UNIVERSITY OF CAMBRIDGE

Integrating Scale Out and Fault Tolerance in Stream Processing using Operator State Management

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Big data …

… in numbers:

- 2.5 billions on gigabytes of data every day (source IBM)
- LSST telescope, Chile 2016, 30 TB nightly

… come from everywhere:

- web feeds, social networking
- mobile devices, sensors, cameras
- scientific instruments
- online transactions (public and private sectors)

… have value:

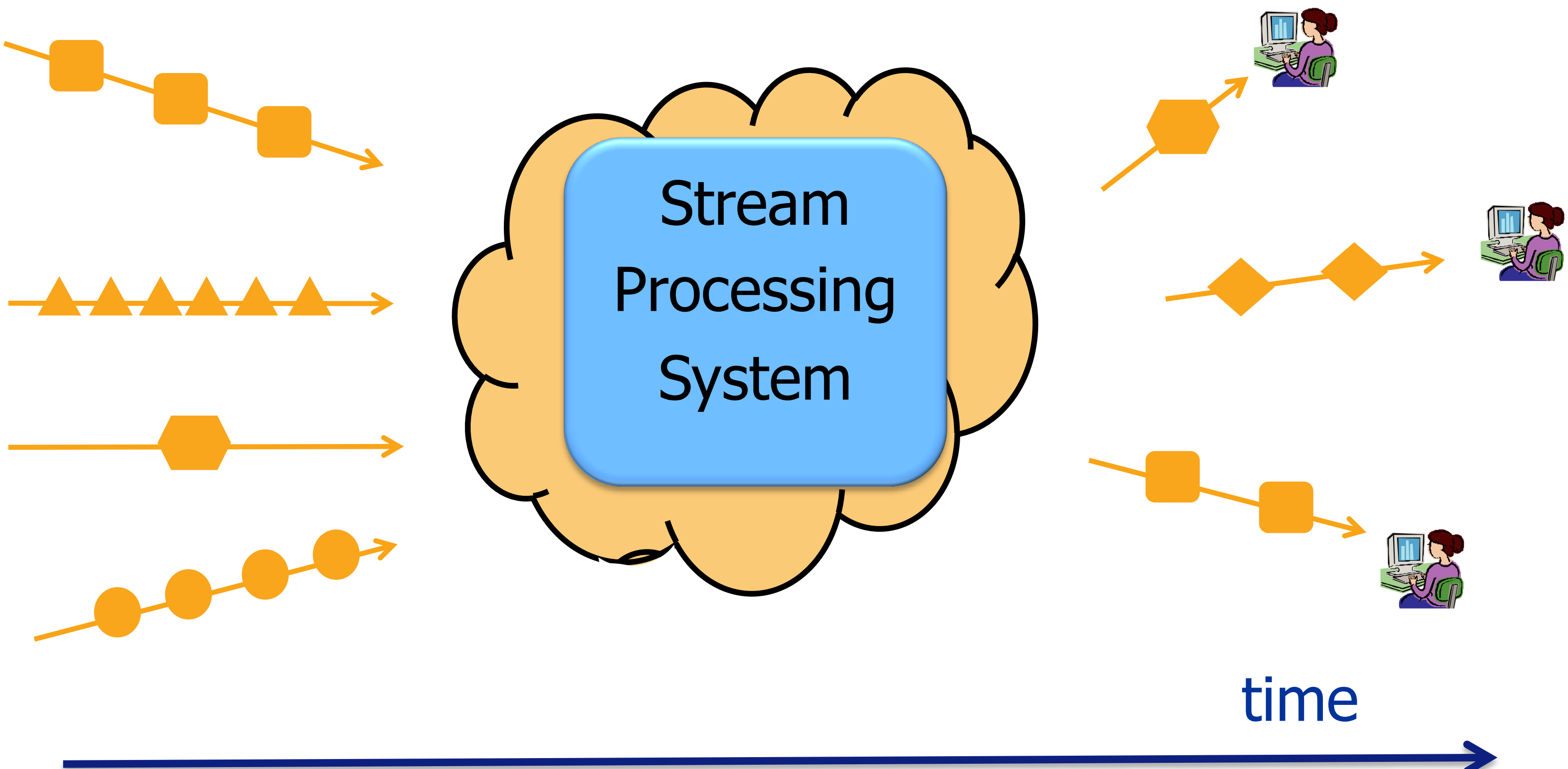
- Global Pulse forum for detecting human crises internationally
- real-time big data analytics in UK £25 billions → £216 billions in 2012-17
- recommendation applications (LinkedIn, Amazon)

☛ processing infrastructure for big data analysis

A black-box approach for big data analysis

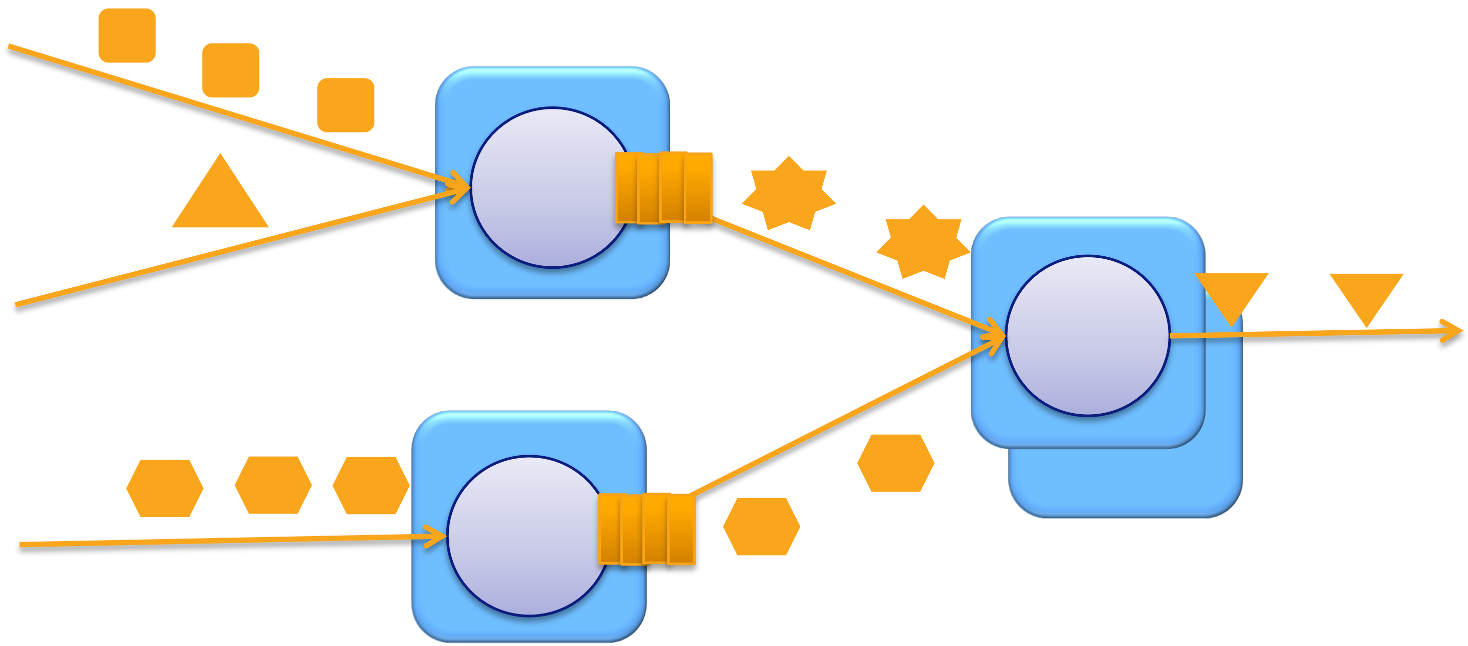
- users issue analysis ***queries*** with real-time semantics
- ***streams*** of data updates, ***time-varying rates***, generated in ***real-time***
- ***streams of result data***

✓ processing in ***near real-time***



Distributed Stream Processing System

- queries consist of **operators** (join, map, select, ..., UDOs)
- operators form graphs
- operators process **streams of tuples** on-the-fly
- operators span nodes



Elastic DSPSs in the Cloud

Real-time big data analysis challenge traditional DSPS:

? what about continuous workload surges?

? what about real-time resource allocation to workload variations?

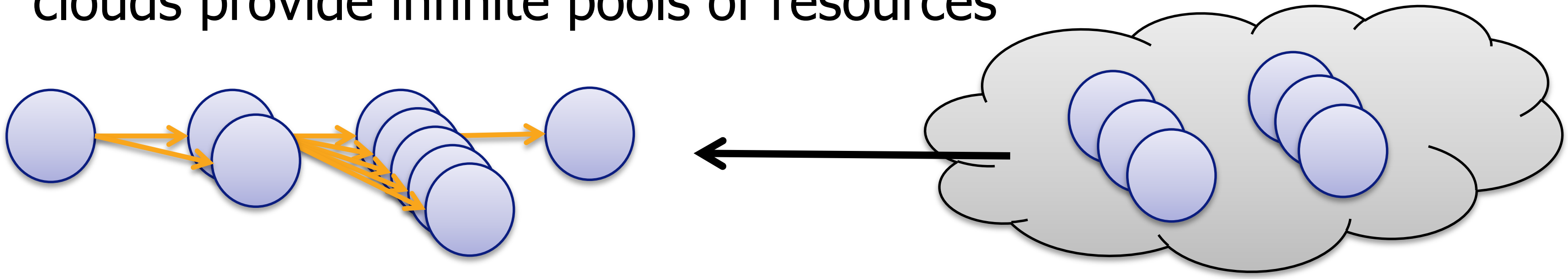
? keeping the state correct for *stateful* operators?

Massively scalable , cloud-based DSPSs [SIGMOD 2013]

1. gracefully handles **stateful** operators' state
2. operator **state management** for **combined** scale out and fault tolerance
3. SEEP system and evaluation
4. related work
5. future research directions

Stream Processing in the Cloud

clouds provide infinite pools of resources



? How do we build a stream processing platform in the Cloud?

Intra-query parallelism:

– provisioning for workload peaks unnecessarily conservative

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

Failure resilience:

– active fault-tolerance needs 2x resources

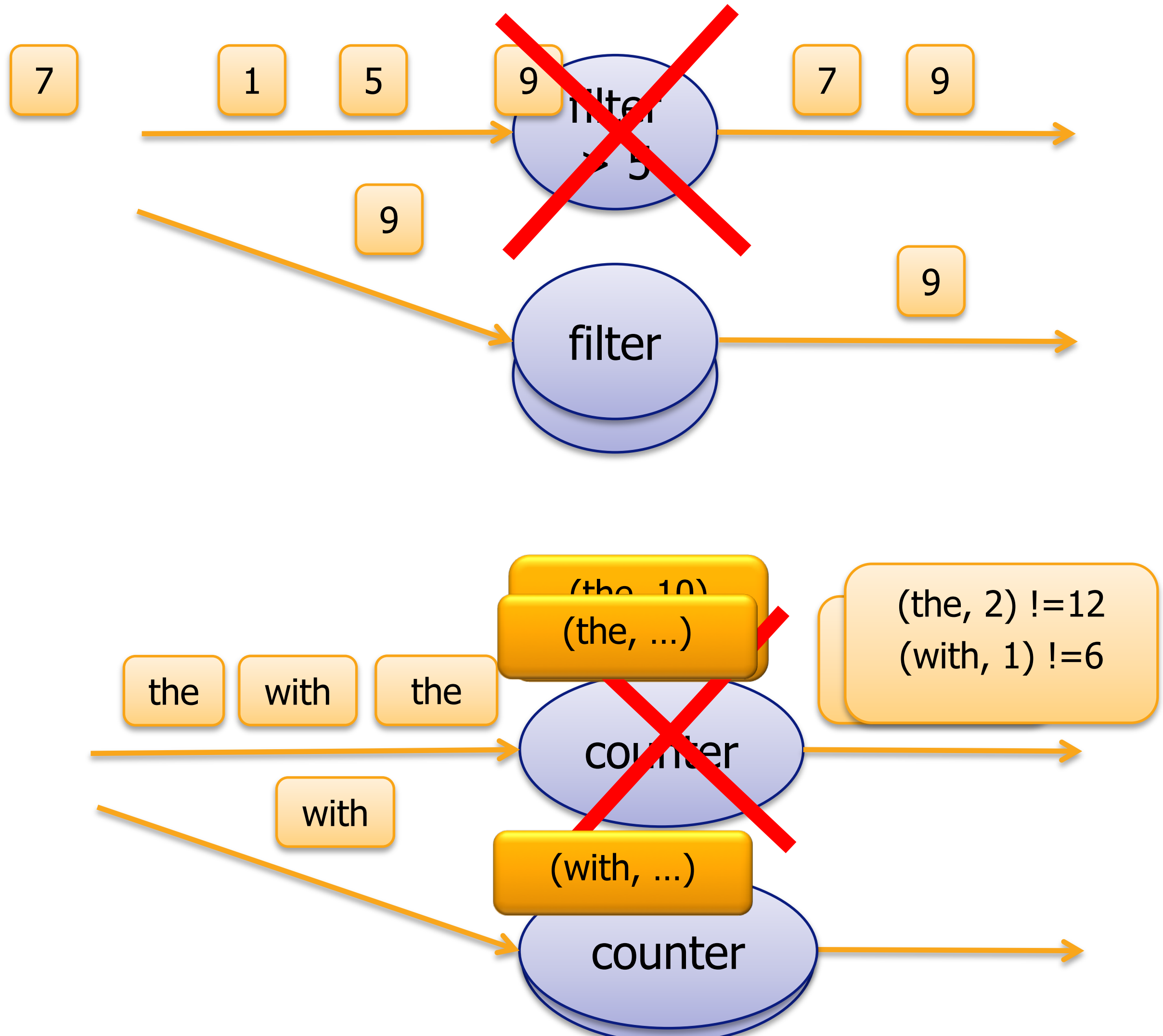
– passive fault-tolerance leads to long recovery times

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

☛ Both mechanisms must support **stateful** operators

Stateless vs Stateful Operators

operator state: a summary of past tuples' processing



stateless:
- ✓ failure recovery
- ✓ scale out

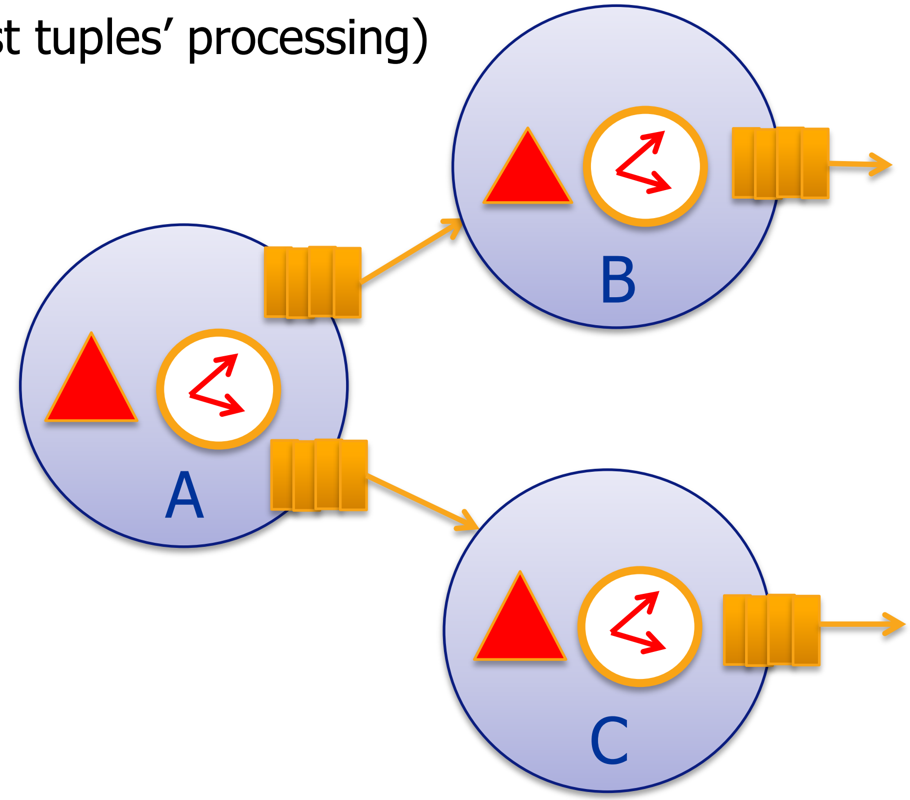
stateful:
- × failure recovery
- × scale out

State Management

processing state: (summary of past tuples' processing)

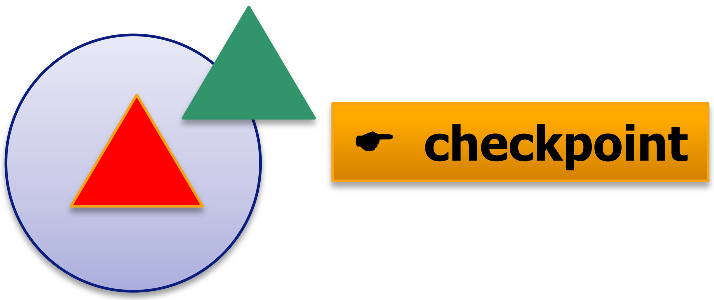
routing state: (routing of tuples)

buffer state: (tuples)

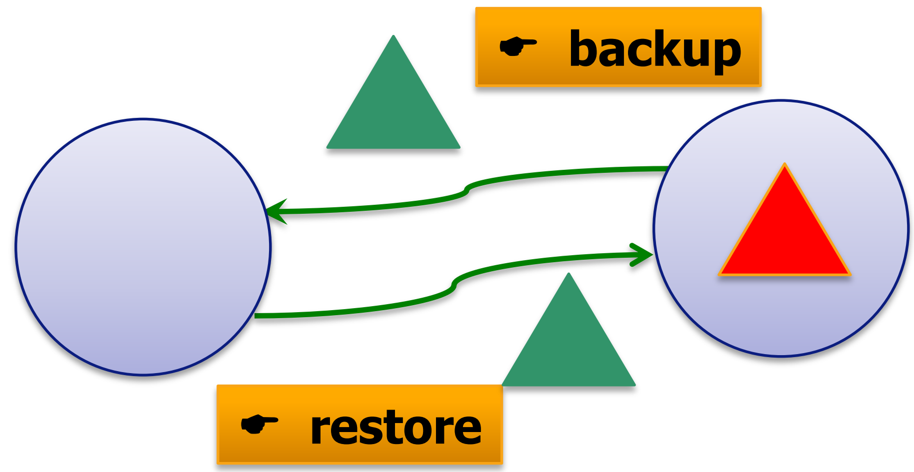


- operator state is an external entity managed by the DSPS
- **primitives** for state management
- **mechanisms** (scale out, failure recovery) on top of primitives
- **dynamic reconfiguration** of the dataflow graph

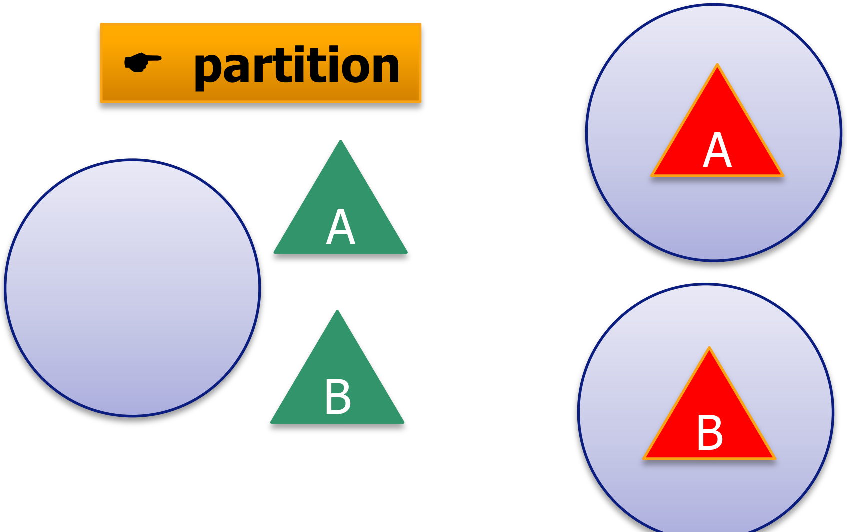
State Management Primitives



takes snapshot of state and
makes it externally available



moves copy of state from
one operator to another

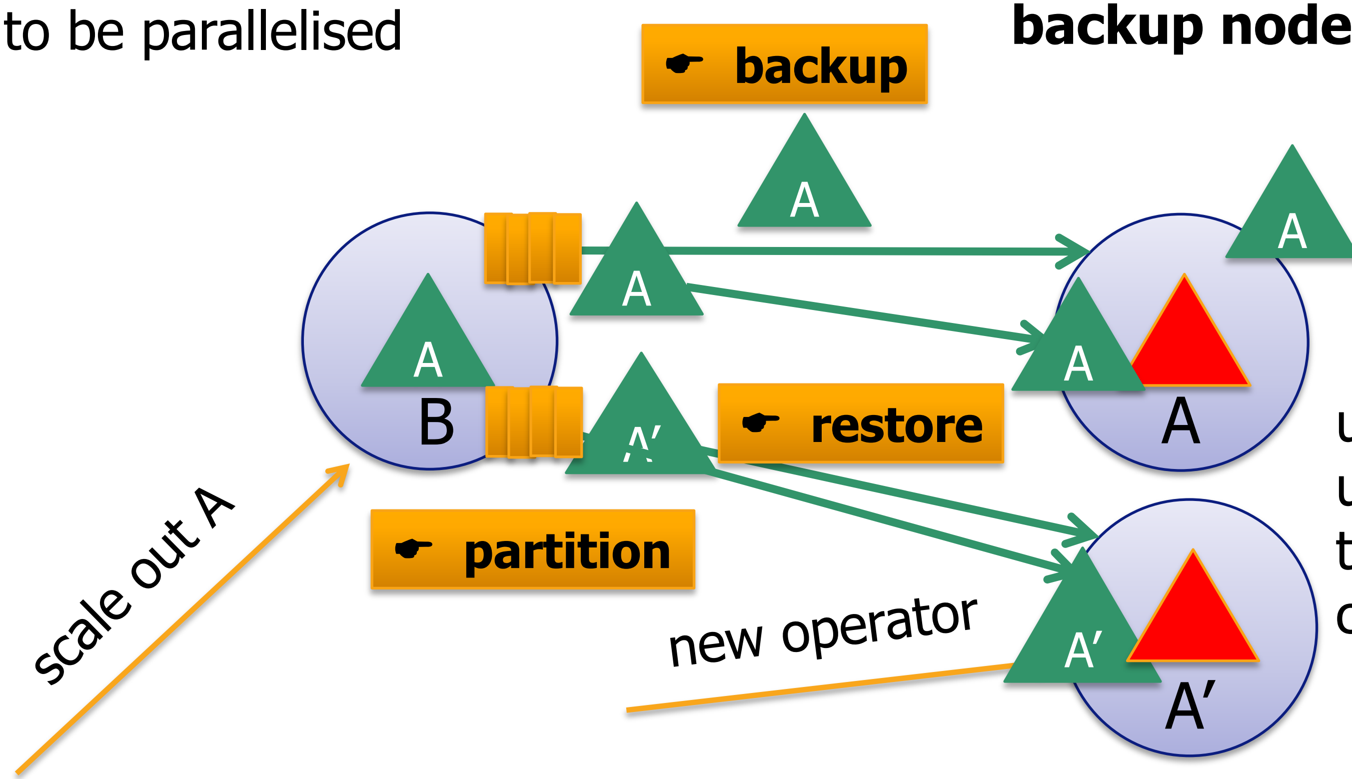


splits state in a semantically correct
fashion for parallel processing

State Management Scale Out, Stateful Ops

backup node already has state of operator to be parallelised

periodically, stateful operators checkpoint and back up state to designated **upstream backup node**, in memory

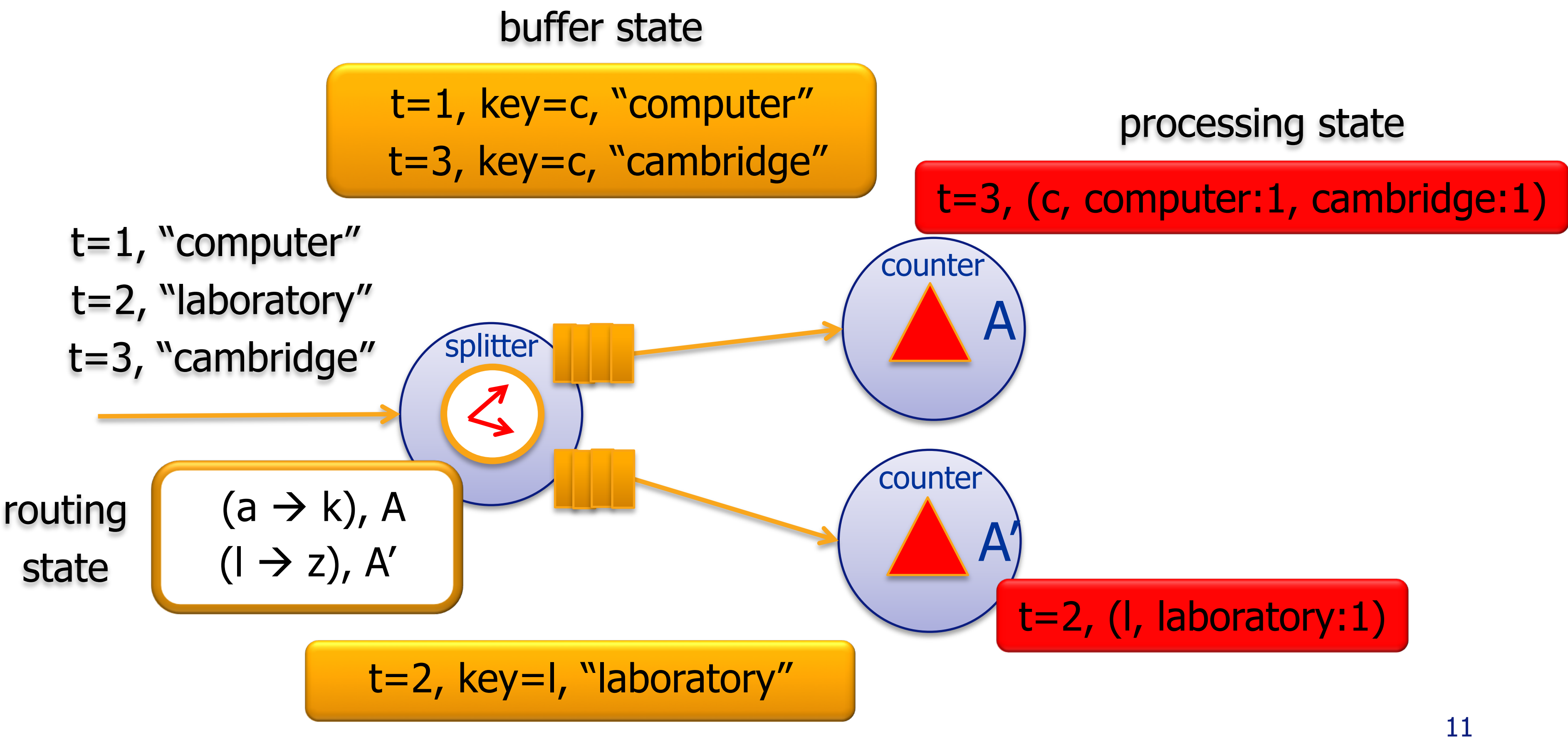


upstream ops send unprocessed tuples to update checkpointed state

☛ How do we partition **stateful** operators?

Partitioning Stateful Operators

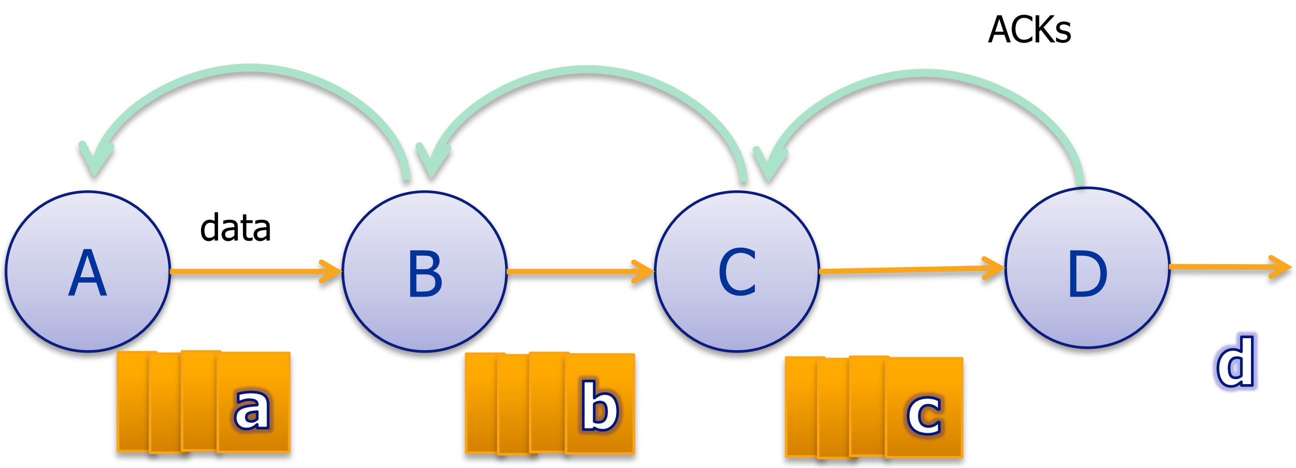
1. Processing state modeled as (key, value) dictionary
2. State partitioned according to key k of tuples
3. Tuples will be routed to correct operator as of k



Passive Fault-Tolerance Model

recreate operator state by replaying tuples after failure:

– **upstream backup**: sends acks upstream for tuples processed downstream



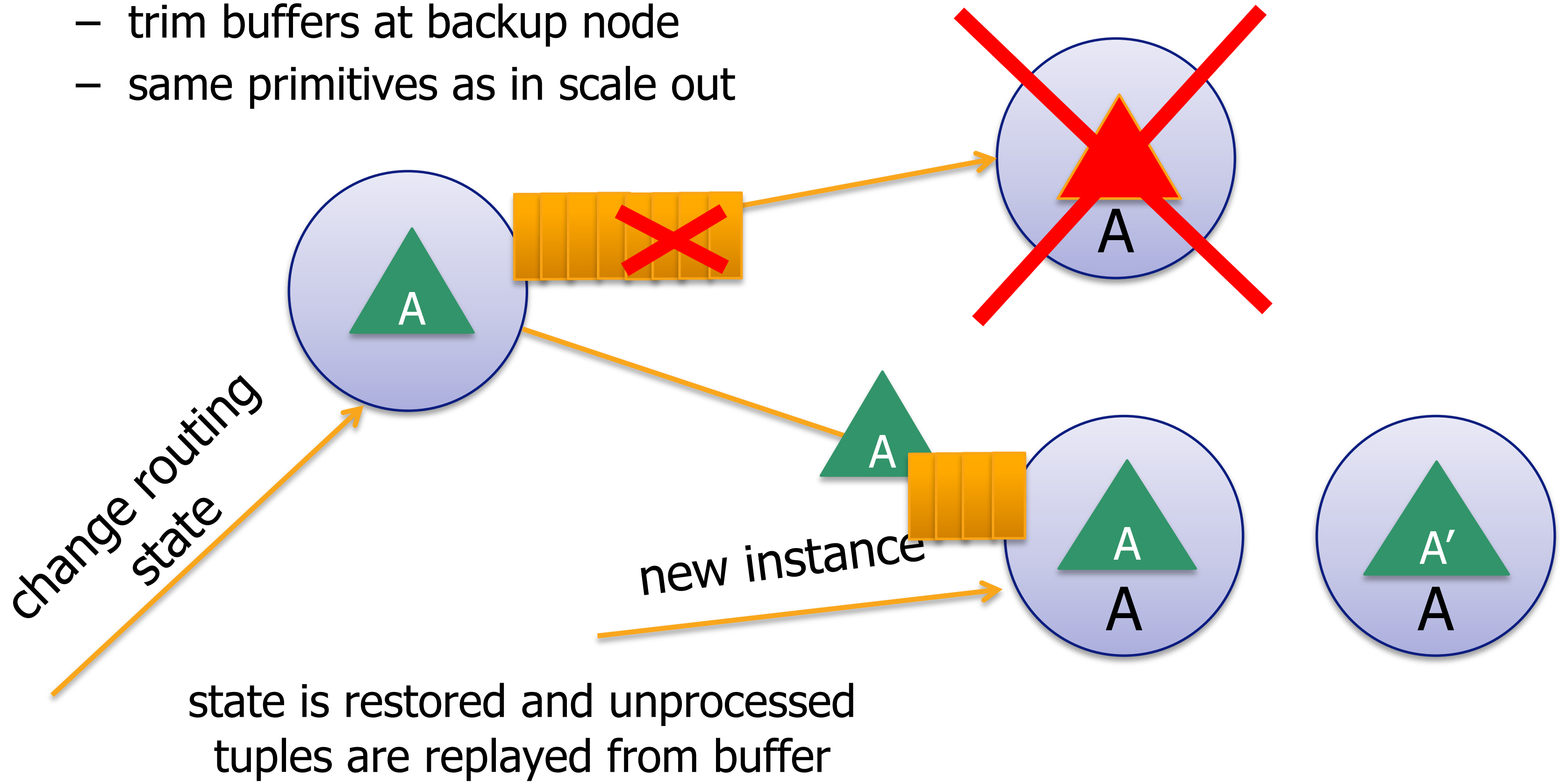
may result in long recovery times due to large buffers:

– system is reprocessing streams after failure ➔ inefficient

Recovering using State Management (R+SM)

Benefit from state management primitives:

- use periodically backed up state on upstream node to recover faster
- trim buffers at backup node
- same primitives as in scale out

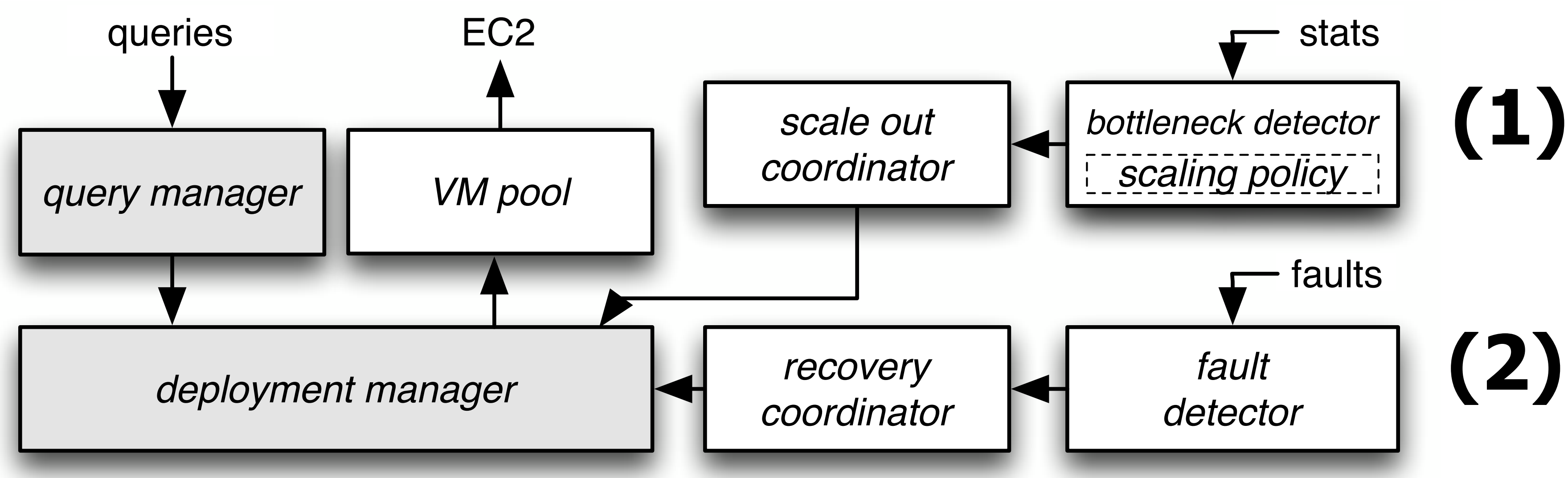


☛ same primitives for parallel recovery

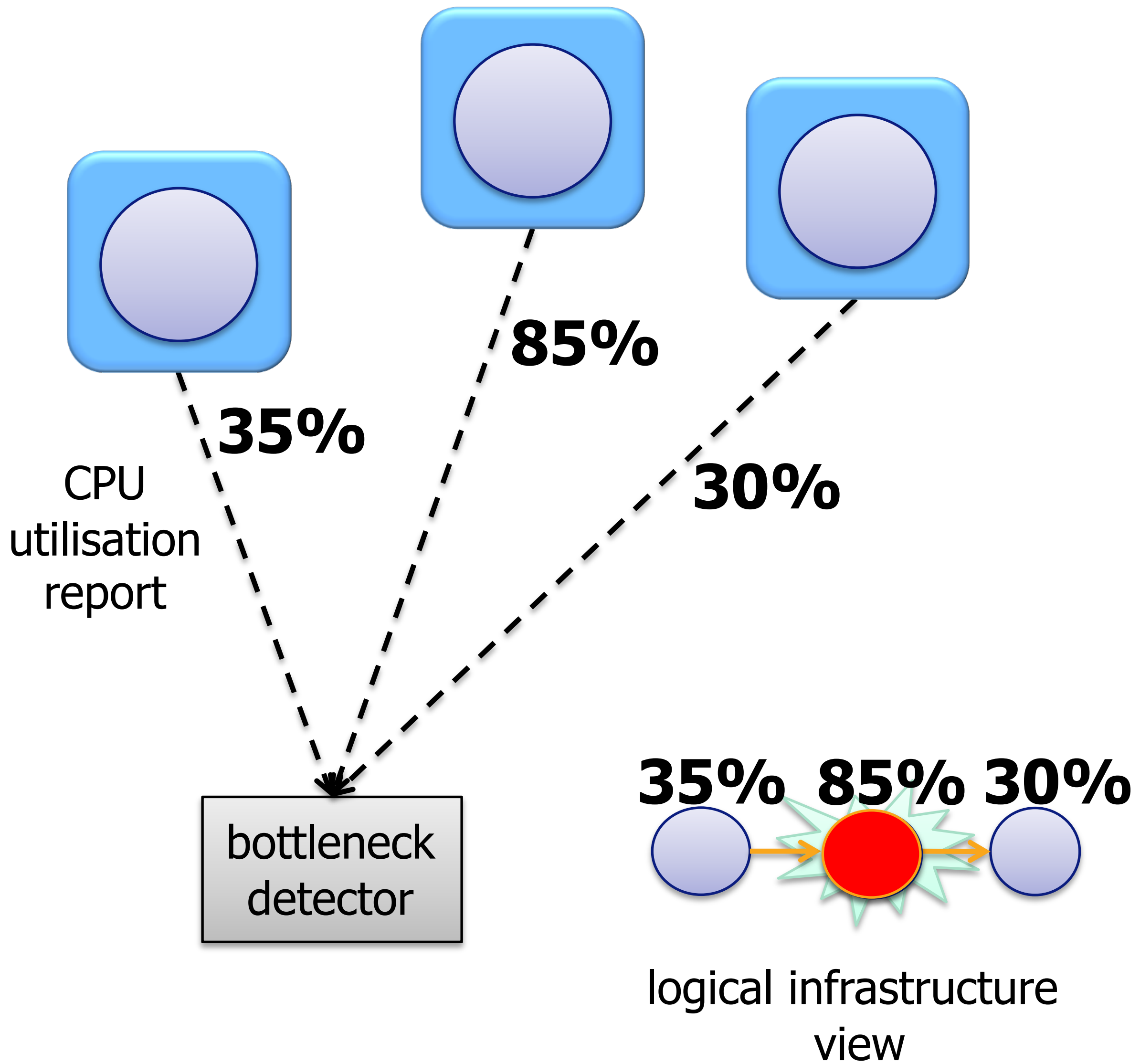
State Management in Action: SEEP

(1) dynamic Scale Out: detect bottleneck , add new parallelised operator

(2) failure Recovery: detect failure, replace with new operator

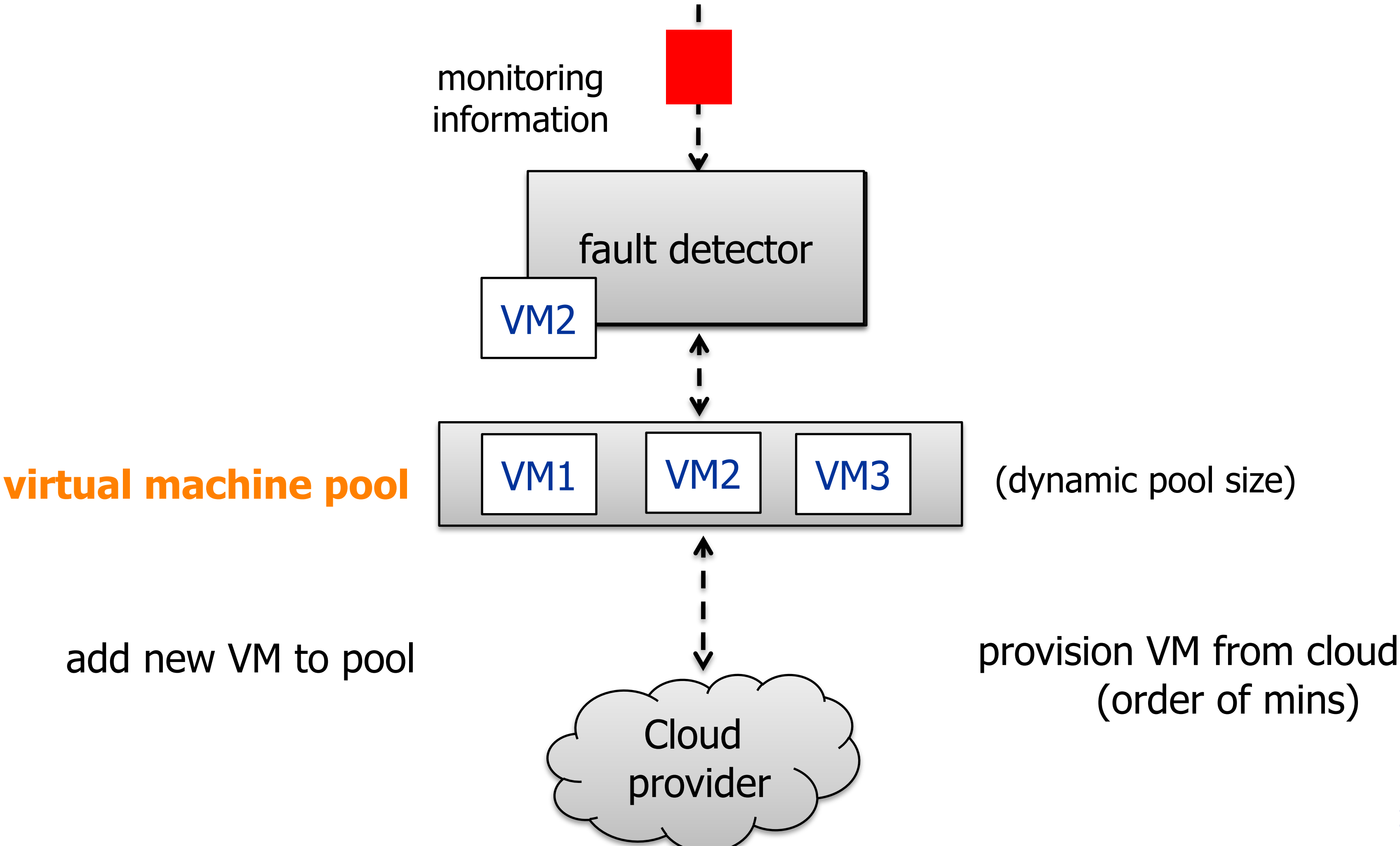


Dynamic Scale Out: Detecting bottlenecks



The VM Pool: Adding operators

problem: allocating new VMs takes minutes...



Experimental Evaluation

Goals:

- investigate effectiveness of **scale out** mechanism
- recovery time after failure using **R+SM**
- overhead of **state management**

Scalable and Elastic Event Processing (SEEP):

- implemented in Java; Storm-like data flow model

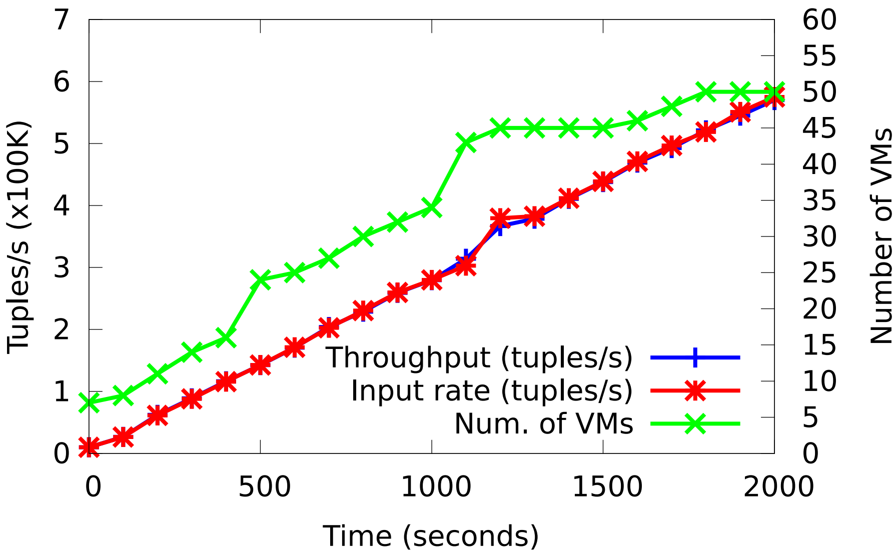
Sample queries + workload

- **Linear Road Benchmark** (LRB) to evaluate scale out [VLDB'04]
  - provides an increasing stream workload over time
  - query with 8 operators, 3 are stateful; SLA: results < 5 secs
- **Windowed word count query** (2 ops) to evaluate fault tolerance
  - induce failure to observe performance impact

Deployment on Amazon AWS EC2

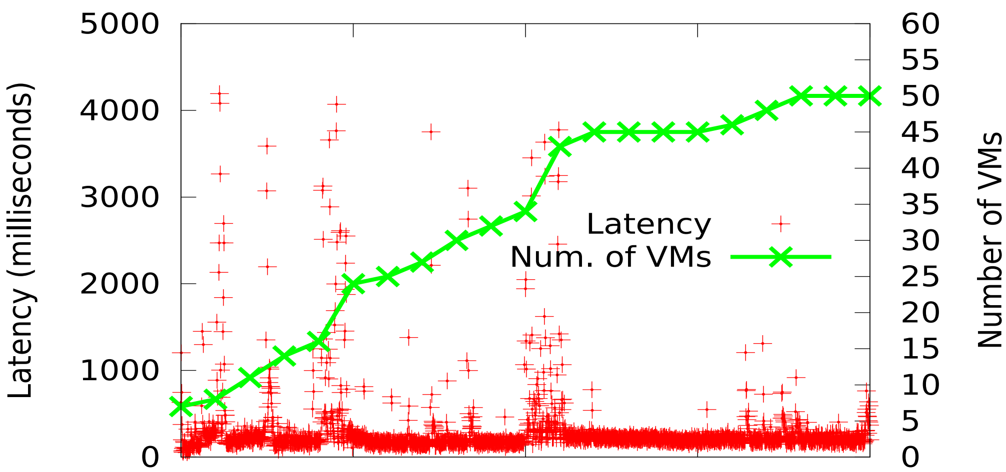
- sources and sinks on high-memory double extra large instances
- operators on small instances

Scale Out: LRB Workload



scales to load factor L=350 with 50 VMs on Amazon EC2
(automated query parallelisation, scale out policy at 70%)

L=512 highest result [VLDB'12]
(hand-crafted query on cluster)



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

☛ SEEP scales out to increasing workload in the Linear Road Benchmark

Conclusions

Stream processing will grow in importance:

- handling the data deluge
- enables real-time response and decision making

Integrated approach for scale out and failure recovery:

- operator state an independent entity
- primitives and mechanisms

Efficient approach extensible for additional operators:

- effectively applied to Amazon EC2 running LRB
- parallel recovery