Context Prediction

FTW Tutorial day on “Personalization and context-dependent service enablers”
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Vision: A „Personal Digital Assistant“ that can live up to its name.

Motivation

Problem:

- Most information appliances are difficult to use for non-technology-savy users
- Devices only react to user input

Aim:

- Make information appliances „smarter“ in a sense that they are easier to use
- Devices should be proactive
- Devices should adapt to the user

Problem statement:

How can an information appliance infer its (or its users) current context and predict future context?

Motivating Example

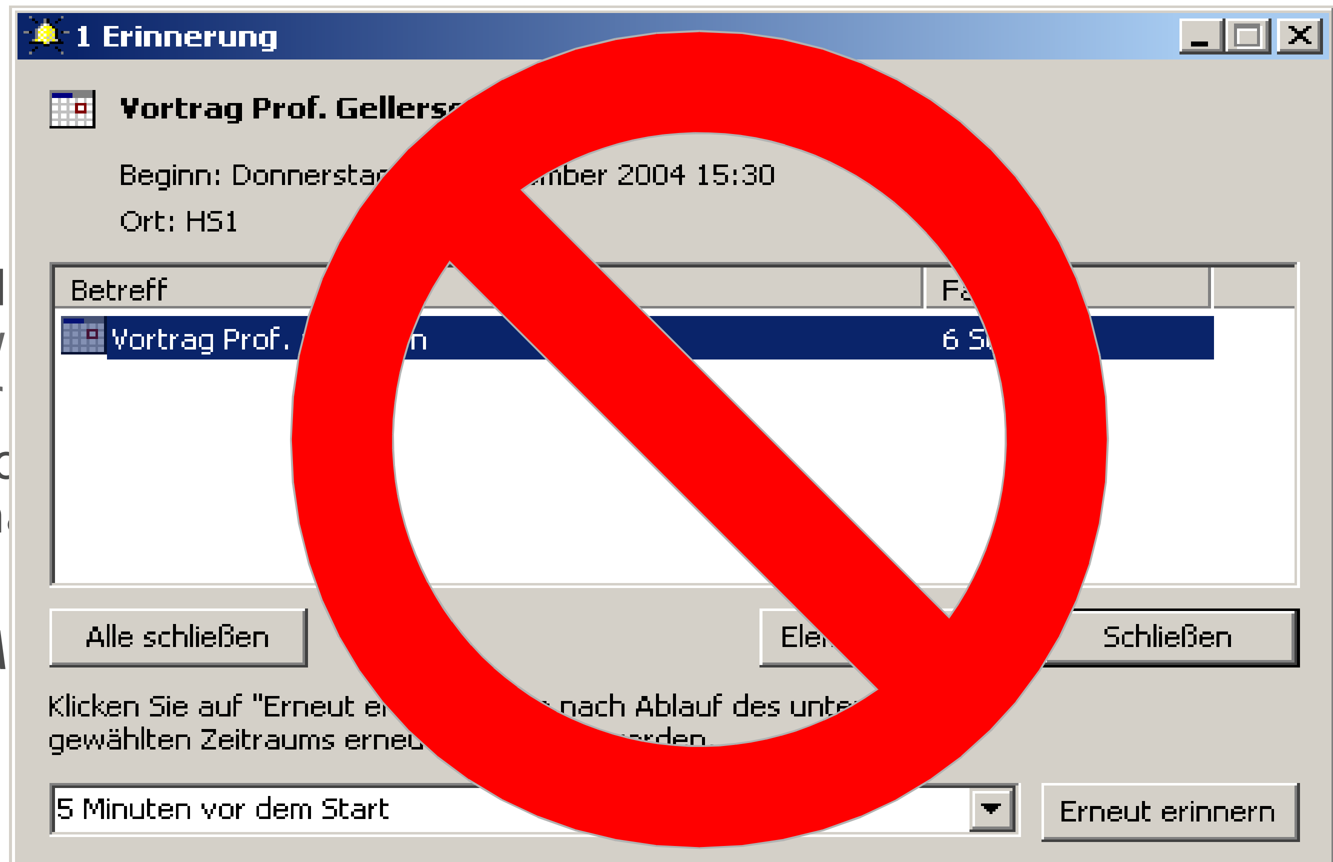
- Reminder to buy milk
- When to deliver: depends …
  - not time/location specific
- How to deliver: depends …
  - appropriate modality

Problem area

What is *Context*?

- e.g. Wikiped … es and conditions w … longer utterance or
- In the area c … hich something h

What is *Context A*

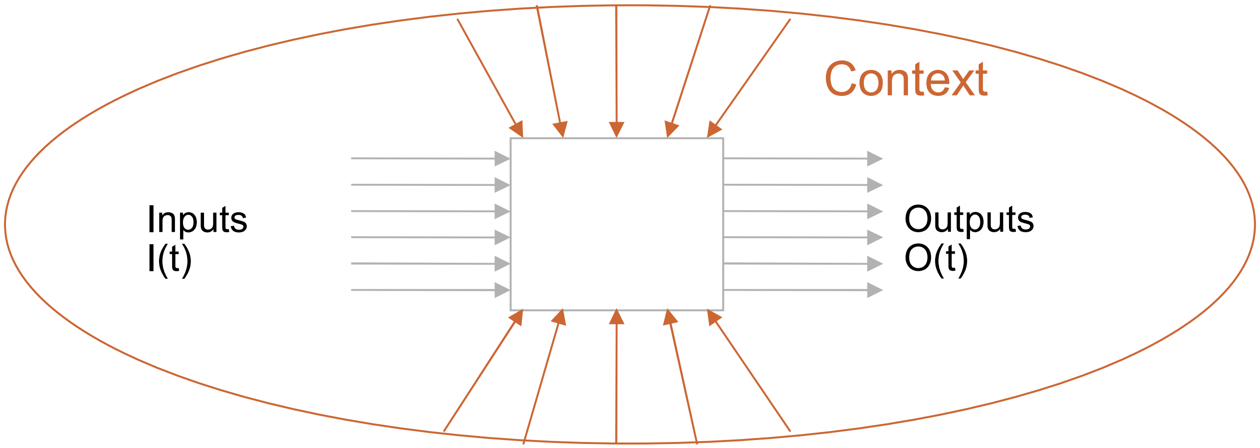


Context Awareness

Many definitions in this sense, e.g..:

- *"Three important aspects of context are: where your are, who you are with, and what resources are nearby […]. Context encompasses more than just the user's location, because other things of interest are also mobile and changing."* [SAW 1994]
- *"any information that can be used to characterize the situation of an entity, where an entity can be a person, place or a physical or computational object"* [Dey 1999]
- A working model for context [Schmidt 2002]

Context is everything **except** the explicit in- and outputs [LS 2000].



[SAW 1994] B.N. Schilit, N. Adams, R. Want: „Context-aware computing applications"
[Schmidt 2002] A. Schmidt: "Ubiquitous Computing – Computing in Context", PhD Thesis, Lancaster Univ.
[Dey 1999] A. Dey, G.D. Abowd, D.Salber: „A Context-based infrastructure for smart environments"
[LS 2000] H. Lieberman, T. Selker: „Out of context: Computer systems that adapt to, and learn from, context"

Context Awareness (2)

Context has a vast multitude of different aspects, e.g.

- time
- location
- physical (temperature, humidity, etc.)
- social (with colleagues / family etc.)

⇒ It seems sensible to use multiple small sensors instead of a single, but more powerful one (cf. Gellersen et.al.)

What is and what isn’t context?

- You, as end user or designer, decide:
  Application dependent and situation-specific

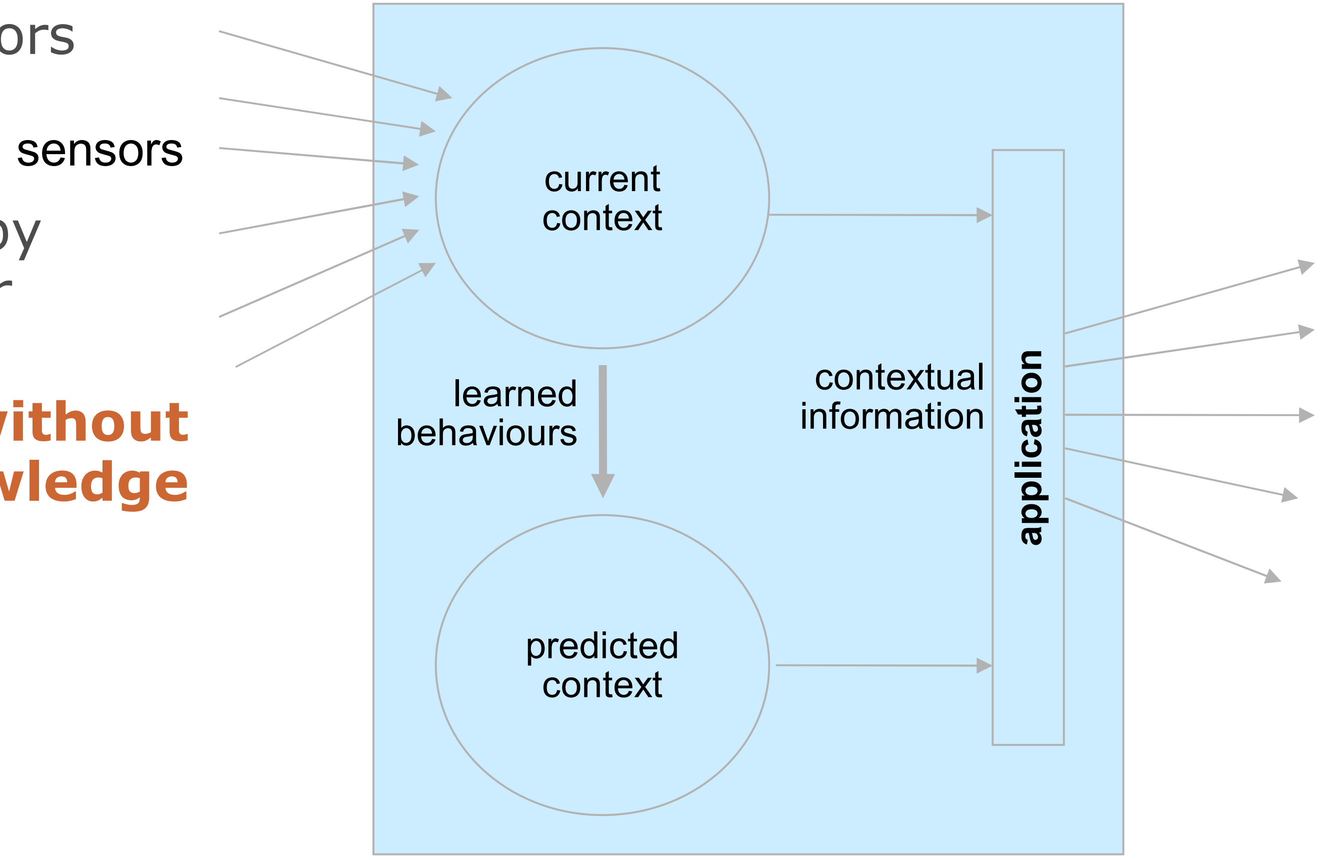
... based on real-world, noisy, and incomplete data

- Domain-specific knowledge helps, but modeling the world is hard!

⇒ How much context can we infer using data-driven machine learning approaches?

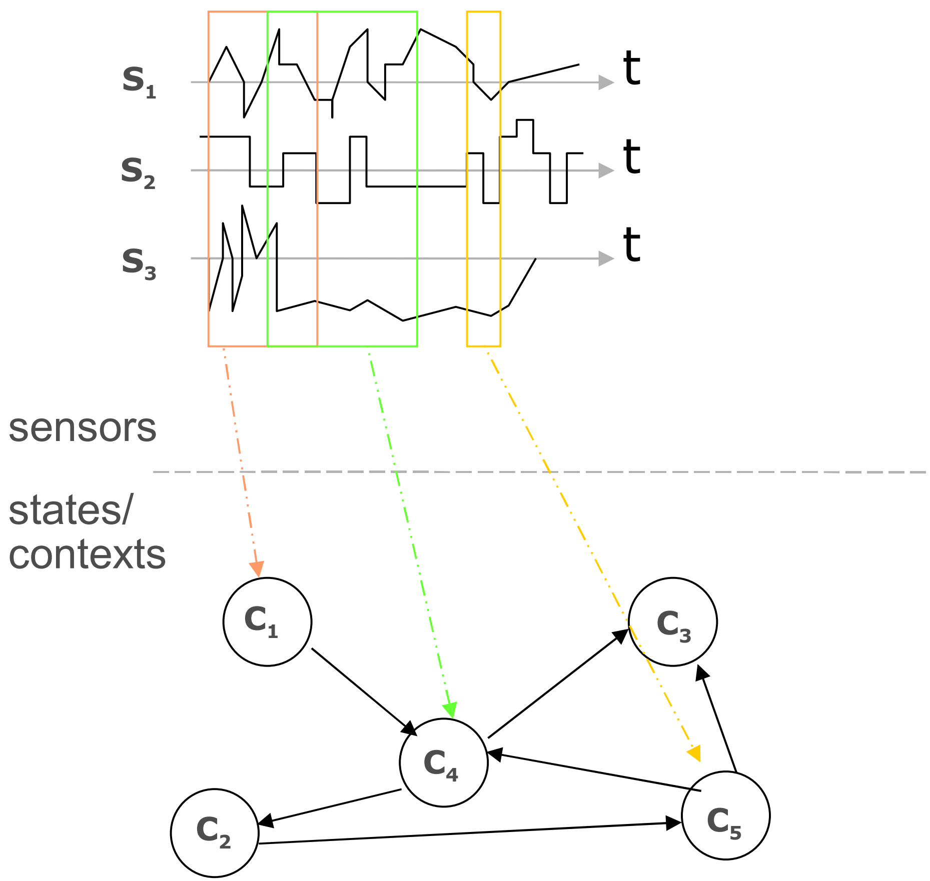
Basic approach to context prediction

- Recognize the current context based on multiple sensors (e.g. [Schmidt 2002])
- Predict future context by learning user behaviour
- ... as far as possible, **without domain specific knowledge**



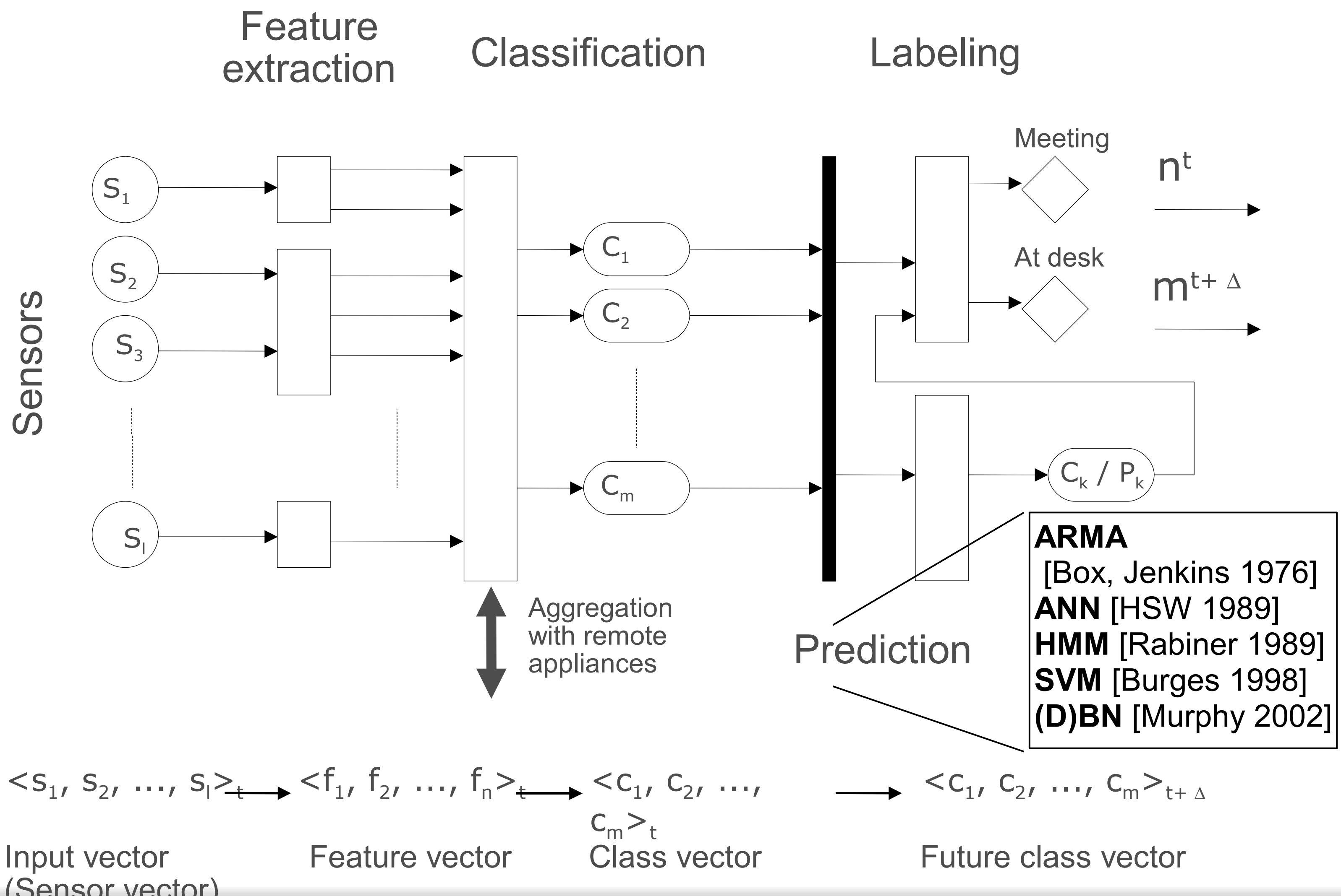
[Schmidt 2002] A. Schmidt: “Ubiquitous Computing – Computing in Context”, PhD Thesis, Lancaster Univ.

Concept



- Sensors yield time series
- Particular patterns in the input streams can be interpreted as the states of a (observable but not controllable) state machine
- These states are understood as the device (or user) contexts
- Then it becomes possible to predict future contexts by extrapolating the state trajectory into the future

Architecture



Step 1: *Sensor data acquisition*

- Sensors yield time series
- Sampled either at regular intervals or based on events
- Examples for currently available “sensors” that can help to determine the current context on a typical mobile off-the-shelf device:
  - time
  - application being used
  - brightness
  - microphone
  - Bluetooth
  - WLAN
  - docked/undocked
- Additional sensors can be connected easily:
  - GPS
  - GSM
  - compass
  - accelerometers
  - tilt sensors
  - temperature sensors
  - pressure sensors, etc.
- Sharing of sensor values between nearby devices

Step 2: *Feature extraction*

- Transforms raw sensor values into more meaningful features
- Applying domain-specific knowledge
- Multiple features can be generated from a single sensor data stream (and vice versa)

⇒ **High dimensional feature space**

- Different types of features:
  - Numerical (continuous): e.g. brightness, heart rate, microphone
  - Numerical (discrete): e.g. number of access points in range
  - Ordinal: e.g. day of week
  - Nominal: e.g. current WLAN SSID, list of WLAN/BT devices in range

- Notice: only two operations are necessary for each feature dimension
  - similarity measure (distance metric)
  - adaptation operator

$$\alpha(f,g,a) : \alpha(f,g,a) := \begin{cases} f & if \quad a \leq 0.5 \\ g & if \quad a > 0.5 \end{cases}$$

[MRF 2003b] R. Mayrhofer, H. Radi, A. Ferscha: „Feature Extraction i
Area Networks“, Proceedings of 6th IFIP MWCN 2003, World Scientil

[MRF 2003b] R. Mayrhofer, H. Radi, A. Ferscha: „Feature Extraction in Wireless Personal and Local Area Networks“, Proceedings of 6th IFIP MWCN 2003, World Scientific, October 2003

Step 3: *Classification*

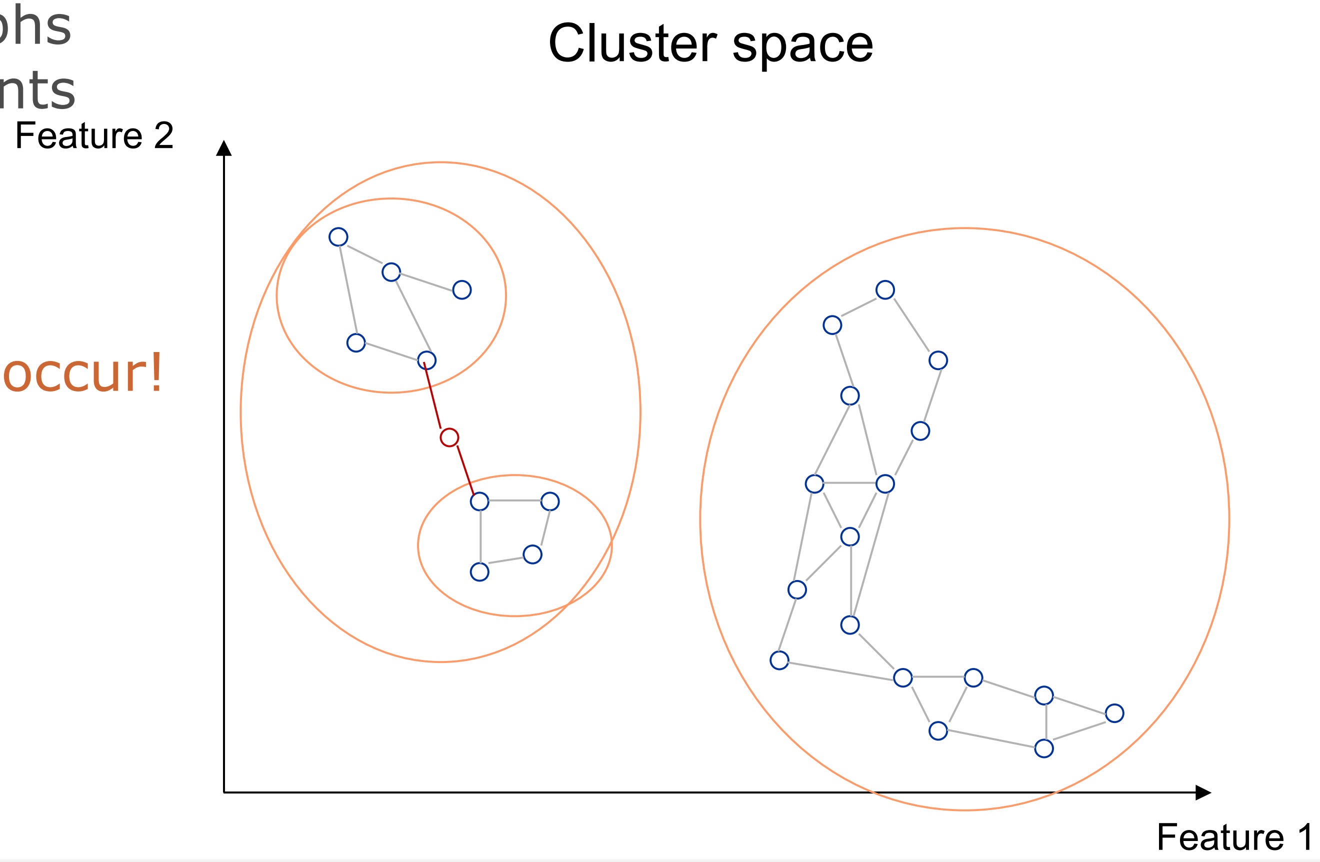
- Classifies features and recognizes common patterns (clusters) in the input data ⇒ possible without user interaction, unobtrusive
- Different types of classification algorithms
  - Type (partitioning / hierarchical)
  - „soft" / „hard" classification
  - supervised / unsupervised
- Requirements on algorithms for context recognition:
  - Online / incremental
  - Adaptive
  - Dynamic number of classes and dynamic structure
  - Finding clusters in sub spaces
  - "Soft" classification
  - Robustness against noise
  - Low resource consumption
  - Simplicity
  - Interpretability of classes / protection of user privacy

Classification: Algorithms

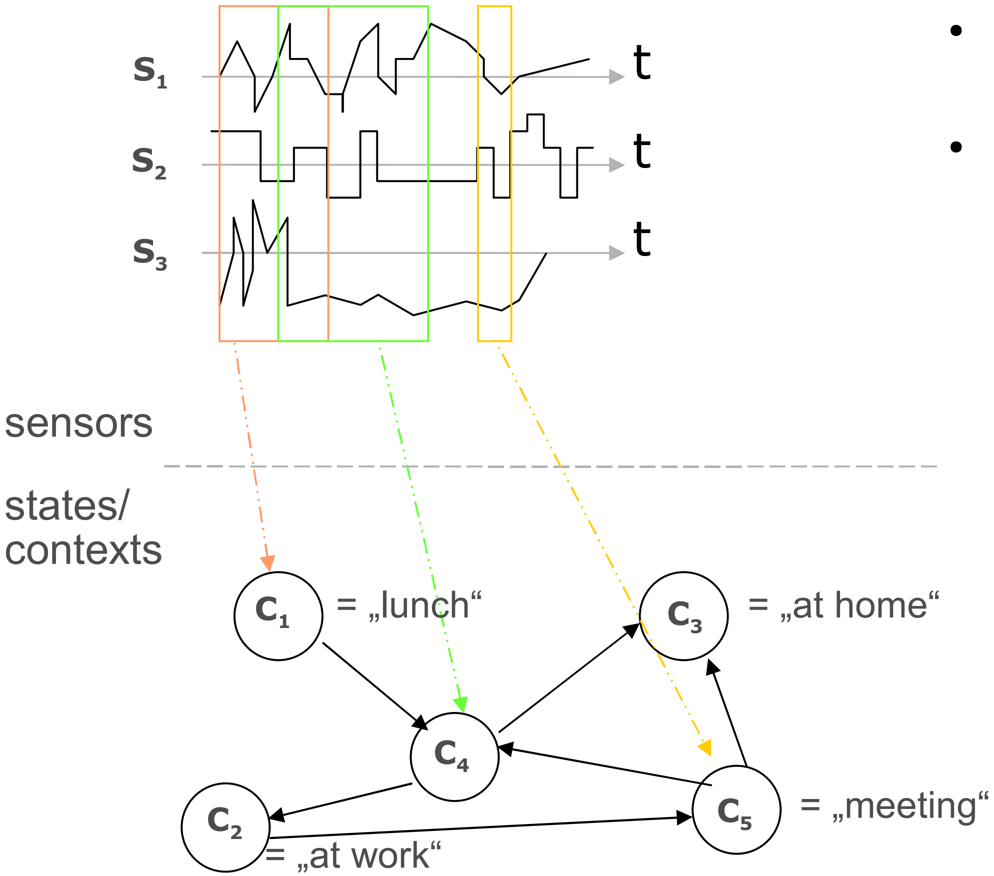
Algorithm	Network topology	Topology preserving	Competitive
SOM [SAT 1999]	fixed	yes	soft
RSOM	fixed	yes	soft
K-Means	fixed	no	hard
Leader	variable	no	hard
Growing K-Means [DWM 2002]	variable	no	hard
Neural Gas	variable	no	soft
Neural Gas + Competitive Hebbian Learning	variable	yes	soft
Growing Neural Gas [Fri 1995]	variable	yes	soft
Incremental DBSCAN [SWX]	variable	No	hard

(LL)GNG: Meta clusters

- Arbitrary shapes in cluster spaces formed by edges between clusters
  ⇒ *Meta-clusters*
- Cyclic, undirected graphs consisting of components
- Each component can be assigned an ID
- But: meta-cluster splits and merges can occur!



Step 4: *Labeling*



- 1:{0,1} mapping of (meta) clusters to context labels
- basically two options:
  - for stable (meta) clusters from classification step: direct mapping of (meta-) cluster ID to labels
  - for significantly varying (meta) clusters (by learning/adaptation): additional, simple clustering step [Lae 2001]

[Lae 2001] K. van Laerhoven and S. Lowette: “Real-time analysis of data from many sensors with neural networks”, Proceedings of ISWC, IEEE Press, October 2001

Step 5: *Prediction*

- Recognized contexts can be interpreted as „states" of a state machine
- Monitoring the state trajectory allows to extrapolate and thus to predict it
- Important aspects of time series prediction:
  - periodical patterns (e.g. week ends, regular meetings)
  - sequential patterns (e.g. travel preparations, preparing a meal)
  - trends (changing behaviours)

- Requirements on algorithms for context prediction:
  - Unsupervised model estimation
  - Online
  - Incremental model growth
  - Confidence estimation
  - Automatic (implicit) feedback
  - Manual (explicit) feedback
  - Long term vs. short term prediction

Options for context prediction

- Based upon the trajectory of context classes
- Advantage over the independent prediction of different feature values: consideration of all aspects of context that are recognized by the available sensors
- Two options:
  - Predict each dimension of the class vector as continuous time series
    ⇒ does not consider relationships between context classes, but allows for overlapped contexts
  - Aggregate all classes to a single, categorical time series *by using the most probably context class at each time step: AACCBCCAAADDDDDDDEEEEEEBBAAAA……..*
    ⇒ implicitly considers relationships between context classes, because they are considered as mutually exclusive

⇒ Flat vs. hierarchical/overlapping **context model**

- Many known methods for time series prediction to select from for a specific application
- Selection is necessary, because the requirements/features of the specific methods are too diverse (there is no “best” method for time series prediction yet)

Prediction: Possible algorithms (1)

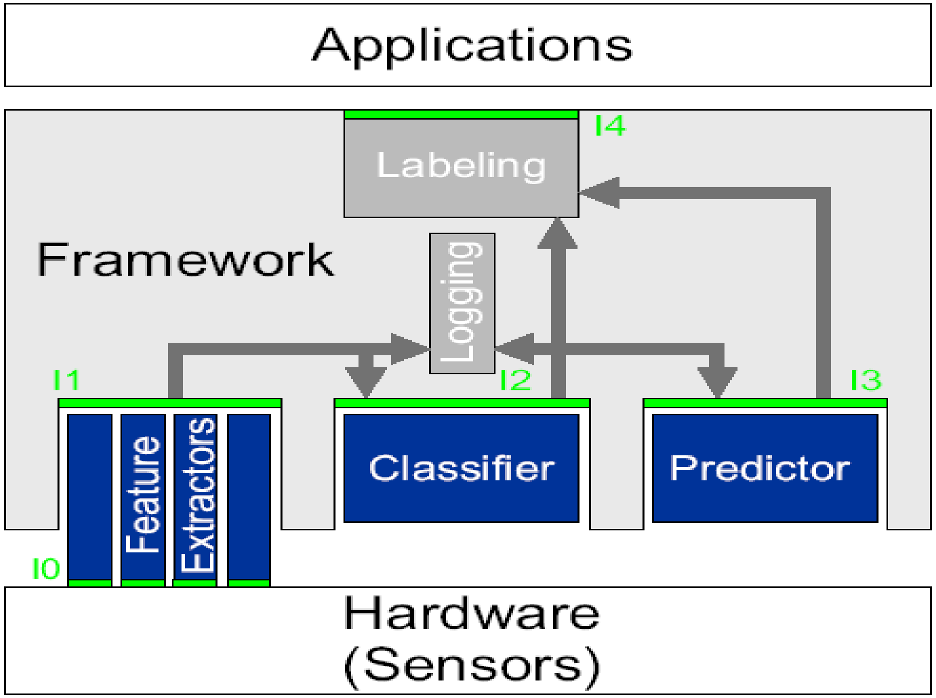
- ARMA: suitable for single-dimension, continuous time series forecast (option 1)
  But: relationship between context classes not regarded
- ANN (e.g. back-propagation MLP): suitable for multi-dimensional, continuous time series forecast
  But: needs known output (supervised learning) and long training time with many samples; no online mode, no incremental model growing, no confidence estimation
- HMM: allows discrete forecast
  But: assumes statistical independence of events, which is definitely not the case for subsequent contexts

Prediction: Possible algorithms (2)

- MavHome project [Das 2002] uses prediction algorithms (currently) for predicting user locations
- Two algorithms for covering both aspects:
  - *Active Lempel-Ziv* for finding and predicting sequential patterns: online / incremental
  - *Episode Discovery (ED)* for identifying events at some regular intervals or in response to other events
- Back propagation ANN for mixing results of both algorithms

[Das 2002] S.K. Das, D.J. Cook, A. Bhattacharya, E. Heiermann, T. Lin: „The role of prediction algorithms in The MavHome smart home environment", IEEE Wireless Communications 9(6)

Implementation as Software Framework



Cross-platform:

- Currently for Win32, Windows CE (>=3.0), Linux IA32 and ARM and (partially) Symbian OS
- Based on modules that are loadable at run-time:
  - Feature extractors (= sensor data acquisition + feature extraction)
  - Classifiers
  - Predictors
- Labeling is realized by providing network transparent interfaces (SOAP) $\Rightarrow$ splitting HCI issues from context recognition/prediction issues
- Designed for resource limited devices

Further Challenges

Taxonomy

- What context is important? When?
- How do you represent context?
- Standards to allow exchange of context?

Real-World Knowledge

- Knowledge about how the world works for advanced reasoning

Interpretation

- Lots of interesting work here
- Most context-awareness deals with simple forms of context
- Sophisticated applications require more sophisticated context
- Machine learning, sensor fusion, modeling uncertainty, etc

Privacy

- Capturing/collecting lots of information about people, places and devices
- Users uncomfortable when they don't know what is being collected and how it's used
- Seemingly harmless information can lead to undesired (and potentially misleading) inferences when combined with other data

QoS

- Context is derived from sensor observation of the world: inherently limited and noisy
  - Coverage, Reliability
  - Resolution, Accuracy, Precision
  - Frequency, Timeliness

Thank you for your attention!

Slides: http://www.mayrhofer.eu.org/presentations
Later questions: rene.mayrhofer@univie.ac.at

OpenPGP key: 0xC3C24BDE
7FE4 0DB5 61EC C645 B2F1 C847 ABB4 8F0D C3C2 4BDE