SPDGI: Meta-Structure and Meta-Path based Deep Graph Infomax

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***Abstract*—Network representation learning aims to learn node representations that preserve both structural and attribute information. Since estimation of mutual information between high dimensional continuous random variables can be achieved by gradient descent, researchers focus on leveraging mutual information to network representation learning. However, most mutual information-based methods focus on handling homogeneous networks. Even if some strategies are designed for heterogeneous networks, they still do not explore the abundant information like the meta-structures. Therefore, in this paper, we propose a meta-Structure and meta-Path based Deep Graph Infomax (SPDGI) method for heterogeneous information networks. Specifically, we first capture rich semantic information via meta-structure and meta-path. Then, we design two methods by considering the different ways in handling meta structure. We further utilize graph convolution module and semantic level attention mechanism to capture local representations of nodes. Finally, we get the global representation for the graph through an averaging operator and learn the final node representations by maximizing the local-global mutual information. The experimental results on three real-world data sets demonstrate that the proposed SPDGI can achieve performance competitive with state-of-the-art unsupervised models.**

***Index Terms*—network representation learning, heterogeneous network, mutual information**

I. Introduction

Network representation learning is to learn the latent and low-dimensional node representations, which preserve the network's topology (e.g., [1–3]), vertex content, and other side information (e.g., [4–7]). After obtaining representations of nodes, the following tasks (e.g., recommender systems [8–10], link prediction [11–13], and node classification [14–16]) can be easily and efficiently carried out by applying conventional machine learning algorithms.

Since random walk-based objectives over-emphasize proximity information at the expense of structural information [17], Belghazi *et al.* [18] offer a general-purpose parametric neural estimator of mutual information based on dual representations of the KL-divergence [19]. It is scalable, flexible, and completely can be trainable via back-propagation. Their work attracts significant attention to mutual information-based methods. For example, Deep InfoMax (DIM) [20], Deep Graph Infomax (DGI) [21], Heterogeneous Deep Graph Infomax (HDGI) [22], and DMGI [23]. Although above mutual information-based algorithms have made great progress, there are still some limitations to be explored. For instance, DIM only focuses on image data; DGI is designed to embed a single network in which only one type of node and edge appear; although HDGI leverages meta-paths to represent the composite relations with different semantics, they still lose some important information, such as when nodes satisfy multiple paths simultaneously; DMGI uses a consensus regularization framework to solve diverse relationships in multiplex networks. However, the relation type they used is similar to meta-paths and thus has the same disadvantages as HDGI. The above representative methods are compared in Table I.

TABLE I: The comparison of representative methods (The symbol ✓ indicates the algorithm exploits the corresponding information, while × means not).

	Methods	DIM	DGI	HDGI	DMGI	SPDGI
Applicable Condition	Image	✓	×	×	×	×
	Homogeneous Network	×	✓	×	×	×
	Heterogeneous Network	×	×	✓	×	✓
	Multiplex Network	×	×	×	✓	×
Used Modules	Meta-path/Relation	×	×	✓	✓	✓
	Meta-structure	×	×	×	×	✓
	Attention	×	×	✓	✓	✓
	Mutual Information	✓	✓	✓	✓	✓

In this paper, we propose a meta-Structure and meta-Path based Deep Graph Infomax (SPDGI) method for heterogeneous information networks (HIN). First, we utilize both meta-structure and meta-path to capture graph heterogeneity rather than meta-paths alone, which allows us to incorporate more complex semantic information. Second, we obtain negative graphs by shuffling node features. Then, we acquire the node's local representations through an attention mechanism on the embedding learned from various meta-structures and meta-paths. Combined nodes' embedding serves as a global representation. Finally, we maximize the mutual information between local node embedding and global graph embedding to obtain the final node representations. According to the different treatment of the meta-structures, we further design SPDGI-A and SPDGI-P. Both of them tend to utilize the nodes that satisfy diverse paths in meta-structures. SPDGI-A tends to combine these paths, while SPDGI-P is likely to choose nodes that meet all paths. The contributions of this work are summarized as follows:

- We propose a heterogeneous network representation learning model called SPDGI, which integrates meta-structures, meta-paths, and mutual information in an appropriate way.
- We further design SPDGI-A and SPDGI-P, inspired by the series connection and parallel connection: confining nodes that satisfy all paths at the same time or any path in meta-structures.
- Extensive experiments are conducted on real-world datasets to evaluate the performance of the proposed model. The experimental results demonstrate that the representations learned by SPDGI are effective for both node classification and clustering tasks.

The remainder of this paper is organized as follows. Section II briefly reviews the related works. The problem to be solved and preliminary knowledge are formulated in Section III. In Section IV, we present the SPDGI methodology. Section V proves the effectiveness of the proposed model with experimental results and analyses. Finally, Section VI concludes the study and discusses our future work.

II. Related Work

Mutual information is based on Shannon entropy to measure dependence between random variables. However, it is difficult to get mutual information when the probability distributions are unknown [18, 24]. For more general problems, Belghazi *et al.* [18] propose a general-purpose mutual information neural estimator based on dual representations of the KL-divergence [19]. Based on the work of Belghazi *et al.*, Hjelm *et al.* [20] find that depending on the downstream task and maximizing mutual information between the complete input and the encoder output is insufficient for learning efficient representations. Therefore, they introduce DIM to learn representations in the image area, which trains a model to maximize the mutual information between global representations and patches. Although these mutual information-based methods are useful, they are not appropriate for graphs. How to apply mutual information to graphs becomes a difficult but interesting problem. Under these circumstances, Velickovic *et al.* [21] successfully apply it into graphs by maximizing mutual information between patch representations and the corresponding high-level summary of the graph. But the disadvantage is that the proposed model is not suitable for heterogeneous networks, while they are common in the real world. To solve this problem, Ren *et al.* [22] further apply it into heterogeneous networks and propose HDGI. To be specific, they use meta-paths, graph convolution module, and semantic-level attention mechanism to capture individual node's local representations. Considering the deficiency that the above strategies only contain relevant information regarding each relation type, and therefore fail to take advantage of the diversity of networks, Park *et al.* [23] present an unsupervised method for embedding attributed multiplex network, which utilizes a consensus regularization framework and a universal discriminator to jointly integrate the embedding from multiple types of relations between nodes. Detailed differences refer to Table I.

III. Problem Definition

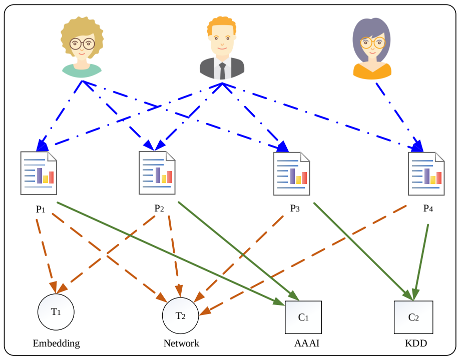
In this section, we first introduce preliminary knowledge. Then, we give the problem definition and summarize the symbols used in this paper in Table II.

Definition 1. Heterogeneous Information Network (HIN) [25–27]. A heterogeneous information network is a directed graph $G = (V, E)$ with a node mapping function $\phi : V \to \mathcal{A}$ and an edge mapping function $\varphi : E \to \mathcal{R}$, where each node $v \in V$ belongs to one node type $\phi(v) \in \mathcal{A}$, and each edge $e \in E$ belongs to a particular relation $\phi(e) \in \mathcal{R}$, respectively. Besides, the type of nodes $|\mathcal{A}|$ and the type of edges $|\mathcal{R}|$ satisfy that $|\mathcal{A}| + |\mathcal{R}| > 2$.

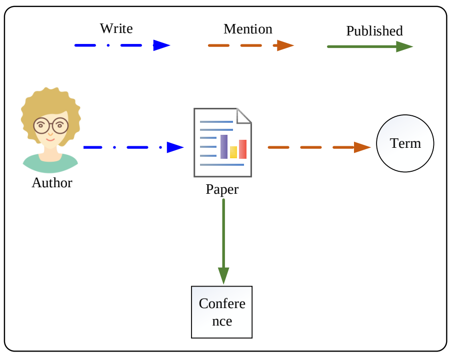
Definition 2. Network Schema [25]. Given a HIN $G = (V, E)$ with a node mapping function $\phi : V \to \mathcal{A}$ and an edge mapping function $\varphi : E \to \mathcal{R}$, its schema T_G is a directed graph defined over node types $\mathcal{A}$ and edge types $\mathcal{R}$, denoted as

TABLE II: The notations used in this paper

Notations	Descriptions
G	The original graph as the input of network embedding.
V, E	The set of nodes/edges in network G.
ϕ, φ	The node/edge mapping function.
$\mathcal{A}, \mathcal{R}$	The type of nodes/edges.
P	The meta-path.
S	The meta-structure.
M	The meta-path or meta-structure, $M \subset \{P, S\}$.
A	The commuting matrix.
$\tilde{A}$	The commuting matrix of negative examples.
$\hat{A}$	The added self-connections commuting matrix.
K	The number of M.
X	The features of nodes.
$\tilde{X}$	The shuffled features of negative nodes.
H	The node representations.
$\tilde{H}$	The node representations of negative examples.
$\mathcal{E}$	The encoder.
$\tilde{s}$	The summary vector of the graph.
$\mathcal{D}$	The discriminator.
I_N	The identity matrix.
W	The adjacency matrix.
W^{M_k}	The layer-specific trainable weight matrix.



(a) HIN example in DBLP data set.



(b) HIN schema in DBLP data set.

Fig. 1: HIN example and abstracted schema in DBLP data set.

$T_G = (\mathcal{A}, \mathcal{R})$. For example, Fig. 1(a) is a HIN in DBLP data set. Then, the abstracted network schema is shown as Fig. 1(b)

Definition 3. Meta-path [25]. A meta-path P is defined on the graph of network schema $T_G = (\mathcal{A}, \mathcal{R})$, which is denoted in the form of $\mathcal{A}_1 \xrightarrow{\mathcal{R}_1} \mathcal{A}_2 \xrightarrow{\mathcal{R}_2} \cdots \xrightarrow{\mathcal{R}_l} \mathcal{A}_{l+1}$. It can be defined with a composite edge $\mathcal{R}_1 \circ \mathcal{R}_2 \circ \cdots \circ \mathcal{R}_{l+1}$ between type $\mathcal{A}_1$ and $\mathcal{A}_{l+1}$, where $\circ$ denotes the composition operator on edges.

Definition 4. Meta-structure [28–30]. Given a HIN $G = (V, E)$ with network schema $T_G = (\mathcal{A}, \mathcal{R})$, a meta-structure S is defined as $S = (\mathcal{A}, \mathcal{R}, v_s, v_t)$, where v_s is the source node, v_t is the target node.

Problem Definition. Meta-structure and meta-path based HIN embedding. Given a HIN $G = (V, E)$ with meta-structures $S = (\mathcal{A}, \mathcal{R}, v_s, v_t)$ and meta-paths P as input, the task is to learn the d-dimensional latent representations H for nodes, which not only contains structural and attribute information, but also includes additional but not redundant semantic information.

IV. SPDGI Methodology

In this section, we propose an unsupervised graph neural network model for heterogeneous information networks. It integrates meta-structures, meta-paths, and mutual information appropriately. Fig. 2 shows the whole framework of SPDGI by taking the DBLP dataset as an example.

TABLE III: Algorithm of SPDGI

Algorithm 1 The overall process of SPDGI.

Input: A HIN graph $G = (V, E)$ with selected meta-structures $S = (\mathcal{A}, \mathcal{R}, v_s, v_t)$ and meta-paths P, initial features X and commuting matrix A.
Output: node representations.
1: Calculate meta-path and meta-structure based commuting matrices A^{M_k} through SPDGI-A and SPDGI-P;
2: Obtain shuffled features $\tilde{X} = Shuffle(X)$;
3: **while** not converged **do**
4: **for** $k = 1...K$ **do**
5: Obtain H^{M_k} and $\tilde{H}^{M_k}$ through Eq. (1);
6: Generate nodes' representations H by Eq. (2);
7: Get a global vector $\vec{s}$ for the whole graph via Eq. (3);
8: Maximize the mutual information with the binary cross-entropy loss of the discriminator through Eq. (4);
9: **end while**

TABLE IV: Computing commuting matrix of SPDGI-A

SPDGI-A: Commuting matrix
$A^{P_1} = W_{AP} \cdot W_{AP}^\top$
$A^{S_A} = W_{AP} \cdot (W_{PC} \cdot W_{PC}^\top + W_{PT} \cdot W_{PT}^\top) \cdot W_{AP}^\top$

A. SPDGI-A and SPDGI-P

According to the different treatment of meta-structures and meta-paths, we divide SPDGI into SPDGI-A and SPDGI-P. Specifically, SPDGI-A allows nodes at intersections to satisfy any path. It is equivalent to separate the meta-structure into meta-paths, and then combine them into one merged graph. We implement it by adding the commuting matrix. Considering redundancy, we leverage meta-paths that are not included in meta-structures and the merged graph. For SPDGI-P, we constrain nodes to meet all paths. It means that the intersected nodes can be reserved when they satisfy all paths in meta-structure. We carry out it via adopting element-wise product between their commuting matrices. The final matrix is combined with meta-path based commuting matrices to obtain the node's local representations. For example, in Fig. 1, there are four types of nodes (Author, Paper, Conference, and Term) and three kinds of edges (Write, Mention, and Publish). From the HIN schema, we select several meta-paths and meta-structures. They are at the left side of the Fig. 2. We employs P_1 and S in SPDGI-A and leverages P_1, P_2, P_3 and S for SPDGI-P. The calculation of the commuting matrix is shown in Table IV and Table V.

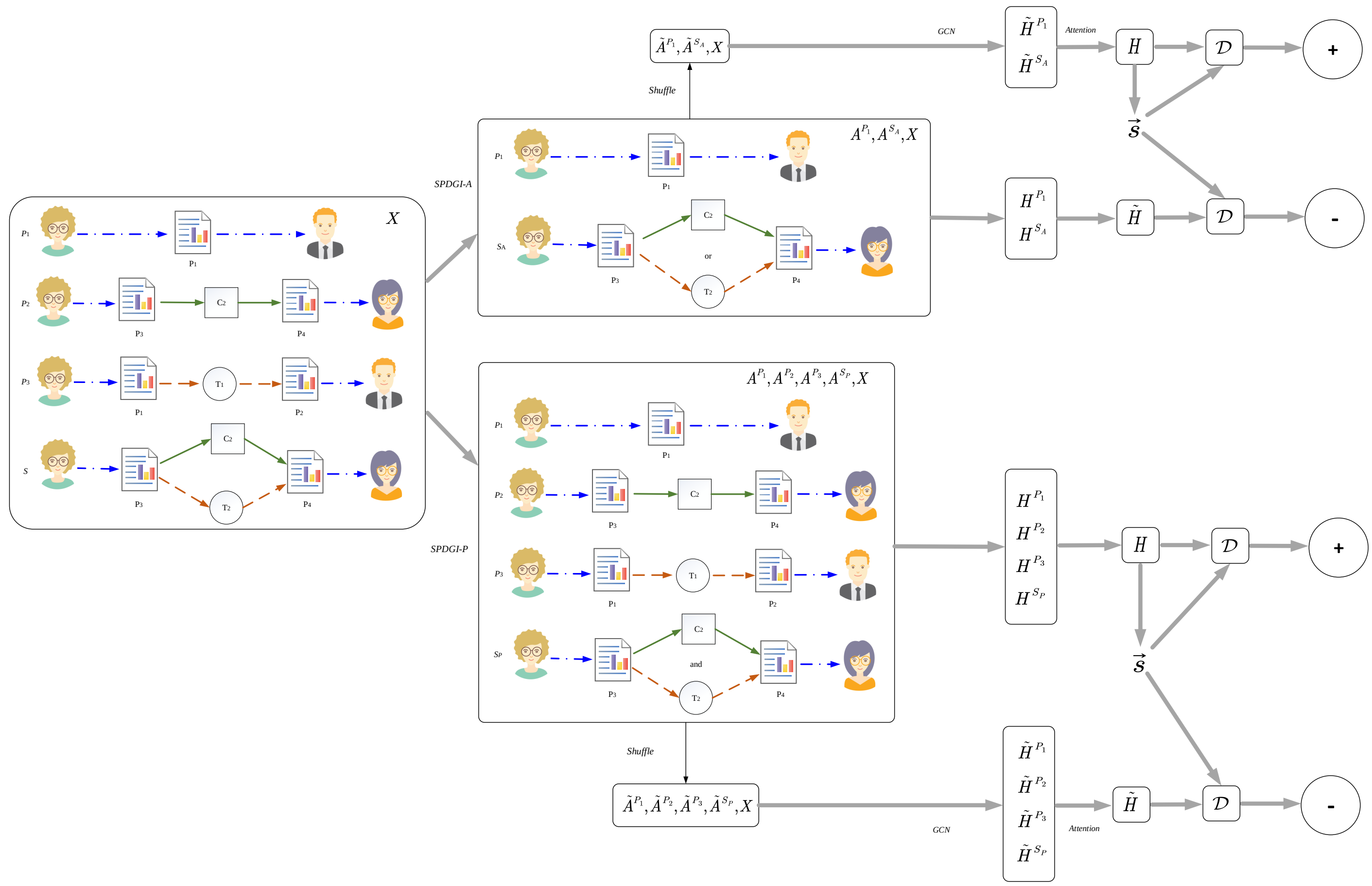


Fig. 2: The overall framework of the proposed SPDGI (Taking DBLP data set as an example)

TABLE V: Computing commuting matrix of SPDGI-P

SPDGI-P: Commuting matrix
$A^{P_1} = W_{AP} \cdot W_{AP}^{\top}$
$A^{P_2} = W_{AP} \cdot W_{PC} \cdot W_{PC}^{\top} \cdot W_{AP}^{\top}$
$A^{P_3} = W_{AP} \cdot W_{PT} \cdot W_{PT}^{\top} \cdot W_{AP}^{\top}$
$A^{S_P} = W_{AP} \cdot [(W_{PC} \cdot W_{PC}^{\top}) \odot (W_{PT} \cdot W_{PT}^{\top})] \cdot W_{AP}^{\top}$

1) Local Representation: SPDGI shuffles the rows of node's feature matrix and keep the commuting matrix unchanged to obtain the negative graph, which is in line with previous works, like [22]. For each M_k ($M \subset \{P, S\}$, k in $[1, K]$), we utilize Graph Convolutional Network (GCN) as our encoder $\mathcal{E}$. Therefore, the node representation for each M_k can be obtained by GCN through Eq. (1).

$$H^{M_k} = \left(\hat{D}^{M_k\ -\frac{1}{2}} \hat{A}^{M_k} \hat{D}^{M_k\ -\frac{1}{2}}\right) X W^{M_k}, \tag{1}$$

where $\hat{A}^{M_k} = A^{M_k} + I_N$, I_N is the identity matrix, $\hat{D}^{M_k}$ is the diagonal node degree matrix of A^{M_k} and W^{M^k} is a layer-specific trainable weight matrix.

Then, inspired by HDGI [22], we also add a semantic attention layer to obtain the final node's representation by combining the learned representation from meta-paths and meta-structures:

$$H = SemanticLevelAttention\left(\left\{H^{M_k}\right\}_1^K\right). \tag{2}$$

2) Global Representation: The objective of SPDGI is to maximize the mutual information between local representations and the global representation. The local node representations are obtained in Section. IV-A1, and we need the summary vector to represent the global information of the entire heterogeneous graph. In this paper, we apply the mean of node representations to get the global summary vector:

$$\vec{s} = \mathcal{R}\left(H\right) = \sigma\left(\frac{1}{N}\sum_{i=1}^{N}\vec{h}_i\right). \tag{3}$$

3) Mutual information based discriminator: Inspired by previous works (e.g. [20–23]), we maximize the mutual information based on the Jensen Shannon divergence between

TABLE VI: Statistics of experimental data sets.

Dataset	Node	Edge	Meta-structure	Average Degree (target node)	Class
IMDB	M [4275] A [5431] D [2082] K [7313]	M-A [12838] M-D [4280] M-K [20529]	MAM MDM MKM M(ADK)M	5.15 18.21 78.00 \	3
DBLP	A [4057] P [14328] C [20] T [8789]	A-P [19645] P-C [14328] P-T [88420]	APA APCPA APTPA AP(CT)PA	2.74 1232.56 1669.28 \	4
ACM	P [3025] A [5835] S [56]	P-A [9744] P-S [3025]	PAP PSP P(AS)P	9.68 730.83 \	3

the joint and the product of marginals and use the following objectives:

$$\mathcal{L} = \frac{1}{N+M}\left(\sum_{i=1}^{N}\mathbb{E}_{(X,A)}\left[\log\mathcal{D}\left(\vec{h}_i,\vec{s}\right)\right] + \sum_{j=1}^{M}\mathbb{E}_{(\tilde{X},\tilde{A})}\left[1-\log\mathcal{D}\left(\vec{\tilde{h}}_j,\vec{s}\right)\right]\right), \quad (4)$$

where N and M denote the number of nodes and negative examples.

V. Experiment

A. Datasets

To make fair comparisons with HDGI [22], which is the most relevant baseline method, we conduct experiments on the datasets used in their original paper [22] in terms of node classification and node clustering tasks.

- **IMDB.** It contains 4275 movies (M), 5431 actors (A), 2082 directors (D), and 7313 keywords (K). We set movies as the target nodes. For the IMDB dataset, the classification task is to classify movies into three classes (Action, Comedy, and Drama) according to their genre.
- **DBLP.** This is a research paper set, which contains 4057 authors (A), 14328 papers (P), 20 conferences (C), and 8789 terms (T). We set authors as the target nodes. For the DBLP dataset, the classification task is to classify authors into four areas (Database, Data Mining, Information Retrieval, and Machine Learning) according to the research topic.
- **ACM.** It is a research paper set, which contains 3025 papers (P), 5835 authors (A), and 56 subjects (S). For the ACM data set, the classification task is to classify the papers into three classes (Database, Wireless Communication, and Data Mining).

B. Baselines

We compare our model with some state-of-the-art baselines to verify the validity of the proposed model.

- **DGI [21]:** It is an unsupervised manner for homogeneous graph, which relies on maximizing mutual information between patch representations and corresponding high-level summaries of the graph. In this paper, we apply DGI to meta-path based homogeneous graph and report the average performance.
- **DMGI [23]:** It is an unsupervised network embedding method for the attributed multiplex network, which jointly integrates the node embeddings from multiple graphs by introducing the consensus regularization framework and the universal discriminator.
- **HDGI-C [22]:** It employs meta-paths and graph convolution module with a semantic-level attention mechanism to capture local representations of nodes in heterogeneous information networks. Then, HDGI learns high-level node representations by maximizing the local-global mutual information.
- **SPDGI-A:** The proposed meta-structure and meta-path based deep graph infomax method, which allows nodes to satisfy any path in meta-structures.
- **SPDGI-P:** The proposed meta-structure and meta-path based deep graph infomax method, which constrains nodes to satisfy all paths in meta-structures.

TABLE VII: Quantitative results on the node classification task.

Dataset	Metrics	Training	DGI	DMGI	HDGI-C	SPDGI-A	SPDGI-P
IMDB	Macro-F1	20%	0.4830	0.6015	0.6068	**0.6501**	0.5899
		40%	0.5028	0.6203	0.6152	**0.6944**	0.6178
		60%	0.4894	0.6395	0.6234	**0.7010**	0.6378
		80%	0.5112	0.6495	0.6228	**0.7186**	0.6665
	Micro-F1	20%	0.5021	0.6010	0.6046	**0.6517**	0.5871
		40%	0.5199	0.6183	0.6127	**0.6950**	0.6131
		60%	0.5048	0.6353	0.6203	**0.7022**	0.6339
		80%	0.5165	0.6502	0.6239	**0.7218**	0.6663
DBLP	Macro-F1	20%	0.7379	0.8225	0.9092	0.8985	**0.9231**
		40%	0.7400	0.8243	**0.9298**	0.9162	0.9233
		60%	0.7361	0.8432	0.9191	0.9107	**0.9335**
		80%	0.7374	0.8450	0.9206	0.9098	**0.9373**
	Micro-F1	20%	0.7478	0.8303	0.9150	0.9040	**0.9272**
		40%	0.7556	0.8307	**0.9336**	0.9198	0.9265
		60%	0.7508	0.8478	0.9269	0.9182	**0.9386**
		80%	0.7475	0.8646	0.9235	0.9126	**0.9412**
ACM	Macro-F1	20%	0.7352	0.9294	0.9167	**0.9322**	0.9044
		40%	0.7220	0.9280	0.9063	**0.9327**	0.9104
		60%	0.7322	0.9223	0.9398	**0.9515**	0.8869
		80%	0.7392	0.9162	0.9236	**0.9583**	0.9138
	Micro-F1	20%	0.7670	0.9298	0.9163	**0.9310**	0.9039
		40%	0.7534	0.9278	0.9050	**0.9326**	0.9089
		60%	0.7648	0.9221	0.9405	**0.9499**	0.8868
		80%	0.7624	0.9109	0.9205	**0.9570**	0.9139

C. Node Classification

We conduct experiments with different training ratios for these three data sets for better comparison. We take fixed 10 percent of data as the validation set. Except for the training data and validation data, the rest data are set as test data. All data are chosen randomly. We use early stopping with the patience of 20, i.e. we stop training if the validation loss does not decrease for 20 consecutive epochs. We tune learning rate from $\{0.00001, 0.00005, 0.0001, 0.0005, 0.001, 0.005, 0.01\}$. The final dimensions refer to Section V-E. To keep the results stable, we repeat the classification process 10 times and report the average Macro-F1 and Micro-F1 in Table VII.

Based on Table VII, we can see that SPDGI has a good performance. For homogeneous graph embedding methods, we apply them to meta-path based homogeneous graphs and report the average values. Compared with DGI, the proposed SPDGI has a better result in these three data sets because of its effectiveness in capturing more semantic information. Besides, SPDGI gives different representations of different weights, while DGI averages the result. For heterogeneous graph embedding methods, we can observe that DMGI and HDGI-C have a good performance in the ACM and DBLP data set. This is because both of them seize heterogeneous information and leverage the strength of mutual information. The proposed SPDGI-A works effectively in most instances while SPDGI-P works well in the DBLP data set. This is due to the properties of data sets and models. SPDGI tends to preserve additional information when nodes satisfy a meta-structure. Particularly, SPDGI-P tends to constrain nodes satisfying each channel in meta-structure, while SPDGI-A is inclined to allow nodes to satisfy any path. Therefore, SPDGI-A is to combine paths in meta-structure, while SPDGI-P is to increase additional information. In the IMDB data set, the degree of nodes is small, thus extra information is able to improve results. In the DBLP data set, the meta-path contains enough information, superfluous information will decrease the performance. Under these circumstances, SPDGI-A performs worse than SPDGI-P and HDGI-C. In the ACM data set, the degree distribution of nodes in 'PAP' and 'PSP' meta-paths varies greatly. Thus, it is important to capture nodes that satisfy different paths at the same time and give them different weights

Through the above analysis, we can find that the proposed SPDGI-A and SPDGI-P can achieve good performances when networks contain little information. When there is enough information, SPDGI-P is appropriate to provide additional but not redundant information. When the nodes' distribution varies greatly in meta-structure, SPDGI-A can make a good balance by merging them into one graph.

D. Node Clustering

We also conduct the node clustering task to evaluate the embedding learned from the previously mentioned algorithms. Once the proposed SPDGI has been trained, we can get the node embedding. Here we utilize the KMeans to conduct node clustering. The number of clusters of IMDB, DBLP, and ACM data set is set to their true label classes. We adopt NMI and ARI to assess the quality of clustering results. Since the performance of KMeans is affected by initial centroids, we repeat the process 100 times. Other parameters are same to Section V-C. The average results are reported in Table VIII

Form Table VIII, we can see that DGI cannot perform well in both IMDB and DBLP data sets because it is not able to balance weights from various meta-path based homogeneous graphs. However, in the ACM data set, the DGI model has good results, even better than DMGI, HDGI-C, and SPDGI-P, while it has a bad performance in the classification task. This probably also because of the distribution of the ACM data set. Papers with the same subjects are likely to be in the same group. Although HDGI-C and DMGI are designed for heterogeneous networks, they still miss some information between nodes that satisfy several meta-paths simultaneously, making the representations not effective enough. The verification based on node clustering tasks also demonstrates that SPDGI can learn effective representations by considering the additional information. Similar to the classification task,

TABLE VIII: Quantitative results on the node clustering task.

Dataset	Metrics	DGI	DMGI	HDGI-C	SPDGI-A	SPDGI-P
IMDB	NMI	0.0275	0.019	0.0387	**0.1367**	0.0117
	ARI	0.0154	0.0181	0.0085	**0.1483**	0.0029
DBLP	NMI	0.3063	0.4339	0.4014	0.6309	**0.7180**
	ARI	0.3013	0.4638	0.3635	0.6955	**0.7798**
ACM	NMI	0.6129	0.5767	0.5116	**0.6525**	0.4909
	ARI	0.5971	0.6074	0.4718	**0.6466**	0.4511

SPDGI-A performs better in IMDB and ACM data sets, SPDGI-P can achieve a good performance in the DBLP data set.

E. Dimension Analysis for the Final Embedding.

In this section, we investigate the effect of the dimension of the final embedding in SPDGI. The result in the three data sets is shown as Fig. 3. We can observe that with the growth of the embedding dimension, the performance raises first and then starts to decrease or be stable. The reason is that the proposed models need suitable dimensions to represent information. A smaller or larger dimension may cause deficient representations or additional redundancies. Therefore, considering the performance of result and operating efficiency, we choose 512, 256, 128 for SPDGI-A and 128, 256, 128 for SPDGI-P in the IMDB, DBLP, and ACM data set, respectively.

VI. Conclusion and Future Work

In this paper, we propose a simple yet effective unsupervised method for heterogeneous information network representation learning, named SPDGI. It integrates several meta-paths and meta-structures through an attention mechanism to obtain local representations of nodes and get the global vector by summarizing them. Finally, through maximizing the local-global mutual information, SPDGI learns high-level representations of nodes. We demonstrate the effectiveness of learned representations for both node classification and clustering tasks on three data sets. We are also optimistic that mutual information maximization is a promising future direction for unsupervised representation learning. In our future work, we will study dynamic networks and try to extend mutual information to this area.

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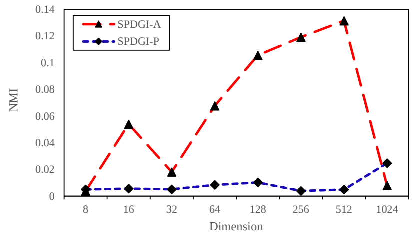
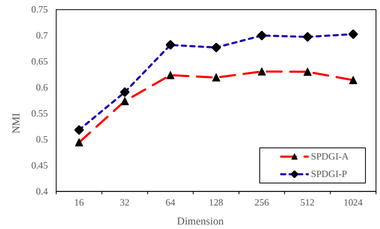
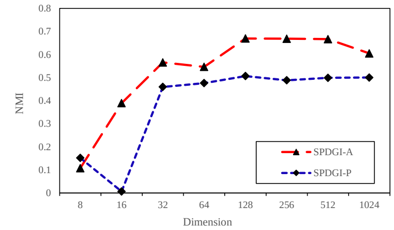


(a) IMDB.



(b) DBLP.



(c) ACM.

Fig. 3: Dimension of the final embedding.

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