Mesos: Multiprograming for Datacenters

Ion Stoica

Joint work with: Benjamin Hindman, Andy Konwinski, Matei Zaharia, Ali Ghodsi, Anthony D. Joseph, Randy Katz, Scott Shenker,

amplab UC BERKELEY

Motivation

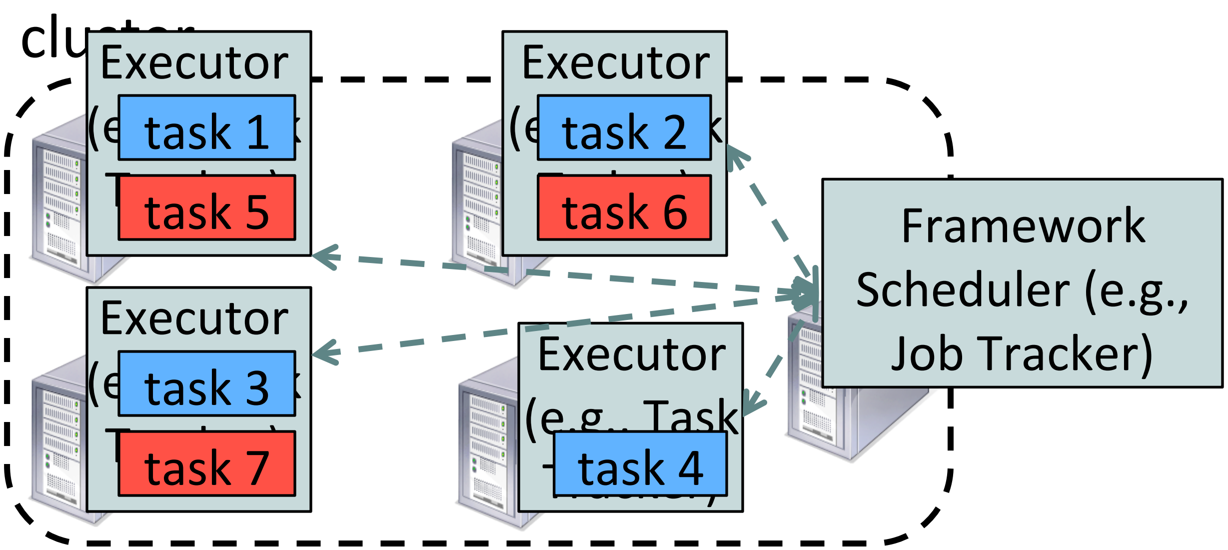
- Rapid innovation in cloud computing

Hypertable Dryad HIVE
H·BASE
hadoop
Cassandra MPI
Pregel mahout

- Today
  - No single framework optimal for all applications
  - Each framework runs on its dedicated cluster or cluster partition

Computation Model: Frameworks

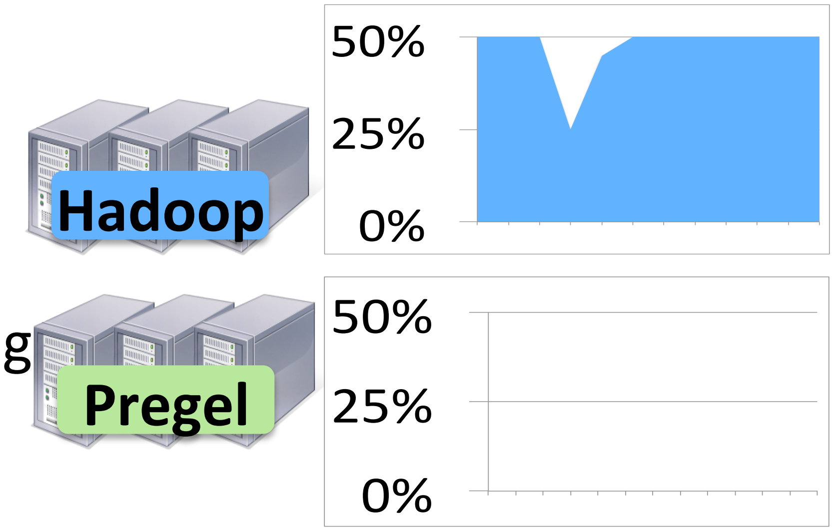
- A ***framework*** (e.g., Hadoop, MPI) manages one or more ***jobs*** in a computer cluster
- A ***job*** consists of one or more ***tasks***
- A ***task*** (e.g., map, reduce) is implemented by one or more processes running on a single machine



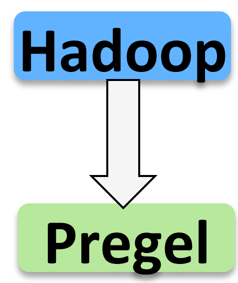
Job 1: tasks 1, 2, 3, 4
Job 2: tasks 5, 6, 7

One Framework Per Cluster Challenges

- Inefficient resource usage
  - E.g., Hadoop cannot use available resources from Pregel's cluster
  - No opportunity for stat. multiplexing



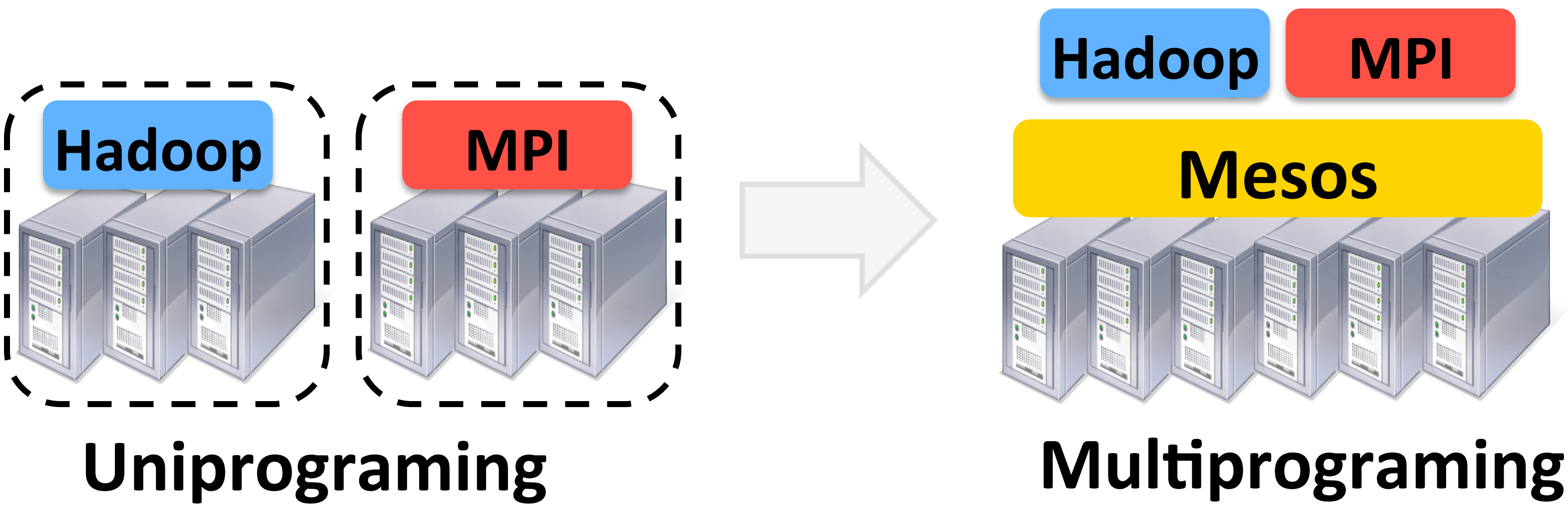
- Hard to share data
  - Copy or access remotely, expensive
- Hard to cooperate
  - E.g., Not easy for Pregel to use graphs generated by Hadoop



Need to run multiple frameworks on same cluster

Solution: Mesos

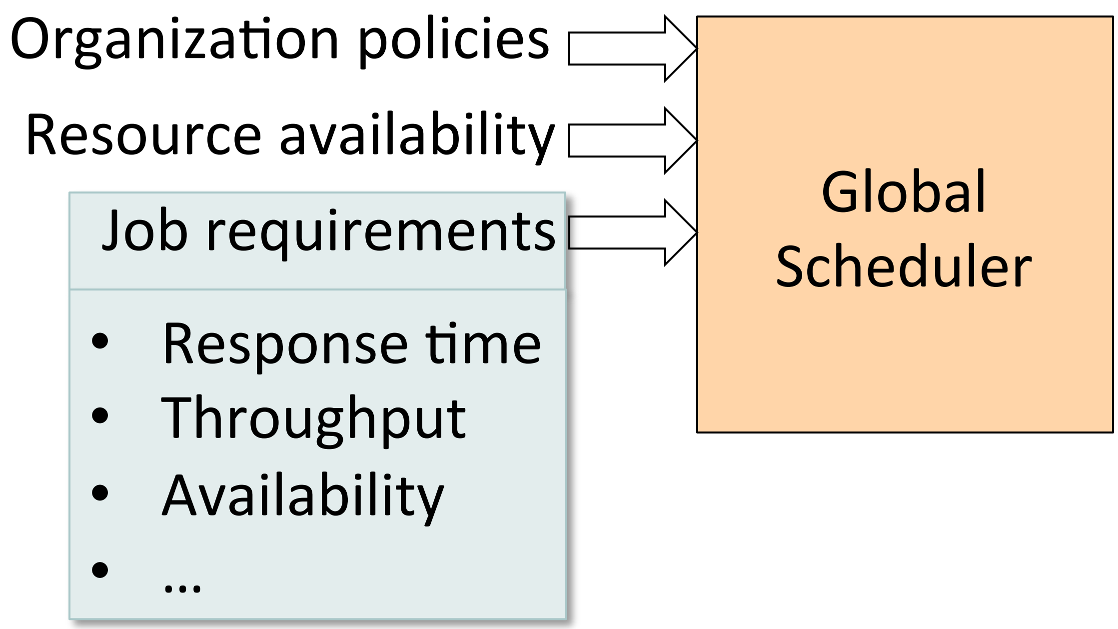
- Common resource sharing layer
  - abstracts ("virtualizes") resources to frameworks
  - enable diverse frameworks to share cluster



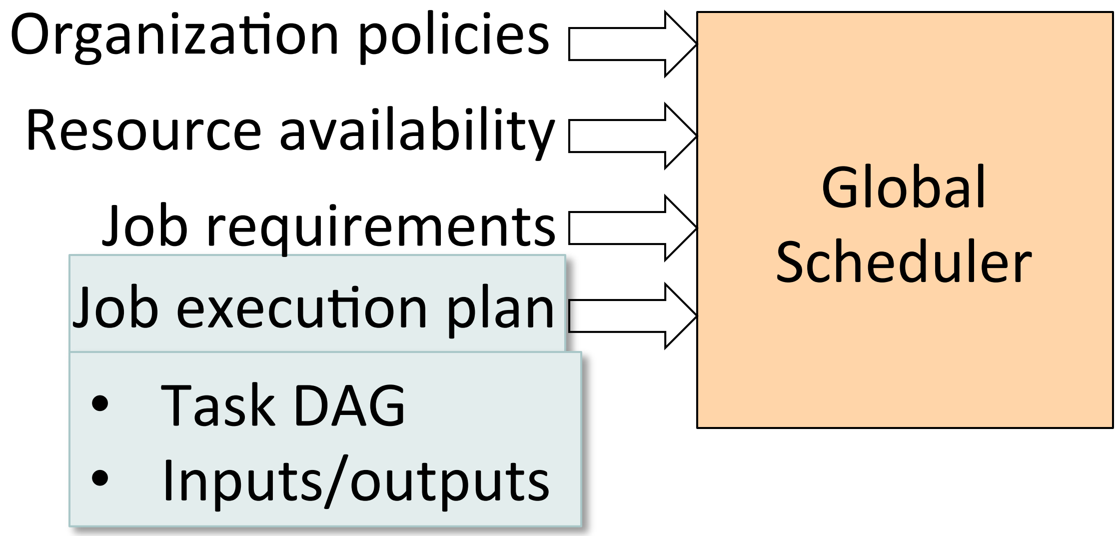
Mesos Goals

- **High utilization** of resources
- **Support diverse frameworks** (existing & future)
- **Scalability** to 10,000's of nodes
- **Reliability** in face of node failures
- Focus of this talk: ***resource management & scheduling***

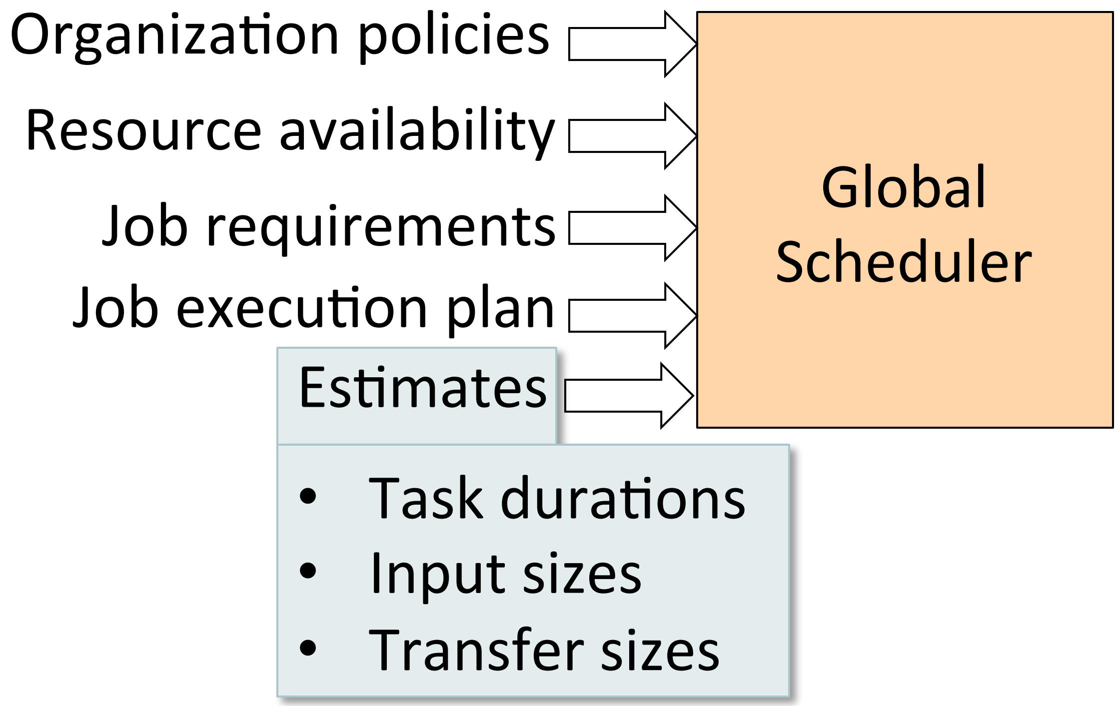
Approach: Global Scheduler



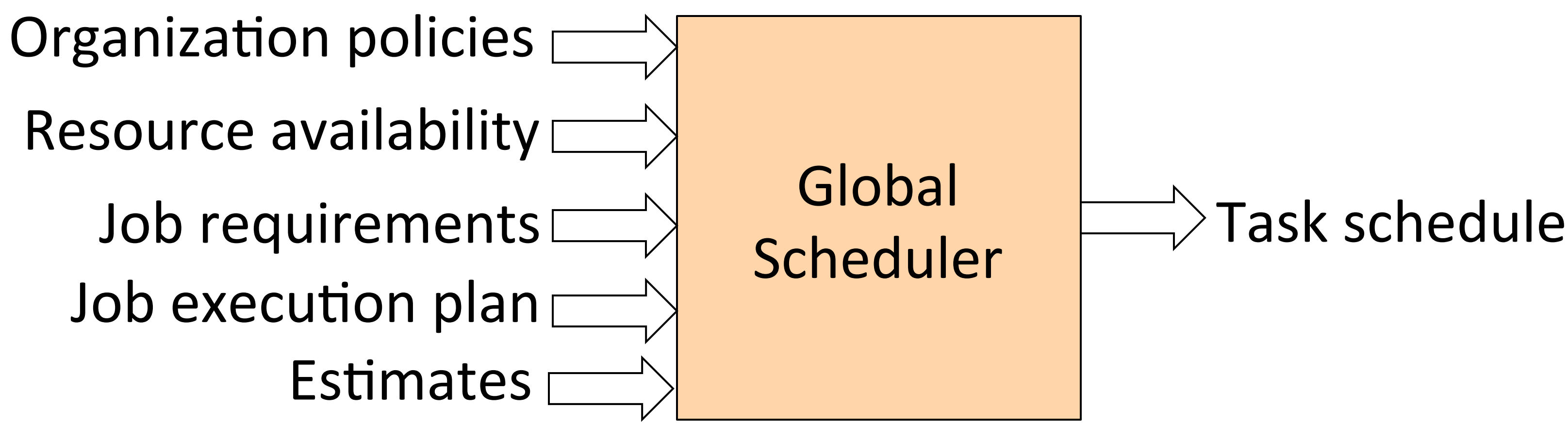
Approach: Global Scheduler



Approach: Global Scheduler

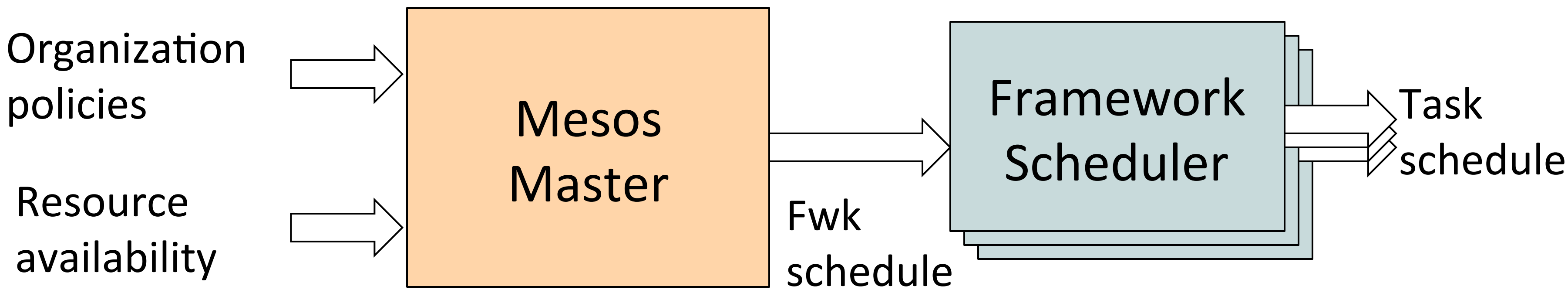


Approach: Global Scheduler



- Advantages: can achieve optimal schedule
- Disadvantages:
  - Complexity → hard to scale and ensure resilience
  - Hard to anticipate future frameworks' requirements
  - Need to refactor existing frameworks

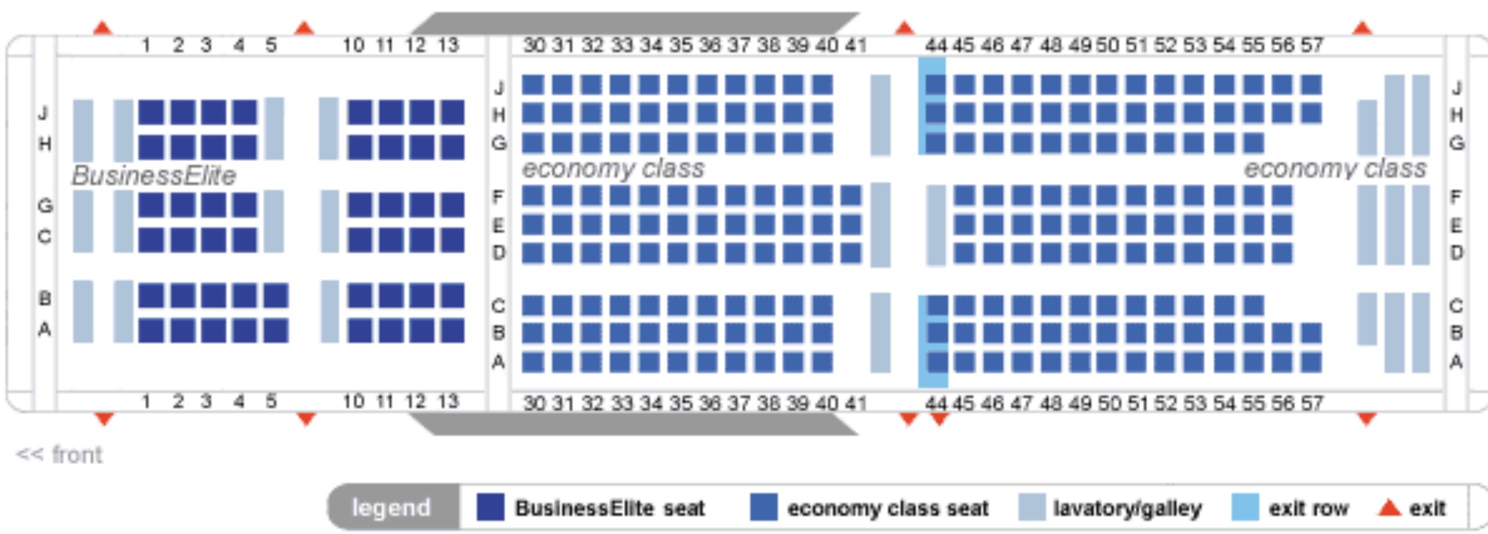
Our Approach: Distributed Scheduler



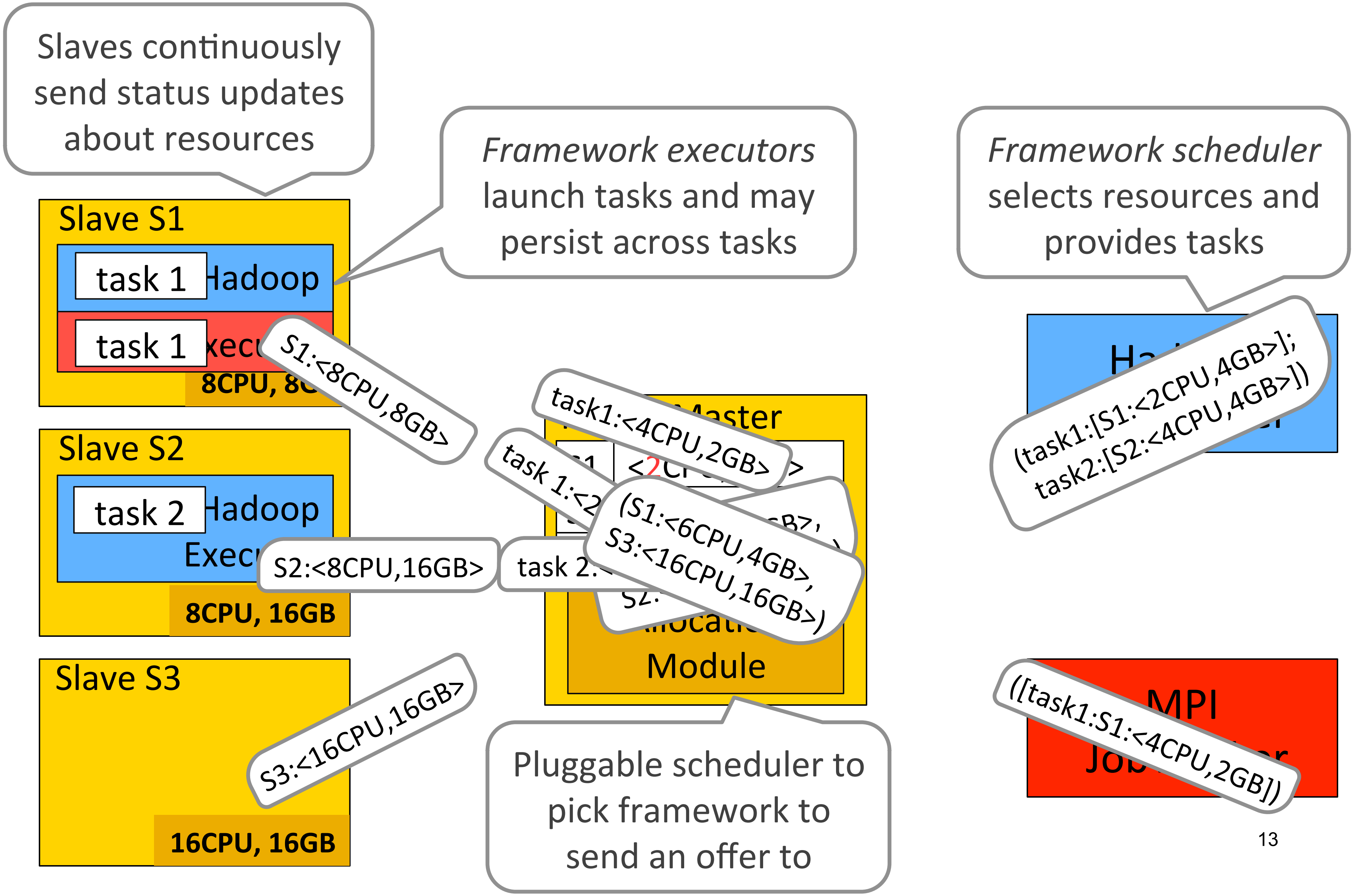
- Advantages:
  - Simple → easier to scale and make resilient
  - Easy to port existing frameworks, support new ones
- Disadvantages:
  - Distributed scheduling decision → not optimal

Resource Offers

- Unit of allocation: ***resource offer***
  - Vector of available resources on a node
  - E.g., node1: <1CPU, 1GB>, node2: <4CPU, 16GB>
- Master sends resource offers to frameworks
- Frameworks select which offers to accept and which tasks to run

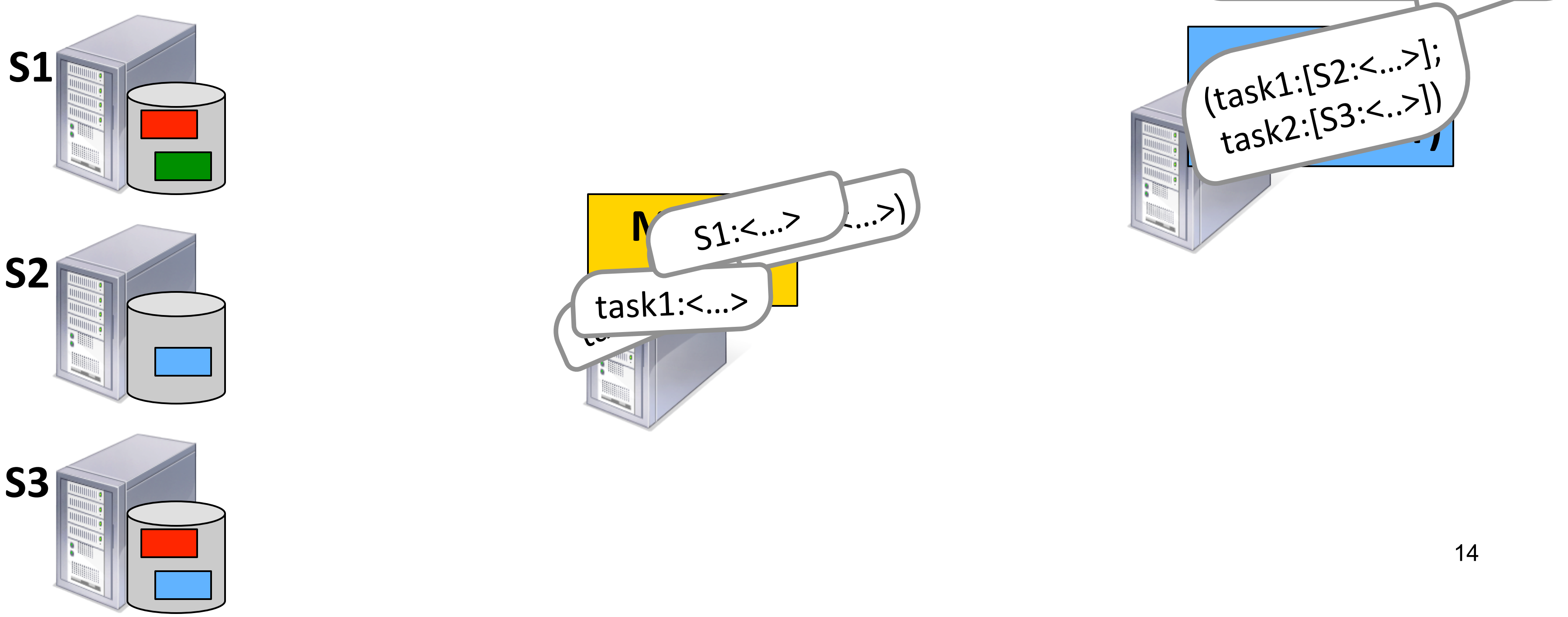


Mesos Architecture: Example



Why does it Work?

- A framework can just wait for an offer that matches its constraints or preferences!
    - Reject offers it does not like
- Example: Hadoop's job input is *blue* file



Two Key Questions

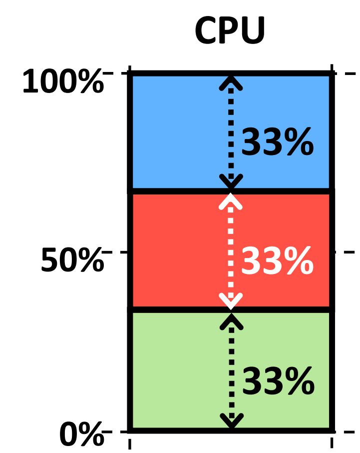
- How long does a framework need to wait?
- How do you allocate resources of different types?

Two Key Questions

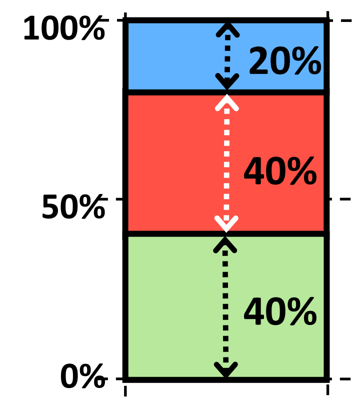
- How long does a framework need to wait?
- How do you allocate resources of different types?

Single Resource: Fair Sharing

- n users want to share a resource (e.g. CPU)
  - Solution: give each $1/n$ of the shared resource



- Generalized by ***max-min fairness***
  - Handles if a user wants less than its fair share
  - E.g. user 1 wants no more than 20%



Why Max-Min Fairness?

Policy	Examples
Proportional Allocation	User 1 gets weight 2, user 2 weight 1
Priority	Give user 1 weight 1000, user 2 weight 1
Reservation	Ensure user 1 gets 10% of a resource Give user 1 weight 10, sum weights ≤ 100
Deadline Guarantees	Given a user job's demand and deadline, compute user's reservation/weight

Isolation: Users cannot affect others beyond their share

Widely Used

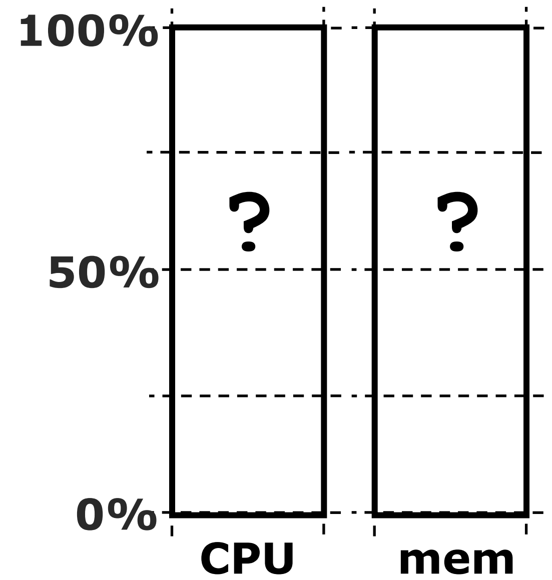
- ***OS:*** proportional sharing, lottery, Linux's cfs, …
- ***Networking:*** wfq, wf2q, sfq, drr, csfq, ...
- ***Datacenters:*** Hadoop's fair sched, capacity sched, Quincy

Why is Max-Min Fairness Not Enough?

- Job scheduling is not only about a ***single*** resource
    - Tasks consume CPU, memory, network and disk I/O


Problem

- 2 resources: CPUs & mem
- User 1 wants **<1 CPU, 4 GB>** per task
- User 2 wants **<3 CPU, 1 GB>** per task
- ***What's a fair allocation?***



A Natural Policy

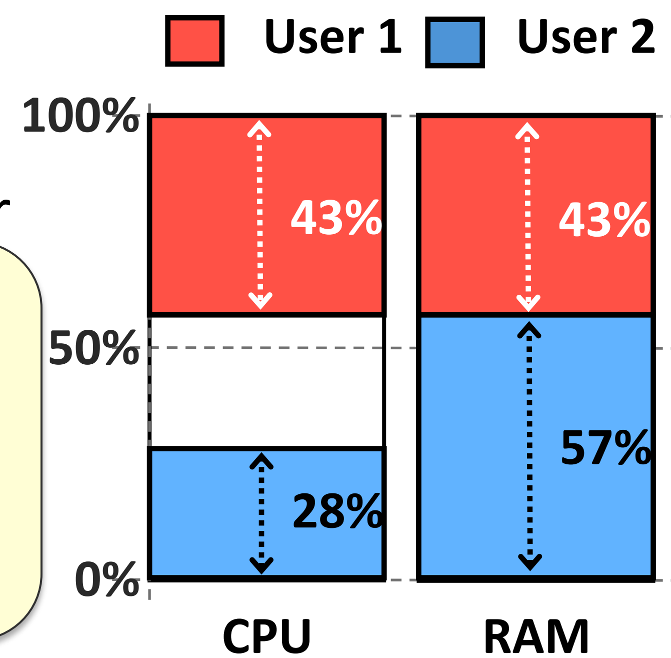
- *Asset Fairness*
  - Equalize each user's ***sum of resource shares***

- Cluster with 28 CPUs, 56 GB RAM
  - U_1 needs <1 CPU, 2 GB RAM> per task, or

Problem: violates share guarantee
User 1 has < 50% of both CPUs and RAM

Better off in a separate cluster with half the resources

- Asset fairness yields
  - U_1: 12 tasks: <43% CPUs, 43% RAM> (∑=86%)
  - U_2: 8 tasks: <28% CPUs, 57% RAM> (∑=86%)



Cheating the Scheduler

- Users willing to *game* the system to get more resources

- Real-life examples
  - A cloud provider had quotas on map and reduce slots
    Some users found out that the map-quota was low
  - **Users implemented maps in the reduce slots!**

  - A search company provided dedicated machines to users that could ensure certain level of utilization (e.g. 80%)
  - **Users used busy-loops to inflate utilization**

Challenge

- Can we find a fair sharing policy that provides
  - Share guarantee
  - Strategy-proofness

- Can we generalize max-min fairness to multiple resources?

Dominant Resource Fairness (DRF)

- A user's *dominant resource* is the resource user has the biggest share of
  - Example:

    Total resources: < **8 CPU**, **5 GB** >

    User 1's allocation: < **2 CPU**, **1 GB** >

    25% CPUs 20% RAM

    Dominant resource of User 1 is CPU (as 25% > 20%)

- A user's *dominant share* is the fraction of the dominant resource she is allocated
  - User 1's dominant share is **25%**

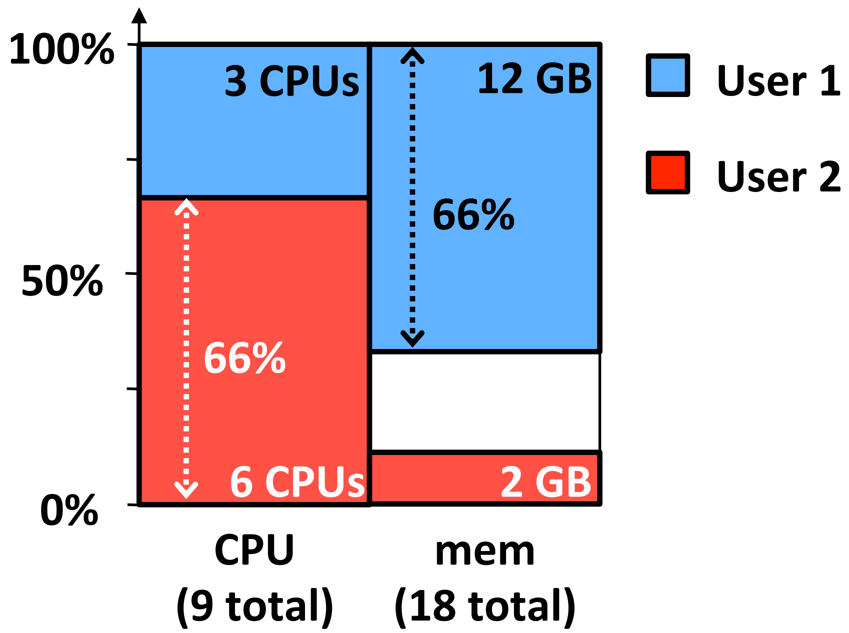
Dominant Resource Fairness (DRF)

- ***Apply max-min fairness to dominant shares***
- Equalize the dominant share of the users
  - Example:

    Total resources: **<9 CPU, 18 GB>**

    User 1 demand: **<1 CPU, 4 GB>;** dom res: **mem** (1/9 < 4/18)

    User 2 demand: **<3 CPU, 1 GB>;** dom res: **CPU** (3/9 > 1/18)



Online DRF Scheduler

Whenever there are available resources and tasks to run:

Schedule a task to the user with smallest dominant share

Properties of Policies

Property	Asset	CEEI	DRF
Share guarantee		✔	✔
Strategy-proofness	✔		✔
Population monotonicity	✔		✔
Resource monotonicity			

Conjecture: Assuming non-zero demands, DRF is the ***only*** allocation that is strategy proof and provides sharing incentive (*Eric Friedman, Cornell*)

Implementation Stats

- 20,000 lines of C++
- Master failover using ZooKeeper
- Isolation using Linux Containers
- Frameworks ported: Hadoop, MPI, Torque
- New specialized framework: Spark, for iterative jobs (up to 30× faster than Hadoop)

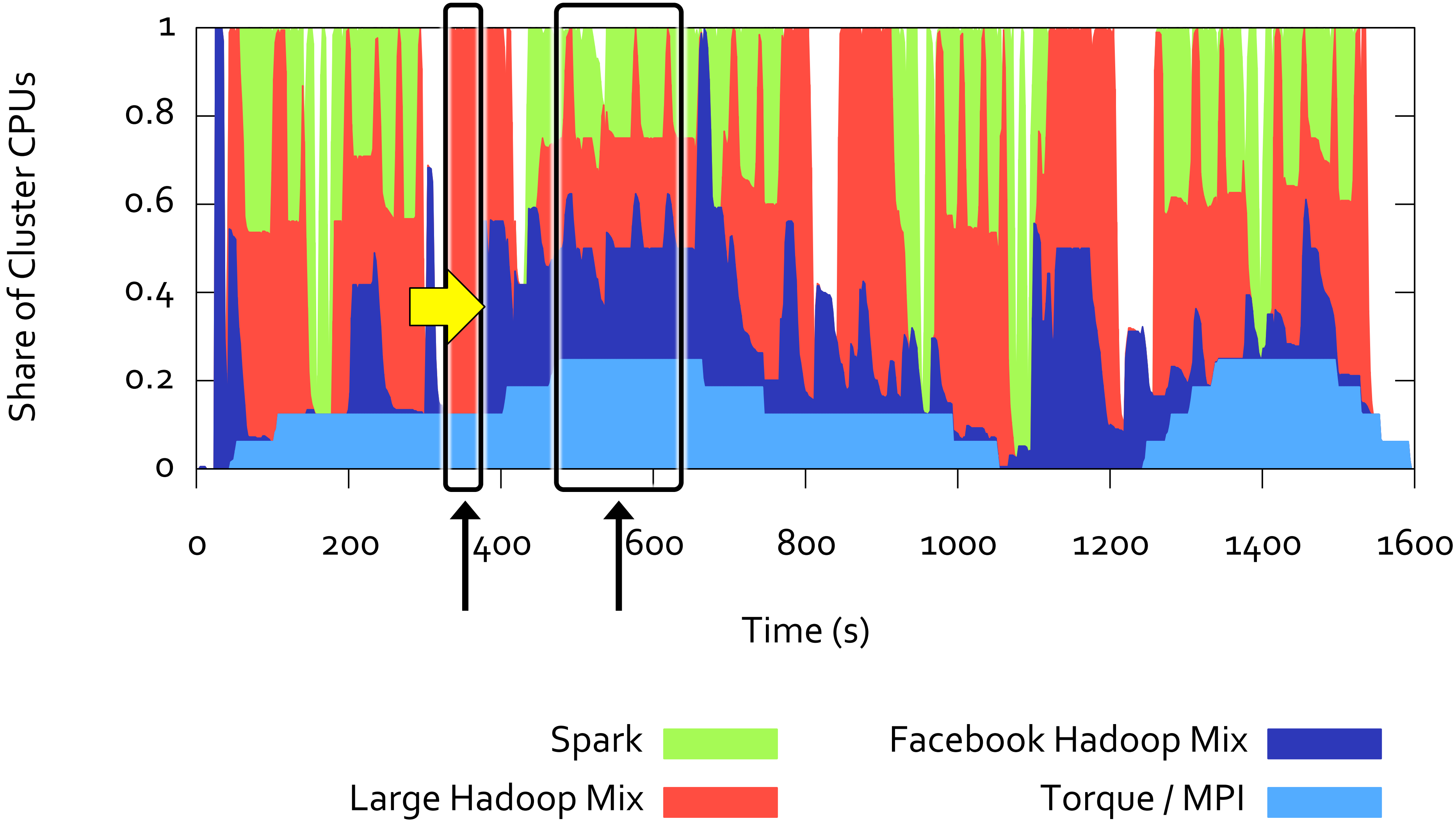
Open source in Apache Incubator

Users

- **Twitter** uses Mesos on > 100 nodes in production to run ~12 production services
- **Berkeley** machine learning researchers are running various algorithms at scale on Spark
- **Conviva** is using Spark for data analytics
- **UCSF** medical researchers are using Mesos to run Hadoop for bioinformatics apps

Dynamic Resource Sharing

- 100 node cluster



Conclusion

- Mesos shares clusters efficiently and dynamically among diverse frameworks
- Enable co-existence of current frameworks and development of new specialized ones
- In use at Twitter, UC Berkeley, Conviva and UCSF

www.mesosproject.org