Generalized Equivariance and Preferential Labeling for GNN Node Classification

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Abstract

Existing graph neural networks (GNNs) largely rely on node embeddings, which represent a node as a vector by its identity, type, or content. However, graphs with unattributed nodes widely exist in real-world applications (e.g., anonymized social networks). Previous GNNs either assign random labels to nodes (which introduces artefacts to the GNN) or assign one embedding to all nodes (which fails to explicitly distinguish one node from another). Further, when these GNNs are applied to unattributed node classification problems, they have an undesired equivariance property, which are fundamentally unable to address the data with multiple possible outputs. In this paper, we analyze the limitation of existing approaches to node classification problems. Inspired by our analysis, we propose a generalized equivariance property and a Preferential Labeling technique that satisfies the desired property asymptotically. Experimental results show that we achieve high performance in several unattributed node classification tasks.1

1 Introduction

Graphs are a widely used type of data structure in computer science. A graph can be represented as $G = (V, E)$, where $V$ is a set of nodes, and $E$ is a set of node pairs known as edges (directed or undirected). With the prosperity of deep learning techniques, graph neural networks (GNNs) are shown to be effective in various graph-related applications, such as program analysis (Mou et al. 2016), social networks (Hamilton, Ying, and Leskovec 2017), knowledge graphs (Hamaguchi et al. 2017), molecule analysis (Scarselli et al. 2009), and the satisfiability (SAT) problem (Zhang et al. 2020).

Existing GNNs highly rely on node embeddings, which are a vector representation of a node, typically based on its identity, type, or content. For example, a GNN for a knowledge graph typically embeds an entity/concept (e.g., “cat” and “mammal”) as a vector (Wang, Ye, and Gupta 2018), whereas a GNN for molecules embeds the atom (e.g., hydrogen and oxygen atoms) as a vector (Scarselli et al. 2009).

In many applications, however, the nodes in a graph may not be attributed, and we call such a graph an unattributed graph. A common scenario is that there is no attribute related to the nodes. For example, community detection for large-scale social networks may lack the identity information of nodes, i.e., a person, possibly due to privacy concerns (Backstrom, Dwork, and Kleinberg 2007). Another scenario is that the attribute of a node is an artefact and captures no semantic meanings. Figure 1 shows a graph that represents a propositional satisfiability (SAT) problem (Selsam et al. 2019), where $x_1$ and $c_1$ are arbitrary namings of the literals (variable or its negations) and clauses (disjunction of literals), and could be renamed without changing the nature of the formula. If such an identifier is represented by table look-up embeddings, it would become an artefact in the GNN, because these embeddings do not represent common knowledge among different training samples. Nor do they generalize to new samples.

To encode unattributed graphs, previous methods typically adopt an arbitrary labeling for nodes and represent them by embeddings (Allamanis, Brockschmidt, and Khademi 2018; Wei et al. 2020). As mentioned, this introduces artefacts to GNNs. Recently, Selsam et al. (2019) have realized that such artefacts are undesired, and assign all nodes with the same embedding. However, this approach may suffer from the problem that the graph neural network becomes insensitive to the nodes.

In this work, we analyze unattributed node classification tasks, which require equivariance, i.e., the change of node labels should be reflected correspondingly in the output. To address the mentioned problems, a naïve idea is to still assign different node embeddings, but to eliminate such artefacts by an ensemble of multiple labelings. For training, the labeling is randomly sampled every time we process a data sample; during inference, an ensemble of multiple random labelings is adopted for a sample. In this way, the nodes are distinguishable given any labeling, but such artefacts are smoothed out by the ensemble average.

Our theoretical analysis, however, shows that such a naïve treatment does not work well for node classification. An equivariant GNN is unable to solve equivariant node classification problems where multiple outputs are appropriate for an input graph.

To this end, we propose a generalized equivariance prop-
In this section, we first present the problem formulation and analyze the equivariance property on unattributed graphs. Then, we present our Preferential Labeling approach to address equivariant node classification.

2.1 Problem Formulation

A problem on unattributed graphs can be formalized as predicting output $Y$ given a graph $X$. A predicate function $H(X,Y)$, specific to a task, determines if $Y$ is appropriate for a given $X$. The predicate is true if and only if $Y$ is an appropriate solution for $X$.

For an unattributed graph $G = (V, E)$, the input can be fully represented by an adjacency matrix $X \in \{0, 1\}^{n \times n}$, where $n$ is the number of nodes. In a node classification task, the output is a matrix $Y \in \mathbb{R}^{n \times k}$ for $n$ nodes and $k$ classes.

To analyze how node indexes affect (or shall not affect) a GNN, we introduce the notation $S_n$ to represent the permutation group for $[n]$. Given $\pi \in S_n$, the action of $\pi$ on an unattributed graph $X \in \{0, 1\}^{n \times n}$ is defined as $(\pi(X))_{i,j} = X_{(\pi^{-1}(i)),(\pi^{-1}(j))}$, and its corresponding action on $Y \in \mathbb{R}^{n \times k}$ is given by $(\pi(Y))_{i,c} = Y_{(\pi^{-1}(i)),c}$, i.e., $\pi$ denotes the same shuffle on the rows and columns of $X$, as well as the rows of $Y$. Here, $\pi$ is the mapping from node indexes to permuted indexes. Thus, $\pi^{-1}$ is retrieving the original node indexes in $X$ and $Y$ from the permuted indexes $i$ and $j$ in $\pi(X)$ and $\pi(Y)$.

**Equivariance.** We now formulate the *equivariance property* of node classification tasks. It essentially asserts that for any permutation $\pi \in S_n$,

$$H(X, Y) \text{ implies } H(\pi(X), \pi(Y))$$

(1)

That is to say, if we permute the order of nodes, the solution should be changed correspondingly.

Suppose for every $X$ there exists a unique $Y$ satisfying $H(X, Y)$, the mapping from $X$ to $Y$ can be modeled by a function $h$ and the equivariance property becomes the form that we commonly see

$$h(\pi(X)) = \pi(h(X))$$

(2)

for every permutation $\pi \in S_n$.

In the above formulation, we define the equivariance property of a node classification task. In fact, equivariance can also be said in terms of GNN output $f(X)$, given by

$$f(\pi(X)) = \pi(f(X))$$

(3)

2.2 Limitations of Existing GNNs on Unattributed Graphs

We analyze the limitations of existing GNNs on unattributed graphs. As mentioned in Section 1, previous approaches for unattributed graph either assign random labels to nodes (Alamanis, Brockschmidt, and Khademi 2018; Wei et al. 2020) or assign the same embedding to all nodes (Li, Chen, and Koltun 2018; Wei et al. 2020). When they are applied to unattributed node classifications, they suffer from at least one of the two limitations: 1) node distinction and 2) equivariance property.

**Node Distinction.** We first consider distinguishing different nodes in a graph. The state-of-the-art approaches (Li, Chen, and Koltun 2018; Selsam et al. 2019; Zhang et al. 2020) assign all nodes with the same embedding, and thus, the model cannot distinguish different nodes effectively. Consider a common graph convolutional network (GCN), which learns the hidden representation for a node by encoding the node vector with the neighbors via a set of fully-connected layers. In the example given by Figure 2, all four nodes will have the same hidden representation, because every node is represented by the same embedding and all nodes have the same neighboring information.

**Equivariance Property.** We now consider the equivariance property of node classification for unattributed graphs, which is believed to be important for various GNN applications (Chen, Li, and Bruna 2018; Azizian et al. 2020).

In node classification for unattributed graphs, if the node index changes, the output would change accordingly, shown in Eqn (1). Thus, it is tempting to design an equivariant GNN satisfying Eqn (3) for node classification tasks, as suggested by Wu et al. (2021). Otherwise, the GNN would be sensitive to labeling artefacts (Allamanis, Brockschmidt, and Khademi 2018; Wei et al. 2020), if it does not satisfy some form of equivariance. Previous work achieves the equivariance property (3) by using the same embeddings for all nodes (Li, Chen, and Koltun 2018; Selsam et al. 2019; Zhang et al. 2020).

However, we hereby show that an equivariant GNN satisfying (3) will fail on node classification problems, where
multiple outputs are appropriate. In other words, the mapping from \( X \) to \( Y \) is not a function, and given an input \( X \), there exists multiple \( Y \) such that \( H(X, Y) \) holds. Usually, GNN predicts one appropriate \( Y \) by a function \( Y = f(X) \).

We show the drawback of equivariant GNNs with an example of a non-trivial auto-isomorphic graph, i.e., there exists a non-identity permutation \( \pi \) such that \( \pi(X) = X \). If (3) holds, then \( \pi(X) = X \) implies \( f(X) = \pi(f(X)) \). This means that GNN output must be the same for all corresponding nodes shuffled by \( \pi \).

This, unfortunately, may be a bad solution for various tasks. Consider the maximum independent set (MIS) problem that selects the largest number of vertices that are not directly connected. In Figure 2, for example, \( \{1, 3\} \) is an MIS and \( \{2, 4\} \) is also an MIS. However, an equivariant GNN cannot predict any MIS in this example, because there exists a permutation \( \pi \) (e.g., \( \pi: 1 \mapsto 2, 2 \mapsto 3, 3 \mapsto 4, 4 \mapsto 1 \)) essentially tying the output of all nodes.

It should be mentioned that we show the limitation by an example of non-trivial auto-isomorphism. Our analysis is suggestive to real applications, where graphs often have similar local structures.

### 2.3 Our Solution

We start with a naïve attempt to address both node distinction and equivariance in GNNs. With further analysis, we propose a generalized equivariance property and our Preferential Labeling approach.

**A Naïve Attempt.** To address the limitation of the node distinction, a naïve idea is to assign node embeddings by randomly labeling the nodes, but to use an ensemble of different node labelings to eliminate artefacts (Murphy et al. 2019; Sato, Yamada, and Kashima 2021). For training, node labels are assigned randomly; this serves as a way of data augmentation, and can be thought of as training an ensemble over epochs. During inference, it assigns multiple random labels and uses an average ensemble for prediction.

However, it is not appropriate if we directly apply such a naïve idea to equivariant node classification. The standard cross-entropy training is essentially to

\[
\text{minimize } \sum_{(X, Y) \in \mathcal{D}} \sum_{\pi \in S_n} \sum_{i=1}^n D_{KL}(\pi(Y) || f_i(\pi(X); \omega)),
\]

where \( \omega \) denotes the trainable parameters in a GNN, \( \mathcal{D} \) is the training set, and \( D_{KL} \) is the Kullback–Leibler divergence between the predictions and the ground truth. \( \pi(Y) \) and \( f_i(\pi(X)) \) are the \( i \)th row in a matrix, representing the target and predicted distributions of a node. However, the training objective will enforce the GNN to learn the same prediction of nodes under auto-isomorphism, because for every \( \pi \in S_n \), the KL objective requires \( \pi(Y) = f(\pi(X)) \).

For some auto-isomorphic permutation \( \tau \), i.e., \( \tau(X) = X \), this implies \( f(X) = f(\tau(X)) = \tau(Y) \). Since \( Y = f(X) \), we will have \( f(X) = \tau(f(X)) \). This is precisely the limitation that we have analyzed in Section 2.2, namely, auto-isomorphism tying the prediction of a GNN.

To address this issue, we propose a desired generalized equivariance property.

**Generalized Equivariance Property.** An equivariant GNN satisfying (3) fails for equivariant node classification, because it unreasonably assumes the output is a function of input, i.e., approximating (1) by (2).

We relax this constraint for multi-output node classification and analyze the desired form of equivariance in this setting. We denote \( H(X) = \{Y : H(X, Y)\} \) be the set of all correct outputs given a graph \( X \). The training set typically provides one ground truth solution \( Y_* \in H(X_*) \) for a specific graph \( X_* \), as usually one solution suffices in real applications (and this coincides with GNNs whose output is a function of input).

We would define \( H_* \) as a minimal equivariant subset of \( H(\cdot) \) due to self-isomorphism \( \gamma \).

Then, the equivariance property suggests \( H_*(X) = \pi \{H_*(X_*)\} \) if \( X = \pi(X_*) \) for some \( \pi \). Here, we abuse the notation \( \pi \{H_*(X_*)\} := \{\pi(Y) : Y \in H_*(X_*)\} \).

We would like to design a neural network predicting a correct solution, i.e.,

\[
f(X_* \in H_*(X_*)),
\]

Due to the equivariance of \( H_* \), we have

\[
f(\pi(X_*)) \in H_*(\pi(X_*)) = \pi(H_*(X_*)).
\]

By the definition of \( H_* \) in (4), Eqn (5) implies that there exists \( \gamma \) such that \( \gamma_1(X_* \in H_* \) and \( f(X_* \in H_*). Likewise, Eqn (6) implies that there exists \( \gamma_2 \) such that \( \gamma_2(X_* = X_* \) and \( f(\pi(X_*)) = \pi_2(Y_*). Combining these and denoting \( \gamma_2 \gamma_1^{-1} \) by \( \gamma \), we see that there exists \( \gamma \in S_n \) such that

\[
\gamma(X_* = X_* \) and \( f(\pi(X_*)) = \pi_2(f(X_*)).
\]

We call (7) the generalized equivariance property. In fact, (3) is a special case of (7), where \( \gamma \) is an identity permutation. However, we relax (3) by allowing an additional auto-isomorphic permutation \( \gamma \) in the solution space, and thus, it does not suffer from the limitation in Section 2.2.

The analysis shows that an ideal GNN for unattributed node classification should satisfy (7) rather than (2).
Theoretical Analysis. We show that the inference of our Preferential Labeling asymptotically satisfies the generalized equivariance property for node classification, if we have enough sampled permutations. We also draw a connection with Expectation–Maximization (EM) algorithms.

During our inference, we assign multiple labelings to a graph, and pick the prediction that has the highest predicted probability as our output. Formally, we consider the joint predicted probability of a graph $X$ with labeling $\tau$ as

$$s(X, \tau) = \prod_{i=1}^{n} \max_{j=1, \ldots, k} f_{ij}(\tau(X)),$$

where $f$ denotes a GNN function, outputing an $n \times k$ matrix ($n$: the number of nodes, $k$: the number of category). The $i$th row is the predicted distribution of the $i$th node.

During inference, we have multiple labelings $\tau$. We pick the best one that maximizes $s(X, \tau)$, given by

$$\tau^*_s(X) = \arg\max_{\tau \in S_n} s(X, \tau).$$

The prediction of our Preferential Labeling is

$$\hat{Y}(X) = \left(\tau^*_s(X)\right)^{-1} \left(f\left(\tau^*_s(X)\right)(X)\right).$$

The formula follows our convention of adjacency matrix representations. When we perform node labeling, we permute the indexes of both $X$ and $Y$ by $\tau^*_s(X)$. After GNN processing, we need an inverse permutation $(\tau^*_s(X))^{-1}$ to obtain the predictions for $X$, because our prediction should be corresponding to the original graph $X$, rather than $\tau^*_s(X)$.

Theorem 1. $\hat{Y}(\cdot)$ achieves generalized equivariance, i.e., for any graph $X$ and permutation $\pi \in S_n$, there exists $\gamma \in S_n$ such that $\gamma(X) = X$ and $\hat{Y}(\pi(X)) = \pi \gamma(\hat{Y}(X))$.

Proof. Consider any graph $X$ and permutation $\pi$. Replacing $X$ by $\pi(X)$ in Eqn (10), we have

$$\tau^*_s(\pi(X)) = \arg\max_{\tau \in S_n} s(\pi(X), \tau).$$

Notice that Eqns (12) and Eqn (10) are essentially the same problem, and that their optima should be achieved by the same element, i.e., $\tau^*_s(X) = \tau^*_s(\pi(X))$. This essentially means that the two permutations $\tau^*_s(X)$ and $\tau^*_s(\pi(X))$ yield the same result on $X$, implying that they are the same, except for an auto-isomorphic permutation.

In other words, there exists $\gamma$ such that $\gamma(X) = X$ and $\tau^*_s(\pi(X)) = \tau^*_s(\pi(\gamma)(X))$, which can be rearranged as

$$\tau^*_s(\pi(X)) = \tau^*_s(\gamma^{-1}(\pi^{-1})).$$

Replacing $X$ by $\pi(X)$ in Eqn (11), we have

$$\hat{Y}(\pi(X)) = \left(\tau^*_s(\pi(X))\right)^{-1} \left(f\left(\tau^*_s(\pi(X))\right)(\pi(X))\right)$$

$$= \pi \gamma(\tau^*_s(\pi(X))^{-1} \left(f\left(\tau^*_s(\gamma^{-1} \pi^{-1})\right)(\pi(X))\right)$$

$$= \pi \gamma(\hat{Y}(X)),$$

The training process can be described as

$$\min_{\omega} \sum_{(X,Y) \in D} \min_{\pi \in S_n} \sum_{i=1}^{n} D_{KL} \left((\pi(Y)); \omega \right),$$

where we train the model with the best labeling $\pi$, which is a permutation of both $X$ and $Y$ matrices (Section 2.1).

Consider the inference of a $k$-way classification problem. The GNN with permutation $\pi_m$ outputs a probability as $\left(p_1^{(m)}, \ldots, p_k^{(m)}\right)$. We pick the prediction that has the highest joint predicted probability (product of node probabilities). Eventually, our Preferential Labeling approach predicts a label by $e = \arg\max_{x \in \mathbb{R}^k} \{p_e\}$.

Our Preferential Labeling does not suffer from the limitation of equivariance, because our network is not an equivariant function as in (2). However, we will achieve the generalized equivariance property (7) asymptotically, because the labeling of $X$ is optimized out (except for auto-isomorphism) during training and inference by taking the preferred $\pi$, detailed below.
where (15) is due to the substitution with (13); (16) is due to the cancellation of \( \pi^{-1}\pi \) and the auto-isomorphism of \( \gamma \), i.e., \( \gamma(X) = X \); and (17) is due to the definition of \( \tilde{Y} \) in (11).

Our Preferential Labeling is also related to EM algorithms.

\textbf{Theorem 2.} \textit{The training of Preferential Labeling in (8) is a hard Expectation–Maximization algorithm with a uniform prior on \( S_n \).

Proof.} The labeling \( \pi \) can be thought of as a latent variable in the task of mapping a graph \( X \) to output \( Y \). The min operator in (8) is to seek \( \pi \in S_n \) maximizing the likelihood of output given input and the latent labeling, denoted by \( P(Y|X, \pi) \). With the assumption of uniform prior \( P(\pi) \) for \( \pi \in S_n \), this is equivalent to cross-entropy training with one latent labeling \( \pi \) that maximizes the posterior \( P(\pi|X, Y) \propto P(Y|X, \pi)P(\pi) \), known as hard EM (Sam-dani, Chang, and Roth 2012).

This easy theorem provides further intuition on our Preferential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach. EM algorithms are known for handling multi-modal mixtures of distributions, similar to differential Labeling approach.

3 Experiments

We conducted experiments on two node classification tasks. We chose state-of-the-art or standard GNN architectures, but compare our approach with various embedding strategies.

3.1 Competing Methods

\textbf{Static Labeling.} The static labeling assigns an embedding based on the identity of a node (e.g., \( x_i \) and \( c_1 \) in Figure 1), although such identity does not represent meaningful semantics in different samples. Static learning is widely applied in previous work (Boldi et al. 2012; Allamanis, Brockschmidt, and Khademi 2018).

\textbf{Same Embedding.} This baseline assigns all nodes in the unattributed graph with the same embedding. This is adopted in previous work (Li, Chen, and Koltun 2018; Zhang et al. 2020) to eliminate the artefacts of node labeling.

\textbf{Random Labeling.} The random labeling assigns an embedding randomly during training and inference. This is a special case of our approach with \( K = 1 \), and no actual preferential training is performed.

\textbf{Degree Feature.} An intuitive way to encode a node without labeling artefact is by its degree information, which captures some local information of the node. In this baseline, we use 1/(\( d_v + 1 \)) as a one-dimensional, non-learnable embedding feature, where \( d_v \) is the degree of node \( v \). We use the above formula so that the feature is in \([0, 1]\).

<table>
<thead>
<tr>
<th>Row #</th>
<th>GCN (Li, Chen, and Koltun 2018)</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Same</td>
<td>75.59%</td>
</tr>
<tr>
<td>2</td>
<td>Degree Feature</td>
<td>73.22%</td>
</tr>
<tr>
<td>3</td>
<td>Degree Ranking Embedding</td>
<td>71.58%</td>
</tr>
<tr>
<td>4</td>
<td>Static Labeling</td>
<td>74.57%</td>
</tr>
<tr>
<td>5</td>
<td>Random Labeling</td>
<td>75.28%</td>
</tr>
<tr>
<td>6</td>
<td>Preferential Labeling-10</td>
<td>85.04%</td>
</tr>
</tbody>
</table>

Table 1: The results for MIS solving. “Preferential Labeling-10” indicates 10 random labelings in both training and inference.

\textbf{Degree Ranking Embedding.} The drawbacks of using degree information as a single numerical feature are its low-dimensionality and non-learnability. In this baseline, we extend the idea by embedding the ranking of node degrees. Specifically, we sort all nodes by the degrees in descending order, and a node having \( i \)th largest degree is encoded by \( i \)th embedding vector \( e_i \).

3.2 Experiment 1: MIS Solving

We first evaluate our Preferential Labeling on solving the maximum independent set (MIS). In graph theory, an independent set is a set of nodes without any edge. An independent set is maximum, if it has the largest number of nodes among all independent sets. MIS solving is an NP-hard problem that aims to find out a maximum independent set from a graph.

For an input graph, the goal of the GNN in this task is to predict a binary label for each node, deciding whether a node is in the MIS. To induce an MIS from model predictions, we use a simple search algorithm. We first sort all nodes in descending order based on the predicted probability that the node is in the MIS. Then, we iterate over nodes in order and select the top node into the MIS; its neighbors are removed from the list. The process is iterated until we have processed the entire node list. In this way, the selected nodes are guaranteed to be an independent set. Our evaluation determines whether it is maximum.

\textbf{Model.} In this experiment, we adopt the state-of-the-art model (GCN; Li, Chen, and Koltun 2018) for MIS solving. Li, Chen, and Koltun (2018) use the same embedding for all nodes. The model contains 20 graph convolutional layers, which are regularized by dropout with rate of 0.1. For the hidden size of all layers used in this model, we set it to 128. For training, we use Adam (Kingma and Ba 2015) to train the model with learning rate \( 10^{-4} \) on a single Titan RTX.

\textbf{Dataset.} We follow the data synthesis process in previous work (Li, Chen, and Koltun 2018) and generate 173,751, 20,000, 20,000 graphs for training, development, and test, respectively. The number of nodes in a graph is generated from a uniform distribution \([100, 150]\).

\textbf{Results.} Table 1 shows the results for MIS solving. Since our post-processing ensures the output is an independent set, the performance evaluation focuses on whether it is maximum. If the predicted set has the same number of nodes as the ground truth MIS, we say the model solves this MIS correctly; otherwise, the model makes an error.
satisfiable. A propositional formula is said to be satisfiable if there exists an assignment of propositional variables to either True or False that makes the formula True; such an assignment is known as a certificate.

We consider a specific setting of SAT solving, where the given formula is known to be satisfiable, and the goal is to predict a certificate, i.e., whether a variable should be assigned with True or False. This is a key step in SAT solvers.

Model. The GNN model and settings are generally adopted from the state-of-the-art NLocalSAT (Zhang et al. 2020).

A SAT formula is represented as a bipartite graph, where a node is either a clause or a literal (see Figure 1 for an example). The nodes are represented by identifiers, which are labeling artefacts. In our experiment, we applied a convolution-based NLocalSAT model (Zhang et al. 2020), which achieves state-of-the-art performance for SAT solving. Zhang et al. (2020) use the same embedding for all clause/literal nodes. The model has 16 convolutional layers, regularized by a dropout rate of 0.1. In our model, we perform Preferential Labeling for literals and clauses from respective candidate labelings/embeddings.

Dataset. We used the SAT dataset in Zhang et al. (2020). The training and development sets contain 500K and 396K SAT formulas, respectively. The number of variables in a formula is generated from a uniform distribution $U[10, 40]$, whereas the number of clauses is generated from $U[2, 6]$. For testing, the dataset contains four sets of different levels of difficulty. Specifically, the number of variables in a formula is 5, 10, 20, or 40 in each test set, denoted by Test-5, Test-10, Test-20, or Test-40, each containing 40K, 20K, 10K, or 5K test formulas.

Results. Table 2 shows the results for SAT solving, where the performance of a model is evaluated by the formula-level error rate, i.e., if the predicted assignment does not make the formula true, we say the model makes an error.

As mentioned, Static Labeling (Row 4) introduces artefacts of node identities, whereas using the same embedding (Row 1) or the degree embedding (Rows 2 and 3) are labeling artefacts. In our experiment, we applied a convolution-based NLocalSAT model (Zhang et al. 2020), which achieves state-of-the-art performance for SAT solving. Zhang et al. (2020) use the same embedding for all clause/literal nodes. The model has 16 convolutional layers, regularized by a dropout rate of 0.1. In our model, we perform Preferential Labeling for literals and clauses from respective candidate labelings/embeddings.

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<table>
<thead>
<tr>
<th>Row #</th>
<th>NLocalSAT (Zhang et al. 2020)</th>
<th>Test-5</th>
<th>Test-10</th>
<th>Test-20</th>
<th>Test-40</th>
<th>Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Same</td>
<td>5.26%</td>
<td>8.17%</td>
<td>15.03%</td>
<td>27.62%</td>
<td>14.02%</td>
</tr>
<tr>
<td>2</td>
<td>Degree Feature</td>
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<td>8.37%</td>
<td>14.25%</td>
<td>24.94%</td>
<td>13.22%</td>
</tr>
<tr>
<td>3</td>
<td>Degree Ranking Embedding</td>
<td>5.45%</td>
<td>10.23%</td>
<td>16.17%</td>
<td>28.04%</td>
<td>14.97%</td>
</tr>
<tr>
<td>4</td>
<td>Static</td>
<td>6.11%</td>
<td>9.86%</td>
<td>16.89%</td>
<td>28.88%</td>
<td>15.44%</td>
</tr>
<tr>
<td>5</td>
<td>Static &amp; Inference-10 (Averaging)</td>
<td>5.00%</td>
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<td>15.74%</td>
<td>29.70%</td>
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</tr>
<tr>
<td>6</td>
<td>Static &amp; Inference-10 (Max Prob.)</td>
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<td>3.65%</td>
<td>7.86%</td>
<td>16.22%</td>
<td>7.38%</td>
</tr>
<tr>
<td>7</td>
<td>Random</td>
<td>3.38%</td>
<td>6.17%</td>
<td>12.70%</td>
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<td>11.48%</td>
</tr>
<tr>
<td>8</td>
<td>Random &amp; Inference-10 (Averaging)</td>
<td>3.39%</td>
<td>6.07%</td>
<td>12.42%</td>
<td>23.34%</td>
<td>11.31%</td>
</tr>
<tr>
<td>9</td>
<td>Random &amp; Inference-10 (Max Prob.)</td>
<td>2.72%</td>
<td>5.03%</td>
<td>11.37%</td>
<td>22.06%</td>
<td>10.30%</td>
</tr>
<tr>
<td>10</td>
<td>Preferential Labeling-10 (Max Prob.)</td>
<td>1.13%</td>
<td>1.68%</td>
<td>1.81%</td>
<td>5.24%</td>
<td>2.47%</td>
</tr>
</tbody>
</table>

Table 2: The results for SAT solving. “Test-k” indicates a test set where each sample has k variables. “Inference-m” indicates m random labelings during inference.
Graph neural networks (GNNs) have been widely researched in recent years (Scarselli et al. 2009; Battaglia et al. 2018). GNNs have a variety of applications in different domains, ranging from social networks (Kipf and Welling 2017; Hamilton, Ying, and Leskovec 2017), knowledge graphs (Hamaguchi et al. 2017), and programming source code (Mou et al. 2016; Mou and Jin 2018).

A common GNN architecture is the graph convolutional network (GCN, Kipf and Welling, 2017). Recently, researchers have designed various GNN architectures, such as gated graph neural network (Li et al. 2016), graph attention networks (Velickovic et al. 2018), and Transformer-based GNN (Cai and Lam 2020). However, the focus of this paper is not the architecture design. Rather, we focus on node representations in unattributed graphs.

To represent a node in graphs, DeepWalk (Perozzi, Al-Rfou, and Skiena 2014) learns the node presentation by predicting the neighbors in an unsupervised way. Such pretraining-style node embedding does not generalize to new graphs. In certain applications, researchers use domain-specific information as labels. For example, a node in a knowledge graph is represented by text (Lin, Liu, and Sun 2016) and a variable in code analysis/generation tasks is often denoted by its name or subtokens (Allamanis, Brockschmidt, and Khademi 2018; Sun et al. 2020; Xiong and Wang 2021).

The embedding of nodes in unattributed graphs is not extensively addressed in previous literature. Existing work generally applies either an arbitrary labeling (Allamanis, Brockschmidt, and Khademi 2018) or the same embedding (Li, Chen, and Koltun 2018; Selsam et al. 2019; Zhang et al. 2020), which suffer from several limitations as discussed in this paper. To address this, we propose Preferential Labeling for unattributed node classification tasks.

Our Preferential Labeling is also related to, but different from Xu et al. (2019) and Garg, Jegelka, and Jaakkola (2020), where they show that GNNs are limited in determining graph isomorphism. We instead showed equivariant GNNs are limited in solving one-to-many equivariant problems, and further proposed the desired generalized equivariant property. Moreover, our Preferential Labeling does not suffer from the above limitation, because it assumes nodes are unlabeled, but we have (preferential) labelings.

5 Conclusion

In this paper, we address the task of node classification of unattributed graphs. We analyze the limitations of existing GNNs, showing that an equivariant GNN may not solve an equivariant node classification task, when multiple outputs are correct. We propose a generalized equivariance property, which allows an additional auto-isomorphic permutation. Based on our analysis, we further propose Preferential Labeling that samples multiple permutations and uses the best one for training and inference; theoretical analysis shows that our Preferential Labeling achieves the desired generalized equivariance property asymptotically. We conducted extensive experiments on MIS solving and SAT solving tasks to demonstrate the effectiveness and generality of our approach.
Acknowledgments

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