Distributed Systems

CS425/ECE428

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Acknowledgements for the materials: Indy Gupta

Logistics

- HW5 and MP3 due next Friday.
- Final exam: May 7-14
  - Please reserve a slot if you haven't yet.
  - Syllabus includes:
    - Midterm 1 syllabus
      - system model, failure detection, clocks and time synchronization, logical clocks and timestamps, global state
    - Midterm 2 syllabus
      - multicast, mutual exclusion, leader election, synchronous consensus, Paxos, Raft
    - Materials covered in class post-midterm 2 syllabus
      - blockchains, transaction processing and concurrency control, distributed transactions, Chord, MapReduce, job scheduling, distributed datastores.

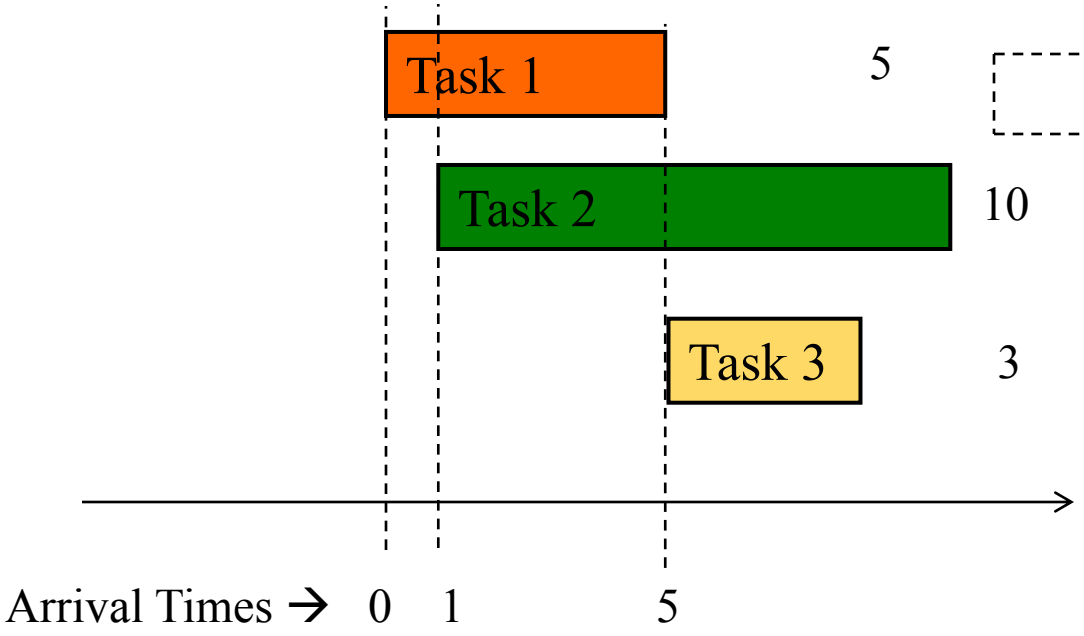
Our agenda for the next 2-3 classes

- Brief overview of key-value stores
- Distributed Hash Tables
  - Peer-to-peer protocol for efficient insertion and retrieval of key-value pairs.
- Key-value stores in the cloud
  - How to run large-scale distributed computations over key-value stores?
    - Map-Reduce Programming Abstraction
    - Job scheduling
  - How to design a large-scale distributed key-value store?
    - Case-study: Facebook's Cassandra

Why Scheduling?

- Multiple "tasks" to schedule
  - The processes on a single-core OS
  - The tasks of a Hadoop job
  - The tasks of multiple Hadoop jobs
  - Replicas of a each service in a microservice application
- Limited resources that these tasks require
  - Processor(s)
  - Memory
  - (Less contentious) disk, network
- Scheduling goals
  1. Good throughput or response time for tasks (or jobs)
  2. High utilization of resources
  3. Fairness (across jobs from multiple users / tenants)

Single Processor Scheduling



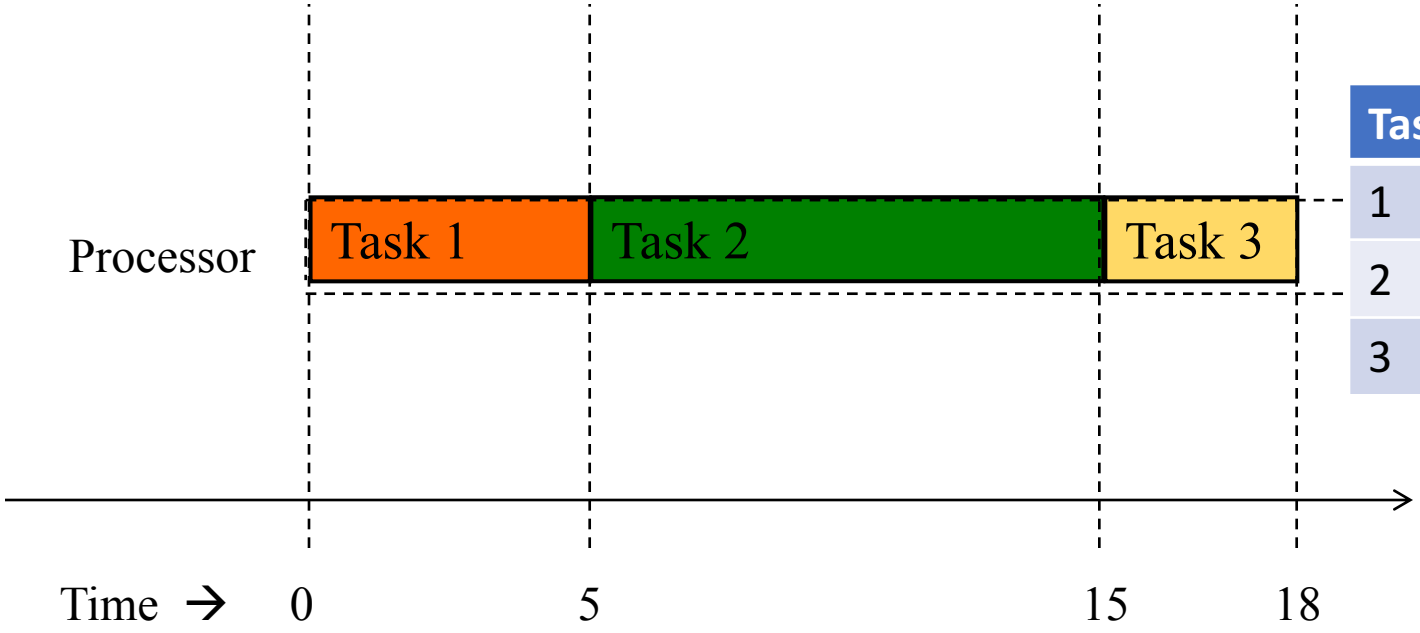
Which tasks run when?

Processor

Task	Length	Arrival
1	5	0
2	10	1
3	3	5

FIFO Scheduling (First-In First-Out)/FCFS

- Maintain tasks in a queue in order of arrival
- When processor free, dequeue head and schedule it



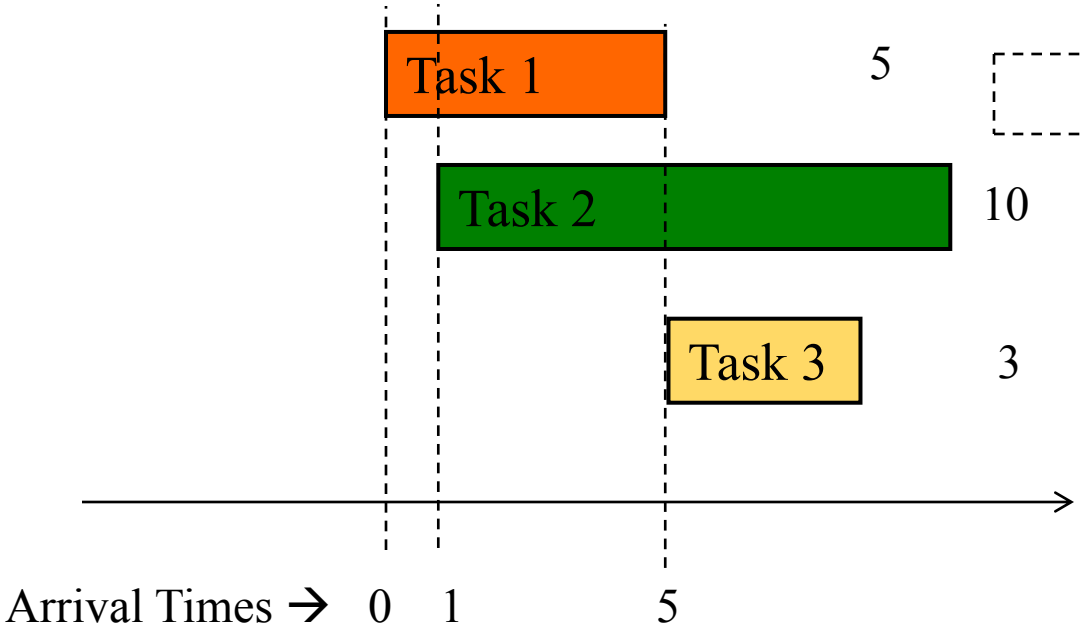
Task	Length	Arrival
1	5	0
2	10	1
3	3	5

FIFO/FCFS Performance

- Average completion time may be high

- For our example on previous slides,
  - Average completion time of FIFO/FCFS =
    (Task 1 + Task 2 + Task 3)/3
  = (5+14+13)/3
  = 10.667

What schedule will minimize avg completion time?



Which tasks run when?

Processor

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2	10	1
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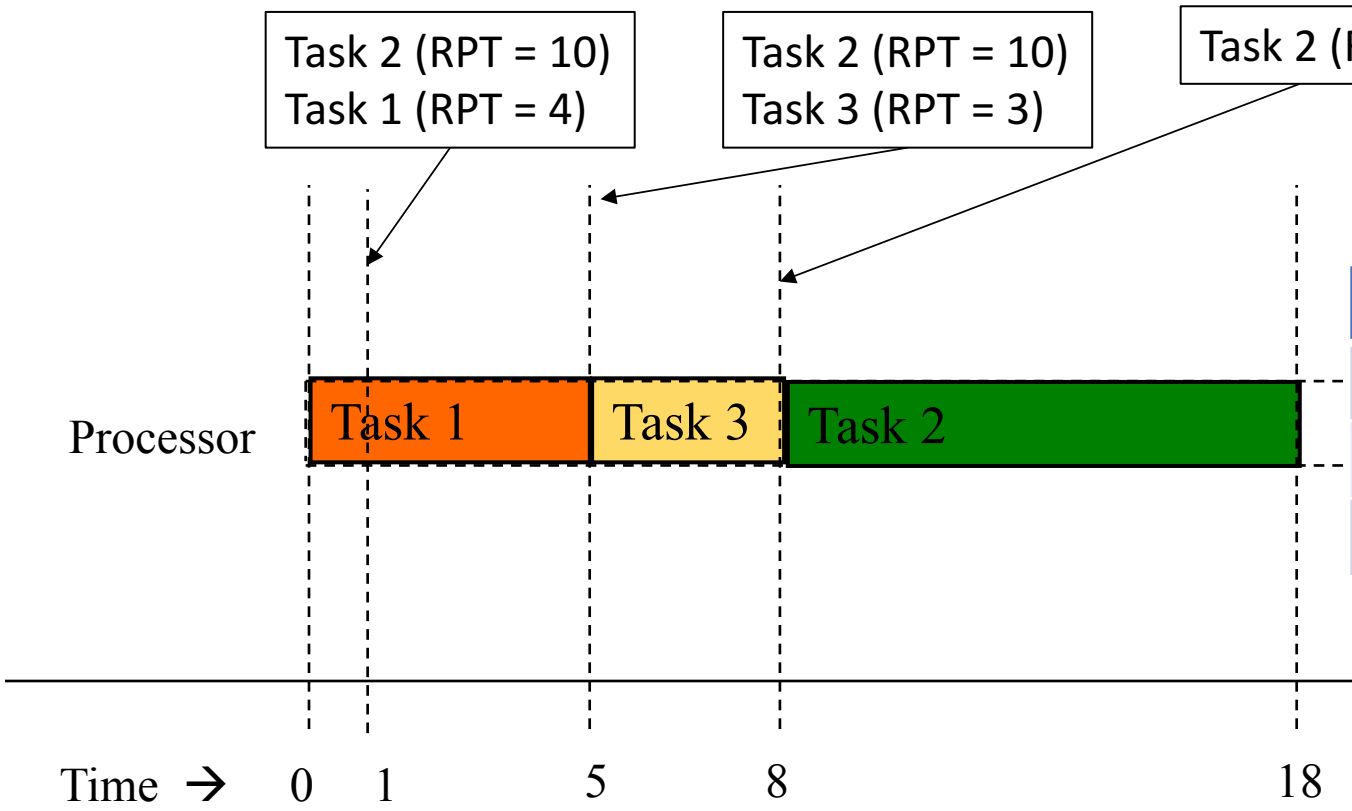
SRPT Scheduling (Shortest Remaining Processing Time)



Task	Length	Arrival
1	5	0
2	10	1
3	3	5

- *Schedule tasks in the order of "remaining processing time" (RPT).*
- *RPT= total processing time required – processing time given so far*

SRPT Is Optimal!

- Average completion of SRPT is the shortest among *all* scheduling approaches!
- For our example on previous slides,
  - Average completion time of SRPT =

    (Task 1 + Task 2 + Task 3)/3

    = (5+17+3)/3

    = 25/3

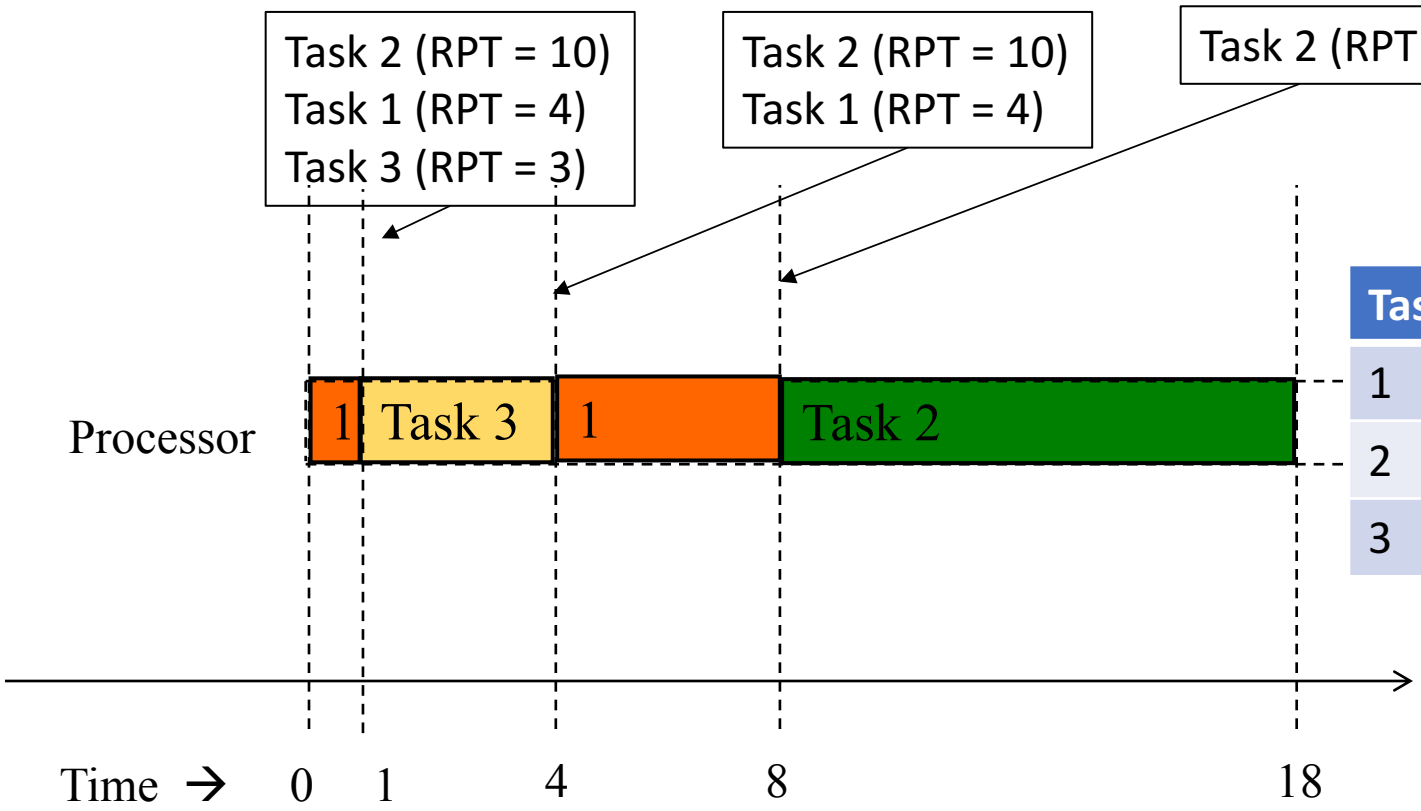
    = 8.333

    (versus 10.667 for FIFO/FCFS)

Priority Scheduling

- In general, SRPT is a special case of *priority scheduling*
  - Schedule tasks in priority order.
    - Maintain a priority queue, and insert tasks into the queue based on their priority value.
  - FIFO/FCFS: use arrival time as priority.
  - SRPT: use remaining processing time as priority
  - STF (shortest task first): use total processing duration as priority
  - Can also use any other user-provided priority.

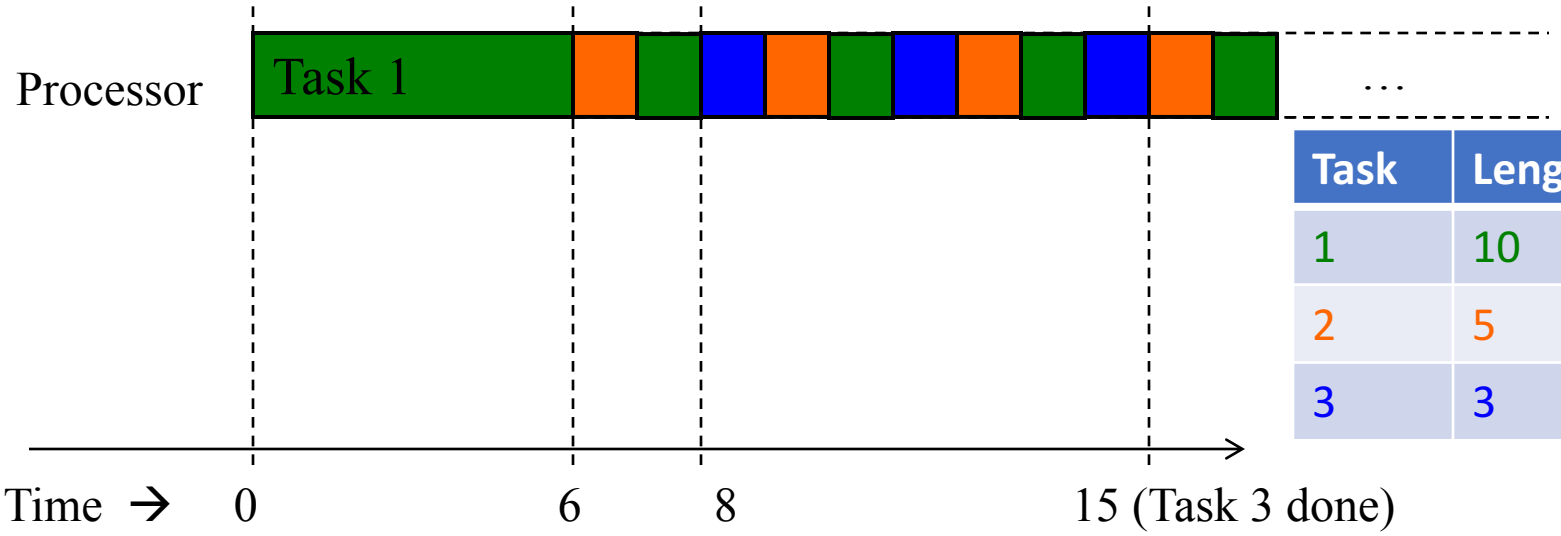
Preemption



Task	Length	Arrival
1	5	0
2	10	1
3	3	1

- SRPT / Priority Scheduling can also cause pre-emption
- (Task 1 pre-empted when higher priority Task 2 arrives at time 1)
- Some systems may choose to implement a non-preemptive priority scheduler for simplicity (wait until currently scheduled task is complete).

Round-Robin Scheduling



Task	Length	Arrival
1	10	0
2	5	6
3	3	8

- *Use a quantum (say 1 time unit) to run portion of task at queue head*
- *Pre-empts processes by saving their state, and resuming later*
- *After pre-empting, add to end of queue*

FIFO vs SRPT vs Round-Robin

- FIFO: lower tail completion time.
- SRPT: lower average completion time.
- Round-robin: Fairness across tasks (from different users).
  - Small task from one user will not be blocked behind large task from another user (as with FIFO)
  - Large task from one user will not starve due to many small tasks from another user (as with SRPT)

Summary

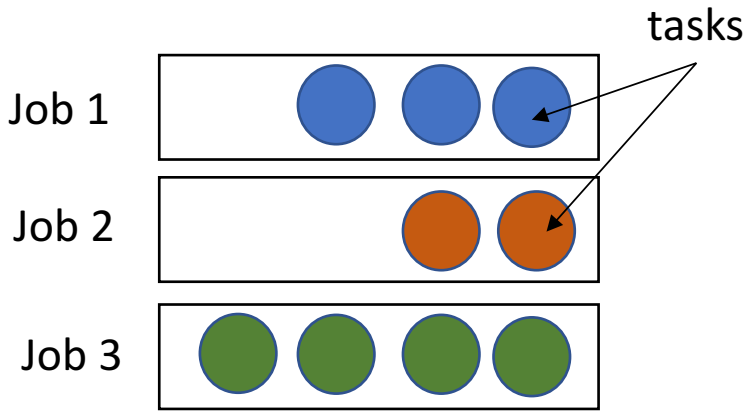
- Single processor scheduling algorithms
  - FIFO/FCFS
  - Shorted remaining processing time first (optimal!)
  - Shortest task first
  - Priority
  - Round-robin
  - (preemption vs non-preemption)
  - Many other scheduling algorithms out there!
- What about cloud scheduling?
  - Next!

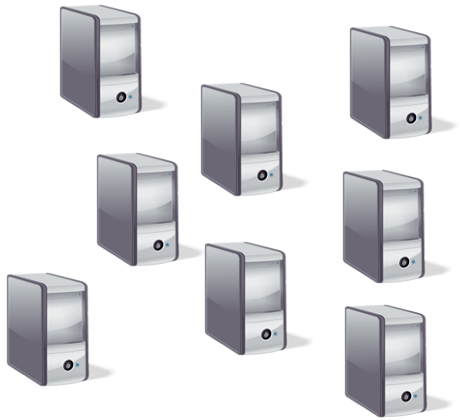
Cloud Scheduling

Single processor scheduling: when should a task start? (order of task)

Cloud/cluster scheduling: additional dimensions

- how many tasks of each job can we run together across the cluster?
  - minimize average job completion time
  - high cluster resource utilization
  - ensure fairness (e.g. across jobs from different users or tenants)
- on which node should we place a given task?
  - data locality, tasks dependencies, minimize inter-task communication latency, etc.





Case-study 1: Hadoop Scheduling

- A Hadoop job consists of Map tasks and Reduce tasks
- Only one job in entire cluster => it occupies cluster
- Multiple customers with multiple jobs
  - Users/jobs = "tenants"
  - Multi-tenant system
- => Need a way to schedule all these jobs (and their constituent tasks)
- => Need to be *fair* across the different tenants
- Hadoop YARN has two popular schedulers
  - *Hadoop Capacity Scheduler*
  - *Hadoop Fair Scheduler*

Hadoop Capacity Scheduler

- Contains multiple queues
- Each queue contains multiple jobs
- Each queue guaranteed some portion of the cluster capacity

  E.g.,
  - Queue 1 is given 80% of cluster resources
  - Queue 2 is given 20% of cluster resources
  - (can specify different percentages for different resource types: memory, compute, etc)
  - Percentages based on business agreements with tenants.
- For jobs within same queue, FIFO typically used

Source: http://hadoop.apache.org/docs/r2.3.0/hadoop-yarn/hadoop-yarn-site/CapacityScheduler.html

Elasticity in HCS

- Administrators can configure each queue with limits
  - Soft limit: how much % of cluster is the queue guaranteed to occupy
  - (Optional) Hard limit: max % of cluster given to the queue
- Elasticity
  - A queue allowed to occupy more of cluster if resources free
  - But if other queues below their capacity limit, now get full, need to give these other queues resources
- Can be configured such that pre-emption not allowed!
  - Cannot stop a task part-way through
  - When reducing % cluster to a queue, wait until some tasks of that queue have finished

Other HCS Features

- Queues can be hierarchical
  - May contain child sub-queues, which may contain child sub-queues, and so on
  - Child sub-queues can share resources equally

Hadoop Fair Scheduler

- Goal: all jobs get equal share of resources
- When only one job present, occupies entire cluster
- As other jobs arrive, each job given equal % of cluster
  - E.g., Each job might be given equal number of cluster-wide YARN containers
  - Each container == 1 task of job

Source: http://hadoop.apache.org/docs/r1.2.1/fair_scheduler.html

Hadoop Fair Scheduler (2)

- Divides cluster into pools
  - Typically one pool per user
- Resources divided equally among pools
  - Gives each user fair share of cluster
- Within each pool, can use either
  - Fair share scheduling, or
  - FIFO/FCFS
  - (Configurable)

Pre-emption in HFS

- Some (higher priority / production) pools may have *minimum shares*
  - Minimum % of cluster that pool is guaranteed
- When minimum share not met in a pool, for a while
  - Take resources away from other pools
  - By pre-empting jobs in those other pools
  - By *killing* the currently-running tasks of those jobs
    - Tasks can be re-started later
    - Ok since tasks are idempotent!
  - To kill, scheduler picks most-recently-started tasks
    - Minimizes wasted work

Other HFS Features

- Can also set limits on
  - Number of concurrent jobs per user
  - Number of concurrent jobs per pool
  - Number of concurrent tasks per pool
- Prevents other cluster resources (disk / external services) from being hogged by one user/job

Estimating Task Lengths

- HCS/HFS use FIFO
  - May not be optimal (as we know!)
  - Why not use SRPT or shortest-task-first instead? It's optimal (as we know!)
- Challenge: Hard to know expected running time of task (before it's completed)
- Solution: Estimate length of task
- Some approaches
  - Within a job: Calculate running time of task as proportional to size of its input
  - Across tasks: Calculate running time of task in a given job as average of other tasks in that given job (weighted by input size)
- Lots of recent research results in this area!

Summary

- Hadoop Scheduling in YARN
  - Hadoop Capacity Scheduler
  - Hadoop Fair Scheduler

- So far we've talked of only one kind of resource
  - How about multi-resource requirements?
  - Next!

Dominant-Resource Fair Scheduling

Challenge

- Jobs may have multi-resource requirements
  - Job 1's tasks: 2 CPUs, 8 GB
  - Job 2's tasks: 6 CPUs, 2 GB
- How do you schedule these jobs in a "fair" manner?
- That is, how many tasks of each job do you allow the system to run concurrently?
- What does fairness even mean?

Dominant Resource Fairness (DRF)

- Proposed by researchers from U. California Berkeley
- Proposes notion of fairness across jobs with multi-resource requirements
- They showed that DRF is
  - Fair for multi-tenant systems
  - Strategy-proof: tenant can't benefit by lying
  - Envy-free: tenant can't envy another tenant's allocations
  - Pareto-efficient: cannot assign more tasks for one tenant, without assigning less tasks for another tenant.

Where is DRF Useful?

- DRF is
  - Usable in scheduling VMs in a cluster
  - Usable in scheduling Hadoop jobs in a cluster
- DRF used in Mesos, an OS intended for cloud environments
- DRF-like strategies also used by some cloud computing company's distributed OS's

How DRF Works

- Our example
  - Job 1's tasks: 2 CPUs, 8 GB
    => Job 1's *resource vector* = <2 CPUs, 8 GB>
  - Job 2's tasks: 6 CPUs, 2 GB
    => Job 2's *resource vector* = <6 CPUs, 2 GB>
- Consider a cloud with <18 CPUs, 36 GB RAM>

- Naïve fairness: each job gets 9CPUs and 18GB RAM.
  - How many tasks for each job?
  - Not Pareto-efficient!

How DRF Works (2)

- Our example
  - Job 1's tasks: 2 CPUs, 8 GB
    => Job 1's *resource vector* = <2 CPUs, 8 GB>
  - Job 2's tasks: 6 CPUs, 2 GB
    => Job 2's *resource vector* = <6 CPUs, 2 GB>
- Consider a cloud with <18 CPUs, 36 GB RAM>
- Each Job 1's task consumes % of total CPUs = 2/18 = **1/9**
- Each Job 1's task consumes % of total RAM = 8/36 = **2/9**
- 1/9 < 2/9
  - => *Job 1's dominant resource is RAM*, i.e., Job 1 is more memory-intensive than it is CPU-intensive

How DRF Works (3)

- Our example
  - Job 1's tasks: 2 CPUs, 8 GB
    => Job 1's *resource vector* = <2 CPUs, 8 GB>
  - Job 2's tasks: 6 CPUs, 2 GB
    => Job 2's *resource vector* = <6 CPUs, 2 GB>
- Consider a cloud with <18 CPUs, 36 GB RAM>
- Each Job 2's task consumes % of total CPUs = 6/18 = 6/18
- Each Job 2's task consumes % of total RAM = 2/36 = 1/18
- 6/18 > 1/18
  - => *Job 2's dominant resource is CPU*, i.e., Job 2 is more CPU-intensive than it is memory-intensive

DRF Fairness

- For a given job, the % of its dominant resource type that it gets cluster-wide, is the same for all jobs
  - Job 1's % of RAM = Job 2's % of CPU
- Can be written as linear equations, and solved
  - Assume J1 has x tasks and J2 has y tasks
  - 2x/9 = 6y/18 (equalize dominant resource shares)
  - 2x + 6y <= 18 (constraint on CPU capacity)
  - 8x + 2y <= 36 (constraint on memory capacity)

DRF Solution, For our Example

- DRF Ensures
  - Job 1's % of RAM = Job 2's % of CPU
- Solution for our example:
  - Job 1 gets **3 tasks** each with <2 CPUs, 8 GB>
  - Job 2 gets **2 tasks** each with <6 CPUs, 2 GB>
  - Job 1's % of RAM

= Number of tasks * RAM per task / Total cluster RAM

= 3*8/36 = 2/3

  - Job 2's % of CPU

= Number of tasks * CPU per task / Total cluster CPUs

= 2*6/18 = 2/3

Other DRF Details

- DRF generalizes to multiple jobs
- DRF also generalizes to more than 2 resource types
  - CPU, RAM, Network, Disk, etc.
- DRF ensures that each job gets a fair share of that type of resource which the job desires the most
  - Hence fairness

Other DRF Details

- DRF may not always equalize dominant resource shares.
  - e.g. when a job's demand is met and does not need more tasks.
  - or, the equations lead to non-integer number of tasks per job
    - need to round down number of tasks.
  - if more tasks of a job cannot be accommodated (insufficient resource available), other jobs using less of that resource can still be scheduled.

DRF Algorithm

Algorithm 1 DRF pseudo-code

$R = \langle r_1, \cdots, r_m \rangle$ ▷ total resource capacities
$C = \langle c_1, \cdots, c_m \rangle$ ▷ consumed resources, initially 0
$s_i \ \ (i = 1..n)$ ▷ user i's dominant shares, initially 0
$U_i = \langle u_{i,1}, \cdots, u_{i,m} \rangle \ \ (i = 1..n)$ ▷ resources given to user i, initially 0

pick user i with lowest dominant share s_i
$D_i \leftarrow$ demand of user i's next task
if $C + D_i \leq R$ **then**
    $C = C + D_i$ ▷ update consumed vector
    $U_i = U_i + D_i$ ▷ update i's allocation vector
    $s_i = \max_{j=1}^{m} \{u_{i,j}/r_j\}$
else
    return ▷ the cluster is full
end if

There is a little bug here!

DRF Algorithm

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else
    remove user i from consideration
end if

(terminates when no more users can be accommodated)

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Our example

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Job 2's tasks: 6 CPUs, 2 GB
=> Job 2's resource vector = <6 CPUs, 2 GB>

Consider a cloud with <18 CPUs, 36 GB RAM>

Summary: Scheduling

- Scheduling very important problem in cloud computing
  - Limited resources, lots of jobs requiring access to these resources
- Single-processor scheduling
  - FIFO/FCFS, STF, Priority, Round-Robin
- Hadoop scheduling
  - Capacity scheduler, Fair scheduler
- Dominant-Resources Fairness
- Highly active area of research!!