

Elastic Memory: Bring Elasticity Back to In-Memory Big Data Analytics

May 18, 2015

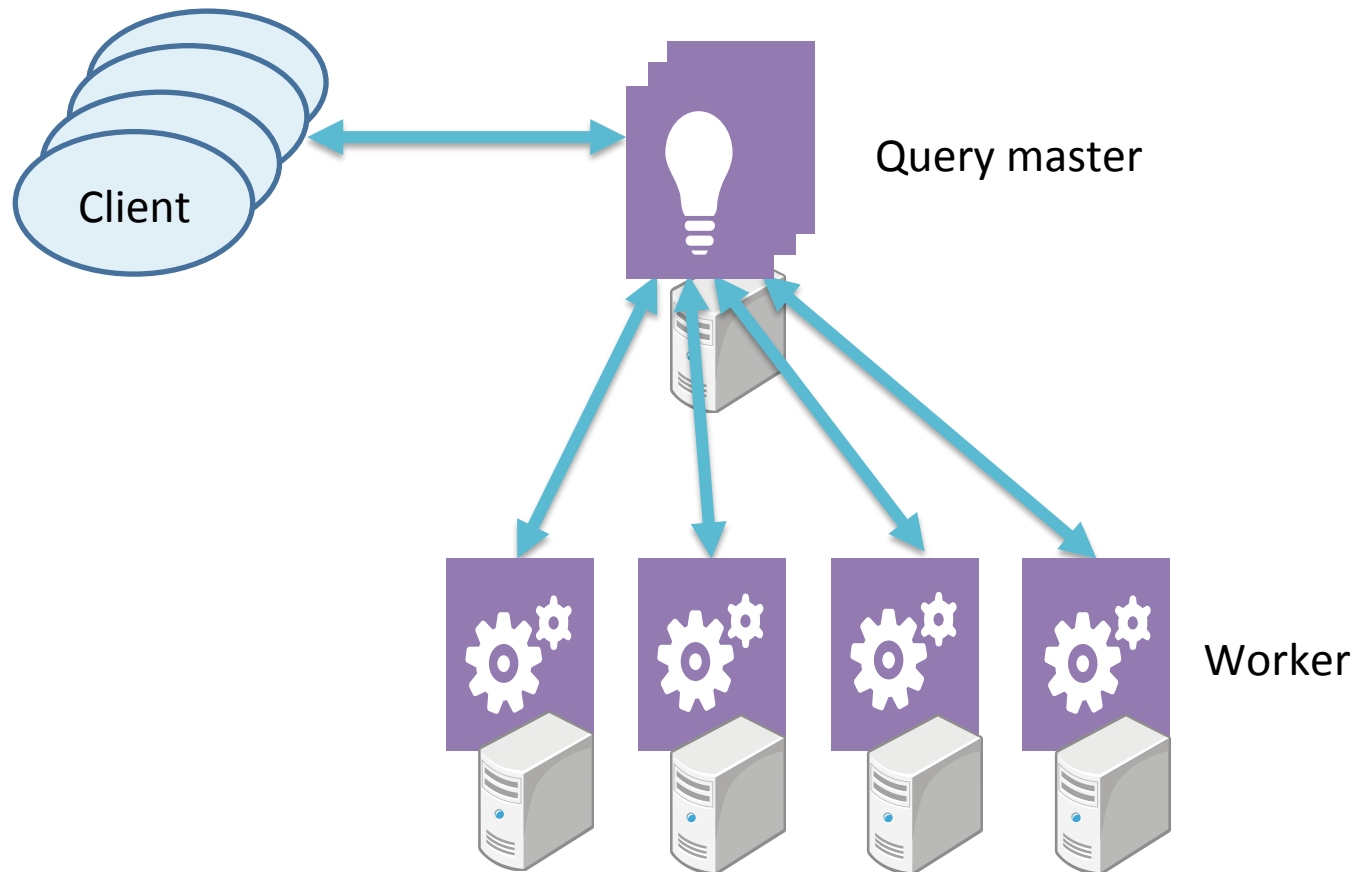
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Elastic Big Data Analytics Jobs

- MapReduce/DAG jobs execute on a runtime that supports elastic scale-out execution
- Distinct MapReduce/DAG jobs run together on a shared cluster, thus improving utilization
- New types of in-memory data analytics do not fit well to this model
 - The interactive query system does not share resources even when the system is idle

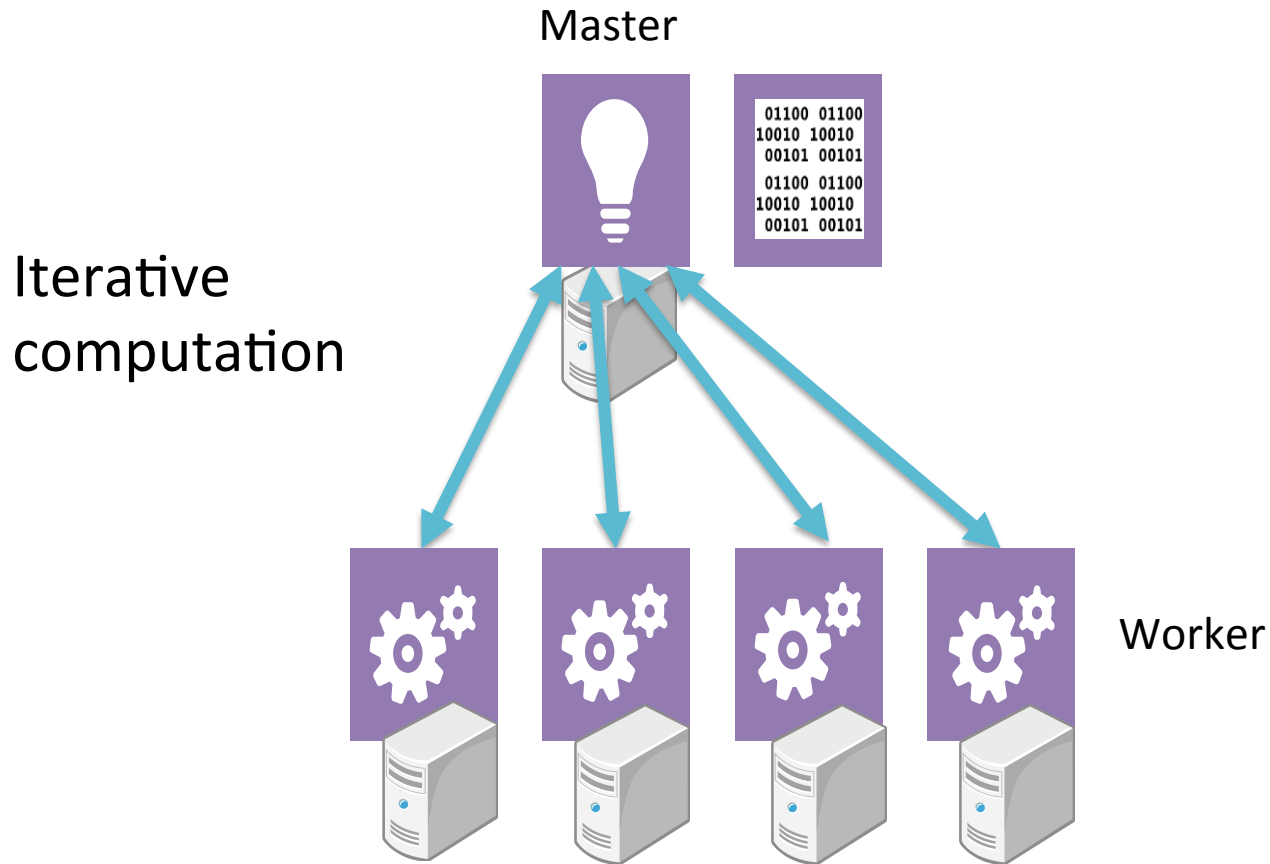
New Types of In-Memory Data Analytics: Interactive Query



The Case for Elasticity: Interactive Query

- Scale-out
 - The workers may spill data to disks when they do not have enough memory resources => expand memory resources to perform in-memory processing
- Scale-in
 - The workers hold on to their resources even while they remain idle during periods without client queries => shrink resources to mitigate reduced cluster utilization

New Types of In-Memory Data Analytics: Machine Learning



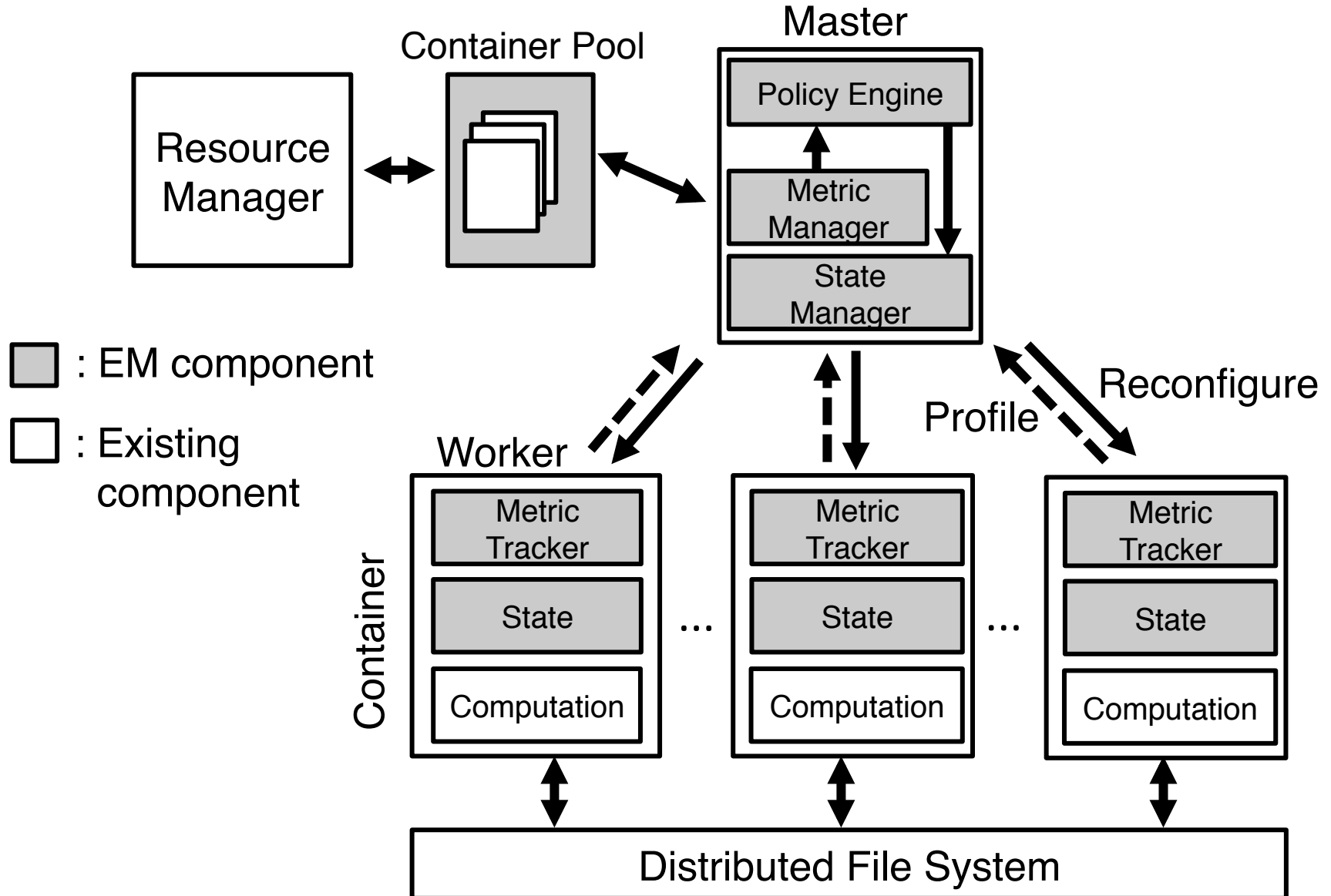
The Case for Elasticity: Machine Learning

- Scale-in
 - The job is communication heavy => shrink the number of machines to reduce communication overheads
- Scale-out
 - The job is computation heavy => allocate more memory in other machines to exploit computation parallelism

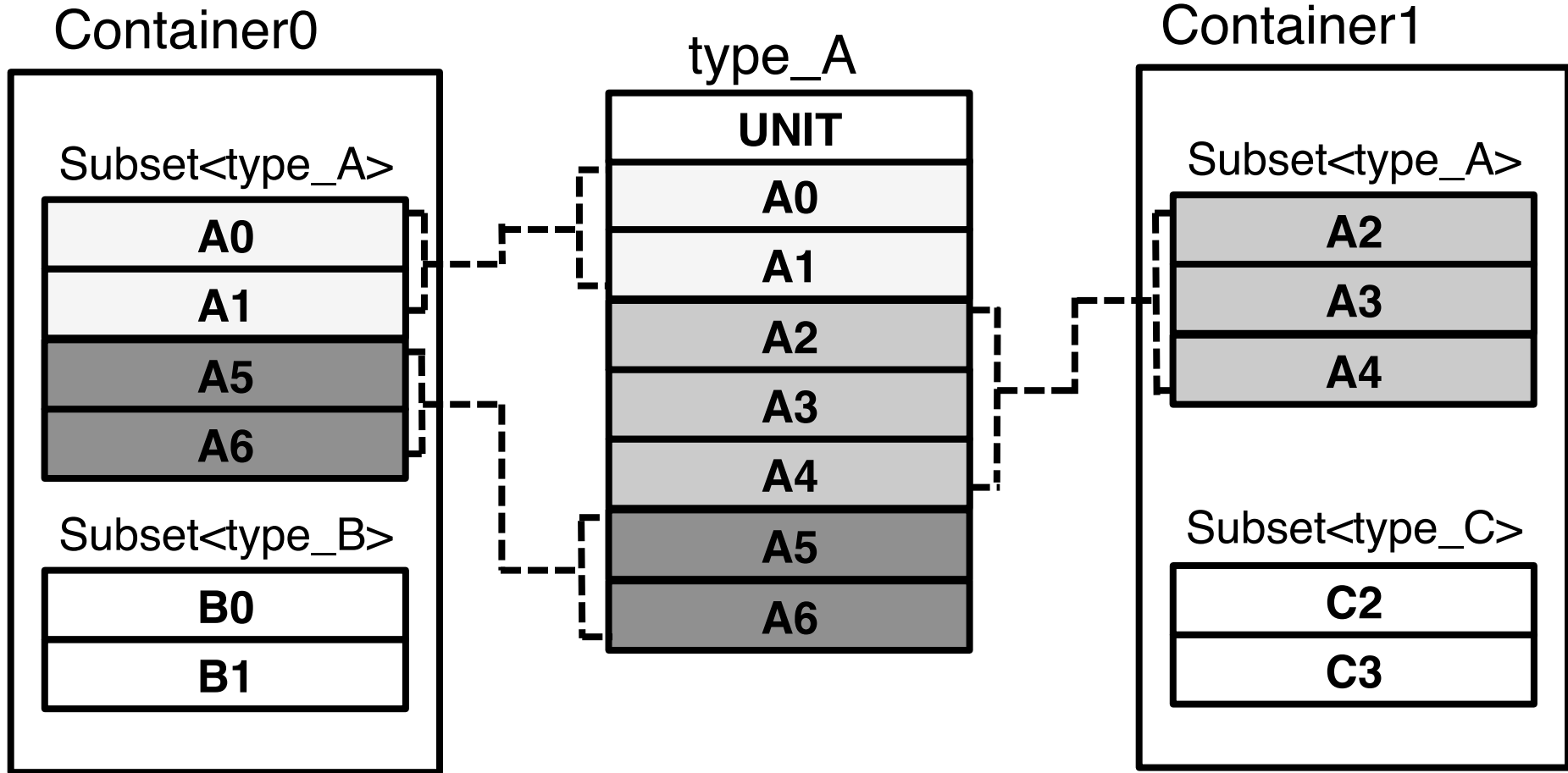
Elastic Memory (EM)

- Abstraction that provides “elastic memory” by dynamically expanding and shrinking memory resources and moving memory state
 - Mechanisms for reconfiguring memory resources and state
 - Policies for automating reconfiguration

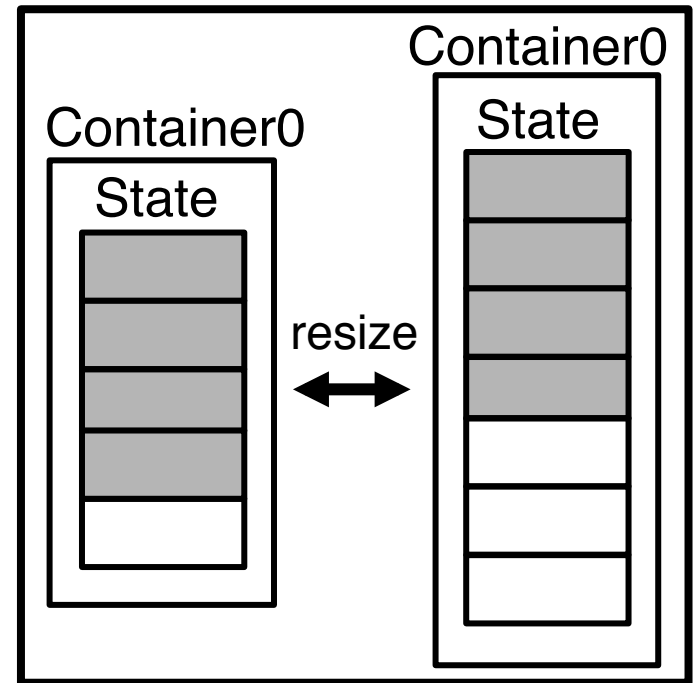
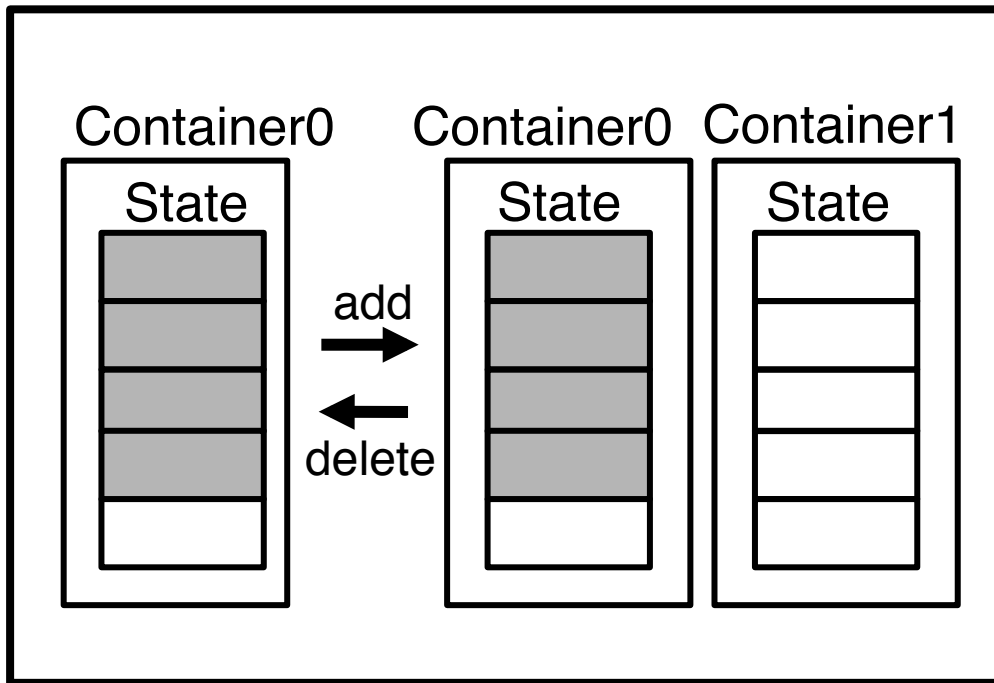
EM Architecture



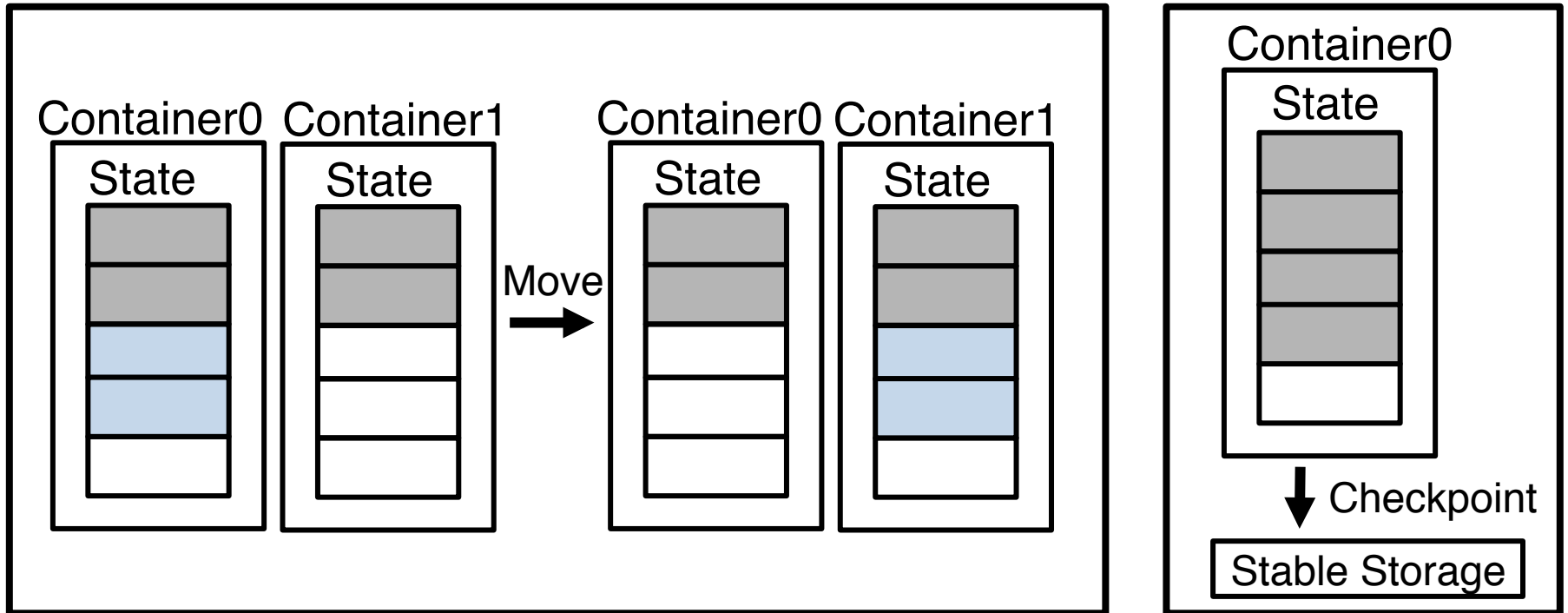
State Representation



Primitives for Reconfiguring State



Primitives for Reconfiguring State



Profiling

- Each worker's metric tracker measures local metrics and sends them to the metric manager
- The metric manager aggregates and processes the received metrics

Policies

- Policy = Rules
- Rule = Condition, Actions
- Condition = Function(metrics)
- Action
 - Add <ResourceSpec>
 - Delete <SelectFunc>
 - Resize <SelectFunc> <ResourceSpec>
 - Merge <SelectFunc> <n>
 - Split <SelectFunc> <n>
 - Migrate <SelectFunc1> <SelectFunc2>

Elastic Interactive Query with EM: Unit, Metrics

- Unit: a row of a table
- Metrics
 - Requests for data per second
 - Memory utilization
 - Idle time
 - ...

Elastic Interactive Query with EM: Policy

- Rule 1 (scale out)
Condition: $avg(load) > 0.8$
Action: `Add(resource-spec)`
- Rule 2 (scale in)
Condition: `idle-time > 10 min`
Action: `Delete(top(idle-time))`

Distributed Machine Learning

- Start by loading data from disk and storing it to memory; access data in memory throughout the job execution
- Iterate
 - The workers run the algorithm independently on its partition of the data
 - The master aggregates the computation results and calculates a model.
 - This model is broadcast to the workers

Elastic Machine Learning with EM: Unit, Metrics

- Unit: an independent observation (e.g., a single number, vector, a matrix)
- Metrics
 - Task time per iteration
 - Computation time per iteration
 - Communication time per iteration
 - ...

Elastic Machine Learning with EM: Policy

- Rule1 (straggler handling)

Condition: *is_straggler*(task-iter-time)

Action: *Migrate*(top1(task-iter-time), bottom1(task-iter-time))

- Rule2 (scale-out)

Condition: *avg*(task-comp-time/task-comm-time) > TH1

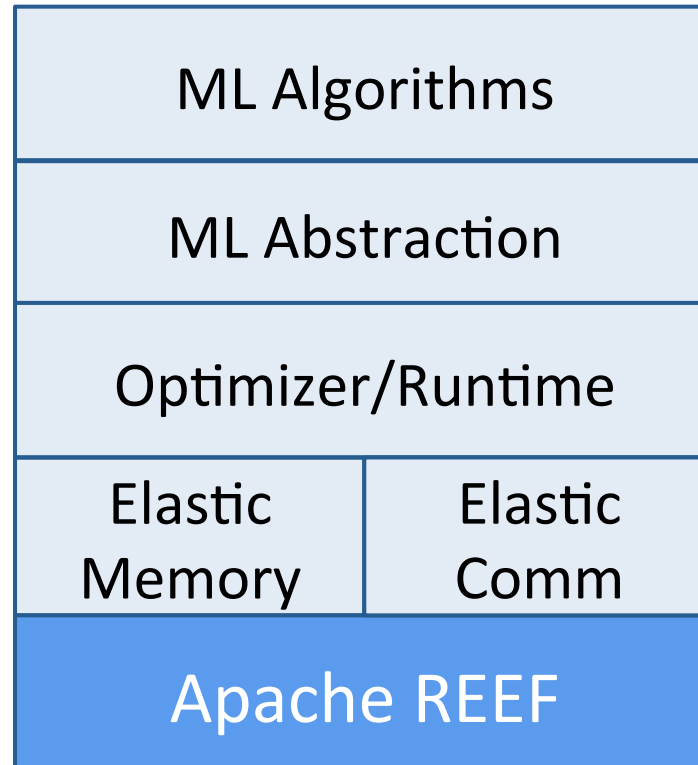
Action: *Split*(top1(task-comp-time/task-comm-time), 2)

- Rule3 (scale-in)

Condition: *avg*(task-comp-time/task-comm-time) < TH2

Action: *Merge*(bottom2(task-comp-time/task-comm-time), 2)

Elastic Machine Learning Framework



Meta-framework
for big data systems

(<http://reef.apache.incubator.org>,
SIGMOD 2015)

Current Status

- Building Elastic Memory on Apache REEF
- Building a new Elastic Machine Learning Framework that runs on Elastic Memory
- Exploring SparkSQL-like engines to work with Elastic Memory

Thank you!
Q & A