SEMANTIC TECHNOLOGY FOR CONTEXT AWARENESS

CRC “Highly Adaptive Energy-efficient computing” (HAEC)

Anni-Yasmin Turhan

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Motivation

Employing ontology-based situation recognition

- support context awareness by logical reasoning
  —in particular coping with incomplete data.

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- enrich raw data by semantic technologies
- providing a high-level, more abstract view by background knowledge captured in ontology
- detect high-level, composite events

Our Setting
in the HAEC project

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We: recognize situations (when adaptations might be beneficial)
Others: perform adaptation

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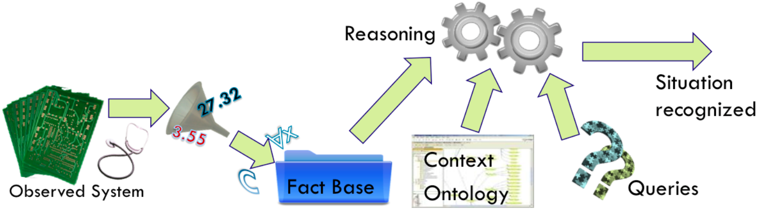
The Setting
- Background ontology: description logics (DL) TBox
- Input data:
  - information on components of observed system (static), sensor data (dynamic)
  - stored in DB, connected to TBox via preprocessors (/mappings)
- Situation descriptions: conjunctive queries (CQs)



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Essentially an OBDA setting, but

- temporal sequence of system states: data items time stamp annotated.
- data items grouped into logical categories with a membership degree

Temporal Query Answering

Motivation and Approach

- System is observed over time yielding sequence of system snapshots.
- "growing" window:
  storing (relevant) data from start until current time point
- Temporal query language: extension of DL by LTL to navigate on the temporal sequence

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Temporal conjunctive queries (TCQs)

- Combine LTL and DLs
- built inductively from CQs using: $\neg$, $\wedge$, $\bigcirc^{-}$, $\Diamond^{-}$, $\Box^{-}$

Temporal Query answering

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Complexity results for TCQ entailment for

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  using temporal DB
- 2-step rewriting: uses atemporal rewriting as black box procedure

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Horn-DLs (include DL-Lite, $\mathcal{EL}$)

- with fixed set of queries ($\sim$ temporal DB monitoring problem): bounded history encodings
- treatment of future operators: gain of one exponent

Fuzzy Queries
Motivation and Approach

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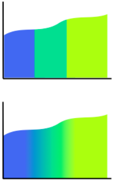

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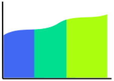
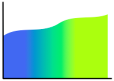
- small change in value should result in similar classification





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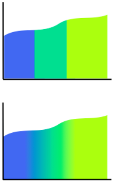

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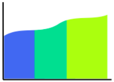

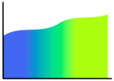

Queries with membership degrees:

- fuzzy query: degrees per atom
- threshold query: degree per CQ

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- data complexity as in the crisp case!

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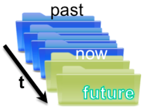

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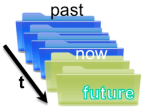

Practical side:

- exploit parallel hardware
- investigate incremental reasoning