Data Stream Query Processing

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Stream Map

- Part I: Motivation
  - Data streams: what, why now, applications, architecture
- Part II: Query processing, system issues

Data Streams: What and Where?

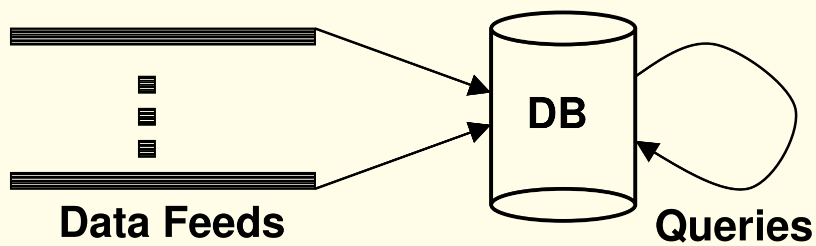
- A **data stream** is a (potentially unbounded) sequence of tuples

- **Transactional** data streams: log interactions between entities
  - Credit card: purchases by consumers from merchants
  - Telecommunications: phone calls by callers to dialed parties
  - Web: accesses by clients of resources at servers

- **Measurement** data streams: monitor evolution of entity states
  - Sensor networks: physical phenomena, road traffic
  - IP network: traffic at router interfaces
  - Earth climate: temperature, moisture at weather stations

Data Streams: Why Now?

- Haven't data feeds to databases always existed? Yes
  - Modify underlying databases, data warehouses
  - Complex queries are specified over stored data

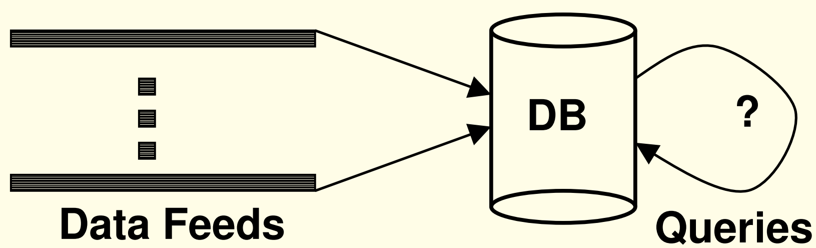


- Two recent developments: application- and technology-driven
  - Need for sophisticated near-real time queries/analyses
  - Massive data volumes of transactions and measurements

Data Streams: Real-Time Queries

- With traditional data feeds
  - Simple queries (e.g., value lookup) needed in real-time
  - Complex queries (e.g., trend analyses) performed offline

- Now need sophisticated near-real time queries/analyses
  - AT&T: fraud detection on call detail tuple streams
  - NOAA: tornado detection using weather radar data



Telecommunications Application: Fraud Detection

- Business Challenge: AT&T wanted to track calling pattern of each of ~100M callers, and raise real-time fraud alerts
- Previous Approach: Handwritten, optimized C code, computing evolving **signatures** for each customer, looking for variations
- Issues: Signature computation is I/O intensive, often modified

- Solution: Using Hancock domain-specific language
  - Abstract logical/physical streams and signatures
  - Express I/O and CPU efficient signature programs cleanly

- Lesson: Essential to consider I/O issues for data streams

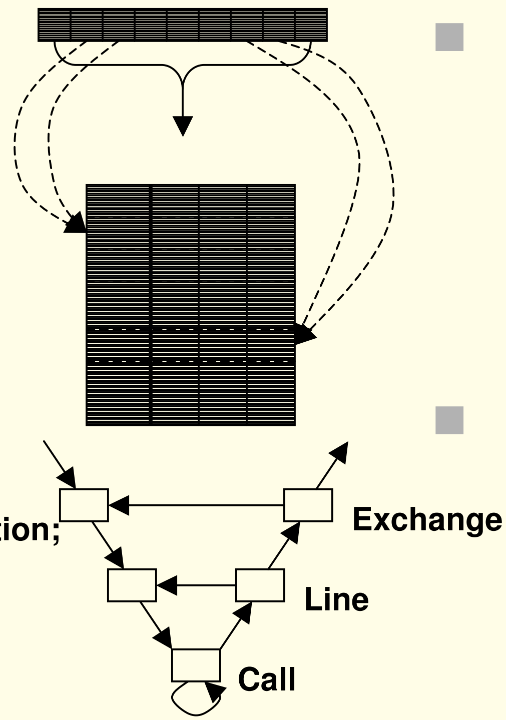
Hancock: Data Streams

```
typedef struct {
    line_t origin;
    line_t dialed;
    date_t connectTime;
    time_t duration;
    char isIncomplete;
    char isIntl;
    char isTollFree;
    …
} callRec_t;
```

- Physical data representation of tuples on disk
  - highly encoded structure
- Logical data representation
  - C struct
- Conversion functions
  - specified in Hancock

Hancock: Signature Programs

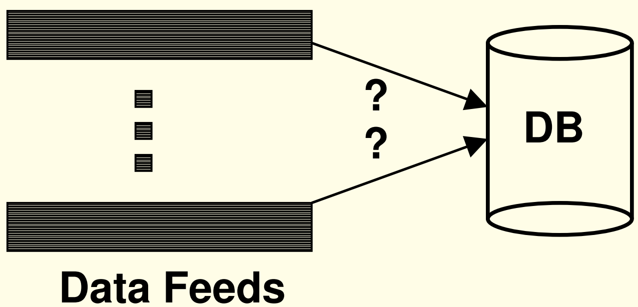
```
iterate (over calls
  sortedby origin
  filteredby noIncomplete
  withevents originDetect){

event line_begin(lpn_t pn){
  cumSec.outTF = 0;
}

event call(callRec_t c){
  if (c.isTollFreeCall)
    cumSec.outTF += c.duration;
}

event line_end(lpn_t pn){
  mySig us = data<:pn:>;
  us.outTF = blend(cumSec.outTF, us.outTF);
  data<:pn:> := us;
}}
```



- Hancock program paradigm:
  - stream-in, relation-out
  - block processing of data
  - multiple passes on block
- Hancock programs support:
  - iterating on sorted data
  - filtering
  - event clause hierarchy
- User-defined aggregation

Data Streams: Massive Volumes

- Now able to deploy transactional data observation points
  - AT&T long-distance: ~300M call tuples/day
  - AT&T IP backbone: >10B IP flows/day
- Now able to generate automated, highly detailed measurements
  - NOAA: satellite-based measurement of earth geodetics
  - Sensor networks: huge number of measurement points



IP Network Application: P2P Traffic Detection

- Business Challenge: AT&T IP customer wanted to accurately monitor P2P traffic evolution within its network
- Previous Approach: Netflow can be used to determine P2P traffic volumes using TCP port number found in Netflow data
- Issues: P2P traffic might not use known P2P port numbers

- Solution: Using Gigascope SQL-based packet monitor
  - Search for P2P related keywords within each TCP datagram
  - Identified 3 times more traffic as P2P than Netflow

- Lesson: Essential to query massive volume data streams

IP Network Application: Web Client Performance Monitoring

- Business Challenge: AT&T IP customer wanted to monitor latency observed by clients to find performance problems
- Previous Approach: Measure latency at “active clients” that establish network connections with servers
- Issues: Use of “active clients” is not very representative

- Solution: Using Gigascope SQL-based packet monitor
  - Track TCP synchronization and acknowledgement packets
  - Report round trip time statistics: latency

- Lesson: Essential to correlate multiple data streams

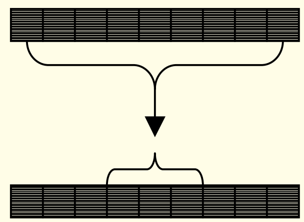
Gigascope: Data Streams

```
PROTOCOL IP (Layer2) {
    uint ipversion
}
PROTOCOL IPv4(IP) {
    uint hdr_length;
    uint service_type;
    uint total_length;
    uint id;
    bool do_not_fragment;
    bool more_fragments;
    uint offset;
    uint ttl;
    uint protocol;
}
```

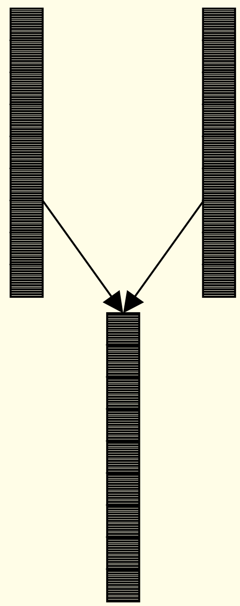
- GSQL queries get raw data from low level schemas
  - defined at packet level
  - inherits from lower layer
- Current schemas include
  - layer 2: ETH/HDLC
  - layer 3: IP/IPv4
  - layer 4: UDP/TCP/ICMP
  - layers 5-7: packet data

Gigascope: GSQL Queries

```
select tb, srcIP, sum(len)
from IPv4
where protocol = 6
group by time/60 as tb, srcIP
having count(*) > 5
```



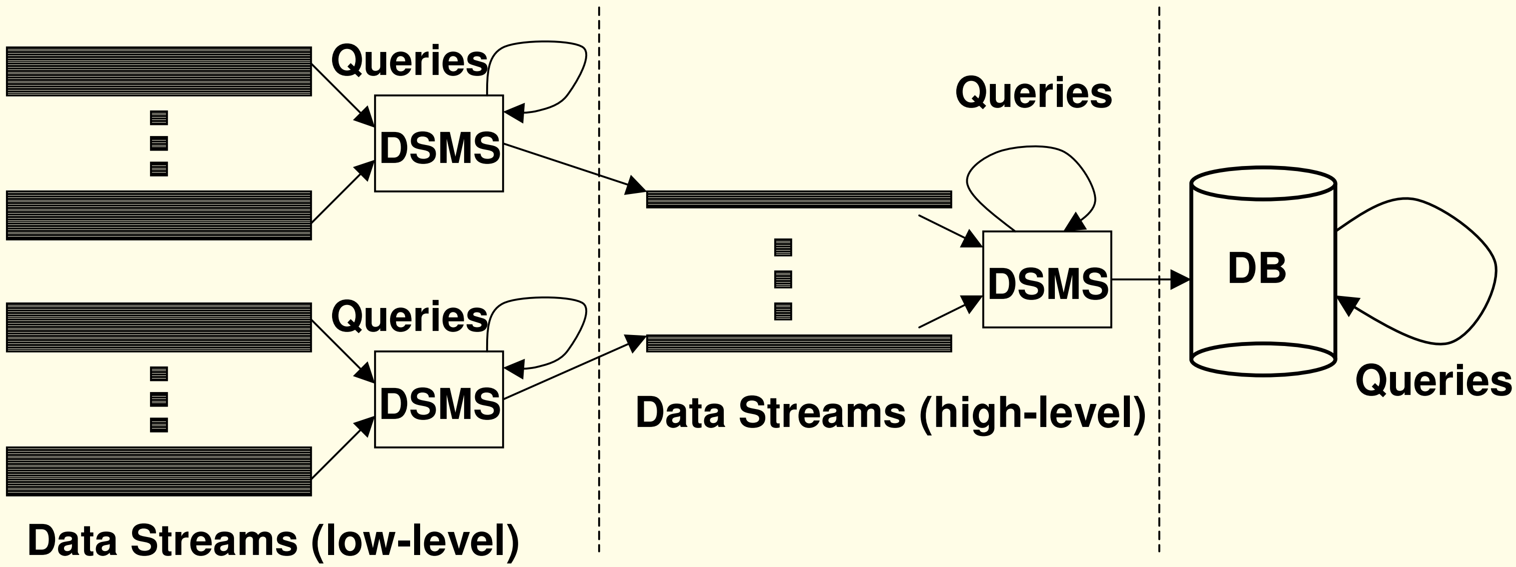
```
select S.tstmp,
       S.srcIP, S.destIP,
       S.srcPort, S.destPort
       (A.tstmp – S.tstmp) as rtt
from tcp_syn S, tcp_syn_ack A
where S.srcIP = A.destIP
       and S.destIP = A.srcIP
       and S.srcPort = A.destPort
       and S.destPort = A.srcPort
       and S.tb = A.tb
```



- GSQL queries support:
  - filtering, aggregation
  - merging data streams
  - joining data streams
  - hand-coded views
  - external functions
- GSQL query paradigm:
  - streams-in, stream-out
  - permits composability
  - permits data reduction

Data Streams: 3-Level Architecture

- Data stream management system at multiple observation points
  - (Voluminous) streams-in, (data reduced) streams-out
- Database management system
  - Data feeds to database can also be treated as data streams



Data Streams: 3-Level Architecture

Data Stream Systems

- Resource (memory, per-tuple computation) limited, especially at low-level
- Reasonably complex, near real time, query processing
- Useful to identify what data to populate in database

Database Systems

- Resource (memory, disk, per-tuple computation) rich
- Useful to audit query results of data stream system
- Supports sophisticated query processing, analyses

Databases vs Data Streams: Issues

Database Systems	Data Stream Systems
Model: persistent relations	Model: transient relations
Relation: tuple set/bag	Relation: tuple sequence
Data Update: modifications	Data Update: appends
Query: transient	Query: persistent
Query Answer: exact	Query Answer: approximate
Query Evaluation: arbitrary	Query Evaluation: one pass
Query Plan: fixed	Query Plan: adaptive

Really a continuum …

Relation: Tuple Set or Sequence?

- Traditional relation = set/bag of tuples
- Tuple sequences have been studied:
  - Temporal databases [TCG+93]: multiple time orderings
  - Sequence databases [SLR94]: integer “position” -> tuple
- Data stream systems:
  - Ordering domains: Gigascope [CJSS03], Hancock [CFP+00]
  - Position ordering: Aurora [CCC+02], STREAM [MWA+03]

Update: Modifications or Appends?

- Traditional relational updates: arbitrary data modifications

- Append-only relations have been studied:
  - Tapestry [TGNO92]: emails and news articles
  - Chronicle data model [JMS95]: transactional data

- Data stream systems:
  - Streams-in, stream-out: Aurora, Gigascope, STREAM
  - Stream-in, relation-out: Hancock

Query: Transient or Persistent?

- Traditional relational queries: one-time, transient
- Persistent/continuous queries have been studied:
  - Tapestry [TGNO92]: content-based email, news filtering
  - OpenCQ, NiagaraCQ [LPT99, CDTW00]: monitor web sites
  - Chronicle [JMS95]: incremental view maintenance
- Data stream systems:
  - Support persistent and transient queries

Query Answer: Exact or Approximate?

- Traditional relational queries: exact answer
- Approximate query answers have been studied [BDF+97]:
  - Synopsis construction: histograms, sampling, sketches
  - Approximating query answers: using synopsis structures
- Data stream systems:
  - Approximate joins: using windows to limit scope
  - Approximate aggregates: using synopsis structures

Query Evaluation: One Pass?

- Traditional relational query evaluation: arbitrary data access

- One/few pass algorithms have been studied:
  - Limited memory selection/sorting [MP80]: *n*-pass quantiles
  - Tertiary memory databases [SS96]: reordering execution
  - Complex aggregates [CR96]: bounding number of passes

- Data stream systems:
  - Per-element processing: single pass to reduce drops
  - Block processing: multiple passes to optimize I/O cost

Query Plan: Fixed or Adaptive?

- Traditional relational query plans: optimized at beginning

- Adaptive query plans have been studied:
  - Query scrambling [AFTU96]: wide-area data access
  - Eddies [AH00]: volatile, unpredictable environments

- Data stream systems:
  - Adaptive query operators
  - Adaptive plans

Data Stream Query Processing: Anything New?

Architecture

- Resource (memory, per-tuple computation) limited, especially at low-level
- Reasonably complex, near real time, query processing

Issues

- Model: transient relations
- Relation: tuple sequence
- Data Update: appends
- Query: persistent
- Query Answer: approximate
- Query Evaluation: one pass
- Query Plan: adaptive

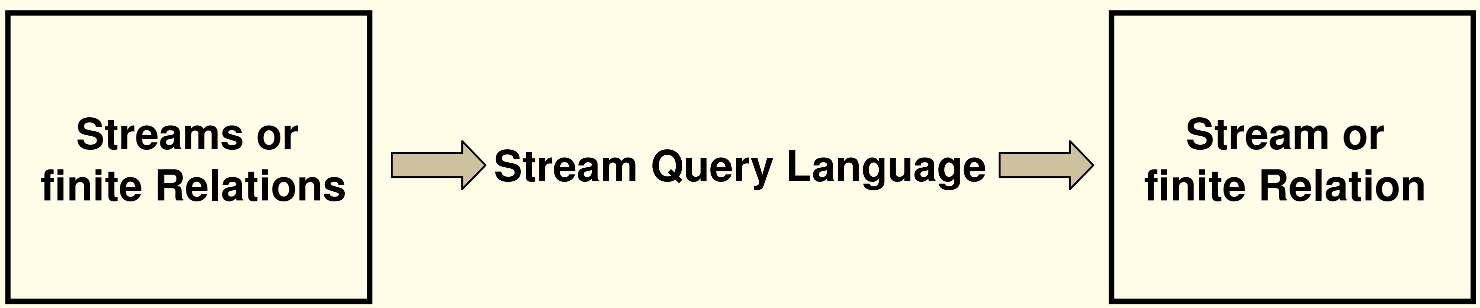
A lot of challenging problems ...

Stream Map

- Part I: Motivation
- Part II: Query processing, system issues
  - Stream query language issues
  - Query operators
  - Optimization objectives
  - Prototype systems
  - Open issues

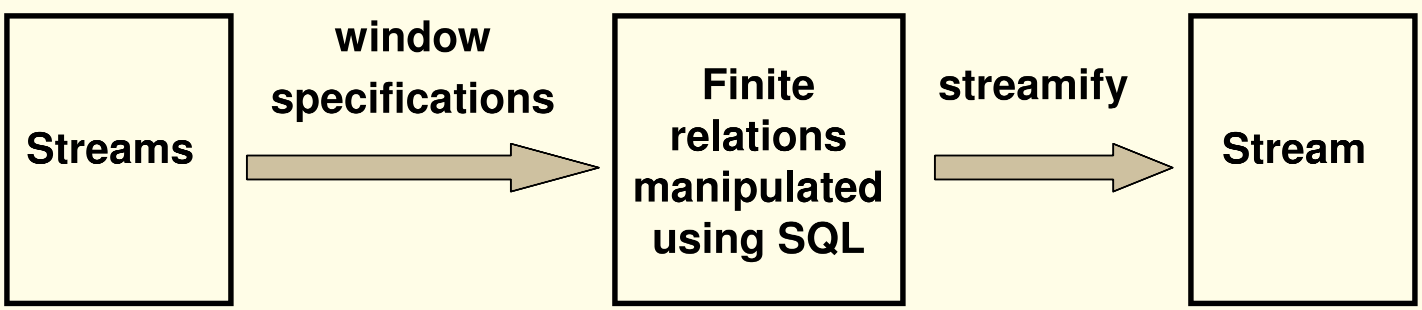
Stream Query Languages

- SQL-like proposals suitably extended for a stream environment:
  - Composable SQL operators
  - Queries reference relations or streams
  - Queries produce relations or streams
- GSQL [CJSS03]: SQL used by Gigascope
- CQL [ABW03]: SQL used by STREAM



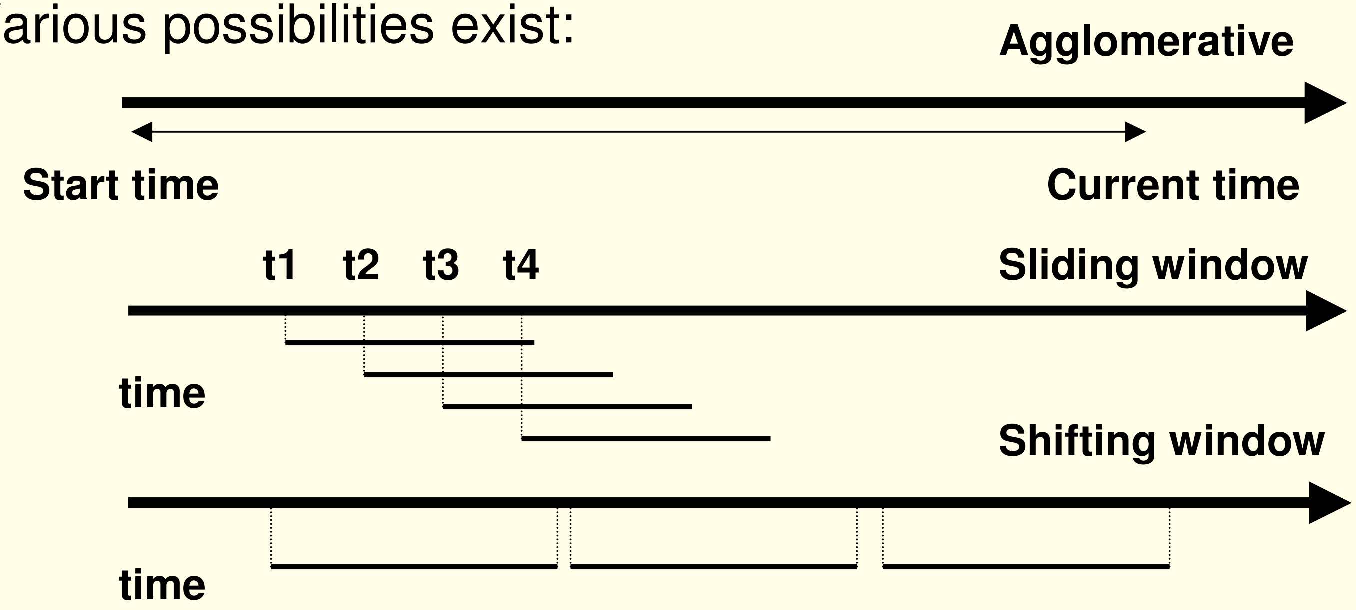
Windows

- Mechanism for extracting a finite relation from an infinite stream
- Various window proposals for restricting operator scope
  - Windows based on ordering attributes (e.g., time)
  - Windows based on tuple counts
  - Windows based on explicit markers (e.g., punctuations)
  - Variants (e.g., partitioning tuples in a window)



Ordering Attribute Based Windows

- Assumes the existence of an attribute that defines the order of stream elements/tuples (e.g., time)
- Let T be the window length (size) expressed in units of the ordering attribute (e.g., T may be a time window)
- Various possibilities exist:



Punctuation Based Windows [TMSF03]

- Application inserted “end-of-processing” markers
  - Each data item identifies “beginning-of-processing”

- Enables data item-dependent variable length windows
  - e.g., a stream of auctions
- Similar utility in query processing
  - Limit the scope of query operators relative to the stream

Selections, Projections

- Selections, (duplicate preserving) projections are straightforward
  - Local, per-element operators
  - Duplicate eliminating projection is like grouping
- Projection needs to include ordering attribute [JMS95]
  - No restriction for position ordered streams

```
Select sourceIP, time
from Traffic
where length > 512
```

Join Operators

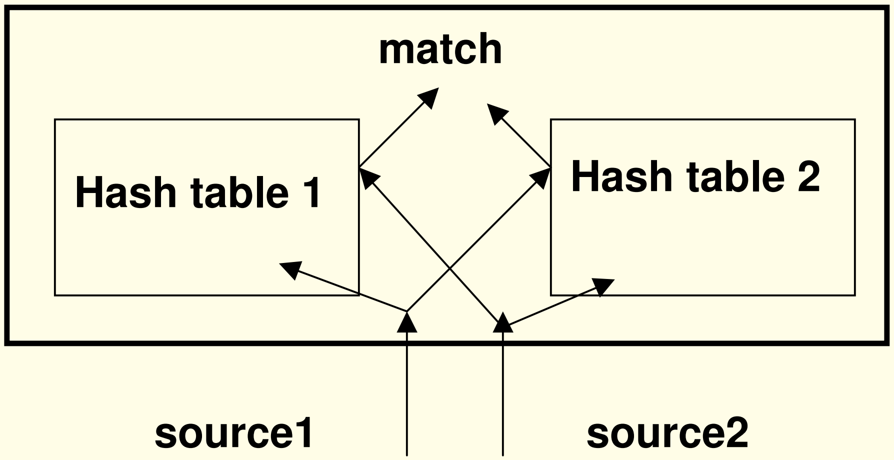
- General case of join operators problematic on streams
  - May need to join arbitrarily far apart stream tuples
  - Equijoin on stream ordering attributes is tractable [JMS95]

- Majority of work focuses on joins between streams with windows specified on each stream

Select A.sourceIP, B.sourceIP
from Traffic1 A [window T1], Traffic2 B [window T2]
where A.destIP = B.destIP

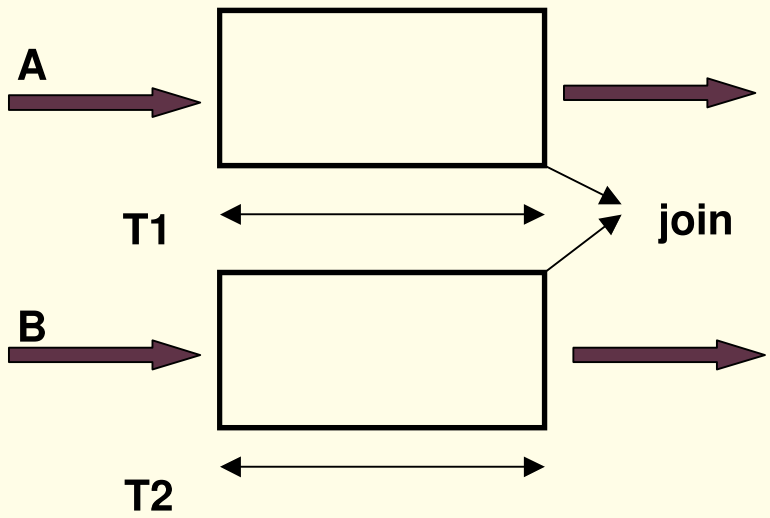
Join Operators: Background

- Symmetric Hash Joins [WA91]
  - Takes into account streaming nature of inputs



- XJoin [UF00]: extends Symmetric Hash Joins
  - overflowing inputs spilled to disk for later evaluation

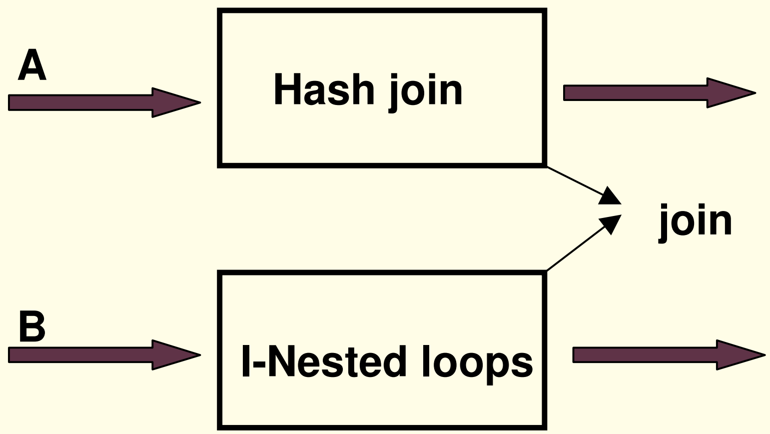
Binary Joins [KNV03]



New A tuple:

- Scan B's window for joining tuples and output result
- Insert tuple into A's window
- **Invalidate** all expired tuples in A's window

Binary Joins: Key Observations



- Asymmetric join processing has advantages if arrival rates differ
- Goal: maximize tuple output
  - limited computational capability but sufficient memory
  - limited memory but sufficient computational capability

Aggregation

- General form:
  - **select** G, F1 **from** S **where** P **group by** G **having** F2 op ϑ
  - G: grouping attributes, F1,F2: aggregate expressions
- Aggregate expressions:
  - distributive: sum, count, min, max
  - algebraic: avg
  - holistic: count-distinct, median

Aggregation in Theory

- An aggregate query result can be streamed if group by attributes include the ordering attribute [JMS95]
- A single stream aggregate query “select G,F from S where P group by G” can be executed in bounded memory if [ABB+02]:
  - every attribute in G is bounded
  - no aggregate expression in F, executed on an unbounded attribute, is holistic
- Arasu et al. [ABB+02] derive conditions for bounded memory execution of aggregate queries on multiple streams

Aggregation in Bounded Memory

- Aggregate query execution not in bounded memory:

```
select length
from Traffic [window T]
where length > 512
group by length
```

$\equiv$

```
select distinct length
from Traffic [window T]
where length > 512
```

- Aggregate query execution in bounded memory:

```
select length, count(*)
from Traffic [window T]
where length > 512 and length < 1024
group by length
```

Aggregation in Gigascope

- Grouping attributes contain window expressions restricting the scope of the group (e.g., temporally)
  - select peerid, tb, count(*) from Traffic group by time/60 as tb, f(destIP,'peerid.tbl') as peerid
  - time/60 is a minute-long shifting window
- Gigascope applies partial-aggregation on low-level data streams
  - bounded number of groups maintained at low level
  - unbounded number of groups maintainable at high level

Aggregation & Approximation

- When aggregates cannot be computed exactly in limited storage, approximation may be possible and acceptable
- Examples:
  - select G, median(A) from S group by G
  - select G, count(distinct A) from S group by G
  - select G, count(*) from S group by G having count(*) > φ |S|
- Use summary structures: samples, histograms, sketches …

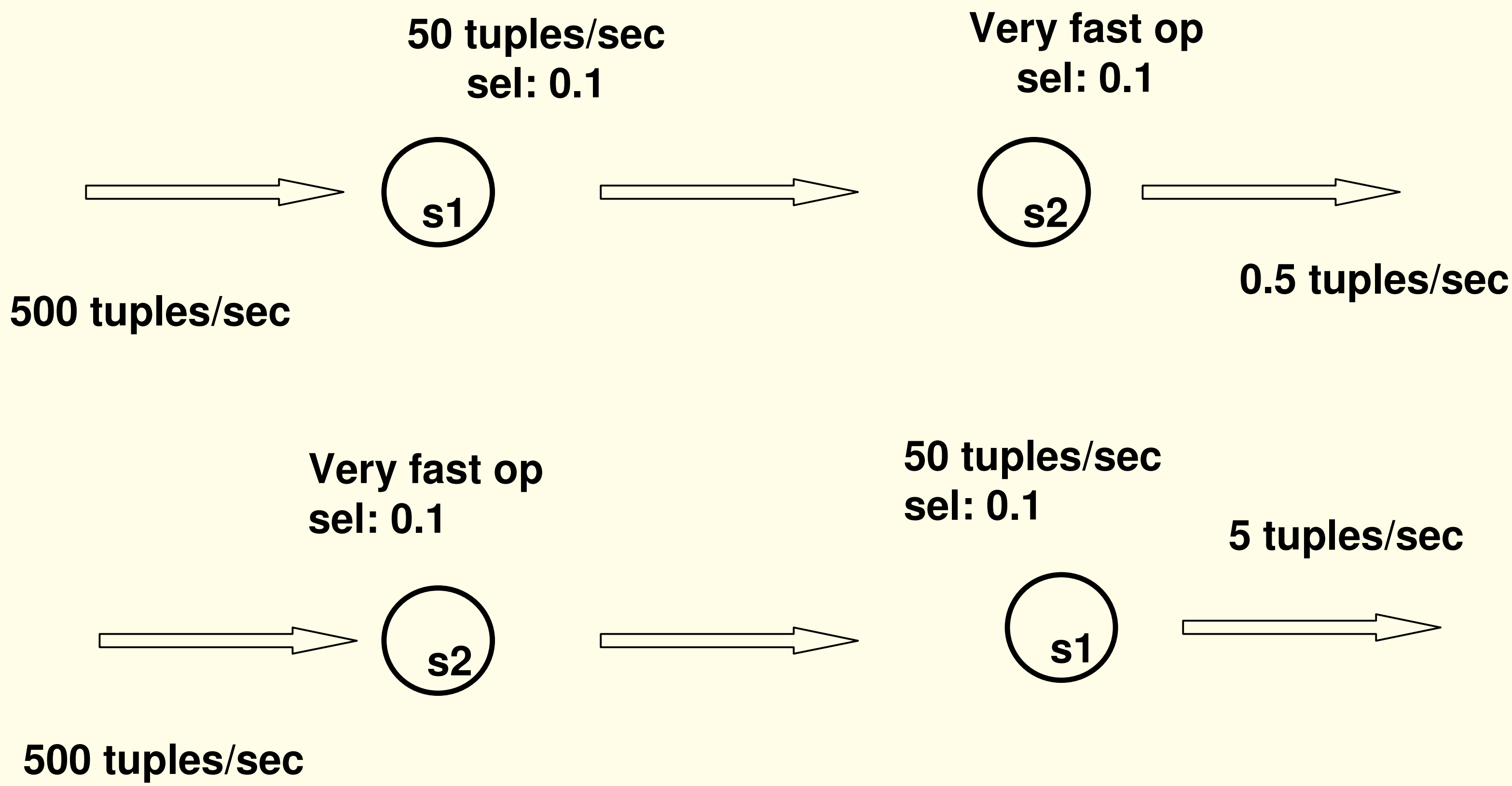
Optimization Objectives: Issues

- Traditionally table based cardinalities used in query optimization
- Problematic in a streaming environment
- Need for novel optimization objectives that are relevant when inputs consist of streaming information sources
  - Rate-based optimization
  - Memory-based optimization
  - QoS-based optimization

Rate-Based Optimization

- Rate-based optimization [VN02]:
  - Take into account the rates of the streams in the query evaluation tree during optimization
  - Rates can be known and/or estimated
- Overall objective is to maximize the tuple output rate for a query
  - Instead of seeking the least cost plan, seek the plan with the highest tuple output rate.

Rate-Based Optimization

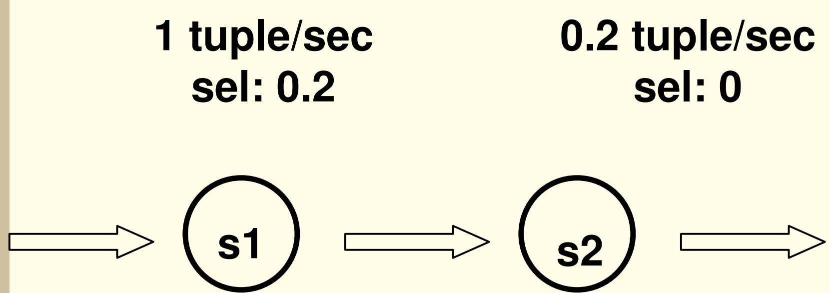


Memory-Based Optimization

- Optimize for resource (memory) consumption
- A query plan consists of interacting operators, with each tuple passing through a sequence of operators
- When streams are bursty, tuple backlog between operators may increase, affecting memory requirements
- Goal: scheduling policies that minimize resource consumption

Operator scheduling [BBDM03]

- When tuple arrival rate is uniform:
  - a simple FIFO scheduling policy suffices
  - let each tuple flow through the relevant operators



Time	Greedy	FIFO
0	1	1
1	1.2	1.2
2	1.4	2.0
3	1.6	2.2
4	1.8	3.0

Average arrival rate: 0.5 tuples/sec

FIFO: tuples processed in arrival order

Greedy: if tuple before s1 schedule it; otherwise process tuples before s2

Load Shedding

- When input stream rate exceeds system capacity a stream manager can shed load (tuples)
- Load shedding affects queries and their answers
- Introducing load shedding in a data stream manager is a challenging problem
- Random and semantic load shedding

Multi-query Processing on Streams

- In traditional multi-query optimization:
  - sharing (of expressions, results etc) among queries can lead to improved performance
- Similar issues arise when processing queries on streams:
  - sharing between select/project expressions
  - sharing between sliding window join expressions

Prototype systems

- Aurora (Brandeis, Brown, MIT) [CCC+02]
- Gigascope (AT&T) [CJSS03]
- Hancock (AT&T) [CFP+00]
- STREAM (Stanford) [MWA+03]
- Telegraph (Berkeley) [CCD+03]
- …

Aurora

- Geared towards monitoring applications (streams, triggers, imprecise data, real time requirements)
- Specified set of operators, connected in a data flow graph
- Optimization of the data flow graph
- Three query modes (continuous, ad-hoc, view)
- Aurora accepts QoS specifications and attempts to optimize QoS for the outputs produced
- Real time scheduling, introspection and load shedding

Gigascope

- Specialized stream database for network applications
- GSQL for declarative query specifications: pure stream query language (stream input/output)
- Uses ordering attributes in IP streams (timestamps and their properties) to turn blocking operators into non blocking ones
- GSQL processor is code generator.
- Query optimization uses a two level hierarchy

Hancock

- A C-based domain specific language which facilitates transactor signature extraction from transactional data streams
- Support for efficient and tunable representation of signature collections
- Support for custom scalable persistent data structures
- Elaborate statistics collection from streams

STREAM

- General purpose stream data manager
- CQL for declarative query specification
- Consider query plan generation
- Resource management:
  - operator scheduling
- Static and dynamic approximations

Telegraph

- Continuous query processing system
- Support for stream oriented operators
- Support for adaptivity in query processing
  - optimization
- Various aspects of optimized multi-query stream processing

Comparative Matrix

System	Data Stream Architecture	Data Model	Query Language	Query Answers	Query Plan
Aurora	low-level	RS-in RS-out	Operators	approximate	QoS-based, load shedding
Gigascope	two level (low, high)	S-in S-out	GSQL	exact	decomposition, avoid drops
Hancock	High-level	RS-in R-out	Procedural	exact, signatures	optimize for I/O, process blocks
STREAM	low-level	RS-in RS-out	CQL	approximate	optimize space, static analysis
Telegraph	high-level	RS-in RS-out	SQL-based	exact	adaptive plans, multi-query

Open Issues: Approximate Aggregates

- Large body of work on approximate aggregates over streams
- Issue: How can this work be used by data stream systems?
  - Engineering summary structures (sketches, samples) for low-level data stream processing
- Current status: Quantile computation is part of Gigascope, and engineered to reduce drops

Open Issues: Query Decomposition

- End-to-end three-level architecture:
  - Low-level and high-level data streams, DBMS
- Issue: How do we decompose a declarative (SQL) query?
  - Need to take resource limitations at each level into account
  - Which sub-queries are evaluated by which level?
- Current status: Gigascope does some automatic decomposition, and provides hooks for manual decomposition

Open Issues: Distributed Evaluation

- Low-level data stream processing may be highly distributed
- Issue: How do we correlate distributed data streams?
  - May not be feasible to bring all relevant data to a single site
  - Can one use techniques from distributed DBMSs?
- Current status: Some preliminary work by Gigascope, Aurora and STREAM people [BO03, CBB+03, OJW03]

Open Issues: I/O and Streaming

- High-level data stream processing can populate DBMS
- Issue: How do we process streams to minimize DBMS I/O?
  - Need to process streams in blocks, using multiple passes
  - How can multiple streams be correlated for this purpose?
- Current status: Hancock pays attention to I/O issues when computing signatures, other stream systems do not focus on I/O

Conclusions

- Data stream query processing has real applications
  - Need for sophisticated near-real time queries
  - Massive data volumes of transactions and measurements
- Wealth of challenging technical problems
  - Resource limitations exist, especially at low-level
  - Important to think of the end-to-end architecture

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