TOWARDS RELIABLE LINK PREDICTION WITH ROBUST GRAPH INFORMATION BOTTLENECK

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ABSTRACT

Link prediction on graphs has achieved great success with the rise of deep graph learning. However, the potential robustness under the edge noise is less investigated. We reveal that the inherent edge noise that naturally perturbs both input *topology* and target *label* leads to severe performance degradation and representation collapse. In this work, we propose an information-theory-guided principle, Robust Graph Information Bottleneck (RGIB), to extract reliable supervision signals and avoid representation collapse. Different from the general information bottleneck, RGIB decouples and balances the mutual dependence among graph topology, target labels, and representation, building new learning objectives toward robust representation. We also provide two instantiations, RGIB-SSL and RGIB-REP, which benefit from different methodologies, i.e., self-supervised learning and data reparametrization, for implicit and explicit data denoising, respectively. Extensive experiments on 6 benchmarks of various scenarios verify the effectiveness of the proposed RGIB.

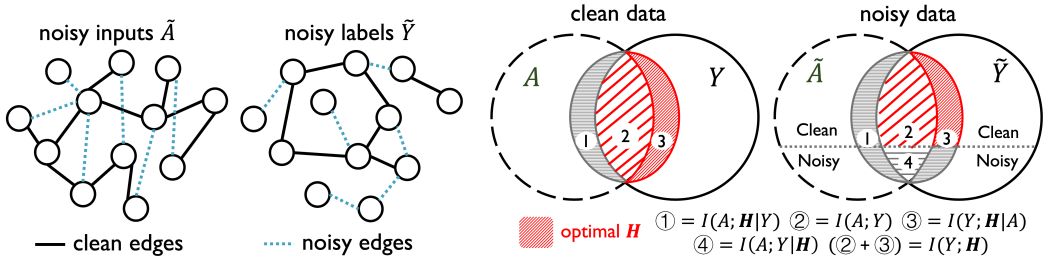
1 INTRODUCTION

As a fundamental problem in graph learning, link prediction (Liben-Nowell & Kleinberg, 2007) has attracted growing interest in real-world applications like drug discovery (Ioannidis et al., 2020), knowledge graph completion (Bordes et al., 2013), and question answering (Huang et al., 2019). Recent advances from heuristic designs (Katz, 1953; Page et al., 1999) to graph neural networks (GNNs) (Kipf & Welling, 2016a; Gilmer et al., 2017; Kipf & Welling, 2016b; Zhang & Chen, 2018; Zhu et al., 2021) have achieved superior performances. Nevertheless, the poor robustness in imperfect scenarios with the inherent edge noise is still a practical bottleneck to the current deep graph models (Gallagher et al., 2008; Ferrara et al., 2016; Wu et al., 2022; Dai et al., 2022).

Early explorations improve the robustness of GNNs for node classification under label noise (Dai et al., 2021; Li et al., 2021) through the smoothing effect of neighboring nodes. Other methods (Rong et al., 2020; Zheng et al., 2020; Luo et al., 2021) achieve a similar goal by actively selecting the informative nodes or edges and pruning the task-irrelevant ones. However, when applying these noise-robust methods to the link prediction with noise, only marginal improvements are achieved. (see Section 5). The attribution is that the edge noise can naturally deteriorate both the input topology and the target labels (as illustrated in Figure 1(a)). Previous works that consider the noise either in the input space or the label space cannot effectively deal with such a coupled scenario. Therefore, it raises a new challenge to understand and tackle the edge noise for robust link prediction.

In this paper, we dive into the inherent edge noise and empirically show the significantly degraded performances it leads to (Section 3.1). Then, we reveal the negative effect of the edge noise through carefully inspecting the distribution of learned representations, and discover that graph representation is severely collapsed, which is reflected by much lower alignment and poorer uniformity (Section 3.2). To solve this challenging problem, we propose the Robust Graph Information Bottleneck (RGIB) principle based on the basic GIB for adversarial robustness (Wu et al., 2020) (Section 4.1). Conceptually, the RGIB principle is with new learning objectives that decouple the mutual information (MI) among noisy inputs $\tilde{A}$, noisy labels $\tilde{Y}$, and the representation $\boldsymbol{H}$. As illustrated in Figure 1(b), RGIB generalizes the basic GIB to learn a robust representation that is resistant to the edge noise.

Technically, we provide two instantiations of RGIB based on different methodologies, i.e., RGIB-SSL and RGIB-REP: (1) the former utilizes contrastive pairs with automatically augmented views



(a) Illustration of inherent edge noise. The GNN predictor takes the input graph as observation (A), and then predicts the potential edges (Y). Under the inherent edge noise, the original training data is with noisy inputs ($\tilde{A}$) and noisy labels ($\tilde{Y}$).

(b) The basic GIB (left) and the proposed RGIB (right). $I(\cdot;\cdot)$ here indicates the mutual information. To solve the intrinsic deficiency of basic GIB in tackling the edge noise, the RGIB learns the graph represenation $\boldsymbol{H}$ via a further balance of informative signals ①, ③, ④ regarding the $\boldsymbol{H}$.

Figure 1: Link prediction with inherent edge noise (a) and the proposed RGIB principle (b).

to form the informative regularization in a self-supervised learning manner (Section 4.2); and (2) the latter explicitly purifies the graph topology and supervision targets with the reparameterization mechanism (Section 4.3). Both instantiations are equipped with adaptive designs, aiming to effectively estimate and balance the corresponding informative terms in a tractable manner. For example, the hybrid augmentation algorithm and self-adversarial alignment loss for RGIB-SSL, and the relaxed information constraints on topology space as well as label space for RGIB-REP. Empirically, we show that these two instantiations work effectively under extensive noisy scenarios and can be seamlessly integrated with various existing GNNs (Section 5). Our main contributions are summarized as follows.

- To our best knowledge, we are the *first* to study the robustness problem of link prediction under the inherent edge noise. We reveal that the inherent noise can bring a severe representation collapse and performance degradation, and such negative impacts are general to common datasets and GNNs.
- We propose a general learning framework, RGIB, with refined representation learning objectives to promote the robustness of GNNs. Two instantiations, RGIB-SSL and RGIB-REP, are proposed upon different methodologies that are equipped with adaptive designs and theoretical guarantees.
- Without modifying the GNN architectures, the RGIB achieves state-of-the-art results on 3 GNNs and 6 datasets under various noisy scenarios, obtaining up to 12.9% AUC promotion. The distribution of learned representations is notably recovered and more robust to the inherent noise.

2 PRELIMINARIES

Notation. We denote $\mathcal{V}=\{v_i\}$ as the set of nodes and $\mathcal{E}=\{e_{ij}\}$ as the set of edges. With adjacent matrix A and node features X, an undirected graph is denoted as $\mathcal{G}=(A,X)$, where $A_{ij}=1$ means there is an edge e_{ij} between v_i and v_j, and $X_{[i,:]}\in\mathbb{R}^D$ is the D-dimension node feature of v_i. Link prediction task is to indicate the existence of query edges with labels Y that are not observed in A.

GNNs for Link Prediction. We follow the common link prediction framework, i.e., graph auto-encoders (Kipf & Welling, 2016b), where the GNN architecture can be GCN (Kipf & Welling, 2016a), GAT (Veličković et al., 2018), or SAGE (Hamilton et al., 2017). Given a L-layer GNN, the graph representations $\boldsymbol{H}\in\mathbb{R}^{|\mathcal{V}|\times D'}$ for each node $v_i\in\mathcal{V}$ are obtained by a L-layer message propagation as the encoding process. For decoding, logits $\boldsymbol{\phi}_{e_{ij}}$ of each query edge e_{ij} are computed with a readout function, e.g., the dot product $\boldsymbol{\phi}_{e_{ij}}=\boldsymbol{h}_i^\top\boldsymbol{h}_j$. Finally, the optimization objective is to minimize the binary classification loss, i.e., $\min\mathcal{L}_{cls}=\sum_{e_{ij}\in\mathcal{E}^{train}}-y_{ij}\log\big(\sigma(\boldsymbol{\phi}_{e_{ij}})\big)-(1-y_{ij})\log\big(1-\sigma(\boldsymbol{\phi}_{e_{ij}})\big)$, where $\sigma(\cdot)$ is the sigmoid function, and $y_{ij}=1$ for positive edges while $y_{ij}=0$ for negative ones.

Topological denoising approaches. A natural way to tackle the input edge noise is to directly clean the noisy graph. Sampling-based methods, such as DropEdge (Rong et al., 2020), NeuralSparse (Zheng et al., 2020), and PTDNet (Luo et al., 2021), are proposed to remove the task-irrelevant edges. Besides, as GNNs can be easily fooled by adversarial network with only a few perturbed edges (Chen et al., 2018; Zhu et al., 2019; Entezari et al., 2020), defending methods like GCN-jaccard (Wu et al., 2019) and GIB (Wu et al., 2020) are designed for pruning adversarial edges.

Label-noise-resistant techniques. For tackling the general problem of noisy label, Co-teaching (Han et al., 2018) lets two neural networks teach each other with small-loss samples based on the memorization effect (Arpit et al., 2017). Besides, peer loss function (Liu & Guo, 2020) pairs independent peer examples for supervision and works within the standard empirical risk minimization framework. As for the graph domain, label propagation techniques proposed by pioneer works (Dai et al., 2021; Li et al., 2021) propagate the reliable signals from clean nodes to noisy ones, which are nonetheless entangled with the node annotations and node classification task that cannot be directly applied here.

3 AN EMPIRICAL STUDY OF THE INHERENT EDGE NOISE

In this section, we attempt to figure out how GNNs behave when learning with the edge noise and what are the latent mechanisms behind it. We first present an empirical study in Section 3.1 and then investigate the negative impact of noise through the lens of representation distribution in Section 3.2.

3.1 HOW DO GNNS PERFORM UNDER THE INHERENT EDGE NOISE?

Since existing benchmarks are usually well-annotated and clean, there is a need to simulate the inherent edge noise properly to investigate the impact of noise. Note the data split manner adopt by most relevant works (Kipf & Welling, 2016b; Zhang & Chen, 2018; Zhu et al., 2021) randomly divides partial edges as observations and the others as prediction targets. The inherent edge noise, if exists, should be *false positive* samples and uniformly distributed to both input observations and output labels. Thus, the training data can be with noisy adjacence $\tilde{A}$ and noisy labels $\tilde{Y}$, i.e., the input noise and label noise. We elaborate the formal simulation of such an *additive* edge noise as follows.

Definition 3.1 (Additive edge noise)**.** *Given a clean training data, i.e., observed graph $\mathcal{G} = (A, X)$ and labels $Y \in \{0, 1\}$ of query edges, the noisy adjacence $\tilde{A}$ is generated by only adding edges to the original adjacent matrix A while keeping the node features X unchanged. The noisy labels $\tilde{Y}$ are generated by only adding false-positive edges to the labels Y. Specifically, given a noise ratio ε_a, the added noisy edges A' ($\tilde{A} = A + A'$) are randomly generated with the zero elements in A as candidates. It satisfies that $A' \odot A = O$ and $\varepsilon_a = {}^{|\texttt{nonzero}(\tilde{A})| - |\texttt{nonzero}(A)|}\big/_{|\texttt{nonzero}(A)|}$. Similarly, noisy labels are generated and added to original labels, where $\varepsilon_y = {}^{|\texttt{nonzero}(\tilde{Y})| - |\texttt{nonzero}(Y)|}\big/_{|\texttt{nonzero}(Y)|}$.*

With the simulated noise, an empirical study is then performed with various GNNs and datasets. As shown in Figure 2, *the edge noise causes a significant drop in performance, and a larger noise ratio generally leads to greater degradation.* It means that these common GNNs normally trained with the stochastic gradient descent are vulnerable to the inherent edge noise, yielding a severe robustness problem. [1] However, none of the existing defending methods are designed for such a coupled noise, which is practical for real-world graph data that can be extremely noisy (Gallagher et al., 2008; Wu et al., 2022). Thus, it is urgent to understand the noise effect and devise the corresponding robust method.

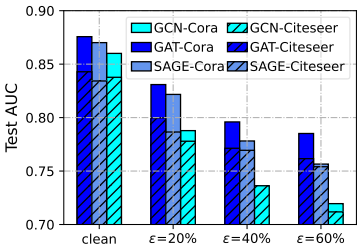


Figure 2: Performances (test AUC) with simulated edge noise. For fair evaluations, results are obtained by repeating 10 times with 4-layer GNNs on each dataset.

3.2 UNDERSTANDING THE IMPACT OF NOISE VIA REPRESENTATION DISTRIBUTION

Denote a GNN as $f_{\boldsymbol{w}}(\cdot)$ with learnable weights $\boldsymbol{w}$. Node representations are extracted by a forward pass as $\boldsymbol{H} = f_{\boldsymbol{w}}(A, X)$ while the backward propagation with stochastic gradient descent optimizes the GNN as $\boldsymbol{w} := \boldsymbol{w} - \eta \nabla_{\boldsymbol{w}} \mathcal{L}(\boldsymbol{H}, Y)$. When encountering noise within $\tilde{A}$ and $\tilde{Y}$, the representation $\boldsymbol{H}$ can be directly influenced, since the training neglects the adverse effect of data corruption. Besides, the GNN readouts the edge logit $\boldsymbol{\phi}_{e_{ij}}$ based on top-layer node representations $\boldsymbol{h}_i$ and $\boldsymbol{h}_j$, which are possibly degraded or even collapsed under the edge noise (Graf et al., 2021; Nguyen et al., 2022).

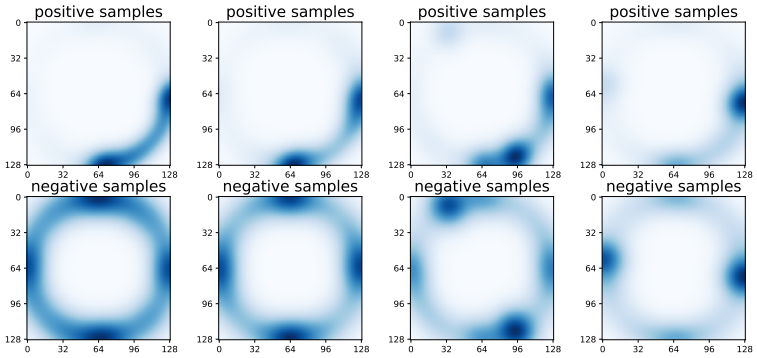
For quantitive and qualitative analysis of $\boldsymbol{H}$ under edge noise, we introduce two concepts (Wang & Isola, 2020) here, i.e., *alignment* and *uniformity*. Basically, a higher alignment means similar

[1] For generality, we provide the full empirical study in Appendix C.

samples tend to have similar representations. On the other hand, a greater uniformity implies that representations of various samples should be uniformly distributed on the unit hypersphere, preserving as much information about the original data as possible. As shown in Table 1 and Figure 3, *a poorer alignment and a worse uniformity are brought by a severer edge noise.* Specifically, the learned GNN $f_{\boldsymbol{w}}(\cdot)$ is more sensitive to input perturbations as the alignment values are sharply increased, and the learned edge representations tend to be less uniformly distributed and gradually collapse to individual points as the noise ratio increases. Thereby, it is discovered that the graph representation is severely collapsed under the inherent edge noise, resulting in the non-discriminative property. This is usually undesirable and potentially risky for downstream applications.

Table 1: Mean values of alignment on Cora dataset, that are calculated as the L2 distance of representations of two randomly perturbed graphs A_1, A_2, i.e., $||\boldsymbol{H}_1 - \boldsymbol{H}_2||_2$, where $\boldsymbol{H}_1 = f_{\boldsymbol{w}}(A_1, X)$ and $\boldsymbol{H}_2 = f_{\boldsymbol{w}}(A_2, X)$.

dataset	Cora	Citeseer
clean	.616	.445
$\varepsilon = 20\%$	.687	.586
$\varepsilon = 40\%$	.695	.689
$\varepsilon = 60\%$	.732	.696



(a) Clean data (b) $\varepsilon = 20\%$ (c) $\varepsilon = 40\%$ (d) $\varepsilon = 60\%$

Figure 3: Uniformity distribution on Cora dataset, which is obtained by mapping query edges of test set to the unit circle in $\mathbb{R}^2$ with normalization, followed by the Gaussian kernel density estimation.

4 On tackling the representation collapse via Robust GIB

As aforementioned, the inherent edge noise brings unique challenges to link-level graph learning. Without prior knowledge like the noise ratio, without the assistance of auxiliary datasets, and even without modifying GNN architectures, how can learned representations be resistant to the inherent noise? Here, we formally build a method to address this problem from the perspective of graph information bottleneck (Section 4.1) and design its two practical instantiations (Section 4.2 and 4.3).

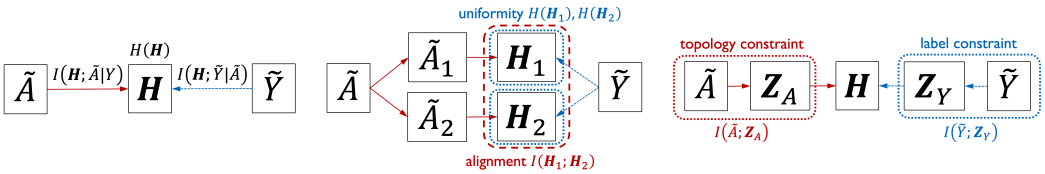
4.1 The Principle of Robust GIB

Recall in Section 3.2, the graph representation $\boldsymbol{H}$ is severely degraded due to incorporating noisy signals in $\tilde{A}$ and $\tilde{Y}$. To robustify $\boldsymbol{H}$, one can naturally utilize the information constraint based on the basic graph information bottleneck (GIB) principle (Wu et al., 2020; Yu et al., 2020), i.e., solving

$$\min \text{GIB} \triangleq -I(\boldsymbol{H}; \tilde{Y}), \ s.t. \ I(\boldsymbol{H}; \tilde{A}) < \gamma. \tag{1}$$

where the hyper-parameter γ constrains the MI $I(\boldsymbol{H}; \tilde{A})$ to avoid $\boldsymbol{H}$ from capturing excess task-irrelevant features from $\tilde{A}$. The basic GIB (Eqn. 1) can effectively withstand the input perturbation (Wu et al., 2020). However, it is intrinsically susceptive to label noise since it entirely preserves the label supervision with maximizing $I(\boldsymbol{H}; \tilde{Y})$. Empirical results in Section 5 show that it becomes ineffective when learning with inherent edge noise simulated as Definition 3.1.

As illustrated in Figure 1(b), the basic GIB decreases $I(\boldsymbol{H}; \tilde{A}|\tilde{Y})$ by directly constraining $I(\boldsymbol{H}; \tilde{A})$ to handle the input noise. Symmetrically, the label noise can be hidden in $I(\boldsymbol{H}; \tilde{Y}|\tilde{A})$, but trivially constraining $I(\boldsymbol{H}; \tilde{Y})$ to regularize $I(\boldsymbol{H}; \tilde{Y}|\tilde{A})$ is not ideal, since it will conflict with Eqn. 1 and also cannot tackle the noise within $I(\tilde{A}; \tilde{Y})$. Thus, it is crucial to decouple the mutual dependence among $\tilde{A}$, $\tilde{Y}$, and $\boldsymbol{H}$, while the noise can exist in areas of $I(\boldsymbol{H}; \tilde{Y}|\tilde{A})$, $I(\boldsymbol{H}; \tilde{A}|\tilde{Y})$, and $I(\tilde{A}; \tilde{Y}|\boldsymbol{H})$. Analytically, $I(\tilde{A}; \tilde{Y}|\boldsymbol{H}) = I(\tilde{A}; \tilde{Y}) + I(\boldsymbol{H}; \tilde{Y}|\tilde{A}) + I(\boldsymbol{H}; \tilde{A}|\tilde{Y}) - H(\boldsymbol{H}) + H(\boldsymbol{H}|\tilde{A}, \tilde{Y})$, where $I(\tilde{A}; \tilde{Y})$ is a constant and redundancy $H(\boldsymbol{H}|\tilde{A}, \tilde{Y})$ can be easily minimized. Thus, the $I(\tilde{A}; \tilde{Y}|\boldsymbol{H})$ can be approximated by the other three terms, i.e., $H(\boldsymbol{H})$, $I(\boldsymbol{H}; \tilde{Y}|\tilde{A})$ and $I(\boldsymbol{H}; \tilde{A}|\tilde{Y})$. Since the two later terms are also with noise, a balance of these three informative terms can be a solution to the problem.



(a) RGIB (Eqn. 2) (b) RGIB-SSL (Eqn. 3) (c) RGIB-REP (Eqn. 4)

Figure 4: Digrams of the proposed RGIB and its two instantiations (best viewed in color).

Based on the above analysis, we propose the *Robust Graph Information Bottleneck (RGIB)*, a new learning objective to balance informative signals regarding $\boldsymbol{H}$, as illustrated in Figure 4(a), i.e.,

$$\min \text{RGIB} \triangleq -I(\boldsymbol{H};\tilde{Y}),\ s.t.\ \gamma_H^- < H(\boldsymbol{H}) < \gamma_H^+,\ I(\boldsymbol{H};\tilde{Y}|\tilde{A}) < \gamma_Y,\ I(\boldsymbol{H};\tilde{A}|\tilde{Y}) < \gamma_A. \quad (2)$$

where constraints on $H(\boldsymbol{H})$ encourage a diverse $\boldsymbol{H}$ to prevent representation collapse ($>\gamma_H^-$) and also limit its capacity ($<\gamma_H^+$) to avoid over-fitting. Another two symmetric terms, $I(\boldsymbol{H};\tilde{Y}|\tilde{A})$ and $I(\boldsymbol{H};\tilde{A}|\tilde{Y})$, mutually regularize posteriors to mitigate the negative impact of inherent noise on $\boldsymbol{H}$.

Note MI terms like $I(\boldsymbol{H};\tilde{A}|\tilde{Y})$ are usually intractable. Next, we introduce two practical implementations of RGIB, i.e., RGIB-SSL and RGIB-REP, based on different methodologies. The former explicitly optimizes the representation $\boldsymbol{H}$ with the self-supervised regularization, while the latter implicitly optimizes $\boldsymbol{H}$ by purifying the noisy $\tilde{A}$ and $\tilde{Y}$ with the reparameterization mechanism.

4.2 Instantiating Robust GIB via Self-Supervised Learning

Recall that the graph representation is deteriorated with the *supervised* learning paradigm. Naturally, we modify it into a *self-supervised* counterpart by explicitly regularizing the representation $\boldsymbol{H}$ (shown in Figure 4(b)) to avoid collapse and to implicitly capture reliable relations among noisy edges, i.e.,

$$\min \text{RGIB-SSL} \triangleq -\underbrace{\lambda_s(I(\boldsymbol{H}_1;\tilde{Y})+I(\boldsymbol{H}_2;\tilde{Y}))}_{\text{supervision}} - \underbrace{\lambda_u(H(\boldsymbol{H}_1)+H(\boldsymbol{H}_2))}_{\text{uniformity}} - \underbrace{\lambda_a I(\boldsymbol{H}_1;\boldsymbol{H}_2)}_{\text{alignment}}. \quad (3)$$

where margins $\lambda_s, \lambda_u, \lambda_a$ balance one supervised and two self-supervised regularization terms. [2]

Note that contrastive learning is a prevalent technique in the self-supervised area to learn robust representation (Chen et al., 2020), where contrasting pair of samples with data augmentation plays an essential role. In practice, we follow such a manner and calculate the supervision term by $\mathbb{E}[I(\boldsymbol{H};\tilde{Y}|\tilde{A})] \leq \mathbb{E}[I(\boldsymbol{H};\tilde{Y})] = \mathbb{E}_{\tilde{A}_s\sim\mathbb{P}(\tilde{A})}[I(\boldsymbol{H}_s;\tilde{Y})] \approx 1/2(I(\boldsymbol{H}_1;\tilde{Y})+I(\boldsymbol{H}_2;\tilde{Y})) = 1/2(\mathcal{L}_{cls}(\boldsymbol{H}_1;\tilde{Y})+\mathcal{L}_{cls}(\boldsymbol{H}_2;\tilde{Y}))$, where $\tilde{A}_1, \tilde{A}_2$ are sampled from $\mathbb{P}(\tilde{A})$. Similarly, we have $\mathbb{E}[H(\boldsymbol{H})] \approx 1/2(H(\boldsymbol{H}_1)+H(\boldsymbol{H}_2))$, and a higher uniformity leads to a high entropy $H(\boldsymbol{H})$ as proved in Proposition 4.1. As for $I(\boldsymbol{H};\tilde{A}|\tilde{Y})$, we approximate it by the alignment term $I(\boldsymbol{H}_1;\boldsymbol{H}_2)$ with the derived upper bound in Proposition 4.2.

Proposition 4.1. *A higher entropy $H(\boldsymbol{H})$ leads to a higher uniformity. Proof. See Appendix B.1.*

Proposition 4.2. *The alignment $I(\boldsymbol{H}_1;\boldsymbol{H}_2)$ is the upper bound of $I(\boldsymbol{H};\tilde{A}|\tilde{Y})$. Since $I(\boldsymbol{H};\tilde{A}|\tilde{Y}) \leq I(\boldsymbol{H};\tilde{A}) \leq 1/2\big(I(\boldsymbol{H}_1;\boldsymbol{H}_2)+I(\tilde{A}_1;\tilde{A}_2)\big) = 1/2\big(I(\boldsymbol{H}_1;\boldsymbol{H}_2)+c\big)$, a constrained alignment estimated by MI $I(\boldsymbol{H}_1;\boldsymbol{H}_2)$ is capable to bound a lower $I(\boldsymbol{H};\tilde{A}|\tilde{Y})$ and $I(\boldsymbol{H};\tilde{A})$. Proof. See Appendix B.2.*

However, directly applying existing contrastive methods like (Chen et al., 2020; Khosla et al., 2020) can be suboptimal, since they are not originally designed for graph data and neglect the internal correlation of topology $\tilde{A}$ and target $\tilde{Y}$. Two following designs are proposed to avoid trivial solutions.

Hybrid graph augmentation. To encourage more diverse views with lower $I(A_1;A_2)$ and to avoid manual selection of augmentation operations, we propose a hybrid augmentation method with four augmentation operations as predefined candidates and ranges of their corresponding hyper-parameters. In each training iteration, two augmentation operators, $\mathcal{T}^1(\cdot)$ and $\mathcal{T}^2(\cdot)$, and their hyper-parameters θ_1 and θ_2 are *automatically* sampled from the search space. Then, two augmented graphs are obtained by applying the two operators on the original graph $\mathcal{G}$. Namely, $\mathcal{G}^1 = \mathcal{T}^1(\mathcal{G}|\theta_1)$ and $\mathcal{G}^2 = \mathcal{T}^2(\mathcal{G}|\theta_2)$. [3]

[2] When $\lambda_s \equiv 1$ and $\lambda_u \equiv 0$, the RGIB-SSL can be degenerated to the basic GIB.

[3] The search space and full augmentation algorithm are elaborated in Appendix D

Self-adversarial alignment & uniformity loss. With representations $\boldsymbol{H}_1$ and $\boldsymbol{H}_2$ from two augmented views, we build the alignment objective by minimizing the representation similarity of the positive pairs $(\boldsymbol{h}_{ij}^1, \boldsymbol{h}_{ij}^2)$ and maximizing that of the randomly-sampled negative pairs $(\boldsymbol{h}_{ij}^1, \boldsymbol{h}_{mn}^2)$, $e_{ij} \neq e_{mn}$. The proposed self-adversarial alignment loss is $\mathcal{R}_{align} = \sum_{i=1}^{N} \mathcal{R}_i^{pos} + \mathcal{R}_i^{neg}$, where $\mathcal{R}_i^{pos} = p^{pos}(\boldsymbol{h}_{ij}^1, \boldsymbol{h}_{ij}^2) \cdot \left\|\boldsymbol{h}_{ij}^1 - \boldsymbol{h}_{ij}^2\right\|_2^2$ and $\mathcal{R}_i^{neg} = p^{neg}(\boldsymbol{h}_{ij}^1, \boldsymbol{h}_{mn}^2) \cdot (\gamma - \left\|\boldsymbol{h}_{ij}^1 - \boldsymbol{h}_{mn}^2\right\|_2^2)$. [4] Importantly, softmax functions $p^{pos}(\cdot)$ and $p^{neg}(\cdot)$ aim to mitigate the inefficiency problem (Sun et al., 2019) that aligned pairs are not informative. Besides, with Gaussian potential kernel, the uniformity loss is as $\mathcal{R}_{unif} = \sum_{ij,mn}^{K} e^{-\left\|\boldsymbol{h}_{ij}^1 - \boldsymbol{h}_{mn}^1\right\|_2^2} + e^{-\left\|\boldsymbol{h}_{ij}^2 - \boldsymbol{h}_{mn}^2\right\|_2^2}$, where e_{ij},e_{mn} are randomly sampled.

Optimization. As Eqn. 3, the overall loss function of RGIB-SSL is $\mathcal{L} = \lambda_s \mathcal{L}_{cls} + \lambda_a \mathcal{R}_{align} + \lambda_u \mathcal{R}_{unif}$.

Remark 4.1. *The inherent noise leads to class collapse, i.e., samples from the same class have the same representation. It comes from trivially minimizing the noisy supervision $I(\boldsymbol{H}; \tilde{Y})$ and results in degraded representations shown in Section 3.2. Fortunately, the alignment and uniformity terms regularizing representations can alleviate such noise effects and avoid collapse (see Section 5).*

4.3 Instantiating Robust GIB via Data Reparameterization

Another realization is by reparameterizing the graph data on both topology space and label space jointly to preserve clean information and discard noise. We propose RGIB-REP that explicitly models the reliability of $\tilde{A}$ and $\tilde{Y}$ via latent variables $\boldsymbol{Z}$ to learn a noise-resistant $\boldsymbol{H}$ (as Figure 4(c)), namely,

$$\min \text{RGIB-REP} \triangleq -\underbrace{\lambda_s I(\boldsymbol{H}; \boldsymbol{Z}_Y)}_{\text{supervision}} + \underbrace{\lambda_A I(\boldsymbol{Z}_A; \tilde{A})}_{\text{topology constraint}} + \underbrace{\lambda_Y I(\boldsymbol{Z}_Y; \tilde{Y})}_{\text{label constraint}}. \tag{4}$$

where latent variables $\boldsymbol{Z}_Y$ and $\boldsymbol{Z}_A$ are clean signals extracted from noisy $\tilde{Y}$ and $\tilde{A}$. Their complementary parts $\boldsymbol{Z}_{Y'}$ and $\boldsymbol{Z}_{A'}$ are considered as noise, satisfying $\tilde{Y} = \boldsymbol{Z}_Y + \boldsymbol{Z}_{Y'}$ and $\tilde{A} = \boldsymbol{Z}_A + \boldsymbol{Z}_{A'}$. [5] The $I(\boldsymbol{H}; \boldsymbol{Z}_Y)$ measures the supervised signals with selected samples $\boldsymbol{Z}_Y$, where the classifier takes $\boldsymbol{Z}_A$ (a subgraph of $\tilde{A}$) as input instead of the original $\tilde{A}$, i.e., $\boldsymbol{H} = f_{\boldsymbol{w}}(\boldsymbol{Z}_A, X)$. Constraints $I(\boldsymbol{Z}_A; \tilde{A})$ and $I(\boldsymbol{Z}_Y; \tilde{Y})$ aim to select the cleanest and most task-relevant information from $\tilde{A}$ and $\tilde{Y}$.

Instantiation. For deriving a tractable objective regarding $\boldsymbol{Z}_A$ and $\boldsymbol{Z}_Y$, a parameterized sampler $f_{\boldsymbol{\phi}}(\cdot)$ sharing the same architecture and weights as $f_{\boldsymbol{w}}(\cdot)$ is adopted here. $f_{\boldsymbol{\phi}}(\cdot)$ generates the probabilistic distribution of edges that include both $\tilde{A}$ and $\tilde{Y}$ by $\boldsymbol{P} = \sigma(\boldsymbol{H}_{\boldsymbol{\phi}} \boldsymbol{H}_{\boldsymbol{\phi}}^\top) \in (0,1)^{|\mathcal{V}| \times |\mathcal{V}|}$, where hidden representations $\boldsymbol{H}_{\boldsymbol{\phi}} = f_{\boldsymbol{\phi}}(\tilde{A}, X)$. Then, the Bernoulli sampling is used to obtain edges of high confidences, i.e., $\boldsymbol{Z}_A = \texttt{SAMP}(\boldsymbol{P}|\tilde{A})$ and $\boldsymbol{Z}_Y = \texttt{SAMP}(\boldsymbol{P}|\tilde{Y})$ [6], where $|\boldsymbol{Z}_A| \leq |\tilde{A}|$ and $|\boldsymbol{Z}_Y| \leq |\tilde{Y}|$.

Optimization. A relaxation is then conducted on the three MI terms in Eqn. 4. With derived bounds in Proposition 4.3 (i.e., $\mathcal{R}_A$ and $\mathcal{R}_Y$) and Proposition 4.4 (i.e., $\mathcal{L}_{cls}$), the final objective is formed as $\mathcal{L} = \lambda_s \mathcal{L}_{cls} + \lambda_A \mathcal{R}_A + \lambda_Y \mathcal{R}_Y$, and the corresponding guarantee is discussed in Theorem 4.5.

Proposition 4.3. *Given the edge number n of $\tilde{A}$, the marginal distribution of $\boldsymbol{Z}_A$ is $\mathbb{Q}(\boldsymbol{Z}_A) = \sum_n \mathbb{P}_\phi(\boldsymbol{P}|n)\mathbb{P}(\tilde{A} = n) = \mathbb{P}(n) \prod_{\tilde{A}_{ij}=1}^{n} \boldsymbol{P}_{ij}$. Then, we derive the upper bound $I(\boldsymbol{Z}_A; \tilde{A}) \leq \mathbb{E}[KL(\mathbb{P}_\phi(\boldsymbol{Z}_A|A)||\mathbb{Q}(\boldsymbol{Z}_A))] = \sum_{e_{ij} \in \tilde{A}} \boldsymbol{P_{ij}} \log \frac{\boldsymbol{P_{ij}}}{\tau} + (1 - \boldsymbol{P_{ij}}) \log \frac{1 - \boldsymbol{P_{ij}}}{1 - \tau} = \mathcal{R}_A$, where τ is a constant. Similarly, the label constraint is bounded as $I(\boldsymbol{Z}_Y; \tilde{Y}) \leq \mathcal{R}_Y$, Proof. See Appendix B.3.*

Proposition 4.4. *Since $I(\boldsymbol{H}; \boldsymbol{Z}_Y) \geq \mathbb{E}_{\boldsymbol{Z}_Y, \boldsymbol{Z}_A}[\log \mathbb{P}_{\boldsymbol{w}}(\boldsymbol{Z}_Y|\boldsymbol{Z}_A)] \approx -\mathcal{L}_{cls}(f_{\boldsymbol{w}}(\boldsymbol{Z}_A), \boldsymbol{Z}_Y)$, the supervision term in Eqn. 4 can be empirically reduced to the classification loss. Proof. See Appendix B.4.*

Theorem 4.5. *Assume the noisy training data $D_{train} = (\tilde{A}, X, \tilde{Y})$ contains a potentially clean subset $D_{sub} = (\boldsymbol{Z}_A^*, X, \boldsymbol{Z}_Y^*)$ and $\boldsymbol{Z}_Y^* \approx Y$, based on which a trained GNN predictor $f_{\boldsymbol{w}}(\cdot)$ satisfies $f_{\boldsymbol{w}}(\boldsymbol{Z}_A^*, X) = \boldsymbol{Z}_Y^* + \epsilon$. The error ϵ is independent from D_{sub} and $\epsilon \to 0$. Then, for any $\lambda_s, \lambda_A, \lambda_Y \in [0,1]$, $\boldsymbol{Z}_A = \boldsymbol{Z}_A^*$ and $\boldsymbol{Z}_Y = \boldsymbol{Z}_Y^*$ minimizes the RGIB-REP (Eqn. 4). Proof. See Appendix B.5.*

[4] Specifically, $p^{pos}(\boldsymbol{h}_{ij}^1, \boldsymbol{h}_{ij}^2) = \frac{\exp(\left\|\boldsymbol{h}_{ij}^1 - \boldsymbol{h}_{ij}^2\right\|_2^2)}{\sum_{i=1}^{N} \exp(\left\|\boldsymbol{h}_{ij}^1 - \boldsymbol{h}_{ij}^2\right\|_2^2)}$, and $p^{neg}(\boldsymbol{h}_{ij}^1, \boldsymbol{h}_{mn}^2) = \frac{\exp(\alpha - \left\|\boldsymbol{h}_{ij}^1 - \boldsymbol{h}_{mn}^2\right\|_2^2)}{\sum_{i=1}^{N} \exp(\alpha - \left\|\boldsymbol{h}_{ij}^1 - \boldsymbol{h}_{mn}^2\right\|_2^2)}$.

[5] When $\boldsymbol{Z}_Y \equiv \tilde{Y}$ and $\boldsymbol{Z}_A \equiv \tilde{A}$, the RGIB-REP can be degenerated to the basic GIB.

[6] $\texttt{SAMP}(\boldsymbol{P}|\tilde{A}) = \{e_{ij} \in \tilde{A} \colon \text{bernoulli}(\boldsymbol{P}_{ij}) = 1\}$, and $\texttt{SAMP}(\boldsymbol{P}|\tilde{Y}) = \{e_{ij} \in \tilde{Y} \colon \text{bernoulli}(\boldsymbol{P}_{ij}) = 1\}$.

Table 2: Method comparison with GCN under inherent noise, i.e., both the input and label noise exist. The **boldface** numbers mean the best results, while the underlines indicate the second-best results.

method	Cora			Citeseer			Pubmed			Facebook			Chameleon			Squirrel		
	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%
Standard	.8111	.7419	.6970	.7864	.7380	.7085	.8870	.8748	.8641	.9829	.9520	.9438	.9616	.9496	.9274	.9432	.9406	.9386
DropEdge	.8017	.7423	.7303	.7635	.7393	.7094	.8711	.8482	.8354	.9811	.9682	.9473	.9568	.9548	.9407	.9439	.9377	.9365
NeuralSparse	.8190	.7318	.7293	.7765	.7397	.7148	.8908	.8733	.8630	.9825	.9638	.9456	.9599	.9497	.9402	.9494	.9309	.9297
PTDNet	.8047	.7559	.7388	.7795	.7423	.7283	.8872	.8733	.8623	.9725	.9674	.9485	.9607	.9514	.9424	.9485	.9326	.9304
Co-teaching	.8197	.7479	.7030	.7533	.7238	.7131	.8943	.8760	.8638	.9820	.9526	.9480	.9595	.9516	.9483	.9461	.9352	.9374
Peer loss	.8185	.7468	.7018	.7423	.7345	.7104	.8961	.8815	.8566	.9807	.9536	.9430	.9543	.9533	.9267	.9457	.9345	.9286
Jaccard	.8143	.7498	.7024	.7473	.7324	.7107	.8872	.8803	.8512	.9794	.9579	.9428	.9503	.9538	.9344	.9443	.9327	.9244
GIB	.8198	.7485	.7148	.7509	.7388	.7121	.8899	.8729	.8544	.9773	.9608	.9417	.9554	.9561	.9321	.9472	.9329	.9302
SupCon	.8240	.7819	.7490	.7554	.7458	.7299	.8853	.8718	.8525	.9588	.9508	.9297	.9561	.9531	.9467	.9473	.9348	.9301
GRACE	.7872	.6940	.6929	.7632	.7242	.6844	.8922	.8749	.8588	.8899	.8865	.8315	.8978	.8987	.8949	.9394	.9380	.9363
RGIB-REP	.8313	.7966	.7591	.7875	.7519	.7312	.9017	.8834	.8652	**.9832**	**.9770**	.9519	**.9723**	**.9621**	**.9519**	**.9509**	**.9455**	**.9434**
RGIB-SSL	**.8930**	**.8554**	**.8339**	**.8694**	**.8427**	**.8137**	**.9225**	**.8918**	**.8697**	.9829	.9711	**.9643**	.9655	.9592	.9500	.9499	.9426	.9425

5 EXPERIMENTS

Setup. In this section, we empirically verify the effectiveness of the proposed RGIB framework. 6 popular datasets and 3 GNNs are taken in the experiments. The inherent edge noise is generated based on Definition. 3.1 after the commonly used data split where 85% edges are randomly selected for training, 5% as the validation set, and 10% for testing. The AUC is used as the evaluation metric as in (Zhang & Chen, 2018; Zhu et al., 2021). The software framework is the Pytorch (Paszke et al., 2017), while the hardware platform is a single NVIDIA RTX 3090 GPU. We repeat all the experiments 10 times to obtain evaluation results with mean values and standard deviations. [7]

Baselines. As existing robust methods separately deal with input noise or label noise, both kinds of methods should be considered as baselines. For input noise, three sampling-based approaches are used for comparison, i.e., DropEdge (Rong et al., 2020), NeuralSparse (Zheng et al., 2020), and PTDNet (Luo et al., 2021). Jaccard (Wu et al., 2019) and GIB (Wu et al., 2020), which are designed for pruning adversarial edges, are also included. Two generic methods are selected for label noise, i.e., Co-teaching (Han et al., 2018) and Peer loss (Liu & Guo, 2020). In addition, two contrastive learning methods are taken into comparison with adaptation to the link prediction task, including SupCon (Khosla et al., 2020) utilizing the full labels for supervision and GRACE (Zhu et al., 2020) that are optimized in a self-supervised manner without labels. All 9 above baseline methods are evaluated w.r.t. their original implementations (see Appendix D for details).

5.1 MAIN RESULTS

Performance comparison. As shown in Table 2, the RGIB achieves the best results in all 6 datasets under the inherent edge noise with various noise ratios, especially on the more challenging datasets, i.e., Cora and Citeseer, where a 12.9% AUC promotion can be gained compared with the second-best methods. When it comes to decoupled noise settings shown in Table 3, RGIB also surpasses all the baselines ad hoc for input noise or label noise by a large margin.

Remark 5.1. *The two instantiations of RGIB can be generalized to different scenarios with their own priority w.r.t. intrinsic graph properties that can be complementary to each other with flexible options in practice. Basically, the RGIB-SSL is more adaptive to sparser graphs, e.g., Cora and Citeseer, where the inherent edge noise presents a considerable challenge and results in greater performance degradation. The RGIB-REP can be more suitable for denser graphs, e.g., Facebook and Chameleon. Meanwhile, two instantiations also work effectively on heterogeneous graphs with low homophily.*

The learned representation distribution. Next, we justify that the proposed method can effectively alleviate the representation collapse. Compared with the standard training, both RGIB-REP and RGIB-SSL bring significant improvements for the alignment with much lower values, as in Table 4. At the same time, the uniformity of learned representation is also enhanced: it can be seen from Figure 5 that the various query edges tend to be more uniformly distributed on the unit circle. As RGIB-SSL explicitly constrains the representation, its recovery power on representation distribution is naturally stronger than RGIB-REP, resulting in comparably better alignment and uniformity measures.

[7] Full evaluation results can be found in Appendix E.

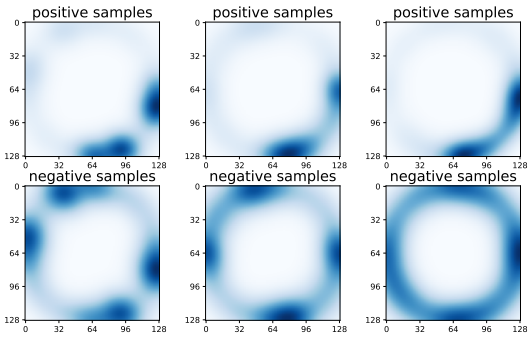
Table 3: Method comparison with GCN under decoupled input or label noise.

input noise																		
method	Cora			Citeseer			Pubmed			Facebook			Chameleon			Squirrel		
	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%
Standard	.8027	.7856	.7490	.8054	.7708	.7583	.8854	.8759	.8651	.9819	.9668	.9622	.9608	.9433	.9368	.9416	.9395	.9411
DropEdge	.8338	.7826	.7454	.8025	.7730	.7473	.8682	.8456	.8376	.9803	.9685	.9531	.9567	.9433	.9432	.9426	.9376	.9358
NeuralSparse	.8534	.7794	.7637	.8093	.7809	.7468	.8931	.8720	.8649	.9712	.9691	.9583	.9609	.9540	.9348	.9469	.9403	.9417
PTDNet	.8433	.8214	.7770	.8119	.7811	.7638	.8903	.8776	.8609	.9725	.9668	.9493	.9610	.9457	.9360	.9469	.9400	.9379
Co-teaching	.8045	.7871	.7530	.8059	.7753	.7668	.8931	.8792	.8606	.9712	.9707	.9714	.9524	.9446	.9447	.9462	.9425	.9306
Peer loss	.8051	.7866	.7517	.8106	.7767	.7653	.8917	.8811	.8643	.9758	.9703	.9622	.9558	.9482	.9412	.9362	.9386	.9336
Jaccard	.8200	.7838	.7617	.8176	.7776	.7725	.8987	.8764	.8639	.9784	.9702	.9638	.9507	.9436	.9364	.9388	.9345	.9240
GIB	.8002	.8099	.7741	.8070	.7717	.7798	.8932	.8808	.8618	.9796	.9647	.9650	.9605	.9521	.9416	.9390	.9406	.9397
SupCon	.8349	.8301	.8025	.8076	.7767	.7655	.8867	.8739	.8558	.9647	.9517	.9401	.9606	.9536	.9468	.9372	.9343	.9305
GRACE	.7877	.7107	.6975	.7615	.7151	.6830	.8810	.8795	.8593	.9015	.8833	.8395	.8994	.9007	.8964	.9392	.9378	.9363
RGIB-REP	.8624	.8313	.8158	.8299	.7996	.7771	.9008	.8822	.8687	**.9833**	**.9723**	**.9682**	**.9705**	**.9604**	.9480	**.9495**	**.9432**	.9405
RGIB-SSL	**.9024**	**.8577**	**.8421**	**.8747**	**.8461**	**.8245**	**.9126**	**.8889**	**.8693**	.9821	.9707	.9668	.9658	.9570	**.9486**	.9479	.9429	**.9429**

label noise																		
method	Cora			Citeseer			Pubmed			Facebook			Chameleon			Squirrel		
	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%
Standard	.8281	.8054	.8060	.7965	.7850	.7659	.9030	.9039	.9070	.9882	.9880	.9886	.9686	.9580	.9362	.9720	.9720	.9710
DropEdge	.8363	.8273	.8148	.7937	.7853	.7632	.9313	.9201	.9240	.9673	.9771	.9776	.9580	.9579	.9578	.9608	.9603	.9698
NeuralSparse	.8524	.8246	.8211	.7968	.7921	.7752	.9272	.9136	.9089	.9781	.9781	.9784	.9583	.9583	.9571	.9633	.9626	.9625
PTDNet	.8460	.8214	.8138	.7968	.7765	.7622	.9219	.9099	.9093	.9879	.9880	.9783	.9585	.9576	.9665	.9633	.9623	.9626
Co-teaching	.8446	.8209	.8157	.7974	.7877	.7913	.9315	.9291	.9319	.9762	.9797	.9638	.9642	.9650	.9533	.9675	.9641	.9655
Peer loss	.8325	.8036	.8069	.7991	.7990	.7751	.9126	.9101	.9210	.9769	.9750	.9734	.9621	.9501	.9569	.9636	.9694	.9696
Jaccard	.8289	.8064	.8148	.8061	.7887	.7689	.9098	.9135	.9096	.9702	.9725	.9758	.9603	.9659	.9557	.9529	.9512	.9501
GIB	.8337	.8137	.8157	.7986	.7852	.7649	.9037	.9114	.9064	.9742	.9703	.9771	.9651	.9582	.9489	.9641	.9628	.9601
SupCon	.8491	.8275	.8256	.8024	.7983	.7807	.9131	.9108	.9162	.9647	.9567	.9553	.9584	.9580	.9477	.9516	.9595	.9511
GRACE	.8531	.8237	.8193	.7909	.7630	.7737	.9234	.9252	.9255	.8913	.8972	.8887	.9053	.9074	.9075	.9171	.9174	.9166
RGIB-REP	.8554	.8318	.8297	.8083	.7846	.7945	.9357	.9343	.9332	**.9884**	**.9883**	**.9889**	**.9785**	**.9797**	**.9785**	**.9735**	**.9733**	**.9737**
RGIB-SSL	**.9314**	**.9224**	**.9241**	**.9204**	**.9218**	**.9250**	**.9594**	**.9604**	**.9613**	.9857	.9881	.9857	.9730	.9752	.9744	.9727	.9729	.9726

Table 4: Alignment comparison. Here, std. is short for *standard training*, and SSL/REP are short for RGIB-SSL/RGIB-REP, respectively.

dataset	Cora			Citeseer		
method	std.	REP	SSL	std.	REP	SSL
clean	.616	.524	**.475**	.445	.439	**.418**
$\varepsilon = 20\%$	.687	.642	**.543**	.586	.533	**.505**
$\varepsilon = 40\%$	.695	.679	**.578**	.689	.623	**.533**
$\varepsilon = 60\%$	.732	.704	**.615**	.696	.647	**.542**



(a) Standard (b) RGIB-REP (c) RGIB-SSL

Figure 5: Uniformity distribution on Citeseer with $\varepsilon = 40\%$.

Optimization schedulers. To reduce the search cost of coefficients in objectives of RGIB-SSL and RGIB-REP, we setup a unified optimization framework that can be formed as $\mathcal{L} = \alpha\mathcal{L}_{cls} + (1-\alpha)\mathcal{R}_1 + (1-\alpha)\mathcal{R}_2$. Here, we attempt 5 different schedulers to tune the only hyper-parameter $\alpha \in [0, 1]$, including (1) constant, $\alpha \equiv c$; (2) linear, $\alpha_t = k \cdot t$, where t is the normalized time step; (3) sine, $\alpha_t = \sin(t \cdot \pi/2)$; (4) cosine, $\alpha_t = \cos(t \cdot \pi/2)$; and (5) exponential, $\alpha_t = e^{k \cdot t}$. As empirical results summarized in Table 5, the selection of optimization schedulers greatly influences the final results. Although there is no gold scheduler that consistently performs the best, the *constant* and *sine* schedulers are generally better than others among the 5 above candidates.

5.2 Ablation Study

In this part, we conduct a thorough ablation study for the RGIB framework. As shown in Table 6, each component contributes to the final performance. For RGIB-SSL, we have the following analysis:

- **Hybrid augmentation.** RGIB-SSL benefits from the hybrid augmentation algorithm that automatically generates graphs of high diversity for contrast. Compared with fixed augmentation, the hybrid augmentation brings consistent improvements with a 3.0% average AUC promotion on Cora.

Table 5: Comparison on different schedulers. Here, SSL/REP are short for RGIB-SSL/RGIB-REP. Experiments are performed with a 4-layer GAT and $\epsilon = 40\%$ inherent edge noise.

dataset	Cora		Citeseer		Pubmed		Facebook		Chameleon		Squirrel	
method	SSL	REP	SSL	REP	SSL	REP	SSL	REP	SSL	REP	SSL	REP
$constant$	.8398	**.7927**	**.8227**	**.7742**	.8596	**.8416**	**.9694**	**.9778**	.9384	**.9498**	.9293	**.9320**
$linear(\cdot)$	.8427	.7653	.8167	.7559	**.8645**	.8239	.9669	.9529	.9434	.9369	.9316	.9265
$sin(\cdot)$	**.8436**	.7924	.8132	.7680	.8637	.8275	.9685	.9594	**.9447**	.9434	**.9325**	.9282
$cos(\cdot)$	.8334	.7833	.8088	.7647	.8579	.8372	.9477	.9629	.9338	.9444	.9251	.9303
$exp(\cdot)$	.8381	.7815	.8085	.7569	.8617	.8177	.9471	.9613	.9402	.9418	.9316	.9299

Table 6: Ablation study for RGIB-SSL and RGIB-REP with a 4-layer SAGE. Here, $\epsilon = 60\%$ indicates the 60% coupled inherent noise, while the ϵ_a/ϵ_y represent ratios of decoupled input/label noise.

variant	Cora			Chameleon		
	$\epsilon = 60\%$	$\epsilon_a = 60\%$	$\epsilon_y = 60\%$	$\epsilon = 60\%$	$\epsilon_a = 60\%$	$\epsilon_y = 60\%$
RGIB-SSL (full)	.8596	.8730	.8994	.9663	.9758	.9762
- w/o hybrid augmentation	.8150 (5.1%↓)	.8604 (1.4%↓)	.8757 (2.6%↓)	.9528 (1.3%↓)	.9746 (0.1%↓)	.9695 (0.6%↓)
- w/o self-adversarial	.8410 (2.1%↓)	.8705 (0.2%↓)	.8927 (0.7%↓)	.9655 (0.1%↓)	.9732 (0.2%↓)	.9746 (0.1%↓)
- w/o supervision ($\lambda_s = 0$)	.7480 (12.9%↓)	.7810 (10.5%↓)	.7820 (13.0%↓)	.8626 (10.7%↓)	.8628 (11.5%↓)	.8512 (12.8%↓)
- w/o alignment ($\lambda_a = 0$)	.8194 (4.6%↓)	.8510 (2.5%↓)	.8461 (5.9%↓)	.9613 (0.5%↓)	.9749 (0.1%↓)	.9722 (0.4%↓)
- w/o uniformity ($\lambda_u = 0$)	.8355 (2.8%↓)	.8621 (1.2%↓)	.8878 (1.3%↓)	.9652 (0.1%↓)	.9710 (0.4%↓)	.9751 (0.1%↓)
RGIB-REP (full)	.7611	.8487	.8095	.9567	.9706	.9676
- w/o edge selection ($Z_A \equiv \tilde{A}$)	.7515 (1.2%↓)	.8199 (3.3%↓)	.7890 (2.5%↓)	.9554(0.1%↓)	.9704 (0.1%↓)	.9661 (0.1%↓)
- w/o label selection ($Z_Y \equiv \tilde{Y}$)	.7533 (1.0%↓)	.8373 (1.3%↓)	.7847 (3.0%↓)	.9484(0.8%↓)	.9666 (0.4%↓)	.9594 (0.8%↓)
- w/o topology constraint ($\lambda_A = 0$)	.7355 (3.3%↓)	.7699 (9.2%↓)	.7969 (1.5%↓)	.9503(0.6%↓)	.9658 (0.4%↓)	.9635 (0.4%↓)
- w/o label constraint ($\lambda_Y = 0$)	.7381 (3.0%↓)	.8106 (4.4%↓)	.8032 (0.7%↓)	.9443(1.2%↓)	.9665 (0.4%↓)	.9669 (0.1%↓)

- **Self-adversarial alignment loss.** Randomly-sampled pairs are with hierarchical information to be learned from, and the proposed re-weighting technique further enhances high-quality pairs and decreases low-quality counterparts. It enables to discriminate the more informative contrasting pairs and thus refines the alignment signal for optimization, bringing to up 2.1% AUC promotion.
- **Information constraints.** Label supervision contributes the most among the three informative terms, even with label noise. Degenerating RGIB-SSL to a pure self-supervised manner without supervision (i.e., $\lambda_s = 0$) leads to an average 11.9% AUC drop. Meanwhile, we show that three regularization terms can be jointly optimized while another two terms are also of significant values.

As for RGIB-REP, its sample selection mechanism and corresponding constraints are also essential:

- **Edge / label selection.** Two sample selection methods are near equally important for learning with the coupled inherent noise that both informative sources are required to be purified. Besides, the edge selection is more important for tackling the decoupled input noise, as a greater drop will come when removed. Similarly, the label selection plays a dominant role in handling the label noise.
- **Topological / label constraint.** Table 6 also shows that the selection mechanism should be regularized by the related constraint; and otherwise, sub-optimal solutions will be achieved. Besides, the topological constraint is generally more sensitive than the label constraint for RGIB-REP.

6 Conclusion

In this work, we study the problem of link prediction with the inherent edge noise and reveal that the graph representation is severely collapsed under such a coupled noise. Based on the observation, we introduce the Robust Graph Information Bottleneck (RGIB) principle, aiming to extract reliable signals via decoupling and balancing the mutual information among inputs, labels, and representation to enhance the robustness and avoid collapse. Regarding the instantiation of RGIB, the self-supervised learning technique and data reparametrization mechanism are utilized to establish the RGIB-SSL and RGIB-REP, respectively. Empirical studies on 6 datasets and 3 GNNs verify the denoising effect of the proposed RGIB under different noisy scenarios. In future work, we will generalize RGIB to more scenarios in the link prediction domain, e.g., multi-hop reasoning on knowledge graphs with multi-relational edges that characterize more diverse and complex patterns.

REPRODUCIBILITY STATEMENT

To ensure the reproducibility of the empirical result in this work, we have stated all the details about our experiments in corresponding contents of Section 3 and Section 5. The implementation details are further elaborated in Appendix D. Besides, we will provide an anonymous Github repository for the source codes during the discussion phase for the reviewers of ICLR 2023.

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Appendix

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A BROADER IMPACT

In this work, we propose the RGIB framework for denoising the inherent edge noise in graphs and for improving the robustness of link prediction. We conceptually derive the RGIB and empirically justify that it enables the various GNNs to learn the input-invariant and label-invariant graph representations, preventing representation collapse and obtaining superior performances against edge noise. Our objective is to protect and enhance the current graph models, and we do not think our work would have negative societal impacts.

B THEORETICAL JUSTIFICATION

B.1 PROOF FOR PROPOSITION 4.1

Proof. As introduced in Section 4.2, the uniformity loss on two augmented graphs is formed as $\mathcal{R}_{unif} = \sum_{ij,mn}^{K} e^{-\|\boldsymbol{h}_{ij}^{1} - \boldsymbol{h}_{mn}^{1}\|_2^2} + e^{-\|\boldsymbol{h}_{ij}^{2} - \boldsymbol{h}_{mn}^{2}\|_2^2}$. For simplicity, we can reduce it to one graph, i.e., $\mathcal{R}_{unif} = \mathbb{E}_{ij,mn \sim p_{\mathcal{E}}}[e^{-\|\boldsymbol{h}_{ij} - \boldsymbol{h}_{mn}\|_2^2}]$. Next, we obtain its upper bound by the following derivation.

$$
\begin{aligned}
\log \mathcal{R}_{unif} &= \log \mathbb{E}_{ij,mn \sim p_{\mathcal{E}}}[e^{-\|\boldsymbol{h}_{ij} - \boldsymbol{h}_{mn}\|_2^2}] \\
&= \log \mathbb{E}_{ij,mn \sim p_{\mathcal{E}}}[e^{2t \cdot \boldsymbol{h}_{ij}^T \boldsymbol{h}_{mn} - 2t}] \\
&\leq \mathbb{E}_{ij \sim p_{\mathcal{E}}}\big[\log \mathbb{E}_{mn \sim p_{\mathcal{E}}}[e^{2t \cdot \boldsymbol{h}_{ij}^T \boldsymbol{h}_{mn}}]\big] \\
&= \frac{1}{N} \sum_{ij}^{N} \big[\log \sum_{mn}^{N} [e^{2t \cdot \boldsymbol{h}_{ij}^T \boldsymbol{h}_{mn}}]\big] \\
&= \frac{1}{N} \sum_{ij}^{N} \log \hat{p}_{\text{vMF-KDE}}(\boldsymbol{h}_{ij}) + \log Z_{\text{vMF}} \\
&\triangleq -\hat{H}(\boldsymbol{H}) + \log Z_{\text{vMF}}
\end{aligned}
\tag{5}
$$

Here, $\hat{p}_{\text{vMF-KDE}}(\cdot)$ is a von Mises-Fisher (vMF) kernel density estimation based on N training samples, and Z_{vMF} is the vMF normalization constant. $\hat{H}(\cdot)$ is the resubstitution entropy estimator of $\boldsymbol{H} = f_{\boldsymbol{w}}(\cdot)$ (Ahmad & Lin, 1976). As the uniformity loss $\mathcal{L}_{unif}$ can be approximated by entropy $\hat{H}(\boldsymbol{H})$, a higher entropy $H(\boldsymbol{H})$ indicates a lower uniformity loss, i.e., a higher uniformity. □

B.2 PROOF FOR PROPOSITION 4.2

Proof. Recall the hybrid graph augmentation technique is adopted by RGIB-SSL for contrasting, we can approximate the expectation $\mathbb{E}[I(\boldsymbol{H}; \tilde{A}|\tilde{Y})]$ by $1/N \sum_{i=1}^{N} I(\boldsymbol{H}_i; \tilde{A}_i|\tilde{Y})$ with N augmented graphs. Based on this, we drive the upper bound of $I(\boldsymbol{H}; \tilde{A}|\tilde{Y})$ as follows.

$$
\begin{aligned}
I(\boldsymbol{H}; \tilde{A}|\tilde{Y}) \leq I(\boldsymbol{H}; \tilde{A}) &= 1/N \sum_{i=1}^{N} \big(I(\boldsymbol{H}_i; \tilde{A}_i)\big) \\
&\approx 1/2\big(I(\boldsymbol{H}_1; \tilde{A}_1) + I(\boldsymbol{H}_2; \tilde{A}_2)\big) \\
&= 1/2\big(H(\boldsymbol{H}_1) + H(\tilde{A}_1) + H(\boldsymbol{H}_2) + H(\tilde{A}_2) - H(\boldsymbol{H}_1, \tilde{A}_1) - H(\boldsymbol{H}_2, \tilde{A}_2)\big) \\
&\leq 1/2\big(H(\boldsymbol{H}_1) + H(\tilde{A}_1) + H(\boldsymbol{H}_2) + H(\tilde{A}_2) - H(\boldsymbol{H}_1, \boldsymbol{H}_2) - H(\tilde{A}_1, \tilde{A}_2)\big) \\
&= 1/2\big(I(\boldsymbol{H}_1; \boldsymbol{H}_2) + I(\tilde{A}_1; \tilde{A}_2)\big) \\
&= 1/2\big(I(\boldsymbol{H}_1; \boldsymbol{H}_2) + c\big)
\end{aligned}
\tag{6}
$$

Thus, a lower $I(\boldsymbol{H}_1; \boldsymbol{H}_2)$ can upper bounded as lower $I(\boldsymbol{H}; \tilde{A})$ and $I(\boldsymbol{H}; \tilde{A}|\tilde{Y})$. □

B.3 PROOF FOR PROPOSITION 4.3

Proof. With the marginal distribution $\mathbb{Q}(\boldsymbol{Z}_A)=\sum_n \mathbb{P}_\phi(\boldsymbol{P}|n)\mathbb{P}(\tilde{A}=n)=\mathbb{P}(n)\prod_{\tilde{A}_{ij}=1}^{n}\boldsymbol{P}_{ij}$, we drive the upper bound of MI $I(\boldsymbol{Z}_A;\tilde{A})$ as:

$$
\begin{aligned}
I(\boldsymbol{Z}_A;\tilde{A}) =& \mathbb{E}_{\boldsymbol{Z}_A,\tilde{A}}[\log(\frac{\mathbb{P}(\boldsymbol{Z}_A|\tilde{A})}{\mathbb{P}(\boldsymbol{Z}_A)})] \\
=& \mathbb{E}_{\boldsymbol{Z}_A,\tilde{A}}[\log(\frac{\mathbb{P}_\phi(\boldsymbol{Z}_A|\tilde{A})}{\mathbb{Q}(\boldsymbol{Z}_A)})] - \mathrm{KL}(\mathbb{P}(\boldsymbol{Z}_A)||\mathbb{Q}(\boldsymbol{Z}_A)) \\
\leq& \mathbb{E}[\mathrm{KL}(\mathbb{P}_\phi(\boldsymbol{Z}_A|A)||\mathbb{Q}(\boldsymbol{Z}_A))] \\
=& \sum_{e_{ij}\in\tilde{A}} \boldsymbol{P_{ij}}\log\frac{\boldsymbol{P_{ij}}}{\tau} + (1-\boldsymbol{P_{ij}})\log\frac{1-\boldsymbol{P_{ij}}}{1-\tau} = \mathcal{R}_A
\end{aligned}
\tag{7}
$$

where the KL divergence on two given distribution $\mathbb{P}(x)$ and $\mathbb{Q}(x)$ is defined as $\mathrm{KL}(\mathbb{P}(x)||\mathbb{Q}(x)) = \sum_x \mathbb{P}(x)\log {}^{\mathbb{P}(x)}/_{\mathbb{Q}(x)}$. Thus, we obtain the upper bound of $I(\boldsymbol{Z}_A;\tilde{A})$ as Eqn. 7. Similarly, the label constraint is bounded as $I(\boldsymbol{Z}_Y;\tilde{Y}) \leq \sum_{e_{ij}\in\tilde{Y}} \boldsymbol{P_{ij}}\log\frac{\boldsymbol{P_{ij}}}{\tau}+(1-\boldsymbol{P_{ij}})\log\frac{1-\boldsymbol{P_{ij}}}{1-\tau} = \mathcal{R}_Y$. □

B.4 PROOF FOR PROPOSITION 4.4

Proof. We derive the lower bound of $I(\boldsymbol{H};\boldsymbol{Z}_Y)$ as follows.

$$
\begin{aligned}
I(\boldsymbol{H};\boldsymbol{Z}_Y) =& I(f_{\boldsymbol{w}}(\boldsymbol{Z}_A);\boldsymbol{Z}_Y) \\
\geq& \mathbb{E}_{\boldsymbol{Z}_Y,\boldsymbol{Z}_A}[\log\frac{\mathbb{P}_{\boldsymbol{w}}(\boldsymbol{Z}_Y|\boldsymbol{Z}_A)}{\mathbb{P}(\boldsymbol{Z}_Y)}] \\
=& \mathbb{E}_{\boldsymbol{Z}_Y,\boldsymbol{Z}_A}[\log\mathbb{P}_{\boldsymbol{w}}(\boldsymbol{Z}_Y|\boldsymbol{Z}_A)-\log(\mathbb{P}(\boldsymbol{Z}_Y))] \\
=& \mathbb{E}_{\boldsymbol{Z}_Y,\boldsymbol{Z}_A}[\log\mathbb{P}_{\boldsymbol{w}}(\boldsymbol{Z}_Y|\boldsymbol{Z}_A) + H(\boldsymbol{Z}_Y)] \\
\geq& \mathbb{E}_{\boldsymbol{Z}_Y,\boldsymbol{Z}_A}[\log\mathbb{P}_{\boldsymbol{w}}(\boldsymbol{Z}_Y|\boldsymbol{Z}_A)] \\
\approx& -\frac{1}{|\boldsymbol{Z}_Y|}\sum_{e_{ij}\in\boldsymbol{Z}_Y}\mathcal{L}_{cls}(f_{\boldsymbol{w}}(\boldsymbol{Z}_A),\boldsymbol{Z}_Y)
\end{aligned}
\tag{8}
$$

Thus, the MI $I(\boldsymbol{H};\boldsymbol{Z}_Y)$ can be lower bounded by the classification loss, and $\min -\lambda_s I(\boldsymbol{H};\boldsymbol{Z}_Y)$ in RGIB-REP (Eqn. 4) is upper bounded by $\min {}^{\lambda_s}/_{|\boldsymbol{Z}_Y|}\sum_{e_{ij}\in\boldsymbol{Z}_Y}\mathcal{L}_{cls}(f_{\boldsymbol{w}}(\boldsymbol{Z}_A),\boldsymbol{Z}_Y)$ as Eqn. 8. □

B.5 PROOF FOR THEOREM 4.5

Proof. With the relaxation via parametrization in B.4, we first relax the standard RGIB-REP to its upper bound as follows.

$$
\begin{aligned}
\min \text{RGIB-REP} \triangleq& -\lambda_s I(\boldsymbol{H};\boldsymbol{Z}_Y) + \lambda_A I(\boldsymbol{Z}_A;\tilde{A}) + \lambda_Y I(\boldsymbol{Z}_Y;\tilde{Y}) \\
\leq& -\lambda_s I(\boldsymbol{Z}_A;\boldsymbol{Z}_Y) + \lambda_A I(\boldsymbol{Z}_A;\tilde{A}) + \lambda_Y I(\boldsymbol{Z}_Y;\tilde{Y})
\end{aligned}
\tag{9}
$$

As $\boldsymbol{Z}_Y^* \approx Y$, Eqn. 9 can be reduced to $\min -\lambda_s I(\boldsymbol{Z}_A;Y) + \lambda_A I(\boldsymbol{Z}_A;\tilde{A}) + \lambda_Y H(Y)$, where $I(Y;\tilde{Y}) = H(Y)$ as $Y \subseteq \tilde{Y}$. Removing the final term with constant $H(Y)$, it can be further reduced to $\min -I(\boldsymbol{Z}_A;Y)+\lambda I(\boldsymbol{Z}_A;\tilde{A})$, where $\lambda = {}^{\lambda_A}/_{\lambda_s}$. Since to minimize the $-I(\boldsymbol{Z}_A;Y)+\lambda I(\boldsymbol{Z}_A;\tilde{A})$

is equal to maximize the $I(\boldsymbol{Z}_A;Y)-\lambda I(\boldsymbol{Z}_A;\tilde{A})$, next, we conduct the following derivation:

$$
\begin{aligned}
&\max I(\boldsymbol{Z}_A;Y)-\lambda I(\boldsymbol{Z}_A;\tilde{A})\\
=&\max\big(I(Y;\boldsymbol{Z}_A,\tilde{A})-I(\tilde{A};Y|\boldsymbol{Z}_A)\big)-\lambda I(\boldsymbol{Z}_A;\tilde{A})\\
=&\max I(Y;\boldsymbol{Z}_A,\tilde{A})-I(\tilde{A};Y|\boldsymbol{Z}_A)-\lambda\big(I(\boldsymbol{Z}_A;\tilde{A},Y)-I(\tilde{A};Y|\boldsymbol{Z}_A)\big)\\
=&\max I(Y;\boldsymbol{Z}_A,\tilde{A})-(1-\lambda)I(\tilde{A};Y|\boldsymbol{Z}_A)-\lambda I(\boldsymbol{Z}_A;\tilde{A},Y)\\
=&\max I(Y;\tilde{A})-(1-\lambda)I(\tilde{A};Y|\boldsymbol{Z}_A)-\lambda I(\boldsymbol{Z}_A;\tilde{A},Y)\\
=&\max(1-\lambda)I(\tilde{A};Y)-(1-\lambda)I(\tilde{A};Y|\boldsymbol{Z}_A)-\lambda I(\boldsymbol{Z}_A;\tilde{A}|Y)\\
=&\max(1-\lambda)c-(1-\lambda)I(\tilde{A};Y|\boldsymbol{Z}_A)-\lambda I(\boldsymbol{Z}_A;\tilde{A}|Y)\\
=&(1-\lambda)c
\end{aligned}
\tag{10}
$$

Since MI $I(\tilde{A};Y|\boldsymbol{Z}_A)\geq 0$ and $I(\boldsymbol{Z}_A;\tilde{A}|Y)\geq 0$ are always true, the optimal $\boldsymbol{Z}_A^*$ should makes $-(1-\lambda)I(\tilde{A};Y|\boldsymbol{Z}_A)-\lambda I(\boldsymbol{Z}_A;\tilde{A}|Y)=0$ to reach the optimal case. Thus, it should satisfy $I(\tilde{A};Y|\boldsymbol{Z}_A)=0$ and $I(\boldsymbol{Z}_A;\tilde{A}|Y)=0$ simultaneously. Therefore, $\boldsymbol{Z}_A=\boldsymbol{Z}_A^*$ maximizes $I(\boldsymbol{Z}_A;Y)-\lambda I(\boldsymbol{Z}_A;\tilde{A})$, which is equal to minimize $-I(\boldsymbol{Z}_A;Y)+\lambda I(\boldsymbol{Z}_A;\tilde{A})$, i.e., the RGIB-REP. Symmetrically, when $\boldsymbol{Z}_A\equiv A$, $\boldsymbol{Z}_Y=\boldsymbol{Z}_Y^*$ maximizes $I(A;\boldsymbol{Z}_Y)-\lambda I(\boldsymbol{Z}_Y;\tilde{Y})$ as $I(A;\boldsymbol{Z}_Y)-\lambda I(\boldsymbol{Z}_Y;\tilde{Y})=(1-\lambda)I(\tilde{Y};A)-(1-\lambda)I(\tilde{Y};A|\boldsymbol{Z}_Y)-\lambda I(\boldsymbol{Z}_Y;\tilde{Y}|A)$. □

C A Further Empirical Study of Noise Effects

This section is the extension of Section 3 in the main content.

C.1 Full evaluation results

Evaluation settings. In this part, we provide a thorough empirical study traversing all combinations of following settings from 5 different aspects.

- 3 GNN architectures: GCN, GAT, SAGE.
- 3 numbers of layers: $2, 4, 6$.
- 4 noise types: clean, mixed noise, input noise, label noise.
- 3 noise ratios: $20\%, 40\%, 60\%$.
- 6 datasets: Cora, CiteSeer, PubMed, Facebook, Chameleon, Squirrel.

Then, we summarize the entire evaluation results of three kinds of GNNs as follows. As can be seen, all three common GNNs, including GCN, GAT, and SAGE, are vulnerable to the inherent edge noise.

- Table 10: full evaluation results with GCN.
- Table 11: full evaluation results with GAT.
- Table 12: full evaluation results with SAGE.

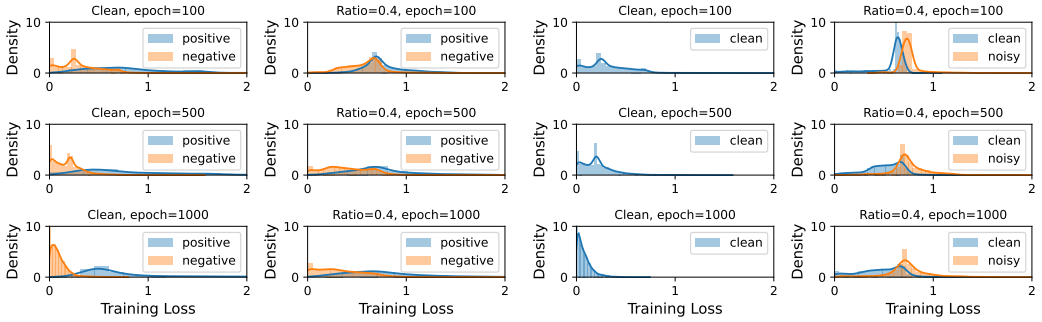
Data statistics. The statistics of the 6 datasets in our experiments are shown in Table 7. As can be seen, 4 homogeneous graphs (Cora, CiteSeer, PubMed, and Facebook) are with the much higher homophily values than the other 2 heterogeneous graphs (Chameleon and Squirrel).

Table 7: Dataset statistics.

dataset	Cora	CiteSeer	PubMed	Facebook	Chameleon	Squirrel
# Nodes	2,708	3,327	19,717	4.039	2,277	5,201
# Edges	5,278	4,676	88,648	88,234	31,421	198,493
Homophily	0.81	0.74	0.80	0.98	0.23	0.22

C.2 FURTHER INVESTIGATION ON THE DECOUPLED NOISE

Loss distribution We visualize the loss distribution under different scenarios to further investigate the memorization effect of GNNs. As shown in Figure 6, two clusters are gradually separated apart with clean data, but such a learning process can be slowed down when training with the noisy-input data, which confuses the model and leads to overlapped distributions. As for the label noise, the model cannot distinguish the noisy samples with a clear decision boundary to separate the clean and noisy samples apart. Besides, it is found that the model can gradually memorize the noisy edges according to the decreasing trend of the corresponding losses, where the loss distribution of noisy edges is minimized and progressively moving towards that of the clean ones.

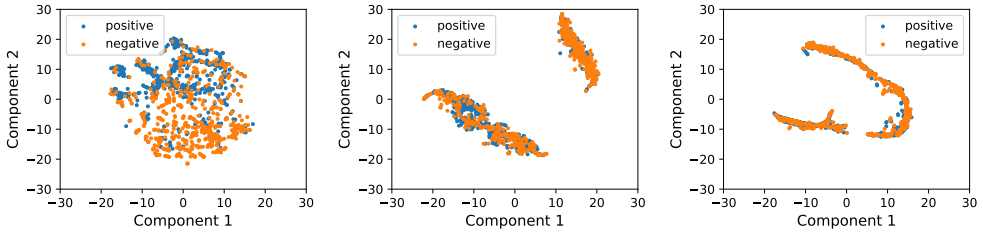


(a) Training loss of positive/nagative samples with clean data (left) and 40% input-noisy data (right).

(b) Training loss of clean/noisy samples with clean data (left) and 40% label-noisy data (right).

Figure 6: Loss distribution of the standard GCN with 40% input noise (a) and 40% label noise (b).

Visualization of edge representations As shown in Figure 7, the dimensionality reduction technique, T-SNE, is utilized here to measure the similarity of the learned edge representations $\boldsymbol{h}_{ij} = [\boldsymbol{h}_i, \boldsymbol{h}_j]$ with edges e_{ij} in the test set $\mathcal{E}^{test}$. Compared with the representation distribution of clean data (Figure 7(a)), which present comparatively distinct cluster boundaries, both the input noise (Figure 7(b)) and the label noise (Figure 7(c)) are with overlapped clusters of the positive and negative samples. Namely, the GCN model is confused by the two patterns of noise, and fails to give a discriminate the true or false edges with their representations.



(a) Clean data

(b) Input noise

(c) Label noise

Figure 7: Visualization of the representations of predictive edges through T-SNE. The edge representations are learned on the Cora dataset by a 4-layer GCN with the standard supervised learning.

D IMPLEMENTATION DETAILS

D.1 GNNS FOR LINK PREDICTION

We provide a detailed introduction forward propagation and backward update of GNNs in this part.

Formally, let $\ell = 1 \dots L$ denote the layer index, h_i^ℓ is the representation of the node i, MESS$(\cdot)$ is a learnable mapping function to transformer the input feature, AGGREGATE$(\cdot)$ captures the 1-hop information from neighborhood $\mathcal{N}(v)$ in the graph, and COMBINE$(\cdot)$ is final combination between neighbour features and the node itself. Then, the l-layer operation of GNNs can be formulated as $\boldsymbol{m}_v^\ell = \text{AGGREGATE}^\ell(\{\text{MESS}(\boldsymbol{h}_u^{\ell-1}, \boldsymbol{h}_v^{\ell-1}, e_{uv}) : u \in \mathcal{N}(v)\})$, where the representation of node v is $\boldsymbol{h}_v^\ell = \text{COMBINE}^\ell(\boldsymbol{h}_v^{\ell-1}, \boldsymbol{m}_v^\ell)$.

After L-layer propagation, the final node representations $\boldsymbol{h}_e^L$ of each $e \in V$ are obtained. Then, for each query edge $e_{ij} \in \mathcal{E}^{train}$ unseen from the input graph, the logit $\boldsymbol{\phi}_{e_{ij}}$ is computed with the node representations $\boldsymbol{h}_i^L$ and $\boldsymbol{h}_j^L$ [8] with the readout function, i.e., $\boldsymbol{\phi}_{e_{ij}} = \text{READOUT}(\boldsymbol{h}_i^L, \boldsymbol{h}_j^L) \to \mathbb{R}$.

Finally, the optimization objective can be defined as minimizing the binary cross-entropy loss, i.e., $\min \mathcal{L}_{cls} = \sum_{e_{ij} \in \mathcal{E}^{train}} -y_{ij} \log(\sigma(\boldsymbol{\phi}_{e_{ij}})) - (1 - y_{ij}) \log(1 - \sigma(\boldsymbol{\phi}_{e_{ij}}))$ where $\sigma(\cdot)$ is the sigmoid function, and $y_{ij} = 1$ for positive edges while $y_{ij} = 0$ for negative ones.

In addtion, we summarize the detailed architectures of different GNNs in the following Table 8.

Table 8: Detailed architectures of different GNNs.

GNN	MESS$(\cdot)$ & AGGREGATE$(\cdot)$	COMBINE$(\cdot)$	READOUT$(\cdot)$
GCN	$\boldsymbol{m}_i^l = \boldsymbol{W}^l \sum_{j \in \mathcal{N}(i)} \frac{1}{\sqrt{\hat{d}_i \hat{d}_j}} \boldsymbol{h}_j^{l-1}$	$\boldsymbol{h}_i^l = \sigma(\boldsymbol{m}_i^l + \boldsymbol{W}^l \frac{1}{\hat{d}_i} \boldsymbol{h}_i^{l-1})$	$\boldsymbol{\phi}_{e_{ij}} = \boldsymbol{h}_i^\top \boldsymbol{h}_j$
GAT	$\boldsymbol{m}_i^l = \sum_{j \in \mathcal{N}(i)} \alpha_{ij} \boldsymbol{W}^l \boldsymbol{h}_j^{l-1}$	$\boldsymbol{h}_i^l = \sigma(\boldsymbol{m}_i^l + \boldsymbol{W}^l \alpha_{ii} \boldsymbol{h}_i^{l-1})$	$\boldsymbol{\phi}_{e_{ij}} = \boldsymbol{h}_i^\top \boldsymbol{h}_j$
SAGE	$\boldsymbol{m}_i^l = \boldsymbol{W}^l \frac{1}{\lvert\mathcal{N}(i)\rvert} \sum_{j \in \mathcal{N}(i)} \boldsymbol{h}_j^{l-1}$	$\boldsymbol{h}_i^l = \sigma(\boldsymbol{m}_i^l + \boldsymbol{W}^l \boldsymbol{h}_i^{l-1})$	$\boldsymbol{\phi}_{e_{ij}} = \boldsymbol{h}_i^\top \boldsymbol{h}_j$

D.2 IMPLEMENTATION DETAILS OF RGIB-SSL

As introduced in Section 4.2, the graph augmentation technique is adopted here to generate the perpetuated graphs of various views.

To avoid manually selecting and tuning the augmentation operations, we propose the hybrid graph augmentation method with the four augmentation operations as predefined candidates and the ranges of their corresponding hyper-parameters. The search space is summarized in Table 9, where the candidate operations cover most augmentation approaches except for those operations modifying the number of nodes that are unsuitable for the link prediction task.

In each training iteration, two augmentation operators $\mathcal{T}^1(\cdot)$ and $\mathcal{T}^2(\cdot)$ and their hyper-parameters θ_1 and θ_2 are randomly sampled from the search space as elaborated in Algorithm. 1. The two operators will be performed on the observed graph $\mathcal{G}$, obtaining the two augmented graphs, namely, $\mathcal{G}^1 = \mathcal{T}^1(\mathcal{G}|\theta_1)$ and $\mathcal{G}^2 = \mathcal{T}^2(\mathcal{G}|\theta_2)$. The edge representations are gained by $\boldsymbol{h}_{ij}^1 = f(\mathcal{G}^1, e_{ij}|\boldsymbol{w}) = \boldsymbol{h}_i^1 \odot \boldsymbol{h}_j^1$, where the node representations $\boldsymbol{h}_i^1$ and $\boldsymbol{h}_i^2$ are generated by the GNN model $f(\cdot|\boldsymbol{w})$ with learnable weights $\boldsymbol{w}$, and so it is for $\boldsymbol{h}_{ij}^2$ with $\mathcal{G}^2$.

Table 9: Search space $\mathcal{H}_T$ of the hybrid graph augmentation.

Operator $\mathcal{T}_i(\cdot)$	hyper-parameter θ_{T_i}	description
`edge removing`	$\theta_{er} \in (0.0, 0.5)$	Randomly remove the observed edges with prob. θ_{er}.
`feature masking`	$\theta_{fm} \in (0.0, 0.3)$	Masking the columns of node features with prob. θ_{fm}.
`feature dropping`	$\theta_{fd} \in (0.0, 0.3)$	Dropping the elements of node features with prob. θ_{fd}.
`identity`	NA.	Do not modify anything.

[8] To avoid abusing notations, we use the $\boldsymbol{h}_i$ to stand for the final representation $\boldsymbol{h}_i^L$ in later contents.

Algorithm 1 Hybrid graph augmentation.

Require: number of augmentation operators n;
1: initialize $\emptyset \rightarrow \mathcal{T}(\cdot)$
2: **for** $i = 1 \ldots n$ **do**
3: randomly select one augmentation operator from operator space $\mathcal{T}_i(\cdot) \in \mathcal{H}_T$;
4: uniformly sample the corresponding hyper-parameter $\theta_i \sim U(\theta_{T_i})$;
5: store the newly sampled operator and combine it with the existing ones $\mathcal{T}(\cdot) \cup \{\mathcal{T}_i(\cdot|\theta_i)\} \rightarrow \mathcal{T}(\cdot)$;
6: **end for**
7: **return** the hybrid augmentation operators $\mathcal{T}(\cdot)$

Then, we learn the self-supervised edge representations by maximizing the edge-level agreement between the same query edge of different augmented graphs (positive pairs) and minimizing the agreement among different edges (negative pairs) with their representations as shown in Figure 8. Note the $\boldsymbol{h}_{ij}$ here is the edge representation. Specifically, we minimize the representation similarity of the positive pairs $(\boldsymbol{h}_{ij}^1, \boldsymbol{h}_{ij}^2)$ and maximize the representation similarity of the randomly-sampled negative pairs $(\boldsymbol{h}_{ij}^1, \boldsymbol{h}_{mn}^2)$, where $e_{ij} \neq e_{mn}$.

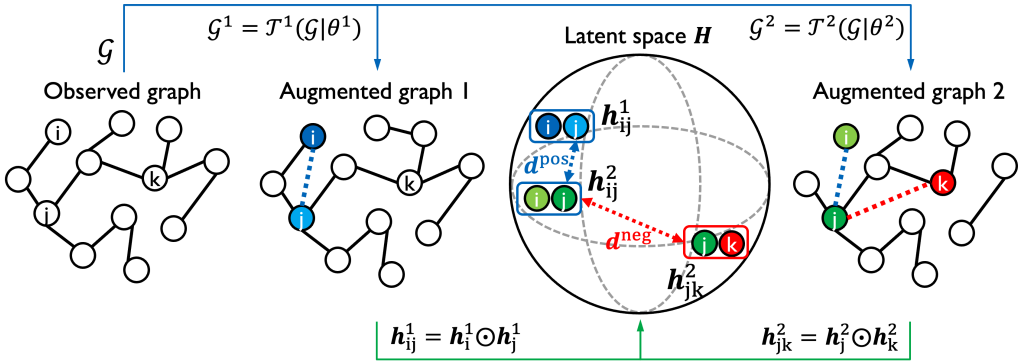


Figure 8: Illustration of the RGIB-SSL model.

D.3 Baseline Implementations

All baselines compared in this paper are based on their own original implementations. We list their source links here.

- DropEdge, `https://github.com/DropEdge/DropEdge`.
- NeuralSparse, `https://github.com/flyingdoog/PTDNet`.
- PTDNet, `https://github.com/flyingdoog/PTDNet`.
- GCN Jaccard, `https://github.com/DSE-MSU/DeepRobust`.
- GIB, `https://github.com/snap-stanford/GIB`.
- Co-teaching, `https://github.com/bhanML/Co-teaching`.
- Peer loss functions, `https://github.com/weijiaheng/Multi-class-Peer-Loss-functions`.
- SupCon, `https://github.com/HobbitLong/SupContrast`.
- GRACE, `https://github.com/CRIPAC-DIG/GRACE`.

E FULL EMPIRICAL RESULTS

Full baseline comparison with decoupled noise. The entire evaluation with 10 baselines and two proposed methods are conducted keeping the same settings as in C.1.

Results on each dataset are summarized as follows.

- Table 13, Table 14, Table 15 : full results of GCN/GAT/SAGE on Cora dataset.
- Table 16, Table 17, Table 18 : full results of GCN/GAT/SAGE on CiteSeer dataset.
- Table 19, Table 20, Table 21 : full results of GCN/GAT/SAGE on PubMed dataset.
- Table 22, Table 23, Table 24 : full results of GCN/GAT/SAGE on Facebook dataset.
- Table 25, Table 26, Table 27 : full results of GCN/GAT/SAGE on Chameleon dataset.
- Table 28, Table 29, Table 30 : full results of GCN/GAT/SAGE on Squirrel dataset.

Table 10: Full results of GCN with edge noise.

layers	clean	mixed noise			input noise			label noise		
		20%	40%	60%	20%	40%	60%	20%	40%	60%
Cora										
2	.9183±.0071	.8870±.0108	.8430±.0145	.7959±.0190	.9091±.0085	.8943±.0085	.8905±.0092	.9020±.0041	.8793±.0099	.8723±.0103
4	.8686±.0102	.8111±.0213	.7419±.0325	.6970±.0377	.8027±.0580	.7856±.0526	.7490±.0498	.8281±.0133	.8054±.0213	.8060±.0172
6	.8256±.0494	.7940±.0133	.7429±.0226	.7177±.0207	.8035±.0370	.7973±.0166	.7546±.0270	.8249±.0112	.7925±.0137	.7901±.0145
Citeseer										
2	.8968±.0092	.8651±.0084	.8355±.0154	.8254±.0066	.8767±.0097	.8615±.0090	.8585±.0085	.8834±.0155	.8649±.0104	.8674±.0122
4	.8317±.0217	.7864±.0145	.7380±.0201	.7085±.0146	.8054±.0240	.7708±.0325	.7583±.0258	.7965±.0124	.7850±.0174	.7659±.0240
6	.8161±.0163	.7355±.0387	.7110±.0222	.7106±.0168	.7720±.0161	.7460±.0401	.7212±.0470	.7900±.0131	.7741±.0157	.7648±.0229
Pubmed										
2	.9737±.0011	.9473±.0019	.9271±.0027	.9141±.0041	.9590±.0022	.9468±.0022	.9337±.0016	.9646±.0024	.9637±.0021	.9597±.0022
4	.9178±.0084	.8870±.0041	.8748±.0031	.8641±.0041	.8854±.0051	.8759±.0031	.8651±.0040	.9030±.0082	.9039±.0029	.9070±.0062
6	.9081±.0056	.8870±.0056	.8731±.0032	.8640±.0036	.8855±.0025	.8742±.0029	.8652±.0041	.9050±.0083	.9112±.0059	.9063±.0036
Facebook										
2	.9887±.0008	.9880±.0007	.9866±.0007	.9843±.0010	.9878±.0008	.9852±.0006	.9834±.0011	.9892±.0006	.9888±.0008	.9888±.0007
4	.9870±.0009	.9829±.0020	.9520±.0424	.9438±.0402	.9819±.0015	.9668±.0147	.9622±.0154	.9882±.0007	.9880±.0007	.9886±.0006
6	.9849±.0009	.9798±.0013	.9609±.0138	.9368±.0179	.9764±.0034	.9502±.0096	.9469±.0160	.9863±.0013	.9865±.0012	.9876±.0010
Chameleon										
2	.9823±.0027	.9753±.0025	.9696±.0022	.9657±.0029	.9784±.0017	.9762±.0016	.9754±.0023	.9775±.0018	.9769±.0018	.9755±.0036
4	.9797±.0021	.9616±.0033	.9496±.0190	.9274±.0276	.9608±.0038	.9433±.0261	.9368±.0271	.9686±.0020	.9580±.0021	.9362±.0035
6	.9752±.0036	.9662±.0042	.9511±.0079	.9286±.0067	.9656±.0045	.9450±.0177	.9276±.0229	.9752±.0027	.9766±.0035	.9745±.0040
Squirrel										
2	.9761±.0011	.9621±.0018	.9519±.0020	.9444±.0024	.9610±.0028	.9490±.0031	.9401±.0036	.9744±.0013	.9731±.0010	.9722±.0011
4	.9725±.0011	.9432±.0036	.9406±.0031	.9386±.0025	.9416±.0042	.9395±.0011	.9411±.0040	.9720±.0016	.9720±.0016	.9710±.0021
6	.9694±.0028	.9484±.0049	.9429±.0038	.9408±.0039	.9489±.0057	.9408±.0021	.9386±.0022	.9688±.0028	.9675±.0027	.9656±.0034

Table 11: Full results of GAT with edge noise.

layers	clean	mixed noise			input noise			label noise		
		20%	40%	60%	20%	40%	60%	20%	40%	60%
					Cora					
2	.9076±.0070	.8786±.0155	.8489±.0131	.8286±.0120	.9014±.0070	.8825±.0097	.8880±.0077	.8991±.0088	.8841±.0097	.8830±.0101
4	.8783±.0103	.8323±.0181	.8005±.0212	.7841±.0095	.8616±.0107	.8454±.0118	.8377±.0146	.8530±.0121	.8357±.0082	.8281±.0114
6	.8650±.0157	.8067±.0302	.7514±.0389	.7032±.0452	.8414±.0127	.7891±.0537	.7678±.0641	.8376±.0097	.8154±.0069	.8024±.0169
					Citeseer					
2	.8911±.0090	.8586±.0125	.8338±.0127	.8207±.0121	.8689±.0096	.8526±.0130	.8512±.0174	.8762±.0076	.8650±.0102	.8648±.0166
4	.8386±.0138	.8026±.0157	.7775±.0248	.7518±.0183	.8191±.0092	.8043±.0105	.7912±.0073	.8174±.0172	.7998±.0143	.7934±.0156
6	.8299±.0098	.7807±.0117	.7373±.0270	.7139±.0251	.7970±.0134	.7860±.0107	.7741±.0126	.7963±.0129	.7883±.0162	.7801±.0161
					Pubmed					
2	.9406±.0032	.9173±.0028	.8984±.0030	.8884±.0033	.9255±.0024	.9176±.0035	.9102±.0030	.9306±.0038	.9271±.0030	.9232±.0034
4	.8960±.0068	.8610±.0045	.8434±.0042	.8339±.0048	.8668±.0040	.8547±.0050	.8476±.0037	.8817±.0042	.8772±.0040	.8696±.0062
6	.8631±.0072	.8315±.0059	.8116±.0073	.8040±.0092	.8374±.0036	.8201±.0321	.8067±.0306	.8480±.0086	.8414±.0116	.8313±.0071
					Facebook					
2	.9874±.0008	.9869±.0005	.9856±.0008	.9836±.0007	.9878±.0006	.9861±.0006	.9858±.0008	.9872±.0006	.9864±.0009	.9857±.0008
4	.9875±.0007	.9857±.0015	.9850±.0012	.9820±.0014	.9855±.0011	.9827±.0019	.9773±.0046	.9873±.0010	.9874±.0010	.9874±.0005
6	.9860±.0007	.9805±.0025	.9658±.0321	.9577±.0314	.9804±.0018	.9738±.0044	.9710±.0036	.9854±.0015	.9860±.0007	.9867±.0012
					Chameleon					
2	.9770±.0044	.9725±.0027	.9650±.0018	.9625±.0018	.9767±.0026	.9747±.0020	.9759±.0018	.9746±.0023	.9743±.0017	.9711±.0041
4	.9734±.0047	.9721±.0035	.9652±.0023	.9605±.0031	.9741±.0028	.9686±.0030	.9674±.0027	.9740±.0037	.9738±.0027	.9712±.0047
6	.9742±.0052	.9659±.0029	.9573±.0036	.9482±.0054	.9644±.0033	.9543±.0075	.9474±.0074	.9722±.0043	.9688±.0055	.9698±.0065
					Squirrel					
2	.9740±.0011	.9680±.0007	.9635±.0017	.9588±.0025	.9702±.0008	.9690±.0010	.9659±.0014	.9719±.0018	.9701±.0017	.9686±.0012
4	.9720±.0023	.9581±.0046	.9436±.0063	.9335±.0062	.9592±.0047	.9455±.0075	.9415±.0061	.9682±.0030	.9690±.0028	.9686±.0021
6	.9578±.0067	.9507±.0050	.9309±.0164	.9254±.0089	.9487±.0065	.9419±.0041	.9255±.0073	.9585±.0097	.9520±.0070	.9507±.0162

Table 12: Full results of SAGE with edge noise.

layers	clean	mixed noise			input noise			label noise		
		20%	40%	60%	20%	40%	60%	20%	40%	60%
					Cora					
2	.9045±.0066	.8733±.0101	.8520±.0137	.8469±.0056	.9006±.0074	.8857±.0093	.8917±.0063	.8868±.0070	.8695±.0106	.8564±.0091
4	.8664±.0109	.8225±.0079	.7833±.0093	.7595±.0259	.8607±.0110	.8437±.0099	.8387±.0183	.8309±.0090	.8046±.0074	.7920±.0191
6	.8426±.0207	.7787±.0423	.7420±.0251	.7180±.0248	.8256±.0222	.7947±.0561	.8005±.0421	.8158±.0168	.7707±.0235	.7660±.0134
					Citeseer					
2	.8648±.0098	.8438±.0143	.8404±.0113	.8279±.0098	.8644±.0109	.8608±.0064	.8647±.0161	.8560±.0120	.8533±.0112	.8412±.0122
4	.8329±.0093	.7914±.0101	.7686±.0213	.7539±.0149	.8171±.0173	.8226±.0141	.8157±.0203	.8068±.0116	.7891±.0136	.7705±.0172
6	.8390±.0187	.7708±.0168	.7223±.0614	.7204±.0236	.8086±.0145	.7997±.0183	.7872±.0145	.7903±.0219	.7690±.0201	.7564±.0096
					Pubmed					
2	.8995±.0044	.9136±.0032	.9094±.0035	.9035±.0040	.9295±.0025	.9378±.0022	.9410±.0023	.8817±.0034	.8793±.0043	.8757±.0041
4	.8446±.0058	.8627±.0056	.8663±.0061	.8619±.0073	.8715±.0080	.8901±.0082	.9033±.0057	.8386±.0085	.8330±.0104	.8268±.0092
6	.8360±.0224	.8314±.0081	.8105±.0279	.8333±.0089	.8224±.0335	.8538±.0105	.8566±.0199	.8242±.0104	.8161±.0071	.8090±.0129
					Facebook					
2	.9882±.0008	.9858±.0008	.9827±.0008	.9788±.0012	.9881±.0008	.9862±.0007	.9862±.0008	.9867±.0006	.9840±.0006	.9825±.0014
4	.9859±.0013	.9824±.0015	.9783±.0025	.9698±.0040	.9849±.0015	.9815±.0024	.9815±.0025	.9844±.0015	.9817±.0007	.9809±.0009
6	.9828±.0024	.9751±.0055	.9603±.0365	.9616±.0091	.9715±.0077	.9672±.0057	.9517±.0228	.9761±.0136	.9788±.0045	.9749±.0151
					Chameleon					
2	.9786±.0030	.9683±.0036	.9605±.0038	.9536±.0028	.9754±.0019	.9734±.0015	.9762±.0018	.9700±.0019	.9670±.0026	.9603±.0049
4	.9743±.0025	.9645±.0035	.9580±.0035	.9505±.0010	.9721±.0017	.9721±.0021	.9721±.0016	.9678±.0026	.9641±.0028	.9605±.0051
6	.9729±.0022	.9606±.0046	.9541±.0058	.9470±.0035	.9679±.0031	.9658±.0041	.9640±.0059	.9673±.0026	.9641±.0038	.9625±.0042
					Squirrel					
2	.9745±.0015	.9680±.0015	.9626±.0015	.9570±.0016	.9737±.0010	.9736±.0010	.9721±.0011	.9692±.0015	.9643±.0012	.9606±.0017
4	.9689±.0052	.9584±.0107	.9577±.0076	.9541±.0021	.9637±.0092	.9630±.0079	.9607±.0090	.9663±.0020	.9612±.0049	.9612±.0020
6	.9682±.0045	.9555±.0065	.9528±.0038	.9461±.0054	.9592±.0053	.9600±.0036	.9551±.0042	.9574±.0192	.9540±.0207	.9583±.0023

Table 13: Full results on Cora dataset with GCN.

GCN										
layers	method	mixed noise			input noise			label noise		
		20%	40%	60%	20%	40%	60%	20%	40%	60%
L=2	Standard	.8870±.0108	.8430±.0145	.7959±.0190	.9091±.0085	.8943±.0085	.8905±.0092	.9020±.0041	.8793±.0099	.8723±.0103
	DropEdge	.8773±.0128	.8305±.0175	.8091±.0104	.9016±.0086	.8692±.0120	.8635±.0099	.9016±.0059	.8791±.0089	.8660±.0095
	NeuralSparse	.8869±.0096	.8497±.0103	.8215±.0158	.9118±.0063	.8903±.0113	.8849±.0086	.8995±.0069	.8797±.0073	.8743±.0088
	PTDNet	.8853±.0127	.8451±.0168	.8180±.0106	.9095±.0108	.8926±.0106	.8825±.0096	.9030±.0080	.8801±.0067	.8702±.0147
	Co-teaching	.8857±.0202	.8419±.0198	.8026±.0237	.9084±.0132	.8959±.0107	.8901±.0101	.9021±.0203	.8929±.0126	.8699±.0115
	Peer loss	.8867±.0115	.8472±.0237	.7970±.0182	.9134±.0147	.8993±.0171	.8806±.0138	.9015±.0021	.8874±.0163	.8813±.0291
	Jaccard	.8912±.0190	.8461±.0168	.7964±.0182	.9107±.0210	.9016±.0270	.8996±.0238	.9094±.0107	.8856±.0093	.8721±.0135
	GIB	.8857±.0296	.8464±.0326	.8037±.0309	.9126±.0065	.8973±.0141	.8937±.0150	.9083±.0136	.8828±.0136	.8807±.0146
	SupCon	.8827±.0125	.8451±.0157	.8125±.0119	.9006±.0074	.8877±.0073	.8846±.0124	.8876±.0082	.8668±.0088	.8721±.0092
	GRACE	.8588±.0158	.8220±.0204	.7987±.0076	.8671±.0121	.8102±.0126	.8048±.0119	.8990±.0092	.8887±.0109	.8896±.0074
	RGIB-REP	.8915±.0091	.8516±.0120	.8358±.0077	.9137±.0060	.8958±.0048	.8911±.0102	.9046±.0107	.8958±.0120	.8935±.0087
	RGIB-SSL	.9272±.0091	.9001±.0145	.8892±.0107	.9342±.0049	.9108±.0063	.9014±.0107	.9473±.0054	.9427±.0051	.9380±.0084
L=4	Standard	.8111±.0213	.7419±.0325	.6970±.0377	.8027±.0580	.7856±.0526	.7490±.0498	.8281±.0133	.8054±.0213	.8060±.0172
	DropEdge	.8017±.0187	.7423±.0335	.7303±.0235	.8338±.0132	.7826±.0377	.7454±.0425	.8363±.0110	.8273±.0106	.8148±.0141
	NeuralSparse	.8190±.0170	.7318±.0379	.7293±.0393	.8534±.0250	.7794±.0285	.7637±.0529	.8524±.0094	.8246±.0111	.8211±.0106
	PTDNet	.8047±.0460	.7559±.0246	.7388±.0216	.8433±.0443	.8214±.0122	.7770±.0624	.8460±.0128	.8214±.0166	.8138±.0151
	Co-teaching	.8197±.0236	.7479±.0372	.7030±.0475	.8045±.0609	.7871±.0564	.7530±.0500	.8446±.0219	.8209±.0481	.8157±.0246
	Peer loss	.8185±.0226	.7468±.0388	.7018±.0473	.8051±.0664	.7866±.0623	.7517±.0492	.8325±.0201	.8036±.0227	.8069±.0193
	Jaccard	.8143±.0218	.7498±.0418	.7024±.0403	.8200±.0772	.7838±.0558	.7617±.0546	.8289±.0177	.8064±.0229	.8148±.0227
	GIB	.8198±.0331	.7485±.0518	.7148±.0455	.8002±.0607	.8099±.0566	.7741±.0584	.8337±.0133	.8137±.0279	.8157±.0270
	SupCon	.8240±.0147	.7819±.0261	.7490±.0230	.8349±.0124	.8301±.0218	.8025±.0210	.8491±.0120	.8275±.0115	.8256±.0108
	GRACE	.7872±.0207	.6940±.0248	.6929±.0140	.7877±.0211	.7107±.0188	.6975±.0124	.8531±.0166	.8237±.0252	.8193±.0246
	RGIB-REP	.8313±.0098	.7966±.0110	.7591±.0142	.8624±.0071	.8313±.0136	.8158±.0193	.8554±.0149	.8318±.0151	.8297±.0150
	RGIB-SSL	.8930±.0072	.8554±.0167	.8339±.0100	.9024±.0097	.8577±.0152	.8421±.0156	.9314±.0066	.9224±.0100	.9241±.0049
L=6	Standard	.7940±.0133	.7429±.0226	.7177±.0207	.8035±.0370	.7973±.0166	.7546±.0270	.8249±.0112	.7925±.0137	.7901±.0145
	DropEdge	.7941±.0172	.7353±.0130	.6909±.0208	.7900±.0560	.7488±.0187	.7170±.0187	.8288±.0148	.8187±.0076	.7990±.0513
	NeuralSparse	.7931±.0201	.7324±.0434	.7018±.0330	.8082±.0418	.7432±.0386	.7393±.0243	.8415±.0167	.8160±.0181	.8081±.0105
	PTDNet	.8037±.0168	.7601±.0225	.7167±.0574	.8129±.0158	.7873±.0199	.7570±.0511	.8348±.0144	.7933±.0538	.7899±.0466
	Co-teaching	.7930±.0132	.7387±.0244	.7151±.0262	.8079±.0469	.8058±.0170	.7623±.0310	.8298±.0365	.8020±.0172	.7976±.0375
	Peer loss	.8015±.0211	.7466±.0320	.7196±.0286	.8068±.0361	.8031±.0169	.7607±.0272	.8409±.0146	.7999±.0289	.7918±.0240
	Jaccard	.8002±.0159	.7492±.0246	.7211±.0250	.8199±.0368	.8041±.0204	.7690±.0364	.8277±.0138	.8005±.0229	.7904±.0230
	GIB	.7961±.0163	.7584±.0313	.7201±.0300	.8036±.0451	.8067±.0331	.7639±.0402	.8347±.0111	.8016±.0156	.7947±.0147
	SupCon	.8092±.0242	.7365±.0227	.6920±.0415	.8021±.0251	.7845±.0280	.7434±.0257	.8273±.0202	.8181±.0234	.8157±.0135
	GRACE	.7576±.0148	.7187±.0243	.6860±.0213	.7693±.0161	.7171±.0223	.6886±.0272	.8209±.0347	.8134±.0310	.8102±.0234
	RGIB-REP	.8103±.0137	.7439±.0221	.7040±.0192	.8282±.0123	.7857±.0142	.7623±.0144	.8365±.0163	.8247±.0142	.8240±.0119
	RGIB-SSL	.8623±.0126	.8080±.0240	.7357±.0342	.8632±.0187	.7878±.0368	.7310±.0483	.9184±.0070	.9120±.0108	.9126±.0081

Table 14: Full results on Cora dataset with GAT.

GAT										
layers	method	mixed noise			input noise			label noise		
		20%	40%	60%	20%	40%	60%	20%	40%	60%
L=2	Standard	.8786±.0155	.8489±.0131	.8286±.0120	.9014±.0070	.8825±.0097	.8880±.0077	.8991±.0088	.8841±.0097	.8830±.0101
	DropEdge	.8741±.0114	.8279±.0172	.8101±.0141	.8930±.0056	.8720±.0063	.8586±.0110	.8954±.0093	.8788±.0083	.8717±.0106
	NeuralSparse	.8820±.0134	.8447±.0151	.8248±.0112	.9051±.0075	.8884±.0121	.8828±.0067	.8982±.0060	.8855±.0110	.8761±.0129
	PTDNet	.8799±.0152	.8487±.0101	.8314±.0075	.9023±.0105	.8838±.0116	.8827±.0090	.9019±.0086	.8772±.0082	.8726±.0060
	Co-teaching	.8883±.0148	.8571±.0192	.8378±.0169	.9069±.0134	.8896±.0173	.8939±.0125	.9289±.0281	.9100±.0358	.8969±.0243
	Peer loss	.8867±.0189	.8562±.0206	.8343±.0140	.9026±.0135	.8908±.0169	.8937±.0073	.9057±.0212	.8848±.0194	.8918±.0217
	Jaccard	.8809±.0180	.8492±.0161	.8334±.0124	.9066±.0142	.8823±.0081	.9065±.0215	.9010±.0092	.8919±.0186	.8929±.0114
	GIB	.8826±.0192	.8564±.0218	.8375±.0294	.9260±.0330	.9092±.0361	.9162±.0213	.9007±.0128	.8928±.0195	.8915±.0098
	SupCon	.8709±.0119	.8462±.0121	.8300±.0132	.8957±.0115	.8827±.0131	.8805±.0116	.8881±.0065	.8730±.0116	.8652±.0143
	GRACE	.8286±.0224	.7564±.0229	.7328±.0213	.8238±.0215	.7615±.0379	.7309±.0297	.8833±.0100	.8805±.0125	.8807±.0119
	RGIB-REP	.8759±.0132	.8374±.0104	.8269±.0134	.9006±.0118	.8833±.0079	.8798±.0131	.8993±.0086	.8838±.0115	.8810±.0125
	RGIB-SSL	.9142±.0092	.8878±.0135	.8777±.0118	.9234±.0053	.8973±.0067	.8866±.0148	.9389±.0053	.9347±.0088	.9311±.0057
L=4	Standard	.8323±.0181	.8005±.0212	.7841±.0095	.8616±.0107	.8454±.0118	.8377±.0146	.8530±.0121	.8357±.0082	.8281±.0114
	DropEdge	.8237±.0157	.7782±.0072	.7515±.0050	.8548±.0144	.8205±.0090	.8000±.0151	.8516±.0100	.8373±.0142	.8374±.0157
	NeuralSparse	.8309±.0154	.7954±.0118	.7769±.0135	.8575±.0174	.8450±.0110	.8277±.0148	.8503±.0123	.8395±.0122	.8348±.0121
	PTDNet	.8364±.0147	.8045±.0096	.7890±.0081	.8669±.0132	.8445±.0155	.8331±.0146	.8507±.0113	.8399±.0096	.8370±.0117
	Co-teaching	.8294±.0222	.8001±.0300	.7895±.0171	.8696±.0196	.8344±.0163	.8423±.0180	.8534±.0145	.8374±.0313	.8544±.0169
	Peer loss	.8344±.0276	.8067±.0254	.7933±.0142	.8520±.0202	.8353±.0145	.8376±.0216	.8533±.0121	.8527±.0075	.8444±.0203
	Jaccard	.8319±.0237	.8001±.0235	.7932±.0107	.8634±.0130	.8449±.0272	.8406±.0141	.8537±.0171	.8402±.0134	.8354±.0152
	GIB	.8352±.0367	.8111±.0244	.7945±.0279	.8860±.0099	.8579±.0163	.8493±.0404	.8604±.0166	.8434±.0094	.8340±.0130
	SupCon	.8324±.0102	.8033±.0099	.7776±.0145	.8620±.0162	.8441±.0098	.8337±.0386	.8514±.0138	.8381±.0092	.8318±.0121
	GRACE	.7403±.0347	.6711±.0695	.6656±.0578	.7707±.0267	.7154±.0366	.7146±.0237	.8040±.0447	.7988±.0292	.8321±.0230
	RGIB-REP	.8274±.0153	.7882±.0134	.7552±.0657	.8652±.0138	.8370±.0118	.8154±.0147	.8480±.0181	.8332±.0129	.8259±.0163
	RGIB-SSL	.8760±.0112	.8469±.0101	.8304±.0176	.8865±.0125	.8553±.0127	.8349±.0130	.9163±.0090	.9075±.0087	.9036±.0087
L=6	Standard	.8067±.0302	.7514±.0389	.7032±.0452	.8414±.0127	.7891±.0537	.7678±.0641	.8376±.0097	.8154±.0069	.8024±.0169
	DropEdge	.8051±.0111	.7375±.0354	.7110±.0388	.8198±.0132	.7514±.0615	.7248±.0511	.8499±.0135	.8312±.0163	.8112±.0079
	NeuralSparse	.8169±.0130	.7726±.0165	.7149±.0596	.8443±.0183	.7997±.0149	.7273±.0592	.8460±.0113	.8257±.0123	.8149±.0224
	PTDNet	.8207±.0166	.7460±.0714	.7145±.0621	.8253±.0514	.8209±.0231	.7759±.0339	.8464±.0106	.8234±.0168	.8159±.0148
	Co-teaching	.8059±.0312	.7576±.0386	.7070±.0455	.8496±.0165	.7969±.0542	.7717±.0691	.8549±.0298	.8204±.0284	.8215±.0369
	Peer loss	.8133±.0336	.7572±.0411	.7070±.0521	.8455±.0214	.7938±.0547	.7679±.0737	.8405±.0229	.8318±.0197	.8049±.0224
	Jaccard	.8155±.0400	.7537±.0466	.7123±.0454	.8495±.0142	.7947±.0561	.7762±.0771	.8374±.0160	.8245±.0067	.8108±.0180
	GIB	.8188±.0386	.7509±.0439	.7014±.0442	.8452±.0392	.8039±.0706	.7923±.0718	.8366±.0137	.8220±.0108	.8090±.0222
	SupCon	.7586±.0629	.6434±.0457	.6115±.0607	.7535±.0856	.7102±.0655	.6241±.0433	.8088±.0568	.8040±.0384	.7869±.0392
	GRACE	.5748±.0659	.5949±.0650	.5611±.0608	.5675±.0788	.6125±.0782	.5537±.0607	.5632±.0583	.5588±.0692	.6176±.0961
	RGIB-REP	.8148±.0158	.7553±.0179	.6842±.0264	.8404±.0129	.8001±.0178	.7433±.0663	.8366±.0107	.8274±.0151	.8192±.0179
	RGIB-SSL	.8613±.0107	.8194±.0158	.7858±.0133	.8657±.0118	.8213±.0189	.8045±.0153	.9049±.0059	.8960±.0141	.8985±.0117

Table 15: Full results on Cora dataset with SAGE.

SAGE										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.8733±.0101	.8520±.0137	.8469±.0056	.9006±.0074	.8857±.0093	.8917±.0063	.8868±.0070	.8695±.0106	.8564±.0091
	DropEdge	.8944±.0105	.8600±.0083	.8478±.0095	.9013±.0080	.9026±.0086	.9050±.0084	.8985±.0079	.8725±.0107	.8699±.0091
	NeuralSparse	.8821±.0123	.8570±.0090	.8491±.0105	.9020±.0090	.8880±.0087	.8949±.0098	.8885±.0111	.8681±.0110	.8638±.0075
	PTDNet	.8860±.0109	.8536±.0101	.8474±.0099	.9040±.0101	.8925±.0085	.8947±.0070	.8902±.0096	.8721±.0068	.8586±.0075
	Co-teaching	.8794±.0097	.8569±.0141	.8557±.0080	.8910±.0099	.8891±.0100	.8935±.0123	.9071±.0216	.8759±.0291	.8632±.0156
	Peer loss	.8817±.0102	.8559±.0132	.8480±.0058	.9042±.0099	.8866±.0174	.8960±.0064	.8876±.0111	.8768±.0251	.8739±.0149
	Jaccard	.8828±.0170	.8513±.0185	.8474±.0081	.9080±.0209	.8975±.0210	.8897±.0045	.8922±.0112	.8695±.0183	.8596±.0133
	GIB	.8765±.0196	.8679±.0125	.8546±.0246	.9089±.0232	.9004±.0098	.8998±.0347	.8938±.0082	.8727±.0101	.8614±.0125
	SupCon	.8844±.0117	.8507±.0135	.8499±.0076	.8974±.0075	.8904±.0076	.8943±.0122	.8916±.0094	.8742±.0092	.8601±.0093
	GRACE	.8123±.0113	.7978±.0090	.7944±.0137	.8082±.0199	.8010±.0160	.7962±.0120	.8280±.0092	.8228±.0170	.8261±.0102
	RGIB-REP	.8748±.0094	.8484±.0149	.8380±.0102	.9016±.0074	.8876±.0075	.8914±.0093	.8863±.0078	.8628±.0089	.8449±.0077
	RGIB-SSL	.9102±.0074	.8967±.0114	.8993±.0076	.9196±.0072	.9059±.0090	.9082±.0084	.9278±.0073	.9174±.0089	.9163±.0076
L=4	Standard	.8225±.0079	.7833±.0093	.7595±.0259	.8607±.0110	.8437±.0099	.8387±.0183	.8309±.0090	.8046±.0074	.7920±.0191
	DropEdge	.8323±.0146	.7944±.0130	.7842±.0149	.8734±.0082	.8635±.0120	.8628±.0146	.8466±.0111	.8199±.0155	.8125±.0059
	NeuralSparse	.8292±.0157	.7930±.0108	.7573±.0198	.8703±.0108	.8549±.0145	.8596±.0061	.8418±.0148	.8025±.0148	.8069±.0106
	PTDNet	.8310±.0149	.7847±.0174	.7690±.0177	.8626±.0141	.8607±.0090	.8630±.0154	.8435±.0112	.8125±.0117	.7961±.0231
	Co-teaching	.8237±.0139	.7855±.0103	.7658±.0343	.8660±.0168	.8533±.0149	.8424±.0196	.8580±.0345	.8117±.0187	.8088±.0275
	Peer loss	.8230±.0107	.7863±.0174	.7626±.0294	.8669±.0175	.8534±.0179	.8451±.0234	.8363±.0142	.8124±.0191	.7904±.0231
	Jaccard	.8261±.0153	.7850±.0115	.7602±.0348	.8619±.0253	.8465±.0227	.8496±.0233	.8378±.0106	.8046±.0084	.7976±.0288
	GIB	.8286±.0059	.7947±.0240	.7729±.0378	.8844±.0280	.8437±.0158	.8574±.0207	.8374±.0185	.8052±.0103	.7947±.0229
	SupCon	.8295±.0143	.7809±.0176	.7383±.0218	.8568±.0115	.8450±.0153	.8445±.0187	.8426±.0105	.8150±.0170	.7943±.0129
	GRACE	.6242±.0245	.6424±.0290	.6711±.0452	.6465±.0381	.6172±.0320	.6496±.0544	.6434±.0384	.6376±.0251	.6438±.0449
	RGIB-REP	.8274±.0112	.7822±.0143	.7692±.0202	.8634±.0121	.8470±.0144	.8528±.0131	.8367±.0149	.8087±.0187	.7991±.0120
	RGIB-SSL	.8837±.0065	.8728±.0116	.8613±.0148	.8960±.0109	.8817±.0119	.8825±.0113	.9130±.0038	.9041±.0075	.9023±.0072
L=6	Standard	.7787±.0423	.7420±.0251	.7180±.0248	.8256±.0222	.7947±.0561	.8005±.0421	.8158±.0168	.7707±.0235	.7660±.0134
	DropEdge	.8035±.0228	.7398±.0560	.7176±.0389	.8262±.0153	.8193±.0679	.8089±.0260	.8340±.0161	.7993±.0091	.7897±.0144
	NeuralSparse	.7953±.0177	.7378±.0180	.7292±.0238	.8384±.0120	.8234±.0288	.7980±.0701	.8214±.0107	.7908±.0136	.7622±.0160
	PTDNet	.7999±.0151	.7604±.0169	.7352±.0202	.8311±.0143	.8267±.0078	.8109±.0140	.8222±.0121	.7823±.0078	.7745±.0231
	Co-teaching	.7817±.0477	.7445±.0312	.7212±.0332	.8306±.0256	.7991±.0595	.8007±.0439	.8324±.0256	.7720±.0263	.7687±.0266
	Peer loss	.7781±.0451	.7445±.0286	.7192±.0277	.8300±.0234	.8020±.0624	.8043±.0449	.8309±.0149	.7734±.0388	.7652±.0262
	Jaccard	.7779±.0437	.7493±.0245	.7277±.0238	.8333±.0323	.8075±.0605	.8037±.0494	.8148±.0186	.7707±.0243	.7709±.0204
	GIB	.7814±.0493	.7473±.0442	.7349±.0437	.8366±.0194	.8106±.0689	.8040±.0617	.8172±.0258	.7806±.0265	.7689±.0180
	SupCon	.7879±.0356	.7019±.0285	.6673±.0317	.8219±.0469	.7648±.0666	.7159±.0717	.8242±.0159	.7880±.0152	.7686±.0148
	GRACE	.6866±.0160	.6437±.0455	.5967±.0248	.6949±.0181	.6536±.0365	.6114±.0394	.7239±.0231	.7035±.0160	.7014±.0111
	RGIB-REP	.8049±.0146	.7157±.0725	.7099±.0473	.8391±.0215	.8149±.0234	.7927±.0171	.8358±.0100	.7974±.0140	.8046±.0135
	RGIB-SSL	.8662±.0130	.8430±.0178	.8306±.0108	.8746±.0091	.8634±.0099	.8603±.0156	.8982±.0089	.8930±.0108	.8940±.0076

Table 16: Full results on Citeseer dataset with GCN.

GCN										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.8651±.0084	.8355±.0154	.8254±.0066	.8767±.0097	.8615±.0090	.8585±.0085	.8834±.0155	.8649±.0104	.8674±.0122
	DropEdge	.8613±.0112	.8317±.0168	.8112±.0158	.8755±.0117	.8557±.0122	.8483±.0164	.8862±.0084	.8695±.0133	.8688±.0143
	NeuralSparse	.8605±.0119	.8402±.0138	.8239±.0069	.8801±.0085	.8634±.0109	.8614±.0134	.8827±.0094	.8753±.0111	.8720±.0156
	PTDNet	.8646±.0155	.8404±.0111	.8223±.0142	.8805±.0095	.8647±.0112	.8571±.0116	.8813±.0074	.8734±.0126	.8708±.0097
	Co-teaching	.8689±.0100	.8416±.0215	.8278±.0061	.8849±.0167	.8659±.0180	.8659±.0090	.8833±.0231	.8744±.0281	.8847±.0094
	Peer loss	.8728±.0159	.8374±.0182	.8308±.0062	.8783±.0089	.8665±.0152	.8638±.0131	.8909±.0144	.8653±.0276	.8808±.0212
	Jaccard	.8682±.0164	.8406±.0230	.8292±.0137	.8725±.0090	.8743±.0186	.8696±.0158	.8849±.0231	.8718±.0105	.8680±.0154
	GIB	.8825±.0119	.8476±.0331	.8306±.0156	.8819±.0381	.8660±.0318	.8688±.0136	.8914±.0253	.8681±.0128	.8707±.0144
	SupCon	.8344±.0101	.8173±.0155	.8140±.0121	.8501±.0100	.8325±.0129	.8387±.0186	.8436±.0128	.8337±.0139	.8269±.0131
	GRACE	.8450±.0123	.8225±.0169	.7898±.0081	.8529±.0074	.8209±.0137	.7967±.0171	.8697±.0110	.8646±.0122	.8699±.0156
	RGIB-REP	.8585±.0088	.8347±.0213	.8167±.0113	.8751±.0074	.8637±.0122	.8600±.0119	.8795±.0101	.8638±.0175	.8644±.0095
	RGIB-SSL	.9199±.0091	.8957±.0099	.8759±.0087	.9271±.0055	.9018±.0090	.8942±.0145	.9495±.0059	.9515±.0049	.9480±.0062
L=4	Standard	.7864±.0145	.7380±.0201	.7085±.0146	.8054±.0240	.7708±.0325	.7583±.0258	.7965±.0124	.7850±.0174	.7659±.0240
	DropEdge	.7635±.0106	.7393±.0170	.7094±.0190	.8025±.0106	.7730±.0147	.7473±.0161	.7937±.0175	.7853±.0109	.7632±.0142
	NeuralSparse	.7765±.0123	.7397±.0168	.7148±.0237	.8093±.0129	.7809±.0160	.7468±.0289	.7968±.0198	.7921±.0129	.7752±.0209
	PTDNet	.7795±.0131	.7423±.0200	.7283±.0130	.8119±.0103	.7811±.0191	.7638±.0167	.7968±.0141	.7765±.0124	.7622±.0215
	Co-teaching	.7533±.0181	.7238±.0245	.7131±.0157	.8059±.0263	.7753±.0408	.7668±.0272	.7974±.0381	.7877±.0291	.7913±.0343
	Peer loss	.7423±.0215	.7345±.0213	.7104±.0242	.8106±.0250	.7767±.0400	.7653±.0315	.7991±.0241	.7990±.0289	.7751±.0245
	Jaccard	.7473±.0160	.7324±.0204	.7107±.0172	.8176±.0283	.7776±.0471	.7725±.0432	.8061±.0187	.7887±.0196	.7689±.0310
	GIB	.7509±.0336	.7388±.0240	.7121±.0210	.8070±.0398	.7717±.0612	.7798±.0421	.7986±.0120	.7852±.0186	.7649±.0275
	SupCon	.7554±.0196	.7458±.0176	.7299±.0218	.8076±.0099	.7767±.0111	.7655±.0164	.8024±.0108	.7983±.0123	.7807±.0166
	GRACE	.7632±.0224	.7242±.0219	.6844±.0226	.7615±.0152	.7151±.0193	.6830±.0232	.7909±.0211	.7630±.0196	.7737±.0307
	RGIB-REP	.7875±.0131	.7519±.0181	.7312±.0227	.8299±.0134	.7996±.0130	.7771±.0178	.8083±.0152	.7846±.0234	.7945±.0203
	RGIB-SSL	.8694±.0108	.8427±.0174	.8137±.0170	.8747±.0144	.8461±.0109	.8245±.0142	.9204±.0085	.9218±.0098	.9250±.0071
L=6	Standard	.7355±.0387	.7110±.0222	.7106±.0168	.7720±.0161	.7460±.0401	.7212±.0470	.7900±.0131	.7741±.0157	.7648±.0229
	DropEdge	.7653±.0139	.7191±.0159	.7006±.0304	.7645±.0441	.7442±.0160	.7209±.0182	.8007±.0152	.7823±.0141	.7656±.0196
	NeuralSparse	.7644±.0180	.7361±.0191	.7036±.0387	.7913±.0152	.7476±.0279	.7391±.0235	.7793±.0391	.7739±.0188	.7688±.0256
	PTDNet	.7661±.0153	.7401±.0134	.7072±.0385	.7882±.0134	.7728±.0164	.7464±.0188	.7913±.0122	.7742±.0155	.7582±.0151
	Co-teaching	.7375±.0468	.7171±.0299	.7188±.0248	.7813±.0185	.7550±.0475	.7310±.0496	.8034±.0117	.7885±.0275	.7701±.0245
	Peer loss	.7398±.0387	.7105±.0288	.7166±.0250	.7783±.0158	.7532±.0488	.7301±.0509	.7915±.0169	.7748±.0299	.7695±.0239
	Jaccard	.7415±.0444	.7162±.0307	.7135±.0171	.7793±.0263	.7459±.0416	.7369±.0473	.7925±.0176	.7825±.0245	.7710±.0298
	GIB	.7370±.0531	.7226±.0268	.7175±.0234	.7743±.0435	.7722±.0697	.7276±.0534	.7948±.0178	.7803±.0221	.7681±.0251
	SupCon	.7714±.0122	.7413±.0166	.7205±.0231	.7907±.0161	.7842±.0109	.7670±.0183	.7745±.0231	.7659±.0114	.7573±.0180
	GRACE	.6995±.0221	.6901±.0210	.6946±.0152	.7041±.0240	.7037±.0247	.6818±.0169	.7752±.0230	.7739±.0151	.7773±.0351
	RGIB-REP	.7725±.0077	.7429±.0202	.7232±.0110	.7781±.0218	.7559±.0130	.7415±.0221	.7900±.0252	.7797±.0181	.7886±.0194
	RGIB-SSL	.8417±.0169	.7995±.0148	.7673±.0137	.8379±.0065	.8026±.0173	.7793±.0207	.8984±.0144	.9062±.0066	.9060±.0098

Table 17: Full results on Citeseer dataset with GAT.

GAT										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.8586±.0125	.8338±.0127	.8207±.0121	.8689±.0096	.8526±.0130	.8512±.0174	.8762±.0076	.8650±.0102	.8648±.0166
	DropEdge	.8566±.0113	.8333±.0183	.8100±.0098	.8750±.0079	.8496±.0101	.8512±.0121	.8820±.0086	.8679±.0112	.8673±.0114
	NeuralSparse	.8573±.0101	.8431±.0151	.8222±.0092	.8743±.0117	.8577±.0067	.8580±.0135	.8826±.0080	.8724±.0076	.8657±.0089
	PTDNet	.8602±.0107	.8381±.0137	.8157±.0075	.8755±.0090	.8560±.0084	.8574±.0154	.8784±.0120	.8693±.0098	.8669±.0142
	Co-teaching	.8628±.0220	.8366±.0124	.8199±.0194	.8720±.0128	.8521±.0139	.8510±.0224	.8924±.0122	.8888±.0365	.8919±.0305
	Peer loss	.8637±.0125	.8378±.0170	.8235±.0120	.8721±.0172	.8529±.0173	.8559±.0216	.8878±.0185	.8653±.0288	.8631±.0258
	Jaccard	.8615±.0197	.8379±.0222	.8223±.0124	.8841±.0079	.8556±.0119	.8498±.0309	.8843±.0143	.8676±.0195	.8661±.0256
	GIB	.8610±.0230	.8462±.0114	.8324±.0316	.8909±.0091	.8823±.0188	.8488±.0276	.8781±.0135	.8739±.0144	.8741±.0156
	SupCon	.8495±.0100	.8138±.0174	.8155±.0099	.8611±.0086	.8454±.0111	.8393±.0172	.8558±.0137	.8459±.0170	.8379±.0185
	GRACE	.8092±.0221	.7564±.0264	.7479±.0278	.8014±.0370	.7628±.0240	.7433±.0245	.8788±.0146	.8768±.0073	.8654±.0172
	RGIB-REP	.8545±.0108	.8310±.0127	.8137±.0091	.8736±.0107	.8566±.0097	.8503±.0159	.8778±.0093	.8696±.0081	.8614±.0084
	RGIB-SSL	.9106±.0102	.8829±.0058	.8677±.0095	.9172±.0072	.8909±.0086	.8785±.0121	.9419±.0071	.9410±.0047	.9410±.0090
L=4	Standard	.8026±.0157	.7775±.0248	.7518±.0183	.8191±.0092	.8043±.0105	.7912±.0073	.8174±.0172	.7998±.0143	.7934±.0156
	DropEdge	.8063±.0079	.7624±.0211	.7434±.0124	.8171±.0132	.7977±.0178	.7814±.0162	.8262±.0148	.8103±.0178	.8057±.0148
	NeuralSparse	.7958±.0142	.7761±.0172	.7550±.0129	.8282±.0130	.8088±.0088	.7911±.0174	.8259±.0119	.8135±.0092	.7986±.0109
	PTDNet	.8000±.0113	.7734±.0198	.7597±.0185	.8254±.0105	.8132±.0089	.7950±.0143	.8137±.0243	.8082±.0094	.8036±.0139
	Co-teaching	.8016±.0184	.7807±.0315	.7521±.0267	.8213±.0173	.8068±.0156	.7903±.0105	.8402±.0220	.8109±.0316	.7947±.0350
	Peer loss	.8064±.0178	.7802±.0253	.7544±.0191	.8246±.0145	.8108±.0122	.7945±.0113	.8160±.0329	.8045±.0185	.7925±.0207
	Jaccard	.8098±.0222	.7771±.0273	.7517±.0186	.8258±.0124	.8083±.0138	.7901±.0073	.8206±.0168	.8036±.0176	.7999±.0215
	GIB	.8170±.0230	.7884±.0341	.7645±.0247	.8422±.0365	.8112±.0212	.7972±.0305	.8192±.0249	.8080±.0155	.8010±.0177
	SupCon	.7940±.0114	.7728±.0125	.7478±.0145	.8137±.0115	.8003±.0116	.7777±.0409	.8038±.0114	.7972±.0198	.7852±.0201
	GRACE	.7319±.0433	.6611±.0395	.6449±.0579	.7216±.0261	.5947±.0660	.6060±.0507	.7775±.1040	.7739±.0475	.7882±.0328
	RGIB-REP	.7991±.0107	.7743±.0164	.7418±.0121	.8155±.0156	.7905±.0157	.7372±.0908	.8108±.0118	.7946±.0180	.7935±.0131
	RGIB-SSL	.8520±.0145	.8306±.0149	.8029±.0098	.8592±.0120	.8251±.0132	.8145±.0110	.9084±.0091	.9101±.0076	.9102±.0117
L=6	Standard	.7807±.0117	.7373±.0270	.7139±.0251	.7970±.0134	.7860±.0107	.7741±.0126	.7963±.0129	.7883±.0162	.7801±.0161
	DropEdge	.7768±.0088	.7477±.0195	.7116±.0119	.7854±.0232	.7640±.0188	.7425±.0362	.8114±.0132	.7840±.0217	.7826±.0186
	NeuralSparse	.7704±.0099	.7462±.0170	.7242±.0138	.8047±.0101	.7647±.0372	.7248±.0596	.8087±.0235	.7855±.0176	.7880±.0148
	PTDNet	.7805±.0193	.7503±.0223	.7286±.0237	.7927±.0287	.7822±.0132	.7579±.0355	.8002±.0085	.7977±.0134	.7890±.0145
	Co-teaching	.7819±.0141	.7399±.0335	.7236±.0292	.7964±.0189	.7809±.0183	.7740±.0185	.7933±.0406	.7918±.0348	.7979±.0245
	Peer loss	.7846±.0214	.7459±.0294	.7187±.0259	.7979±.0172	.7955±.0168	.7796±.0218	.7957±.0273	.7865±.0285	.7912±.0148
	Jaccard	.7902±.0117	.7365±.0332	.7157±.0248	.8056±.0264	.8038±.0226	.7733±.0245	.7964±.0226	.7936±.0255	.7847±.0218
	GIB	.7818±.0230	.7378±.0285	.7137±.0416	.8161±.0267	.7995±.0183	.7762±.0176	.8002±.0155	.7955±.0166	.7794±.0244
	SupCon	.7370±.0524	.7160±.0462	.6670±.0442	.7667±.0402	.7729±.0356	.6999±.0597	.7810±.0219	.7752±.0119	.7591±.0362
	GRACE	.5068±.0128	.5034±.0106	.5108±.0319	.5058±.0096	.4956±.0069	.5379±.0427	.5181±.0547	.5288±.0467	.5068±.0178
	RGIB-REP	.7817±.0129	.7062±.0681	.7254±.0188	.7883±.0160	.7769±.0168	.7620±.0176	.7981±.0092	.7711±.0487	.7817±.0164
	RGIB-SSL	.8275±.0148	.7989±.0136	.7681±.0140	.8261±.0096	.8024±.0087	.7806±.0174	.8855±.0103	.8918±.0143	.8940±.0119

Table 18: Full results on Citeseer dataset with SAGE.

SAGE										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.8438±.0143	.8404±.0113	.8279±.0098	.8644±.0109	.8608±.0064	.8647±.0161	.8560±.0120	.8533±.0112	.8412±.0122
	DropEdge	.8654±.0118	.8593±.0129	.8503±.0125	.8834±.0059	.8791±.0108	.8806±.0101	.8809±.0085	.8734±.0064	.8710±.0170
	NeuralSparse	.8658±.0079	.8478±.0109	.8437±.0069	.8746±.0102	.8674±.0086	.8722±.0183	.8670±.0120	.8645±.0136	.8485±.0105
	PTDNet	.8620±.0125	.8488±.0113	.8477±.0078	.8740±.0094	.8675±.0120	.8702±.0134	.8657±.0138	.8576±.0147	.8530±.0073
	Co-teaching	.8505±.0143	.8436±.0179	.8323±.0144	.8652±.0133	.8606±.0067	.8650±.0247	.8787±.0269	.8660±.0101	.8392±.0363
	Peer loss	.8525±.0157	.8440±.0120	.8319±.0186	.8661±.0199	.8693±.0113	.8735±.0151	.8563±.0278	.8535±.0107	.8563±.0241
	Jaccard	.8514±.0208	.8492±.0143	.8291±.0183	.8691±.0282	.8805±.0205	.8715±.0152	.8616±.0120	.8629±.0210	.8413±.0167
	GIB	.8574±.0192	.8577±.0134	.8323±.0125	.8693±.0186	.8632±.0310	.8739±.0405	.8600±.0197	.8576±.0182	.8403±.0157
	SupCon	.8344±.0106	.8241±.0123	.8168±.0111	.8485±.0133	.8493±.0147	.8484±.0161	.8487±.0109	.8394±.0096	.8323±.0113
	GRACE	.8283±.0295	.8319±.0192	.8253±.0208	.8361±.0190	.8273±.0222	.8351±.0134	.8434±.0193	.8422±.0119	.8400±.0233
	RGIB-REP	.8514±.0120	.8359±.0093	.8213±.0112	.8614±.0118	.8537±.0105	.8664±.0153	.8592±.0111	.8533±.0134	.8455±.0123
	RGIB-SSL	.9003±.0104	.8894±.0119	.8916±.0078	.9045±.0076	.8945±.0097	.8992±.0141	.9143±.0082	.9075±.0080	.9087±.0108
L=4	Standard	.7914±.0101	.7686±.0213	.7539±.0149	.8171±.0173	.8226±.0141	.8157±.0203	.8068±.0116	.7891±.0136	.7705±.0172
	DropEdge	.7889±.0182	.7850±.0117	.7678±.0206	.8300±.0130	.8032±.0953	.8271±.0115	.8058±.0118	.7899±.0173	.7826±.0282
	NeuralSparse	.7934±.0115	.7746±.0195	.7639±.0175	.8331±.0119	.8242±.0176	.8324±.0144	.8111±.0146	.7904±.0229	.7747±.0242
	PTDNet	.7972±.0105	.7804±.0201	.7563±.0230	.8299±.0177	.8259±.0119	.8374±.0110	.8121±.0168	.7892±.0103	.7845±.0166
	Co-teaching	.7928±.0189	.7679±.0230	.7557±.0214	.8226±.0172	.8297±.0202	.8256±.0263	.8233±.0203	.8083±.0218	.7836±.0347
	Peer loss	.7913±.0116	.7710±.0307	.7556±.0238	.8197±.0264	.8321±.0155	.8239±.0275	.8135±.0131	.7940±.0194	.7885±.0195
	Jaccard	.7904±.0108	.7691±.0269	.7626±.0183	.8359±.0251	.8244±.0189	.8290±.0264	.8167±.0119	.7972±.0157	.7744±.0227
	GIB	.7931±.0134	.7739±.0254	.7691±.0291	.8199±.0278	.8306±.0209	.8217±.0273	.8151±.0152	.7947±.0170	.7737±.0266
	SupCon	.7870±.0130	.7672±.0145	.7641±.0125	.8191±.0197	.8081±.0138	.8036±.0211	.7982±.0137	.7898±.0121	.7783±.0172
	GRACE	.6196±.0253	.6404±.0258	.6308±.0323	.6286±.0287	.6365±.0223	.6198±.0157	.6495±.0202	.6431±.0210	.6411±.0191
	RGIB-REP	.7854±.0123	.7703±.0123	.7562±.0200	.8195±.0140	.8151±.0118	.8134±.0221	.8038±.0158	.7863±.0140	.7799±.0212
	RGIB-SSL	.8545±.0157	.8482±.0147	.8352±.0127	.8706±.0074	.8525±.0118	.8564±.0141	.8867±.0088	.8866±.0161	.8903±.0124
L=6	Standard	.7708±.0168	.7223±.0614	.7204±.0236	.8086±.0145	.7997±.0183	.7872±.0145	.7903±.0219	.7690±.0201	.7564±.0096
	DropEdge	.7756±.0143	.7485±.0104	.7290±.0261	.8070±.0125	.8060±.0165	.8026±.0195	.7861±.0174	.7769±.0149	.7534±.0212
	NeuralSparse	.7757±.0175	.7564±.0205	.7306±.0173	.8039±.0144	.8008±.0157	.8016±.0223	.7902±.0189	.7762±.0177	.7588±.0160
	PTDNet	.7844±.0116	.7525±.0270	.7435±.0108	.8070±.0130	.8128±.0108	.8085±.0135	.7948±.0165	.7830±.0182	.7634±.0210
	Co-teaching	.7792±.0246	.7248±.0642	.7268±.0297	.8087±.0136	.8076±.0234	.7864±.0147	.8011±.0394	.7671±.0406	.7626±.0232
	Peer loss	.7796±.0158	.7213±.0628	.7294±.0233	.8135±.0225	.8012±.0206	.7914±.0208	.8005±.0409	.7710±.0316	.7672±.0098
	Jaccard	.7800±.0257	.7267±.0606	.7248±.0330	.8166±.0328	.8058±.0177	.7980±.0250	.7906±.0274	.7749±.0269	.7617±.0147
	GIB	.7823±.0358	.7352±.0808	.7247±.0332	.8180±.0388	.8073±.0241	.8049±.0378	.7967±.0223	.7710±.0267	.7576±.0097
	SupCon	.7649±.0176	.7193±.0426	.7040±.0231	.7864±.0187	.7802±.0219	.7529±.0419	.7775±.0174	.7715±.0206	.7517±.0235
	GRACE	.6608±.0371	.6767±.0441	.6433±.0494	.6591±.0344	.6660±.0366	.6670±.0292	.6966±.0367	.6678±.0682	.6979±.0476
	RGIB-REP	.7766±.0070	.7479±.0150	.7427±.0127	.7981±.0104	.7939±.0149	.7894±.0238	.7959±.0137	.7865±.0163	.7695±.0169
	RGIB-SSL	.8372±.0169	.8226±.0189	.8184±.0135	.8441±.0078	.8252±.0129	.8288±.0114	.8795±.0112	.8802±.0100	.8749±.0178

Table 19: Full results on Pubmed dataset with GCN.

GCN										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9473±.0019	.9271±.0027	.9141±.0041	.9590±.0022	.9468±.0022	.9337±.0016	.9646±.0024	.9637±.0021	.9597±.0022
	DropEdge	.9394±.0025	.9155±.0027	.8994±.0036	.9467±.0022	.9302±.0021	.9146±.0022	.9594±.0026	.9558±.0027	.9519±.0019
	NeuralSparse	.9479±.0021	.9251±.0039	.9120±.0029	.9558±.0019	.9315±.0033	.9269±.0014	.9654±.0015	.9525±.0023	.9588±.0017
	PTDNet	.9467±.0018	.9264±.0025	.9111±.0032	.9554±.0026	.9320±.0035	.9272±.0027	.9651±.0018	.9616±.0021	.9584±.0021
	Co-teaching	.9502±.0085	.9335±.0104	.9160±.0096	.9510±.0098	.9331±.0054	.9255±.0113	.9676±.0018	.9560±.0127	.9608±.0098
	Peer loss	.9500±.0034	.9339±.0044	.9140±.0138	.9558±.0068	.9397±.0019	.9283±.0090	.9615±.0175	.9521±.0178	.9545±.0144
	Jaccard	.9496±.0039	.9325±.0087	.9235±.0081	.9554±.0019	.9327±.0067	.9230±.0159	.9580±.0032	.9532±.0086	.9591±.0054
	GIB	.9509±.0205	.9268±.0074	.9131±.0066	.9599±.0303	.9303±.0047	.9228±.0234	.9559±.0076	.9573±.0040	.9597±.0099
	SupCon	.9345±.0020	.9257±.0017	.9118±.0031	.9583±.0015	.9345±.0030	.9214±.0023	.9625±.0021	.9522±.0018	.9506±.0010
	GRACE	.9341±.0032	.9319±.0027	.9154±.0049	.9409±.0046	.9321±.0032	.9225±.0078	.9489±.0034	.9516±.0027	.9511±.0022
	RGIB-REP	.9537±.0013	.9368±.0018	.9270±.0036	.9579±.0022	.9467±.0023	.9365±.0016	.9696±.0033	.9690±.0023	.9671±.0015
	RGIB-SSL	.9585±.0022	.9471±.0032	.9301±.0021	.9425±.0088	.9305±.0098	.9121±.0125	.9719±.0020	.9724±.0015	.9711±.0012
L=4	Standard	.8870±.0041	.8748±.0031	.8641±.0041	.8854±.0051	.8759±.0031	.8651±.0040	.9030±.0082	.9039±.0029	.9070±.0062
	DropEdge	.8711±.0149	.8482±.0045	.8354±.0062	.8682±.0158	.8456±.0036	.8376±.0046	.9313±.0071	.9201±.0091	.9240±.0077
	NeuralSparse	.8908±.0080	.8733±.0022	.8630±.0049	.8931±.0090	.8720±.0043	.8649±.0041	.9272±.0108	.9136±.0117	.9089±.0084
	PTDNet	.8872±.0071	.8733±.0036	.8623±.0050	.8903±.0087	.8776±.0078	.8609±.0055	.9219±.0122	.9099±.0104	.9093±.0101
	Co-teaching	.8943±.0090	.8760±.0117	.8638±.0093	.8931±.0045	.8792±.0036	.8606±.0083	.9315±.0075	.9291±.0327	.9319±.0324
	Peer loss	.8961±.0130	.8815±.0099	.8566±.0057	.8917±.0076	.8811±.0127	.8643±.0129	.9126±.0116	.9101±.0046	.9210±.0095
	Jaccard	.8872±.0036	.8803±.0060	.8512±.0136	.8987±.0221	.8764±.0099	.8639±.0073	.9098±.0110	.9135±.0116	.9096±.0132
	GIB	.8899±.0239	.8729±.0205	.8544±.0051	.8932±.0256	.8808±.0053	.8618±.0317	.9037±.0089	.9114±.0065	.9064±.0059
	SupCon	.8853±.0061	.8718±.0110	.8525±.0108	.8867±.0080	.8739±.0033	.8558±.0042	.9131±.0068	.9108±.0095	.9162±.0125
	GRACE	.8922±.0034	.8749±.0098	.8588±.0042	.8810±.0034	.8795±.0099	.8593±.0040	.9234±.0088	.9252±.0052	.9255±.0043
	RGIB-REP	.9017±.0044	.8834±.0082	.8652±.0038	.9008±.0033	.8822±.0054	.8687±.0056	.9357±.0028	.9343±.0062	.9332±.0062
	RGIB-SSL	.9225±.0125	.8918±.0065	.8697±.0053	.9126±.0046	.8889±.0052	.8693±.0049	.9594±.0026	.9604±.0028	.9613±.0023
L=6	Standard	.8870±.0056	.8731±.0032	.8640±.0036	.8855±.0025	.8742±.0029	.8652±.0041	.9050±.0083	.9112±.0059	.9063±.0036
	DropEdge	.8623±.0039	.8421±.0044	.8342±.0058	.8623±.0054	.8407±.0051	.8328±.0058	.9140±.0054	.9102±.0082	.9092±.0072
	NeuralSparse	.8814±.0049	.8586±.0029	.8603±.0060	.8792±.0072	.8695±.0031	.8612±.0046	.9140±.0065	.9130±.0047	.9080±.0077
	PTDNet	.8807±.0053	.8610±.0026	.8518±.0040	.8791±.0040	.8708±.0032	.8619±.0040	.9123±.0074	.9086±.0079	.9105±.0072
	Co-teaching	.8850±.0126	.8698±.0101	.8568±.0050	.8773±.0023	.8767±.0113	.8691±.0095	.9103±.0372	.9311±.0290	.9204±.0162
	Peer loss	.8860±.0125	.8633±.0079	.8534±.0048	.8734±.0023	.8775±.0107	.8668±.0042	.9155±.0070	.9172±.0089	.9251±.0107
	Jaccard	.8852±.0092	.8658±.0085	.8555±.0055	.8711±.0031	.8794±.0126	.8670±.0200	.9045±.0137	.9118±.0108	.9065±.0059
	GIB	.8807±.0046	.8738±.0140	.8605±.0193	.8718±.0070	.8767±.0110	.8623±.0114	.9081±.0131	.9136±.0147	.9155±.0106
	SupCon	.8716±.0090	.8627±.0043	.8533±.0045	.8705±.0108	.8733±.0026	.8643±.0047	.9232±.0081	.9294±.0075	.9218±.0092
	GRACE	.8798±.0079	.8664±.0031	.8584±.0051	.8806±.0043	.8675±.0035	.8591±.0045	.9296±.0064	.9190±.0052	.9110±.0049
	RGIB-REP	.8846±.0071	.8715±.0035	.8640±.0043	.8818±.0054	.8716±.0021	.8646±.0047	.9161±.0081	.9156±.0075	.9129±.0095
	RGIB-SSL	.8915±.0062	.8737±.0029	.8633±.0036	.8891±.0057	.8732±.0034	.8639±.0051	.9450±.0042	.9488±.0065	.9484±.0027

Table 20: Full results on Pubmed dataset with GAT.

GAT										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9173±.0028	.8984±.0030	.8884±.0033	.9255±.0024	.9176±.0035	.9102±.0030	.9306±.0038	.9271±.0030	.9232±.0034
	DropEdge	.9102±.0023	.8970±.0032	.8837±.0034	.9208±.0030	.9177±.0028	.9087±.0037	.9374±.0031	.9309±.0020	.9267±.0019
	NeuralSparse	.9106±.0021	.8952±.0031	.8840±.0029	.9179±.0029	.9210±.0032	.9141±.0038	.9310±.0039	.9297±.0026	.9252±.0021
	PTDNet	.9119±.0015	.8943±.0030	.8844±.0037	.9068±.0027	.9210±.0026	.9143±.0025	.9311±.0031	.9280±.0034	.9267±.0024
	Co-teaching	.9163±.0044	.8924±.0050	.8881±.0100	.9058±.0089	.9180±.0089	.9136±.0068	.9556±.0098	.9364±.0207	.9376±.0249
	Peer loss	.9156±.0115	.8968±.0083	.8823±.0041	.9147±.0055	.9171±.0089	.9173±.0070	.9407±.0225	.9296±.0084	.9219±.0229
	Jaccard	.9128±.0057	.8940±.0094	.8831±.0086	.9042±.0092	.9181±.0175	.9228±.0214	.9304±.0039	.9355±.0127	.9282±.0109
	GIB	.9136±.0061	.8965±.0110	.8881±.0115	.9052±.0313	.9208±.0097	.9383±.0268	.9366±.0069	.9291±.0065	.9277±.0089
	SupCon	.9072±.0036	.8881±.0037	.8763±.0027	.9076±.0025	.9080±.0033	.9002±.0037	.9202±.0032	.9123±.0040	.9059±.0027
	GRACE	.8230±.0512	.7882±.0693	.7914±.0767	.8273±.0671	.8053±.0498	.7993±.0695	.8792±.0342	.8926±.0257	.8946±.0211
	RGIB-REP	.9190±.0025	.9034±.0017	.8939±.0056	.9250±.0033	.9164±.0024	.9099±.0029	.9311±.0036	.9306±.0025	.9276±.0022
	RGIB-SSL	.9223±.0027	.9054±.0032	.8960±.0027	.9183±.0021	.9071±.0023	.8977±.0029	.9405±.0027	.9407±.0022	.9378±.0018
L=4	Standard	.8610±.0045	.8434±.0042	.8339±.0048	.8668±.0040	.8547±.0050	.8476±.0037	.8817±.0042	.8772±.0040	.8696±.0062
	DropEdge	.8600±.0034	.8462±.0028	.8325±.0044	.8605±.0041	.8557±.0057	.8454±.0029	.8852±.0052	.8851±.0055	.8871±.0034
	NeuralSparse	.8691±.0034	.8505±.0025	.8402±.0055	.8612±.0042	.8572±.0048	.8459±.0038	.8906±.0059	.8806±.0076	.8796±.0075
	PTDNet	.8614±.0038	.8568±.0026	.8372±.0338	.8640±.0035	.8541±.0050	.8562±.0027	.8909±.0052	.8855±.0054	.8785±.0064
	Co-teaching	.8688±.0125	.8450±.0065	.8413±.0081	.8666±.0066	.8556±.0103	.8468±.0118	.8792±.0107	.8946±.0335	.8968±.0132
	Peer loss	.8613±.0040	.8493±.0105	.8342±.0108	.8652±.0061	.8504±.0143	.8471±.0059	.8851±.0110	.8839±.0085	.8735±.0069
	Jaccard	.8630±.0089	.8502±.0082	.8365±.0136	.8677±.0198	.8495±.0065	.8485±.0116	.8863±.0078	.8846±.0060	.8750±.0119
	GIB	.8616±.0036	.8534±.0143	.8370±.0116	.8814±.0189	.8486±.0059	.8421±.0220	.8828±.0111	.8827±.0066	.8700±.0076
	SupCon	.8534±.0061	.8292±.0128	.8048±.0164	.8625±.0085	.8447±.0069	.8360±.0141	.8768±.0057	.8686±.0062	.8629±.0065
	GRACE	.8355±.0477	.8202±.0387	.8046±.0409	.8439±.0344	.8078±.0649	.7822±.0686	.7878±.0839	.8185±.0702	.8008±.0794
	RGIB-REP	.8656±.0043	.8443±.0057	.8339±.0033	.8674±.0058	.8528±.0043	.8392±.0036	.8909±.0084	.8925±.0051	.8833±.0062
	RGIB-SSL	.8891±.0037	.8651±.0036	.8480±.0068	.8878±.0039	.8650±.0044	.8489±.0055	.9276±.0042	.9277±.0022	.9264±.0024
L=6	Standard	.8315±.0059	.8116±.0073	.8040±.0092	.8374±.0036	.8201±.0321	.8067±.0306	.8480±.0086	.8414±.0116	.8313±.0071
	DropEdge	.8468±.0407	.8236±.0050	.8004±.0071	.8655±.0037	.8303±.0044	.7915±.0334	.8501±.0058	.8568±.0068	.8523±.0381
	NeuralSparse	.8426±.0035	.8234±.0032	.8098±.0067	.8323±.0342	.8258±.0090	.7977±.0295	.8622±.0062	.8563±.0091	.8577±.0075
	PTDNet	.8384±.0319	.8117±.0384	.8031±.0380	.8508±.0044	.8251±.0284	.8204±.0034	.8635±.0064	.8498±.0251	.8452±.0065
	Co-teaching	.8360±.0122	.8111±.0122	.8081±.0113	.8391±.0101	.8246±.0398	.8071±.0312	.8729±.0090	.8647±.0107	.8424±.0079
	Peer loss	.8354±.0128	.8186±.0111	.8044±.0104	.8416±.0122	.8277±.0359	.8133±.0336	.8504±.0132	.8563±.0215	.8310±.0089
	Jaccard	.8333±.0140	.8191±.0073	.8044±.0082	.8408±.0221	.8340±.0424	.8216±.0497	.8528±.0100	.8507±.0210	.8304±.0108
	GIB	.8316±.0125	.8266±.0055	.8064±.0241	.8359±.0136	.8205±.0345	.8274±.0430	.8551±.0149	.8493±.0134	.8361±.0072
	SupCon	.8218±.0236	.7763±.0306	.7113±.0241	.8137±.0821	.8025±.0286	.7555±.0297	.8543±.0139	.8390±.0370	.8540±.0071
	GRACE	.7773±.0737	.7729±.0344	.6821±.1217	.7015±.1340	.6953±.0805	.6643±.1009	.5212±.0262	.5455±.0459	.5743±.0549
	RGIB-REP	.8324±.0039	.8162±.0088	.7934±.0068	.8248±.0070	.8145±.0088	.7892±.0107	.8518±.0056	.8496±.0083	.8492±.0113
	RGIB-SSL	.8738±.0051	.8443±.0033	.8124±.0084	.8709±.0023	.8432±.0046	.8187±.0050	.9208±.0043	.9250±.0029	.9235±.0031

Table 21: Full results on Pubmed dataset with SAGE.

SAGE										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9136±.0032	.9094±.0035	.9035±.0040	.9295±.0025	.9378±.0022	.9410±.0023	.8817±.0034	.8793±.0043	.8757±.0041
	DropEdge	.9142±.0026	.9188±.0029	.9014±.0038	.9179±.0020	.9178±.0013	.9165±.0013	.9021±.0021	.9003±.0018	.9011±.0020
	NeuralSparse	.9118±.0030	.9137±.0031	.9094±.0034	.9271±.0019	.9209±.0026	.9234±.0017	.9033±.0028	.8925±.0030	.8864±.0032
	PTDNet	.9114±.0026	.9138±.0030	.9104±.0037	.9267±.0020	.9211±.0027	.9229±.0024	.9030±.0028	.8941±.0040	.8868±.0033
	Co-teaching	.9164±.0031	.9160±.0027	.9092±.0132	.9362±.0061	.9258±.0072	.9228±.0017	.8827±.0026	.9054±.0236	.8856±.0113
	Peer loss	.9103±.0104	.9174±.0094	.9044±.0087	.9308±.0079	.9238±.0051	.9307±.0076	.9005±.0118	.8833±.0066	.8909±.0058
	Jaccard	.9108±.0123	.9167±.0105	.9109±.0031	.9236±.0098	.9259±.0175	.9308±.0141	.8861±.0052	.8785±.0092	.8842±.0048
	GIB	.9173±.0049	.9125±.0211	.9096±.0020	.9338±.0152	.9294±.0125	.9299±.0194	.8880±.0125	.8865±.0129	.8853±.0058
	SupCon	.9167±.0026	.9148±.0031	.9106±.0035	.9259±.0034	.9305±.0031	.9230±.0033	.9033±.0055	.8929±.0051	.8888±.0034
	GRACE	.8317±.0063	.8291±.0059	.8336±.0068	.8288±.0071	.8344±.0074	.8305±.0052	.8320±.0046	.8344±.0078	.8328±.0075
	RGIB-REP	.9192±.0022	.9136±.0027	.9119±.0037	.9278±.0031	.9322±.0031	.9331±.0034	.9055±.0033	.9015±.0051	.9000±.0043
	RGIB-SSL	.9276±.0052	.9285±.0030	.9313±.0031	.9273±.0056	.9305±.0040	.9334±.0025	.9304±.0017	.9294±.0049	.9274±.0066
L=4	Standard	.8627±.0056	.8663±.0061	.8619±.0073	.8715±.0080	.8901±.0082	.9033±.0057	.8386±.0085	.8330±.0104	.8268±.0092
	DropEdge	.8737±.0060	.8740±.0065	.8816±.0077	.9072±.0120	.9016±.0078	.9087±.0019	.9037±.0024	.9036±.0048	.9048±.0059
	NeuralSparse	.8888±.0037	.8825±.0046	.8822±.0051	.8982±.0067	.9146±.0029	.9190±.0041	.8647±.0075	.8535±.0091	.8472±.0079
	PTDNet	.8842±.0045	.8853±.0059	.8846±.0052	.8885±.0055	.9057±.0055	.9127±.0058	.8464±.0105	.8458±.0066	.8408±.0065
	Co-teaching	.8678±.0104	.8752±.0090	.8667±.0122	.8727±.0079	.8971±.0159	.9061±.0098	.8601±.0240	.8498±.0368	.8514±.0388
	Peer loss	.8683±.0136	.8717±.0100	.8665±.0117	.8736±.0075	.8997±.0079	.9095±.0119	.8510±.0151	.8514±.0115	.8423±.0128
	Jaccard	.8646±.0124	.8725±.0141	.8625±.0140	.8773±.0125	.9017±.0205	.9155±.0164	.8378±.0137	.8383±.0118	.8275±.0083
	GIB	.8816±.0203	.8768±.0098	.8641±.0238	.8824±.0102	.8918±.0095	.9221±.0243	.8479±.0103	.8410±.0151	.8330±.0120
	SupCon	.8765±.0086	.8682±.0100	.8518±.0198	.8907±.0054	.8957±.0104	.8879±.0113	.8865±.0046	.8811±.0052	.8810±.0044
	GRACE	.7142±.0451	.6741±.0484	.7227±.0446	.6578±.0701	.6816±.0536	.7012±.0516	.6498±.0896	.6647±.0535	.6540±.0424
	RGIB-REP	.8746±.0049	.8708±.0064	.8758±.0071	.8800±.0045	.8904±.0048	.8941±.0051	.8504±.0078	.8466±.0070	.8533±.0118
	RGIB-SSL	.9315±.0036	.9237±.0035	.9214±.0033	.9276±.0046	.9310±.0039	.9286±.0035	.9463±.0030	.9448±.0037	.9430±.0021
L=6	Standard	.8314±.0081	.8105±.0279	.8333±.0089	.8224±.0335	.8538±.0105	.8566±.0199	.8242±.0104	.8161±.0071	.8090±.0129
	DropEdge	.8781±.0041	.8665±.0076	.8556±.0081	.8800±.0050	.8731±.0122	.8628±.0152	.8503±.0070	.8698±.0074	.8426±.0096
	NeuralSparse	.8611±.0101	.8589±.0081	.8482±.0182	.8694±.0083	.8858±.0068	.8889±.0057	.8368±.0074	.8344±.0090	.8353±.0081
	PTDNet	.8425±.0073	.8511±.0067	.8525±.0064	.8430±.0107	.8627±.0115	.8739±.0103	.8232±.0076	.8195±.0071	.8198±.0060
	Co-teaching	.8385±.0114	.8202±.0303	.8349±.0147	.8265±.0385	.8607±.0164	.8612±.0190	.8299±.0352	.8243±.0074	.8143±.0409
	Peer loss	.8339±.0162	.8111±.0285	.8335±.0084	.8317±.0412	.8610±.0135	.8605±.0223	.8277±.0224	.8260±.0197	.8204±.0316
	Jaccard	.8355±.0110	.8180±.0272	.8347±.0124	.8298±.0436	.8564±.0107	.8607±.0394	.8260±.0138	.8207±.0130	.8140±.0192
	GIB	.8309±.0062	.8195±.0329	.8336±.0206	.8226±.0355	.8527±.0208	.8647±.0344	.8310±.0142	.8237±.0128	.8141±.0165
	SupCon	.8288±.0109	.8276±.0351	.8174±.0070	.8617±.0122	.8443±.0528	.8365±.0350	.8745±.0071	.8692±.0132	.8661±.0076
	GRACE	.7293±.0133	.7151±.0368	.6737±.0522	.7102±.0296	.7392±.0257	.6751±.0444	.7120±.0166	.7042±.0588	.7230±.0286
	RGIB-REP	.8493±.0057	.8424±.0083	.8373±.0079	.8439±.0063	.8527±.0092	.8536±.0112	.8275±.0218	.8148±.0098	.8211±.0145
	RGIB-SSL	.8915±.0060	.8971±.0051	.8956±.0046	.8948±.0079	.9026±.0042	.8995±.0040	.9313±.0042	.9311±.0036	.9294±.0053

Table 22: Full results on Facebook dataset with GCN.

GCN										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9880±.0007	.9866±.0007	.9843±.0010	.9878±.0008	.9852±.0006	.9834±.0011	.9892±.0006	.9888±.0008	.9888±.0007
	DropEdge	.9865±.0007	.9845±.0008	.9821±.0009	.9764±.0010	.9835±.0007	.9708±.0012	.9783±.0006	.9879±.0008	.9881±.0007
	NeuralSparse	.9877±.0007	.9861±.0008	.9837±.0009	.9772±.0007	.9852±.0007	.9732±.0010	.9788±.0006	.9885±.0007	.9888±.0005
	PTDNet	.9876±.0008	.9862±.0008	.9838±.0008	.9776±.0007	.9848±.0008	.9728±.0011	.9859±.0006	.9786±.0009	.9886±.0006
	Co-teaching	.9871±.0052	.9722±.0104	.9876±.0009	.9738±.0018	.9848±.0077	.9750±.0002	.9716±.0266	.9873±.0121	.9825±.0009
	Peer loss	.9755±.0095	.9737±.0033	.9895±.0096	.9797±.0024	.9855±.0051	.9720±.0019	.9763±.0001	.9732±.0110	.9774±.0034
	Jaccard	.9759±.0043	.9796±.0056	.9707±.0006	.9739±.0098	.9807±.0040	.9793±.0150	.9729±.0030	.9773±.0044	.9729±.0042
	GIB	.9752±.0009	.9735±0.021	.9720±.0154	.9796±.0245	.9820±.0173	.9707±.0024	.9724±.0017	.9774±.1404	.9717±.0086
	SupCon	.9779±.0008	.9748±.0014	.9665±.0022	.9724±.0009	.9803±.0011	.9783±.0010	.9713±.0060	.9569±.0160	.9701±.0024
	GRACE	.8883±.0120	.8811±.0077	.8412±.0224	.8950±.0081	.8792±.0119	.8530±.0221	.8864±.0077	.8826±.0051	.8784±.0104
	RGIB-REP	.9881±.0007	.9866±.0008	.9846±.0009	.9880±.0007	.9854±.0005	.9841±.0011	.9895±.0007	.9891±.0008	.9894±.0008
	RGIB-SSL	.9845±.0005	.9810±.0005	.9765±.0014	.9840±.0011	.9808±.0012	.9787±.0009	.9862±.0005	.9859±.0010	.9866±.0007
L=4	Standard	.9829±.0020	.9520±.0424	.9438±.0402	.9819±.0015	.9668±.0147	.9622±.0154	.9882±.0007	.9880±.0007	.9886±.0006
	DropEdge	.9811±.0028	.9682±.0096	.9473±.0120	.9803±.0016	.9685±.0033	.9531±.0112	.9673±.0008	.9771±.0008	.9776±.0009
	NeuralSparse	.9825±.0020	.9638±.0039	.9456±.0067	.9712±.0022	.9691±.0045	.9583±.0071	.9781±.0007	.9781±.0008	.9784±.0008
	PTDNet	.9725±.0017	.9674±.0131	.9485±.0094	.9725±.0014	.9668±.0089	.9493±.0267	.9879±.0003	.9880±.0008	.9783±.0008
	Co-teaching	.9820±.0113	.9526±.0439	.9480±.0450	.9712±.0084	.9707±.0141	.9714±.0146	.9762±.0070	.9797±.0167	.9638±.0154
	Peer loss	.9807±.0016	.9536±.0503	.9430±.0437	.9758±.0011	.9703±.0204	.9622±.0176	.9769±.0085	.9750±.0128	.9734±.0137
	Jaccard	.9794±.0031	.9579±.0471	.9428±.0452	.9784±.0127	.9702±.0295	.9638±.0340	.9702±.0016	.9725±.0064	.9758±.0035
	GIB	.9773±.0182	.9608±.0548	.9417±.0441	.9796±.0260	.9647±.0200	.9650±.0373	.9742±.0073	.9703±.0023	.9771±.0030
	SupCon	.9588±.0067	.9508±.0100	.9297±.0121	.9647±.0088	.9517±.0113	.9401±.0135	.9647±.0164	.9567±.0149	.9553±.0133
	GRACE	.8899±.0100	.8865±.0226	.8315±.0108	.9015±.0049	.8833±.0285	.8395±.0157	.8913±.0036	.8972±.0046	.8887±.0123
	RGIB-REP	.9832±.0026	.9770±.0032	.9519±.0063	.9833±.0014	.9723±.0062	.9682±.0087	.9884±.0006	.9883±.0007	.9889±.0007
	RGIB-SSL	.9829±.0023	.9711±.0025	.9643±.0029	.9821±.0019	.9707±.0021	.9668±.0040	.9857±.0010	.9881±.0008	.9857±.0007
L=6	Standard	.9798±.0013	.9609±.0138	.9368±.0179	.9764±.0034	.9502±.0096	.9469±.0160	.9863±.0013	.9865±.0012	.9876±.0010
	DropEdge	.9774±.0030	.9635±.0063	.9500±.0103	.9540±.0034	.9579±.0083	.9411±.0084	.9556±.0014	.9642±.0006	.9559±.0012
	NeuralSparse	.9774±.0020	.9596±.0067	.9435±.0114	.9449±.0029	.9496±.0073	.9490±.0087	.9564±.0012	.9562±.0011	.9465±.0016
	PTDNet	.9767±.0066	.9606±.0131	.9449±.0175	.9555±.0034	.9568±.0064	.9416±.0145	.9560±.0011	.9460±.0014	.9569±.0009
	Co-teaching	.9638±.0051	.9565±.0235	.9426±.0261	.9520±.0051	.9568±.0148	.9489±.0228	.9474±.0068	.9458±.0143	.9561±.0169
	Peer loss	.9699±.0045	.9557±.0141	.9362±.0221	.9554±.0053	.9494±.0135	.9445±.0234	.9498±.0063	.9581±.0200	.9650±.0021
	Jaccard	.9641±.0032	.9553±.0137	.9425±.0178	.9507±.0064	.9616±.0125	.9480±.0170	.9528±.0060	.9525±.0075	.9423±.0057
	GIB	.9649±.0145	.9602±.0198	.9416±.0236	.9511±.0333	.9552±.0261	.9555±.0346	.9556±.0099	.9430±.0106	.9578±.0052
	SupCon	.9462±.0050	.9377±.0054	.9282±.0113	.9460±.0073	.9355±.0118	.9253±.0110	.9411±.0088	.9550±.0087	.9510±.0122
	GRACE	.8939±.0118	.8563±.0206	.8259±.0019	.9071±.0077	.8582±.0228	.8274±.0029	.8962±.0093	.9026±.0035	.8977±.0100
	RGIB-REP	.9774±.0031	.9680±.0097	.9501±.0134	.9780±.0024	.9619±.0069	.9423±.0085	.9868±.0008	.9863±.0010	.9872±.0011
	RGIB-SSL	.9751±.0023	.9641±.0037	.9395±.0122	.9763±.0034	.9633±.0040	.9451±.0084	.9845±.0008	.9843±.0012	.9847±.0011

Table 23: Full results on Facebook dataset with GAT.

GAT										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9869±.0005	.9856±.0008	.9836±.0007	.9878±.0006	.9861±.0006	.9858±.0008	.9872±.0006	.9864±.0009	.9857±.0008
	DropEdge	.9645±.0007	.9532±.0010	.9517±.0009	.9652±.0007	.9636±.0007	.9733±.0008	.9755±.0007	.9743±.0010	.9739±.0012
	NeuralSparse	.9661±.0007	.9651±.0009	.9638±.0006	.9765±.0008	.9652±.0007	.9744±.0006	.9662±.0010	.9657±.0006	.9656±.0007
	PTDNet	.9762±.0007	.9551±.0008	.9735±.0007	.9766±.0007	.9650±.0007	.9645±.0009	.9766±.0006	.9759±.0009	.9757±.0008
	Co-teaching	.9723±.0006	.9685±.0054	.9762±.0039	.9632±.0057	.9720±.0001	.9741±.0046	.9703±0.001	.9789±.0232	.9792±.0288
	Peer loss	.9762±.0032	.9644±.0020	.9725±.0076	.9699±.0020	.9720±.0104	.9708±.0103	.9632±.0194	.9807±.0207	.9713±.0078
	Jaccard	.9771±.0038	.9661±.0057	.9736±.0078	.9556±.0064	.9758±.0180	.9780±.0012	.9720±.0100	.9749±.0064	.9701±.0087
	GIB	.9879±.0075	.9616±.0007	.9709±.0199	.9564±.0122	.9746±.0004	.9645±.0225	.9758±.0101	.9738±.0019	.9799±.0094
	SupCon	.9718±.0028	.9646±.0085	.9659±.0087	.9753±.0008	.9737±.0009	.9629±.0009	.9720±.0038	.9456±.0038	.9419±.0029
	GRACE	.8377±.0309	.8716±.0263	.8519±.0264	.8343±.0341	.8502±.0271	.8487±.0407	.8768±.0457	.8370±.0416	.8794±.0319
	RGIB-REP	.9865±.0006	.9854±.0009	.9837±.0006	.9872±.0007	.9855±.0007	.9855±.0008	.9871±.0007	.9861±.0009	.9859±.0006
	RGIB-SSL	.9788±.0011	.9764±.0017	.9717±.0021	.9784±.0012	.9764±.0015	.9734±.0021	.9778±.0008	.9784±.0009	.9791±.0009
L=4	Standard	.9857±.0015	.9850±.0012	.9820±.0014	.9855±.0011	.9827±.0019	.9773±.0046	.9873±.0010	.9874±.0010	.9874±.0005
	DropEdge	.9839±.0009	.9791±.0032	.9767±.0024	.9836±.0009	.9772±.0022	.9705±.0030	.9852±.0005	.9845±.0009	.9844±.0007
	NeuralSparse	.9854±.0009	.9812±.0019	.9768±.0027	.9839±.0012	.9790±.0028	.9736±.0030	.9872±.0009	.9869±.0009	.9868±.0007
	PTDNet	.9843±.0039	.9830±.0018	.9745±.0076	.9844±.0012	.9787±.0039	.9752±.0027	.9872±.0005	.9868±.0010	.9872±.0007
	Co-teaching	.9789±.0039	.9777±.0086	.9717±.0111	.9703±.0050	.9718±.0071	.9782±.0049	.9645±.0105	.9730±.0267	.9646±.0014
	Peer loss	.9944±.0029	.9630±.0105	.9687±.0046	.9610±.0068	.9610±.0064	.9783±.0073	.9677±.0053	.9638±.0050	.9691±.0203
	Jaccard	.9757±.0079	.9863±.0087	.9883±.0015	.9607±.0182	.9616±.0184	.9655±.0151	.9689±.0025	.9625±.0009	.9604±.0036
	GIB	.9809±.0134	.9747±.0077	.9709±.0204	.9721±.0297	.9741±.0199	.9740±.0111	.9747±.0038	.9768±.0093	.9799±.0016
	SupCon	.9709±.0156	.9464±.0254	.9134±.0309	.9824±.0008	.9745±.0062	.9677±.0113	.9600±.0154	.9580±.0183	.9482±.0174
	GRACE	.7803±.0649	.7947±.0600	.7618±.1058	.8259±.0669	.7588±.0963	.7260±.1331	.8440±.0370	.8448±.0337	.8122±.0403
	RGIB-REP	.9855±.0014	.9839±.0016	.9783±.0034	.9838±.0019	.9806±.0013	.9765±.0037	.9872±.0008	.9871±.0008	.9867±.0007
	RGIB-SSL	.9751±.0033	.9707±.0061	.9602±.0043	.9767±.0030	.9683±.0053	.9603±.0062	.9755±.0028	.9772±.0032	.9762±.0047
L=6	Standard	.9805±.0025	.9658±.0321	.9577±.0314	.9804±.0018	.9738±.0044	.9710±.0036	.9854±.0015	.9860±.0007	.9867±.0012
	DropEdge	.9643±.0041	.9638±.0054	.9500±.0274	.9736±.0042	.9589±.0089	.9606±.0055	.9735±.0008	.9726±.0012	.9736±.0009
	NeuralSparse	.9746±.0077	.9667±.0092	.9560±.0122	.9740±.0047	.9668±.0056	.9652±.0043	.9735±.0017	.9742±.0018	.9733±.0030
	PTDNet	.9769±.0037	.9679±.0071	.9582±.0296	.9754±.0027	.9688±.0045	.9645±.0039	.9738±.0041	.9741±.0022	.9756±.0012
	Co-teaching	.9745±.0034	.9686±.0316	.9625±.0408	.9747±.0084	.9833±.0108	.9738±.0035	.9622±.0024	.9676±.0072	.9721±.0215
	Peer loss	.9690±.0114	.9728±.0334	.9588±.0309	.9716±.0028	.9776±.0075	.9766±.0074	.9871±.0207	.9605±.0202	.9768±.0063
	Jaccard	.9789±.0084	.9651±.0360	.9620±.0337	.9673±.0007	.9809±.0110	.9731±.0021	.9652±.0064	.9607±.0004	.9751±.0030
	GIB	.9839±.0037	.9777±.0420	.9584±.0374	.9868±.0290	.9760±.0135	.9791±.0249	.9648±.0054	.9640±.0046	.9774±.0029
	SupCon	.9428±.0194	.9097±.0361	.8779±.0347	.9653±.0171	.9459±.0378	.9312±.0344	.9465±.0173	.9484±.0194	.9023±.0333
	GRACE	.7234±.0687	.6604±.1398	.6075±.1089	.7415±.1242	.6176±.1345	.6216±.1341	.7613±.1157	.7256±.1351	.7062±.1042
	RGIB-REP	.9779±.0031	.9711±.0042	.9433±.0392	.9753±.0041	.9666±.0087	.9614±.0057	.9847±.0017	.9848±.0013	.9856±.0009
	RGIB-SSL	.9653±.0107	.9491±.0105	.9254±.0206	.9676±.0057	.9502±.0087	.9384±.0067	.9737±.0065	.9675±.0052	.9713±.0103

Table 24: Full results on Facebook dataset with SAGE.

SAGE										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9858±.0008	.9827±.0008	.9788±.0012	.9881±.0008	.9862±.0007	.9862±.0008	.9867±.0006	.9840±.0006	.9825±.0014
	DropEdge	.9745±.0008	.9807±.0011	.9765±.0011	.9766±.0007	.9749±.0011	.9752±.0008	.9761±.0008	.9739±.0010	.9719±.0011
	NeuralSparse	.9753±.0008	.9619±.0011	.9683±.0007	.9675±.0008	.9660±.0006	.9659±.0011	.9667±.0007	.9640±.0007	.9627±.0011
	PTDNet	.9755±.0007	.9723±.0009	.9779±.0012	.9775±.0007	.9761±.0008	.9754±.0007	.9766±.0007	.9743±.0007	.9726±.0014
	Co-teaching	.9759±.0101	.9722±.0004	.9728±.0100	.9702±.0050	.9742±.0023	.9739±.0081	.9764±.0125	.9788±.0205	.9700±.0282
	Peer loss	.9765±.0052	.9720±.0072	.9790±.0103	.9787±.0005	.9781±.0105	.9787±.0075	.9721±.0019	.9842±.0136	.9793±.0031
	Jaccard	.9747±.0018	.9720±.0009	.9721±.0096	.9729±.0166	.9760±.0139	.9752±.0102	.9733±.0053	.9706±.0059	.9716±.0098
	GIB	.9798±.0089	.9780±.0040	.9765±.0020	.9774±.0139	.9767±.0287	.9778±.0006	.9780±.0012	.9713±.0067	.9772±.0050
	SupCon	.9482±.0166	.9288±.0046	.9141±.0139	.9793±.0043	.9782±.0072	.9786±.0078	.9278±.0048	.9252±.0074	.9156±.0041
	GRACE	.9113±.0116	.8907±.0295	.9077±.0089	.9012±.0113	.8885±.0177	.9031±.0104	.9053±.0126	.9050±.0173	.9067±.0137
	RGIB-REP	.9860±.0009	.9834±.0008	.9802±.0014	.9878±.0009	.9863±.0007	.9863±.0011	.9875±.0006	.9860±.0007	.9855±.0011
	RGIB-SSL	.9840±.0007	.9829±.0010	.9811±.0006	.9838±.0007	.9821±.0008	.9823±.0004	.9841±.0008	.9839±.0007	.9844±.0010
L=4	Standard	.9824±.0015	.9783±.0025	.9698±.0040	.9849±.0015	.9815±.0024	.9815±.0025	.9844±.0015	.9817±.0007	.9809±.0009
	DropEdge	.9818±.0026	.9764±.0034	.9722±.0022	.9625±.0015	.9601±.0043	.9600±.0023	.9649±.0008	.9627±.0017	.9615±.0012
	NeuralSparse	.9811±.0031	.9776±.0021	.9740±.0031	.9636±.0023	.9600±.0026	.9615±.0016	.9648±.0008	.9628±.0014	.9613±.0025
	PTDNet	.9823±.0012	.9757±.0041	.9735±.0032	.9623±.0041	.9609±.0031	.9607±.0022	.9652±.0007	.9632±.0009	.9623±.0024
	Co-teaching	.9660±.0009	.9653±.0075	.9659±.0114	.9600±.0098	.9634±.0091	.9626±.0079	.9654±.0253	.9706±.0136	.9628±.0263
	Peer loss	.9668±.0105	.9676±.0064	.9716±.0030	.9681±.0079	.9641±.0044	.9603±.0112	.9671±.0204	.9609±.0088	.9660±.0032
	Jaccard	.9621±.0019	.9715±.0056	.9772±.0068	.9662±.0143	.9675±.0094	.9782±.0056	.9725±.0107	.9726±.0063	.9705±9.276
	GIB	.9774±0.000	.9758±.0200	.9732±.0025	.9708±.0195	.9626±.0286	.9679±.0171	.9765±.0101	.9714±.0018	.9710±.0107
	SupCon	.9169±.0144	.9096±.0191	.9001±.0143	.9324±.0208	.9188±.0100	.9185±.0192	.9295±.0114	.9328±.0158	.9325±.0148
	GRACE	.8683±.0292	.8355±.0696	.8545±.0415	.8585±.0424	.8721±.0261	.8413±.0364	.8108±.0213	.8527±.0375	.8376±.0330
	RGIB-REP	.9828±.0016	.9804±.0020	.9750±.0024	.9843±.0014	.9811±.0030	.9808±.0030	.9857±.0004	.9833±.0025	.9830±.0019
	RGIB-SSL	.9817±.0016	.9797±.0014	.9768±.0009	.9828±.0018	.9798±.0014	.9797±.0013	.9821±.0009	.9820±.0011	.9826±.0010
L=6	Standard	.9751±.0055	.9603±.0365	.9616±.0091	.9715±.0077	.9672±.0057	.9517±.0228	.9761±.0136	.9788±.0045	.9749±.0151
	DropEdge	.9652±.0039	.9676±.0088	.9578±.0149	.9734±.0050	.9616±.0126	.9665±.0073	.9631±.0022	.9606±.0046	.9651±.0145
	NeuralSparse	.9640±.0075	.9577±.0222	.9672±.0061	.9647±.0048	.9694±.0156	.9673±.0036	.9632±.0017	.9618±.0037	.9615±.0051
	PTDNet	.9668±.0029	.9633±.0142	.9617±.0111	.9774±.0028	.9693±.0053	.9642±.0055	.9629±.0035	.9736±.0010	.9708±.0037
	Co-teaching	.9644±.0116	.9699±.0463	.9658±.0182	.9730±.0107	.9738±.0076	.9583±.0239	.9742±.0138	.9744±.0106	.9720±.0202
	Peer loss	.9644±.0141	.9602±.0369	.9681±.0085	.9613±.0167	.9728±.0053	.9524±.0288	.9655±.0220	.9769±.0028	.9650±.0256
	Jaccard	.9750±.0119	.9666±.0453	.9686±.0094	.9666±.0261	.9612±.0056	.9683±.0383	.9634±.0170	.9784±.0110	.9781±.0178
	GIB	.9739±.0197	.9656±.0564	.9749±.0125	.9743±.0351	.9717±.0034	.9615±.0291	.9607±.0153	.9779±.0059	.9743±.0222
	SupCon	.9007±.0112	.8859±.0189	.8730±.0140	.8997±.0142	.8940±.0104	.9006±.0232	.9146±.0114	.9166±.0143	.9185±.0122
	GRACE	.8202±.0365	.7225±.0840	.7901±.1065	.8018±.0575	.8224±.0547	.7960±.0915	.8061±.0367	.8262±.0306	.8103±.0351
	RGIB-REP	.9770±.0040	.9557±.0119	.9574±.0149	.9749±.0046	.9683±.0072	.9584±.0093	.9838±.0020	.9829±.0015	.9814±.0029
	RGIB-SSL	.9773±.0032	.9720±.0031	.9678±.0030	.9781±.0027	.9739±.0023	.9692±.0050	.9774±.0016	.9786±.0012	.9786±.0017

Table 25: Full results on Chameleon dataset with GCN.

GCN										
		mixed noise			input noise			label noise		
layers	method	20%	40%	60%	20%	40%	60%	20%	40%	60%
L=2	Standard	.9753±.0025	.9696±.0022	.9657±.0029	.9784±.0017	.9762±.0016	.9754±.0023	.9775±.0018	.9769±.0018	.9755±.0036
	DropEdge	.9716±.0030	.9640±.0025	.9579±.0029	.9646±.0026	.9602±.0024	.9661±.0024	.9686±.0018	.9664±.0029	.9651±.0031
	NeuralSparse	.9741±.0032	.9692±.0030	.9633±.0030	.9682±.0026	.9646±.0023	.9627±.0022	.9679±.0017	.9669±.0029	.9651±.0039
	PTDNet	.9748±.0026	.9682±.0032	.9637±.0031	.9679±.0021	.9649±.0019	.9627±.0025	.9690±.0019	.9674±.0021	.9648±.0033
	Co-teaching	.9679±.0059	.9641±.0086	.9676±.0088	.9767±.0096	.9712±.0084	.9709±.0106	.9790±.0218	.9729±.0015	.9745±.0272
	Peer loss	.9647±.0057	.9662±.0106	.9658±.0059	.9781±.0043	.9784±.0014	.9759±.0095	.9762±.0159	.9695±.0090	.9736±.0036
	Jaccard	.9684±.0103	.9657±.0118	.9660±.0030	.9611±.0190	.9799±.0005	.9774±.0128	.9711±.0010	.9754±.0091	.9750±.0086
	GIB	.9649±.0052	.9711±.0050	.9634±.0177	.9709±.0106	.9714±.0257	.9786±.0012	.9674±.0066	.9660±.0070	.9778±.0089
	SupCon	.9625±.0024	.9677±.0024	.9613±.0032	.9757±.0018	.9718±.0023	.9697±.0034	.9749±.0013	.9755±.0024	.9750±.0030
	GRACE	.9145±.0105	.8978±.0110	.8915±.0033	.9081±.0121	.9005±.0062	.8931±.0042	.9171±.0042	.9184±.0054	.9196±.0058
	RGIB-REP	.9754±.0026	.9698±.0026	.9652±.0027	.9797±.0023	.9757±.0016	.9744±.0028	.9804±.0023	.9798±.0016	.9782±.0028
	RGIB-SSL	.9719±.0023	.9658±.0025	.9595±.0026	.9709±.0017	.9664±.0024	.9638±.0025	.9786±.0016	.9797±.0022	.9789±.0034
L=4	Standard	.9616±.0033	.9496±.0190	.9274±.0276	.9608±.0038	.9433±.0261	.9368±.0271	.9686±.0020	.9580±.0021	.9362±.0035
	DropEdge	.9568±.0044	.9548±.0058	.9407±.0050	.9567±.0039	.9433±.0055	.9432±.0088	.9580±.0020	.9579±.0033	.9578±.0033
	NeuralSparse	.9599±.0026	.9497±.0032	.9402±.0057	.9609±.0027	.9540±.0178	.9348±.0169	.9583±.0017	.9583±.0030	.9571±.0031
	PTDNet	.9607±.0030	.9514±.0036	.9424±.0097	.9610±.0024	.9457±.0194	.9360±.0090	.9585±.0022	.9576±.0030	.9665±.0035
	Co-teaching	.9595±.0112	.9516±.0199	.9483±.0374	.9524±.0123	.9446±.0288	.9447±.0286	.9642±.0079	.9650±.0058	.9533±.0050
	Peer loss	.9543±.0090	.9533±.0192	.9267±.0320	.9558±.0037	.9482±.0280	.9412±.0269	.9621±.0161	.9501±.0055	.9569±.0227
	Jaccard	.9503±.0061	.9538±.0223	.9344±.0364	.9507±.0056	.9436±.0286	.9364±.0385	.9603±.0051	.9659±.0020	.9557±.0070
	GIB	.9554±.0036	.9561±.0292	.9321±.0267	.9605±.0069	.9521±.0231	.9416±.0512	.9651±.0061	.9582±.0100	.9489±.0029
	SupCon	.9561±.0046	.9531±.0043	.9467±.0045	.9606±.0031	.9536±.0031	.9468±.0075	.9584±.0015	.9580±.0051	.9477±.0038
	GRACE	.8978±.0145	.8987±.0050	.8949±.0030	.8994±.0141	.9007±.0045	.8964±.0043	.9053±.0110	.9074±.0136	.9075±.0113
	RGIB-REP	.9723±.0035	.9621±.0036	.9519±.0052	.9705±.0027	.9604±.0052	.9480±.0053	.9785±.0031	.9797±.0017	.9785±.0032
	RGIB-SSL	.9655±.0022	.9592±.0043	.9500±.0053	.9658±.0023	.9570±.0047	.9486±.0029	.9730±.0017	.9752±.0030	.9744±.0032
L=6	Standard	.9662±.0042	.9511±.0079	.9286±.0067	.9656±.0045	.9450±.0177	.9276±.0229	.9752±.0027	.9766±.0035	.9745±.0040
	DropEdge	.9601±.0032	.9484±.0053	.9331±.0066	.9608±.0020	.9481±.0129	.9331±.0073	.9537±.0022	.9559±.0027	.9547±.0024
	NeuralSparse	.9644±.0035	.9550±.0033	.9411±.0046	.9538±.0035	.9468±.0038	.9387±.0053	.9525±.0033	.9541±.0031	.9535±.0037
	PTDNet	.9655±.0043	.9585±.0033	.9384±.0088	.9657±.0024	.9553±.0051	.9391±.0044	.9537±.0037	.9559±.0025	.9543±.0032
	Co-teaching	.9654±.0058	.9582±.0139	.9319±.0163	.9505±.0121	.9534±.0222	.9271±.0308	.9679±.0198	.9557±.0112	.9557±.0282
	Peer loss	.9658±.0120	.9551±.0174	.9308±.0099	.9552±.0040	.9441±.0226	.9358±.0328	.9575±.0164	.9667±.0230	.9593±.0236
	Jaccard	.9754±.0063	.9549±.0088	.9292±.0104	.9637±.0035	.9495±.0213	.9457±.0350	.9500±.0040	.9550±.0128	.9433±.0066
	GIB	.9800±.0203	.9621±.0246	.9329±.0238	.9544±.0212	.9542±.0395	.9456±.0219	.9619±.0072	.9505±.0112	.9536±.0124
	SupCon	.9537±.0054	.9452±.0073	.9352±.0046	.9534±.0068	.9454±.0068	.9375±.0023	.9618±.0036	.9627±.0032	.9557±.0067
	GRACE	.9024±.0098	.8995±.0030	.8936±.0029	.9025±.0097	.8983±.0055	.8952±.0042	.9154±.0092	.9166±.0092	.9151±.0082
	RGIB-REP	.9666±.0028	.9580±.0074	.9467±.0067	.9662±.0027	.9606±.0041	.9453±.0049	.9740±.0033	.9776±.0021	.9753±.0031
	RGIB-SSL	.9633±.0032	.9416±.0036	.9177±.0082	.9627±.0037	.9482±.0037	.9276±.0093	.9712±.0017	.9742±.0025	.9726±.0032

Table 26: Full results on Chameleon dataset with GAT.

GAT										
		mixed noise			input noise			label noise		
layers	method	20%	40%	60%	20%	40%	60%	20%	40%	60%
L=2	Standard	.9725±.0027	.9650±.0018	.9625±.0018	.9767±.0026	.9747±.0020	.9759±.0018	.9746±.0023	.9743±.0017	.9711±.0041
	DropEdge	.9716±.0023	.9630±.0036	.9563±.0023	.9747±.0026	.9717±.0030	.9708±.0025	.9752±.0018	.9726±.0026	.9698±.0035
	NeuralSparse	.9733±.0029	.9667±.0028	.9615±.0028	.9762±.0028	.9748±.0028	.9741±.0015	.9762±.0022	.9742±.0033	.9704±.0042
	PTDNet	.9736±.0028	.9657±.0024	.9620±.0027	.9768±.0023	.9735±.0021	.9739±.0022	.9670±.0021	.9631±.0028	.9611±.0058
	Co-teaching	.9617±.0071	.9629±.0047	.9626±.0051	.9624±.0084	.9645±.0027	.9647±.0104	.9684±.0279	.9610±.0139	.9688±.0092
	Peer loss	.9675±.0064	.9646±.0101	.9683±.0037	.9602±.0046	.9621±.0112	.9611±.0078	.9638±.0045	.9626±.0074	.9620±.0089
	Jaccard	.9662±.0063	.9665±.0062	.9697±.0073	.9652±.0130	.9649±.0051	.9616±.0123	.9608±.0076	.9612±.0047	.9603±.0134
	GIB	.9628±.0018	.9639±.0115	.9625±.0208	.9681±.0091	.9643±.0257	.9601±.0285	.9644±.0119	.9688±.0096	.9631±.0113
	SupCon	.9709±.0059	.9611±.0195	.9607±.0032	.9752±.0011	.9721±.0026	.9706±.0022	.9692±.0035	.9701±.0030	.9689±.0057
	GRACE	.7908±.0348	.7829±.0494	.7598±.0693	.7992±.0371	.7960±.0371	.7913±.0418	.7905±.0261	.7985±.0322	.7894±.0340
	RGIB-REP	.9736±.0031	.9668±.0021	.9629±.0026	.9769±.0018	.9752±.0016	.9752±.0018	.9766±.0021	.9753±.0029	.9732±.0041
	RGIB-SSL	.9635±.0037	.9593±.0037	.9536±.0041	.9640±.0062	.9587±.0048	.9545±.0035	.9709±.0015	.9728±.0028	.9719±.0046
L=4	Standard	.9721±.0035	.9652±.0023	.9605±.0031	.9741±.0028	.9686±.0030	.9674±.0027	.9740±.0037	.9738±.0027	.9712±.0047
	DropEdge	.9666±.0031	.9572±.0034	.9469±.0043	.9659±.0028	.9598±.0024	.9496±.0040	.9749±.0024	.9747±.0016	.9718±.0031
	NeuralSparse	.9687±.0027	.9603±.0026	.9536±.0033	.9699±.0025	.9600±.0036	.9502±.0037	.9748±.0022	.9756±.0022	.9727±.0035
	PTDNet	.9707±.0041	.9640±.0031	.9549±.0034	.9708±.0027	.9602±.0025	.9548±.0058	.9754±.0025	.9761±.0021	.9709±.0041
	Co-teaching	.9726±.0096	.9648±.0030	.9639±.0088	.9551±.0037	.9503±.0027	.9566±.0028	.9691±.0039	.9664±.7565	.9622±.0242
	Peer loss	.9745±.0092	.9714±.0088	.9668±.0103	.9637±.0041	.9602±.0088	.9658±.0064	.9549±.0073	.9531±.0096	.9587±.0068
	Jaccard	.9776±.0089	.9692±.0098	.9663±.0112	.9729±.0024	.9677±.0214	.9744±.0012	.9587±.0078	.9519±.0092	.9573±.0137
	GIB	.9600±.0148	.9646±.0041	.9641±.0089	.9639±.0197	.9642±.0189	.9636±.0047	.9646±.0044	.9624±.0103	.9609±.0064
	SupCon	.9644±.0033	.9537±.0106	.9381±.0125	.9675±.0028	.9631±.0042	.9555±.0068	.9594±.0131	.9442±.0136	.9386±.0102
	GRACE	.5429±.0465	.6085±.1132	.6273±.1475	.6178±.0940	.5839±.1022	.6513±.1544	.5534±.0439	.6195±.1055	.6333±.0818
	RGIB-REP	.9704±.0035	.9645±.0027	.9591±.0036	.9713±.0023	.9654±.0046	.9572±.0047	.9741±.0040	.9745±.0028	.9718±.0039
	RGIB-SSL	.9507±.0034	.9432±.0034	.9389±.0059	.9526±.0037	.9451±.0045	.9360±.0083	.9619±.0037	.9645±.0042	.9643±.0038
L=6	Standard	.9659±.0029	.9573±.0036	.9482±.0054	.9644±.0033	.9543±.0075	.9474±.0074	.9722±.0043	.9688±.0055	.9698±.0065
	DropEdge	.9461±.0082	.9295±.0063	.9062±.0218	.9469±.0059	.9293±.0087	.9182±.0063	.9698±.0036	.9689±.0046	.9694±.0037
	NeuralSparse	.9563±.0079	.9391±.0057	.9185±.0157	.9473±.0149	.9338±.0043	.9250±.0037	.9688±.0037	.9705±.0026	.9696±.0063
	PTDNet	.9508±.0075	.9359±.0222	.9288±.0153	.9535±.0082	.9424±.0053	.9332±.0043	.9723±.0033	.9717±.0036	.9697±.0046
	Co-teaching	.9699±.0033	.9627±.0129	.9501±.0141	.9709±.0129	.9569±.0115	.9482±.0155	.9673±.0285	.9698±.0260	.9631±.0176
	Peer loss	.9736±.0116	.9570±.0133	.9485±.0076	.9659±.0060	.9555±.0157	.9469±.0086	.9704±.0136	.9701±.0196	.9682±.0078
	Jaccard	.9680±.0057	.9607±.0055	.9511±.0106	.9815±.0185	.9563±.0145	.9468±.0100	.9750±.0124	.9732±.0093	.9772±.0120
	GIB	.9652±.0138	.9666±.0113	.9612±.0165	.9776±.0272	.9610±.0322	.9624±.0365	.9587±.0079	.9514±.0078	.9585±.0138
	SupCon	.9481±.0185	.9310±.0171	.9015±.0169	.9455±.0267	.9490±.0157	.9194±.0239	.9413±.0206	.9370±.0174	.9241±.0144
	GRACE	.5681±.0785	.5107±.0287	.5147±.0361	.5599±.0776	.5046±.0124	.5167±.0502	.5850±.0827	.5864±.0795	.5518±.0404
	RGIB-REP	.9612±.0042	.9410±.0069	.9258±.0169	.9531±.0054	.9417±.0058	.9313±.0092	.9716±.0049	.9747±.0036	.9707±.0056
	RGIB-SSL	.9367±.0058	.9233±.0046	.9199±.0053	.9418±.0085	.9236±.0056	.9205±.0050	.9576±.0066	.9562±.0079	.9557±.0083

Table 27: Full results on Chameleon dataset with SAGE.

SAGE										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9683±.0036	.9605±.0038	.9536±.0028	.9754±.0019	.9734±.0015	.9762±.0018	.9700±.0019	.9670±.0026	.9603±.0049
	DropEdge	.9604±.0025	.9614±.0028	.9556±.0022	.9677±.0022	.9659±.0030	.9673±.0026	.9630±.0016	.9678±.0033	.9625±.0047
	NeuralSparse	.9669±.0031	.9584±.0029	.9550±.0029	.9751±.0025	.9735±.0022	.9745±.0021	.9705±.0014	.9661±.0031	.9606±.0051
	PTDNet	.9674±.0035	.9594±.0028	.9538±.0019	.9752±.0022	.9637±.0033	.9651±.0029	.9603±.0016	.9658±.0036	.9598±.0042
	Co-teaching	.9581±.0040	.9549±.0110	.9543±.0093	.9453±.0044	.9425±.0083	.9469±.0089	.9585±.0006	.9595±.0039	.9525±.0309
	Peer loss	.9638±.0096	.9581±.0098	.9512±.0021	.9541±.0091	.9561±.0075	.9557±.0104	.9625±.0146	.9506±.0155	.9587±.0227
	Jaccard	.9672±.0074	.9650±.0123	.9589±.0056	.9503±.0007	.9540±.0190	.9517±.0015	.9592±.0010	.9522±.0027	.9545±.0118
	GIB	.9650±.0066	.9593±.0214	.9530±.0021	.9671±.0007	.9606±0.000	.9639±.0275	.9537±.0055	.9523±.0048	.9586±.0068
	SupCon	.9636±.0031	.9656±.0017	.9599±.0041	.9506±.0022	.9585±.0020	.9593±.0019	.9567±.0024	.9530±.0027	.9516±.0037
	GRACE	.8215±.0332	.8327±.0178	.8372±.0245	.8369±.0146	.8251±.0441	.8295±.0422	.8610±.0055	.8583±.0114	.8641±.0137
	RGIB-REP	.9699±.0028	.9626±.0031	.9577±.0034	.9765±.0022	.9741±.0018	.9770±.0014	.9733±.0017	.9715±.0025	.9670±.0037
	RGIB-SSL	.9740±.0030	.9709±.0027	.9686±.0025	.9752±.0020	.9737±.0031	.9741±.0035	.9789±.0016	.9791±.0028	.9781±.0029
L=4	Standard	.9645±.0035	.9580±.0035	.9505±.0010	.9721±.0017	.9721±.0021	.9721±.0016	.9678±.0026	.9641±.0028	.9605±.0051
	DropEdge	.9674±.0041	.9585±.0026	.9516±.0024	.9652±.0029	.9638±.0039	.9652±.0019	.9602±.0021	.9663±.0030	.9614±.0038
	NeuralSparse	.9649±.0022	.9576±.0035	.9495±.0041	.9619±.0032	.9602±.0022	.9620±.0031	.9675±.0017	.9642±.0031	.9603±.0046
	PTDNet	.9651±.0036	.9574±.0034	.9506±.0037	.9624±.0027	.9622±.0015	.9630±.0035	.9687±.0024	.9646±.0025	.9596±.0056
	Co-teaching	.9722±.0090	.9665±.0040	.9582±.0007	.9683±.0083	.9633±.0101	.9613±.0067	.9617±.0255	.9638±.0070	.9637±.0066
	Peer loss	.9543±.0099	.9663±.0044	.9496±.0096	.9610±.0110	.9667±.0086	.9601±.0060	.9657±.0035	.9679±.0026	.9661±.0180
	Jaccard	.9438±.0076	.9485±.0047	.9444±.0069	.9653±.0115	.9683±.0218	.9697±.0157	.9696±.0043	.9537±.0048	.9685±.0088
	GIB	.9557±.0177	.9574±.0043	.9538±.0117	.9644±.0214	.9614±.0204	.9559±.0038	.9576±.0026	.9464±.0080	.9303±.0065
	SupCon	.9494±.0130	.9351±.0093	.9263±.0065	.9592±.0122	.9538±.0122	.9512±.0125	.9478±.0099	.9501±.0126	.9449±.0099
	GRACE	.8040±.0364	.8542±.0415	.8266±.0443	.8362±.0272	.8251±.0484	.8642±.0383	.7462±.0412	.7970±.0306	.7892±.0341
	RGIB-REP	.9665±.0031	.9582±.0035	.9520±.0035	.9740±.0018	.9719±.0028	.9722±.0022	.9690±.0021	.9696±.0023	.9671±.0058
	RGIB-SSL	.9725±.0027	.9682±.0028	.9655±.0049	.9740±.0021	.9707±.0040	.9721±.0044	.9748±.0023	.9762±.0031	.9754±.0040
L=6	Standard	.9606±.0046	.9541±.0058	.9470±.0035	.9679±.0031	.9658±.0041	.9640±.0059	.9673±.0026	.9641±.0038	.9625±.0042
	DropEdge	.9532±.0028	.9540±.0024	.9487±.0043	.9592±.0028	.9582±.0035	.9580±.0299	.9500±.0014	.9561±.0030	.9537±.0024
	NeuralSparse	.9525±.0043	.9383±.0365	.9480±.0036	.9597±.0027	.9569±.0037	.9530±.0057	.9589±.0024	.9552±.0025	.9515±.0034
	PTDNet	.9536±.0042	.9557±.0038	.9483±.0047	.9706±.0035	.9581±.0040	.9459±.0074	.9580±.0024	.9559±.0021	.9429±.0045
	Co-teaching	.9503±.0070	.9466±.0113	.9355±.0039	.9492±.0031	.9457±.0059	.9403±.0118	.9445±.0009	.9465±.0055	.9497±.0115
	Peer loss	.9553±.0064	.9409±.0086	.9330±.0076	.9697±.0084	.9656±.0110	.9652±.0066	.9521±.0210	.9595±.0195	.9589±.0047
	Jaccard	.9416±.0113	.9535±.0116	.9535±.0111	.9610±.0042	.9568±.0210	.9463±.0085	.9518±.0057	.9421±.0032	.9433±.0137
	GIB	.9609±.0173	.9579±.0050	.9568±.0070	.9691±.0315	.9698±.0037	.9592±.0279	.9433±.0065	.9366±.0074	.9347±.0115
	SupCon	.9310±.0107	.9134±.0087	.9178±.0101	.9291±.0114	.9244±.0271	.9181±.0281	.9342±.0132	.9373±.0116	.9313±.0087
	GRACE	.7479±.0742	.7756±.0708	.7718±.0880	.7275±.0906	.7914±.0755	.8109±.0655	.7754±.0258	.7629±.0508	.7686±.0437
	RGIB-REP	.9636±.0022	.9558±.0032	.9455±.0038	.9703±.0022	.9641±.0075	.9607±.0050	.9683±.0013	.9681±.0033	.9664±.0042
	RGIB-SSL	.9665±.0030	.9601±.0045	.9563±.0036	.9662±.0052	.9654±.0040	.9610±.0032	.9699±.0022	.9716±.0033	.9698±.0031

Table 28: Full results on Squirrel dataset with GCN.

GCN										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9621±.0018	.9519±.0020	.9444±.0024	.9610±.0028	.9490±.0031	.9401±.0036	.9744±.0013	.9731±.0010	.9722±.0011
	DropEdge	.9571±.0015	.9480±.0032	.9370±.0028	.9587±.0011	.9486±.0026	.9349±.0026	.9623±.0015	.9612±.0008	.9604±.0014
	NeuralSparse	.9611±.0019	.9528±.0027	.9409±.0023	.9621±.0017	.9495±.0016	.9364±.0022	.9741±.0013	.9724±.0018	.9722±.0010
	PTDNet	.9612±.0018	.9513±.0026	.9424±.0024	.9619±.0016	.9488±.0035	.9363±.0022	.9744±.0011	.9723±.0015	.9718±.0009
	Co-teaching	.9701±.0076	.9535±.0044	.9465±.0059	.9599±.0097	.9525±.0120	.9454±.0109	.9629±.0047	.9666±.0304	.9631±.0004
	Peer loss	.9610±.0015	.9608±.0057	.9451±.0097	.9636±.0107	.9491±.0125	.9436±.0091	.9694±.0012	.9628±.0134	.9676±.0149
	Jaccard	.9613±.0027	.9568±.0046	.9509±.0014	.9622±.0159	.9594±.0111	.9397±.0119	.9528±.0017	.9405±.0089	.9401±.0010
	GIB	.9522±.0195	.9478±.0094	.9489±.0159	.9494±.0260	.9461±.0091	.9432±.0068	.9457±.0099	.9462±.0017	.9492±.0060
	SupCon	.9494±.0013	.9439±.0009	.9458±.0024	.9421±.0008	.9549±.0013	.9489±.0030	.9444±.0011	.9423±.0015	.9318±.0009
	GRACE	.9292±.0011	.9316±.0010	.9330±.0013	.9290±.0012	.9317±.0010	.9327±.0016	.9054±.0018	.9058±.0015	.9052±.0018
	RGIB-REP	.9614±.0019	.9554±.0026	.9471±.0035	.9611±.0021	.9512±.0032	.9392±.0043	.9761±.0015	.9753±.0011	.9745±.0015
	RGIB-SSL	.9571±.0019	.9476±.0029	.9402±.0020	.9534±.0016	.9486±.0027	.9451±.0031	.9752±.0023	.9749±.0019	.9738±.0023
L=4	Standard	.9432±.0036	.9406±.0031	.9386±.0025	.9416±.0042	.9395±.0011	.9411±.0040	.9720±.0016	.9720±.0016	.9710±.0021
	DropEdge	.9439±.0063	.9377±.0024	.9365±.0045	.9426±.0042	.9376±.0033	.9358±.0023	.9608±.0008	.9603±.0013	.9698±.0016
	NeuralSparse	.9494±.0065	.9309±.0028	.9297±.0033	.9469±.0047	.9403±.0028	.9417±.0062	.9633±.0009	.9626±.0016	.9625±.0016
	PTDNet	.9485±.0056	.9326±.0046	.9304±.0048	.9469±.0048	.9400±.0030	.9379±.0026	.9633±.0018	.9623±.0012	.9626±.0012
	Co-teaching	.9461±.0099	.9352±.0064	.9374±.0051	.9462±.0101	.9425±.0032	.9306±.0053	.9675±.0292	.9641±.0115	.9655±.0264
	Peer loss	.9457±.0117	.9345±.0117	.9286±.0044	.9362±.0038	.9386±.0058	.9336±.0043	.9636±.0012	.9694±.0033	.9696±.0006
	Jaccard	.9443±.0047	.9327±.0079	.9244±.0054	.9388±.0179	.9345±.0146	.9240±.0055	.9529±.0029	.9512±.0089	.9501±.0120
	GIB	.9472±.0127	.9329±.0155	.9302±.0202	.9390±.0045	.9406±.0196	.9397±.0249	.9641±.0025	.9628±.0032	.9601±.0042
	SupCon	.9473±.0010	.9348±.0017	.9301±.0029	.9372±.0010	.9343±.0037	.9305±.0033	.9516±.0042	.9595±.0011	.9511±.0040
	GRACE	.9394±.0008	.9380±.0007	.9363±.0016	.9392±.0011	.9378±.0008	.9363±.0017	.9171±.0019	.9174±.0014	.9166±.0013
	RGIB-REP	.9509±.0046	.9455±.0071	.9434±.0059	.9495±.0053	.9432±.0059	.9405±.0050	.9735±.0013	.9733±.0015	.9737±.0009
	RGIB-SSL	.9499±.0040	.9426±.0019	.9425±.0021	.9479±.0051	.9429±.0017	.9429±.0024	.9727±.0015	.9729±.0019	.9726±.0011
L=6	Standard	.9484±.0049	.9429±.0038	.9408±.0039	.9489±.0057	.9408±.0021	.9386±.0022	.9688±.0028	.9675±.0027	.9656±.0034
	DropEdge	.9460±.0063	.9375±.0028	.9349±.0017	.9474±.0057	.9409±.0030	.9365±.0022	.9669±.0022	.9652±.0031	.9638±.0038
	NeuralSparse	.9508±.0049	.9429±.0047	.9391±.0029	.9532±.0060	.9412±.0044	.9388±.0036	.9681±.0020	.9647±.0018	.9671±.0019
	PTDNet	.9535±.0047	.9451±.0050	.9395±.0033	.9514±.0041	.9432±.0068	.9380±.0020	.9690±.0023	.9667±.0035	.9649±.0025
	Co-teaching	.9480±.0144	.9454±.0074	.9463±.0076	.9538±.0051	.9424±.0048	.9379±.0012	.9672±.0179	.9694±.0283	.9654±.0195
	Peer loss	.9539±.0051	.9420±.0127	.9405±.0060	.9445±.0139	.9446±.0012	.9462±.0081	.9684±.0182	.9639±.0188	.9624±.0189
	Jaccard	.9519±.0138	.9459±.0100	.9398±.0115	.9483±.0070	.9429±.0203	.9428±.0105	.9697±.0074	.9687±.0062	.9673±.0077
	GIB	.9447±.0103	.9459±.0026	.9410±.0108	.9431±.0289	.9413±.0301	.9386±.0238	.9633±.0041	.9619±.0114	.9612±.0064
	SupCon	.9590±.0023	.9507±.0019	.9463±.0028	.9580±.0024	.9519±.0018	.9464±.0026	.9638±.0051	.9524±.0048	.9419±.0012
	GRACE	.9399±.0007	.9372±.0006	.9348±.0017	.9397±.0012	.9370±.0009	.9349±.0017	.9213±.0017	.9218±.0013	.9211±.0014
	RGIB-REP	.9556±.0028	.9492±.0060	.9463±.0063	.9570±.0018	.9496±.0060	.9420±.0056	.9677±.0029	.9676±.0031	.9662±.0018
	RGIB-SSL	.9462±.0029	.9471±.0020	.9448±.0032	.9509±.0032	.9474±.0017	.9449±.0030	.9642±.0012	.9659±.0027	.9647±.0010

Table 29: Full results on Squirrel dataset with GAT.

GAT										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9680±.0007	.9635±.0017	.9588±.0025	.9702±.0008	.9690±.0010	.9659±.0014	.9719±.0018	.9701±.0017	.9686±.0012
	DropEdge	.9619±.0014	.9567±.0020	.9505±.0022	.9627±.0008	.9593±.0014	.9551±.0012	.9684±.0015	.9662±.0026	.9661±.0018
	NeuralSparse	.9656±.0009	.9602±.0012	.9533±.0019	.9662±.0011	.9629±.0010	.9584±.0017	.9709±.0012	.9692±.0014	.9685±.0009
	PTDNet	.9655±.0011	.9602±.0012	.9546±.0024	.9668±.0010	.9630±.0015	.9603±.0021	.9610±.0015	.9698±.0012	.9689±.0016
	Co-teaching	.9566±.0034	.9562±.0066	.9516±.0026	.9505±.0045	.9509±.0092	.9509±.0046	.9591±.0293	.9880±.0174	.9360±.0089
	Peer loss	.9720±.0097	.9726±.0039	.9682±.0106	.9706±6.649	.9715±.0064	.9704±.0107	.9681±.0121	.9635±.0069	.9683±.0116
	Jaccard	.9715±.0098	.9651±.0053	.9648±.0094	.9807±.0202	.9768±.0041	.9645±.0174	.9637±.0081	.9668±.0104	.9627±.0002
	GIB	.9727±.0019	.9820±.0058	.9610±.0069	.9780±0.001	.9965±0.000	.9838±.0123	.9660±.0067	.9611±.0022	.9679±.0061
	SupCon	.9471±.0019	.9386±.0022	.9353±.0026	.9539±.0032	.9463±.0026	.9411±.0034	.9629±.0028	.9631±.0019	.9636±.0021
	GRACE	.7300±.1193	.7583±.1135	.7015±.1383	.7494±.1101	.6903±.1807	.7032±.1659	.8109±.0382	.7780±.1044	.7608±.0620
	RGIB-REP	.9675±.0014	.9631±.0012	.9587±.0023	.9692±.0007	.9660±.0013	.9632±.0016	.9735±.0012	.9719±.0013	.9715±.0010
	RGIB-SSL	.9453±.0020	.9421±.0017	.9385±.0022	.9418±.0024	.9394±.0033	.9362±.0023	.9726±.0007	.9705±.0037	.9695±.0024
L=4	Standard	.9581±.0046	.9436±.0063	.9335±.0062	.9592±.0047	.9455±.0075	.9415±.0061	.9682±.0030	.9690±.0028	.9686±.0021
	DropEdge	.9501±.0041	.9340±.0046	.9234±.0059	.9476±.0054	.9354±.0067	.9292±.0039	.9529±.0047	.9513±.0054	.9510±.0037
	NeuralSparse	.9524±.0041	.9383±.0046	.9320±.0044	.9401±.0071	.9377±.0045	.9334±.0041	.9559±.0031	.9555±.0032	.9556±.0022
	PTDNet	.9416±.0054	.9310±.0059	.9302±.0032	.9447±.0031	.9393±.0053	.9305±.0131	.9574±.0039	.9557±.0025	.9552±.0042
	Co-teaching	.9324±.0109	.9024±.0120	.9029±.0126	.9421±.0074	.9345±.0126	.9371±.0091	.9576±.0124	.9592±.0064	.9551±.0087
	Peer loss	.9520±.0071	.9506±.0145	.9370±.0140	.9560±.0063	.9451±.0086	.9448±.0142	.9548±.0128	.9500±.0088	.9593±.0134
	Jaccard	.9561±.0133	.9423±.0160	.9396±.0117	.9578±.0185	.9583±.0256	.9558±.0050	.9572±.0074	.9572±.0083	.9554±.0089
	GIB	.9353±.0080	.9271±.0093	.9098±.0079	.9545±.0156	.9504±.0240	.9530±.0348	.9544±.0023	.9549±.0073	.9524±.0060
	SupCon	.9397±.0044	.9322±.0038	.9266±.0047	.9365±.0039	.9340±.0021	.9314±.0029	.9574±.0019	.9557±.0065	.9556±.0049
	GRACE	.5710±.1110	.5658±.1143	.6203±.1324	.5694±.1202	.5771±.0945	.6021±.1203	.5291±.0694	.5097±.0139	.5029±.0072
	RGIB-REP	.9541±.0059	.9432±.0059	.9316±.0063	.9526±.0037	.9401±.0072	.9389±.0056	.9681±.0028	.9672±.0029	.9660±.0048
	RGIB-SSL	.9347±.0038	.9321±.0031	.9260±.0032	.9321±.0022	.9327±.0020	.9270±.0028	.9592±.0031	.9651±.0014	.9641±.0021
L=6	Standard	.9507±.0050	.9309±.0164	.9254±.0089	.9487±.0065	.9419±.0041	.9255±.0073	.9585±.0097	.9520±.0070	.9507±.0162
	DropEdge	.9347±.0049	.9279±.0118	.9181±.0078	.9368±.0082	.9262±.0076	.9175±.0127	.9412±.0092	.9431±.0076	.9444±.0090
	NeuralSparse	.9399±.0088	.9279±.0167	.9224±.0051	.9423±.0063	.9342±.0023	.9213±.0115	.9468±.0118	.9474±.0102	.9504±.0051
	PTDNet	.9433±.0105	.9348±.0072	.9213±.0100	.9460±.0048	.9340±.0052	.9273±.0094	.9482±.0088	.9541±.0092	.9453±.0077
	Co-teaching	.9219±.0059	.9329±.0231	.9229±.0185	.9392±.0093	.9352±.0098	.9261±.0100	.9496±.0383	.9445±.0272	.9490±.0284
	Peer loss	.9300±.0136	.9316±.0220	.9349±.0147	.9271±.0119	.9170±.0117	.9057±.0127	.9230±.0221	.9341±.0113	.9187±.0325
	Jaccard	.9577±.0112	.9374±.0225	.9297±.0158	.9469±.0111	.9406±.0111	.9309±.0168	.9393±.0153	.9390±.0151	.9314±.0223
	GIB	.9504±.0239	.9475±.0221	.9445±.0127	.9484±.0211	.9487±.0139	.9438±.0307	.9421±.0133	.9484±.0101	.9486±.0206
	SupCon	.9269±.0089	.9174±.0092	.9107±.0052	.9278±.0057	.9223±.0054	.9210±.0038	.9140±.0072	.9173±.0085	.9182±.0081
	GRACE	.5003±.0009	.5427±.0961	.6004±.1210	.5657±.1221	.6023±.0931	.5342±.0684	.5064±.0145	.5017±.0031	.5074±.0190
	RGIB-REP	.9404±.0067	.9248±.0161	.9218±.0051	.9437±.0084	.9299±.0070	.9238±.0063	.9473±.0071	.9486±.0073	.9397±.0045
	RGIB-SSL	.9286±.0033	.9241±.0055	.9165±.0055	.9276±.0023	.9245±.0015	.9257±.0037	.9593±.0043	.9586±.0027	.9499 ±.0067

Table 30: Full results on Squirrel dataset with SAGE.

SAGE										
layers	method	mixed noise 20%	mixed noise 40%	mixed noise 60%	input noise 20%	input noise 40%	input noise 60%	label noise 20%	label noise 40%	label noise 60%
L=2	Standard	.9680±.0015	.9626±.0015	.9570±.0016	.9737±.0010	.9736±.0010	.9721±.0011	.9692±.0015	.9643±.0012	.9606±.0017
	DropEdge	.9657±.0011	.9602±.0015	.9535±.0020	.9622±.0010	.9625±.0009	.9609±.0020	.9593±.0009	.9530±.0009	.9593±.0007
	NeuralSparse	.9572±.0008	.9517±.0012	.9562±.0019	.9534±.0007	.9534±.0010	.9521±.0016	.9589±.0012	.9534±.0009	.9591±.0010
	PTDNet	.9578±.0009	.9513±.0013	.9559±.0021	.9630±.0010	.9504±.0007	.9524±.0010	.9596±.0014	.9529±.0010	.9596±.0019
	Co-teaching	.9526±.0031	.9560±.0071	.9526±.0029	.9403±.0050	.9585±.0061	.9585±.0101	.9533±.0022	.9533±.0306	.9539±.0026
	Peer loss	.9552±.0079	.9507±.0050	.9588±.0066	.9512±.0052	.9534±.0019	.9599±.0013	.9525±.0105	.9555±.0178	.9510±.0187
	Jaccard	.9658±.0111	.9619±.0068	.9630±.0027	.9600±.0189	.9649±.0173	.9617±.0171	.9620±.0105	.9608±.0068	.9603±.0044
	GIB	.9656±.0079	.9660±.0077	.9661±.0060	.9632±.0260	.9517±.0213	.9565±.0010	.9565±.0009	.9593±.0002	.9548±.0111
	SupCon	.9628±.0015	.9541±.0019	.9409±.0040	.9585±.0061	.9585±.0101	.9533±.0022	.9533±.0306	.9539±.0026	.9400±.0021
	GRACE	.8543±.0076	.8572±.0094	.8528±.0166	.8563±.0068	.8601±.0087	.8528±.0075	.8477±.0119	.8459±.0105	.8452±.0141
	RGIB-REP	.9701±.0010	.9647±.0014	.9597±.0018	.9757±.0009	.9747±.0007	.9737±.0011	.9735±.0010	.9707±.0007	.9682±.0016
	RGIB-SSL	.9536±.0016	.9480±.0027	.9448±.0030	.9734±.0014	.9739±.0015	.9803±.0024	.9765±.0021	.9702±.0015	.9694±.0005
L=4	Standard	.9584±.0107	.9577±.0076	.9541±.0021	.9637±.0092	.9630±.0079	.9607±.0090	.9663±.0020	.9612±.0049	.9612±.0020
	DropEdge	.9518±.0030	.9577±.0021	.9515±.0033	.9656±.0051	.9612±.0093	.9573±.0111	.9683±.0020	.9628±.0014	.9608±.0012
	NeuralSparse	.9604±.0083	.9570±.0040	.9513±.0040	.9644±.0066	.9599±.0084	.9605±.0061	.9652±.0035	.9632±.0023	.9605±.0021
	PTDNet	.9624±.0050	.9581±.0039	.9536±.0033	.9667±.0045	.9668±.0057	.9649±.0052	.9675±.0043	.9635±.0040	.9607±.0026
	Co-teaching	.9518±.0181	.9468±.0093	.9479±.0024	.9525±.0086	.9577±.0159	.9528±.0137	.9625±.0244	.9610±.0220	.9675±.0097
	Peer loss	.9632±.0196	.9662±.0085	.9602±.0088	.9674±.0145	.9626±.0120	.9643±.0145	.9637±.0004	.9617±.0170	.9691±.0016
	Jaccard	.9622±.0135	.9606±.0157	.9587±.0105	.9647±.0084	.9630±.0253	.9640±.0278	.9505±.0026	.9508±.0063	.9599±.0039
	GIB	.9527±.0122	.9538±.0275	.9531±.0174	.9603±.0081	.9620±.0115	.9580±.0330	.9598±.0031	.9523±.0064	.9559±.0091
	SupCon	.9478±.0042	.9412±.0059	.9342±.0039	.9267±.0045	.9368±.0028	.9249±.0026	.9375±.0034	.9335±.0012	.9317±.0021
	GRACE	.8859±.0115	.8751±.0085	.8609±.0212	.8824±.0113	.8805±.0261	.8633±.0178	.8386±.0130	.8466±.0103	.8347±.0180
	RGIB-REP	.9611±.0058	.9578±.0035	.9536±.0037	.9682±.0049	.9667±.0051	.9584±.0074	.9689±.0014	.9664±.0027	.9635±.0022
	RGIB-SSL	.9498±.0032	.9443±.0047	.9422±.0044	.9531±.0071	.9599±.0023	.9551±.0019	.9623±.0021	.9603±.0087	.9601±.0091
L=6	Standard	.9555±.0065	.9528±.0038	.9461±.0054	.9592±.0053	.9600±.0036	.9551±.0042	.9574±.0192	.9540±.0207	.9583±.0023
	DropEdge	.9544±.0069	.9411±.0200	.9463±.0041	.9566±.0070	.9473±.0172	.9519±.0052	.9464±.0023	.9402±.0084	.9396±.0025
	NeuralSparse	.9563±.0060	.9515±.0036	.9457±.0054	.9591±.0046	.9460±.0052	.9415±.0061	.9371±.0025	.9344±.0017	.9319±.0033
	PTDNet	.9565±.0060	.9524±.0050	.9463±.0056	.9593±.0045	.9584±.0044	.9492±.0038	.9384±.0023	.9342±.0018	.9236±.0018
	Co-teaching	.9423±.0071	.9396±.0126	.9251±.0137	.9382±.0063	.9433±.0054	.9388±.0088	.9344±.0232	.9496±.0204	.9374±.0083
	Peer loss	.9473±.0108	.9371±.0040	.9333±.0084	.9339±.0053	.9312±.0058	.9331±.0066	.9396±.0211	.9375±.0195	.9335±.0035
	Jaccard	.9335±.0058	.9305±.0057	.9225±.0146	.9309±.0059	.9386±.0084	.9433±.0147	.9348±.0200	.9210±.0285	.9273±.0029
	GIB	.9437±.0258	.9323±.0155	.9204±.0182	.9492±.0239	.9406±.0137	.9322±.0335	.9407±.0269	.9364±.0274	.9394±.0079
	SupCon	.9392±.0049	.9330±.0098	.9221±.0138	.9266±.0024	.9313±.0102	.9309±.0052	.9264±.0021	.9202±.0084	.9196±.0021
	GRACE	.8418±.0983	.8470±.0823	.8732±.0151	.8747±.0151	.8126±.1348	.8716±.0148	.8385±.0097	.8370±.0295	.8487±.0121
	RGIB-REP	.9558±.0047	.9474±.0066	.9455±.0052	.9583±.0044	.9566±.0035	.9447±.0030	.9662±.0057	.9646±.0021	.9634±.0030
	RGIB-SSL	.9437±.0026	.9391±.0036	.9366±.0042	.9441±.0064	.9549±.0012	.9469±.0012	.9678±.0031	.9613±.0076	.9601±.0041