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CereSZ: Enabling and Scaling Error-bounded Lossy Compression on Cerebras CS-2

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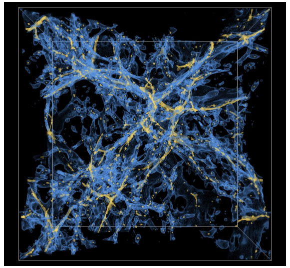
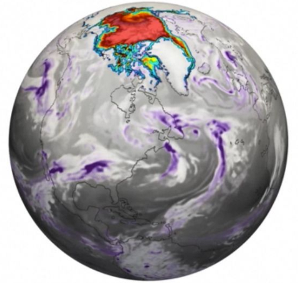
Lossy Compression in AI and HPC

- **Lossy compression** can reduce data size drastically.
  - ***Much higher compression ratio*** than lossless compression (limited to 2:1).
  - Introduced errors are controlled within a certain bound – ***error-bounded***.
- **Error-bounded lossy compression** is used by various domains.

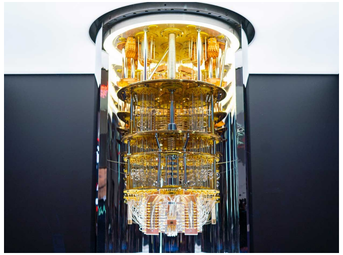
Deep Learning[1]
(e.g. Natural Language Processing)



Cosmology Simulation[2]
(e.g. NYX)



Climate Simulation[3]
(e.g. CESM-ATM)



Quantum Circuit Simulation[4]
(e.g. Grover)

1. [**TelecomReview'2020**] The rise of emotionally intelligent artificial intelligence
2. [**News@CMU'2021**] Machine Learning Accelerates Cosmological Simulations
3. [**TechReview@MIT'2018**] What the hell is a climate model—and why does it matter?
4. **[IEEESpectrum'2020]** IBM's concept of quantum volume tries to measure quantum computing progress in ways beyond counting qubits

An Emerging AI Chip System: Cerebras CS-2

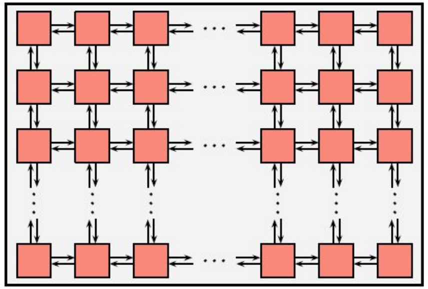
- Cerebras is critical to accelerate many **scientific computing applications**.
  - 3D Fast Fourier Transform: ***959 ms*** for ***512x512x512*** complex input array[1].
  - Matrix-Vector Multiplications: ***92.58 PB/s*** on ***35,784,000*** processing elements[2].
- However, Cerebras CS-2 system is processing **massive data**.
  - Large Language Model Training: GPT-3 had ***175 billion*** parameters, and this number is increasing to ***1 trillion*** in near future models such as MSFT-1T[3].
  - Seismic Imaging: ***1.8 TB*** data for a 4.5 seconds and 45 Hz flat wave[2].

Performing efficient data reduction within Cerebras CS-2 system is necessary!

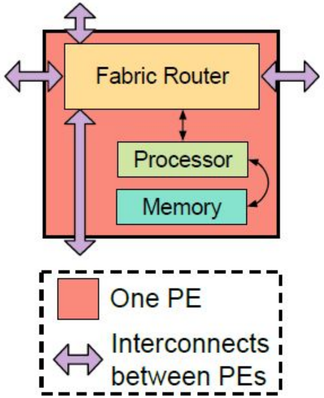
1. **[ICS'2023]** Wafer-Scale Fast Fourier Transforms
2. **[SC'2023]** Scaling the "Memory Wall" for Multi-dimensional Seismic Processing with Algebraic Compression on Cerebras CS-2 Systems.
3. **[IEEE Micro'2023]** Cerebras Architecture Deep Dive: First Look Inside the Hardware/Software Co-Design for Deep Learning

Background: Cerebras CS-2 System

- **Dataflow Architecture:** **Wafer-scale engine (WSE)** is the central processor of Cerebras CS-2 system.

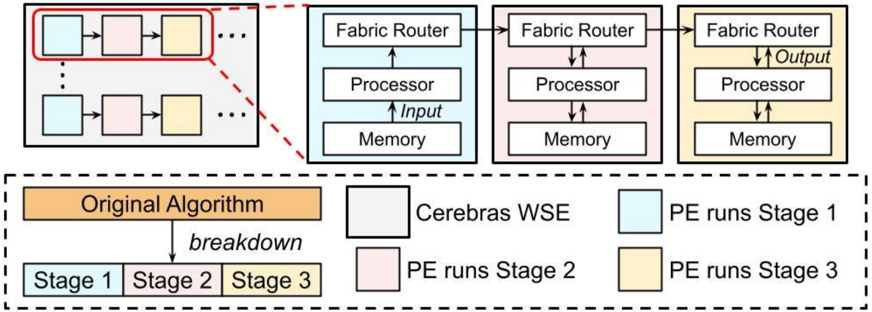


Cerebras WSE, where each node denotes one PE



Structure of a single PE

- **Parallel Processing**: Map computing stages into consecutive PEs in the same row.

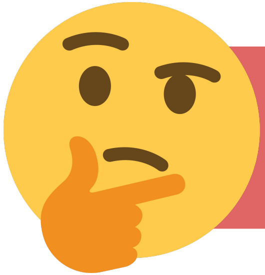


Pipeline parallelization on Cerebras WSE

- **Implementation**: A language called CSL provided by Cerebras.

Challenges: Deploying Compression on Cerebras

- **Cerebras Feature 1: Unconventional Memory Structure**
  - No traditional global memory as NVIDIA GPUs.
  - Local memory for each PE is limited (up to 48 kB).
- **Cerebras Feature 2: Spatial Constraints from Data-Flow Design**
  - Each PE can only access data from its neighbors.
  - The data movement directions could influence the performance.

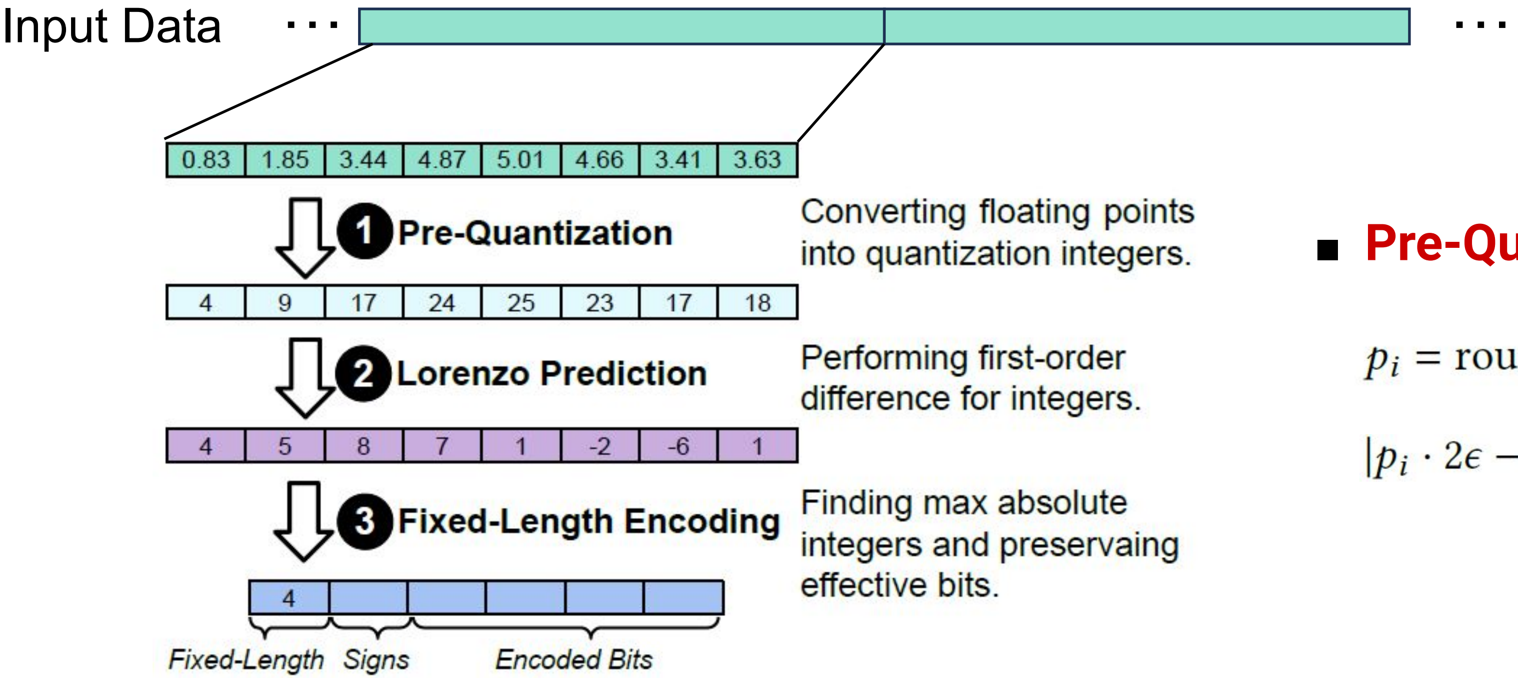


How to perform lossy data compression that efficiently utilizes Cerebras CS-2 architectural characteristics?

1. [**Cerebras White Paper**] Cerebras Systems: Achieving Industry Best AI Performance Through A Systems Approach

CereSZ: Compression Algorithm

- **An overview of the compression algorithm**



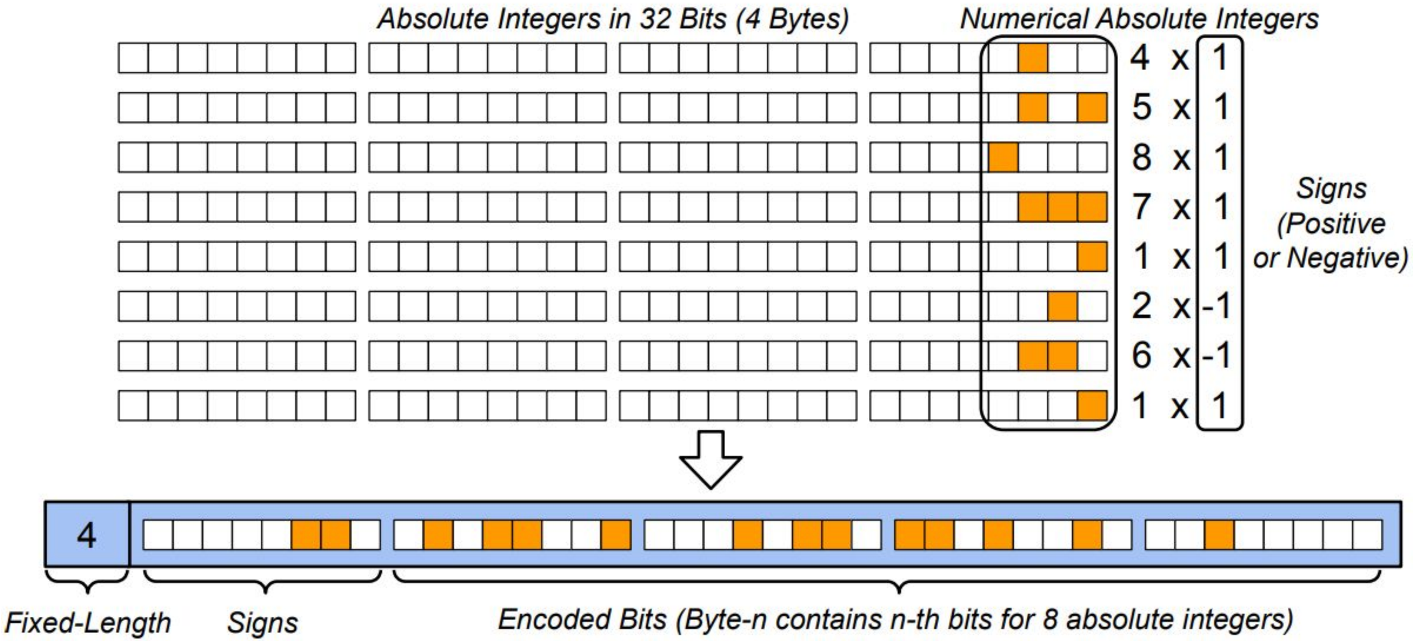
- **Pre-Quantization**

$$p_i = \text{round}\left(\frac{e_i}{2\epsilon}\right)$$

$$|p_i \cdot 2\epsilon - e_i| \leq \epsilon$$

CereSZ: Compression Algorithm

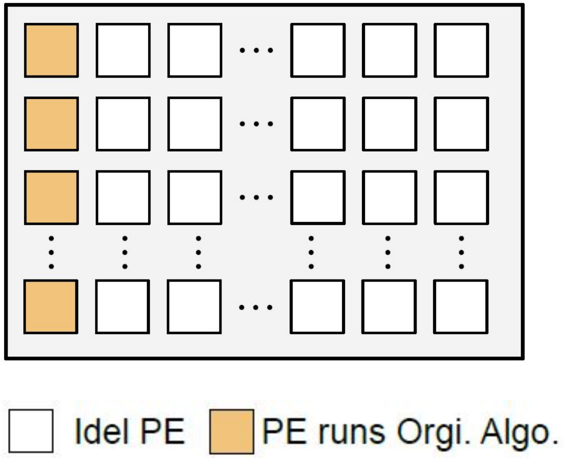
- **Fixed-length Encoding**



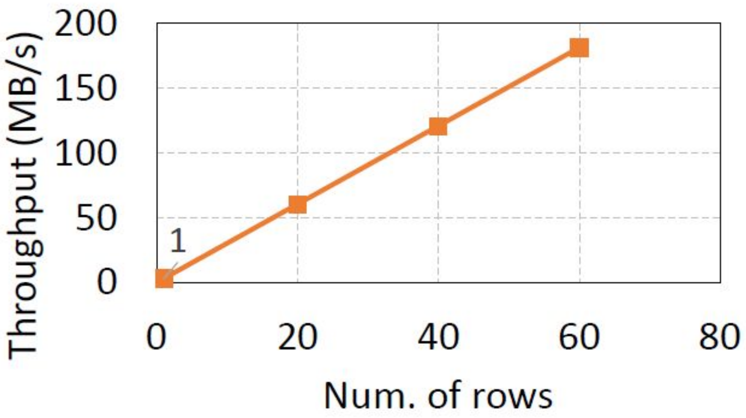
Compression Ratio:
8*4/(1+1+4)=5.33

Perf. Opt. 1: Data Parallelism (Block-level)

- Data Parallelism with Data Blocking



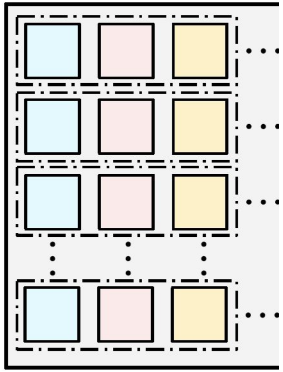
- Throughput with different numbers of PE rows



Throughput = Input Data Size / compression time

Perf. Opt. 2: Pipeline Parallelism (Stage-level)

- Pipeline Parallelism for 3 Stages



Idel PE

PE runs Stage 1 PE runs Stage 3

Algorithm 1: Evenly distributing n sub-stages across m PEs

Input: The stages: $s_1, s_2, ..., s_n$; Total cycles of all stages: C; Number of PEs: m;

Output: Stage group assigned to PEs: $G_1, G_2, ..., G_m$

1 Initialize $G_1 = \{\}, G_2 = \{\}, ..., G_m = \{\}$

2 **for** *each stage group* G_i *in* $\{G_1, G_2, ..., G_{m-1}\}$ **do**

3 **while** *The sum of runtime of the stages in* $G_j < \frac{C}{m}$ **do**

4 move the next s_j to G_i

5 $G_m = \{s_1, s_2, ..., s_n\} - (G1 \cup G2 \cup ... \cup G_{m-1})$

- Breakdown cycles for compression

Encd.
37124
29181
27188

Addition
1033
1038
1049

tLength	Bit-shuffle
1386	33609
1370	25675
1385	23694

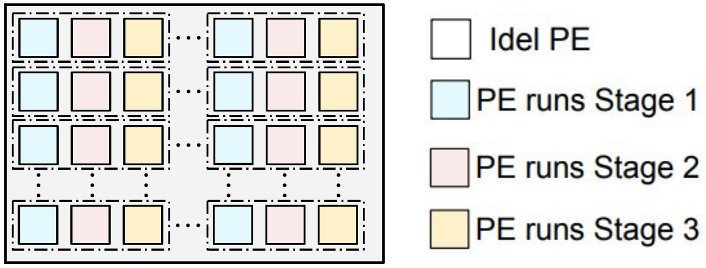
Fixed-Length for CESM-ATM, HACC, and QMCPack: 17, 13, and 12

Bit-shuffle -> several 1-bit shuffle

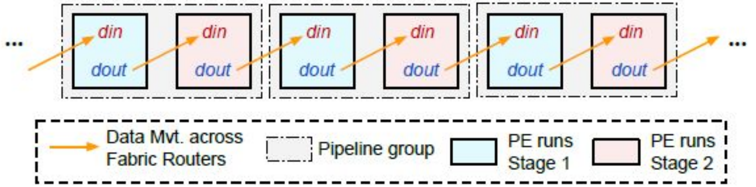
Stages: Multiplication, Addiction, Lorenzo Prediction, Sign, Max, GetLength, 1-bit shuffle

Perf. Opt. 3: Data Parallelism (Pipeline-level)

- Data Parallelism for Multiple Pipelines



- Passing data with 2-length pipeline



- Pseudocode runs on the first PE of each pipeline

```
task relay() void {
    // Receive the input dsd and activate computeColor once the
    // current PE receives it own data block
    if (nblock == (total_cols-cur_col)/pipeline_length)){
        @mov32(data, din, .{.async = true, .activate =
        computeColor}); nblocks = 0;}}
    // Pass the data blocks for right PEs and activate relayColor again
    else{
        @mov32(dout, din, .{.async = true});
        nblocks += 1;
        @activate(relayColor);}

task compute() void {
    // Activate relayColor to run relay task again
    @activate(relayColor);}
    // Execute substages assigned to the PE
    // Send results to next PE in the pipeline}

// Bind two colors to their corresponding tasks
@bind_task(relay, relayColor);
@bind_task(compute, computeColor);
```

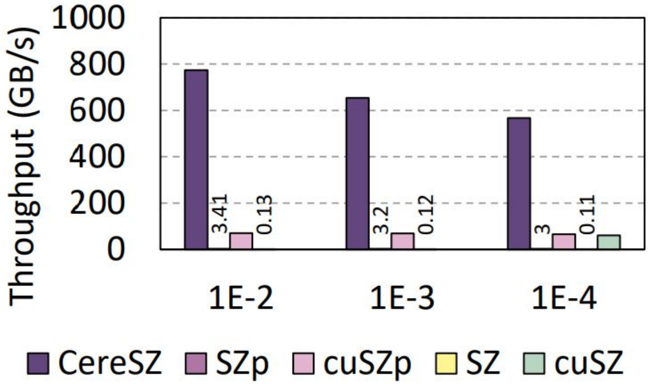
Evaluation: Settings

- **Neocortex Cerebras CS-2**
  - 512×512 processing elements (PEs)
  - 850MHz clock frequency
- **Baseline Compressor**
  - *SZ*[1] : AMD EPYC 7742 CPUs
  - *cuSZp*[2] : NVIDIA A100 GPU (40GB)
  - *SZp*[2] : AMD EPYC 7742 CPUs
  - *cuSZ*[3] : NVIDIA A100 GPU (40GB)
- **Evaluation Metrics**
  - Throughput (GB/s)
  - Compression ratio
  - Reconstructed data quality
- **HPC Datasets**
  - *Hurricane*: weather simulation
  - *NYX*: cosmology simulation
  - *QMCPack*: quantum computing
  - *RTM*: seismic imaging
  - *HACC*: cosmic simulation
  - *CESM-ATM*: climate simulation

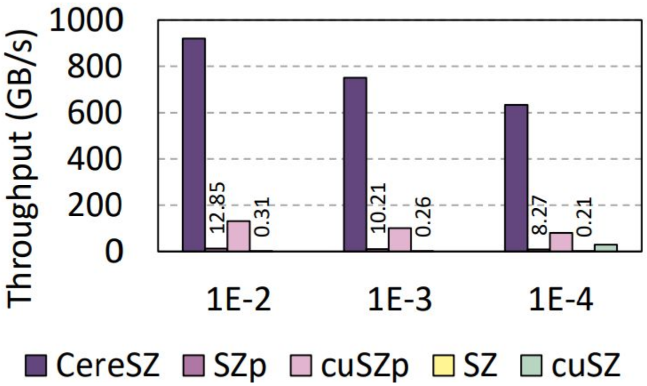
1. [**IEEE TBD'2022**] SZ3: A Modular Framework for Composing Prediction-Based Error-Bounded Lossy Compressors
2. [**SC'2023**] cuSZp: An Ultra-fast GPU Error-bounded Lossy Compressor with Optimized End-to-End Performance
3. [**PACT'2020**] cuSZ: An Efficient GPU-Based Error-Bounded Lossy Compression Framework for Scientific Data

Evaluation: Throughput

- Compression and decomrpession throughput on RTM dataset



Compression



Decompression

- On average, CereSZ can achieve **457.35 GB/s** and **581.31 GB/s** for compression and decompression throughput, which is **4.9** and **4.8** times faster compared with cuSZp.

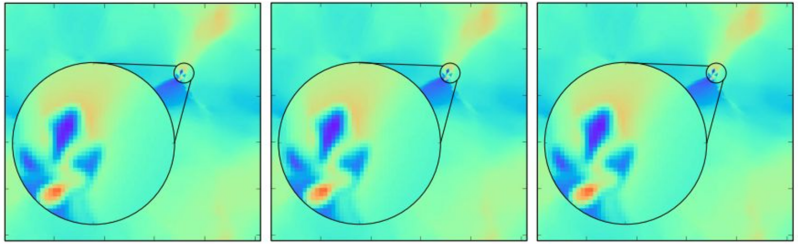
Evaluation: Compression Ratio

	REL	CESM-ATM range	CESM-ATM avg	HACC range	HACC avg	Hurricane range	Hurricane avg	NYX range	NYX avg	QMCPack range	QMCPack avg	RTM range	RTM avg
CereSZ	1E-2	2.67~21.60	8.73	4.66~9.18	6.82	5.21~28.82	17.10	7.83~31.98	20.22	9.59~19.67	14.63	10.52~31.99	23.46
	1E-3	2.13~16.10	6.49	3.18~4.91	4.05	3.41~24.37	12.57	4.54~31.84	14.05	5.31~9.02	7.16	5.94~31.98	17.73
	1E-4	1.68~13.42	5.11	2.38~3.20	2.83	2.53~19.71	9.64	3.10~29.74	9.61	3.48~4.97	4.23	3.79~31.96	12.87
SZp	1E-2	9.91~70.48	23.72	10.16~13.62	11.56	10.80~88.94	40.26	12.21~127.80	67.58	12.44~22.45	17.45	14.22~127.94	67.51
	1E-3	6.70~69.15	20.14	3.82~9.63	5.39	7.44~57.42	23.92	8.62~125.55	40.16	6.08~11.60	8.84	7.91~127.79	43.40
	1E-4	4.22~67.65	17.03	3.49~5.51	3.57	4.49~37.08	15.29	4.91~98.23	23.41	3.79~6.57	5.18	4.73~127.51	28.19
cuSZp	1E-2	2.84~43.75	12.56	5.24~10.08	7.63	5.94~88.88	38.70	9.60~127.80	66.73	12.44~22.21	17.33	13.97~127.95	66.97
	1E-3	2.25~25.86	8.46	3.43~5.20	4.31	3.71~56.88	22.31	5.09~125.55	38.44	6.08~10.08	8.08	6.90~127.80	42.29
	1E-4	1.75~19.59	6.24	2.53~3.39	2.96	2.70~36.66	14.36	3.35~98.23	22.14	3.79~5.56	4.68	4.17~127.52	27.43
SZ	1E-2	26.13~4.0E+4	2.2E+3	16.58~931.76	217.94	23.76~404.71	110.33	1.3E+3~1.2E+5	2.3E+4	17.10~727.13	372.11	23.57~1.3E+5	4.4E+3
	1E-3	9.30~2.9E+4	941.39	6.11~30.97	15.57	8.81~105.49	35.67	84.55~1.8E+4	3.2E+3	6.37~221.11	113.74	9.27~2.3E+4	894.69
	1E-4	5.04~2.9E+4	825.49	3.74~8.92	5.75	4.63~48.46	18.72	14.38~2.6E+3	471.61	3.88~66.09	34.99	5.30~1.6E+4	548.91
cuSZ	1E-2	19.18~25.33	22.89	N/A	N/A	15.35~28.62	22.53	28.71~31.57	30.22	7.50~21.55	14.53	N/A	N/A
	1E-3	11.34~25.16	18.48	N/A	N/A	8.91~23.61	15.97	N/A	N/A	4.26~17.70	10.98	N/A	N/A
	1E-4	5.38~24.43	12.47	N/A	N/A	3.37~17.25	8.36	10.75~31.28	16.22	N/A	N/A	3.67~30.84	11.63

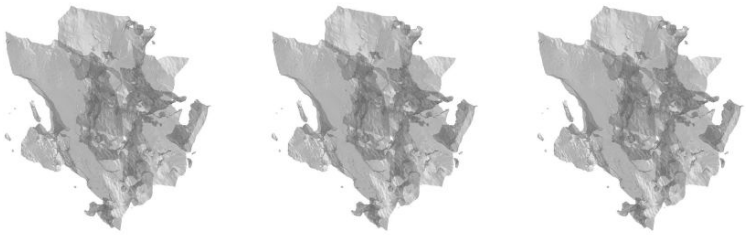
- CereSZ has lower compression ratios than CPU-based compressor SZ
- But CereSZ is inline with GPU-based alternatives such as cuSZ and cuSZp.

Evaluation: Data Quality

- Slice and Isosurface visualization analysis



(a) Ori. Slice (b) cuSZp Slice (c) CERESZ Slice



(d) Ori. Isosurface (e) cuSZp Isosurface (f) CERESZ Isosurface

- CereSZ has **the same** data quality as cuSZp

Summary

- CereSZ is **the first** error-bounded lossy compressor on Cerebras CS-2 system.
- **457.35 GB/s and 581.31 GB/s** for compression/decompression throughput.
- CereSZ has linear speedups across the rows and columns of the 2D mesh of computing units (i.e. PEs) on Cerebras.
- CereSZ also achieves **similar compression ratio** with GPU alternatives.
- CereSZ demonstrates potential to preserve high data quality.

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