

Statistical Prediction of Lossy Compression Ratios for 3D Scientific Data

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Introduction

Why Study Lossy Compressibility?

- Error bounded lossy compressors are used within scientific research due to larger compression ratios (CRs) in relation to lossless compressors
- Entropy[1] is the mathematical limit on lossless compression; however, there is no known bound of lossy compression
- Use of data correlation structures, heterogeneity and error bounds in lossy compression techniques
- Establish entropy-like metric for lossy compression algorithms which can guide lossy compression community to an optimal development and usage
- Anticipate compression performances and adapt compressors to correlation structures to get the best CR performance possible



Goals:

- (1) Explore possible models of CR and quality metrics for 3D data
- (2) Next step towards the theoretical limit for lossy compressibility

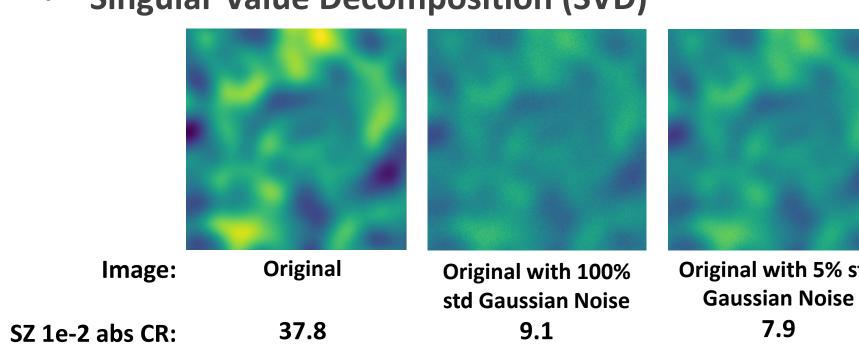
Our Previous Work

Statistical Methods & Compression Statistics for 2D

Statistical predictors trained with datasets using notions of correlation, entropy and lossy-ness. The model, Eq. (1), relies on:

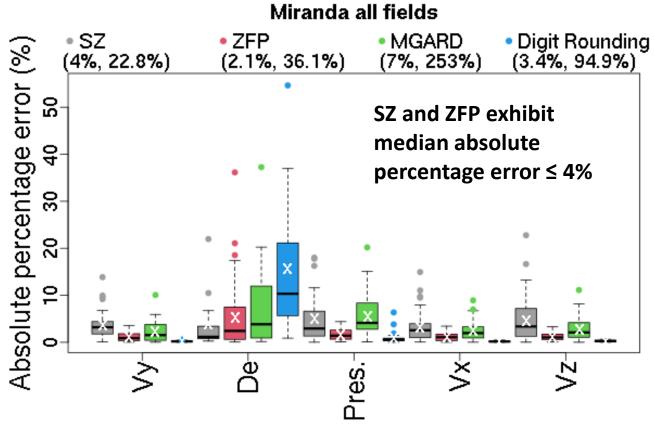
- Quantized entropy
- Singular Value Decomposition (SVD)

5.1



How Well Does This Work?

SZ 1e-5 abs CR:

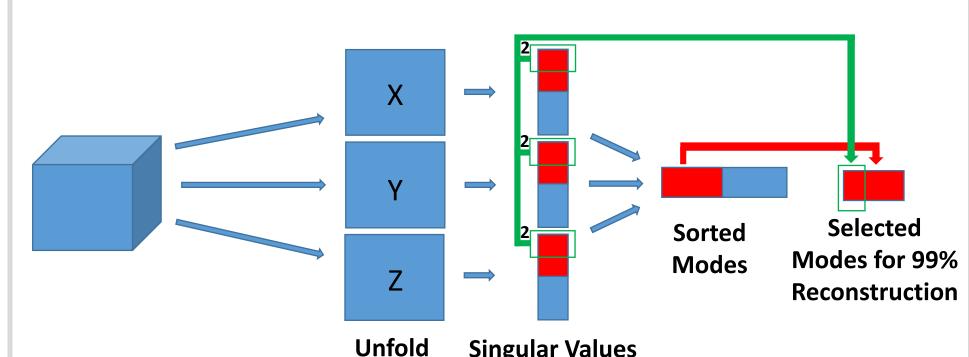


Does this extend to 3D?

Methodology

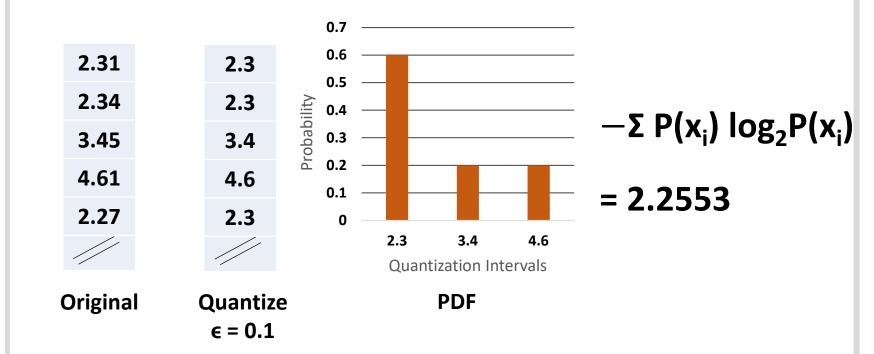
Statistical Methods & Compression Statistics: Predictors for 3D Datasets

What Is Higher Order SVD (HOSVD)?



- 1. Unfold a tensor along each dimension
- 2. Perform SVD on each unfolding to obtain singular values
- 3. Combine singular values using at least two from each unfolded dimension to reconstruct 99% of the data
- 4. Perform SVD truncation (percentage of singular values needed to reconstruct 99.9% of the data)

What Is Quantized Entropy (Qentropy)?



- 1. Discretize original data into intervals based off the user defined error bound (ϵ)
- 2. Create a probability distribution function (PDF) of the different symbols used
- 3. Calculate the entropy using the PDF

Compressors and Software

Lossy Compressors:

- SZ[2] @2.1.12.2
- ZFP[3] @0.5.5 MGARD[4] @1.0.0
- Bit Grooming[5] @2.9.0
- TTHRESH[6] @0.0.5

Software:

- Libpressio[7] @0.83.1
- LLVM @12.0.1
- Julia @1.7.2
- CUDA @11.7.0
- CUSOLVER @11.3.5

Regression Model for 2D and 3D

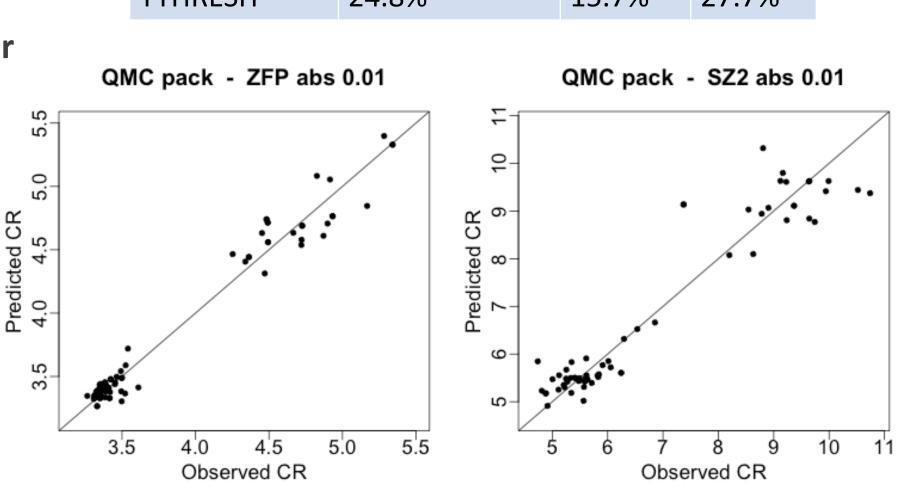
- Regression models, Eq. (1), are trained on observed CR of the studied datasets and the statistical predictors
- Least-square techniques estimate parameters from observed training datasets and then used to make CR predictions from new predictor values
- K-fold cross-validation assesses without bias or over-fitting the predictive capabilities of the regression models

$$\log(\text{CR}) = a + b \times \log(\text{Qentropy}) + c \times \log\left(\frac{\text{SVD-trunc}}{\sigma}\right) + d \times \log(\text{Qentropy}) \times \log\left(\frac{\text{SVD-trunc}}{\sigma}\right) + \epsilon$$
 (1)

Results **How Accurate Is The 3D Approach?**

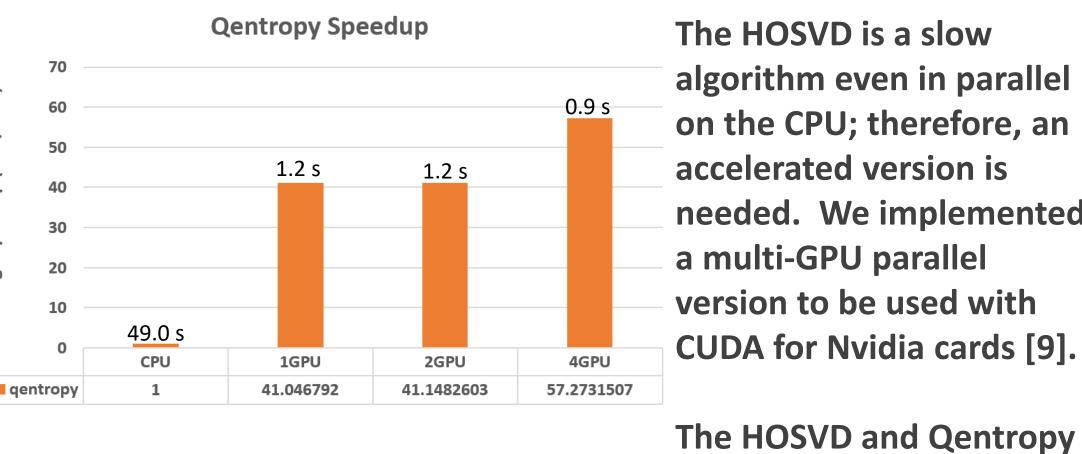
- Data: 288 3D orbitals from QMCPack from SDRBENCH [8] containing structures of atoms, molecules, and solids.
- Median absolute percentage errors (MAPE) is the difference between the predicted and observed CRs on the validation set
- The predicted CR exhibits low MAPEs (< 7.5%) for SZ2, ZFP, MARD, and Bit Grooming
- However, TTHRESH produces a higher error

Compressor	MAPE (median percentage error)	10% Quantile	90% Quantile
SZ2	4.5%	3.2%	5.7%
ZFP	1.7%	1.3%	3.5%
MGARD	0.6%	0.4%	1.3%
Bit Grooming	7.4%	5%	9.3%
TTHRESH	24.8%	15.7%	27.7%



Performance

How Fast Is The 3D Approach?



The HOSVD is a slow algorithm even in parallel on the CPU; therefore, an accelerated version is needed. We implemented a multi-GPU parallel version to be used with CUDA for Nvidia cards [9].

HOSVD Speedup 2GPU 42.20032994 HOSVD

were measured on average performance over 6 runs on the baryon_density buffer (512x512x512) from the NYX dataset [8].

NVIDIA A100 GPU scaling with DGX node on the Palmetto Cluster [10].

The maximum speedup (CPU / GPU) is 57x

Conclusions

- Ability to accurately predict CRs in 3D is comparable to 2D
- Flexible across compressors, error bounds, and datasets
- Statistical predictor reuse allows for comparison of different compressors to find largest CR
- Next step towards theoretical quantification of lossy compressibility

Future Work

- Further reduction of computation costs
- **➢** Generate training samples from blocks of the 3D tensor data
- Estimate CR using the samples and our predictors



[1]C. E. Shannon, "A mathematical theory of communication," in The Bell System Technical Journal, vol. 27, no. 3, pp. 379-423, July 1948, doi: 10.1002/j.1538-7305.1948.tb01338.x.

2.1

[4] https://github.com/CODARcode/MGARD

[5] Zender, C. S.: Bit Grooming: statistically accurate precision-preserving quantization with compression, evaluated in the netCDF Operators (NCO, v4.4.8+), Geosci. Model Dev., 9, 3199–3211, https://doi.org/10.5194/gmd-9-3199-2016, 2016.

[6] https://github.com/rballester/tthresh

[7]R. Underwood, S. Di, J. C. Calhoun, and F. Cappello, "FRaZ: A Generic High-Fidelity Fixed-Ratio Lossy Compression Framework for Scientific Floating-point Data," presented at the 34th IEEE International Parallel and Distributed Processing Symposium, New Orleans, May 2020.

https://github.com/robertu94/libpressio

[8]F. Cappello et al., "Scientific Data Reduction Benchmarks," Scientific Data Reduction Benchmarks, Jun. 18, 2018. https://sdrbench.github.io/ (accessed Jun. 02, 2020).

[2]https://github.com/disheng222/SZ