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# Data Stream Query Processing

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# Stream Map

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- Part I: Motivation (45 min)
  - Data streams: what, why now, applications
  - Data streams: architecture and issues
- Part II: Query processing (90 min)
- Part III: XML, open issues (45 min)

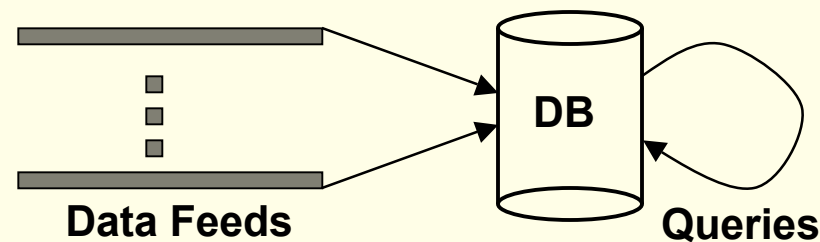
# Data Streams: What and Where?

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- 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
  - IP network: traffic at router interfaces
  - Sensor networks: physical phenomena, road traffic
  - Earth climate: temperature, moisture at weather stations

# Data Streams: Why Now?

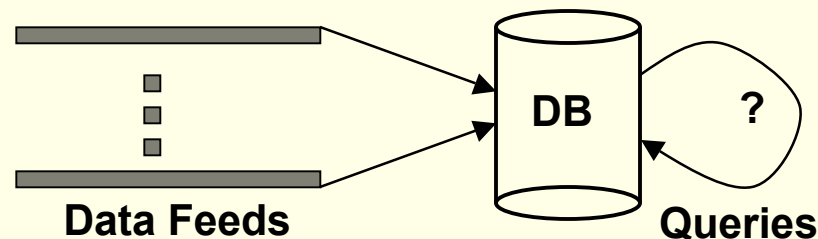
- Haven't data feeds to databases always existed? Yes
  - Modify underlying databases, data warehouses
  - Complex queries are specified over stored data



- 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

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- 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

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```
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

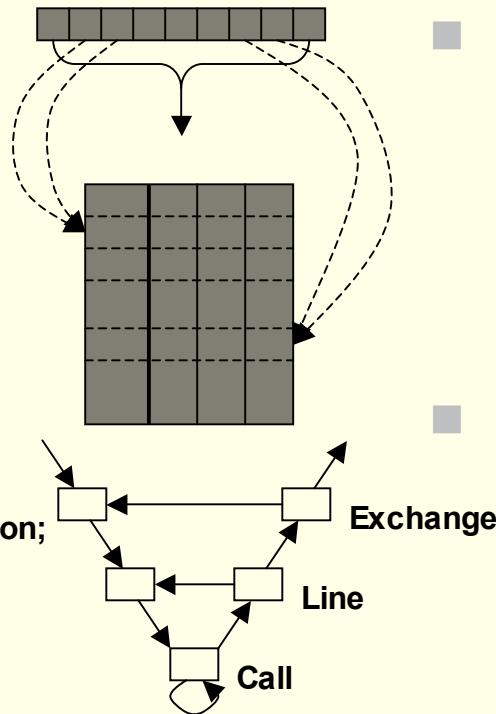
# Hancock: Signature Programs

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

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

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

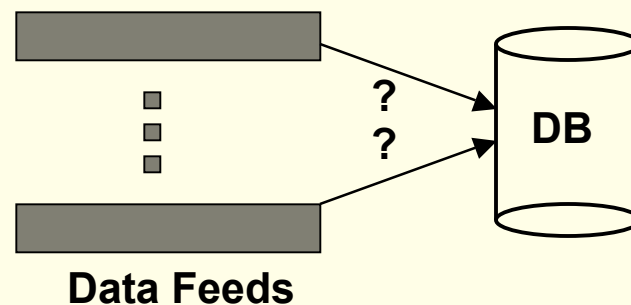
```
event line_end(lp_n_t pn){
mySig us = data<:pn:>;
us.outTF = blend(cumSec.outTF, us.outTF);
data<:pn:> := us;
}}
```



- 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: ~50B 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: Hidden P2P Traffic Detection

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- Business Challenge: AT&T IP customer wanted to accurately monitor peer-to-peer (P2P) traffic evolution within its network
- Previous Approach: 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 DSMS
  - Search for P2P related keywords within each TCP datagram
  - Identified 3 times more traffic as P2P than using Netflow
- Lesson: Essential to query massive volume data streams

# IP Network Application: Web Client Performance Monitoring

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- 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 DSMS
  - Track TCP synchronization and acknowledgement packets
  - Report round trip time statistics: latency
- Lesson: Essential to correlate multiple data streams

# Gigascop: Features and Functions

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- Gigascop is a fast, flexible data stream management system
  - High performance at speeds up to OC48 (2 \* 2.48 Gbit/sec)
- Developed at AT&T Labs-Research
  - Collaboration between database and networking research
- Current libraries include
  - Traffic matrix by site or autonomous system
  - Detection of hidden P2P traffic
  - End-to-end TCP performance monitoring
  - Detailed custom performance statistics

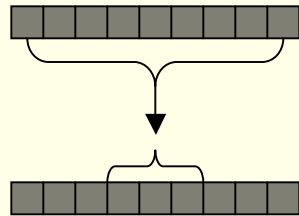
# Gigascop: Data Streams

```
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;
}
```

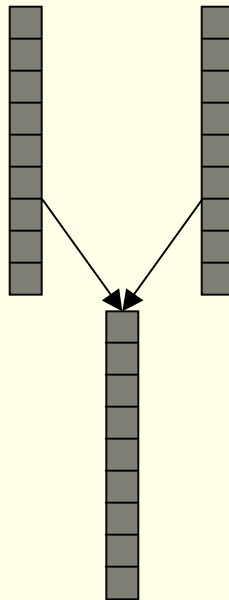
- GSQL queries get raw data from low level schemas
  - defined at packet level
  - inherits from lower layer
- Current schemas include
  - layer 2: ETH/HDLC
  - layer 3: IP/IPv4
  - layer 4: UDP/TCP/ICMP
  - layers 5-7: packet data

# Gigascop: 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

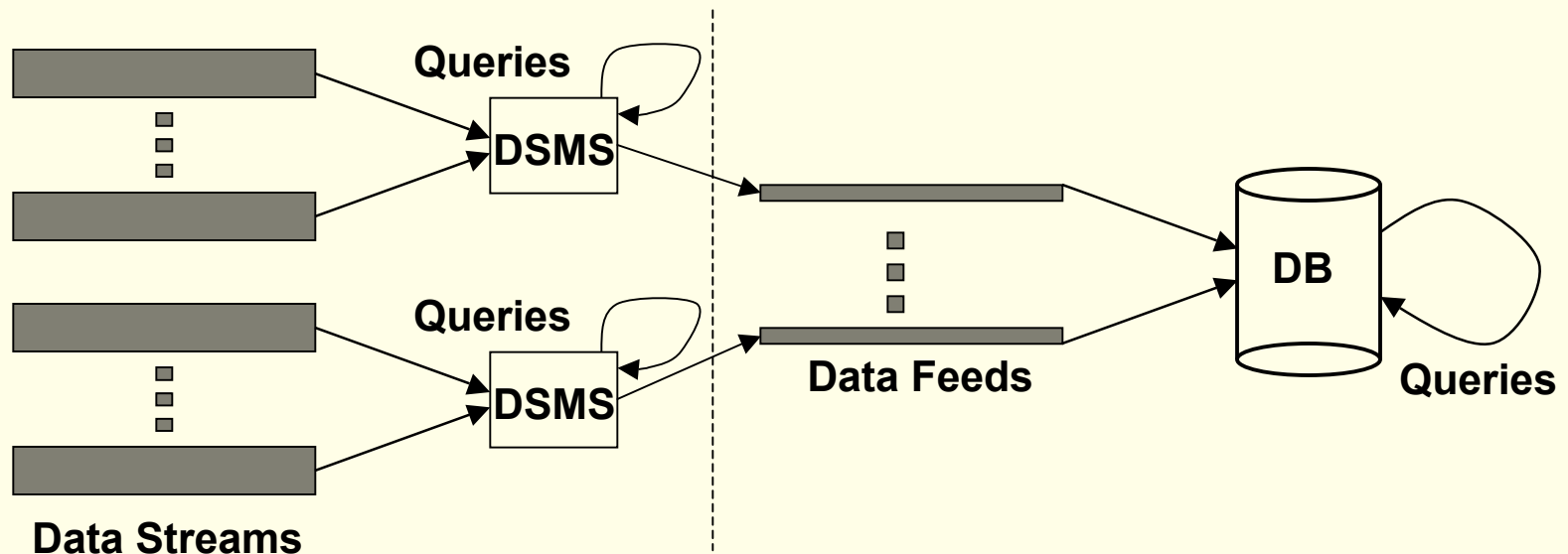
# Stream Map

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- Part I: Motivation (45 min)
  - Data streams: what, why now, applications
  - Data streams: architecture and issues
- Part II: Query processing (90 min)
- Part III: XML, open issues (45 min)

# DSMS + DBMS: Architecture

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



# DSMS + DBMS: Architecture

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## Data Stream Systems

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

# Databases vs Data Streams: Issues

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## Database Systems

- Model: persistent relations
- Relation: tuple set/bag
- Data Update: modifications
- Query: transient
- Query Answer: exact
- Query Evaluation: arbitrary
- Query Plan: fixed

## Data Stream Systems

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

Really a continuum ...

# Relation: Tuple Set or Sequence?

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- 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?

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- 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?

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- 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?

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- 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?

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- 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?

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- 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?

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## Architecture

- Resource (memory, per-tuple computation) limited
- 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 ...

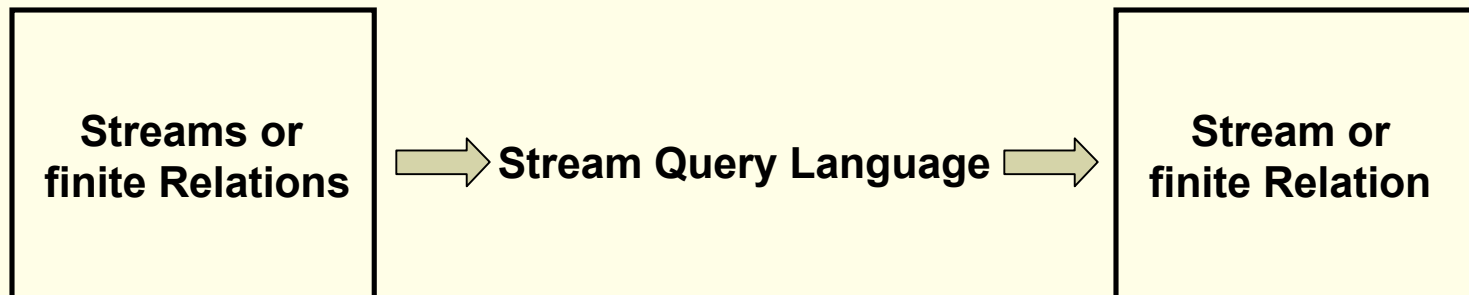
# Stream Map

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- Part I: Motivation (45 min)
- Part II: Query processing (90 min)
  - Stream query language issues (compositionality, windows)
  - Query operators
  - Optimization objectives
  - Multi-query execution
  - Prototype systems
- Part III: XML, open issues (45 min)

# Stream Query Languages

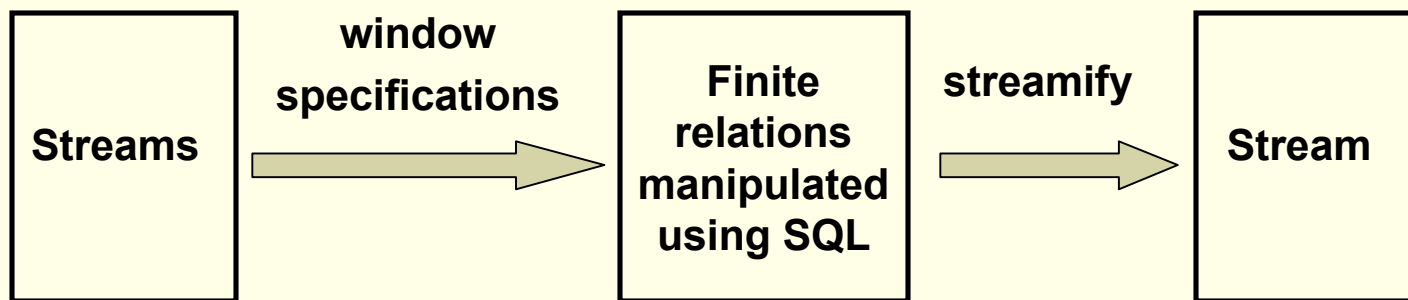
- SQL-like proposals suitably extended for a stream environment:
  - Composable SQL operators
  - Queries reference/produce relations or streams
  - GSQL [CJSS03]: SQL used by Gigascope
  - CQL [ABW03]: SQL used by STREAM



- UDA-SQL [LWZ04]: Monotonic sequence based queries

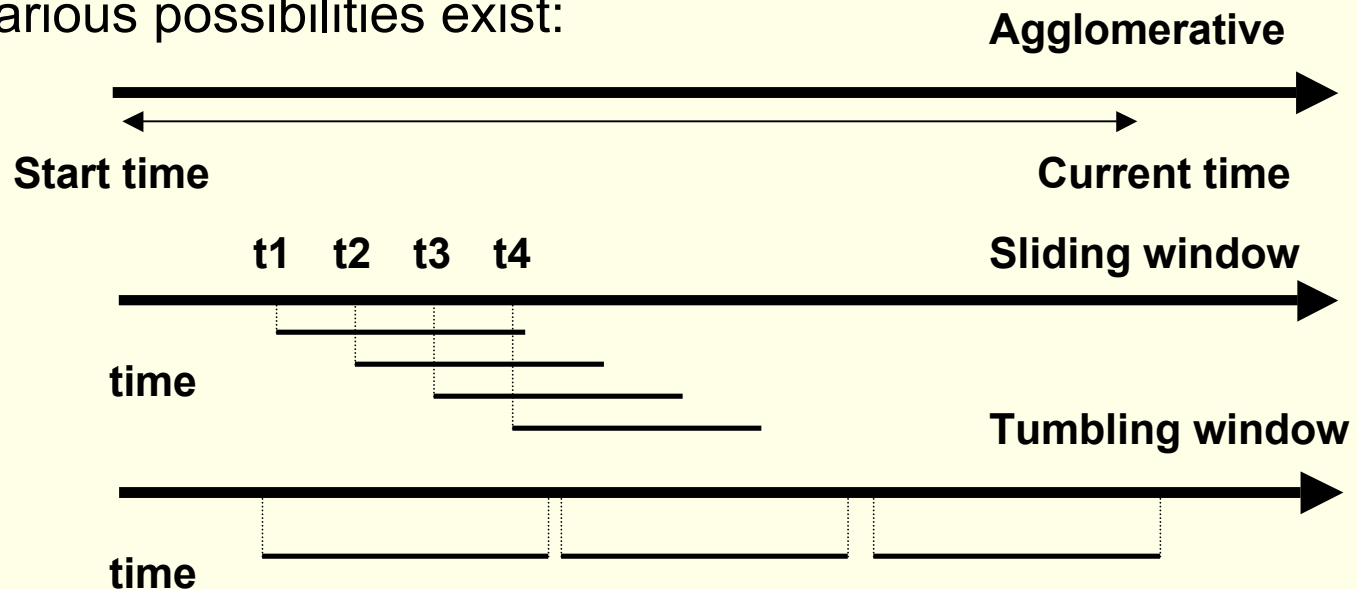
# Windows

- 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)



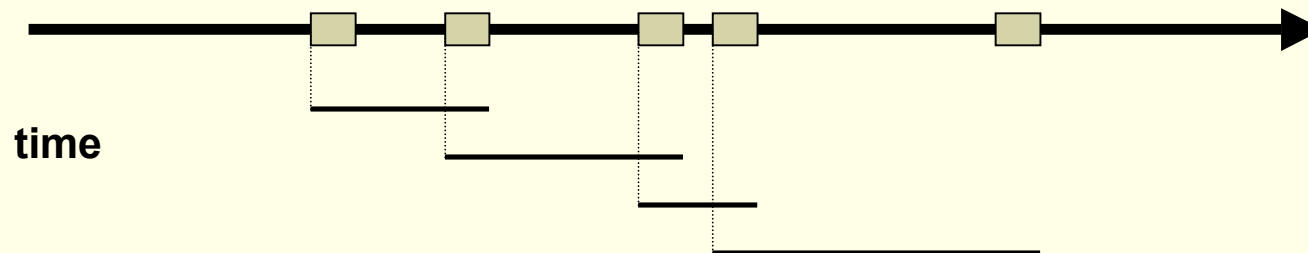
# Ordering Attribute Based Windows

- 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:



# Tuple Count Based Windows

- Window of size N tuples (sliding, tumbling) over the stream
- Problematic with non-unique time stamps associated with tuples
- Ties broken arbitrarily may lead to non deterministic output



# Punctuation Based Windows

## [TMSF03]

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- 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

# UDA-SQL [LWZ04]

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- Key Idea: Only permit non-blocking queries on data streams
  - Non-blocking queries = monotonic queries
- Non-blocking RA cannot express all monotonic FO queries
  - Set difference (-) in RA is blocking wrt its second argument
  - Expression of “coalesce” and “until” use set difference
- Proposal: Support non-blocking user-defined aggregates
  - INITIALIZE, ITERATE: process tuples in an ordered fashion
  - NB-UDAs + Union = computable monotonic functions

# Stream Map

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- Part I: Motivation (45 min)
- Part II: Query processing (90 min)
  - Stream query language issues
  - Query operators (selections/projections, joins, aggregations)
  - Optimization objectives
  - Multi-query execution
  - Prototype systems
- Part III: XML, open issues (45 min)

# Query Operators: Sample Stream

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```
Traffic ( sourceIP      -- source IP address
         sourcePort    -- port number on source
         destIP        -- destination IP address
         destPort      -- port number on destination
         length        -- length in bytes
         time          -- time stamp
);
```

# Selections, Projections

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- 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

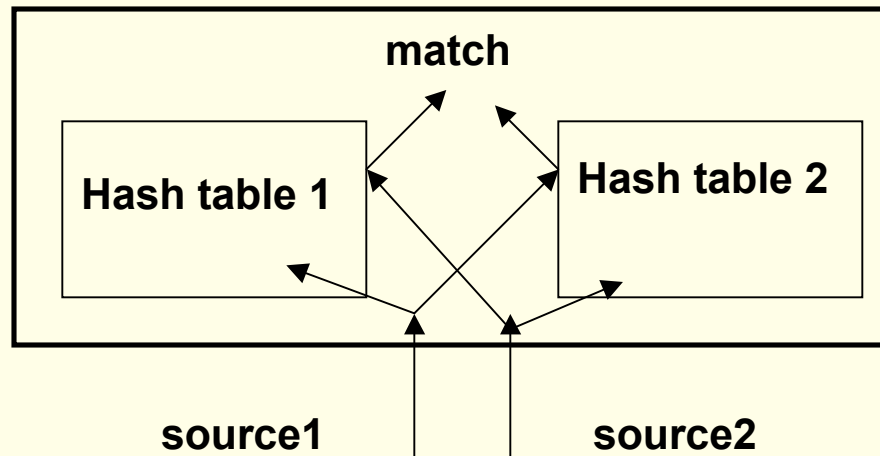
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- General case of join operators problematic on streams
  - May need to join arbitrarily far apart stream tuples
  - Equijoin on stream ordering attributes is tractable [JMS95]
- Majority of work focuses on joins between streams with windows specified on each stream

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

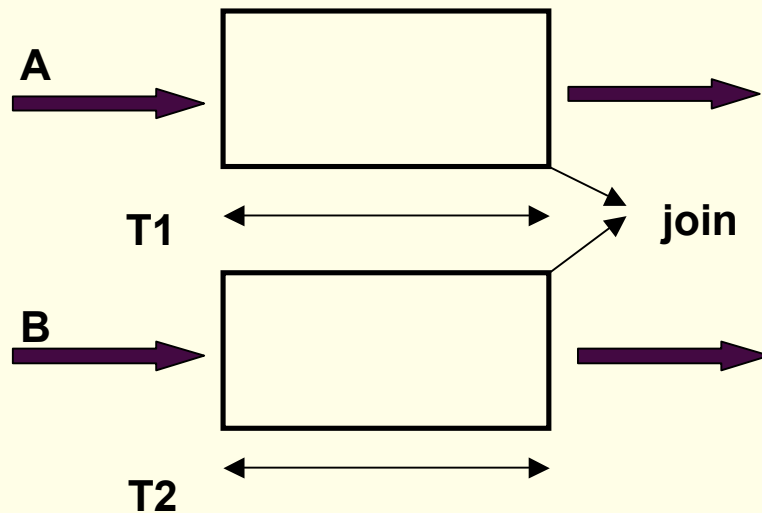
# Join Operators: Background

- 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:

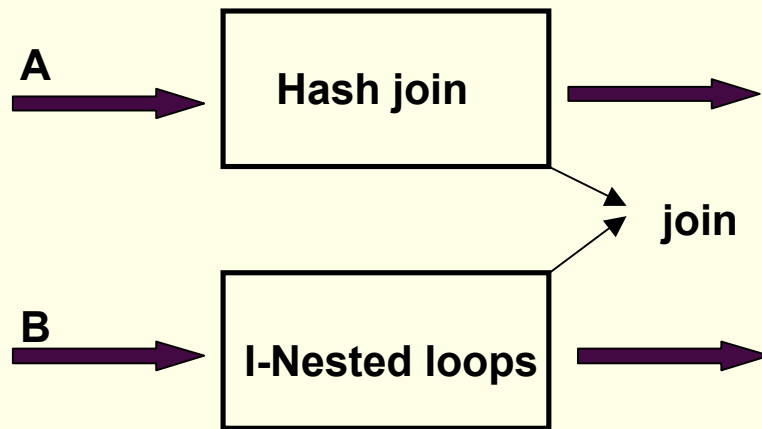
- Scan B's window for joining tuples and output result
- Insert tuple into A's window
- **Invalidate** all expired tuples in A's window

# Binary Joins: Issues

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- How do existing join algorithms apply in this setting?
- Impact of stream arrival rate and resources in join processing
  - Introduce a cost model for each operator as a function of individual stream arrival rates (unit time based cost model)
  - Utilize the cost model to identify tradeoffs

# 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

# Joining Punctuated Streams

## [DMRH'04]

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- Binary hash-based equi-join:
  - optimized for *reducing memory overhead*
  - optimized for *increasing data output rate*
- Fine-tunable execution logic: targeting various optimization goals
  - minimum memory overhead
  - maximum tuple output rate

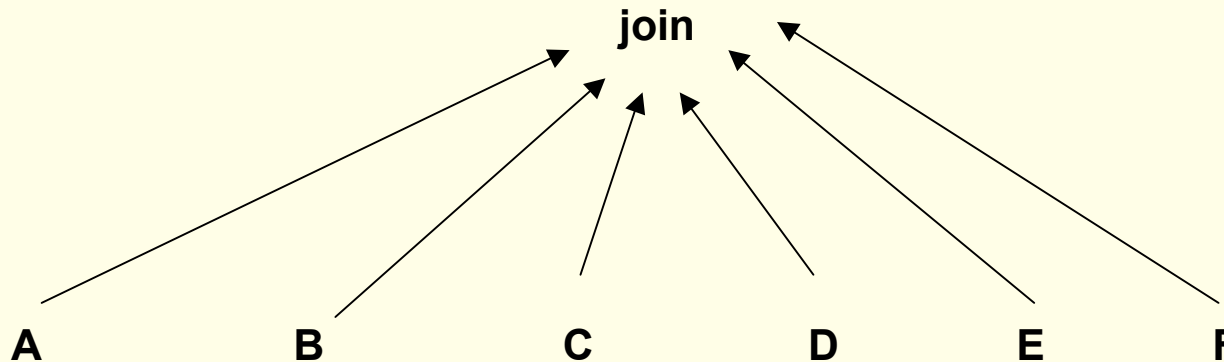
# Multi-way Joins

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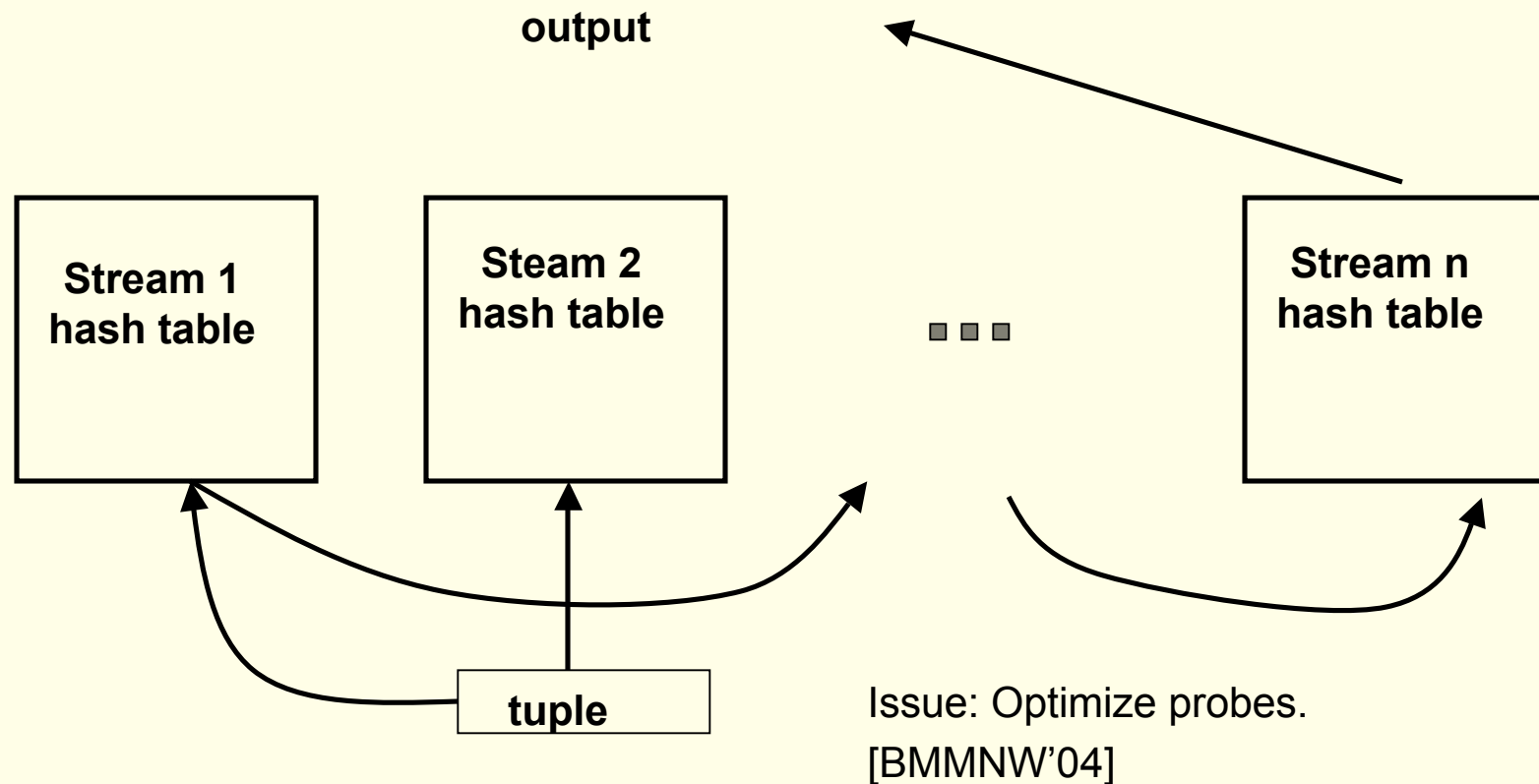
- Challenges during evaluation of n-way joins on streams:
  - evaluation order important
  - how to adapt traditional algorithms in this setting?
  - issues with varying arrival rates

# Mjoin Operator [VNB03]

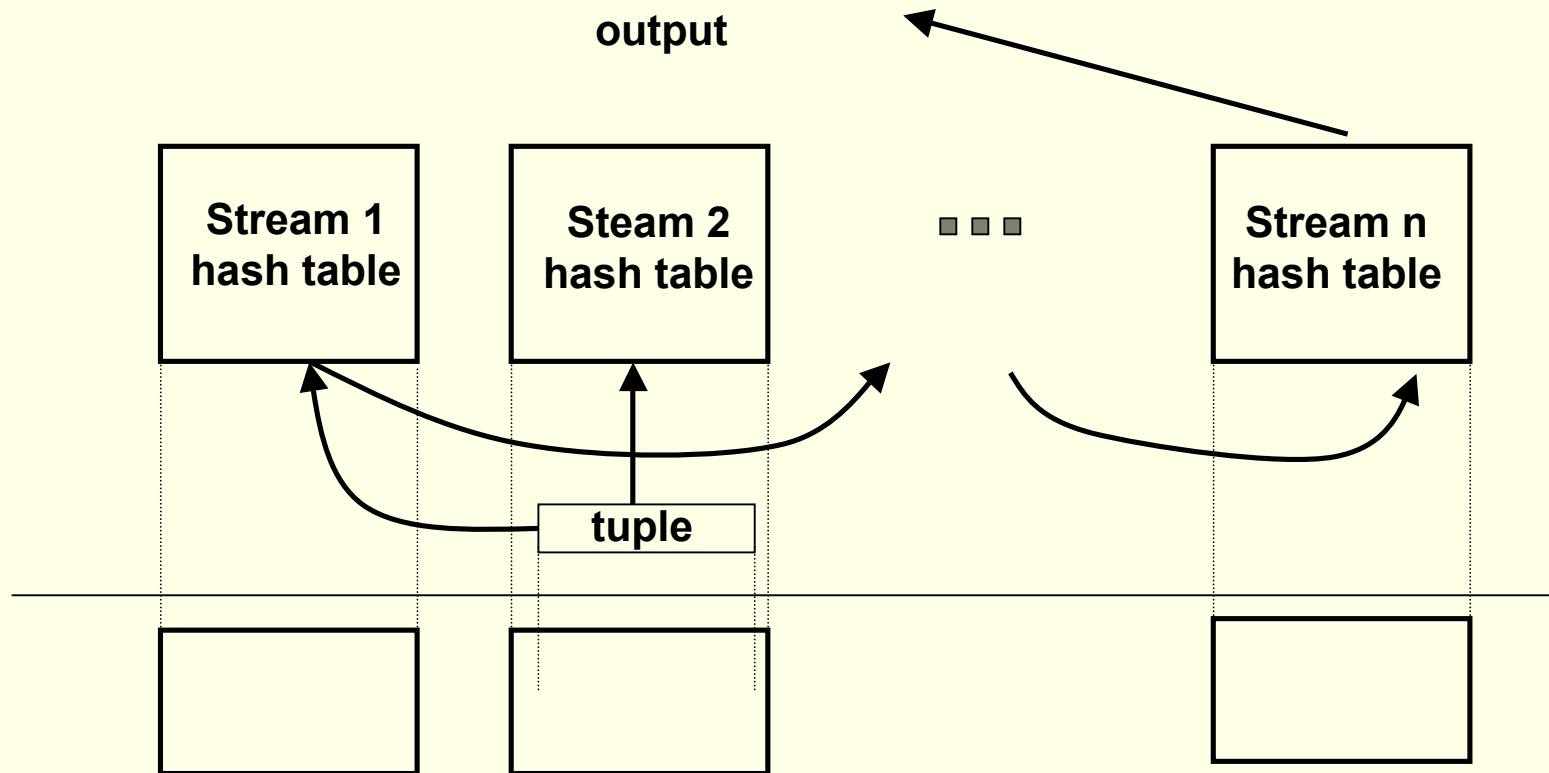
- Mjoin generalizes symmetric binary hash joins to work with multiple inputs
- Equijoins over attribute common to all streams
- Objective: maximize the output rate of the join operation



# Mjoin: In-memory Operation

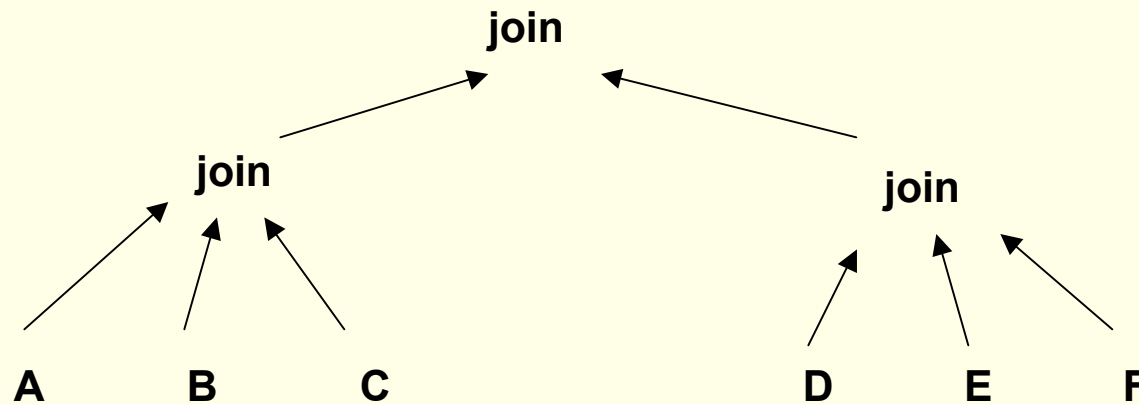


# Mjoin: Disk to Memory



# Mjoin: Observations

- As the number of input streams increases, the processing cost per input tuple increases
- In such cases, bushy plans of smaller (fewer input streams) Mjoin operators can be beneficial



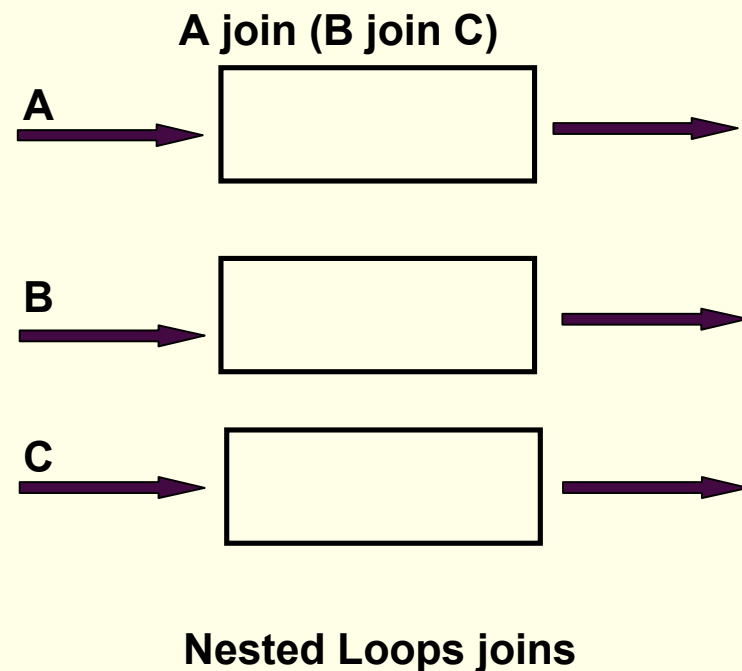
# Multi-way Sliding Window Joins [GO03]

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- Evaluation of n-way sliding window joins queries
  - n streams with associated sliding windows
  - continuously evaluate the joins of all n windows
- Two natural join strategies
  - **eager**: join is evaluated each time a new tuple arrives in any of the input streams
  - **lazy**: join is evaluated with some pre-specified frequency, e.g., every t time units
- Relationship with incremental, bottom-up evaluation of recursive rules [BR87]

# Eager Multi-way Joins

- Naïve approach extends the binary case
- Improved:
  - adapt join orders wrt origin of new tuple
  - Arrival on A
    - (A join B) join C
  - Arrival on B
    - (B join A) join C
  - Arrival on C
    - (C join A) join B



# Lazy multi-way joins

- Adapt eager multi-way joins in a lazy scenario
- Process all tuples that arrived since the last re-execution
- Imperative to apply lazy expiration for correctness

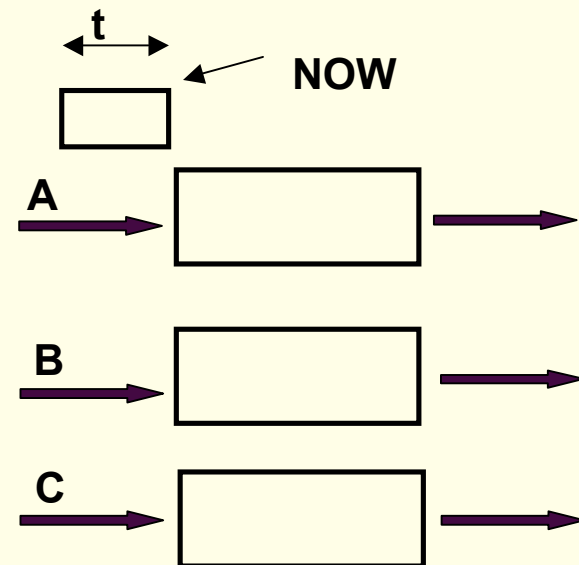
Insert new tuple into its window on arrival

At re-execution:

for each stream  $S_i$ , for all  $k$  in  $S_i$

where  $NOW - t \leq \text{timestamp of } k \leq NOW$

ComputeJoin( $k, \{S_1, \dots, S_{i-1}, S_{i+1}, \dots, S_n\}$ )



# Multi-way joins





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- Analytical model (using stream rates) to evaluate performance:
  - Eager algorithms better than the naïve approach
  - Improved lazy algorithms never worse than eager
- Similar algorithms can be instantiated for hash join strategies
  - Multi-way hash join algorithms more efficient than NL
  - More buckets for larger windows
  - Larger re-evaluation interval => larger hash tables

# Strategies and Expirations

**Eager tuple expiration**

**Lazy tuple expiration**

**Eager  
Evaluation**

**Lazy  
Evaluation**

# Aggregation

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

# Aggregation in Theory

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- 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
```

≡

```
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
```

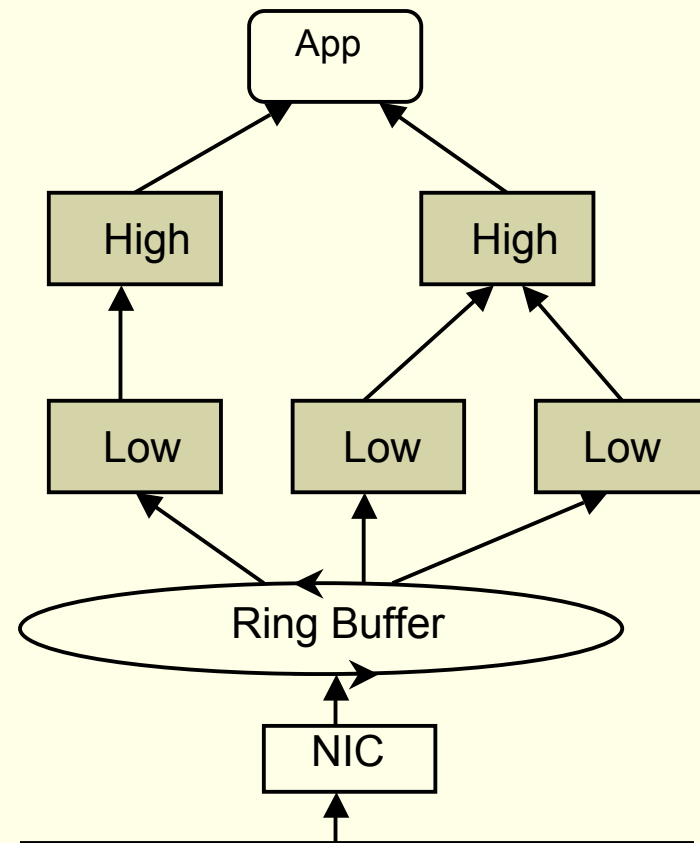
# Aggregation in Gigascope

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- 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 tumbling window (epoch)
- 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

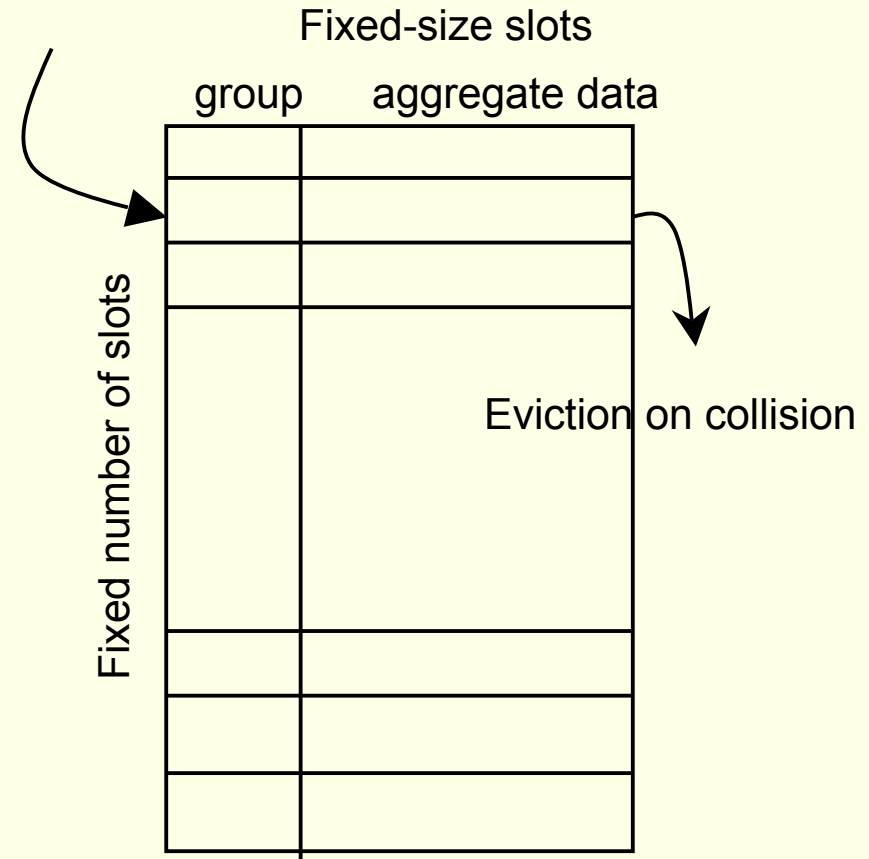
# Gigascoppe: Run-Time Architecture

- Low-level queries perform fast selection, aggregation
- High-level queries complete complex aggregation



# Gigascop: Low-Level Aggregation

- Fixed number of slots for groups, fixed size slot for each group
- Direct-mapped hashing
- Optimizations
  - Limited hash chaining reduces eviction rate
  - Slow eviction of groups when epoch changes



# Gigascop: Query Splitting

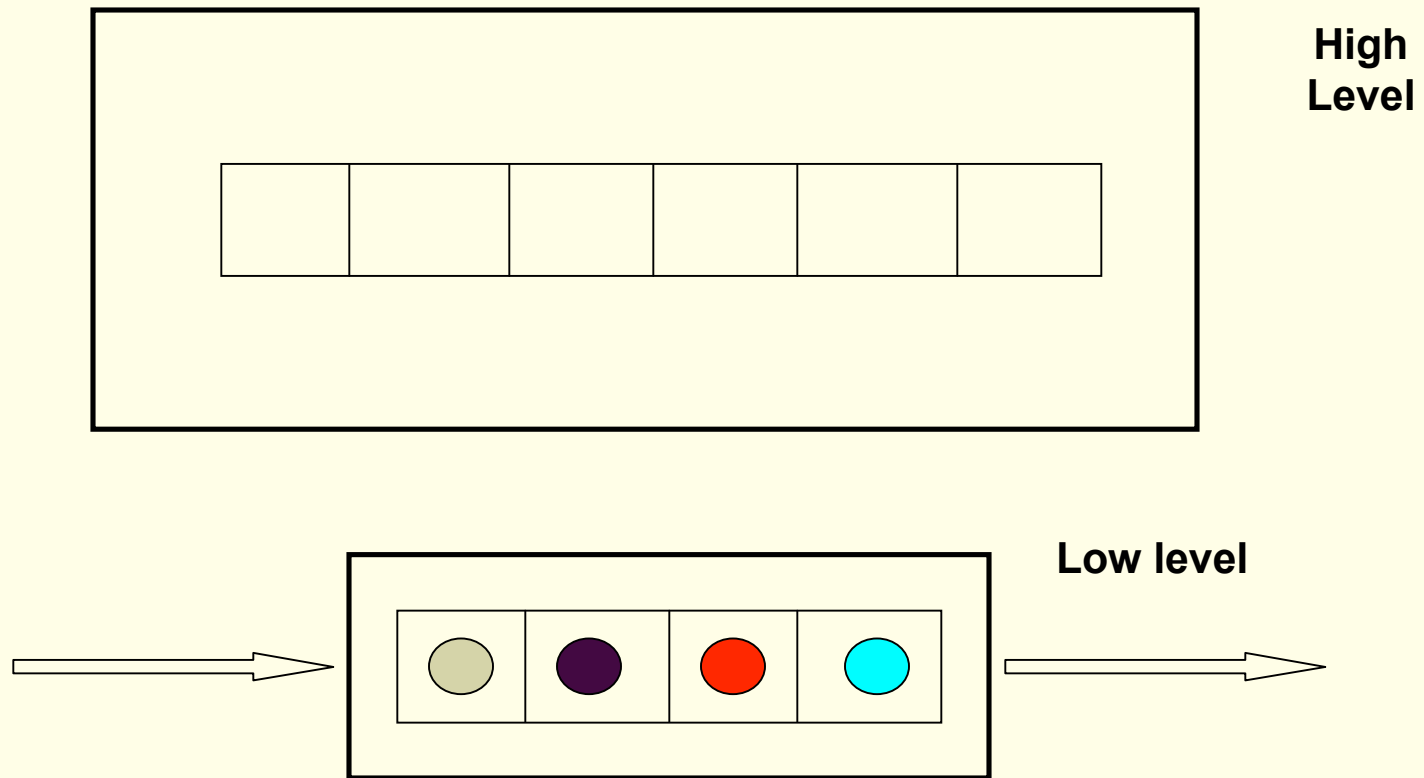
```
select tb, srcIP, sum(len)
from IPv4
where protocol = 6
group by time/60 as tb, srcIP
having count(*) > 5
```

```
select tb, srcIP, sum(sumLen)
from SubQ
group by tb, srcIP
having sum(cnt) > 5
```

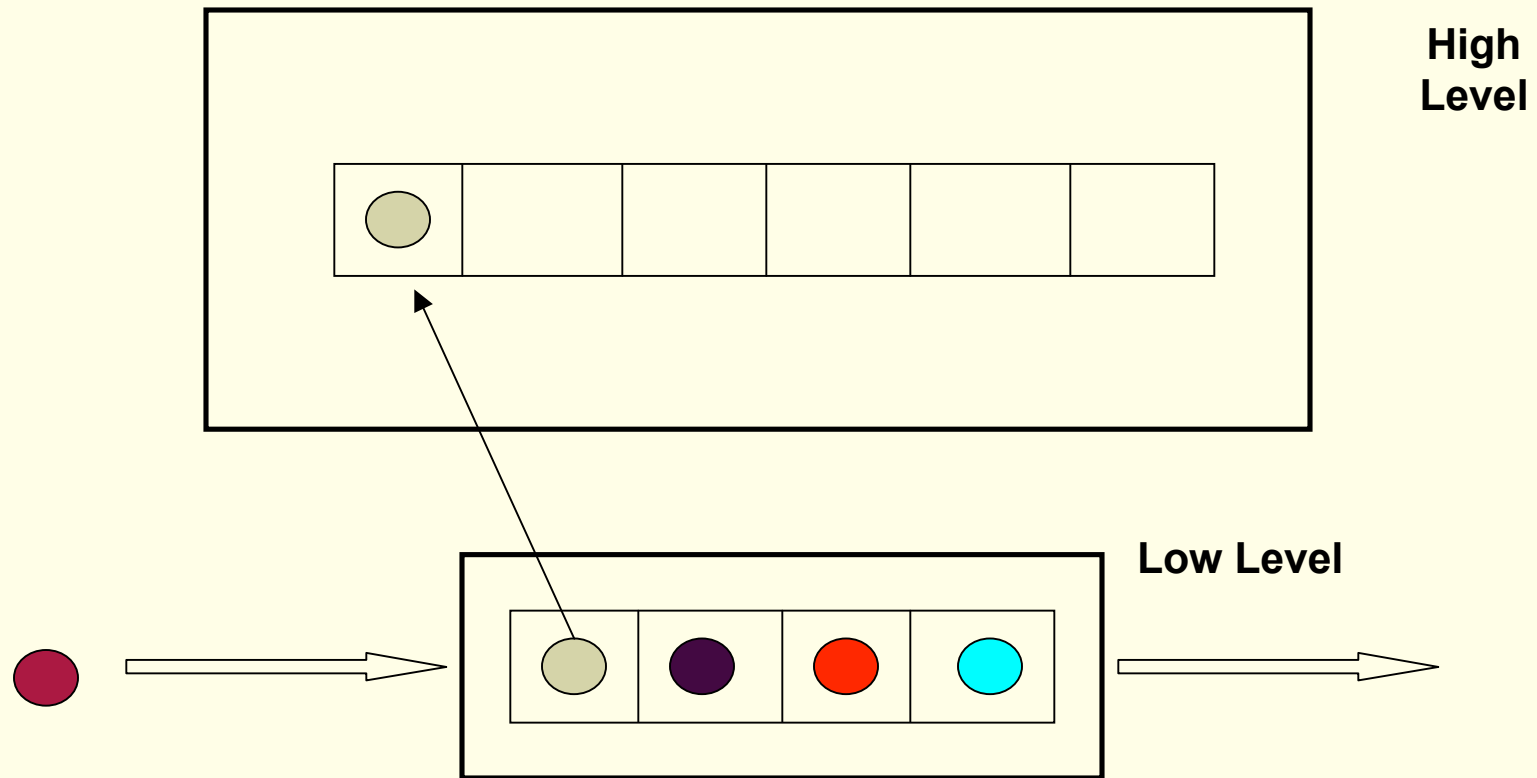
**SubQ:**

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

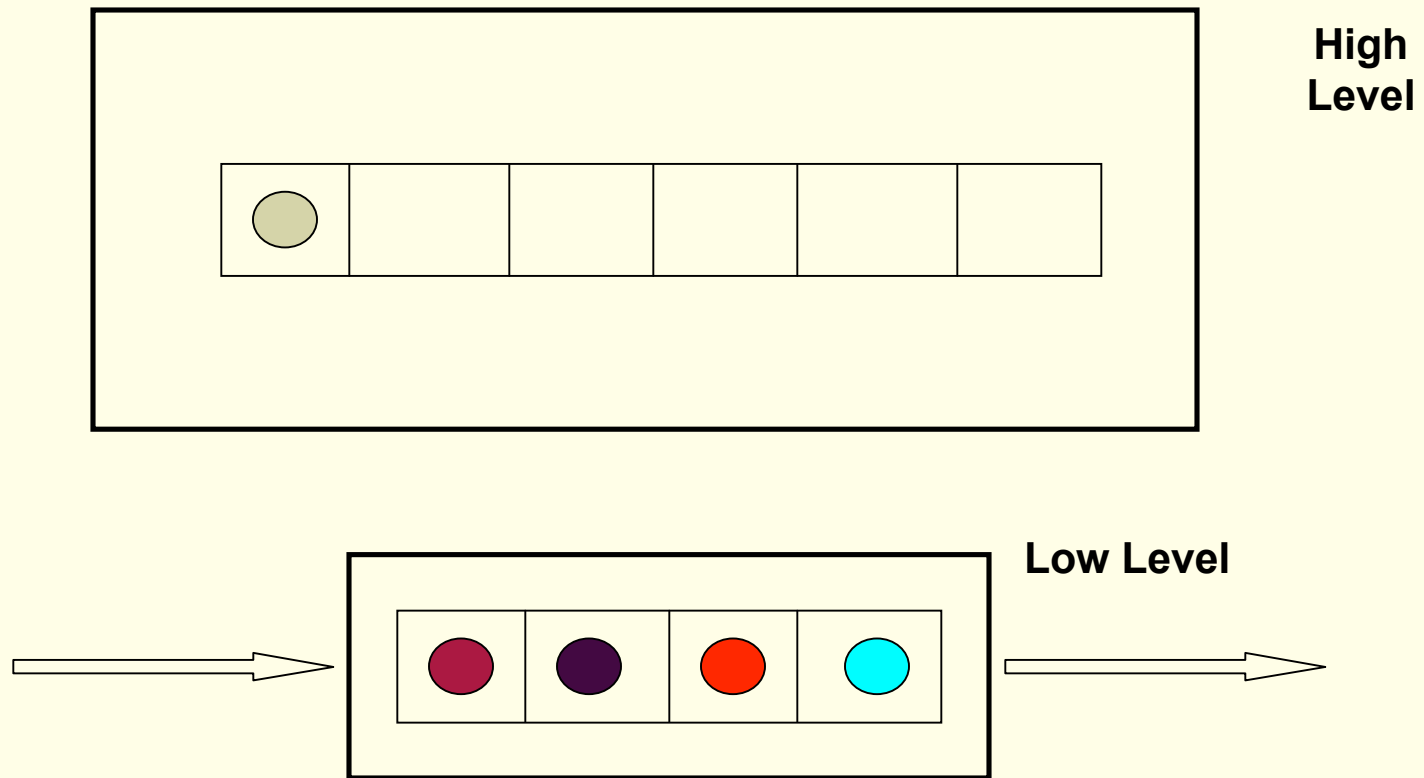
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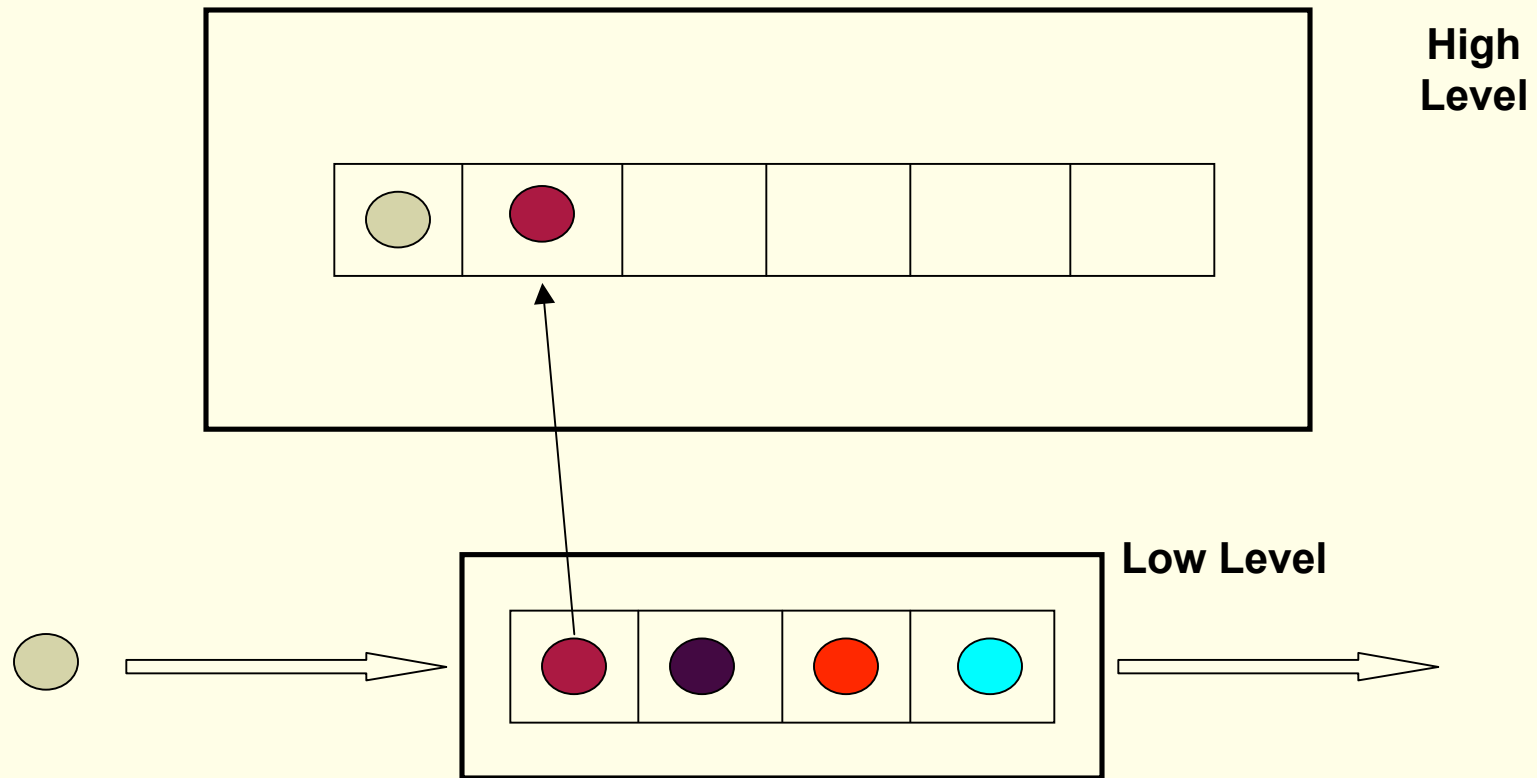
# Aggregation in Gigascope



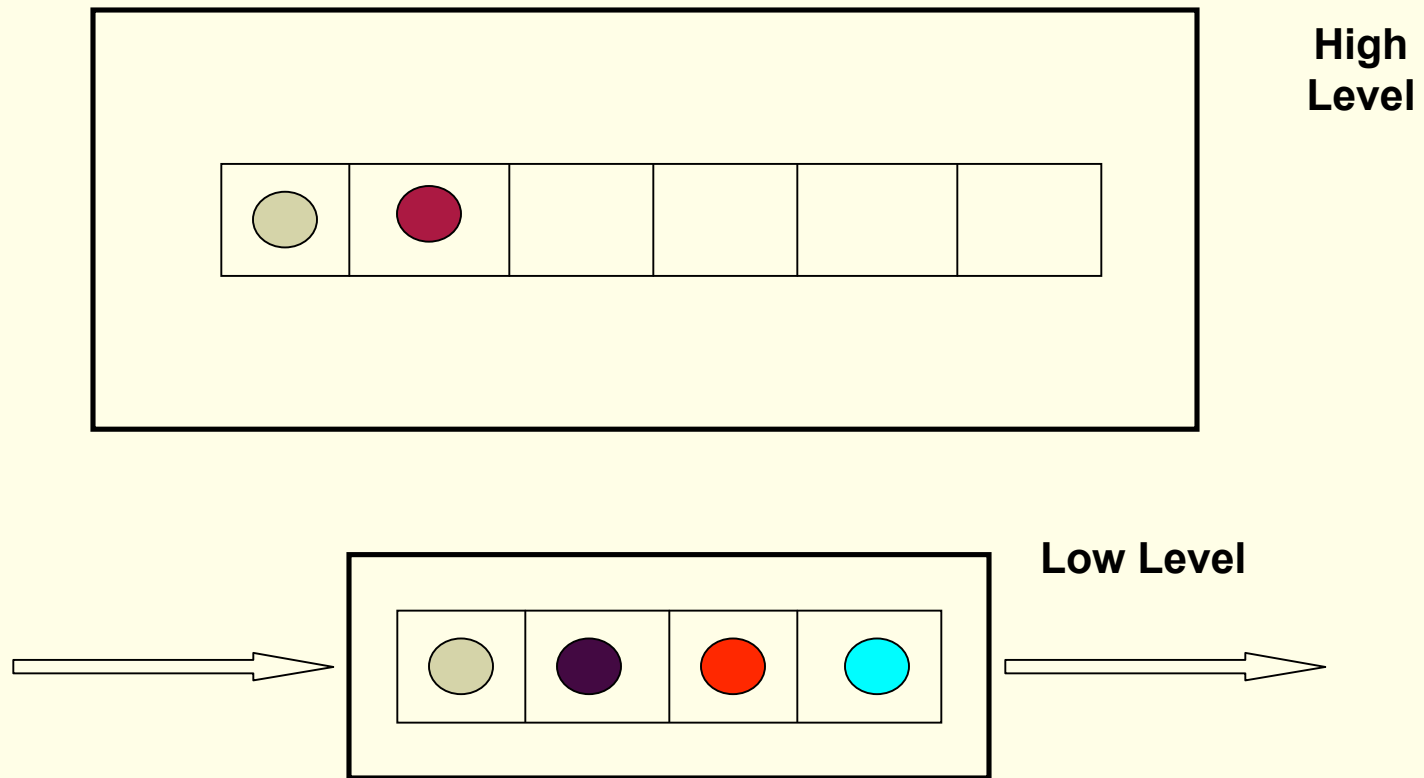
# Aggregation in Gigascope



# Aggregation in Gigascope



# Aggregation in Gigascope



# 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(*) >  $\varphi$  |S|`
- Use summary structures: samples, histograms, sketches ...
- Focus of different tutorial [GGR02]

# Stream Map

---

- Part I: Motivation (45 min)
- Part II: Query processing (90 min)
  - Stream query language issues
  - Query operators
  - Optimization objectives (stream rate, resource limits, QoS)
  - Multi-query execution
  - Prototype systems
- Part III: XML, open issues (45 min)

# Optimization Objectives: Issues

---

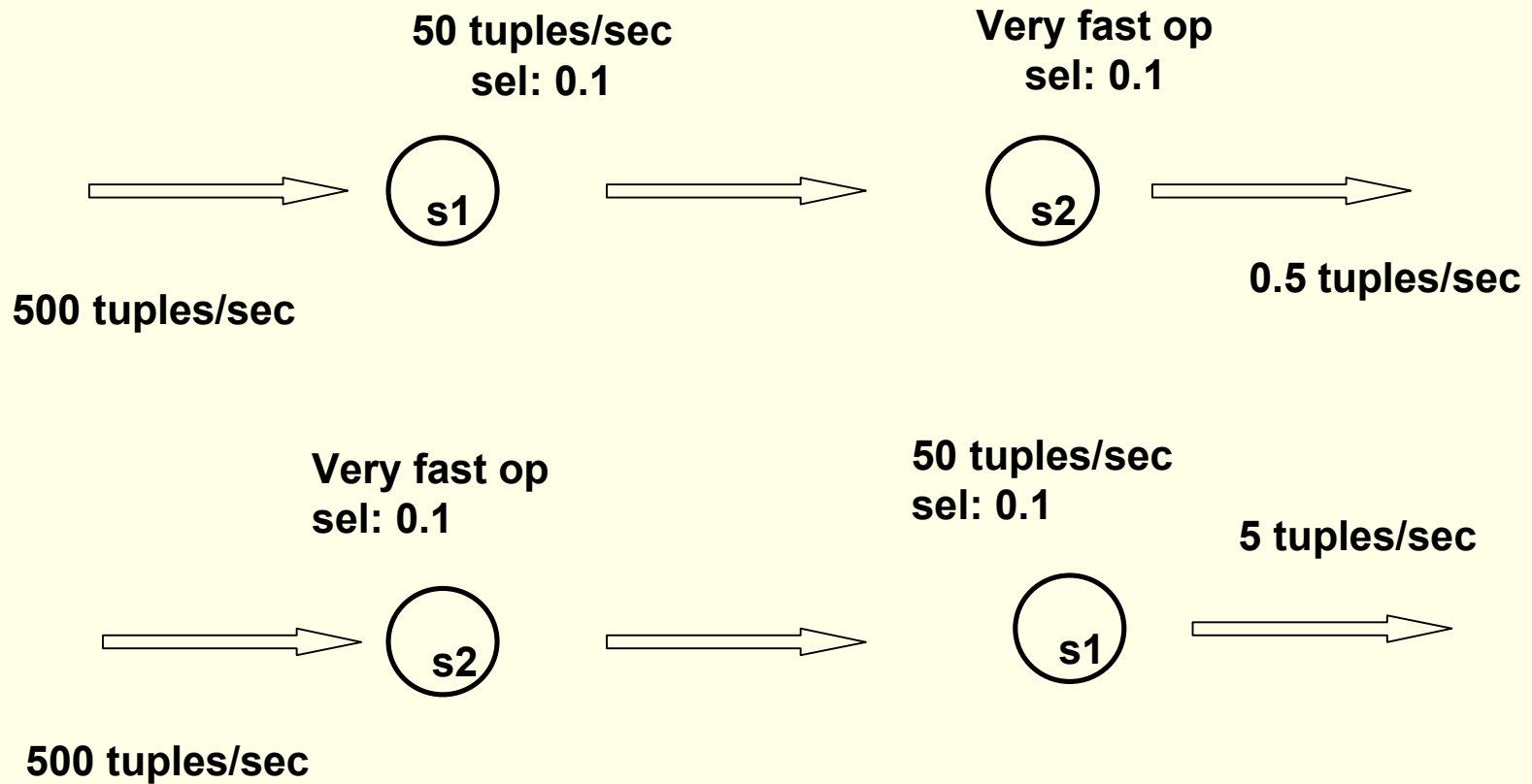
- Traditionally table based cardinalities used in query optimization
- Problematic in a streaming environment
- Need for novel optimization objectives that are relevant when inputs consist of streaming information sources

# Optimization Objectives

---

- 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



# Rate Based Optimization

---

- Output rate of a plan: number of tuples produced per unit time
- Derive expressions for the rate of each operator
- Combine expressions to derive expression  $r(t)$  for the plan output rate as a function of time:
  - Optimize for a specific point in time in the execution
  - Optimize for the output production size

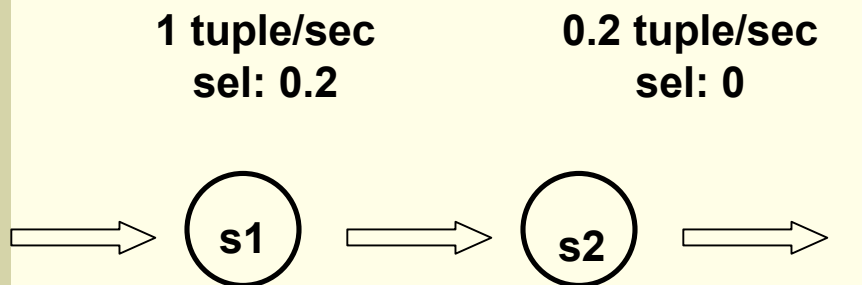
# Optimization Objectives

---

- 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



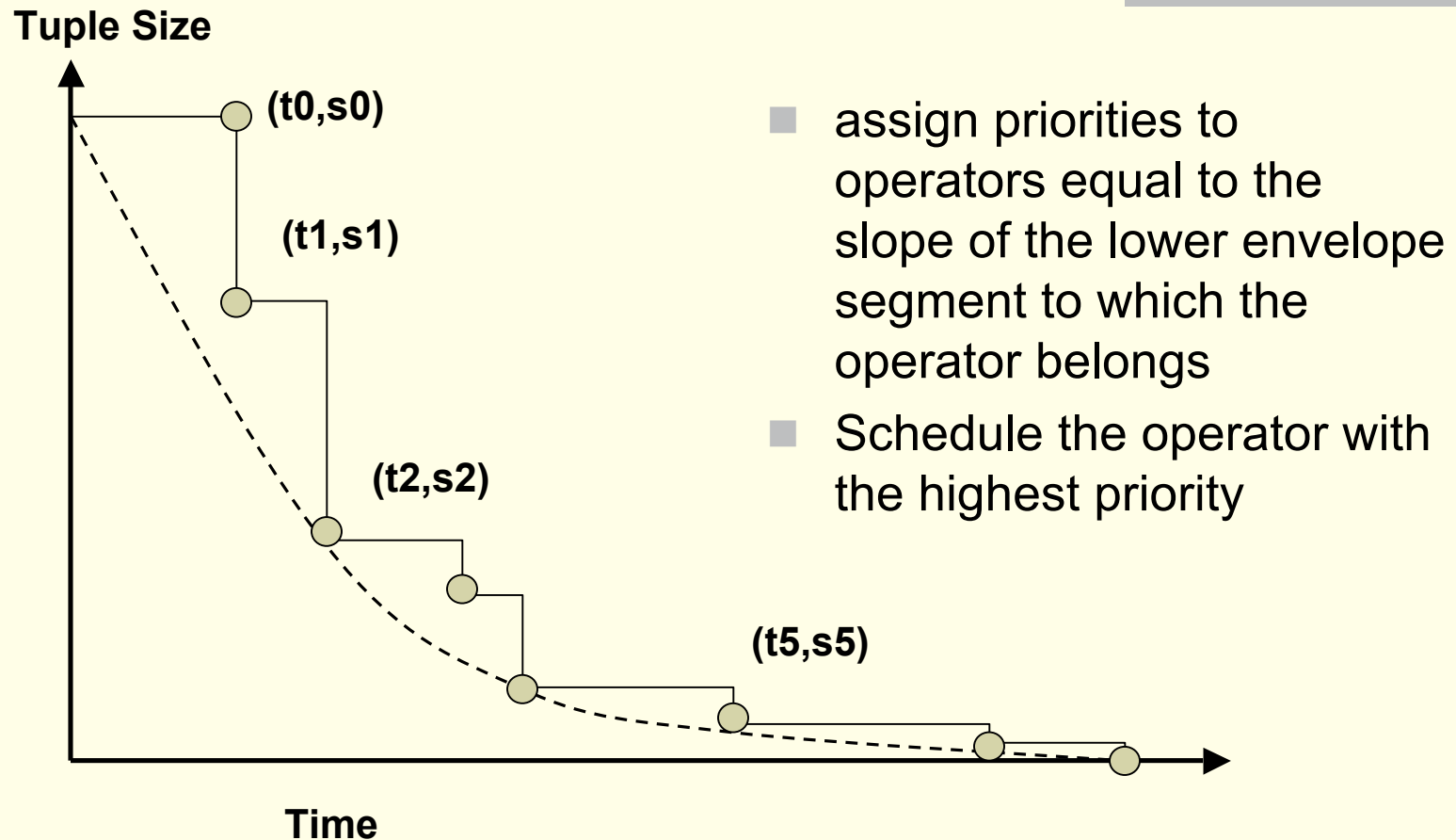
Average arrival rate: 0.5 tuples/sec

FIFO: tuples processed in arrival order

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

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

# Progress Chart: Chain Scheduling



# QoS Based Optimization [CCR+03]

---

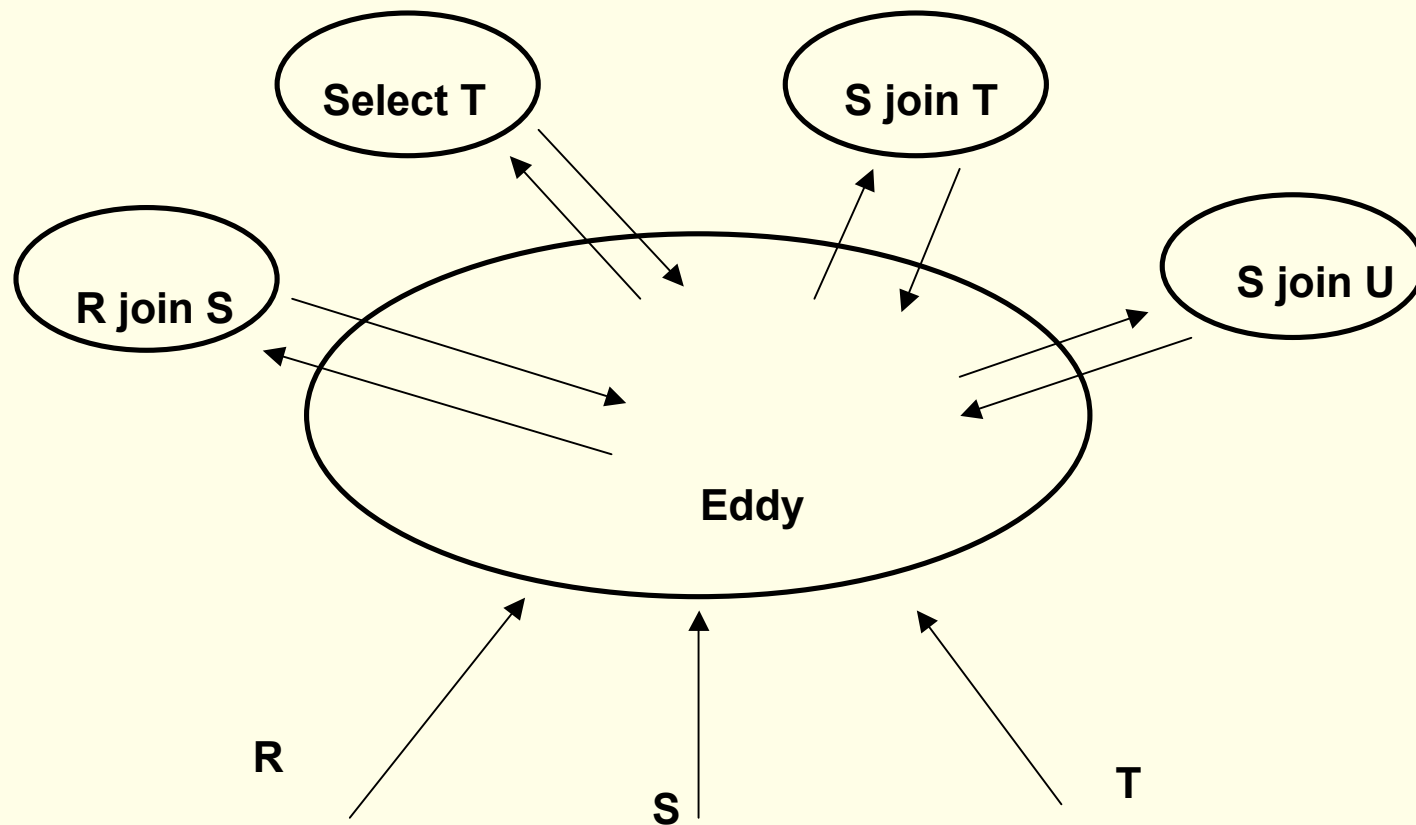
- Query and operator scheduling based on performance and QoS requirements
- Two-level scheduling policy:
  - Operator batching: superbox selection, superbox traversal based on avg throughput, avg latency, minimizing memory
  - Tuple batching

# Optimization Objectives

---

- Multi-way join techniques proposed:
  - start with a fixed plan
  - moderately adjust it as tuples arrive
- Eddies framework for adaptive query optimization:
  - Continuously adapt the evaluation order as tuples arrive

# Eddies [AH00]



# Optimization Objectives: Summary

---

- Novel notions of optimization
  - stream rate based
  - resource based
  - QoS based
  
- Continuously adaptive optimization
  
- Possibility that objectives cannot be met:
  - resource constraints
  - bursty arrivals under limited processing capability

# 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

# Load Shedding in Aurora [TCZ+03]

---

- QoS for each application as a function relating output to its utility
  - value based, loss tolerance based
- Techniques for introducing load shedding operators in a plan such that QoS is disrupted the least
  - Determining when, where and how much load to shed

# Load Shedding in STREAM

## [BDM03]

---

- Formulate load shedding as an optimization problem for multiple sliding window aggregate queries
  - Minimize inaccuracy in answers subject to output rate matching or exceeding arrival rate
- Consider placement of load shedding operators in query plan
  - Each operator sheds load uniformly with probability  $p_i$

# Benchmark: Linear Road [ACG+04]

---

- Goal: Compare performance of DSMSs and DBMSs
- Linear Road Benchmark: Challenges
  - Semantically valid input: high-volume simulated data
  - Performance metrics: real-time query response, load
  - No query language: queries specified in predicate calculus

# Benchmark: Linear Road [ACG+04]

- Input data: Generated using MIT Traffic Simulator
  - Vehicles, accidents, congestion on multiple expressways
  - Position reports: (Time, VID, Spd, Xway, Lane, Dir, Seg, Pos)
  - Historical data: TollHistory, SegmentHistory
- Queries
  - Continuous query requests:
    - Toll notifications, toll assessments
    - Accident detection, accident notification
  - Historical query requests:
    - Account balance: (Time, VID, QID)
    - Daily expenditure: (Time, VID, Xway, QID, Day)
    - Travel time: (Time, VID, Xway, QID, Sinit, Send, DOW, TOD)

# Stream Map

---

- Part I: Motivation (45 min)
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  - Prototype systems
- Part III: XML, open issues (45 min)

# Multi-query Processing on Streams

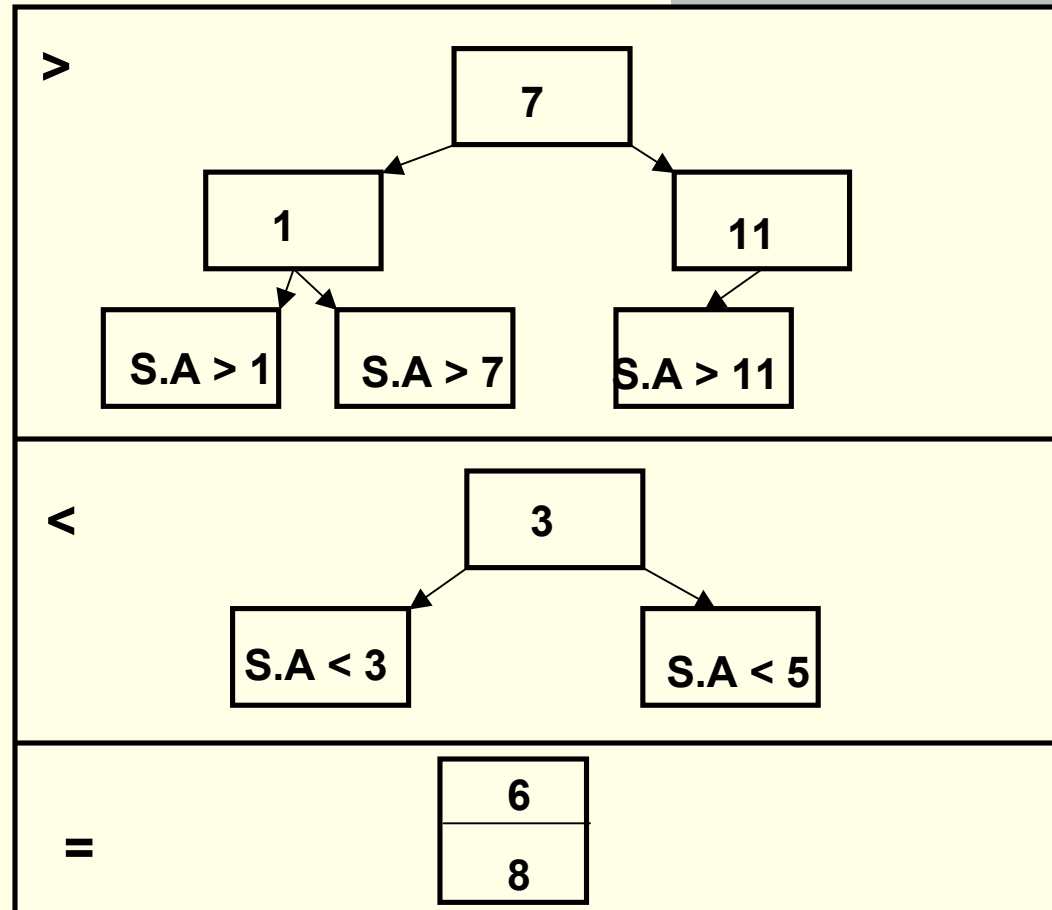
---

- 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

# Grouped Filters [MSHR02]

Select Predicates for Stream S.A
<p>S.A &gt; 1 S.A &gt; 7 S.A &gt; 11</p>
<p>S.A &lt; 3 S.A &lt; 5</p>
<p>S.A = 6 S.A = 8</p>

Tuple S.A = 8



# Shared Window Joins [HFAE03]

---

- Consider the two queries:

```
select sum (A.length)
from Traffic1 A [window 1hour], Traffic2 B [window 1 hour]
where A.destIP = B.destIP
```

```
select count (distinct A.sourceIP)
from Traffic1 A [window 1 min], Traffic2 B [window 1 min]
where A.destIP = B.destIP
```

# Shared Window Joins

---

- Great opportunity for optimization as windows are highly shared
- Strategies for scheduling the evaluation of shared joins:
  - Largest window only
  - Smallest window first
  - Process at any instant the tuple that is likely to benefit the largest number of joins (maximize throughput)

# Shared Window Aggregates [AW04]

---

- Great opportunity for optimization as windows are highly shared
- Sliding window aggregates
  - Various classes of aggregation functions (e.g., distributive, algebraic, etc)
  - Various window types (time, tuple based)
  - Input models (single, multiple streams)

# Stream Map

---

- Part I: Motivation (45 min)
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# Prototype systems

---

- Aurora (Brandeis, Brown, MIT) [CCC+02]
- Gigascope (AT&T) [CJSS03]
- Hancock (AT&T) [CFP+00]
- Nile (Purdue) [AEA+04]
- 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

# Gigascop

---

- 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

# Nile

---

- Stream-in stream-out paradigm
- Summary Manager with the notion of promising tuples
- Sliding and predicate windows
- Negative tuples
- Shared execution
- Admission control and quality of service support
- Context-aware query processing and optimization
- Built-in online data mining
- Sensor network support
- Disk-based data 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
Nile	high level	RS-in RS-out	SQL-based	approximate	incremental evaluation, multi-query
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

# Stream Map

---

- Part I: Motivation (45 min)
- Part II: Query processing (90 min)
- Part III: XML, open issues (45 min)
  - XML streams: motivation, query processing
  - XML streams: connection to tuple streams
  - Open Issues

# XML Data Streams: Applications

---

- An **XML data stream** is a sequence of **tokens**
- Data and application integration
  - Distributed monitoring of computing systems
- Message-based web services
  - Purchase orders, retail transactions
- Personalized content delivery

# XML Data Streams: Why XML?

---

- XML data model
  - Self-describing data representation
  - Natural for both structured and unstructured data
  - XML schema provides rich typing and structural constraints
- XML query languages
  - Declarative matching of structured data and text
  - Easy restructuring to meet needs of data consumers

# Data Integration Application: Distributed Monitoring [MCC03]

---

- Business Challenge: Monitor the performance of a very large number (federation of clusters, grids) of computing devices
- Issues: Scalability, robustness, extensibility
- Solution: In Ganglia's hierarchical design
  - Monitoring daemons of single cluster report state in XML
  - Meta-daemons aggregate and export lower-level XML data
  - Permits queries based on path expressions, time windows
- Lesson: Essential to query distributed data streams

# Web Services Application: Purchase Orders Workflow [FHK+03]

---

- Business Challenge: Automate enterprise business processes
- Issues: Need strong support for data transformations
- Solution: WLI uses XML and XQuery to
  - Transform purchase order data as it flows through system
  - Specify data-driven workflow logic (looping, branching)
- Lesson: Essential to transform and personalize data streams

# WLI: Data Streams

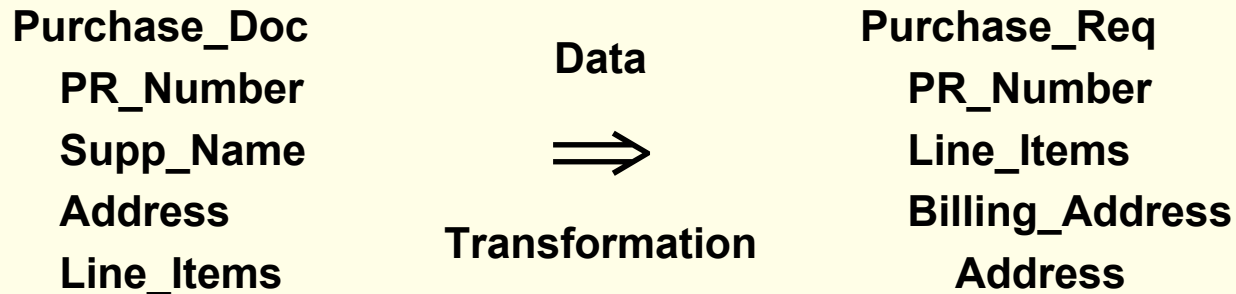
- XML data: tree structure

```
<Purchase_Doc>
  <PR_Number val = "50"/>
  <Supp_Name>ABC</Supp_Name>
  <Address>
    <City>Florham Park</City>
    <State>New Jersey</State>
  </Address>
  <Line_Items>
    <Item>
      <Part_Number val= "1050"/>
      <Quantity val="20"/>
    </Item>
```

- Data stream: ~ SAX events

```
[element Purchase_Doc anyType]
[element PR_Number anyType]
[attribute val anySimpleType]
[chardata 50]
[end-attribute]
[end-element]
[element Supp_Name anyType]
[text ABC]
[end-element]
...
```

# WLI: Data Transformation Query



```
<Purchase_Req> {  
  for $d in document("doc.xml")/Purchase_Doc  
  where $d//State = "New Jersey"  
  return  
    { $d/PR_Number } { $d/Line_Items }  
    <Billing_Address> { $d/Address } </Billing_Address>  
} </Purchase_Req>
```

# XML Stream Processing: Key Ideas

---

- Obtain bindings of **for** clause path expression variables
  - Ordered sequence, no duplicates
- Filter bindings using **where** clause path expression predicates
  - Existential check suffices
- Compute bindings of **return** clause path expressions
  - Ordered (possibly null) sequence
- Goal: Efficient matching/binding of XML path expressions
  - Very large number of path expressions

# Result Generation: Alternatives

Path Matching	Result Generation
<b>for</b> clause paths	Navigation for <b>where</b> clause paths Navigation for <b>return</b> clause paths
<b>for-where</b> clause paths	Semijoins for <b>where</b> clause paths Navigation for <b>return</b> clause paths
<b>for-where-return</b> clause paths	Semijoins for <b>where</b> clause paths Left outerjoins for <b>return</b> clause paths

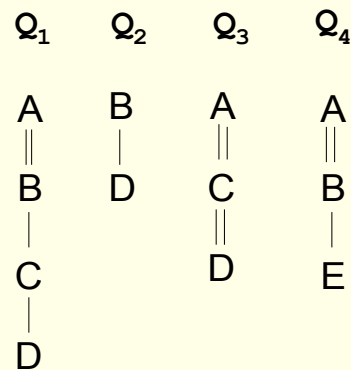
# Shared Path Matching: Overview

---

- Automata-based techniques:
  - XFilter [AF00]: finite state machine per path expression
  - XTrie [CFGR02]: shares common sub-paths of PC paths
  - **YFilter** [DF03]: single NFA for all path expressions
  - [GMOS03]: single DFA, limitations on flexibility
  - XPush [GS03]: pushdown automaton for tree patterns
- Index-based techniques:
  - MatchMaker [LP02]: shared tree patterns
  - **IndexFilter** [BGKS03]: shared path expressions, comparison

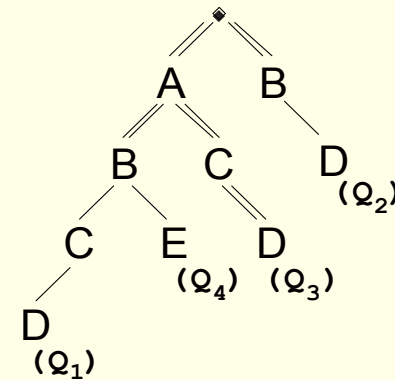
# Prefix Sharing for Path Expressions

- Used by automata- and index-based techniques
- Eliminates redundant processing
- Tradeoff between “compression” and “amount of bookkeeping”



Set of Path Expressions

Prefix sharing →



Path Prefix Tree

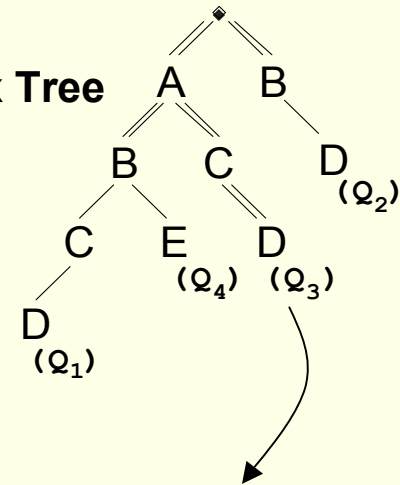
# Solution Representation

[element A anyType]  
 [element C anyType]  
 [element A anyType]  
 [element C anyType]  
 [element B anyType]  
 [element D anyType]  
 [end-element]  
 [end-element]  
 [end-element]  
 [end-element]  
 [end-element]  
 [end-element]

A<sub>1</sub>  
 C<sub>1</sub>  
 A<sub>2</sub>  
 C<sub>2</sub>  
 B<sub>1</sub>  
 D<sub>1</sub>

XML Data

Path Prefix Tree

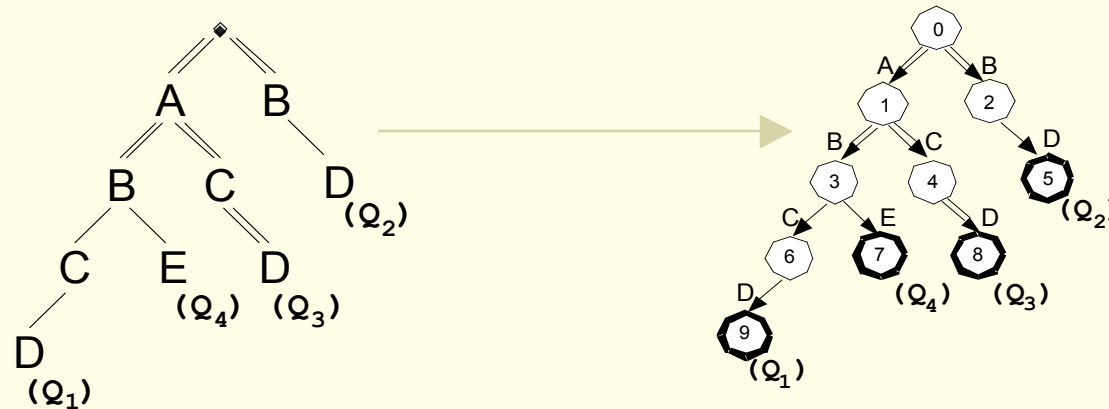


A	C	D
A <sub>1</sub>	C <sub>1</sub>	D <sub>1</sub>
A <sub>1</sub>	C <sub>2</sub>	D <sub>1</sub>
A <sub>2</sub>	C <sub>2</sub>	D <sub>1</sub>

Matches

# YFilter: Automata-based Technique

- Augment the path prefix tree into an NFA



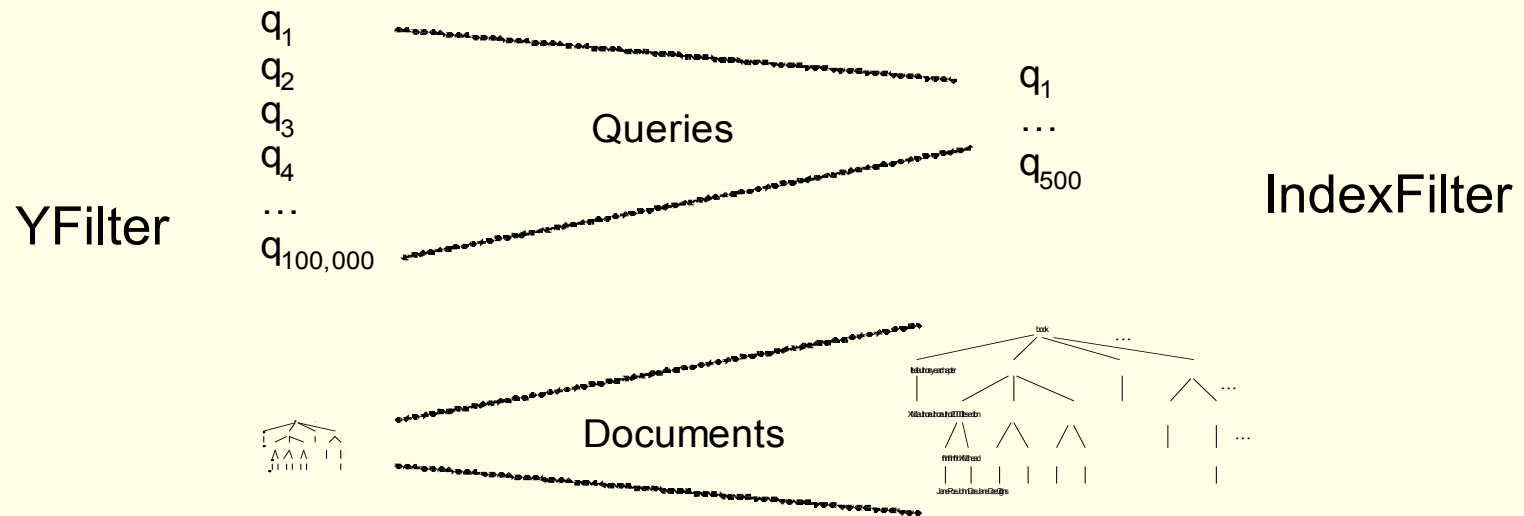
- Implemented as a tree of hash tables for efficiency
- Set of active states maintained in a runtime stack
  - Adds sets of states to stack when encountering open-tags
  - Backtracks stack when encountering close-tags

# IndexFilter: Index-based Technique

---

- Build and exploit (start, end, level) indexes on XML tags
- Each node  $q$  in path prefix tree contains:
  - $T_q$ : Indexed stream of tags sorted by “start”
  - $S_q$ : Stack to track all matches
  - $P_q$ : Dynamic access to  $q$ 's children with minimal start value
- Tradeoff index building cost with unnecessary matching in NFA
  - Use of indexes focuses matching to relevant tags

# YFilter versus IndexFilter: Summary



- Other relevant factors:
  - Document/query structure, selectivity of path expressions

# Stream Map

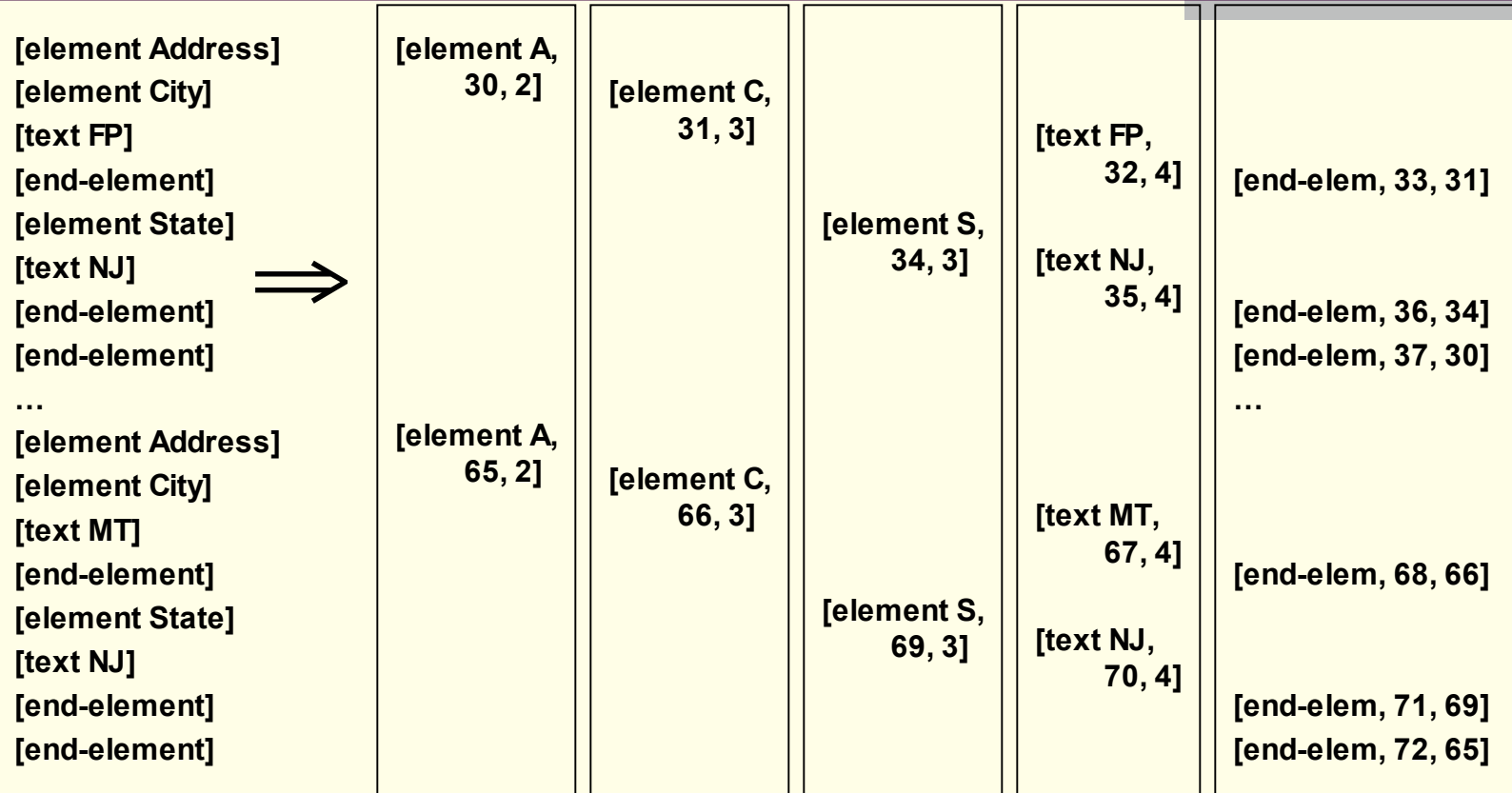
---

- Part I: Motivation (45 min)
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  - XML streams: motivation, query processing
  - XML streams: connection to tuple streams
  - Open Issues

# Connections

XML Streams	Tuple Streams
One heterogeneous stream of XML tokens	Multiple homogeneous sub-streams of tuples
(Shared) path matching	(Shared) multi-way joins
Explicit [end-element] and [end-attribute] tokens	Explicit punctuations to identify “end of processing”

# Sub-streams of an XML Stream



# Path Matching as Multi-way Joins

- Path: //A/S[. = "NJ"]
- SQL query:

```

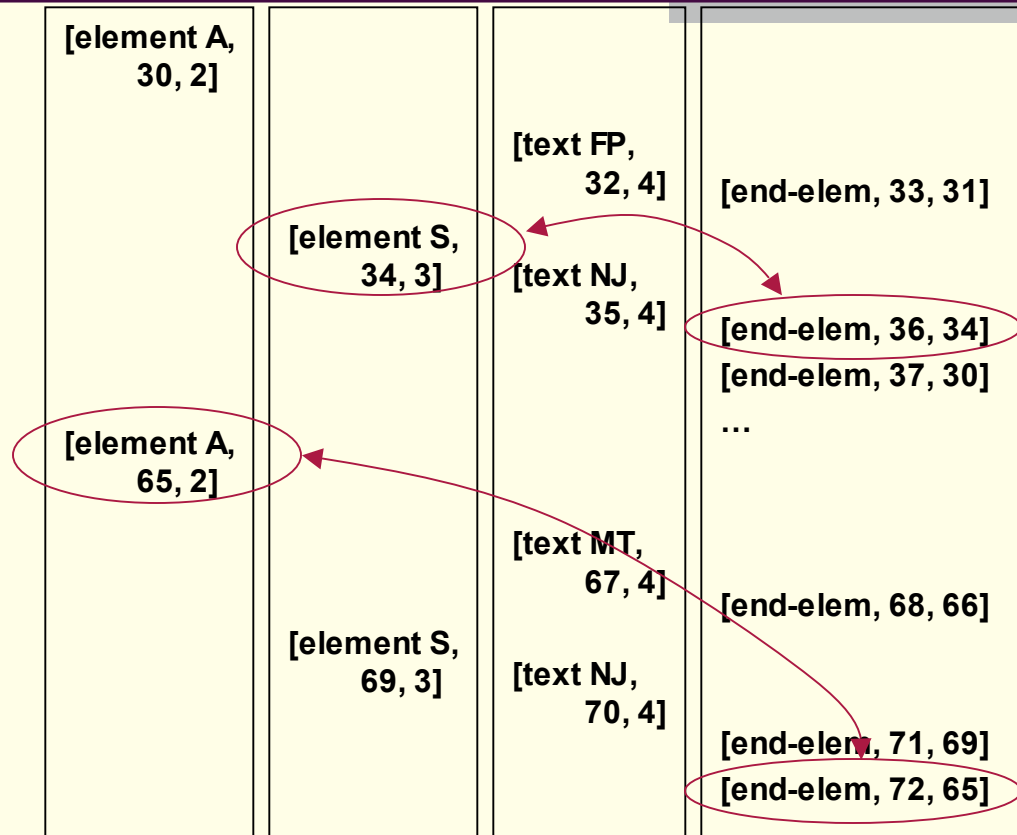
select A.id, S.id
from A, S, text T, end E E1
where S.id > A.id AND
      S.level = A.level+1 AND
      T.id > S.id AND
      T.level = S.level+1 AND
      T.value = "NJ" AND
      E.id > T.id AND
      E.back = S.id AND
      E1.id > E.id AND
      E1.back = A.id
    
```

[element A, 30, 2]		[text FP, 32, 4]	[end-elem, 33, 31]
	[element S, 34, 3]	[text NJ, 35, 4]	[end-elem, 36, 34] [end-elem, 37, 30] ...
[element A, 65, 2]		[text MT, 67, 4]	[end-elem, 68, 66]
	[element S, 69, 3]	[text NJ, 70, 4]	[end-elem, 71, 69] [end-elem, 72, 65]

# End-element as Punctuation

- Limits query scope
- Nested structure

```
select A.id, S.id
from A, S, text T, end E E1
where S.id > A.id AND
      S.level = A.level+1 AND
      T.id > S.id AND
      T.level = S.level+1 AND
      T.value = "NJ" AND
      E.id > T.id AND
      E.back = S.id AND
      E1.id > E.id AND
      E1.back = A.id
```



# Stream Map

---

- Part I: Motivation (45 min)
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# Open Issues: Multi-way Joins

---

- Recent work on multi-way joins with equality predicates
- Issue: How do we use constraints and punctuations effectively?
  - Self-joins: looking for patterns in a single stream
  - Natural constraints other than “nesting” constraints
- Current status:
  - XML path matching is a special case

# 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 two-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 Aurora and STREAM people [BO03, CBB+03, OJW03]

# Open Issues: Query Optimization

---

- Data stream properties (arrival rate, sortedness) may vary a lot
- Issue: How do we evaluate queries efficiently?
  - Adaptive strategies like Eddies have high overheads, and may not be directly feasible for data stream systems
  - Can one borrow ideas from queuing theory?
- Current status: Preliminary cost models developed by various data stream projects

# 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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