Heterogeneity-Aware Cluster Scheduling Policies for Deep Learning Workloads

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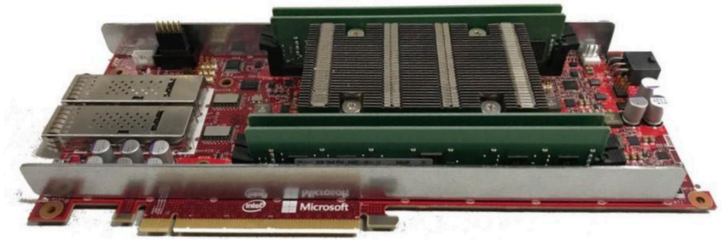
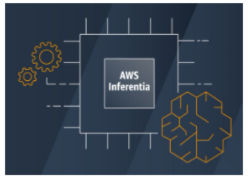
Hardware for ML training is becoming highly specialized and heterogeneous!

Nvidia GPUs: K80, P100, V100, A100

Google TPU



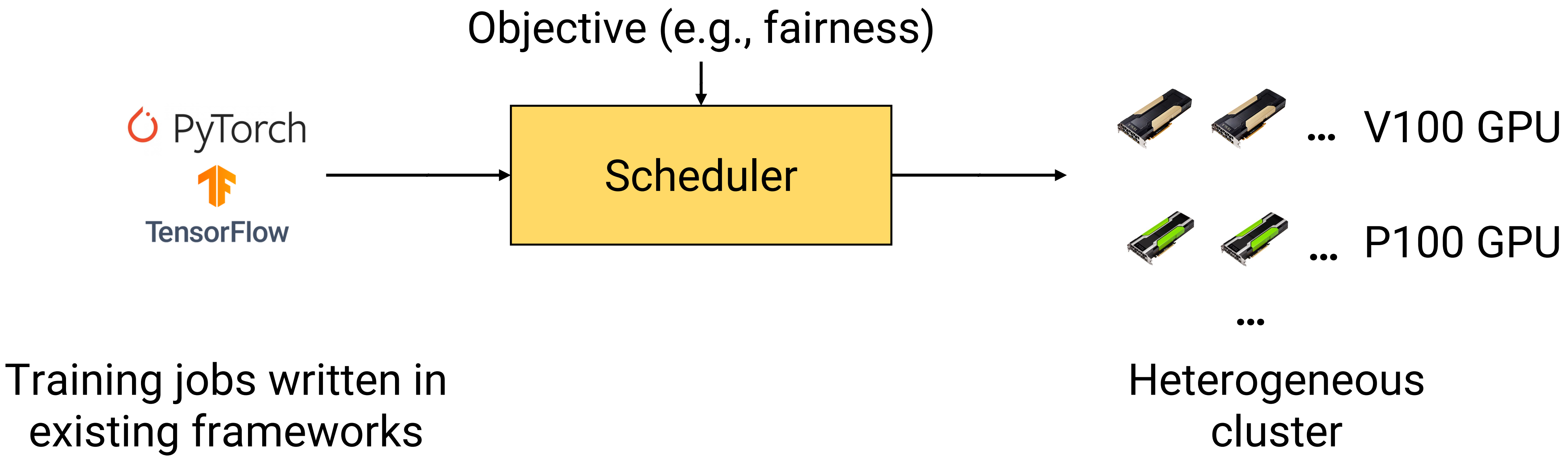
FPGAs in Azure



cerebras SambaNova SYSTEMS GRAPHCORE

...and others

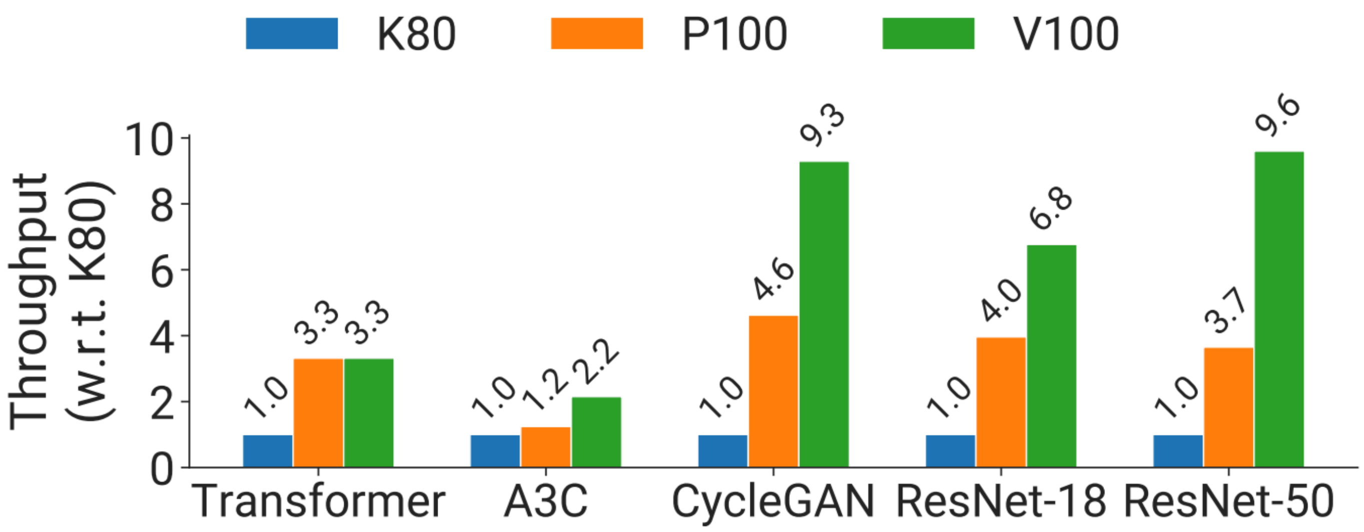
How should we allocate heterogeneous resources?



How should one allocate **heterogeneous resources** to DL training jobs from multiple users while optimizing **different objectives**?

Challenge 1: Heterogeneous performance

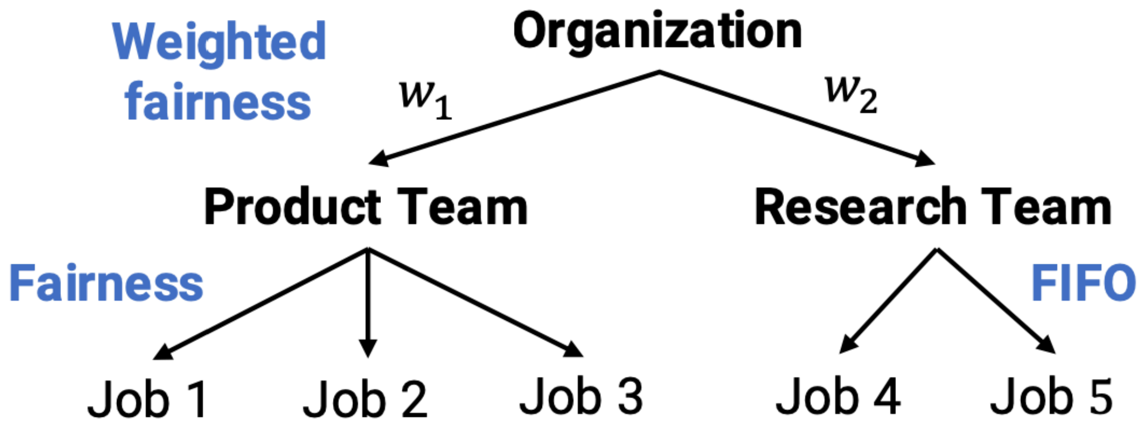
- Models and operators (e.g., convolution, attention) perform differently across hardware architectures
- Disregarding heterogeneity can lead to unfair allocations



Magnitude of speedup across GPU generations varies significantly

Challenge 2: Diverse scheduling objectives

- Single-job objectives: “maximize throughput” or “minimize cost”
  - Minimizing cost subject to SLOs involves moving between fast but expensive, and slow but cheap instances
- Multi-job objectives: fairness or more complicated hierarchical policies



Hierarchical policy: Weighted fairness across sub-organizations, FIFO and fairness within

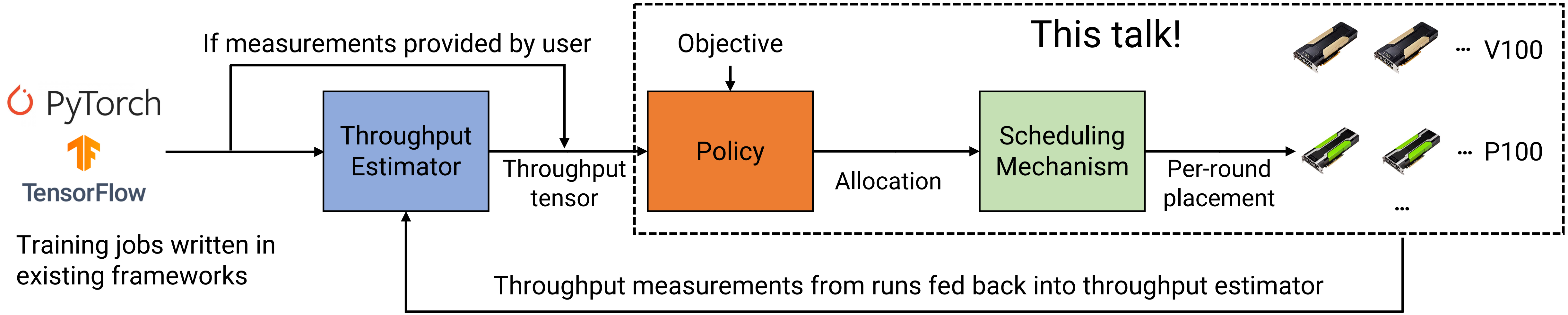
Related work

- Most existing cluster schedulers for deep learning (e.g., Gandiva [1], Themis [2], Tiresias [3]) disregard heterogeneity
- AlloX [4] and Gandiva_fair [5] do consider performance heterogeneity, but tightly couple their target objective to scheduling mechanism
  - Average JCT for AlloX, max-min fairness for Gandiva_fair

[1] Gandiva: Introspective Cluster Scheduling for Deep Learning, OSDI 2019, Xiao et al.
[2] Themis: Fair and Efficient GPU Cluster Scheduling, NSDI 2020, Mahajan et al.
[3] Tiresias: A GPU Cluster Manager for Distributed Deep Learning, NSDI 2019, Gu et al.
[4] AlloX: Compute Allocation in Hybrid Clusters, EuroSys 2020, Le et al.
[5] Balancing Efficiency and Fairness in Heterogeneous GPU Clusters for Deep Learning, EuroSys 2020, Chaudhary et al.

Gavel: A new heterogeneity-aware cluster scheduler

- Generalizes a wide range of existing scheduling policies by expressing policies as optimization problems over the allocation
- Provides abstraction to incorporate performance heterogeneity
- Round-based scheduling mechanism ensures jobs receive optimal allocation
- Improves objectives such as average job completion time by 3.5×



Outline

- Background and Motivation
- Challenges with allocating resources over heterogeneous resources
- **Heterogeneity-aware Policies**
- Round-based Scheduling Mechanism
- Evaluation

Scheduling policies to be made heterogeneity-aware

- **FIFO:** First in, first out
- **Shortest Job First:** Minimize time taken by shortest job
- **Minimize Makespan:** Minimize time taken by batch of jobs
- **Minimize cost (w/ SLOs):** Minimize total cost in public cloud (subject to SLOs)
- **LAS [1]:** Max-min fairness by total compute time
- **LAS w/ weights:** Max-min fairness by total compute time with weights
- **Finish Time Fairness [2]:** Maximize minimum job speedup
- **Hierarchical:** Multi-level policy with fairness as top-level policy, and FIFO or fairness as lower-level policies. Per-job weights can be specified

[1] Tiresias: A GPU Cluster Manager for Distributed Deep Learning, NSDI 2019, Gu et al.
[2] Themis: Fair and Efficient GPU Cluster Scheduling, NSDI 2020, Mahajan et al.

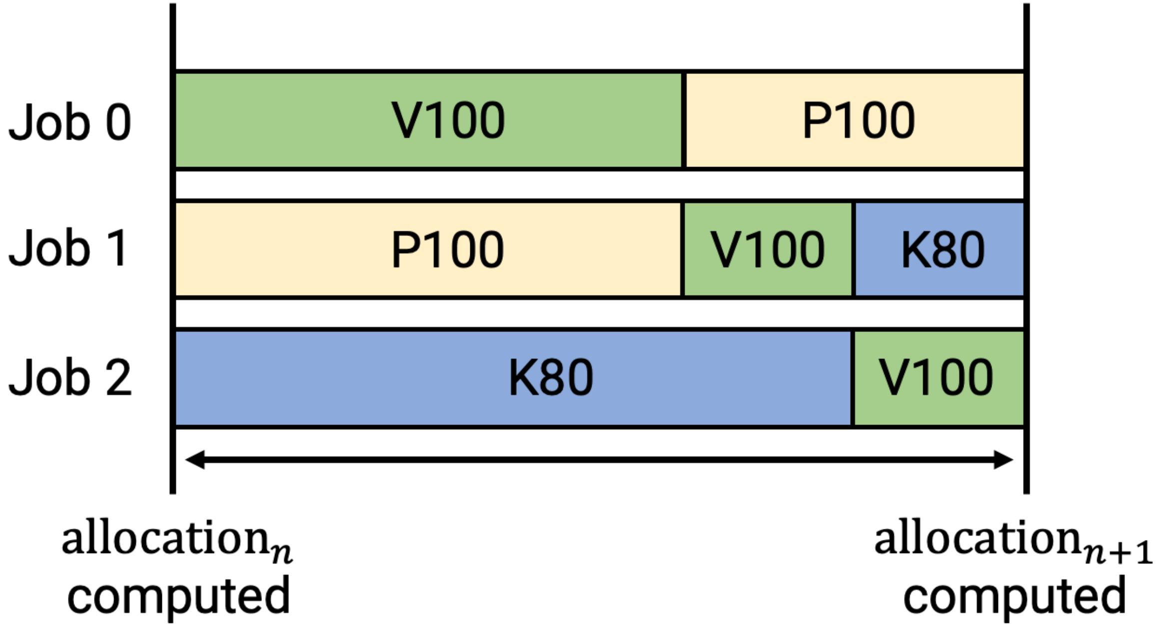
Policies as optimization problems

- In a homogeneous cluster, policy objectives are functions of throughput (e.g., duration = training steps / throughput) and allocation
- On a homogeneous cluster, **Least Attained Service** policy is a max-min fairness policy that equalizes the total compute time each job receives
- Jobs can see unequal throughput reductions on heterogeneous clusters

Allocations (X) as time fractions

X specifies the fraction of time a job spends on each accelerator between allocation recomputations

$$X^{\text{example}} = \begin{array}{cccc} V100 & P100 & K80 & \\ \left(\begin{array}{c} 0.6 \\ 0.2 \\ 0.2 \end{array}\right. & \begin{array}{c} 0.4 \\ 0.6 \\ 0.0 \end{array} & \left.\begin{array}{c} 0.0 \\ 0.2 \\ 0.8 \end{array}\right) & \begin{array}{c} \text{job } 0 \\ \text{job } 1 \\ \text{job } 2 \end{array} \end{array}$$



Allocations recomputed either at periodic intervals of time, or on a reset event (new job arrives, or old job completes)

Effective throughput

To make policies heterogeneity-aware, policy objectives can be expressed in terms of **effective throughput** (given allocation X and throughputs T):

$$\text{throughput}(\text{job } m, X) = \sum_{\substack{\text{accelerator} \\ \text{type } j}} T_{mj} \cdot X_{mj}$$

T is matrix of raw throughputs of each job on each accelerator type

$$\begin{array}{cc} & \begin{array}{cc} V100 & K80 \end{array} \\ T = & \begin{pmatrix} 40.0 & 10.0 \\ 12.0 & 4.0 \\ 100.0 & 50.0 \end{pmatrix} \end{array} \begin{array}{l} \\ \text{job } 0 \\ \text{job } 1 \\ \text{job } 2 \end{array}$$

Policies as optimization problems

- In a homogeneous cluster, policy objectives are functions of throughput (e.g., duration = training steps / throughput)
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$$\text{Maximize}_X \min_m X_m$$

- Jobs can see unequal throughput reductions on heterogeneous clusters
- Instead, compute max-min fairness over effective throughputs:

$$\text{Maximize}_X \min_m \frac{\text{throughput}(m, X)}{\text{normalizing\_factor}_m}$$

Scheduling policies to be made heterogeneity-aware

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See paper for details!

Performance optimizations: space sharing and placement

- Gavel can also deploy existing performance optimizations like space-sharing and placement awareness [1, 2] in a heterogeneity-aware way
- Objectives in terms of $\mathrm{throughput}(m, X)$ unchanged
- X needs to be modified to account for performance optimization (e.g., allocation for each job combination)
- Raw throughputs (T) for concurrently running applications might need to be measured / estimated on the fly (see paper for details)

[1] Gandiva: Introspective Cluster Scheduling for Deep Learning, OSDI 2018, Xiao et al.
[2] Themis: Fair and Efficient GPU Cluster Scheduling, NSDI 2020, Mahajan et al.

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How do we realize an optimal allocation?

Given an optimal heterogeneity-aware allocation by a policy, how do we assign resources to jobs?

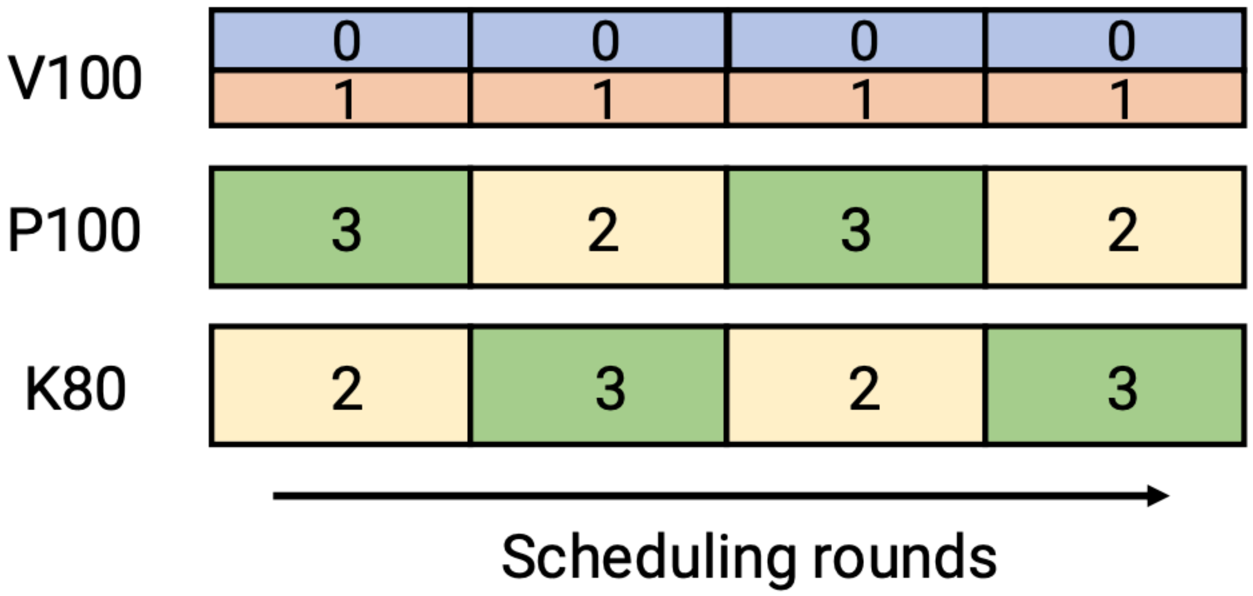
$$
\begin{array}{cl}
\text{V100} \mid \text{P100} \mid \text{K80} & \\
\begin{pmatrix} 1.0 & 0.0 & 0.0 \\ 0.0 & 0.5 & 0.5 \\ 0.0 & 0.5 & 0.5 \end{pmatrix} & \begin{array}{l} \text{jobs 0+1} \\ \text{job 2} \\ \text{job 3} \end{array} \\
X^{\text{het.}+SS} &
\end{array}
\xrightarrow{\quad ? \quad}
$$

Assignments of jobs to heterogeneous cluster resources

Gavel's round-based scheduling

- Round-based scheduler ensures jobs receive time on accelerator types according to the computed optimal allocation X

$$
\begin{array}{cc}
\text{V100} \mid \text{P100} \mid \text{K80} & \\
\begin{pmatrix} 1.0 & 0.0 & 0.0 \\ 0.0 & 0.5 & 0.5 \\ 0.0 & 0.5 & 0.5 \end{pmatrix} & \begin{array}{c} \text{jobs 0+1} \\ \text{job 2} \\ \text{job 3} \end{array} \\
X^{\text{het.}+SS} &
\end{array}
$$



Gavel's round-based scheduling

- Round-based scheduler ensures jobs receive time on accelerator types according to the computed optimal allocation X
- Priority score for every (job, accelerator) combination
  - $\text{priorities} = X^{\text{target}} / \text{rounds\_received}$ (element-wise division of matrices)

$$X^{\text{example}} = \begin{array}{c} \begin{array}{ccc} V100 & P100 & K80 \end{array} \\ \begin{pmatrix} 0.6 & 0.4 & 0.0 \\ 0.2 & 0.6 & 0.2 \\ 0.2 & 0.0 & 0.8 \end{pmatrix} \end{array} \begin{array}{l} \\ \text{job 0} \\ \text{job 1} \\ \text{job 2} \end{array}$$

$$\begin{array}{c} \text{V100 | P100 | K80} \\ \begin{pmatrix} 3 & 1 & 0 \\ 1 & 3 & 0 \\ 0 & 0 & 4 \end{pmatrix} \end{array} \begin{array}{l} \\ \text{job 0} \\ \text{job 1} \\ \text{job 2} \end{array}$$

rounds_received_n

$$\begin{array}{c} \text{V100 | P100 | K80} \\ \begin{pmatrix} 0.2 & \mathbf{0.4} & 0 \\ 0.2 & 0.2 & \infty \\ \infty & 0 & 0.2 \end{pmatrix} \end{array} \begin{array}{l} \\ \text{job 0} \\ \text{job 1} \\ \text{job 2} \end{array}$$

priorities_n

Jobs placed on resources where they have high priority (marked in **red**)

$$\begin{array}{c} \text{V100 | P100 | K80} \\ \begin{pmatrix} 3 & \mathbf{2} & 0 \\ 1 & 3 & \mathbf{1} \\ \mathbf{1} & 0 & 4 \end{pmatrix} \end{array} \begin{array}{l} \\ \text{job 0} \\ \text{job 1} \\ \text{job 2} \end{array}$$

$\text{rounds\_received}_{n+1}$

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- **Evaluation**

Main questions

- Do Gavel’s policies improve objective metrics in a heterogeneous cluster?
- What is the impact of input load on objectives using Gavel’s policies?
- Can Gavel’s policy framework support hierarchical policies?
- How do Gavel’s policies scale with the number of active jobs?

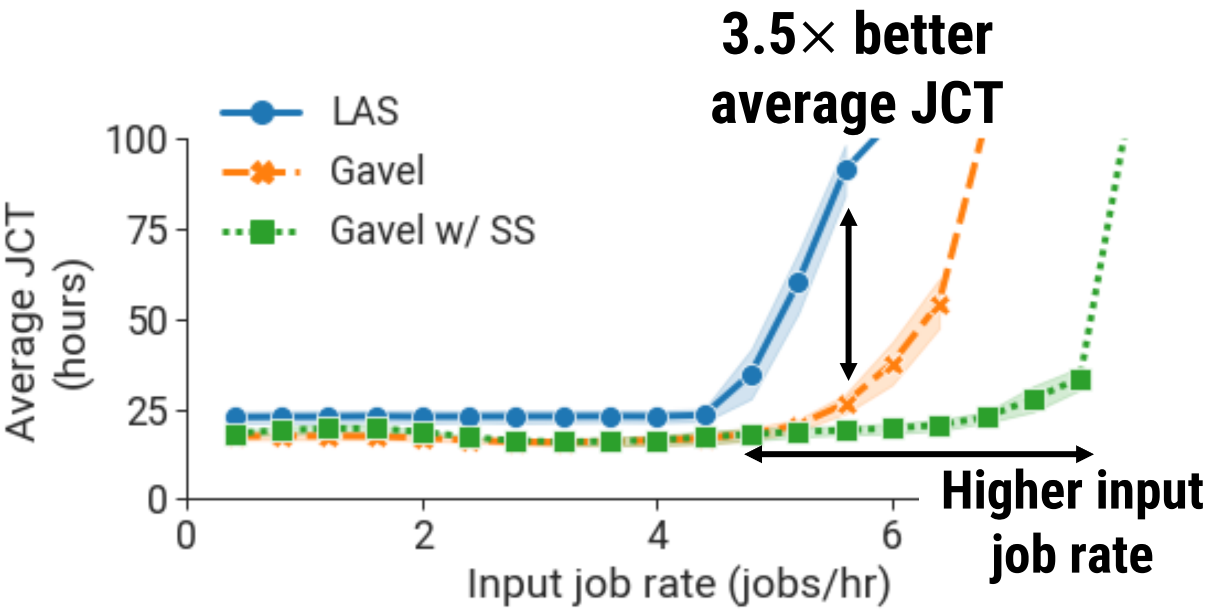
Gavel improves objectives on a heterogeneous cluster

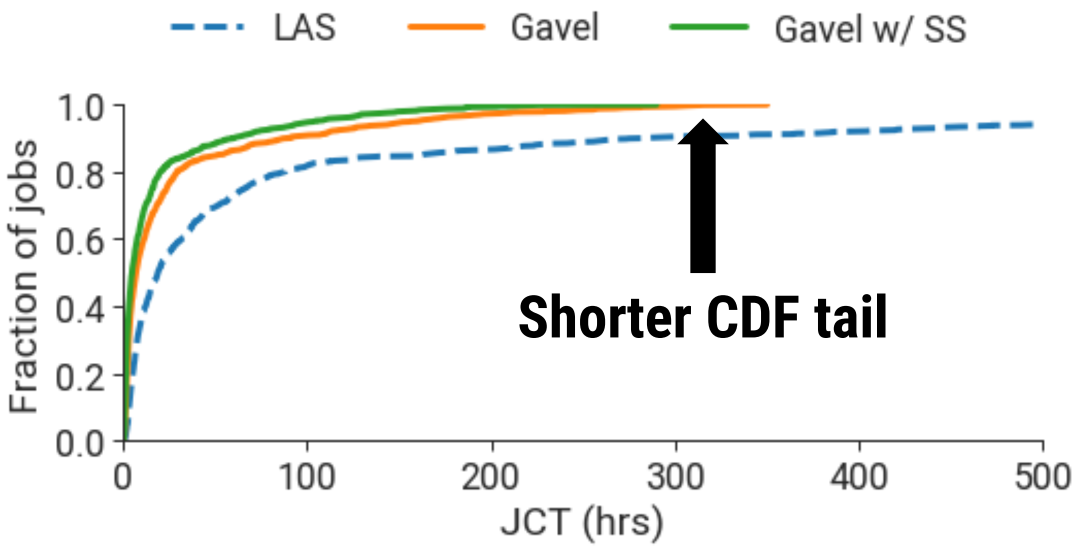
Physical cluster with
8 V100 GPUs,
16 P100 GPUs,
24 K80 GPUs

System	Policy	Physical	Simulated
Heterogeneity-agnostic	Least Attained Service (average JCT)	5.1 hrs	5.4 hrs
Heterogeneity-aware		3.4 hrs	3.7 hrs
Heterogeneity-agnostic (w/ ad hoc space sharing)	Makespan	21.3 hrs	22.1 hrs
Heterogeneity-aware		17.7 hrs	17.6 hrs

- Gavel reduces average JCT by 1.5x
- Gavel without space sharing reduces makespan by 1.2x compared to a baseline that uses ad-hoc space sharing
- Results in simulation reflect reality ($< 8\%$ difference)

Gavel can enable the same heterogeneous cluster to support higher input load



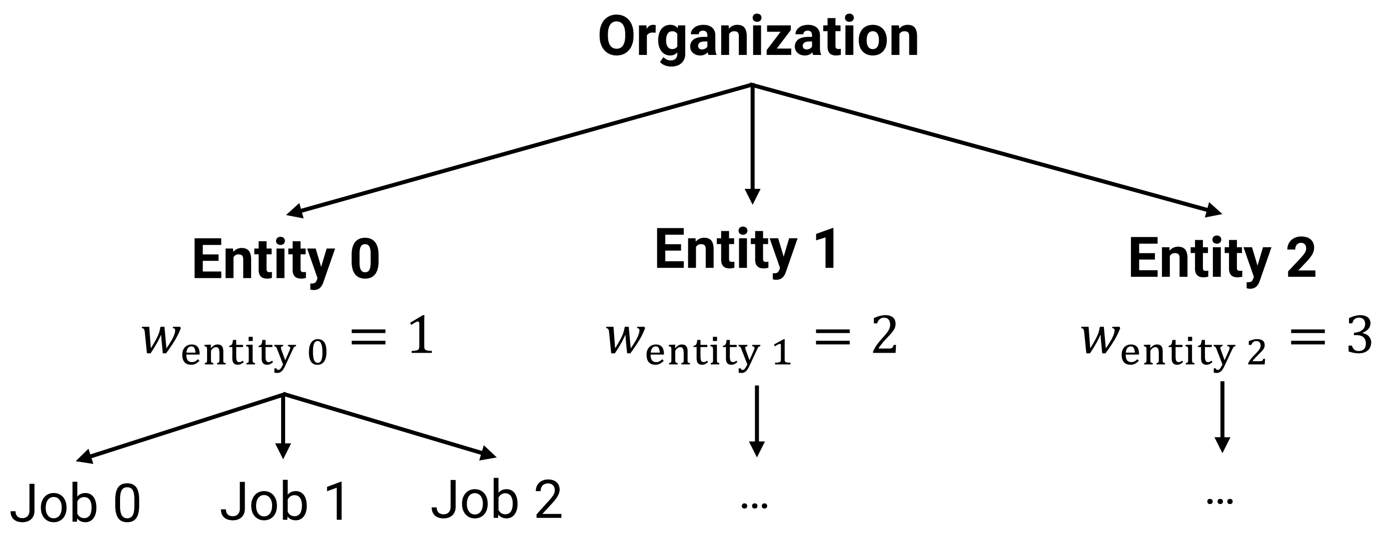


JCT CDF (input job rate = 5.6 jobs/hr)

- **Simulated cluster** with 36 V100 GPUs, 36 P100 GPUs, 36 K80 GPUs
- Each policy evaluated on multiple traces (different Poisson arrival rates)

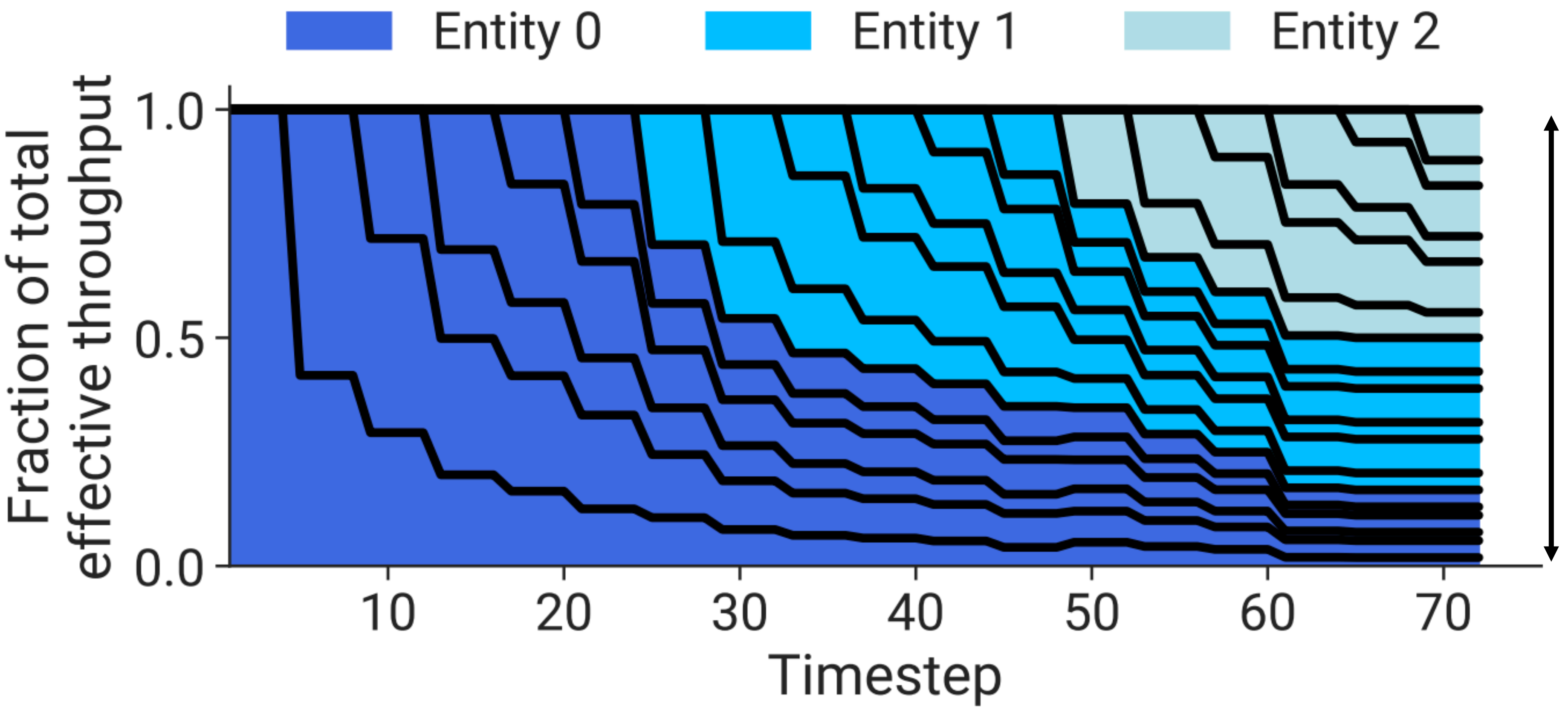
Gavel can support hierarchical policies

Weighted fairness
at both levels



- Six jobs per entity
- $w_{\text{entity 0}} < w_{\text{entity 1}} < w_{\text{entity 2}}$
- $w_{\text{entity 1}} = 2$ implies that entity 1 should get 2× resources as entity 0

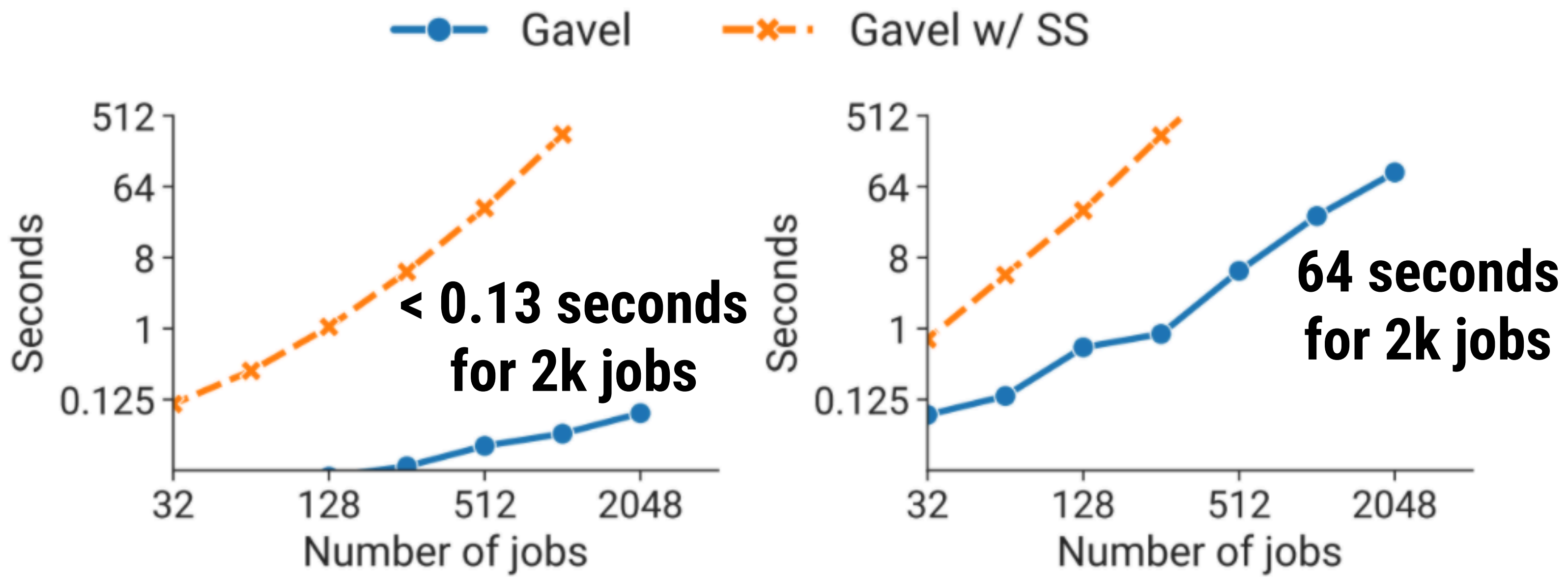
Gavel can support hierarchical policies



Allocation in ratio of 3:2:1

Widths of bars indicate that inter- and intra-entity weights are respected

Gavel scales to clusters with hundreds of active jobs



(a) LAS. (b) Hierarchical.

Gavel can compute heterogeneity-aware allocations over 2048 jobs in a minute

Main questions

- Do Gavel's policies improve objective metrics in a heterogeneous cluster?
- What is the impact of input load on objectives using Gavel's policies?
- Can Gavel's policy framework support hierarchical policies?
- How do Gavel's policies scale with the number of active jobs?
- How well does Gavel's scheduling mechanism realize optimal allocations?
- What is the overhead of preemption in Gavel?

More results (including more objectives) in paper!

Conclusion

- Gavel is a heterogeneity-aware cluster scheduler able to optimize for many high-level objectives such as fairness, makespan, and cost
- Gavel formulates existing policies as optimization problems, and extends these optimization problems to be heterogeneity-aware
- Gavel can reduce average job completion time by **3.5**×

Code open sourced at https://github.com/stanford-futuredata/gavel

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