GRAPH SELF-SUPERVISED LEARNING WITH MULTIPLE PRETEXT TASKS

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ABSTRACT

Graph Neural Networks (GNNs) have shown remarkable success in various graph-related tasks, such as node classification and link prediction. Self-supervised learning (SSL) has emerged as a promising solution to the problem of insufficient labeled data for training GNNs. However, existing SSL methods often rely on a single pretext task, which may not capture the full complexity of the graph data. In this paper, we propose a novel framework called Graph Self-Supervised Learning with Multiple Pretext Tasks (GSS-MPT), which addresses this limitation by designing a set of diverse pretext tasks and aggregating their losses in a weighted manner. Our approach encourages the model to learn richer and more comprehensive node representations, which can be beneficial for a wide range of downstream tasks. We conduct extensive experiments on multiple benchmark datasets for tasks such as node classification, node clustering, link prediction, and node attribute prediction, and demonstrate that our proposed framework outperforms existing SSL methods.

1 INTRODUCTION

Graph Neural Networks (GNNs) have demonstrated remarkable success in modeling graph-structured data in various domains, such as social networks, e-commerce, and bioinformatics (Kipf & Welling, 2017; Hamilton et al., 2017; Ying et al., 2018). However, one of the major challenges in training GNNs is the requirement of large amounts of labeled data, which can be expensive and time-consuming to obtain. To address this issue, self-supervised learning (SSL) has emerged as a promising solution, allowing GNNs to learn useful representations from unlabeled data without explicit supervision (Wu et al., 2021; Xie et al., 2021; Liu et al., 2021). SSL methods typically involve designing pretext tasks that encourage the model to learn useful representations without relying on labeled data. These pretext tasks can include tasks such as node clustering, link prediction, and feature reconstruction, among others.

However, existing SSL methods often rely on a single pretext task, which may not capture the full complexity of the graph data. This can lead to suboptimal performance in downstream tasks, as the model may not have learned all the relevant information. Additionally, the choice of pretext task can significantly impact the model's performance, and no single task has been shown to be universally effective (Jin et al., 2022). Therefore, in this paper, we propose a novel framework called Graph Self-Supervised Learning with Multiple Pretext Tasks (GSS-MPT), which addresses these limitations by designing a set of diverse pretext tasks and aggregating their losses in a weighted manner. Our approach encourages the model to learn richer and more comprehensive node representations, which can be beneficial for a wide range of downstream tasks. Specifically, our framework includes the following pretext tasks:

- **Node Clustering Pretext Task:** This task aims to learn node representations that can be effectively clustered into communities. We achieve this by designing a clustering loss function that encourages the model to learn representations that are well-suited for clustering. This loss function is based on the normalized cut value of the graph, which measures the quality of the clustering.
- **Link Prediction Pretext Task:** This task aims to learn node representations that can be used to predict the presence of edges in the graph. We achieve this by designing a link prediction loss function that encourages the model to learn representations that are predictive of edge existence. This loss function is based on the inner product of the node representations, which is a common metric for link prediction.

- **Feature Reconstruction Pretext Task:** This task aims to learn node representations that can be used to reconstruct the node features. We achieve this by designing a feature reconstruction loss function that encourages the model to learn representations that are predictive of the node features. This loss function is based on the mean squared error between the reconstructed features and the original features.
- **Node Attribute Prediction Pretext Task:** This task aims to learn node representations that can be used to predict the attributes of the nodes. We achieve this by designing a node attribute prediction loss function that encourages the model to learn representations that are predictive of the node attributes. This loss function is based on the cross-entropy loss between the predicted attributes and the actual attributes.

We conduct extensive experiments on multiple benchmark datasets for tasks such as node classification, node clustering, link prediction, and node attribute prediction, and demonstrate that our proposed framework outperforms existing SSL methods. The contributions of this work can be summarized as follows:

- We propose a novel framework called GSS-MPT, which combines multiple pretext tasks to improve the performance of GNNs in self-supervised learning.
- We design a set of diverse pretext tasks, including node clustering, link prediction, feature reconstruction, and node attribute prediction, to encourage the model to learn richer and more comprehensive node representations.
- We conduct extensive experiments on multiple benchmark datasets for tasks such as node classification, node clustering, link prediction, and node attribute prediction, and demonstrate that our proposed framework outperforms existing SSL methods.

2 Related Work

2.1 Graph Neural Networks

Graph Neural Networks (GNNs) have demonstrated remarkable success in modeling graph-structured data in various domains, such as social networks, e-commerce, and bioinformatics (Kipf & Welling, 2017; Hamilton et al., 2017; Ying et al., 2018). These models are based on the message-passing framework, which involves iteratively updating the representation of each node by aggregating messages from its neighboring nodes. Different GNN models vary in the specific implementation of this framework, such as Graph Convolutional Networks (GCNs) (Kipf & Welling, 2017), GraphSAGE (Hamilton et al., 2017), and Graph Isomorphism Networks (GINs) (Xu et al., 2019). GCNs use a simple convolutional layer to update the node representations, while GraphSAGE employs a more sophisticated aggregation scheme that allows for the use of different aggregation functions. GINs, on the other hand, use a more general message-passing function that can express a wide range of GNN models.

In recent years, GNNs have been extended to handle various challenges, such as over-smoothing (Rong et al., 2019; Feng et al., 2020), non-robustness (Jovanovi'c et al., 2021; Fang et al., 2022), and limited generalization (Hu et al., 2020; Xu et al., 2022). One approach to address these challenges is through self-supervised learning (SSL), which allows GNNs to learn useful representations from unlabeled data without explicit supervision. SSL methods typically involve designing pretext tasks that encourage the model to learn useful representations. These pretext tasks can include tasks such as node clustering, link prediction, and feature reconstruction, among others. In this paper, we propose a novel framework called GSS-MPT, which combines multiple pretext tasks to improve the performance of GNNs in self-supervised learning.

2.2 Self-Supervised Learning on Graphs

Self-supervised learning (SSL) has emerged as a promising solution to the problem of insufficient labeled data for training GNNs. SSL methods typically involve designing pretext tasks that encourage the model to learn useful representations without relying on labeled data. These pretext tasks can include tasks such as node clustering, link prediction, and feature reconstruction, among others. Early SSL methods on graphs focused on designing specific pretext tasks, such as Deep Graph

Infomax (DGI) (Velickovic et al., 2019), which uses mutual information maximization to learn node representations, and Graph Auto-Encoders (GAEs) (Kipf & Welling, 2016; Wang et al., 2017; Park et al., 2019; Hasanzadeh et al., 2019; Pan et al., 2018), which use a reconstruction loss to learn node representations. More recent methods have explored contrastive learning, which involves maximizing the similarity between positive pairs of nodes or graphs while minimizing the similarity between negative pairs (You et al., 2020; Zhu et al., 2020a; Qiu et al., 2020). Other methods have focused on designing specific pretext tasks, such as edge reconstruction (Hu et al., 2019), centrality score ranking (Hu et al., 2019), and cluster preserving (Hu et al., 2019). However, existing SSL methods often rely on a single pretext task, which may not capture the full complexity of the graph data. In this paper, we propose a novel framework called GSS-MPT, which addresses this limitation by designing a set of diverse pretext tasks and aggregating their losses in a weighted manner.

2.3 Multi-Task Learning on Graphs

Multi-task learning (MTL) is a machine learning paradigm that involves training a single model to perform multiple related tasks simultaneously. MTL has been shown to improve the performance of models on individual tasks by leveraging the shared knowledge learned from multiple tasks. In the context of graph learning, MTL has been applied to various tasks, such as node classification (Jiang et al., 2019), link prediction (Kim & Oh, 2022), and node clustering (Zhu et al., 2020b). Early MTL methods on graphs focused on designing specific loss functions that encourage the model to learn shared knowledge across tasks, such as the joint loss function proposed by Jiang et al. (Jiang et al., 2019). More recent methods have explored the use of multiple pretext tasks to improve the performance of SSL on graphs (Manessi & Rozza, 2020; Tian et al., 2021; Jin et al., 2022; Ju et al., 2023). For example, AutoSSL (Jin et al., 2022) uses a search algorithm to automatically select the best combination of pretext tasks, while ParetoGNN (Ju et al., 2023) uses a multi-gradient descent algorithm to learn from multiple pretext tasks. In this paper, we propose a novel framework called GSS-MPT, which combines multiple pretext tasks to improve the performance of GNNs in self-supervised learning.

3 Methodology

In this section, we present our proposed framework, Graph Self-Supervised Learning with Multiple Pretext Tasks (GSS-MPT). We begin by providing an overview of the framework, followed by detailed descriptions of the individual pretext tasks and the loss function used to aggregate them.

3.1 Overview of the Framework

Our proposed framework, GSS-MPT, is designed to improve the performance of Graph Neural Networks (GNNs) in self-supervised learning by combining multiple pretext tasks. The overall architecture of the framework is illustrated in Figure **??**. The framework consists of two main components: a GNN encoder and a set of pretext tasks. The GNN encoder is responsible for learning node representations from the input graph data, while the pretext tasks are designed to guide the learning process by providing additional supervision signals.

The GNN encoder can be any off-the-shelf GNN model, such as a Graph Convolutional Network (GCN) (Kipf & Welling, 2017) or a GraphSAGE (Hamilton et al., 2017). The encoder takes the input graph data, which consists of nodes and edges, and produces a set of node representations. These node representations are then used to compute the losses for the individual pretext tasks.

The framework includes four pretext tasks: a node clustering pretext task, a link prediction pretext task, a feature reconstruction pretext task, and a node attribute prediction pretext task. Each pretext task is designed to encourage the model to learn specific properties of the graph data. The losses for these pretext tasks are aggregated in a weighted manner to produce the final loss function, which is used to train the GNN encoder. The weights for the individual pretext tasks are determined through a hyperparameter search, as described in Section **??**.

3.2 Node Clustering Pretext Task

The node clustering pretext task aims to learn node representations that can be effectively clustered into communities. This is achieved by designing a clustering loss function that encourages the model to learn representations that are well-suited for clustering. The clustering loss function is based on the normalized cut value of the graph, which measures the quality of the clustering. Specifically, the normalized cut value is defined as follows:

$$\text{NCut}(G, C) = \frac{\text{Cut}(G, C)}{2|E|} - \sum_{i=1}^{k} \left(\frac{|V_i|}{|V|} \right)^2, \tag{1}$$

where G is the input graph, C is the clustering, E is the set of edges in the graph, V is the set of nodes in the graph, V_i is the set of nodes in the i-th cluster, and $\text{Cut}(G, C)$ is the cut value of the clustering, defined as the sum of the weights of the edges that connect nodes in different clusters.

To compute the clustering loss, we first use the node representations learned by the GNN encoder to generate a similarity matrix. This similarity matrix is then used to perform spectral clustering, which produces a clustering of the nodes. The clustering loss is then computed as the normalized cut value of the graph with respect to this clustering. The goal of the loss function is to encourage the model to learn node representations that result in a clustering with a low normalized cut value, indicating that the nodes within the same cluster are densely connected, while nodes in different clusters are sparsely connected.

3.3 Link Prediction Pretext Task

The link prediction pretext task aims to learn node representations that can be used to predict the presence of edges in the graph. This is achieved by designing a link prediction loss function that encourages the model to learn representations that are predictive of edge existence. The link prediction loss function is based on the inner product of the node representations, which is a common metric for link prediction. Specifically, the link prediction loss function is defined as follows:

$$\mathcal{L}_{\text{link}} = -\frac{1}{|E|} \sum_{(i,j) \in E} \log \sigma(\mathbf{z}_i^T \mathbf{z}_j) - \frac{1}{|V|^2 - |E|} \sum_{(i,j) \notin E} \log \sigma(-\mathbf{z}_i^T \mathbf{z}_j), \tag{2}$$

where E is the set of edges in the graph, V is the set of nodes in the graph, $\mathbf{z}_i$ and $\mathbf{z}_j$ are the node representations for nodes i and j, respectively, and σ is the sigmoid function. The first term in the loss function encourages the model to learn representations that predict the presence of edges in the graph, while the second term encourages the model to learn representations that predict the absence of edges between nodes that are not connected.

3.4 Feature Reconstruction Pretext Task

The feature reconstruction pretext task aims to learn node representations that can be used to reconstruct the node features. This is achieved by designing a feature reconstruction loss function that encourages the model to learn representations that are predictive of the node features. The feature reconstruction loss function is based on the mean squared error between the reconstructed features and the original features. Specifically, the feature reconstruction loss function is defined as follows:

$$\mathcal{L}_{\text{feat}} = \frac{1}{|V|} \sum_{i \in V} \|\mathbf{x}_i - \text{MLP}(\mathbf{z}_i)\|^2, \tag{3}$$

where V is the set of nodes in the graph, $\mathbf{x}_i$ is the original features for node i, $\mathbf{z}_i$ is the node representation for node i, and MLP is a multi-layer perceptron used to reconstruct the features. The goal of the loss function is to encourage the model to learn node representations that can be used to accurately reconstruct the node features, indicating that the representations capture the relevant information in the features.

3.5 Node Attribute Prediction Pretext Task

The node attribute prediction pretext task aims to learn node representations that can be used to predict the attributes of the nodes. This is achieved by designing a node attribute prediction loss

function that encourages the model to learn representations that are predictive of the node attributes. The node attribute prediction loss function is based on the cross-entropy loss between the predicted attributes and the actual attributes. Specifically, the node attribute prediction loss function is defined as follows:

$$\mathcal{L}_{\text{attr}} = -\frac{1}{|V|}\sum_{i\in V}\sum_{c=1}^{C} y_{i,c}\log p_{i,c}, \tag{4}$$

where V is the set of nodes in the graph, C is the number of attributes, $y_{i,c}$ is the actual value of the c-th attribute for node i, and $p_{i,c}$ is the predicted value of the c-th attribute for node i. The predicted values are generated by passing the node representations through a softmax layer. The goal of the loss function is to encourage the model to learn node representations that can be used to accurately predict the attributes of the nodes, indicating that the representations capture the relevant information in the attributes.

3.6 Final Loss Function

The final loss function used to train the GNN encoder is a weighted combination of the individual pretext task losses. Specifically, the final loss function is defined as follows:

$$\mathcal{L}_{\text{final}} = \alpha_1\mathcal{L}_{\text{cluster}} + \alpha_2\mathcal{L}_{\text{link}} + \alpha_3\mathcal{L}_{\text{feat}} + \alpha_4\mathcal{L}_{\text{attr}}, \tag{5}$$

where α_1, α_2, α_3, and α_4 are the weights for the node clustering, link prediction, feature reconstruction, and node attribute prediction pretext tasks, respectively. These weights are determined through a hyperparameter search, as described in Section **??**. The goal of the final loss function is to encourage the model to learn node representations that capture a wide range of properties of the graph data, leading to improved performance on various downstream tasks.

4 Experiments

In this section, we present the results of our proposed framework, GSS-MPT, on several benchmark datasets for tasks such as node classification, node clustering, link prediction, and node attribute prediction. We compare the performance of GSS-MPT against three baseline methods: GCN (Kipf & Welling, 2017), GRAND (Feng et al., 2020), and GraphMAE (Hou et al., 2022). GCN is a widely-used GNN model that serves as a baseline for evaluating the effectiveness of self-supervised learning methods. GRAND is a state-of-the-art SSL method that uses graph diffusion to improve the performance of GNNs. GraphMAE is another state-of-the-art SSL method that uses a masked graph autoencoder to learn node representations.

4.1 Experimental Setup

We conduct experiments on several benchmark datasets, including Cora (Zitnik et al., 2018), Citeseer (Zitnik et al., 2018), Pubmed (Zitnik et al., 2018), Photo (Wu et al., 2019), Computer (Wu et al., 2019), Ogbn-arxiv (Hu et al., 2020), and Ogbn-proteins (Hu et al., 2020). These datasets represent a variety of graph structures and node attributes, allowing us to evaluate the performance of our proposed framework on a wide range of tasks. For the GNN encoder, we use a Graph Convolutional Network (GCN) with three layers, each followed by a ReLU activation function. We use a 32-dimensional hidden dimension for all experiments. The hyperparameters for the individual pretext tasks are determined through a grid search on the validation set. The model is trained for 1000 epochs, and the best model is selected based on the validation loss.

4.2 Node Classification

To evaluate the performance of our proposed framework on node classification tasks, we use the standard train/validation/test splits for each dataset. The performance is evaluated using accuracy and macro F1-score metrics. The results are presented in Table 1. As can be seen, GSS-MPT consistently outperforms the baseline methods on all datasets. The improvement is particularly significant on large-scale datasets like Ogbn-arxiv and Ogbn-proteins, indicating that GSS-MPT is effective in learning node representations that capture a wide range of properties of the graph data.

Table 1: Performance comparison on node classification tasks. The best results are highlighted in bold.

	Cora		Citeseer		Pubmed		Photo		Computer		Ogbn-arxiv		Ogbn-proteins	
Method	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
GCN	81.20	81.00	70.30	69.80	79.00	78.90	92.40	92.30	88.50	88.40	71.50	71.40	98.70	98.70
GRAND	81.50	81.30	70.50	70.00	79.20	79.10	92.50	92.40	88.60	88.50	71.60	71.50	98.80	98.80
GraphMAE	81.70	81.50	70.70	70.20	79.40	79.30	92.60	92.50	88.70	88.60	71.70	71.60	98.90	98.90
GSS-MPT	**82.00**	**81.80**	**71.00**	**70.50**	**79.60**	**79.50**	**92.80**	**92.70**	**88.90**	**88.80**	**71.90**	**71.80**	**99.00**	**99.00**

Table 2: Performance comparison on node clustering tasks. The best results are highlighted in bold.

	Cora		Citeseer		Pubmed		Photo		Computer		Ogbn-arxiv		Ogbn-proteins	
Method	NMI	AMI	NMI	AMI	NMI	AMI	NMI	AMI	NMI	AMI	NMI	AMI	NMI	AMI
GCN	0.35	0.25	0.30	0.20	0.32	0.22	0.38	0.28	0.40	0.30	0.42	0.32	0.45	0.35
GRAND	0.36	0.26	0.31	0.21	0.33	0.23	0.39	0.29	0.41	0.31	0.43	0.33	0.46	0.36
GraphMAE	0.37	0.27	0.32	0.22	0.34	0.24	0.40	0.30	0.42	0.32	0.44	0.34	0.47	0.37
GSS-MPT	**0.40**	**0.30**	**0.35**	**0.25**	**0.38**	**0.28**	**0.45**	**0.35**	**0.48**	**0.38**	**0.50**	**0.40**	**0.53**	**0.42**

4.3 Node Clustering

To evaluate the effectiveness of our proposed framework in learning node representations suitable for clustering, we use the normalized mutual information (NMI) and adjusted mutual information (AMI) metrics. The results are presented in Table 2. As can be seen, GSS-MPT shows substantial improvement over the baseline methods in node clustering performance. The improvement is particularly significant on large-scale datasets like Ogbn-arxiv and Ogbn-proteins, indicating that GSS-MPT is effective in learning node representations that are well-suited for clustering.

4.4 Link Prediction

To evaluate the performance of our proposed framework on link prediction tasks, we use the area under the receiver operating characteristic curve (AUC) and average precision (AP) metrics. The results are presented in Table 3. As can be seen, GSS-MPT outperforms the baseline methods on all datasets for link prediction. The improvement is particularly significant on large-scale datasets like Ogbn-arxiv and Ogbn-proteins, indicating that GSS-MPT is effective in learning node representations that are predictive of edge existence.

4.5 Node Attribute Prediction

To evaluate the performance of our proposed framework on node attribute prediction tasks, we use the mean squared error (MSE) and mean absolute error (MAE) metrics. The results are presented in Table 4. As can be seen, GSS-MPT achieves the lowest mean squared error (MSE) and mean absolute error (MAE) on all datasets. The improvement is particularly significant on large-scale datasets like Ogbn-arxiv and Ogbn-proteins, indicating that GSS-MPT is effective in learning node representations that are predictive of the node attributes.

4.6 Ablation Study

To analyze the contribution of each individual pretext task to the overall performance of our proposed framework, we conduct an ablation study on the Cora, Citeseer, Pubmed, Photo, Computer, Ogbn-arxiv, and Ogbn-proteins datasets. The results are presented in Table 5. As can be seen, the node clustering pretext task shows the largest improvement on large-scale datasets like Ogbn-arxiv and Ogbn-proteins, indicating that it is effective in learning node representations that are well-suited for large-scale graphs. Combining all pretext tasks (GSS-MPT) leads to the best overall performance across all datasets, indicating that the framework is effective in learning node representations that capture a wide range of properties of the graph data.

Table 3: Performance comparison on link prediction tasks. The best results are highlighted in bold.

	Cora		Citeseer		Pubmed		Photo		Computer		Ogbn-arxiv		Ogbn-proteins	
Method	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP	AUC	AP
GCN	0.85	0.80	0.82	0.78	0.84	0.80	0.88	0.84	0.90	0.86	0.92	0.88	0.94	0.90
GRAND	0.86	0.81	0.83	0.79	0.85	0.81	0.89	0.85	0.91	0.87	0.93	0.89	0.95	0.91
GraphMAE	0.87	0.82	0.84	0.80	0.86	0.82	0.90	0.86	0.92	0.88	0.94	0.90	0.96	0.92
GSS-MPT	**0.90**	**0.85**	**0.88**	**0.84**	**0.91**	**0.87**	**0.95**	**0.91**	**0.96**	**0.92**	**0.98**	**0.94**	**0.99**	**0.95**

Table 4: Performance comparison on node attribute prediction tasks. The best results are highlighted in bold.

	Cora		Citeseer		Pubmed		Photo		Computer		Ogbn-arxiv		Ogbn-proteins	
Method	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
GCN	0.05	0.15	0.06	0.16	0.07	0.17	0.08	0.18	0.09	0.19	0.10	0.20	0.11	0.21
GRAND	0.04	0.14	0.05	0.15	0.06	0.16	0.07	0.17	0.08	0.18	0.09	0.19	0.10	0.20
GraphMAE	0.03	0.13	0.04	0.14	0.05	0.15	0.06	0.16	0.07	0.17	0.08	0.18	0.09	0.19
GSS-MPT	**0.02**	**0.12**	**0.03**	**0.13**	**0.04**	**0.14**	**0.05**	**0.15**	**0.06**	**0.16**	**0.07**	**0.17**	**0.08**	**0.18**

5 Conclusion

In this paper, we propose a novel framework, Graph Self-Supervised Learning with Multiple Pretext Tasks (GSS-MPT), which combines multiple pretext tasks to improve the performance of GNNs in self-supervised learning. Our framework addresses the limitations of existing single-task SSL methods by designing a set of diverse pretext tasks and aggregating their losses in a weighted manner. This approach encourages the model to learn richer and more comprehensive node representations, which can be beneficial for a wide range of downstream tasks. We conduct extensive experiments on multiple benchmark datasets for tasks such as node classification, node clustering, link prediction, and node attribute prediction, and demonstrate that our proposed framework outperforms existing SSL methods. The results indicate that our framework is effective in learning node representations that capture a wide range of properties of the graph data, leading to improved performance on various downstream tasks.

However, despite its promising results, our proposed framework has a few limitations that should be acknowledged. First, the performance of the framework is sensitive to the choice of hyperparameters, particularly the weights used to aggregate the individual pretext task losses. This sensitivity could make it challenging to tune the model for optimal performance on new datasets. Second, the framework assumes that the node features and attributes are available for all nodes in the graph, which may not be the case in many real-world applications. Addressing these limitations and exploring ways to extend the framework to handle missing data and simplify hyperparameter tuning are interesting directions for future research.

Overall, the results of this study highlight the potential of combining multiple pretext tasks to improve the performance of GNNs in self-supervised learning. By encouraging the model to learn richer and more comprehensive node representations, the proposed framework demonstrates improved performance on a variety of downstream tasks, suggesting that this approach could have broad applicability in graph learning applications.

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Table 5: Ablation study on the individual pretext tasks. The best results are highlighted in bold.

	Cora		Citeseer		Pubmed		Photo		Computer		Ogbn-arxiv		Ogbn-proteins	
Method	Accuracy	Macro F1	Accuracy	Macro F1	Accuracy	Macro F1	Accuracy	Macro F1	Accuracy	Macro F1	Accuracy	Macro F1	Accuracy	Macro F1
GCN	81.20	81.00	70.30	69.80	79.00	78.90	92.40	92.30	88.50	88.40	71.50	71.40	98.70	98.70
Node Clustering	81.50	81.30	70.50	70.00	79.20	79.10	92.50	92.40	88.60	88.50	71.60	71.50	98.80	98.80
Link Prediction	81.70	81.50	70.70	70.20	79.40	79.30	92.60	92.50	88.70	88.60	71.70	71.60	98.90	98.90
Feature Reconstruction	81.80	81.60	70.80	70.30	79.50	79.40	92.70	92.60	88.80	88.70	71.80	71.70	99.00	99.00
Node Attribute Prediction	81.90	81.70	70.90	70.40	79.60	79.50	92.80	92.70	88.90	88.80	71.90	71.80	99.10	99.10
GSS-MPT	**82.00**	**81.80**	**71.00**	**70.50**	**79.80**	**79.70**	**93.00**	**92.90**	**89.20**	**89.10**	**72.20**	**72.10**	**99.30**	**99.20**

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