Doing more with less: Training large DNN models on commodity servers for the masses

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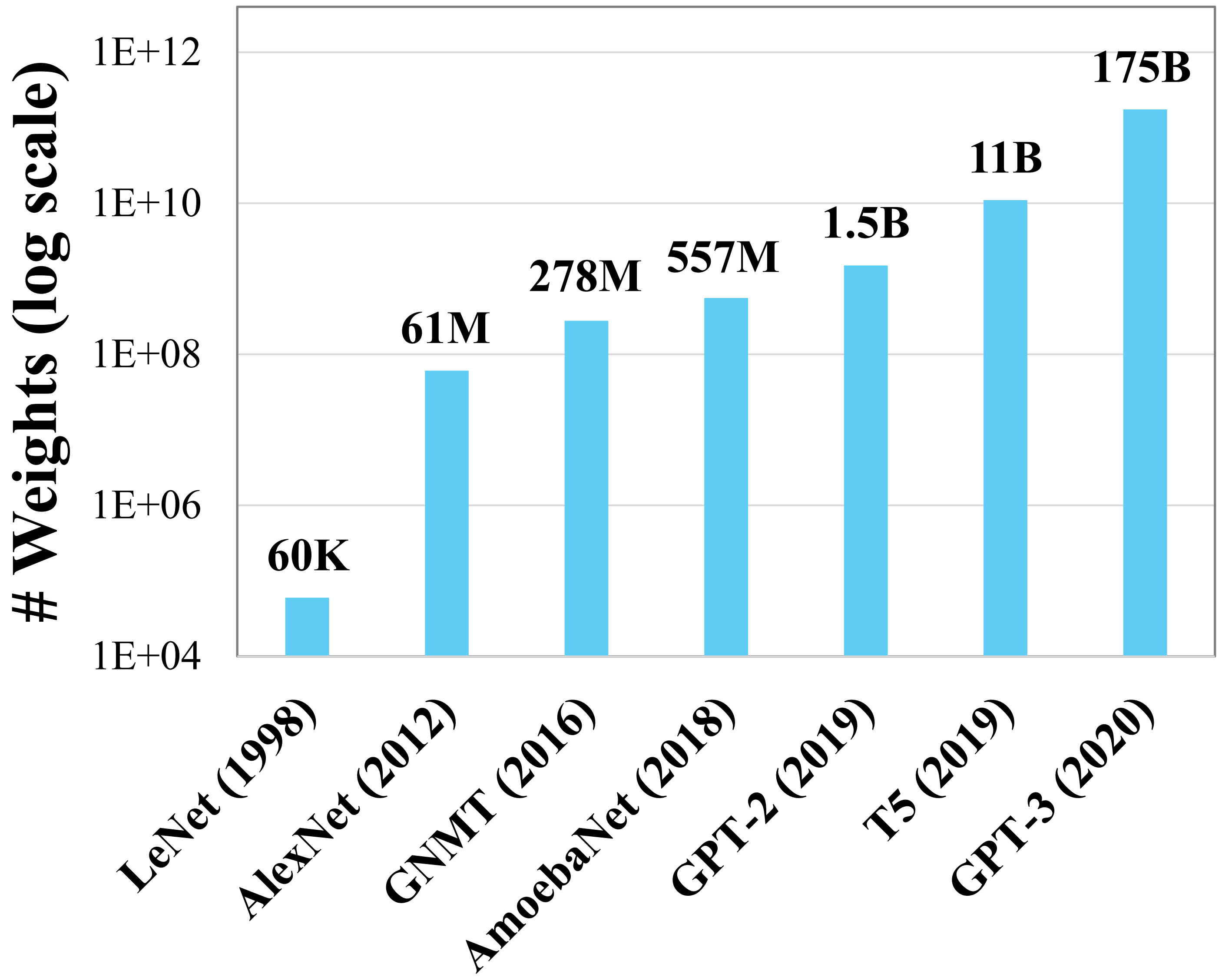
HotOS 2021

DNN model size are growing exponentially!



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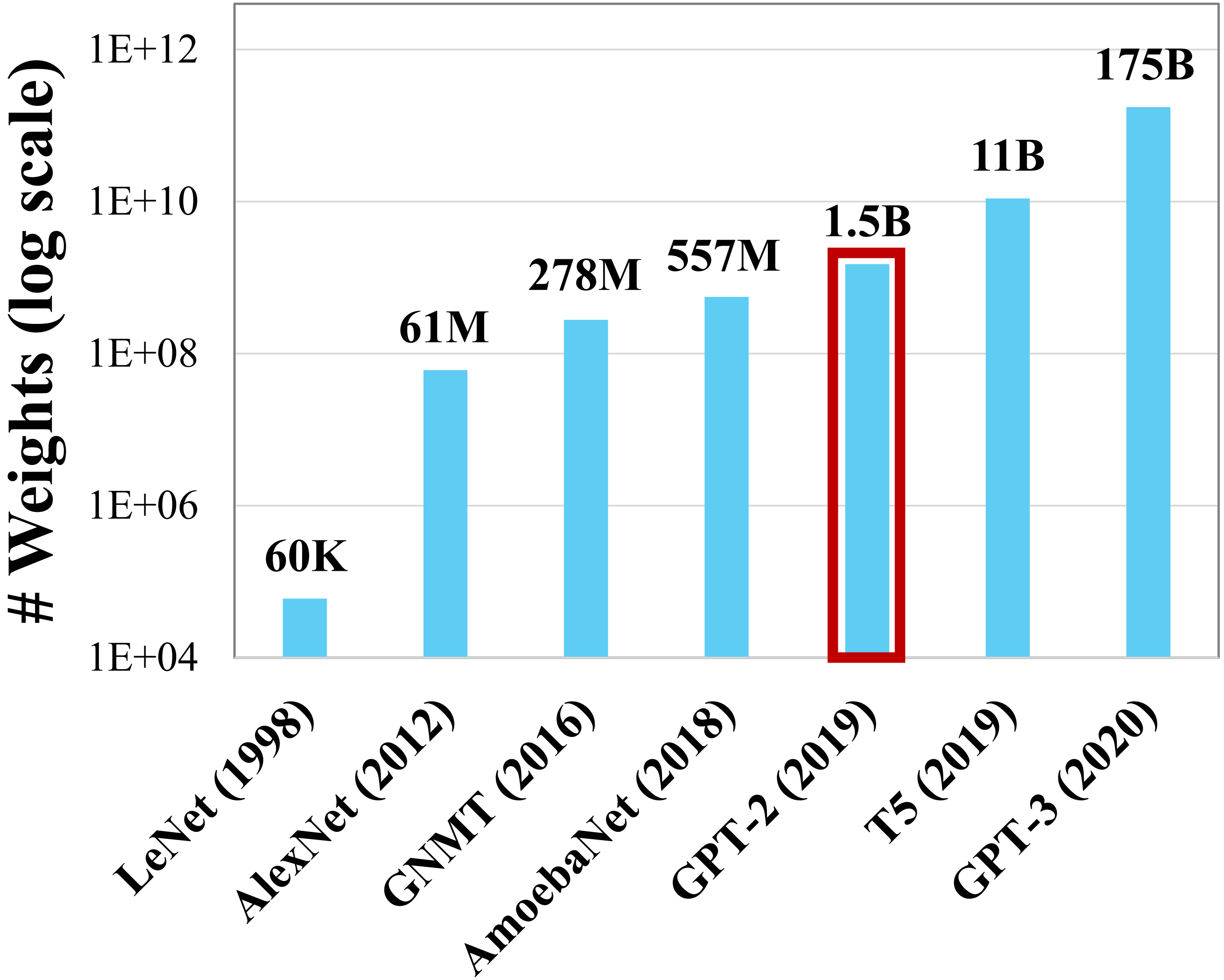

128 GB footprint for training GPT2*

Breakdown	Mem Usage	Percent
Weight	3 GB	2.3%
Gradient	3 GB	2.3%
Optimizer	18 GB	14.1%
Stashing	60 GB	46.9%
Buffer	6 GB	4.7%
Other	38 GB	29.7%
Total	128 GB	100%

*[GPT2, arXiv'19][Zero, SC'20]

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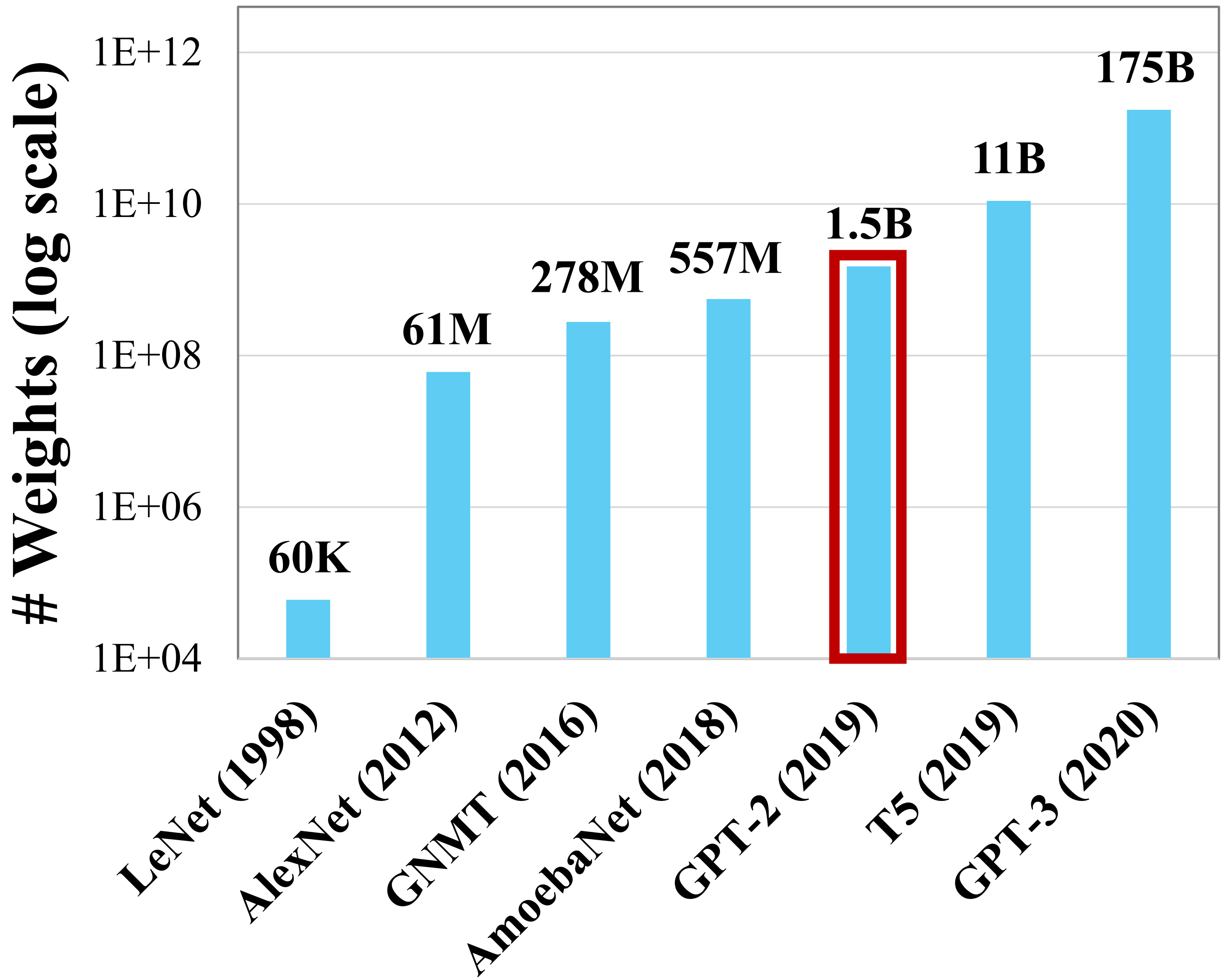

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Weights are only a fraction of total memory usage!

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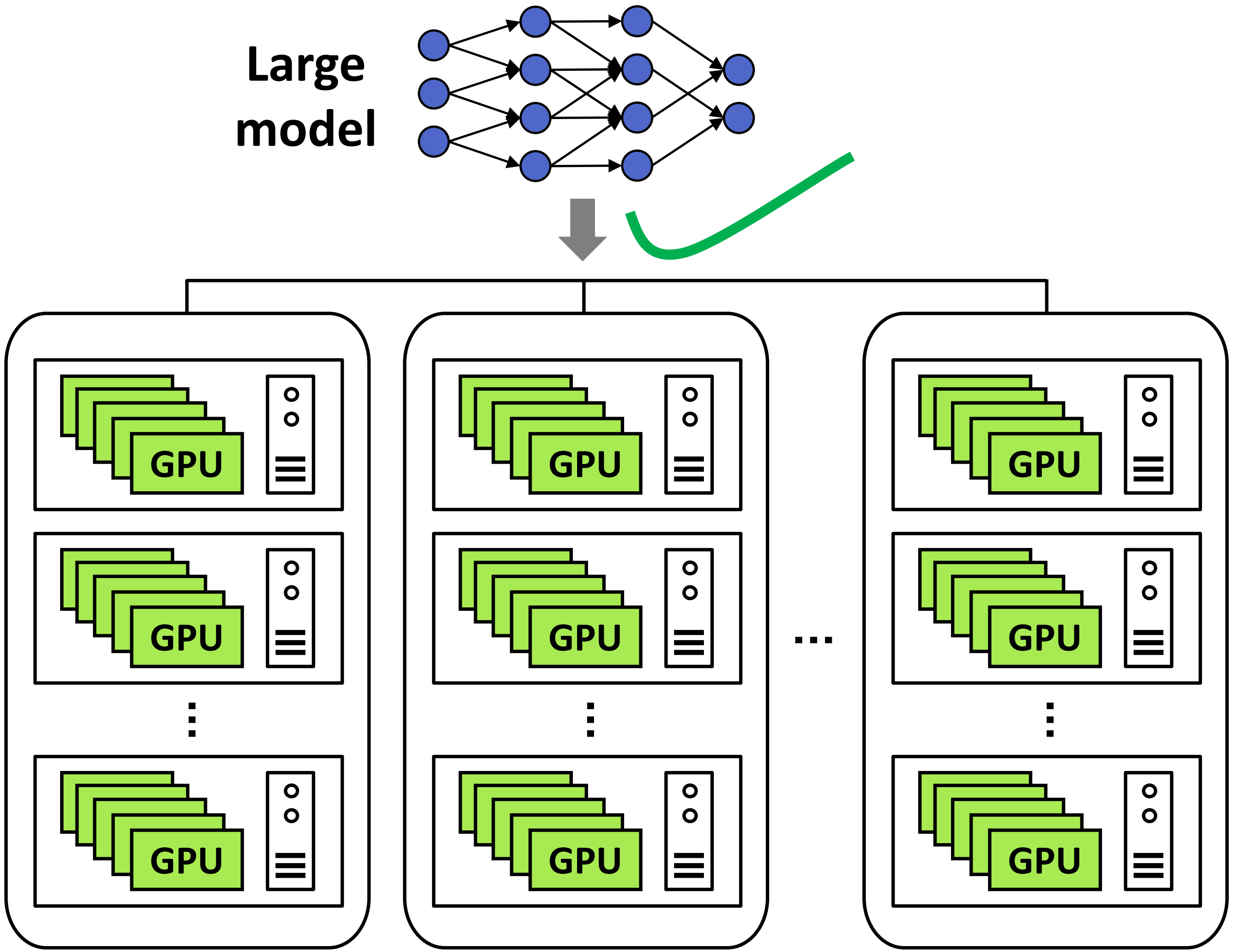
Now, only “elites” can train large models



A hyper-scale accelerator cluster of the elites

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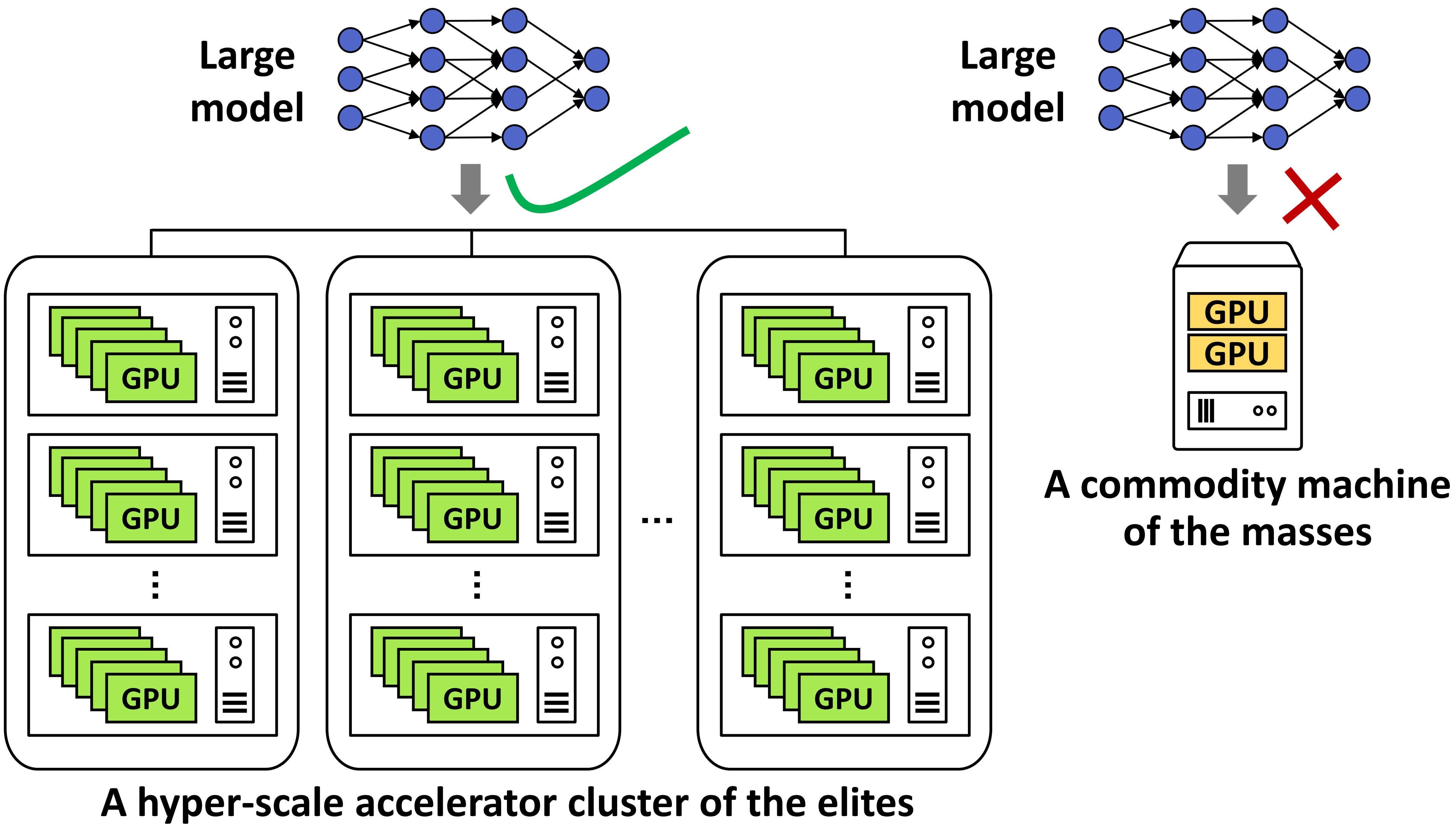

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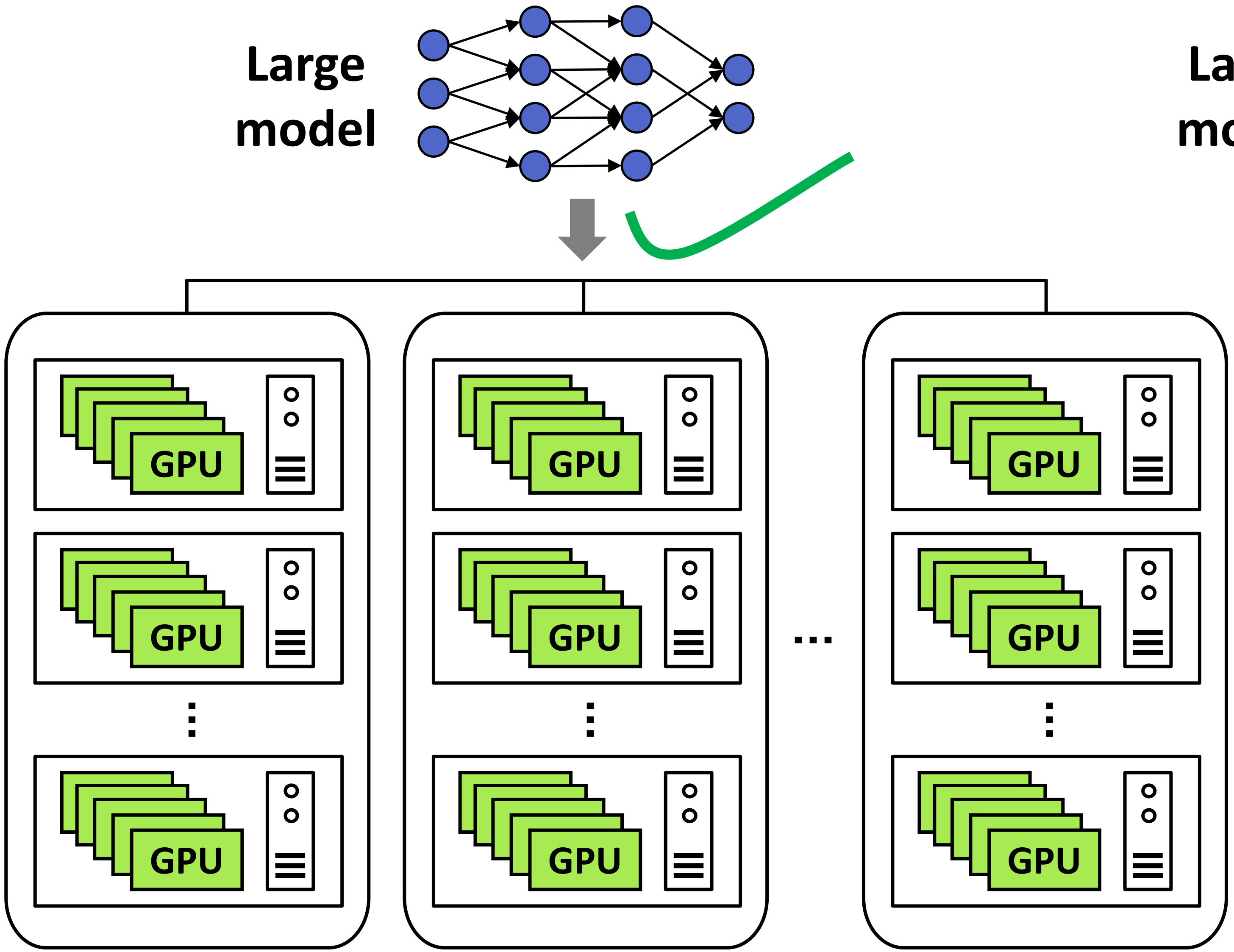

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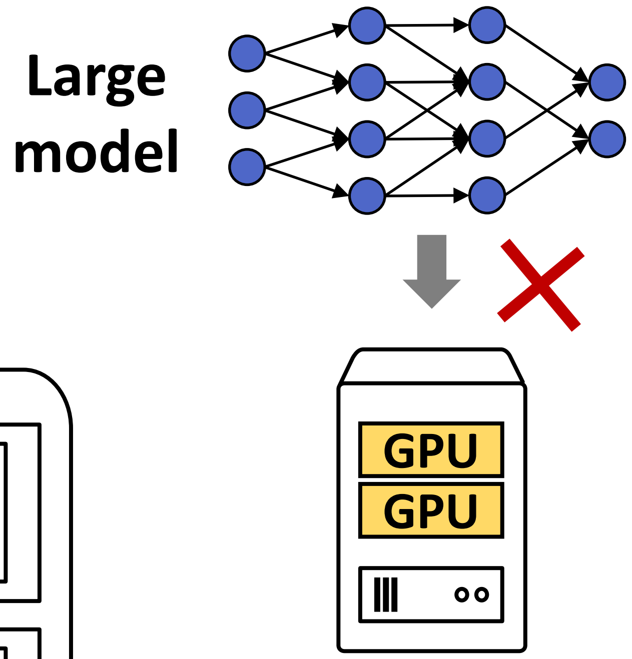
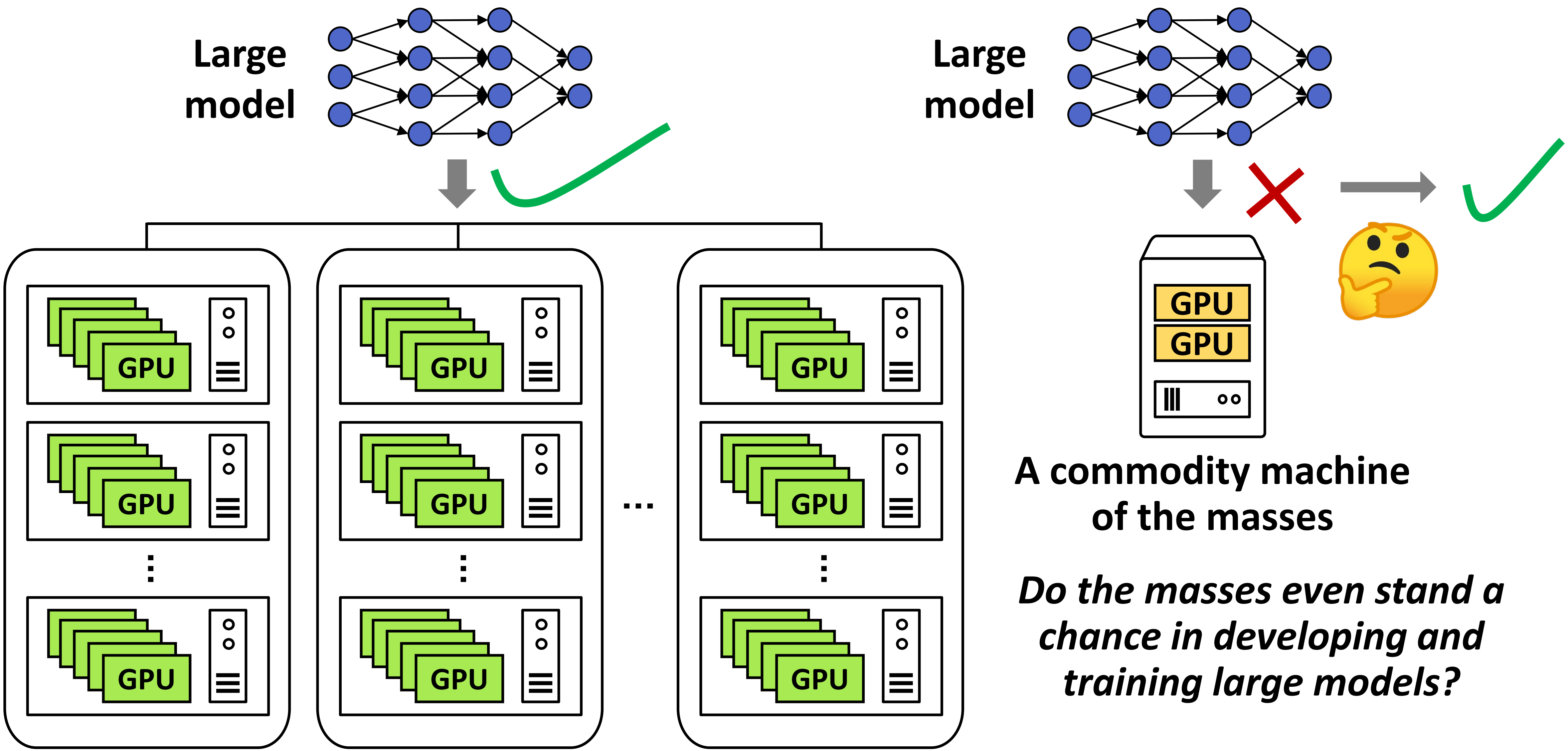


A commodity machine of the masses

Do the masses even stand a chance in developing and training large models?

Now, only “elites” can train large models



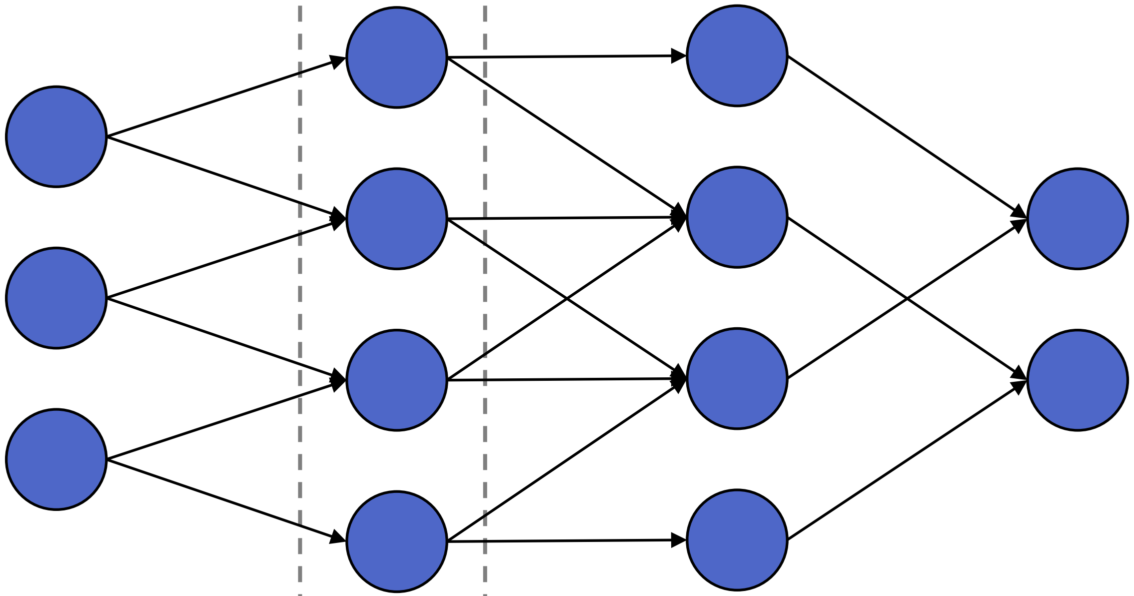
A hyper-scale accelerator cluster of the elites

A commodity machine of the masses

Do the masses even stand a chance in developing and training large models?

The main challenge:

training memory footprint > accelerator memory capacity

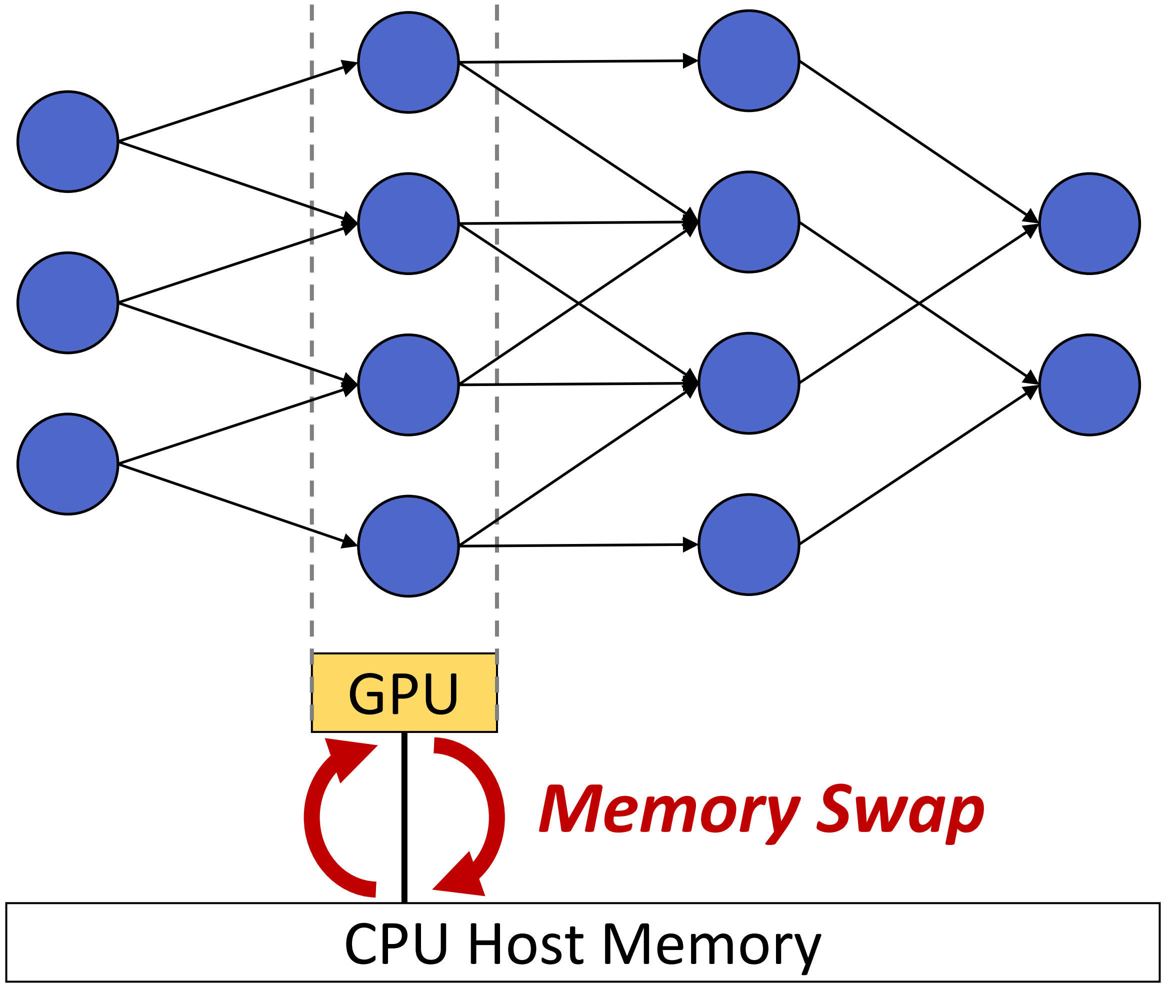


128 GB footprint for training GPT2

GPU

16 GB V100

Promising technique #1: *Single-GPU Memory Virtualization**



*[vDNN, MICRO'16]
[LMS, SysML'18]
[SwpAdv, ASPLOS'20]
[Sentinel, HPCA'21]

Excessive overhead: Repeated swaps across data batches

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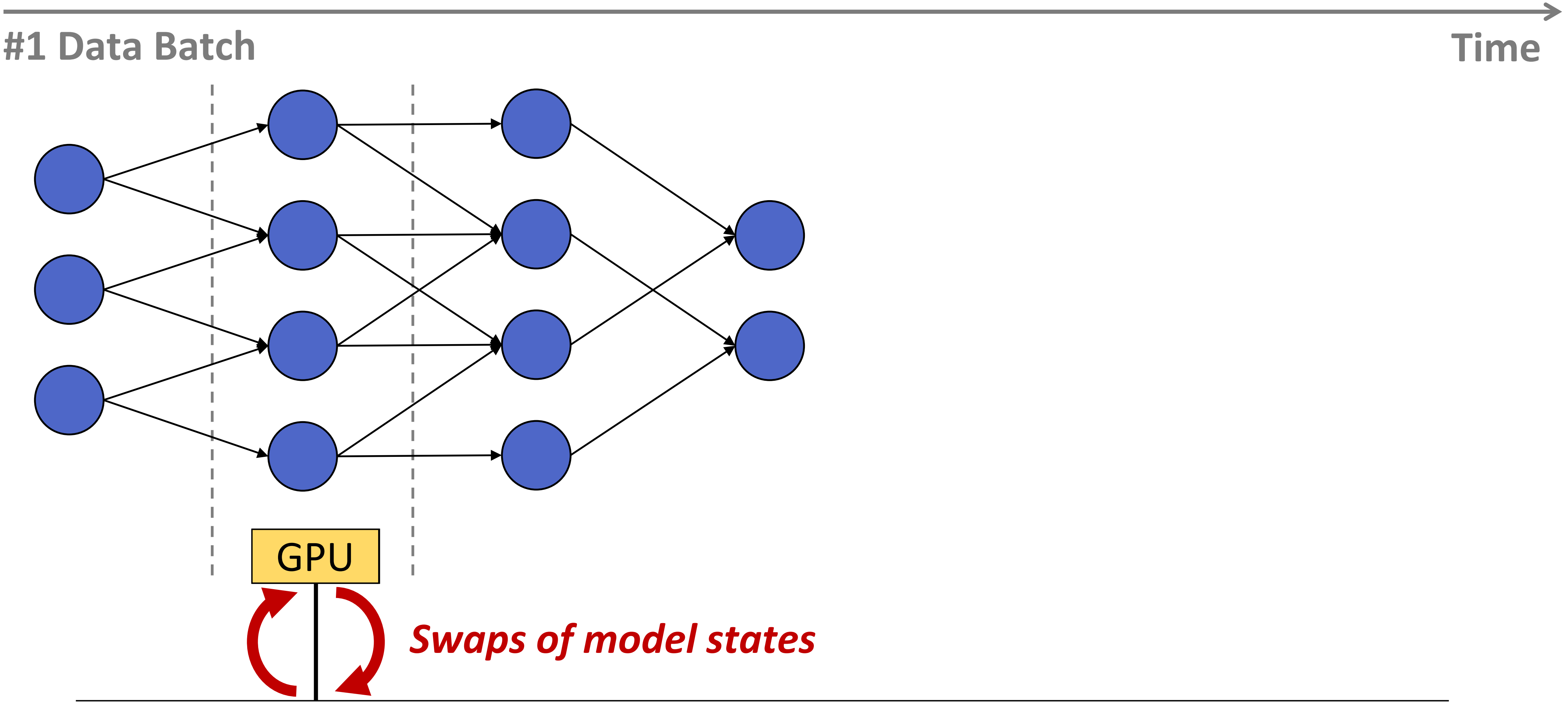

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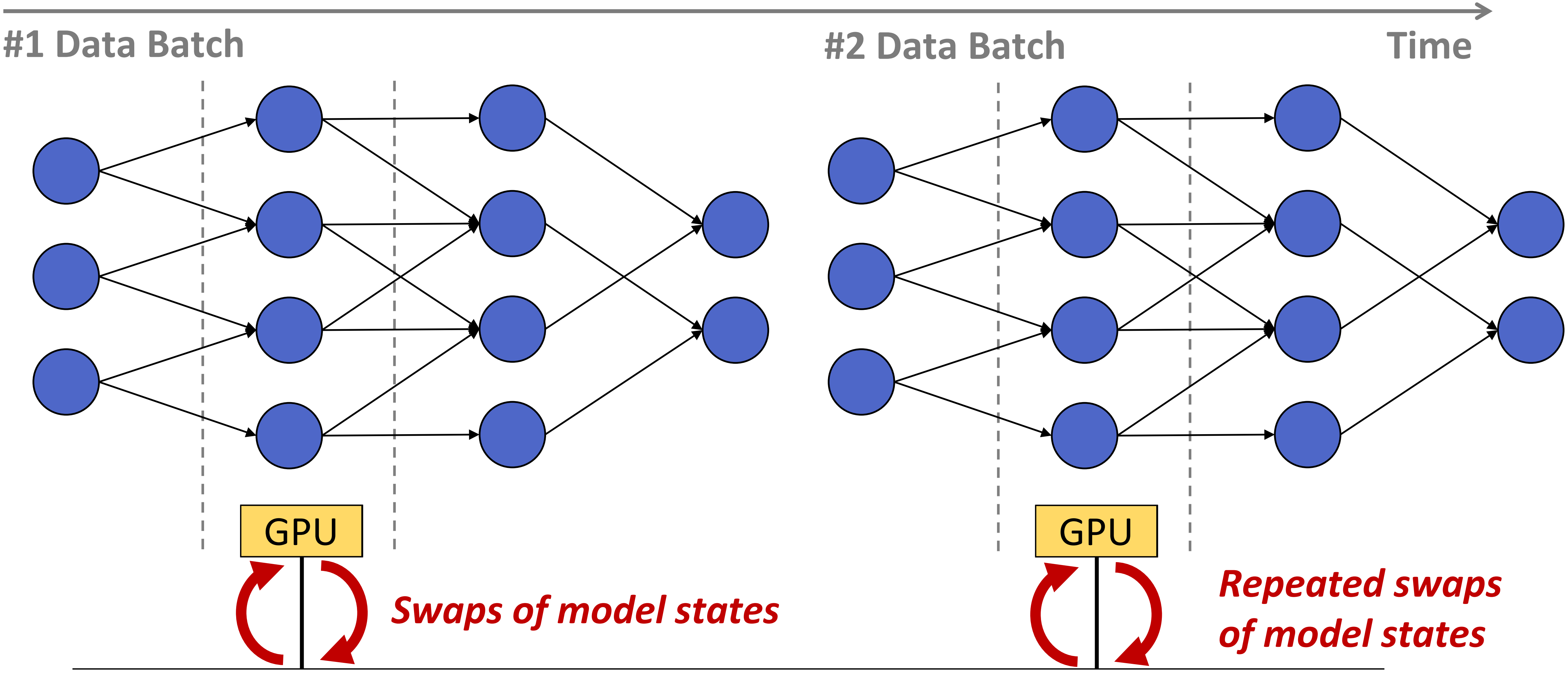
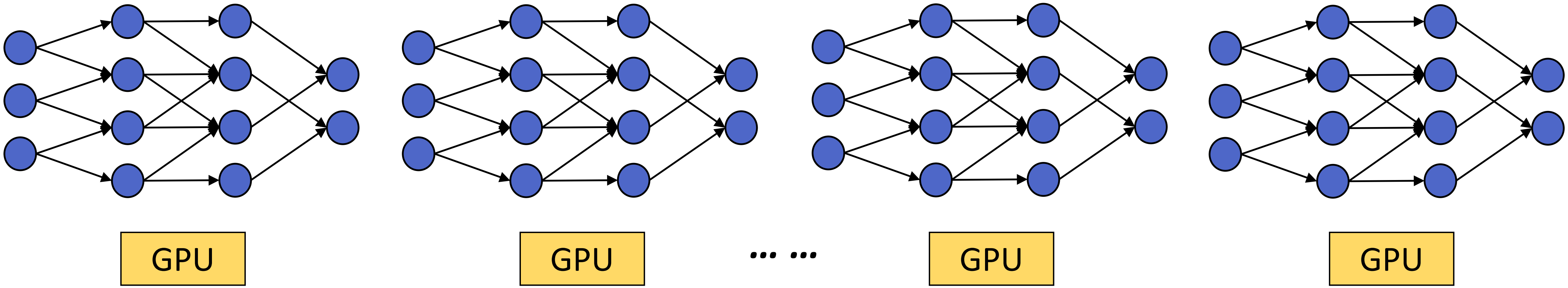


Swapping bottleneck: All GPU swaps via a root link



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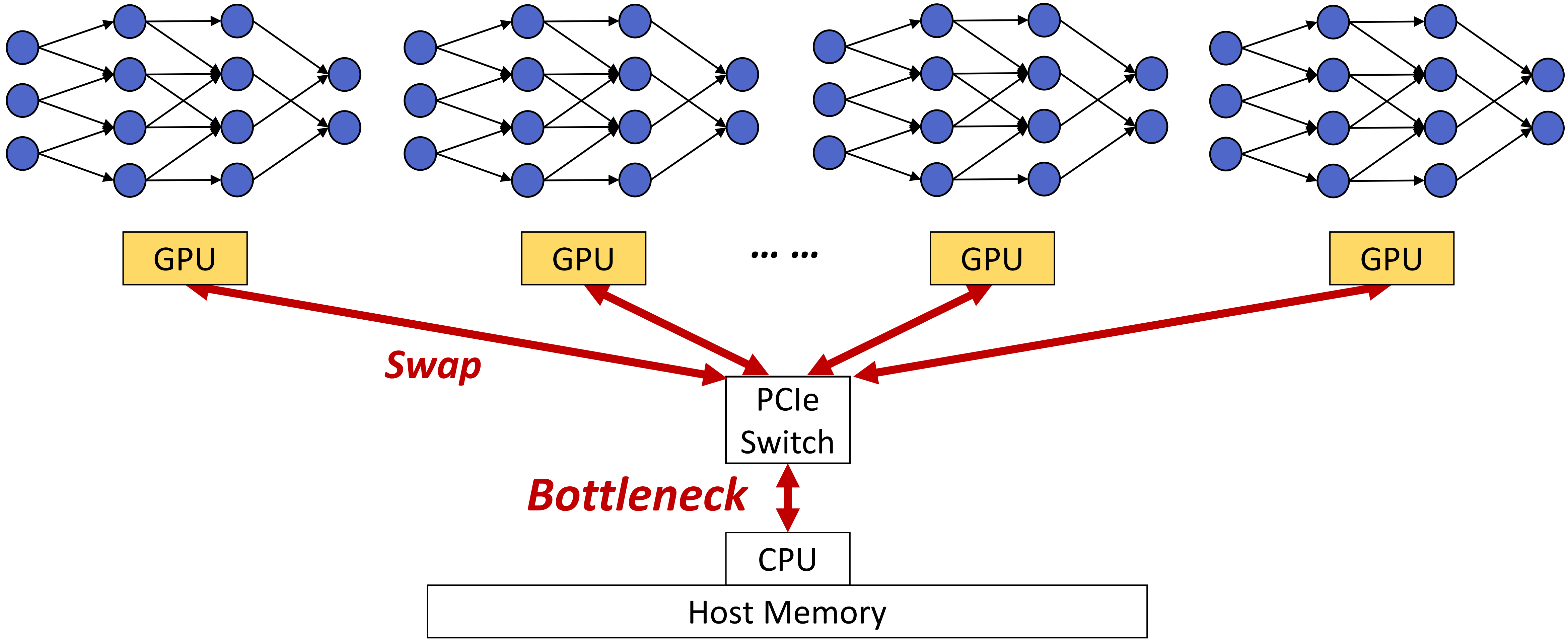
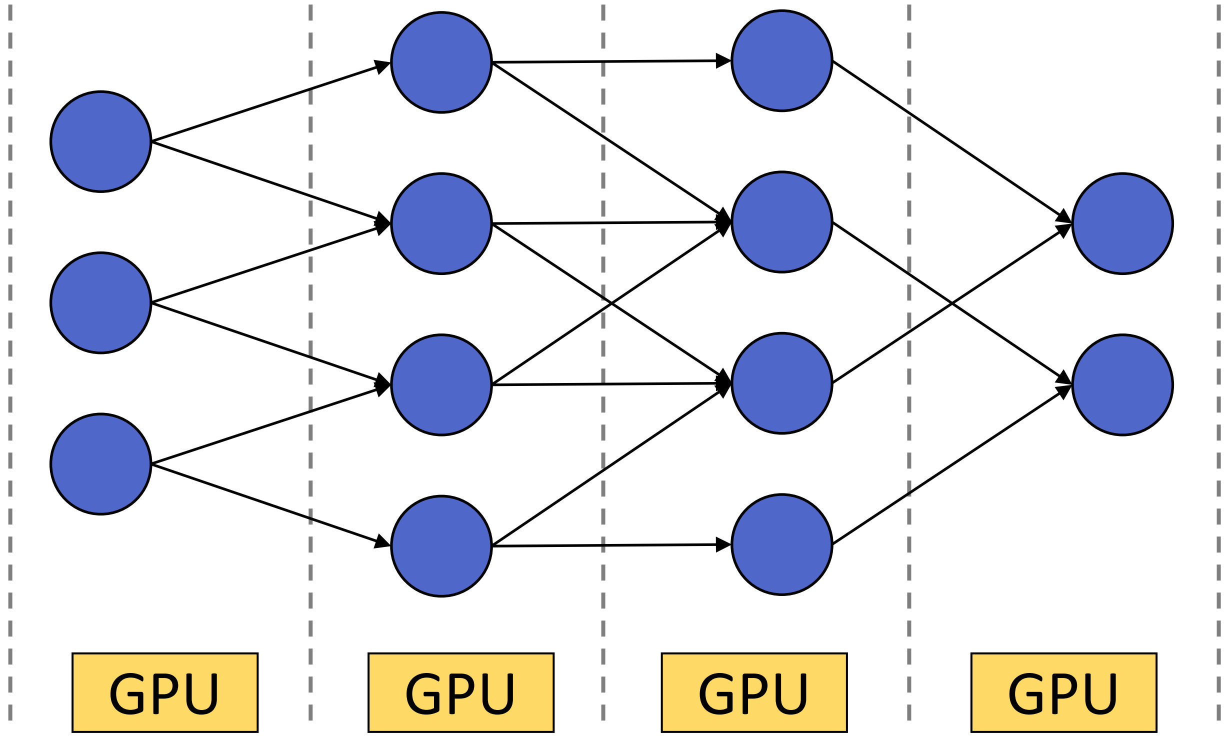


Intra-server Interconnects

Promising technique #2: *Model/Pipeline Parallel Training*



- **Model-parallel training** [Megatron, arXiv'19]
- **Pipeline-parallel training** [GPipe, NeurIPS'19] [PipeDream, SOSP'19]

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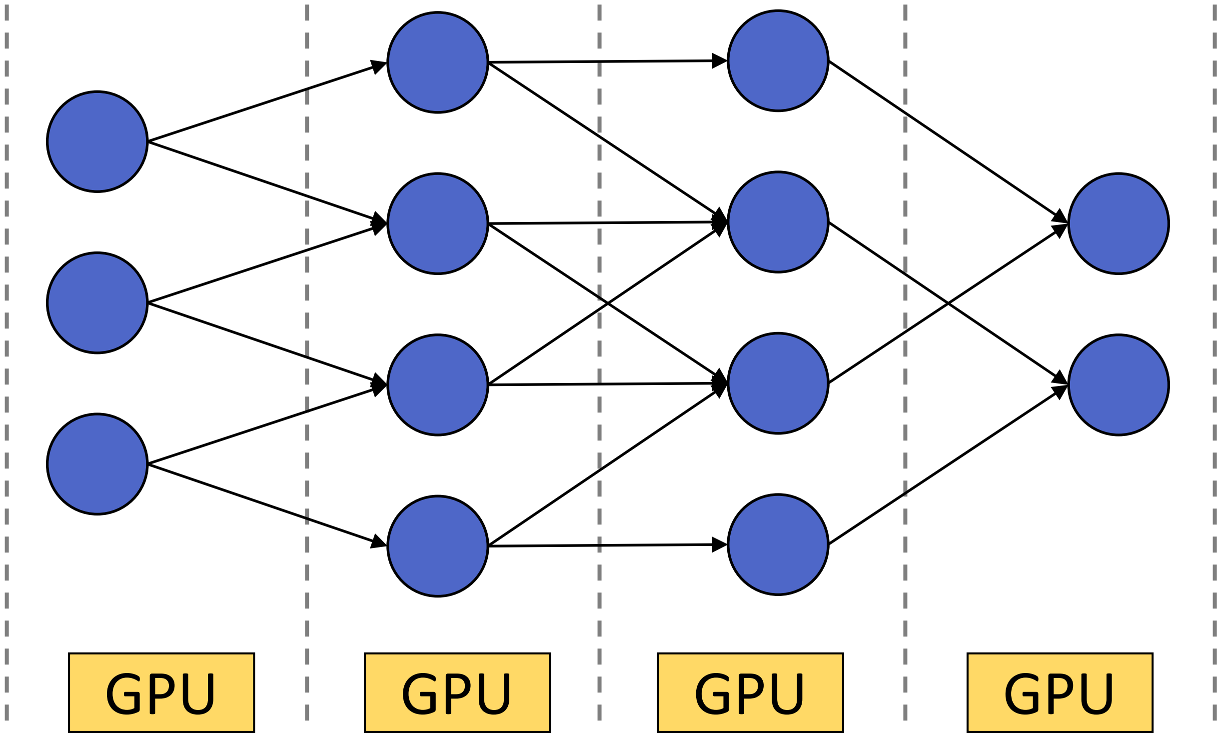

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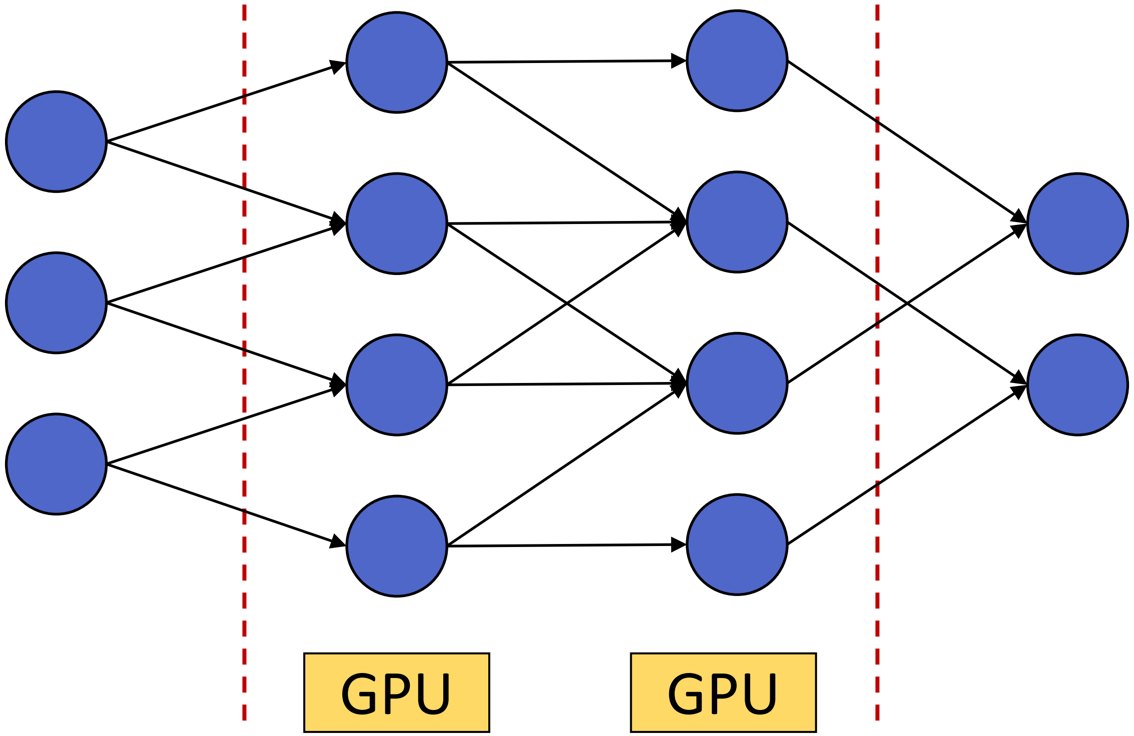
Great for models that fit collective memory capacity :)

Quite often, on commodity servers:

training memory footprint > collective accelerator memory capacity



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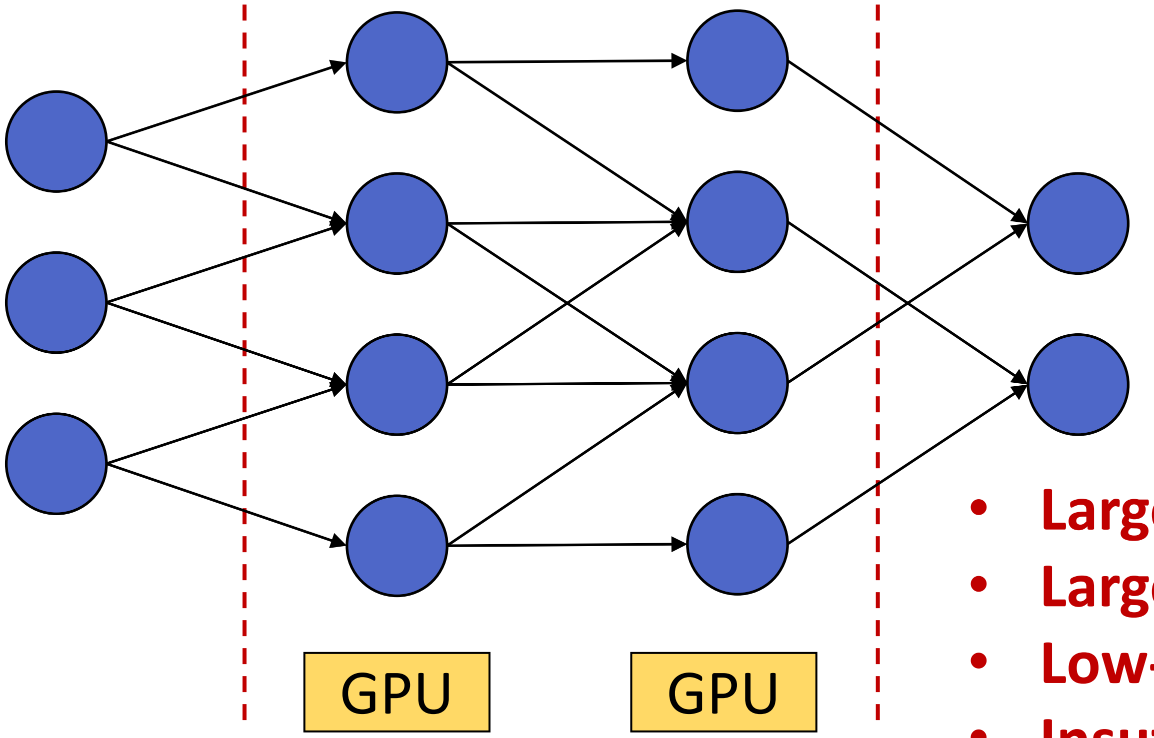

- **Large Model Size**
- **Large Data Size**
- **Low-End GPUs**
- **Insufficient # of GPUs**

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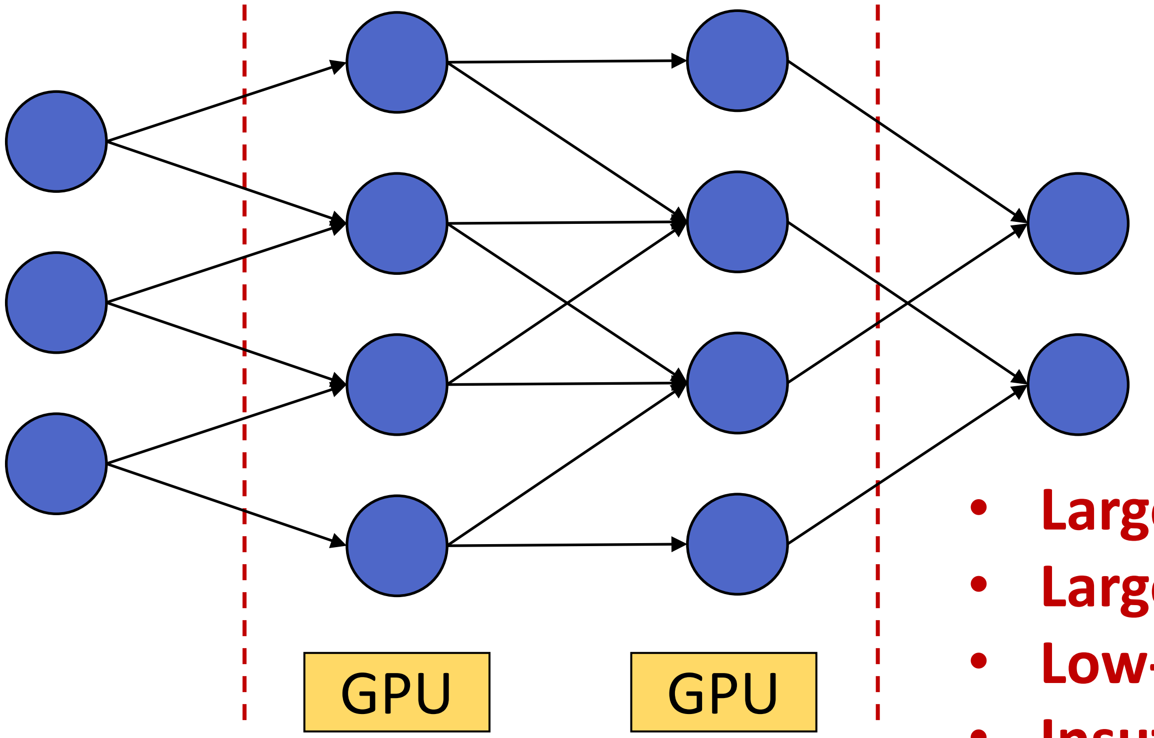

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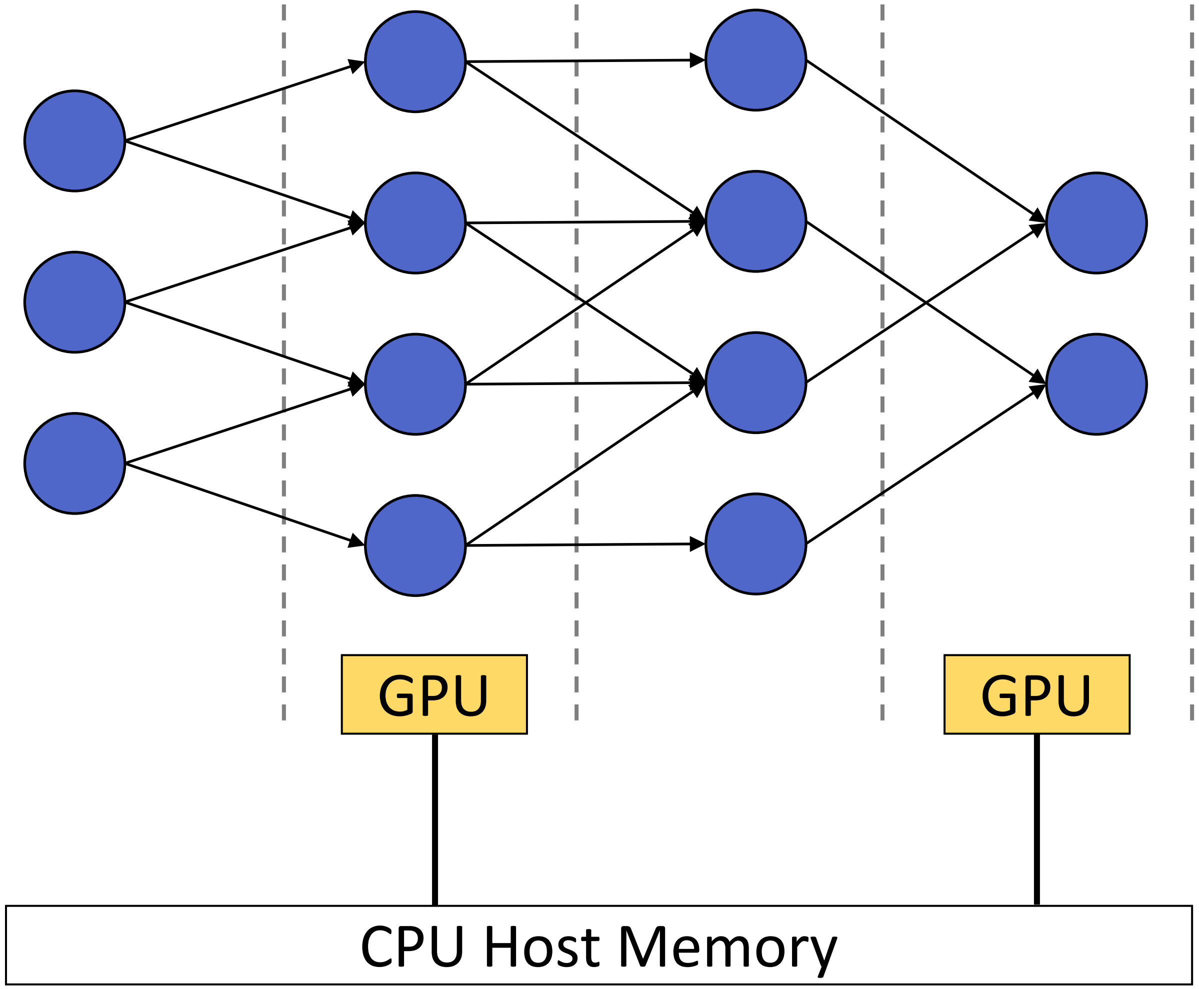
How to train large models on commodity servers? efficiently?

-- Open questions

How about combine existing techniques?



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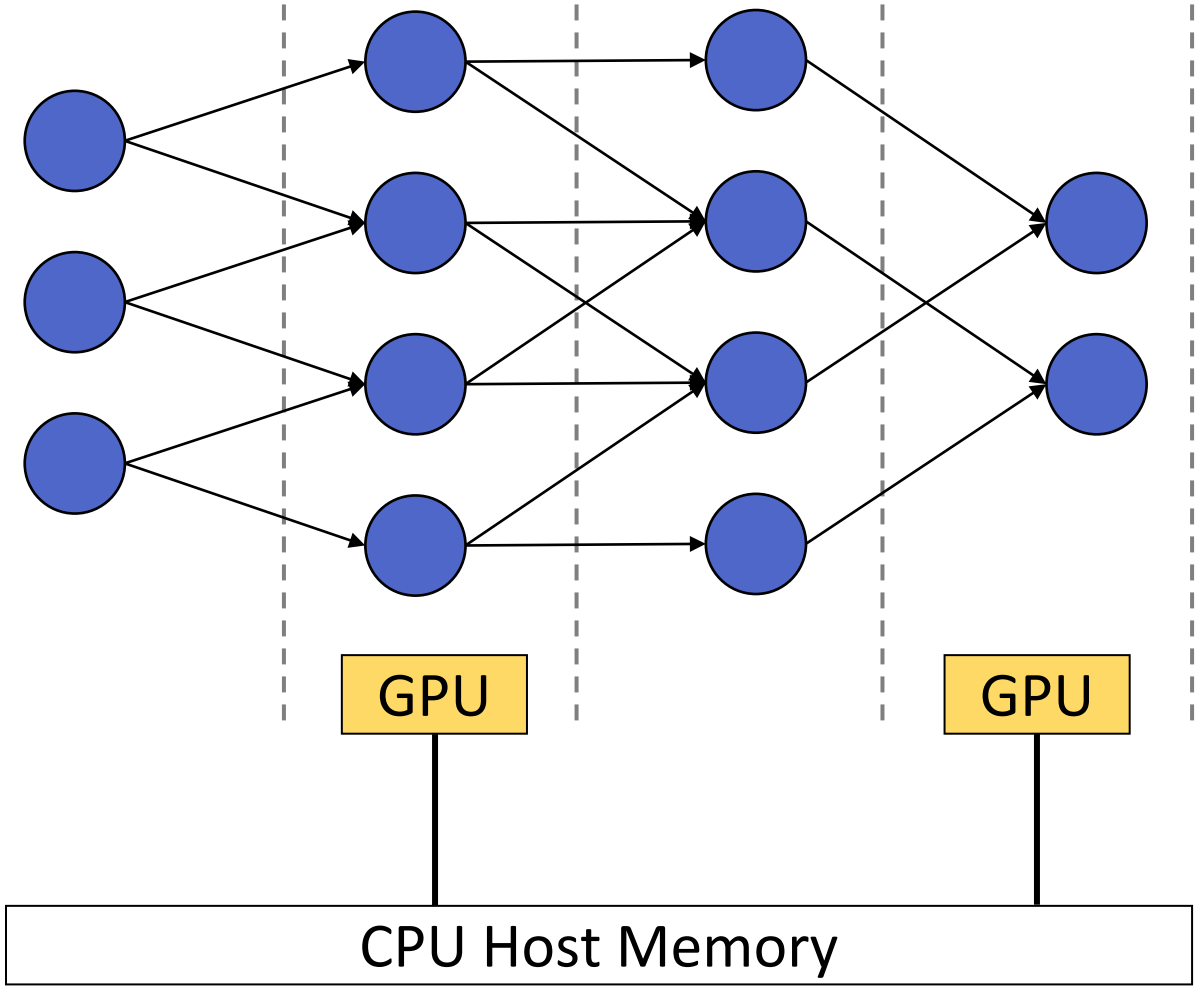

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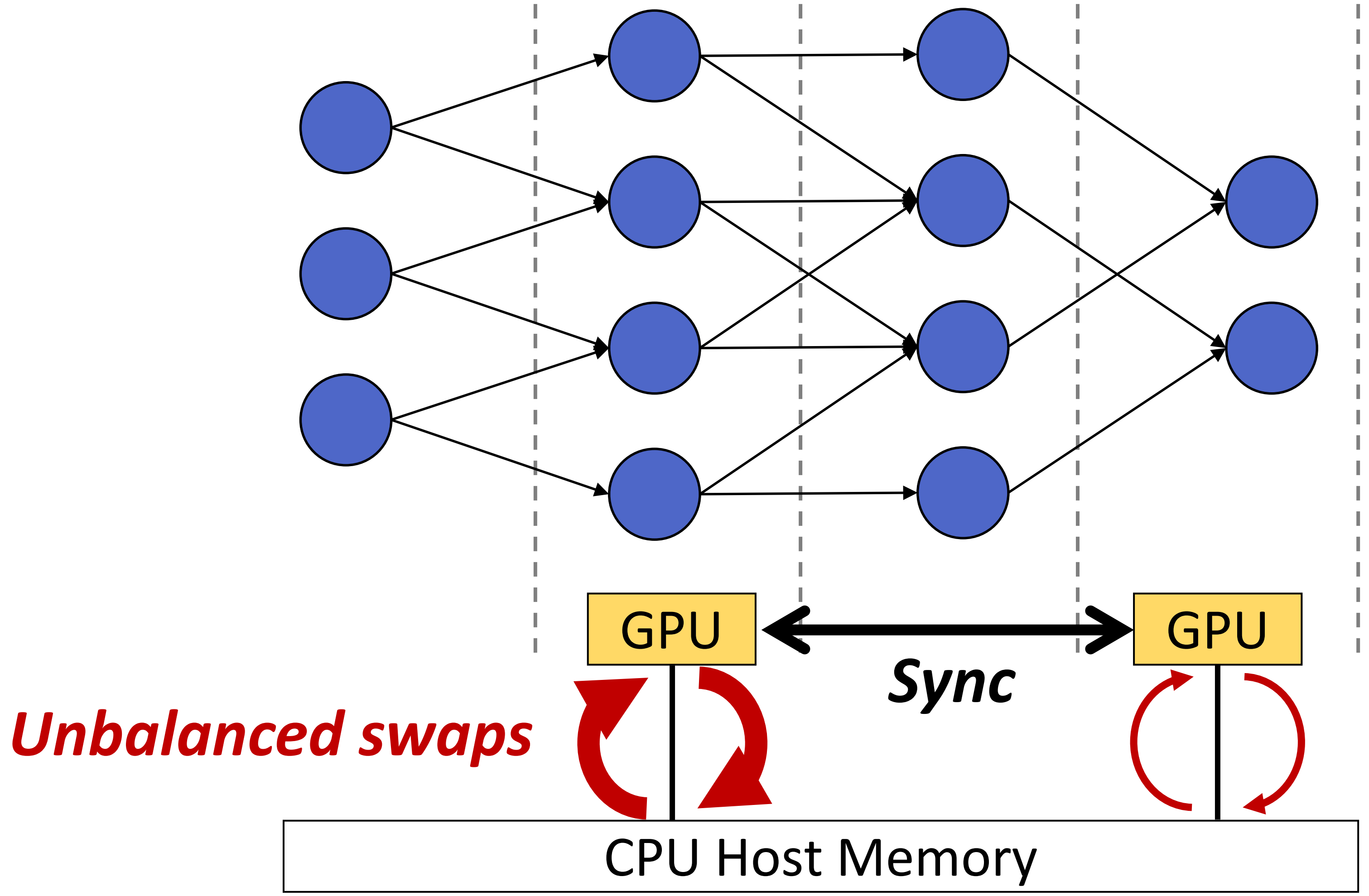

These inefficiencies are hard to solve

- *Excessive swap overhead*
- *CPU-GPU swap bottleneck*
- *Unbalance swaps*

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   (e.g., PyTorch schedules an entire model to compute the 1st data batch, before the 2nd data batch)

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→ ***Not flexible & poor resource utilization***

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Key Idea

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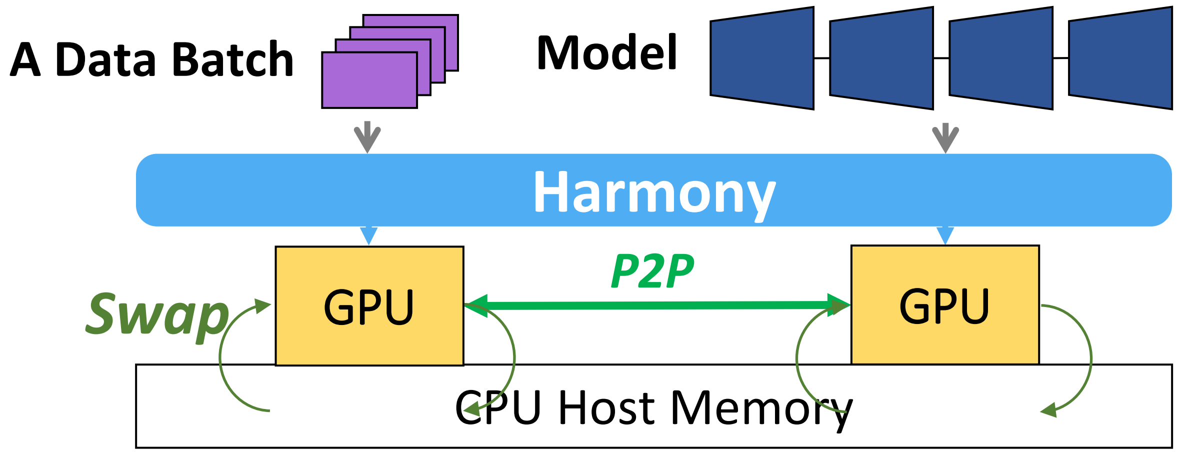
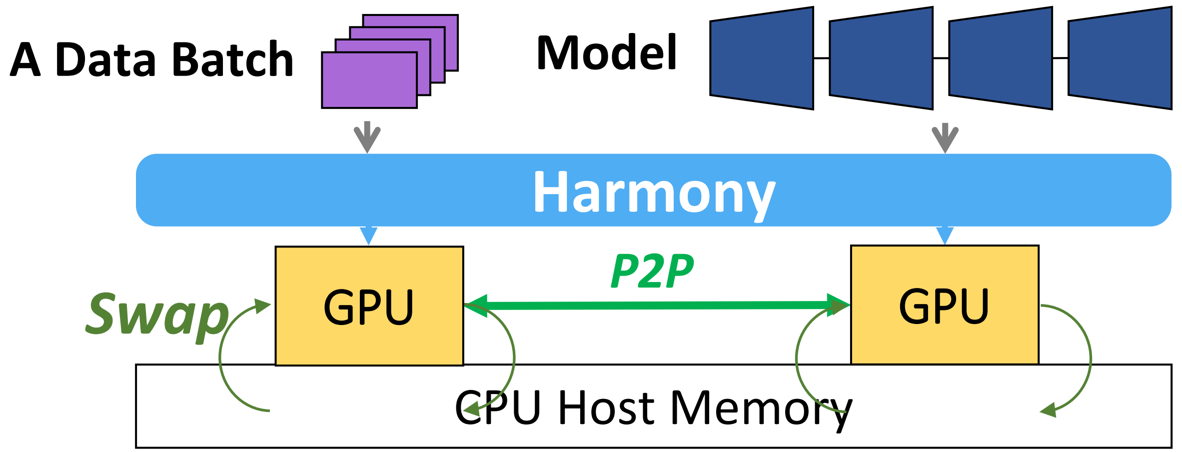
Goal

- Maximize **system efficiency** for training large models

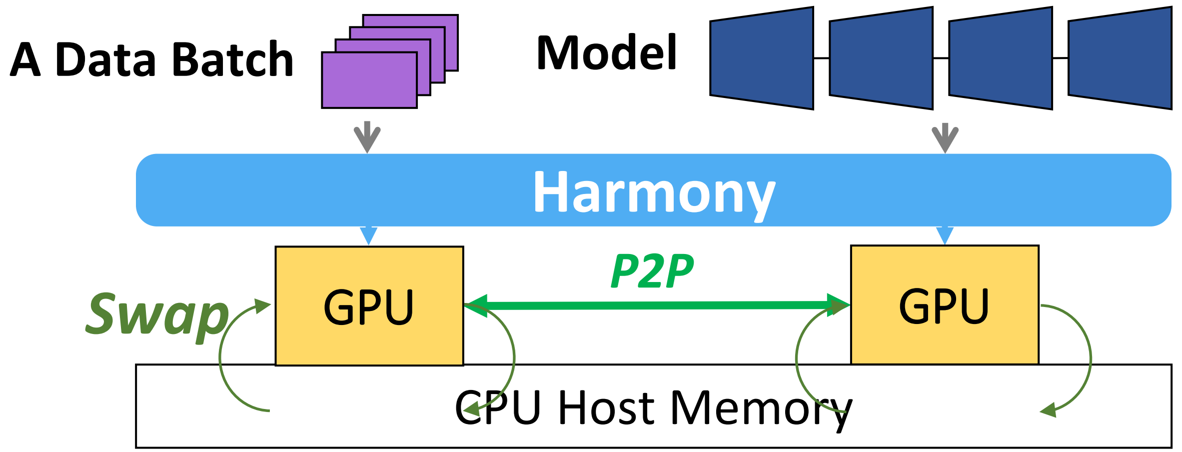

A Data Batch
Model
Harmony
P2P
Swap
GPU
GPU
CPU Host Memory



Four Principles

- **Minimize memory swaps**

  (e.g., *group* tasks to reuse shared states in memory)



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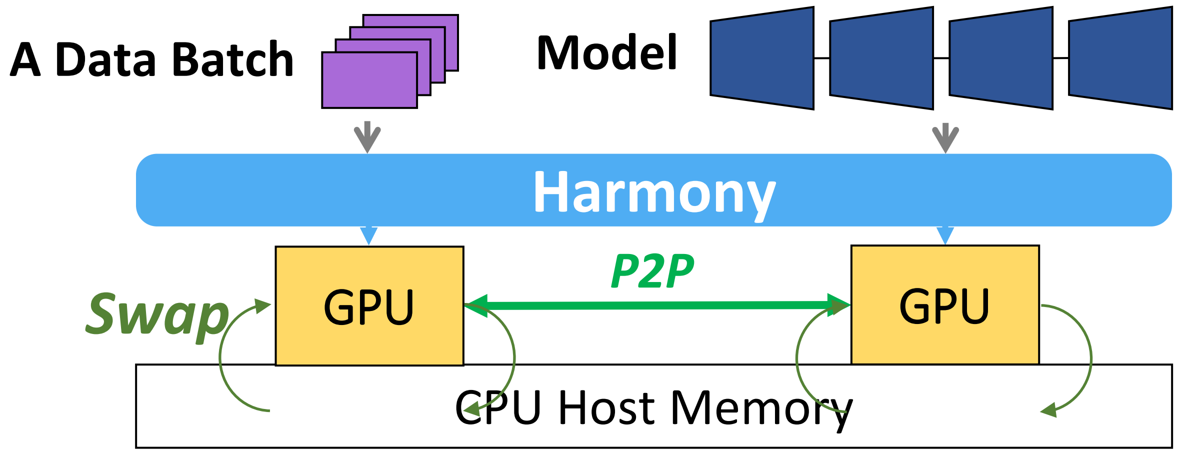

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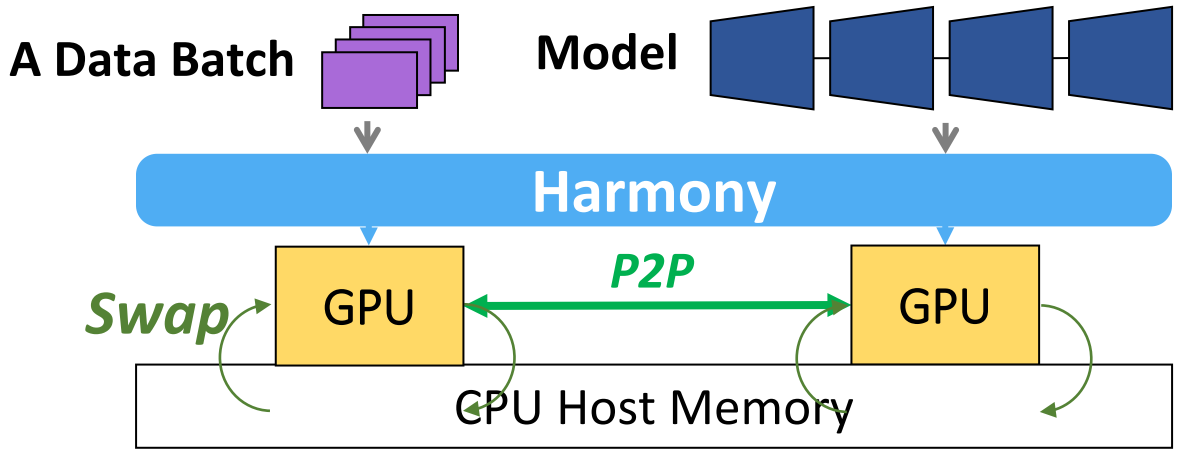

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- **Balance load**
  (e.g., *pack* tasks for similar compute & swap loads)

A toy example: *training 4-layer DNN on 2 GPUs with Harmony*

Forward Pass	Backward Pass	Update
Microbatch Idx Layer Idx	Microbatch Idx Layer Idx	Layer Idx

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Grouping	Peer2Peer	Just-In-Time

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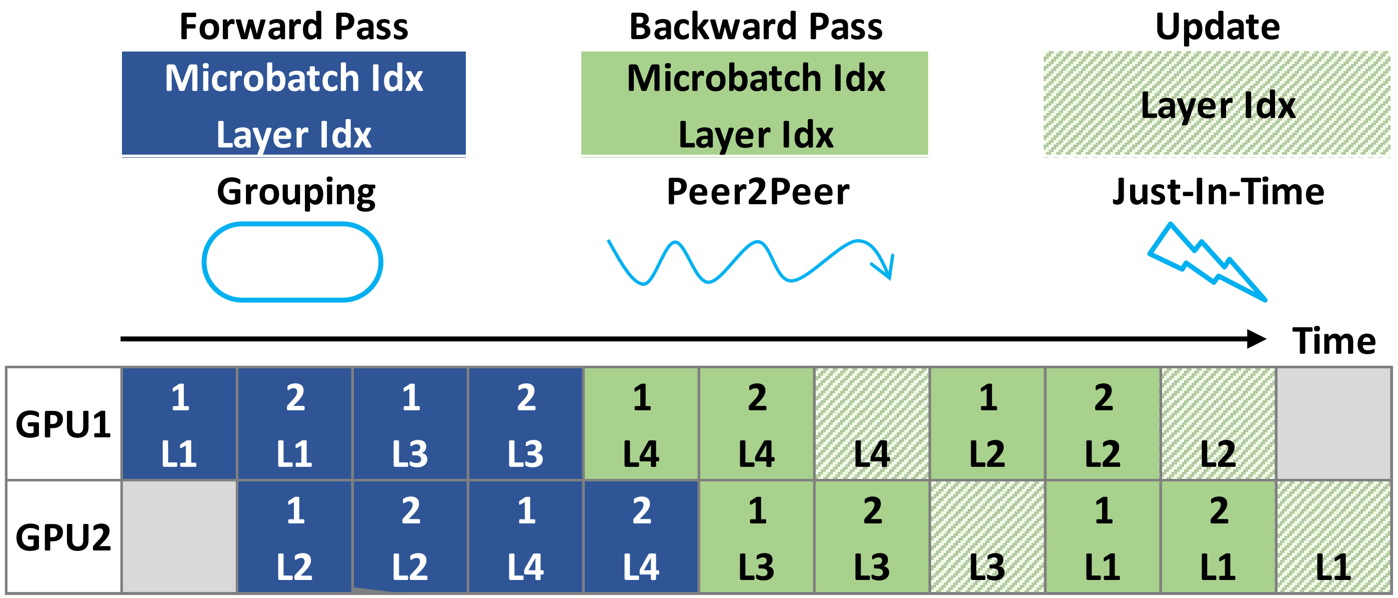

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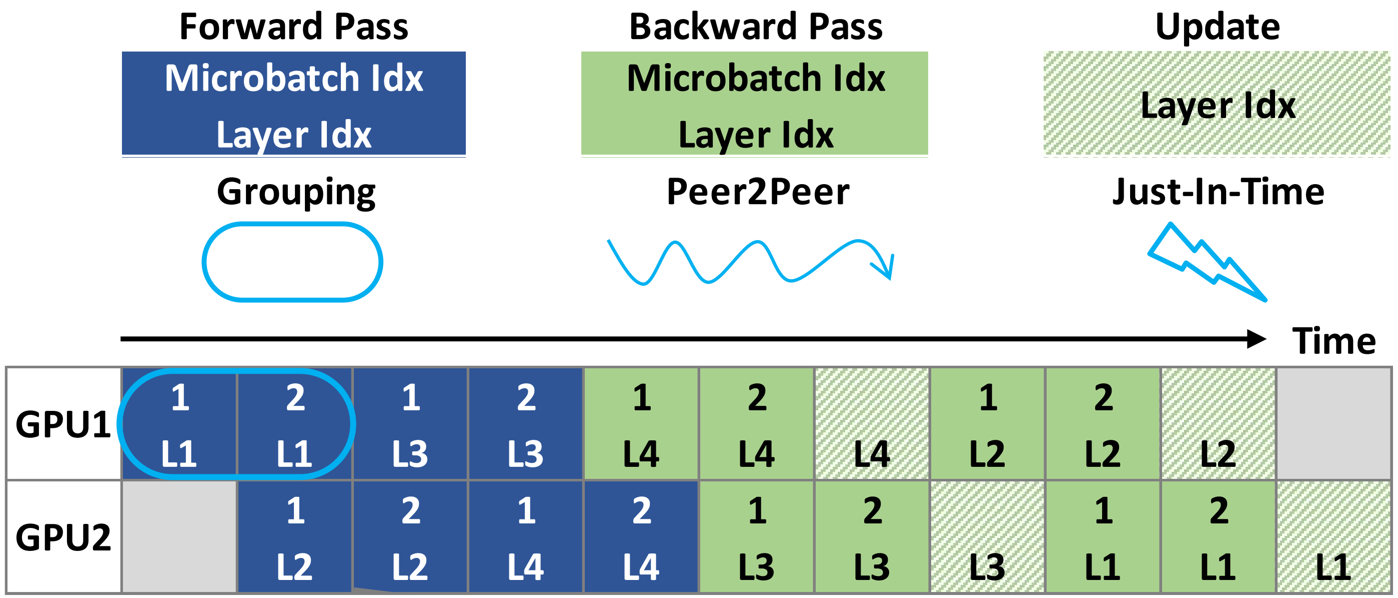

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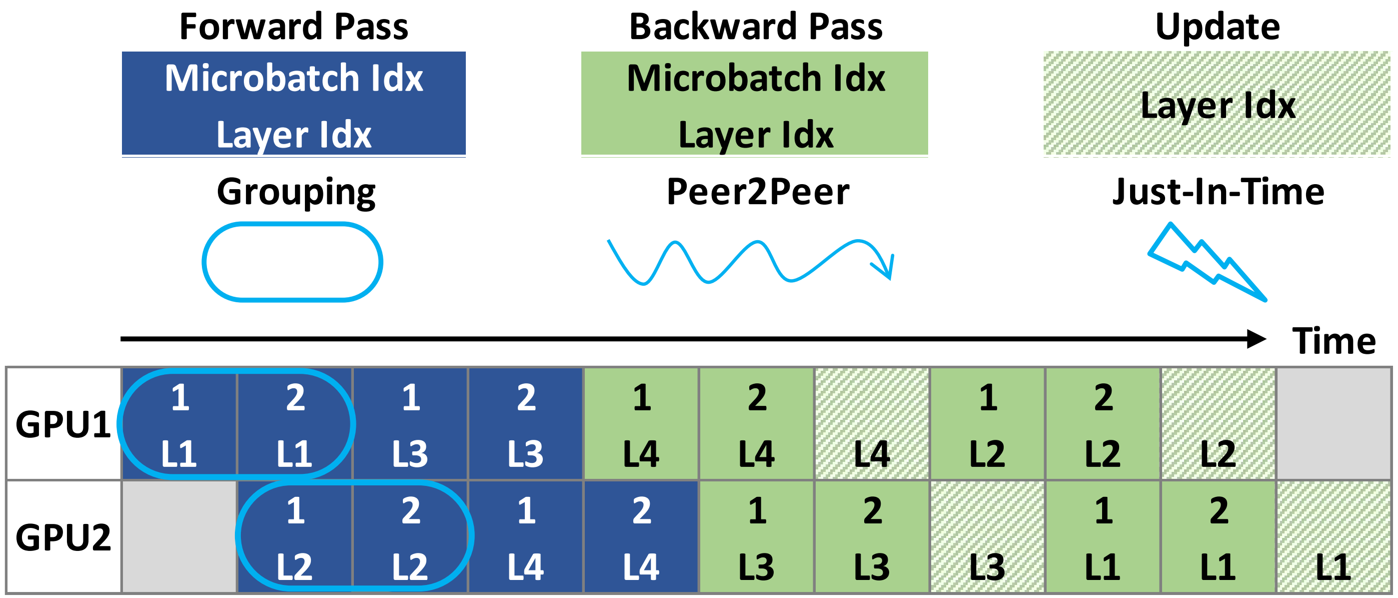

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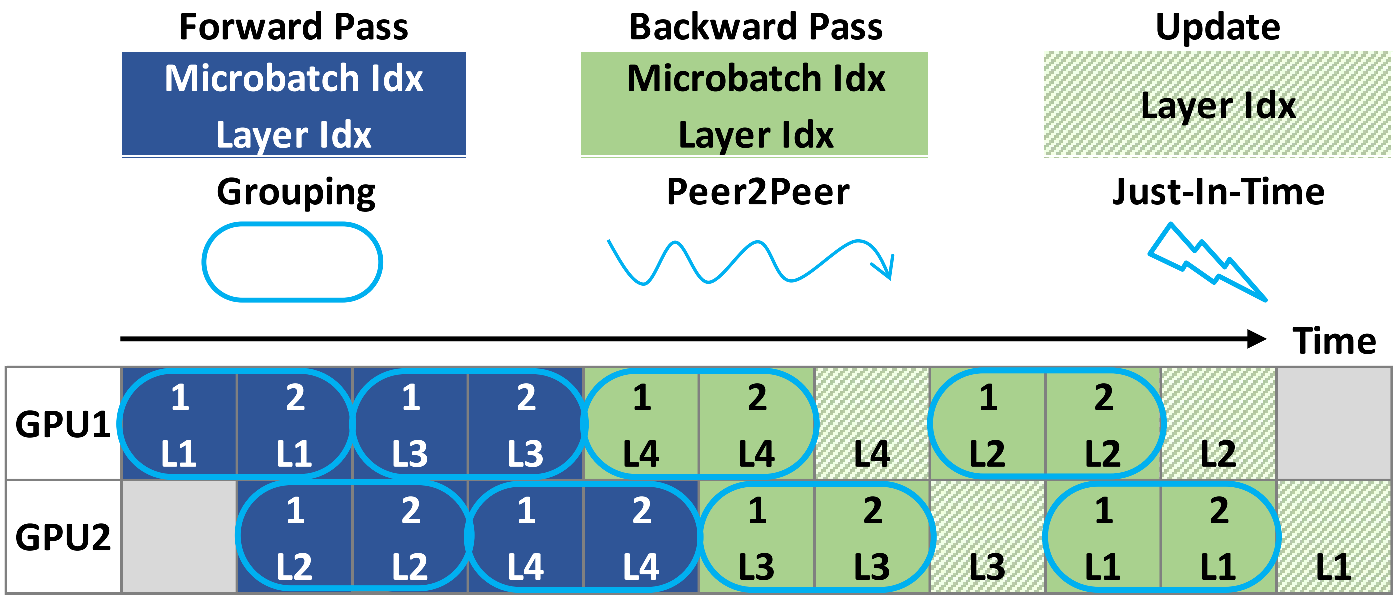

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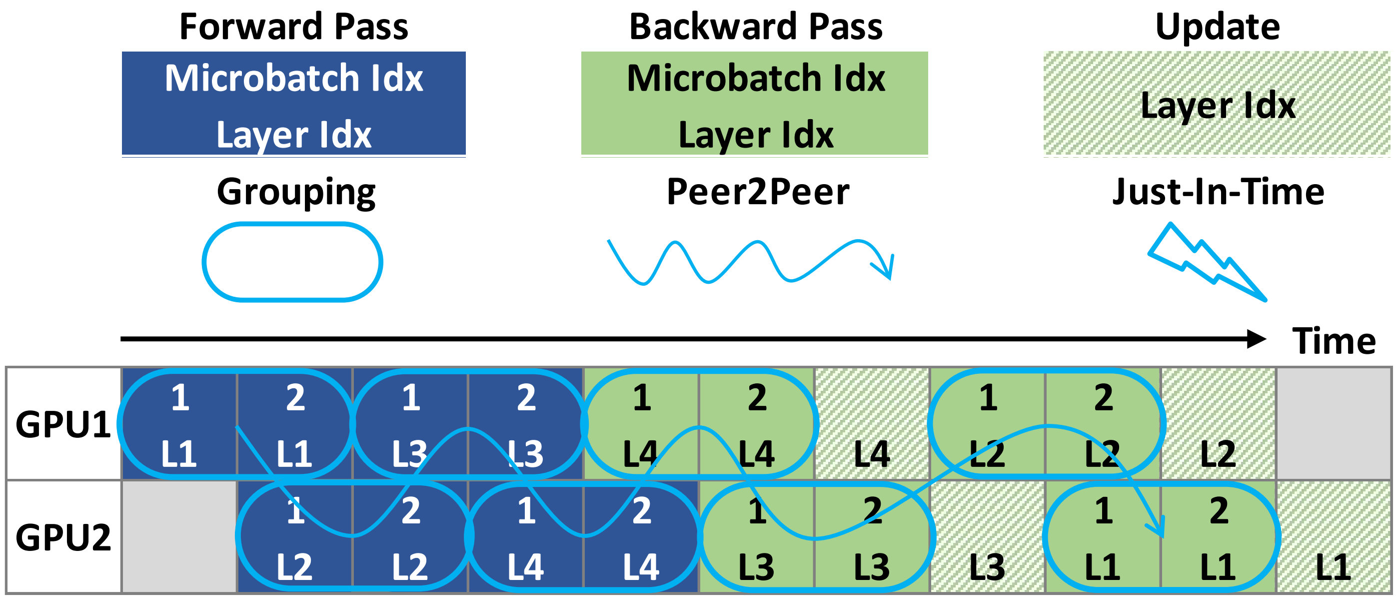

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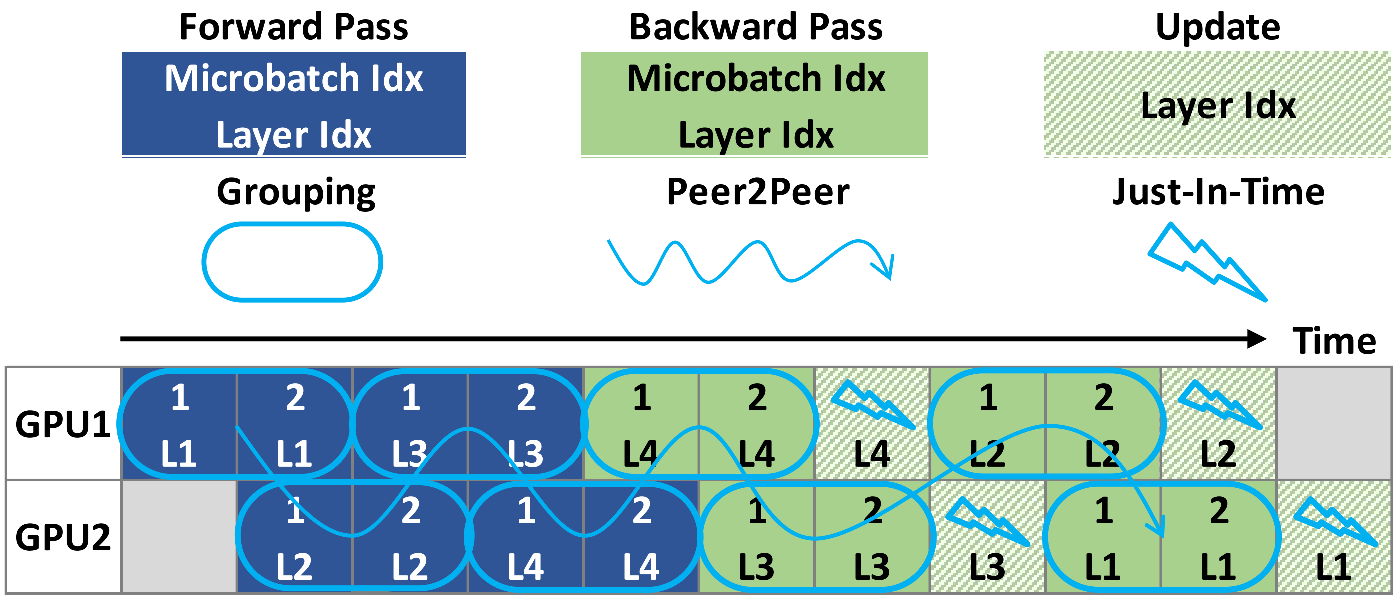

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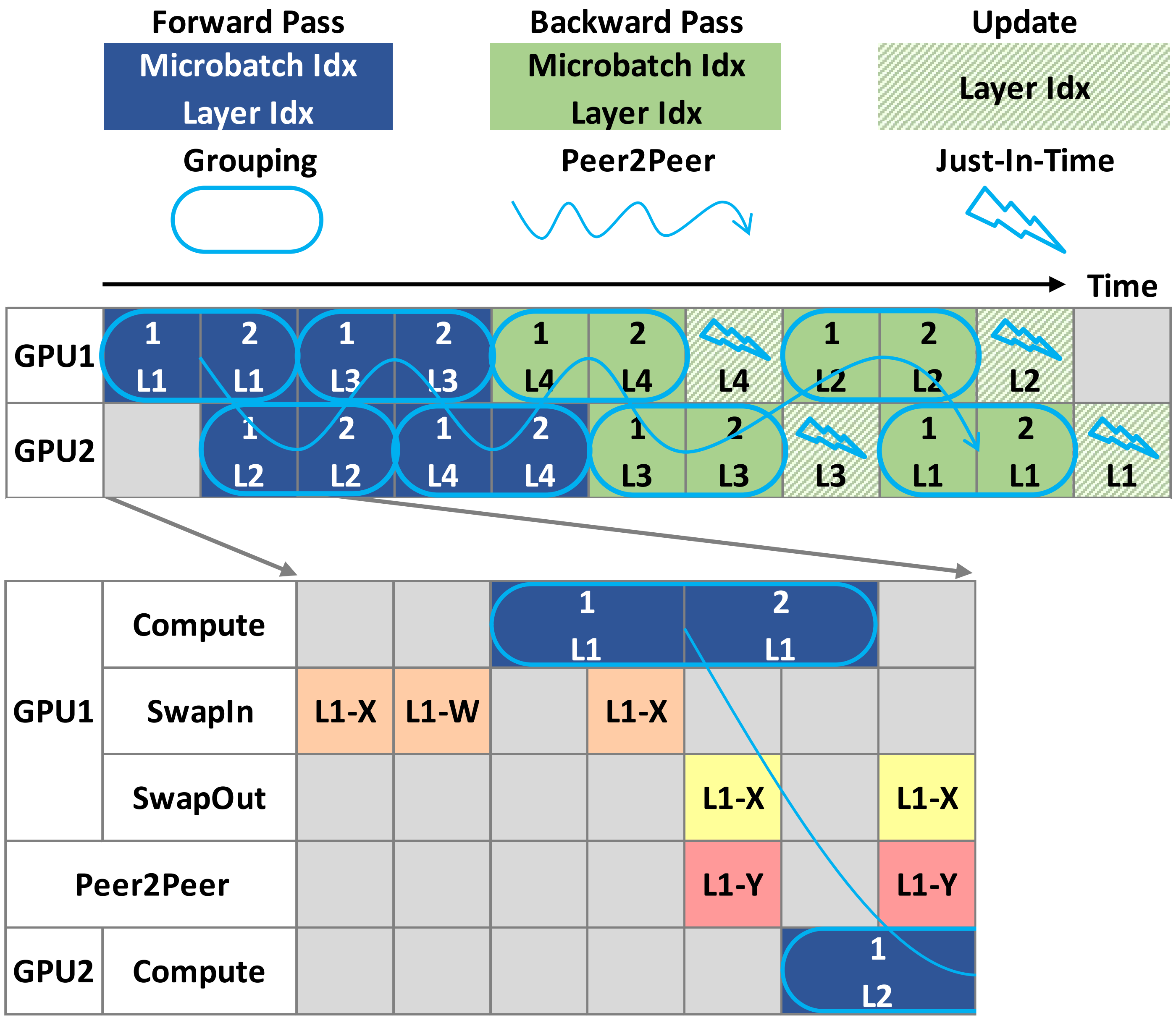


More of Harmony in the paper :)

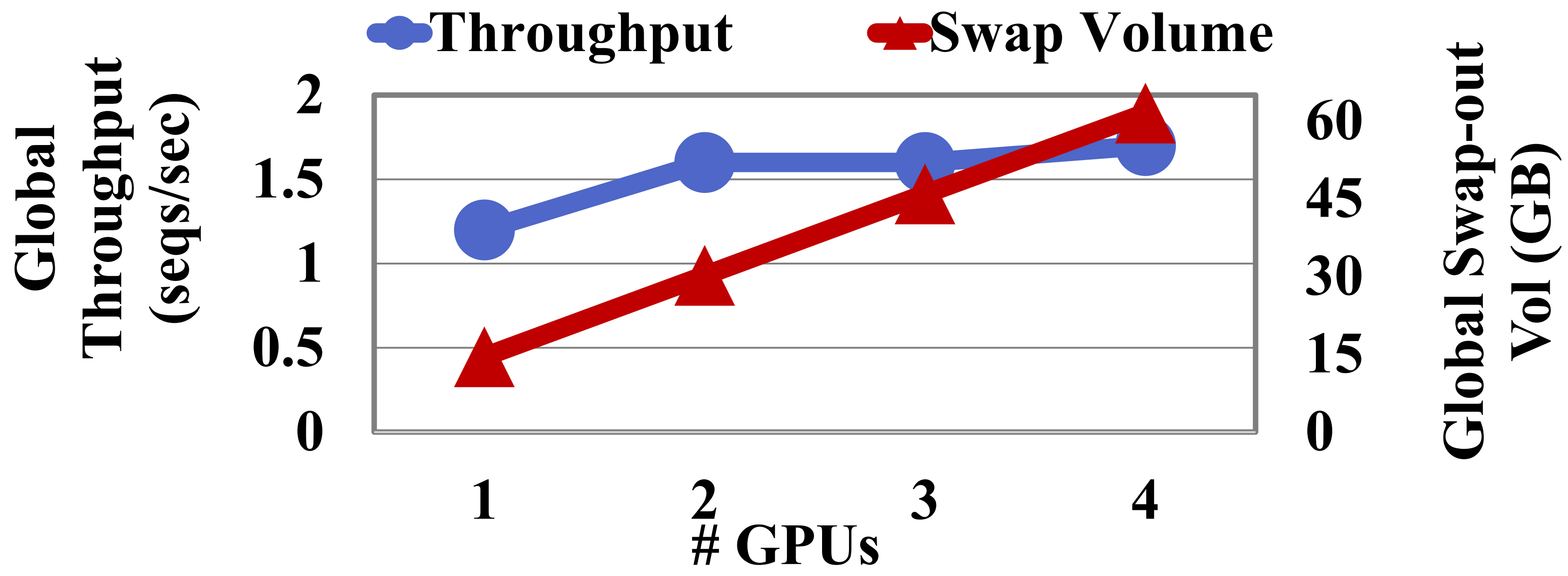
- Single-accelerator abstraction for multi-GPU training
- Virtualization of different parallel training techniques
- Analytical evaluation
- Multi-machine training
- Memory-performance trade-offs
- Feasibility for end-to-end training on modest deployments

Conclusion

- Large model training can also be for the "masses"!
- Large model training requires huge accelerator memory.
- Memory virtualization incurs excessive swap overhead.
- We advocate rethinking how ML frameworks schedule compute and move data for – *efficiently training large models on commodity servers.*

Backup Slides

Data-Parallelism with per-GPU memory virtualization



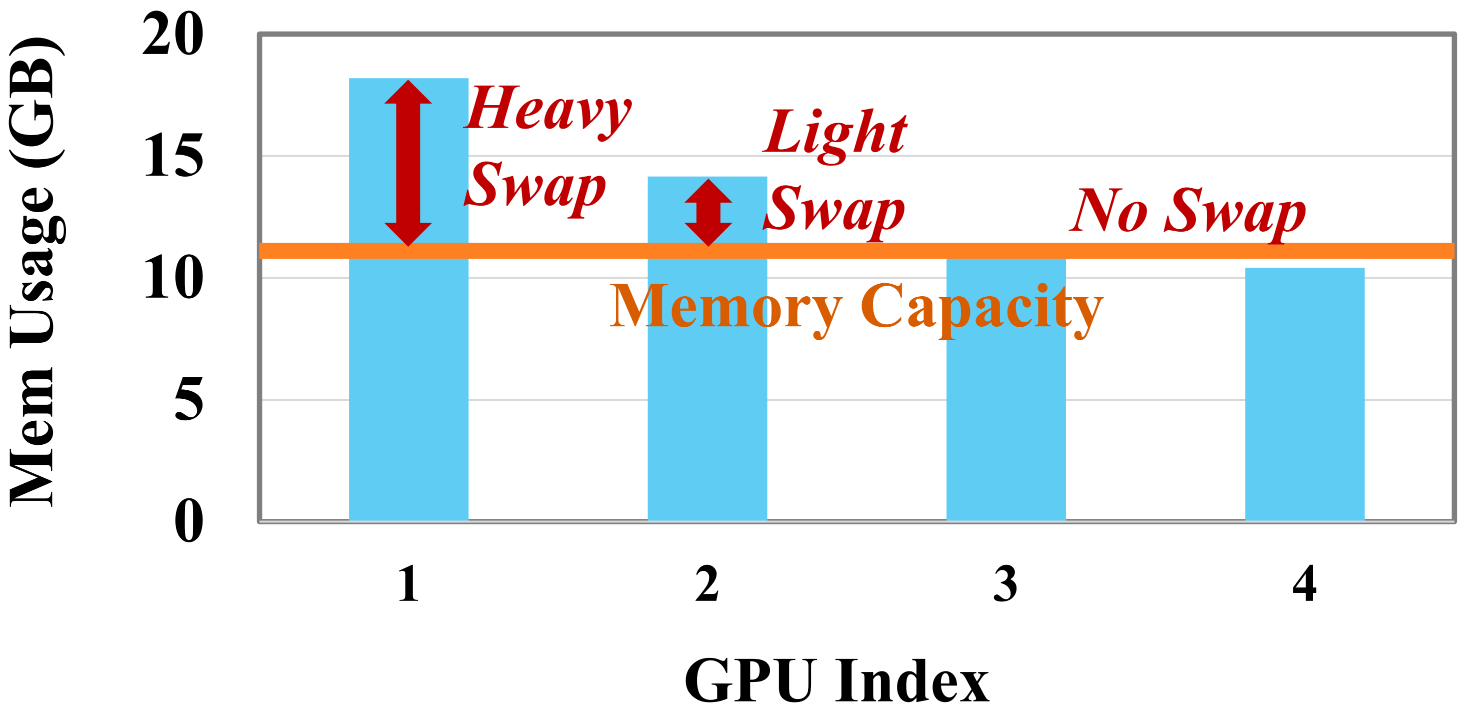
Setting: 4x GTX-1080Ti (11GB) + Bert-Large + Per-GPU batchsize=5 + PyTorch Data Parallel + IBM-LMS

Linearly increased swap volume plagues throughput

(Reason: swap load across replicated models is proportional to GPU count)

* [LMS, SysML'18]

Pipeline-Parallel training with per-GPU memory virtualization



Setting: 4x GTX-1080Ti (11GB) + Bert-Large + MicrobatchSize 32+ PipeDream2BW + IBM-LMS

Unbalanced swap load across GPUs

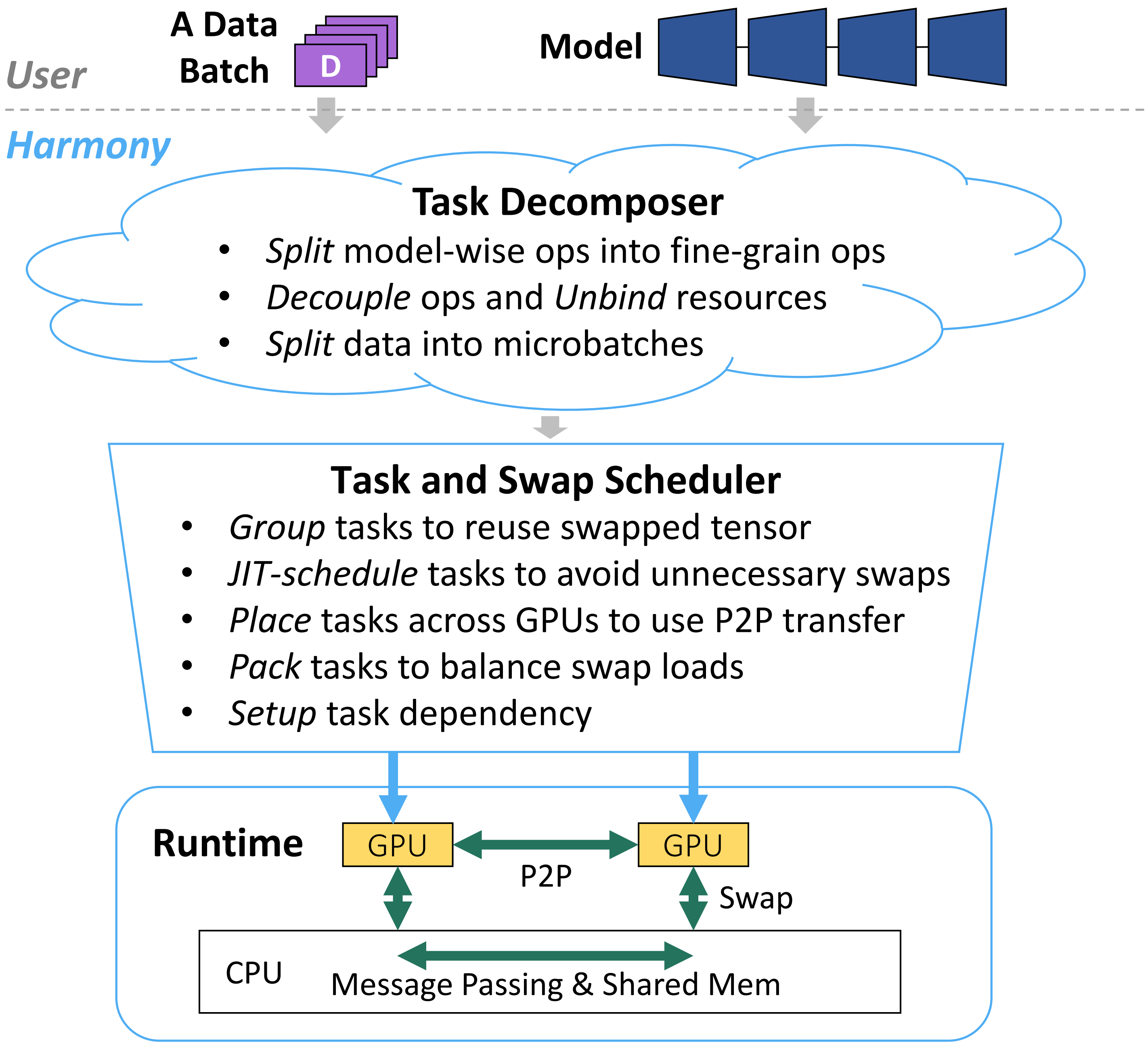
→ The heaviest swap happens on GPU-0 while GPU2-3 has no swap issue

→ Pipeline is always synchronous across all GPUs

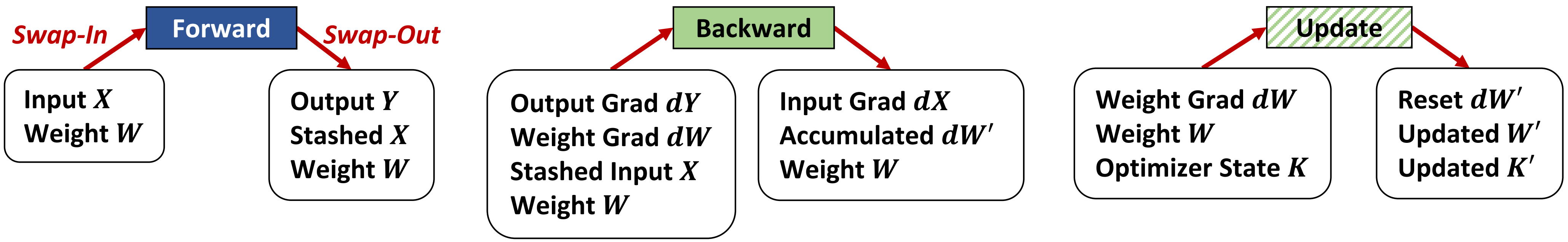
→ The system throughput is bottlenecked by GPU-0

* [LMS, SysML'18]

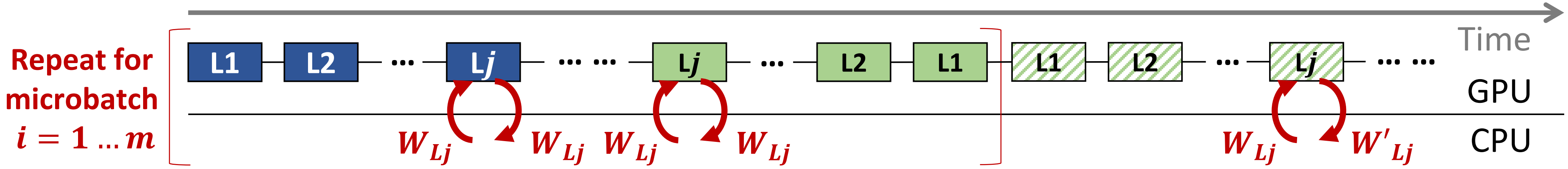
Overview


A Data Batch
D
Model
User
Harmony
Task Decomposer
• Split model-wise ops into fine-grain ops
• Decouple ops and Unbind resources
• Split data into microbatches
Task and Swap Scheduler
• Group tasks to reuse swapped tensor
• JIT-schedule tasks to avoid unnecessary swaps
• Place tasks across GPUs to use P2P transfer
• Pack tasks to balance swap loads
• Setup task dependency
Runtime
GPU
GPU
P2P
Swap
CPU
Message Passing & Shared Mem

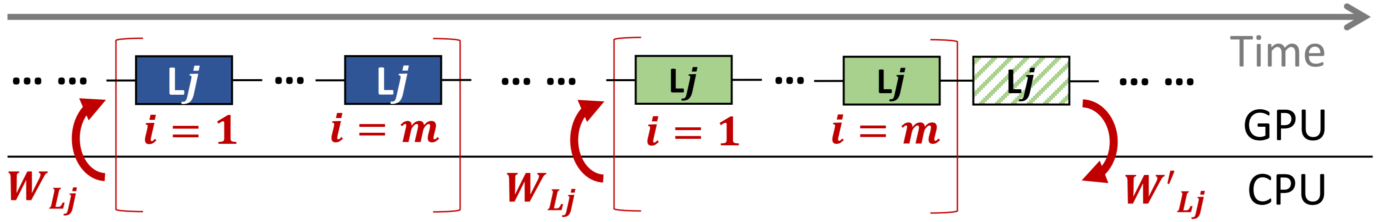
Analyzing the swap load



(a) Swap model.



(b) Swapping of weights for layer Lj in "DP with per-GPU memory virtualization."



(c) Swapping of weights for layer Lj in "Harmony DP."

Analytical comparison

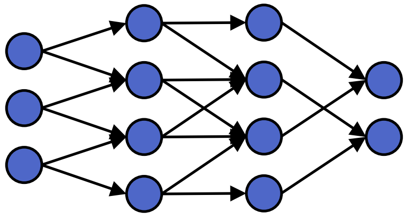
Different Approaches			DP with Per-GPU Swap	Harmony DP (vDP)	PP with Per-GPU Swap	Harmony PP (vPP)
Total Comm. Volume of One Data Batch	Swap Volume (In + Out)	W	$(4M + 2N) \times$	$3N \times$	$(4M + 2) \times$	$3 \times$
		dW	$(2M + 2N) \times$	$0 \times$	$(2M + 2) \times$	$0 \times$
		K	$2N \times$	$2N \times$	$2 \times$	$2 \times$
		X	$2M \times$	$2M \times$	$2M \times$	$2M \times$
		Y & dX	-	$2M \times$	-	-
	P2P Volume	AllReduce dW	$N \times$	$N \times$	-	-
		Send Y & dX	-	-	$\left(\frac{N-1}{R}\right) M \times$	$M \times$
Balanced Memory Usage (CPU + GPU)			Yes	Yes	No (Stashed X across GPUs is $1:2:\ldots:N$)	Yes

Feasibility for end-to-end training on commodity GPU servers

End-to-End Training Timeline

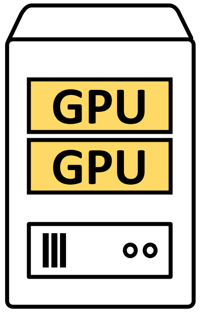
Large model

1. Development & Debugging

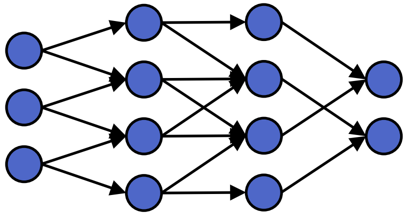


Training FLOPs: up-to 10^{19} *or*
Training Time: several hours/days

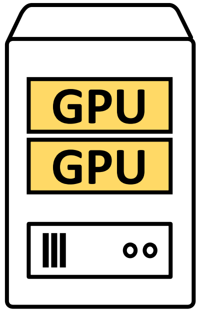
Commodity machine(s) with only GTX GPU



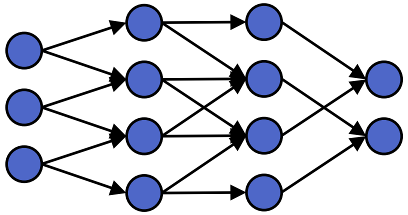
2. Pre-training from Scratch



Training FLOPs: beyond 10^{23} *or*
Training Time: months/years



3. Fine-tuning to Best Accuracy



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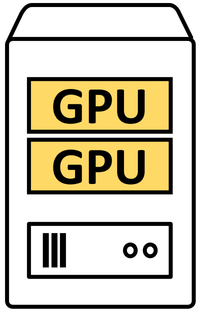

Estimated Training Time

Model	Pre-training		Fine-Tuning Wikitext-103 for 5 epoch			Fine-Tuning GLUE for 3 epoch		
	# FLOP	Single 1080Ti Time (days)	# Tokens	# FLOP	Single 1080Ti Time (days)	# Tokens	# FLOP	Single 1080Ti Time (days)
BERT-Large	5.33E+20	581	5.1E+08	1.24E+18	1	6.09E+08	1.49E+18	2
GPT-2	2.38E+21	2,592	5.1E+08	6.30E+18	7	6.09E+08	7.56E+18	8
T5-11B	3.30E+22	36,002	5.1E+08	1.35E+19	15	6.09E+08	1.62E+19	18
GPT-3	3.14E+23	342,564	5.1E+08	7.16E+20	781	6.09E+08	8.59E+20	937