

Beyond low-rankness: nonparametric models for tensor completion and regression

Nonparametric signal tensor estimation via sign series

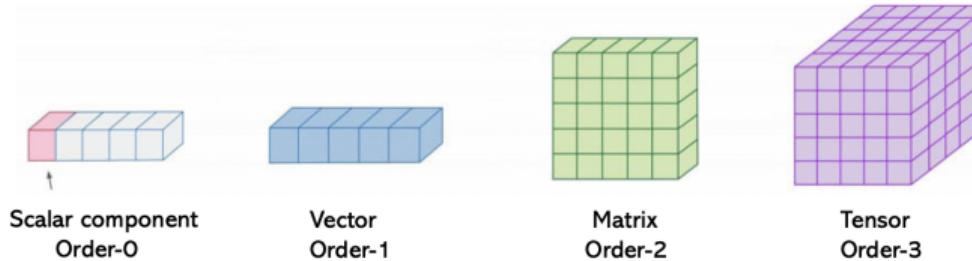
Chanwoo Lee

Department of Statistics
University of Wisconsin - Madison

Preliminary Exam

What is tensor?

- Tensors are generalizations of vectors and matrices:



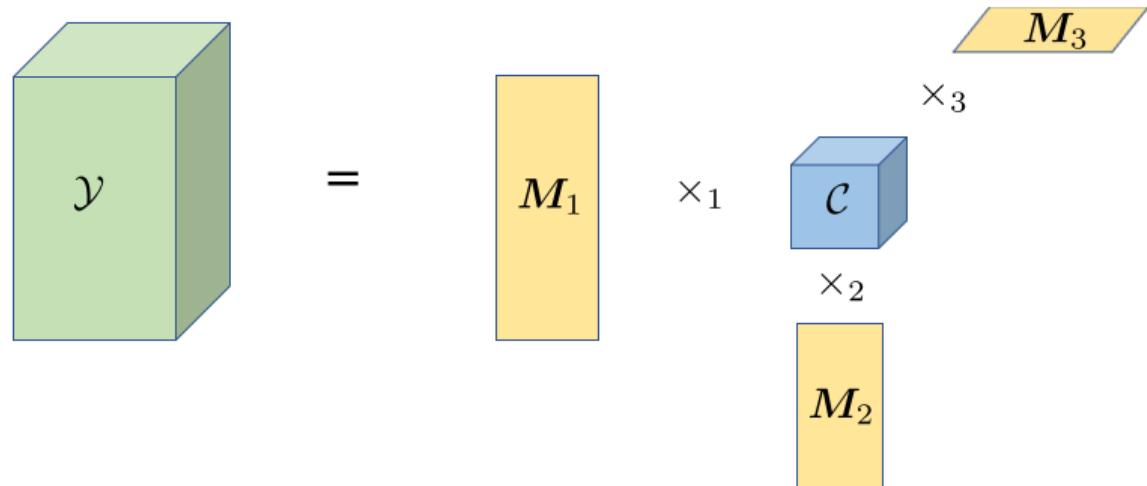
- We focus on tensors of order 3 or greater, also called **higher-order tensors**.
- Denote an order- $K(d_1, \dots, d_K)$ dimensional tensor as $\mathcal{Y} = [\![y_\omega]\!] \in \mathbb{R}^{d_1 \times \dots \times d_K}$ where $\omega \in [d_1] \times \dots \times [d_K]$.

Tensor decomposition (Tucker decomposition)

Delete

- Tucker decomposition (De Lathauwer et al., 2000).
 - $\mathcal{Y} = \mathcal{C} \times_1 \mathbf{M}_1 \times_2 \mathbf{M}_2 \times_3 \mathbf{M}_3$.
 - Generalization of matrix SVD to higher orders: $\mathbf{Y} = \mathbf{U}\Sigma\mathbf{V}^T (= \Sigma \times_1 \mathbf{U} \times_2 \mathbf{V})$
 - Tucker rank of an order-3 tensor is defined as

$$r(\mathcal{Y}) = (r_1, r_2, r_3).$$

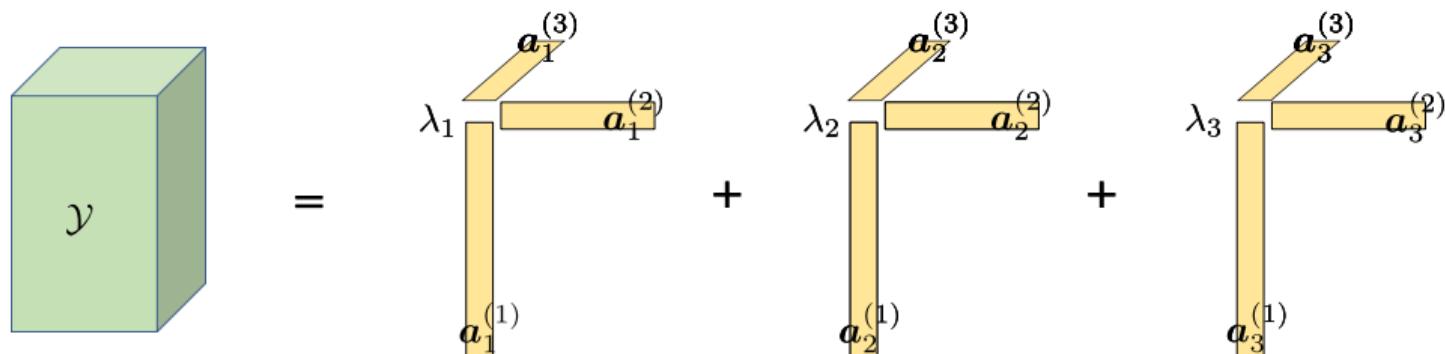


Tensor decomposition (CP decomposition)

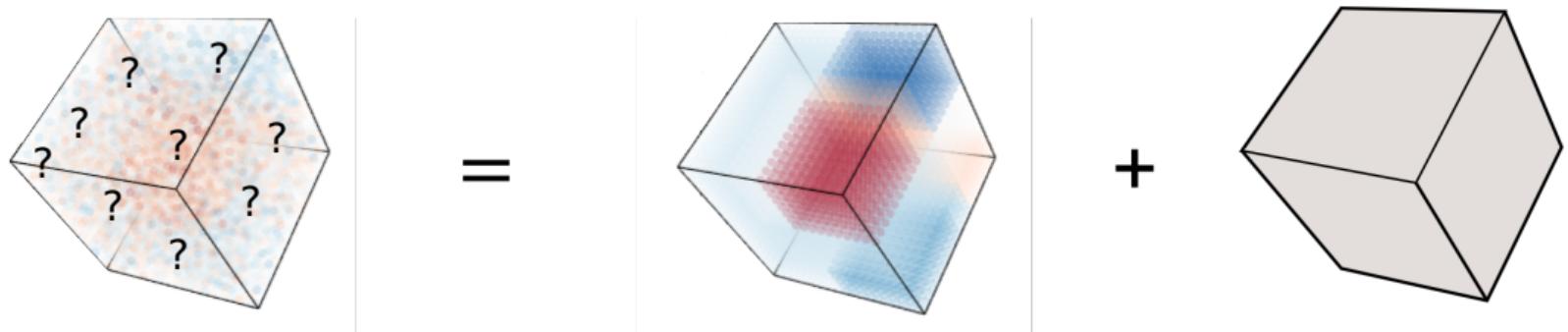
Delete

- Canonical Polyadic (CP) decomposition (Hitchcock, 1927).

- $\mathcal{Y} = \sum_{s=1}^r \lambda_s \mathbf{a}_s^{(1)} \otimes \cdots \otimes \mathbf{a}_s^{(K)}$.
- Generalization of matrix SVD to higher orders: $\mathbf{Y} = \sum_{s=1}^r \lambda_s \mathbf{u}_s \otimes \mathbf{v}_s$
- CP rank is defined as the minimal r for which the above equation holds.
- Today, we use the tensor rank as **CP rank**.



Main problems: the signal plus noise model



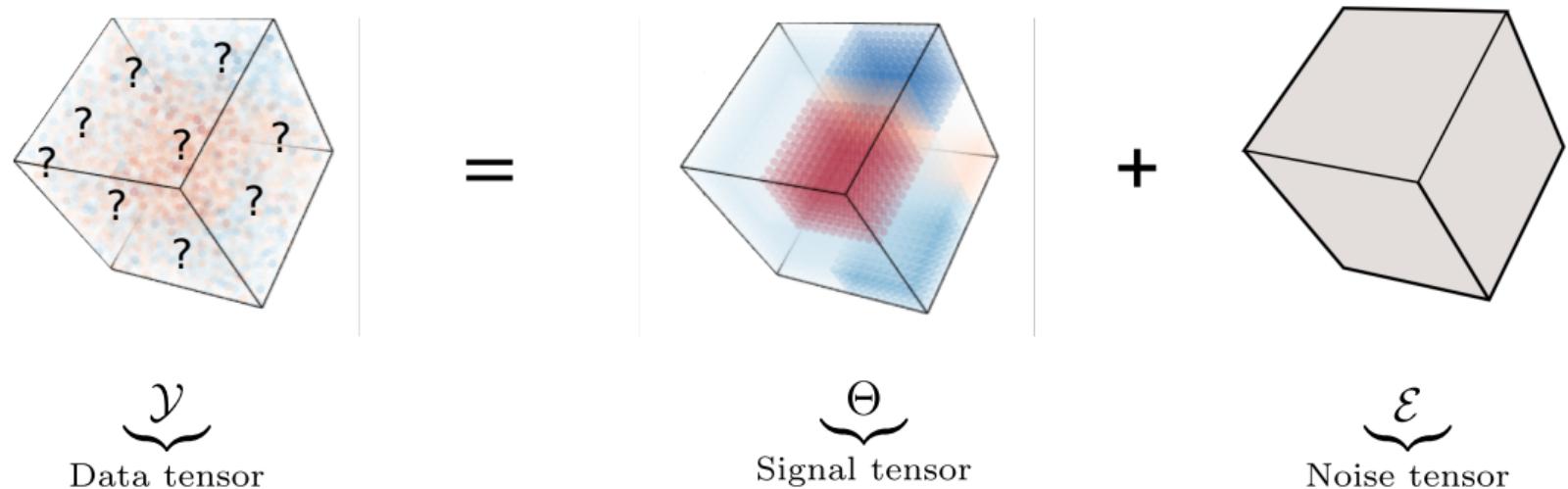
Rewrite pages 1-5. Check my slides <http://pages.stat.wisc.edu/~miaoyan/faculty.ppt>

- My research (my p2)
Data tensor
- What is tensor (your p2 + p5)
- Challenges (my p6. Structure + Data type)
- Talk outline (three bullets)
 1. Previous work. Parametric models for ordinal tensor completion (p5+1~2 slides)
 2. Current work. Nonparametric models for tensor completion and regression.
 3. Future work. Other approaches for nonparametric tensor modeling.

Signal tensor

Noise tensor

Main problems: the signal plus noise model



We focus on the two problems

1. **Nonparametric tensor estimation:** How to estimate the signal tensor Θ ?
2. **Complexity of tensor completion:** How many observed tensor entries do we need?

Tensor based learning is challenging

High-rank matrix model

- **Matrix based model** (Cai and Zhou, 2013; Davenport et al., 2014; Ganti et al., 2015; Fan et al., 2019) update citation as well

Tensor based learning is challenging

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 - Applying matrix methods to higher-order tensor destroys structural information.
 - Tensor is different from matrix and more challenging.

Tensor based learning is challenging

- **Matrix based model** (Cai and Zhou, 2013; Davenport et al., 2014; Ganti et al., 2015; Fan et al., 2019)
 - Applying matrix methods to higher-order tensor destroys structural information.
 - ~~Tensor is different from matrix and more challenging~~ (vage)
tensors are more challenging because tensor rank may exceed dimension
- **Low rank tensor model** (Jain and Oh, 2014; Montanari and Sun, 2018; Cai et al., 2019)

- **Matrix based model** (Cai and Zhou, 2013; Davenport et al., 2014; Ganti et al., 2015; Fan et al., 2019)
 - Applying matrix methods to higher-order tensor destroys structural information.
 - Tensor is different from matrix and more challenging.
- **Low rank tensor model** (Jain and Oh, 2014; Montanari and Sun, 2018; Cai et al., 2019)
 - Low rank models are inadequate in many cases.

Inadequacies of low rank models

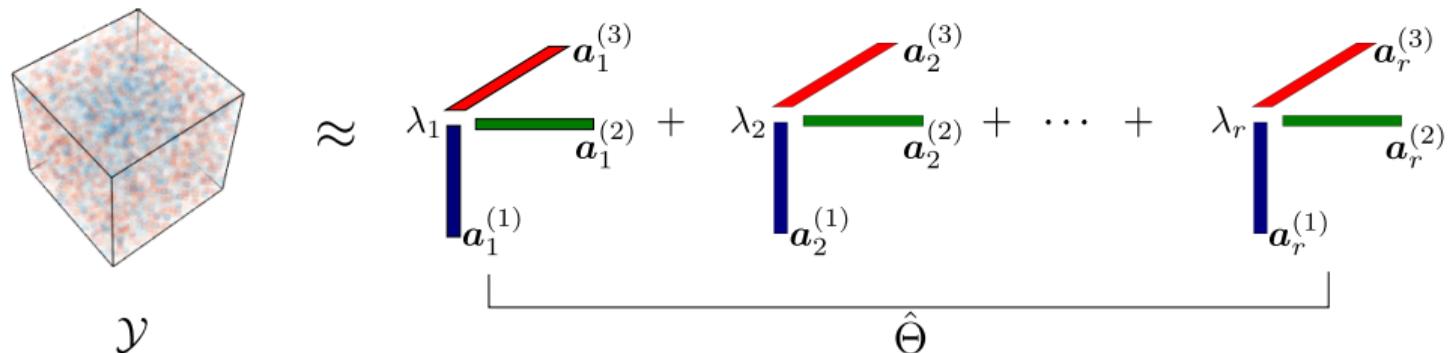
- Low rank models. (citation)

The diagram illustrates the decomposition of a 3D tensor y into a sum of low-rank tensors. On the left, a 3D cube represents the tensor y , filled with a pattern of red and blue dots. To its right is the approximation symbol (\approx). Following this are three terms separated by plus signs: $\lambda_1 a_1^{(1)} a_1^{(2)} a_1^{(3)}$, $\lambda_2 a_2^{(1)} a_2^{(2)} a_2^{(3)}$, and $\dots + \lambda_r a_r^{(1)} a_r^{(2)} a_r^{(3)}$. These terms represent the product of three vectors ($a_i^{(1)}, a_i^{(2)}, a_i^{(3)}$) for each component i . A bracket under the terms $\lambda_2 a_2^{(1)} a_2^{(2)} a_2^{(3)}$ through $\lambda_r a_r^{(1)} a_r^{(2)} a_r^{(3)}$ is labeled $\hat{\Theta}$, indicating they belong to a matrix $\hat{\Theta}$.

Inadequacies of low rank models

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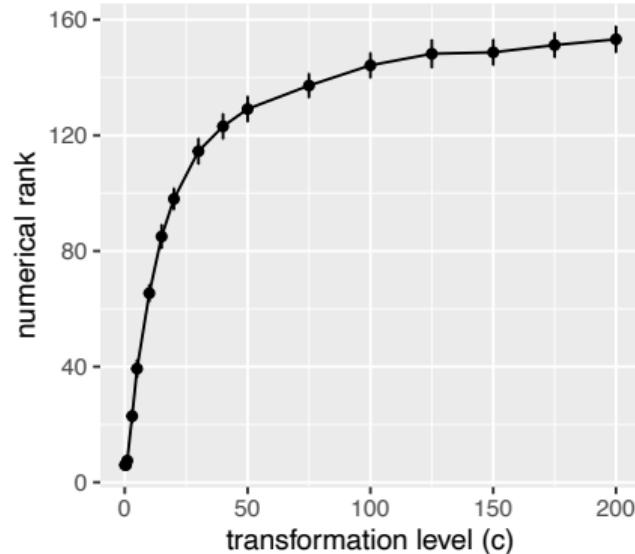
- Low rank models.



- There are two limitations of the model
 1. The sensitivity to order-preserving transformation.
 2. The inadequacy for special structures.

Inadequacies of low rank models

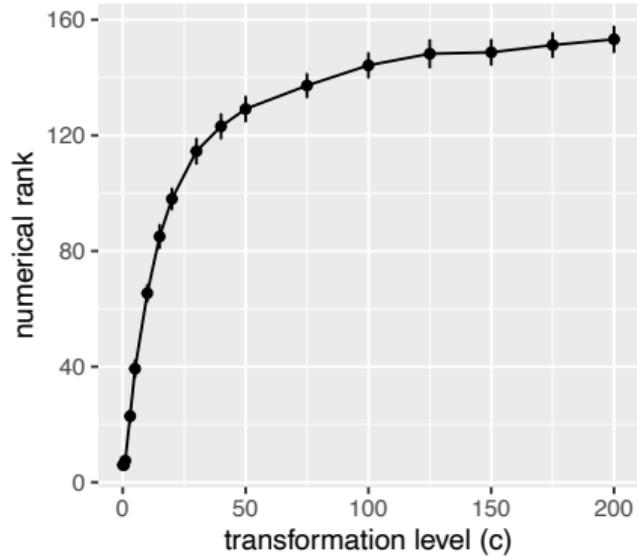
- The **sensitivity** to order-preserving transformation



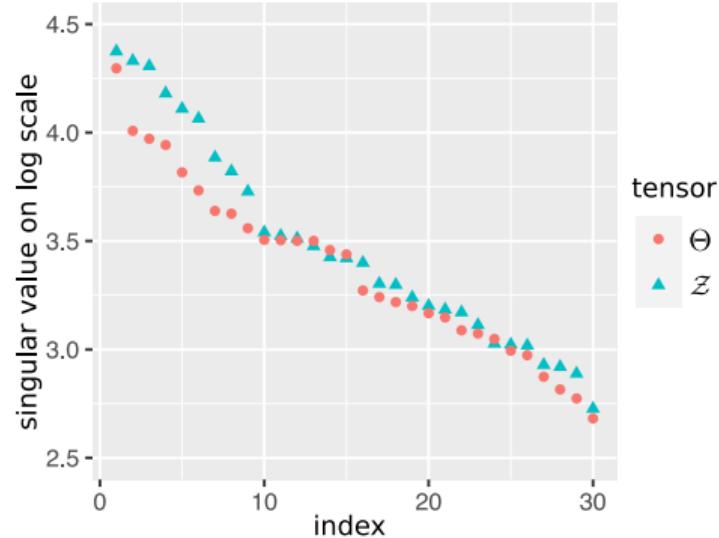
$$\Theta = \frac{1}{1 + \exp(-c(\mathcal{Z}))}, \quad \text{where}$$
$$\mathcal{Z} = \mathbf{a}^{\otimes 3} + \mathbf{b}^{\otimes 3} + \mathbf{c}^{\otimes 3}.$$

Inadequacies of low rank models

- The **sensitivity** to order-preserving transformation
- The **inadequacy** for special structures.



$$\Theta = \frac{1}{1 + \exp(-c(\mathcal{Z}))}, \quad \text{where}$$
$$\mathcal{Z} = \mathbf{a}^{\otimes 3} + \mathbf{b}^{\otimes 3} + \mathbf{c}^{\otimes 3}.$$



$$\Theta = \log(1 + \mathcal{Z}), \quad \text{where}$$
$$\mathcal{Z}(i, j, k) = \frac{1}{d} \max(i, j, k).$$

Motivating toy example in noiseless case

Delete.

$$\underbrace{\begin{pmatrix} -1 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & 1 & 1 \end{pmatrix}}_{\Theta} \xrightarrow[\pi \in \{-1, -0.5, 0, 0.5, 1\}]{\text{Dichotomization}} \underbrace{\left\{ \begin{array}{lll} \pi = -1 & \pi = -0.5, 0 & \pi = 0.5, 1 \\ \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}, & \begin{pmatrix} -1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}, & \begin{pmatrix} -1 & -1 & 1 \\ -1 & -1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \end{array} \right\}}_{\text{sign}(\Theta - \pi)} \xrightarrow{\text{Aggregation}} \underbrace{\begin{pmatrix} -\frac{3}{5} & \frac{1}{5} & 1 \\ \frac{1}{5} & \frac{1}{5} & 1 \\ 1 & 1 & 1 \end{pmatrix}}_{\tilde{\Theta} = \frac{1}{2H+1} \sum_{\pi \in \Pi} \text{sign}(\Theta - \pi)}$$

~~Motivating toy example in noiseless case~~

Why sign matters?

* For a bounded tensor Theta in $[-1, 1]^{d_1 \dots d_K}$

$\Theta \sim \frac{1}{H} \sum_{\pi \in \Pi} \text{sign}(\Theta - \pi)$, where $\Pi = \{-1, \dots, -1/H, 0, 1/H, \dots, 1\}$

$$\underbrace{\begin{pmatrix} -1 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & 1 & 1 \end{pmatrix}}_{\Theta} \xrightarrow[\pi \in \{-1, -0.5, 0, 0.5, 1\}]{\text{Dichotomization}} \left\{ \begin{array}{lll} \pi = -1 & \pi = -0.5, 0 & \pi = 0.5, 1 \\ \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}, & \begin{pmatrix} -1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}, & \begin{pmatrix} -1 & -1 & 1 \\ -1 & -1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \end{array} \right\}_{\text{sign}(\Theta - \pi)} \xrightarrow{\text{Delete } \Pi \setminus \{0\} \text{ Aggregation}} \underbrace{\begin{pmatrix} -\frac{3}{5} & \frac{1}{5} & 1 \\ \frac{1}{5} & \frac{1}{5} & 1 \\ 1 & 1 & 1 \end{pmatrix}}_{\tilde{\Theta} = \frac{1}{2H+1} \sum_{\pi \in \Pi} \text{sign}(\Theta - \pi)}$$

Sign (*not signed*) tensors are invariant to order-preserving transformation.

- Signed tensors are much simpler in the sense of rank.
- With a series of sign tensors, we successfully preserve all information in the **More flexible signal tensors allowed by using sign tensor series representation.**
- In **noise** case, we estimate $\text{sgn}(\Theta - \pi)$ from the tensor data $\text{sgn}(\mathcal{Y} - \pi)$.
noisy

Sign rank

* Key idea: we use a local notion of low-rankness to allow a richer family of signal tensors

- Two tensors are sign equivalent denoted as $\Theta \simeq \Theta'$ if $\text{sgn}(\Theta) = \text{sgn}(\Theta')$.
- Sign rank is defined as

$$\text{srank}(\Theta) = \min\{\text{rank}(\Theta') : \Theta' \simeq \Theta, \Theta' \in \mathbb{R}^{d_1 \times \dots \times d_K}\}.$$

Sign rank

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ex) $\Theta = \begin{matrix} & \text{blue} \\ & \text{light blue} \\ & \text{orange} \\ \text{red} & \end{matrix}$, $\text{sgn}(\Theta) = \begin{matrix} & \text{blue} \\ & \text{dark red} \\ & \text{blue} \end{matrix} \implies \text{rank}(\Theta) = d, \text{srank}(\Theta) = 2.$

Sign rank

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remove (ex)

ex) $\Theta = \begin{matrix} & \text{highlight } d \text{ and } 2 \\ \begin{matrix} & \text{blue} \\ \text{orange} & \text{red} \end{matrix} & , \text{sgn}(\Theta) = \begin{matrix} & \text{blue} \\ \text{dark red} & \text{blue} \end{matrix} \end{matrix} \implies \text{rank}(\Theta) = d, \text{srank}(\Theta) = 2.$

- More generally, for any strictly monotonic function $g: \mathbb{R} \rightarrow \mathbb{R}$ with $g(0) = 0$,

$$\text{srank}(\Theta) \leq \text{rank}(g(\Theta)).$$

Sign representable tensors

Sign representable tensors

A tensor Θ is called ***r*-sign representable** if the tensor $(\Theta - \pi)$ has sign rank bounded by r for all $\pi \in [-1, 1]$.

- Most existing structure tensors belong to sign representable family:
 - Low-rank CP tensors, Tucker tensors, stochastic block models.
 - High-rank tensors from GLM, single index models,
 - Tensors with repeating patterns, e.g. $\Theta(i_1, \dots, i_K) = \log(1 + \max(i_1, \dots, i_K))$ is 2-sign representable.

Sign representable tensors

Sign representable tensors

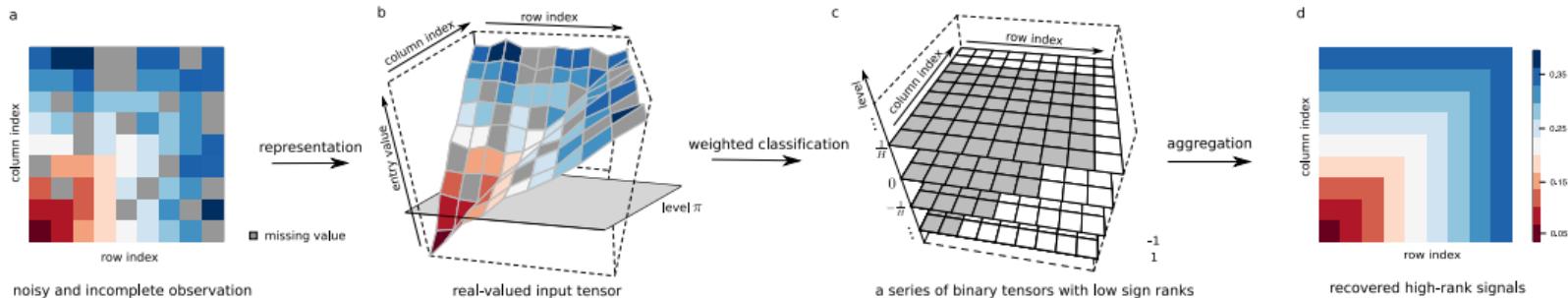
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 - Tensors with repeating patterns, e.g. $\Theta(i_1, \dots, i_K) = \log(1 + \max(i_1, \dots, i_K))$ is 2-sign representable.
- Instead of the classical low rank assumption, we propose the **sign representable tensor family**

$$\Theta \in \mathcal{P}_{\text{sgn}}(r) := \{\Theta : \text{srank}(\Theta - \pi) \leq r \text{ for all } \pi \in [-1, 1]\}.$$

~~Our new approach~~ Our solution: sign signal helps!

general principle: slide title should be informative

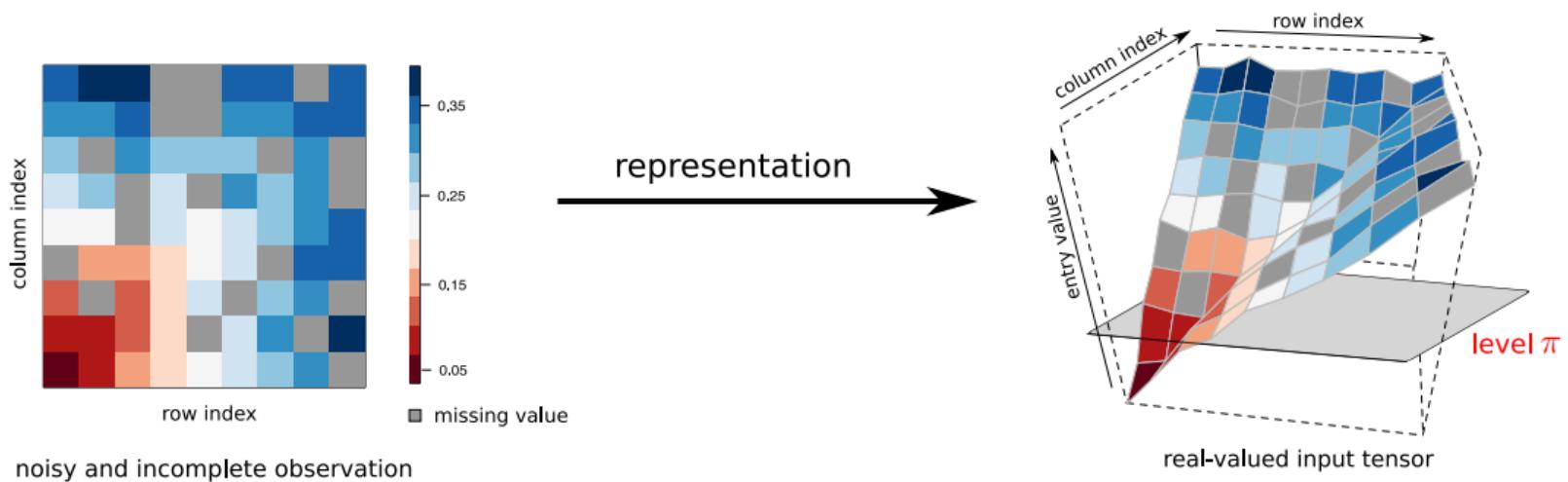


your earlier clock layout in 992 is better.
(current figure too small to see).

two slides:

first figure shows a and d (with a question mark on top of question mark)
second shows a-d (four pictures in a clock).

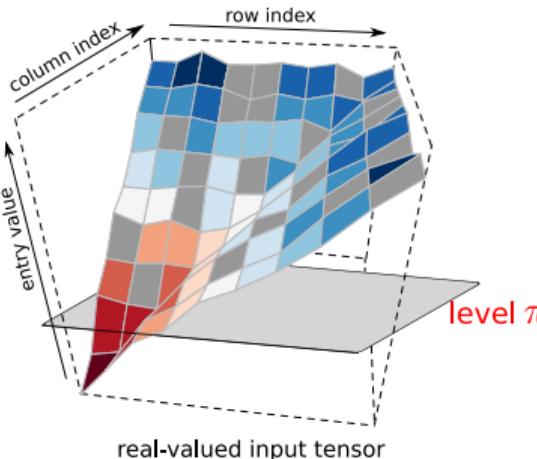
Step 1: representation



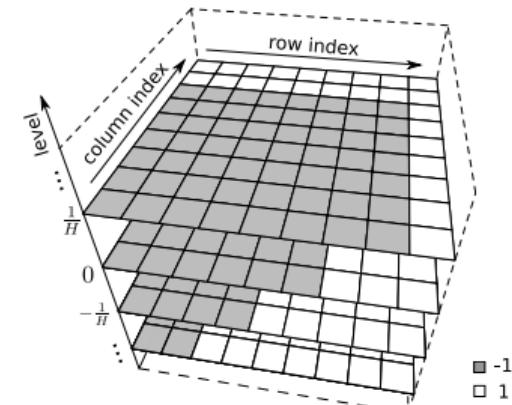
- We observe a noisy incomplete tensor $\mathcal{Y}_\Omega \in [-1, 1]^{d_1 \times \dots \times d_K}$ with observed index set $\Omega \subset [d_1] \times \dots \times [d_K]$.
- We dichotomize the data into a series of sign tensors:

$$\{\text{sgn}(\mathcal{Y}_\Omega - \pi)\}_{\pi \in \mathcal{H}}, \quad \text{where } \mathcal{H} = \left\{-1, \dots, -\frac{1}{H}, 0, \frac{1}{H}, \dots, 1\right\}.$$

Step 2: weighted classification



weighted classification



a series of binary tensors with low sign ranks

- We estimate $\text{sgn}(\Theta - \pi)$ through $\text{sgn}(\mathcal{Y}_\Omega - \pi)$ via weighted classification.
- Objective function of weighted classification is

$$L(\mathcal{Z}, \mathcal{Y}_\Omega - \pi) = \frac{1}{|\Omega|} \sum_{\pi \in \Omega} \underbrace{|\mathcal{Y}(\omega) - \pi|}_{\text{weight}} \times \underbrace{|\text{sgn}(\mathcal{Z}(\omega)) - \text{sgn}(\mathcal{Y}(\omega) - \pi)|}_{\text{classification loss}}$$

Do you mean weight |Y-pi|?

- Magnitude $|\Theta(\omega) - \pi|$ plays important role in estimation.

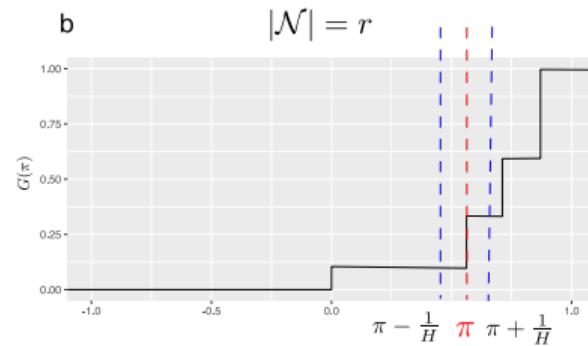
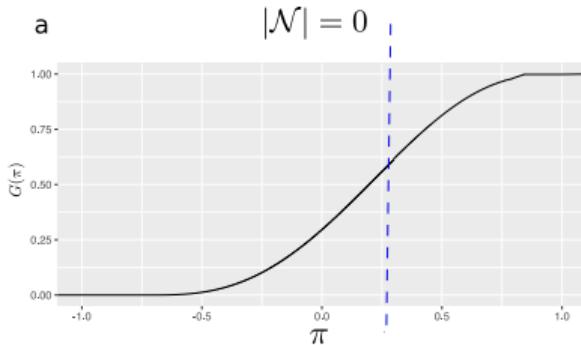
Main assumption

S2

Combine S2+S2'. No need to explain much on N.

- We quantify difficulty of the problem using CDF $G(\pi) = \mathbb{P}_{\omega \in \Pi}[\Theta(\omega) \leq \pi]$.
- We define classification hard region \mathcal{N} at which point mass concentrates,

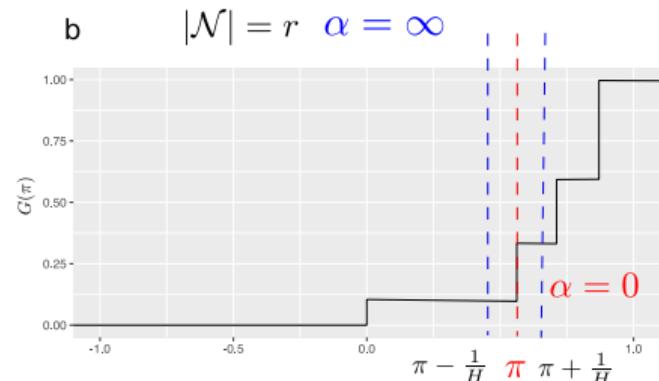
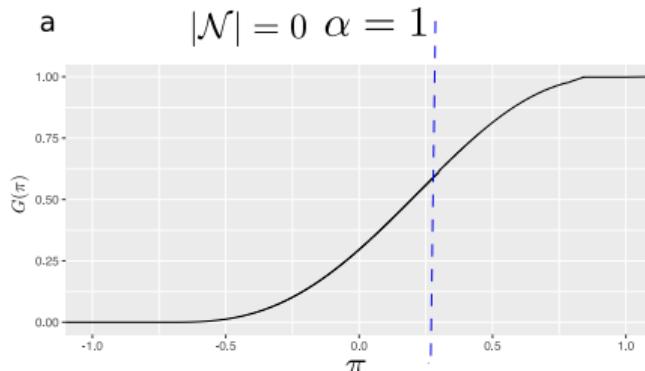
$$\mathcal{N} = \left\{ \pi : \frac{G(\pi + \Delta s) - G(\pi - \Delta s)}{\Delta s} \geq C \right\}, \text{ where } \Delta s = 1 / \prod_k^K d_k.$$



α smoothness

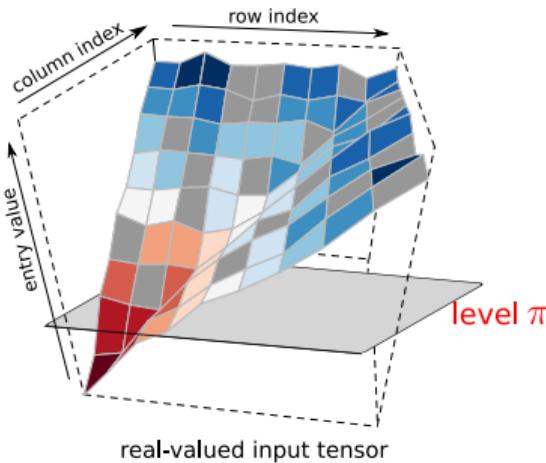
For fixed $\pi \in \mathcal{N}^c$, we call Θ is α smooth if there exist $\alpha = \alpha(\pi) > 0, c = c(\pi) > 0$, such that

- * Partition $[-1, 1] = N + N^c$, where N^c consists of levels whose pseudo density is uniformly bounded, and N otherwise.
 - * G is globally alpha-smooth in that for all $\pi \in N^c$,
-
 where $\rho(\pi, N) = \min_{\pi' \in N} |\pi - \pi'| + \Delta s$. If α and c are global constants for all π 's, we call Θ is α -globally smooth.
- Keep only global.
no need to say local.



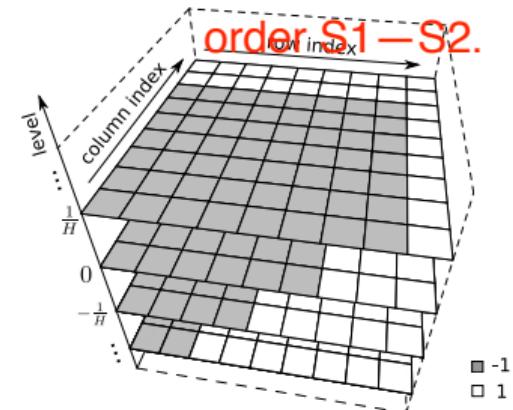
Step 2: weighed classification

S1



weighted classification

highlight



a series of binary tensors with low sign ranks

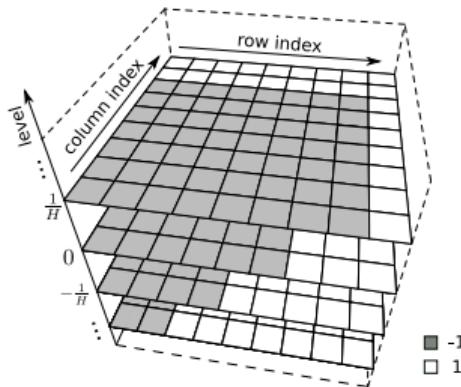
- If $\Theta \in \mathcal{P}_{\text{sgn}}(r)$ is α smooth ($\alpha > 0$), we have **a unique optimizer** such that

$$\text{sgn}(\Theta - \pi) = \arg \min_{\mathcal{Z}: \text{rank}(\mathcal{Z}) \leq r} \mathbb{E}_{\mathcal{Y}_\Omega} L(\mathcal{Z}, \mathcal{Y}_\Omega - \pi).$$

- So we obtain a series of optimizers $\{\hat{\mathcal{Z}}_\pi\}_{\pi \in \mathcal{H}}$ as

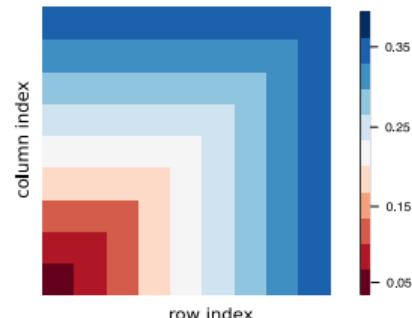
$$\hat{\mathcal{Z}}_\pi = \arg \min_{\mathcal{Z}: \text{rank}(\mathcal{Z}) \leq r} L(\mathcal{Z}, \mathcal{Y}_\Omega - \pi).$$

Step 3: aggregation



a series of binary tensors with low sign ranks

aggregation →



recovered high-rank signals

- From a series of optimizers $\{\hat{\mathcal{Z}}_\pi\}_{\pi \in \mathcal{H}}$ in the weighted classification, we obtain the tensor estimate

$$\hat{\Theta} = \frac{1}{2H+1} \sum_{\pi \in \mathcal{H}} \text{sgn} \hat{\mathcal{Z}}_\pi.$$

Sign tensor estimation error

For two tensor Θ_1, Θ_2 , define $\text{MAE}(\Theta_1, \Theta_2) = \mathbb{E}_{\omega \in \Pi} |\Theta_1(\omega) - \Theta_2(\omega)|$.

Sign tensor estimation for fixed π (L. and Wang, 2021)

Suppose $\Theta \in \mathcal{P}_{\text{sgn}}(r)$ is α smooth for fixed π . Denote $d_{\max} = \max_{k \in [K]} d_k$. Then, with very high probability over \mathcal{Y}_Ω ,

, and $d_1 = \dots = d_K = d$

add footnote on \lessim (footnote: log _{α} term suppressed)

$$\text{MAE}(\text{sgn} \hat{\mathcal{Z}}_\pi, \text{sgn}(\Theta - \pi)) \lesssim \left(\frac{d_{\max} r \log |\Omega|}{|\Omega|} \right)^{\frac{\alpha}{\alpha+2}}.$$

- Sign estimation error shows a polynomial decay with the number of observed entries.
principle: always present the simplest case in talk.

Tensor estimation error

Tensor estimation error (L. and Wang 2021)

Suppose $\Theta \in \mathcal{P}_{\text{sgn}}(r)$ is α -globally smooth. Then, with very high probability over \mathcal{Y}_Ω ,
with bounded INI

$$\text{MAE}(\hat{\Theta}, \Theta) \lesssim \left(\frac{d_{\max} r \log |\Omega| \log H}{|\Omega|} \right)^{\frac{\alpha}{\alpha+2}} + \frac{1 + |\mathcal{N}|}{H} + \frac{d_{\max} r \log |\Omega| \log H}{|\Omega|}.$$

In particular, setting $H \asymp \left(\frac{(1+|\mathcal{N}|)|\Omega|}{d_{\max} r \log |\Omega|} \right)^{1/2}$ yields the tightest error bound.

add Bracket to each of the term:
errors inherited from sign estimation
Bias
Variance

* see paper for general case that allows unbounded IN^cl and sub-Gaussian noise.

Tensor estimation error (L. ~~and~~ Wang 2021) (power of d) | Previous results

Suppose $\Theta \in \mathcal{P}_{\text{sgn}}(r)$ is α -globally smooth. Then, with very high probability over \mathcal{Y}_Ω ,

$$\text{MAE}(\hat{\Theta}, \Theta) \lesssim \left(\frac{d_{\max} r \log |\Omega| \log H}{|\Omega|} \right)^{\frac{\alpha}{\alpha+2}} + \frac{1 + |\mathcal{N}|}{H} + \frac{d_{\max} r \log |\Omega| \log H}{|\Omega|}.$$

In particular, setting $H \asymp \left(\frac{(1+|\mathcal{N}|)|\Omega|}{d_{\max} r \log |\Omega|} \right)^{1/2}$ yields the tightest error bound.

- For full observation case with equal dimension $d_1 = \dots = d_K = d$ and bounded $|\mathcal{N}| \leq C$,

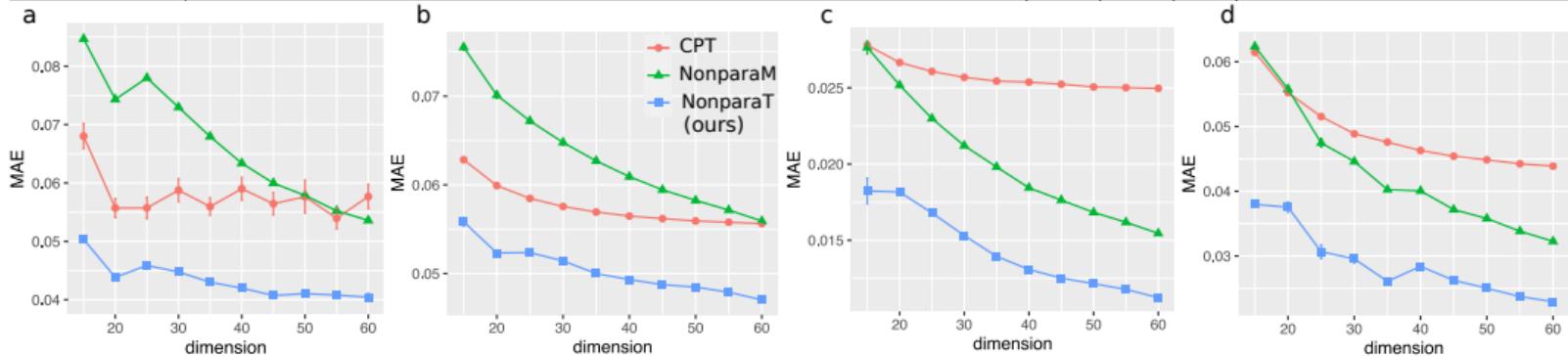
$$\text{MAE}(\hat{\Theta}, \Theta) \lesssim \tilde{\mathcal{O}} \left(d^{-(K-1) \min\left(\frac{\alpha}{\alpha+2}, \frac{1}{2}\right)} \right).$$

- Tensor estimation is generally no better than sign tensor estimation.
- Sample complexity: $\text{MAE}(\hat{\Theta}, \Theta) \rightarrow 0$, as $\frac{|\Omega|}{d_{\max} r \log^2 |\Omega|} \rightarrow \infty$.

Simulations for estimation error vs tensor dimension

Delete

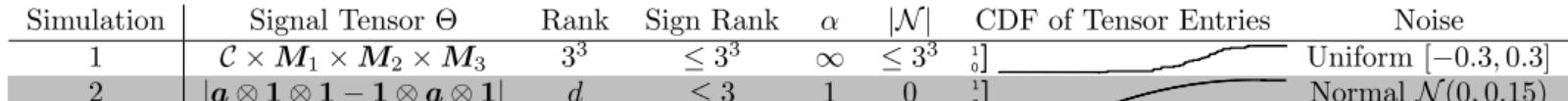
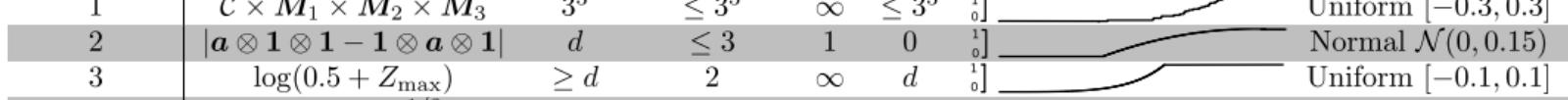
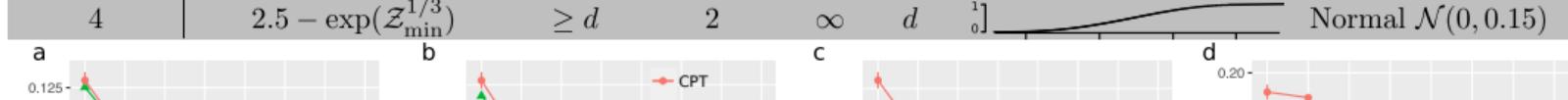
Simulation	Signal Tensor Θ	Rank	Sign Rank	α	$ \mathcal{N} $	CDF of Tensor Entries	Noise
1	$\mathcal{C} \times M_1 \times M_2 \times M_3$	3^3	$\leq 3^3$	∞	$\leq 3^3$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	Uniform $[-0.3, 0.3]$
2	$ \mathbf{a} \otimes \mathbf{1} \otimes \mathbf{1} - \mathbf{1} \otimes \mathbf{a} \otimes \mathbf{1} $	d	≤ 3	1	0	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	Normal $\mathcal{N}(0, 0.15)$
3	$\log(0.5 + Z_{\max})$	$\geq d$	2	∞	d	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	Uniform $[-0.1, 0.1]$
4	$2.5 - \exp(Z_{\min}^{1/3})$	$\geq d$	2	∞	d	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	Normal $\mathcal{N}(0, 0.15)$

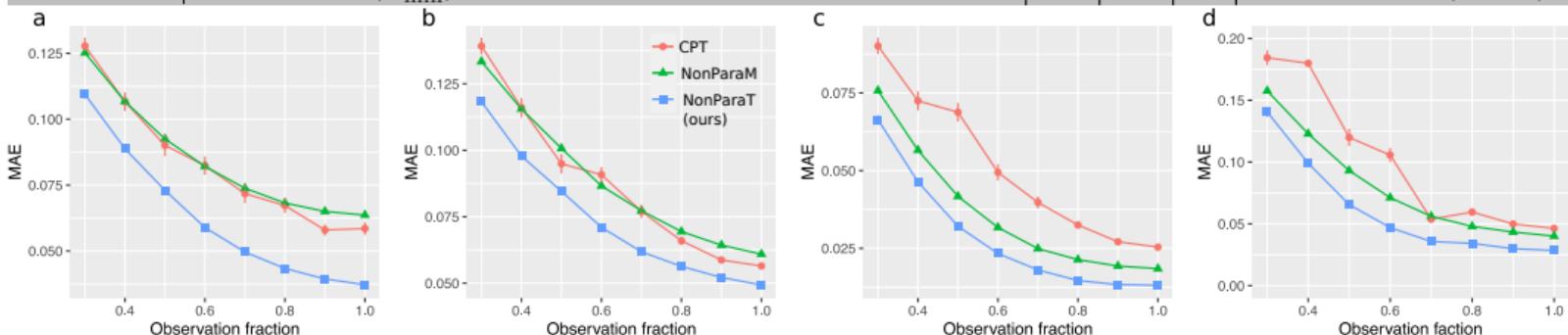


- **NonPraT**: Our nonparametric tensor method, **CPT**: low rank tensor CP decomposition, **NonPraraM**: the matrix version of our method.
- Our method (NonparaT) achieves the best performance.

Simulations for estimation error vs the observation fraction

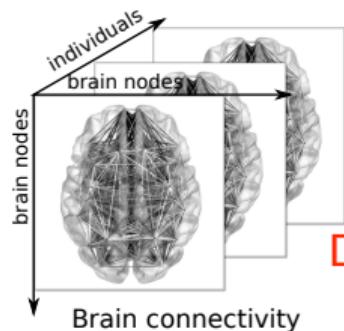
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Simulation	Signal Tensor Θ	Rank	Sign Rank	α	$ \mathcal{N} $	CDF of Tensor Entries	Noise
1	$\mathcal{C} \times \mathbf{M}_1 \times \mathbf{M}_2 \times \mathbf{M}_3$	3^3	$\leq 3^3$	∞	$\leq 3^3$		Uniform $[-0.3, 0.3]$
2	$ \mathbf{a} \otimes \mathbf{1} \otimes \mathbf{1} - \mathbf{1} \otimes \mathbf{a} \otimes \mathbf{1} $	d	≤ 3	1	0		Normal $\mathcal{N}(0, 0.15)$
3	$\log(0.5 + Z_{\max})$	$\geq d$	2	∞	d		Uniform $[-0.1, 0.1]$
4	$2.5 - \exp(Z_{\min}^{1/3})$	$\geq d$	2	∞	d		Normal $\mathcal{N}(0, 0.15)$



- Our method (NonparaT) achieves the best performance in completion.

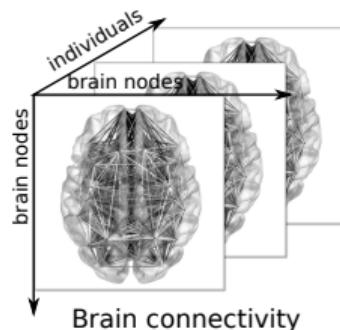
Data application: Brain connectivity



- The MRN-114 human brain connectivity data consists of 68 brain regions for 114 individuals along with their IQ scores (Wang et al., 2017).

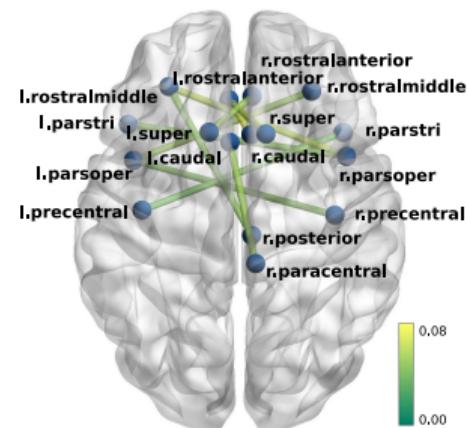
Data tensor $\mathcal{Y} \in \{0, 1\}^{68 \times 68 \times 114}$.

Data application: Brain connectivity

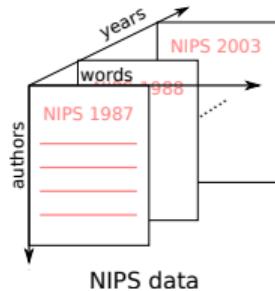


- The MRN-114 human brain connectivity data consists of 68 brain regions for 114 individuals along with their IQ scores (Wang et al., 2017).
- $\mathcal{Y} \in \{0, 1\}^{68 \times 68 \times 114}$.

- We examine the estimated signal tensor $\hat{\Theta}$.
- Top 10 brain edges based on regression analysis show inter-hemisphere connections.

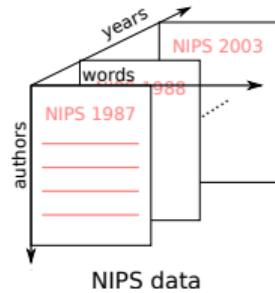


Data application: NIPS



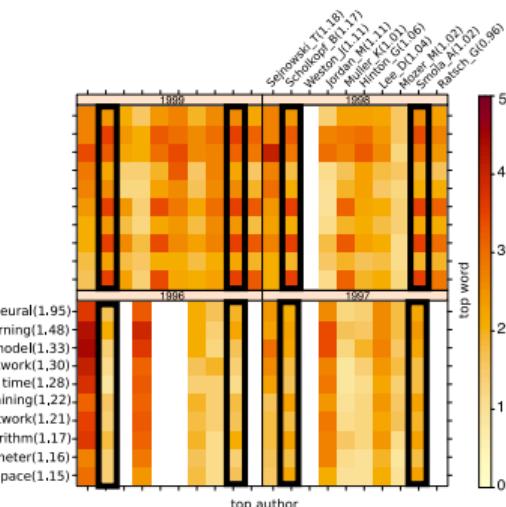
- The NIPS dataset consists of word occurrence counts in papers published from 1987 to 2003 (Globerson et al., 2007).
- Log transformation yields the dataset $\mathcal{Y} \in \mathbb{R}^{100 \times 200 \times 17}$.

Data application: NIPS



- The NIPS dataset consists of word occurrence counts in papers published from 1987 to 2003 (Globerson et al., 2007).
- Log transformation yields the dataset $\mathcal{Y} \in \mathbb{R}^{100 \times 200 \times 17}$.

- We examine the estimated signal tensor $\hat{\Theta}$.
- Most frequent words are consistent with the active topics
- There are strong heterogeneity among word occurrences across authors and years.
- Similar word patterns (B. Schölkopf and A. Smola).



Data application: Brain connectivity + NIPS

MRN-114 brain connectivity dataset					
Method	$r = 3$	$r = 6$	$r = 9$	$r = 12$	$r = 15$
NonparaT (Ours)	0.18(0.001)	0.14(0.001)	0.12(0.001)	0.12(0.001)	0.11(0.001)
Low-rank CPT	0.26(0.006)	0.23(0.006)	0.22(0.004)	0.21(0.006)	0.20(0.008)
NIPS word occurrence dataset					
Method	$r = 3$	$r = 6$	$r = 9$	$r = 12$	$r = 15$
NonparaT (Ours)	0.18(0.002)	0.16(0.002)	0.15(0.001)	0.14(0.001)	0.13(0.001)
Low-rank CPT	0.22(0.004)	0.20(0.007)	0.19(0.007)	0.17(0.007)	0.17(0.007)
Naive imputation (Baseline)			0.32(.001)		

5-folded cross-validation.

Table: MAE comparison in the brain data and NIPS data on ~~cross-validation (5 repetitions 5 folds)~~.
~~Standard errors are reported in parenthesis.~~

- Our method substantially outperforms the low-rank CP method for every configuration under consideration.

Nonparametric trace regression via sign series

Add transition slide:

Outline (three bullet points)

Current bullet (visible).

Other bullet in gray fonts (less visible)

L26-28. Write in terms of tensor.

- $\mathbf{X} \in \mathcal{X} \subset \mathbb{R}^{d_1 \times d_2}$ denotes the matrix predictor, $Y \in \mathbb{R}$ the scalar response. We consider the regression model,

$$Y = f(\mathbf{X}) + \epsilon,$$

where $f: \mathcal{X} \rightarrow \mathbb{R}$ is an unknown regression function of interest, and ϵ is mean-zero noise.

- Trace regression (Fan et al., 2019; Hamidi and Bayati, 2019) assumes that

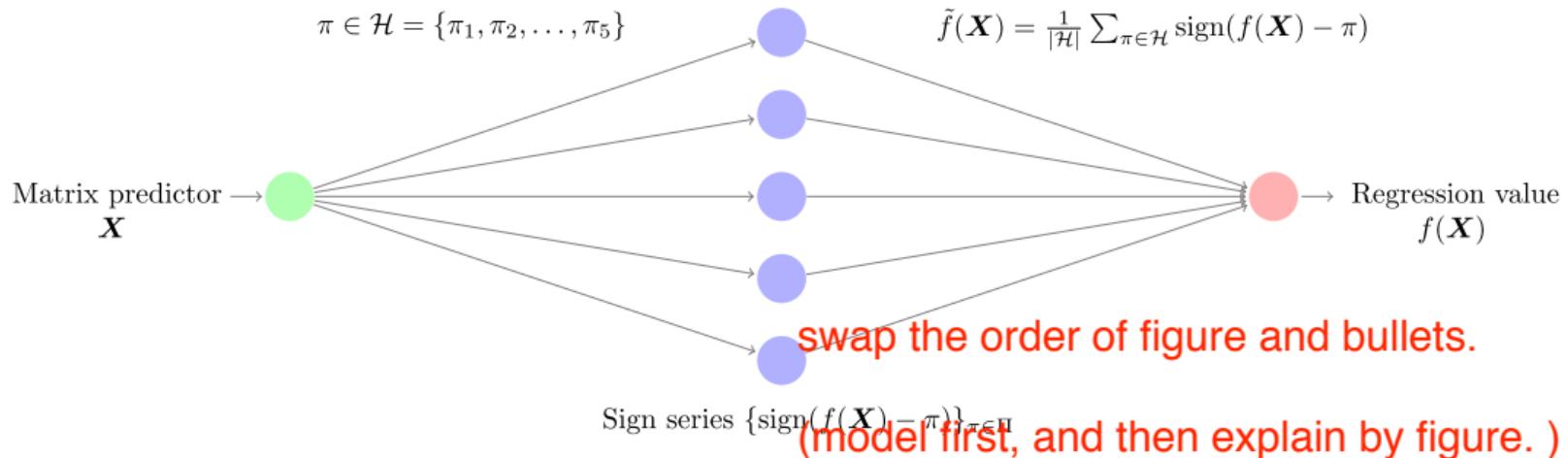
$$f(\mathbf{X}) = \langle \mathbf{B}, \mathbf{X} \rangle + b, \text{ for all } \mathbf{X} \in \mathcal{X},$$

where \mathbf{B} is usually a low rank matrix.

Functional form of $f(\mathbf{X})$

- Low rank assumption on \mathbf{B} is not adequate in many cases.

Nonparametric trace regression via sign series



- We apply our framework for the regression problem.

- We assume that for given π , **sign of regression function** is represented by **Add a slide after this slide: two examples:**

$$\text{sign}(f(\mathbf{X}) - \pi) = \text{sign} (\langle \mathbf{B}_\pi, \mathbf{X} \rangle + b_\pi)$$

where \mathbf{B}_π is a low rank matrix.

1. single index model
2. tensor completion.

Nonparametric trace regression via sign series

- Based on **the sign rank** assumption, we estimate the series of sign functions $\{\text{sign}(f - \pi)\}_{\pi \in \mathcal{H}}$ from the weighted classification,

$$L(\phi; \{(\mathbf{X}_i, \text{sign}(Y_i - \pi))\}_{i=1}^n) = \frac{1}{n} \sum_{i=1}^n |Y_i - \pi| \times |\text{sign}(Y_i - \pi) - \text{sign}(\phi(\mathbf{X}_i))|.$$

(add one sentence about learning reduction + meta/base algorithm + no need to reinvent the wheel)

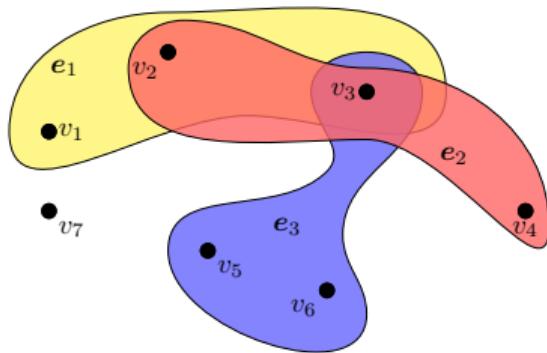
- Our framework enjoys theoretical guarantees.

- We detailed the trace regression problem in Lee et al. (2021).

Our extend the broad nonparametric paradigm to many important matrix/tensor learning problems, including regression, completion, multi-task learning, and compressed sensing

Nonparametric probability tensor estimation from hypergraph

add transition slide



- Hypergraph considers higher-way interaction among nodes.
- An observed adjacency tensor $\mathcal{A} \in \{0, 1\}^{d \times \dots \times d}$ corresponding to a hypergraph is generated by

$$\mathcal{A}_\omega \sim \text{Bernoulli}(\Theta_\omega), \text{ for all } \underbrace{\omega \in [d] \times \dots \times [d]}_K.$$

- The **block model** (Ahn et al., 2018; Wang and Zeng, 2019; Han et al., 2020) has

$$\Theta_\omega = \mathcal{Q}_{z(\omega_1), z(\omega_2), \dots, z(\omega_K)}, \text{ for all } \omega \in [d] \times \dots \times [d],$$

where $\mathcal{Q} \in [0, 1]^{m \times \dots \times m}$ and $z: [d] \rightarrow [m]$ is a hidden partition.

- We will take **nonparametric** approach considering **smooth function f** such that

$$\Theta_\omega = f(\xi_{\omega_1}, \xi_{\omega_2}, \dots, \xi_{\omega_K}), \text{ for all } \omega \in [d] \times \dots \times [d],$$

where $\{\xi_i\}_{i=1}^d$ are i.i.d. random variables sampled from $\text{Unif}[0, 1]$.

Thank you!

Appendix: Algorithm

Algorithm 1 Nonparametric tensor completion

Input: Noisy and incomplete data tensor \mathcal{Y}_Ω , rank r , resolution parameter H .

- 1: **for** $\pi \in \mathcal{H} = \{-1, \dots, -\frac{1}{H}, 0, \frac{1}{H}, \dots, 1\}$ **do**
- 2: Random initialization of tensor factors $\mathbf{A}_k = [\mathbf{a}_1^{(k)}, \dots, \mathbf{a}_r^{(k)}] \in \mathbb{R}^{d_k \times r}$ for all $k \in [K]$.
- 3: **while** not convergence **do**
- 4: **for** $k = 1, \dots, K$ **do**
- 5: Update \mathbf{A}_k while holding others fixed: $\mathbf{A}_k \leftarrow \arg \min_{\mathbf{A}_k \in \mathbb{R}^{d_k \times r}} \sum_{\omega \in \Omega} |\mathcal{Y}(\omega) - \pi| F(\mathcal{Z}(\omega) \text{sgn}(\mathcal{Y}(\omega) - \pi))$,
where $F(\cdot)$ is the large-margin loss, and $\mathcal{Z} = \sum_{s \in [r]} \mathbf{a}_s^{(1)} \otimes \dots \otimes \mathbf{a}_s^{(K)}$ is a rank- r tensor.
- 6: **end for**
- 7: **end while**
- 8: Return $\mathcal{Z}_\pi \leftarrow \sum_{s \in [r]} \mathbf{a}_s^{(1)} \otimes \dots \otimes \mathbf{a}_s^{(K)}$.
- 9: **end for**

Output: Estimated signal tensor $\hat{\Theta} = \frac{1}{2H+1} \sum_{\pi \in \mathcal{H}} \text{sgn}(\mathcal{Z}_\pi)$.

Theoretical guarantees for a large-margin loss classification

- we consider the estimation

$$\hat{\mathcal{Z}}_\pi = \arg \min_{\substack{\text{rank}(\mathcal{Z}) \leq r \\ \omega \in \Omega}} \sum |\mathcal{Y}(\omega) - \pi| \times F(\mathcal{Z}(\omega)\text{sign}(\mathcal{Y}(\omega) - \pi)) + \lambda \|\mathcal{Z}\|_F^2,$$

where $\lambda > 0$ is the penalty parameter and F is a large-margin loss satisfying the following assumption,

Assumption 1

- (a) (Approximation error) For any given $\pi \in [-1, 1]$, there exists a sequence of tensors $\mathcal{Z}_\pi^{(n)} \in \mathcal{P}_{\text{sgn}}(r)$, such that $\text{Risk}_F(\mathcal{Z}_\pi^{(n)}) - \text{Risk}_F(\Theta - \pi) \leq a_n$, for some sequence $a_n \rightarrow 0$ as $n \rightarrow \infty$. Furthermore, assume $\|\mathcal{Z}_\pi^{(n)}\|_F \leq J$ for some constant $J > 0$.
- (b) $F(z) = (1 - z)_+$ is hinge loss.

Theoretical guarantees for a large-margin loss classification

Estimation error for a large margin loss (L. and Wang 2021)

Denote $t_n = \frac{d_{\max} r K \log n}{n}$. Suppose the surrogate loss F satisfies Assumption 1 with $a_n \lesssim t_n^{(\alpha+1)/(\alpha+2)}$. Set $\lambda \asymp t_n^{(\alpha+1)/(\alpha+2)} + t_n/\rho(\pi, \mathcal{N})$. Then, with high probability, we have:

1. (Sign tensor estimation). For all $\pi \in [-1, 1]$ except for a finite number of levels,

$$\text{MAE}(\text{sign}(\hat{\mathcal{Z}}_\pi), \text{sign}(\Theta - \pi)) \lesssim t_n^{\frac{\alpha}{2+\alpha}} + \frac{1}{\rho^2(\pi, \mathcal{N})} t_n.$$

2. (Tensor estimation).

$$\text{MAE}(\hat{\Theta}, \Theta) \lesssim (t_n \log H)^{\frac{\alpha}{2+\alpha}} + \frac{1 + |\mathcal{N}|}{H} + t_n H \log H.$$

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