# Compression of Scientific Data with SZ

Franck Cappello

**Argonne National Laboratory** 

University of Illinois at Urbana Champaign

With:

Sheng Di, Robert Underwood, Julie Bessac, Dingwen Tao, Xin Liang, Kai Zaho, Xiaodong Lu, Jon Calhoun, Hanqi Guo, Jiannan Tian, Jinyang Liu, Codi Rivera, Ali Murat Gok and more...



### Lossy compression of scientific data

- Consist in reducing scientific data volume by leveraging correlations and reducing precision (lossless compression does not reduce scientific data enough)
- Compression ratios (with current compressors) vary depending on use-cases, typically:
  - CR=5 for hard to compress dataset and demanding data/analysis quality preservation
  - CR=10-100 for scientific data presenting high correlation and medium data/analysis quality preservation
  - CR=x100 for visualization (low data/analysis quality preservation)
- Goal: keep the same science (satisfy user's quality requirements WRT QoIs features)
  - WARNING: You will see images because this is the easiest way to show distortion but compression of scientific data is NOT only for images
- Getting significant traction in the scientific community (climate, cosmology, seismic, etc.), IoT community as well (sensors, EKG)



### Huge Progress in performance in the past 5-6 year $(\hat{c})$ P

Evolution of SZ compression quality and performance using a large-eddy simulation of multicomponent flows with turbulent mixing: Miranda - density field.



Visualization of Miranda - density data for SZ's different versions (EB: VRAE 1E-2), Performance on single core CPU (Intel Broadwell)

### SZx compresses at 300GB/s on NVIDIA A100 → Bottleneck is not compression but PCIe

# Many Applications Domains



### Climate

- Combustion
- Cosmology
- Deep Learning
  - Activation data
  - Model coefficients
  - Training data
- Extreme Weather
- Fusion Energy
- Hydrodynamics
- IoT

We

worked

directly

for all

these

SZ

domains

to develop

- Light Sources (LCLS, APS, etc.)
- Materials Science
- Molecular Dynamics
- Quantum Chemistry
- Quantum Circuit Simulation
- Seismic Imaging



### Many Use-Cases

We are seeing an increasing diversity/number of use-cases

"Classic" use-cases:

1) Visualization

2) Reducing storage footprint (offline compression)

3) Reducing I/O, communication time (on-line, in-situ compression)

#### Recently identified use-cases:

4) Reducing streaming intensity (recent for generic floating-point compressors)

5) Lossy checkpoint/restart from lossy state

- reduce checkpoints footprint on storage adjoint, accelerate checkpointing
- 6) Re-computation Avoiding by reducing the memory footprint  $\rightarrow$  GAMESS
- 7) Running larger simulations by reducing the memory footprint
- 8) Accelerating CPU/GPU memory transfer
- 9) Reduce DNN model size
- 10) Accelerate training (I/O read time) of DNNs



Cappello, F., Di, S., Li, S., Liang, X., Gok, A. M., Tao, et Al., Use cases of lossy compression for floating-point data in scientific data sets. *The International Journal of High Performance Computer Source Source Applications*, 33(6), 1201–1220, 2019



## General Principle of Error Bounded Lossy Compression

### Typical design of a lossy compressor for scientific data



SZ as a Software (Responds to ECP users) https://szcompressor.org



- Compress/decompress by blocks for nearly random-access decompression
- Can compress 1D, 2D, 3D datasets. and unstructured datasets as 1D
- Multiple // implementations: CPU Core (Vector Instructions), Multi-core (OpenMP), GPU (Cuda, Kokkos, HIP\*, DPC++\*), FPGA (proto)
- Integration in HDF5, ADIOS and PnetCDF
- Production quality. test infrastructure, scripts for regression testing





### Linear-regression



the constructed hyperplane must be based on "decompressed" coefficients

And many others: Multi-level interpolation, pattern based, DNN, Wavelet, etc. For 1D, 2D, 3D and 4D (3D + time) datasets.



# Example: SZ Interpolation based Predictor



Predictor based on multilevel, multidimensional tri-cubic spline interpolation

Spline method	Prediction Value $p_i$		
Linear spline	$p_i = \frac{1}{2}d_{i-1} + \frac{1}{2}d_{i+1}$		
Cubic spline	$p_i = -\frac{1}{16}d_{i-3} + \frac{9}{16}d_{i-1} + \frac{9}{16}d_{i+1} - \frac{1}{16}d_{i+3}$		

#### 1D case (linear spline):

. . .

• Known data points $\bigcirc$ Unknown data points (to be predicted) $d_i$ Original raw data $d_i'$ Reconstructed data
$d_1 \ d_2 \ d_3 \ d_4 \ d_5 \ d_6 \ d_7 \ d_8 \ d_9$
evel 0 $\bigcirc$ Use 0 to predict d <sub>1</sub>
evel 1 • Use d <sub>1</sub> ' to predict d <sub>9</sub>
evel 2 $\bigcirc$ $\bigcirc$ $\bigcirc$ Use d <sub>1</sub> ' and d <sub>9</sub> ' to predict d
evel 3 $\bigcirc$
evel 4 ● ● Use d₁', d₃', d₅', d⁊', and d₀
to predict $d_2$ , $d_4$ , $d_6$ , $d_8$

At level 0, 0 to predict d1,  $\rightarrow$  Store quantized error (e0) At level 1, d1+e0 to predict d9,  $\rightarrow$  Store quantized error (e9) At level 2, d1+e0 and d9+e9 to predict d5,  $\rightarrow$  Store error (e5)





Figure 25: Visualization of RTM, original data



(c) ZFP (PSNR:51.7,CR:258)

(d) MGARDx (PSNR:62.5,CR:310)

### Generic with App Specific Performance: Customization

Too specific:

Expensive to

Develop,

Maintain,

Update

Goal: reach performance (ratio, speed, accuracy) as close as possible to application specific data reduction without requiring expensive development/maintenance/update costs.



### What makes SZ3 different: a Highly **Modular**/ **Customizable** Compression Framework





**SZ 3 (C++)** library of algorithms for lossy compression and examples of SZ compressors built from the library of algorithms.

To compose and tune a compression pipeline we analyze the data to compress and user requirements in compression speed, ratio and accuracy.



### Example: Cosmology 1/2 (Storage Footprint Reduction)

HACC: N-body problem with domain decomposition, medium/long-range force solver (particle-mesh method), short-range force solver (particle-particle/ particle-mesh algorithm). SZ 2.0: CR ~5

Particle dataset: 6 x 1D array (x, y, z, vx, vy ,vz)

Preferred error controls:

- Point wise max error (Relative) bound
- Absolute (position), Relative (Velocity)

ANL: Cosmological Simulations for Large-Scale Sky Surveys





# Example: Cosmology 2/2



S. Li, S. Di, X. Liang, Z. Chen, F. Cappello, Optimizing Lossy Compression with Adjacent Snapshots for N-body Simulation Data, IEEE BigData 2018

ORATORY

### Example: Crystallography (Streaming intensity) Chuck Yoon: (Stanford, LCLS)

**LCLS-II Data System** 



#### 2: Diffraction



#### 3: Reduction

1 PF

Ā

P

pipeline

compression

oiBinSZ

Offline

(shared by all)

Ethernet 10 Gb/s

100 PB

Offline Analysi

Diffraction before destruction Number of pulses/sec: 120 Millions of diffraction patterns from crystals

Context: LCLS II. Goal: Definition of reduction method Detector produces:

- 2D images @ 250GB/s
- 4M pixel/event unsigned integers, in binary XTC2 format

Compression objectives: CR of 10 or more with error bound @ 500 MB/s/core → RoiBinSZ algorithm (regions of interest extraction + background binning + SZ background compression)



# Crystallography: First Level of Analysis Distortion: Indexing



### **Chuck Yoon: Stanford**

### Roibin SZ on Se-SAD SFX Dataset (Selenium)

selenobiotinyl-streptavidin on a cspad detector

- Number of hits: An image with at least 15 peaks is considered a hit
- Number indexed: Number of crystals extracted from hits
- Rsplit: measure precision of averaged intensities/amplitudes
- CCano: The correlation coefficient of the Bijvoet differences of acentric reflections
- CC1/2: Pearson correlation coefficient.
- Rwork: measure of the agreement between the crystallographic model and the experimental X-ray diffraction data
- Rfree: Rwork computed on a small, random sample of data
- Map-model CC: cross-correlation between electron density map and model.

	Original	Riobin SZ
Total compression ratio	1	70.65
Number of hits	744,150	744,150
Number indexed	255,065	255,918
Rsplit 🗸	7.58%	7.08%
CC1/2 <b>↑</b>	0.997	0.997
CCano 个	0.087	0.104
Rwork 🦊	0.206	0.199
Rfree 🗸	0.231	0.223
Map-model CC ↑	0.81	0.8

 $\uparrow$ : higher the better

 $\downarrow$ : lower the better

# Crystallography: Final Level of Analysis Distortion: Protein Reconstruction



### Reconstruction of Electron Densities Lysozyme

Very important role in our immune system: breaks up (digests) components of the cell walls of bacteria.



Lysozyme on a jungfrau4m detector

(a) original

(b) roibin-sz

The data on the right is 196x smaller (or 631× if also using Non-Hit Rejection)



#### Example: Ptychography (Storage Footprint Reduction) Tekin Bicer (DSL and XSD) Beamline Scientists: Junjing Deng, Jeff Klug and others

Compression and reconstructions: Sheng Di, Tekin Bicer

Timing: Bebop cluster, Intel Xeon E5-2695v4 (1 core).

**Original dataset:** Catalyst Particle Compressed with SZ2.1 (not Riobin SZ) Single scan (diffraction patterns): 1856x1030x514 Compressed 1856 images of 514x1030 pixels.

For the spatial compression, the dataset is treated as a 3D dataset, so the predictor adopts a 3D Lorenzo + 3D Linear regression;

For the temporal compression, the compressor predicts each data point only based on its temporal dimension

Tested absolute error bound from 2 to 64. Absolute error bound of 2 translates to (+/-) 2 photon count error on the detector.

PSNR computed from the diffraction patterns (not reconstruction result)

_	Absolute error bound				bounds		
	RATIO	2	4	8	16	32	64
	Spatial	72.9	97.2	117.7	144.7	147.2	181.1
*	Temporal	90.2	123.2	245.1	307.3	354.4	465.1
	Timing (secs, comp/decomp)	2	4	8	16	32	64
	Spatial	18.6/ 8.3	18.5/ 7.6	18.6/ 7.4	18.8/ 7.1	18.5/ 7.4	17.5/ 7.6
	Temporal	28.1/ 16	29.4/ 15.6	27.8/ 15	27.7/ 14.9	27.6/ 14.9	29/ 14.7
	GB/s (comp)	2	4	8	16	32	64
	Spatial	201.5	202.6	201.5	199.3	202.6	214.1
	Temporal	133.3	127.4	134.8	135.3	135.8	129.2
	PSNR	2	4	8	16	32	64
	Spatial	200.1	196.7	192.7	188.5	180.5	175.7
	Temporal	194.2	187.9	185.0	181.9	167.9	165.6

### Ptychography: Reconstruction from Diffraction Pattern Tekin Bicer (DSL and XSD) Beamline Scientists: Junjing Deng, Jeff Klug and others Compression and reconstructions: Sheng Di, Tekin Bicer

Ptychographic experiment: reconstruction on (sz) decompressed diffraction patterns.

Reconstruction parameters: Iter=300; Alg.:Conjugate Gradient (Tike)

Ptycho.

recon.



(de)compressed diff. patterns





Spatial error bound: 4 Compression ratio: 97 SSIM: >0.96



Temporal error bound: 8 Compression ratio: 245 SSIM: >0.94



### Conclusion

Lossy Compression for scientific data:

- Very popular topic among application teams
- SZ is the only customizable compressor
- ... designed to enable science preservation
- Can tune compression ratio, speed and accuracy according to specific constraints
- Tested on many different applications and experiments
- Generic SZ good enough for Ptychography
- Specific RiobinSZ needed for Crystalography
- Open-source, production quality, integrated in HDF5 and other I/O libs (Adios, NetCDF)



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### SZp: Design Principle

- Pre-quantization: raw data → integers (based on error bound)
- 1D 3-layer Lorenzo: Data prediction
   based on only three previous values
- Compute difference between predicted value and raw data value
- Search 0-pattern blocks: search all-0 blocks (block size = 16)
- Encode quantization bins: simplified bit-shuffle-similar encoding



### SZp: High Speed Compression

- We have implemented the CPU version to verify SZp's compression ratio and GPU version for speed.
- Compression quality: SZp has much higher quality than SZx on seismic pressure datasets. SZx may have obvious artifacts at high-compression cases (i.e., error bound is relatively high), while SZp has no such issue.



• Compression speed: cuSZp significantly outperforms the BitComp on CUDA A100 when including kernel launch cost: 400GB/s vs. 200GB/s.

# More Lossy Compressors

**ZFP** (LLNL): Transform (DCT) ECP ZFP Overpreserves data, lower Compression ratio compared to SZ, Better speed.

**SPERR** (NCAR): Wavelet Works well on wave propagation problem (Climate, Seismic)

MGARD (ORNL) ECP CODAR Multigrid adaptive reduction MGARD controls the compression errors in quantities of interest (*Q*): Linear expression of the error Largest Compression Ratio For Each Compressor that Satisfies Each Pinard et al (2020) Requirements

Compressor	Pearson R^2	Spatial Error	KS-test
SZ_Interp	93	93	21
SZ (regression)	14.34	14.34	14.34
ZFP	5.45	5.45	2.36
MGARD	27.1	4.69	Х
MGARDx	14.7	6.49	Х
TThresh	16.1	16.1	2.98
BitGrooming	1.51	1.51	1.51
Digit Rounding	1.86	1.86	1.86
FPZip	1.95	1.95	1.95
NDZip	1.64	1.64	1.64
Zstd	1.35	1.35	Argonne

# More Lossy Compressors

#### TTRESH (LLNL):

HoSVD (Tucker Decomposition)
Quantize the Core tensor
Very high compression ratio
Tendency to blur the overall data
(loose details)
1 or 2 orders of magnitude slower
than SZ or ZFP

#### **Autoencoders**

Overall architecture of convolutional autoencoder (A. Glaws, R. King, and M. Sprague, "Deep learning for in situ data compression of large turbulent flow simulations," Physical Review Fluids, vol. 5, no. 11, p. 114602, 2020.)

12 residual blocksfor feature extraction+ 3 compression layers

Largest Compression Ratio For Each Compressor that Satisfies Each Pinard et al (2020) Requirements

Compressor	Pearson R^2	Spatial Error	KS-test
SZ_Interp	93	93	21
SZ (regression)	14.34	14.34	14.34
ZFP	5.45	5.45	2.36
MGARD	27.1	4.69	Х
MGARDx	14.7	6.49	X
TThresh	16.1	16.1	2.98
BitGrooming	1.51	1.51	1.51
Digit Rounding	1.86	1.86	<sup>1.86</sup> Smoothing
FPZip	1.95	1.95	1.95
NDZip	1.64	1.64	1.64
Zstd	1.35	1.35	Argonne

# Methodologies

#### https://sdrbench.github.io/



#### https://github.com/robertu94/libpressio





#### https://github.com/CODARcode/Z-checker





### VSZ

**Features** to preserve are mathematically formalized and integrated into compressor error controls

- VSZ (SZ-Critical points): Preserves Critical points in 2D, 3D piecewise linear vector fields (Important in flow visualization, keep each critical point in its original cell, retain each critical point type).
  - Compute error bound on each data point.



X. Liang *et al.*, Toward Feature-Preserving 2D and 3D Vector Field Compression, *IEEE Pacific Visualization Symposium (PacificVis)*, 2020

Provides excellent compression performance and feature preservation.

### Limitations:

- Expressing feature mathematically could be too complex.
- Requires specific compression algorithm designs for each feature to preserve.
- Preservation of combination of features has not been addressed.

