CS 425 / ECE 428
Distributed Systems
Fall 2020

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Lecture 24: Scheduling

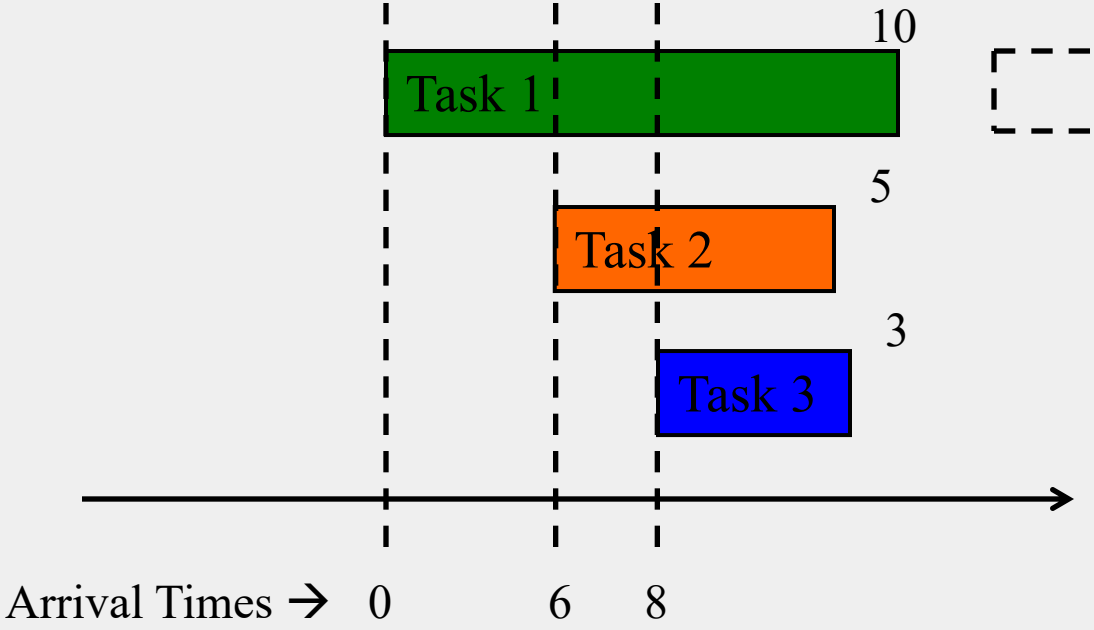
Jokes for this Topic

- **Batman, Robin, and The Joker were out eating, when Batman said to Robin, “Stop eating so much. You might become a Round Robin!” Joker laughed and said, “Yeah, Round Robin, don’t hide in the shadows -- I heard you are good for interactive tasks!”**
- **What did Shortest Job/Task First say to the shy baby robin? Hey, Round Robin, you’re supposed to be for Interactive Scheduling! Batman got angry and said to The Joker, “I’m gonna make short work out of you!” To which Robin replied (with a mouthful of food), “I heard that’s optimal”.**

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
- 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

Single Processor Scheduling

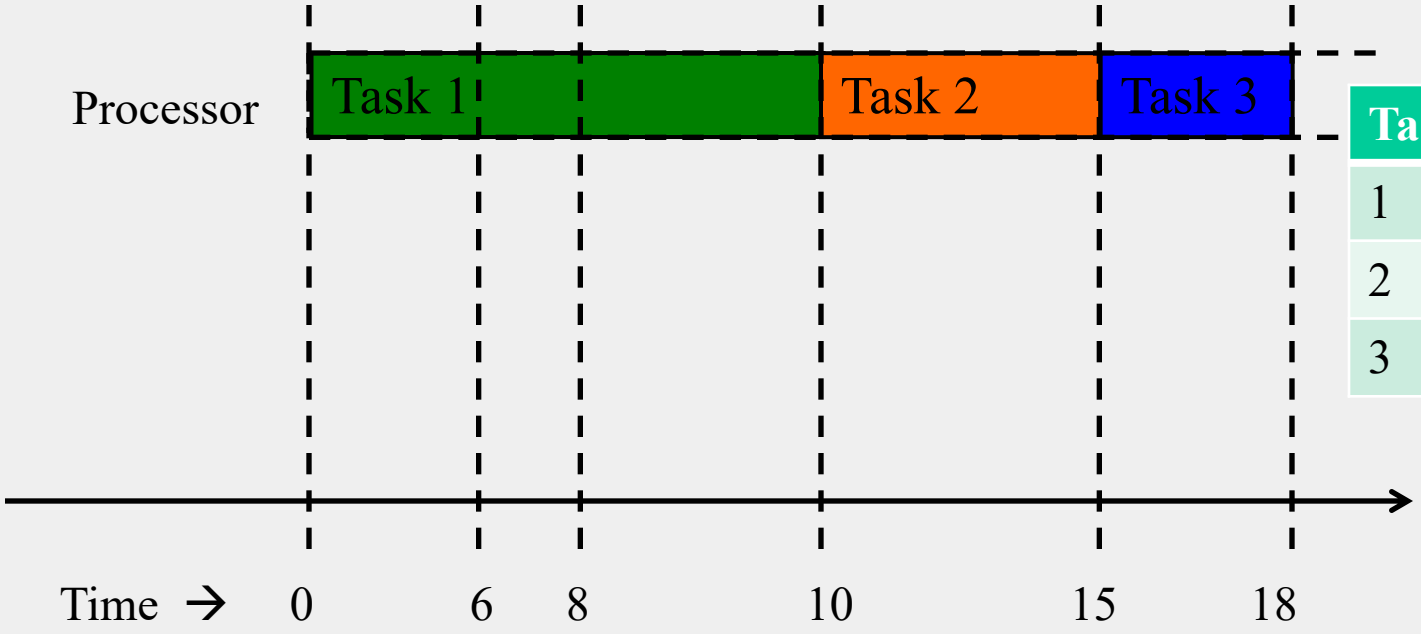


Which tasks run when?

Processor

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

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



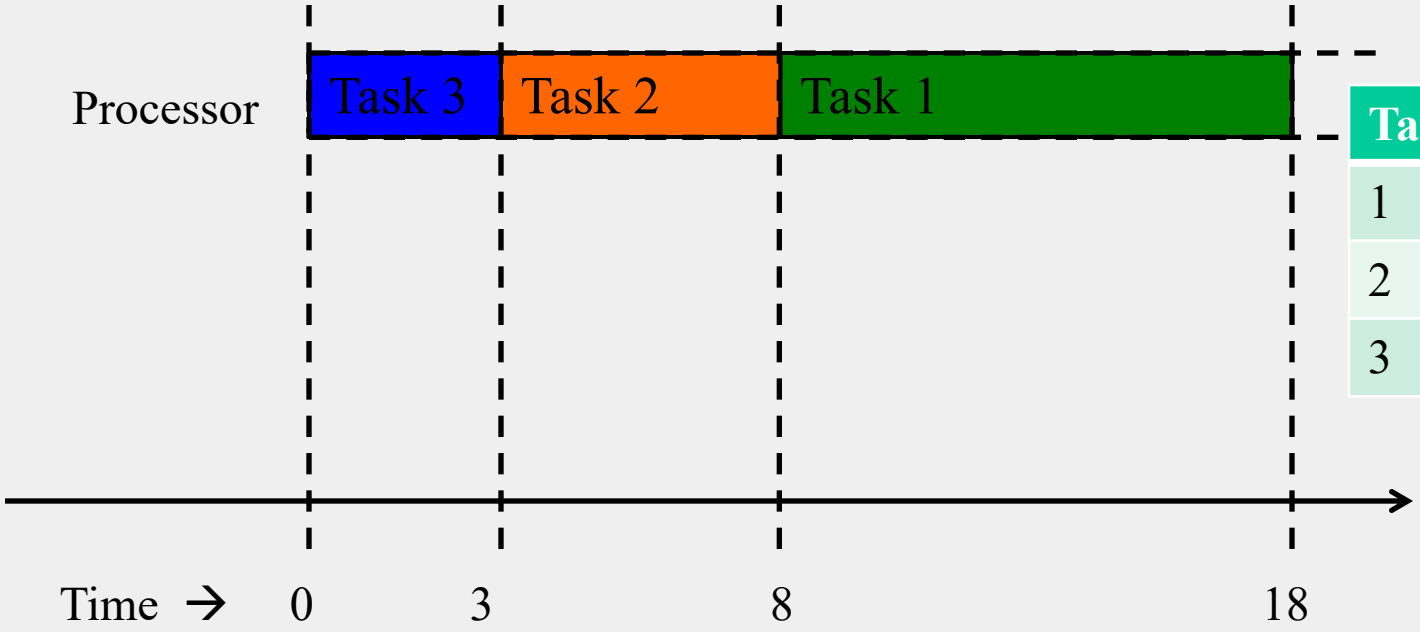
Task	Length	Arrival
1	10	0
2	5	6
3	3	8

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

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
  = (10+15+18)/3
  = 43/3
  = 14.33

STF Scheduling (Shortest Task First)



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

- *Maintain all tasks in a queue, in increasing order of running time*
- *When processor free, dequeue head and schedule*

STF Is Optimal!

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

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

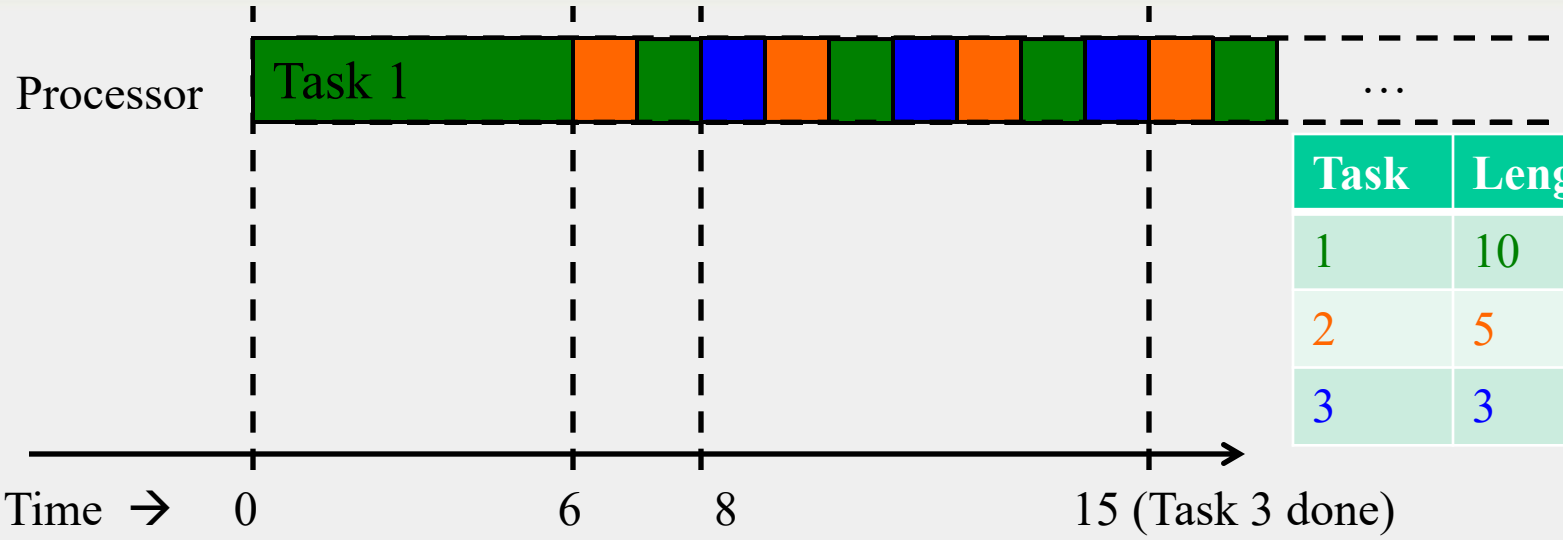
    = (18+8+3)/3

    = 29/3

    = 9.66

    (versus 14.33 for FIFO/FCFS)
- In general, STF is a special case of *priority scheduling*
  - Instead of using time as priority, scheduler could use user-provided priority

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*

Round-Robin vs. STF/FIFO

- Round-Robin preferable for
  - Interactive applications
  - User needs quick responses from system
- FIFO/STF preferable for Batch applications
  - User submits jobs, goes away, comes back to get result

Summary

- Single processor scheduling algorithms
  - FIFO/FCFS
  - Shortest task first (optimal!)
  - Priority
  - Round-robin
  - Many other scheduling algorithms out there!
- What about cloud scheduling?
  - Next!

Hadoop Scheduling

Hadoop Scheduling

(Hadoop 2.0)

- 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
  - Queue 2 is given 20% of cluster
  - Higher-priority jobs go to Queue 1
- For jobs within same queue, FIFO typically used
- Administrators can configure queues

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
- 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
- Scheduling can take memory requirements into account (memory specified by user)

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 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 cluster from being hogged by one user/job

Estimating Task Lengths

- HCS/HFS use FIFO
  - May not be optimal (as we know!)
  - Why not use 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

- Yet, so far we've talked of only one kind of resource
  - Either processor, or memory
  - How about multi-resource requirements?
  - Next!

Dominant-Resource Fair Scheduling

Challenge

- What about scheduling VMs in a cloud (cluster)?
- 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

Where is DRF Useful?

- DRF is
  - Usable in scheduling VMs in a cluster
  - Usable in scheduling Hadoop in a cluster
- DRF used in Mesos, an OS intended for cloud environments
- DRF-like strategies also used 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>

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

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

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

Announcements

- MP4 and HW4 due right after Thanksgiving, so please start early (before the break)
- Collect MP3 reports

- Group numbers
- 1-30 on YOUR LEFT 31-60 MIDDLE 61+ ON YOUR RIGHT