

Sharp threshold for alignment of graph databases with Gaussian weights

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The logo for INRIA, featuring the word "Inria" in a stylized, red, cursive script.

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Minimizing disagreements: Find a bijection $f : V \rightarrow V'$ that minimizes

$$\sum_{(i,j) \in V^2} (\mathbf{1}_{(i,j) \in E} - \mathbf{1}_{(f(i),f(j)) \in E'})^2,$$

or, equivalently solve

$$\max_{\Pi} \langle G, \Pi G' \Pi^T \rangle,$$

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where Π runs over all permutation matrices. \leftarrow *NP-hard in the worst case*

Planted Alignment with gaussian weights

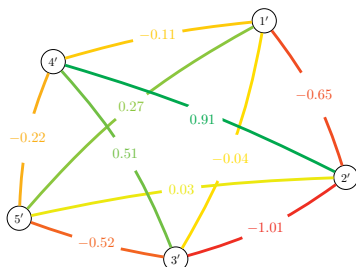
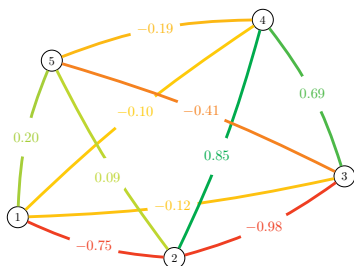
Correlated Wigner model:

- Draw the planted permutation π^* uniformly at random in S_n .
- $(A_{i,j}, B_{\pi^*(i),\pi^*(j)})_{1 \leq i < j \leq n}$ are i.i.d. $\mathcal{N}\left(0, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$ with $\rho \in [0, 1]$.

In other words:

$$B = \rho \cdot \Pi^{*T} A \Pi^* + \sqrt{1 - \rho^2} \cdot H,$$

where H is an independent copy of A , and $\Pi_{i,j}^* = \mathbf{1}_{j=\pi^*(i)}$.



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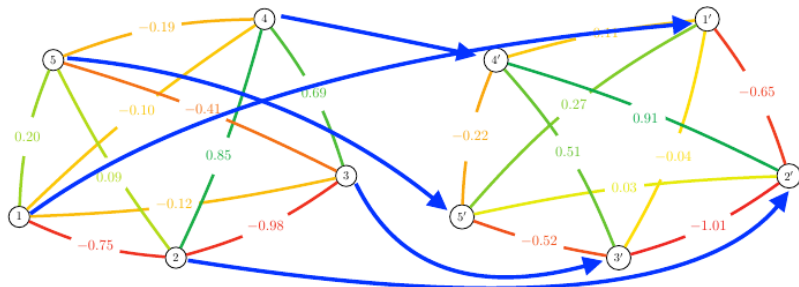
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$$p_{\pi^*|A,B}(\pi|a,b) \propto p_{\pi^*,A,B}(\pi, a, b) \\ \propto \exp\left(-\frac{1}{2(1-\rho^2)} \sum_{1 \leq i < j \leq n} (B_{\pi(i),\pi(j)} - \rho A_{i,j})^2\right),$$

where \propto indicates equality up to some factors that do not depend on σ . The MAP estimator is given by

$$\hat{\pi}_{\text{MAP}} := \arg \max_{\pi} p_{\pi^*|A,B}(\pi|A, B) = \arg \max \langle A, \Pi B \Pi^T \rangle.$$

Theorem (Achievability part)

If for n large enough

$$\rho^2 \geq \frac{(4 + \varepsilon) \log n}{n} \quad (1)$$

for some $\varepsilon > 0$, then there is an estimator (namely, the MAP estimator) $\hat{\pi}$ of π given A, B such that $\hat{\pi} = \pi^*$ with probability $1 - o(1)$.

Theorem (Converse part)

Conversely, if

$$\rho^2 \leq \frac{4 \log n - \log \log n - \omega(1)}{n} \quad (2)$$

then any estimator $\hat{\pi}$ of π given A, B verifies $\hat{\pi} = \pi^*$ with probability $o(1)$.

- Achievability result: analysis of the MAP estimator

$$\hat{\pi}_{\text{MAP}} = \arg \min_{\pi} \mathcal{L}(\pi, \mathbf{A}, \mathbf{B}),$$

with

$$\mathcal{L}(\pi, \mathbf{A}, \mathbf{B}) := \sum_{1 \leq i < j \leq n} (B_{\pi(i), \pi(j)} - \rho A_{i,j})^2.$$

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- Converse result: we show that when $\rho^2 \leq \frac{4 \log n - \log \log n - \omega(1)}{n}$, w.h.p. there exists a perturbation of π^* (namely $\pi^* \circ \tau$ for some transposition τ) s.t. $\mathcal{L}(\pi^* \circ \tau, A, B) < \mathcal{L}(\pi^*, A, B)$.

Linear Assignment problem: $\pi^* \sim U(\mathcal{S}_N)$ and u, v are random vectors such that $(u_i, v_{\pi^*(i)})_{1 \leq i \leq n}$ are i.i.d. $\mathcal{N}\left(\mathbf{0}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$ with $\rho \in [0, 1]$.

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(Dai-Cullina-Kiyavash '19): sharp threshold for exact recovery at $-\frac{1}{2} \log(1 - \rho^2) \gtrsim 2 \log N$, for $N = n(n - 1)/2$, i.e. at

$$1 - \rho^2 \lesssim n^{-8}.$$

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→ vector alignment (resp. LAP) is a very bad relaxation of matrix alignment (resp. QAP).

State-of-the art algorithms for (almost) exact recovery

- Degree profiles (Ding-Ma-Wu-Xu 18'), spectral method (Fan-Mao-Wu-Xu 19') with time complexity $\mathcal{O}(n^3)$ requires

$$\sqrt{1 - \rho^2} \leq \mathcal{O}(\log^{-1} n).$$

- A simpler spectral method with complexity $\mathcal{O}(n^2)$ (G-Massoulié-Lelarge 19') requires

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→ *hard phase* conjectured to be really wide for this reconstruction problem.

Thank you!