Accelerating MPI Message Matching and Reduction Collectives For Multi-/Many-core Architectures

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Adaptive and Dynamic Design for MPI Tag Matching

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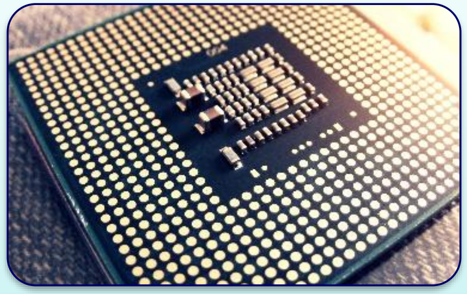
Current Trends in HPC



Supercomputing systems scaling rapidly

- Multi- and Many-core architectures
- High-performance Interconnects

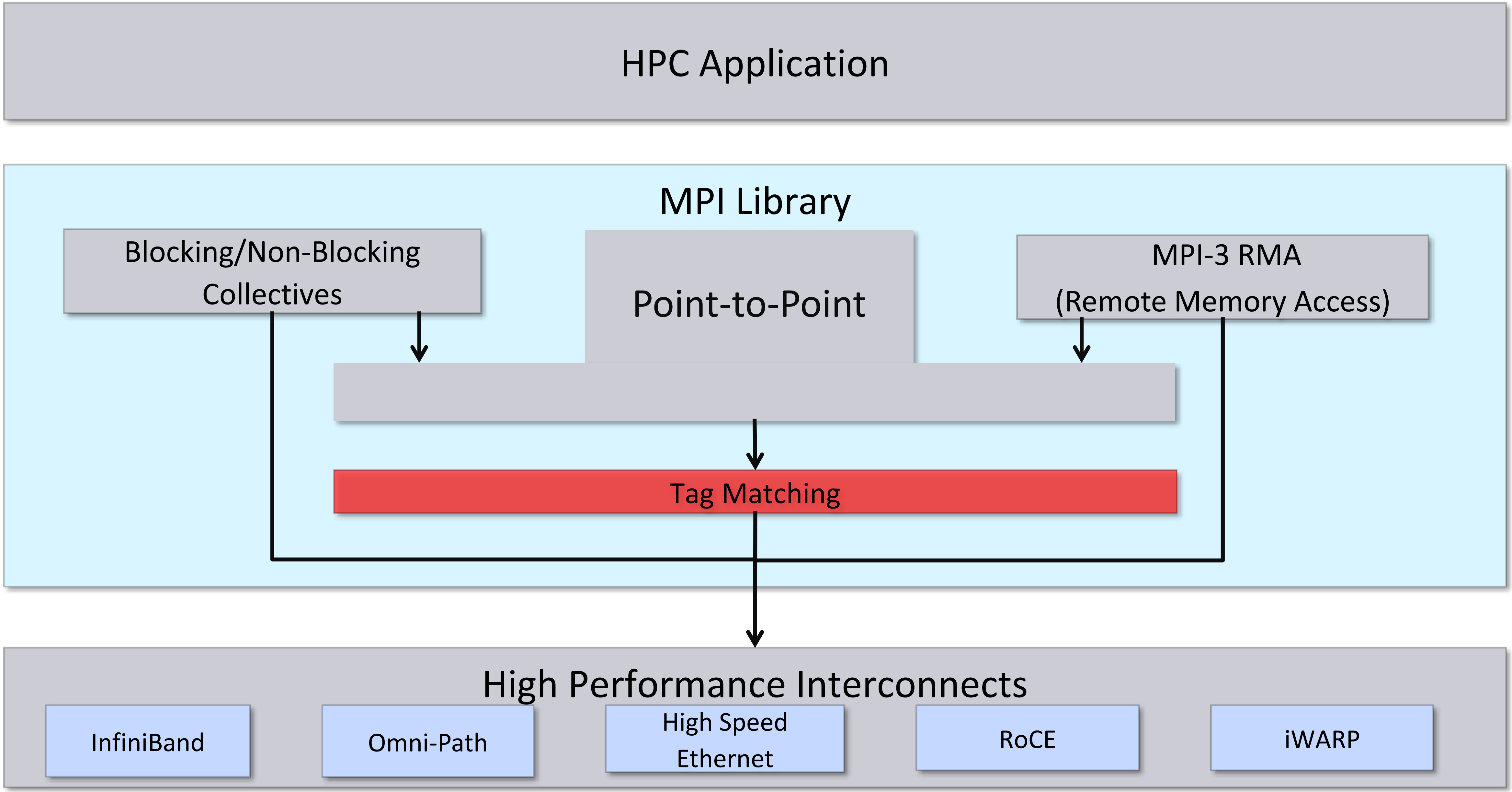
InfiniBand and Omni-Path are popular HPC Interconnects

- Low-latency and High-bandwidth
- 192 systems (39%) in Jun’17 Top500 use IB

MPI used by vast majority of HPC applications

- Helping applications scale to thousands of cores
- Large systems exposing new scalability issues

Components of an MPI Library



MPI Tag Matching 101

- On the receiver side, one needs to match the incoming message with the message that was posted by receiver
- Three parameters should match
  - Context id, Source Rank, Tag
  - Wildcards (MPI_ANY_SRC, MPI_ANY_TAG) introduce additional complexity
- Two kinds of the queues are involved in the receiver side
  - Posted queue
  - Unexpected queue

Search Time Analysis of the Default Double Linked List Design

- Most MPI libraries use double linked list for unexpected and posted queues
- Message to be removed could be in any position of the queue
  - Removal time in the best case is O(1) and in the average case is linear O(N)
- Tag matching is in the critical path for point-to-point based operations
- Number of the processes in a job is increasing
  - Future extreme-scale systems are expected to have millions of cores*
  - Multithreaded programming models
- All can push the search functions to go deeper in the lists
  - Impose significant overhead on the performance

* Thakur R, Balaji P, Buntinas D, Goodell D, Gropp W, Hoefler T, Kumar S, Lusk E, Träff JL. MPI at Exascale. Proceedings of SciDAC. 2010 Jul;2:14-35.

Proposed Adaptive Design

- Based on the Bin-based and default simple double linked list scheme
- Three phases
  - Starts with the default design
  - Observes the communication pattern for each process during the runtime
  - If all the conditions are held, it begins to convert the default scheme to the Bin-based scheme
- Each process can have its own scheme
  - Some may stay at the default scheme, some may need to convert to bin-based scheme

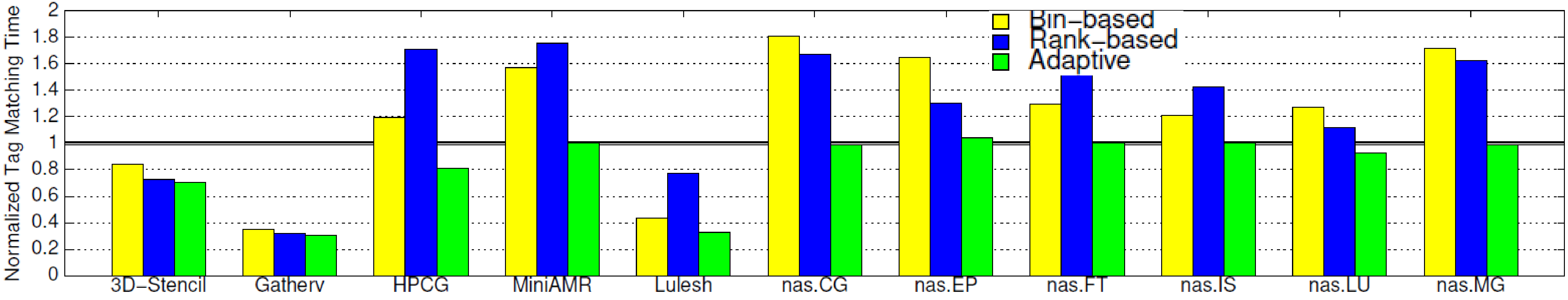
Proposed Adaptive Design (Cont'd)

- For each of the posted and unexpected queues, we consider the following thresholds
  - Number of the calls to the tag matching functions in the library (CALLS_NUM)
  - The average number of queue look-up attempts per CALLS_NUM (MACTCH_ATTMPS)
- Each process maintains both during the runtime
- If both thresholds are crossed
  - Adaptive design changes from the double linked list scheme to the bin-based scheme

Proposed Adaptive Design (Cont'd)

- Currently, conversion is one way from default to bin-based scheme and may occur only one time through the entire runtime
- These thresholds are fixed through entire runtime and they are configurable
  - We have tuned them based on empirical analysis using OSU micro benchmarks
- We consider two possible sizes for NUM_BINS
  - ¼ JOB_SIZE and ½ JOB_SIZE
  - Based on MATCH_ATTMPS, we decide which one to choose

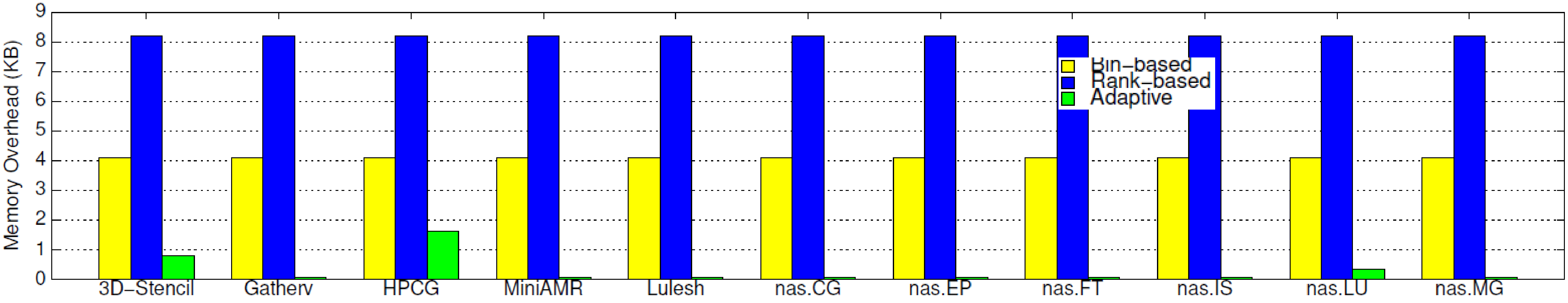
Summary of Tag Matching Performance



(b) Total Tag Matching Time, Normalized to Default (Lower is Better)

- Comparison of different designs/benchmarks at 512 processes on RI
- Adaptive design shows the best performance

Summary of Memory Consumed for Tag Matching



(a) Memory Overhead per Process, Compared to Default (Lower is Better)

- Comparison of different designs/ benchmarks at 512 processes on RI with default design
- Adaptive design shows minimal memory overhead

MVAPICH
MPI, PGAS and Hybrid MPI+PGAS Library

Scalable Reduction Collectives with Data Partitioning-based Multi-Leader Design

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MPI Reduction Collectives 101

- Convenient abstraction to implement group communication operations
- Widely used across various scientific domains
  - Owing to their ease of use and performance portability
- One of the most popular collective operations: MPI_Allreduce
  - 37% of communication time
- MPI_Allreduce reduces values from all processes and distribute the result back to all processes

Existing Designs for MPI_Allreduce

- Hierarchical strategy
  - A two-level approach
    - Intra-node reduction by root + inter-node Allreduce
    - Computations are done by the root process of each node
- Tree-based strategies
  - Recursive Doubling
    - Based on point-to-point operation
    - High parallelism for computation
      - All the process are involved in computation
    - Pairs distance doubles after each step
    - Log (P*) steps

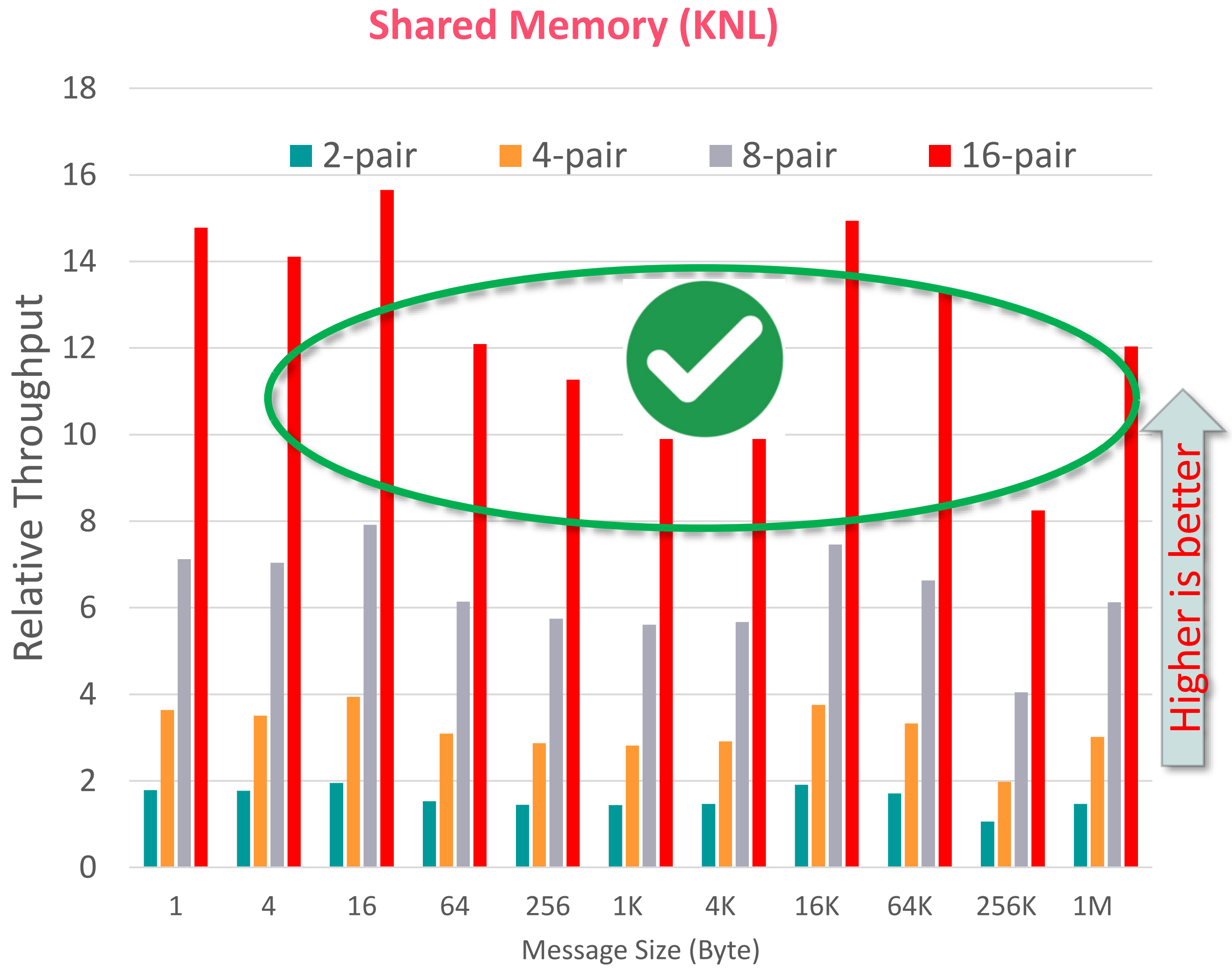
* Bloch et al. Scalable Hierarchical Aggregation Protocol (SHArP): A Hardware Architecture for Efficient Data Reduction

Relative Throughput of Different Architectures

- Using OSU Micro benchmark suite*
- “Multiple Bandwidth Test”
  - Back-to-back messages
    - Sent to a pair before waiting for receive
- Evaluates the aggregate unidirectional bandwidth between multiple pairs of processes
- 1) Xeon + IB, 2)Xeon + Omni-Path, and 3) KNL + Omni-Path

* http://mvapich.cse.ohio-state.edu/benchmarks/

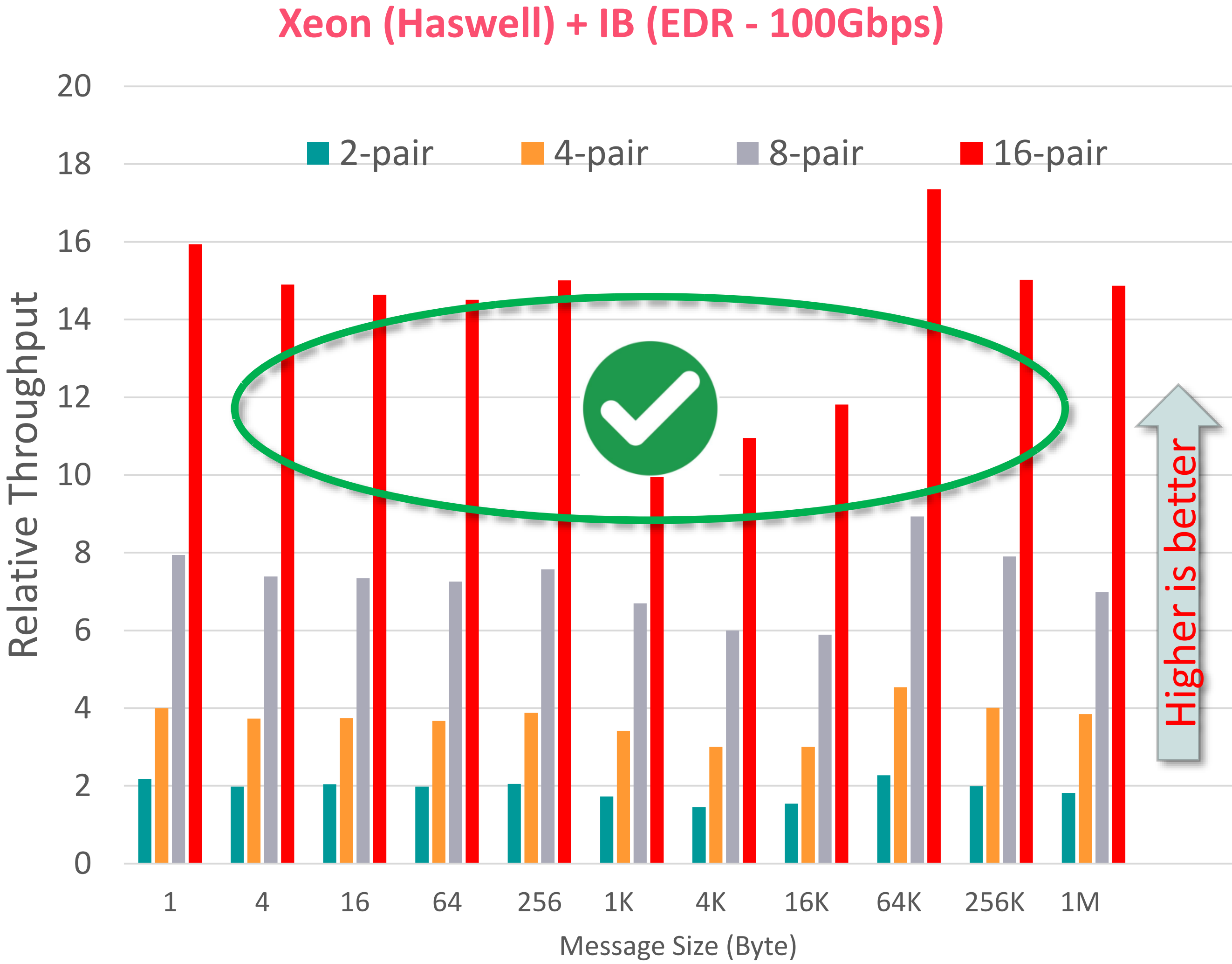
Communication Characteristics of Modern Architectures: Intra-node Communication



Multiple pair test vs. one pair test

- The relative throughput very close to the number of pairs
- Support many concurrent intra-node communication

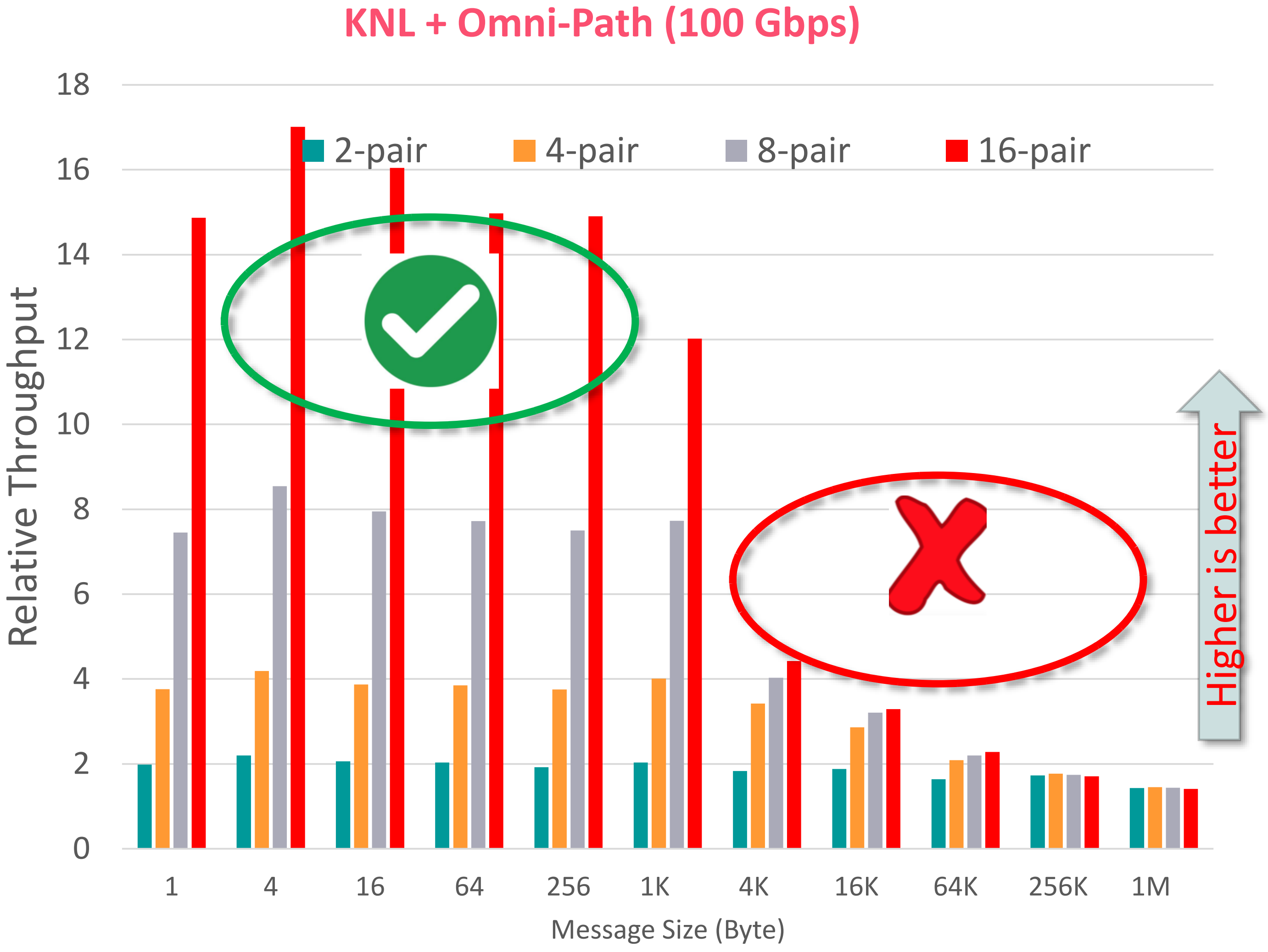
Communication Characteristics of Modern Architectures: InfiniBand Interconnect



Multiple pair test vs. one pair test

- The relative throughput close to the number of communicating processes per node
- Support many concurrent intra-node communication

Communication Characteristics of Modern Architectures: Omni-Path Interconnect



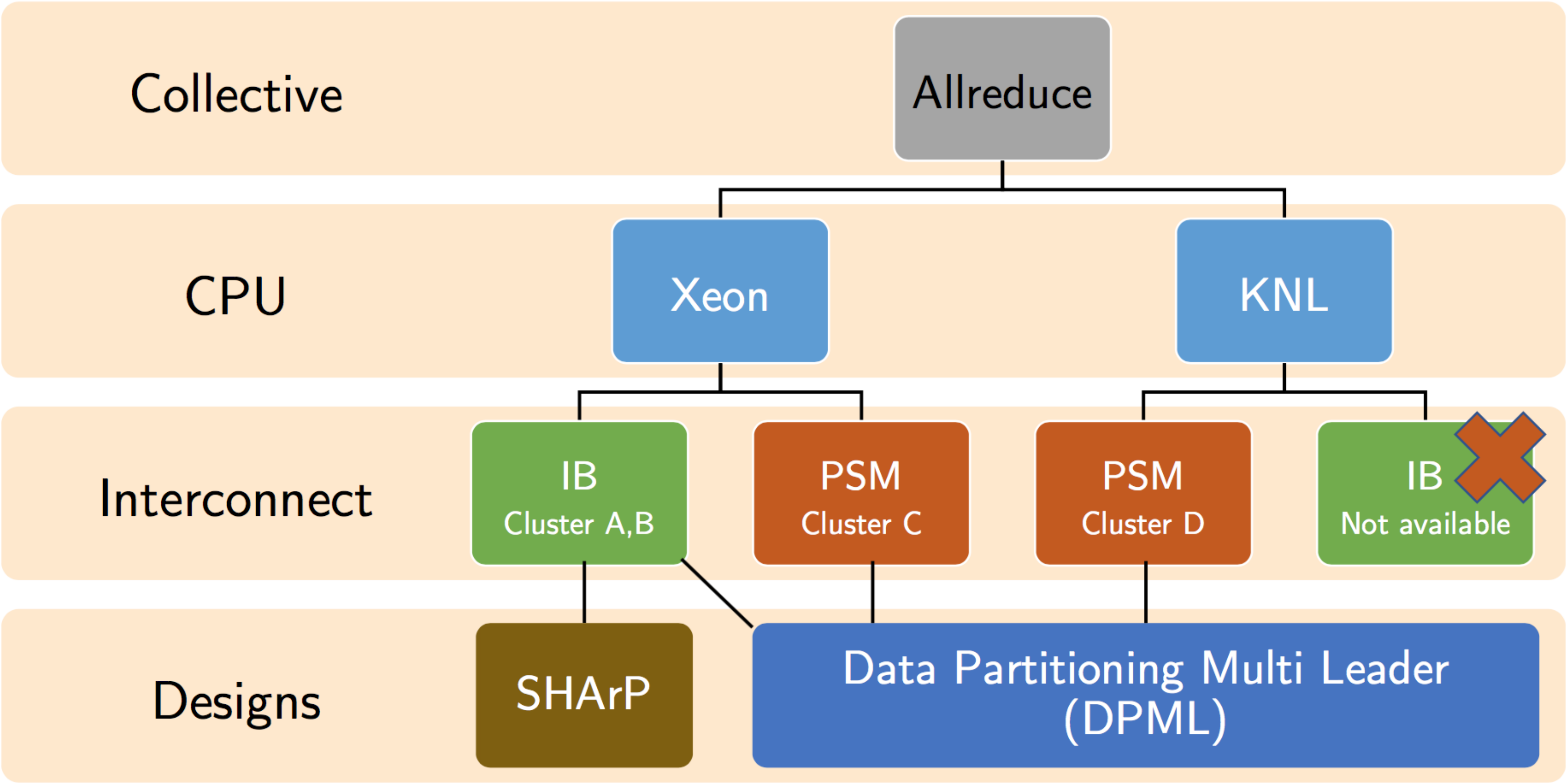
Multiple pair test vs. one pair test

- The relative throughput of one for large messages
- Supports many concurrent communications for small and medium message range
- Similar behavior observed for Xeon + Omni-Path

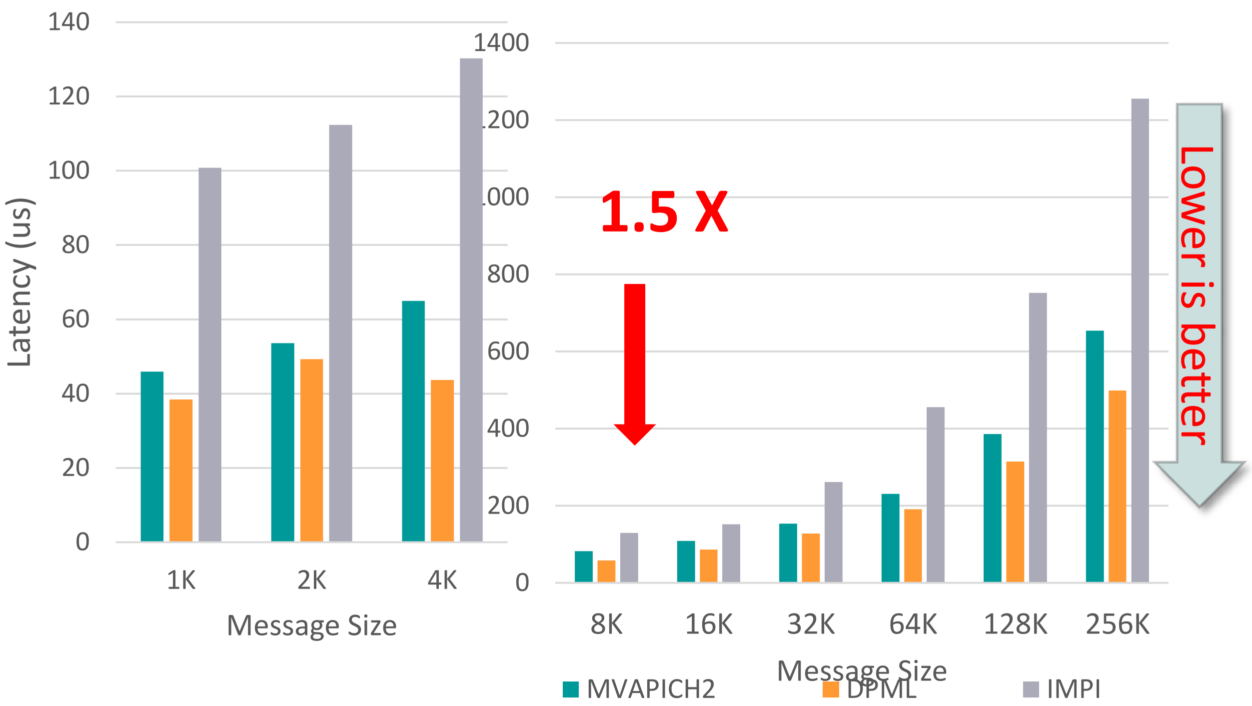
Performance limitations of Existing Designs for MPI_Allreduce

- Does not take advantage of large number of cores and high concurrency in communication
- Does not take advantage of shared memory collectives
  - Needs kernel support for zero-copy communication for large messages in same node
- Too many inter-node communication for large PPNs
- Limited performance due to extra QPI transfers
- Limited computing power of switches limits its performance for medium and large message ranges

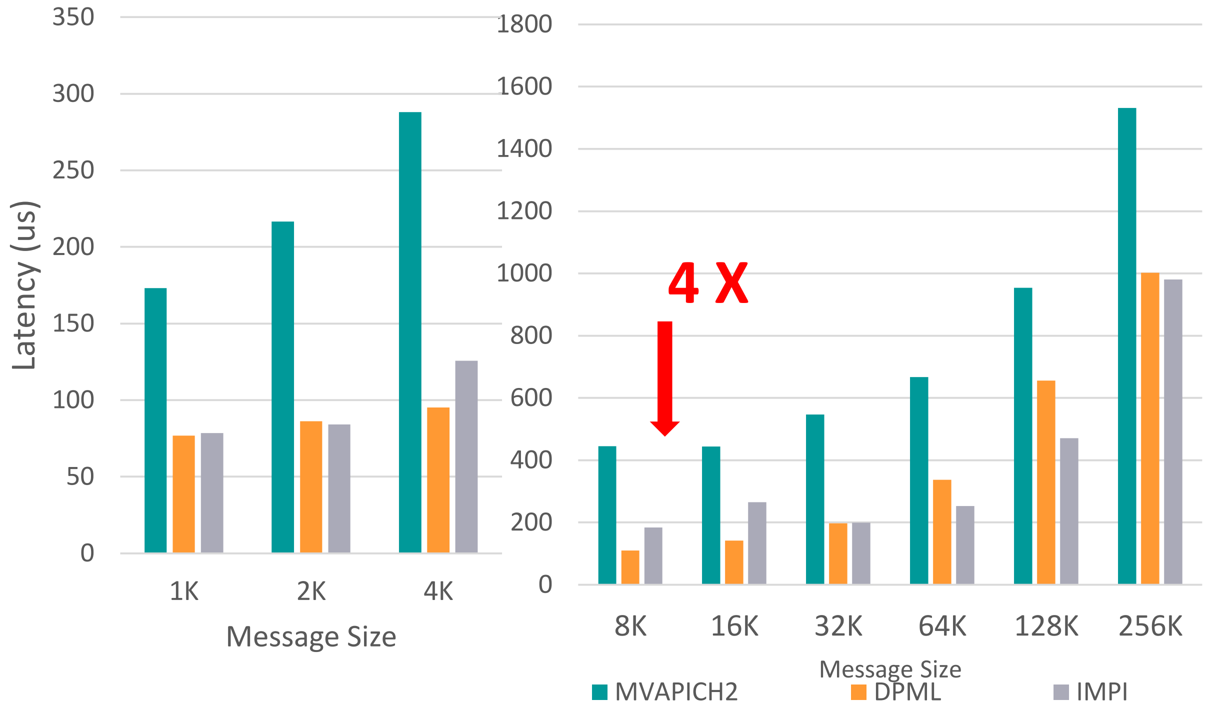
Design Outline



Performance of MPI_Allreduce On Omni-Path



XEON + Omni-Path (64 Nodes, 28 PPN*)

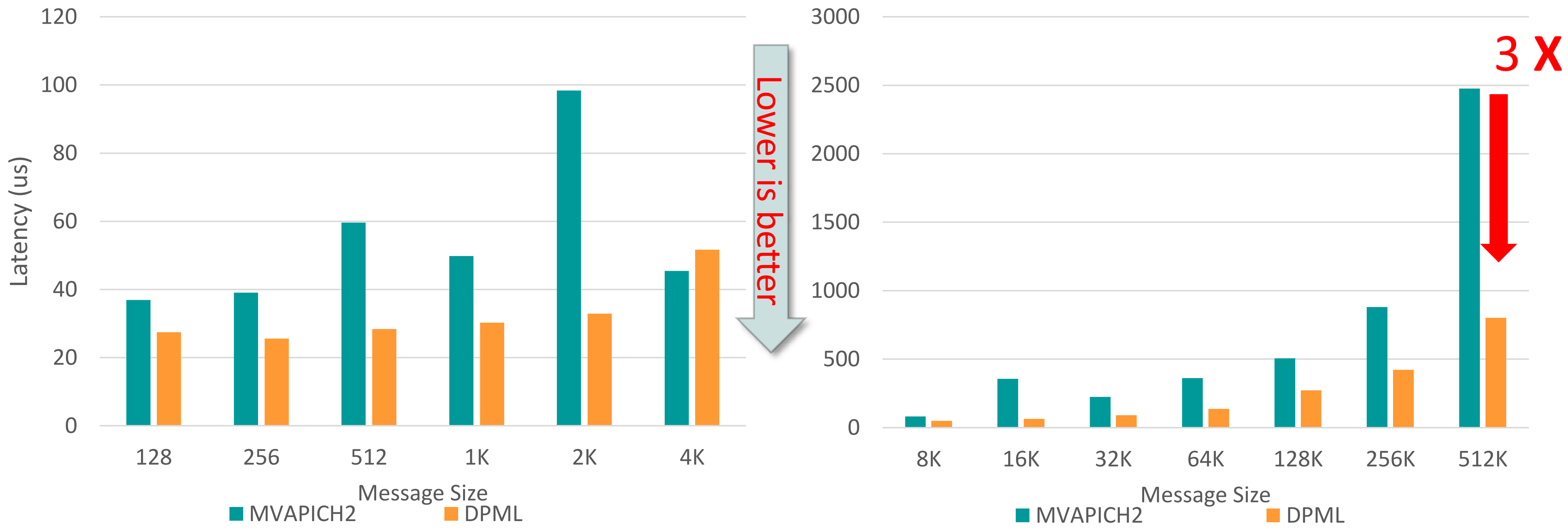


KNL + Omni-Path (32 Nodes, 32 PPN)

- DPML always outperform MVAPICH2 for all medium and large message range
- DPML outperform IMPI in medium message range
- High parallelism of DPML benefits KNL more than XEON

*Processes Per Node

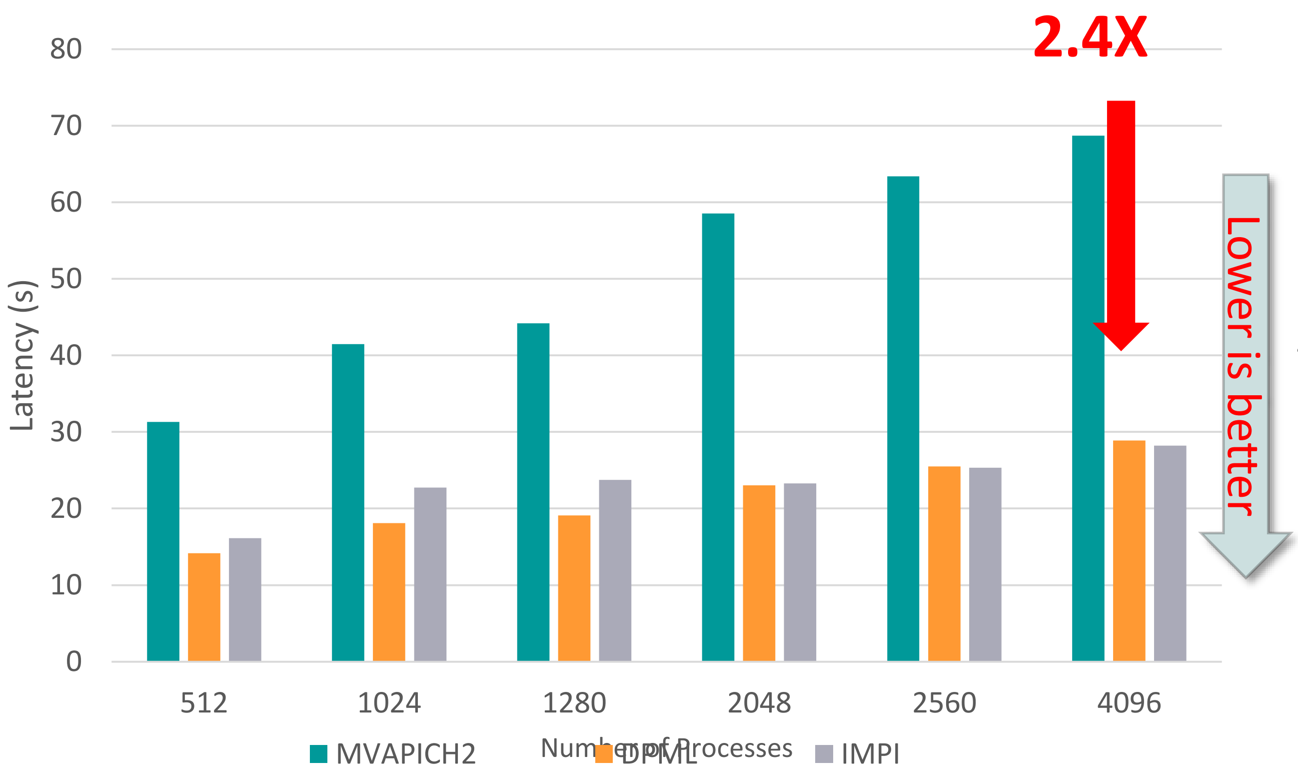
Performance of MPI_Allreduce On InfiniBand



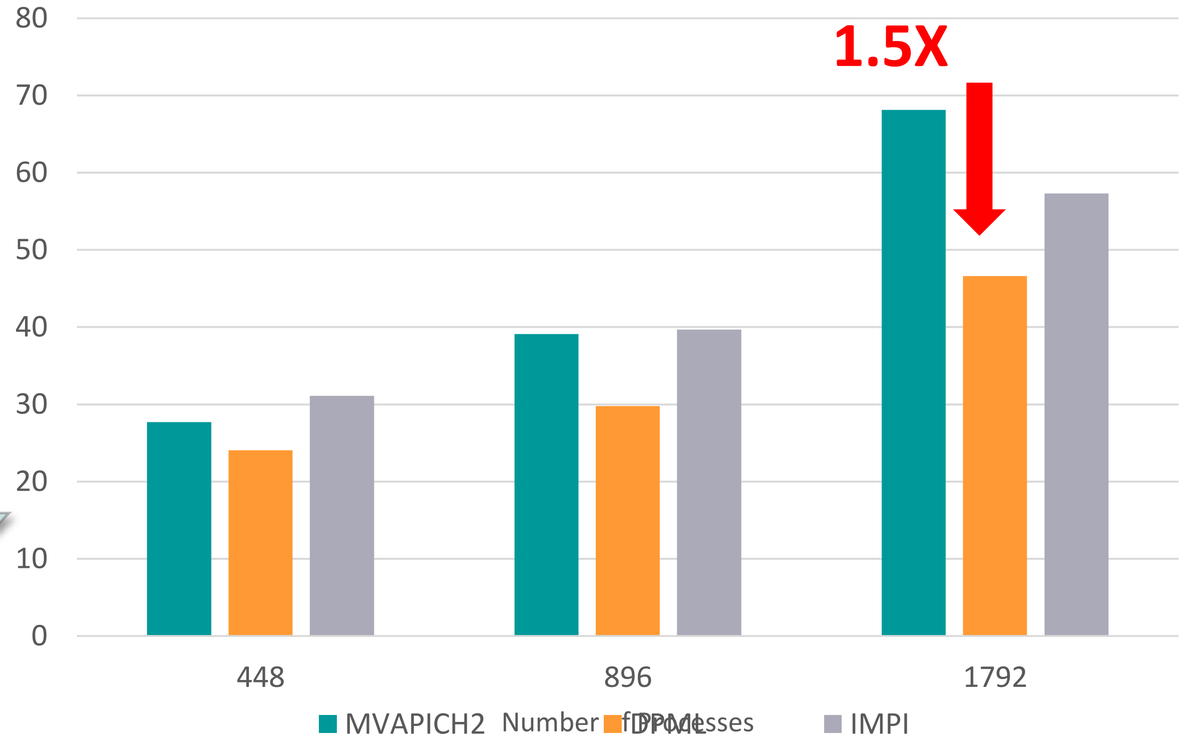
XEON + IB (64 Nodes, 28 PPN)

- DPML outperform MVAPICH2 for most of the medium and large message range
  - With 512K bytes, 3X improvement of DPML
- Higher benefits of DPML as the message size increases

Performance Benefits for MiniAMR Application



KNL + Omni-Path (32 PPN)



XEON + Omni-Path (28 PPN)

- For MiniAMR Application with 4096 processes, DPML can reduce the latency by 2.4X on KNL + Omni-Path cluster
- On XEON + Omni-Path, with 1792 processes, DPML can reduce the latency by 1.5X

MVAPICH
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SALaR: Scalable and Adaptive Designs for Large Message Reduction Collectives

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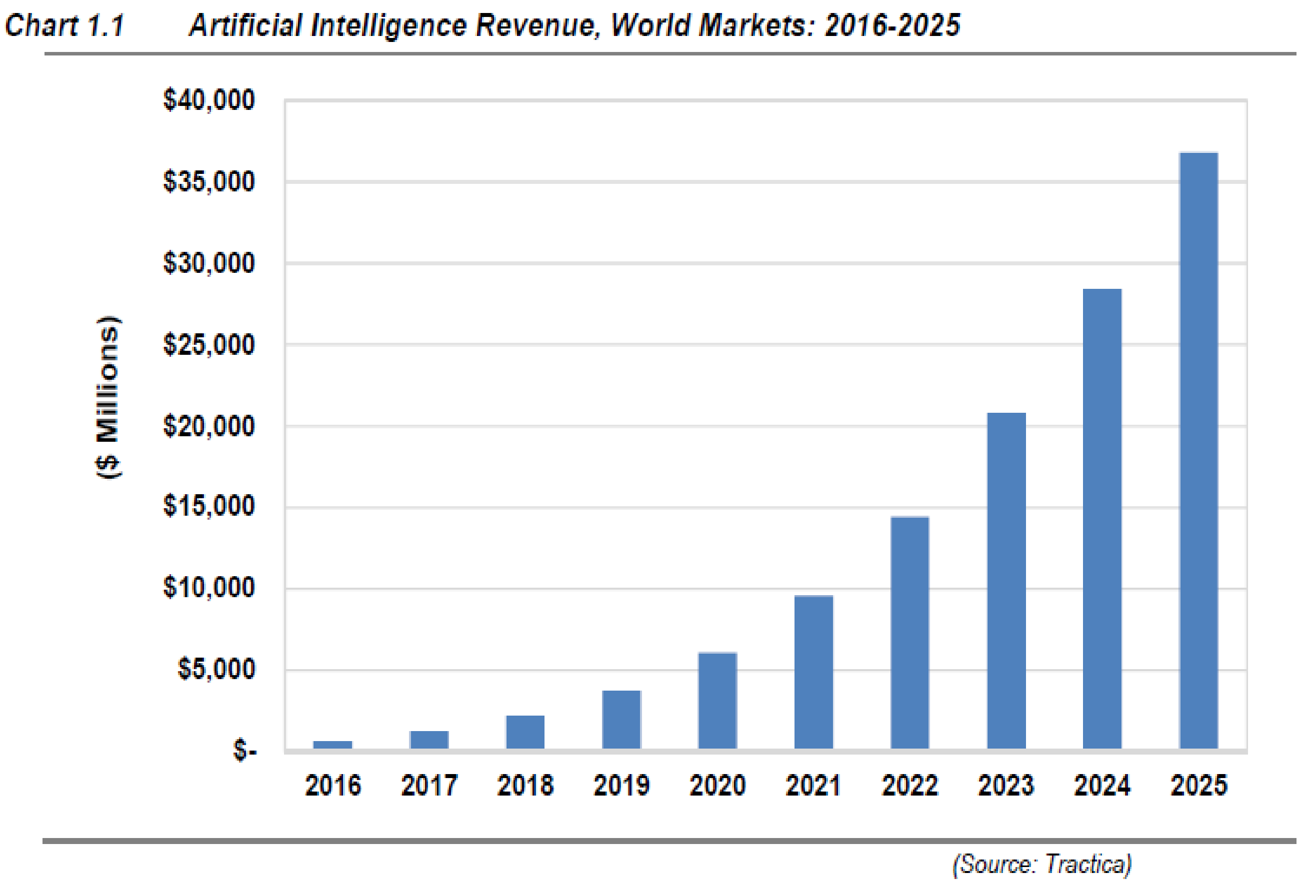
Deep Learning (DL) Frameworks and Trends

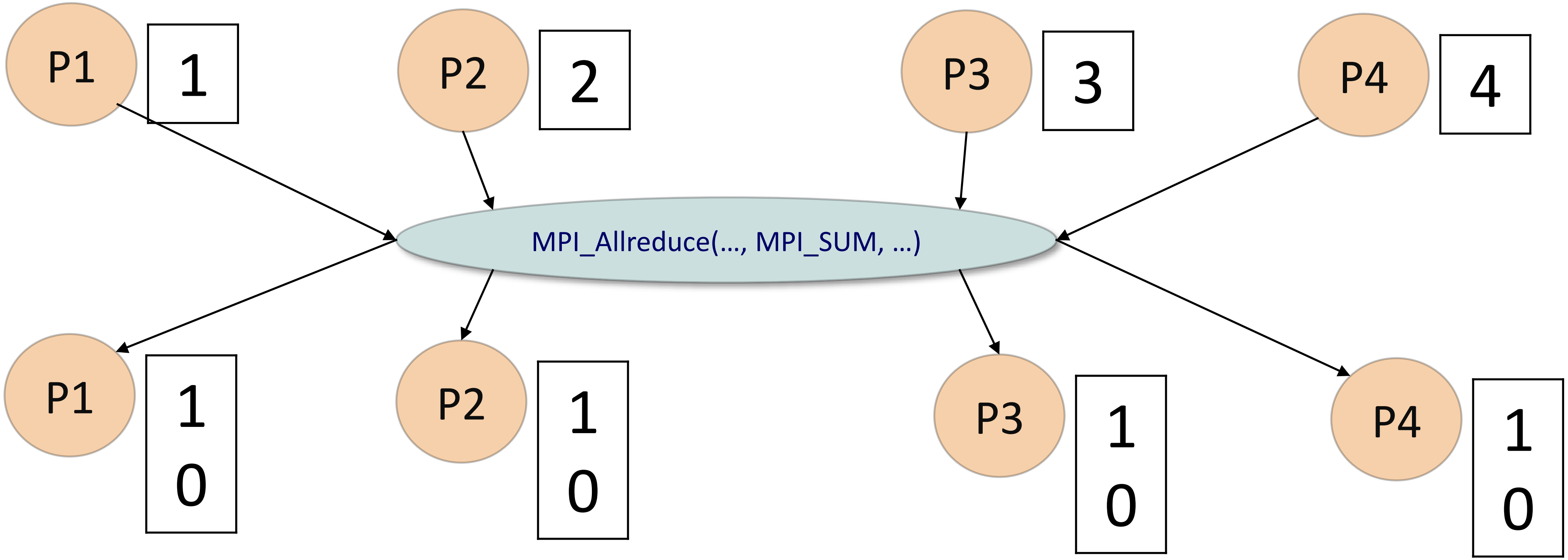
- Renewed interest in DL
  - Deep Neural Networks (DNNs)
- Tensorflow, CNTK and many more
- Excellent accuracy for deep/convolutional neural networks
- Diverse applications – Image Recognition, Cancer Detection, Self-Driving Cars, Speech Processing etc.



https://www.top500.org/news/market-for-artificial-intelligence-projected-to-hit-36-billion-by-2025/

MPI Allreduce Collective

- MPI_Allreduce – Walkthrough Example



Performance limitations of Existing Designs for MPI_Allreduce

1. Load-balancing the computation and network resources
2. Overlap of communication and computation
3. Avoiding data copies and data staging
4. Avoiding the unnecessary synchronization overheads
5. Heuristic based adaptive design

State-of-the-art Allreduce Designs	**Feature being used**				
	1	**2**	**3**	**4**	**5**
Baidu-Allreduce [a]	✔	✔	✘	✘	✘
Linear Pipelining [b]	✔	✔	✘	✘	✘
Reduce-scatter followed by Allgather [c,d]	✔	✘	✘	✘	✘
Segmented Ring [e]	✔	✔	✘	✘	✘
XPMEM-based Reduction [f]	✘	✘	✔	✘	✘
Proposed "**SALaR**"	✔	✔	✔	✔	✔

Research Contribution

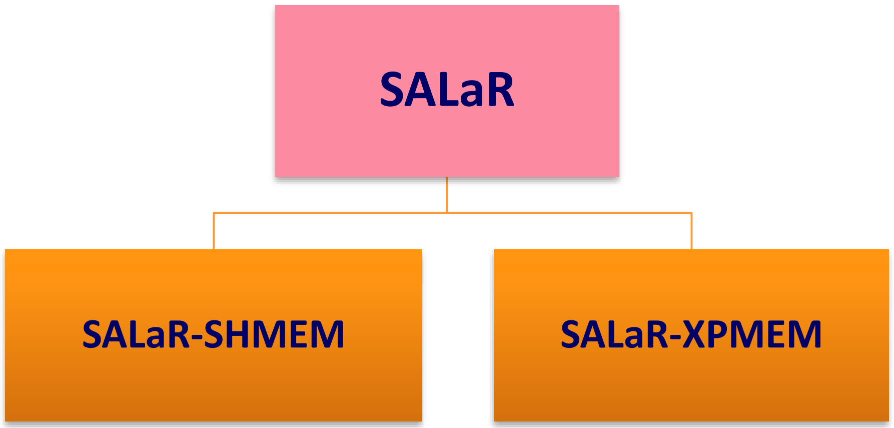
- Designing high-performance Allreduce
  - Pipelined design for efficient overlap of computation and communication
  - Exploiting process Shared Address Space based truly zero-copy intra-node reduction
  - One-sided inter-node communication to reduce synchronizations
  - Efficient load-balanced inter-node communication
  - Heuristic based adaptive design
- Modeling the proposed design
- Improved the AlexNet training time on CNTK by up to 46%
- Reduced the latency of osu_allreduce by up to 5X at scale

Outline

- Introduction
- Motivation
- Contributions
- Proposed Designs
  - Design Optimizations
  - Modeling
- Experimental Results
- Conclusions & Future Work

Summary of Proposed SALaR Designs

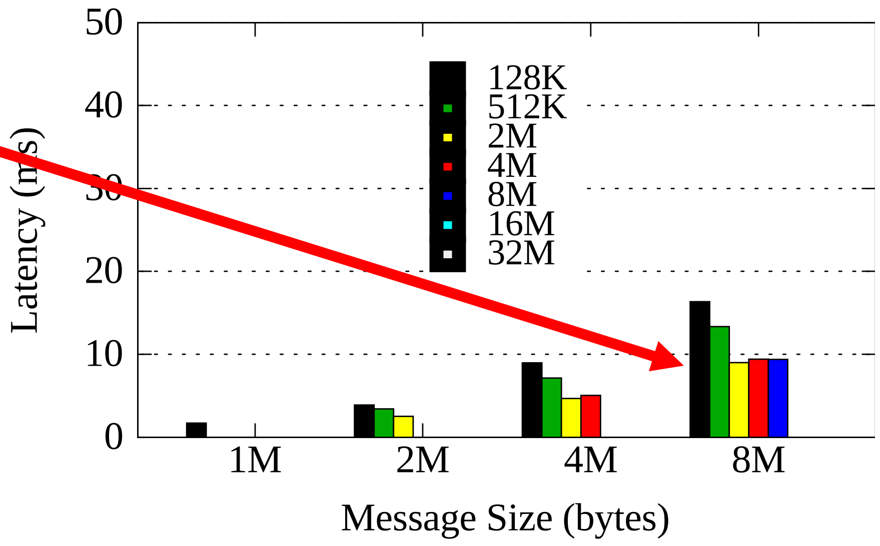
- SALaR-XPMEM
  - Efficient Pipeline of Inter-node Allreduce with Intra-node Reduce
  - Uses XPMEM as intra-node zero copy mechanism
- SALaR-SHMEM
  - In case of lack of XPMEM module, shared memory is being used as the intra-node mechanism



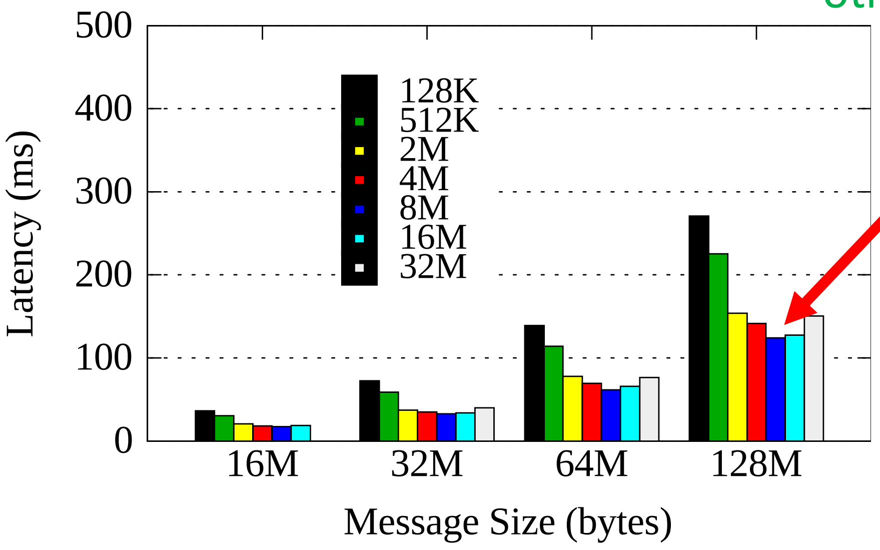
Impact of Chunk Size on Allreduce Performance

8MB is optimal among other chunk sizes

2MB is optimal among other chunk sizes



SALaR-XPMEM



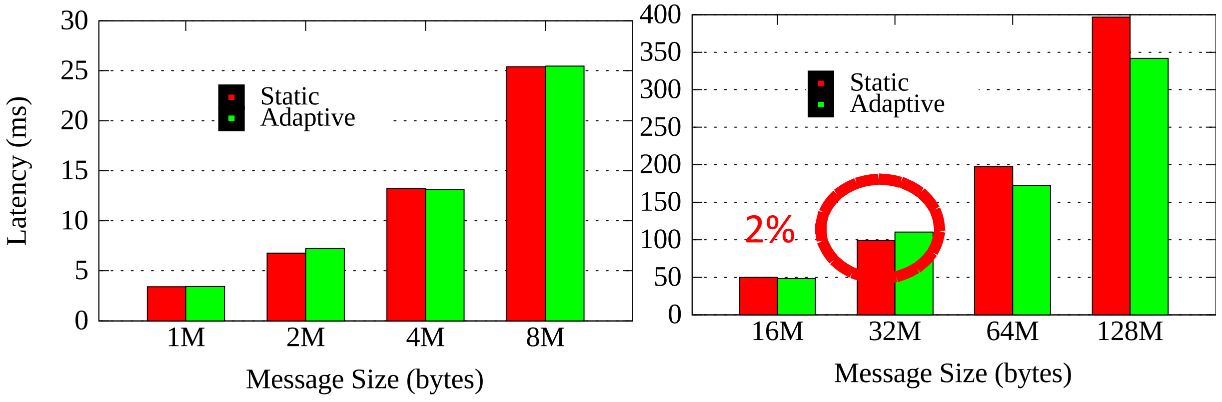
SALaR-XPMEM (Larger Messages)

Latency of MPI_Allreduce on 224 processes and 28 processes per node on Cluster A

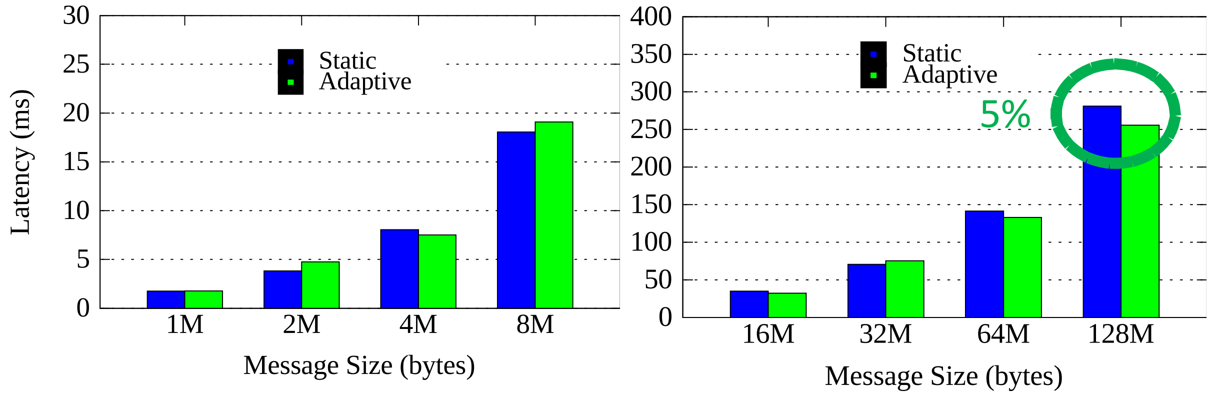
- Selecting the proper chunk size can have a big impact on the performance
- Different chunk is optimal for each message range

Impact of Heuristic based Design on Allreduce Performance

- Adaptive design is close and in some cases, even has better performance compared to the Static version
- Effectively removes the hassle of static tuning



SALaR-SHMEM design on 896 processes on Cluster A



SALaR-XPMEM designs 896 processes on Cluster A

Outline

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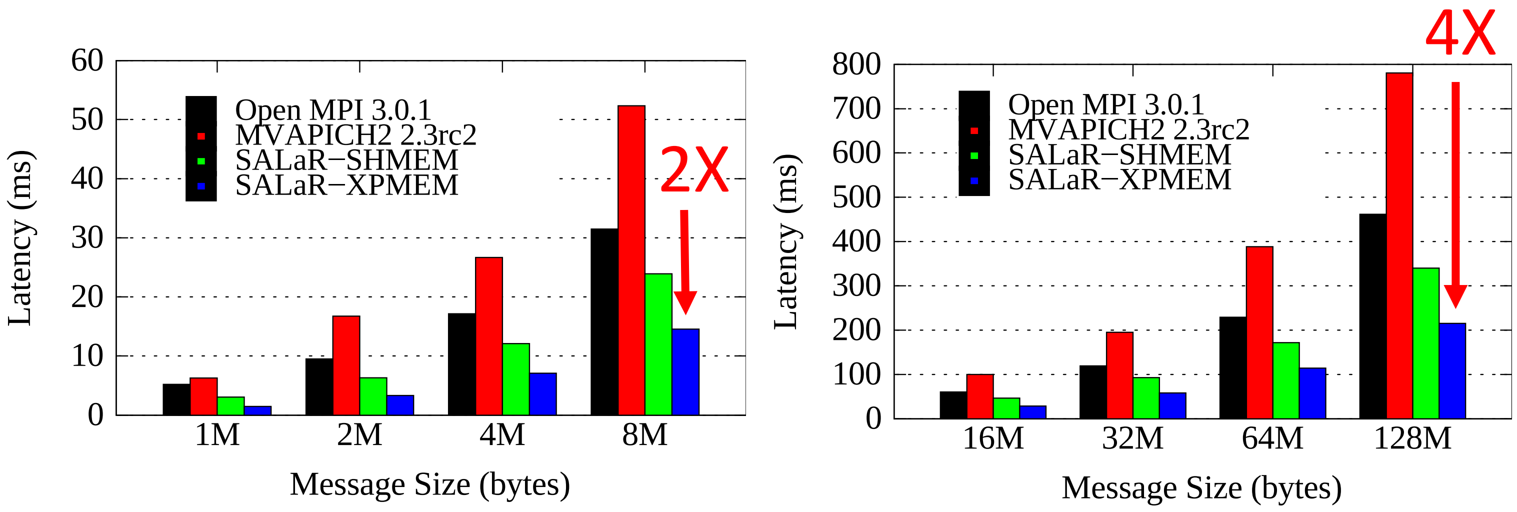
Experimental Setup

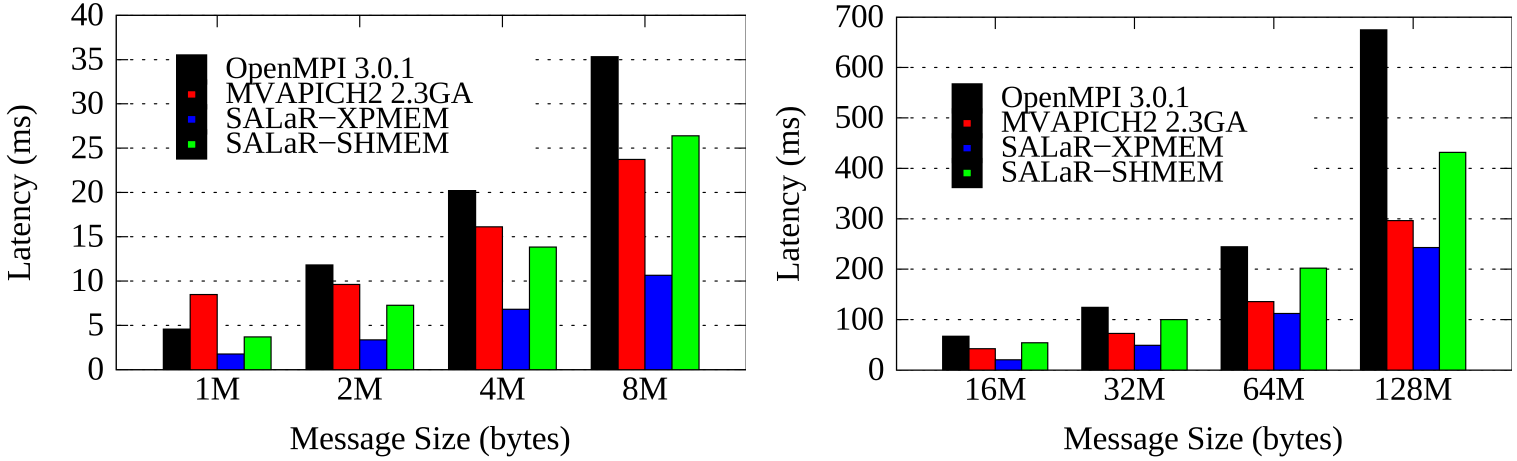
Hardware		Software	
Cluster A RI2	Cluster B Comet	MPI Benchmark	DL Frameworks
40 Dual socket Intel Xeon series CPUs 14-core Broadwell processors of 2.40 GHz	1944 Dell PowerEdge C6320 two- socket servers with 12-core Intel Xeon processors of 2.50 GHz	OSU Microbenchmarks v5.4.1	Microsoft Computational Network Toolkit (CNTK) v.2.3.1
Mellanox MT4115 EDR ConnectX-4 HCAs	Mellanox MT4099 FDR ConnectX-3 HCAs		Horovod: Uber implementation of Tensorflow v0.12.1

Performance Comparison of MPI_Allreduce

- Using osu_allreduce benchmark from OSU Microbenchmarks on Cluster A with 28 processes per node
- SALaR outperforms Open MPI and MVAPICH2 up to 2X and 4X
- In the latest release of MVAPICH2, we have incorporated some of similar SALaR ideas and enhanced the performance



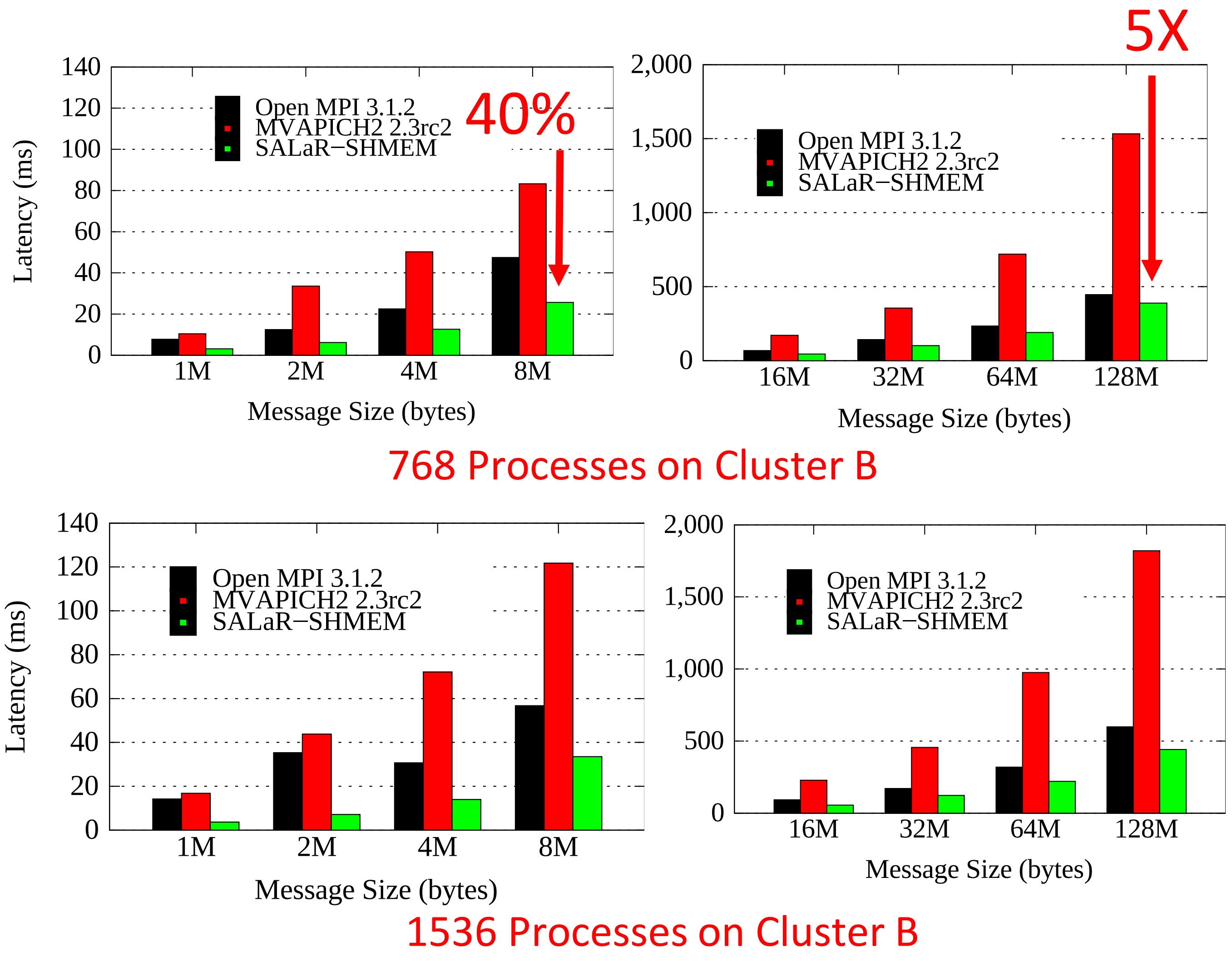
448 Processes (Same as in the Paper)



756 Processes (Latest Numbers)

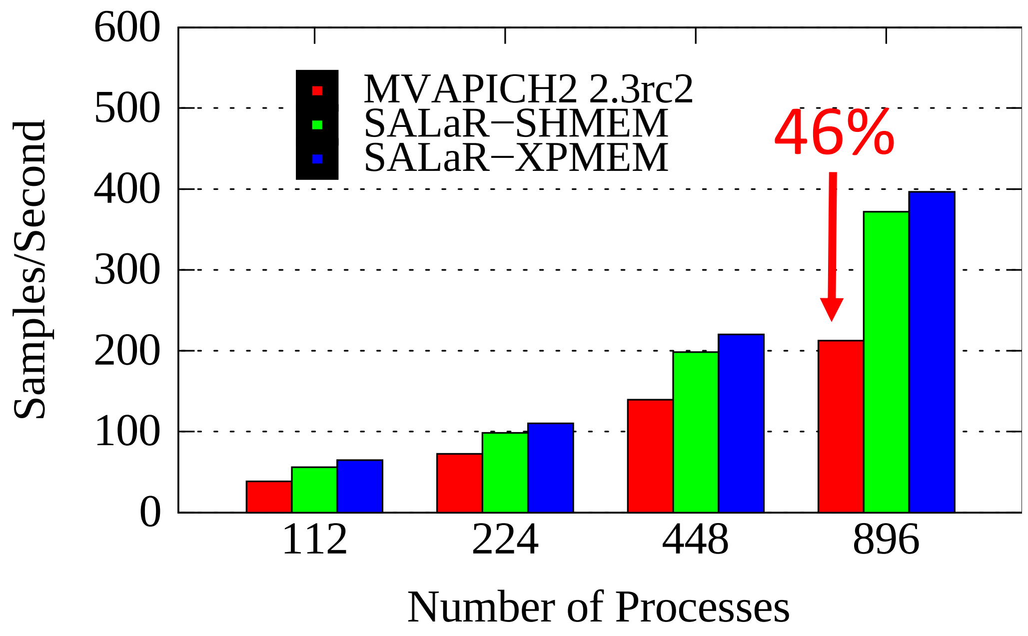
Performance Comparison of MPI_Allreduce (cont'd)

- Using osu_allreduce benchmark from OSU Microbenchmarks on Cluster B with 24 processes per node
- SALaR outperforms Open MPI v3.1.2 and MVAPICH2 v2.3rc2 up to 40% and 5X respectively



Impact of SALaR Designs on CNTK

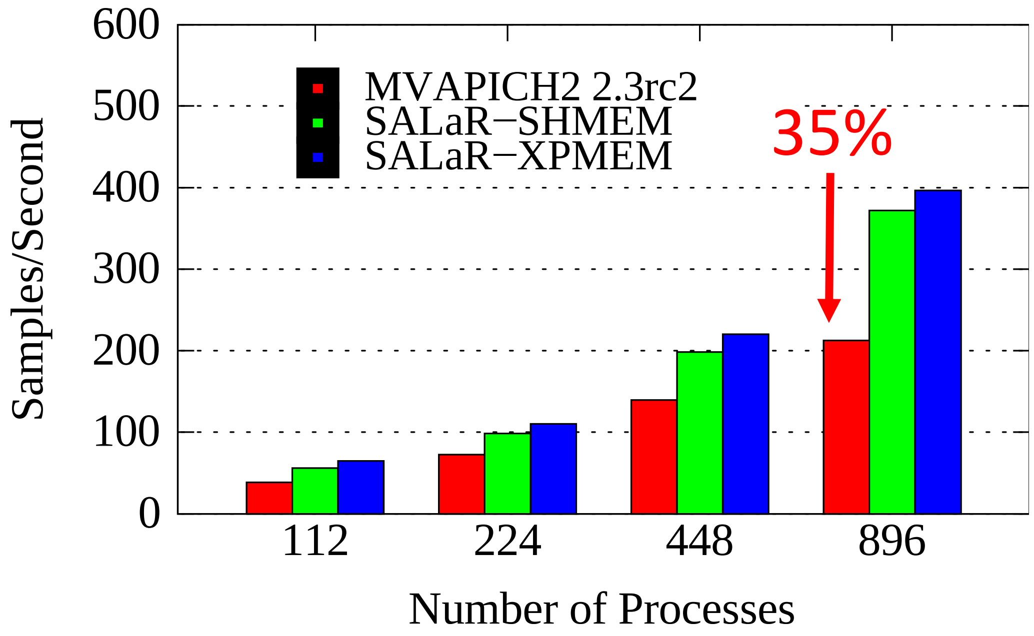
- CPU-based training AlexNet neural network ILSVRC2012 dataset from the ImageNet
- SALaR designs perform up to 46% better than the MVAPICH2 library at 896 processes
- Increasing the scale, the benefits of the proposed designs also increases



CNTK Samples per Second on Cluster A (higher is better)

Impact of SALaR Designs on TensorFlow

- CPU-based tf_cnn_benchmarks for distributed tests from TensorFlow Benchmarks (TF)
  - Training AlexNet neural network from the synthetic datasets
- 15% and 35% improvements in the number of images per second at 448 and 896 processes jobs
- Increasing the job size, the benefits of SALaR compared to MVAPICH2 keep increasing



TensorFlow Images per Second (higher is better)

Conclusions & Future Work

- Designed multi-leader based collective operations
  - Capable of taking advantage of high-end features offered by modern network interconnects
- Modeled and analyzed proposed design theoretically
- The benefits were evaluated on different architectures
- The DPML design is released as a part of MVAPICH2-X 2.3b! Check out:
  - http://mvapich.cse.ohio-state.edu/overview/#mv2X
- Studied the interplay between communication pattern of applications and different tag matching schemes
- Proposes, designed and implemented a dynamic and adaptive tag matching scheme capable to adapting dynamically to the communication characteristics of applications
- The adaptive approach opens up a new direction to design tag matching schemes for next-generation exascale systems

Conclusion and Future Work (cont'd)

- Proposed scalable and adaptive Allreduce design
  - Capable of taking advantage of high-end features offered by modern network interconnects and increased parallelism of Multi-/Many-core architectures
- Modeled and analyzed proposed design theoretically
- The benefits were evaluated on different architectures and Deep Learning frameworks
- Improved the AlexNet training time on CNTK by up to 46%
- Reduced the latency of osu_allreduce by up to 5X at scale
- In the future:
  - Exploring the SALaR for other collective operations
- The SALaR design will be as a part of MVAPICH2! Check out:
  - http://mvapich.cse.ohio-state.edu/

References

[a] Baidu Allreduce Design: https://github.com/baidu- research/baidu-allreduce

[b] Efficient communications in training large scale neural networks, Zhao et al, Thematic Workshops ACMMM2017

[c] MVAPICH2 2.3rc2

[d] Bandwidth optimal all-reduce algorithms for clusters of workstations, Patarasuk et al, Journal of Parallel and Distributed Comp '09

[e] OpenMPI 1.8.5 and later

[f] Designing Efficient Shared Address Space Reduction Collectives for Multi-/Many-cores, Hashmi et al, IPDPS '17

Thank you! Questions?