Improving MPI Reduction Performance for Manycore Architectures with OpenMP and Data Compression

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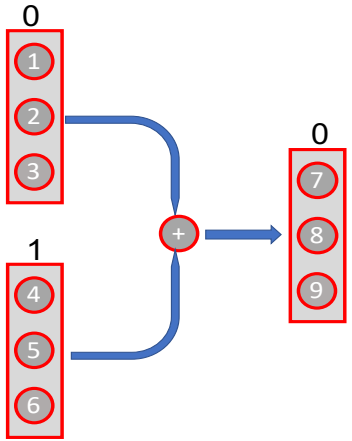
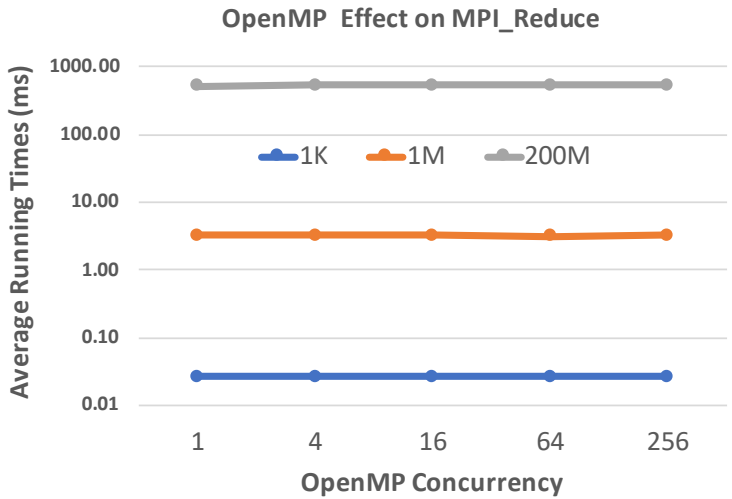
Background

- When parallelized, many numerical methods require dot or norm calculations, result in global reduction on scalar values
- In multidimensional parallelization, lead to global broadcast and reduction on large vectors of size $N/\sqrt{P}$ (could be megabytes or gigabytes)
- MPI_Reduce succinctly express such requisite functionality and are widely used in many applications
  - int MPI_Reduce(
    - const void *sendbuf,
    - void *recvbuf,
    - int count,
    - MPI_Datatype datatype,
    - MPI_Op op,
    - int root,
    - MPI_Comm comm)



Motivation

- MPI_Reduce on large vectors often become the performance scaling bottleneck
- Most optimizations focus on latency and bandwidth



- **Problem:**
  - Low single core performance
  - Idle threads
  - No performance improvement

Approach

- Two new perspectives to improve reduce performance:
  - Using OpenMP threads to accelerate local reduction
  - Using data compression to reduce communication volume
- Accomplishments:
  - Could perform up to 4X better than the Cray implementation on large vector size
  - Improve application BIGSTICK performance up to 2.6X

Outline

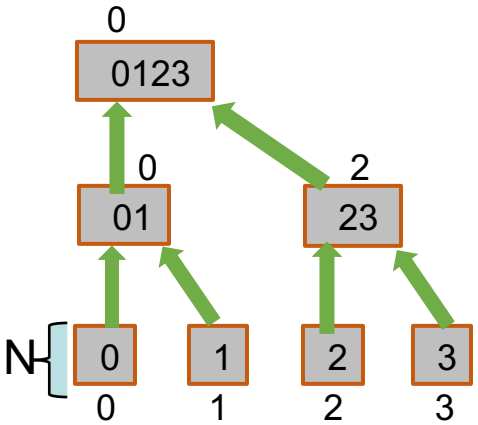
- Background and Motivation
- Algorithms for MPI_Reduce and their performance characteristics
  - Binomial, Reduce-Scatter, Ring
- Performance analysis for MPI_Reduce
- Performance analysis for application BIGSTICK
- Summary and future work

Algorithms

- MPI_Reduce:
  - Binomial for short messages
  - Reduce-Scatter for long messages
  - Ring
- Simple Cost Model ($\alpha + N\beta + N\gamma$)
  - N: vector size
  - α: latency
  - β: transfer time per byte
  - γ: compute time per byte (aggregate)

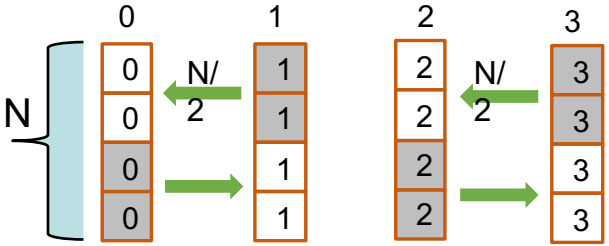
Binomial

- **Cost:**
  - $log(P)\times(\alpha + N\beta + N\gamma)$
- **Case: P = 4**
  - The numbers in the block represent the process ranks whose data has already been reduced.
  - The shaded blocks represents the communication data.

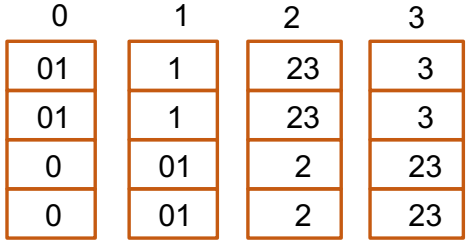


Algorithm: Reduce-Scatter

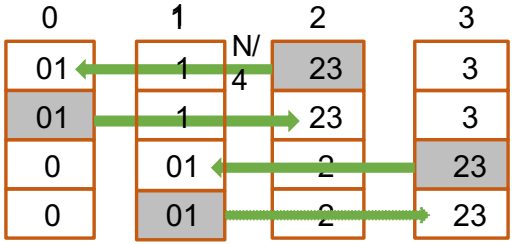
- **Cost Model:** $2\alpha log(P) + 2\frac{P-1}{P}N\beta + \frac{P-1}{P}N\gamma$



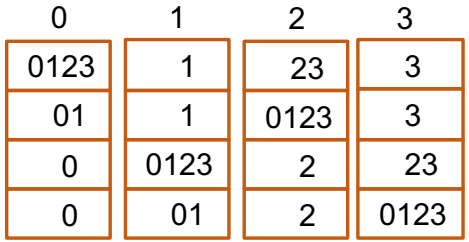
a) Initial status and communication in 1st step



b) After 1st step status



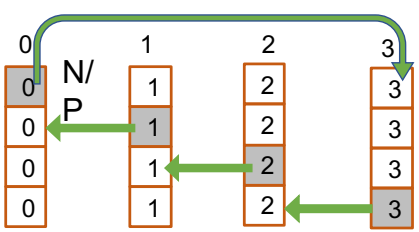
c) 2rd step communication



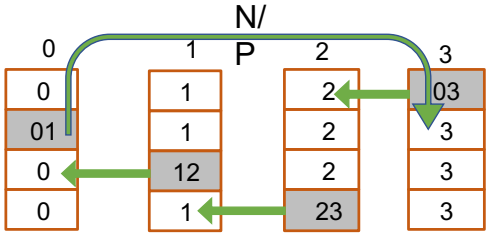
d) After 2rd step status

Algorithm: Ring

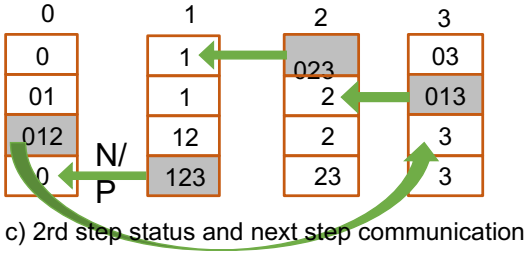
- **Cost Model:** $(\log(P) + P)\alpha + 2\frac{P-1}{P}N\beta + \frac{P-1}{P}N\gamma$



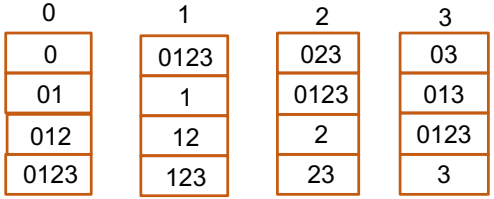
a) Initial status and communication in 1st step



b) 1st step status and next step communication

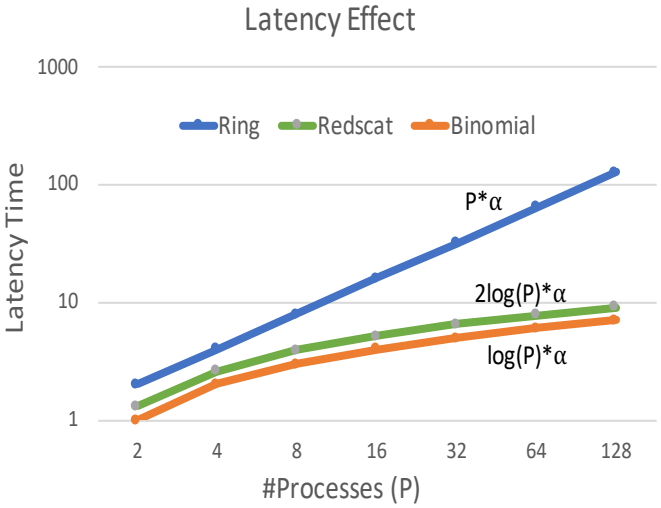


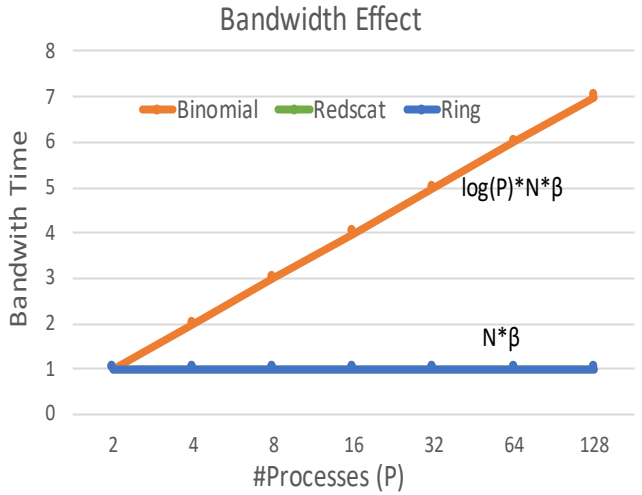
c) 2rd step status and next step communication



d) Final status

Performance Characteristics





- **Binomial:** $log(P)\alpha + lop(P)N\beta + lop(P)N\gamma$
- **RedScat:** $2log(P)\alpha + 2\frac{P-1}{P}N\beta + \frac{P-1}{P}N\gamma$
- **Ring:** $(\log(P) + P)\alpha + 2\frac{P-1}{P}N\beta + \frac{P-1}{P}N\gamma$

OpenMP Implementation

- Each thread has its own independent buffers
  - Float *rbuffer[NTHREADS]
- Using OpenMP parallel Region to implement workload partition:
  - #pragma omp parallel
  - {
    - tid = omp_get_thread_num()
    - nthreads = omp_get_num_threads()
    - partition the work manually
    - perform the assigned work
  - }

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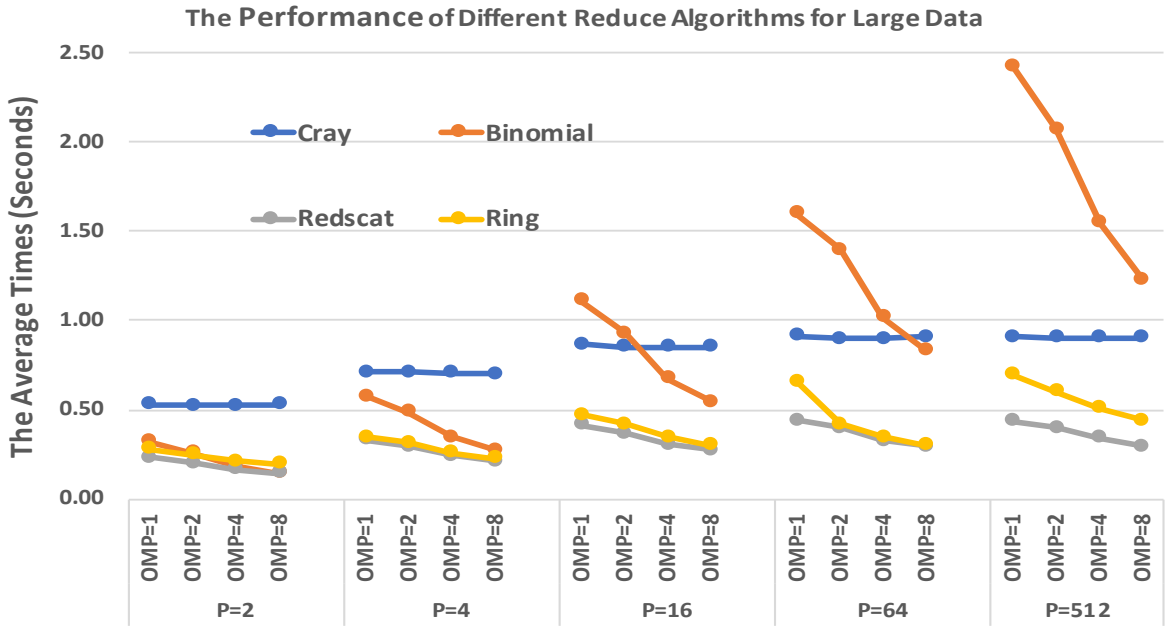
Platform

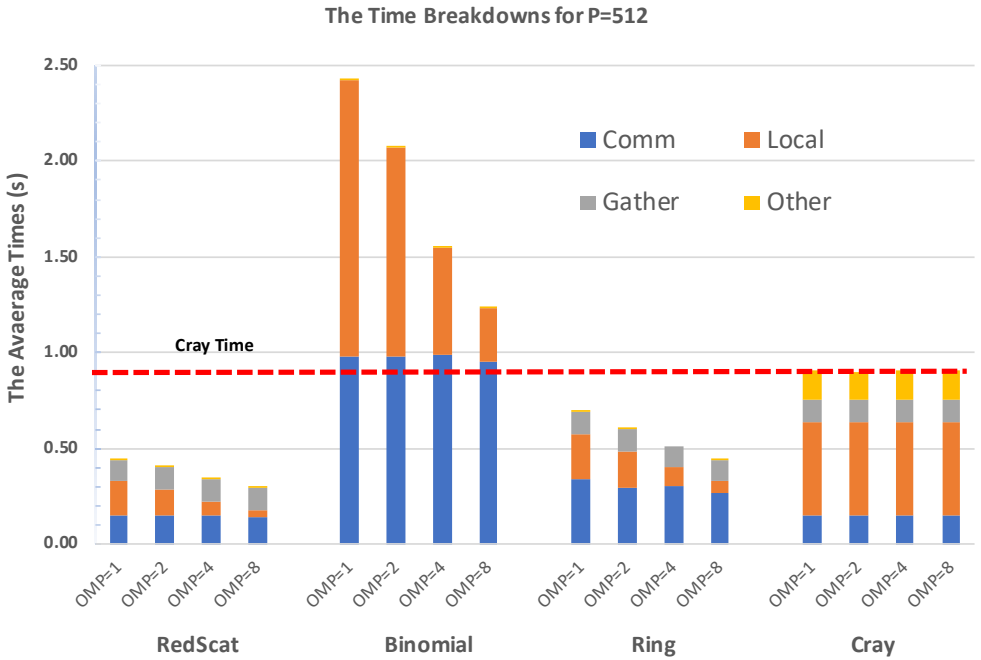
- Cori-KNL, located at NERSC
- Programming Environment:
  - PrgEnv-intel/6.0.4
  - MPI Version: cray-mpich/7.7.0
  - Compiler: Intel/18.0.1.163
- Baseline: DMAPP enabled Cray implementation
  - MPICH_NEMESIS_ASYNC_PROGRESS=MC
  - MPICH_MAX_THREAD_SAFETY=multiple
  - MPICH_USE_DMAPP_COLL=1
- Using OMP_NUM_THREADS to set the number of OpenMP threads

Performance: Micro Large Messages



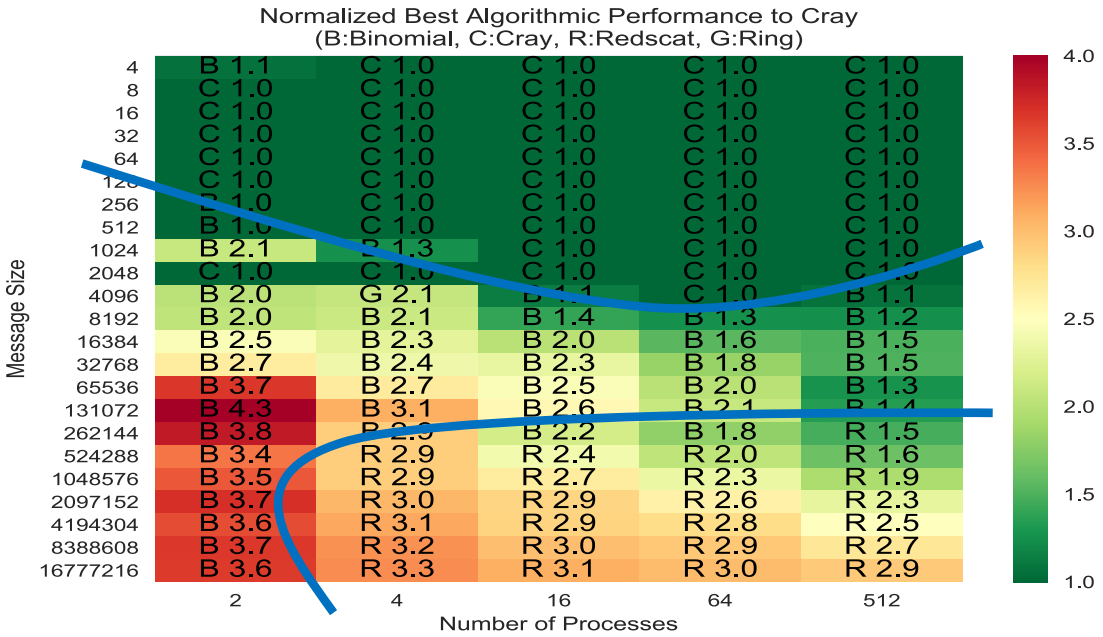
- N=200M floats, one MPI process/node
- Redscat performs best, significant better performance than Cray
- Threading is important

Time Breakdown: Micro Large Messages



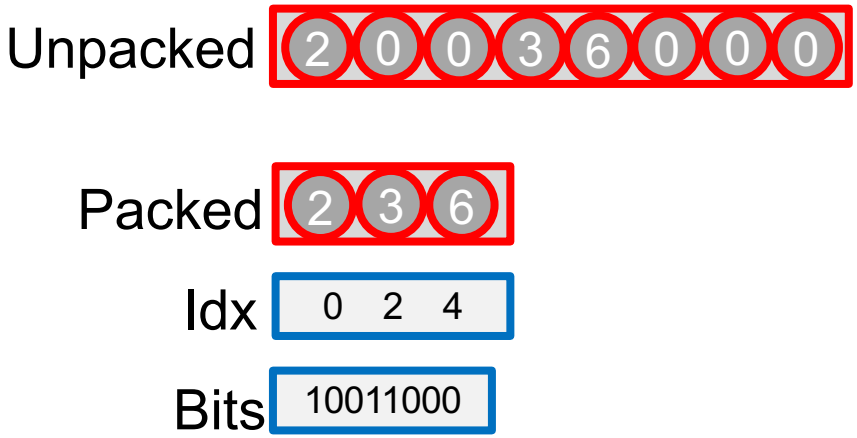
- **Cray: local time dominate, threading does not help**
- **Other three: threading reduce the local time significantly; the "other" time has been eliminated**

Performance: Micro
Small Messages



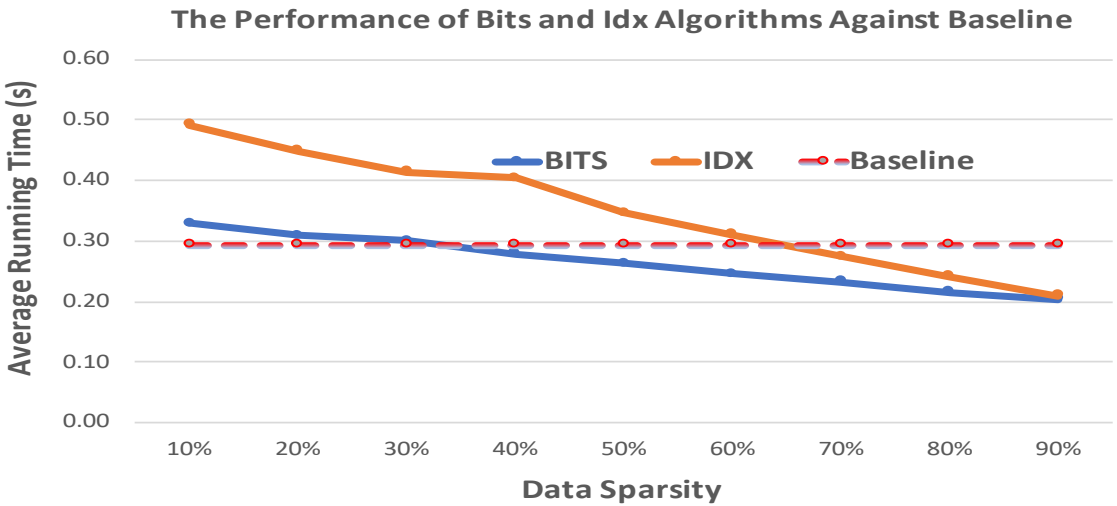
- **Msg sizes < 2K floats, Cray performs best**
- **Msg sizes > 512K floats, Redscat performs best**
- **Msg sizes between 2K – 512K, binomial performs best**

Data Sparsity



- **Algorithm IDX: using an extra index array**
- **Algorithm BITS: using one bit to indicate whether the element is zero or not**

Performance: Data Sparsity



- Implemented on top of threading and the packing/unpacking is vectorized efficiently
- The break-even point is around 35% for BITS and 65% for IDX

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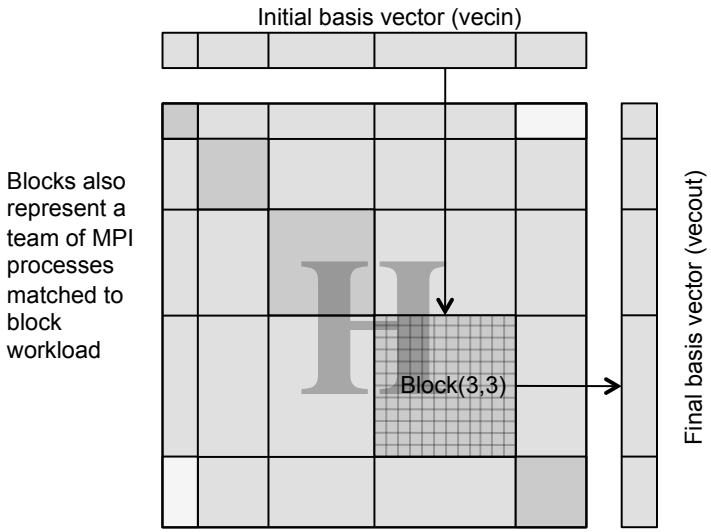
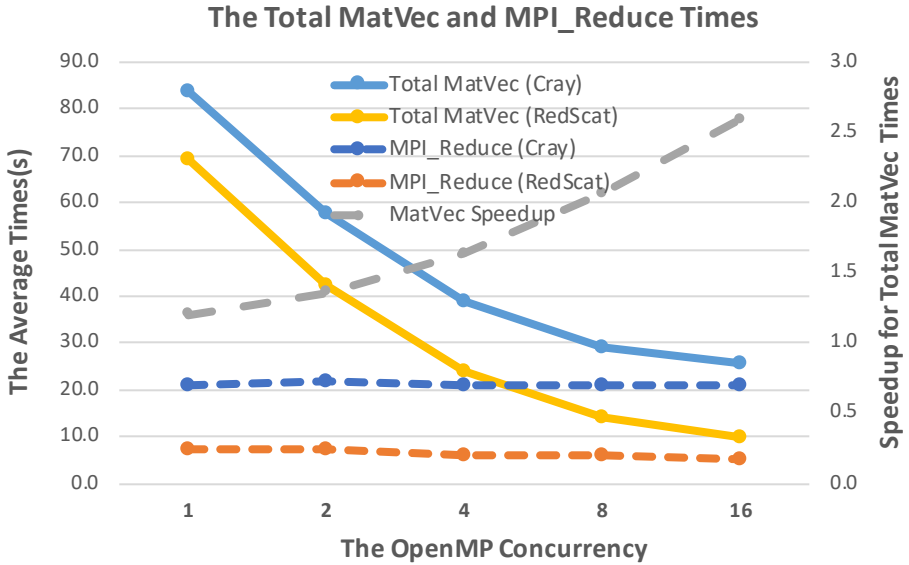
BIGSTICK



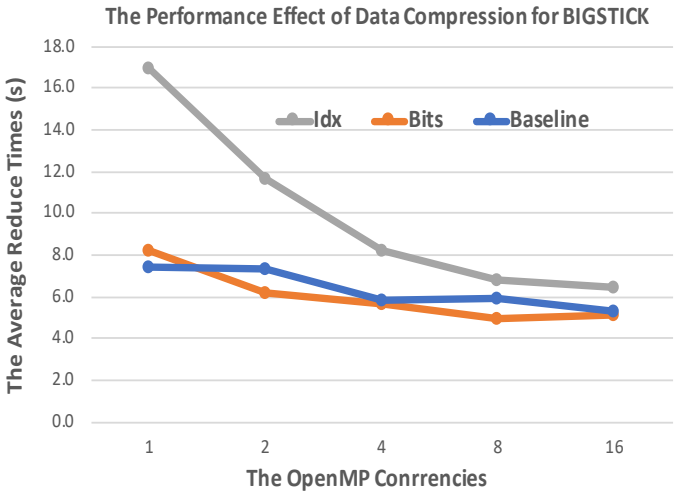
- Dominated by sparse matrix vector multiplication
- Vector size is big, around 10.6 billion elements for ^{130}Cs
- Communication: MPI_Reduce in row direction; MPI_Bcast in col direction

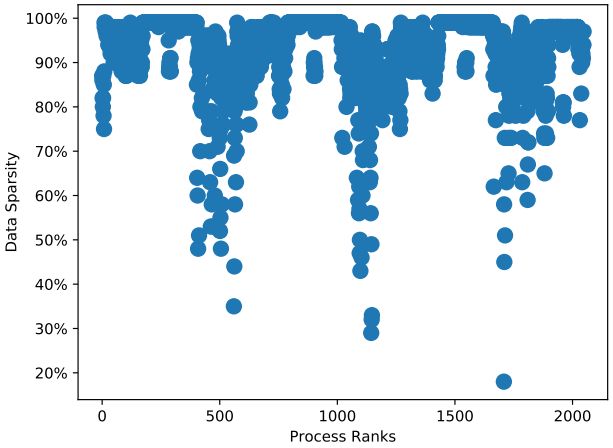
Performance: BIGSTICK Threading



- BIGSTICK scaling performance is highly related with MPI_Reduce
- Using threading could improve the performance up to 2.5X

Performance: BIGSTICK Data Compression





- Data compression does not help performance though the average data sparsity is over 90%
- The density imbalance destroys the performance advantage of data compression

Conclusion

- Making effective use of the idling threads on the manycore architectures could significantly improve large MPI_Reduce performance
- Our threading algorithms performs up to 4x better than the Cray implementation and improve the BIGSTICK performance up to 2.6x.
- Compressing the sparse data could also help the performance, but may suffer from density imbalance.

Future Work

- Extend out algorithms to more applications and other HPC platforms
- Using threads to increase network injection bandwidth
- Develop smart algorithms to address the density imbalance problem
- Develop hierarchical algorithms to combine advantages of different ones
- Develop auto-tuning framework for MPI persistent reduce functions

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