Mesos and YARN

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Motivation

- Rapid innovation in cloud computing.
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- No single framework optimal for all applications.
- Running each framework on its dedicated cluster:
  - Expensive
  - Hard to share data

Proposed Solution

Running multiple frameworks on a single cluster

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Running multiple frameworks on a single cluster

Maximize utilization
Share data between frameworks

Two Resource Management Systems ...

- Mesos

- YARN

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Mesos

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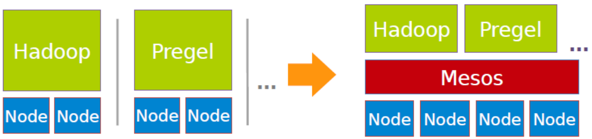

Mesos Goals

- High utilization of resources
- Support diverse frameworks (current and future)
- Scalability to 10,000's of nodes
- Reliability in face of failures

Computation Model

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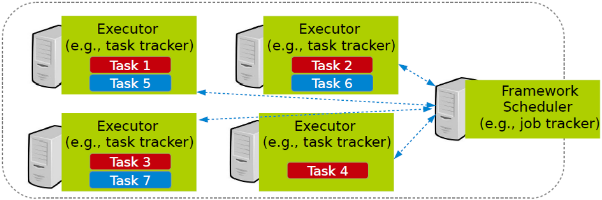


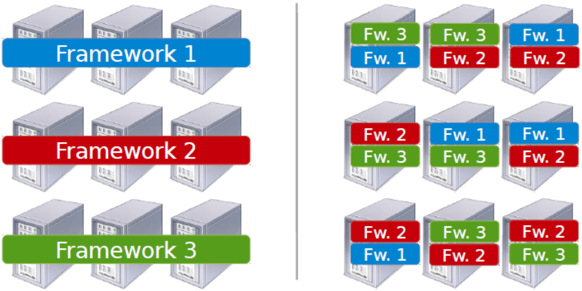
Mesos Design Elements

- Fine-grained sharing

- Resource offers

Fine-Grained Sharing

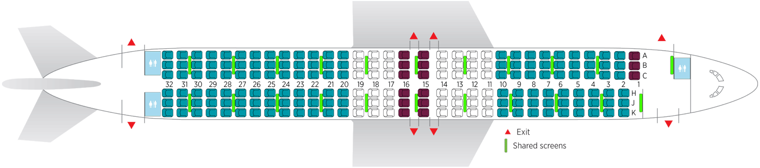
- Allocation at the level of tasks within a job.
- Improves utilization, latency, and data locality.



Coarse-grained sharing   Fine-grained sharing

Resource Offer

- 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.



Question?

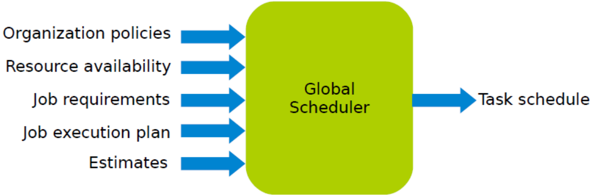
How to schedule resource offering among frameworks?

Schedule Frameworks

- Global scheduler
- Distributed scheduler

Global Scheduler (1/2)

- Job requirements
  - Response time
  - Throughput
  - Availability
- Job execution plan
  - Task DAG
  - Inputs/outputs
- Estimates
  - Task duration
  - Input sizes
  - Transfer sizes

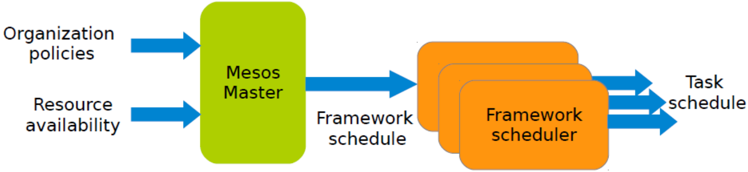


Global Scheduler (2/2)

- Advantages
  - Can achieve optimal schedule.

- Disadvantages
  - Complexity: hard to scale and ensure resilience.
  - Hard to anticipate future frameworks requirements.
  - Need to refactor existing frameworks.

Distributed Scheduler (1/3)



Distributed Scheduler (2/3)

- Unit of allocation: resource offer
  - Vector of available resources on a node
  - For example, node1: $\langle 1CPU, 1GB \rangle$, node2: $\langle 4CPU, 16GB \rangle$

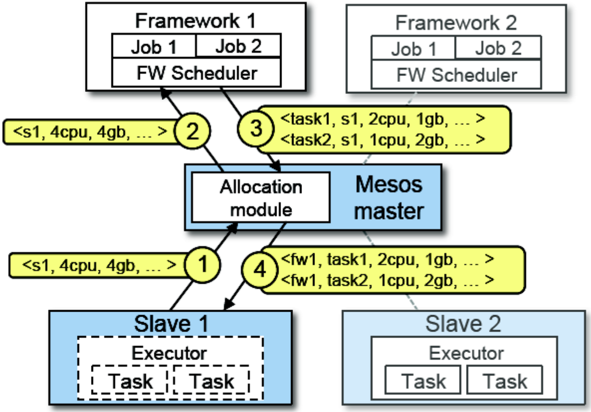
- Master sends resource offers to frameworks.

- Frameworks select which offers to accept and which tasks to run.

Distributed Scheduler (3/3)

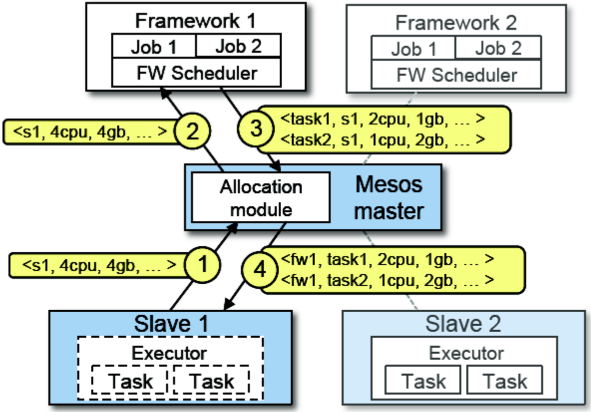
- Advantages
  - Simple: easier to scale and make resilient.
  - Easy to port existing frameworks, support new ones.
- Disadvantages
  - Distributed scheduling decision: not optimal.

Mesos Architecture (1/4)



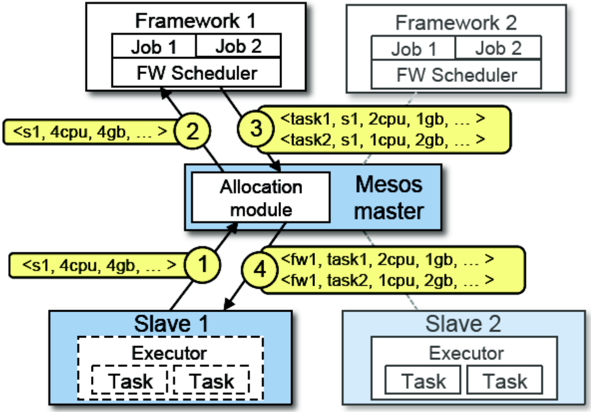
- Slaves continuously send status updates about resources to the Master.

Mesos Architecture (2/4)



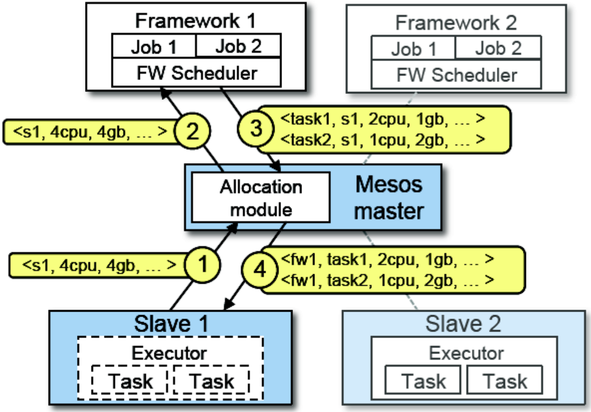
- Pluggable scheduler picks framework to send an offer to.

Mesos Architecture (3/4)



- Framework scheduler selects resources and provides tasks.

Mesos Architecture (4/4)



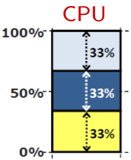
- Framework executors launch tasks.

Question?

How to allocate resources of different types?

Single Resource: Fair Sharing

- n users want to share a resource, e.g., CPU.
  - Solution: allocate each $\frac{1}{n}$ of the shared resource.



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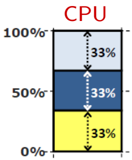
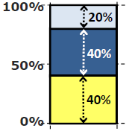


- Generalized by max-min fairness.
  - Handles if a user wants less than its fair share.
  - E.g., user 1 wants no more than 20%.



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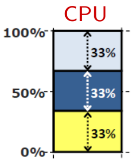

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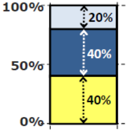
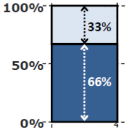


- Generalized by weighted max-min fairness.
  - Give weights to users according to importance.
  - E.g., user 1 gets weight 1, user 2 weight 2.



Max-Min Fairness

- 1 resource: CPU
- Total resources: 20 CPU
- User 1 has x tasks and wants $\langle 1CPU \rangle$ per task
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  subject to
  $x + 2y \leq 20$ (CPU constraint)
  $x = 2y$
  so
  $x = 10$
  $y = 5$

Why is Fair Sharing Useful?

- Proportional allocation: user 1 gets weight 2, user 2 weight 1.
- Priorities: give user 1 weight 1000, user 2 weight 1.
- Reservations: ensure user 1 gets 10% of a resource, so give user 1 weight 10, sum weights ≤ 100.
- Isolation policy: users cannot affect others beyond their fair share.

Properties of Max-Min Fairness

- Share guarantee
  - Each user can get at least $\frac{1}{n}$ of the resource.
  - But will get less if her demand is less.
- Strategy proof
  - Users are not better off by asking for more than they need.
  - Users have no reason to lie.

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- Max-Min fairness is the only reasonable mechanism with these two properties.
- Widely used: OS, networking, datacenters, ...

Question?

When is Max-Min Fairness NOT Enough?

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When is Max-Min Fairness NOT Enough?

Need to schedule multiple, heterogeneous resources, e.g., CPU, memory, etc.

Problem

- Single resource example
  - 1 resource: CPU
  - User 1 wants $\langle 1CPU \rangle$ per task
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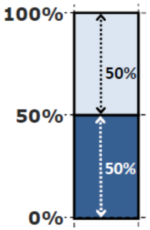

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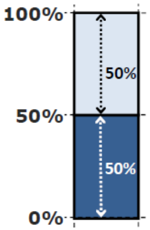

- Multi-resource example
  - 2 resources: CPUs and mem
  - User 1 wants $\langle 1CPU, 4GB \rangle$ per task
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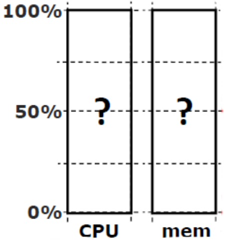

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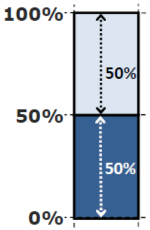

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  - 2 resources: CPUs and mem
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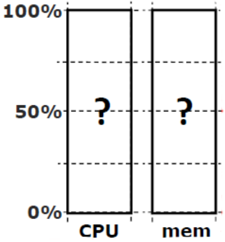
  - What is a fair allocation?



A Natural Policy (1/2)

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- Total resources: 28 CPU and 56GB RAM (e.g., 1 CPU = 2 GB)
  - User 1 has x tasks and wants $\langle 1CPU, 2GB \rangle$ per task
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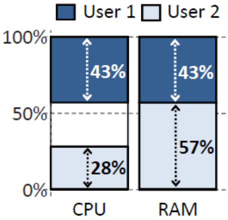
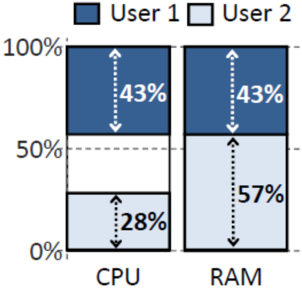
- Asset fairness yields:



$\max(x, y)$
$x + y \leq 28$
$2x + 4y \leq 56$
$4x = 6y$
User 1: $x = 12$: $\langle 43\%CPU, 43\%GB \rangle$ $(\sum = 86\%)$
User 2: $y = 8$: $\langle 28\%CPU, 57\%GB \rangle$ $(\sum = 86\%)$

A Natural Policy (2/2)



- Problem: violates share grantee.
- User 1 gets less than 50% of both CPU and RAM.
- Better off in a separate cluster with half the resources.

Challenge

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

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

Proposed Solution

Dominant Resource Fairness (DRF)

Dominant Resource Fairness (DRF) (1/2)

- Dominant resource of a user: the resource that user has the biggest share of.
    - Total resources: $\langle 8CPU, 5GB \rangle$
    - User 1 allocation: $\langle 2CPU, 1GB \rangle$
      $\frac{2}{8} = 25\%\texttt{CPU}$ and $\frac{1}{5} = 20\%\texttt{RAM}$
    - Dominant resource of User 1 is CPU $(25\% > 20\%)$

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- Dominant share of a user: the fraction of the dominant resource she is allocated.
  - User 1 dominant share is 25%.

Dominant Resource Fairness (DRF) (2/2)

- Apply max-min fairness to dominant shares: give every user an equal share of her dominant resource.

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- Equalize the dominant share of the users.
  - Total resources: $\langle 9CPU, 18GB \rangle$
  - User 1 wants $\langle 1CPU, 4GB \rangle$; Dominant resource: RAM $\frac{1}{9} < \frac{4}{18}$
  - User 2 wants $\langle 3CPU, 1GB \rangle$; Dominant resource: CPU $\frac{3}{9} > \frac{1}{18}$

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- $\mathtt{max}(x, y)$

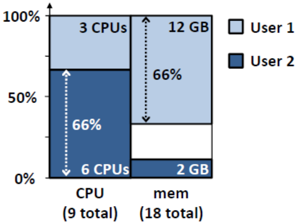
  $x + 3y \leq 9$

  $4x + y \leq 18$

  $\frac{4x}{18} = \frac{3y}{9}$

  User 1: $x = 3$: $\langle 33\% CPU, 66\% GB \rangle$

  User 2: $y = 2$: $\langle 66\% CPU, 16\% GB \rangle$



Online DRF Scheduler

- Whenever there are available resources and tasks to run:
  Schedule a task to the user with the smallest dominant share.

Two Resource Management Systems ...

- Mesos
- YARN

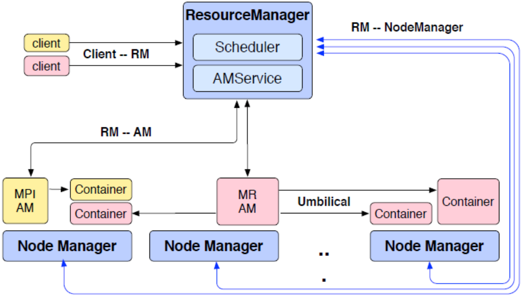
YARN

YARN

Yet Another Resource Negotiator

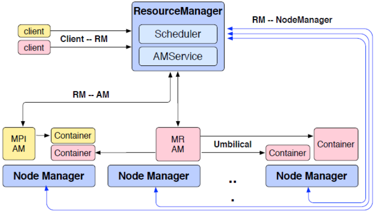
YARN Architecture

- Resource Manager (RM)
- Application Master (AM)
- Node Manager (NM)



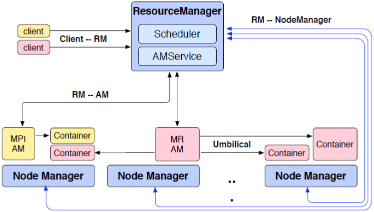
YARN Architecture - Resource Manager (1/2)

- One per cluster
  - Central: global view
  - Enable global properties
  - Fairness, capacity, locality
- Job requests are submitted to RM.
  - To start a job (application), RM finds a container to spawn AM.
- Container
  - Logical bundle of resources (CPU/memory).
- No static resource partitioning.



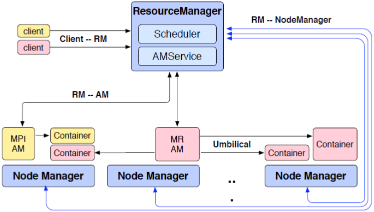
YARN Architecture - Resource Manager (2/2)

- Only handles an overall resource profile for each application.
  - Local optimization is up to the application.
- Preemption
  - Request resources back from an application.
  - Checkpoint snapshot instead of explicitly killing jobs / migrate computation to other containers.



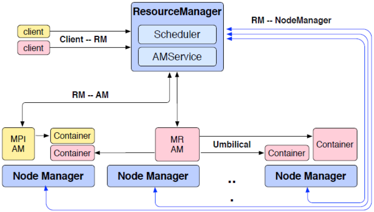
YARN Architecture - Application Manager (1/2)

- The head of a job.
- Runs as a container.
- Request resources from RM.
  - # of containers/resource per container/locality ...
- Dynamically changing resource consumption, based on the containers it receives from the RM.



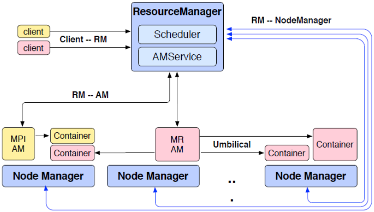
YARN Architecture - Application Manager (2/2)

- Requests are late-binding.
  - The process spawned is not bound to the request, but to the lease.
  - The conditions that caused the AM to issue the request may not remain true when it receives its resources.
- Can run any user code, e.g., MapReduce, Spark, etc.
- AM determines the semantics of the success or failure of the container.



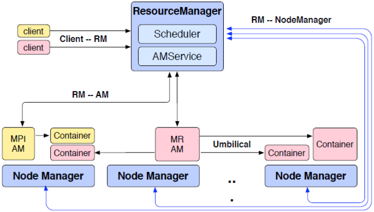
YARN Architecture - Node Manager (1/2)

- The worker daemon.
- Registers with RM.
- One per node.
- Report resources to RM: memory, CPU, ...
- Containers are described by a Container Launch Context (CLC).
  - The command necessary to create the process
  - Environment variables
  - Security tokens
  - ...



YARN Architecture - Node Manager (2/2)

- Configure the environment for task execution.
- Garbage collection.
- Auxiliary services.
  - A process may produce data that persist beyond the life of the container.
  - Output intermediate data between map and reduce tasks.



YARN Framework (1/2)

- Submitting the application: passing a CLC for the AM to the RM.
- When RM starts the AM, it should register with the RM.
  - Periodically advertise its liveness and requirements over the heartbeat protocol.

YARN Framework (2/2)

- Once the RM allocates a container, AM can construct a CLC to launch the container on the corresponding NM.
  - It monitors the status of the running container and stop it when the resource should be reclaimed.

- Once the AM is done with its work, it should unregister from the RM and exit cleanly.

Mesos vs. YARN

- Similarities:
  - Both have schedulers at two levels.
- Differences:
  - Mesos is an offer-based resource manager, whereas YARN has a request-based approach.
  - Mesos uses framework schedulers for inter-job scheduling, whereas YARN uses per-job optimization through AM (however, per-job AM has higher overhead compare to Mesos).

Summary

- Resource management: Mesos and YARN

- Mesos
  - Offered-based
  - Max-Min fairness: DRF

- YARN
  - Request-based
  - RM, AM, NM

Questions?

Acknowledgements

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