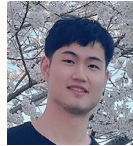


# Tree Decomposed Graph Neural Network

**Yu Wang**



**Tyler Derr**



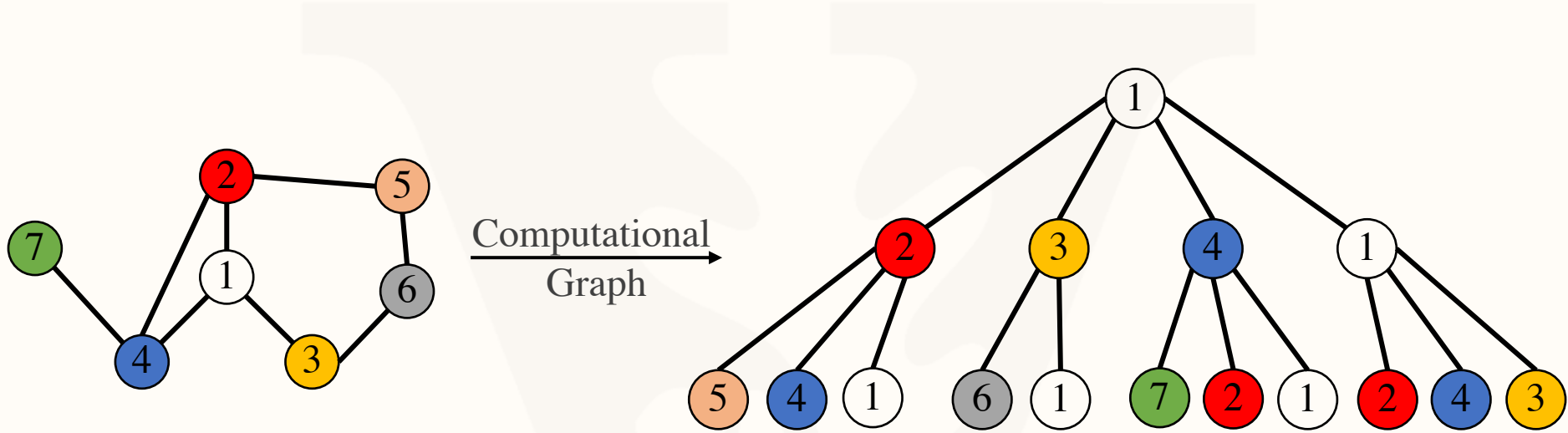
Network and Data Science Lab  
Department of Computer Science

Vanderbilt University

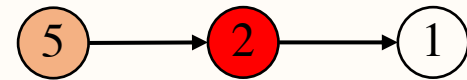
[yu.wang.1@Vanderbilt.edu](mailto:yu.wang.1@Vanderbilt.edu)  
<https://yuwvandy.github.io/>

# Motivation – Tree Decomposition

## Iterative propagation framework



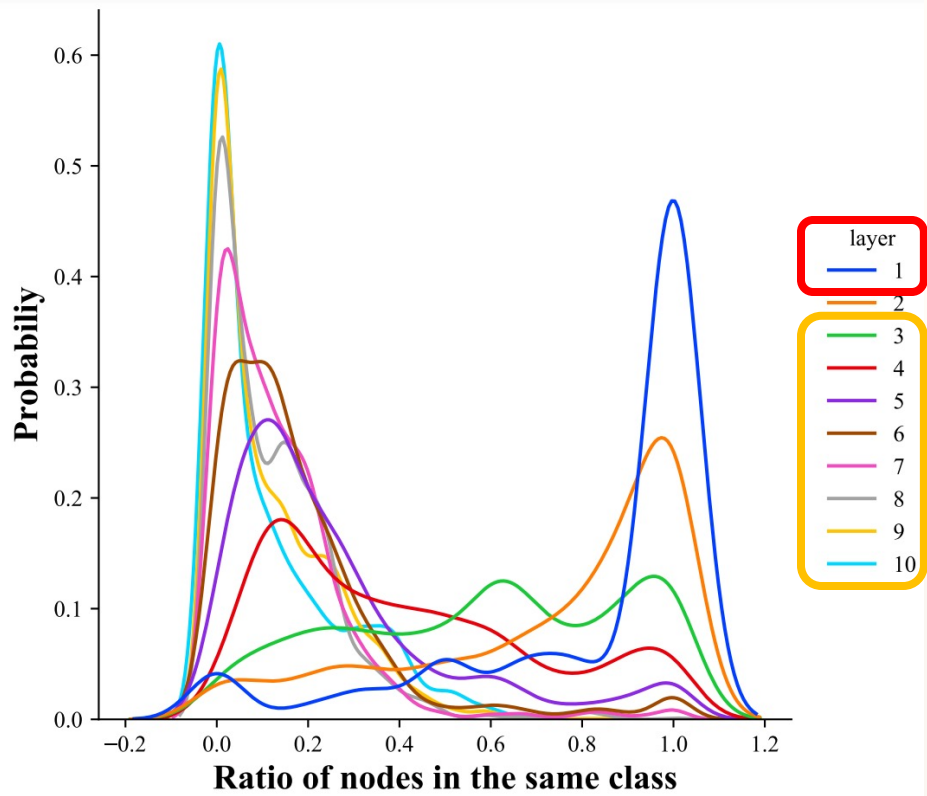
$$\hat{\mathbf{h}}_i^l = \text{AGGREGATION}^l(\mathbf{h}_i^{l-1}, \{\mathbf{h}_j^{l-1} | j \in \mathcal{N}_i\}),$$



Feature smoothing between different layers!

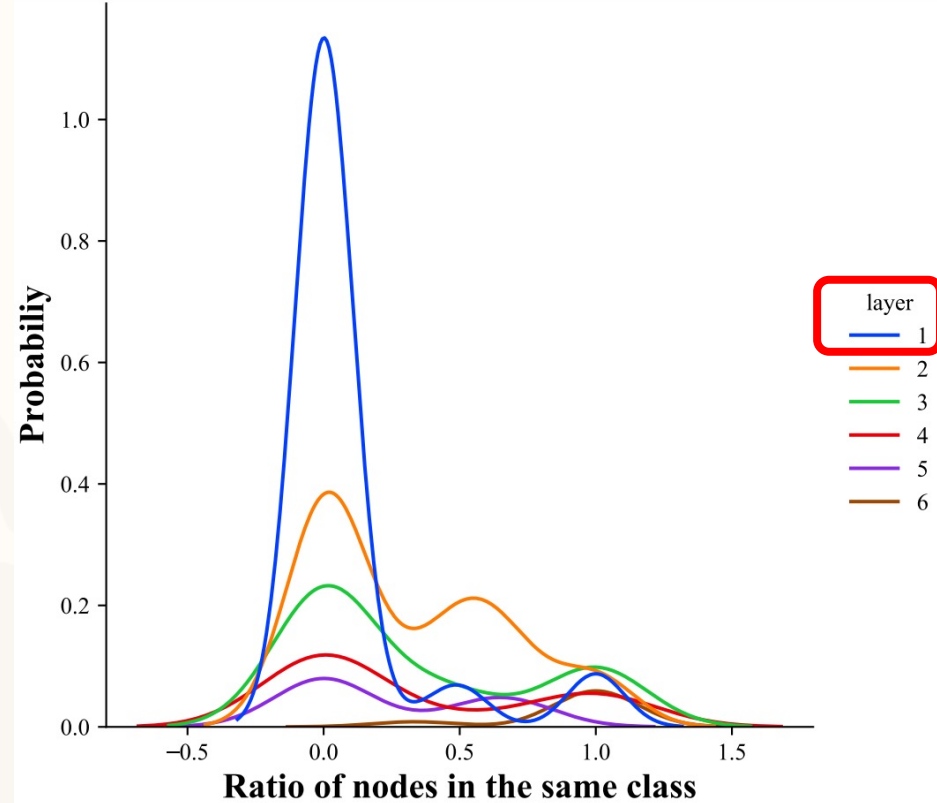
# Motivation – Tree Decomposition

## Cora



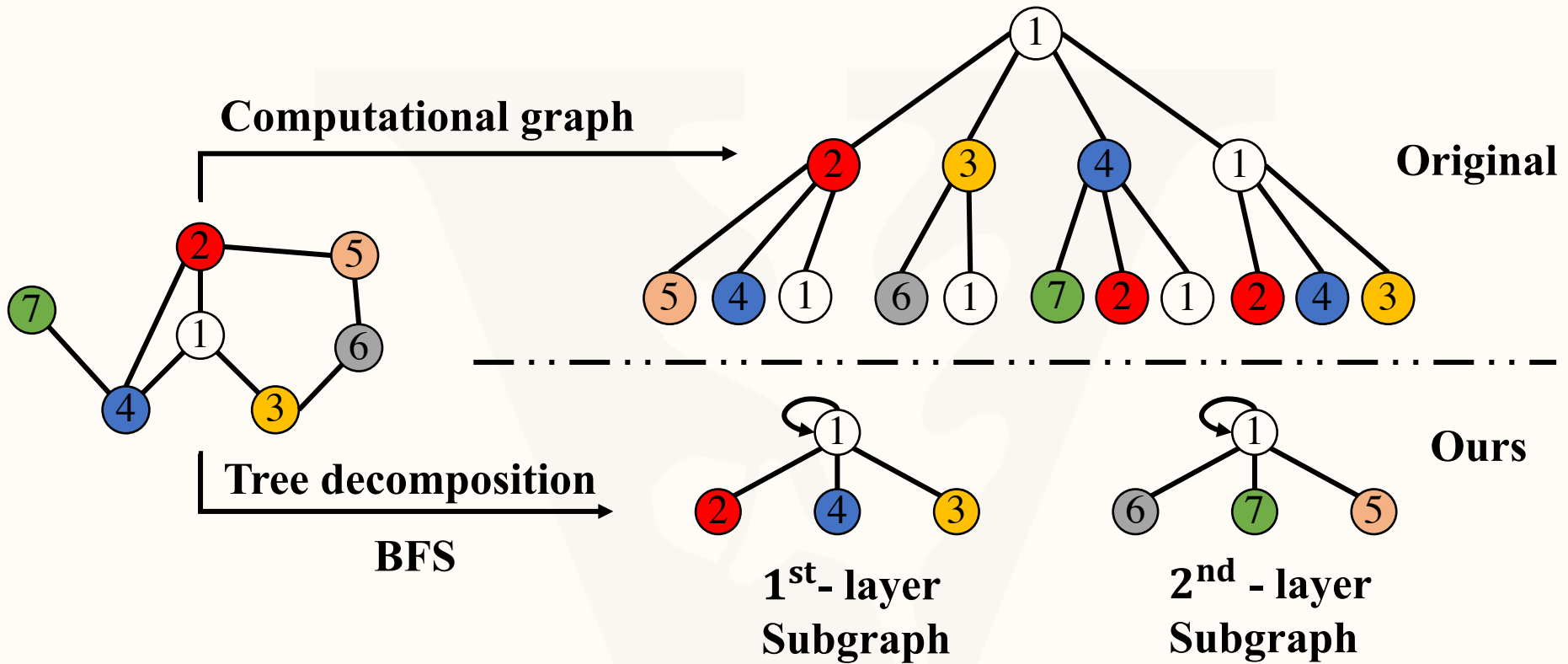
## Homophily

## Texas



## Heterophily

# Method – Tree Decomposition

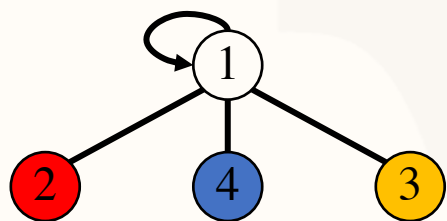


$$\mathbf{T}^k = \text{sign}(\widehat{\mathbf{A}}^k) - \text{sign}(\widehat{\mathbf{A}}^{k-1}) + \mathbf{I}$$

$$\text{sign}(\widehat{\mathbf{A}}^k)_{ij} = \begin{cases} 1, & \text{if } \widehat{\mathbf{A}}_{ij}^k > 0 \\ 0, & \text{if } \widehat{\mathbf{A}}_{ij}^k = 0 \end{cases}$$

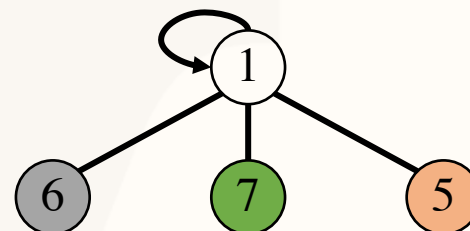
# Motivation – Multi-hop dependency

What's the weight for these edges?

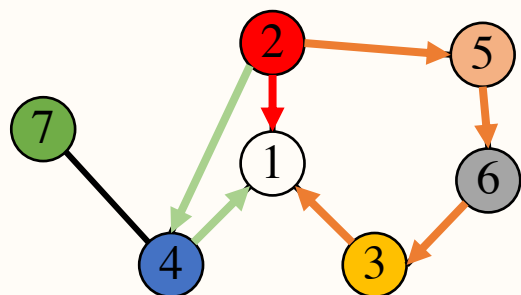


1<sup>st</sup>- layer Subgraph

Difference



2<sup>nd</sup> - layer Subgraph



$v_2 \rightarrow v_1$

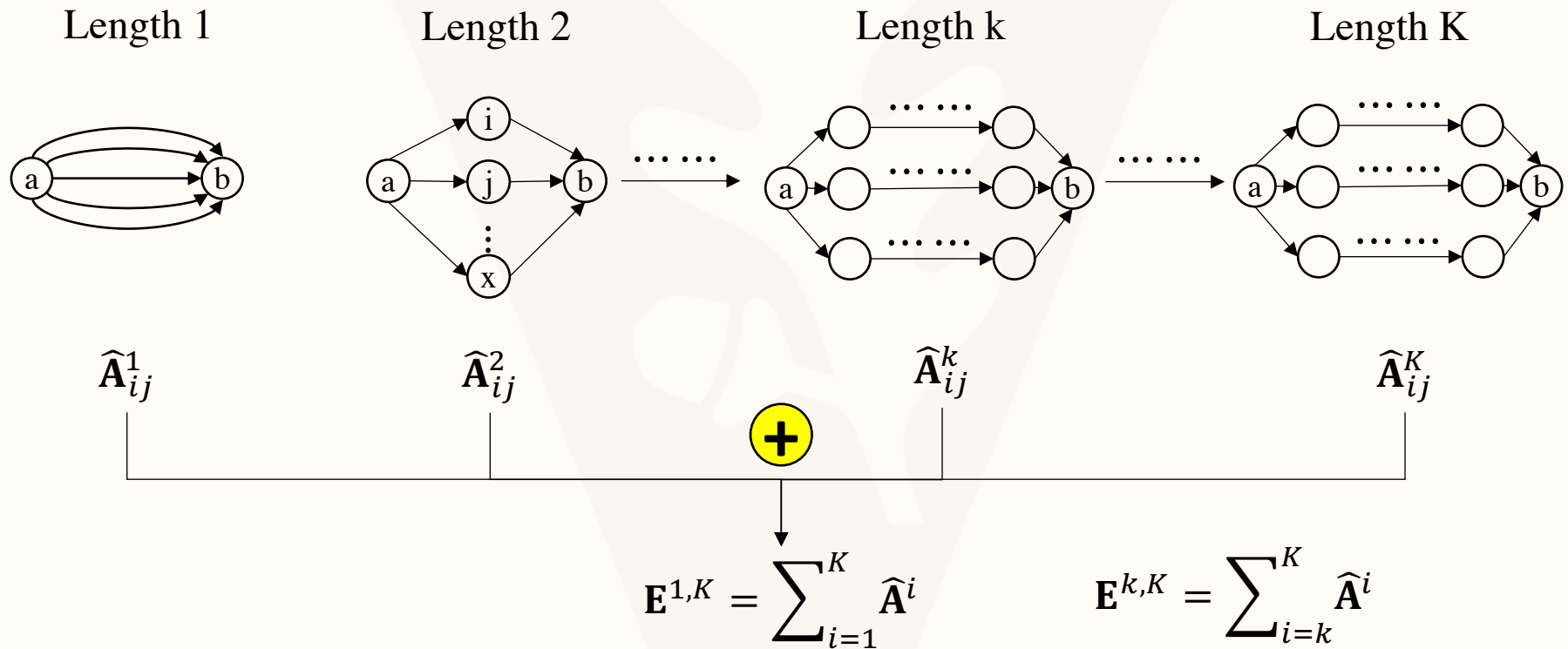
$v_2 \rightarrow v_5 \rightarrow v_6 \rightarrow v_3 \rightarrow v_1$

$v_2 \rightarrow v_4 \rightarrow v_1$

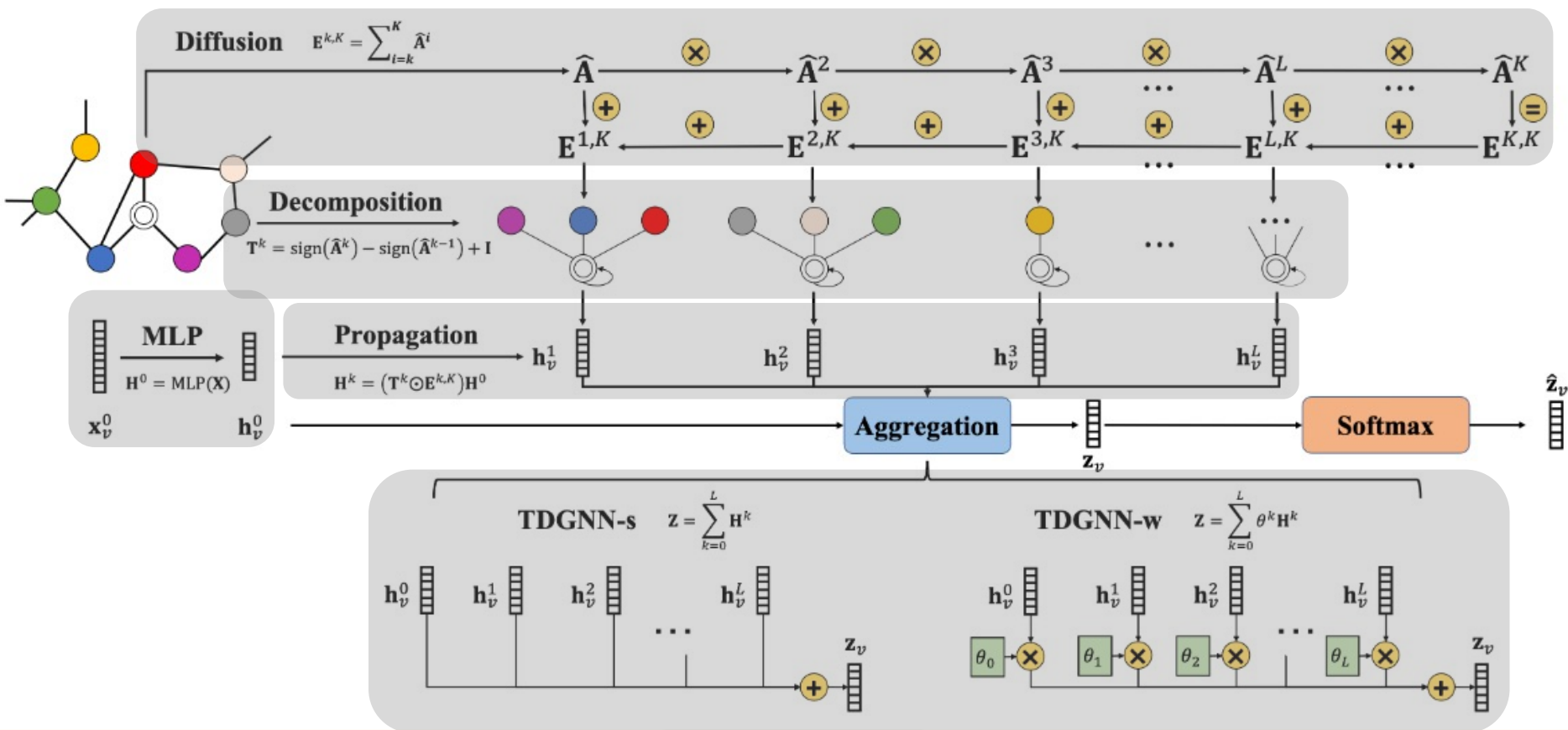
Multi-hop dependency  
Width of GNNs

# Method – Multi-hop dependency

## Graph Diffusion



# Framework - TDGNN



# Experiment

**Table 1: Statistics of datasets.**

Networks		Nodes	Edges	Features	Classes	Train/Val/Test	Type
<b>Homophily</b>	Cora	2708	5429	1433	7	140/500/1000	Citation network
	Citeseer	3327	4732	3703	6	120/500/1000	Citation network
	Pubmed	19717	44338	500	3	60/500/1000	Citation network
<b>Non-homophily</b>	Cornell	183	295	1703	5	48%/32%/20%	Webpage network
	Texas	183	309	1703	5	48%/32%/20%	Webpage network
	Wisconsin	251	499	1703	5	48%/32%/20%	Webpage network
	Actor	7600	33544	931	5	48%/32%/20%	Actor co-occurrence network

## Semi-supervised setting

- (1) 20 training nodes each class
- (2) Fixed splitting and random splitting

## Full-supervised setting

- (1) 48% training nodes each class
- (2) Fixed splitting



# Experiment - Semi-supervised classification

Table 2: Summary of semi-supervised classification accuracy (%)  $\pm$  stdev over Cora, Citeseer, and Pubmed datasets.

Method	Cora		Citeseer		Pubmed		Avg. Rank
	Fixed	Random	Fixed	Random	Fixed	Random	
GCN	81.50 $\pm$ 0.79 (0-2)	79.91 $\pm$ 1.64 (0-2)	71.42 $\pm$ 0.48 (0-2)	68.78 $\pm$ 2.01 (0-2)	79.12 $\pm$ 0.46 (0-2)	77.84 $\pm$ 2.36 (0-2)	7.17
GAT	83.10 $\pm$ 0.40 (0-2)	80.80 $\pm$ 1.60 (0-2)	70.80 $\pm$ 0.50 (0-2)	68.90 $\pm$ 1.70 (0-2)	79.10 $\pm$ 0.40 (0-2)	77.80 $\pm$ 2.10 (0-2)	7.00
SGC	82.63 $\pm$ 0.01 (0-2)	80.18 $\pm$ 1.57 (0-2)	72.10 $\pm$ 0.14 (0-2)	69.33 $\pm$ 1.90 (0-2)	79.12 $\pm$ 0.10 (0-2)	76.74 $\pm$ 2.84 (0-2)	6.83
APPNP	83.34 $\pm$ 0.56 (0-10)	82.26 $\pm$ 1.39 (0-10)	72.22 $\pm$ 0.50 (0-10)	70.53 $\pm$ 1.57 (0-10)	80.14 $\pm$ 0.24 (0-10)	79.54 $\pm$ 2.23 (0-10)	3.83
DAGNN	84.88 $\pm$ 0.49 (0-10)	83.47 $\pm$ 1.18 (0-10)	73.39 $\pm$ 0.17 (0-9)	70.87 $\pm$ 1.44 (0-10)	<b>80.51<math>\pm</math>0.42 (0-20)</b>	79.52 $\pm$ 2.19 (0-20)	2.33
GCNII*	<b>85.57<math>\pm</math>0.45 (0-64)</b>	82.58 $\pm$ 1.68 (0-64)	73.24 $\pm$ 0.61 (0-32)	70.04 $\pm$ 1.72 (0-10)	80.00 $\pm$ 0.48 (0-16)	79.03 $\pm$ 1.68 (0-16)	3.83
TDGNN-s	85.35 $\pm$ 0.41 (0-4)	<b>83.84<math>\pm</math>1.45 (0-6)</b>	<b>73.78<math>\pm</math>0.50 (0-8)</b>	<b>71.27<math>\pm</math>1.71 (0-8)</b>	80.20 $\pm$ 0.33 (0-5)	<b>80.01<math>\pm</math>1.95 (0-5)</b>	<b>1.33</b>
TDGNN-w	84.42 $\pm$ 0.51 (0-4)	83.43 $\pm$ 1.35 (0-6)	72.14 $\pm$ 0.19 (0-6)	70.32 $\pm$ 1.17 (0-6)	80.12 $\pm$ 0.14 (0-5)	79.77 $\pm$ 2.04 (0-5)	3.67

TDGNN-s, TDGNN-w rank 1<sup>st</sup> and 3<sup>rd</sup>

TDGNN-s, TDGNN-w utilize less layers of neighborhoods

Random setting – more robustness to data distribution

# Experiment - Full-supervised classification

Table 3: Summary of full-supervised classification accuracy (%)  $\pm$  stdev over 8 datasets

Method	Cora	Cite.	Pub.	Corn.	Tex.	Wisc.	Act.	Avg. Rank
MLP	75.78 $\pm$ 1.84 (0)	73.81 $\pm$ 1.74 (0)	86.90 $\pm$ 0.37 (0)	80.97 $\pm$ 6.33 (0)	81.32 $\pm$ 4.19 (0)	85.38 $\pm$ 3.95 (0)	36.60 $\pm$ 1.25 (0)	5.57
GCN	86.97 $\pm$ 1.32 (0-2)	76.37 $\pm$ 1.47 (0-2)	88.19 $\pm$ 0.48 (0-2)	58.57 $\pm$ 3.57 (0-2)	58.68 $\pm$ 4.64 (0-2)	53.14 $\pm$ 6.25 (0-2)	28.65 $\pm$ 1.38 (0-2)	8.14
GAT	87.30 $\pm$ 1.01 (0-2)	75.55 $\pm$ 1.32 (0-2)	85.33 $\pm$ 0.48 (0-2)	61.89 $\pm$ 5.05 (0-2)	58.38 $\pm$ 6.63 (0-2)	55.29 $\pm$ 4.09 (0-2)	28.45 $\pm$ 0.89 (0-2)	8.00
SGC	87.07 $\pm$ 1.20 (0-2)	76.01 $\pm$ 1.78 (0-2)	85.11 $\pm$ 0.52 (0-2)	58.68 $\pm$ 3.75 (0-2)	60.43 $\pm$ 5.11 (0-2)	53.49 $\pm$ 5.13 (0-2)	27.46 $\pm$ 1.46 (0-2)	8.57
Geom-GCN*	85.35 $\pm$ 1.57 (0-2)	<b>78.02<math>\pm</math>1.15 (0-2)</b>	89.95 $\pm$ 0.47 (N/A)	60.54 $\pm$ 3.67 (0-2)	66.76 $\pm$ 2.72 (N/A)	64.51 $\pm$ 3.66 (N/A)	31.63 $\pm$ 1.15 (N/A)	5.86
APPNP	86.76 $\pm$ 1.74 (0-10)	77.08 $\pm$ 1.56 (0-10)	88.45 $\pm$ 0.42 (0-10)	74.59 $\pm$ 5.11 (0-10)	74.30 $\pm$ 4.74 (0-10)	81.10 $\pm$ 2.93 (0-10)	34.36 $\pm$ 1.09 (0-10)	5.43
DAGNN	87.26 $\pm$ 1.42 (0-10)	76.47 $\pm$ 1.54 (0-10)	87.49 $\pm$ 0.63 (0-20)	80.97 $\pm$ 6.33 (0)	81.32 $\pm$ 4.19 (0)	85.38 $\pm$ 3.95 (0)	36.60 $\pm$ 1.25 (0)	4.71
GCNII*	<b>88.27<math>\pm</math>1.31 (0-64)</b>	77.06 $\pm$ 1.67 (0-64)	<b>90.26<math>\pm</math>0.41 (0-64)</b>	76.70 $\pm$ 5.40 (0-16)	77.08 $\pm$ 5.84 (0-32)	80.94 $\pm$ 4.94 (0-16)	35.18 $\pm$ 1.30 (0-64)	3.71
TDGNN-s	88.26 $\pm$ 1.32 (0-4)	76.64 $\pm$ 1.54 (0-8)	89.13 $\pm$ 0.39 (0-1)	80.97 $\pm$ 6.33 (0)	82.95 $\pm$ 4.59 (0, 4-5)	85.47 $\pm$ 3.88 (0, 4-5)	36.70 $\pm$ 1.28 (0, 3-4)	2.86
TDGNN-w	88.01 $\pm$ 1.32 (0-5)	76.58 $\pm$ 1.40 (0-2)	89.22 $\pm$ 0.41 (0-1)	<b>82.92<math>\pm</math>6.61 (0, 2-6)</b>	<b>83.00<math>\pm</math>4.50 (0, 2)</b>	<b>85.57<math>\pm</math>3.78 (0, 3-5)</b>	<b>37.11<math>\pm</math>0.96 (0, 3-4)</b>	<b>2.14</b>

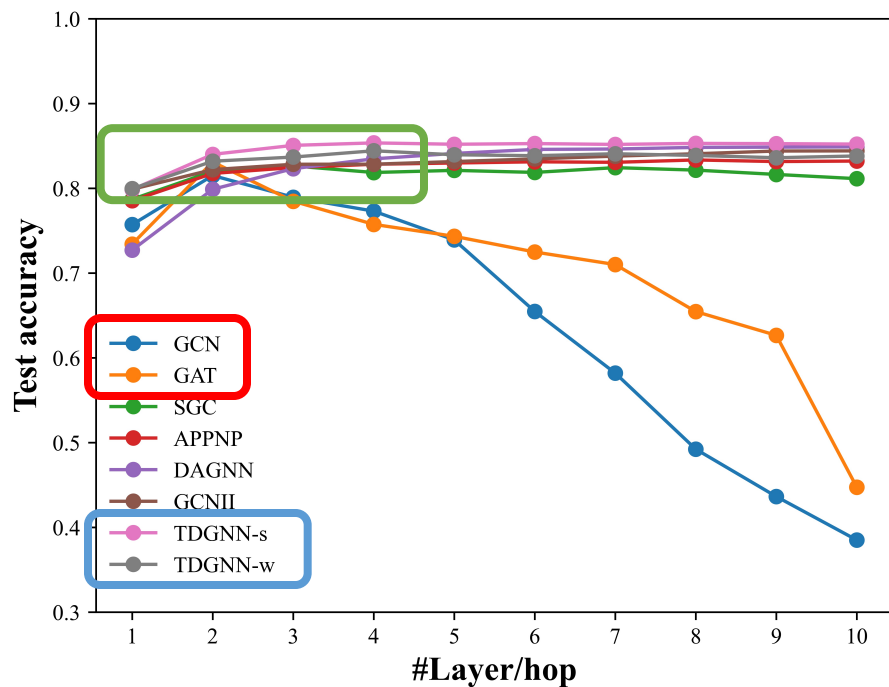
\* We reuse the results reported in [33] for Geom-GCN. 'N/A' indicate the corresponding layers are not reported in the paper.

TDGNN-w, TDGNN-s rank 1<sup>st</sup> and 2<sup>nd</sup>

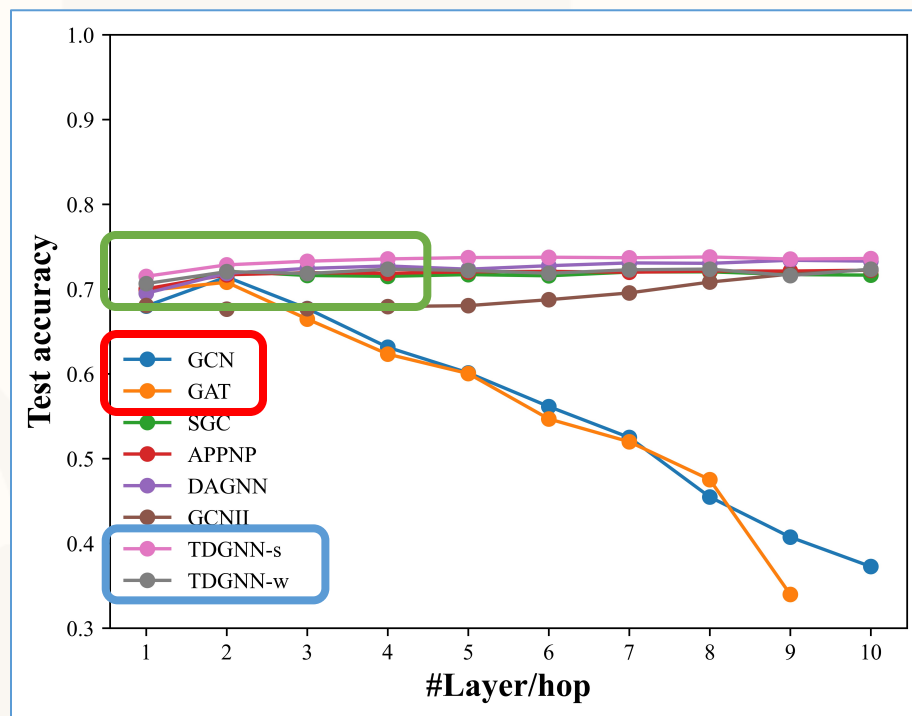
TDGNN-s, TDGNN-w leverage different layers of neighborhoods

# Experiment – Further Probe

## Alleviate over-smoothing

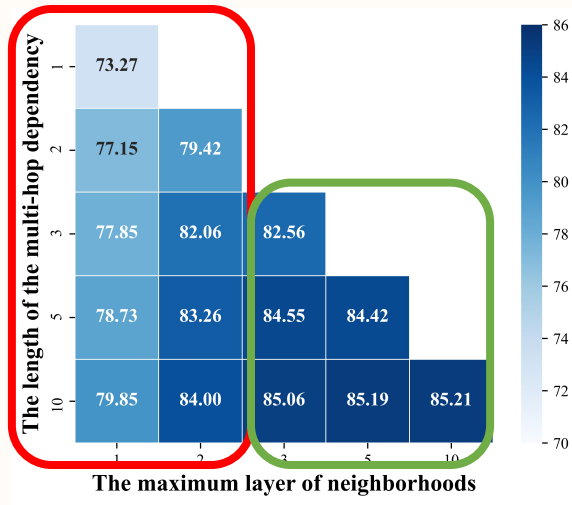


Cora

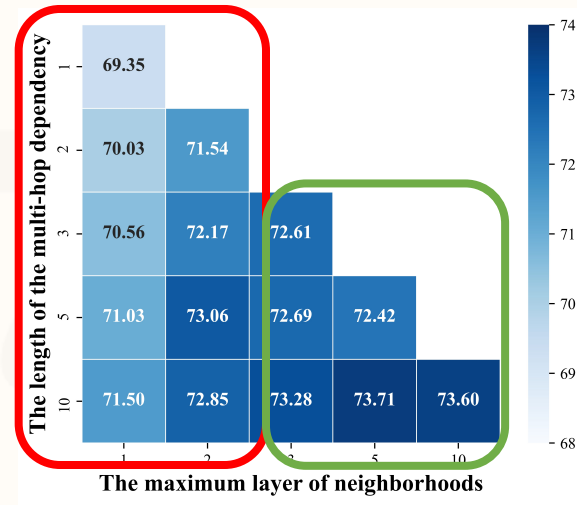


Citeseer

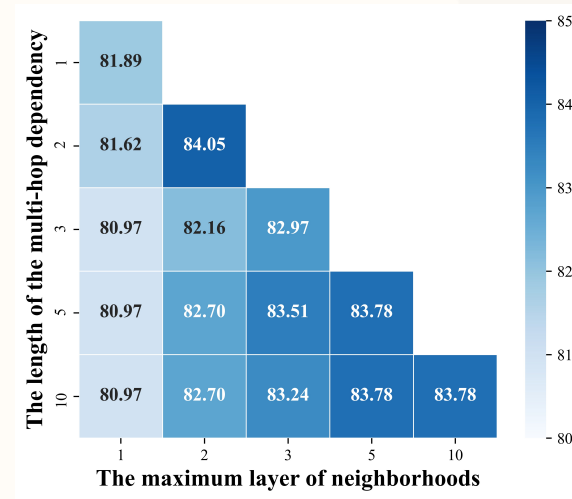
# Experiment – Further Probe



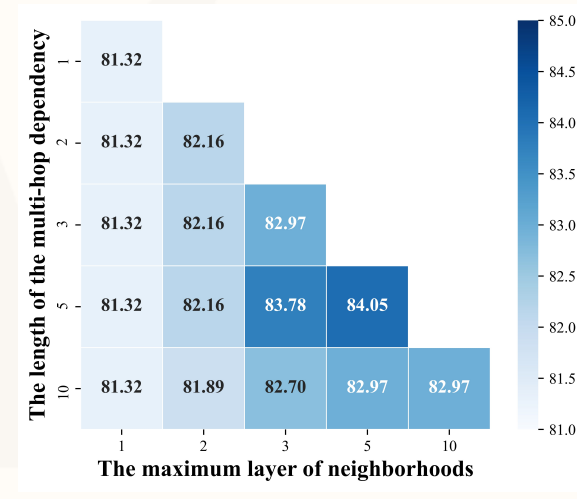
**Cora**



**Citeseer**



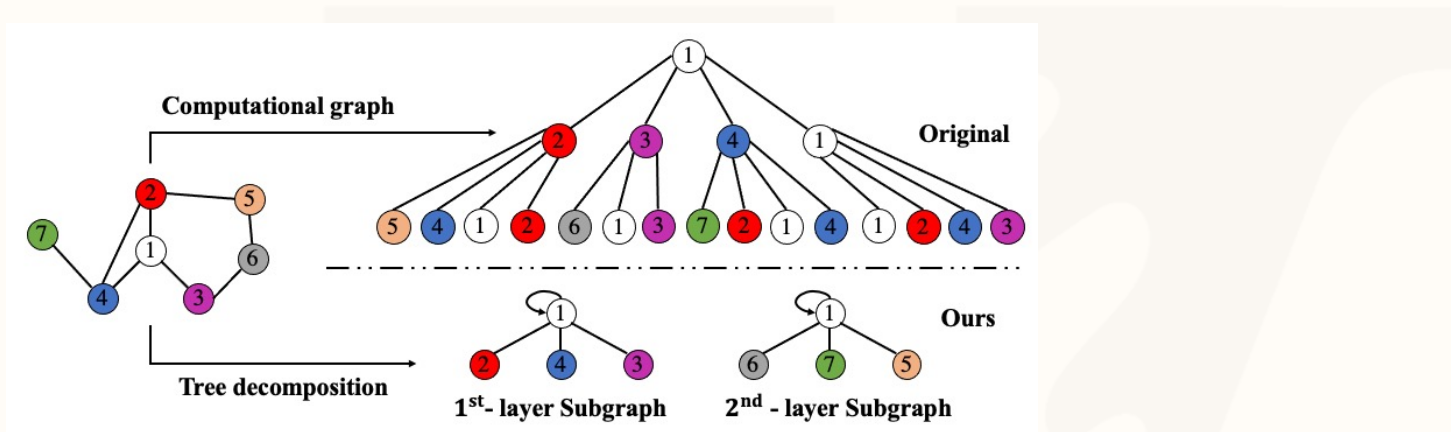
**Texas**



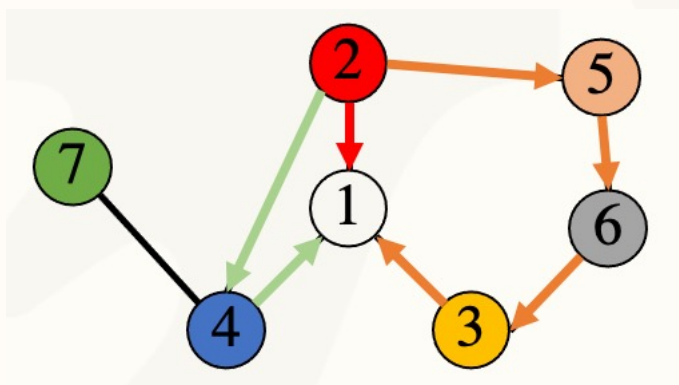
**Wisconsin**

# Conclusion

## Tree decomposition to alleviate over-smoothing between different layers



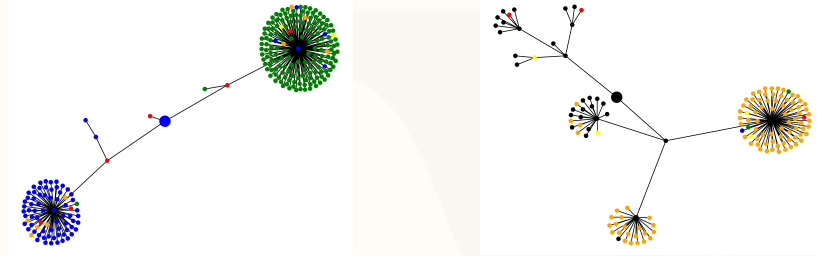
## Graph diffusion to incorporate multi-hop dependencies



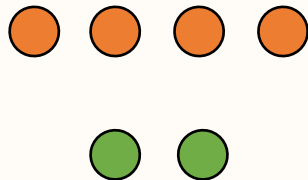
**Width is also important compared with depth!**

# Future Directions

Layer adaptive -> node adaptive

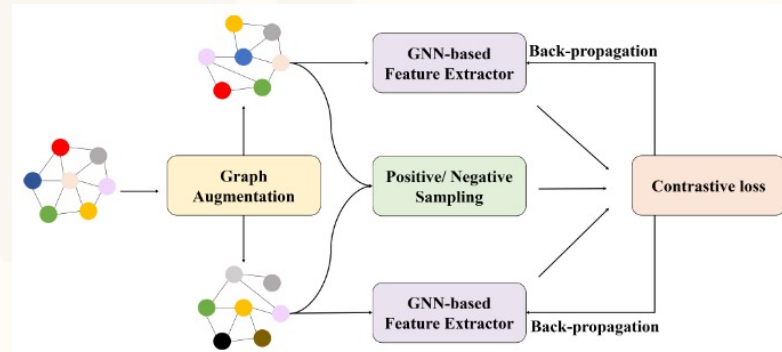
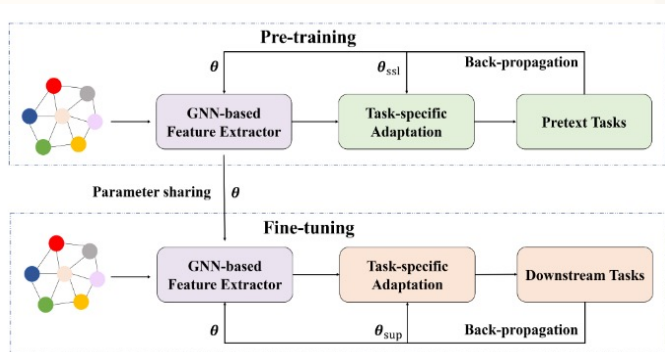


Node/Graph imbalance classification



$$\mathcal{L} = \mathcal{L}_{\min} + \mathcal{L}_{\text{maj}}$$

Incorporate self-supervised learning with deeper GNNs



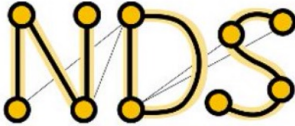
# Acknowledgement

Project webpage:  
<https://github.com/YuWVandy/TDGNN>

**SIGIR**  
Special Interest Group  
on Information Retrieval



**CIKM**  
2021  
1-5 NOVEMBER

 **Network and Data Science Lab**

**PhD**

**MS**

**BS**

**Summer Interns**

**High School**

A collage of portraits of students and interns, categorized by their education level: PhD, MS, BS, Summer Interns, and High School. The NDS Lab logo is prominently displayed at the top left of the collage.



Please see my homepage for  
more details!

<https://yuwvandy.github.io/>

**Thank you!**  
**Any question?**