TAC: Optimizing Error-Bounded Lossy Compression for Three-Dimensional Adaptive Mesh Refinement Simulations

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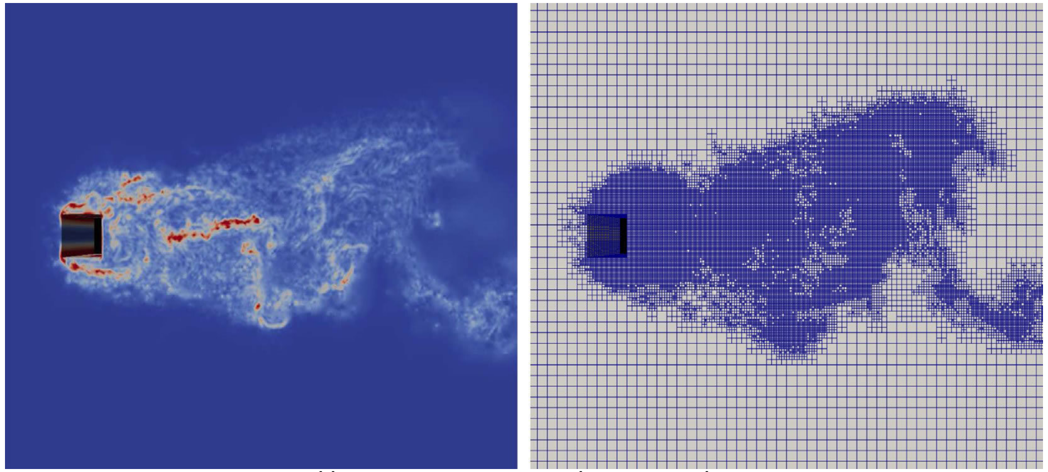
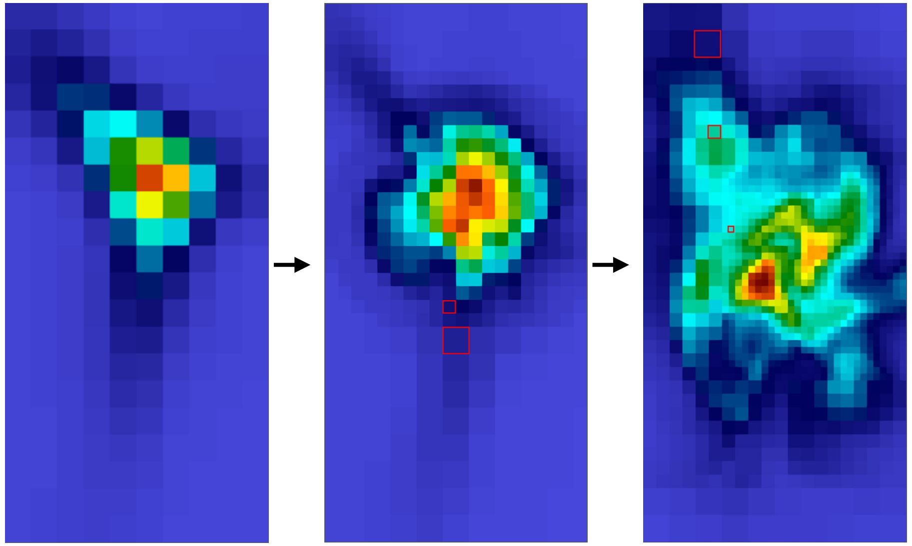
Background: Adaptive Mesh Refinement

- **Adaptive Mesh Refinement**
  - Increase **resolution** in regions of most **interest**
  - Reduce **computational** and **storage** overhead
  - Result in hierarchical AMR data with different resolutions
  - One of the most widely used frameworks for HPC applications



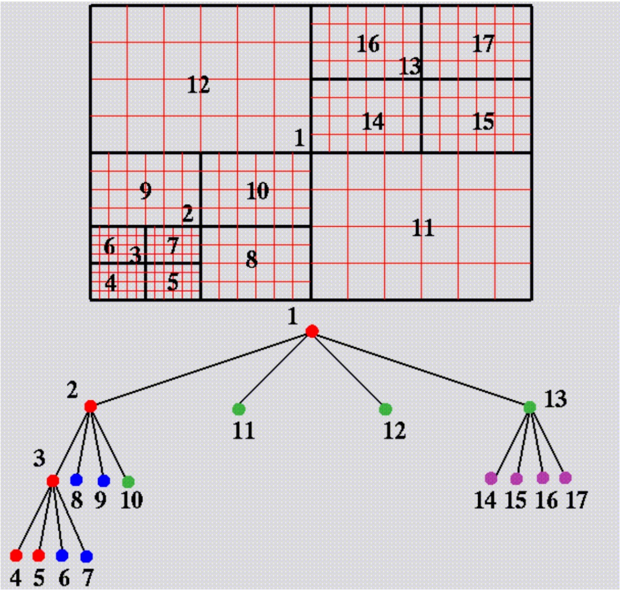
https://www.cttc.upc.edu/?q=node/165

- **Example of AMR**
  - The mesh will be refined when the value **meets the refinement criteria** (i.e., greater than the threshold)
  - The grid structure changes with the universe's evolution
  - The red boxes indicate **different resolutions** within one AMR level

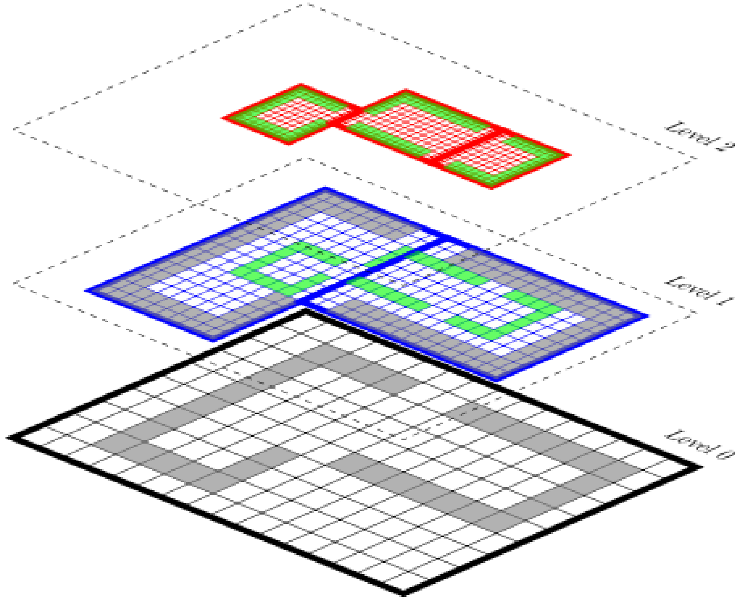


Vis of three key timesteps of an AMR-based cosmology simulation

Different type of AMR



http://cucis.ece.northwestern.edu/projects/DAMSEL



AMReX: Building a Block-Structured AMR Application

- **Tree-based AMR**

- Tree-based AMR organizes the grids as leaves on the tree and has **no redundant** data across different level
- Tree-based AMR can be more **complex** and time consuming to perform visualization and analysis

- **Patch-based AMR**

- Patch-based AMR saves the data that will be refined at the fine level in the coarse level **redundantly**
- The **redundant coarse data** will not be used in post analysis and vis
- We focus on patch-based AMR and discard the redundant coarse data while doing the compression

Motivation: Why Compression

➢ **Even with AMR, the size of data generated by apps could still be prodigious**

- One Nyx AMR dataset ($\frac{1}{2} * 2048^3$ mesh points in the coarse level; $\frac{1}{2} * 4096^3$ in the fine level) → **1.8 TB**
- Running the simulation 5 times with 200 snapshots dumped per simulation → **1.8 PB**

➢ **Trend of Supercomputing Systems**

- The **compute capability** is developed much faster than **storage and bandwidth**: a widening gap
  (1) between compute unit and storage bandwidth (PF–SB), or
  (2) between main memory size and storage bandwidth (MS–SB)

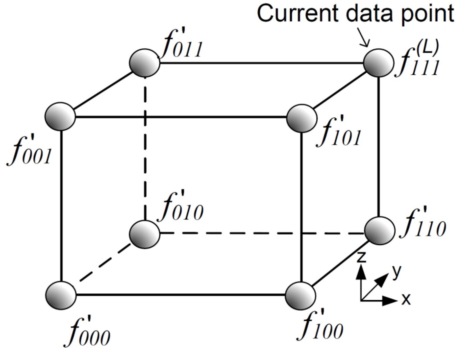
supercomputer	year	class	PF	MS	SB	MS/SB	PF/SB
Cray Jaguar	2008	1 PFLOPS	1.75 PFLOPS	360 TB	240 GB/S	1.5k	7.3k
Cray Blue Waters	2012	10 PFLOPS	13.3 PFLOPS	1.5 PB	1.1 TB/S	1.3k	13k
Cray CORI	2017	10 PFLOPS	30 PFLOPS	1.4 PB	1.7 TB/S*	0.8k	17k
IBM Summit	2018	100 PFLOPS	200 PFLOPS	>10 PB**	2.5 TB/S	>4k	80k

PF: peak FLOPS   * when using burst buffer   ** counting only DDR4   *Source: F. Cappello (ANL)*

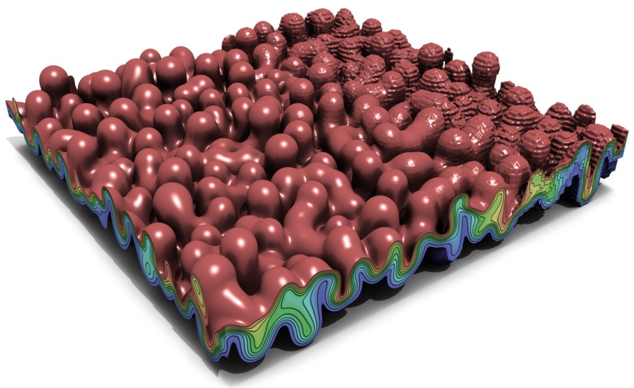
Background: Lossy Compression

- **Lossy compression on scientific data**

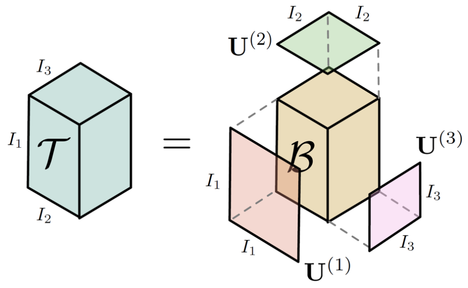
- Offers much **higher compression ratios** than lossless compression by trading a little bit of accuracy
- Traditional lossy compressors (e.g., **JPEG**) are designed for **images** (integer) → bad performance on **scientific data** (floating-point data)
- New generation of lossy compressors:
  1. **SZ** (Prediction based), nice compression ratio
  2. **ZFP** (Transform based), high throughput
  3. **TThresh** (HOSVD based), works nice in 3d but slow



Prediction (SZ)



Compressed data of ZFP
16x (left); 64x (right)



HOSVD (TThresh)

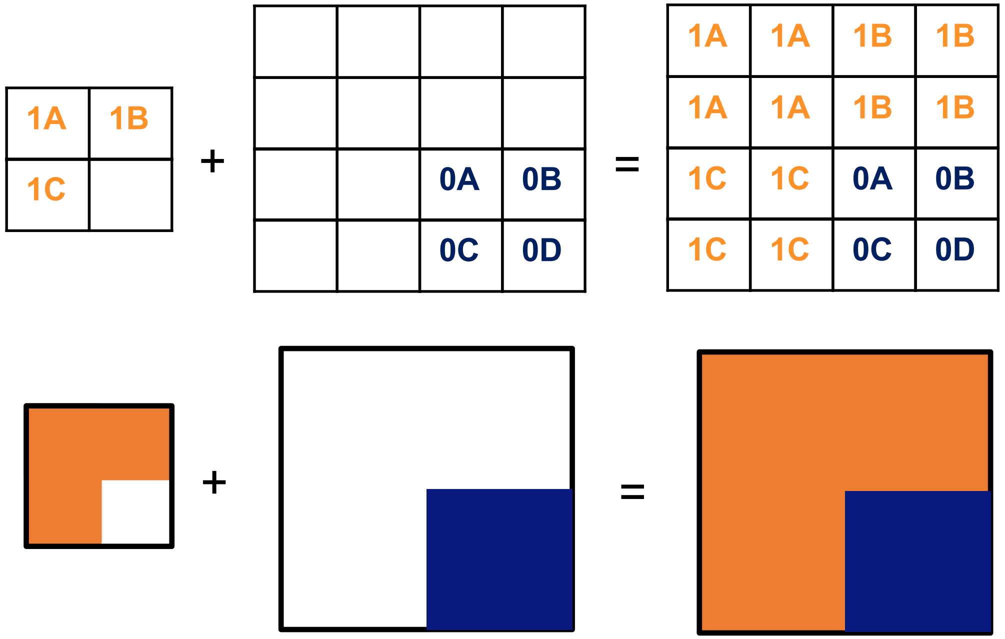
[Error-Controlled Lossy Compression Optimized for High Compression Ratios of Scientific Datasets]
[Fixed-Rate Compressed Floating-Point Arrays]
[TTHRESH: Tensor Compression for Multidimensional Visual Data]
[COMET: A Novel Memory-Efficient Deep Learning Training Framework by Using Error-Bounded Lossy Compression]

Basic AMR Compression

➢ **Challenges**

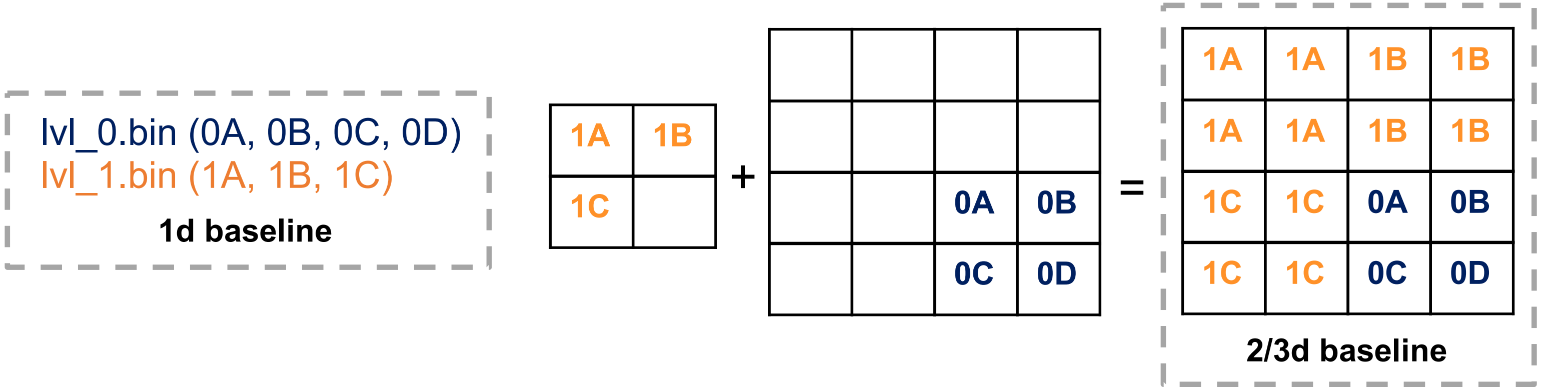
- Compared to non-AMR data, the structure of AMR data is more **comprehensive**
- The data of each level are **stored separately** in 1D, could be **reshaped** & convert to uniform resolution & combined for vis/post-analysis.

lvl_0.bin (0A, 0B, 0C, 0D)
lvl_1.bin (1A, 1B, 1C)



Basic AMR Compression

- **1D Baseline Compression**
  - Compress the 1d directly → lose almost all the **spatial information**
- **2/3D Baseline Compression**
  - Compress in 2/3d with an up-sampled coarse level → **redundant data**

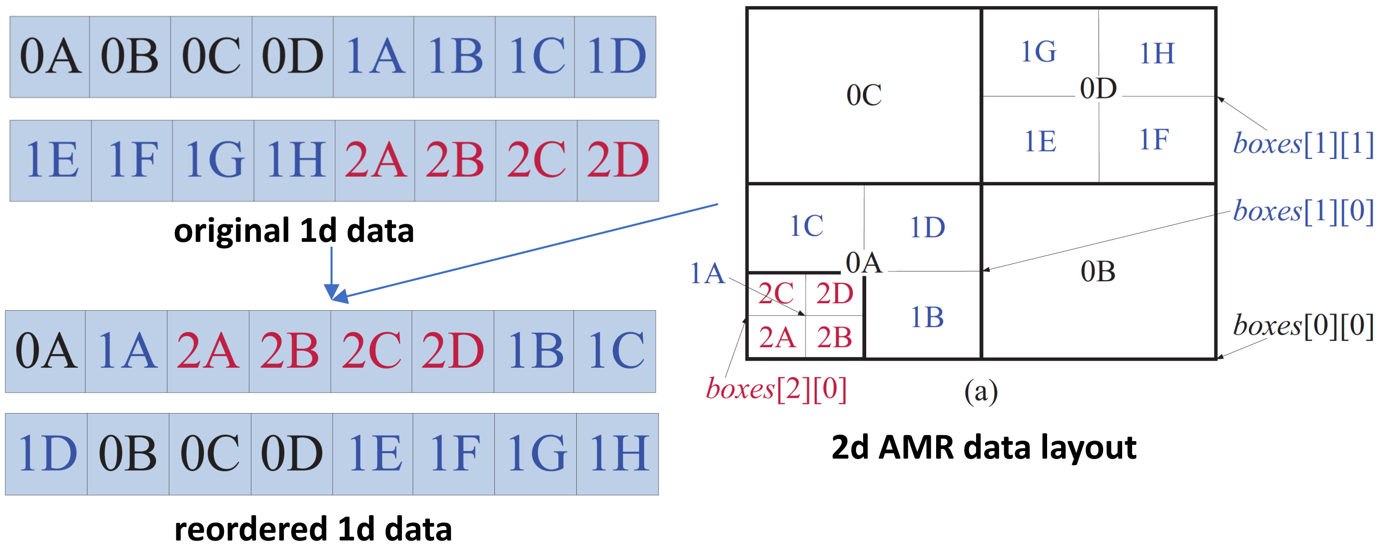


No matter which method is used, we are faced with the problem of either **low locality or redundant data**

SOTA AMR Compression: zMesh

➢ An alternative solution of the 1d baseline

- **Smooth** (preprocess) the 1D data by **reordering** to help compression
- Puts the points neighbored in the 2D layout closer in the 1D array



➢ Limitation

- Cannot apply different error bound for different lvls, different AMR lvls will have different “importance” based on the need for post-analysis.
- Compress the data in 1D, can not fully utilize spatial information of high dimension data

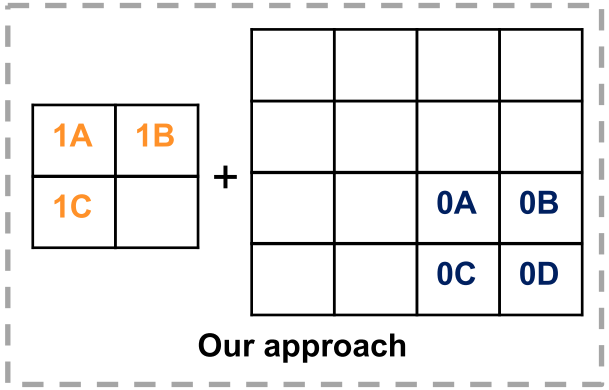
Overview of TAC

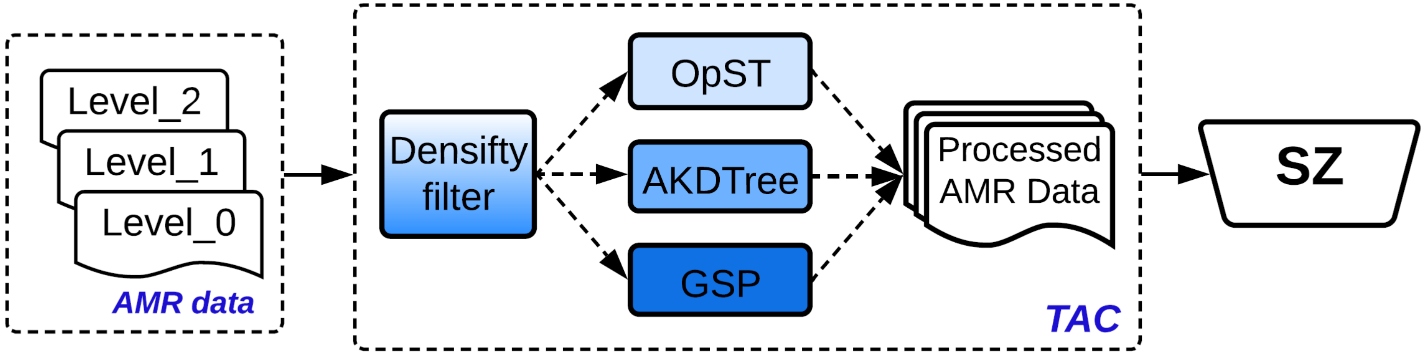
➢ **Compress Each Level Separately in high dimension**

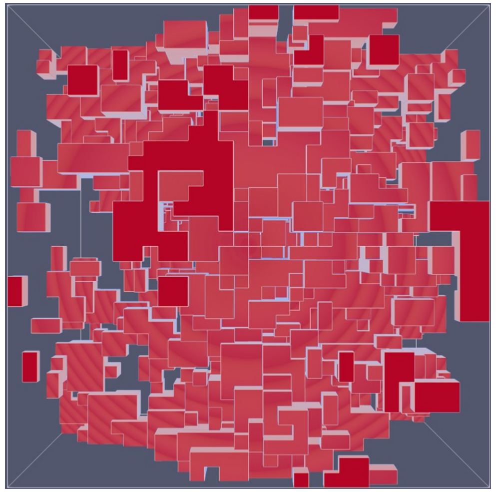
- Each level contain **empty regions** that decrease the **data smoothness** and increase the **data size**

➢ **Our Hybrid Pre-process Strategies**

- Three pre-processing strategies that can adapt based on the density of each AMR level
  1. Optimized Sparse Tensor Representation (**OpST**) for low-density level
  2. Adaptive k-D Tree (**AKDTree**) for medium-density level
  3. Ghost-Shell Padding (**GSP**) for high-density level





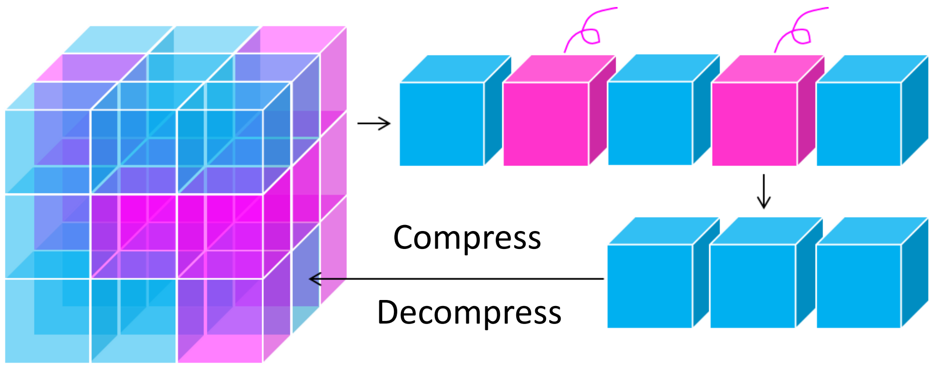


Visualization of data distributions of an example AMR dataset (finest level)

OpST for Low-density Data

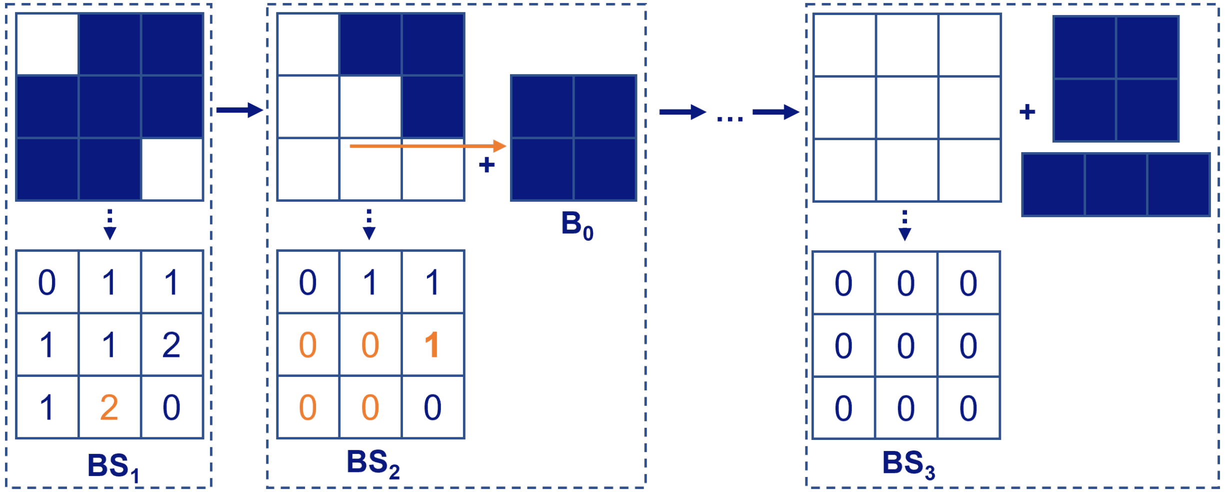
- **Naïve Sparse Tensor Representation (NaST)**

- Partition → Linearize blocks → Remove empty blocks → Pass to SZ → Reconstruct
- Needs a **small unit-block size** to effectively remove the empty regions (e.g., 16^3 vs 512^3) → high proportion of boundary data → low compression performance



OpST for Low-density Data

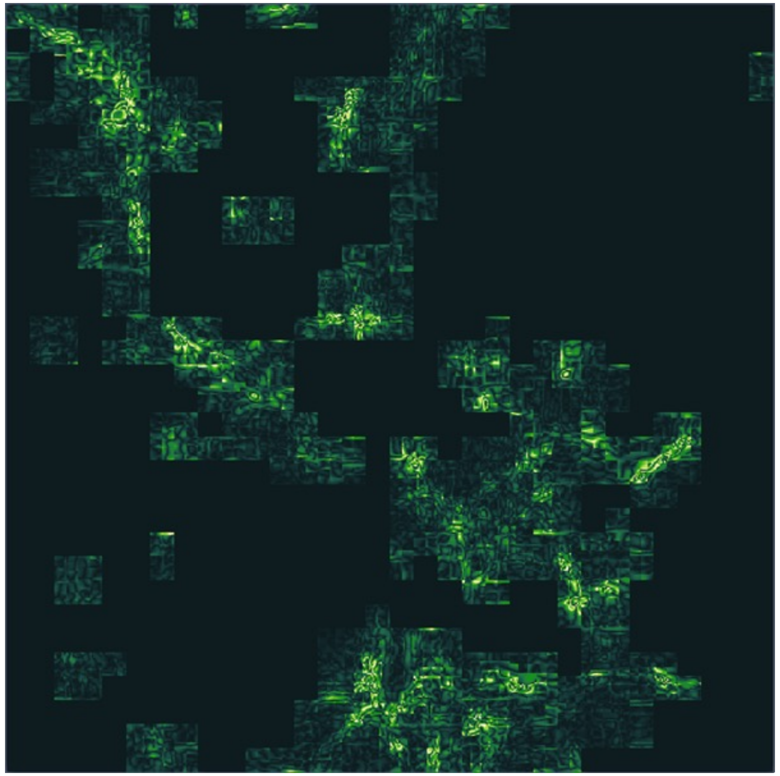
- **OpST: larger sub-block**
- Partition → Use Dynamic Programming to initiate an array BS to save the size of the **maximum square** whose **bottom-right corner** is that unit block → Extract the big sub-block → Update BS → Pass to SZ after done extraction



A 2D example of OpST. The subblocks are extracted according to BS.
E.g., a 2-by-2 sub-block B_0 is extracted according to BS_1 [2] [1].

OpST vs NaST

- OpST can significantly reduce the overall compression error



NaST (CR = 233.8, PSNR = 76.9 dB)

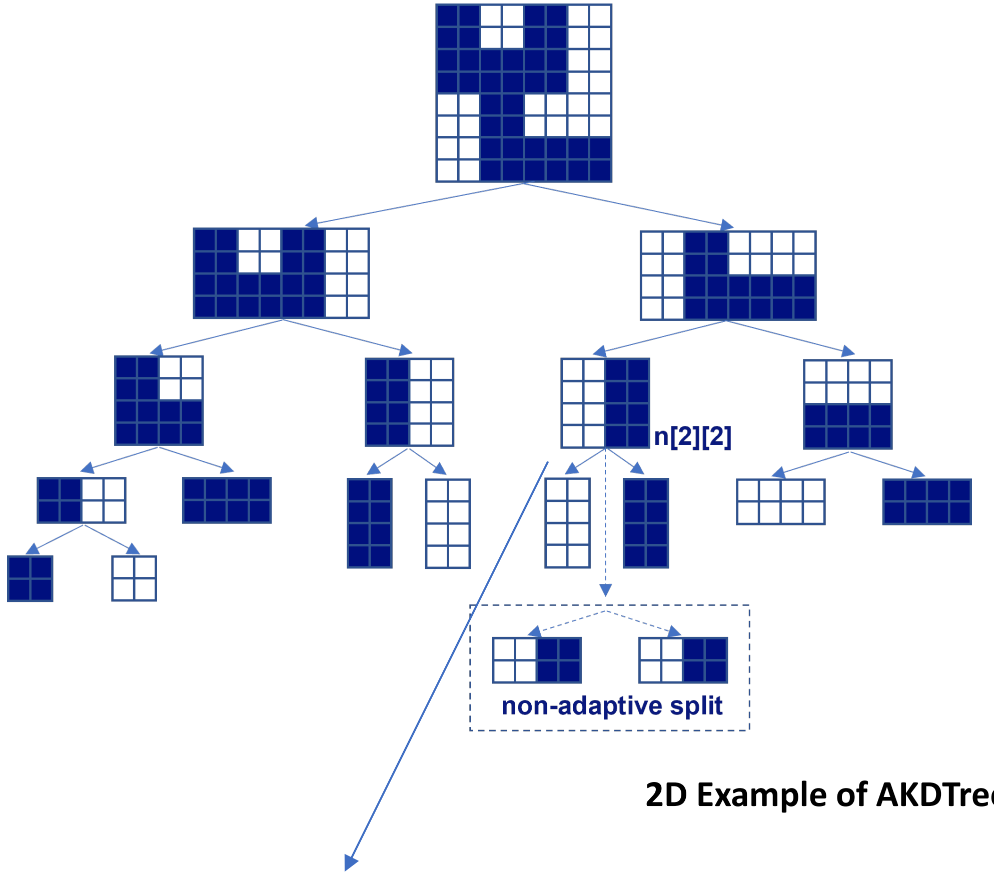
Visual (one slice) of **compression errors** of two approaches using SZ based on Nyx "baryon density" field

AKDTree for Medium-density Data

- **Address high overhead issue of OpST for denser data**
  - Time complexity of OpST: O($N^2 d$), N is the unit block number and d is the density
  - Time complexity of AKDTree: O($\frac{1}{3} N log N$)

- **Remove empty regions and extract sub-blocks**

1. Partition
2. Use a tree to represent the data, each node is associated with a sub-block
3. Adaptively split each sub-block from the middle among one of the dimension
4. Keep splitting a node until it is full or empty
5. Collect all the leaf nodes and send them to the compressor



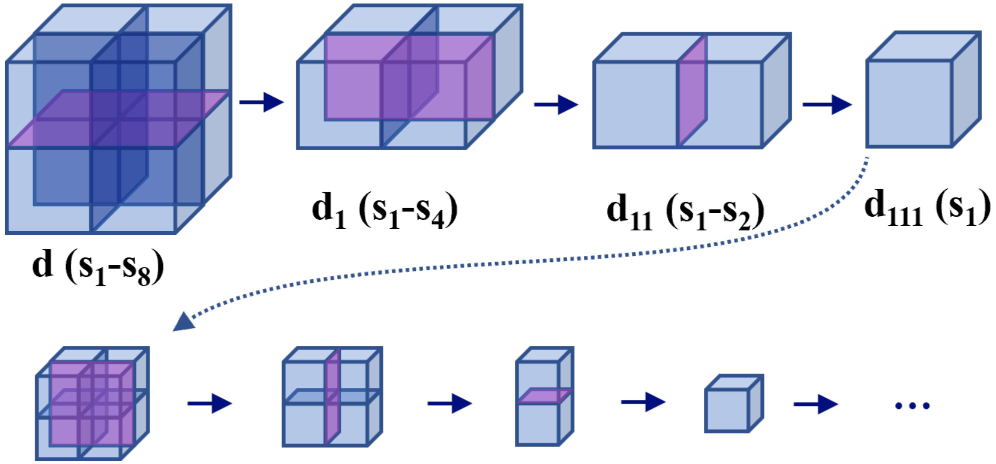
2D Example of AKDTree

Select the dimension which can **maximize the difference** of the numbers of non-empty unit blocks of the **two children**

AKDTree for Medium-density Data

➢ **Adaptive splitting**

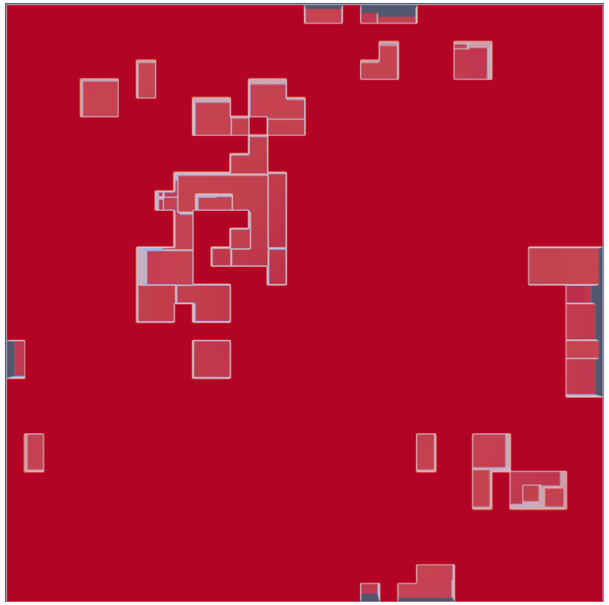
1. Categorize nodes into three different types: **"cube"** (1:1:1), **"flat"** (2:2:1), and **"slim"** (1:2:2)
2. Divide cube node d into eight oct-blocks, s_1,…, s_8 → get the counts of non-empty unit blocks $\boldsymbol{c_1,\dots,c_8}$ of s_1,…,s_8 → decide along which dimension to split
3. For the flat node d_1, we can reuse $\boldsymbol{c_1,\dots,c_4}$ to decide how to spilt
4. Simply split the slim node d_{11} along x-axis
5. This process (i.e., cube nodes → flat nodes → slim nodes) will be looped until the node is empty or full



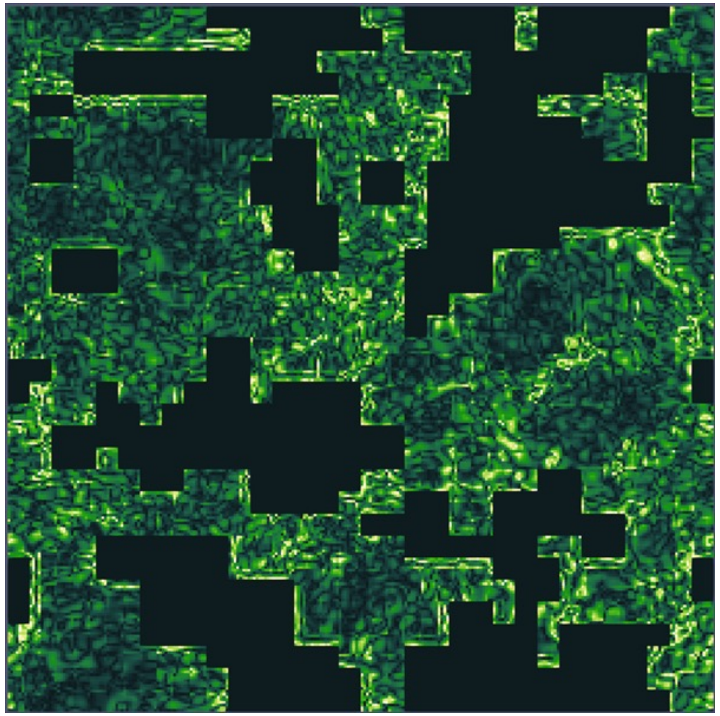
Only count every three step (i.e., only for the "cube" nodes) → $O(\frac{1}{3}NlogN)$

GSP for High-density Data

- **Not much room for removing empty regions for dense data**
- OpST and AKDTree will hurt the data locality/smoothness
- **Pad zeros** into the few empty regions→ **higher error** at the **boundary**



Visualization of data distributions of an example AMR dataset (coarse level)

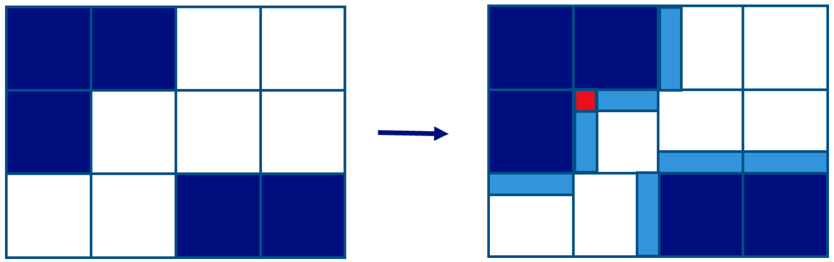


Zero Filling (CR = 156.7, PSNR = 32.8 dB)

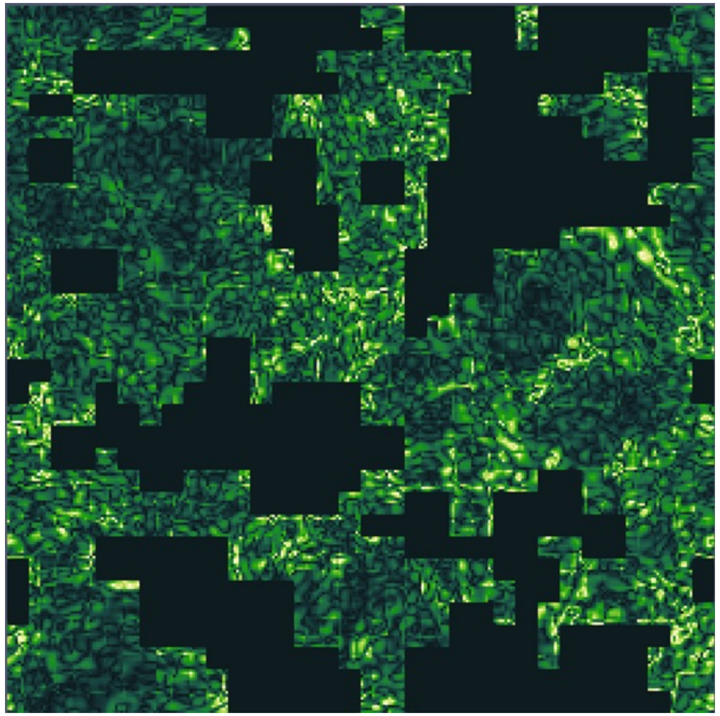
GSP for High-density Data

- **Ghost Shell Padding (GSP)**

- Partition → pad empty unit block using the average of its **non-empty neighbors'** boundary data values
- For empty unit blocks have more than one non-empty neighbors → use the avg value of all its neighbors for padding



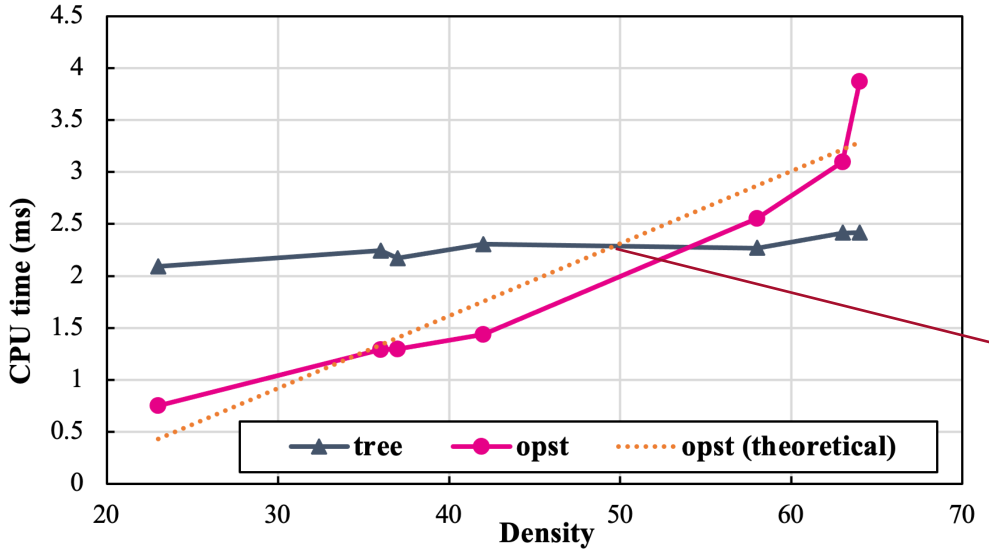
2D Example of GSP. Non-empty blocks are in **navy blue**; padded blocks are in **light blue**/red; padded blocks based on more than one non-empty neighbors are in **red**.



GSP (CR = 161.3, PSNR = 33.5 dB)

Hybrid Compression Strategy

- **Adaptively choose a best-fit pre-process strategy**
  - We have: OpST (low-density), AKDTree (medium-density), and GSP (high density)
  - Use **two data-density thresholds** to determine when to use OpST, AKDTree, or GSP
- **First threshold T_1 for switching between OpST and AKDTree**
  - OpST and AKDTree have almost same compression performance in terms of bit-rate and PSNR
  - Time cost of OpST **increases linearly** with **data density**



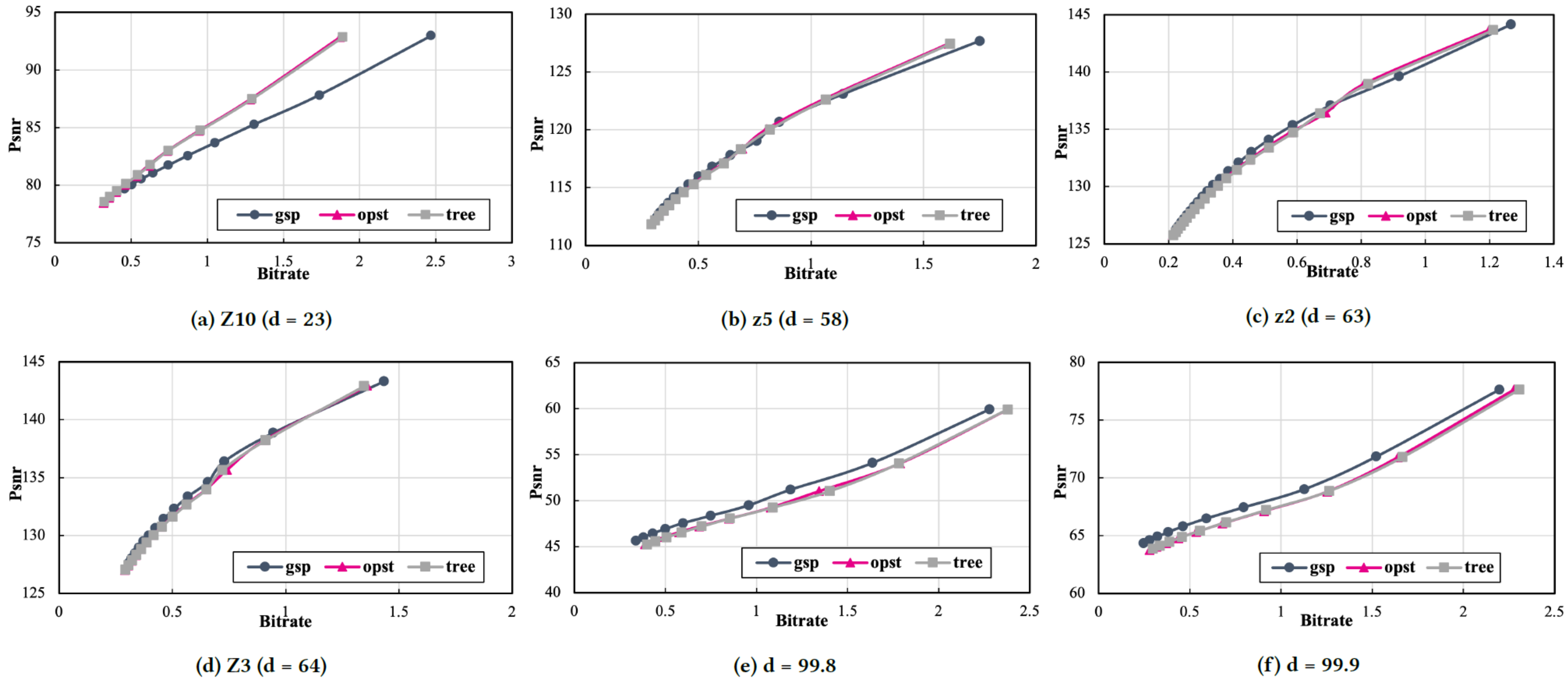
$T_1 = 50$

Time overhead of OpST and AKDTree on different datasets with different densities.

Hybrid Compression Strategy

➢ **Second threshold T_2 for switching between AKDTree and GSP**

- When the density is low, AKDTree is better; when the density gets higher, GSP gradually outperforms AKDTree
- AKDTree and GSP have **similar compression performance** when the density is around **60%** → **T_2= 60%**



Compression performance comparison (PSNR vs Bitrate) of GSP, OpST and AKDTree on six datasets with different densities

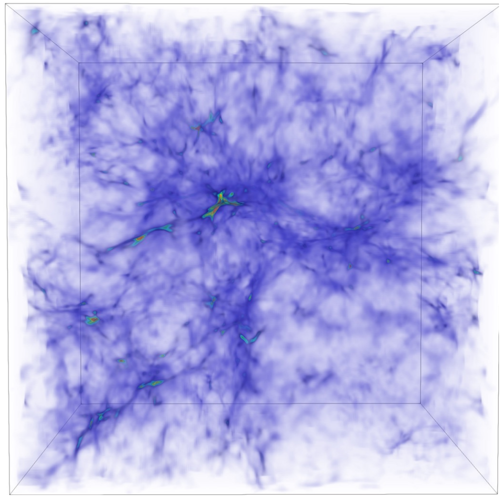
Evaluation

➢ **Experimental Setup**

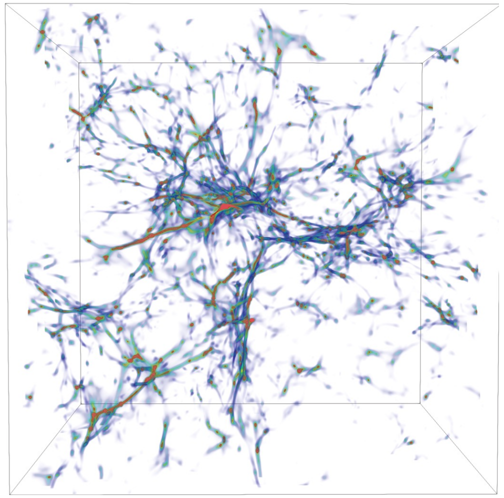
- Real-word application: Nyx cosmology simulation based on AMReX
- Datasets: 7 datasets generated by 2 runs with different numbers of AMR levels, simulating a region of 64 megaparsecs (Mpc)
- Platform: two 28-core Intel Xeon Gold 6238R processors and 384 GB DDR4 memory

Dataset	# Levels	Grid Size of Each Level (Fine to Coarse)	Density of Each Level (Fine to Coarse)
Run1_Z10	2	512, 256	23%, 77%
Run1_Z5	2	512, 256	58%, 42%
Run1_Z3	2	512, 256	64%, 36%
Run1_Z2	2	512, 256	63%, 37%
Run2_T2	2	256, 128	0.2%, 99.8%
Run2_T3	3	512, 256, 128	0.02%, 0.56%, 99.42%
Run2_T4	4	1024, 512, 256, 128	3E-5, 0.02%, 2.2%, 97.7%

Our tested datasets



Visual of baryon density field of z10 (early timestep)

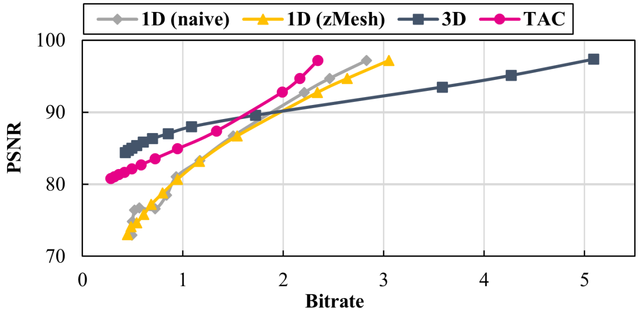


z5 (later timestep)

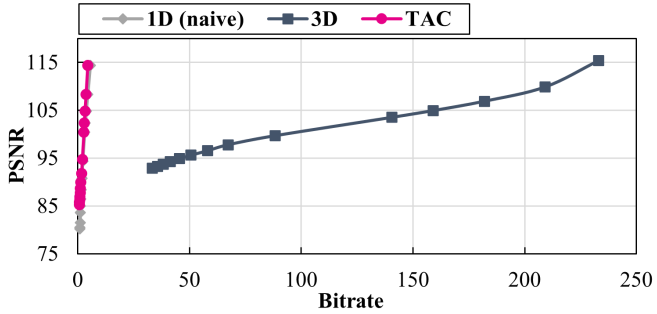
Evaluation

➢ Evaluation on Rate-distortion

- Outperforms naïve 1D baseline & zMesh (up to **3.3x**)
- Perform much better than 3D baseline when
  (1) finest level has a relatively **low density**, or
  (2) decompressed data has a **high PSNR**



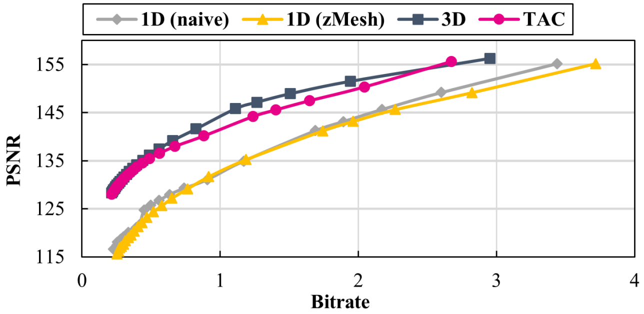
Run1_Z10 (finest-level density = 23%)



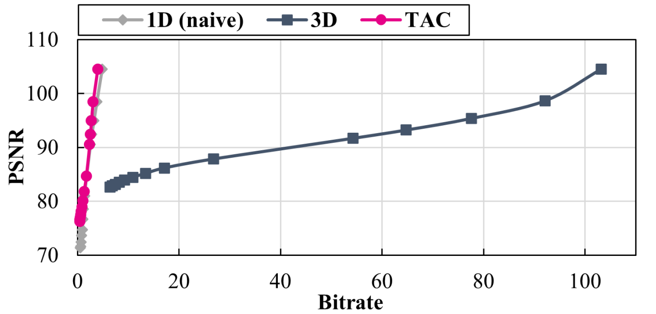
Run2_T4 (finest-level density = 0.02%)

➢ Discussion on Comparison with Baselines

- 3D baseline works better when finest level is dense
  - Dense finest lvl → similar to **non-AMR dataset** → no need to use AMR compress strategies
- zMesh cannot improve the smoothness if there is **no data redundancy** in the AMR datasets



Run1_Z2 (finest-level density = 63%)



Run2_T3 (finest-level density = 3E-5)

Evaluation

- **Evaluation on Time Overhead**

- Up to **75x** faster than 3D baseline on the Run2 datasets and **2.4x** faster on the Run1
  - Due to Run2 has higher overhead of redundant data for the 3D baseline
- Throughput degrades on the small datasets
  - Due to a relatively heavy launching time compared to the overall time on the small datasets

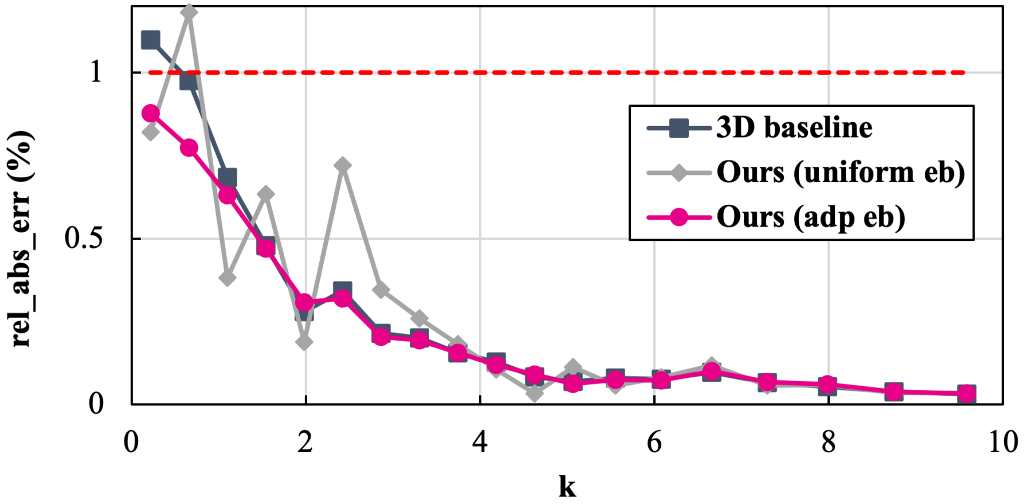
EB_{abs}	Run1_Z2			Run1_Z3			Run1_Z5			Run1_Z10			Run2_T2			Run2_T3			Run2_T4		
	1D	3D	TAC	1D	3D	TAC	1D	3D	TAC	1D	3D	TAC	1D	3D	TAC	1D	3D	TAC	1D	3D	TAC
1E+08	169	94	97	166	90	94	161	76	99	160	40	95	152	17	76	143	2.4	60	125	0.4	30
1E+09	219	115	121	213	120	127	208	109	123	208	63	117	193	27	91	184	3.9	66	159	0.5	32
1E+10	259	125	135	256	125	136	253	117	137	250	65	135	242	30	102	229	4.0	72	197	0.5	34

Overall compression/decompression throughput (MB/s) of different approaches with different absolute error bounds

Evaluation

- **Evaluation on Post-analysis Quality with Adaptive Error Bound**

- TAC can apply different error bounds to different AMR levels based on (1) the **post-analysis metrics**, (2) the **up-sampling rates** of coarse levels, and (3) the rate-distortion trade-off between different AMR levels
- Power spectrum (PS) eb ratio: (1) 1:1, **PS focus on the global quality** → (2) 8:1, up-sample rate is 2^3 → (3) 3:1
- Halo finder (HF) eb ratio: (1) 2:1 **HF focus on finer data**→ (2) 4:1 → (3) 2:1



PS error of the 3D baseline and TAC (both uniform and adp eb) on run1-Z2.
We compare the PS $p'(k)$ of decompressed data with the original $p(k)$ and accept a maximum relative error within 1% (red dashed line) for all k < 10.

	CR	Rel Mass Diff	Cell Nums Diff
3D baseline	198.5	6.66E-04	39.00
TAC (uniform eb)	198.5	4.97E-04	28.00
TAC (adp eb)	**198.6**	**4.49E-04**	**25.00**

The mass change, and the number of cells change for the biggest halo identified using the 3D baseline, TAC with uniform and, TAC with adaptive error bound

Conclusion & Future Work

- **Conclusion**

- Propose TAC, an error-bounded lossy compression for **3D AMR data**
- Propose **three pre-processing** strategies that can adapt based on the density of each AMR level
- Improve the **compression ratio** compared to the STOA approach by up to **3.3x** under the same data quality loss
- Tune the error-bound ratio of fine and coarse levels for better **post analysis quality**

- **Future work**

- Apply our hybrid compression approach to more AMR simulations.
- Address the issue of low throughput on small AMR datasets.

Thank you!

Any questions and ideas are welcomed

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