Geometry-Aware Edge Pooling for Graph Neural Networks

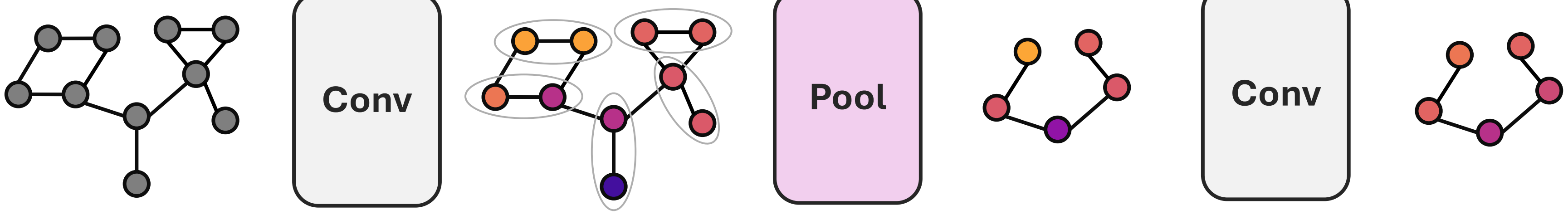
Katharina Limbeck[†], Lydia Mezrag[†], Guy Wolf[‡], Bastian Rieck[‡]

Paper

Code

Why graph pooling?

Hierarchical Graph Pooling



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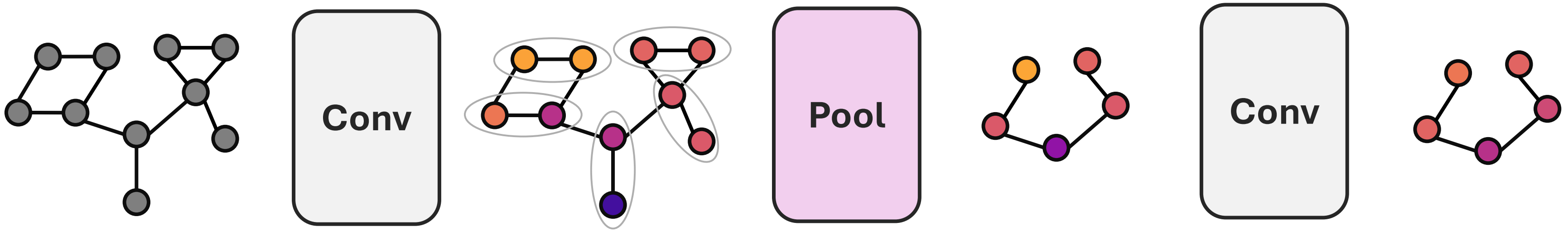

Aim to preserve:

Graph structure and topology	Task performance
Computational efficiency	Expressivity

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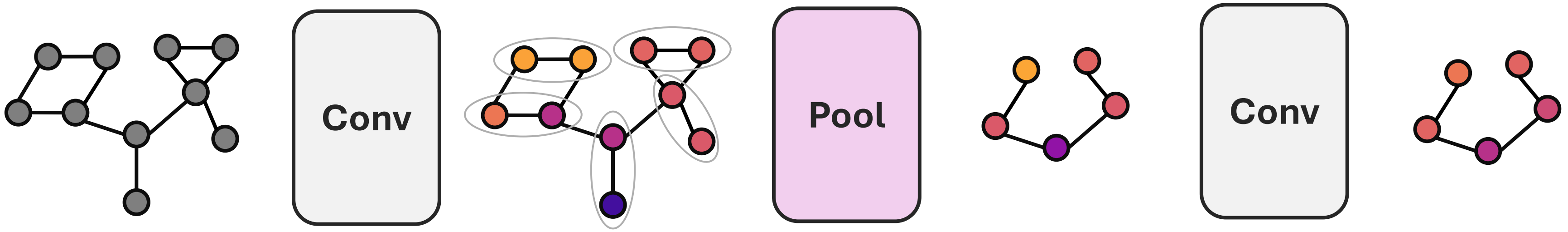

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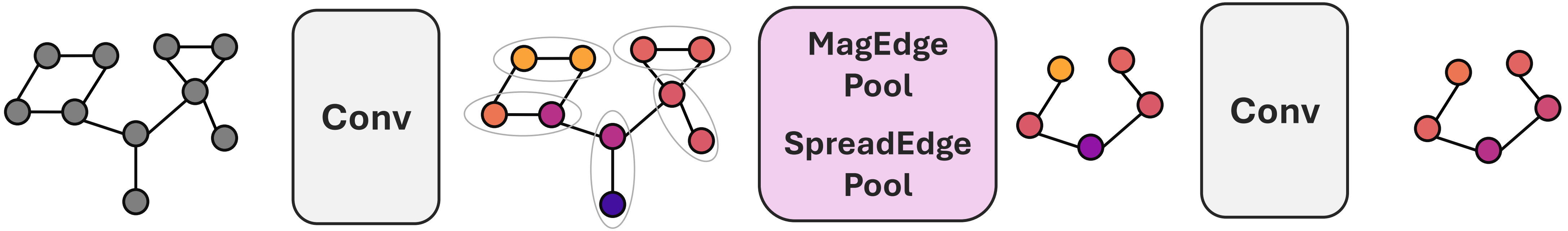
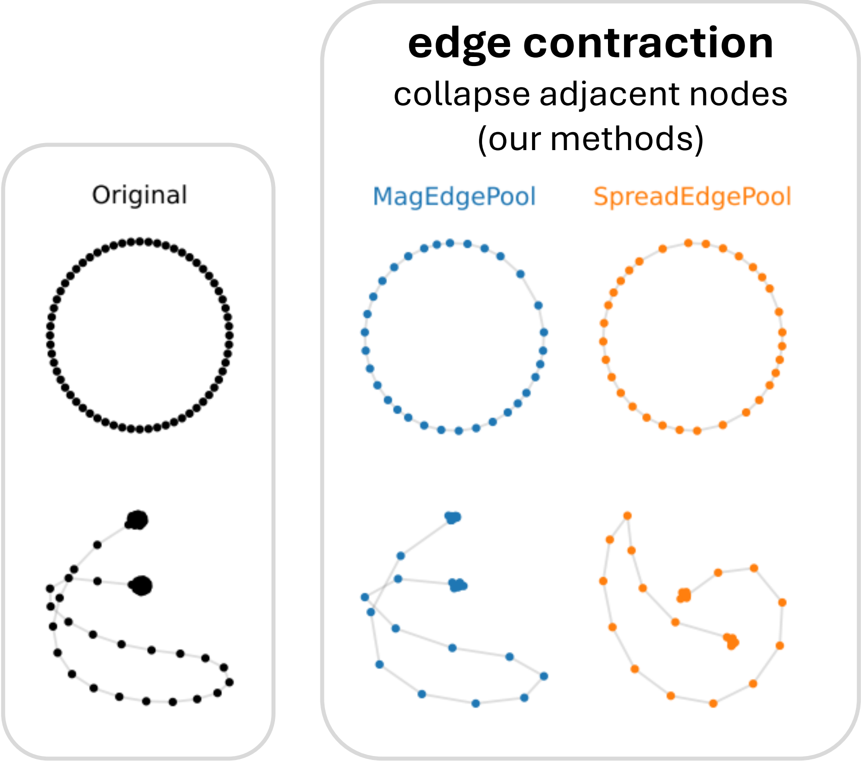
Addressing these goals, we propose novel geometry-aware edge contraction-based pooling methods, **MagEdgePool and SpreadEdgePool.**


Conv
MagEdge
Pool
SpreadEdge
Pool
Conv

Why do we need geometry-aware graph pooling?

Examples of pooled graphs. Our methods **respect the original graphs' geometry**.



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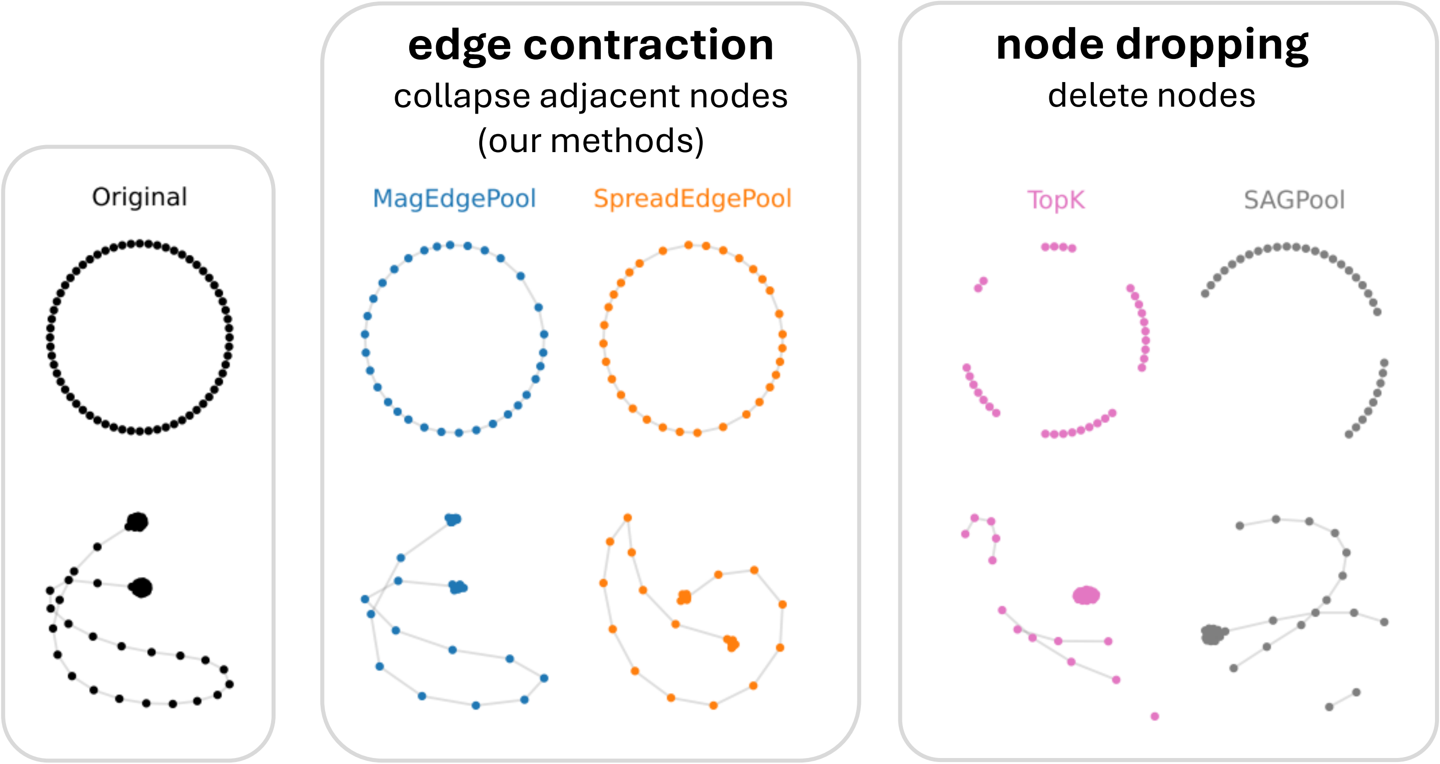

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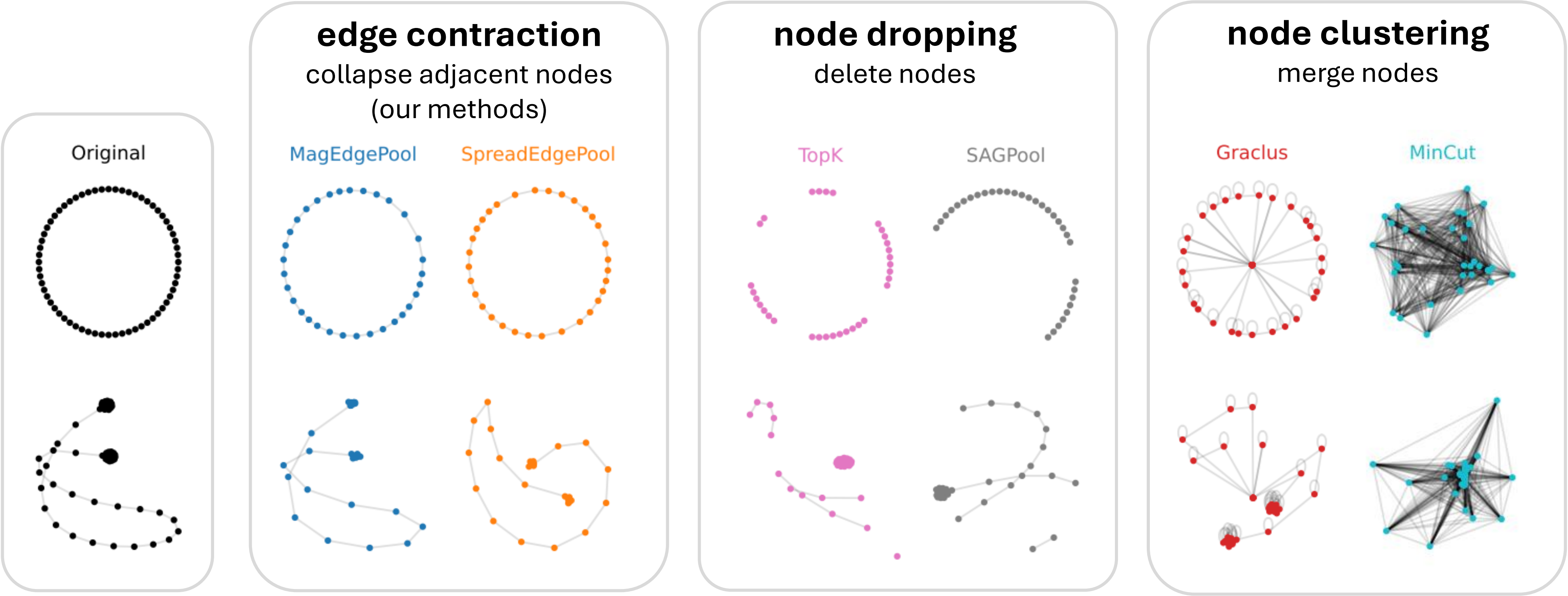
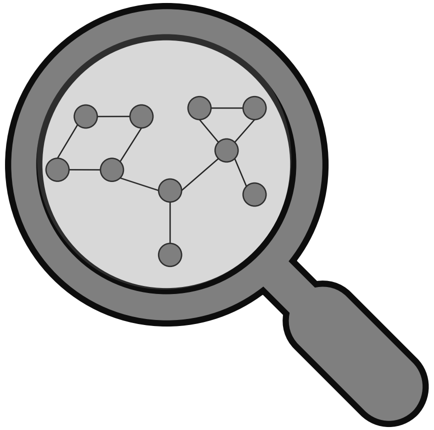


Geometry-aware edge pooling

Contract the edges least relevant for the graph’s structural diversity.



structural diversity ≈
magnitude ≈ spread

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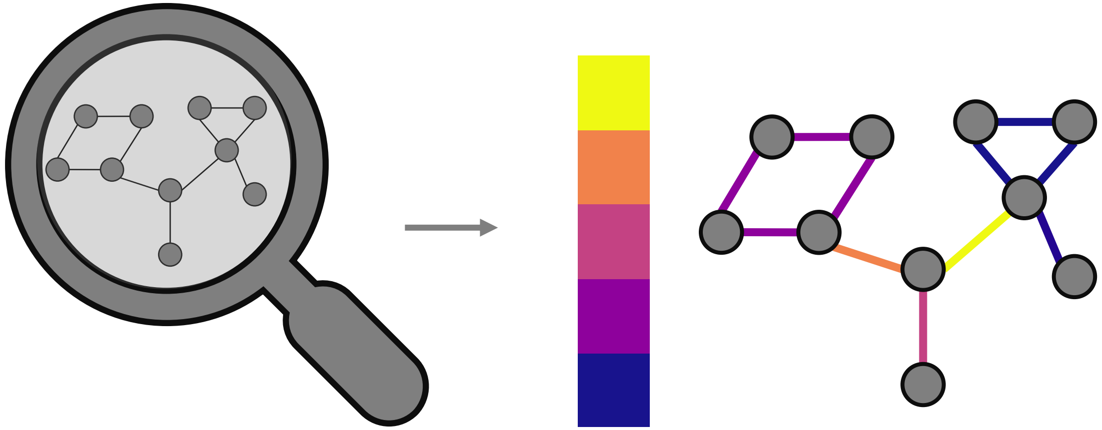

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edge importance
for the graph structure

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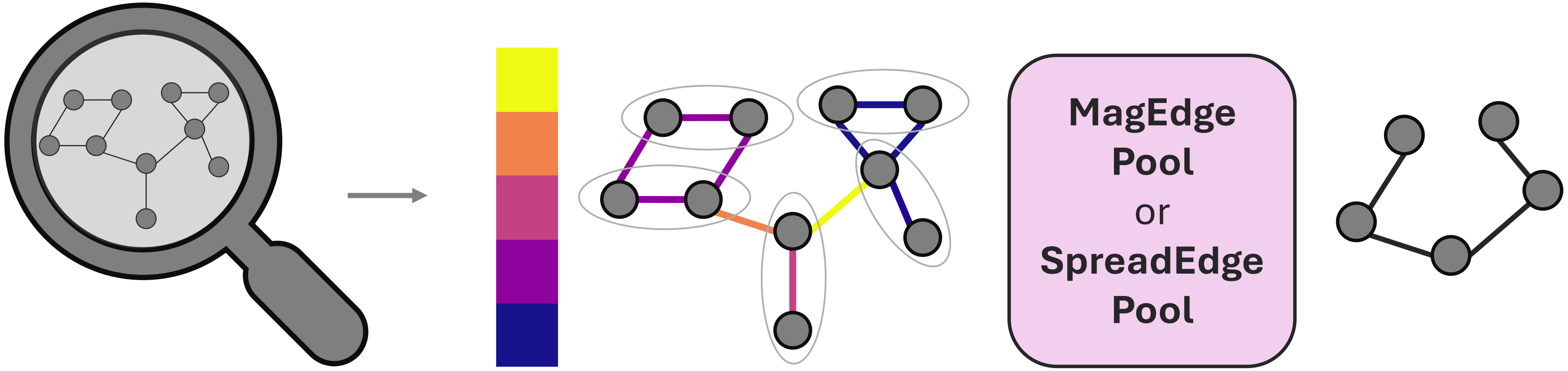

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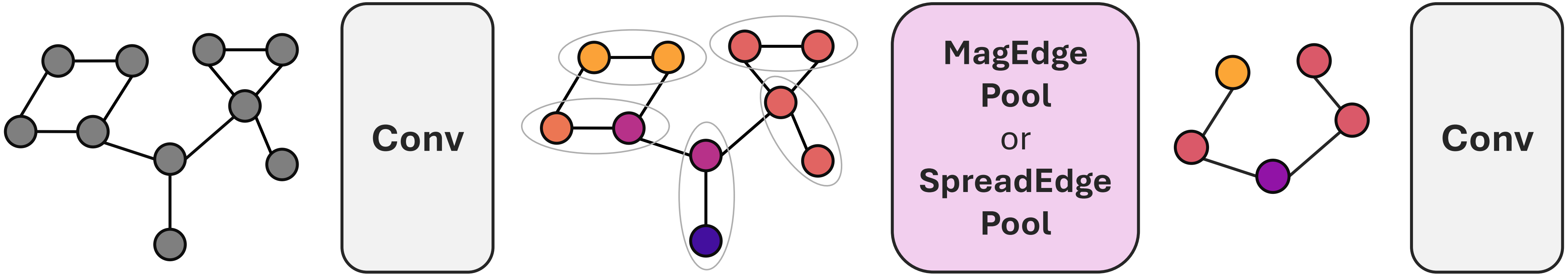
Geometry-aware edge pooling

During GNN training, use the edge selection and average the node features.



Evaluation

It works! Our pooling methods perform well across tasks.

Top graph classification and regression **performance**

Method	Mean Rank
MagEdge	**2.4**
SpreadEdge	**3.0**
NDP	3.6
Graclus	5.6
NMF	6.0
TopK	4.9
SAGPool	4.7
DiffPool	7.6
MinCut	7.4

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Robust performance
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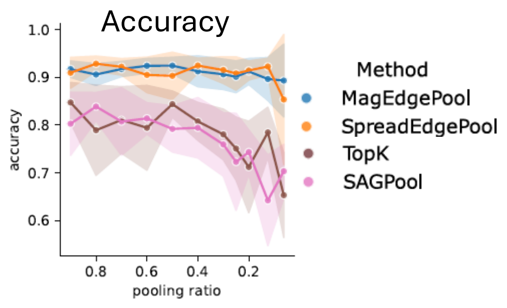

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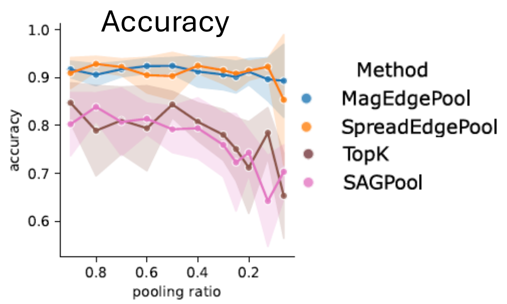
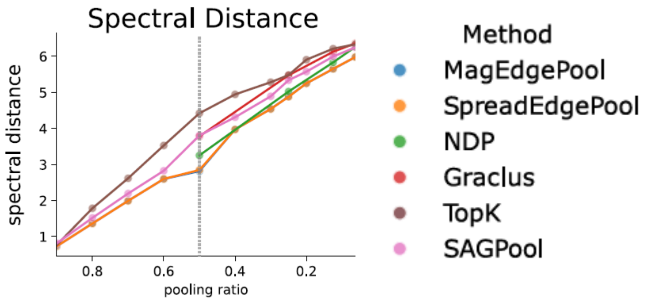


Superior **preservation of graph structure**



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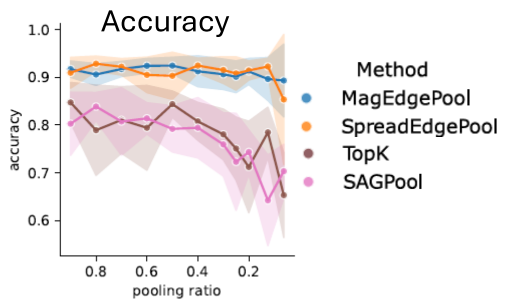

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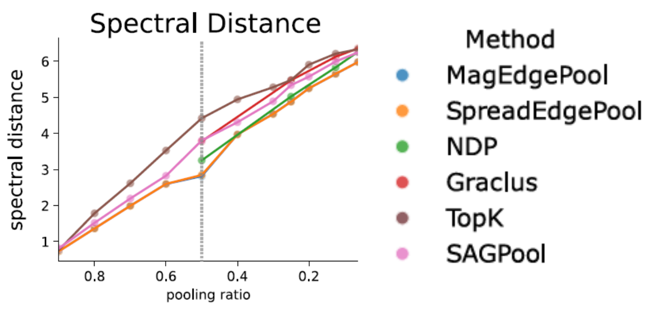

More **efficient GNN training** compared to trainable methods

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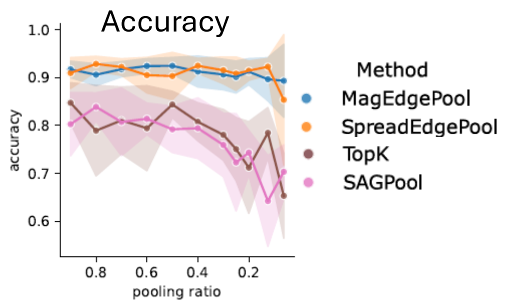

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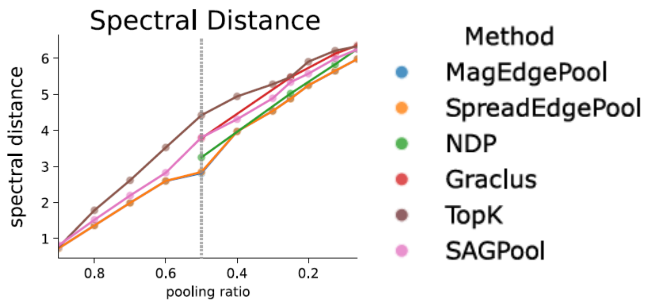


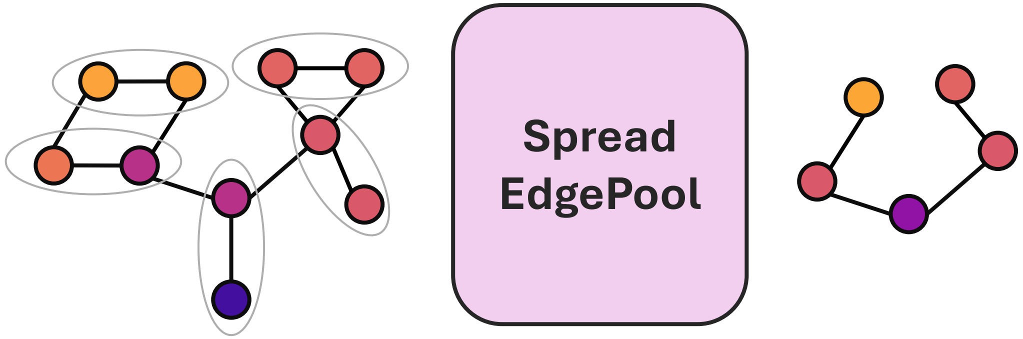
More **efficient GNN training** compared to trainable methods

Theoretical guarantees:

Expressivity, isometry-invariance, etc.

Geometry-aware edge pooling

We propose **novel edge contraction based pooling methods** that preserve graphs' structural diversity and geometry.



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