LayoutGKN: Graph Similarity Learning of Floor Plans

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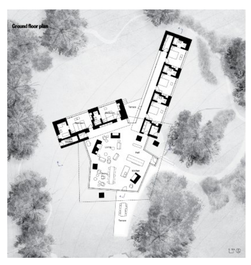
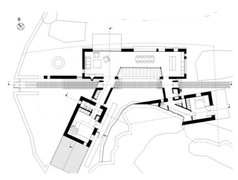
1 Challenge

The question of spatial similarity



Secular Retreat, England (Zumthor, 2018)

How similar?
How to compute?

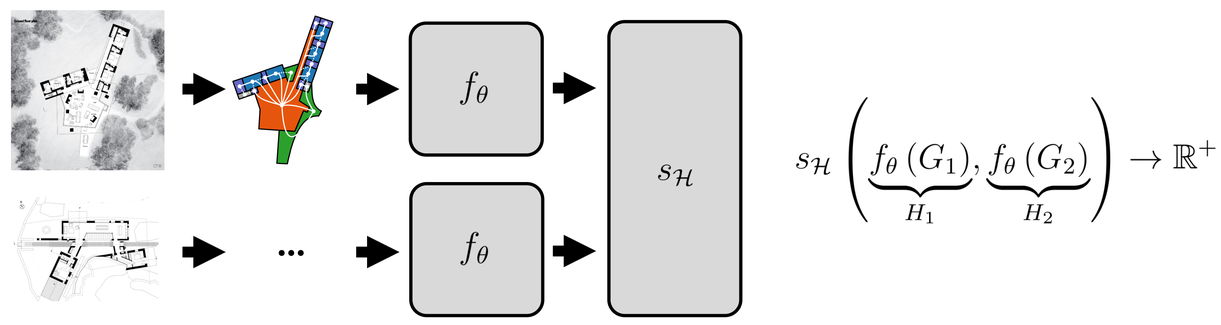


Volax House, Greece (Aristides Dallas Architects, 2016).

- The built-environment can be adequately described as a hierarchy of spatial networks: road networks, neighborhood compositions, floor plans, etc.
- Computing spatial similarity is essential to spatial machine understanding

2 Problem formulation

Spatial similarity as graph comparison problem

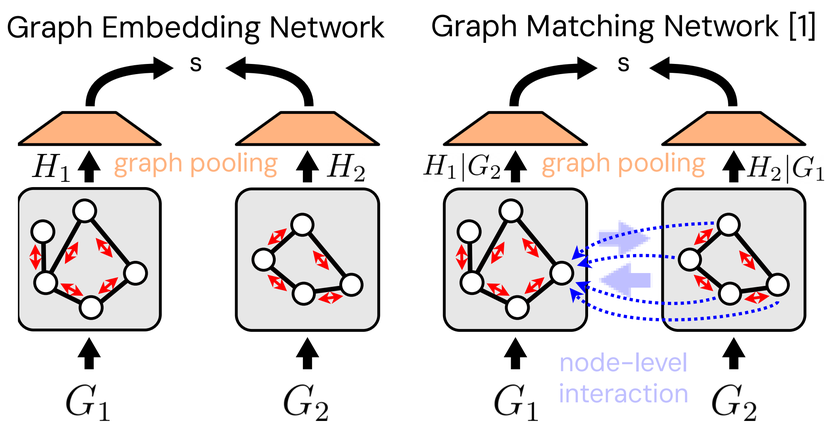


Spatial data as graphs. (Not our focus in this work. We start from the graphs!) → learn node-level embeddings → similarity between embeddings → s.t. similarities mimic a ground truth ranking

- Tackling the question of spatial similarity by casting it as a deep metric learning problem over graphs

3 Efficient or effective (gap)

Node-level interactions are computationally expensive

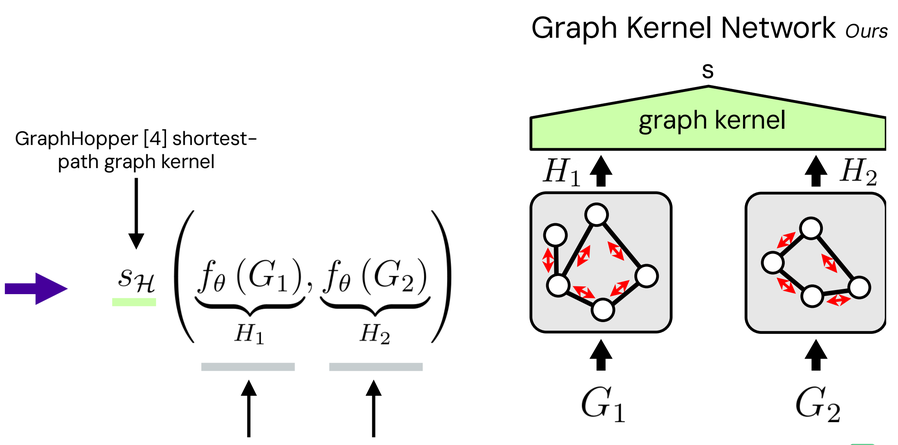


RQ
How to model node-level interactions less expensively?

- Graph Matching Networks model node-level interactions across graph-based encoders → boosts effectiveness
- Problem: node-level interactions are computationally expensive → inference is slow

4 Efficient and effective

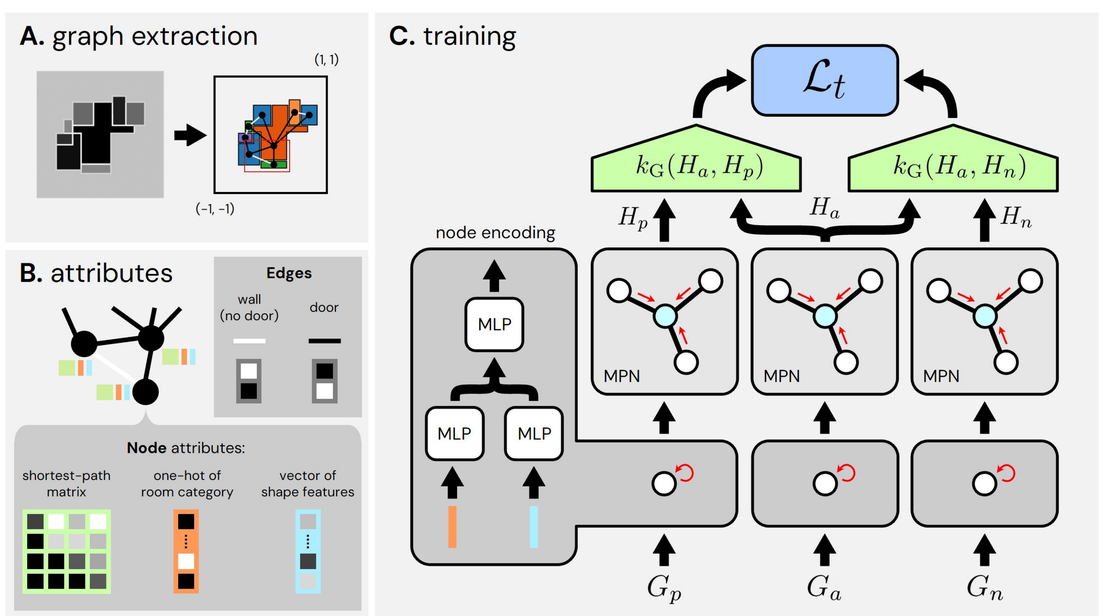
Less expensive node-level interactions



- Model node-level interactions in the similarity metric by using a (differentiable) graph kernel. This postpones interactions to the end of the pipeline → inference is fast

5 Training

Triplet network training to mimic (expensive) GED-based similarity



- Graphs contain a rich set of spatial attributes
- Specifically designed Graph Neural Network for spatial graphs
- (Hard) triplet mining using GED-based similarity

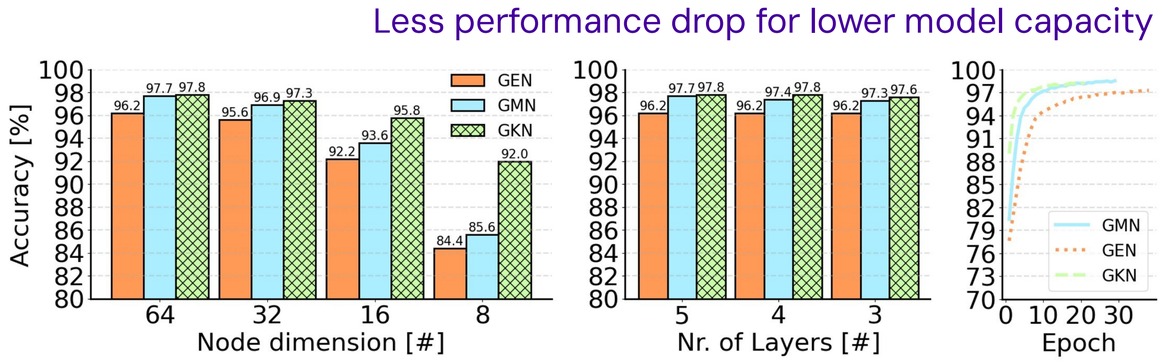
Graph edit distance (GED) [3] measures the "effort" it takes to transform one graph into the other, by adding, deleting, substituting nodes and edges. Known NP-hard problem.

6 Results

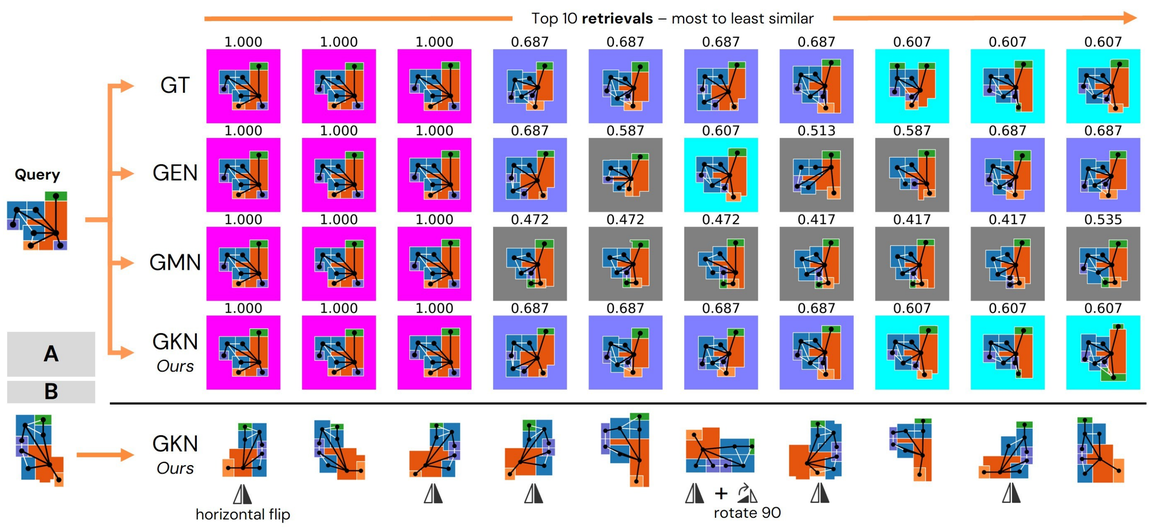
Effective yet efficient

	RPLAN				Zero-shot to MSD	
	Accuracy (↑)	P@5 (↑)	P@10 (↑)	t [s] (↓)	P@5 (↑)	P@10 (↑)
LayoutGK (*baseline*)	65.63±0.00	0.389±0.000	0.439±0.000	1.2±0.4	na	na
LayoutGEN (*baseline*)	96.24±0.07	0.603±0.007	0.665±0.004	**0.7±0.1**	0.595±0.015	0.605±0.018
LayoutGMN* CVPR'21	**97.74±0.05**	0.616±0.004	0.675±0.002	35.6±10.5	0.585±0.026	0.596±0.020
LayoutGKN (*ours*)	**97.78±0.10**	**0.623±0.004**	**0.683±0.002**	1.8±0.5	**0.674±0.024**	**0.697±0.017**

Less performance drop for lower model capacity



Retrievals (A) show better ranking and (B) are often flip, rot90 invariant



7 References

[1] Yujia Li, Chenjie Gu, Thomas Dullien, Oriol Vinyals & Pushmeet Kohli. Graph Matching Networks for Learning the Similarity of Graph Structured Objects. In ICML, 2019. [→GMN]
[2] Akshay Gadi Patil, Manyi Li, Matthew Fisher, ManolisSavva & Hao Zhang. LayoutGMN: Neural Graph Matching for Structural Layout Similarity. In CVPR, 2021. [→LayoutGMN]
[3] Alberto Sanfeliu & King-Sun Fu. A Distance Measure Between Attributed Relational Graphs for Pattern Recognition. In IEEE Trans. on Systems, Man, and Cybernetics, 1983. [→GED]
[4] Aasa Feragen, Niklas Kasenburg, Jens Petersen, Marleende Bruijne & Karsten Borgwardt. Scalable Kernels for Graphs with Continuous Attributes. In NIPS, 2013. [→GraphHopper]