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| **PAPER NAME** | **YEAR** | **AUTHOR** | **PAPER LINK** | **DESCRIPTION** | **ADVANTAGES** | **DISADVANTAGES** |
| AEGAN: A Novel Machine Learning Model to Attribute Network Community Detection | 2024 | Long Chen; Zhenyu Zhang; Xiaoming Li; Guangquan Xu | https://ieeexplore.ieee.org/document/10650897 | The **AE-GAN (Autoencoder-enhanced Graph Attention Network)** model for attribute network community detection integrates a **self-attention mechanism**, **self-encoder module**, and **GCN**. It also includes a **triple self-supervised module** for improved unsupervised learning. | - Enhances **attribute network community detection** by combining content and topology information effectively.  - Extends GCN depth and balances information fusion.  - Significant improvements in **ACC** and **NMI** metrics. | - The model's complexity may lead to increased computational requirements.  - Implementation may be challenging due to integration of multiple advanced components.  - Performance might vary depending on the specific dataset and network structure. |
| Machine Learning Approaches for Community Detection in Online Social Networks | 2024 | Aurélio Ribeiro Costa; Rafael Henrique Nogalha de Lima; Célia Ghedini Ralha | https://ieeexplore.ieee.org/document/10371982 | A comparison of five state-of-the-art machine learning-based community detection methods—**Graph-GAN, SDNE, ComE, AC2CD, and CLARE**—evaluated on real-world social network datasets. The study shows that **graph neural networks** and **deep reinforcement learning** are superior for community detection. | - **Graph neural networks** and **deep reinforcement learning** provide better performance in community detection based on **micro-F1, macro-F1, and NMI** scores.  - Demonstrates effectiveness across multiple datasets. | - Some of the compared methods, especially **probabilistic** or **shallow networks**, may struggle with scalability or accuracy in large, complex networks.  - Deep learning approaches may require more computational resources and training time. |
| Dynamic Community Detection Based on Similarity of Social Network Nodes | 2023 | Junjie Jia; LiFang Li | https://ieeexplore.ieee.org/document/10061958 | **DCDSN (Dynamic Community Detection based on Similarity of Nodes)** improves dynamic community detection by integrating both static and dynamic node similarities, considering direct, common, and exclusive neighbors. It uses the Louvain method for detection. | - **Incorporates dynamic characteristics** of node attributes and connections.  - **Higher quality detection** compared to traditional methods.  - Utilizes a **weighted dynamic network** approach for better accuracy | - May require complex calculations for **dynamic similarity** between nodes.  - Performance depends on the effectiveness of the similarity metrics used.  - The method might be computationally intensive for very large networks. |
| Community Detection Based on Node Influence and Similarity of Nodes | 2022 | Yanjie Xu;Tao Ren ; Shixiang Sun | https://www.mdpi.com/2227-7390/10/6/970 | An **agglomerative community detection algorithm** based on **node influence** and **node similarity**. It includes steps for identifying central nodes, expanding communities with similar nodes, and merging small communities. Evaluation is done using **modularity** and **NMI**. | - Effectively integrates **node influence** and **similarity** for realistic community detection.  - Structured approach with clear steps for community formation and expansion.  - Comparable performance to classic methods in **modularity** and **NMI**. | - Performance might vary depending on the quality of node influence and similarity measures.  - Computational complexity may increase with network size due to multiple steps in the algorithm.  - Effectiveness might be influenced by the specific structure of the network. |
| Dynamic Local Community Detection Algorithms | 2022 | Sahar Bakhtar; Hovhannes A. Harutyunyan | https://ieeexplore.ieee.org/document/9789847 | The paper investigates **local community detection** algorithms in **dynamic social networks**, where complete network information is often unavailable. **Algorithm P** is found to outperform others in terms of speed within dynamic structures | **Algorithm P** demonstrates superior performance and **faster processing** in dynamic networks.  - Addresses the challenge of detecting communities with incomplete network information.  - Provides insights into effective local detection in evolving networks. | - Focuses on **dynamic networks**, which may not be as applicable to static networks.  - The effectiveness of Algorithm P may vary with different types of dynamic changes in the network.  - Limited discussion on the limitations of other algorithms. |
| Community detection in social networks by incorporating the preferential selection | 2021 | Shyam Sundar Meena ; Vrinda Tokekar; Ernesto Estrada | https://ieeexplore.ieee.org/document/9684800 | A community detection algorithm based on the **preferential selection of neighbors** in online social networks (OSNs). The method is evaluated using real-world and computer-generated datasets, showing superior performance in terms of **NMI** and **F1-measure** compared to other algorithms. | - Superior performance in community detection based on **NMI** and **F1-measure**.  - The preferential selection mechanism allows for more accurate community formation in OSNs.  - Effective for both real-world and synthetic datasets. | - The effectiveness may depend on the specific criteria used for preferential selection, which might not generalize well to all types of networks.  - May not perform as well on networks where neighbor preference is less relevant for community formation. |
| Information Granulation-Based Community Detection for Social Networks | 2020 | Ebin Deni Raj; Gunasekaran Manogaran; Gautam Srivastava; Yulei Wu | https://ieeexplore.ieee.org/document/8977552 | The **GBCD algorithm** detects communities in OSNs by modeling the network as a **Rough Set Granular Social Network (RGSN)**. It incorporates **granular computing** and defines two key measures: **granular community factor** and **object community factor** to guide the detection process. | - Incorporates **granular computing** and rough sets, which are novel approaches for handling uncertainty and imprecision in social networks.  - Outperforms state-of-the-art algorithms in terms of modularity, NMI, Omega index, accuracy, and F1-score. | - The complexity of granular computing and rough sets may make the algorithm more difficult to implement and understand.  - May require fine-tuning of parameters specific to granular computing to achieve optimal performance in various datasets. |
| Community Detection Based on Co-regularized Nonnegative Matrix Tri-Factorization in Multi-view Social Networks | 2018 | Longqi Yang; Liangliang Zhang; Zhisong Pan; Guyu Hu; Yanyan Zhang | https://ieeexplore.ieee.org/document/8367103 | **CoNMTF (Co-regularized Nonnegative Matrix Tri-Factorization)** integrates multi-view adjacency data using a **relaxed pairwise regularization**. It includes an iterative algorithm with proven correctness and convergence for improved community detection. | - Effectively combines **multi-view data** to improve community detection performance.  - Proven **correctness and convergence** of the iterative algorithm.  - Outperforms state-of-the-art algorithms in **accuracy** and **NMI**. | - May require careful tuning of regularization parameters.  - Complexity of the iterative algorithm might increase computational demands.  - Performance might vary based on the quality and number of views integrated. |
| LPANNI: Overlapping Community Detection Using Label Propagation in Large-Scale Complex Networks | 2018 | Meilian Lu ; Zhenglin Zhang; Zhihe Qu; Yu Kang | https://ieeexplore.ieee.org/abstract/document/8443129 | **LPANNI (Label Propagation Algorithm with Neighbor Node Influence)** improves overlapping community detection by using a fixed label propagation sequence and label update strategies based on node importance and neighbor influence. It operates with linear time complexity. | - **Improves accuracy and stability** in community detection for large-scale networks.  - **Detects overlapping communities** effectively.  - Maintains **linear time complexity**, making it suitable for large networks. | - May require tuning of parameters related to node importance and label update strategies.  - Performance might vary with the specific network characteristics and the extent of overlap in communities.  - May still face challenges with very dense networks. |
| Local community detection algorithm based on links and content | 2017 | [Cuijuan Wang](https://ieeexplore.ieee.org/author/37085794836); [Wenzhong Tang](https://ieeexplore.ieee.org/author/37656258100); [Yanyang Wang](https://ieeexplore.ieee.org/author/37085797489); [Jing Fang](https://ieeexplore.ieee.org/author/37085742767); [Shan Yao](https://ieeexplore.ieee.org/author/37086132595) | https://ieeexplore.ieee.org/document/8054324/authors#authors | A local community detection method based on links and content, focusing on specific users' communities rather than the global network. Tested on the Enron email dataset, it aims to improve accuracy despite missing links or low communication frequency. | - More accurate in networks with missing or sparse links.  - Combines structural (links) and content information for better community detection.  - Faster and more efficient for large networks due to local analysis. | - May not capture global community patterns effectively.  - Content data extraction can be resource-intensive.  - Depends on availability and quality of content, which may not always be present in all types of networks. |
| An efficient modularity based algorithm for community detection in social network | 2016 | Ranjan Kumar Behera; Santanu Ku. Rath | https://ieeexplore.ieee.org/abstract/document/7562715 | A **modularity-based community detection algorithm** for large-scale social networks. The algorithm is evaluated against existing methods using metrics like **modularity**, **clustering coefficient**, and **execution time** on popular social network datasets. | - Efficient for detecting communities in **large-scale networks**.  - Evaluated with various metrics, providing a comprehensive performance assessment.  - Addresses challenges in big data analytics for social networks. | - Performance may vary depending on the specific network characteristics and dataset.  - May require fine-tuning of parameters for optimal results.  - Computational complexity could be high for very large networks. |
| Finding research groups using modularity based community detection algorithm | 2016 | S Rao Chintalapudi; M H M Krishna Prasad | https://ieeexplore.ieee.org/document/7724229 | A **modularity-based community detection algorithm** applied to **co-authorship networks** to identify research groups. The method is evaluated using two real-world datasets (netscience and DBLP), and results are measured by **modularity** and **NMI**. | - Effective in identifying modular research groups in co-authorship networks.  - The use of modularity ensures that the detected communities (research groups) are well-formed and cohesive.  - Evaluated using strong metrics like modularity and NMI. | - Modularity-based methods may struggle with very large or dense networks.  - Performance could be affected by resolution limits of modularity, which may not detect smaller research groups within large networks. |
| A survey on community detection algorithms in large scale real world networks | 2015 | S Rao Chintalapudi; M H M Krishna Prasad | https://ieeexplore.ieee.org/document/7100465 | The paper reviews community detection algorithms for both disjoint and overlapping communities, tested on Zachary's karate club dataset. It evaluates algorithms using modularity, NMI, and Omega index. It concludes that high-performance computing frameworks are needed to address quality and scalability issues. | - Comprehensive review of both **disjoint and overlapping** community detection algorithms.  - Evaluation using multiple **quality measures** (modularity, NMI, Omega index).  - Provides solutions for improving **scalability** and **quality**. | - Community detection algorithms may require **high computational power** for large networks.  - Performance and quality depend on the framework used (e.g., GPU or Hadoop).  - Review may not cover all recent algorithms or techniques. |
| Overlapping Local Community Detection in Directed Weighted Networks | 2015 | [Shidong Li](https://ieeexplore.ieee.org/author/37085529858); [Sheng Ge](https://ieeexplore.ieee.org/author/37653079100) | https://ieeexplore.ieee.org/document/7023742 | A **distributed algorithm** for detecting **overlapping local communities** in directed, weighted networks. It defines **Local Community Modularity** and **Tightness** to guide the process. The algorithm has two phases: initial local community detection and merging of similar communities based on tightness. | - Efficient for large-scale networks due to its distributed nature.  - Handles **overlapping communities**, which is common in real-world networks.  - Incorporates local community modularity to improve detection accuracy. | - May be computationally intensive depending on network size.  - The tightness and local modularity calculations could be complex for very large or dense networks.  - Might struggle in networks with less clear community structures. |
| Overlapping community detection in social networks | 2014 | Zeineb Dhouioui; Jalel Akaichi | https://ieeexplore.ieee.org/document/6732729 | A method for **overlapping community detection** that uses the **edge betweenness** principle to identify communities in complex networks. It aims to address the challenge of high complexity in detecting overlapping communities as network size increases. | - Efficiently detects **overlapping communities**, which are common in real-world networks.  - Uses **edge betweenness**, a well-known measure that is effective in finding community boundaries.  - Performs well in large networks compared to existing methods. | - Edge betweenness can be computationally expensive to calculate in very large or dense networks.  - May struggle with networks where the community structure is not well defined by edge betweenness or when communities overlap significantly. |
| Structure and attributes community detection benchmark and a novel selection method | 2014 | Haithum Elhadi; Gady Agam | https://ieeexplore.ieee.org/document/6785910 | A new **benchmark** for evaluating graph clustering methods that includes both structure and attributes. The **Selection method** uses graph structure ambiguity to switch between structure-based and attribute-based clustering methods. | - Integrates both **structure and attributes** for a more comprehensive evaluation.  - The **Selection method** effectively uses structure ambiguity to improve clustering results.  - Outperforms existing state-of-the-art methods in **NMI**. | - May require careful tuning to balance between structure and attribute-based clustering.  - Complexity in switching methods might increase computational overhead.  - Effectiveness depends on the quality of the benchmark and data attributes. |
| An Improved Community Detection Algorithm Based on Local Information in Social Networks | 2013 | Xia Lei; Zhang Lejun; Zhang Jianpei; Yang Jing; Guo Lin | https://ieeexplore.ieee.org/document/6405846 | The **LPA-SNA algorithm** is an enhanced version of the **Label Propagation Algorithm (LPA)**, incorporating **similarity of nodes' attributes** to improve community detection and overcome the random partitioning issue in standard LPA. | - Reduces the randomness of standard LPA by incorporating node similarity, leading to **more stable and optimal community detection** results.  - Efficient and scalable due to its label propagation mechanism. | - The algorithm may require additional computation for calculating node attribute similarity, which could increase complexity.  - The effectiveness heavily depends on the availability and quality of node attribute information. |
| Enhancing community detection using a network weighting strategy | 2013 | Pasquale De Meo , Emilio Ferrara , Giacomo Fiumara , Alessandro Provetti | https://www.sciencedirect.com/science/article/abs/pii/S0020025512005488 | A **pre-processing strategy** for community detection algorithms that weights edges based on **centrality** to improve accuracy. The centrality is computed using multiple random walks, making the method scalable for large networks. Tested with **Louvain, COPRA,** and **OSLOM**. | - **Improves accuracy** of community detection algorithms by incorporating edge centrality.  - Scalable to **large networks** due to efficient centrality computation.  - Enhances existing algorithms such as **Louvain, COPRA,** and **OSLOM**. | - Additional pre-processing step may increase overall computational complexity.  - Effectiveness depends on the quality of edge centrality computation.  - Performance gains might vary with different network structures and sizes. |