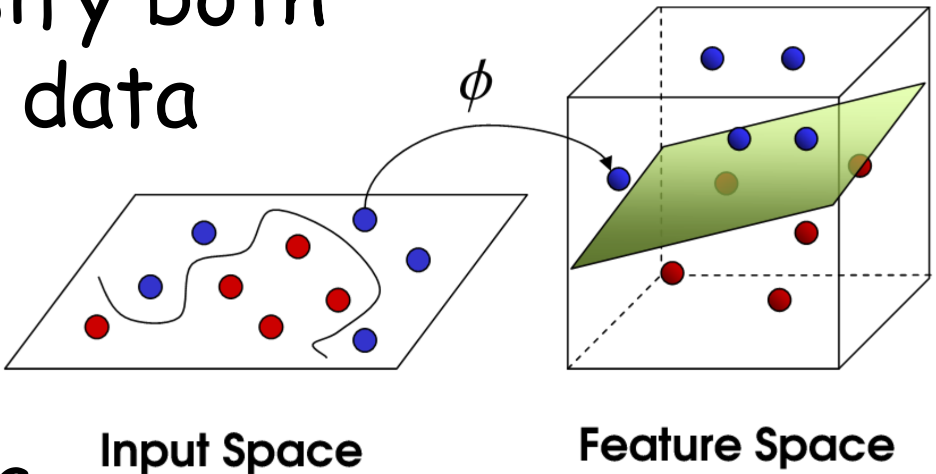
- A decision tree (DT) is a predictive model where each leaf represents a classification and each branch represents a conjunction of features that lead to the target classifications



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

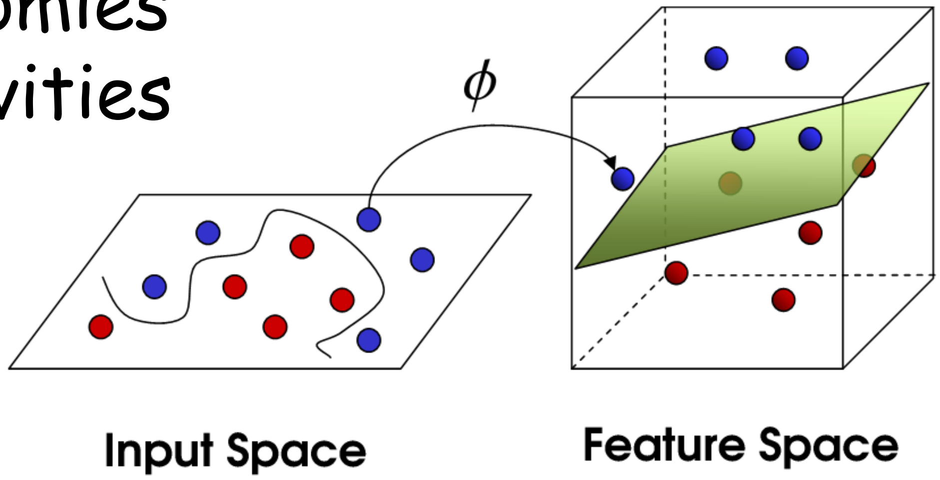
Support Vector Machines (1)

- 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)

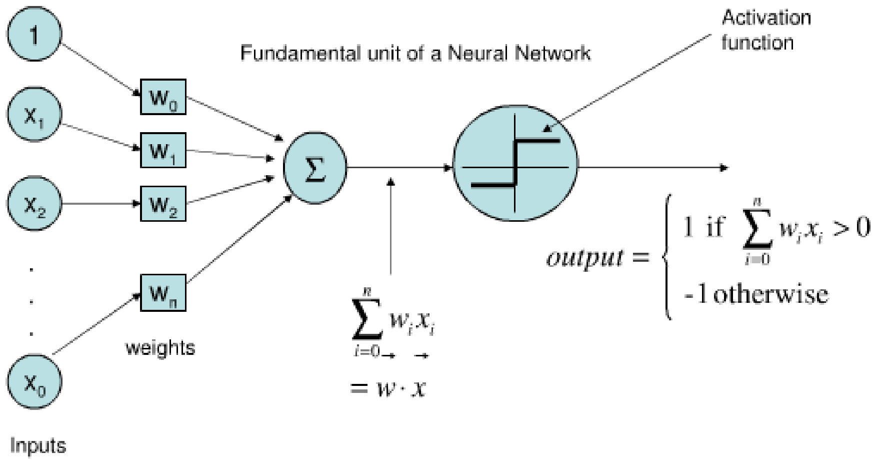
- Supervised binary classification
  - This activity or another
- Combined with other learning techniques
  - E.g., Learning taxonomies (e.g., these two activities are not compatible)



Krishnan, Cook, Activity recognition on streaming sensor data. Pervasive Mob. Comput. 2014

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 methods**