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Drinking From The Fire Hose: The Rise of Scalable Stream Processing Systems

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Cambridge MPhil – February 2013


THE
END
IS
NEAR

The Data Deluge

150 Exabytes (billion GBs) created in 2005 alone

- Increased to 1200 Exabytes in 2010

Many new sources of data become available

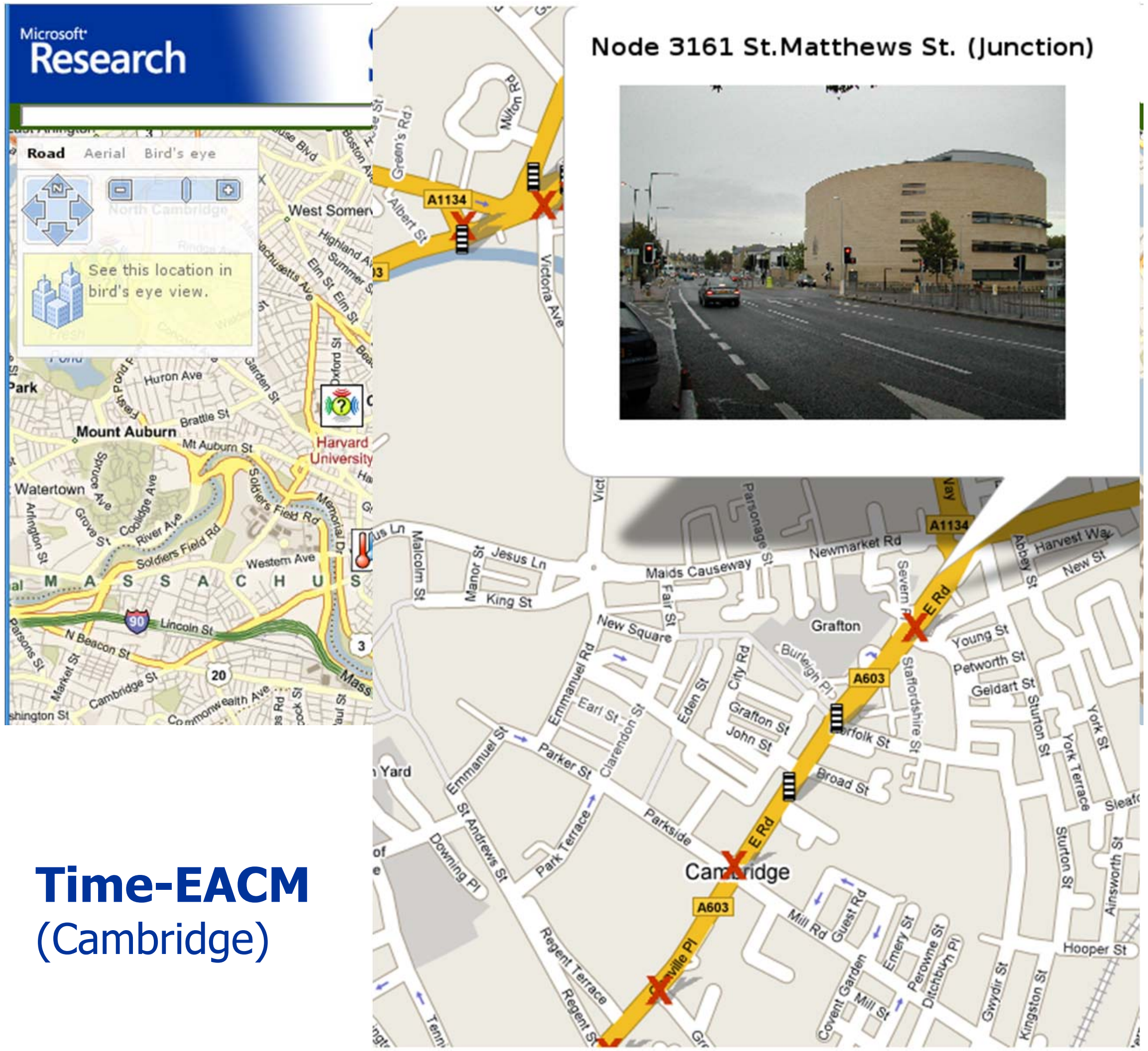
- Sensors, mobile devices
- Web feeds, social networking
- Cameras
- Databases
- Scientific instruments

☛ **How can we make sense of all data ?**

- Most data is not interesting
- New data supersedes old data
- Challenge is not only storage but also querying

Real Time Traffic Monitoring

Instrumenting country's transportation infrastructure



Time-EACM
(Cambridge)

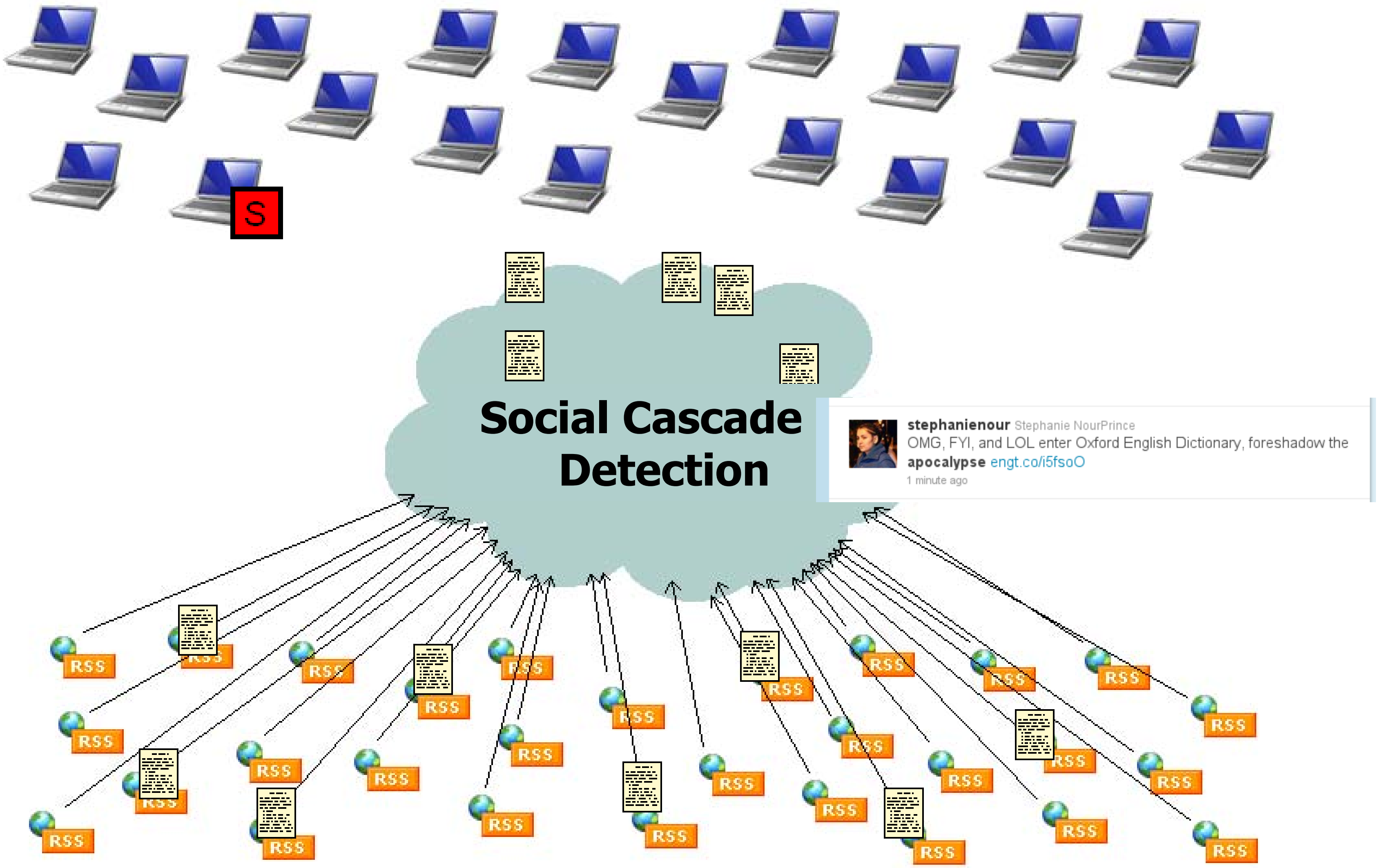
Many parties interested in data

- Road authorities, traffic planners, emergency services, commuters
- But access not everything: Privacy

High-level queries

- "What is the best time/route for my commute through central London between 7-8am?"

Web/Social Feed Mining



Detection and reaction to social cascades

Fraud Detection

How to detect identity fraud as it happens?

Illegal use of mobile phone, credit card, etc.

- Offline: avoid aggravating customer
- Online: detect and intervene

Huge volume of call records

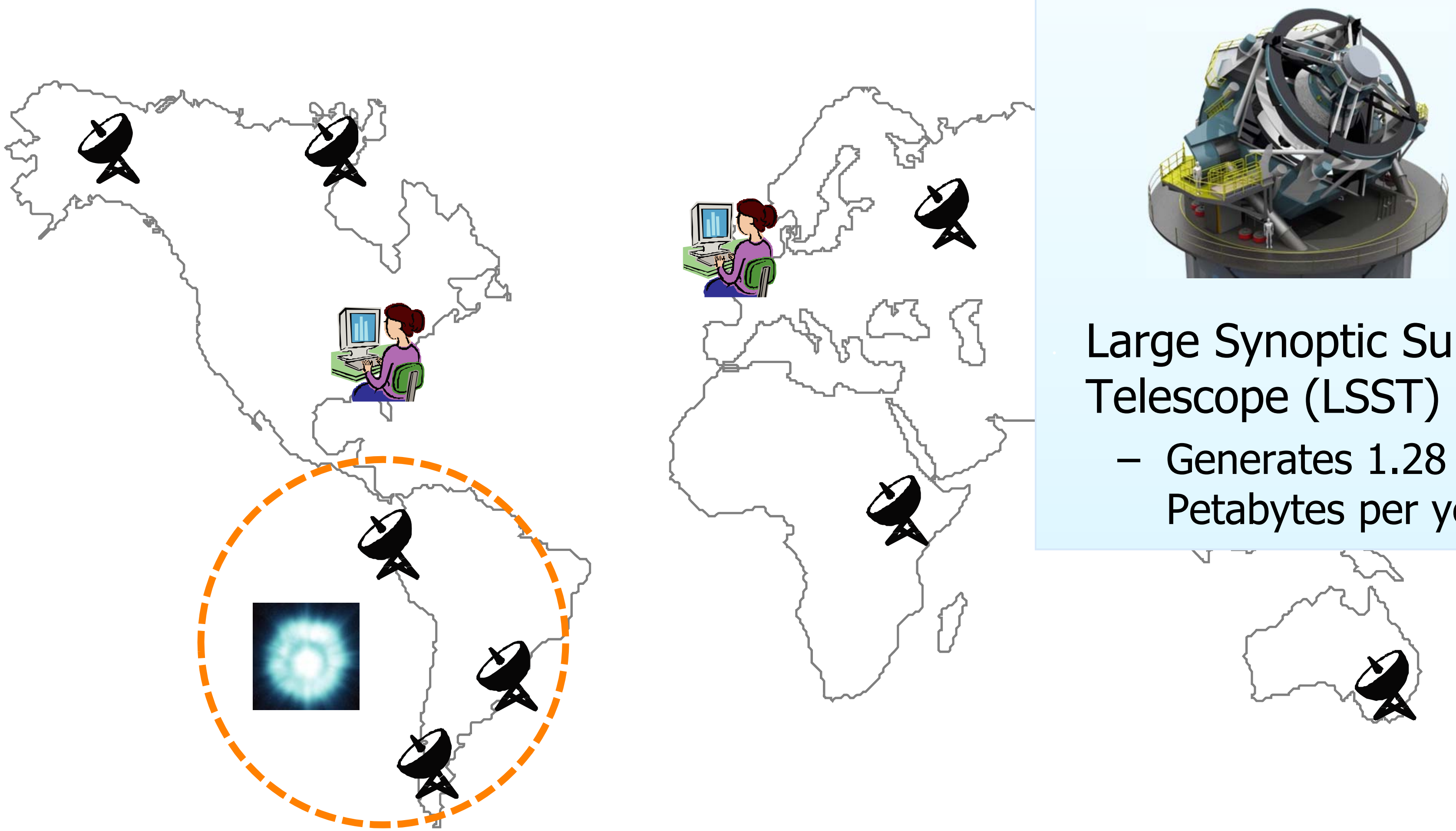
More sophisticated forms of fraud

- e.g. insider trading

Supervision of laws and regulations

- e.g. Sabanes-Oxley, real-time risk analysis

Astronomic Data Processing



Large Synoptic Survey Telescope (LSST)

- Generates 1.28 Petabytes per year

Analysing transient cosmic events: γ-ray bursts

Stream Processing to the Rescue!

☛ Process data streams on the fly without storage

Stream data rates can be high

- High resource requirements for processing (clusters, data centres)

Processing stream data has real-time aspect

- Latency of data processing matters
- Must be able to react to events as they occur

Traditional Databases (Boring)

D

Qu

es

Data Stream Processing System

result stream

- Indexing?

Overview

Why Stream Processing?

Stream Processing Models

- Streams, windows, operators
- Data mining of streams

Stream Processing Systems

- Distributed Stream Processing
- Scalable Stream Processing in the Cloud

Stream Processing

Need to define

1. Data model for streams

2. Processing (query) model for streams

Data Stream

"A **data stream** is a real-time, continuous, ordered (implicitly by arrival time or explicitly by timestamp) **sequence of items**. It is impossible to control the order in which items arrive, nor is it feasible to locally store a stream in its entirety."
[Golab & Ozsu (SIGMOD 2003)]

Relational model for stream structure?

– Can't represent audio/video data
– Can't represent analogue measurements

Relational Data Stream Model

Streams consist of infinite sequence of tuples

- Tuples often have associated time stamp
  - e.g. arrival time, time of reading, ...

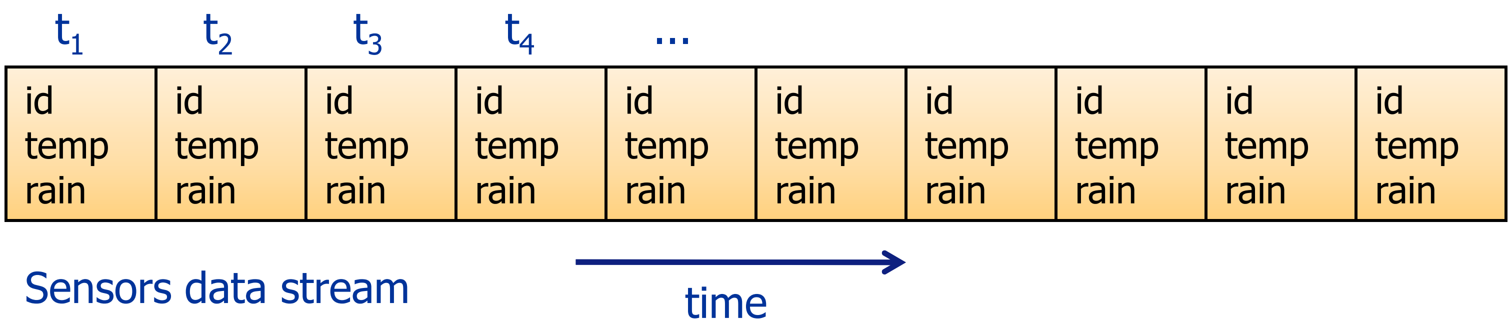
Tuples have fixed relational schema

- Set of attributes

id = 27182
temp = 24 C
rain = 20mm

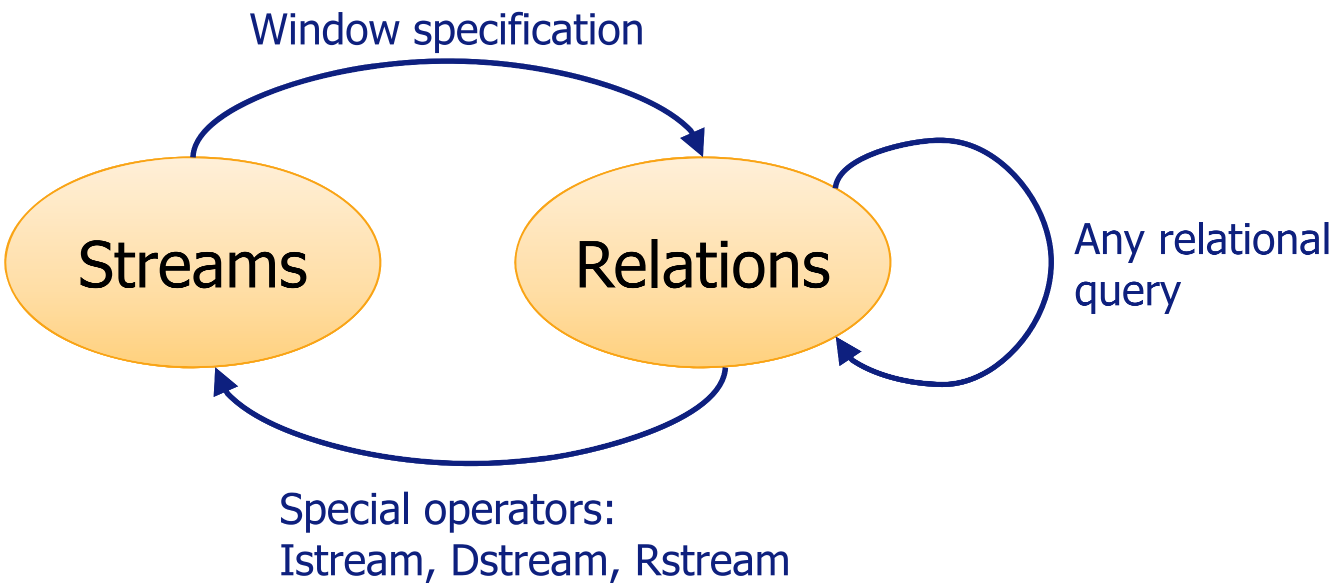
sensor output

`Sensors(id, temp, rain)`



Sensors data stream

Stream Relational Model



Window converts stream to dynamic relation

- Similar to maintaining view
- Use regular relational algebra operators on tuples
- Can combine streams and relations in single query

Sliding Window I

How many tuples should we process each time?

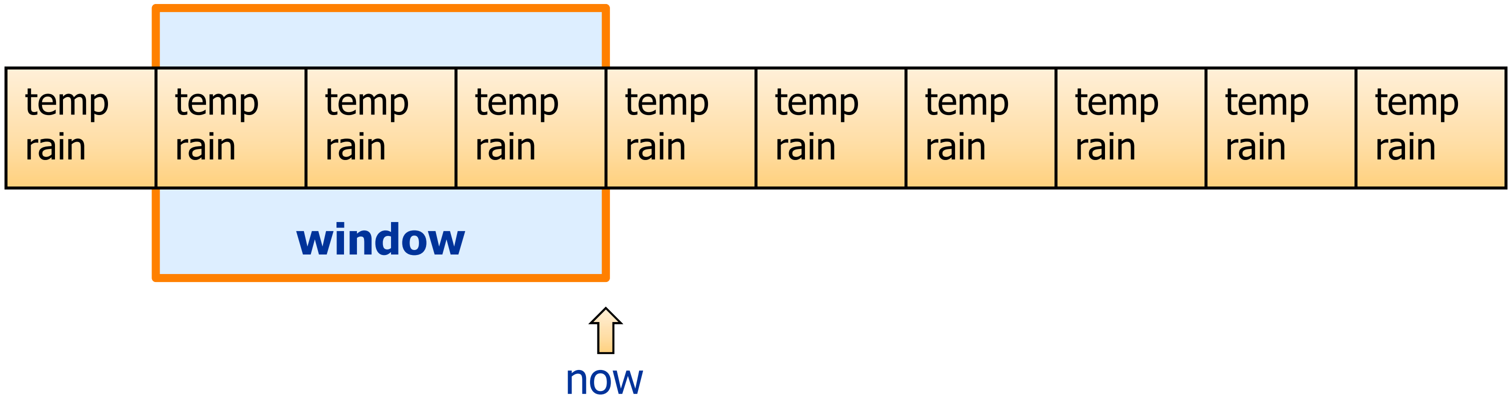
Process tuples in window-sized batches

Time-based window with size τ at current time t

[t - τ : t]	`Sensors [Range τ seconds]`
[t : t]	`Sensors [Now]`

Count-based window with size n:

last n tuples	`Sensors [Rows n]`



Sliding Window II

How often should we evaluate the window?

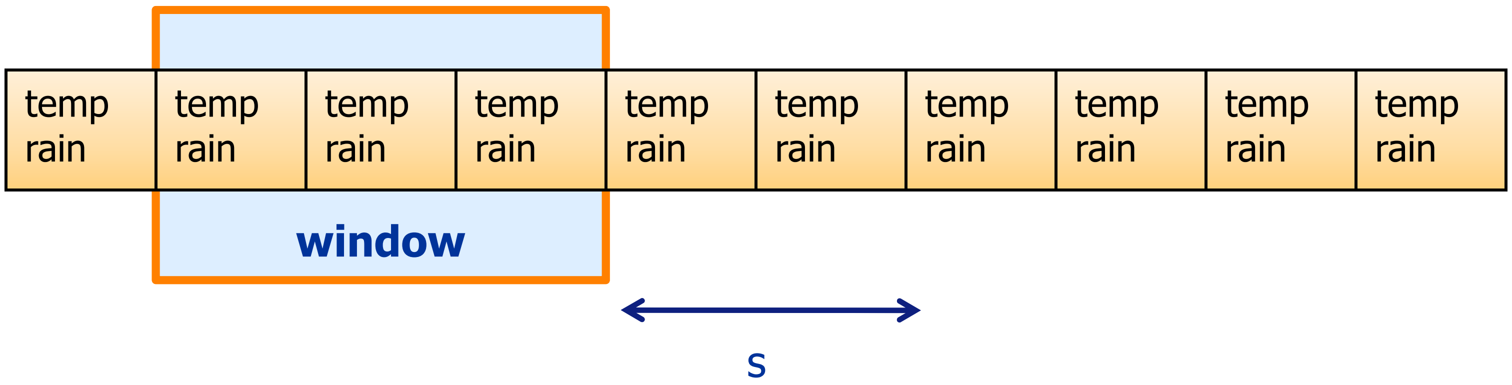
1. Output new result tuples as soon as available
   – Difficult to implement efficiently

2. Slide window by s seconds (or m tuples)

```
Sensors [Slide s seconds]
```

Sliding window: s < T

Tumbling window: s = T



Continuous Query Language (CQL)

Based on SQL with streaming constructs

- Tuple- and time-based windows
- Sampling primitives

```
SELECT temp
FROM Sensors [Range 1 hour]
WHERE temp > 42;
```

```
SELECT *
FROM S1 [Rows 1000],
     S2 [Range 2 mins]
WHERE S1.A = S2.A
   AND S1.A > 42;
```

Apart from that regular SQL syntax

Join Processing

Naturally supports joins over windows

```
SELECT *
FROM S1, S2
WHERE S1.a = S2.b;
```

Only meaningful with window specification for streams

- Otherwise requires unbounded state!

Sensors(time, id, temp, rain) **Faulty(time, id)**

```
SELECT S.id, S.rain
FROM Sensors [Rows 10] as S, Faulty [Range 1 day] as F
WHERE S.rain > 10 AND F.id != S.id;
```

Converting Relations ➔ Streams

Define mapping from relation back to stream

- Assumes discrete, monotonically increasing timestamps
  $\tau, \tau+1, \tau+2, \tau+3, \ldots$

Istream(R)

- Stream of all tuples (r, τ) where $r \in R$ at time τ but $r \notin R$ at time $\tau-1$

Dstream(R)

- Stream of all tuples (r, τ) where $r \in R$ at time $\tau-1$ but $r \notin R$ at time τ

Rstream(R)

- Stream of all tuples (r, τ) where $r \in R$ at time τ

Data Mining in Streams

Stream Data Mining

Often continuous queries relate to long-term characteristics of streams

- Frequency of stock trades, number of invalid sensor readings, ...

May have insufficient memory to evaluate query

- Consider stream with window of 10^9 integers
  - Can store this in 4GB of memory
- What about 10^6 such streams?
  - Cannot keep all windows in memory

☛ Need to compress data in windows

Limitations of Window Compression

Consider window compression for following query:

```
SELECT SUM(num)
FROM Numbers [Rows 10⁹];
```

Assume that W can be compressed as $C(W) = W_C$

- Then $W_1 \neq W_2$ must exist, with $C(W_1) = C(W_2)$
- Let t be oldest time in window for which W1 and W2 differ:

W_1	**3**	5	8	9	2	3	9	7	8	9
W_2	**4**	5	8	2	0	7	0	7	2	1

⇧

t

- For W_1: subtract $W_1(t) = 3$; for W_2: subtract $W_2(t) = 4$
  - Cannot distinguish between cases from C(W1) = C(W2)
- No correct compression scheme C(W) possible

Approximate Sum Calculation

Keep sums Σ_i for each n tuples in window

- Compression ratio is 1/n

v_1	v_2	…	v_n	v_{n+1}	v_{n+2}	…	v_{2n}	…	v_{2n+1}	v_{2n+2}

n tuples

n tuples

2 tuples
(incomplete group)

$$\Sigma_W = \boxed{\Sigma_1} + \boxed{\Sigma_2} + \ldots + \boxed{\Sigma_{incomplete}}$$

- Estimate of window sum Σ_W is total of group sums Σ_i

Now v_1 leaves window and v_{2n+3} arrives:

$$\Sigma_W = \boxed{(n\text{-}1/n) * \Sigma_1} + \boxed{\Sigma_2} + \ldots + \boxed{\Sigma_{incomplete}}$$

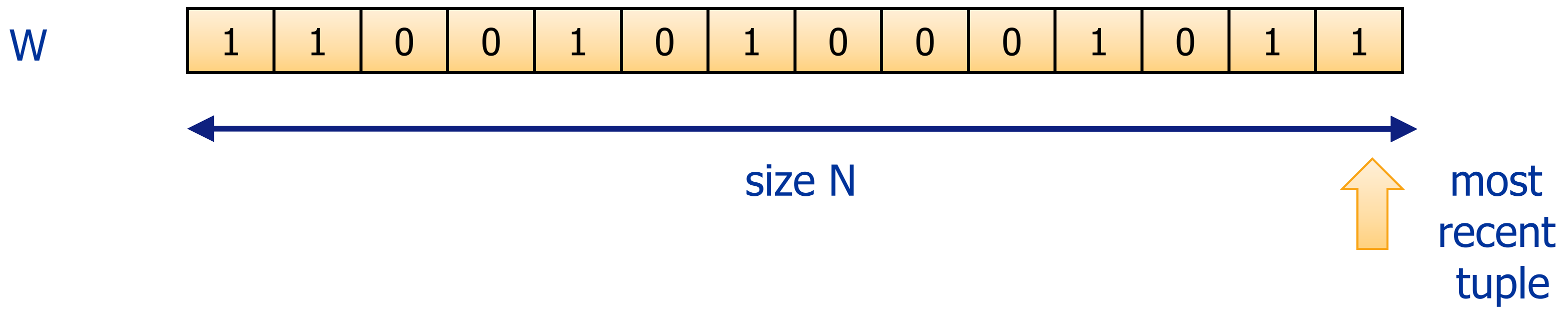
3 tuples
(incomplete group)

- Accuracy of approximation depends on variance

Counting Bits

Assume sliding window W of size N contains bits 1 and 0

– How many 1s are there in the most recent k bits?
  ($1 \le k \le N$)



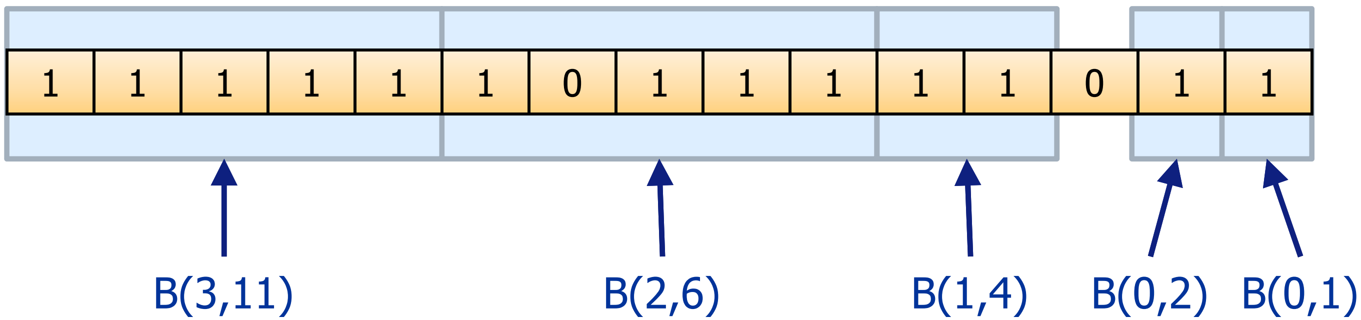
Could answer question trivially with O(N) storage

– But can we approximate answer with, say, logarithmic storage?

Approximate Counting with Buckets

Divide window into multiple buckets B(m, t)

- B(m, t) contains 2^m 1s and starts at t
- Size of buckets does not decrease as t increases
- Either one or two buckets for each size m
- Largest bucket only partially filled



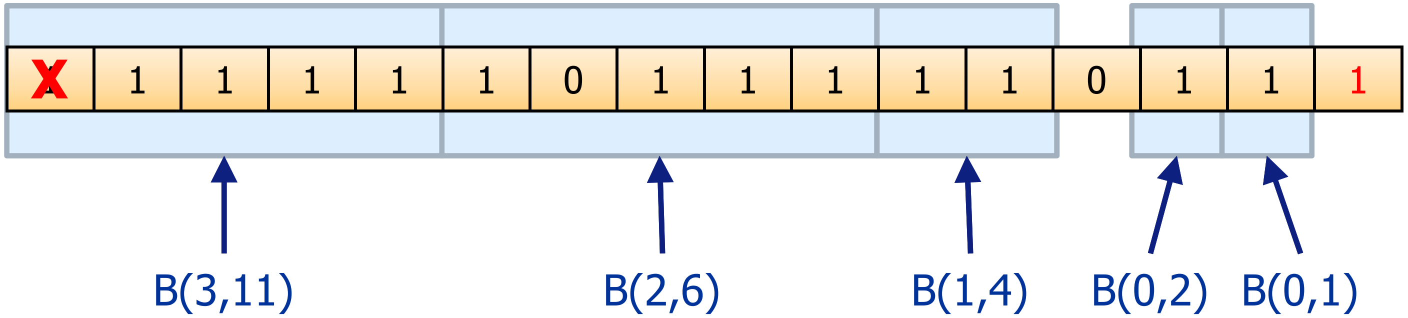
Estimate sum of last k tuples Σ_k:

Σ_k = {sizes of buckets within k} + ½ {last partial bucket}

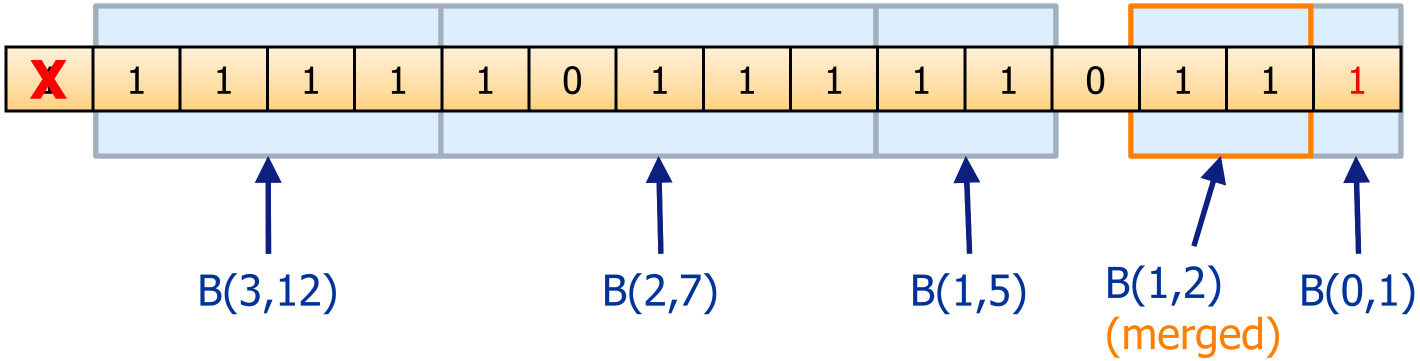
$\Sigma_N = 2^0 + 2^0 + 2^1 + 2^2 + ½ * 2^3 = 12$ (exact answer: 13)

Maintaining Buckets

Discard/merge buckets as window slides



- Discard largest bucket once outside of window
- Create new bucket B(0,1) for new tuple if 1
- Merge buckets to restore invariant of at most 2 buckets of each size m



Space Complexity

Need $O(\log N)$ buckets for window of size N

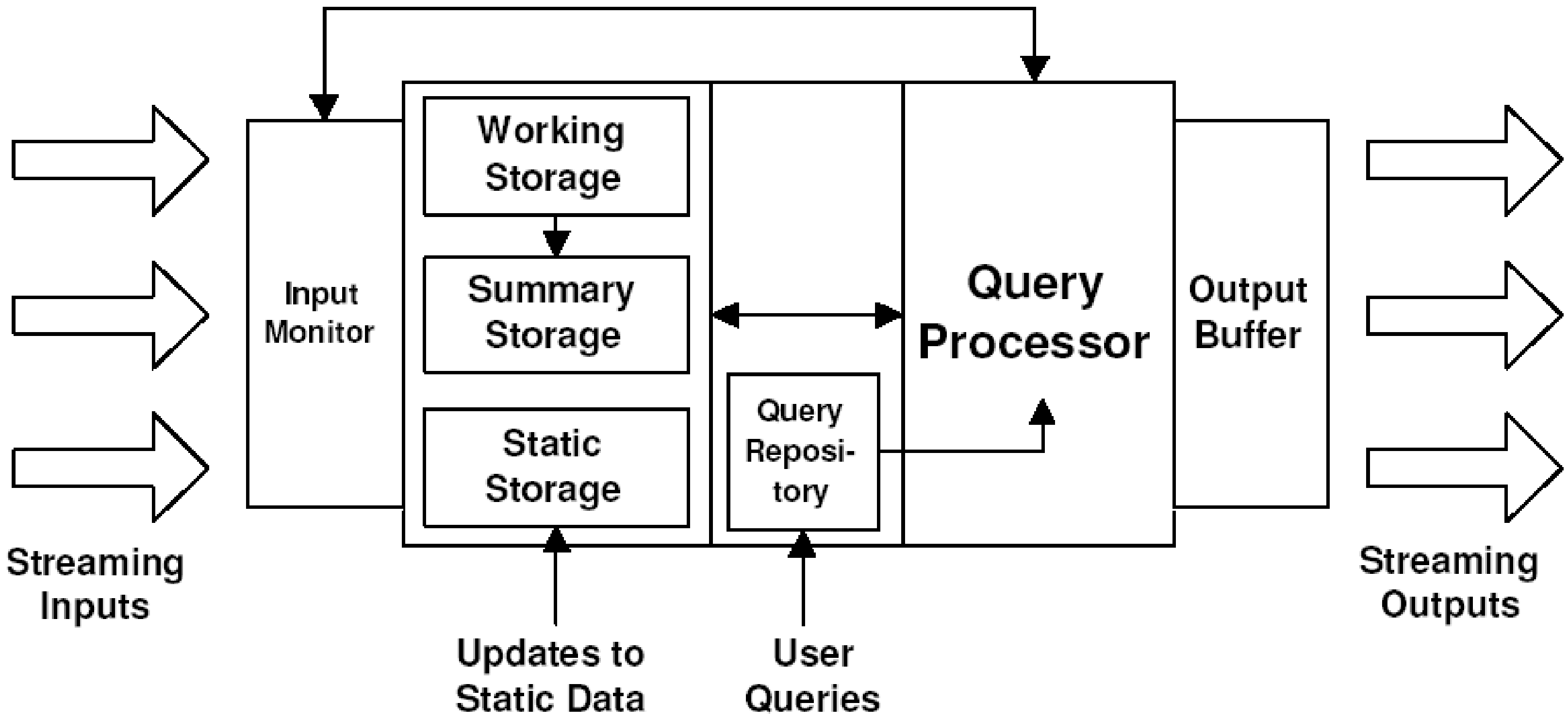
Need $O(\log N)$ bits to represent bucket B(m, t):

- **m** is power of 2, so representable as $\log_2 m$
  m can be represented with $O(\log \log N)$ bits
- t is representable as t mod N
  t can be represented with $O(\log N)$ bits

Overall window compressed to $\mathbf{O(\log^2 N)}$ bits

Stream Processing Systems

General DSPS Architecture



Source: Golab & Ozsu 2003

Stream Query Execution

Continuous queries are long-running
➔ properties of base streams may change

- Tuple distribution, arrival characteristics, query load, available CPU, memory and disk resources, system conditions, ...

Solution: Use **adaptive query plans**

- Monitor system conditions
- Re-optimise query plans at run-time

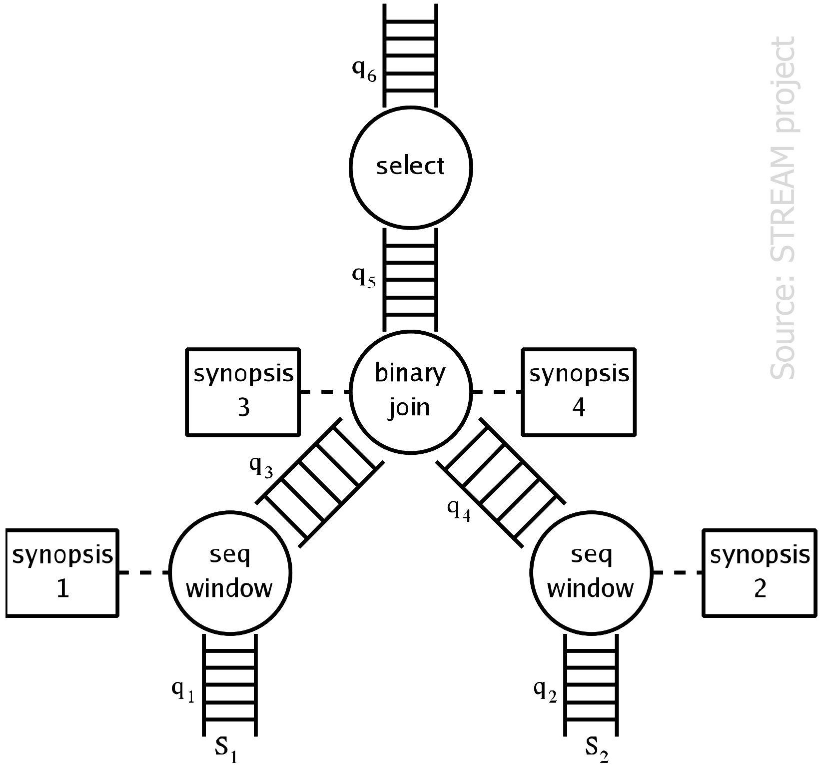
DBMS didn’t quite have this problem...

Query Plan Execution

Executed query plans include:

- **Operators**
- **Queues** between operators
- **State**/“Synposis” (windows, ...)
- **Base streams**

```
SELECT *
FROM S1 [Rows 1000],
     S2 [Range 2 mins]
WHERE S1.A = S2.A
   AND S1.A > 42;
```



Source: STREAM project

Challenges

- State may get large (e.g. large windows)

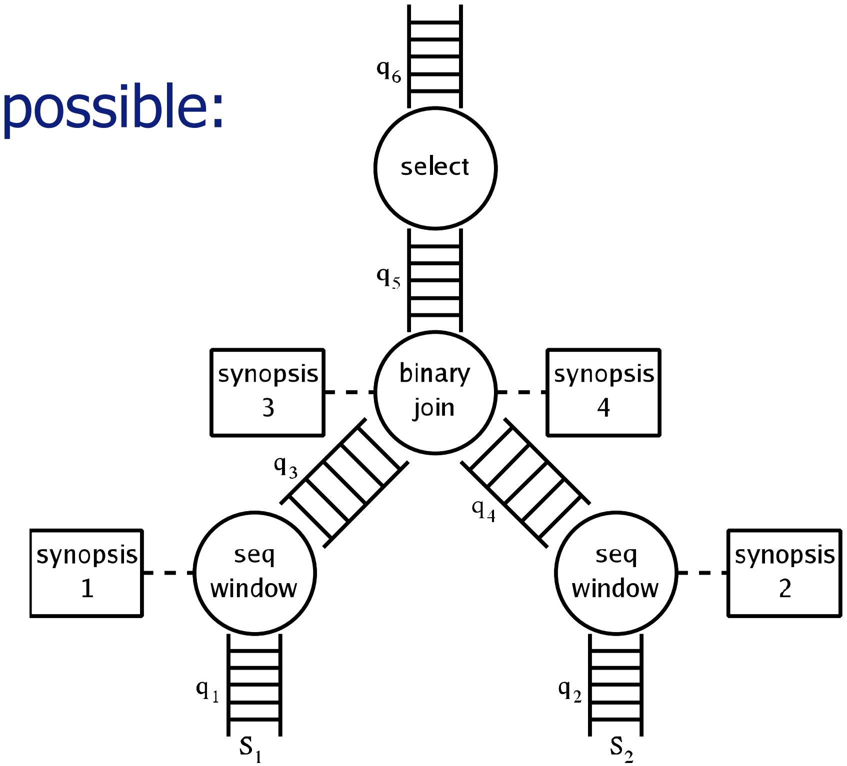
Operator Scheduling

Need scheduler to invoke operators (for time slice)

– Scheduling must be adaptive

Different scheduling disciplines possible:

1. Round-robin
2. Minimise queue length
3. Minimise tuple delay
4. Combination of the above



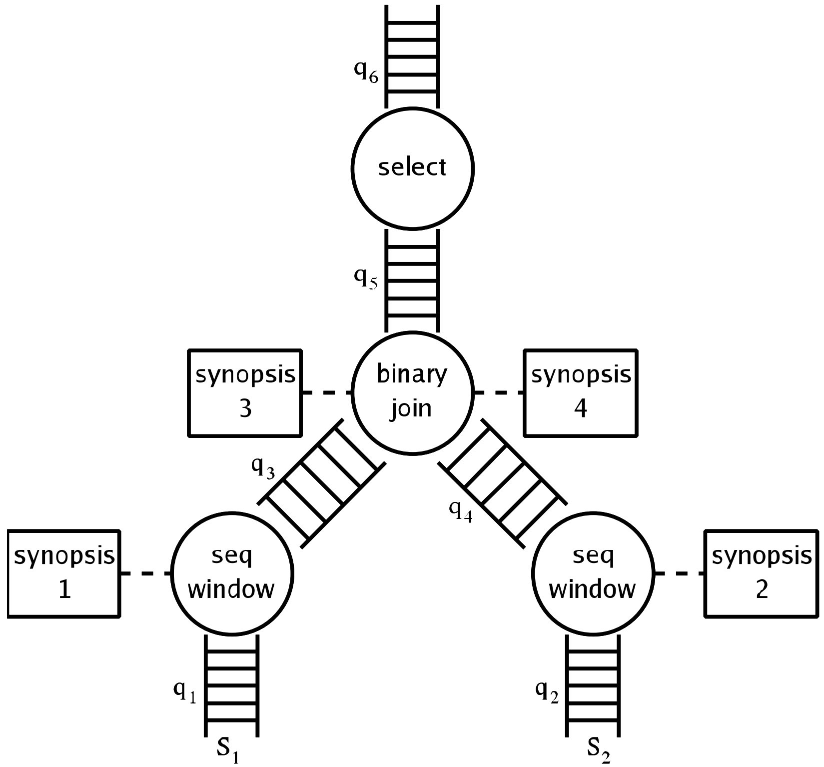
Load Shedding

DSMS must handle overload:
Tuples arrive faster than processing rate

Two options when overloaded:

1. **Load shedding**: Drop tuples
   - Much research on deciding which tuples to drop: c.f. result correctness and resource relief
   - e.g. sample tuples from stream

2. **Approximate processing**: Replace operators with approximate processing
   - Saves resources

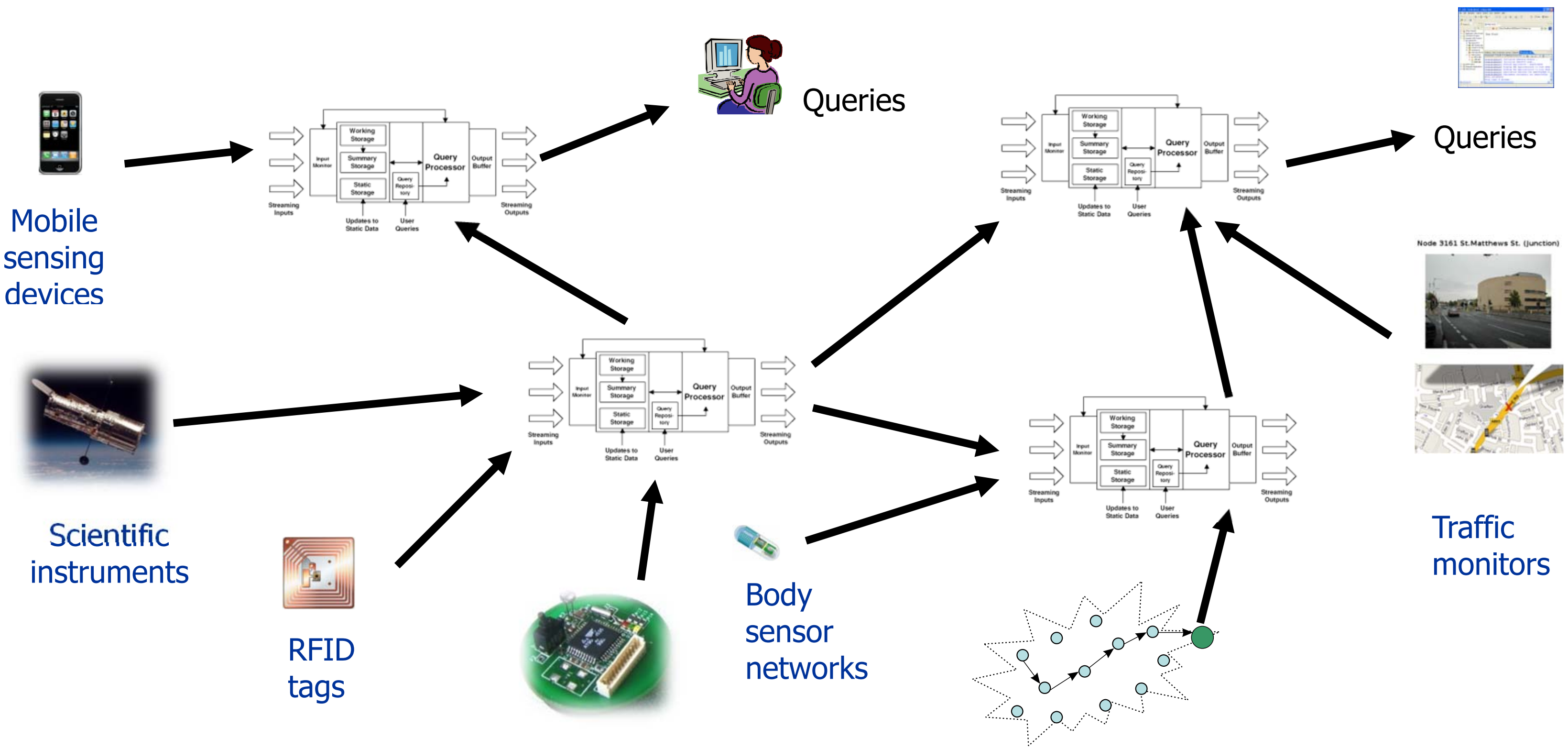


Distributed DSPS

Distributed DSPS

Interconnect multiple DSPSs with network

– Better scalability, handles geographically distributed stream sources

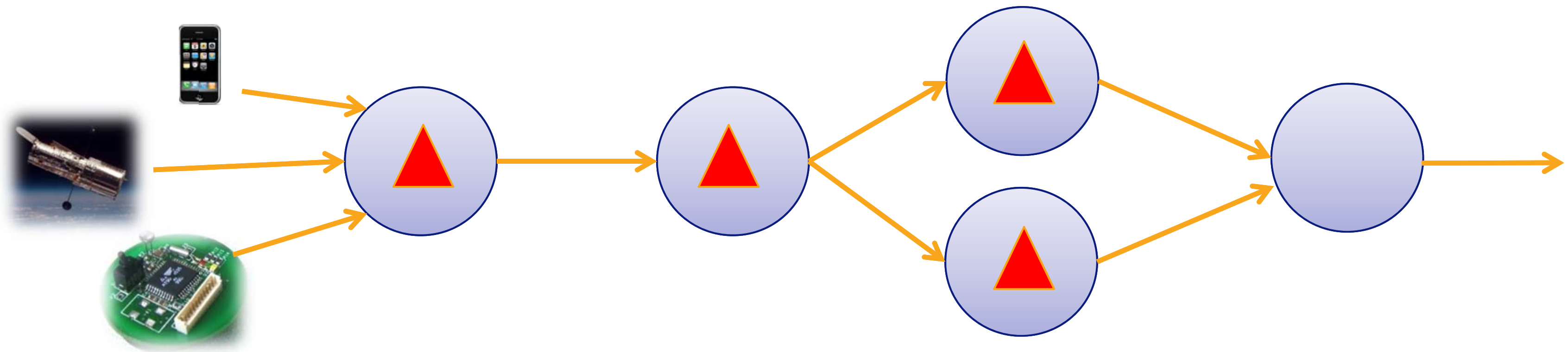


Interconnect on LAN or Internet?

– Different assumptions about <u>time</u> and <u>failure</u> models

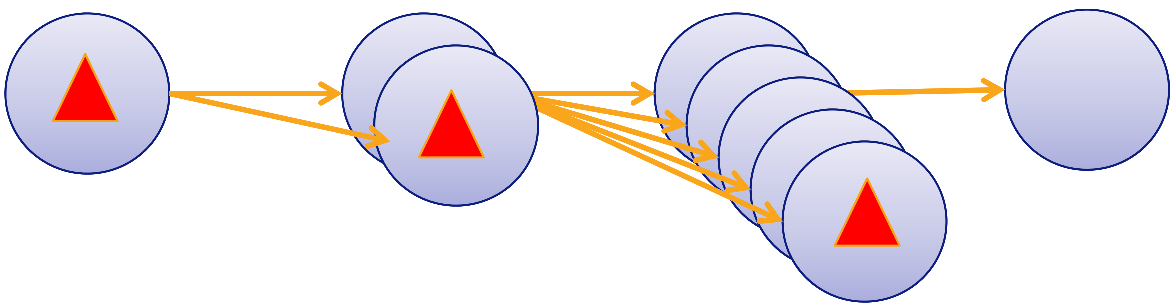
Stream Processing to the Rescue!

☛ Process data streams on-the-fly:
Apache S4, Twitter Storm, Nokia Dempsy, …

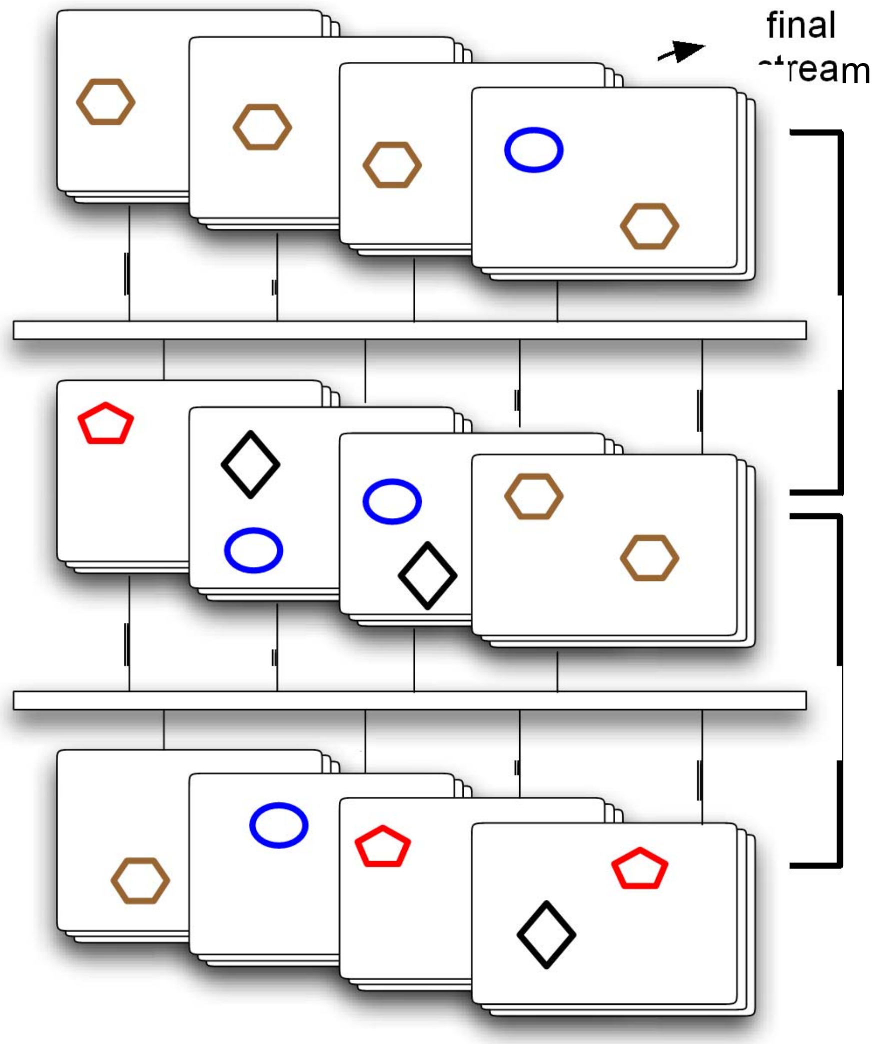


▲ Most interesting operators are **stateful**

☛ Exploit intra-query parallelism for scale out



Query Planning in DSPS



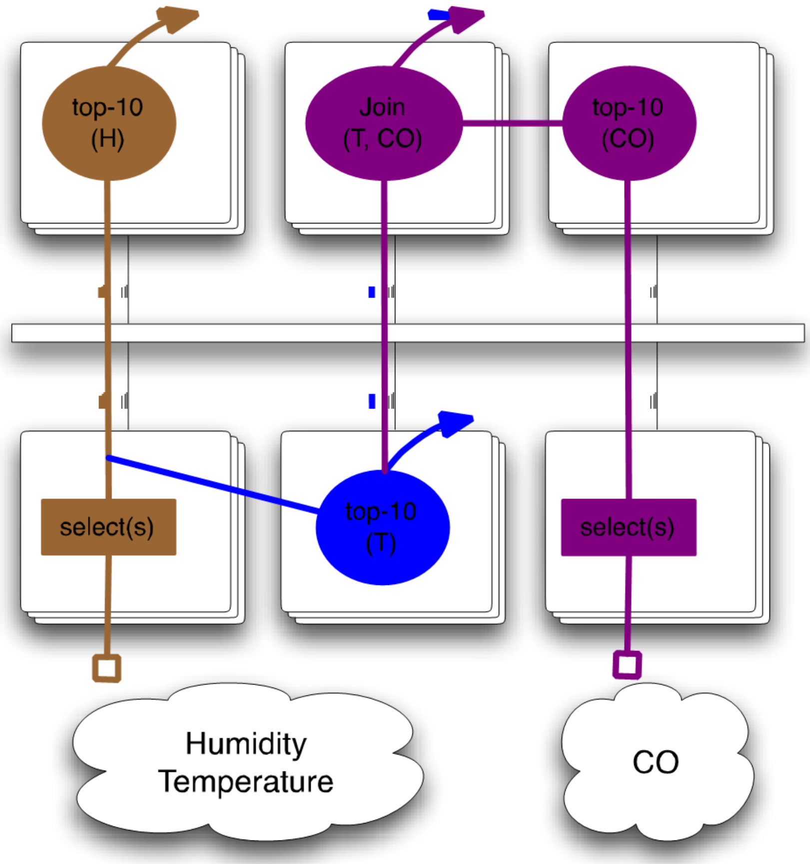
Query Plan

– Operator placement
– Stream connections
– Resource allocation: CPU, network bandwidth, ...

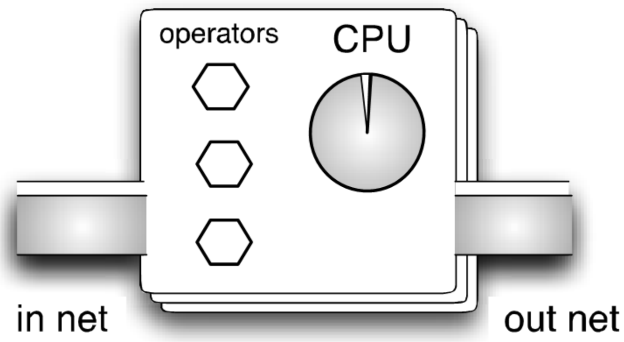
State-of-the-art planners

– Based on heuristics (eg IBM's SODA)
– Assume over-provisioned system
  - Simplifies query planning
  - Not true when you pay for resources...

Planning Challenges



Waste of resources due to query overlap ➔ reuse streams



Premature exhaustion of resources ➔ multi-resource constraints

SQPR: Stream Query Planning with Reuse [ICDE'11]

Unified optimisation problem for

- query admission
- operator allocation
- stream reuse

maximise:

λ_1 * (no of satisfied queries) – λ_2 * (CPU usage) – λ_3 * (net usage) – λ_4 * (balance load)

subject to constraints:

1. availability: streams for operators exist on nodes
2. resource: allocations within resource limits
3. demand: final query streams are generated eventually
4. acyclicity: all streams come from real sources

This is hard!

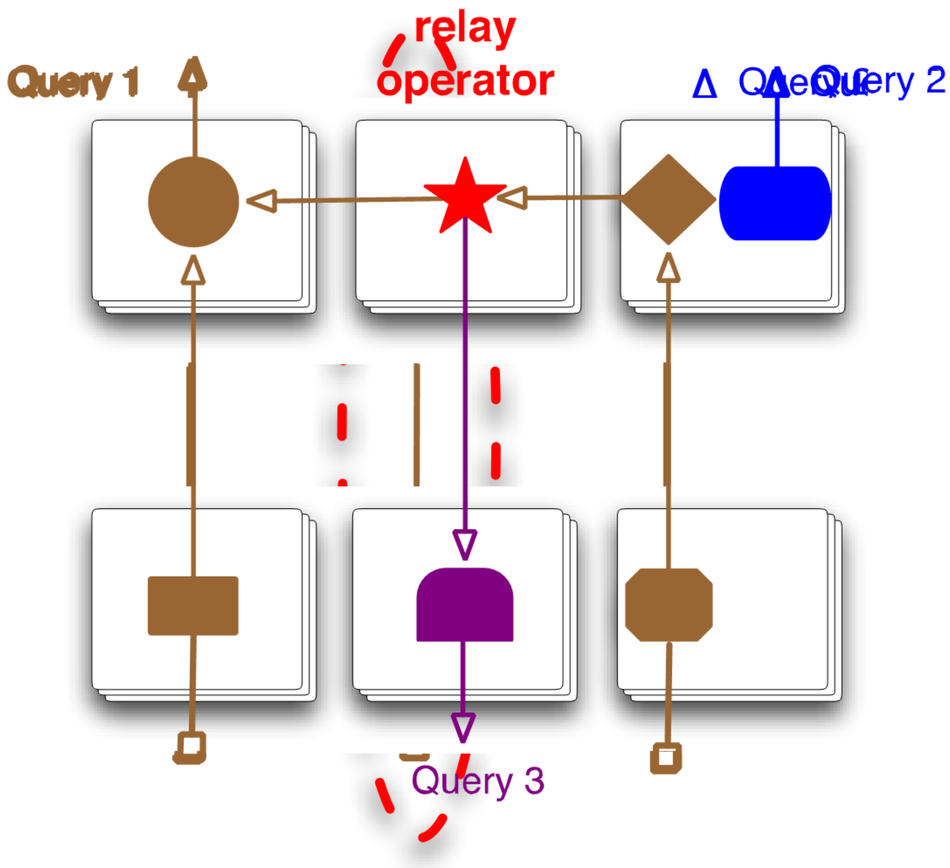
- Solve approximate problem to obtain tractable solution

Evangelia Kalyvianaki, Wolfram Wiesemann, Quang Hieu Vu and Peter Pietzuch, **"SQPR: Stream Query Planning with Reuse"**, IEEE International Conference on Data Engineering (ICDE), Hannover, Germany, April 2011

Tractable Optimisation Model

Idea: Only optimise over streams related to new query

- Add relay operators to work around constraints under reuse

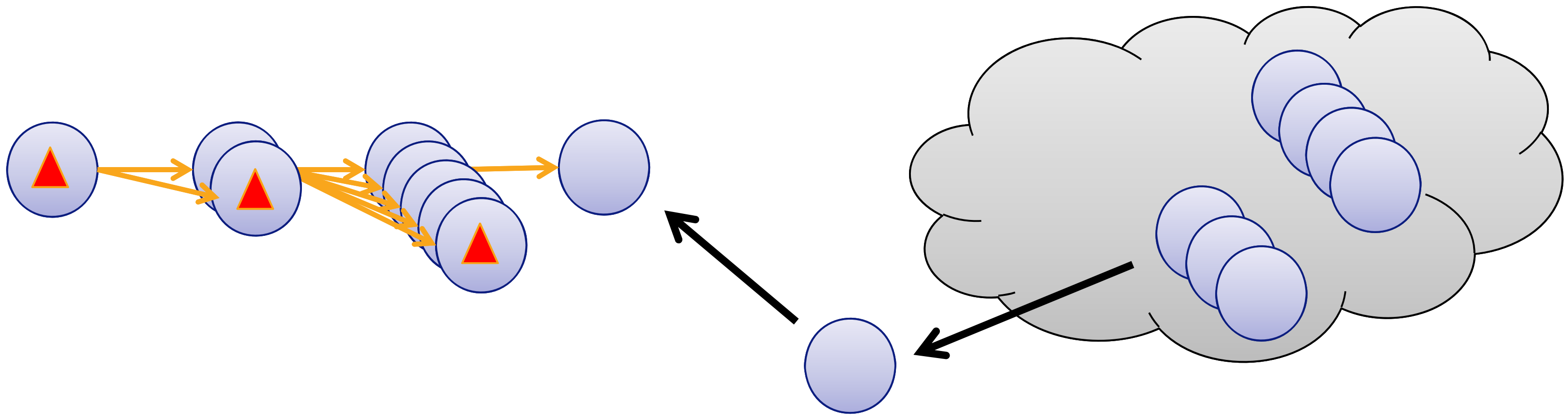


Scalable Stream Processing

Stream Processing in the Cloud

Clouds provide virtually infinite pools of resources

- Fast and cheap access to new machines for operators



In a utility-based pricing model:

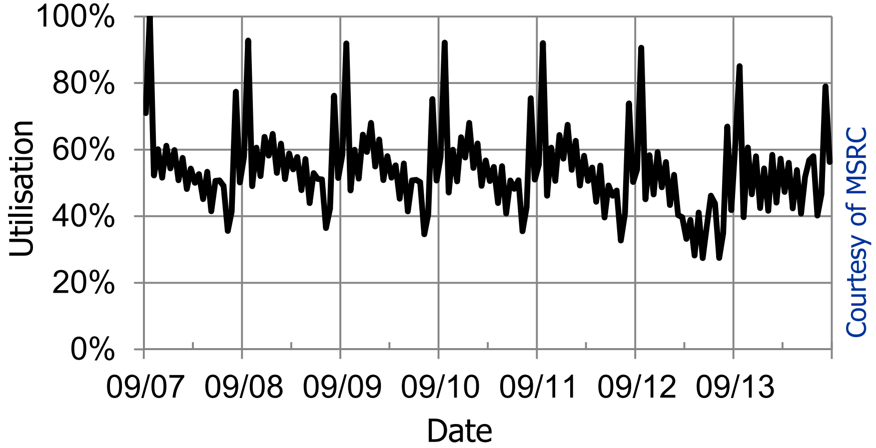
☛ How do you use the optimal number of resources?

- Needlessly overprovisioning system is expense
- Using too few resources leads to poor performance

Challenges in Cloud-Based Stream Processing

Intra-query parallelism

– Provisioning for workload peaks unnecessarily conservative



☛ **Dynamic scale out:** increase resources when peaks appear

Failure resilience

– Active fault-tolerance requires 2x resources
– Passive fault-tolerance leads to long recovery times

☛ **Hybrid fault-tolerance:** low resource overhead with fast recovery

☛ **Stateful operators:** both mechanisms must support stateful operators

SEEP Stream Processing System [SIGMOD'13]

Operator State Management in stream processing

Two state-aware mechanisms:

1. **Dynamic Operator Scale Out**
2. **Upstream Backup with Checkpointing** (UBC)

Evaluation results

Raul Castro Fernandez, Matteo Migliavacca, Evangelia Kalyvianaki, and Peter Pietzuch, **"Integrating Scale Out and Fault Tolerance in Stream Processing using Operator State Management"**, ACM International Conference on Management of Data (SIGMOD), New York, NY, June 2013

Operator State Management

State cannot be lost, or stream results are affected

On **scale out**:

- Partition operator state correctly, maintaining consistency

On **failure recovery**:

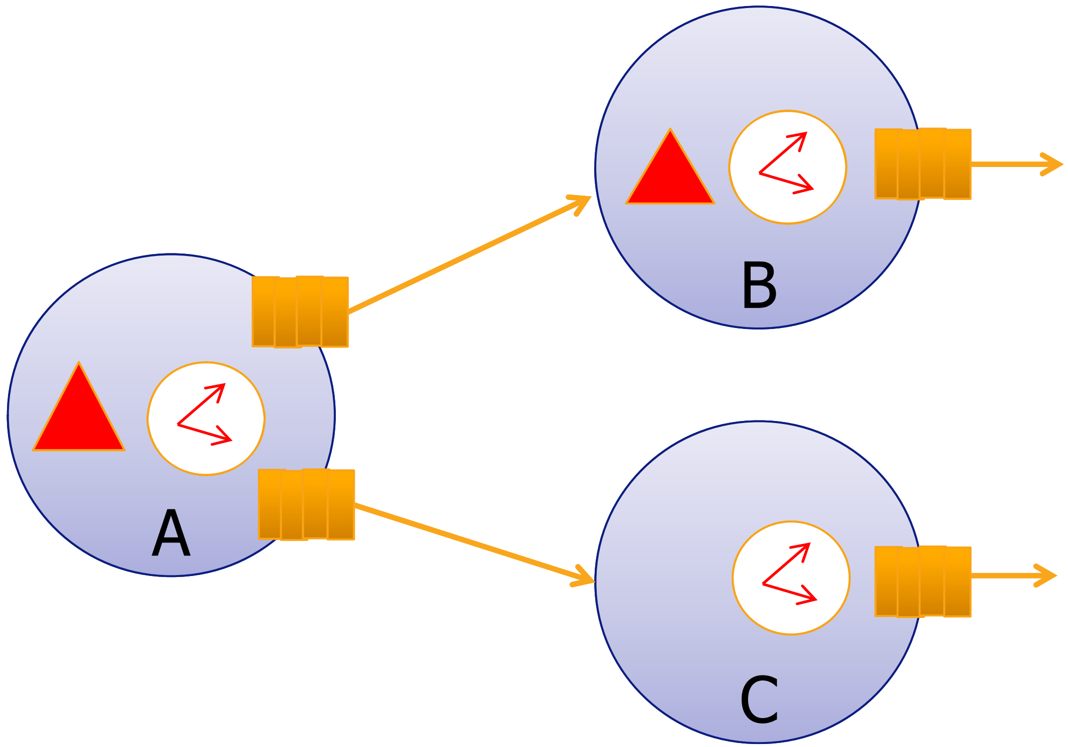
- Restore state of failed operator

☛ Make operator state an external entity that can be managed by the stream processing system

- Define primitives for state management and build other mechanisms on top of them

State Management

What is state in stream processing system?



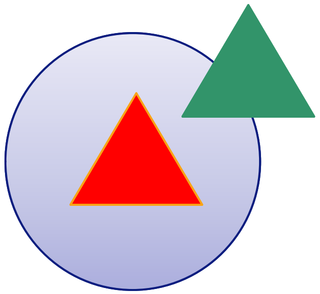
Processing state

Routing state

Buffer state

– Need to externalise processing state of operators

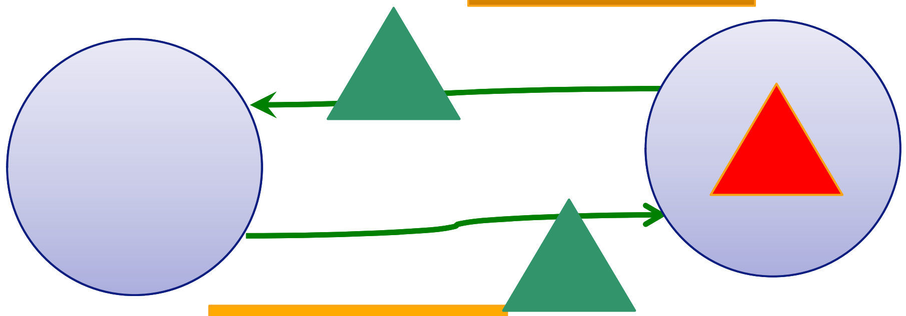
State Management Primitives



☛ **Checkpoint**

Takes snapshot of state and makes it externally available

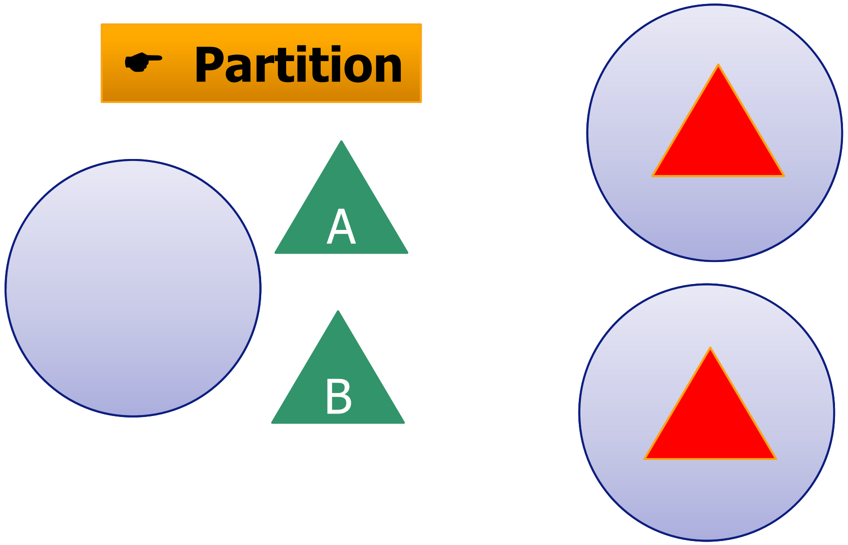
☛ **Backup**



Moves copy of state from one operator to another

☛ **Restore**

☛ **Partition**



Splits state in a semantically correct fashion for parallel processing

State Partitioning

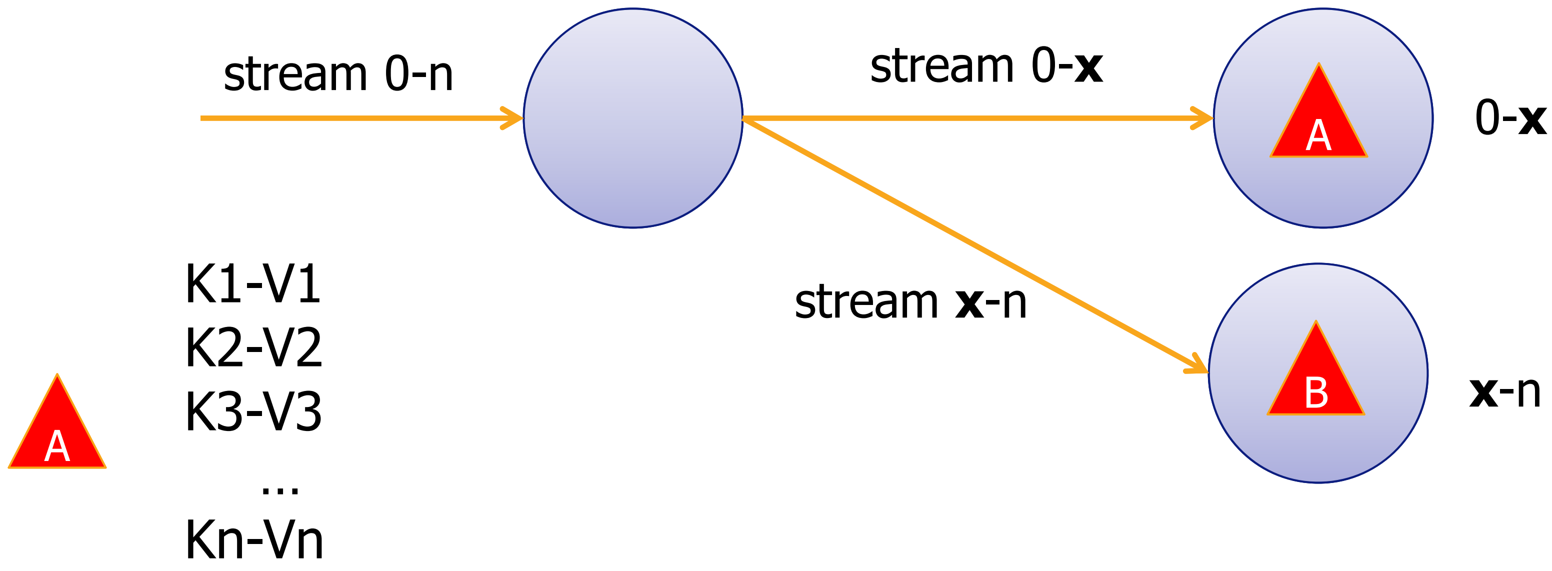
Processing state modeled as (key, value) dictionary

State partitioned according to key k of tuples

- Same key used to partition incoming streams

Tuples will be routed to correct operator

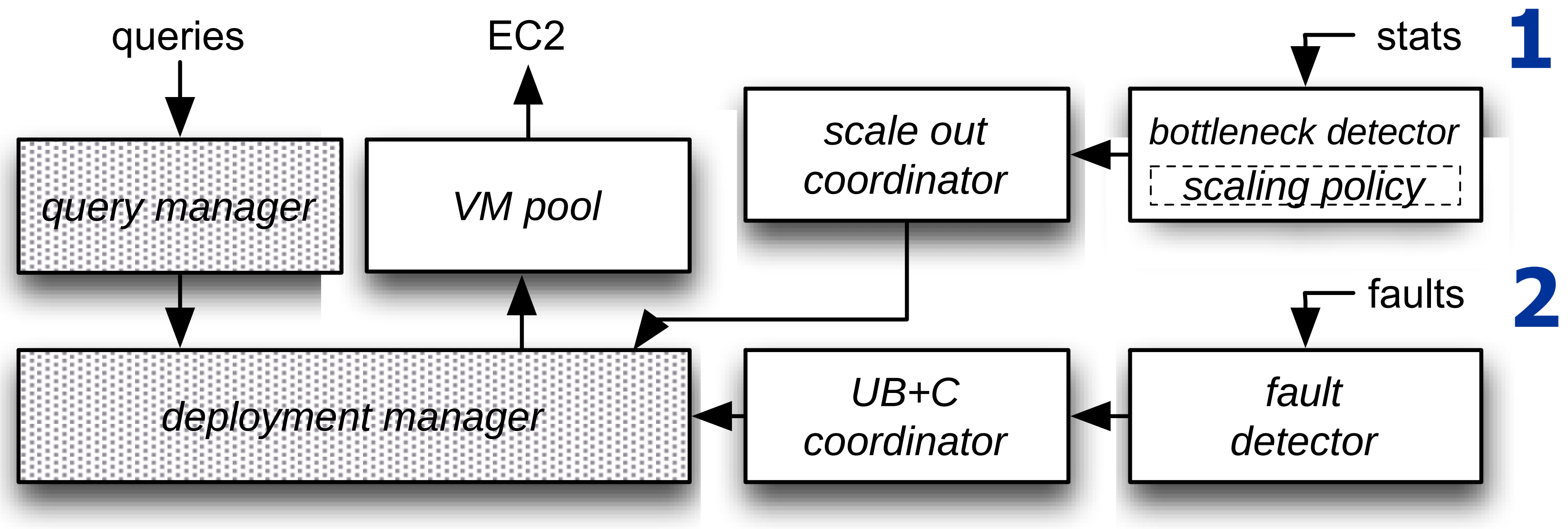
- x is splitting key that partitions state



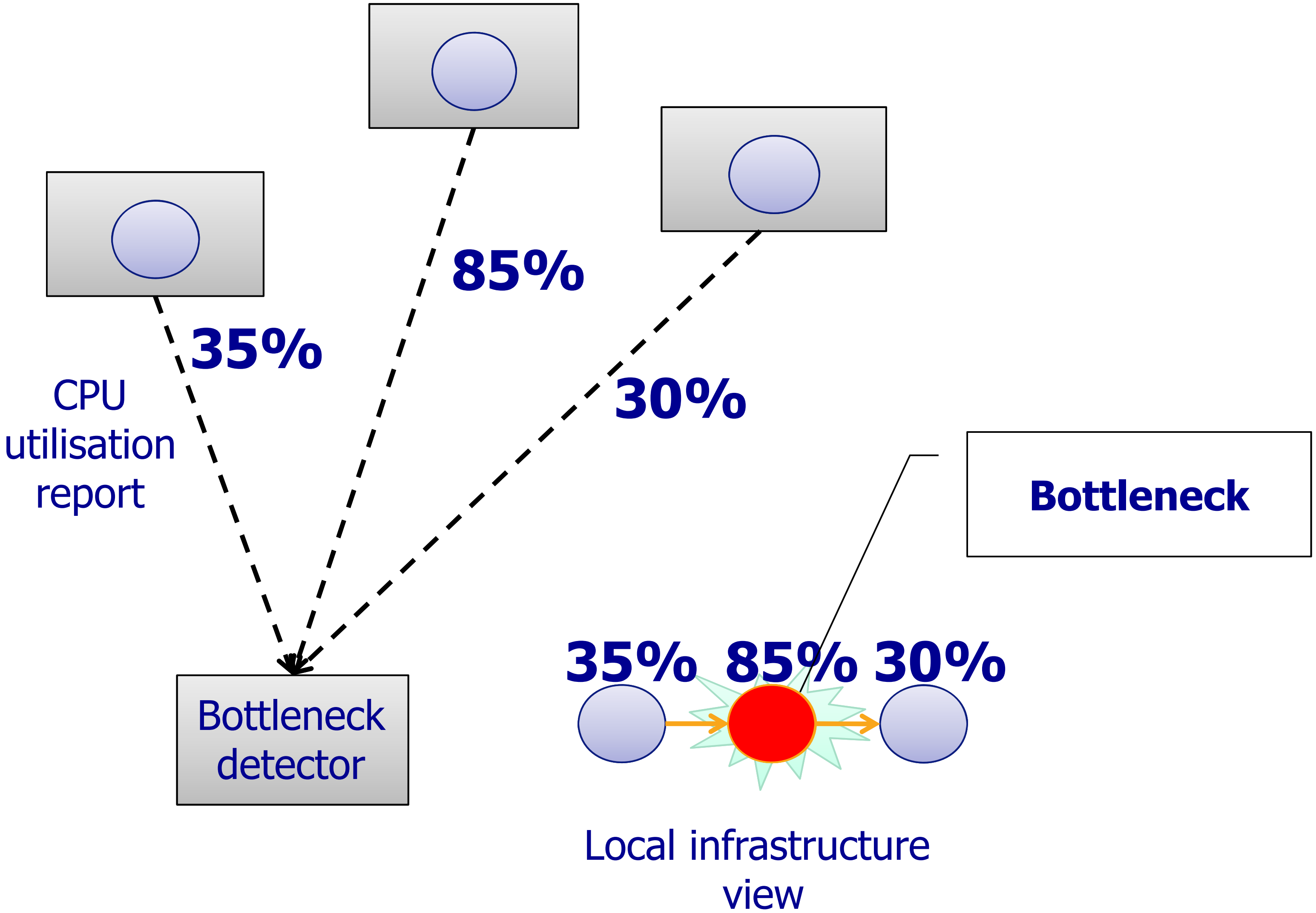
State Management in Action

1. Dynamic Scale Out: Detect bottleneck, remove by adding new parallelised operator

2. Failure Recovery: Detect failure, replace with new operator

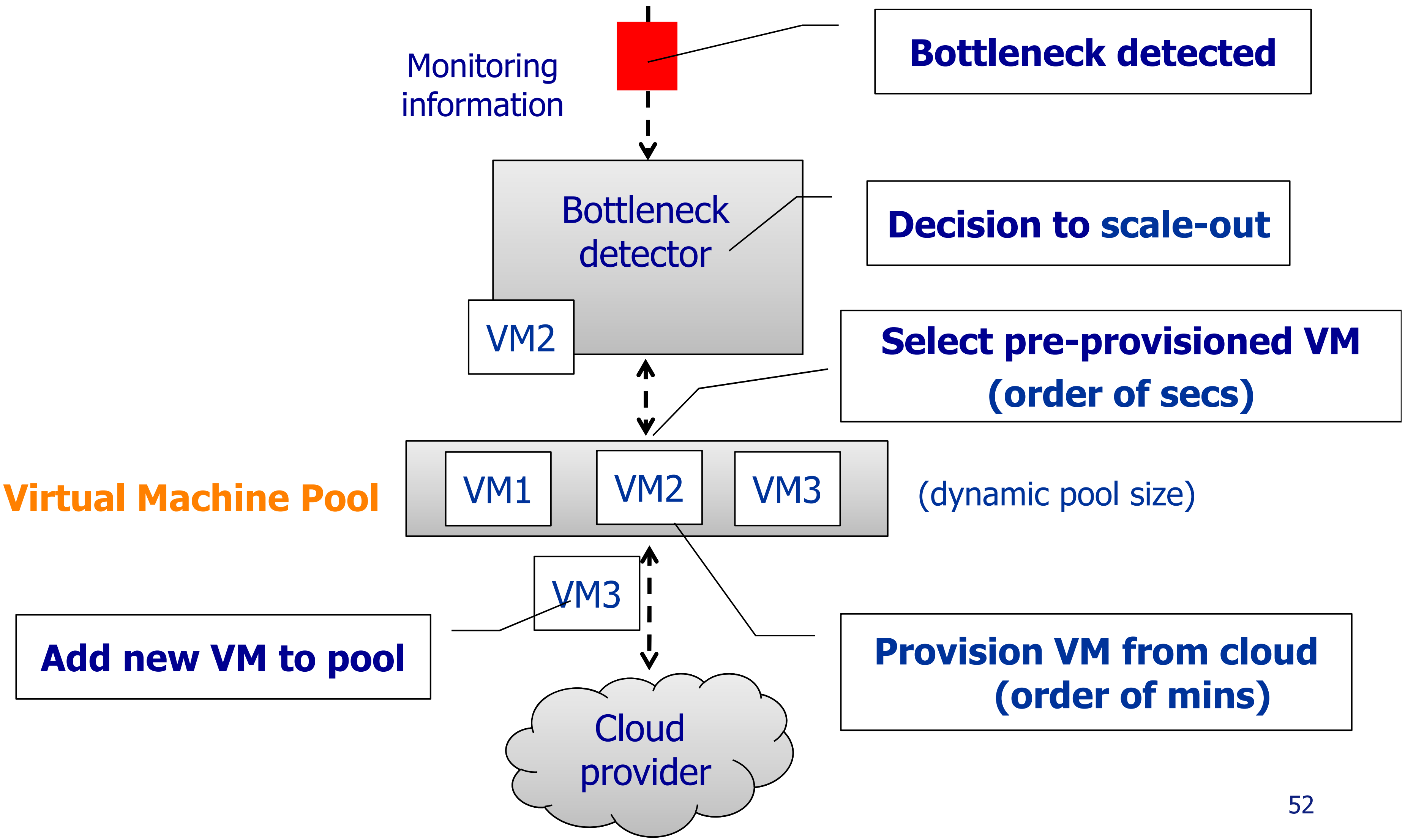


Dynamic Scale Out: Detecting bottlenecks



The VM Pool: Adding operators

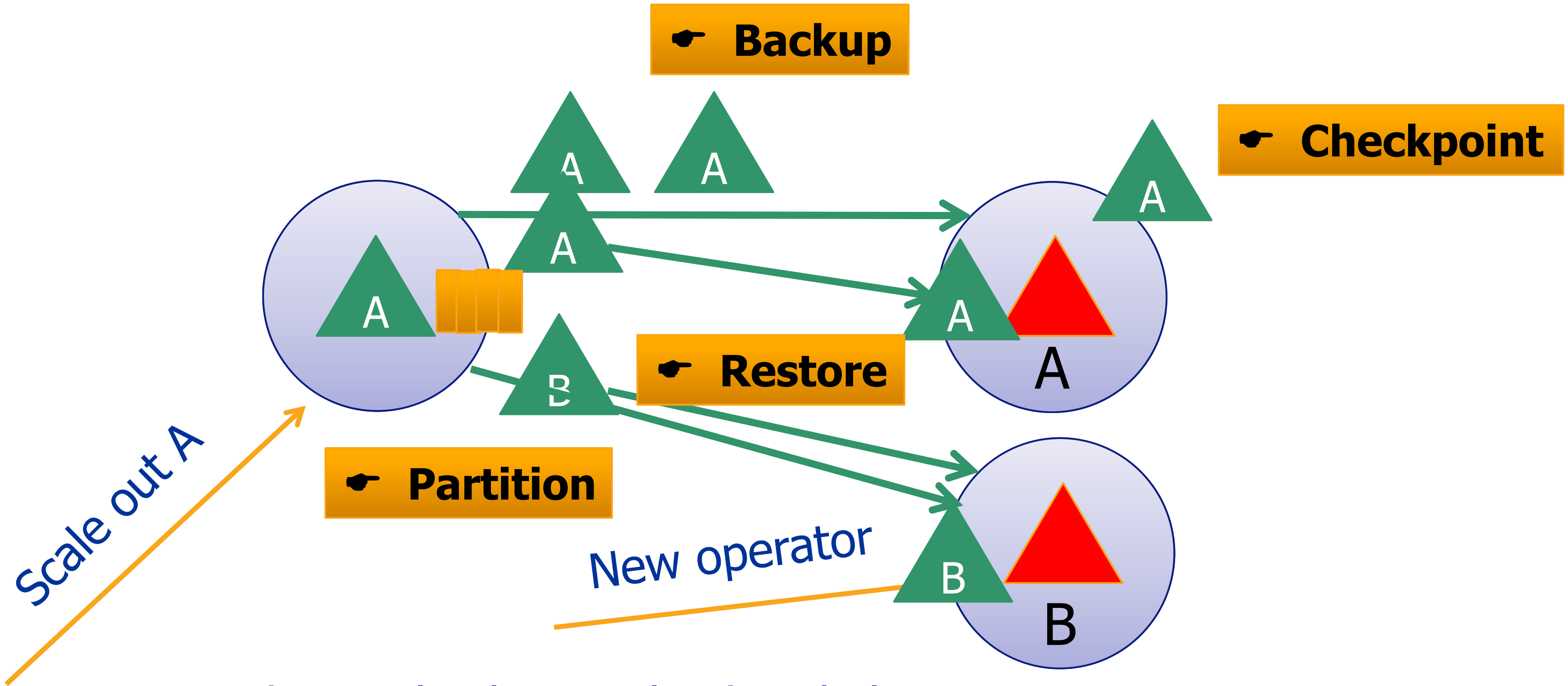
Problem: Allocating new VMs takes minutes...



Scaling Out Stateful Operators

Finally, upstream operators replay unprocessed tuples to update checkpointed state

Periodically, stateful operators checkpoint and back up state to designated **upstream backup node**

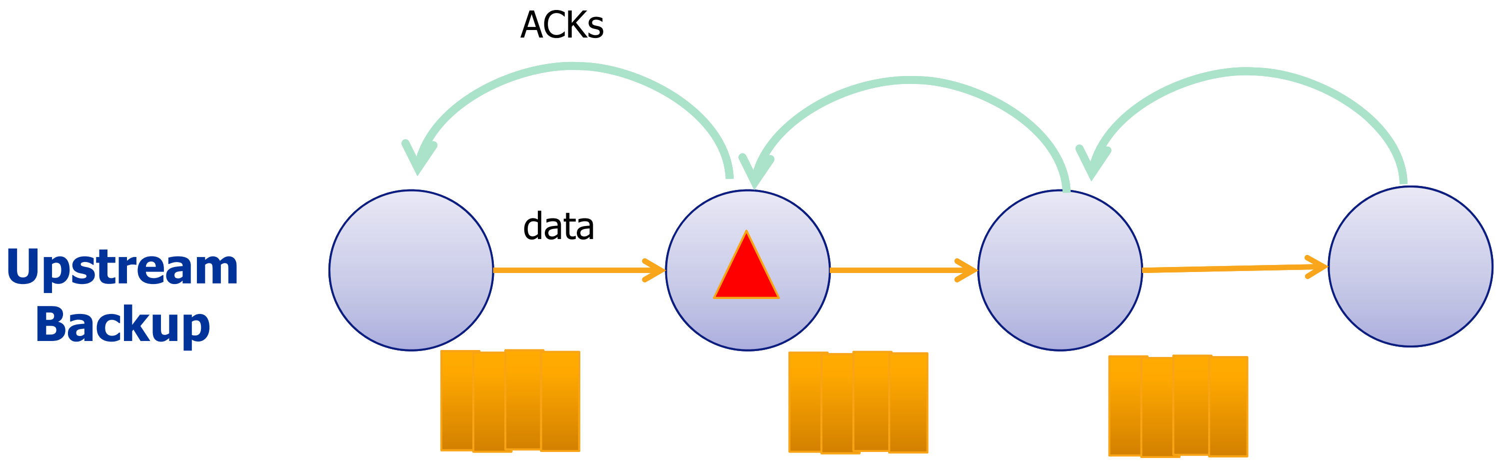


For scale out, backup node already has state of operator to be parallelised

Passive Fault-Tolerance Model

Recreate operator state by replaying tuples after failure

- Send acknowledgements upstream for tuples processed downstream



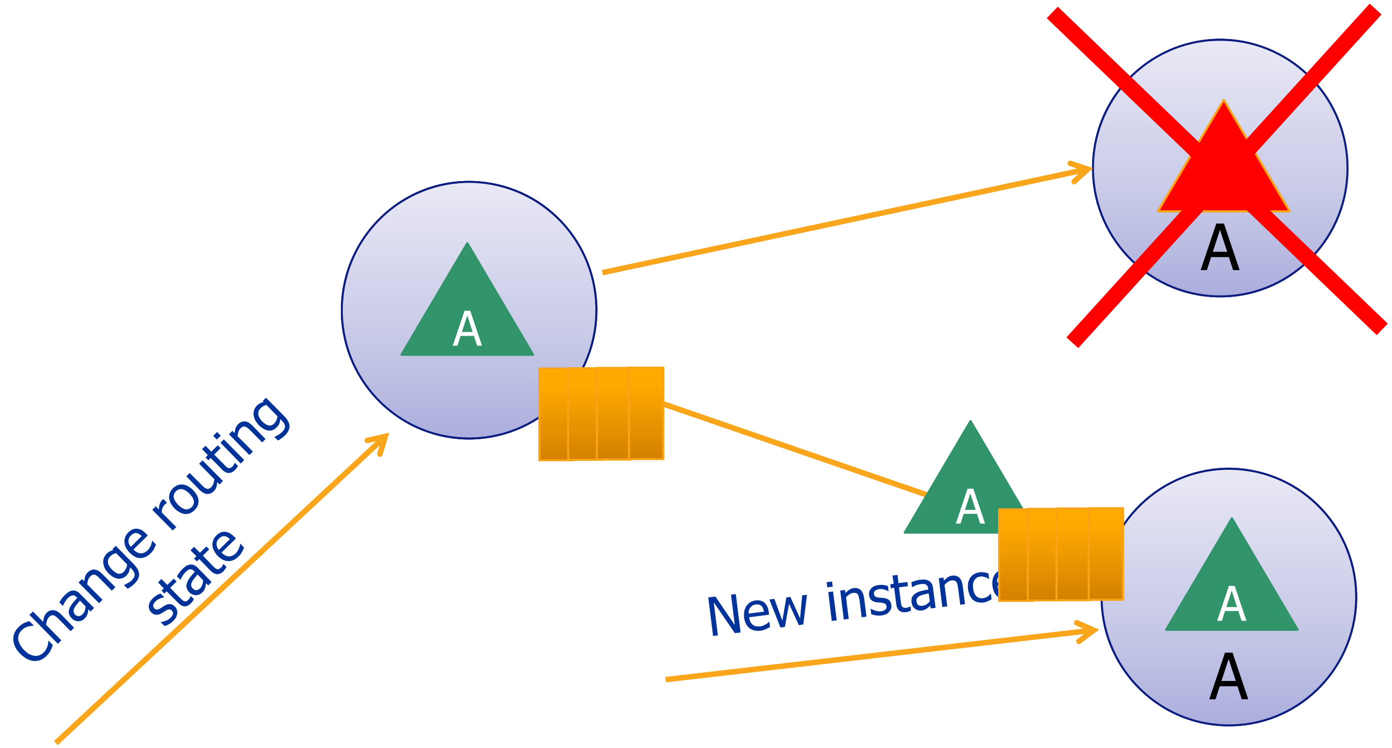
May result in long recovery times due to large buffers

- System is reprocessing streams after failure ➔ inefficient

Upstream Backup + Checkpointing

Benefit from state management primitives

- Use periodically backed up state on upstream node to recover faster



State is restored and unprocessed tuples are replayed from buffer

Experimental Evaluation

Goals

- Investigate effectiveness of scale out mechanism
- Recovery time after failure using UBC
- Overhead of state management

Prototype system: Scalable and Elastic Event Processing (SEEP)

- Implemented in Java; Storm-like data flow model

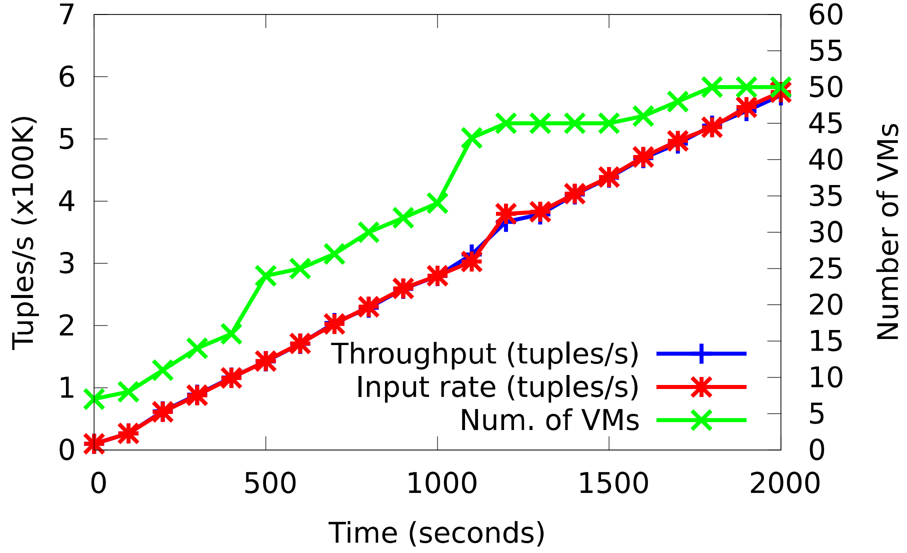
Sample queries + workload

- **Linear Road Benchmark** (LRB) to evaluate scale out [VLDB'04]
  - Provides an increasing stream workload over time for given load factor
  - Query with 8 operators; SLA: results < 5 secs
- **Windowed word count query** to evaluate fault tolerance
  - Induce failure to observe performance impact

Deployment on Amazon AWS EC2

- Sources and sinks on high-memory double extra large instances
- Operators on small instances

Scale Out: LRB Workload

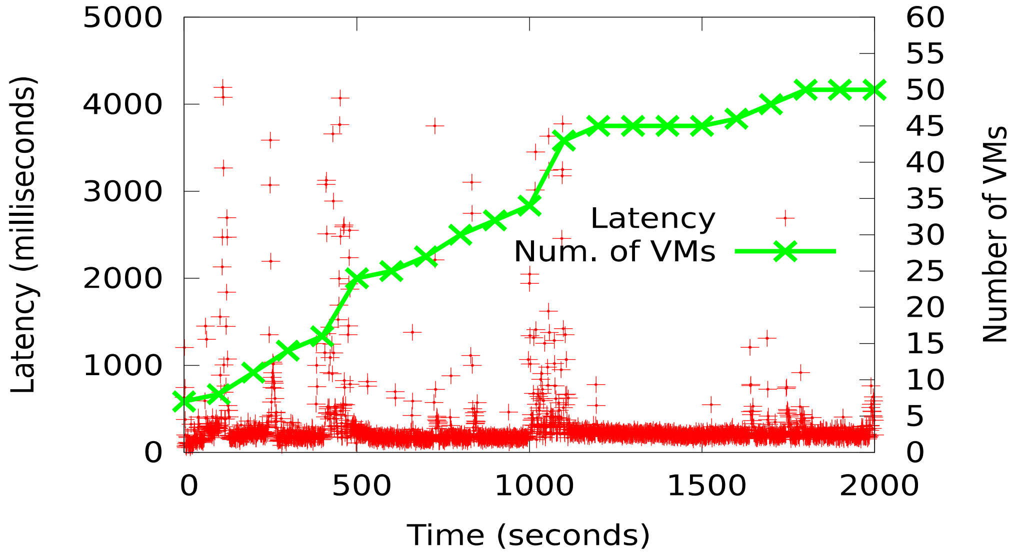


Scales to load factor L=350 with 60 VMs on Amazon EC2

- Automated query parallelisation

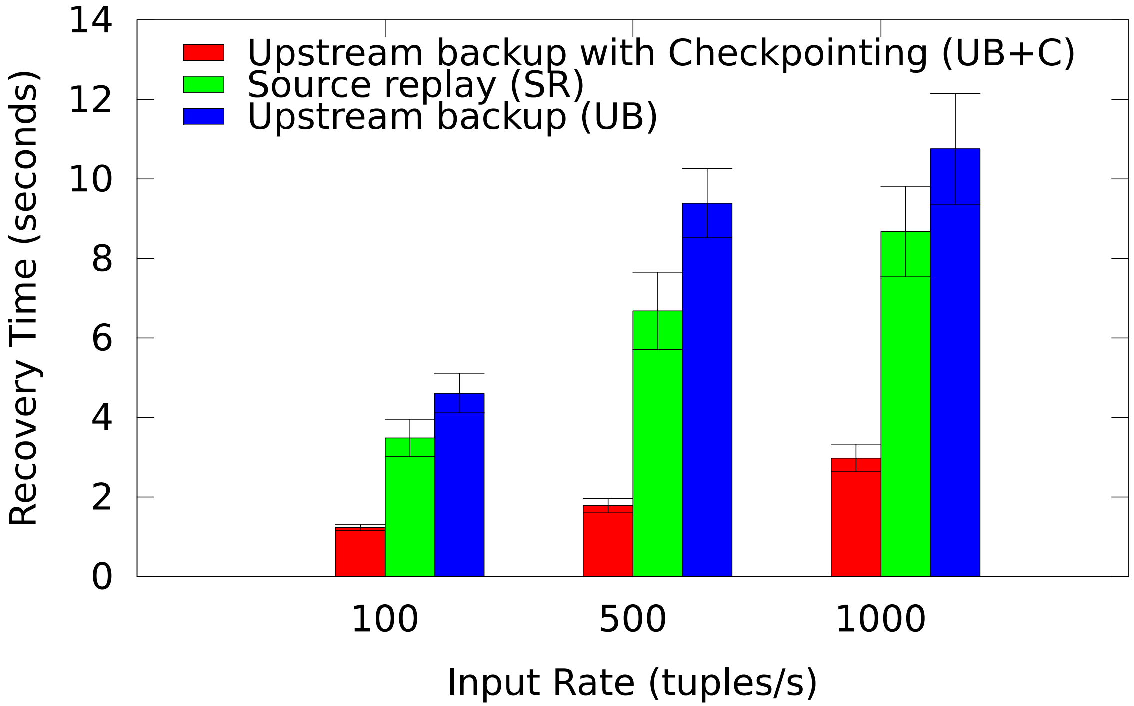
L=512 highest report result [VLDB'12]

- Hand-crafted query on dedicated cluster



Scale out leads to latency peaks, but remains within LRB SLA

UB+C: Recovery Time

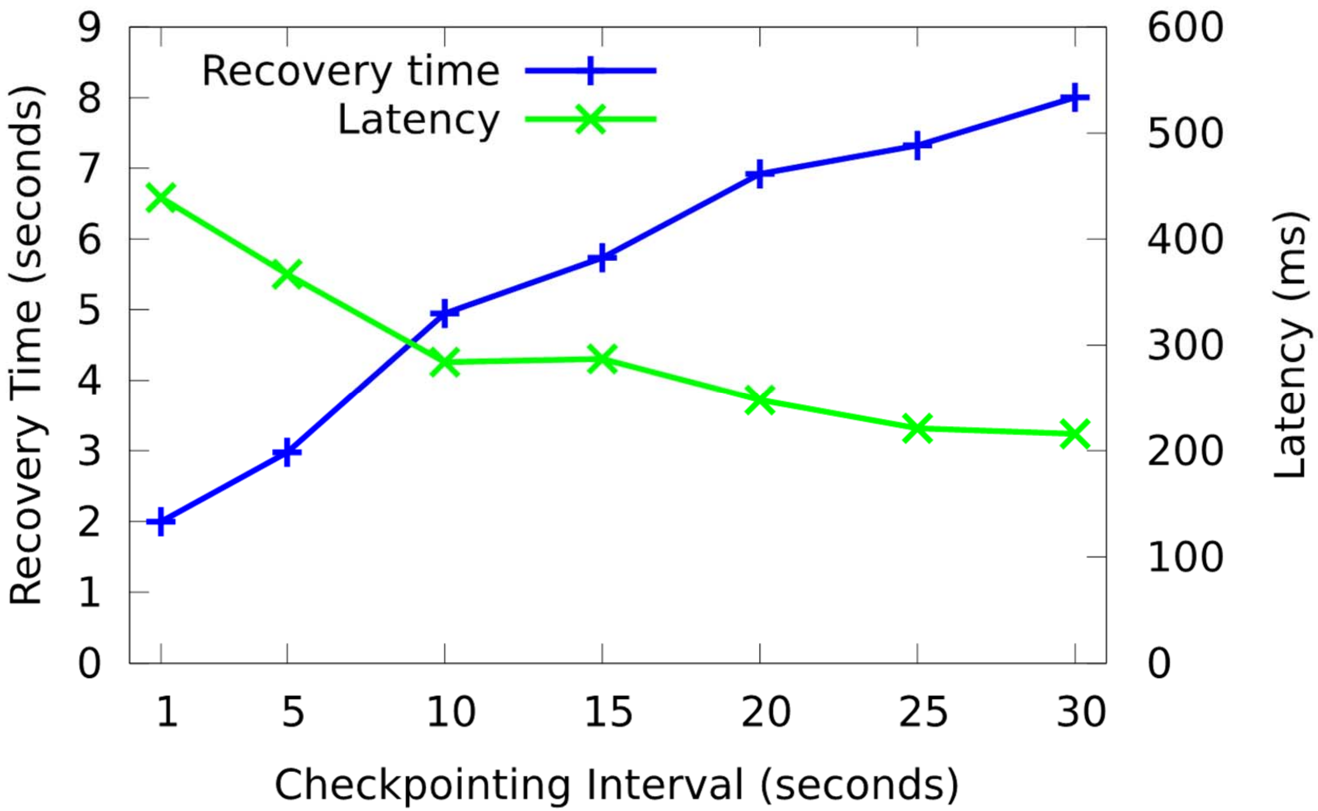


Source Replay:
Upstream Backup with tuples replayed by source only

State backed up every 5 seconds in UB+C

☛ UB+C achieves faster recovery, especially for fast stream rates

Tradeoff of Checkpointing Interval



☛ Shorter checkpointing interval leads to faster recovery times
But also incurs more overhead, impacting tuple processing latency

Related Work

Scalable stream processing systems

- **Twitter Storm, Yahoo S4, Nokia Dempsey**
  Exploit operator parallelism mainly for stateless queries
- **ParaSplit operator** [VLDB'12]
  Partition stream for intra-query parallelism

Support for elasticity

- **StreamCloud** [TPDS'12]
  Dynamic scale out/in for subset of relational stream operators
- **Esc** [ICCC'11]
  Dynamic support for stateless scale out

Resource-efficient fault tolerance models

- **Active Replication at (almost) no cost** [SRDS'11]
  Use under-utilized machines to run operator replicas
- **Discretized Streams** [HotCloud'12]
  Data is checkpointed and recovered in parallel in event of failure

Conclusions

Stream processing will grow in importance

- Handling the data deluge
- Just provide a view/window on subset of data
- Enables real-time response and decision making

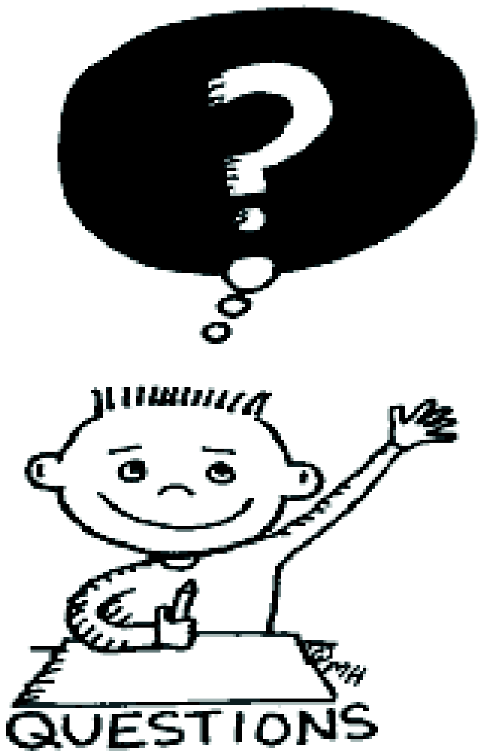
Principled models to express stream processing semantics

- Enables automatic optimisation of queries, e.g. finding parallelism
- What is the right model?

Resource allocation matters due to long running queries

- High stream rates and many queries require scalable systems
- Handling overload becomes crucial requirement
- Volatile workloads benefit from elastic DSPS in cloud environments

Thank You! Any Questions?



Peter Pietzuch
<prp@doc.ic.ac.uk>
http://lsds.doc.ic.ac.uk

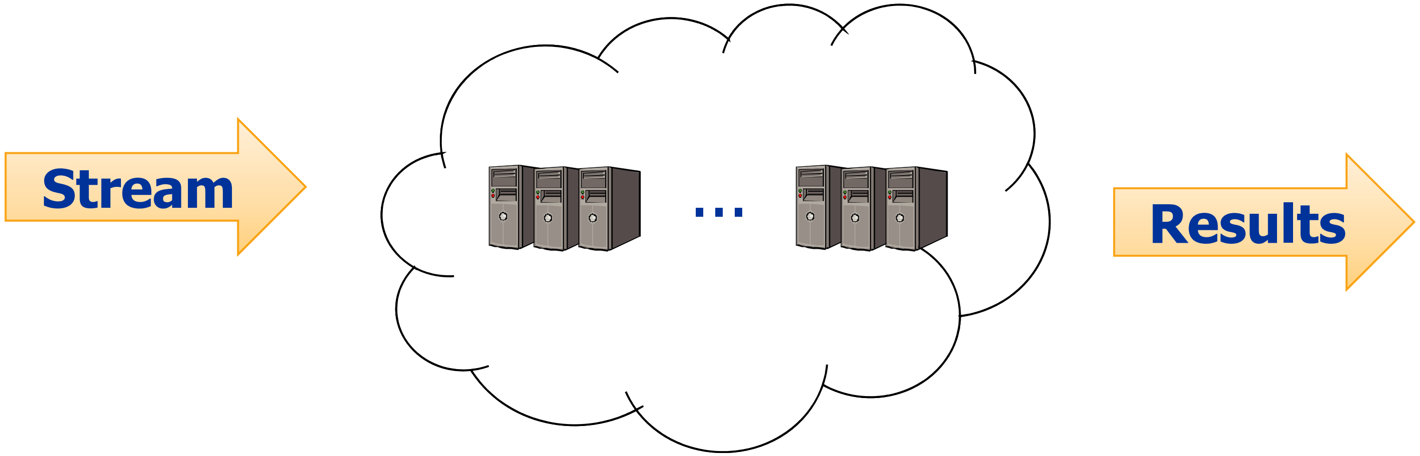
Backup

Global Sensor Applications: EarthScope

Using sensors to understand geological evolution

- Many sources: 400 seismometers, 1000 GPS stations, …

Stream Processing in the Cloud



n servers in cloud DC

Scalability: Scale horizontally across 1000 VMs to support

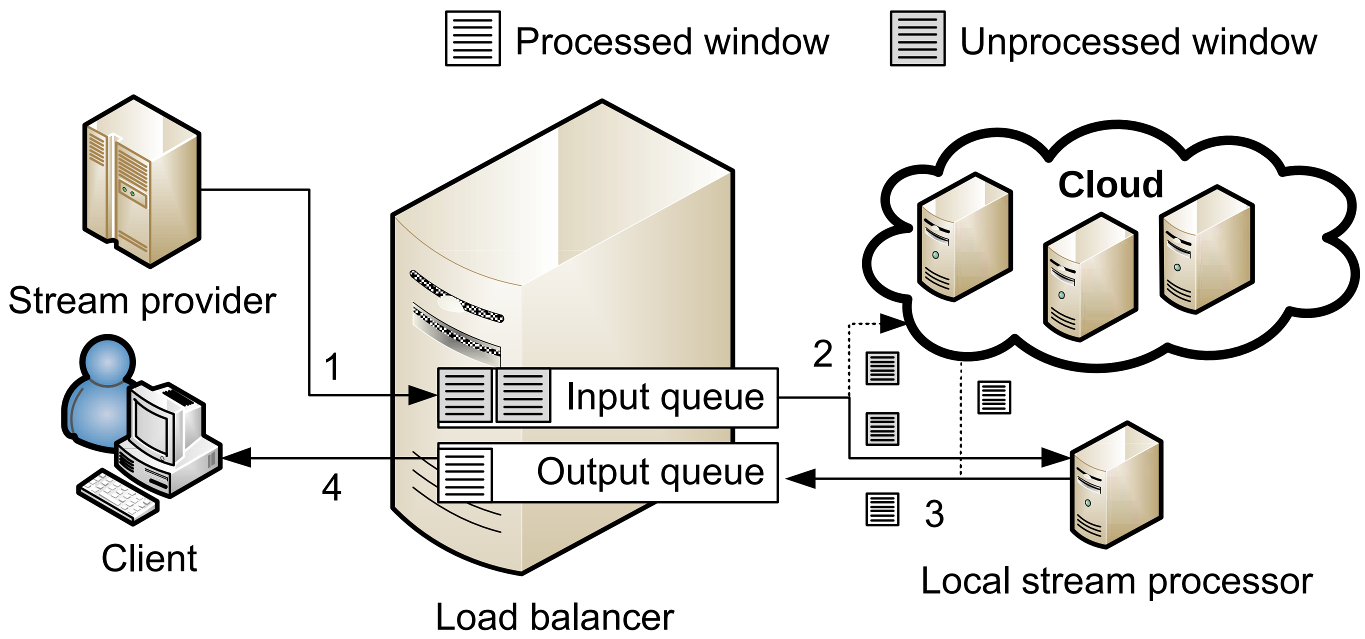
- larger number of queries
- high stream rates

Elasticity: Dynamically tune number of processing servers

- Tune n to affect stream processing throughput

Load Balancing with the Cloud

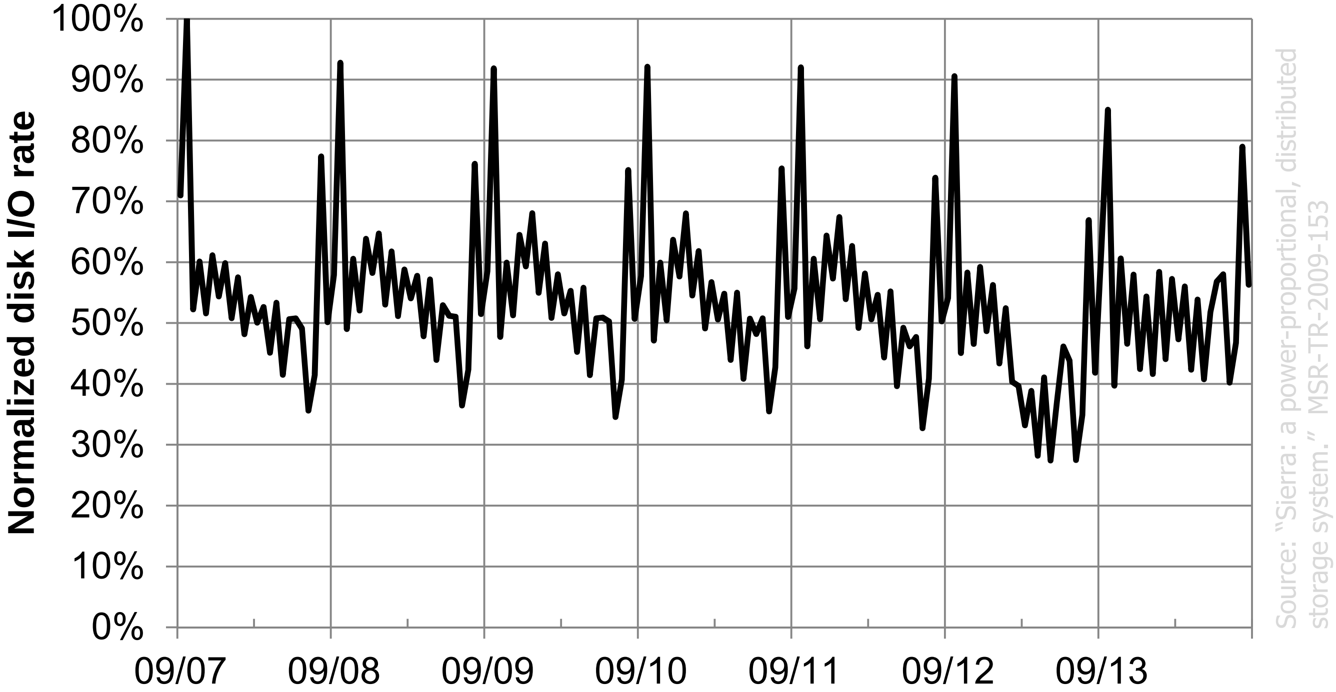
Idea: Using cloud resources for handling peak processing demand



– Network latency to cloud major issue
– Partitioning granularity important

☛ How do you perform stream processing in the cloud?

Typical Processing Workload



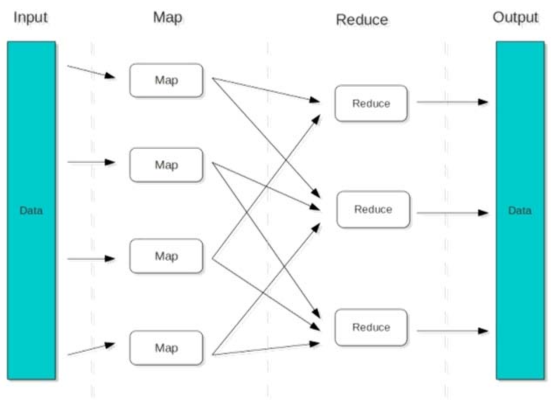
Existing workloads have peaks and troughs

– Scope for improvement in terms of **elasticity and adaptability**

Current solutions in distributed stream processing

– Over-provisioning to handle peak demand
– Load-shedding to discard data during peaks

The Map/Reduce Hammer?



Strawman idea:

- Adapt batch processing model
- Pipelined implementation of map/reduce

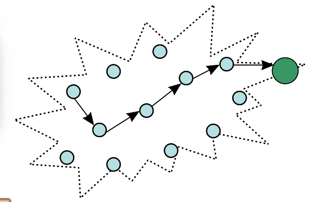
Partitioning granularity?

- Window = job?
- Apache Hadoop has large per job overhead

Stream processing semantics?

Data exchange based on distributed file system

Application Domains for Stream Processing



Processing sensor data

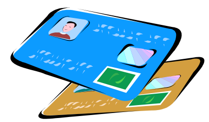
- Readings of physical quantity from sensors
- Readings of RFID tags

Scientific experiments

- Result streams from particle accelerators
- Photon sightings from radio telescopes

Financial transactions

- Detection of credit card fraud
- Debit card transactions from shops
- Trades from stock markets



Network monitoring

- Packet monitoring in intrusion detection systems

Detecting Transient Sky Objects

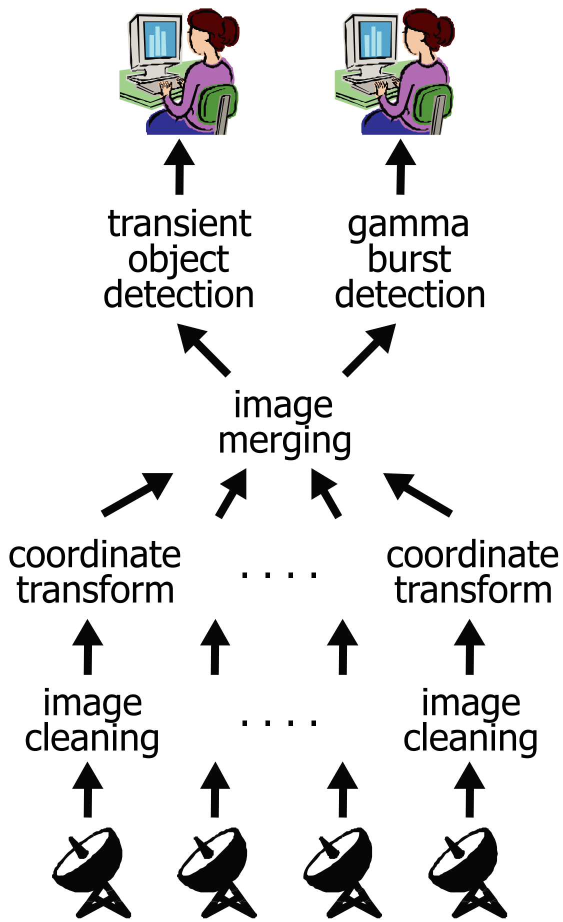
Detection requires non-trivial processing

- Needs to happen within minutes
- Can't express it in SQL

Where do we do the computation?

- What data do we store?

Often looking for needle in haystack



Database Triggers

Database triggers are stored queries

- Triggered by stream of updates

```
CREATE TRIGGER PrizeStudent
AFTER UPDATE OF mark ON Exam
FOR EACH ROW
WHEN (mark > 80)
BEGIN
        INSERT Prizes(name, mark)
        VALUES (...)
END
```

Often written as event-condition-action rules

- Action can be any stored procedure

Hard to support efficiently

- Difficult to take advantage of overlap between triggers
- Low performance with high update rates

Sliding Windows

How many tuples should we process each time?

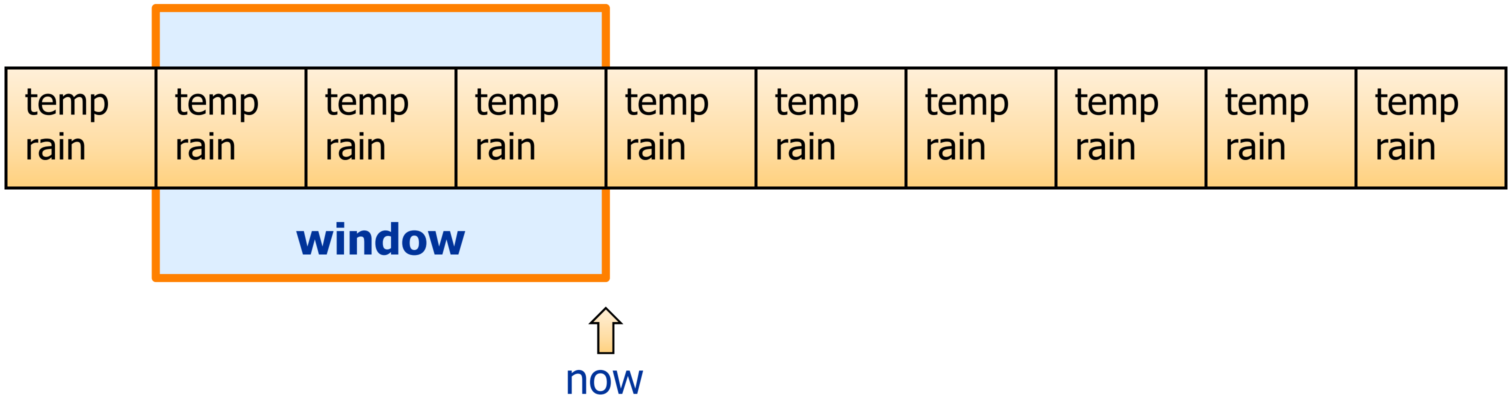
Process tuples in window-sized batches

Time-based window with size τ at current time t

- **$[t - \tau : t]$** `Sensors [Range τ seconds]`
- **$[t : t]$** `Sensors [Now]`

Count-based window with size n:

- **last n tuples** `Sensors [Rows n]`



Memory Overhead

Queues & State kept in memory

- Keep in memory for fast access
- Large state swapped out to disk?

Goal: Minimise memory usage

1. Detect and exploit constraints on streams to reduce state
2. Share state within and between queries
3. Schedule operators intelligently to keep queues short

Exploiting Stream Constraints

Exploit query semantics to bound windows

- Provide additional information about streams:
  - Stream semantics
  - Ordering
  - Referential integrity

```
Sensors(time, id, temp, rain)        Faulty(time, id)
```

```
SELECT S.id, S.rain
FROM Sensors [Rows 10] as S, Faulty as F
WHERE S.rain > 10 AND F.id != S.id;
```

[Range 1 day]

Assume all sensors checked once a day:

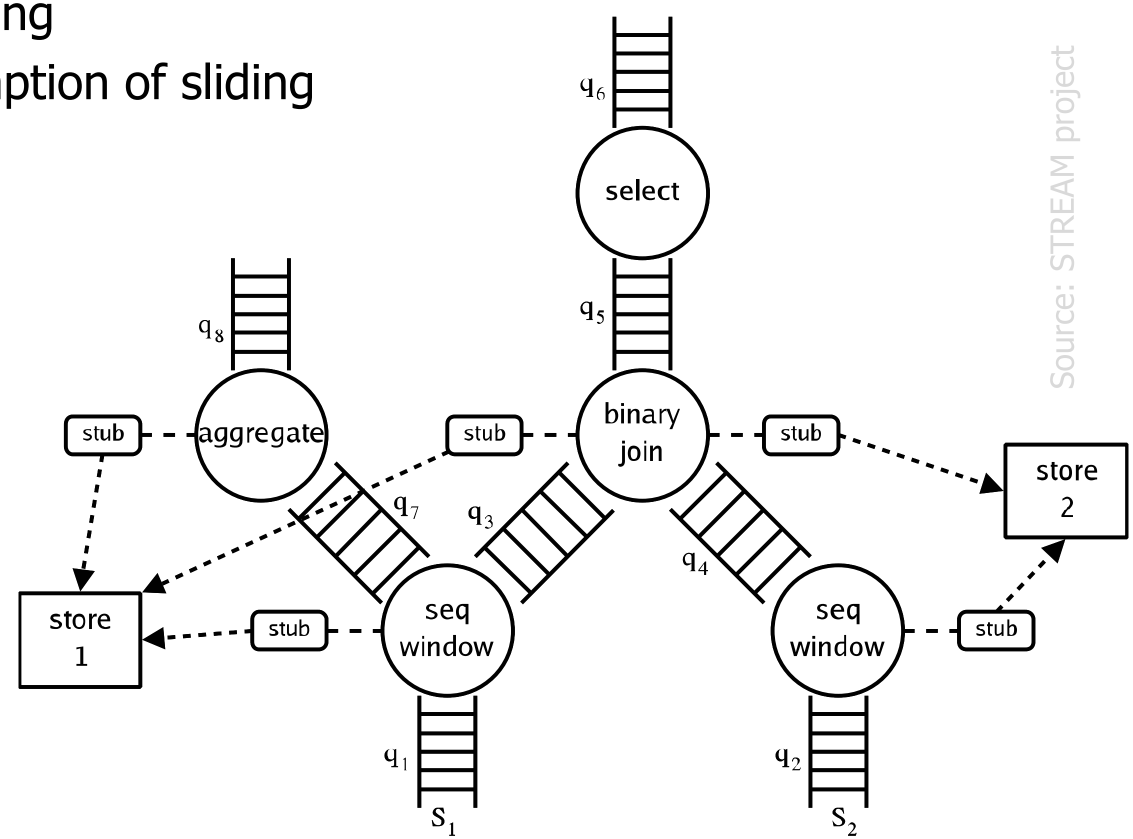
Sharing State + Processing

Base streams: Shared by all queries

– Maintain single maximum window

Intermediate streams: Shared by some queries

– Share state and processing
– Reduce memory consumption of sliding window aggregates



Source: STREAM project

Open Questions

Where will be the bottleneck in the system?

- Can we partition/filter the stream fast enough?

Are EPMs expressive enough to be useful?

- Other computational models possible

How can we adapt to workload changes?

- Migration of EPMs?

☛ Currently building a prototype system to play around with...

Space Complexity

Need O(log N) buckets for window of size N

Need O(log N) bits to represent bucket B(m, t):

- **m** is power of 2, so representable as $\log_2 m$
  m can be represented with O(log log N) bits
- t is representable as t mod N
  t can be represented with O(log N) bits

Overall window compressed to **$O(\log^2 N)$** bits

Estimation error at most 50%:

- Assume partial bucket has size m
  Average contribution of partial bucket: ½ m
- Sum of smaller buckets: m/2 + m/4 + ... = m
  Worst case: estimate too low by half
- Reduce error: keep between p and p+1 buckets of each size

This Talk

Efficiency

How can a stream processing system allocate resources efficiently?

SQPR:
Stream Query Planning with Reuse

– Initial allocation of processing operators to machines in a cluster
– Treat query planning as an optimisation problem

Scalability

How can a stream processing system scale to arbitrary workloads?

SEEP:
Scalable and Elastic Stream Processing

– Elastic architecture for stream processing in the cloud
– Two phase architecture: filtering and transformation

SQPR Query Planner

```
wait until new query q arrives
if q is already satisfied then
    reuse stream
else
    add demand constraint for q
    fix optimisation variables relating to unrelated streams
    solve optimisation model (MILP problem) using
    standard branch & bound techniques
    update solution
    notify hosts of changed streams and operators
```

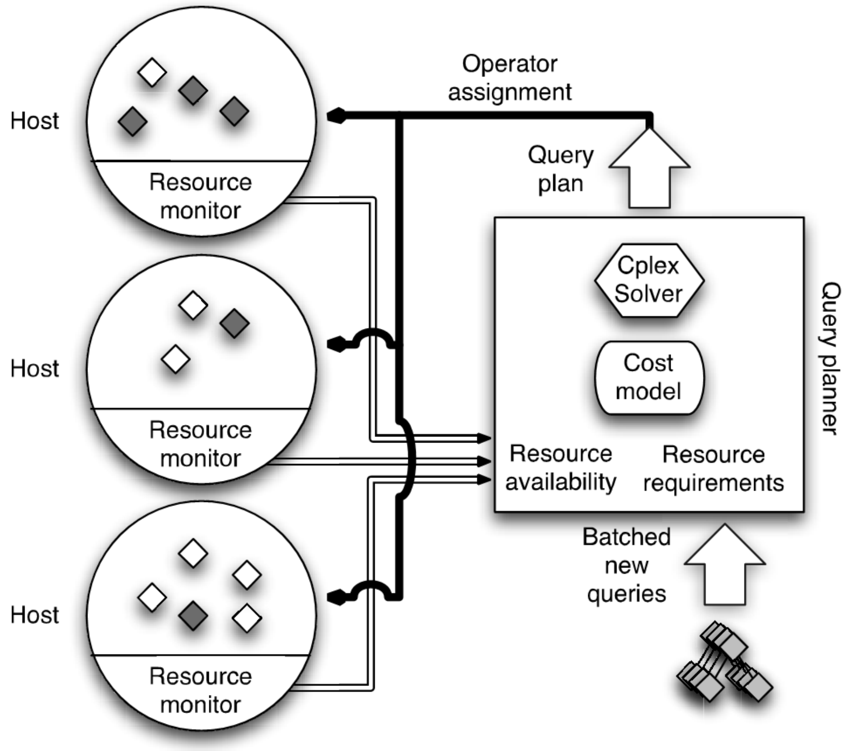
Evaluation Results

Custom simulator

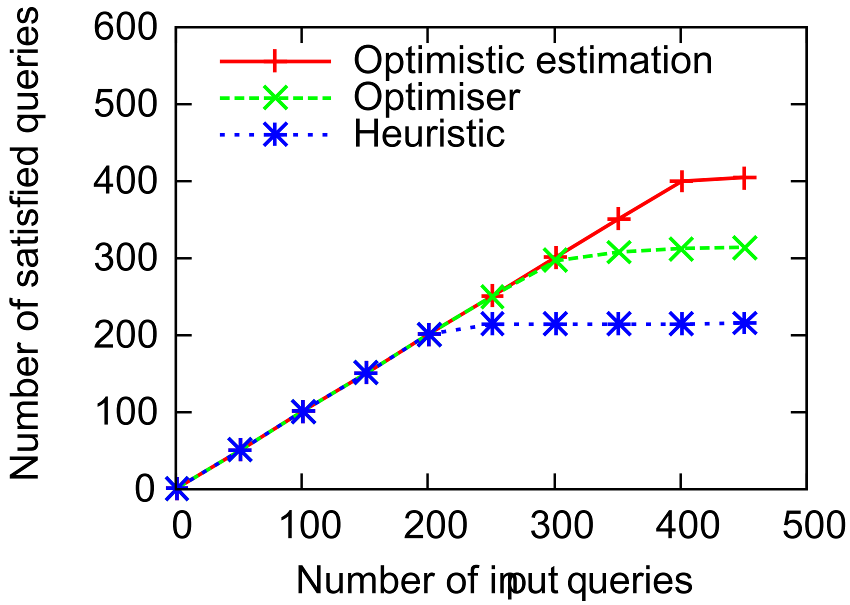
- Workload based on multi-way join queries
- CPU and network constrained environments

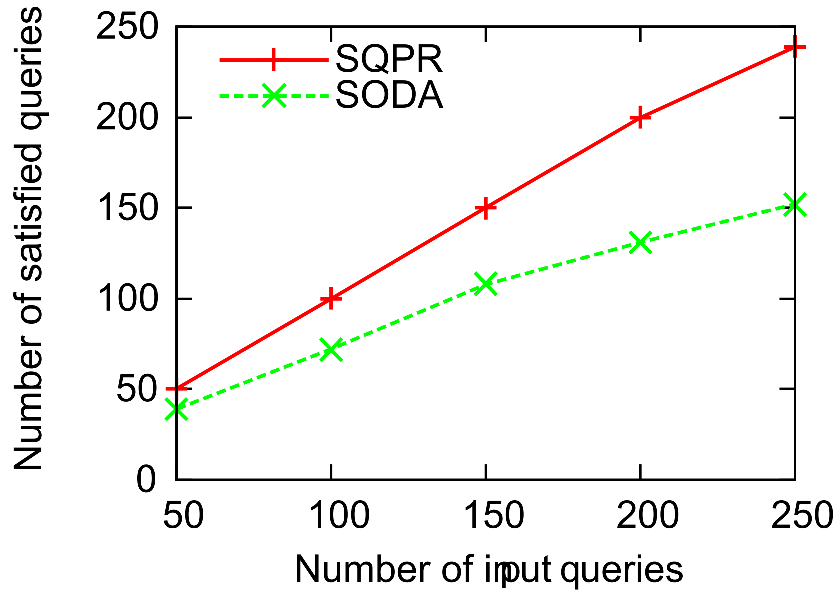
Prototype deployment with DISSP platform

- 15 nodes with 10Mbps network bandwidth
- Comparison with IBM's SODA scheduler



Planning Efficiency



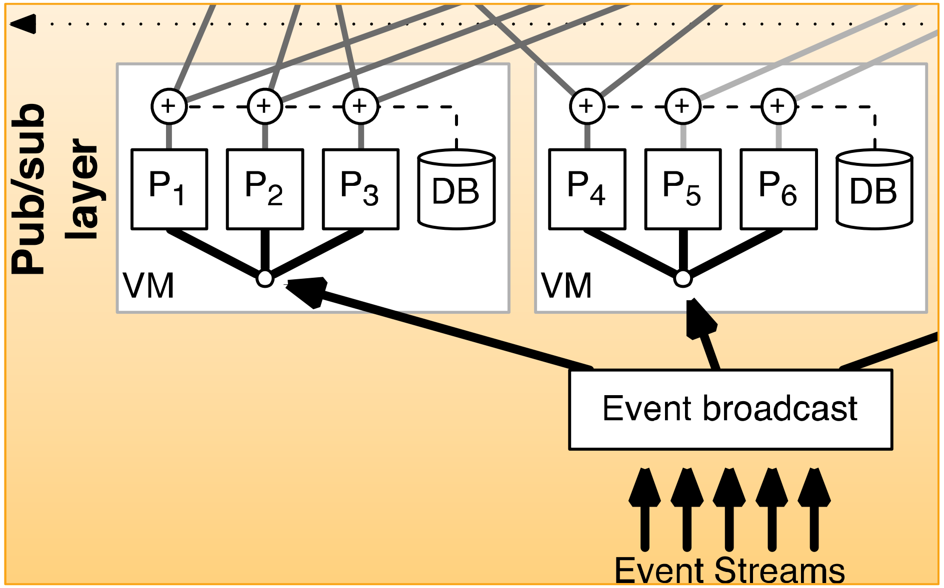


SQPR manages to place more queries than heuristics/SODA

Publish/Subscribe Layer

Incoming streams broadcast to P/S layer VMs

- Match predicates (P_1, P_2, ..., P_n) on incoming streams
- Matched tuples dispatched to VMs in partitioning layer



Inverted index created over predicates to speed up matching

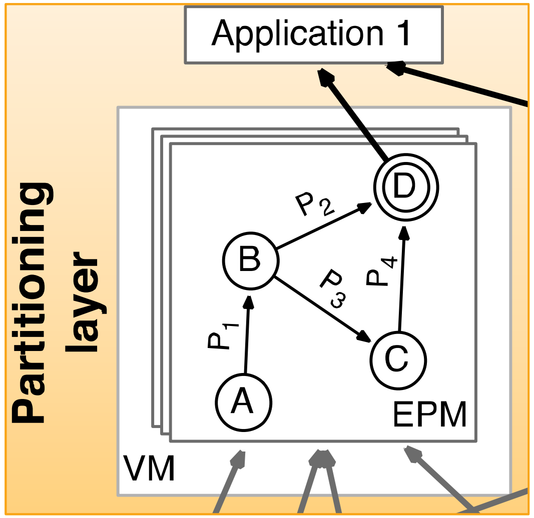
- Predicates composed from language for efficient indexing
- Indexed according to matched attributes, operators and values
- Rich literature on efficient matching

Stream augmentation with stored data

Partitioning Layer

Event Processing Machines (EPMs) transform streams

- Implemented as non-deterministic FSAs
- Composed of detection/aggregation states
  - Each EPM instance contains state S derived by tuples processed so far
  - States linked by edge predicates (computed in P/S layer)



When matched tuples dispatched to EPM:

1. Makes transition to new state
   - Transition might generate new EPM instances (non-determinism)
2. Aggregation function incorporates new tuple in S
3. On accepting state, state S becomes part of result stream

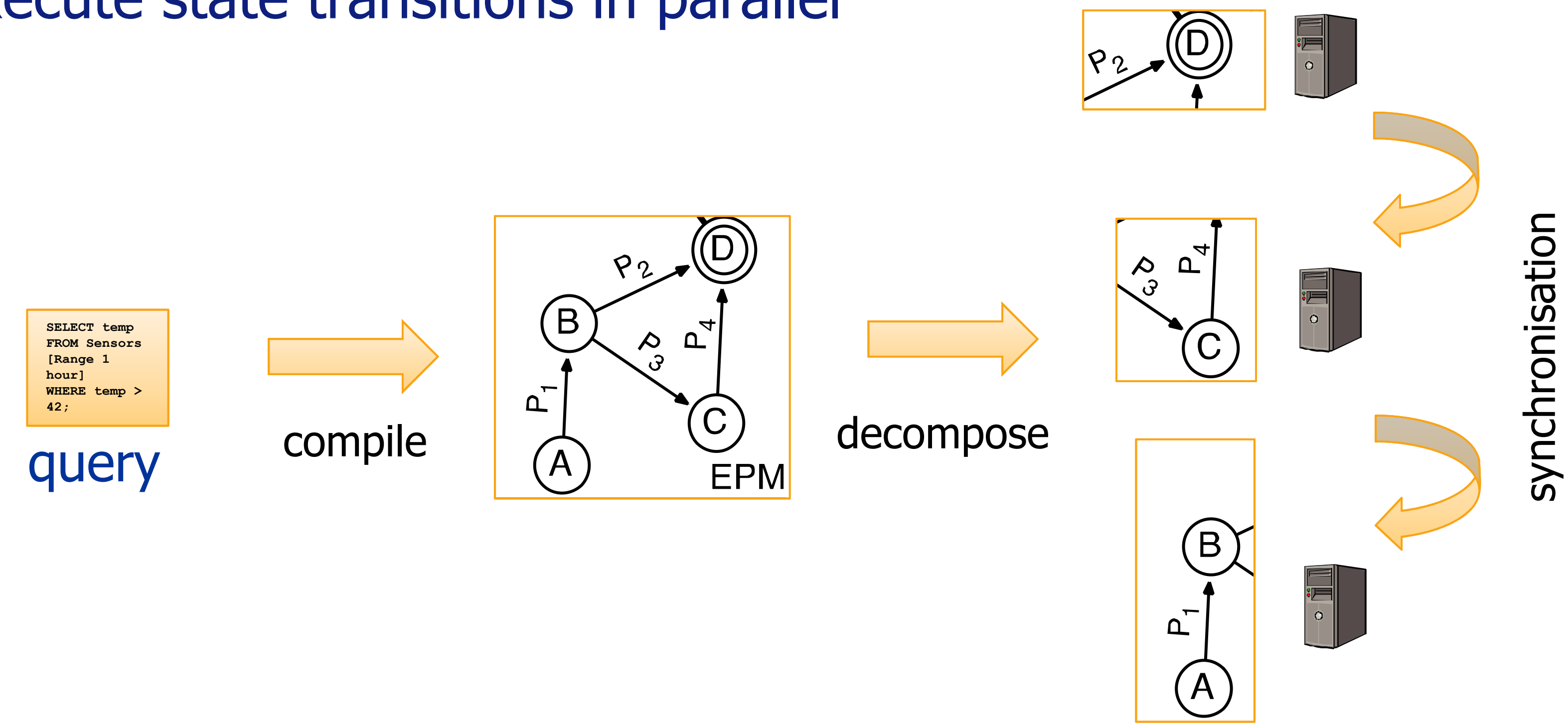
EPM Decomposition

Decompose EPM into fragments hosted on different VMs

– Pipelines EPM execution

Support EPMs with large state requirements

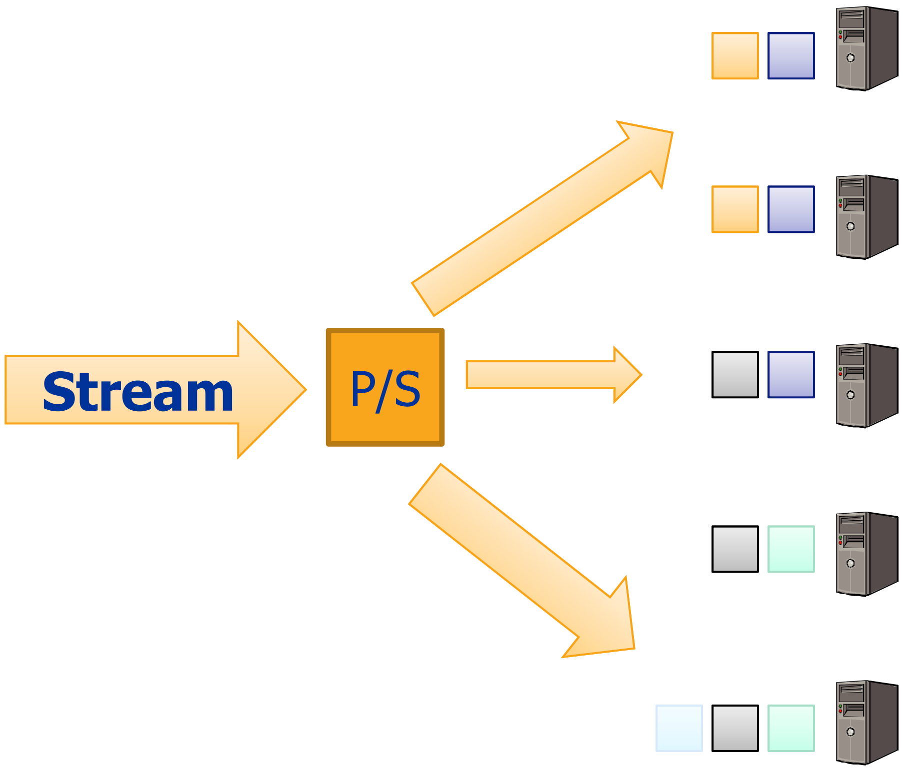
Execute state transitions in parallel



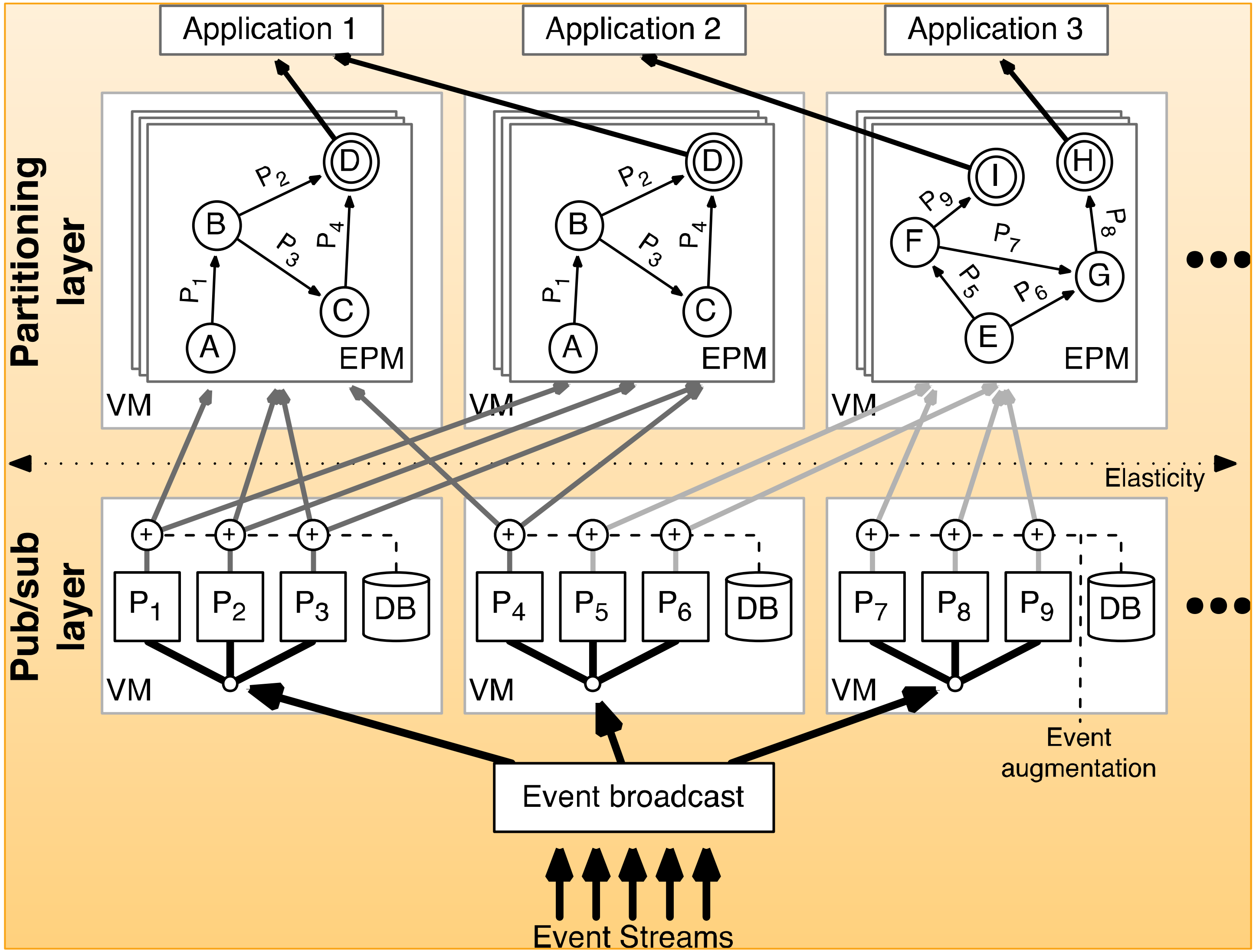
Resource Allocation

Allocate EPM fragments to VMs in partitioning layer

- Must balance CPU load across all VMs
- Observe network bandwidth constraints



SEEP Architecture



Scratch

Two Layers: Dispatching and Processing

Structured architecture for stream processing

- Separates stream partitioning from computation
- Partitioning reduces amount of data for computation

Simple function in each operators:

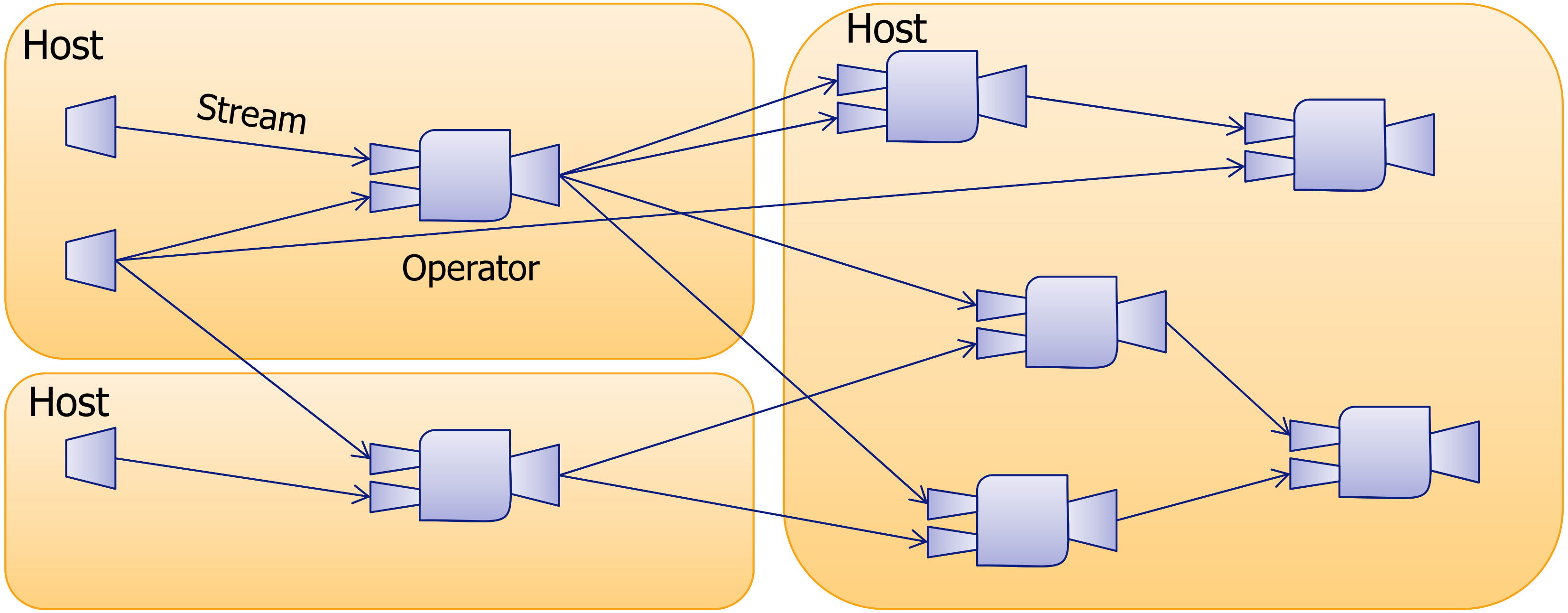
1. Stream partitioning performed by **dispatching layer**
   - Identify relevant data for queries
   - Partitioning of data streams and multicast to multiple operators

2. Computation done by **processing layer**
   - Execution of query operators

SEEP: Scalable & Elastic Event Processing

Decompose queries into multiple stream processing operators

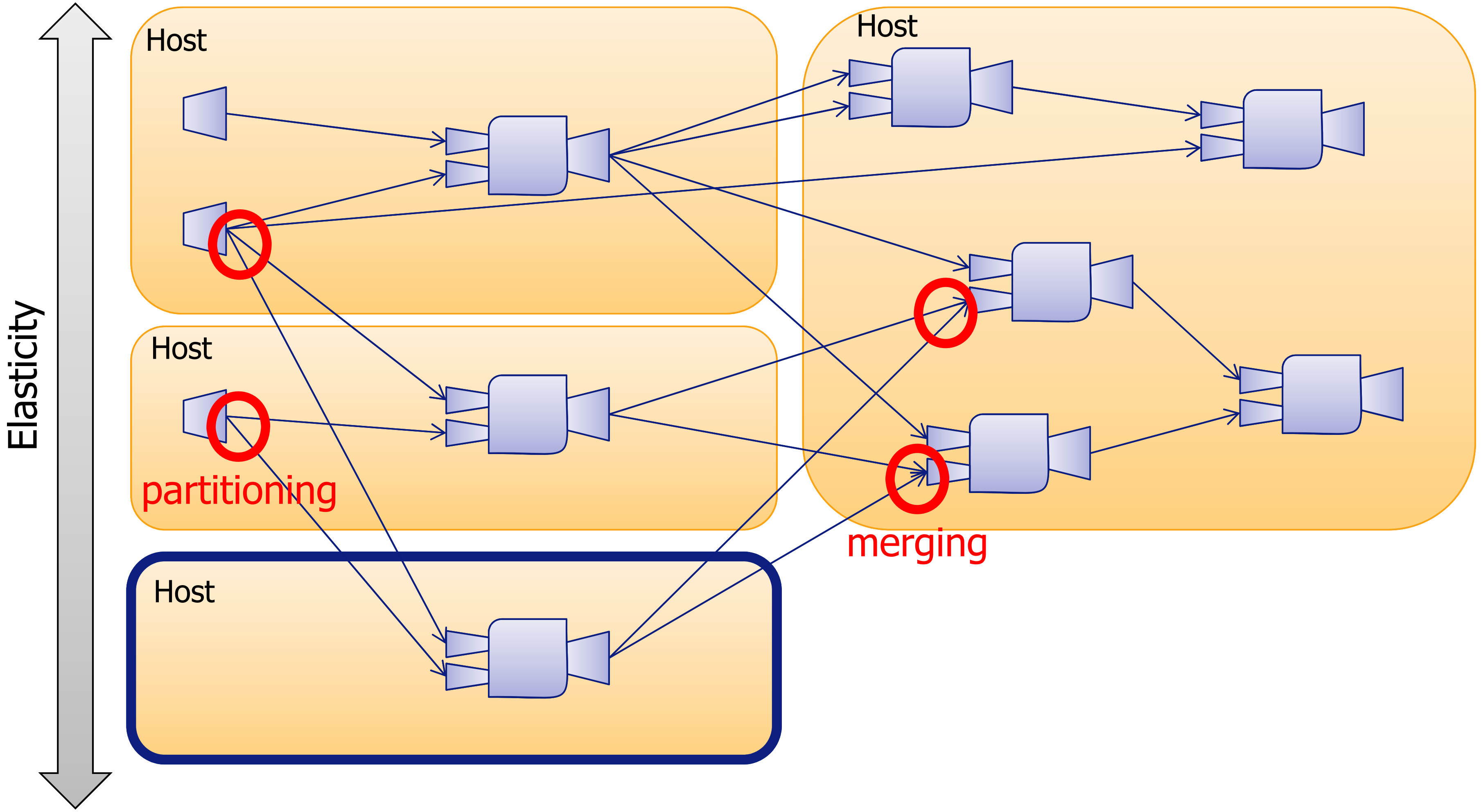
- System exploits intra-query parallelism



Adapt to variations in workload by scaling out

SEEP: Scalable & Elastic Event Processing

Partition and merge streams to utilise more hosts



Twitter Storm & Yahoo S4

Yahoo! S4 (http://incubator.apache.org/s4/)

– Java framework for implementing stream processing applications
– Hides stream "plumbing" from developers
– Uses Zookeeper for coordination

Twitter Storm (https://github.com/nathanmarz/storm)

– Focus on fault-tolerance: acknowledgement of processed tuples
– Spouts produce data; bolts process data
– Different mechanisms for stream partitioning and bolt parallelisation

This is just the beginning... lots of open challenges...