







# **NEUKRON: Constant-Size Lossy** Compression of Sparse Reorderable **Matrices and Tensors**



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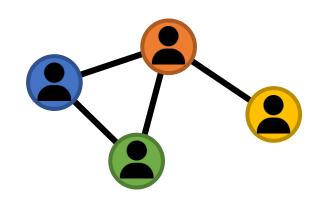


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Kijung Shin

#### **Sparse matrices from Web applications**





Publication 1

Publication 2

Publication 3

Publication 4

Publication 4

**Authors** 

Friendship in Social Media

 2
 2
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 2
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Counting Clicks on Ads By Search Engine

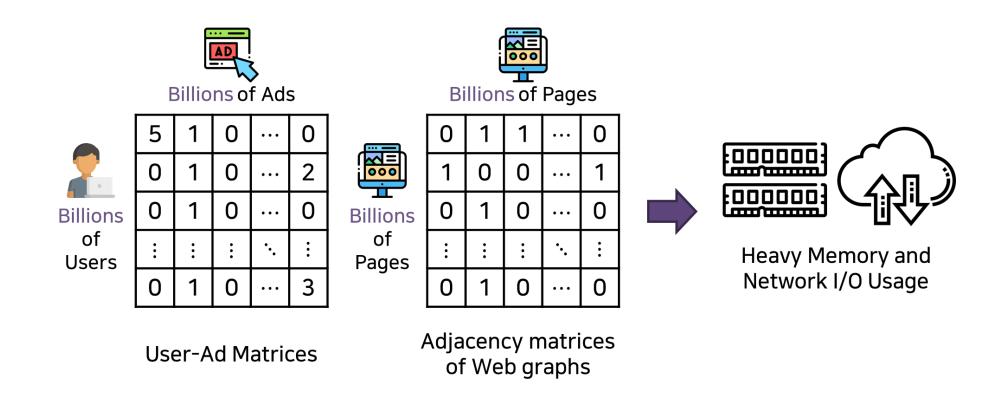
	AD	AD	AD	AD
<b>9</b>	5	1	0	0
2	0	1	0	2
3	0	1	0	0
4	0	1	0	3

Publication Records from Academic Databases

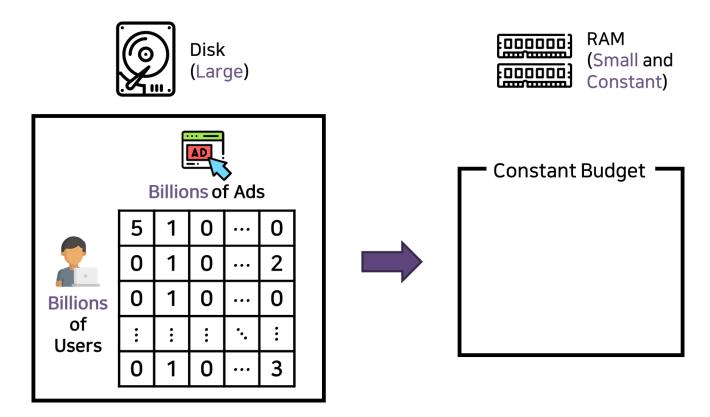
	1	2	3	4
<b>Q</b> A	0	0	1	0
Oβ	1	0	1	0
<b>ာ</b> ပ	0	1	1	0
<b>O</b>	1	1	1	1

## Real-world sparse matrices are large-scale

- Real-world sparse matrices often containing billions of rows or columns
  - ⇒ requires heavy memory or network I/O usage
  - ⇒ compressing these large sparse matrices is important!



## Our goal: constant-size compression



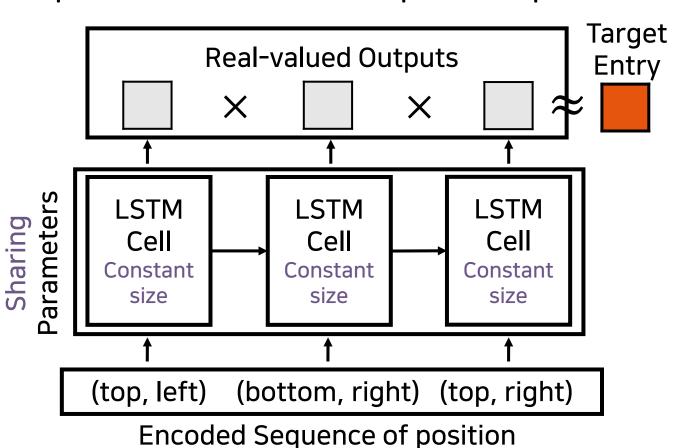
- Given: a sparse and reorderable matrix  $A \in \mathbb{R}^{N \times M}$  / a constant k = O(1)
- Find: a model  $\Theta$  whose size is at most k
- To minimize: the approximation error  $\|A-\widetilde{A}_{\mathbf{\Theta}}\|_F^2$

**Experiments** 

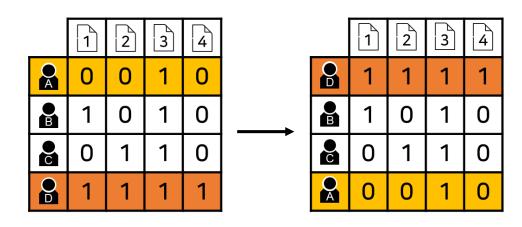
#### Overview of Neukron

 Recurrent Neural Network: having a constant number of parameters but also expressive power

Introduction

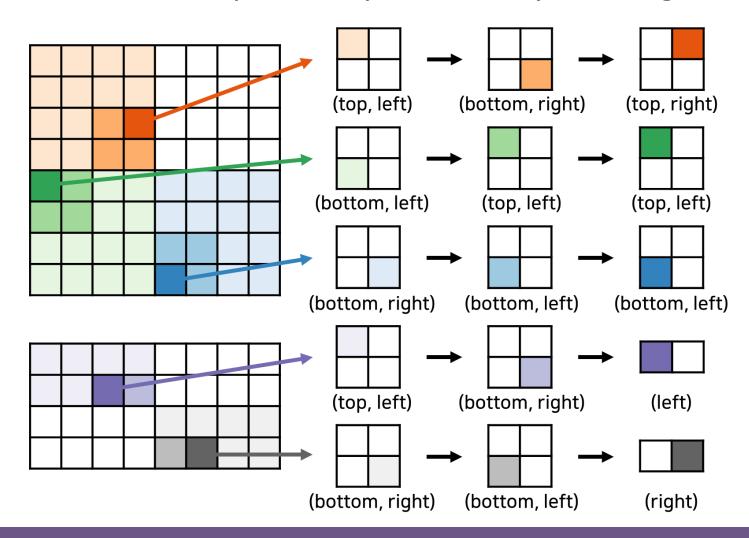


Reordering: extract and exploit structural patterns for better compression

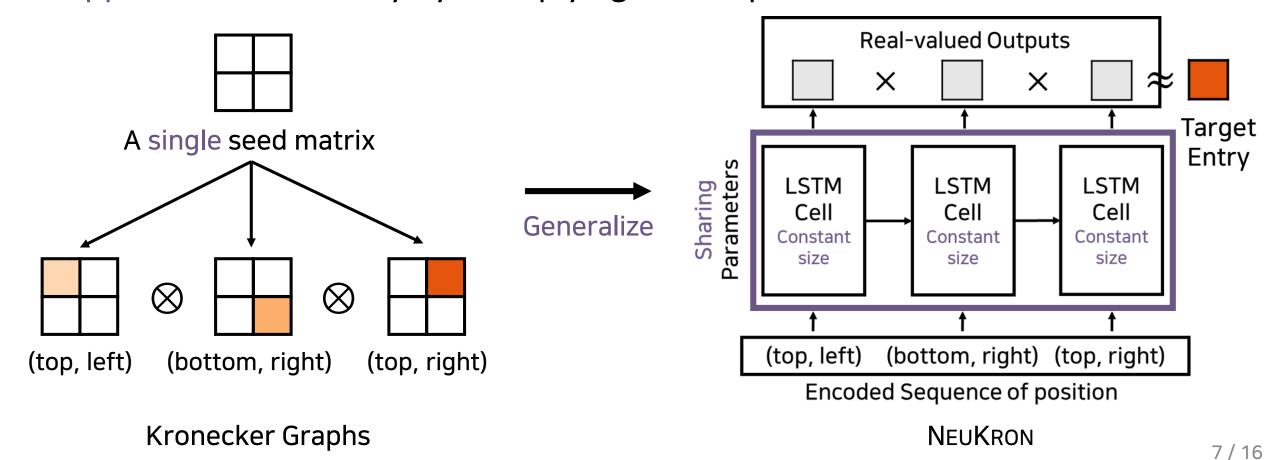


#### **Model of NEUKRON**

• Encode the position in a sequence by recursively dividing the input matrix



- Feed the sequence to LSTM to compute seed matrices
- Approximate the entry by multiplying the outputs of the LSTM cells



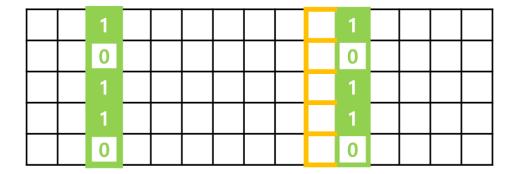
# **Order optimization**

- Many real-world sparse matrices are reorderable
  - ⇒ Exploit structural patterns for compression!

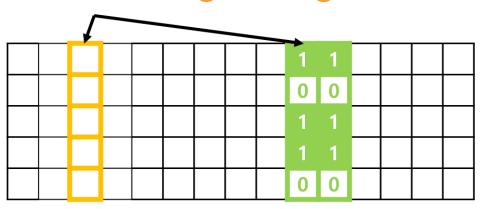
	1	2	3	4			3	2	1	4						
A	0	0	1	0			1	1	1	1						
B	1	0	1	0	<b>→</b>	B	1	0	1	0	<b>→</b>			$\otimes$		1
e	0	1	1	0		e c	1	1	0	0		_1	0		1	O
B	1	1	1	1		A	1	0	0	0						

# **Order optimization**

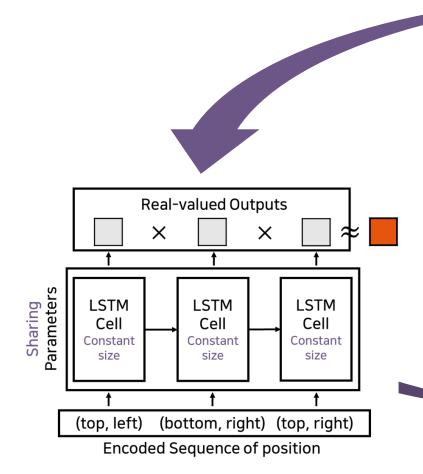
• Step 1. Find similar pairs of slices using Min-Hashing



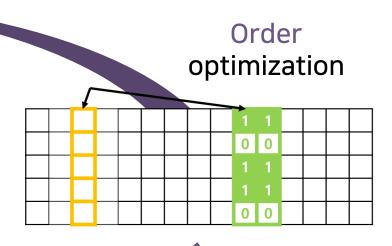
• Step 2. Exchange slices with the neighboring slices when loss decreases



## Overall training procedure



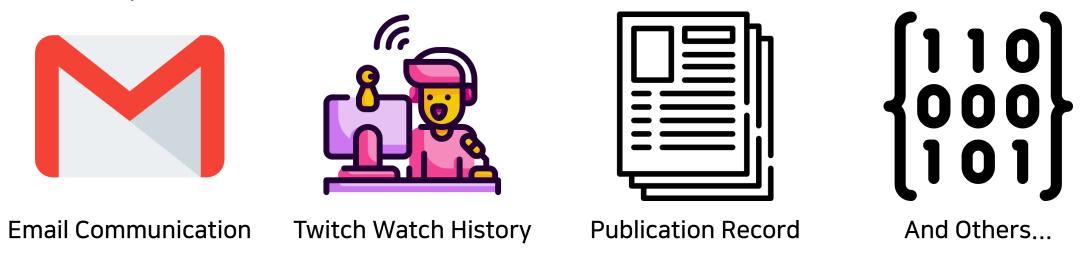
Iterative update until convergence



Model optimization

## **Experimental settings**

• 10 real-world datasets: 6 sparse matrices and 4 sparse tensors (up to 233M non-zeros)



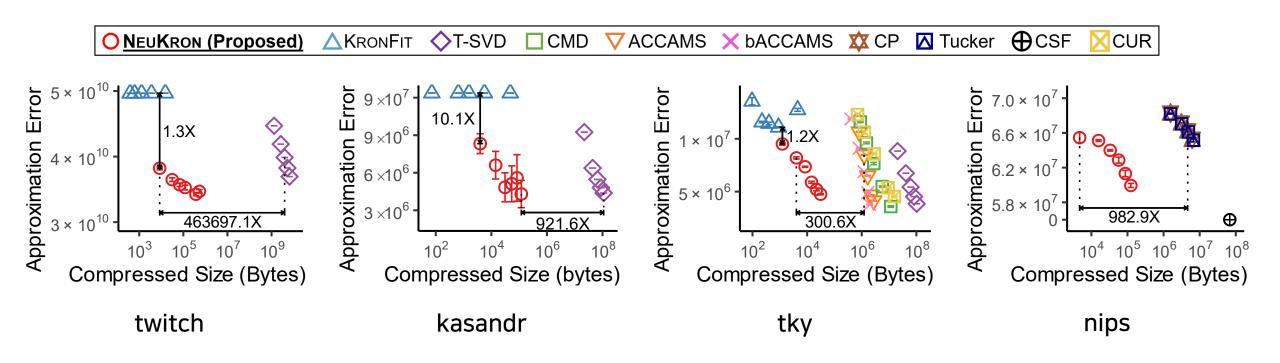
• 9 SOTA competitors

## **Experimental settings**

- 10 real-world datasets: 6 sparse matrices and 4 sparse tensors
- 9 SOTA competitors
  - Factorization-based matrix compression
    - T-SVD, CMD, CUR
  - Co-clustering-based matrix compression
    - ACCAMS, bACCAMS
  - Kronecker product-based matrix compression
    - KronFit
  - Factorization-based tensor compression
    - CP, Tucker
  - Lossless tensor compression
    - CSF (Compressed Sparse Fiber)

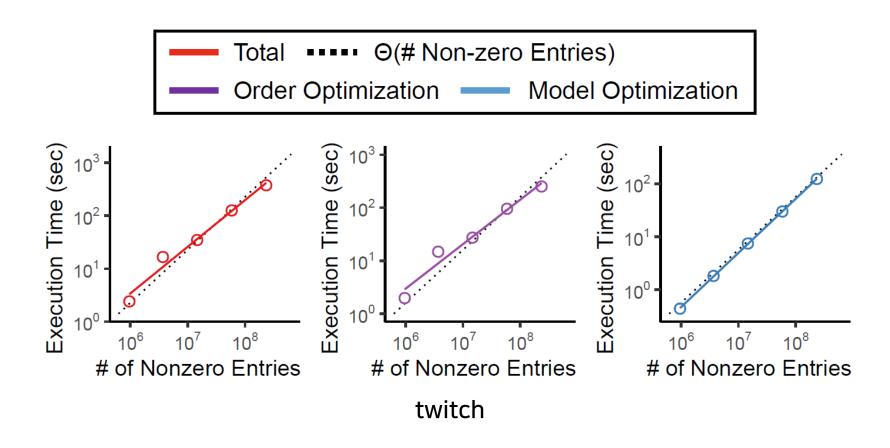
### **NEUKRON** is compact and accurate

- The outputs of Neukron are up to 5 orders of magnitude smaller
- The approximation error was up to 10.1X smaller in the outputs of NEUKRON



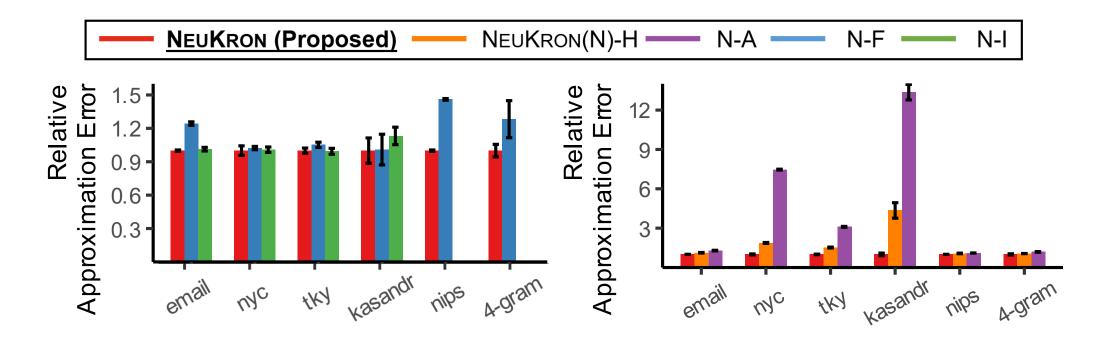
#### Neukron is scalable

Compression by Neukron scaled linearly with the number of non-zeros



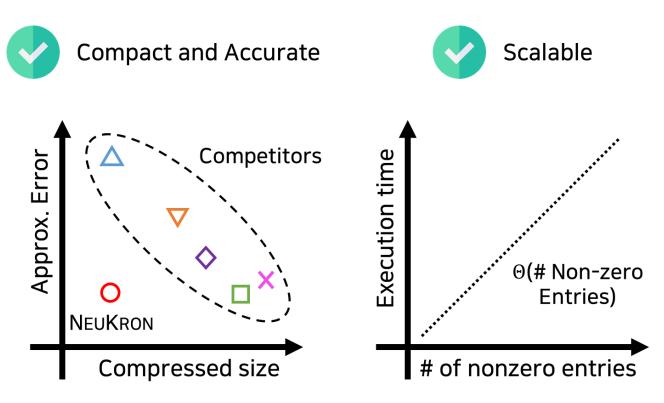
## **Ablation Study**

- All components of NEUKRON are effective
  - the variants of Neukron with missing components (Neukron-H, -A, -F, -I) were outperformed by the original Neukron, equipped with all components



#### Conclusion

• We propose Neukron, a lossy compression algorithm for reorderable and sparse matrices and tensors



Code and datasets are available at https://github.com/kbrother/NeuKron









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