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

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The Data Deluge

150 Exabytes (billion GBs) created in 2005 alone

- Increased to 1200 Exabytes in 2010

Many new sources of data become available

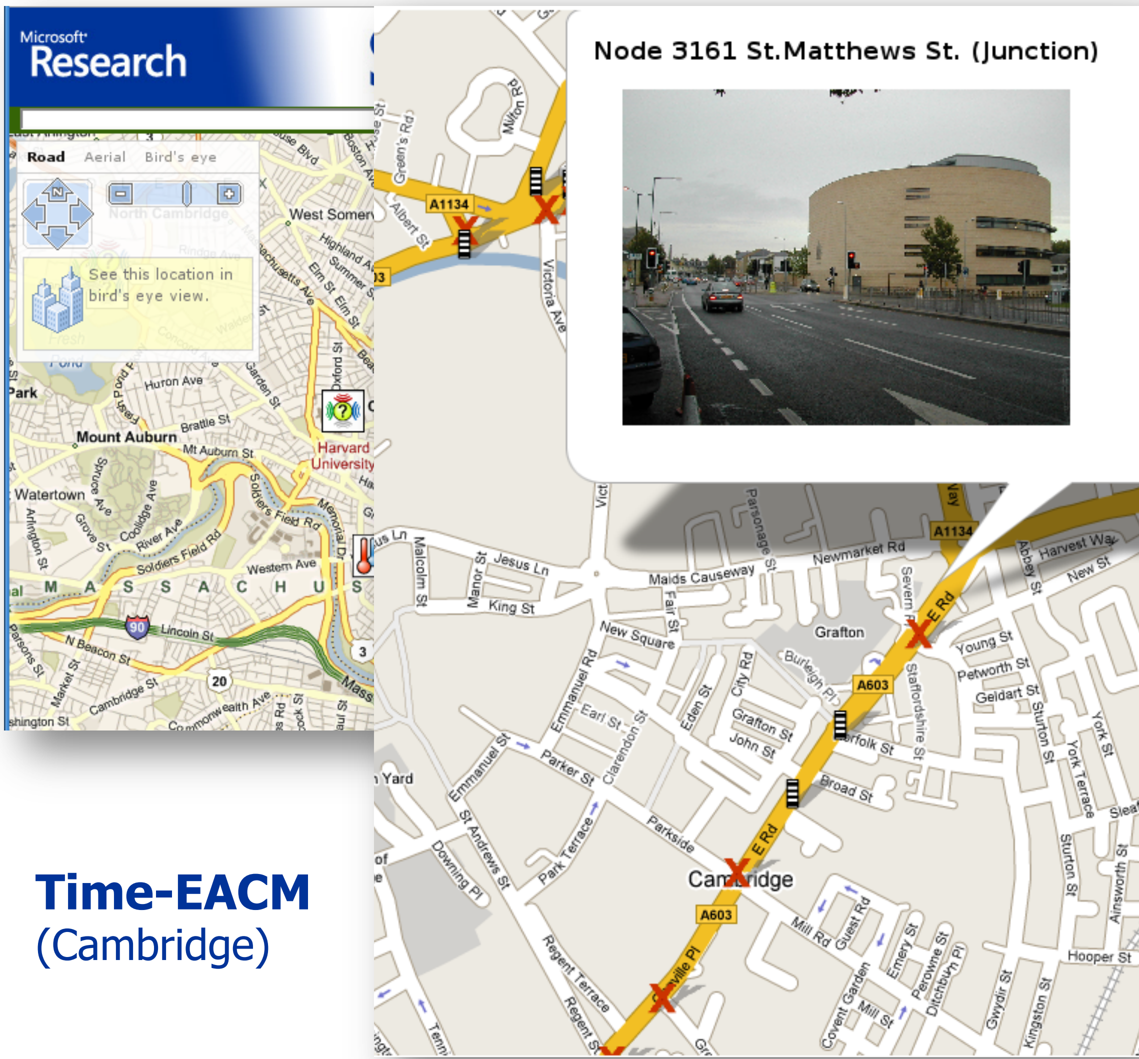
- Sensors, mobile devices
- Web feeds, social networking
- Cameras
- Databases
- Scientific instruments

☛ **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)

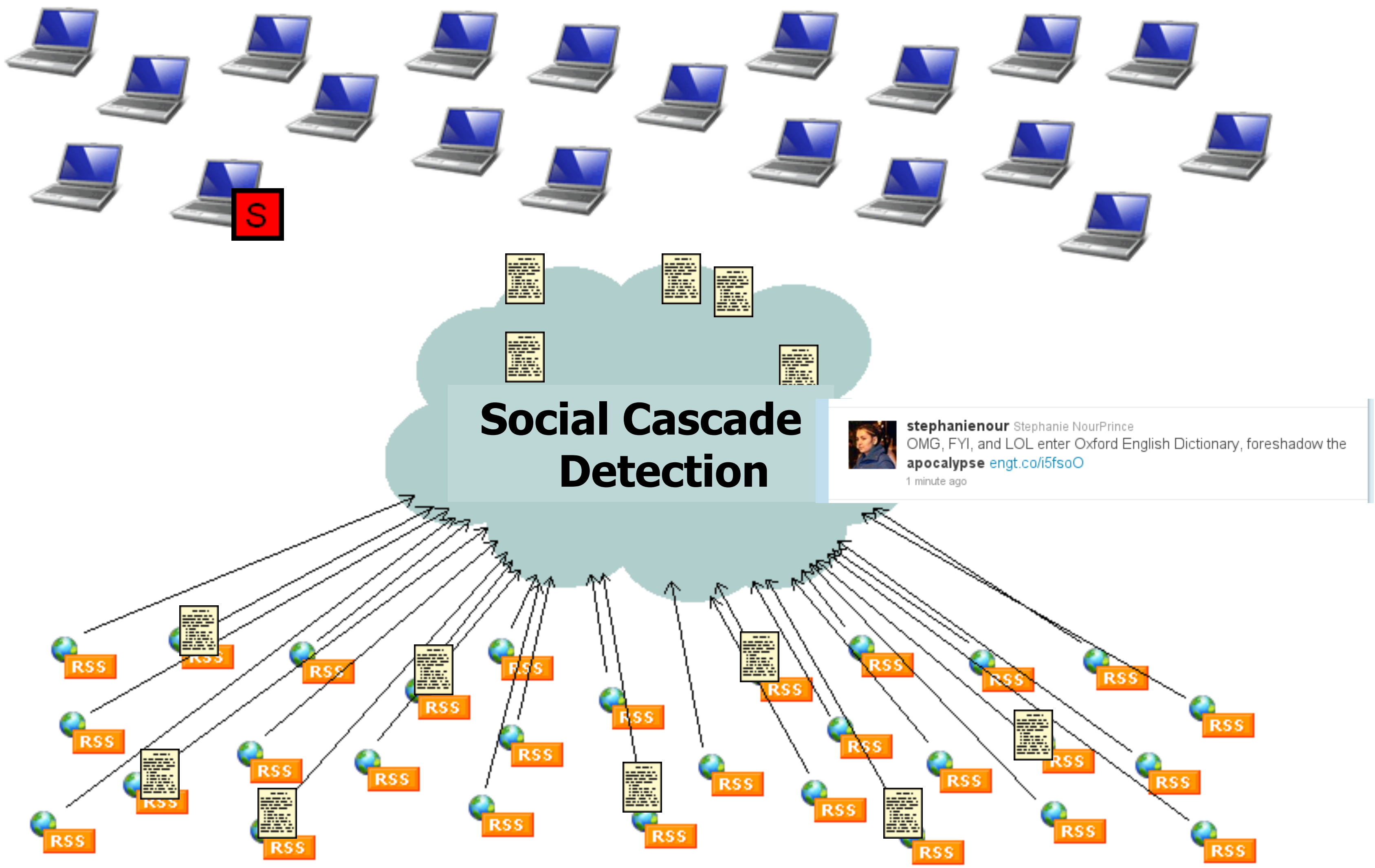
Many parties interested in data

- 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

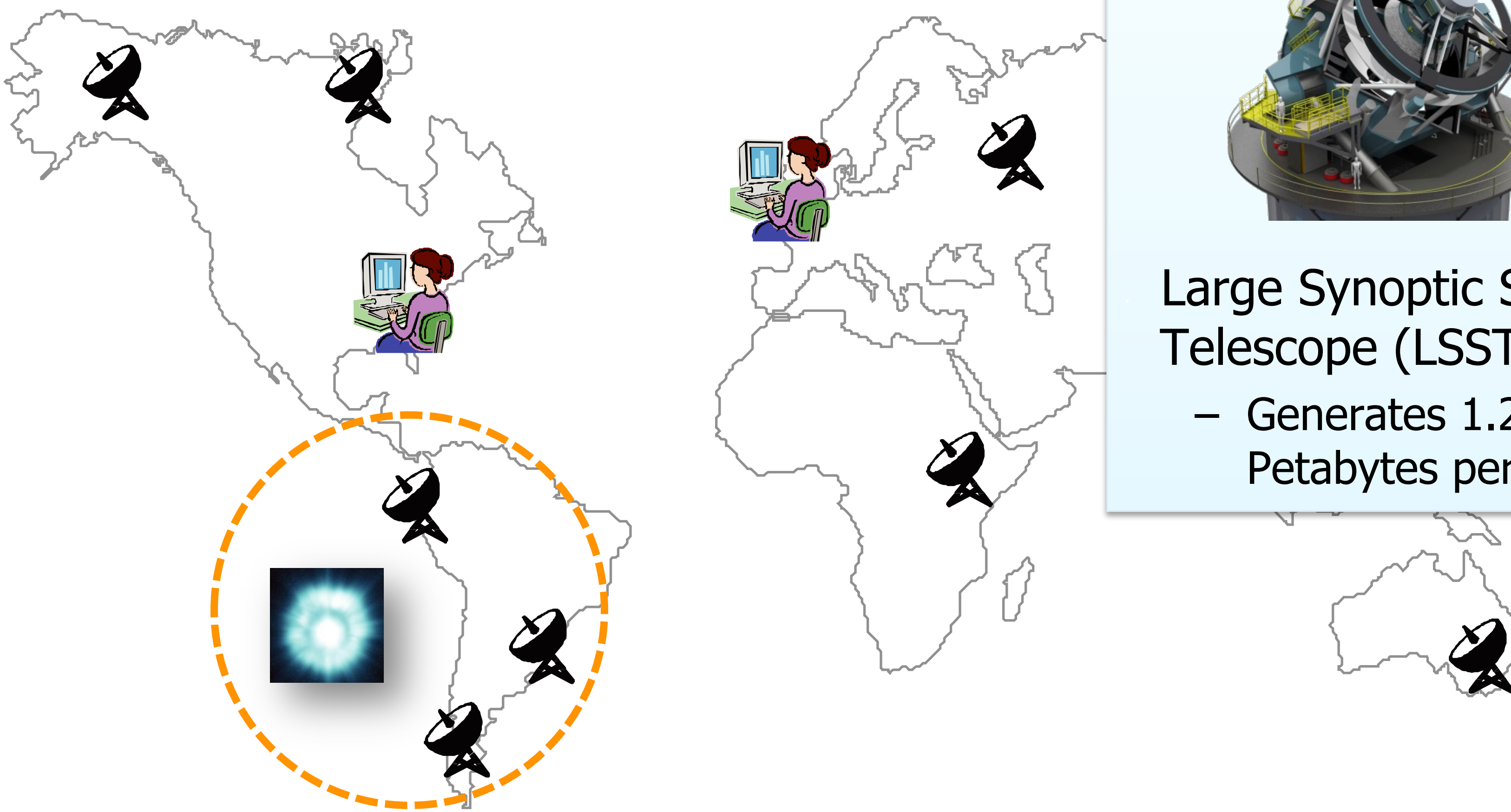
More sophisticated forms of fraud

- 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

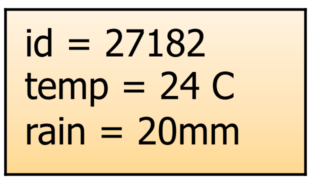
Relational Data Stream Model

Streams consist of infinite sequence of tuples

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

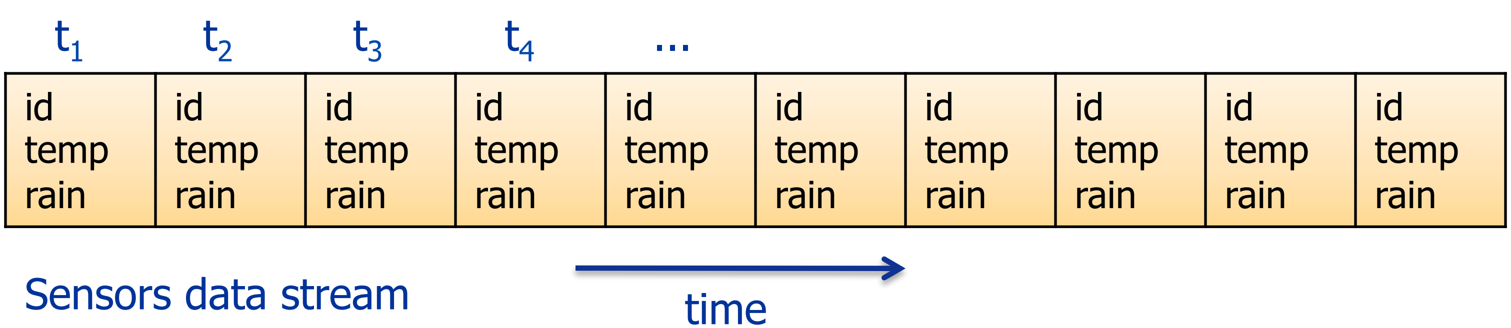
Tuples have fixed relational schema

- Set of attributes



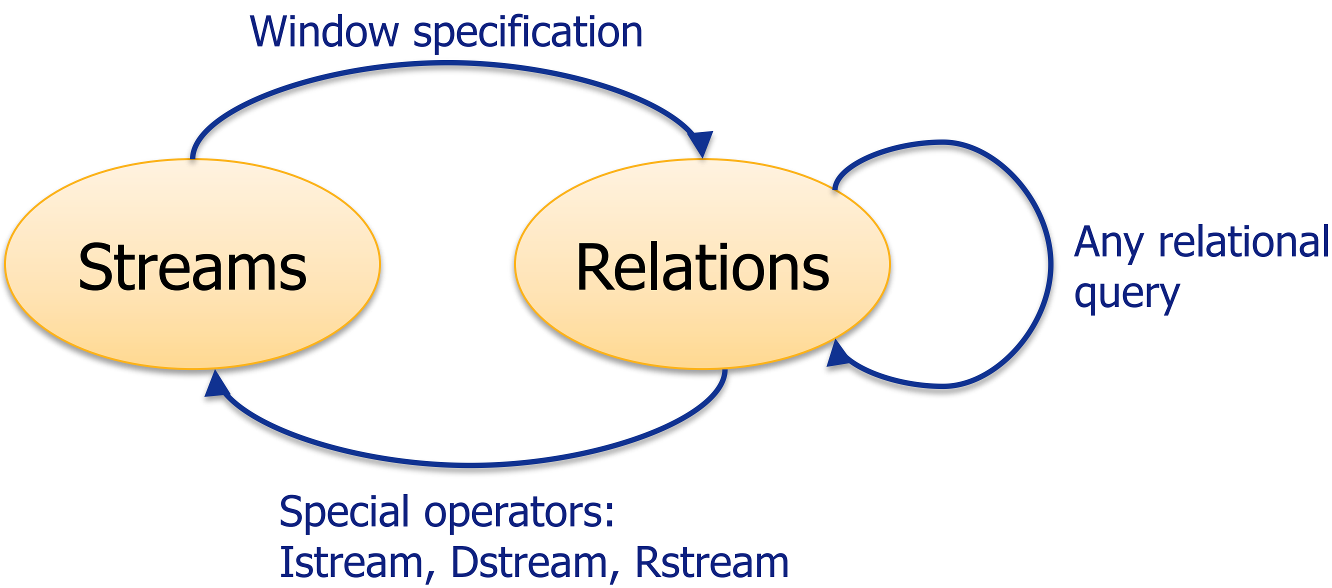
sensor output

`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?

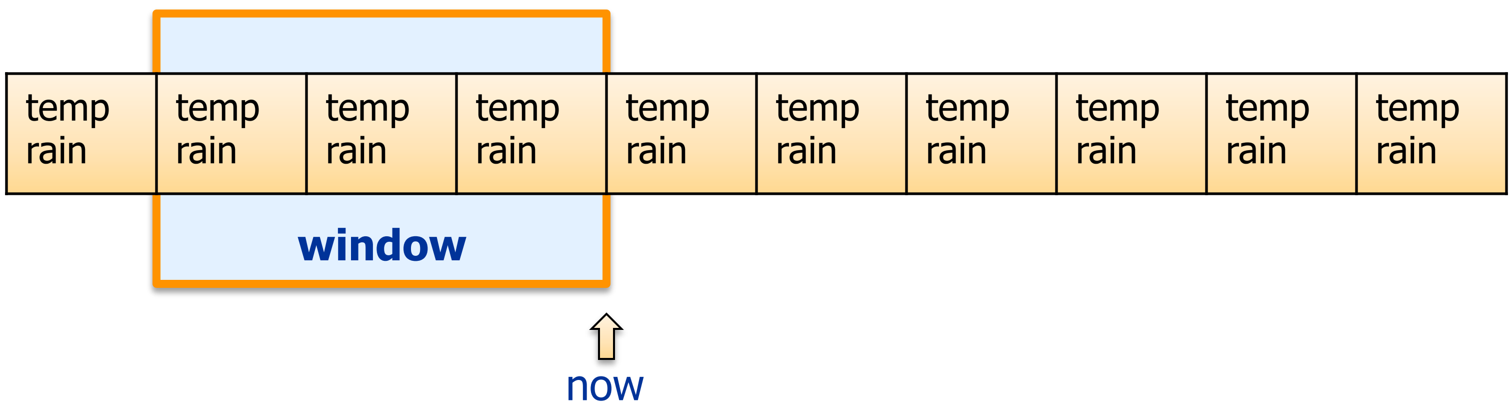
Process tuples in window-sized batches

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?

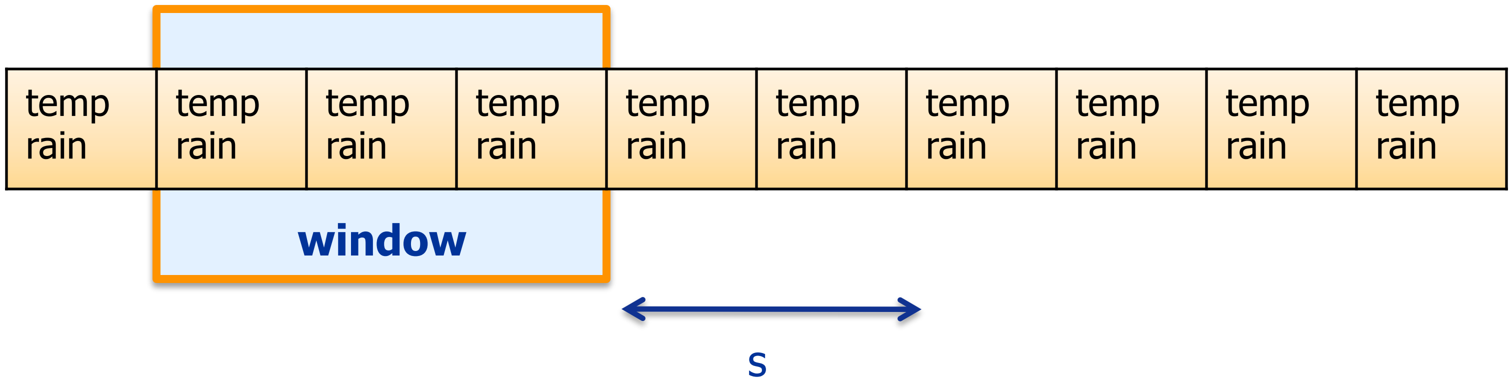
1. Output new result tuples as soon as available
   - Difficult to implement efficiently

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 10^9];
```

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:

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

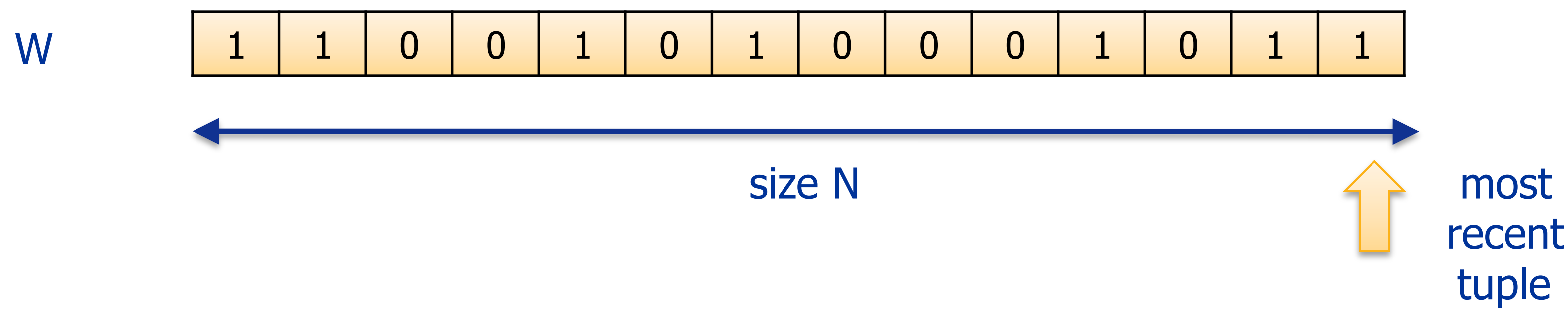
3 tuples (incomplete group)

– 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?
  ($1 \leq k \leq N$)



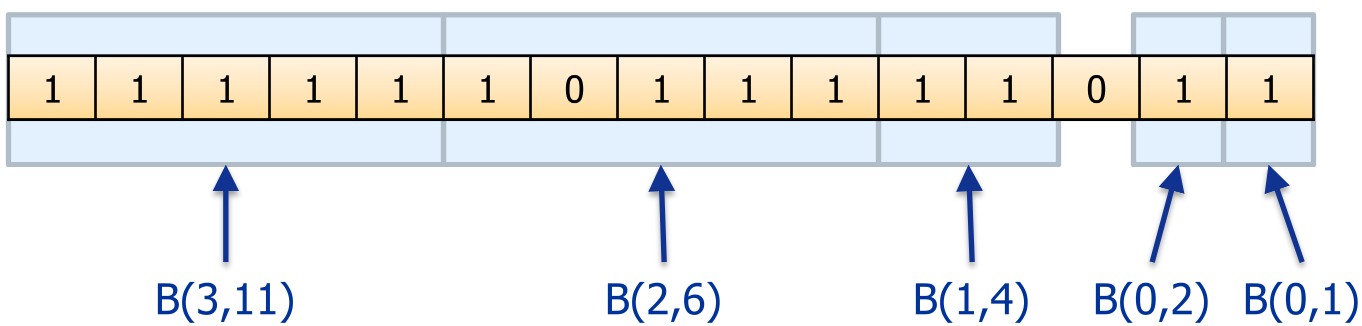
Could answer question trivially with O(N) storage

- 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



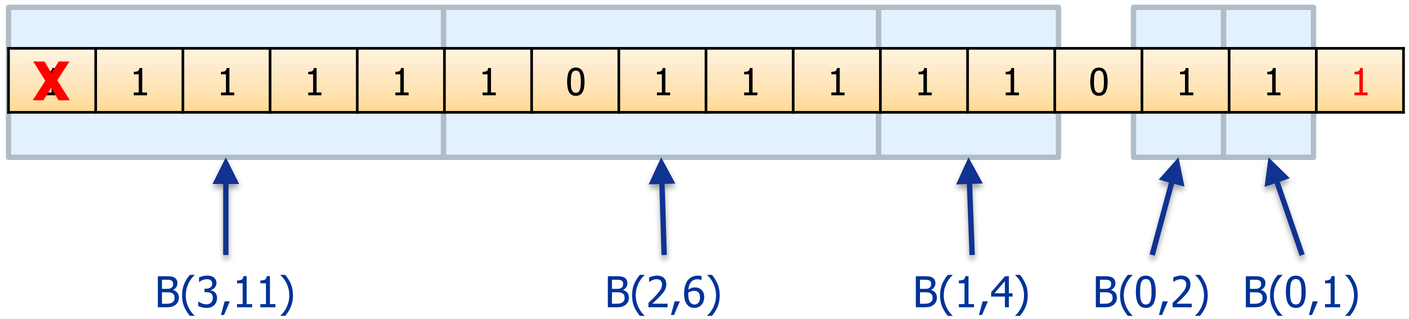
Estimate sum of last k tuples Σ_k:

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

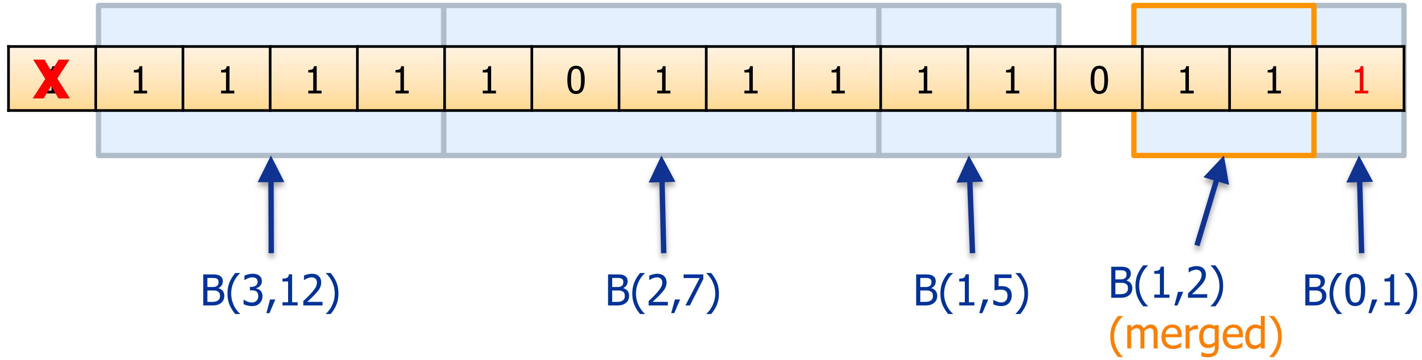
$\Sigma_N = 2^0 + 2^0 + 2^1 + 2^2 + ½ * 2^3 = 12$ (exact answer: 13)

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

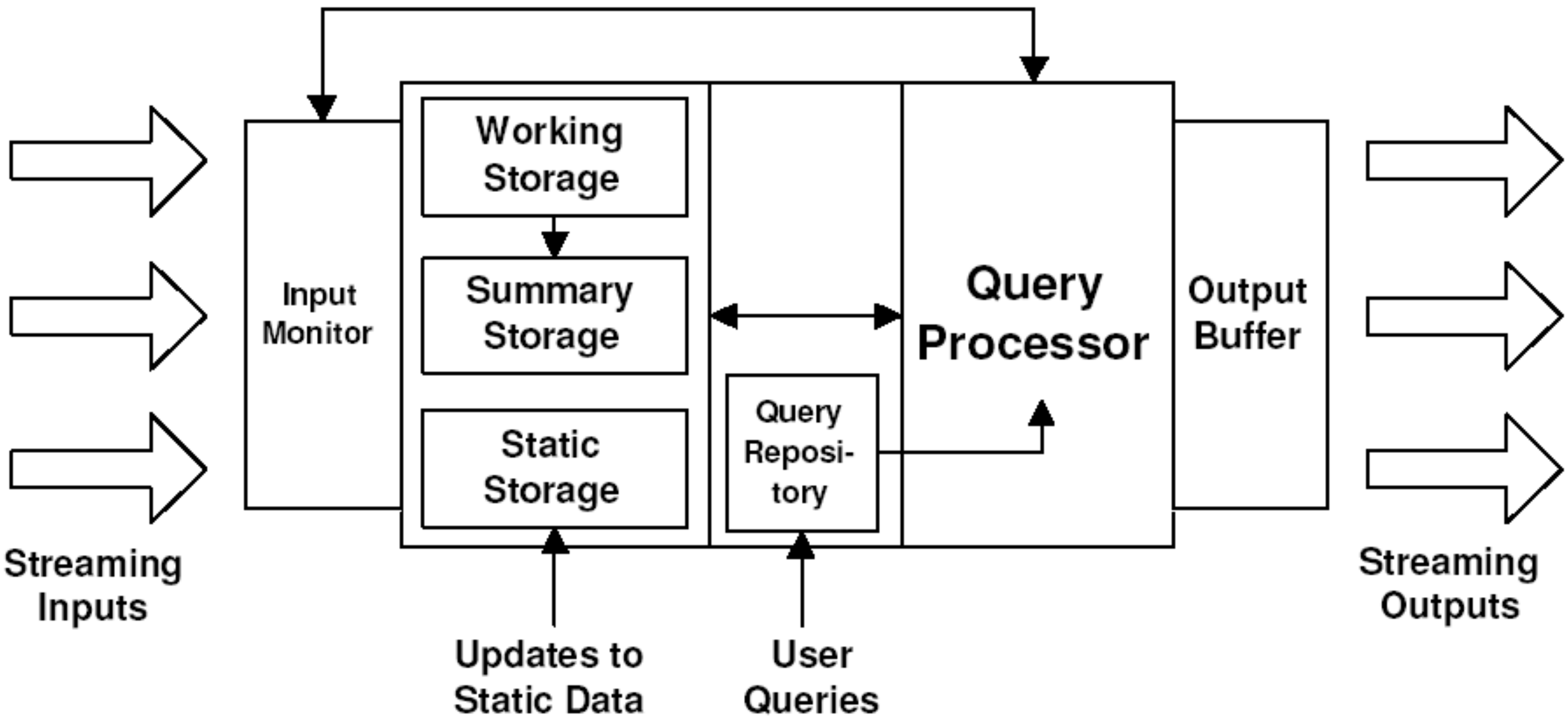
Need O(log N) bits to represent bucket B(m, t):

- **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 **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

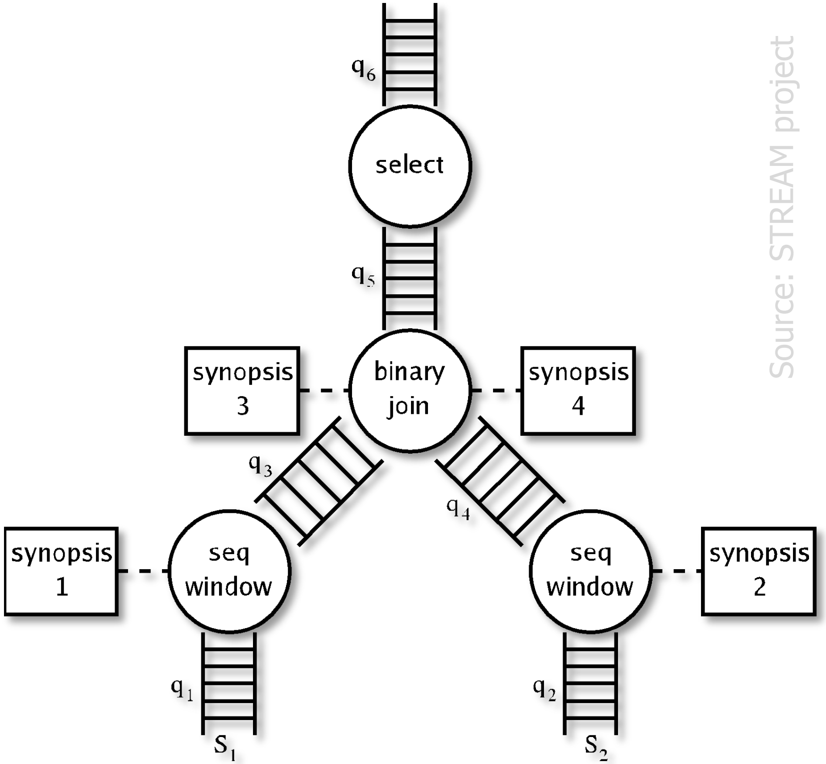
DBMS didn’t quite have this problem...

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)

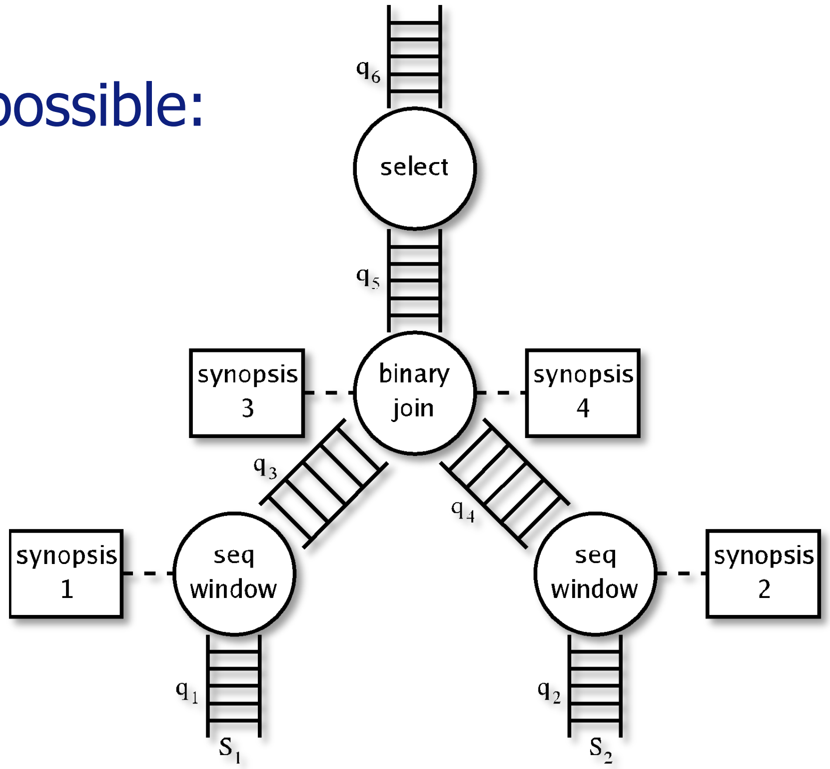
Operator Scheduling

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



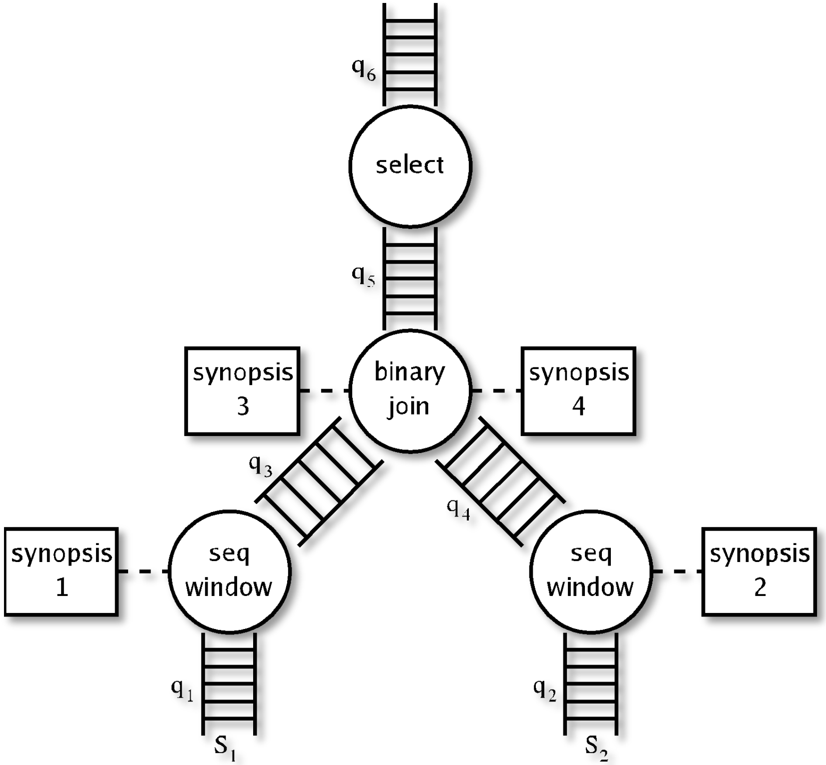
Load Shedding

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

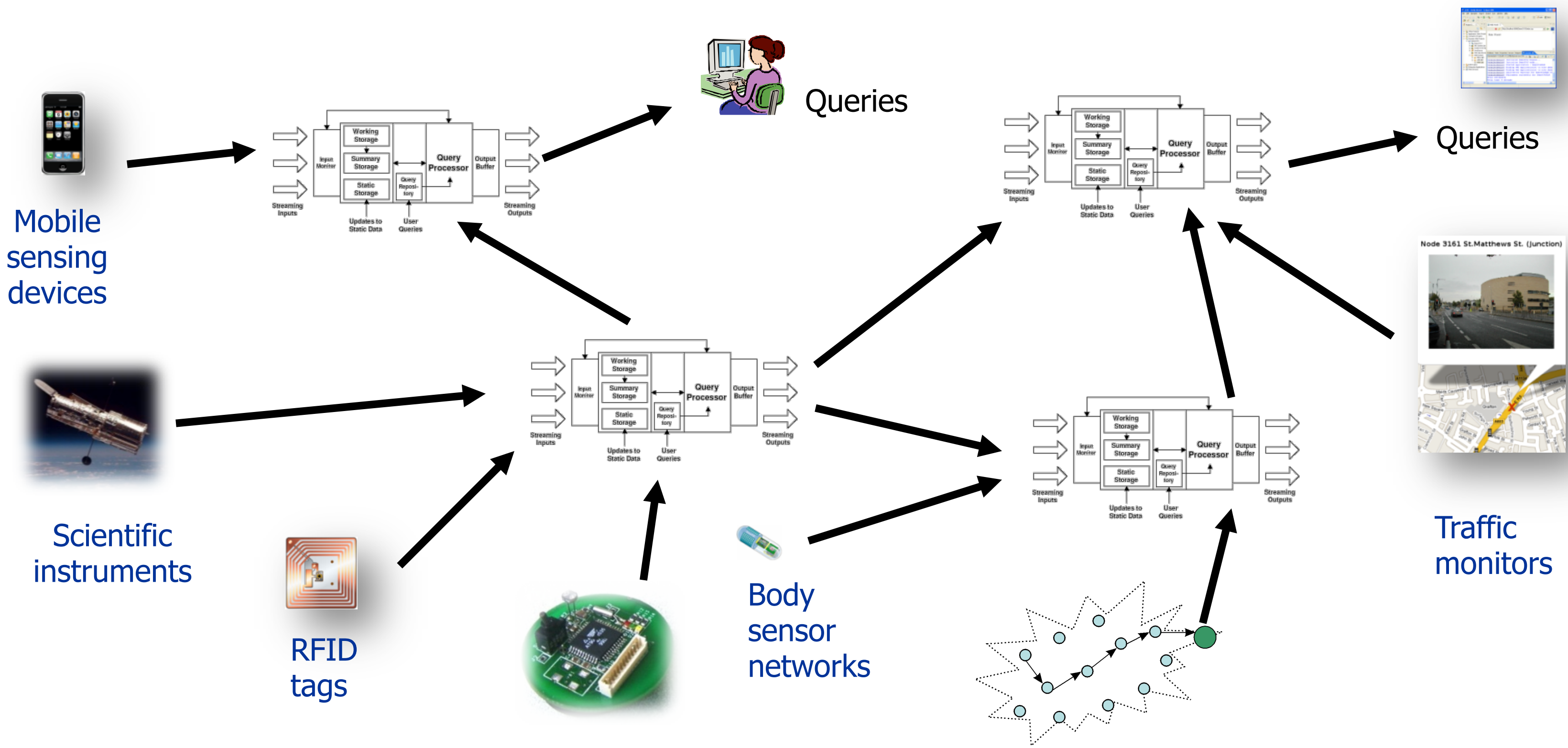


Distributed DSPS

Distributed DSPS

Interconnect multiple DSPSs with network

– Better scalability, handles geographically distributed stream sources

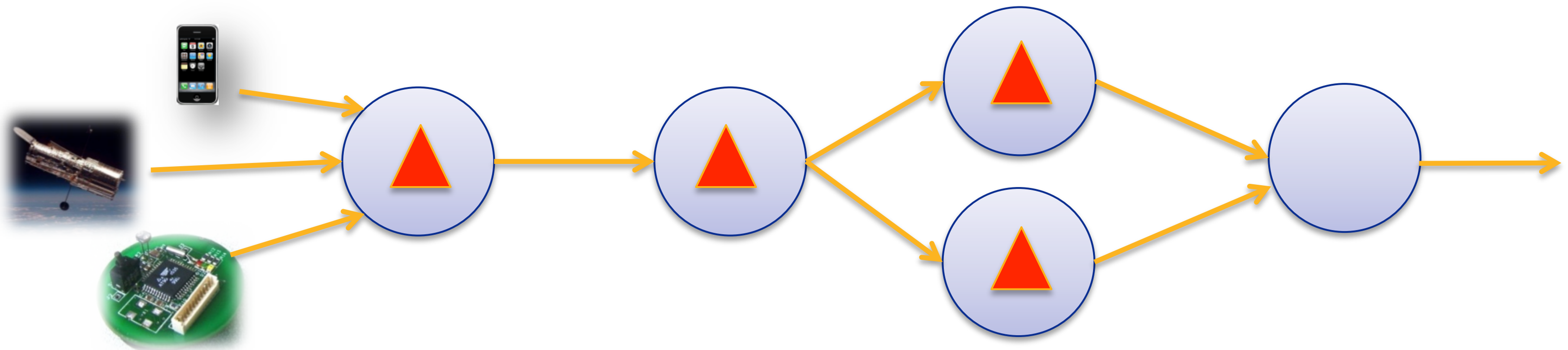


Interconnect on LAN or Internet?

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

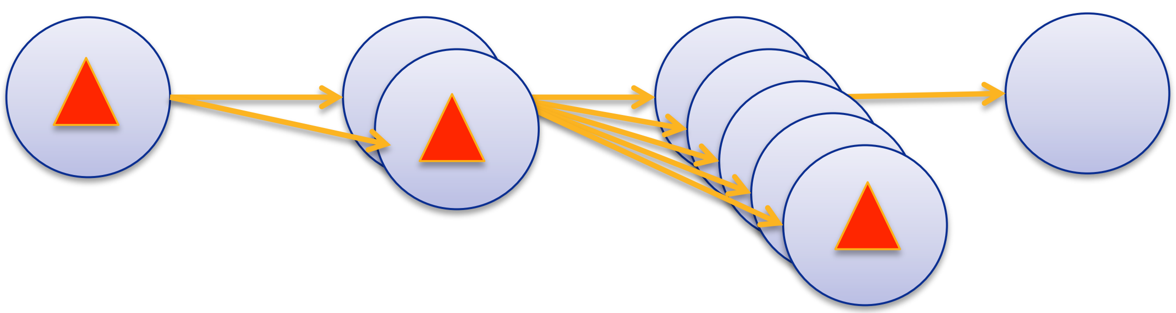
Stream Processing to the Rescue!

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

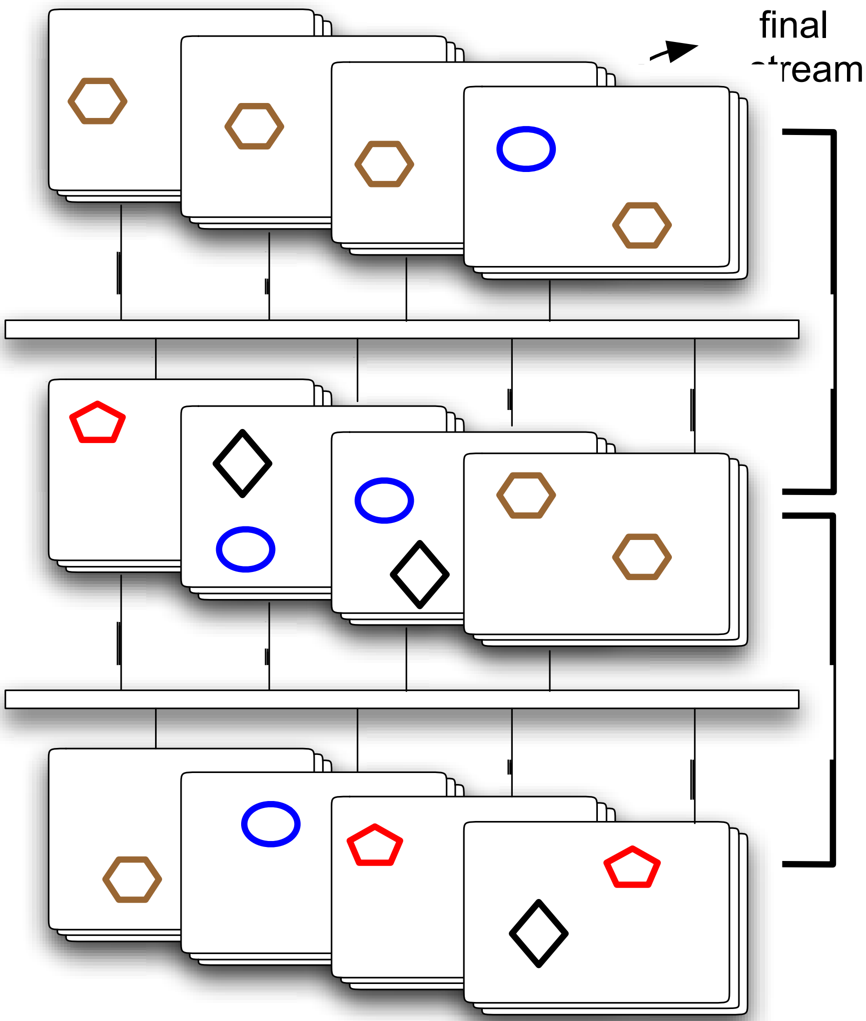


Most interesting operators are **stateful**

- Exploit intra-query parallelism for scale out



Query Planning in DSPS



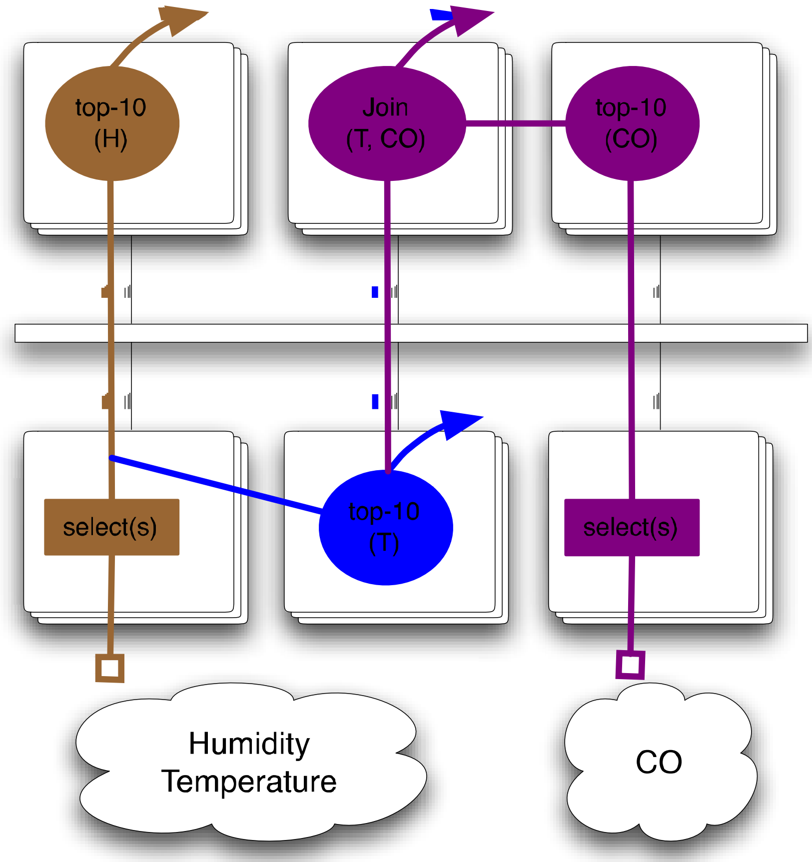
Query Plan

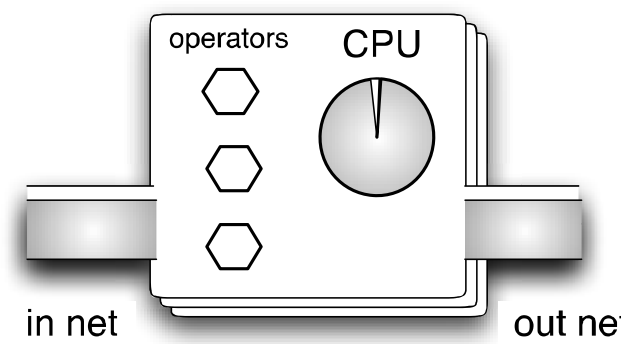
- Operator placement
- Stream connections
- Resource allocation: CPU, network bandwidth, ...

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!

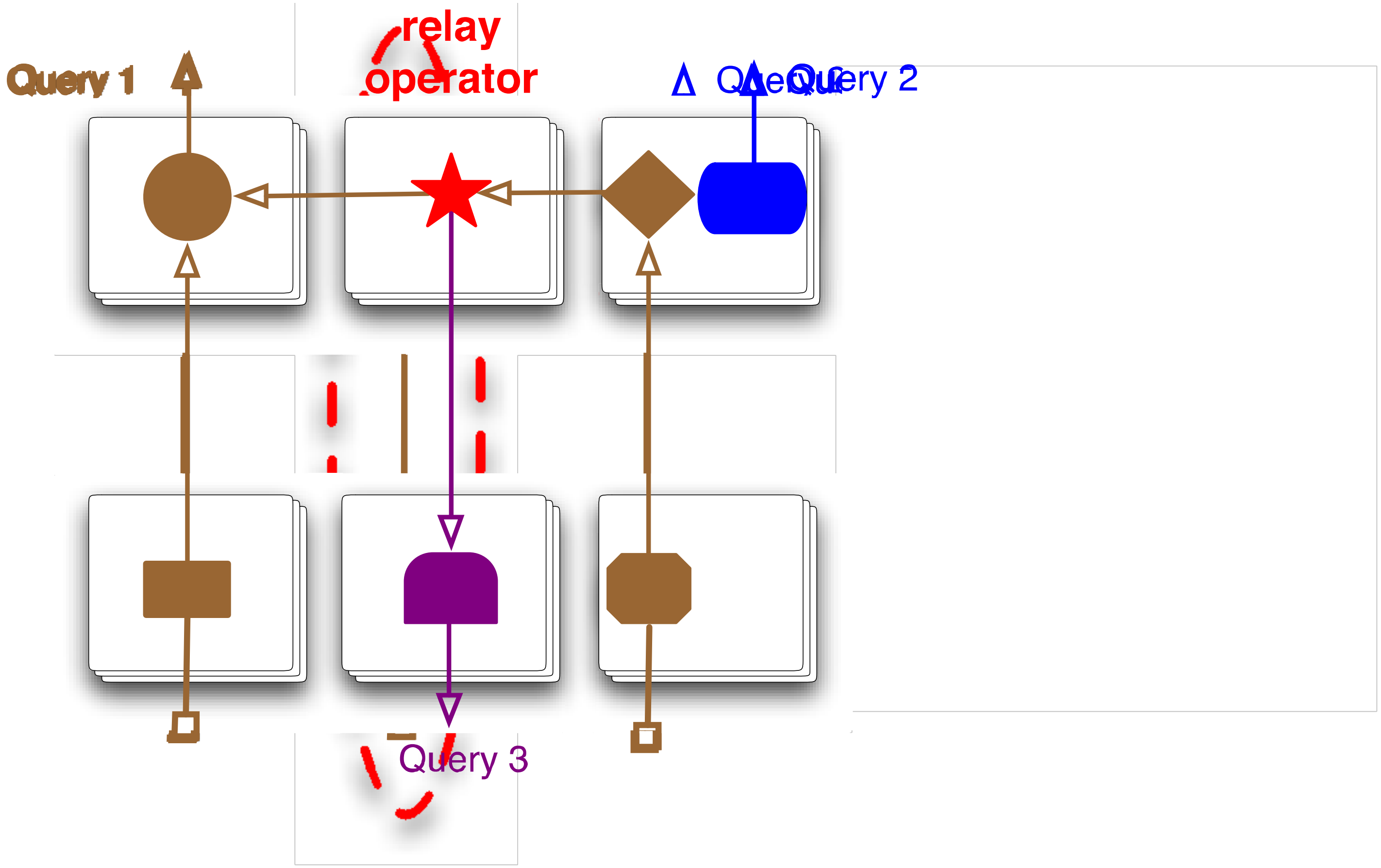
- Solve approximate problem to obtain tractable solution

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

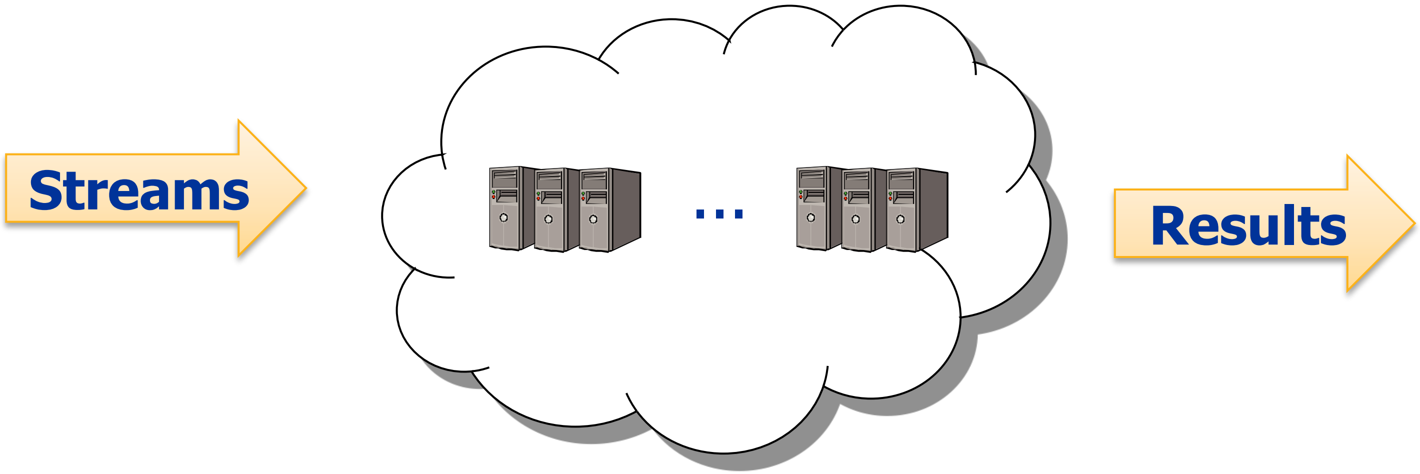


Scalable Stream Processing

Stream Processing in the Cloud

Clouds provide virtually infinite pools of resources

- Fast and cheap access to new machines for operators



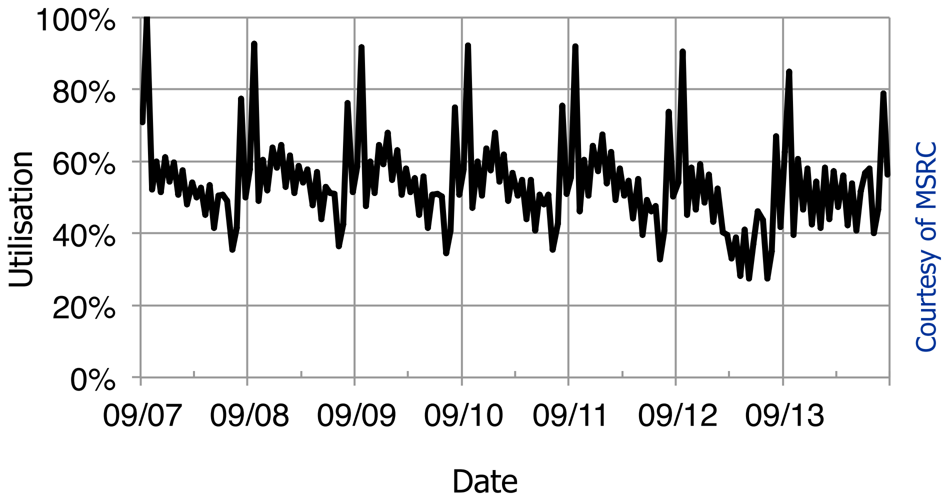
n virtual machines in cloud data centre

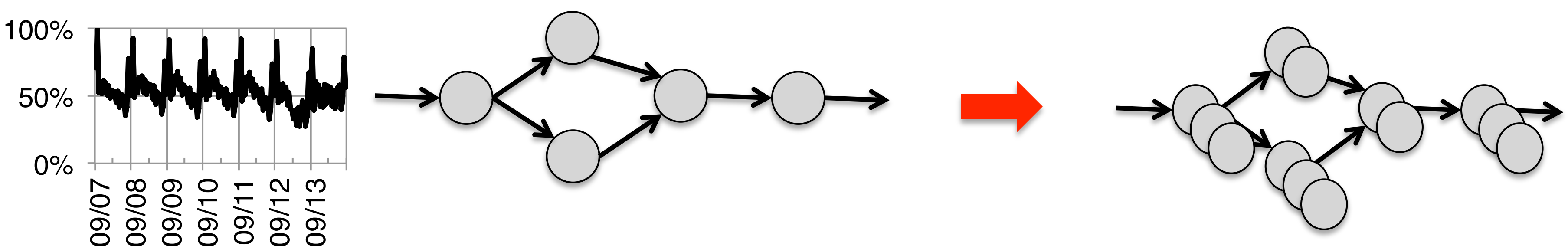
☛ How do you decide on the optimal number of VMs?

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

Challenge 1: Elastic Data-Parallel Processing

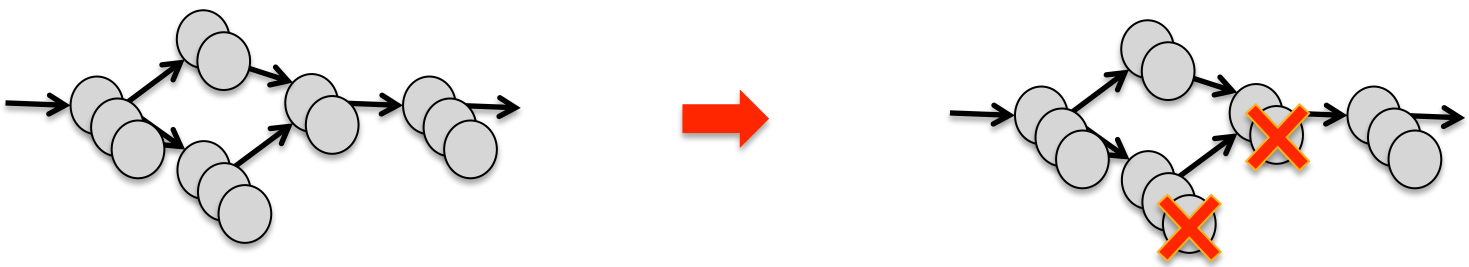
Typical stream processing workloads are bursty





High + **bursty** input rates ➔ Detect **bottleneck** + **parallelise**

Challenge 2: Fault-Tolerant Processing



Large scale deployment ➔ Handle node **failures**

Failure is a common occurrence

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

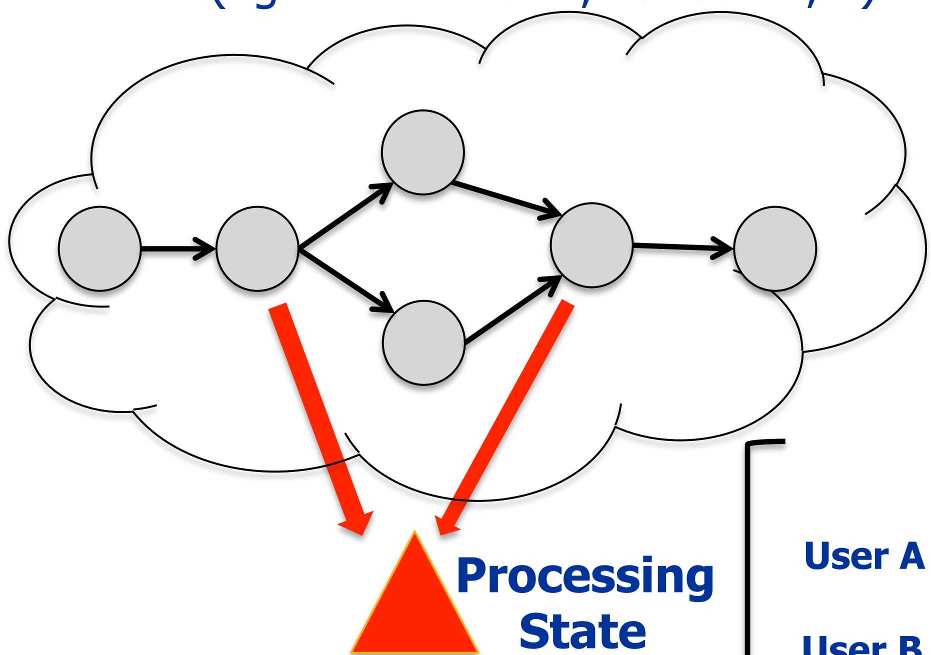
State in Stream Processing

Consider a streaming recommender application (collaborative filtering)

Stream Processing System
(eg Twitter Storm, Yahoo S4,…)

User Activities

(eg item purchases, page views, clicks, …)



Recommendations

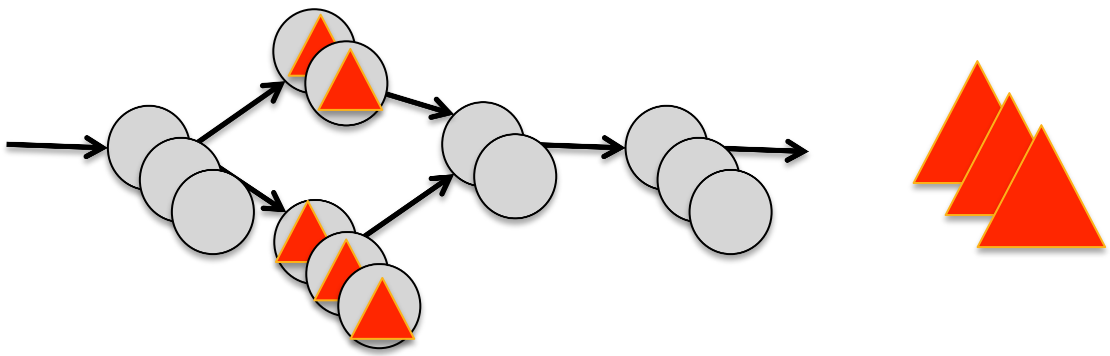
Processing State

	Item 1	**Item 2**
User A	2	5
User B	4	1

☛ Most online machine learning algorithms require state

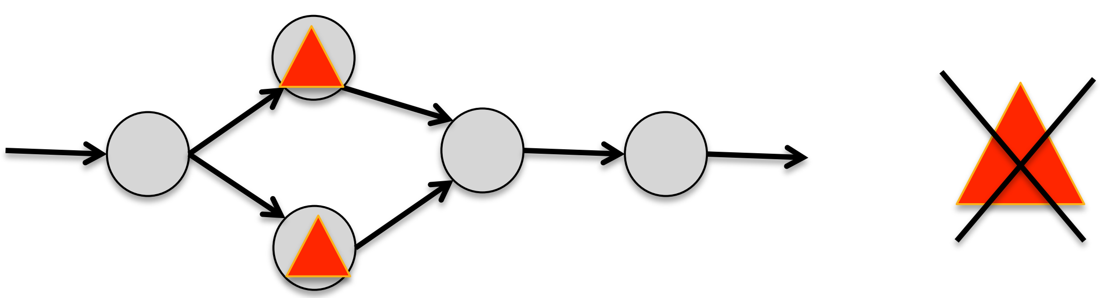
State Complicates Things…

1. Dynamic scale out impacts state



Partitioning of state

2. Recovery from failures

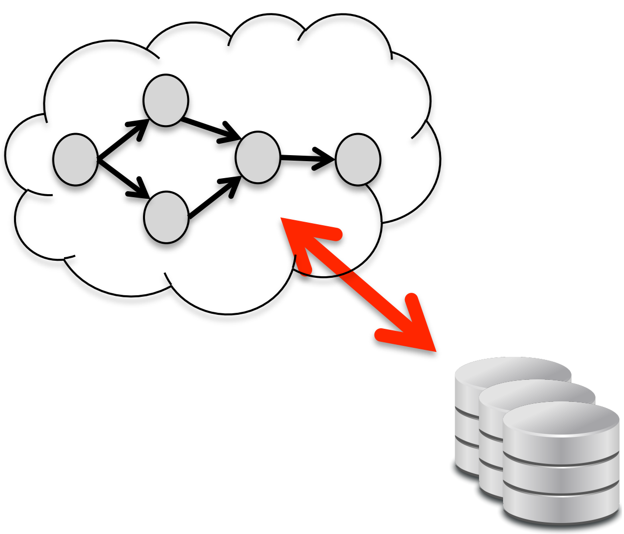


Loss of state after node failure

Current Approaches for Stateful Processing

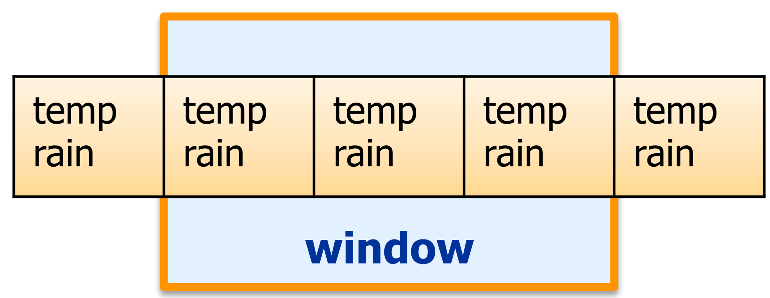
Stateless stream processing systems (eg Yahoo S4, Twitter Storm, …)

- **Developers manage state**
- Typically combine with external system to store state (eg Cassandra)
- Design complexity

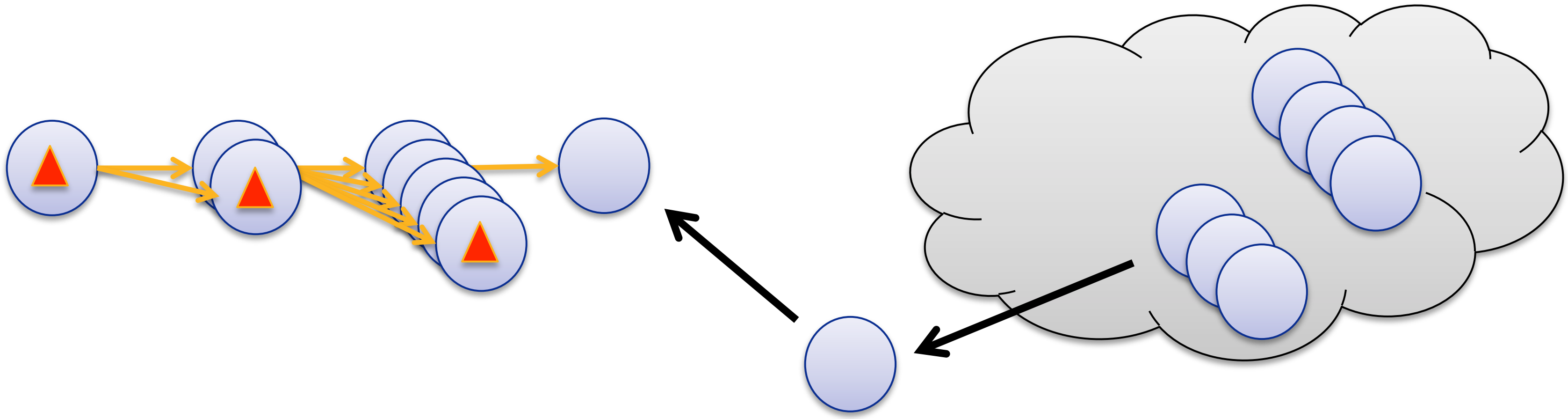


Relational stream processing systems (eg Borealis, Stream)

- State is **window** over stream
- No support for arbitrary state
- Hard to realise complex ML algorithms



Stateful Stream Processing Model



Operators can maintain **arbitrary state**

State management primitives to:

- Backup and recover state
- Partition state

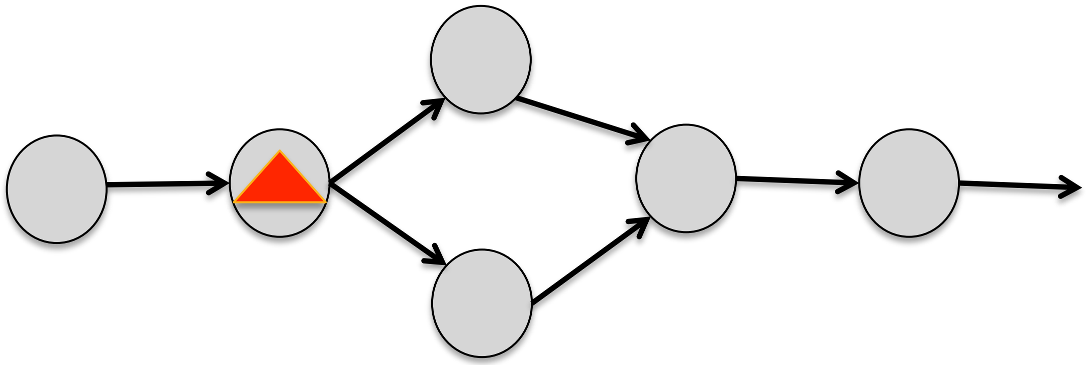
Integrated mechanism for scale out and failure recovery

- Operator recovery and scale out equivalent from state perspective

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

Idea: State as First Class Citizen

☛ Expose operator state as external entity so that it can be managed by stream processing system



Operators have direct access to state

System manages state

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

What is State?

Processing state

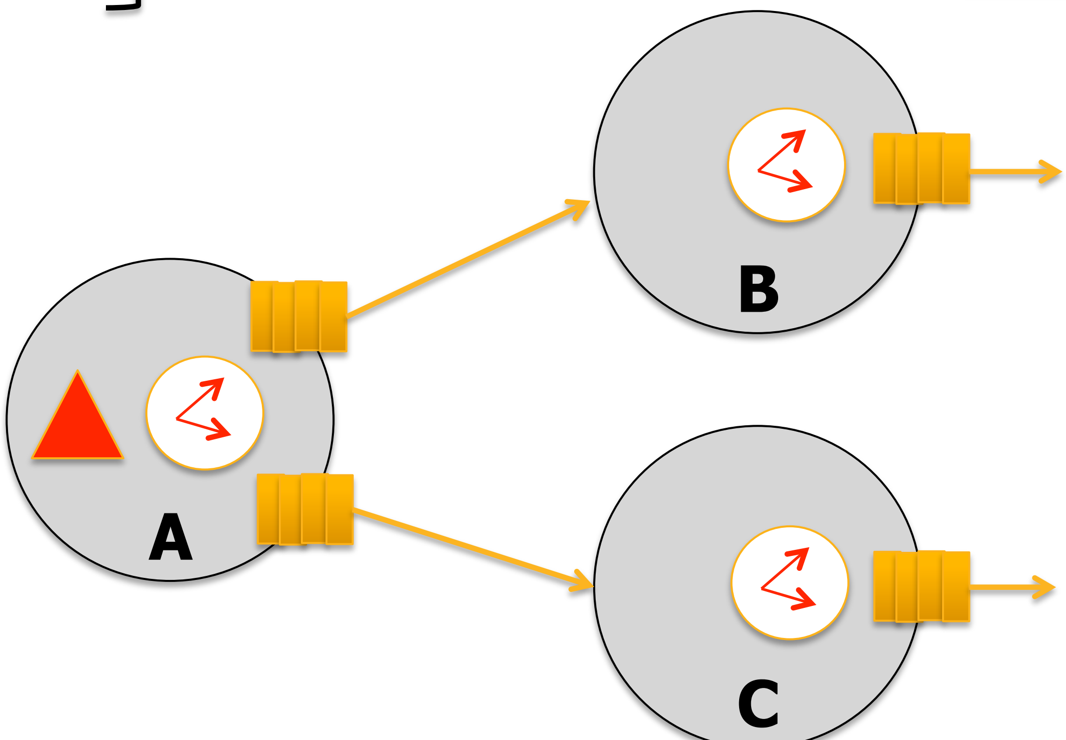
	Item 1	Item 2
User A	2	5
User B	4	1

Routing state

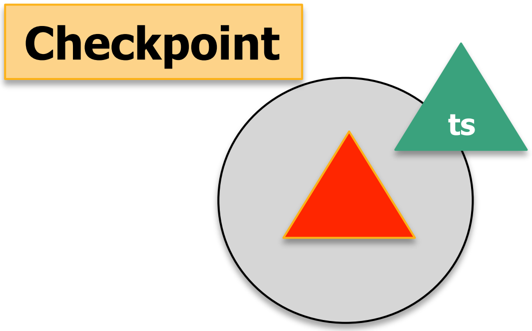
Dynamic data flow graph:
Based on data, A ➔ B or A ➔ C

Buffer state

Data ts1	Data ts2	Data ts3	Data ts4

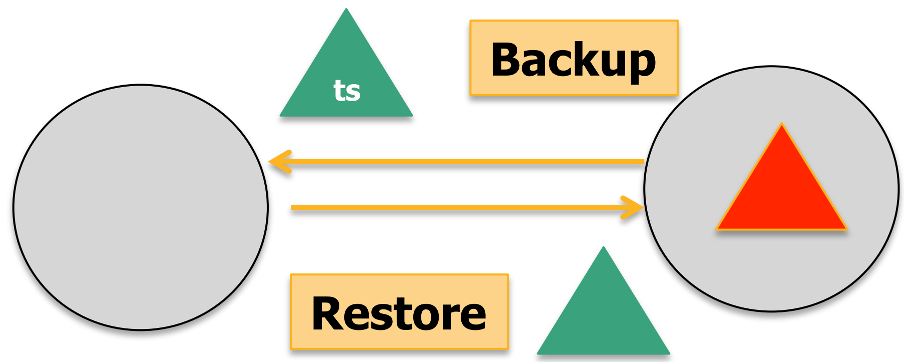


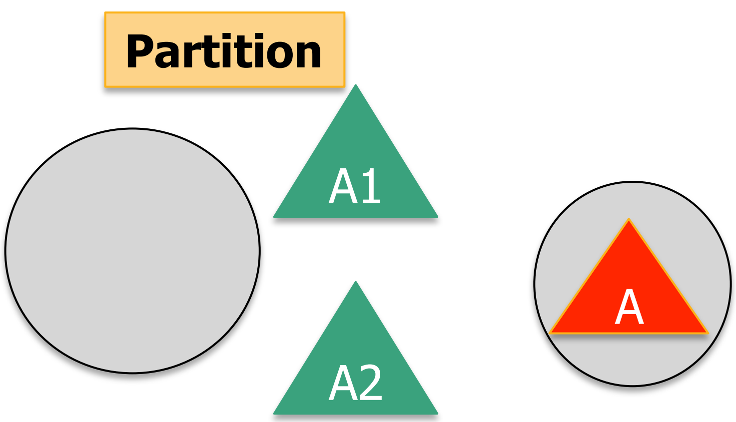
State Management Primitives



- Makes state available to system
- Attaches **last processed tuple timestamp**

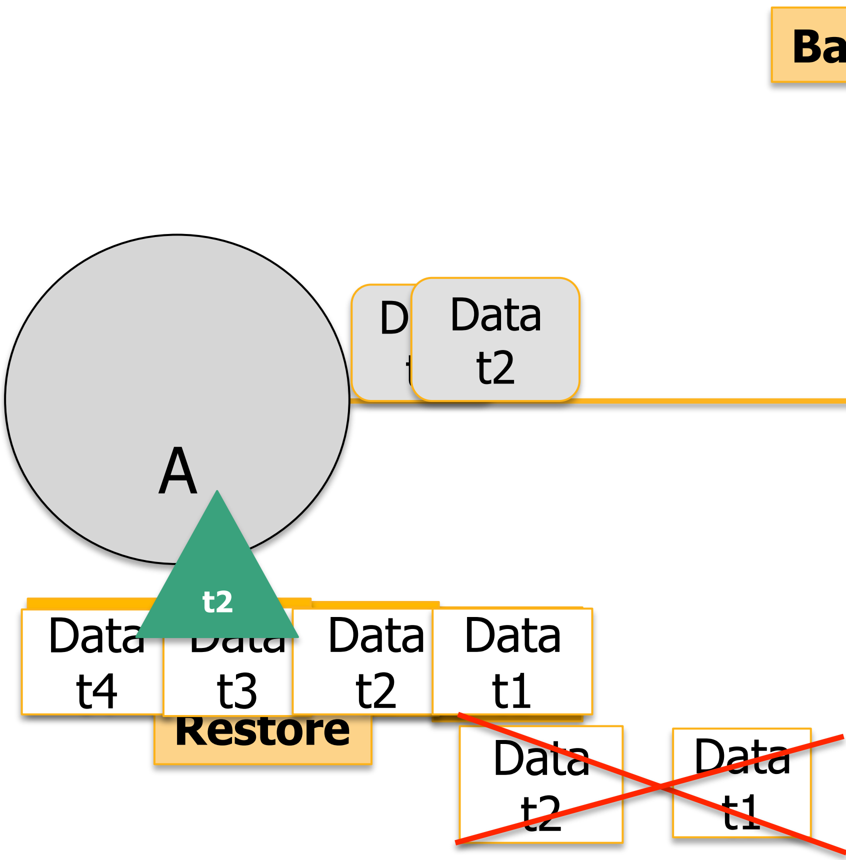
- Moves copy of state from one operator to another





- Splits state to scale out an operator

State Primitives: Backup and Restore

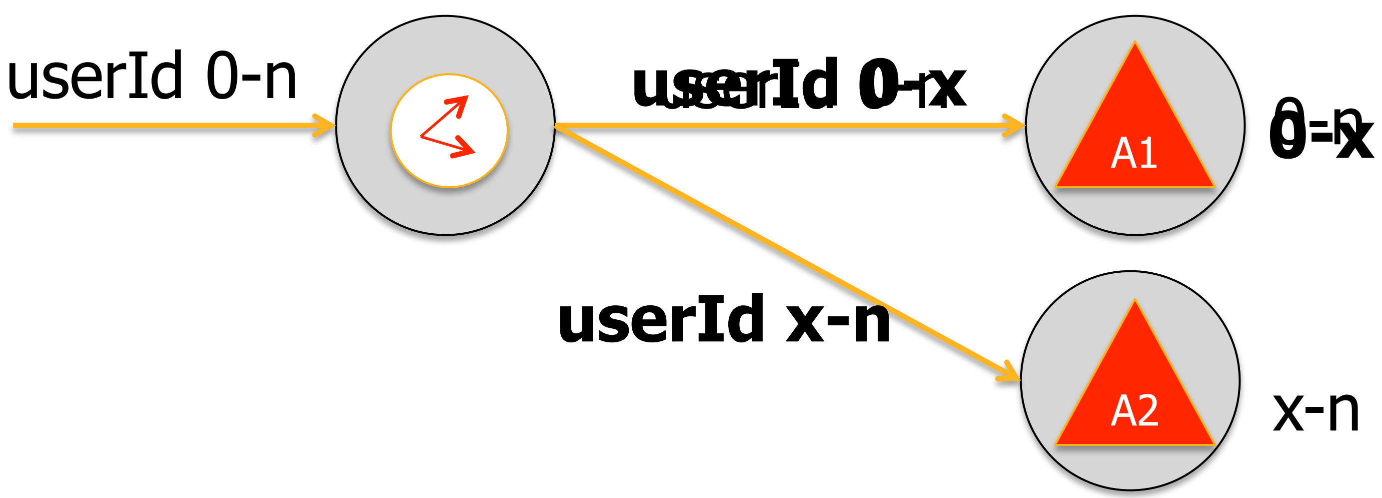


State Primitives: Partition

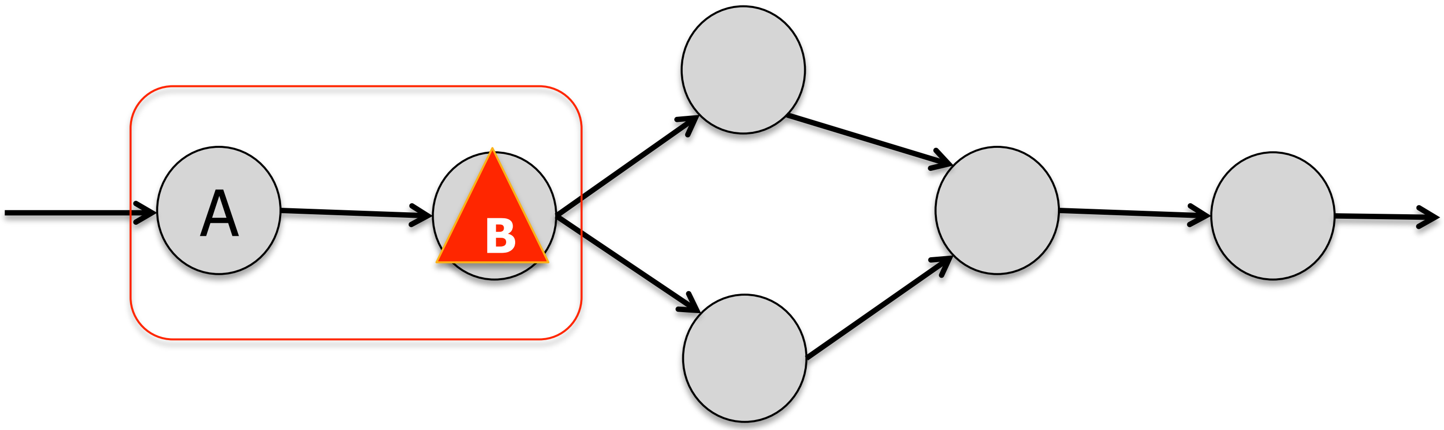
Processing state modeled as (key, value) dictionary

State partitioned according to **key** *k* of tuples

- Same key used to partition streams



Scale Out and Failure Recovery



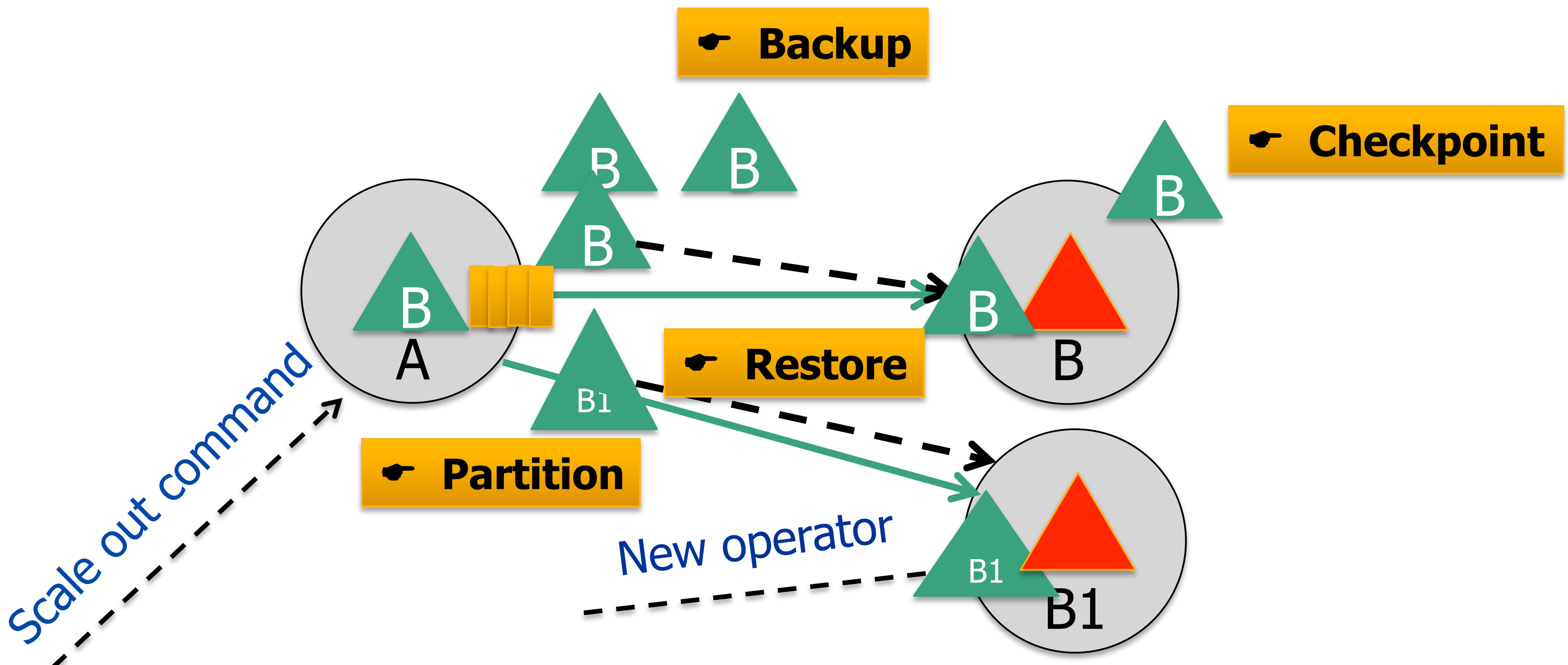
Two cases:

- Operator B becomes **bottleneck ➔ Scale out**
- Operator B **fails ➔ Recover**

Scaling Out Stateful Operators

Finally, upstream operators replay unprocessed tuples to update checkpointed state

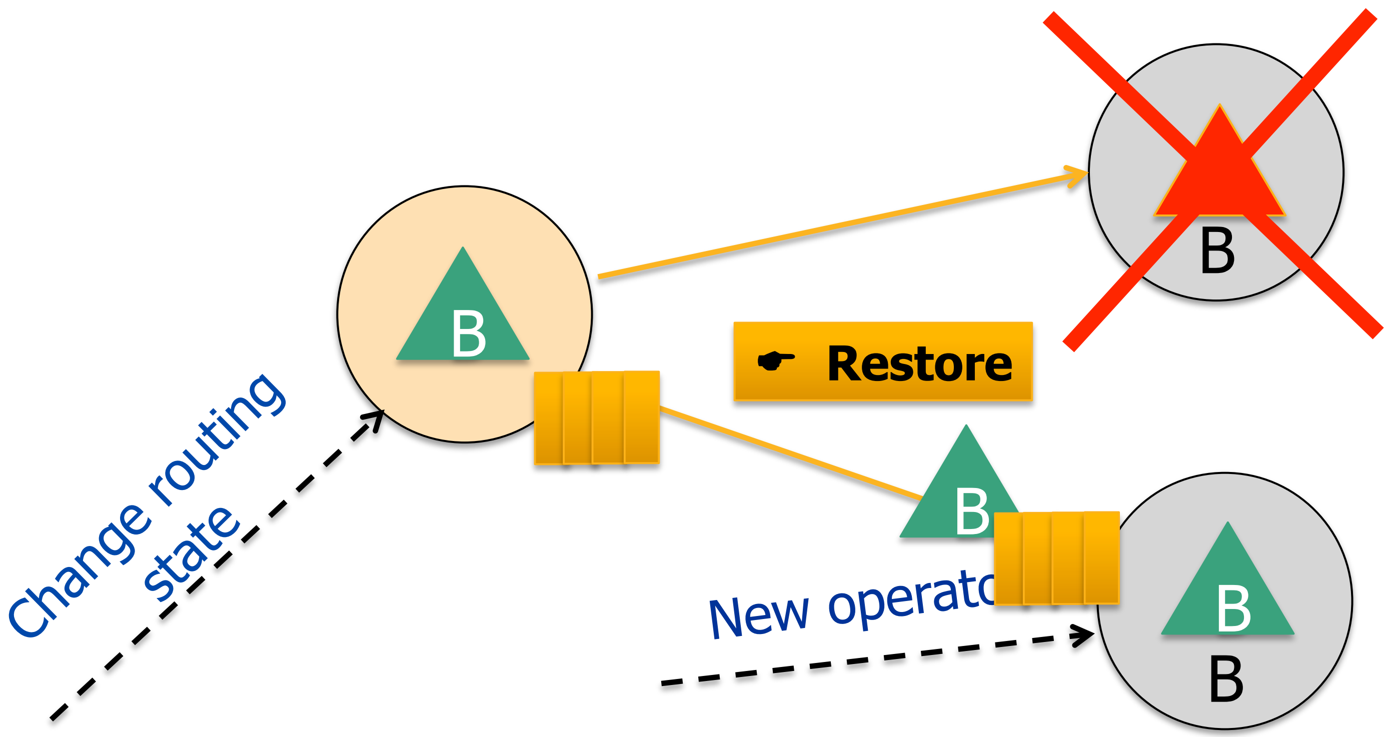
Periodically, stateful operators checkpoint and back up state to designated **upstream backup node**



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

Recovering Failed Operators

Use backed up state to recover quickly



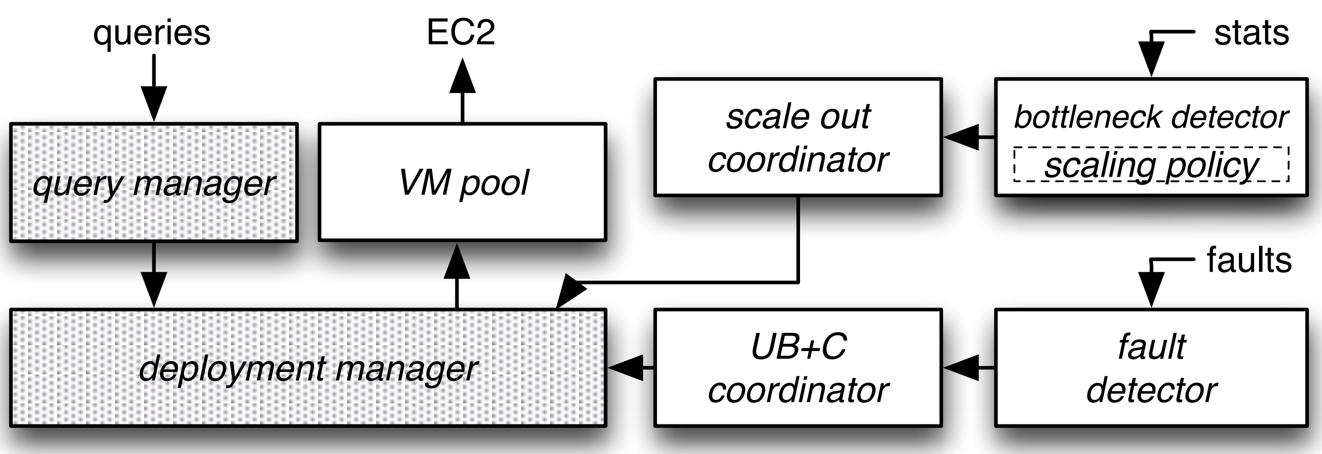
State restored and unprocessed tuples replayed from buffer

SEEP Stream Processing System

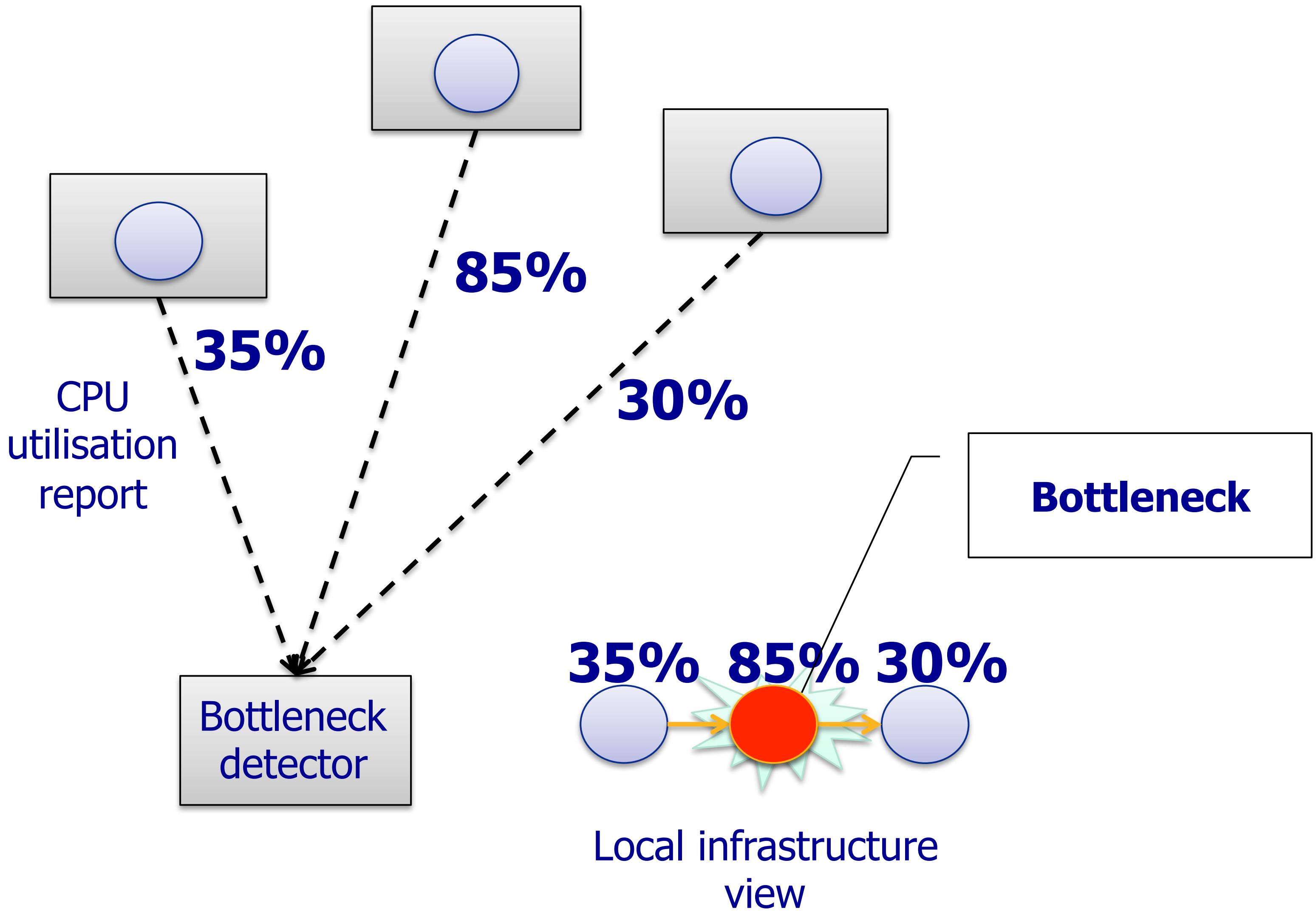
Experimental stateful stream processing platform

Implements dynamic scale out and recovery

- Detect failed or overloaded operators
- Have fast access to new VMs

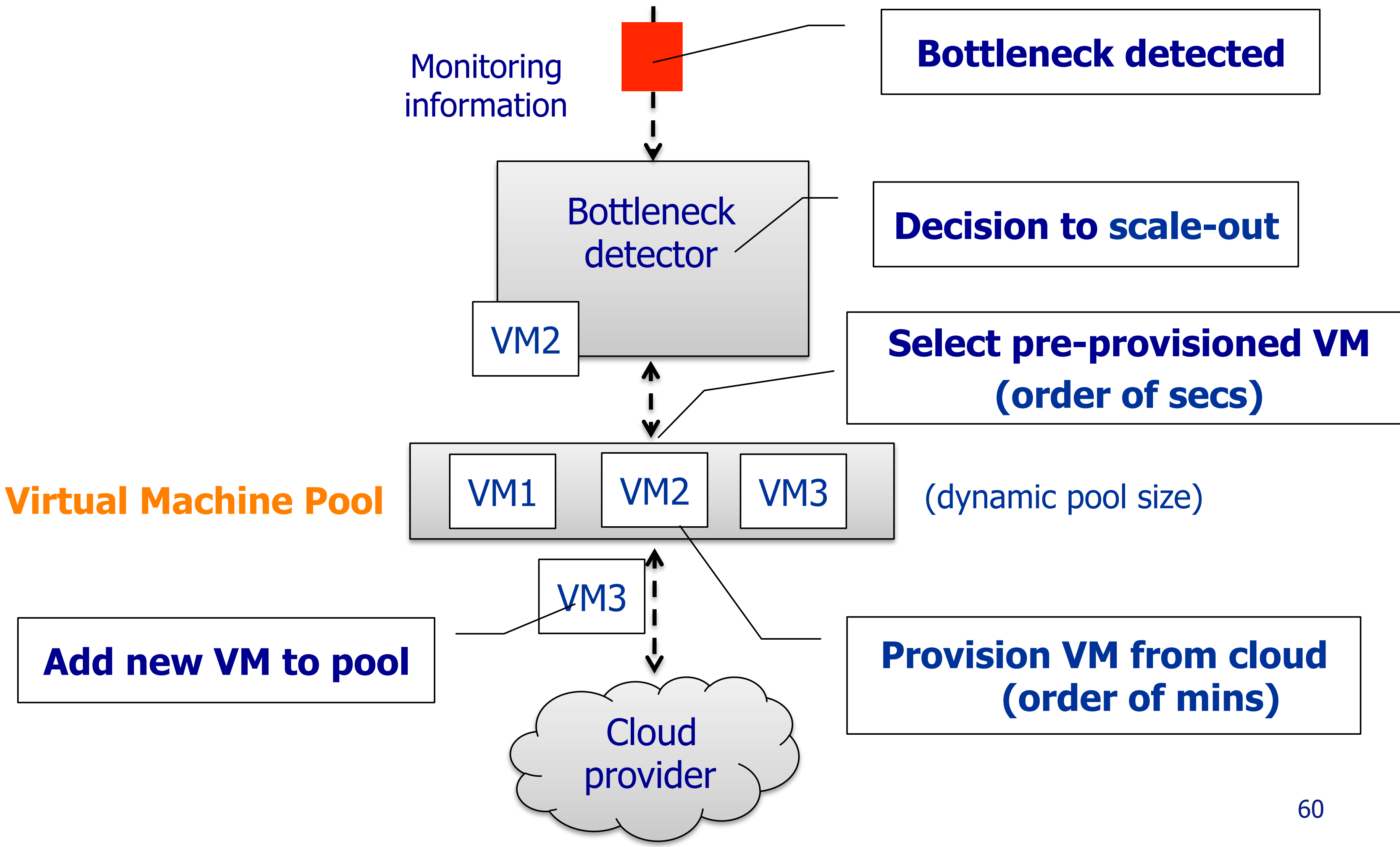


Detecting Bottlenecks



VM Pool for Adding Operators

Problem: Allocating new VMs takes minutes...



Evaluation: Goals and Methodology

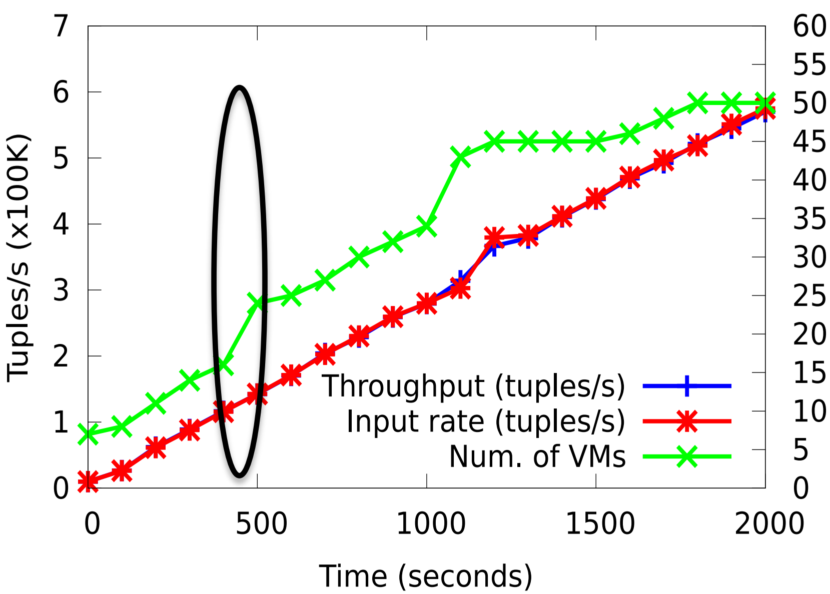
1. Effectiveness of dynamic scale out
2. Measurement of failure recovery time
3. Overhead of state management

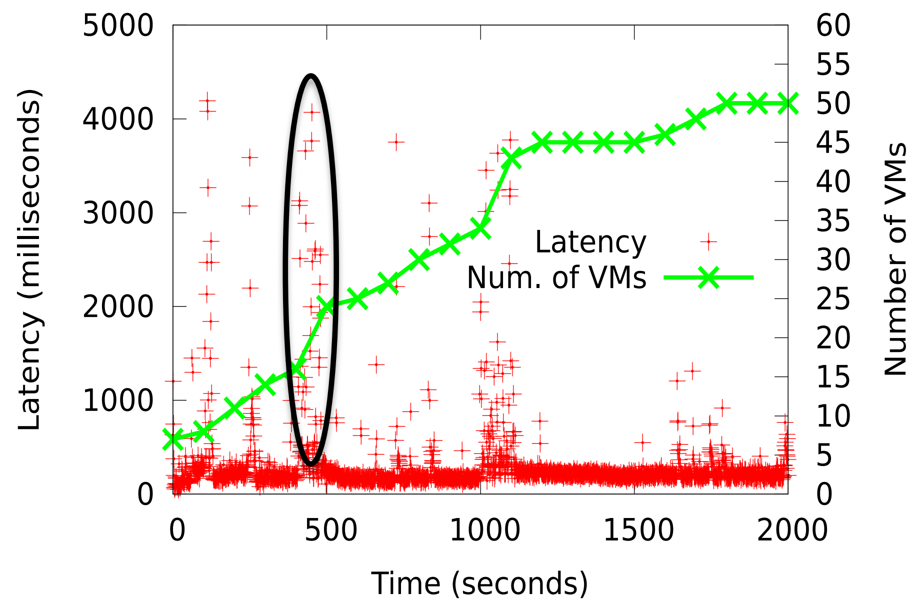
Workload: **Linear Road Benchmark** [VLDB'04]

- Operator state depends on whole stream history
- Input stream rate increases over time according to Load Factor L
- SLA: results $<$ 5 secs
- Data flow graph with 7 operators

Deployed SEEP on **Amazon AWS EC2**

Scale Out with Elastic Workload





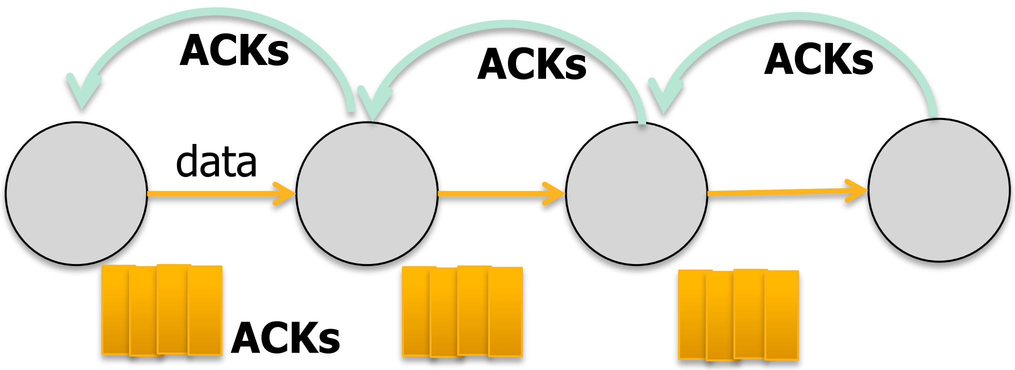
Scales to load factor L=350 with 60 VMs on Amazon EC2

– L=512 highest report result [VLDB'12]

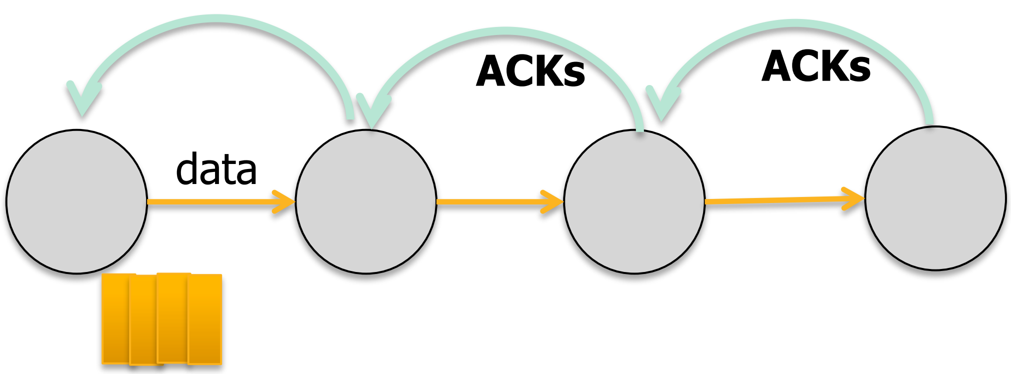
☛ **SEEP scales out dynamically with low impact on latency**

Upstream Backup

Upstream Backup saves all tuples in buffers



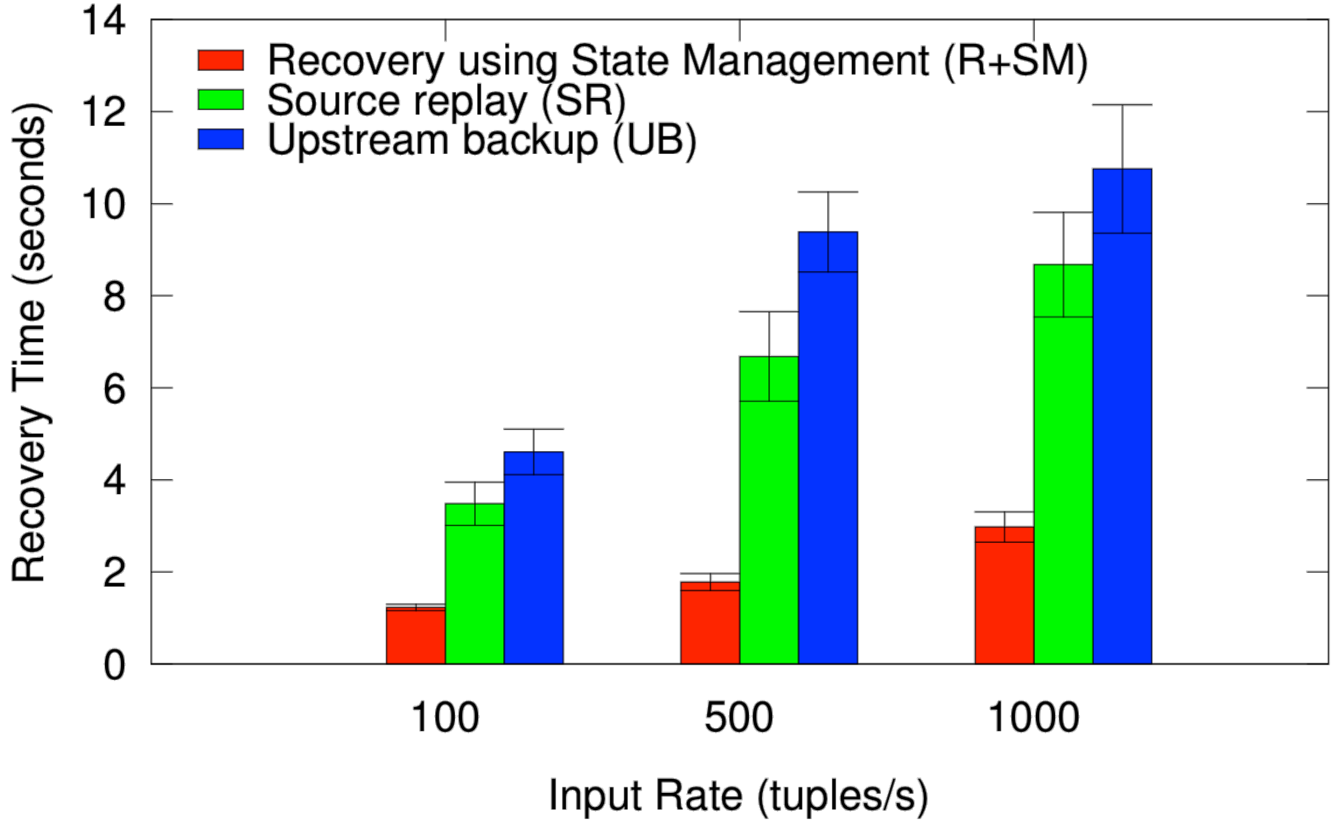
Source Replay saves tuples only in the source



Failure Recovery Time

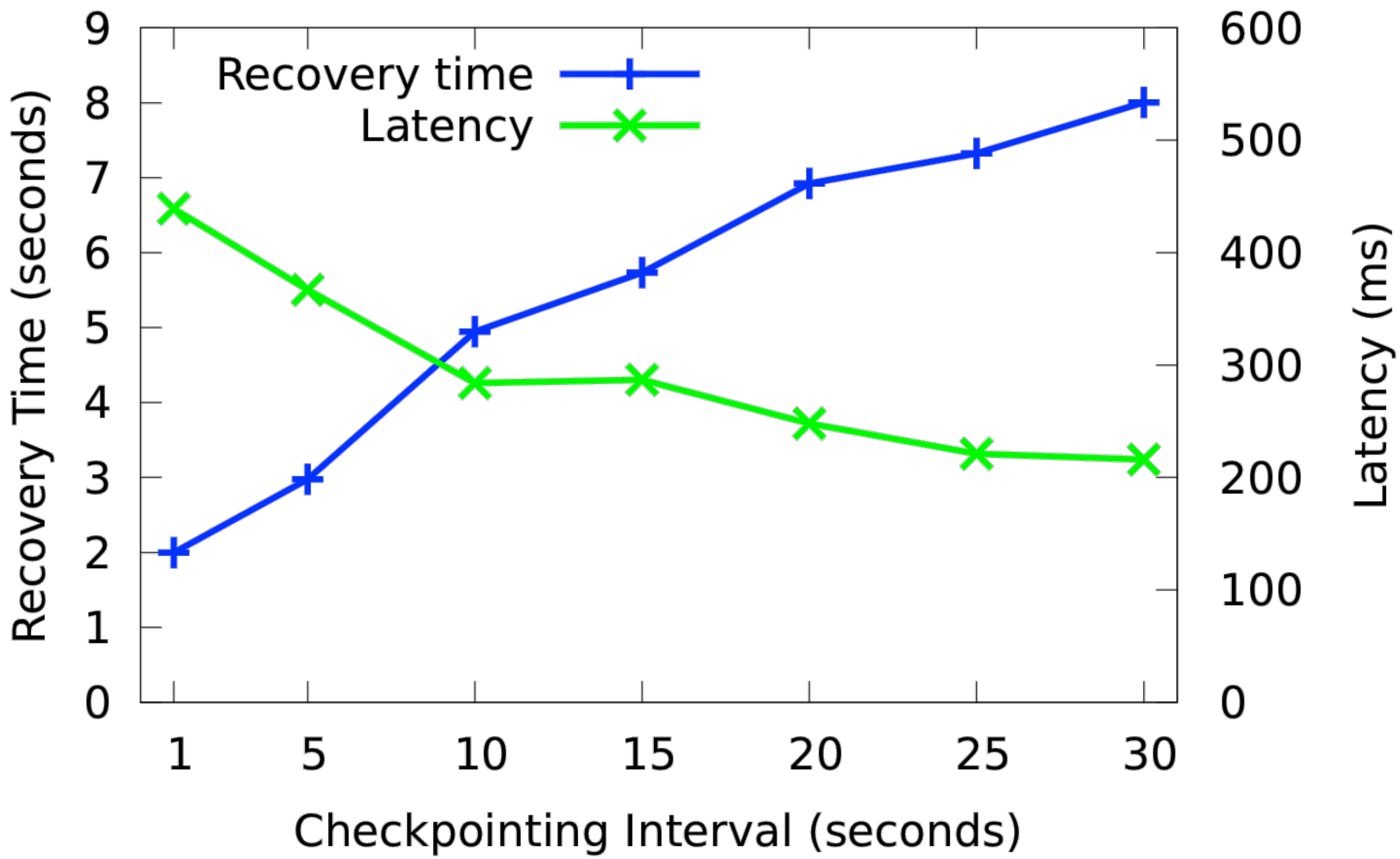
Workload: Windowed word counting query

– 30 sec window with 5 sec checkpointing interval



☛ **Checkpointing leads to smaller buffers**

Overhead of Checkpointing



☛ **Tradeoff between latency and recovery time**

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?

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