

Are Graph Transformers Necessary? Efficient Long-Range Message Passing with Fractal Nodes in MPNNs



Jeongwan Choi¹, Seungjun Park¹, Sumin Park¹, Sung-Bae Cho², Noseong Park¹

¹Korea Advanced Institute of Science & Technology ²Yonsei University

Fractal Nodes: Long-Range Message Passing Without Graph Transformers!

Mitigating **over-squashing** and enabling long-range interactions at MPNN efficiency.



Motivation: Limitations of MPNNs and Graph Transformers

Table: Comparison of GNN Approaches

Method	Long-Range	Efficiency	Locality
MPNN	✗	$\mathcal{O}(\mathcal{E})$	✓
Graph Transformer	✓	$\mathcal{O}(\mathcal{V} ^2)$	✗
MPNN + Fractal Nodes	✓	$\mathcal{O}(\mathcal{E})$	✓

Key Question: Can we enhance long-range message passing while preserving MPNN efficiency?

Our Answer: Yes! Graph partitioning induces **fractal structure** that enables long-range interactions.

Main Idea: Fractal Nodes Architecture

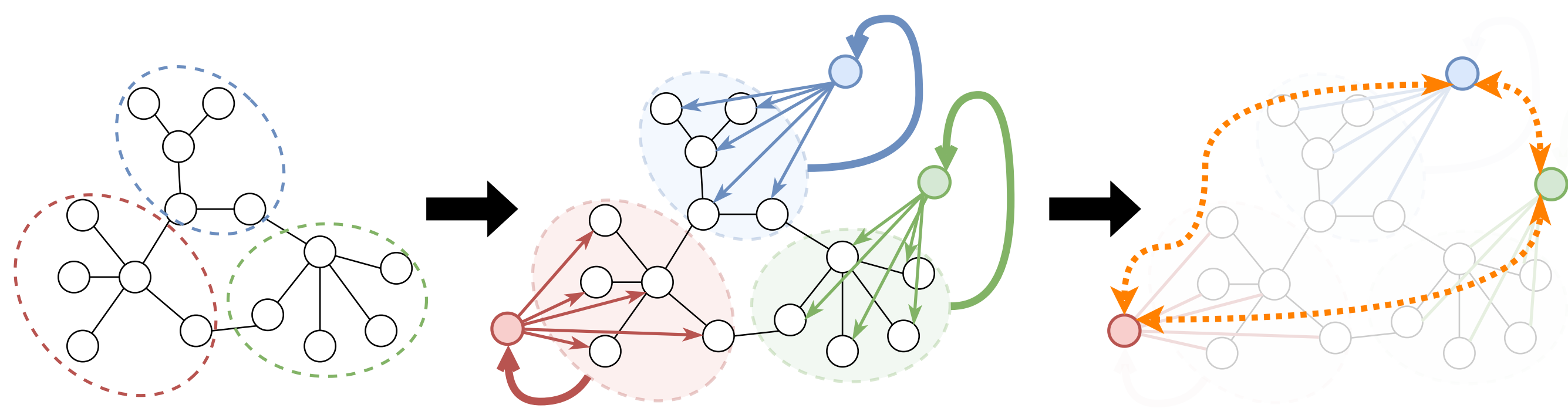


Figure: *Fractal nodes* (●, ●, ●) coexist with original nodes, aggregate subgraph-level features, and enable long-range interactions via MLP-Mixer (orange dashed lines).

Method: Message Passing with Fractal Nodes

Three-step update process:

$$\tilde{h}_{v,c}^{(\ell+1)} = \varphi^{(\ell)}(h_{v,c}^{(\ell)}, \psi^{(\ell)}(\{h_{u,c}^{(\ell)} : u \in \mathcal{N}_v\})) \quad (\text{Node update}) \quad (1)$$

$$f_c^{(\ell+1)} = \underbrace{\text{LPF}(\{h_{v,c}^{(\ell)}\})}_{\text{Sub-global}} + \omega_c^{(\ell)} \cdot \underbrace{\text{HPF}(\{h_{v,c}^{(\ell)}\})}_{\text{Local}} \quad (\text{Fractal node}) \quad (2)$$

$$h_{v,c}^{(\ell+1)} = \tilde{\varphi}^{(\ell)}(\tilde{h}_{v,c}^{(\ell+1)}, f_c^{(\ell+1)}) \quad (\text{Final update}) \quad (3)$$

Key Insight: Mean pooling captures only the **DC component** (0-th Fourier basis, i.e., constant/average). Our fractal nodes capture richer **subgraph-level** frequency information:

- ▶ $\text{LPF} = \frac{1}{|\mathcal{V}_c|} \sum_{v \in \mathcal{V}_c} h_v$: DC component (sub-global mean)
 - ▶ $\text{HPF} = h_v - \text{LPF}$: Higher-freq components (deviation from mean)
 - ▶ $\omega_c^{(\ell)}$: Learnable weight balancing low + high freq
- ⇒ FN: fractal nodes only.
⇒ FN_M : + MLP-Mixer for inter-subgraph interaction.

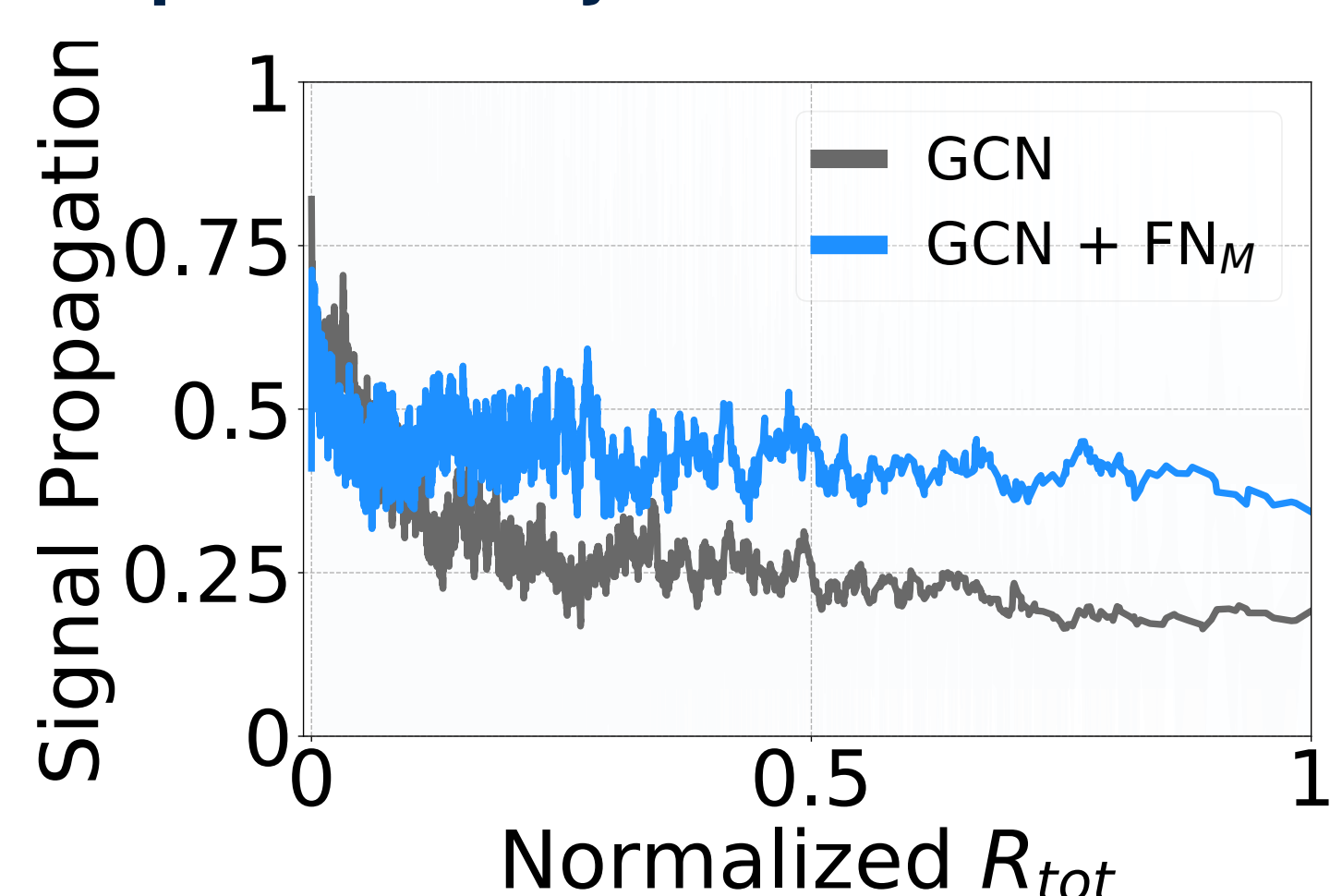
Theoretical Analysis: Over-squashing Mitigation

Over-squashing: information from distant nodes compressed into fixed-size vectors. Fractal nodes mitigate this by reducing **effective resistance**.

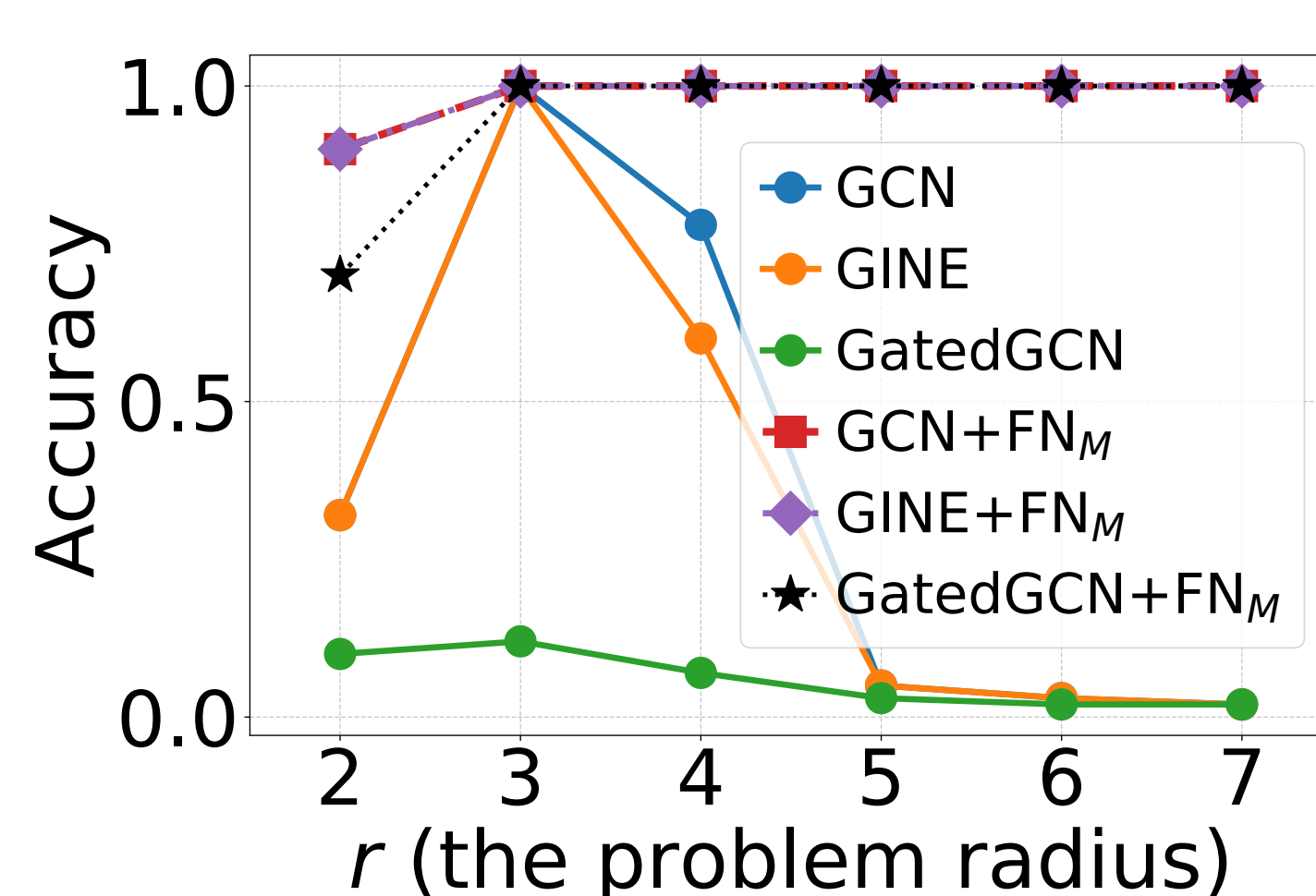
Theorem 1: For augmented graph $\mathcal{G}_f$ with fractal nodes: $R_f(u, v) \leq R(u, v)$
→ Adding fractal nodes creates shortcuts that **lower effective resistance** between nodes.

Theorem 2: After ℓ layers: $\|h_u^{(\ell)} - h_v^{(\ell)}\| \leq \exp(-\ell/R_f(u, v)) \|h_u^{(0)} - h_v^{(0)}\|$
→ Lower resistance enables **faster signal propagation** between distant node pairs.

Empirical Analysis:



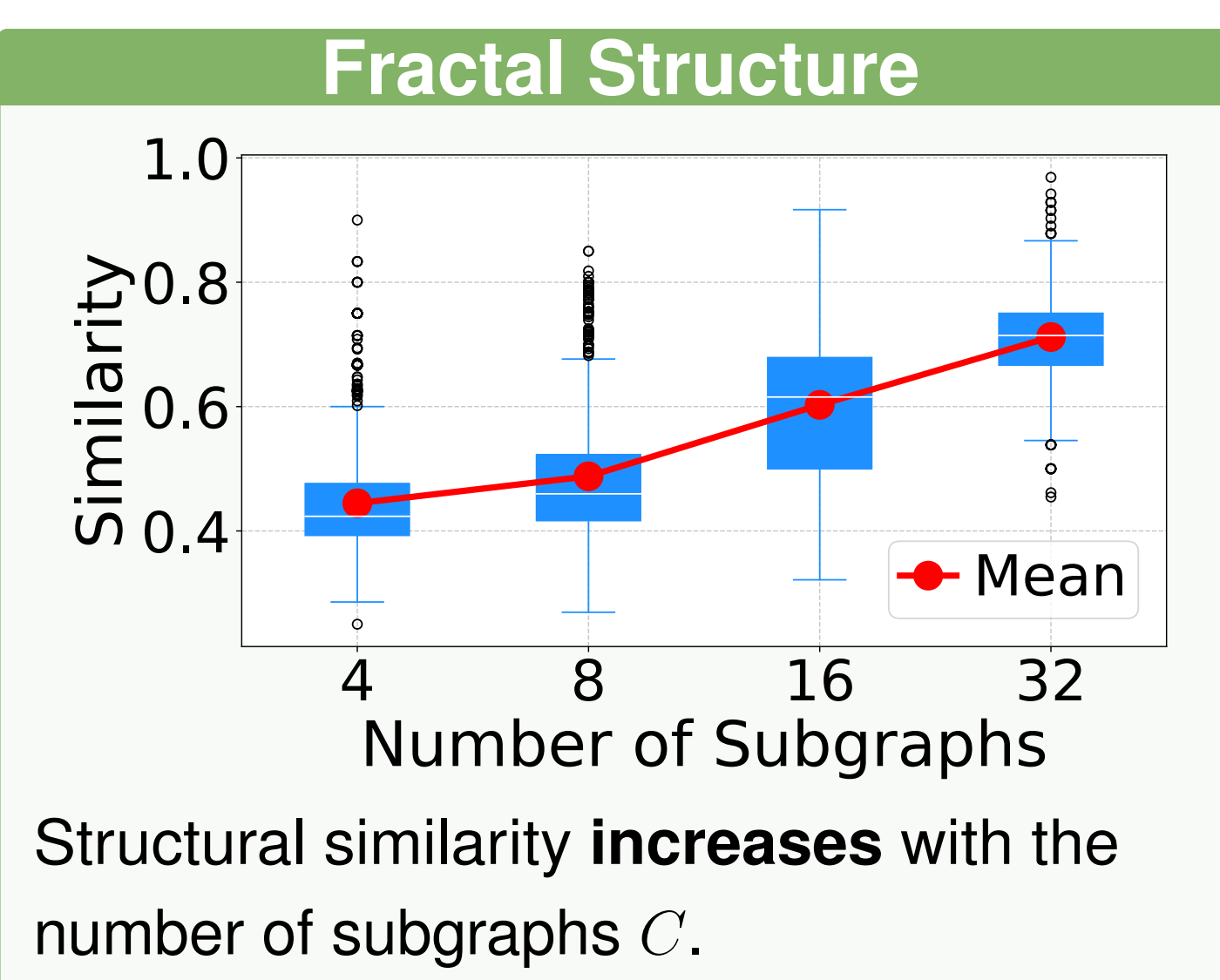
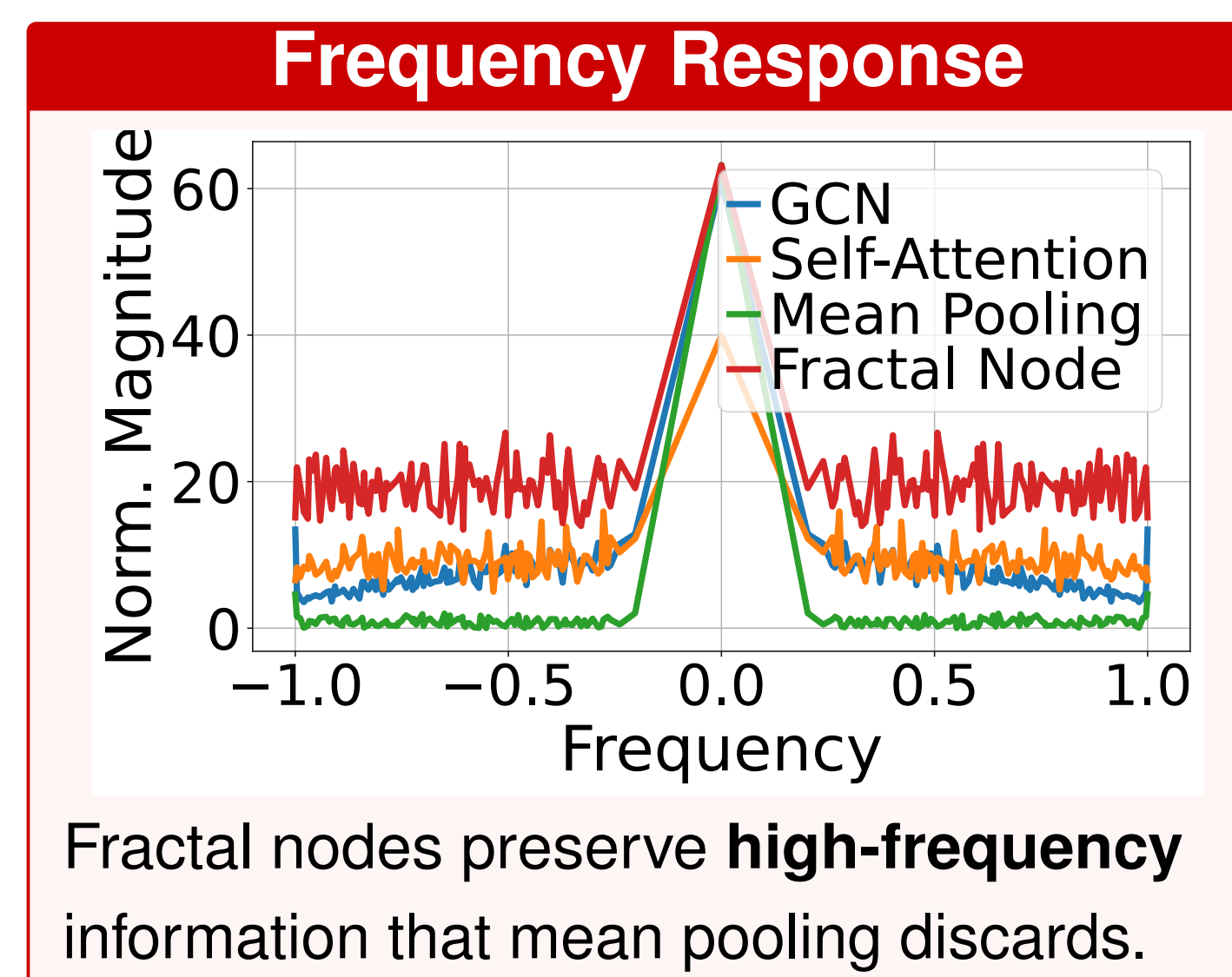
(a) Signal propagation on PEPTIDES-FUNC



(b) TreeNeighbourMatch accuracy

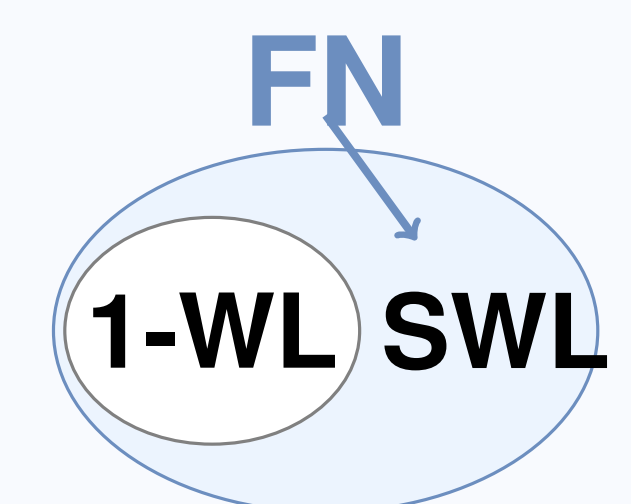
Figure: (a) GCN+ FN_M maintains higher signal flow. (b) MPNNs fail for $r > 3$.

Properties of Fractal Nodes



Expressive Power: Beyond 1-WL Test

Method	CSL	SR25	EXP
GCN	10.00	6.67	52.17
GINE	10.00	6.67	51.35
GatedGCN	10.00	6.67	51.25
GCN + FN_M	39.67	100.0	86.40
GINE + FN_M	47.33	100.0	95.58
GatedGCN + FN_M	49.67	100.0	96.50



100% on SR25!
(MPNNs: 6.67%)

⇒ Standard MPNNs **fail** on graphs indistinguishable by 1-3 WL tests!

Experimental Results: Graph-Level Benchmarks

Table: Performance comparison on 6 benchmark datasets

Method	PEP-FUNC	PEP-STRUCT	MNIST	CIFAR10	MOLHIV	MOLTox21
	AP ↑	MAE ↓	Acc ↑	Acc ↑	ROC ↑	ROC ↑
GCN	0.6328	0.2758	0.9269	0.5423	0.7529	0.7525
GINE	0.6405	0.2780	0.9705	0.6131	0.7885	0.7730
GatedGCN	0.6300	0.2778	0.9776	0.6628	0.7874	0.7641
GraphGPS	0.6534	0.2509	0.9805	0.7230	0.7880	0.7570
GRIT	0.6988	0.2460	0.9811	0.7647	-	-
Graph-ViT	0.6970	0.2449	0.9846	0.7158	0.7997	0.7910
Expformer	0.6527	0.2481	0.9841	0.7469	-	-
GECO	0.6975	0.2464	-	-	0.7980	-
GNN-AK+	0.6480	0.2736	-	0.7219	0.7961	-
CRaWI	0.6963	0.2506	0.9794	0.6901	0.7707	-
GCN + FN_M	0.6787	0.2464	0.9455	0.6413	0.7866	0.7882
GINE+FN_M	0.7018	0.2446	0.9786	0.6672	0.8127	0.7926
GatedGCN+FN_M	0.6950	0.2453	0.9848	0.7526	0.8097	0.7922

⇒ Fractal nodes outperform Graph Transformers and Subgraph-based methods!

Large-Scale Node Classification & Efficiency

Table: Results on large-scale graphs (%)

Method	ogbn-arxiv	ogbn-products
GraphGPS	70.97	OOM
Expformer	72.44	OOM
GCN	71.74	75.64
GCN + FN	73.03	81.29
GraphSAGE + FN_M	72.54	83.11

Table: Runtime & Memory (ogbn-arxiv)

Method	Time (s)	Mem (GB)
GCN	1.27	16.49
GraphGPS	1.32	38.91
Expformer	0.74	34.04
GCN + FN	1.27	16.49
GCN + FN_M	1.27	16.49

⇒ Graph Transformers **fail to scale** (OOM), while Fractal Nodes maintain **zero overhead**!

Comparison with Graph Rewiring Methods & Virtual Nodes

Method	PEP-FUNC	PEP-STRUCT
	AP ↑	MAE ↓
GCN	0.5930±0.0023	0.3496±0.0013
+ FoSR	0.5947±0.0035	0.3473±0.0007
+ SDRF	0.5947±0.0126	0.3478±0.0013
+ BORF	0.5994±0.0037	0.3514±0.0009
+ PANDA	0.6028±0.0031	0.3272±0.0001
+ LASER	0.6440±0.0010	0.3043±0.0019
+ FN	0.6445±0.0057	0.2535±0.0012

Table: GCN + Rewiring methods

Method	PEP-FUNC	PEP-STRUCT
	AP ↑	MAE ↓
GCN + VN	0.6455±0.0060	0.2745±0.0015
GINE + VN	0.6575±0.0080	0.2683±0.0020
GatedGCN + VN	0.6823±0.0075	0.2475±0.0012
GatedGCN + VN_G	0.6822±0.0077	0.2458±0.0017
GCN + FN_M	0.6787±0.0048	0.2464±0.0014
GINE + FN_M	0.7018±0.0074	0.2446±0.0018

Table: Virtual Node methods

⇒ Fractal nodes outperform both graph rewiring and virtual node approaches!