Beware of Fragmentation:

Scheduling GPU-Sharing Workloads with Fragmentation Gradient Descent

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Agenda

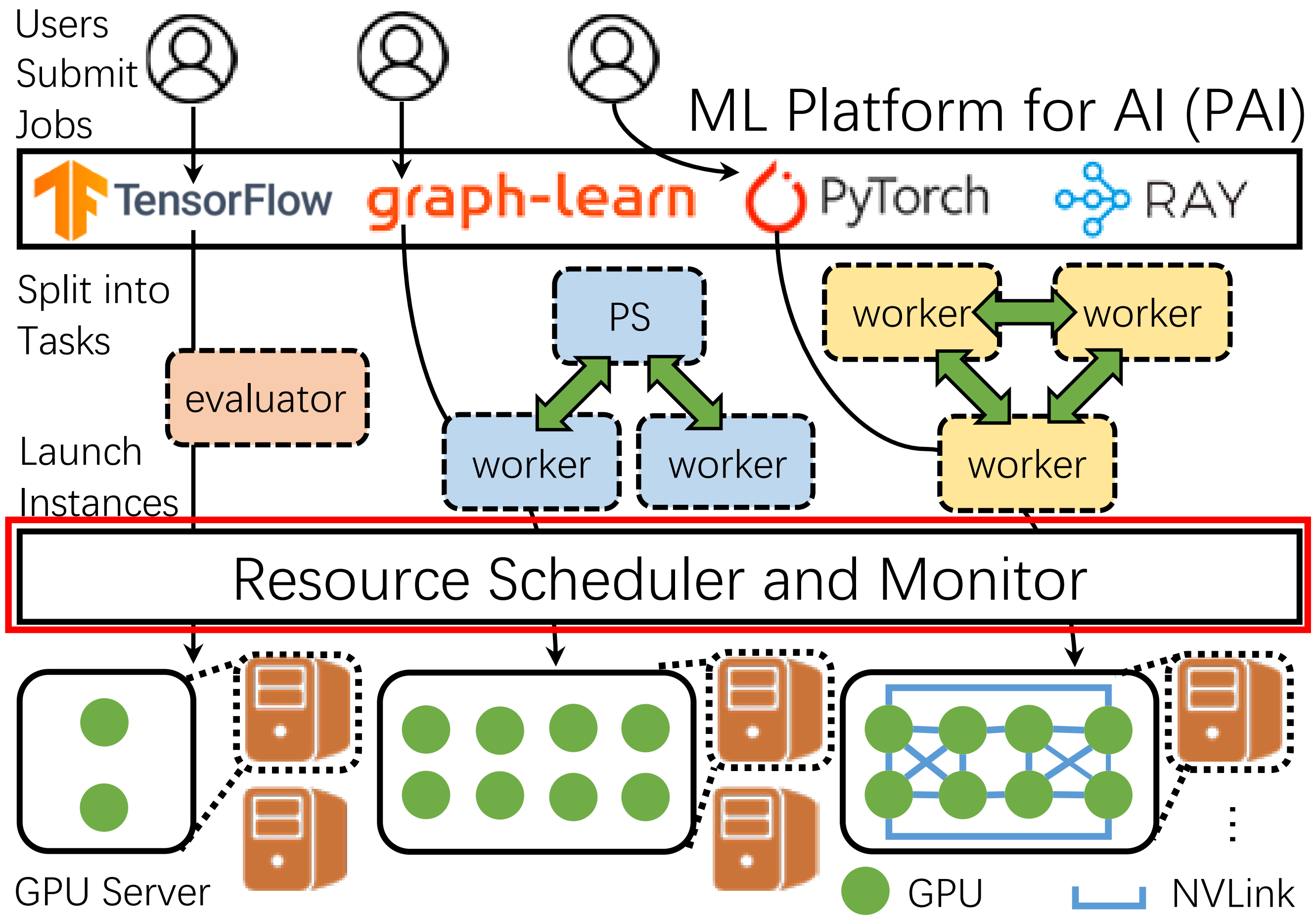
- GPU Sharing & Fragmentation in ML Cluster
- Inefficiency of Existing Approaches
- The Fragmentation Measure
- Fragmentation Gradient Descent
- Implementation and Evaluation
- Conclusion

ML-as-a-Service (MLaaS) Cloud

All-in-one platform for users using different ML frameworks

Support various workloads: training, inference, evaluation …

ML tasks running in containers scheduled to >1000 GPU servers

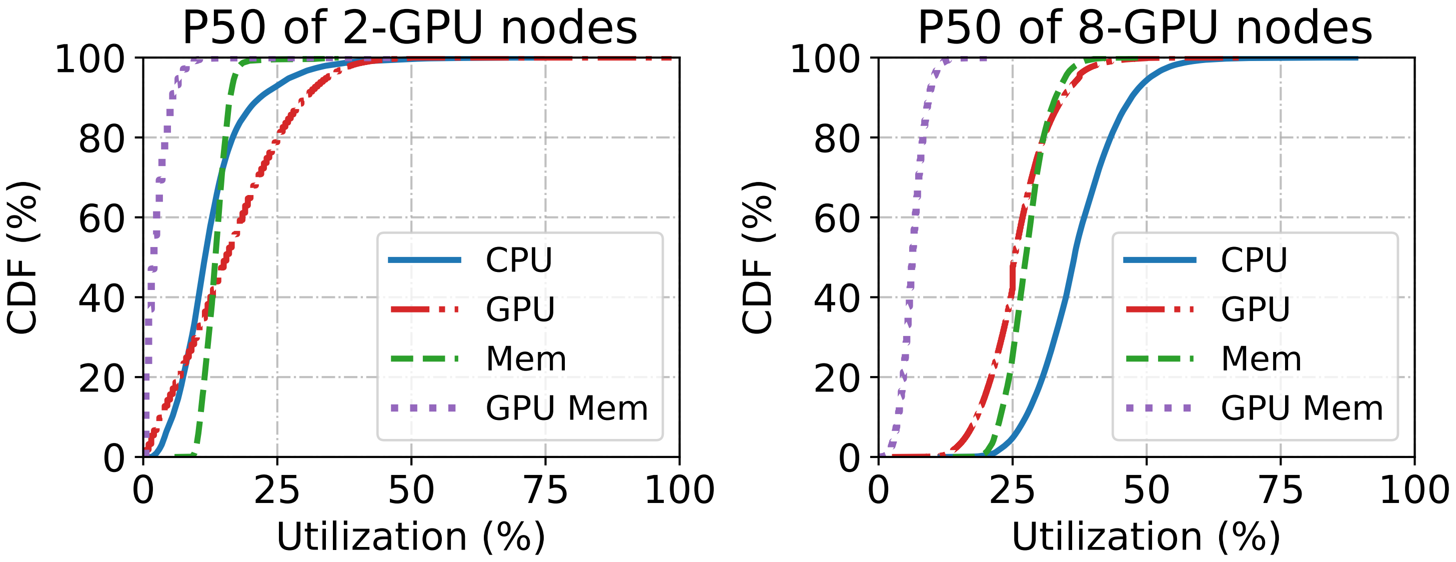


[1] Weng et al., "MLaaS in the Wild: Workload analysis and scheduling in large-scale heterogeneous GPU clusters," in NSDI 2022.

GPU underutilization

25-50% GPU utilization in production ML clusters [1-4]

- Most ML tasks cannot fully utilize the capability of modern GPUs

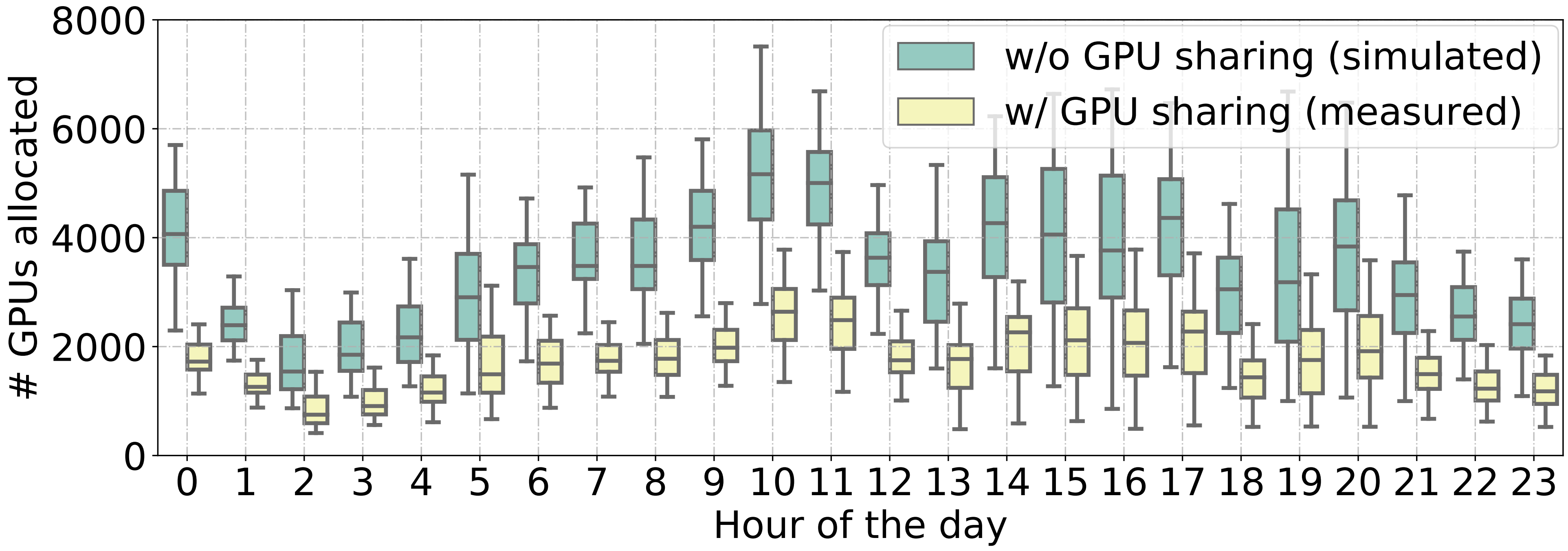


Alibaba PAI trace [1]

[1] Weng et al., "MLaaS in the Wild: Workload analysis and scheduling in large-scale heterogeneous GPU clusters," in NSDI 2022.
[2] Narayanan et al., "Heterogeneity-aware cluster scheduling policies for deep learning workloads," in OSDI 2020
[3] Hu et al., "Characterization and prediction of deep learning workloads in large-scale GPU datacenters," in SC 2021.
[4] Li et al., "Lyra: Elastic scheduling for deep learning clusters," in EuroSys 2023.

The need for GPU sharing

- GPU sharing lets multiple tasks run on a single GPU
    - e.g., via DL framework, CUDA API interception, or hardware support (MIG)
- Sharing saves 50% GPUs in Alibaba PAI [1]

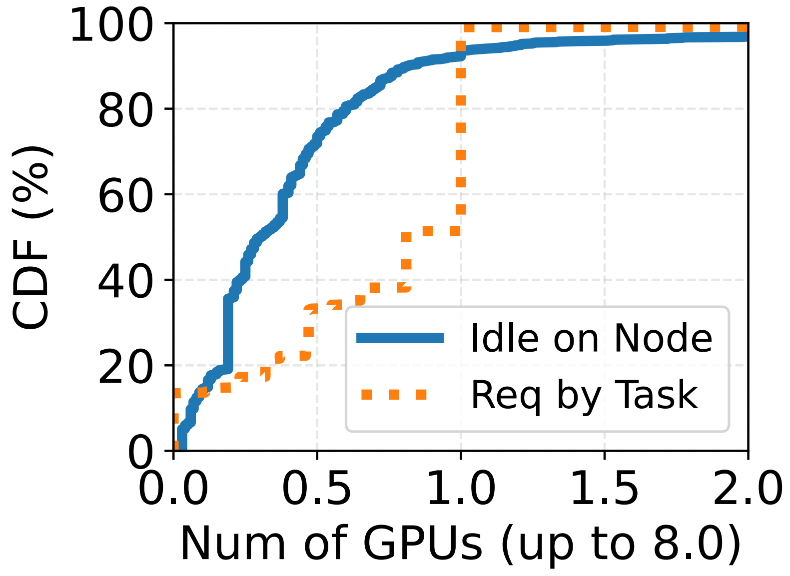


[1] Weng et al., "MLaaS in the Wild: Workload analysis and scheduling in large-scale heterogeneous GPU clusters," in NSDI 2022.

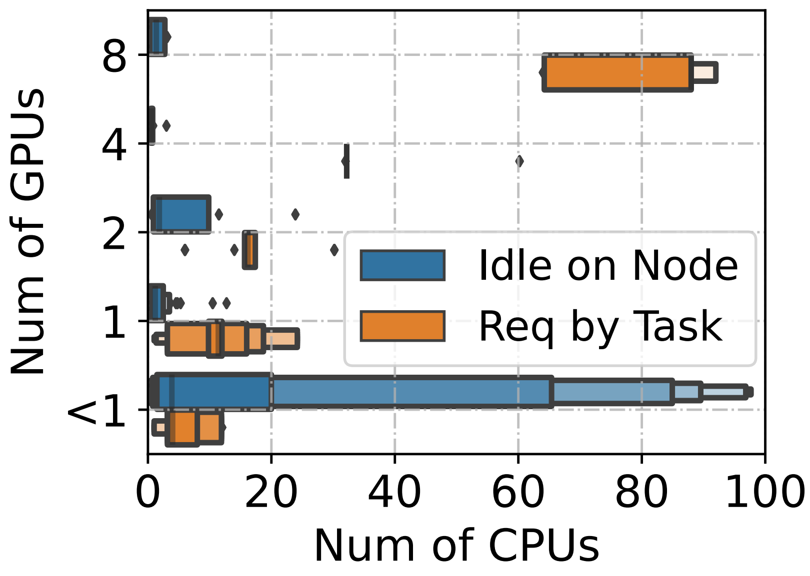
Yet, partial GPU allocation results in fragmentation and limits allocation rate

GPU-sharing cluster H with 1.2k nodes, 6.2k GPUs, 8k tasks (Alibaba)

- Fully packed after allocating 92% GPUs, wasting ~500 GPUs
- User experience scheduling failures even with sufficient GPU allocation quotas



Insufficient GPUs



Insufficient CPUs (stranded GPU)

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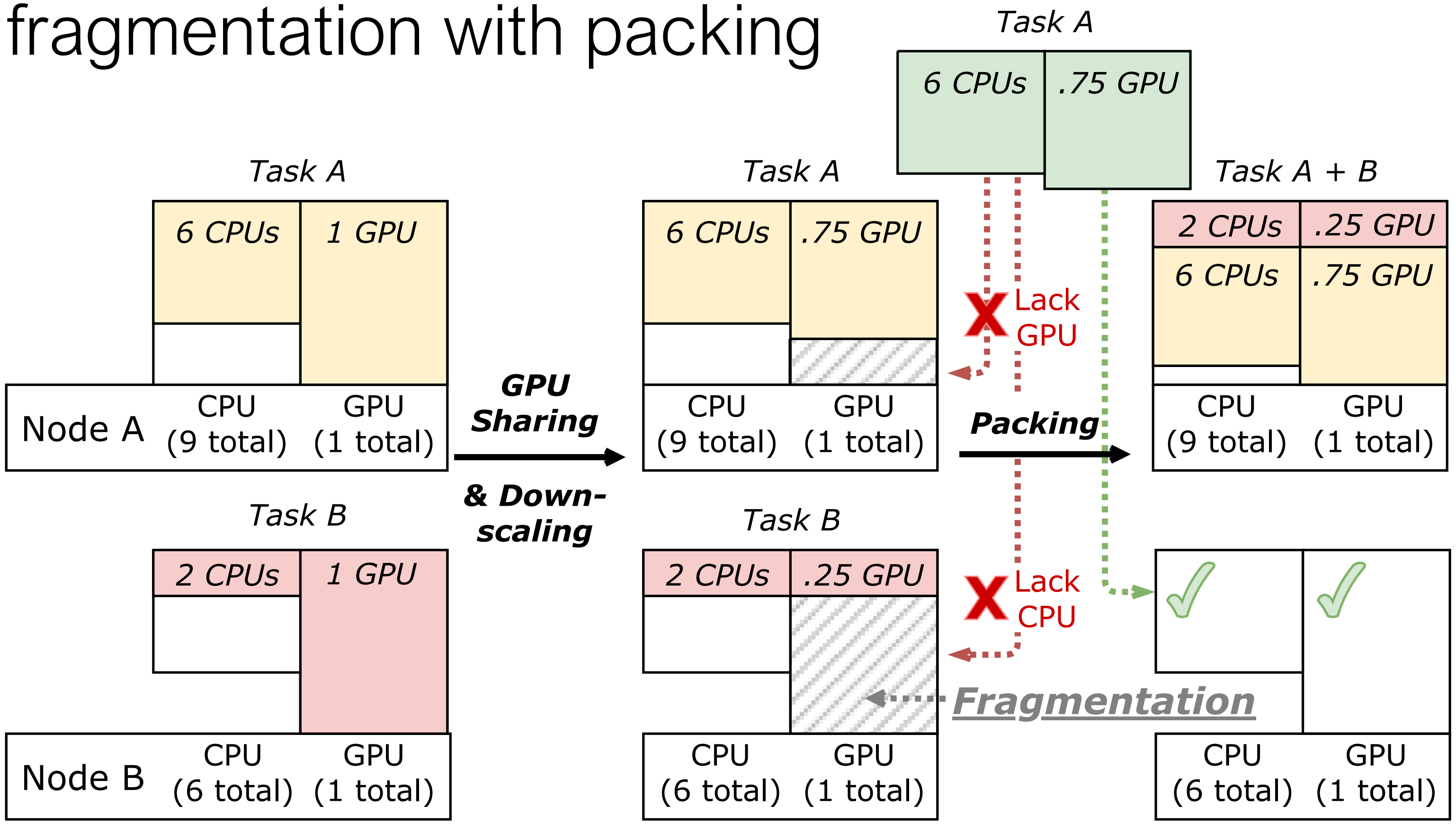
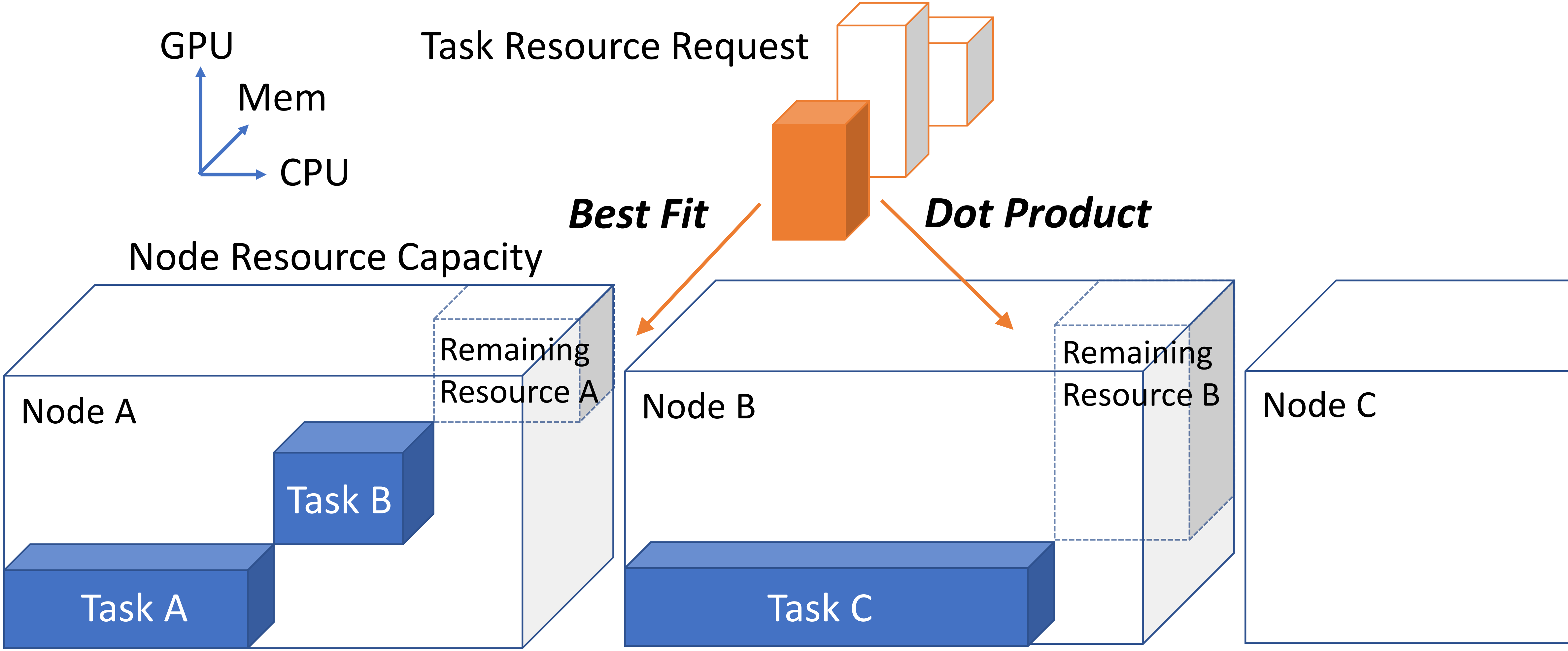
Packing improves allocation

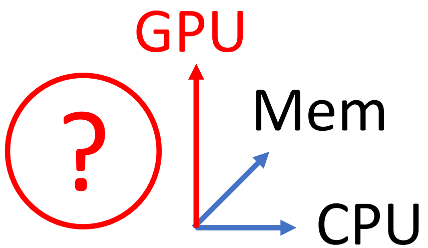
- After GPU sharing, "1 GPU" left in idle but not allocatable to Task A
- Mitigate fragmentation with packing



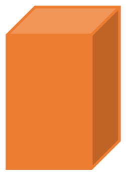
Recap: Multi-Resource Bin-Packing



Best Fit: Verma *et al.* "Borg" *EuroSys* '15
Dot Product: Grandl *et al.* "Tetris" *SIGCOMM* '14



Task Resource Request



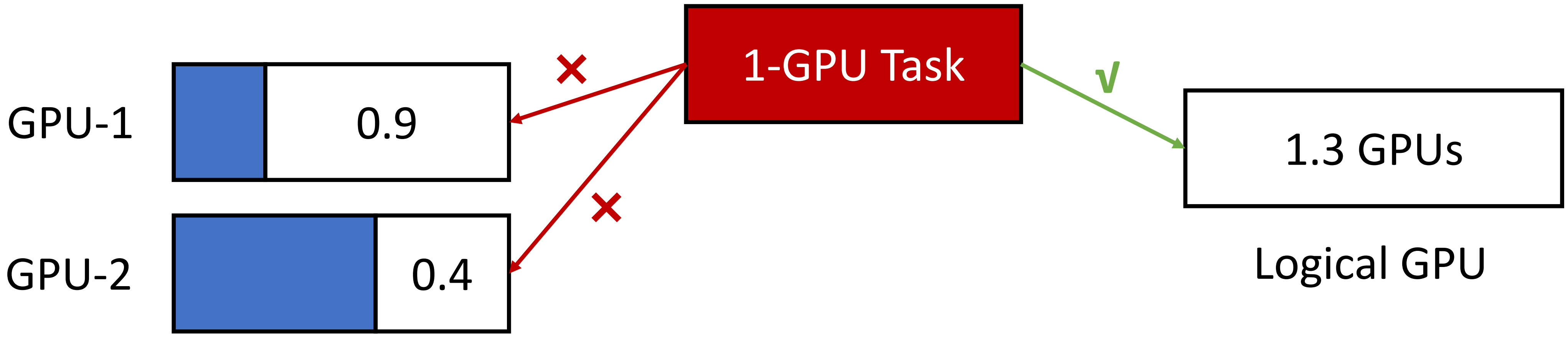
Node Resource Capacity

Does classical multi-resource bin-packing work for GPUs?

How to formulate GPUs into a resource dimension?

Attempt #1

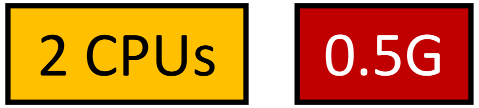
- Pool together a node's multiple available GPUs into one logical GPU
  - e.g., 2-GPU node with <0.9 GPUs, 0.4 GPUs> => having 1.3 GPUs idle
- Problem:
  - GPU pooling ignores the allocation boundary between GPUs
  - Unable to differentiate the fragmentation on individual GPUs

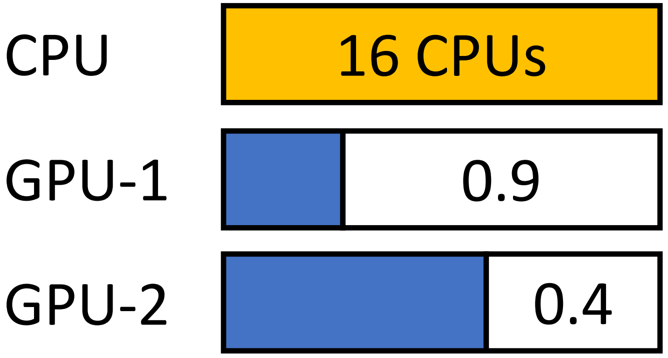


Attempt #2

- Treat each GPU as an independent resource dimension
  - e.g., 2-GPU node has 3D-resource vector <16 CPUs, 0.9 GPUs, 0.4 GPUs>
- Problem:
  - Choosing the wrong expansion of task resource vectors may block allocation

Task <2 CPUs, 0.5 GPUs>





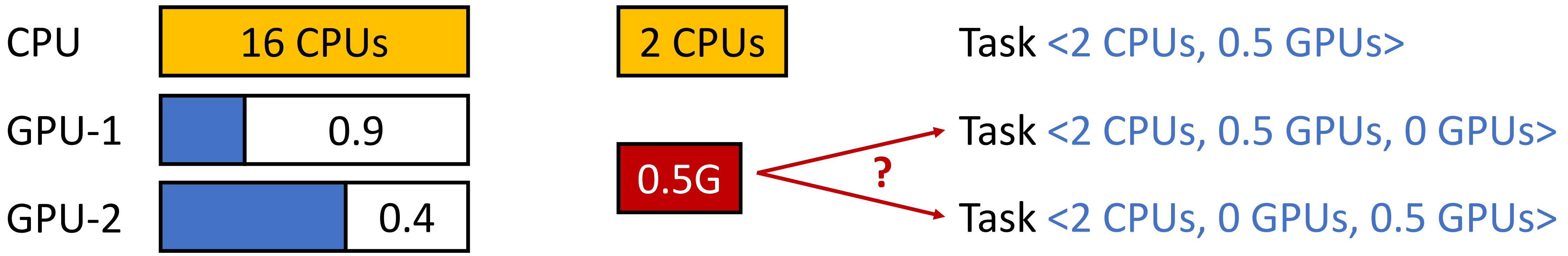
Task <2 CPUs, 0.5 GPUs, 0 GPUs>

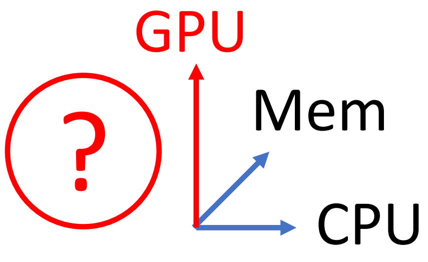
Task <2 CPUs, 0 GPUs, 0.5 GPUs>

Attempt #2

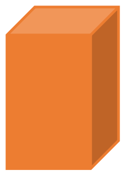
- Treat each GPU as an independent resource dimension
  - e.g., a 2-GPU node with resource vector <16 CPUs, 0.9 GPUs, 0.4 GPUs>
- Problem:
  - Unlike other resources, GPUs are interchangeable!

A GPU task has a "deformable" resource vector wrt available GPUs on the nodes, invalidating the conventional bin-packing formulation!

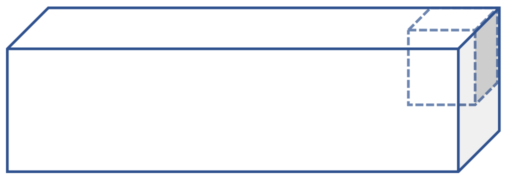




Task Resource Request



Node Resource Capacity



Does classical multi-resource bin-packing work for GPUs?

Not for shared GPUs! Need a new approach to address the fragmentation problem of scheduling GPU-sharing workloads

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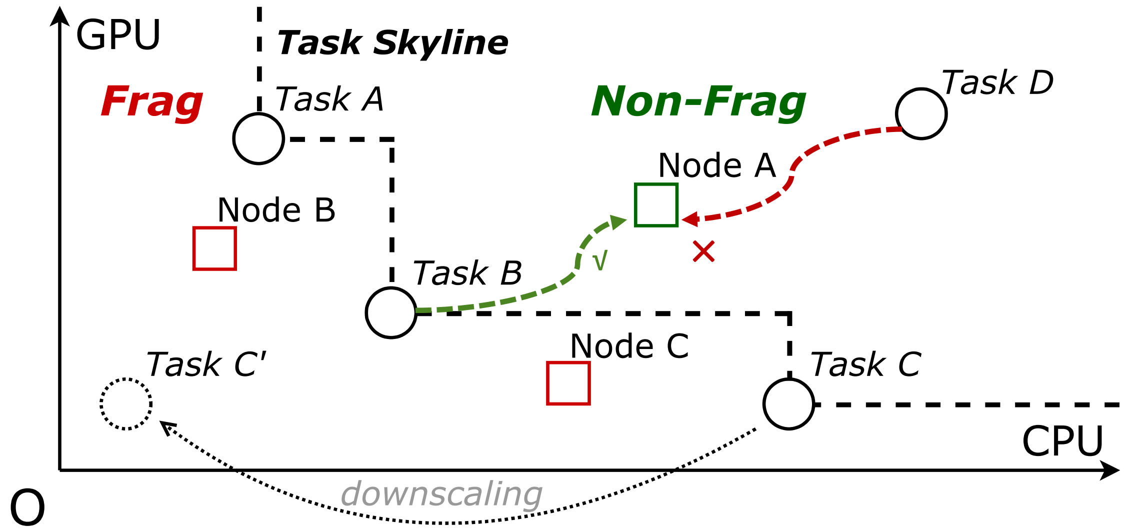
"To Measure is the First Step to Improve"

- How to formally define fragmentation?
  - "You keep using that word. I do not think it means what you think it means."
- How to further reason the sources of fragmentation?
  - Insufficient GPUs, stranded GPUs, or both, how much do they contribute?
- How to efficiently mitigate fragmentation?
  - Simpler and more explainable than using ML techniques

Fragmentation in absolute term ☹

Bad Def.: "A node is fragmented if and only if it cannot run any task"



Y(X)-axis: Idle GPU (CPU) on nodes or Requested GPU (CPU) of tasks

① Ignorant of high-demanding workloads (e.g., Task D has no say on fragmentation)

② Skyline tasks (A, B, C) dominate others, regardless of their tiny population (0.06% in our traces).

- Average skyline task demand: <3.2 CPUs, 0.07 GPUs> is far below avg. task demand: <9.4 CPUs, 0.9 GPUs>

③ Vulnerable to small workload changes (C -> C').
Unable to differentiate fragmentation sources.

The absolute measure is overly restrictive in fragmentation identification

- Scheduling 8k tasks to 6.2k GPUs

Fragmentation stays at a **low level (<5%)** throughout the scheduling — Failing to provide early feedbacks to the scheduling quality

A statistical fragmentation measure ☺

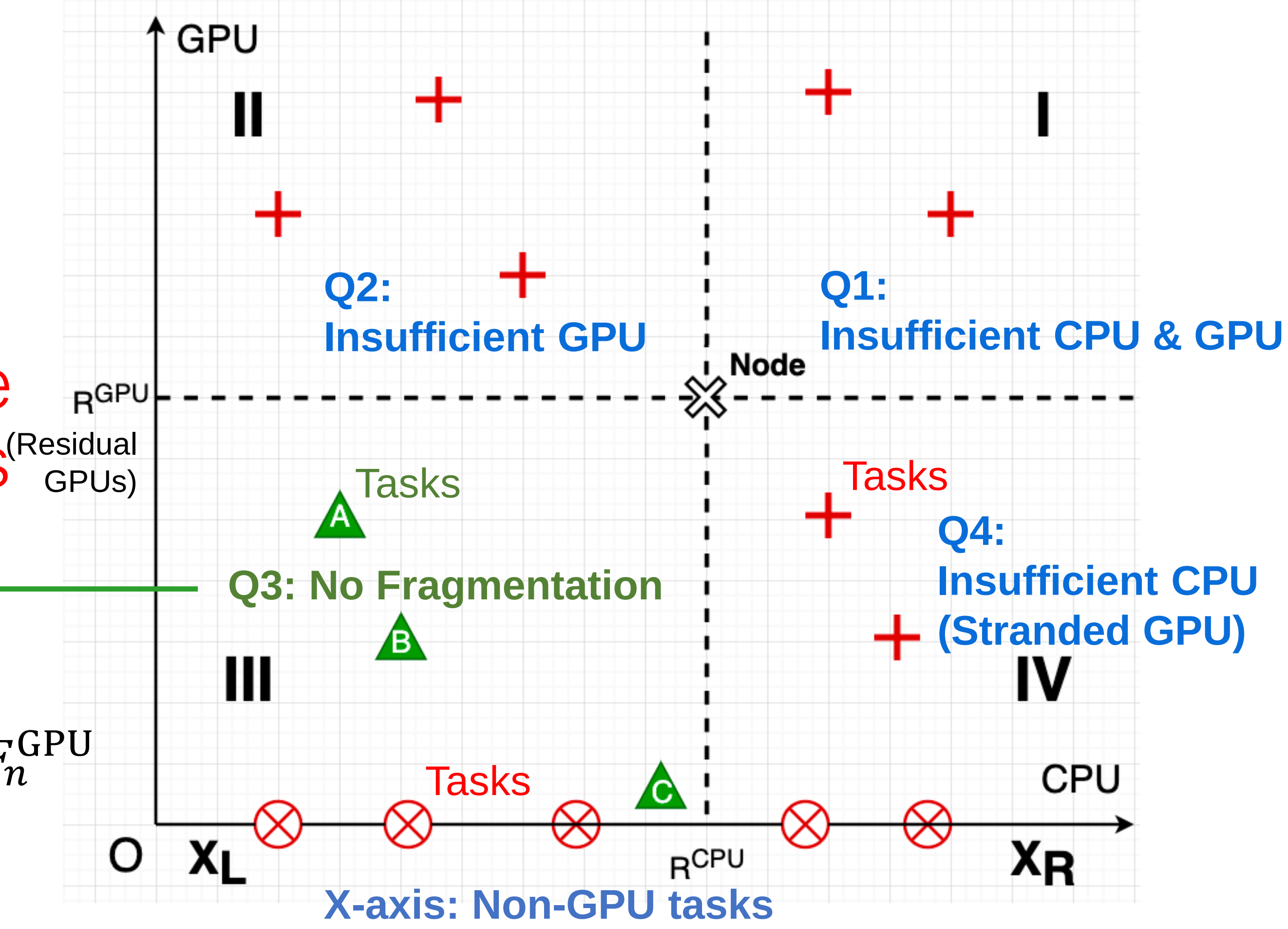
The next task to arrive is considered to be randomly sampled from typical workloads

Fragmentation region

- Q1 & Q2: Insufficient GPU
- Q4: Stranded GPU
- X-axis: Non-GPU tasks

Frag rate: the likelihood that the arriving task falls in frag regions

- Frag rate*: $f_n^{\mathrm{GPU}} \cong 1 - \sum_{m \in Q_3} p_m$
  ($p_m \in (0, 1]$: task popularity)
- Frag amount: $F_n^{\mathrm{GPU}} = f_n^{\mathrm{GPU}} R_n^{\mathrm{GPU}}$
- Cluster frag amount: $F_N^{\mathrm{GPU}} = \sum_n F_n^{\mathrm{GPU}}$

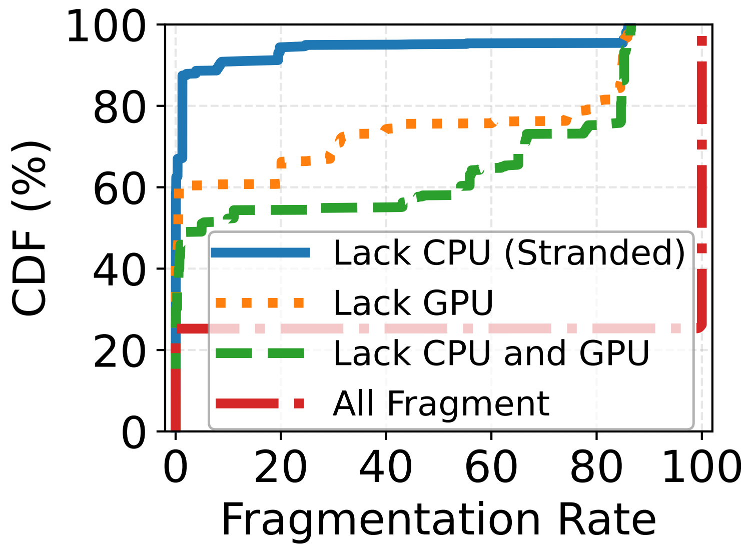


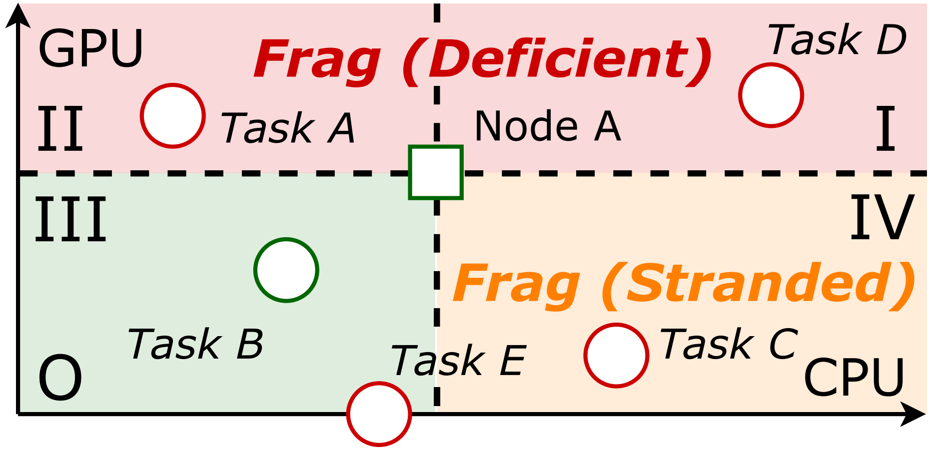
* Roughly, as finer-grained calculation should consider fragmentation at per-GPU level. See more in the §3.2 of the paper.

A statistical fragmentation measure ☺

Given the task distribution of a target workload, it measures the expected GPU resources that cannot be allocated

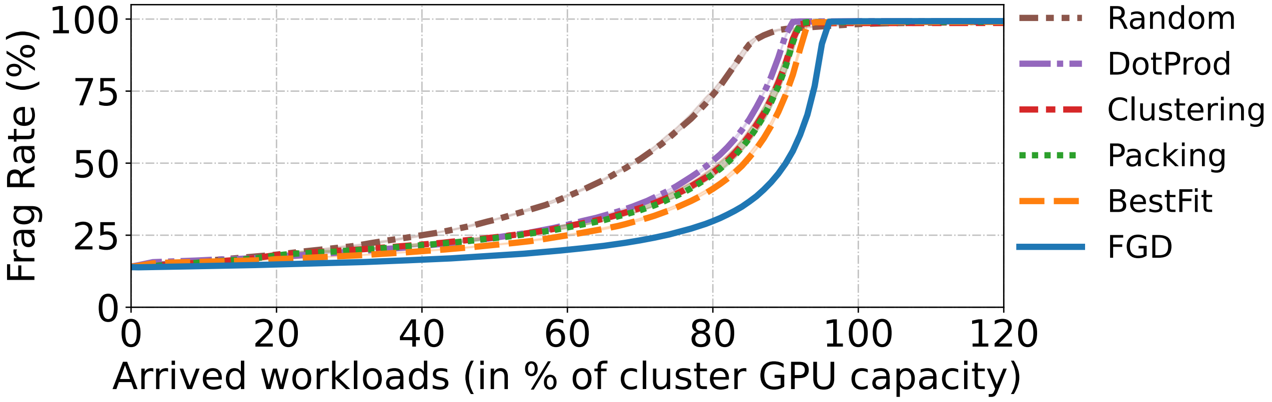
- Further broken down into different sources of fragmentation: Insufficient GPU (Q2), stranded GPU (Q4), lack both (Q1), non-GPU tasks (X-axis).

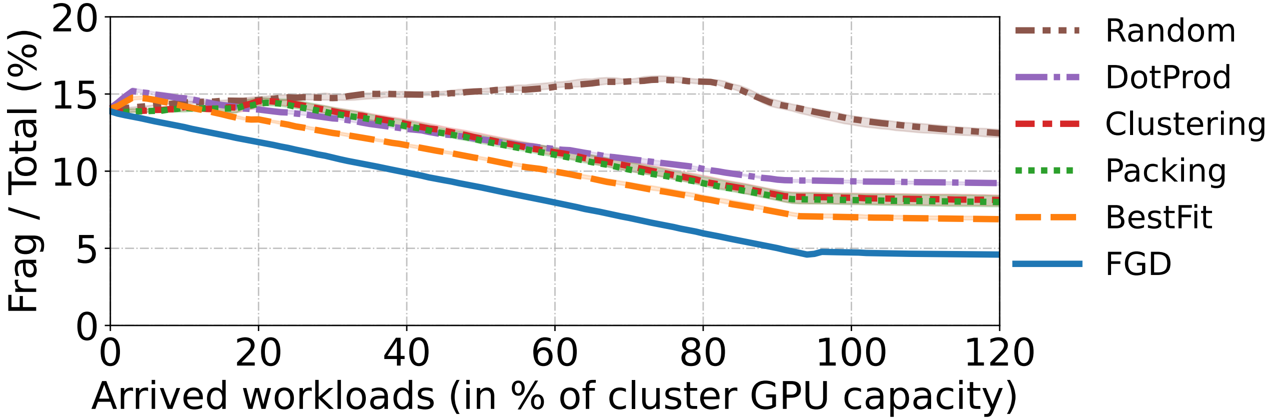




A statistical fragmentation measure ☺

- Sensitive to scheduling quality; useful feedback at early stages
- Scheduling: Frag rate f_n^{GPU} ↑ Remaining resources R_n^{GPU} ↓ Until all remaining resources are unallocatable to any tasks (i.e., Frag rate = 100%).
- Cluster Frag = $\sum_n (f_n^{\text{GPU}} R_n^{\text{GPU}})$ / Total (%): normalized by cluster GPU capacity





Clustering: Xiao *et al.* “Gandiva" *OSDI* '18
Packing: Weng *et al.* “MLaaS" *NSDI* '22

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Fragmentation Gradient Descent (FGD)

Heuristic: schedule tasks towards the ***steepest descent*** of fragmentation

FGD scores nodes in parallel, thus scaling to large clusters: each decision can be made in *hundred of milliseconds* in cluster with 1200 nodes

Algorithm 1: Task scheduling of FGD

Input : Cluster N, incoming task m, target workload 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

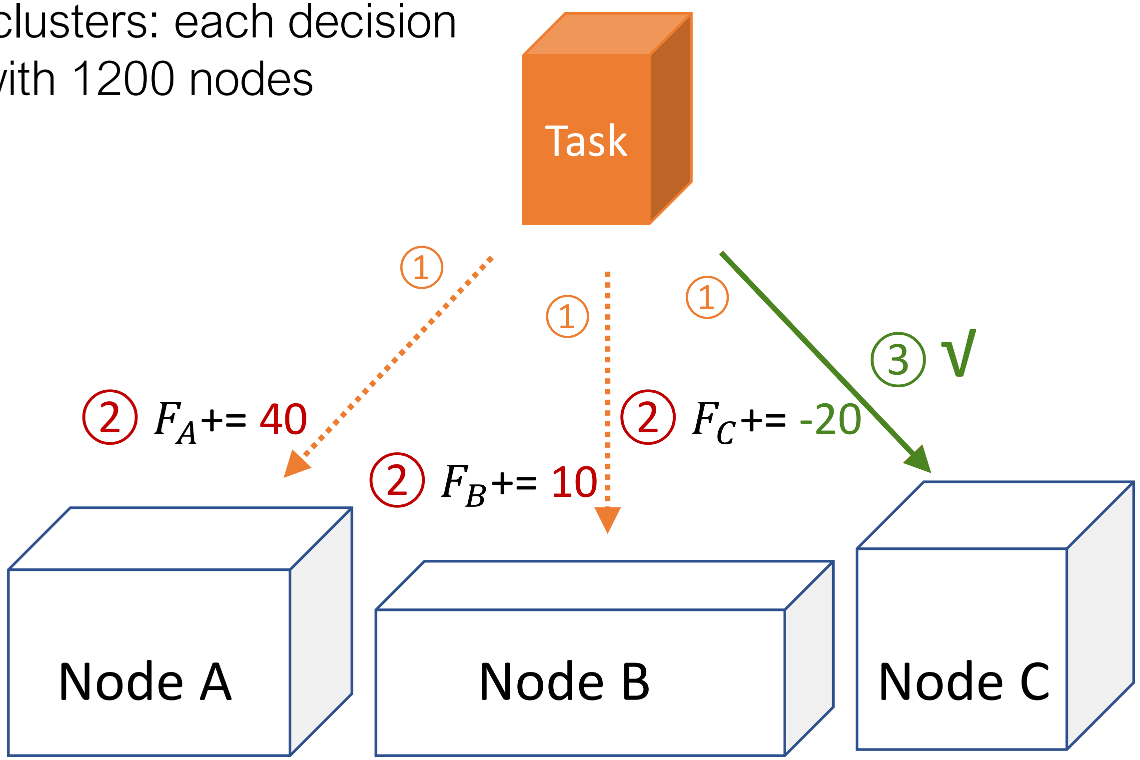
  $n^- \leftarrow \text{AssignTaskToNode}(m, n)$ ▷ Hypothetically

2 $\Delta \leftarrow F_{n^-}(M) - F_n(M)$ ▷ Fragmentation increment

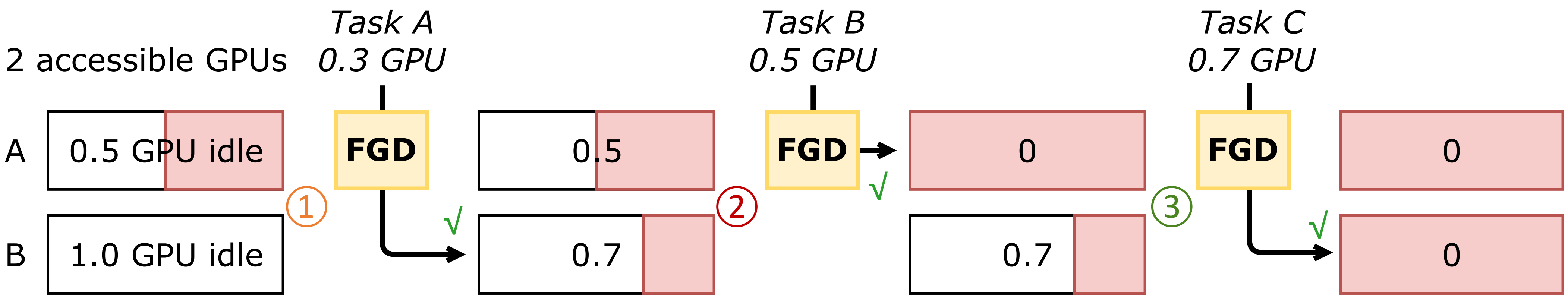
  $\mathcal{S} \leftarrow \mathcal{S} \cup (n, \Delta)$

if $\mathcal{S} \neq \varnothing$ **then**

3 $n^* \leftarrow \arg\min_{n \in \mathcal{S}} \Delta$ ▷ pick the node with the least Δ.



A running example of FGD scheduling



after alloc. before alloc.

Frag amount:
$F_n^{\text{GPU}} = f_n^{\text{GPU}} R_n^{\text{GPU}}$

1 To GPU A: A will be fragmented to Task A, B, C $(F_A^{GPU} \mathrel{+}= \underline{100\% * 0.2} - 33\% * 0.5)$
To GPU B: B will be no fragmentation to any Task $(F_B^{GPU} \mathrel{+}= \underline{0\% * 0.7} - 0)$ √

2 To GPU A: A will have no GPU left, thus no fragmentation $(F_A^{GPU} \mathrel{+}= \underline{0} - 33\% * 0.5)$ √
To GPU B: B will be fragmented to Task A, B, C $(F_B^{GPU} \mathrel{+}= \underline{100\% * 0.2} - 0)$

3 To GPU A: Impossible
To GPU B: B will have no GPU left, thus no fragmentation $(F_B^{GPU} \mathrel{+}= \underline{0} - 0\% * 0.7)$ √

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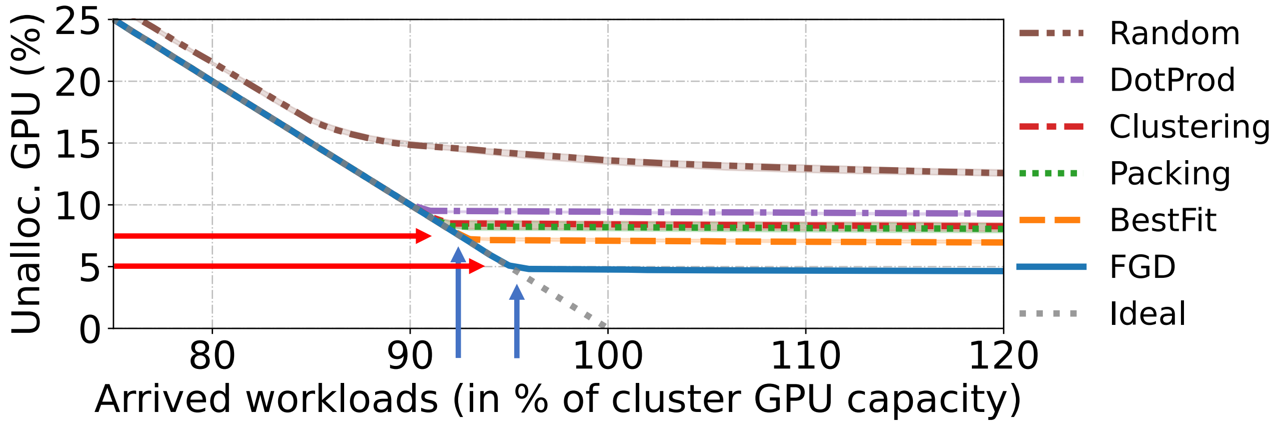
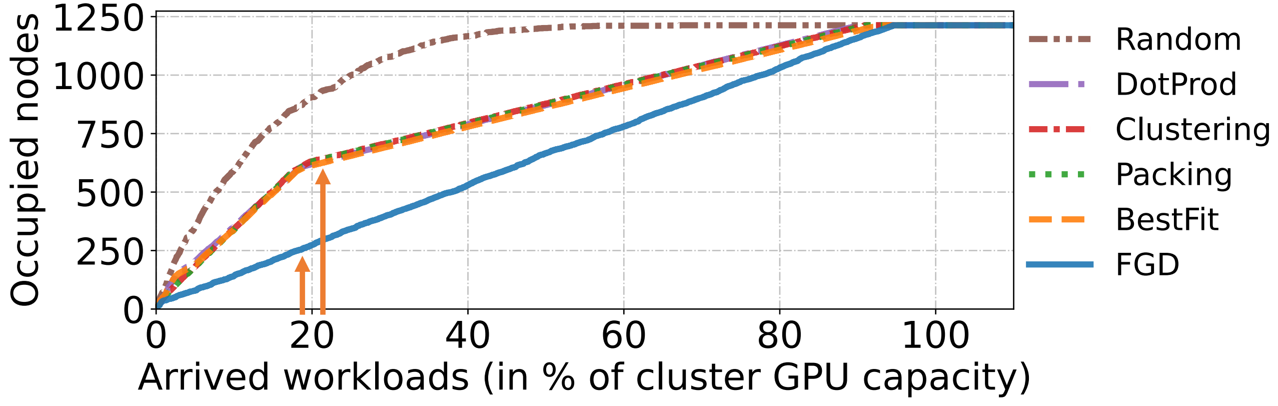
Large-scale trace-driven emulation

- **Implementation**: a pluggable scheduler in Kubernetes
- **High-fidelity event-driven emulator**
  - Cluster-H: 1.2k nodes, 6.2k GPUs
  - Production trace of 8k tasks as input
  - Plugin + Emulator: 10k lines of code



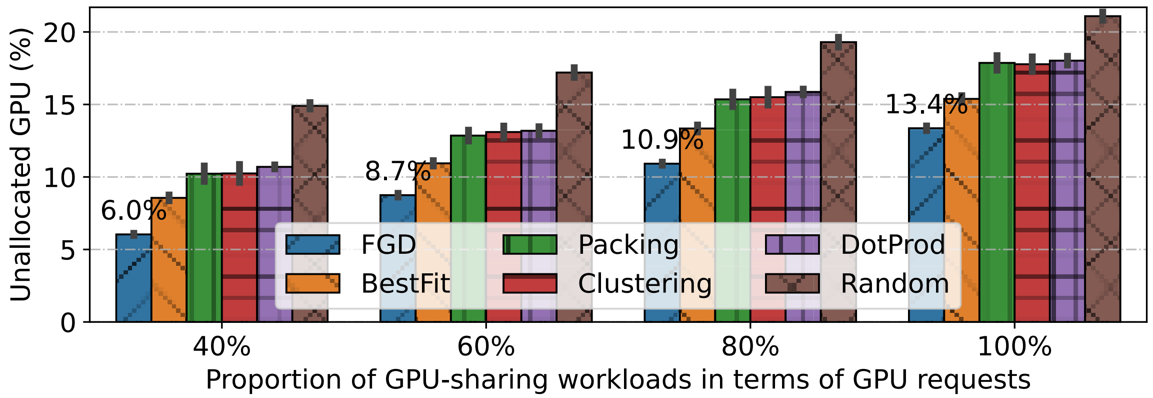
- FGD outperforms all heuristics
  1. Has the **least** amount of GPU fragment
  2. Hosts more tasks before saturation
  3. Packs tasks to 250+ fewer nodes
  4. Reduces unallocated GPUs by 33-49% (utilizes additional 150-290 GPUs)



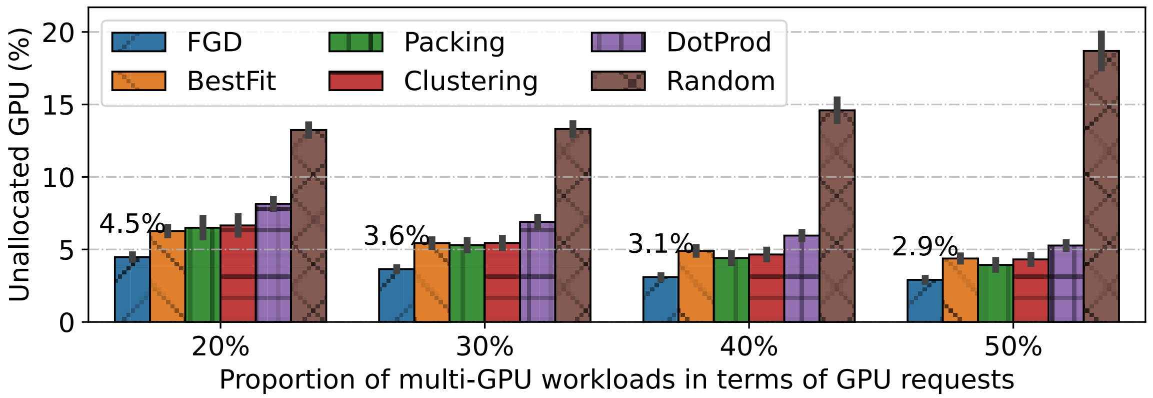
- Emulator: https://github.com/hkust-adsl/kubernetes-scheduler-simulator
- Traces: https://github.com/alibaba/clusterdata/tree/master/cluster-trace-gpu-v2023
- Clustering: Xiao et al. "Gandiva" OSDI '18
- Packing: Weng et al. "MLaaS" NSDI '22

Under varying workload distribution

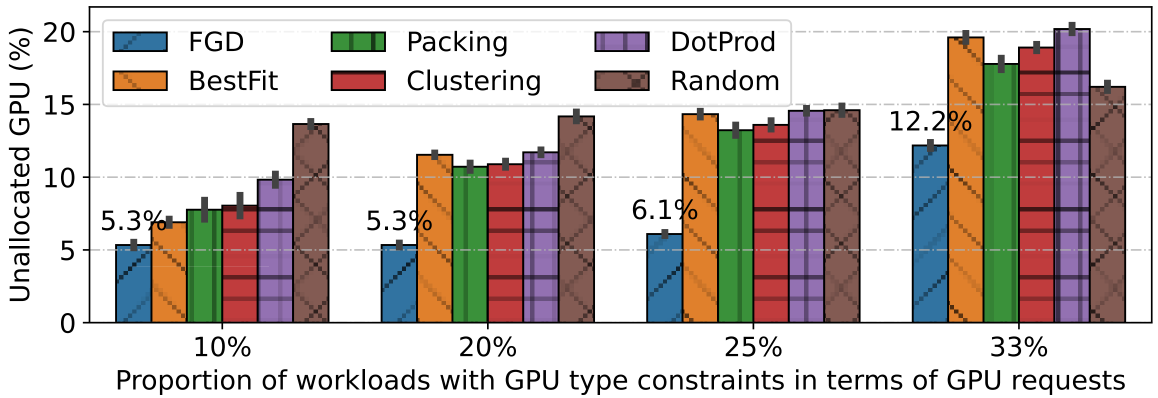
GPU-Sharing Tasks



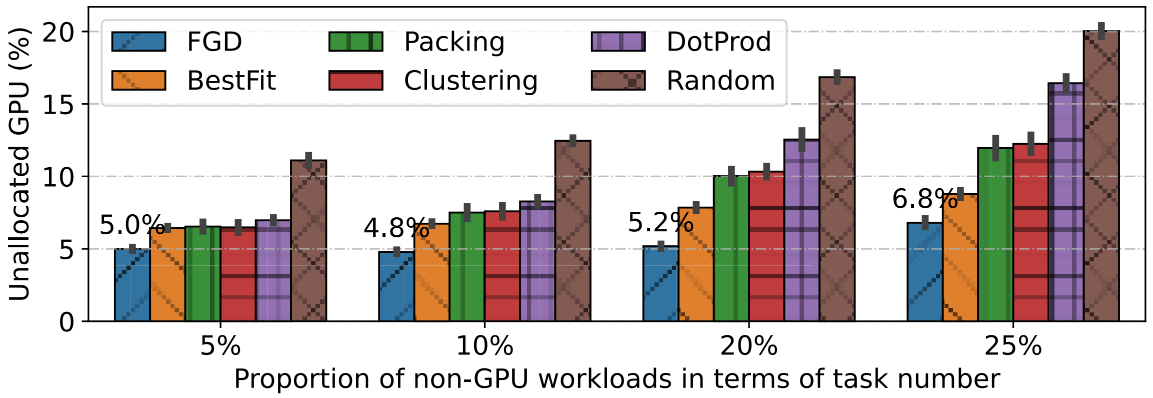
Multi-GPU Tasks



Tasks with GPU-type constraints



Non-GPU Tasks



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Trace & Code

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Conclusion

Allocating partial GPUs results in severe fragmentation

- A new challenge that cannot be addressed using conventional bin-packing approaches

A new fragmentation metrics

- Measure the expected GPU resources that cannot be allocated given a workload distribution
- Support breakdown analysis to reason about fragmentation

Fragmentation Gradient Descent (FGD)

- Schedules tasks towards the steepest descent of GPU fragmentation
- Packs tasks to fewer nodes, substantially reducing unallocated GPUs
- Easy to implement

Paper