

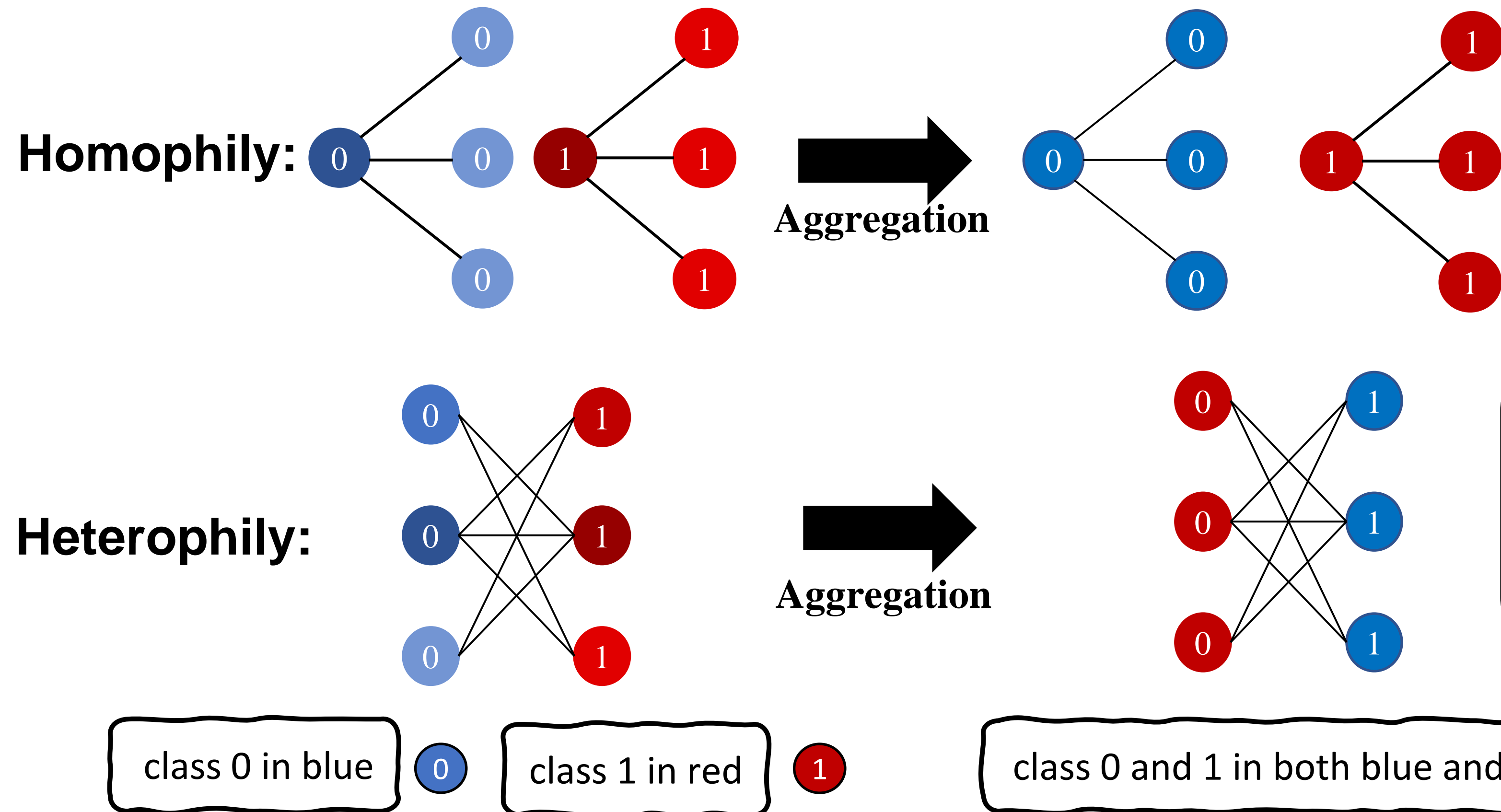
# Demystifying Structural Disparity in Graph Neural Networks: Can One Size Fit All?

Haitao Mao, Zhikai Chen, Wei Jin, Haoyu Han, Yao Ma, Tong Zhao, Neil Shah, Jiliang Tang



## When do Graph Neural Networks work and when not?

### Toy example with mixed patterns



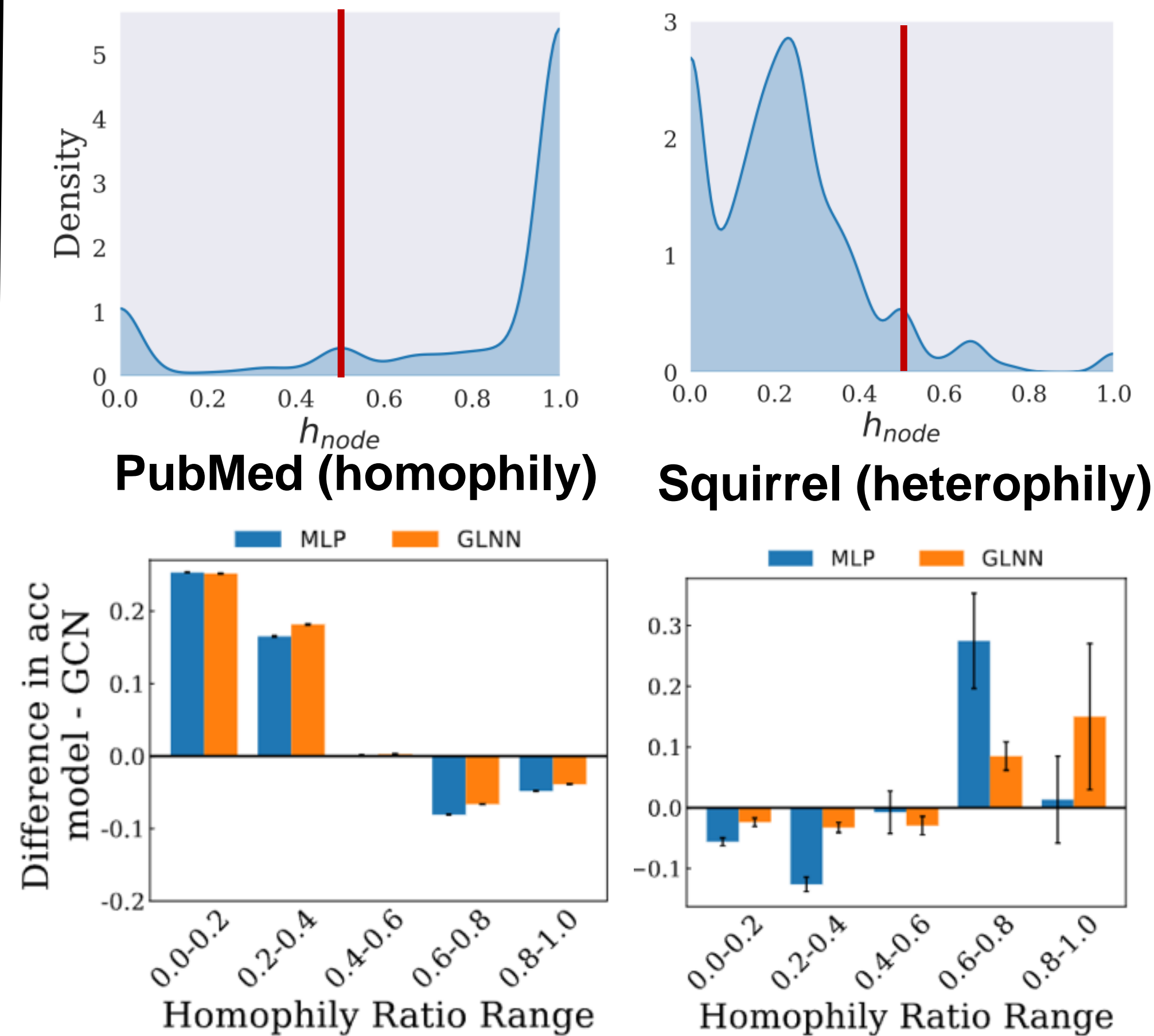
- If graph with only single pattern, GNN can work well
- If graph with mixed patterns, GNNs may fail

#### Homophily:

nodes tend to connect with similar ones

$$h_i = \frac{|\{u \in \mathcal{N}(v_i): y_u = y_v\}|}{|\mathcal{N}(v_i)|}$$

### Empirical evidence



### Theoretical understanding

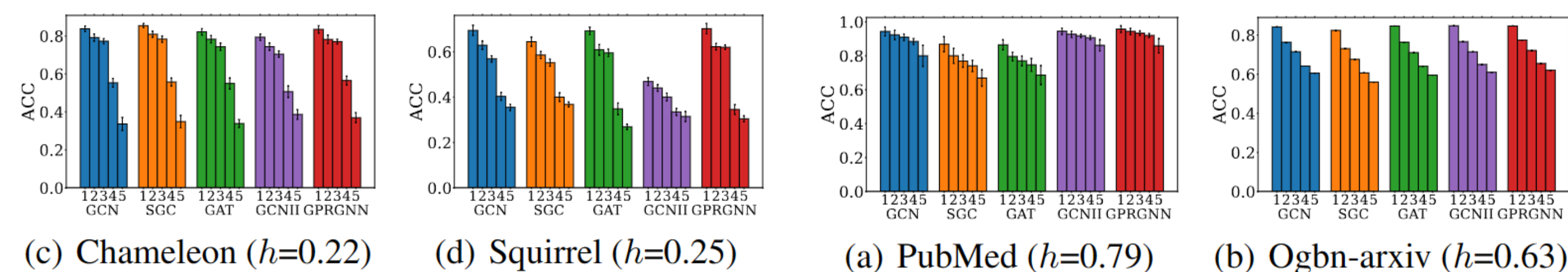
$$\mathcal{L}_m^0(\tilde{h}) \leq \hat{\mathcal{L}}_{tr}^0(\tilde{h}) + O\left(\underbrace{\frac{K\rho}{\sqrt{2\pi}\sigma} \epsilon_m}_{(a)} + \underbrace{[h_{tr} - h_m] \cdot \rho}_{(b)} + \frac{b \sum_{l=1}^L \|\tilde{W}_l\|_F^2}{(\gamma/8)^{2/L} N_{tr}^\alpha} (\epsilon_m)^{2/L} + R\right)$$

Loss gap between train and test set

**Aggregated feature disparity**  $\epsilon_m = |f_i - f_j|_F^2$  is the aggregated feature distance between train and test subgroup(s).

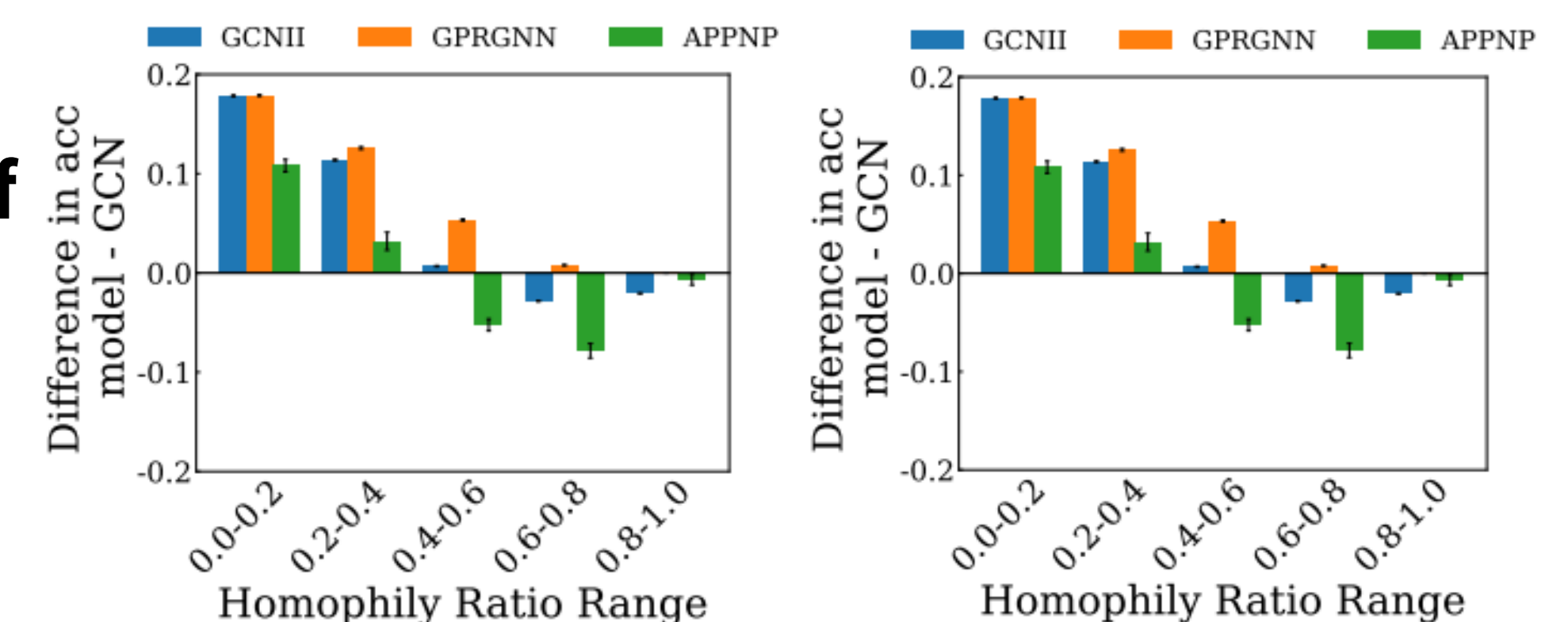
**Structural disparity**  $|h_{tr} - h_m|$  is the homophily ratio difference between train and test subgroup(s).

Large aggregation feature distance and structural disparity lead to large generalization gap



### Implications

#### Effectiveness of Deeper GNNs



#### Performance on new OOD split

	Pubmed	Ogbn-Arxiv	Squirrel
GCN(i.i.d)	89.18±0.15	72.99±0.14	58.09±0.71
GCN	51.04±0.16	34.94±0.07	32.13±4.93
MLP	68.38±0.43	33.17±0.37	24.57±0.77
GCNII	67.76±0.36	36.81±0.14	37.15±1.39
SRGNN	57.91±0.10	40.37±1.65	37.62±1.74
EERM	65.37±1.35	34.23±0.46	40.93±0.57

#### New OOD scenario

#### Paper



#### Code

