

Edge-Based Graph Component Pooling

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Motivation

Message-passing propagates features to local neighbourhoods
 But **costly** for large and sparse graphs
 Pooling improves efficiency by changing the graph structure
 Improves connectivity by reducing the longest path
 Crucial when handling large, sparsely connected graphs
 Two categories: Node drop pooling and cluster pooling

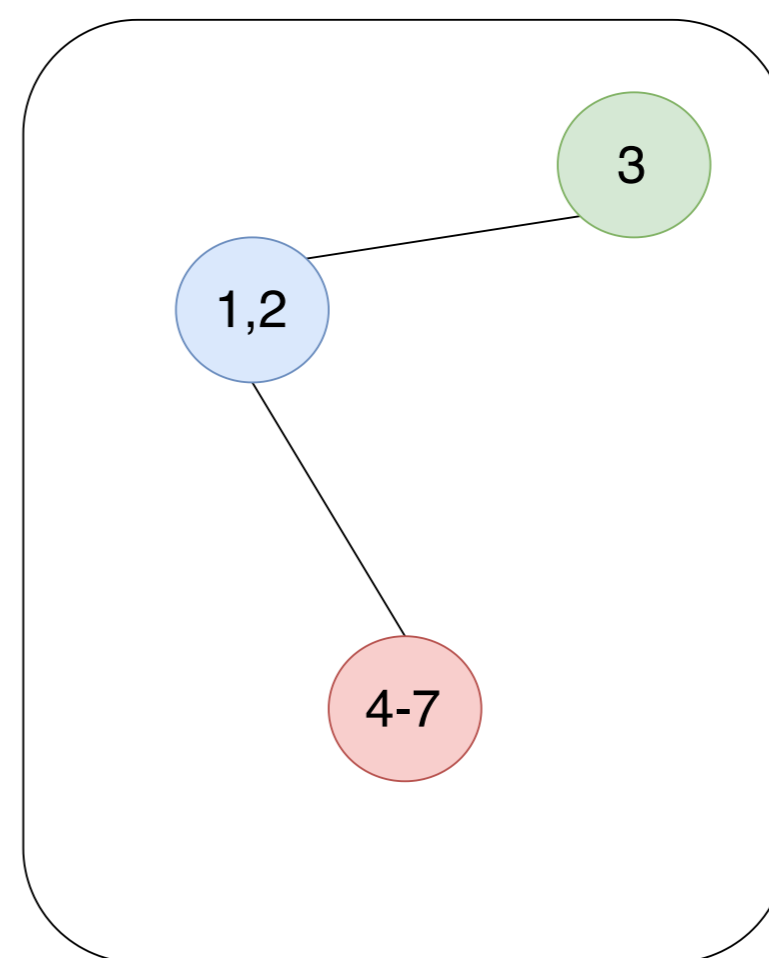
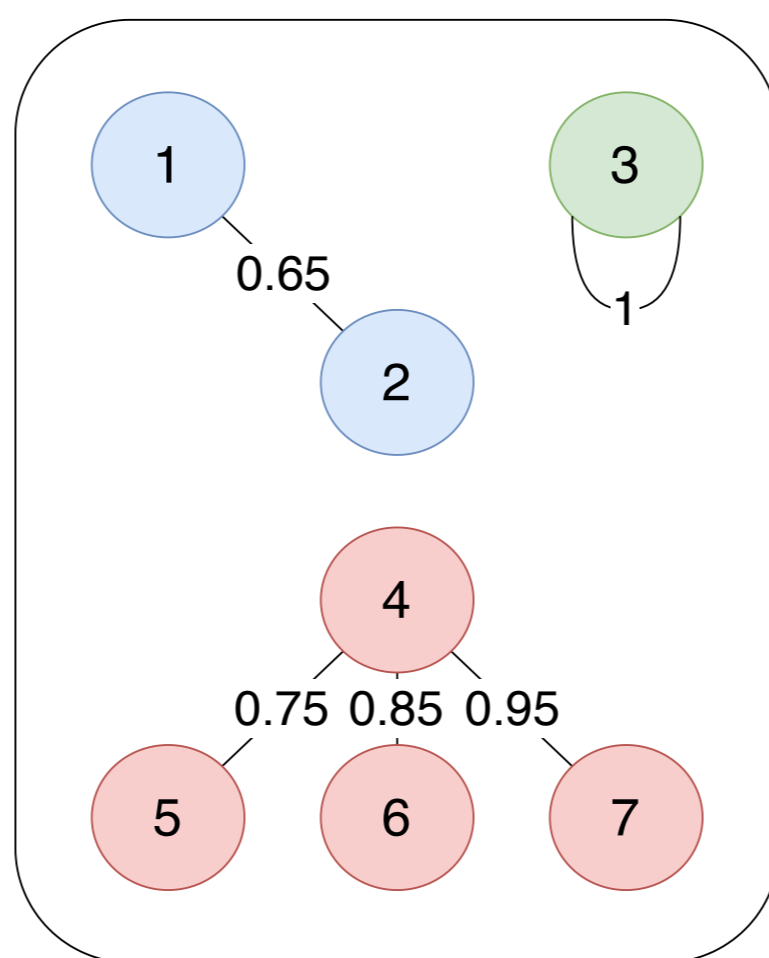
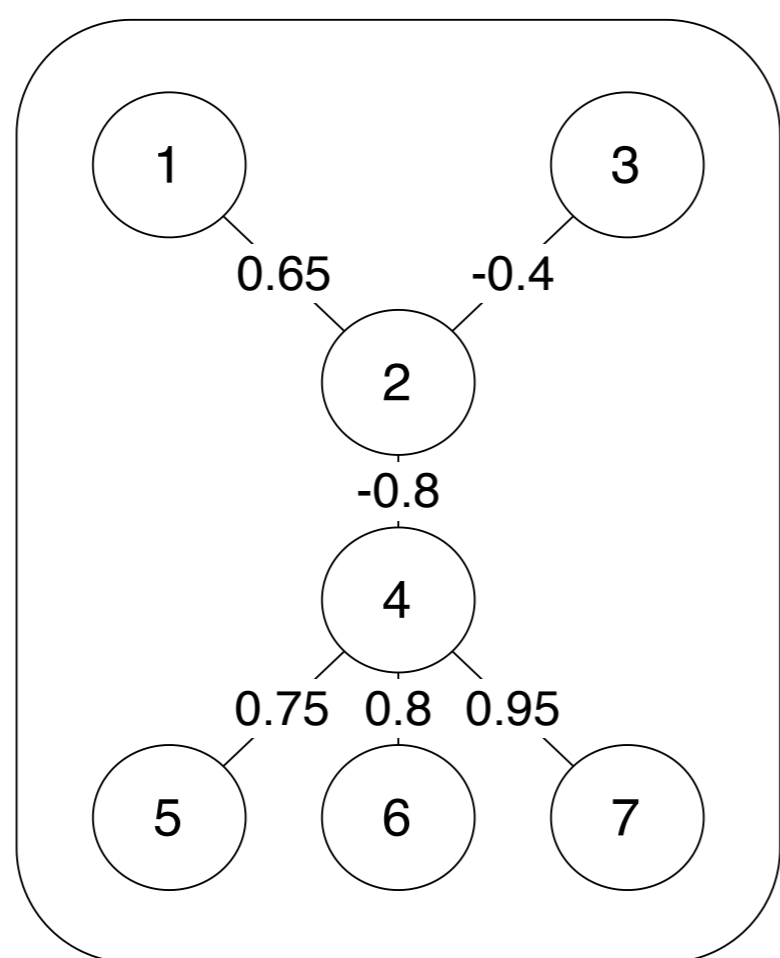
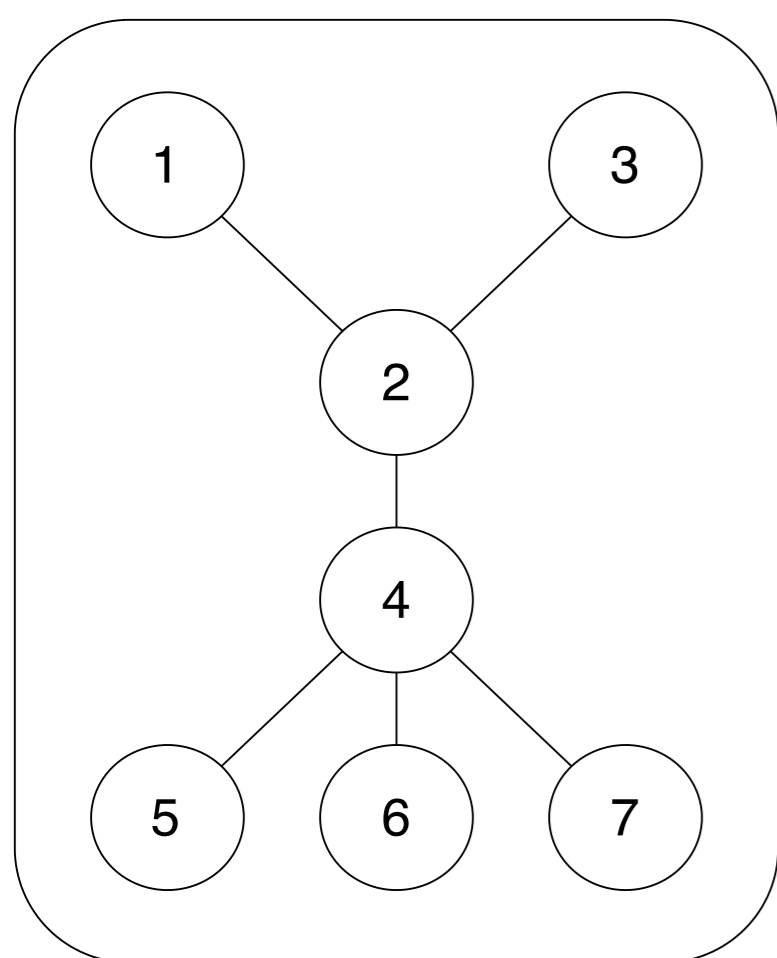
Contributions

We propose an improved pooling method by Diehl et al. (2019):

Hard constraints removal: # nodes merged, # nodes per cluster
 Reduced **complexity**: from $\mathcal{O}(n^2 \cdot \log(n))$ to $\mathcal{O}(n^2)$
 Improved accuracy in seven benchmarks
 Efficient implementation
 Bridges the gap between drop pooling and cluster pooling
 Comparable performance to message-passing GNN

Cluster Assignment Matrix C and weights W

Coarsen

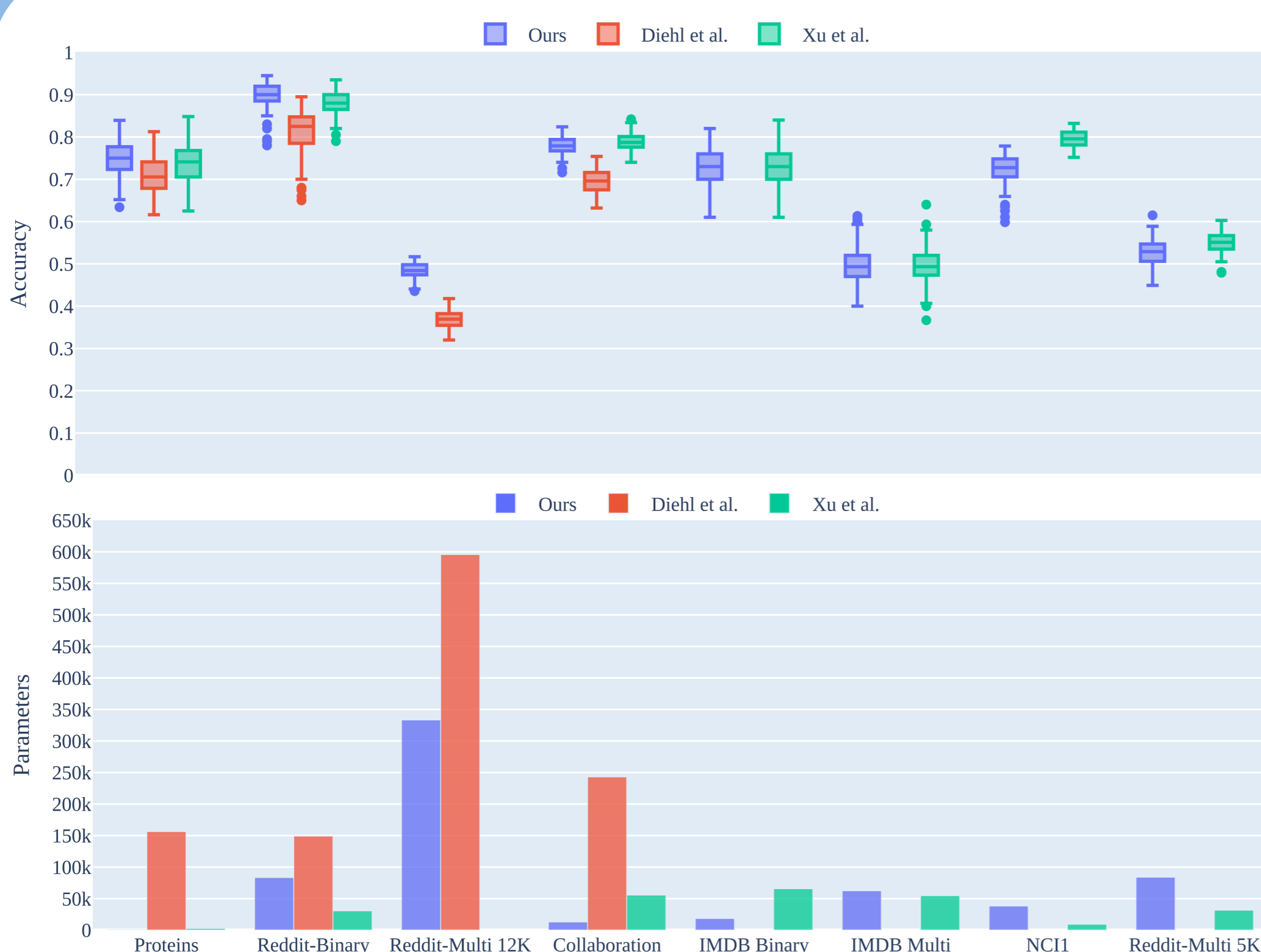


$$W_{ij} = S_{ij} \text{ if } S_{ij} > t$$

$$W_{ij} = 1 \text{ if } i = j \text{ and not merging } i$$

$$W_{ij} = 0 \text{ otherwise}$$

$$S_{ij} = \sigma(\psi(x_i, x_j) + b)$$



Results

Compared to Diehl et al. (2019):

Significantly outperforms Diehl et al. (2019) in terms of accuracy and learnable parameters

Compared to Xu et al. (2019):

Higher accuracy on **two**, outperformed on **three** benchmarks
 Smaller model in three cases, but larger in four of which three very substantially larger

Concluding

- Efficient, maximally expressive, information retaining method
- Significant increase of accuracy and reduction of learnable parameters compared to the original method
- Competes with MP GNN, but is outperformed in several benchmarks in terms of accuracy and model size

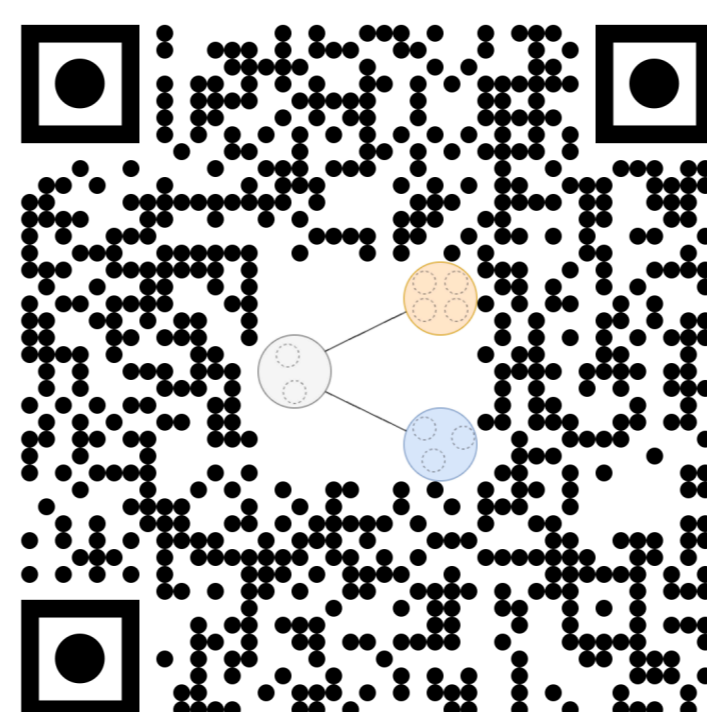


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