

Beyond Homophily in Graph Neural Networks: And the average accuracy and the average accuracy and standard **Current Limitations and Effective Designs Current Limitations and Effective Designs** we observe similar trends on both benchmarks: H2GCN has been been benchmarks: H2GCN has been benchmarks: H2GCN \sim

Jiong Zhu, Yujun Yan, Lingxiao Zhao, Mark Heimann, Leman Akoglu, Danai Koutra n Akoglu, Danai Koutra $\begin{bmatrix} 1 & 0 \end{bmatrix}$ n also use the contractor in $\begin{bmatrix} 26 & 0 \end{bmatrix}$

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Limitations of GNNs Beyond Homophily

Problem: many popular GNN models (e.g. GCN) rely on assumed **homophily** and fail to generalize in **heterophily**.

Observation: In heterophily, existing methods have worse classification accuracy than graph-agnostic MLP.

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Effective Designs for GNNs in Heterophily

Design D1: Model the of ego- and neighbor-embeddings distinctly (per layer). • In heterophily, neighbors may have information complementary to ego. assigned a class label based on the research field. These datasets use a bag of words α

Design D2: Leverage representations of neighbors at different hops distinctly (per layer). • Under heterophily, higher-order neighborhoods may still show homophily.

Design D3: Leverage the intermediate representations distinctly (at the final layer). \parallel Method Opesigns) Average Rank • Information with different locality contains different frequency components.

Empirical Analysis 0.3 ly widely used benchmarks for semi-supervised benchmarks for semi-supervised node classification \vert TeVW AccXUac\ homophily. The performance of GCN, GAT and MixHop, respect to the homophily level. But, while they achieve near-• Cora, Pubmed and Citeseer are citation graphs originally introduced in [30, 22], which are among

0.6

Edge homophily ratio $h = \frac{intra-class edges}{total edges}$ Figure 2: Performance of GNN mod-(D1) *Ego- and Neighbor-embedding Separation.* We con- $\text{Edge homophily ratio } h = \frac{intra - \text{cuts}}{\text{total edges}}$

- $GR(\lbrace \bullet \rbrace))$. H₂GCN, our base model effectively combining all embedding the model inductive model of the model of the model interversion in the completed of the control of t
Experimental control of the designs, has the best trend overall. istinctly (per layer). **In our synthetic experiments (§ G), we use of the 1-hope of the 1-hope of to general control overall.**
- ophily. \bullet Ablation study on H₂GCN shows effectiveness of each design, which results in up to 40% performance gain in (NS1) only the 1-hop neighborhood *N₁*. In Fig. 3a, we see that the two variants that learn separate the two variants of embedding functions significantly outperform the others (NS0/1) in heterophily settings (*h <* 0*.*7) strong heterophily (Table 5). The same that said, the said of the said relatively small relatively smal \mathbb{R} benchmarks), and \mathbb{R} are class of \mathbb{R} and \mathbb{R} labels in \mathbb{R} and \mathbb{R} labels labels labels labels in \mathbb{R} and \mathbb{R} and \mathbb{R} and \mathbb{R} and \mathbb{R} and \mathbb{R} and \mathbb{R} a

real for success in heterophilia. Vanilla H2GCN-1 is critical for success in heterophilia. Vanilla H2GCN-1 is c $\bigcup_{\mathcal{S} \in \mathcal{S}}$ performs best for all homophilips $\bigcup_{\mathcal{S} \in \mathcal{S}}$

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- $\begin{cases} \begin{matrix} 0 \\ \frac{1}{2} \end{matrix} \end{cases}$. In heterophily, models leveraging all or subsets of the $\left(\begin{array}{ccc} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{array} \right)$ designs perform significantly better than methods (N₁) with *N₂*(*v*); and (*n*₂) without *N₂*(*v*), and (*n*₂) without *N₂*(*n*₂) shows that H2GCN-1 consistently performs that H2GCN-1 consistently performs that H2GCN-1 consistently performs that $\frac{1}{2}$ \mathcal{L} encourage function more diverse datasets with different levels of the homophily, models level aging all or subsets of the
	- \mathbf{c} than \mathbf{b} the variants, \mathbf{c} indicating \mathbf{c} and \mathbf{c} in \mathbf{c} and \mathbf{c} in \mathbf{c} and \mathbf{c} in $\mathbf{$ • GraphSAGE (D1) vs. GCN: up to +23%
- \cdot GCN-Cheby (D2) vs. GCN: up to +20%
- AGGR((0))) CON-UNEDY (DZ) vs. OUN. up to +20% higher-order neighborhoods contribute the most in homophilian homophilian homophilian allows it to the design of H2GCN allo

Detailed Results,

