Models and Issues in Data Stream Systems (with changes by CZ)

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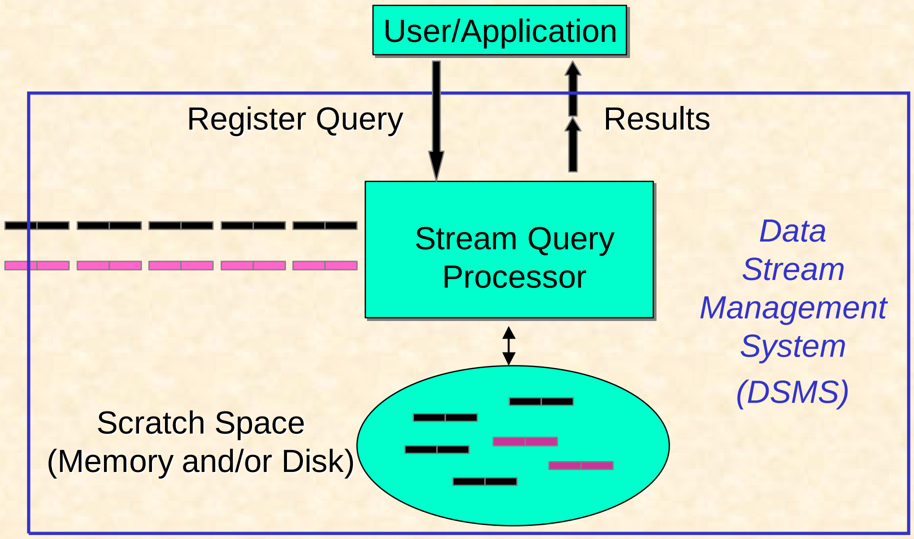
Data Streams

- Traditional DBMS – data stored in finite, persistent data sets
- New Applications – data input as continuous, ordered data streams
  - Network monitoring and traffic engineering
  - Telecom call records
  - Network security
  - Financial applications
  - Sensor networks
  - Manufacturing processes
  - Web logs and clickstreams
  - Massive data sets

Data Stream Management System



Sample Applications

- Network security
  (e.g., iPolicy, NetForensics/Cisco, Niksun)
  - Network packet streams, user session information
  - Queries: URL filtering, detecting intrusions & DOS attacks & viruses
- Financial applications
  (e.g., Traderbot)
  - Streams of trading data, stock tickers, news feeds
  - Queries: arbitrage opportunities, analytics, patterns
  - SEC requirement on closing trades

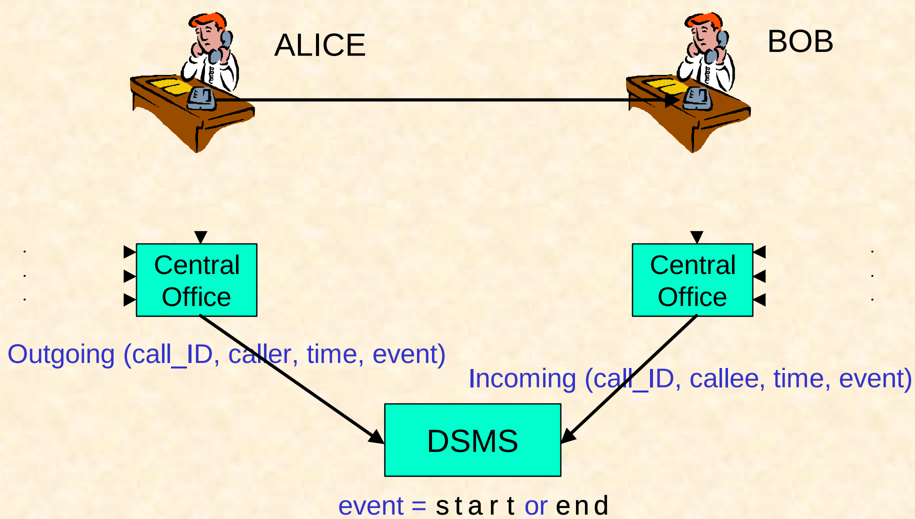
Executive Summary

- Data Stream Management Systems (DSMS)
  - Highlight issues and motivate research
  - Not a tutorial or comprehensive survey
- Caveats
  - Personal view of emerging field
  - ✍ Stanford STREAM Project bias
  - ✍ Cannot cover all projects in detail

DBMS versus DSMS

• Persistent relations	• Transient streams
• One-time queries	• Continuous queries
• Random access	• Sequential access
• "Unbounded" disk store	• Bounded main memory
• Only current state matters	• History/arrival-order is critical
• No real-time services	• Real-time requirements
• Assume precise data	• Data stale/imprecise

Making Things Concrete



Query 1 (self-join)

- Find all outgoing calls longer than 2 minutes

  SELECT O1.call_ID, O1.caller
  FROM Outgoing O1, Outgoing O2
  WHERE (O2.time – O1.time > 2
  AND O1.call_ID = O2.call_ID
  AND O1.event = start
  AND O2.event = end)

- Result requires unbounded storage
- Can provide result as data stream
- Can output after 2 min, without seeing end

Query 2 (join)

- Pair up callers and callees

```
SELECT   O.caller, I.callee
FROM     Outgoing O, Incoming I
WHERE    O.call_ID = I.call_ID
```

- Can still provide result as data stream
- Requires unbounded temporary storage …
- … unless streams are near-synchronized

Query 3 (group-by aggregation)

- Total connection time for each caller

```
SELECT      O1.caller, sum(O2.time – O1.time)
FROM        Outgoing O1, Outgoing O2
WHERE       (O1.call_ID = O2.call_ID
             AND O1.event = start
             AND O2.event = end)
GROUP BY    O1.caller
```

- Join: a very inefficient solution (CZ)
- sum: some window must be specified

Outline of Remaining Talk

- Stream Models and DSMS Architectures
- Query Processing
- Runtime and Systems Issues
- Algorithms
- Conclusion

Data Model

- Append-only
  - Call records
- Updates
  - Stock tickers
- Deletes
  - Transactional data
- Meta-Data
  - Control signals, punctuations

System Internals – probably need all above

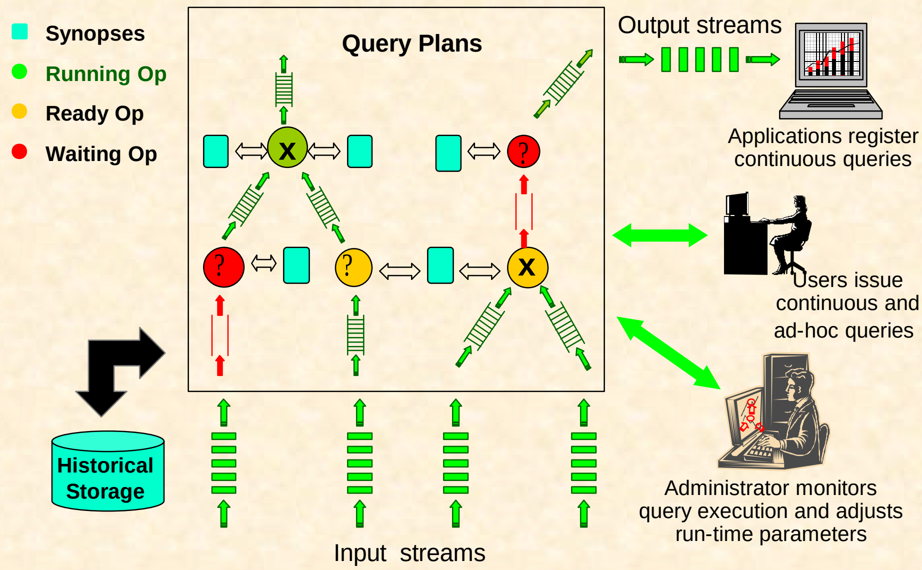
Related Database Technology

- DSMS must use ideas, but none is substitute
  - Triggers, Materialized Views in Conventional DBMS
  - Main-Memory Databases
  - Distributed Databases
  - Pub/Sub Systems
  - Active Databases
  - Sequence/Temporal/Timeseries Databases
  - Realtime Databases
  - Adaptive, Online, Partial Results
- Novelty in DSMS
  - Semantics: input ordering, streaming output, …
  - State: cannot store unending streams, yet need history
  - Performance: rate, variability, imprecision, …

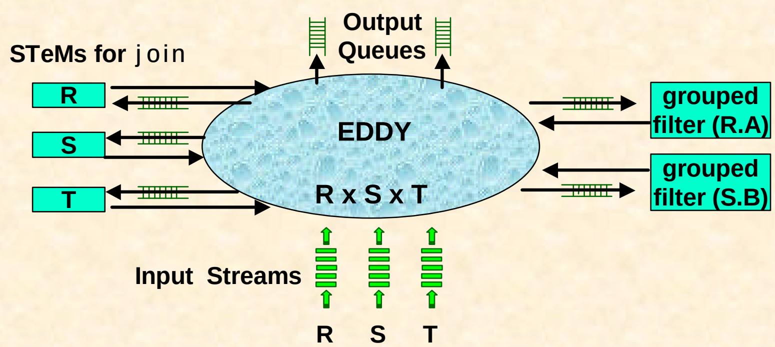
Stream Projects

- Amazon/Cougar (Cornell) – sensors
- Aurora (Brown/MIT) – sensor monitoring, dataflow
- Hancock (AT&T) – telecom streams
- Niagara (OGI/Wisconsin) – Internet XML databases
- OpenCQ (Georgia) – triggers, incr. view maintenance
- Stream (Stanford) – general-purpose DSMS
- Tapestry (Xerox) – pub/sub content-based filtering
- Telegraph (Berkeley) – adaptive engine for sensors
- Tribeca (Bellcore) – network monitoring
- ATLAS(UCLA) – Query power: DB/DS integration.

Aurora/STREAM Overview

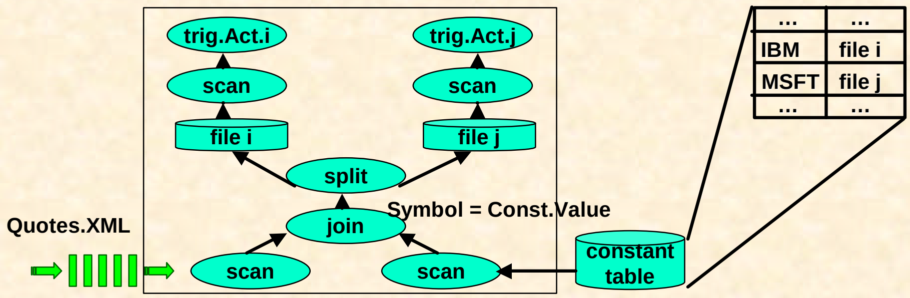


Adaptivity (Telegraph)



- Runtime Adaptivity
- Multi-query Optimization
- Framework – implements arbitrary schemes

Query-Split Scheme (Niagara)



- Aggregate subscription for efficiency
- Split – evaluate trigger only when file updated
- Triggers – multi-query optimization

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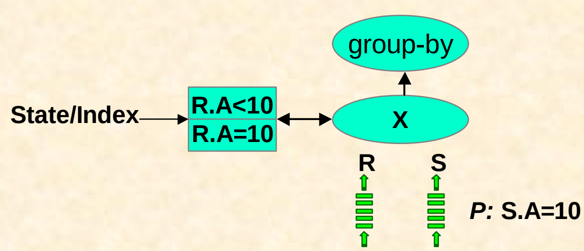
Blocking Operators

- Blocking
  - No output until entire input seen
  - Streams – input never ends
- Aggregates – output "update" stream
- Set Output (sort, group-by)
  - Intermediate nodes – try non-blocking analogs
  - Example – j u g g l e for sort [Raman,R,Hellerstein]
  - Punctuations and constraints
- Join
  - sliding-window restrictions

Punctuations [Tucker, Maier, Sheard, Fegaras]

- Assertion about future stream contents
- Unblocks operators, reduces state



- Future Work
  - Inserted at source or internal (operator signaling)?
  - Does ***P*** unblock ***Q***? Exists ***P***? Rewrite ***Q***?
  - Relation between ***P*** and memory for ***Q***?

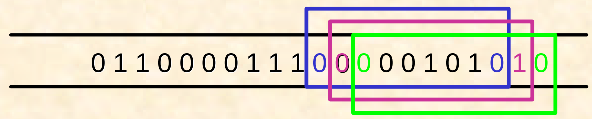
Impact of Limited Memory

- Continuous streams grow unboundedly
- Queries may require unbounded memory
- [ABBMW 02]
  - a priori memory bounds for query
  - Conjunctive queries with arithmetic comparisons
  - Queries with join need domain restrictions
  - Impact of duplication elimination
- Open – general queries

Approximate Query Evaluation

- Why?
  - Handling load – streams coming too fast
  - Avoid unbounded storage and computation
  - Ad hoc queries need approximate history
- How? Sliding windows, synopsis, samples, load-shed
- Major Issues?
  - Metric for set-valued queries
  - Composition of approximate operators
  - How is it understood/controlled by user?
  - Integrate into query language
  - Query planning and interaction with resource allocation
  - Accuracy-efficiency-storage tradeoff and global metric

Sliding Window Approximation

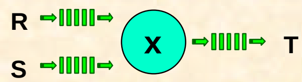


- Why?
  - Approximation technique for bounded memory
  - Natural in applications (emphasizes recent data)
  - Well-specified and deterministic semantics
- Issues
  - Extend relational algebra, SQL, query optimization
  - Algorithmic work
  - Timestamps?

Timestamps

- Explicit
  - Injected by data source
  - Models real-world event represented by tuple
  - Tuples may be out-of-order, but if near-ordered can reorder with small buffers
- Implicit
  - Introduced as special field by DSMS
  - Arrival time in system
  - Enables order-based querying and sliding windows
- Issues
  - Distributed streams?
  - Composite tuples created by DSMS?

Timestamps in JOIN Output



Approach 1

- User-specified, with defaults
- Compute output timestamp
- Must output in order of timestamps
- Better for Explicit Timestamp
- Need more buffering
- Get precise semantics and user-understanding

Approach 2

- Best-effort, no guarantee
- Output timestamp is exit-time
- Tuples arriving earlier more likely to exit earlier
- Better for Implicit Timestamp
- Maximum flexibility to system
- Difficult to impose precise semantics

Approximate via Load-Shedding

Handles scan and processing rate mismatch

Input Load-Shedding

- Sample incoming tuples
- Use when scan rate is bottleneck
- Positive – online aggregation [Hellerstein, Haas, Wang]
- Negative – join sampling [Chaudhuri, Motwani, Narasaya]

Output Load-Shedding

- Buffer input infrequent output
- Use when query processing is bottleneck
- Example – XJoin [Urhan, Franklin]
- Exploit synopses

Stream Query Language?

- SQL extension
- Sliding windows as first-class construct
  - Awkward in SQL, needs reference to timestamps
  - SQL-99 allows aggregations over sliding windows
- Sampling/approximation/load-shedding/QoS support?
- Stream relational algebra and rewrite rules
  - Aurora and STREAM
  - Sequence/Temporal Databases

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DSMS Internals

- Query plans: operators, synopses, queues
- Memory management
  - Dynamic Allocation – queries, operators, queues, synopses
  - Graceful adaptation to reallocation
  - Impact on throughput and precision
- Operator scheduling
  - Variable-rate streams, varying operator/query requirements
  - Response time and QoS
  - Load-shedding
  - Interaction with queue/memory management

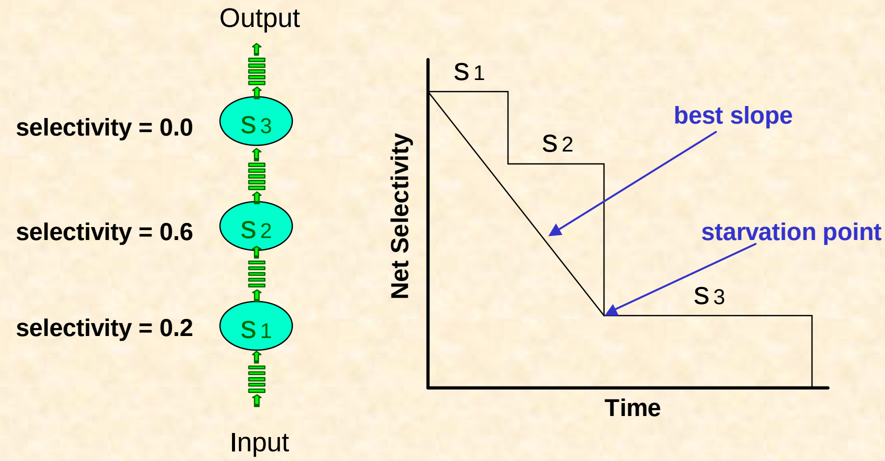
Queue Memory and Scheduling

[Babcock, Babu, Datar, Motwani]

- Goal
  - Given – query plan and selectivity estimates
  - Schedule – tuples through operator chains
- Minimize total queue memory
  - Best-slope scheduling is near-optimal
  - Danger of starvation for some tuples
- Minimize tuple response time
  - Schedule tuple completely through operator chain
  - Danger of exceeding memory bound
- Open – graceful combination and adaptivity

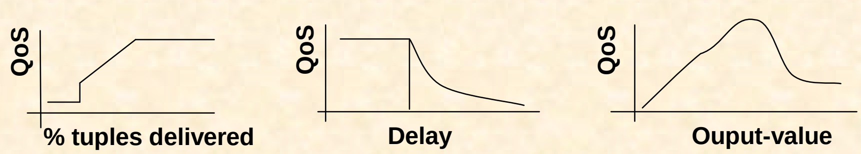
Queue Memory and Scheduling

[Babcock, Babu, Datar, Motwani]



Rate-Based & QoS Optimization

- [Viglas, Naughton]
  - Optimizer goal is to increase throughput
  - Model for output-rates as function of input-rates
  - Designing optimizers?
- Aurora – QoS approach to load-shedding



Static: drop-based Runtime: delay-based Semantic: value-based

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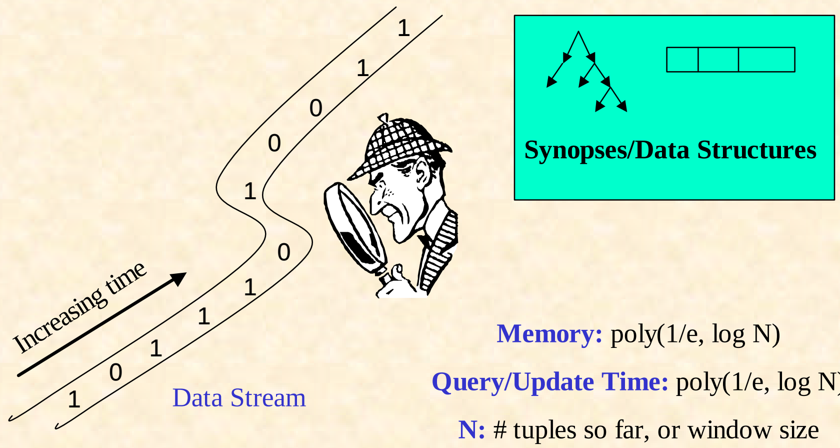
Synopses

- Queries may access or aggregate past data
- Need bounded-memory history-approximation
- Synopsis?
  - Succinct summary of old stream tuples
  - Like indexes/materialized-views, but base data is unavailable
- Examples
  - Sliding Windows
  - Samples
  - Sketches
  - Histograms
  - Wavelet representation

Model of Computation



Memory: poly(1/e, log N)

Query/Update Time: poly(1/e, log N)

N: # tuples so far, or window size

e: error parameter

Many other results …

- Histograms
  - V-Opt Histograms
    [Gilbert, Guha, Indyk, Kotidis, Muthukrishnan, Strauss], [Indyk]
  - End-Biased Histograms (Iceberg Queries)
    [Manku, Motwani], [Fang, Shiva, Garcia-Molina, Motwani, Ullman]
  - Equi-Width Histograms (Quantiles)
    [Manku, Rajagopalan, Lindsay], [Khanna, Greenwald]
  - Wavelets
    Seminal work [Vitter, Wang, Iyer] + many others!
- Data Mining
  - Stream Clustering
    [Guha, Mishra, Motwani, O'Callaghan]
    [O'Callaghan, Meyerson, Mishra, Guha, Motwani]
  - Decision Trees
    [Domingos, Hulten], [Domingos, Hulten, Spencer]

Conclusion: Future Work

- Query Processing
  - Stream Algebra and Query Languages
  - Approximations
  - Blocking, Constraints, Punctuations
- Runtime Management
  - Scheduling, Memory Management, Rate Management
  - Query Optimization (Adaptive, Multi-Query, Ad-hoc)
  - Distributed processing
- Synopses and Algorithmic Problems
- Systems
  - UI, statistics, crash recovery and transaction management
  - System development and deployment

Thank You!