TensorCodec: Compact Lossy Compression of Tensors without Strong Data Assumptions

Best Student Paper Runner-up

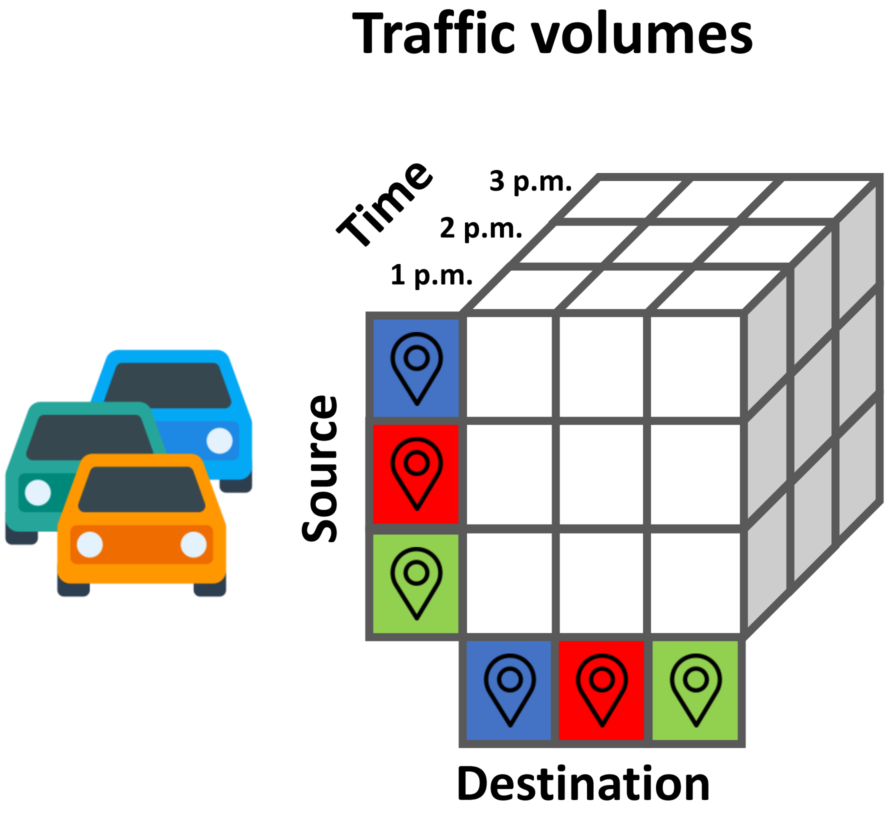

Taehyung Kwon

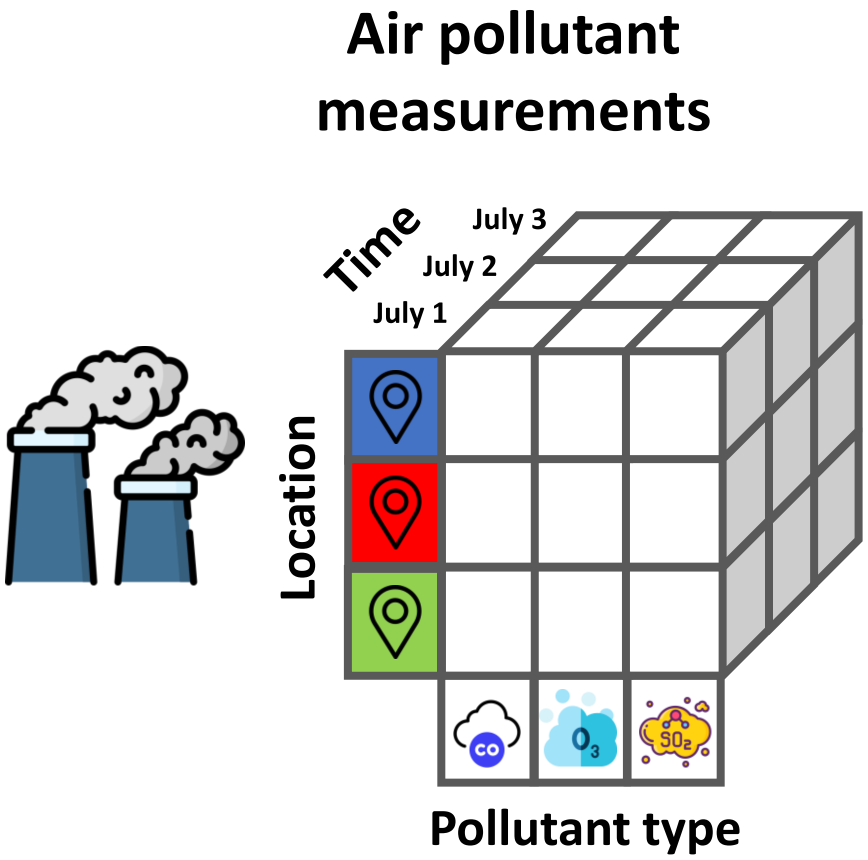

Jihoon Ko


Jinhong Jung

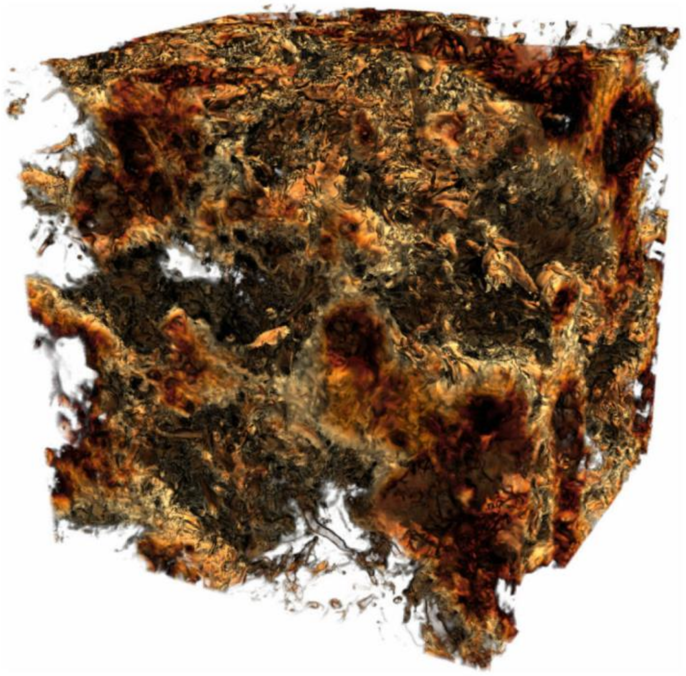

Kijung Shin

Various data can be expressed as tensors





Why do we need to compress tensors?



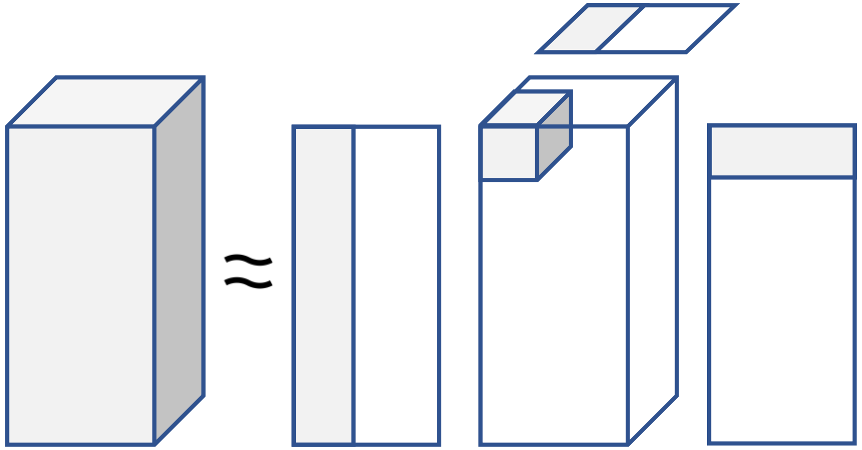
E.g.,) Scientific simulation data

1. Network I/O

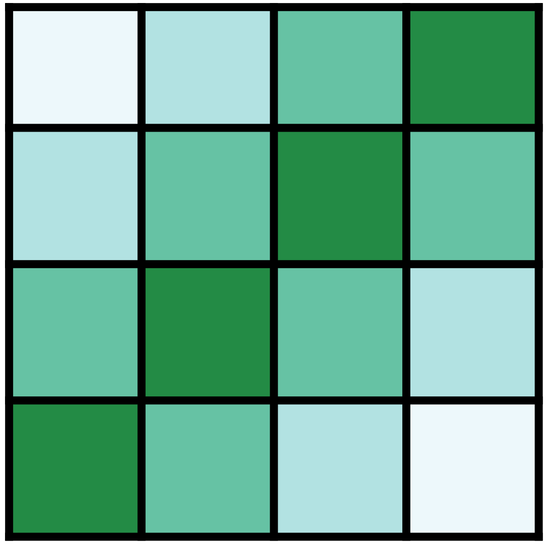
2. Memory requirement

Limitations of existing approaches

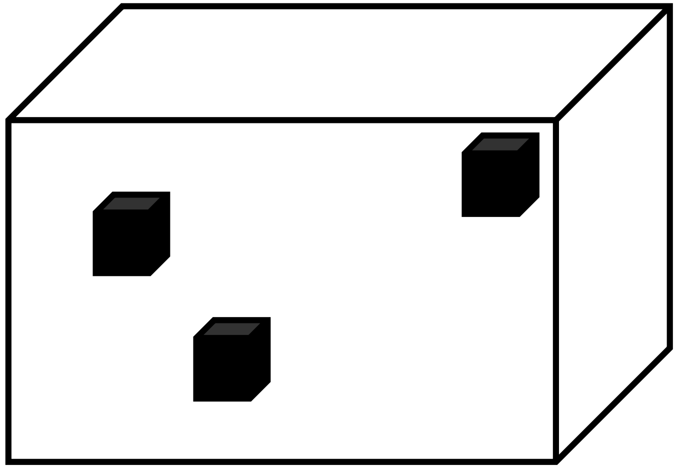
- Existing methods heavily rely on assumptions on input data.



Low-rank structure



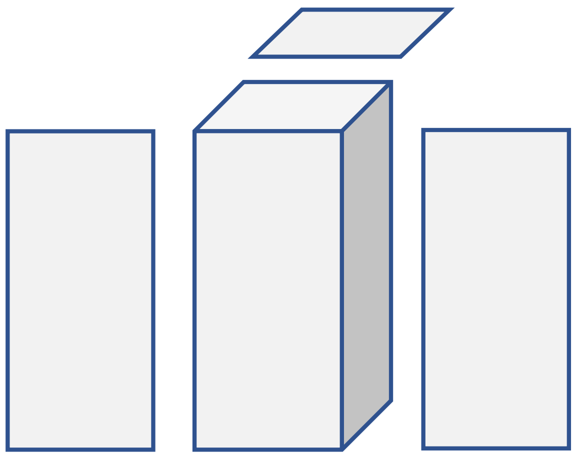
Smooth (e.g., videos)

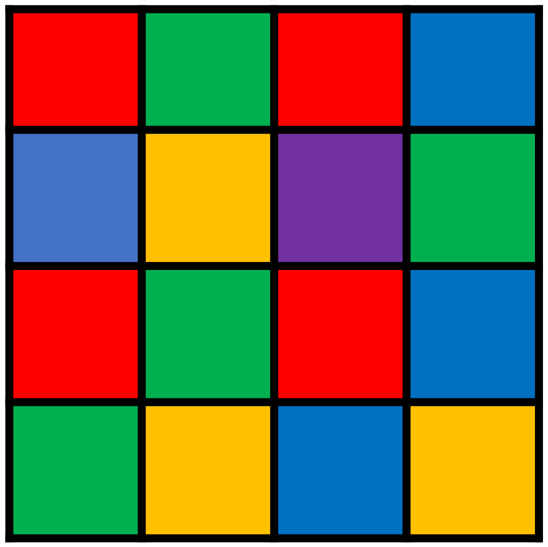


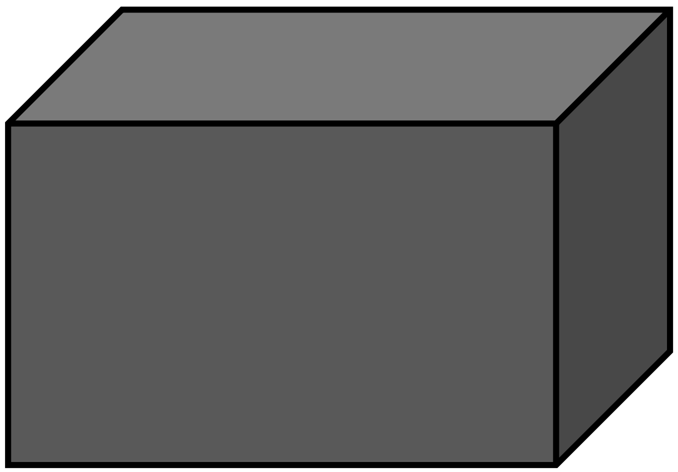
Sparse

Our objective: compression w/o assumptions

- However, not all real-world tensors meet the assumptions.



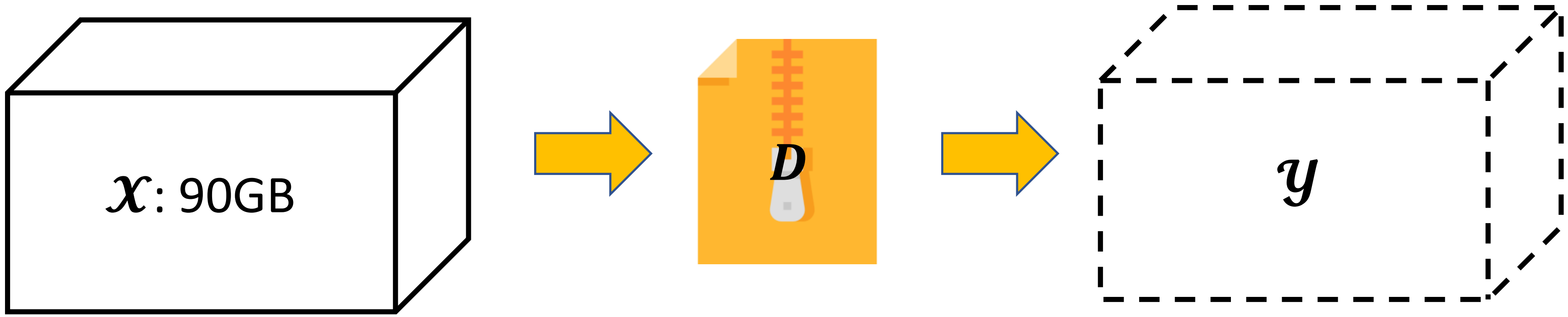




- How can we compress such general tensors?

Problem definition

Lossy compression of tensors **without** any **data assumption**.



- **Given**: a general tensor $\boldsymbol{\mathcal{X}} \in \mathbb{R}^{N_1 \times \cdots \times N_d}$.
- **Find**: the compressed data D.
- **To minimize**: (1) the size of D and (2) the reconstruction error $||\boldsymbol{\mathcal{X}} - \boldsymbol{\mathcal{Y}}||$

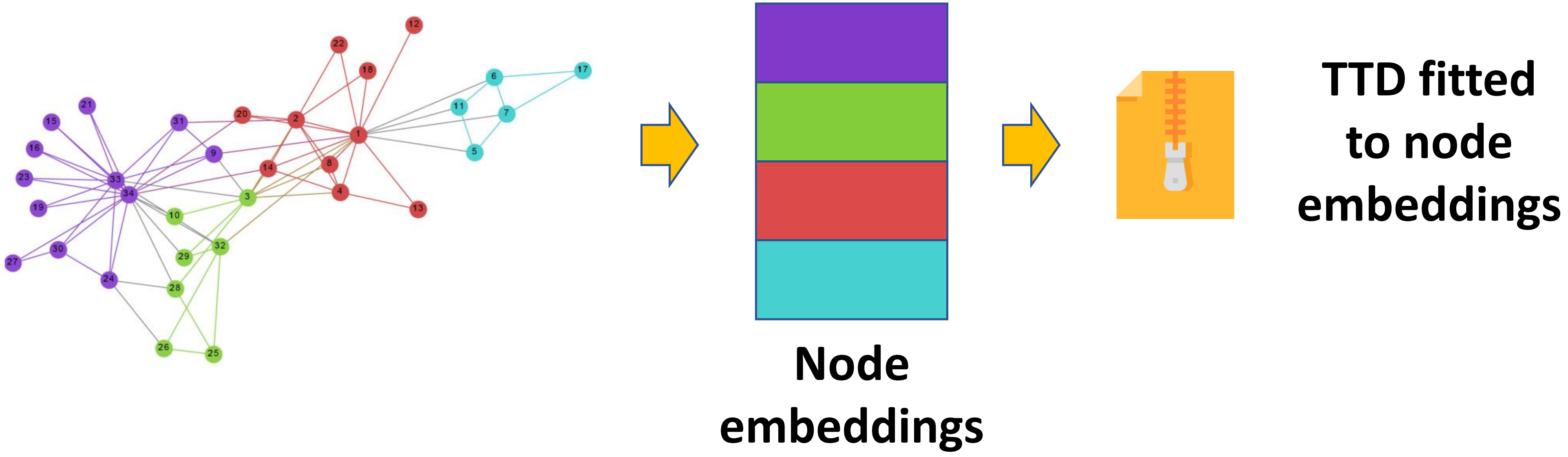
  where $\boldsymbol{\mathcal{Y}}$ is the tensor reconstructed from D.

Outline

1. Introduction.
2. Preliminaries.
3. Proposed method.
4. Experiments.
5. Conclusion.

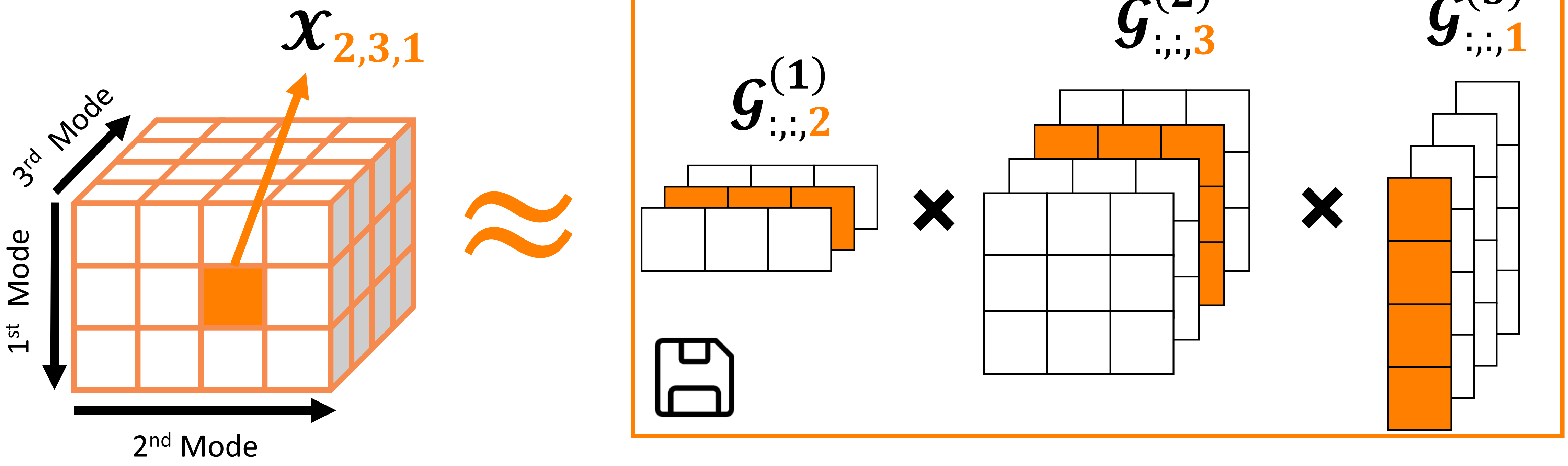
Tensor-Train decomposition (TTD)

- Our approach is founded on the Tensor-Train decomposition (TTD).
- TTD efficiently compresses large matrices.
  - E.g., Compression of node embeddings for efficiency of GNNs



Tensor-Train decomposition (TTD)

- TT-cores ($\mathcal{G}$) can be **stored** instead of the input tensor.
- They can be used to **approximately restore** the input tensor.
  → lossy compression.



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Overview of TensorCodec

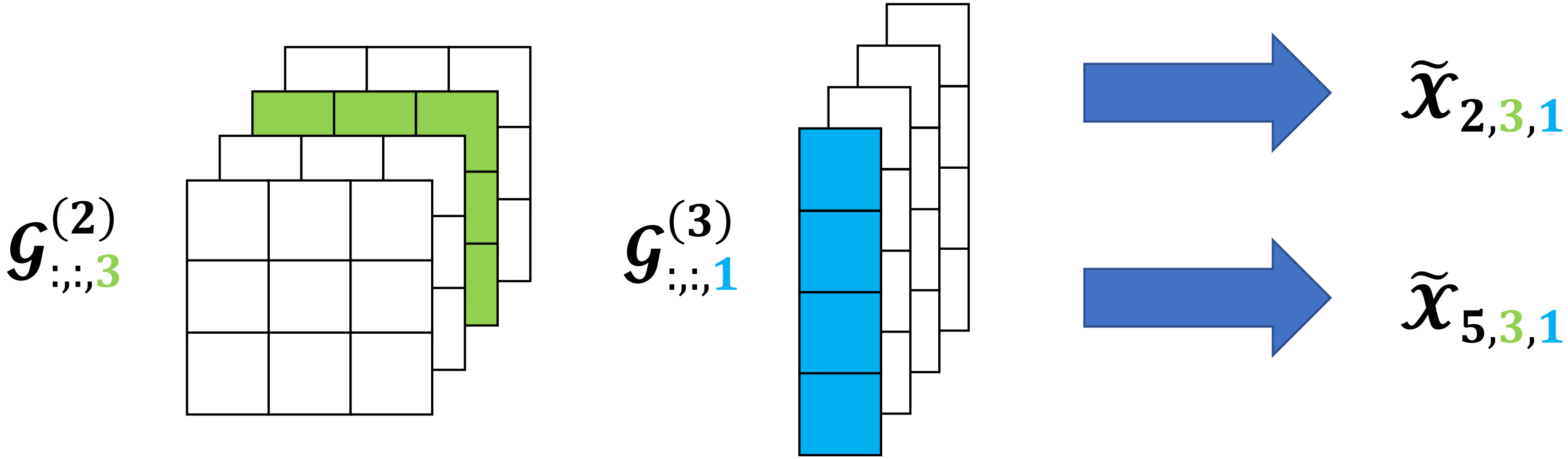
- Our compression algorithm, **TensorCodec**, makes TTD more expressive, concise, and accurate.

- Q1 Expressiveness: How can we enhance the **expressiveness** of TTD?
- Q2 Conciseness: How can we **reduce the parameters** of TTD?
- Q3 Accuracy: How can we **improve approximation accuracy** of TTD?

- **TensorCodec** employs Neural TTD, Folding, and reordering ↑↓

Limited Expressiveness of TTD

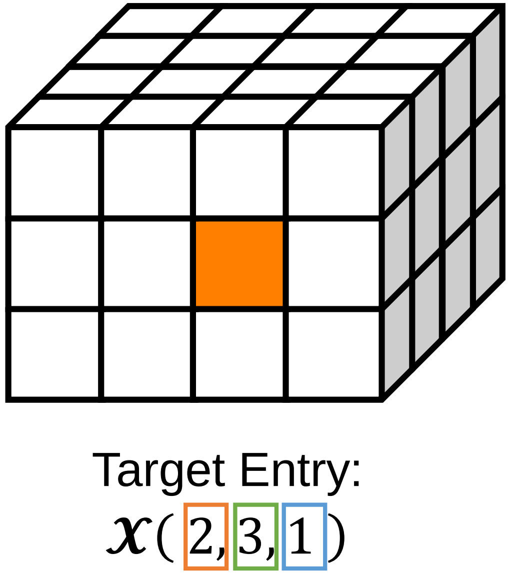
- TT-cores are **fixed** for all tensor entries.

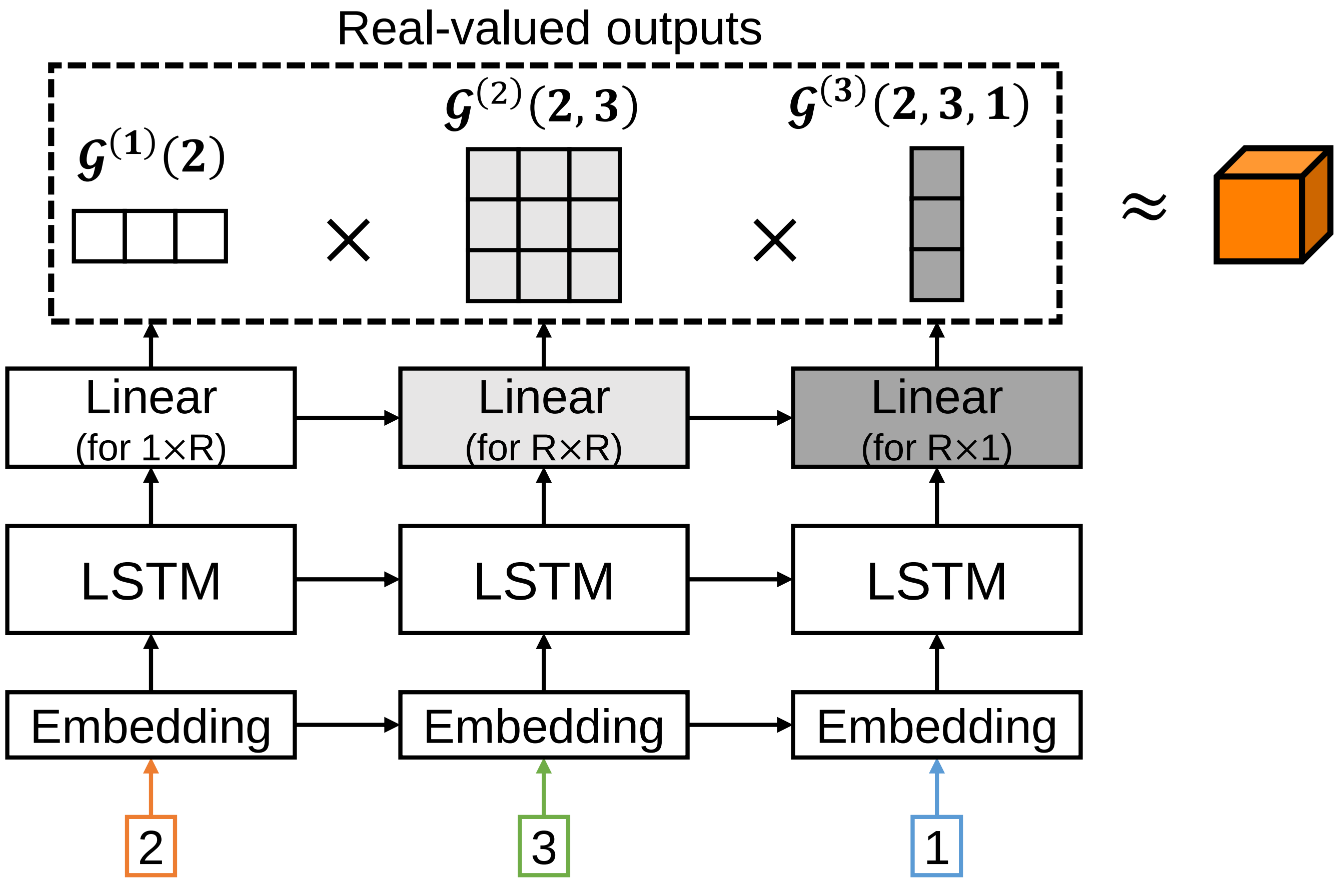


- How can we make TT-cores **adaptive** to each tensor entry?

A1. Neural TTD (NTTD)

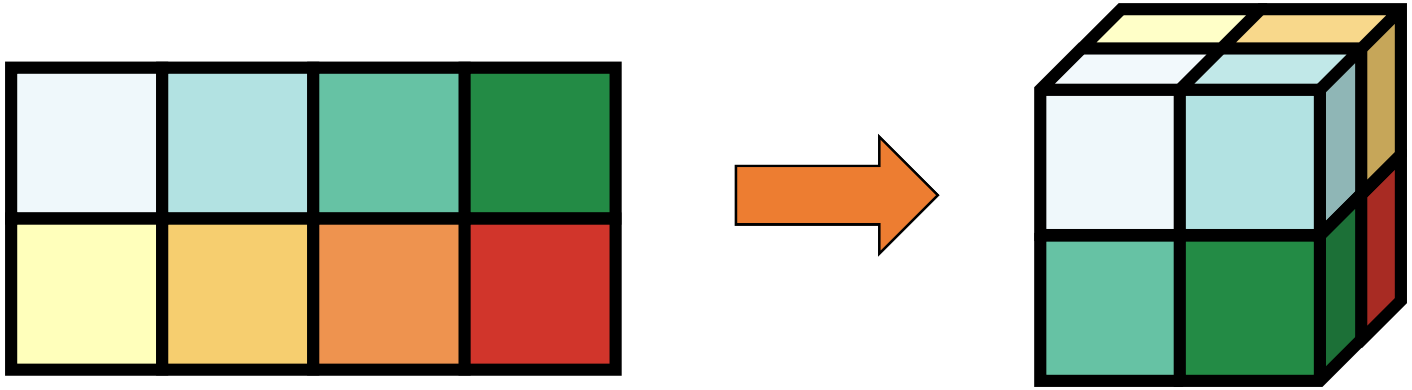
- We make TT-cores **adaptive** to each entry using LSTM returning TT-cores.





A2. Folding

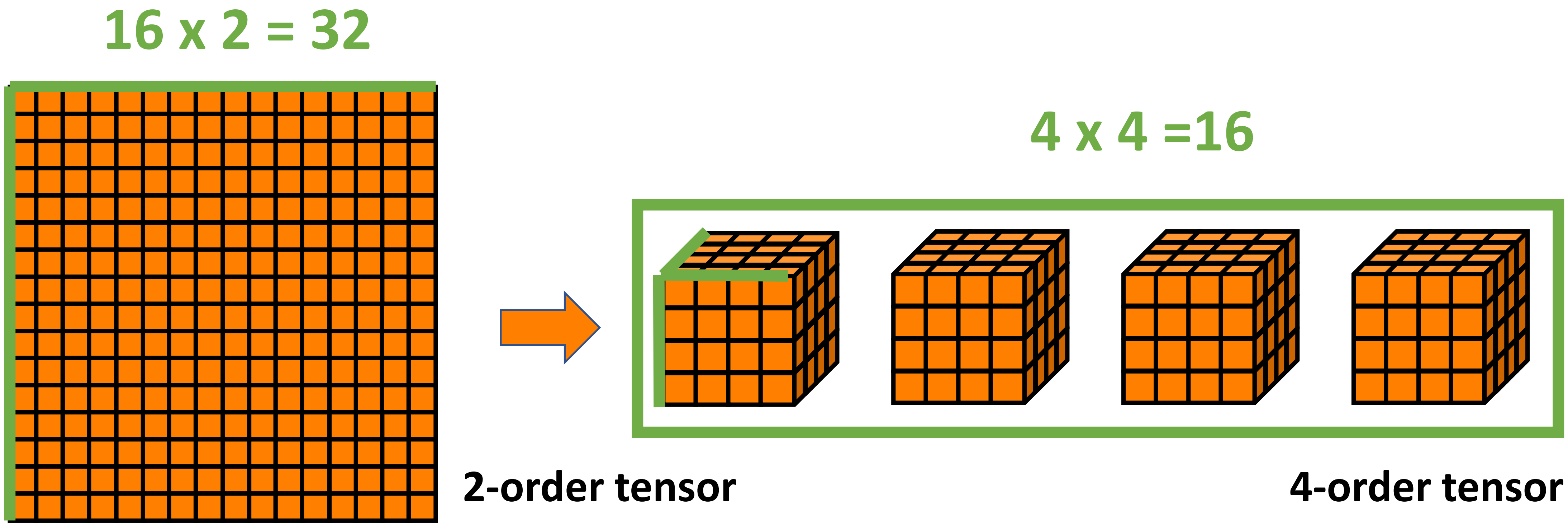
- **Folding** is the process of mapping each entry of a low-order tensor to an entry of a high-order tensor by splitting dimensions.



2-order tensor 3-order tensor

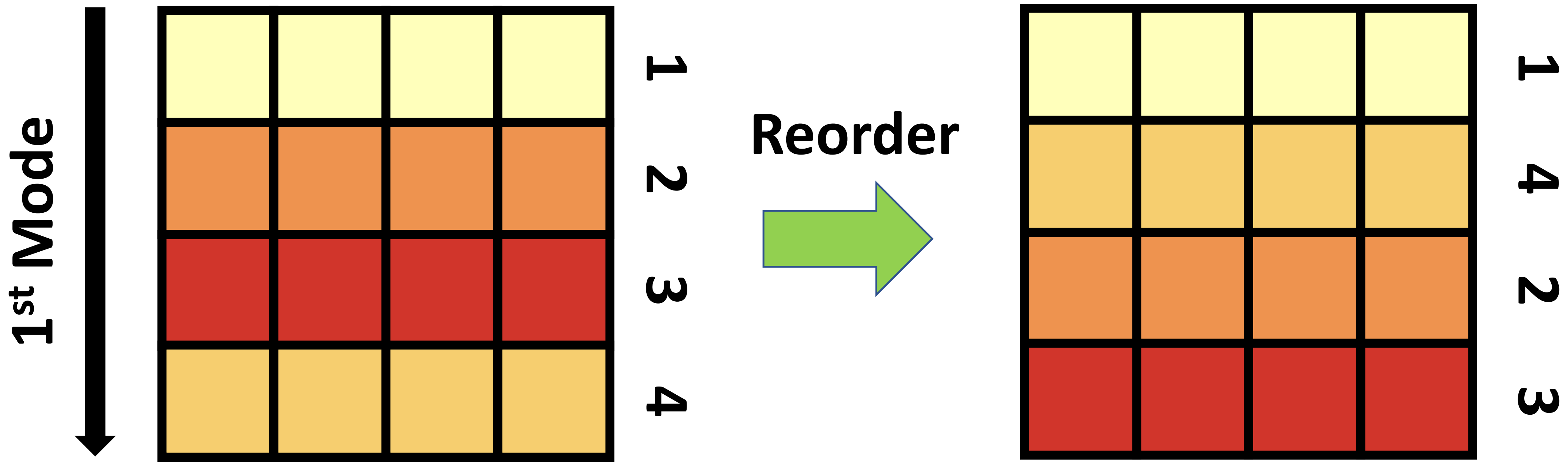
A2. Folding

- The sum of the mode-sizes of a tensor decreases by folding.
- The **number of parameters of NTTD** is proportional to the sum.



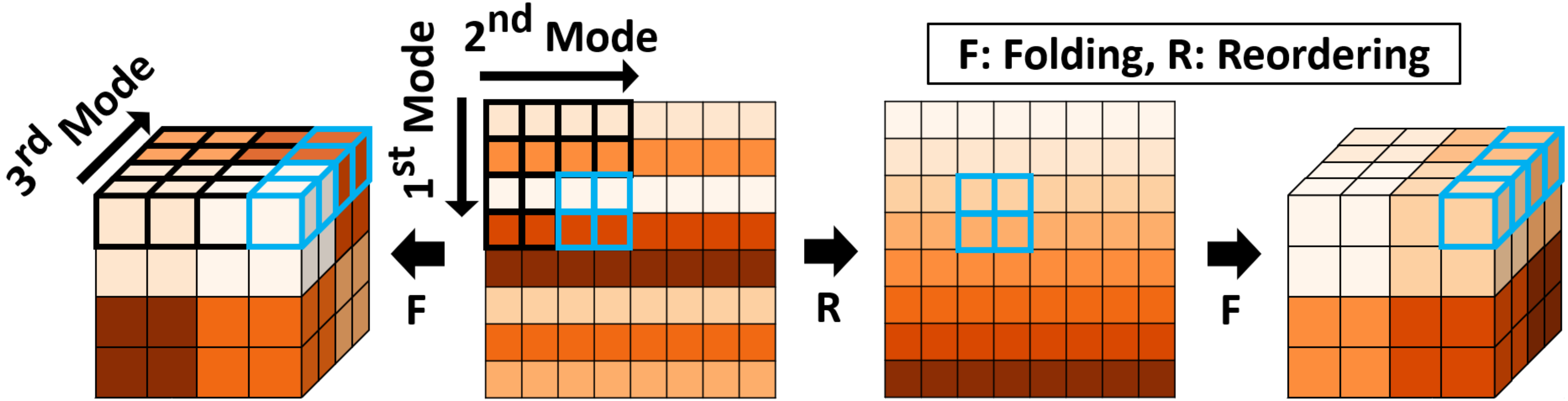
A3. Reordering

- **Reordering** is the process of changing the orders of indices of all modes so that the similar entries are located nearby.



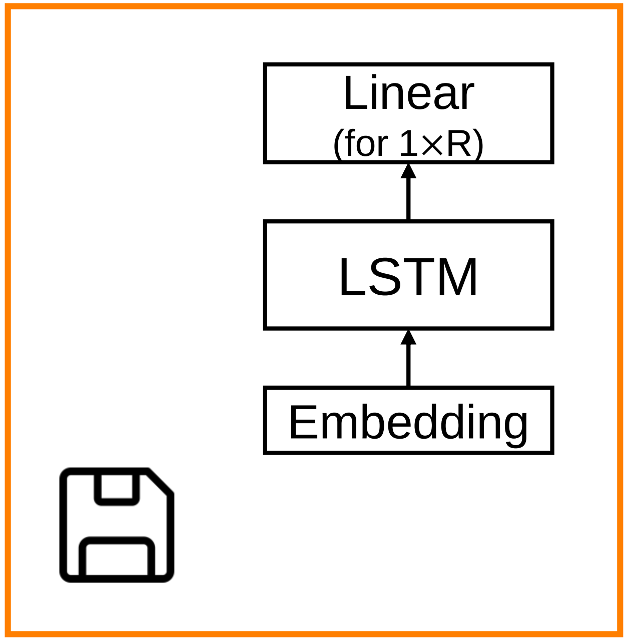
↑↓ A3. Reordering

- The **closer** the entries are in the original tensor, the **closer they are** in the folded tensor.
- **Reordering** helps the model fit the tensor because they share more inputs to LSTM.

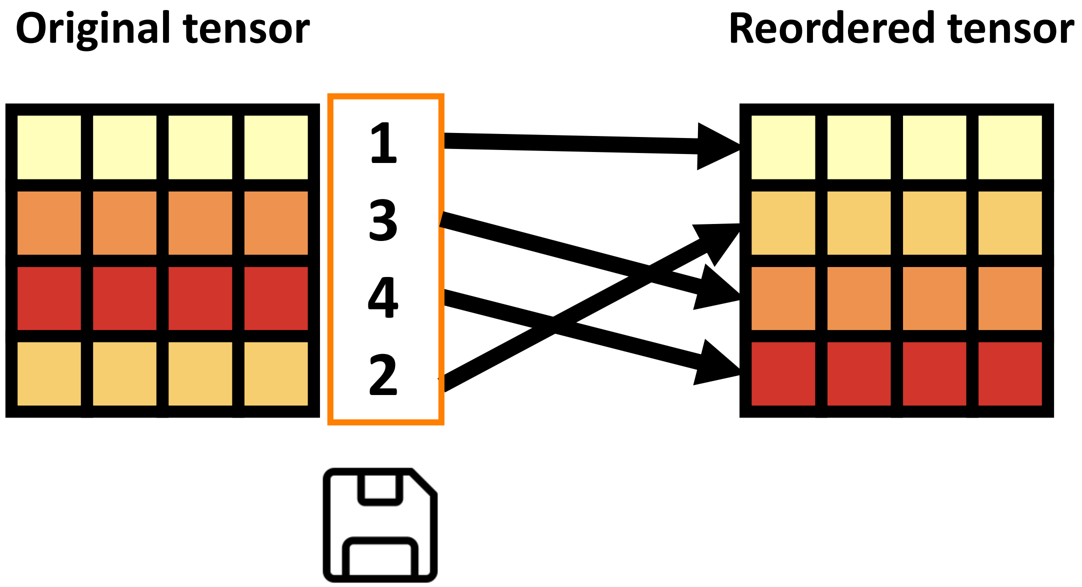


Outputs of TensorCodec

- The **outputs** of compression are (1) **neural-network parameters** and (2) an **index mapping** after reordering

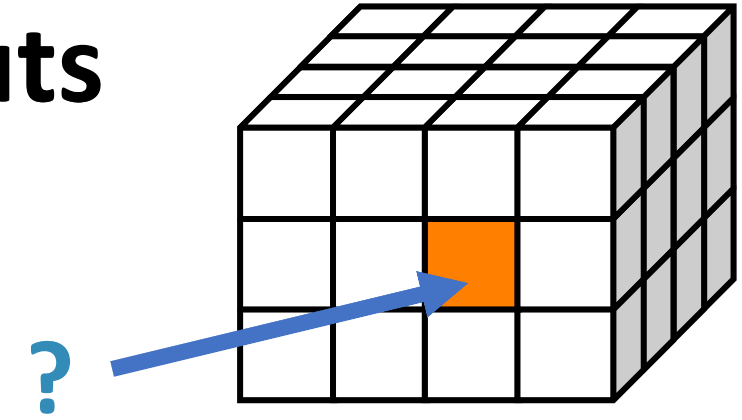


neural network parameters

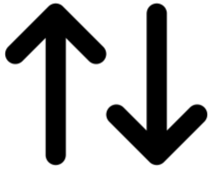


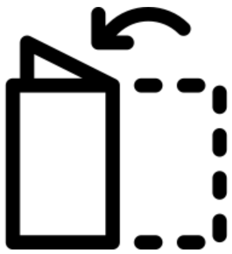
Index mapping

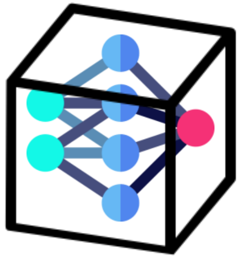
Reconstruction from the outputs



Entry indices		Reordered indices		Folded indices		Reconstructed value
(2, 3, 1)	→ Reordering	(12, 23, 2)	→ Folding	(2, 4, 6, 3, 2)	→ NTTD	2.17







Summary: contributions of each component

A1. NTTD → Better Expressiveness of TTD

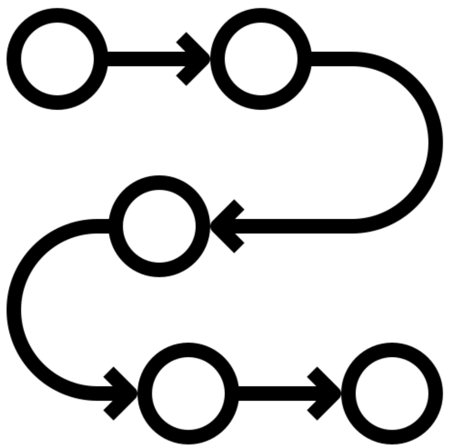
A2. Folding → Better Conciseness of NTTD

A3. Reordering → Better Fitness of NTTD → Better Accuracy

Details

Overall training process for fitting the input

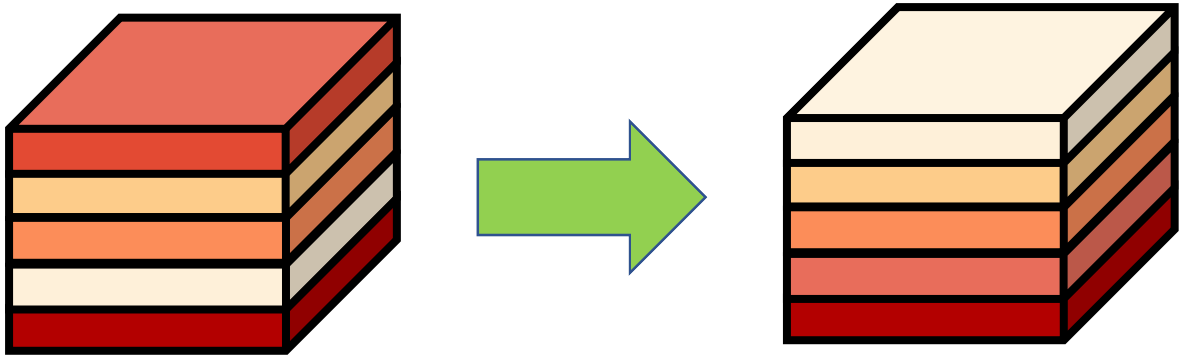
1. Initialize orders (**A3-1**).
2. Update **NTTD** using a **gradient descent**.
3. Update the orders as in (**A3-2**).
4. Repeat 2 and 3 until the error converges.



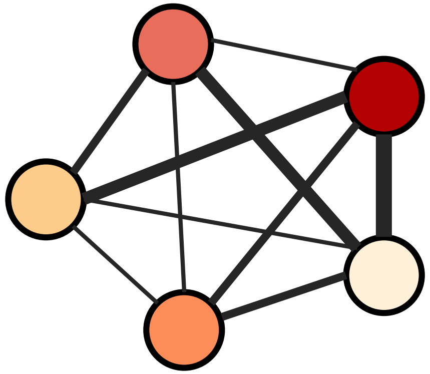
Details

A3-1. Order initialization

- Our goal: minimize the differences between neighboring slices.



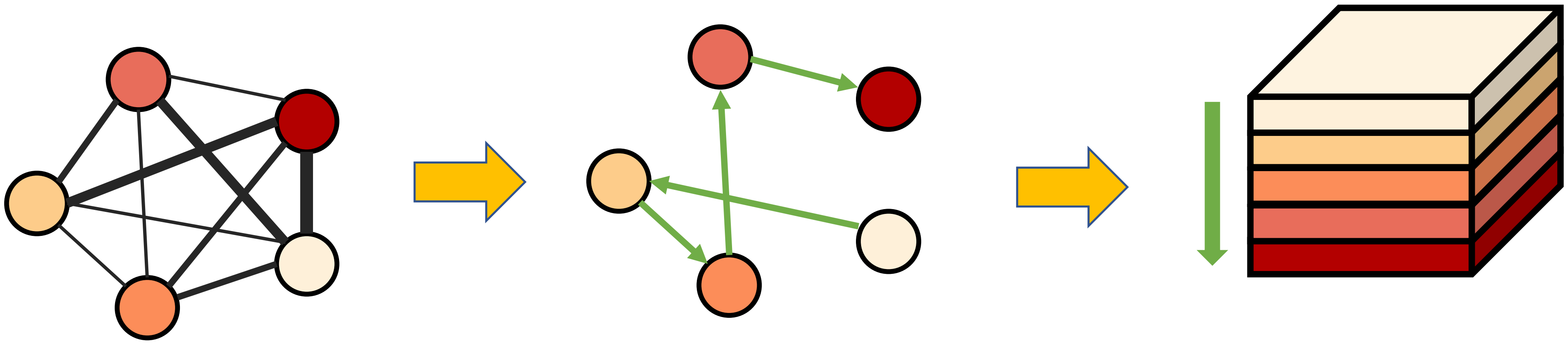
- Consider a **complete graph.**
  - Nodes: slices (i.e., mode indices)
  - Edge weights: L2 distances between the slices.



Details

A3-1. Order initialization

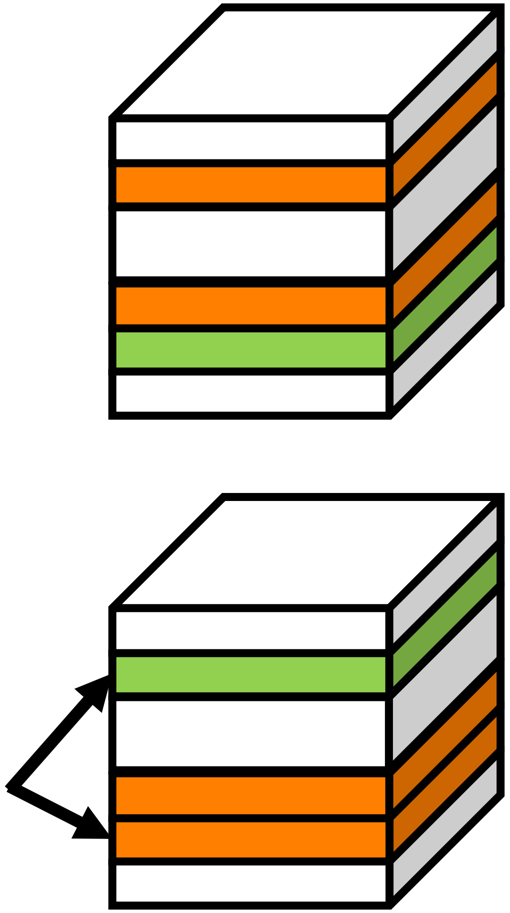
- Find a short cycle with a 2-approximate solution of the TSP.
- Then, remove the largest-weight edge.
- The path becomes the order of slices.



Details

A3-2. Order update using hill climbing

- Finding **similar pairs** of slices using locality-sensitive hashing (LSH) for L2 distance.
- Swap **one slice** with the **neighboring slice of the other** if fitting loss decreases.
- Repeat the above steps.



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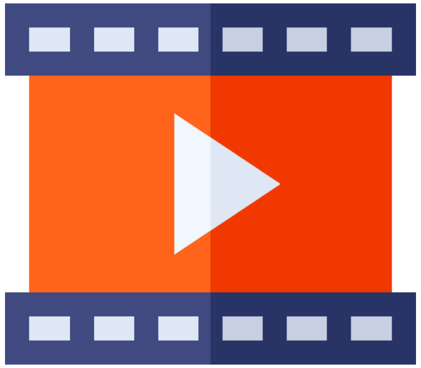
Experimental settings

- Eight real-world datasets: six 3-order tensors and two 4-order tensors.

Air quality measurement

Traffic volume



Video feature

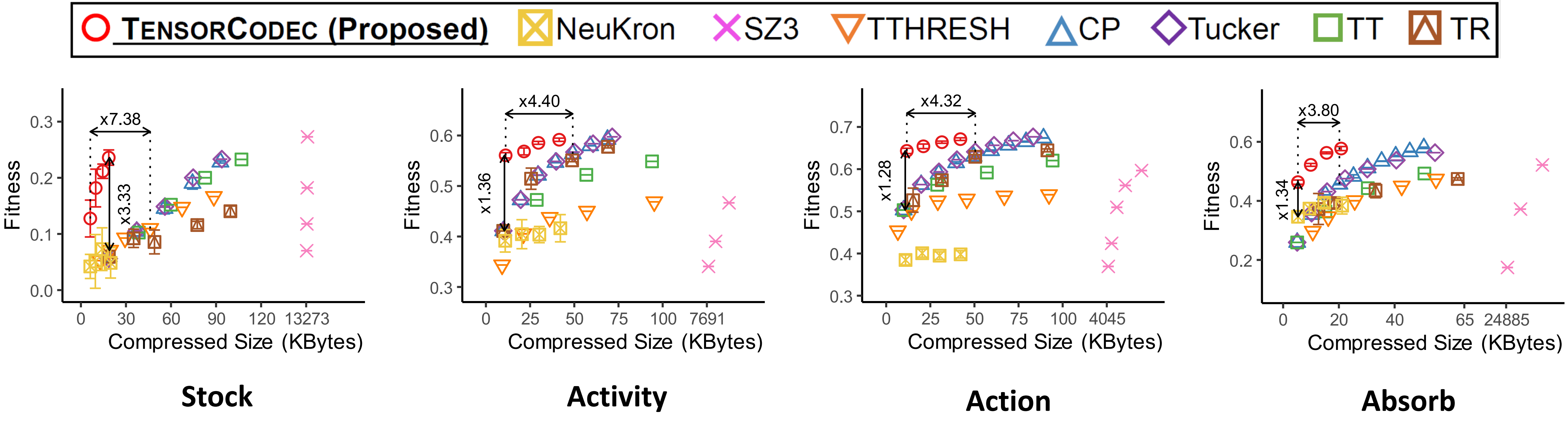
Stock datum

Experimental settings

- Lossy-compression baselines:
  - **Low-rank tensor** compression methods
    - CP, Tucker, TT, and TR decompositions.
  - **Smooth-tensor** compression methods
    - TTHRESH and SZ3.
  - **Sparse-tensor** compression methods
    - NeuKron.

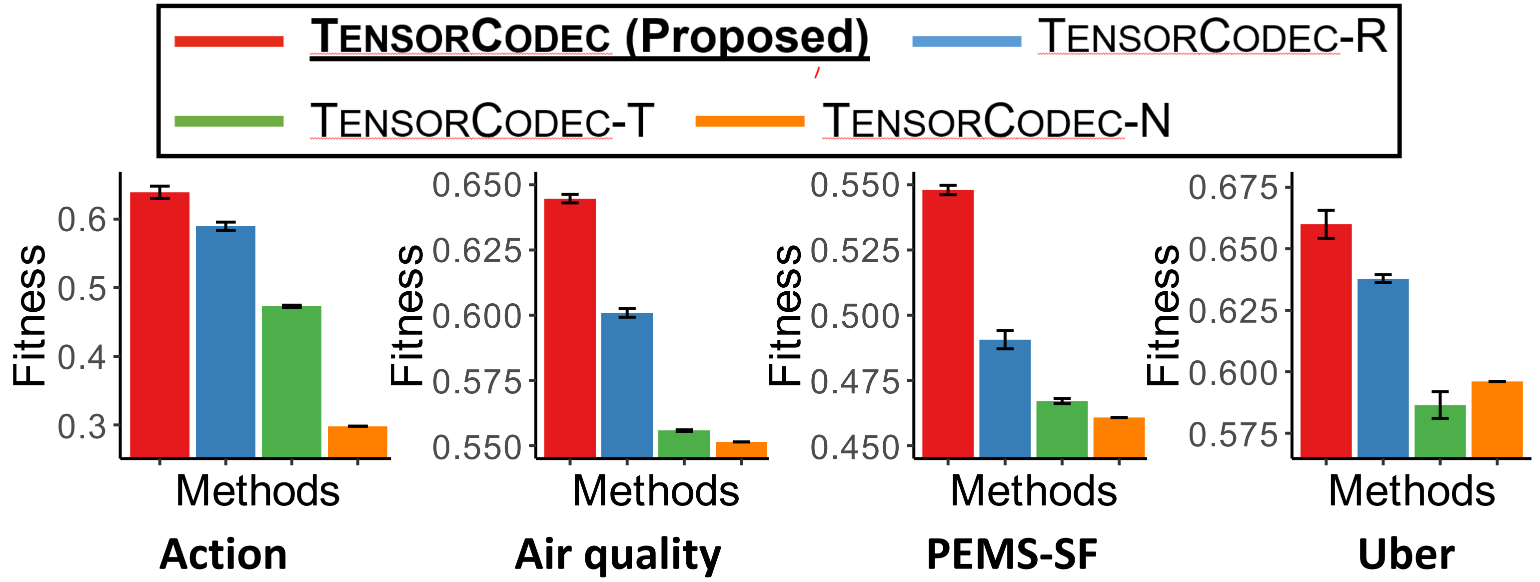
TensorCodec is concise and precise

- The compressed outputs of TensorCodec is up to 7.38x smaller.
- TensorCodec shows up to 3.33x better accuracy.



All components of TensorCodec are useful

- TensorCodec outperforms all of its variants with missing components.



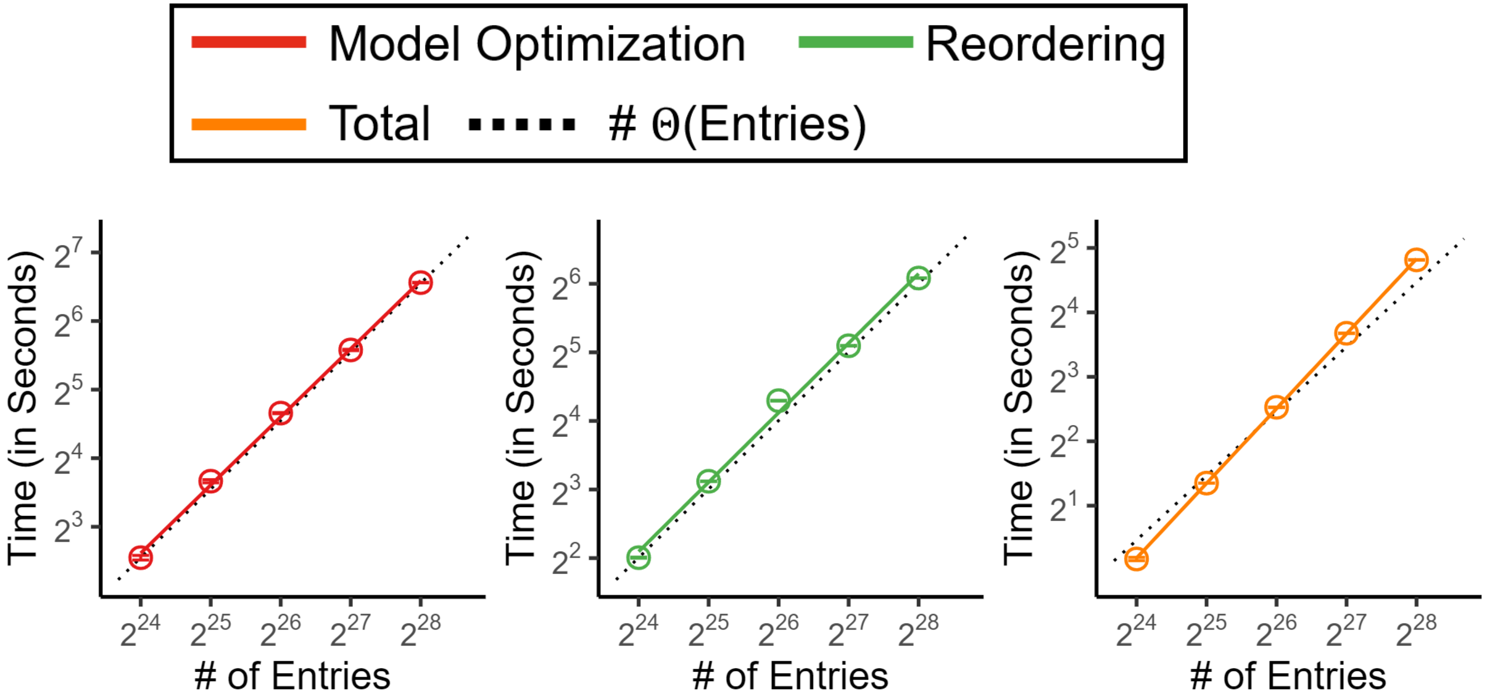
TensorCodec (TC)-R: variant of TC without reordering.

TC-T: variant of TC-R without order initialization.

TC-N: variant of TC-T without a neural network.

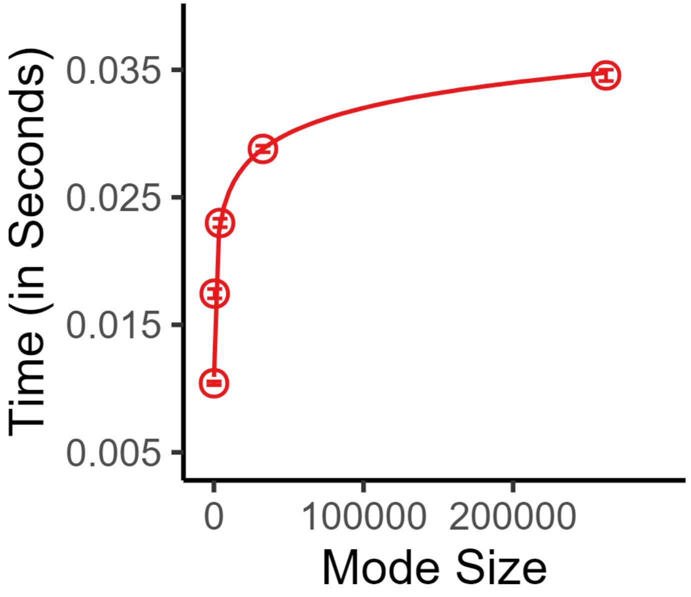
TensorCodec is scalable

- Compression time of TensorCodec is linear in the tensor entry count.

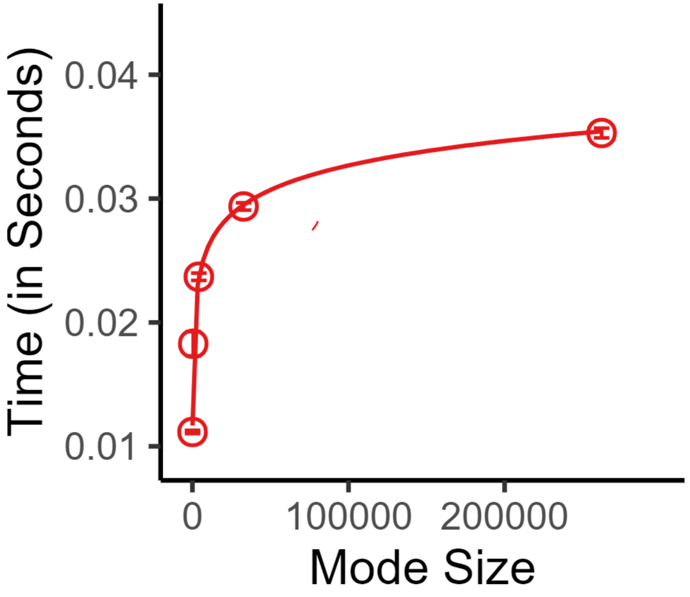


TensorCodec is scalable

- Its reconstruction time is **sub-linear** in the tensor entry count.



3-order tensor



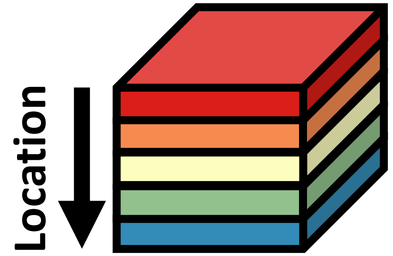
4-order tensor

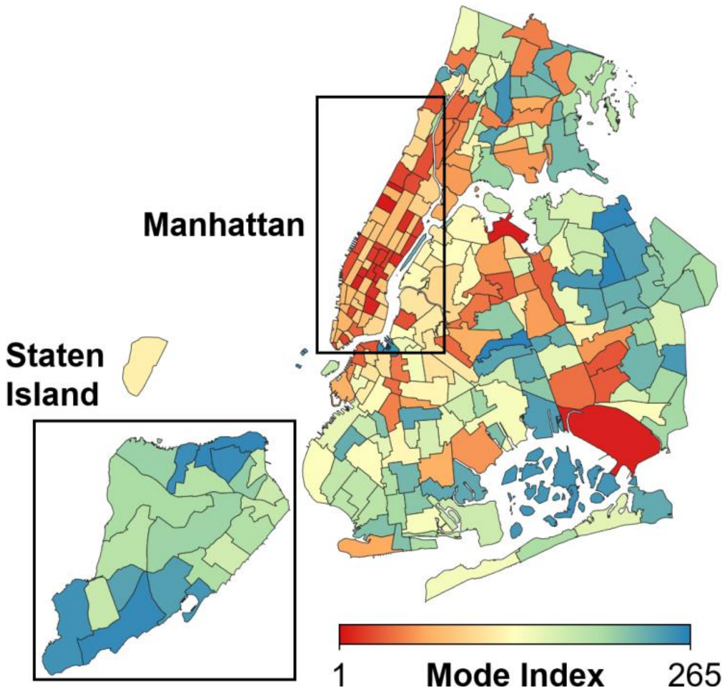
Further Analysis

- Which slices are **closely** ordered by TensorCodec?
- Can TensorCodec approximate **high-rank tensors** with few parameters?

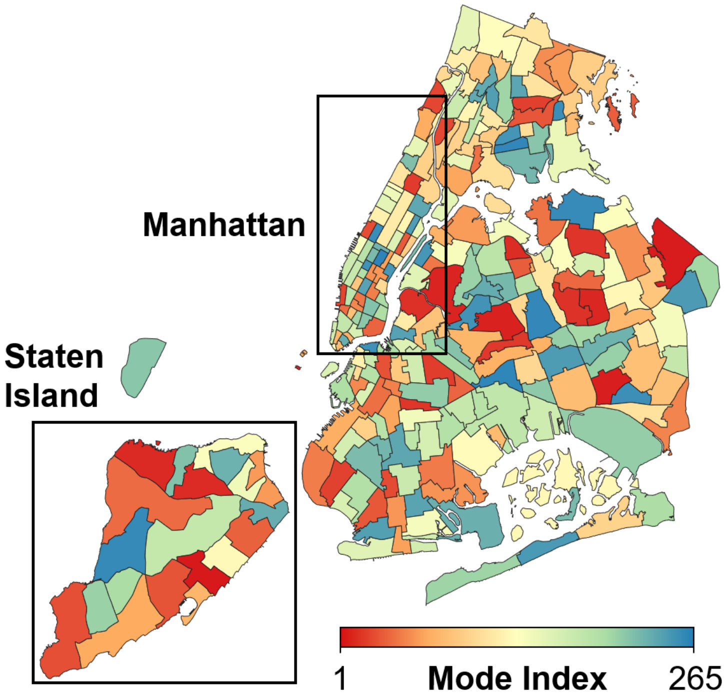
Reordering by TensorCodec is effective

- Reordered results of TensorCodec align with our intuition.





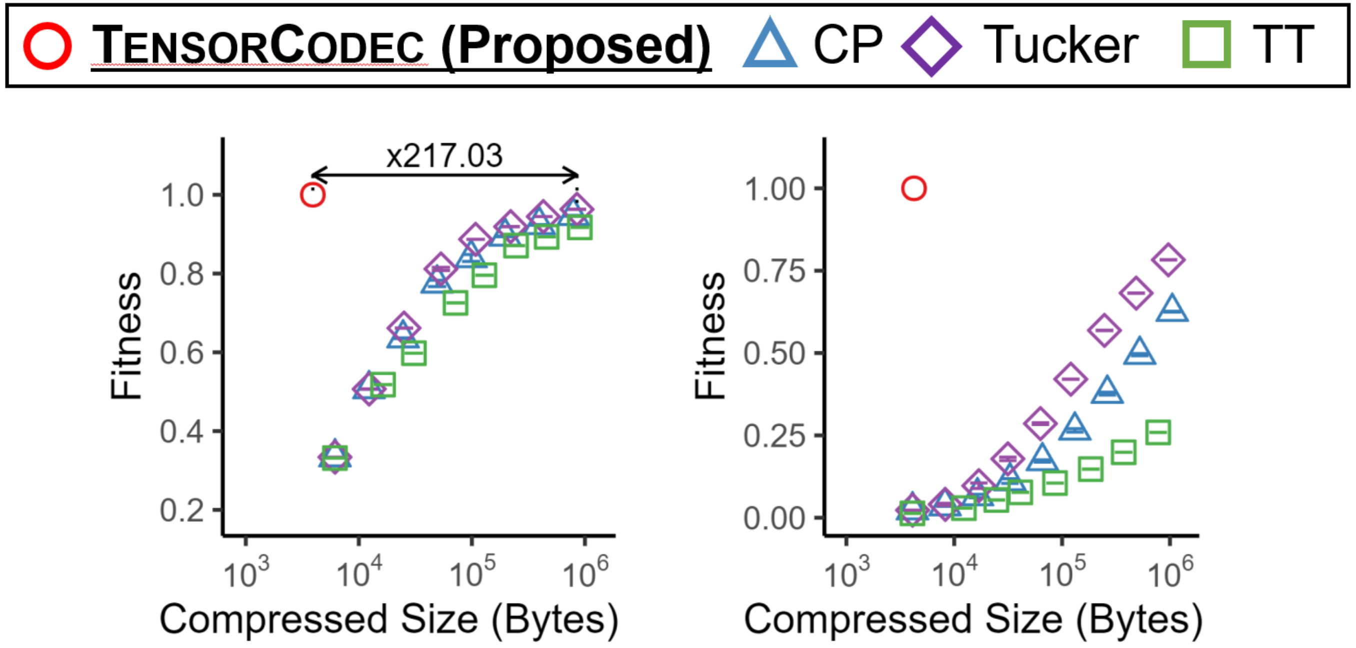
Reordering by TensorCodec



Reordering by NeuKron

TensorCodec is expressive

- TensorCodec fits high-rank tensors with a small number of parameters.



3-order tensor **4-order tensor**

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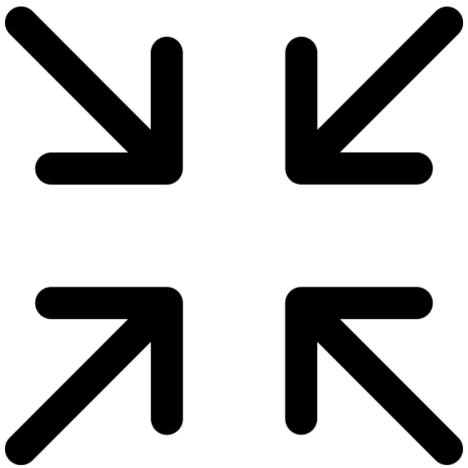
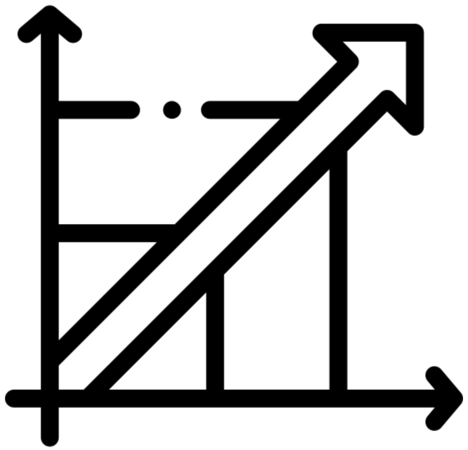
Conclusion

- We propose **TensorCodec** for **lossy compression** of general tensors.
- **TensorCodec** is **concise**, **accurate**, and **scalable**.



Concise

Accurate



Scalable

Thank you for listening!

Any question?

Code & Datasets: https://github.com/kbrother/TensorCodec