

Matching Wishart matrices via Umeyama algorithm

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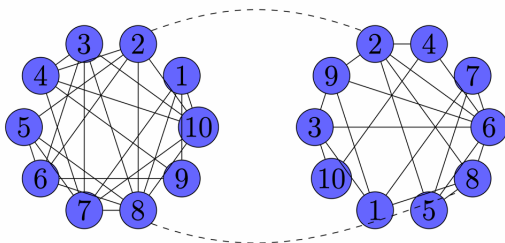
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Motivations: random graph matching

- **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 σ the noise parameter. Let $Z_i \sim \mathcal{N}(0, I_d)$ be independent of X_i 's.
- Plant a latent permutation π^* (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 σ is this possible?)

Informational upper bound

Define the estimator

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

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

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

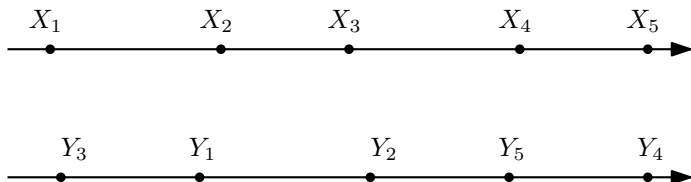
- Suppose that $\sigma^2 \leq d/40$ and

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

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 σ .

- 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 σ 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

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

By concentration of eigenvalues, we can define

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

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

Computation: the Umeyama algorithm

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!