

ncclsee: A Lightweight Profiling Tool for NCCL Ioannis Vardas, Ruben Laso Rodriguez, and Majid Salimi Beni

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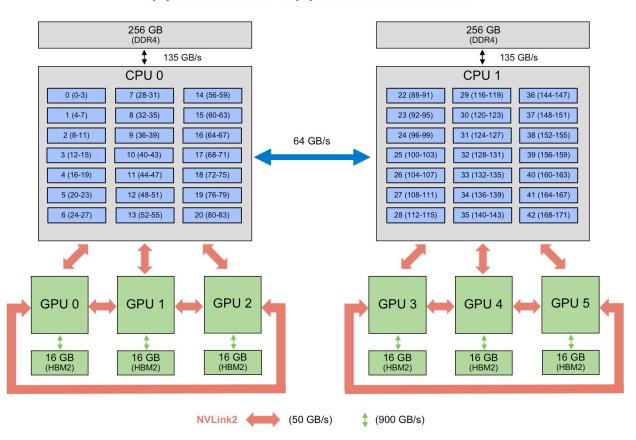
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Scaling Al: Distributed Training

- Training State-of-the-art AI models (especially LLMs) on a single GPU:
 - Too large to fit into the memory.
 - Slower training times.
- Distributed training: Facilitates such models by parallelizing the workload across multiple GPUs.
 - Either within a single machine or across multiple interconnected machines (nodes).
 - New challenge: Communication and co-operation of multiple GPUs.

(2) IBM Power9 + (6) NVIDIA Volta V100

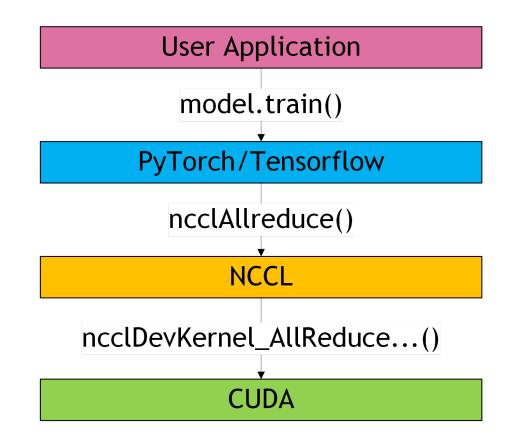


HTTPS://WWW.OLCF.ORNL.GOV/CALENDAR/PROGRAMMING-METHODS-FOR-SUMMITS-MULTI-GPU-NODES

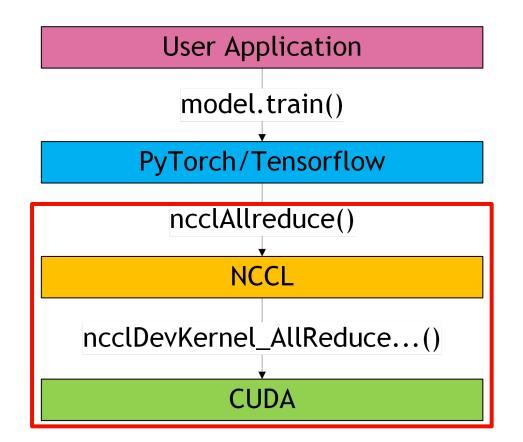
NCCL: Addressing the Inter-GPU Communication Challenge

- **NCCL**: NVIDIA Collective Communications Library.
 - Provides collectives optimized for NVIDIA GPUs and interconnects.
 - Collective Operation: A group of GPUs exchanges data and/or performs computations for a global result, e.g., AllReduce, Broadcast.
 - Performs such operations using optimized CUDA kernels.
 - Reduces memory copies.
 - Developers do not need to optimize their applications for specific machines.
 - GPU-communication backend for frameworks as PyTorch and TensorFlow.







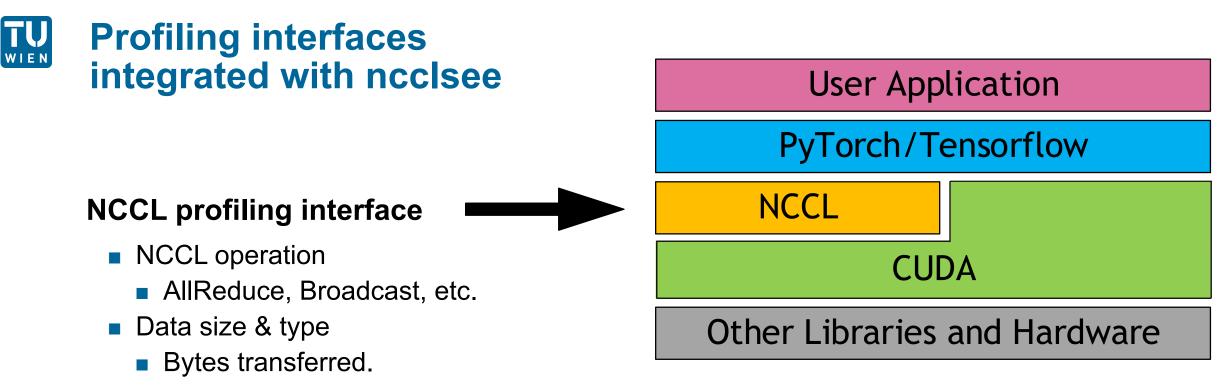


The Challenge: Measuring NCCL Time at Scale

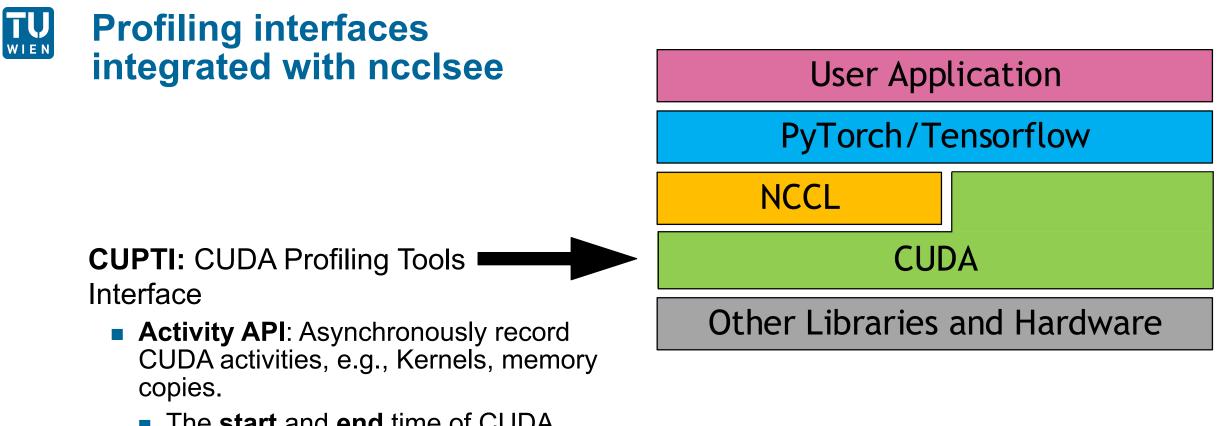
- Inter-GPU communication can impose significant overhead.
- To measure the communication time + time NCCL operations.
 - Existing tool: NVIDIA Nsight Systems.
 - **Tracing**: produces a detailed event timeline.
 - Massive data files (prohibitive at large scales)
 - May introduce high overhead.
 - Distort execution.
 - For large scale runs **profiling** is more suitable:
 - Summarizes the time spent on different operations.
 - Concise, aggregated statistics.
 - Light overhead and smaller data files.

Introducing ncclsee: Lightweight NCCL Profiling

- Key Features & Approach:
 - Profiling: Aggregated statistics (call counts, average duration per NCCL operation).
 - Categorizes NCCL operations by buffer size (buckets).
 - **Low overhead**: Minimize impact on application performance.
 - Smaller data files suited for large-scale runs.
 - Interfaces with:
 - NCCL's built-in profiling interface.
 - CUPTI (CUDA Profiling Tools Interface) for timing CUDA kernels related to NCCL operations.

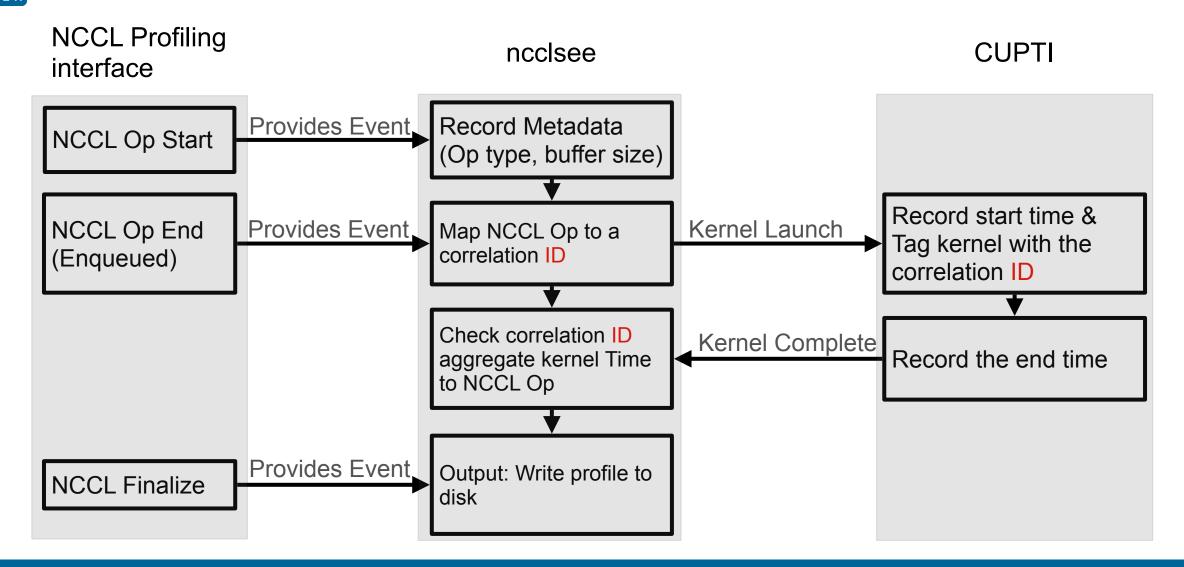


- integer, float, bfloat16, etc.
- Asynchronous operations: Only provides the time until the NCCL operation is enqueued.
- **Missing:** The actual time to execute the operation (CUDA kernel).



- The start and end time of CUDA kernels.
- External Correlation API: Correlating NCCL operations with CUDA events

ncclsee: Combining NCCL profiling interface and CUPTI

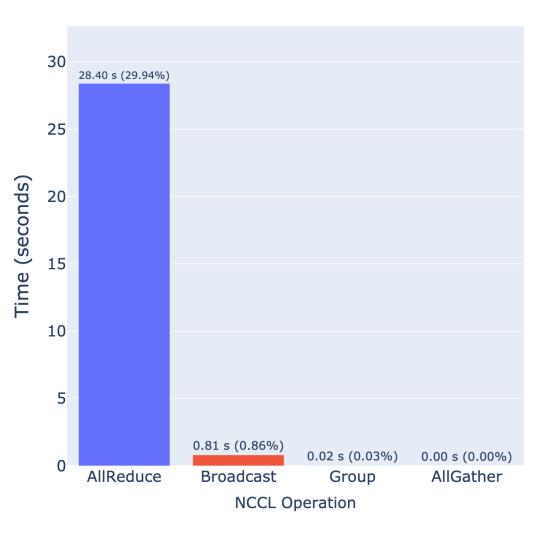




Profiling with ncclsee: ResNet50 training with PyTorch on two NVIDIA Tesla T4 GPUs

- Aggregate times among operations
- Despite only running with 2 GPUs, the time spent in NCCL operations is still significant.
 - AllReduce 30% of the total application time.
 - Broadcast is less than 1%.

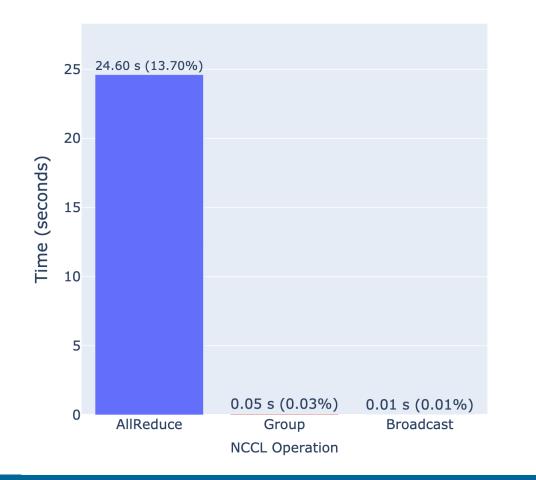




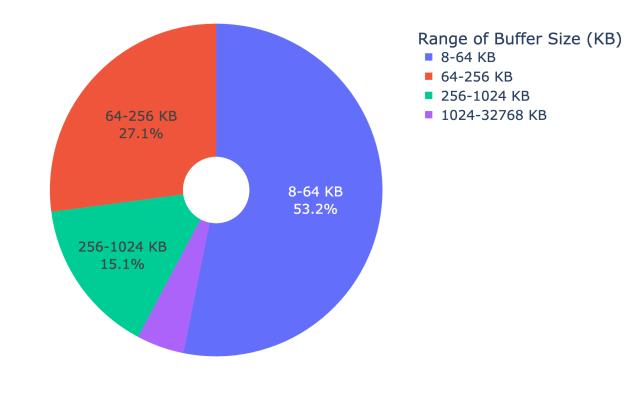


Profiling with ncclsee: ResNet50 training with Tensorflow+horovod on two NVIDIA Tesla T4 GPUs

NCCL Operations Time Breakdown (Total App: 179.58s)









- Measuring Inter-GPU communication at scale is challenging.
 - **Tracing**: produces a detailed event timeline but higher overhead.
 - **Profiling**: more lightweight providing concise, aggregated statistics.
- **ncclsee** a lightweight NCCL profiler:
 - Times NCCL collectives (incl. GPU kernels).
 - Statistics per range of buffer size.
- Al training:
 - Profile of ResNet50 training using either PyTorch or Tensorflow.
 - Identify optimization opportunities for NCCL operations.



Thank you!



ncclsee is under development and hosted on GitHub: <u>https://github.com/variemai/ncclsee</u>

NCCL on GitHub: <u>https://github.com/NVIDIA/nccl</u>

CUPTI: https://docs.nvidia.com/cupti/overview/overview.html

