MIPS 2004 Tutorial

Data Stream Management Systems (DSMS)

- Applications, Concepts, and Systems -

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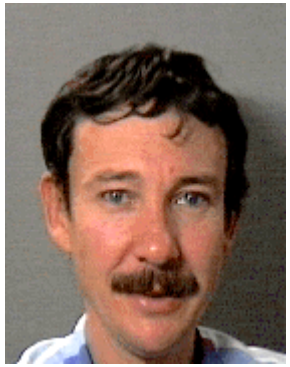
DSMS Tutorial Outline

- Introduction:
  - What are DSMS? (terms)
  - Why do we need DSMS? (applications)
- Example 1:
  - Network monitoring with TelegraphCQ
- Concepts and issues:
  - Architecture(s)
  - Data modeling
  - Query processing and optimization
  - Data reduction
  - Stream Mining
- Overview of existing systems
- Example 2:
  - DSMS for sensor networks
- Summary:
  - Open issues
  - Conclusions

Why did we started this?

- Vera & Thomas on sabbatical at Eurecom
- Questions to Vera:



Ernst Biersack:

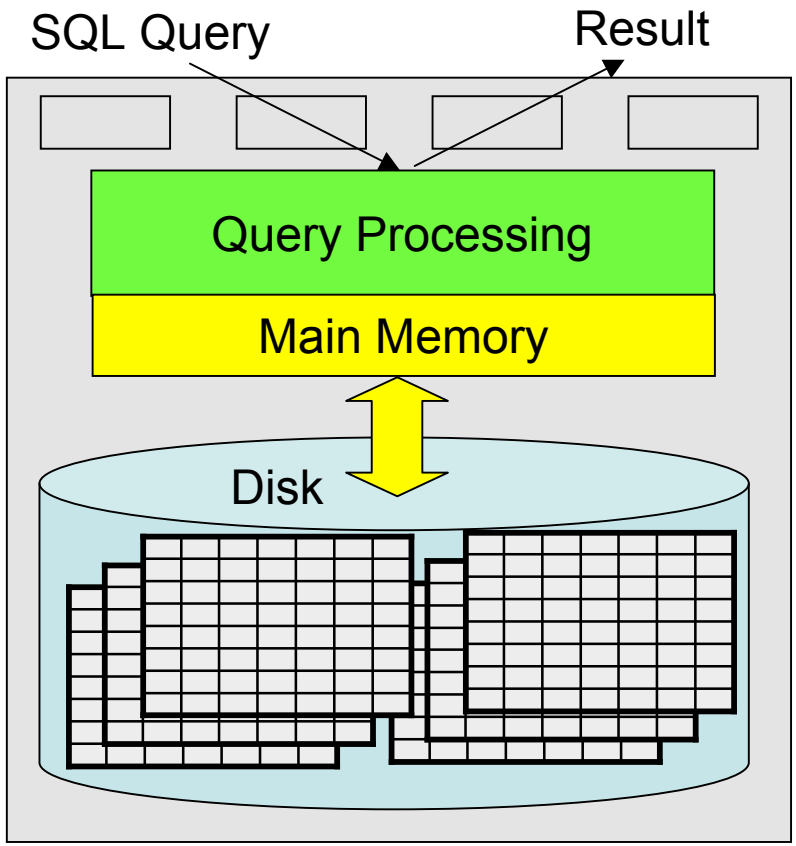
- *We have so many measurement data can't we use a DBMS for more systematic management?*
- *I have seen a tool from AT&T which seems to be very useful for network monitoring, tomography, etc.*

Marc Dacier:

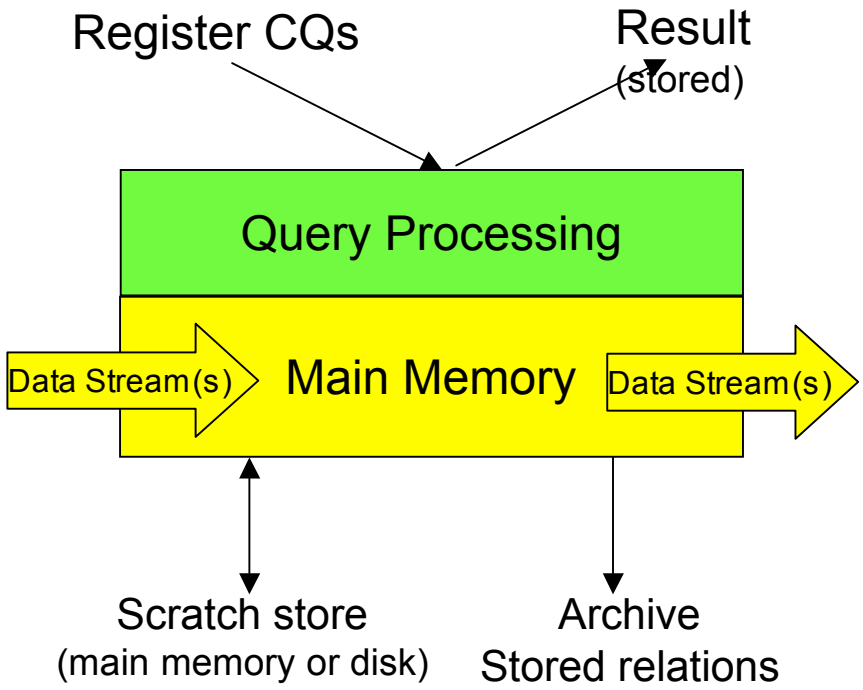
- *To perform intrusion detection we have to analyze in detail just a small subset of all network packets. Can't we use a DBMS to select efficiently and continuously only the relevant packets?*

Handle Data Streams in DBS?

Traditional DBS



DSMS



Data Management:
Comparison - DBS versus DSMS

Database Systems (DBS)

- Persistent relations
  (relatively static, stored)
- One-time queries
- Random access
- “Unbounded” disk store
- Only current state matters
- No real-time services
- Relatively low update rate
- Data at any granularity
- Assume precise data
- Access plan determined by query processor, physical DB design

DSMS

- Transient streams
  (on-line analysis)
- Continuous queries (CQs)
- Sequential access
- Bounded main memory
- Historical data is important
- Real-time requirements
- Possibly multi-GB arrival rate
- Data at fine granularity
- Data stale/imprecise
- Unpredictable/variable data arrival and characteristics

Adapted from [Motawani: PODS tutorial]

Related DBS Technologies

- Continuous queries
- Active DBS (triggers)
- Real-time DBS
- Adaptive, on-line, partial results
- View management (materialized views)
- Sequence/temporal/timeseries DBS
- Main memory DBS
- Distributed DBS
- Parallel DBS
- Pub/sub systems
- Filtering systems
- …

=> Must be adapted for DSMS!

DSMS Applications

- Sensor Networks:
  - Monitoring of sensor data from many sources, complex filtering, activation of alarms, aggregation and joins over single or multiple streams
- Network Traffic Analysis:
  - Analyzing Internet traffic in near real-time to compute traffic statistics and detect critical conditions
- Financial Tickers:
  - On-line analysis of stock prices, discover correlations, identify trends
- On-line auctions
- Transaction Log Analysis, e.g., Web, telephone calls, …

Data Streams - Terms

- 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

DSMS: Why Now?

- Massive volumes: deploy transactional data observation points, e.g.,
  - AT&T long-distance: ~300M call tuples/day
  - AT&T IP backbone: ~10B IP flows/day
- Massive volumes: generate automated, highly detailed measurements
  - NOAA: satellite-based measurement of earth geodetics
  - Sensor networks: huge number of measurement points
- Data feeds to DBSs: not new
  - Modify underlying DBSs, data warehouses
  - Complex queries are specified over stored data
- Recent developments: application- & technology-driven
  - Need sophisticated near real-time queries/analyses
  - Massive data volumes of transactions and measurements
- Traditional data feeds
  - Simple queries (e.g., value lookup) needed in real-time
  - Complex queries (e.g., trend analyses) performed off-line
- Near real-time queries/analyses, e.g.,
  - AT&T: fraud detection on call detail tuple streams
  - NOAA: tornado detection using weather radar data

Telecomm. Applications:
Fraud Detection

- Telcos/ISPs want to track calling pattern of each of ~100M callers, and raise real-time fraud alerts
- **Current 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 DSMS 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

IP Network Application:
P2P Traffic Detection

- AT&T IP customer wanted to accurately monitor P2P traffic evolution within its network
  - **Current 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
  - **DSMS 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

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

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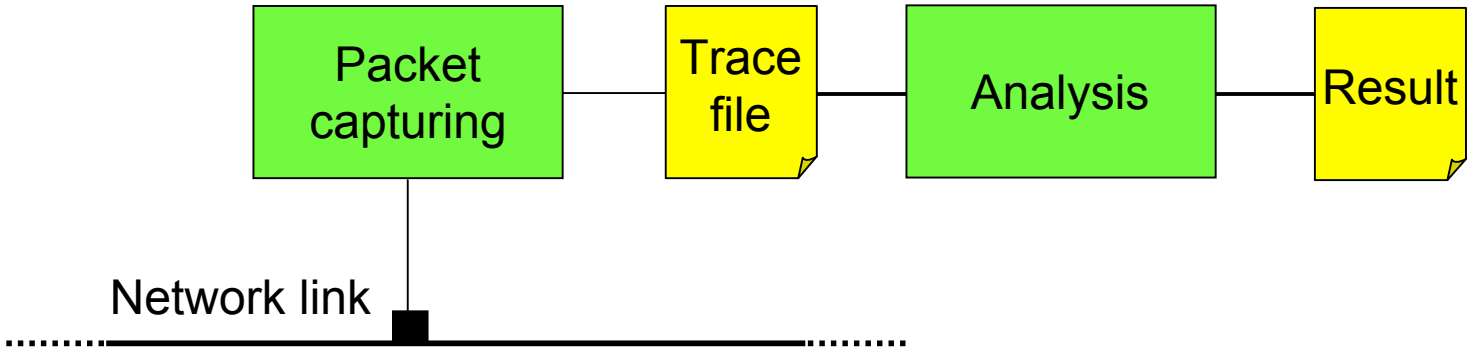
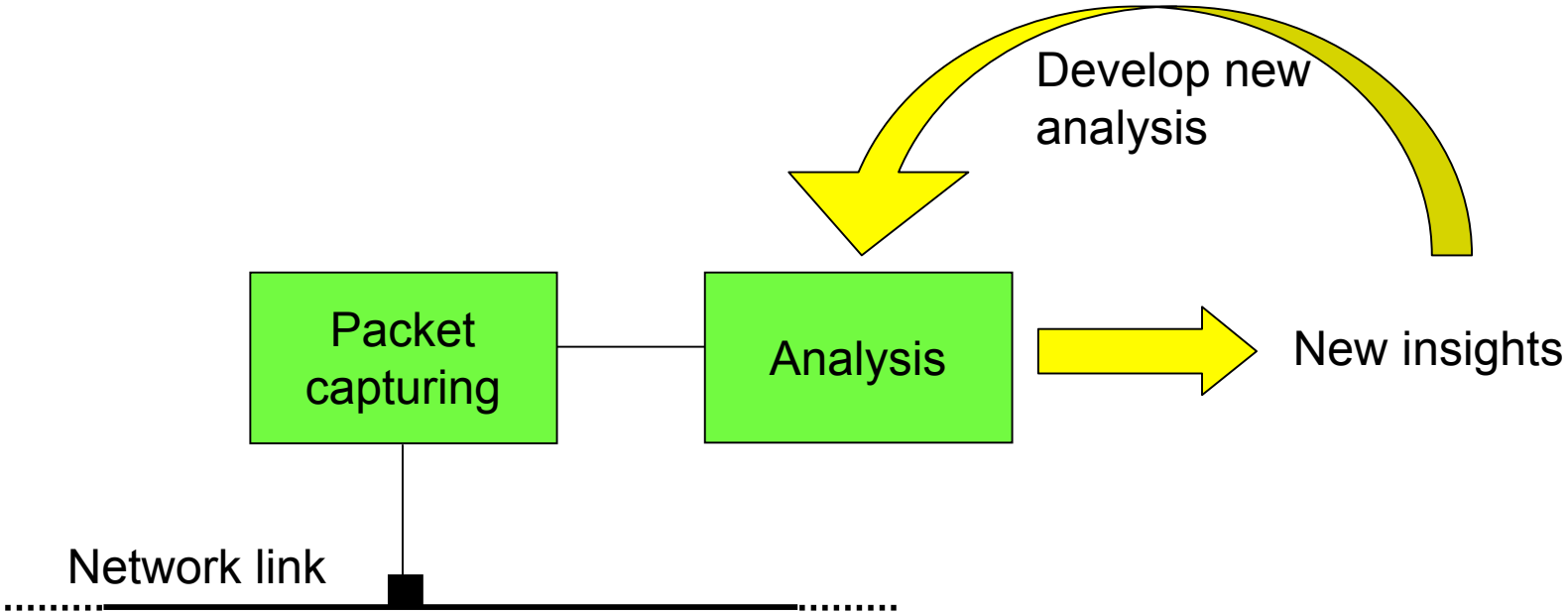
Example 1: Traffic Analysis

- Need to analyze Internet traffic is increasing ....
- .... and so is the number of tools for this
- Examples:
  - ISP monitor service levels, look for bottlenecks,etc.
  - development of new protocols, like P2P
- Basic structure of tools:



Traffic Analysis (cont.)

- Performing traffic analysis to gain new knowledge is an iterative process:



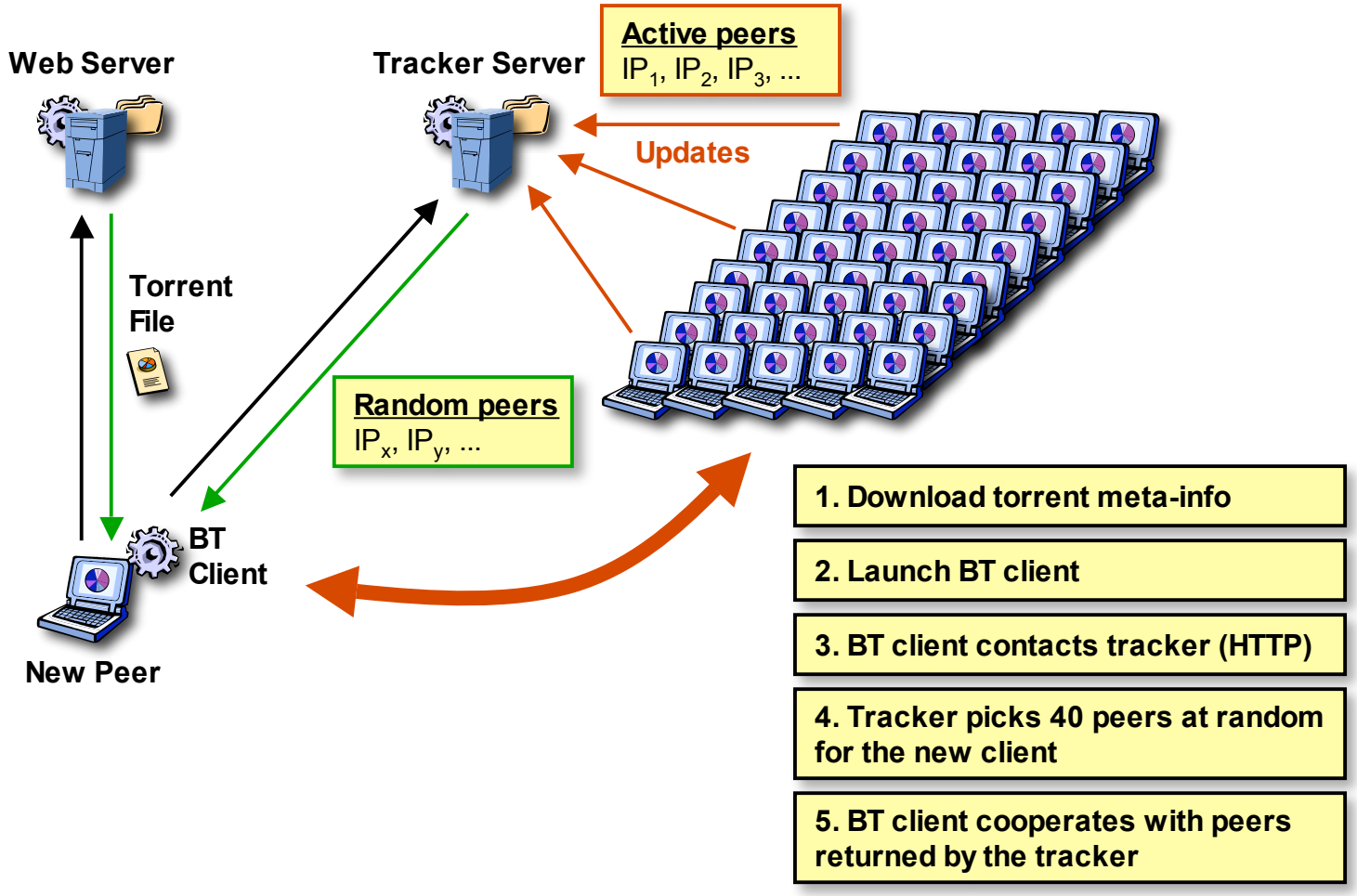
Example: BitTorrent Analysis

- Designed for the transfer of large files to many clients
  - based on **swarming**: a server sends different parts of a file to different clients, and the clients exchange chunks with one another
- One session = distribution of a single (large) file
- Elements
  - ordinary web server
  - static “meta-info” file
  - tracker
  - initial client with the complete file
  - on end user side: web browser + BitTorrent client

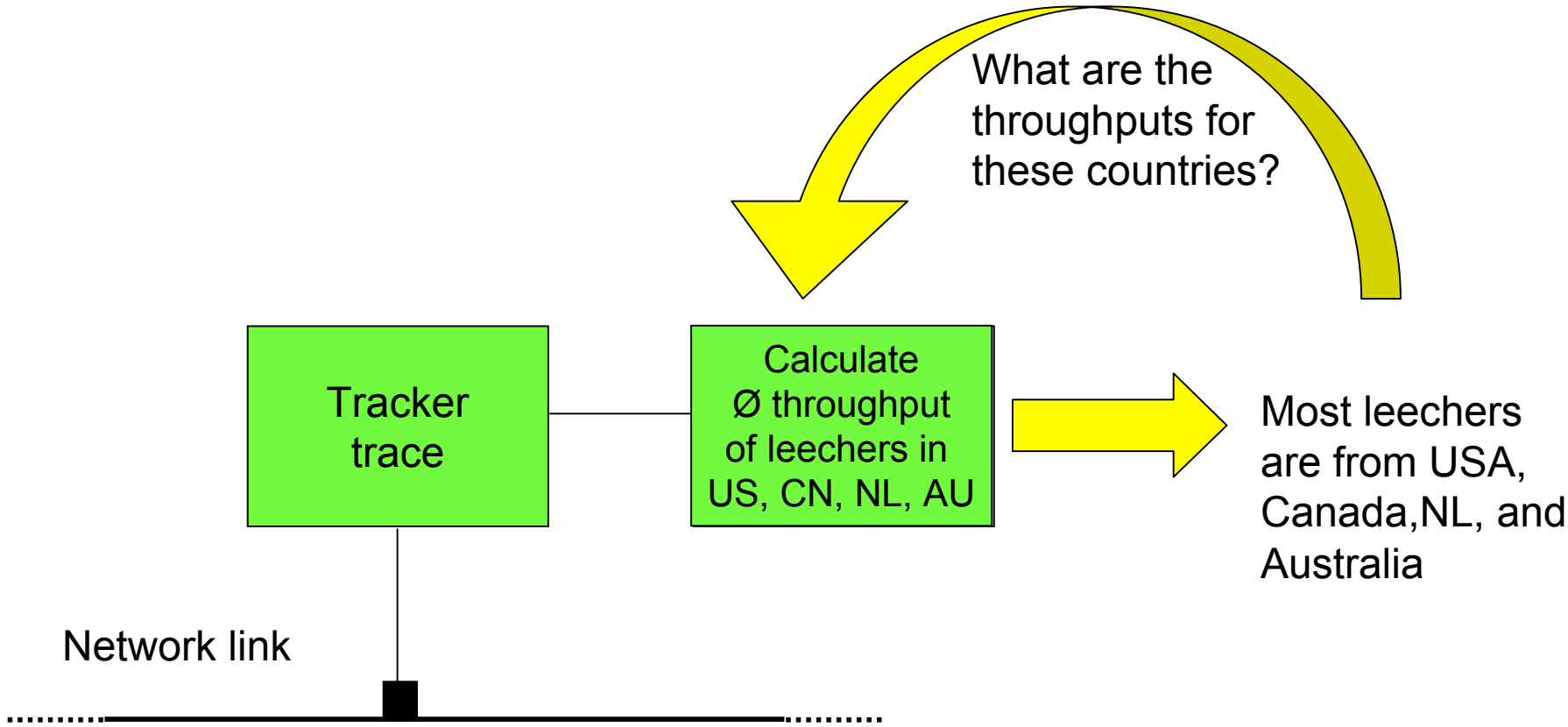
Example: BitTorrent Analysis (cont.)

- Start running a web server that hosts a torrent file
  - torrent file contains the IP address of the tracker
- The tracker (often not on web server) tracks all peers
  - initially, it must know at least one peer with the complete file
  - peer with full file: **seed**
  - peer still downloading file: **leecher**
- On client side
  - BT client reads tracker IP address and contacts the tracker (through HTTP or HTTPS)
  - tracker provides to the BT client a set of active peers (leechers and seeds, typically 40) to cooperate with
  - clients regularly report state (% of download) to the tracker

Example: BitTorrent Analysis (cont.)



Example: BitTorrent Analysis (cont.)



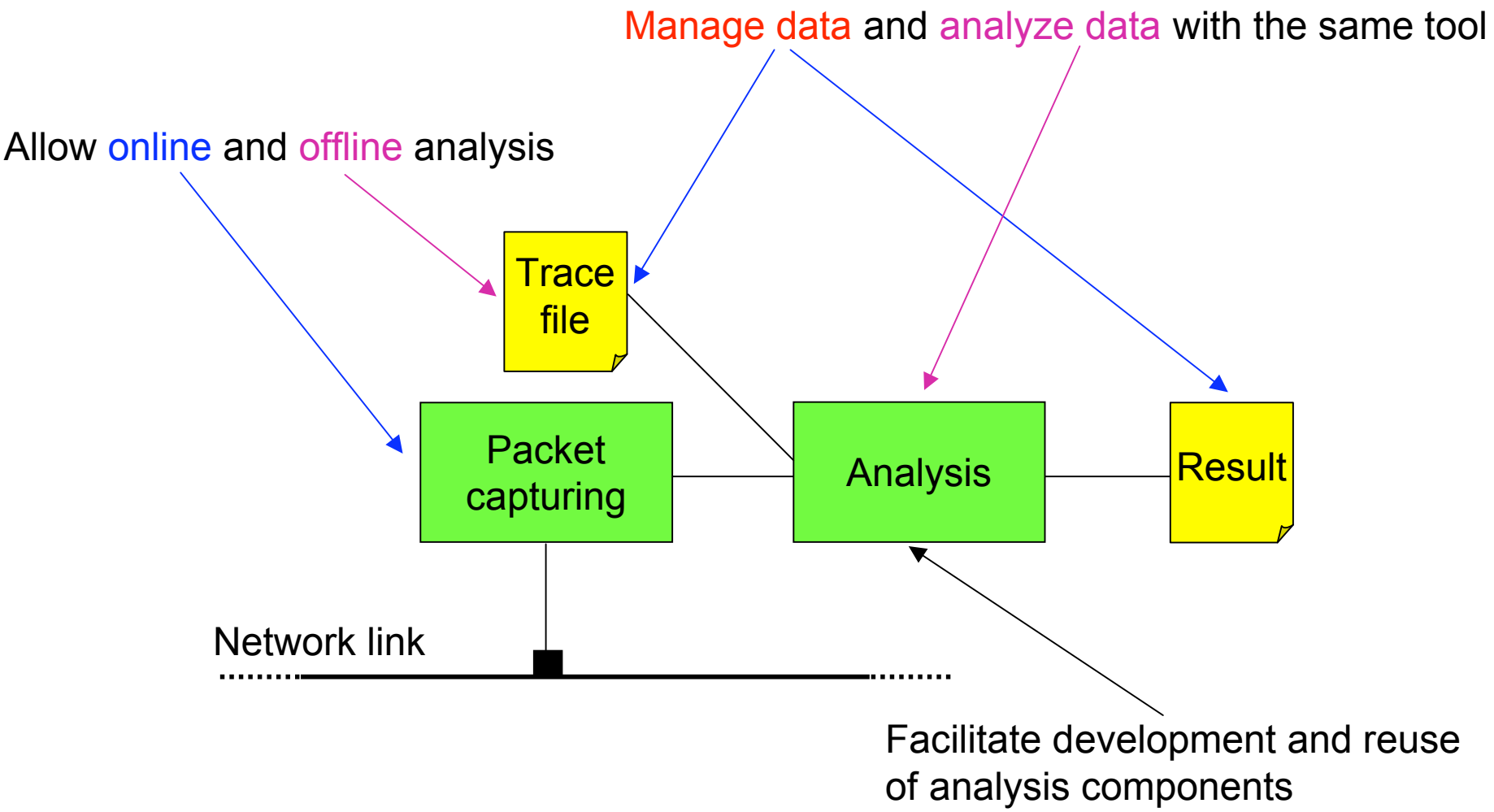
.... and so on and so on .....

By the end of the day 66 scripts have been implemented

Expectations

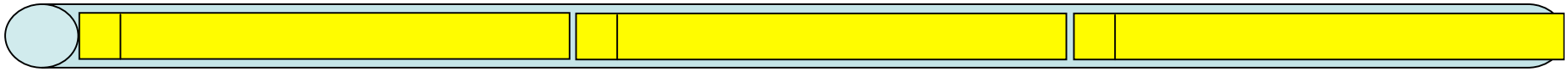
- Be helpful for typical traffic analysis tasks:
  - the load of a system
    - how often are certain ports, like FTP, or HTTP, of a server contacted
    - which share of bandwidth is used by different applications
    - which departments use how much bandwidth on the university backbone
  - characteristics of flows
    - distribution of life time and size of flows
    - relation between number of lost packets and life time of flows
    - what are the reasons for throughput limitations, or
  - characteristics of sessions:
    - how long do clients interact with a web server
    - which response time do clients accept from servers
    - how long are P2P clients on-line after they have successfully downloaded a file

Expectations (cont.)

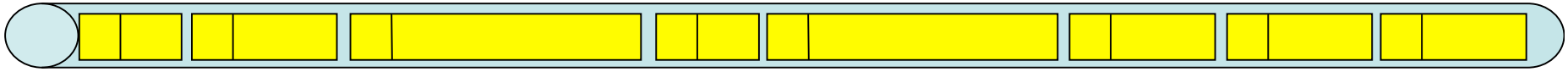


Expectations (cont.)

- Provide sufficient performance:
  - idealized gigabit/s link



    - all packets 1500 byte, TCP/IP header 64 byte
    - 42 megabit/s of header information
  - more realistic: compression of 9:1 or less



    - approx. 880 megabit/s on gigabit/s link
    - approx. 11 megabit/s for 100 megabit/s network

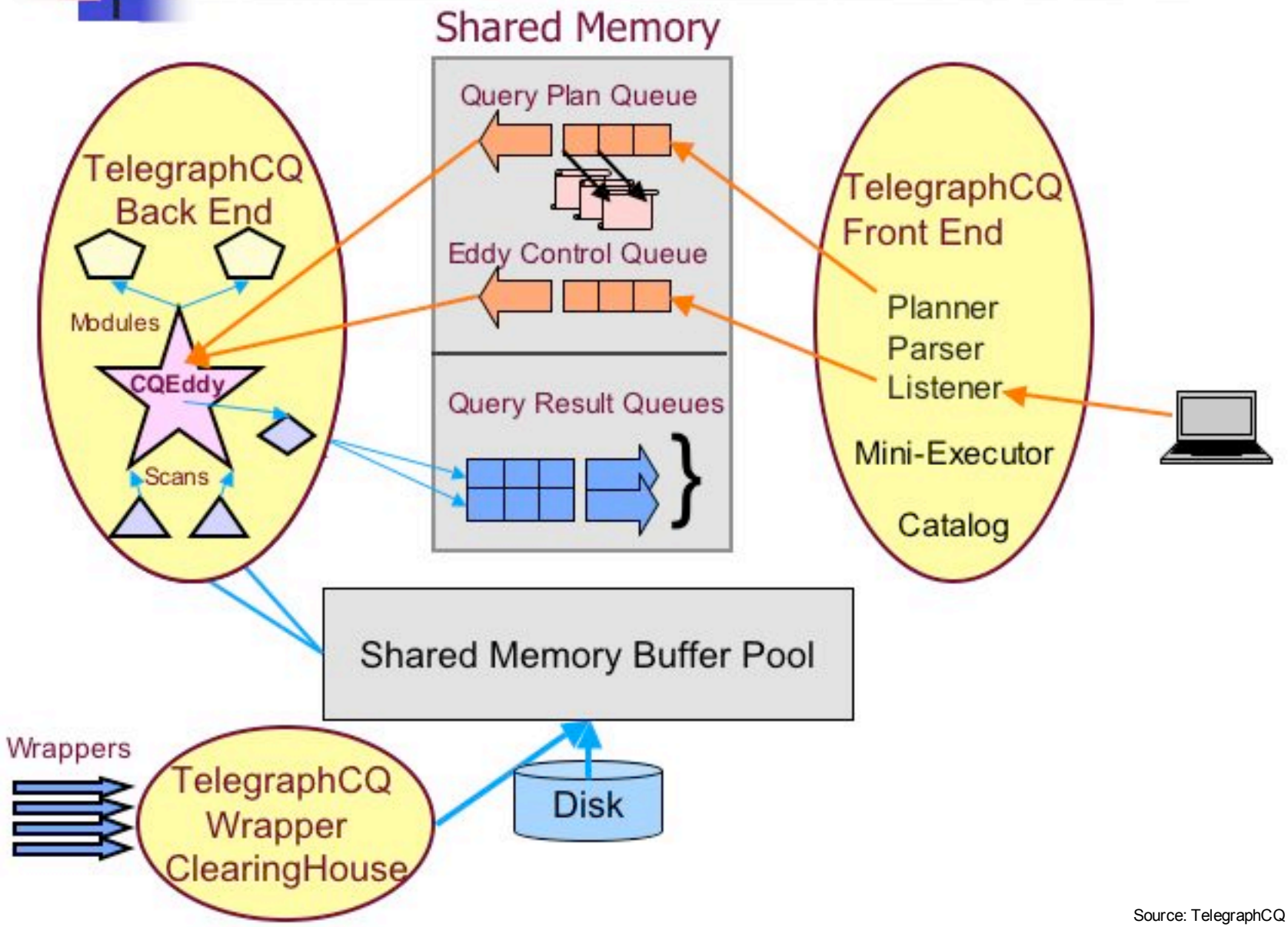
Approach

- Public domain DSMS (fall 2003):
  - TelegraphCQ
  - Aurora ... only source tree, complete???
- Student project by A. Bergamini & G. Tulo:
  - install TelegraphCQ
  - connect it to wrappers, i.e., sources
  - model TCP traces/streams
  - develop queries for simple but typical tasks
  - try to re-implement an existing complex tool
  - identify performance bounds

TelegraphCQ

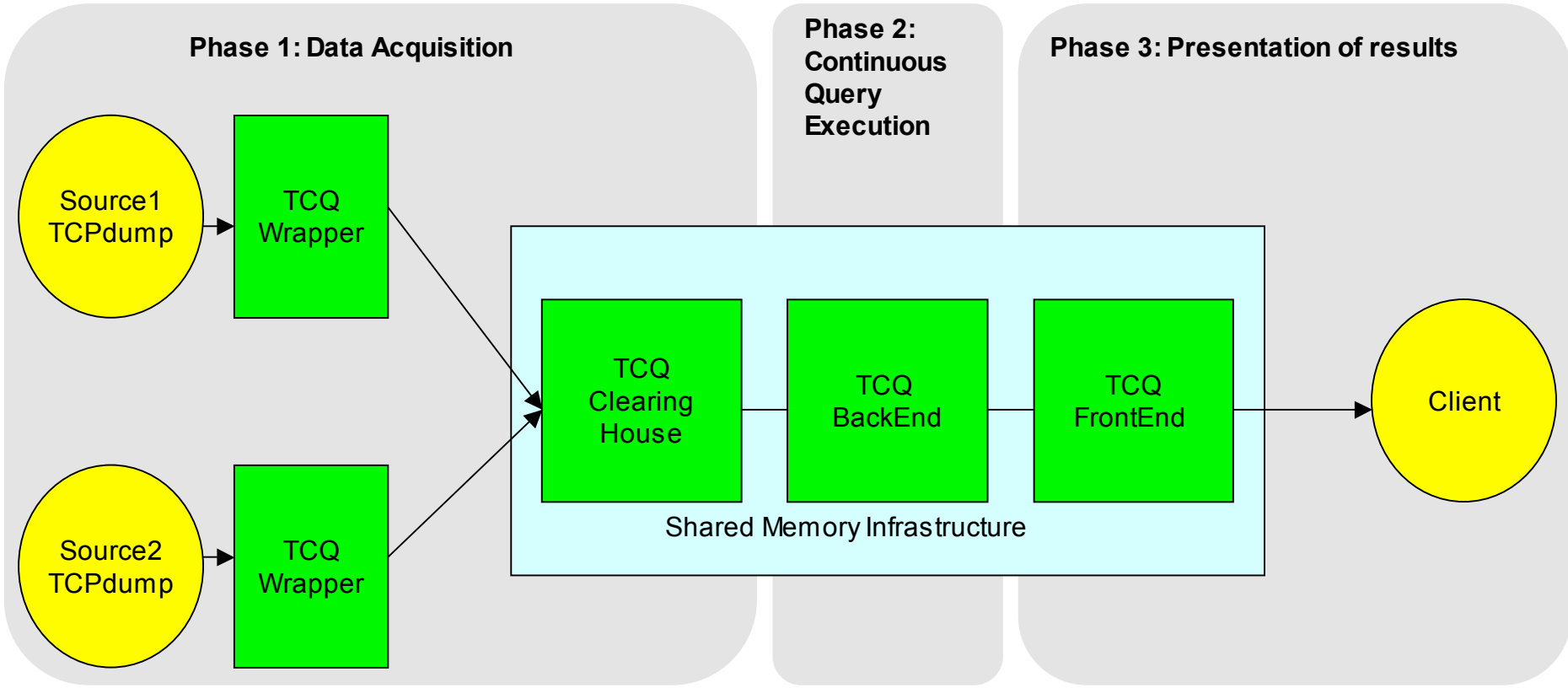
- Characterization of it's developers:
  - "*a system for continuous dataflow processing*"
  - "*aims at handling large streams of continuous queries over high-volume highly variable data streams*"
- Extends PostgreSQL
  - adaptive query processing operators
  - shared continuous queries
  - data ingress operations

The TelegraphCQ Architecture



Source: TelegraphCQ getting started Guide

TelegraphCQ Architecture



Continous Queries in TCQ

- Data streams are defined in DDL with CREATE STREAM (like tables)

```
SELECT      <select_list>
FROM        <relation_and_pstream_list>
WHERE       <predicate>
GROUP BY    <group_by_expressions>
WINDOW      stream[interval], ...
ORDER BY    <order_by_expressions>
```

Continous Queries in TCQ (cont.)

- Restrictions in TelegraphCQ 0.2 alpha release [9]:
  - windows can only be defined over streams (not for PostgreSQL tables)
  - `WHERE` clause qualifications that join two streams may only involve attributes, not attribute expressions or functions
  - `WHERE` clause qualifications that filter tuples must be of the form attribute operand constant
  - `WHERE` clause may only contain `AND` (not `OR`); sub queries are not allowed
  - `GROUP BY` and `ORDER BY` clauses are only allowed in window queries

Stream Definition

- CREATE STREAM p6trace.tcp (ip_src cidr, ip_dst cidr, hlen bigint, tos int, length bigint, id bigint, frag_off bigint, ttl bigint, prot int, ip_hcsum bigint, port_src bigint, port_dst bigint, sqn bigint, ack bigint, tcp_hlen bigint, flags varchar(10), window bigint, tcp_csum bigint, tcqtime timestamp TIMESTAMPCOLUMN) type ARCHIVED;

Task 1

- How many packets have been sent during the last five minutes to certain ports?
- Store all ports of interests in a table and join with the stream
- ```
  CREATE TABLE services (port bigint,
  counter bigint);
  ```
- ```
  SELECT services.port, count(*)
  FROM p6trace.tcp, services
  WHERE
  p6trace.tcp.port_dst=services.port
  GROUP BY services.port
  WINDOW p6trace.tcp ['5 min'];
  ```

Task 2

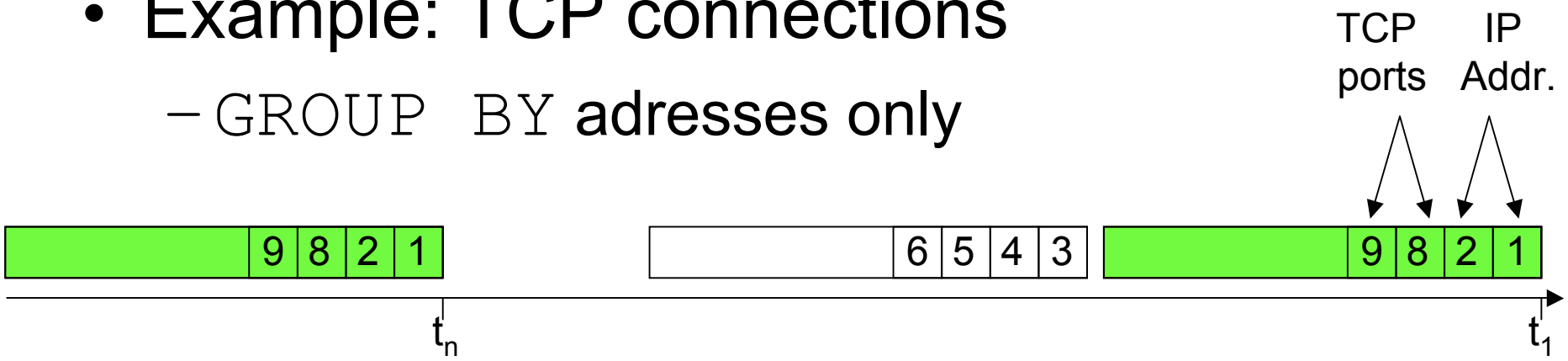
- How many bytes have been exchanged on each connection during the last minute?
- Simple heuristic to identify connections:
  - during a one minute window all packets with the same sender and receiver IP addresses and port numbers belong to the same connection
-
```
SELECT ip_src, port_src, ip_dst,
port_dst, sum(length-ip_len-tcphlen)
FROM p6trace.tcp
GROUP BY ip_src, port_src, ip_dst,
port_dst
WINDOW p6trace.tcp ['1 min'];
```

Task 3

- How many bytes are exchanged over the different connections during each week?
- Two problems to handle this in a CQ:
  - GROUP BY clause can only be used together with a WINDOW clause
    - window smaller than one week
    - payload of each packet would contribute several times to intermediate results
    - how to remove this redundancy?
    - tumbling or jumping windows are needed
  - identification of connections
    - simple heuristic from task 2 does not work
    - boils down to the generic problem of association identification

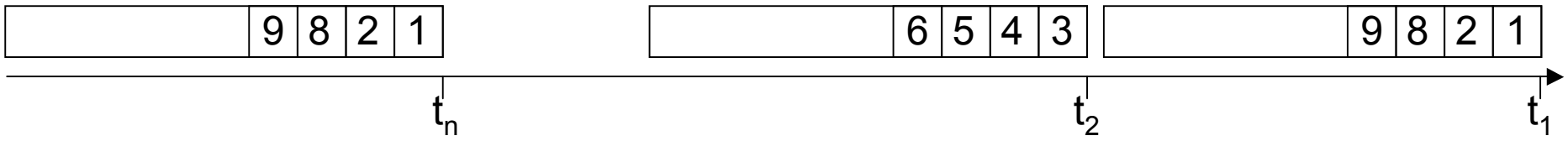
Identification of Associations

- Use address fields and rules
- Example: TCP connections
  - `GROUP BY` adresses only



  - rule: if $t_n - t_1 < T$ then same connection
    else new connection

Identification of Associations (cont.)

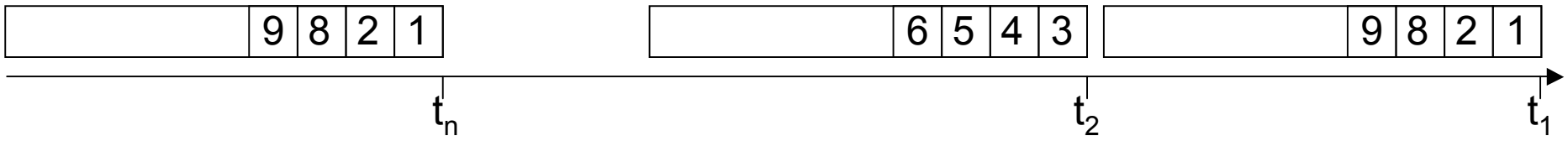


A priori no address values are known

Check for each new packet:
-is address combination known?
NO: insert new entry
YES: is it a new or old connection?
OLD: update statistics
NEW: insert new connection

IP d.	IP s.	Port d.	Port s.	Statistics	Time
1	2	8	9	1	t_1
3	4	5	6	1	t_2
1	2	8	9	1	t_n

Identification of Associations (cont.)



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IP d.	IP s.	Port d.	Port s.	Statistics	Time
1	2	8	9	2	t_n
3	4	5	6	1	t_2

With a single pass over the data this is only possible with sub-queries in SQL

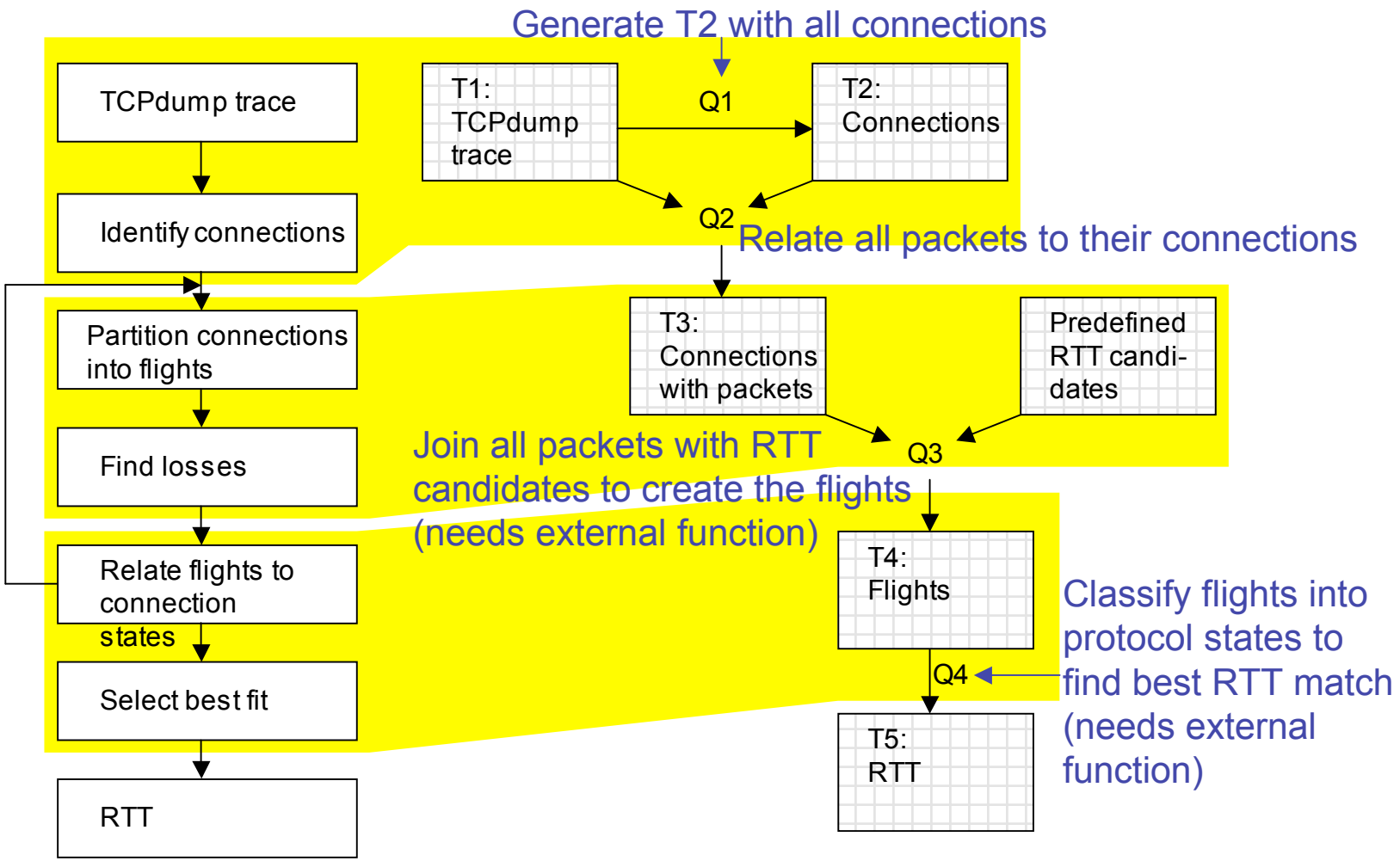
Task 4

- Which department has used how much bandwidth on the university backbone in the last five minutes?
- Store address ranges of all departments in a table
- Check with “>>” which address range contains the IP address of the packet in the data stream
-
```
CREATE TABLE departments (name varchar(30),
prefix cidr, traffic bigint);

SELECT departments.name, sum(length-hlen-tcp_hlen)
FROM p6trace.tcp, departments
WHERE departments.prefix >> p6trace.tcp.ip_src
GROUP BY departments.name
WINDOW p6trace.tcp ['5 min'];
```
- TelegraphCQ prototype produces incorrect results if “>>” is used in a join, but works correctly with “=”

Task 4 (cont.)

- ”Solution”: use ”=” and enumerate all adresses in a stored table
-
```
CREATE TABLE departments (name
varchar(30), ip_addr cidr, traffic
bigint);

SELECT departments.name, sum(length-hlen-
tcp_hlen)
FROM p6trace.tcp, departments
WHERE departments.ip_addr =
p6trace.tcp.ip_src
GROUP BY departments.name
WINDOW p6trace.tcp ['5 min'];
```

T-RAT Re-Design with TCQ



Main Insights from T-RAT Exercise

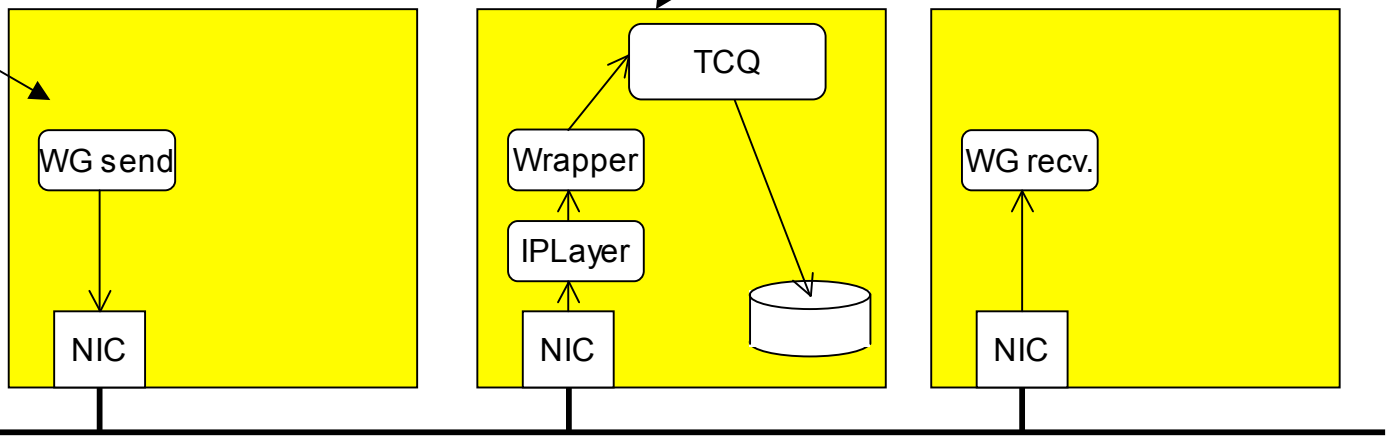
- It is not possible to do this in a continuous query (identification of connections and flights)
- Main functionality of T-RAT has to done in PostgreSQL
  - T-RAT is using complex heuristics which cannot be expressed in SQL
  - the extensibility of TelegraphCQ & PostgreSQL, allows to increase the expressiveness of queries with external functions
- T-RAT and other complex analysis can be performed off-line with TelegraphCQ, even if the main functionality is then hidden in external functions instead of SQL statements

Performance Evaluation

- We just want to get a rough idea...
- Experimental set-up:

Pentium 4 machine with a 2Ghz CPU
524 MB RAM, 100 Mb/s Ethernet card
Linux version 2.4.18-3

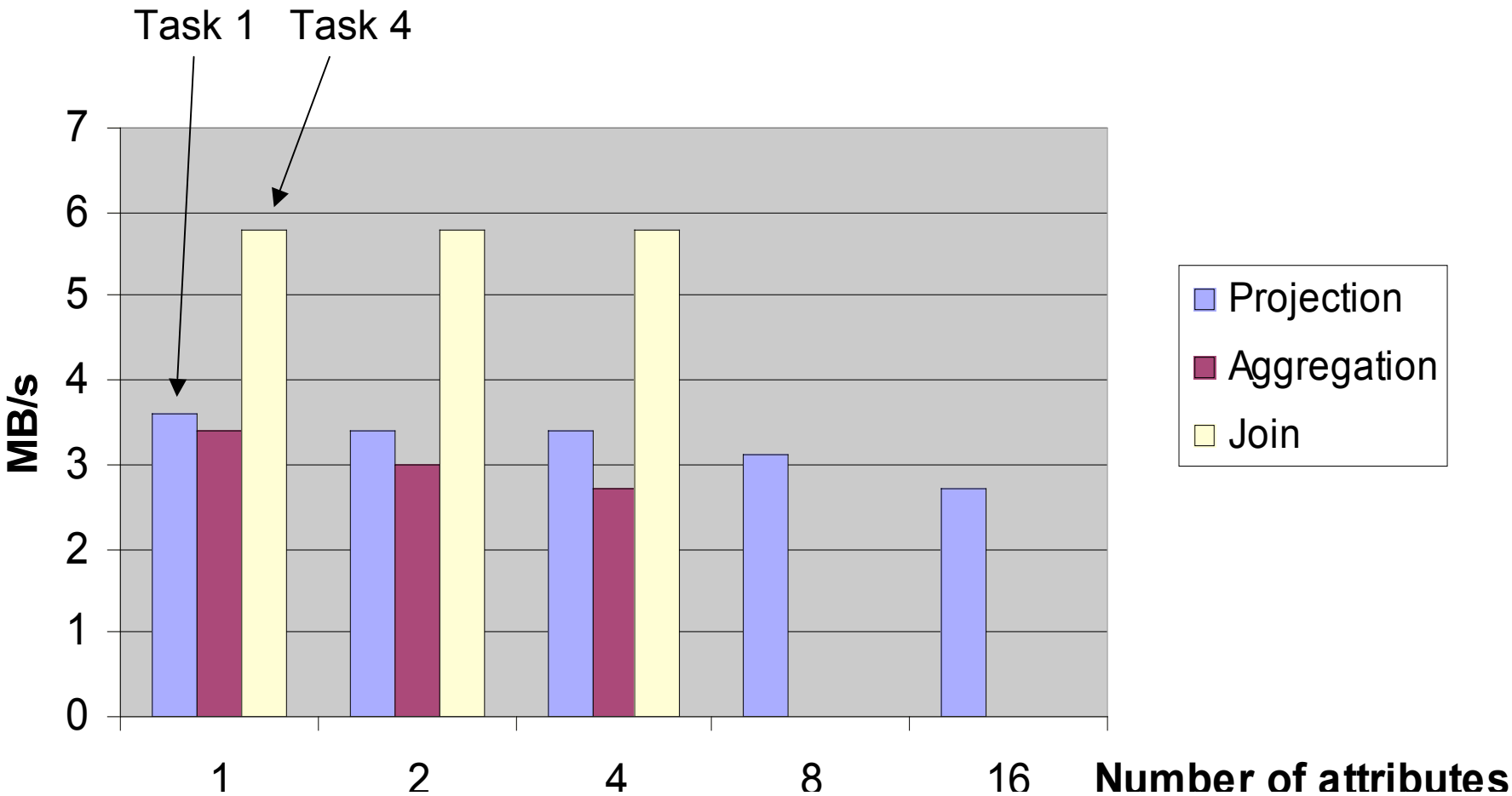
Workload generator streams data over TCP connection with different fixed rates



Eurecoms play-ground
100 megabit/s
Outside of firewall
Nearly no traffic

Start different types of queries
increase the load
identify when TCQ looses data

Performance Evaluation (cont.)



Performance of `JOIN` is surprising!

Performance Evaluation (cont.)

- Some additional investigations on the `JOIN` performance:
  - number of matches between table and stream does impact performance
  - size of table and position of the matching entry influence performance
  - but with 100000 entries and matching entry is the last one, TelegraphCQ can still handle more than 2 MB/s of network data without loss
- Disclaimer: this was no in-depth evaluation
- TelegraphCQ is fast enough to perform meaningful network analysis tasks on a commodity PC up to network loads of 2,5 MB/s

Lessons Learned

- TelegraphCQ is quite useful for many on-line monitoring tasks (sliding window!)
- Performance is not too bad
- In-build C functions can help
- Not all features are fully implemented, i.e. only equi-joins, but “>>” might be helpful for many tasks
- Sub queries are not supported, i.e., all tasks that require to identify associations by inspecting the data stream twice cannot be solved on-line
- Jumping or tumbling windows are not supported and redundancy by sliding window cannot be removed
- On-line and off-line handling is not integrated
- TelegraphCQ team has been very helpful!

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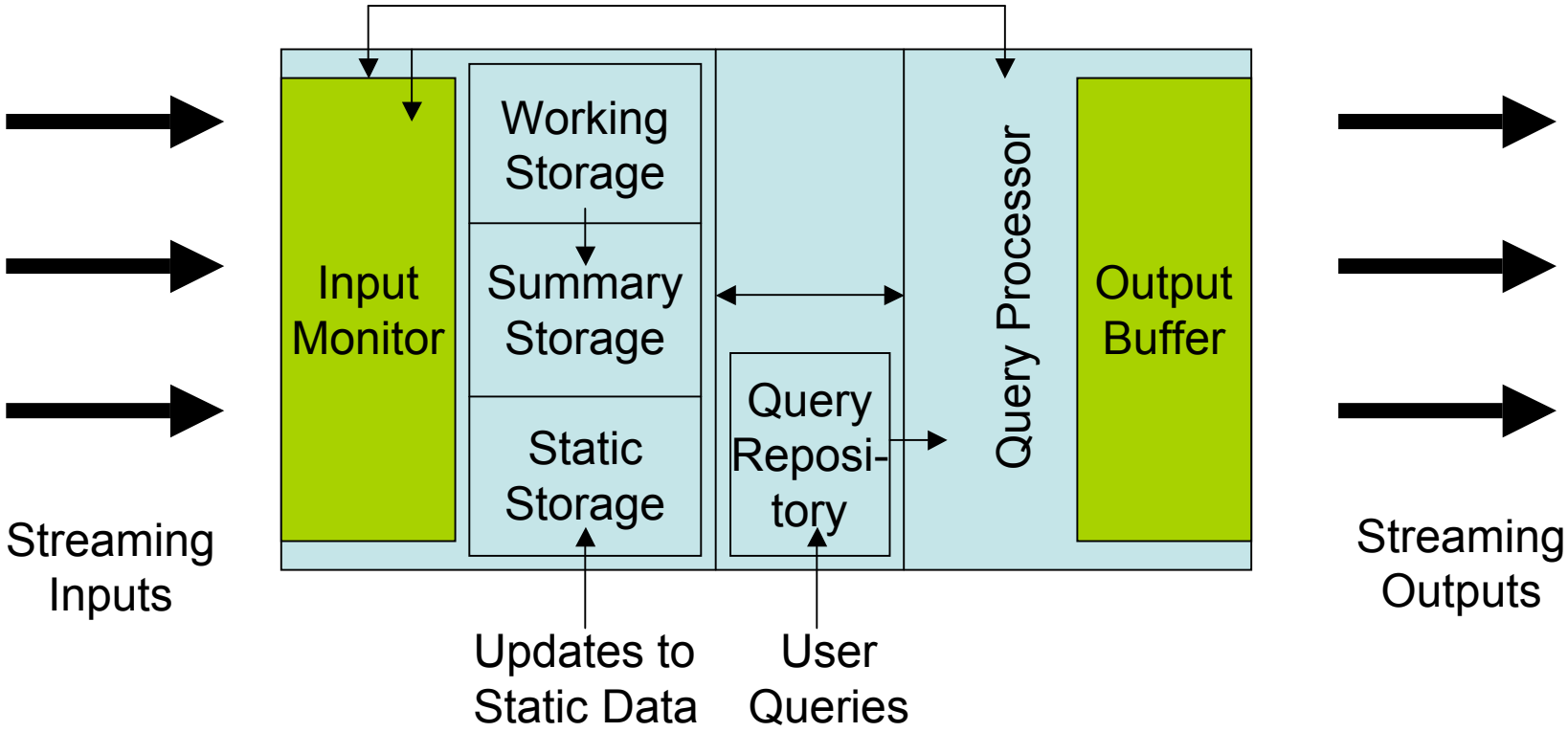
DSMS – Concepts and Issues

- **Applications requirements**
- **Architecture(s)**
- **Data modeling**
  - Relation-based models
  - Object-based models
  - Procedural models
- **Query languages / operators**
  - Declarative (relational or object-oriented) query languages
  - Other (procedural) approaches using higher level graphical approach to compose queries
  - Query repositories
  - New types of query operators: windows, …
- **Query processing and optimization**
  - Approaches towards optimizing stream queries
- **Data reduction techniques**
  - Filters, Punctuation, Synopsis, Sketches, Wavelets, …
- **Stream Mining**

Application Requirements

- Data model and query semantics: order- and time-based operations
  - Selection
  - Nested aggregation
  - Multiplexing and demultiplexing
  - Frequent item queries
  - Joins
  - Windowed queries
- Query processing:
  - Streaming query plans must use non-blocking operators
  - Only single-pass algorithms over data streams
- Data reduction: approximate summary structures
  - Synopses, digests => no exact answers
- Real-time reactions for monitoring applications => active mechanisms
- Long-running queries: variable system conditions
- Scalability: shared execution of many continuous queries, monitoring multiple streams
- Stream Mining

Generic DSMS Architecture



[Golab & Özsu 2003]

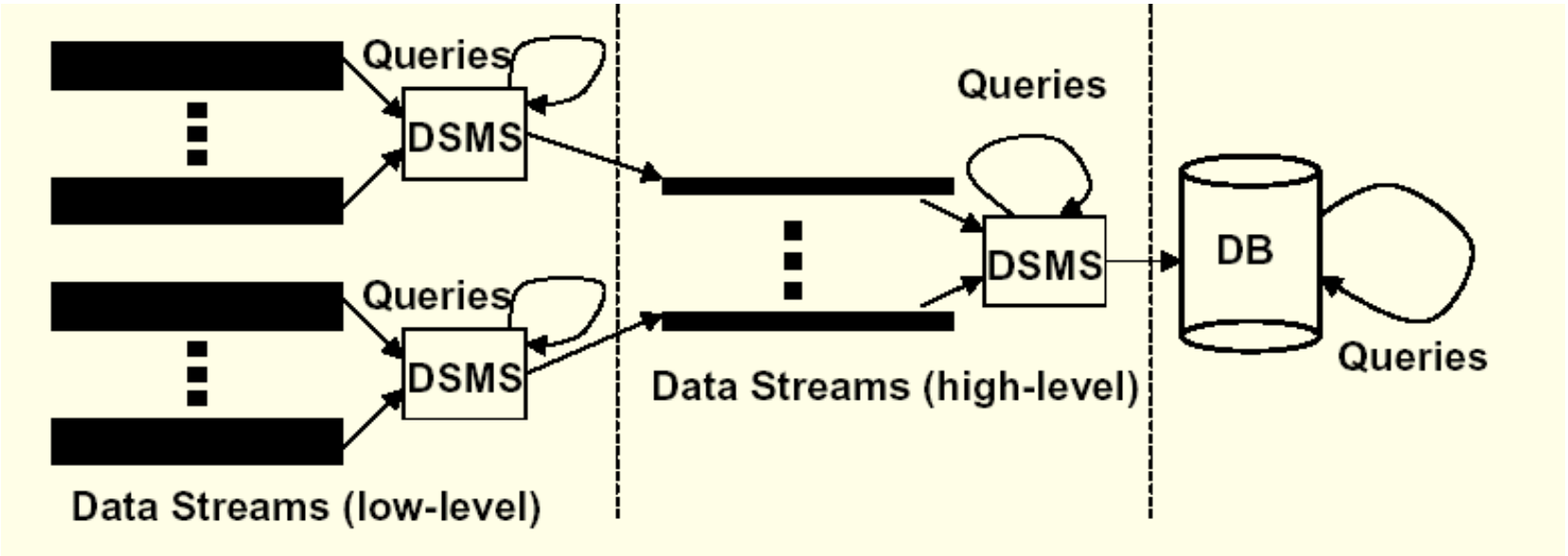
DSMS: 3-Level Architecture

DBS

- Data feeds to database can also be treated as data streams
- Resource (memory, disk, per-tuple computation) rich
- Useful to audit query results of DSMS
- Supports sophisticated query processing, analyses

DSMS

- DSMS at multiple observation points, (voluminous) streams-in, (data reduced) streams-out
- Resource (memory, per tuple computation) limited, esp. at low-level
- Reasonably complex, near real-time, query processing
- Identify what data to populate in DB



DBS versus DSMS: Issues

DBS

- Persistent relations
- Tuple set/bag
- Modifications
- Transient queries
- Exact query answers
- Arbitrary query processing
- Fixed query plans

DSMS

- Transient relations
- Tuple sequence
- Appends
- Persistent queries
- Approximate query answers
- One-pass query processing
- Adaptive query plans

Data Models

- Real-time data stream: sequence of data items that arrive in some order and may be seen only once.
- Stream items: like relational tuples
  - relation-based models, e.g., STREAM, TelegraphCQ; or instanciations of objects
  - object-based models, e.g., COUGAR, Tribeca
- Window models:
  - Direction of movement of the endpoints: fixed window, sliding window, landmark window
  - Physical / time-based windows versus logical / count-based windows
  - Update interval: eager (update for each new arriving tuple) versus lazy (batch processing -> jumping window), non-overlapping tumbling windows

Relation: Tuple Set or Sequence?

- Traditional relation = set/bag of tuples
- Tuple sequences:
  - Temporal databases: multiple time orderings
  - Sequence databases: integer “position” -> tuple
- DSMS:
  - Ordering domains: Gigascope, Hancock
  - Position ordering: Aurora, STREAM

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?

Time

- Easiest: global system clock
  - Stream elements and relation updates timestamped on entry to system
- Application-defined time
  - Streams and relation updates contain application timestamps, may be out of order
  - Application generates “heartbeat”
    - Or deduce heartbeat from parameters: stream skew, scrambling, latency, and clock progress
  - Query results in application time

Update: Modifications or Appends?

- Traditional relational updates: arbitrary data modifications
- Append-only relations have been studied:
  - Tapestry: emails and news articles
  - Chronicle data model: transactional data
- DSMS:
  - Streams-in, stream-out: Aurora, Gigascope, STREAM
  - Stream-in, relation-out: Hancock

Queries - I

- DBS: one-time (transient) queries
- DSMS: continuous (persistent) queries
  - Support persistent and transient queries
  - Predefined and ad hoc queries (CQs)
  - Examples (persistent CQs):
    - Tapestry: content-based email, news filtering
    - OpenCQ, NiagaraCQ: monitor web sites
    - Chronicle: incremental view maintenance
- Unbounded memory requirements
- Blocking operators: window techniques
- Queries referencing past data

Queries - II

- DBS: (mostly) exact query answer
- DSMS: (mostly) approximate query answer
  - Approximate query answers have been studied:
    - Synopsis construction: histograms, sampling, sketches
    - Approximating query answers: using synopsis structures
    - Approximate joins: using windows to limit scope
    - Approximate aggregates: using synopsis structures
- Batch processing
- Data reduction: sampling, synopses, sketches, wavelets, histograms, …

Queries – III
Continuous Query Semantics

- Monotonic continuous queries
  re-evaluate the query over newly arrived items and append qualifying tuples to the result
- Non-monotonic continuous queries
  may need to be re-computed from scratch during every re-evaluation
- Challenges (problems to be solved):
  - Unbounded memory requirements
  - Approximate query answering
  - Sliding windows
  - Batch processing, sampling, synopses
  - Blocking operators
  - Queries referencing past data

One-pass Query Evaluation

- DBS:
  - Arbitrary data access
  - One/few pass algorithms have been studied:
    - Limited memory selection/sorting: *n*-pass quantiles
    - Tertiary memory databases: reordering execution
    - Complex aggregates: bounding number of passes
- DSMS:
  - Per-element processing: single pass to reduce drops
  - Block processing: multiple passes to optimize I/O cost

Query Plan

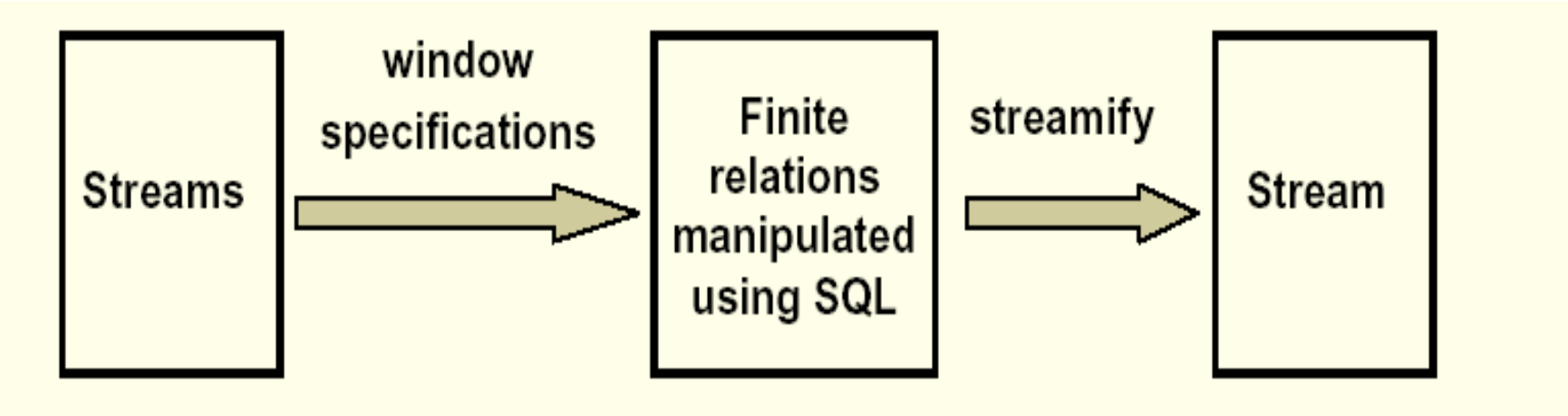
- DBS: fixed query plans optimized at beginning
- DSMS: adaptive query operators
  - Adaptive plans Adaptive query plans have been studied:
    - Query scrambling: wide-area data access
    - Eddies: volatile, unpredictable environments

Query Languages & Processing

- Stream query language issues (compositionality, windows)
- SQL-like proposals suitably extended for a stream environment:
  - Composable SQL operators
  - Queries reference relations or streams
  - Queries produce relations or streams
- Query operators (selection/projection, join, aggregation)
- Examples:
  - GSQL (Gigascope)
  - CQL (STREAM)
- Optimization objectives
- Multi-query execution

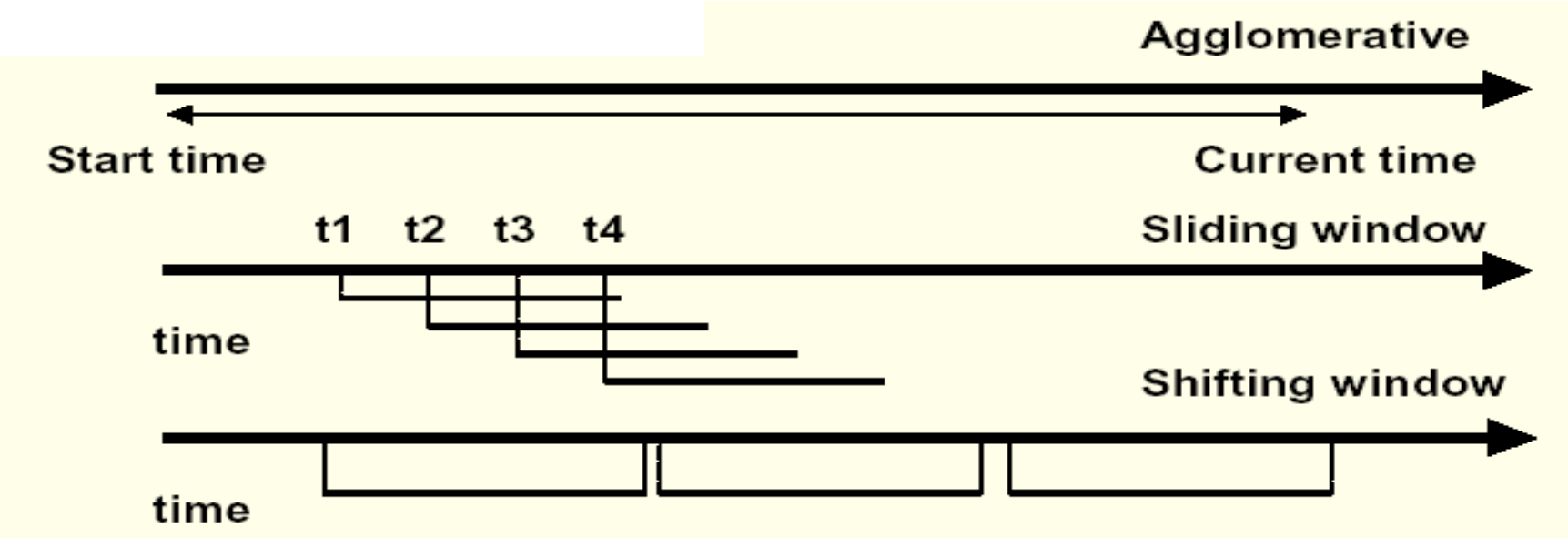
Windows

- 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)



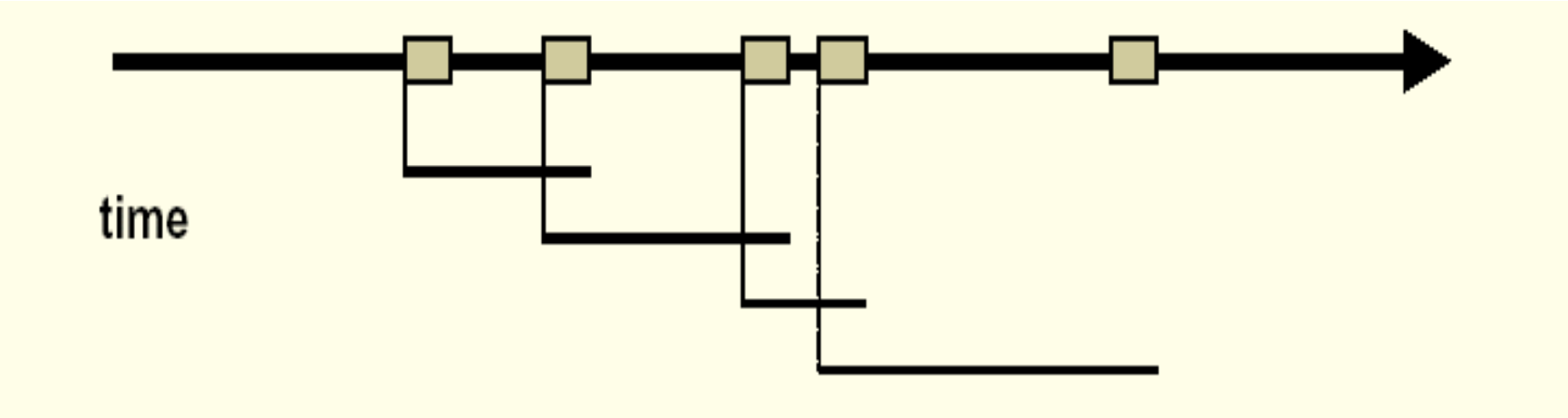
Ordering Attribute Based Windows

- 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

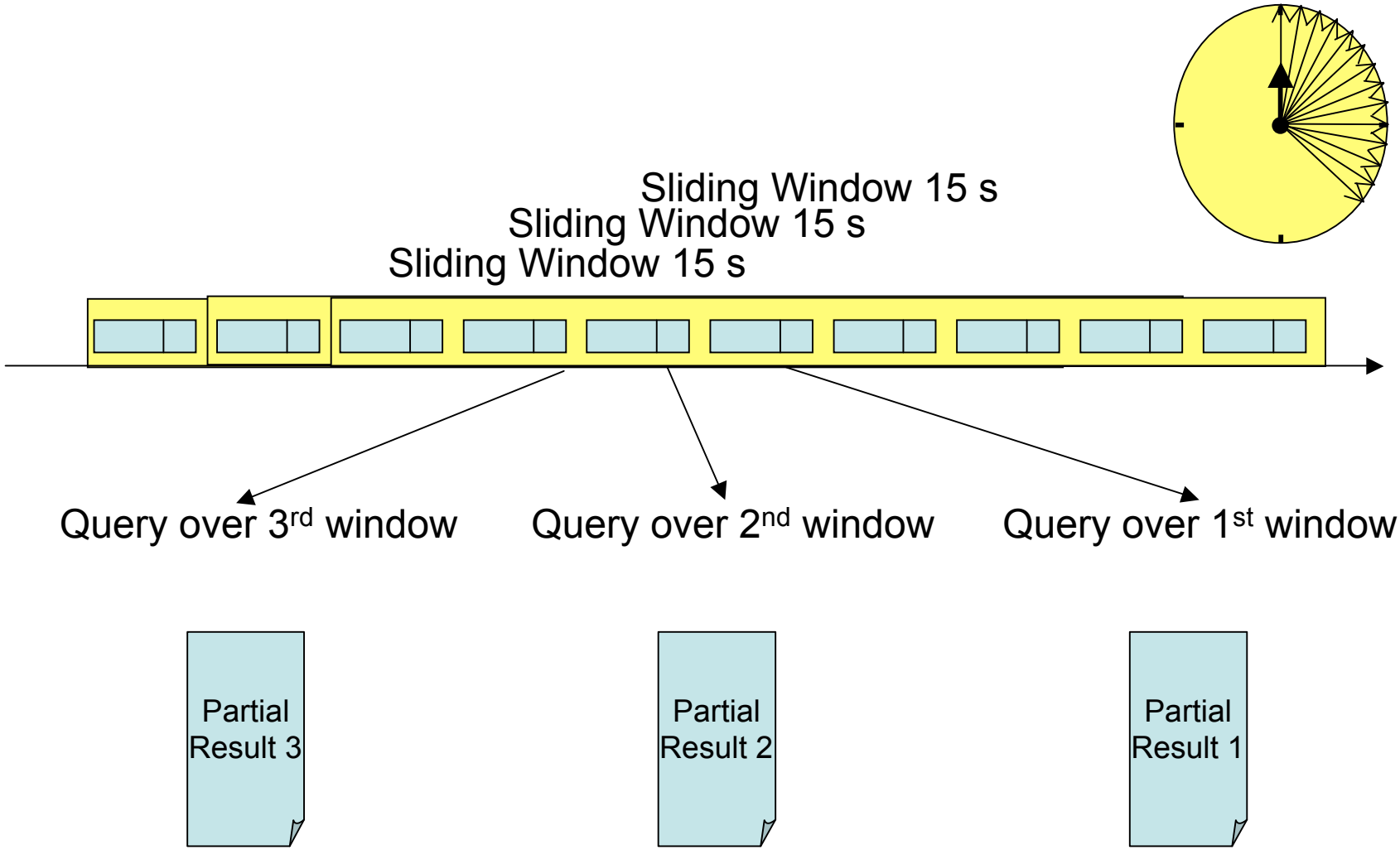
- Window of size N tuples (sliding, shifting) over the stream
- Problematic with non-unique time stamps associated with tuples
- Ties broken arbitrarily may lead to non deterministic output



Punctuation Based Windows

- 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

Sliding Window



Sample Stream

```
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

- Selections, (duplicate preserving) projections are straightforward
  - Local, per-element operators
  - Duplicate eliminating projection is like grouping
- Projection needs to include ordering attribute
  - 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
- 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
```

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

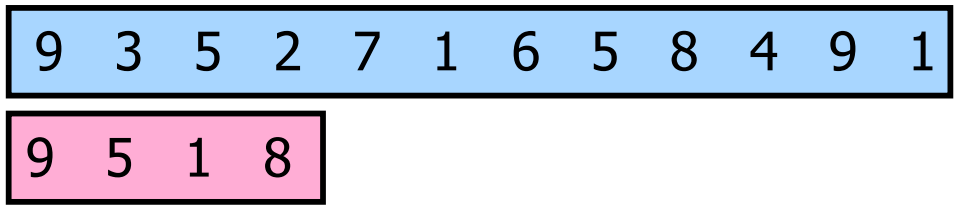
- An aggregate query result can be streamed if group by attributes include the ordering attribute
- A single stream aggregate query "select G,F from S where P group by G" can be executed in bounded memory if:
  - every attribute in G is bounded
  - no aggregate expression in F, executed on an unbounded
  - attribute, is holistic
- Conditions for bounded memory execution of aggregate queries on multiple streams

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(*) > f|S|
- Data reduction: use summary structures
  - samples, histograms, sketches …
- Focus of different tutorial

Sampling

- A small random sample S of the data often well-represents all the data
  - Example: select agg from R where R.e is odd (n=12)



  - If agg is avg, return average of odd elements in S

answer: 5

  - If agg is count, return average over all elements e in S of
    - n if e is odd
    - 0 if e is even

answer: 12*3/4 =9

Unbiased!

Histograms

- Histograms approximate the frequency distribution of element values in a stream
- A histogram (typically) consists of
  - A partitioning of element domain values into buckets
  - A count C_B per bucket B (of the number of elements in B)
- Long history of use for selectivity estimation within a query optimizer

Wavelets

- For hierarchical decomposition of functions/signals
- Haar wavelets
  - Simplest wavelet basis => Recursive pairwise averaging and differencing at different resolutions

Resolution	Averages	Detail Coefficients
3	[2, 2, 0, 2, 3, 5, 4, 4]	----
2	[2, 1, 4, 4]	[0, -1, -1, 0]
1	[1.5, 4]	[0.5, 0]
0	[2.75]	[-1.25]

Haar wavelet decomposition: [2.75, -1.25, 0.5, 0, 0, -1, -1, 0]

Disorder in Data Streams

- Many queries over data streams rely on some kind of order on the input data items
  - Can often use more efficient operator implementations if the input is sorted on “interesting attributes” (e.g. aggregates)
- What causes disorder in streams?
  - Items from the same source may take different routes
  - Many sources with varying delays
  - May have been sorted on different attribute
- Sorting a stream may be undesirable
- May be more than one possible interesting order over a stream
  - For example, data items may have *creation time* and *arrival time*
  - Sorted on arrival time, but creation time also interesting

Punctuations

- Punctuations embedded in stream denote end of subset of data
  - Unblocks blocking operators
  - Reduces state required by stateful operators
- New operator: Punctuate
  - Has special knowledge regarding the input stream
    - timer-based, k-constraints, communication with stream source
  - Emits punctuations in source schema based on special knowledge
- Punctuations can help in two ways:
- Maintain order – Punctuations unblock sort
  - Similar to approach in Gigascope
  - Order-preserving operators include sort behavior for punctuations
- Allow disorder – Punctuations define the end of subsets
  - Operators use punctuations, not order, to output results
  - Reduces tuple latency

Example - I: Queries for Network Traffic Management

- Large network, e.g., backbone network of ISP
- Monitor a variety of continuous data streams that may be unpredictable and have high data rates
- Provide a ”general-purpose” system for monitoring
- Traditional DBS do not support on-line continuous query processing
- Example: network packet traces from multiple network links, here only two specific links: customer link C, backbone link B, we consider only five packet header fields: src, desr, id, len, time

Example - II: Queries for Network Traffic Management

- Compute load on link *B* averaged over one-minute intervals, notifying the network operator when the load crosses a specified threshold *t*. Two special functions: getminute, notifyoperator

```
SELECT      notifyoperator(sum(len))
FROM        B
GROUP BY    getminute(time)
HAVING      sum(len) > t
```

Example - III: Queries for Network Traffic Management

- Isolate flows in the backbone link and determine amount of traffic generated by each flow. Flow: sequence of packets grouped in time, and sent from a specific source to a specific destination.

```
SELECT    flowid, src, dest, sum(len) AS flowlen
FROM      (SELECT src, dest, len, time
           FROM B
           ORDER BY time)
GROUP BY  src, dest, getfbwid(src, dest, time)
          AS flowid
```

Example - IV: Queries for Network Traffic Management

- Ad hoc continuous queries when network is congested to determine whether the customer network is the cause.

```
SELECT    count(*)
FROM      C, B
WHERE     C.src = B.src and C.dest = B.dest
          and C.id = B.id /
          (SELECT count (*) FROM B)
```

Example - V: Queries for Network Traffic Management

- Continuous query for monitoring the source-destination pairs in the top 5% in terms of backbone traffic.

```
WITH Load AS
    (SELECT   src, dest, sum(len) AS traffic
     FROM     B
     GROUP BY       src, dest)
SELECT       src, dest, traffic
FROM         Load AS L1
WHERE        (SELECT      count (*)
              FROM                Load AS L2
              WHERE       L2.traffic > L1.traffic) >
             (SELECT      0.95xcount(*) FROM Load)
ORDER BY   traffic
```

Query Languages

3 querying paradigms for streaming data:

1. Relation-based: SQL-like syntax and enhanced support for windows and ordering, e.g., CQL (STREAM), StreaQuel (TelegraphCQ), AQuery, GigaScope
2. Object-based: object-oriented stream modeling, classify stream elements according to type hierarchy, e.g., Tribeca, or model the sources as ADTs, e.g., COUGAR
3. Procedural: users specify the data flow, e.g., Aurora, users construct query plans via a graphical interface

(1) and (2) are declarative query languages,
currently, the relation-based paradigm is mostly used.

Query Processing - I

- Continuous query plans:
  - push-based approaches - data is pushed to the DSMS by the source(s)
  - trad.DBS approaches are pull-based, queue problems (overflows)
  - open problems: redesign disk-based data structures and indices
- Processing multiple continuous queries:
  - sharing query plans
  - indexing query predicates
- Distributed query processing:
  - multiple data streams arriving from remore sources
    => distributed optimization strategies

Query Processing - II

(1) Non-blocking operators - 3 techniques for unblocking stream operators:
- windowing
- incremental evaluation
- exploiting stream constraints (*punctuations*)

(2) Approximate algorithms – if (1) does not work, compact stream summaries may be stored and approximate queries may be run over the summaries
-> Trade-off: *accuracy* vs. *amount of memory*
Methods of generating synopses: counting methods, hashing methods, sampling methods, sketches, wavelet transformations

(3) Sliding window algorithms:
- windowed sampling
- symmetric hash join

(4) On-line data stream mining (single pass): computing stream signatures, decision trees, forecasting, *k*-medians clustering, nearest neighbour queries, regression analysis, similarity detection, pattern matching

Approximate Query Answering Methods

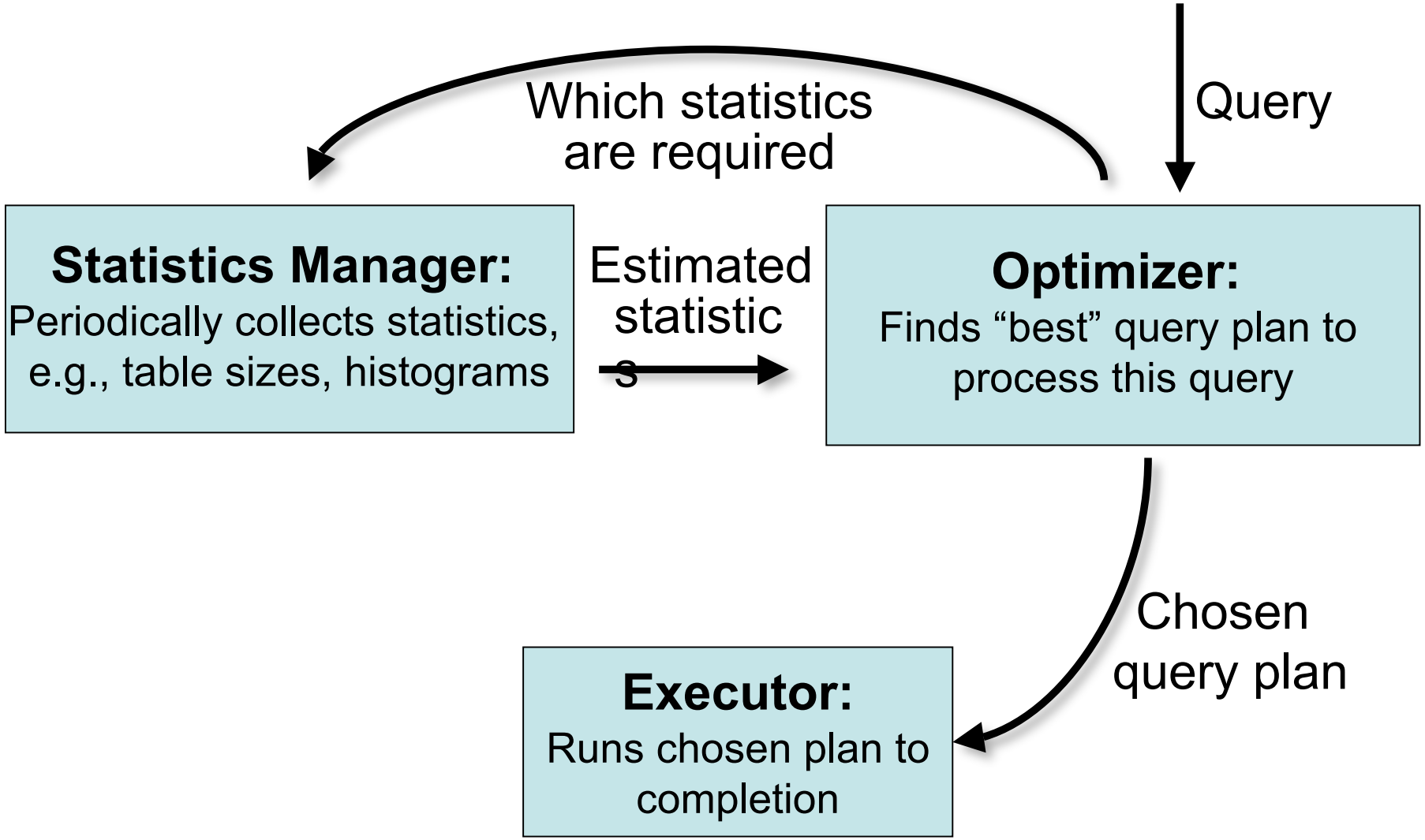
- Sliding windows
  - Only over sliding windows of *recent stream data*
  - Approximation but often more desirable in applications
- Batched processing, sampling and synopses
  - Batched if update is fast but computing is slow
    - Compute periodically, not very timely
  - Sampling if update is slow but computing is fast
    - Compute using sample data, but not good for joins, etc.
  - Synopsis data structures
    - Maintain a small *synopsis* or *sketch* of data
    - Good for querying historical data
- Blocking operators, e.g., sorting, avg, min, etc.
  - Blocking if unable to produce the first output until seeing the entire input

[Han 2004]

Query Optimization

- DBS: table based cardinalities used in query optimization
  => Problematic in a streaming environment
- Cost metrics and statistics: accuracy and reporting delay vs. memory usage, output rate, power usage
- Query optimization: query rewriting to minimize cost metric, adaptive query plans, due to changing processing time of operators, selectivity of predicates, and stream arrival rates
- Query optimization techniques
  - stream rate based
  - resource based
  - QoS based
- Continuously adaptive optimization
- Possibility that objectives cannot be met:
  - resource constraints
  - bursty arrivals under limited processing capability

Traditional Query Optimization



[Babu 2004]

STREAM - Optimizing CQs

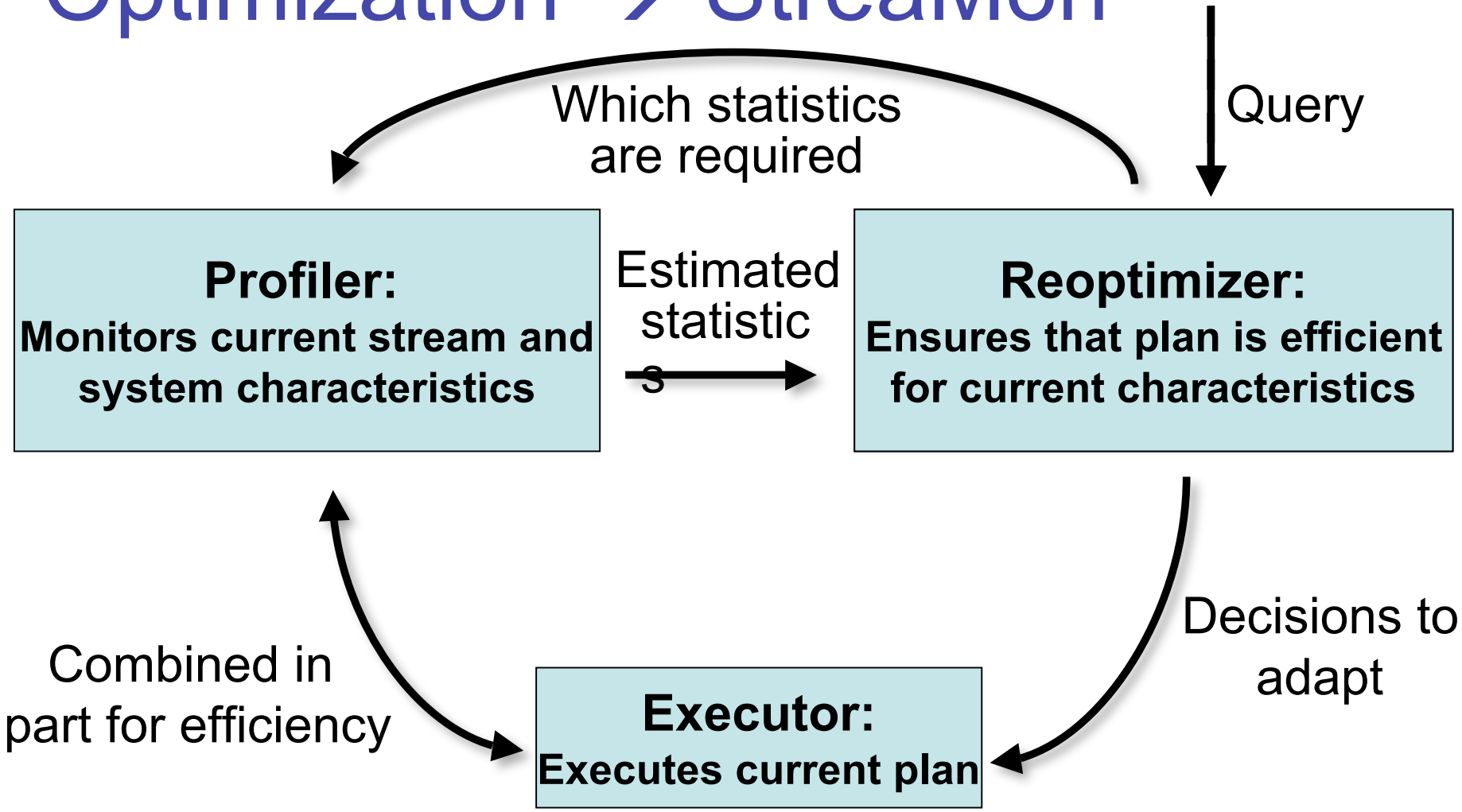
- Continuous queries are long-running
- Stream characteristics can change over time
  - Data properties: Selectivities, correlations
  - Arrival properties: Bursts, delays
- System conditions can change over time

➔ Performance of a fixed plan can change significantly over time

➔Adaptive processing: find best plan for current conditions

[Babu 2004]

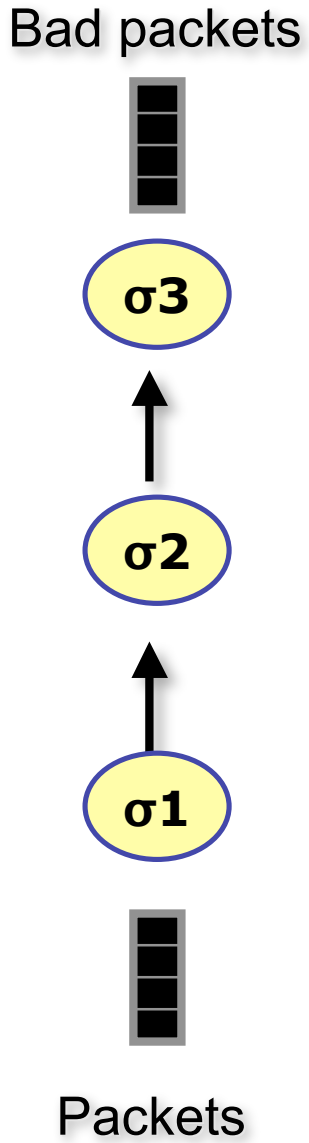
STREAM - Traditional Optimization → StreaMon



[Babu 2004]

STREAM - Pipelined Filters

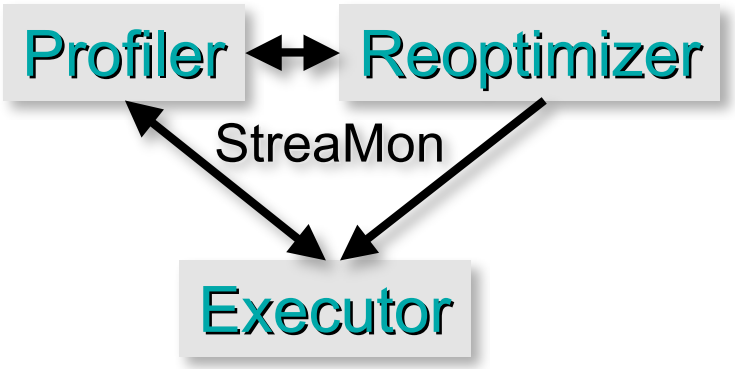
- Order commutative filters over a stream
- Example: Track HTTP packets with destination address matching a prefix in given table and content matching “*\.ida”
- Simple to complex filters
  - Boolean predicates
  - Table lookups
  - Pattern matching
  - User-defined functions
  - Joins as we will see later



[Babu 2004]

STREAM - Metrics for an Adaptive Algorithm

- Speed of adaptivity
  - Detecting changes and finding new plan
- Run-time overhead
  - Collecting statistics, reoptimization, plan migration
- Convergence properties
  - Plan properties under stable statistics

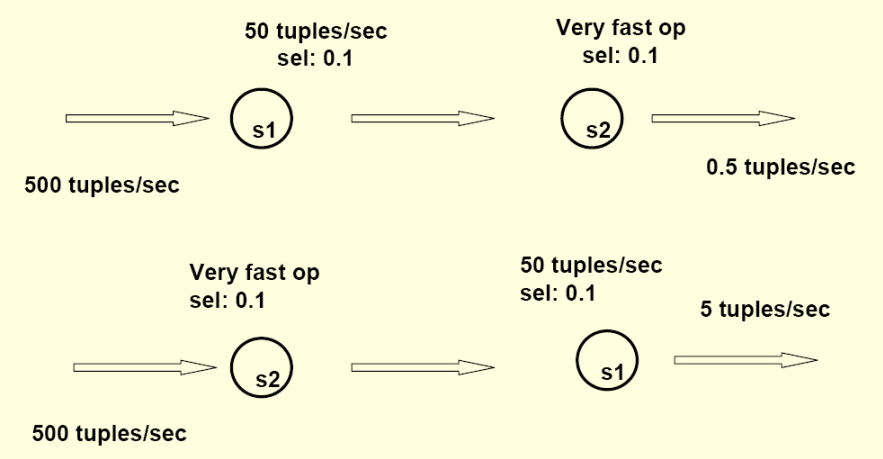


[Babu 2004]

Optimization Objectives

- Rate-based optimization:
  - Take into account the rates of the streams in the query evaluation tree during optimization
  - Rates can be known and/or estimated
- Maximize 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 – I



- 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

Rate Based Optimization – II

- 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

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

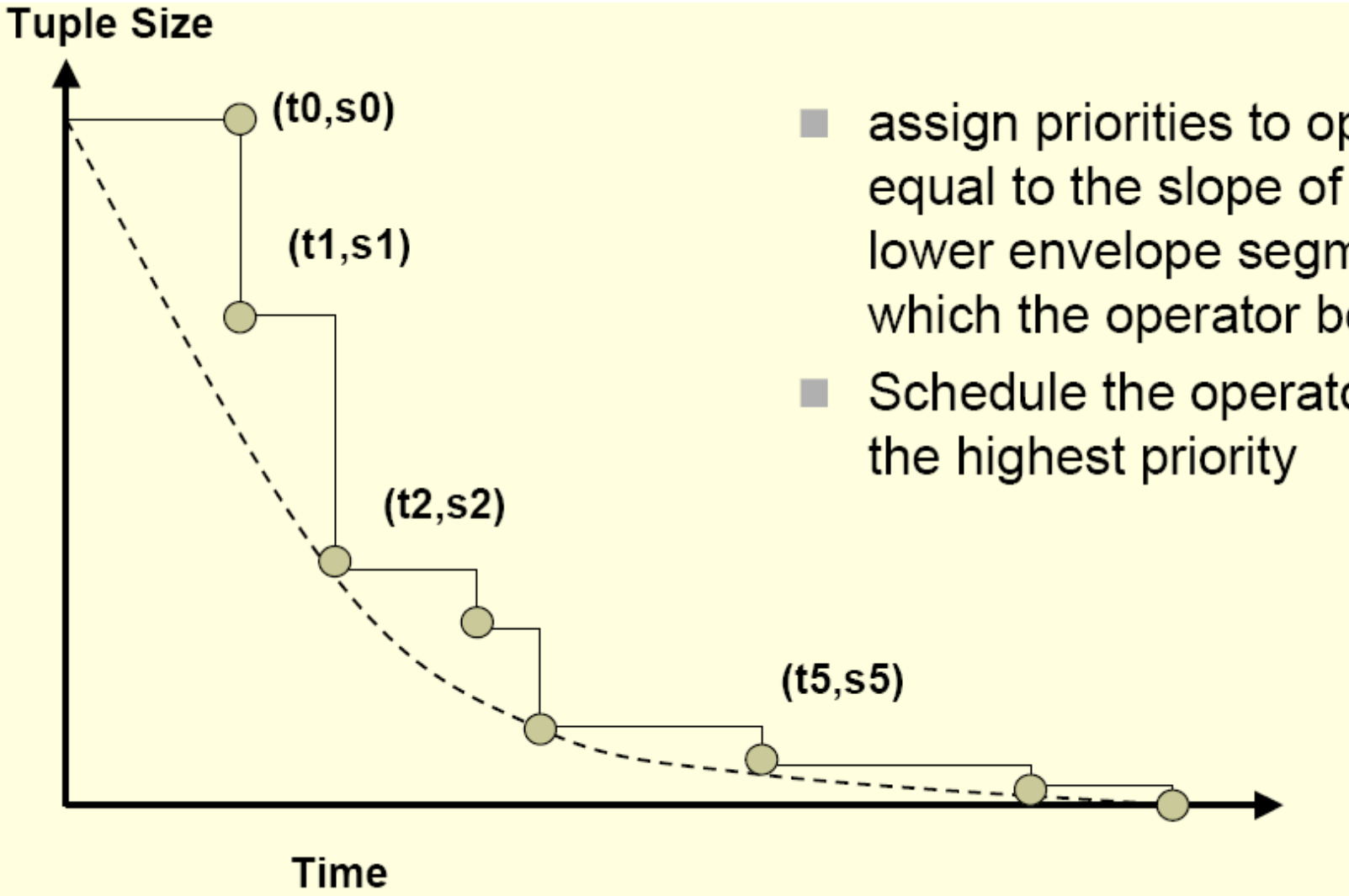
Average arrival rate: 0.5 tuples/sec

FIFO: tuples processed in arrival order

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

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

Progress Chart: Chain Scheduling



- assign priorities to operators equal to the slope of the lower envelope segment to which the operator belongs
- Schedule the operator with the highest priority

QoS Based Optimization

- Query and operator scheduling based on 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

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

- QoS for each application as a function relating output to its utility
  - Delay based, drop based, value 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

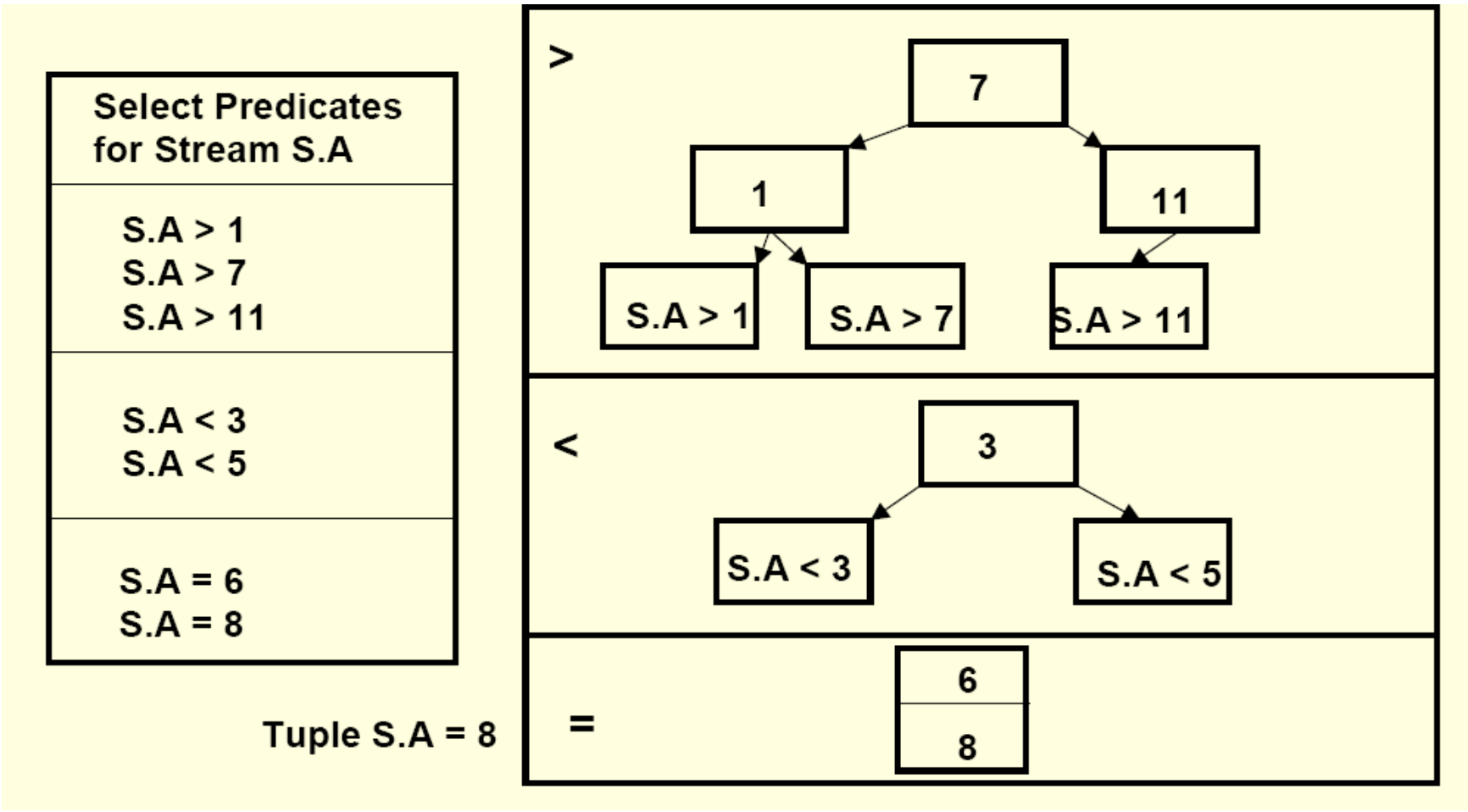
Load Shedding in STREAM

- 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 pi

Multi-query Processing

- 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



Shared Window Joins

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
```

- 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)

Stream Data Mining

- Stream mining
  - It shares most of the difficulties with stream querying
  - Patterns are hidden and more general than querying
  - It may require exploratory analysis
    - Not necessarily continuous queries
- Stream data mining tasks
  - Multi-dimensional on-line analysis of streams
  - Mining outliers and unusual patterns in stream data
  - Clustering data streams
  - Classification of stream data

[Han 2004]

Stream Mining - Challenges

- Most stream data are at pretty low-level or multi-dimensional in nature: needs ML/MD processing
- Analysis requirements
  - Multi-dimensional trends and unusual patterns
  - Capturing important changes at multi-dimensions/levels
  - Fast, real-time detection and response
  - Comparing with data cube: Similarity and differences
- Stream (data) cube or stream OLAP: Is this feasible?
  - Can we implement it efficiently?

[Han 2004]

Examples:
Multi-Dimensional Stream Analysis

- Analysis of Web click streams
  - Raw data at low levels: seconds, web page addresses, user IP addresses, …
  - Analysts want: changes, trends, unusual patterns, at reasonable levels of details
  - E.g., *Average clicking traffic in North America on sports in the last 15 minutes is 40% higher than that in the last 24 hours.”*
- Analysis of power consumption streams
  - Raw data: power consumption flow for every household, every minute
  - Patterns one may find: *average hourly power consumption surges up 30% for manufacturing companies in Chicago in the last 2 hours today than that of the same day a week ago*

[Han 2004]

Stream Data Reduction

Challenges of OLAPing stream data

- Raw data cannot be stored
- Simple aggregates are not powerful enough
- History shape and patterns at different levels are desirable: multi-dimensional regression analysis

Proposal

- A scalable multi-dimensional stream “data cube” that can aggregate regression model of stream data efficiently without accessing the raw data

Stream data compression

- Compress the stream data to support memory- and time-efficient multi-dimensional regression analysis

[Han 2004]

Data Warehouse:
Stream Cube Architecture

- A tilt time frame
  - Different time granularities (second, minute, quarter, hour, day, week, …)
- Critical layers
  - Minimum interest layer (m-layer)
  - Observation layer (o-layer)
  - User: watches at o-layer and occasionally needs to drill-down down to m-layer
- Partial materialization of stream cubes
  - Full materialization: too space and time consuming
  - No materialization: slow response at query time
  - Partial materialization: what do we mean “partial”?
- On-line materialization
  - Materialization takes precious resources and time
    - Only incremental materialization (with slide window)
  - Only materialize “cuboids” of the critical layers?
    - Some intermediate cells that should be materialized
  - Popular path approach vs. exception cell approach
    - Materialize intermediate cells along the popular paths
    - Exception cells: how to set up exception thresholds?
    - Notice exceptions do not have monotonic behaviour
- Computation problem
  - How to compute and store stream cubes efficiently?
  - How to discover unusual cells between the critical layer?

[Han 2004]

Data Warehouse: Stream Cube Computation

- Cube structure from m-layer to o-layer
- Three approaches
  - All cuboids approach
    - Materializing all cells (too much in both space and time)
  - Exceptional cells approach
    - Materializing only exceptional cells (saves space but not time to compute and definition of exception is *not flexible*)
  - Popular path approach
    - Computing and materializing cells only along a popular path
    - Using H-tree structure to store computed cells (which form the *stream cube—a selectively materialized cube*)

[Han 2004]

Other Approaches for Mining Unusual Patterns in Stream Data

- Beyond multi-dimensional regression analysis
  - Other approaches can be effective for mining unusual patterns
- Multi-dimensional gradient analysis of multiple streams
  - Gradient analysis: finding substantial changes (notable gradients) in relevance to other dimensions
  - E.g., those stocks that increase over 10% in the last hour
- Clustering and outlier analysis for stream mining
  - Clustering data streams
  - History-sensitive, high-quality incremental clustering
- Decision tree analysis of stream data
  - Evolution of decision trees
  - Incremental integration of new streams in decision-tree induction

[Han 2004]

Research Problems: Stream Classification

- What about decision tree may need dramatic restructuring?
  - Especially when new data is rather different from the existing model
  - Efficient detection of outliers (far away from majority) using constructed models
- Weighted by history of the data: pay more attention to new data?
- Mining evolutions and changes of models?
- Multi-dimensional decision tree analysis?
- Stream classification with other classification approaches?
- Constraint-based classification with data streams?

[Han 2004]

Research Problems: Stream Data Mining

- Stream data mining: should it be a general approach or application-specific ones?
  - Do stream mining applications share common core requirements and features?
- Killer applications in stream data mining
- General architectures and mining language
- Multi-dimensional, multi-level stream data mining
  - Algorithms and applications
- How will stream mining make good use of user-specified constraints?
- Stream association and correlation analysis
  - Measures: approximation? Without seeing the global picture?
  - How to mine changes of associations?

[Han 2004]

DSMS Tutorial Outline

- Introduction:
  - What are DSMS? (terms)
  - Why do we need DSMS? (applications)
- Example 1:
  - Network monitoring with TelegraphCQ
- Concepts and issues:
  - Architecture(s)
  - Data modeling
  - Query processing and optimization
  - Data reduction
  - Stream Mining
- Overview of existing systems
- Example 2:
  - DSMS for sensor networks
- Summary:
  - Open issues
  - Conclusions

Systems

- Aurora (Brandeis, Brown, MIT, http://www.cs.brown.edu/research/aurora): workflow-oriented system, sensor monitoring, dataflow
- COUGAR (Cornell, http://www.cs.cornell.edu/database/cougar): sensor database, time series
- GigaScope (AT&T): distributed network monitoring architecture, proprietary system
- Hancock (AT&T): telecom streams
- NiagaraCQ (OGI/Wisconsin, http://www.cs.wisc.edu/niagara): continuous XML query system for dynamic web content
- OpenCQ (Georgia Tech, http://disl.cc.gatech.edu/CQ): continuous query system for monitoring streaming web content, triggers, incr. view maintenance
- StatStream (http://cs.nyu.edu/cs/faculty/shasha/papers/statstream.html): multi-stream monitoring system for on-line statistics
- STREAM (Stanford, http://www-db.stanford.edu/stream): general-purpose relation-based system
- Streaminer (UIUC): stream data mining project
- Tapestry (Xerox): pub/sub content-based filtering
- TelegraphCQ (UC Berkeley, http://telegraph.cs.berkeley.edu): adaptive engine for sensors, continuous query processing system
- Tradebot (www.tradebot.com): stock tickers & streams
- Tribeca (Bellcore): network monitoring, early on-line Internet traffic monitoring tool

Aurora

- Data processing system targeted towards monitoring applications:
  - Streams: for each monitorind task DBA adds 1-n triggers into trigger network
  - Large network of triggers
  - Imprecise data
  - Real-time requirements
- Specified set of operators, connected in a data flow graph
- Each trigger is data flow graph (each node is one of seven built-in operators)
- Optimization of:
  - Data flow graph
  - Compile-time and run-time optimization of trigger network
- Three query modes (continuous, ad-hoc, view)
- Detects resource overload: accepts QoS specifications and attempts to optimize QoS for 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

NiagaraCQ

- CQs for monitoring persistent data sets distributed over WAN
- Scalability (# queries) by grouping CQs for efficient evaluation
- Problem of blocking operators in query plans for streams

OpenCQ

- CQs for monitoring persistent data sets distributed over WAN
- QP based on incremental view maintenance

STREAM

- General purpose stream data manager
  - Data streams and stored relations
- CQL (continuous query language) for declarative query specification
- Timestamps in streams
- Flexible query plan generation
- Query processing architecture
- Resource management:
  - Operator scheduling
  - Graceful approximation: can handle high data rates
- Static and dynamic approximations

Tapestry

- CQs for content-based filtering
  - Over append-only database containing email and bulletin board messages
- Restricted subset of SQL
  - To guarantee efficient evaluation and append-only results

Telegraph

- CQ processing system
  - Uses adaptive query engine
  - Query execution strategies over data streams generated by sensors
  - Processing techniques for multiple CQs
- Support for stream oriented operators
- Support for adaptivity in query processing
  - optimization
- Various aspects of optimized multi-query stream processing

Tribeca

- Restricted querying capability over network packet streams

System Comparison

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

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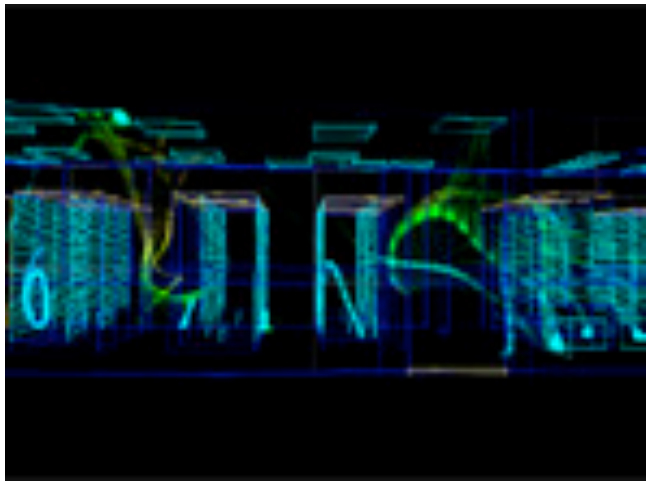
Some Sensornet Applications

ZebraNet

Redwood forest
microclimate monitoring

Smart cooling in data centers



http://www.hpl.hp.com/research/dca/smart_cooling/

Principles of Sensor Networks

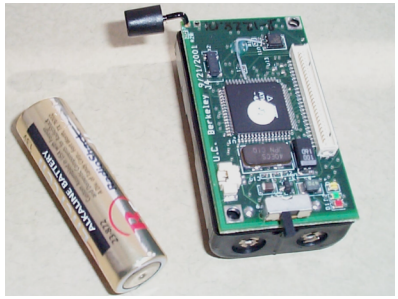
- A large number of low-cost, low-power, multifunctional, and small sensor nodes
- Sensor node consists of sensing, data processing, and communicating components
- A sensor network is composed of a large number of sensor nodes,
  - which are densely deployed either inside the phenomenon or very close to it.
- The position of sensor nodes need not be engineered or pre-determined.
  - sensor network protocols and algorithms must possess self-organizing capabilities.

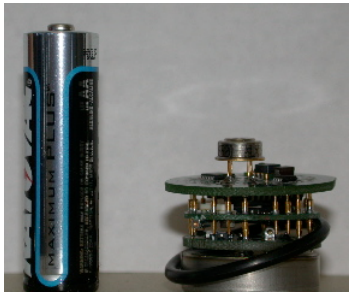
Sensor Hardware

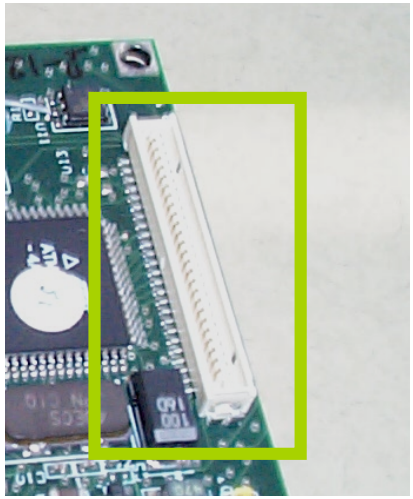
- A sensor node is made up of four basic components
  - a sensing unit
    - usually composed of two subunits: sensors and analog to digital converters (ADCs).
  - processing unit,
    - Manages the procedures that make the sensor node collaborate with the other nodes to carry out the assigned sensing tasks.
  - A transceiver unit
    - Connects the node to the network.
  - Power units (the most important unit)
- Matchbox-sized module
  - consume extremely low power,
  - operate in high volumetric densities,
  - have low production cost and be dispensable,
  - be autonomous and operate unattended,
  - be adaptive to the environment.

Sensor Hardware (cont.)

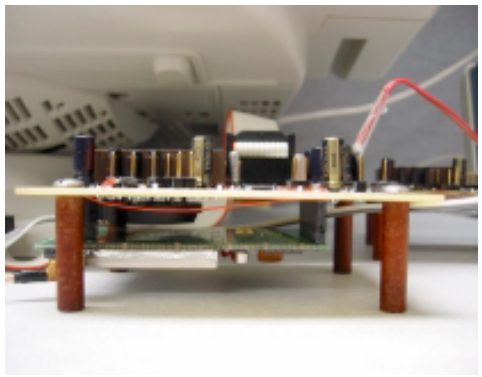
- Motes:

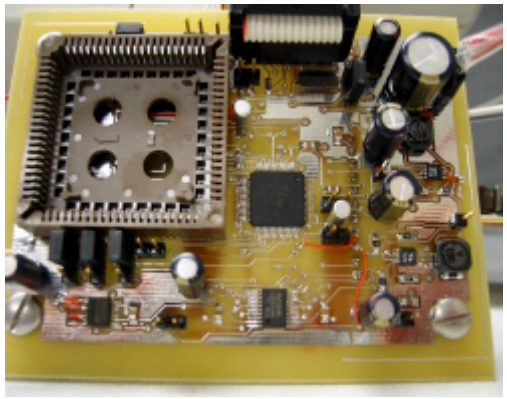




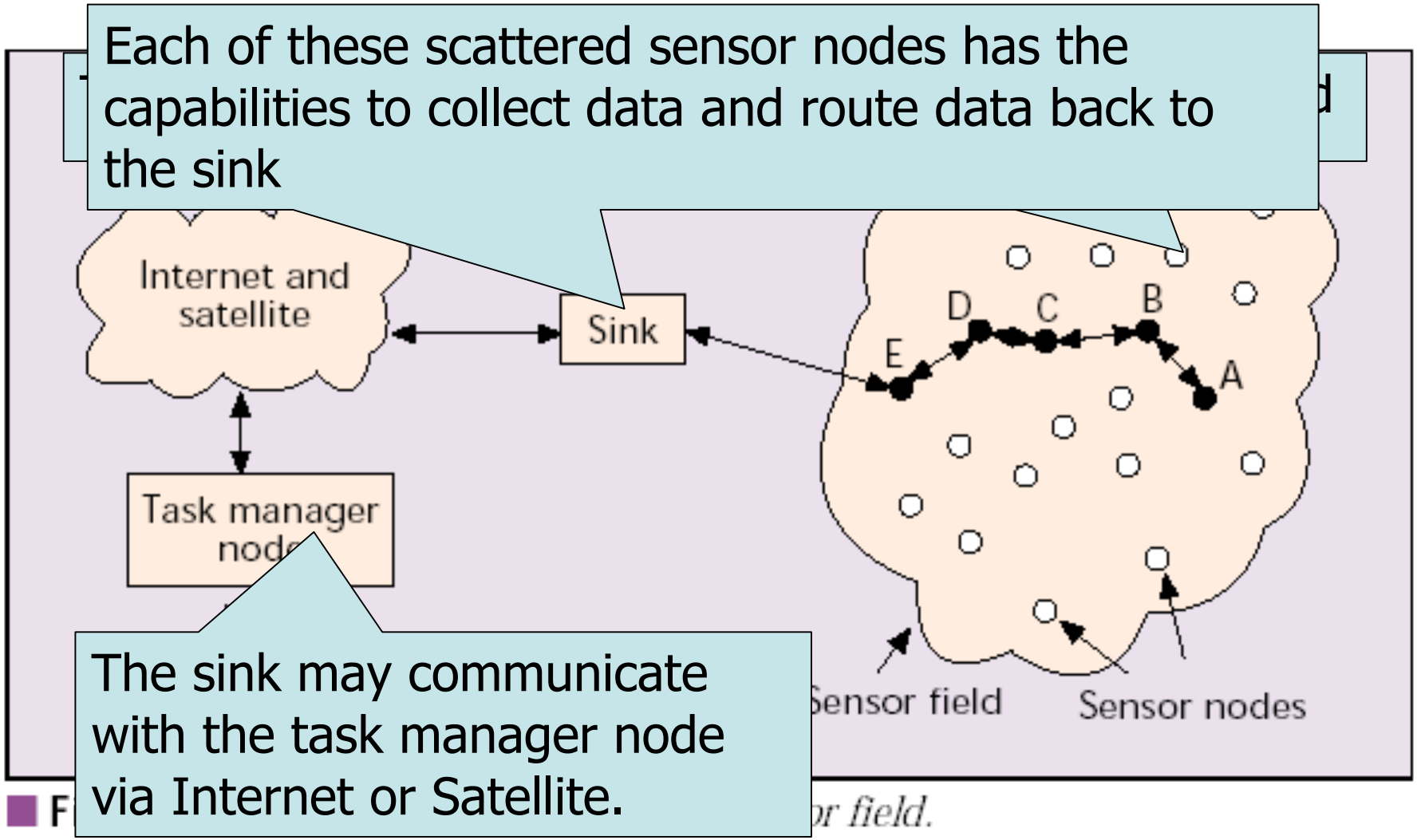


- ZebraNet II:





Sensor networks communication architecture



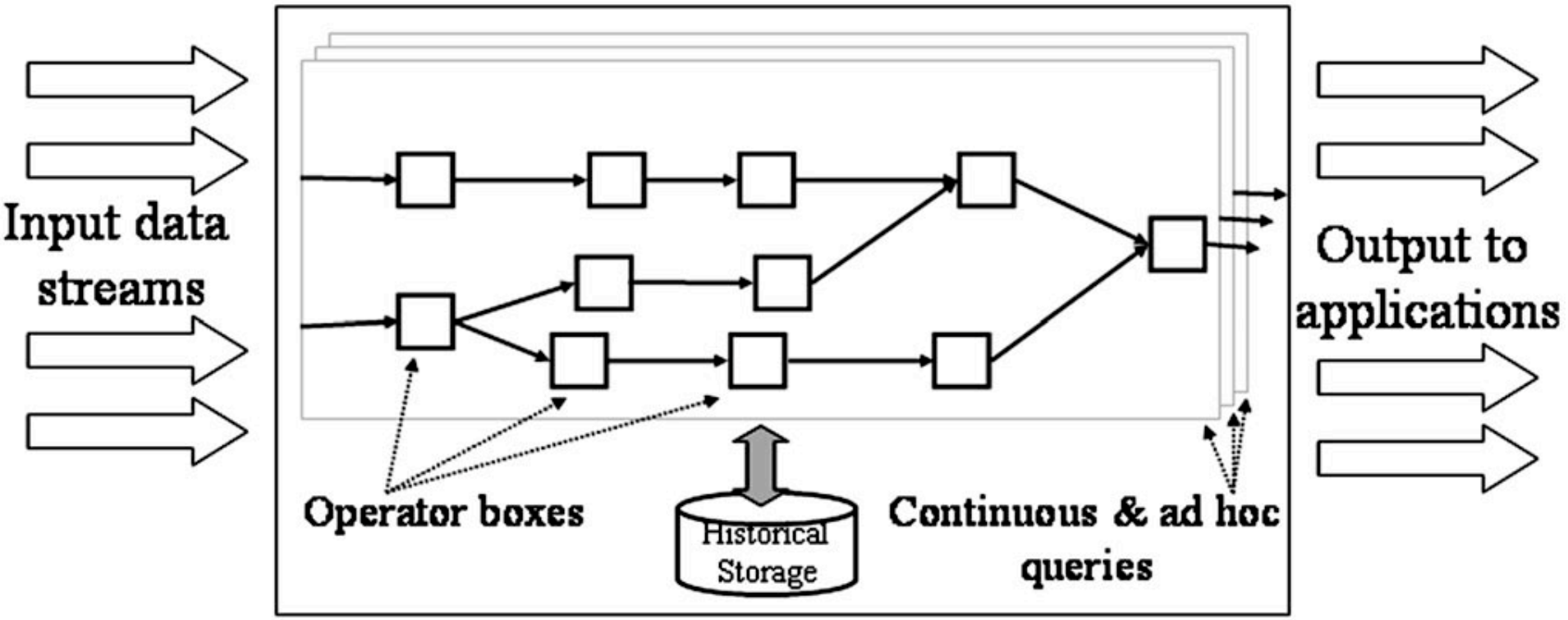
Aurora & Medusa

- Aurora: single-site high performance stream processing engine
- Aurora*: connecting multiple Aurora workflows in a distributed environment
- Medusa: distributed environment where hosts belong to different organizations and no common QoS notion is feasable

Important Aspects of Aurora

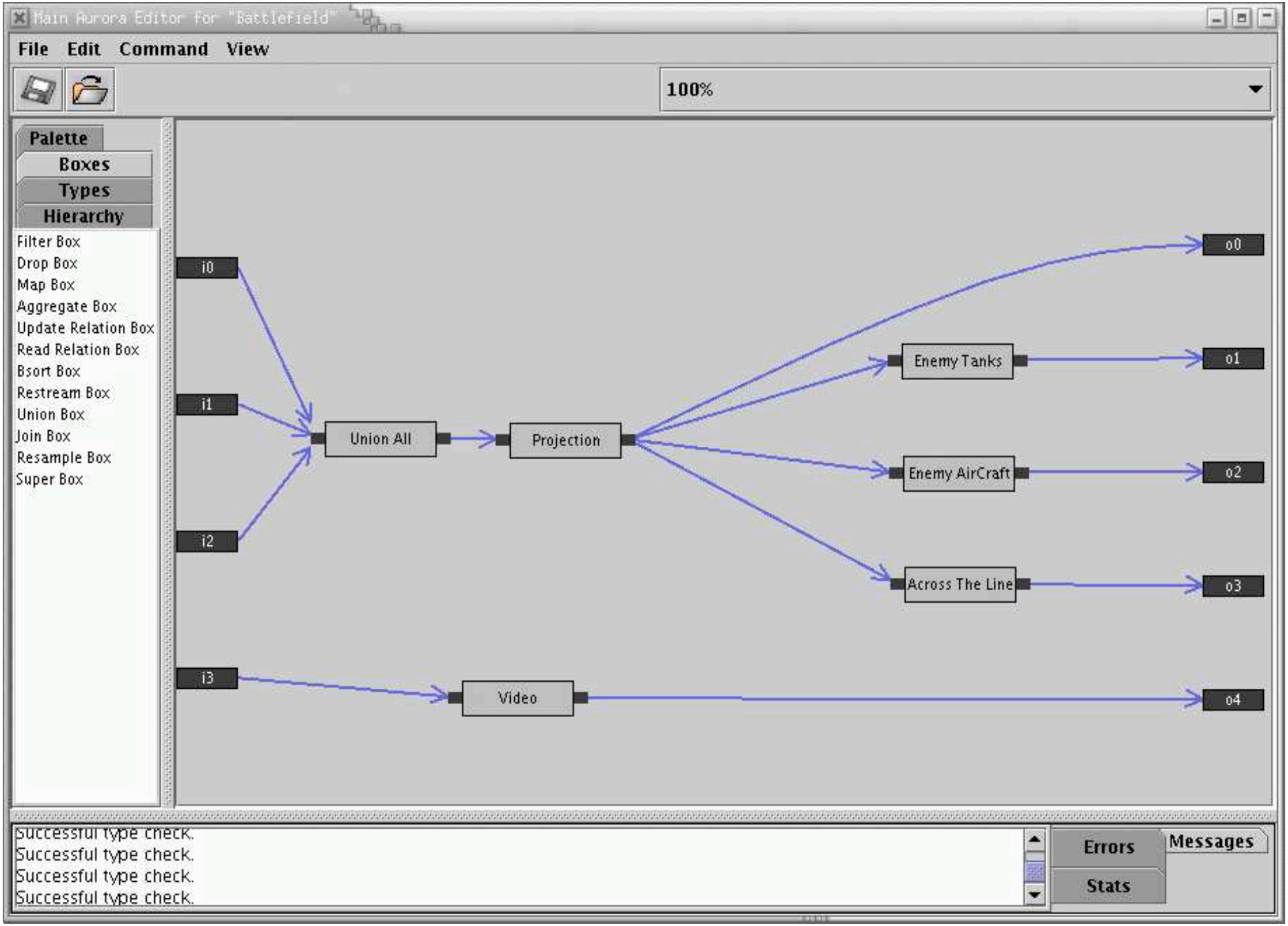
- Workflow orientation
- Operators
- Scheduler
- Quality of Service
- Optimizations

Aurora System Model



Aurora Workflows

- Two reasons to build Aurora as a workflow system:
  - Most monitoring applications contain a component that performs sensor fusion or data cleansing
    - This can be part of DSMS or a different sub-system (less control and more boundary crossings)
  - Query optimization: application designers locate the correct place in workflow diagram to add needed functionality ⇒ reduces complexity of query optimization


Main Aurora Editor for "Battlefield"
File
Edit
Command
View
100%
Palette
Boxes
Types
Hierarchy
Filter Box
Drop Box
Map Box
Aggregate Box
Update Relation Box
Read Relation Box
Bsort Box
Restream Box
Union Box
Join Box
Resample Box
Super Box
i0
i1
i2
i3
Union All
Projection
Enemy Tanks
Enemy AirCraft
Across The Line
Video
o0
o1
o2
o3
o4
Successful type check.
Successful type check.
Successful type check.
Successful type check.
Errors
Messages
Stats

Aurora Operators

- Windowed operations have timeout capability
- Handling out-of-order messages
- Extendability
- Resample operator

Aurora Operators (cont.)

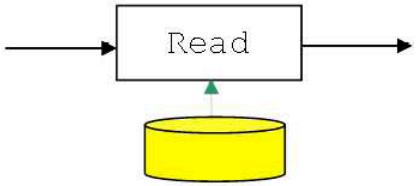
Filter ($p_1,\ldots,p_m$) (S)  *Selection: route tuples to output with 1st predicate match*	*BSort (Using O) (S)*  *Bounded-Pass Bubble Sort: Sort over order attribute. Number of passes = slack*
Map ($A_1=f_1,\ldots,A_m=f_m$) (S)  *Mapping: Map input tuples to outputs with m fields*	*Aggregate (F, Assume O, Size s, Advance i) (S)*  *Sliding Window Aggregate: Apply F to windows of size, s. Slide by i between windows.*
Union ($S_1,\ldots,S_m$)  *Merging: Merge n input streams into 1*	*Join (P, Size s, Left Assume O_1, Right Assume O_2) (S_1,S_2)*  *Band Join: Join s-sized windows of tuples from S_1 and S_2*

Aurora Operators (cont.)

Resample (F, Size s, Left Assume O_1, Right Assume O_2) (S_1,S_2)

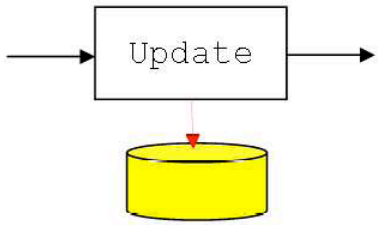
Interpolation: Interpolate missing points in S_2 as determined with S_1

Read (Assume O, SQL Q) (S)



SQL Read: Apply SQL query Q for each input in S. Output as stream.

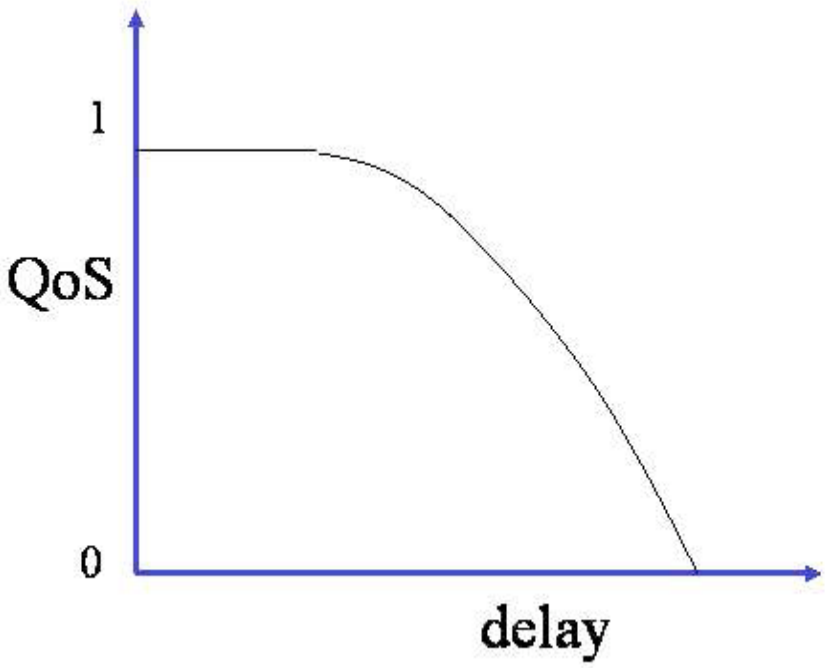
Update (Assume O, SQL U, Report t) (S)



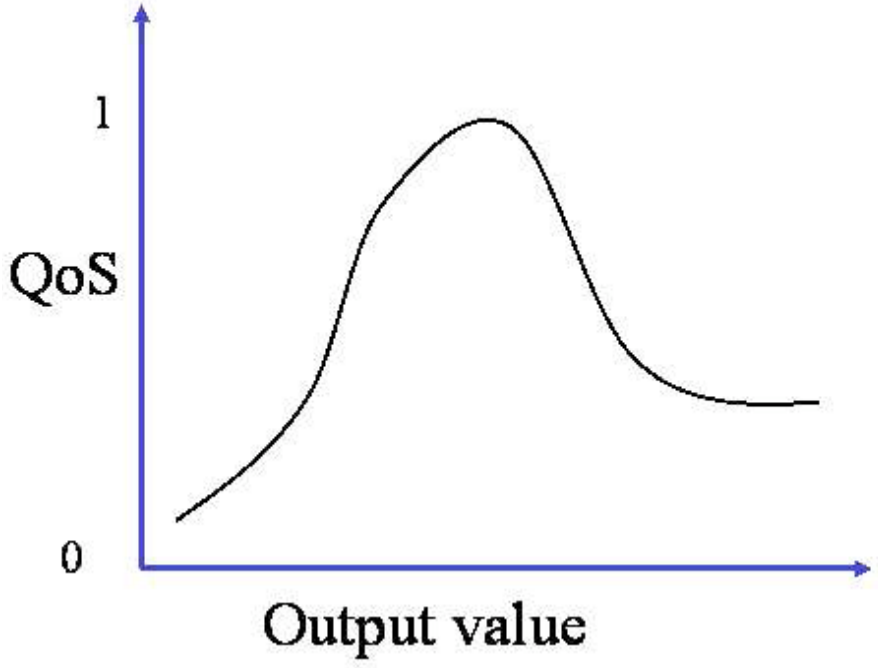
SQL Write: Apply SQL update query U for each input in S. Report t for each update.

Aurora: Quality of Service

- Basic idea: use human specified QoS graphs at Aurora output

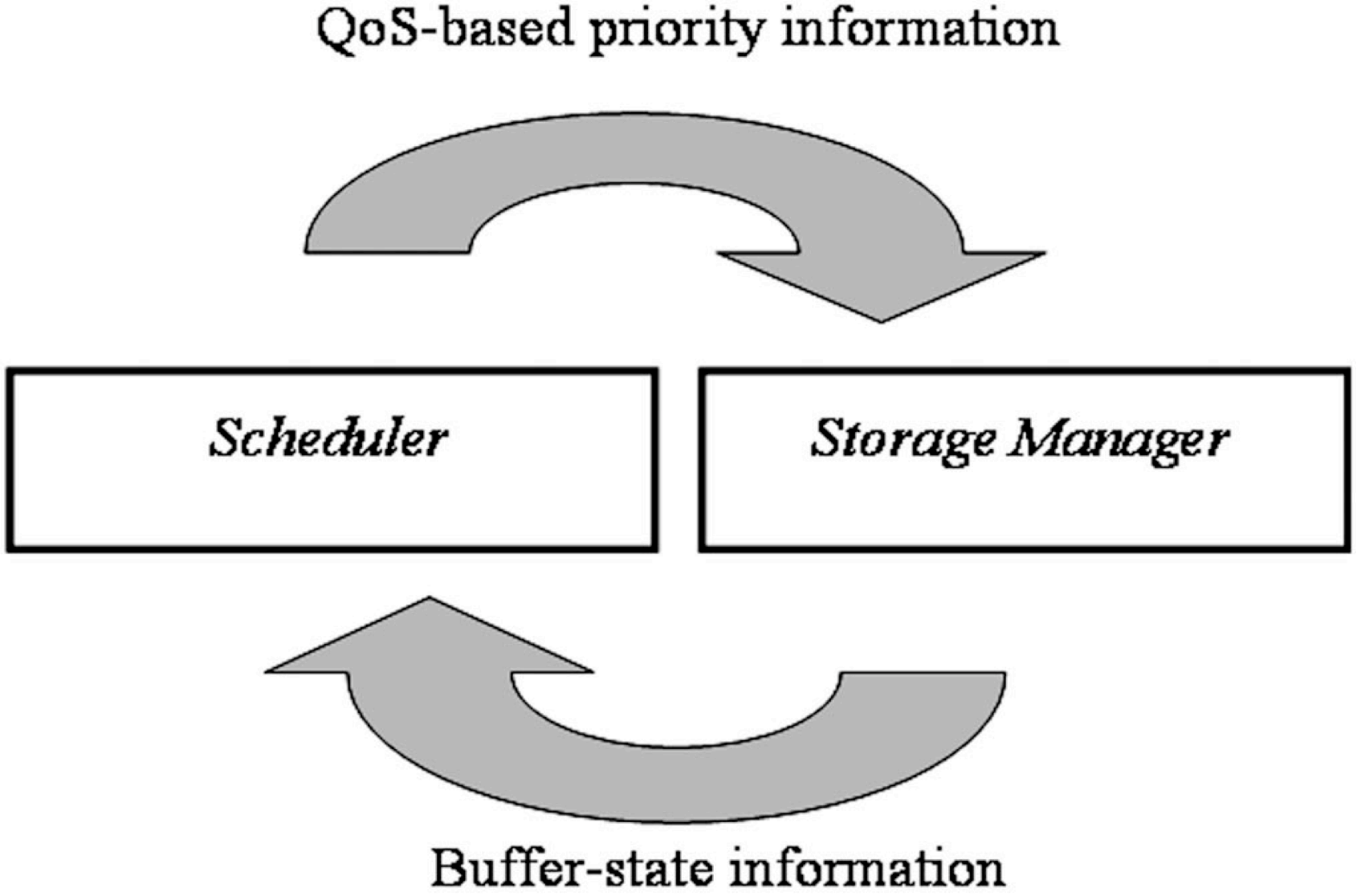


Drop based

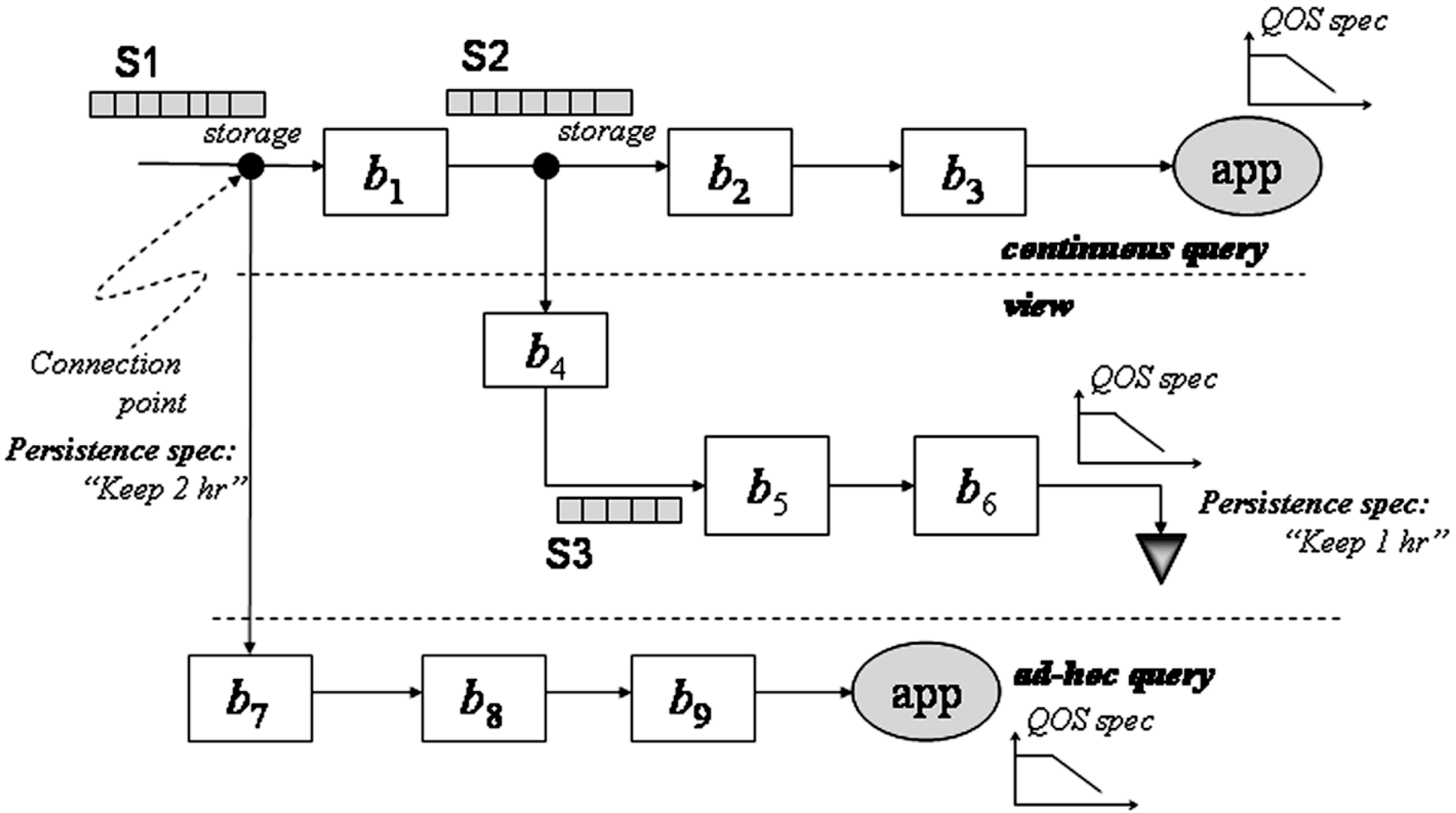


Value-based

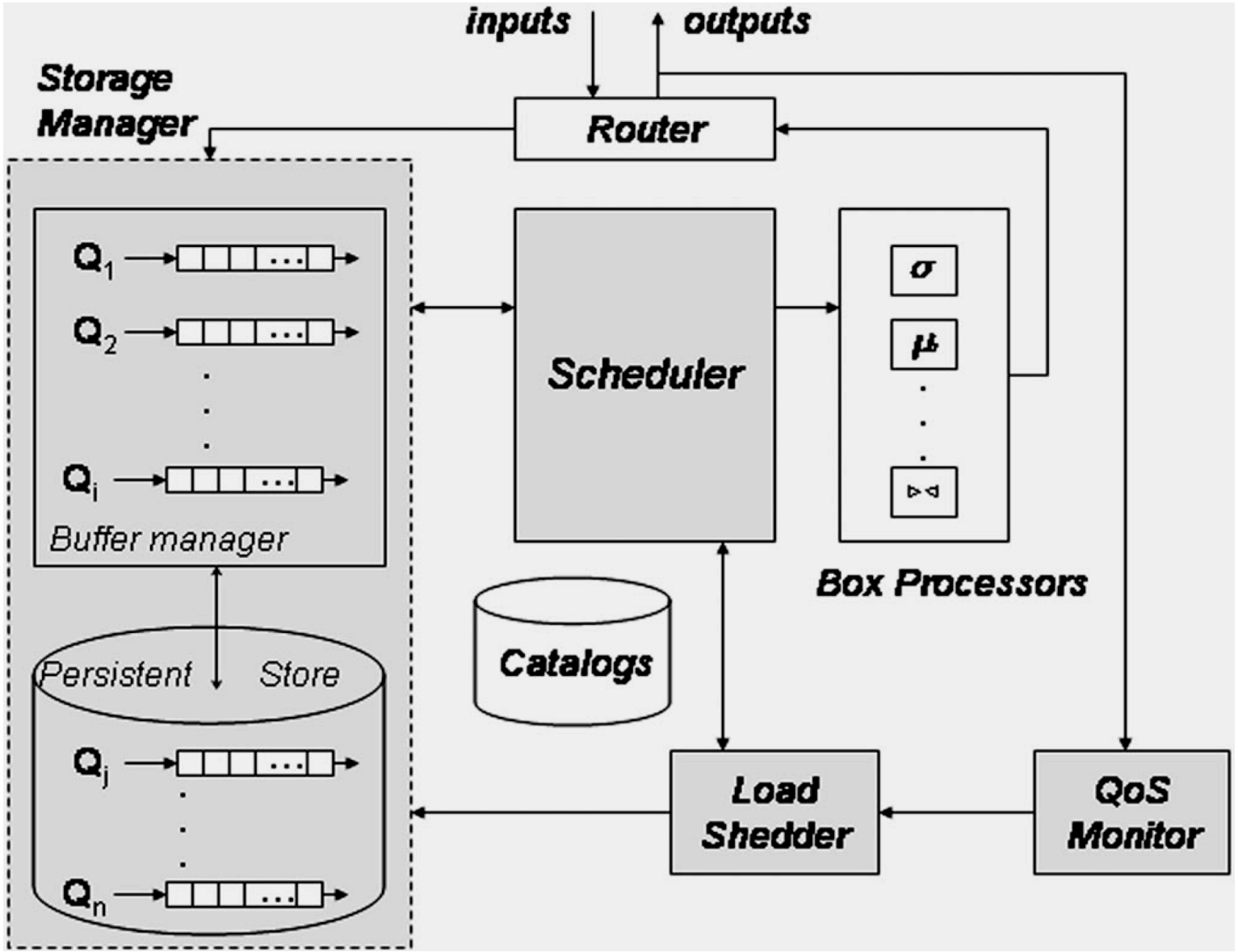
Aurora: Scheduler ↔ Storage



Aurora Query Model

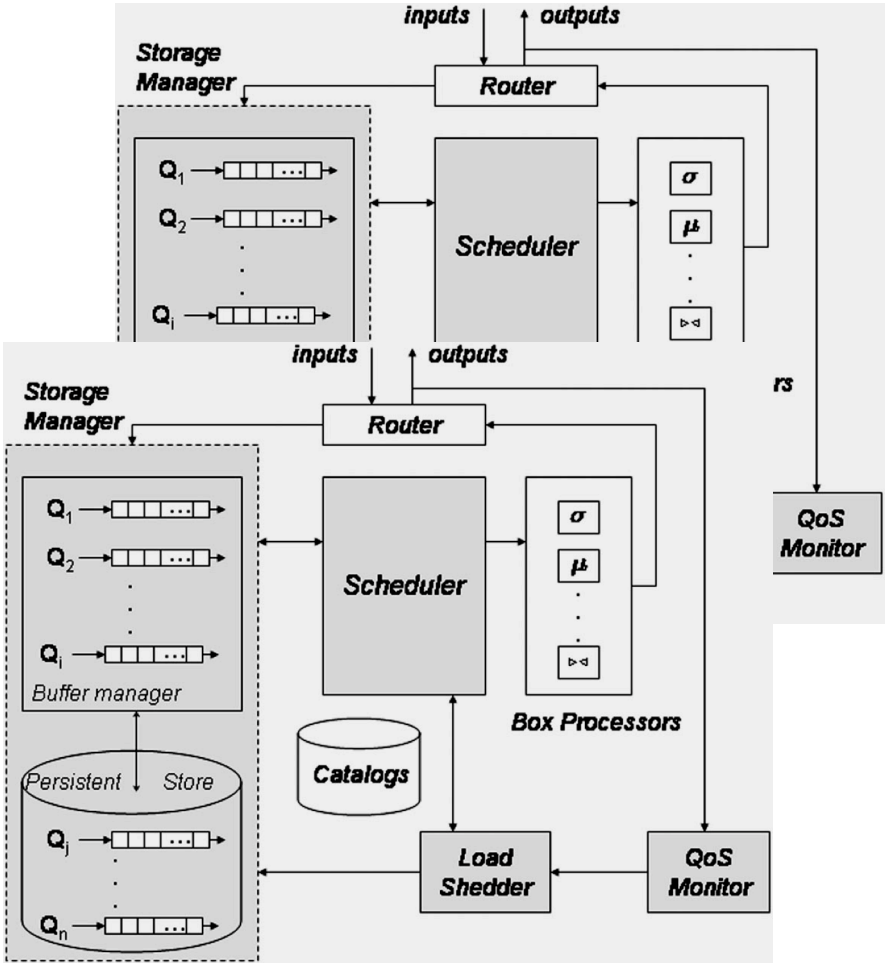


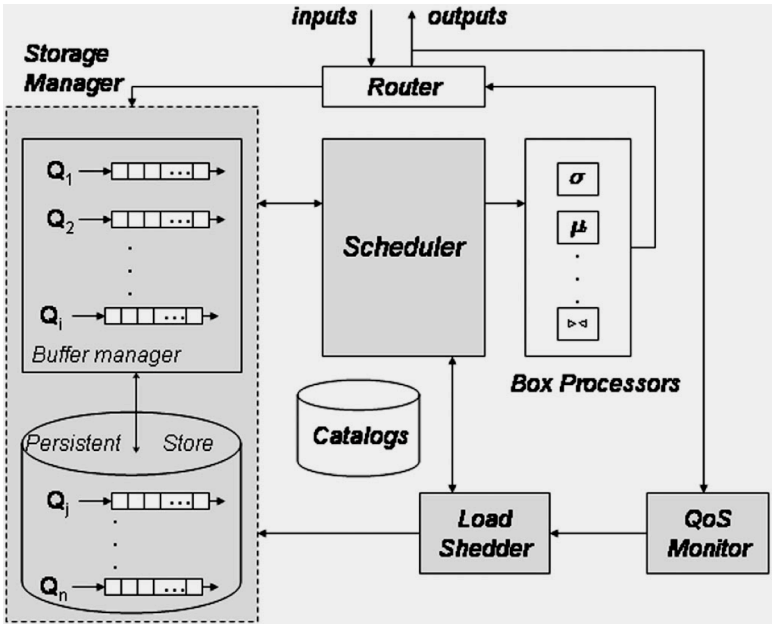
Aurora Architecture



Aurora* Architecture

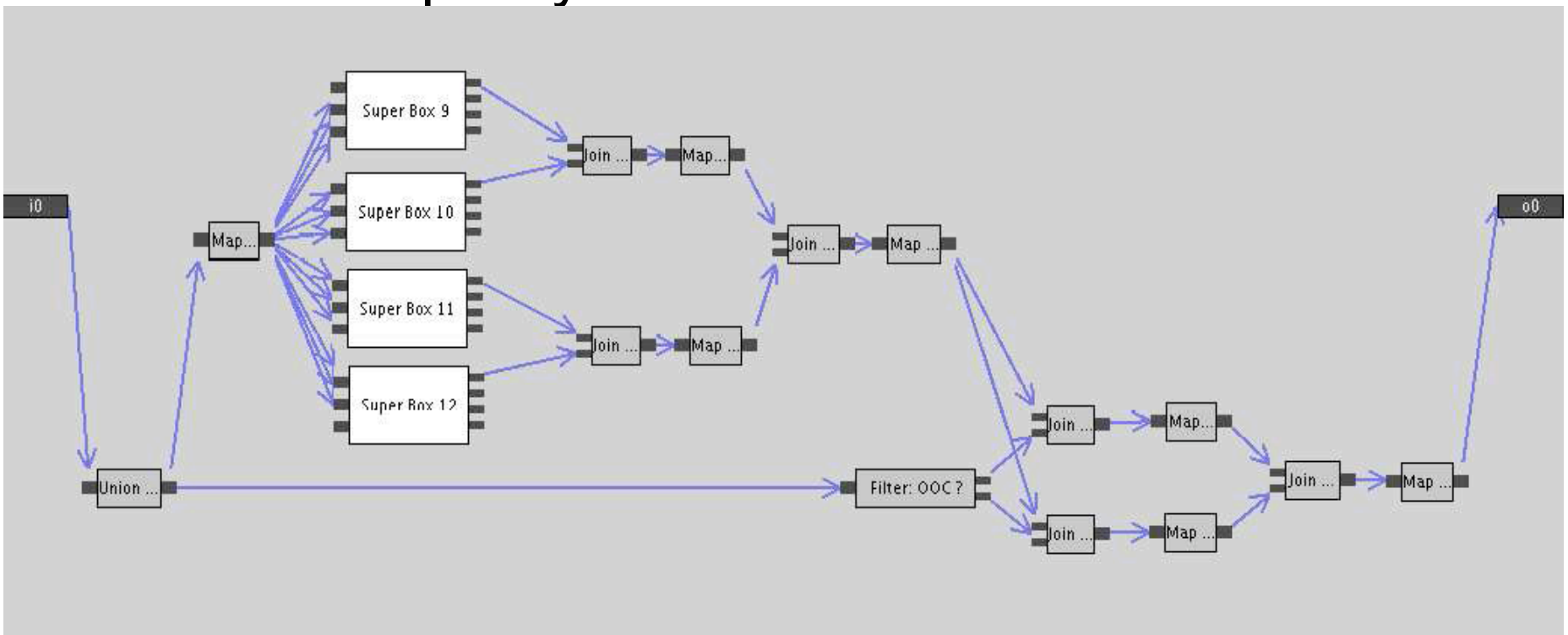
External QoS Monitor



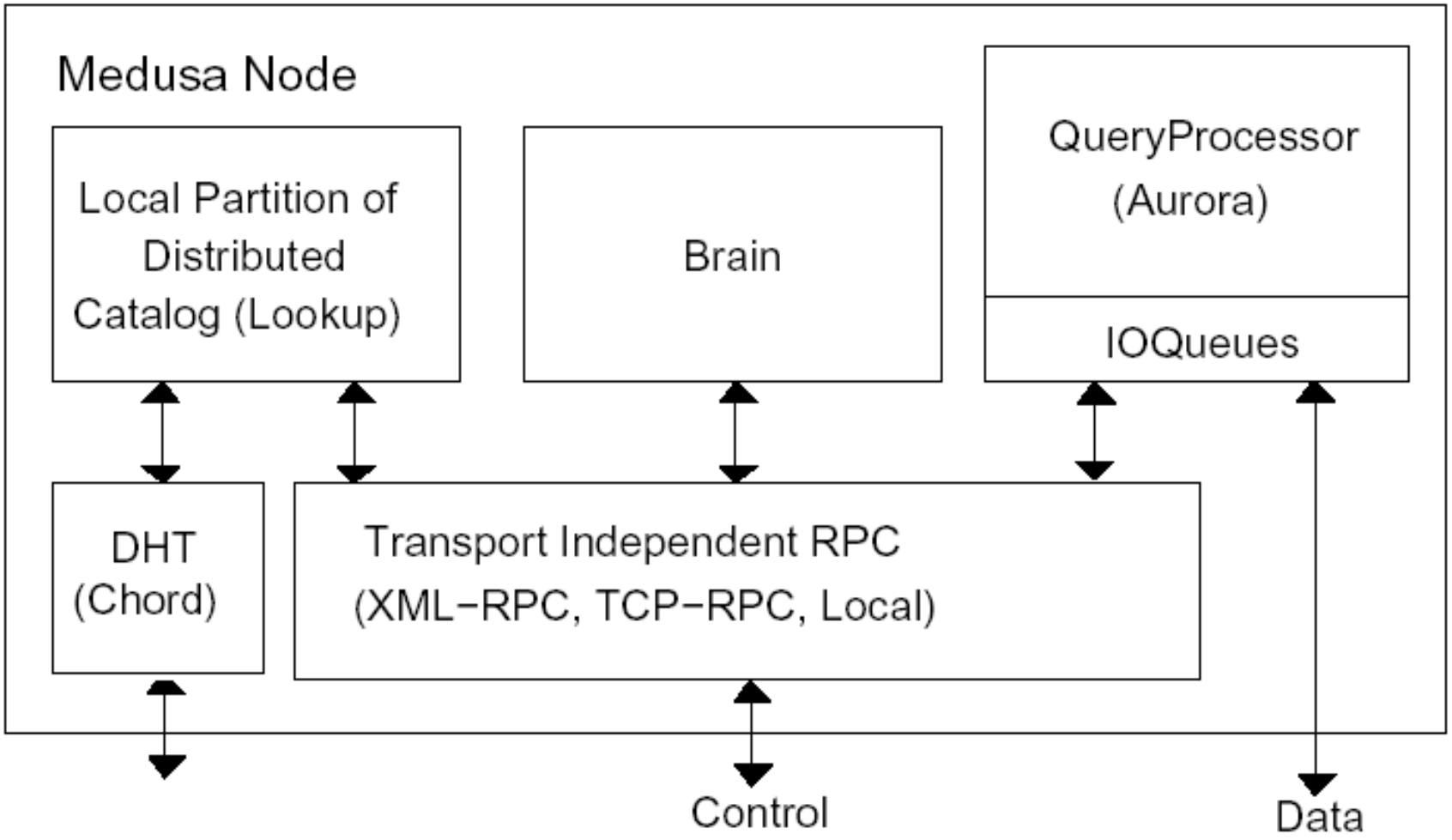


Example: Enviromental Monitoring

- Monitoring toxins in the water
  - Fish behaviour
  - Water quality

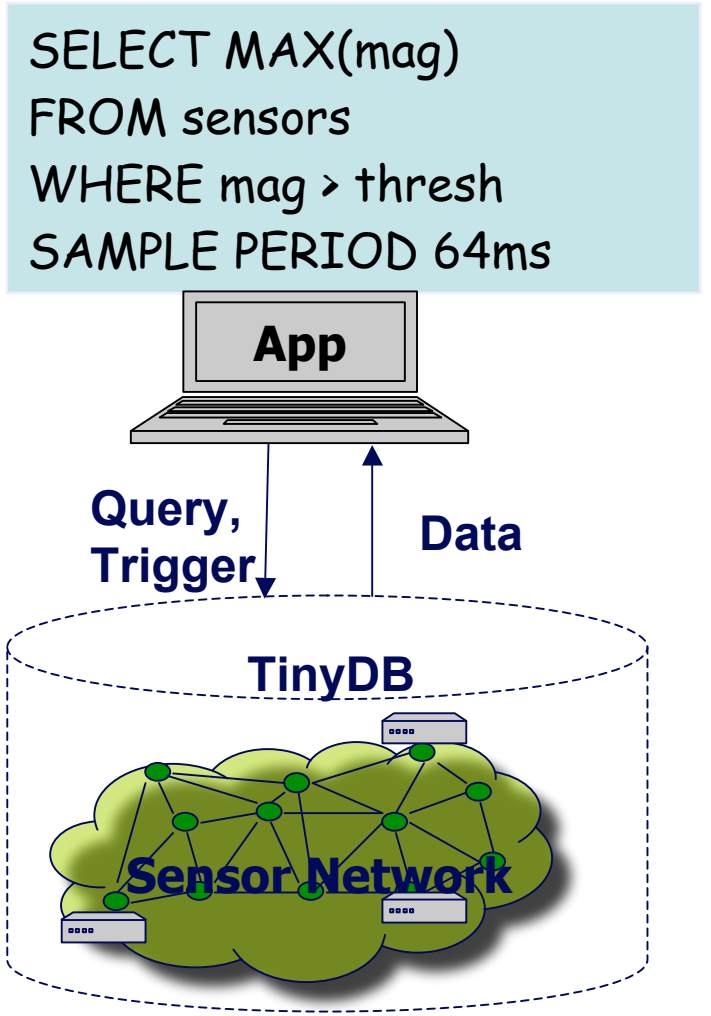


Medusa


Medusa Node
Local Partition of Distributed Catalog (Lookup)
Brain
QueryProcessor (Aurora)
IOQueues
DHT (Chord)
Transport Independent RPC (XML-RPC, TCP-RPC, Local)
Control
Data

TinyDB

- High level abstraction:
  - Data centric programming
  - Interact with sensor network as a whole
  - Extensible framework
- Under the hood:
  - Intelligent query processing: query optimization, power efficient execution
  - Fault Mitigation: automatically introduce redundancy, avoid problem areas



[Source: Sam Madden]

Feature Overview

- Declarative SQL-like query interface
- Metadata catalog management
- Multiple concurrent queries
- Network monitoring (via queries)
- In-network, distributed query processing
- Extensible framework for attributes, commands and aggregates
- In-network, persistent storage

[Source: Sam Madden]

NesC/TinyOS

- NesC: a C dialect for embedded programming
  - Components, “wired together”
  - Quick commands and asynch events
- TinyOS: a set of NesC components
  - hardware components
  - ad-hoc network formation & maintenance
  - time synchronization

Think of the pair as a programming environment

[Source: Sam Madden]

TinyDB Architecture

TinyDB GUI

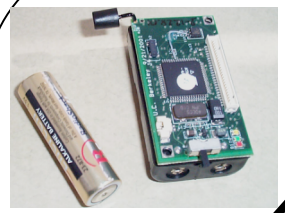
TinyDB Client API

JDBC

DBMS

PC side

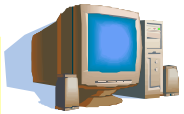
Mote side



[Source: Sam Madden]

Inside TinyDB

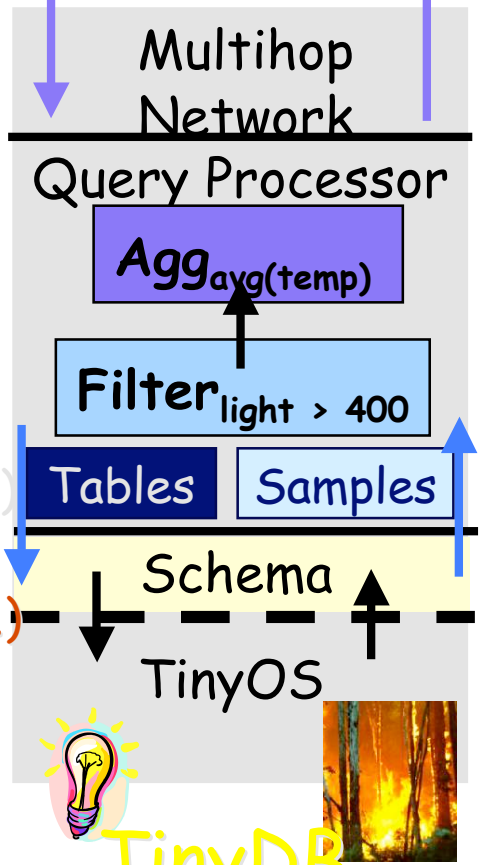
```
SELECT
AVG(temp)
WHERE
light > 400
```



Queries

Results

```
T:1, AVG: 225
T:2, AVG: 250
```



get ('temp')

got('temp')

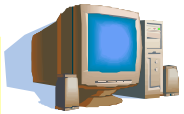
getTempFunc(...)

Name: temp
Time to sample: 50 uS
Cost to sample: 90 uJ
Calibration Table: 3
Units: Deg. F
Error: ± 5 Deg F

Get *f* : `getTempFunc()`...

[Source: Sam Madden]

Inside TinyDB



SELECT
AVG(temp)
WHERE
light > 400

Queries

Results

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T:2, AVG: 250

Multihop
Network

Query Processor

~10,000 Lines Embedded C Code

~5,000 Lines (PC-Side) Java

~3200 Bytes RAM (w/ 768 byte heap)

~58 kB compiled code

(3x larger than 2nd largest TinyOS Program)

[Source: Sam Madden]

TinyDB Status

- Latest released with TinyOS 1.1 (9/03)
  - Install the task-tinydb package in TinyOS 1.1 distribution
  - First release in TinyOS 1.0 (9/02)
  - Widely used by research groups as well as industry pilot projects
- Successful deployments in Intel Berkeley Lab and redwood trees at UC Botanical Garden
  - Largest deployment: ~80 weather station nodes
  - Network longevity: 4-5 months

[Source: Sam Madden]

TinyDB Data Model

- Entire sensor network as one single, infinitely-long logical table: *sensors*
- Columns consist of all the *attributes* defined in the network
- Typical attributes:
  - Sensor readings
  - Meta-data: node id, location, etc.
  - Internal states: routing tree parent, timestamp, queue length, etc.
- Nodes return NULL for unknown attributes
- On server, all attributes are defined in catalog.xml
- Discussion: other alternative data models?

[Source: Sam Madden]

TinySQL

SELECT <aggregates>, <attributes>
[FROM {sensors | <buffer>}]
[WHERE <predicates>]
[GROUP BY <exprs>]
[SAMPLE PERIOD <const> | ONCE]
[INTO <buffer>]
[TRIGGER ACTION <command>]

[Source: Sam Madden]

TinySQL Examples

"Find the sensors in bright nests."

1

```
SELECT nodeid, nestNo, light
FROM sensors
WHERE light > 400
EPOCH DURATION 1s
```

Sensors

Epoch	Nodeid	nestNo	Light
0	1	17	455
0	2	25	389
1	1	17	422
1	2	25	405

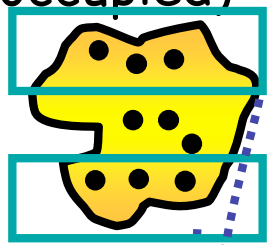
[Source: Sam Madden]

TinySQL Examples (cont.)

2
```
SELECT AVG(sound)
FROM sensors
EPOCH DURATION 10s
```

"Count the number occupied nests in each loud region of the island."

3
```
SELECT region, CNT(occupied)
       AVG(sound)
FROM sensors
GROUP BY region
HAVING AVG(sound) > 200
EPOCH DURATION 10s
```



Epoch	region	CNT(…)	AVG(…)
0	North	3	360
0	South	3	520
1	North	3	370
1	South	3	520

Regions w/ AVG(sound) > 200

[Source: Sam Madden]

Event-based Queries

- ON event SELECT …
- Run query only when interesting events happens
- Event examples
  - Button pushed
  - Message arrival
  - Bird enters nest
- Analogous to triggers but events are user-defined

[Source: Sam Madden]

Query over Stored Data

- Named buffers in Flash memory
- Store query results in buffers
- Query over named buffers
- Analogous to materialized views
- Example:
  - CREATE BUFFER name SIZE x (field1 type1, field2 type2, …)
  - SELECT a1, a2 FROM sensors SAMPLE PERIOD d INTO name
  - SELECT field1, field2, … FROM name SAMPLE PERIOD d

[Source: Sam Madden]

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Open Issues

- Multi-way joins equality predicates
  - How do we use constraints and punctuations effectively?
  - Self-joins: looking for patterns in a single stream
  - Natural constraints other than “nesting” constraints
- Approximate aggregate:
  - How can this work be used by data stream systems?
  - Engineering summary structures (sketches, samples) for low-level data stream processing

Open Issues (cont.)

- Query decomposition:
  - Three-level architecture (low-level and high-level data streams, DBMS)
  - 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?
- Distributed evaluation:
  - 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?

Open Issues (cont.)

- Query optimization:
  - Data stream properties (arrival rate, sortedness) may vary a lot
  - 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 queueing theory?
- I/O and streaming:
  - High-level data stream processing can populate DBMS
  - 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?

Conclusions

- Applications of Data Stream Management Systems
  - Near real-time queries and potentially massive data volumes
  - Sensor networks, network monitoring, intrusion detection, ….
- Stream data analysis: A rich and largely unexplored field
  - Current research focus in database community: DSMS system architecture, continuous query processing, supporting mechanisms, QoS issues, distribution
- Data mining and OLAP analysis of streams
  - Powerful tools for finding general and unusual patterns
  - Largely unexplored: current studies only touched the surface
- Many challenging technical problems
  - Resource limitations exist, especially at low-level
  - Important to think of the end-to-end architecture

Conclusions (cont.)

- Some research prototypes are available
  - TelegraphCQ
  - Aurora
  - Niagara
- Very active research area is promising many new results