Cluster Scheduling

COS 518: *Advanced Computer Systems*
Lecture 13

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[Heavily based on content from Ion Stoica]

Key aspects of cloud computing

1. Illusion of infinite computing resources available on demand, eliminating need for up-front provisioning

2. The elimination of an up-front commitment

3. The ability to pay for use of computing resources on a short-term basis

From "Above the Clouds: A Berkeley View of Cloud Computing"

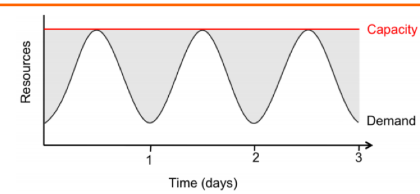
Two main sources of resource demand

- "Services"
  - External demand, scale supply to match demand

- "Data analysis"
  - Tradeoff scale & completion time
    - E.g., use 1 server for 10 hours vs. 10 servers for 1 hour
  - Source of demand elasticity!

Type of contract	Price (m4.xlarge)
Spot - 1 hr duration	$0.139 / hour
Spot– 6 hr duration	$0.176 / hour
On-demand	$0.215 / hour

Towards fuller utilization



- Source of variable demand?
  - Search, social networks, e-commerce, usage have diurnal patterns
  - Apocryphal story: AWS exists because Amazon needed to provision for holiday shopping season, wanted to monetize spare capacity

- But…if provision for peak, what around remaining time?
  - Fill-in with non-time-sensitive usage, e.g., various data crunching
  - E.g., Netflix using AWS at night for video transcoding

Today's lecture

- Metrics / goals for scheduling resources
- System architecture for big-data scheduling

Scheduling: An old problem

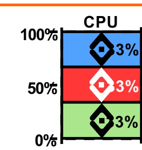
- **CPU allocation**
  - Multiple processors want to execute, OS selects one to run for some amount of time
- **Bandwidth allocation**
  - Packets from multiple incoming queue want to be transmitted out some link, switch chooses one

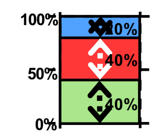
What do we want from a scheduler?

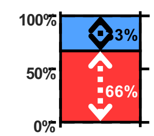
- **Isolation**
  - Have some sort of guarantee that misbehaved processes cannot affect me "too much"
- **Efficient resource usage**
  - Resource is not idle while there is process whose demand is not fully satisfied
  - "*Work conservation*" – not achieved by hard allocations
- **Flexibility**
  - Can express some sort of priorities, e.g., strict or time based

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%
  - *Work conserving* or *work preserving*
    - No unused capacity if there's demand.
- Generalized by ***weighted max-min fairness***
  - Give weights to users according to importance
  - User 1 gets weight 1, user 2 weight 2







Max-Min Fairness is Powerful

- **Weighted Fair Sharing / Proportional Shares**
  - User u1 gets weight 2, u2 weight 1
- **Priorities:** Give u1 weight 1000, u2 weight 1
- **Reservations**
  - Ensure u1 gets 10%: Give u1 weight 10, sum weights ≤ 100
- **Deadline-based scheduling**
  - Given a job's demand and deadline, compute user's reservation / weight
- **Isolation:** Users cannot affect others beyond their share

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Max-min Fairness via Fair Queuing

- Fair queuing explained in a fluid flow system: reduces to bit-by-bit round robin among flows
  - Each flow receives $min(r_i, f)$, where
    - r_i – flow arrival rate
    - f – link fair rate (see next slide)
- Weighted Fair Queuing (WFQ)
  - Associate a weight with each flow

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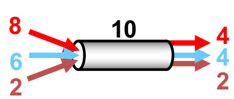
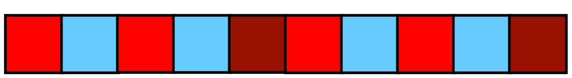
Fair Rate Computation

- If link congested, compute f such that

$$\sum_i \min(r_i, f) = C$$



***f* = 4:**
min(8, 4) = 4
min(6, 4) = 4
min(2, 4) = 2



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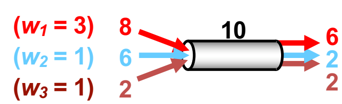
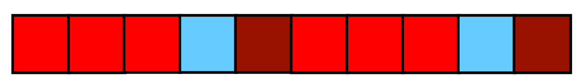
Fair Rate Computation

- Associate a weight w_i with each flow i
- If link congested, compute f such that

$$\sum_i \min(r_i, f \times w_i) = C$$



***f* = 2:**
min(8, 2*3) = 6
min(6, 2*1) = 2
min(2, 2*1) = 2



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Theoretical Properties of Max-Min Fairness

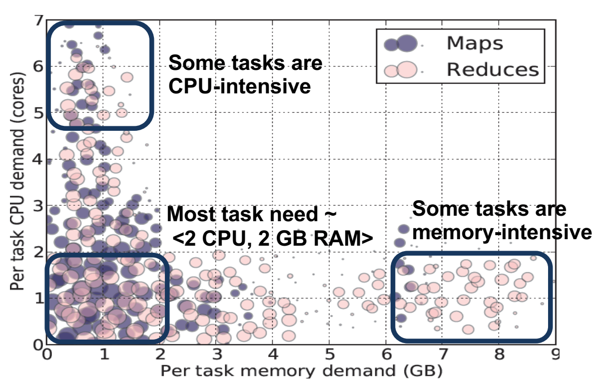
- **Share guarantee**
  - Each user gets at least 1/n of the resource
  - But will get less if her demand is less
- **Strategy-proof**
  - Users are not better off by asking for more than they need
  - Users have no reason to lie

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


- What are task demands today?

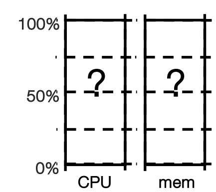
Heterogeneous Resource Demands



2000-node Hadoop Cluster at Facebook (Oct 2010)

How to allocate?

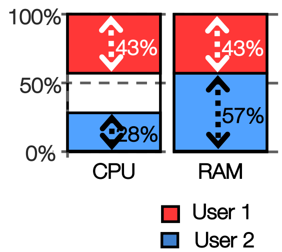
- 2 resources: CPUs & memory
- User 1 wants **<1 CPU, 4 GB>** per task
- User 2 wants **<3 CPU, 1 GB>** per task



- ***What's a fair allocation?***

A Natural Policy

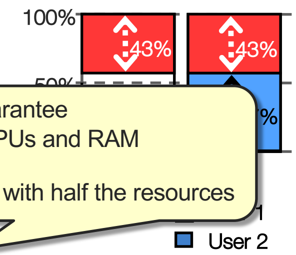
- ***Asset Fairness:*** Equalize each user's ***sum of resource shares***
- Cluster with 28 CPUs, 56 GB RAM
  - U_1 needs <1 CPU, 2 GB RAM> per task, or <3.6% CPUs, 3.6% RAM> per task
  - U_2 needs <1 CPU, 4 GB RAM> per task, or <3.6% CPUs, 7.2% RAM> per task



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

Strawman for asset fairness

- Approach: 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 <…
  - U_2 …
    or <…



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

Better off in 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.
- How achieve **share guarantee** + **strategy proofness** for sharing?
  - Generalize max-min fairness to multiple resources/

Dominant Resource Fairness (DRF)

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

Total resources:	8 CPU	5 GB
User 1's allocation:	2 CPU	1 GB
	25% CPUs	**20% RAM**

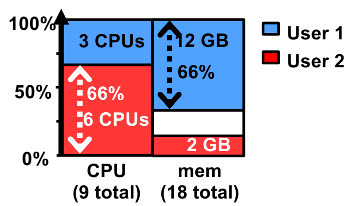
Dominant resource of User 1 is CPU (as 25% > 20%)

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

Dominant Resource Fairness: Fair Allocation of Multiple Resource Types
Ali Ghodsi, Matei Zaharia, Benjamin Hindman, Andy Konwinski, Scott Shenker, Ion Stoica, NSDI'11

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 available resources and tasks to run:

Schedule task to user with smallest dominant share

Today's lecture

1. Metrics / goals for scheduling resources
2. System architecture for big-data scheduling

Many Competing Frameworks

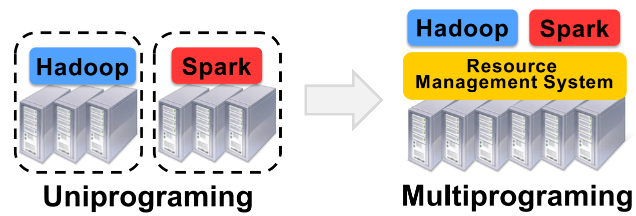
- Many different "Big Data" frameworks
  - Hadoop | Spark
  - Storm | Spark Streaming | Flink
  - GraphLab
  - MPI
- Heterogeneity will rule
  - No single framework optimal for all applications
  - So…each framework runs on dedicated cluster?

One Framework Per Cluster Challenges

- Inefficient resource usage
  - E.g., Hadoop cannot use underutilized resources from Spark
  - Not work conserving
- Hard to share data
  - Copy or access remotely, expensive
- Hard to cooperate
  - E.g., Not easy for Spark to use graphs generated by Hadoop

Common resource sharing layer ?

- Abstracts ("virtualizes") resources to frameworks
- Enable diverse frameworks to share cluster
- Make it easier to develop and deploy new frameworks



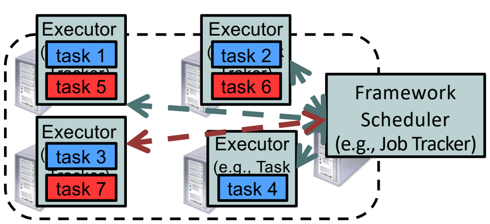
Abstraction hierarchy 101

In a cluster:

… a ***framework*** (e.g., Hadoop, Spark) manages 1+ ***jobs***

  … *a* ***job*** consists of 1+ ***tasks***

    … a ***task*** (e.g., map, reduce) involves 1+ processes executing on single machine



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

Abstraction hierarchy 101

In a cluster:

… a ***framework*** (e.g., Hadoop, Spark) manages 1+ ***jobs***

  … *a* ***job*** consists of 1+ ***tasks***

    … a ***task*** (e.g., map, reduce) involves 1+ processes executing on single machine

- Seek fine-grained resource sharing
  - Tasks typically short: median ~= 10 sec – minutes
  - Better data locality / failure-recovery if tasks fine-grained

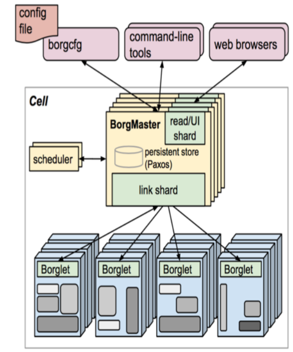
Approach #1: Global scheduler

- Global scheduler takes input, outputs task schedule
  - **Organization policies**
  - **Resource Availability**
  - **Estimates:** Task durations, input sizes, xfer sizes, …
  - **Job requirements:** Latency, throughput, availability…
  - **Job execution plan:** Task DAG, inputs/outups
- Advantages: "Optimal"
- Disadvantages
  - More complex, harder to scale (yet Google: 10,000s servers/scheduler)
  - Anticipate future requirements, refactor existing

Google's Borg

- Centralized Borgmaster + Localized Borglet (manage/monitor tasks)
- Goal: Find machines for a given job

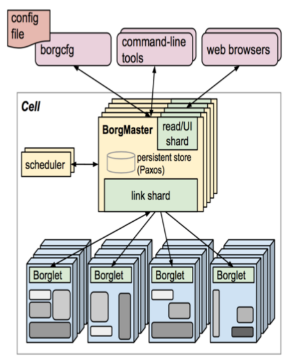
```
job hello = {
  runtime = { cell = "ic" }
  binary = '../hello_webserver'
  args = { port = '%port%' }
  requirements = {
    RAM = 100M
    disk = 100M
    CPU = 0.1
  }
  replicas = 10000
}
```



Large-scale cluster management at Google with Borg
A. Verma, L. Pedrosa, M. Korupolu, D. Oppenheimer, E. Tune, J. Wilkes, EuroSys 15

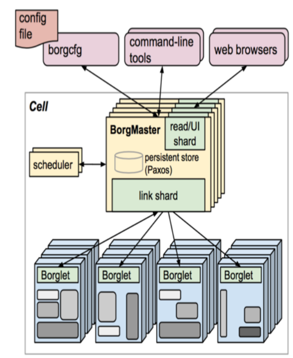
Google's Borg

- Centralized Borgmaster + Localized Borglet (manage/monitor tasks)
- Goal: Find machines for a given job
- Used across all Google services
  - Services: Gmail, web search, GFS
  - Analytics: MapReduce, streaming
    - Framework controller sends master allocation request to Borg for full job



Google's Borg

- Centralized Borgmaster + Localized Borglet (manage/monitor tasks)
- Goal: Find machines for a given job
- Allocation
  - Minimize # / priority preempted tasks
  - Pick machines already having copy of the task's packages
  - Spread over power/failure domains
  - Mix high/low priority tasks



Approach #2: Offers, not schedule

- Unit of allocation: ***resource offer***
  - Vector of available resources on a node
  - E.g., node1: <1CPU, 1GB>, node2: <4CPU, 16GB>

1. Master sends resource offers to frameworks
2. Frameworks:
   - Select which offers to accept
   - Perform task scheduling
   - Unlike global scheduler, requires another level of support

Mesos: A Platform for Fine-Grained Resource Sharing in the Data Center
Benjamin Hindman, Andy Konwinski, Matei Zaharia, Ali Ghodsi, Anthony D. Joseph, Randy Katz, Scott Shenker, Ion Stoica, NSDI'11

How to allocate resources? DRF!

	CPU	Memory
Cluster Supply	10	20
A's Demand	4 (**40%**)	2 (10%)
B's Demand	1 (10%)	5 (**25%**)

Cluster: Remaining	Cluster: Offer	A's Allocation	B's Allocation
(10cpu, 20gb)	(2cpu, 2gb) to A	(0cpu, 0gb, 0%)	(0cpu, 0gb, 0%)
(10cpu, 20gb)	(4cpu, 3gb) to A	**(4cpu, 3gb, 40%)**	(0cpu, 0gb, 0%)
(6cpu, 17gb)	(1cpu, 3gb) to B	(4cpu, 3gb, 40%)	(0cpu, 0gb, 0%)
(5cpu, 12gb)	(1cpu, 5gb) to B	(4cpu, 3gb, 40%)	**(1cpu, 5gb, 25%)**
(1cpu, 10gb)	(4cpu, 2gb) to A	**(8cpu, 5gb, 80%)**	(1cpu, 5gb, 25%)
(0cpu, 4gb)	(1cpu, 6gb) to B	(8cpu, 5gb, 80%)	**(2cpu, 11gb, 55%)**

Today's lecture

- Metrics / goals for scheduling resources
  - Max-min fairness, weighted-fair queuing, DRF
- System architecture for big-data scheduling
  - Central allocator (Borg), two-level resource offers (Mesos)