Structure-Enhanced Heterogeneous Graph Contrastive Learning

Yanqiao Zhu*†‡ Yichen Xu*§ Hejie Cui‖ Carl Yang¶ Qiang Liu†‡ Shu Wu†‡‖

Abstract
Recent years have seen a growing interest in Graph Contrastive Learning (GCL), which trains Graph Neural Network (GNN) model to discriminate similar and dissimilar pairs of nodes without human annotations. Most prior GCL work focuses on homogeneous graphs and little attention has been paid to Heterogeneous Graphs (HG) that involve different types of nodes and edges. Moreover, earlier studies reveal that the explicit use of structure information of underlying graphs is useful for learning representations. Conventional GCL methods merely measure the likelihood of contrastive pairs according to node representations, which may not align with the true semantic similarities. How to leverage such structure information for GCL is not yet well-understood. To address the aforementioned challenges, this paper presents a novel method dubbed STENCIL for brevity. At first, we generate multiple semantic views for HGs based on metapaths. Unlike most methods that maximize the consistency among these views, we propose a novel multiview contrastive aggregation objective to adaptively distill information from each view. In addition, we advocate the explicit use of structure embedding, which enriches the model with local structural patterns of the underlying HGs, so as to better mine true and hard negatives for GCL. Empirical studies on three real-world datasets show that our proposed method consistently outperforms existing state-of-the-art methods and even surpasses several supervised counterparts.

1 Introduction
Many real-world complex interactive objectives can be represented in Heterogeneous Graphs (HG) or heterogeneous information networks. Recent development in heterogeneous Graph Neural Networks (GNNs) has achieved great success in analyzing heterogeneous data [27, 29]. However, most existing models require a large amount of labeled data for proper training [7, 14, 35, 36], which may not be accessible in reality. As a promising strategy of leveraging abundant unlabeled data, Graph Contrastive Learning (GCL) is proposed to learn representations by distinguishing semantically similar samples (positives) over dissimilar samples (negatives) in the latent space without human annotations. Most existing GCL models follow a multiview paradigm [35, 46, 47], where multiple views of the input data are constructed via stochastic augmentations and the model is then trained to maximize the consistency of representations among these views.

Though multiview GCL has achieved promising performance in many tasks, it is still non-trivial to adopt multiview GCL on HG data. In HGs, multiple types of nodes and edges convey rich semantic information. It is therefore natural to construct multiple views based on metapaths. Then, following the multiview contrastive objective [46, 47], its embeddings in different views constitute positives and all other embeddings are regarded as negative examples. Nevertheless, this scheme fails to consider the inter-view dependency of different views (e.g., complementary or redundant information [28]) and may lead to suboptimal performance. For example, consider an academic network, where nodes correspond to four types of entities: Papers (P), Conferences (C), Topics (T), and Authors (A). Two views created by APA and ACPA share common co-authorship information, while two other metapaths ACPA and APTPA connect authors from two dissimilar sources: conferences and topics. Therefore, it is insufficient to distill comprehensive information from HGs by only contrasting node representations within each metapath-induced view.

Furthermore, conventional GCL methods usually ran-
At first, our model works by constructing multiple views. Previous work has established that explicitly incorporating structure and semantics in GCL, we argue that it is not only important to consider individual node representations but also local structural representations. These structural embeddings enhance the graph model by encoding additional graph-based closeness between nodes and thus carry local positional information and context of the given graph-structured data.

In this paper, we propose STENCIL for brevity. At first, our model works by constructing multiple views corresponding to metapaths and obtaining node embeddings within each view through a heterogeneous GNN. Then, we propose a novel multiview contrastive aggregation objective that adaptively learn information from each semantic view.

- To further improve the performance of negative sampling in GCL for HGs, we propose to enrich the model with structurally hard negatives.
- Extensive experiments on three real-world datasets from various domains demonstrate the effectiveness of the proposed method. Particularly, our STENCIL method outperforms representative unsupervised baselines, achieves competitive performance with supervised counterparts, and even exceeds several of them.

To foster reproducible research, we make all the code publicly available at https://github.com/CRIPAC-DIG/STENCIL.

2 Preliminaries

2.1 Problem Definition. We introduce several key definitions of heterogeneous graphs and the problem of unsupervised graph representation learning.

DEFINITION 2.1. A Heterogeneous Graph (HG), denoted by \( G = (V, E, X, R, \phi, \varphi) \), is a graph with multiple types of nodes and edges, where \( V, E \) denote the node set and the edge set respectively. The node type mapping function \( \phi : V \rightarrow S \) associates each node \( v_i \in V \) with a node type \( s = \phi(v_i) \), the edge type mapping function \( \varphi : E \rightarrow R \) associates each edge \( e_{ij} \in E \) with an edge type \( r = \varphi(e_{ij}) \), with \( |S| + |R| > 2 \). Moreover, each node \( v_i \) and each edge \( e_{ij} \) is possibly associated with attribute \( x_i \) and \( r_{ij} \). Note that the edge type \( r = \varphi(e_{ij}) \) implicitly defines types of its two end nodes \( v_i \) and \( v_j \).

DEFINITION 2.2. A metapath \( P \) defines a path on the network schema in the form of \( s_1 \xrightarrow{r_1} s_2 \xrightarrow{r_2} \cdots \xrightarrow{r_{l-1}} s_l \). It represents a composite relation \( r_1 \circ r_2 \circ \cdots \circ r_l \) between two nodes \( v_1 \) and \( v_{l+1} \) that captures the proximity between the two nodes from a particular perspective, where \( \circ \) is the composite operator. We further denote the set of all considered metapaths as \( \mathcal{P} \).

DEFINITION 2.3. Given a HG \( G \), the problem of heterogeneous graph representation learning aims to learn node representations \( H \in \mathbb{R}^{|V| \times d} \) that encode both structural and semantic information, where \( d \ll |V| \) is the dimension of the embedding space.
where \( \parallel \) concatenates \( K \) standalone node representations in each attention head, \( \mathcal{N}_v(v_i) \) defines the neighborhood of \( v_i \) that is connected by metapath \( p \), \( W^p \in \mathbb{R}^{d \times m} \) is a linear transformation matrix for metapath \( p \), and \( \sigma(\cdot) \) is the activation function, such as \( \text{ReLU}(\cdot) = \max(0, \cdot) \). The attention coefficient \( \alpha_{ij}^p \) can be computed by a softmax function

\[
\alpha_{ij}^p = \frac{\exp(\sigma(a_p^i [h_i^p \parallel h_j^p]))}{\sum_{v_k \in \mathcal{N}_v(v_i)} \exp(\sigma(a_p^i [h_i^p \parallel h_k^p]))},
\]

where \( a_p \in \mathbb{R}^{2d} \) is a trainable metapath-specific linear weight vector.

Finally, we combine node representation in each view to an aggregated representation. We employ another attentive network to obtain the aggregated representation \( h_i \) that combines information from every semantic space by

\[
h_i = \sum_{p=1}^{P} \beta_p h_i^p.
\]

The coefficients are given by

\[
\beta_p = \frac{\exp(w^p)}{\sum_{p' \in P} \exp(w^{p'})},
\]

\[
w^p = \frac{1}{|V|} \sum_{v_i \in V} q^\top \cdot \tanh(W h_i^p + b),
\]

where \( q \in \mathbb{R}^{d_m} \) is the aggregation attention vector, \( W \in \mathbb{R}^{d_m \times d} \), \( b \in \mathbb{R}^{d_m} \) is the weight matrix and the bias vector respectively, and \( d_m \in \mathbb{R} \) is a hyperparameter.

### 3 The Proposed Method: STENCIL

In the following section, we present the proposed STENCIL in detail. There are three major components in the proposed STENCIL framework: (a) a heterogeneous graph encoder, which embeds nodes under each metapath-induced view into low-dimensional vectors and aggregates these embeddings into a final representation, (b) a multiview contrastive aggregation objective that adaptively encodes node representations in a self-supervised manner, and (c) structure-enriched negative mining, which discovers and reweights structurally hard samples.

#### 3.1 Multiview Contrastive Aggregation

As described in Section 2.2, we first generate multiple views according to metapaths and learn node representations under these views independently using heterogeneous GNN models. Then, to comprehensively learn the information encoded in different metapaths, we propose a novel multiview contrastive aggregation objective that adaptively distills essential information from each view.

This contrastive aggregation scheme is shown in Figure 2. Its learning objective can be mathematically expressed as

\[
\max \frac{1}{|V|} \sum_{v_i \in V} \left( \frac{1}{|P|} \sum_{p \in P} \frac{1}{2} (I(h_i^p; h_i) + I(h_i; h_i^p)) \right),
\]

where \( h_i^p \) is a metapath-specific embedding for node \( v_i \) under metapath \( p \) and \( h_i \) is the aggregated embedding for node \( v_i \) that collects information of all its relations.

Following previous work [10, 32, 45], to estimate the mutual information \( I(h_i^p; h_i) \) in Eq. (3.6), we empirically choose the InfoNCE estimator. Concretely, for node representation \( h_i^p \) in one specific metapath-induced view, we construct its positive sample as the aggregated representation \( h_i \), while embeddings of all other nodes in the semantic and the aggregated embeddings are considered as negative samples. The contrastive loss can be expressed by

\[
\mathcal{L}(h_i^p, h_i) = -\log e^{\theta(h_i^p, h_i)/\tau} \sum_{j \neq i} e^{\theta(h_i^p, h_j)/\tau} e^{\theta(h_j^p, h_j)/\tau},
\]

where \( \tau \in \mathbb{R} \) is a temperature parameter. We define the critic function \( \theta(\cdot, \cdot) \) by

\[
\theta(h_i, h_j) = \frac{g(h_i)^\top g(h_j)}{\|g(h_i)\| \|g(h_j)\|},
\]

where \( g(\cdot) \) is parameterized by a non-linear multilayer perceptron to enhance the expressive power [2].
3.2 Structure Embeddings for Metapath-Induced Views.
In the context of HGs, we observe that metapath-level node representations are not sufficient to calculate the similarity of each negative pair. Therefore, in this work, to effectively measure the likelihood of each negative sample with respect to the anchor, we propose to digest the structural characteristics of the underlying graphs.

In this paper, we propose two model variants STENCIL-PPR and STENCIL-PE, which use Laplacian positional embeddings and personalized PageRank scores for modeling local structural patterns of the metapath-induced view, respectively. Note that in order to empower the model with inductive capabilities, we prefer a local measure to a global one. Specifically, we introduce a structural metric \( s(i, j, p) \) representing the distance measure of a negative node \( v_j \) to the anchor \( v_i \) given structural embeddings in metapath-induced view \( p \).

- The Personalized PageRank (PPR) score \([12, 18]\) of node \( v \) is defined as the stationary distribution of a random walk starting from and returning to node \( v \) at a probability of \( c \) at each step. Formally, the PPR vector of node \( v \) under semantic view \( p \) satisfies the following equation

\[
\mathbf{s}_v^p = (1 - c) \mathbf{A}^p \mathbf{s}_v^p + c \mathbf{I} \mathbf{p}_v,
\]

where \( c \) is the returning probability and \( \mathbf{p}_v \) is the preference vector with \((\mathbf{p}_v)_i = 1 \) when \( i = v \) and all other entries set to 0. \( \mathbf{A}^p \) denotes the adjacency matrix induced by metapath \( p \). The structural similarity \( s(v, k, p) \) between node \( v \) and \( k \) can be represented by the PPR score of node \( k \) with respect to \( v \), i.e. \((\mathbf{s}_v^p)_k\).

- The Laplacian positional embedding of one node is defined to be its \( k \) smallest non-trivial eigenvectors \([5]\). We simply define the structure similarity \( s(v, k, p) \) as the inner product between \( \mathbf{s}_v^p \) and \( \mathbf{s}_k^p \).

3.3 Structure-Enhanced Negative Mining. Previous studies \([1, 25, 41]\) demonstrate that CL benefits from hard negative samples, i.e. samples close to the anchor node such that cannot be distinguished easily. As illustrated in Figure 3, after obtaining structural embeddings for each metapath-induced view, we perform negative mining by giving larger weights to structurally harder negative samples. To be specific, we sort negatives according to the hardness metric \( s(i, j, p) \) and pick the top-\( T \) negatives to form a candidate list for metapath-induced view \( p \). Then, we synthesize \( M \ll |V| \) samples by creating a convex linear combination of them. The generated sample \( \mathbf{h}_{i}^p \) can be written as

\[
\mathbf{h}_{i}^p = \alpha_m \mathbf{h}_i^p + (1 - \alpha_m) \mathbf{h}_j^p,
\]

where \( \mathbf{h}_i^p, \mathbf{h}_j^p \in \mathcal{B}^p \) are randomly picked from the memory bank, \( \alpha_m \sim \text{Beta}(\alpha, \alpha) \), and \( \alpha \in \mathbb{R} \) is a hyperparameter, fixed to 1 in our experiments. These interpolated samples will be added into negative bank when estimating mutual information \( I(h_i^p; h_j) \), as given in sequel

\[
\mathcal{L}'(h_i^p, h_j) = -\log \frac{e^{\theta(h_i^p, h_j)/\tau}}{\sum_{h \in \mathcal{B}^p} e^{\theta(h_i^p, h)/\tau}},
\]

where the negative bank

\[
\mathcal{B}^p = \{h_j^p\}_{j \neq i} \cup \{h_j\}_{j \neq i} \cup \{\mathbf{h}_{i}^p\}_{m=1}^M
\]

consists of all inter-view and intra-view negatives as well as synthesized hard negatives.

3.4 Model Training and Complexity Analysis. The contrastive objective \( \ell(h_i; h_i^p) \) for the aggregated node representation \( h_i \) can be defined similarly as Eq. (3.10). The final objective is an average of the losses from all contrastive pairs, formally given by

\[
\mathcal{J} = \frac{1}{|V|} \sum_{v_i \in V} \left[ \frac{1}{|P|} \sum_{p \in P} \frac{1}{2} \left( \mathcal{L}'(h_i^p; h_i) + \mathcal{L}'(h_i; h_i^p) \right) \right].
\]

We use stochastic gradient descent algorithms to update all model parameters. We summarize the training procedure in Appendix A in the supplementary material.

Most computational burden of the STENCIL framework lies in the contrastive objective, which involves computing \((|V|^2|P|)\) node embedding pairs. For structure-enhanced negative mining, the synthesized samples incur an additional computational cost of \( O(M|V||P|) \), which is equivalent to increasing the memory size by \( M \ll |V| \). Since the construction of the candidate list of hard negatives only depends on metapath-induced views, it can be regarded as a preprocessing step and will not incur heavy computation.

3.5 Discussions. The proposed multiview contrastive aggregation objective Eq. (3.6) conceptually relates to contrastive knowledge distillation \([31]\), where several teacher
models (the metapath-induced views) and one student model (the aggregation view) are employed. By forcing the embeddings between several teachers and a student to be the same, these aggregated embeddings adaptively collect information of all relations.

Moreover, the proposed structure-enhanced negative mining scheme generally resembles many studies in domains of metric learning [9, 41] and visual contrastive learning [1, 13, 23, 39]. Nevertheless, none of these methods can be directly applied to graph-structured data, as the hardness score defined simply by inner product of node representations is not sufficient to distinguish negative nodes in graphs and even results in amplifying false negatives.

4 Experiments

We empirically evaluate the effectiveness of our proposed STENCIL in this section. The purpose of empirical studies is to answer the following questions.

- **RQ1.** How does our proposed STENCIL outperform representative baseline models?
- **RQ2.** How does the proposed structure-enhanced negative mining scheme affect the model performance?

4.1 Datasets. For a comprehensive comparison, we use three widely-used heterogeneous datasets from various domains: DBLP, ACM, and IMDb, where DBLP and ACM are two academic networks, and IMDb is a movie network. The statistics of these three used datasets is summarized in Table 1. For details on datasets, please refer to Appendix B in the supplementary material.

4.2 Baselines. We compare our model against a comprehensive set of baselines, including both traditional and deep graph representation learning methods.

- **DeepWalk** [20] generates several sequences by random walk and training the embeddings using the skip-gram objective [17].
- **ESim** [26] captures node semantics from sampled metapath instances with a preset weight. In our experiments, we simply treat all metapaths equally.
- **metapath2vec** [4] performs metapath-based random walks and learns node representations using the skip-gram model similar to DeepWalk. Since metapath2vec only utilizes one metapath, we experiment with all available metapaths and report the best performance.
- **HERec** [27] converts the heterogeneous graph into metapath-based graphs and utilizes the skip-gram model to embed them. Similarly, we test all metapaths and report the best performance.
- **GCN** [14] is a deep semi-supervised baseline for homogeneous graphs, which works by aggregating information from neighborhoods.
- **GAT** [34] is also a homogeneous graph model. It further leverages the self-attention mechanism to model anisotropic neighborhood information.
- **HAN** [36] is a semi-supervised baseline for heterogeneous graphs, which proposes node- and semantic-level attention for learning node representations. We also include the unsupervised version of HAN (denoted by HAN-U) trained with link prediction loss, for further comparison with our proposed contrastive objective.
- **DGI** [35] is a deep contrastive learning model for homogeneous graphs, which maximizes the agreement of node representations and a global summary vector.
- **GRACE** [46] is the state-of-the-art contrastive learning model for homogeneous graphs. It uses a node-level contrastive objective by generating two graph views and maximizing the agreement between them.
- **HeCo** [37] is the state-of-the-art heterogeneous contrastive learning model. HeCo constructs two views with metapaths and the network schema and leverages a collective contrastive scheme to align the two views.

Among these baselines, DeepWalk, DGI, GRACE, GCN, and GAT are designed for homogeneous graphs, and the others are for heterogeneous graphs. Following HAN [36], for DeepWalk, we simply discard node and edge types and treat the heterogeneous graph as a homogeneous graph; for DGI, GRACE, GCN, and GAT, we construct homogeneous graphs according to all metapaths and report the best performance.

4.3 Performance Comparison (RQ1)

4.3.1 Evaluation Protocols. For comprehensive evaluation, we follow HAN [36] and perform experiments on two
Table 2: Performance comparison on three datasets. We report node classification performance in terms of Macro-F1 (Ma-F1) and Micro-F1 (Mi-F1) and node clustering performance in terms of Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI). Available training data is shown in the second column, where \( A \) denotes adjacency matrices, \( X \) denotes node features, and \( Y \) denotes ground-truth labels. The highest performance of unsupervised and supervised models is boldfaced and underlined, respectively.

<table>
<thead>
<tr>
<th>Method</th>
<th>Training Data</th>
<th>Node Classification</th>
<th>Node Clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>ACM</td>
<td>IMDb</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mi-F1</td>
<td>Ma-F1</td>
</tr>
<tr>
<td>DeepWalk</td>
<td>( A )</td>
<td>76.92</td>
<td>77.25</td>
</tr>
<tr>
<td>ESim</td>
<td>( A )</td>
<td>76.89</td>
<td>77.32</td>
</tr>
<tr>
<td>metapath2vec</td>
<td>( A )</td>
<td>65.00</td>
<td>65.09</td>
</tr>
<tr>
<td>HERec</td>
<td>( A )</td>
<td>66.03</td>
<td>66.17</td>
</tr>
<tr>
<td>HAN-U</td>
<td>( A, X )</td>
<td>82.63</td>
<td>81.89</td>
</tr>
<tr>
<td>DGI</td>
<td>( A, X )</td>
<td>89.15</td>
<td>89.09</td>
</tr>
<tr>
<td>GRACE</td>
<td>( A, X )</td>
<td>88.72</td>
<td>88.72</td>
</tr>
<tr>
<td>HeCo</td>
<td>( A, X )</td>
<td>88.15</td>
<td>88.25</td>
</tr>
<tr>
<td>STENCIL-PE</td>
<td>( A, X )</td>
<td>90.76</td>
<td>90.72</td>
</tr>
<tr>
<td>STENCIL-PPR</td>
<td>( A, X )</td>
<td>90.75</td>
<td>90.70</td>
</tr>
<tr>
<td>GCN</td>
<td>( A, X, Y )</td>
<td>86.77</td>
<td>86.81</td>
</tr>
<tr>
<td>GAT</td>
<td>( A, X, Y )</td>
<td>86.01</td>
<td>86.23</td>
</tr>
<tr>
<td>HAN</td>
<td>( A, X, Y )</td>
<td>89.22</td>
<td>89.40</td>
</tr>
</tbody>
</table>

4.3.2 Performance and Analysis. Experiment results are presented in Table 2. Overall, our proposed STENCIL achieves the best unsupervised performance on almost all datasets on both node classification and clustering tasks. It is worth mentioning that our STENCIL is competitive to and even better than several supervised counterparts.

The performance difference of two variants STENCIL-PE and STENCIL-PPR is negligible, which demonstrates that both Laplacian positional embedding and Personalized PageRank scores that calculate local structural similarities are suitable for structure-enhanced negative mining.

Compared with traditional approaches based on random walks and matrix decomposition, our proposed GNN-based STENCIL outperforms them by large margins. Particularly, STENCIL improves metapath2vec and HERec by over 25% on ACM, which demonstrates the superiority of GNN that can leverage rich node attributes to learn high quality node representations for heterogeneous graphs.

Compared to other deep unsupervised methods, our STENCIL obtains promising improvements as well. The performance of the unsupervised version HAN-U trained with a simple reconstruction loss is even inferior to HERec on IMDb and DBLP despite its utilization of node attributes. This indicates that the reconstruction loss is insufficient to fully exploit the structural and semantic information for node-centric tasks such as node classification and clustering. Compared to DGI, GRACE, and HeCo, state-of-the-art graph contrastive learning methods, STENCIL accomplishes excelled performance on all datasets and evaluation tasks, which validates the effectiveness of our proposed contrastive aggregation objective and structure-enhanced negative mining.

Furthermore, experiments show that STENCIL even outperforms its supervised baselines on ACM and IMDb datasets. It remarkably improves HAN by over 4% in terms of node classification Micro-F1 score on IMDb. The outstanding performance of STENCIL certifies the superiority of our proposed framework such that it can distill useful information from each metapath-induced view.

4.4 Close Inspections on Structure-Enhanced Negative Mining Module (RQ2)

4.4.1 Effectiveness of the Module. We modify the negative bank in our contrastive objective to study the impact of structure-enhanced negative mining component:
We study how the two key parameters in the negative mining module affect the performance of STENCIL: the number of synthesized hard negatives $M$ and the threshold $T$ in selecting top-$T$ candidate hard negatives. We perform node classification on the ACM dataset under different parameter settings by only varying one specific parameter and keeping all other parameters the same.

As is shown in Figure 4a, the performance of STENCIL improves as the number of synthesized negatives $M$ increases, which indicates that the learning of STENCIL benefits from more synthesized hard negatives. For the parameter $T$, as presented in Figure 4b, the model performance first rises with a larger $T$, but soon the performance levels off and decreases as $T$ increases further. We suspect that this is because a larger $T$ will result in the selection of less hard negatives, reducing the benefits brought by our proposed structure-enhanced negative mining strategy.
aforementioned traditional approaches could be regarded as shallow node embedding and thus have difficulty in leveraging rich node attributes, due to the fact that they are essentially factorizing a preset proximity matrix [21].

Deep learning approaches. There has been many attempts adopting GNNs into HGs. R-GCN [24] introduces multiple graph convolutional layers, each corresponding to one edge type. GTN [43] firstly generates all possible connections via graph transformer layers and performs graph convolution on the new graph afterwards. Following GAT [34], HAN [36] introduces self-attention mechanisms [33] to aggregate features from metapath-based neighborhoods and weigh different metapaths. Similarly, HetGNN [44] adopts node-type-based neighborhood aggregation, where the neighborhood is sampled using random walk with restart. Moreover, MAGNN [7] further proposes to aggregate intermediate node features along each metapath. When performing neighborhood aggregation, HGT [11] implicitly learns metapaths by modeling heterogeneous attention over each edge.

5.2 Graph Contrastive Learning. Recently, considerable attention has grown up around the theme of Graph Contrastive Learning (GCL), which marries the power of GNN and unsupervised learning. We refer readers to [38] for a comprehensive survey.

The very first work DGI [35] proposes to maximizes mutual information (MI) between node embeddings and a global summary embedding. To be specific, DGI constructs negative graphs by random shuffling node attributes. Then, it requires an injective readout function to produce a graph-level embedding. Mirroring DGI, HDGI [22] adopts CL into heterogeneous graphs. DMGI [19] proposes to align the original network and a corrupted network on each view induced by metapaths and designs a consensus regularization term to aggregate different metapaths. However, the injective property is hard to fulfill in practice and thus these methods may cause information loss due to non-injectivity. Follow-up work GRACE [46] eschews the need of an injective readout function and propose a node-level contrastive framework. Following their work, GCA [47] further proposes stronger adaptive augmentation schemes.

For HG data, prior work proposes various strategies for the contrastive objective. HeCo [37] constructs two views based on metapaths and the network schema and proposes a co-contrastive objective to learn high-level semantic information. Nevertheless, these methods fail to explicitly leverage structural information for GCL, leading to suboptimal performance. We argue that inner product of node embeddings is inefficient to encode similarity between nodes. In our work, we propose to define similarity of examples via structural embeddings, which yields true and hard negative samples in the context of HGs.

6 Conclusion
This paper has developed a novel heterogeneous graph contrastive learning framework. To alleviate the label scarcity problem, we leverage contrastive learning techniques that enables self-supervised training for HGs. Specifically, we propose a novel multiview contrastive aggregation objective that encodes information adaptively from each semantic view. Furthermore, we propose a novel hard negative mining scheme to improve the embedding quality, considering the complex structure of HGs and smoothing nature of heterogeneous GNNs. The proposed structure-aware negative mining scheme discovers and reweights structurally hard negatives so that they contribute more to contrastive learning. Extensive experiments show that our proposed method not only consistently outperforms representative unsupervised baseline methods, but also achieves on par performance with supervised counterparts and even surpasses several of them.

Acknowledgements
This work is supported by National Natural Science Foundation of China (61772528 and U19B2038).

References


[10] O. J. Hénaff, A. Srinivas, J. De Fauw, A. Razavi, C. Doersch, S. M. A. Eslami, and A. van den Oord,


[29] Y. Sun, R. Barber, M. Gupta, C. C. Aggarwal, and J. Han, Co-author Relationship Prediction in Heterogeneous Bibliographic Networks, in ASONAM, 2011, pp. 121–128.


