Recap: Ontology Change

- Considered ontology change from BR perspective
- Required adaptations and extensions for BR
  - non-classical logics
  - revision of finite belief bases
  - multiple revision
  - iterated revision
- Considered Infinite Iteration and Idea of Formal Learning Theory
- Stabilization/convergence conditions

End of Recap
This Lecture

- Infinite sequences from stream processing perspective
  - Additional aspects: temporality of data, recency, data-driveness, velocity

- Resume OBDA and consider how to lift them to temporal OBDA and streaming OBDA
  - Temporal OBDA: Add time aspect (somewhere)
  - Stream OBDA: Higher-level stream w.r.t. ontology (and mappings)
Temporalized OBDA
A Confession

- Ontology-Based Data Access on temporal and Streaming Data
- But: Streams are temporal streams and we talk about local temporal reasoning
Adding a Temporal Dimension to OBDA

- Most conservative strategy: handle time as “ordinary” attribute $time$

$$\begin{align*}
meas(x) \land \\
val(x, y) \land \\
time(x, z)
\end{align*} \leftarrow \text{SELECT } f(MID) \text{ AS } m, \text{ Mval AS } y, \text{ MtimeStamp AS } z \text{ FROM MEASUREMENT}$$

- Classical Mapping

- Pro: Minimal (no) adaptation

- Contra:
  - No control on “logic of time”
  - Need reification
    - sometimes necessary (because DLs provided only predicates up to arity 2)
    - but not that “natural”
Flow of Time

- Flow of time \((T, \leq_T)\) is a structure with a time domain \(T\) and a binary relation \(\leq_T\) over it.
- Flow metaphor hints on directionality and dynamic aspect of time.
- But still different forms of flow are possible.

- One can consider concrete structures of flow of (time), as done here.
- Or investigate them additionally axiomatically.
- An early model-theoretic and axiomatic treatise:
  
The Family of Flows of Time

 Domain $T$
  - points (atomic time instances)
  - pairs of points (application time, transaction time)
  - intervals etc.

 Properties of the time relation $\leq_T$
  - Non-branching (linear) vs. branching
    Linearity:
      - reflexive: $\forall t \in T: t \leq_T t$
      - antisymmetric: $\forall t_1, t_2 \in T: (t_1 \leq_T t_2 \land t_2 \leq_T t_1) \Rightarrow t_1 = t_2$
      - transitive: $\forall t_1, t_2, t_3 \in T: (t_1 \leq_T t_2 \land t_2 \leq_T t_3) \Rightarrow t_1 \leq_T t_3$
      - total: $\forall t_1, t_2 \in T: t_1 \leq_T t_2 \lor t_2 \leq_T t_1 \lor t_1 = t_2$

 Existence of first or last element

 Discreteness (Example: $T = \mathbb{N}$); also used for modeling state sequences;

 Density (Example: $T = \mathbb{Q}$);

 Continuity (Example: $T = \mathbb{R}$)
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Temporalized OBDA: General Approach

- Semantics rests on family of interpretations \((\mathcal{I}_t)_{t \in T}\)
- Temporal ABox \(\tilde{\mathcal{A}}\): Finite set of \(T\)-tagged ABox axioms

**Example**

\[\text{val}(s_0, 90^\circ)\langle 3s \rangle\] holds in \((\mathcal{I}_t)_{t \in T}\) iff \(\mathcal{I}_{3s} \models \text{val}(s_0, 90^\circ)\)

“sensor \(s_0\) has value \(90^\circ\) at time point \(3s\)”

- Alternative sequence representation of temporal ABox \(\tilde{\mathcal{A}}\)
  - \((\mathcal{A}_t)_{t \in T'}\) (where \(T'\) are set of timestamps in \(T\))
  - \(\mathcal{A}_t = \{ax \mid ax\langle t \rangle \in \tilde{\mathcal{A}}\}\)

**Definition (Adapted notion of OBDA rewriting)**

\[\text{cert}(Q, (\text{Sig}, T, (\mathcal{A}_t)_{t \in T'})) = \text{ans}(Q_{\text{rew}}, (\text{DB}(\mathcal{A}_t))_{t \in T'})\]
Temporalized OBDA: TCQs

- Different approaches based on modal (temporal) operators
- LTL operators only in QL (Borgwardt et al. 13)

Example

\[ \text{Critical}(x) = \exists y. \text{Turbine}(x) \land \text{showsMessage}(x, y) \land \text{FailureMessage}(y) \]

\[ Q(x) = \circ^{-1} \circ^{-1} \circ^{-1} (\lozenge (\text{Critical}(x) \land \circ \lozenge \text{Critical}(x))) \]

“turbine has been at least two times in a critical situation in the last three time units”

- CQ embedded into LTL template
- Special operators taking care of endpoints of state sequencing
- Not well-suited for OBDA as non-safe
- Rewriting simple due to atemporal TBox

Temporalized OBDA: TQL

- LTL operators in TBox and T argument in QL

Example

TBox axiom : \( \text{showsAnomaly} \sqsubseteq \Box \text{UnplanedShutDown} \)
“if turbine shows anomaly (now) then sometime in the future it will shut down”

Query : \( \exists t. 3s \leq t \leq 6s \land \text{showsAnomaly}(x, t) \)

- Can formulate rigidity assumptions
- Rewriting not trivial

Stream Basics
Definition (Stream)

A stream $S$ is a potentially infinite sequence of objects $d$ over some domain $D$.

- “Streams are forever”
  

- “Order matters!”
  

- “It’s a streaming world!”
  
Streams

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Adding a Time Dimension

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- Consider non-branching (or: linear) time, i.e., $\leq_T$ is
- We assume that there is no last element in $T$
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Arrival Ordering

- Sequence fixed by arrival ordering fixed $<_{ar}$
- $<_{ar}$ is a strict total ordering on the elements of $S$
  - Synchronous streams: $\leq_T$ compatible with $<_{ar}$
  - Compatibility: For all $d_1(t_1), d_2(t_2) \in S$: If $d_1(t_1) <_{ar} d_2(t_2)$, then $t_1 \leq_T t_2$.
- Asynchronous streams: $\leq_T$ not necessarily compatible with $<_{ar}$

Convention for the following:

- Consider only temporal streams
- Consider only synchronous streams $\implies$ neglect $<_{ar}$.
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Stream Stack and Stream Research

- **Low-level sensor perspective** (semantic sensor networks)
  - Develop fast algorithms on high-frequency streams with minimal space consumption
  - Considers approximate algorithms for aggregation functions
  - See lecture “Non-standard DBs” by Ralf Möller

- **Data stream management system (DSMS) perspective**
  - Provide whole DB systems for streams of structured (relational) data
  - Deals with all aspects relevant in static DBMS adapted to stream scenario
  - See lecture “Non-standard DBs” by Ralf Möller and this lecture
  - Stream Query Language

- **High-level and Ontology layer streams**
  - Processing stream of assertions (RDF triples) w.r.t. an ontology
  - Related: Complex Event Processing (CEP)
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Local vs. Global Stream Processing

- **Global aim: Learn** about the whole by looking at the parts
  - Examples: inductive learning, ontology change, iterated belief revision (see slides before), robotics oriented stream processing with plan generation
  - May produce also an output stream
  - But in the end the whole stream counts

- **Local aim: Monitor** window contents with time-local
  - Examples: Real-time monitoring, simulation for reactive diagnostics

- Categories not exclusive
  - In learning one applies operation on (NOW)-window to learn about stream
  - In predictive analytics one monitors with window in order to predict upcoming events
Domain Objects for Streams

Definition (Temporal Stream)

A stream $S$ is a sequence of timestamped objects $d\langle t \rangle$ over some domain $D$ and flow of time $(T, \leq_T)$.

Streamified OBDA has to deal with different types of domains.
Domain Objects for Streams

Definition (Temporal Stream)

A stream $S$ is a sequence of timestamped objects $d\langle t \rangle$ over some domain $D$ and flow of time $(T, \preceq_T)$.

Streamified OBDA has to deal with different types of domains

$D_1 = \text{a set of typed relational tuples adhering to a relational schema}$

- Streams at the backend sources
- $S_{rel} = \{(s_1, 90^\circ)\langle 1s \rangle, (s_2, 92^\circ)\langle 2s \rangle, (s_1, 94^\circ)\langle 3s \rangle, \ldots \}$
- Schema: hasSensorRelation(Sensor:string, temperature:integer)
Domain Objects for Streams

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A stream $S$ is a sequence of timestamped objects $d\langle t \rangle$ over some domain $D$ and flow of time $(T, \leq T)$.

Streamified OBDA has to deal with different types of domains

$D_2 = \text{set of untyped tuples}$ (of the same arity)

- Stream of tuples resulting as bindings for subqueries
Domain Objects for Streams

**Definition (Temporal Stream)**

A stream $S$ is a sequence of timestamped objects $d\langle t \rangle$ over some domain $D$ and flow of time $(T, \leq_T)$.

Streamified OBDA has to deal with different types of domains

$D_3 = \text{set of assertions (RDF tuples)}.$

- $S_{rdf} = \{ \text{val}(s_0, 90^\circ)\langle 1s \rangle, \text{val}(s_2, 92^\circ)\langle 2s \rangle, \text{val}(s_1, 94^\circ)\langle 3s \rangle, \ldots \}$
Domain Objects for Streams

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Streamified OBDA has to deal with different types of domains

$D_4 = \text{set of RDF graphs}$
Nearly all stream processing approaches provide a fundamental means to cope with potential infinity of streams, namely ...
Taming the Infinite

Nearly all stream processing approaches provide a fundamental means to cope with potential infinity of streams, namely ...

- Stream query continuous, not one-shot activity
- Window content continuously updated
Nearly all stream processing approaches provide a fundamental means to cope with potential infinity of streams, namely...

- Here a time-based window of width 3 seconds
- and slide 1 second is applied
Window Operators: Classification

- Direction of movement of the endpoints
  - Both endpoints fixed (needed for “historical” queries)
  - Both moving/sliding
  - One moving the other not

- Window size
  - Temporal
  - Tuple-based
  - Partitioned window
  - Predicate window

- Window update
  - tumbling
  - sampling
  - overlapping
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Why is the Window Concept so Important?

- We give an answer using the word perspective on stream processing according to (Gurevich et al. 07)
- Streams = finite or infinite words over an alphabet (domain) $D$
  - $D^* =$ finite words over $D$
  - $D^\omega =$ infinite ($\omega$-) words over $D$
  - $D^\infty =$ finite and infinite words over $D$
  - $\circ =$ word concatenation (usually not mentioned)
- Stream operators $Q$ are functions/queries of the form

\[ Q : D_1^\infty \rightarrow D_2^\infty \]

- Assume w.l.o.g that $D_1 = D_2 = D$.

Genuine Streams are Finite Prefix Determined

- **Open ball around** $u$:
  \[
  B(u) := uD^\infty = \{ s \in D^\infty \mid \text{There is } s' \in D^\infty \text{ s.t. } s = u \circ s' \}
  \]

**Definition (Axiom of finite prefix determinedness (FP))**

For all $s \in D^\infty$ and all $u \in D^*$:
If $Q(s) \in uD^\infty$, there is $w \in D^*$ s.t. $s \in wD^\infty \subseteq Q^{-1}(uD^\infty)$

- (FP) expresses a continuity condition w.r.t. a topology
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- (FP) expresses a continuity condition w.r.t. a topology
- Reminder: A **topology** is a structure \((X, \mathcal{O})\) where
  - \( \mathcal{O} \subseteq \text{Pow}(X) \)
  - \( \emptyset, X \in \mathcal{O} \)
  - \( \mathcal{O} \) closed under finite intersections
  - \( \mathcal{O} \) closed under arbitrary unions
- A **basis** for \( \mathcal{O} \) is a set \( \mathcal{B} \subseteq \text{Pow}(X) \) s.t.: Every \( S \in \mathcal{O} \) is a union of elements of \( \mathcal{B} \).
Genuine Streams are Finite Prefix Determined

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- (FP) expresses a continuity condition w.r.t. a topology
- Gurevich topology
  \[
  T_G = (D^\infty, \{ AD^\infty | A \subseteq D^* \})
  \]
- \( B(u) \) for \( u \in D^* \) are basis for \( T_G \).
- A function \( Q : D^\infty \to D^\infty \) is continuous iff for every open ball \( B : Q^{-1}(B) \) is open.
- i.e., iff \( Q \) fulfills (FP)
For $K : D^* \longrightarrow D^*$

Repeated application of $K$

\[
\text{Repeat}(K) : \quad D^\infty \longrightarrow D^\infty \\
\quad s \mapsto \bigcirc_{i=0}^{\text{length}(s)} K(s \preceq i)
\]

**Definition (Gurevich et al. 2007)**

$K$ is a kernel for $Q$ iff $Q = \text{Repeat}(K)$.

$Q$ is abstract computable (AC) iff it has a kernel.
Abstract Computability

- For $K : D^* \rightarrow D^*$
- Repeated application of $K$

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\text{Repeat}(K) : \quad D^\infty \quad \rightarrow \quad D^\infty \\
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Abstract Computability

- For $K : D^* \rightarrow D^*$ (window function)
- Repeated application of $K$

$$
\text{Repeat}(K) : D^\infty \rightarrow D^\infty \\
\text{length}(s) \atop \circ_{i=0}^{length(s)} \quad K(s \leq i)
$$

Definition (Gurevich et al. 2007)

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$Q$ is abstract computable (AC) iff it has a kernel.
A Representation Theorem

**Theorem**

The set of AC functions are exactly those stream functions fulfilling FP (i.e. that are continuous) and mapping finite streams to finite streams

- Further interesting representation results by considering restrictions on window
- Gurevich et al. also describe computation model (abstract state machines)
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- Further interesting representation results by considering restrictions on window
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Example for non-continuuous stream functions

Example

Query CHECK

- $a, b \in D$
- CHECK($s$) = (a) if $b$ does not occur in $s$
- Otherwise $CHECK(s) = () = \text{empty stream}$

- CHECK is not continuous (and hence not an AC function):
  - Consider open ball $B(a)$.
  - $(()) \in CHECK^{-1}(B(a))$
  - But the only open ball containing $(())$ is $B((())) = D^\infty$
  - But $B((())) \not\subseteq CHECK^{-1}(B(a))$ because
  - $CHECK(b) = () \notin B(a)$
Relational Stream Processing with CQL
Relational Data Stream Processing

- Different groups working on DSMS around 2004
  - Academic prototypes: STREAM and CQL (Stanford); TelgraphCQ (Berkeley) (extends PostGreSQL); Aurora/Borealis (Brandeis, Brown and MIT); PIPES from Marburg University
  - Commercial systems: StreamBase, Truviso (Standalone), extensions of commercial DBMS (MySQL, PostgreSQL, DB2 etc.)

- Though well investigated and many similarities there is no streaming SQL standard

- First try for standardization:
  

- But if development speed similar to that for introducing temporal dimension into SQL, then we have to wait...
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CQL (Continuous Query Language)

- Early relational stream query language extending SQL
- Developed in Stanford as part of a DSMS called STREAM
- Semantics theoretically specified by denotational semantics
- Practically, development of CQL was accompanied by the development the Linear Road Benchmark (LRB) (http://www.cs.brandeis.edu/~linearroad/)
- Had immense impact also on development of early RDF streaming engines in RSP community


CQL Operators

- Special data structure next to streams: relations R
  - R maps times $t$ to ordinary (instantaneous) relations $R(t)$
  - Motivation: Use of ordinary SQL operators on instantaneous relations

- Operators
  - Stream-to-relation = window operator
  - Relation-to-relation = standard SQL operators at every single time point
  - relation-stream = for getting streams agains

- Non-predictability condition for operators $op$:  
  - If two inputs $S_1$, $S_2$ are the same up to $t$, then $op(S_1)(t) = op(S_2)(t)$.
  (This is related to (FP))
CQL Windows

- Window operators are stream-to-relation operators
- CQL knows tuple-based, partition based, and time-based windows

**Definition (Semantics of Window Operator)**

\[ R = S \ [\text{Range wr Slide sl}] \]

- with slide parameter sl and range wr
- \( t_{\text{start}} = \lfloor t/sl \rfloor \cdot sl \)
- \( t_{\text{end}} = \max\{t_{\text{start}} - \text{wr}, 0\} \)

\[ R(t) = \begin{cases} \emptyset & \text{if } t < sl \\ \{s \mid s \langle t' \rangle \in S \text{ and } t_{\text{end}} \leq t' \leq t_{\text{start}}\} & \text{else} \end{cases} \]

- Standard slide = 1: [RANGE wr]
- Left end fixed: [Range UNBOUND]
- Width 0: [NOW]
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\[ R = S \ [\text{Range wr Slide } sl] \]
- with slide parameter \( sl \) and range \( wr \)
- \( t_{\text{start}} = \lfloor t/sl \rfloor \cdot sl \)
- \( t_{\text{end}} = \max \{ t_{\text{start}} - wr, 0 \} \)

\[ R(t) = \begin{cases} 
\emptyset & \text{if } t < sl \\
\{ s \mid s\langle t' \rangle \in S \text{ and } t_{\text{end}} \leq t' \leq t_{\text{start}} \} & \text{else}
\end{cases} \]

- Standard slide = 1: [RANGE \( wr \)]
- Left end fixed: [Range UNBOUND]
- Width 0: [NOW]
CQL Windows

- Window operators are stream-to-relation operators
- CQL knows tuple-based, partition-based, and time-based windows

**Definition (Semantics of Window Operator)**

\[ R = S [\text{Range wr Slide sl}] \]

- with slide parameter sl and range wr
- \[ t_{\text{start}} = \lfloor t / sl \rfloor \cdot sl \]
- \[ t_{\text{end}} = \max\{t_{\text{start}} - \text{wr}, 0\} \]

\[ R(t) = \begin{cases} \emptyset & \text{if } t < sl \\ \{s \mid s\langle t'\rangle \in S \text{ and } t_{\text{end}} \leq t' \leq t_{\text{start}}\} & \text{else} \end{cases} \]

- Standard slide = 1: [RANGE wr]
- Left end fixed: [Range UNBOUND]
- Width 0: [NOW]
Sliding Window Example in CQL

▶ Flow of time \((\mathbb{N}, \leq)\)

▶ Input stream

\[
S = \{(s_0, 90^\circ)\langle 0 \rangle, (s_1, 94^\circ)\langle 0 \rangle, (s_0, 91^\circ)\langle 1 \rangle, (s_0, 92^\circ)\langle 2 \rangle, \\
(s_0, 93^\circ)\langle 3 \rangle, (s_0, 95^\circ)\langle 5 \rangle, (s_0, 94^\circ)\langle 6 \rangle\ldots\}
\]

▶ Output relation \(R = S\) [Range 2 Slide 1]

\[
\begin{array}{cccccccc}
\text{t} & 0 & 1 & 2 & 3 & 4 & 5 & 6 \\
R(\text{t}) & \{(s_0, 90), (s_1, 94)\} & \{(s_0, 90), (s_1, 94), (s_0, 91)\} & \{(s_0, 90), (s_1, 94), (s_0, 91), (s_0, 92)\} & \{(s_0, 91), (s_0, 92), (s_0, 93)\} & \{(s_0, 92), (s_0, 93)\} & \{(s_0, 92), (s_0, 93), (s_0, 95)\} & \{(s_0, 93), (s_0, 94)\}
\end{array}
\]
Sliding Window Example in CQL

\[ S = \{(s_0, 90)\langle 0\rangle, (s_1, 94)\langle 0\rangle, (s_0, 91)\langle 1\rangle, (s_0, 92)\langle 2\rangle, (s_0, 93)\langle 3\rangle, (s_0, 95)\langle 5\rangle, (s_0, 94)\langle 6\rangle\} \]

Output relation \( R = S \) [Range 2 Slide 1]
Sliding Window Example in CQL

\[ S = \{(s_0, 90)\langle 0\rangle, (s_1, 94)\langle 0\rangle, (s_0, 91)\langle 1\rangle, (s_0, 92)\langle 2\rangle, (s_0, 93)\langle 3\rangle, (s_0, 95)\langle 5\rangle, (s_0, 94)\langle 6\rangle\} \]

Output relation \( R = S \) [Range 2 Slide 1]

<table>
<thead>
<tr>
<th>( t )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R(t) )</td>
<td>{(s_0, 90), (s_1, 94)}</td>
<td>{(s_0, 90), (s_1, 94), (s_0, 91)}</td>
<td>{(s_0, 90), (s_1, 94)}</td>
<td>{(s_0, 91), (s_0, 93)}</td>
<td>{(s_0, 92), (s_0, 93)}</td>
<td>{(s_0, 93), (s_0, 95)}</td>
<td>{(s_0, 95), (s_0, 94)}</td>
</tr>
</tbody>
</table>
Sliding Window Example in CQL

\[ S = \{(s_0, 90), (s_1, 94), (s_0, 91), (s_0, 92), (s_0, 93), (s_0, 95)\} \]

Output relation \( R = S \ [\text{Range 2 Slide 1}] \)

<table>
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<tr>
<th>( t )</th>
<th>0</th>
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<th>3</th>
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<td>{(s_0, 92), (s_0, 95)}</td>
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<td>{(s_0, 95), (s_0, 94)}</td>
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</tbody>
</table>
Sliding Window Example in CQL

\[ S = \{(s_0, 90)\langle 0\rangle, (s_1, 94)\langle 0\rangle, (s_0, 91)\langle 1\rangle, (s_0, 92)\langle 2\rangle, (s_0, 93)\langle 3\rangle, (s_0, 95)\langle 5\rangle, (s_0, 94)\langle 6\rangle\} \]

Output relation \( R = S \) [Range 2 Slide 1]
Sliding Window Example in CQL

\[ S = \{(s_0, 90)\langle 0\rangle, (s_1, 94)\langle 0\rangle, (s_0, 91)\langle 1\rangle, (s_0, 92)\langle 2\rangle, (s_0, 93)\langle 3\rangle, (s_0, 95)\langle 5\rangle, (s_0, 94)\langle 6\rangle\} \]

Output relation \( R = S \) [Range 2 Slide 1]
Sliding Window Example in CQL

\[ S = \{(s_0, 90)\langle 0\rangle, (s_1, 94)\langle 0\rangle, (s_0, 91)\langle 1\rangle, (s_0, 92)\langle 2\rangle, (s_0, 93)\langle 3\rangle, (s_0, 95)\langle 5\rangle, (s_0, 94)\langle 6\rangle\} \]

Output relation \( R = S \) [Range 2 Slide 1]
Sliding Window Example in CQL

\[ S = \{(s_0, 90)\langle 0 \rangle, (s_1, 94)\langle 0 \rangle, (s_0, 91)\langle 1 \rangle, (s_0, 92)\langle 2 \rangle, (s_0, 93)\langle 3 \rangle, (s_0, 95)\langle 5 \rangle, (s_0, 94)\langle 6 \rangle\} \]

Output relation \( R = S \) [Range 2 Slide 1]
Relation vs. Stream

\[ S = \{(s_0, 90^\circ)\langle 0\rangle, (s_1, 94^\circ)\langle 0\rangle, (s_0, 91^\circ)\langle 1\rangle, (s_0, 92^\circ)\langle 2\rangle, \\
(s_0, 93^\circ)\langle 3\rangle, (s_0, 95^\circ)\langle 5\rangle, (s_0, 94^\circ)\langle 6\rangle \ldots\} \]

- Output relation \( R = S \) [Range 2 Slide 1]

<table>
<thead>
<tr>
<th>( t )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
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<td>{(s_0, 90), (s_1, 94), (s_0, 91)}</td>
<td>{(s_0, 90), (s_1, 94), (s_0, 91), (s_0, 92)}</td>
<td>{(s_0, 91), (s_0, 92), (s_0, 93)}</td>
<td>{(s_0, 92), (s_0, 93)}</td>
<td>{(s_0, 93), (s_0, 95)}</td>
<td>{(s_0, 93), (s_0, 94)}</td>
</tr>
</tbody>
</table>

- Note that there are also entries for second 4
- Note that timestamps are lost in the bags
- Slides are local to streams and may be different over different streams
Relation-To-Stream Operators

- Output stream of input relation \( R \):

\[
Istream(R) = \bigcup_{t \in T} (R(t) \setminus R(t-1)) \times \{t\}
\]
stream of inserted elements

\[
Dstream(R) = \bigcup_{t \in T} (R(t-1) \setminus R(t)) \times \{t\}
\]
stream of deleted elements

\[
Rstream(R) = \bigcup_{t \in T} R(t) \times \{t\}
\]
stream of all elements

- In CQL, \( IStream \) and \( DStream \) are syntactic sugar
Sensor Measurement CQL Example

Example

```sql
SELECT Rstream(m.sensorID)
FROM Msmt[Range 1] as m, Events[Range 2] as e
WHERE m.val > 30 AND
  e.category = Alarm AND
  m.sensorID = e.sensorID
```

- Stream join realized by join of window contents
- Output is a stream
Non-discrete Time Flows

- Taken literally, CQL window definitions work only for discrete flows of times
- Time flow: \((T, \leq) = (\mathbb{R}, \leq)\)
- Input stream: \(S = \{i\langle i \rangle \mid i \in \mathbb{N}\}\)
- \(RStream(S[RANGE 1 SLIDE 1])\) is “stream” with cardinality of \(\mathbb{R}\)
- “Solution” in CQL hidden in stream engine layer
- Heartbeat with smallest possible time granularity
Linear City

10 Expressways (L: performance measure)

Linear City

Reports every 30 seconds

100 segments of 1 mile each

Main Input Stream: Car Locations (CarLocStr)

<table>
<thead>
<tr>
<th>car_id</th>
<th>speed</th>
<th>exp_way</th>
<th>lane</th>
<th>x_pos</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>55</td>
<td>5</td>
<td>3 (Right)</td>
<td>12762</td>
</tr>
<tr>
<td>1035</td>
<td>30</td>
<td>1</td>
<td>0 (Ramp)</td>
<td>4539</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Linear Road Benchmark

- 10 years old benchmark for stress testing relational DSMS

- Suite of continuous queries based on real traffic management proposals.
  - Stream car segments based on x-positions (easy)
  - Identify probable accidents (medium)
  - Compute toll whenever car enters segment (hard)

- Metric: Scale to as many expressways as possible without falling behind

Toll Query

- Preconditions and Postconditions

<table>
<thead>
<tr>
<th>Trigger</th>
<th>Position report, $q$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preconditions</td>
<td>$q.\text{Seg} \neq \overleftarrow q.\text{Seg}, l \neq \text{EXIT}$</td>
</tr>
<tr>
<td>Output</td>
<td>$(\text{Type}: 0, \text{VID}: v, \text{Time}: t, \text{Emit}: t', \text{Spd}: \text{Lav}(M(t),x,s,d)$, Toll: $\text{Toll}(M(t),x,s,d)$)</td>
</tr>
<tr>
<td>Recipient</td>
<td>$v$</td>
</tr>
<tr>
<td>Response</td>
<td>$t' - t \leq 5$ Sec</td>
</tr>
</tbody>
</table>

- $\text{Toll}(M(t),x,s,d) = 0$ if in last 5 minutes either
  - congestion below 50 cars in the segment or
  - average speed $\text{Lav}(M(t),x,s,d)$ is below a given threshold or
  - segment is in vicinity of an accident
- else $\text{Toll}(M(t),x,s,d) = 2 \times (\#(\text{cars in } x, s, d) - 50)^2$

- Requires identification of accidents
Toll Query

- **Toll(M(t), x, s, d) = 0** if in last 5 minutes either
  - congestion below 50 cars in the segment or
  - average speed $Lav(M(t), x, s, d)$ is below a given threshold or
  - segment is in vicinity of an accident
- **else** $Toll(M(t), x, s, d) = 2 \times (\#(\text{cars in } x, s, d) - 50)^2$

Query 6 **TollStr(vehicleId, toll):** This is the final output toll stream.

```
Select Rs
tream(E.vehicleId,
      2 * (V.numVehicles-50)
   * (V.numVehicles-50)
   as toll)
From VehicleSegEntryStr [Now] as E,
   CongestedSegRel as C,
   SegVolRel as V
Where E.segNo = C.segNo and
     C.segNo = V.segNo
```
High-Level Declarative Stream Processing
Local Reasoning Service

- Need to apply calculation/reasoning $CR_{loc}$ locally, e.g.
  - arithmetics, timeseries analysis operations
  - SELECT querying, CONSTRUCT querying, abduction, revision, planning
High-Level and Declarative

- **Declarative:**
  Stream elements have “assertional status” and allow for symbolic processing

**Example (Relational data streams)**

Stream element \((\text{sensor}, \text{val})\langle3\text{sec}\rangle\) “asserts” that sensor shows some value at second 3

- **High-Level:**
  Streams are processed with respect to some background knowledge base such as a set of rules or an ontology.

**Example (Streams of time-tagged ABox assertions)**

Streams elements of form \(\text{val}(\text{sensor}, \text{val})\langle3\text{sec}\rangle\) evaluated w.r.t. to an ontology containing, e.g., axiom \(\text{tempVal} \sqsubseteq \text{val}\)
High-Level and Declarative

▶ Declarative:
Stream elements have “assertional status” and allow for symbolic processing

Example (Relational data streams)
Stream element \((sensor, val)(3sec)\) “asserts” that sensor shows some value at second 3

▶ High-Level:
Streams are processed with respect to some background knowledge base such as a set of rules or an ontology.

Example (Streams of time-tagged ABox assertions)
Streams elements of form \(val(sensor, val)(3sec)\) evaluated w.r.t. to an ontology containing, e.g., axiom \(tempVal \sqsubseteq val\)
Need to apply calculation/reasoning $\text{CR}_{\text{loc}}$ locally, e.g.

- arithmetics, timeseries analysis operations
- SELECT querying, CONSTRUCT querying, abduction, revision, planning (⇒ high-level & declarative)
Streamified OBDA

- Nearly ontology layer stream processing
  - CEP (Complex event processing)
  - EP-SPARQL/ETALIS, T-REX/ TESLA, Commonsens/ESPER
- RDF-ontology layer stream processing
  - C-SPARQL (della Valle et al. 09), CQELS
- Classical OBDA stream processing
  - SPARQL$_{Stream}$ (Calbimonte et al. 12) and MorphStream
- All approaches rely on CQL window semantics
- extend SPARQL or use some derivative of it
- Treat timestamped RDF triples but use reification
Example of Reified Handling

Example

SELECT `windspeed` `tidespeed`
FROM NAMED STREAM <http://swiss-experiment.ch/data#WannengratSensors.srdf>
[NOW-10 MINUTES TO NOW-0 MINUTES]
WHERE
  ?WaveObs a ssn:Observation;
    ssn:observationResult `windspeed`;
    ssn:observedProperty sweetSpeed:WindSpeed.
  ?TideObs a ssn:Observation;
    ssn:observationResult `tidespeed`;
    ssn:observedProperty sweetSpeed:TideSpeed.
FILTER (`tidespeed`<`windspeed`)
SRBench (Zhang et al. 2012)

- Benchmark for RDF/SPARQL Stream Engines
- Contains data from LinkedSensorData, GeoNames, DBPedia
- Mainly queries for functionality tests, with eye on SPARQL 1.1. functionalities

Example (Example Query (to test basic pattern matching))

Q1. Get the rainfall observed once in an hour.

- Tested on CQELS, SPARQL Stream and C-SPARQL

Test results (for engine versions as of 2012)

- Basic SPARQL features supported
- SPARQL 1.1 features (property paths) rather not supported
- Only C-SPARQL supports reasoning (on RDFS level) (tested subsumption and sameAs)
- Combined treatment of static data plus streaming data only for CQELS and C-SPARQL
Language Comparison of SOTA Stream Engines

- Update in 2016
- We also mention Lübecks contribution STARQL (to be discussed in more detail in next lecture)

<table>
<thead>
<tr>
<th>Name</th>
<th>Data Model</th>
<th>Union, Join</th>
<th>IF</th>
<th>Aggregate</th>
<th>Property Paths</th>
<th>Time Windows</th>
<th>Triple Windows</th>
</tr>
</thead>
<tbody>
<tr>
<td>Streaming SPARQL</td>
<td>RDF streams</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>C-SPARQL</td>
<td>RDF streams</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>CQELS</td>
<td>RDF streams</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
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<tr>
<td>SPARQLStream</td>
<td>virt. RDF streams</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>EP-SPARQL</td>
<td>RDF streams</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>TEF-SPARQL</td>
<td>RDF streams</td>
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<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>STARQL</td>
<td>virt. RDF streams</td>
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<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
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</table>

<table>
<thead>
<tr>
<th>Name</th>
<th>W-to-S Op.</th>
<th>Cascading Streams</th>
<th>Intra window time</th>
<th>Sequencing</th>
<th>Pulse</th>
<th>Historic data</th>
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<tbody>
<tr>
<td>Streaming SPARQL</td>
<td>RStream</td>
<td>No</td>
<td>No</td>
<td>No</td>
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<td>No</td>
</tr>
<tr>
<td>C-SPARQL</td>
<td>RStream</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>CQELS</td>
<td>RStream</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
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<tr>
<td>SPARQLStream</td>
<td>R-,I-,D-Stream</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
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<tr>
<td>EP-SPARQL</td>
<td>RStream</td>
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<td>STARQL</td>
<td>RStream</td>
<td>Yes</td>
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<td>Yes</td>
<td>Yes</td>
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</tbody>
</table>
Architecture Comparison of SOTA Stream Engines

<table>
<thead>
<tr>
<th>Used Language</th>
<th>Input</th>
<th>Execution</th>
<th>Query Optimization</th>
<th>Stored Data</th>
<th>Reasoning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Streaming SPARQL</td>
<td>RDF streams</td>
<td>physical stream algebra</td>
<td>Static plan optimization</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>C-SPARQL</td>
<td>RDF streams</td>
<td>DSMS based evaluation</td>
<td>Static plan optimization</td>
<td>Internal triple store</td>
<td>RDF entailment</td>
</tr>
<tr>
<td>CQELS</td>
<td>RDF streams</td>
<td>RDF stream processor</td>
<td>Adaptive query processing operators</td>
<td>Stored linked data</td>
<td>No</td>
</tr>
<tr>
<td>SPARQLStream</td>
<td>Relational streams</td>
<td>external query processing</td>
<td>Static algebra optimizations host evaluator specific</td>
<td>Data source dependent</td>
<td>No</td>
</tr>
<tr>
<td>EP-SPARQL</td>
<td>RDF streams</td>
<td>logic programming</td>
<td>No</td>
<td>No</td>
<td>RDFS, Prolog equivalent</td>
</tr>
<tr>
<td>TEF-SPARQL</td>
<td>RDF streams</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes (DL-Lite, A)</td>
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<tr>
<td>STARQL</td>
<td>Relational streams</td>
<td>external query processing</td>
<td>Static algebra optimizations</td>
<td>Datasonce dependent</td>
<td>Yes (DL-Lite, A)</td>
</tr>
</tbody>
</table>


A stream reasoning community is forming

Everyone is interested in (high-level) stream processing now

- Various new stream reasoners (based on Datalog extensions)
- Stream reasoning + Machine Learning
- Stream reasoning + Verification
- Further benchmark ambitions and testing frameworks
- For recent progress see, e.g., 3rd stream reasoning workshop