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# Final Project

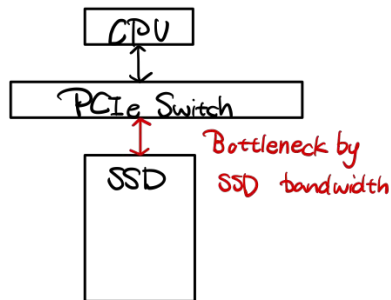
蕭泓佐 林胤辰 方淑玲 王俊閔

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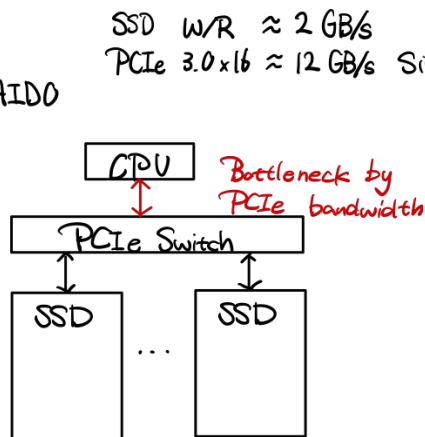
# Computational Storage Device (CSD) - SmartSSD

Scale internal bandwidth with # of CSDs

Single SSD



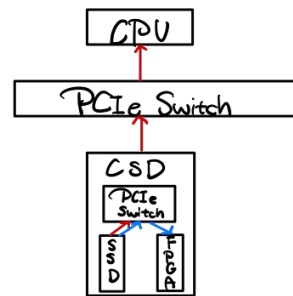
RAID0



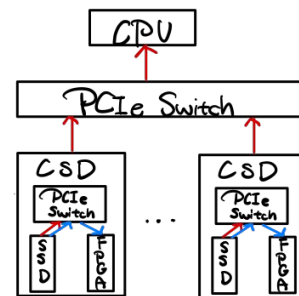
SSD W/R  $\approx 2$  GB/s

PCIe 3.0x16  $\approx 12$  GB/s

Single CSD { Storage to Host  $\times 1$   
Storage to FPGA  $\times 1$



Multiple CSD { Storage to Host  $\times 1$   
Storage to FPGA  $\times N$

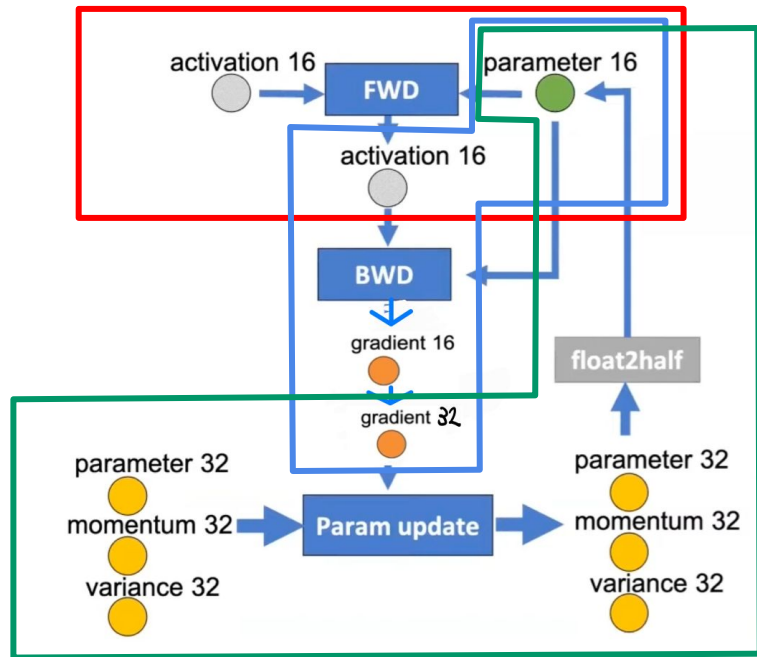


# Smart-Infinity

## Problem Statement

- Workload: Heterogeneous (GPU+CPU+SSD) mixed precision DL training
- Existing method (storage-offload training) comes at the cost of storage bandwidth bottleneck

# Existing Method (ZeRO-Infinity)



Mixed precision training iteration for a layer.

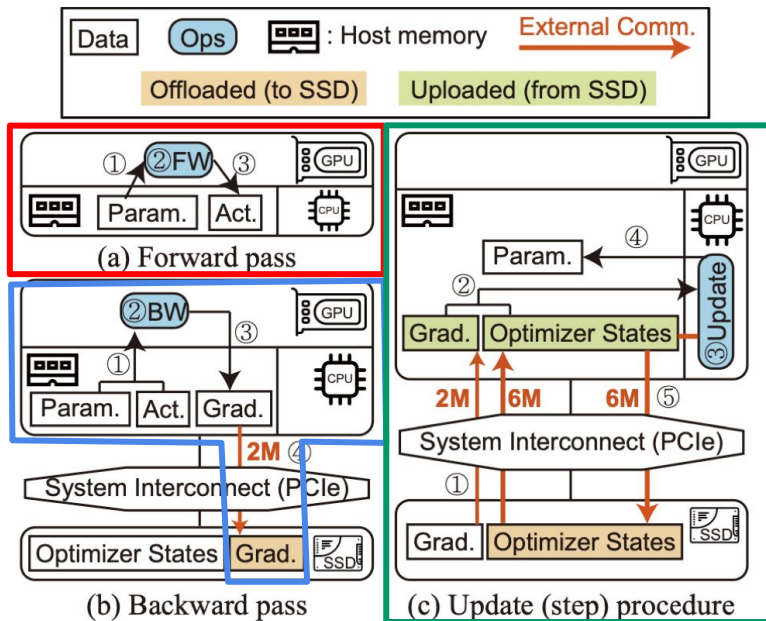
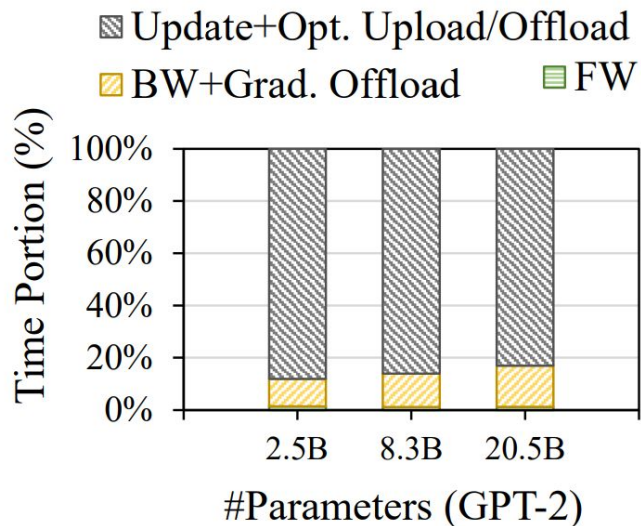
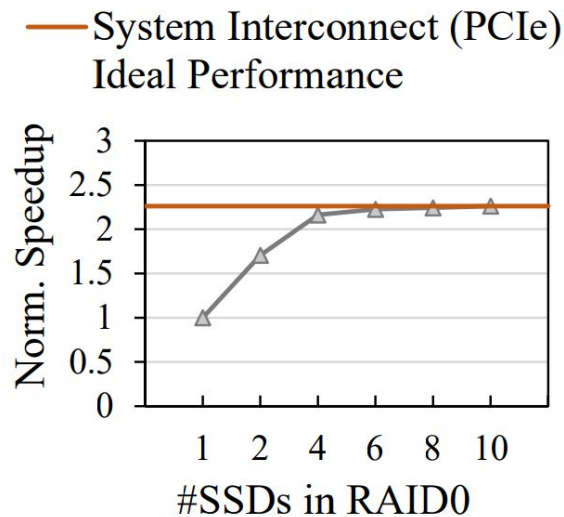


Fig. 1: A conceptual diagram of the storage-offloaded LLM training. Overview of (a) the forward pass, (b) the backward pass, and (c) the update (step) procedure.

# Bottleneck Analysis



(a) Breakdown of baseline

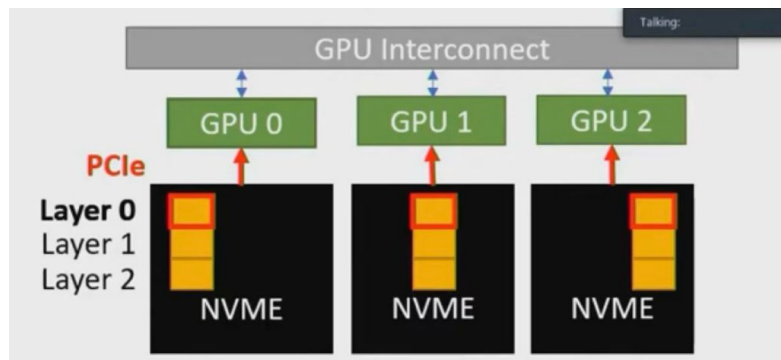


(b) RAID0 performance

# Existing Method (ZeRO-Infinity)

Scaling node (i.e. PCIe lane) is proposed as the solution in ZeRO-Infinity

→ Smart-Infinity: scale CSDs instead of compute nodes



Nodes	GPUs	Aggregate Memory (TB)			GPU-GPU Bandwidth (GB/s)	Memory Bandwidth/GPU (GB/s)		
		GPU	CPU	NVMe		GPU	CPU	NVMe
1	1	0.032	1.5	28.0	N/A	600-900	12.0	12.0
1	16	0.5	1.5	28.0	150-300	600-900	3.0	1.6
4	64	2.0	6.0	112.0	60-100	600-900	3.0	1.6
16	256	8.0	24.0	448.0	60-100	600-900	3.0	1.6
64	1024	32.0	96.0	1792.0	60-100	600-900	3.0	1.6
96	1536	48.0	144.0	2688.0	60-100	600-900	3.0	1.6

(b)

ZeRO Infinity

GPUs	Data Type	Required	NVMe memory	CPU Memory
1024	Params/Grads	60 GB/s	70 GB/s	70 GB/s
1024	Optimizer States	1500 GB/s	1792 GB/s	4096 GB/s
1024	Activations	4 GB/s	1.75GB/s	4GB/s

# Smart Update

1. By offloading parameter update to CSDs, we can scale bandwidth with # of CSDs.
2. Gradient & Param transfer still goes through CPU-PCIe → The CSD scaling upper bound occur when gradient and param transfer become the new bottleneck.

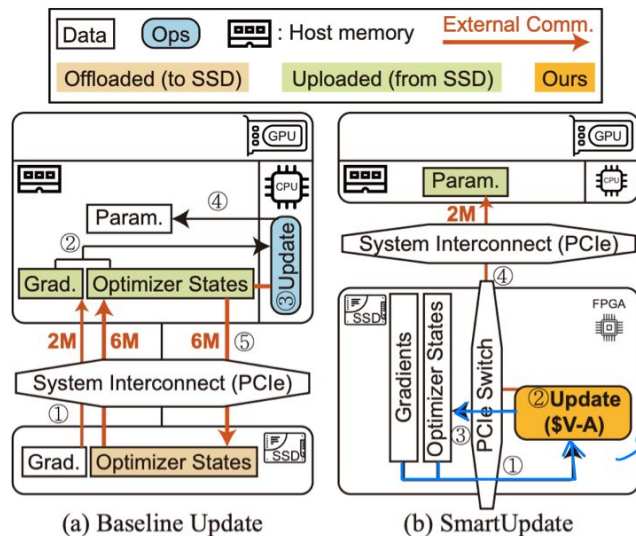


Fig. 4: Update procedure of the storage-offloaded training with (a) baseline [96] and (b) SmartUpdate.

TABLE I  
SYSTEM INTERCONNECT TRAFFIC FOR STORAGE-OFFLOADED TRAINING WITH ADAM OPTIMIZER.

Type	Optimizer States		Gradients	
	Read	Write	Read	Write
ZeRO-Inf [96]	6M	6M	2M	2M
SmartUpdate	2M	—	—	2M
SmartComp (c%)	2M	—	—	$c\% \times 2M$

Internal bandwidth scales linearly with # of CSDs (Scale CSDs instead of compute nodes)

\* Gradient and param transfer still goes through CPU-PCIe  
⇒ The CSD scaling upper bound occur when gradient and Param transfer become new bottleneck.

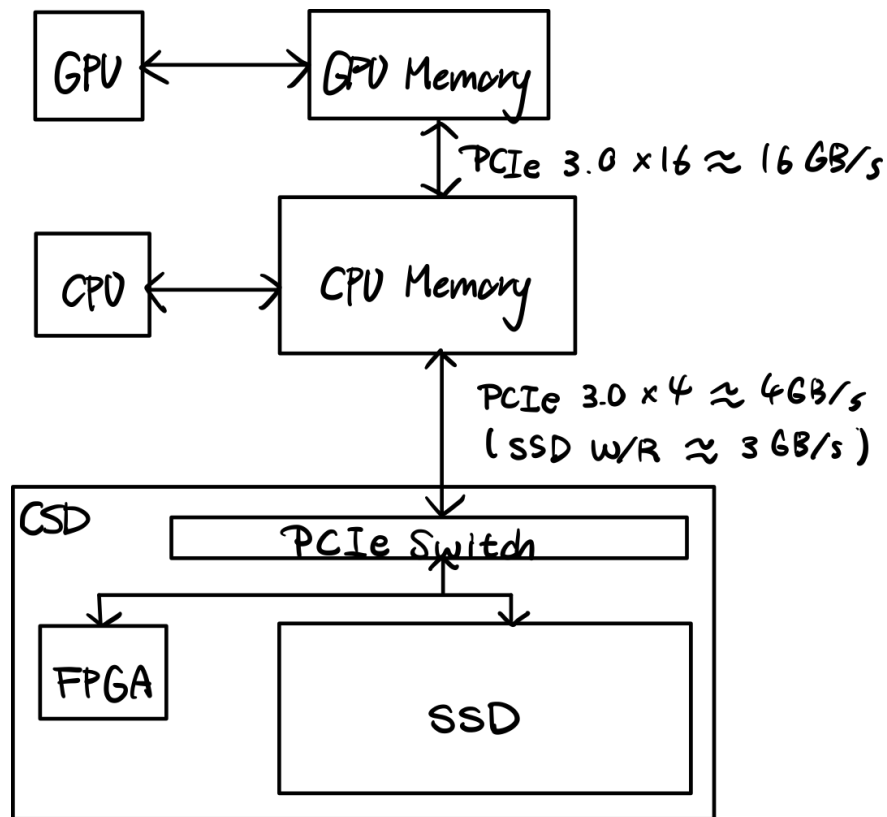
# Environment - System Configuration

## Hardware

1. NVIDIA RTX 3090-GPU (24GB)
2. 16-core Intel I7 12700 CPU
3. 128GB RAM
4. Samsung SmartSSD

## Software

1. Ubuntu 20.04 with Linux kernel 5.4.0-164
2. CUDA 11.6
3. PyTorch 1.13
4. DeepSpeed v0.9.3





# Environment - Challenges

## System Support

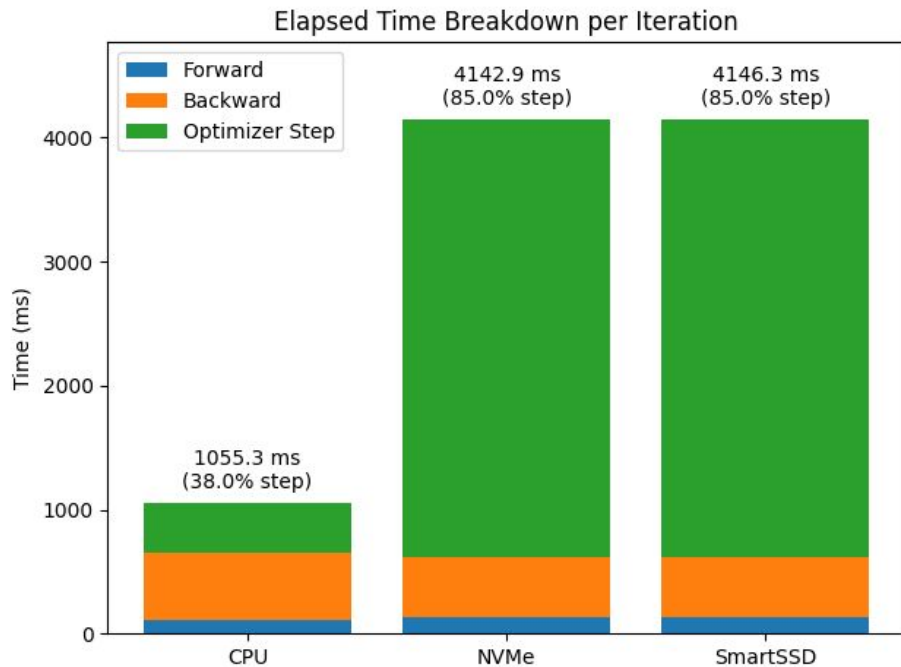
1. The SmartSSD product line has been discontinued, making it difficult to find systems with compatible configurations or support.  
→ We find the compatible system configuration by trial and error.

## Cooling

1. The SmartSSD is designed for installation in servers with controlled airflow for effective cooling, which makes local installation in a standard PC challenging due to potential overheating.  
→ We use an external fan to cool down the SmartSSD.

# Experiment Result

1. As we only have one SmartSSD device we conduct a scalability analysis to verify the result from the paper.
2. From configuration 2, we can observe that **most time spent during an iteration is in optimizer step.**
3. From configuration 1 and 2, we can derived that **most of the time spent during optimizer step is used in IO not computation.**



# Scalability Analysis

There are no data-dependencies  
between each parameter in optimizer  
step

→ Optimizer step scales linearly with  
# of CSDs.

*For each Parameter  $w^j$*

*(j subscript dropped for clarity)*

$$\nu_t = \beta_1 * \nu_{t-1} - (1 - \beta_1) * g_t$$

$$s_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2$$

$$\Delta\omega_t = -\eta \frac{\nu_t}{\sqrt{s_t} + \epsilon} * g_t$$

$$\omega_{t+1} = \omega_t + \Delta\omega_t$$

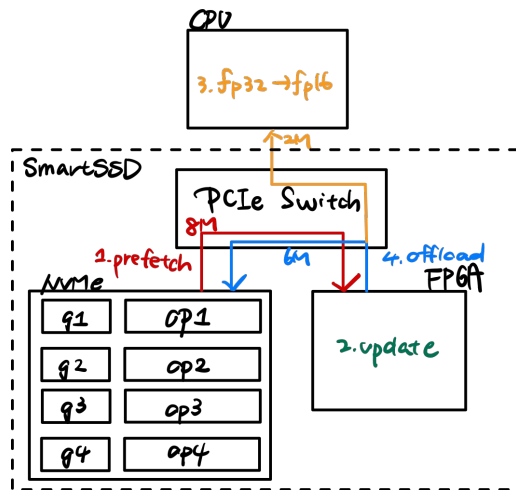
# Scalability Analysis

**Weakly Parallelizable** : Scaling upper bounded by PCIe bandwidth

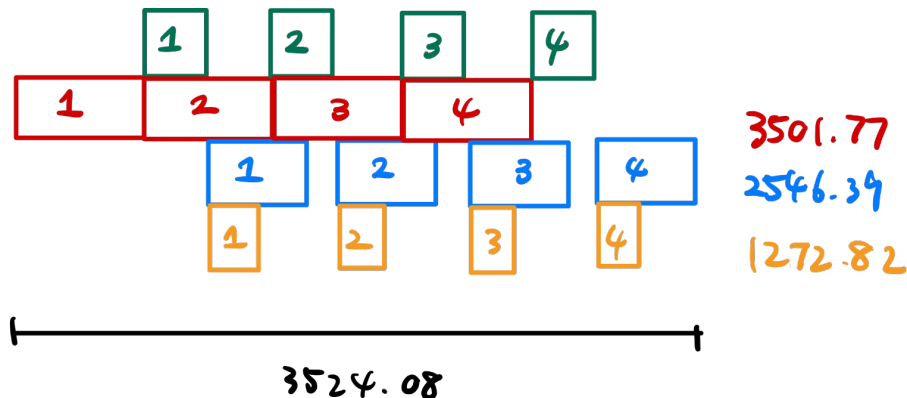
1. FPGA → CPU Communication

**Parallelizable** : Scale linearly with # of CSDs

1. FPGA computation
2. NVMe → FPGA communication
3. FPGA → NVMe communication



FPGA  
NVMe → FPGA  
FPGA → NVMe  
FPGA → CPU



# Scalability Analysis

$$T_{opt,n} = \max\left(\frac{T_{opt}}{n}, \frac{T_{param\_swap}}{\min(n, \frac{B_{PCIe}}{B_{SSD}})}\right)$$

$$T_{total,n} = T_{opt,n} + T_{fwd} + T_{bwd}$$

$n$ : number of CSDs

$T_{opt}$ : time of optimizer step using 1 CSD

$T_{fwd}$ : time of forward pass

$T_{bwd}$ : time of backward pass

$T_{opt,n}$ : time of optimizer step using  $n$  CSDs

$T_{param\_swap}$ : time of swapping in parameters to CPU

$B_{PCIe}$ : PCIe bandwidth

$B_{SSD}$ : SSD bandwidth

