

Understanding Oversubscribed Memory Management for Deep Learning Training

Mao Lin and Hyeran Jeon University of California Merced

March 31, 2025 · Rotterdam, Netherlands

Backgrounds: GPU Memory Is No Longer Enough!



Image source: https://arxiv.org/abs/2403.14123 https://www.substratus.ai/blog/llama-3-1-405b-gpu-requirements



Backgrounds: SOTA Solutions

- Multi-GPU Parallelism
 - GPU may not always be readily available
 - e.g., Megatron-LM@SC'21, MegaScale@NSDI'24, HAP@EuroSys'24, etc.
- Data Offloading/Checkpointing
 - Requires complex memory copy orchestration
 - e.g., ZeRO-Offload@ATC'21, ZeRO-infinity@SC'21, POET@PMLR'22, etc.
- Intermediate Result Recomputation
 - Introduces extra computation overhead
 - e.g., Skipper@MICRO'22, Aceso@EuroSys'24, AdaPipe@ASPLOS'24, etc.
- Memory compression & Quantization
 - Adds overhead and potential accuracy loss
 - e.g., ZeroQuant(4+2)@arXiv'24 (Deepspeed), FP6-LLM@arXiv'24 (Deepspeed), etc.



UVM Can Be Another Solution!

- Unified Virtual Memory
 - On-demand migration
 - Memory oversubscription
 - Workloads' memory footprint > GPU memory capacity
- The challenges
 - UVM overhead (page fault)
 - Interaction with DL framework



GPT-2 performance w/ and w/o UVM and memory usage across varying batch sizes



PyTorch Caching Allocator (PCA)

- Memory hierarchy:
 - Allocator -> Pools -> Allocations -> Subranges (tensors)





• Explore the potential of using UVM for deep learning (DL) workloads

• Examine, for the first time, how DL frameworks' unique memory management (PCA) interacts with UVM

• *Provide insights for efficiently adopting UVM in DL systems*



Evaluation Platform & Targeting DL Models

Evaluation Platform

CPU	GPU	System	System	GPU	CUDA	Nsight
			Memory	Driver	Toolkit	Systems
Intel(R) Xeon(R)	NVIDIA A100		128 GB	550.90.12	12.1	v.2023.1.2
Gold 5320	80GB PCIe	Linux 5.14				

Evaluated DL Models

Model	Туре	Layers	Architecture	Batch Size	Memory Footprint ^(MB)
AlexNet	CNN	8	Convolutional Full Connected	128	5316
ResNet50	CNN	50	Residual Block	32	15952
ResNet101	CNN	101	Residual Block	32	22588
GPT-2	Transformer	12	Transformer (Decoder)	8	12008
BERT	Transformer	12	Transformer (Encoder)	16	12350
Whisper (small)	Transformer	12	Transformer (En/De-coder)	16	9824



UVM Is Good for DL Workloads



Performance under diverse oversubscription factors.





UVM Is Good for DL Workloads



Performance under diverse oversubscription factors.

<u>**Observation 1**</u>: LLMs, such as GPT-2 and BERT, benefit more from UVM than simpler CNNs under a high oversubscription factor, due to intensive computation overlapping with page fault handling.

Observation 2: Despite recommendations to limit the oversubscription factor to 1.25, our findings show acceptable overhead even at higher values for DL workloads.



Why?



Memory usage per kernel over time for various models.

The memory footprint is large, but memory usage per kernel is not that large.



Understanding Oversubscribed Memory Management for Deep Learning Training

PCA Trades Pages Faults for Migrations



<u>**Observation 3**</u>: PCA's pool-based memory management effectively reduces substantial page faults. Given that the main performance bottleneck of UVM is expensive page faults, pool-based memory management can be a solution.

<u>**Observation 4**</u>: PCA trades page fault overhead for memory migration overhead. As UVM's smart prefetching and pre-eviction mechanisms effectively remove memory migrations from the critical path, the cumbersome page fault overhead of UVM can be tackled by integrating the UVM with PCA.





• *DL* workloads' memory behaviors suit UVM, enabling large-scale execution on limited GPU memory without needing multiple GPUs.

• UVM, once seen as inefficient for DL due to page faults, benefits from modern techniques like PCA.

• UVM with PCA is effective, but further DL-specific, context-aware optimizations (prefetching/pre-eviction) can enhance performance.



