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

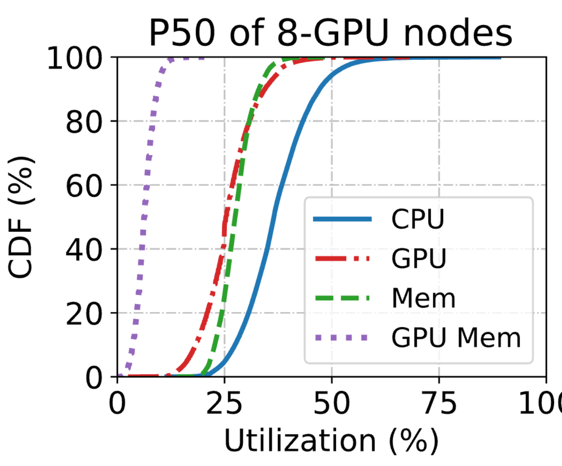
Qizhen Weng†* Lingyun Yang†* Yinghao Yu^† Wei Wang† Xiaochuan Tang^ Guodong Yang^ Liping Zhang^

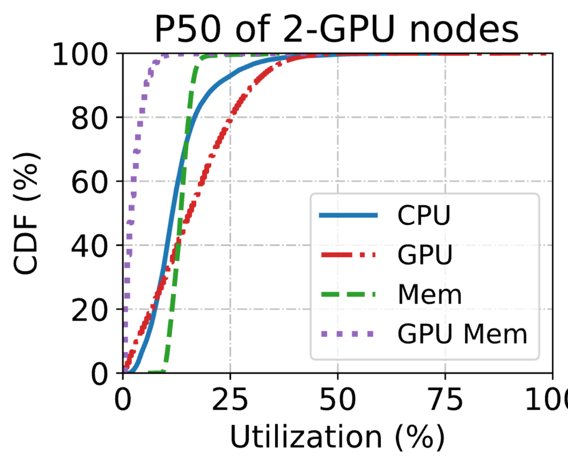
†: Hong Kong University of Science and Technology ^: Alibaba Group (*: equal contribution)

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***

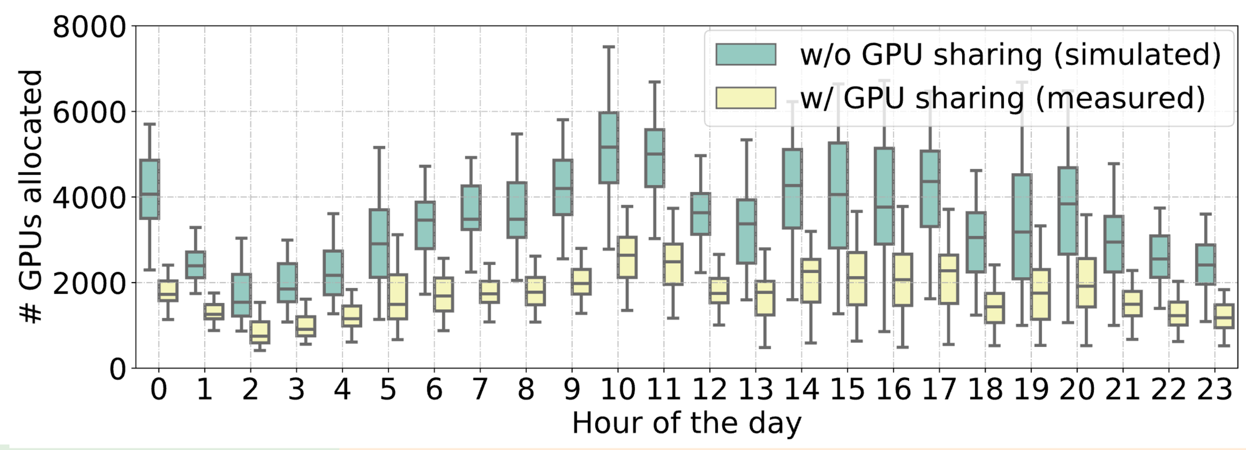
Avg. **25-50% GPU utilization** in production MLaaS clouds [1-3].





[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).

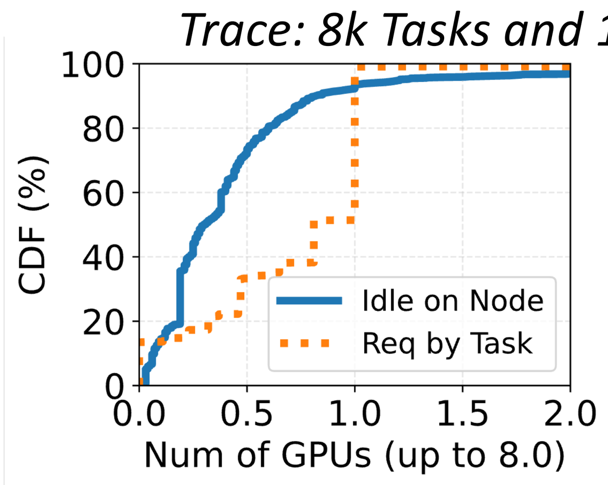
← ***Sharing*** saves **50%** GPUs in Alibaba [1].

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

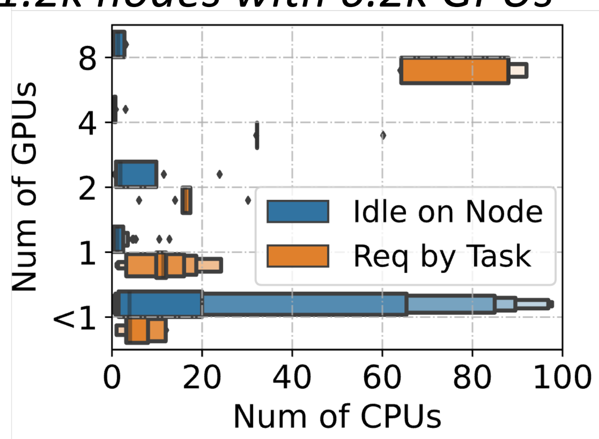
In many clusters, the GPU allocation rate can reach **85-90%** maximum, **leaving hundreds of GPUs unable to allocate!**

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

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



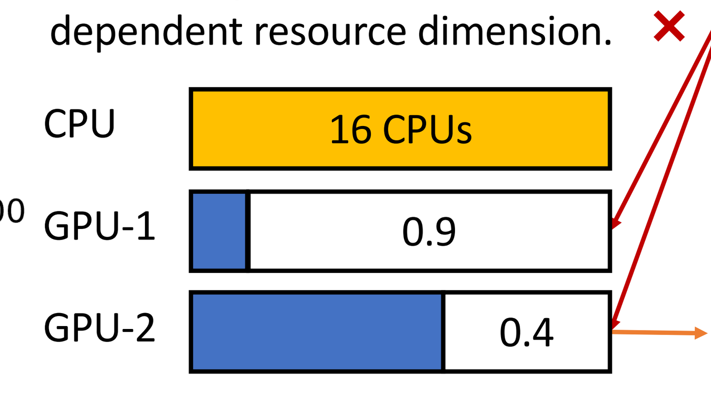
Insufficient GPUs on nodes given the requests of tasks

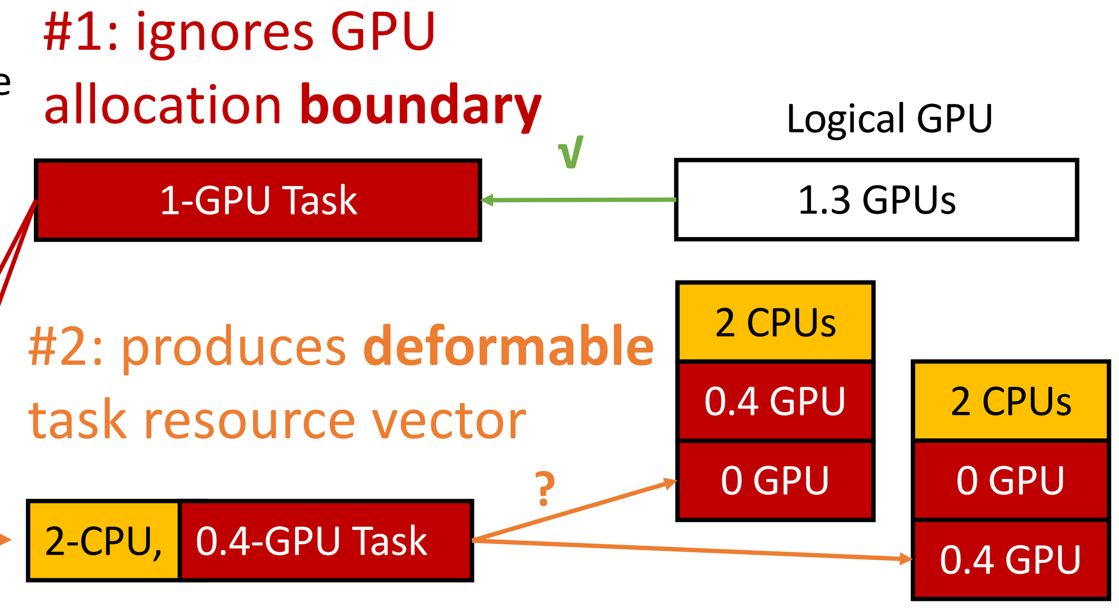


Insufficient CPUs (or stranded GPUs)

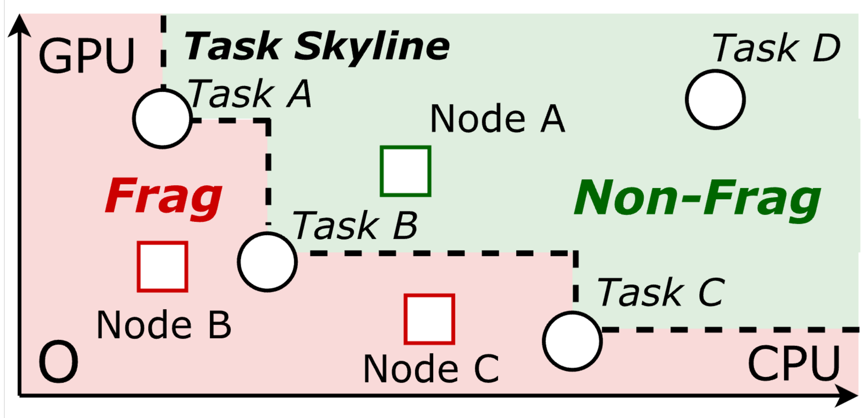
*Classical multi-resource bin-packing **cannot** work effectively on GPUs due to **formulation mismatch***

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***

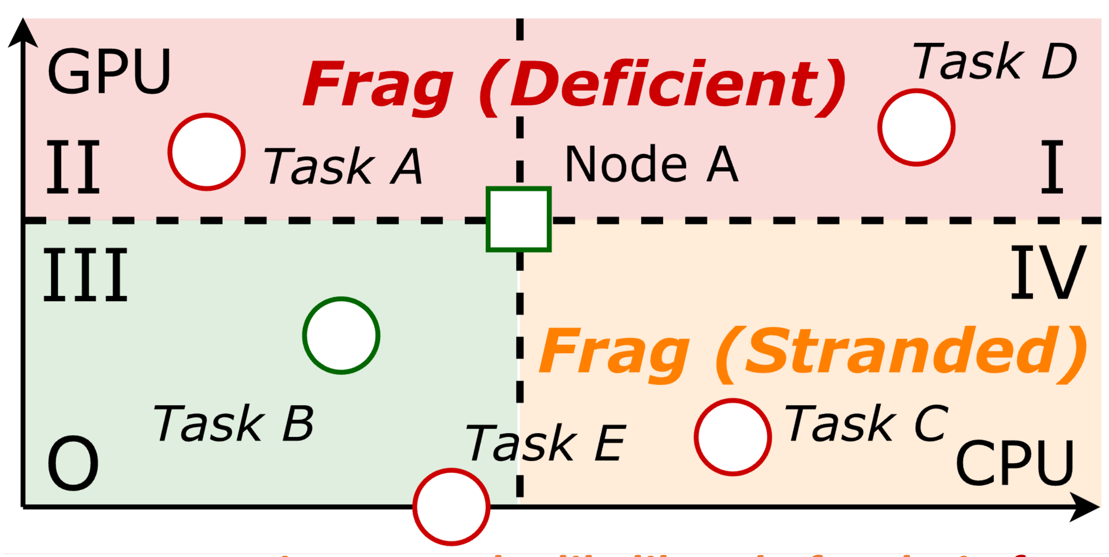


A **defective** definition of **fragmentation** in **absolute** terms — *"a node is fragmented **if and only if** it cannot run any task". **Task skyline** determines the frag / non-frag boundary, yet, only **0.06%** task instances belong to the skyline* ☹

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***



Our **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.

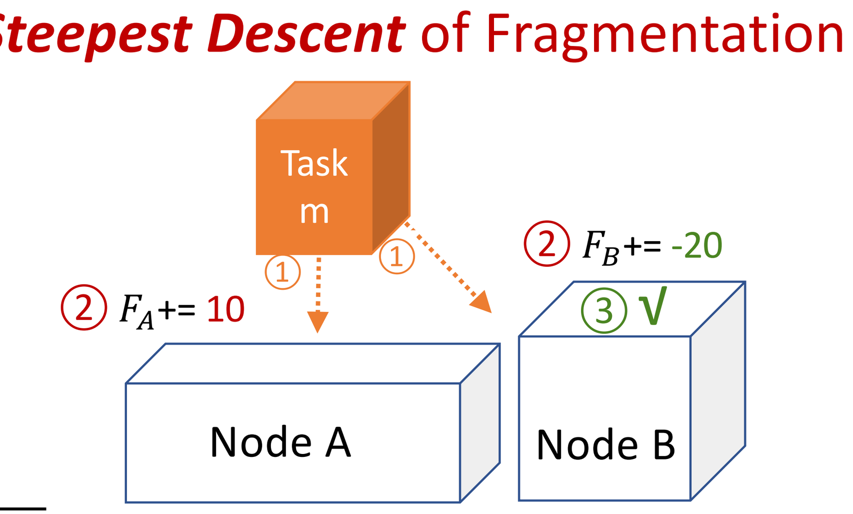
*Schedule Alg.: Fragmentation **G**radient **D**escent*

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 $\mathcal{S} \leftarrow \emptyset$, and output $n^* \leftarrow \emptyset$.
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 $\Delta \leftarrow F_{n^-}^{\text{GPU}}(M) - F_n^{\text{GPU}}(M)$ ▷ Fragmentation increment
  $\mathcal{S} \leftarrow \mathcal{S} \cup (n, \Delta)$
if $\mathcal{S} \neq \emptyset$ **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):

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

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

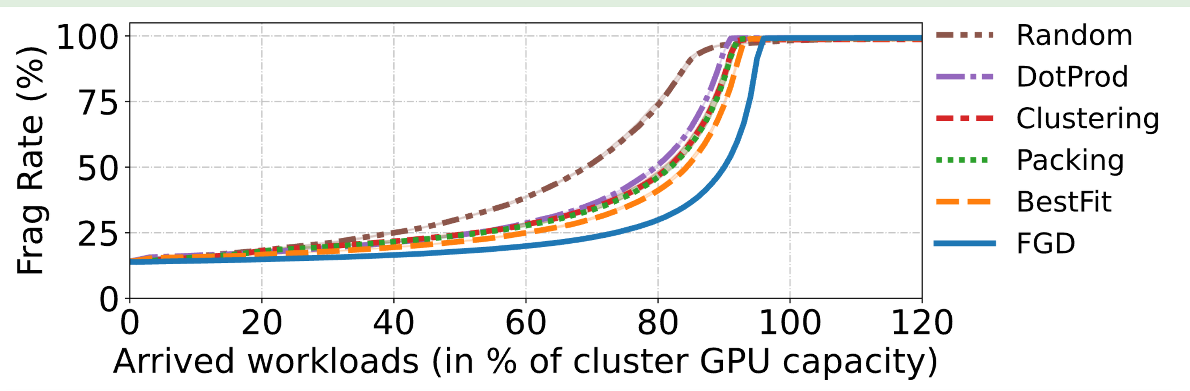
- Case 2: Partial or No Residuals are Frag. (Q-III):

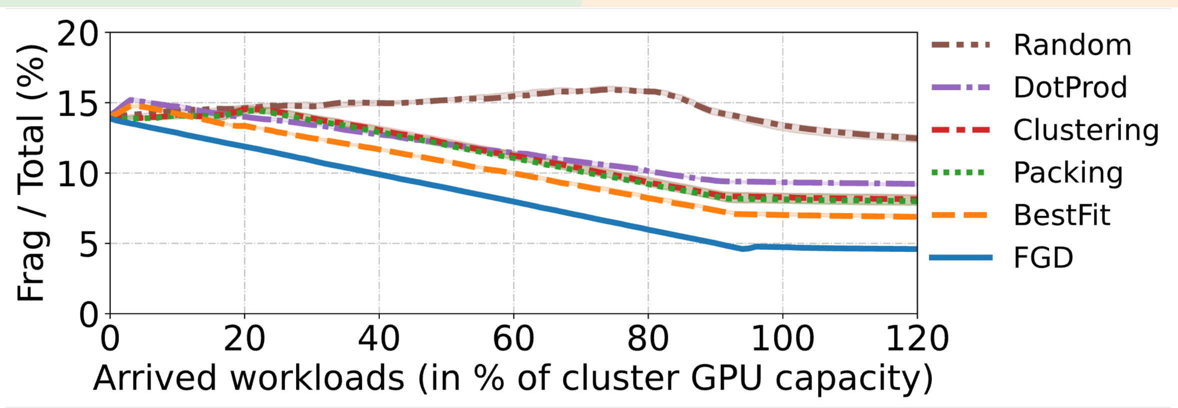
$$F_n(m) = \sum_{1 \le g \le G_n} R_{n,g}^{GPU} \mathbb{1}\left(R_{n,g}^{GPU} < \min\{D_m^{GPU}, 1\}\right)$$

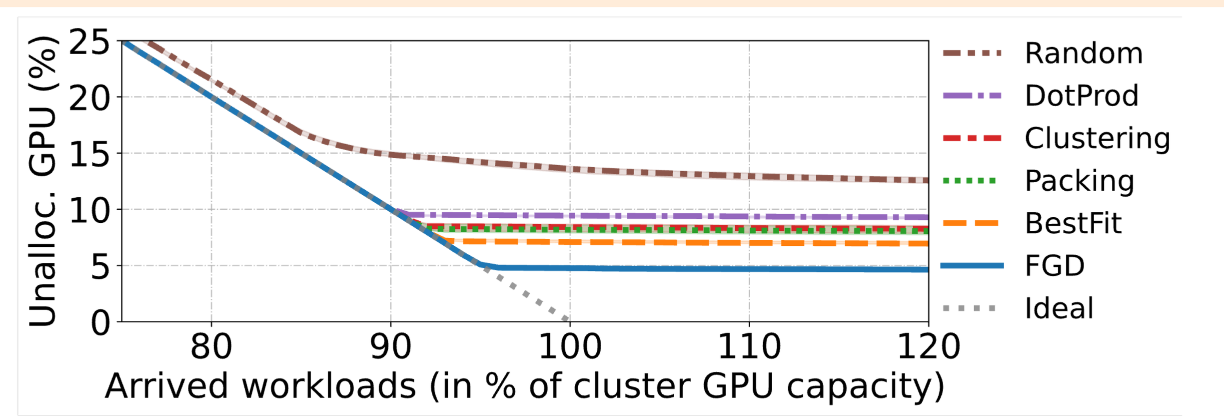
1, if remaining resource is smaller than the demand of task m, else 0.

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

FGD: Lowest Frag. Rate & Fewest GPUs Unallocated







Compared to existing packing-based schedulers, FGD pursues the lowest fragmentation and fewest GPUs unallocated: **FGD reduces unallocated GPUs by up to 49%, utilizing additional 290 GPUs.**

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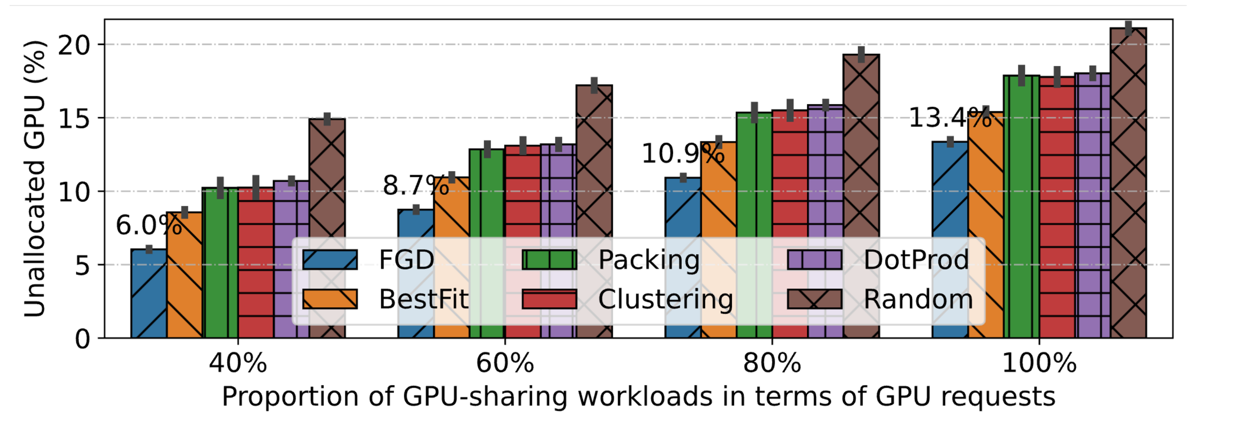

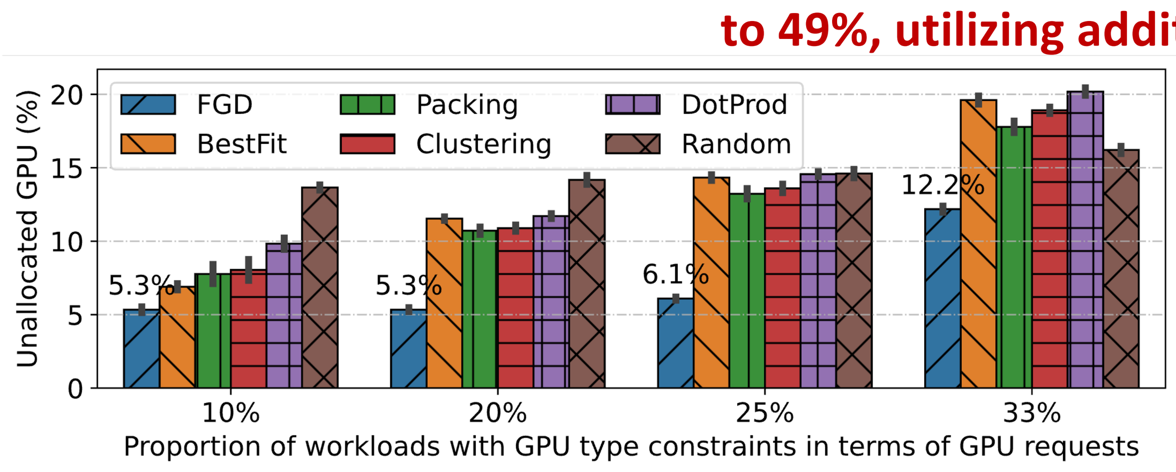

FGD allocates more GPUs across a variety of settings. See more results and task distributions in paper and code.

Paper

Trace & Code