Benchmarking MPI for Deep Learning and HPC Workloads

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Benchmarking in the Data Center: Expanding to the Cloud
Febuary 25th 2023

Outline

Introduction
- Open MPI + UCX

Benchmarking for MPI-Based Deep Learning
- RMA and Collective Communication Design
- Micro-Benchmarks
- Application Results

Benchmarking for MPI-Partitioned Communication
- MPI Partitioned Point-to-Point Communication
- Overhead
- Perceived Bandwidth
- Sweep3D Communication Pattern

Conclusion And Future Work

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  - Communication is one of the main bottlenecks in applications
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- The Message Passing Interface (MPI)
  - Popular parallel programming model in HPC
  - Provides multiple communication APIs
    - Point-to-point
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    - RMA
    - Collective Communication (`MPI_Allreduce`, `MPI_Bcast`, etc.)

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- MPI based Deep Learning on HPC systems
  - As the complexity of DL models grow we move towards using the aggregate power of HPC systems

Open MPI + UCX

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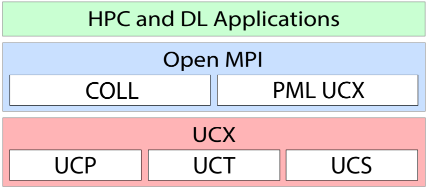
  - Point-to-point implemented upon RMA Put/Get operations



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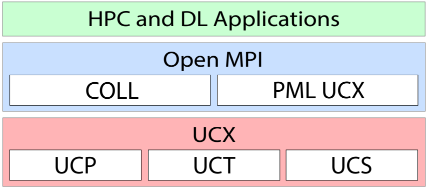

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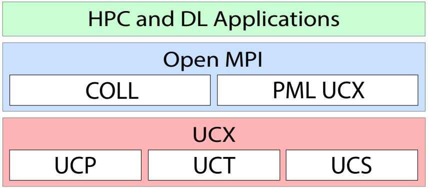


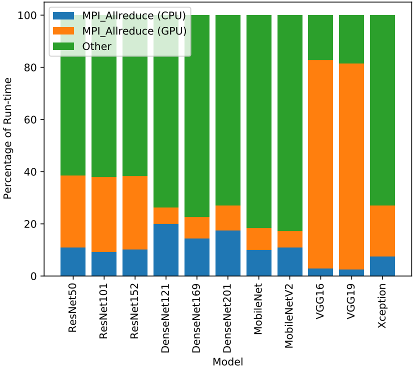
Research Goals

- Improve the performance of GPU MPI communication for Deep Learning
- Obtain a better understanding of the MPI Partitioned Interface

Benchmarking for MPI-Based Deep Learning

MPI-based Deep Learning

- Distributed Deep Learning using Horovod is possible with models from:



Impact of MPI_Allreduce on a single IBM AC922 node

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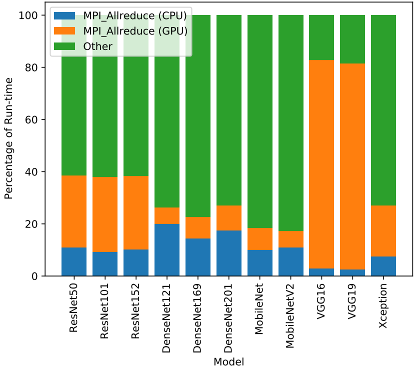

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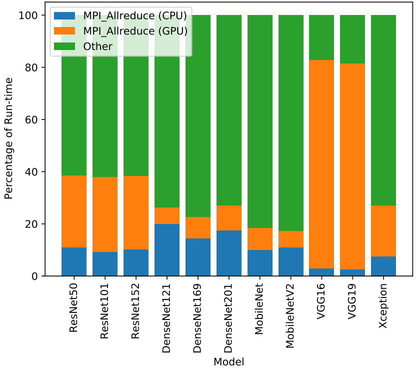

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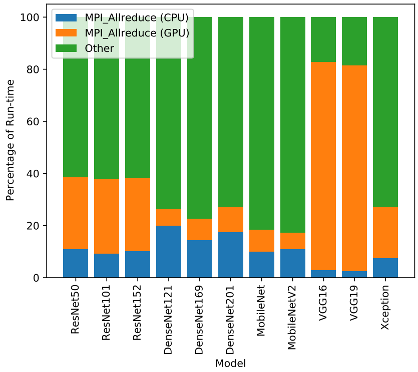

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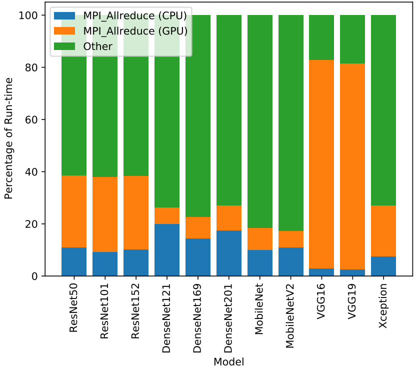
  - Up to 80% of runtime was spent in a GPU based `MPI_Allreduce`



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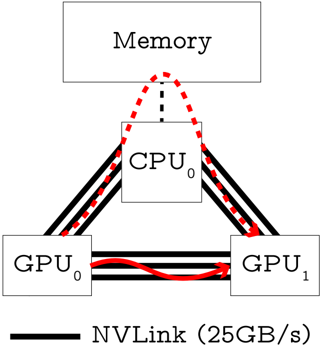

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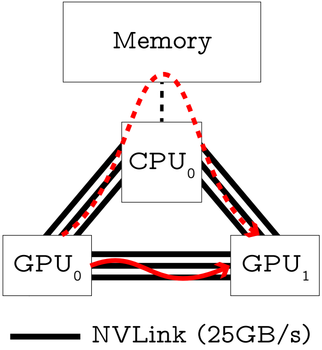

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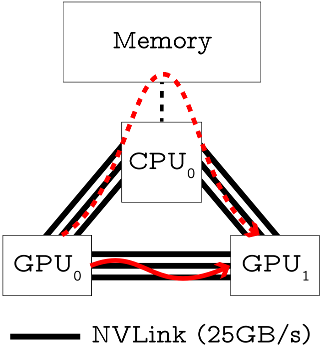

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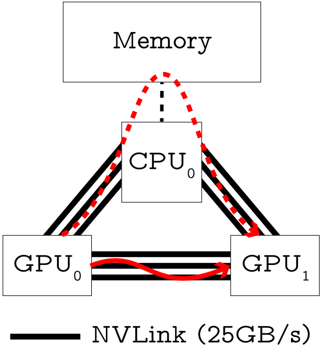

Research Question

Can we design a mechanism to use all communication paths?

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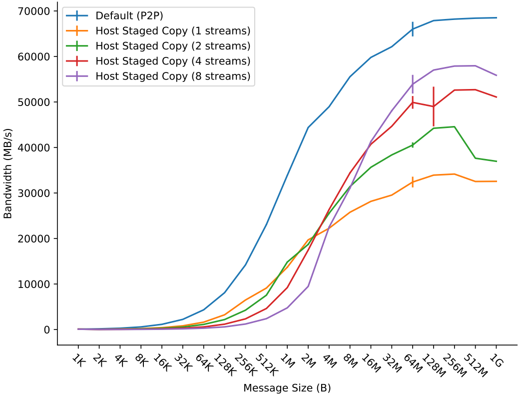
- We used the `ucx_perftest` micro-benchmarks to assess the viability of our design idea



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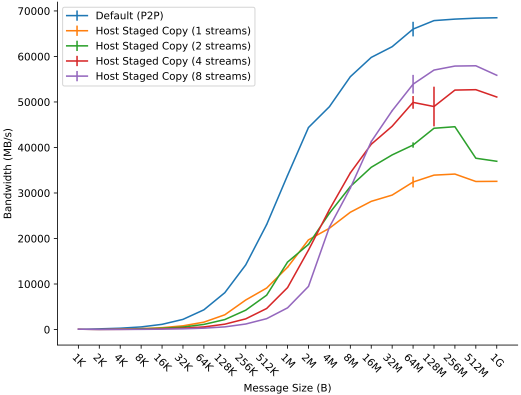

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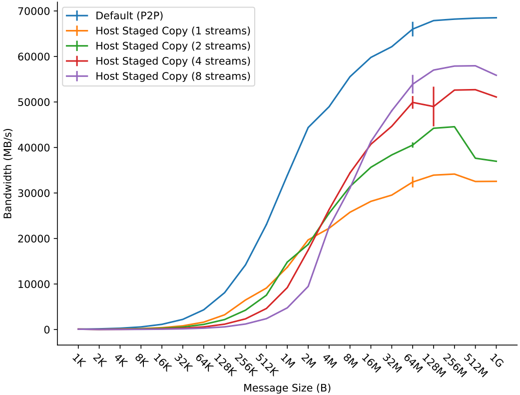

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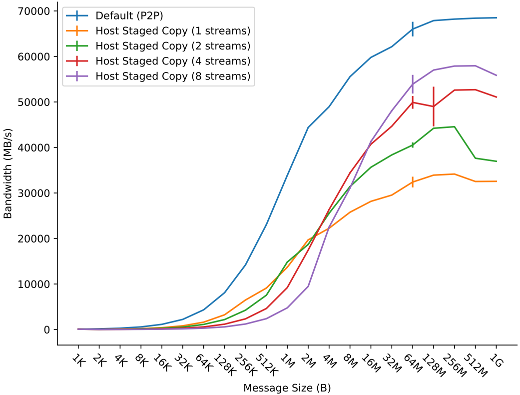

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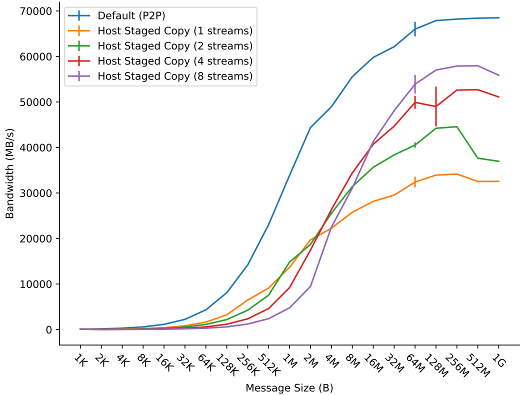

Hierarchical Allreduce with Multi-Path Copy

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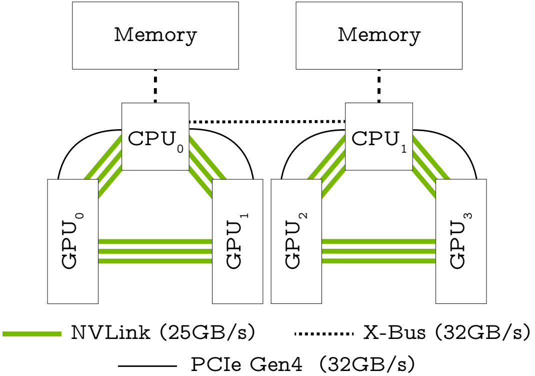

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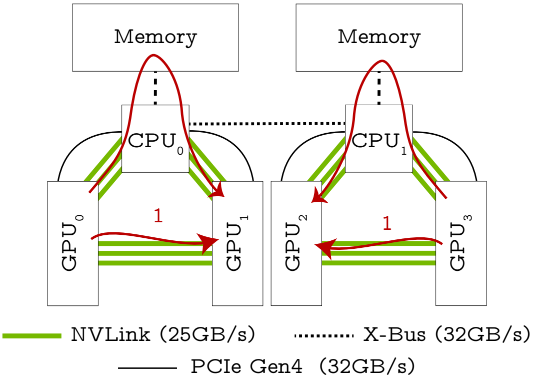

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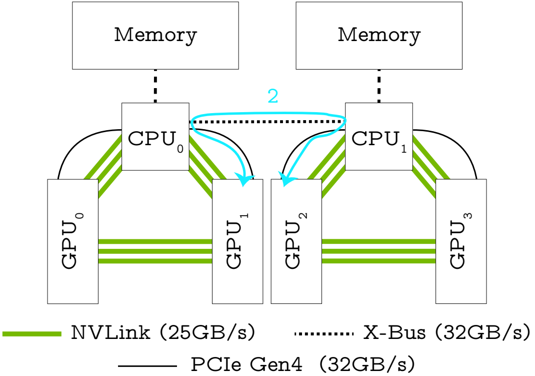

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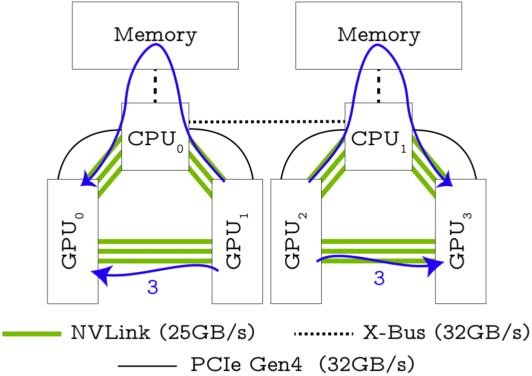

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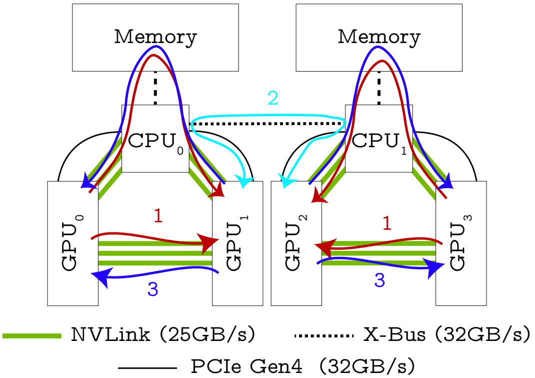

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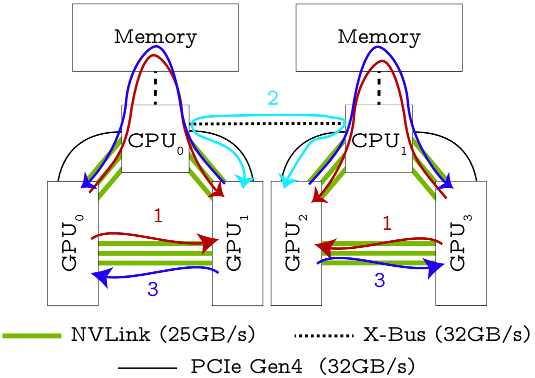

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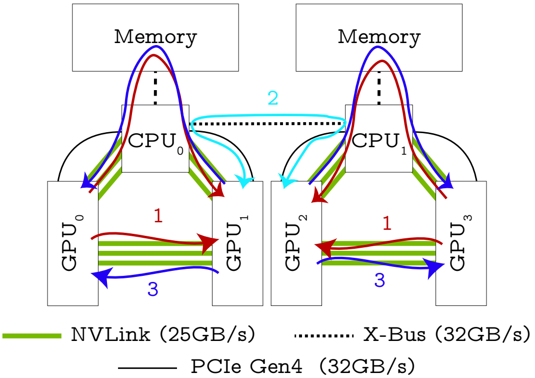

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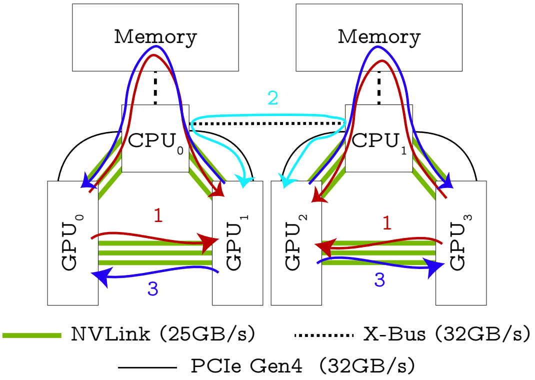

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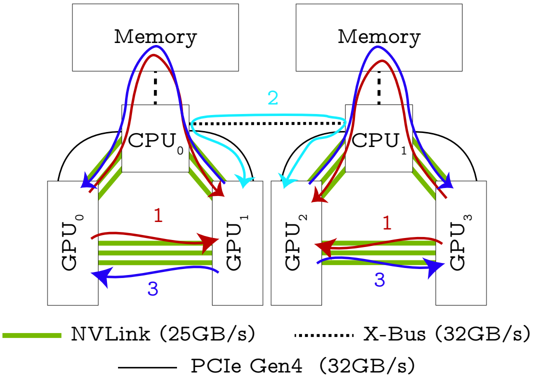
    - Minimise intra-socket congestion



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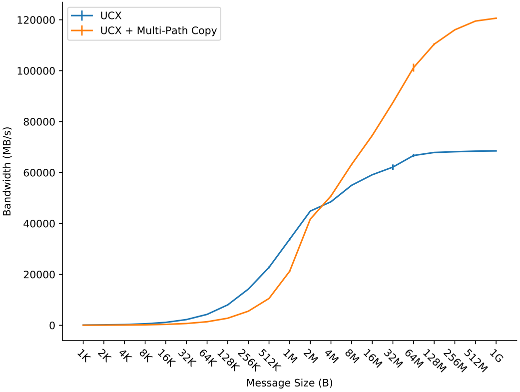
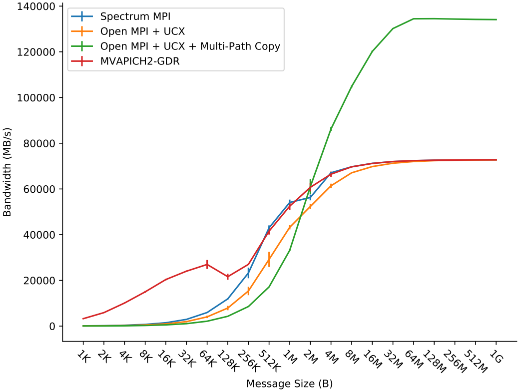
  - UCX 1.8.0
  - Open MPI + HPC-X v2.7
  - Spectrum-MPI 10.3.1
  - MVAPICH2-GDR 2.3.5
  - NCCL 2.5.6
  - Horovod 0.20.3
  - TensorFlow 1.15.2

ADVANCED RESEARCH COMPUTING at the UNIVERSITY OF TORONTO

UCX Put and MPI Point-to-Point Results



UCX Put Bandwidth



MPI Unidirectional Bandwidth

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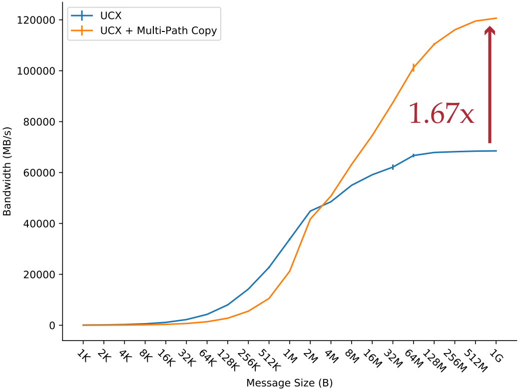

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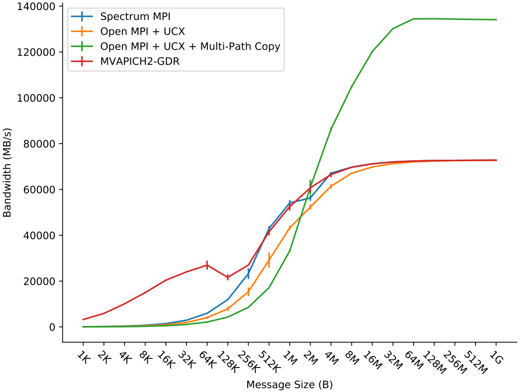

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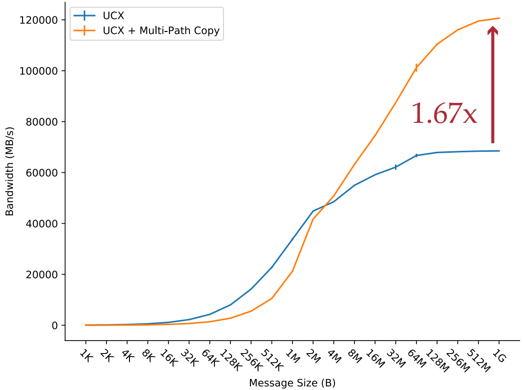

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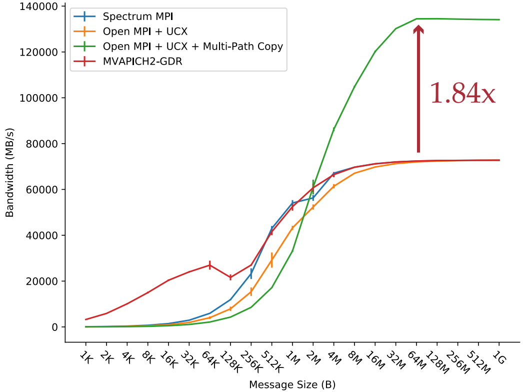

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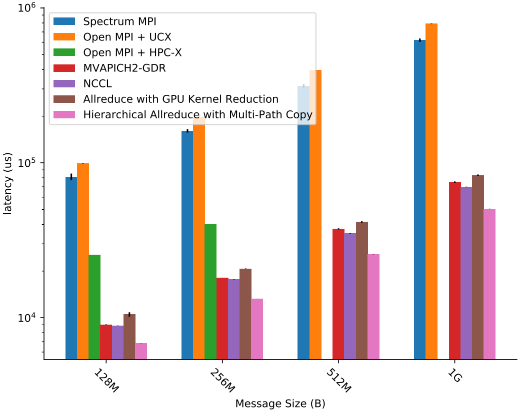
MPI_Allreduce OSU Microbenchmark Results



MPI_Allreduce latency on 4 GPUs for very large message sizes

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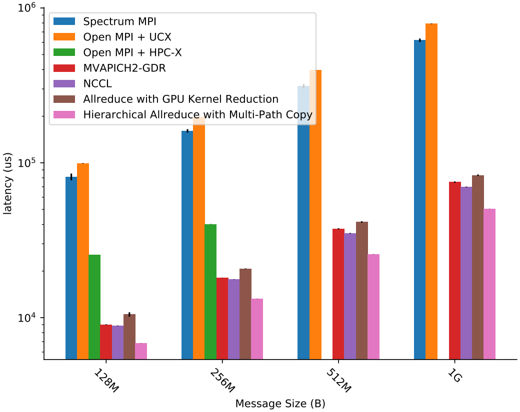

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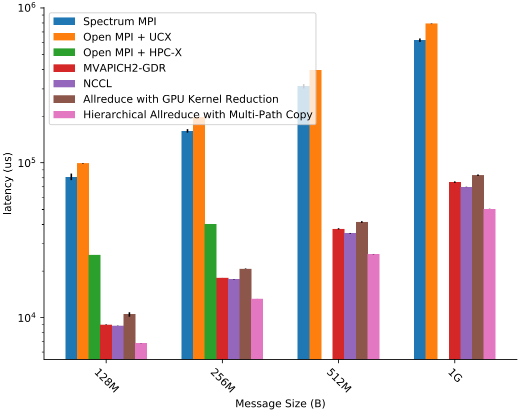

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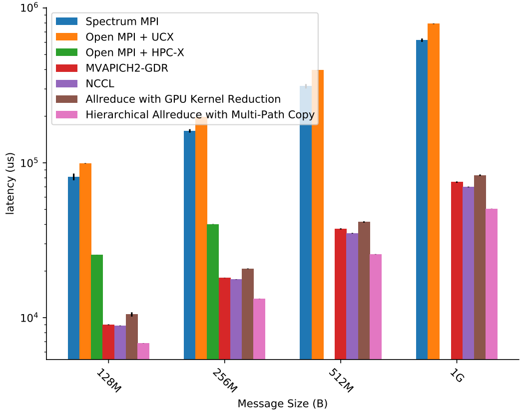

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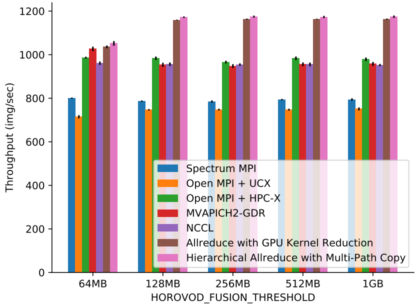
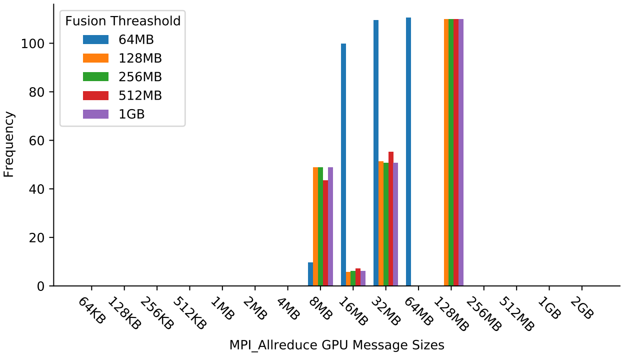
Application Results

- ResNet50 up to 1.56x speedup



Synthetic Horovod + TensorFlow benchmarks for ResNet50



GPU Message Sizes for different `HOROVOD_FUSION_THREASHOLD`

Application Results

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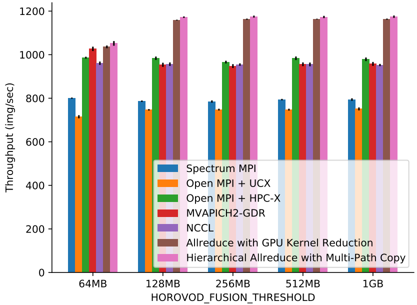
- Modifying fusion threshold increases message sizes to 128MB



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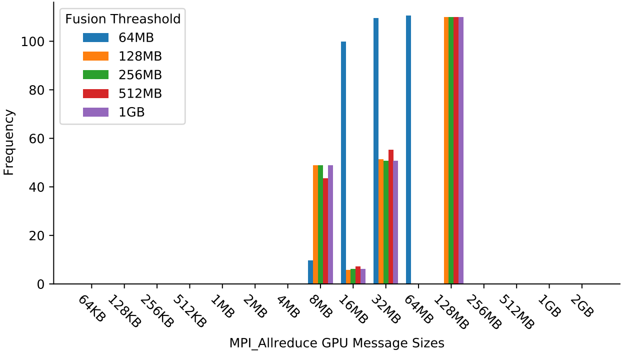

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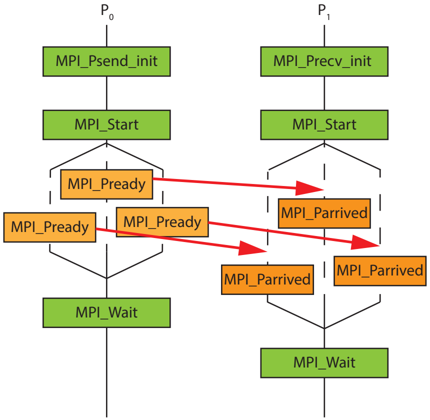

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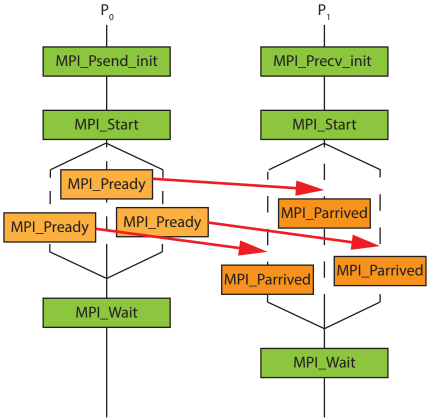

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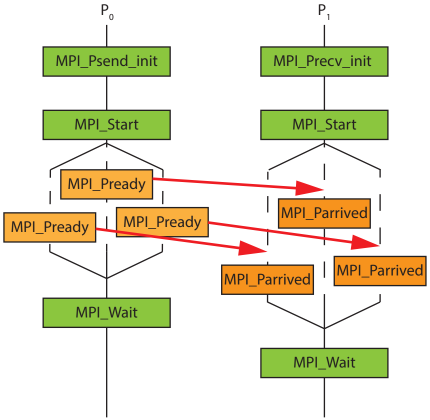

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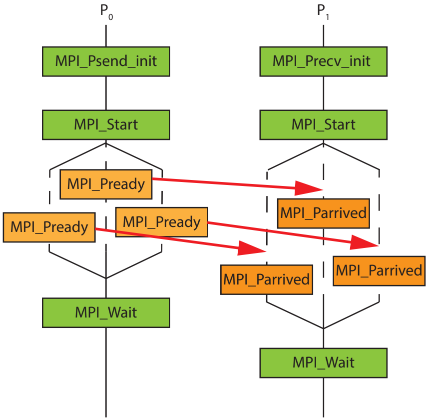

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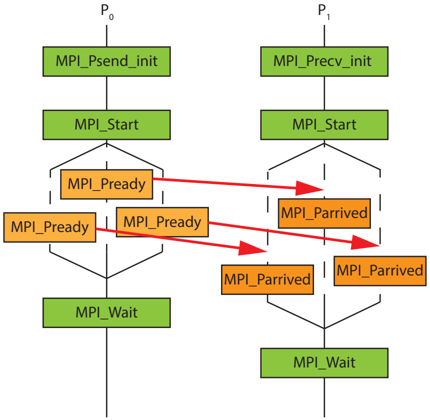
  - Message matching occurs here
  - MPI Partitioned does not accept wildcards
- `MPI_Start` is called to start communication
- A parallel for loop is launched
  - Work is Computed
  - Once data is ready, `MPI_Pready` is called
  - Optionally, `MPI_Parrived` to check if incoming data has arrived



MPI Partitioned Point-to-Point Communication

- `MPI_Psend_init/MPI_Precv_init` is used to initialize communication between processes
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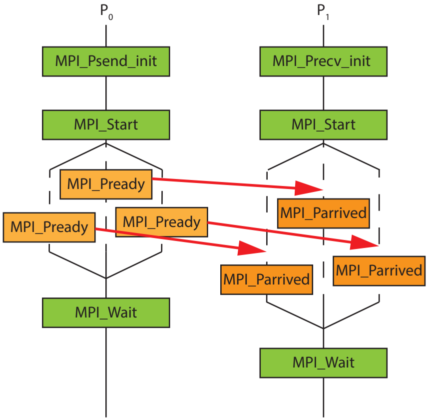

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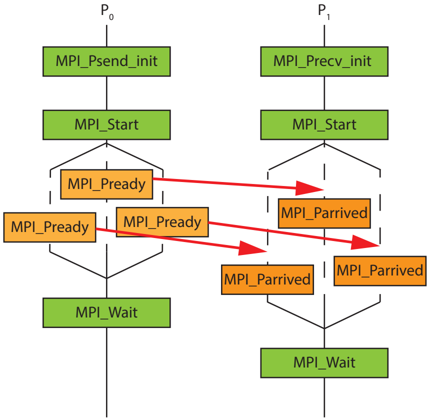

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Can we design an MPI Partitioned Micro-benchmark to address the following:

- How can we understand the behaviour and performance of MPI Partitioned?
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- What are appropriate partition sizes for application developers to use?

Experiment Setup

- Niagara Supercomputer at SciNet[1]
  - 2x 20 Core Intel Skylake at 2.4GHz
  - EDR InfiniBand Network
  - GNU/Linux - CentOS 7.6
  - Open MPI (master branch)
  - UCX v1.11.0
  - MPIPCL

[1]SciNet is funded by: the Canada Foundation for Innovation; the Government of Ontario; Ontario Research Fund - Research Excellence; and the University of Toronto This research was enabled in part by support provided by the Digital Research Alliance of Canada

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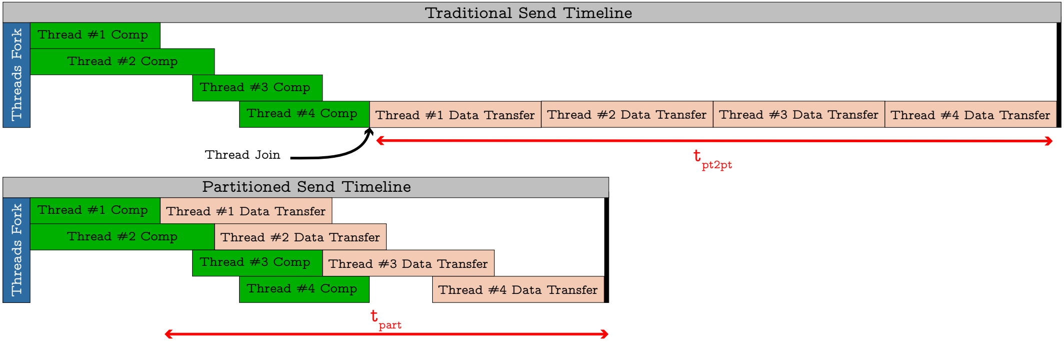

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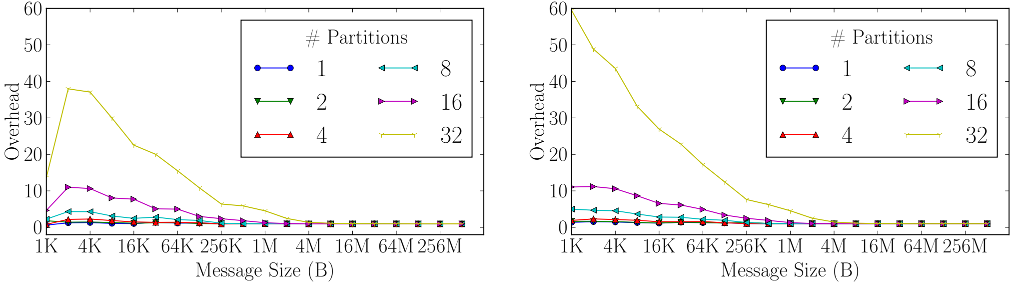


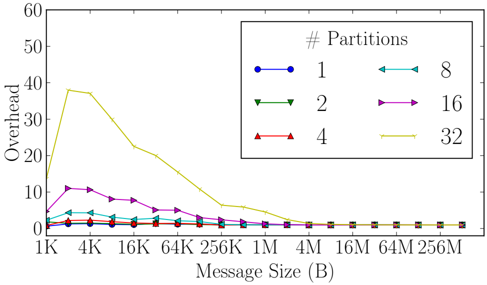
(a) Cold Cache

(b) Hot Cache

Overhead of Partitioned Point-to-Point Communication Relative to Point-to-Point Communication for 10ms of Compute

Overhead Results

- Partition count correlates with overhead



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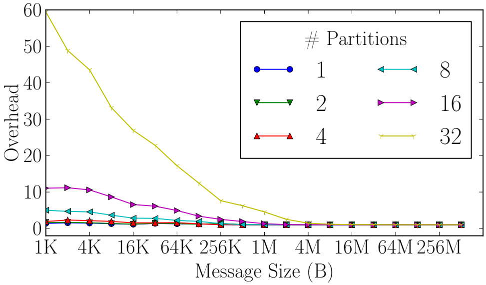

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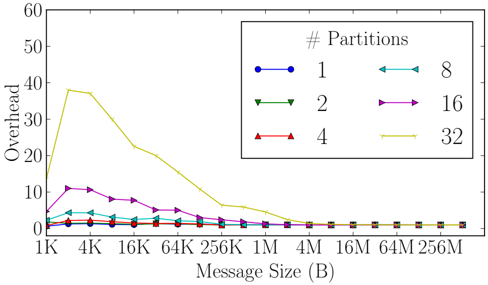

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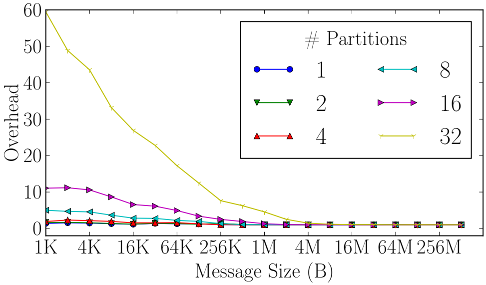

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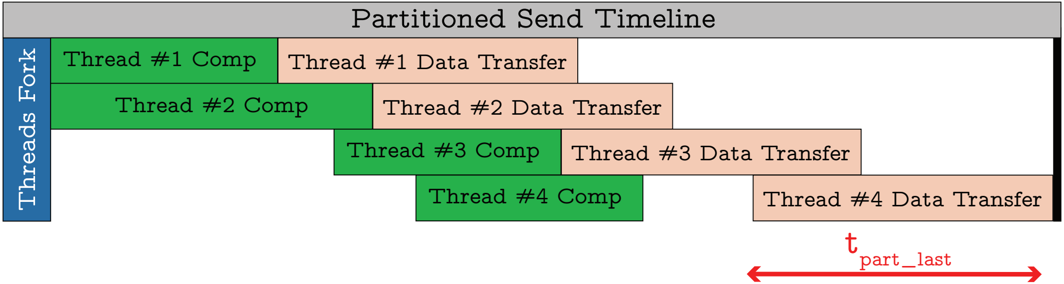

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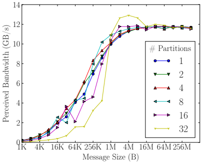

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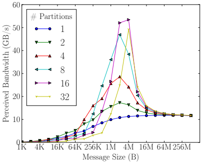

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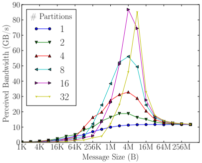

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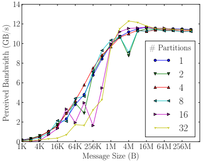

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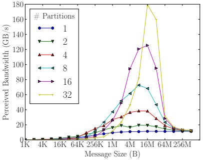

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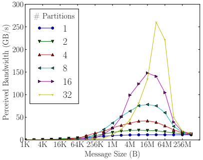

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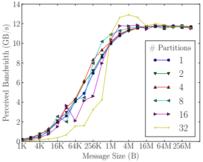

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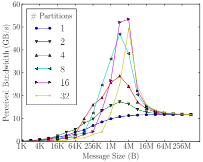

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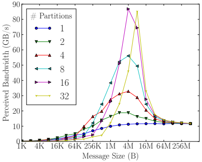

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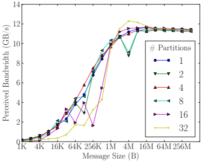

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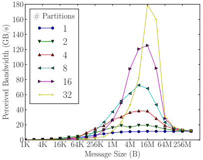

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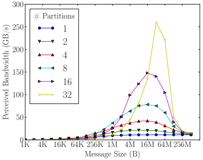

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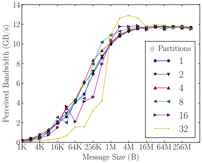

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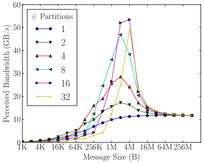

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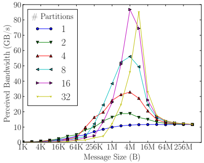

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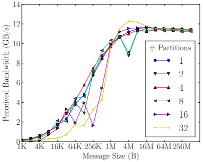

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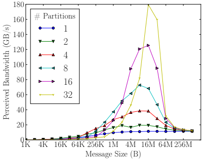

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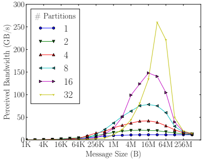

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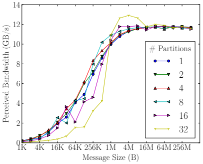

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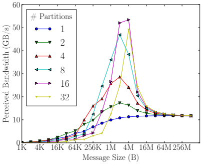

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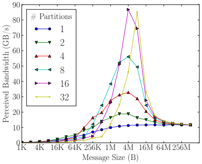

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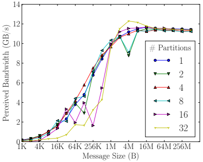

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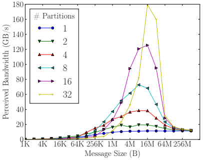

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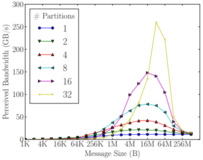

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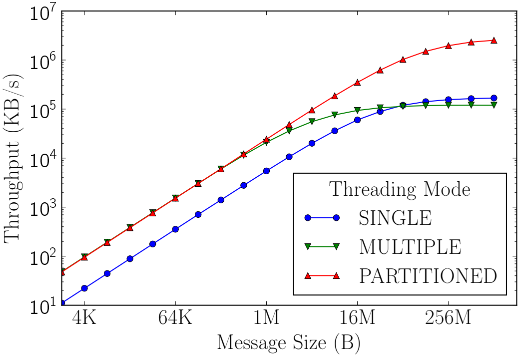

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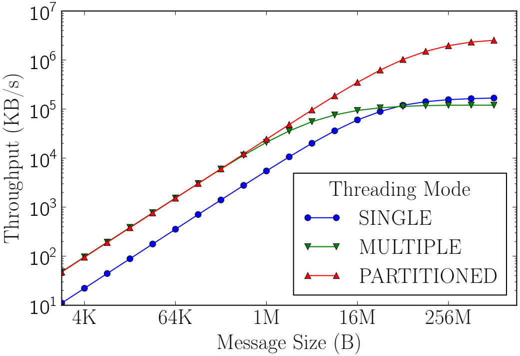

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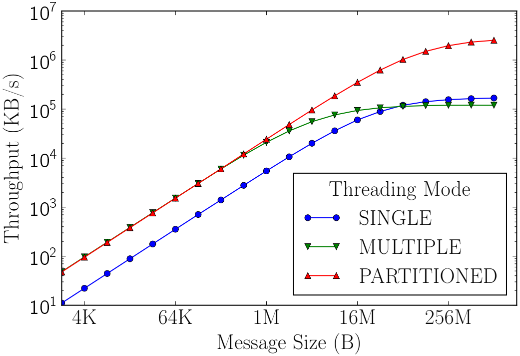

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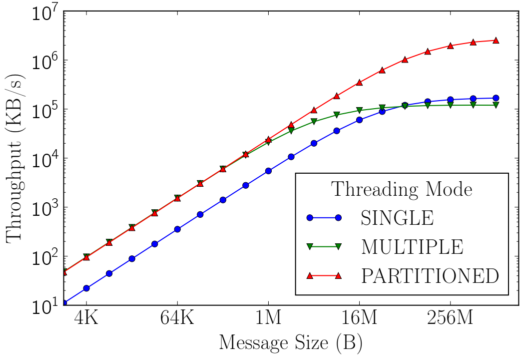

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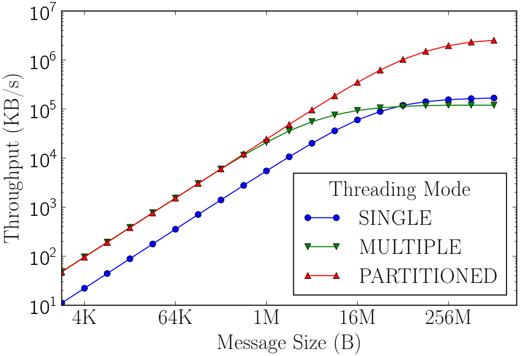

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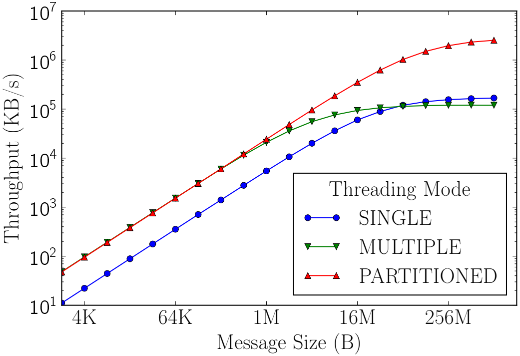

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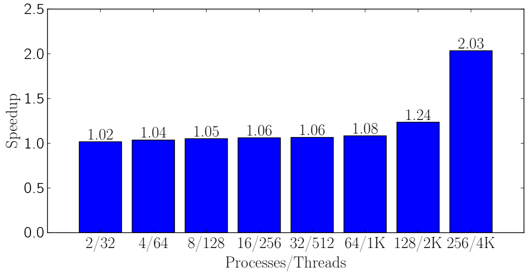

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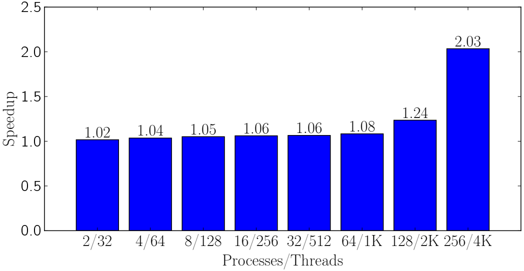

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- SNAP uses a Sweep3D communication
  - We profiled SNAP's communication
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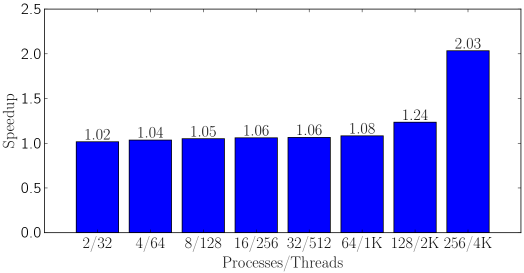

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Thank You!

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