Using Lossy Compression for Interactive Analysis Over Network

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Introduction

- To gain scientific insights from simulation results stored in High performance computing (HPC) centers, researchers conduct post-processing by using:
  1. Batch jobs managed by job schedulers such as Slurm.
  2. **Interactive data analysis tools such as Jupyter Notebook**
- In certain scenarios, transferring the simulation results directly from the center is essential.
  - e.g., the cases where special hardware and/or licensed software is available only on a particular system remote from the HPC center.
- To achieve interactive data processing, only a necessary part of the data could be streamed over the network. Under this assumption, there are two challenges for achieving interactivity:
  1. **Limited network bandwidth.**
  2. **Long network latency.**

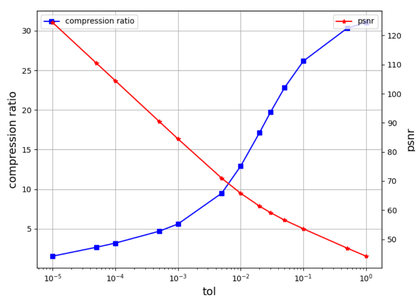
Error-bounded Lossy Compression

- For certain data analyses that allow degradation in quality, error-bounded lossy compression can be applied.
- Features of error-bounded lossy compression are:
  1. A higher compression ratio can be achieved for floating-point data by allowing a larger error.
  2. Acceptable error by lossy compression can be adjusted by users.

$$PSNR = 10\ log\frac{MAX_I^2}{MSE}$$

MAX_I : *Maximum value of the data*

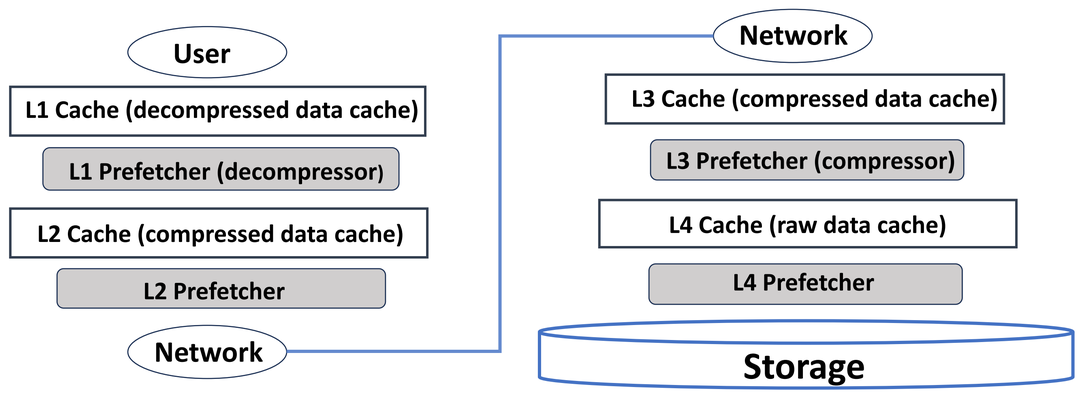
This work proposes a mechanism to properly use error-bounded lossy compression that can find a good trade-off point.



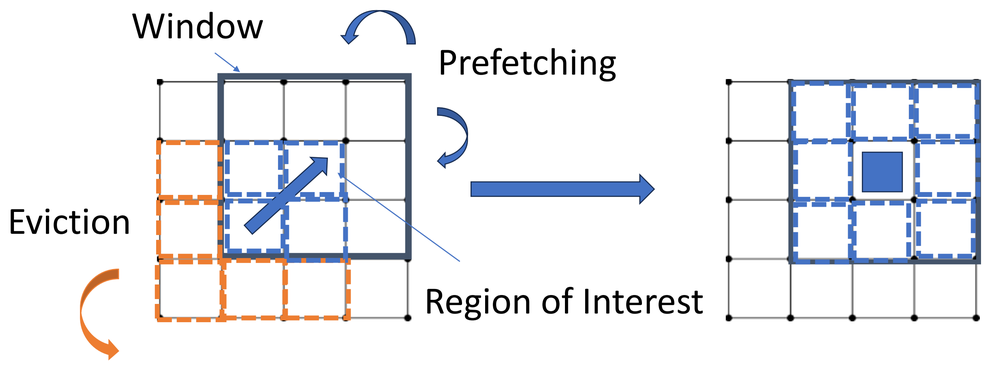
Proposed Middleware

We propose middleware with the following features to support interactive array analysis over network.

1. Using **error-bounded lossy compression** to increase the effective network bandwidth.
2. Using **multi-level caching and prefetching** to hide the network latency.
   - At each step of data transfer from server to client (reading, compressing, transferring over network and decompressing), we introduce:
     1. Caches to take advantage of data access locality.
     2. Prefetchers to improve the cache hit ratio.



- Considering that the access pattern of interactive analysis on a multidimensional array exhibits a spatial locality,
  1. **Prefetcher at each level keeps fetching the blocks around the last accessed block until the cache becomes full.**
  2. **Each cache evicts blocks located farther than a certain distance from the last accessed block.**



Evaluation

Evaluation settings

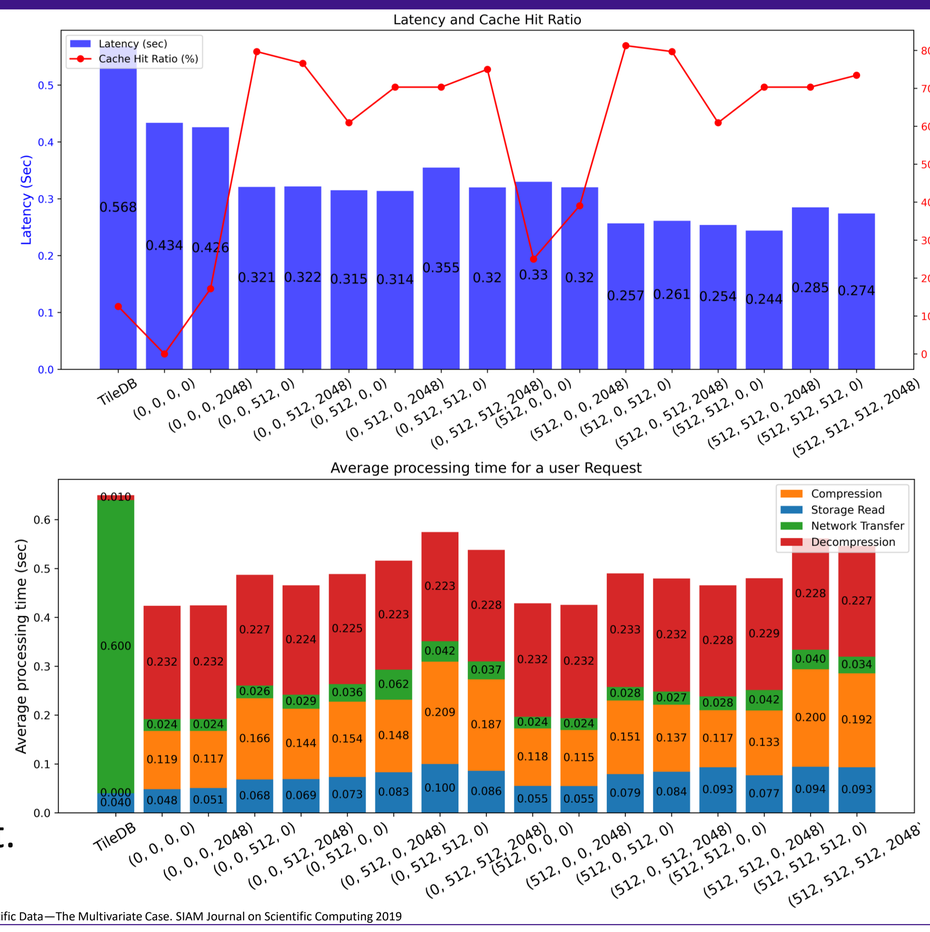
- L1, L2, and L3 cache sizes were set to either 0 MiB or 512 MiB. L4 cache size was set to either 0 MiB or 2048 MiB. The cache size of 0 represents that the cache is turned off and unused.
- Turbulence Flow simulation data [1] is used for the data to analyze.
- Each user requests retrieves a 64MiB block of 3-dimensional array. 64 Requests in total are sent at the interval of 1 second to simulate user's interactive data analysis.
- Error tolerance is set to 10% of the original data value.
- The proposed middleware is compared with TileDB [2], a state-of-the-art array databases with lossless compression and Least-Recently-Used cache replacement policy (no prefetching).

Evaluation metrics

- The average latency from the time the user request a block to obtaining the block.

Implementation details

- TileDB is used for array management in storage, MGARD [3] for error-bounded lossy compression and Python's standard library for key-value store of cache management.
- The server and client communicate over HTTP.



[1] Johns hopkins turbulence databases. https://turbulence.pha.jhu.edu/
[2] S. Papadopoulos, K. Datta, S. Madden, and T. Mattson. 2016. The TileDB Array Data Storage Manager. 2016
[3] M. Ainsworth, O. Tugluk, B. Whitney, and S. Klasky. 2019. Multilevel Techniques for Compression and Reduction of Scientific Data—The Multivariate Case. SIAM Journal on Scientific Computing 2019

Conclusion

- Compared to TileDB, our proposal reduced the average latency by up to **57%** because
  1. Introducing **lossy compression reduced the average network transfer time** from **0.6 sec to 0.042 sec.**
  2. Introducing **multi-level caching and prefetching improved the cache hit ratio** from **12.5% to 70.3%.**
- In the future work, machine learning will be applied to selecting blocks to be prefetched to improve the cache hit ratio.

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