Community Detection Methods: From Statistical Modeling to Deep Learning, Leveraging Attributes and Interactions on Social Networks: A Survey and Future Directions

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Abstract—

Community detection is a fundamental task and an important area of research, aimed at partitioning a network into multiple substructures. This process helps uncover the underlying functions or causes behind large, complex networks, which has garnered significant attention within the scientific community. Numerous studies have been published on this topic. The primary goal of community detection is to identify subgraphs—referred to as "communities"—in which nodes are more densely interconnected with each other than with other parts of the network. Nodes within these communities are expected to share similar features, indicating a common role or property. Classic approaches to community detection often use probabilistic graphical models that statistically infer the most likely community structures. These methods also integrate prior knowledge to guide algorithms and enhance the accuracy of the detected partitions. By using these techniques, researchers and data scientists can transform a convoluted web of connections into a clear map of meaningful communities, providing critical insights across various fields, including social media analysis and biological network studies. Community detection has vital applications in various areas of social networking, such as sociology, business, criminal detection systems, and recommendation systems. As network data becomes increasingly complex, addressing challenges related to computational efficiency due to the large size and dynamic nature of social networks is essential. Despite substantial advancements in the field, there remains a significant gap: a comprehensive understanding of the theoretical and methodological foundations of community detection. Bridging this gap is crucial for unlocking the next generation of breakthroughs in network analysis. This article provides a comprehensive overview of existing community detection methods and introduces a new taxonomy that categorizes these approaches based on network substructures, mining attributes, and interaction systems. We classify the methods into several fundamental categories: probabilistic graphical models, deep learning-based approaches, node content-based methods, edge content-based methods, and hybrid methods that incorporate both node and edge content. Each method is examined in detail, highlighting its core principles and applicability to social network data. The discussion emphasizes the strengths and limitations of various techniques, offering readers a clear understanding of the current landscape in community detection. Finally, we address key challenges in the field and provide actionable suggestions for future research, aiming to inspire advancements in scalable, accurate, and interpretable community discovery. This survey serves as a valuable resource for researchers and practitioners working with complex network data.

Keywords: Latency Reduction,Serverless Computing,Machine Learning, Performance Optimization, Distributed Systems

1. INTRODUCTION

Network science explores complex systems by analyzing the structures of the networks that represent them. For instance, Figure 1 illustrates the community definitions of SubroGFS network motifs. Network structure detection, or community detection, identifies groups of nodes that are strongly interconnected within a group while being loosely connected to nodes in other groups. Understanding the organization of mining networks is crucial for discovering, interpreting, and explaining the principles that govern complex network systems. Community detection is employed in various applications, such as recommendation systems, anomaly detection, and the identification of terrorist groups. This area of research is extensive and continues to evolve. Additionally, the analysis of network structural characteristics involves examining global effects, such as the average distances between nodes. It also explores properties like the distribution of node degrees, which often follows a power law distribution.

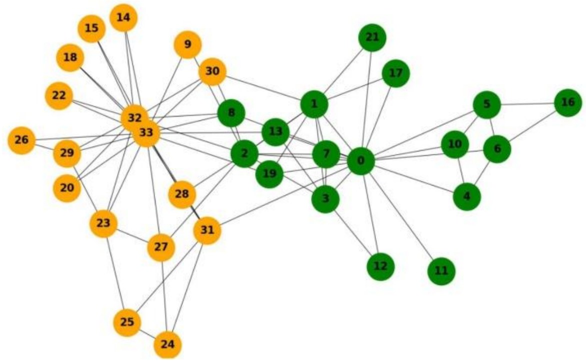

Fig. 1: An illustrative example (Zacharys karate club network [7]) showing community structure.

The nodes of this network are classified into two groups, where the majority of connections occur within the same group and only a few between different clusters. Several community detection algorithms have been proposed, most of which rely solely on network topology. Examples include hierarchical clustering, modularity optimization, spectral clustering, and statistical inference methods.

Recently, new methods have been introduced that utilize the semantics of nodes or node attributes alongside community topology. These approaches aim to improve the quality of identified communities while also providing explanations for the results. Notable among these are heuristic optimization (multi-objective), matrix factorization, and Bayesian models.

When facing more complex problems within a network, it becomes necessary to integrate detailed information from multiple aspects, including topology and node semantics. This presents challenges for conventional methods, particularly in performing data fusion for extremely large datasets with many features. Recently, deep learning techniques have been employed to handle high-dimensional network information and facilitate the understanding of low-dimensional representations of networks. Instances of this include variational autoencoders and generative adversarial networks.

A key and successful approach to identifying communities is to consider an appropriate representation of network structures. Methods based on this principle focus on community detection as they involve training processes. One well-studied example is the Stochastic Block Model (SBM), which models the generative process of networks as a series of rigid probability distributions. Various extensions and enhancements have been proposed to improve the performance of SBMs.

Other learning models, such as Markov Random Fields (MRF), leverage the benefits of local conditions within networks. Recent advancements in learning techniques have explored deep learning methods that can work with smaller datasets. For example, CNN-based networks have been utilized to enhance community detection, measuring network data in ways that improve community identification. Graph Convolutional Networks (GCN), which inherit the advantages of CNNs, further handle structured network data, although research continues into their effectiveness for community representation recovery.

Despite numerous efforts to develop effective community detection methods, there is still a gap in understanding the theoretical and methodological shortcomings of community-based findings. This paper aims to provide a comprehensive overview of representative methods, focusing particularly on two main approaches: stochastic modeling and deep learning-based methods.

We will begin with a detailed discussion on why these approaches are relevant, followed by a comparison of methods. Additionally, we will explore various applications of community detection across different domains, concluding with a discussion of some key issues in network analysis and areas for future research. One goal of our research is to identify new methods that help address fundamental problems and improve community detection algorithms.

Our survey differs from existing literature in three significant ways. First, we review current work on vital issues in community modeling, such as community discovery, whereas existing papers often focus on temporal evolution. Second, we present recent trends in developing community detection methods, highlighting the shift from statistical modeling to advanced learning techniques, while some studies focus merely on individual methods. Third, our work showcases the unique architecture of existing methods, providing a synthesized perspective on both statistical modeling and deep learning-based approaches.

As network data continues to grow in complexity, there is an urgent need to explore the relationships between existing community detection methods. We aim to provide general guidance for researchers and practitioners interested in scientific data and networks, creating our own contributions to this field.
To achieve our goal, as outlined below, we adopt the following experimental protocol. One of our main objectives in this survey is to contribute to defining new perspectives on current approaches that may enhance our understanding of the fundamental problems and methods in community detection.

Our survey stands out from others in three key respects:

1. **Focus on Learning**: We review current methods with a focus on learning, which is crucial for community modeling and detection. Many current reviews [37][38] primarily discuss the developmental phases of recent algorithms.

2. **Development Techniques**: We highlight the latest trends in community detection techniques, ranging from statistical modeling to deep learning. In contrast to other surveys that concentrate on individual methods—such as evolutionary computation [39], statistical inference [40], or deep learning [41]—we provide a more comprehensive overview.

3. **System-Level Architecture**: We introduce a system-level architecture that synthesizes existing approaches, offering a new perspective on techniques based on statistical modeling and deep learning. This goes significantly deeper than some current surveys [42][43].

In the realm of deep learning, where network data becomes increasingly complex, it is essential to conduct a survey that thoroughly explores the inherent relationships among contemporary strategies for network detection. As an effort to provide a common resource for researchers and practitioners in network science and statistical analysis, we include:

- **Two Categories**: We classify learning-based community detection into two categories: Probabilistic Graphical Models and Deep Learning. To the best of our knowledge, this is the first effort focused on community discovery from a learning perspective.

- **Solid Foundation**: This work lays a solid foundation for understanding the principles behind community detection and serves as a guide for designing and implementing various community detection methods.

- **Comprehensive Overview**: We present the most extensive and widespread overview of learning-based community detection, categorizing the methods into probabilistic graphical models and deep learning. This survey also offers a thorough theoretical analysis of these methods, discussing their similarities and differences, identifying critical challenges that remain inadequately addressed, and outlining five directions for future development.

- **Abundant Resources**: We compile abundant resources on learning-based community detection, including state-of-the-art benchmark datasets and applications.

The remainder of this study is structured as follows:
- **Section 2**: Provides an overview and classification of community detection approaches.
- **Section 3**: Presents a technical investigation of advancements in statistical modeling for community detection.
- **Section 4**: Investigates learning-based community detection methods.
- **Section 5**: Explains how to detect communities within assigned networks.
- **Section 6**: Suggests various datasets for experimentation.
- **Section 7**: Concludes the study.

2. PRELIMINARIES AND CATEGORIZATION

We first present the terms and specifications, and then we present a classification of how communities can be detected. Discuss this article.

2.1 **Definitions, Terms, and Notations**

1. **Network**: A network can be formally represented as consisting of $n$nodes, $m$edges, and up to $q$attributes associated with each node. Collectively, these attributes form an **attribute matrix** that captures the feature information of all nodes in the network. The **topological structure** of the network is described by an **adjacency matrix**$A = (A_{ij})_{n\times n}$, where

$$A_{ij} = \begin{cases} 1, & \text{if there exists an edge from node } i \text{ to node } j, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The network is said to be **undirected** if $A_{ij} = A_{ji}$, indicating mutual connections between nodes, and **directed** otherwise, where edges have an orientation from one node to another.

2. **Community**: A network comprises one or more **communities**, where each community Crepresents a **subgraph** of the overall network. Within a community, nodes are **densely connected** to one another, whereas connections between nodes belonging to different communities are **sparse**. Formally, communities are considered **non-overlapping** if, for any two distinct communities $C_1$and C_2, their intersection is empty, i.e.,

$$C_1 \cap C_2 = \emptyset. \tag{2}$$

This implies that each node in the network belongs to exactly one community.

3. **Community Detection**: Given a network G, the objective of **community detection** is to define a **mapping function**

$$f: V \to C, \tag{3}$$

that assigns each node $v \in V$to at least one of the $k$communities, thereby labeling $v$with a corresponding community identity $c \in C$. Equivalently, the task can be viewed as deriving a **community assignment** for all nodes in the network, such that structurally or semantically similar nodes are grouped into the same community.

Taxonomy of Community Detection Methods

In order to facilitate a better understanding of the existing approaches and to foster discussion in the remainder of this article, we propose a taxonomy for community detection methods (Table 1). Approaches can be further roughly categorized into two classes: probabilistic graphical models, and deep learning. Graphical model based probabilistic approaches rely on graph-based heuristics and/or mechanisms to generate communities in network topologies. Such approaches often follow the view of an underlying model of the network structure and entities (nodes) wandering over links in this network. First, with respect to the type of stochastic graphical model considered, community detection falls into one of three categories: directed graphical models or undirected graphical models or ambiguous graphical models. - Graphical Models: More precisely, directed graphical models are built on hidden variables which capitalize on connection patterns among the nodes (or block structures) to generate edges observed in a network. Directed Graphical models are commonly used in star-clique structures with unary and pair-wise potential constraints for community discovery. Hybrid Graphical Models by combining two types of graphical models into one joint factor graph are introduced to improve community detection. - Deep Learning based Approaches: These approaches often concentrate on finding salient structures by using novel community-centric network architectures. They learn new network representations by employing specially designed training mechanisms that project network data from an original input space to a lower-dimension functional space. This operation has low computational complexity and good parallelism. According to the learning strategies, deep learning-based {{approaches can be divided into} four} categories: autoencoder-based models, graph convolutional networks (GCNs), integrated calendaring methods as well as ambiguous graphical models

More specifically, autoencoder-based methods use unsupervised learning techniques to create low-dimensional representations of hidden spaces, reconstructing network and community structures from these low-dimensional representations. Generative adversarial network (GAN) methods discover communities through competitive learning between generators and discriminators. Graph neural networks extract communities by applying distributing and aggregating functions within the network topology. Hybrid graphical model approaches integrate graph beam networks with wave graphical models, for instance, by converting Markov random fields (MRFs) into GCN layers to leverage the advantages of both models.

Table.1. Taxonomy of the methods for community detection

<table>
<tr><td colspan="4">Learning based Community Detection</td></tr>
<tr><td colspan="3">A. Probabilistic Graphical Model-based Community Detection</td><td>B.Deep Learning based Community Detection</td></tr>
<tr><td>1. DirectedGraphical Models</td><td>2.Undirected Graphical Models</td><td>3.Integrating Directed and Undirected Graphical Models</td><td>1. Autoencoder-based methods</td></tr>
<tr><td>1.a.Stochastic Block Model-based Methods</td><td rowspan="3">2.a. Random Field-Based Methods</td><td rowspan="3">3.a. Factor Graph-based Methods</td><td>2. Generative Adversarial Network-based Methods</td></tr>
<tr><td>1.b. Topic Model-based Methods</td><td>3. Graphical Convolutional Network-based Methods</td></tr>
<tr><td>1.c. Matrix Factorization-based Methods</td><td>4. Combining Graph Convolutional Networks with Undirected Graphical Models.</td></tr>
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3. COMMUNITY DETECTION USING PROBABILISTIC GRAPHICAL MODELS

Strategies utilizing probabilistic graphical models generally find communities through network modeling, meaning they apply graphical models to elucidate the process of network formation. Here, we will examine three common methods: directed graphical models, undirected graphical models, and hybrid graphical models that integrate directed and undirected graphs.

3.1 Directed Graphical Models

We will explore the latest advancements in directed graphical models for identifying communities, specifically focusing on the stochastic block model, topic model, and matrix factorization. These methods are based on a solid theoretical framework and demonstrate strong performance, with extensive applications.

3.1.1 Stochastic Block Model-based Methods

The stochastic block model (SBM) provides a positive generative framework for network block structures, utilizing statistical modeling to detect communities. One version of the model employs various parameters so that network blocks are represented as aspect membership functions, while another version takes a more general approach to block structures. By calculating the likelihood distance of node membership, we can determine the probability of individual nodes belonging to specific communities, thereby identifying latent communities within the network.

It is important to note that although there are many versions of SBM for community identification, they all share a consistent foundational generation method. The fundamental process for SBM consists of two steps: first, we iteratively allocate the community for each node in the graph; second, we establish or update a probability value for every pair of connected nodes to indicate the strength of their connection.

Using a social network as an example, SBM can capture a stochastic process where the hidden variable represents community distribution. By maximizing the node community membership likelihood function, we can effectively reconstruct communities. This becomes the likelihood function:

$$P(A, C/\omega, \pi) = P(A/C, \pi)\, P(C/\omega) = \prod_{t=1}^{n} \prod_{r=1}^{k} \omega_r^{c_{ir}} * \prod_{t<1}^{n} \prod_{r,s}^{k} (\pi_{rs}^{a_{ij}} (1-\pi_{rs})^{(1-a_{ij})})^{c_{ir} c_{ja}} \tag{4}$$

Based on the likelihood function, Gibbs sampling and the expectation-maximization (EM) algorithm can be used to attain the model parameters, e.g., ω and π. Finally, we can derive the community partition with the interaction model between communities.

3.1.2 Topic Model-based Methods

The topic model, such as Latent Dirichlet Allocation (LDA), is a statistical framework used to uncover hidden themes in texts within the field of natural language processing. LDA identifies topics by utilizing latent variables, which have gained considerable attention and have been extensively used to identify communities. Topic models can be categorized into two types: one that models network structures as documents and another that analyzes network characteristics, such as user preferences, to identify communities.

Modeling network frameworks as documents.

LDA (Latent Dirichlet Allocation) serves as an example to illustrate the principles of methods in the initial category of community detection techniques. Specifically, one approach within this group posits that each node in a network can belong to multiple communities. This leads to the interpretation that communities function as "themes," while the nodes are seen as "files." The method begins by selecting multiple communities and progressively updates them based on the network's topology to derive the final communities.

A notable model in this context is SSN-LDA, a hierarchical Bayesian algorithm based on LDA applied to link networks, where communities are represented as hidden variables. In this type of social network, nodes are treated as social actors, while edges symbolize social interactions. The social interaction profile (SIP) of each social actor consists of a collection of neighbours and weights, which are used to highlight the actor's characteristics with respect to social network attributes.

Several topic models implicitly utilize social network attributes, such as user interests, for community detection. Yin et al. propose the fusion of community detection and topic models, leading to a method known as Latent Community Topic Analysis (LCTA). Their approach breaks the sampling process into two parts: user node sampling and link sampling.

During this procedure, all network links are sampled after selecting a user node, and the results from the two-stage sampling are used as the outcome for user-node sampling. LCTA assigns each user node and link a community membership attribute. After performing these role-based random walks, user nodes can be clustered into communities based on their community memberships. The advantage of this method lies in the two-stage sampling, which constructs a sampling area that focuses on user nodes, providing a more accurate representation of community structures.
Recently, Xu et al. combined Bayesian systems with topic models to define a joint probability distribution for all possible attributed networks. In this model, every potential clustering of nodes in a given network is associated with a probability, transforming the clustering problem into one of identifying clusters with the highest probability. The algorithm for clustering attribute communities is detailed in Appendix C.

To address the inverse formulation, He et al. proposed a generative model that simultaneously identifies communities and generates their semantic descriptions. They employ a nested EM algorithm combined with belief propagation, seeking correlations between these two components to enhance the resultant communities and their descriptions. Attributes typically have a hierarchical semantic structure, which Jin et al. tackled by proposing a variation of the Bayesian topic model called the BTLSC model. This model differentiates between background words and both general and specialized topics. Unlike traditional topic models that treat topics in social networks as independent, topic embedding methods aim to describe the relationships between topics by embedding words and topics within topical models.

Matrix Factorization-based Methods

Specifically, **ComDetect** can be formulated using **Non-negative Matrix Factorization (NMF)**, which serves as a directed graphical model for community detection. NMF-based approaches operate under the assumption that meaningful community structures exist within a given network.
Given a network represented by an adjacency matrix

$$A = (a_{ij})_{n\times n} \in \mathbb{R}^+, \tag{5}$$

where each element a_{ij}denotes the probability of a connection between nodes $v_i$and v_jThe objective is to factorize Ainto two non-negative matrices:

$$A \approx WH^T, \tag{6}$$

where
$W = (w_{ir})_{n\times k} \in \mathbb{R}^+$and $H = (h_{jr})_{n\times k} \in \mathbb{R}^+$.
The elements $w_{ir}$and h_{jr}represent the probabilities that node $v_i$and v_j, respectively, belong to community r.
Two classic loss functions are commonly used to measure the quality of the NMF approximation:

1. **Frobenius norm loss**:

$$J = \| A - WH^T \|_F^2 \tag{7}$$

2. **Kullback–Leibler (KL) divergence loss**:

$$J = D_{KL}(A \parallel WH^T) \tag{8}$$

For **undirected networks**, where $A$is symmetric, it is typical to assume $W = H = B$. Under this condition, the factorization simplifies to:

$$A \approx BB^T, \tag{9}$$

and the corresponding loss function can be expressed as:

$$J = \min_{A\approx BB^T} F, \text{subject to } B \geq 0. \tag{10}$$

Non-negative Matrix Factorization (NMF) is primarily employed for detecting **non-overlapping communities** within networks. However, it has been extensively adapted to handle a wide range of community detection scenarios, including **overlapping**, **attributed**, **dynamic**, and **semi-supervised** communities, as summarized in *Table 3*.
The original NMF approach for non-overlapping community detection has evolved as researchers extend beyond basic matrix factorization techniques. NMF-based community detection methods generally assume that a network consists of $k$communities, and that its adjacency matrix

$$A = (a_{ij})_{n\times n} \in \mathbb{R}^+ \tag{11}$$

can be decomposed into non-negative components, such that

$$A \approx WH^T, \tag{12}$$

where $W$and Hrepresent the latent feature matrices associated with community memberships. The quality of this factorization is typically evaluated using one of two classical loss functions: the **Frobenius norm** or the **Kullback–Leibler divergence**.

Building upon this foundation, several enhanced NMF-based techniques have been proposed to improve community detection performance. **Kuang et al.** introduced a method known as *Non-negative Assignment of Graph Transformation*, which extends traditional NMF by enforcing nonnegativity constraints directly on clustering assignments, thereby improving interpretability. **Shi et al.** developed a *Pairwise Constrained Non-negative Symmetric Matrix Factorization (PCSNMF)* model, which incorporates pairwise constraints derived from ground-truth community information to enhance detection accuracy. **Sun et al.** further proposed a *Non-negative Symmetric Encoder–Decoder* framework that refines latent representations to generate higher-quality community structures. Unlike most NMF-based methods that focus solely on decoder loss, their approach jointly optimizes both **encoder and decoder losses** within a unified objective function, resulting in clearer and more interpretable community memberships.

Overlapping NMF

Overlapping community detection is an important problem partly because most real-world networks do indeed contain overlapping and nested communities. Wang et al. [21] introduced a Non-negative Matrix Factorization (NMF) counterpart to the sweet-and-sour community structures and suggested symmetric formulae of NMF in undirected networks. They also described how to do asymmetric and joint NMF. The former scans community for directed network, and the latter is more efficient in a composite network such as computer automated movie recommendation system which includes user-network, film-network and user-film networks. Yang et al. [82] presented a BIGCLAM model to find dense hierarchical networks which are large, overlapping nested and non-overlapping for nodes in large network. In detail, BIGCLAM generates communities according to node-community links: every node is assumed to be connected with the community by assigning a particular non-negative latent variable for each node-community pair. It then extends NMF with a block stochastic gradient descent algorithm to compute these non-negative latent variables and identify communities in big networks.

Attribute NMF

Recently, there has been considerable attention on the semantic information of community structures using NMF, particularly at Texas A&M University [83], [84], [88]. For instance, Pei et al. [83] employed both social relations and user content to discover communities using a non-negative matrix tri-factorization (NMTF)-based clustering algorithm with three types of graph regularization. However, this work only utilized network topology and content to mine communities, failing to consider how the discovered content, or semantic information, could explain the concepts behind each community. In response to this issue, Wang et al. [84] introduced a semantic community identification method called SCI. This method determines community affiliations based on the attributes of the communities rather than relying solely on each node's community membership matrix and its contribution proportion to the network topology.

Dynamic and Semi-supervised NMF

In recent years, there are also several works that NMF has been generalized in which dynamic and semi-supervised community detection and have reported good performance. For dynamic community discovery, Wang et al. [85] used a Bayesian model by NMF to detect overlapping communities in temporal networks, in which they represented the number of communities for each network snapshot using automatic relevance determination. Later, Ma et al. [86] showed that there is an NMF approach for dynamic community detection, and explained the connection between evolutionary spectral clustering, evolutionary NMF and evolutionary modularity density optimization. They exploited such a connection to develop an semi-supervised evolutionary NMF method, called sENMF, that exploits prior knowledge of communities for the dynamic detection of patterns on temporal networks. Yang et al. [87] presented a unified semi-supervised algorithm that integrates the prior information with the topology information of two non-negative matrices obtained from NMF.

3.2 Undirected Graphical Models

To the best of our knowledge, there is no existing literature on undirected graphical models specifically designed for community detection that relies on Markov random fields (MRF). In this context, we focus on applying MRF to community detection, and MRF-based methods can generally be categorized into three groups (see Table 4):

1. **Topology-based MRF:** He et al. proposed a method that applies MRF to networks and addresses the organization of data within complex network shapes. They introduced NetMRF, a network variant of MRF for community detection. This approach captures the structural information of irregular networks to infer optimal community structures through an energy function.

2. **Topology and Attribute MRF:** Recent trends involve joint modeling of MRF and node semantic attributes. However, not all methods that directly integrate MRF with node-level semantics yield satisfactory performance. This limitation arises primarily because the two models are not easily separable or tunable, making it challenging to leverage their strengths effectively. He et al. introduced a new model, attrMRF, which coherently integrates Latent Dirichlet Allocation (LDA) and MRF into an end-to-end learning framework that allows for the concurrent learning of corpus-specific parameters.

In this model, attrMRF integrates LDA (a directed graphical model) and MRF (an undirected graphical model) into a consistent factor graph. They also propose a belief propagation (BP) algorithm for parallel parameter learning, enabling both models to be learned end-to-end.

3. **Undirected Graphical Models:** Undirected graphical models rely on the properties of MRF, specifically utilizing unary and pairwise potentials for network structures and node attribute layouts to identify community structures. However, it may be necessary to retrain other energy functions.

3.3 Integrating Directed and Undirected Models

One area of research focuses on merging directed and undirected graph models to address the community detection problem in complex networks. This integration is often realized using a factor graph model, which is defined as a tuple (V, F, ε). Here, V represents the set of variable nodes, F is the set of factor nodes, and ε is the set of edges that connect variable nodes to factor nodes.

Yang et al. propose a foundational model based on this concept, presenting a 3-layer structure: the bottom layer consists of observed nodes, the middle layer comprises hidden vectors, and the top layer includes latent variables representing communities. This model employs node-feature and edge-feature maps to capture the dependencies between the nodes in the bottom layer and those in the top layer, thereby enhancing the efficacy of community detection.

Additionally, Jia et al. utilize the factor graph model in ego-centered networks—a type of human social network where an individual (the ego) is connected to others as friends or foes. They suggest an approach that shifts towards an ego-centered method for examining the social academic effects within co-author networks. This approach integrates ego-centered community detection, topic-level social influence, the strength of social relationships among nodes, and community structures into a single generative process within the factor graph model. They also propose an algorithm for jointly learning the model parameters.

Factor graph models, which effectively blend directed and undirected graphical models, have significantly improved community detection performance. However, these probabilistic graph models typically rely on variational inference or Markov Chain Monte Carlo (MCMC) sampling for model learning, which can lead to a substantial computational burden. Recent advancements in deep learning may offer a solution, as they can optimize high-dimensional network data more efficiently, potentially improving community detection methods.

4. COMMUNITY DETECTION WITH DEEP LEARNING

Community detection has attracted many attentions and becomes increasingly more effective to solve a variety of problems, even the community detection itself. The previous deep learning mechanisms were purely limited to the applications of CNNs and probability models in community detection tasks. For example, Sperl'i et al. [32] presented a new approach that exploits CNNs and the topological properties of an adjacency matrix to learn to detect communities automatically. Sun et al. [117] suggests the vGraph, a probabilistic generative model that learns overlapping and non-overlapping communities with nodes and communities representation jointly. vGraph models each node as a community mixture and defines a community as one kind of nodal distribution. Moreover, Cavallari et al. [86] developed a feedback dynamic correlation between community detection, community embedding, and node embedding. Motivated by this discovery, they proposed a multi-task learning formulation for community embedding and called their method ComE, which aims to jointly learn the community embedding in order to collaboratively enhance all the three tasks together. He et al. developed a self-translation network embedding (STNE) approach, which can map content sequence into node identity sequence to improve community detection. Although these approaches are successful in finding communities, they frequently ignore the essential network features such as intricate connections and irregular network properties. In this section, we peruse four class of methods for complex network and Markov blanket recovery: Auto-encoder based, GAN based, Graph Convolutional Networkbased (CC-GNNNo [4]), Graph Convolutional directed methods [5].

4.1Auto-encoder-based Methods

Auto-encoders are a variant of the simple and effective neural models, which aims to compress the high dimensional network data. As to auto-encoders specifically, they typically refer to a pair of coding algorithms that learn a new representation for their input in an unsupervised way. These models are usually composed of many hidden layers and the architecture is symmetric, where the output of each layer becomes the input for the next. 'other to find a compressed version of the input This underlying manual form (20BV.2 06) is an auto-encoder trying.. reduce the error between input and recast inputgiene else we are prepared based on character vectors are based end.

Stacked Auto-encoders (SdA)

The **semi-DNR** method [100] extends the *Deep Nonlinear Reconstruction* (DNR) framework by concatenating multiple autoencoders to achieve a deep, nonlinear reconstruction of the input network. In this approach, each encoder layer contains fewer neurons than the preceding one, enabling progressive dimensionality reduction and the extraction of the most salient structural features from the network data.

To incorporate prior knowledge, the semi-DNR model embeds **pairwise constraints** between node pairs (v_i, v_j)that are known to belong to the same community. This is achieved through an a priori information matrix

$$O = (o_{ij})_{n\times n}, \tag{13}$$

where $o_{ij} = 1$if nodes $v_i$and $v_j$are confirmed to share the same community, and $o_{ij} = 0$otherwise. By integrating this supervised information into the learning process, the semi-DNR method enhances the accuracy and robustness of community detection by guiding the model toward more meaningful latent representations.

Sparse Auto-encoders

Given the challenges associated with storing and processing large-scale networks, a sparse representation is often necessary. This variant of auto-encoders focuses on determining the optimal representation while adding constraints to the network. The Graph Encoder [107] introduces a regularization term at the hidden layer to limit the size of the hidden representation.

Variational Auto-encoders

Several recent approaches employ **Variational Autoencoders (VAEs)** for community detection, where the hidden representation is modeled as a **latent variable** with an assumed prior distribution. Within the framework of **variational inference**, these models approximate the intractable true posterior distribution $p(H \mid X)$of the latent variables using a more tractable distribution $q(H \mid X)$. The learning objective is then to minimize the **Kullback–Leibler (KL) divergence** between the approximate posterior $q(H \mid X)$and the prior distribution $p(H)$, thereby ensuring that the learned latent representations are consistent with the assumed prior. This probabilistic formulation allows VAEs to capture complex, nonlinear community structures and model uncertainty in the latent space more effectively than traditional deterministic approaches[101][102].

4.2 Generative Adversarial Network-based Methods

Generative Adversarial Networks (GANs), inspired by the minimax two-player game concept, have achieved significant success across a wide range of applications. GANs typically consist of two components: a generator (G) and a discriminator (D). The role of the generator is to model the data distribution and produce samples that are indistinguishable from real data. In contrast, the discriminator's job is to determine whether a given sample originates from real data or is synthetic data generated by the generator.

The motivation for using GANs stems from their unique ability to perform unsupervised learning while generating new data that theoretically maintains the same distribution as actual data. This capability provides robust network analysis potential.

Jia et al. [26] introduced an innovative approach called Community GAN, which incorporates the concept of AGM (adversarial game mechanics) to enhance performance through a minimax competition between a network motif-level generator and discriminator. Initially, this method creates representation vectors for nodes based on the relationships between each node and the communities to which it belongs. This process leads to optimized representations generated by a specially designed GAN tailored for community detection.

4.3 Graph Convolutional Network-based Methods

Graph convolutional networks (GCNs) represent one of the most successful approaches in graph neural networks for representation learning on graph-based data. Recently, they have gained popularity due to their effectiveness in supervised and semi-supervised classification of nodes. Several newly developed GCN-based algorithms have been designed to leverage the capabilities of GCNs in modeling and inferring high-dimensional complex network data for community detection (CD) applications[103].

Jin et al. argue that GCN embeddings are not community-based, emphasizing that community detection is primarily an unsupervised task. In response, they propose an unsupervised model for community detection called Joint GCN Embedding for Community Detection (JGE-CD). This model consists of three key modules:

1. **Dual Encoder**: This generates two embeddings using the original attribute network and its variant.

2. **Community Detection Module**: This module, which rests on top of the dual encoder, is responsible for detecting communities.
3. **Topology Reconstruction Module**: This module is used for reconstructing the network topology.

More recently, some research on community detection has incorporated GCNs that account for graph heterogeneity, where different types of nodes and relationships exist. For instance, Zheng et al. propose a Heterogeneous-Temporal GCN (HTGCN) for detecting communities in heterogeneous and temporal networks. This approach first generates feature representations for each heterogeneous network at every time point[104][105].

4.4 Integrating Graph Convolutional Networks and Undirected Graphical Models

In recent years, several studies have aimed to combine Graph Convolutional Networks (GCNs) with undirected graphical models, such as Markov Random Fields (MRFs) or Conditional Random Fields (CRFs), for community detection. The rationale behind this research direction is that GCNs primarily generate node embeddings by smoothing local features. This process often overlooks community structures, leading to node embeddings that are not community-specific.

While undirected graphical models offer a robust global objective for modeling communities, they tend to lack node-specific information and can be computationally intensive to learn. Therefore, combining GCNs with undirected graphical models allows each to complement the other’s strengths. One notable work in this area is MRFasGCN, which merges GCN and MRF to tackle semi-supervised community detection using attribute information in networks. This approach generalizes the initial NetMRF (as discussed in Section 3.2) into an extended MRF (eMRF) by incorporating both unary potentials and attribute information and then reparameterizes the MRF model to align with the GCN architecture..

5. Community Detection Methods on Attributed Networks

Community detection is an emerging research area within social network analysis. Recently, this topic has garnered significant attention, leading to a variety of community detection approaches applied to social networks. Many of these approaches focus on detecting communities by analyzing the attributes of the networks. With the rapid growth of network data and the abundance of user information, researchers are increasingly interested in using attribute information to identify communities. In this section, we will describe existing community detection methods for social networks developed in recent years, focusing specifically on techniques that leverage the node and edge attributes of the networks.

5.1. Node Content-Based Approaches

Community detection often relies on the topological structure of a network, which may encompass multiple topics. To better understand the fundamental semantics of communities, Wang et al. examined the correlations between different topics within these communities. They proposed a model for edge formation based on the assumption that users are more likely to communicate when they belong to the same community and their topics are closely related. This model includes three components: (1) generating all user content based on community membership and their respective topics, (2) generating link content based on the community memberships and topics of the connected users, and (3) creating directed links that consider both community memberships and topic correlations.

Jiang et al. explored how individual-level topics impact the formation of network topology and content. They noted that individual topics play a crucial role in community generation, suggesting that if two individuals are part of the same community and share similar interests, they are more likely to interact. Furthermore, the existence of relationships among individuals depends on the relationships between their communities and their topics of interest. Nodes within the same community are likely to be interconnected, and individual nodes can belong to multiple overlapping communities. When two nodes share multiple common communities, the likelihood of their connection increases compared to simply sharing a single community.

Nodes within the same community typically share common attributes. An efficient method for detecting overlapping communities is network topology potential analysis. However, many methods overlook the mass differences between nodes, which can lead to inaccuracies in the topological potential values assigned to nodes. Node mass reflects inherent properties such as importance and influence. Zhixiao et al. developed an overlapping community detection method based on node location analysis within the topology potential field. This method associates node mass with the node's importance and influence, utilizing the PageRank algorithm to calculate it. The community affiliation of nodes is determined based on their positions within the inherent peak-valley structure of the topology potential field. They defined three types of node positions: peak nodes (representative nodes), valley nodes (overlapping nodes among communities), and slope nodes (internal nodes).

In another study, it was found that the influence of nodes, the information linking communities from these nodes, and the similarity of community topologies all play vital roles. Researchers proposed an effective node representation strategy and designed a community detection method that combines local node embedding with global community embedding.

5.2. Edge content-based approaches

Most community detection methods primarily focus on either network topology or node attributes in isolation. However, both aspects provide valuable insights for characterizing communities. In reference 32, Liu et al. proposed a method that integrates the topological structure of a network with node attributes from the perspective of content propagation to detect communities in social networks. They treat the network as a dynamic graph, where the interactions among nodes form the community structure. In this framework, a community is seen as a stable state shared by its members. The authors describe interactions using two approaches: a linear model to approximate influence propagation and a direct modeling of interactions through a random walk.

In many social networks, a user can join a group without knowing the other members. Interactions within a group are typically based on membership. Guidi et al. introduced a dynamic community detection method for the user structures in Facebook Groups (reference 33). In their model, a group is represented as a graph, where an edge between two nodes indicates interaction within the group. To address community dynamics, they consider that edges may be added when new pairs of nodes interact, and edges may be removed if the corresponding nodes do not interact again within a fixed timeframe. By analyzing member interactions, they aim to detect dynamic communities, focusing on identifying dense communication groups of users and the evolution of these groups over time.

User interactions are particularly significant in reflecting peer relationships. Luo et al. utilized a cascading analysis of user interactions to identify communities (reference 34). They extracted both direct and indirect interactions, such as reply comments, comments on retweets, and retweets of retweets, from a broad range of social activities, including posting and sharing. Their approach involves a user interaction-oriented community detection method based on cascading analysis. By analyzing both direct and indirect interactions associated with each instance of social object sharing, they construct an event graph that captures cascading relationships among all interactions. From this event graph, small user groups, referred to as sub-events, are identified, which consist of users from the same community who have actively interacted with each other during a particular sharing event. A super graph is then created, with each node representing an extracted user group. This super graph is utilized to discover communities, with each community representing a group of users who have frequently interacted over multiple sharing events. The method aims to detect active communities based on user interaction behaviors rather than infrequent friendships. The process involves four main steps: generating event graphs, clustering sub-events, constructing a super graph, and performing community detection.

In social networks, individuals with shared interests and habits often communicate with one another, establishing a "comfort zone" in their lives. This comfort zone consists of a group of people with whom each individual routinely interacts, limiting their daily activities to this group. Typically, users frequently engage with certain individuals within their comfort zone while rarely interacting with others outside of it. In reference 35, researchers proposed a community detection method based on human social behavior. This model automatically identifies communities within the network by simulating natural human social interactions. The underlying concept is to delineate the social comfort zone of individuals and to simulate the evolution of the social network structure during the information-spreading process. The model consists of three phases: (1) identifying the comfort zone for each node, (2) selecting associated nodes from the comfort zone to reconstruct a simplified network, and (3) adjusting and optimizing the structure of the simplified network by simulating information spreading within human society.

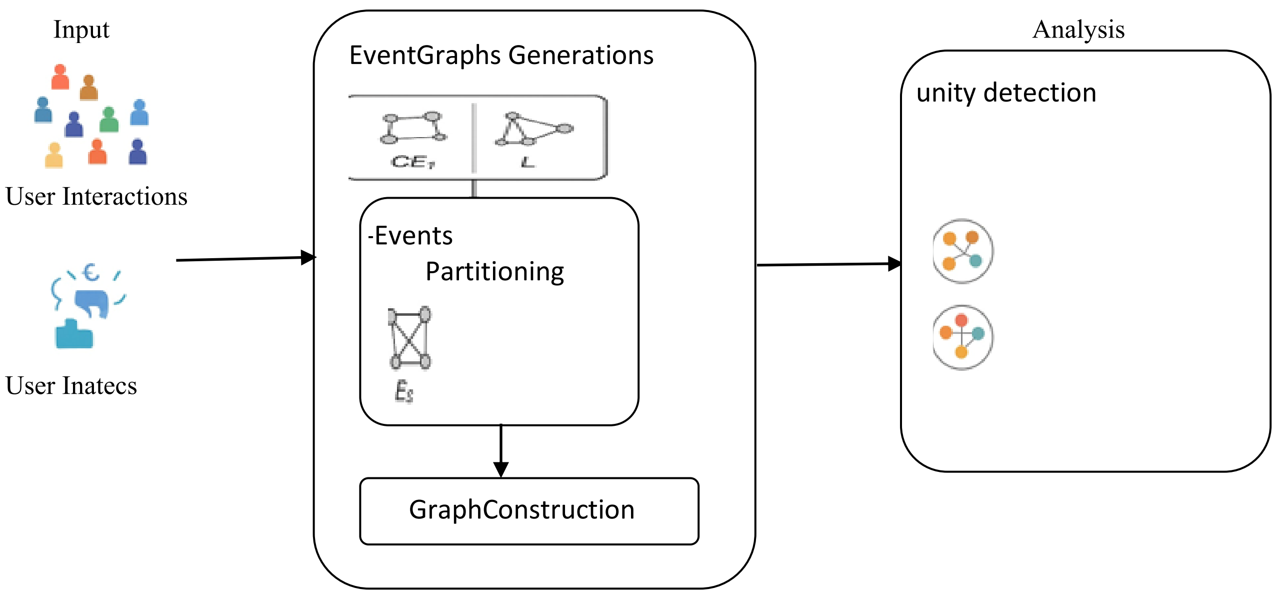

Fig. 3. The overall framework of the user interaction-oriented community detection based on cascading analysis.34

5.3. Edge and node content combination-based approaches

Classical approaches to community detection typically focus solely on the structure of the network, often overlooking the features of the nodes themselves. However, most real-world social networks provide additional information about the users, such as age, gender, and interests. These attributes can enhance our understanding of the actors and their relationships, thereby providing context to the detected communities. This necessity has led to the development of community detection methods that integrate both the structural and attribute information of the network.

Wang et al. raised two key research questions: (1) How does a link between two nodes emerge based on the community structure? (2) What contribution does each user make to the network's semantics? Addressing the second question involves two main aspects: the various types of content present in networks (namely, edge and node content) and a user’s interest in multiple topics. After analyzing a wide range of networks, they concluded that social behaviors among users are hidden mechanisms that shape community structure. Group dynamics include the interaction network, user posting behaviors, other topics of interest for users, and the dynamic evolution of these interests over time. These behaviors reflect internal relationships within community structures, the semantics of a community, the network topology, and its content. Users' social activities help define the topology and content of the network. In social networks, users interact by sharing news and commenting, thereby forging connections. The news posted by users constitutes the content of the network, encapsulating the users' concerns and the overall semantics. User actions significantly influence community structure and semantics.

To address these challenges, Wang et al. studied four types of user social behaviors to investigate information propagation, community structure detection, and influence spread. They proposed a unified community detection model that incorporates network topological structures, node content, edge content, and the four types of user social behavior.

Most community detection algorithms rely solely on linkage structures. However, social networks encode rich information in their content—such as node and edge content—which is vital for discovering topically significant communities. To tackle this, Wang et al. combined linkage structure, node content, and edge content to identify structurally and topically meaningful communities in dynamic networks. They transformed the content-based network into a node-edge interaction network, consistently embedding the structures of links, nodes, and edges along with their contents. The nodes are categorized into two types: n-nodes (representing nodes in the raw content-based network) and e-nodes (representing edges). The edges represent three types of similarity: structural similarity, node content similarity, and edge content similarity. A random walk-based algorithm was then employed to identify communities that are meaningful both structurally and topically within this multi-mode network.

Social networks serve as valuable information sources for analyzing network structures, such as users' topics of interest and interactions. Akachar et al. posed two research questions: (1) How can communities be discovered that reflect both the strengths of users' interactions and their interests? (2) How can the community structure be updated to detect new communities without needing to recompute them at every snapshot of the network? They designed a two-phase framework to discover and update community structures. In the first phase, a static community detection algorithm that utilizes both content and structural information identifies initial community structures. This algorithm leverages a hybrid approach based on statistical and semantic measures to extract users' interesting topics. The network is then partitioned into groups, each representing a distinct topic, and the relationships within each group are analyzed for verification. In the second phase, an adaptive method for detecting and updating the community structure uses the interesting topics of modified nodes to identify their appropriate groups. This algorithm consists of four main steps.

Liu et al. explored community detection in weighted networks, such as the relationships among users on social networks. They proposed a graph clustering algorithm based on the concepts of density and attractiveness for these weighted networks, defining user attractiveness as edge weight and user degree as node weight.

Finally, Zhao et al. proposed a topic-oriented community detection approach that combines social object clustering with link analysis. They initiated their method with subspace clustering...

Entities in real-world networks often possess attributes that are valuable for discovering communities. However, community detection methods that solely rely on the original network topology can lead to low accuracy because they overlook the inherent structures of communities. Li et al. proposed a model for community detection based on community structure embeddings. This model incorporates community structures and node attributes using the underlying community memberships. They formulated attributed community detection as a nonnegative matrix factorization optimization problem.

In social networks, nodes typically feature a variety of attributes, including age, gender, place of residence, preferences, and interactions. Each attribute can be considered as forming a distinct attribute layer. In their work, Li et al. also introduced a multi-layer local community detection model that combines attribute and structural information. This method effectively leverages node attribute information and the similarities in social interactions.

6. Datasets

In community detection research, experimental datasets are commonly referenced in the literature. There are generally two types of network data: real-world datasets and synthetic datasets. Real-world datasets are collected from actual networks, while synthetic datasets are generated using specific models based on manually designed rules. Real-world datasets are more commonly utilized than synthetic ones. Some studies experiment with both types, while most focus solely on real data.
The common datasets used for community detection are listed in Table 2. In this section, we introduce the datasets commonly used in experiments and describe how social networks are represented as graphs.

6.1. Real-World Datasets

Real-world datasets are widely published and typically derived from social networks, which are preprocessed to convert them into graph format. For instance, in the study by Wang et al., two real-world dynamic social networks—the Reddit and DBLP datasets—were employed. These datasets have also been used in several research studies. The Reddit dataset consists of threads from three sub-forums (Movies, Politics, and Science) from www.reddit.com. The nodes in this dataset represent users, while the content of their submissions serves as the node content. The undirected edges illustrate interactions between users who have posted and those who have replied.

The DBLP dataset comprises three research fields classified as three communities: machine learning, image processing, and data mining. Authors are represented as nodes, and undirected edges are formed between nodes when they have co-authored papers. If a paper has an author, the paper title is the node content; otherwise, it is linked to the titles of the collaborating authors. In another study by Akachar et al., three real-world community datasets (Enron email, Cora, and DBLP) were used for community detection experiments. In the Enron email corpus, each node stands for an email address, and an edge is created if two addresses have sent at least one email to each other. In the CORA dataset, nodes represent scientific papers, and edges represent citation relations—if two papers cite each other, an edge is formed. The DBLP dataset consists of three publication types: articles, collections, and proceedings, with nodes representing authors and edges symbolizing co-authorship. Additionally, in the Karate network, nodes represent members of a karate club, and edges represent interactions among them. The Dolphins network features nodes representing dolphins, with edges indicating common contact. In the Football network, nodes correspond to teams, while edges represent relationships between them.

6.2. Synthetic Datasets

LFR benchmark networks are widely employed in community detection experiments due to their capability to simulate realistic network structures with known ground-truth communities. These synthetic networks are particularly useful for testing and comparing the performance of different community detection algorithms.

One significant advantage of LFR benchmark networks is their inclusion of heterogeneity in both node degree and community size distributions—characteristics commonly found in real-world networks. Unlike simpler synthetic models, LFR networks generate data that adheres to power-law distributions for both node degrees and community sizes, making them more representative of actual complex systems, such as social, biological, or information networks.

The LFR model's flexibility allows researchers to fine-tune network properties through adjustable parameters, including:
- Number of nodes
- Average degree
- Mixing parameter (the fraction of a node’s neighbors outside its community)
- Minimum and maximum community sizes
- Number of overlapping nodes (in overlapping community benchmarks)

This high degree of control makes LFR networks an ideal tool for systematically evaluating the accuracy, robustness, and scalability of community detection methods.

In practice, it is common to utilize both real-world networks and LFR-generated synthetic networks in experimental setups. This dual approach helps validate algorithms under controlled conditions while also testing their performance on empirical data, ensuring broader applicability and reliability of the results.

Table 2: The statistics of the real-world network datasets in the literature

Sources	Communities	Nodes	Edges	References
Wisconsin	5	265	530	42, 44, 45
Wiki	19	2,405	17,981	31
Weibo		6,216	13,924	34, 38
Washington	5	230	446	42, 44
UmbcBlog	2	404	4,764	35
Twitter	3140	125,120	2,248,406	29
Twitter	8	171	796	44
Tieba		8,444	25,190	34
Texas	5	187	187	44, 42
Reddit	3	23,371	38,939	15, 27, 28, 36, 41
QQ Zone Sales		632,056	10,239,865	43
PubMed Diabetes	3	19,717	44,338	32
Political Blogs	2	1,490	19,090	39
Polbooks	3	105	882	35, 46
Philosophers	1220	1,218	5,972	29, 42
MoscowAthletics2013		103,319	144,591	43
LiveJ		3,987	26,268	34
Last.fm	38	1,892	12,712	44
Karate	2	34	78	30, 35, 45, 46
Google+	437	250,469	30,230,905	29
Football	12	115	613	35, 38, 46
Flickr	5436	16,710	716,063	29, 42
Facebook	10	4,089	88,234	29, 32, 42, 44
Enron	13	974	1,557	37, 39, 44, 41
Dolphins	2	62	159	30, 35, 45, 46
DBLP	3	2,554	9,963	15, 27, 28, 36, 37
Cornell	5	195	304	44, 42, 45
Cora	7	2,708	5,429	39, 32, 44, 42, 31, 37
Citeseer	6	3,312	4,732	32, 35, 44, 42
BlogCatalog	39	10,312	333,983	31
Airlines		417	3,588	43
AGBlogs	6	1,222	33,428	35
Aarhus employee		61	620	43

7. Conclusion

Community detection remains one of the most fundamental and challenging problems in network science. We conducted a large-scale study of learning-based community detection, categorizing the approaches into two main groups: probabilistic graphical models and deep learning methods. These approaches aim to extract meaningful structures in complex networks through statistical inference, generative modeling, and representation learning.

Traditional probabilistic models, such as the Stochastic Block Model (SBM), Markov Random Fields (MRF), and Non-negative Matrix Factorization (NMF), have established a theoretical foundation for these tasks by capturing the generative mechanisms behind network structures. In contrast, recent advancements in deep learning—with techniques like autoencoders, variational autoencoders, generative adversarial networks (GANs), and graph convolutional networks (GCNs)—have demonstrated superior performance in understanding nonlinear and high-dimensional relationships within large-scale and dynamic networks.
However, several open issues remain. The scalability of these models when applied to large, dynamic, and heterogeneous networks continues to be a significant challenge. Additionally, further investigation is needed to interpret deep representations and determine how to effectively fuse temporal, semantic, and attribute-based information. Future research could explore hybrid architectures that combine the theoretical guarantees of probabilistic modeling with the expressive capabilities and flexibility of deep neural networks.

In summary, learning-based community detection represents a promising research frontier with rapid advancements. This research has the potential to lead to more accurate, interpretable, and adaptive community discovery methods, bridging the gap between statistical modeling and deep learning approaches. Such synergy will further advancements in various applications, including social network analysis, cybersecurity, biological networks, and recommender systems.

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