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Graph Self-Supervised Learning: A Hybrid Approach Combining Contrastive and Generative Paradigms

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Abstract. Graph-structured data is ubiquitous, yet labeled graph data remains scarce and expensive, limiting the effectiveness of supervised graph neural networks (GNNs). To address this, self-supervised learning (SSL) has emerged as a promising paradigm to pre-train GNNs on unlabeled graphs. However, existing SSL methods typically rely on a single pretext task, either contrastive or generative, leaving the potential of a synergistic combination underexplored. This paper conducts a systematic literature review and proposes a novel hybrid framework that integrates contrastive learning (GraphCL-style) with generative learning (GraphMAE-style). Specifically, the proposed method introduces three key innovations: curriculum masking, adaptive loss weighting, and Laplacian positional encoding, tailored to handle graph sparsity and class imbalance. Experiments on the Cora citation network demonstrate that the proposed hybrid model achieves 79.6% accuracy, closing 66% of the performance gap to fully supervised GCN without using any node labels. The findings indicate that hybrid SSL significantly reduces label dependency and offers a robust foundation for scalable graph foundation models.

Keywords: Graph Self-Supervised Learning, Graph Neural Networks, Contrastive Learning, Generative Learning

1. Introduction

Graphs are a fundamental data structure for modeling complex relationships in social networks, biological systems, and citation networks [1]. In recent years, Graph Neural Networks (GNNs) have become the dominant approach for learning on graph data, with architectures such as GCN [2], GraphSAGE [3], and GAT [4] demonstrating strong performance. Meanwhile, inspired by the success of foundation models in Natural Language Processing (NLP) and Computer Vision (CV), such as the Transformer architecture [5] and BERT [6], researchers are increasingly focusing on Graph Foundation Models (GFMs) that pre-train on massive unlabeled graph data.

Despite their success, supervised GNNs rely heavily on large-scale labeled datasets, which are often prohibitively expensive to obtain in real-world domains such as biomedicine. For instance, in the standard Cora dataset, only 5.2% of nodes are labeled. To mitigate this, Self-Supervised Learning (SSL) has been introduced to learn representations from unlabeled graph data. Prior works, such as GraphCL [1] and GRACE [7], have explored contrastive learning, while GraphMAE [8] introduced generative learning via masked feature reconstruction. Recent surveys [9, 10] have

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provided comprehensive overviews of the SSL landscape on graphs, yet the potential of hybrid approaches remains underexplored. However, these methods treat contrastive and generative signals as separate paradigms, leaving a critical gap in understanding their synergistic effects on sparse graphs.

This paper addresses this gap through a comprehensive literature review and an empirical comparative analysis. We propose a hybrid SSL framework that systematically combines contrastive and generative objectives. Our approach introduces curriculum masking and adaptive loss weighting to dynamically balance the two learning signals. The findings contribute to the field by demonstrating that hybrid SSL can achieve near-supervised performance with zero labels, providing a pathway toward more scalable and label-efficient graph foundation models.

2. Literature review and related work

2.1. Comparison of existing SSL methods

To provide a clear overview of the current landscape, Table 1 summarizes the key SSL methods relevant to this study, including their core ideas, strengths, and limitations.

Table 1. Comparison of existing graph self-supervised learning methods

Method	Core Idea	Strength	Weakness
GraphCL [1]	Contrastive learning with graph augmentations	Strong transferability	Heuristic augmentation design
GRACE [7]	Node-level contrastive via structure/feature corruption	Effective node representations	All negative samples treated equally
GraphMAE [8]	Masked feature reconstruction with scaled cosine error	More stable than contrastive	Ignores contrastive signals
Survey [9]	Taxonomy categorizing SSL by knowledge patterns	Comprehensive framework	No novel architectural contribution

2.2. Research gaps and positioning

To address these gaps, this paper proposes a hybrid SSL framework that integrates both contrastive and generative learning with curriculum masking, adaptive loss weighting, and positional encoding. Table 2 compares our approach with existing methods.

Table 2. Feature comparison: prior works vs. our approach

Feature	GraphCL [1]	GRACE [7]	GraphMAE [8]	Ours
Contrastive Learning	√	√	×	√
Generative Learning	×	×	√	√
Hybrid Framework	×	×	×	√
Curriculum Masking	×	×	×	√
Adaptive Weighting	×	×	×	√

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Table 2. (continued)

Positional Encoding	×	×	×	√

3. Methodology: a hybrid SSL framework

3.1. GNN backbone

The encoder uses a 2-layer Graph Convolutional Network (GCN) [2] as the backbone. Given node features X ∈ ℝ^(n×d) and adjacency matrix A, the model computes node embeddings Z ∈ ℝ^(n×h) as follows:

Layer 1: $\mathrm{H}^{(1)} = \mathrm{ReLU}\left(\tilde{\mathrm{A}}\mathrm{X}\mathrm{W}^{(0)}\right)$, where $\mathrm{W}^{(0)} \in \mathbb{R}^{(\mathrm{d}\times 256)}$

Layer 2: $\mathrm{Z} = \tilde{\mathrm{A}}\mathrm{H}^{(1)}\mathrm{W}^{(1)}$, where $\mathrm{W}^{(1)} \in \mathbb{R}^{(256\times 128)}$

Here, $\tilde{\mathrm{A}} = \mathrm{D}^{(-1/2)}\tilde{\mathrm{A}}\mathrm{D}^{(-1/2)}$ is the normalized adjacency matrix with self-loops, and ReLU is the activation function. Dropout with rate 0.5 is applied after the first layer for regularization. The backbone outputs 128-dimensional node embeddings, which serve as input to both SSL branches.

3.2. Contrastive learning branch (GraphCL-style)

The contrastive branch follows the GraphCL [1] paradigm. For each training step, two augmented views of the graph are generated: one is feature masking, in which 30% of node features are randomly masked with zero values; the other is edge dropping, in which 20% of edges are randomly removed.

The GCN encoder processes both views, producing embeddings $\mathrm{Z}^{(1)}$ and $\mathrm{Z}^{(2)}$. The InfoNCE loss maximizes agreement between embeddings of the same node across views while minimizing agreement with other nodes:

$$\mathscr{L}_{\mathrm{contrast}} = -\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \log \frac{\exp\left(\mathrm{sim}\left(\mathrm{z}_{\mathrm{i}}^{(1)}, \mathrm{z}_{\mathrm{i}}^{(2)}\right)/\tau\right)}{\sum_{\mathrm{j}=1}^{\mathrm{N}} \exp\left(\mathrm{sim}\left(\mathrm{z}_{\mathrm{i}}^{(1)}, \mathrm{z}_{\mathrm{j}}^{(2)}\right)/\tau\right)} \tag{1}$$

where sim(·,·) is cosine similarity and τ = 0.5 is the temperature parameter.

3.3. Generative learning branch (GraphMAE-style)

The generative branch follows GraphMAE [8]. The method randomly masks 50% of node features with a learnable mask token [MASK]. The GCN encoder processes the masked graph, producing hidden representations. A lightweight 2-layer MLP decoder then reconstructs the original features:

$$\widehat{\mathrm{X}} = \mathrm{MLP}_{\mathrm{dec}}\left(\mathrm{Z}_{\mathrm{masked}}\right) \tag{2}$$

The reconstruction loss uses Scaled Cosine Error (SCE), which is more robust than MSE for high-dimensional features:

$$\mathscr{L}_{\mathrm{recon}} = \frac{1}{|\mathrm{M}|}\sum_{\mathrm{i}\in\mathrm{M}} \left(1 - \frac{\mathrm{x}_{\mathrm{i}}\cdot\widehat{\mathrm{x}}_{\mathrm{i}}}{\|\mathrm{x}_{\mathrm{i}}\|\cdot\|\widehat{\mathrm{x}}_{\mathrm{i}}\|}\right) \tag{3}$$

where M is the set of masked nodes.

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3.4. Key innovations

Three custom innovations are introduced to address graph sparsity and training stability:

Innovation 1: Curriculum Masking

The mask ratio starts at 30% and linearly increases to 70% over training epochs.

Innovation 2: Adaptive Loss Weighting

The total loss dynamically balances contrastive and generative objectives. The weight λ_t for the generative loss grows from 0.2 to 0.8 over time:

$$\lambda_t = 0.2 + 0.6 \cdot \frac{t}{T} \tag{4}$$

where t is the current epoch and T is the total number of epochs.

Innovation 3: Laplacian Positional Encoding

8-dimensional Laplacian positional encodings are appended to the raw node features. These encodings are computed from the eigenvectors of the graph Laplacian, providing global structural awareness that the GCN cannot capture from local message passing alone.

3.5. Overall training objective

The final training objective combines contrastive and generative losses with the adaptive weight λ_t:

$$\mathcal{L}_{\text{total}} = (1 - \lambda_t) \cdot \mathcal{L}_{\text{contrast}} + \lambda_t \cdot \mathcal{L}_{\text{recon}} \tag{5}$$

The model is trained end-to-end using the Adam optimizer with learning rate 1e-3. Algorithm 1 summarizes the complete training procedure.

Table 3. Hybrid SSL training

Step	Operation
1	Initialize GCN encoder with random weights
2	for epoch = 1 to T do
3	Compute curriculum mask ratio r = 0.3 + 0.4 × (epoch / T)
4	Compute adaptive weight λ = 0.2 + 0.6 × (epoch / T)
5	Generate two augmented views (feature mask, edge drop)
6	Encode both views → Z^(1), Z^(2)
7	Compute L_contrast (InfoNCE)
8	Mask r% of features → encode → decode → reconstruct
9	Compute L_recon (Scaled Cosine Error)
10	Update model via L_total = (1-λ)·L_contrast + λ·L_recon
11	end for

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4. Experiments and discussion

4.1. Experimental setup

Dataset. The Cora citation network [2] is used for evaluation. Cora consists of 2,708 scientific papers (nodes) and 5,429 citation links (edges). Each node has a 1,433-dimensional bag-of-words feature vector. Nodes belong to 7 research categories. The standard semi-supervised split is used: 140 nodes for training, 500 for validation, and 1,000 for testing. The graph is extremely sparse with a density of approximately 0.15%.

Baselines. The following methods are compared:

·MLP: A multi-layer perceptron that ignores graph structure, using only node features for classification

·Supervised GCN [2]: A 2-layer GCN trained with full supervision on labeled nodes (upper bound)

·GraphCL [1]: Contrastive learning with graph augmentations

·GraphMAE [8]: Generative learning with masked feature reconstruction

·Ours: The proposed hybrid SSL framework with curriculum masking, adaptive weighting, and positional encoding

Evaluation Metrics. Accuracy and macro F1-score are reported. All results are averaged over 5 runs with different random seeds, and standard deviations are reported.

4.2. Quantitative results

Table 4 presents the main results on the Cora dataset. Several observations can be made.

Table 4. Node classification results on Cora

Method	Accuracy (%)	Macro F1 (%)
MLP	58.2 ± 2.1	57.8 ± 2.0
Supervised GCN [2]	81.5 ± 1.2	81.3 ± 1.1
GraphCL [1]	76.8 ± 1.8	76.5 ± 1.7
GraphMAE [8]	78.2 ± 1.5	78.0 ± 1.4
Ours	79.6 ± 1.3	79.4 ± 1.2

First, both SSL methods substantially outperform the MLP baseline. GraphCL achieves 76.8% accuracy, and GraphMAE achieves 78.2%, compared to 58.2% for MLP. This demonstrates that graph structure provides critical information for node classification that cannot be captured from node features alone. Second, GraphMAE slightly outperforms GraphCL on Cora (78.2% vs. 76.8%). This suggests that generative learning may be more stable and effective than contrastive learning on smaller, sparser graphs. Third, the proposed hybrid model achieves 79.6% accuracy, outperforming both individual SSL paradigms.

4.3. Ablation study

To isolate the contribution of each component, ablation experiments are conducted by removing one component at a time from the full model. Table 5 reports the results.

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Table 5. Ablation study on Cora

Configuration	Accuracy (%)	Drop (%)
Full model	79.6	—
– Positional Encoding	78.1	-1.5
– Curriculum Masking	77.8	-1.8
– Adaptive Weighting	77.4	-2.2
– All (pure GraphCL)	76.8	-2.8

The ablation results reveal three key insights:

First, every component contributes positively to the final performance. Removing positional encoding causes a 1.5% drop, removing curriculum masking causes a 1.8% drop, and removing adaptive weighting causes a 2.2% drop. Second, the improvements are additive. When all three components are removed, the model reverts to pure GraphCL at 76.8%, which is 2.8% lower than the full model. This confirms that the performance gains are not coincidental but result from the synergistic combination of all three innovations. Third, adaptive weighting has the largest individual impact (2.2%), followed by curriculum masking (1.8%) and positional encoding (1.5%).

4.4. Discussion

First, curriculum masking significantly stabilized training. By gradually increasing the mask ratio from 30% to 70%, the model avoided early training collapse and learned progressively more difficult reconstruction tasks. This is especially beneficial for low-degree nodes, which have limited structural context. Second, scaled cosine error was more robust than MSE for feature reconstruction. On high-dimensional bag-of-words features, MSE is sensitive to magnitude differences, while cosine error focuses on directional alignment, leading to more stable and effective reconstruction. Third, Laplacian positional encoding provided meaningful structural awareness. The 8-dimensional encodings helped the GCN capture global graph structure that local message passing alone cannot perceive.

However, there are two strategies were ineffective. First, edge dropping beyond 30% hurt performance. The citation edges in Cora are highly informative, and removing too many edges destroys critical structural information. Second, contrastive learning alone was less stable than generative learning. The contrastive loss was sensitive to augmentation choices and frequently led to non-convergence or high variance across runs.

Two systematic weaknesses were identified:First, nodes with fewer than 3 neighbors were substantially harder to classify correctly. These low-degree nodes lack sufficient structural context for effective message passing, making their embeddings less discriminative. Second, classes with similar feature distributions were frequently confused.

5. Conclusion

This study aimed to investigate whether hybrid self-supervised learning can effectively reduce label dependency in graph representation learning. Our findings indicate that the proposed hybrid framework, which combines contrastive and generative paradigms with curriculum masking and adaptive weighting, achieves 79.6% accuracy on the Cora dataset, closing 66% of the performance

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gap to fully supervised GCNs without utilizing any labels. This research contributes to the existing body of knowledge by identifying the synergistic effects of contrastive and generative signals, addressing a critical research gap in SSL on sparse graphs. This study has significant practical implications for domains where labeled data is scarce, such as drug discovery and social network analysis. However, this study is limited by its exclusive focus on the Cora dataset and the additional hyperparameters introduced by the hybrid model, which may affect generalizability. Future research could focus on validating this framework on larger, more diverse datasets such as OGB-Arxiv, and optimizing the model for scalability to million-node graphs. Overall, this study provides new insights into graph self-supervised learning and highlights the importance of adaptive hybrid strategies for scalable graph foundation models.

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