

# Novelty Assessment Report

**Paper:** Efficient Learning on Large Graphs using a Densifying Regularity Lemma

**PDF URL:** <https://openreview.net/pdf?id=kK7PbRzqGk>

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## Abstract

Learning on large graphs presents significant challenges, with traditional Message Passing Neural Networks suffering from computational and memory costs scaling linearly with the number of edges. We introduce the Intersecting Block Graph (IBG), a low-rank factorization of large directed graphs based on combinations of intersecting bipartite components, each consisting of a pair of communities, for source and target nodes. By giving less weight to non-edges, we show how an IBG can efficiently approximate any graph, sparse or dense. Specifically, we prove a constructive version of the weak regularity lemma: for any chosen accuracy, every graph can be approximated by a dense IBG whose rank depends only on that accuracy. This improves over prior versions of the lemma, where the rank depended on the number of nodes for sparse graphs. Our method allows for efficient approximation of large graphs that are both directed and sparse, a crucial capability for many real-world applications. We then introduce a graph neural network architecture operating on the IBG representation of the graph and demonstrating competitive performance on node classification, spatio-temporal graph analysis, and knowledge graph completion, while having memory and computational complexity linear in the number of nodes rather than edges.

### Disclaimer

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Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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## Core Task Landscape

This paper addresses: **Efficient Learning on Large Graphs Using Low-Rank Factorization**

A total of **50 papers** were analyzed and organized into a taxonomy with **15 categories**.

### Taxonomy Overview

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

- **Low-Rank Graph Neural Network Architectures**
- **Graph Structure Learning and Denoising**
- **Matrix Factorization for Clustering and Community Detection**
- **Representation Learning via Low-Rank Constraints**
- **Link Prediction and Knowledge Graphs**
- **Specialized Applications and Domain-Specific Methods**
- **Theoretical Foundations and Algorithmic Frameworks**

### Complete Taxonomy Tree

- Efficient Learning on Large Graphs Using Low-Rank Factorization Survey Taxonomy
- Low-Rank Graph Neural Network Architectures
  - Low-Rank Message Passing and Attention Mechanisms (3 papers)
  - [20] Tiny Graph Neural Networks for Radio Resource Management (Ghasemi Ahmad, 2024) [View paper](#)
  - [26] Graph Contrastive Learning with Low-Rank Regularization and Low-Rank Attention for Noisy Node Classification (Wang, 2024) [View paper](#)
  - [45] Semi-Supervised Classification on Non-Sparse Graphs Using Low-Rank Graph Convolutional Networks (Alfke, 2019) [View paper](#)
  - Alternative GNN Paradigms Without Propagation (2 papers)
  - [2] Implicit svd for graph representation learning (Abu-El-Haija, 2021) [View paper](#)
  - [30] Graph neural networks without propagation (Liang Yang, 2023) [View paper](#)
  - Low-Rank Adaptation for Transfer Learning (2 papers)
  - [8] Graphlora: Structure-aware contrastive low-rank adaptation for cross-graph transfer learning (Zhe-Rui Yang, 2025) [View paper](#)
  - [33] LoRA-NCL: Neighborhood-Enriched Contrastive Learning with Low-Rank Dimensionality Reduction for Graph Collaborative Filtering (Honghui Chen, 2023) [View paper](#)
- Graph Structure Learning and Denoising
  - Adversarial Robustness via Low-Rank Graph Purification (4 papers)
  - [13] Speedup robust graph structure learning with low-rank information (Hui Xu, 2021) [View paper](#)
  - [16] Efficient low-rank gnn defense against structural attacks (Abdullah Alchihabi, 2023) [View paper](#)
  - [23] All you need is low (rank) defending against adversarial attacks on graphs (Negin Entezari, 2020) [View paper](#)
  - [32] Garnet: Reduced-rank topology learning for robust and scalable graph neural networks (Deng Chenhui, 2022) [View paper](#)
  - Topological Denoising and Graph Regularization (2 papers)
  - [12] Learnable Graph-regularization for matrix decomposition (Penglong Zhai, 2023) [View paper](#)
  - [14] Learning to drop: Robust graph neural network via topological denoising (Dongsheng Luo, 2021) [View paper](#)
- Matrix Factorization for Clustering and Community Detection
  - Single-View Graph Clustering (5 papers)

- [1] Symmetry and Graph Bi-Regularized Non-Negative Matrix Factorization for Precise Community Detection (Zhigang Liu, 2024) [View paper](#)
- [5] Graph regularized sparse non-negative matrix factorization for clustering (Ping Deng, 2022) [View paper](#)
- [7] Sparse Feature-Weighted Double Laplacian Rank Constraint Non-Negative Matrix Factorization for Image Clustering (Hu Ma, 2024) [View paper](#)
- [24] Exponential Graph Regularized Non-Negative Low-Rank Factorization for Robust Latent Representation (Guowei Yang, 2022) [View paper](#)
- [27] Community detection using nonnegative matrix factorization with orthogonal constraint (Yaoyao Qin, 2016) [View paper](#)
- Multi-View Clustering and Fusion (6 papers)
- [3] Multiview spectral clustering via structured low-rank matrix factorization (Yang Wang, 2018) [View paper](#)
- [6] Learnable Multi-View Matrix Factorization With Graph Embedding and Flexible Loss (Sheng Huang, 2023) [View paper](#)
- [10] Multi-View Clustering via High-Order Bipartite Graph Learning and Tensor Low-Rank Representation (Chuan Tang, 2025) [View paper](#)
- [21] Low-rank graph completion-based incomplete multiview clustering (Jinrong Cui, 2022) [View paper](#)
- [31] One-step incomplete multiview clustering with low-rank tensor graph learning (Guangyan Ji, 2022) [View paper](#)
- [43] Rank consistency induced multiview subspace clustering via low-rank matrix factorization (Jipeng Guo, 2021) [View paper](#)
- Representation Learning via Low-Rank Constraints
  - Contrastive Learning with Low-Rank Regularization (3 papers)
  - [9] Low-rank graph contrastive learning for node classification (Yan-Cheng Wang, 2024) [View paper](#)
  - [34] Noise-disentangled graph contrastive learning via low-rank and sparse subspace decomposition (Gehang Zhang, 2024) [View paper](#)
  - [44] Self-supervised graph neural networks via low-rank decomposition (L Yang, 2023) [View paper](#)
  - Dimensionality Reduction and Subspace Learning (6 papers)
  - [15] Low-rank preserving projection via graph regularized reconstruction (Jie Wen, 2018) [View paper](#)
  - [18] Low-rank discriminant embedding for multiview learning (Jingjing Li, 2016) [View paper](#)
  - [19] Unsupervised large graph embedding (F. Nie, 2017) [View paper](#)
  - [40] Non-negative low rank and sparse graph for semi-supervised learning (Liansheng Zhuang, 2012) [View paper](#)
  - [49] Enhanced Multi-View Low-Rank Graph Optimization for Dimensionality Reduction (Haohao Li, 2024) [View paper](#)
  - [50] Sparsity Enhanced Correntropy-based Low-Rank Matrix Factorization with Adaptive Bipartite Graph Learning for Feature Extraction (Qiuyan Zhang, 2025) [View paper](#)
- Link Prediction and Knowledge Graphs (4 papers)
  - [36] Collaborative filtering with graph information: Consistency and scalable methods (Nikhil Rao, 2015) [View paper](#)
  - [38] Neural graph embeddings as explicit low-rank matrix factorization for link prediction (Asan Agibetov, 2023) [View paper](#)
  - [46] LowFER: Low-rank Bilinear Pooling for Link Prediction (Amin, 2020) [View paper](#)
  - [48] Learning first-order logic embeddings via matrix factorization. (William Yang Wang, 2016) [View paper](#)
- Specialized Applications and Domain-Specific Methods (2 papers)
  - Federated and Distributed Learning (2 papers)
  - [4] Communication-Efficient Personalized Federal Graph Learning via Low-Rank Decomposition (Liu Ruyue, 2024) [View paper](#)
  - [25] Efficient Wireless Federated Learning via Low-Rank Gradient Factorization (Mingzhao Guo, 2024) [View paper](#)
  - Reinforcement Learning and Markov Decision Processes (2 papers)
  - [11] Flambe: Structural complexity and representation learning of low rank mdps (Alekh Agarwal, 2020) [View paper](#)
  - [39] Representation learning for general-sum low-rank markov games (Ni, 2022) [View paper](#)
  - Causal Structure Learning and Probabilistic Models (2 papers)
  - [17] On low-rank directed acyclic graphs and causal structure learning (Zhuangyan Fang, 2023) [View paper](#)
  - [35] On varimax asymptotics in network models and spectral methods for dimensionality reduction (J Cape, 2023) [View paper](#)
  - Domain-Specific Prediction Tasks (5 papers)
  - [22] Graphs regularized robust matrix factorization and its application on student grade prediction (Yupei Zhang, 2020) [View paper](#)
  - [28] SEMA: Semantic Attention for Capturing Long-Range Dependencies in Egocentric Lifelogs (Pravin Nagar, 2024) [View paper](#)
  - [37] A traffic flow forecasting model based on dynamic graph learning and temporally adaptive attention (H Zhang, 2026) [View paper](#)
  - [42] SparGE: Sparse coding-based patient similarity learning via low-rank constraints and graph embedding (Yingjie Liu, 2023) [View paper](#)
  - [47] Graph Low-Rank Non-Negative Matrix Factorization with Auto-Encoders for Fault Detection (Yabing Liu, 2024) [View paper](#)
- Theoretical Foundations and Algorithmic Frameworks ★ (3 papers)
  - [0] Efficient Learning on Large Graphs using a Densifying Regularity Lemma (Anon et al., 2026) [View paper](#)
  - [29] Predicting global label relationship matrix for graph neural networks under heterophily (L Liang, 2023) [View paper](#)
  - [41] Algorithmic Inductive Biases for Graph Representation Learning (Dupty, 2022) [View paper](#)

## Narrative

Core task: efficient learning on large graphs using low-rank factorization. The field organizes around several complementary branches that exploit low-rank structure to scale graph learning. Low-Rank Graph Neural Network Architectures focus on designing efficient GNN layers through factorized weight matrices and reduced-rank message passing, as seen in works like GraphLoRA[8] and Efficient Lowrank GNN[16]. Graph Structure Learning and Denoising emphasizes refining or learning adjacency matrices by imposing low-rank constraints to remove noise and discover latent connectivity, while Matrix Factorization for Clustering and Community Detection applies non-negative and spectral factorizations to partition nodes into communities, exemplified by Orthogonal NMF Community[27] and Multiview Spectral Clustering[3]. Representation Learning via Low-Rank Constraints leverages factorization to learn compact embeddings that preserve graph topology, and Link Prediction and Knowledge Graphs use low-rank decompositions to infer missing edges or relations. Specialized Applications and Domain-Specific Methods adapt these techniques to domains such as federated learning and wireless networks, while Theoretical Foundations and Algorithmic Frameworks provide the mathematical underpinnings and convergence guarantees that justify low-rank approximations.

Several active lines explore trade-offs between expressiveness and scalability: some methods prioritize computational efficiency by aggressively reducing rank, while others balance rank with regularization to preserve critical graph structure. A recurring theme is the tension between global low-rank assumptions and local heterogeneity in real-world graphs. The original paper, Densifying Regularity Lemma[0], resides in the Theoretical Foundations and Algorithmic Frameworks branch alongside works like Algorithmic Inductive Biases[41] and Global Label Relationship[29]. Unlike application-focused neighbors that directly optimize GNN architectures or

clustering objectives, Densifying Regularity Lemma[0] emphasizes foundational algorithmic principles, potentially offering new theoretical tools for understanding when and why low-rank factorizations succeed on large graphs. This positions it as a bridge between abstract graph theory and the practical design choices seen in neighboring branches.

## Related Works in Same Category

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The following **2 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Predicting global label relationship matrix for graph neural networks under heterophily

**Authors:** L Liang, X Hu, Z Xu, Z Song | **Year/Venue:** 2023 | **URL:** [View paper](#)

#### Abstract

and heterophilous graphs, namely Low-Rank Graph Neural Network (LRGNN). Our low rank. This insight inspires us to predict the label relationship matrix by solving a robust low-rank

#### Relationship Analysis

Both papers belong to the Theoretical Foundations and Algorithmic Frameworks category, providing theoretical analysis for low-rank graph learning methods. The original paper introduces a densifying regularity lemma for approximating large directed graphs using Intersecting Block Graphs (IBGs) with complexity linear in nodes rather than edges, while the candidate paper focuses on predicting a global label relationship matrix via low-rank matrix completion for handling heterophily in GNNs. The key difference is that the original paper addresses general graph approximation and scalability through low-rank factorization, whereas the candidate paper specifically targets the heterophily problem by recovering label relationships through matrix completion techniques.

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### 2. Algorithmic Inductive Biases for Graph Representation Learning

**Authors:** Mohammed Haroon Dupty | **Year/Venue:** 2022 | **URL:** [View paper](#)

#### Abstract

In this section, we derive the FGNN model through neuralizing the Sum-Product loopy belief propagation that utilizes the low rank decomposition of higher order potentials. Then we

#### Relationship Analysis

Both papers belong to the Theoretical Foundations and Algorithmic Frameworks category, providing theoretical analysis for low-rank graph learning methods. They share an overlapping focus on using low-rank factorization techniques to improve computational efficiency on large graphs, with both developing neural network architectures that leverage these decompositions. However, the original paper focuses on densifying regularity lemmas and Intersecting Block Graphs (IBG) for approximating sparse directed graphs with theoretical guarantees independent of graph size, while the candidate paper derives models through neuralizing Sum-Product loopy belief propagation with low-rank decomposition of higher-order potentials, representing a different algorithmic approach to incorporating low-rank structure.

## Contributions Analysis

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**Overall novelty summary.** The paper introduces the Intersecting Block Graph (IBG) representation and proves a constructive weak regularity lemma showing that any graph can be approximated by a dense IBG with rank depending only on accuracy, not node count. It sits in the Theoretical Foundations and Algorithmic Frameworks leaf, which contains only three papers total. This is one of the sparsest branches in the taxonomy, contrasting sharply with crowded application-focused areas like Matrix Factorization for Clustering (eleven papers) or Low-Rank Message Passing (three papers). The leaf's scope emphasizes theoretical analysis and general algorithmic frameworks rather than domain-specific implementations.

The taxonomy reveals that most low-rank graph learning research concentrates on architectural design (Low-Rank GNN Architectures with three subtopics) and clustering applications (Matrix Factorization with two subtopics totaling eleven papers). The paper's theoretical focus diverges from these empirical branches: neighboring leaves like Contrastive Learning with Low-Rank Regularization and Adversarial Robustness via Low-Rank Graph Purification apply low-rank constraints to specific learning objectives, while this work provides foundational guarantees about approximation quality. The exclude\_note for Specialized Applications explicitly separates general-purpose methods like this from domain-tailored techniques, reinforcing the paper's position as a bridge between abstract graph theory and practical design.

Among twenty-nine candidates examined, the IBG representation itself shows no clear refutation across ten candidates. However, the densifying weak regularity lemma faces one refutable candidate among nine examined, and the IBG neural network architecture encounters one refutable candidate among ten. The limited search scope means these statistics reflect top-K semantic matches rather than exhaustive coverage. The representation contribution appears more novel within this sample, while the theoretical lemma and architecture face some prior overlap. Given the sparse theoretical foundations leaf and the concentration of prior work in application-driven branches, the paper's core theoretical contributions occupy relatively unexplored territory within the examined literature.

Based on the limited search of twenty-nine candidates, the work appears to contribute primarily through theoretical foundations rather than architectural innovation. The taxonomy structure suggests that foundational algorithmic frameworks remain underexplored compared to application-specific methods. However, the analysis cannot assess whether deeper theoretical graph learning literature outside the top-K semantic matches contains closer precedents for the regularity lemma or IBG construction. The positioning in a sparse leaf with only two siblings indicates potential novelty, but exhaustive verification would require broader coverage of theoretical graph approximation literature.

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

### Contribution 1: Intersecting Block Graph (IBG) representation for directed graphs

**Description:** The authors propose IBG as a novel low-rank graph representation that extends prior work to directed graphs. Each IBG consists of overlapping bipartite components defined by pairs of source and target node communities, enabling efficient approximation of large directed graphs.

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.

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#### 1. Ranking hubs and authorities using matrix functions

**URL:** [View paper](#)

##### Brief Assessment

Ranking Matrix Functions[63] focuses on ranking hubs/authorities in directed networks using matrix exponentials and bipartization techniques, not on low-rank graph approximation using overlapping bipartite components for efficient learning.

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#### 2. Predicting directed links using nondiagonal matrix decompositions

**URL:** [View paper](#)

### **Brief Assessment**

Nondiagonal Matrix Decomposition[67] focuses on DEDICOM decompositions for trust prediction in social networks, not on general low-rank graph representations for machine learning. The candidate addresses link prediction in trust networks using matrix decompositions, while the original paper proposes IBG as a general framework for efficient learning on large directed graphs with theoretical guarantees via the densifying regularity lemma.

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### **3. A link prediction algorithm based on low-rank matrix completion**

URL: [View paper](#)

#### **Brief Assessment**

Lowrank Matrix Completion[64] focuses on link prediction using low-rank matrix completion techniques for general networks. The candidate does not demonstrate prior work on IBG's specific approach of using overlapping bipartite components defined by pairs of source and target node communities for directed graph approximation.

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### **4. A Spectral Framework for Tracking Communities in Evolving Networks**

URL: [View paper](#)

#### **Brief Assessment**

Spectral Tracking Communities[66] focuses on spectral methods for community detection in evolving networks using Grassmann manifolds, not on low-rank factorization of directed graphs using bipartite components as in IBG.

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### **5. RMFSVD: robust graph clustering based on matrix factorization and singular value decomposition**

URL: [View paper](#)

#### **Brief Assessment**

RMFSVD[65] focuses on matrix factorization and SVD for graph clustering, not on low-rank representations of directed graphs using bipartite components. The candidate's bipartite graph construction is for clustering purposes, not for approximating directed graphs as in the original paper.

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### **6. Structural identifiability in low-rank matrix factorization**

URL: [View paper](#)

#### **Brief Assessment**

Structural Identifiability Factorization[69] focuses on bipartite graph representations in the context of matrix factorization identifiability, not on low-rank approximations of large directed graphs for neural network processing.

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### **7. Temporal link prediction using matrix and tensor factorizations**

URL: [View paper](#)

#### **Brief Assessment**

Temporal Link Factorization[61] focuses on temporal link prediction using matrix/tensor factorizations for bipartite graphs evolving over time, not on low-rank representations of directed graphs using intersecting bipartite components as a general graph approximation method.

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### **8. Community Detection in Directed Networks and its Application to Analysis of Social Networks**

URL: [View paper](#)

#### **Brief Assessment**

Directed Community Detection[68] focuses on detecting communities in directed networks using spectral methods and connectivity analysis, not on low-rank graph representation using bipartite components for efficient approximation.

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### **9. Low-rank matrix factorization and co-clustering algorithms for analyzing large data sets**

URL: [View paper](#)

#### **Brief Assessment**

Lowrank Coclustering[70] focuses on low-rank matrix factorization and co-clustering for general data analysis, not specifically on directed graph representation using overlapping bipartite components as defined in the original paper's IBG framework.

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### **10. Link prediction on evolving data using matrix and tensor factorizations**

URL: [View paper](#)

#### **Brief Assessment**

Evolving Link Factorization[62] focuses on temporal link prediction using matrix and tensor factorizations for bipartite graphs, not on low-rank graph representations for directed graphs using overlapping bipartite components as IBG does.

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## **Contribution 2: Densifying Weak Regularity Lemma with rank independent of graph properties**

**Description:** The authors establish a theoretical result showing that any graph (sparse or dense) can be approximated by an IBG with a number of communities that depends only on the desired approximation accuracy, not on graph size or sparsity. This improves over prior regularity lemmas where rank scaled with graph properties for sparse graphs.

This contribution was assessed against **9 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### **1. Regularity properties of Fourier integral operators**

URL: [View paper](#)

#### **Brief Assessment**

Fourier Integral Regularity[52] focuses on regularity properties of Fourier integral operators in mathematical analysis, not graph approximation or weak regularity lemmas for graphs.

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### **2. Learning on large graphs using intersecting communities**

URL: [View paper](#)

#### **Brief Assessment**

Intersecting Communities[51] focuses on undirected graphs with standard cut metric, requiring  $k \propto n^{2/e}$  communities for sparse graphs. The candidate does not demonstrate rank independence from sparsity for general graphs.

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### 3. An efficient sparse regularity concept

URL: [View paper](#)

#### Prior Art Analysis

Efficient Sparse Regularity[56] demonstrates that sparse matrices can be approximated with a number of summands (rank) that is independent of the matrix size, provided certain boundedness conditions are met. This directly challenges the novelty claim that the original paper is the first to establish rank independence from graph properties for sparse graphs. The candidate explicitly states their decomposition uses a number of summands independent of the size of the matrix, which parallels the original paper's claim about rank being independent of graph size and sparsity.

#### Evidence

Evidence 1 - **Rationale:** Both papers claim to approximate graphs/matrices with rank independent of size. The candidate explicitly states 'the number of summands is independent of the size  $m \hat{a} n$  of  $a$ ' for sparse matrices (density  $p$ ), while the original claims their rank 'depends only on that accuracy' and improves over prior work where 'rank depended on the number of nodes for sparse graphs.' - **Original:** we prove a constructive version of the weak regularity lemma: for any chosen accuracy, every graph can be approximated by a dense ibg whose rank depends only on that accuracy. this improves over prior versions of the lemma, where the rank depended on the number of nodes for sparse graphs. - **Candidate:** let  $a$  be a 0/1 matrix of size  $m \hat{a} n$ , and let  $p$  be the density of  $a$  (i.e., the number of ones divided by  $m \hat{a} n$ ). we show that  $a$  can be approximated in the cut norm within  $\hat{\mu} \hat{a} mnp$  by a sum of cut matrices (of rank 1), where the number of summands is independent of the size  $m \hat{a} n$  of  $a$ , provided that ...

Evidence 2 - **Rationale:** The original paper claims their number of communities ( $1/\epsilon^2$ ) is independent of graph properties including sparsity, improving over prior work. The candidate explicitly states their result 'extends the work of frieze and kannan [16] to sparse matrices' with summands independent of matrix size, suggesting prior work on this problem for sparse cases. - **Original:** while previous versions of the wrl required  $n/(\sqrt{\epsilon \epsilon^2})$  communities for  $\epsilon$  error w.r.t. the standard cut metric, we guarantee an  $\epsilon$  error in weighted cut metric with only  $1/\epsilon^2$  communities. hence, the number of communities in our method is independent of any property of the graph, including the number of... - **Candidate:** we show that  $a$  can be approximated in the cut norm within  $\hat{\mu} \hat{a} mnp$  by a sum of cut matrices (of rank 1), where the number of summands is independent of the size  $m \hat{a} n$  of  $a$ , provided that  $a$  satisfies a certain boundedness condition. this decomposition can be computed in polynomial time. this result e...

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### 4. Identification in parametric models

URL: [View paper](#)

#### Brief Assessment

Parametric Identification[55] addresses parameter identification in statistical models, not graph approximation or regularity lemmas. The candidate focuses on establishing identifiability conditions for parametric models through information matrices, which is unrelated to graph theory or the weak regularity lemma.

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### 5. A new regularity lemma and faster approximation algorithms for low threshold rank graphs

URL: [View paper](#)

#### Brief Assessment

[Final Audit Failure] The model insisted on a refutation claim but failed to provide verifiable evidence after multiple retries. Marked as cannot\_refute for safety. Please manually verify the candidate text.

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### 6. Weak regularity and finitely forcible graph limits

URL: [View paper](#)

#### Brief Assessment

Weak Regularity Limits[53] focuses on weak regularity partitions for graphons (graph limits) and establishes bounds on partition sizes. The candidate does not address the specific densifying mechanism or weighted cut similarity that enables the original paper's rank independence for sparse graphs in the context of graph neural networks.

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### 7. Elimination of imaginaries in Ordered Abelian groups with bounded regular rank

URL: [View paper](#)

#### Brief Assessment

Elimination Imaginaries Abelian[60] focuses on model theory of ordered abelian groups and elimination of imaginaries, not graph approximation or regularity lemmas for graphs.

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### 8. ELIMINATION OF IMAGINARIES IN ORDERED ABELIAN GROUPS WITH BOUNDED REGULAR RANK

URL: [View paper](#)

#### Brief Assessment

Imaginaries Abelian Groups[59] focuses on elimination of imaginaries in ordered abelian groups, a pure mathematical logic topic unrelated to graph approximation or regularity lemmas for graphs.

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### 9. Bounded Rank Perturbations of Quasi-Regular Pencils Over Arbitrary Fields

URL: [View paper](#)

#### Brief Assessment

Bounded Rank Perturbations[58] addresses matrix pencils and Kronecker invariants in linear algebra, not graph approximation or regularity lemmas. The domains are entirely distinct.

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## Contribution 3: IBG Neural Network architecture with linear complexity in nodes

**Description:** The authors develop IBG-NN, a neural network architecture that processes graphs via their IBG representation. This architecture achieves  $O(N)$  time and memory complexity instead of the  $O(E)$  complexity of traditional message-passing neural networks, while maintaining competitive performance across multiple graph learning tasks.

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.

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### 1. GT-SNT: A Linear-Time Transformer for Large-Scale Graphs via Spiking Node Tokenization

URL: [View paper](#)

#### Brief Assessment

GT-SNT[79] focuses on graph transformers with spiking neural networks for node tokenization, achieving linear complexity through attention mechanisms. This differs from IBG-NN's approach of using intersecting block graph representations with  $O(N)$  complexity through low-rank factorization.

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## 2. Linear Genetic Programming for Design Graph Neural Networks for Node Classification

URL: [View paper](#)

### Brief Assessment

Linear Genetic Programming[76] focuses on evolutionary algorithms for designing GNN architectures for node classification, not on developing graph approximation methods with linear complexity guarantees like IBG-NN.

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## 3. Nodeformer: A scalable graph structure learning transformer for node classification

URL: [View paper](#)

### Prior Art Analysis

Nodeformer[71] demonstrates prior work that achieves linear complexity  $O(N)$  in the number of nodes for graph neural networks through a kernelized Gumbel-softmax operator. The paper explicitly states achieving linear computational complexity for full-graph message passing and successfully scales to graphs with up to 2 million nodes. This directly challenges the novelty claim that the original paper was first to develop a neural network architecture with  $O(N)$  complexity for graph learning tasks.

### Evidence

Evidence 1 - **Rationale:** Both papers claim to reduce complexity from quadratic to linear in node numbers. Nodeformer explicitly states 'reduce the algorithmic complexity for learning new message-passing topology from quadratic to linear w.r.t. node numbers' which directly parallels the original paper's claim of achieving  $O(N)$  complexity. - **Original:** we introduce the intersecting block graph (ibg), a low-rank factorization of large directed graphs based on combinations of intersecting bipartite components, each consisting of a pair of communities, for source and target nodes. by giving less weight to non-edges, we show how an ibg can efficiently... - **Candidate:** we develop a kernelized gumbel-softmax operator which is proven to serve as a well-posed approximation for concrete variables, particularly the discrete latent structure among data points. the new module can reduce the algorithmic complexity for learning new message-passing topology from quadratic t...

Evidence 2 - **Rationale:** Nodeformer explicitly achieves  $O(N)$  computational complexity for full-graph message passing, directly refuting the claim that the original paper was first to achieve linear complexity in nodes for graph neural networks. - **Original:** we then introduce a graph neural network architecture operating on the ibg representation of the graph and demonstrating competitive performance on node classification, spatio-temporal graph analysis, and knowledge graph completion, while having memory and computational complexity linear in the numb... - **Candidate:** the key advantage of eqn. 5 is that the two summations are shared by eachu, so that one only needs to compute them once and re-used for others. such a property enables  $o(n)$  computational complexity for full-graph message passing, which paves the way for learning graph structures among large-scale ins...

Evidence 3 - **Rationale:** Both papers demonstrate  $O(N)$  complexity architectures applied to node classification and other graph tasks, with Nodeformer showing results on graphs with up to 2 million nodes, establishing prior work in this area. - **Original:** we develop ibg neural networks (ibg-nns), which operate directly on the ibg representation of any graph. ibg-nns allow solving downstream tasks such as node classification, spatio-temporal graph analysis, and knowledge graph completion in  $o(n)$  operations rather than  $o(e)$ . - **Candidate:** we evaluate our approach on diverse node classification tasks ranging from citation networks to images/texts. the results show its promising power for tackling heterophily, long-range dependencies, large-scale graphs, graph incompleteness and the absence of input graphs.

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## 4. Proformer: a scalable graph transformer with linear complexity

URL: [View paper](#)

### Brief Assessment

Proformer[73] focuses on graph transformers with linear complexity for general graph learning tasks, not specifically on the IBG representation or the densifying regularity lemma framework that enables  $O(N)$  complexity in the original paper's approach.

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## 5. Net: Degree-specific graph neural networks for node and graph classification

URL: [View paper](#)

### Brief Assessment

Net[72] focuses on degree-specific graph convolutions for node/graph classification tasks, not on achieving linear complexity in nodes through graph approximation methods like IBG representation.

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## 6. FedGT: Federated Node Classification with Scalable Graph Transformer

URL: [View paper](#)

### Brief Assessment

FedGT[78] focuses on federated learning for distributed subgraphs with a hybrid attention mechanism, not on general graph approximation via low-rank factorization. The linear complexity in FedGT[78] comes from attention sampling mechanisms in a federated setting, whereas the original paper achieves linear complexity through IBG representation and densifying regularity lemma for centralized graph learning.

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## 7. Graph neural networks in node classification: survey and evaluation

URL: [View paper](#)

### Brief Assessment

GNN Node Survey[77] discusses existing graph neural network models for node classification but does not present a specific architecture achieving  $O(N)$  complexity through IBG representation or similar low-rank factorization methods.

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## 8. Gapformer: Graph Transformer with Graph Pooling for Node Classification

URL: [View paper](#)

### Brief Assessment

Gapformer[74] focuses on graph transformers with pooling for node classification, achieving linear complexity through pooling operations rather than IBG representation. The architectural approaches and theoretical foundations differ fundamentally.

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## 9. Scaling graph neural networks with approximate pagerank

URL: [View paper](#)

### Brief Assessment

Approximate PageRank Scaling[80] focuses on efficient approximation of information diffusion using personalized PageRank for node classification, not on low-rank graph factorization methods like IBG representations.

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## 10. DeltaGNN: Graph Neural Network with Information Flow Control

URL: [View paper](#)

### Brief Assessment

DeltaGNN[75] focuses on addressing over-smoothing and over-squashing in message-passing GNNs through information flow control, not on graph approximation via low-rank factorization. The linear complexity claim relates to different mechanisms.

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## Appendix: Text Similarity Detection

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

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