Distributed Systems

CS425/ECE428

Instructor: Radhika Mittal

Acknowledgements for the materials: Indy Gupta

Grade distribution

	3-credit	4-credit
Homework	33%	16% (drop 2 worst HWs)
Midterms	33%	25%
Final	33%	25%
MPs	N/A	33%
Participation	1%	1%

Grading

- Midterms curving formula (tentative)
  - relative: 80 + 10*(your score – avg_UG_score) / standard_dev
  - We will use max(absolute, relative) to get final score out of 100.
  - Relevant Stats:
    - Midterm1: avg_UG_score = 76.119, std_dev = 14.96
    - Midterm2: avg_UG_score = 75.94, std_dev = 13.28
  - Multiply the final score (out of 100) for each midterm by:
    - 0.165 for 3-credit students
    - 0.125 for 4-credit students

- Finals will be similarly curved, but has higher weightage.

Grading

- Homeworks will not be curved.
  - For 3-credit students:
    - (sum of all 5 homework scores) * 100 * 0.33 / 200
  - For 4-credit students:
    - (sum of best 3 homework scores) * 100 * 0.16 / 120

- MPs will not be curved.
  - (sum of all four MP scores) * 100 * 0.33 / 330

- Participation score: directly taken from Campuswire
  - if reported score > 100, you get full 1%
  - Else you get (reported score /100)%
    - Bonus for active participation in class.

Grading

- Grading for active in-class participation
  - Will match faces with roster photograph.
  - If you have actively participated in class, and think you look very different from your roster photograph, please email me a more representative photo.

Tentative Grades Cutoff

- <u>Tentative</u> mapping from score to grade (*<u>rough</u> estimate):*
  - Cutoff for B: 80%
  - Bump up a grade for each 4% leap above 80%.
    - B+ 84%, A- 88%, A 92%, A+ 96%
  - Bump down a grade for each 4% leap below 80%
    - B- 76%, C+ 72%, …..

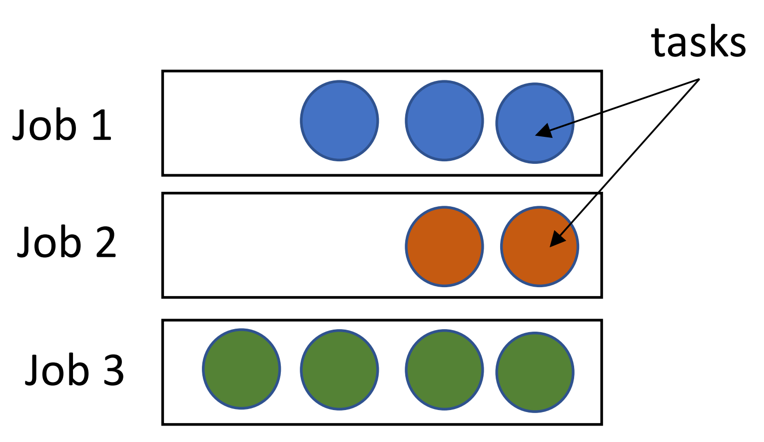
- <u>This is subject to change!</u>

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
- 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
- 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

- 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 jobs 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>

- 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 <u>*resource vector*</u> = <2 CPUs, 8 GB>
  - Job 2's tasks: 6 CPUs, 2 GB
    => Job 2's <u>*resource vector*</u> = <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
  - => <u>*Job 2's dominant resource is CPU*</u>, 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
  - $2x/9 = 6y/18$
  - $2x + 6y <= 18$
  - $8x + 2y <= 36$

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 <u>equalize</u> dominant resource shares.
  - e.g. when a job's demand is met and does not need more tasks.
  - or if one resource gets exhausted, jobs not using that resource can still be served.

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

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

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>

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!!