Efficient LLM Checkpointing with Memory and Storage

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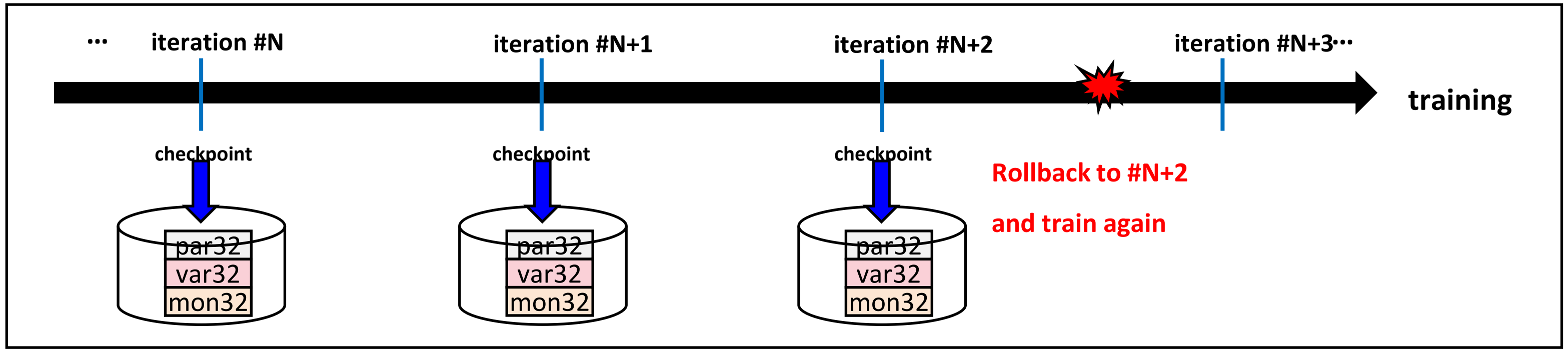
SK hynix

Checkpointing for LLM Training System

Dealing with various issues while training such as H/W, power, interrupt issues, LLM systems need to be checkpointed frequently to be rolled back to a stable state

To restore the specific version for Model-Tuning : Resume from specific meaningful version for a model-tune training



LLM checkpointing writes the model parameters and optimizer state to persistent storage

Challenges on LLM Checkpointing

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Large Checkpoint Size !!

With growing model size, total checkpoint size grow.

→ Large size of LLMs incurs significant I/O overheads

Model	# params (p)	Model size (p*2byte)	total checkpoint state size
GPT-3	175 B	350 GB	2.4 TB
LLaMa	544 B	1088 GB	7 TB
GPT	1 T	2 TB	13.8 TB

https://arxiv.org/pdf/2406.10707v1, DataStates-LLM: Lazy Asynchronous Checkpointing for LLMs

Frequent Checkpointing !!

More frequent LLM checkpoints (becomes mandatory due to frequent GPU failures with large LLM data)

→ incurs system overheads such LLM training performance degradation and storage capacity

Checkpointing every 5 iterations

Iteration	1	2	3	4	5	6	7	8	9	10
Para32										
Mon32										
Var32										

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Para32										
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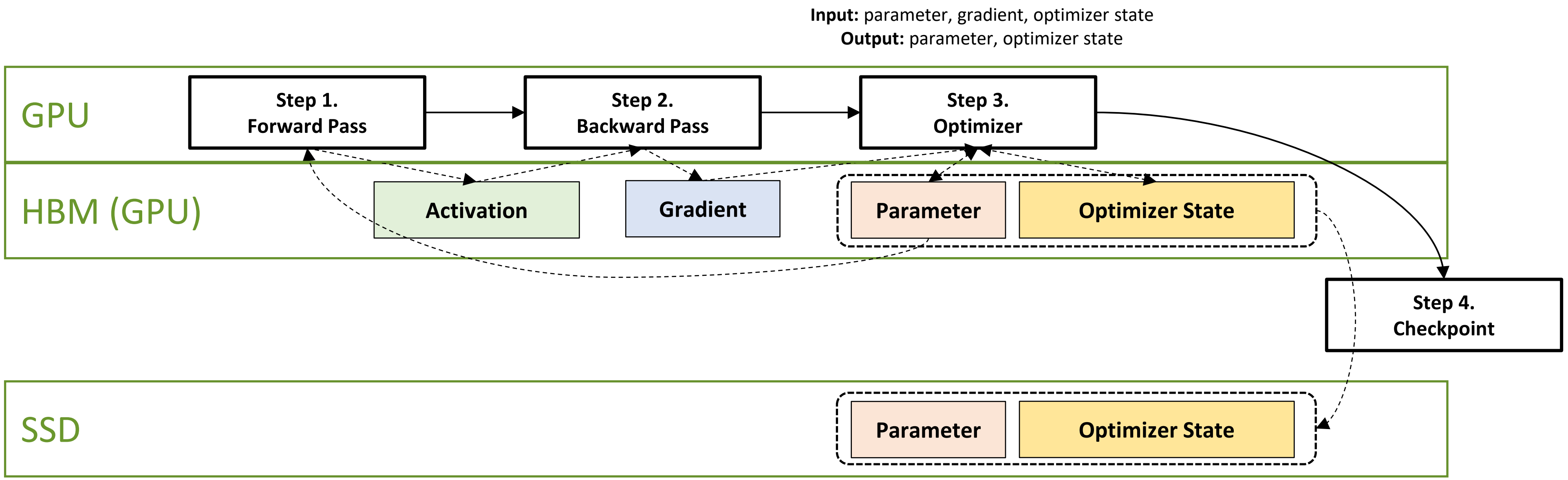
Var32										

LLM Training

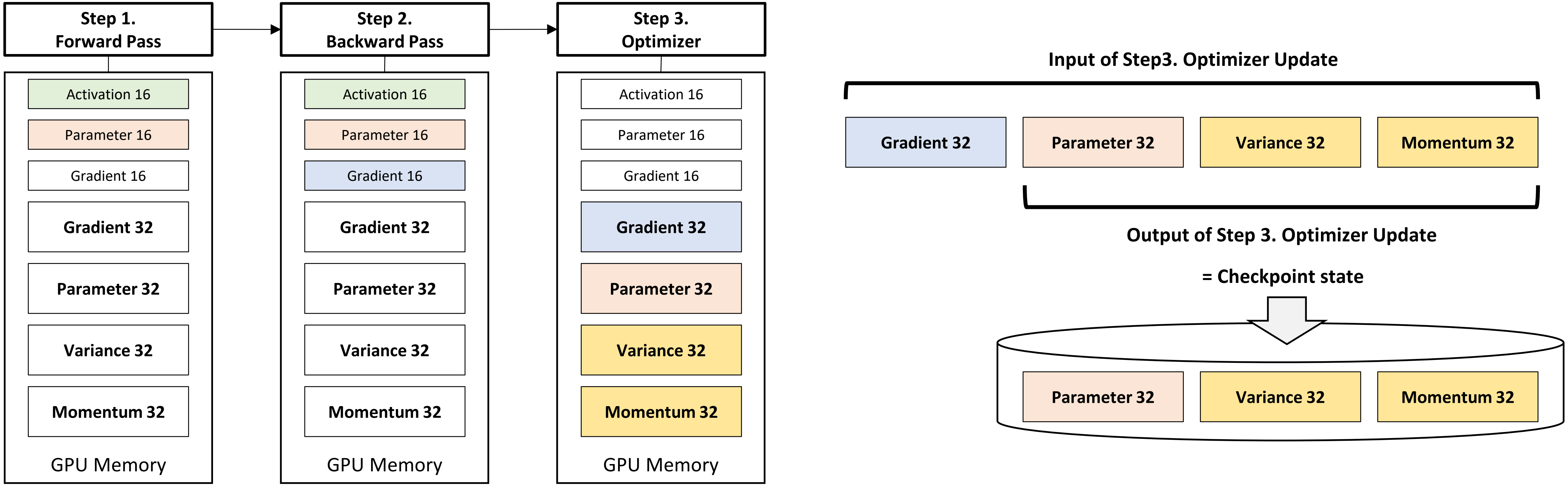
Forward → Backward → Optimizer Update → Checkpoint



Memory Inefficiency

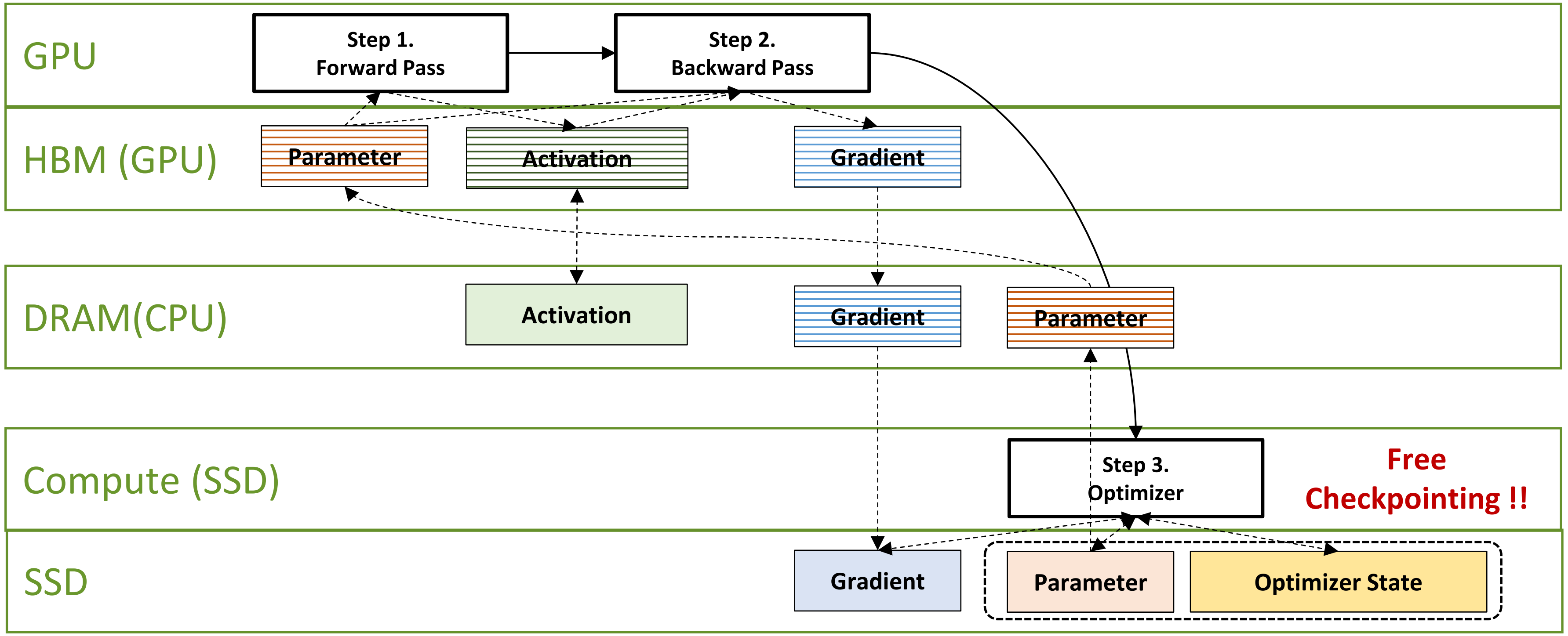
Forward & Backward only use paramter16, activation16, and gradient16

Optimizer state is kept in high precision (FP32 – G32, P32, V32, M32)



Offloading Optimizer to SSD

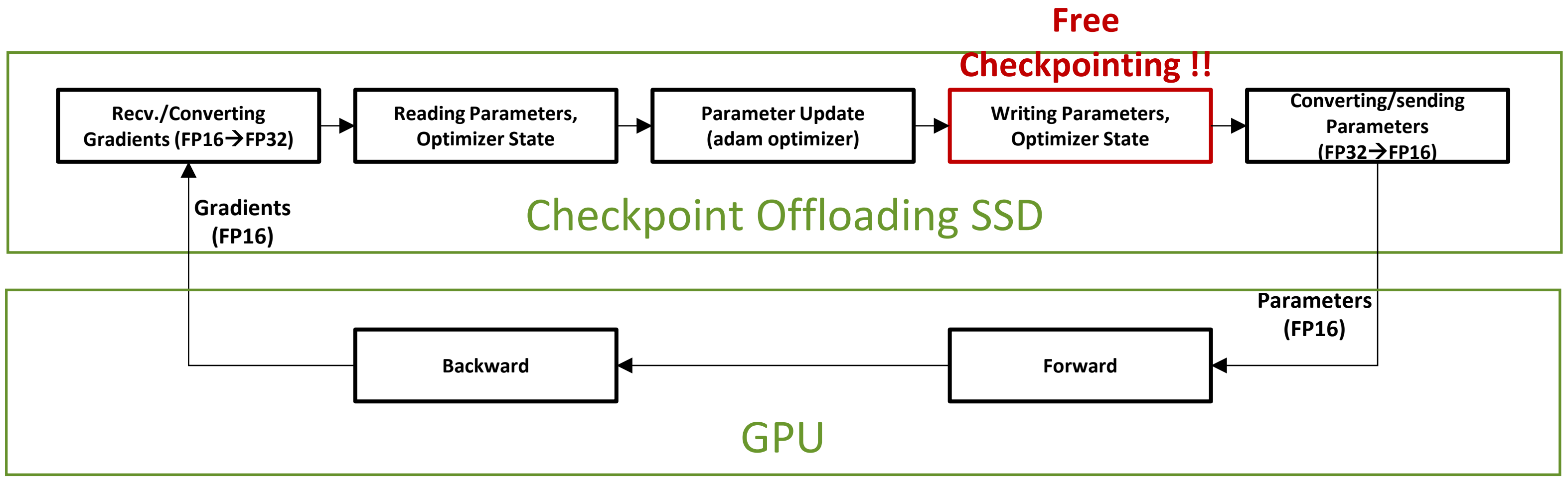
Forward → Backward → Optimizer Update



Checkpoint Offloading SSD

Checkpoint Offloading SSD generates checkpoint states in SSD

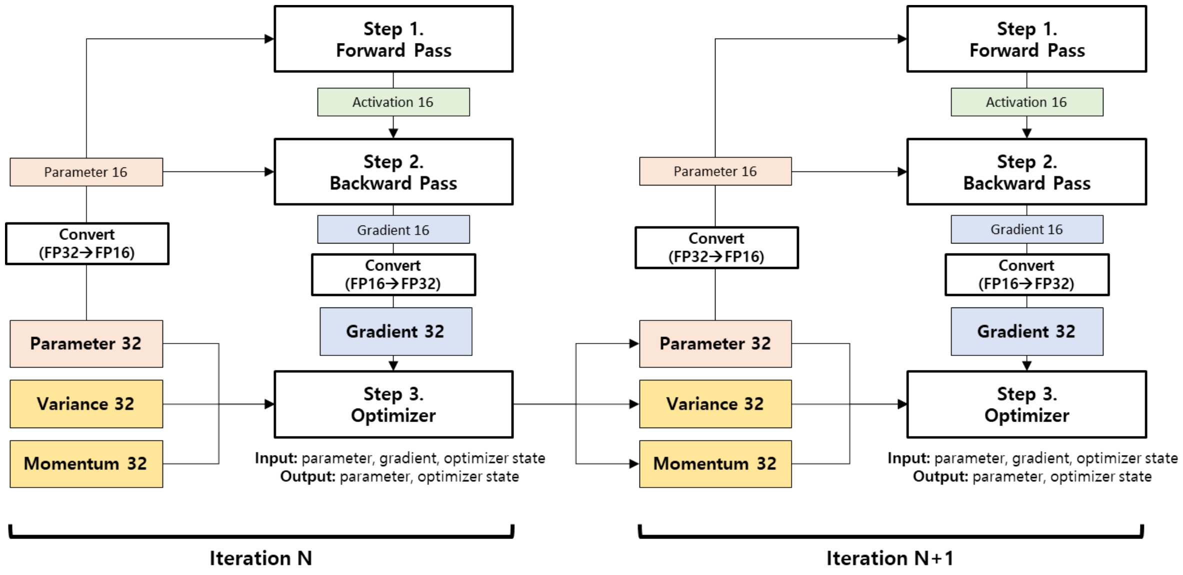
- Generating checkpoint states is an elementwise operation with low operational intensity (# arith. ops. / # mem. ops.) → can be offloaded from GPU
- GPU memory saving → larger model training
- Parameter restore (not optimizer) → shorten checkpoint restoration time
- high frequency checkpointing → Save PCIe + network B/W by avoiding transfer of optimizer state



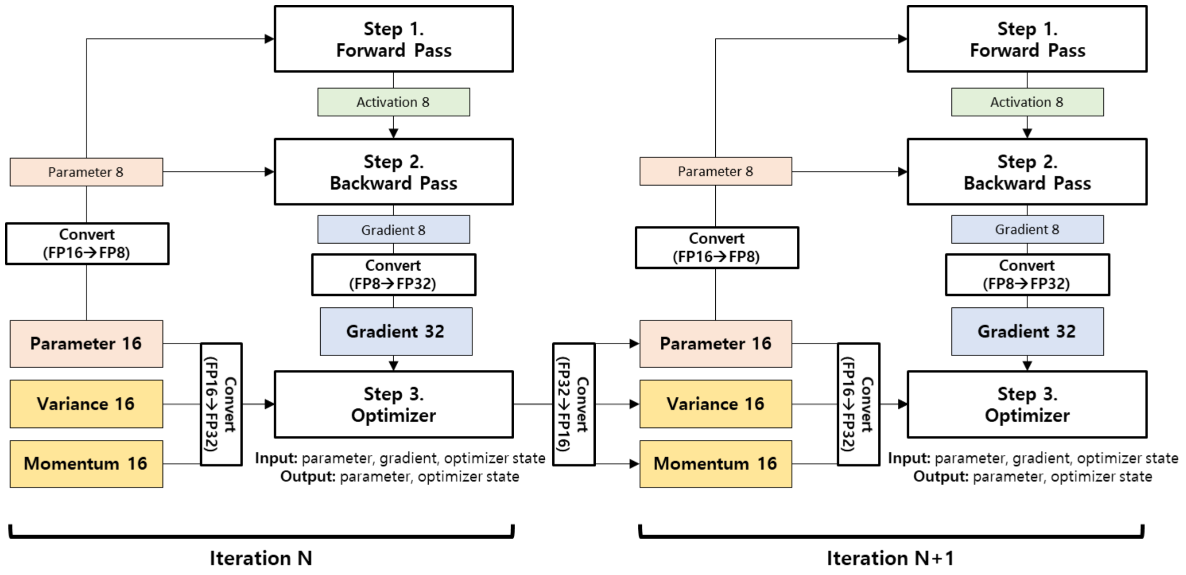
Mixed Precision and Optimizer

Support mixed-precision training to take advantage of low precision compute speedup while maintaining accuracy

- Fwd./Bwd.: High compute, low memory requirement (low precision model, gradients, activations)
- Optimizer: Low compute, high memory requirement (high precision optimizer state)



[Mixed Precision (FP32 ←→ FP16)]

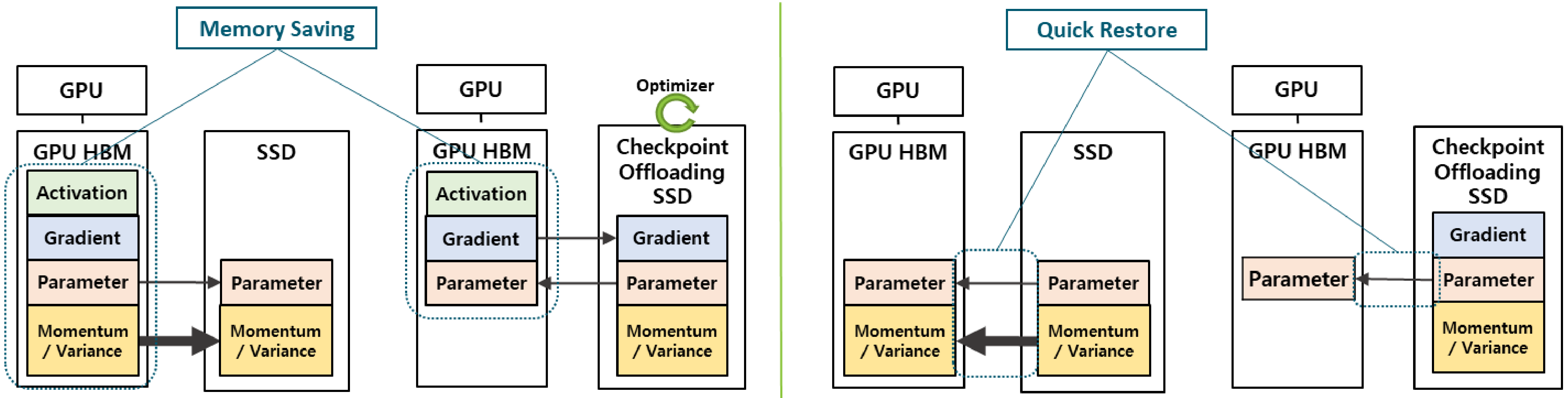


[Mixed Precision (FP16 → FP8, FP32 ←→ FP16, FP8 → FP32)]

Benefit of Checkpoint Offloading SSD

Can save GPU memory usage to train a larger model or increase the batch size

Shorten checkpoint restoration time



[LLM Training System]

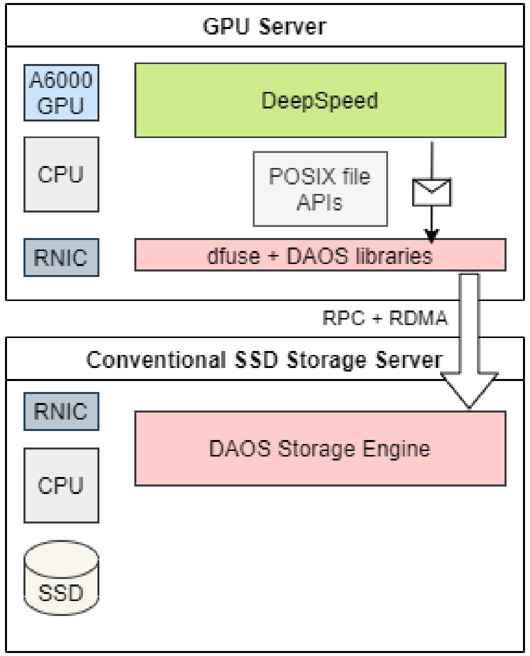
[LLM Training System w/ Checkpoint offloading SSD]

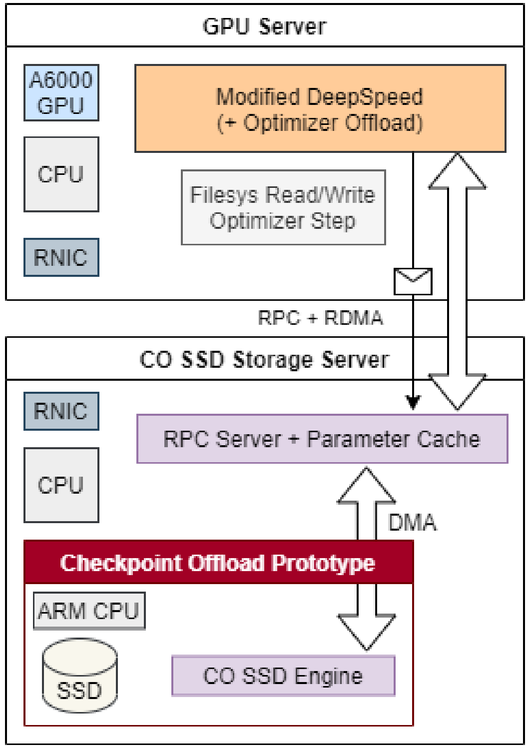
Free Checkpointing !!

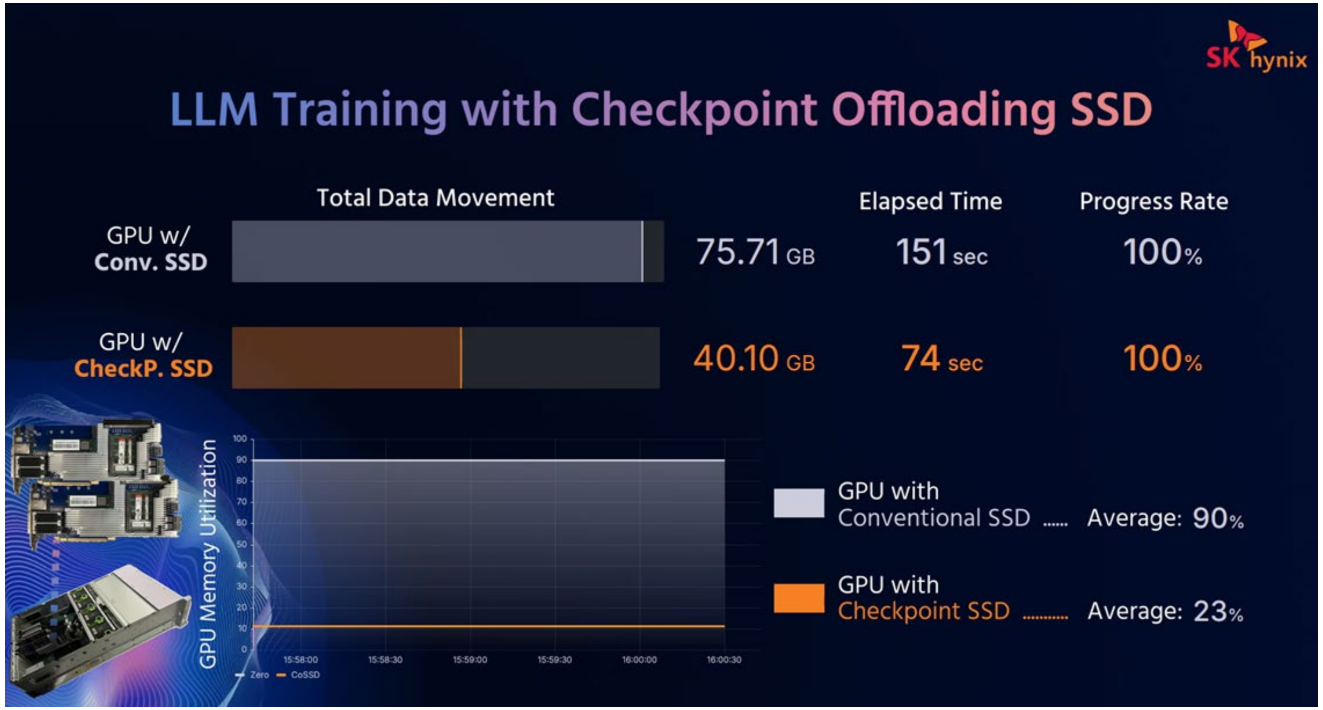
[LLM Training System]

[LLM Training System w/ Checkpoint offloading SSD]

Performance

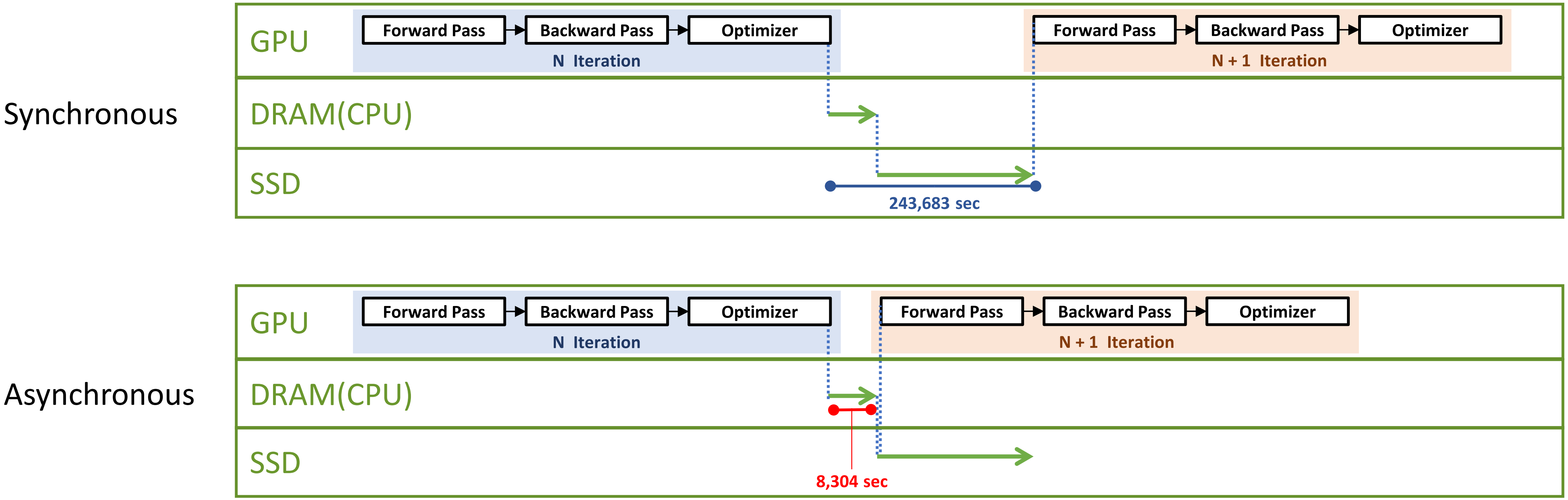




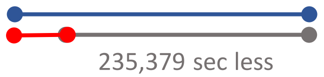


Asynchronous Checkpointing

* Benchmarked with GPT2-2B

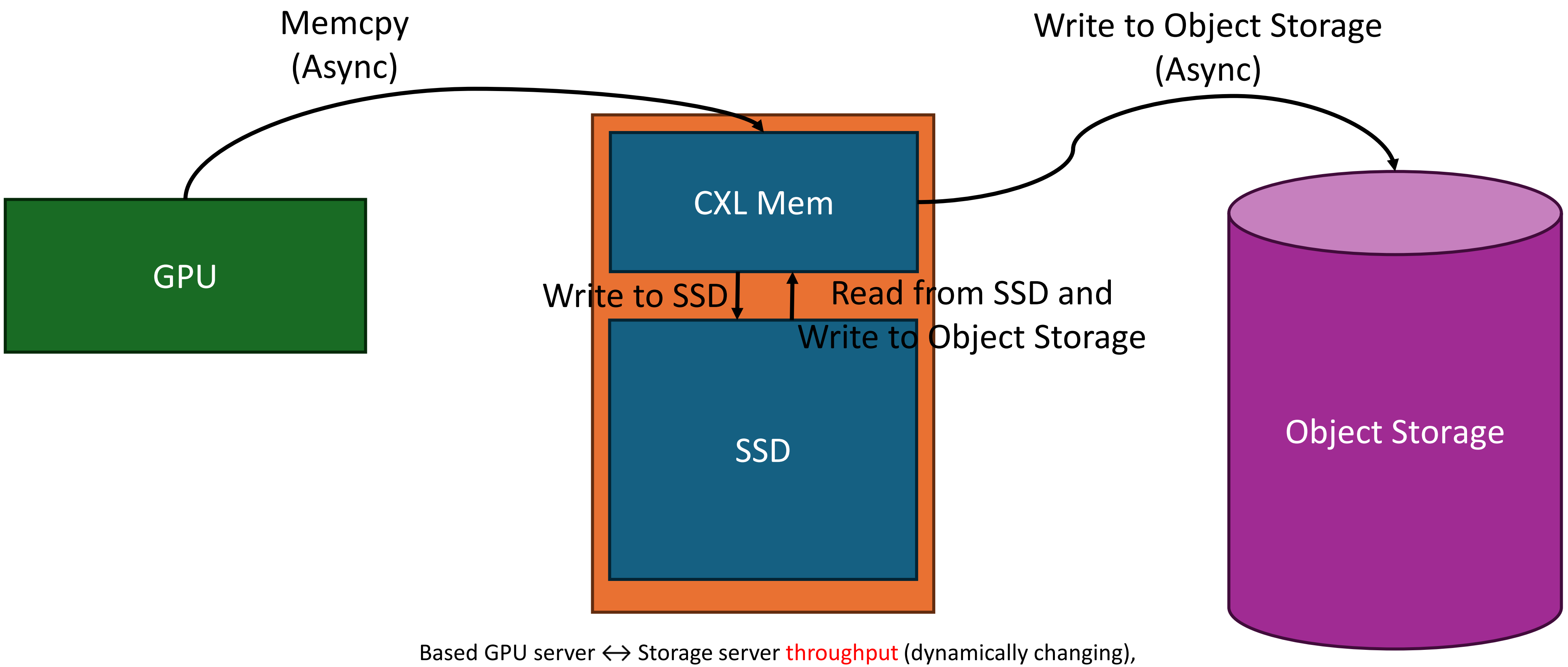


- Asynchronous checkpointing is much faster



- GPU is making progress faster, but the CPU memory can get filled quickly due to slow SSD

Asynchronous Checkpointing with Hybrid CXL Memory



Based GPU server ↔ Storage server throughput (dynamically changing), policy determines whether to write/keep checkpoint data in local SSD or move to remote object storage.

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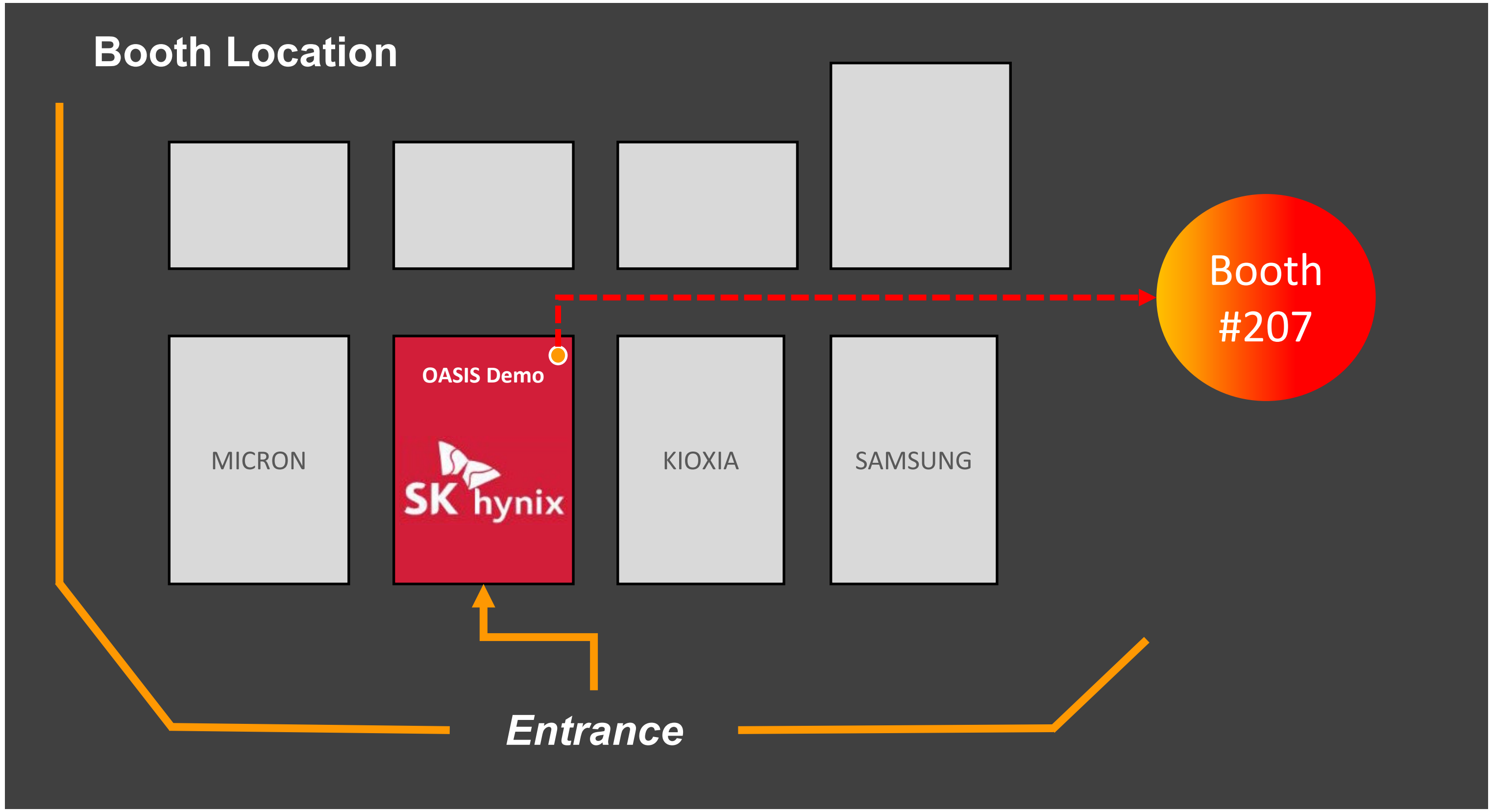

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