Appendix: Rethinking Graph Neural Networks for Graph Coloring

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A. Graph Terminology

Here we list the following graph theoretic terms encountered in our work:

Basic graph terminology. Let $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ and $\mathcal{G}' = (\mathcal{V}', \mathcal{E}')$ be graphs on vertex set $\mathcal{V}$ and $\mathcal{V}'$, we define

- *isomorphism*: we say that a bijection $\pi : \mathcal{V} \to \mathcal{V}'$ is an *isomorphism* if any two vertices $u, v \in \mathcal{V}$ are adjacent in $\mathcal{G}$ if and only if $\pi(u), \pi(v) \in \mathcal{V}'$ are adjacent in $\mathcal{G}'$, i.e., $\{u, v\} \in \mathcal{E}$ iff $\{\pi(u), \pi(v)\} \in \mathcal{E}'$.
- *isomorphic nodes*: If there exists the isomorphism between $\mathcal{G}$ and $\mathcal{G}'$, we say that $\mathcal{G}$ and $\mathcal{G}'$ are *isomorphic*.
- *automorphism*: When π is an isomorphism of a vertex set onto itself, i.e., $\mathcal{V} = \mathcal{V}'$, π is called an *automorphism* of $\mathcal{G}$.
- *topologically equivalent*: We say that the node pair $\{u, v\}$ is *topologically equivalent* if there is an automorphism mapping one to the other, i.e., $v = \pi(u)$.
- *equivalent*: $\{u, v\}$ is *equivalent* if it is topologically equivalent by π and $\boldsymbol{x}_w = \boldsymbol{x}_{\pi(w)}$ holds for every $w \in \mathcal{V}$, where $\boldsymbol{x}_w$ is the node attribute of node w.
- *r-local isomorphism*: A bijection π_r is an *r-local isomorphism* that maps u to v if π_r is an isomorphism that maps $\mathcal{T}_{\mathcal{G}}(u, r)$ to $\mathcal{T}_{\mathcal{G}}(v, r)$.

B. Proofs

B.1. Proof of Proposition 1

We first recall the proposition.

Proposition 1. *All AC-GNNs cannot discriminate any equivalent node pair.*

Proof. Let π be the automorphism mapping u to v, here, we propose a stronger proposition:

Property 1. *Given an AC-GNN and an equivalent node pair $\{u, v\}$ by π, $\boldsymbol{h}_w^i = \boldsymbol{h}_{\pi(w)}^i$ holds for any iteration i and any node $w \in \mathcal{V}$.*

This apparently holds for $i = 0$ since $\boldsymbol{x}_w = \boldsymbol{x}_{\pi(w)}, \forall w \in \mathcal{V}$. Suppose this holds for iteration j, i.e., $\boldsymbol{h}_w^j = \boldsymbol{h}_{\pi(w)}^j, \forall w \in \mathcal{V}$. By definition, AC-GNN $\mathcal{A}$ produces the feature vector $\boldsymbol{h}_v^{j+1}$ of node v in the $(j+1)_{th}$ iteration as follows:

$$\boldsymbol{h}_v^{(j+1)} = \mathrm{COM}^{(j+1)}(\boldsymbol{h}_v^{(j)}, \mathrm{AGG}^{(j+1)}(\{\boldsymbol{h}_u^{(j)} : u \in \mathcal{N}(v)\})). \tag{1}$$

Since an automorphism π remains the set of edges, i.e., $\{u, v\} \in \mathcal{E}$ iff $\{\pi(u), \pi(v)\} \in \mathcal{E}$, the connection relation between two neighbors is preserved after the permutation by π, that is, $\mathcal{N}(\pi(v)) = \{\pi(u), u \in \mathcal{N}(v)\}$ for any $v \in \mathcal{V}$. Then, the input of $\mathrm{AGG}^{(j+1)}$ for $\pi(v)$ is given by $\{\boldsymbol{h}_u^{(j)} : u \in \mathcal{N}(\pi(v))\}$, which is $\{\boldsymbol{h}_{\pi(u)}^{(j)} : u \in \mathcal{N}(v)\}$. Since $\boldsymbol{h}_w^j = \boldsymbol{h}_{\pi(w)}^j, \forall w \in \mathcal{V}$, the input of $\mathrm{AGG}^{(j+1)}$ for v is equal to the one of $\mathrm{AGG}^{(j+1)}$ for v, i.e., $\{\boldsymbol{h}_{\pi(u)}^{(j)} : u \in \mathcal{N}(v)\} = \{\boldsymbol{h}_{\pi(u)}^{(j)} : u \in \mathcal{N}(v)\}$ and makes their output equal, i.e., $\boldsymbol{m}_v^{j+1} = \boldsymbol{m}_{\pi(v)}^{j+1}$. Therefore, the input of $\mathrm{COM}^{(j+1)}$ for v, $(\boldsymbol{h}_v^{(j)}, \boldsymbol{m}_v^{j+1})$, is also equal to the one of $\mathrm{COM}^{(j+1)}$ for $\pi(v)$, which makes the vector features of v and $\pi(v)$ equal after $(j+1)_{th}$ iteration for any node $v \in \mathcal{V}$ and proves the proposition 1. Thus, the AC-GNN $\mathcal{A}$ always produces the same node embeddings for the nodes in the equivalent node pair, which results in the same color.

□

B.2. Proof of Proposition 2

We first recall the proposition.

Proposition 2. *There is a graph in which at least one distinct node pair is not discriminated by any integrated AC-GNN.*

Proof. The proof starts with a simple fact: a classifier $CLS(\cdot)$ always assigns two nodes with the same node embedding to the same category.

Consider the following graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, in which two connected nodes u and v share the same neighborhood except each other, i.e., $\mathcal{N}(u) \backslash \{v\} = \mathcal{N}(v) \backslash \{u\}$. The node pair $\{u, v\}$ is distinct since they are connected. It follows that the inputs for the node features of u and v after iteration

k are exactly the same since $\mathcal{N}(u) \cup \{u\} = \mathcal{N}(u) \backslash \{v\} \cup \{u, v\} = \mathcal{N}(v) \backslash \{u\} \cup \{u, v\} = \mathcal{N}(v) \cup \{v\}$. Therefore, the outputs are the same, which means that $\boldsymbol{h}_u^{(j)} = \boldsymbol{h}_v^{(j)}$ holds for any iteration k and any aggregation and combine functions $\mathrm{AGG}(\cdot), \mathrm{COM}(\cdot)$. Combining with the fact that $CLS(\boldsymbol{h}_u) = CLS(\boldsymbol{h}_v)$ if $\boldsymbol{h}_u = \boldsymbol{h}_v$, the proof is finished. □

B.3. Proof of Corollary 1

We first recall the corollary.

Corollary 1. *A local coloring method is non-optimal in the random d-regular graph as $d \to \infty$.*

Proof. A random d-regular graph $\mathcal{G}_d^n$ is a graph with n nodes and each node pair is connected with a probability d/n. We start the proof from the following non-trivial proposition:

Property 2 ([1]). *The largest density of factor of i.i.d. independent sets in a random d-regular graph is asymptotically at most $(\log d)/d$ as $d \to \infty$. The density of the largest independent sets in these graphs is asymptotically $2(\log d)/d$.*

The proposition above limits the size of an independent set produced by local method for the random d-regular graph with an upper bound, $n(\log d)/d$ as $d \to \infty$. Given an upper bound of the independent set, the following corollary on the graph coloring problem is introduced:

Corollary 3. *The lower bound of k with a zero conflict constraint obtained by a local coloring method for the random d-regular graph is $d/\log d$ as $d \to \infty$.*

The proof is based on the Proposition 2: if a local coloring method f obtains a smaller k', s.t. $k' < d/\log d$ by coloring $\mathcal{G}_d^n$ without conflict using k' colors, all node sets classified by the node color will be independent sets and the size of the maximum one will be larger than $(n \log d)/d$, a contradiction with Proposition 2.

The Corollary 3 reveals the lower bound of k by local methods for a random d-regular graph. Another important observation of k by [2] specifies that exact value of the chromatic number (i.e., the minimum k) of a random d-regular graph. The proposition is described as follows:

Property 3 ([2]). *Let t_d be the smallest integer t such that $d < 2t \log t$. The chromatic number of a random d-regular graph is either t_d or $t_d + 1$.*

It follows directly from Corollary 3 and Proposition 3 that, we can finish the proof of Corollary 1 by showing that the lower bound of k by local methods is always greater than the exact chromatic number:

$$d/\log d > t_d + 1 \text{ for } d \to \infty. \tag{2}$$

Let $f(t) = 2t \log t$ and define t_0 s.t. $d = f(t_0) = 2t_0 \log t_0$. Since t_d is the smallest integer t such that $d < f(t)$, we have $f(t_0) = d \geq f(t_d - 1)$. Since f is monotonically increasing, $t_0 \geq t_d - 1$ and thus $d/\log d - t_d - 1 \geq d/\log d - t_0 - 2$ always holds. Let $d = 2t_0 \log t_0$, we further derive the objective below:

$$\begin{aligned} & d/\log d - t_d - 1 \geq d/\log d - t_0 - 2 \\ =& \frac{2t_0 \log t_0}{\log(2t_0 \log t_0)} - t_0 - 2 > 0, \text{ for } d, t_0 \to \infty. \end{aligned}$$

we first prove that

$$\begin{aligned} & \frac{\log t_0}{\log(2t_0 \log t_0)} > 2/3 \\ \Rightarrow & 3 \log t_0 > 2 \log(2t_0 \log t_0) \\ \Rightarrow & 3 \log t_0 > 2(1 + \log t_0 + \log(\log t_0)) \\ \Rightarrow & \log t_0 > 2 + 2 \log(\log t_0) \text{ when } t_0 \to \infty. \end{aligned}$$

The above inequality holds obviously. Following the objective, we have:

$$\begin{aligned} & \frac{2t_0 \log t_0}{\log(2t_0 \log t_0)} - t_0 - 2 \\ > & \frac{4}{3} t_0 - t_0 - 2 > 0 \text{ when } t_0 \to \infty. \end{aligned}$$

Therefore, we finish the proof.

□

B.4. Proof of Corollary 2

We first recall the corollary.

Corollary 2. *AC-GNN is a local coloring method.*

Proof. Given an AC-GNN $\mathcal{A}$ with L layers, let's consider a L-local equivalent node pair $\{u, v\}$ in $\mathcal{G}$ by an L-local automorphism π_L, which means that two rooted subtrees $\mathcal{T}_{\mathcal{G}}(u, L)$ and $\mathcal{T}_{\mathcal{G}}(v, L)$ are isomorphic and $\boldsymbol{x}_w = \boldsymbol{x}_{\pi_r(w)}$ holds for every $w \in \mathcal{T}_{\mathcal{G}}(u, r)$. Since two rooted subtrees are isomorphic, the WL test [3] decides $\mathcal{T}_{\mathcal{G}}(u, L)$ and $\mathcal{T}_{\mathcal{G}}(v, L)$ are isomorphic and assigns the same color to w and $\pi_L(w)$ for any $w \in \mathcal{T}_{\mathcal{G}}(u, L)$. To connect the WL test with AC-GNN, the following proposition is used:

Property 4 ([4, 5, 6]). *If the WL test assigns the same color to two nodes in a graph, then every AC-GNN maps the two nodes into the same node embedding.*

Therefore, $\mathcal{A}$ maps the u and v into the same node embedding. It follows that $\mathcal{A}$ is L-local and thus local. □

B.5. Proof of Theorem 2

We first recall the theorem.

Theorem 2. *Let $\mathcal{A}$ be a simple AC-GNN and both input and output of each layer in $\mathcal{A}$ be the probability distribution $\boldsymbol{h} \in \mathbb{R}^k$ of k colors, $\mathcal{A}$ is color equivariant if and only if the following conditions hold:*

- *For any layer i, all the off-diagonal elements of $\boldsymbol{C}^{(i)}$ are tied together and all the diagonal elements are equal as well. That is,*

$$\boldsymbol{C}^{(i)} = \lambda_C^{(i)}\boldsymbol{I} + \gamma_C^{(i)}(\boldsymbol{1}\boldsymbol{1}^\top)$$
$$\lambda_C^{(i)}, \gamma_C^{(i)} \in \mathbb{R} \ ; \boldsymbol{1} = [1, ..., 1]^\top \in \mathbb{R}^k. \tag{3}$$

- *For any layer i, all the off-diagonal elements of $\boldsymbol{A}^{(i)}$ are also tied together and all the diagonal elements are equal as well. That is,*

$$\boldsymbol{A}^{(i)} = \lambda_A^{(i)}\boldsymbol{I} + \gamma_A^{(i)}(\boldsymbol{1}\boldsymbol{1}^\top)$$
$$\lambda_A^{(i)}, \gamma_A^{(i)} \in \mathbb{R} \ \boldsymbol{1} = [1, ..., 1]^\top \in \mathbb{R}^k. \tag{4}$$

- *For any layer i, all elements in $\boldsymbol{b}^{(i)}$ are equal. That is,*

$$\boldsymbol{b}^{(i)} = \beta^{(i)}\boldsymbol{1} \quad \beta^{(i)} \in \mathbb{R} \ \boldsymbol{1} = [1, ..., 1]^\top \in \mathbb{R}^k. \tag{5}$$

Proof. Let $\text{AGG}^{(i)}$ and $\text{COM}^{(i)}$ be the aggregation and combination functions in the i_{th} layer of $\mathcal{A}$. $\mathcal{A}$ is color equivariant if and only if all functions in $\{\text{AGG}^{(i)}, \text{COM}^{(i)} : i \in 1, ..., L\}$ are color equivariant. the aggregation function is color equivariant clearly and thus we are left to consider the color equivariance of combination functions. Considering the definition of color equivariant in Definition 4, the color equivariance of combination function $\text{COM}^{(i)} = \sigma(\boldsymbol{x}\boldsymbol{C}^{(i)} + \boldsymbol{y}\boldsymbol{A}^{(i)} + \boldsymbol{b}^{(i)})$ is given by:

$$\sigma(\boldsymbol{x}\boldsymbol{C}^{(i)} + \boldsymbol{y}\boldsymbol{A}^{(i)} + \boldsymbol{b}^{(i)})\boldsymbol{P} = \sigma(\boldsymbol{x}\boldsymbol{P}\boldsymbol{C}^{(i)} + \boldsymbol{y}\boldsymbol{P}\boldsymbol{A}^{(i)} + \boldsymbol{b}^{(i)}). \tag{6}$$

$\text{COM}^{(i)}$ is color equivariant if and only if the equation above holds for any permutation matrix $\boldsymbol{P} \in \mathbb{R}^{k\times k}$ and any vectors $\boldsymbol{x}, \boldsymbol{y}$. Considering it holds for any vectors $\boldsymbol{x}, \boldsymbol{y}$, We first find three special cases of $\boldsymbol{x}$ and $\boldsymbol{y}$, which are necessary conditions and correspond to three conditions respectively:

Case 0. When $\boldsymbol{y} = \boldsymbol{0}$, we have that $\sigma(\boldsymbol{x}\boldsymbol{C}^{(i)})\boldsymbol{P} = \sigma(\boldsymbol{x}\boldsymbol{P}\boldsymbol{C}^{(i)})$ holds for any $\boldsymbol{P}$ and $\boldsymbol{x}$. That is, $\boldsymbol{x}(\boldsymbol{C}^{(i)}\boldsymbol{P} - \boldsymbol{P}\boldsymbol{C}^{(i)}) = \boldsymbol{0}$ always holds, which reveals that $\boldsymbol{C}^{(i)}\boldsymbol{P} = \boldsymbol{P}\boldsymbol{C}^{(i)}$. $\boldsymbol{C}^{(i)}\boldsymbol{P} = \boldsymbol{P}\boldsymbol{C}^{(i)}$ holds for any $\boldsymbol{P}$ follows that $C^{(i)}_{m,m} = C^{(i)}_{n,n}$ and $C^{(i)}_{m,n} = C^{(i)}_{n,m}$ for any $m, n \in \{1, ..., k\}$. Therefore, all the off-diagonal elements of $\boldsymbol{C}^{(i)}$ are tied together and all the diagonal elements are equal as well.

Case 1. When $\boldsymbol{x} = \boldsymbol{0}$, we can prove that all the off-diagonal elements of $\boldsymbol{A}^{(i)}$ are tied together and all the diagonal elements are equal as well following the similar induction in case 1.

Case 2. When $\boldsymbol{x} = \boldsymbol{y} = \boldsymbol{0}$, we have that $\sigma(\boldsymbol{b}^{(i)})\boldsymbol{P} = \sigma(\boldsymbol{b}^{(i)})$ holds for any $\boldsymbol{P}$. Therefore, all elements in $\boldsymbol{b}^{(i)}$ are equal.

After proving that these conditions are necessary for a color equivariant $\mathcal{A}$, we proceed to prove that the conditions above are already sufficient. Let $\boldsymbol{C}^{(i)} = \lambda_C^{(i)}\boldsymbol{I} + \gamma_C^{(i)}(\boldsymbol{1}\boldsymbol{1}^\top)$, $\boldsymbol{A}^{(i)} = \lambda_A^{(i)}\boldsymbol{I} + \gamma_A^{(i)}(\boldsymbol{1}\boldsymbol{1}^\top)$ and $\boldsymbol{b}^{(i)} = \beta^{(i)}\boldsymbol{1}$, $\text{COM}^{(i)}$ is then calculated by:

$$\begin{aligned}
\text{COM}^{(i)}\boldsymbol{P} &= \sigma(\boldsymbol{x}\boldsymbol{C}^{(i)} + \boldsymbol{y}\boldsymbol{A}^{(i)} + \boldsymbol{b}^{(i)})\boldsymbol{P} \\
&= \sigma(\boldsymbol{x}\lambda_C^{(i)}\boldsymbol{I}\boldsymbol{P} + \boldsymbol{x}\gamma_C^{(i)}(\boldsymbol{1}\boldsymbol{1}^\top)\boldsymbol{P} + \boldsymbol{y}\lambda_A^{(i)}\boldsymbol{I}\boldsymbol{P} \\
&\quad + \boldsymbol{y}\gamma_A^{(i)}(\boldsymbol{1}\boldsymbol{1}^\top)\boldsymbol{P} + \beta^{(i)}\boldsymbol{1}\boldsymbol{P}) \\
&= \sigma(\boldsymbol{x}\boldsymbol{P}\lambda_C^{(i)}\boldsymbol{I} + \boldsymbol{x}\boldsymbol{P}\gamma_C^{(i)}(\boldsymbol{1}\boldsymbol{1}^\top) + \boldsymbol{y}\boldsymbol{P}\lambda_A^{(i)}\boldsymbol{I} \\
&\quad + \boldsymbol{y}\boldsymbol{P}\gamma_A^{(i)}(\boldsymbol{1}\boldsymbol{1}^\top) + \beta^{(i)}\boldsymbol{1}) \\
&= \sigma(\boldsymbol{x}\boldsymbol{P}\boldsymbol{C}^{(i)} + \boldsymbol{y}\boldsymbol{P}\boldsymbol{A}^{(i)} + \boldsymbol{b}^{(i)}).
\end{aligned} \tag{7}$$

Therefore, $\text{COM}^{(i)}$ is color equivariant if and only if the conditions hold, which completes the proof. □

C. Related Works

C.1. Graph Neural Networks.

Analysis on the power of GNNs. With the overwhelming success of GNNs in various fields ranging from recommendation system and VLSI design, recently, the study on the power of GNNs becomes more and more important and necessary, and has attracted extensive interest. The two recent papers [4, 6] formalize the power as the capability to map two equivalent nodes to the same node embedding. They explore the power by establishing a close connection between GNNs and 1-Weisfeiler-Lehman (WL) test, a classical algorithm for the graph isomorphism test. More specifically, they independently showed that every time when two nodes are assigned the same embedding by any GNN, the two nodes will always be labeled the same by the 1-WL test, which means that GNNs are upper-bounded by 1-WL test in terms of the representation power. To develop a more powerful GNN that breaks through the limit by 1-WL test, many attempts are made from different perspectives. Some GNNs [7, 8, 9, 4] are proposed by mimicking a higher-order-WL test based on higher-order tensors. Another direction is to introduce more informative features/operations to make the model sensitive to the substructure [10] or global structure [5, 11, 12]. We leave the detailed discussion of such a non-local scheme in Appendix E. Besides the study on the comparison with WL-test, many other works investigate the power of GNNs from different angles and a lot of interesting conclusions are obtained. Xu et al. [13] shows that GNNs align with DP and thus are expected to solve tasks that are solvable by DP. This interesting conclusion leaves

us a future work to study GNN in the coloring problem by learning previous DP-based coloring algorithms. Loukas et al. [14] concludes that the product of the GNN's depth and width must exceed a polynomial of the graph size to obtain the optimal solution of some problems, e.g., Maximum Independent Set (MIS) problem, and coloring problem. This conclusion motivates our experiments on the model depth, which is covered in Appendix F.3. Another work [15] explores the design space for GNNs and gives some best parameters in various design dimensions, where best means the selected parameters make the corresponding GNNs more effective than others. We follow the guidance of this work to select most hyper-parameters and model architectures, as shown in Appendix F.1. GeomGCN [16] points the limits of AC-GNNs from the perspective of network geometry, the node can only exchange information with its neighbors, while the long-range dependencies are missed and similar nodes (may be very distant) are more likely to be proximal. To overcome the issues, a novel geometric aggregation scheme was proposed. Generally, instead of aggregating information from graph neighborhoods directly, the original graph is mapped to a latent continuous space according to pre-calculated node embedding. Then, a structural neighbor relation is constructed based on the distance and relative direction in the latent space. However, their motivation is not applicable for the coloring problem: the coloring results are totally not relevant with the similarity of nodes.

GNNs for NP problem. Recently, the applications of GNNs on NP problems received great attention. Some works integrate GNNs to a sophisticated heuristic algorithm designed for a specific NP problem. Li et al. [17] proposes a GNN-based framework to solve the MIS problem, where the adopted GNN generates multiple probability maps to represent the likelihood of each vertex being in the optimal solution. However, the following heuristic algorithm to handle the *multiple* probability maps is time-consuming. In their experiments, a graph with 1,000 vertices will yield up to 100K diverse solutions and the heuristic algorithm is processed up to 10 minutes. Not saying that the runtime may explode when applied in the k-coloring problem. Another work [18] uses GNNs to solve the subgraph matching problem, a problem of determining whether a given query graph is a subgraph of a large target graph. They designed a particular loss function, to ensure that the subgraph relations are preserved in the embedding space. Besides these direct applications, some theoretical works discussed the power of GNNs to solve the NP problem. If P $\neq$ NP, GNNs cannot exactly solve these problems. Under this assumption, Sato [19] demonstrates the approximation ratios of GNNs for some combinatorial problems such as the minimum vertex cover problem. They study the ratio by building the connection between GNNs and distributed local algorithms. Specifically, they show that the set of graph problems that GNN classes can solve is the same as the one that distributed local algorithm classes can solve. Besides a pure GNN, Dai et al. [20] develops a framework that combines reinforcement learning and graph embedding to address some NP problems. Generally, the reinforcement learning model uses the graph embedding obtained by Structure2Vec [21].

GNNs on tasks under heterophily. To the best of our knowledge, Zhu et al. [22] is the first and only work that formally addressed the drawbacks of previous GNNs on tasks under heterophily. Beyond homophily, they proposed three designs that can be beneficial for the learning under heterophily: 1) The node embedding and aggregated embeddings should be separated. This statement aligns with our Proposition 2, addressing the limitation of an integrated AC-GNN in the coloring problem. Although most previous works focus on the homophily scenario, some of them [15, 23] also pay attention to the separation of neighbor embeddings and ego-embedding (i.e., a node's embedding). 2) The aggregation function should involve higher-order neighborhoods. The intuition is that higher-order neighborhoods may be homophily-dominant. Take the coloring problem as an example, if two nodes, say u, v, are connected with another same node t, then u, v are more likely to be assigned the same color. This design is also employed in previous works [24, 25] for homophily, considering that a higher order polynomials of the normalized adjacency matrix indicates a low-pass filter. 3) The final results should combine intermediate representations from all layers. The design is originally introduced in jumping knowledge networks [26] and motivated by the fact that each layers contains information from neighborhoods of different depth.

C.2. Coloring methods.

The graph coloring problem is crucial in domains ranging from network science and database systems to VLSI design. Here, we classify previous coloring methods as learning-based methods and non-learning-based methods.

Non-learning-based methods. As a classical problem in the NP-hard classes and graph theory, graph coloring problem has received considerable attention in past decades. Here, we only cover some representative non-learning-based methods that are related to our method from some perspectives. Braunstein et al. [27] proposed Belief propagation (BP) and Survey propagation (SP) to solve the k-coloring problem, where both methods belong to a message-passing scheme. The key idea is that, each node is randomly assigned a probability distribution of colors, then the probability is updated based on the probabilities of neighbors. Formally, define $\eta^k_{e\to u}$ as the probability that edge $e = \{u, v\}$ refutes u as the color k, for the k-coloring problem, $\eta^k_{e\to u}$ is updated

by:

$$\eta^k_{e\to u} = \frac{\prod_{v'\in\mathcal{N}(v)/\ u}(1-\eta^k_{\{v,v'\}\to v})}{\sum_{r=1}^{k}\prod_{v'\in\mathcal{N}(v)/\ u}(1-\eta^r_{\{v,v'\}\to v})} \tag{8}$$

The numerator indicates the possibility that v is colored by the color k (without considering node u). And the fraction is for normalization, making that the sum equals to one. The SP procedure is a little different, it did not normalize the probability directly, but introduced a joker state, $\eta^\star_{e\to u}$, representing that the edge can not refute any colors, i.e., $1 = \eta^\star_{e\to u} + \sum_{r=1}^{k}\eta^r_{e\to u}$. The method is simple and very close to our non-training version. However, the method is more theoretical and less practical because it is easy to fall into a trivial solution, i.e., all edges are assigned into the joker state. Even though a non-trivial solution can be found, a large number of iterations may be required due to its randomness. Apart from message passing, Takefuji [28] proposed an Artificial Neural Network (ANN) based method for the four-coloring problem. The basic conclusion is that the probability distribution[1] can be updated by subtracting the aggregated probability distributions of neighbors, which aligned with the intuition for our parameter initialization.

Learning-based methods. Although our work is the first one that tries and analyzes the power of GNNs in the graph coloring problem, there is a surge of learning-based methods for coloring. Lemos et al. [29] integrated Recurrent Neural Networks (RNNs) into the message passing framework, i.e., two RNNs were employed to computes the embedding update from aggregated messages for each vertex and color. Finally, the graph embedding was used to predict the chromatic number, and the node embedding was used to predict exact node color by clustering. However, the clustering-based method generated a prohibitive conflict number as shown in Table 1 of our paper, making the method not practical. Huang et al. [30] introduced a fast heuristics coloring algorithm using deep reinforcement learning. For each step (state), the model predicts the next node and its best color solution with a win/lose feedback. The prediction depends on previous coloring results and a graph embedding generated by an LSTM. The method can give relatively accurate coloring results, but still only comparable with some simple heuristic algorithms such as dynamic order coloring. On the contrary, our supplementary results in Appendix F.2 demonstrates that our method outperforms these simple heuristic algorithms significantly. Zhou et al. [31] also borrowed the idea of reinforcement learning. However, the proposed method did not use a training scheme: the actions towards the environment is defined by a deterministic update function of the coloring probability distributions. The method achieves a state-of-the-art result quality. However, the framework contains a descent-based local search with a portion of randomness, which requires a repeated execution with different random seeds. Moreover, the local search algorithm may require extensive iterations to find a local optimum. Due to these limitations, the method suffers from the runtime, in their experiments, the coloring process for a 500-node graph costs more than 100 seconds.

[1] In their work, the node attribute is not probability distribution but a binary vector indicating the selected colors. Nevertheless, the conclusion still holds for a probability case.

Algorithm 1 IterativeRemoval

Input: $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\} \to$ Target graph.
Input: $k \to$ Number of available colors.
1: **while** $\exists u \in \mathcal{V}$ s.t. degree of $u < k$ **do**
2: Update degree of the neighbor of u by subtracting one.
3: Remove u in $\mathcal{G}$.
4: **end while**

D. Preproces & Postprocess

In our method, we add preprocess and postprocess procedures to reduce the problem complexity and improve the result quality. Note that these techniques are not necessary for our method, in Appendix F.5, we list the experimental results without any postprocess procedures. At the same time, we have implemented these techniques in DGL or by a series of tensor operations, so that both of them can be efficiently processed by GPU.

Preprocess In the preprocess part, we remove the node with a degree less than k iteratively. Because a node with degree less than k will always not contribute to a conflict in the optimal solution, this kind of removal will not introduce any redundant conflicts. The algorithm is shown in Algorithm 1. There are many other graph simplification techniques in the practical applications such as bridge detection [32], we do not focus on these techniques, because the aim of our work is not to develop a very effective coloring method by powerful pre-process and post-process procedures, but to study the power of GNNs on the coloring problems.

Postprocess In the postprocess part, we iteratively detect 1) whether a color change in a single node will decrease the conflict number or 2) whether a swap of colors between connected nodes will decrease the conflict number. The algorithm is shown in Algorithm 2. Generally, we iteratively check (L2 - L18) each node (L4 - L11) and each conflict edge (L12 - L17), if one better solution is found, we modify the coloring result to the better one and continue the iteration.

E. Global method

During the exploration of GNNs, the locality of GNNs has been widely observed as an intrinsic nature. The main

Algorithm 2 POSTPROCESS

Input: $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\} \rightarrow$ Target graph.
Input: $f \rightarrow$ Coloring results.

```
Is_changed ← True;
while Is_changed do
    Is_changed ← False;
    for u ∈ V do
        for r ∈ {1, ..., k} do
            if the conflict # reduces when set f(u) to r then
                f(u) ← r;
                Is_changed ← True;
            end if
        end for
    end for
    for e = {u, v} ∈ E do
        if the conflict # reduces when swap color of u, v then
            swap color of u, v;
            Is_changed ← True;
        end if
    end for
end while
```

concern in previous works is that the locality inhibits GNNs from detecting the global graph structure, thereby harming the representation power. In this section, we use the notation of the local method defined in our paper, and look back on previous solutions to see whether they provide a truly global scheme by our definition. We hope that our analysis can provide some insights on the global GNNs for future research. We first recap the definition of a local method:

Definition 3 (local method [33])**.** *A coloring method f is r-local if it fails to discriminate any r-local equivalent node pair. A coloring method f is local if f is r-local for at least one positive integer r.*

To determine whether a coloring method is local or not, we need to, by definition, determine whether the method is able to discriminate two local equivalent nodes. Consider a local equivalent node pair, say u, v, we can exam previous global methods by testing whether the node embeddings of u and v are the same. To simplify the discussion and only focus on the main point, we summarize and distill the most representative techniques as follows:

E.1. Distance encoding [10].

Distance Encoding is a general class of structure-related features to enrich the sub-structure or even global structure information. In their work, the distance can be represented in various forms and the distance encoding can be used in two different ways, i.e., extra node features and a controller for message passing. For simplicity, we only consider the case where shortest path distance is used to measure distance and employed as the extra node features. Formally, the input features with distance encoding is:

$$\boldsymbol{h}_v^0 = \boldsymbol{x}_v^0 \oplus \sum_{v \in \mathcal{S}} d(u, v) \tag{9}$$

Here, $\boldsymbol{x}_v^0$ is the original node attribute, $d(u, v)$ is the shortest path distance between u and v, $\oplus$ is the concatenation mark, and $\mathcal{S}$ is the target structure defined in the original paper, which can be the whole graph, i.e., $\mathcal{S} = \mathcal{V}$, or a substructure, i.e., $\mathcal{S} \in \mathcal{V}$. We make the following statements:

Proposition 3. *AC-GNNs enhanced by distance encoding ARE global.*

Proof. Note that a local method cannot discriminate *any* local equivalent node pair. We can finish the proof by contradiction. Assume there exists $r > 0$ such that the enhanced AC-GNN is a r-local method, i.e., it fails to discriminate any r-local equivalent node pair. We build a connected graph containing $2r + 3$ nodes like a linked list. A figure illustration is given in Figure 1, where the number represents the node index. Assume all nodes share the same node attribute, i.e., $\boldsymbol{x}_i^0 = \boldsymbol{x}_j^0, \forall i, j \in \{0, ..., 2r + 2\}$. Consider the two nodes, v_r and v_{r+1}, their depth-r neighborhood are topologically equivalent, i.e., $\mathcal{T}_{\mathcal{G}}(v_r, r) = \mathcal{T}_{\mathcal{G}}(v_{r+1}, r)$. Therefore, $\{v_r, v_{r+1}\}$ is a r-local equivalent node pair. However, the distance encoding of the two nodes are different, where $\sum_{v \in \mathcal{G}} d(v_r, v) = r^2 + 3r + 3$ but $\sum_{v \in \mathcal{G}} d(v_{r+1}, v) = r^2 + 3r + 2$, resulting in a difference between $\boldsymbol{h}_r^0$ and $\boldsymbol{h}_{r+1}^0$. Similarly, the neighbors of v_r and v_{r+1} have the different distance encodings. Therefore, the distance encoding makes the two local equivalent nodes differentiable by providing a different input for both aggregation and combination functions, which completes the proof. [2] □

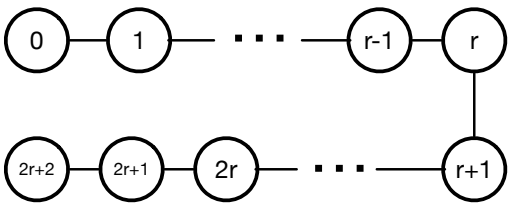

Figure 1: A contradiction example to prove that the distance encoding makes an AC-GNN global.

E.2. Readout function [5].

Barcel et al. [5] proposed a scheme to update node features by aggregating not only neighbor information, but also the global attribute vector. The function considering a global attribute vector is also called the readout function. In their work, it is demonstrated that even a very simple readout function, i.e., summation of all node features, can capture all

[2] We do not discuss extreme cases here, e.g. COM(·) = 0.

FOC_2 classifiers, which means that the representation power is improved. Indeed, the global feature vectors contain some information across the whole graph, and the distance encoding discussed in Section E.1 is also a kind of readout function in the form of distance measurement. But can we declare that *AC-GNNs become global methods as long as we use a readout function?* Here, we discuss the simplest form used in [5], aggregate-combine-readout GNNs (ACR-GNNs), where the readout is calculated by the summation of all node features. An ACR-GNN is formalized as follows:

$$\begin{aligned}\boldsymbol{h}_v^{(i)} =&\text{COM}^{(i)}(\boldsymbol{h}_v^{(i-1)}, \text{AGG}^{(i)}(\{\boldsymbol{h}_u^{(i-1)} : u \in \mathcal{N}(v)\}),\\ &\text{READ}^{(i)}(\{\boldsymbol{h}_u^{(i-1)} : u \in \mathcal{V}\})),\end{aligned} \tag{10}$$

We make the following statement:

Proposition 4. *ACR-GNNs are NOT global.*

Proof. The intuition for proof comes from the fact that the used readout function, i.e., summation of all node features, keeps the same for all nodes. We first prove the following:

Corollary 4. *If an ACR-GNN succeeds in discriminating a node pair, an AC-GNN will also discriminate it.*

Given a node pair $\{u, v\}$ in the graph $\mathcal{G}$. Let $\boldsymbol{h}_u^{(k)'}$ and $\boldsymbol{h}_u^{(k)}$ represents the node embedding of u after k layers by an ACR-GNN $\mathcal{A}'$ and an AC-GNN $\mathcal{A}$ respectively. Suppose after k layers, $\mathcal{A}'$ discriminate them, i.e., $\boldsymbol{h}_u^{(k)'} \neq \boldsymbol{h}_v^{(k)'}$, while $\mathcal{A}$ fails to discriminate them, i.e., $\boldsymbol{h}_u^{(k)} = \boldsymbol{h}_v^{(k)}$. It follows that during the layer t from 0 to $k-1$, $\boldsymbol{h}_u^{(t)'} = \boldsymbol{h}_v^{(t)'}$ and $\boldsymbol{h}_u^{(t)} = \boldsymbol{h}_v^{(t)}$. That is, for any t from 0 to $k-1$, we can create a valid mapping ϕ such that $\boldsymbol{h}_v^{(t)'} = \phi(\boldsymbol{h}_v^{(t)})$ for any node $v \in \mathcal{V}$.

Consider the inequality after k layers, since node u and v always have the same readout term, i.e., $\text{READ}^{(k)}(\{\boldsymbol{h}_u^{(k-1)'} : u \in \mathcal{V}\})$, combing with Equation 10, it must be the case that:

$$\begin{aligned}&(\boldsymbol{h}_v^{(k-1)'}, \{\boldsymbol{h}_s^{(k-1)'} : s \in \mathcal{N}(v)\}) \neq\\ &(\boldsymbol{h}_u^{(k-1)'}, \{\boldsymbol{h}_s^{(k-1)'} : s \in \mathcal{N}(u)\})\end{aligned} \tag{11}$$

That is,

$$\begin{aligned}&(\phi(\boldsymbol{h}_v^{(k-1)}), \{\phi(\boldsymbol{h}_s^{(k-1)}) : s \in \mathcal{N}(v)\}) \neq\\ &(\phi(\boldsymbol{h}_u^{(k-1)}), \{\phi(\boldsymbol{h}_s^{(k-1)}) : s \in \mathcal{N}(u)\})\end{aligned} \tag{12}$$

However, according to the assumption, the AC-GNN fails to discriminate the two nodes, indicating that the inequality above cannot hold. Hence we have reached a contradiction.

Therefore, we can conclude that the ACR-GNN also cannot discriminate any local equivalent node pair, making it a local method. Actually, this proof also demonstrates that such an ACR-GNN is upper-bounded by AC-GNNs in the terms of the discrimination power. □

E.3. Identity-aware Graph Neural Networks [12].

Identity-aware Graph Neural Networks (ID-GNNs) focus on solving the problem that the embeddings are only related to the local subtree. The key insight is to inductively consider the root node during message passing, i.e., whether the aggregated node is the target node itself. If the aggregated node is the target node, a different aggregation and combination channel is used so that the ID-GNN is a heterogeneous one. Formally, let the target node is u, i.e., we are calculating the node embedding of u, then, the mediate features of other nodes are given by:

$$\boldsymbol{h}_{v,u}^{(i)} = \text{COM}^{(i)}(\boldsymbol{h}_{v,u}^{(i-1)}, \{\text{AGG}_{\mathbf{1}[s=u]}^{(i)}(\boldsymbol{h}_{s,u}^{(i-1)}) : s \in \mathcal{N}(v)\}), \tag{13}$$

Here, $\boldsymbol{h}_{v,u}^{(i)}$ represents the mediate feature of node v after i_{th} layer when calculating the node embedding of u, $\text{AGG}^{(i)}$ contains two functions, where $\text{AGG}_1^{(i)}$ is applied to the target node, and $\text{AGG}_0^{(i)}$ is for other nodes. The simple heterogeneous scheme makes the target node different from other nodes and therefore sensitive to the identity. However, such a scheme still fails to discriminate c, d in the Figure 1(a) of our paper. Based on this observation, we claim the following proposition:

Proposition 5. *ID-GNNs are NOT global.*

Proof. We can finish the proof by showing that ID-GNNs cannot discriminate any local equivalent node pair. Given an ID-GNNs $\mathcal{A}$ with L layers, let's consider a L-local equivalent node pair $\{u, v\}$ in $\mathcal{G}$ by an L-local isomorphism π_L, which means that the two subgraphs $\mathcal{T}_\mathcal{G}(u, L)$ and $\mathcal{T}_\mathcal{G}(v, L)$ are isomorphic and $\boldsymbol{x}_w = \boldsymbol{x}_{\pi_r(w)}$ holds for every $w \in \mathcal{T}_\mathcal{G}(u, r)$. Here, we propose a stronger proposition:

Corollary 5. *Given a L-depth ID-GNN and a L-local equivalent node pair $\{u, v\}$ by π, $\boldsymbol{h}_{s,v}^i = \boldsymbol{h}_{\pi(s),u}^i$ holds for any iteration i and any node $w \in \mathcal{T}_\mathcal{G}(u, r)$ if $i + d(s, v) \leq L$, where d represents the shortest distance.*

We prove the corollary by a nested induction.

First induction:

This statement, i.e., $\boldsymbol{h}_{s,v}^i = \boldsymbol{h}_{\pi(s),u}^i$, apparently holds when $i + d(s, v) \leq 0$. Suppose this holds if $i + d(s, v) \leq k$ (first assumption), we now prove that the statement will also hold when $i + d(s, v) = k + 1$ as long as $k + 1 \leq L$.

Induction in the induction: For those nodes, say s_{k+1}, whose shortest distance with v is $k + 1$, i.e., $d(s_{k+1}, v) = k + 1$, we have $\boldsymbol{h}_{s_{k+1},v}^0 = \boldsymbol{h}_{\pi(s_{k+1}),u}^0$ since $\{u, v\}$ is a L-local equivalent node pair and $k + 1 \leq L$. Suppose $\boldsymbol{h}_{s,v}^i = \boldsymbol{h}_{\pi(s),\pi(v)}^i$ holds if $i = t$ and $d(s, v) = k + 1 - t$ (second assumption), we continue to prove that this will hold if $i = t + 1$ and $d(s, v) = k - t$.

Consider those nodes, say s_{k-t}, whose shortest distance between v is $k-t$, i.e., $d(s_{k-t}, v) = k-t$, then $\boldsymbol{h}^{t+1}_{s_{k-t},v}$ is given by:

$$\begin{aligned}\boldsymbol{h}^{t+1}_{s_{k-t},v} =& \text{COM}^{(t+1)}(\boldsymbol{h}^{t}_{s_{k-t},v}, \\ & \{\text{AGG}^{(t+1)}_{\mathbf{1}[s=v]}(\boldsymbol{h}^{(t)}_{s,v}) : s \in \mathcal{N}(s_{k-t})\}),\end{aligned} \tag{14}$$

According to the first assumption, $\boldsymbol{h}^{t}_{s_{k-t},v} = \boldsymbol{h}^{t}_{\pi(s_{k-t}),u}$ since $i + d(s_{k-t}, v) = k$. We then consider the second term in Equation 14, $\boldsymbol{h}^{(t)}_{s,u} : s \in \mathcal{N}(s_{k-t})$. The distance between the neighbors of s_{k-t} and the root node v ranges from $k-t-1$ to $k-t+1$. For the neighbor nodes $s_{k-t-1} \in \mathcal{N}(s_{k-t})$ with a distance $k-t-1$ between v, we have $\boldsymbol{h}^{t}_{s_{k-t-1},v} = \boldsymbol{h}^{t}_{\pi(s_{k-t-1}),u}$ since $t + d(s_{k-t-1}, v) = k-1 \leq k$ (first assumption). Similarly, for the neighbor nodes $s'_{k-t} \in \mathcal{N}(s_{k-t})$, the equation still holds since $t + d(s'_{k-t}, v) = k \leq k$ (first assumption). For the neighbor nodes $s_{k-t+1} \in \mathcal{N}(s_{k-t})$, the equation $\boldsymbol{h}^{t}_{s_{k-t+1},v} = \boldsymbol{h}^{t}_{\pi(s_{k-t+1}),u}$ also holds since $i = t$ and $d(s_{k-t+1}, v) = k+1-t$ (second assumption).

End of the induction in the induction: Hence by mathematical induction $\boldsymbol{h}^{i}_{s,v} = \boldsymbol{h}^{i}_{\pi(s),\pi(v)}$ is correct for all positive integers i and $d(s, v)$. Therefore, we show that $\boldsymbol{h}^{i}_{s,v} = \boldsymbol{h}^{i}_{\pi(s),\pi(v)}$ holds when $i + d(s, v) = k+1 \leq L$, $d(s, v)$ and i are positive integers.

End of the induction: Hence by mathematical induction, $\boldsymbol{h}^{i}_{s,v} = \boldsymbol{h}^{i}_{\pi(s),u}$ holds for any iteration i and any node $w \in \mathcal{T}_{\mathcal{G}}(u, r)$ if $i + d(s, v) \leq L$, such completes the proof of Corollary 5.

Based on Corollary 5, we can conclude that $\boldsymbol{h}^{L}_{v,v} = \boldsymbol{h}^{L}_{u,u}$, indicating that the L-depth ID-GNN fails to discriminate u and v, which completes the proof. □

E.4. Randomness.

In the development of GNNs, random schemes are widely-used and studied. Ryoma et al. [34] and Andreas et al. [14] both prove that the distinct node attributes (even initialized randomly) enhance the representation power significantly. George et al. [35] propose a randomly coloring methods to distinguish different nodes and break the local equivalence. Position-aware GNN [11] makes use of the distance encoding to design a position-aware GNN, where one of the differences between distance encoding [10] is that the distance is not measured with a pre-defined set $\mathcal{S}$, but with a set of *randomly* selected anchor node sets. In our work, we also demonstrated that the randomness enhances the discrimination power of AC-GNNs, because nodes are not possible to be local equivalent considering that their node attributes are initialized randomly. Therefore, we want to know:

Q: *Does randomness make AC-GNNs global?*

Unfortunately, we are not able to answer the question now. We can only declare that a random scheme indeed helps to distinguish local equivalent node pair, but it *may* be still local. The reason is that the AC-GNNs are not deterministic anymore if we add some randomness, therefore, the definition of local methods is not available here. In some cases, the upper bound (or lower bound) remains when the function becomes not deterministic, but a formal proof is needed in our case. We look forward to a deeper discussion on the discrimination power of randomness in AC-GNNs, and leave this as our future work.

E.5. Deep Network.

A lot of efforts [36, 37, 26] are made to make GNNs deeper. However, as we discussed in the paper, according to the definition of local method, the AC-GNN is still local, no matter how deep it is. Nevertheless, a deep network can detect wider substructure information, which may contribute to the discrimination power. A supplementary experiment on the model depth can be found in Section F.3.

F. Supplementary Experiments

F.1. Experiment & model settings.

Experiments. Besides GNN-GCP and tabucol compared in the paper, we also implement integer linear programming (ILP) based solver by Gurobi [38], and three heuristics coloring methods which are used as baselines in [30]. In the supplementary experiments, 80% randomly selected samples in the layout dataset are separated into the training dataset (for trainable models) and the testing dataset contains the remaining samples. In the paper, we only run our model once with a specified k and obtain the cost (conflict number), in the supplementary experiments, we sometimes need to calculate the chromatic number by our model, i.e., calculate the minimum k that achieves a zero cost. To do this, we iteratively run our model and add k by one after each iteration until a zero cost is received.

Model hyperparameters. If not specified, all AC-GNN variations have 2 layers and the hidden dimension is 64. Other training parameters of these variations keep the same with our proposed GDN . We use the Adam [39] optimizer with a 1024 batched graph (if batch-graph is possible) and a learning rate 0.001. Training proceeds for 10 epochs and takes about one hour. More detailed default hyperparameter values can be found in our released code, i.e., `color_arg.py`.

F.2. Comparison with other methods.

We compare our method with the other three heuristics coloring methods use in [30] and ILP based method. We only compare these methods in the layout dataset, because ILP even cannot solve others within 24 hours. The three heuristic algorithms are summarized as follows:

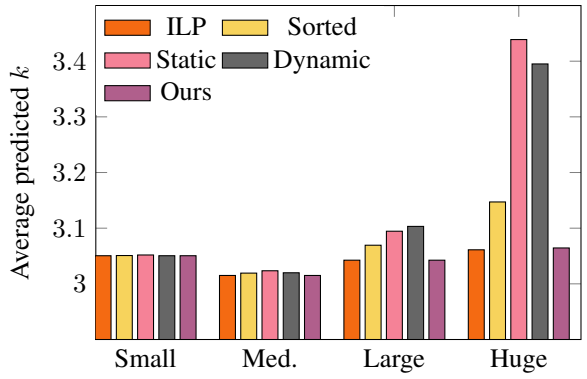

Figure 2: Comparison with other heuristic methods.

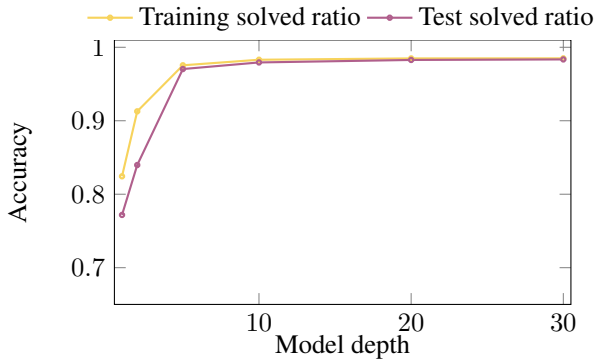

Figure 3: Comparison with different model depth.

Static-ordered: Coloring nodes in the order of node IDs.

Sorted-ordered: Coloring nodes in the largest degree first manner.

Dynamic-ordered: Coloring nodes in the largest degree first manner, while the degree is updated when coloring nodes, i.e., the neighbors of the colored node will decrease their degree by one.

The results are shown in Figure 2. We measure the average predicted k (minimal color number to be conflict-free) on four different graph size $|\mathcal{V}|$, i.e., small ($|\mathcal{V}|$ <8), Medium ($8 \leq |\mathcal{V}| < 16$), Large ($16 \leq |\mathcal{V}| < 32$), Huge ($32 \leq |\mathcal{V}|$). All methods contain a pre-process procedure for a fair comparison. From the results, we can see that *Our method achieves exactly the same performance with ILP in all graphs except the huge one.* Note that ILP is an optimal coloring solver, indicating that our method reaches the optimality for relatively small graphs. However, even for such small cases, three heuristic algorithms fail to be close to ILP or our method. For large and huge graphs, the average k is increased by more than 10% for static and dynamic algorithms. With the growth of the graph size, our method becomes more and more advanced compared with these heuristic algorithms.

F.3. Model depth

We also study the influence of model depth on the coloring results. The results are shown in Figure 3, where the solved ratio is defined as in paper, i.e., the ratio between the number of edges without introducing conflicts and the number of total edges. According to the results, we can conclude that a deeper model indeed has a more positive influence on the results. However, the ratio improvement gradually slows down and eventually stops as the model goes deeper. The phenomenon also demonstrates the idea in [14], i.e., the product of the GNN's depth and width must exceed a polynomial of the graph size to obtain an optimal result.

F.4. Model interpretation.

One of the advantages of our model is that the trainable weights represent a meaningful value. For example, α is the importance of the global summation feature, and the ratio between λ_C and λ_A indicates the relative importance between the features of each node and its neighbors. Therefore, our model provides a straightforward way to interpret the model by analyzing the values of these trainable weights directly. The results of λ_C and α are shown in Figure 4 and the results of λ_A are given in 5. We do not discuss γ and β here because they are actually bias values, which are less crucial compared with λ and α. From the results, we can find some interesting phenomenons: 1) the absolute value of λ_A is larger than λ_C, indicating that GDN believes that neighbor information is much more important than the ego-information for the coloring problem. 2) the ego-information and global information is relatively critical in 5 or 6 layers, we posit that this happens because GDN thinks the ego-information containing the message from neighborhood with depth 5 or 6 is enough. 3) λ_C reaches the peak at the final layer while α is near to zero, which shows that GDN thinks the ego-information is important while the global summation information is not needed in the final layer.

F.5. Other discussion.

Postprocess. We discuss the influence of our proposed GPU-friendly postprocess on the result quality and runtime. We compare our method with postprocess and without postprocess on layout dataset (Table 1) and normal dataset (Table 2). In the layout dataset, the relatively simple one, our post process can reduce the average predicted k by 1%. More importantly, the postprocess part makes our method optimal for more than 99.9% layout graphs except for the huge one, which occupies less than 0.1% in the total dataset. In the harder normal dataset, the conflict will increase by 73.4% if postprocess is not used, as a scarifies, the runtime is increased by 12.8% when using postprocess. However, compared with the significant accuracy improvement, the

Table 1: The results of our methods without postprocess and with concatenation on the layout dataset. k is the average predicted chromatic number, and the $\uparrow$ (%) is the increase compared with Our original model.

		Small	Med.	Large	Huge
ILP	k	3.0505	3.0151	3.0425	3.0612
Ours	k	3.0505	3.0151	3.0425	3.0645
Ours	k	3.0548	3.0181	3.0451	3.0669
w.o. post	$\uparrow$ (%)	1.4	1.0	0.9	0.8
Ours	k	3.0512	3.0151	3.0425	3.0653
w. concat	$\uparrow$ (%)	0.3	0	0	0.3

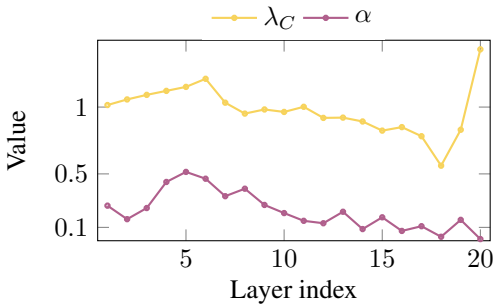

Figure 4: Values of trainable variables λ_C and α among different layers.

time loss is acceptable, especially under the occasion that our method is 500$\times$ faster than a heuristic algorithm with a similar-quality. In Table 2, our method without postprocess sometimes even results in a better solution than the one with postprocess, this happens because we randomly initialize our node attribute, resulting in a slightly different solution everytime. Actually, we can further improve our performance by a repeated running like previous coloring methods [31, 27, 28], but our target is to provide insights for powerful GNNs on coloring problems instead of developing a powerful coloring solver by some simple tricks.

Other techniques for heterophily. In [22], they propose a concatenation technique for tasks under heterophily, i.e., concatenate all features in the middle layers, and compute the final embedding using the concatenated result. We also implement it for comparison, the results are shown in Table 1. According to the table, we can see that it fails to be effective in the coloring problem, which even increases k a little bit. Nevertheless, it is still an open and interesting question to find the effective techniques in the coloring tasks, and even in the general tasks under heterophily.

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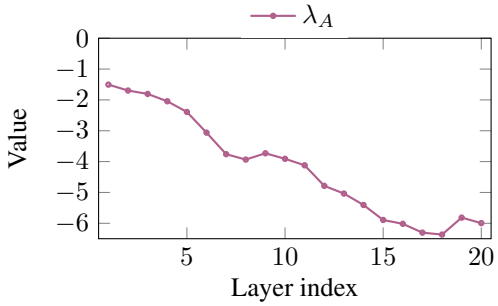

Figure 5: Values of trainable variables λ_A among different layers.

Table 2: The results of our method without postprocess on the normal dataset.

	Ours		Ours w.o. post	
	cost	time	cost	time
jean	0	0.13	0	0.11
anna	0	0.17	0	0.15
huck	0	0.13	5	0.11
david	1	0.19	0	0.17
homer	1	0.29	1	0.26
myciel5	0	0.12	0	0.10
myciel6	0	0.21	1	0.18
games120	0	0.08	0	0.07
Mug88_1	0	0.01	0	0.01
1-Insertions_4	0	0.07	0	0.07
2-Insertions_4	2	0.08	1	0.07
Queen5_5	0	0.05	7	0.04
Queen6_6	4	0.05	5	0.04
Queen7_7	11	0.06	15	0.05
Queen8_8	7	0.06	16	0.05
Queen9_9	10	0.09	18	0.06
Queen8_12	7	0.09	14	0.08
Queen11_11	24	0.07	38	0.07
Queen13_13	42	0.08	68	0.08
ratio	1.000	1.000	1.734	0.872

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