





Titan: A Scheduler for Foundation Model Fine-tuning Workloads

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- Background about Foundation Models
- Limitations of Existing Solutions
- Proposed Solution: Titan



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Foundation Model (FM)



Foundation models achieve impressive performance over many AI tasks

Fine-tuning FMs will become important workloads in GPU datacenters

- The "pretrain-then-finetune" technique emerges as a new paradigm for building AI systems
 - OpenAI releases fine-tuning GPT-3 as a paid service for language understanding
 - AliCloud provides a service of fine-tuning M6 which supports various down-stream tasks, e.g., image-text matching, visual question answer



FM fine-tuning workloads demand extensive GPUs for a short time

- FM fine-tuning workloads tends to request more GPUs
 - Single GPU device cannot hold the foundation models



- The duration of FM fine-tuning workloads is relative short
 - Fine-tuning workloads converge relatively fast





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Existing Deep Learning (DL) schedulers cannot mitigate the significant context-switch overhead

- Most DL schedulers assume the context-switch overhead is acceptable
 - Gandiva [OSDI'18] & Gavel [OSDI'20] frequently make resource reallocations
- However, this is not applicable to FM fine-tuning workloads



Existing DL schedulers manage each job separately

• Existing schedulers do not consider the *multi-task adaptivity* of FMs

- Applying multi-task learning on foundation models can accelerate the convergence of fine-tuned tasks
 - Jointly fine-tuning FashionMnist and cifar100 can reduce the 1.55x timeto-accuracy



The animation is borrowed from https://ai.googleblog.com/2022/04/pathways-language-model-palm-scaling-to.html



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Titan contains three key designs

Task merger leverages the multi-task adaptivity

- Objective
 - Retain the accuracy
 - Reduce the latency



- Method Overview
 - A rule-based method to determine whether tasks can be merged without accuracy loss calculate classes similarity by internal semantic hierarchy similarity('cat', 'dog') > similarity('cat', 'car')
 - Formulate task combination as an Integer Linear Programming (ILP) Problem

	A	В	Task Merger	SRTF
Case 1	20	20	25	30
Case 2	10	20	21	20
Case 3	5	100	102	55

Pipeline switch can address the significant overhead of context switch

- Objective
 - Reduce the overhead of context switch

- Method Overview
 - Overlap parameter transfer and gradient computation
 - Reversed parameter load





Titan achieves significant performance improvement

Scheduler Policy	Average JCT	Makespan
SRTF	1.68h(ours)	33.09h
Tiresias	1.67h	33.09h
TITAN (w/o task merger)	1.23h	33.11h
TITAN (w/o pipeline switch)	1.16h	29.01h
TITAN	1.04h	29.01h

 Table 3: Summary of evaluation results.



Figure 5: Performance across various workload density.

 Titan can reduce up to 38% average JCT and 12% makespan compared to baseline schedulers

 Titan can maintain its competitive advantage over baseline schedulers with the job density increasing

Conclusion and Future Works

- We present a scheduling system tailored for FM fine-tuning workloads in GPU datacenters
- We need to conduct thorough analysis about the multi-task adaptivity of FM fine-tuning workloads
- We need to extend the pipeline switch to support the single-GPU training







