Systems Infrastructure for Data Science

Web Science Group
Uni Freiburg
WS 2012/13

Data Stream Processing

Topics

- **Model Issues**
- System Issues
- Distributed Processing
- Web-Scale Streaming

Data Streams

- Continuous sequences of data elements that are typically:
  - **Push-based** (data flow controlled by sources)
  - **Ordered** (e.g., by arrival time, or by explicit timestamps)
  - **Rapid** (e.g., ~ 100K messages/second in market data)
  - **Potentially unbounded** (may have no end)
  - **Time-sensitive** (usually representing real-time events)
  - **Time-varying** (in content and speed)
  - **Unpredictable** (autonomous data sources)

Example Applications

- Financial Services

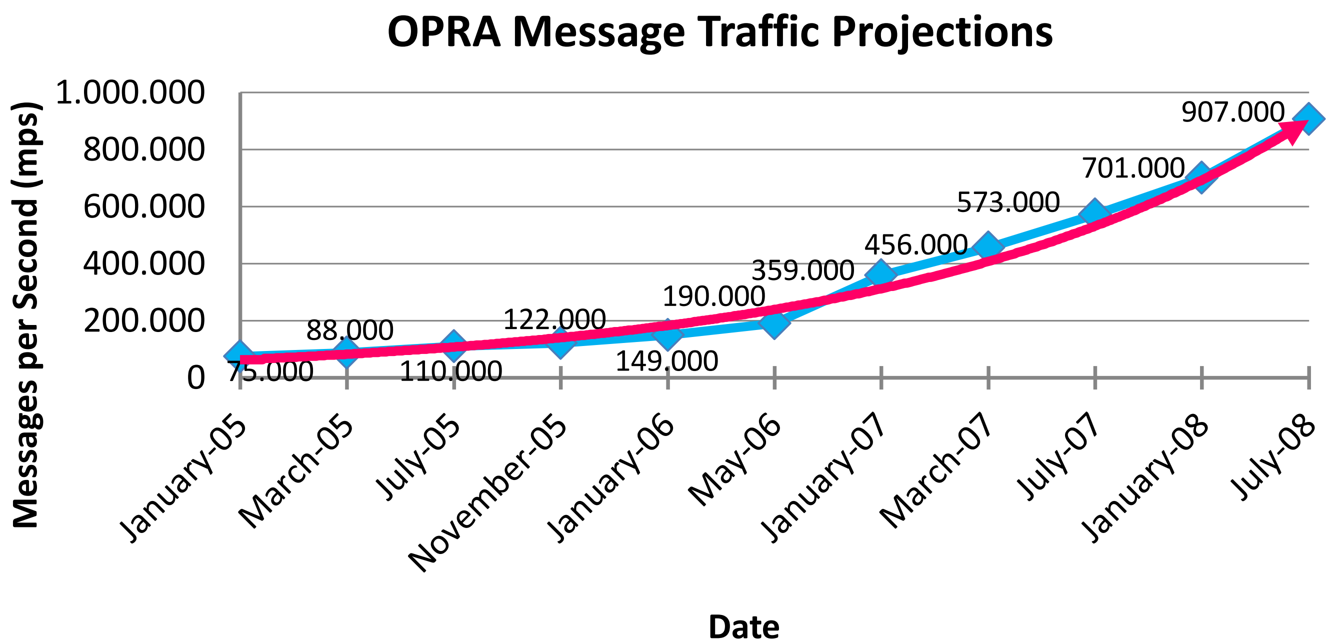
Example:

- Trades(time, symbol, price, volume)

Typical Applications:

- Algorithmic Trading
- Foreign Exchange
- Fraud Detection
- Compliance Checking

Financial Services: Skyrocketing Data Rates



[Source: Options Price Reporting Authority, http://www.opradata.com]

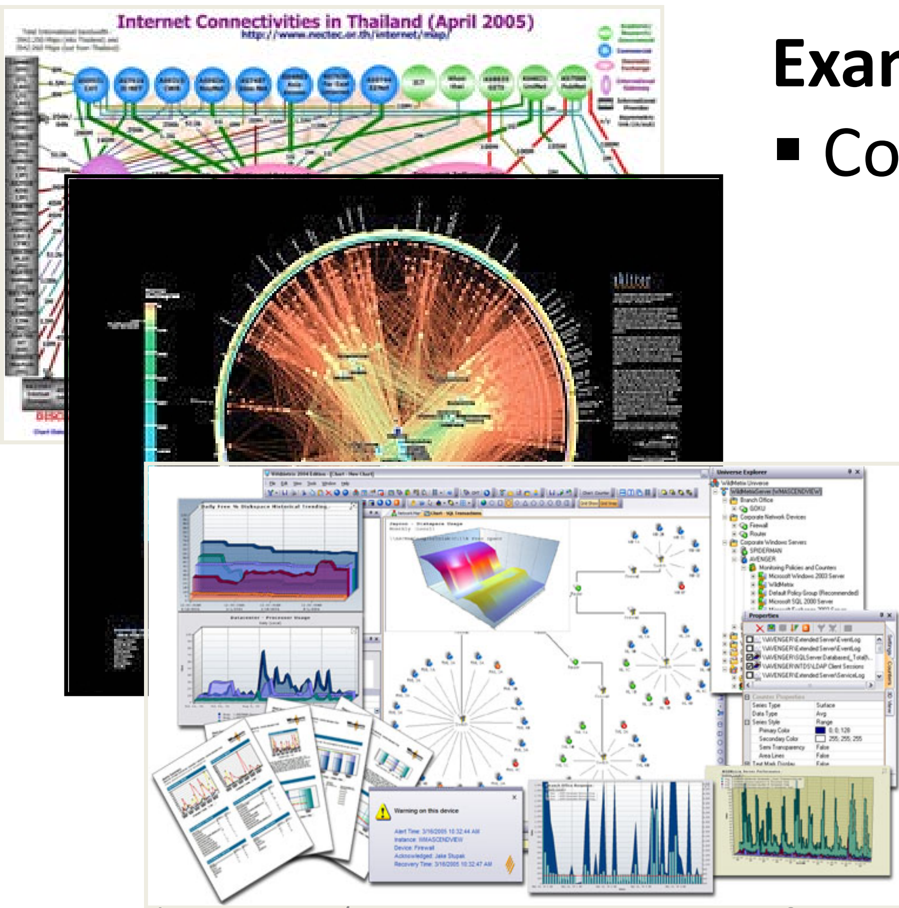
Some more up-to-date rates from http://www.marketdatapeaks.com/:

- 4 M mps on January 25, 2013
- 6.65 M mps on October 7, 2011

Low response time critical (think high frequency trading)!

Example Applications

- System and Network Monitoring



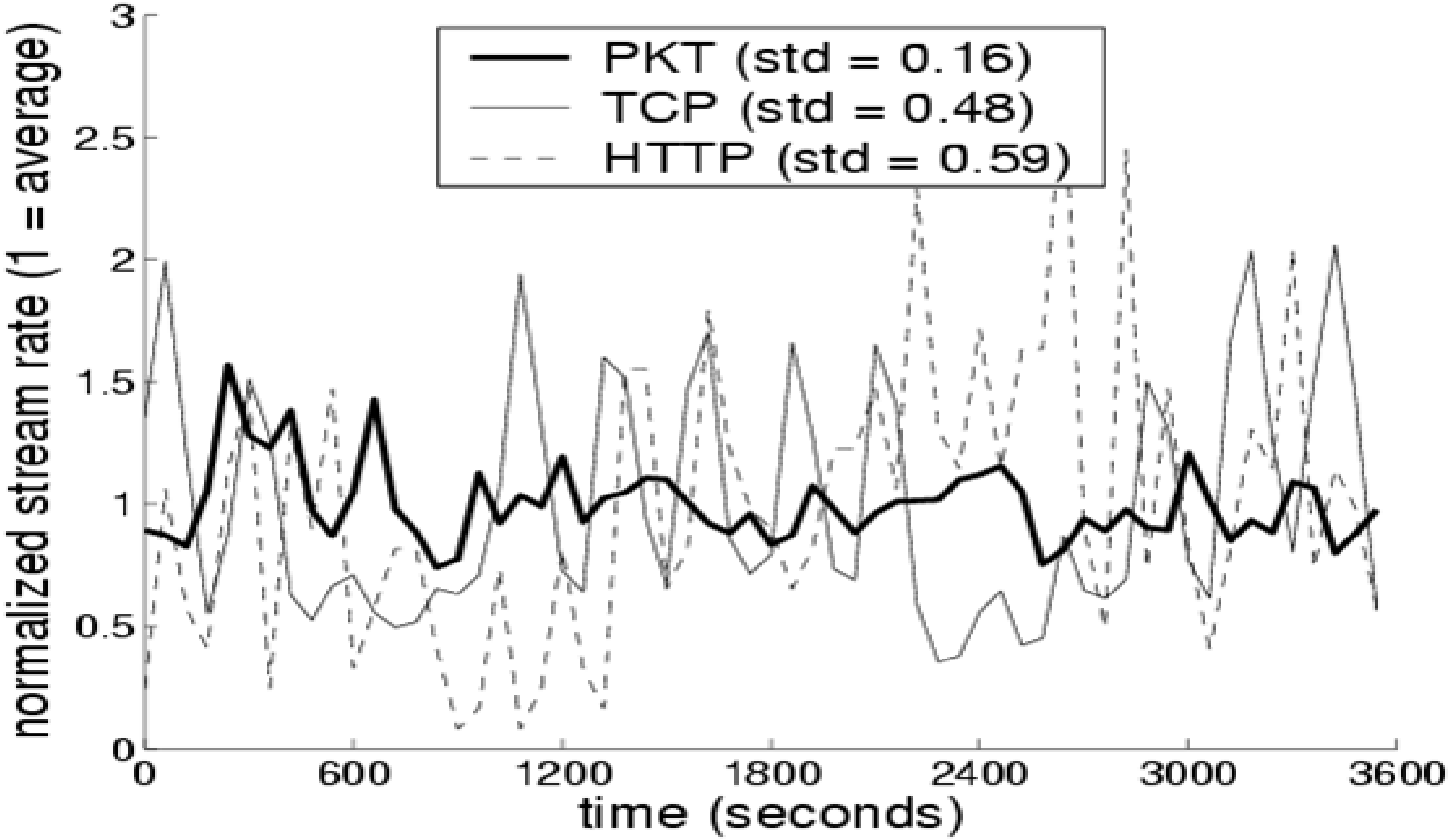
Example:

- Connections(time, srcIP, destIP, destPort, status)

Typical Applications:

- Server load monitoring
- Network traffic monitoring
- Detecting security attacks
  - Denial of Service
  - Intrusion

Network Monitoring: Bursty Data Rates



[Source: Internet Traffic Archive, http://ita.ee.lbl.gov/]

Example Applications

- Sensor-based Monitoring

Example:

- CarPositions(time, id, speed, position)

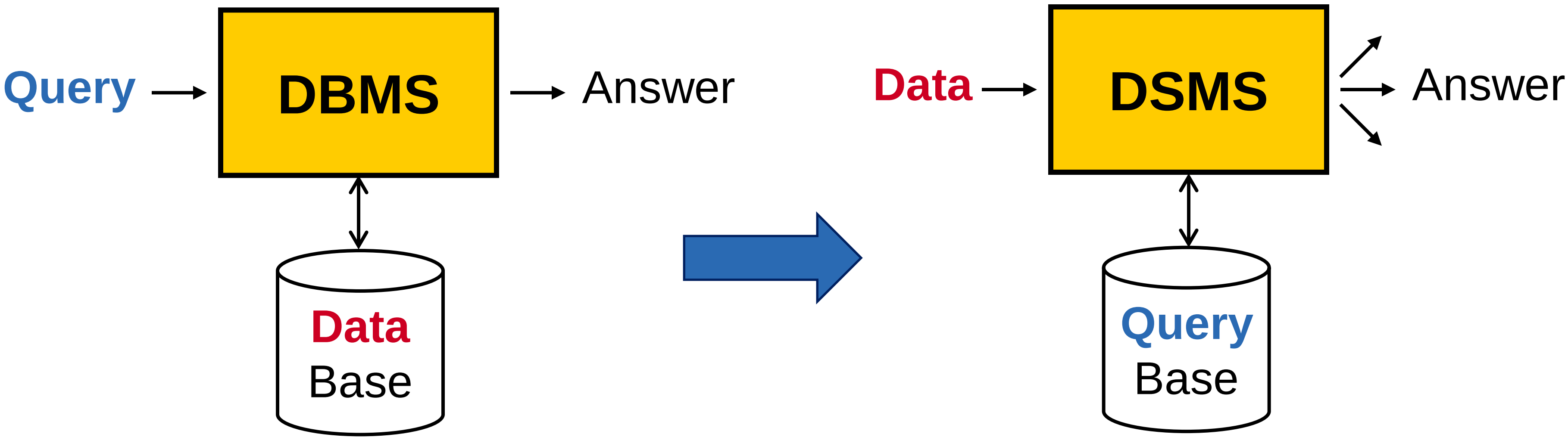
Typical Applications:

- Monitoring congested roads
- Route planning
- Rule violations
- Tolling

Historical Background

- 1990s: Various extensions to traditional database systems
  - Triggers in Active DB's, Sequence DB's, Continuous Queries, Pub/Sub, etc.
- Early 2000s: Data Stream Management Systems
  - Aurora [Brandeis-Brown-MIT]
  - STREAM [Stanford]
  - TelegraphCQ [UC Berkeley]
  - Many others (NiagaraCQ, Gigascope, Nile, PIPES, …)
- 2003: Start-ups
  - Aurora -> StreamBase, Inc.
    -> Borealis (= distributed Aurora)
  - STREAM -> Coral8, Inc.
- 2005: More Start-ups
  - TelegraphCQ -> Truviso, Inc.
- Today: Growing industry interest and standardization efforts

A Paradigm Shift in Data Processing Model



Traditional Data Management

Data Stream Management

DBMS vs. DSMS

- Persistent relations
- Read-intensive
- One-time queries
- Random access
- Access plan determined by query processor and physical DB design

- Transient streams
- Update-intensive
- Continuous queries (*a.k.a., long-running, standing, or persistent queries*)
- Sequential access
- Unpredictable data characteristics and arrival patterns

Model Issues

- Data models
  - Relational-based vs. XML-based vs Object-based
  - Time and Order
- Query models
  - Declarative vs. Procedural
  - Window-based Processing

Example Models

- STREAM / CQL [*Stanford*]
  - Relational-based data model
  - Declarative query language (SQL extensions)
- Aurora / SQuAl [*Brandeis-Brown-MIT*]
  - Relational-based data model
  - Procedural query language (Relational algebra extensions)
- MXQuery [*ETH Zurich*]
  - XML-based data model
  - Declarative query language (XQuery extensions)

Window-based Processing

- Windows are finite excerpts of a potentially unbounded stream.
- Most streaming applications are interested in the readings of the recent past.
- Windows help us unblock operators such as aggregates.
- Windows help us bound the memory usage for operators such as joins.

Window Example

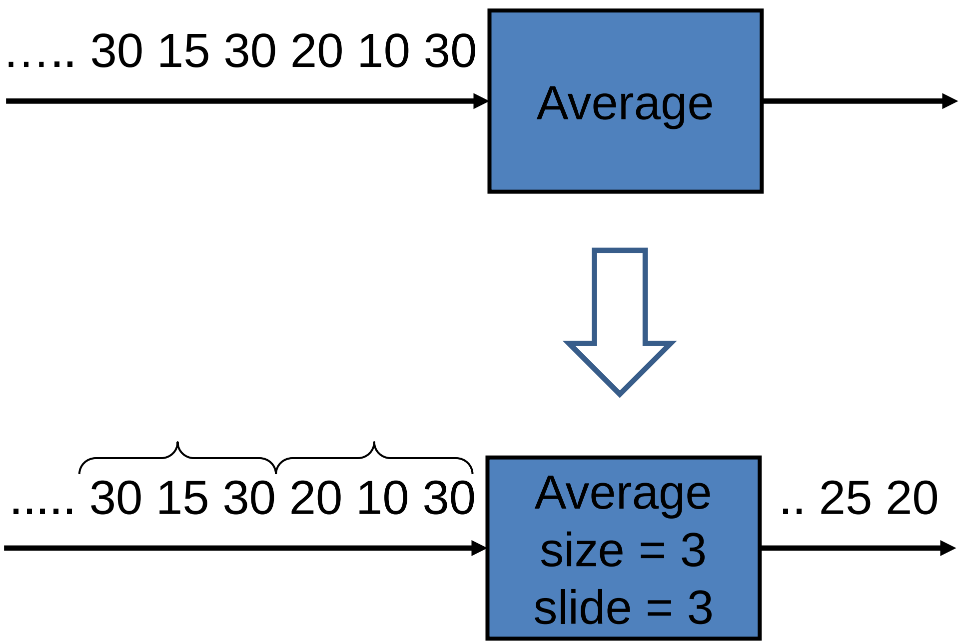
- Two basic parameters: size and slide
- Example: **`Trades(time, symbol, price, volume)`**

size = 10 min

slide by 5 min

```
(10:00, “IBM”,  20, 100)
(10:00, “INTC”, 15, 200)
(10:00, “MSFT”, 22, 100)
(10:05, “IBM”,  18, 300)
(10:05, “MSFT”, 21, 100)
(10:10, “IBM”,  18, 200)
(10:10, “MSFT”, 20, 100)
(10:15, “IBM”,  20, 100)
(10:15, “INTC”, 20, 200)
(10:15, “MSFT”, 20, 200)
.
.
```

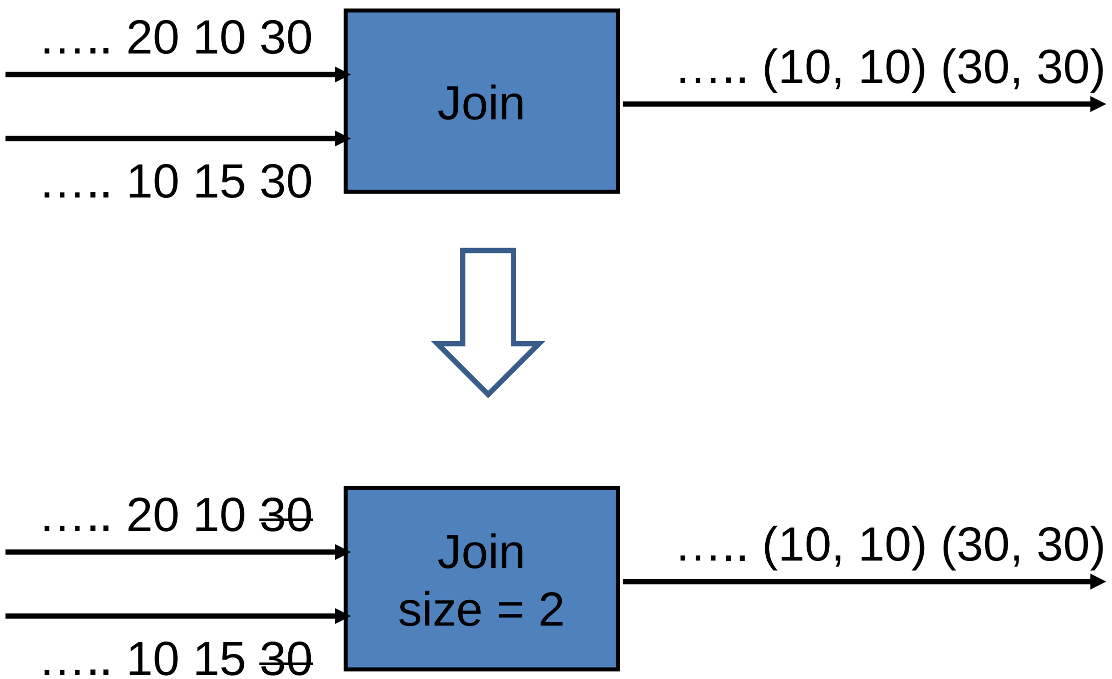
Windows: Unblocking Aggregate Operation



- **Problem:**
  No results can be produced until the stream ends.
  - ➢ Average is "blocked".

- **Solution:**
  Average can be computed on sliding windows.
  - ➢ Average is "unblocked".

Windows: Bounding Join State



- Problem:
  Join must buffer its inputs until both streams end.
  ➢Join state is "unbounded".

- Solution:
  Join must only buffer the latest window on its inputs.
  ➢Join state is "bounded".

STREAM CQL: **C**ontinuous **Q**uery **L**anguage

- SQL for Relation-to-Relation operations
- Additionally:
  - "Stream" as a new data type (in addition to "Relation")
  - Continuous instead of one-time query semantics
  - Stream-to-Relation operations:
    - Window specifications derived from SQL-99
  - Relation-to-Stream operations:
    - Three special operators: Istream, Dstream, Rstream
  - Simple sampling operations on streams

CQL: Streams vs. Relations

- T: discrete, ordered time domain

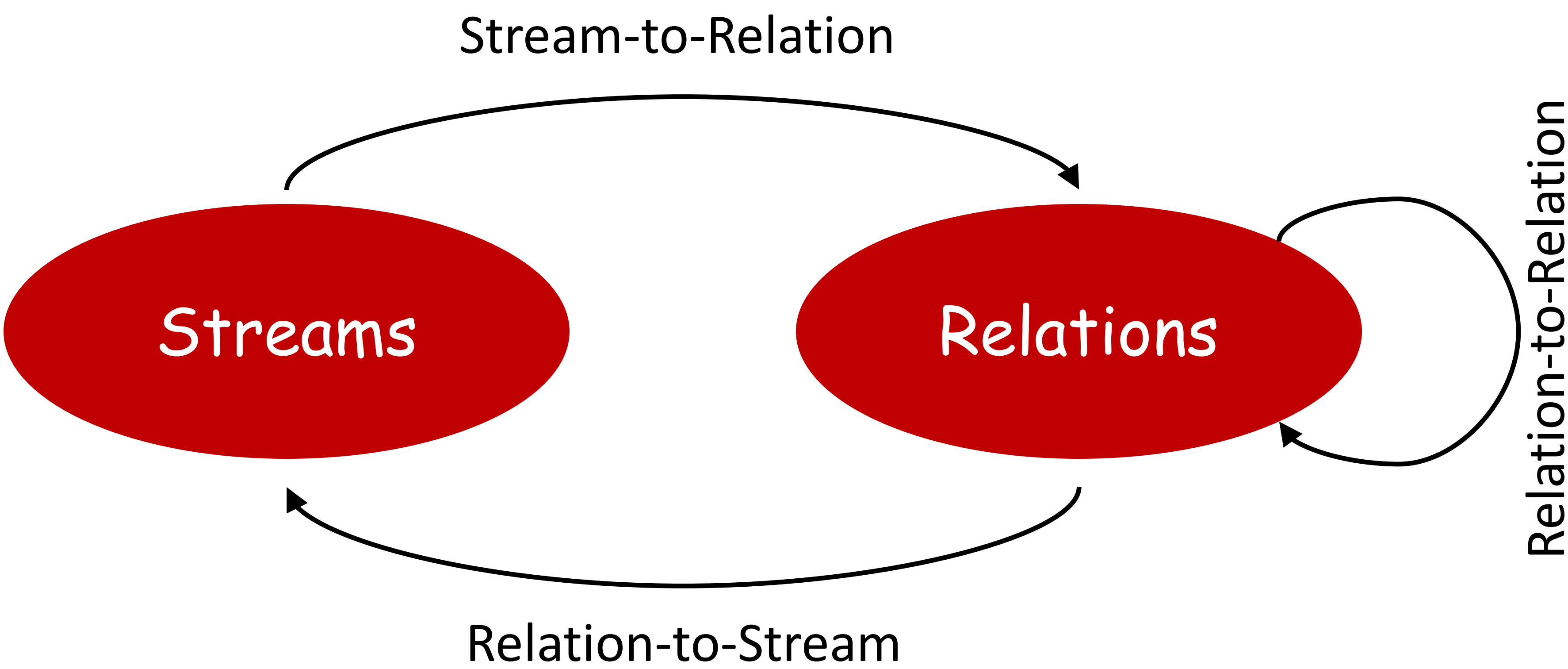
- A stream S is a possibly infinite bag of elements <s, t>, where s is a tuple with the schema of S and t ϵ T is the timestamp of the element.
  - Note: Timestamp is not part of the tuple schema!

- A relation R is a mapping from each time instant in T to a finite but unbounded bag of tuples with the schema of R.

CQL: Continuous Query Semantics

- Time “advances” from t-1 to t, when all inputs up to t-1 have been processed.
- For a query producing a stream:
  - At time t ϵ T, all inputs up to t are processed and the continuous query emits any new stream result elements with timestamp t.
- For a query producing a relation:
  - At time t ϵ T, all inputs up to t are processed and the continuous query updates the output relation to state R(t).

CQL: Mappings between Streams and Relations



- Stream-to-Stream = Stream-to-Relation + Relation-to-Stream

CQL: Stream-to-Relation Operators

- Time-based sliding windows
  - FROM S[RANGE T]
- Tuple-based sliding windows
  - FROM S[ROWS N]
- Partitioned windows
  - FROM S[PARTITION BY A_1, …, A_k RANGE T]
  - FROM S[PARTITION BY A_1, …, A_k ROWS N]
- Windows with a “slide” parameter
  - FROM S[RANGE T SLIDE L]
  - FROM S[ROWS N SLIDE L]
  - FROM S[PARTITION BY A_1, …, A_k RANGE T SLIDE L]
  - FROM S[PARTITION BY A_1, …, A_k ROWS N SLIDE L]

CQL: Relation-to-Stream Operators

- Insert stream

$$Istream(R) = \bigcup_{t \geq 0} ((R(t) - R(t-1)) \times \{t\})$$

- Delete stream

$$Dstream(R) = \bigcup_{t > 0} ((R(t-1) - R(t)) \times \{t\})$$

- Relation stream

$$Rstream(R) = \bigcup_{t \geq 0} (R(t) \times \{t\})$$

- SELECT Istream(..), SELECT Dstream(..), SELECT Rstream(..)

CQL: Example Queries

Trades (time, symbol, price, volume)
NYSE_Trades (time, symbol, price, volume)
SWX_Trades (time, symbol, price, volume)

- **Streaming Filter**

```
SELECT  Istream(*)
FROM    Trades[RANGE Unbounded]
WHERE price > 20
```

- **Streaming Aggregation**

```
SELECT  Istream(Count(*))
FROM    Trades[PARTITION BY symbol
               RANGE 10 Minutes
               SLIDE 1 Minute]
```

- **Sliding-window Join**

```
SELECT  Istream(*)
FROM    NYSE_Trades[RANGE 10 Minutes], SWX_Trades[RANGE 10 Minutes]
WHERE NYSE_Trades.symbol = SWX_Trades.symbol
```

CQL: Example Query Execution

- Stream: S(A)
- Query:
  SELECT Istream(*)
  FROM S[ROWS 1]
  WHERE <Filter>
- Operations:
  LastRow: S-to-R
  Filter: R-to-R
  Istream: R-to-S
- Assumption:
  (a_0), (a_2), (a_4) satisfy the filter.

Time	S	LastRow	Filter	Istream
0	$\langle(a_0),0\rangle$	(a_0)	(a_0)	$\langle(a_0),0\rangle$
1	$\langle(a_0),0\rangle$ $\langle(a_1),1\rangle$	(a_1)	ϕ	$\langle(a_0),0\rangle$
2	$\langle(a_0),0\rangle$ $\langle(a_1),1\rangle$ $\langle(a_2),2\rangle$	(a_2)	(a_2)	$\langle(a_0),0\rangle$ $\langle(a_2),2\rangle$
3	$\langle(a_0),0\rangle$ $\langle(a_1),1\rangle$ $\langle(a_2),2\rangle$ $\langle(a_3),3\rangle$	(a_3)	ϕ	$\langle(a_0),0\rangle$ $\langle(a_2),2\rangle$
4	$\langle(a_0),0\rangle$ $\langle(a_1),1\rangle$ $\langle(a_2),2\rangle$ $\langle(a_3),3\rangle$ $\langle(a_4),4\rangle$	(a_4)	(a_4)	$\langle(a_0),0\rangle$ $\langle(a_2),2\rangle$ $\langle(a_4),4\rangle$
⋮	⋮	⋮	⋮	⋮

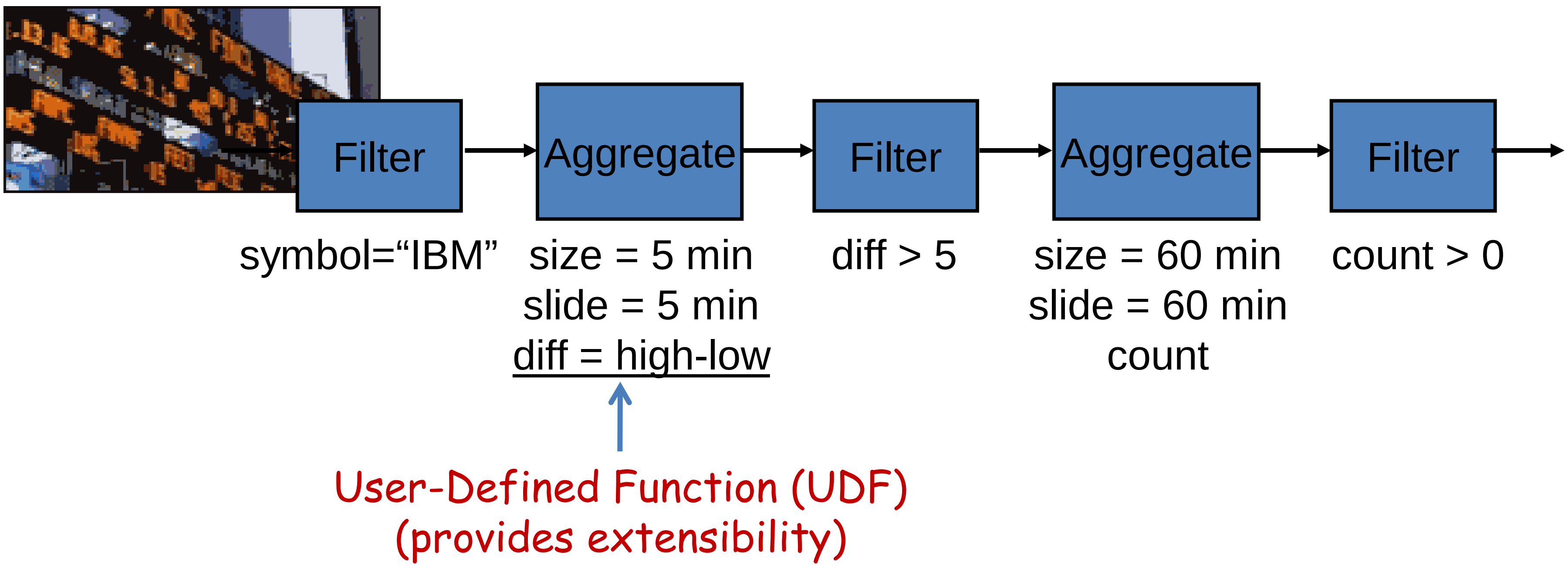
Aurora SQuAl: **S**tream **Qu**ery **Al**gebra

- A stream is an append-only sequence of tuples with a uniform schema.
- The system stamps each tuple with its time of arrival.
- Disorder is allowed.
- Queries are represented with data-flow diagrams consisting of operators.
- Order-agnostic operators:
  - Filter, Map, Union
- Order-sensitive operators:
  - BSort, Aggregate, Join, Resample

SQuAl: Operators

- **Filter** applies a predicate on each stream tuple.
- **Map** applies a function on each stream tuple. *(* extensibility)*
  - e.g., projection
- **Union** merges two or more streams into one.
  - “order-preserving” version also exists.
- **BSort** is a buffer-based approximate sort.
  - equivalent to n-pass bubble sort
- **Aggregate** applies window functions to sliding windows over its input. *(* extensibility)*
- **Join** applies a predicate to pairs of tuples from two input streams that are within a certain window distance from each other.
- **Resample** applies an interpolation function on a stream to align it with another stream.

SQuAl: Example Query



- Boxes and arrows data-flow diagram instead of a declarative specification.
- Same query can also be written in STREAM CQL as a nested query.

SQuAl: Slack & Timeout Parameters

- **Slack** is a stream parameter to specify the degree of disorder in that stream.
  - Out of order tuples beyond the slack parameter are simply discarded.
- **Timeout** is a parameter for sliding window operators to specify the maximum time period that a window is allowed to remain open.
  - Delayed tuples beyond the timeout parameter are simply discarded.

Streaming XQuery

- Extend existing turing-complete processing language
- Benefit: Data Model already sequence-based, no mapping needed
- Extend for infinite sequences, define formal semantics for existing operators
- Define predicate-based window operator to produce finite sequences, can be fully nested
- Time not part of data model, operate on item values
- No implicit constraints
- Limitation: FLWOR semantics difficult for join

Streaming XQuery Example

Most valuable customer per day

```
declare variable $seq external;
forseq $w in $seq/sequence/* sliding window
start curItem $cur, prevItem $prev when day-from-date(xs:dateTime($cur/@date)) ne day-from-
      date(xs:dateTime($prev/@date)) or empty($prev)
end when newstart
return
<mostValuableCustomer endOfDay="{xs:dateTime($cur/@date)}">{
let $companies :=
for $x in distinct-values($w/@billTo )
return
<amount company="{$x}">{sum($w[/@billTo eq $x]/@total)}</amount>
let $max := max($companies)
for $company in $companies
where $company eq xs:untypedAtomic($max)
return $company
 }
</mostValuableCustomer>
```

Common Window Types

- Sliding window
  - A window that slides (i.e., both of its end-points move) as new stream tuples arrive.
- Tumbling window
  - A sliding window for which window size = window slide (i.e., consecutive windows do not overlap).
- Landmark window
  - A window which is moving only on one of its end-points (usually the forward end-point).

Common Window Types

- Time-based window
  - A window whose size and content is determined by tuples that arrived within a “time period”.
  - Note: The actual size of such a window may depend on the stream arrival rate.
- Tuple-based window (a.k.a., count-based window)
  - A window whose size and content is determined by the number of tuples arrived.
  - Note: The actual size is always fixed.
- Semantic window (a.k.a., predicate-based window)
  - A window whose size and content is determined by the tuple contents.
  - Note: Time-based window is a very simple form of semantic window when the time field carried in the tuple is used for windowing.

A Final Note on Window Execution Semantics

- Currently, there is no standard model for defining and executing stream windows.
  - Example: Even “time-based window” works differently in different systems, producing different query results.

- Example differentiators:
  - What triggers window state change? (e.g., time in STREAM vs. tuple arrival in Aurora)
  - When is a window result reported? (e.g., at window close in Aurora vs. at each window state change in Coral8)
  - …

Time in DSMS

- „A window of 30 seconds, starting every 5 seconds"
- What is the precise meaning of these time values?
- Two main approaches to handle time:
  - System Time: take 30 seconds of execution time
  - Application Time: 30 seconds of data time fields
- System Time leads to non-deterministic results
- Application Time might cause system-time delays

=> Heartbeats to synchronize

- Application Time desirable, in practice often system time
- Other time aspects:
  - Point in Time or Time Period
  - Start, End, ...

Stream Constraints

- Metadata about streams that can be used for their optimized processing, in particular:
  - to reduce, bound, eliminate memory state
  - could be an alternative to windowing
- Metadata can be affect to static and dynamic parts of stream processing
- Schema-level constraints
  - Clustering (e.g., contiguous duplicates)
  - Ordering (e.g., slack parameter in SQuAl)
  - Referential integrity (e.g., timestamp synchronization)
  - In relaxed form: k-constraints (k: adherence parameter)
- Data-level constraints
  - Punctuations
  - Partitions
  - Pattern

Punctuations

- Punctuations are special annotations embedded in data streams to specify the end of a subset of data.
  - ➢ No more tuples will follow that match the punctuation.
- A punctuation is represented as an ordered set of patterns, where each pattern corresponds to an attribute of a tuple.
  - ➢ Patterns: *, constants, ranges [a, b] or (a b), lists {a, b, ..}, Ø
  - ➢ Example: < item_id, buyer_id, bid >

    < {10, 20}, *, * >   => all bids on items 10 and 20.