LARS: A Logic-Based Framework for Analyzing Reasoning over Streams

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Motivation

Different communities looked at different aspects

- **Data Management:**
  - stream processing approach
  - continues queries
  - low-level, high rate input data (cross-joins, pattern matching, etc.)
  - windows for partial data snapshots

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- **Semantic Web:**
  - lifting stream data to a semantic level
  - linked stream data (coupling tuples with timestamps)
  - several extensions of SPARQL

Observations

- *Lack of (unified) formal foundations*

  stream processing:
  - often operational semantics; unpredictable
  - systems may give for same query different results

- *Comparisons / benchmarks unsatisfactory*
  - semantics outcome not / weakly addressed (tuple counting)
  - benchmarks geared towards high-frequency / limits
  - no general methods, no reference semantics

- *Advanced features missing*
  - controlled nondeterminism, incomplete information, negation, model generation

Aims

“Towards a Logic-Based Framework for Analyzing Stream Reasoning”

- Stream Reasoning

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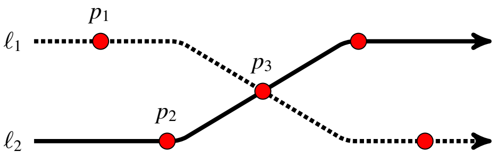
Note: Relates to Complex Event Processing

(e.g., ETALIS [Anicic *et al.*, 2012], RTEC [Artikis *et al.*, 2014])

Example: Public Transportation Monitoring

Samantha with her baby & stroller on public transport, line ℓ_2



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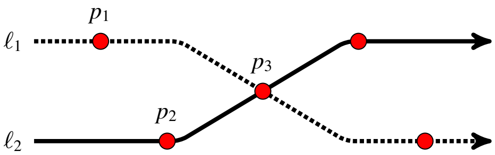
Samantha with her baby & stroller on public transport, line ℓ_2, tram a_2

PLAN			
L	$From$	To	Dur
ℓ_1	p_1	p_3	8
ℓ_2	p_2	p_3	3
...			

LINE	
ID	L
a_1	ℓ_1
a_2	ℓ_2
...	



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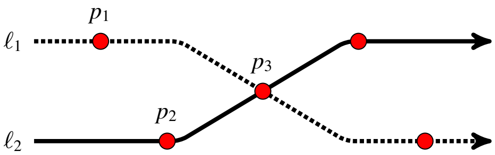

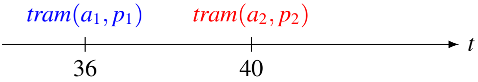

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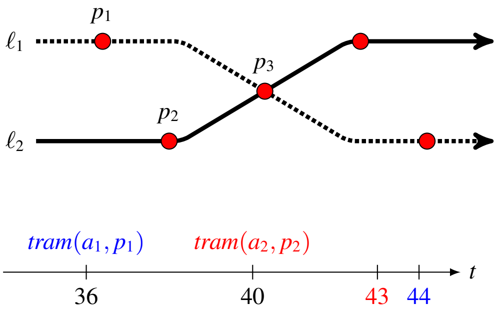

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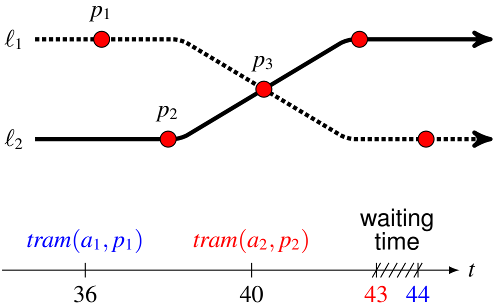

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- Report good connections between two lines at a given stop: ≤ 5 mins waiting

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a_2
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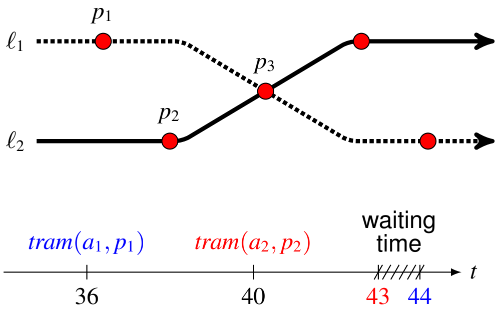

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Stream Model

- Model streams in a simple way
- Elements:
  - data items: set $\mathcal{A}$ of facts (atoms)
  - timeline: interval $T = [l, u] = \{l, l+1, \ldots, u\} \subseteq 2^{\mathbb{N}_0}$ of integers

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Example:

- stream $T = [0, 50]$, $\upsilon = \{36 \mapsto \{tram(a_1, p_1)\}, 40 \mapsto \{tram(a_2, p_2)\}\}$
- substream $T' = [30, 40]$, $\upsilon' = \{36 \mapsto \{tram(a_1, p_1)\}\}$

Window Functions

- Important aspect of stream processing: use only *window* view of data, i.e., limited observability at each point in time
- Different types of windows:
  - time-based windows (within time bounds)
  - tuple-based windows (number of tuples, count)
  - partition-based windows (split input data, process separately)
  - orthogonal, sliding or tumbling (consider atom repeatedly / once)

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  - orthogonal, sliding or tumbling (consider atom repeatedly / once)
- Model windows abstractly as functions

$$w_\iota : (S, t, \mathbf{x}) \mapsto S'$$

assigning each stream $S = (T, \upsilon)$ and time point $t \in T$ depending on parameters $\mathbf{x}$ for window type ι a substream S' of S.

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- Various ways for time references
- Nesting of window operators:

$$\boxplus^{60}_{\tau}\Box\,\boxplus^{5}_{\tau}\,\Diamond tramAt(p_1)$$

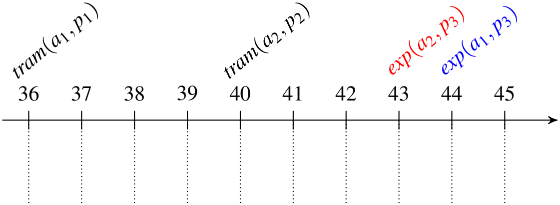
$$\boxplus^{n}_{\#}\,\boxplus^{5}_{\tau}\,\Diamond tramAt(p_1)$$

$$\boxplus^{5}_{\tau}\,\boxplus^{n}_{\#}\,\Diamond tramAt(p_1)$$

Semantics: Evaluation in Stream Context

- Structure: tuple $M = \langle T^\star, \upsilon^\star, W, B \rangle$ where
  - $S^\star = (T^\star, \upsilon^\star)$ is a stream
  - $W = W_1, W_2, \ldots$ are window functions
  - $B \subseteq \mathcal{A}$ is (static, fixed) background knowledge

- Entailment: $M, S^\star, t \Vdash \alpha\,?$ for query α and stream $S^\star$



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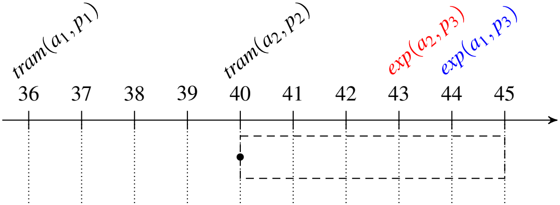

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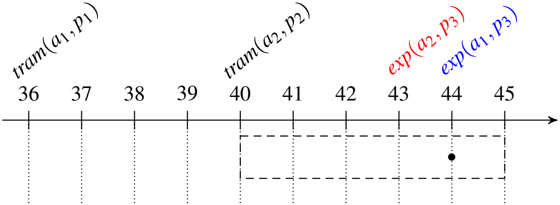

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$$M, S, 44 \Vdash exp(a_1, p_3)$$

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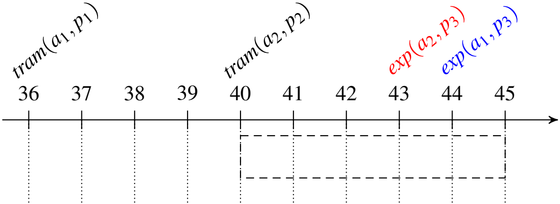

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$$M, S, 44 \Vdash exp(a_1, p_3)\ \checkmark$$

LARS Rules

Intensional part: define data using rules

- Allows to define auxiliary data, output (result) data
- Use datalog-style rules (i.e., variables and grounding)

$$
\begin{aligned}
tramAt(P) &\leftarrow tram(ID, P). \\
gc(ID_1, ID_2, P) &\leftarrow @_T exp(ID_1, P), \\
&\quad\;\; @_T \boxplus_\tau^{+5} \Diamond exp(ID_2, P), \\
&\quad\;\; \text{not } old(ID_2).
\end{aligned}
$$

- Negation: extend answer set semantics: *answer streams*
- Inherit properties of stable / stratified semantics
  - minimality (pointwise $\subseteq$)
  - supportedness
- Exploit ASP features (nondeterminism, preferences & recursion)

Capturing CQL Queries

- A set Q of CQL queries can be captured via a translation $\Delta(P)$ into a LARS program:

> The result of Q on input streams $\mathbb{S}$ at time t corresponds to the (unique) answer stream of $\Delta(P)$ on stream $\triangledown(\mathbb{S})$ at time t.

- **Translation Idea**
  - stream-to-relation
    - Δ_{SRC} translating source (input streams) to table names, using $\boxplus$ and $\Diamond$ and formulas as names
  - for *relation-to-relation* operators:
    - Δ_ρ translating SQL to relational algebra
    - Δ_δ translating relational algebra to datalog
  - for *relation-to-stream* operators:
    - rule heads produce output streams
  - $\Delta(Q) = \bigcup_{q \in Q} \Delta(q)$, where $\Delta(q) = \Delta_\delta(\Delta_\rho(\Delta_{\text{SRC}}(q)))$

ETALIS Encoding

- ETALIS: rules for complex event processing $a \leftarrow x \text{ SEQ } y$
- interval semantics: $\mathcal{I}(a) = \{\langle t_1, t_4\rangle \mid \langle t_1, t_2\rangle \in \mathcal{I}(x), \langle t_3, t_4\rangle \in \mathcal{I}(y), t_2 < t_3\}$

LARS answer streams can capture ETALIS models for integer timelines, if each atom's intervals do not overlap or meet

Translation idea:

- Encode intervals by serial time points labeled with atom
- Window operator $\boxplus^{[\ell,u]}$: selects substream of interval $[\ell, u]$
- Use syntactic sugar:
  - $[\![\ell, u]\!]$: select interval from ℓ to u
  - $\langle\!\langle \ell, u\rangle\!\rangle\alpha$: holds if $[\ell, u]$ is a *maximal* interval where α holds
- Example: $[\![t_1, t_4]\!]\Box\, a \;\leftarrow\; \langle\!\langle t_1, t_2\rangle\!\rangle\Box\, x, \langle\!\langle t_3, t_4\rangle\!\rangle\Box\, y, t_2 < t_3.$

Further and Ongoing Work

- Complexity analysis
- Modeling of streaming processing / reasoning approaches
  - e.g. when do C-SPARQL (pull) and CQELS (push) coincide?
- Algorithms and implementation
  - answer update (incremental methods)
  - optimization (equivalence)
- Distributed streams (multi-context systems)
- Applications (with KLU, NUI Galway, Siemens)

see `http://www.kr.tuwien.ac.at/research/projects/dhsr/`

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Related Work

- *SPARQL streaming*
  - CQELS [Phuoc *et al.*, 2011]
  - C-SPARQL [Barbieri *et al.*, 2010a]
  - EP-SPARQL [Anicic *et al.*, 2011]
  - SPARQLstream [Calbimonte *et al.*, 2010]

  snapshot approaches; advanced extensions (non-mononicity, nondeterminism, missing data) difficult

- *ASP / Datalog*
  - periodic ASP solver calls [Do *et al.*, 2011]
  - time-decaying logic programs [Gebser *et al.*, 2011]
  - StreamLog [Zaniolo, 2012]: stratified datalog extension, using "progressive" CWA to "unblock" query evaluation; no windows

- *Ontology Streams:* incremental reasoning
  - materialization [Volz *et al.*, 2005], [Barbieri *et al.*, 2010b]
  - OSMS [Ren and Pan, 2011]: ontology streams with new, obsolete and invariant axioms
  - classification [Grau *et al.*, 2010]