



Dual-level Hypergraph Contrastive Learning with Adaptive Temperature Enhancement

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ABSTRACT

Inspired by the success of graph contrastive learning, researchers have begun exploring the benefits of contrastive learning over hypergraphs. However, these works have the following limitations in modeling the high-order relationships over unlabeled data: (i) They primarily focus on maximizing the agreements among individual node embeddings while neglecting the capture of group-wise collective behaviors within hypergraphs; (ii) Most of them disregard the importance of the temperature index in discriminating contrastive pairs during contrast optimization. To address these limitations, we propose a novel dual-level **HyperGraph Contrastive Learning** framework with **Adaptive Temperature (HyGCL-AdT)** to boost contrastive learning over hypergraphs. Specifically, unlike most works that merely maximize the agreement of node embeddings in hypergraphs, we propose a dual-level contrast mechanism that not only captures the individual node behaviors in a local context but also models the group-wise collective behaviors of nodes within hyperedges from a community perspective. Besides, we design an adaptive temperature-enhanced contrastive optimization to improve the discrimination ability between contrastive pairs. Empirical experiments conducted on seven benchmark hypergraphs demonstrate that HyGCL-AdT exhibits excellent effectiveness compared to state-of-the-art baseline models. The source code is available at <https://github.com/graphprojects/HyGCL-AdT>.

CCS CONCEPTS

• **Computing methodologies** → **Unsupervised learning; Neural networks.**

KEYWORDS

Hypergraph, Contrastive learning, Hypergraph learning

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WWW '24 Companion, May 13–17, 2024, Singapore, Singapore

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ACM ISBN 979-8-4007-0172-6/24/05...\$15.00

<https://doi.org/10.1145/3589335.3651493>

ACM Reference Format:

Yiyue Qian, Tianyi Ma, Chuxu Zhang, and Yanfang Ye. 2024. Dual-level Hypergraph Contrastive Learning with Adaptive Temperature Enhancement. In *Companion Proceedings of the ACM Web Conference 2024 (WWW '24 Companion)*, May 13–17, 2024, Singapore, Singapore. ACM, New York, NY, USA, 4 pages. <https://doi.org/10.1145/3589335.3651493>

1 INTRODUCTION

Hypergraphs, which introduce versatile structures through hyperedges connecting multiple nodes to represent intricate relationships, have been investigated across diverse domains such as social networks and knowledge graphs [2, 7, 8]. Inspired by the success of graph contrastive learning, recent works [7, 16] extend contrastive learning to hypergraphs for modeling hypergraph structures via hypergraph neural networks (HyGNNs) over unlabeled data. However, current contrastive methods over hypergraphs [15, 16] still have limitations in modeling the high-order relationships and collective behaviors within hypergraphs over unlabeled data: (i) These works primarily focus on maximizing agreements among node embeddings while neglecting the capture of group-wise behaviors within hypergraphs; (ii) They consider the temperature index in contrastive learning as a hyper-parameter while underestimating the importance of temperature in differentiating contrastive pairs during contrast optimization.

To handle these challenges, in this work, we design a novel dual-level **HyperGraph Contrastive Learning** framework with **Adaptive Temperature** called **HyGCL-AdT** to enhance hypergraph contrastive learning. Specifically, we first introduce a noise-enhanced module over augmented hypergraphs to generate challenging hypergraph pairs. Afterward, the noise-enhanced hypergraph augmentations are fed to the HyGNNs encoder to obtain the node embeddings and the hyperedge embeddings. To address the first challenge, we design a dual-level contrast mechanism that aims to maximize the agreements among individual node embeddings at the node level and also focuses on capturing the group-wise behaviors within hyperedges at the community level, simultaneously. To handle the second challenge, we design an adaptive temperature-enhanced optimization to dynamically adjust the temperature during dual-level contrast optimization. This adaptation serves to enhance the discriminative capacity between contrastive pairs. To conclude, this work makes the following contributions:

- **Novelty:** We design a novel dual-level hypergraph contrastive learning framework that is enhanced by adaptive temperature optimization to pre-train HyGNNs encoder over unlabeled data.
- **Generalization:** HyGCL-AdT is designed as a general framework that unifies various hypergraph augmentations to boost hypergraph representation learning and enhance the model performance over various downstream tasks.
- **Effectiveness:** Empirical experiments over seven benchmark hypergraphs demonstrate the effectiveness of HyGCL-AdT.

2 RELATED WORK

Inspired by existing graph contrastive learning works [10, 22] over graph datasets [13, 14, 18, 20, 21, 23–25], researchers start to explore the benefits of contrastive learning over hypergraphs [7, 16]. For instance, HyperGCL [16] proposes a generative method to create generative augmentations of hypergraphs. CHGNN [15] designs an adaptive augmentation strategy for hypergraph augmentation and further proposes the updated hypergraph encoder to learn the node embedding over the unlabeled data. However, these works still have limitations in describing the group-wise collective node behaviors during hypergraph contrastive learning. However, these works do not consider the influence of temperature index in contrastive optimization. Motivated by these works, we design a dual-level hypergraph contrastive learning with an adaptive temperature framework to reach agreements among node embeddings and group-wise community embeddings.

3 METHODOLOGY

In this section, we present the details of HyGCL-AdT: (i) noise-enhanced augmentation; (ii) dual-level hypergraph contrastive strategy; (iii) adaptive temperature enhanced optimization.

Noise-Enhanced Hypergraph Augmentation. Given the hypergraph augmentation set $\mathcal{T}$ including hyperedge removal, edge perturbation, attribute masking, node dropping, and subgraph, we randomly select one pair of hypergraph augmentation methods from $\mathcal{T}$ and further obtain the augmented hypergraph pair $(\mathcal{G}_1, \mathcal{G}_2)$. Inspired by the conclusion that relatively challenging contrastive learning tasks can enhance the ability of representation learning compared with easy contrastive learning tasks [9, 11, 12, 17, 22], we propose to generate challenging augmented hypergraph pairs by performing random noise over the augmented hypergraphs. Specifically, with the augmented graph pair $(\mathcal{G}_1, \mathcal{G}_2)$, for each node $v_i \in \mathcal{V}$, we perform a random noise δ_i following a specific distribution (e.g., uniform distribution) to the node attribute feature x_i . The attribute feature with noise is formulated as $\tilde{X} = X + \delta = [x_1 + \delta_1; x_2 + \delta_2; \dots; x_N + \delta_N]$, where X is the original node attribute feature, $[\cdot; \cdot]$ is the concatenation operator among attribute features. Afterward, we obtain two noise-enhanced hypergraphs $[\tilde{\mathcal{G}}_1 = (\mathcal{V}_1, \mathcal{E}_1, \tilde{X}_1), \tilde{\mathcal{G}}_2 = (\mathcal{V}_2, \mathcal{E}_2, \tilde{X}_2)]$, where $\mathcal{V}_*$ and $\mathcal{E}_*$ are the set of nodes and the hyperedges in the corresponding $\tilde{\mathcal{G}}_*$.

Dual-Level Hypergraph Contrastive Strategy. After obtaining noise-enhanced augmented hypergraphs, a dual-level contrastive strategy is devised to align the node embeddings locally and match the group-wise community embeddings globally.

Node-Level Hypergraph Contrastive Learning. Following existing works (e.g., HyperGCL [16]), we also employ a node-level hypergraph contrastive learning (HyGCL) module to ensure that the same nodes from different augmented hypergraphs are encoded closely, while different nodes are embedded farther apart. Specifically, given two nodes (v_i, v_j) from $(\tilde{\mathcal{G}}_1, \tilde{\mathcal{G}}_2)$, we obtain the node embeddings $(\mathbf{u}_i^1, \mathbf{u}_j^2)$ by feeding the augmented graph $(\tilde{\mathcal{G}}_1, \tilde{\mathcal{G}}_2)$ to any HyGNNs encoder. Here we employ AllDeepSet [5] as the encoder. We then feed $(\mathbf{u}_i^1, \mathbf{u}_j^2)$ to projection head $h(\cdot)$. (v_i, v_j) is a positive contrastive pair if $i = j$. Otherwise, it is a negative pair in node-level HyGCL.

Community-Level Hypergraph Contrastive Learning. Although the node-level HyGCL captures the information of individual nodes, it may not be sufficient for capturing the collective node behaviors within hyperedges. Therefore, we propose the community embeddings to capture the collective node behaviors within hyperedges. Consider two hyperedges (e_i^1, e_j^2) from augmented graphs $(\tilde{\mathcal{G}}_1, \tilde{\mathcal{G}}_2)$ where e_i^1 contains nodes $\{v_1, v_2, v_3, v_4\}$ and e_j^2 contains nodes $\{v_3, v_4, v_7\}$, as illustrated in Figure 1. Contrastive learning on hyperedge embeddings might be insufficient to distinguish negative hyperedge pair e_i^1 and e_j^2 , as they share most of the nodes during information propagation. In light of this, we design a community-level HyGCL module to capture the group behaviors within hyperedges from a global perspective. Specifically, for each hyperedge $e_i \in \mathcal{E}$, we first get the hyperedge embedding $\mathbf{z}_i$ via the HyGNNs encoder. Then the community embedding is formulated as:

$$\mathbf{h}_i = \mathbf{z}_i \oplus \frac{1}{d(e_i)} \sum_{m \in e_i} \mathbf{u}_m, \quad (1)$$

where $\mathbf{h}_i$ denotes the community embedding distinguished by hyperedge e_i , $\mathbf{u}_m$ represents the embedding of node v_m within the hyperedge e_i , $d(e_i)$ denotes the degree of e_i , and $\oplus$ is the concatenation operator. With community embeddings $\mathbf{h}_i^1$ and $\mathbf{h}_j^2$ from $\tilde{\mathcal{G}}_1$ and $\tilde{\mathcal{G}}_2$, we consider the community embeddings distinguished by the same hyperedge from different augmented hypergraphs as the positive contrastive community pairs, and we expect that their community embeddings would stay closer than others. On the contrary, the community embeddings distinguished by different hyperedges from different augmented hypergraphs should be far apart. To make it clear, $(\mathbf{h}_i^1, \mathbf{h}_j^2)$ will be viewed as positive contrastive pair if $i = j$. Otherwise, it would be a negative contrastive community pair.

Adaptive Temperature Enhanced Contrastive Optimization.

To make positive contrastive pairs closer and negative pairs farther, several contrastive losses are designed, e.g., NT-Xent loss [4]. All contrastive losses occupy the temperature index τ as a proxy to scale the embeddings and control the penalties on negative samples. However, most consider τ as a hyper-parameter to scale the representations but ignore the fact that a fixed temperature may not be optimal during the whole training process.

Adaptive Temperature in Dual-Level Hypergraph Contrastive Learning. In light of this, we design a module where the temperature can be learned at an adjustable pace based on the distance among these negative contrastive pairs. If the distance among negative contrastive pairs is small (hard negative pairs), the temperature decreases rapidly, while it decreases slowly when the distance among

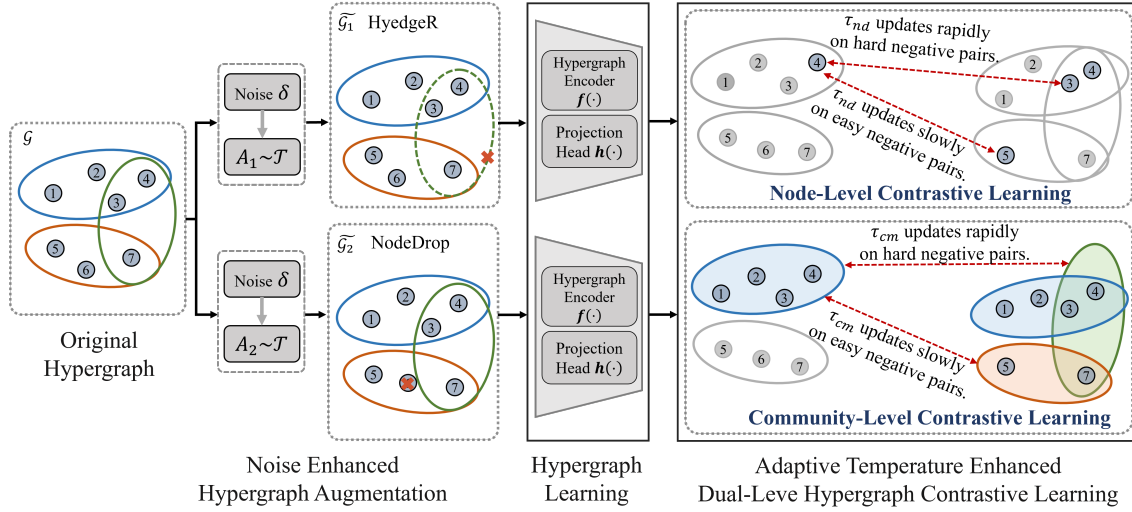


Figure 1: The framework of HyGCL-AdT: (i) given a hypergraph $\mathcal{G}$, HyGCL-AdT samples A_1, A_2 from hypergraph augmentation set $\mathcal{T}$. Here A_1 and A_2 denote hyperedge removal and node dropping, respectively. With the augmented hypergraphs, it performs noise δ over augmented graphs for generating challenging hypergraph pairs; (ii) augmented graphs $\tilde{\mathcal{G}}_1$ and $\tilde{\mathcal{G}}_2$ are fed into HyGNNs encoder $f(\cdot)$ and projection head $h(\cdot)$ to get node and hyperedge embeddings. (iii) a dual-level contrastive strategy is designed to reach agreements among node embeddings from a local view and agreements among community embeddings from a global perspective. The dual-level contrast optimization is enhanced via the adaptive temperature τ_{nd} and τ_{cm} , respectively.

negative pairs is large (easy negative pairs). Eventually, the temperature will converge to an optimal value. Formally, the adaptive module in dual-level HyGCL is formulated as:

$$\tau_{nd}^{(t)} = \max \left\{ \tau_{nd}^{(t-1)} - \eta \left[\frac{1}{\log \frac{\sum_i |\mathcal{V}| \sum_{j \neq i} \exp(\rho * ||\mathbf{u}_i^{(t)1} - \mathbf{u}_j^{(t)2}||^2)}{|\mathcal{V}| * (|\mathcal{V}| - 1)}} \right], \tau_{low} \right\}, \quad (2)$$

$$\tau_{cm}^{(t)} = \max \left\{ \tau_{cm}^{(t-1)} - \eta \left[\frac{1}{\log \frac{\sum_i |\mathcal{E}| \sum_{j \neq i} \exp(\rho * ||\mathbf{h}_i^{(t)1} - \mathbf{h}_j^{(t)2}||^2)}{|\mathcal{E}| * (|\mathcal{E}| - 1)}} \right], \tau_{low} \right\}.$$

Here $\tau_{nd}^{(t)}$ is the adaptive temperature in node-level HyGCL at the current training epoch t . $\tau_{cm}^{(t)}$ is the adaptive temperature in community-level HyGCL. $||\mathbf{u}_i^{(t)1} - \mathbf{u}_j^{(t)2}||$ and $||\mathbf{h}_i^{(t)1} - \mathbf{h}_j^{(t)2}||$ are the pairwise distances among nodes and communities in the embedding space from different augmented hypergraphs $\tilde{\mathcal{G}}_1$ and $\tilde{\mathcal{G}}_2$ at time t . η denotes the learning rate; ρ is the scaling factor to control the influence of distance among embeddings; τ_{low} is the hyperparameter to control the lower bound. Mention that, the lower bound τ_{low} is to prevent the temperature from becoming too small or approaching zero, ensuring a more reliable learning process.

Overall Optimization. With the designed adaptive temperature in both node-level and community-level HyGCL-AdT, the overall contrastive loss $\mathcal{L}_{nd_cm}$ can be formulated as:

$$\mathcal{L}_{nd_cm} = \lambda_1 * \mathcal{L}_{nd} + \lambda_2 * \mathcal{L}_{cm}, \text{ where}$$

$$\mathcal{L}_{nd} = -\log \sum_{v_i \in \mathcal{V}} \frac{\exp(\text{sim}(\mathbf{u}_i^1, \mathbf{u}_i^2) / \tau_{nd}^*)}{\sum_{k \neq i} \exp(\text{sim}(\mathbf{u}_i^1, \mathbf{u}_k^2) / \tau_{nd}^*) + \exp(\text{sim}(\mathbf{u}_i^1, \mathbf{u}_i^2) / \tau_{nd}^*)}, \quad (3)$$

$$\mathcal{L}_{cm} = -\log \sum_{e_i \in \mathcal{E}} \frac{\exp(\text{sim}(\mathbf{h}_i^1, \mathbf{h}_i^2) / \tau_{cm}^*)}{\sum_{k \neq i} \exp(\text{sim}(\mathbf{h}_i^1, \mathbf{h}_k^2) / \tau_{cm}^*) + \exp(\text{sim}(\mathbf{h}_i^1, \mathbf{h}_i^2) / \tau_{cm}^*)}.$$

Here λ_1 and λ_2 are hyper-parameters to balance node-level and community-level HyGCL-AdT. τ_{nd}^* and τ_{cm}^* are the adaptive temperatures at both levels.

4 EXPERIMENTS

Experimental Setup

Dataset: We employ seven benchmark datasets from existing HyGNNs literature, including three co-citation and co-authorship networks from [19] (i.e., Cora, CiteSeer, Cora-CA), one drug trafficking hypergraph for user role classification classification (Twitter-HyDrug [7]), two hypergraph datasets (i.e., Zoo and Mushroom) from the UCI categorical machine learning repository [1], one computer vision hypergraph data (i.e., NTU2012) from [3]. **Baseline Methods:** To evaluate the performance of HyGCL-AdT, we consider three baseline methods, including three HyGNNs (i.e., HCHA [2], UniGCNII [6], and AllDeepSets [5]) and one recent contrastive learning method over hypergraphs, i.e., HyperGCL [16]. **Experimental Settings:** All experiments are conducted under the environment of the Ubuntu 16.04 OS, plus an Intel i9-9900k CPU, two GeForce GTX 2080 Ti Graphics Cards, and 64 GB of RAM. To make fair comparisons, we exactly follow the settings of HyperGCL: (i) We train all methods with 500 epochs; (ii) The train/val/test ratio is 10%/10%/80%; (iii) We adopt AllDeepSets [5] as the encoder over all datasets. nd the average performance multiplied by 100 on testing data is reported. In Equation 3, λ_1 and λ_2 are set as 1.0.

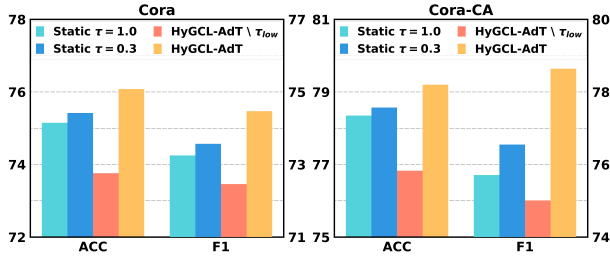
Experiment Analysis

HyGCL-AdT Enhances Semi-supervised Learning. Table 1 shows the accuracy performance of all methods over seven datasets for node classification tasks. From this table, we conclude that: (i) contrastive learning over unlabeled data boosts the representation learning in hypergraphs as HyperGCL outperforms AllDeepSets over all datasets. (ii) HyGCL-AdT outperforms all baseline methods, showing the effectiveness of HyGCL-AdT in enhancing hypergraph representation learning, showing the effectiveness of our dual-level HyGCL and the adaptive temperature optimization.

Table 1: Accuracy performance comparison for node classification. Purple shaded numbers indicate the best result and gray shade numbers represent the runner-up performance.

	Cora	Citeseer	Cora-CA	Twitter-HyDrug	Zoo	Mushroom	NTU2012
HCHA	72.20 $\pm$ 1.69	65.33 $\pm$ 0.57	75.12 $\pm$ 0.99	66.69 $\pm$ 0.74	69.51 $\pm$ 10.02	97.65 $\pm$ 0.45	73.88 $\pm$ 1.74
UniGCNII	71.23 $\pm$ 0.66	65.71 $\pm$ 1.48	77.35 $\pm$ 0.27	66.59 $\pm$ 1.38	69.09 $\pm$ 10.64	99.85 $\pm$ 0.04	74.27 $\pm$ 1.41
AllDeepSets	68.14 $\pm$ 1.31	63.60 $\pm$ 1.27	68.52 $\pm$ 2.67	67.65 $\pm$ 1.18	58.48 $\pm$ 9.13	99.72 $\pm$ 0.18	72.54 $\pm$ 1.42
HyperGCL	73.52 $\pm$ 1.05	66.82 $\pm$ 0.98	76.57 $\pm$ 1.70	68.45 $\pm$ 1.05	58.77 $\pm$ 6.09	99.76 $\pm$ 0.15	76.16 $\pm$ 1.26
Ours	76.20 $\pm$ 0.44	79.39 $\pm$ 1.32	78.59 $\pm$ 0.51	68.76 $\pm$ 0.41	69.88 $\pm$ 12.45	99.92 $\pm$ 0.05	77.64 $\pm$ 0.84

Temperature Analysis in HyGCL-AdT. We conducted additional experiments to study the influence of temperature on HyGCL-AdT. Figure 2 illustrates the performance of HyGCL-AdT with static τ , and HyGCL-AdT without the lower bound constraint τ_{low} . We find out that the static values of τ achieve excellent performance but still do not yield the best performances. Besides, HyGCL-AdT without τ_{low} decreases obviously over these datasets. These findings show the rationality of our adaptive contrast optimization.

**Figure 2: Performance of HyGCL-AdT under different contrast optimization strategies over Cora and Cora-CA datasets. The left axis is for accuracy and the right axis is for Macro-F1.**

5 CONCLUSION

The paper designs an adaptive temperature-enhanced dual-level hypergraph contrastive learning model to enhance hypergraph contrastive learning. To handle the limitations of existing hypergraph contrastive learning w.r.t. underestimating group-wise behaviors and ignoring the importance of temperature in contrast optimization, HyGCL-AdT introduces a dual-level contrast mechanism to capture individual behaviors and group-wise behaviors simultaneously. Besides, it designs adaptive temperature-enhanced contrast optimization to improve discrimination ability between contrastive pairs. Empirical experiments on seven hypergraphs demonstrate the effectiveness of HyGCL-AdT.

ACKNOWLEDGEMENTS

This work was partially supported by the NSF under grants IIS-2321504, IIS-2334193, IIS-2203262, IIS-2217239, CNS-2203261, IIS-2340346, and CMMI-2146076. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the sponsors.

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