

# Impossibility of Partial Recovery in the Graph Alignment Problem

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Luca Ganassali, Marc Lelarge and Laurent Massoulié  
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INRIA, DI/ENS, PSL Research University, Paris, France

*Inria*



## The Graph Alignment problem

**Question:** Given two graphs  $G = (V, E)$  and  $G' = (V', E')$  with  $|V| = |V'|$ , what is the best way to match nodes of  $G$  with nodes of  $G'$ ?

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

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

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

# Planted Graph Alignment

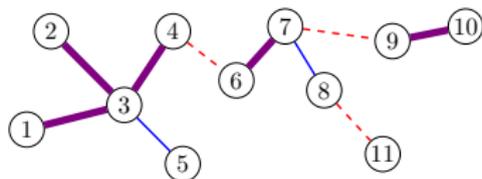
## Correlated Erdős-Rényi model $\mathcal{G}(n, q, s)$ :

- Draw two graphs  $\mathcal{G}, \mathcal{G}'$  with same node set  $[n]$ , s.t. for all  $(i, j) \in \binom{[n]}{2}$ :

$$\left( \mathbf{1}_{i \sim_{\mathcal{G}} j}, \mathbf{1}_{i \sim_{\mathcal{G}'} j} \right) = \begin{cases} (1, 1) & \text{w.p. } qs & \text{two-coloured edge} \\ (0, 1), (1, 0) & \text{w.p. } q(1-s) & \text{red or blue edge} \\ (0, 0) & \text{w.p. } 1 - q(2-s) & \text{non-edge} \end{cases}$$

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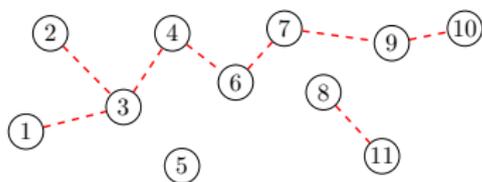
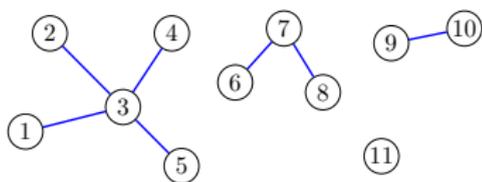
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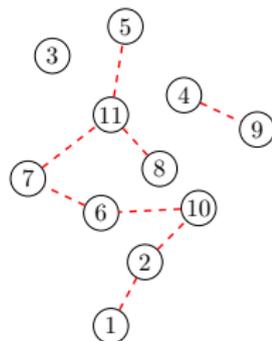
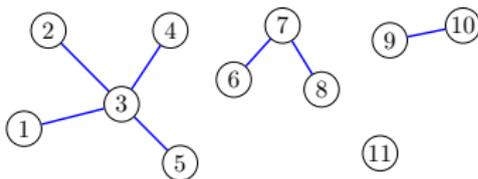
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- Relabel the vertices of  $\mathcal{G}'$  with a uniform independent permutation  $\pi^*$ :  
 $\mathcal{H} := \mathcal{G}' \circ \pi^*$ .



## Planted Graph Alignment: state-of-the art

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**Notion of performance:** for any  $\mathcal{S}_n$ -valued estimator  $\hat{\pi}(\mathcal{G}, \mathcal{H})$ , define its overlap with the planted permutation  $\pi^*$

$$\text{ov}(\hat{\pi}(\mathcal{G}, \mathcal{H}), \pi^*) := \frac{1}{n!} \sum_{\sigma \in \mathcal{S}_n} \sum_{i=1}^n \mathbf{1}_{\hat{\pi}(\mathcal{G}^\sigma, \mathcal{H})(i) = \pi^* \circ \sigma^{-1}(i)},$$

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**Questions:** can we hope for  $\text{ov}(\hat{\pi}, \pi^*) > \alpha n$  w.h.p. (no computational restrictions)? What is the maximal fraction  $\alpha$ ?

**State-of-the art:** in the sparse case where  $\lambda > 0$  and  $s \in [0, 1]$  are fixed constants: partial recovery is IT-feasible if  $\lambda s > 4 + \varepsilon$  [Wu-Xu-Yu '21].

## Main result: maximal reachable overlap

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**Theorem 1**

For  $\lambda > 0$  and  $s \in [0, 1]$ , we have for any  $\alpha > 0$ , for any estimator  $\hat{\pi}$ :

$$\mathbb{P}(\text{ov}(\hat{\pi}, \pi^*) > (c(\lambda s) + \alpha)n) \xrightarrow[n \rightarrow \infty]{} 0,$$

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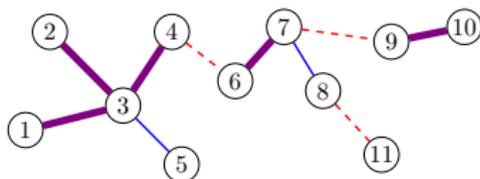
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**Corollary: Partial recovery is IT-infeasible if  $\lambda s \leq 1$ .**

## Intuition: exchanging small tree components

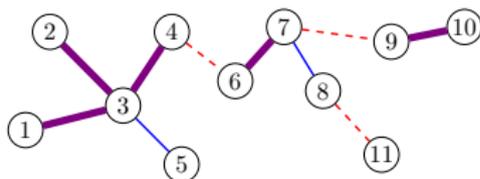
1. Information contained in the **intersection graph**  $\mathcal{G} \wedge \mathcal{G}'$ :



In our model  $\mathcal{G} \wedge \mathcal{G}'$  is an Erdős-Rényi graph:  $\mathcal{G} \wedge \mathcal{G}' \sim G(n, \lambda s/n)$ .

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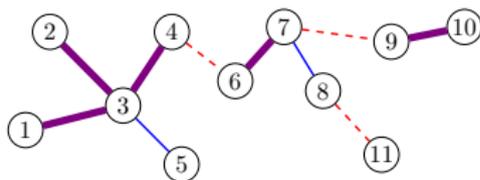


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2. [Erdős, Rényi, Bollobás] typical fraction  $c(\lambda s)$  of nodes in the giant component of  $\mathcal{G} \wedge \mathcal{G}' \rightarrow$  the remaining  $(1 - c(\lambda s))n$  nodes are almost all on **small tree components**.

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3. For any small tree **T**, a large number of copies of **T** will appear in  $\mathcal{G} \wedge \mathcal{G}'$ . **Reshuffle them in  $\mathcal{G}$**   $\rightarrow$  a lot of unnoticed corrupted candidates for  $\hat{\pi}$  that are far from  $\pi^*$ .

## Intuition: exchanging small tree components

Let  $\mathbb{T} := \{\mathbf{T}_1, \dots, \mathbf{T}_M\}$  be the set of all trees (up to isomorphism) of size less than  $K := K(n) = \lfloor \log n \rfloor$ .

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### Algorithm 1: Recursive construction of $\sigma$

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Initialize  $\sigma_0 \leftarrow \text{id}$ ;

**for**  $i = 1$  to  $M$  **do**

    Consider  $\mathbf{T} = \mathbf{T}_i$  and draw uniformly at random the tree permutation

$\Sigma_{\mathbf{T}} \in \mathcal{S}_{X_{\mathbf{T}}}$ , independently from the past;

    Consider  $\sigma_{\mathbf{T}}$  the node permutation associated with  $\Sigma_{\mathbf{T}}$ ;

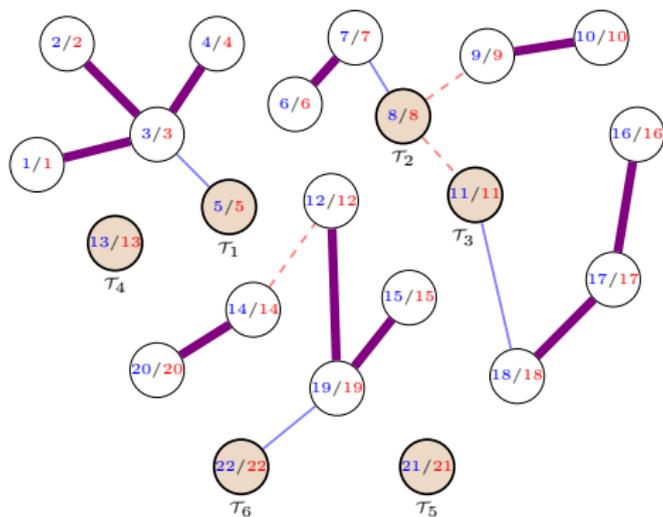
$\sigma_i \leftarrow \sigma_{\mathbf{T}} \circ \sigma_{i-1}$ ;

**end**

**return**  $\sigma = \sigma_M$

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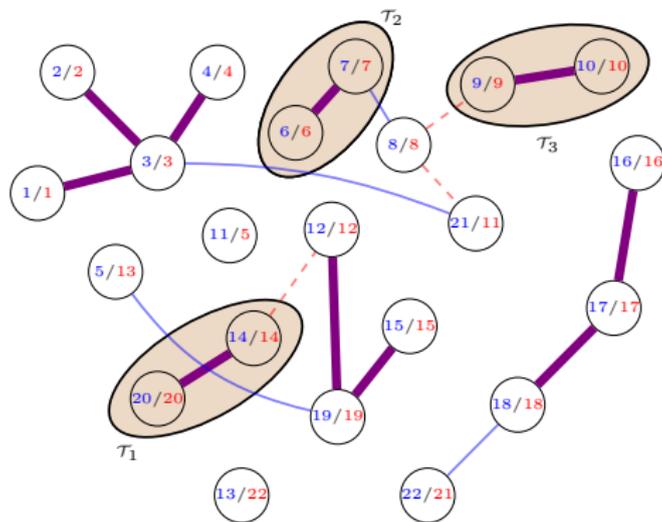
## Intuition: exchanging small tree components



$$\Sigma_{T_1} = (2)(1\ 3\ 5\ 6\ 4)$$

$$\sigma_{T_1} = (8)(5\ 11\ 21\ 22\ 13)$$

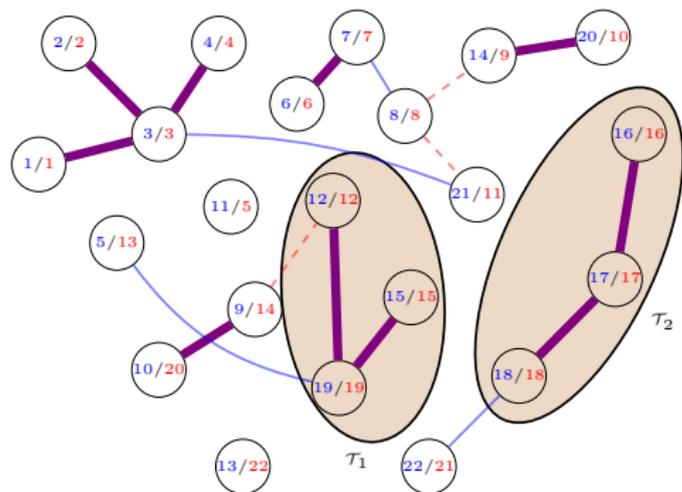
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$$\Sigma_{T_2} = (2)(13)$$

$$\sigma_{T_2} = (6)(7)(9\ 14)(10\ 20)$$

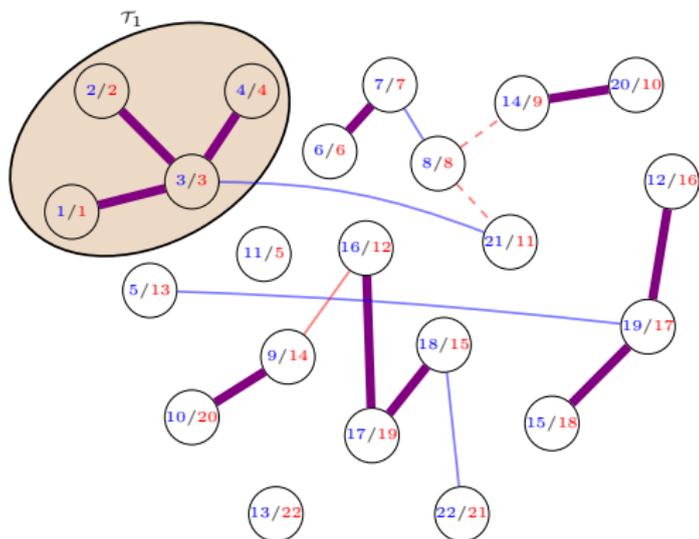
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$$\Sigma_{\mathbf{T}_3} = (1\ 2)$$

$$\sigma_{\mathbf{T}_3} = (15\ 18)(19\ 17)(12\ 16)$$

## Intuition: exchanging small tree components



$$\Sigma_{\mathbf{T}_4} = (1)$$

$$\sigma_{\mathbf{T}_4} = (1)(2)(3)(4)$$

4. Joint distribution for  $\mathcal{G}, \mathcal{G}'$ :

$$\mathbb{P}(\mathcal{G} = \mathbf{G}, \mathcal{G}' = \mathbf{G}') = \frac{1}{\mathcal{Z}_{\lambda,s}(\mathbf{G})\mathcal{Z}_{\lambda,s}(\mathbf{G}')} \left[ \frac{s(n - \lambda(2 - s))}{\lambda(1 - s)^2} \right]^{|E(\mathbf{G} \wedge \mathbf{G}')|}$$

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### Theorem 2

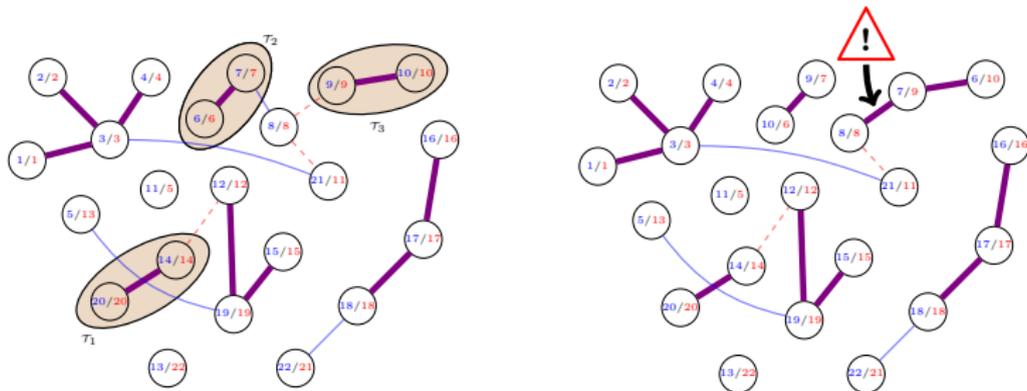
Fix an integer  $p > 0$ . Consider  $(\mathcal{G}, \mathcal{G}')$  drawn under the correlated Erdős-Rényi model. Then, with high probability, there exists  $\{\sigma_i\}_{i \in [p]}$  that depend on the intersection graph  $\mathcal{G} \wedge \mathcal{G}'$  – such that

- (i)  $\forall i \in [p], |E(\mathcal{G}^{\sigma_i} \wedge \mathcal{G}')| = |E(\mathcal{G} \wedge \mathcal{G}')|$ ,
- (ii)  $\forall i, j \in [p], i \neq j \implies \sum_{\ell=1}^n \mathbf{1}_{\sigma_i(\ell)=\sigma_j(\ell)} \leq c(\lambda s)n + o(n)$ , where the  $o(n)$  is independent of  $i, j \in [p]$ .

## Proof sketch for Theorem 2

- Point (ii) (**all permutations are far apart**): lower bound for  $X_T$ , number of components isomorphic to  $\mathbf{T}$  in  $\mathcal{G} \wedge \mathcal{G}'$  holding uniformly w.h.p. + standard random permutation arguments.
- Point (i) (**same number of double edges**): Define  $\mathcal{S} : \{u, v\} \in \mathcal{S}$  if edge  $\{u, v\}$  is not double. Control of the number of extra double edges:

$$\Delta(\sigma) := \sum_{\{u,v\} \in \mathcal{S}} \mathbf{1}_{u \leftrightarrow v} \mathbf{1}_{\sigma(u) \not\leftrightarrow \sigma(v)}.$$



$$\Sigma_{T_2} = (1)(2\ 3)$$

$$\sigma_{T_2} = (14)(20)(7\ 9)(6\ 10)$$

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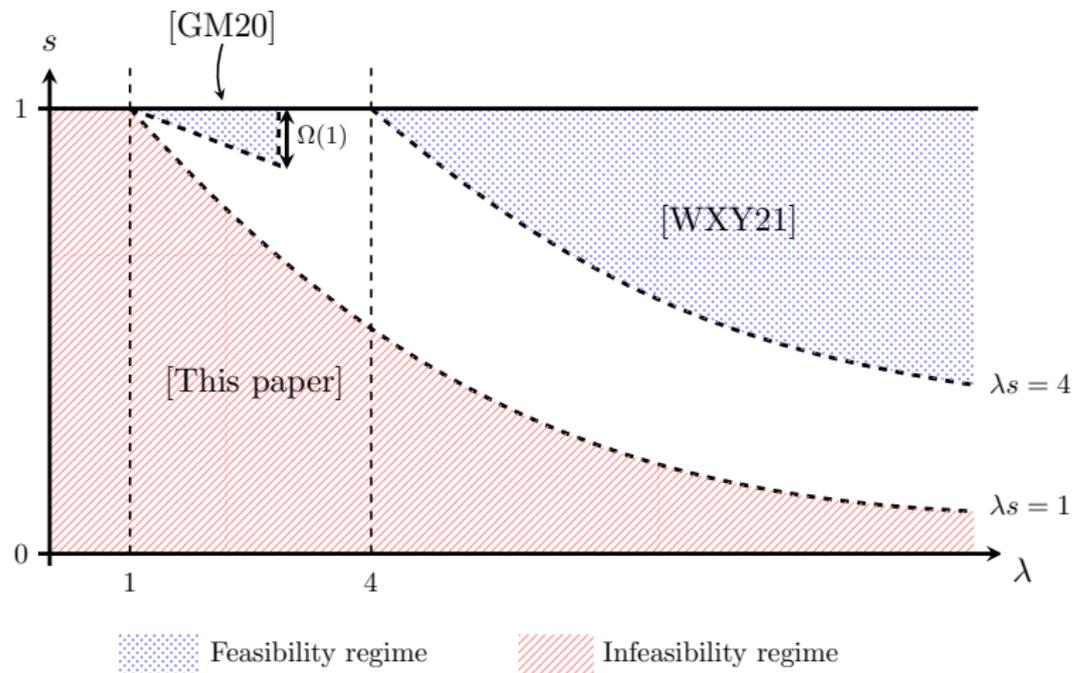
$$\Delta(\sigma) := \sum_{\{u,v\} \in \mathcal{S}} \mathbf{1}_{u \leftrightarrow v} \mathbf{1}_{\sigma(u) \leftrightarrow \sigma(v)}.$$

Conditionally to the two-coloured edges and to  $\sigma$ ,  $\Delta(\sigma)$  is asymptotically Poisson with parameter

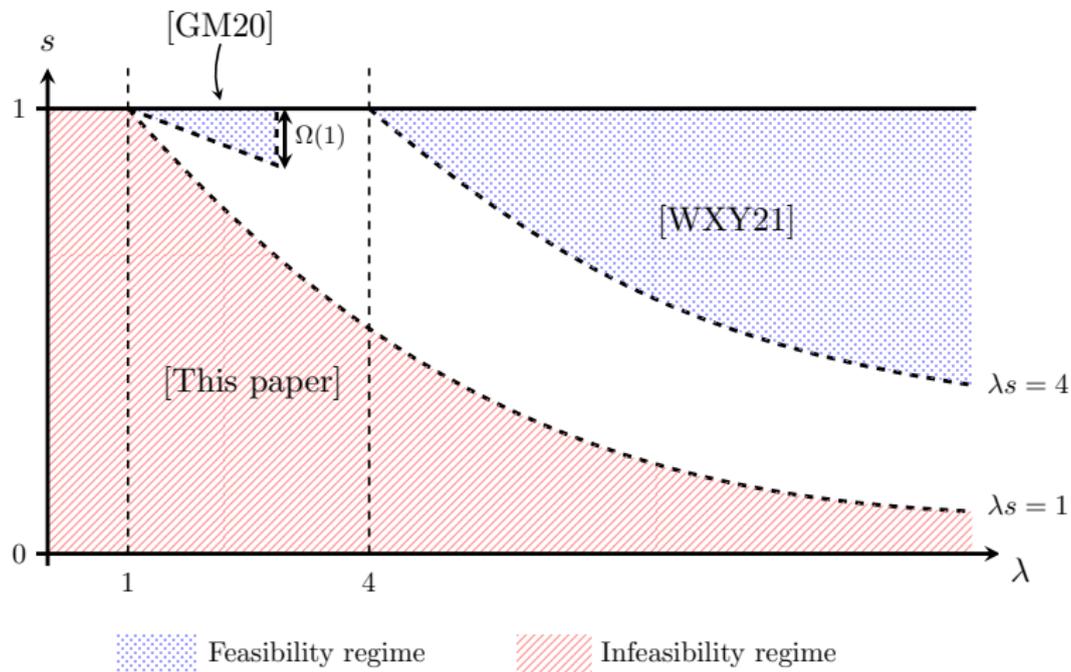
$$\frac{(1 - c(\lambda s)n)^2}{2} \times \frac{\lambda^2(1 - s)^2}{n^2} = \frac{\lambda^2(1 - s)^2(1 - c(\lambda s))^2}{2}.$$

→ probabilistic method.

## Conclusion: diagram for partial recovery



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**Conjecture:**  $\lambda_s = 1$  is the sharp threshold.

Thank you!