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Beware of Fragmentation: Scheduling GPU-Sharing Workloads with Fragmentation Gradient Descent

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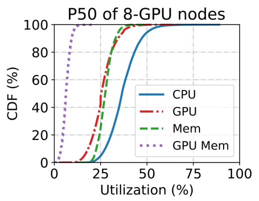
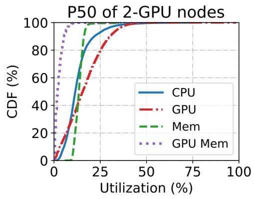
TL;DR: We propose a novel measure of fragmentation to statistically quantify the degree of GPU fragmentation caused by different sources. Based on this measure, we invent a scheduling policy **FGD** that packs tasks to minimize the growth of fragmentation and maximize GPU allocation.

*ML-as-a-Service clouds suffer **low GPU utilization***

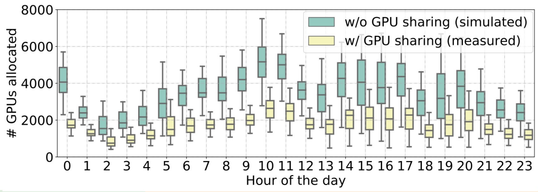
Avg. **25-50% GPU utilization** in production MLaaS clouds [1-3].

[1] Weng et al., "MLaaS in the Wild: Workload analysis and scheduling in large-scale heterogeneous GPU clusters," in NSDI 2022.
[2] Hu et al., "Characterization and prediction of deep learning workloads in large-scale GPU datacenters," in SC 2021.
[3] Narayanan et al., "Heterogeneity-aware cluster scheduling policies for deep learning workloads," in OSDI 2020





GPU sharing comes to rescue



GPU sharing lets multiple tasks run on a single GPU, via DL framework manipulation, or CUDA API interception, or hardware-assisted methods (e.g., MIG).

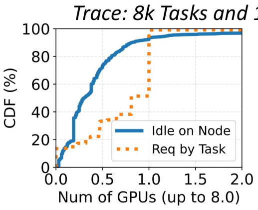
← ***Sharing*** saves **50%** GPUs in Alibaba [1].

*Yet, GPU sharing doesn't always improve allocation. Often, allocating partial GPUs results in **fragmentation***

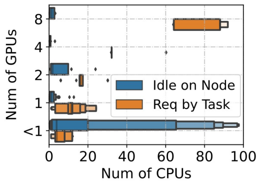
In many clusters, the GPU allocation rate can reach **85-90%** maximum, **leaving hundreds of GPUs unable to allocate!**

Many users experienced **scheduling failures even with sufficient GPU allocation quotas.**

Trace: 8k Tasks and 1.2k nodes with 6.2k GPUs



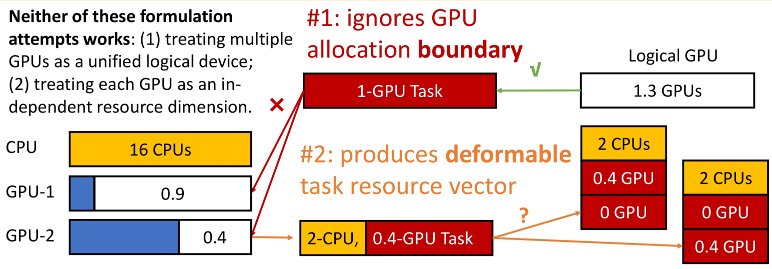
Insufficient GPUs on nodes given the requests of tasks



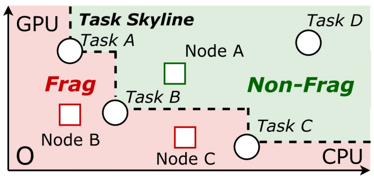
Insufficient CPUs (or stranded GPUs)

*Classical multi-resource bin-packing **cannot** work effectively on GPUs due to **formulation mismatch***

Neither of these formulation attempts works: (1) treating multiple GPUs as a unified logical device; (2) treating each GPU as an independent resource dimension.



*Definition of GPU Fragmentation: The absolute measure is defective. Be **statistical***

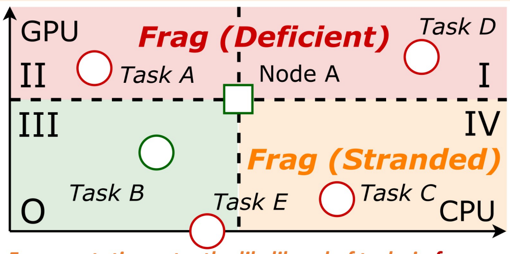


A **defective** definition of **fragmentation** in **absolute** terms — *"a node is fragmented **if and only if** it cannot run any task". **Task skyline*** determines the frag / non-frag boundary, yet, only **0.06%** task instances belong to the skyline ☹

Absolute fragmentation stays low (**<5%**) throughout scheduling simulation (8k tasks to 6.2k GPUs) — ☹ fail to provide useful feedback to the scheduling quality

$$F_n(M) = \sum_{m\in M} p_m F_n(m) \quad (p_m\text{: task popularity})$$

*For each task m in task set M, Sum the fragmentation **viewed by task m***



A **statistical** definition: summed by each task's own view of node fragmentation, weighted by their popularity.

Fragmentation region:
Q-I, Q-II: insufficient GPU
Q-IV: Stranded GPU
X-axis: Non-GPU tasks

Fragmentation rate: the likelihood of tasks in fragmentation regions:
☺ Aware of workload distribution while stable to small changes.
☺ Break down fragmentation into Deficient and Stranded.
☺ Independent of scheduling policy and node distribution.

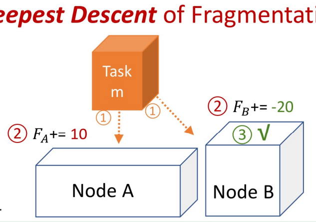
*Schedule Alg.: **Fragmentation Gradient Descent***

Algorithm 1: Node selecting process of FGD

Input : Node set N, incoming task m, workload set M
Output: Assigned node n^*

Initialize node score set $\mathcal{S} \leftarrow \varnothing$, and output $n^* \leftarrow \varnothing$.
① **parallel for** *node* $n \in N$ **do**
  if *Insufficient resources* ∥ *constraints not met* **then**
    Return ▷ Filter out unavailable nodes
  $n^- \leftarrow$ AssignTaskToNode(m, n) ▷ Hypothetically
② $\Delta \leftarrow F^{GPU}_{n^-}(M) - F^{GPU}_{n}(M)$ ▷ Fragmentation increment
  $\mathcal{S} \leftarrow \mathcal{S} \cup (n, \Delta)$
if $\mathcal{S} \neq \varnothing$ **then**
③ $n^* \leftarrow \arg\min_{n\in\mathcal{S}} \Delta$ ▷ pick the node with the least Δ.

Schedule Tasks towards the ***Steepest Descent*** of Fragmentation



Formal Description of Computation $F_n(m)$

- Case 1: All Residuals are Frag. (Q-I, Q-II, Q-IV, **x-axis**):

$$F_n(m) = \sum_{1\le g\le G_n} R^{GPU}_{n,g}$$

Residual resource on GPU g Node n
G_n: GPU set on node n

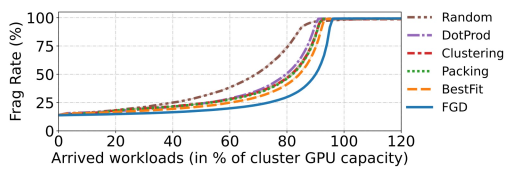
- Case 2: Partial or No Residuals are Frag. (Q-III):

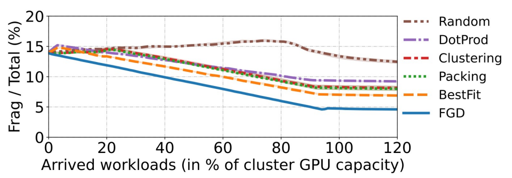
$$F_n(m) = \sum_{1\le g\le G_n} R^{GPU}_{n,g}\,\mathbb{1}\left(R^{GPU}_{n,g} < \min\{D^{GPU}_m, 1\}\right)$$

1, if remaining resource is smaller than the demand of task m, else 0.

Evaluation: Schedule 8k tasks to 6.2k GPUs (1.2k nodes)

FGD: Lowest Frag. Rate & Fewest GPUs Unallocated





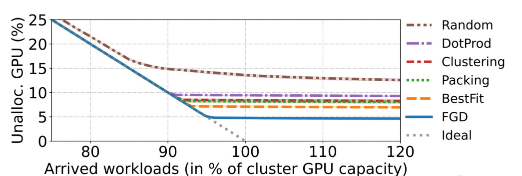


Fig 4a: FGD pursues the lowest fragmentation among various policies in scheduling production workloads, leading to fewest GPUs unallocated.

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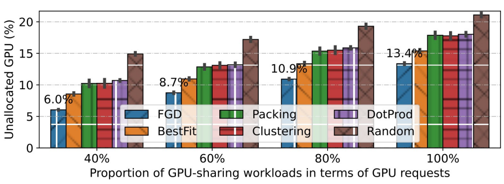

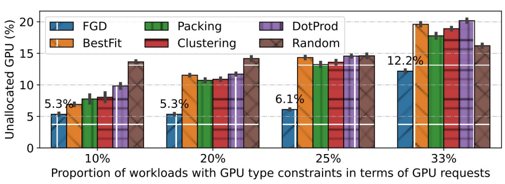

Fig 4b: FGD allocates more GPUs across a variety of settings. See more results and task distributions in paper and code.

Paper

Trace & Code