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GRADUATED ASSIGNMENT FOR MULTI-GRAPH MATCHING

Project Presentation

AGENDA

- Motivation
- Graduated Assignment for Multi-Graph Matching
- Methodology
- Results & Discussion
- Future Work
- Conclusion

MOTIVATION

WHAT IS GRAPH MATCHING?

"Are graphs 1 and 2 isomorphic?"

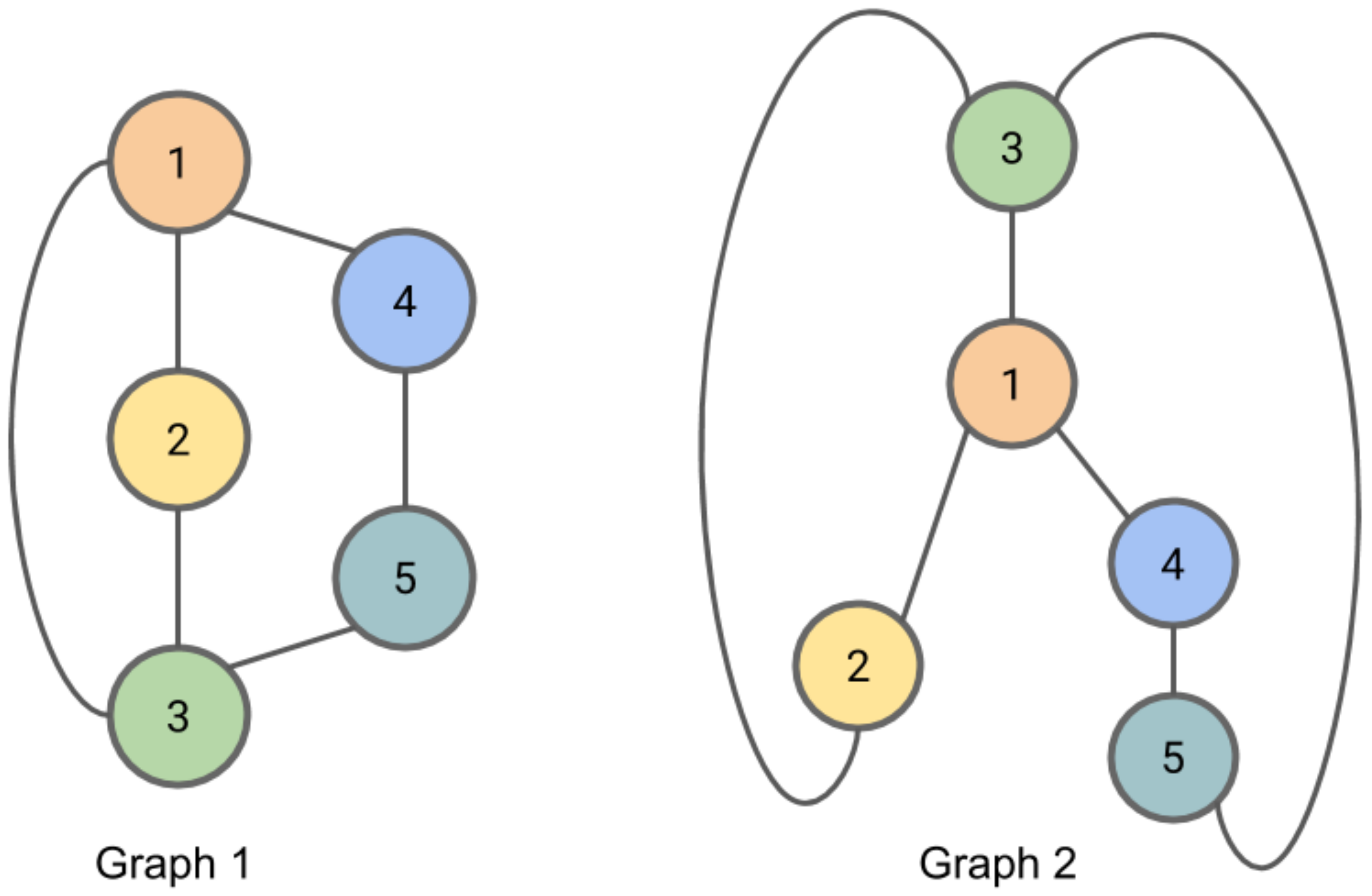
- $PA_1P^\top = A_2$
- $PX_1 = X_2$

How to solve?

- $\min_{P \in \mathscr{P}} \left\| PA_1P^\top - A_2 \right\| + \left\| PX_1 - X_2 \right\|$

Approximation Methods

- **VF2**
- **Deep Learning**

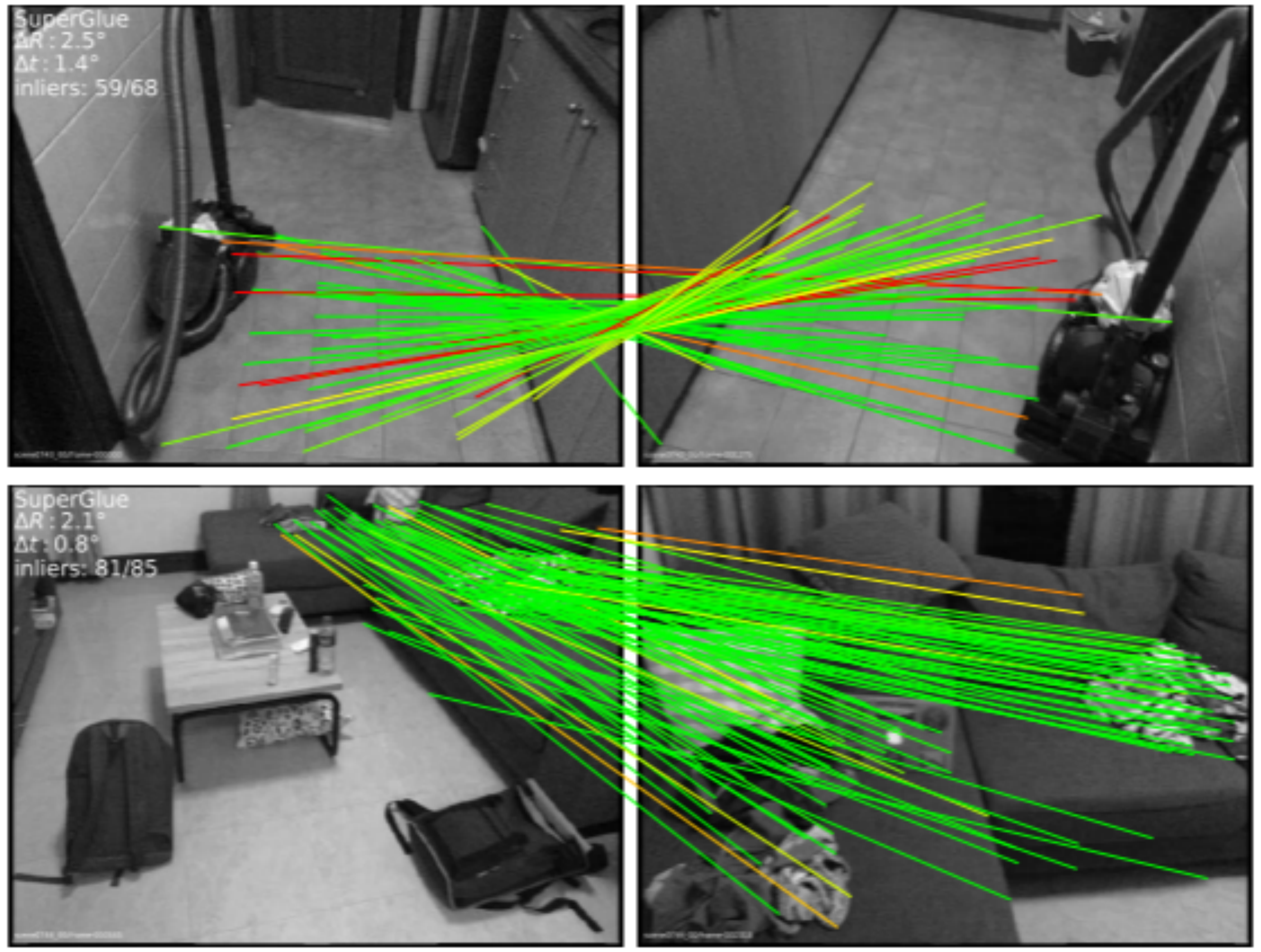


APPLICATION IN COMPUTER VISION

Graph matching algorithms can encode geometric relationships between feature points.

Applications

- Face recognition
- Action recognition
- Duplicate detection



RESEARCH QUESTION

How robust is state of the art graph matching algorithms to noisy data?

Hypothesis

- Deep learning methods are generally more precise
- Learning free methods are more stable

GRADUATED ASSIGNMENT

CONCEPTS

Quadratic Assignment Problem

- Fundamental combinatorial optimisation problem

Taylor Series

- $\sum_{n=0} \frac{f^{(n)}(a)}{n!}(x-a)^n$

Sinkhorn / Hungarian

- Iterative algorithms solving Linear Assignment Problem

APPROACH

Iteratively solving the first-order Taylor expansion of the Multi-Graph QAP.

Before iteration

- Initialise matching matrix using similarity heuristic

Each iteration

- Update matching matrix using Sinkhorn

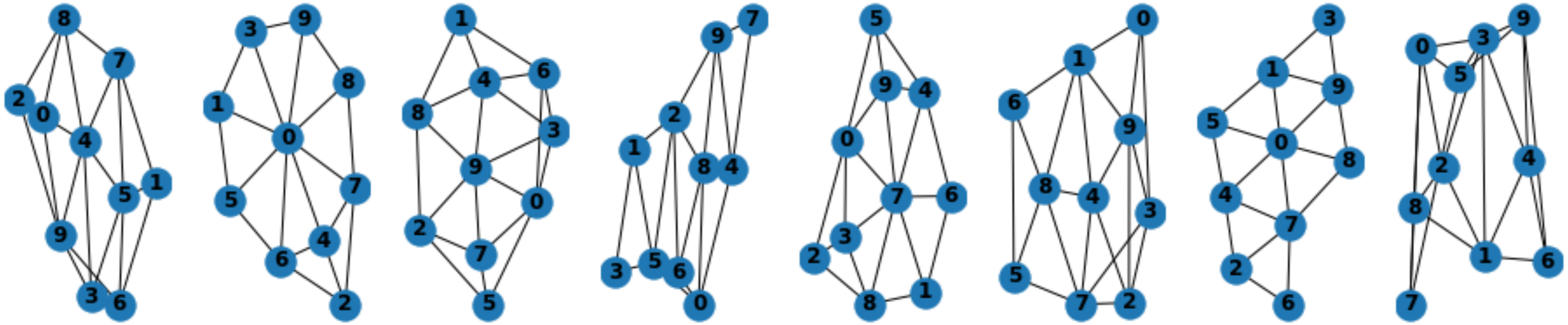
Final iteration

- Update matching matrix using Hungarian

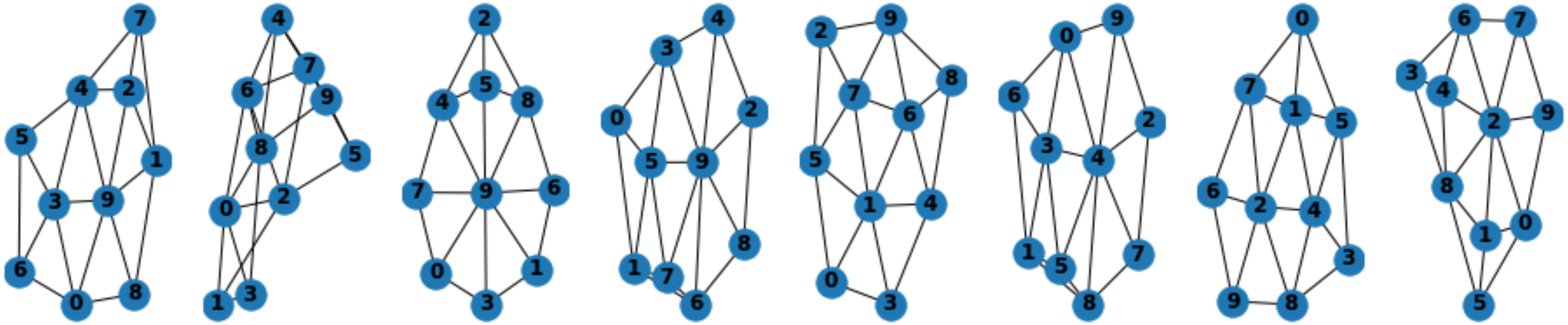
METHODOLOGY

STATUS QUO

Source Graph



Target Graph



GRAPH PERTURBATION

Insight: Graphs appear to be very similar.

Idea: Add noise to evaluate the robustness.

Approach:

- Calculate Katz-Centrality for each node
- Select node with lowest score
- Remove edges from selected node

EXPERIMENT SETUP

Dataset:

- Willow Object Dataset

Algorithms (pre-trained weights):

- Graduated Assignment - MGM
- Graduated Assignment Neural Network - MGM
- Permutation loss and Cross-graph Affinity - MGM

Hyperparameters:

- Remove 0-3 edges

RESULTS & DISCUSSION

UNPERTURBED RESULTS

Training Algorithm	F1-Score	Time (s)
GA	0.8646	**0.575278**
GANN	**0.9739**	11.566146
PCA	0.9048	1.305027

GA RESULTS

Edge Removals	F1-Score	Time (s)
0	**0.8646**	0.575278
1	0.8578	0.555186
2	0.8546	0.593917
3	0.8498	**0.542628**

GANN RESULTS

Edge Removals	F1-Score	Time (s)
0	**0.9739**	**11.566146**
1	**0.9739**	12.194371
2	**0.9739**	12.170296
3	0.9712	12.906036

PCA RESULTS

Edge Removals	F1-Score	Time (s)
0	**0.9048**	1.305027
1	0.8967	1.324514
2	0.8935	1.308162
3	0.8985	**1.296206**

FUTURE WORK

PROPOSAL

Evaluate algorithms on different datasets

Choose more sophisticated perturbation methods

- Based on embeddings
- Based on node / edge features

CONCLUSION

SUMMARY

This project evaluated the performance and robustness of state-of-the-art multi-graph matching algorithms in computer vision.

Main contributions

- Noise injection through graph perturbation
- Demonstration of GA's robustness to noisy data

QUESTIONS?