Exploring Lossy Compressibility through Statistical Correlations of Scientific Datasets

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Goals

In lossless compression, entropy provides theoretical limit on compressibility (associated with coding) of data
-> 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

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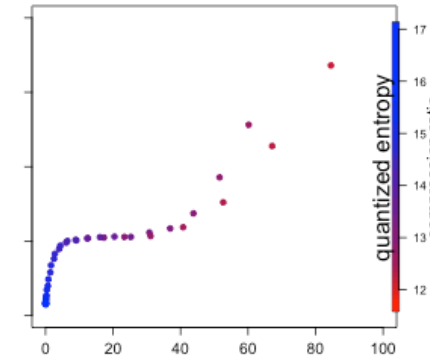
Procedure and quantities of interest

- 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: Miranda, SCALE-LETKF available on SDRBench [1]

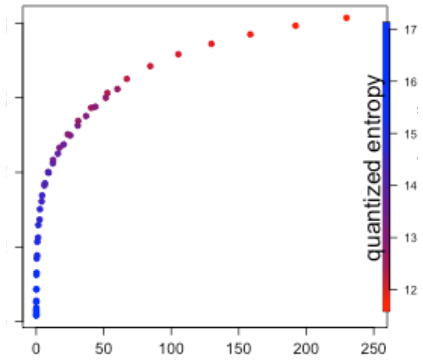
- Lossy compressors: SZ [2], ZFP [3], MGARD [4], BitGrooming, Digit Rounding
  - > compression ratios (impacted by error bound, compressor used, and structures within data)

- Statistics of interest: independent of the compressors
  - > correlation strength across grid-points
  - > variance: value range, variability
  - > quantized entropy: entropy $-\sum_{i=1}^{n} P(q(x_i))\log(P(q(x_i)))$ of quantized data

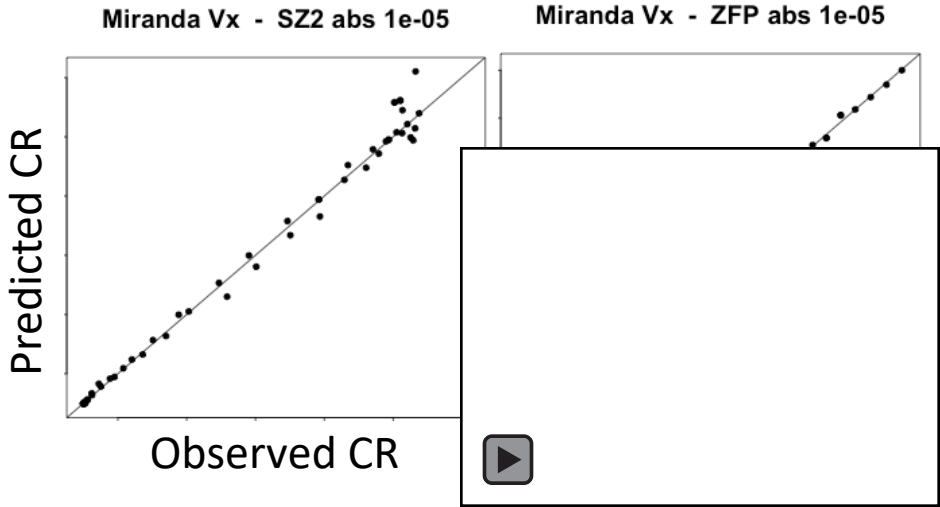
Miranda velocity x – SZ abs=1e-4



Miranda velocity x – ZFP abs=1e-4



Spline regression model to predict compression ratio



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