Data Stream Management: 30,000 feet

- DBMS world:
  - Static data, dynamic queries
- Data Stream Management world:
  - Dynamic data, static queries

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10,000 feet …

- DBMS world:
  - Data is stored, pre-indexed, ~static
  - Queries are ad-hoc and arrive unexpectedly
- Data Stream Management world:
  - Data arrives in continuous, unbounded streams
    - Examples: sensor readings, stock tickers, …
  - Queries are ~static (multiple concurrent "standing queries")
    - Example: alert me when any stock jumps by 5%

"DSMS" = Data Stream Management System

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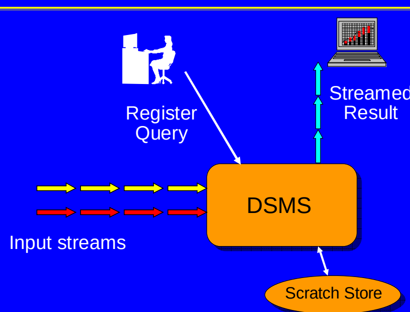
5000 feet: DSMS Architecture



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Research Issues (1/2)

- Languages & formal semantics for data streams and continuous queries
  (what is correct output?)
- Memory requirements & constraints
  (many queries require unbounded memory in worst case)
- Timestamp management & heartbeats
  (data sources tend to have differing latencies)
- Load shedding & approximation
  (keep up with data w/o having to overprovision system)

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Research Issues (2/2)

- Work sharing
  (concurrent, standing queries --> opportunity to share work)
- Adaptation
  (data characteristics fluctuate, queries persist for long time)
- Operator scheduling
  (data is pushed, not pulled)
- Distributed processing
  (stream sources distributed; improve scalability)

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Players

- Berkeley [“Telegraph” project]
  – Franklin, Hellerstein
- MIT/Brown/Brandeis [“Aurora” project]
  – Stonebraker, Zdonik, Cherniack
- Stanford [“STREAM” project]
  – Motwani, Widom
- Wisconsin [“Niagara” project]
  – DeWitt, Naughton

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Players <--> Topics

- STREAM: Languages & formal semantics
- STREAM: Memory requirements & constraints
- STREAM: Timestamp management & heartbeats
- Aurora, STREAM: Load shedding & approximation
- Work sharing: Niagara, Telegraph
- Telegraph, STREAM: Adaptation
- Operator scheduling: Aurora, STREAM
- Aurora: Distributed processing

The Stanford Data Stream Management System

Jennifer Widom

Stanford University

stanfordstreamdatamanager

Formula for a Database Research Project

- Pick a simple but fundamental assumption underlying traditional database systems
  - **Drop it**
- Reconsider all aspects of data management and query processing
  - **Many Ph.D. theses**
  - **Prototype from scratch**

Following the Formula

- We followed this formula once before
  - The **LORE** project
  - Dropped assumption:
    Data has a fixed schema declared in advance
  - Semistructured data (→ XML)
- The **STREAM** Project
  - Dropped assumption:
    First load data, then index it, then run queries
  - Continuous data streams (+ continuous queries)

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Data Streams

- Continuous, unbounded, rapid, time-varying streams of data elements
- Occur in a variety of modern applications
  - Network monitoring and traffic engineering
  - Sensor networks, RFID tags
  - Telecom call records
  - Financial applications
  - Web logs and click-streams
  - Manufacturing processes
- DSMS = Data Stream Management System

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DBMS versus DSMS

DBMS	DSMS
Persistent relations	Transient streams (and persistent relations)
One-time queries	Continuous queries
Random access	**Sequential access**
Access plan determined by query processor and physical DB design	**Unpredictable data characteristics and arrival patterns**

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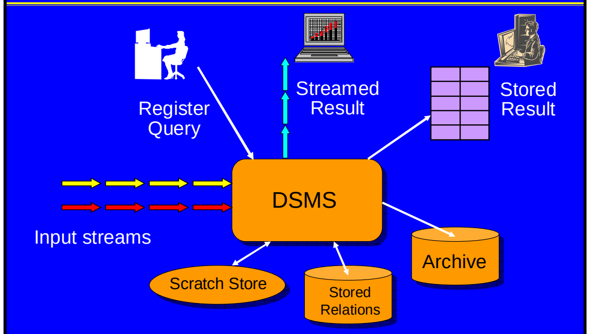
The (Simplified) Big Picture



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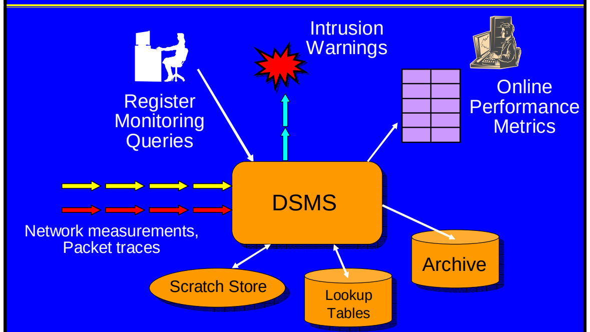
(Simplified) Network Monitoring



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Using Conventional DBMS

- Data streams as relation inserts, continuous queries as triggers or materialized views
- Problems with this approach
  - Inserts are typically batched, high overhead
  - Expressiveness: simple conditions (triggers), no built-in notion of sequence (views)
  - No notion of approximation, resource allocation
  - Current systems don't scale to large # of triggers
  - Views don't provide streamed results

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The STREAM System

- Data streams and stored relations
- Declarative language for registering continuous queries
- Flexible query plans and execution strategies
- Textual, graphical, and application interfaces
- Relational, centralized (for now)

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STREAM System Challenges

- Must cope with:
  - Stream rates that may be high,variable, bursty
  - Stream data that may be unpredictable, variable
  - Continuous query loads that may be high, variable

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STREAM System Challenges

- Must cope with:
  - Stream rates that may be **high**,variable, **bursty**
  - Stream data that may be unpredictable, variable
  - Continuous query loads that may be **high**, variable

Ø **Overload**

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STREAM System Challenges

- Must cope with:
  - Stream rates that may be high, **variable**, bursty
  - Stream data that may be **unpredictable, variable**
  - Continuous query loads that may be high, **variable**

Ø **Overload**

Ø **Changing conditions**

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STREAM System Features

- Aggressive sharing of state and computation
- Careful resource allocation and use
- Continuous self-monitoring and reoptimization
- Graceful approximation as necessary

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Rest of This Talk

- Query language
- Query plans and execution issues
- Coping with overload
- Coping with changing conditions
- **Live system demonstration**

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Continuous Query Language – CQL

Start with SQL
Then add…

- Streams as new data type
- Continuous instead of one-time semantics
- Windows on streams (derived from SQL-99)
- Sampling on streams (basic)
- Three relation-to-stream operators
  Istream, Dstream Rstream

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CQL (cont'd)

- Syntactic shortcuts and defaults
  - So easy queries are easy to write
- Equivalences
  - Basis for query-rewrite optimizations
  - Includes all relational equivalences, plus new stream-based ones
- Based on formally-defined abstract semantics

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CQL Example Query 1

Two streams, contrived for ease of examples:

Orders (orderID, customer, cost)
Fulfillments (orderID, clerk)

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CQL Example Query 1

Two streams, contrived for ease of examples:

Orders (orderID, customer, cost)
Fulfillments (orderID, clerk)

Total cost of orders fulfilled over the last day by clerk "Sue" for customer "Joe"

```
Select Sum(O.cost)
From Orders O, Fulfillments F [Range 1 Day]
Where O.orderID = F.orderID And F.clerk = "Sue"
  And O.customer = "Joe"
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CQL Example Query 1

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```

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CQL Example Query 2

Using a 10% sample of the Fulfillments stream, take the 5 most recent fulfillments for each clerk and return the maximum cost

```
Select F.clerk, Max(O.cost)
From Orders O,
  Fulfillments F [Partition By clerk Rows 5] 10% Sample
Where O.orderID = F.orderID
Group By F.clerk
```

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33

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```

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CQL Example: Result Type

Simpler version of Example Query 2:

```
Select F.clerk, Max(O.cost)
From O, F [Rows 100]
Where O.orderID = F.orderID
Group By F.clerk
```

- Result is a relation, updated as stream elements arrive

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CQL Example: Result Type

Simpler version of Example Query 2:

```
Select Istream( F.clerk, Max(O.cost) )
From O, F [Rows 100]
Where O.orderID = F.orderID
Group By F.clerk
```

- Streamed result: Emits <clerk,max> stream element whenever max changes for a clerk (or new clerk)

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CQL Example Query 4

Relation **CurPrice(stock, price)**

Select stock, Avg(price)
From Istream(CurPrice) [Range 1 Day]
Group By stock

- Average price over last day for each stock
- *Istream* provides history of *CurPrice*
- Window on history (back to relation), group and aggregate

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Query Execution

- When a continuous query is registered, generate a query plan
  - New plan merged with existing plans
  - Users can also create & manipulate plans directly
- Plans composed of three main components:
  - Operators
  - Queues (input and inter-operator)
  - State (windows, operators requiring history)
- Global scheduler for plan execution

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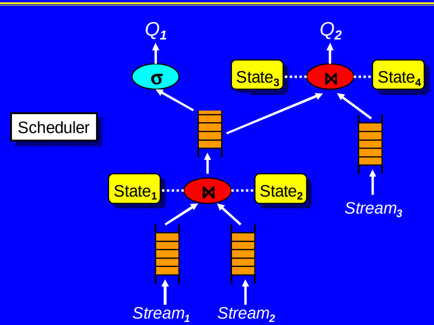
Simple Query Plan



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Memory Overhead in Query Processing

- Queues + State
- Continuous queries keep state indefinitely
- Online requirements suggest using memory rather than disk
  - But we realize this assumption is shaky
- Goal: minimize memory use while providing timely, accurate answers

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Reducing Memory Overhead

1) Exploit constraints on streams to reduce state
2) Enable state sharing within and across queries
3) Specialized operator scheduling to reduce queue sizes

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Exploiting Stream Constraints

- For many queries, large or unbounded state is required for arbitrary streams

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Exploiting Stream Constraints

- For many queries, large or unbounded state is required for arbitrary streams
- But streams may exhibit constraints that reduce, bound, or even eliminate state
  - **Clustered**
  - **Ordered**
  - **Stream-based referential integrity**

  Relaxed version: *k*-constraints

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Stream Constraints: Simple Example

Orders (orderID, customer, cost)
Fulfillments (orderID, portion, clerk)

If **Fulfillments** is *k*-clustered on **orderID**, can infer when to discard **Orders**

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Exploiting Constraints

- Continuously monitor streams to identify *k*-constraints relevant to queries
- Query execution plans reduce or eliminate state based on *k*-constraints
- If constraints violated, get approximate result

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State Sharing

- Baseline: Input streams shared by all queries
  - Maintain maximum window
- Subplans and synopses also can be shared
  - Currently must hook up manually
- Sophisticated techniques for sharing and memory minimization in sliding-window aggregates

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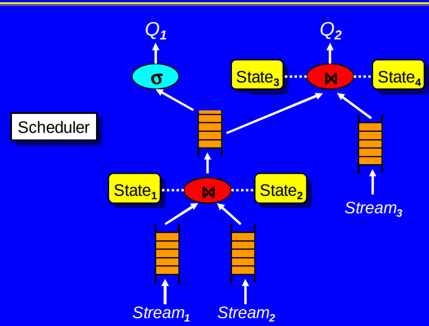
Reminder: Query Plans



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Operator Scheduling

- Global scheduler invokes **run** method of query plan operators with “timeslice” parameter
- Many possible scheduling objectives: minimize latency, memory use, computation, inaccuracy, starvation, …
  1) Round-robin
  2) Minimize queue sizes
  3) Minimize combination of queue sizes and latency
  4) Parallel versions of above

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Coping with Overload

- "Load-shedding" ≈ discarding tuples
- Goal: deliver best possible approximate answer while not falling behind
- What is definition of "best"?
  - Maximum subset
  - Maximum random sample
- We have techniques with provable guarantees for specific query types
  - Extremely hard problem for general plans

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Coping with Changing Conditions

- Continuous queries are long-running; conditions may change
  - Data characteristics, arrival characteristics, query load, available resources, system conditions, …
- Solution: self-monitoring and adaptivity
  - We already saw one example (what was it?)
  - Other results:
    - Adaptive operator reordering
    - Adaptive caching

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A Note on Time

- All stream elements have timestamps
  - Necessary for time-based windows
  - Necessary for consistent well-defined semantics over multiple streams and updatable relations
- Basic correctness requirement: query processor must see stream elements in timestamp order
- Easy when time is centralized system clock
  - Stream elements timestamped on entry to system

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Application-Defined Time

- Streams may contain application timestamps
  - Sensor readings, financial transactions, etc.
- Elements may arrive out of order at DSMS
  - Distributed streams with time skew among them
  - Latency reaching DSMS
  - Reordering on transmission channel
- Our solution: heartbeats
  - Provided by application or deduced from measured parameters (skew, latency, etc.)

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The Stream Systems Landscape

- (At least) three general-purpose DSMS prototypes underway
  - STREAM (Stanford)
  - Aurora - Borealis (Brown, Brandeis, MIT)
  - TelegraphCQ - HiFi (Berkeley)
- Stream system benchmark
  - Main goal: demonstrate that conventional systems are far inferior for data stream applications

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http://www-db.stanford.edu/stream/
Google: "stanford stream"

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