

Mixture of Weak and Strong Experts on Graphs

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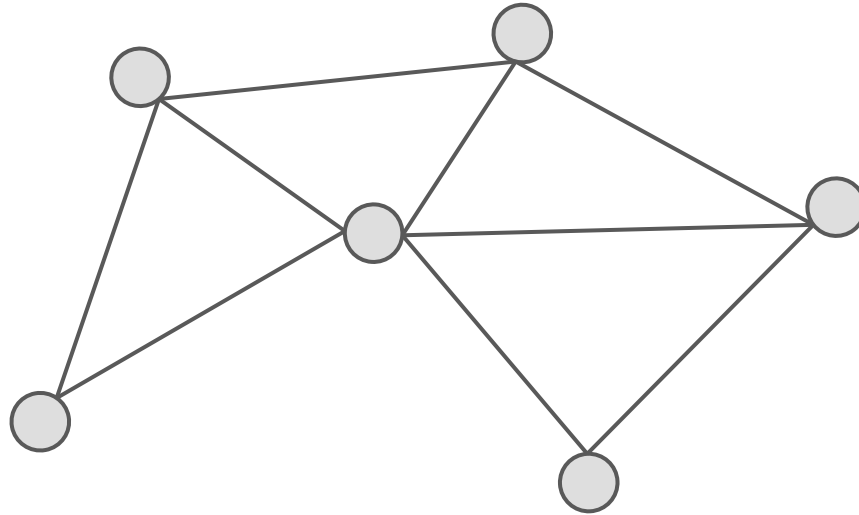
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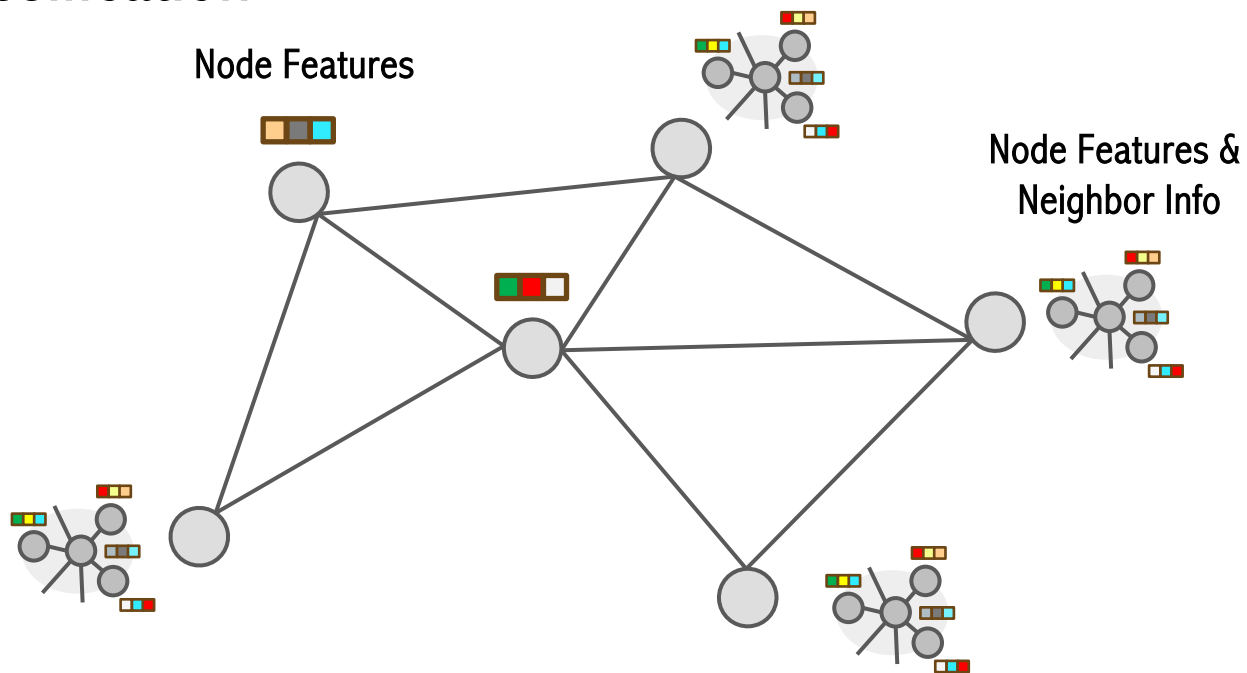
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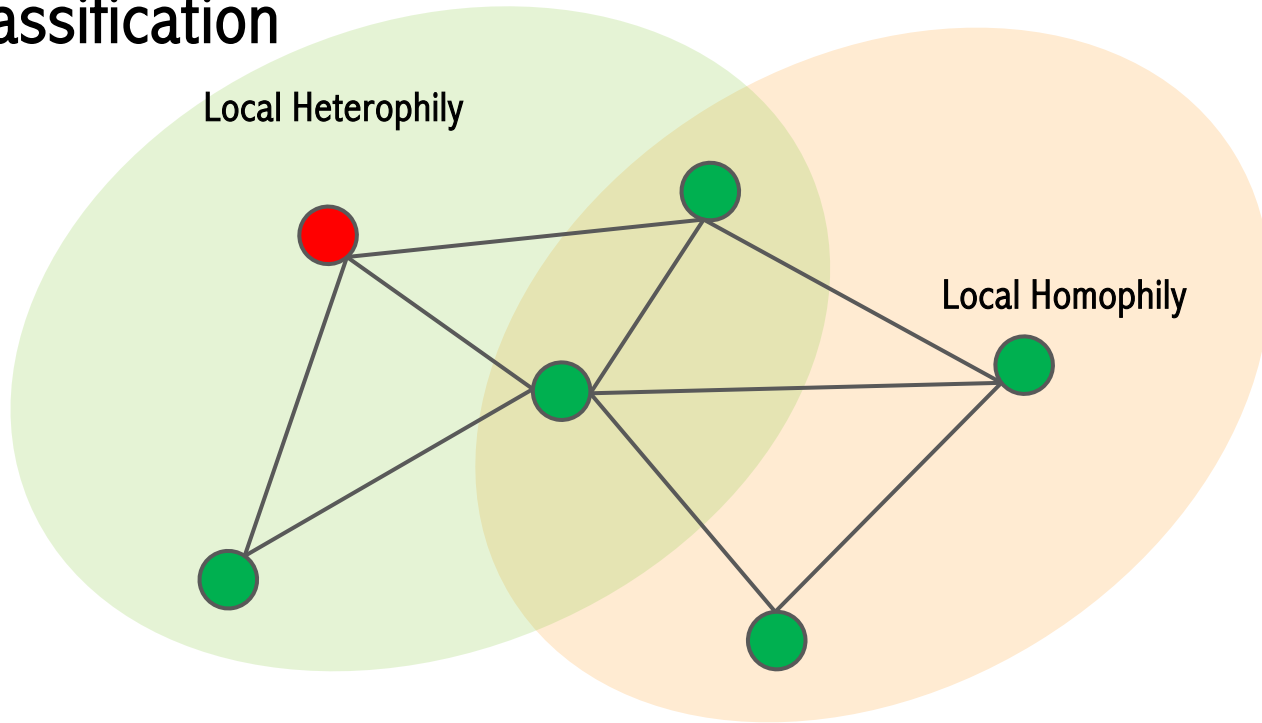
Node Classification

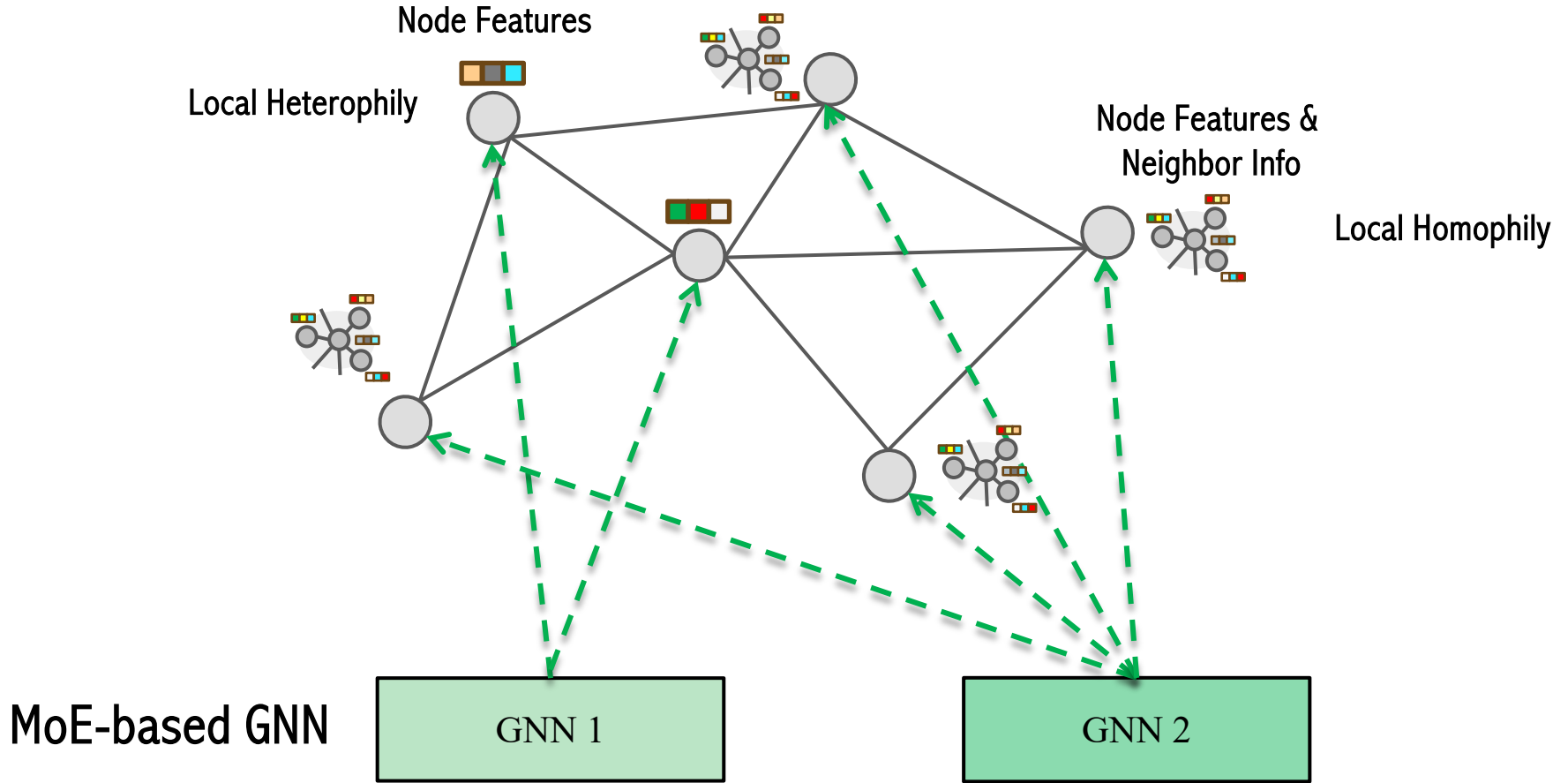


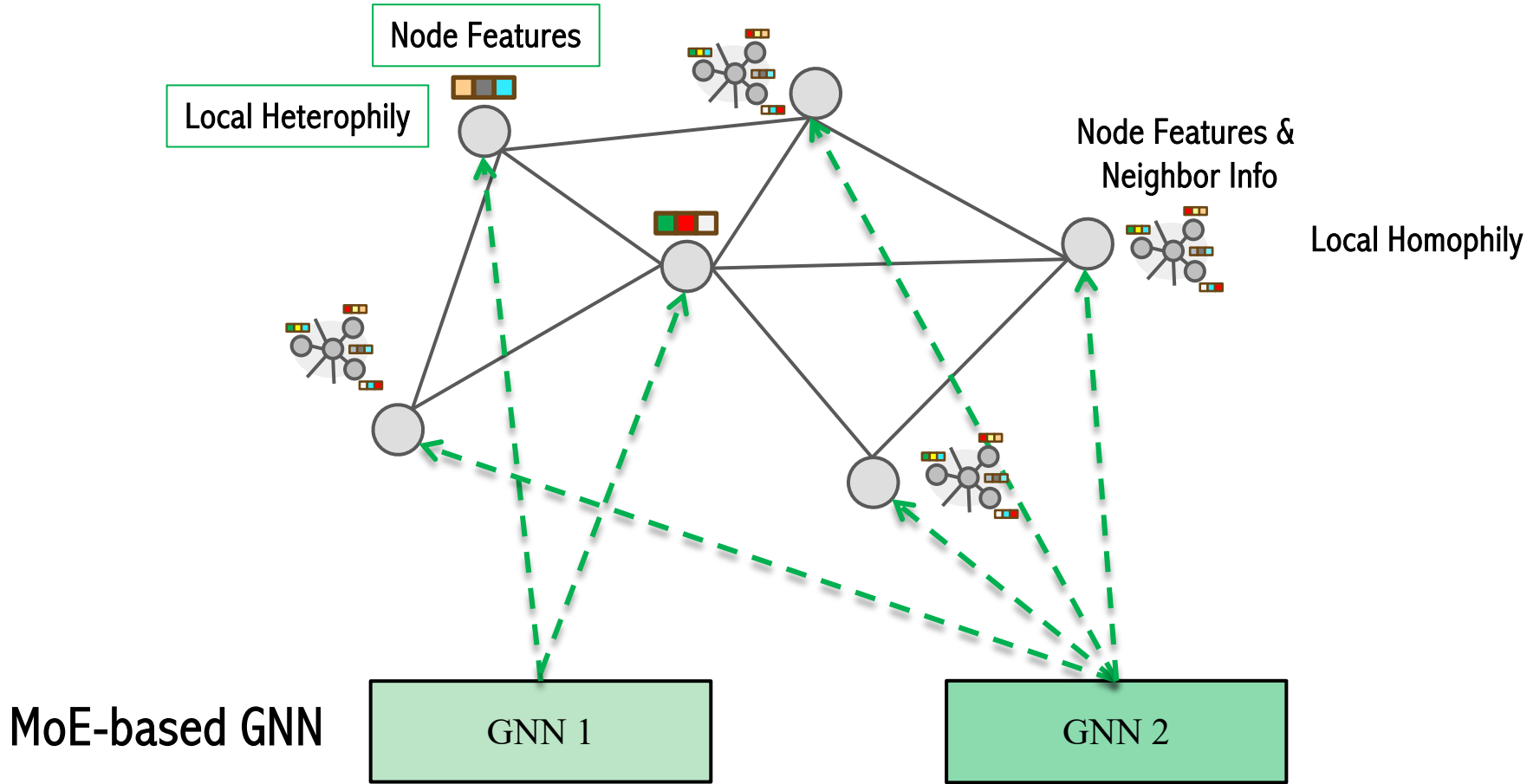
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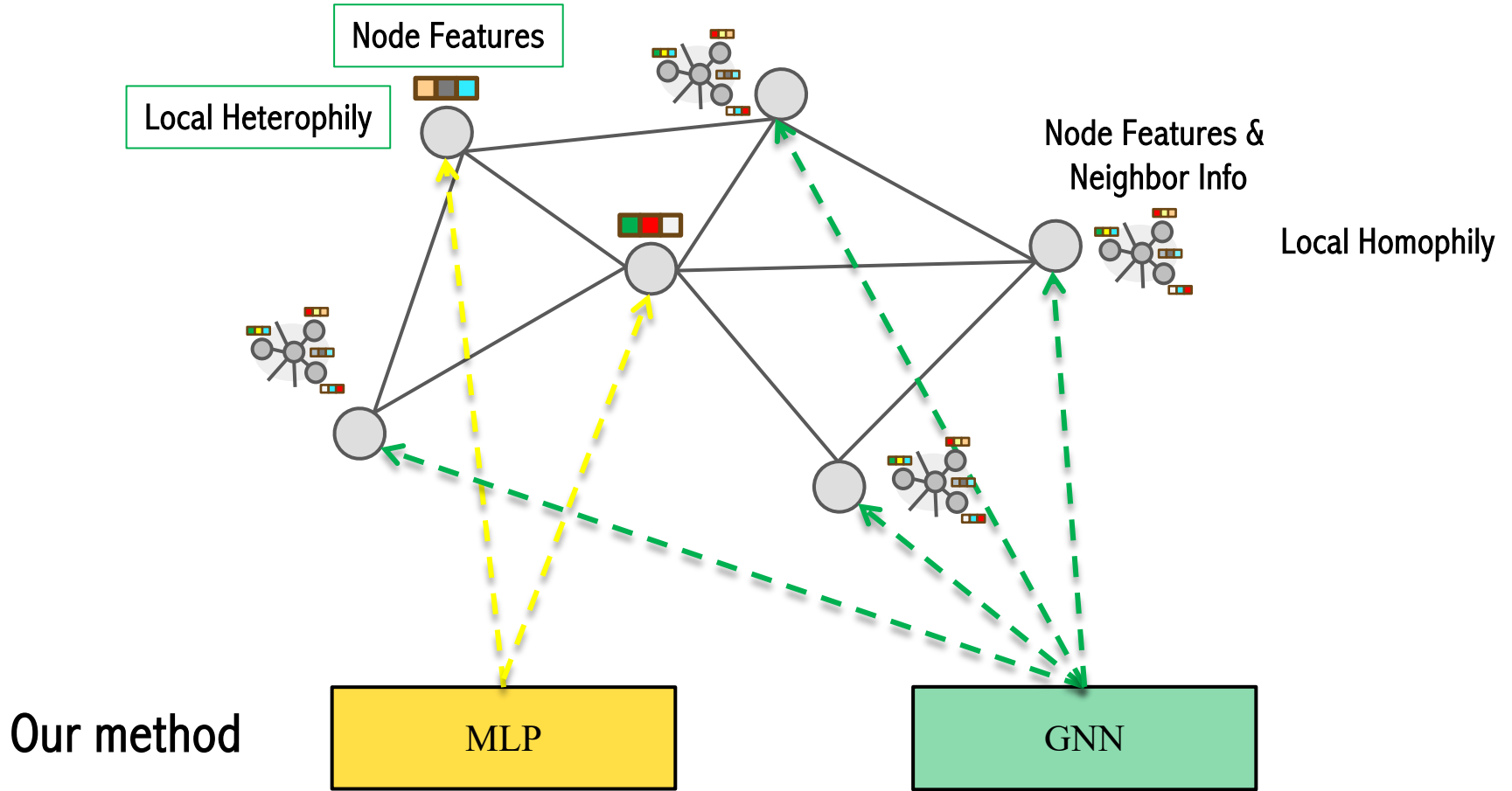


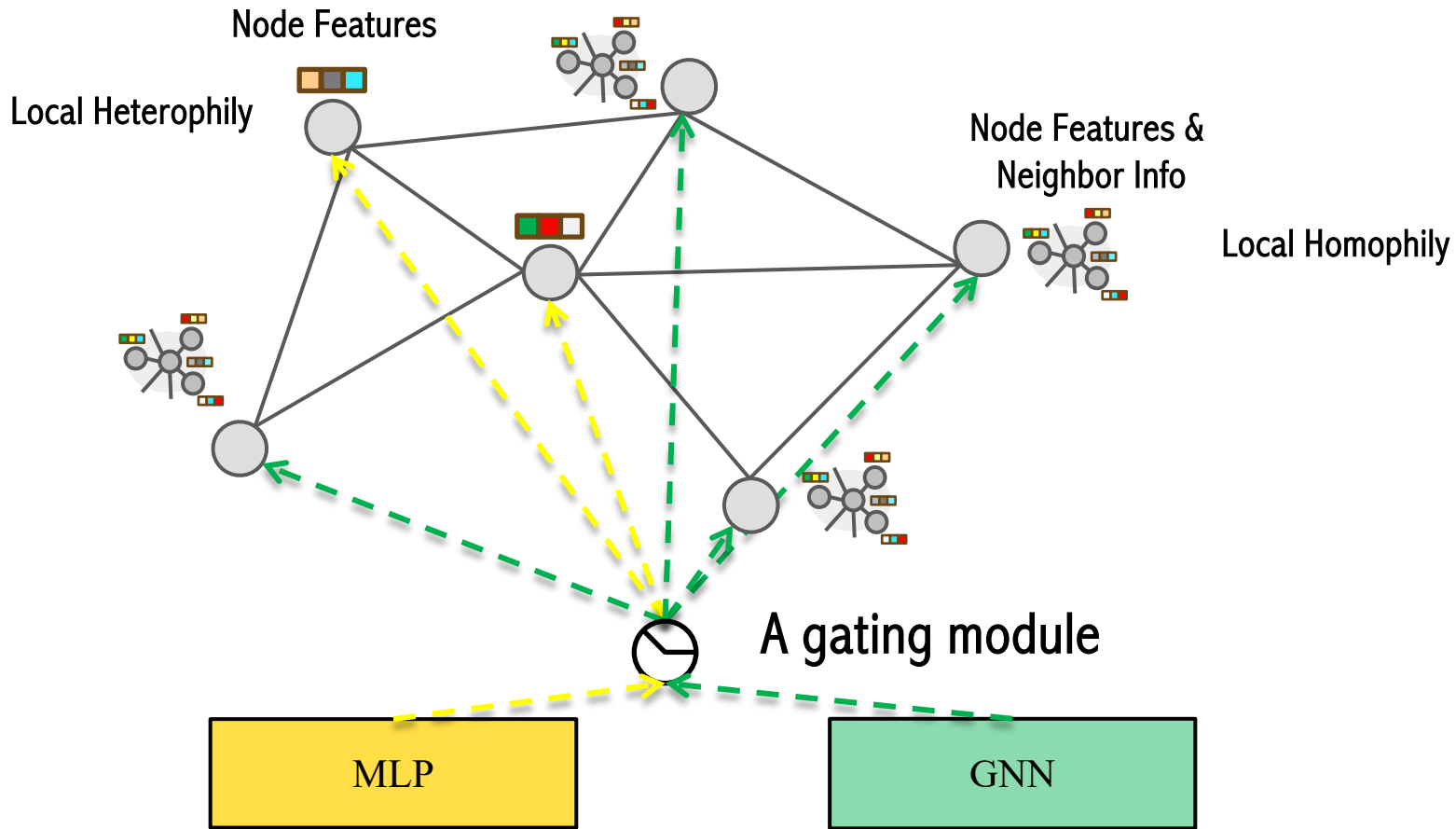
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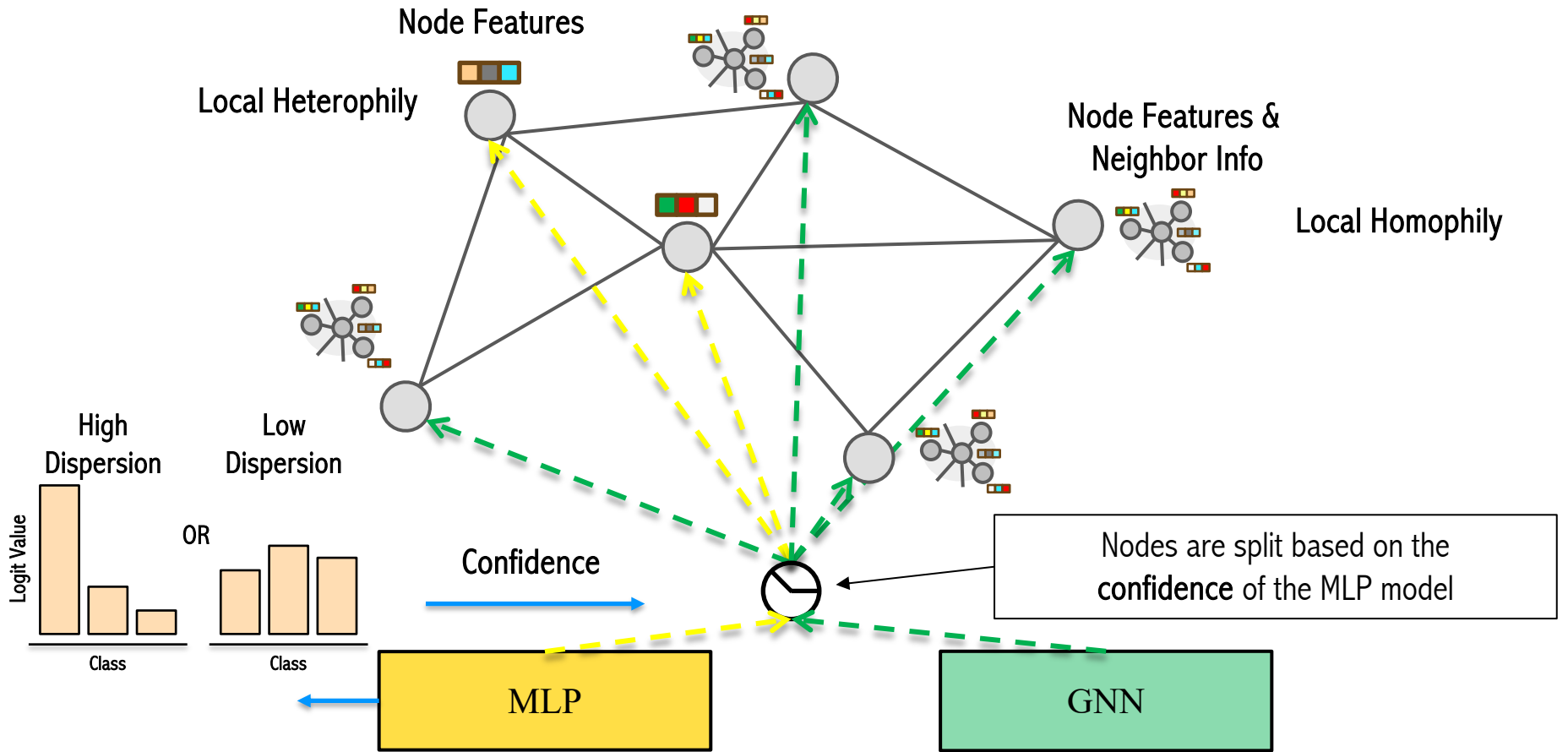




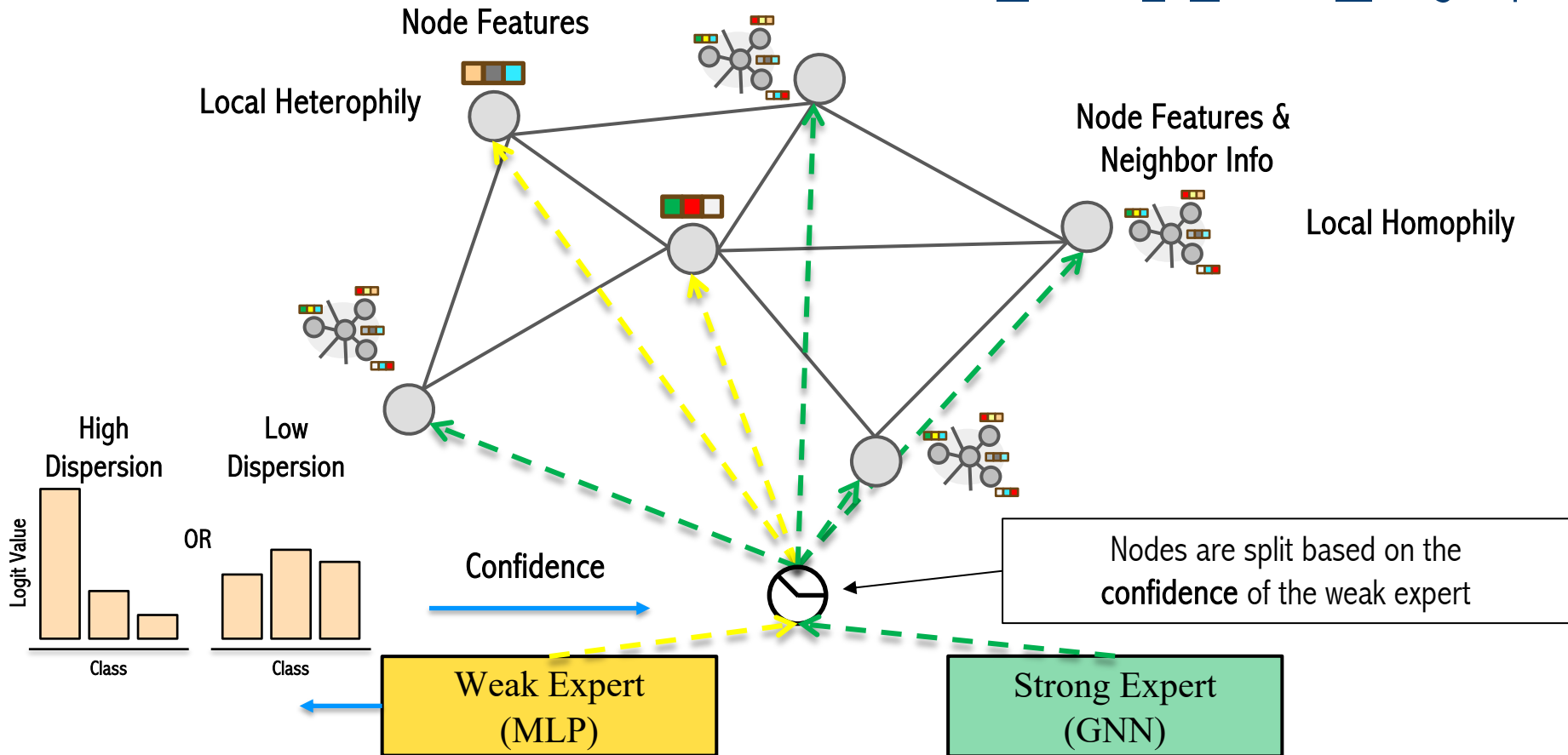








Mowst: Mixture of Weak & Strong Experts



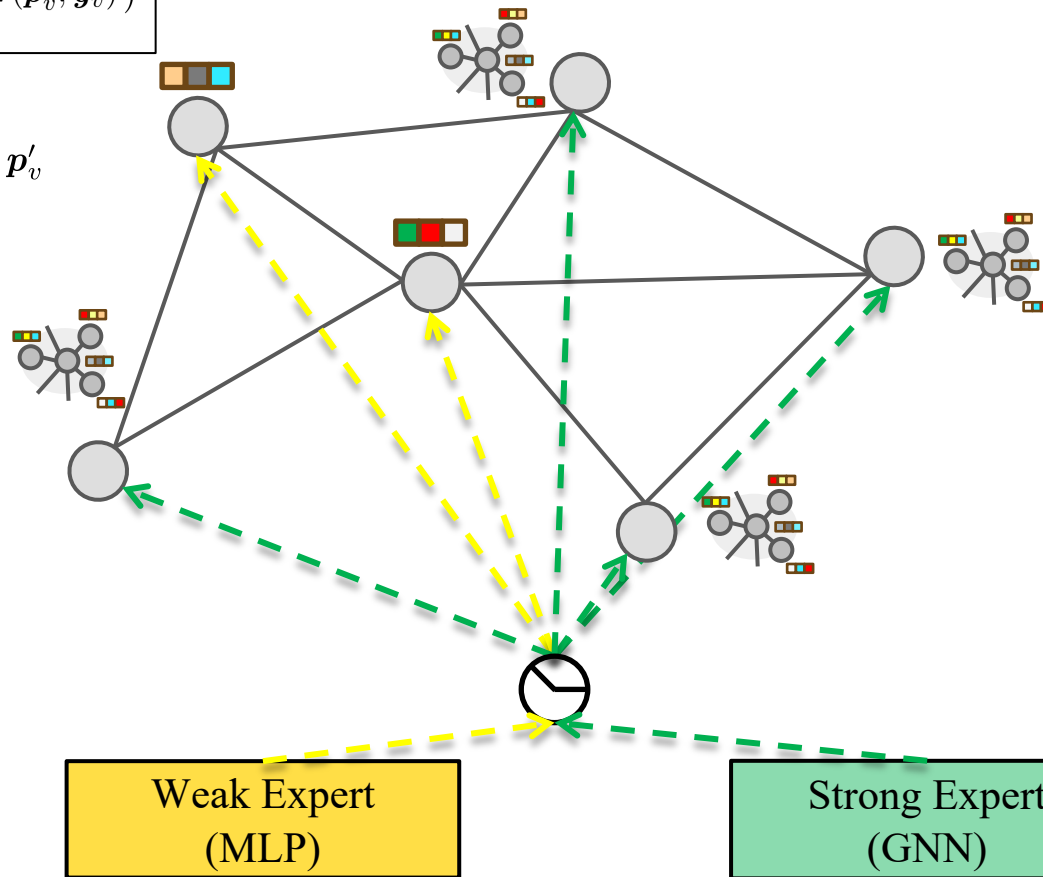
Mowst: Mixture of Weak & Strong Experts

$$L_{\text{Mowst}} = \frac{1}{|\mathcal{V}|} \sum_{v \in \mathcal{V}} (C(\mathbf{p}_v) \cdot L(\mathbf{p}_v, \mathbf{y}_v) + (1 - C(\mathbf{p}_v)) \cdot L(\mathbf{p}'_v, \mathbf{y}_v))$$

Target node: v

MLP's prediction: \mathbf{p}_v GNN's prediction: \mathbf{p}'_v

How confident is MLP: $C(\mathbf{p}_v)$



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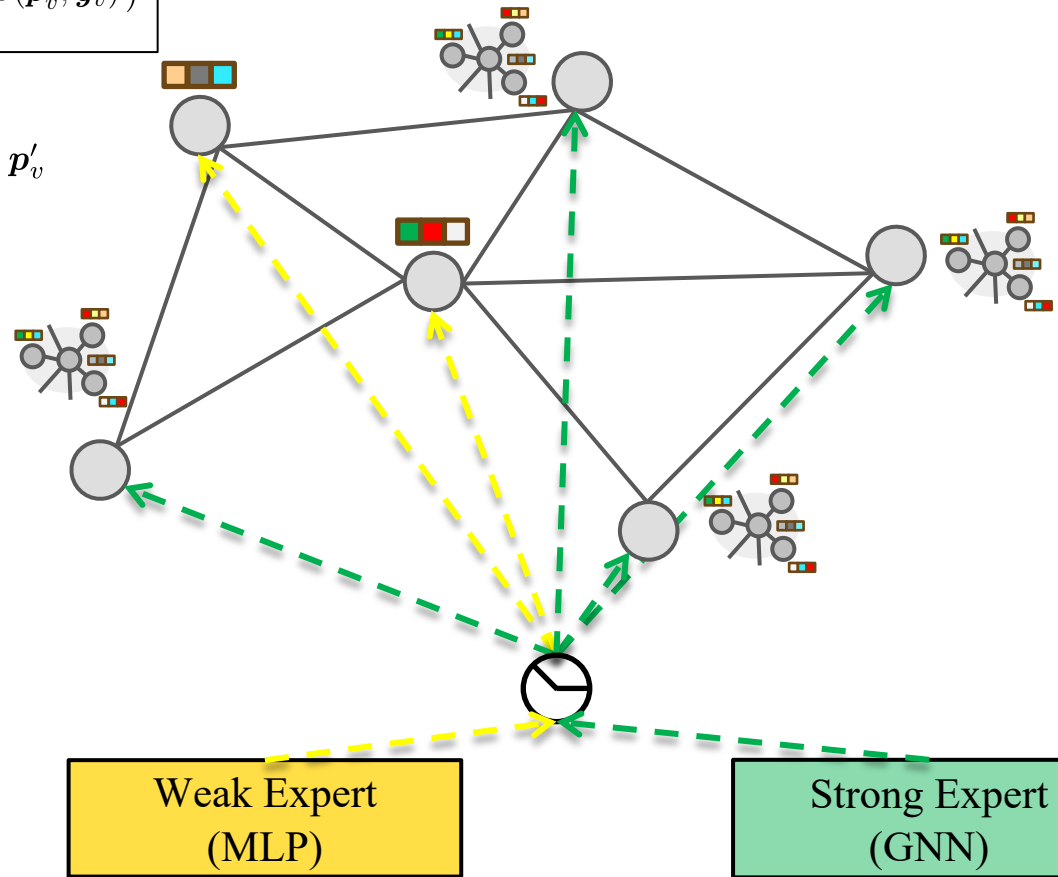
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Case 1:

If the node's self features are sufficient



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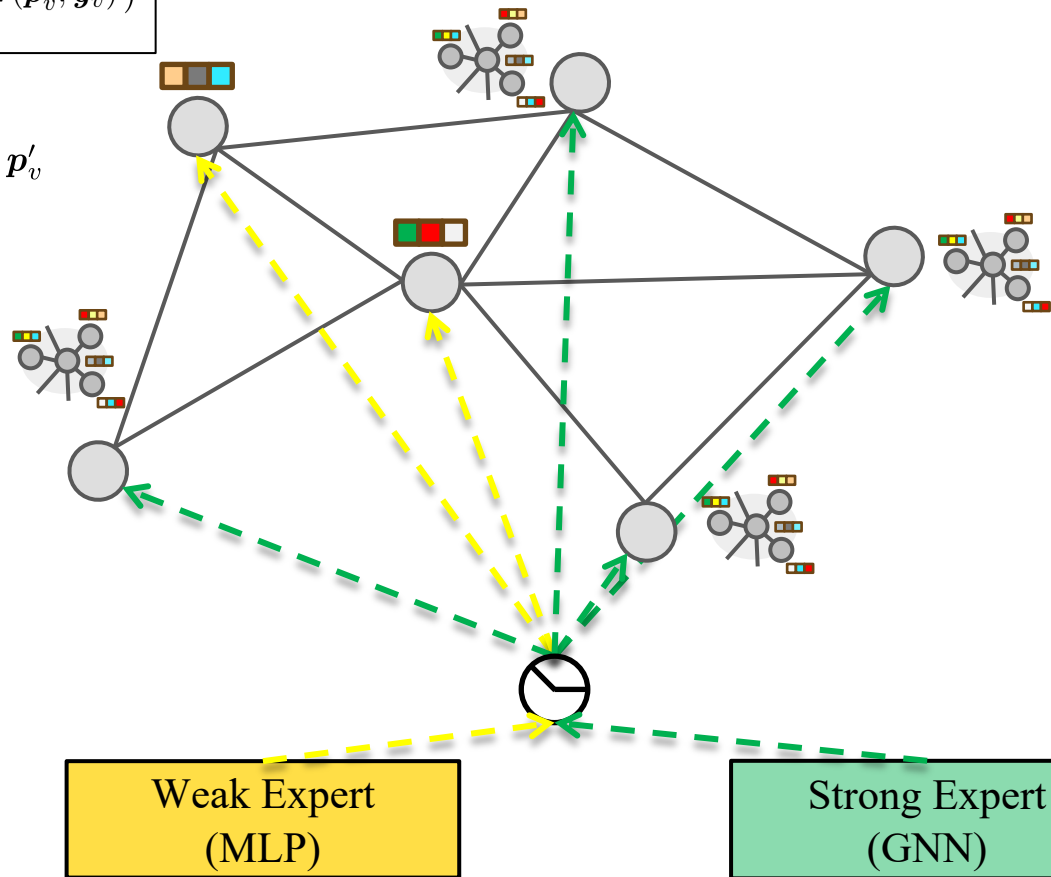
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Case 2:

If the node's self features are insufficient

- MLP is certain
- MLP is not certain



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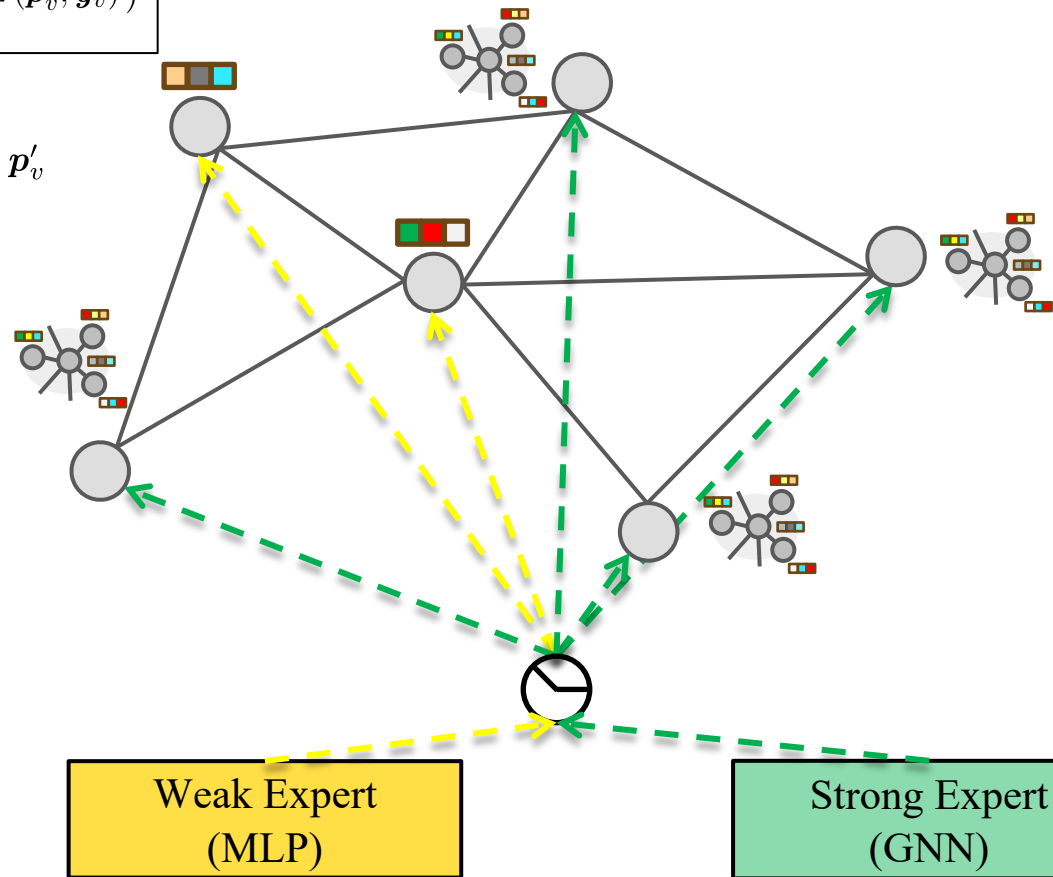
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- Mowst is at least as expressive as the MLP or GNN expert alone



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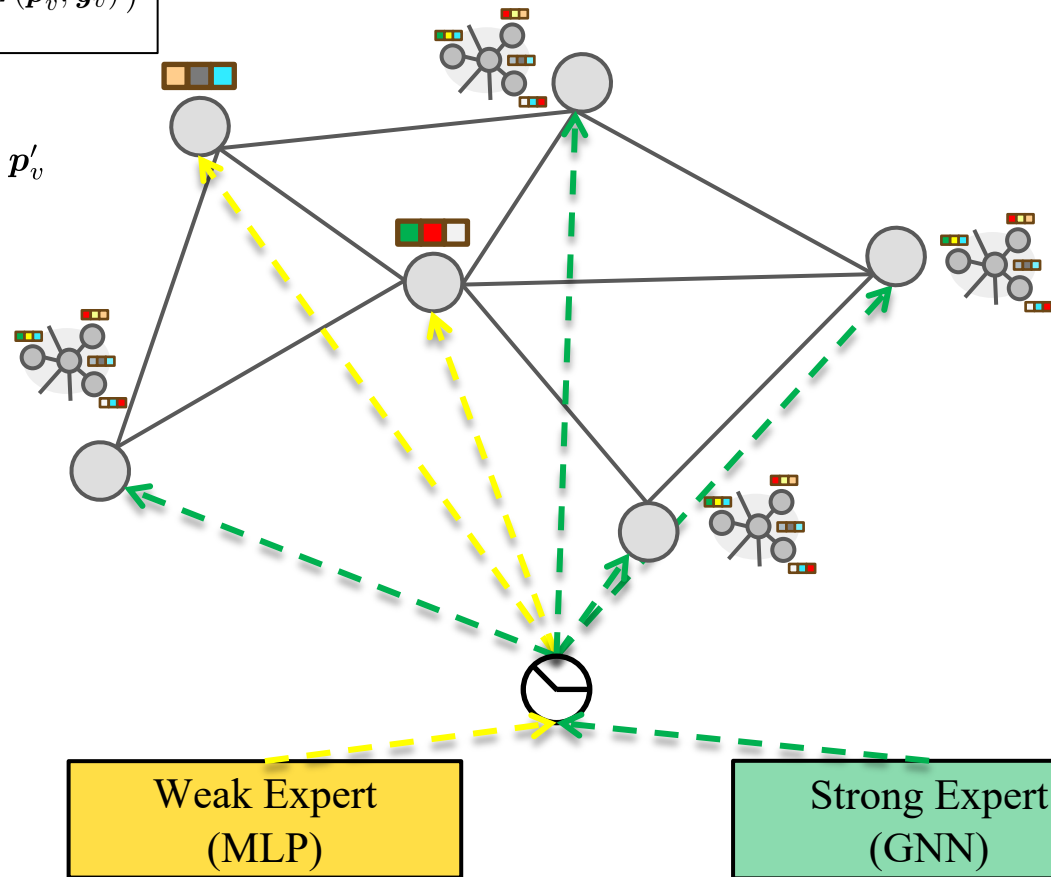
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- Mowst-GCN is more expressive than the GCN expert alone



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- Mowst is at least as expressive as the MLP or GNN expert alone
- Mowst-GCN is more expressive than the GCN expert alone
- The worst-case cost of Mowst-GCN is similar to that of a vanilla GCN

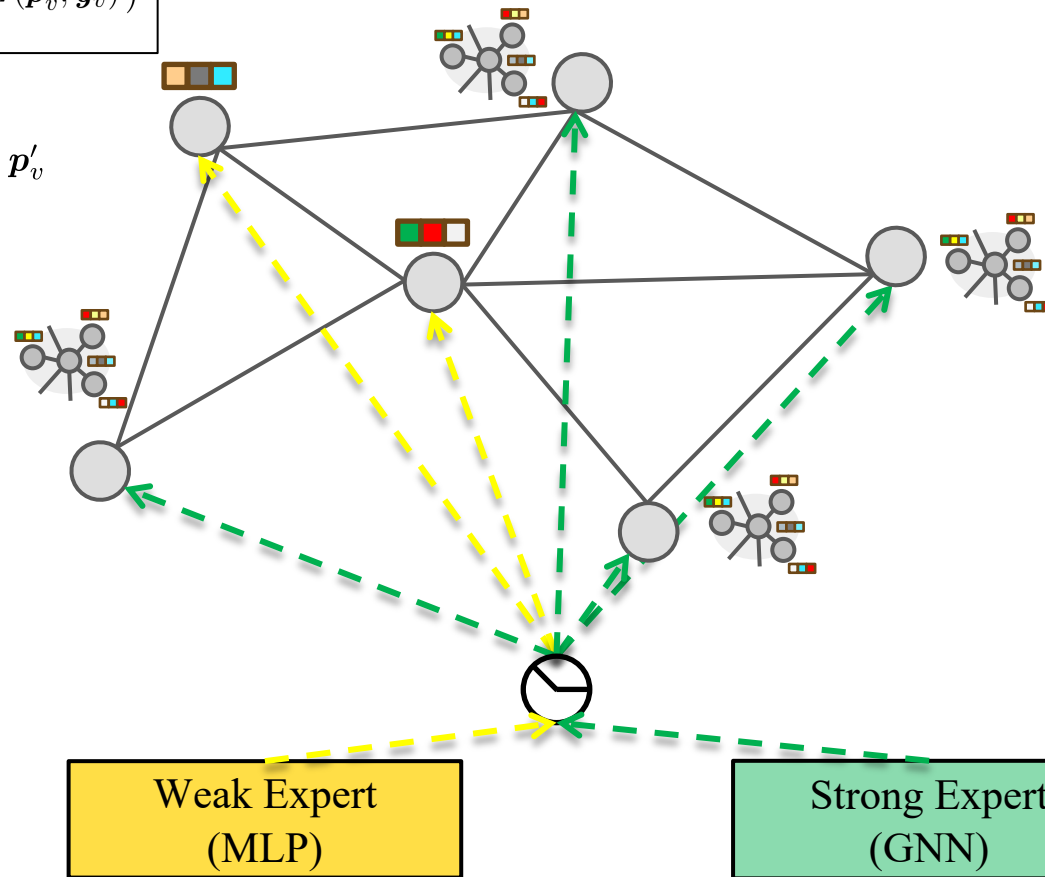
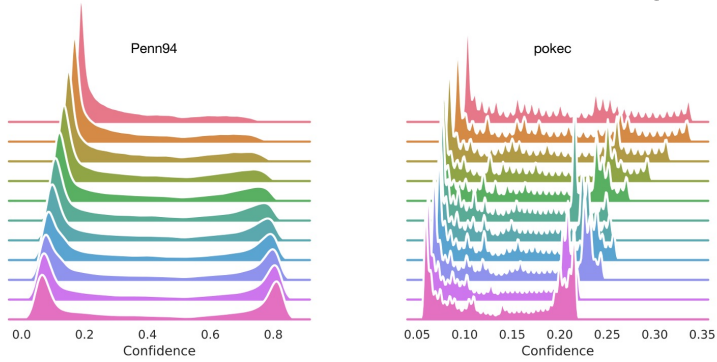


Table 1: Mowst outperforms baselines under the same number of layers and hidden dimension. Values with ‘†’, ‘‡’ and ‘††’ are from Hu et al. (2020), Lim et al. (2021), and Wang et al. (2023). For each graph, we show the **best** and second best results, and **absolute gains** against the GNN counterparts (e.g., Mowst(*)-GCN vs. GCN and GraphMoE-GCN). All results are averaged over 10 runs.

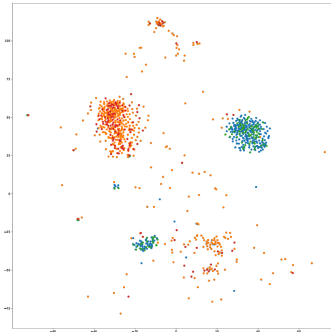
	Flickr	ogbn-products	ogbn-arxiv	Penn94	pokec	twitch-gamer
MLP	46.93 ±0.00	61.06 [†] ±0.08	55.50 [†] ±0.23	73.61 [‡] ±0.40	62.37 [‡] ±0.02	60.92 [‡] ±0.07
GAT	52.47 ±0.14	OOM	71.58 ±0.17	81.53 [‡] ±0.55	71.77 [‡] ±6.18	59.89 [‡] ±4.12
GPR-GNN	53.23 ±0.14	72.41 ±0.04	71.10 ±0.22	81.38 [‡] ±0.16	<u>78.83[‡]</u> ±0.05	61.89 [‡] ±0.29
AdaGCN	48.96 ±0.06	69.06 ±0.04	58.45 ±0.50	74.42 ±0.58	55.92 ±0.35	61.02 ±0.14
GCN	53.86 ±0.37	75.64 [†] ±0.21	71.74 [†] ±0.29	82.17 ±0.04	76.01 ±0.49	62.42 ±0.53
Mowst(*)-GCN	<u>54.62</u> ±0.23 (+0.76)	76.49 ±0.22 (+0.85)	72.52 ±0.07 (+0.64)	<u>83.19</u> ±0.43 (+1.02)	77.28 ±0.08 (+0.29)	63.74 ±0.23 (+0.83)
GIN	53.71 ±0.35	-	69.39 ±0.56	82.68 ±0.32	53.37 ±2.15	61.76 ±0.60
Mowst(*)-GIN	55.48 ±0.32 (+1.77)	-	71.43 ±0.26 (+2.04)	84.56 ±0.31 (+1.88)	76.11 ±0.39 (+22.74)	64.32 ±0.34 (+2.56)
GIN-skip	52.70 ±0.00	-	71.28 ±0.00	80.32 ±0.43	76.29 ±0.51	64.27 ±0.25
Mowst(*)-GIN-skip	53.19 ±0.31 (+0.49)	-	71.79 ±0.23 (+0.51)	81.20 ±0.55 (+0.88)	79.70 ±0.23 (+3.41)	64.91 ±0.22 (+0.64)
GraphSAGE	53.51 ±0.05	<u>78.50[†]</u> ±0.14	71.49 [†] ±0.27	76.75 ±0.52	75.76 ±0.04	61.99 ±0.30
GraphMoE-SAGE	52.16 ±0.13	77.79 ±0.00	71.19 ±0.15	77.04 ±0.55	76.67 ±0.08	63.42 ±0.23
Mowst(*)-SAGE	53.90 ±0.18 (+0.39)	79.38 ±0.44 (+0.88)	<u>72.04</u> ±0.24 (+0.55)	79.07 ±0.43 (+2.03)	77.84 ±0.04 (+1.33)	<u>64.38</u> ±0.14 (+1.05)

More details in our paper

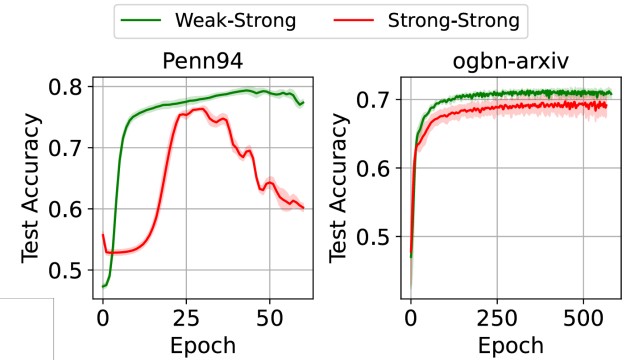
Specialization via data splitting



Denoised Fine-tuning

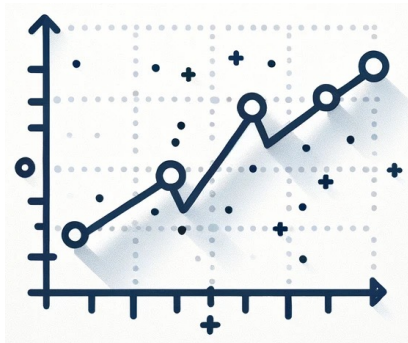


Weak-strong vs. Strong-strong



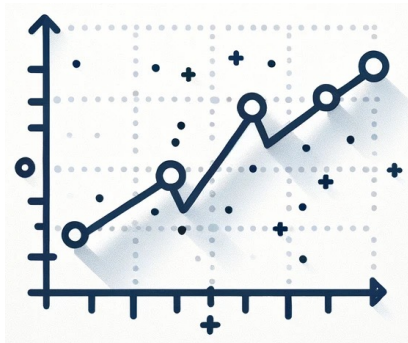
Future work

- More experts
- Other non-graph domains



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Thank you!

