Cloud Computing
Resource management

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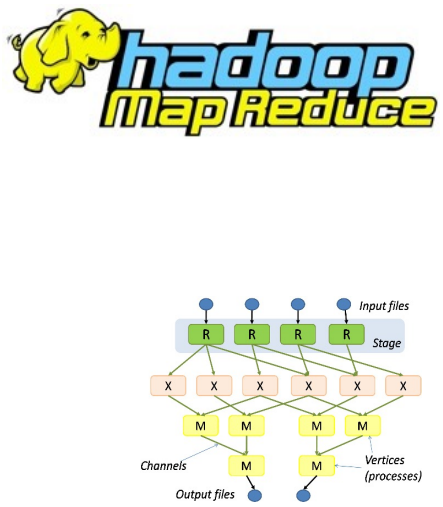
SCHOOL OF
DATA SCIENCE
數據科學學院

Background

Rapid innovation in cluster computing frameworks



Dryad

Ciel

S4 distributed stream computing platform

Google Percolator

Google Pregel

MPI-2

Background

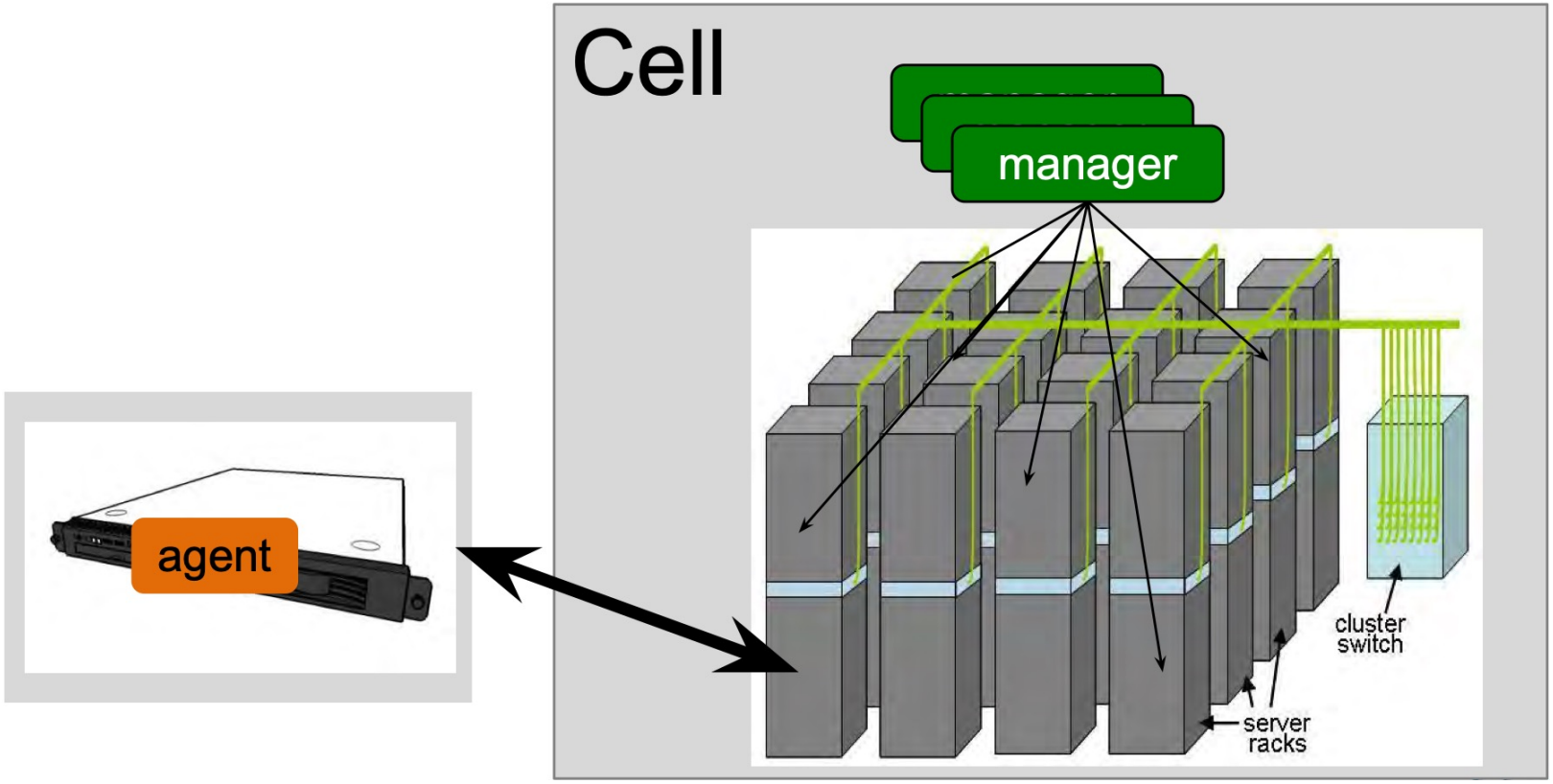
- Data centers are built from clusters of commodity hardware
- These clusters run a diverse set of applications: e.g., MapReduce, Spark, etc.
- Each application has its own execution framework
- Multiplexing a cluster between frameworks improves resources utilization and so reduces costs

Background

- It is very difficult and challenging for a single framework (application-specific) to efficiently manage the resources of clusters
- The aim of the cluster management is to be able to run multiple frameworks in a single cluster to:
  - maximize utilization
  - share data between frameworks

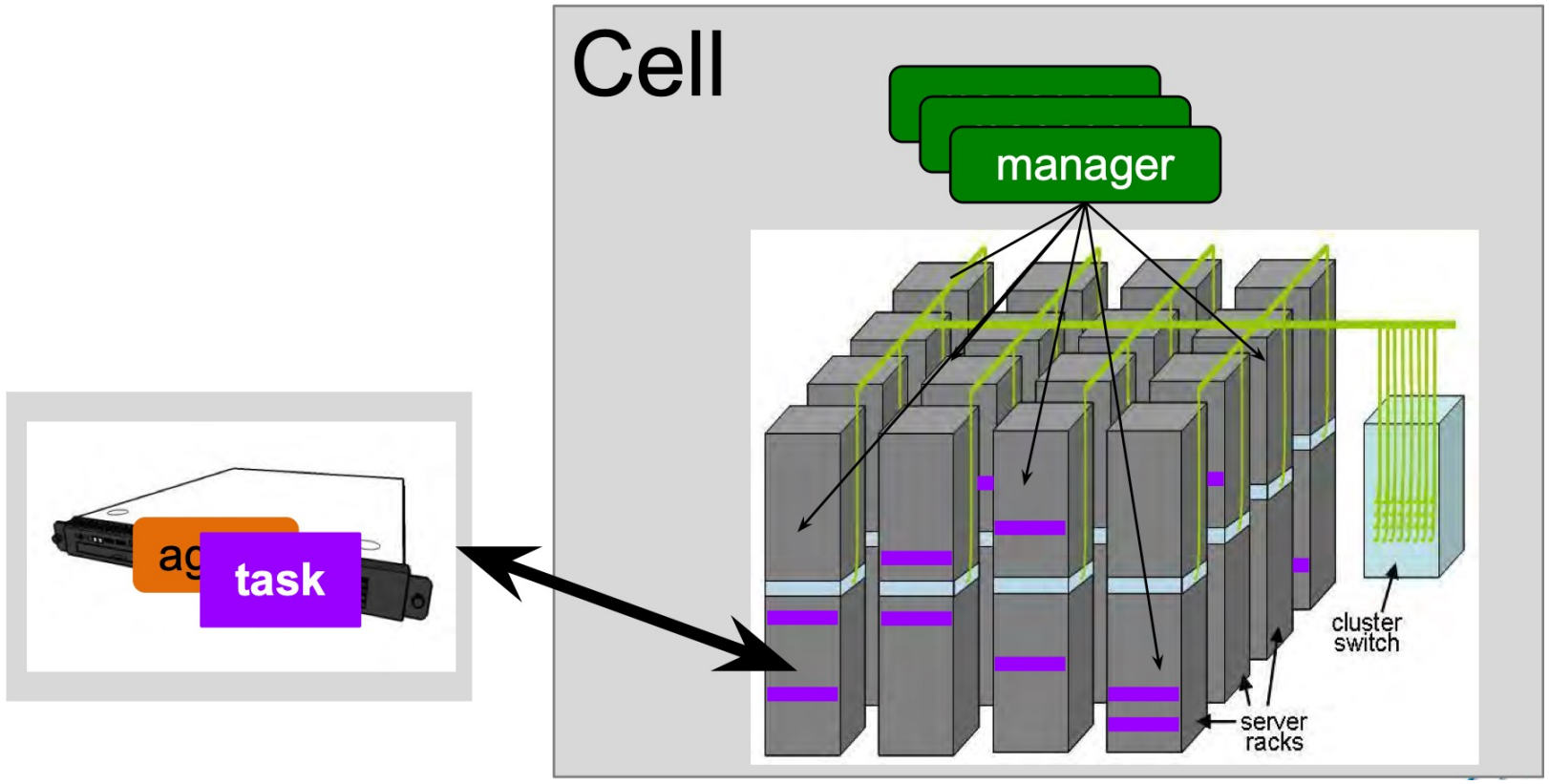
Cluster management: what is it?

A cluster is managed as 1 or more *cells*



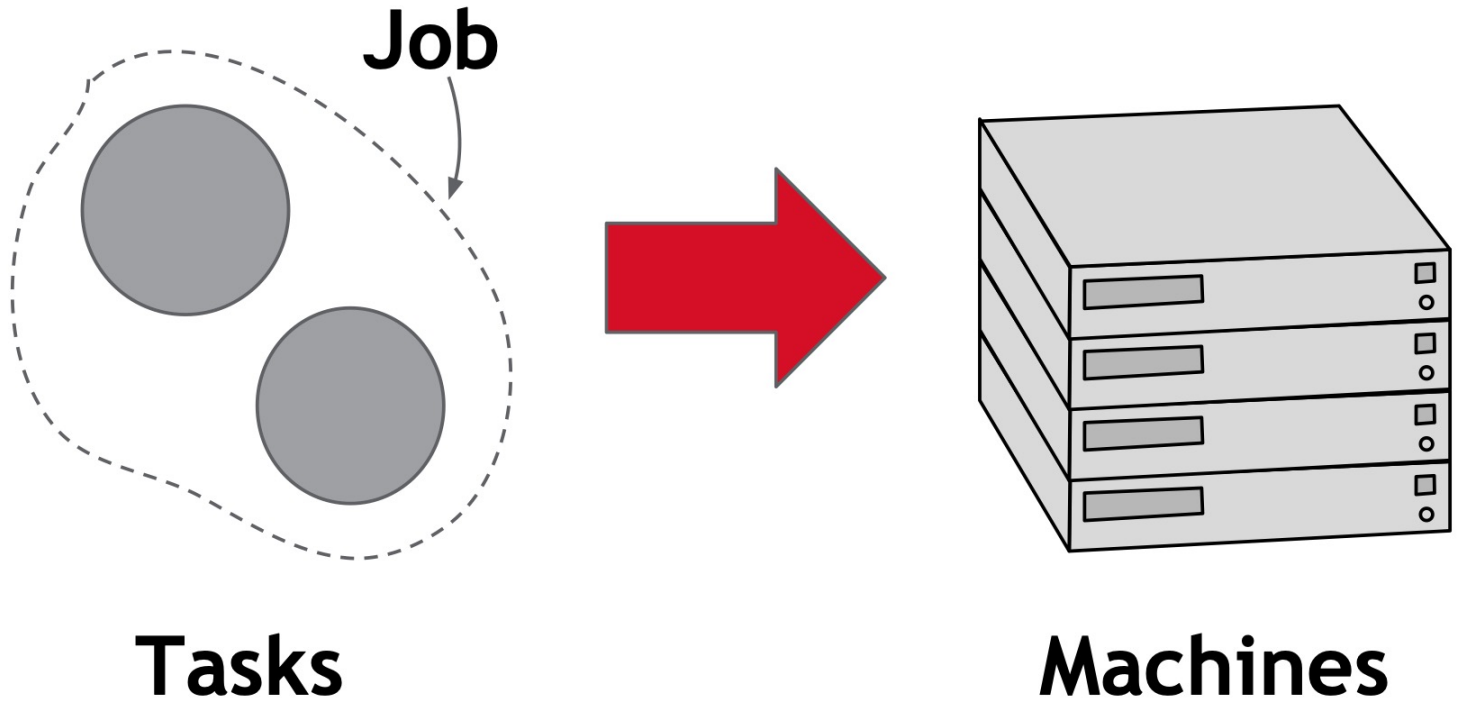
Cluster management: what is it?

A cell runs *jobs*, made up of *tasks*, for internal users



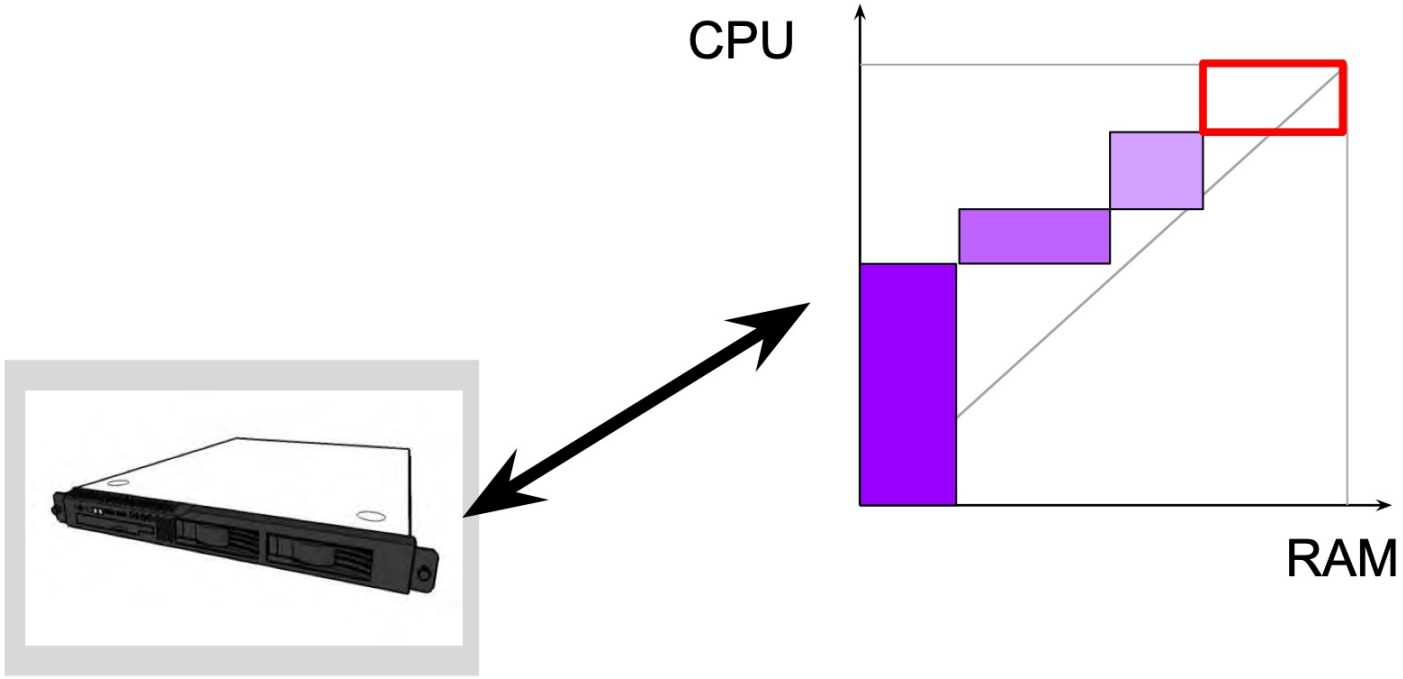
Cluster management: what is it?

The scheduling problem

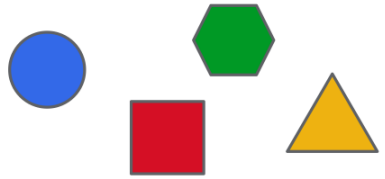


Cluster management: what is it?

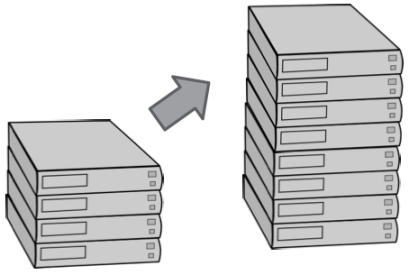
Placing tasks onto machines is just a ***knapsack problem***, with constraints



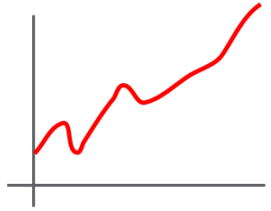
Cluster management is hard!



Diverse workloads



Increasing cluster sizes



Growing job arrival rates

Diverse workloads

Batch

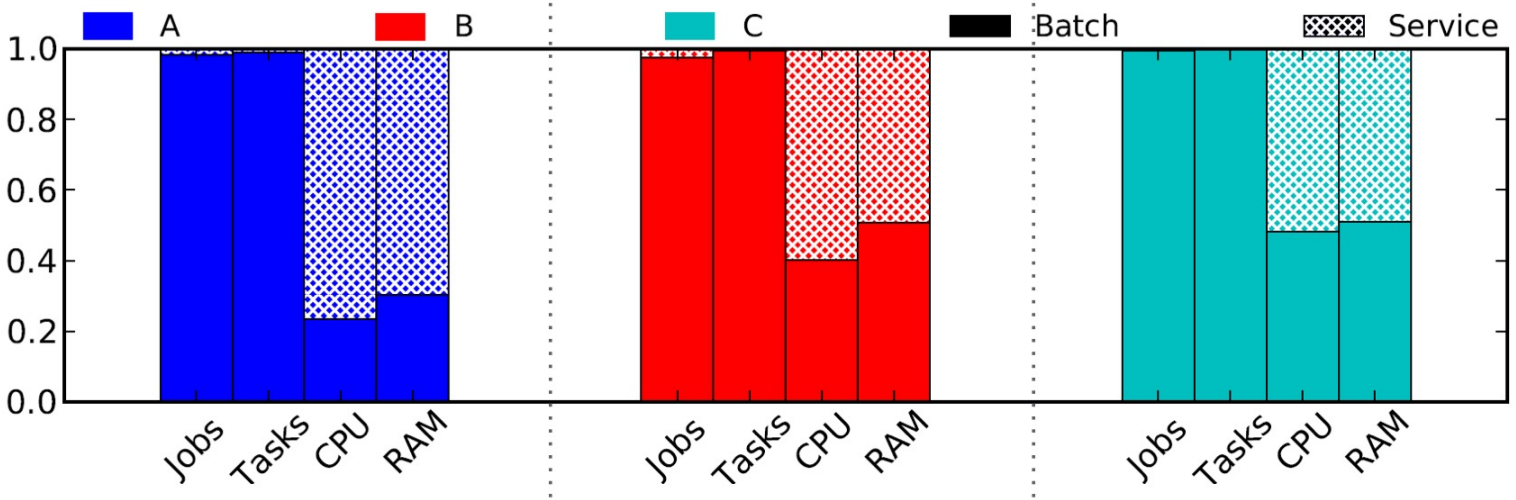
Service

Batch/service split

Cluster A
Medium size
Medium utilization

Cluster B
Large size
Medium utilization

Cluster C
Medium (12k mach.)
High utilization
Public trace



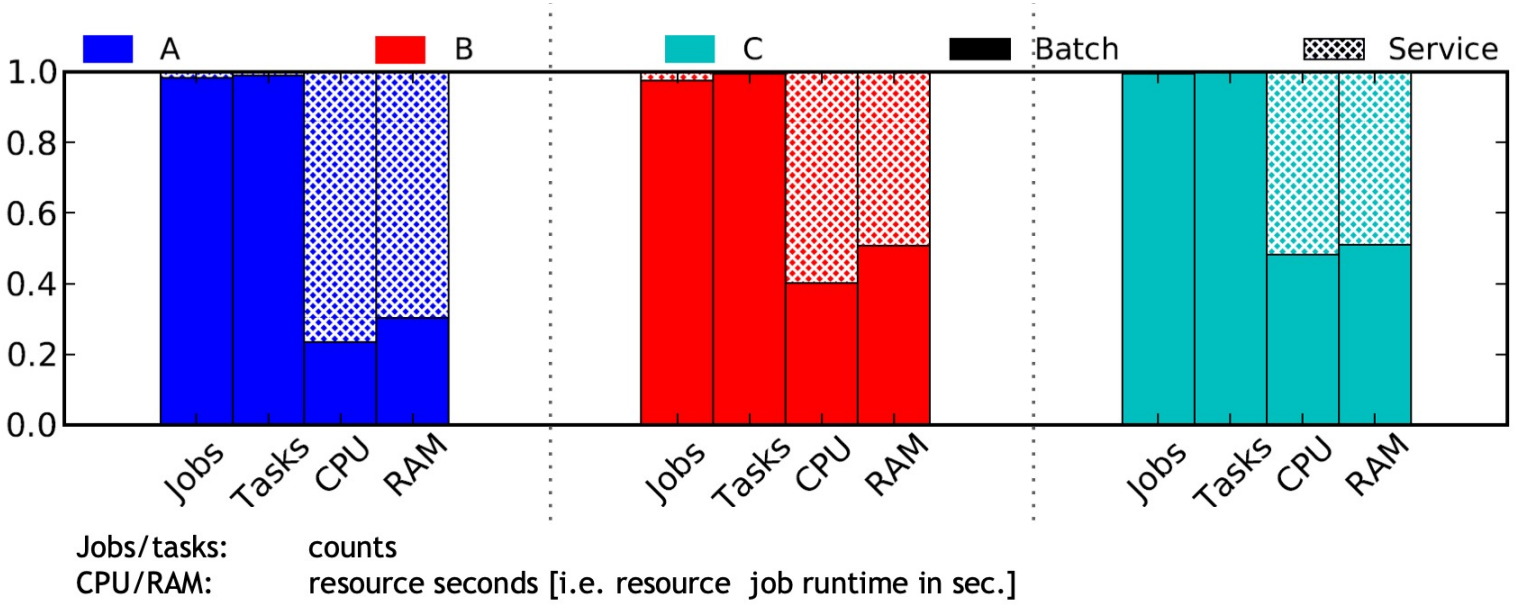
Jobs/tasks: counts
CPU/RAM: resource seconds [i.e. resource job runtime in sec.]

M. Schwarzkopf, A. Konwinski, M. Abd-El-Malek, and J. Wilkes. Omega: flexible, scalable schedulers for large compute clusters. In ACM EuroSys, 2013.

Batch/service split

TAKEAWAY

Most jobs are batch, but most resources are consumed by service jobs.



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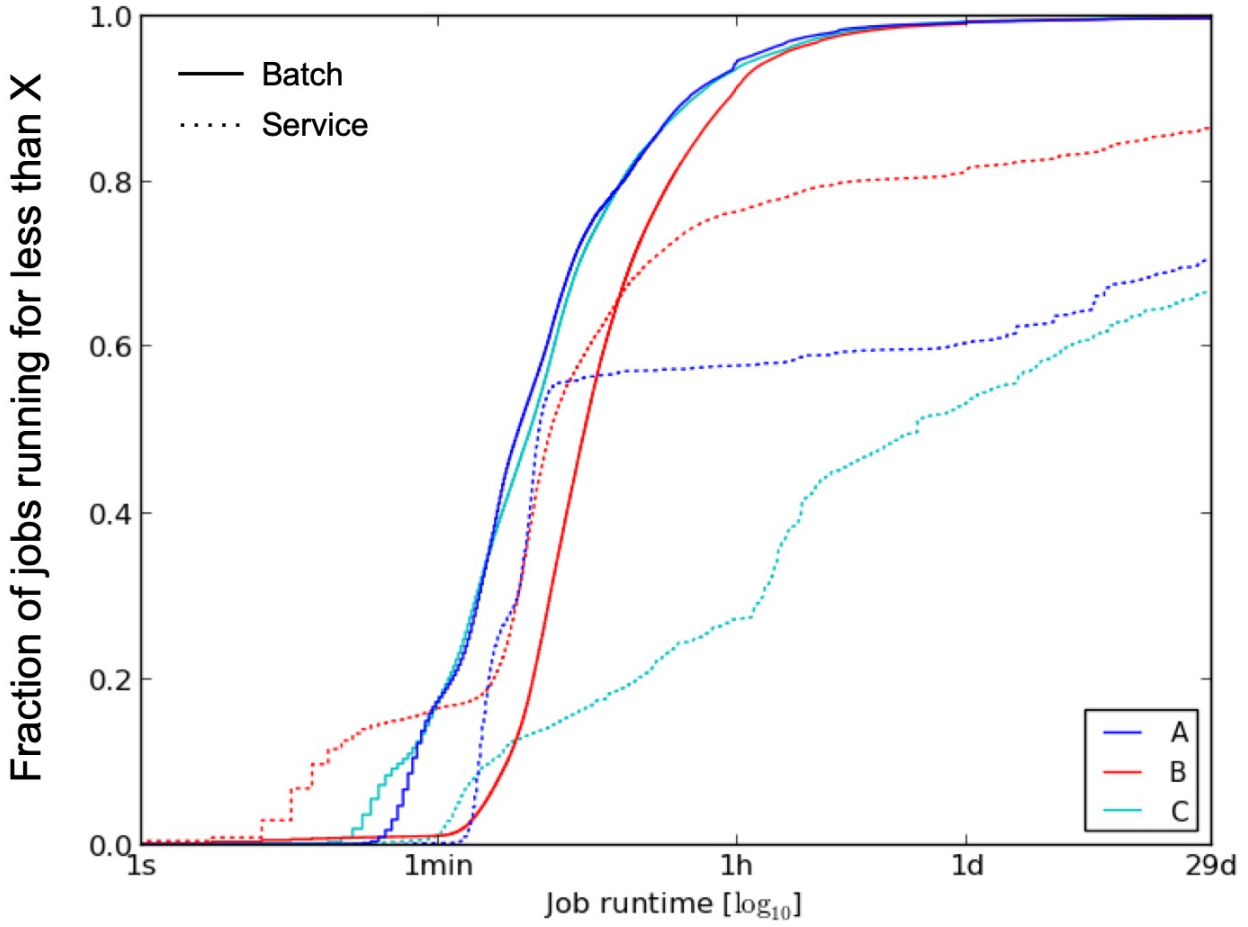
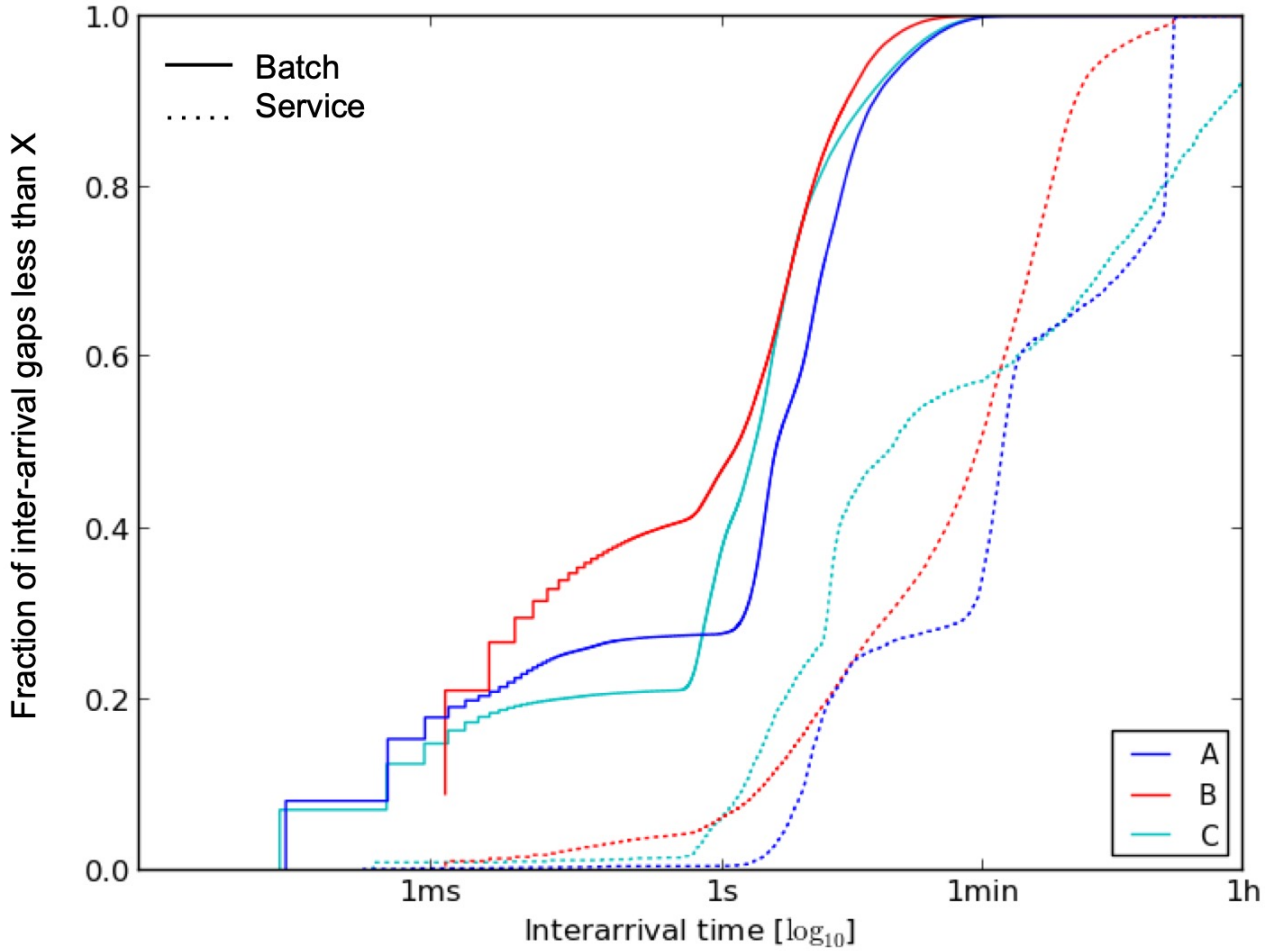
Job runtime distributions



M. Schwarzkopf, A. Konwinski, M. Abd-El-Malek, and J. Wilkes. Omega: flexible, scalable schedulers for large compute clusters. In ACM EuroSys, 2013.

Inter-arrival time distributions



M. Schwarzkopf, A. Konwinski, M. Abd-El-Malek, and J. Wilkes. Omega: flexible, scalable schedulers for large compute clusters. In ACM EuroSys, 2013.

Batch/service split

Batch jobs	*Service jobs*
80th %ile **runtime**	
12-20 min.	**29 days**
80th %ile **inter-arrival time**	
4-7 sec.	**2-15 min.**

Scale matters

Big

- The storage system *holds* a Petabyte of data

Google

- The storage system pages you when there is only a few Petabytes of space left

Scale matters: faults

> 1%	Rate of uncorrectable DRAM errors per machine year
2-10%	Annual failure rate of disk drives
~2	Crashes/machine year
2-6	OS upgrades/machine year
> 1	Power utility events per year

Consequence: a 2000-machine service will have >10 machine crashes per day!

Scale matters: stragglers

High tail latency due to variability of response time

A toy example: a task that

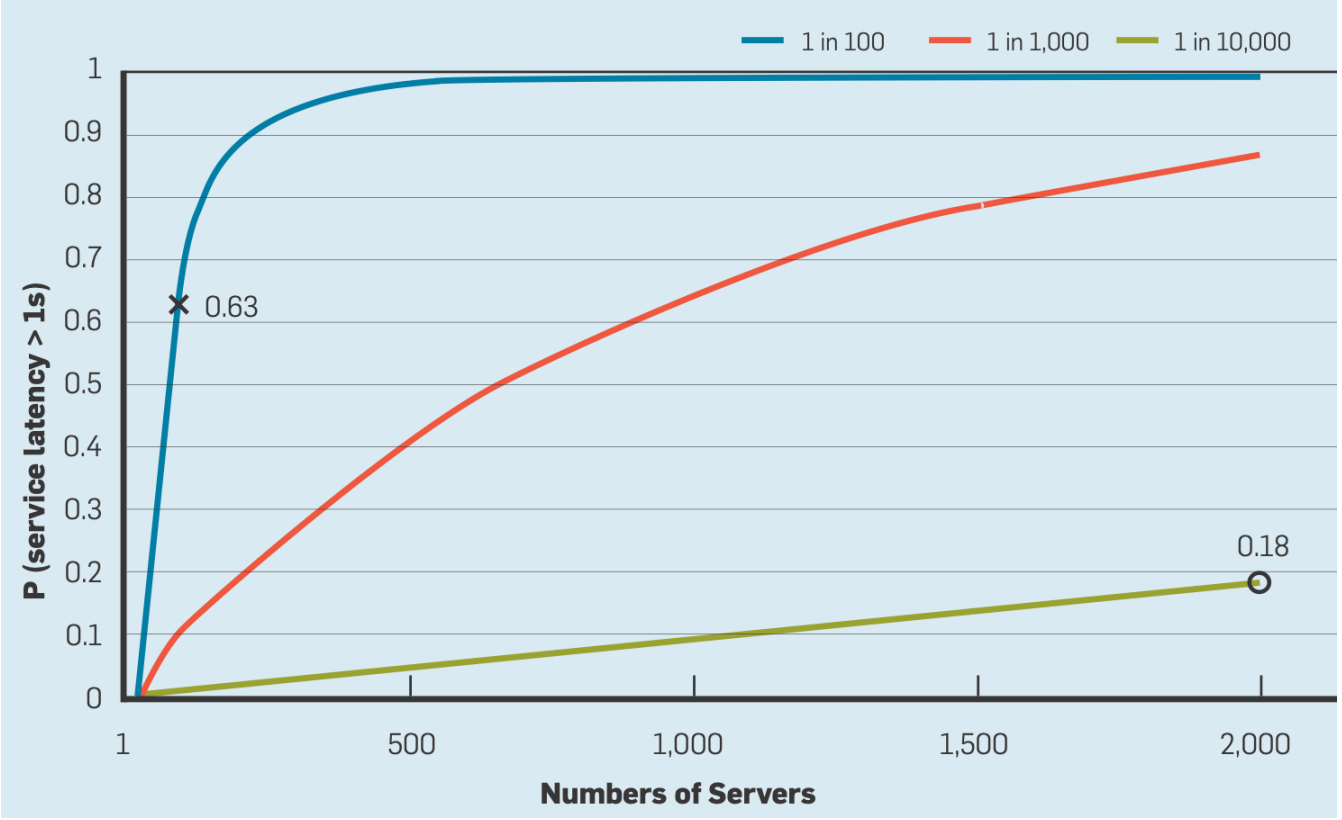
- completes in 1s w/ probability 0.9
- completes in 100s w/ probability 0.1

For a job with ***N*** tasks, what's the distribution of the job completion time?

- ***N*** = 10, 100, 1000

Stragglers: A non-toy

Probability of one-second Google service-level response time as the system scales and frequency of server-level high-latency outliers varies.



J. Dean and L. A. Barroso. The tail at scale. Commun. ACM, 56(2):74–80, 2013.

Cluster management: goals

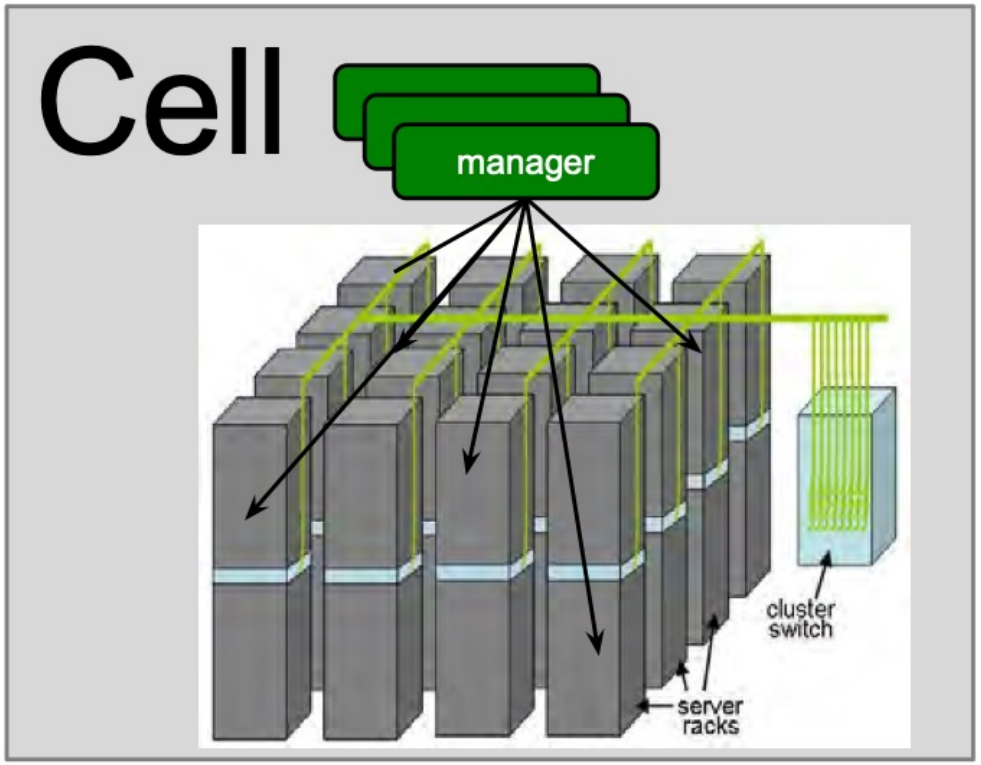
Run everything

Tolerate failures

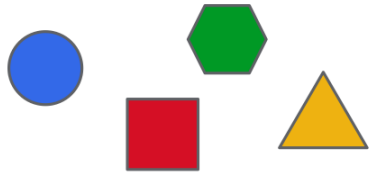
Predictable behavior

High utilization

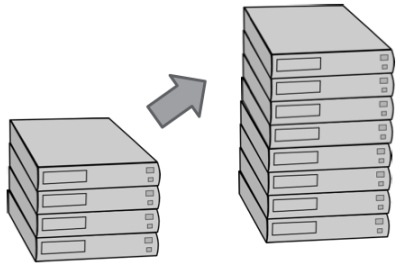
With very few people!



Let’s build a cluster scheduler



Diverse workloads



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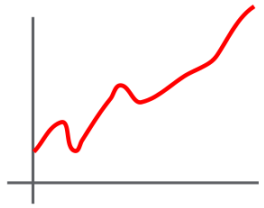
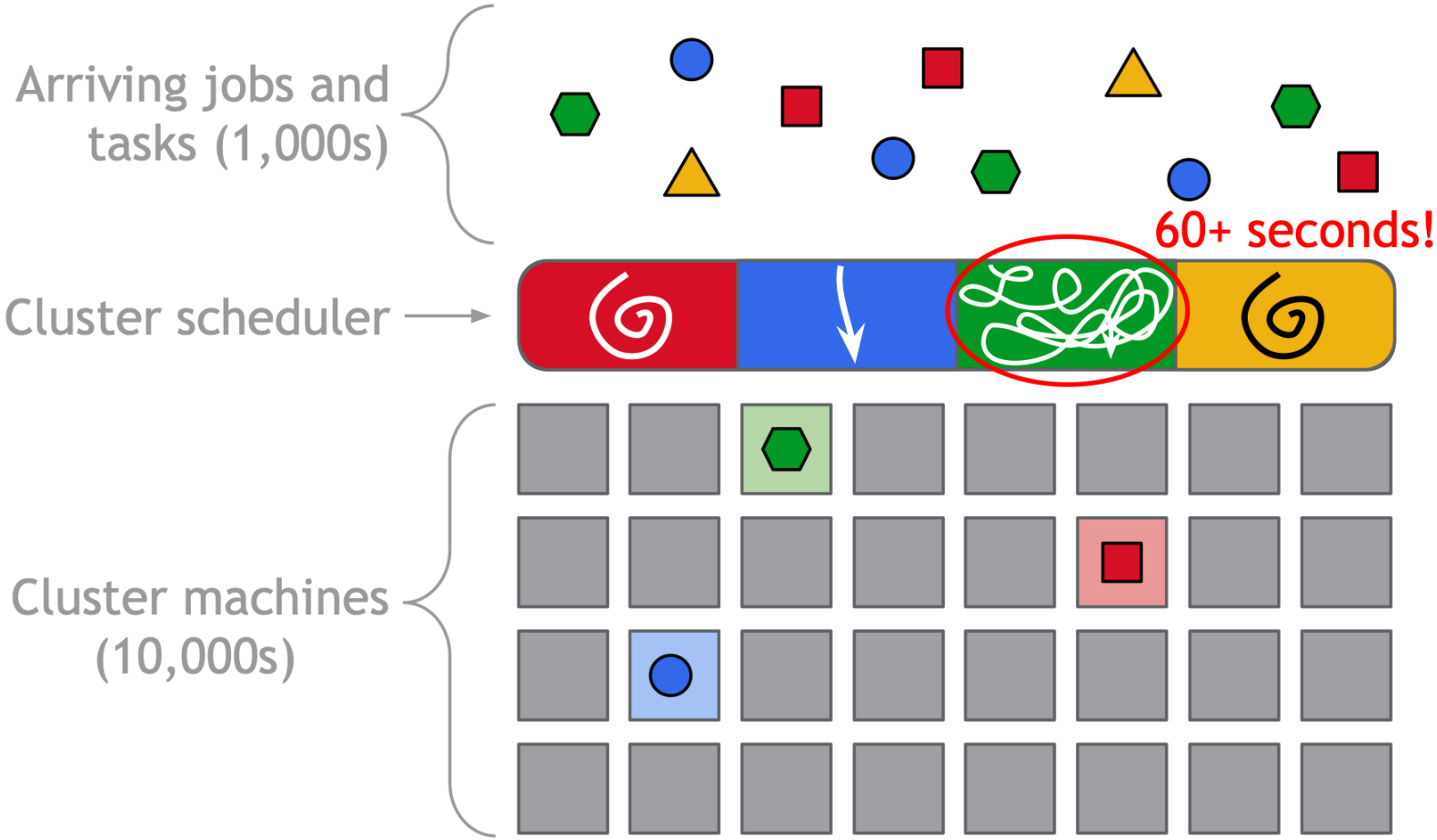


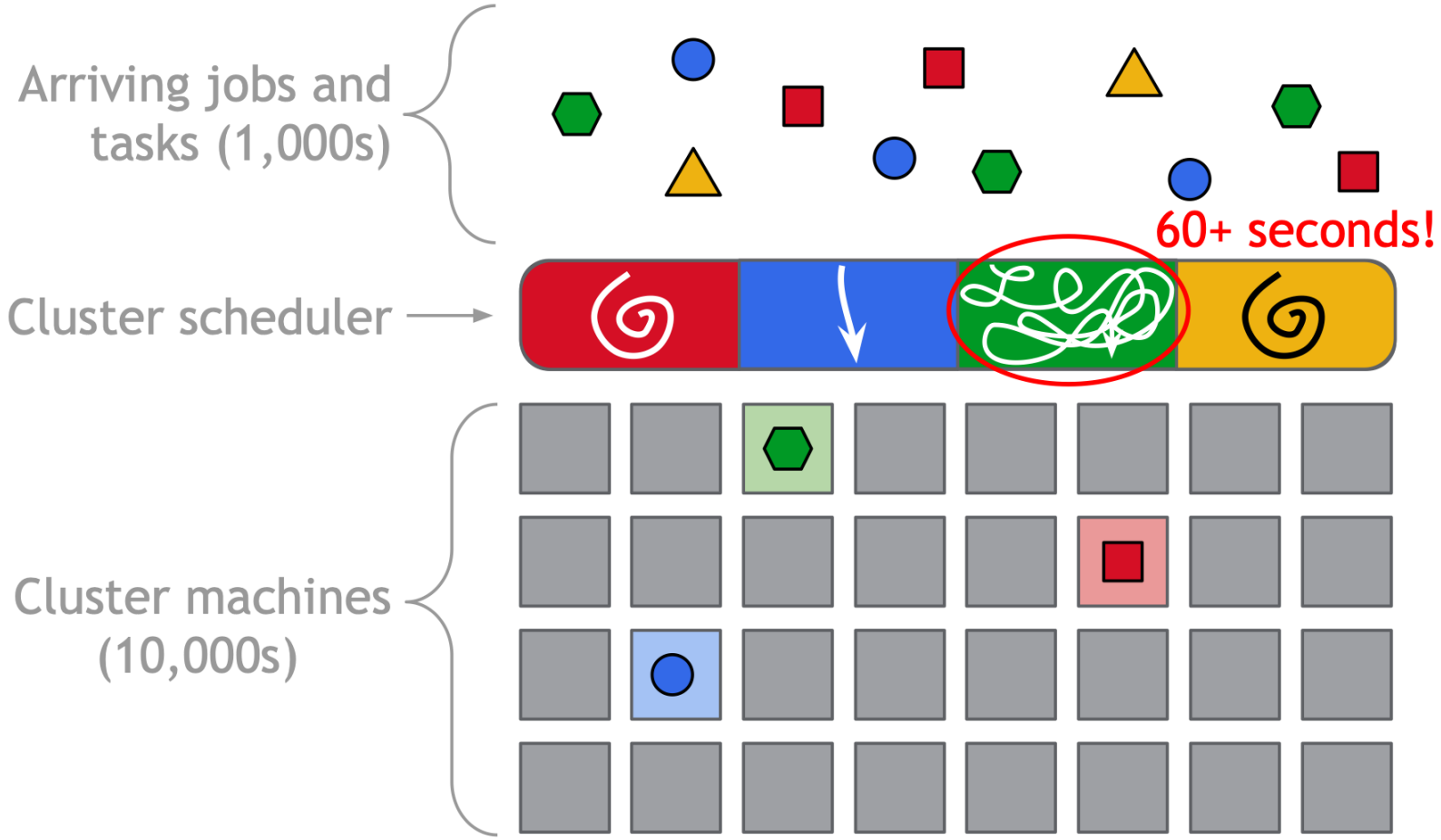
Growing job arrival rates


Arriving jobs and tasks (1,000s)
60+ seconds!
Cluster scheduler
Cluster machines (10,000s)

Why might scheduling take 60+ s?

Large jobs

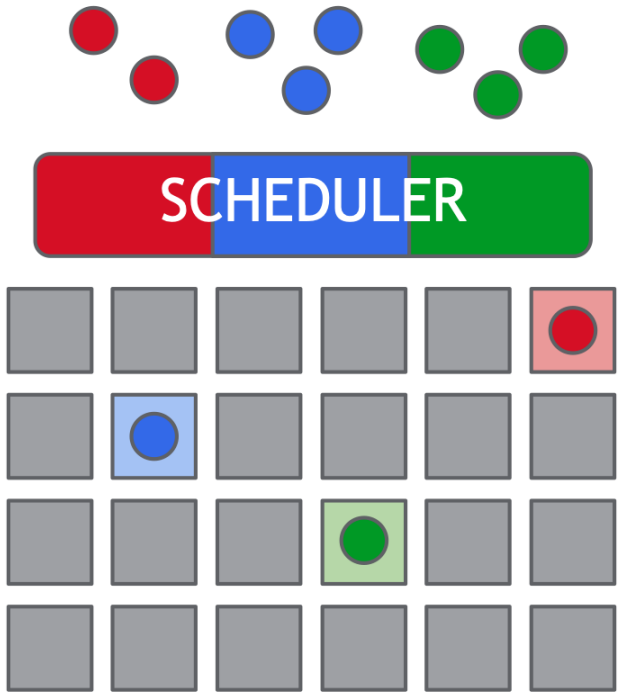
- tens of thousands of tasks
- optimization algorithms (constraints, bin packing w/ knock-on preemption)
- picky jobs in a full cluster



Hence: break up into independent schedulers, and arbitrate resources between them

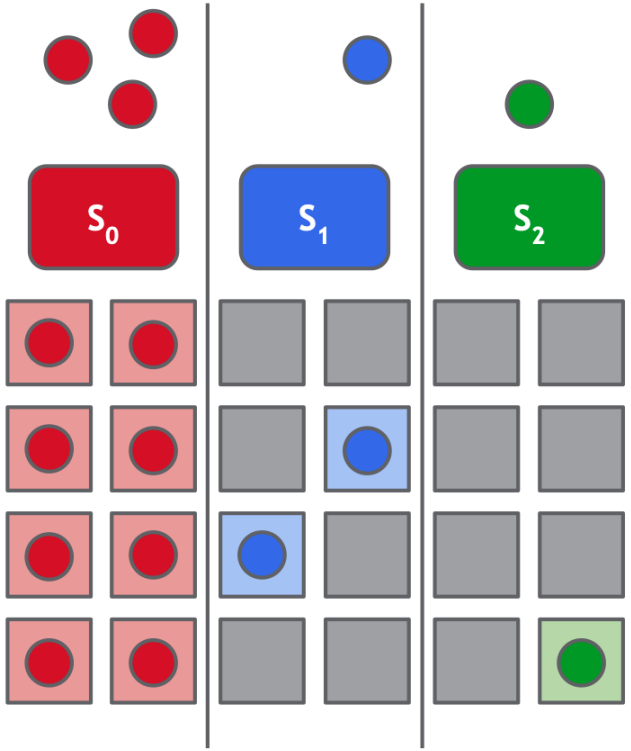
How to arbitrate resources?

monolithic scheduler



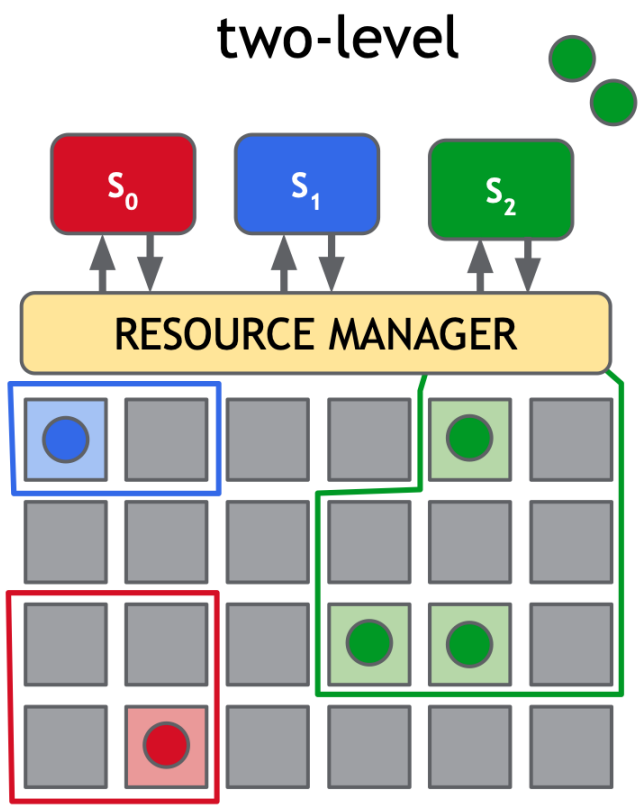
- hard to diversify
- code growth
- scalability bottleneck

static partitioning

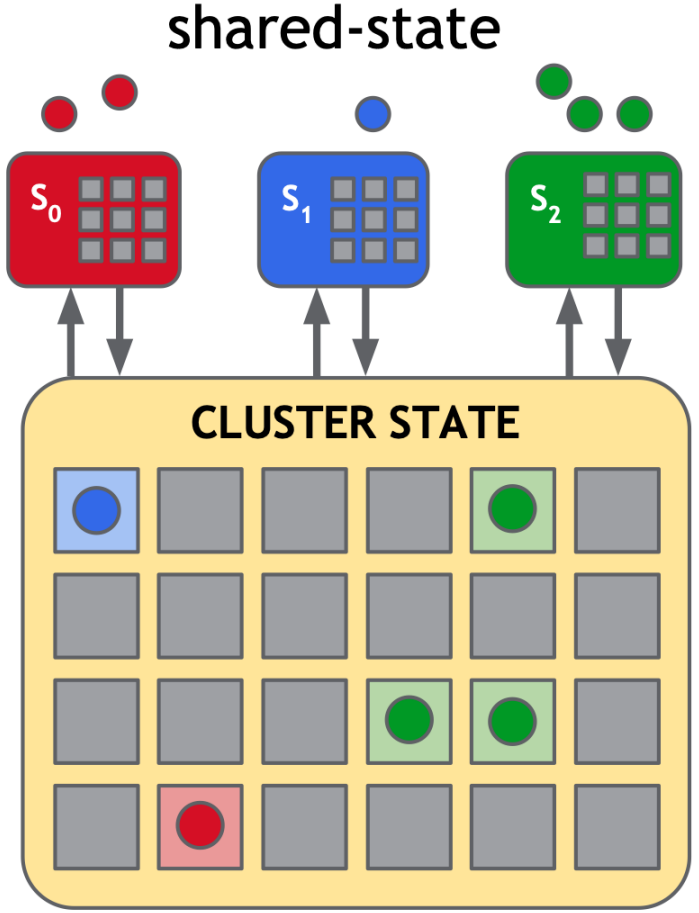


- poor utilization
- inflexible

Existing approaches



Mesos, YARN



Google's Omega

Mesos

A Platform for Fine-Grained Resource Sharing in the Data Center

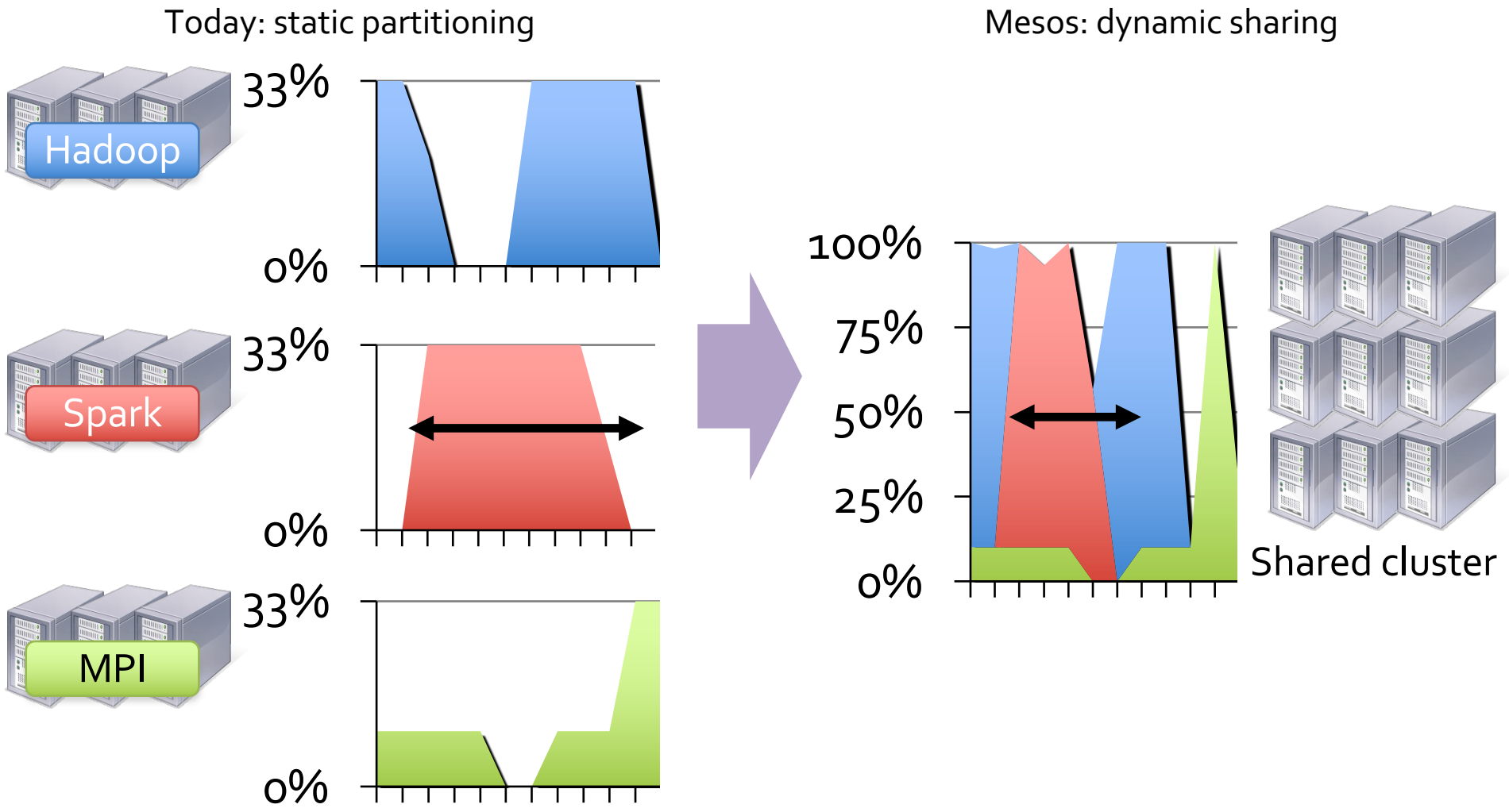
Benjamin Hindman, Andy Konwinski, Matei Zaharia,
Ali Ghodsi, Anthony Joseph, Randy Katz, Scott Shenker, Ion Stoica

University of California, Berkeley

Challenges and goals

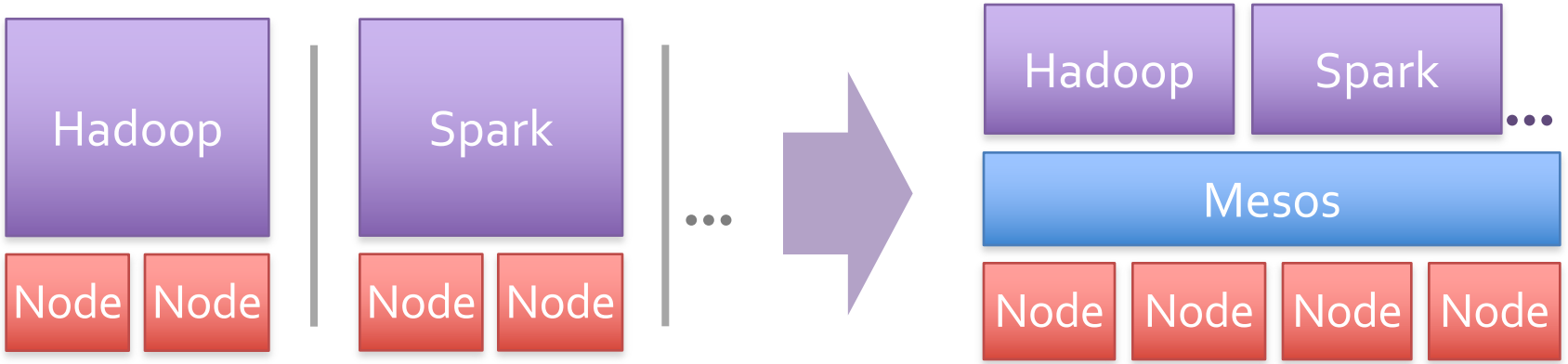
- High utilization
- Support diverse frameworks: each framework will have different scheduling needs
- Scalability: the scheduling system must scale to clusters of 1,000s of nodes running 100s of jobs with 1,000,000s of tasks
- Reliability: because all applications would depend on Mesos, the system must be **fault-tolerant** and **highly available.**

Where We Want to Go



Mesos

A thin resource sharing layer that enables fine-grained sharing across diverse cluster computing frameworks, by giving frameworks a common interface for accessing cluster resources.



Design Elements

Fine-grained sharing

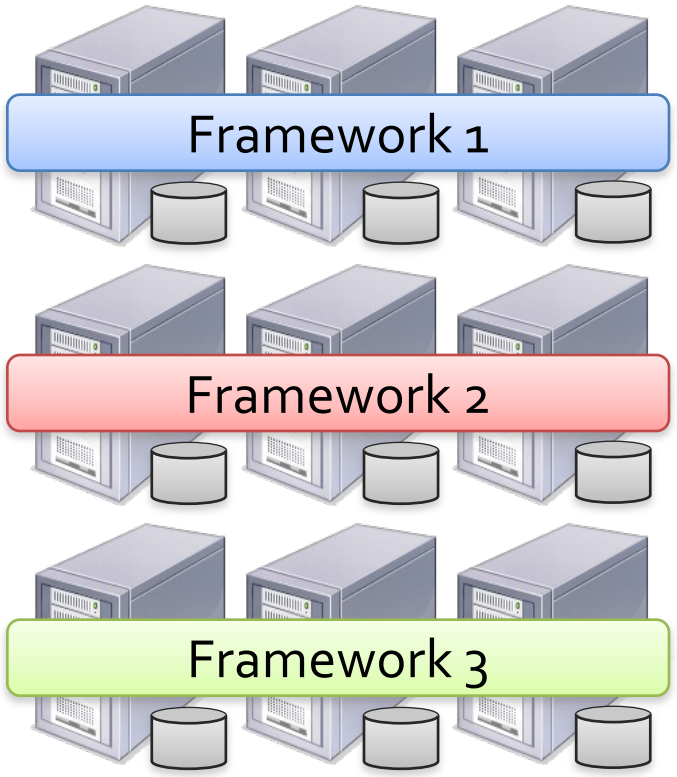
- Allocation at the level of tasks within a job
- Improves utilization, latency, and data locality

Resource offers

- Simple, scalable application-controlled scheduling mechanism

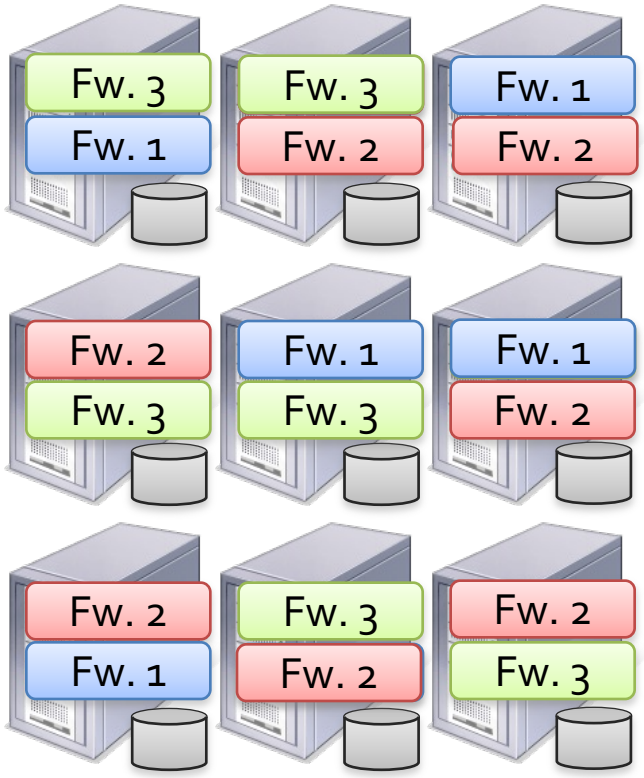
Element 1: Fine-Grained Sharing

Coarse-Grained Sharing (HPC):



Storage System (e.g. HDFS)

Fine-Grained Sharing (Mesos):



Storage System (e.g. HDFS)

+ Improved utilization, responsiveness, data locality

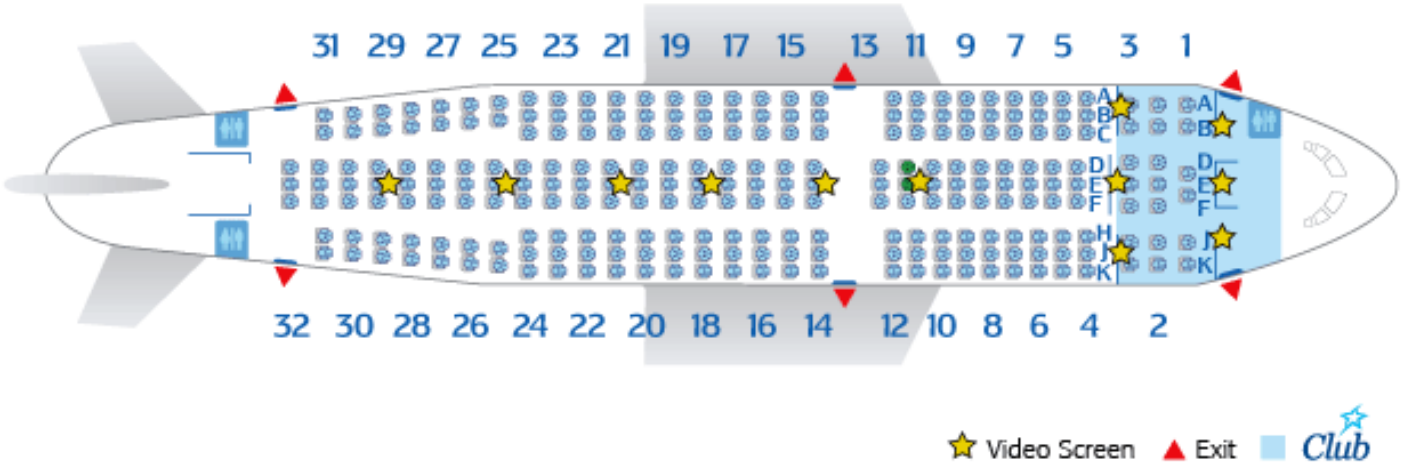
Element 2: Resource Offers

Mesos: Resource offers

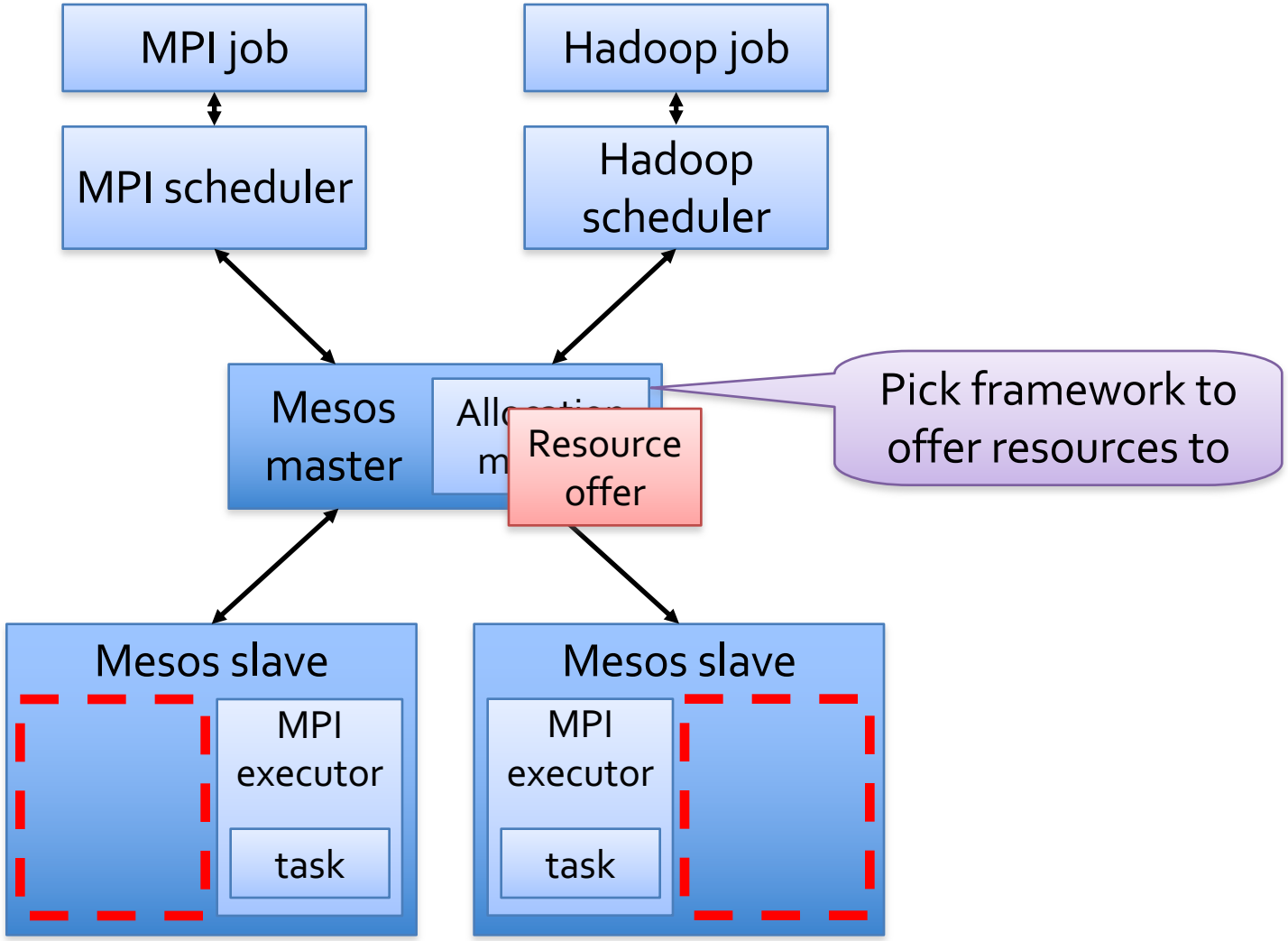
- Offer available resources to frameworks, let them pick which resources to use and which tasks to launch

\+ Keeps Mesos simple, lets it support future frameworks

– Decentralized decisions might not be optimal



Mesos Architecture



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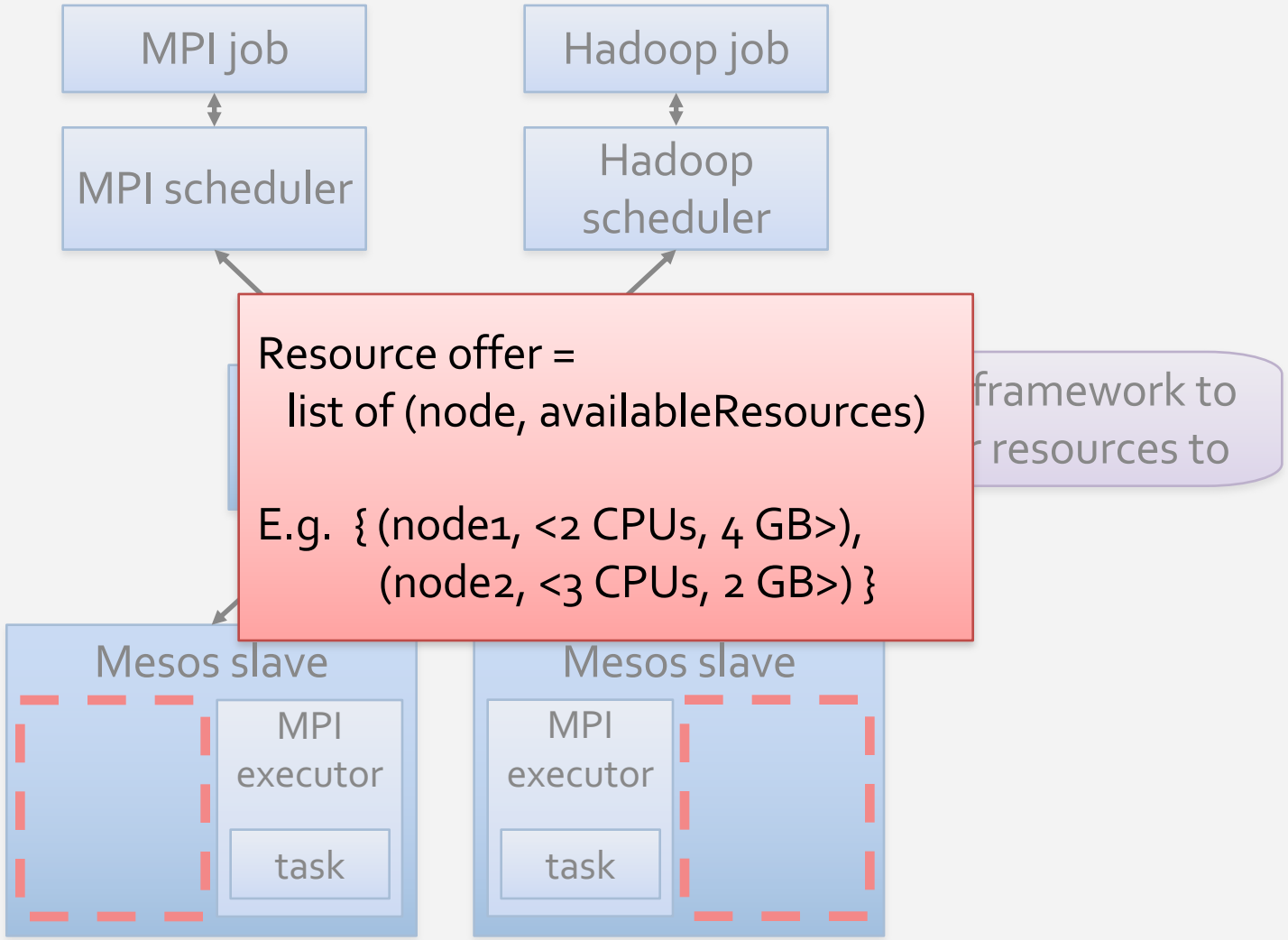
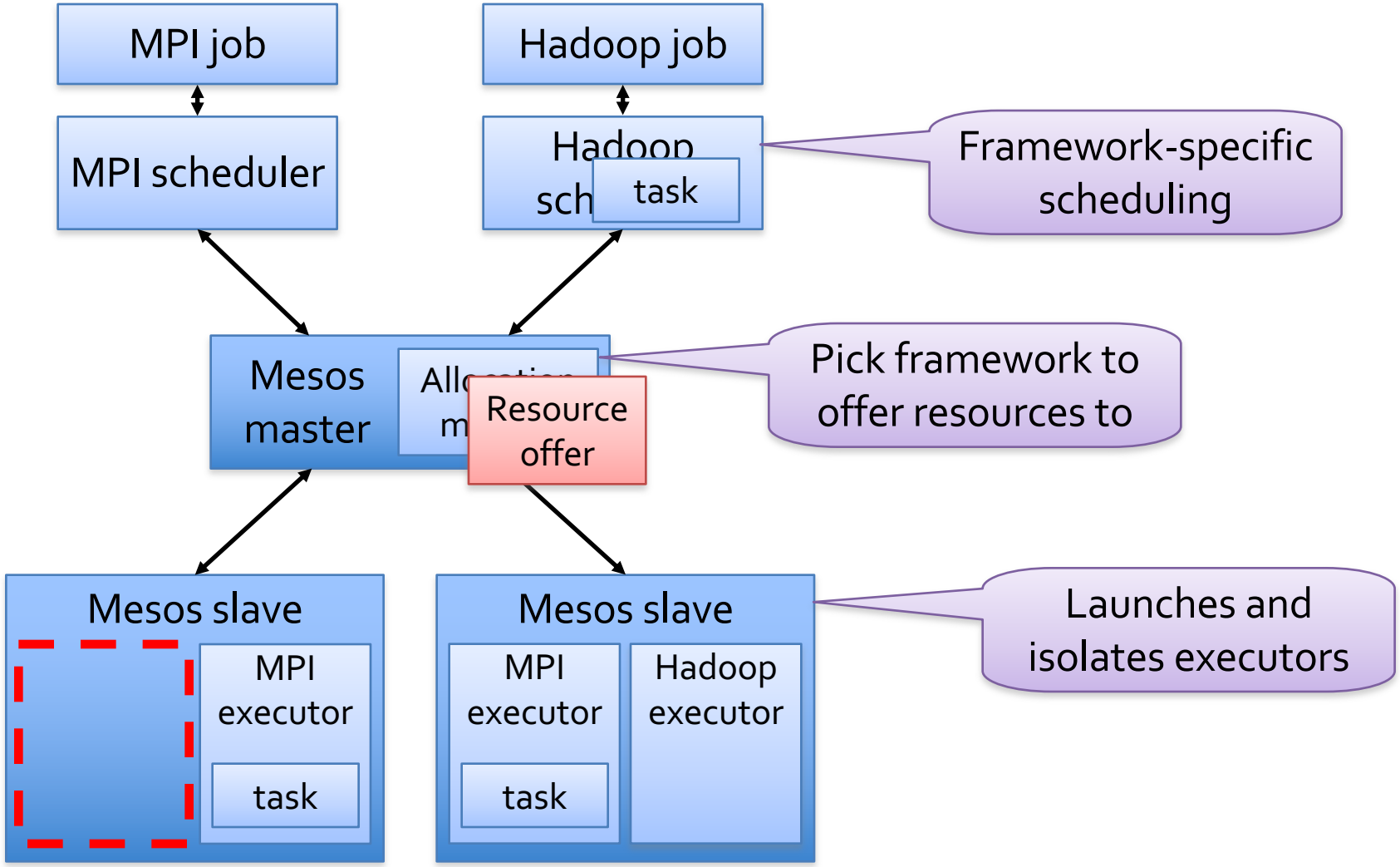


Mesos Architecture



Mesos Architecture

- Mesos master: fine-grained sharing across frameworks
- Mesos slave on each node
- Frameworks that run tasks on slave nodes
- Framework schedulers

“While the Mesos master determines how many resources to offer to each framework, the frameworks’ schedulers select which of the offered resources to use”.

Optimization: Filters

Let frameworks short-circuit rejection by providing a predicate on resources to be offered

- E.g. “nodes from list L” or “nodes with > 8 GB RAM”
- Could generalize to other hints as well

Ability to reject still ensures correctness when needs cannot be expressed using filters

Analysis

Resource offers work well when:

- Frameworks can scale up and down elastically
- Task durations are homogeneous
- Frameworks have many preferred nodes

These conditions hold in current data analytics frameworks (MapReduce, Dryad, …)

- Work divided into short tasks to facilitate load balancing and fault recovery
- Data replicated across multiple nodes

Revocation

Mesos allocation modules can revoke (kill) tasks to meet organizational SLOs

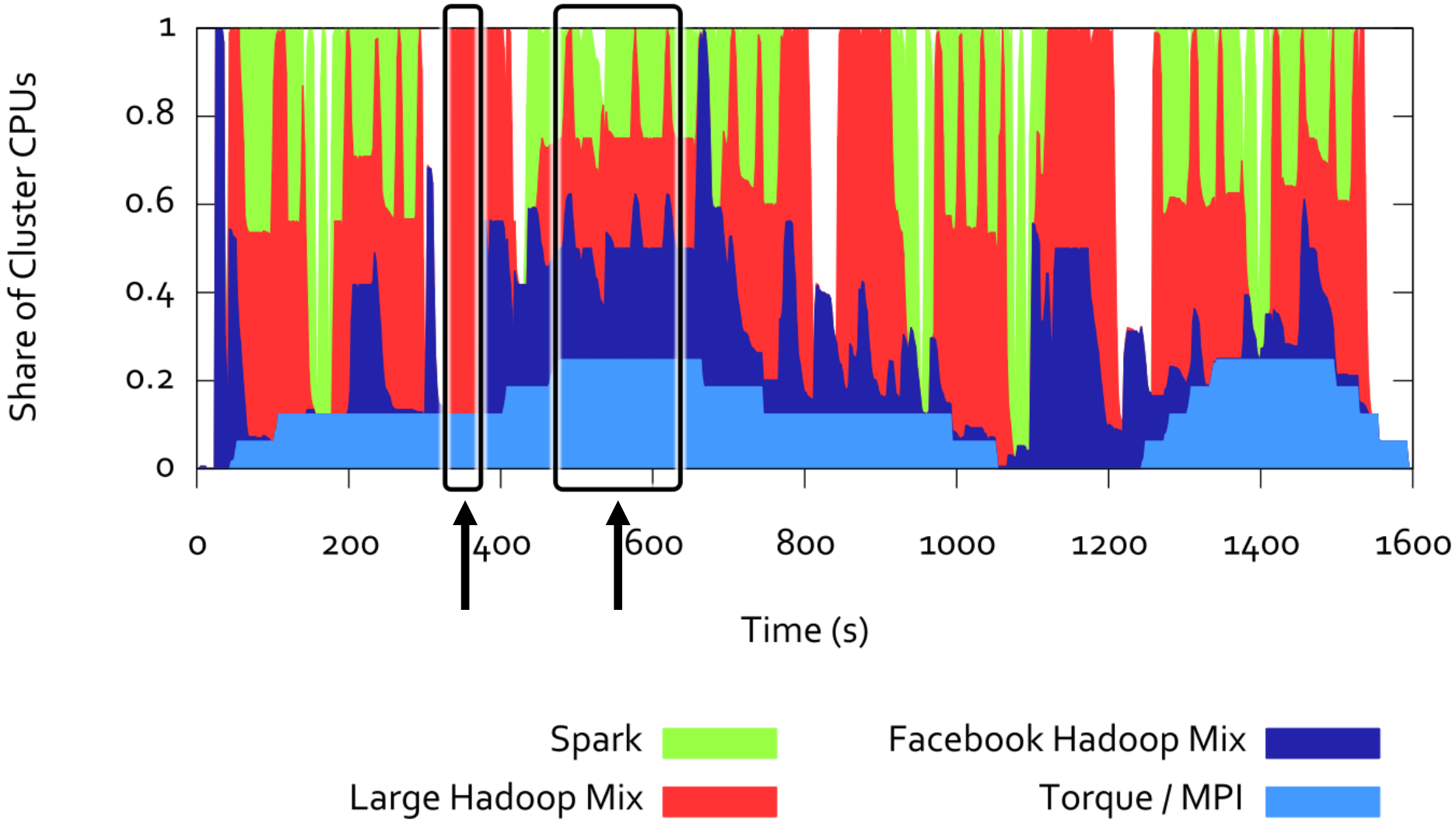
Framework given a grace period to clean up

“Guaranteed share” API lets frameworks avoid revocation by staying below a certain share

Results

- Utilization and performance vs static partitioning
- Framework placement goals: data locality
- Scalability
- Fault recovery

Dynamic Resource Sharing



Mesos vs Static Partitioning

Compared performance with statically partitioned cluster where each framework gets 25% of nodes

Framework	Speedup on Mesos
Facebook Hadoop Mix	1.14×
Large Hadoop Mix	2.10×
Spark	1.26×
Torque / MPI	0.96×

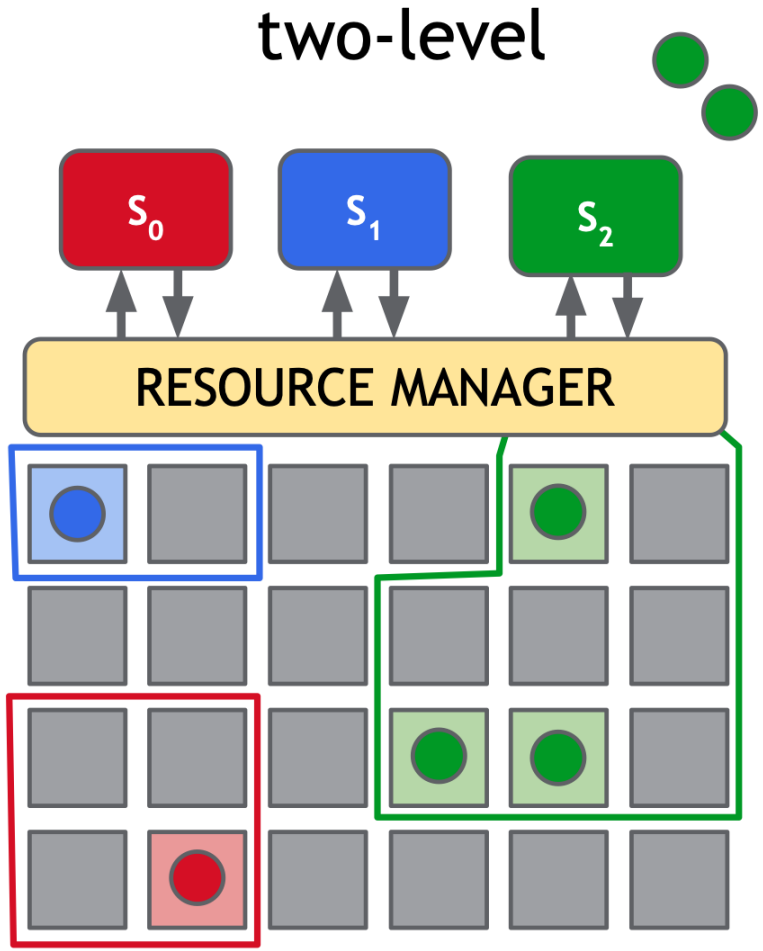
Mesos's problem

Hoarding

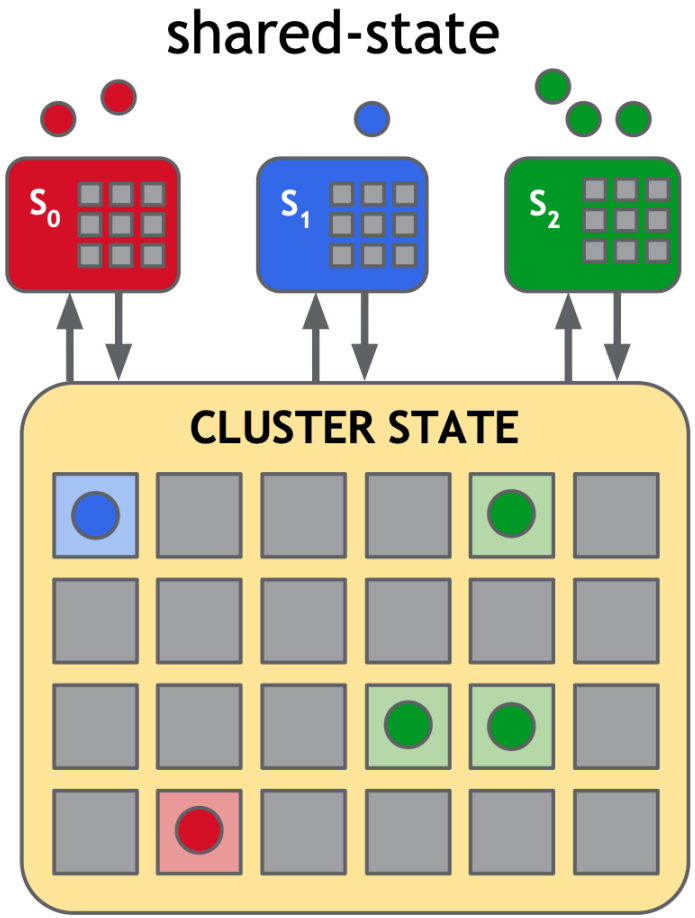
- Mesos avoids conflicts by offering a given resource to one framework at-a-time. Mesos chooses the order. One framework holds the lock of the resources for the duration of the decision → slow

Information hiding

- A framework does not have access to all the cluster state. Hard for preemption or getting all resources.



Omega: shared-state



Cell state

- a resilient master copy of the resource allocations of the cluster

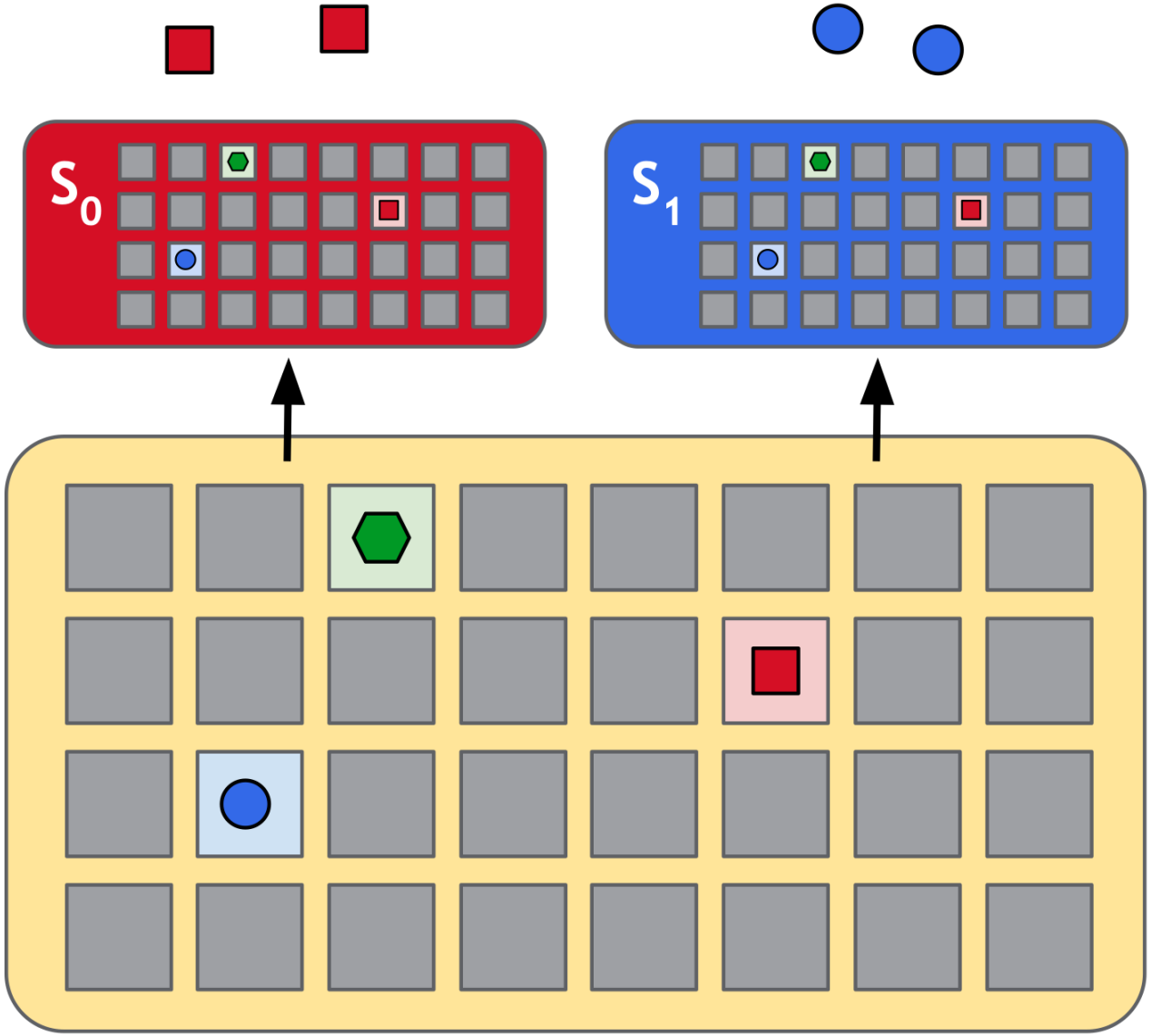
No centralized scheduler

- Each framework maintains its own scheduler. Each scheduler has its own private, local, frequently-updated copy of the cell state which uses to make decisions

Omega shared-state scheduling

- A framework's scheduler makes a decision
- Updates the shared cell state copy in an atomic commit
- At most one such commit will succeed
- The scheduler resyncs its local copy and if needed re-schedules

how does omega work?



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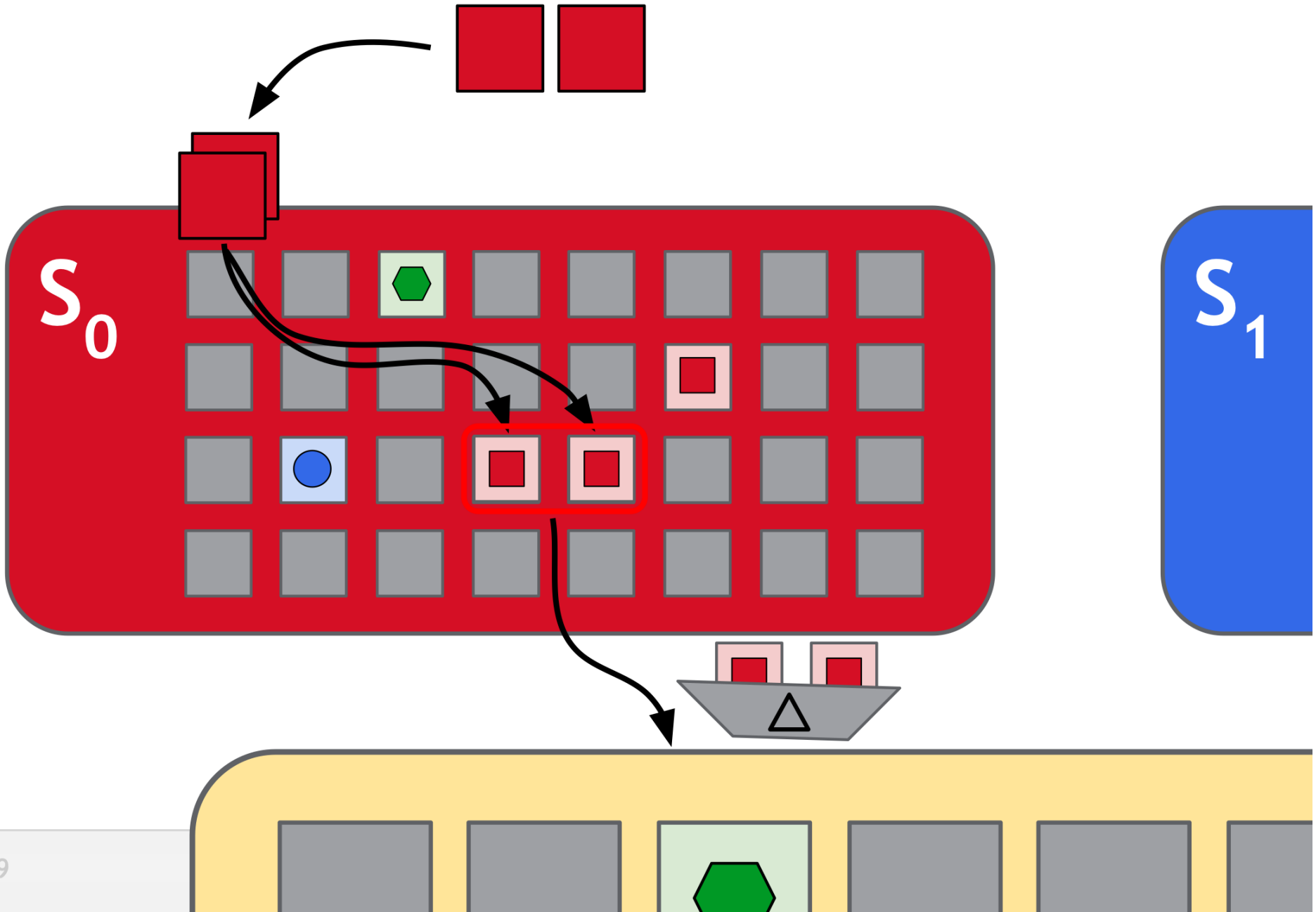

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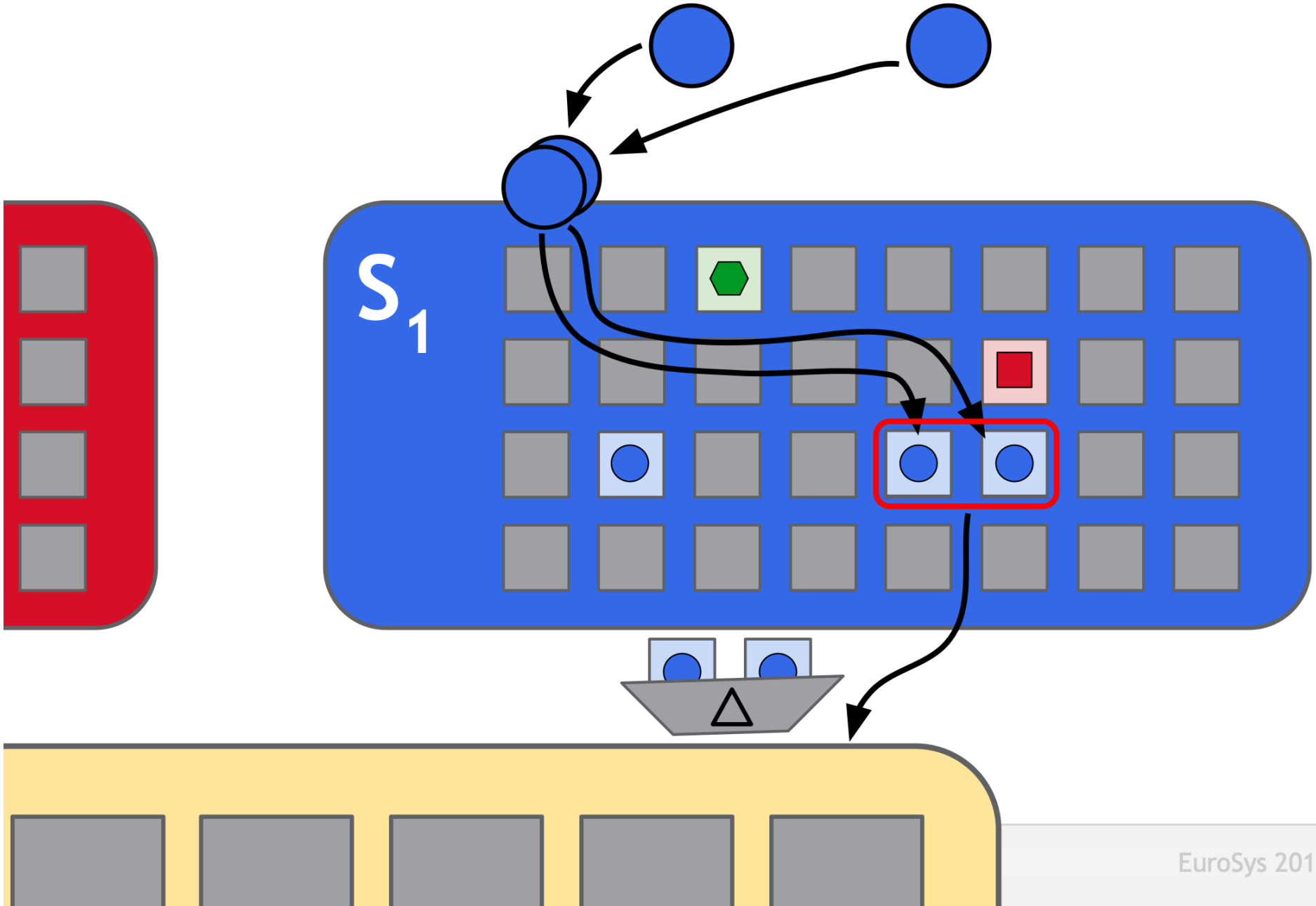

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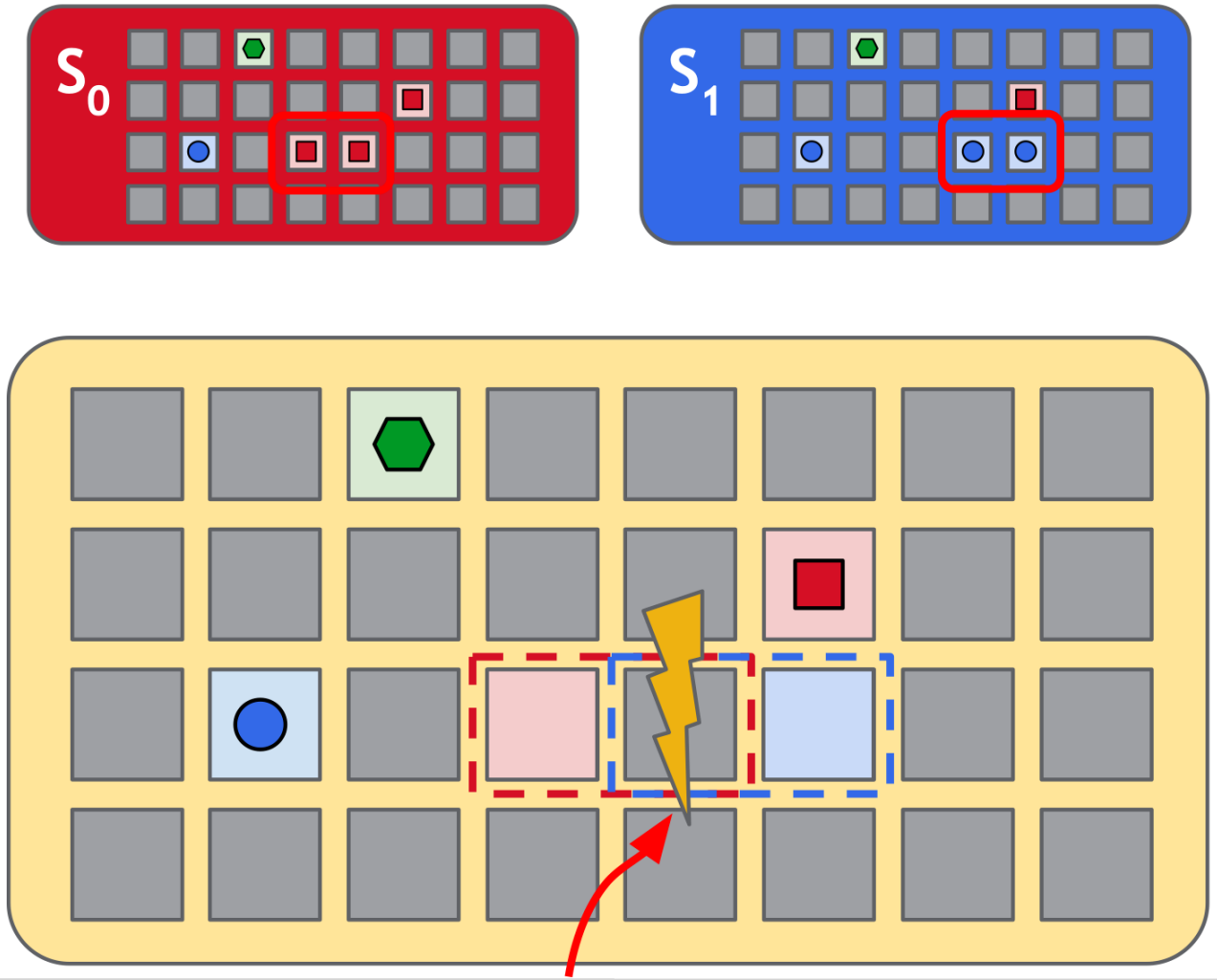

Omega's Takeaways

- Flexibility and scale require parallelism
- Parallel scheduling works if you do it right
- Using shared state is the way to do it right

Credits

John Wilkes, Google

- M. Schwarzkopf, A. Konwinski, M. Abd-El-Malek, and J. Wilkes. Omega: flexible, scalable schedulers for large compute clusters. In ACM EuroSys, 2013.

Matei Zaharia, Stanford & Databricks

- B. Hindman, A. Konwinski, M. Zaharia, A. Ghodsi, A. D. Joseph, R. Katz, S. Shenker, and I. Stoica. Mesos: A platform for fine-grained resource sharing in the data center. In USENIX NSDI, 2011.