

Hello

# CS 744: DRF

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Fall 2022

# ADMINISTRIVIA

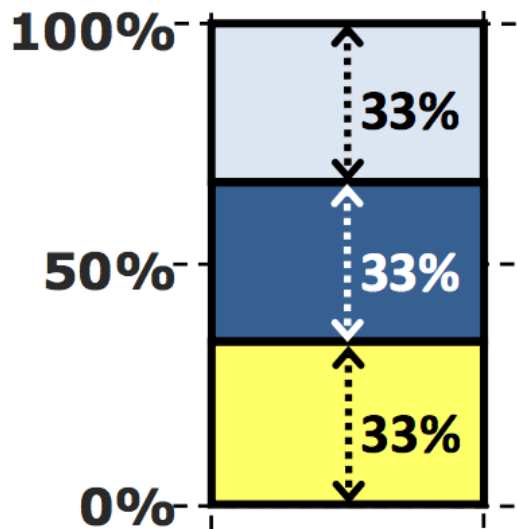
- Assignment 2 out! → *~ 2 weeks* *Pytorch / Machine Learning*
- Course Project
  - Project list by Oct 4 → *seed ideas*
  - Form groups and submit project bids by Oct 11
  - Assigned project by Oct 15
  - Introductions due Oct 25

3 clients in system  
one resource

# SETTING: FAIR SHARING

→ work conserving  
= no resources  
are wasted

Equal Share



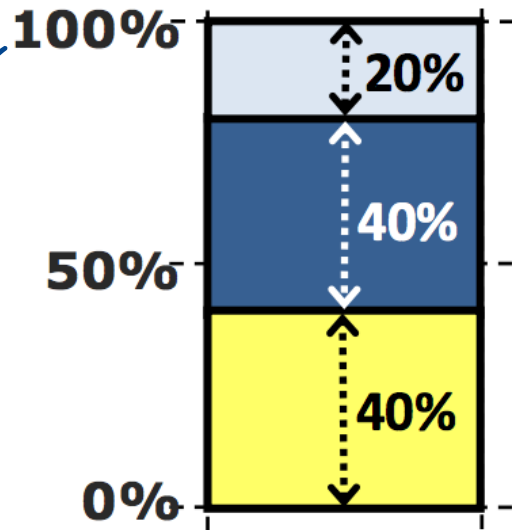
Max-Min Share

↖ network

↘ CPU lottery scheduling

Maximize the allocation  
for most poorly treated  
users

Maximize the minimum



# SLOT-BASED MODEL

Slot: Fixed quantity of CPU and memory

Example: Hadoop MapReduce

Mapper: 2 CPU and 1 GB

Reducer: 1 CPU and 2 GB

Allocate in units of slots →

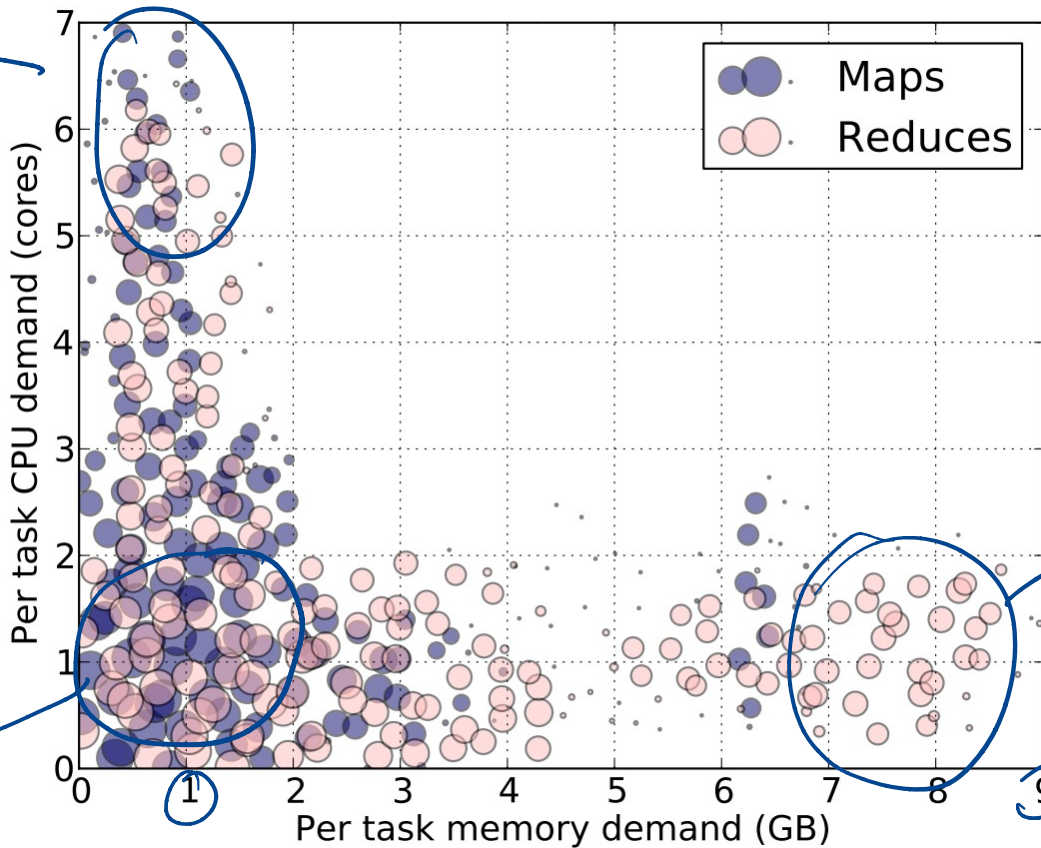
2 map slots in machine 1  
to job 1  
2 reduce slots of job 2 in  
machine 1 ....

# MOTIVATION: MULTI RESOURCES

→ Not based model

CPU intensive  
not memory intensive

large range of resource demands



majority of tasks

Reduce tasks  
memory intensive

# DRF: MODEL

Users have a demand vector

<2, 3, 1> means user's task needs 2 R1, 3 R2, 1 R3 }

<CPU, Mem, Disk> example

requirements of  
one task

Resources given in multiples of demand vector

i.e., users might get <4,6,2>

# PROPERTIES

## Sharing Incentive

Users should not  
fare worse than  
having  $1/n$  cluster

## Strategy Proof

Users should not be  
able to lie to  
get a large share

## "Pareto Efficiency"

We cannot increase  
allocation of one user  
without decreasing  
others

## Envy free

Users should not  
desire allocation  
of another user.

# PROPERTIES

## Sharing Incentive

User is no worse off than a cluster with  
 $1/n$  resources

## Strategy Proof

User should not benefit by  
lying about demands

## Pareto Efficiency

Not possible to increase  
one user without  
decreasing another

## Envy free

User should not desire the  
allocation of another user



# DRF: APPROACH

## Dominant Resource

Resource user has the **biggest** share of

## Dominant Share

Fraction of the dominant resource user is allocated

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Total: <10 CPU, 4 GB>

User 1: <1 CPU, 1 GB>

Dominant resource is **memory**

E.g., for User 1 this is **25% or 1/4**

$$\frac{1}{10} < \left( \frac{1}{4} \right) \longrightarrow \text{Dominant Share}$$

# DRF: APPROACH

x tasks for u1  
y tasks for u2

Equalize the dominant share of users

Total: <9 CPU, 18 GB>

User1: <1 CPU, 4 GB>  
dom res: mem

User2: <3 CPU, 1 GB>  
dom res: CPU

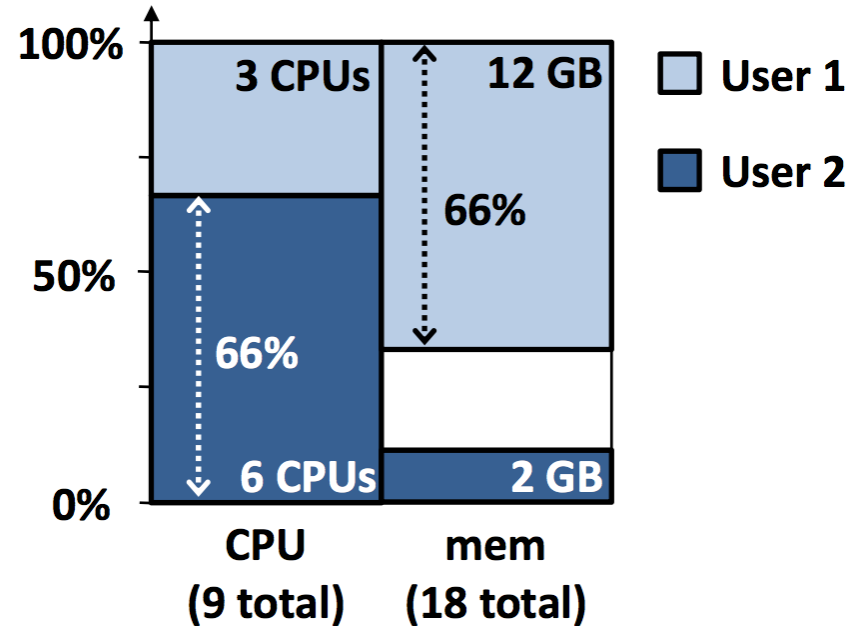
User	Allocation	Dominant Share
User1	<p>&lt;0 CPU, 0 GB&gt;                      &lt;1 CPU, 4 GB&gt;                      &lt;2 CPU, 8 GB&gt;                      &lt;3 CPU, 12 GB&gt;                      3 tasks</p>	<p>0  <math>4/18 = 2/9</math>  <math>8/18 = 4/9</math>  <math>12/18 = 2/3</math></p>
User2	<p>&lt;0 CPU, 0 GB&gt;                      &lt;3 CPU, 1 GB&gt;                      &lt;6 CPU, 2 GB&gt;                      2 tasks</p>	<p>0  <math>3/9 = 1/3</math>  <math>6/9 = 2/3</math></p>

# DRF: APPROACH

Total: <9 CPU, 18 GB>

User1: <1 CPU, 4 GB> per task  
<3 CPU, 12 GB> for 3 tasks  
dom res: mem  
dom share:  $12/18 = 2/3$

User2: <3 CPU, 1 GB>  
<6 CPU, 2 GB> for 2 tasks  
dom res: CPU  
dom share:  $6/9 = 2/3$



# DRF ALGORITHM

Whenever there are available resources:

Schedule a task to the user with **smallest dominant share**

*similar to max-min fairness but on  
dominant share*

# DRF ALGORITHM

$n$  users  
 $m$  resource types

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## Algorithm 1 DRF pseudo-code

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$R = \langle r_1, \dots, r_m \rangle$   $\triangleright$  total resource capacities  
 $C = \langle c_1, \dots, c_m \rangle$   $\triangleright$  consumed resources, initially 0  
 $s_i$  ( $i = 1..n$ )  $\triangleright$  user  $i$ 's dominant shares, initially 0  
 $U_i = \langle u_{i,1}, \dots, u_{i,m} \rangle$  ( $i = 1..n$ )  $\triangleright$  resources given to user  $i$ , initially 0

$\rightarrow$  cluster limitation / capacity

$\rightarrow$  dominant share

$\rightarrow$  Prior allocations made

**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**

$C = C + D_i$   $\triangleright$  update consumed vector

$U_i = U_i + D_i$   $\triangleright$  update  $i$ 's allocation vector

$s_i = \max_{j=1}^m \{u_{i,j}/r_j\}$

**else**

**return**

**end if**

give me the resource vector  
check if it fits

dominant share update

Instantaneous fairness

$\triangleright$  the cluster is full

# COMPARISON: ASSET FAIRNESS

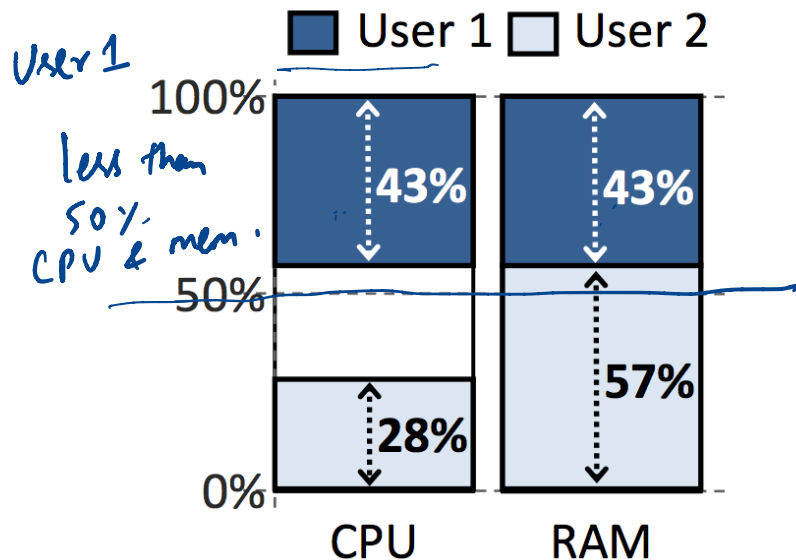
Asset Fairness: Equalize each user's sum of resource shares

Consider total of 70 CPUs, 70 GB RAM  
U1 needs <2 CPU, 2 GB RAM> per task  
U2 needs <1 CPU, 2 GB RAM> per task

Asset Fair Allocation:

U1: 15 tasks: 30 CPU, 30 GB (Sum = 60)

U2: 20 tasks: 20 CPU, 40 GB (Sum = 60)



# COMPARISON: ASSET FAIRNESS

Asset Fairness: Equalize each user's sum of resource shares

Violates Sharing Incentive

Consider total of 70 CPUs, 70 GB RAM

U1 needs <2 CPU, 2 GB RAM> per task

U2 needs <1 CPU, 2 GB RAM> per task

Sharing incentive?

Half of the cluster is 35 CPU, 35 GB RAM

U1: 17 tasks      34 CPU, 34 GB RAM

U2:

→ better than 15 tasks  
with Asset Fairness

# COMPARISON: CEEI

CEEI: Competitive Equilibrium from Equal Incomes

- Each user receives initially  $1/n$  of every resource,
- Subsequently, each user can trade resources with other users in a perfectly competitive market
- Nash solution: Maximize **product of utilities** across users

→ reaches market equilibrium



# COMPARISON: CEEI

Total: <9 CPU, 18 GB>

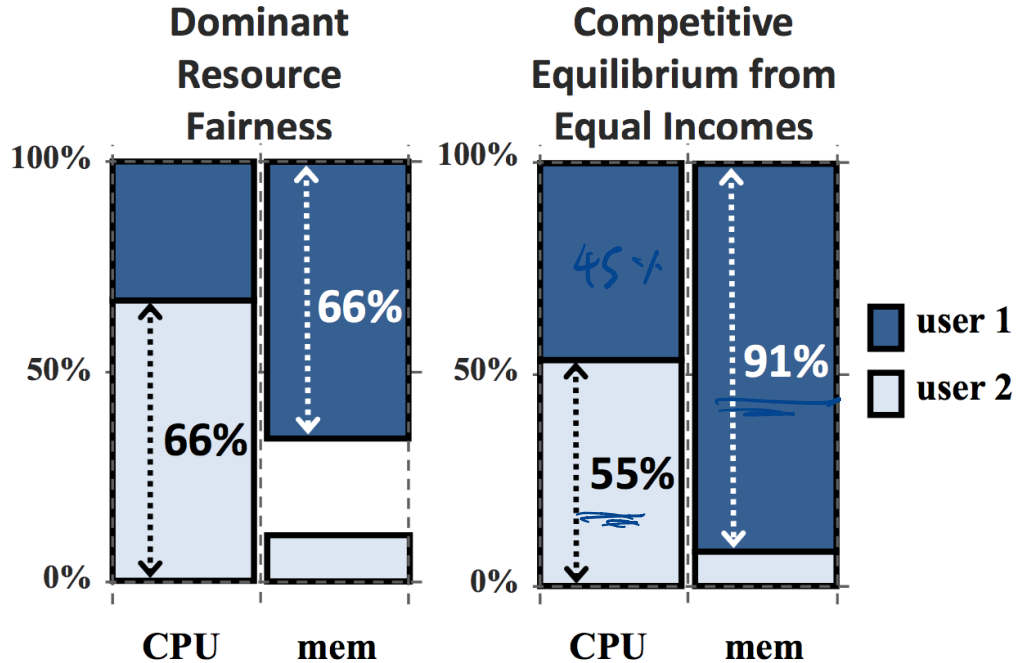
User1: <1 CPU, 4 GB>

User2: <3 CPU, 1 GB>

$\max(x \cdot y)$  *product of utilities*  
subject to  
 $x + 3y \leq 9$  *CPU*  
 $4x + y \leq 18$  *Mem*

$x = 4.05$

$y = 1.62$



# CEEI: STRATEGY PROOFNESS

Total: <9 CPU, 18 GB>

User2 Before:

CEEI: 55% CPU, 9% mem

Total: <9 CPU, 18 GB>

User1: <1 CPU, 4 GB>

User2: <3 CPU, 1 GB>

User2: <3 CPU, 2 GB>

max  $x \cdot y$

$x = 3.6$

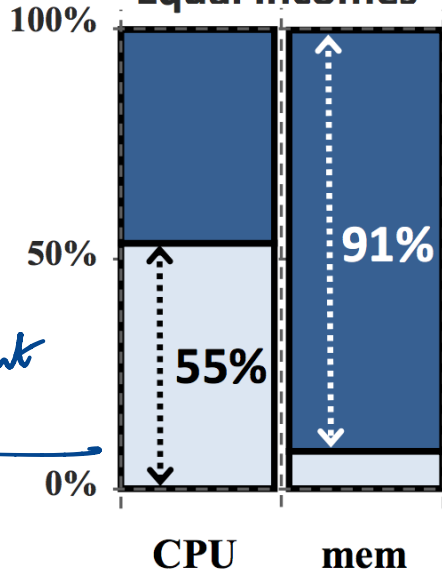
$y = 1.8$

*lied about mem req.*

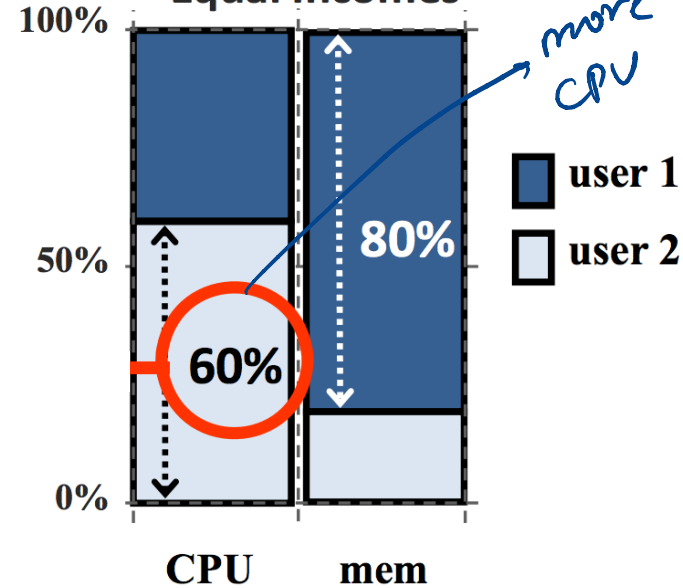
$x + 3y \leq 9$

$4x + 2y \leq 18$

Competitive Equilibrium from Equal Incomes



Competitive Equilibrium from Equal Incomes



# COMPARISON

<b>Property</b>	<b>Allocation Policy</b>		
	Asset	CEEI	DRF
Sharing Incentive		✓	✓
Strategy-proofness	✓		✓
Envy-freeness	✓	✓	✓
Pareto efficiency	✓	✓	✓
Single Resource Fairness	✓	✓	✓
Bottleneck Fairness		✓	✓
Population Monotonicity	✓		✓
Resource Monotonicity			

Table 2: Properties of Asset Fairness, CEEI and DRF.

# SUMMARY

DRF: Dominant Resource Fairness

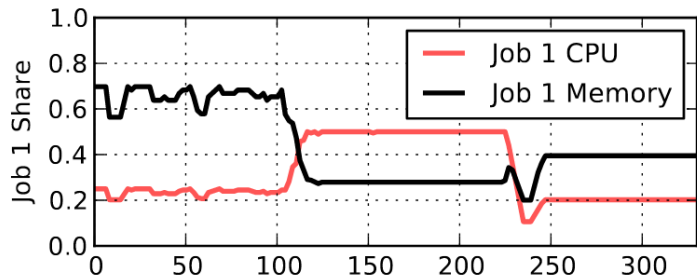
Allocation policy for scheduling

Provides multi-resource fairness

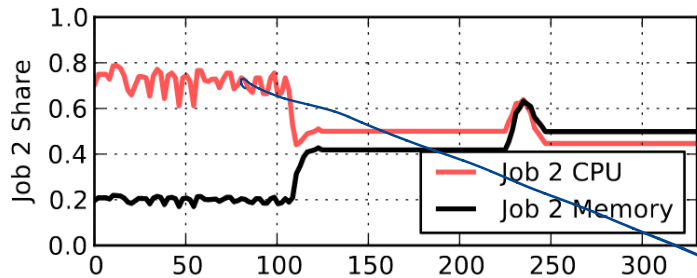
Ensures sharing incentive, strategy proofness

# DISCUSSION

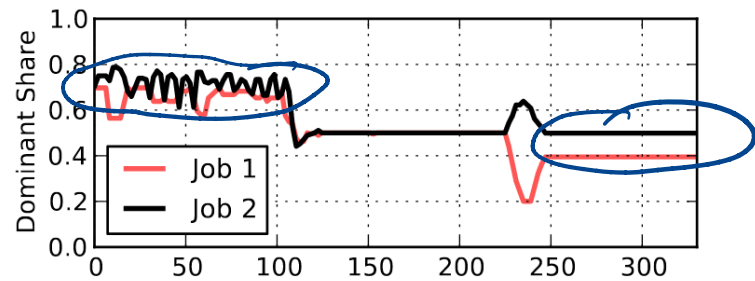
<https://forms.gle/n97b12Qcs8Xv3C6L6>



(a)



(b)



(c)

- Task requirements change and DRF adapts to the changes

- There is a gap between Job 1 / Job 2 (discretization)

- Both jobs have dom. share  $> 0.5$

Task arrival / discretization?

What could be one workload / cluster scenario where DRF implemented on Mesos will NOT be optimal?

- Users diff between dominant resource & next dom. resource is small → will this lead to strategy proof violations ??
- If you cannot fit the user with smallest dominant share, resource waste?
- Handling locality / affinity preferences is challenging

# NEXT STEPS

Next Week: Machine Learning

Assignment 2 out!