Towards Robust Graph Neural Networks for Noisy Graphs with Sparse Labels

Enyan Dai[†], Wei Jin[‡], Hui Liu[‡], Suhang Wang[†]
† The Pennsylvania State University, ‡ Michigan State University
{emd5759,szw494}@psu.edu,{jinwei2,liuhui7}@msu.edu

ABSTRACT

Graph Neural Networks (GNNs) have shown their great ability in modeling graph structured data. However, real-world graphs usually contain structure noises and have limited labeled nodes. The performance of GNNs would drop significantly when trained on such graphs, which hinders the adoption of GNNs on many applications. Thus, it is important to develop noise-resistant GNNs with limited labeled nodes. However, the work on this is rather limited. Therefore, we study a novel problem of developing robust GNNs on noisy graphs with limited labeled nodes. Our analysis shows that both the noisy edges and limited labeled nodes could harm the message-passing mechanism of GNNs. To mitigate these issues, we propose a novel framework which adopts the noisy edges as supervision to learn a denoised and dense graph, which can down-weight or eliminate noisy edges and facilitate message passing of GNNs to alleviate the issue of limited labeled nodes. The generated edges are further used to regularize the predictions of unlabeled nodes with label smoothness to better train GNNs. Experimental results on real-world datasets demonstrate the robustness of the proposed framework on noisy graphs with limited labeled nodes.

CCS CONCEPTS

• **Computing methodologies** → **Semi-supervised learning settings**; **Neural networks**.

KEYWORDS

Noisy Edges; Robustness; Graph Neural Networks

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1 INTRODUCTION

Graph Neural Networks (GNNs) [15, 22] have made remarkable achievements in modeling graphs from various domains such as social networks [15], financial system [35], and recommendation system [36]. The success of GNNs relies on the message-passing mechanism [15, 22], where node representations are updated by aggregating the information from neighbors. With this mechanism, the node representations capture node features, information of neighbors and local graph structure, which facilitate various tasks, especially semi-supervised node classification.

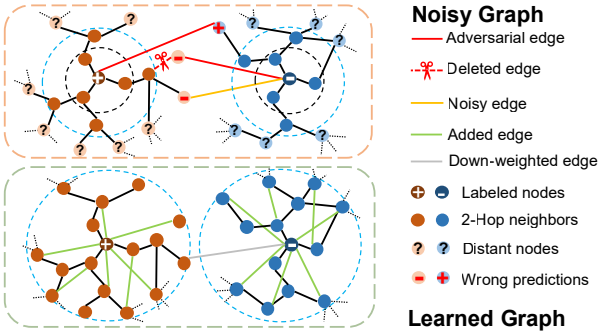

Figure 1: An illustration of down-weighting/removing noise edges and densifying the graph for better performance.

Although GNNs have shown great ability in modeling graphs, their performance can degrade significantly when trained on graphs with *noisy edges* and/or *limited labeled nodes*. *First*, due to the message passing, GNNs are vulnerable to adversarial or noisy edges. For example, as shown in Fig. 1, poisoning attacks [46] add/delete carefully chosen edges to the graph. These adversarial edges (shown in red) usually connect nodes of different labels or features, thus contaminating the neighborhoods of nodes, propagating noises/errors to node representations. In addition, inherent edge noises also exist in real-world graphs. For instance, in social networks, bots tend to build connections with normal users to spread misinformation [11], which can also harm the performance of GNNs for bot detection. *Second*, for many applications, graphs are often sparsely labeled such as cell phone network for fraud detection [13]. Label sparsity can severely reduce the involvement of unlabeled nodes during message passing, leading to poor performance. Generally, in a K-layer GNN, a labeled node aggregates its K-hop neighborhood information, thus making many unlabeled nodes in K-hop neighborhood participate in the training, which is one major reason that GNNs can leverage unlabeled nodes for semi-supervised node classification. However, as verified in our preliminary analysis in Fig. 2a of Sec. 3.3, when the number of labeled nodes decreases, the amount of unlabeled nodes participating in training drops quickly, making message passing less effective. These shortcomings of GNNs hinder the adoption of GNNs for many real-world applications. Thus, it is important to develop robust GNNs that can simultaneously handle noisy graphs with sparse labels.

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However, developing robust GNNs for graphs with noisy edges and limited labeled nodes is challenging. *First*, the training graph itself is noisy, i.e., noisy edges are mixed with the normal edges. Thus, we need supervision in down-weighting or eliminating noisy edges. *Second*, alleviating the limited label issue requires more labels, while obtaining more labeled nodes is time-consuming and expensive. Hence, we need alternative approaches to more effectively utilize the limited labels. Some initial efforts [20, 20, 33, 38] have been taken to alleviate the effects of the adversarial edges such as pruning edges by using node similarity [38], and adopting Gaussian distribution as node representations to absorb noises [43]. To address the problem of sparsely labeled graphs, some methods [24, 30, 32] propose to obtain better representations by training GNNs with self-supervised learning tasks such as pseudo label prediction [24, 32] and global context predictions [30]. However, little efforts are taken for robust GNNs that can simultaneously handle noisy edges and label sparsity.

Since both the noisy edges and limited labeled nodes harm the message passing of GNNs and message passing is directly related to the graph structure, we argue that learning a denoised and dense graph guided by the raw attributed graph is promising to facilitate message passing for robust GNNs. *First*, for many graphs such as social networks, nodes with similar features and labels tend to be linked [26], while noisy edges would link nodes of dissimilar features [38]. Thus, we can use node attributes to predict the links. For existing links, the link predictor will assign small weights to links connecting nodes of dissimilar features while large weights to links connecting nodes of similar features, thus alleviating negative issue of noisy edges during message passing. *Second*, real-world graphs are usually very sparse, containing many missing edges. With the link predictor, nodes that are potentially to be linked could be identified. Densifying the graph by linking similar nodes would induce more unlabeled nodes to become neighbors of labeled nodes with the same labels as shown in Fig. 1, which can alleviate the label sparsity issue. In addition, since adjacent nodes tend to have the same labels, the predicted new links can be used to further regularize the label predictions of unlabeled nodes. Though promising, the work on down-weighting noisy edges and densifying graph for robust GNN on noisy graphs with sparse labels are rather limited.

Therefore, in this paper, we investigate a novel problem of developing robust noise-resistant GNNs with limited labeled nodes by learning a denoised and densified graph. In essence, we need to solve two challenges: (i) how to effectively learn a link predictor from the noisy graph which can eliminate noisy edges and densify the graph; and (ii) how to simultaneously use the learned graph to learn a structural noise-resistant GNNs with limited labeled nodes. To address these challenges, we propose a novel framework named robust structural noise-resistant GNN (RS-GNN) [1]. RS-GNN adopts the node attributes and supervision from the noisy edges to denoise and dense graph, which can alleviate the negative effects of noisy edges and facilitate the message passing between unlabeled nodes and labeled nodes. The learned graph is used as input for learning a GNN. RS-GNN also adopts the predicted edges to further explicitly regularize the predictions of unlabeled nodes to alleviate the label sparsity issue. In summary, our main contributions are:

- We study a new problem of learning robust noise-resistant GNNs with limited labeled nodes;
- We propose a novel framework RS-GNN, which can simultaneously learn a denoised and densified graph and a robust GNN on noisy graphs with limited labeled nodes; and
- We conduct extensive experiments on real-world datasets to demonstrate the robustness of RS-GNN on both noisy/clean graphs with limited labeled nodes.

2 RELATED WORK

2.1 Graph Neural Networks

Graph Neural Networks (GNNs) have shown their great power in modeling graph structured data for various applications [7, 35, 37, 41, 42]. To generalize neural networks for graphs, two categories of GNNs are proposed, i.e., spectral-based [1, 17, 22, 23] and spatial-based [2, 5, 15, 34]. Bruna et al. [1] first propose spectral-based GNNs by defining graph convolution with spectral graph theory. For instance, GCN [22] simplifies the convolutional operation by using the first order approximation. Spatial-based graph convolution is defined in spatial domain, which updates node representation by aggregating its neighbors' representations [14, 15, 29]. For example, self-attention of neighbor nodes is leveraged in graph attention network (GAT) [34]. Moreover, various spatial methods are proposed to solve the scalability issue [2, 5] and learn deeper GNNs [3]. Recently, to alleviate the problem of lacking labeled nodes, many efforts are taken to explore GNNs using self-supervision, which aims to learn better node representations with pretext tasks [8, 19, 21, 24, 32, 44]. For instance, superGAT [21] deploys edge prediction in GAT to guide the learning of attention for better representations. SE-GNN [8] deploys contrastive learning to benefit the similarity modeling for self-explainable GNN.

Inspired by the great success of GNNs, methods that construct graphs and adopt GNNs for data without explicit relational structure are also explored [4, 6, 17, 18]. Generally, a graph would be built based on certain rules [4, 17] or be learned in an end-to-end model [6, 18]. Our RS-GNN is inherently different from these methods as we eliminate/down-weight the noisy edges and predict the missing edges for robust GNNs on noisy graphs with limited labels.

2.2 Robust GNNs

Although GNNs have obtained great achievements, they are vulnerable to adversarial attacks [9, 38, 45, 46]. Based on the objective, the adversarial attacks on GNNs can be split into two categories, i.e., targeted attack [9, 45] and non-targeted attack [46]. Targeted attack methods aim to degrade the performance of the GNNs on target nodes. For instance, *nettack* [45] adds adversarial perturbations to a graph to attack targeted nodes. Non-targeted attack aims to reduce the overall performance of GNNs. For example, *metattack* [46] poisons the graph globally to achieve non-targeted attack with meta-learning. To defend against adversarial attacks, many efforts are taken recently [10, 20, 33, 38, 40, 43]. [38] prune the perturbed edges based on Jaccard similarity of node features. Another preprocessing method by low-rank approximation of adjacent matrix is investigated [10]. Pro-GNN [20] is the most similar work to ours, which learns a clean graph structure by low-rank constraint. However, they only tackle the adversarial edges and their computational

[1] Codes are available at: https://github.com/EnyanDai/RSGNN

cost is very large due to the direct learning of the graph and the sparse low-rank constraint. This work is inherently different from these methods as: (i) we study a novel problem of developing robust GNN for both noisy graphs and label sparsity issues; and (ii) the proposed RS-GNN simultaneously tackles the two issues by learning an link predictor to down-weight noisy edges and connecting nodes with high similarity to facilitate message-passing; and (iii) RS-GNN uses link predictor instead of direct graph learning to save computational cost.

3 PRELIMINARY ANALYSIS

In this section, we discuss the inner working of GNNs, conduct preliminary analysis to show the issues of GNN with sparse labels and verify that densifying graphs by connecting similar nodes can potentially alleviate the issue.

3.1 Notations

We use $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{X})$ to denote an attributed graph, where $\mathcal{V} = \{v_1, ..., v_N\}$ is the set of N nodes, $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is the set of edges, and $\mathbf{X} = \{\mathbf{x}_1, ..., \mathbf{x}_N\}$ is the set of attributes of $\mathcal{V}$. $\mathbf{A} \in \mathbb{R}^{N \times N}$ is the adjacency matrix of the graph $\mathcal{G}$, where $\mathbf{A}_{ij} = 1$ if nodes v_i and v_j are connected, otherwise $\mathbf{A}_{ij} = 0$. In our setting, only a limited number of nodes $\mathcal{V}_L = \{v_1, ..., v_l\}$ are provided with labels $\mathcal{Y} = \{\mathbf{y}_1, ..., \mathbf{y}_l\}$, where $\mathbf{y}_i \in \mathbb{R}^C$ is a one-hot vector of node v_i's label for multi-class classification. Note that the topology of the graph $\mathcal{G}$ could be noisy such as poisoned by adversarial edges or containing inherent noises, which leads to poor performance.

3.2 Basic Design and Inner Working of GNNs

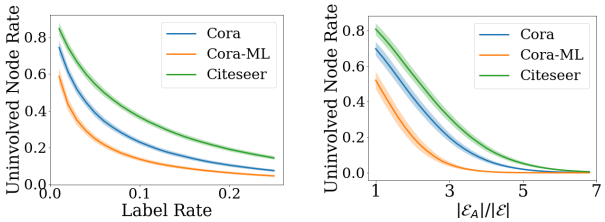
In this subsection, we briefly introduce the common architecture of graph neural networks (GNNs). Generally, GNNs adopt message-passing mechanism to learn node representations, i.e., they update the representation of a node by aggregating the representations of the neighborhood nodes. The updating process of the k-th layer in GNNs could be written as:

$$\begin{aligned} \mathbf{a}_v^{(k)} &= \text{AGGREGATE}^{(k-1)}(\{\mathbf{h}_u^{(k-1)} : u \in \mathcal{N}(v)\}), \\ \mathbf{h}_v^{(k)} &= \text{COMBINE}^{(k)}(\mathbf{h}_v^{(k-1)}, \mathbf{a}_v^{(k)}), \end{aligned} \tag{1}$$

where $\mathbf{h}_v^{(k)}$ is the representation vector of node $v \in \mathcal{V}$ at the k-th layer and $\mathcal{N}(v)$ is the set of neighborhoods of v. During the training of node classification, the representations of labeled nodes are used to give prediction and obtain the training loss to minimize. With the message-passing mechanism, after K-layers of GNN, the node representation of v_i would capture the node features and structure information of the K-hop neighborhoods of v_i, and thus facilitating downstream tasks. In other words, in GNN, *one labeled node would make the K-hop neighborhood participate in the training of GNN*, which is one reason that GNNs have great ability in leveraging unlabeled nodes for semi-supervised node classification.

3.3 Analysis of GNNs with Sparse Labels

In this subsection, we conduct preliminary analysis on real-world graphs to show the issues of GNNs when limited labeled nodes are available for training, which paves us a way to design robust GNNs for alleviating the label sparsity issue. The analysis is based on three widely used datasets, i.e., Citeseer [31], Cora and Cora-ML [27].



(a) Impacts of label rate **(b) Impacts of graph density**

Figure 2: The impacts of label rate and density of graph to uninvolved node rate in the training phase.

Generally, GNNs, such as GCN and GAT, rely on the classification loss of the labeled nodes to learn the parameters, which is effective when we have adequate labeled nodes. However, when the size of labeled node set $\mathcal{V}_L$ is small and the graph is sparse, only a small portion of nodes would be involved in the training. This may lead to poor performance of GNNs. More specifically, for a K-layer GNN, the nodes involved in the training phase include the labeled nodes and the unlabeled nodes within K-hop distance of labeled nodes. We usually set K as 2 to 3 because deep GNNs have over-smoothing issue [24]. Since real-world graphs are usually sparse, the K-hop neighbors of the labeled nodes would be limited as well. Thus, when $\mathcal{V}_L$ is small, only a small portion of nodes would be involved in training, making GNNs less effective in leveraging unlabeled nodes.

We analyze how the label rate affects the rates of uninvolved nodes of real-world datasets for a two layer GNN. We vary label rates from 0.01 to 0.25. The average uninvolved node rates and the standard deviations are shown in Fig. 2a. From the figure, we observe that **(i)** when the label rate is high, say above 0.1, most of the nodes are involved in training GNN. The benefit of further increasing label rate is marginal as the 2-hop neighbors of labeled nodes could overlap. This is one reason that GNNs have great ability for semi-supervised node classification with small but adequate amount of labeled nodes, and the increase of labeled nodes can marginally improve the performance; **(ii)** As the label rate decreases from 0.1, the uninvolved node rate increases significantly, i.e., the majority of nodes are not involved in the training. This indicates that GNNs would have difficulty in handling sparsely labeled graphs.

Although a higher label rate could help to reduce the uninvolved node rate, it can be expensive to obtain more labels [12]. Thus, we need an alternative approach to effectively use the labels. From the analysis above, one potential solution is to make the graph denser so that one labeled node could have more neighbors to be involved in the training of GNN. To verify it, we randomly add different amount of edges to the three graphs. We denote the number of edges of the new graph as $|\mathcal{E}_A|$ and that of raw graph as $|\mathcal{E}|$. We fix label rate as 0.01. The impact of the graph density on the uninvolved node rate is presented in Fig. 2b. From the figure, we observe that when $|\mathcal{E}_A|/|\mathcal{E}|$ increases from 1 to 3, i.e., we add two times the number of original edges, the uninvoled node rate drops significantly. For example, it drops from 0.8 to around 0.3 on Citeseer.

As real-world graphs such as social networks have many pairs of nodes who are similar but not connected together, the analysis above shows that it is promising to predict links to densify the graph, which can help the message passing of GNNs to alleviate the

issue of limited labeled nodes. In addition, these predicted edges can also be directly used to regularize the predicted labels of unlabeled nodes, i.e., if two nodes are more likely to have a link, they are more likely to have the same labels.

3.4 Problem Definition

Our preliminary analysis shows that predicting links to densify the graph can potentially alleviate the label sparsity issue. In addition, the link prediction can potentially down-weight or eliminate noisy edges as noisy edges usually connect nodes with low node attribute similarity. Therefore, we aim to simultaneously eliminate noisy edges and densify the graph with a link predictor and train a robust GNN on the new graph. The problem is formally defined as:

Problem 1. *Given an attributed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{X})$ with edge set $\mathcal{E}$ might contain a small amount of noisy edges, and a small set of labeled nodes $\mathcal{V}_L \in \mathcal{V}$ with the corresponding labels in $\mathcal{Y}$, simultaneously learn adjacency matrix $\mathbf{S} \in [0,1]^{N\times N}$ which down-weights/removes noisy edges and completes missing links by a link predictor $f_E : (v_i, v_j) \rightarrow \mathbf{S}_{ij}$, and a GNN on the learned graph for node classification, i.e., $f_{\mathcal{G}} : (\mathbf{S}, \mathbf{X}) \rightarrow \hat{\mathcal{Y}}$, where $\mathbf{S}_{ij}$ indicates the weight of edge linking v_i and v_j and $\hat{\mathcal{Y}}$ is the set of predictions for unlabeled nodes.*

4 PROPOSED FRAMEWORK – RS-GNN

In this section, we present the details of the proposed RS-GNN. The main challenges are: (i) given the noisy graph, how can we learn a link predictor which can down-weight/eliminate noisy edges and densify the graph; and (ii) how to simultaneously use the learned graph for node classification. As the graph topology is noisy, we cannot directly apply a GNN on $\mathcal{G}$ to predict edges because the message passing would magnify the negative effects of the noisy edges. Generally, nodes sharing similar features tend to connect to each other; while noisy edges tend to connect nodes of dissimilar nodes. Thus, we propose to learn a MLP-based link predictor which predicts links using node attributes. The more similar the node features of two nodes are, the larger weights the link predictor will assign. Thus, the link predictor is able to down-weight or eliminate noisy edges in the initial graph. Meanwhile, the edge predictor can predict missing links to alleviate label sparsity issue. We design a novel feature similarity weighted edge-reconstruction loss to train the link predictor so as to reduce the negative effects of noisy edges on the link predictor. An illustration of the framework is shown in Figure 3, which contains a link predictor f_E and a GCN classifier $f_{\mathcal{G}}$. The link predictor f_E takes node features as input to learn a dense adjacency matrix $\mathbf{S}$, aiming to remove adversarial edges and assign edges that benefit predictions. The GCN classifier $f_{\mathcal{G}}$ takes $\mathbf{S}$ and node features $\mathbf{X}$ to predict the node labels with the node features. Finally, label smoothness constraint based on the predicted edges will be added to the predictions of unlabeled nodes to further alleviate label sparsity issue. Next, we give the details of each component.

4.1 Link Prediction

As the given graph contains structural noises and has missing edges, we propose to learn a new graph that down-weights noisy edges to eliminate their negative effects and completes the missing links to facilitate GNN in dealing noisy graphs with sparse labels.

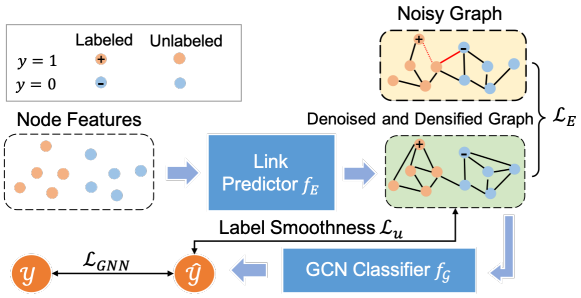


Figure 3: An illustration of the proposed RS-GNN.

Building Link Predictor. Generally, noisy edges connect two nodes with dissimilar node features; while nodes of similar features are likely to have similar labels and should be connected. Therefore, we propose to predict edge weights and missing edges between nodes using nodes features. Specifically, for node v_i, a MLP takes its node attributes $\mathbf{x}_i$ to learn its node representation as: $\mathbf{z}_i = MLP(\mathbf{x}_i)$. With the node representations, we predict the weight $w(i,j)$ between $v_i \in \mathcal{V}$ and $v_j \in \mathcal{V}$ as:

$$w(i,j) = f(\mathbf{z}_i^T \mathbf{z}_j), \tag{2}$$

where f is the activation function. For f, we use ReLU instead of sigmoid as we find that when the learned adjacency matrix is used as the input of GCN, the use of sigmoid function will lead to gradient vanishing, which is consistent with previous observations [16]. Note that we use MLP instead of a GNN as the link predictor because the graph structure is noisy and the message passing of GNN could magnify the negative effects.

Learning Link Predictor. Our goal is to learn a link predictor which can (i) assign small weights to two nodes of different features so as to eliminate noisy edges; and (ii) assign larger weights to two nodes of similar node features so as to densify the graph to facilitate message passing. As for many real-world graphs, similar nodes tend to link together and linked nodes usually have high feature similarity. Thus, to learn a good link predictor f_E, we utilize the adjacency matrix reconstruction as the loss function. Since the graph is sparse, the adjacency matrix $\mathbf{A}$ contains many zero entries. Directly adopting adjacency matrix reconstruction as the loss function would (i) result in poor performance as the link predictor will be biased on predicting missing links; and (ii) require large computational cost as we need to calculate N^2 edges. To address this problem, negative sampling [28] is adopted, i.e., for each $v_j \in \mathcal{N}(v_i)$, we randomly sample Q nodes that's not connected to v_i and use them as negative samples.

However, a small portion of edges in $\mathbf{A}$ are noisy, which might have negative effects in training the predictor. To mitigate the negative effects of noisy edges and to learn a link predictor that can assign lower weights to edges that link dissimilar nodes, we propose to reweight the positive and negative samples based on the feature similarity of two nodes. Specifically, for node v_i and its positive sample $v_j \in \mathcal{N}(v_i)$, we minimize $\exp(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{\sigma^2})(w(i,j) - 1)^2$, where σ is the hyperparameter to control the variance of the sample weights. Thus, if the node features of v_i and v_j are similar, A_{ij} is likely to be a clean edge and $\exp(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{\sigma^2})$ would be large.

Minimizing the loss will force $w(i,j)$ to be close to 1; while if the features are dissimilar, then A_{ij} is likely to be a noisy edge and $\exp(-\frac{\|\mathbf{x}_i-\mathbf{x}_j\|^2}{\sigma^2})$ would be small, thus minimizing the loss will have little effect on $w(i,j)$. Similarly, for v_i and its negative sample v_n, we minimize $\exp(\frac{\|\mathbf{x}_i-\mathbf{x}_n\|^2}{\sigma^2})(w(i,n)-0)^2$. If the node features of v_i and v_n are dissimialr, then $\exp(\frac{\|\mathbf{x}_i-\mathbf{x}_n\|^2}{\sigma^2})$ is large, minimizing the loss would make $w(i,n)$ close to 0 as expected. With the weight defined in this way, the loss for training the link predictor is:

$$\mathcal{L}_E = \sum_{v_i\in\mathcal{V}}\sum_{v_j\in\mathcal{N}(v_i)}\Big[\exp(-\frac{\|\mathbf{x}_i-\mathbf{x}_j\|^2}{\sigma^2})(w(i,j)-1)^2 + \sum_{n=1}^{Q}\cdot\mathbb{E}_{v_n\sim P_n(v_i)}\exp(\frac{\|\mathbf{x}_i-\mathbf{x}_n\|^2}{\sigma^2})(w(i,n)-0)^2\Big], \tag{3}$$

where $P_n(v_i)$ is the distribution of sampling negative nodes for v_i, which is a uniform distribution. With the loss function Eq.(3), the link predictor would be able to downweight the noisy edges and densify the graph to facilitate the learning of robust GNN on noisy graph with limited labels.

Graph Denoising and Densification. With the link predictor, we could apply the learned weights to the existing edges and drop edges whose predicted weights are small to eliminate the negative effects of noisy/adversarial edges. Moreover, to increase the involvement of unlabeled nodes to facilitate the message passing of GNNs, we also link nodes that have large weights predicted by the link predictor. However, if we predict weights of all pairs of nodes, the computation cost will be very large because we will train a link predictor and a GNN classifier end-to-end as shown in Sec. 4.4, which means we need to do prediction in each iteration. To save the computational cost, for each node v_i, we first construct a candidate subset $\mathcal{S}(v_i)$, which contains K nodes having the largest cosine similarities with v_i in the raw feature space $\mathbf{X}$. Note that this only needs to be done once. Since nodes not in $\mathcal{S}(v_i)$ are not likely to be connected with v_i, we only need to compute weights between v_i and $\mathcal{S}(v_i)$. The whole process of obtaining a clean and dense adjacency matrix $\mathbf{S}$ could be formally stated as:

$$\mathbf{S}_{ij} = \begin{cases} w(i,j) & \text{if } w(i,j) > T_l \text{ and } v_j \in \mathcal{N}(v_i)\cup\mathcal{S}(v_i); \\ 0 & \text{else,} \end{cases} \tag{4}$$

where $\mathcal{N}(v_i)$ are neighbors of v_i in the noisy graph, and T_l is a threshold to determine whether we should keep/add the edge. With the above operation, those noisy edges would be assigned smaller weights or even dropped, which mitigate the negative effects of noisy edges. Meanwhile, more edges are introduced to facilitate the message passing of GNNs during training.

4.2 GNN for Node Classification

With the learned adjacency matrix $\mathbf{S}$, we can apply GNNs to learn the node representation as $\mathbf{H} = GNN(\mathbf{S},\mathbf{X})$. Note that the proposed framework is a flexible framework which can facilitate various GNNs such as GAT [34] and GIN [39]. With the node representation, the label of node v_i can be predicted as $\hat{y}_i = softmax(\mathbf{h}_i)$, where $\mathbf{h}_i$ is the representation of node v_i. Then, the training loss is:

$$\mathcal{L}_{GNN} = \sum_{v_i\in\mathcal{V}_L} l(\hat{\mathbf{y}}_i, \mathbf{y}_i) \tag{5}$$

where $l(\hat{\mathbf{y}}_i,\mathbf{y}_i)$ is the cross entropy between $\hat{y}_i$ and $\mathbf{y}_i$. Since $\mathbf{S}$ is denser than the original graph, more unlabeled nodes are involved in the training even with limited amount of labeled nodes, thus making the propagation of information more efficient.

4.3 Label Smoothness on Unlabeled Nodes

Though the dense graph $\mathbf{S}$ can help to include more unlabeled nodes in the loss function, their information is propagated through the message-passing mechanism instead of being directly used in the training loss. To further alleviate the issue of limited labeled nodes, we propose to adopt the predicted weighted edges for label smoothness regularization. The basic idea is the larger weights of an edge S_{ij} is, the more likely that v_i and v_j have the same label [36]. Thus, for an unlabeled node v_i, if its edge weight with node v_j is larger than a threshhold T_h, i.e., $S_{ij} > T_h$, we want their predicted labels to be similar with each other. This can be formally written as

$$\mathcal{L}_u = \sum_{v_i\in\mathcal{V}_u}\sum_{v_j\in\mathcal{V}} \mathbf{T}_{ij}\|\hat{\mathbf{y}}_i - \hat{\mathbf{y}}_j\|^2, \tag{6}$$

where $\mathcal{V}_u$ denotes the set of unlabeled nodes, $\hat{\mathbf{y}}_i$ and $\hat{\mathbf{y}}_j$ represent the predictions of node $v_i\in\mathcal{V}_u$ and $v_j\in\mathcal{V}$, respectively. $\mathbf{T}_{ij} = \mathbf{S}_{ij}$ if $\mathbf{S}_{ij} > T_h$; otherwise 0. In this way, we explicitly smooth the predicted labels between unlabeled nodes and nodes that are similar to them. By including $\mathbf{T}_{ij}$ in $\mathcal{L}_u$, edge weights are also considered.

4.4 Final Objective Function of RS-GNN

With the link predictor denoising and densifying the graph with the supervision from $\mathbf{A}$, the GNN adopting the learned graph for label prediction and the label smoothness regularization from the generated graph, the final loss function can be written as

$$\arg\min_{\theta_E,\theta_{\mathcal{G}}} \mathcal{L}_{GNN} + \alpha\mathcal{L}_E + \beta\mathcal{L}_u, \tag{7}$$

where θ_E and $\theta_{\mathcal{G}}$ are parameters of link predictor f_E and GNN classifier $f_{\mathcal{G}}$, respectively. α and β are hyperparameters to balance the contributions of reconstructing the adjacency matrix with f_E and label smoothness regularization. The proposed framework is an end-to-end framework where we simultaneously learn the link predictor and utilize the predicted edges for training a robust GNN to alleviate the noisy graph and limited labeled nodes issues. The training algorithm is shown in the supplementary material.

5 EXPERIMENTS

In this section, we evaluate the proposed RS-GNN on noisy graphs with limited labels to answer the following research questions:

- **RQ1** How robust is the proposed framework on various types of noisy graphs with limited labeled nodes?
- **RQ2** How does the proposed framework perform under various label rates and graph sparsity levels?
- **RQ3** What are the contributions of link predictor and label smoothness regularization from predicted edges on RS-GNN?

5.1 Experimental Settings

5.1.1 Datasets. For a fair comparison, we conduct experiments on four widely used benchmark datasets, i.e., Cora, Cora-ML, Citeseer and Pubmed [31]. The statistics of the datasets are presented in the

Table 1: Node classification performance (Accuracy(%)±Std) on various types of noisy graphs

Dataset	Graph	GCN	SuperGAT	Self-Training	RGCN	GCN-jaccard	GCN-SVD	Pro-GNN	Ours
Cora	Raw Graph	65.5 ±0.5	69.0 ±1.7	67.9 ±0.9	63.0 ±0.7	65.7 ±0.6	62.9 ±1.1	65.9 ±1.3	**75.3 ±0.6**
	Random Noise	59.2 ±0.7	58.8 ±0.4	63.1 ±0.5	51.5 ±0.7	57.8 ±1.4	51.5 ±0.7	56.1 ±3.0	**71.8 ±1.5**
	Non-Targeted Attack	26.8 ±2.5	41.5 ±1.6	29.6 ±0.4	30.4 ±1.0	48.3 ±2.0	37.1 ±1.4	41.7 ±5.7	**70.8 ±0.7**
	Targeted Attack	45.3 ±1.2	44.4 ±1.3	46.7 ±2.1	40.3 ±1.0	49.5 ±1.0	44.8 ±0.7	49.7 ±0.9	**67.8 ±1.2**
Cora-ML	Raw Graph	72.4 ±0.8	73.8 ±1.4	72.7 ±1.4	72.9 ±0.7	71.0 ±1.2	71.1 ±1.0	62.0 ±1.5	**75.6 ±0.4**
	Random Noise	62.3 ±0.6	63.7 ±0.9	62.8 ±1.3	61.4 ±1.1	61.3 ±0.5	62.6 ±0.6	57.1 ±2.1	**72.9 ±0.7**
	Non-Targeted Attack	13.2 ±1.4	18.6 ±1.5	15.0 ±0.7	11.0 ±1.0	48.9 ±5.3	16.3 ±0.6	18.2 ±2.4	**73.2 ±1.2**
	Targeted Attack	55.7 ±0.7	56.5 ±1.7	57.7 ±1.2	54.6 ±0.6	61.2 ±0.9	53.0 ±0.8	55.1 ±1.6	**70.8 ±0.7**
Citeseer	Raw Graph	64.8 ±1.4	64.2 ±1.7	65.7 ±1.1	56.6 ±1.2	62.2 ±2.0	61.3 ±2.0	60.6 ±2.0	**71.2 ±1.4**
	Random Noise	57.0 ±1.2	54.6 ±1.3	58.7 ±2.1	48.2 ±1.2	61.1 ±2.8	48.3 ±1.6	54.4 ±2.6	**68.8 ±1.5**
	Non-Targeted Attack	26.6 ±2.5	42.3 ±2.6	28.8 ±2.7	26.6 ±1.1	57.9 ±2.7	41.7 ±1.6	41.6 ±3.1	**68.0 ±0.4**
	Targeted Attack	43.9 ±1.7	42.9 ±0.4	47.6 ±1.2	35.3 ±1.5	52.5 ±2.3	40.5 ±0.7	48.1 ±1.6	**67.2 ±1.3**
Pubmed	Raw Graph	85.9 ±0.1	86.0 ±1.2	86.1 ±0.2	85.1 ±0.1	86.0 ±0.1	83.0 ±0.1	86.1 ±0.1	**86.9 ±0.1**
	Random Noise	80.5 ±0.1	79.8 ±0.1	81.2 ±0.2	79.7 ±0.1	83.0 ±0.1	82.0 ±0.1	85.1 ±0.2	**86.4 ±0.1**
	Non-Targeted Attack	73.7 ±0.2	73.8 ±0.2	73.5 ±0.3	73.8 ±0.3	84.4 ±0.1	83.0 ±0.1	86.0 ± 0.1	**86.3 ±0.1**
	Targeted Attack	76.5 ±0.1	75.6 ±0.1	76.8 ±0.2	76.2 ±0.2	82.7 ±0.2	78.1 ±1.3	79.1 ±0.1	**84.3 ±0.2**

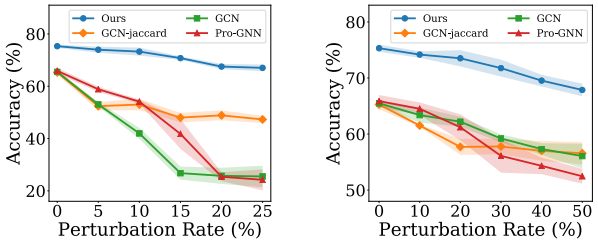
Table 3 in Appendix. Note that the split of validation and testing on all datasets are the same as described in the cited papers to keep consistence. For the training set, we randomly sample 1% of nodes as the labeled set for Cora, Cora-ML and Citeseer. For Pubmed, we randomly sample 10% of nodes to compose the labeled set. The training node set doesn't overlap with the validation and test sets.

5.1.2 Noisy Graphs. To show RS-GNN is robust to various structural noises, we evaluate RS-GNN on the following types of noises:

- **Raw Graphs**: They are the original graphs of the benchmark datasets which may contain inherent structural noise.
- **Random Noise**: We randomly inject fake edges and remove normal edges to add random noise to graphs.
- **Non-Targeted Attack**: We adopt *metattack* [46] to poison the graph structures by adding and removing edges, which aims to reduces the overall performance of GNNs on the whole graph.
- **Targeted Attack**: It aims to lead the GNN to misclassify target nodes. Following [33], we randomly select 15% nodes as target nodes and apply *nettack* [45] to perturb the graph structure.

5.1.3 Baselines. We compare RS-GNN with the representative and state-of-the-art GNNs, and robust GNNs against adversarial attacks:

- **GCN** [22]: GCN is a representative GNN which defines Graph convolution with spectral analysis.
- **SuperGAT** [21]: This extends GAT [34] with self-supervised learning. Edge prediction is deployed as the pretext task to guide the learning of attention to facilitate the message-passing.
- **Self-Training** [24]: This is a self-supervised learning method. A GCN is firstly trained on given labels. Then, confident pseudo labels would be added to the label set to improve the GCN.
- **RGCN** [43]: It uses Gaussian distributions as representations to absorb the effects of adversarial edges.
- **GCN-jaccard** [38]: GCN-Jaccard eliminates edges that connect nodes with low Jaccard similarity, then apply GCN on the graph.
- **GCN-SVD** [10]: This preprocessing method is based on low rank assumption. Low-rank approximation of the perturbed graph is used to train GNNs against adversarial attacks.
- **Pro-GNN** [20]: It applies low-rank and sparsity constraints to learn a clean graph structure close to the noisy graph structure.



(a) Metattack **(b) Random Noise**

Figure 4: Robustness under different Ptb rates on Cora.

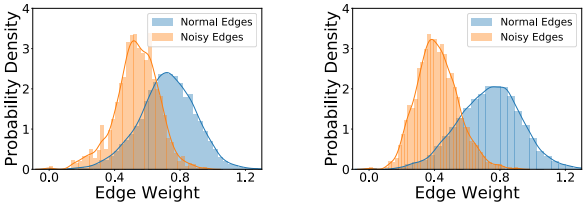
For all the baselines, we use the implementation from the repository DeepRobust [25]. All the hyperparameters of the baselines are tuned on the validation set to make a fair comparison with RS-GNN.

5.1.4 Implementation Details. Each experiment is conducted 5 times and average results with standard deviations are reported. The hyperparameters are tuned based on the performance of validation set. More specifically, for RS-GNN, we vary α as {0.003, 0.03, 0.3, 3, 30 }, and β as {0.01, 0.03, 0.1, 0.3, 1}. For all experiments, T_l, T_h, σ, and Q are fixed as 0.1, 0.8, 100, and 50, respectively. K is set as 100, 300, 400 and 10 for Cora, Cora-ML, Citeseer and Pubmed, respectively. More details about the hyperparameters sensitivity is discussed in Sec. 5.6. A one-hidden layer MLP with 64 filters is applied as the link predictor. We use GCN as the backbone of RS-GNN. Various GNNs can be used in RS-GNN and we leave it as a future work.

5.2 Performance on Noisy Graphs

To answer **RQ1**, we first compare RS-GNN with the baselines on various noisy graphs. We then evaluate the performance of RS-GNN on the graphs with different levels of structural noise.

5.2.1 Comparisons with baselines. We conduct experiments on four types of noisy graphs, i.e., raw graphs, graphs with random noise, non-targeted attack perturbed graphs and targeted attack perturbed graphs. The perturbation rate of non-targeted attack and targeted attack is 0.15. The perturbation rate of random noise is set as 0.3. Since we focus on noisy graph with sparse labels, we set the label rates as 0.01 for Cora, Cora-ML, Citeseer and 0.1 for Pubmed. The results are reported in Table 1, where we can observe:



(a) Cora (b) CoraML

Figure 5: Distributions of the weights of normal and noisy edges on the generated graph.

- With limited labeled nodes, GCN even hardly performs well on raw graph, which indicates the necessity of investigating method to address the challenge of sparsely labeled graphs. Though recent GNNs such as SuperGAT and Self-Training can improve the performance with self-supervised learning, our RS-GNN still outperforms them by a large margin. This shows the effectiveness of graph densification in dealing with sparsely labeled graphs.
- The structural noise further degrades the performance of GCN, but its impact to RS-GNN is negligible. RS-GNN achieves better results than the state-of-the-art robust GNNs. This indicates RS-GNN could eliminate the effects of the noisy edges.
- Compared with the preprocessing methods and Pro-GNN, RS-GNN achieves higher accuracy on the sparsely labeled graphs perturbed by attack methods. This is because the baselines only focus on eliminating potential noisy edges, which will even result in less involvement of unlabeled nodes. By contrast, RS-GNN can down-weights/removes the adversarial edges to defend the adversarial attacks and densify the graph to facilitate the message passing for predictions of unlabeled nodes.

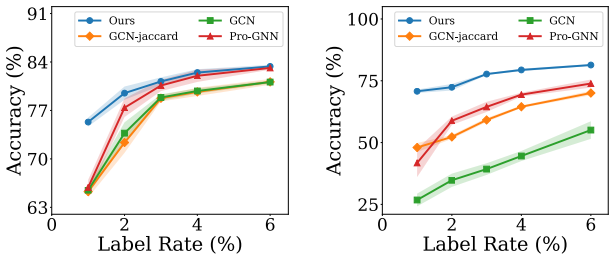
5.2.2 Robustness Under Different Ptb Rates . To show that RS-GNN is resistant to different levels of structural noise, we vary the perturbation rate as $\{0\%, 5\%, 10\%, \ldots, 25\%\}$ and compare the performance of RS-GNN with the most effective baselines. The label rate is fixed as 0.01. Since we have similar observations on other datasets, we only report the average accuracy and standard deviation on Cora in Figure 4. From the figure, we make following observations:

- As the perturbation rate increases, the performance of all the baselines drop significantly, which is as expected. Though the performance of RS-GNN also drops, it is much stable and consistently outperforms the baselines, which shows the robustness of RS-GNN against various levels of attacks and random noise; and
- Compared with GCN, RS-GNN uses GCN as backbone but significantly outperforms GCN, especially when the perturbation rate is large, which shows the effectiveness of eliminating the effects of noisy edges and densifying the graph to benefit the predictions given limited labels.

5.3 Analysis of the Learned Graph

To demonstrate that RS-GNN could alleviate negative effects of noisy edges by downweighting the noisy edges, we investigate the distribution of the learned edge weights $\mathbf{S}_{ij}$ of normal and noisy edges in this subsection. The edge weight distributions of graphs perturbed by random noise with 30% perturbation rate on Cora and Cora-ML are shown in Fig. 5. From this figure, we observe: **(i)** The weights of noisy edges are significantly lower than the weights of normal edges, which indicates RS-GNN manages to reduce the effects of noisy edges for robust GNN; and **(ii)** Although most normal edges have higher weights, some of their weights are very low, which implies inherent noise exists in the graph and RS-GNN is able to get rid of such inherent structural noise.

We also provide more details about the number of involved unlabeled nodes with the learned graph in Appendix B, which proves RS-GNN can enhance the involvement of unlabeled nodes.



(a) Raw Graph (b) Metattack with 15% Ptb

Figure 6: Performance on Cora with different label rates.

5.4 Impacts of Label Rate and Graph Sparsity

To answer **RQ2**, we study the impacts of the number of labeled nodes and sparsity of the graph by varying the label rate and edge rate of the graph. The hyperparameters are selected with the process described in Sec. 5.1.4. Each experiment is conducted 5 times and average accuracy with standard deviation are reported.

5.4.1 Impacts of Label Rate. We vary label rates as {0.01, 0.02,..., 0.06}. Experiments are conducted on raw graphs and graphs perturbed by *mettack* to study the effectiveness of RS-GNN under various label rates. The results on Cora are shown in Fig. 6. We have similar observations on other datasets. From Fig. 6, we observe:

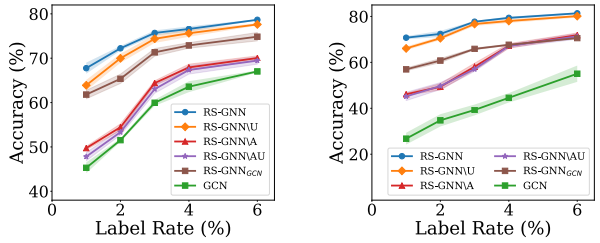
- Generally, as the increase of label rate, the performances of all the methods increase, which is as expected.
- For the raw graph, though RS-GNN consistently outperforms the baselines, as the label rate increases, the improvement of RS-GNN becomes marginal. This is because the raw graph doesn't contain much noise. Thus, as label rate increases to 6%, there are already adequate labels. Since higher label rates would result in more unlabeled nodes involving in the training, the effects of densifying graphs and label smoothness become less significant;
- For the metattack graph, as the label rate increases, RS-GNN still significantly outperforms baselines. That's because the training graph contains a lot of adversarial edges. Though we have enough training labels, the adversarial edges can still contaminate the message passing of GNNs. But RS-GNN can eliminate noisy edges and densify the graph, thus having better results.

5.4.2 Impacts of Graph Sparsity. As RS-GNN can generate dense graphs, it should have the ability to handle sparse graphs. Thus, we randomly select $x\%$ edges from the raw graph to build graphs of different sparsity levels. We vary edge rate $x\%$ from 20% to 100% with a step of 40%. Since we are interested in how the sparsity of the graph could affect RS-GNN in generating dense graphs, we only focus on the performance on raw graphs. The average results of 5 runs on Citeseer are reported in Table 2. From the table, we have the following observations:

Table 2: Accuracy (%) on Citeseer in different sparsity levels.

Edge Rate (%)	GCN	Pro-GNN	RS-GNN
20	54.5 ±1.2	55.2 ±1.6	**63.7 ±2.2**
60	58.7 ±1.8	58.3 ±2.4	**69.8 ±1.1**
100	64.8 ±1.4	60.6 ±2.0	**71.2 ±1.4**

- As the edge rate decreases, the performance of all the methods decrease, which is because message-passing of GNNs becomes ineffective on very sparse graphs;
- RS-GNN consistently outperforms the baselines. In particular, when the graph becomes more sparse, the improvement of RS-GNN over the baselines becomes larger. For example, the improvement of RS-GNN over GCN on Citeseer is 6.4% when Edge Rate is 100%, and becomes 9.2% when Edge Rate is 20%, which shows the importance of generating edges for densifying the graph and smoothing predictions with the learned graph.



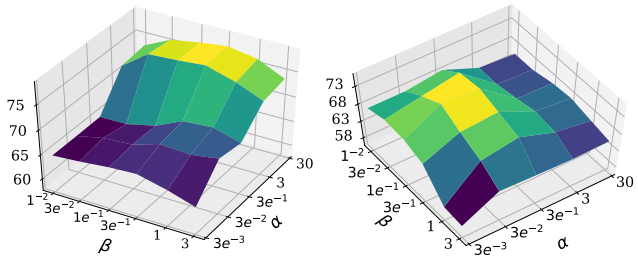
(a) Nettack **(b) Metattack with 15% Ptb**

Figure 7: Ablation studies on Cora with different label rates.

5.5 Ablation Study

To answer **RQ3**, we conduct ablation studies to understand the effects of graph densification, graph purification and label smoothness regularization. In RS-GNN, the link predictor densify the graph to enhance the performance on unlabeled nodes. To demonstrate the effects of adding edges with the link predictor, we remove the process of adding edges and obtain RS-GNN\A. To testify the effectiveness of the label smoothness regularization based on the generated graph, we eliminate the label smoothness regularization and get RS-GNN\U. To show our link predictor can eliminate the effects of noisy edges, we compare a variant named as RS-GNN\AU which only use the link predictor to denoise graphs. Graph desification and label smoothness are not applied in RS-GNN\AU. We also implement a variant named as RS-GNN$_{GCN}$ which uses GCN as link predictor to show that the noisy edges would largely affects the GNNs for link prediction. Hyperparameters selection follows the process in Sec 5.1.4. We only show the results on the Cora graph perturbed with *metattack* and random noise, because similar trends are observed on other datasets. Results are presented in Fig. 7. From this figure, we observe that:

- RS-GNN performs much better than RS-GNN\A and RS-GNN\U, which shows that densifying graphs and label smoothness with the learned graph can address the label sparsity issue;
- With the increase of label rate, the gap between RS-GNN and RS-GNN\U will be narrowed. This is consistent with our analysis that higher label rates would involve more unlabeled nodes;
- RS-GNN$_{GCN}$ performs much worse than RS-GNN, which indicates adversarial edges would impair GCN and result in a poor link predictor for denoising and densification.



(a) Raw Graph **(b) Metattack with 15% Ptb**

Figure 8: Parameter sensitivity analysis on Cora.

5.6 Parameter Sensitivity Analysis

In this subsection, we explore the sensitivity of the most crucial hyperparameters α and β which are in the final objective function of RS-GNN. The analysis about other hyperparameters is presented in the supplementary material. α controls how well the link predictor reconstructs the noisy graph and β controls the contribution of label smoothness. To investigate the effects of α and β, we vary the values of α as $\{0.003, 0.03, 0.3, 3, 30\}$ and β as $\{0.01, 0.03, 0.1, 0.3, 1, 3\}$ on Cora. The results are shown in Fig 8. In the raw graph, when α is large, the accuracy is stable and high. But if the α is too large in the perturbed graph, the performance would decrease. This difference is due to the noise levels of the raw graph and the perturbed graph. The structural noise in the perturbed graph is severe, faithfully reconstructing the perturbed graph with high α would lead to a poor link predictor. As for the β, a value between 0.03 to 0.3 generally gives good performance, which eases the parameter selection.

6 CONCLUSION AND FUTURE WORK

In this paper, we study a novel problem of learning robust GNNs on noisy graphs with limited labeled nodes. We demonstrate that noisy edges and limited labeled nodes would largely impair the performance of GNNs. A novel RS-GNN is proposed to mitigate these issues. More specially, we adopt the edges in the noisy graph as supervision to obtain a denoised and densified graph to facilitate the message passing for predictions of unlabeled nodes. Moreover, we also utilize the supervision from the generated graph to explicitly involve unlabeled nodes. Extensive experiments on real-world datasets demonstrate the robustness of the proposed framework on noisy graphs with limited labeled nodes. There are several directions requiring further investigation. First, we focus on structural noise in this paper. However, for some applications, such as social networks, users may provide fake attributes for privacy. Thus, we will extend it to graphs with structural noise as well as attribute noise under the setting of limited labeled nodes. Second, the labels may also contain noise which may degrade the performance of GNNs due to the message passing. Therefore, we will also explore methods that handle noisy graphs with limited and noisy labels.

7 ACKNOWLEDGEMENT

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REFERENCES

[1] Joan Bruna, Wojciech Zaremba, Arthur Szlam, and Yann LeCun. 2014. Spectral networks and locally connected networks on graphs. *ICLR* (2014).

[2] Jie Chen, Tengfei Ma, and Cao Xiao. 2018. Fastgcn: fast learning with graph convolutional networks via importance sampling. *ICLR* (2018).

[3] Ming Chen, Zhewei Wei, Zengfeng Huang, Bolin Ding, and Yaliang Li. 2020. Simple and deep graph convolutional networks. In *ICML*. PMLR, 1725–1735.

[4] Zhao-Min Chen, Xiu-Shen Wei, Peng Wang, and Yanwen Guo. 2019. Multi-label image recognition with graph convolutional networks. In *CVPR*. 5177–5186.

[5] Wei-Lin Chiang, Xuanqing Liu, Si Si, Yang Li, Samy Bengio, and Cho-Jui Hsieh. 2019. Cluster-GCN: An efficient algorithm for training deep and large graph convolutional networks. In *SIGKDD*. 257–266.

[6] Enyan Dai, Charu Aggarwal, and Suhang Wang. 2021. NRGNN: Learning a Label Noise Resistant Graph Neural Network on Sparsely and Noisily Labeled Graphs. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 227–236. https://doi.org/10.1145/3447548.3467364

[7] Enyan Dai and Suhang Wang. 2021. Say no to the discrimination: Learning fair graph neural networks with limited sensitive attribute information. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*. 680–688.

[8] Enyan Dai and Suhang Wang. 2021. Towards Self-Explainable Graph Neural Network. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*. 302–311.

[9] Hanjun Dai, Hui Li, Tian Tian, Xin Huang, Lin Wang, Jun Zhu, and Le Song. 2018. Adversarial attack on graph structured data. *ICML* (2018).

[10] Negin Entezari, Saba A Al-Sayouri, Amirali Darvishzadeh, and Evangelos E Papalexakis. 2020. All You Need Is Low (Rank) Defending Against Adversarial Attacks on Graphs. In *WSDM*. 169–177.

[11] Emilio Ferrara, Onur Varol, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2016. The rise of social bots. *Commun. ACM* 59, 7 (2016), 96–104.

[12] Brian Gallagher and Tina Eliassi-Rad. 2008. Leveraging label-independent features for classification in sparsely labeled networks: An empirical study. In *International Workshop on Social Network Mining and Analysis*. Springer, 1–19.

[13] Brian Gallagher, Hanghang Tong, Tina Eliassi-Rad, and Christos Faloutsos. 2008. Using ghost edges for classification in sparsely labeled networks. In *SIGKDD*. 256–264.

[14] Justin Gilmer, Samuel S Schoenholz, Patrick F Riley, Oriol Vinyals, and George E Dahl. 2017. Neural message passing for quantum chemistry. *ICML* (2017).

[15] Will Hamilton, Zhitao Ying, and Jure Leskovec. 2017. Inductive representation learning on large graphs. In *NeurIPS*. 1024–1034.

[16] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In *WWW*. 173–182.

[17] Mikael Henaff, Joan Bruna, and Yann LeCun. 2015. Deep convolutional networks on graph-structured data. *arXiv preprint arXiv:1506.05163* (2015).

[18] Bo Jiang, Ziyan Zhang, Doudou Lin, Jin Tang, and Bin Luo. 2019. Semi-supervised learning with graph learning-convolutional networks. In *CVPR*. 11313–11320.

[19] Wei Jin, Tyler Derr, Haochen Liu, Yiqi Wang, Suhang Wang, Zitao Liu, and Jiliang Tang. 2020. Self-supervised learning on graphs: Deep insights and new direction. *arXiv preprint arXiv:2006.10141* (2020).

[20] Wei Jin, Yao Ma, Xiaorui Liu, Xianfeng Tang, Suhang Wang, and Jiliang Tang. 2020. Graph structure learning for robust graph neural networks. In *SIGKDD*. 66–74.

[21] Dongkwan Kim and Alice Oh. 2021. How to find your friendly neighborhood: Graph attention design with self-supervision. In *International Conference on Learning Representations*.

[22] Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907* (2016).

[23] Ron Levie, Federico Monti, Xavier Bresson, and Michael M Bronstein. 2018. Cayleynets: Graph convolutional neural networks with complex rational spectral filters. *IEEE Transactions on Signal Processing* 67, 1 (2018), 97–109.

[24] Qimai Li, Zhichao Han, and Xiao-Ming Wu. 2018. Deeper insights into graph convolutional networks for semi-supervised learning. *AAAI* (2018).

[25] Yaxin Li, Wei Jin, Han Xu, and Jiliang Tang. 2020. DeepRobust: A PyTorch Library for Adversarial Attacks and Defenses. *arXiv preprint arXiv:2005.06149* (2020).

[26] David Liben-Nowell and Jon Kleinberg. 2007. The link-prediction problem for social networks. *JASIST* 58, 7 (2007), 1019–1031.

[27] Andrew Kachites McCallum, Kamal Nigam, Jason Rennie, and Kristie Seymore. 2000. Automating the construction of internet portals with machine learning. *Information Retrieval* 3, 2 (2000), 127–163.

[28] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In *NeurIPS*. 3111–3119.

[29] Mathias Niepert, Mohamed Ahmed, and Konstantin Kutzkov. 2016. Learning convolutional neural networks for graphs. In *ICML*. 2014–2023.

[30] Zhen Peng, Yixiang Dong, Minnan Luo, Xiao-Ming Wu, and Qinghua Zheng. 2020. Self-Supervised Graph Representation Learning via Global Context Prediction. *arXiv preprint arXiv:2003.01604* (2020).

[31] Prithviraj Sen, Galileo Namata, Mustafa Bilgic, Lise Getoor, Brian Galligher, and Tina Eliassi-Rad. 2008. Collective classification in network data. *AI magazine* 29, 3 (2008), 93–93.

[32] Ke Sun, Zhanxing Zhu, and Zhouchen Lin. 2020. Multi-stage self-supervised learning for graph convolutional networks. *AAAI* (2020).

[33] Xianfeng Tang, Yandong Li, Yiwei Sun, Huaxiu Yao, Prasenjit Mitra, and Suhang Wang. 2020. Transferring Robustness for Graph Neural Network Against Poisoning Attacks. In *WSDM*. 600–608.

[34] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2018. Graph attention networks. *ICLR* (2018).

[35] Daixin Wang, Jianbin Lin, Peng Cui, Quanhui Jia, Zhen Wang, Yanming Fang, Quan Yu, Jun Zhou, Shuang Yang, and Yuan Qi. 2019. A Semi-supervised Graph Attentive Network for Financial Fraud Detection. In *ICDM*. IEEE, 598–607.

[36] Hongwei Wang, Fuzheng Zhang, Mengdi Zhang, Jure Leskovec, Miao Zhao, Wenjie Li, and Zhongyuan Wang. 2019. Knowledge-aware graph neural networks with label smoothness regularization for recommender systems. In *SIGKDD*. 968–977.

[37] Zhichun Wang, Qingsong Lv, Xiaohan Lan, and Yu Zhang. 2018. Cross-lingual knowledge graph alignment via graph convolutional networks. In *EMNLP*. 349–357.

[38] Huijun Wu, Chen Wang, Yuriy Tyshetskiy, Andrew Docherty, Kai Lu, and Liming Zhu. 2019. Adversarial examples on graph data: Deep insights into attack and defense. *arXiv preprint arXiv:1903.01610* (2019).

[39] Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. 2018. How powerful are graph neural networks? *arXiv preprint arXiv:1810.00826* (2018).

[40] Xiang Zhang and Marinka Zitnik. 2020. Gnnguard: Defending graph neural networks against adversarial attacks. *arXiv preprint arXiv:2006.08149* (2020).

[41] Tianxiang Zhao, Xianfeng Tang, Xiang Zhang, and Suhang Wang. 2020. Semi-Supervised Graph-to-Graph Translation. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*. 1863–1872.

[42] Tianxiang Zhao, Xiang Zhang, and Suhang Wang. 2021. GraphSMOTE: Imbalanced Node Classification on Graphs with Graph Neural Networks. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*. 833–841.

[43] Dingyuan Zhu, Ziwei Zhang, Peng Cui, and Wenwu Zhu. 2019. Robust graph convolutional networks against adversarial attacks. In *SIGKDD*. 1399–1407.

[44] Qikui Zhu, Bo Du, and Pingkun Yan. 2020. Self-supervised Training of Graph Convolutional Networks. *arXiv preprint arXiv:2006.02380* (2020).

[45] Daniel Zügner, Amir Akbarnejad, and Stephan Günnemann. 2018. Adversarial attacks on neural networks for graph data. In *SIGKDD*. 2847–2856.

[46] Daniel Zügner and Stephan Günnemann. 2019. Adversarial attacks on graph neural networks via meta learning. *arXiv preprint arXiv:1902.08412* (2019).

Table 5: The impacts of hyperparameter K.

K	50	100	200	400
Cora	66.4 ±1.8	**70.8 ±0.7**	69.5 ±2.9	68.2 ±3.3
Cora-ML	44.8 ±1.2	53.8 ±2.7	**73.2 ±1.2**	69.0 ±5.0
Citeseer	63.3 ±2.0	66.0 ±1.4	**68.0 ±0.4**	67.8 ±1.4

Table 6: The impacts of hyperparameter T_h.

T_h	0.6	0.7	0.8	0.9
Cora	68.3 ±0.7	68.9 ±1.5	**70.8 ±0.7**	69.8 ±2.1
Cora-ML	64.8 ±4.1	68.2 ±3.6	**73.2 ±1.2**	69.2 ±4.8
Citeseer	66.6 ±1.7	67.5 ±2.1	**68.0 ±0.4**	67.8 ±2.2

Table 7: The impacts of hyperparameter T_l.

T_l	0.0	0.05	0.1	0.2
Cora	65.5 ±2.8	68.5 ±3.3	**70.8 ±0.7**	70.3 ±1.4
Cora-ML	65.9 ±2.6	72.5 ±1.3	**73.2 ±1.2**	69.6 ±3.9
Citeseer	65.8 ±0.6	66.8 ±0.8	**68.0 ±0.4**	66.6 ±1.3

Table 8: The impacts of hyperparameter σ.

σ	30	100	300	1000
Cora	70.2 ±1.2	**70.8 ±0.7**	70.1 ±1.1	68.9 ±2.8
Cora-ML	72.7 ±1.0	**73.2 ±1.2**	72.5 ±0.8	72.4 ±0.5
Citeseer	66.1 ±1.3	**68.0 ±0.4**	67.3 ±0.9	66.5 ±1.0

Table 3: Statistics of datasets.

	Cora	Cora-ML	Citeseer	Pubmed
#nodes	2,485	2,810	2,110	19,717
#edges	5,069	7,981	3,668	44,338
#features	1,433	2,879	3,703	500
#classes	7	7	6	3

Algorithm 1 Training Algorithm of RS-GNN.

Input: $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{X})$, $\mathcal{Y}$, K, Q T_l, T_h, σ, α and β.
Output: $f_{\mathcal{G}}$ and f_E

1: Randomly initialize the parameters of $f_{\mathcal{G}}$ and f_E.
2: **repeat**
3: Get the denoised and densified graph $\mathbf{S}$ with f_E by Eq.(4).
4: Input the learned graph $\mathbf{S}$ and node attributes $\mathbf{X}$ to GCN classifier $f_{\mathcal{G}}$ to get robust predictions.
5: Jointly optimize the GCN classifier parameters $\theta_{\mathcal{G}}$ and the link predictor parameters θ_E by Eq.(7).
6: **until** convergence
7: **return** $f_{\mathcal{G}}$ and f_E

A A TRAINING ALGORITHM OF RS-GNN

The training algorithm of RS-GNN is presented in Algorithm 1. In line 1, link predictor f_E and GCN classifier $f_{\mathcal{G}}$ are randomly initialized. In line 2, we generate the graph with f_E. Then the link predictor and GCN classifier are jointly trained in an end-to-end manner by Eq. (7) in line 3. Adam optimizer with learning rate set as 0.001 is applied to update all the parameters.

Table 4: Number of involved unlabeled nodes

Dataset	Cora	CoraML	Citeseer	Pubmed
Raw Graph	212	447	168	12,430
Generated Graph	1,383	2,161	955	18,555

B MORE DETAILS OF THE LEARNED GRAPH

Since RS-GNN aims to densify the graphs to benefit predictions in sparsely labeled graphs, we compare the number of involved unlabeled nodes in raw and generated graphs. More specially, in a two layer GNN, the neighbors of labeled nodes within two hops will participate in the training process. The generated graphs are attained by training RS-GNN on graphs perturbed by random noise. We binarize weighted edges by setting 0.5 as the threshold. The comparisons are given in Table 4. We can find that more unlabeled nodes are involved in the training with the generated graphs, which implies that RS-GNN could promote predictions of unlabeled nodes by densifying graphs.

C THE IMPACTS OF HYPERPARMETERS

Impacts of K. When we add edges with the link predictor, for each node, we select K nodes with the largest cosine similarity as candidate node set to predict the links to reduce the computational cost. To investigate how the selection of K would influence the training, we vary K as {50, 100, 200, 400} and report the average accuracy of 5 runs on Cora, Cora-ML and Citeseer that are perturbed by *metattack* in Table 5. The perturbation rate is set as 0.15. The label rate is set as 0.01 which is the same as that of main paper. We can observe that with the increase of K, the performance would firstly increase a lot then slightly decrease. Because when K is small, there are not adequate candidate nodes to predict links for each node. In this situation, the learned graph will be still sparse, which leads to poor performance on the noisy graphs with sparse labels. When K is very large, for a node v, nodes that dissimilar with v in raw features space would also be added into the candidate set. As a result, the performance slightly decrease.

Impacts of T_h. When we apply the label smoothness regularization based on the generated graph, we will smooth the predictions of nodes linked by predicted links whose weights are larger than T_h. To investigate how the setting of T_h affects the label smoothness regularization, we vary T_h as $\{0.6, 0.7, 0.8, 0.9\}$. We conduct experiments on the graphs perturbed by *metattack*. The perturbation rate is set as 0.15. The label rate is set as 0.01. Other parameters follows the same settings in the main paper. Average results of 5 runs are reported in Table 6. It shows that T_h should be set as an appropriate value such as 0.8 to benefit the predictions with label smoothness.

Impacts of T_l. When we deniose and desify the graph, a T_l is applied to the results of link predictor to determine whether we should keep/add the links. We vary the value of T_l as $\{0.0, 0.05, 0.1, 0.2\}$ to investigate the influence of T_l. Experiments are conducted on the graphs perturbed by *metattack* with the perturbation rate set as 0.15. The average results of 5 runs are reported in Table 7. As we can see, with the increase of T_l, the performance will firstly increase and then decrease. Because when T_l is very small, a lot

of down-weighted noisy edges are not removed, which degrades the performance of RS-GNN. If T_l is too large, the size of assigned links will be limited and some normal edges are likely to be deleted. Thus, the performance will drop when T_l is too large.

Impacts of σ. In Eq.(3) of our main paper, a parameter σ is used to control the variance of the weights of positive samples and negative samples when we train the link predictor with the loss of reconstructing the noisy graph. We vary the value of σ as $\{30, 100, 300, 1000\}$ and fix other hyperparameters. Similarly, experiments are conducted of the Cora, Cora-ML, and citeseer graphs perturbed by *metattack* with the perturbation rate set as 0.15. The results are presented in Table 8. From this table we could observe that when the σ is set too large, the performance will decrease. When σ is very large, the weights of all the negative samples and positive samples will be similar, which results a poor link predictor affected by noisy edges. This demonstrates the effectiveness of reweighting the samples based on raw feature similarity. However, if the σ is too small, the variance of sample weights would be too large, which negatively affects the learning of link predictor.