SURER: Structure-Adaptive Unified Graph Neural Network for Multi-View Clustering

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Abstract

Deep Multi-view Graph Clustering (DMGC) aims to partition instances into different groups using the graph information extracted from multi-view data. The mainstream framework of DMGC methods applies graph neural networks to embed structure information into the view-specific representations and fuse them for the consensus representation. However, on one hand, we find that the graph learned in advance is not ideal for clustering as it is constructed by original multi-view data and localized connecting. On the other hand, most existing methods learn the consensus representation in a late fusion manner, which fails to propagate the structure relations across multiple views. Inspired by the observations, we propose a Structure-adaptive Unified Graph Neural Network for multi-view clustering (SURER), which can jointly learn a heterogeneous multi-view unified graph and robust graph neural networks for multi-view clustering. Specifically, we first design a graph structure learning module to refine the original view-specific attribute graphs, which removes false edges and discovers the potential connection. According to the view-specific refined attribute graphs, we integrate them into a unified heterogeneous graph by linking the representations of the same sample from different views. Furthermore, we use the unified heterogeneous graph as the input of the graph neural network to learn the consensus representation for each instance, effectively integrating complementary information from various views. Extensive experiments on diverse datasets demonstrate the superior effectiveness of our method compared to other state-of-the-art approaches.

Introduction

In the big data era, the exploration of a comprehensive understanding of heterogeneous features such as images, videos, speech, and text is an important research problem (Wu et al. 2023). Multi-view clustering (MVC) algorithms (Ling et al. 2023; Xu et al. 2023) have found widespread application across many fields. Benefiting from the modeling capacity of deep neural networks, Deep Multi-view Clustering (DMVC) (Li et al. 2019; Yang et al. 2022) methods emerge to provide an effective solution for handling high-dimensional and complex multi-view data. DMVC usually aims at learning the consensus representation by exploiting the consistency and complementarity of multi-view data. For instance, Xu et al. (Xu et al. 2022) utilize view-specific deep autoencoders to extract view-specific instance-level and cluster-level representations. After that, the contrastive losses are introduced to learn discriminative features and reliable clustering labels. Zhou et al. (Zhou and Shen 2020) also adopt deep networks to learn view-specific representations and introduce the adversarial learning mechanism to align the latent representations. Although DMVC achieves impressive clustering performance, its effectiveness is constrained by its failure to leverage the topological structure information among instances. To address this issue, many Deep Multi-view Graph Clustering (DMGC) methods (Huang et al. 2023; Xia et al. 2021) are proposed recently. The mainstream framework of DMGC methods, as depicted in Figure 1, initially utilizes multi-view data to construct topological graphs in advance. Subsequently, view-specific Graph Convolutional Networks (GCNs) are employed to encode the graph information into view-specific representations, which are then merged to create the consensus representation. For example, Wang et al. (Wang et al. 2021) adopt GCNs to explore the complementarity of multi-view data and introduce a mutual information maximization module to guide the consensus representation maintaining the structure information of multiple views. However, the graph used in the above methods is constructed by original multi-view data and remains fixed throughout the entire representation learning process. These graphs inherently incorporate...
noise from the raw data, failing to guide the subsequent representation learning. Furthermore, existing DMGC methods usually learn the consensus representation in a late fusion manner, which only considers the intra-view structure information failing to propagate the structure relations across different views.

To alleviate the limitations of existing DMGC methods, we propose a structure-adaptive unified graph neural network for multi-view clustering, which can provide a robust structure graph and comprehensively fuse information from multiple views to learn the consensus representation. Specifically, we first utilize the original attribute graphs to update the instances latent representations with GCNs, which are further employed to refine the view-specific structure graphs via graph decoders. Then, we integrate the above refined view-specific structure graphs into the unified heterogeneous graph by connecting the latent representations, which are from the same instance. Furthermore, we utilize a heterogeneous graph neural network to simultaneously propagate both the inter-view and intra-view relations, aiming to learn the consensus representation for each instance. Here, the inter-view relations reflect the instance alignment relationship and the intra-view relations denote the local structure relation within the same view. Finally, the consensus representation is employed to generate the final clustering results by the clustering layer. The contributions are summarized as follows:

- We propose a novel structure-adaptive unified graph neural network for MVC. By introducing a graph structure learning module, SURER can generate a structure-adaptive graph, enhancing the robustness of the structure graph used for subsequent representation learning.
- The proposed SURER learns the consensus representation from a unified heterogeneous attribute graph, which can not only effectively fuse the intra-view structure relations but also propagate the structure relations across multiple views.
- Extensive experimental results across eight datasets demonstrate the superior performance of our proposed method in comparison to other state-of-the-art multi-view clustering algorithms.

**Related Work**

In this section, we briefly review multi-view clustering methods, which can be roughly divided into three categories, namely, subspace-based methods (Cao et al. 2015), kernel-based methods (Liu 2021), and graph-based methods (Lin and Kang 2021). The subspace-based methods usually learn a low-dimensional subspace representation from multi-view data, which aims to handle the high-dimensional complex multi-view data. For example, Cuo (Guo 2013) formulates the subspace learning with multiple views as a unified optimization problem, incorporating a common subspace representation matrix and a group sparsity inducing norm. Zhang et al. (Zhang et al. 2019) propose an end-to-end framework, which utilizes the pseudo label to supervise the training of the deep convolutional network, resulting in superior performance. Kernel-based methods aim to provide an optimal combination of a group of pre-specified base kernels to improve the clustering performance. However, kernel-based MVC methods suffer from the problem of high computational complexity. For instance, Zhou et al. (Zhou et al. 2021) propose an efficient sampling strategy in multi-kernel clustering to enhance performance and speed, reducing memory and computational complexity to $O(n)$ and $O(n^2)$, respectively. These multi-view methods show satisfactory performance but they rarely consider the structure information between instances.

The graph-based methods for MVC primarily focus on identifying a consensus graph and obtaining the clustering result through spectral clustering. For instance, Tang et al. (Tang, Lu, and Dhillon 2009) propose a linked matrix factorization technique to fuse the information from multiple graphs. In order to reduce the computational complexity of graph-based methods, the anchor graph has been introduced, which selects a small set of representative samples named anchors to capture the manifold structure of each view. Lu et al. (Lu and Feng 2023) adopt a structure fusion strategy to integrate the view-specific anchor graphs for clustering, which greatly improves the representation capability of the target structure optimal graph. With the widespread adoption of deep learning, deep multi-view graph clustering has become increasingly popular to model graph information, which fully explores the structure information by graph neural networks. Xia et al. (Xia et al. 2021) utilize the clustering label to guide the representation learned by the multi-view shared graph attention encoder. Huang et al.

**Method**

In this paper, we propose a structure-adaptive unified graph neural network to provide robust topological structure and fully explore complementary information from multiple views for improving the performance of clustering. Figure 2 illustrates the framework of SURER.

**Graph Structure Learning Module**

Graph Neural Networks (GNNs) can fully discover the potential structure hidden in multi-view data and achieve better clustering performance. However, GNNs are highly sensitive to the quality of the given graph structures. In pursuit of an optimal graph for downstream tasks, we propose an adaptive graph structure learning module to refine the original graph. Specifically, given a multi-view dataset \( \{X^v \in \mathbb{R}^{d_v \times n}\}_{v=1}^V \) that includes \( n \) samples with \( m \) views. Here, the \( i \)-th column \( x_{vi} \in \mathbb{R}^{d_v} \) in \( X^v \) represents the \( d_v \)-dimensional feature vector of sample \( i \) under the \( v \)-th view.

In most existing DMGC methods, the view-specific graph \( A^v \in \mathbb{R}^{n \times n} \) is constructed using an unsupervised method, such as Euclidean distance, to identify the nearest neighbors of each node. However, they utilize the original feature and local relationship to obtain the structure graph and assume \( A^v \) is fixed, adversely impacting the learning of representations in graph neural networks. Thus, we adopt the graph autoencoder networks to obtain the refined structure graph \( \hat{A}^v \in \mathbb{R}^{n \times n} \).
the computation of the

Then, we build a unified heterogeneous graph \( G \) by linking all view-specific graphs \( \{A_v\}_{v=1}^m \) through the instance alignment relationship across multiple views. Furthermore, we adopt the heterogeneous graph neural network to propagate the structure information across different views and obtain an instance consensus representation matrix \( H \). Finally, the consensus representation \( H \) is treated as the input of the clustering layer to get clustering results, which are supervised by the clustering information contained in latent representations \( \{Z^v\}_{v=1}^m \) and KL divergence loss.

(a) **View-specific graph encoders.** Based on the original structure graph \( A^v \), we utilize the GCN to embed the neighbor structure relationship into instance latent representations \( Z^{v,l} \in \mathbb{R}^{d_{v,l} \times n} \), which can be obtained by following graph convolutional operation:

\[
Z^{v,l} = f^{v,l}(Z^{v,(l-1)}, \hat{A}^v; \theta^v)
\]

where, the computation of the \( l \)-th graph convolutional layer \( f^{v,l} \) is formulated as follows:

\[
Z^{v,l} = \sigma(D^{-\frac{1}{2}}_v \hat{A}^v D^{-\frac{1}{2}}_v Z^{v,(l-1)} W^{v,l} + b^{v,l})
\]

where, \( \hat{A}^v = A^v + I_n \in \mathbb{R}^{n \times n} \) is the self-connection variant of \( A^v \), and \( D^v_i = \sum_j A^v_{ij} \in \mathbb{R}^{n \times n} \) is the degree matrix of \( A^v \). Furthermore, \( \sigma \) denotes the activation function of the \( l \)-th layer. Besides, the input of the first layer is the multi-view data \( \{X^v \in \mathbb{R}^{d_v \times n}\}_{v=1}^m \), and the corresponding latent representations \( Z^{v,1} \) is obtained by:

\[
Z^{v,1} = \sigma(D^{-\frac{1}{2}}_v \hat{A}^v D^{-\frac{1}{2}}_v X^v W^{v,1} + b^{v,1})
\]

(b) **View-specific feature decoders.** After obtaining \( m \) view-specific latent representations \( \{Z^v\}_{v=1}^m \) by graph encoder networks, the view-specific feature decoders are introduced to extract the content information of instances underlying different views. Specifically, we use the view-specific decoder network \( g^v(\cdot) \) with parameters \( \mu^v \) to reconstruct multi-view data \( \hat{X}^v = g^v(Z^v; \mu^v) \), where the decoder network is composed of fully-connected layers. In order to learn the content information of instances, the reconstruction loss between the original data and their corresponding reconstructed features is defined by:

\[
\mathcal{L}_{r,rec} = \frac{1}{m} \sum_{v=1}^m \| X^v - \hat{X}^v \|_F^2
\]

(c) **View-specific graph decoders.** For mitigating the negative impact of noise present in the original data, we utilize the features extracted by the graph encoders to reconstruct the clean graph \( \{A^v\}_{v=1}^m \). Since the representations \( \{Z^v\}_{v=1}^m \) extracted by view-specific graph encoders contain comprehensive structure and view-specific content information, we directly employ an inner product decoder to predict the affinity relationships between instances, resulting in a more robust graph. The graph decoder network of \( v \)-th view can be written as:

\[
\hat{A}^v = \text{sigmoid}(Z^v W^v Z^v^T)
\]

where \( W^v \) is the learned parameter of the \( v \)-th decoder.

To preserve the structure of the refined graph \( \hat{A}^v \), we minimize the graph reconstruction error for each individual view:

\[
\mathcal{L}_{g,rec} = \frac{1}{m} \sum_{v=1}^m \| A^v - \hat{A}^v \|_F^2
\]

**Unified Heterogeneous Graph Construction**

The view-specific graph \( \{\hat{A}^v\}_{v=1}^m \) and latent representations \( \{Z^v\}_{v=1}^m \) retain a lot of view-private information. By fully analyzing complementary information from multiple views, we can achieve more accurate clustering results compared to relying on a single view. Existing deep multi-view graph clustering methods usually use different methods, such as
contrastive learning to learn the consensus representation, or perform convolutions on a fusion graph to obtain the consensus representation. However, they focus on exploring the structure relationships within a single view and fail to propagate the structure relationships across different views.

In our work, we construct a novel unified attribute heterogeneous graph, which simultaneously contains the intra-view edges and inter-view edges. Specifically, we establish connections between distinct representations \( Z_i^v \) and \( Z_i^v \), which correspond to the same instance \( i \) observed from different views. The operation contributes to uncovering the structure relationships across different views. According to the above operation, we can obtain the consensus representation \( H \) by minimizing the following cross-entry loss:

\[
L_{KL} = KL(Q||P) = \sum_{i=1}^{n} \sum_{j=1}^{C} q_{ij} \log \frac{q_{ij}}{p_{ij}}
\]

As the number of convolutional layers increases, instance representation tends to become increasingly similar, leading to the reduction of diversity and information. Thus, we leverage the clustering information contained in the latent representations \( \{Z^v\}_{v=1}^{m} \) to achieve the clustering effectiveness of the soft assignments \( P \). Specifically, we first weighted fuse the latent representations, i.e., \( Z = \frac{1}{m} \sum_{v=1}^{m} Z^v \), which is treated as the input of \( K \)-means to achieve the clustering result \( \hat{P} \in \mathbb{R}^{n \times C} \). Then, we regard \( \hat{P} \) as anchors to modify \( P \) by minimizing the following cross-entry loss:

\[
L_{con} = H(\hat{P}, P) = -\sum_{i=1}^{N} \hat{P}_i \log P_i
\]

Concretely, the clustering result of the \( i \)-th instance is obtained by:

\[
y_i = \arg \max_j p_{ij}
\]

The Overall Loss Function of SURER

In summary, we have introduced a structure-adaptive unified graph neural network for multi-view clustering. In the training stage, the graph structure learning module, heterogeneous graph neural network, and the clustering layer are jointly optimized according to the following objective function:

\[
\mathcal{L} = \mathcal{L}_{g-rec} + \mathcal{L}_{g-rec} + \lambda_1 \mathcal{L}_{con} + \lambda_2 \mathcal{L}_{KL}
\]

where \( \lambda_1 \) and \( \lambda_2 \) are hyper-parameters to balance the weight of different loss functions. The whole learning process of SURER is summarized in Algorithm 1.

**Experiments**

In this section, we evaluate the proposed SURER model on eight widely used multi-view datasets to verify the effect-
Datasets. In our experiments, we employ eight widely-used multi-view datasets to evaluate the performance of SURER, whose detailed characteristics are illustrated in Table 1. MSRCv1 (Winn and Jojic 2005) contains 210 objects from 7 clusters, each of which is represented by five visual features. BBCSports (Greene and Cunningham 2006) is a document dataset containing 544 instances with 5 distinct classes, each image is characterized by two features. 100leaves (Wang, Yang, and Liu 2019) contains 1600 leaves from 100 clusters with three kinds of features. Mfeat (Wang, Yang, and Liu 2019) contains 1600 leaves from 100 clusters with three kinds of features. Mfeat (Wang, Yang, and Liu 2019) contains 1600 leaves from 100 clusters with three kinds of features. Mfeat (Wang, Yang, and Liu 2019) contains 1600 leaves from 100 clusters with three kinds of features.

Baseline models. All compared methods are implemented according to the source codes released by the authors, and the optimal parameters are set according to the suggestion in the corresponding literature.

- MCGC (Zhan et al. 2019) proposes a novel approach by using a disagreement cost function to align view-specific graphs towards the consensus graph.
- LMSC (Zhang et al. 2017) extracts latent representations from multi-view data, facilitating the generation of an accurate instance structure graph to enhance downstream clustering tasks.
- LMVSC (Kang et al. 2020) introduces an anchor graph construction method and a graph fusion mechanism simultaneously to effectively tackle the challenge of large-scale multi-view subspace clustering.
- CDIMC (Wen et al. 2020) uses a cognitive-inspired self-paced $K$-means clustering layer that identifies high-confidence samples, effectively mitigating the influence of outliers.
- SiMVC (Trosten et al. 2021) is a deep multi-view clustering approach that leverages autoencoder networks to acquire view-specific representations and subsequently merge them into a unified final representation.
- CoMVC (Trosten et al. 2021) extends the SiMVC by introducing a selective contrastive learning mechanism to formulate the consensus representation, where the positive pairs consist of samples sharing the same pseudo-label assignments.
- MFLVC (Xu et al. 2022) simultaneously applies instance-level and cluster-level contrastive objects, enhancing feature extracting and clustering results in an end-to-end manner.
- DFP-GNN (Xiao et al. 2023) is composed of three sub-modules, namely view-specific, cross-view propagation, and fusion module, which aims at capturing consistency and complementarity information from multi-view data.

Metrics. Seven commonly employed metrics, specifically ACC, NMI, PUR, ARI, PRE, REC, and F-score, are utilized to evaluate the clustering performance of all algorithms. The detailed definitions of these metrics are elaborated in the (Cao et al. 2015).

![Figure 3](image-url)  
Figure 3: (a), (b), and (c) The visualizations of the consensus representation of LMVSC, DFP-GNN, and SURER on the Mfeat dataset. (d) Ablation study on the Mfeat dataset.

Implementation Details. For all datasets, the view-specific graph encoder module consists of a three-layer graph convolutional encoder with a ReLU activation function, and the dimension is set as \( \{d_v, 512, 2048, 256\} \). The view-specific feature decoders are formed by four fully-connected layers and the dimensions are respectively set as
explore the structure relations between instances. The phe-
tably, DFP-GNN also adopts deep graph neural networks to
MCGC), our SURER obtains the best clustering results. No-
mentary information. (2) Compared with other multi-view
structure relations and fully consider the multi-view comple-
most cases. The encouraging performance demonstrates that
outperforms all compared multi-view clustering methods in
Figure 3, we adopt
on all evaluation metrics. Notably, the best and sub-optimal
results from
$\{0.1, 0.1, 0.5, 1.0, 2.0, 5.0, 10.0\}$. In order to enhance the robustness of refined attribute graphs,
we first conduct an initial pre-training phase for the GSL
module spanning some epochs. Subsequently, we optimize
GSL and the HGNN jointly.

Comparison Results
In Table 2 and 3, we present a comprehensive comparison of
our proposed method with the other eight compared methods on all evaluation metrics. Notably, the best and sub-optimal performances are indicated by bold and underlined formatting, respectively. In Figure 3, we adopt t-SNE to visualize the consensus representation learned by LMVSC, DFP-GNN, and SURER on the Mfeat. By analyzing the data in Table 2-3, and Figure 3 we can observe that:

1. The proposed SURER significantly and consistently outperforms all compared multi-view clustering methods in most cases. The encouraging performance demonstrates that our graph structure learning module and unified heterogeneous graph construction method can provide more robust structure relations and fully consider the multi-view complementary information.

2. Compared with other multi-view graph clustering methods (i.e., DFP-GNN, LMVSC, and MCGC), our SURER obtains the best clustering results. Notably, DFP-GNN also adopts deep graph neural networks to explore the structure relations between instances. The phenomenon indicates that our graph structure learning module can mitigate the influence of noise from the original attribute graphs. Furthermore, the unified heterogeneous graph constructed in our method can propagate the structure information across different views. (3) As illustrated in Figure 3(a),(b), and (c), SURER is capable of acquiring more distinct cluster structures. This observation demonstrates the capacity of SURER to effectively explore structure relationships among samples, thereby grouping similar instances into the same cluster.

Ablation Study
To analyze the effectiveness of the graph structure learning module and the construction of the unified heterogeneous graph, we perform an ablation study and compare our proposed SURER with its degenerated methods. In Figure 3(d), we analyze the following cases:

- **A1**: SRUER w/o. the graph structure learning module. In this case, we use original structure graph $\{A^v\}_{v=1}^m$ and latent representation $\{Z^v\}_{v=1}^m$ to construct the unified heterogeneous graph.

- **A2**: SRUER w/o. the construction of the unified heterogeneous graph. The heterogeneous GNN is replaced by the view-specific graph neural networks to obtain multiple representations, which are fused into a consensus one for subsequent clustering.

- **A3**: SRUER w/o. the graph structure learning module and unified heterogeneous graph. We adopt view-specific GNNs to learn the latent representations $\{Z^v\}_{v=1}^m$, subsequently merging them into the consensus representation.
Parameter Sensitivity Analysis

In this subsection, we analyze the parameter sensitivity of SURER with respect to its two employed parameters $\lambda_1$ and $\lambda_2$. Specifically, we adopt the cross-validation strategy to fine-tune $\lambda_1$ and $\lambda_2$ within the range of $\{0.01, 0.1, 0.5, 1.0, 2.0, 5.0, 10.0\}$. Figure 4 illustrates the experiment results of ACC, NMI, and PUR on the Mfeat dataset. These experiment results indicate that our approach achieves good performance across an extensive parameter range, further emphasizing the insensitivity of our SURER framework to variations in $\lambda_1$ and $\lambda_2$.

Conclusions

In this work, we propose a structure-adaptive unified graph neural network to perform multi-view clustering. To provide a robust structure graph for each view, the graph structure learning module is employed, which explores both structure and content information to reconstruct the corresponding refined graph. The heterogeneous unified graph is further constructed to propagate the structure relations within and across different views, serving to obtain the final consensus representation. By fully capturing the topological structure from multiple views and comprehensively fusing them for clustering, our framework enjoys more powerful clustering performance, which has been verified on various multi-view datasets as compared with state-of-art methods.

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