DataStates-LLM: Lazy Asynchronous Checkpointing for Large Language Models

HPDC'24. Authors: Avinash Maurya, Robert Underwood, M. Mustafa Rafique, Franck Cappello, Bogdan Nicolae

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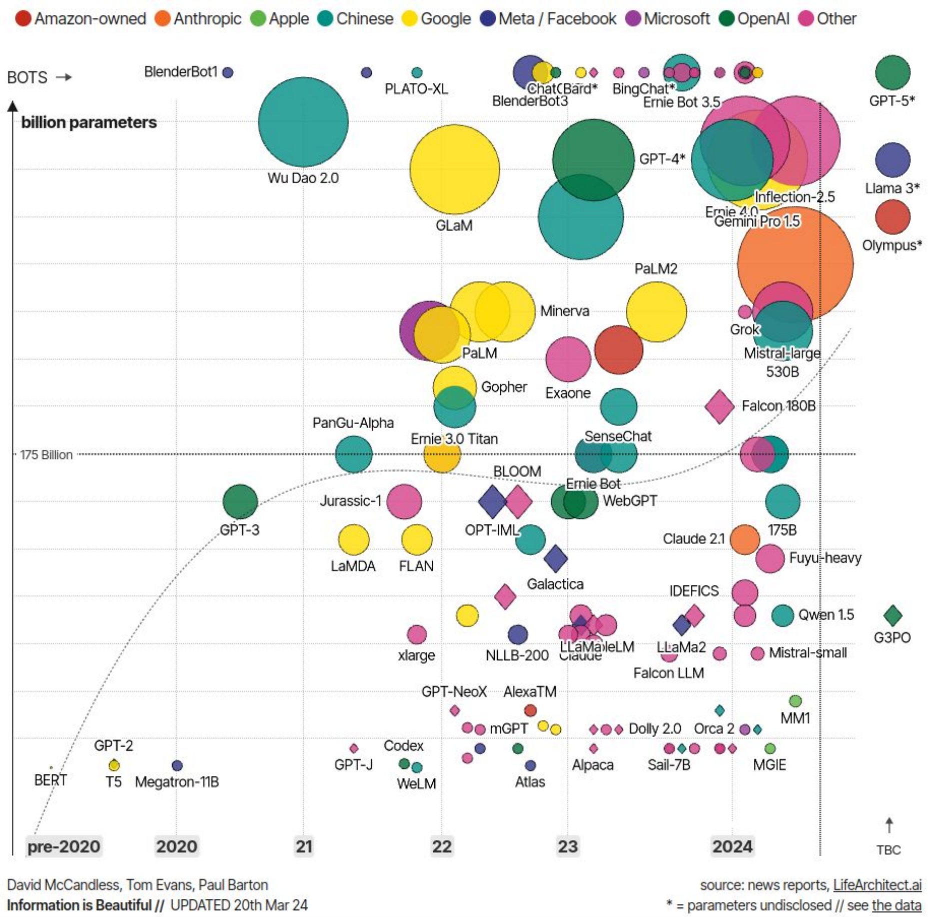
Motivation: LLM Pre-Training is Expensive



Model	Number of GPUs	Duration
GPT-3 (175B)	10,000	34 days
GPT-4	25,000	Several months
PaLM (540B)	6,144	2 months
Turing NLG	560	Several months
Bloom (176B)	384	3 months
Chinchilla (70B)	4,096	1 month
T5 (11B)	1,024	1 month

LLM pre-training: How much does it cost?

Model Size (B)	Tokens (Trillion)	Aurora Time (h)	Polaris Time (h)	Aurora Time (Days)	Polaris Time (Days)	Cloud Cost ($3 GPU/hr)
7	2	2.29	333	0.10	14	$437K
7	3	3.34	500	0.14	21	$656K
70	2	22.88	3,333	0.95	139	$4,374K
70	3	34.31	5,000	1.43	208	$6,561K
200	6	196.08	28,571	8.17	1,190	$37,496K
200	10	326.80	47,619	13.62	1,984	$62,494K
1000	10	1633.99	238,095	68.08	9,921	$312,470K
1000	20	3267.97	476,190	136.17	19,841	$624,941K

LLM Pretraining is Resource-intensive & Time-consuming

Datacenter Traces Reveal Urgent need for Efficient Resilience

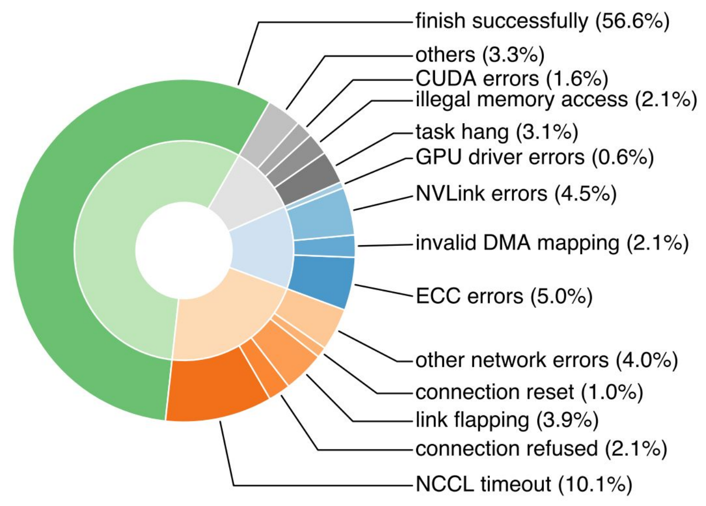


Fig: Failures on Alibaba Cloud consisting of 256 NVIDIA H800 GPUs running LLM training*

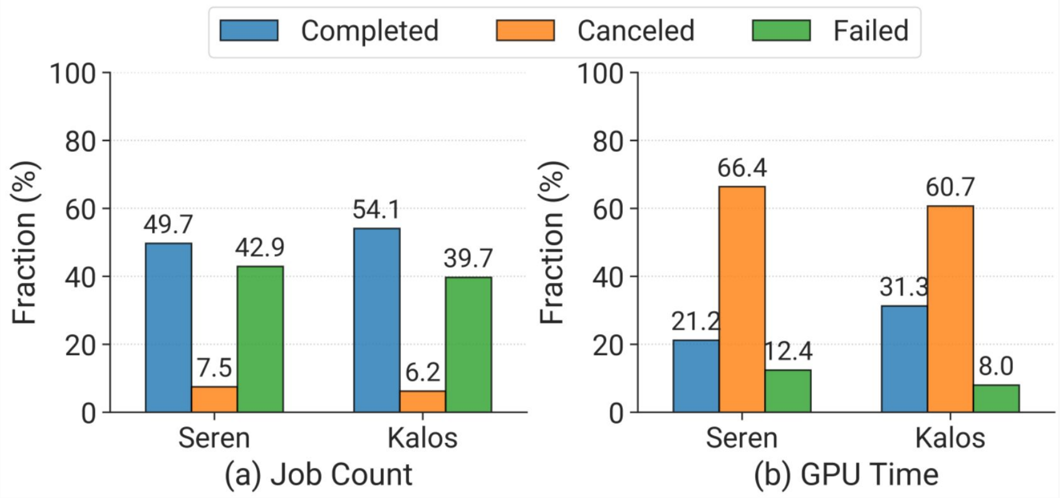
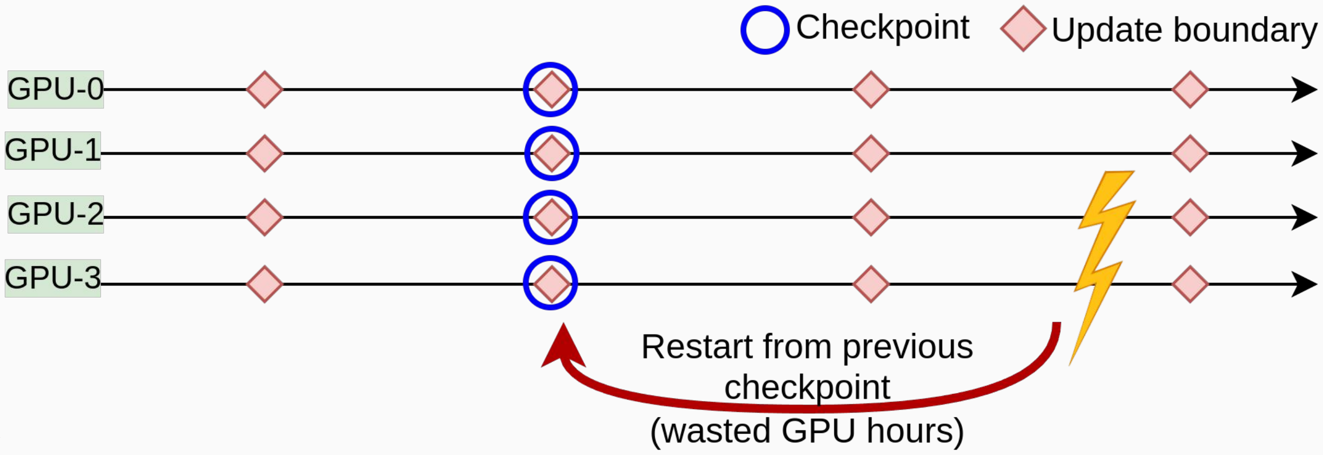


Fig: Failures on Shanghai AI Laboratory's LLM Clusters: Seren and Kalos, housing a total of 4704 A100 GPUs in total^

*Unicron: Economizing Self-Healing LLM Training at Scale; He, Tao, et. al. 2023, https://arxiv.org/pdf/2401.00134
^Characterization of Large Language Model Development in the Datacenter, Hu, Qinghao, et. al., 2024, https://arxiv.org/pdf/2403.07648v2

Checkpointing as a Fundamental Primitive for LLMs



Scenarios:

Failures

- NCCL timeout
- NVLink error
- Invalid DMA mapping
- Task hung up
- Link flapping

Impacts one or more processes

Undesirable training trajectories

- Google PaLM reported model spikes at arbitrary training points
- Restart from checkpoints taken 100s of timesteps ago
- Costly fine-grained checkpointing due to lack of efficient checkpoint engine

Productive and Administrative

- Understanding Model Evolution
- Forensics, Biases & Ethics: periodic evaluation in the background
- Suspend-resume (e.g. every 6 hours)
- Elastic training: Vary number of GPUs

3D Parallelism: How to Scale LLM Pre-Training (1)

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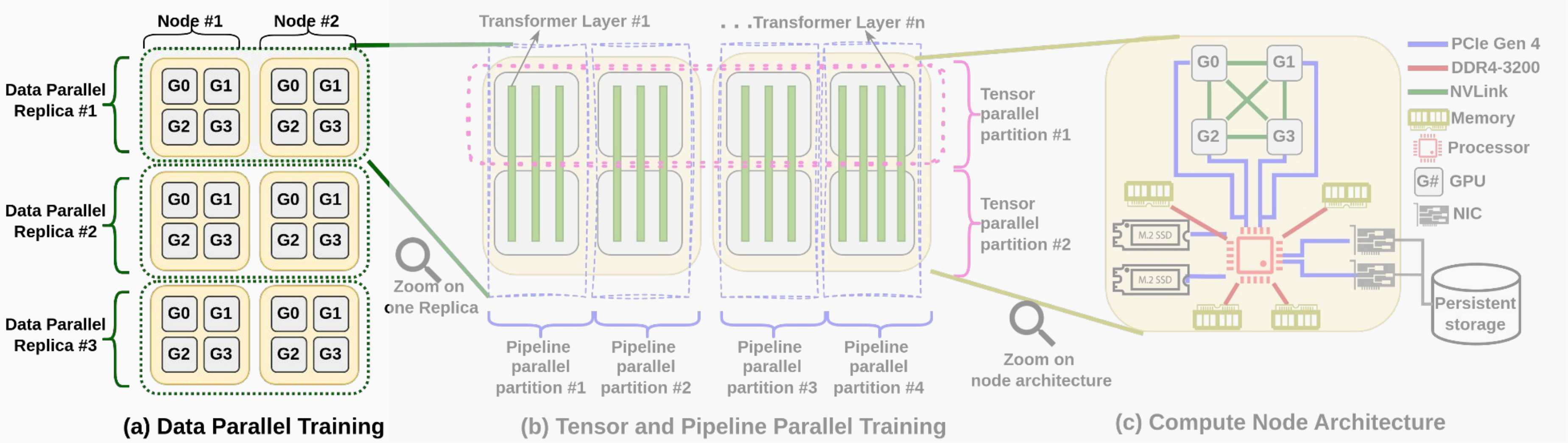

- Input data is split across data-parallel instances to improve training throughput
- Gradients are averaged using all-reduce to keep the replicas in sync and learn the same pattern

3D Parallelism: How to Scale LLM Pre-Training (2)

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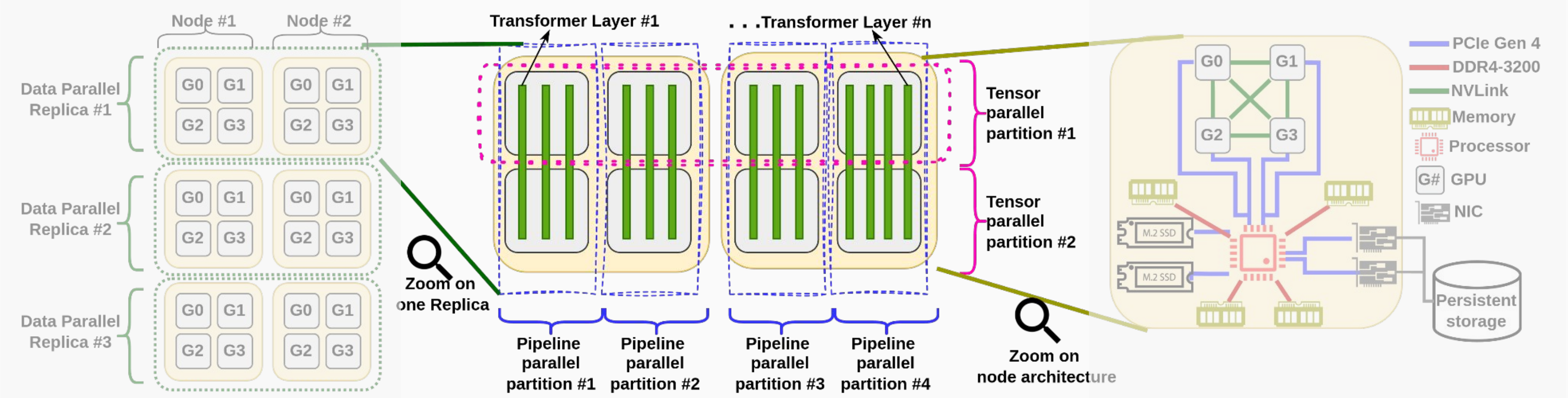
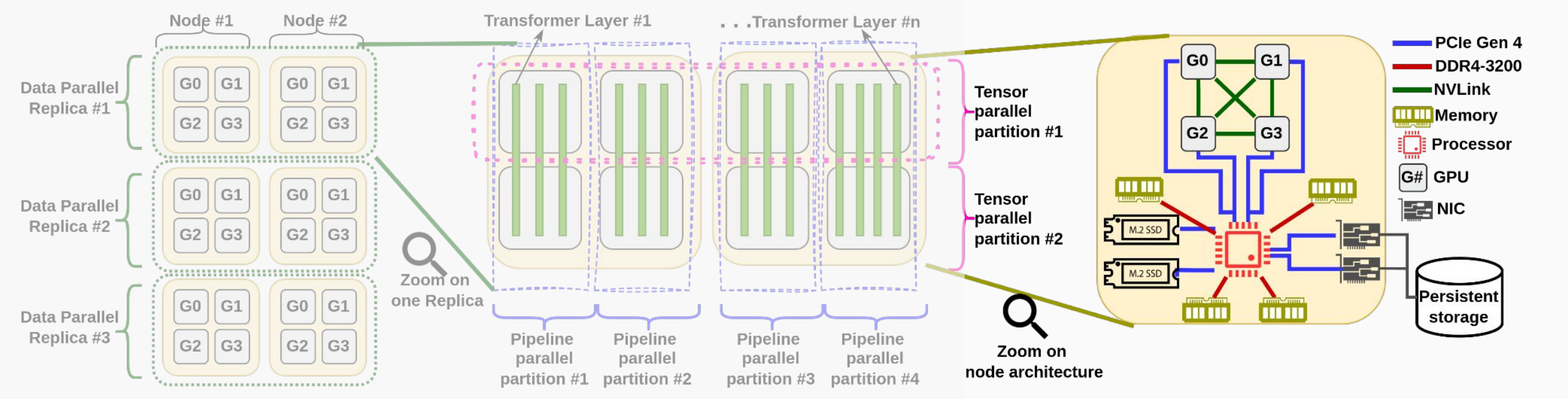


(a) Data Parallel Training (b) Tensor and Pipeline Parallel Training (c) Compute Node Architecture

- Tensor parallelism splits individual layers horizontally across multiple GPUs
- Pipeline parallelism groups multiple layer together into successive stages

Checkpointing under 3D Parallelism: Use Heterogeneous Storage



(a) Data Parallel Training

(b) Tensor and Pipeline Parallel Training

(c) Compute Node Architecture

- PCIe Interconnects (25GB/s+) are used to capture checkpoints to host memory
- From there, multi-level storage hierarchy: node-local NVMe, remote storage (PFS)

What Do We Need to Checkpoint?

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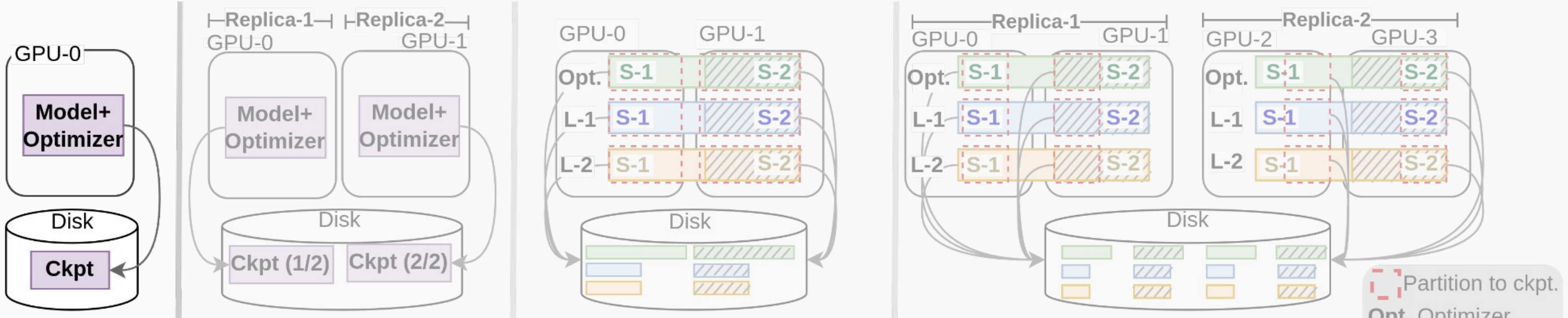

(a) Conventional DNN (PP=1, TP=1, DP=1)

(b) Conventional DNN (PP=1, TP=1, DP=2)

(c) LLM training (PP=1, TP=2, DP=1) Ckpt. single file per layer shard

(d) LLM training (PP=1, TP=2, DP=2) Partition each layer shard across DP instances

- Produces a single checkpoint file
- What do we need to checkpoint: Metadata (e.g. PRNG state), model parameters, optimizer state

Data Parallelism: Parallel Checkpointing

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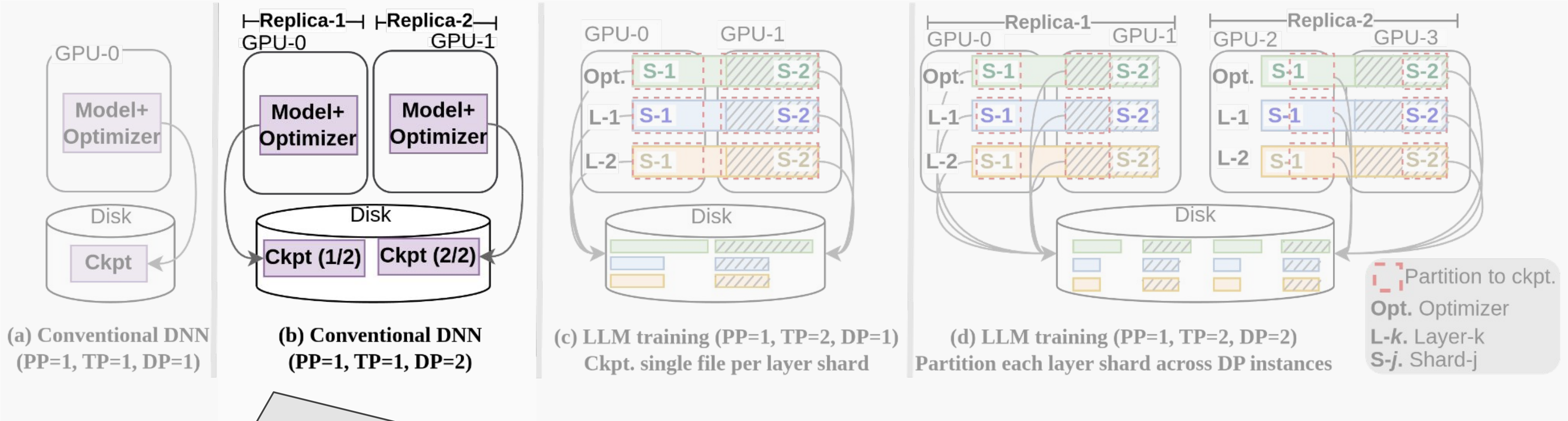
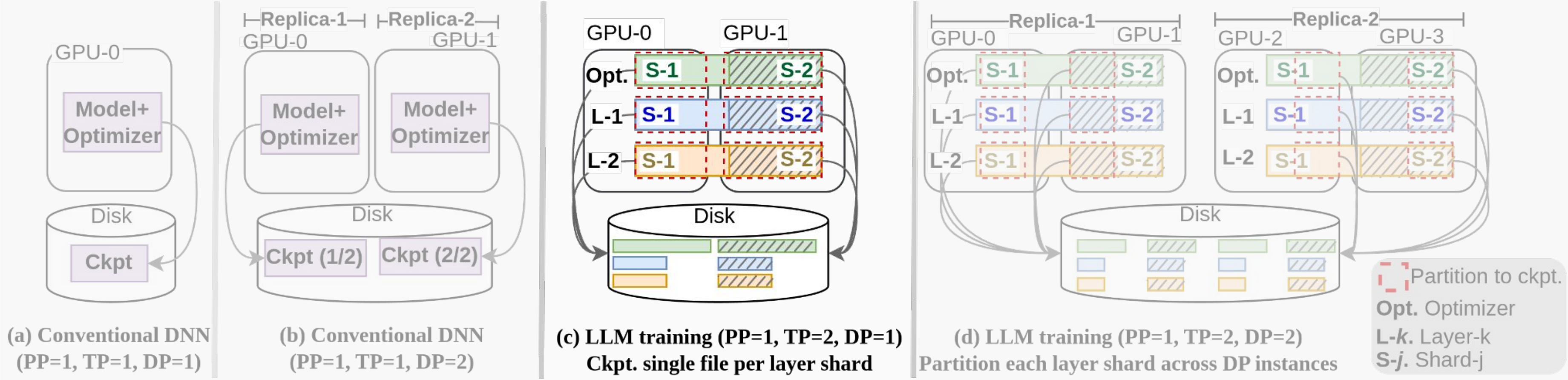


- Each data-parallel replica owns a complete copy of the model
- Checkpointing in parallel exploits the I/O bandwidth of all GPUs/nodes
- Examples: DeepFreeze, TorchSnapshot, etc.

Model and Optimizer State Fine-Grain Sharding (1)



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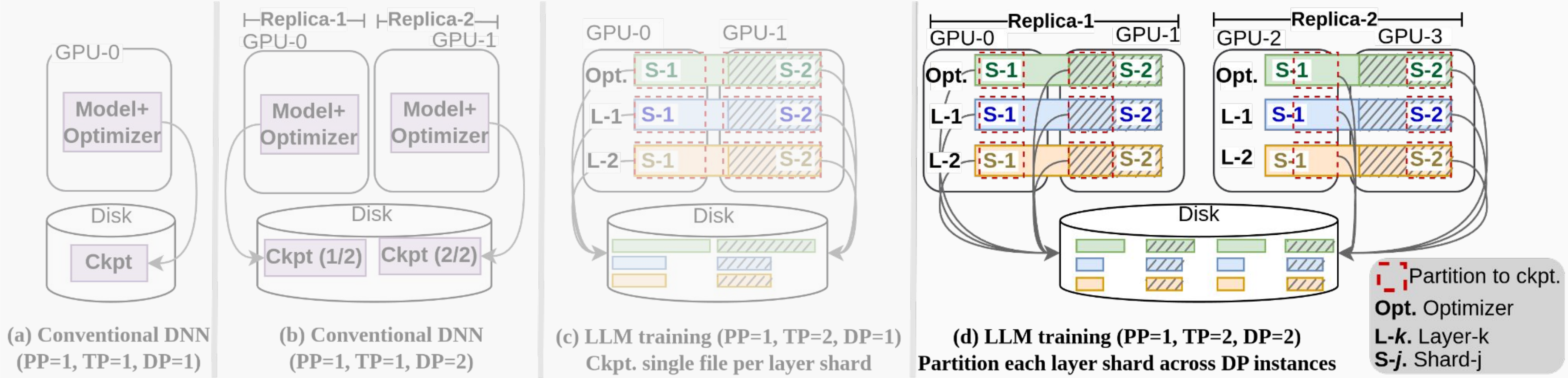
- Each model layer and optimizer shard produces a different checkpoint file for each GPU (e.g. DeepSpeed)
- Helpful for elastic/universal checkpoint-restart (use different data, tensor, pipeline-parallelism on restart)
- All shards need to be consistently captured for a successful checkpoint

Model and Optimizer State Fine-Grain Sharding (2)



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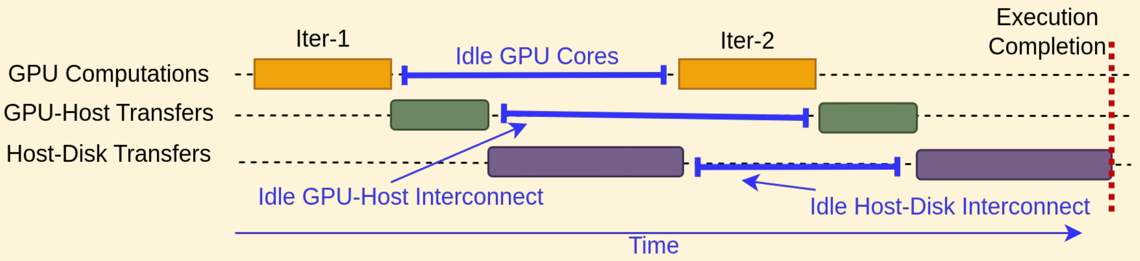
- Independent files per shard enables highly parallel I/O, but too many files may introduce I/O bottlenecks on shared storage (PFS)

Goal: High-Performance, Scalable Checkpointing that Masks I/O Overheads

Synchronous and Asynchronous Data Movement Techniques

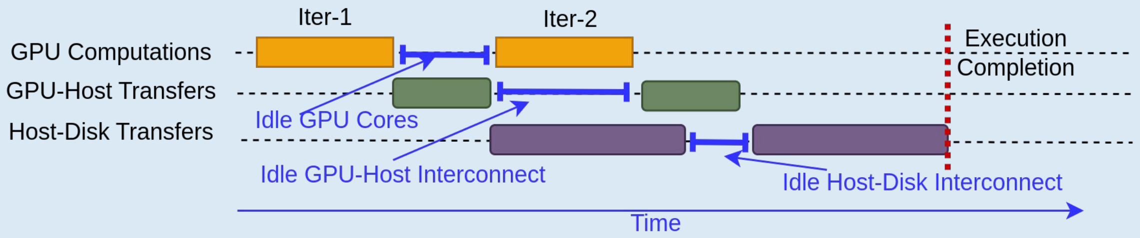
Synchronous Data Movement

- ✔ Easy to design and debug
- ✔ Avoids CPU oversubscription
- ✖ Underutilized computational resources, memory tiers and interconnects

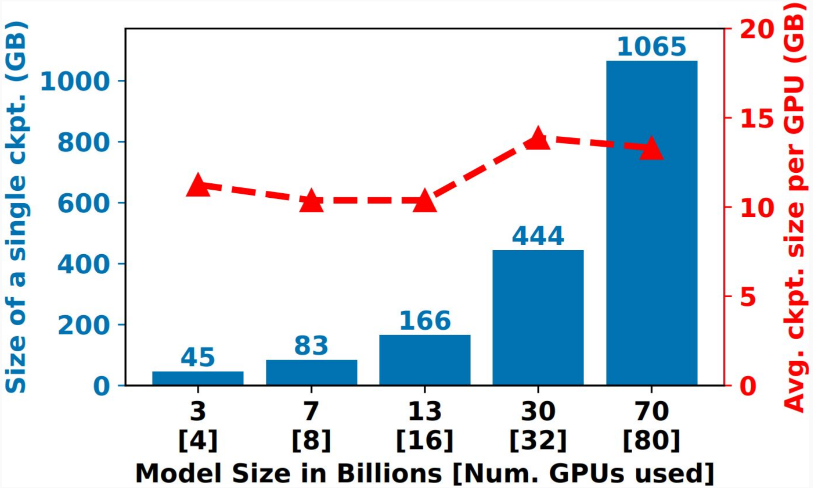


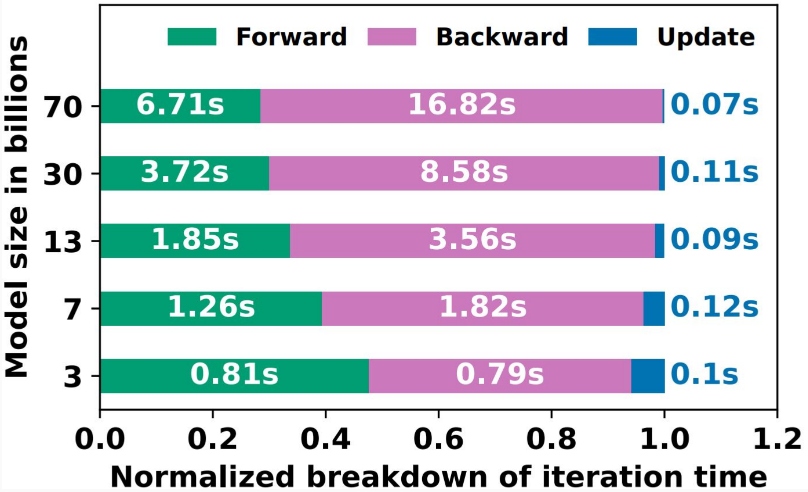
Partially Asynchronous Data Movement

- ✔ Easy extension of existing engines
- ✔ Mitigates slow I/O bottlenecks beyond the host tier
- ✖ Underutilization of spare GPU memory and GPU-host interconnect



Observations Driving Our Design





- Checkpoint size increases linearly with the number of model parameters
- Checkpoint **shard per GPU is load balanced** and remains the similar for different model sizes
- Forward and backward pass consume majority of the iteration duration (>95%) during training
- **Model and optimizer states are immutable** during forward and backward passes

DataStates-LLM: Key Ideas and Design Principles

- Leverage Immutability: Lazy Non-Blocking Copies Overlapping with Forward and Backward Pass
  - Model and optimizer states do not change during forward and backward passes
  - Keep copying until the start of update phase; block updates if previous copies are pending
- Coalescing of GPU Model/Optimizer Shards to Host Memory
  - Prepare the host memory for efficient GPU-host data transfers (pre-pinning)
  - Optimize host memory layout for bulk transfer of shards from multiple GPUs
- Streamlined Multi-level Flushing to Persistent Storage
  - Start streaming to disk as soon as partial checkpointing data is copied from GPU to host memory
  - Parallel use of two physical links: GPU-to-host and host-to-disk
- Asynchronous Distributed Consolidation of Model and Optimizer Shards
  - Asynchronous multi-level flushing necessitate consensus to commit a valid and consistent checkpoint version

Synchronous and Asynchronous Data Movement Techniques

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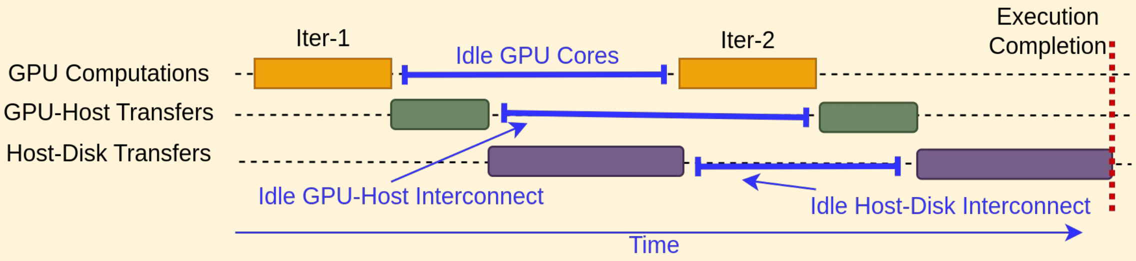

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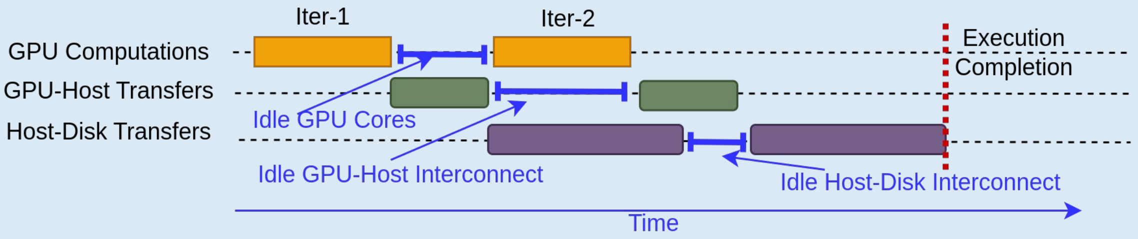
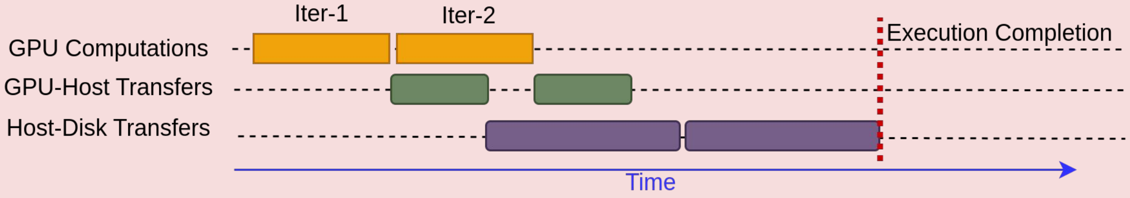
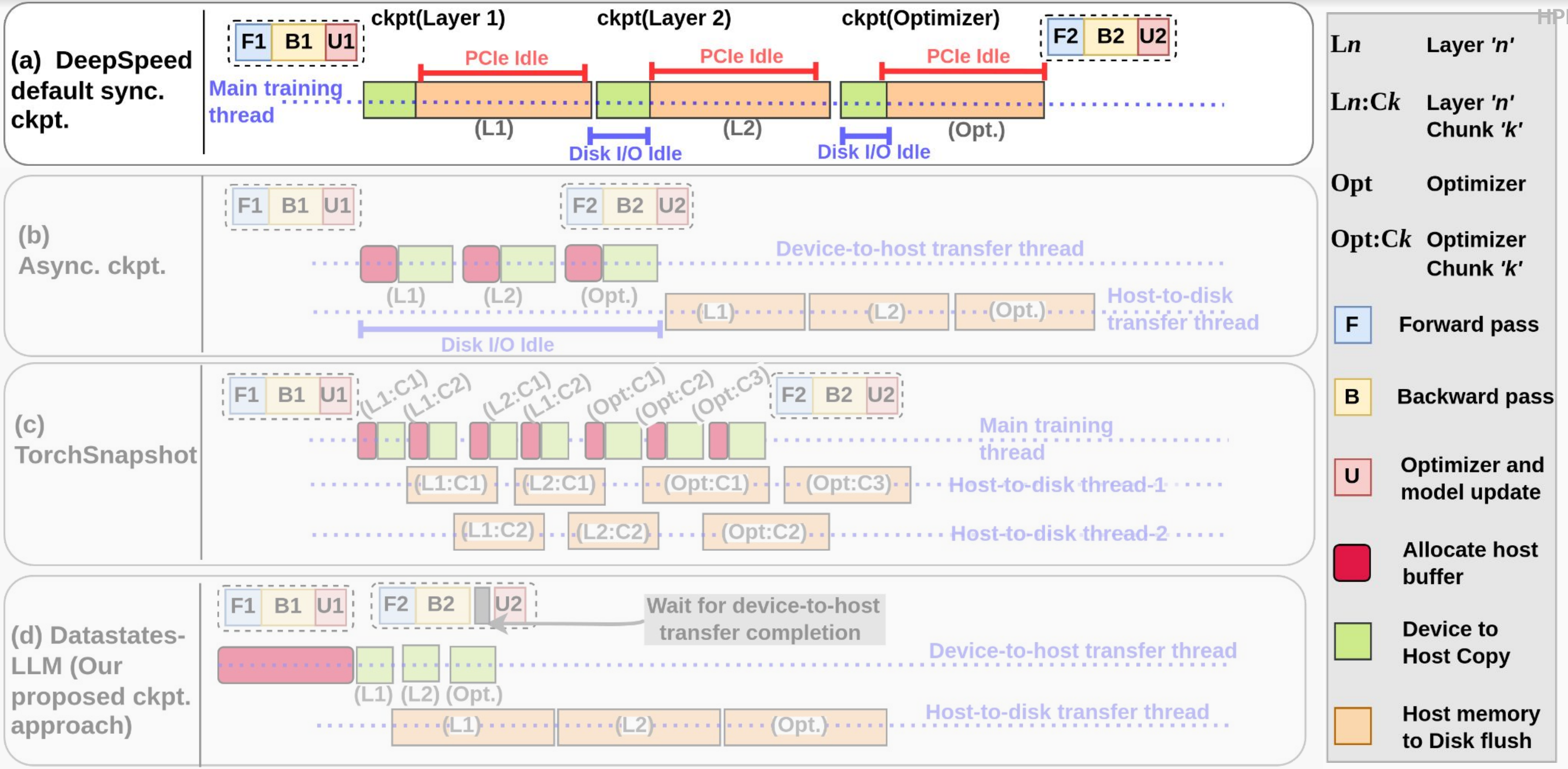


Asynchronous Data Movement

- ✔ Mitigates slow I/O bottlenecks and memory utilization for all tiers
- ✖ Complex overlap centric design makes it challenging to design & debug



Comparison with State of Art Checkpointing Approaches



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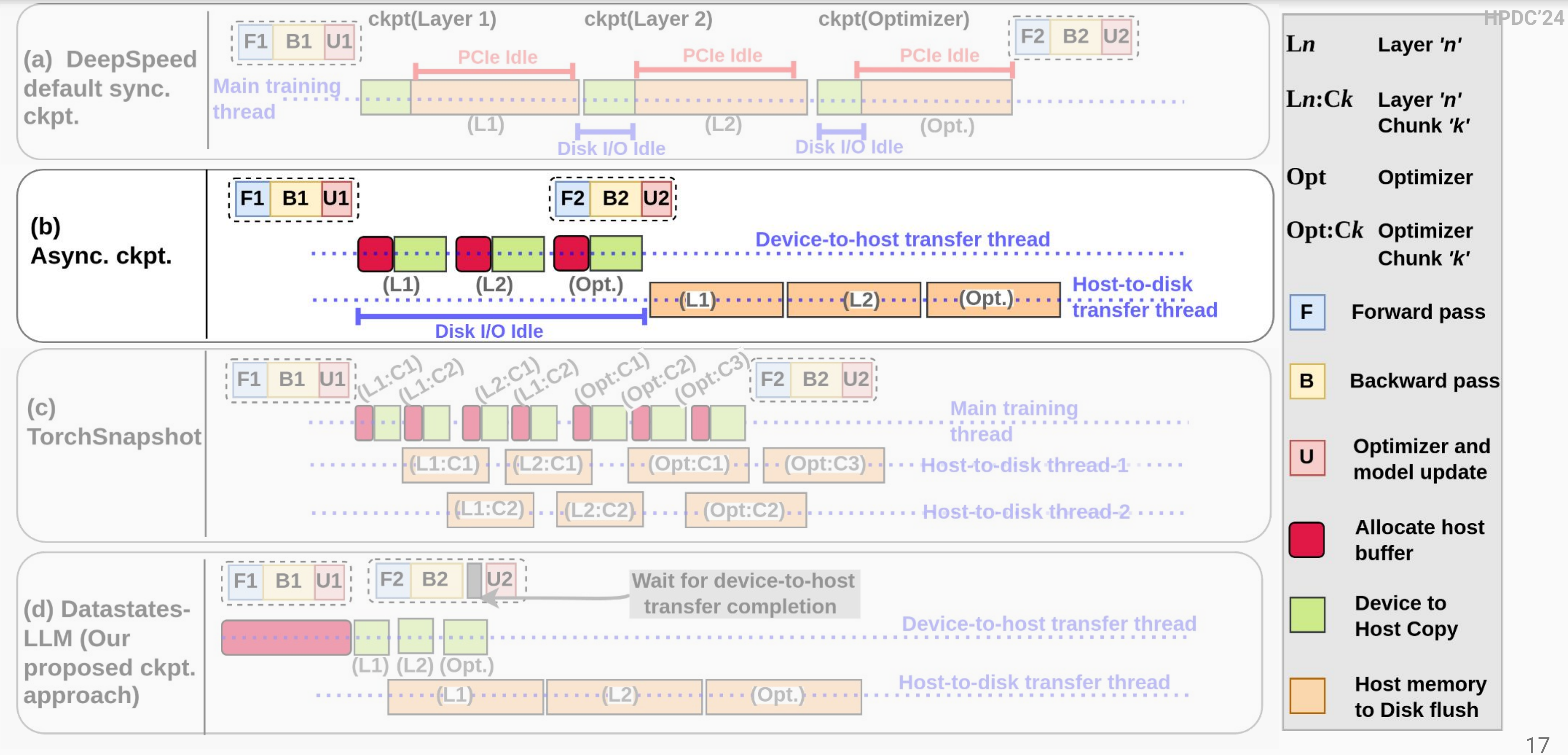

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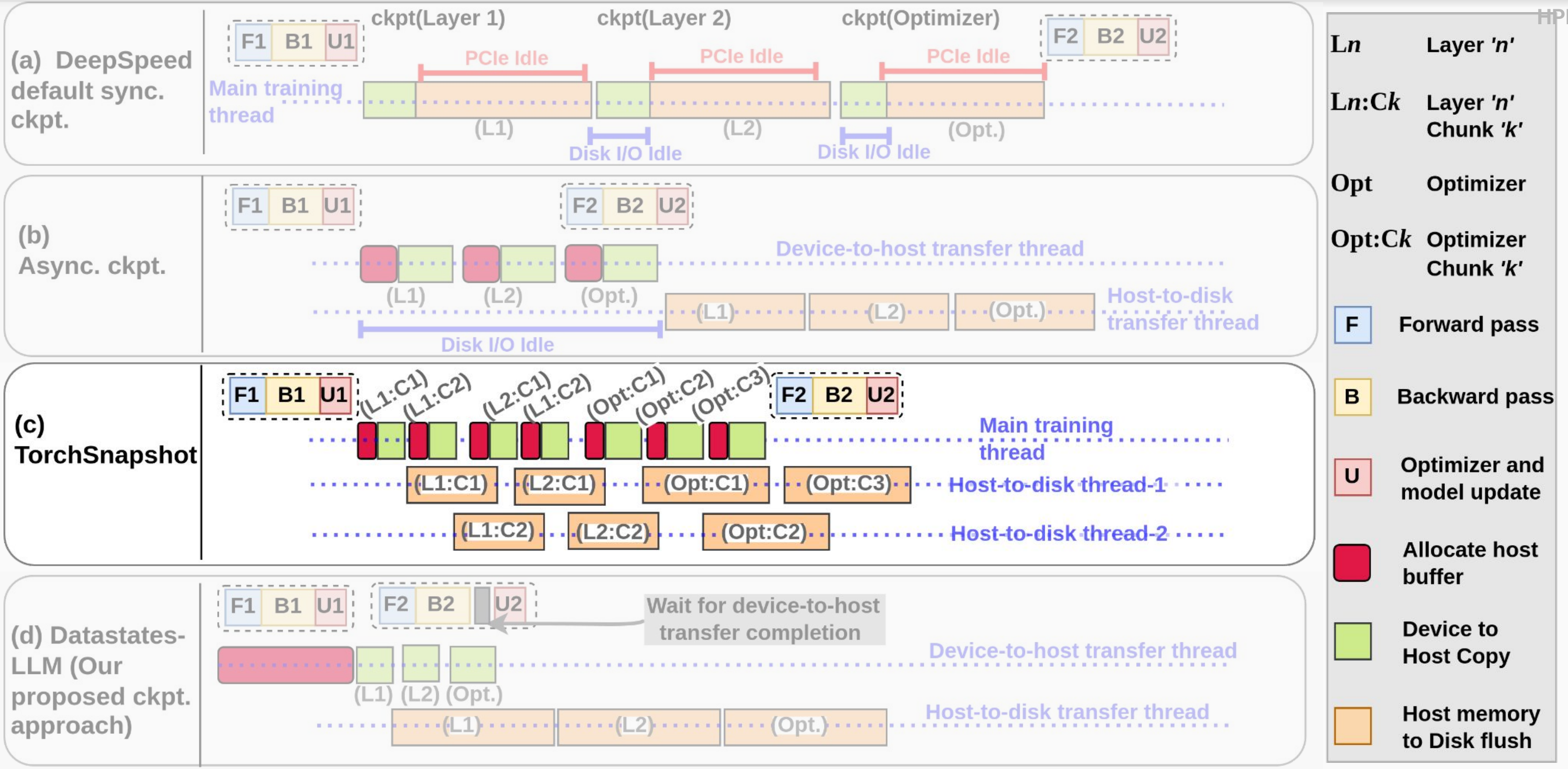

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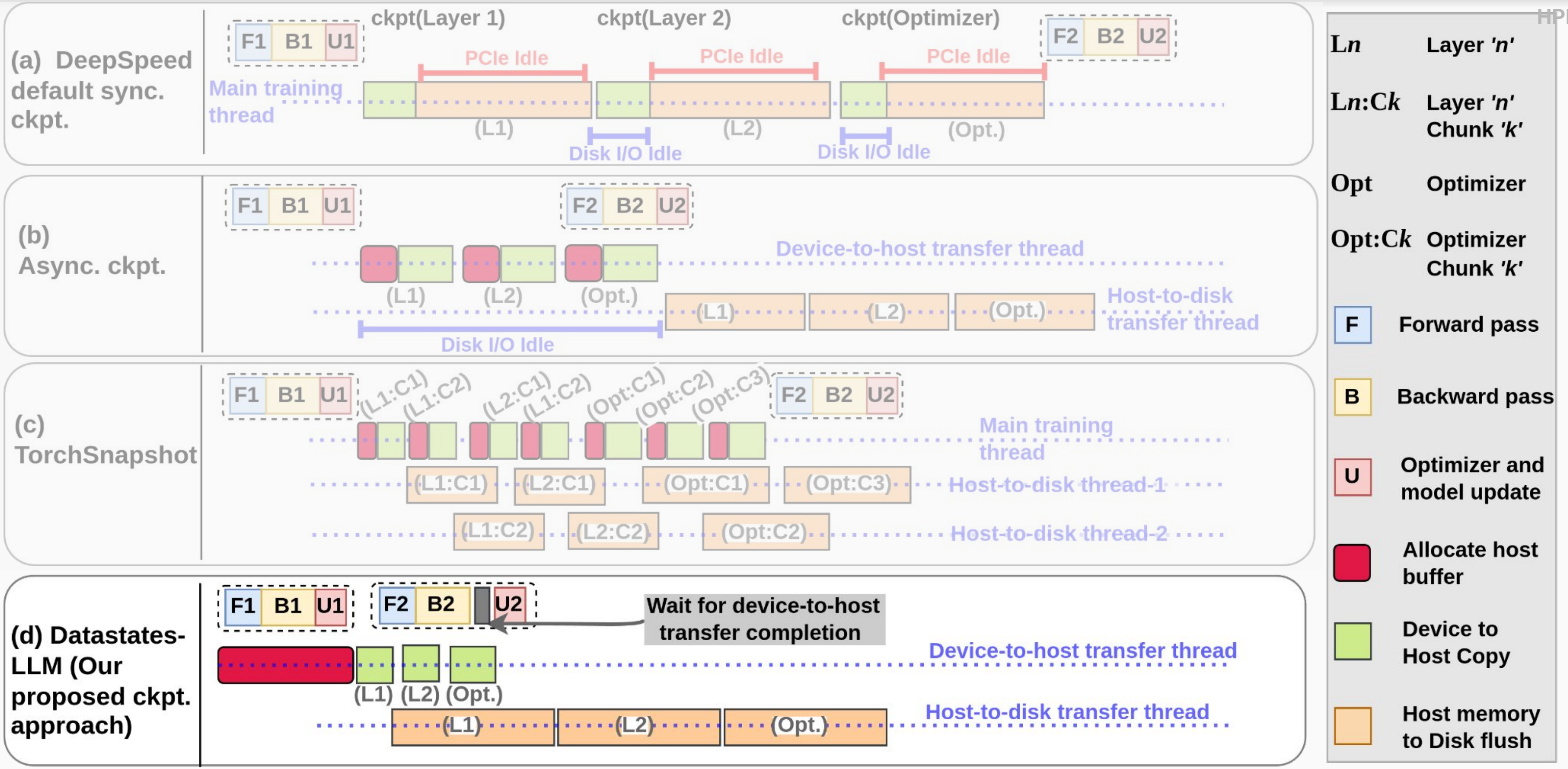
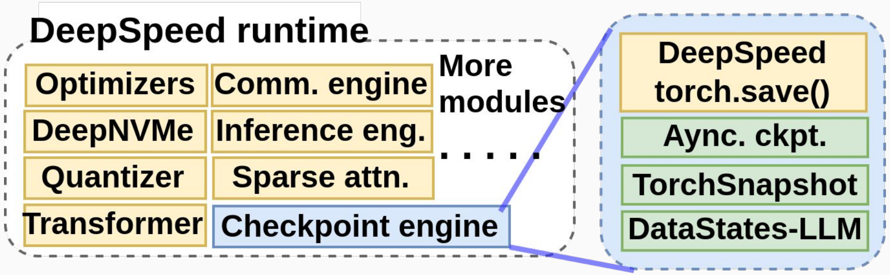


Implementation and Integration with DeepSpeed

- Module extension to DeepSpeed, state-of-art LLM training runtime
- Written in C++/CUDA and exposed through Python and C++ APIs
  - Eliminates inefficiencies arising from Python Global Interpreter Lock (GIL)
  - Uses dedicated CUDA-streams overlapping D2H and H2D transfers using hardware copy engines
  - Leverages PyBind11
- Openly available and extensible to other accelerators and runtimes (e.g., Pytorch Lightning)

DataStates-LLM

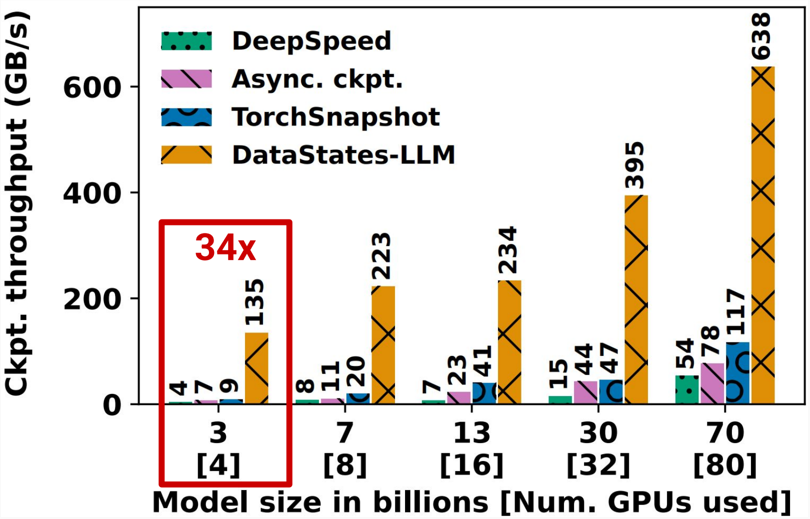


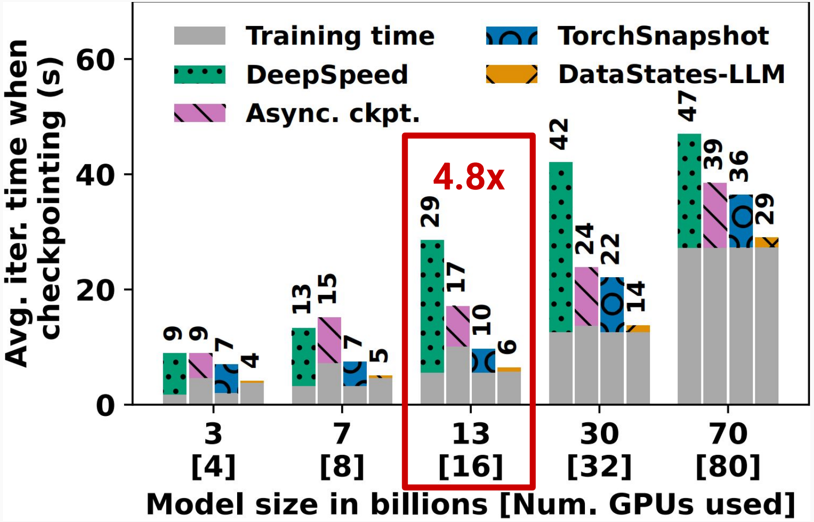
Experimental Evaluation

- Experimental Setup: ALCF Polaris testbed
  - Every node: 4xA100 40GB GPUs and 512 GB host memory
  - We use up to 512 GPUs
  - Each GPU mapped to a different NUMA domain with PCIe Gen 4 device-host throughput: 25 GB/s
  - Luster file system for persistence with 160 OST and 40 metadata servers with aggregated bandwidth of 650 GB/s

- Model and runtime configuration
  - 5 models from real-world setups: 3B, 7B, 13B, 30B, 70B
  - Tensor-parallelism: 4 (max GPUs per node), pipeline parallelism: number of nodes, ZeRO stage-1
- Compared approaches
  - DeepSpeed, Asynchronous checkpointing, TorchSnapshot, DataStates-LLM (Ours)
- Performance metrics
  - Checkpointing throughput — Measures checkpoint_size/total_blocking_time
  - Iteration slowdown — Measures impact of I/O overheads incurred by checkpointing
  - End-to-end training time — Measures impact of slow asynchronous flushes to disk

Checkpointing Performance for Different Model Sizes

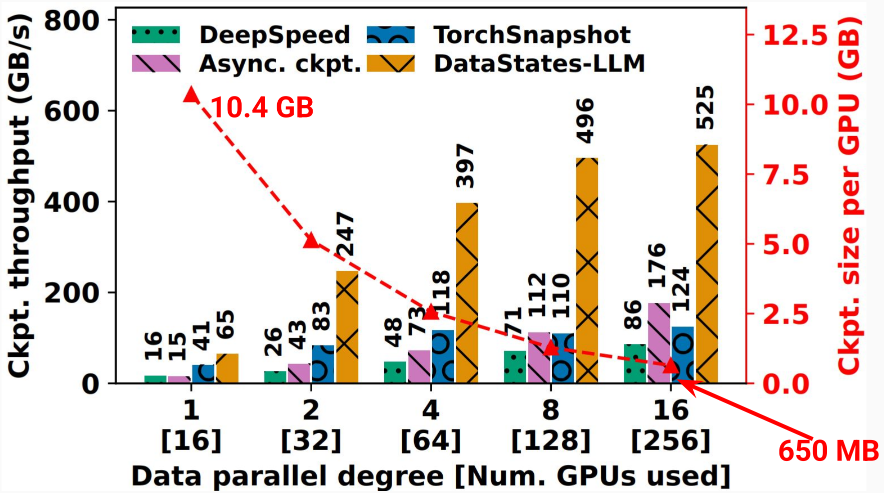




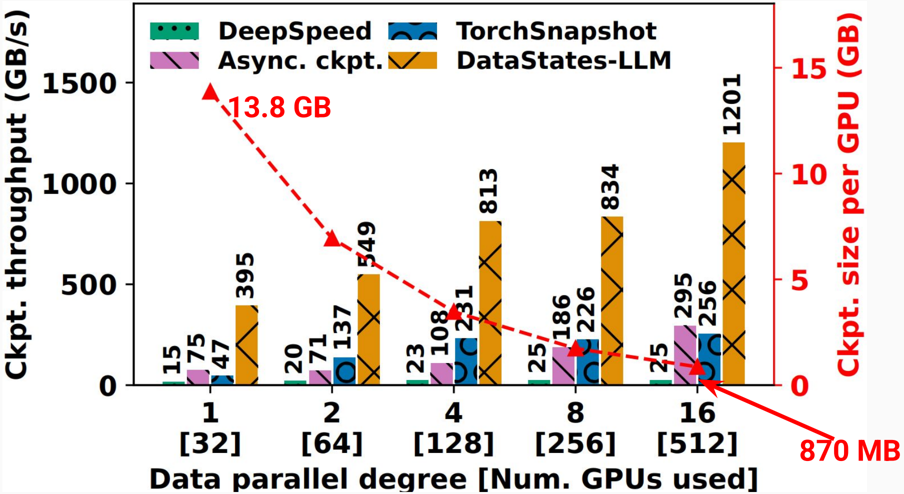
- DataStates-LLM achieves **4x – 34x faster checkpointing** throughput compared to state-of-art
- Checkpointing throughput increases for larger models because all GPUs flush in parallel

- DataStates-LLM achieves **1.3x – 4.8x faster iterations** compared to state-of-art
- DataStates-LLM shows negligible overheads on the training iteration when checkpointing

Increasing Data-Parallelism: Strong Scalability of Checkpoint Performance



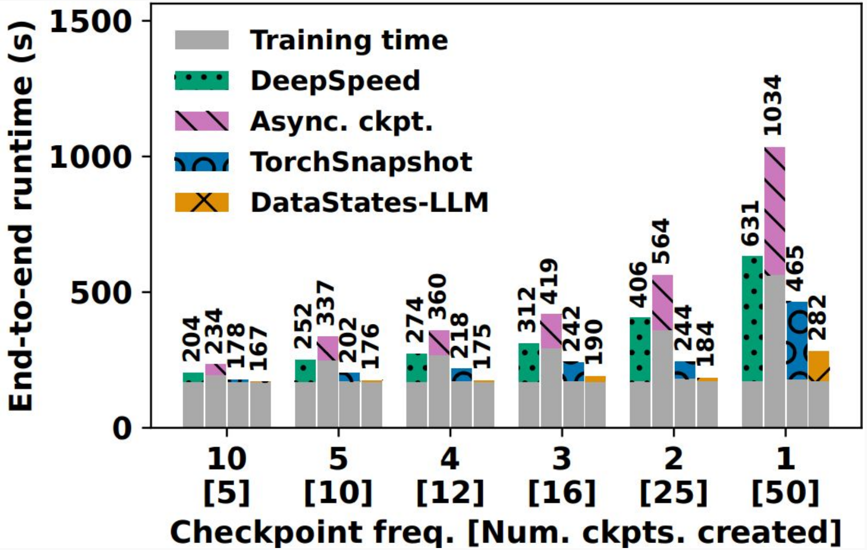
13B model



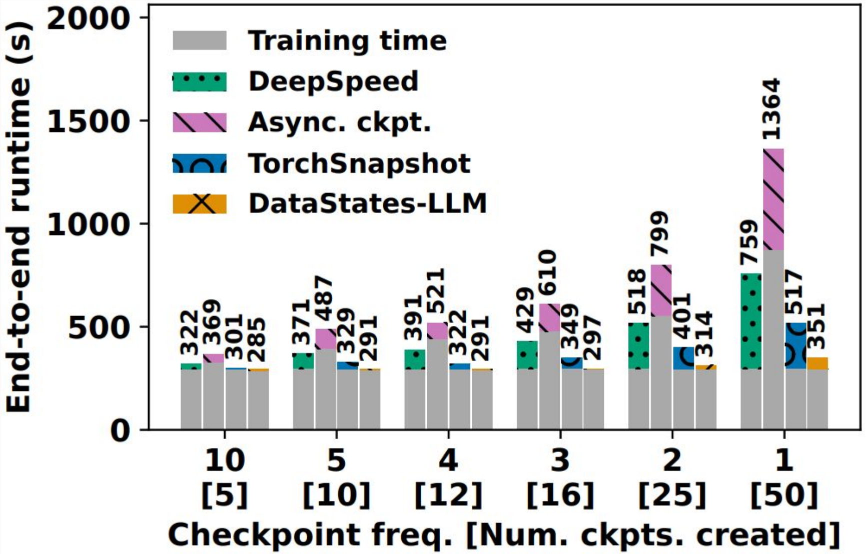
30B model

- All approaches scale well to increasing data parallel replicas due to more parallel channels for flushes
- Our approach achieves **1.75x – 48x faster checkpointing** compared to state-of-art

End-to-end Runtime for Increasing Checkpointing Frequency



7B model



13B model

Our overlap centric design achieves **3x – 4.2x faster** end-to-end training compared to state-of-art checkpointing engines, irrespective of the I/O pressure due to increasing checkpointing frequency

Key takeaways: Asynchronous Checkpointing for LLMs

- Large-scale distributed LLM training running with advanced hybrid parallelism strategies are prone to failures and undesirable trajectories, necessitating checkpointing
- State-of-the-art checkpointing engines are inefficient because
  - They do not exploit immutable training phases to overlap checkpoint I/O
  - They underutilize available interconnect and memory resources
- DataStates-LLM efficiently and transparently captures globally consistent checkpoints
  - Uses preallocated pinned buffers for fast DMA
  - Coalescing of model/optimizer shards
  - Lazy non-blocking checkpoint snapshotting overlapping with immutable phases
  - Streaming multi-level flushing to persistent storage
  - Asynchronous distributed consensus of checkpoint
- DataStates-LLM achieves **4x – 48x faster checkpointing** and **1.3x – 4.8x faster iterations** compared to state-of-the-art approaches

DataStates
DataStates EvoStore
DataStates LLM
DataStates AI

DataStates LLM

Our Current and Future Research Directions

Pre-training

- Optimized hybrid GPU-CPU computations with optimizer offloading (*Middleware'24*)
  - Accelerate updates by 2.5x using overlapping I/O and combined computations of CPU and GPU
- Accelerated training for memory-constrained scenarios requiring disk-offloaded optimizers
  - Leveraging idle remote storage bandwidth for 3x faster backward and update phases
- Utilizing low rank linear layer representations for accelerated and memory efficient pre-training (ArXiv'25)

Inferencing

- Characterizing KV cache access patterns under concurrency (*IPDPS'25*)
  - Report key findings for optimizing KV cache movement and request scheduling
- Unified, dynamic, asynchronous model and KV cache offloading

More…

- EAIRA: A Methodology for Evaluating AI Models as Scientific Research Assistants (*IJHPC'25*)
- DataStates-LLM Elastic Checkpoint, Evaluations, and Recovery