Novelty Assessment Report

Paper: Compactness and Consistency: A Conjoint Framework for Deep Graph Clustering
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Abstract

Graph clustering is a fundamental task in data analysis, aiming at grouping nodes with similar characteristics in the graph into clusters. This problem has been widely explored using graph neural networks (GNNs) due to their ability to leverage node attributes and graph topology for effective cluster assignments. However, representations learned through GNNs typically struggle to capture global relationships between nodes via local message-passing mechanisms. Moreover, the redundancy and noise inherently present in the graph data may easily result in node representations lacking compactness and robustness. To address the aforementioned issues, we propose a conjoint framework called CoCo, which captures compactness and consistency in the learned node representations for deep graph clustering. Technically, our CoCo leverages graph convolutional filters to learn robust node representations from both local and global views, and then encodes them into low-rank compact embeddings, thus effectively removing the redundancy and noise as well as uncovering the intrinsic underlying structure. To further enrich the node semantics, we develop a consistency learning strategy based on compact embeddings to facilitate knowledge transfer from the two perspectives. Our experimental findings indicate that our proposed CoCo outperforms state-of-the-art counterparts on various benchmark datasets.

Core Task Landscape

This paper addresses: **deep graph clustering with node representation learning**

A total of **50 papers** were analyzed and organized into a taxonomy with **27 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Contrastive Learning-Based Graph Clustering**
- **Autoencoder-Based Graph Clustering**
- **Representation Enhancement and Augmentation**
- **Joint Embedding and Clustering Optimization**
- **Scalable and Large-Scale Graph Clustering**
- **Specialized Graph Clustering Applications**
- **Semi-Supervised and Few-Shot Graph Clustering**
- **Graph Clustering with Auxiliary Tasks**
- **Theoretical and Methodological Foundations**
- **Graph Clustering with Specialized Constraints**
- ... and 1 more categories

Complete Taxonomy Tree

- deep graph clustering with node representation learning Survey Taxonomy
- Contrastive Learning-Based Graph Clustering
  - Dual-View Contrastive Clustering (2 papers)
  - [1] Deep graph clustering via aligning representation learning (Zhikui Chen, 2024) View paper
  - [3] Deep Graph Clustering via Dual Correlation Reduction (Yue Liu, 2021) View paper
  - Multi-Modal and Multi-View Contrastive Clustering (3 papers)
  - [8] Graph embedding contrastive multi-modal representation learning for clustering (Wei Xia, 2023) View paper
  - [12] Clustering enhanced multiplex graph contrastive representation learning (Ruiwen Yuan, 2023) View paper
  - [19] Deep Multi-View Clustering via View-Specific Representation and Global Graph (Jingyu Pu, 2023) View paper
  - Cluster-Aware Contrastive Learning (3 papers)
  - [16] Attributed graph clustering under the contrastive mechanism with cluster-preserving augmentation (Yimei Zheng, 2024) View paper
  - [28] Community-aware graph debiased contrastive representation learning (Peng Wu, 2024) View paper
  - [49] CC-GNN: A Clustering Contrastive Learning Network for Graph Semi-Supervised Learning (Peng Qin, 2024) View paper
  - Self-Supervised Contrastive Clustering Without Negatives (3 papers)
  - [5] Carl-g: Clustering-accelerated representation learning on graphs (William Shiao, 2023) View paper
  - [22] Graph infoclust: Leveraging cluster-level node information for unsupervised graph representation learning (Mavromatis, 2020) View paper
  - [44] Neighborhood contrastive representation learning for attributed graph clustering (Tong Wang, 2023) View paper
- Autoencoder-Based Graph Clustering
  - Variational Graph Autoencoders (1 papers)
  - [6] Graph clustering via variational graph embedding (Lin Guo, 2022) View paper
  - Hierarchical and Pooling-Based Autoencoders (2 papers)

- [11] HC-GAE: The Hierarchical Cluster-based Graph Auto-Encoder for Graph Representation Learning (Xu Zhuo, 2024) View paper
    - [33] Hierarchical graph representation learning with differentiable pooling (Ying, 2018) View paper
    - Dual Autoencoder and Multi-Task Embedding (2 papers)
    - [30] Attributed graph clustering with multi-task embedding learning (Xiaotong Zhang, 2022) View paper
    - [36] SDAC-DA: Semi-Supervised Deep Attributed Clustering Using Dual Autoencoder (Kamal Berahmand, 2024) View paper
- Representation Enhancement and Augmentation
    - Disentangled Representation Learning (1 papers)
    - [2] Deep Graph Clustering with Disentangled Representation Learning (Yifan Wang, 2025) View paper
    - Structure and Feature Augmentation (3 papers)
    - [4] Deep graph clustering with enhanced feature representations for community detection (Jie Hao, 2022) View paper
    - [7] Deep graph clustering method with improved cluster structure feature learning (Peng Lv, 2025) View paper
    - [10] Improved Attributed Graph Clustering with Representation and Structure Augmentation (Jipeng Guo, 2024) View paper
    - Attention-Based Representation Learning (3 papers)
    - [13] Adaptive graph clustering based on feature adversarial and graph transformer (Wei-tong Zhang, 2025) View paper
    - [20] Attributed Graph Clustering: A Deep Attentional Embedding Approach (Chun Wang, 2019) View paper
    - [26] Deep Attentional Implanted Graph Clustering Algorithm for the Visualization and Analysis of Social Networks (Fernando Escobedo, 2024) View paper
- Joint Embedding and Clustering Optimization
    - Compact Embedding with Consistency Constraints ★ (1 papers)
    - [0] Compactness and Consistency: A Conjoint Framework for Deep Graph Clustering (Anon et al., 2026) View paper
    - Dynamic Embedding and Adaptive Clustering (2 papers)
    - [27] Graph clustering with dynamic embedding (Yang, 2017) View paper
    - [37] Graph Clustering with Embedding Propagation (Carl Yang, 2020) View paper
    - Reinforcement and Unknown Cluster Number (1 papers)
    - [29] Reinforcement Graph Clustering with Unknown Cluster Number (Yue Liu, 2023) View paper
    - Fuzzy and Soft Assignment Clustering (1 papers)
    - [41] Fuzzy-Based Deep Attributed Graph Clustering (Yue Yang, 2024) View paper
- Scalable and Large-Scale Graph Clustering (2 papers)
    - [21] Dink-net: Neural clustering on large graphs (Liu Yu-e, 2023) View paper
    - [25] Graph Neural Network-Based Node Clustering for Dual-Focused Power Network Partitioning (Maymouna Ez Eddin, 2024) View paper
- Specialized Graph Clustering Applications
    - Temporal and Dynamic Graph Clustering (2 papers)
    - [9] DECRL: A Deep Evolutionary Clustering Jointed Temporal Knowledge Graph Representation Learning Approach (Chen Qian, 2024) View paper
    - [43] Interpretable clustering on dynamic graphs with recurrent graph neural networks (Yuhang Yao, 2021) View paper
    - Heterogeneous and Multiplex Graph Clustering (2 papers)
    - [15] A node clustering algorithm for heterogeneous information networks based on node embeddings (Dongjiang Liu, 2024) View paper
    - [23] An efficient graph embedding clustering approach for heterogeneous network (Zahra Sadat Sajjadi, 2024) View paper
    - Signed and Attributed Network Clustering (1 papers)
    - [18] Deep network embedding for graph representation learning in signed networks (X. Shen, 2018) View paper
    - Domain-Specific Graph Clustering (3 papers)
    - [38] A community-aware graph neural network applied to geographical location-based representation learning and clustering within GIS (Phu Pham, 2025) View paper
    - [39] Deep Multi-Graph Embedded Clustering for Community Detection in FMRI Functional Brain Networks Across Individuals (Kai-Jun See, 2024) View paper
    - [48] Human Clustering Based on Graph Embedding and Space Functions of Trajectory Stay Points on Campus (Ke Xie, 2025) View paper
- Semi-Supervised and Few-Shot Graph Clustering (3 papers)
    - [17] Semi-supervised clustering with deep metric learning and graph embedding (Xiaocui Li, 2020) View paper
    - [35] Cluster-HGNN: Deep Local Features Clustering for Few-Shot Image Classification With Hybrid Graph Neural Networks (Wu Hongxuan, 2025) View paper
    - [40] A heterogeneous graph-based semi-supervised learning framework for access control decision-making (Jiao Yin, 2024) View paper
- Graph Clustering with Auxiliary Tasks
    - Community Detection and Embedding Co-Learning (1 papers)
    - [31] Learning community embedding with community detection and node embedding on graphs (Sandro Cavallari, 2017) View paper
    - Clustering with Graph Neural Network Enhancements (2 papers)
    - [14] Graph Neural Networks Powered by Encoder Embedding for Improved Node Learning (Chen Shiyu, 2025) View paper
    - [34] CAGNN: Cluster-aware graph neural networks for unsupervised graph representation learning (Zhu Yanqiao, 2020) View paper
- Theoretical and Methodological Foundations (1 papers)
    - [32] Deep Graph Representation Learning and its Application on Graph Clustering (Hua, 2024) View paper
- Graph Clustering with Specialized Constraints
    - Homophily-Aware and Trustworthy Neighborhood Mining (1 papers)
    - [47] Trustworthy Neighborhoods Mining: Homophily-Aware Neutral Contrastive Learning for Graph Clustering (Liang Peng, 2025) View paper
    - Optimal Graph Structure Learning (1 papers)
    - [24] Structured optimal graph-based clustering with flexible embedding (Pengzhen Ren, 2019) View paper
    - Heterogeneous Feature Clustering (1 papers)
    - [50] QGRL: Quaternion Graph Representation Learning for Heterogeneous Feature Data Clustering (Junyang Chen, 2024) View paper

- Application-Driven Graph Clustering (3 papers)
  - [42] A Graph-Based Blocking Approach for Entity Matching Using Contrastively Learned Embeddings (John Bosco Mugeni, 2022) View paper
  - [45] Graph-Augmented Open-Domain Multi-Document Summarization (X Shen, 2025) View paper
  - [46] Graph Clustering Techniques for Community Detection in Social Networks (Fatemeh Daneshfar, 2025) View paper

Narrative

Core task: deep graph clustering with node representation learning. The field has evolved into a rich landscape organized around several major methodological branches. Contrastive learning-based approaches leverage self-supervised signals to learn discriminative node embeddings, while autoencoder-based methods reconstruct graph structure or node features to capture latent representations. Representation enhancement and augmentation techniques focus on improving embedding quality through data transformations or multi-view learning, as seen in works like Dual Correlation Reduction[3] and Enhanced Feature Representations[4]. Joint embedding and clustering optimization methods, including Compactness Consistency[0], tightly couple the representation learning and cluster assignment processes to ensure that learned embeddings are directly optimized for clustering objectives. Additional branches address scalability for large graphs, specialized applications ranging from brain networks to entity matching, and semi-supervised or few-shot settings where label scarcity is a key challenge.

A particularly active line of work centers on enforcing consistency and compactness constraints during joint optimization, balancing the need for expressive embeddings with stable cluster assignments. Compactness Consistency[0] exemplifies this direction by imposing dual constraints that encourage compact cluster structures and consistent assignments across training iterations, closely aligning with methods like Aligning Representation Learning[1] and Disentangled Representation[2] that also emphasize coherent embedding spaces. In contrast, Carl-g[5] and Variational Graph Embedding[6] explore probabilistic or contrastive frameworks that may prioritize flexibility over strict compactness. Meanwhile, works such as Improved Cluster Structure[7] and DECRL[9] integrate auxiliary objectives or multi-stage refinement to enhance cluster quality. The original paper sits within this joint optimization branch, sharing the emphasis on consistency with nearby efforts but distinguishing itself through its specific compactness regularization strategy, offering a complementary perspective to the probabilistic and contrastive alternatives prevalent in the field.

Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

Taxonomy-Level Summary

The original leaf focuses on learning compact, low-dimensional embeddings with consistency regularization to jointly optimize clustering. Sibling subtopics explore alternative joint embedding-clustering strategies: dynamic iterative refinement, fuzzy/soft assignments for uncertainty modeling, and reinforcement learning for automatic cluster number determination. All approaches share the goal of jointly optimizing node representations and clustering, but differ in their optimization mechanisms and architectural constraints.

Similarities: - All subtopics perform joint optimization of node embeddings and clustering rather than treating them as separate stages - Each approach aims to improve clustering quality by learning task-specific representations - All methods operate within deep graph clustering frameworks that leverage graph structure

Differences: - The original leaf emphasizes compactness (low-rank embeddings) and consistency constraints, while siblings focus on dynamics, uncertainty, or adaptivity - Dynamic Embedding uses iterative refinement between embeddings and assignments; the original leaf uses consistency regularization as the coupling mechanism - Fuzzy and Soft Assignment methods model uncertainty through probabilistic assignments, whereas the original leaf likely uses deterministic consistency constraints - Reinforcement and Unknown Cluster Number approaches automatically determine cluster counts, while the original leaf (and other siblings) typically assume predefined cluster numbers

Suggested Search Directions: - Investigate whether compact embeddings with consistency constraints can be extended to handle unknown cluster numbers - Explore hybrid approaches combining consistency regularization with fuzzy assignments for robust clustering - Examine trade-offs between embedding compactness and dynamic adaptivity in iterative clustering frameworks

Sibling Subtopics

- **Dynamic Embedding and Adaptive Clustering** (leaves: 1, papers: 2)
- Scope: Methods jointly optimizing dynamic node embeddings and cluster assignments through iterative refinement.
- Exclude: Static embedding methods or those without adaptive clustering belong to sibling categories.
- **Fuzzy and Soft Assignment Clustering** (leaves: 1, papers: 1)
- Scope: Methods using fuzzy logic or soft assignments to model uncertainty in joint embedding-clustering frameworks.
- Exclude: Hard assignment methods without fuzzy or probabilistic components belong to sibling categories.
- **Reinforcement and Unknown Cluster Number** (leaves: 1, papers: 1)
- Scope: Approaches using reinforcement learning or adaptive mechanisms to determine cluster numbers during joint optimization.
- Exclude: Methods requiring predefined cluster numbers belong to sibling categories.

Contributions Analysis

Overall novelty summary. The paper proposes CoCo, a framework for deep graph clustering that learns compact, low-rank node embeddings while enforcing consistency constraints across training iterations. It resides in the 'Compact Embedding with Consistency Constraints' leaf of the taxonomy, which currently contains only this paper as its sole member. This positioning suggests a relatively sparse research direction within the broader 'Joint Embedding and Clustering Optimization' branch, where methods tightly couple representation learning with cluster assignment. The taxonomy reveals that while joint optimization approaches are well-represented, the specific combination of compactness and consistency constraints appears less explored.

The taxonomy tree shows that CoCo's parent branch, 'Joint Embedding and Clustering Optimization', contains sibling leaves focused on dynamic embeddings, reinforcement learning for unknown cluster numbers, and fuzzy assignments. Neighboring branches include contrastive learning methods (dual-view, multi-modal, cluster-aware) and autoencoder-based approaches (variational, hierarchical, dual-task). The taxonomy narrative indicates that while consistency and compactness themes appear in works like 'Aligning Representation Learning' and 'Disentangled Representation' under the 'Representation Enhancement' branch, CoCo's joint optimization setting distinguishes it from these representation-focused methods. The exclude_note clarifies that two-stage methods separating embedding from clustering belong elsewhere.

Among 30 candidates examined, the overall CoCo framework (Contribution 1) showed no clear refutations across 10 candidates, suggesting some novelty in the integrated approach. However, the compactness learning via low-rank subspace training (Contribution 2) and consistency learning strategy (Contribution 3) each encountered one refutable candidate among 10 examined. This indicates that while the specific combination may be novel, individual components have precedent in the limited search scope. The statistics reflect a focused semantic search rather than exhaustive coverage, meaning additional related work may exist beyond the top-30 matches analyzed.

Based on the limited search scope of 30 semantically similar papers, the work appears to occupy a relatively underexplored niche within joint optimization methods, though individual technical components show some overlap with prior efforts. The taxonomy structure suggests the field has diversified into multiple methodological branches, and CoCo's specific leaf remains sparsely populated. A more comprehensive literature review would be needed to fully assess novelty across the broader graph clustering landscape.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: CoCo framework for deep graph clustering

Description: The authors introduce CoCo, a novel framework that learns node representations by capturing both compactness (through low-rank embeddings) and consistency (through similarity alignment) from local and global graph views to improve deep graph clustering performance.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Attribute-missing graph clustering network

URL: View paper

Brief Assessment

Attribute-Missing Graph[71] addresses a different problem (clustering with missing node attributes) rather than the general deep graph clustering framework proposed in the original paper. The candidate focuses on imputation-then-clustering for incomplete data, not on capturing compactness and consistency in complete graph representations.

2. Attributed Graph Clustering: A Deep Attentional Embedding Approach

URL: View paper

Brief Assessment

Deep Attentional Embedding[20] focuses on attributed graph clustering using graph attention networks with autoencoder reconstruction and self-training, not on the specific compactness-consistency framework with low-rank embeddings and dual-view consistency learning proposed in CoCo.

3. Deep Graph Clustering via Dual Correlation Reduction

URL: View paper

Brief Assessment

Dual Correlation Reduction[3] focuses on reducing information correlation at sample and feature levels to avoid representation collapse, while the original paper's CoCo framework addresses different challenges: capturing global relationships via graph diffusion and eliminating redundancy through low-rank subspace learning with GMM. The technical approaches and problem formulations are fundamentally different.

4. Graph embedding contrastive multi-modal representation learning for clustering

URL: View paper

Brief Assessment

Contrastive Multi-modal[8] focuses on multi-modal clustering across different data modalities (e.g., image, text), not single-graph clustering with local/global views. The technical approaches differ fundamentally: CoCo uses low-rank embeddings via GMM for graph structure, while [8] uses contrastive learning across modalities.

5. Clustering using graph convolution networks

URL: View paper

Brief Assessment

Graph Convolution Clustering[77] focuses on unsupervised graph clustering using modularity-based objectives and pooling methods, not on learning node representations through compactness (low-rank embeddings) and consistency (similarity alignment) from local and global views as proposed in the original paper.

6. Deep learning powered single-cell clustering framework with enhanced accuracy and stability

URL: View paper

Brief Assessment

Single-Cell Clustering[72] focuses on single-cell RNA sequencing data clustering using dual-topology adaptive graph convolutional networks, not general deep graph clustering frameworks with compactness and consistency learning as proposed in the original paper.

7. Simple contrastive graph clustering

URL: View paper

Brief Assessment

Simple Contrastive[75] focuses on contrastive learning with simple MLPs and low-pass filtering for graph clustering, while the original paper proposes a framework combining compactness (low-rank embeddings via GMM) and consistency (similarity alignment) from local and global views. These are fundamentally different technical approaches to graph clustering.

8. Structure-adaptive multi-view graph clustering for remote sensing data

URL: View paper

Brief Assessment

Structure-Adaptive Multi-view[74] focuses on multi-view graph clustering for remote sensing data with superpixel-based anchor selection and spatial correlation refinement. The original paper addresses deep graph clustering with compactness and consistency learning through low-rank embeddings and dual-view feature extraction, which are fundamentally different technical approaches and application domains.

9. Multi-view contrastive graph clustering

URL: View paper

Brief Assessment

Multi-view Contrastive[76] focuses on multi-view graph clustering with contrastive learning at the graph-level, not on learning low-rank compact embeddings via GMM or consistency learning between local/global views as in CoCo.

10. Deep fuzzy clusteringâa representation learning approach

URL: View paper

Brief Assessment

Deep Fuzzy Clustering[73] focuses on fuzzy clustering with autoencoder-based representation learning for general data, not specifically graph-structured data. It does not address graph neural networks, local-global view learning, or graph topology exploitation that are central to the original paper's CoCo framework.

Contribution 2: Compactness learning via low-rank subspace training

Description: The method uses Gaussian mixture models to learn an optimal low-dimensional subspace that reconstructs node representations from both local and global views, eliminating redundancy and noise while preserving the intrinsic data structure through low-rank factorization.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Partial multi-label learning via multi-subspace representation

URL: View paper

Brief Assessment

Partial Multi-label[57] focuses on partial multi-label learning with label disambiguation and feature noise reduction, not graph clustering. The low-rank decomposition is applied to label matrices and feature spaces in a supervised multi-label context, fundamentally different from the original paper's unsupervised graph clustering with GMM-based node representation learning.

2. Multi-level Graph Subspace Contrastive Learning for Hyperspectral Image Clustering

URL: View paper

Brief Assessment

Multi-level Subspace Contrastive[59] focuses on hyperspectral image clustering using graph contrastive learning at multiple levels (node and graph), not on low-rank subspace training via GMM for general graph clustering as in the original paper.

3. Robust dimensionality reduction via low-rank laplacian graph learning

URL: View paper

Brief Assessment

Low-Rank Laplacian[53] focuses on dimensionality reduction via low-rank Laplacian graph construction for classification/clustering tasks, not on learning low-rank subspaces through Gaussian mixture models for graph neural network embeddings as in the original paper.

4. Cluster-infused low-rank subspace learning for robust multi-label classification

URL: View paper

Prior Art Analysis

Cluster-Infused Subspace[54] demonstrates prior work on using low-rank subspace learning to remove redundancy and noise in graph embeddings. The candidate paper explicitly describes a subspace clustering component that removes redundant noise through low-rank embedding, which directly addresses the same technical challenge of eliminating redundancy and noise while preserving intrinsic data structure. Both papers employ low-rank factorization techniques to achieve compact representations that filter out noise and redundancy from high-dimensional graph data.

Evidence

Evidence 1 - **Rationale**: Both papers explicitly target the same problem of removing noise and redundancy through low-rank techniques in graph data. - **Original**: we encode node representations into low-rank compact embeddings, which learns the optimal low-dimensional subspace to characterize the intrinsic underlying structure, thereby fully eliminating redundancy and noise - **Candidate**: aim to transcend the challenges of noise, redundancy, and high

Evidence 2 - **Rationale**: The candidate paper's subspace clustering component indicates prior work on the same low-rank subspace approach for handling graph data. - **Original**: low-rank representations can effectively exploit the inherent underlying correlation structure among data and suppress the impact of noise under the assumption that high-dimensional data points often intrinsically lie on a low-dimensional subspace - **Candidate**: to be specific, the subspace clustering component

Evidence 3 - **Rationale**: Both papers use low-rank embedding techniques specifically to remove redundant noise from node representations, demonstrating the same core technical approach. - **Original**: we leverage the gaussian mixture model (gmm, in appendix a) (richardson & green, 1997) to learn the optimal low-dimensional subspace that can represent the localand global-view node embeddings - **Candidate**: while the low-rank embedding further removes redundant noise and

5. A novel robust adaptive subspace learning framework for dimensionality reduction

URL: View paper

Brief Assessment

Robust Adaptive Subspace[55] focuses on general dimensionality reduction for removing noise and redundancy, but does not specifically address graph embeddings or the dual local-global view reconstruction framework proposed in the original paper.

6. Robust recovery of subspace structures by low-rank representation

URL: View paper

Brief Assessment

Low-Rank Representation[52] focuses on subspace clustering and recovering subspace structures from corrupted data, not on learning compact embeddings for graph neural networks or eliminating redundancy in graph embeddings specifically.

7. Error-robust multi-view subspace clustering with nonconvex low-rank tensor approximation and hyper-Laplacian graph embedding

URL: View paper

Brief Assessment

Hyper-Laplacian Tensor[51] focuses on multi-view subspace clustering with tensor approximation for multi-view data, not graph clustering with GMM-based low-rank subspace learning for node representations.

8. Semisupervised Subspace Learning With Adaptive Pairwise Graph Embedding

URL: View paper

Brief Assessment

Adaptive Pairwise Embedding[56] focuses on semisupervised subspace learning with graph construction in original space, not on eliminating redundancy through GMM-based low-rank factorization of GNN representations as in the original paper.

9. Multiview Subspace Clustering via Low-Rank Symmetric Affinity Graph

URL: View paper

Brief Assessment

Low-Rank Symmetric Affinity[58] focuses on multiview subspace clustering using Gaussian mixture models for low-rank structure learning across multiple views, while the original paper addresses graph clustering with GNNs using GMM for node representation learning from local and global graph views. The application domains and technical contexts differ substantially.

10. Unsupervised graph denoising via feature-driven matrix factorization

URL: View paper

Brief Assessment

Feature-Driven Factorization[60] focuses on graph denoising through matrix factorization techniques, but the provided context is too fragmentary to establish whether it uses Gaussian mixture models for low-rank subspace learning or addresses redundancy elimination in the same manner as the original paper's dual-view (local/global) reconstruction approach.

Contribution 3: Consistency learning strategy for semantic enhancement

Description: A consistency learning approach is proposed that aligns similarity distributions of nodes across local and global views using anchor samples, enabling knowledge transfer between perspectives and enriching node semantics for improved clustering.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Consistency Enhancement-Based Deep Multiview Clustering via Contrastive Learning

URL: View paper

Brief Assessment

Consistency Enhancement Multiview[68] focuses on multi-view clustering with consistency across different data views (e.g., different feature sets), whereas the original paper addresses consistency between local and global graph perspectives within a single graph structure. These are fundamentally different problem settings and technical approaches.

2. Local-Global Representation Enhancement for Multi-View Graph Clustering

URL: View paper

Brief Assessment

Local-Global Representation Enhancement[69] focuses on multi-view graph clustering with attention-based fusion and contrastive learning, not on consistency learning across local and global views using anchor samples for knowledge transfer as in the original paper.

3. Efficient multi-view graph clustering with local and global structure preservation

URL: View paper

Brief Assessment

Local Global Preservation[64] focuses on anchor-based multi-view graph clustering with local and global structure preservation through anchor graphs, not on consistency learning across views using similarity distributions for semantic enhancement in deep graph clustering.

4. GLAC-GCN: Global and Local Topology-Aware Contrastive Graph Clustering Network

URL: View paper

Prior Art Analysis

GLAC-GCN[63] demonstrates prior work on consistency learning across local and global views for semantic enhancement in clustering. Both papers employ consistency learning strategies that align similarity distributions between local and global perspectives using KL-divergence. GLAC-GCN[63] explicitly describes a 'self-adaptive learning mechanism' that 'ensure[s] consistency between multiple learning pipelines via the kullbackâleibler (kl)-divergence' for graph clustering, which directly parallels the original paper's approach of aligning similarity distributions across views. The candidate paper's abstract clearly states this consistency mechanism was used to refine graph clustering by leveraging both local topology and global semantic information, predating the original submission.

Evidence

Evidence 1 - **Rationale**: Both papers describe consistency learning mechanisms for semantic enhancement. GLAC-GCN[63] explicitly uses KL-divergence to ensure consistency between learning pipelines, while the original paper uses KL-divergence to align similarity distributions for knowledge transfer between local and global views. - **Original**: To further enrich the node semantics, we develop a consistency learning strategy based on compact embeddings to facilitate knowledge transfer from the two perspectives. - **Candidate**: a self-adaptive learning mechanism is devised to ensure consistency between multiple learning pipelines via the kullbackâleibler (kl)-divergence

Evidence 2 - **Rationale**: Both papers use KL-divergence to enforce consistency between local and global views. The original paper explicitly defines consistency loss using KL-divergence between similarity distributions, while GLAC-GCN[63] describes using KL-divergence to ensure consistency between multiple learning pipelines that process local and global topology information. - **Original**: with the localand global-view similarity distributionsp i = (pi 1, . . . , pi m)andq i = (qi 1, . . . , qi m), we encourage the consistency of them to facilitate the knowledge transfer and mutually enhance the representation semantics. formally, we define the consistency learning loss as: l= 1 2n ... - **Candidate**: the local topology structure, and global semantic information are simultaneously utilized to refine the graph. then a paralleled graph convolutional network (gcn) learning mechanism is designed, where i) both the original graph and the globally and locally refined graph are treated as input graphs, ...

Evidence 3 - **Rationale**: Both papers identify the need to bridge local and global views for enhanced clustering. GLAC-GCN[63] explicitly addresses the limitation of single-pipeline approaches and proposes joint optimization of multiple pipelines leveraging local and global topology, which aligns with the original paper's consistency learning approach across local and global views. - **Original**: In summary, contrastive learning focuses on sample discriminability at the instance level, whereas our consistency learning considers to bridge the gap between the considered local and global views at the relational distribution level. - **Candidate**: first, in the input space, they primarily rely on the original topology structure as the input (to some graph network), lacking the ability to jointly leverage local and global topology information to refine the graph. second, in the learning process, they usually employ a single graph learning pipe...

5. Deep contrastive coordinated multi-view consistency clustering

URL: View paper

Brief Assessment

Coordinated Multi-view Consistency[61] focuses on multi-view clustering with semantic label alignment, while the original paper develops consistency learning for graph clustering using anchor-based similarity distributions across local/global views.

6. Cluster alignment with target knowledge mining for unsupervised domain adaptation semantic segmentation

URL: View paper

Brief Assessment

Cluster Alignment Mining[67] focuses on domain adaptation for semantic segmentation using clustering and contrastive strategies across source-target domains, not consistency learning across local-global views within a single domain for graph clustering.

7. Self-Supervised, Multi-View, Semantics-Aware Anchor Clustering

URL: View paper

Brief Assessment

Semantics-Aware Anchor[70] focuses on multi-view anchor clustering with dual-level contrastive learning between views, not on consistency learning across local and global views of a single graph for semantic enhancement in graph clustering.

8. MCoCo: Multi-level Consistency Collaborative Multi-view Clustering

URL: View paper

Brief Assessment

MCoCo[66] focuses on aligning semantic labels across views in multi-view clustering using contrastive learning, not on consistency learning between local and global views for node representation enhancement in graph clustering.

9. Global and local combined contrastive learning for multi-view clustering

URL: View paper

Brief Assessment

Global Local Contrastive[65] focuses on multi-view clustering with contrastive learning methods, while the original paper proposes consistency learning that aligns similarity distributions across local and global views using anchor samples for graph clustering. The candidate's limited context does not provide sufficient detail to assess whether similar consistency learning mechanisms were previously proposed.

10. Self-supervised graph-level representation learning with local and global structure

URL: View paper

Brief Assessment

Local Global Structure[62] focuses on aligning graph/subgraph embeddings via contrastive learning and uses hierarchical prototypes for global semantic clustering, not consistency learning across local-global views with anchor samples as in the original paper.

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

- [0] Compactness and Consistency: A Conjoint Framework for Deep Graph Clustering View paper
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