# Logical Foundations of Continuous Query Languages for Data Streams

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# Data Streams

- Unbounded, rapid, time-varying streams of data elements, continuous flowing on the internet and broad-band
- **Data Stream Management Systems** (DSMS) are designed to process them continuously, with immediate response to new arriving tuples.
- Typical applications involve database like queries. Many adaptations of SQL proposed for continuous queries.
- Continuous (i.e., persistent) queries on transient data, are very different from the transient queries on persistent data creating difficult issues needing better formal models.
  - **blocking queries must be disallowed on data streams**
  - **Previous formal treatments have have focused on streams without time-stamps and proved that for queries:** blocking = non-monotonic !

# The Renaissance of Datalog

- Many DSMS projects were developed during Datalog's Dark Ages, …
- The time has come to revisit data stream query languages with the insights and formal tools provided by logic--surprising results:
  - **Negation is a simpler problem here than in Datalog or Prolog,**
  - **Datalog with minor adjustments becomes a powerful and natural language for data streams.**
- These results hold directly on time-stamped data streams.

# Outline

- Analysis and Design of Logic-based languages for Data streams
  - One time-stamped Data Stream
  - Closed World Assumption (CWA) for data streams.
  - Several time-stamped data streams and the synchronization problem,
  - Streamlog, vs. Datalog and Prolog.

# Time-Stamped Data Streams

A. **Input tuples enter operators in time-stamp order,**
B. **Output of query operators must also be ordered.**

*A stream of messages (ground facts):* **msg(Time, MsgCode)**

*Repeated occurrences of a "red" alarm:*

**repeated(T, X) ← msg(T, X), msg(T0, X), T0 < T .**

**? repeated(T, red)**

*When 'red alarm' occurs at time* **T** *event , an output tuple is produced if the red alarm had also occurred earlier, i.e. at time* **T0 < T.**

# The Importance of Order

*For repeated occurrence of code 'red' we write:* **? repeated(T, red)**

*This is OK:* **repeated(T, X) ← msg(T, X), msg(T0, X), T0 <T.**

*This is not OK:* **repeated(T0, X) ← msg(T, X), msg(T0, X), T0 < T.**

*Thus the* **T0** *event comes first and then when the* **T** *event occurs, an output tuple is produced at once.*

*An immediate response produces out-of-order outputs. Input ($t_1$ a) … ($t_2$ b), … ($t_3$ b), … ($t_4$ a) produces ($t_2$ b) , ($t_1$ a)*

*of course, we do not want wait until we can output tuples in the right order, this would produce a blocking behavior.*

# Progressively Closed World Assumption (PCWA) for Data Streams

- PCWA for a single data stream revises the standard CWA of deductive databases with the provision that the world knowledge is expanding according to the timestamps of the arriving data stream tuples.
- CWA: Once the **p** is not entailed by the given set of facts and Horn rules, then **¬p** can be safely assumed.
- PCWA: Once a **streamfact(T, . . .)** is observed in the input stream, the PCWA allows us to assume **¬streamfact(T0, . . .)** provided that **T0 < T** , and **streamfact(T0, . . .)** is not entailed by the *fact base* augmented with the stream facts having timestamp **< T.**

# Negated Goals

- First occurrence of code red: $?\mathtt{first}(\mathtt{T}, \mathtt{red})$

$$\mathtt{first}(\mathtt{T}, \mathtt{X}) \leftarrow \quad \mathtt{msg}(\mathtt{T}, \mathtt{X}), \neg \mathtt{previous}(\mathtt{T}, \mathtt{X}).$$
$$\mathtt{previous}(\mathtt{T}, \mathtt{X}) \leftarrow \quad \mathtt{msg}(\mathtt{T0}, \mathtt{X}), \mathtt{T0} < \mathtt{T}.$$

This query uses negation on events that, according to their timestamps, are past events. The query can be answered in the present: it is non-blocking.

- Last occurrence of code red: $?\mathtt{last}(\mathtt{T}, \mathtt{red})$

$$\mathtt{last}(\mathtt{T}, \mathtt{Z}) \leftarrow \quad \mathtt{msg}(\mathtt{T}, \mathtt{Z}), \neg \mathtt{next}(\mathtt{T}, \mathtt{Z}).$$
$$\mathtt{next}(\mathtt{T}, \mathtt{Z}) \leftarrow \quad \mathtt{msg}(\mathtt{T1}, \mathtt{Z}), \mathtt{T1} > \mathtt{T}.$$

We do not know if the current red is the last one until we have seen the all stream. Obviously, a **blocking** query. **Thus negation can cause blocking but not always. We must understand when.**

# Sequentiality of Rules & Predicates

*A Sequential rule. The TS of the goals are less or equal than that of the head.*

repeated(T, X) ← msg(T, X), msg(T0, X), T0 < T.

Sequentiality is required for all goals.

**Strict** sequentiality required for negated goals:

$$\begin{aligned} \texttt{first}(\texttt{T},\texttt{X}) &\leftarrow \quad \texttt{msg}(\texttt{T},\texttt{X}), \neg\texttt{previous}(\texttt{T},\texttt{X}). \\ \texttt{previous}(\texttt{T},\texttt{X}) &\leftarrow \quad \texttt{msg}(\texttt{T0},\texttt{X}), \texttt{T0} < \texttt{T}. \end{aligned}$$

*A strictly sequential rule: time-stamp in the head is > than that of every goal. A predicate is strictly sequential when all the rules defining it are strictly sequential.*

# Stratification in Datalog

minpath(X, Y, D) ← path(X, Y, D), ¬shorter(X, Y, D).

shorter(X, Z, D) ← path(X, Z, D1), D1 < D.

path(X, Y, D) ← arc(X, Y, D).

path(X,Z,D) ← path(X,Y,D1), path(Y,Z,D2), D =D1+D2,

- Inefficient computation, since non-minimal paths are eliminated at the end of the recursive iteration, rather than as-soon-as generated.

- More general kinds of stratifications can solve this problem. E.g., XY-stratification, or Statelog, that are based on the introduction of an additional temporal argument—a complication for the users.

- But in Streamlog the temporal argument is already there!!!!!!

# Shortest Path in Streamlog

$$\mathtt{path}(T,X,Y,D) \leftarrow \quad \mathtt{arc}(T,X,Y,D), \neg\mathtt{shorter}(T,X,Y,D).$$
$$\mathtt{shorter}(T,X,Y,D) \leftarrow \mathtt{path}(T',X,Y,D'), T' < T, D' \leq D.$$

$$\begin{aligned}
\mathtt{path}(T,X,Z,Ds) \leftarrow\ & \mathtt{path}(T,X,Y,D), \mathtt{path}(T',Y,Z,D'),\\
& T' < T,\ Ds = D{+}D'.\\
\mathtt{path}(T,X,Z,Ds) \leftarrow\ & \mathtt{path}(T',X,Y,D'), \mathtt{path}(T,Y,Z,D),\\
& T' < T,\ Ds = D'{+}D.\\
\mathtt{path}(T,X,Z,Ds) \leftarrow\ & \mathtt{path}(T',X,Y,D'), \mathtt{path}(T,Y,Z,D),\\
& T' = T,\ Ds = D'{+}D.
\end{aligned}$$

- Arriving arcs are check against previous paths $T' < T,$
- now $\neg\mathtt{shorter}(T,X,Y,D)$ can be added in the last three rules too
- The last three rules can be condensed into one:

$$\begin{aligned}
\mathtt{path}(T3,X,Z,Ds) \leftarrow\ & \mathtt{path}(T2,X,Y,D), \mathtt{path}(T1,Y,Z,D'),\\
& \mathtt{lgr}(T1,T2,T3)\ Ds = D{+}D'.
\end{aligned}$$

# Bistate Version of a Program

1. Rename all the predicates in the body whose temporal argument is less than that of the head by the suffix **_old**

$$\mathtt{path}(T,X,Y,D) \leftarrow \quad \mathtt{arc}(T,X,Y,D), \neg\mathtt{shorter}(T,X,Y,D).$$

2. $\mathtt{shorter}(T,X,Y,D) \leftarrow \mathtt{path}(T',X,Y,D'), T' < T, D' \leq D.$

$$\begin{aligned}
\mathtt{path}(T,X,Z,Ds) &\leftarrow \mathtt{path}(T,X,Y,D), \mathtt{path}(T',Y,Z,D'),\\
&\quad T' < T,\ Ds = D{+}D'.\\
\mathtt{path}(T,X,Z,Ds) &\leftarrow \mathtt{path}(T',X,Y,D'), \mathtt{path}(T,Y,Z,D),\\
&\quad T' < T,\ Ds = D'{+}D.\\
\mathtt{path}(T,X,Z,Ds) &\leftarrow \mathtt{path}(T',X,Y,D'), \mathtt{path}(T,Y,Z,D),\\
&\quad T' = T,\ Ds = D'{+}D.
\end{aligned}$$

The bistate version of the program is stratified: e.g.

- **old_path** and **shorter** at lower stratum and
- **path** at stratum next stratum.

Thus, the original program is locally stratified in the same way.

# Semantics: formal and Operational

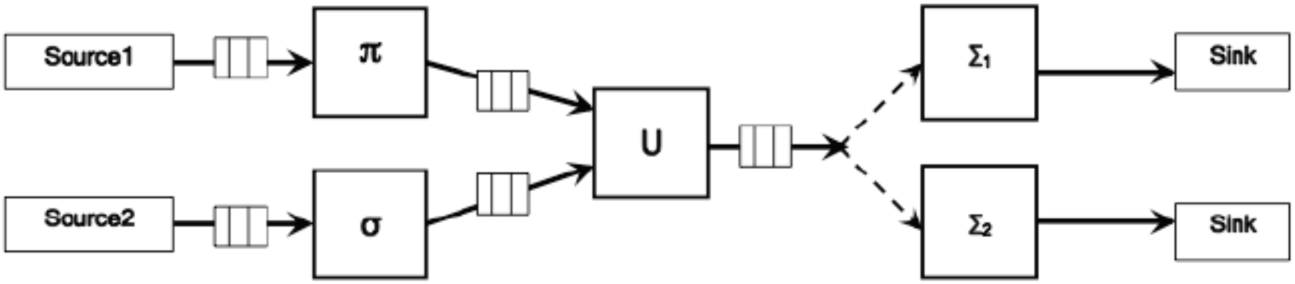
Theorem 1: if the bistate version of the program is stratified then the original program is locally stratified.

Theorem 2: if the original program is strictly sequential then its bistate version is stratified.

Perfect Model of a strictly sequential program is simple to compute:

For each new arriving data stream fact
begin
if the fact has a timestamp larger than that of the previous one, then update the old_ tables;
compute the implications of the new fact according to the stratified bistate version of the program.
end

# Multiple Streams: Unions

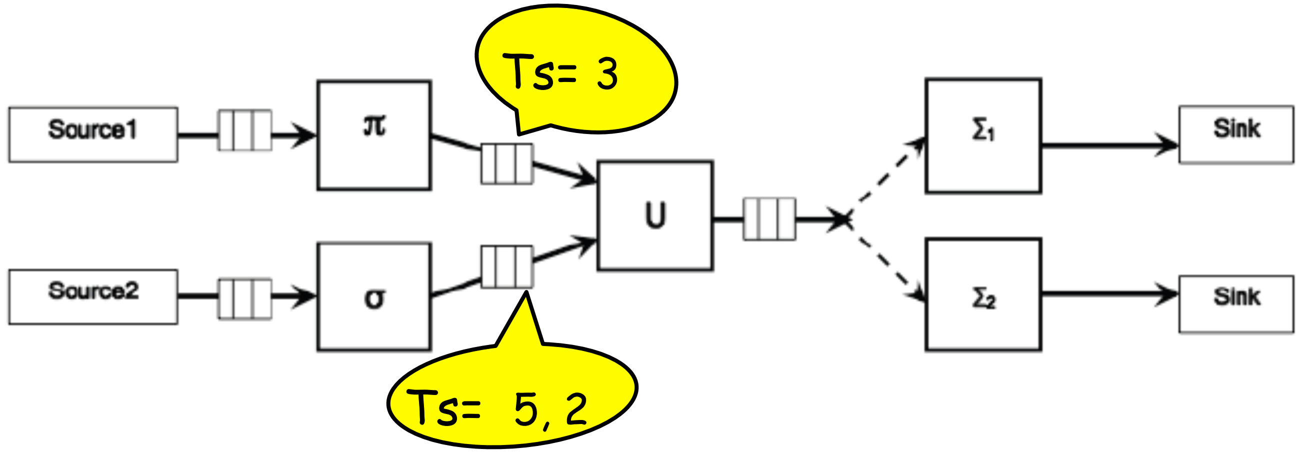



msg(T, S) ← sensr1(T, S).

msg(T, S) ← sensr2(T, S).

- ***On stored data, multiple rules simply define disjunction.***
- ***But on data streams there is also a time-stamp order constraint.***

# Multiple Streams: Unions

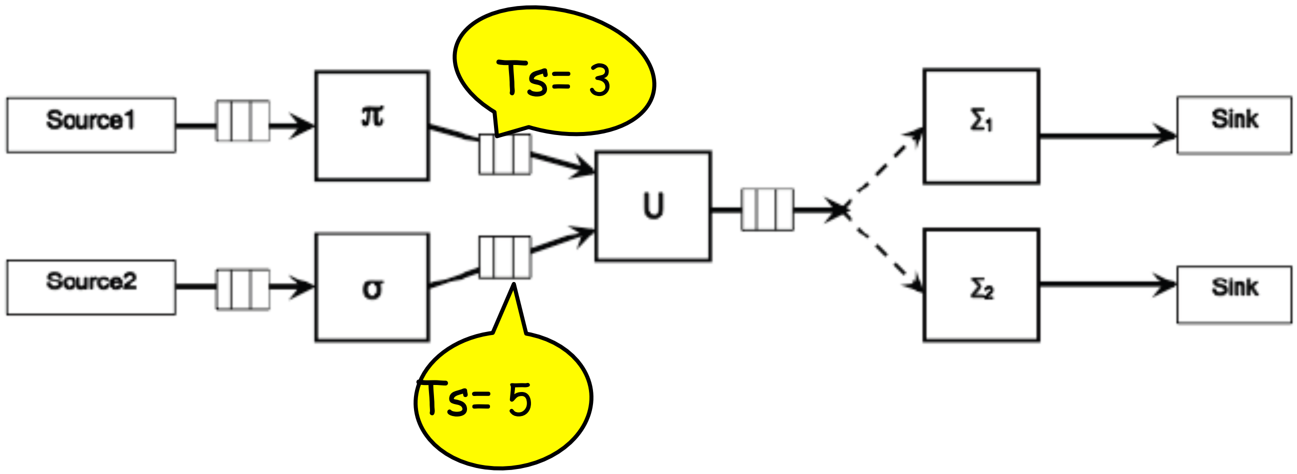



msg(T, S) ← sensr1(T, S).

msg(T, S) ← sensr2(T, S).

When both input buffers have tuples, simply take a tuple that has a mininimal timestamp.

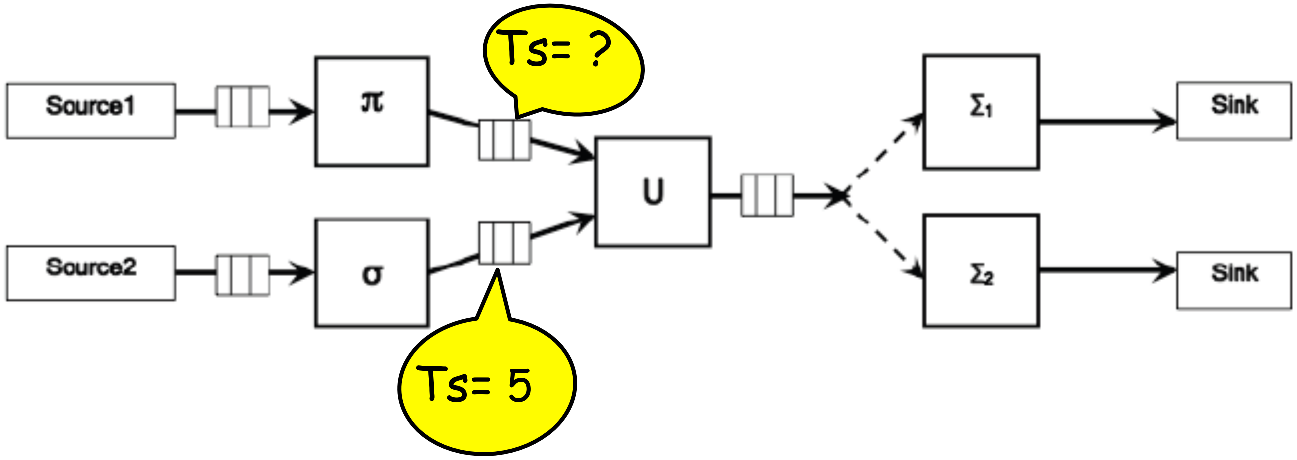
# Multiple Streams: Unions




msg(T, S) ← sensr1(T, S).

msg(T, S) ← sensr2(T, S).

# Multiple Streams: Unions




msg(T, S) ← sensr1(T, S).

msg(T, S) ← sensr2(T, S).

- In order to perform a correct sort-merge, when one of the imput buffer is empty , we must wait until a new tuple arrives.
- This strategy can cause long waits, and stop working when one streams stops.
- System-added punctuation tuples can be used to addres this problem.

# Multiple Streams and Synchronization

**A. The union of two streams:**

$$\mathtt{msg}(\mathtt{T1},\mathtt{S1}) \leftarrow \mathtt{sensr1}(\mathtt{T1},\mathtt{S1}).$$
$$\mathtt{msg}(\mathtt{T2},\mathtt{S2}) \leftarrow \mathtt{sensr2}(\mathtt{T2},\mathtt{S2}).$$

**B. Sort-Merge of two streams:**

$$\mathtt{msg}(\mathtt{T1},\mathtt{S1}) \leftarrow \mathtt{sensr1}(\mathtt{T1},\mathtt{S1}), \mathtt{sensr2}(\mathtt{T2},\_), \mathtt{T2} \geq \mathtt{T1}.$$
$$\mathtt{msg}(\mathtt{T2},\mathtt{S2}) \leftarrow \mathtt{sensr2}(\mathtt{T2},\mathtt{S2}), \mathtt{sensr1}(\mathtt{T1},\_), \mathtt{T1} \geq \mathtt{T2}.$$

**C. Synchronized union of two streams:**

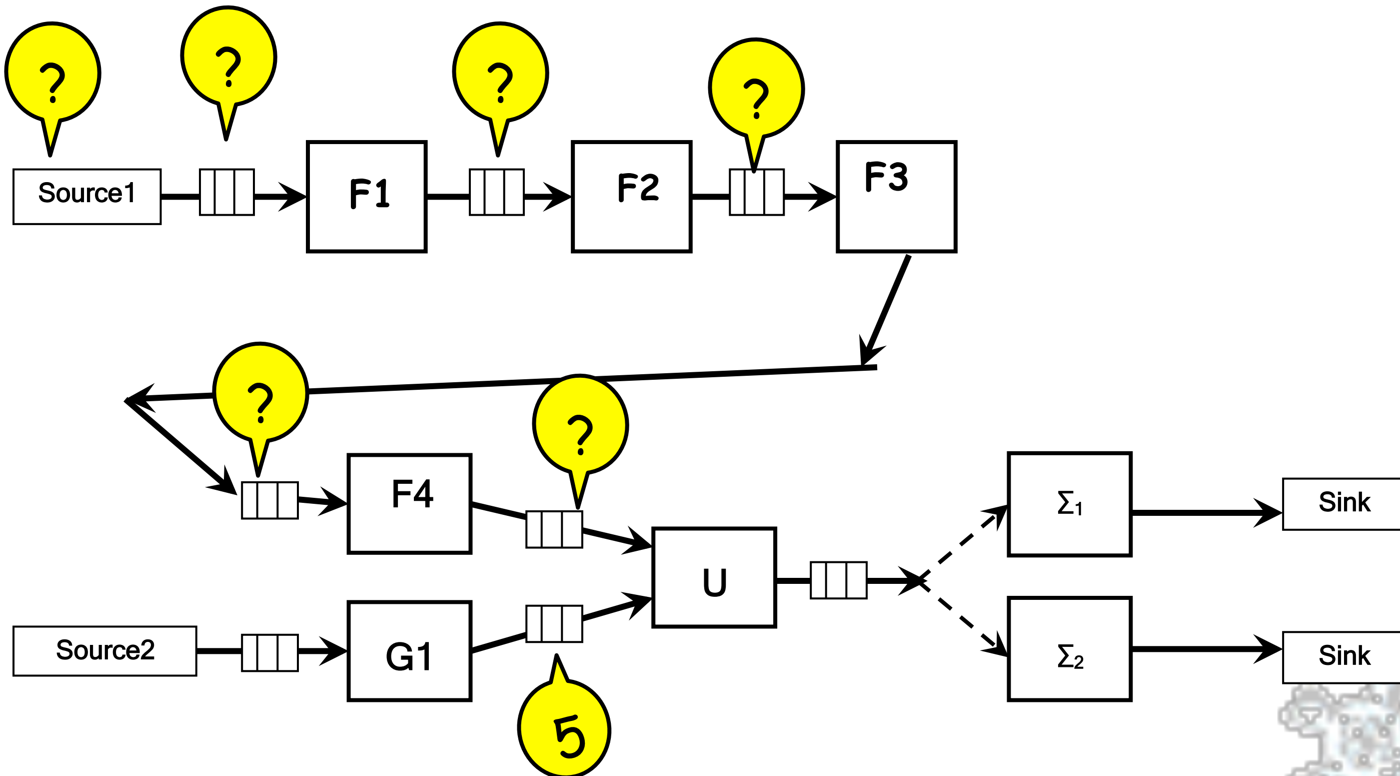
$$\mathtt{msg}(\mathtt{T1},\mathtt{S1}) \leftarrow \mathtt{sensr1}(\mathtt{T1},\mathtt{S1}), \neg \mathtt{missing2}(\mathtt{T1}).$$
$$\mathtt{msg}(\mathtt{T2},\mathtt{S2}) \leftarrow \mathtt{sensr2}(\mathtt{T2},\mathtt{S2}), \neg \mathtt{missing1}(\mathtt{T2}).$$

$$\mathtt{missing2}(\mathtt{T1}) \leftarrow \mathtt{sensr2}(\mathtt{T2},\mathtt{S}), \mathtt{T2} < \mathtt{T1}.$$
$$\mathtt{missing1}(\mathtt{T2}) \leftarrow \mathtt{sensr1}(\mathtt{T1},\mathtt{S}), \mathtt{T1} < \mathtt{T2}.$$

A: what users write.
B: the partially blocking way in which it is often treated now.
C: the proper characterization using negation.

From correct semantics to better implementation:

# Backtracking on Idle Branches



# Minimizing Idle Waiting in Implementation

- Generation of punctuation tuples (carrying enabling time stamps ETS) to unblock idle waiting union operators.
- At regular intervals or, on demand, via backtracking.

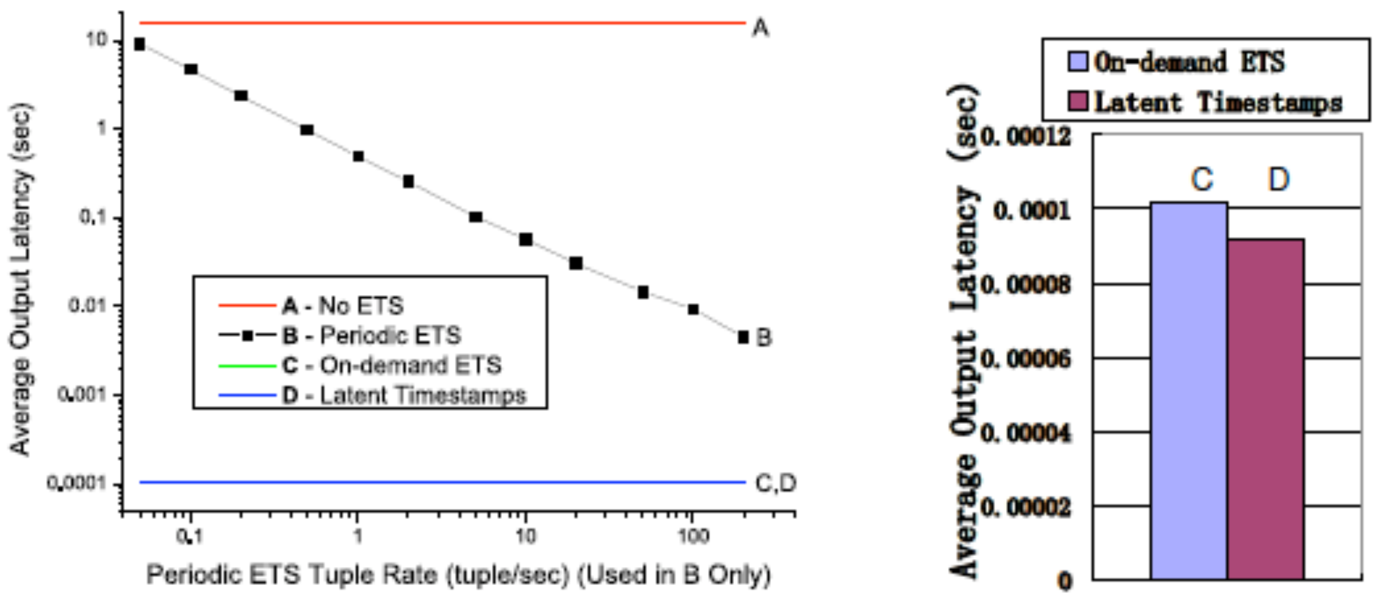



Fig. 2. Average Output Latency

Latent: same as no timestamp

# Conclusion

- Non-monotonic reasoning for data streams can be supported quite naturally and efficiently using simple extensions of Datalog.
- We introduced rigorous logical foundations for continuous query languages.
- These are practical solutions that significantly enhance the expressive power of continuous query languages.
- Streamlog extends Datalog but also benefits from Prolog.
- Current work: data streams without timestamps, and beyond strictly sequential.
- Future directions: a unified language for stored data and data streams: SAUL (Scalable Analytics Unification Language).

# Conclusion

Exciting progress in overcoming disabilities suffered by DSMS query languages in the dark age of our field.

# Thank you!

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