Sia: Heterogeneity-aware, goodput-optimized ML-cluster scheduling

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Slides

Sia: Heterogeneity-aware, goodput-optimized ML-cluster scheduling

- Introduction
- Background details and related work
- Sia design and implementation
- Experiments
- Conclusion

Slides

Introduction

Scheduling of deep learning (DL) clusters:

- Multiple users submit jobs to DL clusters to train their models.
- A scheduler assigns resources (i.e. GPU time) to jobs.
- Current clusters might consist of mixed types of GPUs
  - (Homogenous – same type in a cluster)
  - **(Heterogenous – mixed types)**

Overview of Sia

What is Sia?

- A deep learning (DL) clusters' scheduler.
- Outperforms (at least matches) representative schedulers.

Features of Sia?

- Match jobs (configurations) with resources (GPU)
- Adaptable to changes (e.g. batchsize)
- Support elastic scaling of "hybrid" parallel jobs

Key features

Sia- a new scheduler designed for DL clusters that are BOTH...

- **Heterogeneous** *-containing different types of GPUs, and
- **Resource-adaptive** *-able to adjust the resources allocated to jobs dynamically.

(* More details following)

to optimize the *goodput* of these DL clusters, while original schedulers usually only focus on one of the criteria.

Goodput:
A measure of useful work done.

Background details and related work

Training a deep neural network (DNN)...

- Iterate through epochs with the dataset, in each epoch/ minibatch in epochs,
- minimizes loss function over the minibatch of samples.
- updates model parameters (optimizer)

The DL jobs are usually able to be **parallelized** across multiple GPUs on a single/multiple node

Parallelization of DL jobs

Most training jobs use *synchronous data parallelism (DP)*

- a set of GPUs,
- each GPU receives a model replica,
- computes gradients on a partition of the minibatch(local batch size).
- gradients reduced on all GPUs (synchronizes)

Some jobs use *model parallelism*

- when the model being trained is too large to fit in a single GPU’s memory

(Other strategies exist)

*Elastic and resource-adaptive DL jobs

Elastic Resizing & Adaptive Job :

- Data-parallel DL jobs (minibatch sizes) can be **resized** over time.
- Achieved by checkpointing and restarting on a different number of GPUs.
- Jobs can adapt to assigned resources.

  Example: Minibatch size can be increased with more GPUs.
- Different minibatch sizes have different impacts.

  increaed per-GPU compute and scalability.

*Resource heterogeneity

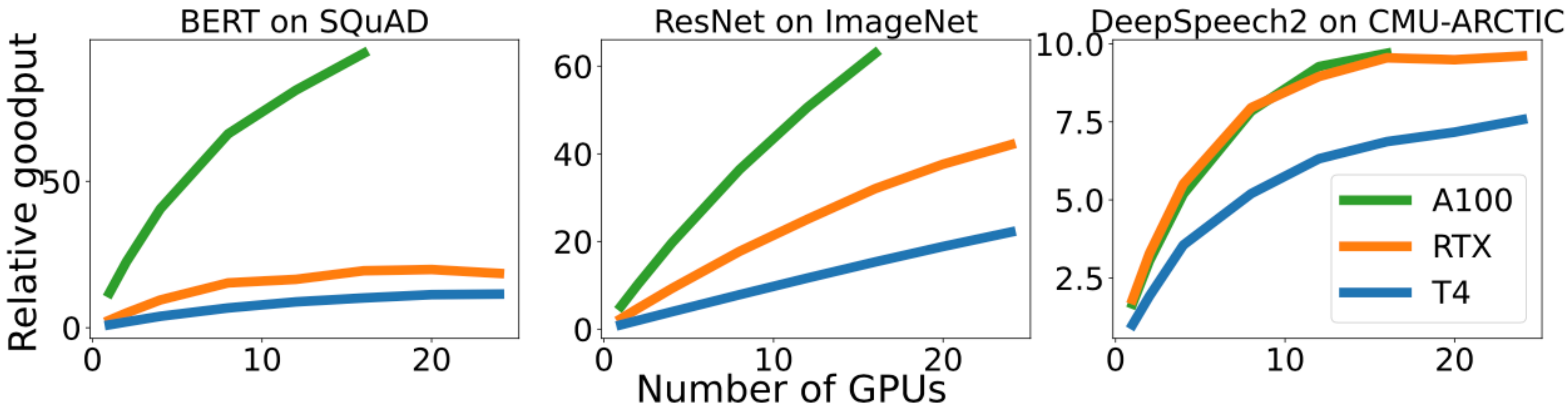
Different types of GPUs might be deployed to a cluster.

(e.g. the cluster upgrades meet the rapid advancement of GPUs)

(may be differed in memory size, performance etc.)

DL jobs might perform differently over varied GPU types.

(figure: different speedups/scalability of 3 DL jobs on 3 types of GPUs)



*Current DL cluster schedulers -example

Heterogeneity-aware schedulers

(Gavel, as state of art example)

- Consider differences among GPU **types**
- Run the jobs with user-specified **number** of GPUs ("*Rigid*" jobs)

- No elastic scaling, not adaptable to resource assignments.

Adaptivity-aware schedulers

(Pollux)

- Assume the cluster is deployed with same **type** of GPUs
- Adaptable with **number** of GPUs involved ("No-*rigid*" jobs)

- Allows adjustment in resources (e.g. specify different batchsize ...)

Current DL cluster schedulers

Heterogeneity-aware schedulers (Gavel)

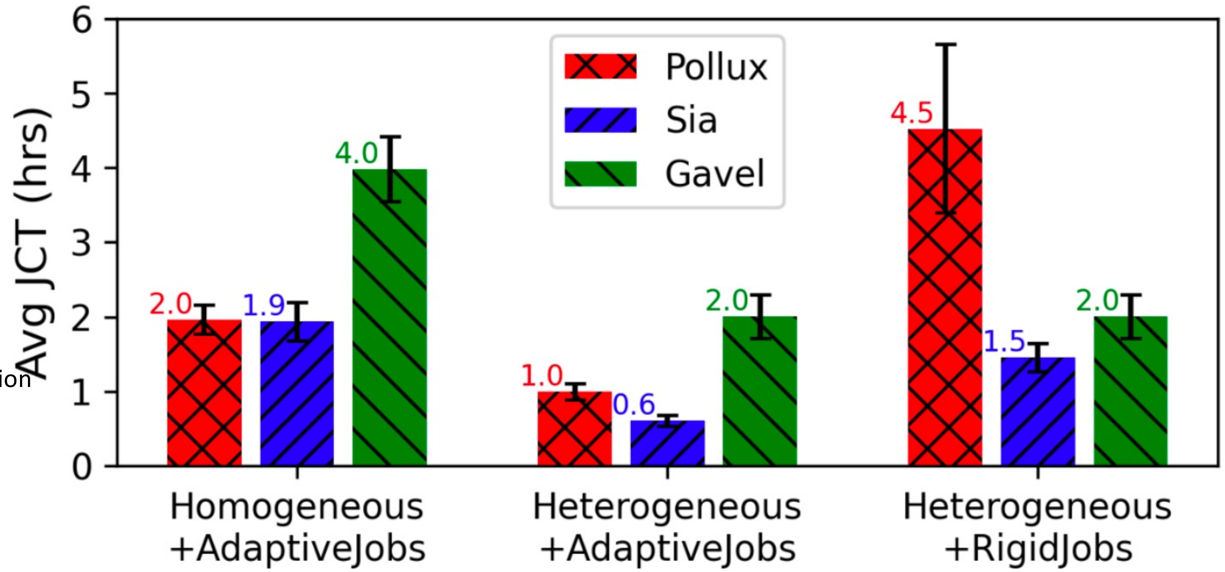
RIGHT✅ Good with rigid jobs on **<u>hetero</u>**geneous cluster (3 GPU types)

Adaptivity-aware schedulers (Pollux)

LEFT✅ Good with non-rigid jobs on **<u>homo</u>**geneous cluster

MIDDLE❌ Both not perfect with non-rigid jobs on **<u>hetero</u>**geneous cluster (still faster?)

JCT-
Job
Completion
Time



DL cluster schedulers summary

Many DL cluster schedulers only accommodate fix **number** of GPUs, not

- elasticity (**resizing**),
- resource-**adaptivity**,
- and heterogeneity (**types**)

Sia is designed to solve the issues.

Sia design and implementation

For Sia's workflow to...

- considers every possible assignment of GPUs (number and type)
- selects the best resource assignment

which is challenging because,

- the search space is huge, and
- profiling all possible job-allocations is prohibitively expensive,

Features

‚Sia introduces a new **scheduling approach**...

- ILP formulation
- efficiently manage the large search space of possible resource assignments
- addresses both the GPU types and numbers* (*job adaptability).

And to find optimized configurations (per-job && per-GPU-type throughput models), Sia ...

- at first bootstraps from observing **a few mini-batches**
- effectively refine as the job runs.

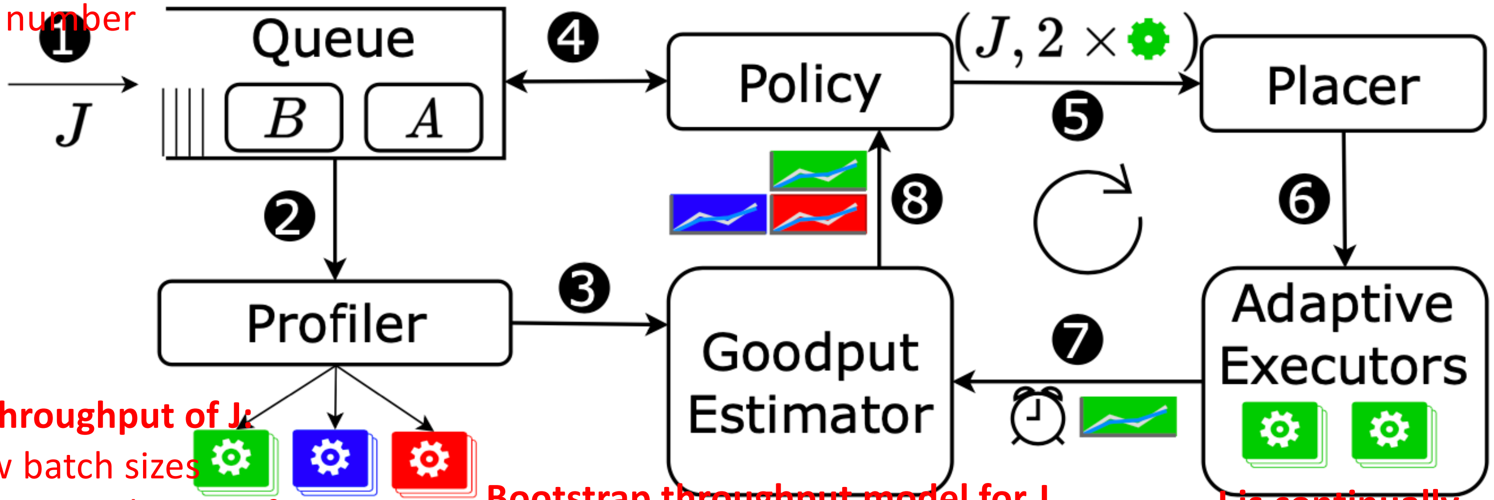
Job lifecycle

J declares its demands:

1- max batch size

2- max GPU number

J stays in queue until allocated GPUs



Sia "profile" the throughput of J:

1- using a few batch sizes

2- attempting on each type of GPUs

Bootstrap throughput model for J

(on each each type of GPUs)

J is continually monitored/optimized

Bootstrap throughput model

- Sia obtained the throughput of a Job on ONE(1) GPU of a new type (says, type B).
- How to estimate throughput of such Job on multiple (N) type B GPUs?

$$\text{est-xput}_B(N) = \frac{\text{xput}_B(1)}{\text{xput}_A(1)} * \text{xput}_A(N)$$

Used a ratio to a known type of GPU

Experiments shows this kind of bootstrap is accurate enough

Implementation

Open-source AdaptDL framework AdaptDL

https://github.com/petuum/adaptdl

- *Resource-adaptive* DL training & scheduling framework
- Claimed efficient resource management and lower training time compared to others

Experiments

Sia is compared with state-of-the-art schedulers in

- both homogeneous and heterogeneous clusters
- using real-world workloads

Experimental workloads

Real world workloads used for evaluation:

- Philly
  - 100k jobs executed over two months
  - multiple GPU types at Microsoft
- Helios
  - 3.3M jobs over six months
  - heterogeneous cluster, 6k GPUs

...

Hardware

4 types of GPUs used to build the experiment environment (physical + simulated **Homogeneous/Heterogeneous** clusters)

- `t4` – [Cloud] `g4dn.12xlarge` AWS EC2 instance with 4 NVIDIA T4 (16GB VRAM) GPUs.
- `rtx` – [On-prem] *commodity* node with 8 NVIDIA RTX 2080Ti (11GB VRAM) GPUs and 50Gb/s Ethernet.
- `a100` – [On-prem] *high-performance* NVIDIA DGX-A100 node with 8 NVIDIA A100 (40GB VRAM) GPUs and 1.6Tb/s Infiniband.
- `quad` – [On-prem] *workstation* node with 4 NVIDIA Quadro RTX6000 (24GB VRAM) GPUs and 200 Gb/s Infiniband.

Models involved

- Real world DL training tasks

Table 2. Models used in our evaluations.

Size	Task	Model	Dataset	Target Metric	Batch Sizes	Optimizer
S	Image Classification	ResNet18 [16]	CIFAR-10 [30]	94% Top-1 acc	[128 - 4096]	SGD
M	Question-Answering	BERT [12]	SQuAD [46]	0.88 F1 score	[12 - 384]	AdamW [33]
	Speech Recognition	DeepSpeech2 [6]	CMU-ARCTIC [28]	25% word err	[20 - 640]	SGD
L	Object Detection	YOLOv3 [47]	PASCAL-VOC [14]	85% mAP	[8 - 512]	SGD
XL	Image Classification	ResNet50 [16]	ImageNet-1k [11]	75% Top-1 acc	[200, 12800]	SGD
XXL	LLM Finetuning	2.8B GPT [45]	SQuAD	0.88 F1 score	[48, 384]	AdamW

Results

- Sia overperforms current state-of-the-art schedulers.

Trace	Policy	JCT		Makespan	Avg. GPU-hours/job	Contention		Avg. job restarts
		Avg.	p99			Avg.	Max.	
Philly	Sia	**0.6h ± 0.1**	**9.5h**	**14.2 ± 1.9h**	**4.0 ± 0.7**	**6.9**	**31**	**2.9**
	Pollux	1.0 ± 0.1h	14.9h	24.5 ± 7.9h	5.6 ± 1.1	7.2	42	5.8
	Gavel+TJ	1.9 ± 0.3h	30.0h	33.8 ± 8.6h	9.0 ± 6.3	9.9	56	5.7
Helios	Sia	**0.7 ± 0.1h**	**10.9h**	**14.9 ± 1.7h**	**4.8 ± 0.7**	**7.4**	**32**	**3.4**
	Pollux	1.0 ± 0.2h	15.0h	25.5 ± 8.0h	5.9 ± 0.7	6.9	47	5.3
	Gavel+TJ	2.5 ± 0.9h	38.7h	43.0 ± 10.9h	12.1 ± 3.7	9.2	48	7.5
new-Trace	Sia	**0.7 ± 0.1h**	**4.6h**	**52.2 ± 1.3h**	**3.0 ± 0.1**	**13**	**69**	5.0
	Pollux	1.5 ± 0.2 h	10.3h	62.3 ± 4.6h	3.4 ± 0.2	22	85	5.4
	Gavel+TJ	11.3 ± 3.0h	98.1h	110 ± 21.5h	6.4 ± 1.1	96	243	**4.5**

Results

- Sia overperforms current state-of-the-art schedulers.

- Adapting hybrid parallel jobs
- Attribution of primary benefits
- Finish Time Fairness
- ...

Conclusion

- Sia improves job completion times (JCT) by 30-93% while using 12-60% fewer GPU hours.
  - derived from 3 real-world environments

- Quick to evaluate GPU clusters with many GPU types and thousands of GPUs.
  - scalability up to 2000 GPUs

Performance of Sia

Matches state-of-the-art schedulers in their target domains (Gavel, Pollux etc.);

Outperforms state-of-the-art schedulers in **union** of their domains (Adaptivity + Heterogeneity), and;

The **first** cluster scheduler able to elastically scale hybrid parallel jobs.

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Q & A

Slides