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Context prediction based on learning user habits: A next step towards "smart" systems

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Guest lecture 1

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Problem area

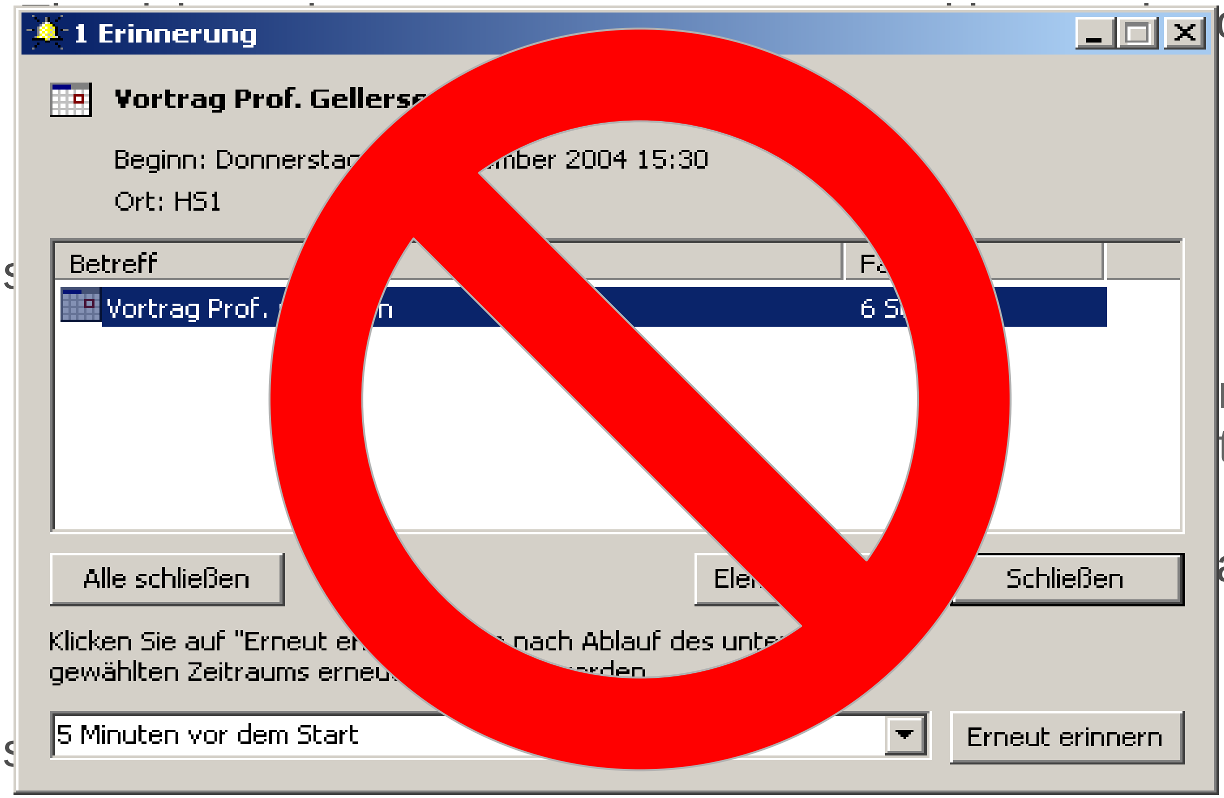
What is *Pervasive Computing*?

- ... objects
-

What is ...

- ... ntext ... the
- ... ation in

What is ...

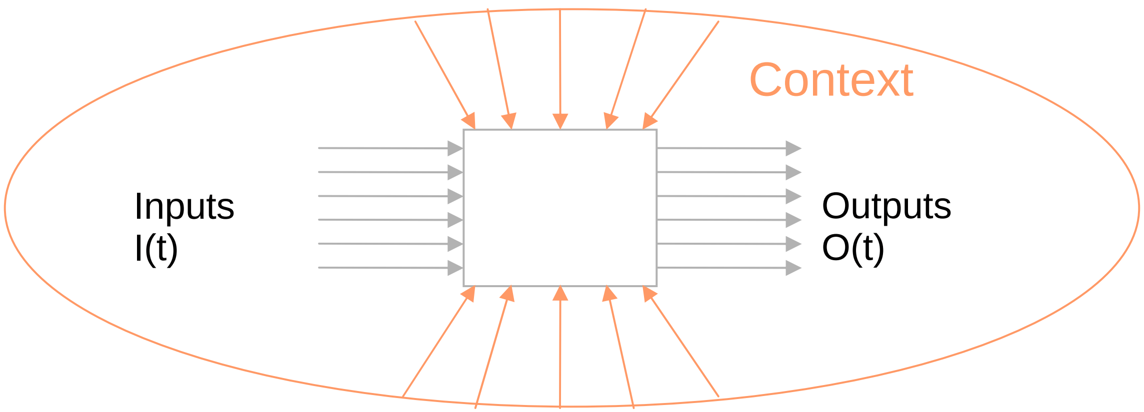


Context Awareness

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].



Problem description of this research:

How can the **current context** of a device or its user be determined autonomously from sensor information and the **future context** be predicted from recorded context histories?

[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.)

Proactivity

Proactive vs. reactive behaviour of a (computer-) systems

- Determines the capabilities of a system to merely react to changes in the environment or to act in advance
- Important feature of software agents
- Here: definition of proactivity based on system states [MRF 2003a]

- The current internal state of a (Moore) state machine depends on the last system state and its current inputs:

$$q_t = \delta(q_{t-1}, a_{t-1})$$

- Reactive system: determine the output depending on the current state

$$b_t = \lambda(q_t)$$

- Proactive system: additional dependency on **predicted** future states

$$b_t = \lambda\langle q_t, \overline{q}_{t+1}, \overline{q}_{t+2}, \ldots, \overline{q}_{t+m} \rangle$$

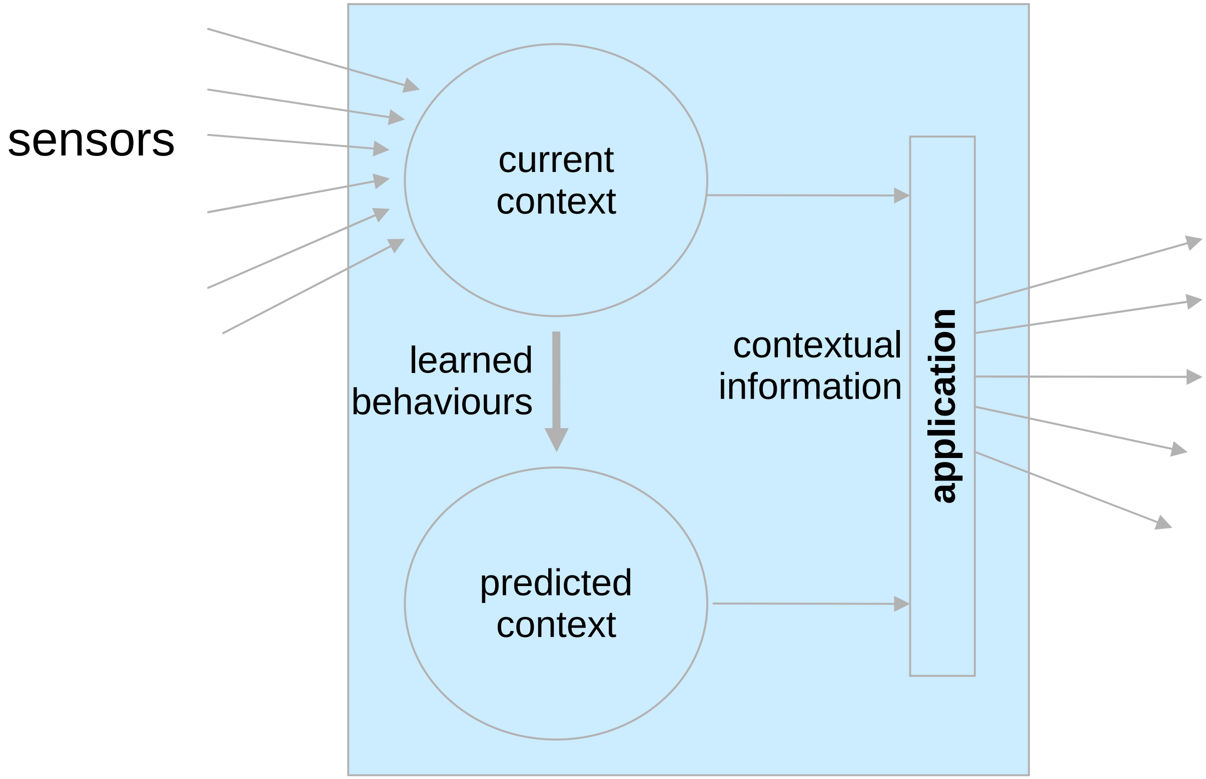
[MRF 2003a] R. Mayrhofer, H. Radi, A. Ferscha: „Recognizing and Predicting Context by Learning From User Behavior“, Proceedings of MoMM2003, OCG, September 2003

Related work

- TEA
- Smart-Its
- University of Helsinki
- Context Toolkit
- Robotics
- CIS
- Neural Network House
- Aware Home
- MavHome
- ContextCube
- Portolano
- University of Washington
- …

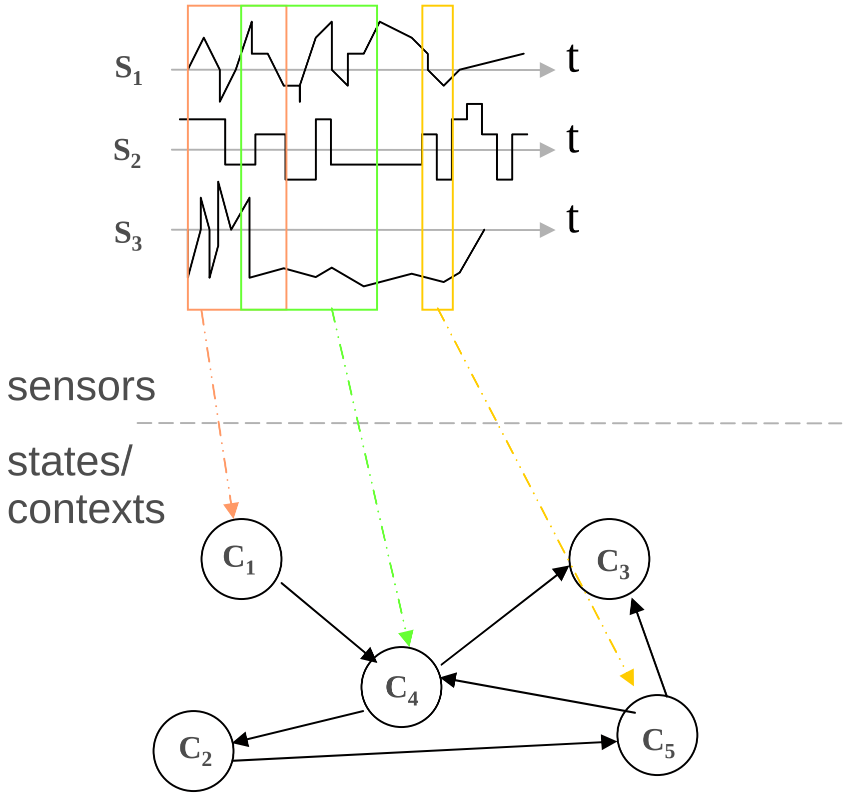
Basic approach to context prediction

- 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



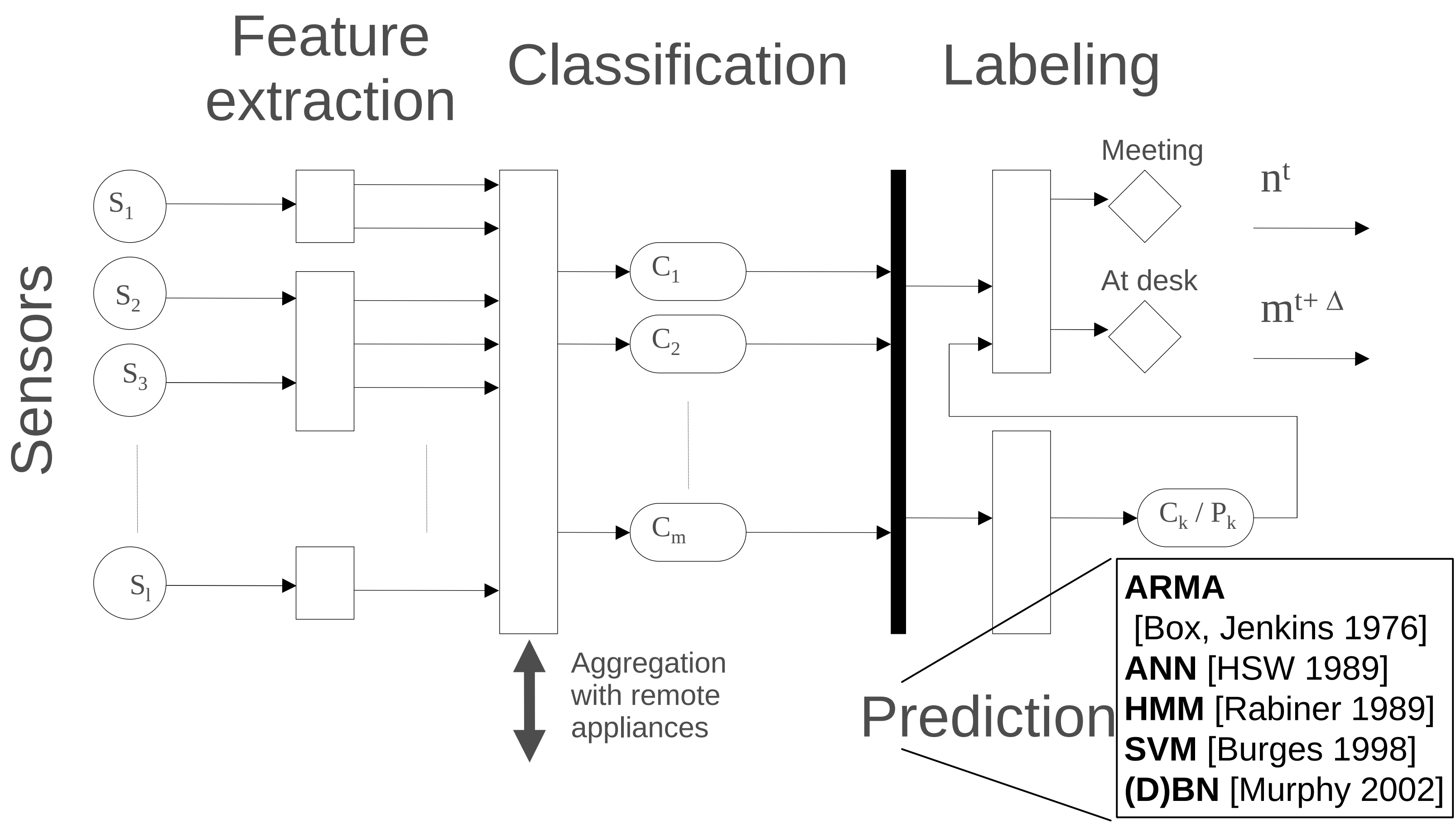
[Schmidt 2002] A. Schmidt: “Ubiquitous Computing – Computing in Context”, PhD Thesis, Lancaster Univ.

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



$<s_1, s_2, \ldots, s_l>_t \rightarrow <f_1, f_2, \ldots, f_n>_t \rightarrow <c_1, c_2, \ldots, c_m>_t \rightarrow <c_1, c_2, \ldots, c_m>_{t+\Delta}$

Input vector (Sensor vector) — Feature vector — Class vector — Future class vector

[MRF 2003a] R. Mayrhofer, H. Radi, A. Ferscha: „Recognizing and Predicting Context by Learning From User Behavior", Proceedings of MoMM2003, OCG, September 2003

Introduction
Approach
Architecture
Implementation
Results
Contribution

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
  - ....

- 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 op

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

[MRF 2003b] R. Mayrhofer, H. Radi, A. Ferscha: „Feature Extraction 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 / unsupverised
- 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

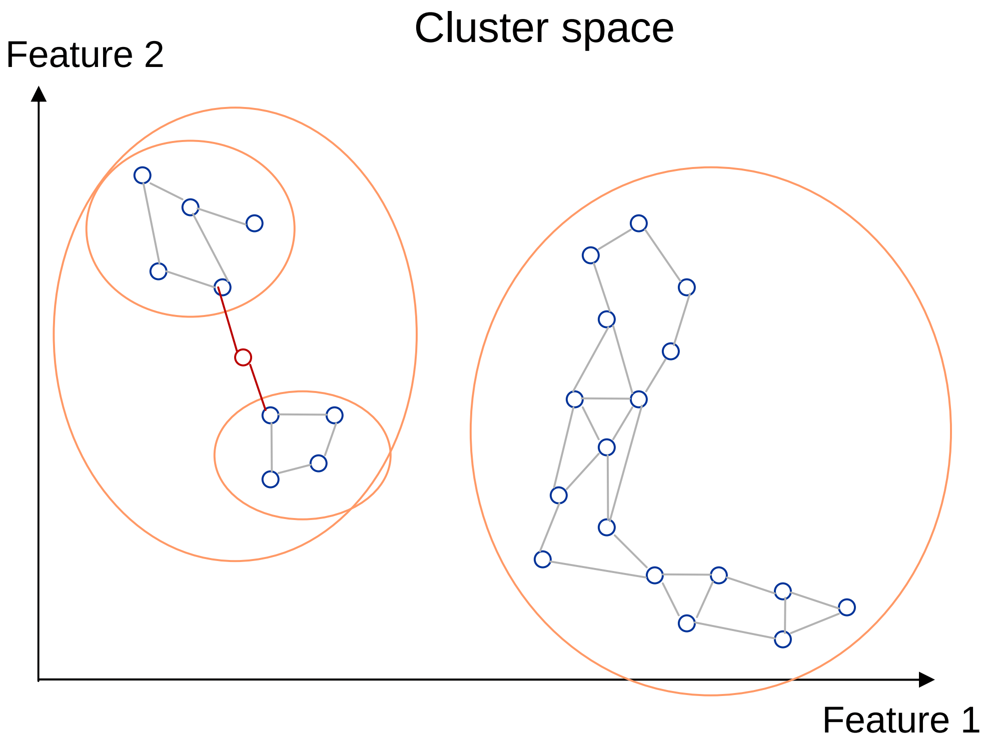
Classification algorithms

Algorithm	Topology / number of classes	Online / incremental	Adaptive	Hard / soft
K-Means	fixed	yes	yes	hard
FCM	fixed	yes	no	soft
Neural Gas	fixed	yes	no	partially
SOM	fixed	no	no	soft
ART	variable	yes	no	soft
IDBSCAN	variable	incremental, but not online	no	soft
SNN	fixed or variable	yes	no	soft
Growing Neural Gas [Fri 2003]	variable	yes	yes	soft

[Fri 2003] B. Fritzke: „A Growing Neural Gas Network learns Topologies“, Advances in Neural Information Processing Systems (7), MIT Press

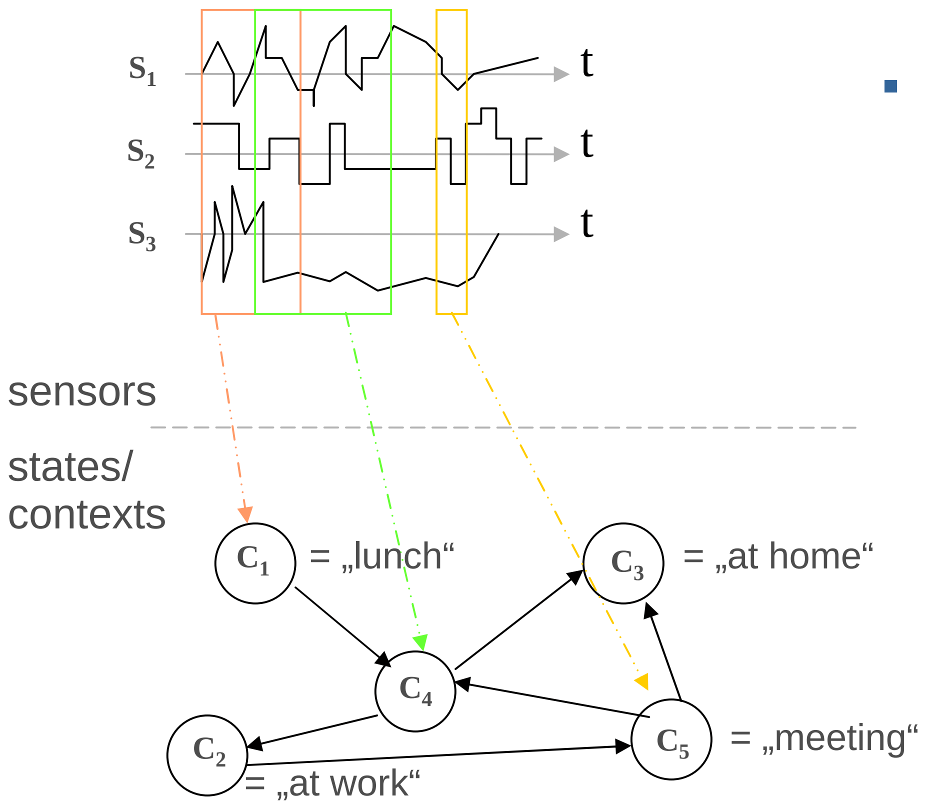
Variation: Lifelong Growing Neural Gas (LLGNG)

- Modification of GNG for life-long learning [Ham 2001]
- Difference: applies local criteria for each cluster to prevent the unbounded insertion of new clusters (instead of a global limit on the number of clusters)
- Extensions to LLGNG for context recognition:
  - Usage of a heterogeneous feature space
  - Utilising the internal topology to allow arbitrarily shaped clusters
    $\Rightarrow$ Meta clusters
    as additional level of abstraction



[Ham 2001] F.H. Hamker: „Life-long Learning Cell Structures – continuously learning without Catastrophic Interference", Neural Networks (14)

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*

Introduction
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Architecture
Implementation
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- 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

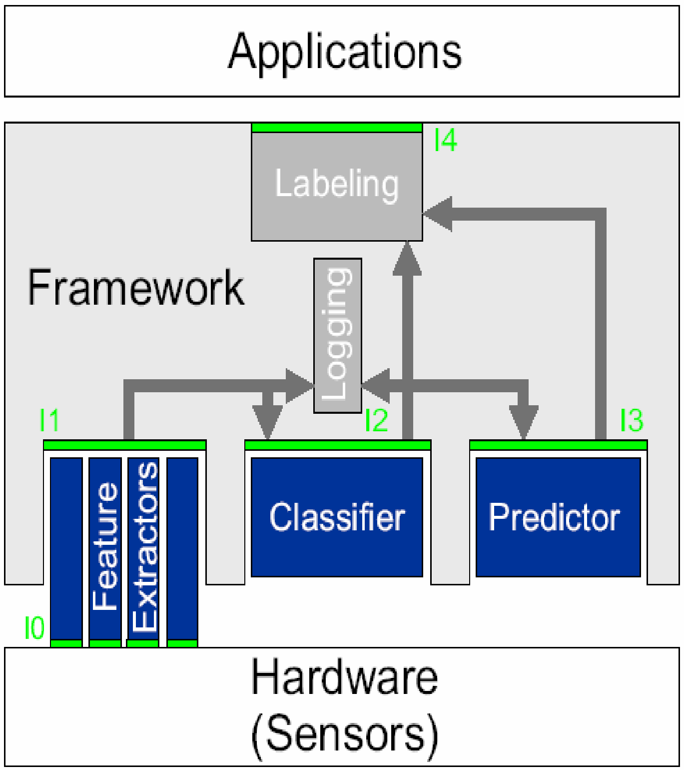
Options for context prediction

- 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
    $\Rightarrow$ 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: AAACCBCCAAADDDDDDDEEEEEEBBAAAA……..*
    $\Rightarrow$ implicitly considers relationships between context classes, because they are considered as mutually exclusive

$\Rightarrow$ 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)

Implementation as Software Framework

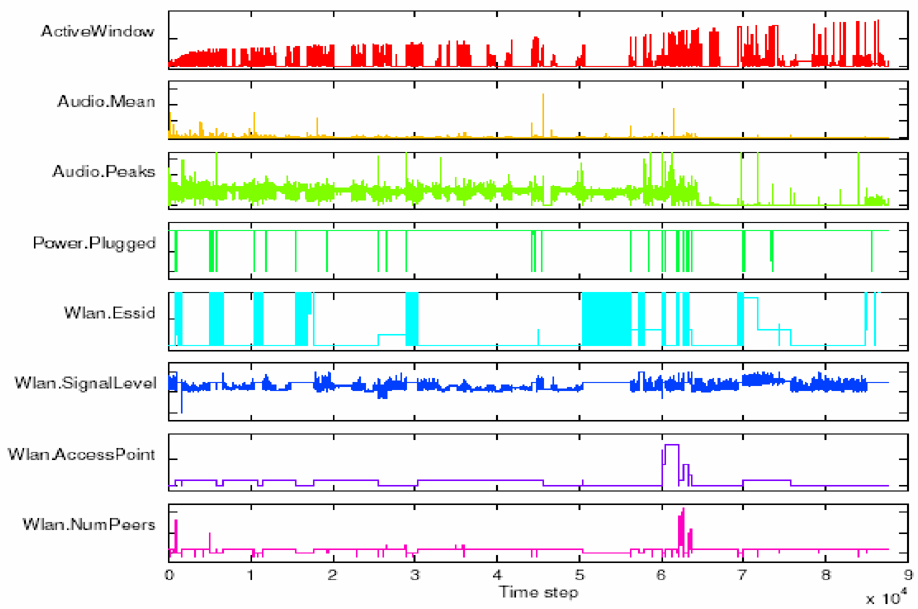


Cross-platform:

- 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

Initial evaluation with real-world data

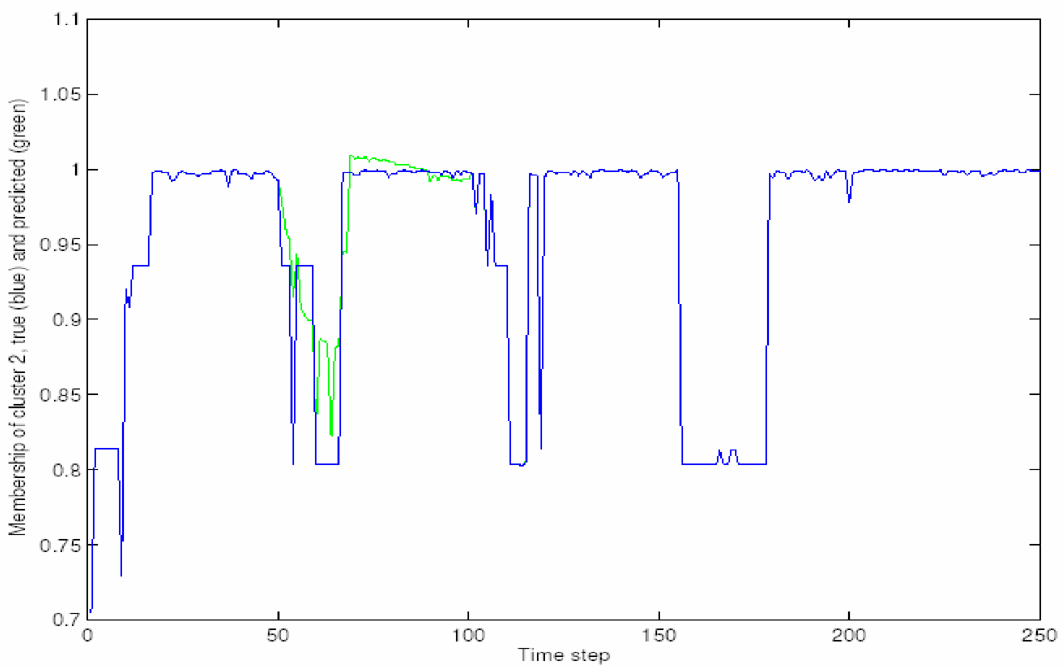
- Recorded with a standard laptop
- Recording completely in the background ⇒ unobtrusive operation
- Time frame: ca. 2 months
- 28 feature dimensions
- ~ 90000 data points



Classification:

- Evaluation of K-means, SOM and LLGNG
  - K-means: smallest error with 6 clusters: 0,7451
  - SOM: smallest error with 71x21 (=1491) neurons in output layer: 0,5659
  - Extended LLGNG: 9 meta clusters with 109 clusters: 0,0069
- LLGNG produces a smaller error with less clusters than SOM
- Extended variant offers the additional concept of meta cluster

Evaluation with real-world data (2)



Algorithm	Error
ARMA	0,04
MLP	0,62
SVR	0,24
Central tendency	0,46
ALZ	0,46
ALZ + Duration	0,44
HMM	0,46
SVM	0,46

Prediction:

- Currently best results with ARMA and seasonal correction in pre-processing
- HMM, SVM etc. less suitable (for this data set, no general statements should be deducted)

Contribution of this project

Development of an architecture for context prediction:

- Predicting context on a high level instead of predicting individual aspects of context. This is achieved by interpreting contexts as states and monitoring the emerging state trajectory.
- Flexibility due to simple, clearly defined interfaces between the 5 steps
- Classification, labeling, and prediction are exchangeable plug-ins
- Able to deal with heterogeneous input data in a unified manner

Requirements / methods for context classification and prediction

Implementation of the architecture in terms of an open software framework:

- Direct use of different sensor types without re-coding of non-numerical data
- Extension of LLGNG by the concept of meta clusters and various optimisations
- Supporting different platforms
- Developed for resource limited devices

Open Issues and Outlook

- Wide open: exploring the area of applications that employ context prediction and user studies
  $\Rightarrow$ new research issues expected
- Gather new data sets with ground truth
  $\Rightarrow$ should allow better quantitative comparison of algorithms
- User interface for labeling

- Evaluate new prediction algorithms (e.g. [EAE 2004]), especially for online recognition of periodicities
- Support for event based features in the architecture
- Optional use of domain-specific knowledge for recognition and prediction, if available
- Implementation of additional classification and prediction algorithms within the framework
- Porting the framework to new platforms, e.g. Familiar or Montavista-based mobile phones (sensor and UI support)

[EAE 2004] M. G. Elfeky, W. G. Aref, and A. K. Elmagarmid: “Using convolution to mine obscure periodic patterns in one pass”, EDBT 2004

Summary

- Upcoming applications of computer systems that go beyond the usual desktop demand new ways of user interaction.
- Recognizing current and predicting future context opens manifold possibilities for more intuitive and “smart” user interaction.
- This research project proposes a modular architecture for context prediction based on 5 steps. it allows an automatic recognition and prediction of high-level context from low-level, simple sensor data and focuses on unobtrusive operation. The proposed steps are:
  - Sensor data acquisition
  - Feature extraction
  - Classification
  - Labeling
  - Prediction
- This architecture has been developed for online, life-long learning with continuous adaptation to new situations and explicitly considers low resource requirements and protecting user privacy.
- To directly use heterogeneous feature values without internal conversation, only two operations need to be implemented for each feature.

- This is only the beginning, many issues are still open…

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“It is hard to predict, especially the future.”

LANCASTER
UNIVERSITY

Niels Bohr

Winner of the 1922 Nobel Prize in Physics

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“If we knew what it was we were doing, it would not be called research, would it?”

Albert Einstein

Winner of the 1921 Nobel Prize in Physics

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Thank you for your attention!

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