Exploring Lossy Compressibility through Statistical Correlations of Scientific Datasets

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Goals

In lossless compression, entropy provides theoretical limit on compressibility of data but there are no equivalent for lossy compressors

1. Characterize statistics of the data that impact lossy compression, e.g. correlation structures of scientific datasets, patterns, range of values, …

2. Explore their relationships, through functional regression models, to compression ratios

-> These models form the first step towards evaluating theoretical limits of lossy compressibility

> how far are existing compressors to optimality

> help optimize compressors

> allow maximum efficiency for storing scientific datasets

Exploring Lossy Compressibility through Statistical Correlations of Scientific Datasets
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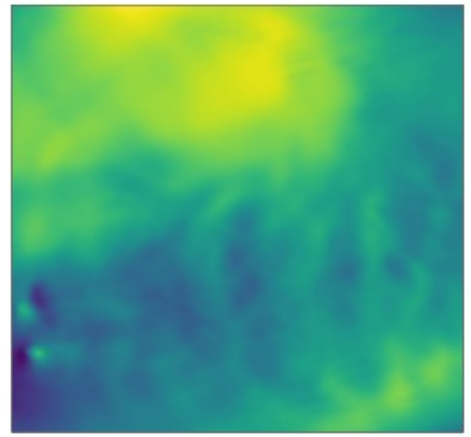
https://arxiv.org/pdf/2111.13789.pdf

Procedure and quantities of interest



- Performed statistical and compression analysis on several datasets
  - > analysis of 2D slices as a start
  - > synthetic 2D-Gaussian samples with controllable correlation structured
  - > Scientific datasets: CESM, SCALE-LETKF, Hurricane Isabel available on SDRBench [1]

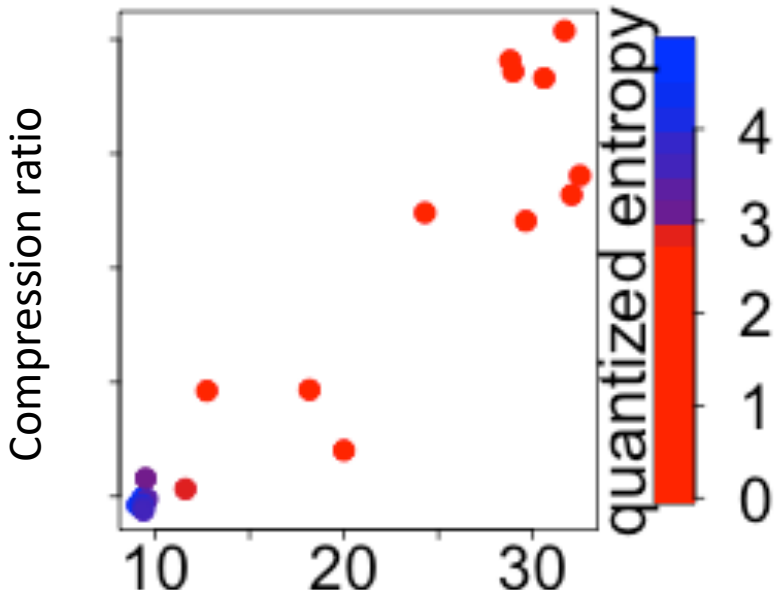
- Compressors: SZ [2], ZFP [3], MGARD [4], BitGrooming, Digit Rounding
  - > compression ratios (impacted by error bound, compressor used, and structures within data)

- Statistics of interest: independent of the compressors
  - > correlation strength across grid-points: truncation level of singular value decomposition as proxy
  - > variance: value range, variability
  - > quantized entropy: entropy $-\sum_{i=1}^{n} P(q(x_i))\log(P(q(x_i)))$ of quantized data $\forall x_i \in x, q(x_i) = \left\lceil \frac{x_i - \min(x)}{\epsilon} \right\rceil$ at given error bound [given sequence of symbols, provides average minimum number of bits required to represent data]

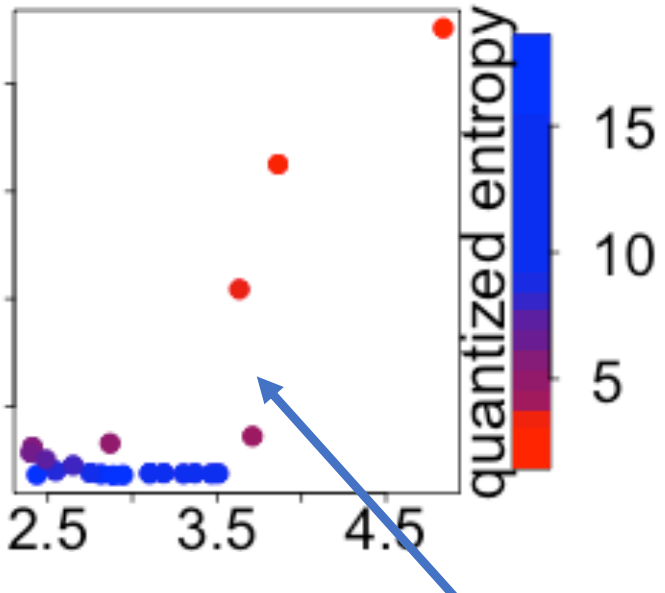
[1] K. Zhao, S. Di, X. Lian, S. Li, D. Tao, J. Bessac, Z. Chen, and F. Cappello, "SDRBench: Scientific data reduction benchmark for lossy compressors," in 2020 IEEE International Conference on Big Data (Big Data). IEEE, 2020, pp. 2716–2724. [Online]. Available: https://sdrbench.github.io
[2] X. Liang, S. Di, D. Tao, S. Li, S. Li, H. Guo, Z. Chen, and F. Cappello, "Error-controlled lossy compression optimized for high compression ratios of scientific datasets," in 2018 IEEE International Conference on Big Data (Big Data). IEEE, Dec. 2018. [Online]. Available: https://doi.org/10.1109/bigdata.2018.862252
[3] P. Lindstrom and M. Isenburg, "Fast and efficient compression of floating-point data," IEEE Transactions on Visualization and Computer Graphics, vol. 12, no. 5, pp. 1245–1250, Sep. 2006. [Online]. Available: https://doi.org/10.1109/tvcg.2006.143
[4] M. Ainsworth, O. Tugluk, B. Whitney, and S. Klasky, "Multilevel techniques for compression and reduction of scientific data- the multivariate case," SIAM Journal on Scientific Computing, vol. 41, no. 2, pp. A1278–A1303, Jan. 2019. [Online]. Available: https://doi.org/10.1137/18m1166651

Addition of quantized entropy as explanatory statistics

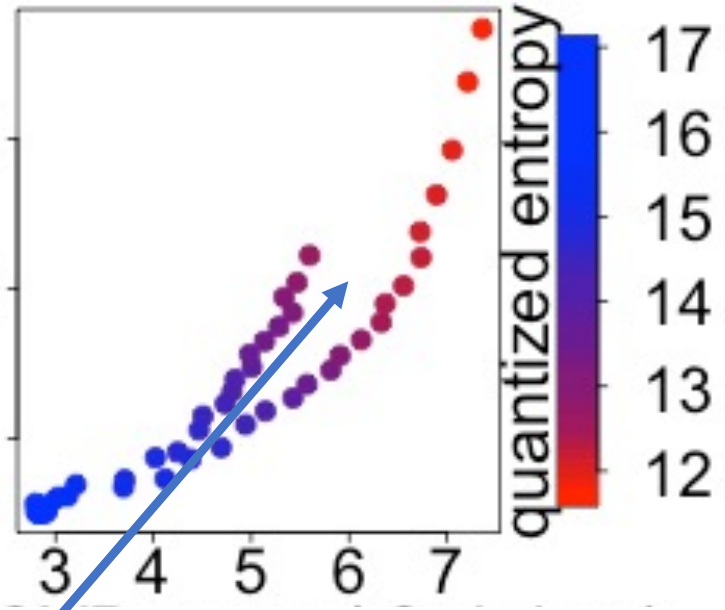
Hurricane QR – SZ abs=1e-3



CESM CLOUD– ZFP abs=1e-5



Miranda velocity x – MGARD abs=1e-4



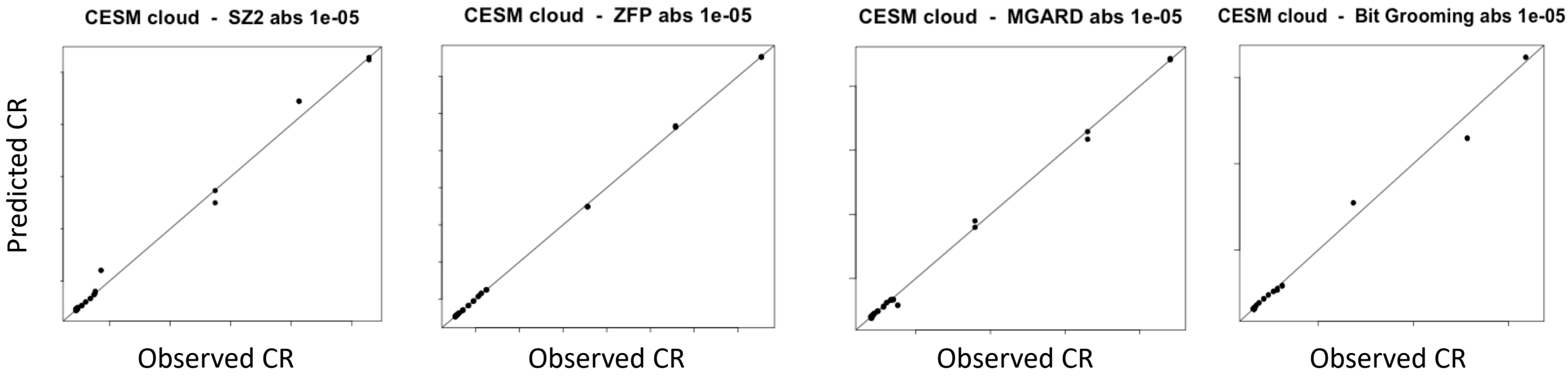
-> Quantized entropy enables to further characterize further compression ratios

-> Matching and complementary information to previous statistics

Use of regression models to predict compression ratios

log(CR) ~ spline(correlation/std dev) + spline(quantized entropy) + spline(interaction)

Models trained for each compressor and each data field



> Very good (out-of-sample) prediction of compression ratios based on selected statistics

> Regression model adequate for several studied compressors

> Need to access compression ratios to train these models

Conclusions

- Correlation ranges combined with other statistics: variance or gradient and quantized entropy, can explain most compression ratios through various regression functionals for some compressors and given error bounds [1]

- Next: Explore a unified way (across compressors) of expressing compression ratios as functions of these statistics

- Next: How to go about in a compressor-free framework?
  Now, rely on compressors to train regression models

[1] Exploring Lossy Compressibility through Statistical Correlations of Scientific Datasets
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