Multi-tenancy in Datacenters: to each according to his …

Lecture 15, cs262a
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UC Berkeley, March 10, 2018

Cloud Computing

- IT revolution happening in-front of our eyes

Above the Clouds: A Berkeley View of Cloud Computing

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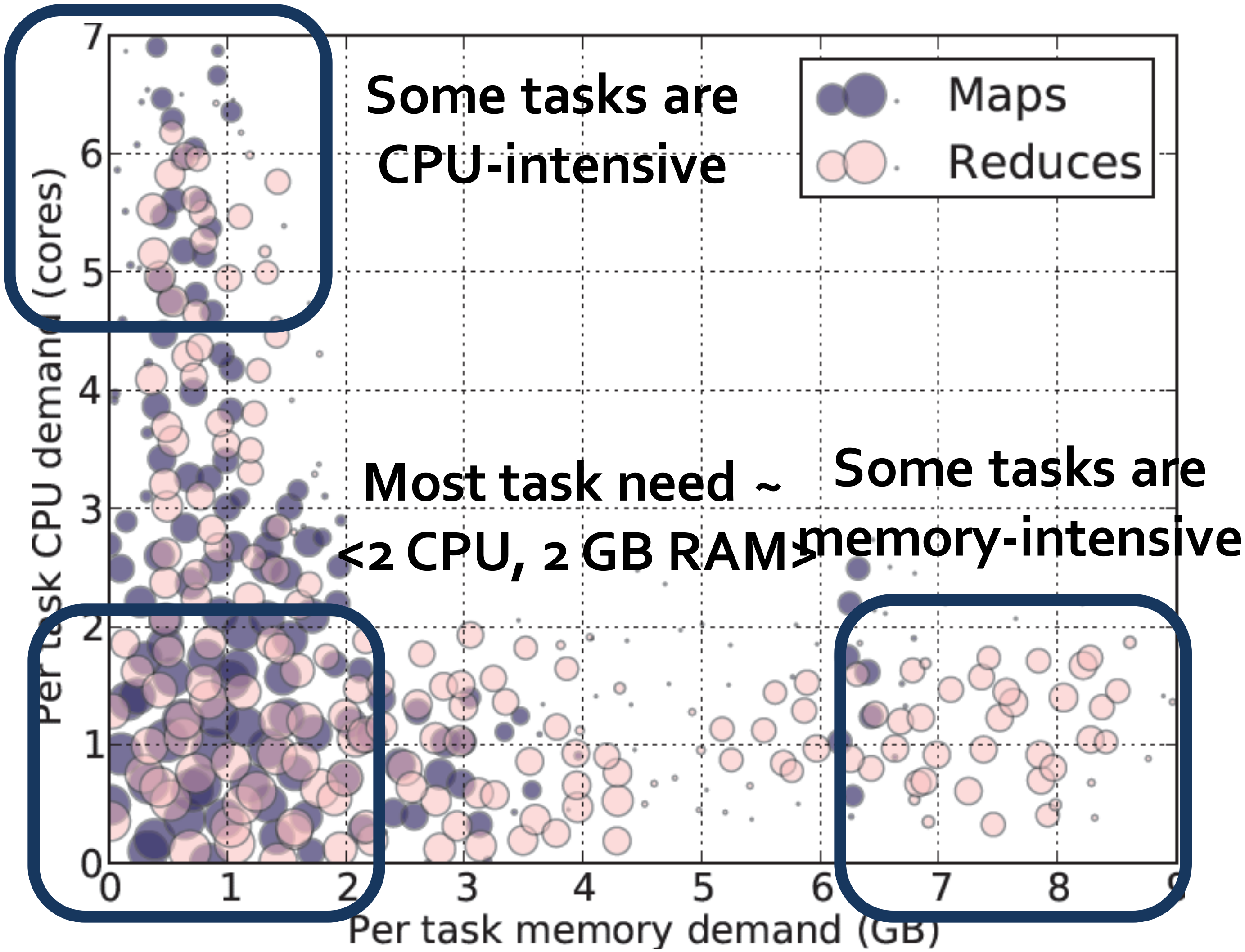
KEYWORDS: Cloud Computing, Utility Computing, Internet Datacenters, Distributed System Economics

Basic tenet of cloud computing

- Consolidate workloads into datacenters
  - Better resource utilization

- Goal: consolidate workloads onto one cluster
  - Now powering most of Twitter, Netflix, eBay, etc

Workload Study



Tasks have heterogeneous resource demands

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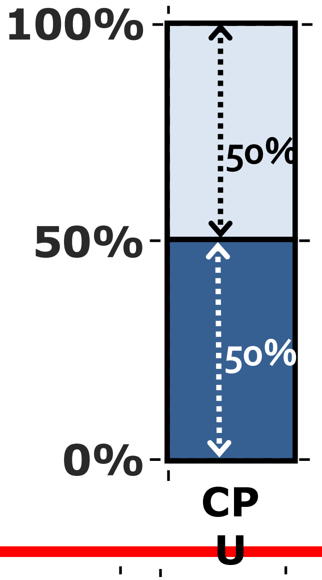
How to allocate resources to jobs with heterogeneous resource demands?

How to allocate resources to jobs with heterogeneous resource demands?

- Terminology
  - Synonymous: jobs, users, applications
  - A job can consist of many tasks
  - A task is a program running on one machine
  - Fine-grained scheduling (schedule one task at a time)

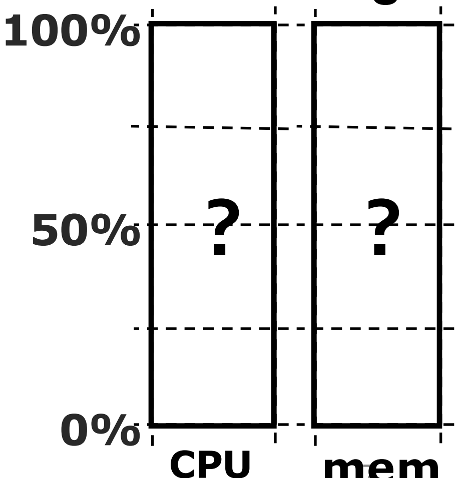
Example Problem

Assume two users with equal entitlement
- Infinite request of tasks



Single *resource example*
- 1 resource: 1,000,000 CPU
- User 1 wants **<1 CPU>** per task
- User 2 wants **<3 CPU>** per task

Multi-resource example
- 2 resources: CPUs & mem
- User 1 wants **<1 CPU, 4 GB>** per task
- User 2 wants **<3 CPU, 1 GB>** per task
- What's a fair allocation?



Why fairness? Equal entitlements?

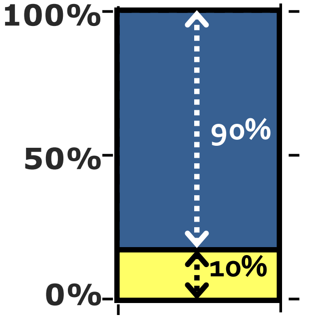
Fairness policy equivalent to isolation policy

Users cannot affect others beyond their fair share

Weighted fairness implements many policies

Not equal: user 1 weight 9, User 2 weight 1, …

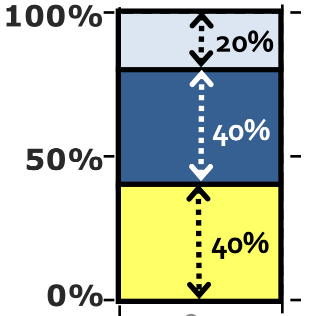
Priority: User 1 weight 10^{10}, User 2 weight 10, …



Fairness generalized by Max-Min Fairness

Handles if a user uses less than her fair share

e.g. user 1 only uses 20% of it's 33% entitlement



Talk from Bird's-eye View

	Allocation Policy
Single-Resource Fairness	**Max-Min Fairness**
Multi-Resource Fairness	↓ **?**

- Fair scheduling well studied in many contexts
  - Surprisingly little work on multi-resource fairness

Multi-resource scenario opens many new fundamental challenges

Talk Outline

- Multi-resource fairness – DRF
- DRF deployments in organizations
- Applying DRF to modern network routers
- Follow-up work on DRF
- Other research

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Talk Outline

- Multi-resource fairness – DRF
  - What properties do we want?
  - Our proposed solution (DRF)
  - How would an economist solve this?
  - How well does this work in practice?

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Properties of policies
Share guarantee
Strategy-proofness
Pareto efficiency
Envy-freeness
Single resource fairness
Bottleneck resource fairness
Population monotonicity
Resource monotonicity

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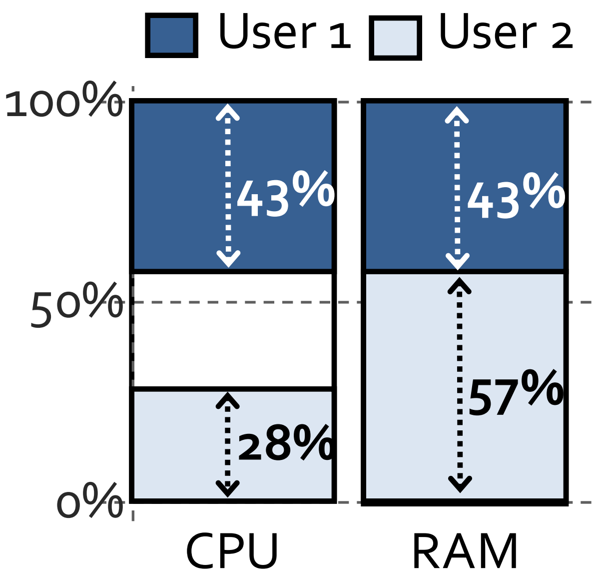
A Natural Policy

- *Asset Fairness*
  - Equalize each user's *sum of resource shares*



Problem
User 1 has < 50% of both CPUs and RAM

Better off in a separate cluster with 50% of the resources

- Asset fairness yields
  - U_1: 15 tasks: 30 CPUs, 30 GB (∑=60)
  - U_2: 20 tasks: 20 CPUs, 40 GB (∑=60)

Share Guarantee

- Every user should get $1/n$ of at least one resource
- Intuition:
  - "You shouldn't be worse off than if you ran your own cluster with 1/n of the resources"

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Cheating the Scheduler

- Users willing to *game* the system to get more resources
- Real-life examples
  - A familiar company provided dedicated machines to users that could ensure certain level of utilization (e.g. 80%)
  - **Users used busy-loops to inflate utllization**
  - A cloud provider had quotas on map and reduce slots
    Some users found out that the map-quota was low
  - **Users implemented map-reduce in the reduce phase!**

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Strategy-proofness

- A user should not be able to increase her allocation by lying about her demand
- Intuition:
  - Users are incentivized to make truthful resource requirements

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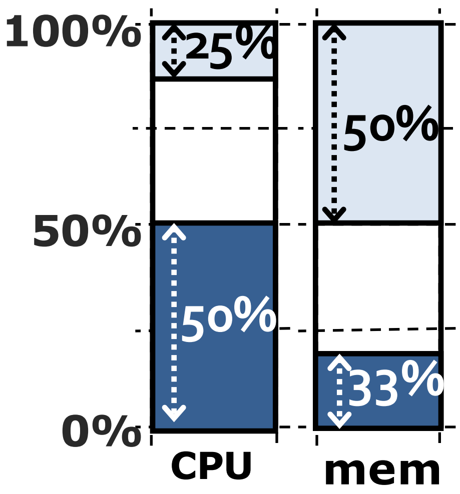
Pareto efficiency

- There should not exist another allocation where at least one user is better off and no user is worse off.

- Avoid inefficient solutions
  User 1 wants **<1 CPU, 4 GB>** per task
  User 2 wants **<3 CPU, 1 GB>** per task



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Challenge

- Max-min fairness for a single resource trivially satisfies all these properties

- Can we find a multi-resource fair sharing policy that provides:
  - Strategy-proofness
  - Share guarantee
  - Pareto efficiency

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Dominant Resource Fairness

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

    Total resources: **<10 CPU, 4 GB>**

    User 1's allocation: **<2 CPU, 1 GB>**

    Dominant resource is memory as 1/4 > 2/10 (1/5)

- A user's *dominant share* is the fraction of the dominant resource she is allocated
  - User 1's dominant share is **25%** (1/4)

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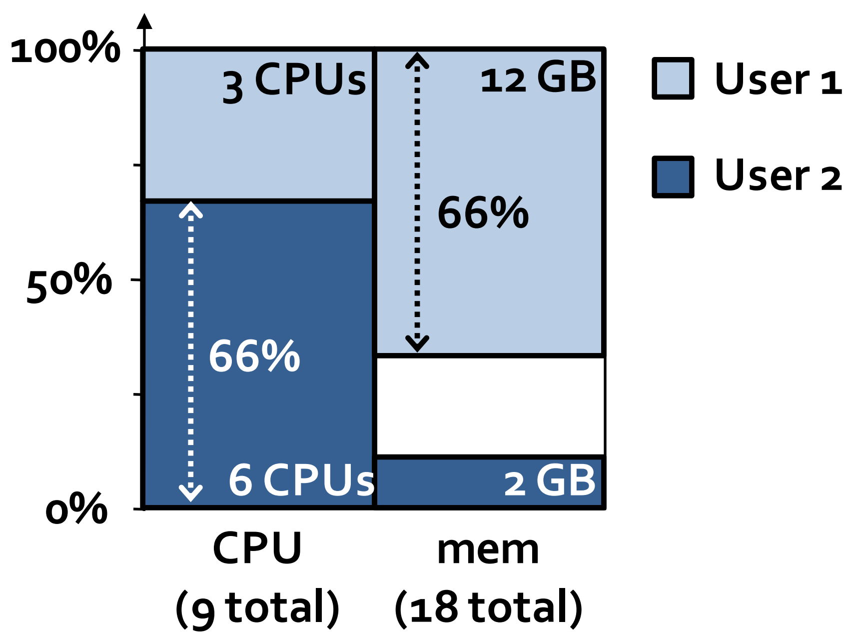
Dominant Resource Fairness (2)

- 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**

    User 2 demand: **<3 CPU, 1 GB>** dom res: **CPU**



Online DRF Scheduler

Whenever there are available resources and tasks to run:

Schedule a task to the user with smallest dominant share

- O(log *n*) time per decision using binary heaps

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How would an economist solve it?

- Use pricing
  - Set prices for each good
  - Give each user the same budget
  - Let users buy what they want

- Problem
  - How do we determine the right prices for different goods?

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The market approach

- Let the market determine the prices

- Competitive Equilibrium from Equal Incomes (CEEI)
  - Give each user 1/n of every resource
  - Let users trade in a perfectly competitive market
  - Analytical solution: max of product of dominant shares

- **Violates strategy-proofness**

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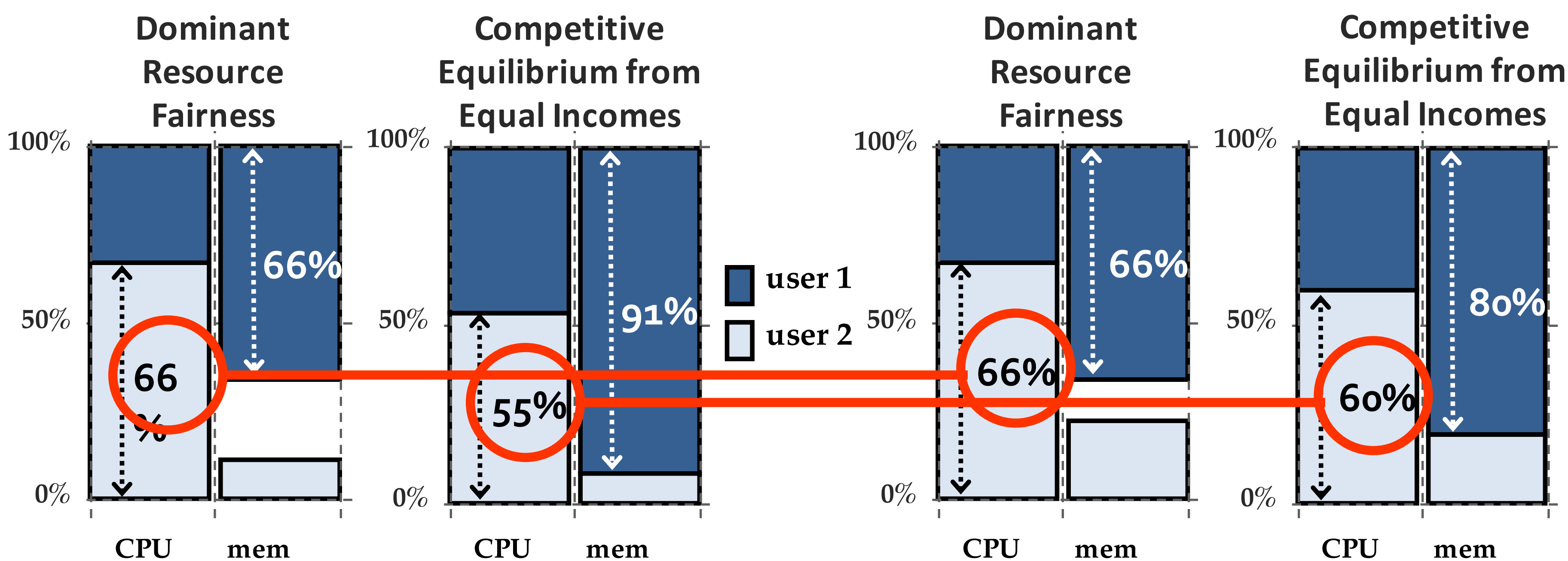
DRF vs CEEI

- User 1: <1 CPU, 4 GB> User 2: <3 CPU, 1 GB>
  - DRF more fair, CEEI better utilization



- User 1: <1 CPU, 4 GB> User 2: <3 CPU, 2 GB>
  - User 2 increased her share of both CPU and memory

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Properties of DRF

- We proved DRF is strategy-proof
  - Assuming linear utilities
  - Others proved it's the only policy satisfying Strategy-proofness, sharing incentive, Pareto

Results carried over the economics literature

Properties of Policies

Property	Asset	CEEI	DRF
Share guarantee		✔	✔
Strategy-proofness	✔		✔
Pareto efficiency	✔	✔	✔
Envy-freeness	✔	✔	✔
Single resource fairness	✔	✔	✔
Bottleneck res. fairness		✔	✔
Population monotonicity	✔		✔
Resource monotonicity			

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Talk Outline

- Multi-resource fairness – DRF
  - What properties do we want?
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  - How would an economist solve this?
  - DRF variants?

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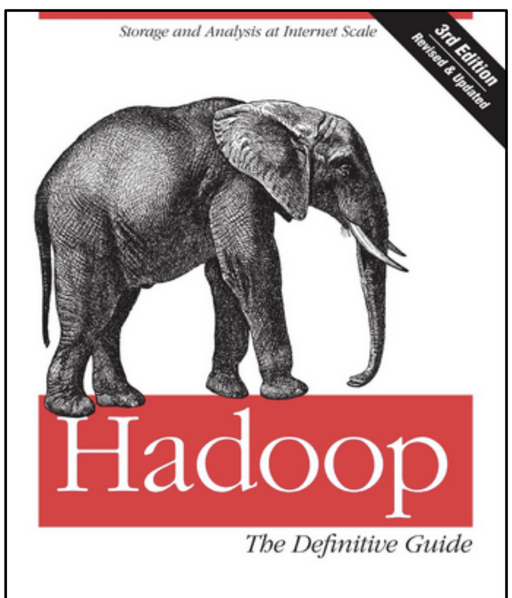
Follow-up papers

	Allocation in Space	Allocation in Time
Single-Resource Fairness	Max-Min Fairness	Fair Queueing
Multi-Resource Fairness	DRF	

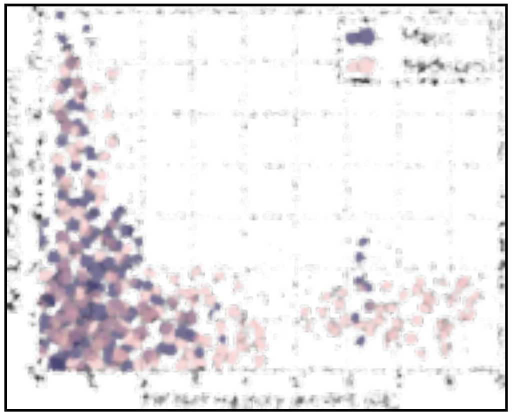
DRFQ broadly applicable: VMs, OSs

DRF in the wild

- DRF de-facto scheduler in Hadoop & Mesos
  - DRF capacity scheduler (HortonWorks)
  - DRF fair scheduler (Cloudera)
  - Mesos cluster of O(10k) nodes at Twitter



Multi-Resource Scheduling **Hierarchical Policies**



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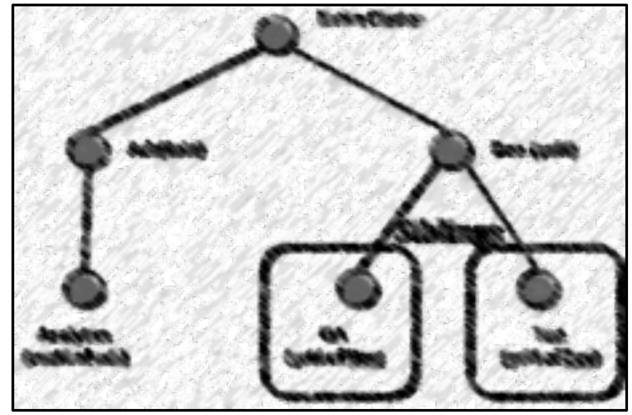
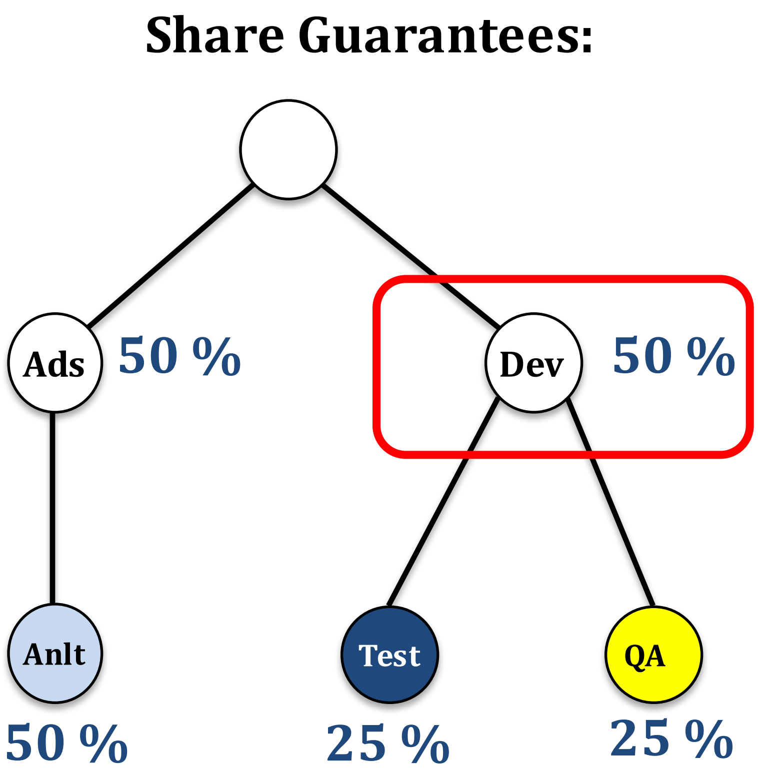
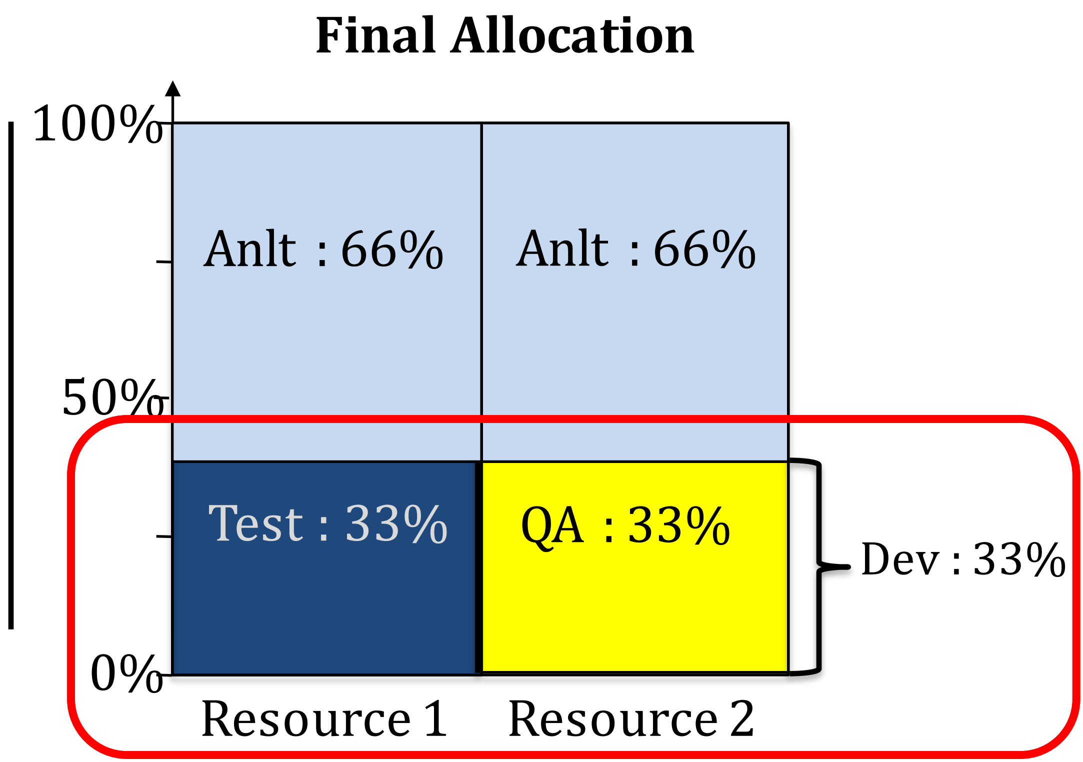


Challenging

- Hadoop DRF schedulers can break down
  - Leave resources unallocated (not Pareto) or
  - Starve users

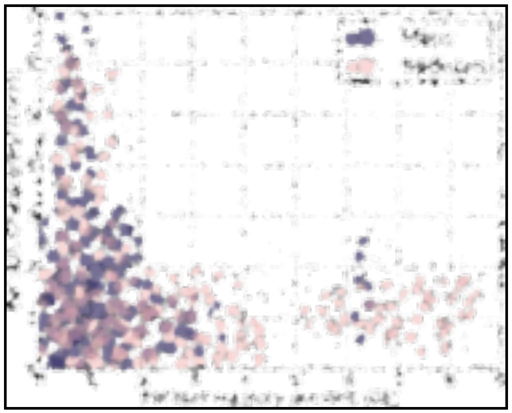
Hierarchical Share Guarantee Violated





Follow-up papers

Dominant Resource Fairness



- **Share guarantee**
  1/n share to leafs
- **Pareto efficiency**
  Work-conservation

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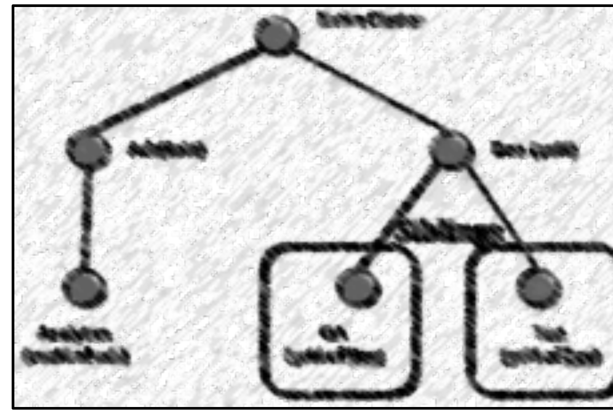
H-DRF



- **Hierarchical share guarantee**
  1/n to every node
- **Pareto efficiency**
  Work-conservation

Talk Outline

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  - What properties do we want?
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  - How would an economist solve this?
  - DRF variants?
  - DRF evaluation

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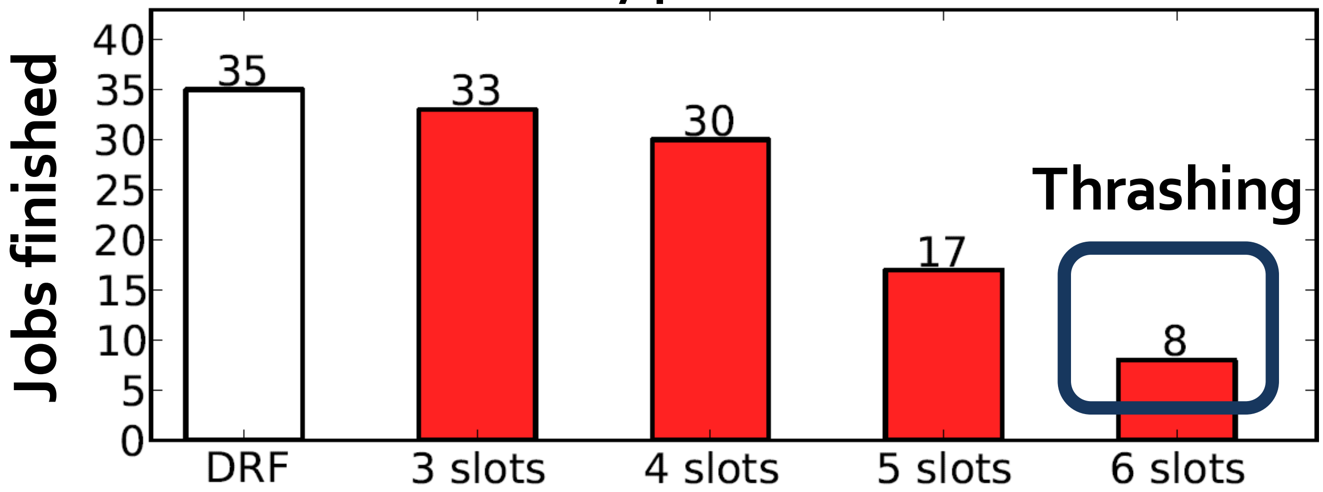
Previous approach: slot-based scheduling

- Hadoop Fair Scheduler
  - Each machine consists of k *slots* (e.g. k=14)
  - Run at most one task per slot
  - Give jobs "equal" number of slots,

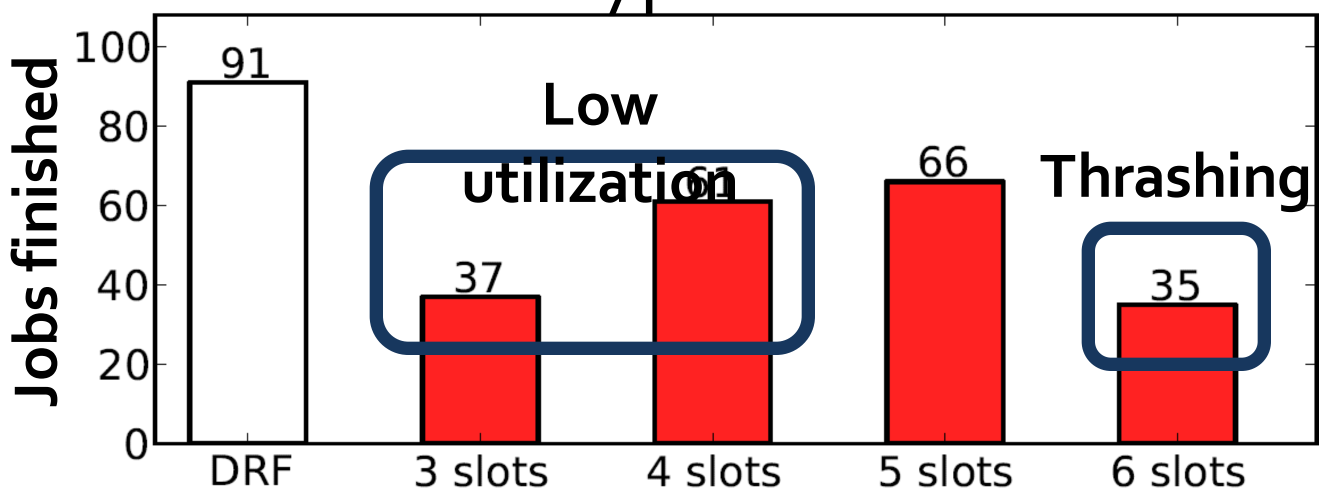
This is what we compare against

Experiment: DRF vs Slots

Number of Type 1 Jobs Finished



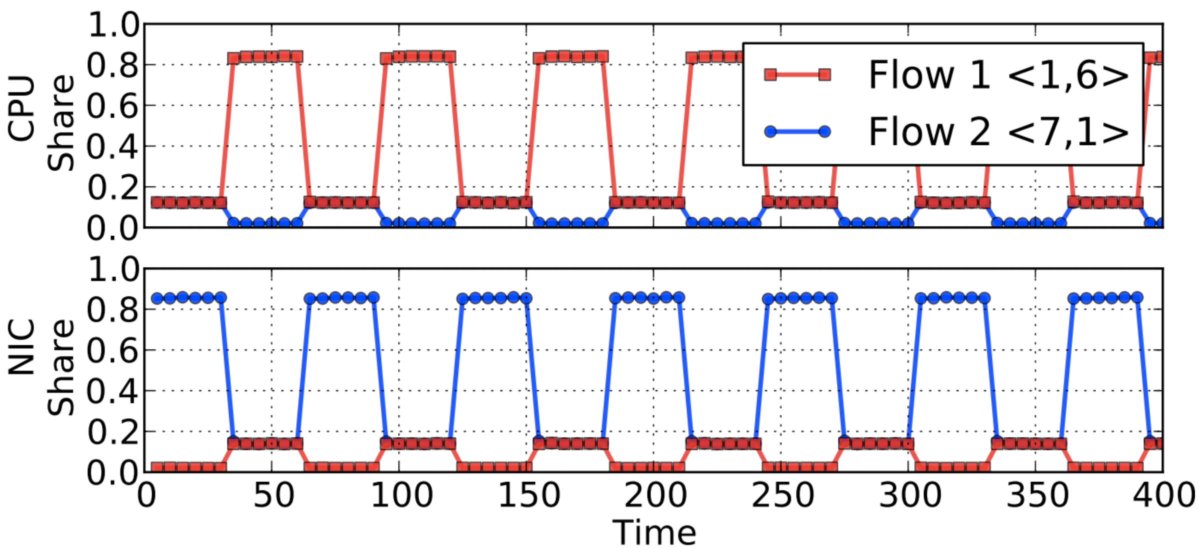
Number of Type 2 Jobs Finished



Type 1 jobs <2 CPU, 2 GB> **Type 2 jobs <1 CPU, 0.5GB>**

State-of-the-art: bottleneck fairness

- 2 flows and 2 res. <CPU μs, NIC μs>
  - Demands <1,6> and <7,1> → *bottleneck unclear*



- Especially bad for TCP and video/audio traffic

TCP and oscillations

- Implemented Bottleneck Fairness in Click
  - Bottleneck determined every 300 ms
  - 1 BW-bound flow and 1 CPU-bound flow

Scenario	Flow 1 (BW-bound)	Flow 2 (CPU-bound)
Running alone	191 Mbps	33 Mbps
Bottleneck	75 Mbps	32 Mbps
DRFQ	160 Mbps	28 Mbps

Oscillations in Bottleneck degrade performance of TCP

Thank you!

Questions?