

Multilevel Network Alignment

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Multiple Networks Are Prevalent!

Scenarios

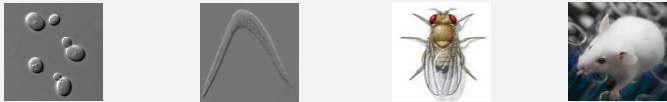
social networks



transaction networks



PPI networks



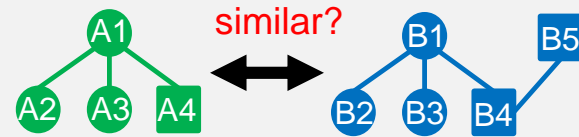
yeast elegans fly mouse

knowledge graphs



Tasks

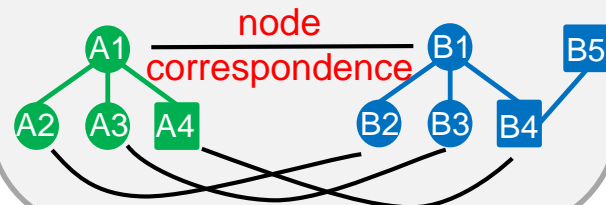
graph level



subgraph level

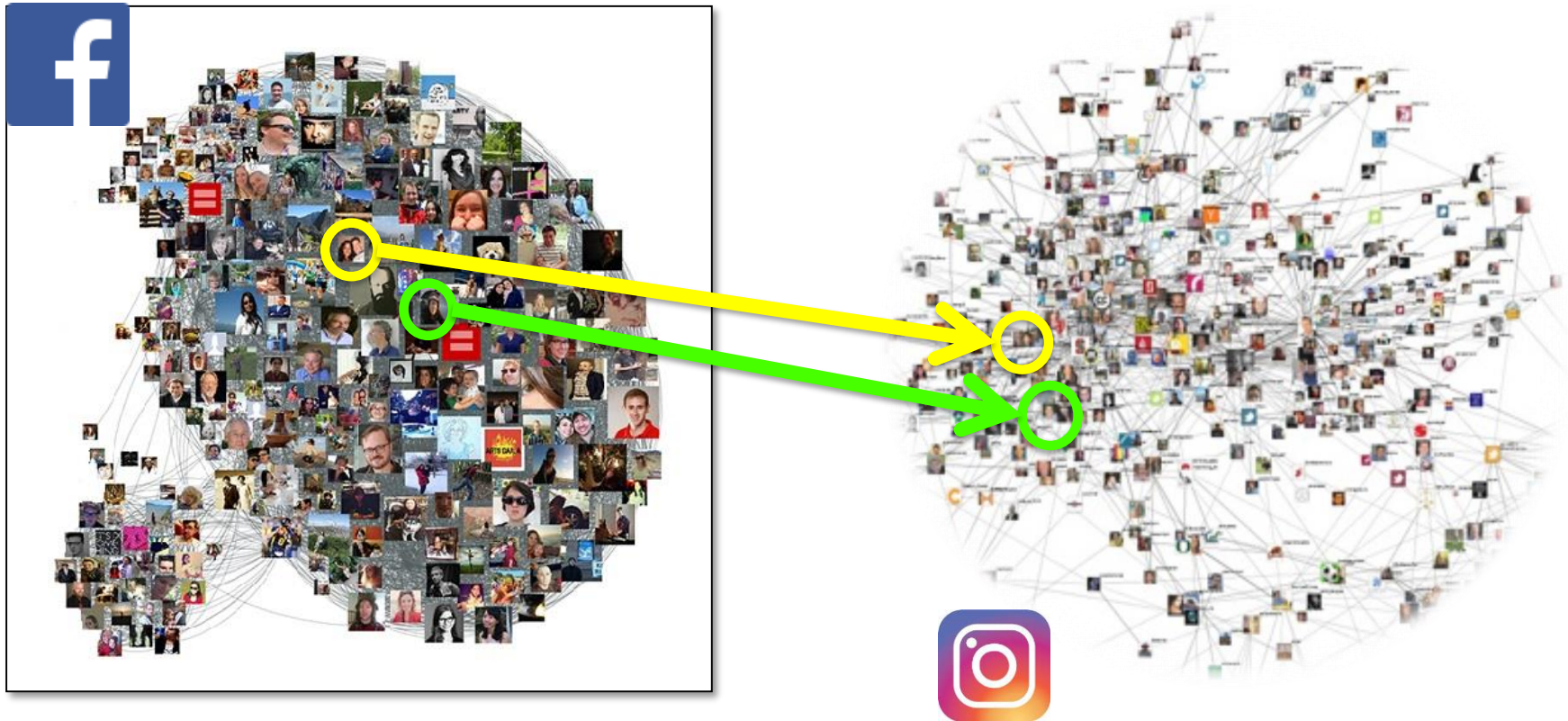


node level



What Is Network Alignment?

- Find node correspondence across networks



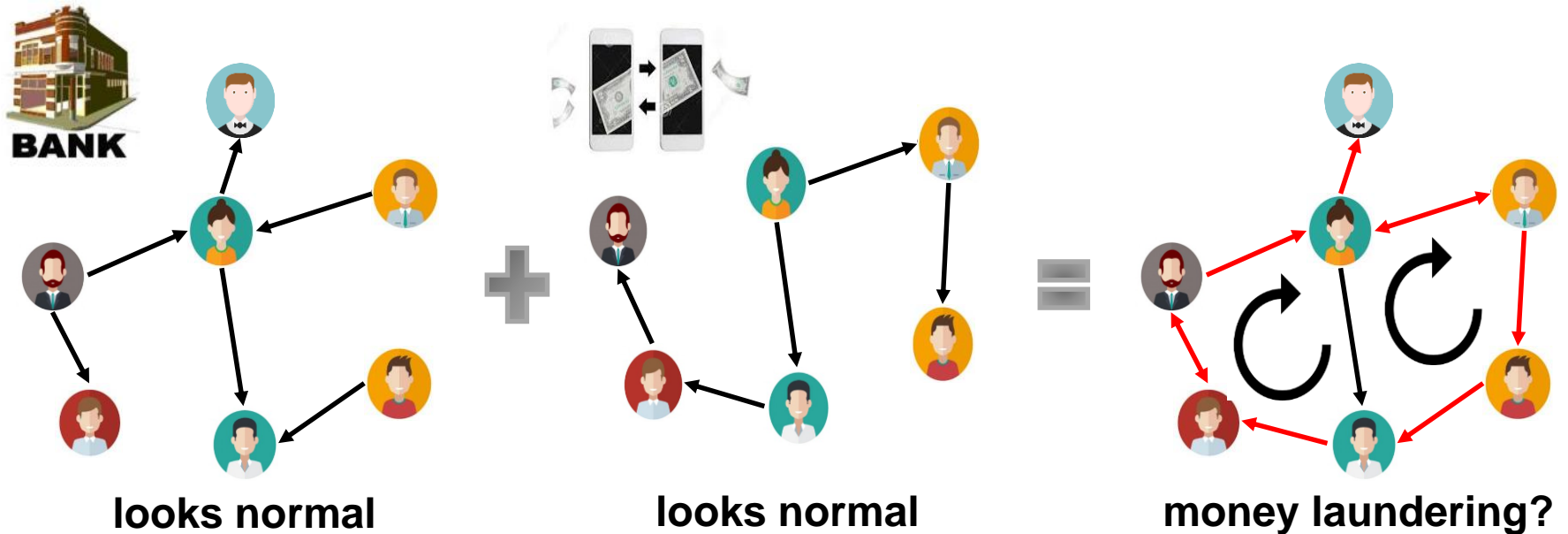
Other Applications

- Knowledge completion



Other Applications

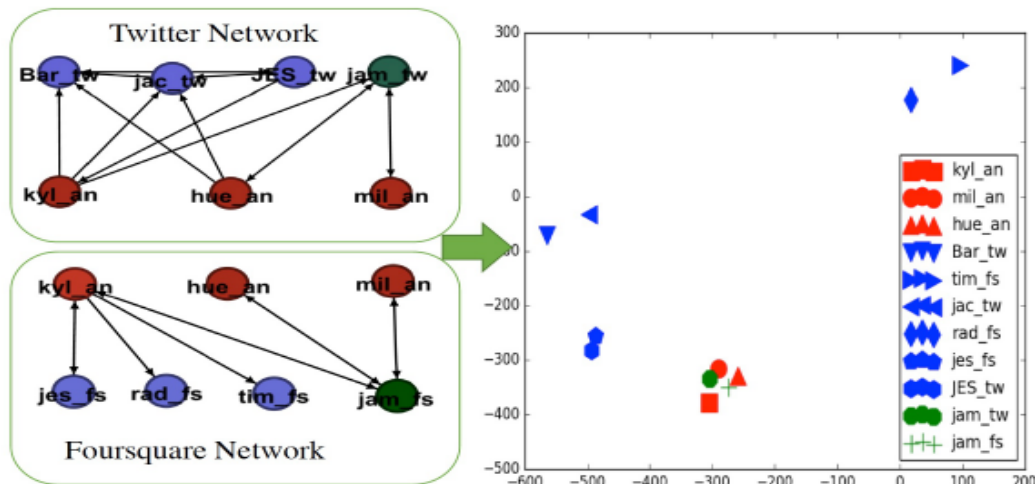
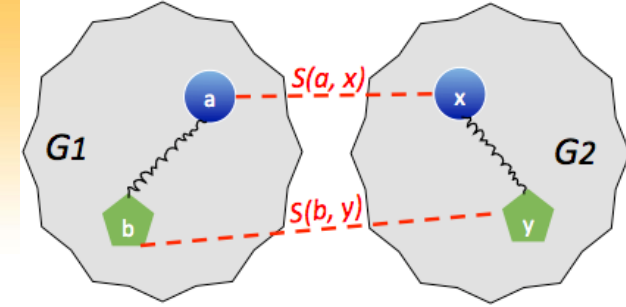
■ Fraud detection



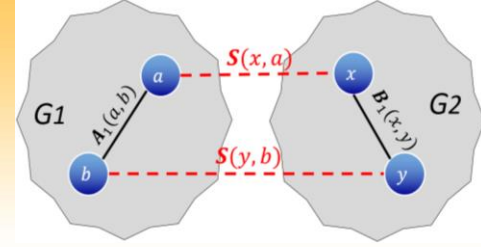
- Unsuspicious patterns become suspicious!
- **Question:** How to identify the correspondences across networks?

Network Alignment: How to

- Topological alignment
 - If two nodes are aligned, their neighbors are likely to be aligned
- Attributed alignment [Zhang'16]
 - Consider both topological and attribute consistency
- Embedding-based alignment [Liu'16]
 - Aligned nodes are closed in the embedding space



Network Alignment: How to (con't)



- Topological alignment: FINAL-P [Zhang'16]
 - if two nodes are likely to be aligned (i.e., similar)
 - their close neighbors are likely to be aligned (similar)

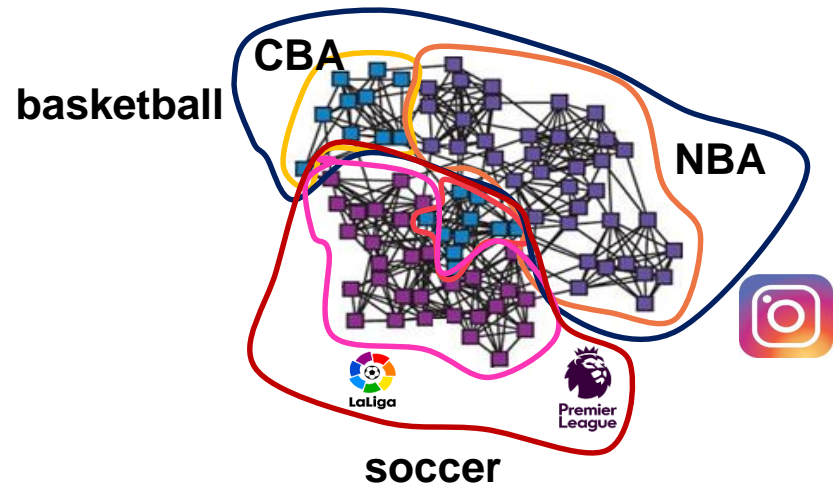
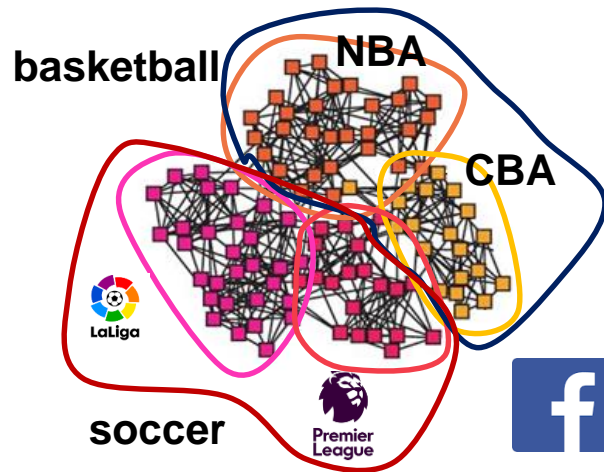
- Optimization formulation

$$\min_{\mathbf{s}_1} \alpha \mathbf{s}_1^T (\mathbf{I} - \mathbf{A}_1 \otimes \mathbf{B}_1) \mathbf{s}_1 + (1 - \alpha) \|\mathbf{s}_1 - \mathbf{h}_1\|_2^2$$

- $\mathbf{A}_1, \mathbf{B}_1$ are symmetrically normalized adjacency matrices
 - $\mathbf{s}_1, \mathbf{h}_1$ are the vectorization of alignment \mathbf{S}_1 and preference \mathbf{H}_1
 - **convex** optimization \rightarrow **global** optimal solution
- Optimization algorithm
 - fixed point solution: $\mathbf{S}_1 = \alpha \mathbf{B}_1 \mathbf{S}_1 \mathbf{A}_1 + (1 - \alpha) \mathbf{H}_1$

Network Alignment: Limitations

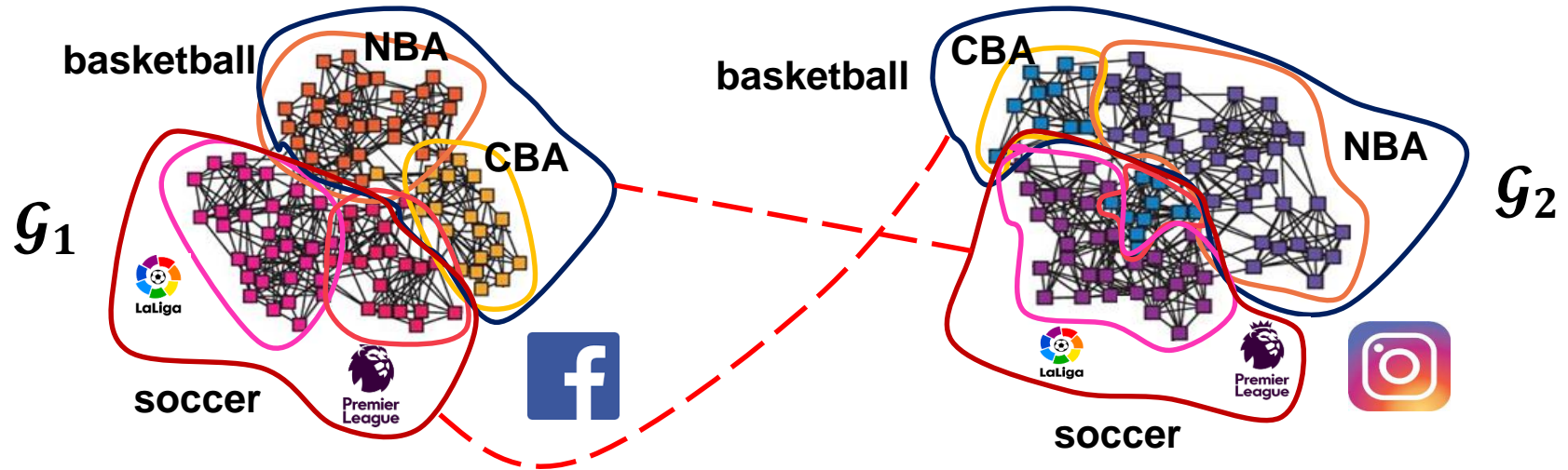
- Existing methods
 - Align networks at node level (and cluster level)
 - Have an at least **quadratic** computational complexity
- Rich patterns in networks
 - E.g., hierarchical cluster-within-clusters structure







- **Question:** how to align networks at different granularities?

Challenge #1: Alignment Accuracy

- Error propagation through different levels




- If soccer in \mathcal{G}_1 is aligned with basketball in \mathcal{G}_2
 - Next cluster level:  in \mathcal{G}_1 cannot be aligned with  in \mathcal{G}_2
 - Node level: nodes in cluster  in \mathcal{G}_1 can't be aligned with nodes in cluster  in \mathcal{G}_2
- **Question:** How to mitigate error propagation?

Challenge #2: Scalability

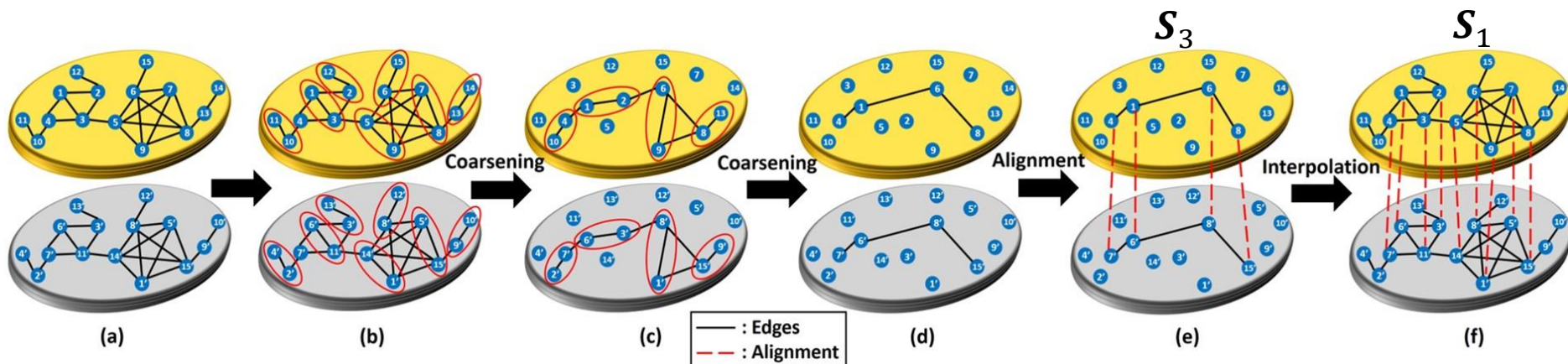
- Time complexity
 - At least $O(n^2)$ due to dense matrix multiplication
- Space complexity
 - At least $O(n^2)$ to store the dense alignment matrix
- **Question:** How can we reduce the complexity?

Outline

- Motivations 
- Q1: Moana Formulation
- Q2: Moana Algorithm
- Experimental Results
- Conclusions

Prob. Def: Multilevel Network Alignment

- Given:
 - (1) adjacency matrices \bar{A}_1, \bar{B}_1 of two undirected networks;
 - (2) a sparse prior alignment preference H_1 ;
 - (3) the number of levels $L \geq 2$ of interests.
- Find: a set of alignment matrices S_l at level- l , $l = 1, \dots, L$
 - where S_1 indicates the alignment at the node level
- An illustrative example



Moana Formulation #1: Multilevel Optimization

- Generic strategy

- coarsening → alignment → interpolation

- Alignment interpolations

- bilinear interpolations by $P_l \in R^{p_l \times n_1}$, $Q_l \in R^{q_l \times n_2}$ ($p_l \leq n_1, q_l \leq n_2$)

- w.l.o.g., $S_1 = Q_1^T S_2 P_1$ between level-1 & level-2

- Multilevel alignment formulation

Level-1:
$$\min_{s_1} \alpha s_1^T (I - A_1 \otimes B_1) s_1 + (1 - \alpha) \|s_1 - h_1\|_2^2$$

FINAL-P
at node level



If $P_1 P_1^T = I$ and $Q_1 Q_1^T = I$

Level-2:
$$\min_{s_2} \alpha s_2^T (I - A_2 \otimes B_2) s_2 + (1 - \alpha) \|s_2 - h_2\|_2^2$$

- where $A_2 = P_1 A_1 P_1^T$, $B_2 = Q_1 B_1 Q_1^T$ and $H_2 = Q_1 H_1 P_1^T$

- same properties (e.g., convexity) and algorithm as FINAL-P

- ‘good’ (semi-) orthogonal P_1, Q_1 can make A_2, B_2 well-represented

Moana Formulation #2: Perfect Interpolation

- Alignment error propagation
 - imperfect interpolations bring errors to S_l even from optimal S_{l+1}^*
 - mathematically, $S_l^* \neq Q_l^T S_{l+1}^* P_l$ if P_l, Q_l are not well-chosen
 - errors can be propagated or diverged to level- $(l - 1)$
- Perfect interpolation
 - if P_l, Q_l ($l = 1, \dots, L - 1$) are orthogonal
 - then $S_l^* = Q_l^T S_{l+1}^* P_l$ where S_l^*, S_{l+1}^* are optimal solutions at level- l and level- $(l + 1)$
 - proof in the paper

Outline

- Motivations ✓
- Q1: Moana Formulation ✓
- Q2: Moana Algorithm
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Moana Algorithm #1: Coarsening

- Generic strategy
 - **coarsening** → alignment → interpolation
- Network coarsening by P_l, Q_l
 - $A_{l+1} = P_l A_l P_l^T, B_{l+1} = Q_l B_l Q_l^T$
- Requirements on P_l, Q_l
 - **perfect interpolation**: they are **orthogonal** matrix
 - **efficient computation**: they are **sparse** matrix
 - **informative coarsening**: they can uncover **hierarchical cluster-within-clusters** structures

Moana Algorithm #1: Coarsening (Con't)

- Multiresolution matrix factorization [Kondor'14]

$$\begin{pmatrix} \square_{\mathcal{S}_{L-1}} \\ \vdots \\ \square_{\mathcal{S}_2} \\ \vdots \\ \square_{\mathcal{S}_1} \end{pmatrix} \cdots \begin{pmatrix} \square_{\mathcal{S}_{L-1}} \\ \vdots \\ \square_{\mathcal{S}_2} \\ \vdots \\ \square_{\mathcal{S}_1} \end{pmatrix} \begin{pmatrix} \square \\ \vdots \\ \square \\ \vdots \\ \square \end{pmatrix} \Pi \begin{pmatrix} \square \\ \vdots \\ \square \\ \vdots \\ \square \end{pmatrix} \Pi^T \begin{pmatrix} \square \\ \vdots \\ \square \\ \vdots \\ \square \end{pmatrix} \begin{pmatrix} \square \\ \vdots \\ \square \\ \vdots \\ \square \end{pmatrix} \cdots \begin{pmatrix} \square \\ \vdots \\ \square \\ \vdots \\ \square \end{pmatrix} \approx \begin{pmatrix} \square_{\mathcal{S}_L} \\ \vdots \\ \square_{\mathcal{S}_2} \\ \vdots \\ \square_{\mathcal{S}_1} \end{pmatrix} \begin{pmatrix} \tilde{A}_{L_1} \\ \vdots \\ \tilde{A}_{L_2} \\ \vdots \\ \tilde{A}_L \end{pmatrix}$$

P_{L-1} P_2 P_1 A_1 P_1^T P_2^T P_{L-1}^T \tilde{A}_L

- Π is to reorder for visualization (no need to calculate)
- P_l contains: (1) a rotation matrix block, (2) an identity matrix block
- active set \mathcal{S}_l indicates nodes at the l -th granularity (i.e., clusters)

- Coarsening procedure

$$\begin{aligned}
 - P_{L-1} \cdots P_2 P_1 A_1 P_1^T P_2^T \cdots P_{L-1}^T &= A_L \rightarrow \tilde{A}_L \\
 - Q_{L-1} \cdots Q_2 Q_1 B_1 Q_1^T Q_2^T \cdots Q_{L-1}^T &= B_L \rightarrow \tilde{B}_L
 \end{aligned}$$

- Orthogonality ✓
- Sparsity ✓
- Informativeness ✓

- Remark: $\mathcal{S}(\mathcal{S}_{B_l}, \mathcal{S}_{A_l})$ indicates the alignment among clusters at the l -th granularity

Moana Algorithm #2: Alignment

- Generic strategy

- coarsening → **alignment** → interpolation

$$\tilde{\mathbf{A}}_L = \Pi_A \begin{bmatrix} \tilde{\mathbf{A}}_{L_1} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{A}}_{L_2} \end{bmatrix} \Pi_A^T$$

$$\tilde{\mathbf{B}}_L = \Pi_B \begin{bmatrix} \tilde{\mathbf{B}}_{L_1} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{B}}_{L_2} \end{bmatrix} \Pi_B^T$$

- Alignment across the coarsest networks

$$\tilde{\mathbf{S}}_L = \alpha \begin{bmatrix} \tilde{\mathbf{B}}_{L_1} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{B}}_{L_2} \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{S}}_{L_1} & \tilde{\mathbf{S}}_{L_2} \\ \tilde{\mathbf{S}}_{L_3} & \tilde{\mathbf{S}}_{L_4} \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{A}}_{L_1} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{A}}_{L_2} \end{bmatrix} + (1 - \alpha) \begin{bmatrix} \tilde{\mathbf{H}}_{L_1} & \tilde{\mathbf{H}}_{L_2} \\ \tilde{\mathbf{H}}_{L_3} & \tilde{\mathbf{H}}_{L_4} \end{bmatrix}$$



block-wise computation

$$\tilde{\mathbf{S}}_{L_1} = \alpha \tilde{\mathbf{B}}_{L_1} \tilde{\mathbf{S}}_{L_1} \tilde{\mathbf{A}}_{L_1} + (1 - \alpha) \tilde{\mathbf{H}}_{L_1}$$

$$\tilde{\mathbf{S}}_{L_2} = \alpha \tilde{\mathbf{B}}_{L_1} \tilde{\mathbf{S}}_{L_2} \tilde{\mathbf{A}}_{L_1} + (1 - \alpha) \tilde{\mathbf{H}}_{L_2}$$

$$\tilde{\mathbf{S}}_{L_3} = \alpha \tilde{\mathbf{B}}_{L_2} \tilde{\mathbf{S}}_{L_3} \tilde{\mathbf{A}}_{L_2} + (1 - \alpha) \tilde{\mathbf{H}}_{L_3}$$

$$\tilde{\mathbf{S}}_{L_4} = (1 - \alpha) (\mathbf{I} - \alpha \tilde{\mathbf{A}}_{L_2} \otimes \tilde{\mathbf{B}}_{L_3})^{-1} \tilde{\mathbf{h}}_{L_4}$$

- matrix composition: e.g., $\mathbf{S}_L(\mathcal{S}_{B_L}, \mathcal{S}_{A_L}) = \tilde{\mathbf{S}}_{L_1}$, $\mathbf{S}_L(\bar{\mathcal{S}}_{B_L}, \bar{\mathcal{S}}_{A_L}) = \tilde{\mathbf{S}}_{L_4}$

- Alignment at finer levels

- perfect interpolations: $\mathbf{S}_l = \mathbf{Q}_l^T \mathbf{S}_{l+1} \mathbf{P}_l$

Moana Algorithm: Analysis

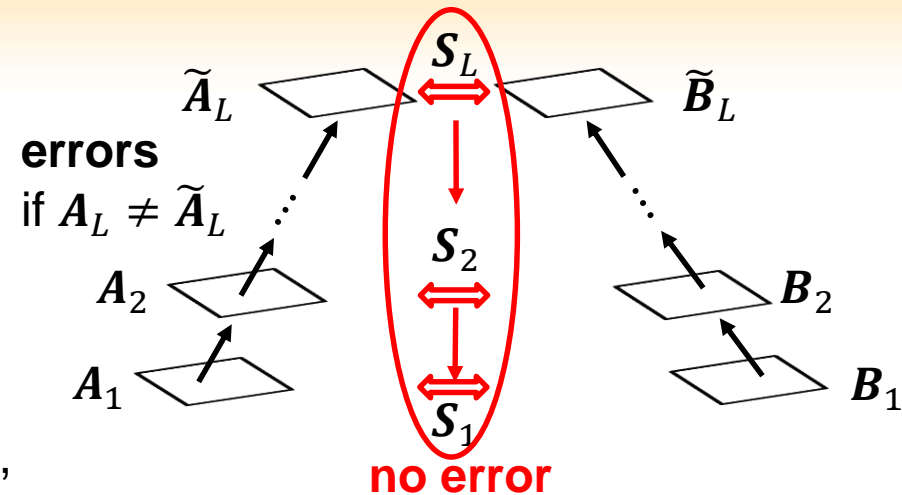
- Alignment error bound

$$\frac{\|\mathbf{S}_l^* - \mathbf{S}_l\|_F}{\|\mathbf{S}_l\|_F} \leq \frac{2\epsilon\kappa}{1 - \epsilon\kappa}, \forall l = 1, \dots, L$$

where $\epsilon = \sqrt{\frac{\alpha}{2n}} (\delta_1 r_2 + \delta_2 r_1 + \delta_1 \delta_2)$,

$$\delta_1 = \|\mathbf{A}_L - \tilde{\mathbf{A}}_L\|_F, \delta_2 = \|\mathbf{B}_L - \tilde{\mathbf{B}}_L\|_F,$$

κ is condition number, r_1, r_2 are ranks



- Complexity analysis

- linear time and space complexity

Outline

- Motivations ✓
- Q1: Moana Formulation ✓
- Q2: Moana Algorithm ✓
- **Experimental Results**
- Conclusions

Experimental Setup

■ Datasets

- Gr-Qc network vs. its permutation (nodes: 5,241 vs. 5,241)
- Google+ network vs. its permutation (nodes: 23,628 vs. 23,628)
- Amazon co-purchasing networks (nodes: 74,596 vs. 66,951)
- ACM vs DBLP coauthor networks (nodes: 9,872 vs. 9,916)

■ Evaluation objectives

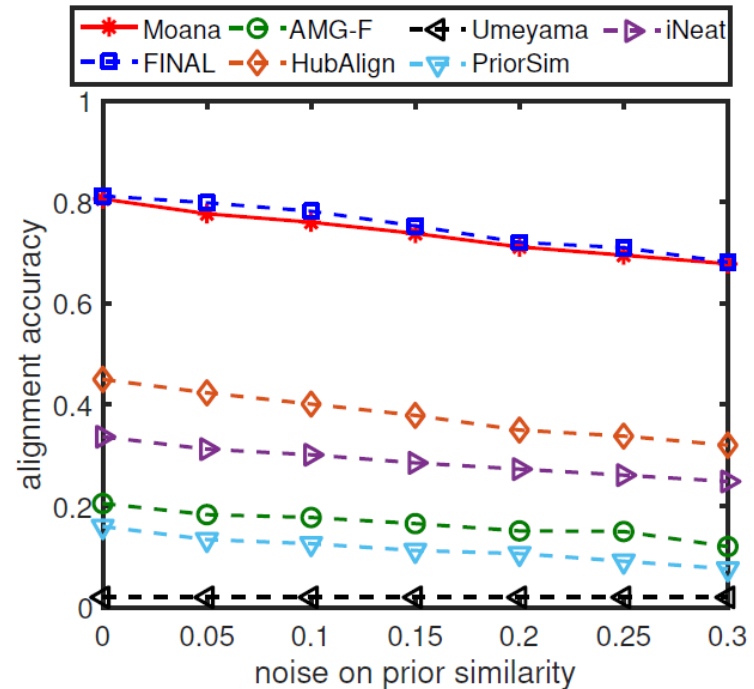
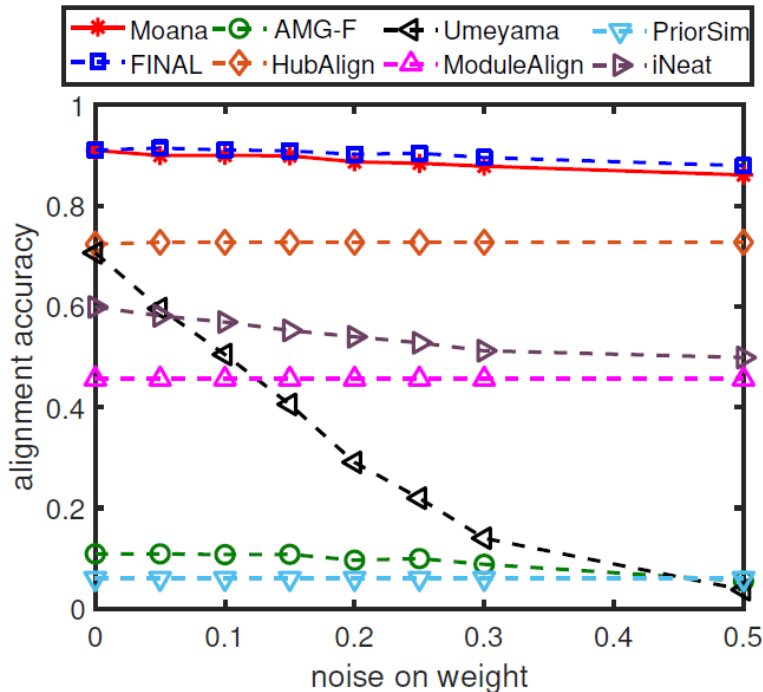
- Effectiveness: how accurate is our algorithm in aligning networks?
- Efficiency: how fast and scalable is our algorithm?

■ Comparison methods

Moana	AMG-FINAL	Umeyama	PriorSim
FINAL-P	HubAlign	ModuleAlign	iNeat

R1: Effectiveness Results

■ Effectiveness in node-level alignment

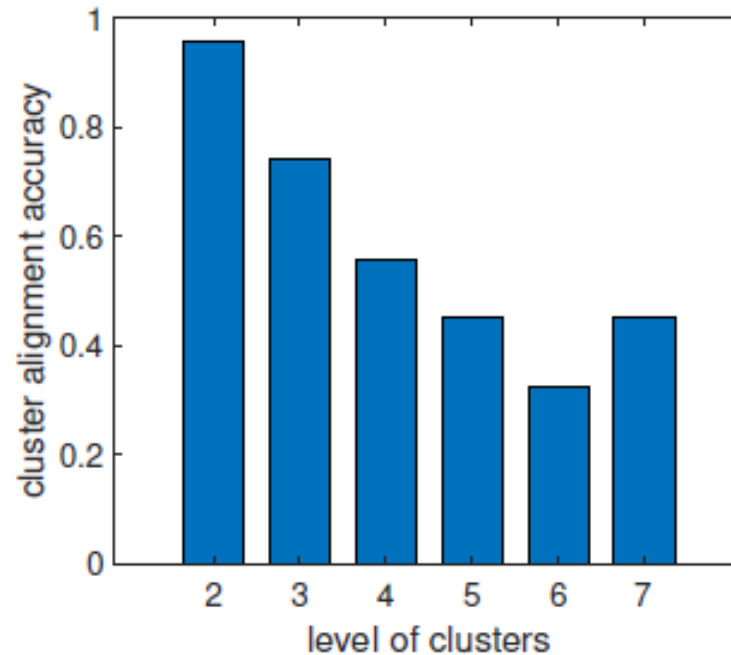


Observations:

- (1) the performance of Moana is close to FINAL-P;
- (2) Moana outperforms all other methods.

R2: Effectiveness Results

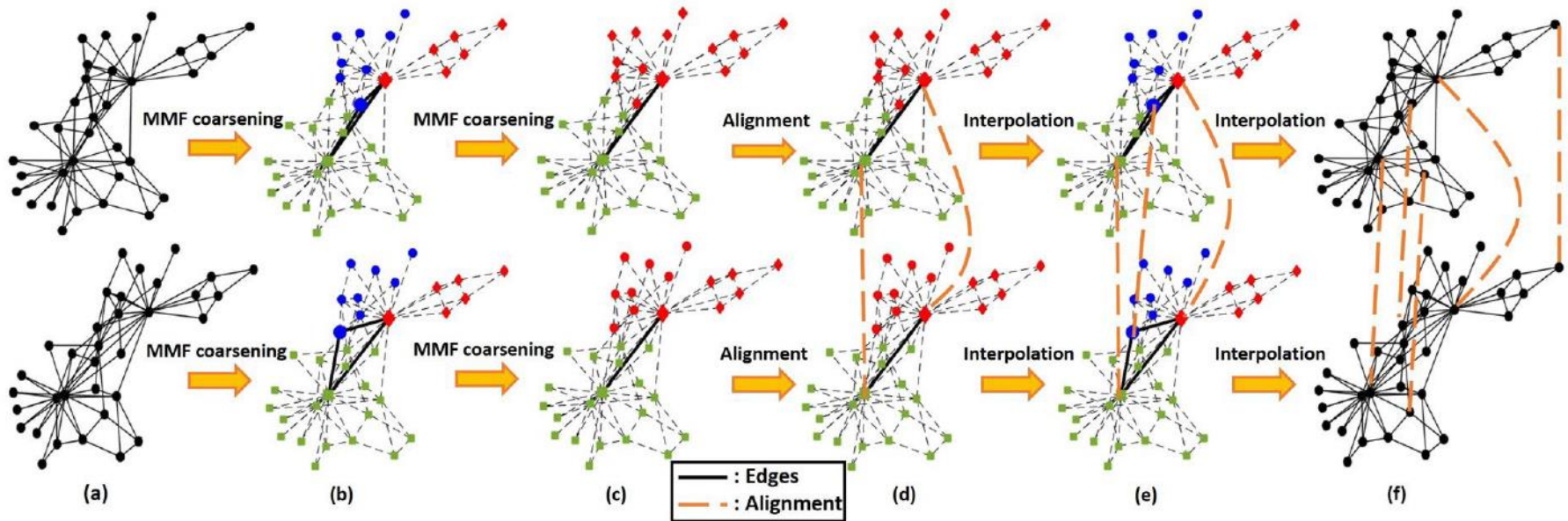
- Effectiveness in cluster-level alignment



Observations: Moana achieves a good performance in cluster alignment at different levels.

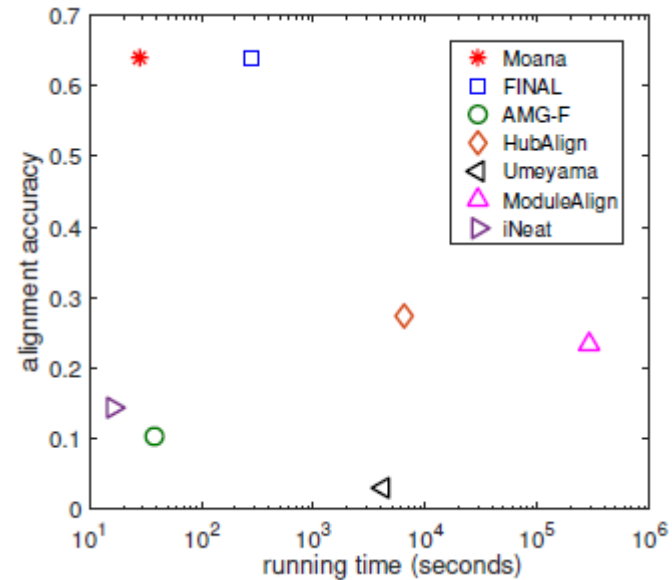
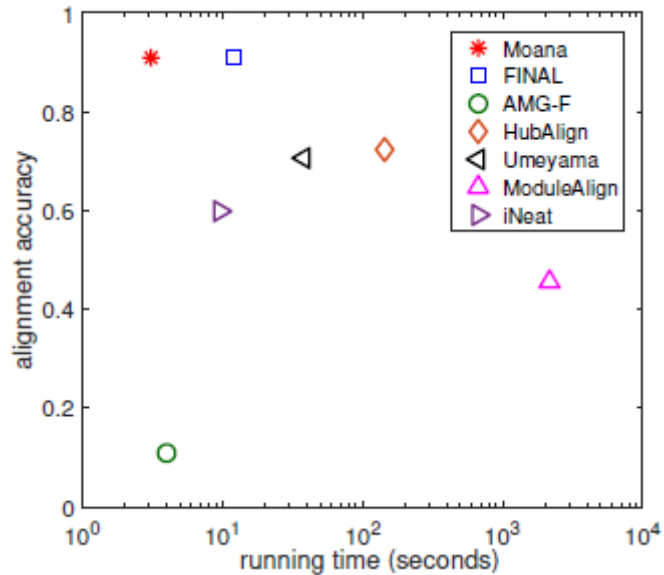
R3: Case Study on Multilevel Alignment

- A case study on Zachary's Karate networks



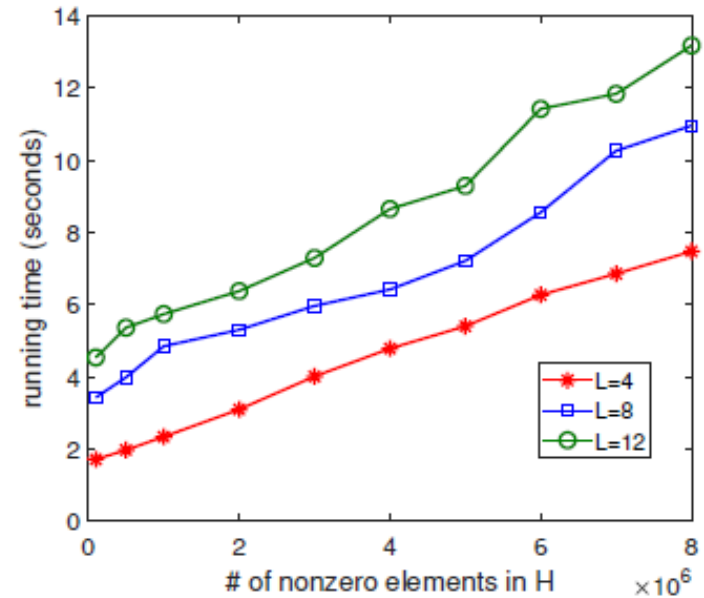
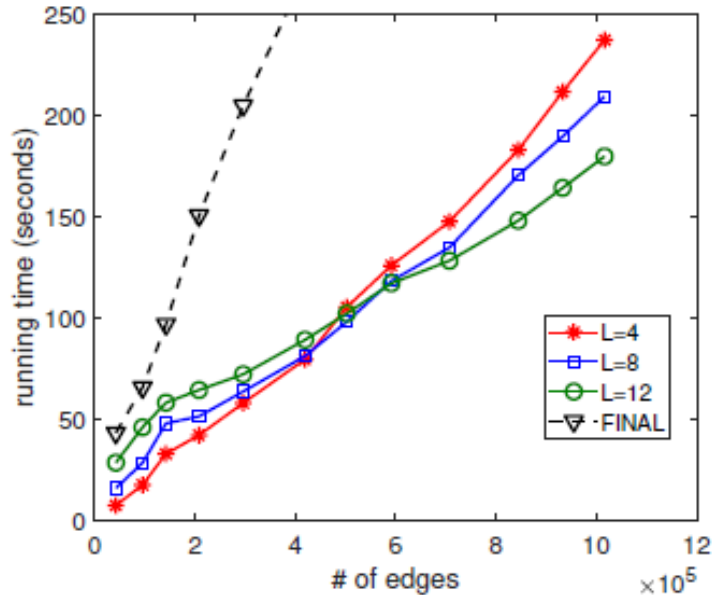
Observations: Moana can unveil meaningful alignment of clusters at different granularities.

R4: Quality-Speed Balance



Observations: Moana can achieve a better quality-speed balance.

R5: Scalability



Observations:

- (1) Moana scales linearly w.r.t. the number of edges;
- (2) Moana scales linearly w.r.t. the number of nonzero elements in H_1 .

Outline

- Motivations ✓
- Q1: Moana Formulation ✓
- Q2: Moana Algorithm ✓
- Experimental Results ✓
- **Conclusions**

Conclusions

- Multilevel network alignment
 - Q1: Formulation
 - A1: Multilevel optimization + perfect interpolation
 - Q2: Scalability
 - A2: Moana algorithm
- Results
 - Moana outperforms most baseline methods in node alignment
 - Moana achieves good performance in cluster alignment
 - Moana has linear complexity
- More in paper
 - Proof of algorithm analysis & more experimental results