

# Dominant Resource Fairness: Fair Allocation of Multiple Resource Types



Ali Ghodsi, Matei Zaharia  
Benjamin Hindman, Andy Konwinski,  
Scott Shenker, Ion Stoica  
University of California, Berkeley

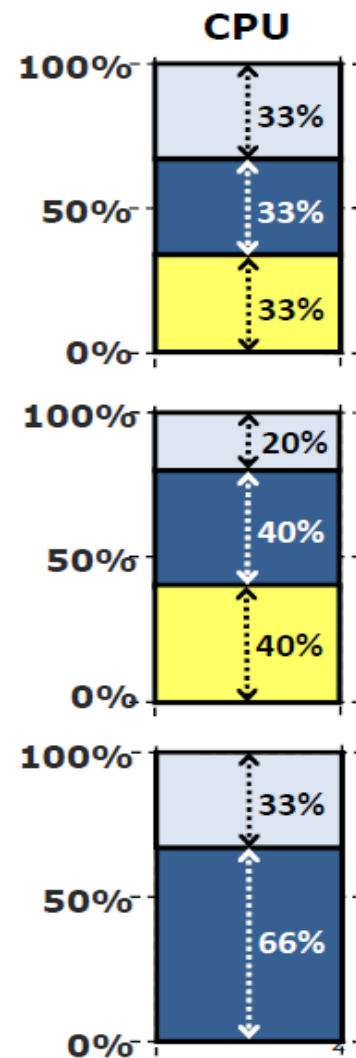
NSDI'11



# What is fair sharing?



- $n$  users want to share a resource
  - Solution:  
Allocate each  $1/n$  of the shared resource
- Generalized by max-min fairness
  - Handles if a user wants less than its Fair share
- Generalized by weighted max-min fairness
  - Give weights to users according to importance





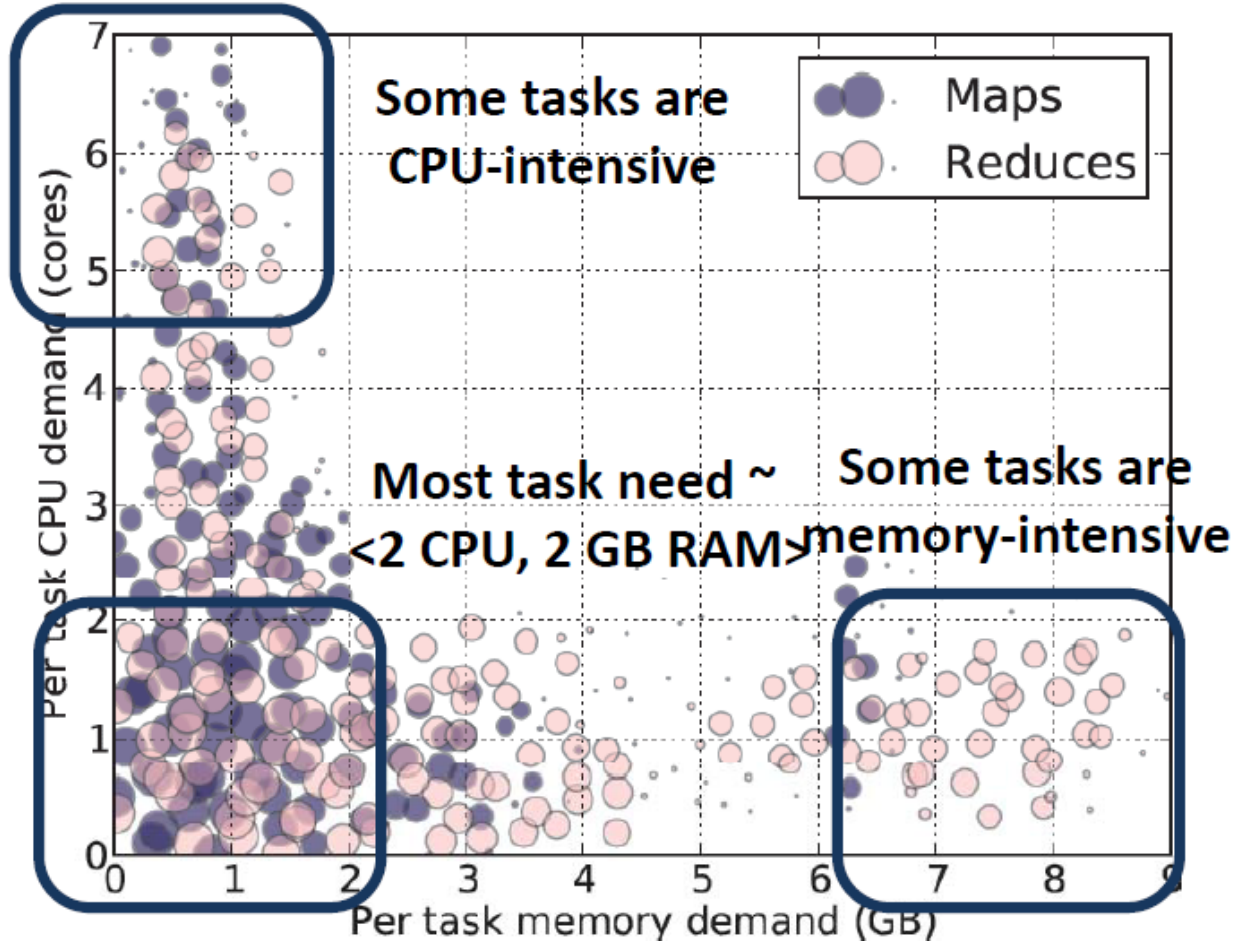
# Why is max-min fairness not enough?



- Job scheduling in datacenters is not only about CPUs
  - Jobs consume CPU, memory, disk, and I/O
- Does this pose any challenge



# Heterogeneous Resource Demands

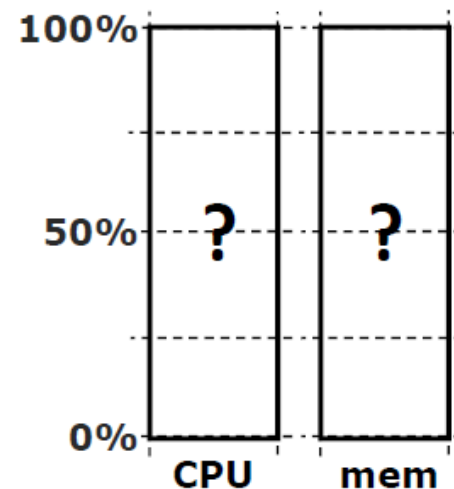
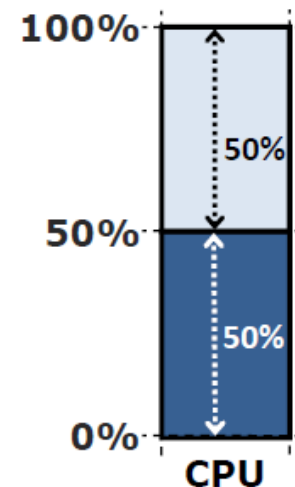


2000-node Hadoop Cluster at Facebook

# Problem



- Single resource example
  - 1 resource: 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





# Problem definition



- How to fairly share multiple resources when users have heterogenous demands on them?





# Allocation Properties

- Share Guarantee
  - Every user should get  $1/n$  of at least one resource
- Strategy proofness
  - A user should not be able to increase her allocation by lying about her demand vector
- Envy freeness
- Pareto efficiency





# Dominant Resource Fairness

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

- Example:

Total resources:  $\langle 10 \text{ CPU}, 4 \text{ GB} \rangle$

User 1's allocation:  $\langle 2 \text{ CPU}, 1 \text{ GB} \rangle$

Dominant resource is memory as  $1/4 > 2/10$

- A user's dominant share is the fraction of the dominant resource she is allocated
  - User 1's dominant share is 25%







# Dominant Resource Fairness(2)

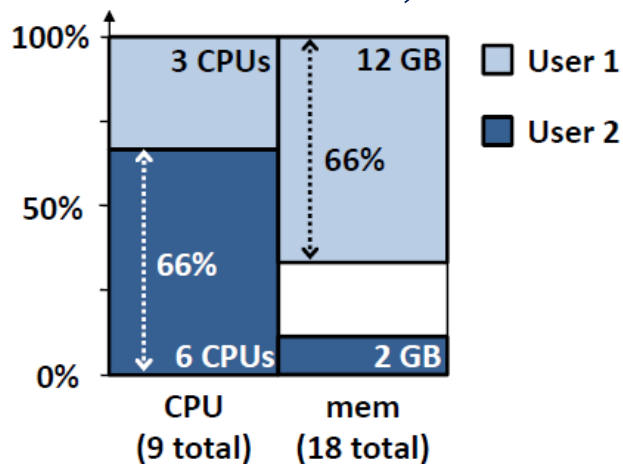


- Apply max-min fairness to dominant shares
- Equalize the dominant share of the users
  - Example:

Total resources:  $\langle 9 \text{ CPU}, 18 \text{ GB} \rangle$

User 1 demand:  $\langle 1 \text{ CPU}, 4 \text{ GB} \rangle$  dom res: mem

User 2 demand:  $\langle 3 \text{ CPU}, 1 \text{ GB} \rangle$  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

Schedule	User <i>A</i>		User <i>B</i>		CPU total alloc.	RAM total alloc.
	res. shares	dom. share	res. shares	dom. share		
User <i>B</i>	$\langle 0, 0 \rangle$	<b>0</b>	$\langle 3/9, 1/18 \rangle$	1/3	3/9	1/18
User <i>A</i>	$\langle 1/9, 4/18 \rangle$	<b>2/9</b>	$\langle 3/9, 1/18 \rangle$	1/3	4/9	5/18
User <i>A</i>	$\langle 2/9, 8/18 \rangle$	4/9	$\langle 3/9, 1/18 \rangle$	<b>1/3</b>	5/9	9/18
User <i>B</i>	$\langle 2/9, 8/18 \rangle$	<b>4/9</b>	$\langle 6/9, 2/18 \rangle$	2/3	8/9	10/18
User <i>A</i>	$\langle 3/9, 12/18 \rangle$	<b>2/3</b>	$\langle 6/9, 2/18 \rangle$	<b>2/3</b>	1	14/18





# Compare with Asset Fairness and CEEI



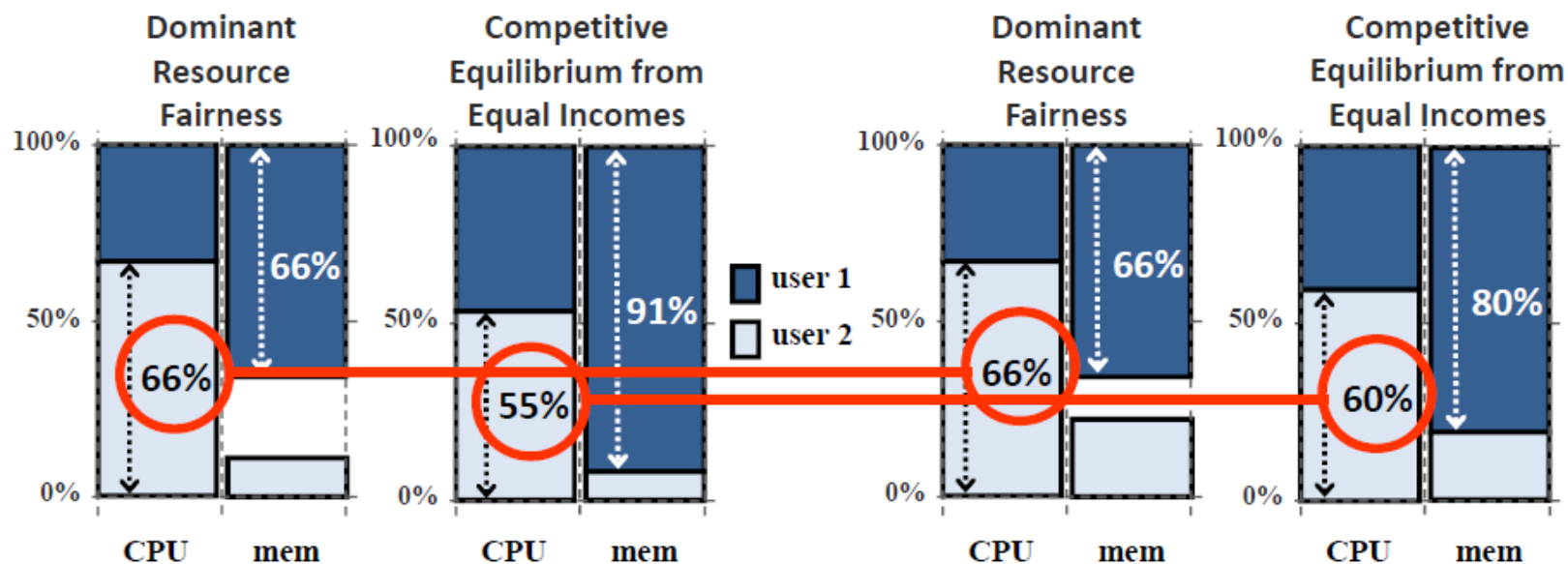
- Asset Fairness: Equalize each user's sum of resource shares
- CEEI: Competitive Equilibrium from Equal Incomes
  - Give each user  $1/n$  of every resource
  - Let users trade in a perfectly competitive market





# DRF vs CEEI

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

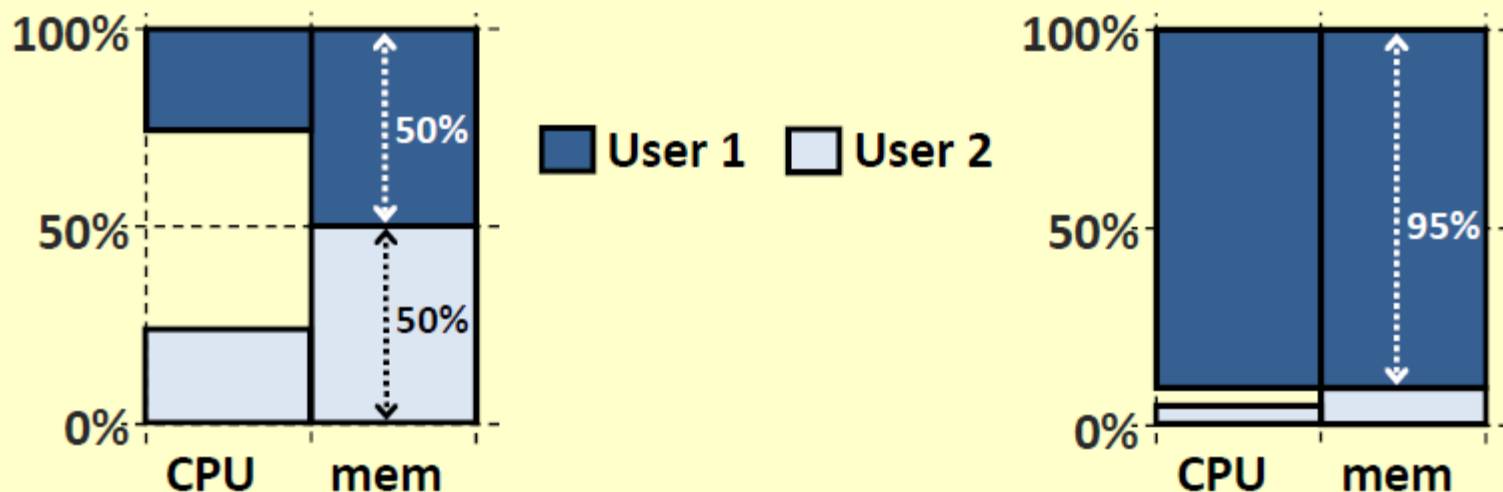


- User 1: <1 CPU, 4 GB> User 2: <3 CPU, 2 GB>
  - User 2 increased her share of both CPU and memory



# Gaming Utilization-Optimal Schedulers

- Cluster with **<100 CPU, 100 GB>**
- 2 users, each demanding **<1 CPU, 2 GB>** per task

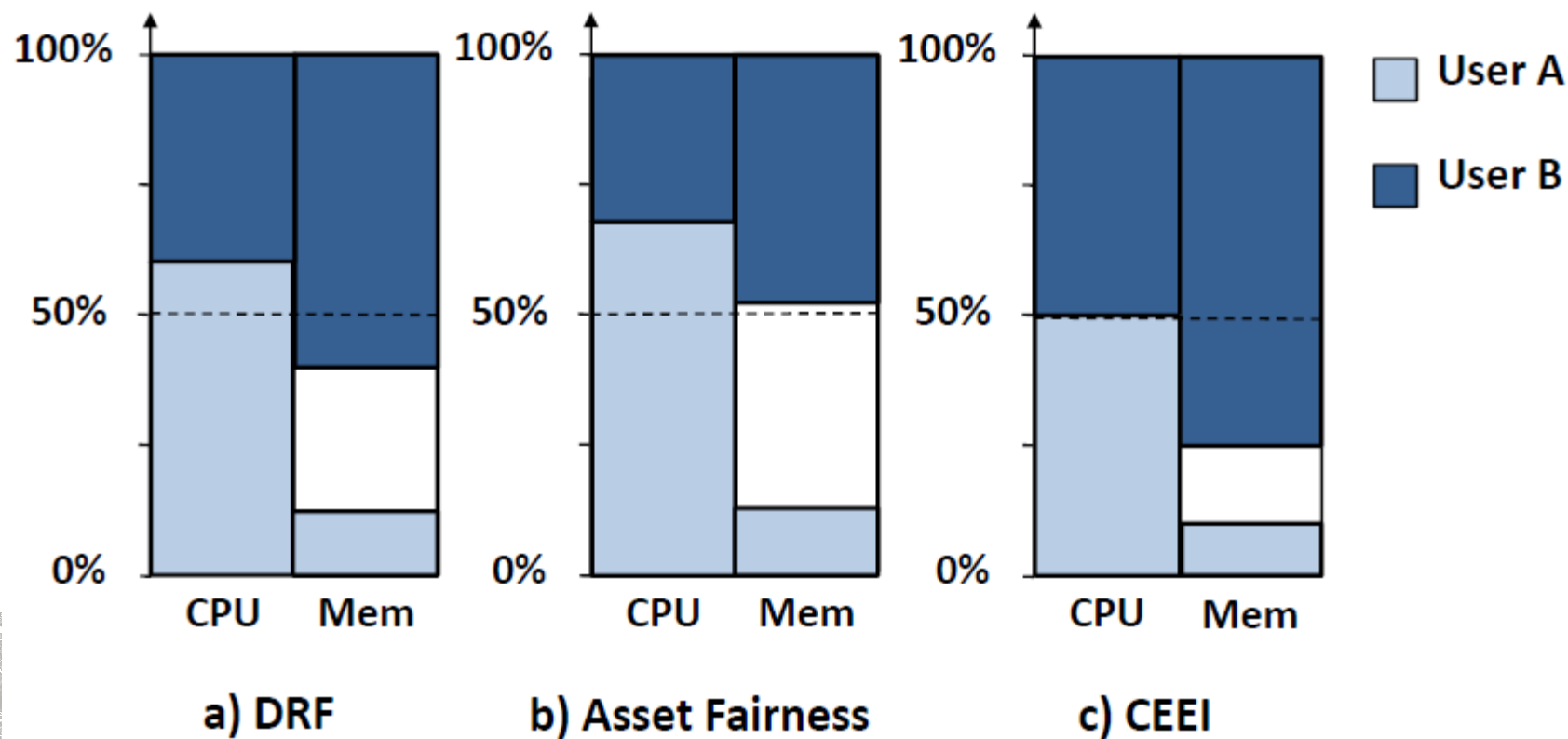


- User 1 lies and demands **<2 CPU, 2 GB>**
- Utilization-Optimal scheduler prefers user 1



# Example of DRF vs Asset vs CEEI

- Resources  $\langle 1000 \text{ CPUs}, 1000 \text{ GB} \rangle$
- 2 users A:  $\langle 2 \text{ CPU}, 3 \text{ GB} \rangle$  and B:  $\langle 5 \text{ CPU}, 1 \text{ GB} \rangle$





# 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			





# Evaluation Methodology



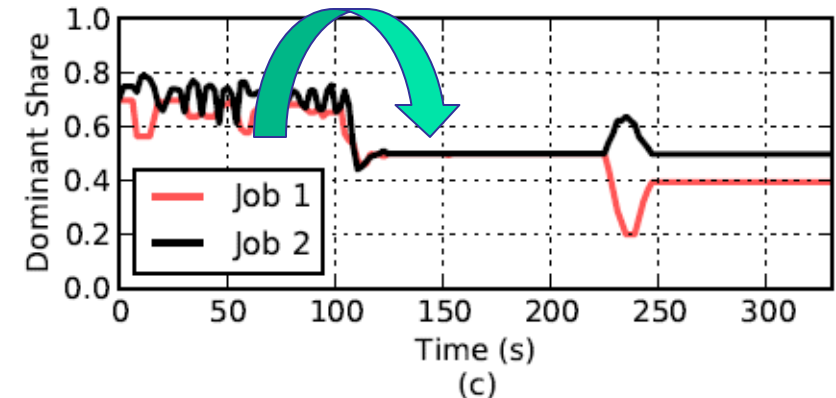
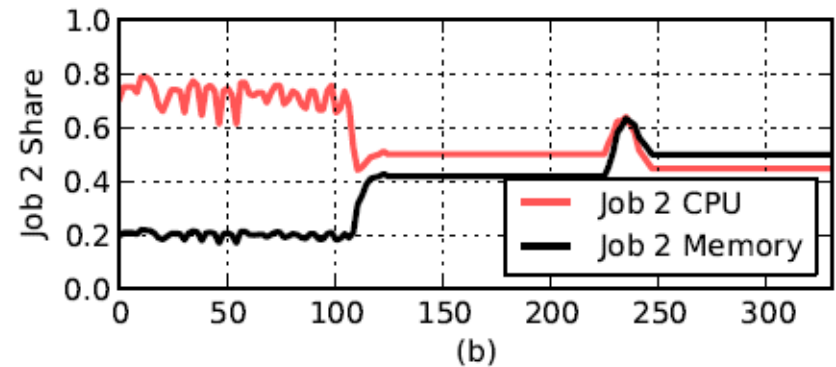
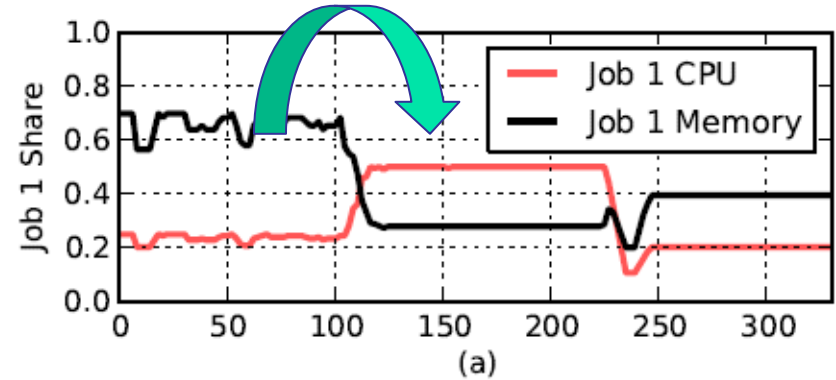
- Micro-experiments on EC2
  - Evaluate DRF's dynamic behavior when demands change
  - Compare DRF with current Hadoop scheduler
- Macro-benchmark through simulations
  - Simulate Facebook trace with DRF and current Hadoop scheduler



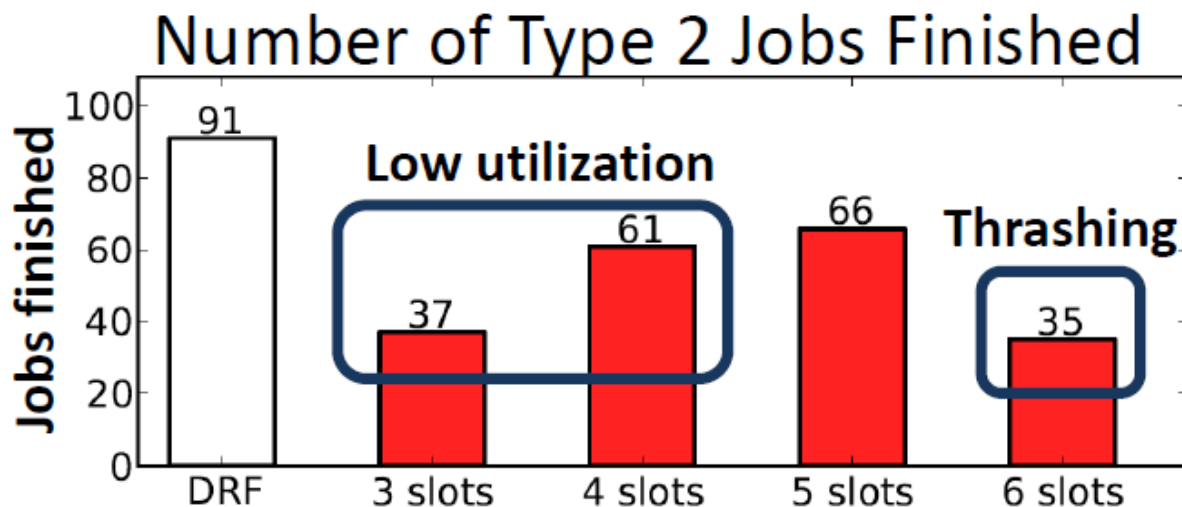
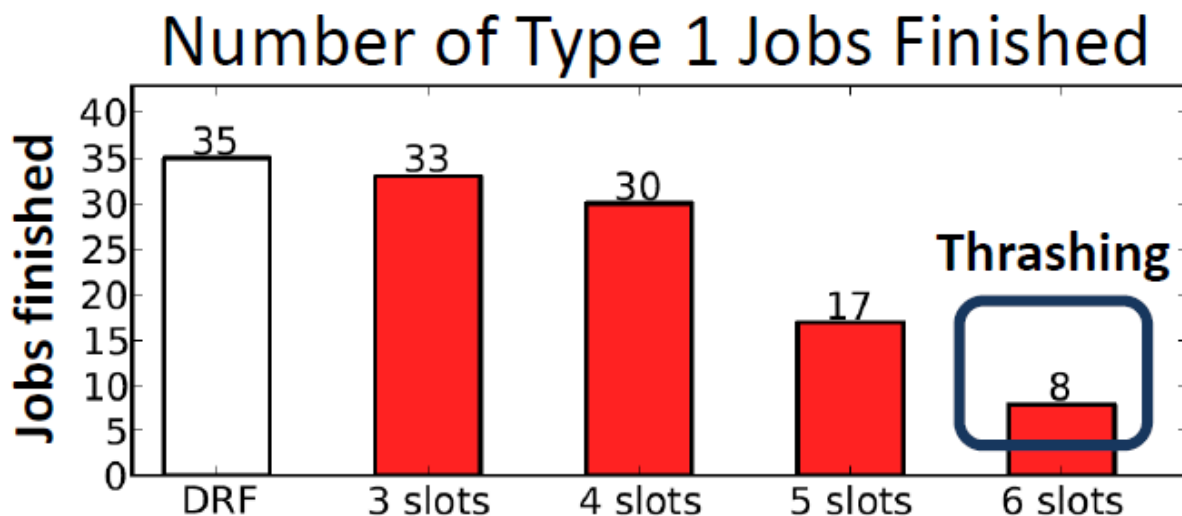




- Dominant shares are equalized
  - Job 1's dominant resource changes from Memory to CPU
- Share guarantee changes from 70% to 50%



# Experiment: DRF vs Slots

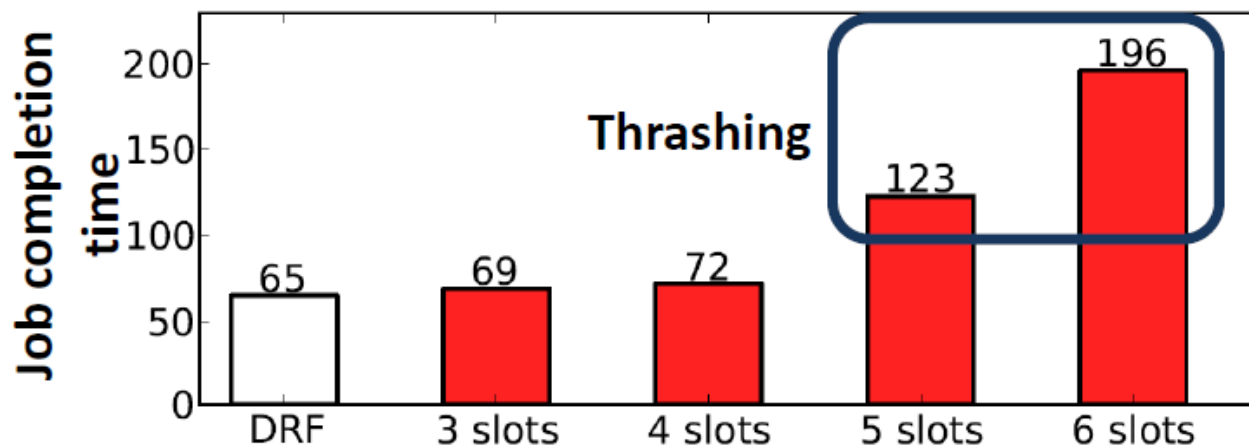


Type 1 jobs <2 CPU, 2 GB>    Type 2 jobs <1 CPU, 0.5GB>

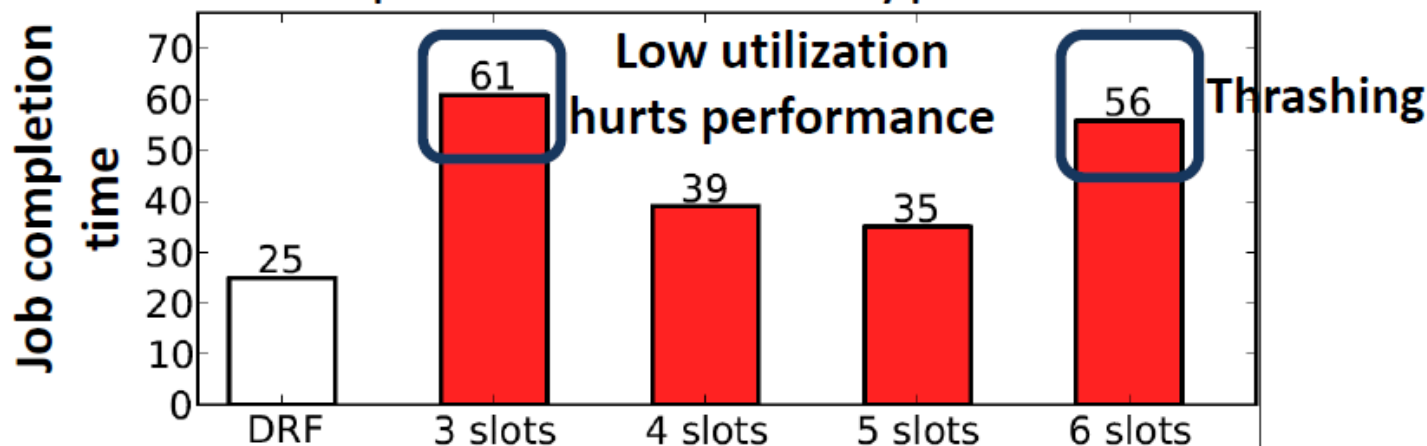


# Experiment: DRF vs Slots

## Completion Time of Type 1 Jobs



## Completion Time of Type 2 Jobs

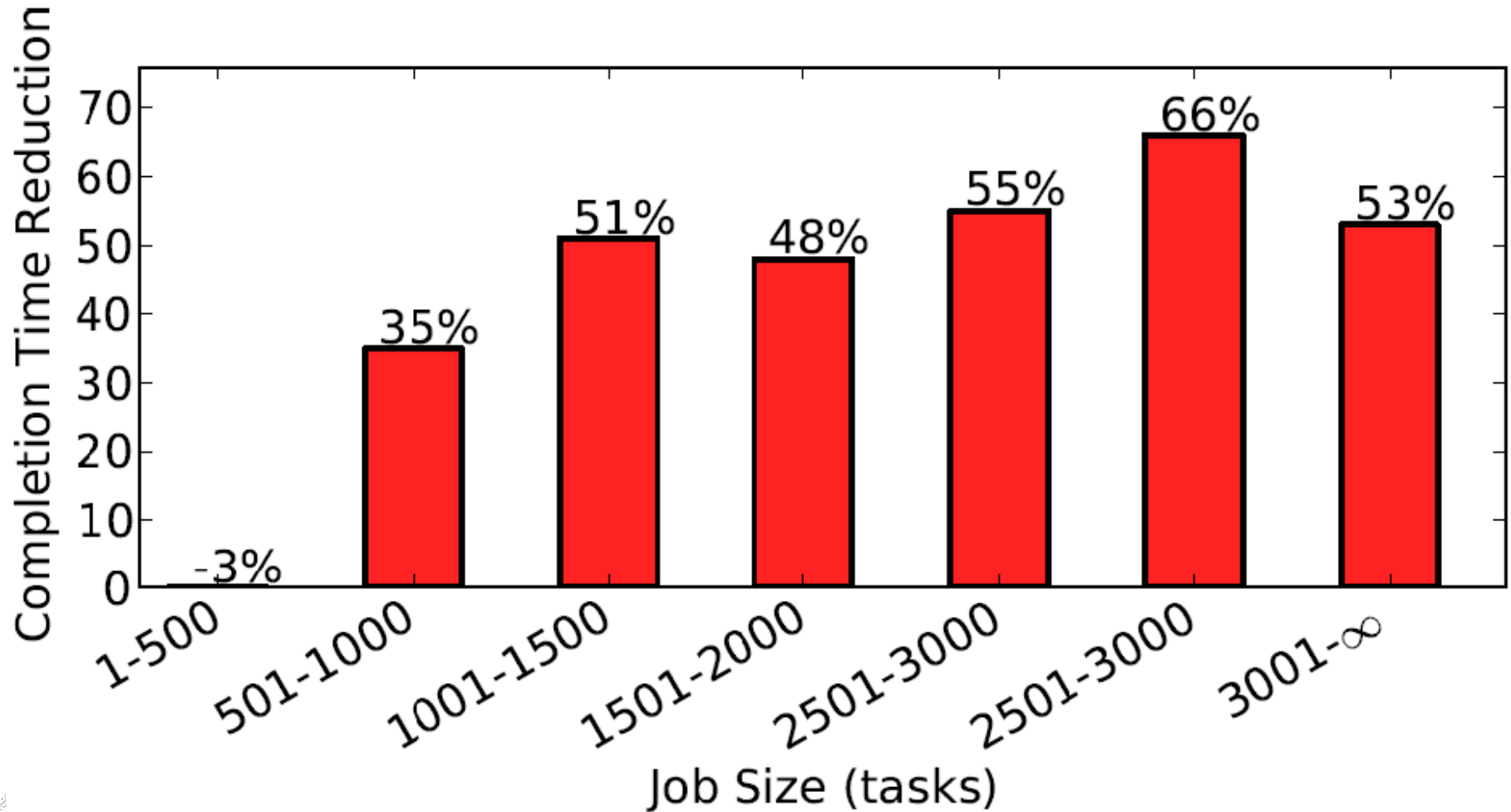


Type 1 job <2 CPU, 2 GB>    Type 2 job <1 CPU, 0.5GB>

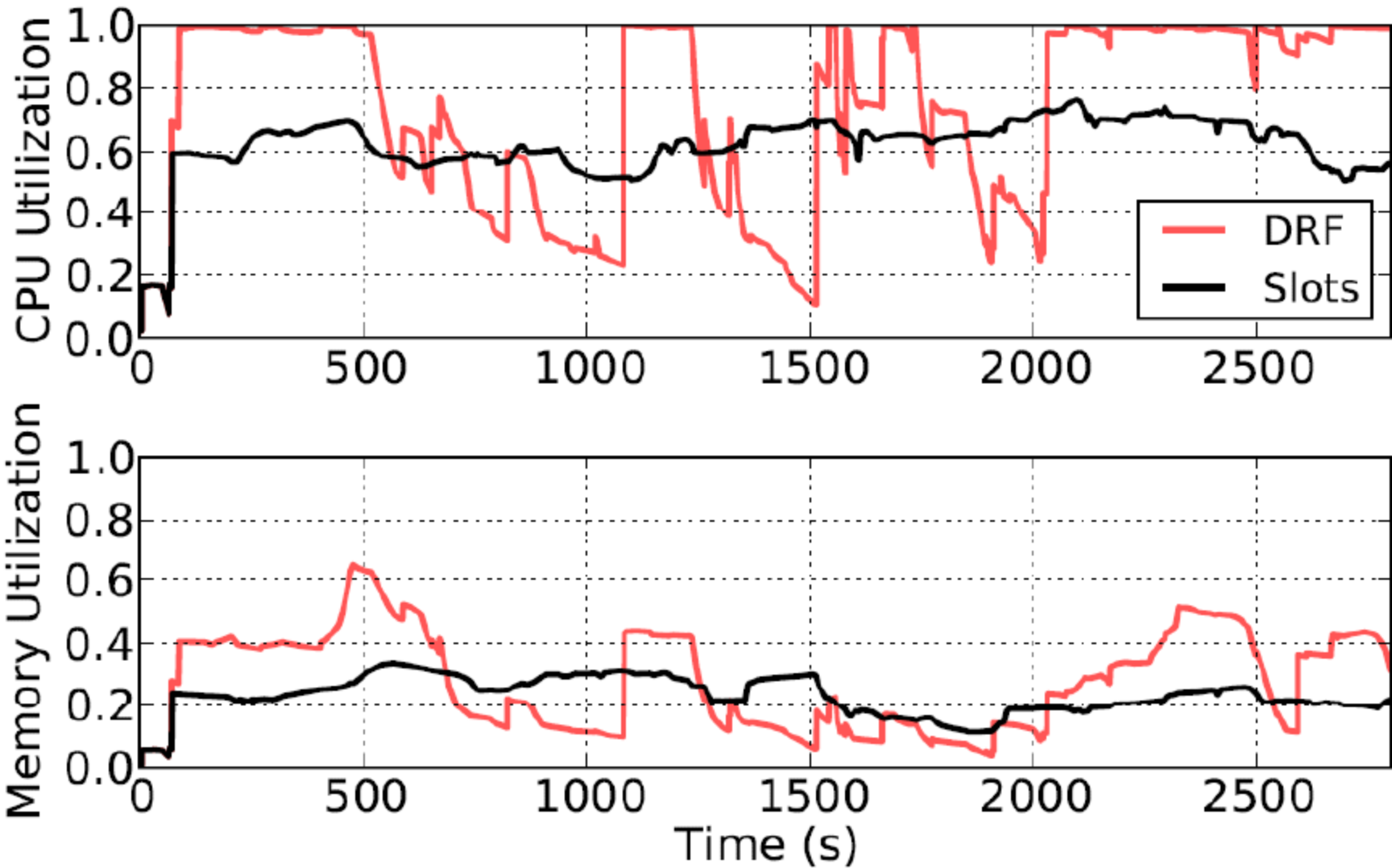




# Simulations using Facebook Traces



# Simulations using Facebook Traces





# Conclusion

- DRF provides multiple-resource fairness in the presence of heterogeneous demand
  - First generalization of max-min fairness to multiple-resources
- DRF's properties
  - Share guarantee
  - Strategy-proofness
  - Performs better than current approaches





# Thanks

