Improving Prediction-Based Lossy Compression Dramatically via Ratio-Quality Modeling

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Introduction

Why Compression
- Large-scale scientific simulations generate extremely large amounts of data
- Limited storage capacity even for large-scale parallel computers
- The I/O bandwidth required to save this data to disk can create bottlenecks in the transmission

Lossy Compression
- High compression ratio
- Controllable compression error

Jin, Sian, et al. "Understanding GPU-based lossy compression for extreme-scale cosmological simulations." 2020 IEEE International Parallel and Distributed Processing Symposium (IPDPS). IEEE, 2020.
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Take Advantage Of Lossy Compressors
- Identify the optimal trade-off between the compression ratio and compressed data quality
- No analytical model available
- Trial-and-error experiments
  - High computational cost
  - Identified configuration setting is dependent on specific conditions and input data
Introduction

Our Ratio-Quality Modeling
- Estimate compression ratio and compressed data quality
  - General model suiting most scientific datasets and applications
  - High accuracy
  - Low computational overhead

Contributions
- We decouple prediction-based lossy compressors to build a modularized model
- We theoretically analyze how to estimate the encoder efficiency and provide essential parameters for compression ratio estimation
- We propose a theoretical analysis to estimate the qualification of lossy decompressed data on post-hoc analysis
- We evaluate our model using 10 real-world scientific datasets involving 17 fields.
Background

Data Management in Scientific Applications
- HDF5, netCDF, and Adaptable IO System (ADIOS)
- Compression techniques are often adopted

Error Bounded Lossy Compressors
- Transform-based lossy compressor (ZFP)
- Prediction-based lossy compressor (SZ)
- Data distortion metrics
  - Peak signal-to-noise ratio (PSNR)
  - Structural similarity (SSIM)

Compression Mode
- Error bounded mode
  - Absolute error bound (ABS)
  - Relative error bound (REL)
  - Point-wise relative error bound (PW_REL)
- Fix rate mode

Scientific data management with compression
Background

Prediction-Based Lossy Compression

- Each data point’s value is predicted based on its neighboring data points by an adaptive, best-fit prediction method.
- Each floating-point weight value is converted to an integer number by a linear-scaling quantization based on the difference between the real value and predicted value and a specific error bound.
- Lossless compression is applied to reduce the data size thereafter.

Main Challenges

- How to decompose prediction-based lossy compression into multiple stages and model the compression ratio for each stage?
- How to reduce the time cost of extracting data information needed by the model?
- How to model the quality degradation in terms of diverse post-analysis metrics?
- How does our model benefit real-world applications?
Rate-Quality Model

Overview

• Compression ratio
  • Predictor (prediction error histogram)
  • Quantizor (quantization code histogram)
  • Encoder (encode efficiency)

• Post-hoc analysis quality
  • Estimated error distribution

Analysis

• Model compression ratio of popular encoders
• Refine compression ratio modeling for various predictors and quantizers
• Model quality degradation for both generic and specific post-hoc analysis

An overview of ratio-quality modeling workflow for prediction-based lossy compression and scientific data analysis
Rate-Quality Model

Modeling Encoder Efficiency
- Quantization code is highly randomized
- Encoding efficiency provided by Huffman encoding is highly separated from that provided by the optional lossless encoders
- Zero would always dominate the Huffman codes after the red dashed line

Huffman Encoding
\[
B = \sum_{i=0}^{n} P(s_i)L(s_i) \approx -\sum_{i=0}^{n} P(s_i) \log_2 P(s_i),
\]
\[
e^* = 2^{B - B^*} e,
\]

Run-Length Encoding (After Huffman)
\[
R_{rle} = 1/(C_1(1 - p_0)P_0 + (1 - P_0)).
\]
\[
p_0 = \sqrt{1 - R_{rle}^{-1} - ((C_1 - 1)/2)^2 + (C_1 - 1)/2}
\]

Compression ratio from Huffman encoder and optional lossless encoder from Zstandard and Gzip on quantization code
Rate-Quality Model

Modeling Quantized Prediction Error Histogram
  • Prediction error histogram: different sampling solutions for different predictors
    • Lorenzo Predictor
    • Linear Interpolation Predictor
    • Linear Regression Predictor
  • Quantization code histogram
    • Based on sampled prediction error
    • Large distortion under large error bounds
      • Bin transfer scheme

\[ N_{\text{tran}} = P_{\text{tran}} \cdot N = C_2 \cdot (1 - p_0) \cdot N, \text{ when } p_0 \geq \theta_2. \]

Original Value  [..., 0.0, 1.3]
Quantization Code  [..., 0, 1]  [..., 0, 0]
Ours  Actual

Error rate between sampled prediction error and original prediction error under different sampling rates with three predictors. The error bar indicates the max and min values
Rate-Quality Model

Post-hoc Analysis Quality Model

- Error distribution, described by its variance

\[ \sigma(E)^2 = \sum_{i=0}^{N} (E[i]^2 - \mu^2) \approx \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{x^2}{2}} dx = \frac{1}{3} e^2 \]

\[ \sigma(E)^2 = \sum_{i=0}^{(1-p_0)N} (E[i]^2 - \mu^2) + \sum_{i=0}^{p_0N} (E[i]^2 - \mu^2) = (1-p_0)^\frac{1}{3} e^2 + p_0 \sigma(B[0]), \]

- Peak signal-to-noise ratio (PSNR)
- Structural similarity index (SSIM)
- Data-specific post-hoc analysis

\[ PSNR(D', D) = 20 \log_{10}(minmax) - 10 \log_{10}(\sigma(E)^2) \]

\[ SSIM(D', D) = \frac{2\sigma_{D'} + C_3}{2\sigma_{D'} + C_3 + \sigma(E)^2} \]

Unified distribution

Refined centralized distribution at high error bounds

FFT quality degradation estimation compared to measurement. Evaluated on Nyx temperature field at ABS 500
Evaluation

Ratio-Quality Model Accuracy
- Accuracy of Compression Ratio Model
- Accuracy of Post-Hoc Analysis Quality Model

Compression ratio (bit-rate) estimation accuracy compared to measurement by the encoders

PSNR estimation accuracy compared to measurement

SSIM estimation accuracy compared to measurement
## Evaluation

| Name       | Field                  | Dim       | Sample Err. | Huff Err. | Lossless Err. | Huff+LL. Err. | PSNR Err. | SSIM Err. |
|------------|------------------------|-----------|-------------|-----------|---------------|---------------|------------|-----------|
| RTM        | 1000                   | 235x449x449 | 0.03%      | 5.67%    | **9.82%**     | 8.72%         | 0.77%      | **9.34%** |
|            | 2000                   | 235x449x449 | 0.02%      | 3.32%    | **9.01%**     | 7.76%         | 1.56%      | **6.56%** |
|            | 3000                   | 235x449x449 | 0.06%      | 1.88%    | **9.15%**     | 7.57%         | 2.84%      | **4.12%** |
| CESM       | TS                     | 1800x3600  | 0.06%      | 6.88%    | **11.26%**    | 8.85%         | **3.97%**  | 2.54%     |
|            | TROP_Z                 | 1800x3600  | 0.20%      | 7.56%    | **10.52%**    | 9.66%         | 2.97%      | **4.44%** |
| Hurricane  | \( U \)                | 100x500x500 | 0.10%      | 4.62%    | 3.46%         | 5.75%         | 1.56%      | **5.43%** |
|            | \( TC \)               | 100x500x500 | 0.12%      | **5.44%** | 2.96%         | 5.95%         | 2.42%      | **3.80%** |
| Nyx        | Dark Matter            | 512x512x512 | 0.14%      | **7.53%** | 4.36%         | 7.67%         | 1.78%      | **6.55%** |
|            | Temperature            | 512x512x512 | 0.13%      | 3.92%    | **5.13%**     | 3.99%         | 1.89%      | **4.34%** |
|            | \( \text{Velocity Z} \) | 512x512x512 | 0.07%      | 6.85%    | **8.65%**     | 8.08%         | 2.64%      | **3.90%** |
| HACC       | \( xx \)               | 2808953867  | 0.26%      | **2.29%** | 1.34%         | 3.22%         | 1.98%      | -         |
|            | \( vx \)               | 2808953867  | 0.27%      | **3.71%** | 1.49%         | 3.83%         | 3.67%      | -         |
| Brown      | Pressure               | 8388699    | 0.11%      | **5.99%** | 5.68%         | 6.46%         | 4.42%      | -         |
| Miranda    | \( vx \)               | 256x384x384 | 0.13%      | **7.90%** | 6.95%         | 8.71%         | 2.55%      | **8.92%** |
| QMCPACK    | einspline              | 69x69x115  | 0.13%      | 6.84%    | **8.83%**     | 6.28%         | 5.67%      | **7.43%** |
| SCALE      | PRES                   | 98x1200x1200 | 0.16%      | 1.63%    | **2.79%**     | 2.36%         | 1.72%      | **5.35%** |
| EXAFEL     | raw                    | 10x32x185x388 | 0.12%      | **5.64%** | 4.25%         | 6.23%         | 3.80%      | -         |
| **Average**|                        |           | 0.12%      | 5.16%    | **6.21%**     | 6.53%         | 2.72%      | **5.59%** |

* Bold items highlight the larger prediction error between the two encoders and between the two post analyses.

Details of Evaluation Results on Tested Data and Fields

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Use Cases

- Predictor Selection
  - Select the most efficient predictor for a given dataset & error bound
- Memory Limitation Control
  - Efficiently utilize available memory
- In-Situ Compression Optimization
  - Optimize the compression performance individually for each partition with overall compression ratio and overall analysis quality as objectives

Rate-distortion curve of multiple predictors with different error bound. Evaluated with RTM dataset.
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Ratio of measured space consumption to assigned space. Evaluated with RTM dataset, randomly choose time steps and error bound for 15 groups.
Evaluation

Use Cases

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Error bound optimization for RTM dataset with multiple time steps in consideration for post-hoc analysis
Evaluation

Performance
- Significantly lower overhead compared to previous solution
- One sampling, prediction on all error bound setting
- Outperforms the trial-and-error solution by $18.7\times$ on average when considering 7 candidate error bounds to estimate with the Lorenzo and interpolation predictors as candidates

Performance comparison between proposed modeling solution and previous trial-and-error approach
Evaluation

Overall Performance of Data Management

- Optimize the most efficient compression configuration for each snapshot
- Provide consistent and the fastest data dumping time

Overall data dumping performance with parallel HDF5. Comparison between traditional method, trial-and-error and our modeling-based method. Dashed lines highlight the maximum dumping time occurred in the simulation. “Tr” refers to the traditional approach, “TAE” refers to the in-situ trial-and-error approach. ‘Comp’, ‘I/O’, and ‘Op’ refer to times of compression, I/O, and optimization, respectively.

Comparison between our modeling-based method with offline optimization method in terms of both bit-rate and corresponding PSNR across different snapshots when target PSNR is 56 dB.
Thank you!

Any questions are welcome!

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