Graph Aggregation Beyond Homophily Assumption

— a more meaningful way to model networks

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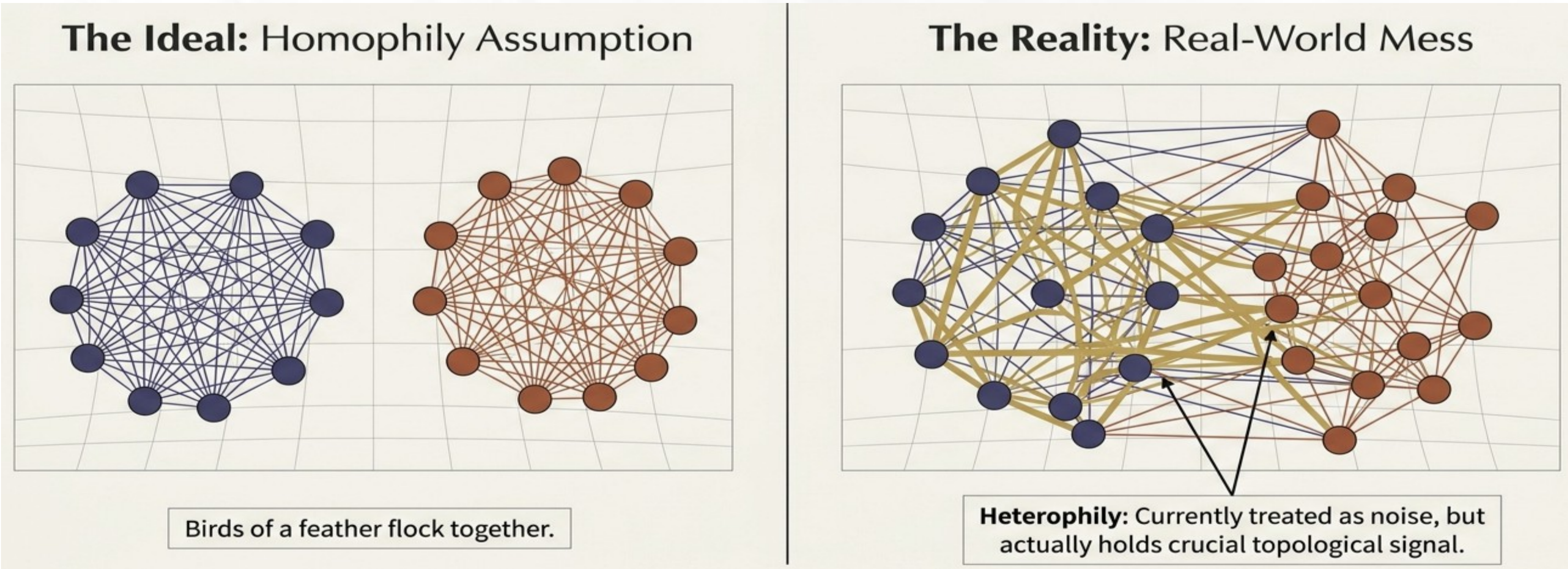
Outline

- Introduction
- Related Work
- Motivating Observations
- Graph Weighted Aggregation
- Performance
- Conclusion

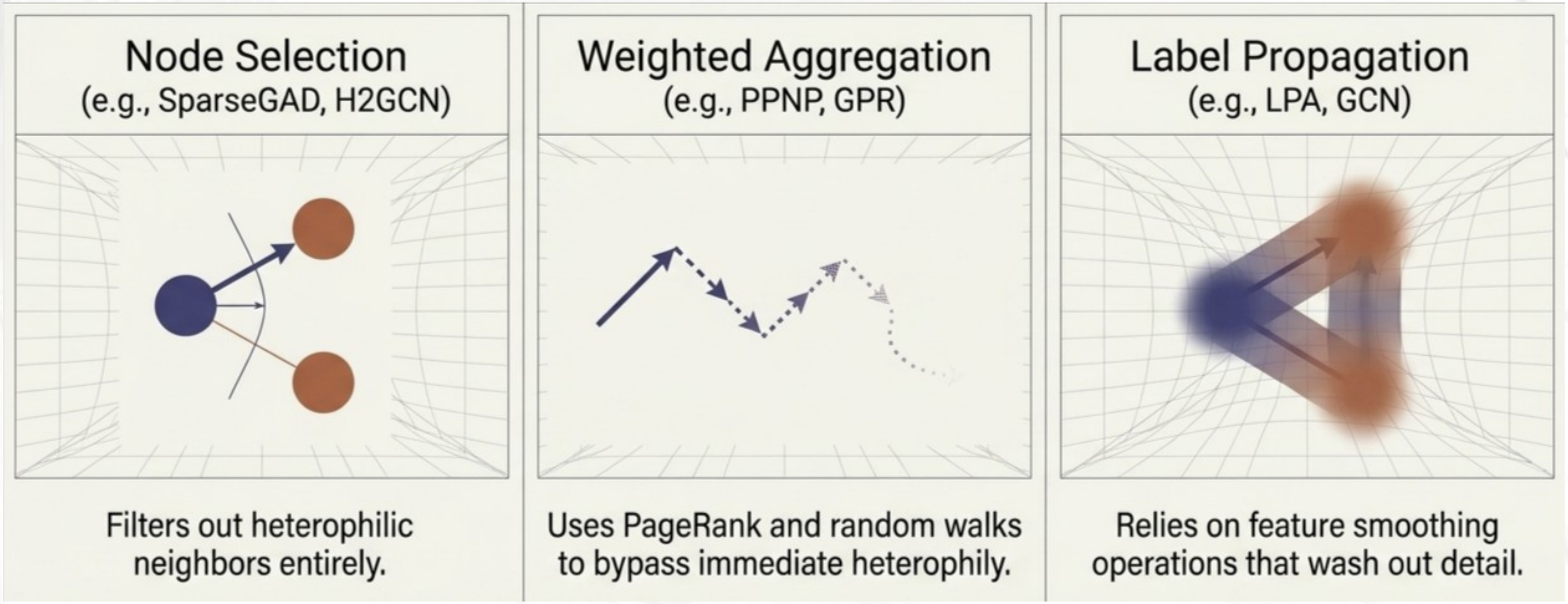
Introduction

- Space Networks vs. Social Networks
- Feature Engineering
- Connectedness and Categorization are distinct phenomena



Related Work

- All rely on the Homophily Assumption



Motivating Observation

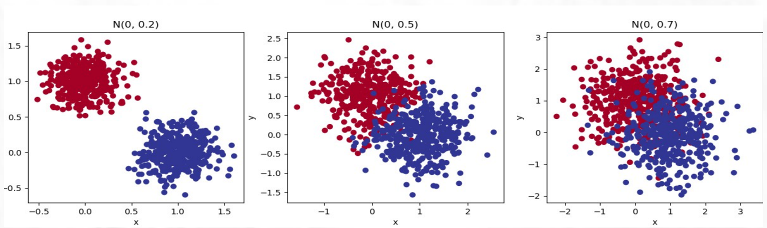


Figure 1. Sample Networks

1. Standard Aggregation destroys problem-specific patterns
2. Aggregation Strategy needs to be problem-specific.

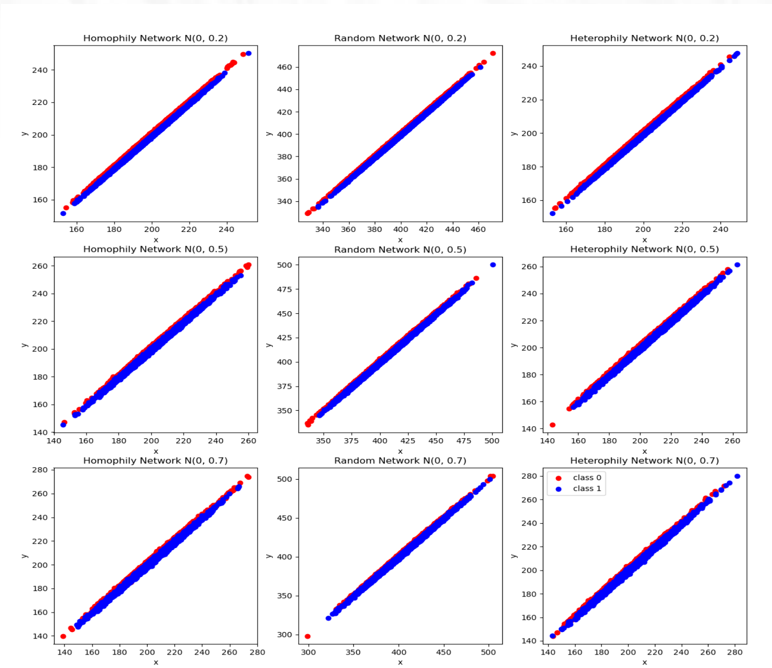


Figure 2. Standard Aggregation

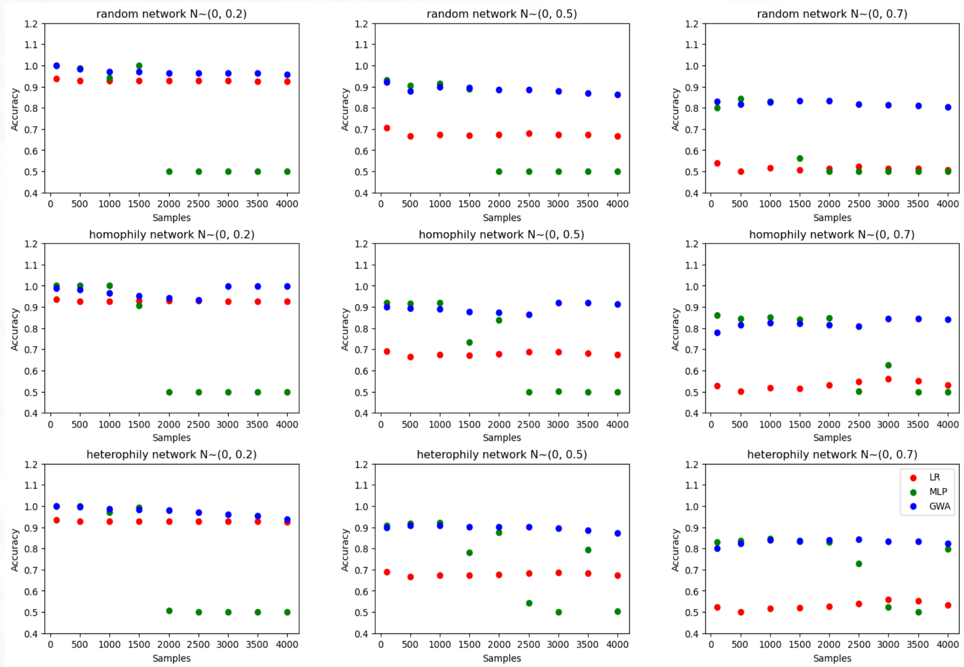
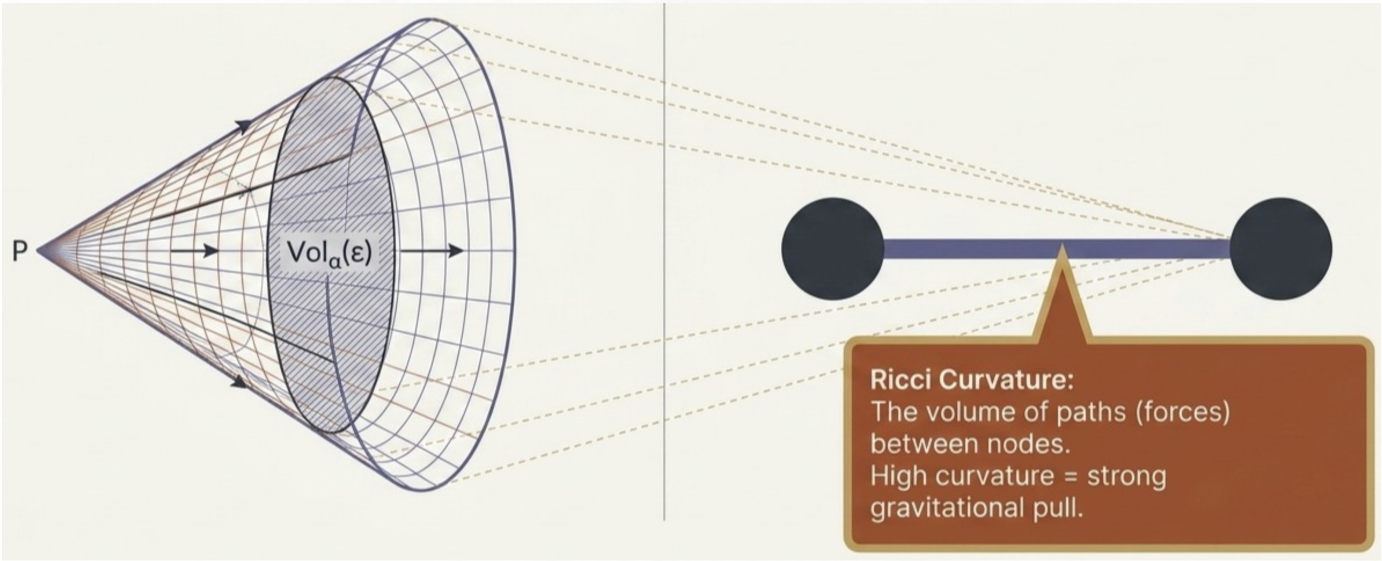


Figure 3. Accuracy of different Aggr. Strategy

Graph Weighted Aggregation (GWA)

- Translating Spacetime to Social Networks
- When Riemannian manifolds are mapped to the Tangent Space, Ricci tensor encodes all essential properties.

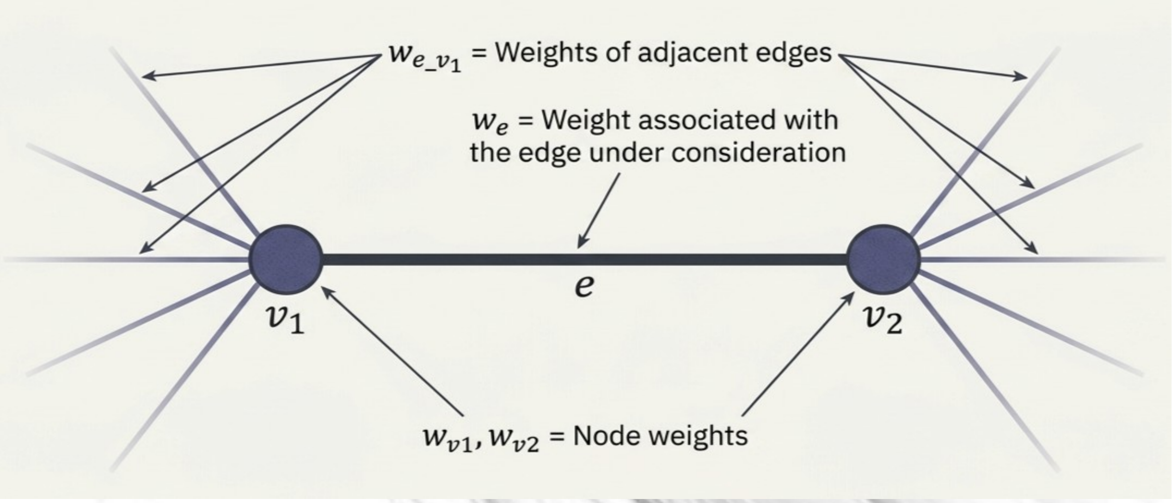


Ricci Tensor

- Traditional Forman-Ricci calculation is computationally heavy

$$F(a) = w_a\left(\frac{w_{v_1}}{w_a} + \frac{w_{v_2}}{w_a} - \sum_{e_{v_1} \sim a,\, e_{v_2} \sim a}\left(\frac{w_{v_1}}{\sqrt{w_a w_{e_{v_1}}}} + \frac{w_{v_2}}{\sqrt{w_a w_{e_{v_2}}}}\right)\right)$$

- Use graph properties to compute Forman-Ricci curvature



Edge Curvature

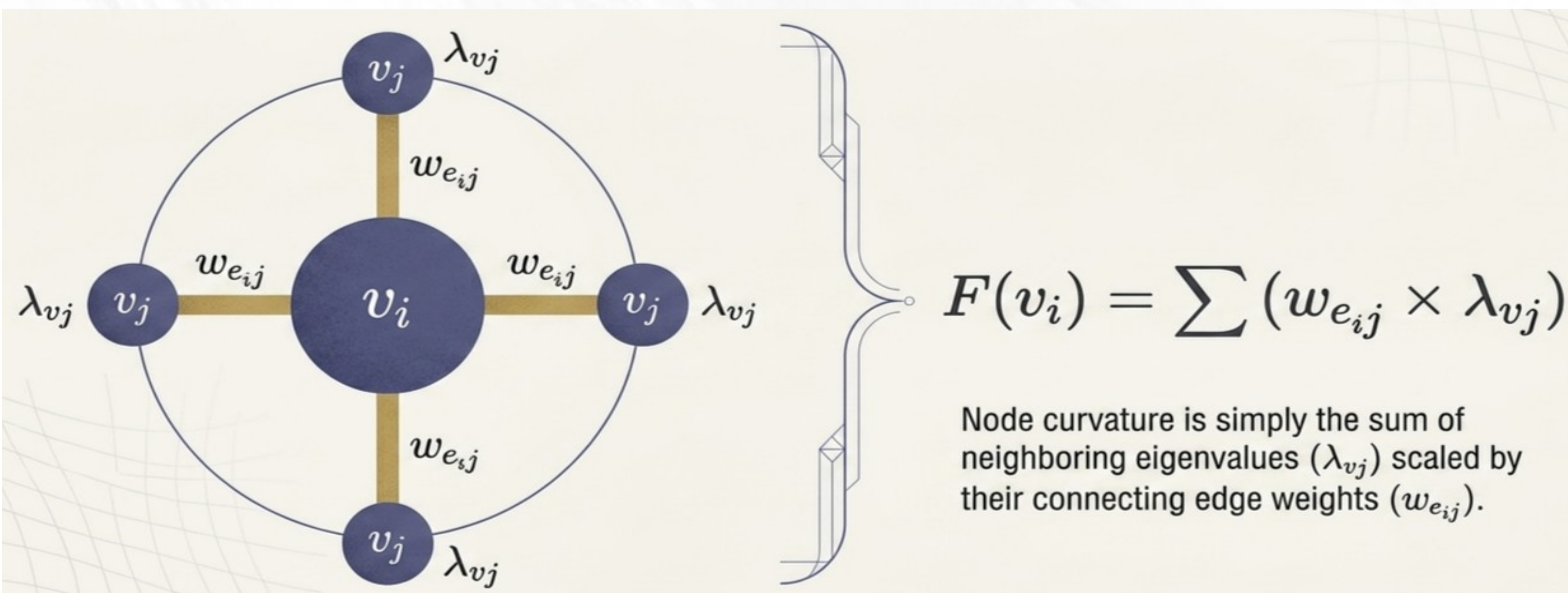
- Theorem 1: when graphs or networks become stabilized and reach the lowest energy, the following formula holds

$$F(e) = w_e(\lambda_{v_1} + \lambda_{v_2})$$

w_e = Edge weight, λ_v = Eigenvalue of the node.

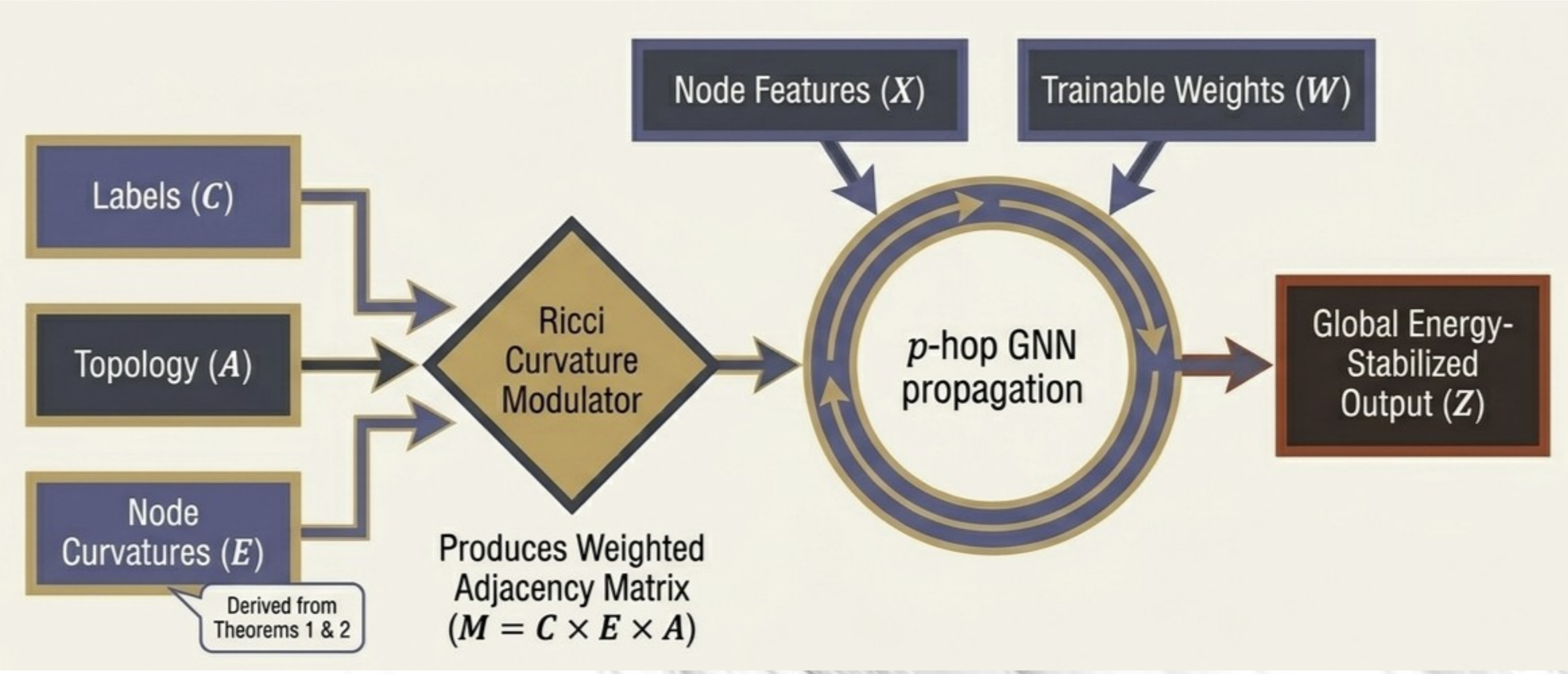
Node Curvature

- Theorem 2: a node's curvature is the weighted sum of the stabilized momentum of its immediate neighbors.



GWA Pipeline

- GWA fuses label, topology, node curvature information, aggregating across n hops until the network achieves global stabilization.

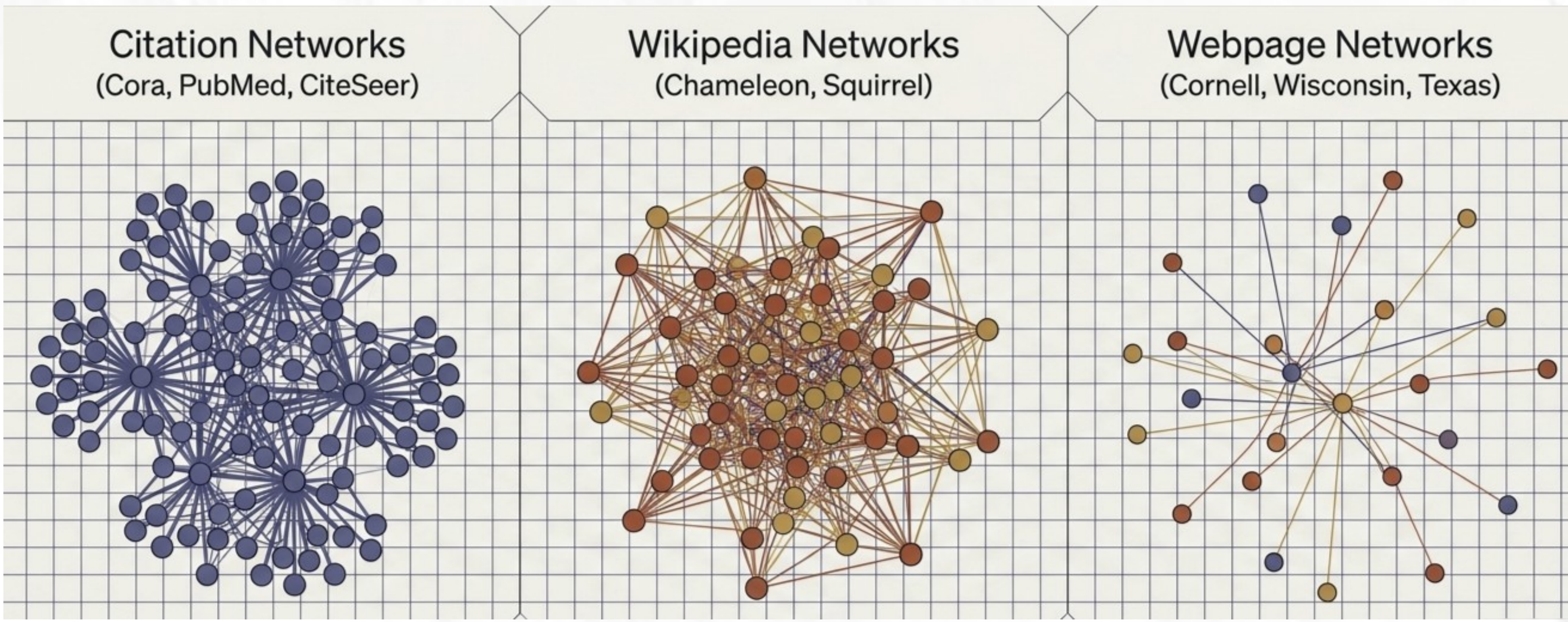


GNN vs. GWA

- By treating a graph as a physical space rather than a map of similarities, we can fuse topology, features, and labels into a single unified momentum.

	Legacy GNNs (Homophily)	GWA (Geometric Force)
Core Premise	Similarity-based grouping	Geometric curvature and physical space
Heterophily	Noise to be eliminated	Valid topological signal
Mechanism	Smoothing operations	Energy stabilization
Inputs	Node features primarily	Features + Topology + Labels

Evaluating Across 8 Real-world Datasets, 10 baseline models



Alg.	Cora	PubMed	CiteS.	Cornell	Cha.	Squ.	Wis.	Tex.
GCN	82.9	83.3	73.1	46.5	52.3	33.1	47.7	52.7
GAT	83.1	84.4	72.0	48.1	51.4	32.3	46.6	49.6
SSP	81.1	79.5	71.1	55.0	21.9	19.7	49.4	55.0
JK-N	81.3	**86.2**	71.7	52.7	54.0	33.5	48.3	51.9
G-S	82.2	83.0	71.4	53.5	42.3	26.9	56.8	53.5
G-G	74.3	83.5	73.8	54.3	38.7	32.2	53.4	64.3
G-L	82.3	85.8	72.3	49.6	52.7	33.5	50.6	48.8
U-G	**84.0**	85.2	**74.1**	**69.8**	**54.1**	**34.4**	**69.9**	**71.7**
MLP	63.3	83.1	67.7	65.9	41.4	29.4	64.2	65.9
GWA	99.5	89.7	99.6	96.2	91.7	74.6	96.4	98.4

Conclusion

- GWA outperformed 10 state-of-the-art baselines across all 8 datasets, achieving an average accuracy improvement of 25.29%
- By interpreting networks as geometric fields rather than mere similarity maps, GWA unlocks massive performance gains – particularly on chaotic, high-heterophily networks like Wikipedia and webpages.

Q & A

Thank You