Checkmate: Zero Performance Overhead Model Checkpointing via Network Gradient Replication

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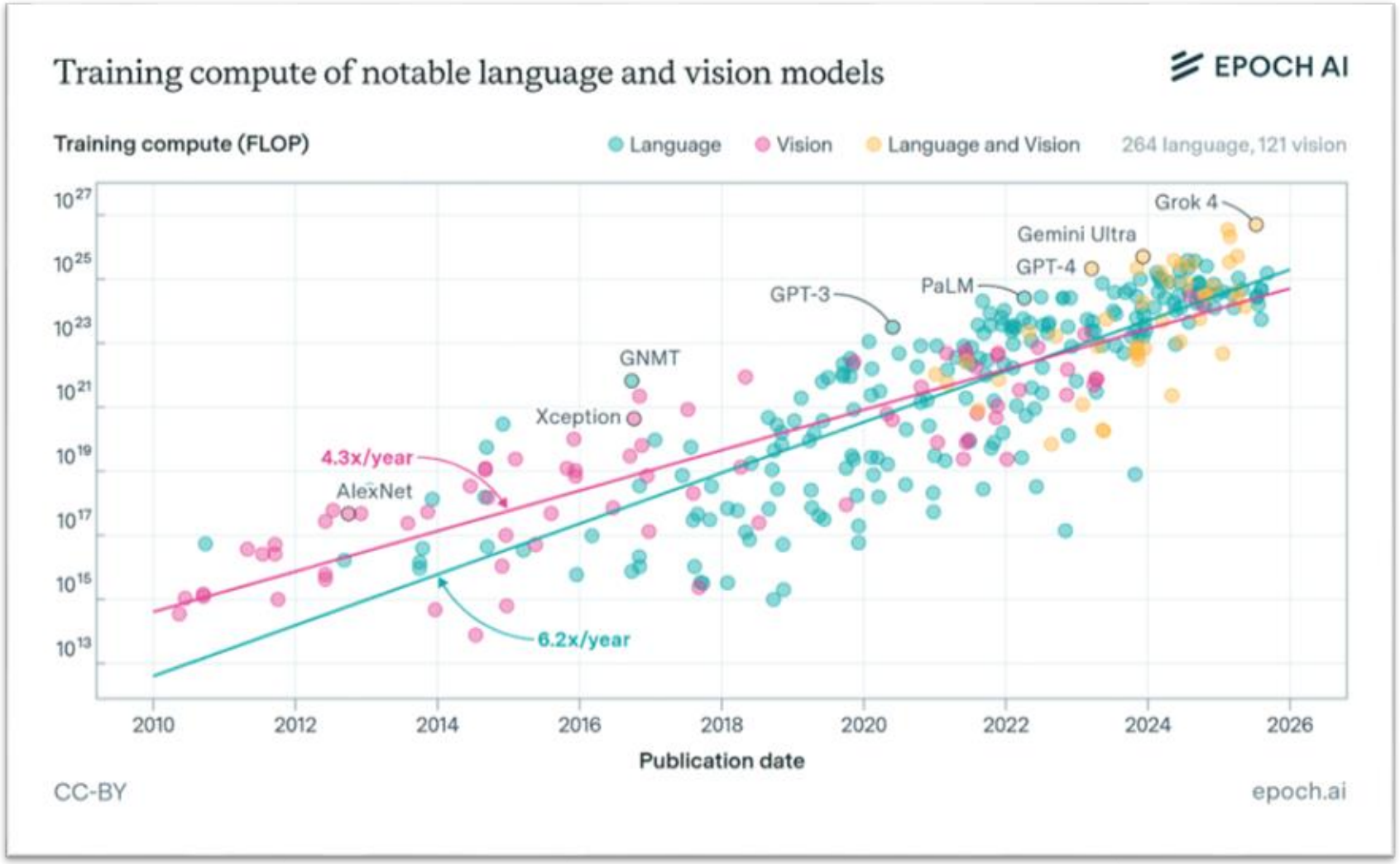
Modern machine learning (ML) is demanding



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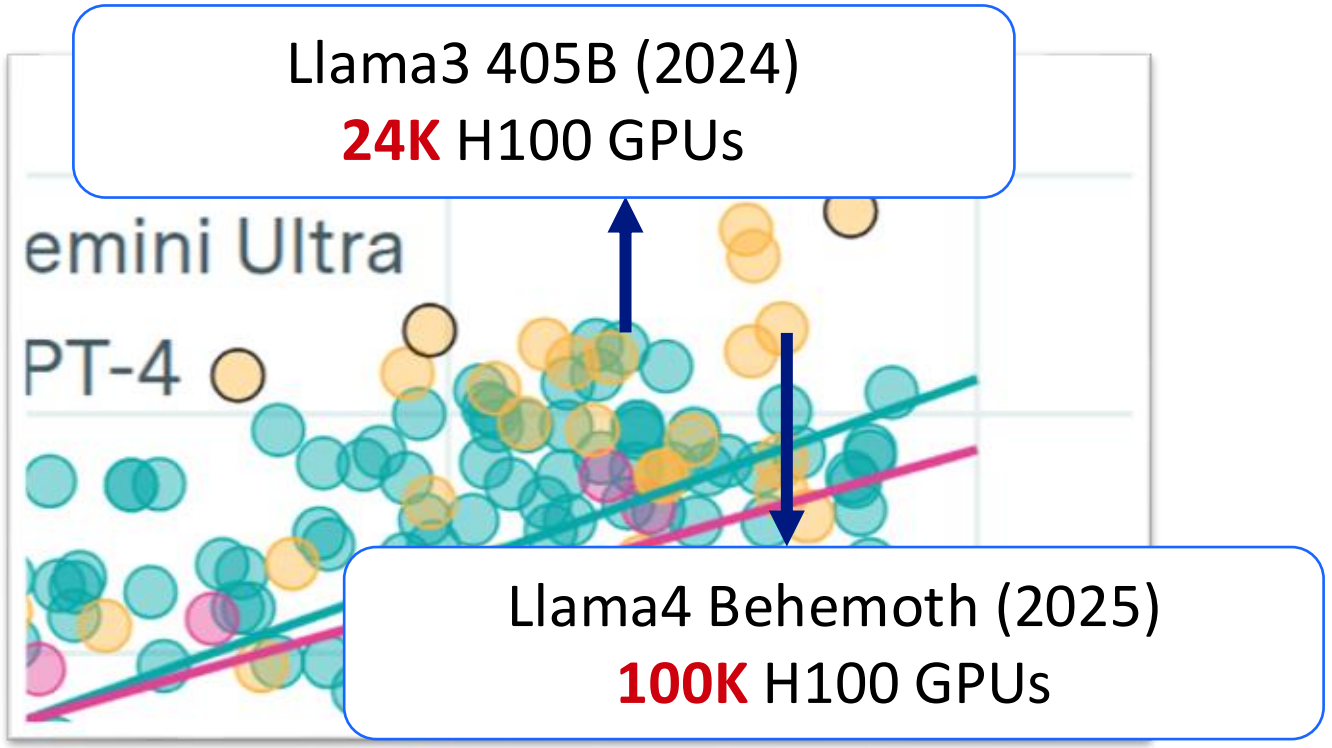
Scaling out ML: More GPUs, more network



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Problem: Failures are common at scale

Component	Category	Interruption Count	% of Interruptions
Faulty GPU	GPU	148	30.1%
GPU HBM3 Memory	GPU	72	17.2%
Software Bug	Dependency	54	12.9%
Network Switch/Cable	Network	35	8.4%
Host Maintenance	Unplanned Maintenance	32	7.6%
GPU SRAM Memory	GPU	19	4.5%
GPU System Processor	GPU	17	4.1%
NIC	Host	7	1.7%
NCCL Watchdog Timeouts	Unknown	7	1.7%
Silent Data Corruption	GPU	6	1.4%
GPU Thermal Interface + Sensor	GPU	6	1.4%
SSD	Host	3	0.7%
Power Supply	Host	3	0.7%
Server Chassis	Host	2	0.5%
IO Expansion Board	Host	2	0.5%
Dependency	Dependency	2	0.5%
CPU	Host	2	0.5%
System Memory	Host	2	0.5%

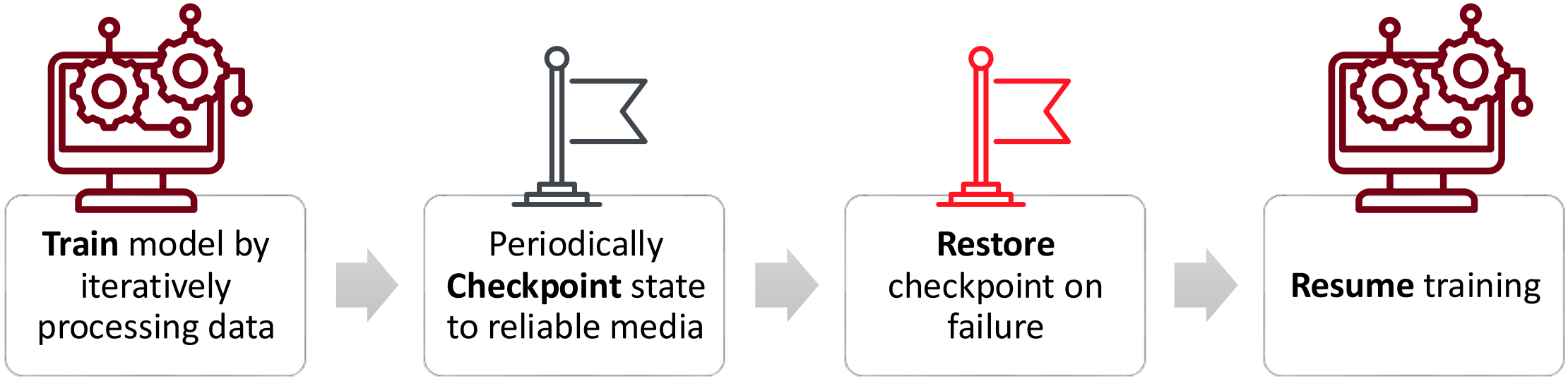
Table 5 Root-cause categorization of unexpected interruptions during a 54-day period of Llama 3 405B pre-training. About 78% of unexpected interruptions were attributed to confirmed or suspected hardware issues.

Failure types during Llama 3 training

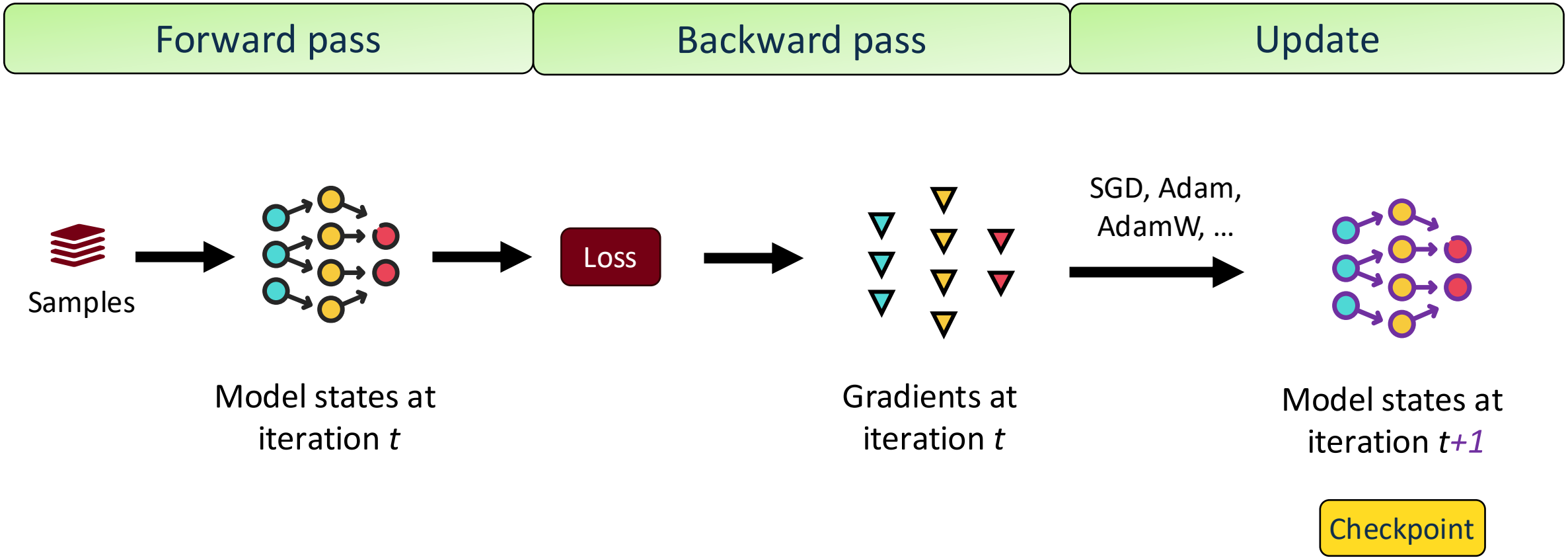
419 unexpected interruptions over 54 days

~2 million wasted GPU-hours

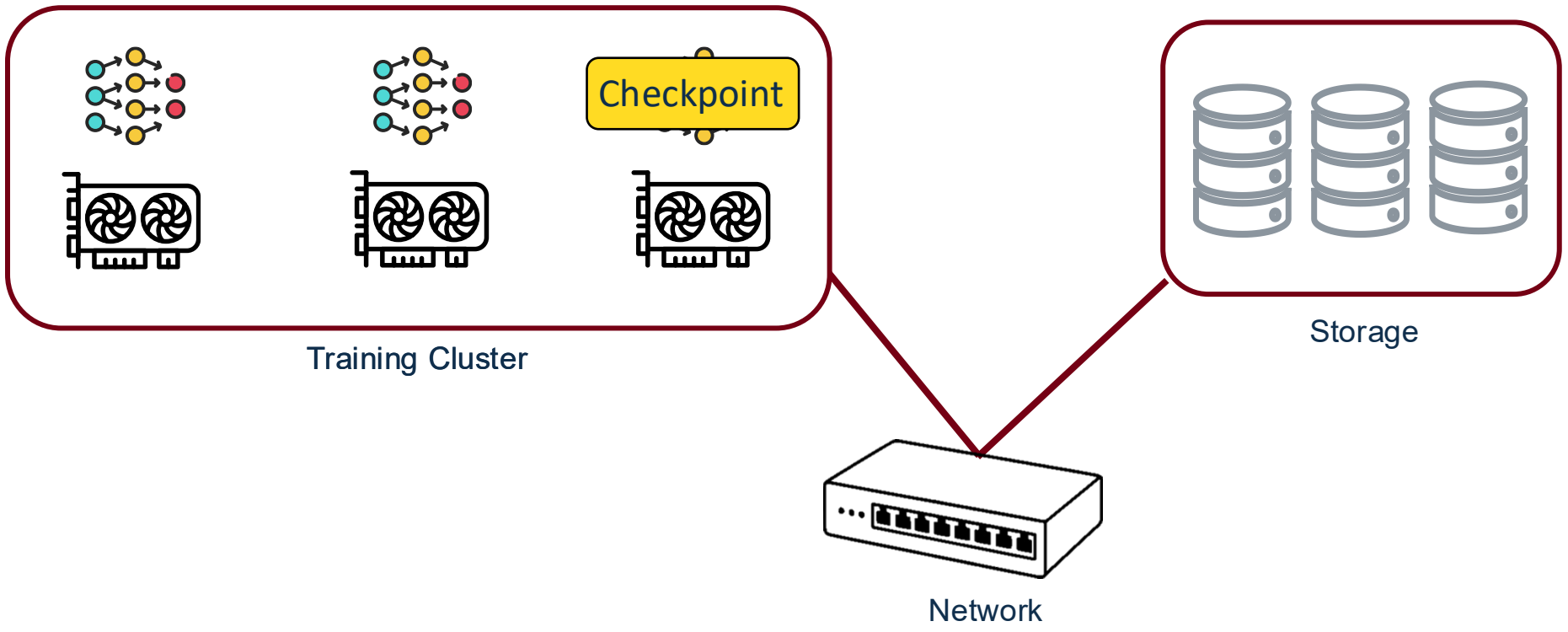
Checkpoint for failure recovery



Background: DNN training iteration and model update



Step 1: `copy` out of GPU memory



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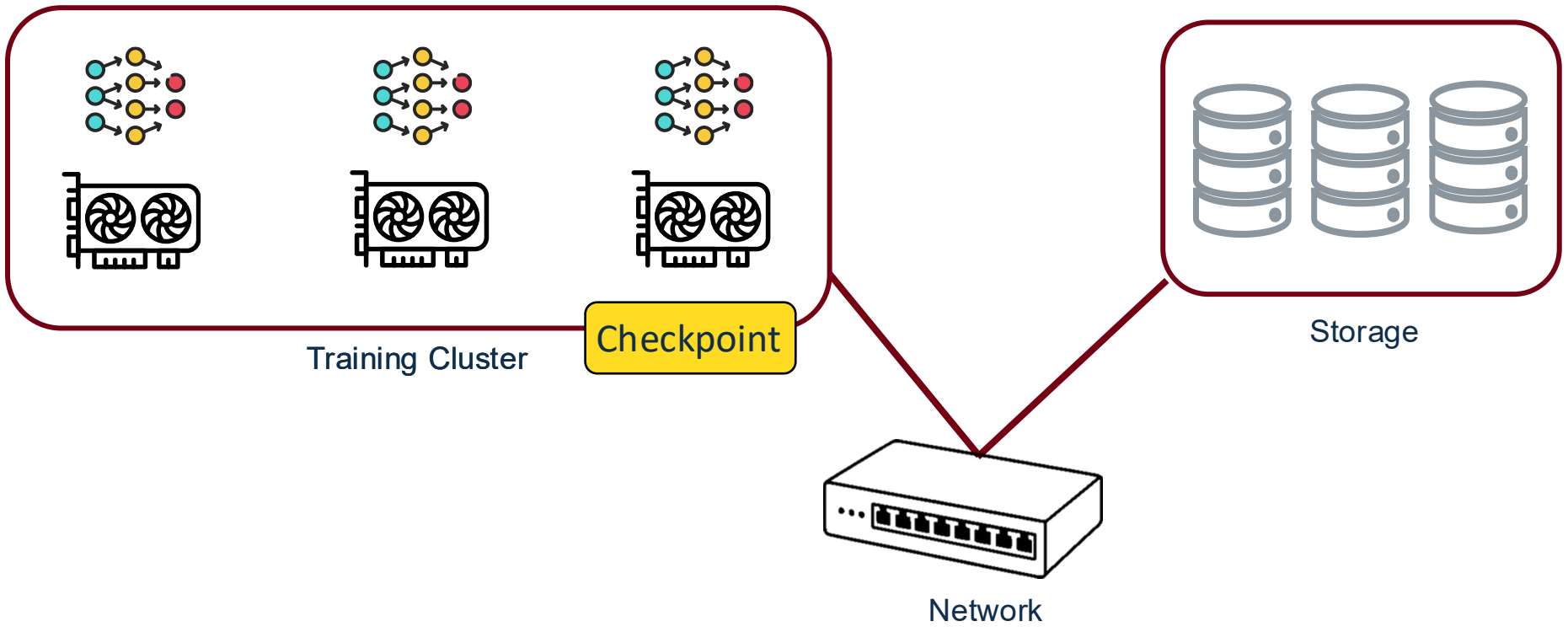

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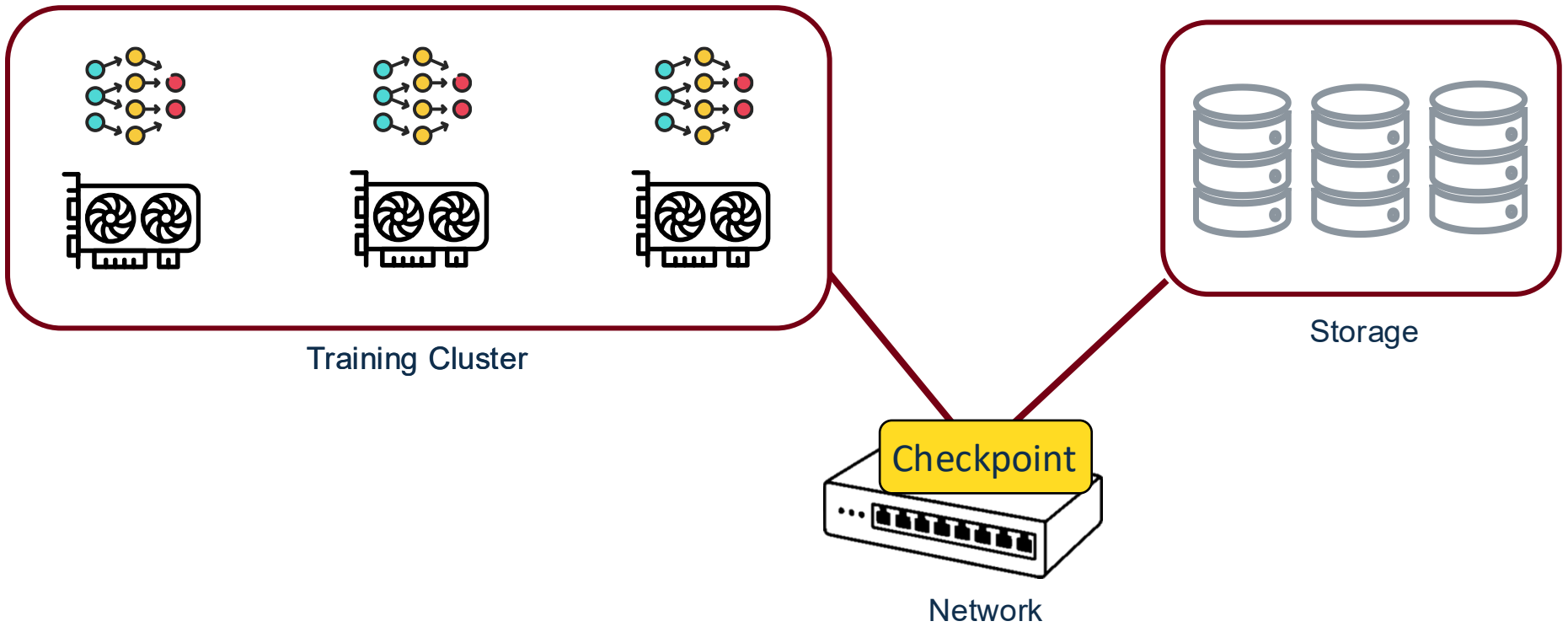
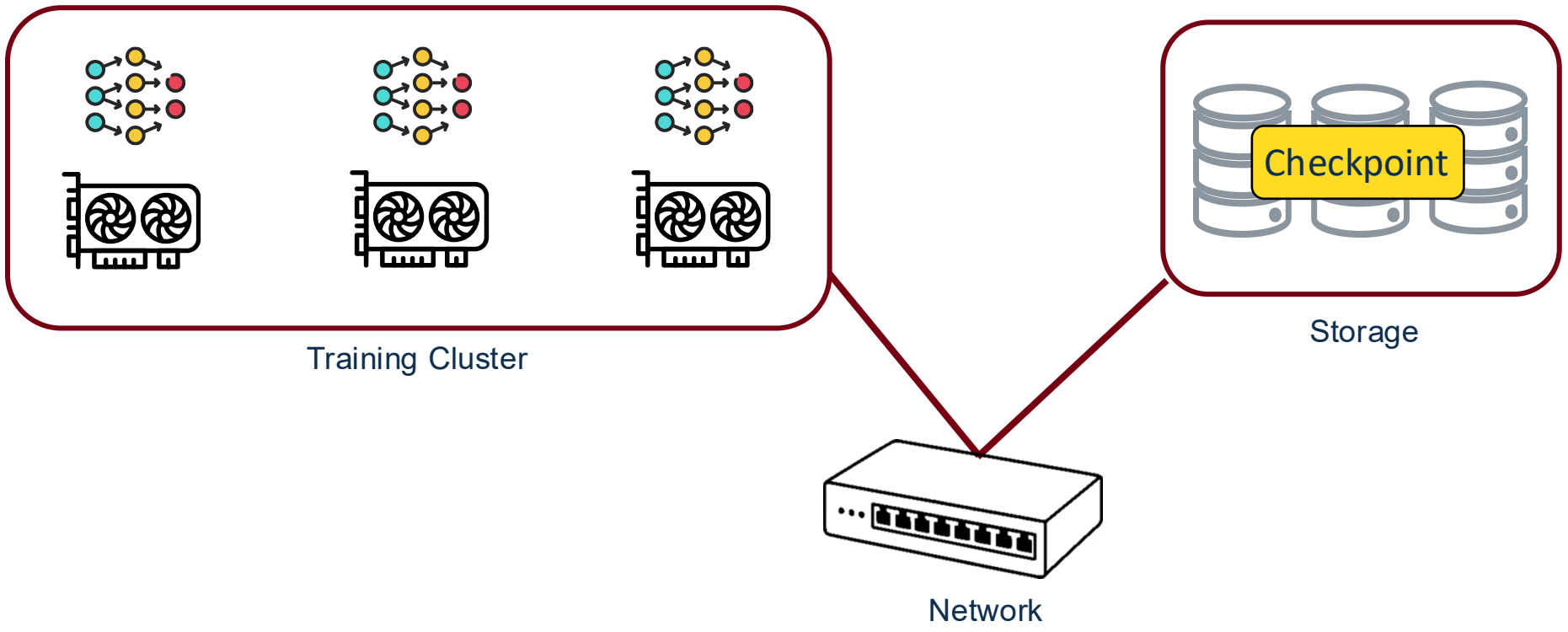
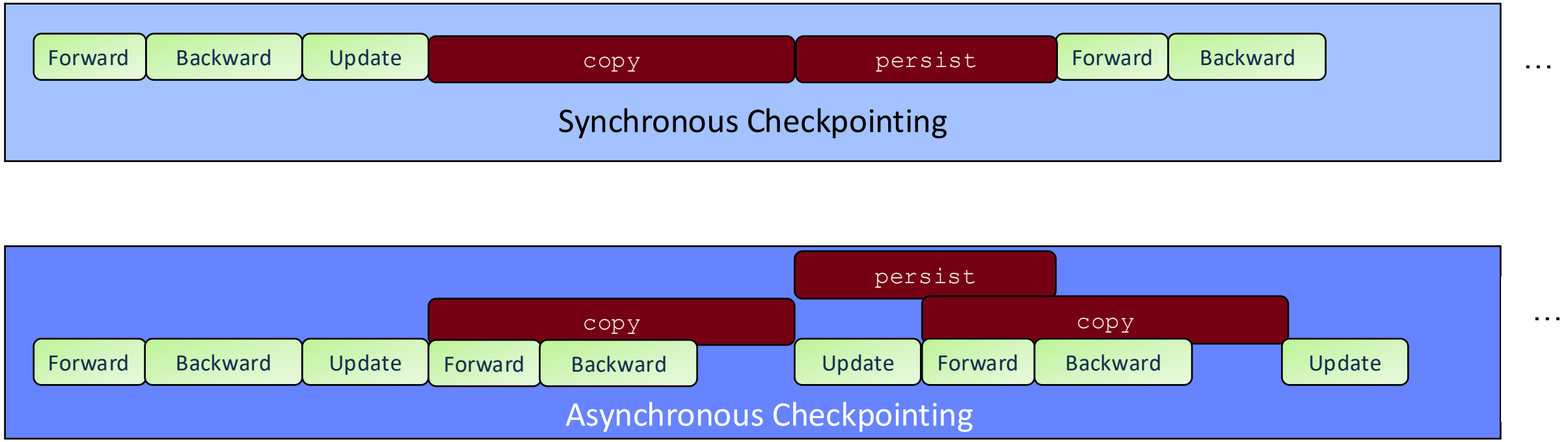


Step 2: `persist` to remote storage

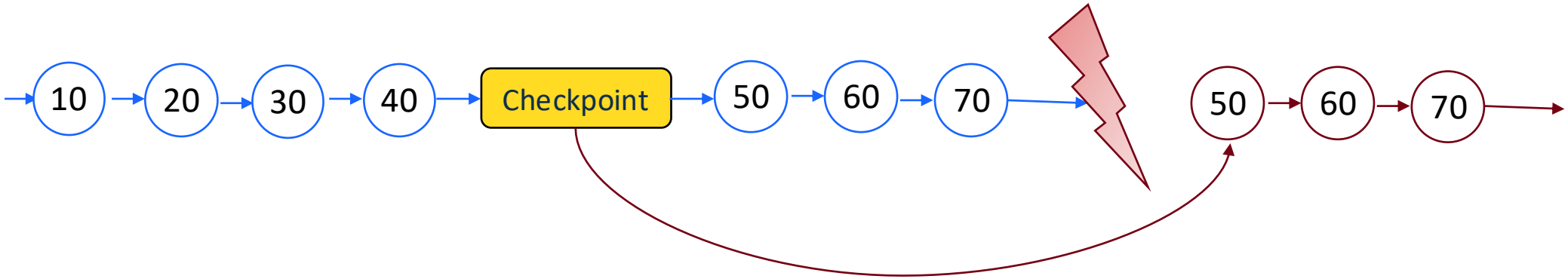


`copy-persist` stalls GPUs



Low checkpointing frequency

Low checkpointing frequency leads to repeated work

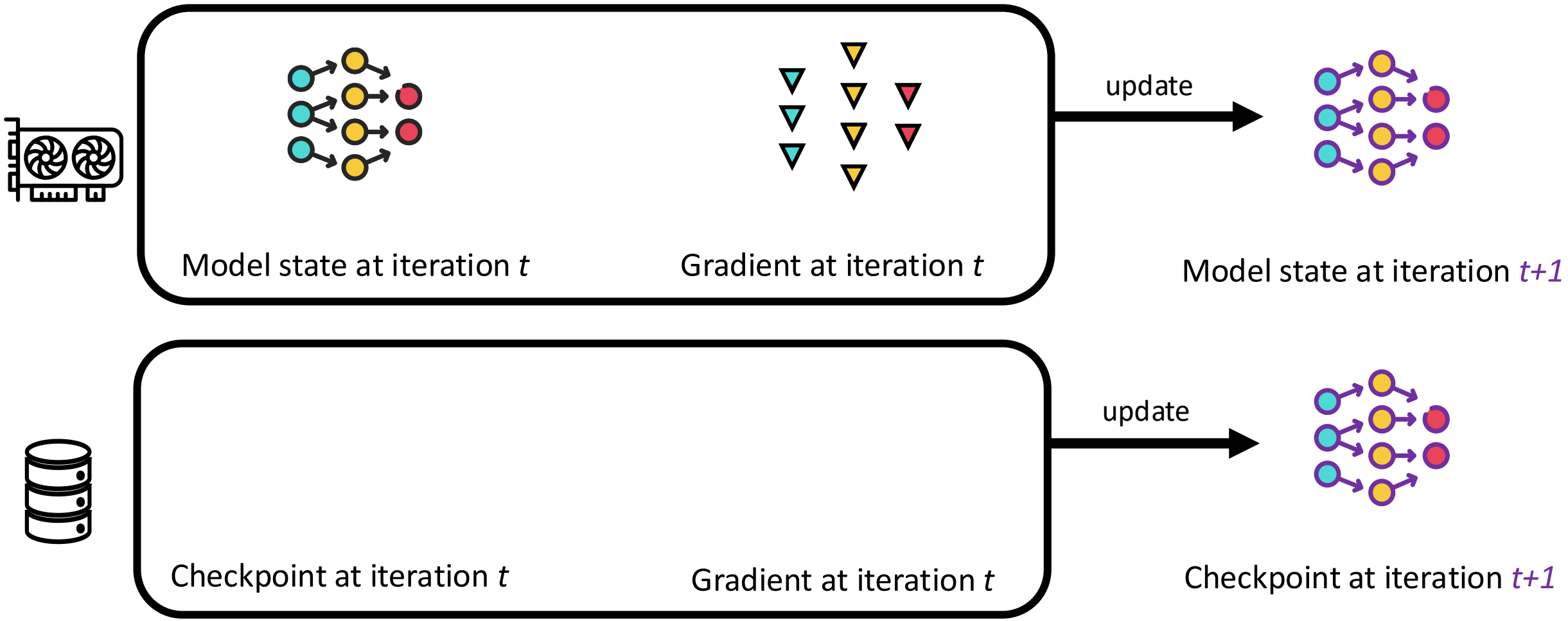


Trade-off:
checkpointing often - high GPU overhead
checkpointing seldomly - more repeated work

“We aim to minimize GPU pause time during checkpointing and increase checkpoint frequency to reduce the amount of lost work after a recovery.”
– Llama-3 Paper

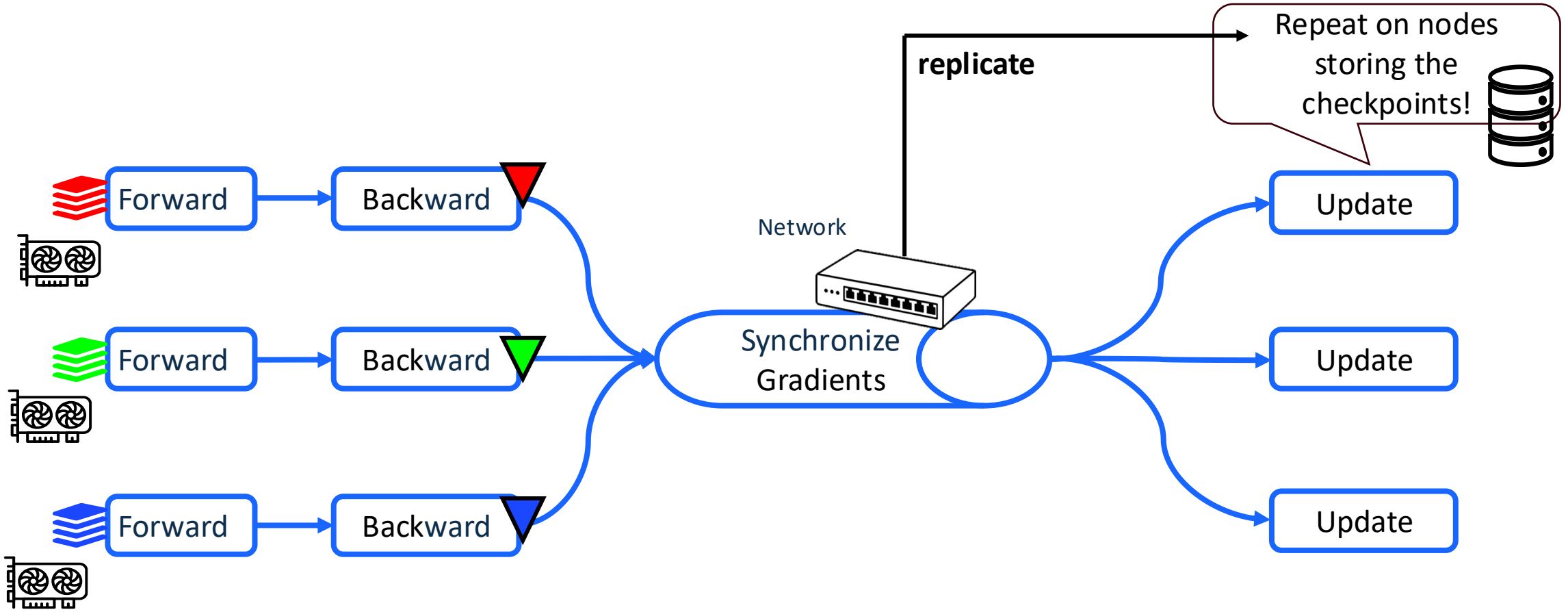
Checkmate: per-iteration checkpointing without GPU overhead

Observation: Model update step on the checkpoint



Great, where do we get the gradients for the nodes storing checkpoints?

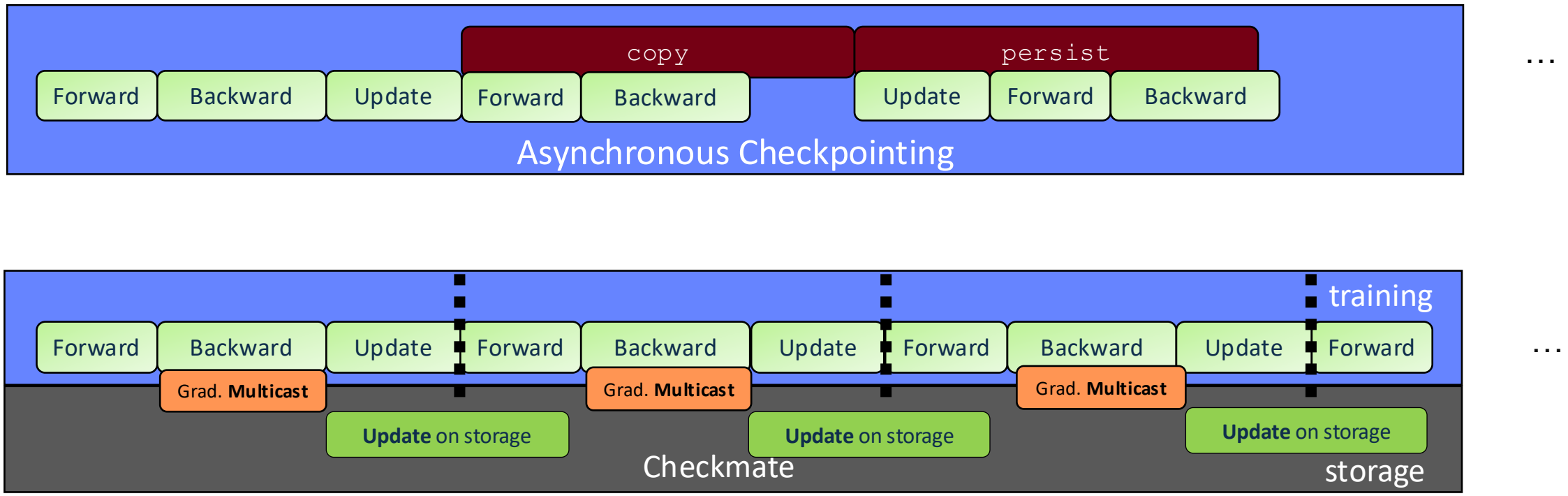
Key idea 2: Checkpointing gradients for optimization



Checkmate Overview

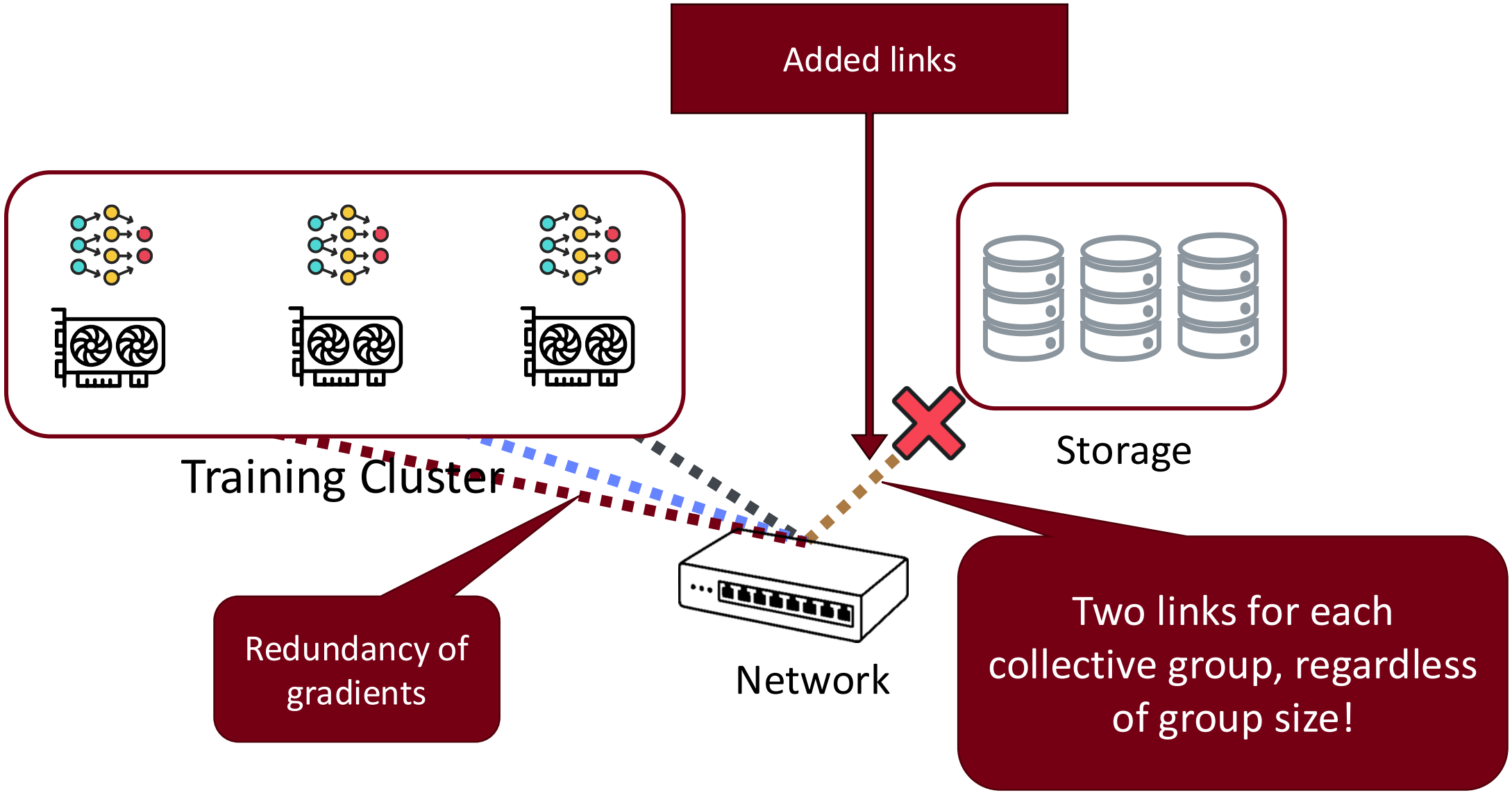
1. Un-interrupted and unmodified DNN training
   - NCCL-Plugin to assist network gradient replication
2. Programmable Switch
   - **Multicast** gradients to training and storage nodes in parallel
3. Storage node
   - Use gradients to maintain the **shadow** model and optimizer

`Multicast-update` abstraction in Checkmate



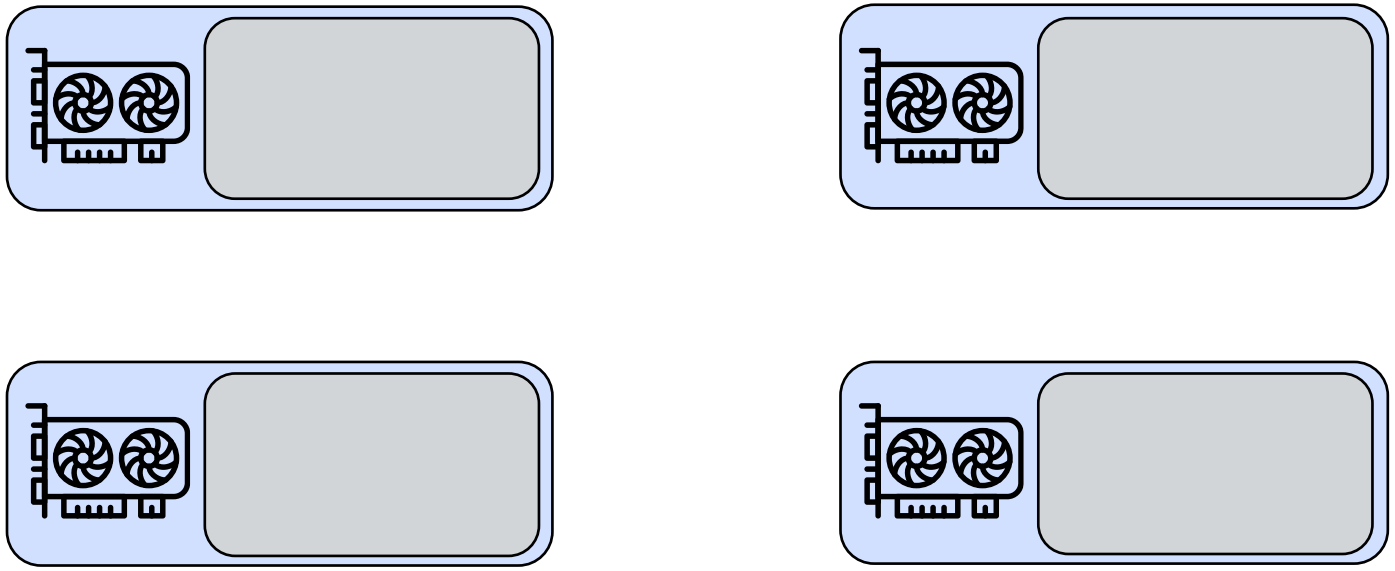
Time

Challenge 1: Too much gradient traffic



Solution 1: Selectively replicate gradients during AllReduce

- Synchronizing gradients  across four GPUs



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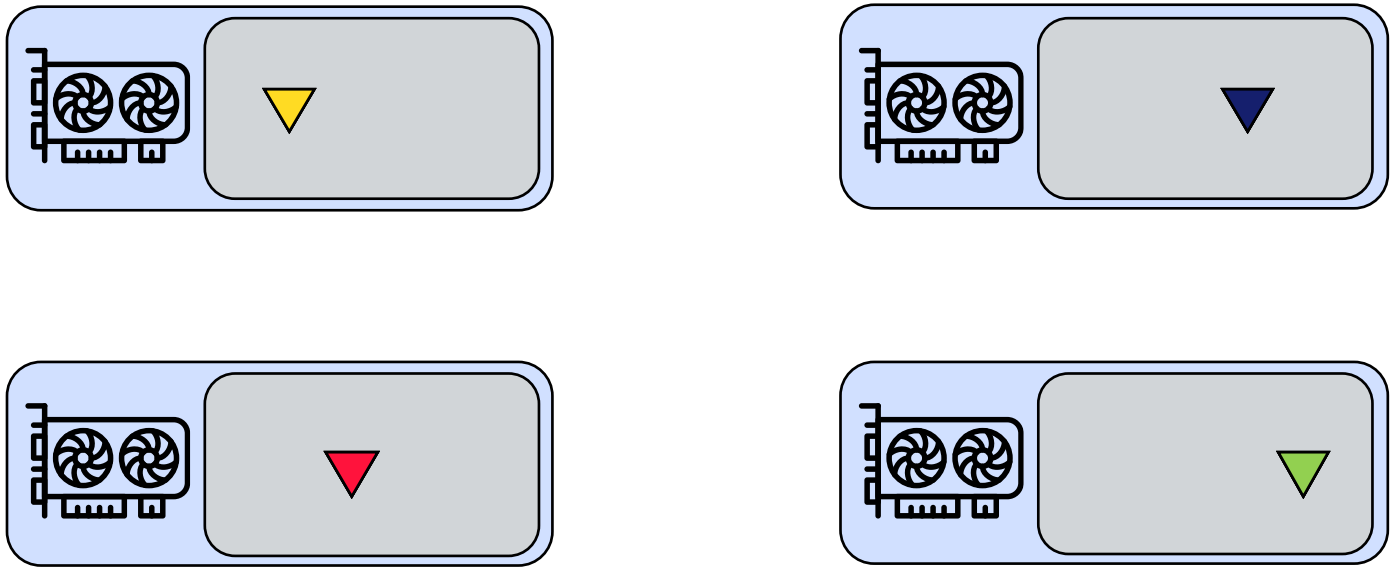

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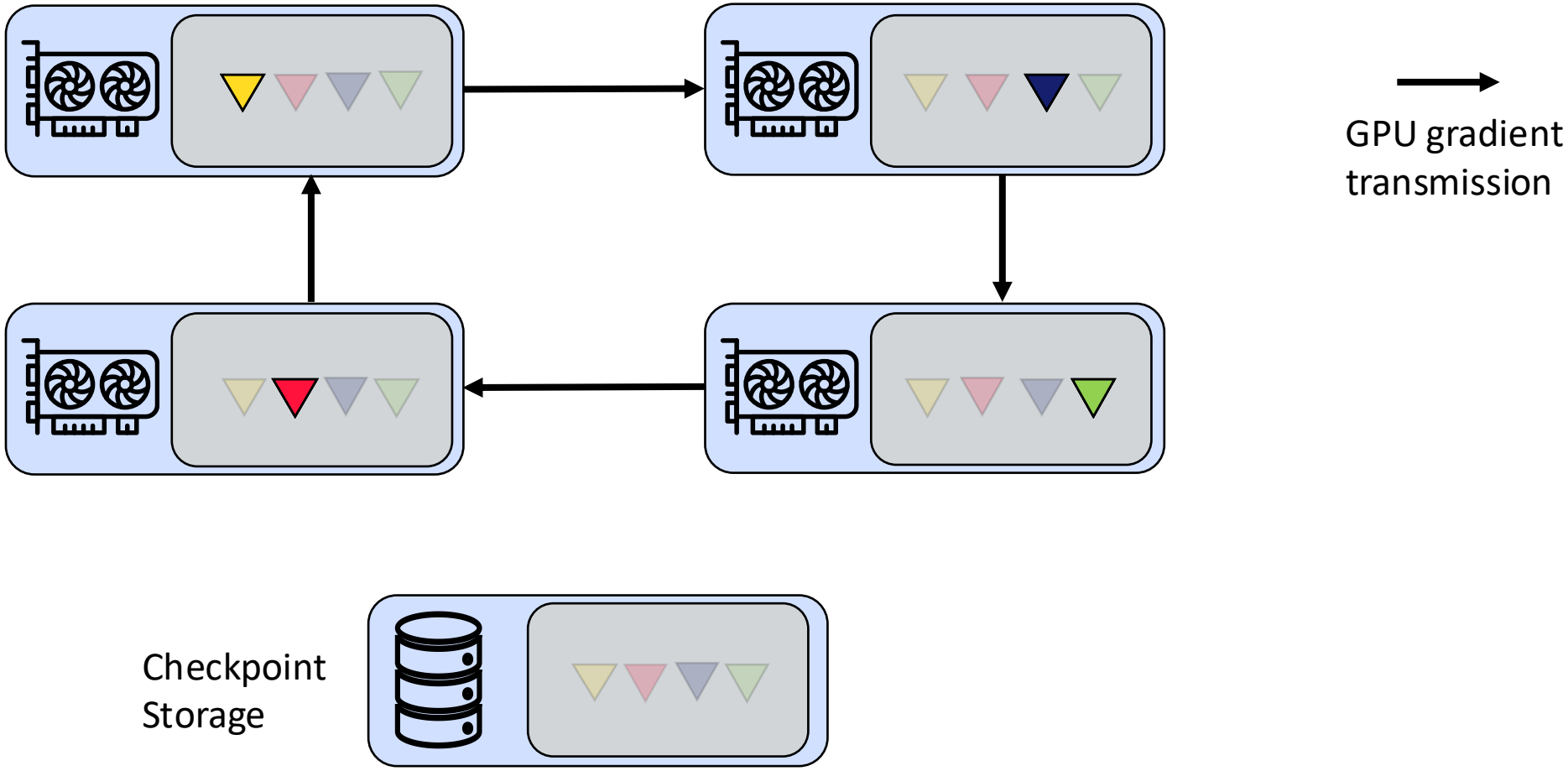

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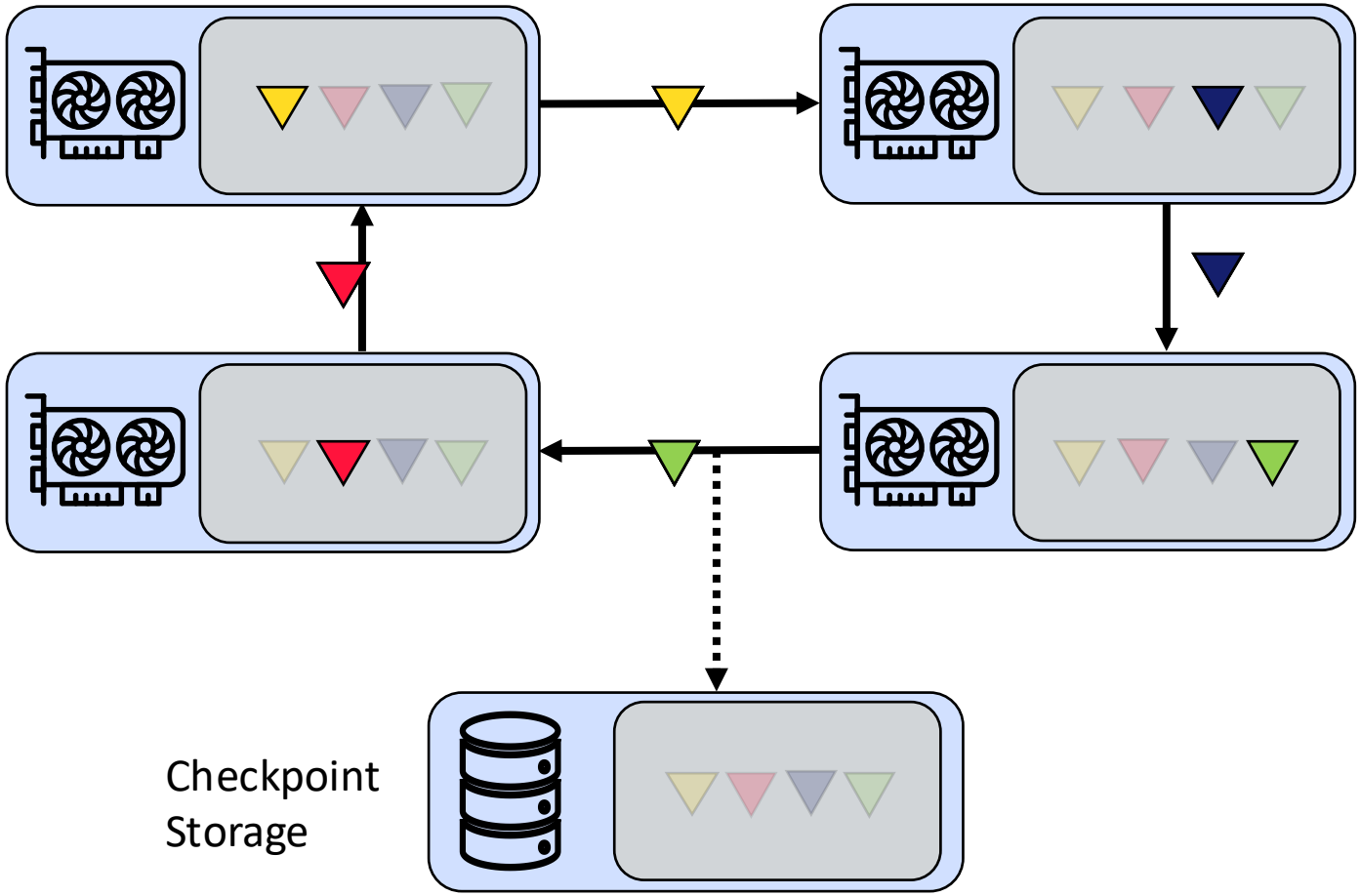

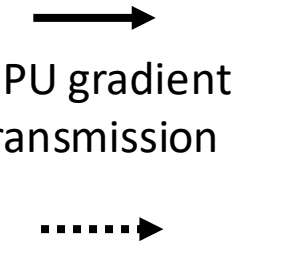

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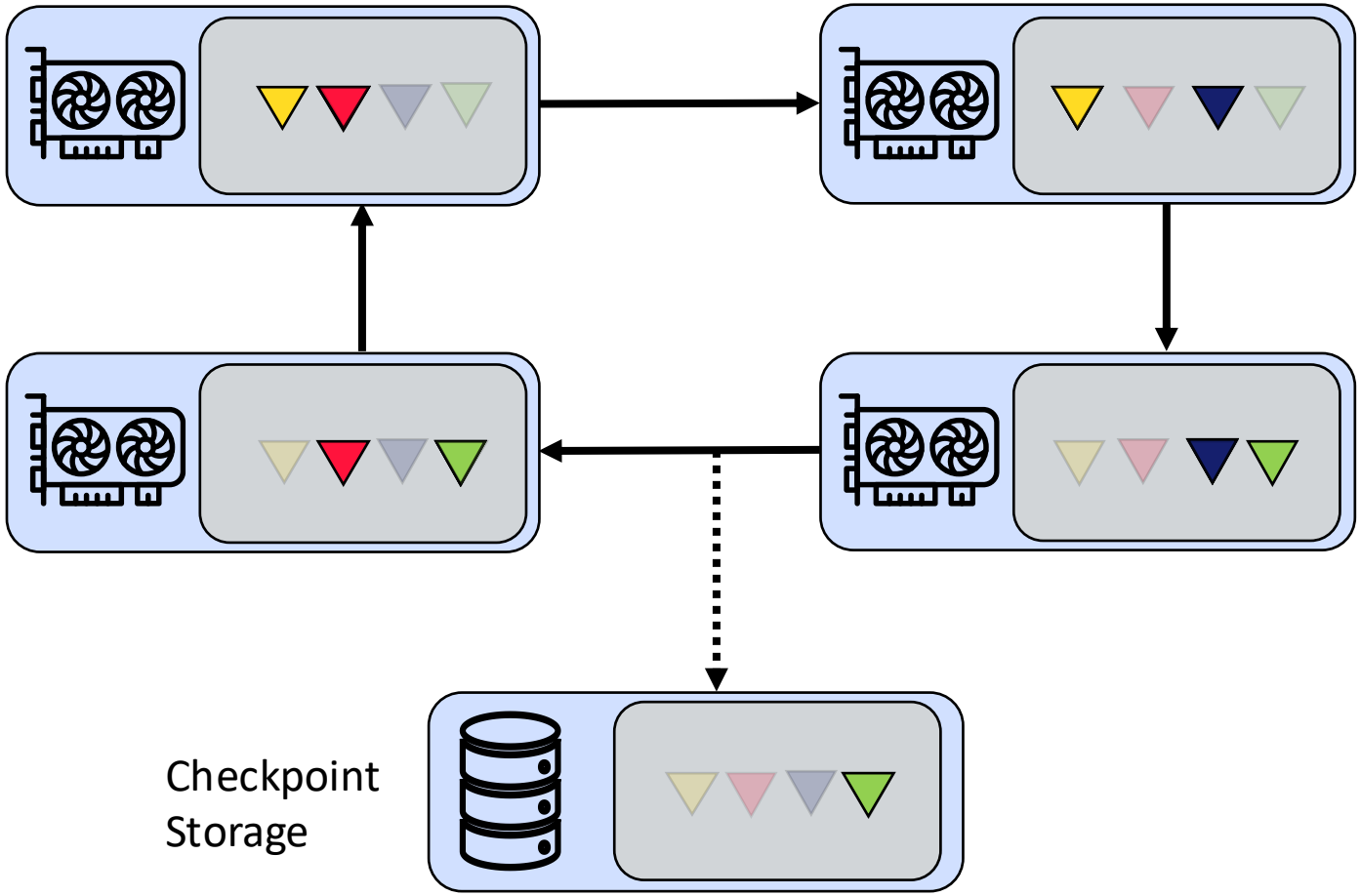

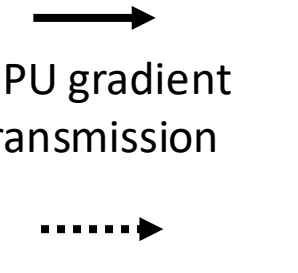

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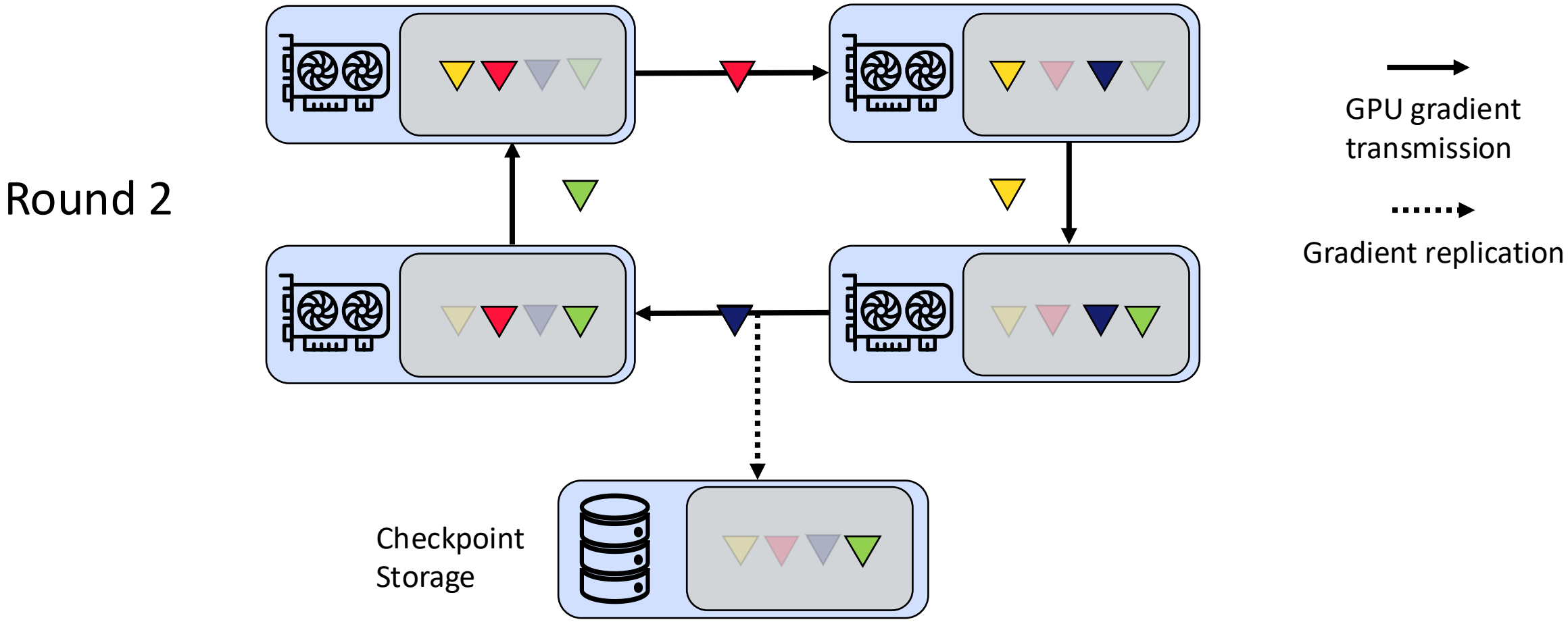

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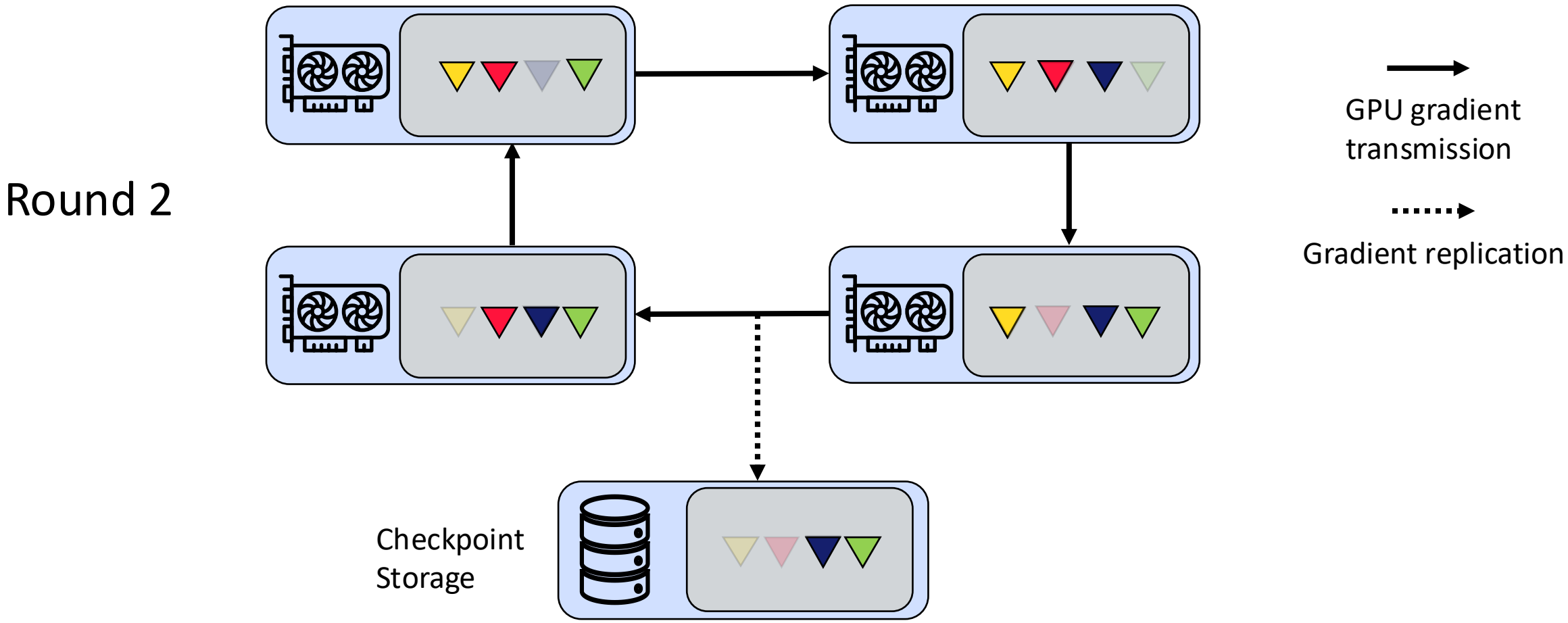

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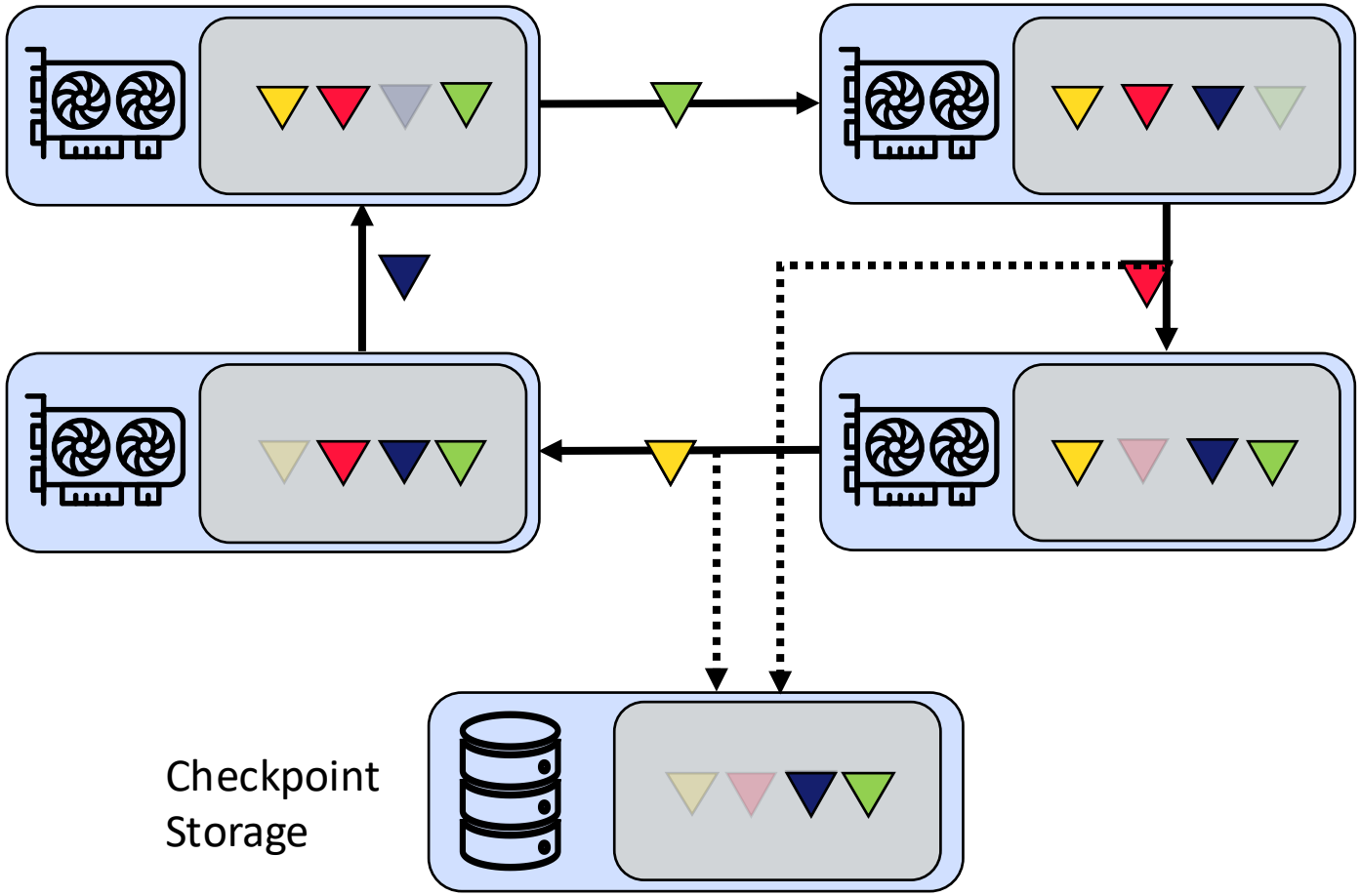
Round 3

Last round!

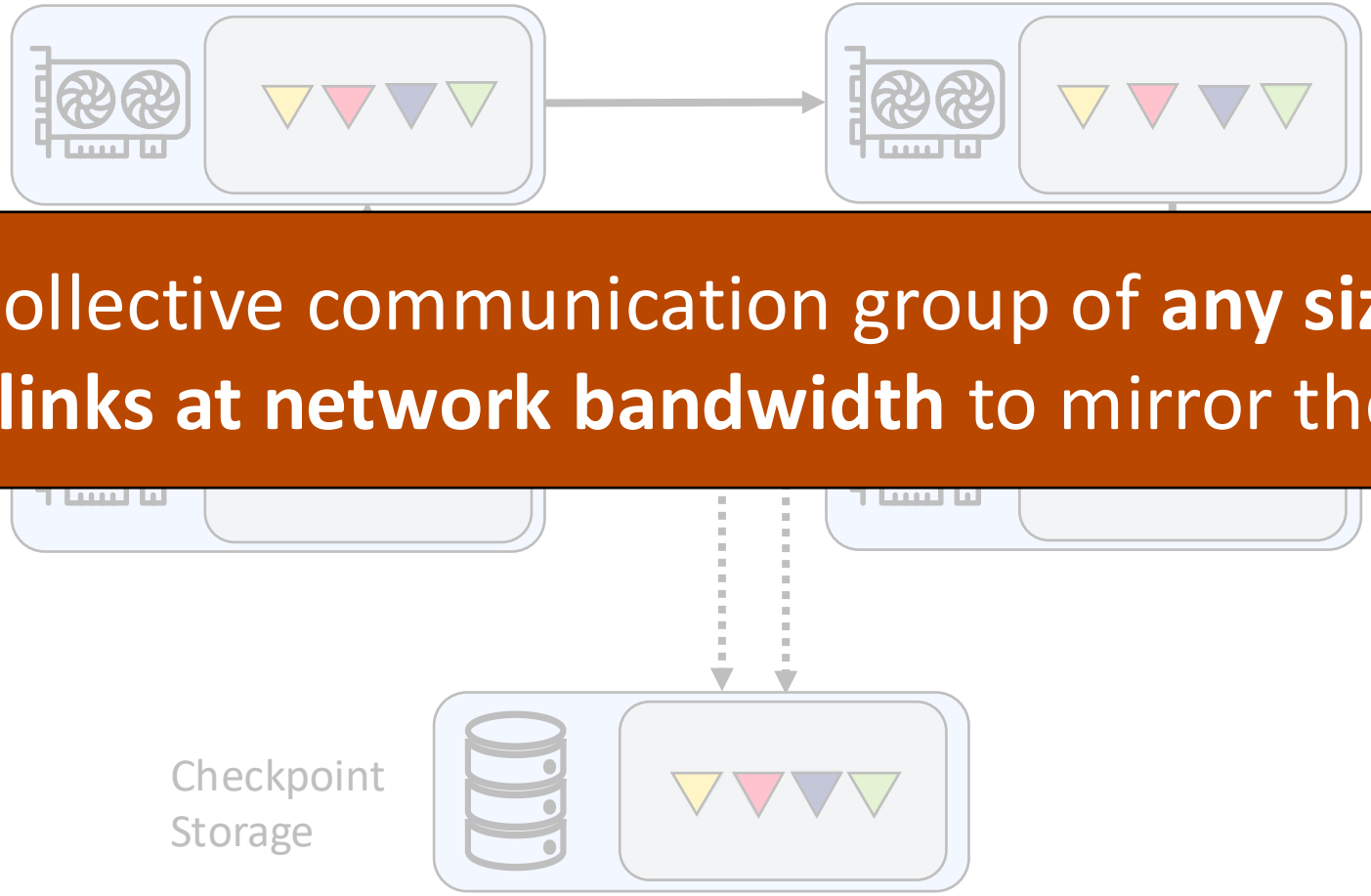


GPU gradient transmission

Gradient replication

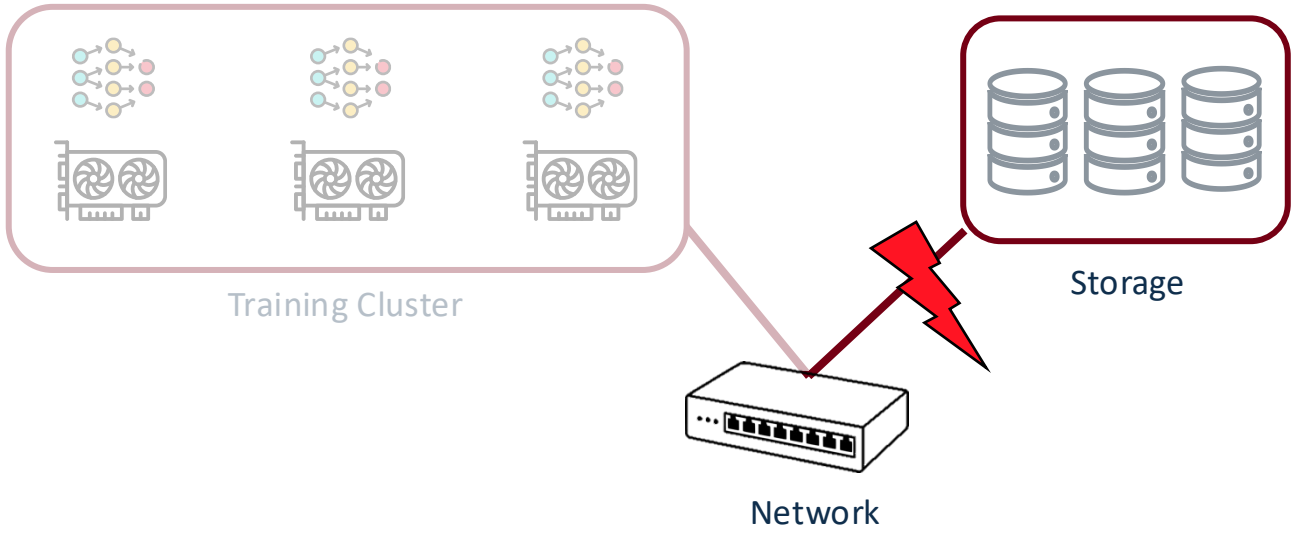
Solution 1: Selectively replicate gradients during AllReduce

- Synchronizing gradients  across four GPUs



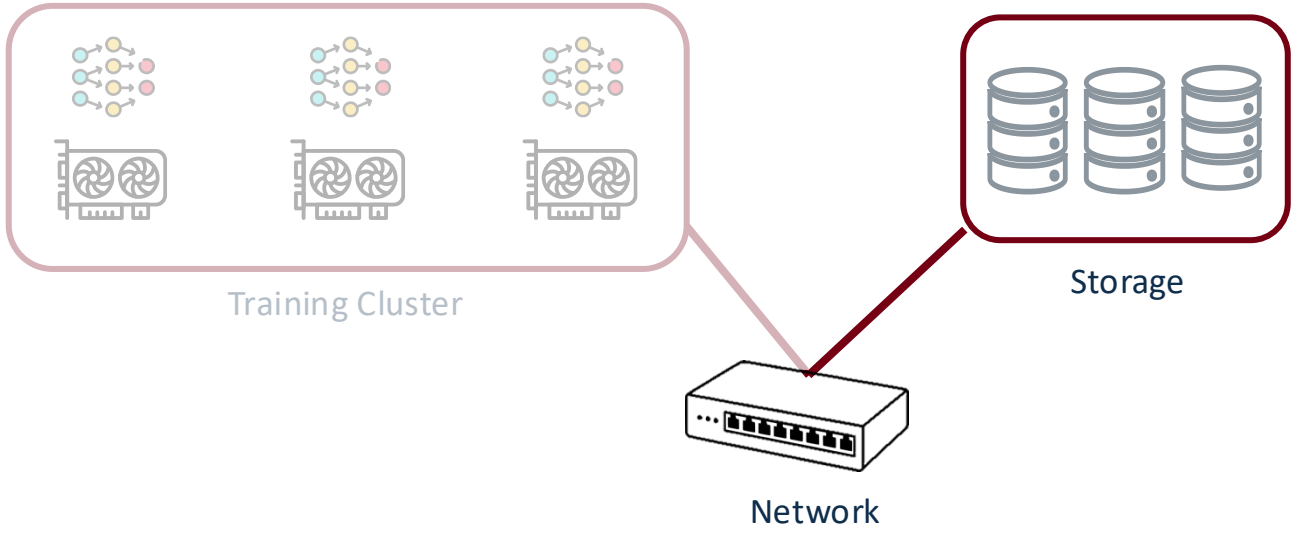
For each collective communication group of **any size**, we only need **two links at network bandwidth** to mirror the gradients

Challenge 2: Reliable delivery



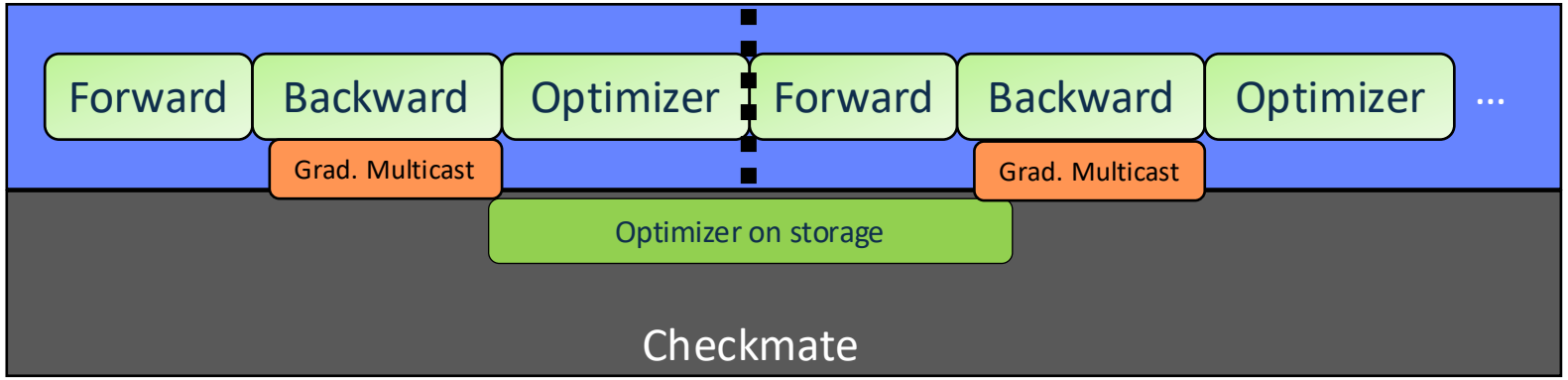
- The network must replicate *all* gradients to the storage cluster for consistency
- Need reliable communication for the multicast streams

Solution 2: Reliable delivery



- Priority-based Flow Control (PFC)
  - Pause transmission when buffer is full
  - All streams in a multicasting flow can backpressure upstream sender
  - Tuned switch and NIC buffers
- Switch to storage connection
  - Handshake mechanism between switch and storage
  - Forward error correction (FEC) codes to handle data corruption

Challenge 3: Compute resource constraint on storage nodes



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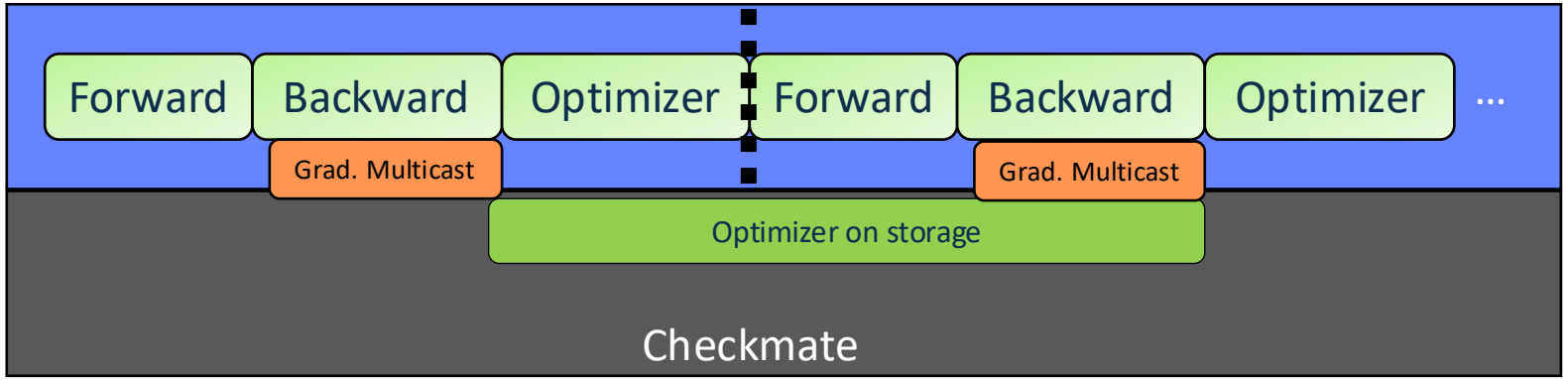

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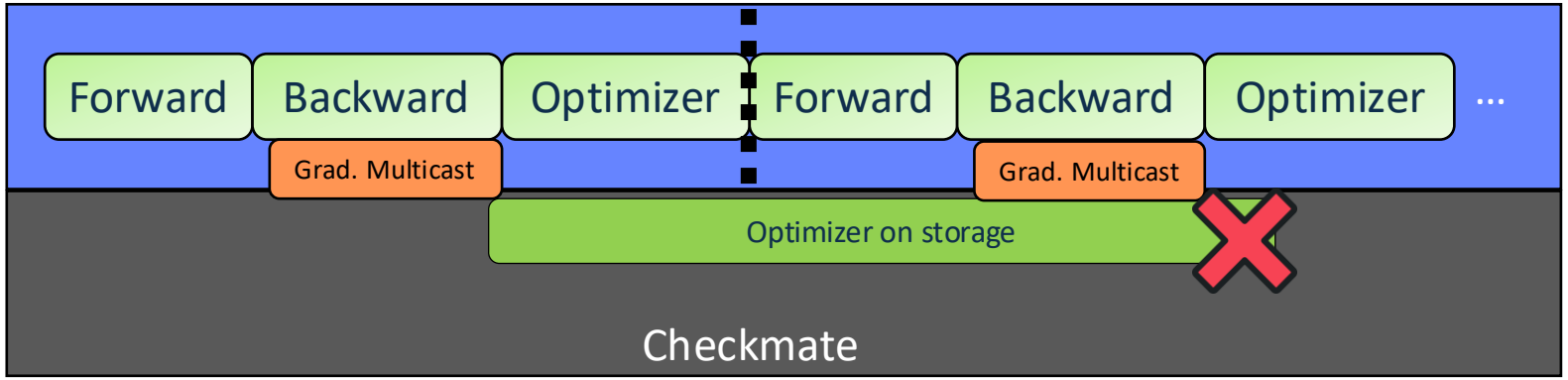
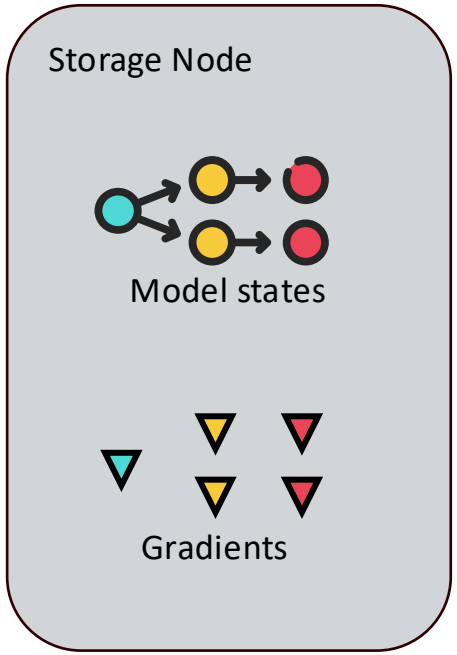


Solution 3: partition the checkpoint

- Most popular optimizers (e.g. SGD, Adam, AdamW) are *functional* and *independent:*
  - Each parameter updates independently, and the update depends only on the parameter itself, the gradient and the optimizer state



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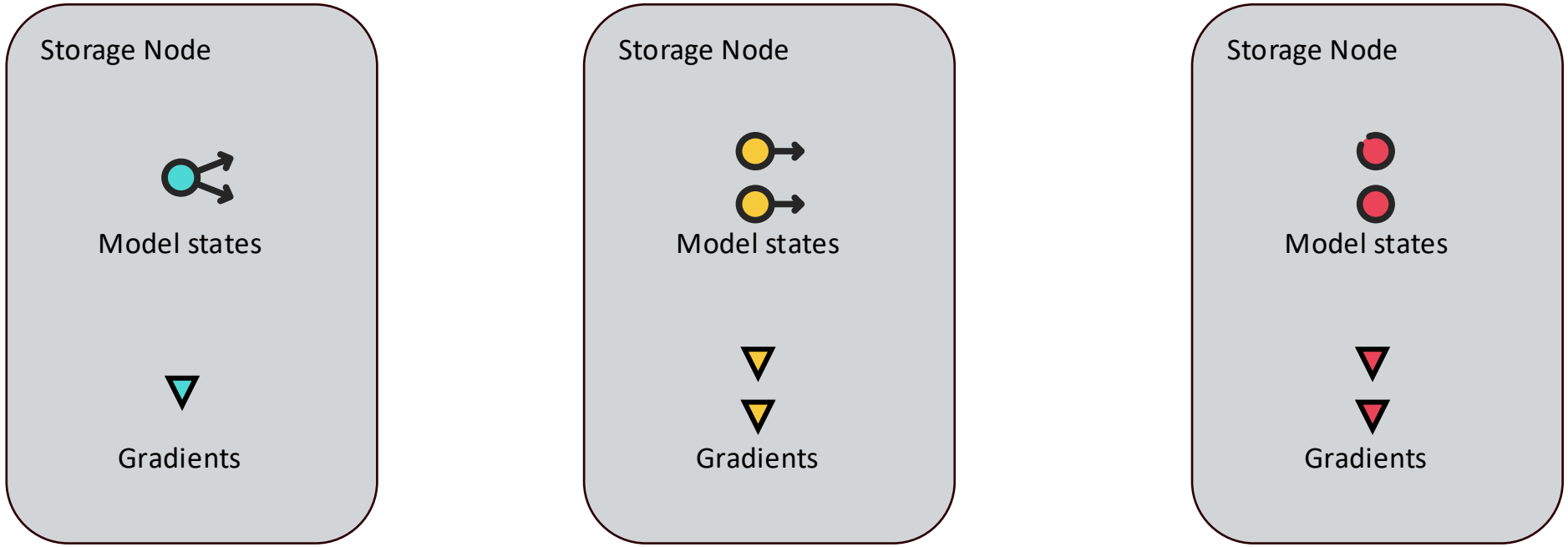
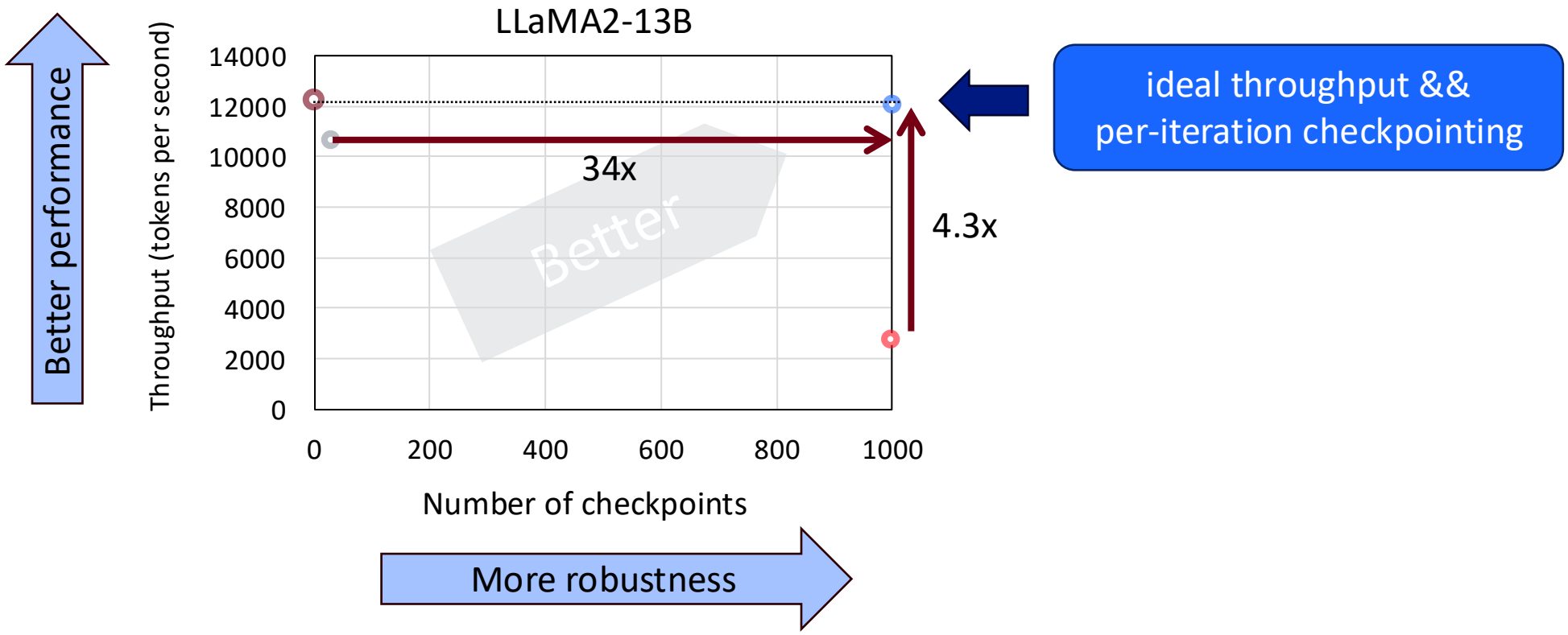


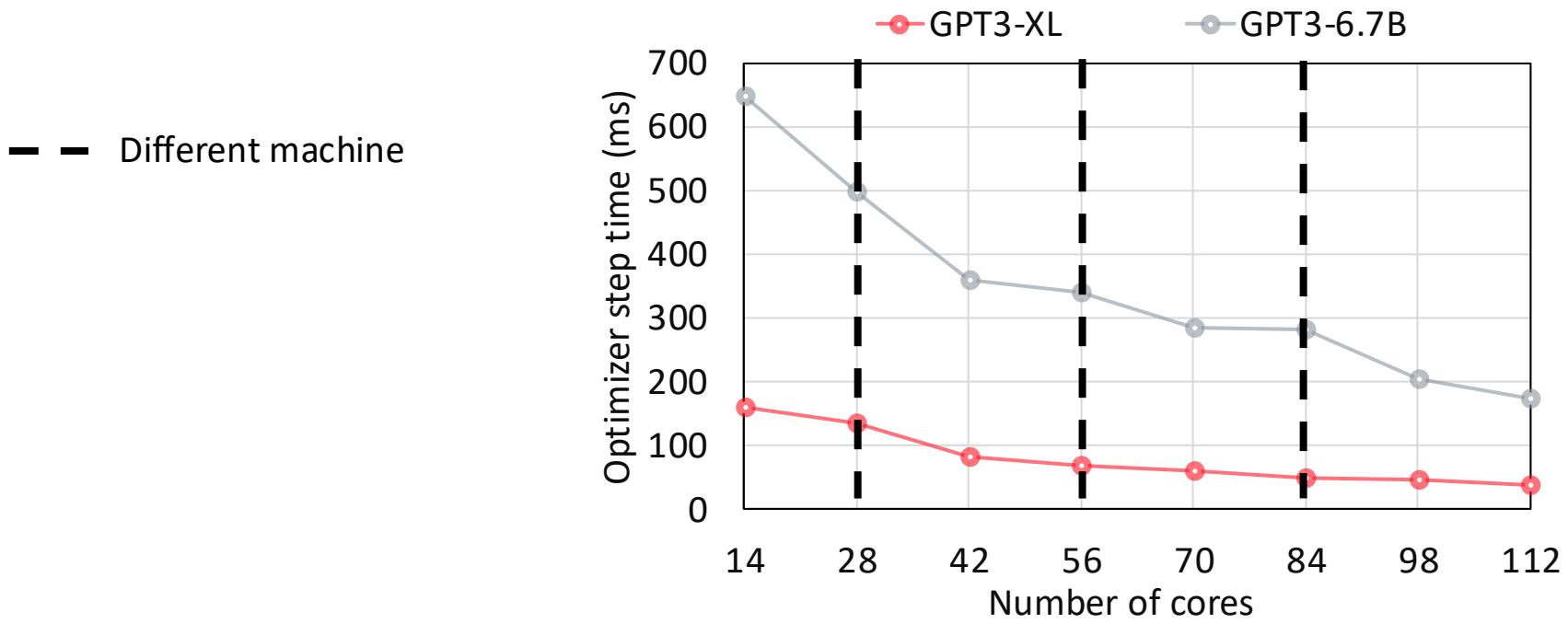
Result: Robustness at the ideal throughput

- Twelve A100 GPUs with 100 Gbps network; four storage CPU servers



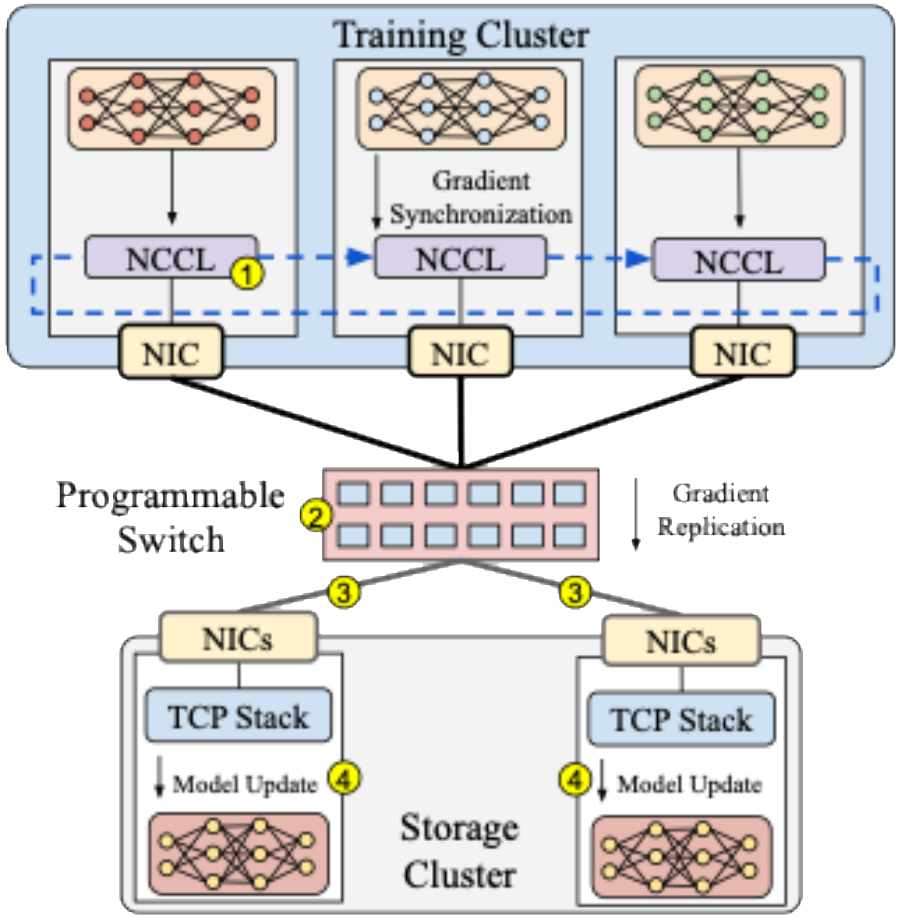
Result: Storage optimizer performance scaling

- One to four 28-core CPU servers running optimizer steps



- A single 28-core CPU server keeps up with training a 6.7B-parameter GPT model with reasonable batch size (local batch size of 5 sequences)

Summary



- Checkmate: zero-GPU overhead checkpointing with network assistant
- Multicast-update abstraction to replicate gradient in the network and repeat update step on the storage node
- 5 - 34.5× more frequent checkpointing
- 1.3 - 6.5× throughput at the same checkpointing frequency
- https://github.com/hipersys-team/checkmate