Interference-aware Multiplexing for Deep Learning in GPU Clusters: A Middleware Approach

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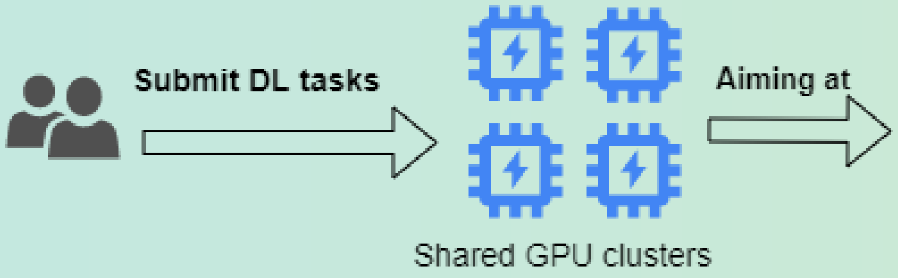
Deep learning: An important cloud workload

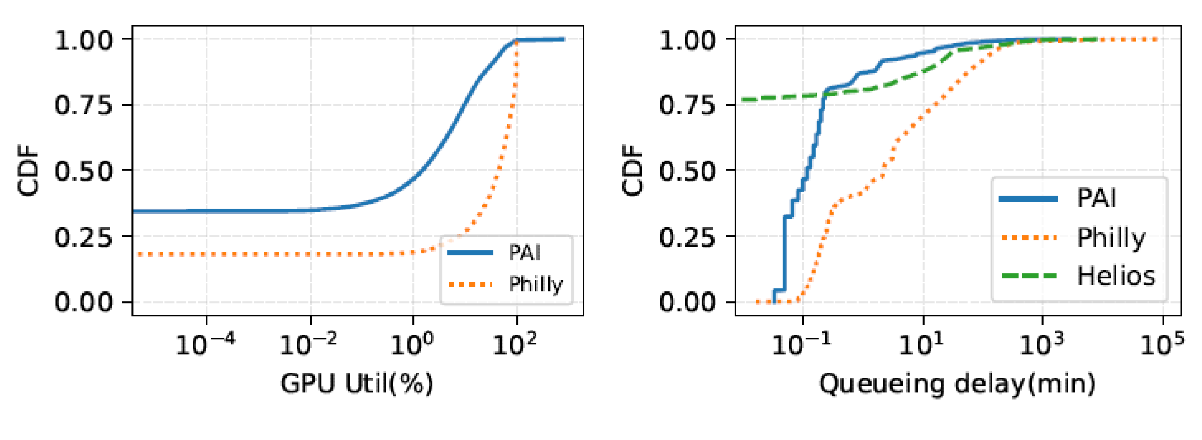
- **Deep learning (DL)** are widely adopted as intelligent applications
  - Computer Vision
  - Natural Language Processing
  - E-commerce Recommendation
  - …
- DL tasks are often trained in GPU clusters to achieve specific validations



DL task	validations
VGG16	85% top1 acc
NCF	69% hit rate
Bert	88% F1 score
YOLOv5	84% mAP

GPU Schedulers for Deep Learning Today

- Underutilization and long queueing delay of deep learning
  - Up to 60% GPUs are below 10% utilization of Philly trace in Microsoft[1] and PAI trace in Alibaba[2]
  - The longest delay spans more than 1,000 minutes in Philly trace and Helios trace in SenseTime[3]

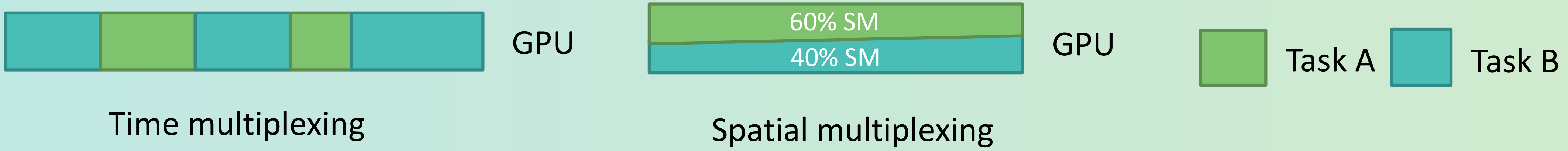


(a) GPU Utilization (b) Queueing delay

[1] Jeon, Myeongjae, et al. "Analysis of Large-Scale Multi-Tenant GPU Clusters for DNN Training Workloads." *In Proceedings of ATC*. 2019.
[2] Weng, Qizhen, et al. "MLaaS in the wild: Workload analysis and scheduling in Large-Scale heterogeneous GPU clusters.“ *In Proceedings of NSDI*, 2022.
[3] Hu, Qinghao, et al. "Characterization and prediction of deep learning workloads in large-scale gpu datacenters." *In Proceedings of SC*, 2021.

GPU Schedulers for Deep Learning Today

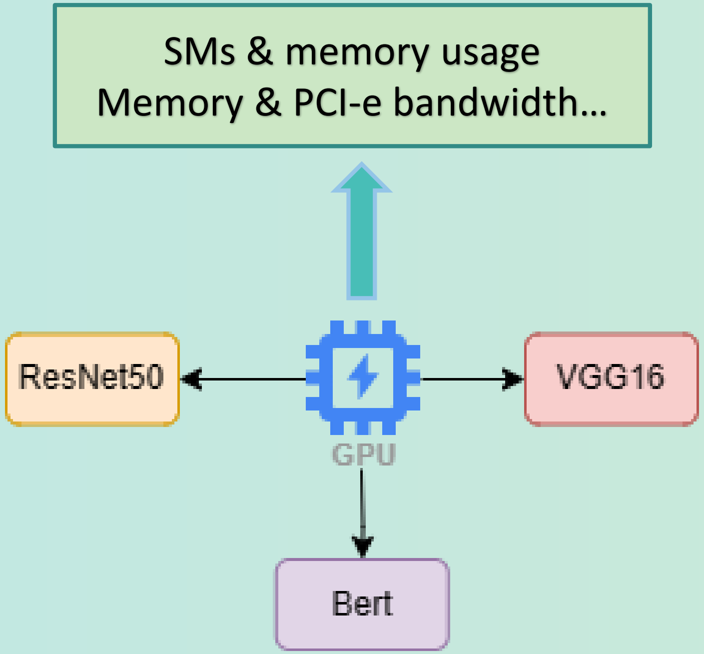
- Packing tasks via time or spatial multiplexing to improve GPU utilization

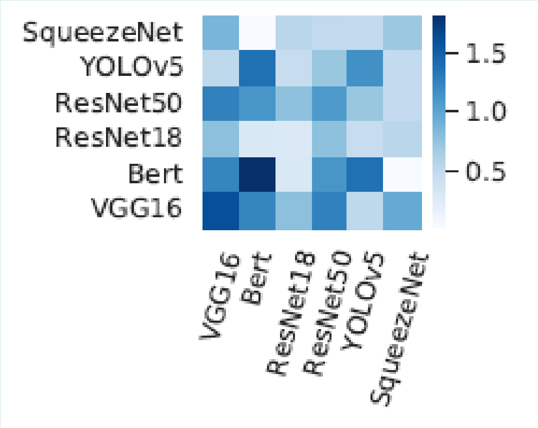


- Time multiplexing: AntMan (OSDI’20), PilotFish (ATC’22), PipeSwitch (OSDI’20)…
- Spatial multiplexing: MPS and MIG in NVIDIA

Is Always Good for Multiplexing?

- Multiple tasks may compete for the same required resources
- Severe interference among multiplexing tasks

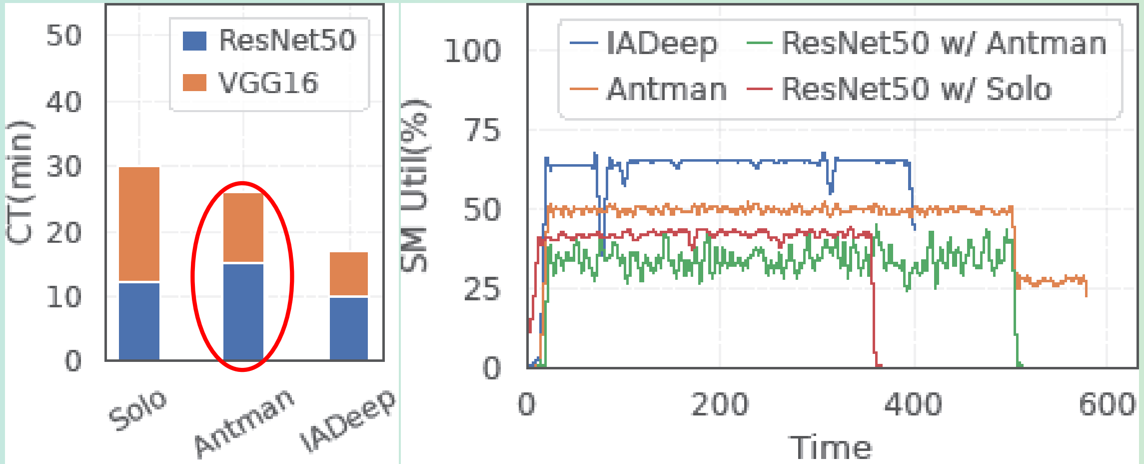




Slowdown of multiplexing tasks

Inefficiencies in Low-level Multiplexing Solutions

- **Kernel-level** solutions: AntMan[1] (OSDI’20)
  - Too fine-grained
  - Can not effectively overlap the kernel computation with copy operations among different tasks
  - Need tailored modifications for different DL frameworks such as Tensorflow and Pytorch



[1] Xiao, Wencong, et al. "AntMan: Dynamic Scaling on GPU Clusters for Deep Learning." *In Proceedings of OSDI*. 2020.

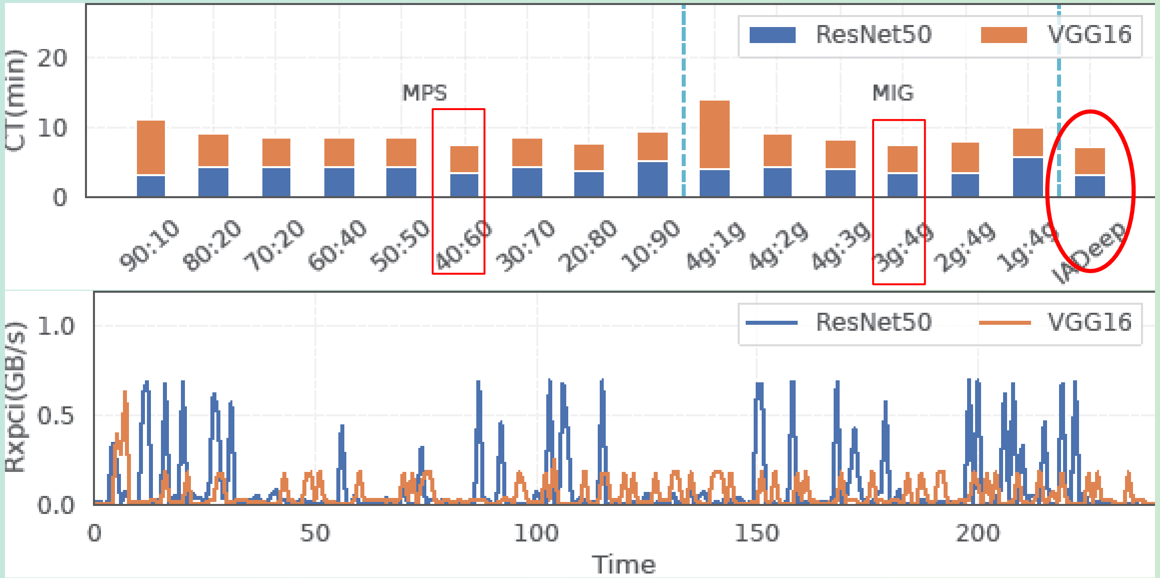
Inefficiencies in Low-level Multiplexing Solutions

- **Hardware-level** isolation solutions: MPS[1] and MIG[2]
  - MPS: A soft isolation solution for GPU multiplexing provided by NVIDIA
    - Require application knowledge to properly set resource partitions
    - Weak fault isolation: when a task fails, other co-located tasks may be affected
  - MIG: A hard isolation solution for GPU multiplexing provided by NVIDIA
    - Only supported by high-end GPU models
    - Inflexible for dynamically allocating resources to tasks

[1] NVIDIA Multi-Process Service. https://docs.nvidia.com/deploy/mps/index.html
[2] NVIDIA Multi-Instance GPU. https://www.nvidia.com/en-us/technologies/multi-instance-gpu

Inefficiencies in Low-level Multiplexing Solutions

- **Hardware-level** isolation solutions: MPS[1] and MIG[2]
  - Too course-grained
  - MPS and MIG can not separate PCI-e bandwidth



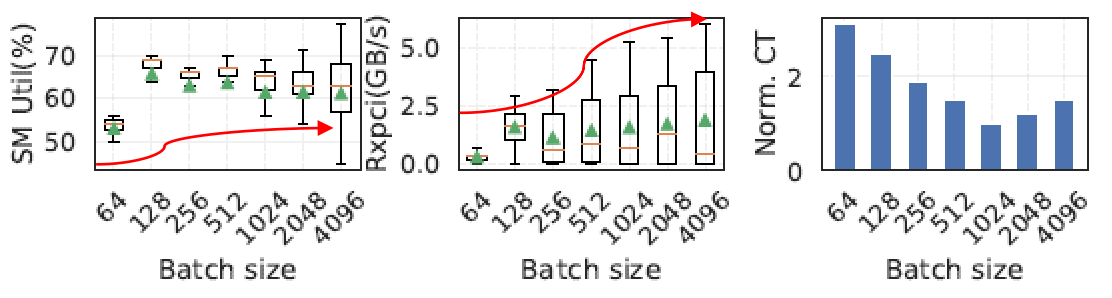
[1] NVIDIA Multi-Process Service. https://docs.nvidia.com/deploy/mps/index.html
[2] NVIDIA Multi-Instance GPU. https://www.nvidia.com/en-us/technologies/multi-instance-gpu

A middleware Solution: IADeep

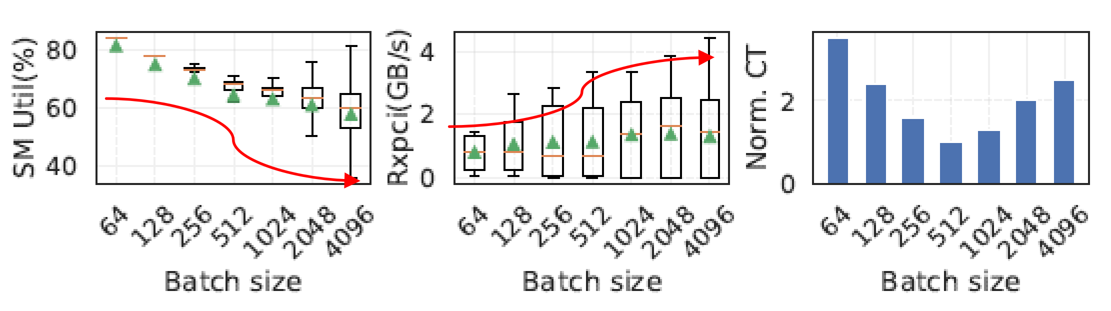
- ✓ Dynamic
- ✓ Less fine-grained
- ✓ Better control all shared resources to mitigate the interference

A middleware Solution: IADeep

- Opportunities and Challenges
  - Training-related configurations, such as *batch size* exhibit strong correlations with various resource metrics



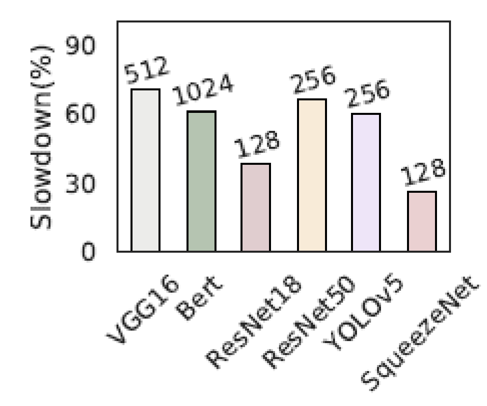
(a) ResNet50



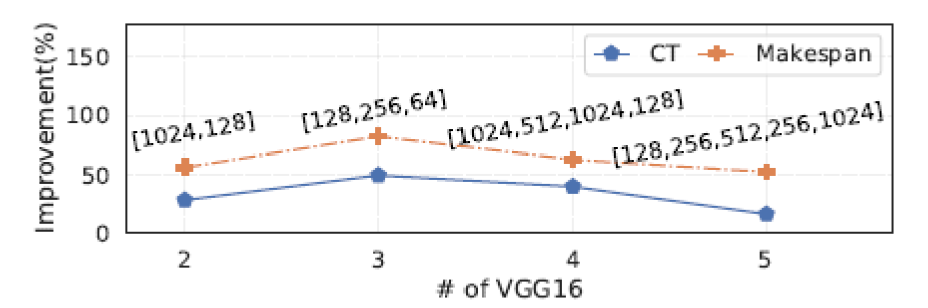
(b) VGG16

A middleware Solution: IADeep

- **Opportunities**
  - Q1: Which tasks to be co-located?
    - Choose appropriate tasks to multiplex on a GPU can mitigate interference
  - Q2: How many tasks should be co-located?
    - Co-locate a suitable number of tasks can balance the waiting time and training time



(a) Slowdown of VGG16



A middleware Solution: IADeep

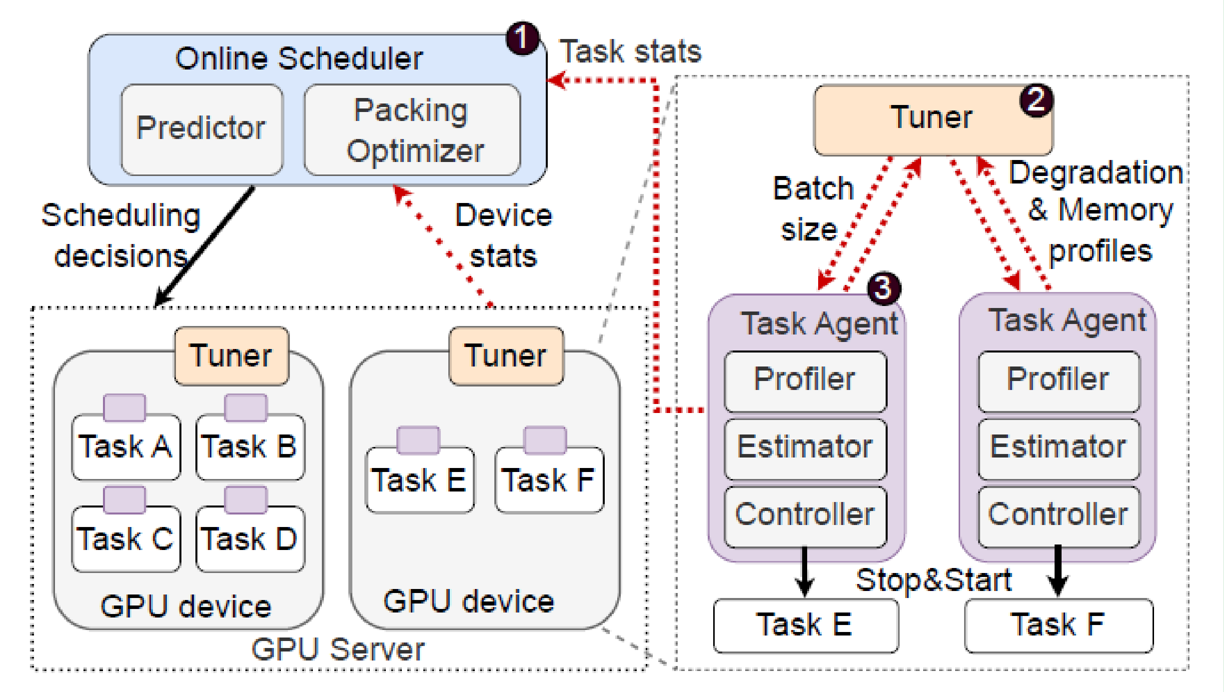
- **Challenges**
  - **C1:** Task configurations heavily influence both interference and training progress
  - **C2:** Vast search space of task configurations
  - **C3:** Intricate coupling between adjusting task configurations and designing task placement policies

IADeep: System Design

① **Online Scheduler**: Find the optimal device to place the new arrival task

② **Tuner**: Tune configurations (batch sizes) to mitigate the interference

③ **Task Agent**: Update the configurations for each co-located task



IADeep: Basic Optimization Problem

- Performance degradation (PD)

Drop in training throughput

$$PD_d^k(*^k) = \boxed{IF_d^k(*^k)} \times \boxed{DT^k(*^k)} \times \boxed{\frac{1}{EFFICIENCT_d^k(*^k)}}$$

Co-location interference

Statistical efficiency

This expression takes interference (IF) and training progress (EFFICIENCY) into PD to address Challenge 1.

IADeep: Basic Optimization Problem

- Co-location interference

$$IF(*) = T^{co}(m) \div T(m)$$

- Drop in throughput

$$DT(*) = m_0/T(m_0) \div \mathrm{m}/\mathrm{T}(\mathrm{m})$$

- Statistical efficiency

Gradient noise scale[1]

$$EFFICIENCY(*) = \frac{\varphi_t + m_0}{\varphi_t + m}$$

$$\boxed{PD(*) = \frac{T^{co}(m)}{T(m_0)} \cdot \frac{m_0}{m} \cdot \frac{\varphi_t + m}{\varphi_t + m_0}}$$

[1] Qiao, Aurick, et al. "Pollux: Co-adaptive Cluster Scheduling for Goodput-Optimized Deep Learning." *In Proceedings of OSDI*, 2021.

IADeep: Basic Optimization Problem

- **Objective**
  - Minimize the overall performance degradation of all co-located tasks on each device
- **Constraint**
  - The memory capacity limitation of each device

x_d^k is a binary variable indicating whether task k is placed on device d

$$\min \sum_{d=1}^{D} \sum_{k=1}^{N} \boxed{x_d^k} \cdot \mathrm{PD}_d^k(\star^{\mathrm{k}})$$

$$\text{s.t.,} \sum_{k=1}^{N} x_d^k \cdot \mathrm{PM}^k(\star^{\mathrm{k}}) \leq \mathrm{C}_d, \forall d,$$

$$\sum_{d=1}^{D} x_d^k = 1, \forall k, \text{ and } x_d^k \in \{0, 1\}.$$

IADeep: Online Task Placement

- **Online Prediction**
  - Use an alternative solution that predicts co-location performance based only on co-location patterns
  - Collect training samples online and train the prediction model incrementally
- **Task Placement**
  - Find the device with minimal performance degradation to place the task (**Q1**)

IADeep: Task Configuration Selection

- Finding task configurations
  - Bayesian Optimization (GP-LCB)

$$\min_{\Delta \in \Re} \mu(\Delta) - \beta_n^{1/2} \sqrt{k(\Delta, \Delta)}, \text{ s.t., } \sum_{k \in \mathcal{T}} \mathrm{PM}^k(\star^k) \leq \mathrm{C}_d$$

    - Able to handle noise
    - Efficient to find an optimal configuration from a vast search space (Challenge 2)
- Profiling memory usage
  - Fit functions of batch size and memory usage to avoid OOM (memory limitation constraint)
  - Use cubic polynomial regression with an average testing error 0.06

IADeep: Co-location Optimization

- Optimization 1
  - Regulate the average resource utilization of both SM and memory on each device
- Optimization 2
  - Evaluate the performance gain of co-location (**Q2**)
  - Find a tradeoff between *waiting time* and *interference mitigation* of assigning a task

$$\boxed{E_i} = (1 + \boxed{\epsilon_i}) \cdot \sum_{l=1}^{n} \frac{\epsilon_i}{1 + \epsilon_l} - 1, \quad 1 \le i \le n - 1$$

If positive, schedule the task n, the overall CT will be worse.

The change of PD for each co-located task i.

IADeep Implementation

- **Online Scheduler** *(5500 LOC in Go)*
  - On top of *Kubernetes*
  - Develop a *device plugin* to expose device status
  - Use *etcd* to store intermediate results
- **Tuner** *(300 LOC in Python)*
  - On each GPU device
  - Provides well-tuned *batch sizes* to each task agent
- **Task Agent** *(360 LOC in Python)*
  - On each DL task
  - Collect GPU memory and task runtime information and upload them to *ectd*

Evaluation: Experiment setup

- Testbed
  - A GPU cluster of 20 RTX 3090 GPUs managed by Kubernetes 1.18.13
  - CUDA 11.4 & CUDNN 7 & NVIDIA Driver 470.57
- Workloads
  - With job arrival process follows Microsoft trace

Task Name	Dataset	Validation	m_0 (batch size)	Optimizer	Size	Frac. Tasks	Filed
VGG16 [60]	CIFAR10 [42]	85% top1 acc.	512	Adam	S	14%	
SqueezeNet [35]	CIFAR10	50% top1 acc.	512	Adam	S	14%	Image Classification
ResNet50 [32]	CIFAR100 [42]	75% top1 acc.	1024	Adam	S	14%	
NCF [33]	MovieLens [31]	69% hit rate	1024	SGD	M	12%	Recommend System
AD-GCL [62]	REDDIT-MULTI-12K[3]	40% acc.	32	Adam	M	12%	Social Network
LSTM [55]	Wikitext-2 [51]	4.0 PPL	256	Adadelta	M	12%	Text Generation
Bert(finetune) [22]	SQuAD [57]	88% F1 score	8	AdamW	L	10%	Question Answering
YOLOv5 [39]	COCO [46]	84% mAP	32	SGD	L	10%	Object Detection
ResNet18 [32]	ImageNet [21]	75% top1 acc.	128	SGD	XL	2%	Image Classification

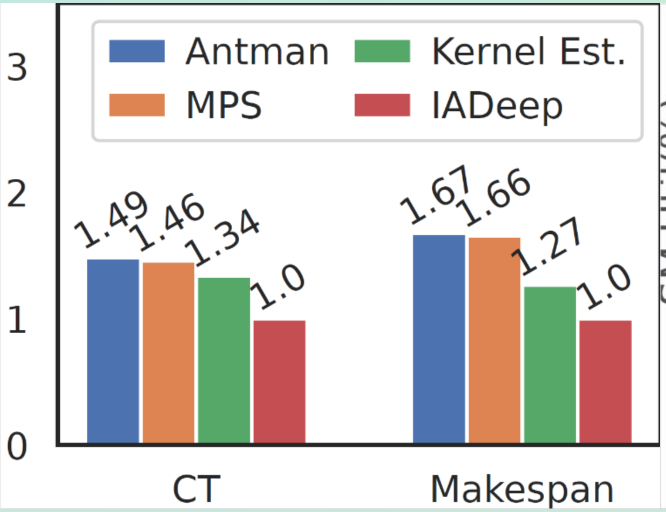
Evaluation: Experiment setup

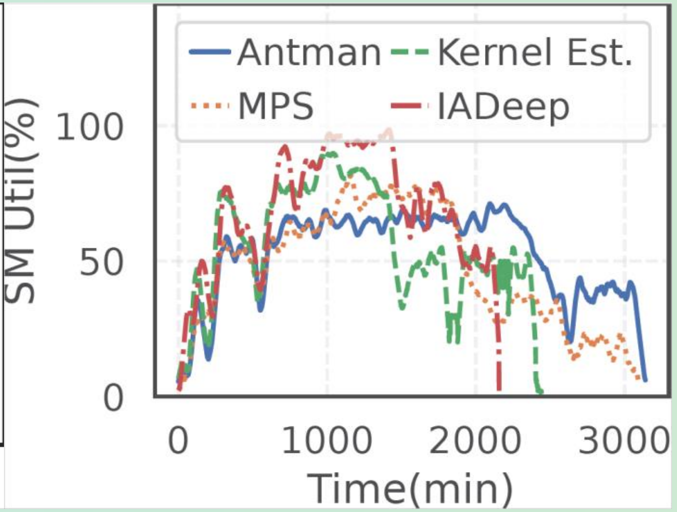
- **Baselines**
  - AntMan[1] , Tencent’s solution based on MPS[2] , Kernel Est.[3]
- **Evaluation metrics**
  - CT: Average Complete Time of the overall tasks
  - Makespan: The total time it takes to complete all tasks
  - GPU resource utilization: SM utilization and memory utilization

[1] Xiao, Wencong, et al. "AntMan: Dynamic Scaling on GPU Clusters for Deep Learning." In Proceedings of OSDI. 2020.
[2] NVIDIA Multi-Process Service. https://docs.nvidia.com/deploy/mps/index.html
[3] Xu, Xin, et al. "Characterization and Prediction of Performance Interference on Mediated Passthrough GPUs for Interference-aware Scheduler." *In Proceedings of HotCloud*. 2019.

Evaluation: End-to-end performance

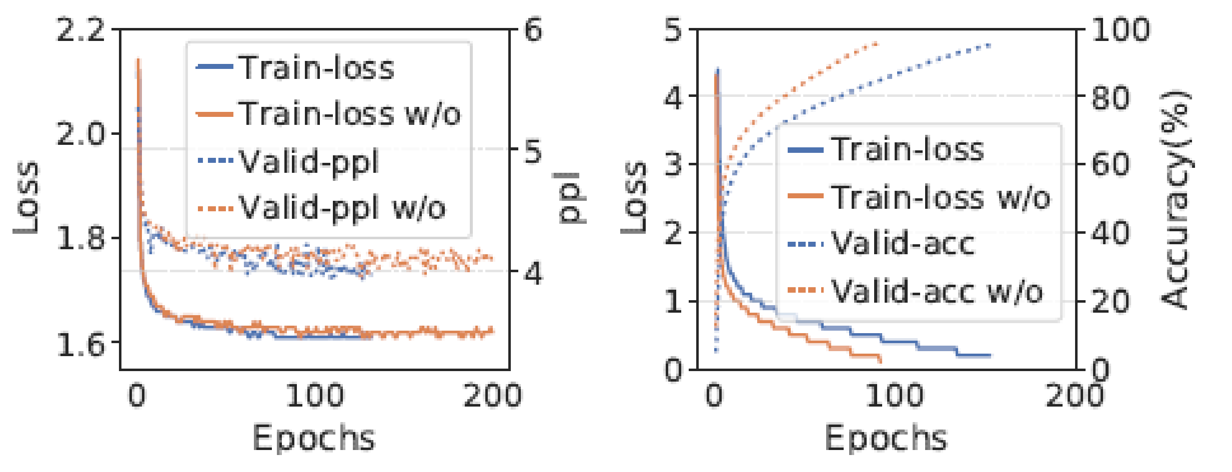
- A task stream contains 300 DL training tasks
  - Up to 49% **CT reduction** compared to baselines
  - Up to 67% **makespan reduction** compared to baselines
  - 31% **GPU utilization improvement**





Evaluation: End-to-end performance

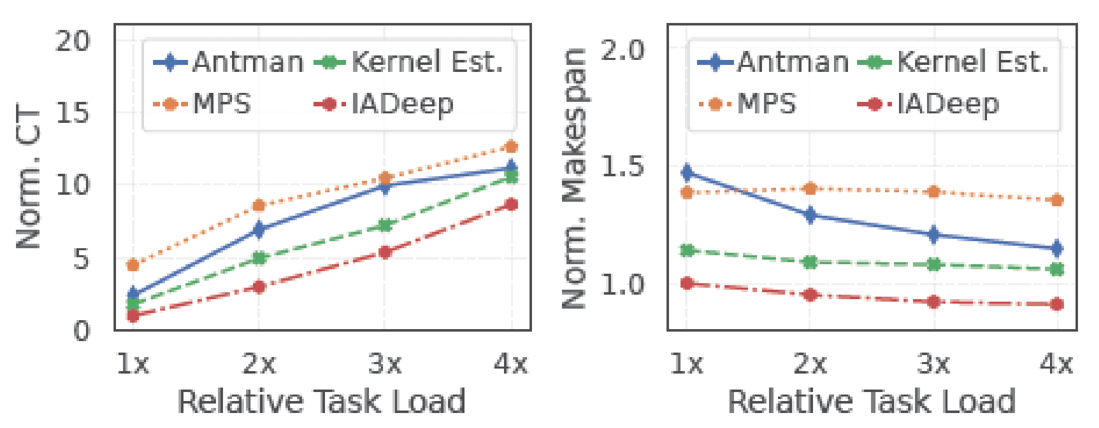
- A task stream contains 300 DL training tasks
  - **Convergence**
    - The training tasks can converge at several epochs to achieve the target validations



(a) LSTM (b) ResNet18

Evaluation: End-to-end performance

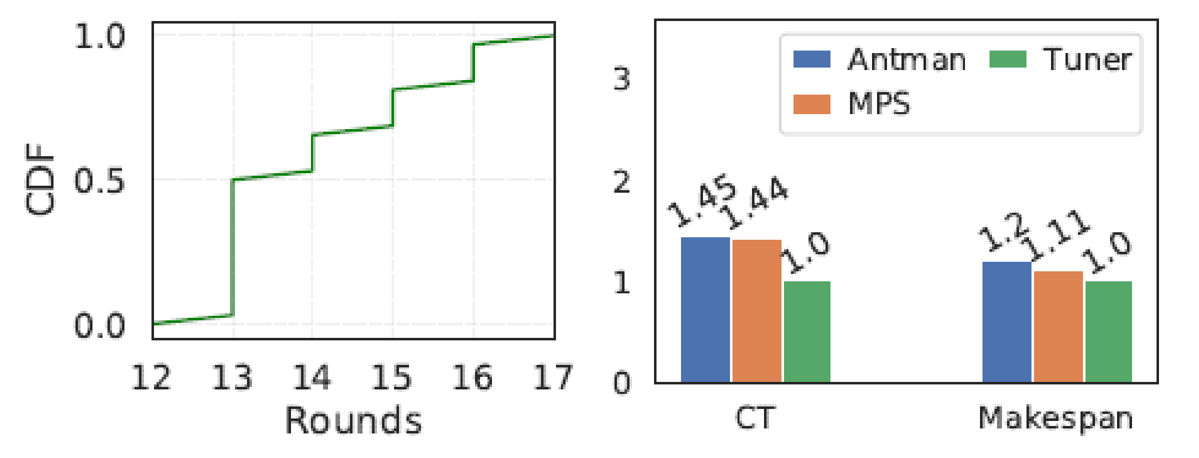
- A task stream contains 300 DL training tasks
  - **Sensitivity to task arrival rate**
    - IADeep always outperforms other baselines concerning the overall CT
    - For makespan, IADeep achieves a linear speedup with the increase of task arrival rate



(a) CT (b) Makespan

Evaluation: Effectiveness of Interference Mitigation

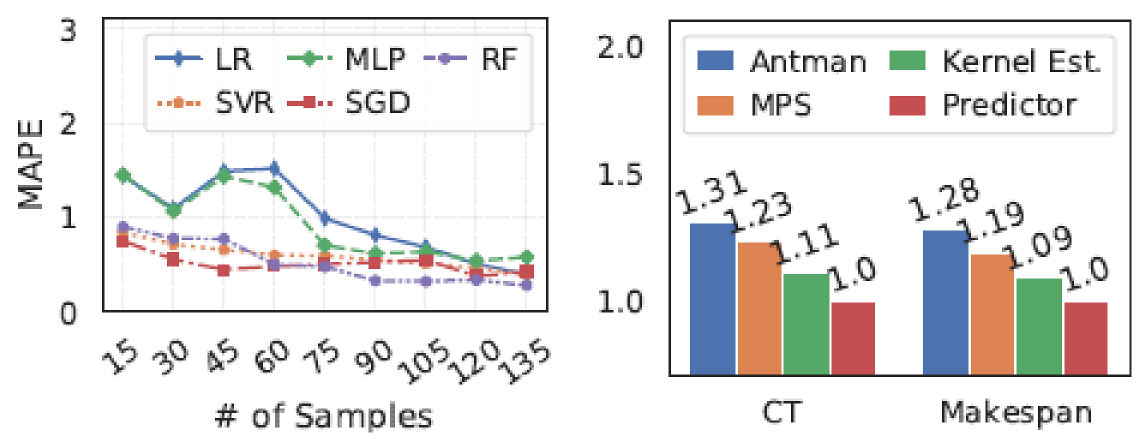
- A task stream contains 300 DL training tasks
  - GP-LCB (in Tuner) converges within 17 rounds and all search cost is within 2s
  - Tuner alone improves CT and makespan by up to 45% and 20%



(a) CDF of search rounds (b) Performance improvement

Evaluation: Effectiveness of Task Assignment

- A task stream contains 300 DL training tasks
  - RF as the Predictor achieves only 27.8% MAPE within 135 samples
  - Online Predictor alone achieves up to 31% CT and 28% makespan reduction



(a) Prediction error (b) Performance improvement

More Evaluations in our Paper

- Performance of Online Optimizer
  - Optimizer alone performance improvement
  - Scheduling overhead

Conclusion

Interference-aware Multiplexing for Deep Learning in GPU Clusters

- Propose a formulation that quantifies co-location performance by combining interference and job training progress
- Co-optimize cluster-level job assignment and per device interference control
- Achieve up to 49% in CT and up to 31% in GPU resource utilization

Thanks & QA

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