Cake

Enabling High-level SLOs on Shared Storage Systems

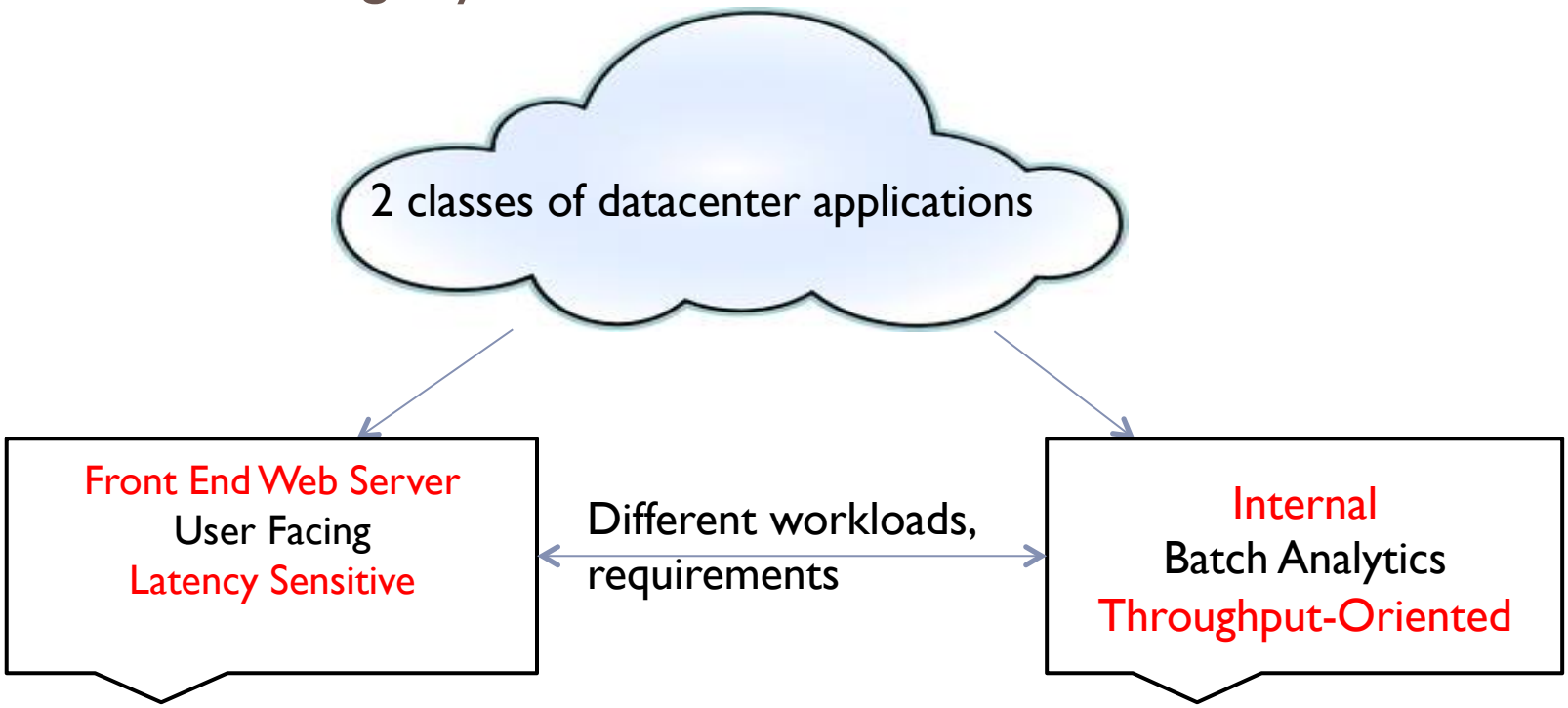
AMPLab – UCBerkeley

Introduction

- Cake
  - Coordinated (multiresource) 2-level scheduling system for shared storage systems
  - Enforces SLO requirements of the clients.

Introduction

- Cake
  - Coordinated 2-level scheduling system for shared storage systems



Service Level Objective

Performance Metric (Ex: 99th percentile latency)

of

Requirement (Ex:100 ms)

for

Type of Request (Ex: get request)

Service Level Objective (Examples)

- Latency SLO:
  - 99th percentile latency of 100ms for get requests
- Throughput SLO:
  - 100 8KB scan requests per second
- 90% of calls to the helpdesk should be answered in less than 20 seconds…

Introduction

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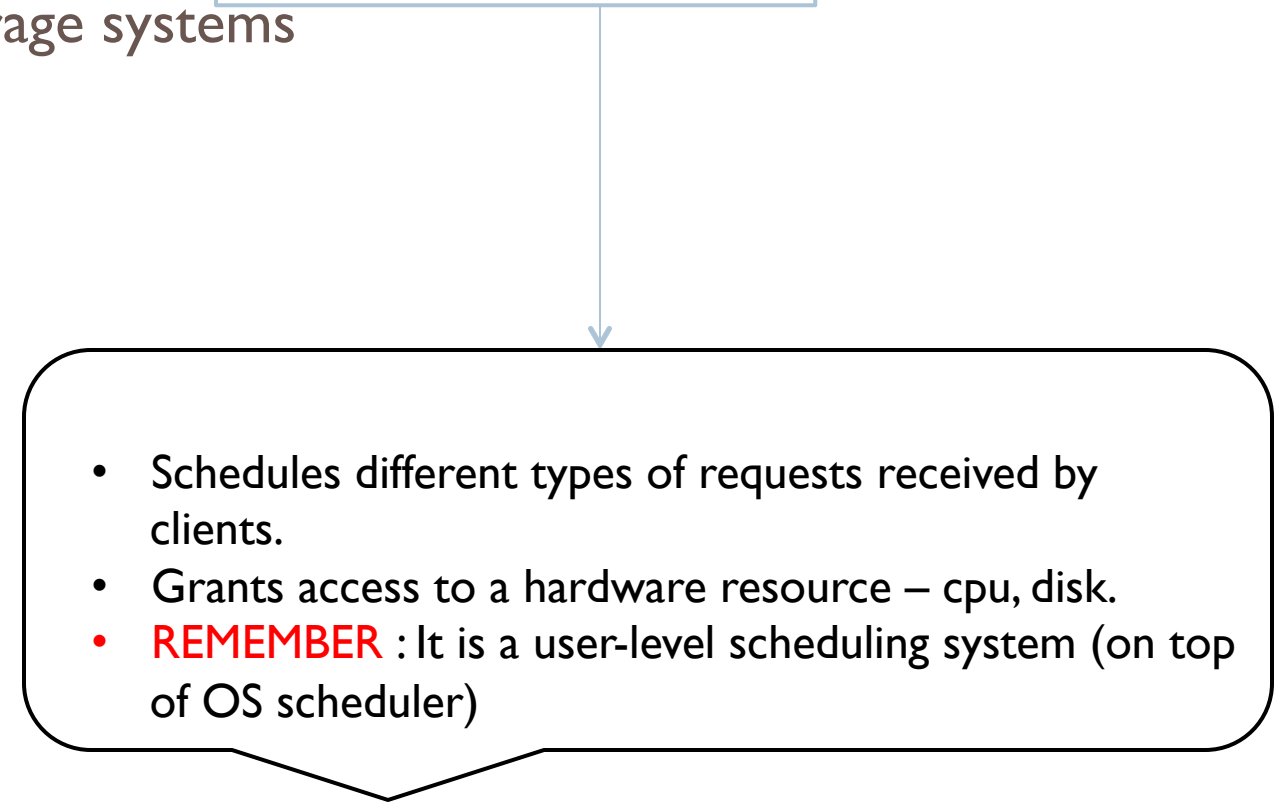


Introduction

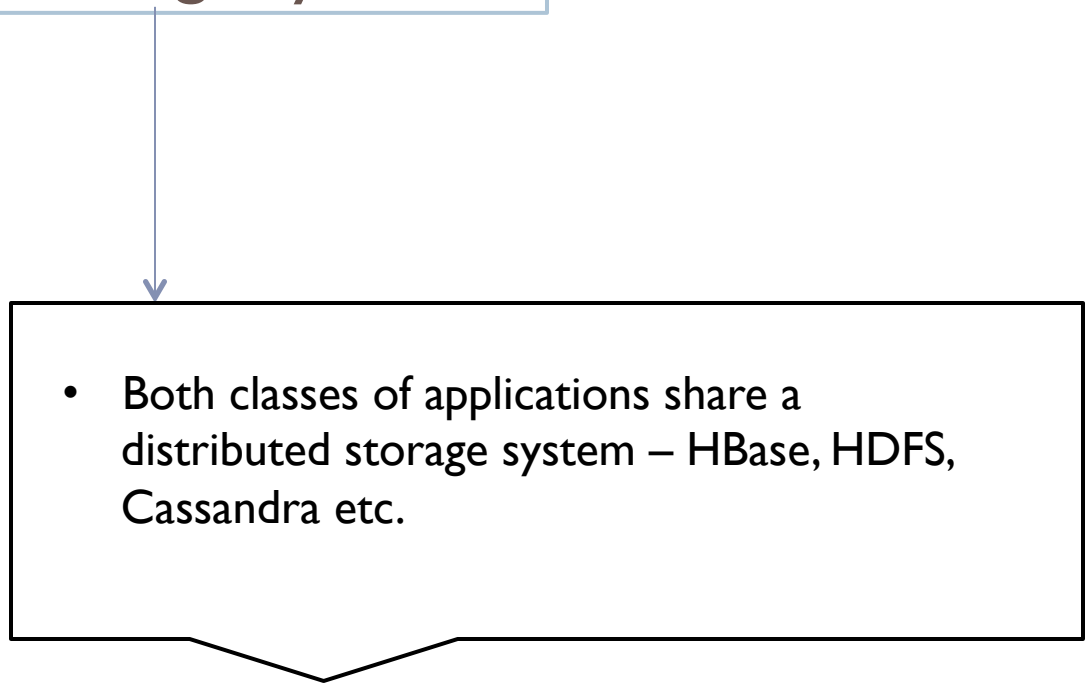
- Cake
  - Coordinated 2-level scheduling system for shared storage systems

- Provides scheduling at multiple resources – cpu, disk.
- Scheduling at different resources is coordinated. Why?

Introduction

- Cake
  - Coordinated 2-level scheduling system for

shared storage systems

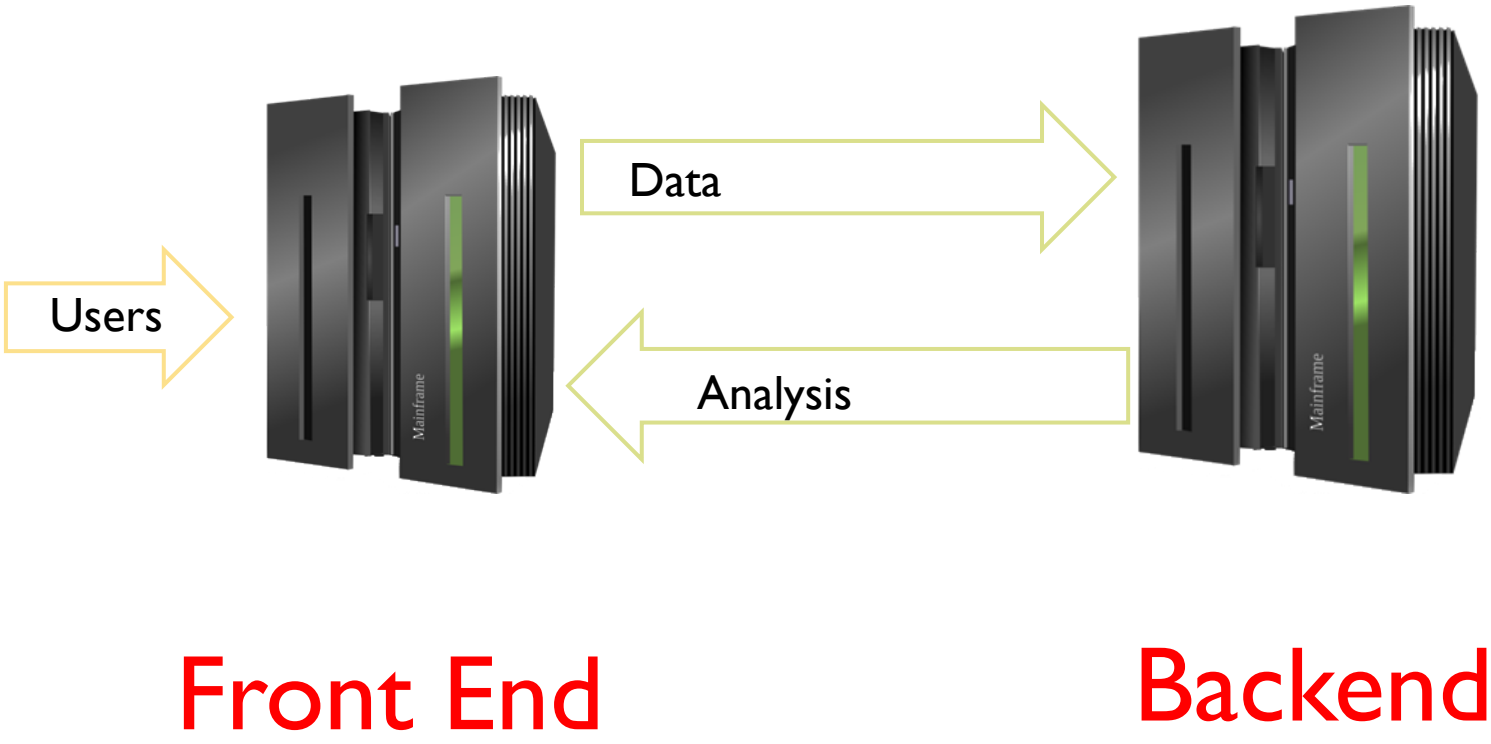


Motivation

- Separate storage systems for both the classes of applications.
  - Hard to multiplex front-end (web server) storage and backend (analytics) storage.
  - Different workloads and requirements for both these classes.
  - We don't want to violate SLOs of web-clients.

Motivation

Motivation



Cake in one slide

- Observation:
  - Separate storage systems for front-end and back-end applications
- Problem:
  - Hard to multiplex latency sensitive applications and throughput-oriented applications.
  - Why? – inherent latency v/s throughput tradeoff in rotational media storage
- Solution:
  - Have separate queue each for latency sensitive applications requests and throughput-oriented applications requests
  - Schedule them by giving higher priority for latency sensitive applications so that SLOs are met

Cake Objectives

- Combine both the workloads
  - consolidate separate front-end and batch storage clusters
- Meet front-end latency requirements
- Then maximize batch throughput

Cake Benefits

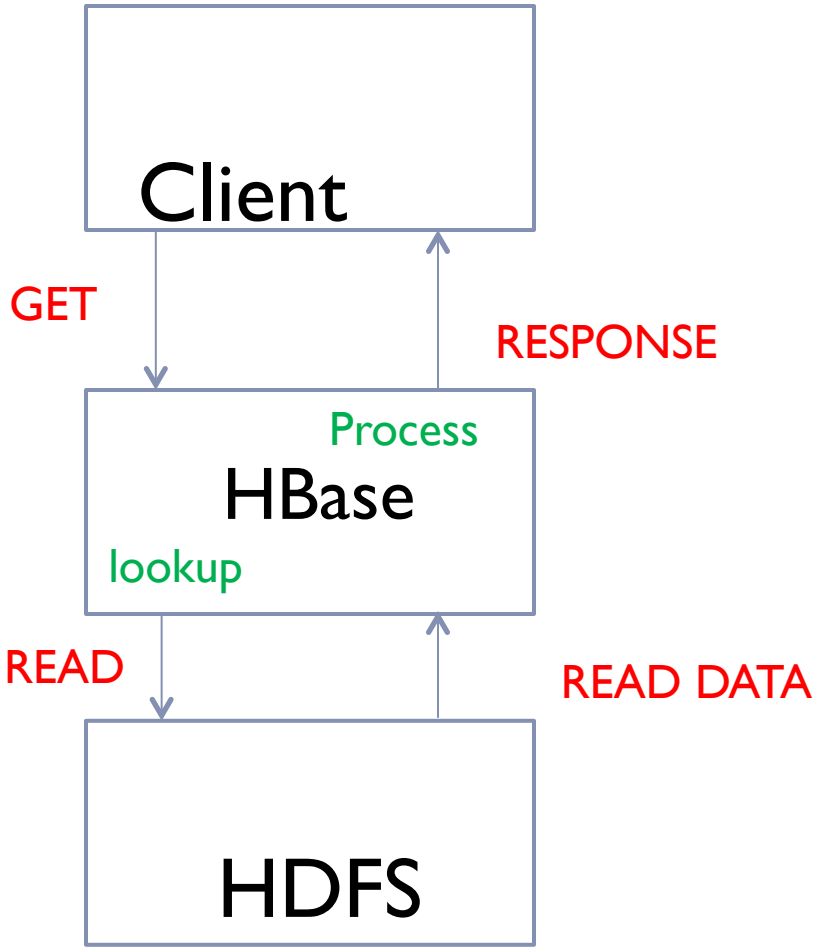
Consolidated

- Lower cost of provisioning
- Better cluster utilization
- Improved performance.
- Also meets SLOs

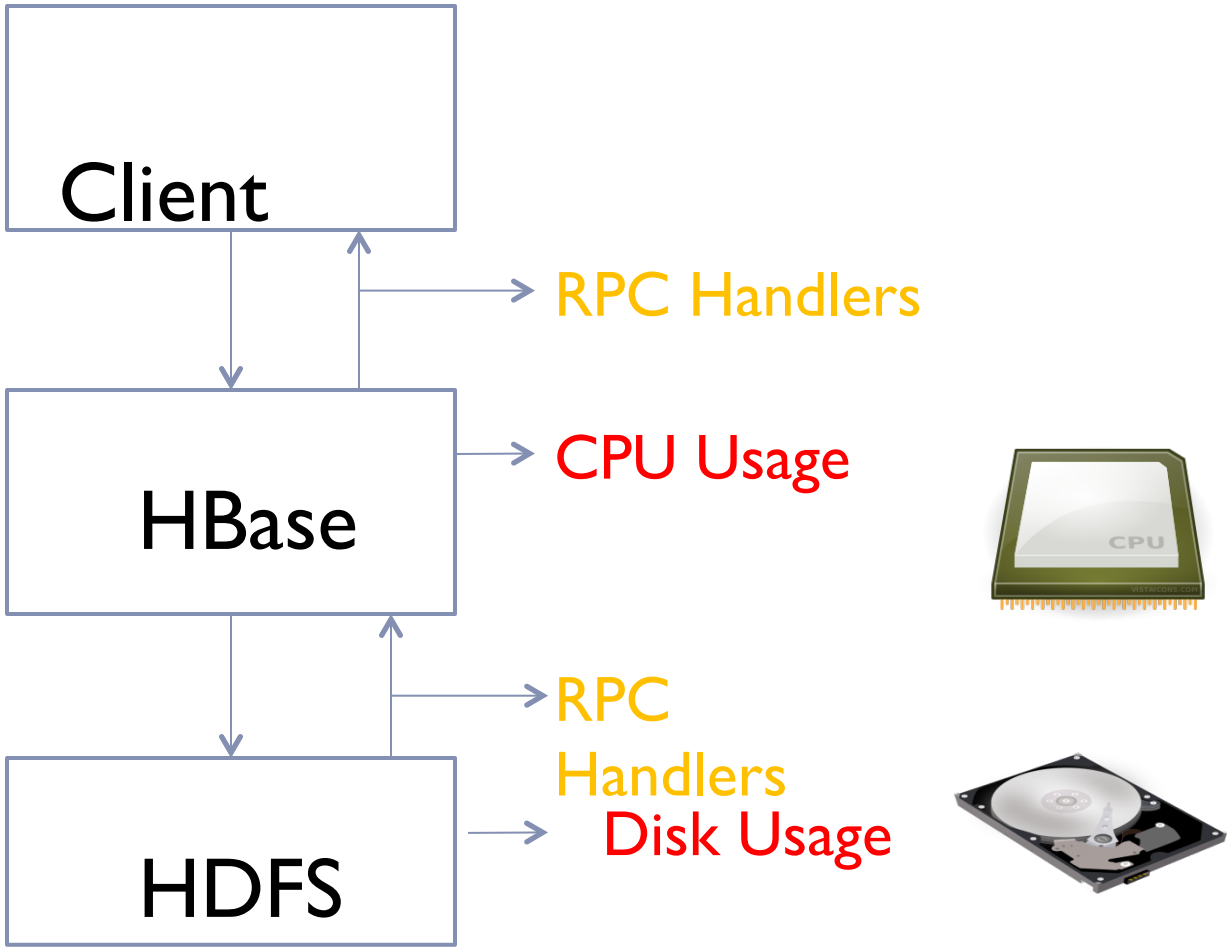
Recap

- Cake
  - Coordinated mutliresource scheduler
  - Can consolidate storage systems for different types of workloads (latency sensitive vs throughput-oriented)
  - Also meets SLO requirements

System Design

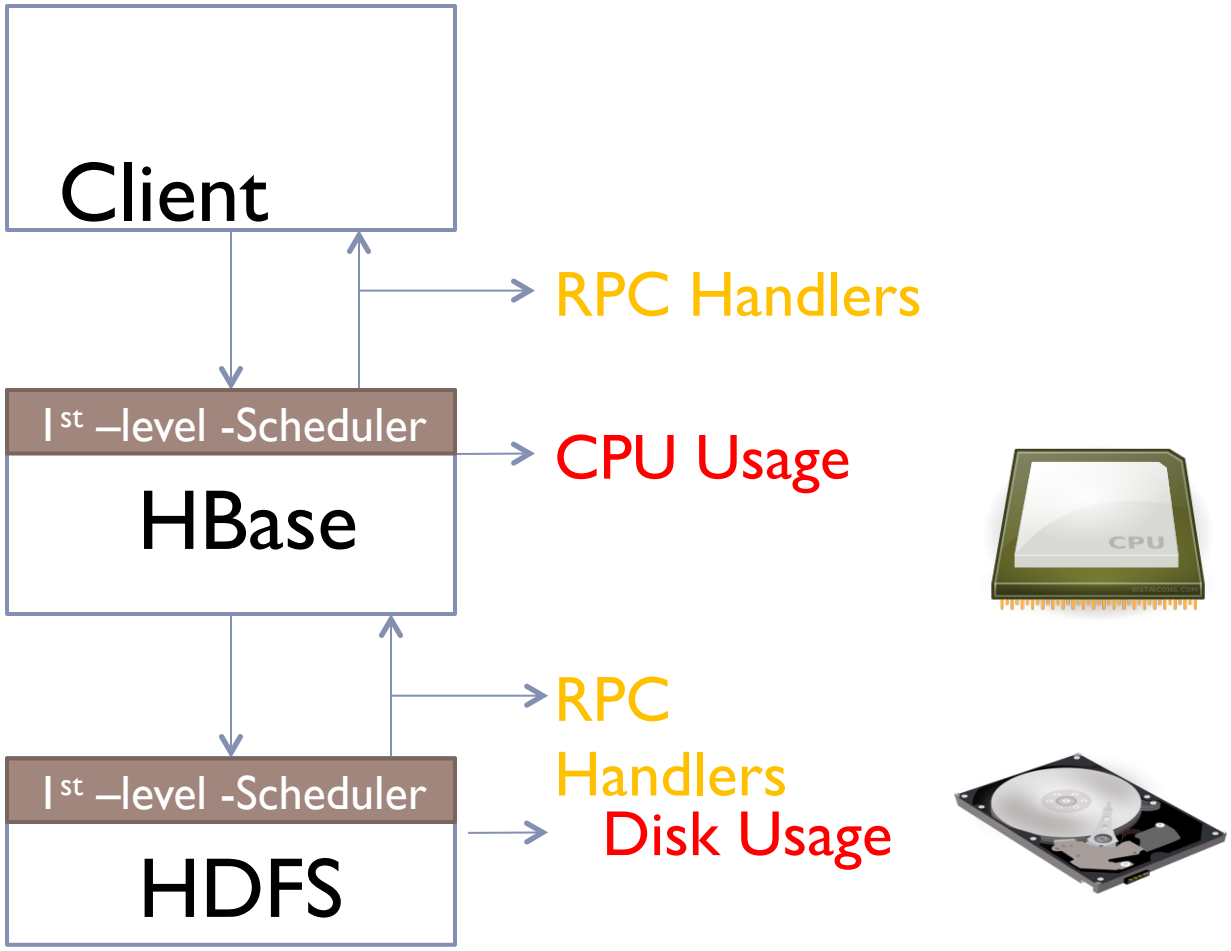


System Design

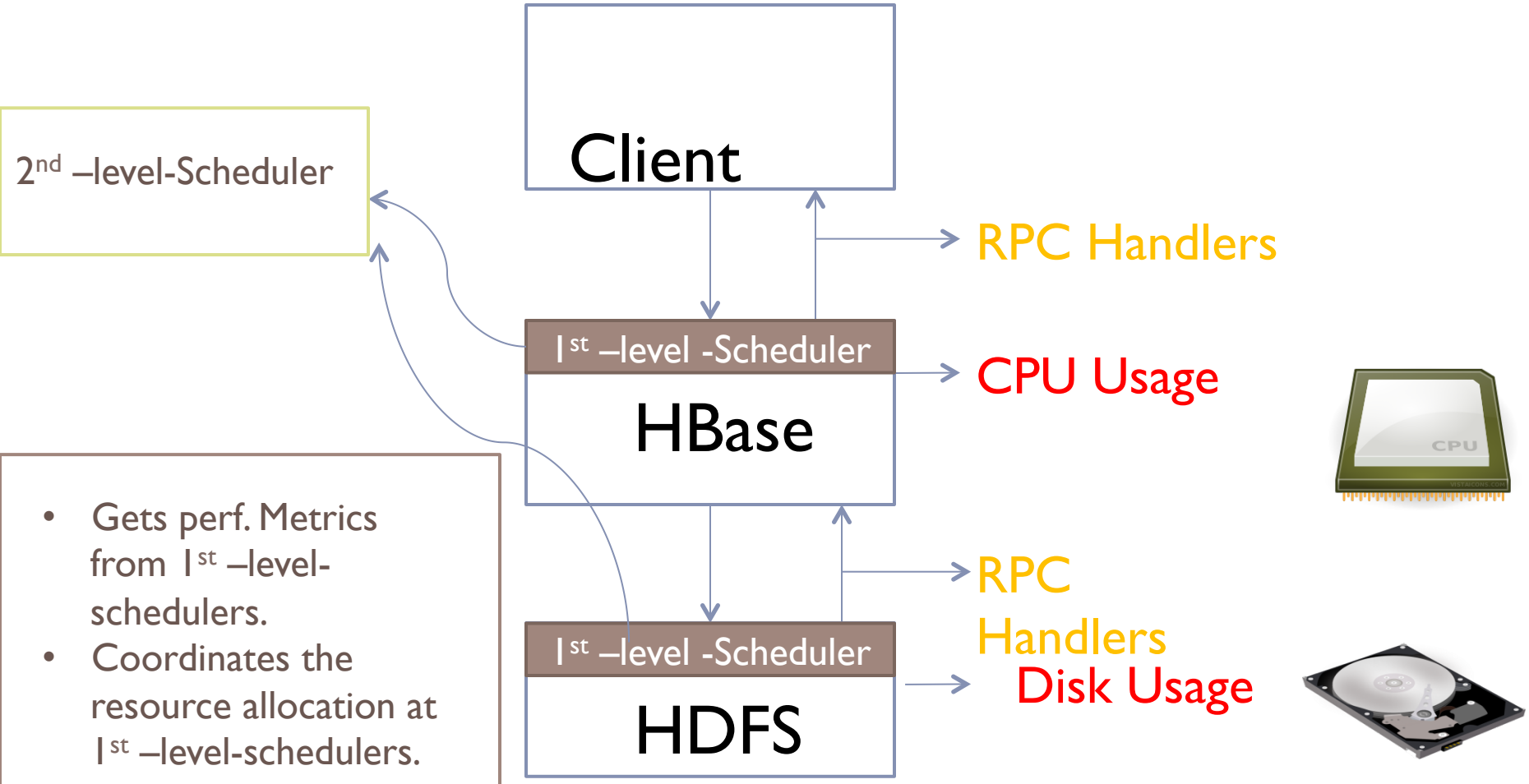


System Design

- Responsible for scheduling at single resource (disk, cpu etc)
- Built into RPC layer of each software component



System Design



- Gets perf. Metrics from 1st –level-schedulers.
- Coordinates the resource allocation at 1st –level-schedulers.
- Enforces SLOs

System Design

- Add scheduling points within the system
- Dynamically adjust allocations to meet SLO requirements.
- Evaluated on HBase/HDFS system.

Schedulers : Overview

- First-Level Schedulers
  - Give control over underlying hardware resource : cpu, disk
  - Implemented at different layers of software stack (HBase, HDFS)
- Second-Level Scheduler
  - Coordinates first-level schedulers to decide allocations
  - Enforces SLO requirements

System Design
First-Level Schedulers

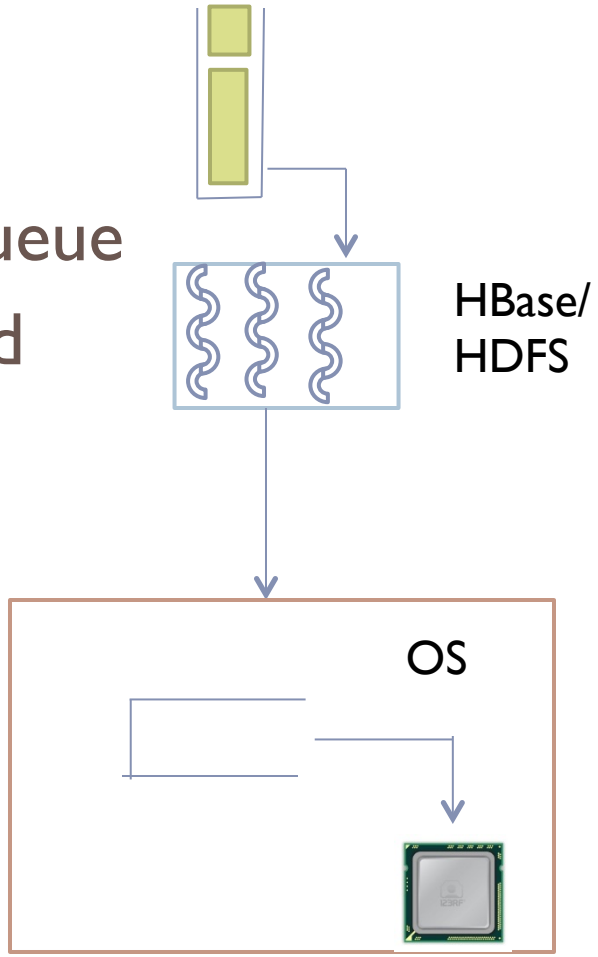
- Provide effective control over the underlying hardware – cpu, disk etc.
- Coordinate with second-level-scheduler

System Design
First-Level Schedulers

- Effective scheduler requirements
  - Differentiated Scheduling
  - Split large requests
  - Control number of outstanding requests

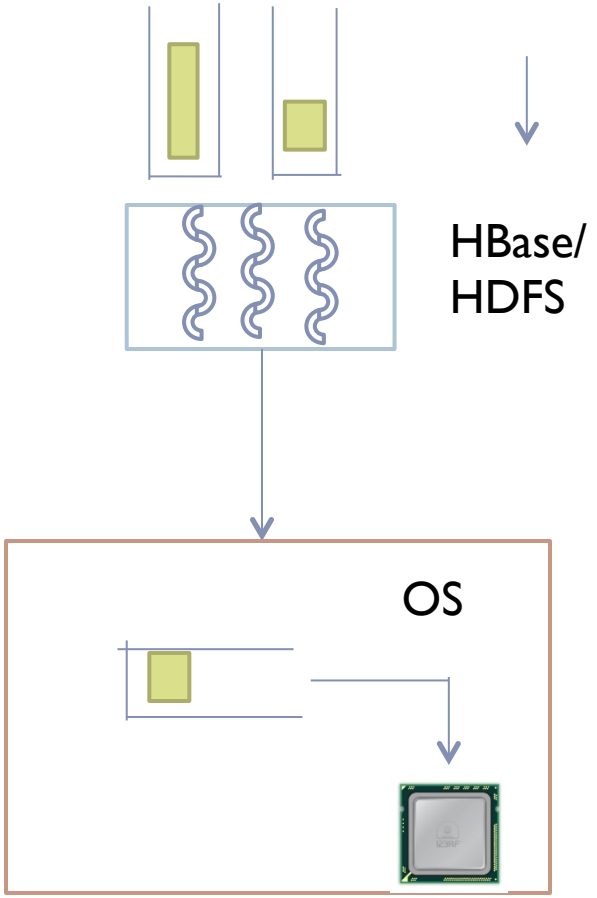
System Design
First-Level Schedulers – Differentiated Scheduling

- FIFO Scheduling Scheme
- Problems
  - Unfairness with a single FIFO queue
  - Front-end requests block behind batch requests
- Solution :
  - Separate queues for both classes of applications



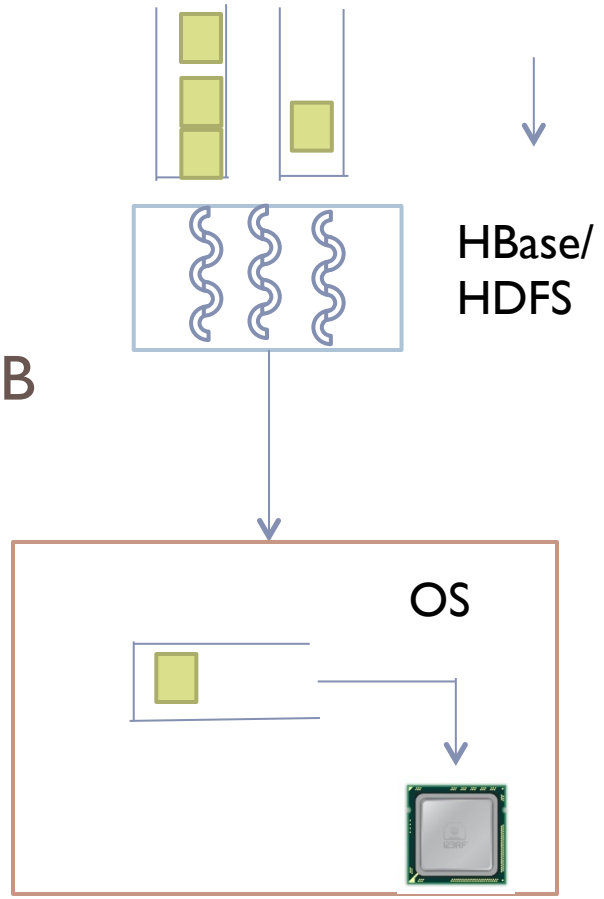
System Design
First-Level Schedulers – Differentiated Scheduling

- Schedule based on allocations set by the 2nd –level scheduler
- Allocations :
  - Proportional share allocation
  - Reservations
- Problems:
  - Large requests might tie up resources
  - Requests can be non-prememptible
- Solution : split large requests



System Design
First-Level Schedulers – Splitting large requests

- Split large requests into multiple chunks
- Only wait for a chunk than an entire large request
- Tradeoff :
  - Lower latency but lesser throughput
- For the experiments performed, 64KB chunk size was found to be optimal



System Design
First-Level Schedulers – Limiting outstanding requests

- A device can only handle a certain number of concurrent executions
- Need to make sure the thread pool size at HBase/ HDFS is optimal
  - Not overwhelming the device
  - Not underloading the device

System Design

First-Level Schedulers – Limiting outstanding requests

- TCP congestion control technique : AIMD (additive increase multiplicative decrease)
  - Periodically determine the device latency
  - If device underloaded, additively increase # of threads
  - If device overloaded, multiplicatively decrease # of threads
  - Claim : converges in general case

System Design
Second-Level Scheduler

- Decides allocation at first-level schedulers
  - Collects performance and queue occupancy metrics from first-level schedulers.
  - Every interval (10 secs) – uses these metrics to decide scheduling allocations at first-level schedule
  - Enforces front-end client's SLOs.

System Design
Second-Level Scheduler

- 2 phases in allocation
  - SLO Compliance-based
    - Adjusts allocations at HDFS.
  - Queue Occupancy-based
    - Adjusts HBase allocation based on queue occupancy at HDFS and HBase

System Design
Second-Level Scheduler : SLO Compliance-Based Phase

- Adjusts HDFS allocations
- Disk is the bottleneck in storage workloads
- Clients performance < SLO
  - Increase allocation when performance < SLO
- However, if client's performance is very good
  - Decrease allocation

System Design
Second-Level Scheduler : Queue Occupancy-Based Phase

- Disk bottleneck workloads. But HBase can be bottleneck too (processing of get requests at HBase can be expensive)
- HBase can throttle HDFS
- Balance HBase/HDFS allocation
- Queue occupancy metric:
  - % of time a client's requests is waiting in the queue at a resource
- Increase allocation when more queuing at HBase
- Decrease allocation when more queuing at HDFS

Evaluation

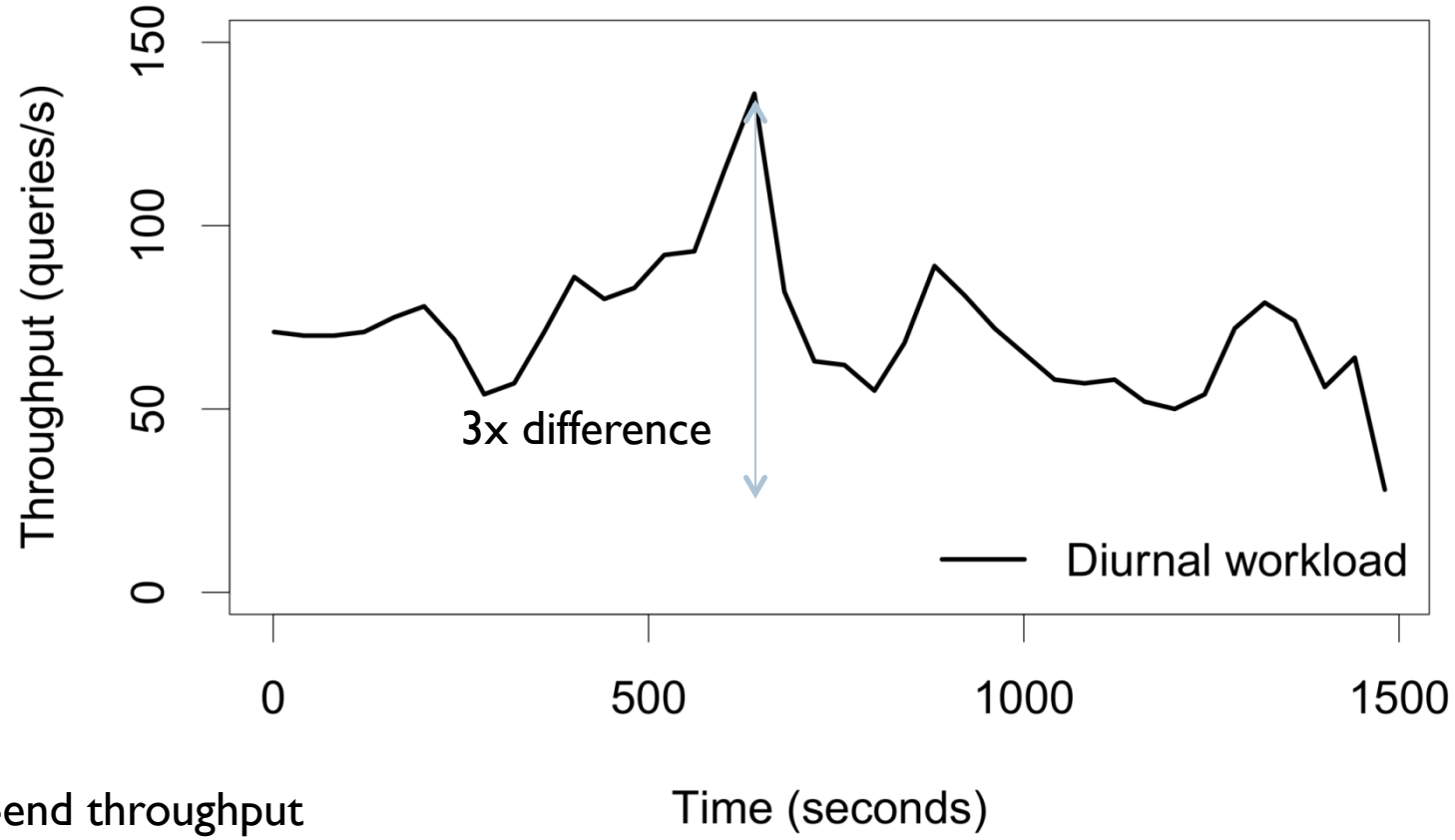
- Several challenging consolidated workload scenarios
- Yahoo! Cloud Serving Benchmark (YCSB) clients to generate simulated front-end and batch load.
- Front-end clients – configured to make single-row requests (8KB data)
- Batch MapReduce clients configured to make 500-row scans (4MB data)
- C1.xlarge EC2 instances

Evaluation : Diurnal Workload Scenario

- Traces obtained from a web-server workload of an "industrial partner"
- Front-end running web serving workload
- Batch client running at max throughput

- Goals
  - Evaluate ability to adapt to dynamic workload patterns
  - Evaluate latency v/s throughput trade-off

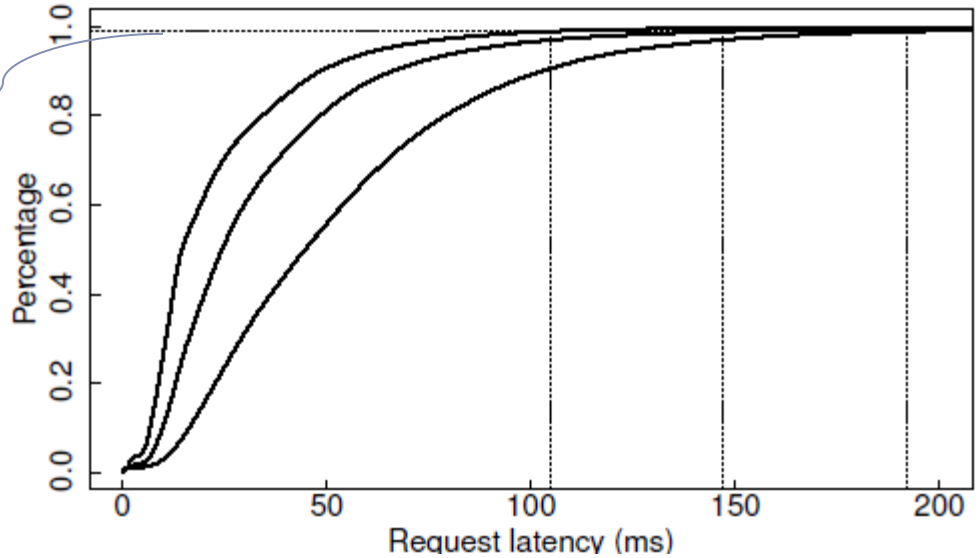
Evaluation : Diurnal Workload Scenario



Front-end throughput according to diurnal pattern

Evaluation : Diurnal Workload Scenario

99% line



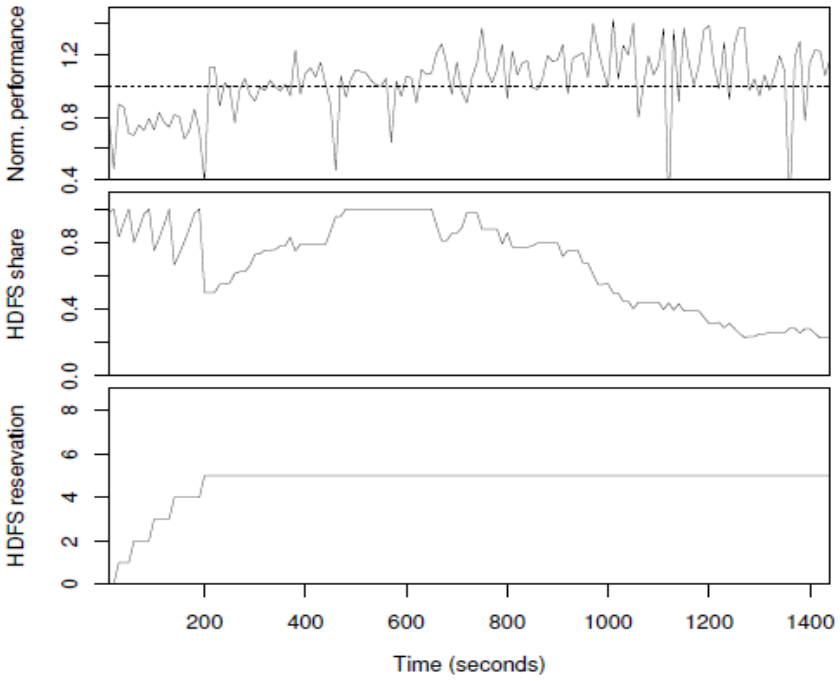
Details/Observations

- 3 experiments with different front-end latency SLOs (100ms, 150ms, 200ms)
- Observe that we miss the 100ms SLO slightly. The 99th percentile latency for this experiment is at 105ms.
- Throughput increases as latency requirements relax. Traditional in rotational storage media

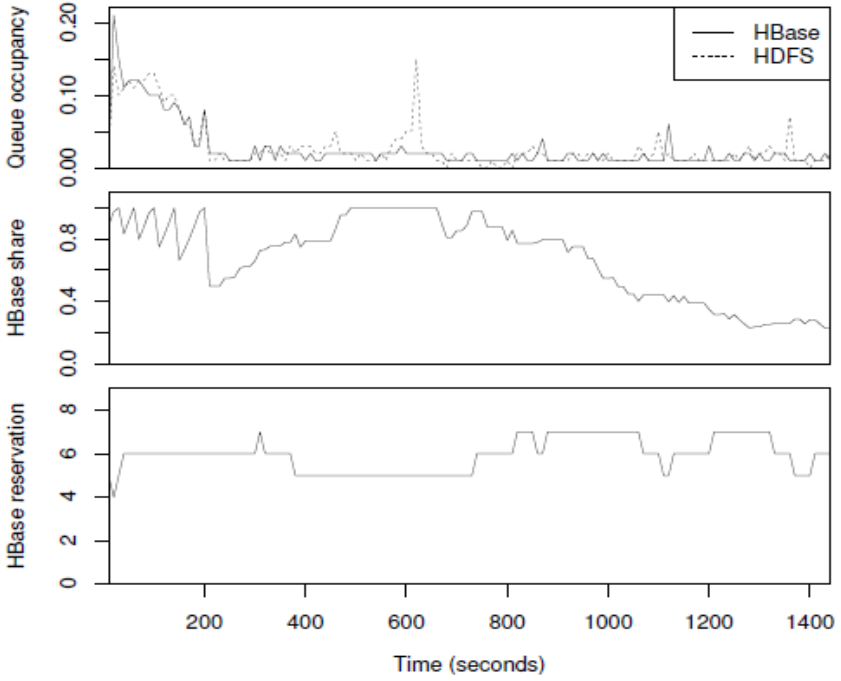
Front-end 99th SLO (in ms)	% of requests meeting latency requirements	Batch Throughput
100	98.77	24.6 queries/s
150	99.72	41.2 queries/s
200	99.88	41.2 queries/s

Evaluation : Diurnal Workload Scenario

Second-level scheduler actions at HBase and HDFS for 100ms SLO



SLO compliance-based algorithm

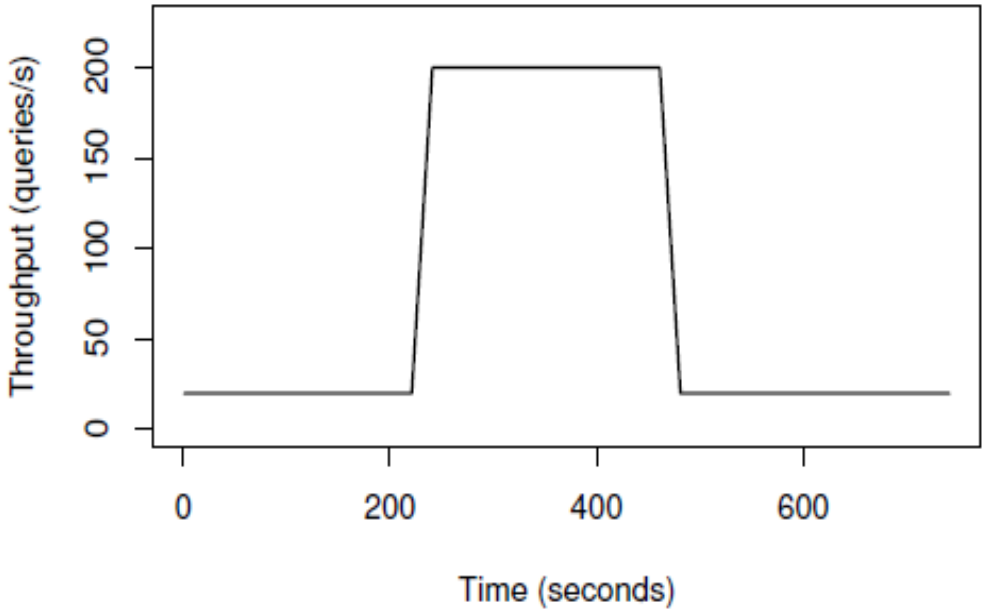


Queue occupancy-based algorithm

Evaluation : Spike Workload Scenario

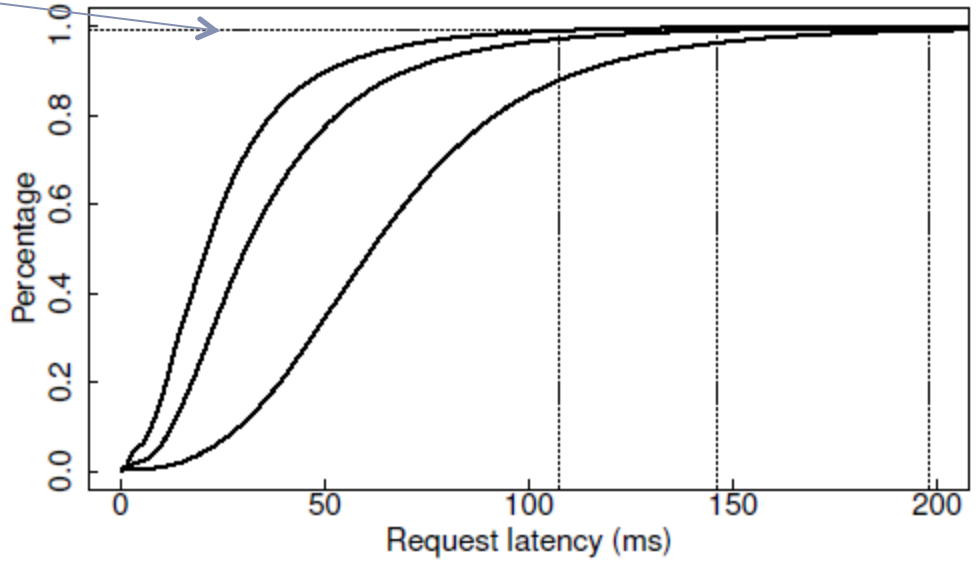
- Goal – evaluate the ability of the system to deal with sudden traffic spikes

The spike workload considered for the experiment



Evaluation : Spike Workload Scenario

99% line



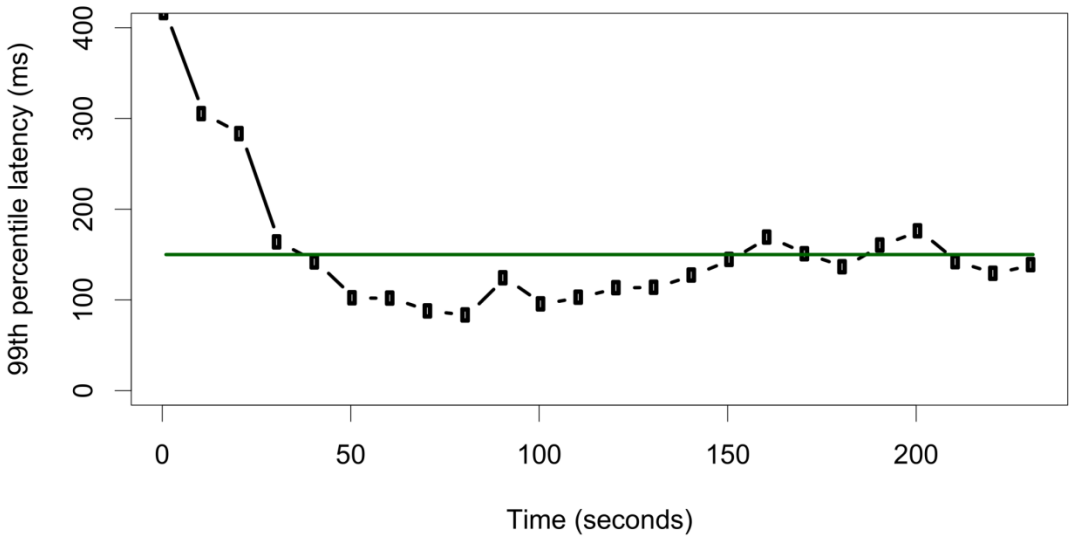
Observations

- 3 experiments with different front-end latency SLOs (100ms, 150ms, 200ms)
- Observe that we miss the 100ms SLO slightly. The 99th percentile latency for this experiment is at 107ms.
- Throughput increases as latency requirements relax. Traditional in rotational storage media
- 200 ms SLO achieves higher throughput than diurnal case.

Front-end latency SLO (ms)	Batch Throughput
100	22.9 queries/s
150	38.4 queries/s
200	45 queries/s

Evaluation : Convergence Time

Workload :
Front-End workload : 100 qps + Unthrottled batch client
Latency SLO placed: 150 ms 99th percentile
Scheduler Interval : 10s



Observations

- 40 secs to fall below SLO
- 150 secs to stabilize.

Convergence for dynamic workloads like diurnal?

Evaluation : Analytics

- 20-node EC2 cluster
- Front-end YCSB client running diurnal pattern
- Batch MapReduce scanning over 386GB data

- Goals:
  - Quantifying benefits of consolidating separate front-end and backend storage clusters
  - Evaluate analytics time and provisioning cost
  - Evaluate SLO compliance

Evaluation : Analytics

Performance Gains:
1.7x speedup +
50% provisioning cost

Scenario	Time	Speedup	Nodes
Unconsolidated	1722s	1.0x	40
Consolidated	1030s	1.7x	20

Front-end 99th SLO	% Requests Meeting SLO
100ms	99.95%

Evaluation : Summary

- Can adapt to changing workload pattern
- Can adapt to spike workload pattern
- Can adjust SLOs to give control over latency v/s throughput tradeoff
- Performance:
  - 1.7 x speedup in batch/analytics jobs
  - 50% provisioning cost

Discussion

- Convergence times on dynamic workload? Is Cake guaranteed to converge?
- SLOs on throughput?
- No experiments on write workloads. Some SLOs were violated for read requests. They could be more severe for writes
- Extensibility to new storage abstractions?
  - Not possible to implement 1st level scheduling criteria at all layers. Chunking not applied at HBase
- Future Work : SLO admission control, Application-level SLOs, use of SSDs, parameter tuning, multiple SLOs

Dominant Resource Fairness: Fair Allocation of Multiple Resource Types

Ali Ghodsi, Matei Zaharia, Benjamin Hindman, Andy Konwinski,
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NSDI 2011

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Presented By

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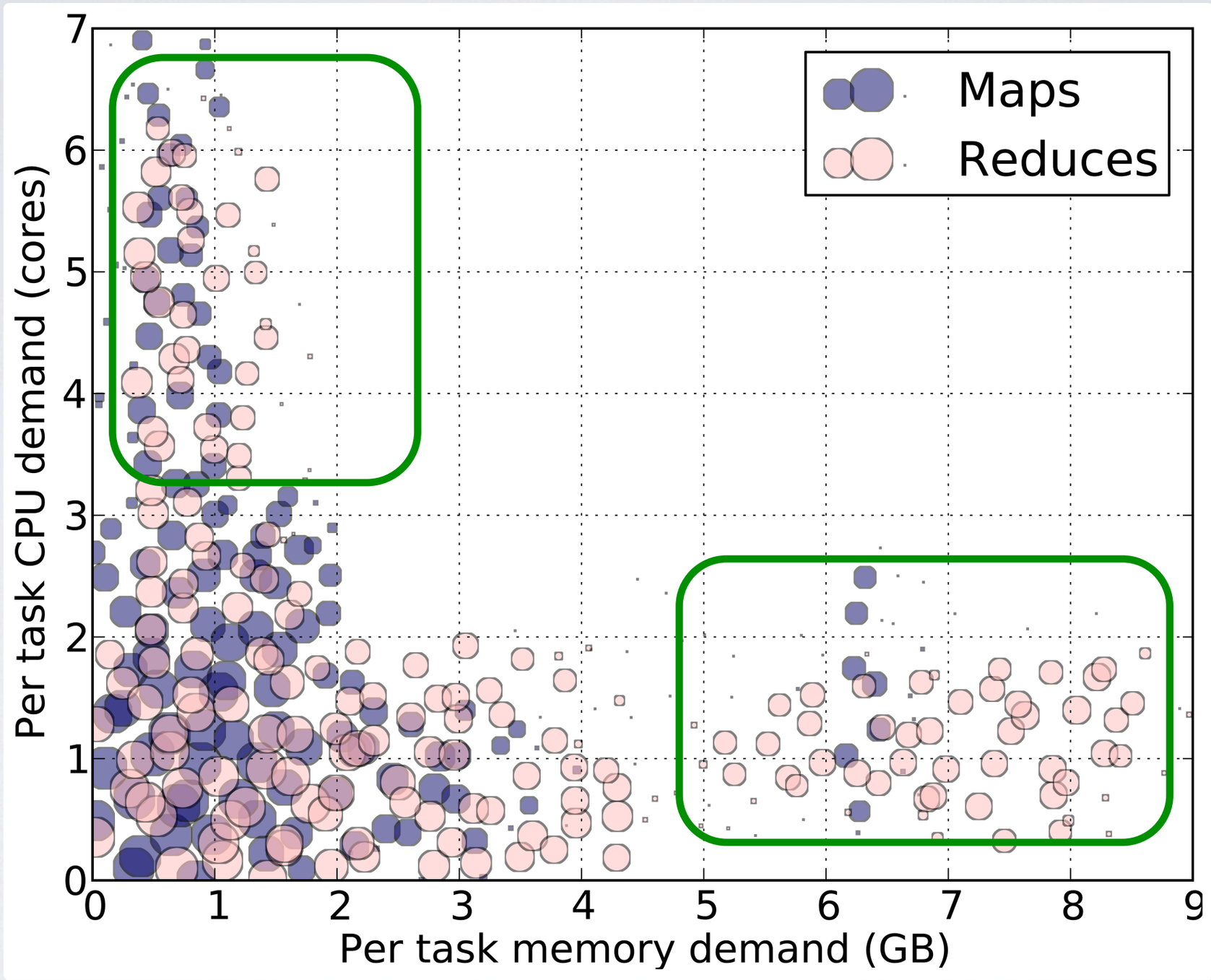
Resource Demands in a Datacenter



One month (Oct 2010) trace of CPU and Memory demands
2000-node Hadoop cluster at Facebook

Schedulers in Practice

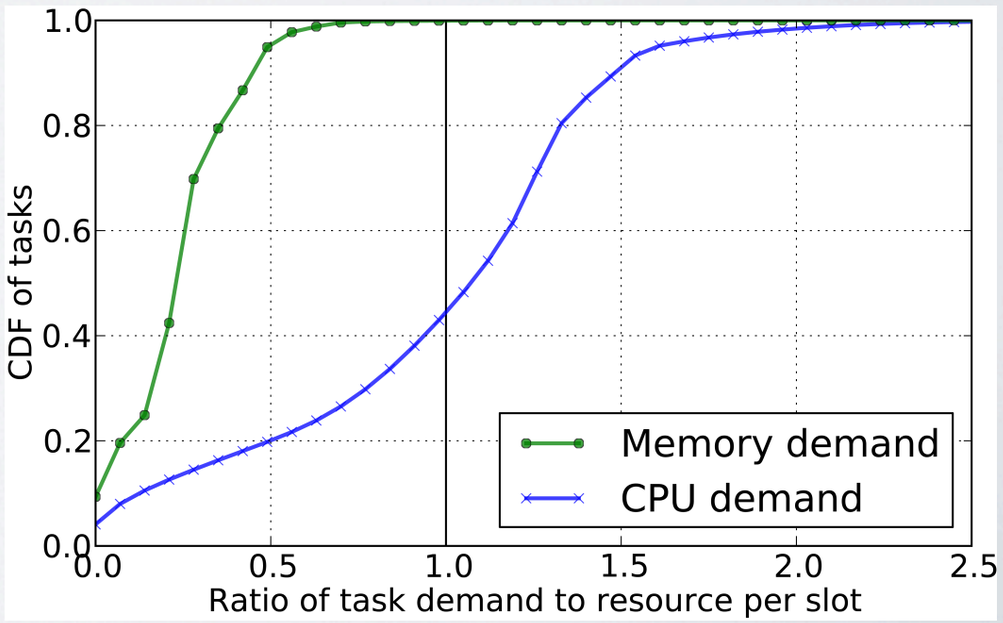
- Slot based schedulers
  - Allocate resources at the granularity of slots
  - Slot is a fixed fraction of a node
  - Agnostic of user demand heterogeneity
- Example
  - Quincy (Dryad)
  - Hadoop's Fair Scheduler
- Outcome?
  - Underutilization
  - Thrashing
  - Users can game the system

It really happens!

- Users game the system (Not strategy-proof)
  - Yahoo! Hadoop cluster allocated more slots for Reduce
    - User launched all his jobs as long reduce phases
  - A "Big" search company provided dedicated machines for jobs that had high utilization
    - Users inserted artificial infinite loops
- Underutilization and Over-utilization
  - CDF of demand to slot ratio in the Facebook example.

    ratio < 1 : Underutilizing

    ratio > 1 : Over-utilizing



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  - A "Big" search company provided dedicated machines for jobs that had high utilization
    - U

60% tasks need more CPU

95% had atleast double of what really required

- Underutilization and Over-utilization
  - CDF of demand to slot ratio in the Facebook example.

    ratio < 1 : Underutilizing

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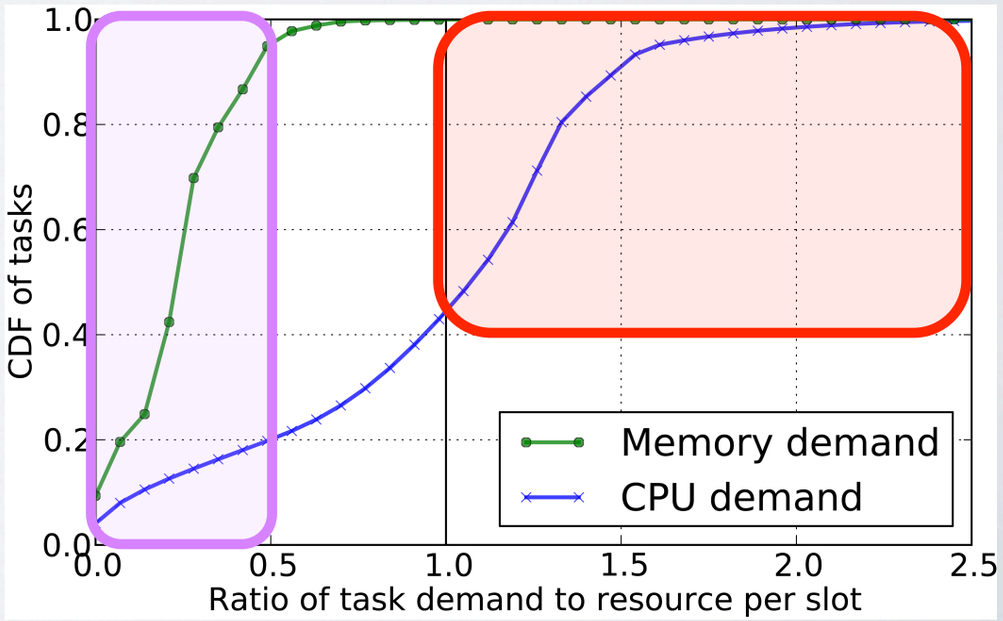

Problem Definition

- How to
  - Fairly Share
  - Multiple type of resources
- Among
  - Different Users
- When users have
  - Heterogeneous demands

Fairness Policy

- Sharing incentive
  - Each user should get at-least 1/n fraction of the cluster
- Strategy-proof
  - One cannot ‘cheat’ by lying about demand
- Envy-free
  - User should not prefer allocation of the other
- Pareto-efficiency
  - Cannot increase allocation of a user without the expense of another

Fairness Policy

- Single resource fairness
  - Reduce to max-min fairness in single resource scenario
- Bottleneck fairness
  - Reduce to max-min on bottleneck resource if it is the only dominant resource
- Population monotonicity
  - A user leaves ➔ Other users allocation do not decrease
- Resource monotonicity
  - Resource added ➔ No users allocation decrease

Single Resource Fairness

- Max-Min Fairness strategy
  - Allocate chunks in the order of increasing demand
  - Nobody gets more than what it asks
  - All unsatisfied demands get an equal share

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*Animation adapted from https://theone.ece.cmu.edu/drupal/sites/default/files/papers/Dominant%20Resource%20Fairness.pptx

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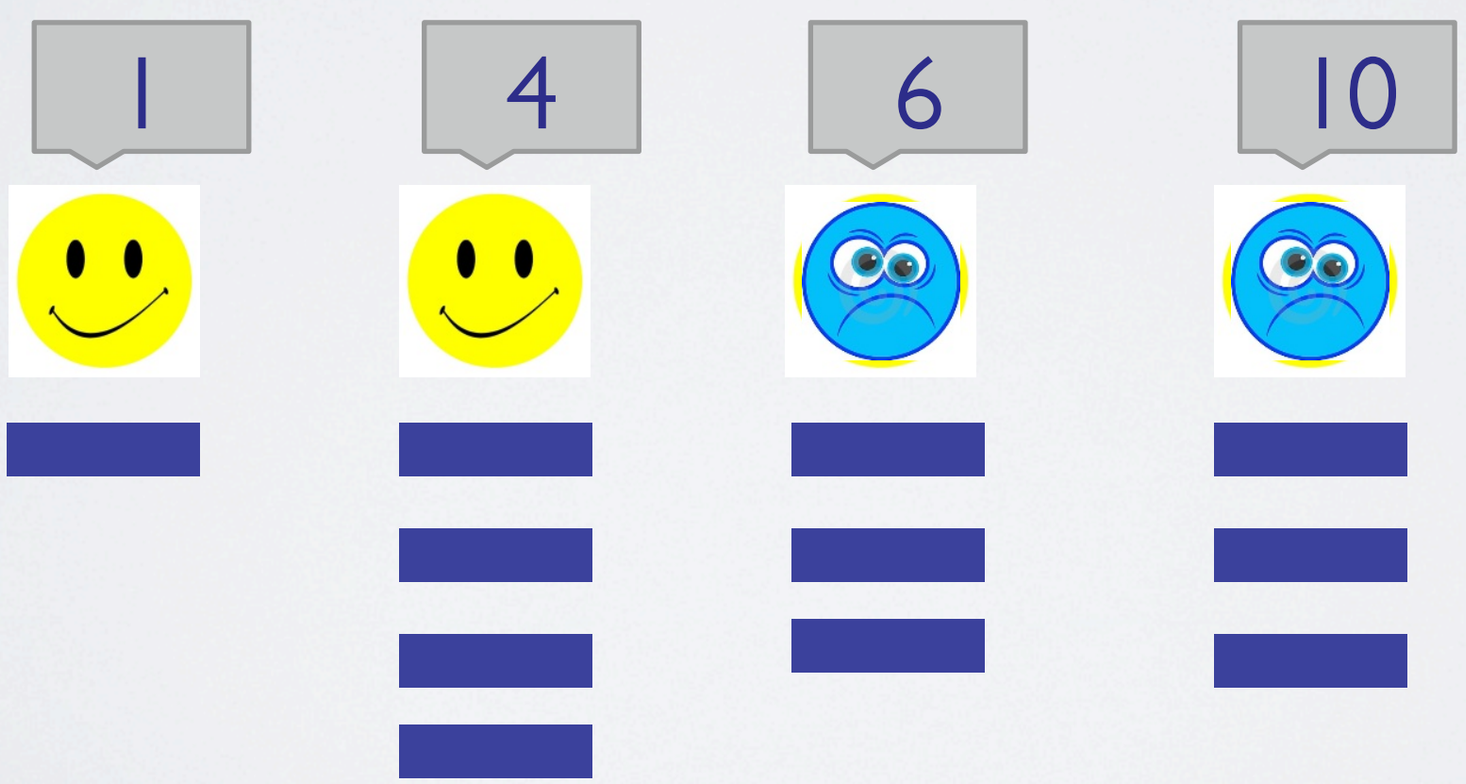

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Single Resource Fairness

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Maximizes the Minimum share of the unsatisfied ones

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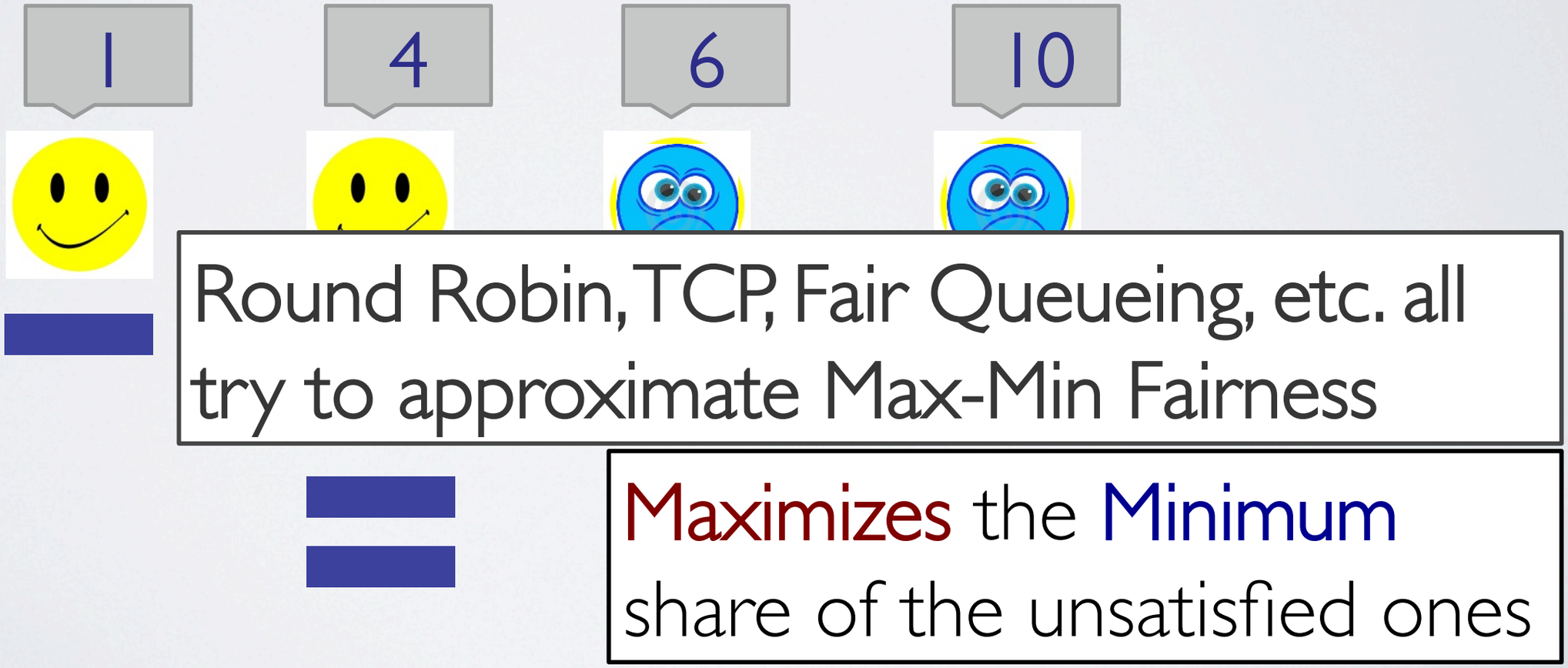

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Single Resource Fairness

- Max-Min Fairness strategy
  - Allocate chunks in the order of increasing demand
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Only "reasonable" mechanism with Sharing incentive and Strategy-proof properties

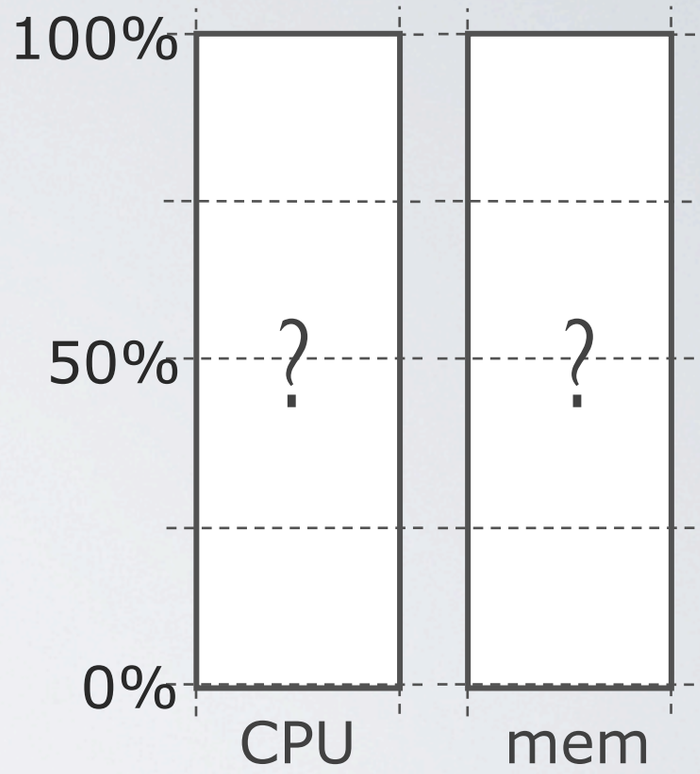
Round Robin, TCP, Fair Queueing, etc. all try to approximate Max-Min Fairness

Maximizes the Minimum share of the unsatisfied ones

*Animation adapted from https://theone.ece.cmu.edu/drupal/sites/default/files/papers/Dominant%20Resource%20Fairness.pptx

Max-Min Fairness

- Multiple Resource
  - 2 resources: CPUs & memory
  - User 1 wants <1 CPU, 4 GB> per task
  - User 2 wants <3 CPU, 1 GB> per task
  - What is a fair allocation?

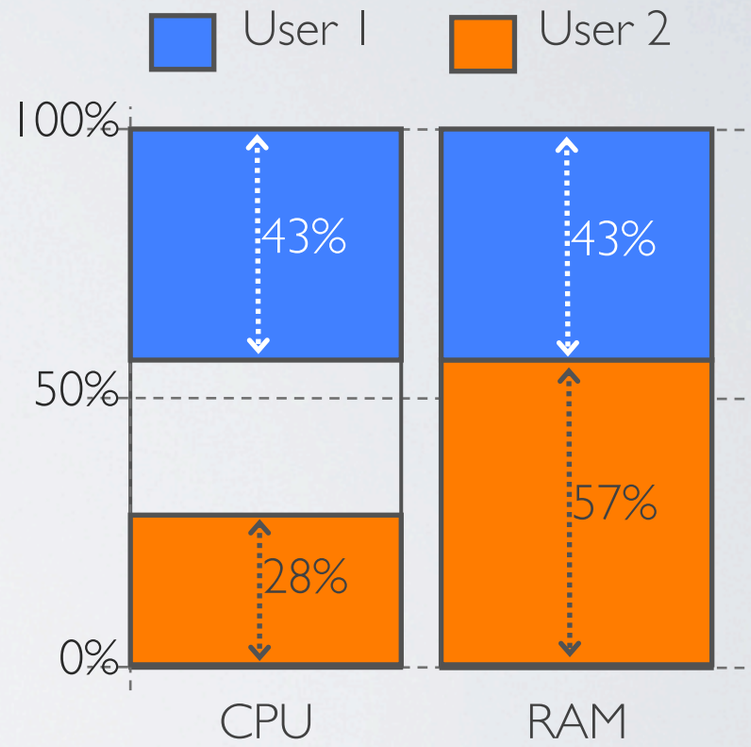


- Users have tasks according to a demand vector
  - Not needed in practice, can simply measure actual consumption
  - Assume divisible resources

Slide adapted from: John Kubiatowicz and Anthony D. Joseph, Advanced Topics in Computer Systems, Lecture 13, http://www.eecs.berkeley.edu/~kubitron/cs262

A Natural Policy: Asset Fairness

- Asset Fairness
  - Equalize each user's *sum of resource shares*
- Cluster with 70 CPUs, 70 GB RAM
  - U_1 needs <2 CPU, 2 GB RAM> per task
  - U_2 needs <1 CPU, 2 GB RAM> per task



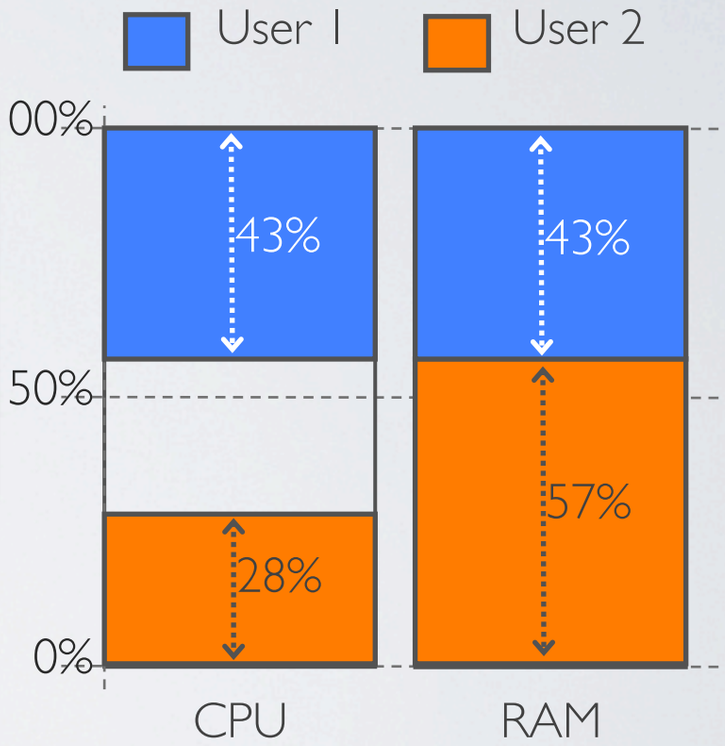
- Asset fairness yields
  - U_1: 15 tasks: 30 CPUs, 30 GB (Σ=60)
  - U_2: 20 tasks: 20 CPUs, 40 GB (Σ=60)

A Natural Policy: Asset Fairness

- Asset Fairness
  - Equalize each user's *sum of resource shares*
- Cluster with 70 CPUs, 70 GB RAM

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 (Σ=60)
  - U_2: 20 tasks: 20 CPUs, 40 GB (Σ=60)

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)

Dominant Resource Fairness

Example:

Total resources: <9 CPU, 18 GB>

User 1 demand: <1 CPU, 4 GB> dominant res: mem

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

$$\max(x, y)$$

$$s.t$$

$$x + 3y \leq 9$$

$$4x + y \leq 18$$

$$\frac{2x}{9} = \frac{y}{3}$$

$$\therefore x = 3, y = 2$$

Dominant Resource Fairness

Example:

Total resources: <9 CPU, 18 GB>

User 1 demand: <1 CPU, 4 GB> dominant res: mem

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

$\max(x, y)$ x tasks from User1, y tasks from User2

$s.t$

$x + 3y \leq 9$ CPU Constraint

$4x + y \leq 18$ Memory Constraint

$\frac{2x}{9} = \frac{y}{3}$ DRF Equalize

User 1: <3 CPU, 12 GB>, User2: <6 CPU, 2 GB>

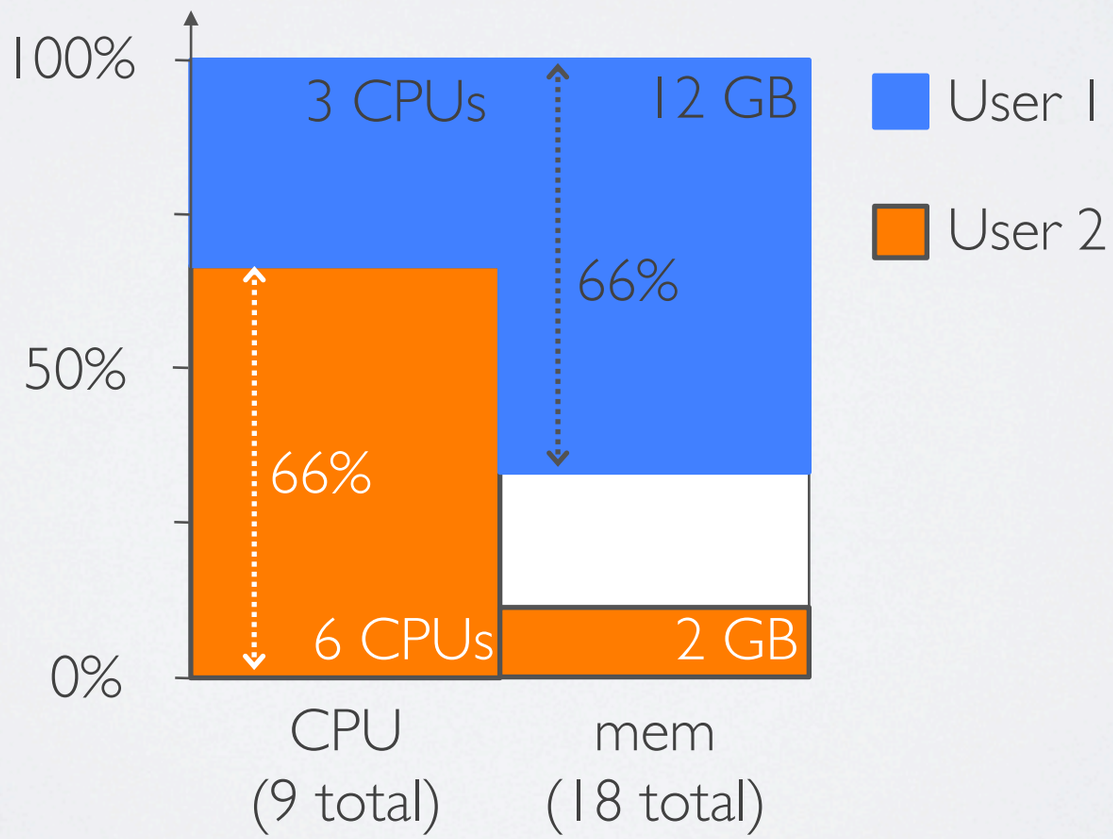
Dominant Resource Fairness

Example:

Total resources: <9 CPU, 18 GB>

User 1 demand: <1 CPU, 4 GB> dominant res: mem

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



Online DRF Scheduler

Whenever there are available resources and tasks to run:

Schedule a task to the user with smallest dominant share

- Easy computation
  - O(log *n*) time per decision using binary heaps
- How to determine demand vectors?

Alternative: CEEI

- Approach
    - Set prices for each good
    - Let users buy what they want
- How do we determine the right prices for different goods?
    - 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
- Not strategy-proof!

CEEI

$$\max(x.y)$$

$$s.t$$

$$x+3y\le 9$$

$$4x+y\le 18$$

$$\therefore x=\frac{45}{11},y=\frac{18}{11}$$

CEEI

$\max(x.y)$ Product of Nash Products

$s.t$

$x + 3y \leq 9$ CPU Constraint

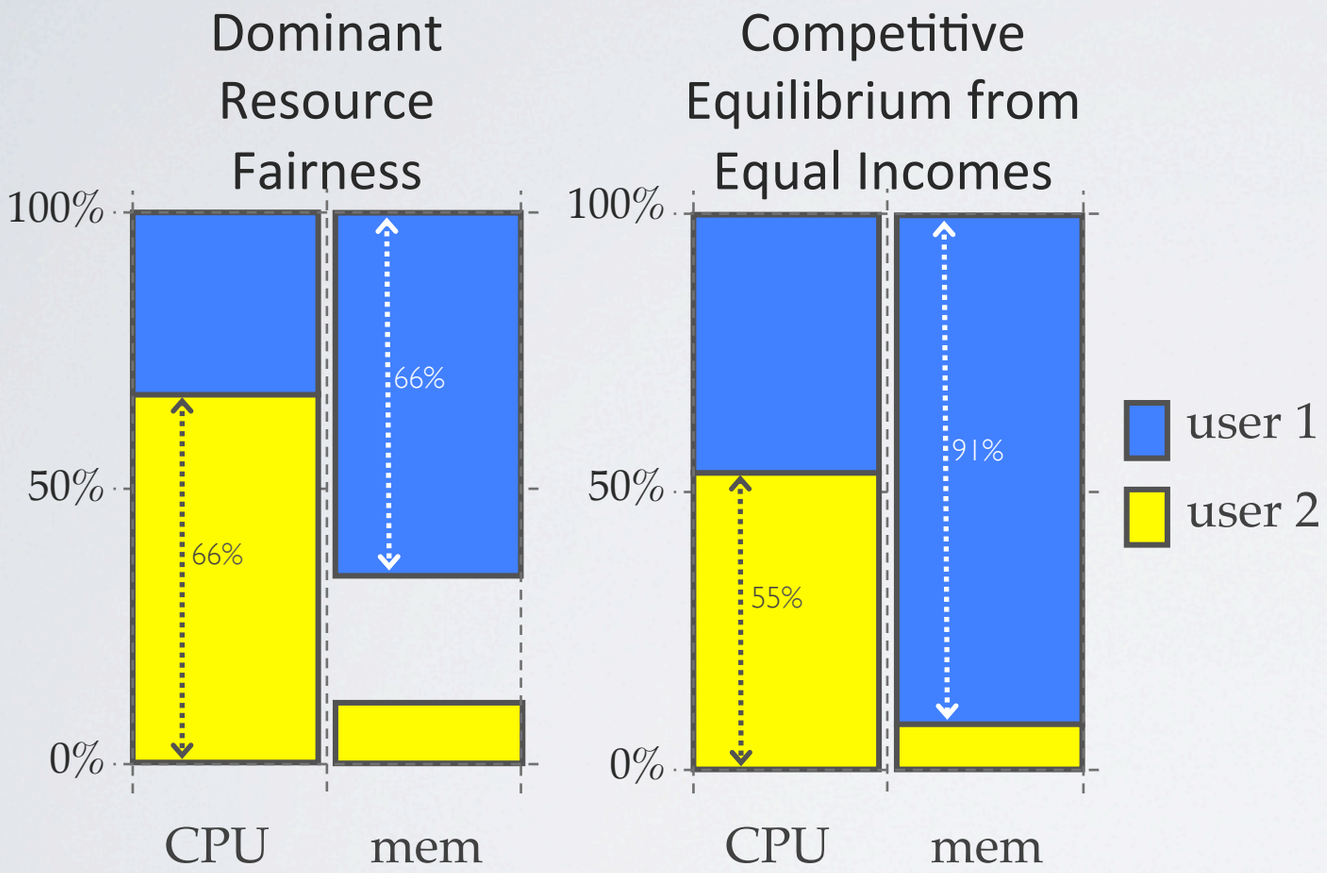
$4x + y \leq 18$ Memory Constraint

$$\therefore x = \frac{45}{11}, y = \frac{18}{11}$$

User 1: <4.1 CPU, 16.4 GB>,
User2: <4.9 CPU, 1.6 GB>

DRF vs CEEI

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



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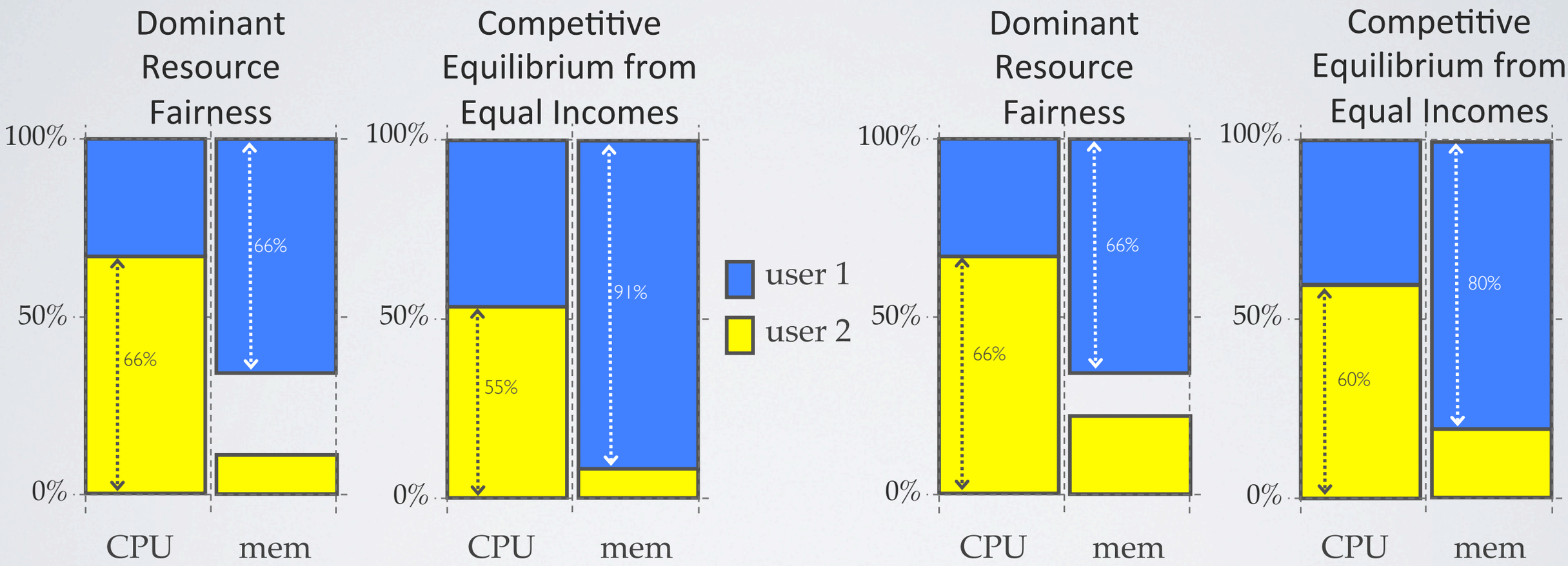

User 1: <1 CPU, 4 GB> User 2: <3 CPU, 2 GB>

User 2 increased her share of both CPU and memory

Slide adapted from: John Kubiatowicz and Anthony D. Joseph, Advanced Topics in Computer Systems, Lecture 13, http://www.eecs.berkeley.edu/~kubitron/cs262

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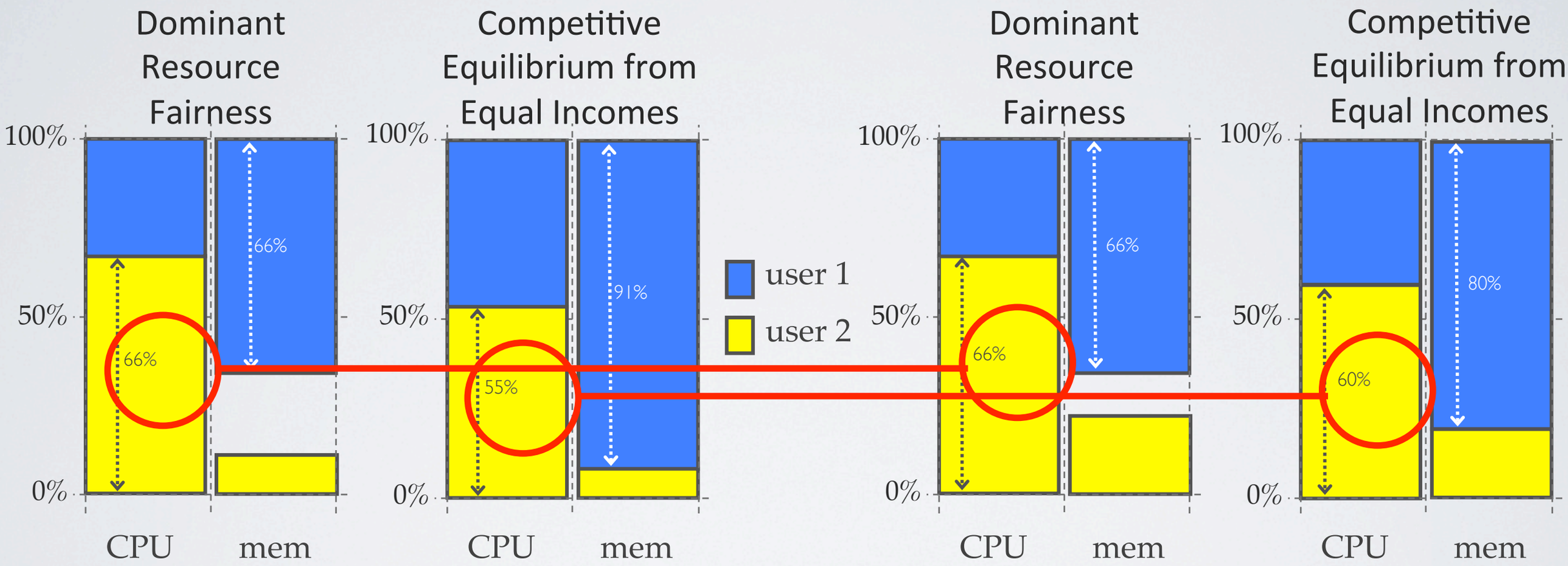

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User 2 increased her share of both CPU and memory

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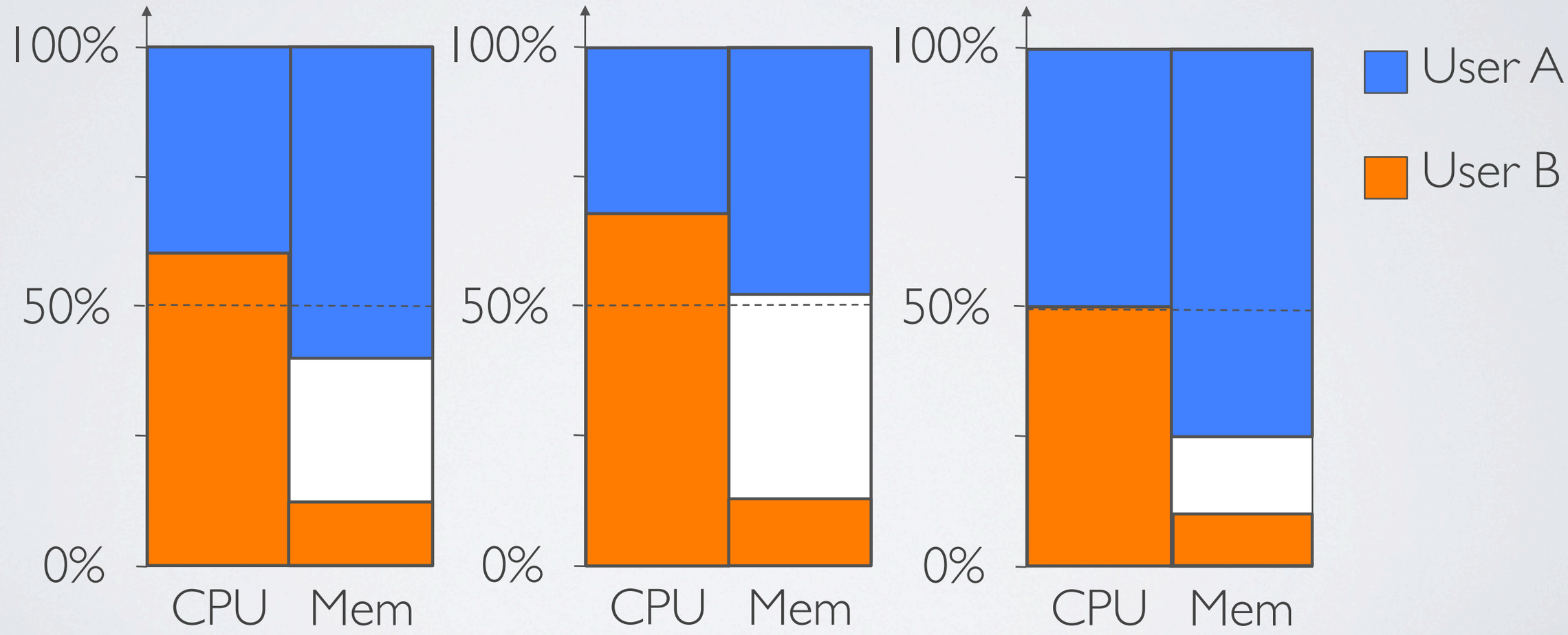
DRF vs Asset Fairness vs CEEI

- Resources <1000 CPUs, 1000 GB>
- 2 users A: <2 CPU, 3 GB> and B: <5 CPU, 1 GB>



a) DRF b) Asset Fairness c) CEEI

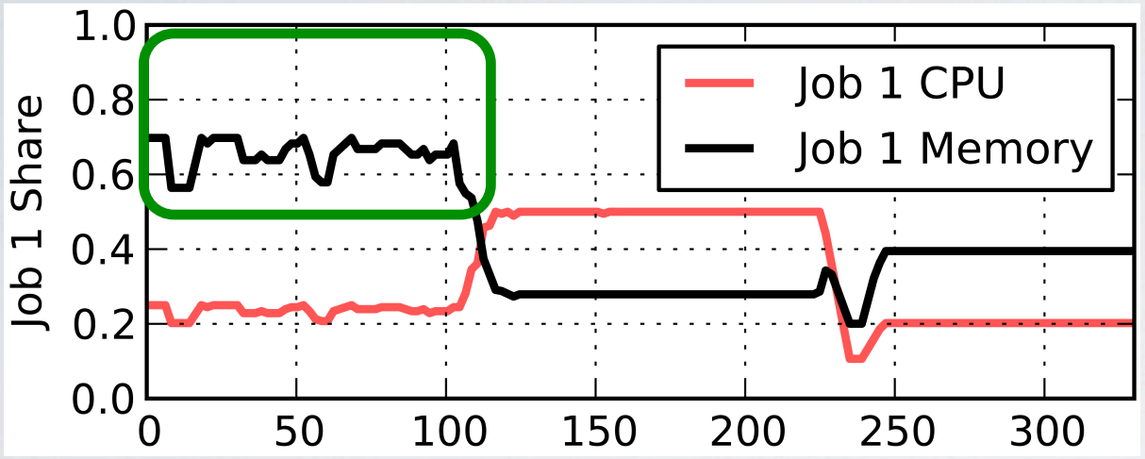
Comparison

Property	Asset Fairness	CEEI	DRF
Sharing Incentive	✗	✓	✓
Strategy-Proofness	✓	✗	✓
Envy-freeness	✓	✓	✓
Pareto efficiency	✓	✓	✓
Single Resource Fairness	✓	✓	✓
Bottleneck Fairness	✗	✓	✓
Population Monotonicity	✓	✗	✓
Resource Monotonicity	✗	✗	✗

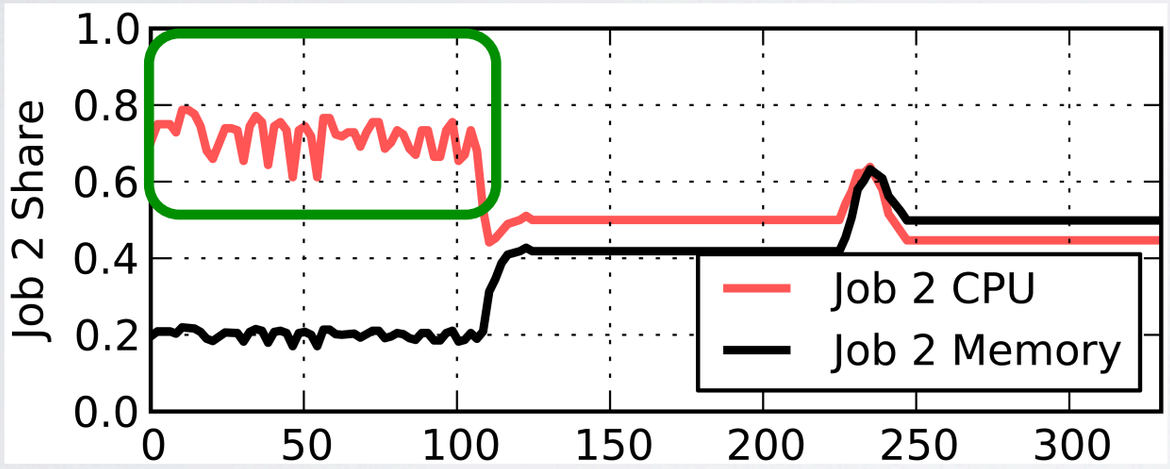
Evaluation

- Micro-experiments
    - 48 node Mesos cluster on EC2
    - Extra large instances with 4 CPU cores and 15 GB of RAM
        - Two jobs, one CPU intensive, one memory intensive
            - Compare DRF with current Hadoop scheduler
- Macro-benchmark through simulations
    - Simulate Facebook trace with DRF and current Hadoop scheduler

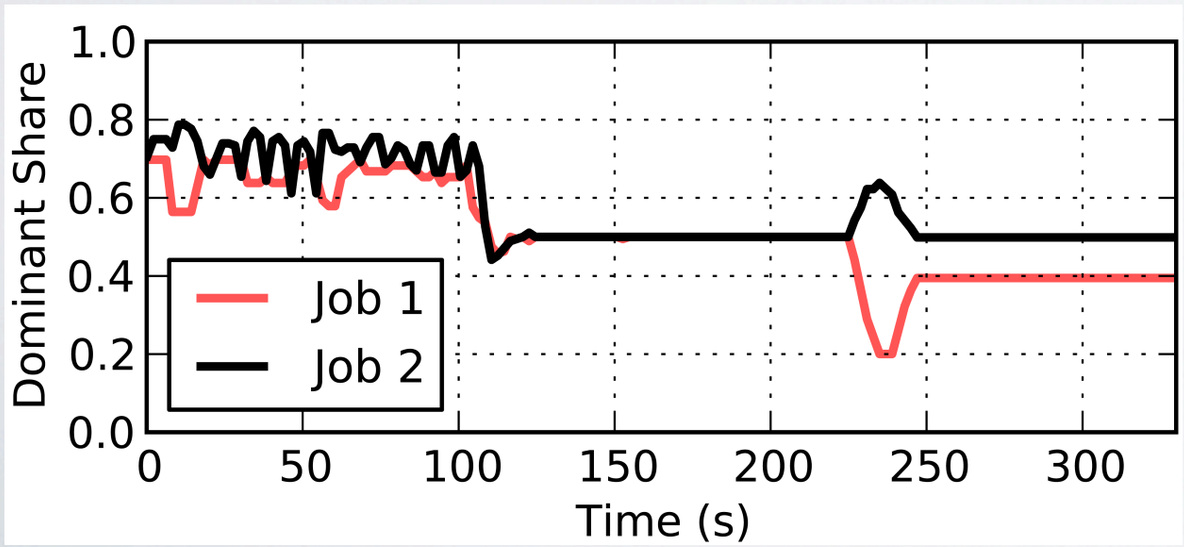
Micro Experiments



Job 1's Share



Job 2's share

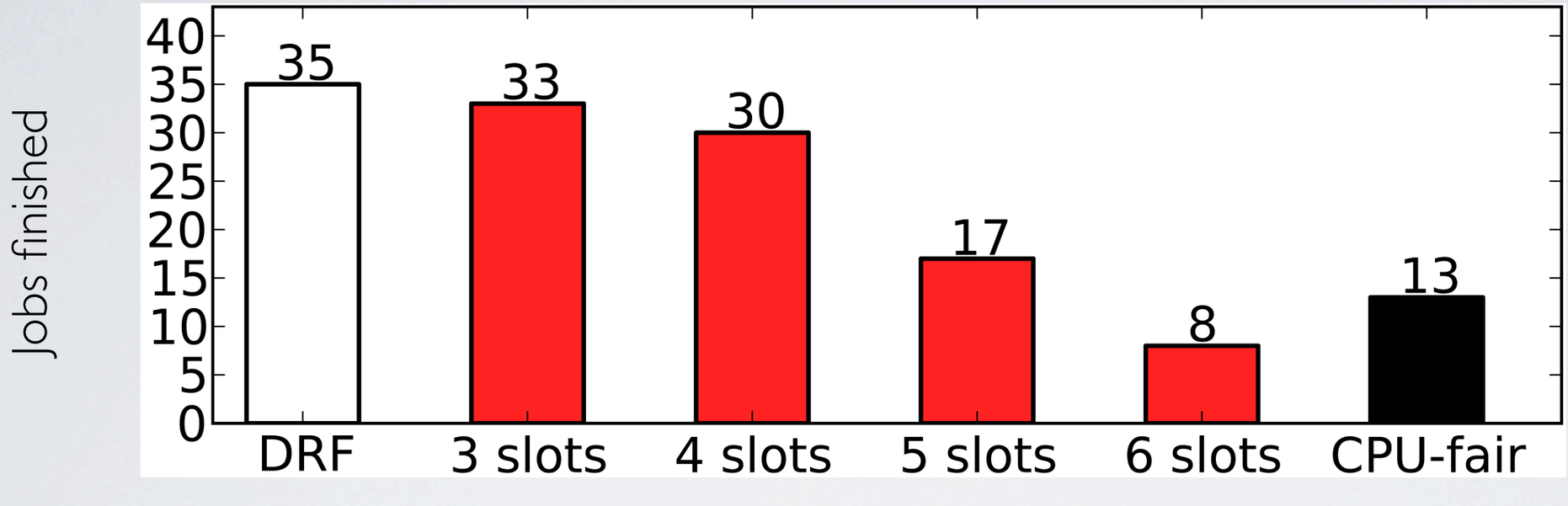


Dominant Share

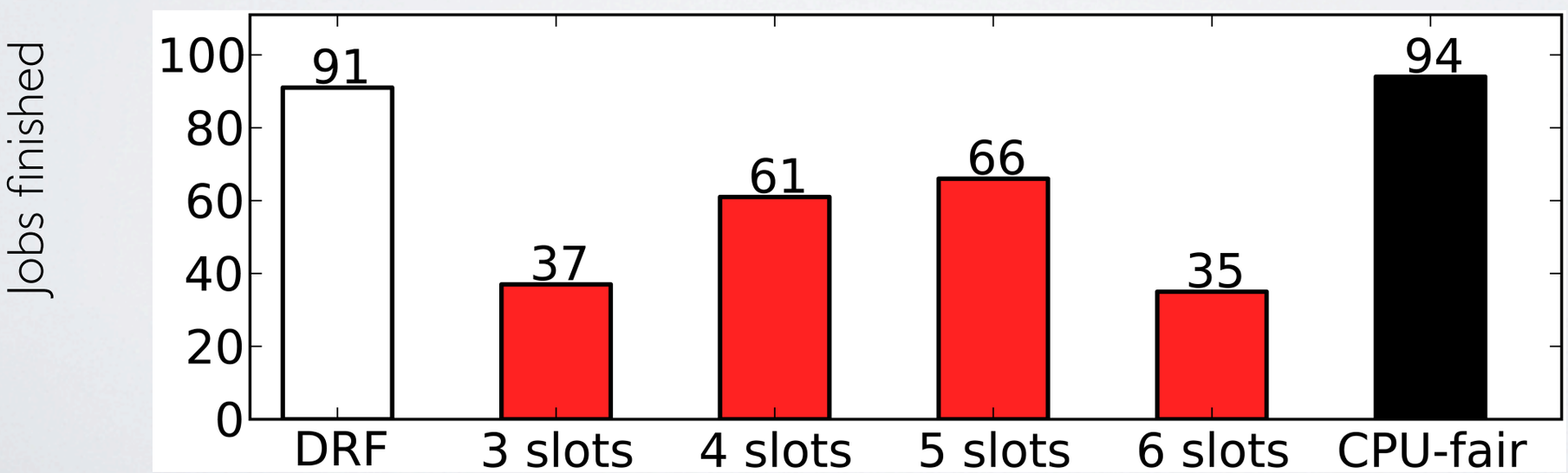
Hadoop Fair Scheduler Experiments

- Hadoop Fair Scheduler/capacity/Quincy
  - Each machine consists of k *slots* (e.g. k=2~6)
- Run at most one task per slot
  - apply max-min fairness to slot-count

Micro Experiments

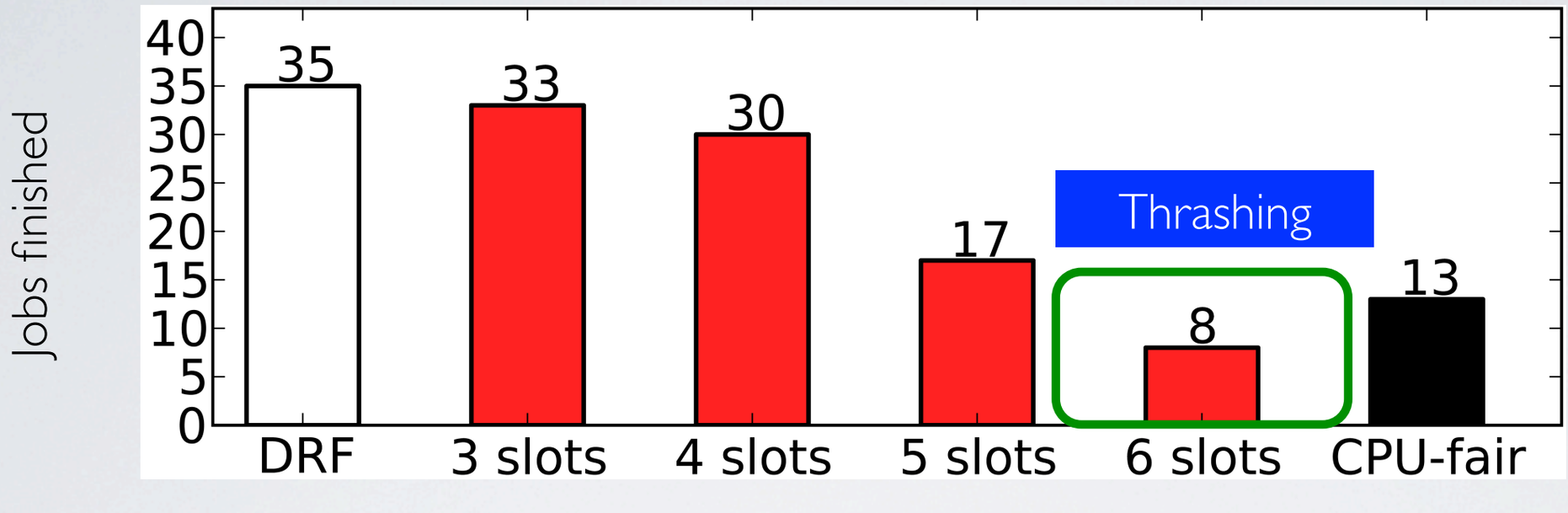


Number of large jobs completed

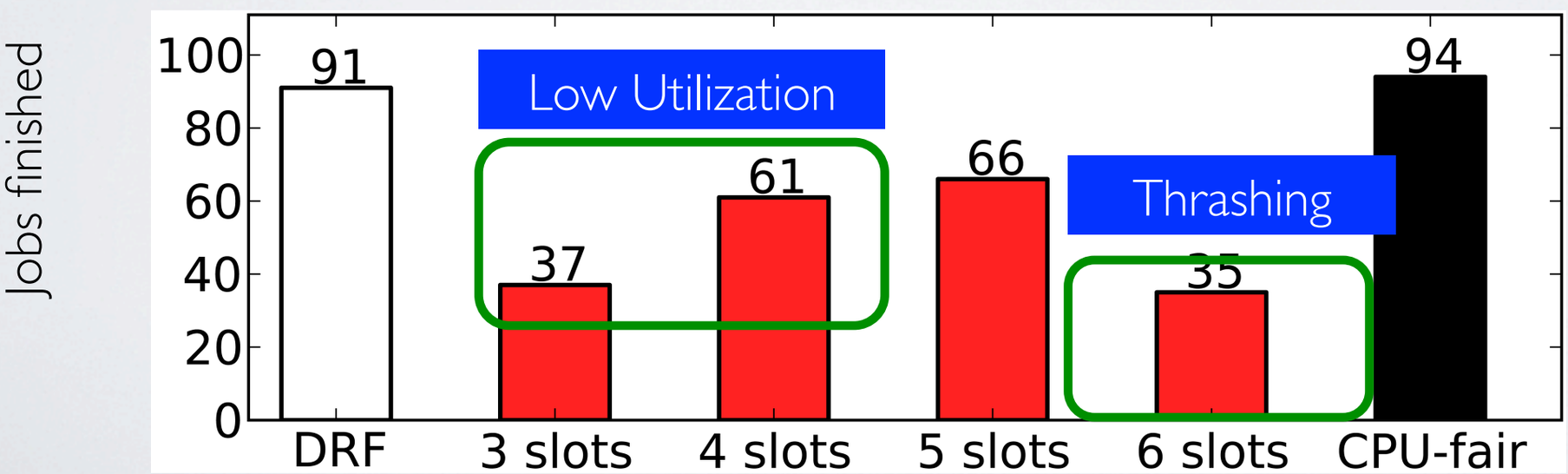


Number of small jobs completed

Micro Experiments

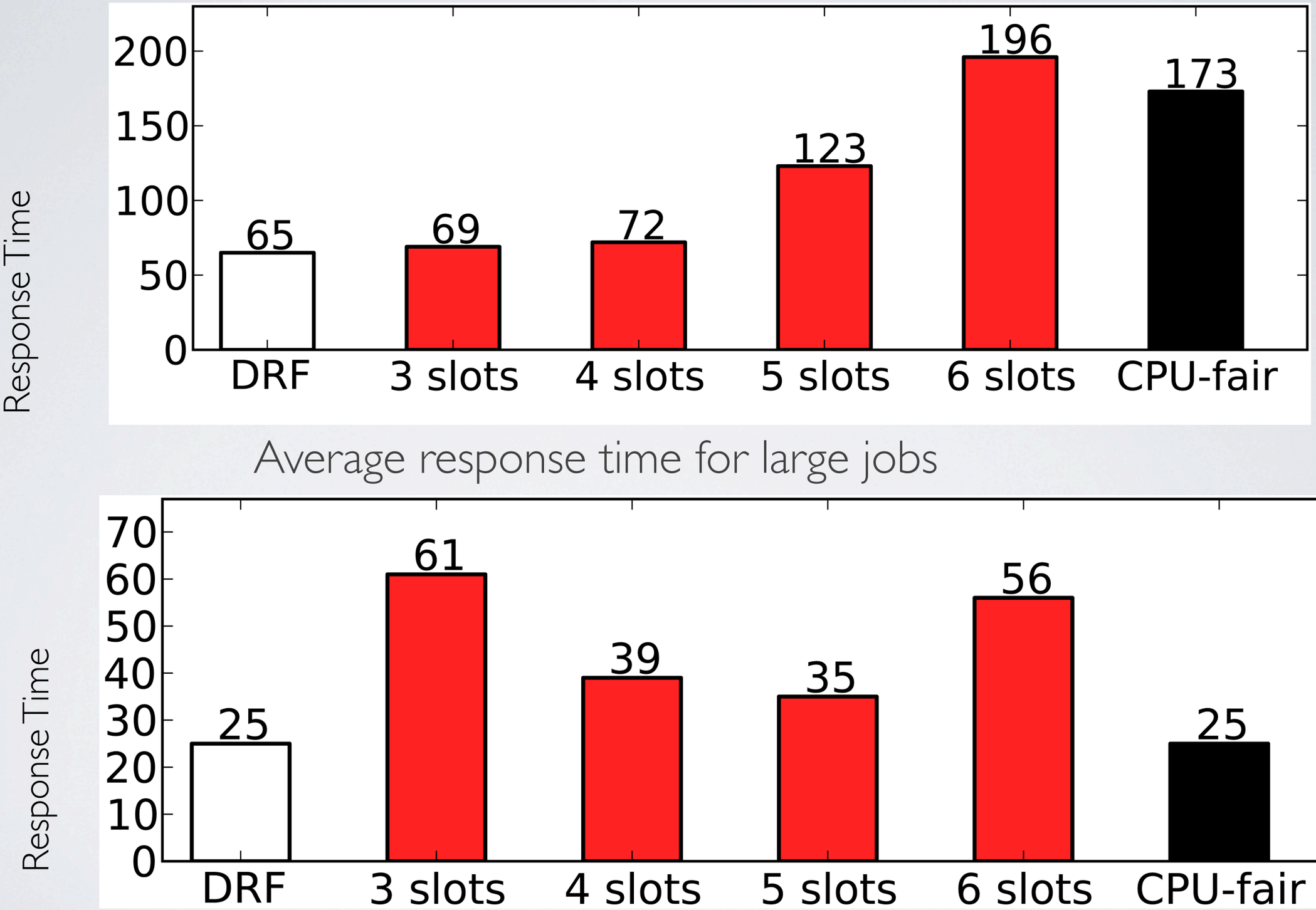


Number of large jobs completed



Number of small jobs completed

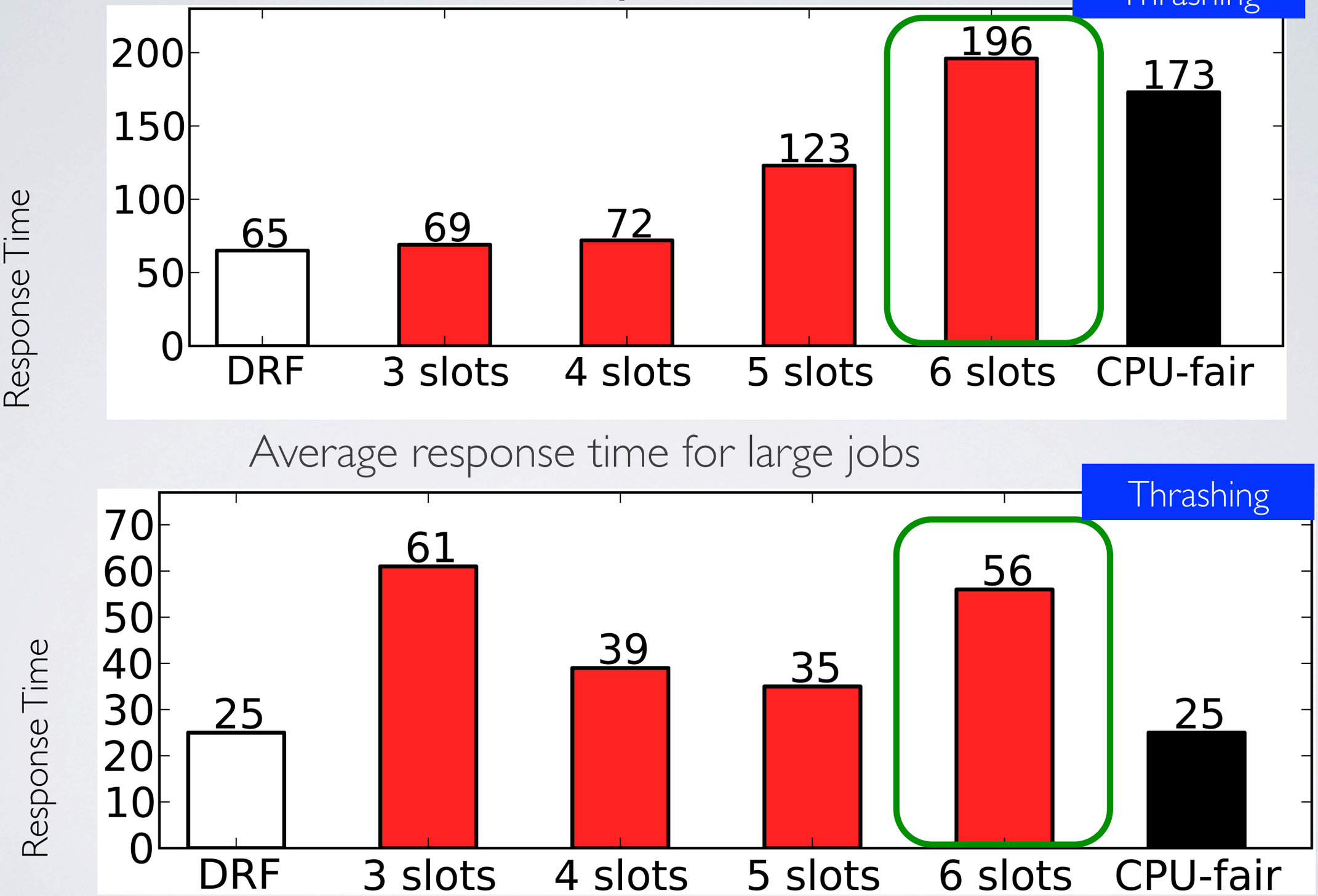
Micro Experiments



Average response time for large jobs

Average response time for small jobs

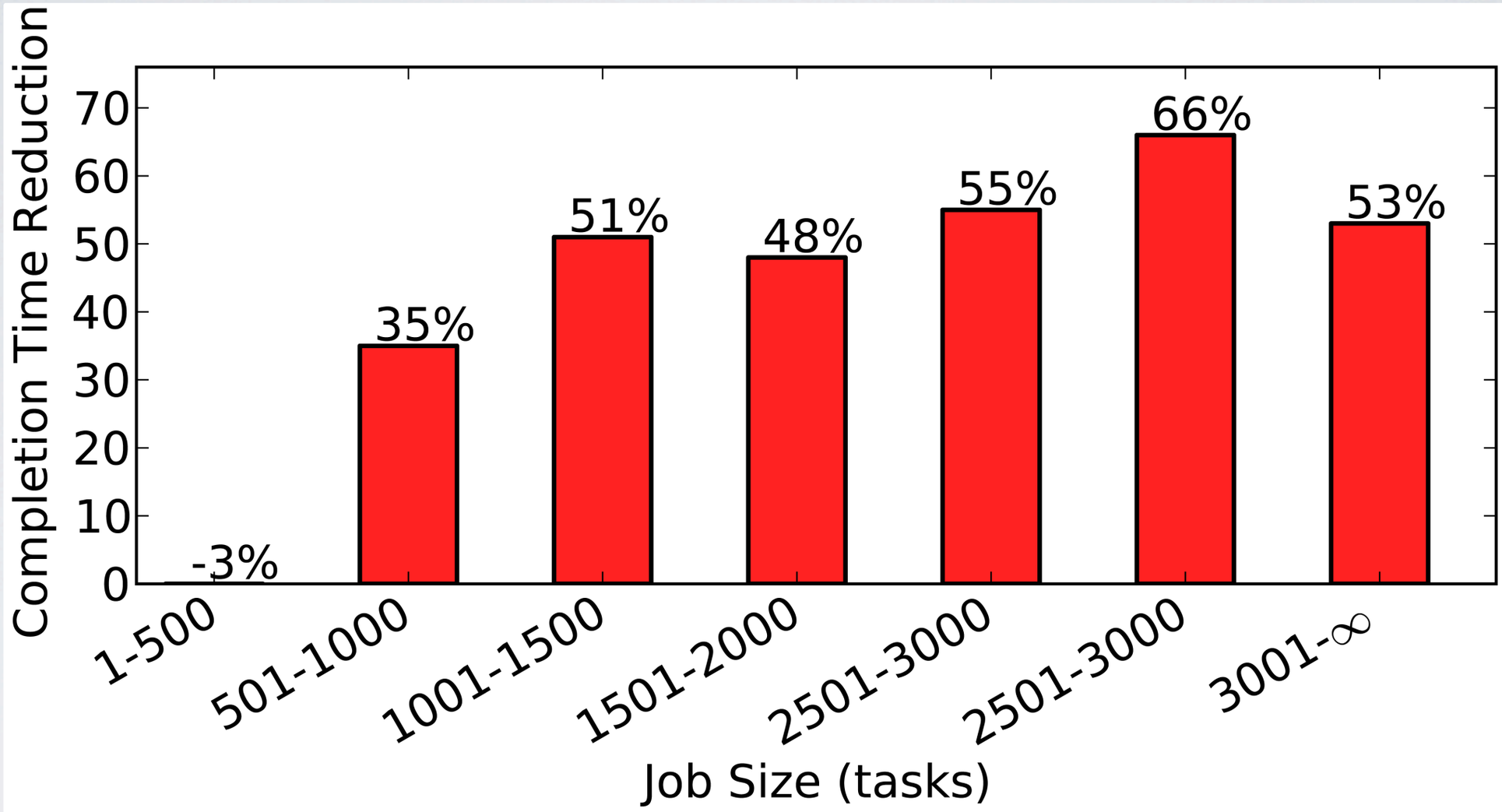
Micro Experiments



Average response time for large jobs

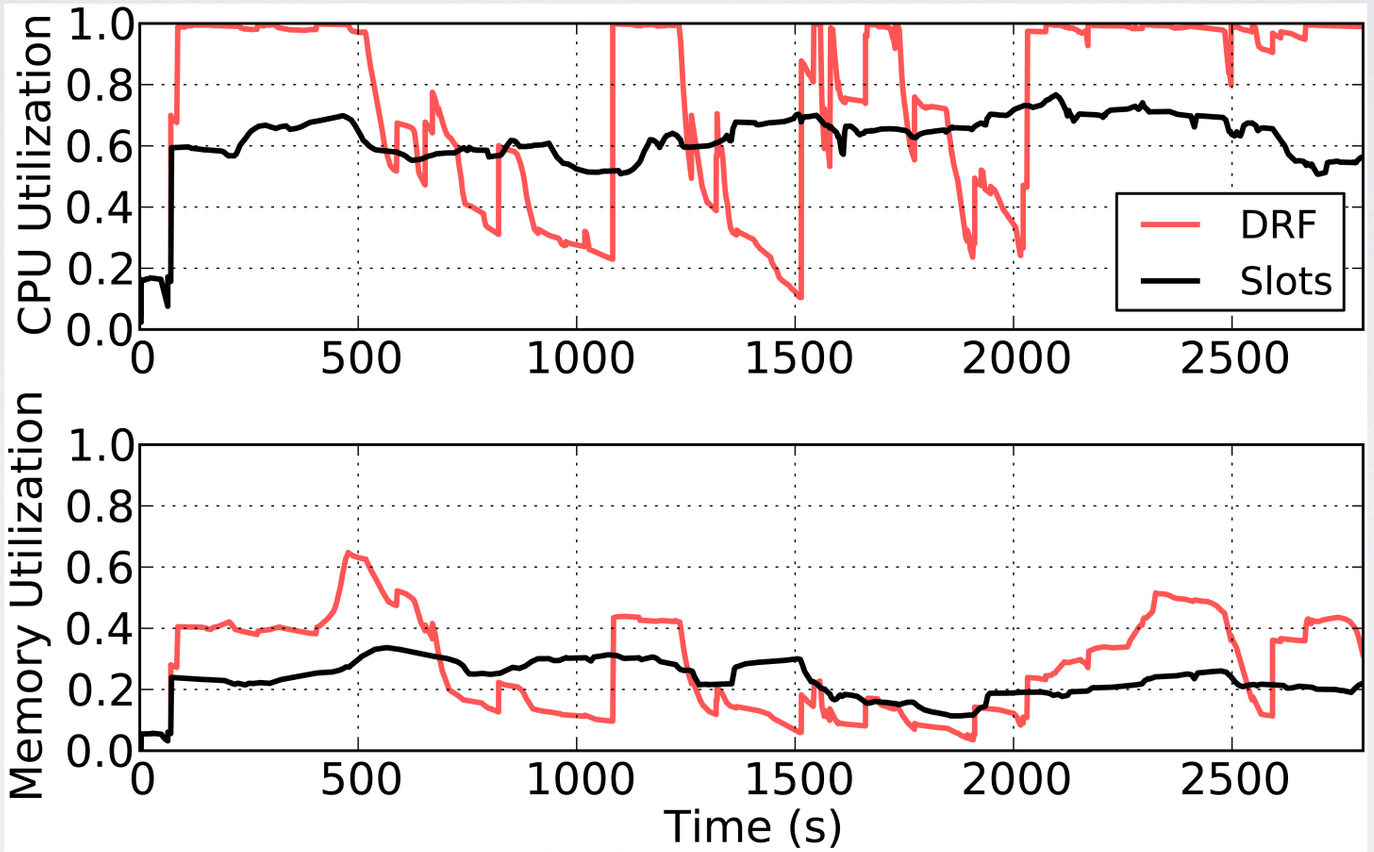
Average response time for small jobs

Macro Benchmarks



Average reduction of the completion times for different job sizes for a trace from a Facebook Hadoop cluster

Utilization



CPU and Memory utilization for DRF and slot fairness for a trace from Facebook Hadoop Cluster

Discussions

- Fair sharing vs. Meeting Deadlines? (Indy)
  - Is the job throughput only concern?
- What is the cloud specific requirement behind this research?
  - Why don't we require / apply this fairness in a single machine OS?
  - Is multi-tenancy of a cloud the only reason for this scheduling?
- Only Memory and CPU ! IO, Network, Disk is absent from experiments?
  - Hadoop stores the intermediate results in persistence storage
- They are considering exclusive resources. What about shared resources in the Datacenter? How to share the network?
  - Multi-Resource Fair Queueing for Packet Processing: SIGCOMM 2012
  - Schedule multiple resources in a Middleboxes (IDS, VPN, Firewall, Wan Optimizer etc)
- What about the task placement constraints?
- Integrate DRF with Hadoop?
- Leaves some resource unutilized
- Adding more resources to the system may decrease the allocations for existing users.
  - Proved in the paper that satisfying everything is not possible