

# Matching Wishart matrices via Umeyama algorithm

Shuyang Gong

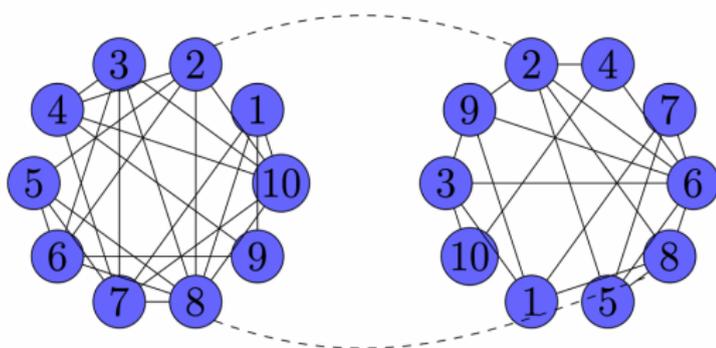
School of Mathematical Sciences, Peking University

September 9, 2024

Joint work with Zhangsong Li (PKU)

# Motivations: random graph matching

- **Random Graph Matching** is an extensively studied topic in recent years, which lies in the intersection of **probability, statistics and theoretical computer science**.
- **Goal**: find a bijection between two vertex sets which maximizes the number of common edges (i.e. minimize the adjacency disagreements)
- $\max_{\pi \in \mathcal{S}_n} A_{i,j} B_{\pi(i),\pi(j)}$  and  $\arg \max_{\pi \in \mathcal{S}_n} A_{i,j} B_{\pi(i),\pi(j)}$ .



- Sample  $n$  i.i.d Gaussian vectors  $X_1, X_2, \dots, X_n \sim \mathcal{N}(0, I_d)$ .
- Denote  $\sigma$  the noise parameter. Let  $Z_i \sim \mathcal{N}(0, I_d)$  be independent of  $X_i$ 's.
- Plant a latent permutation  $\pi^*$  (unknown). Define  $Y_i = X_{\pi^*(i)} + \sigma Z_i$ .
- The observations:  $A = XX^\top$  and  $B = YY^\top$ .
- **Goal:** Is it possible to recover the latent permutation based on the observations? (i.e., for which values of  $\sigma$  is this possible?)

# Informational upper bound

Define the estimator

$$\hat{\Pi} := \arg \max_{\Pi \in S_n} \max_{Q \in O(d)} \langle B^{1/2}, \Pi A^{1/2} Q \rangle, \quad (1)$$

where  $A = U^\top \Lambda U$  and  $A^{1/2} := U^\top \Lambda^{1/2}$ .

## Theorem (H. Wang, Y. Wu, J. Xu, I. Yelou, 22)

For  $d = o(\log n)$ , the following holds:

- For  $\sigma = o(n^{-1/d})$ , we have

$$\mathbb{P} \left( \frac{\text{dist}(\hat{\pi}, \pi^*)}{n} = o(1) \right) = 1 - o(1).$$

- For  $\sigma = o(n^{-2/d})$ , we have

$$\mathbb{P}(\hat{\pi} = \pi^*) = 1 - o(1).$$

- Computation of  $\hat{\pi}$  requires  $n^{O(d^2)}$  time, which is not efficient when  $d = \omega(1)$ .  
( $d = \omega(1)$  means  $d = d_n \rightarrow \infty$ )

# Informational lower bound

For the “easier” model (linear assignment model), where the observations are  $X$  and  $Y = \Pi^* X + \sigma Z$ .

## Theorem (H. Wang, Y. Wu, J. Xu, I. Yelou, 22)

- For any  $\epsilon \in (0, 1)$ , if there exists an estimator  $\hat{\pi} = \hat{\pi}(X, Y)$  such that  $\mathbb{E} \text{dist}(\pi^*, \hat{\pi}) \leq \epsilon n$ , then

$$\frac{d}{2} \log \left( 1 + \frac{1}{\sigma^2} \right) - (1 - \epsilon) \log n + 1 + \frac{\log(n+1)}{n} \geq 0.$$

- Suppose that  $\sigma^2 \leq d/40$  and

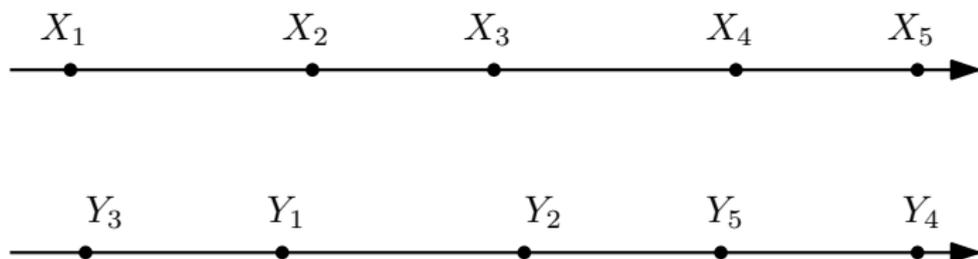
$$\frac{d}{4} \log \left( 1 + \frac{1}{\sigma^2} \right) - \log n + \log d \leq C, \quad (2)$$

for a constant  $C > 0$ . Then there exists a constant  $c$  that only depend on  $C$  such that for any estimator  $\hat{\pi}$ ,  $\mathbb{P}(\hat{\pi} \neq \pi^*) \geq c$ .

- When  $d = o(\log n)$ , the necessary conditions become  $\sigma = O\left(n^{-(1-\epsilon)/d}\right)$  and  $\sigma \leq n^{-2/d}$ . When  $d = O(1)$ , there is **no sharp phase transition** in  $\sigma$ .

# Intuition

- The “typical” minimal distance for a given vector  $X_i$ ,  $\min_{j:j \neq i} \|X_j - X_i\| \sim n^{-1/d}$ .
- The minimal distance of all the vectors,  $\min_{(i,j):i \neq j} \|X_i - X_j\| \sim n^{-2/d}$ .
- To recover the permutation, the noise  $\sigma$  should not exceed the minimal distances (the correspondence is not “blurred”).



$$\pi^* = (132)(45)$$

# Computation: the Umeyama algorithm

- In [WWXY22], the authors proposed the Umeyama algorithm and conducted numerical experiments.
- Heuristic I: consider

$$\begin{aligned}\widehat{\Pi}_{\text{Diag}(\{\pm 1\}^d)} &:= \arg \max_{\Pi \in \mathcal{S}_n} \max_{Q \in \text{Diag}(\{\pm 1\}^d)} \langle B^{1/2}, \Pi A^{1/2} Q \rangle \\ &= \arg \max_{\Pi \in \mathcal{S}_n} \max_{Q \in \text{Diag}(\{\pm 1\}^d)} \langle V \Sigma^{1/2}, \Pi U \Lambda^{1/2} Q \rangle.\end{aligned}$$

By concentration of eigenvalues, we can define

$$\begin{aligned}\widehat{\Pi}_{Ume} &:= \arg \max_{\Pi \in \mathcal{S}_n} \max_{Q \in \text{Diag}(\{\pm 1\}^d)} \langle V, \Pi U Q \rangle \\ &= \arg \max_{\Pi \in \mathcal{S}_n} \max_{q \in \{\pm 1\}^d} \left\langle \Pi, \sum_{i=1}^d q_i v_i u_i^\top \right\rangle.\end{aligned}$$

- Running time:  $O(2^d n^3)$ .

## Theorem (G. and Li 24+)

When  $d = O(\log n)$ , for  $\hat{\Pi}_{Ume}$  (output of the Umeyama algorithm) we have

- if  $\sigma = o(d^{-3}n^{-2/d})$ ,  $\mathbb{P}(\hat{\Pi}_{Ume} = \Pi^*) = 1 - o(1)$ .
- if  $\sigma = o(d^{-3}n^{-1/d})$ ,  $\mathbb{P}(\text{dist}(\hat{\Pi}_{Ume}, \Pi^*) = o(n)) = 1 - o(1)$ .
- This result approaches the informational threshold up to a  $d^3$  factor.
- For  $d = O(1)$ , there is **no information computation gap**. For  $d = \omega(1)$ , it remains an open question.

# Heuristic II

(Assume  $\Pi^* = \text{Id}$ , thus  $Y = X + \sigma Z$ )

- Expect  $\langle X, Y \rangle$  to be the maximizer of all  $\langle X, \Pi Y \rangle$ 's.
- **Singular value decomposition:**  $X = U\Lambda^{1/2}Q_1^\top$  and  $Y = V\Sigma^{1/2}Q_2^\top$ .
- $\langle X, Y \rangle = \langle U\Lambda^{1/2}Q_1^\top, V\Sigma^{1/2}Q_2^\top \rangle = \langle U\Lambda^{1/2}, V\Sigma^{1/2}Q_2^\top Q_1 \rangle$ .
- Then  $\hat{\Pi}_{Ume}$  works if  $Q_2^\top Q_1$  is approximately an element in  $\text{Diag}(\{\pm 1\}^d)$ .

## Proposition (G. and Li 24+)

There exists a  $\Psi_0 \in \text{Diag}(\{\pm 1\}^d)$  such that

$$\|Q_1\Psi_0 - Q_2\|_F \leq d^3\sigma.$$

# Proof of proposition

- Write  $Q_1 = [q_1^{(1)}, \dots, q_d^{(1)}]$  and  $Q_2 = [q_1^{(2)}, \dots, q_d^{(2)}]$ .
- By **Davis-Kahan** theorem

$$\sin \angle(q_i^{(1)}, q_i^{(2)}) \leq \frac{2\|X^\top X - Y^\top Y\|_{op}}{\min_{j:j \neq i} |\lambda_j - \lambda_i|}.$$

- By standard result, it can be shown  $\|X^\top X - Y^\top Y\|_{op} \leq \sigma d \sqrt{n}$ .
- For minimal spacing term, we compare the eigenvalues of a  $d * d$  Wishart matrices to standard GOE. For GOE, the limiting distribution of the minimal spacing has been derived in [**Feng-Tian-Wei19**].
- We have  $\min_{(i,j):i \neq j} |\lambda_i - \lambda_j| \geq \frac{1}{2d} \sqrt{n}$ .

## Take-home messages

- When  $d = O(1)$ , there is no information-computation gap for this problem.
- When  $d = \omega(1)$ , the Umeyama algorithm approaches the informational thresholds up to a  $\text{poly}(d)$  factor in the low-dimensional regime.
- When  $d = \omega(1)$ , it remains an intriguing question to answer if I-C gap phenomenon occurs.

Thank you!