Efficient Multi-Path NVLink/PCIe-Aware UCX based Collective Communication for Deep Learning

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Outline

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- HPC is used to solve large complex problems in many domains
  - Communication is one of the main bottlenecks in applications
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  - Provides multiple communication APIs
    - Point-to-point
    - Partitioned point-to-point
    - RMA
    - Collective Communication (`MPI_Allreduce`, `MPI_Bcast`, etc.)

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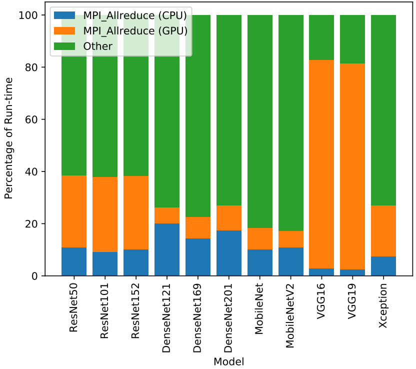
    - Collective Communication (`MPI_Allreduce`, `MPI_Bcast`, etc.)
- MPI based Deep Learning on HPC systems
  - As the complexity of DL models grow we move towards using the aggregate power of HPC systems

MPI-based Deep Learning

- Distributed Deep Learning Using Horovod is one of the most popular training method.



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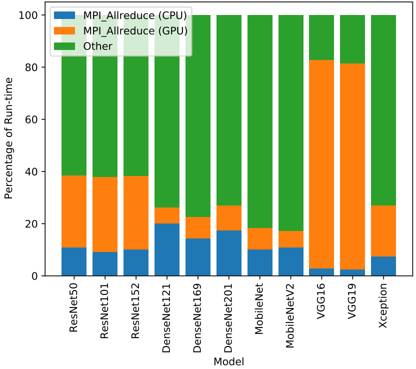

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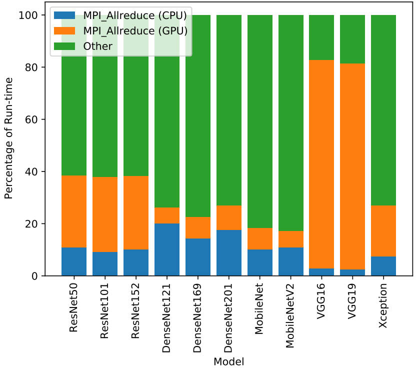

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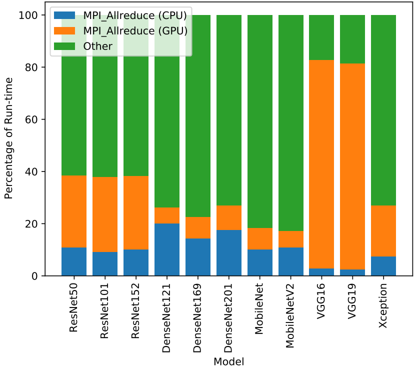

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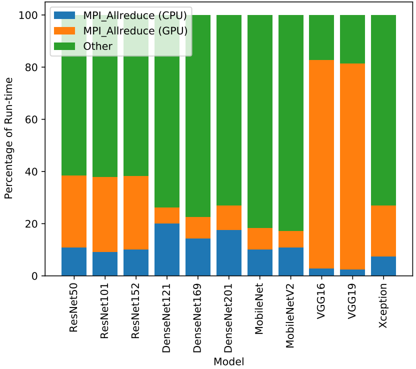

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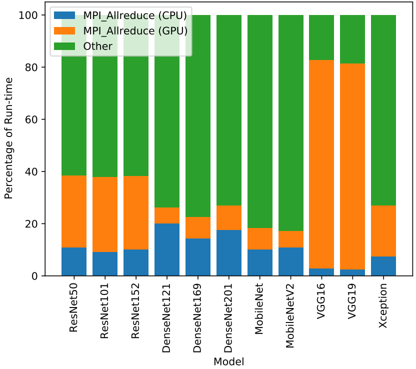
- MPI communication is a major bottleneck in these applications



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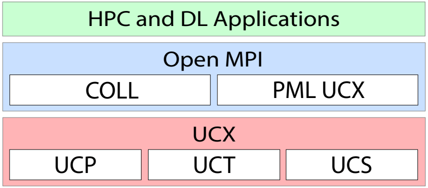

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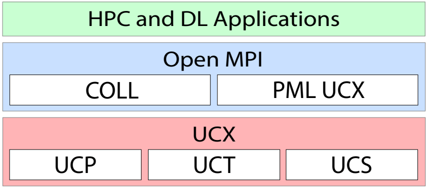

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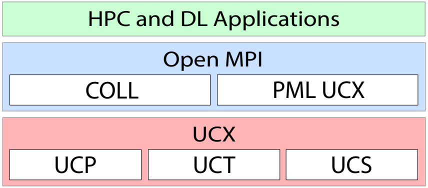
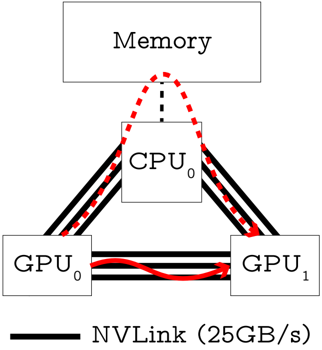


Research Goal

- Improve the performance of Deep Learning applications
- Enhance point-to-point and collective communication for MPI's large GPU messages

Multi-Path Copy Motivation

- Currently data transfers between GPUs, send the data directly between devices using a zero copy put operation in UCX.
  - (As shown by the solid red line)



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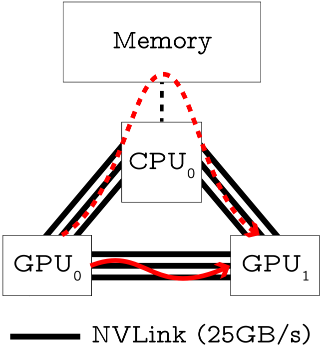

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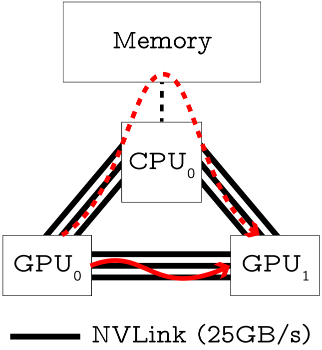

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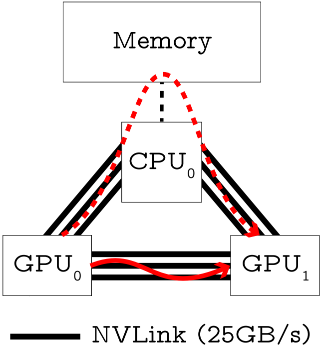

Research Question

Can we design a mechanism to use all communication paths?

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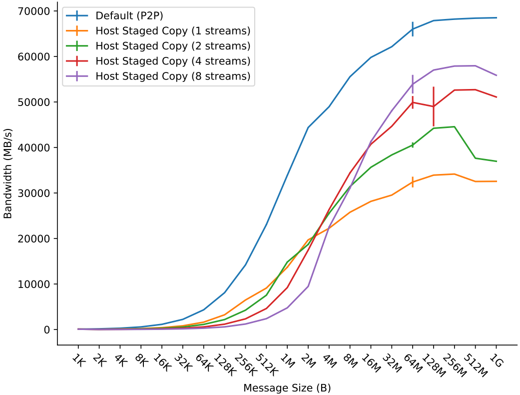

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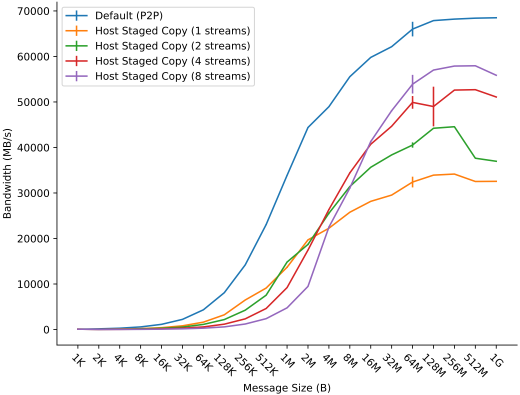

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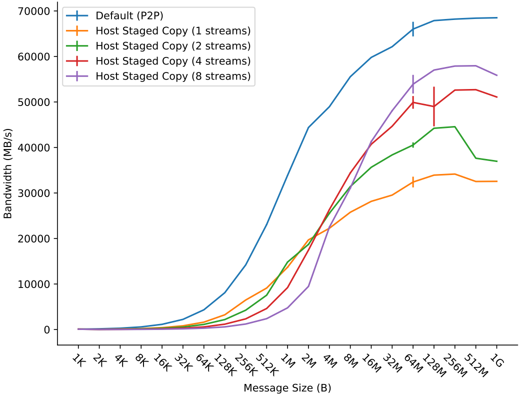

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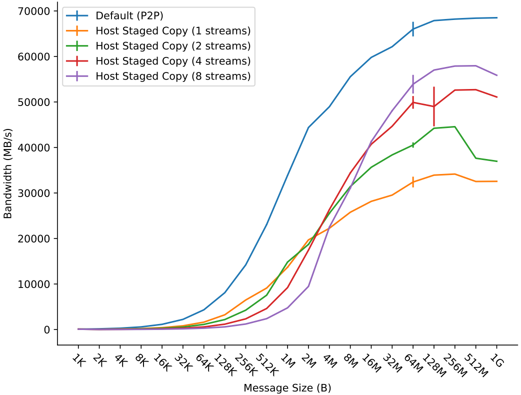

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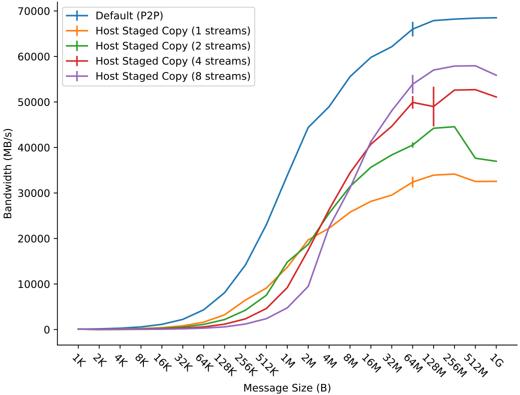
- Good potential for our Multi-Path design



Multi-Path Copy Design

Algorithm: Multi-Path Copy Algorithm

Input: sbuf, host_buf, data_size, host_share, n_host_streams
Output: dbuf

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host_dsize = data_size * host_share;
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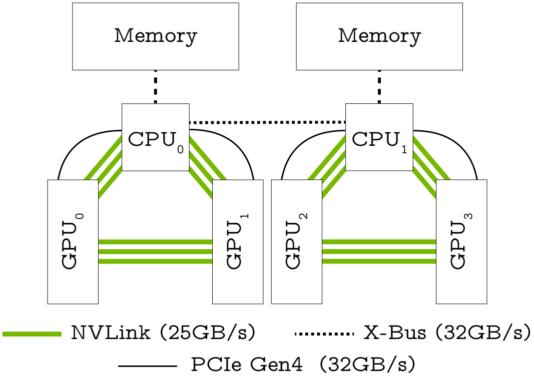

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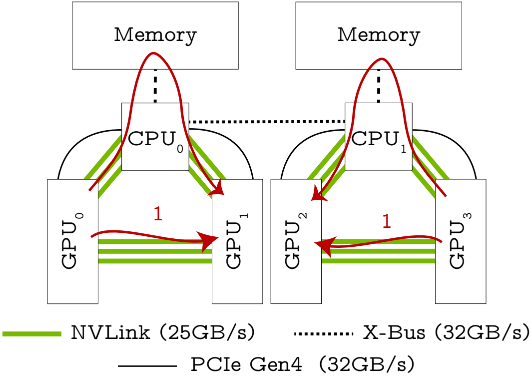

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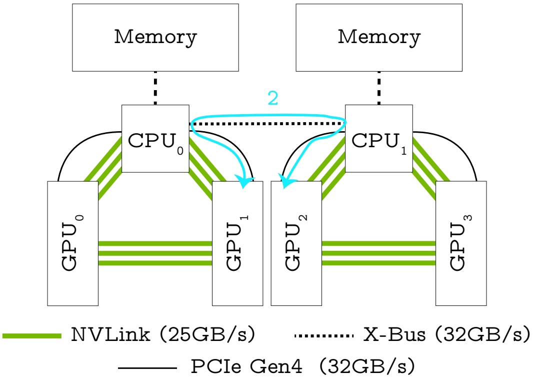

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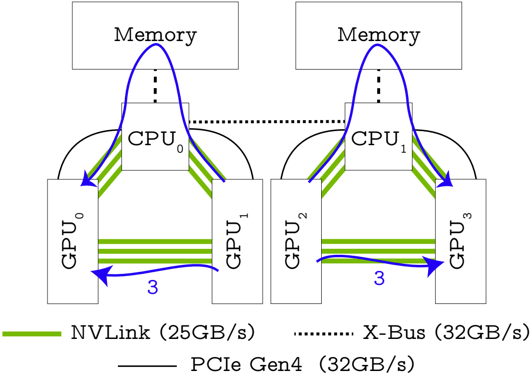

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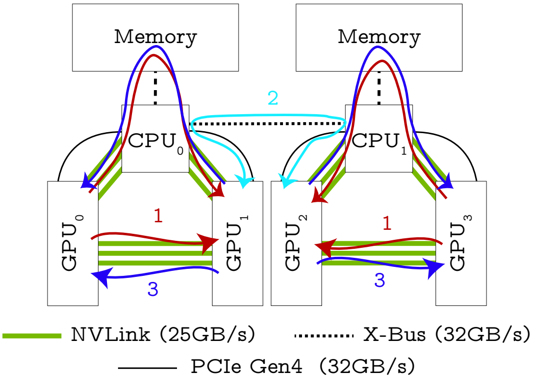

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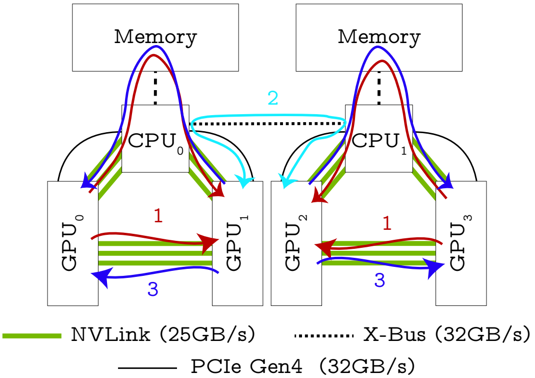

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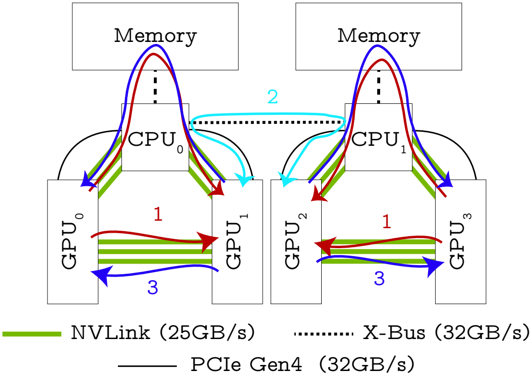

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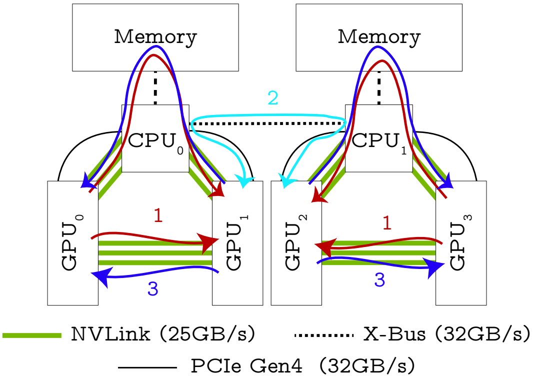

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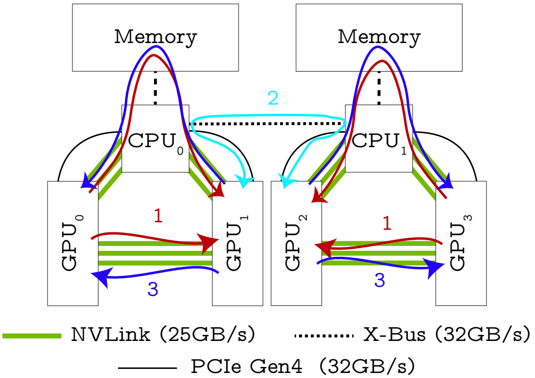

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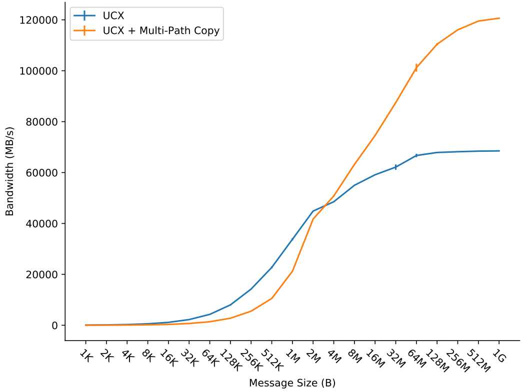
  - UCX 1.8.0
  - Open MPI + HPC-X v2.7
  - Spectrum-MPI 10.3.1
  - MVAPICH2-GDR 2.3.5
  - NCCL 2.5.6
  - Horovod 0.20.3
  - TensorFlow 1.15.2

UCX Put and MPI Point-to-Point Results



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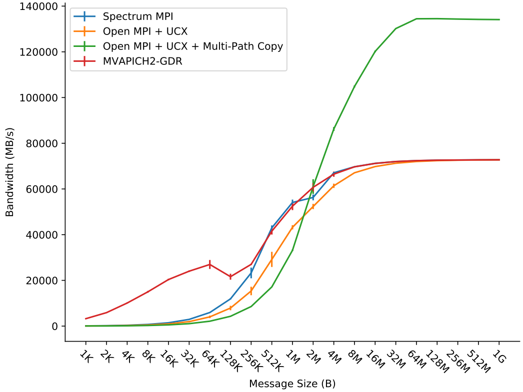

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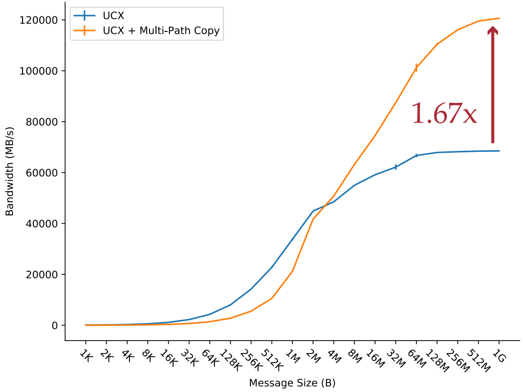

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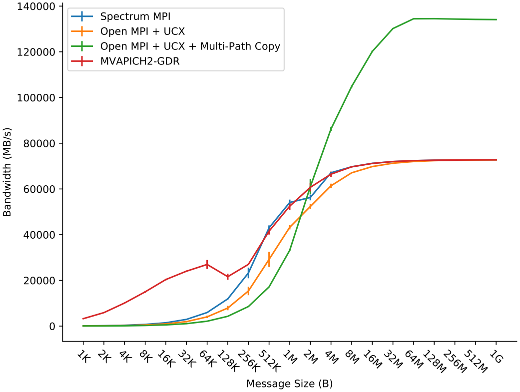

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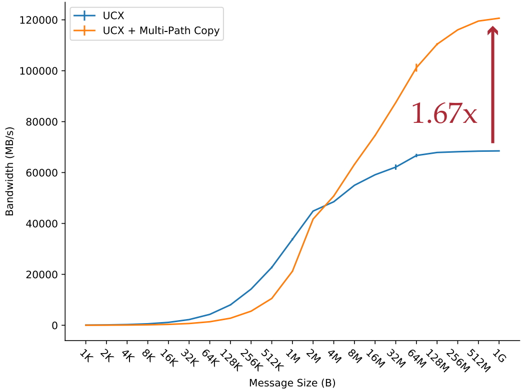

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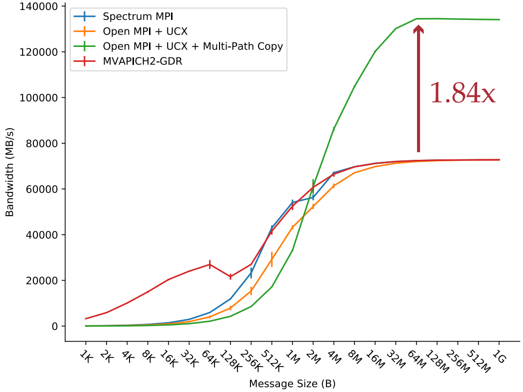

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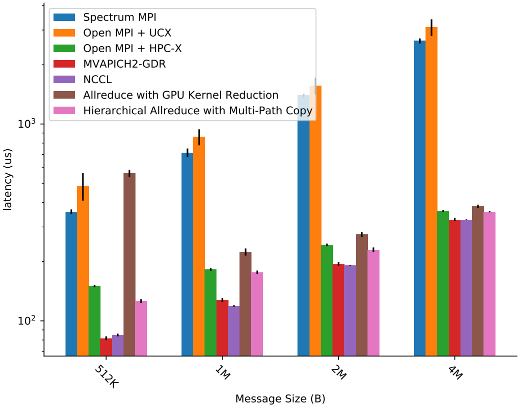

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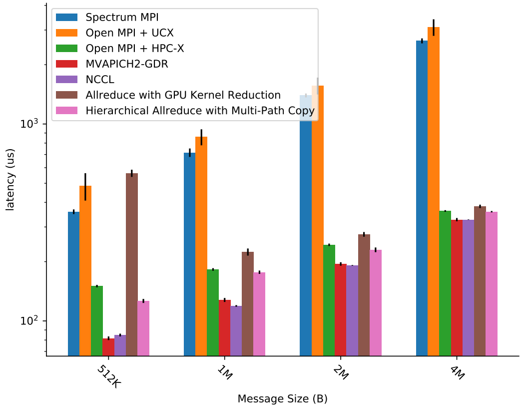

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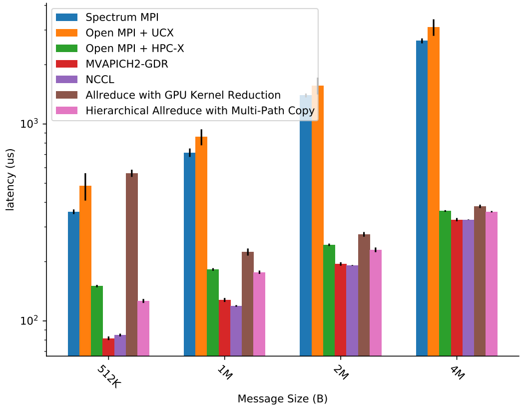

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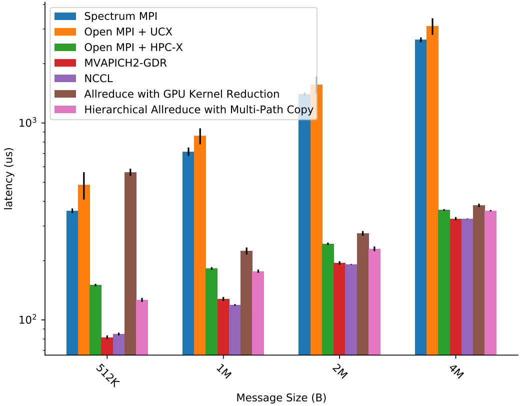

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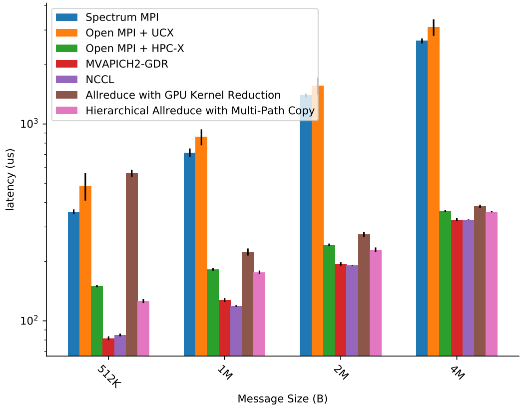
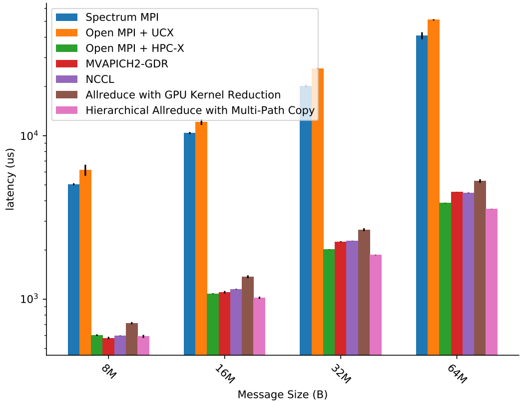


`MPI_Allreduce` latency on 4 GPUs for medium to large message sizes

- 2.75x speedup over Open MPI + UCX at 1MB
- 2.03x speedup over Spectrum MPI at 1MB
  - We suspect a host-staged implementation of Spectrum MPI
- Comparable performance to Open MPI + HPC-X

MPI_Allreduce Results (Large Message Sizes)



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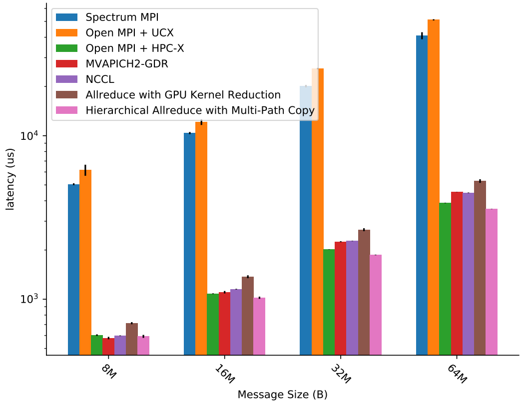

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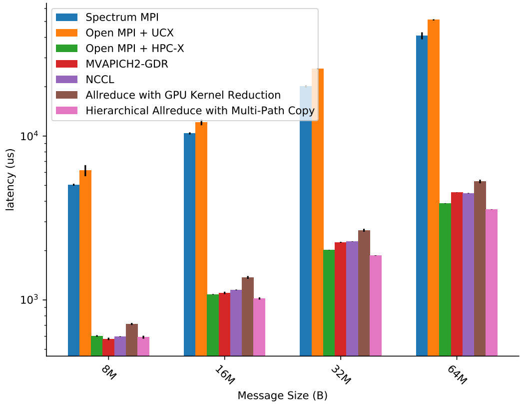

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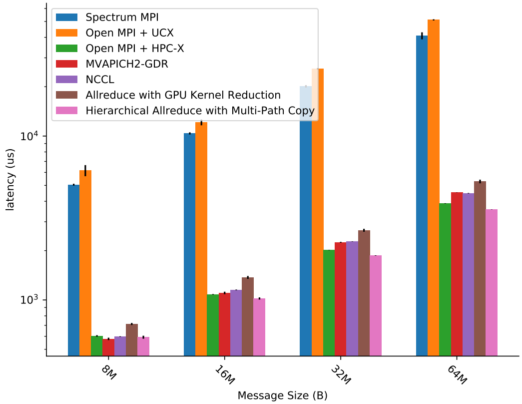
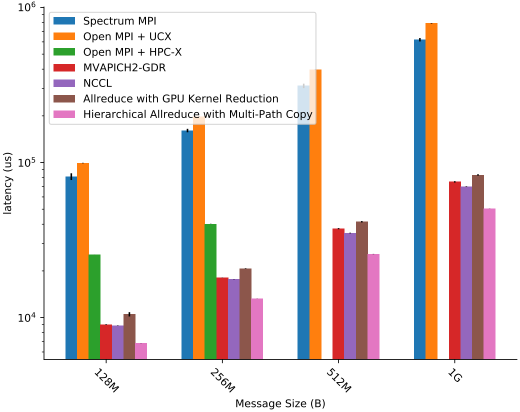


`MPI_Allreduce` latency on 4 GPUs for large message sizes

- Comparable performance to optimised libraries at 8MB
- Outperformed all libraries after 16MB
  - Open MPI + HPC-X by 1.09x
  - MVAPICH2-GDR by 1.26x
  - NCCL by 1.25x

MPI_Allreduce Results (Very Large Message Sizes)



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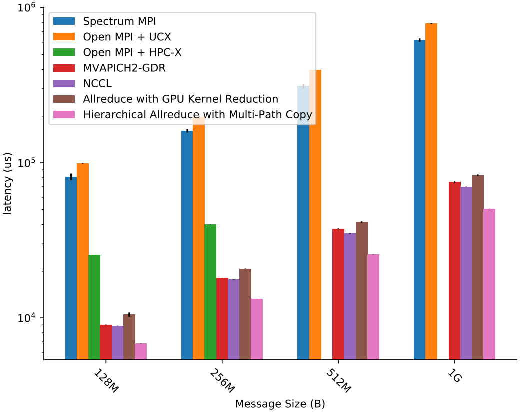
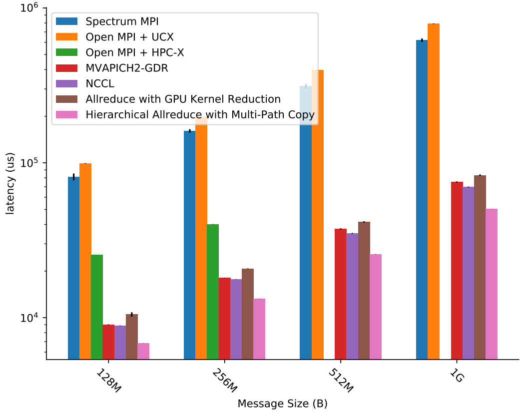


MPI_Allreduce latency on 4 GPUs for very large message sizes

- Much lower latency than Open MPI + HPC-X

MPI_Allreduce Results (Very Large Message Sizes)



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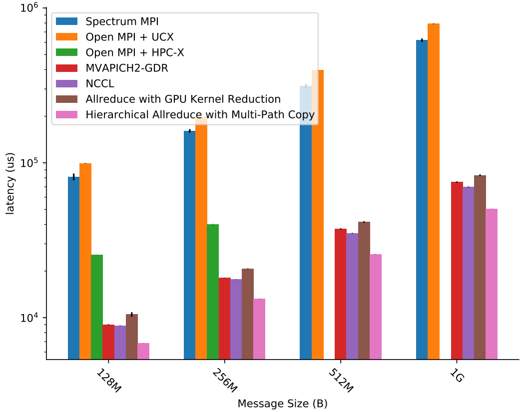
MPI_Allreduce Results (Very Large Message Sizes)

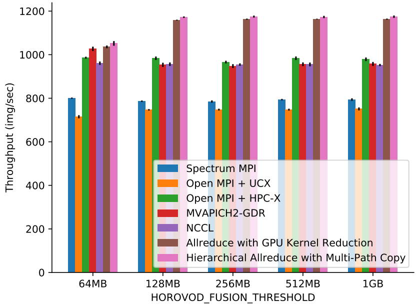


`MPI_Allreduce` latency on 4 GPUs for very large message sizes

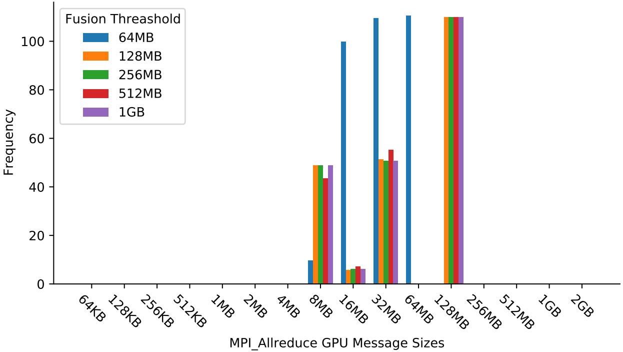
- Much lower latency than Open MPI + HPC-X
- At 1GB we see speedup of:
  - 1.47x over MVAPICH2-GDR
  - 1.38x over NCCL

Application Results (ResNet50)

- ResNet50 up to 1.56x speedup



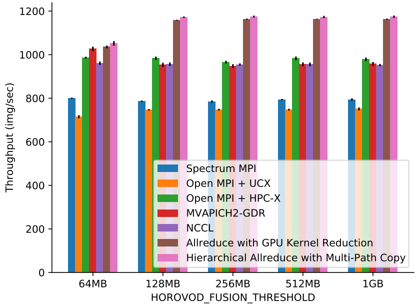
Synthetic Horovod + TensorFlow benchmarks for ResNet50



GPU Message Sizes for different `HOROVOD_FUSION_THREASHOLD`

Application Results (ResNet50)

- ResNet50 up to 1.56x speedup
- Modifying fusion threshold increases message sizes to 128MB



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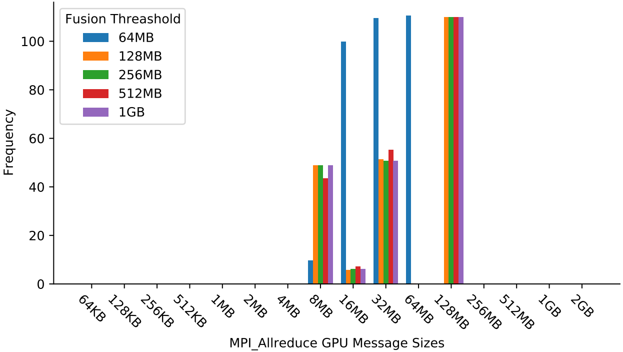
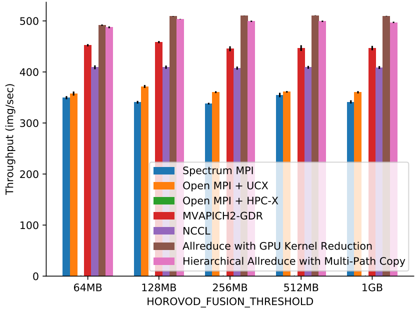


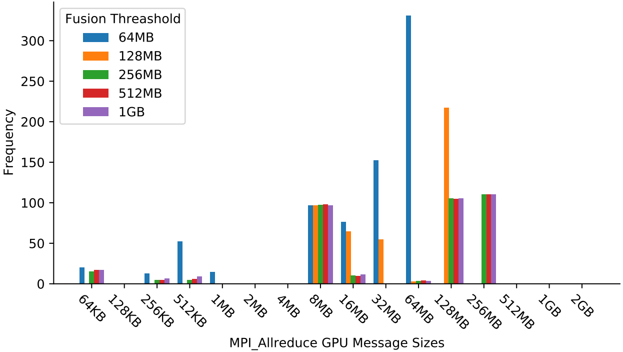
GPU Message Sizes for different `HOROVOD_FUSION_THREASHOLD`

Application Results (ResNet152)

- ResNet152 up to 1.40x speedup



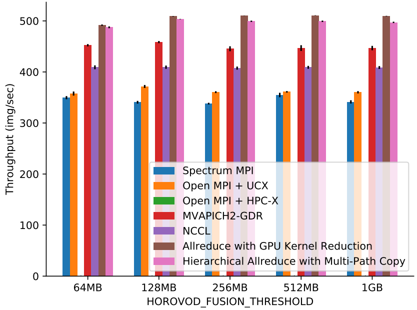
Synthetic Horovod + TensorFlow benchmarks for ResNet152



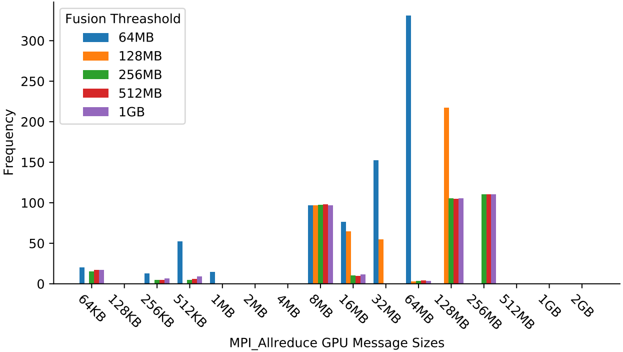
GPU Message Sizes for different `HOROVOD_FUSION_THRESHOLD`

Application Results (ResNet152)

- ResNet152 up to 1.40x speedup
- Modifying fusion threshold increases message sizes to 256MB
  - Also results in smaller messages



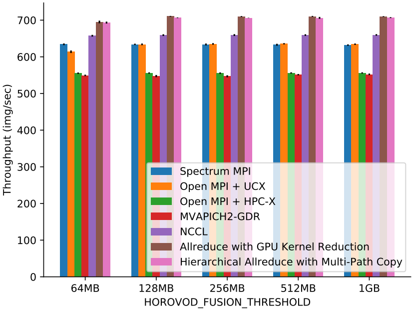
Synthetic Horovod + TensorFlow benchmarks for ResNet152



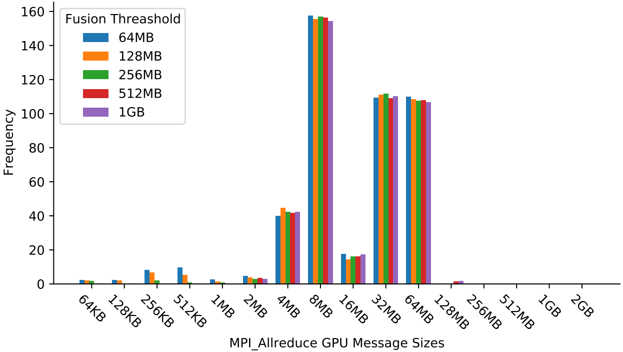
GPU Message Sizes for different `HOROVOD_FUSION_THRESHOLD`

Application Results (DenseNet201)

- DenseNet201 up to 1.26x speedup



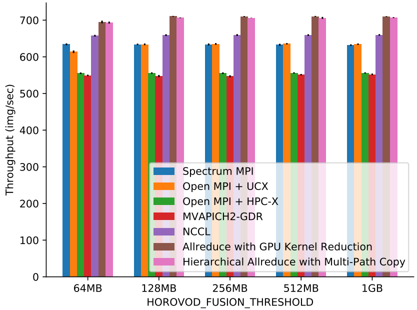
Synthetic Horovod + TensorFlow benchmarks for DenseNet201



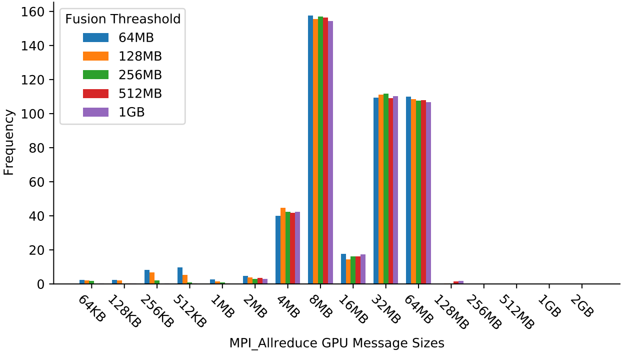
GPU Message Sizes for different `HOROVOD_FUSION_THRESHOLD`

Application Results (DenseNet201)

- DenseNet201 up to 1.26x speedup
- Modifying fusion threshold has minimal impact on message sizes



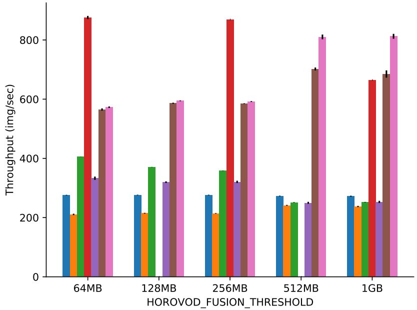
Synthetic Horovod + TensorFlow benchmarks for DenseNet201



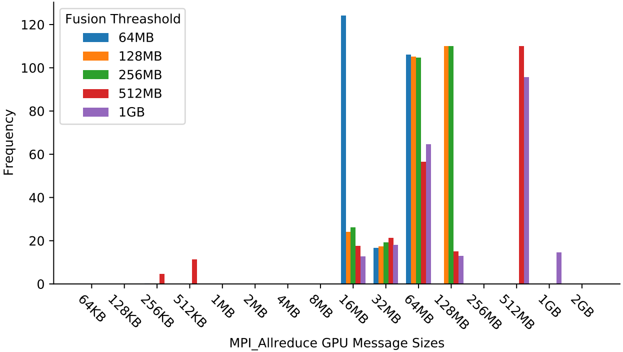
GPU Message Sizes for different `HOROVOD_FUSION_THRESHOLD`

Application Results (VGG16)

- VGG16 up to 3.42x speedup



Synthetic Horovod + TensorFlow benchmarks for VGG16



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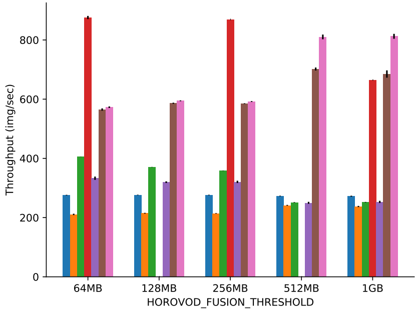
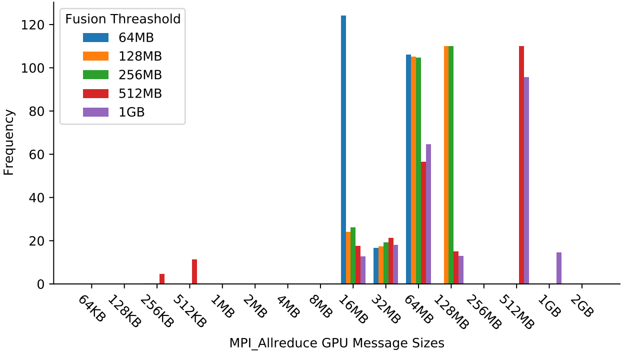
Application Results (VGG16)

- VGG16 up to 3.42x speedup
- Modifying fusion threshold increases message sizes to 1GB



Synthetic Horovod + TensorFlow benchmarks for VGG16



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- For Deep Learning Applications we see up to 3.42x speedup with these proposed ideas

Future Work

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- We would like to study dynamic tuning approaches

Thank You!

Acknowledgements

Queen's University

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ADVANCED RESEARCH COMPUTING at the UNIVERSITY OF TORONTO

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