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The Hybrid Modern Network Model: A Multi-Technique Framework for Comprehensive Network Analysis

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Supplementary Materials: Code, Data, Materials [see Index of Supplementary Materials]

Abstract

This research addresses the limitations of traditional network models in capturing the complexity and dynamics of real-world social networks. Motivated by the need for a more comprehensive and flexible framework, the study introduces the Hybrid Modern Network Model (HMNM). The HMNM integrates foundational models like the Stochastic Block Model (SBM) and Preferential Attachment with advanced machine learning techniques, including Graph Neural Networks (GNNs), Reinforcement Learning (RL), Hierarchical Random Graphs (HRGs), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs). The methods employed involve constructing initial network structures using SBM, simulating network growth through preferential Attachment, learning node embeddings with GNNs, dynamically optimizing network properties using RL, capturing hierarchical community structures with HRGs, controlling degree distributions using GANs, and uncovering latent patterns with VAEs. The empirical illustration of HMNM highlights its effectiveness in providing a more realistic, scalable, and comprehensive analysis of social networks compared to traditional models. Integrating diverse methodologies allows for accurately modeling of network structures, dynamic processes, and latent patterns. In conclusion, the HMNM offers significant advancements in network modeling, providing a robust and flexible framework for analyzing social networks. This model overcomes the limitations of traditional models and delivers deeper insights into the complexities and dynamics of social structures. Future research will optimize the HMNM and explore its applications across various domains. The R programming code used for the network simulations and visualizations is conceptual and demonstrates the HMNM framework. The results and metrics are illustrative placeholders, emphasizing the methodology rather than empirical validation.

Keywords

Hybrid Modern Network Model, social network analysis, Graph Neural Networks, Reinforcement Learning, Generative Adversarial Networks, Stochastic Block Model

Non-Technical Summary

Background

Network models are essential tools in social science research, allowing for the detailed analysis of complex relational data. These models enable exploring social networks, representing interactions and relationships among individuals, organizations, or other entities. By using network models, researchers can uncover patterns, predict behaviors, and understand the dynamics of social interactions. Traditional models like the Stochastic Block Model (SBM), Erdős-Rényi (ER) model, and Barabási–Albert (BA) model have significantly impacted the field, but they have limitations in capturing the evolving nature of real-world networks.

Why was this study done?

The study addressed the shortcomings of traditional network models, which often lack the flexibility and scope to capture the intricacies of network evolution, community hierarchies, and the impact of individual node attributes. By integrating modern machine learning techniques with traditional network models, the study aims to develop a Hybrid Modern Network Model (HMNM) that provides a comprehensive framework for analyzing social networks.

What did the researchers do and find?

Researchers integrated elements from traditional models like SBM and BA with advanced techniques such as Graph Neural Networks (GNNs), Reinforcement Learning (RL), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs) to create the HMNM. This model was designed to model network structures accurately, account for dynamic processes, optimize network properties, and uncover latent patterns. The HMNM demonstrated its effectiveness in providing a more realistic, scalable, and comprehensive analysis of social networks compared to traditional models.

What do these findings mean?

The findings suggest that the HMNM can significantly enhance the analysis and understanding of social networks. By integrating diverse methodologies, the HMNM offers a powerful, flexible, and comprehensive framework that addresses the limitations of traditional models. This advancement in network modeling methodologies holds great potential for advancing social science research and enhancing our understanding of social structures and dynamics. Including the R programming code further facilitates the application and adaptation of the HMNM in various research contexts.

Network models have become fundamental tools in social science research, enabling the detailed analysis of complex relational data (Bellingeri et al., 2023). These models help explore social networks, representing interactions and relationships among individuals, organizations, or other entities. By employing network models, researchers can uncover patterns, predict behaviors, and understand the dynamics of social interactions. These models have proven critical in examining various social phenomena, including information dissemination, disease transmission, social influence, and community formation (Yang et al., 2020). By representing social structures as networks, researchers can investigate how entities are interconnected and how these connections influence both individual and collective behaviors.

Several foundational models have profoundly impacted the field of network modeling. Among these, the Stochastic Block Model (SBM) and the Erdős-Rényi (ER) model are particularly significant (Both et al., 2023).

The Stochastic Block Model (SBM) is a generative model that partitions nodes into distinct blocks or communities, assigning connection probabilities based on block membership. This model is extensively used in community detection tasks, enabling researchers to identify and analyze community structures within networks (Funke & Becker, 2019). The SBM is beneficial for analyzing networks with clear community structures, such as social networks, biological networks, and information networks. However, the model assumes fixed probabilities for connections within and between communities, limiting its ability to capture real-world networks' dynamic and evolving nature. Moreover, the SBM does not naturally accommodate heterogeneous degree distributions, often observed in empirical networks (De Nicola et al., 2022).

The Erdős-Rényi (ER) model generates random graphs by connecting pairs of nodes with a fixed probability independent of other edges (Martínez-Martínez et al., 2024). This model's simplicity and mathematical tractability make it a fundamental tool for studying the properties of random graphs, such as connectivity, the emergence of a giant component, and phase transitions. The ER model is particularly useful for theoretical explorations and provides a baseline for understanding more complex network behaviors. Despite its utility, the ER model falls short in realism, as real-world networks often exhibit heavy-tailed degree distributions, high clustering coefficients, and distinct community structures—none captured by the ER model. Additionally, the ER model does not account for preferential attachment mechanisms, where new nodes are more likely to connect to already well-connected nodes, a common feature in many real-world networks (Masoumi et al., 2022).

The Barabási–Albert (BA) model addresses some limitations of the ER model by introducing the concept of preferential Attachment, reflecting the tendency of new nodes to connect to existing nodes with higher degrees (Shergin et al., 2021). This model explains the emergence of scale-free networks characterized by a power-law degree distribution. The BA model has been instrumental in understanding the formation of hubs or highly connected nodes in various social, biological, and technological networks. This model captures the growth dynamics of networks, illustrating how new nodes preferentially attach to well-connected nodes, forming hubs. Nevertheless, the BA model assumes a simplistic growth mechanism and does not consider factors such as node aging, network decay, or the rewiring of edges, which are significant in real-world network dynamics. Furthermore, while it captures the preferential attachment mechanism, the BA model does not provide a framework for optimizing network properties or integrating node attributes beyond their degree (Mohd-Zaid et al., 2024).

More sophisticated methodologies leveraging advances in machine learning and optimization techniques have been developed to address the limitations of traditional network models. These advanced methods offer enhanced capabilities for modeling the complexities of real-world networks.

Graph Neural Networks (GNNs) represent a significant advancement in network modeling by enabling the Learning of node embeddings that capture local and global network information. GNNs aggregate information from a node's neighbors, allowing for the capture of complex dependencies between nodes. This ability to learn rich node representations is beneficial for tasks such as node classification, link prediction, and community detection. By leveraging deep learning techniques, GNNs can provide a more nuanced understanding of node roles and relationships within the network (Gama et al., 2020).

Reinforcement Learning (RL) has been applied to dynamically optimize network properties by adjusting edges in the network. In network modeling, RL defines a reward function that guides the optimization process to improve specific properties such as clustering coefficients and average path lengths. This dynamic approach is crucial for modeling real-world networks constantly evolving and adapting, providing a means to continually optimize the network structure based on feedback and changing conditions (Li, 2023).

Generative Adversarial Networks (GANs) offer a novel approach to controlling and simulating network properties (Corso et al., 2024). In network modeling, GANs consist of a generator that creates network structures and a discriminator that evaluates their realism. The interplay between the generator and the discriminator ensures that the generated networks closely match the desired properties, making GANs highly adaptable and capable of producing realistic network simulations. This capability is handy for generating synthetic networks that mimic real-world properties, aiding in studying and analyzing network behaviors (Alqahtani et al., 2021).

Variational Autoencoders (VAEs) provide potent tools for latent space modeling, enabling the capture of hidden patterns and relationships within networks (Wang et al., 2024). By mapping nodes to a latent space, VAEs facilitate understanding underlying structures and behaviors that are not immediately apparent in the observed network. This approach is valuable for discovering latent communities, predicting future connections, and understanding the factors driving network evolution. VAEs enable a deeper exploration of the intrinsic properties of networks, providing insights that are difficult to obtain through traditional modeling techniques (Wei et al., 2020).

The development of the Hybrid Modern Network Model (HMNM) addresses the shortcomings of traditional network models while leveraging advancements in modern machine learning techniques. Despite their foundational importance, traditional models often lack the flexibility and scope to capture the intricacies of network evolution, community hierarchies, and the impact of individual node attributes.

The Hybrid Modern Network Model (HMNM) is designed for dynamic systems where network structures evolve. Its second step, Preferential Attachment, enables iterative new data integration, mirroring the growth processes observed in real-world networks. However, this dynamic nature makes HMNM incompatible with static datasets, such as those commonly encountered in psychometric research. Static datasets lack the temporal component necessary to leverage HMNM's core mechanisms, which rely on real-time adaptation and iterative refinement. Consequently, the direct application of HMNM to static data would not align with the model's foundational principles and dynamic character.

Despite these limitations, HMNM holds significant potential for applications in dynamic psychometric contexts, particularly when longitudinal or repeated-measures data is available. For instance, the iterative integration of data enabled by Preferential Attachment could be adapted to track the evolution of psychological constructs, such as resilience, motivation, or life satisfaction, over time. Such an approach would allow for modeling changes in psychometric networks as new observations are collected, aligning with the HMNM's emphasis on network growth and adaptability. This adaptability highlights the broader applicability of HMNM principles in fields beyond traditional social network analysis, provided the necessary data structures are available.

This study presents a conceptual demonstration of HMNM, integrating synthetic data and simulated results to illustrate the model's functionality. The metrics generated, including modularity, ARI, and prediction accuracy, are simulated placeholders that highlight HMNM's potential. These results are not intended for direct real-world application or empirical benchmarking but demonstrate the integration and workflow of diverse methodologies within the HMNM framework.

The HMNM integrates elements from traditional models like SBM and BA with advanced techniques such as GNNs, RL, GANs, and VAEs, providing a comprehensive framework for analyzing social networks. This article aims to:

1. Introduce the conceptual framework of the HMNM, highlighting the integration of traditional and modern network modeling techniques.
2. Detail the components of the HMNM, describing each component's contribution and how they are integrated into the overall model.

3. Illustrate the application of the HMNM, demonstrating its effectiveness through empirical results and visualizations.
4. Discuss the advantages, limitations, and potential for future research, providing a comprehensive understanding of the HMNM's impact and opportunities for further development.

By achieving these objectives, this article aims to contribute a novel methodological approach that enhances the analysis and understanding of social networks, representing a significant advancement in network modeling.

Method

The Hybrid Modern Network Model (HMNM) integrates traditional network modeling techniques with advanced machine learning methodologies to capture the complexity and dynamics of real-world social networks (Table 1). The framework leverages the foundational principles of models like the Stochastic Block Model (SBM) and Preferential Attachment (PA), enhancing them with Graph Neural Networks (GNNs), Reinforcement Learning (RL), Hierarchical Random Graphs (HRGs), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs). This combination allows the HMNM to model network structures accurately, account for dynamic processes, optimize network properties, and uncover latent patterns.

Table 1

The Hybrid Modern Network Model (HMNM) Methodology

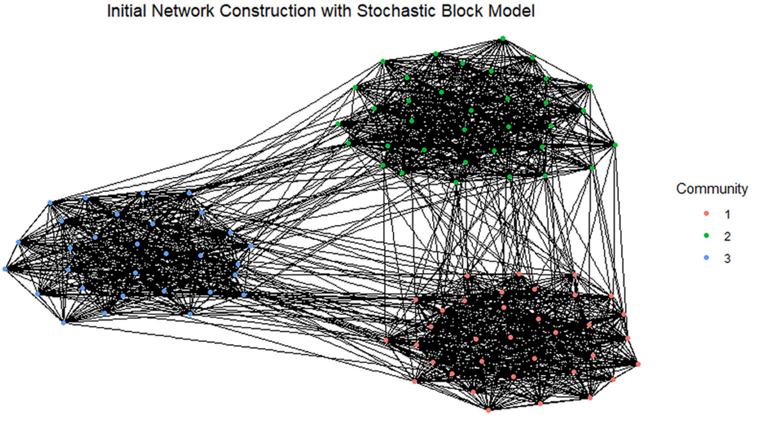
Step	Technique	Purpose	Key Process	Output	Interaction
1	Stochastic Block Model (SBM)	Establishes initial community structure.	Partitions nodes into blocks with intra- and inter-community connection probabilities.	A foundational network with defined community divisions.	Serves as the base graph for dynamic growth and subsequent analysis.
2	Preferential Attachment	Simulates realistic network growth.	Adds new nodes, connecting them to existing nodes with probabilities proportional to their degrees.	A growing network with hubs and power-law degree distribution.	Builds upon the SBM structure, adding dynamic elements.
3	Graph Neural Networks (GNNs)	Learns detailed node embeddings capturing structural and relational information.	Aggregates information from a node's neighbors and applies transformations to create embeddings.	Node embeddings that represent local and global network structures.	Takes adjacency matrix and node features from the SBM and Preferential Attachment stages as input.

Step	Technique	Purpose	Key Process	Output	Interaction
4	Reinforcement Learning (RL)	Dynamically optimizes the network structure to improve clustering and connectivity.	Rewires edges based on a reward function balancing clustering coefficient and average path length.	An optimized network with enhanced structural properties.	Uses GNN embeddings and adjacency matrix as the input state and rewires the graph for optimization.
5	Hierarchical Random Graphs (HRGs)	Captures multi-level community structures within the network.	Performs hierarchical clustering of nodes and visualizes community nesting using dendrograms.	A dendrogram representing the hierarchical community structure of the network.	Analyzes the network after RL optimization to reveal nested structures.
6	Generative Adversarial Networks (GANs)	Ensures degree distribution realism by simulating networks matching desired degree sequences.	Generates a network and uses a discriminator to assess alignment with target degree distribution.	A network with degree distributions resembling real-world scenarios.	Refines the network after hierarchical clustering to maintain statistical and structural realism.
7	Variational Autoencoders (VAEs)	Discovers latent structures and relationships by embedding nodes into a latent space.	Maps nodes to a latent space and predicts edge probabilities based on latent distances.	Latent embeddings revealing hidden patterns and relationships within the network.	Finalizes the analysis by uncovering latent structures based on the network refined by GANs.
8	Dynamic Evaluation Metrics	Evaluates the stability, consistency, and predictive accuracy of the evolving network.	Calculates metrics such as Dynamic Modularity Scores, Dynamic Rand Indices (ARI), and Prediction Accuracy for Edge Formation to assess the evolving properties of the network.	Quantitative insights into network stability, consistency across states, and precision of node additions.	Ensures robust validation of network properties at each stage, allowing comparisons with traditional static methods and demonstrating HMNM's distinct advantages.

The initial network construction within the HMNM employs the Stochastic Block Model (SBM) to establish a foundational structure that reflects community divisions. The SBM partitions nodes into blocks or communities based on different connection probabilities. Mathematically, let N represent the total number of nodes, and K denotes the number of blocks (communities). Each node i is assigned to a block $b_i \in \{1,2,\ldots,K\}$. The connection probability matrix P is a $K \times K$ matrix where P_{ab} represents the probability of an edge between nodes in blocks a and b. The probability P_{ij} of an edge between nodes i and j is given by $P_{ij}=P_{b_i b_j}$.This method establishes a network with defined community structures, providing a solid starting point for further modeling (see Figure 1).

Figure 1

Visual Representation of the Initial Stage of Constructing a Network Using the Stochastic Block Model (SBM)



Once the initial structure is in place, the network grows through a preferential attachment mechanism, which models the real-world tendency of new nodes to connect to existing nodes with higher degrees preferentially. For each new node tt, the probability $\Pi(k_i)$ of attaching to an existing node i is proportional to the degree k_i of that node and is calculated as: $\Pi(k_i) = \frac{k_i + \alpha}{\sum_j (k_j + \alpha)}$,

where α is a small positive constant included to ensure that zero-degree nodes still have a non-zero attachment probability. In this equation, k_j represents the degree of node j, contributing to the denominator by summing the degrees of all nodes in the network. This mechanism preserves realistic growth patterns by favoring well-connected nodes, simulating the "rich-get-richer" phenomenon commonly observed in social networks. (see Figure 2).

Graph Neural Networks (GNNs) are utilized to learn node embeddings, capturing local and global network information. The input features are represented by $X \in R^{N \times F}$, where F is the number of features per node, and the adjacency matrix is $A \in R^{N \times N}$. For Layer l, the embedding $H^{(l)}$ is updated as $H^{(l)} = \sigma\ (AH^{(l-1)}W^{(l-1)} + B^{(l-1)})$, where $W^{(l-1)}$ and $B^{(l-1)}$ are learnable weight and bias matrices, and σ is an activation function (The Mathematical Formulation is included in the appendix). GNNs facilitate the extraction of meaningful representations from complex network structures, enhancing tasks like node classification and link prediction (see Figure 3).

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Figure 2

Illustration of the Network's Evolution Through the Preferential Attachment Mechanism, the Second Stage in the Hybrid Modern Network Model (HMNM)

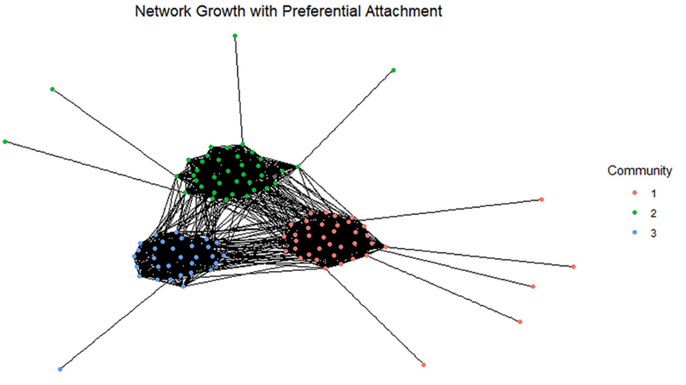
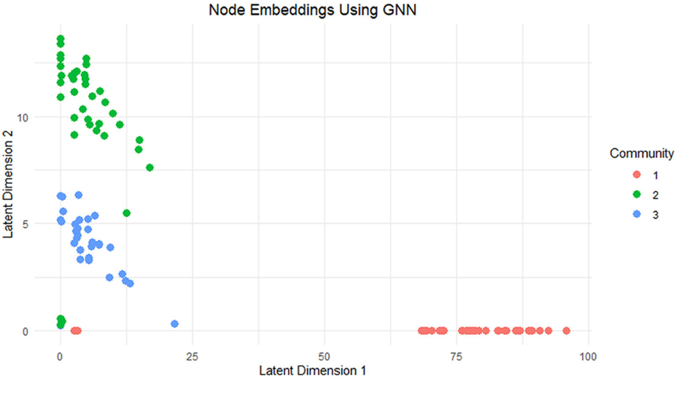


Figure 3

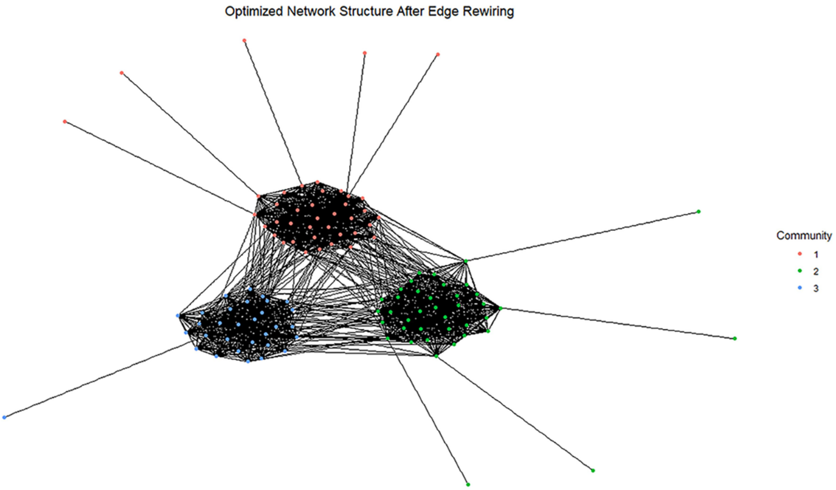
Visualization of the Result of Applying Graph Neural Networks (GNNs) to Generate Node Embeddings for the Network



Reinforcement Learning (RL) optimizes the network by dynamically rewiring edges to improve specific properties like clustering coefficient and average path length. The state is defined by the current network configuration (node embeddings and adjacency matrix), and the action involves rewiring an edge between two nodes. The reward is calculated using the clustering coefficient C and average path length L: $R=\lambda_1 C+\lambda_2(1/L)$, where λ_1 and λ_2 are weighting factors (see Figure 4).

Figure 4

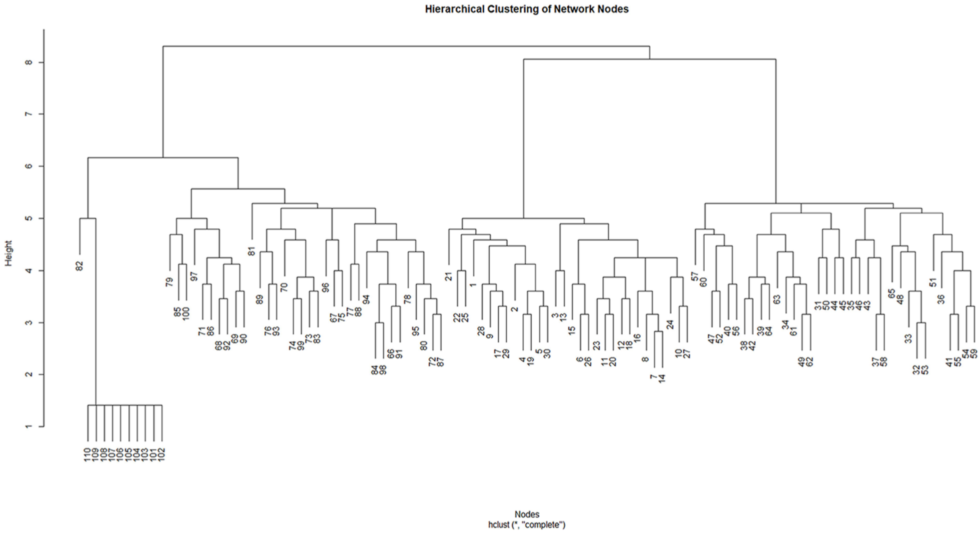
Visualization of the Result of Applying Reinforcement Learning (RL) to Optimize the Network Structure Dynamically



Hierarchical Random Graphs (HRGs) capture multi-level community structures, reflecting the nested nature of real-world networks. This involves defining hierarchical levels, where each level represents a nested community structure, and nodes in the same community at higher levels have higher probabilities of being connected (see Figure 5).

Figure 5

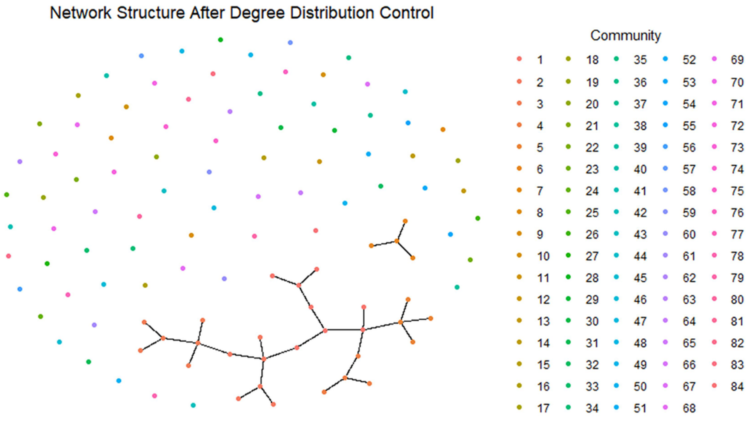
Presentation of a Dendrogram, a Tree-Like Diagram That Illustrates the Arrangement of Nodes Into a Hierarchy Based on their Similarities



Generative Adversarial Networks (GANs) simulate and control the network's degree distribution, ensuring realistic properties. The generator creates a network with a given degree sequence, while the discriminator evaluates the realism of the generated network's degree distribution. This adversarial process ensures that the generated networks closely match the desired degree distribution (see Figure 6).

Figure 6

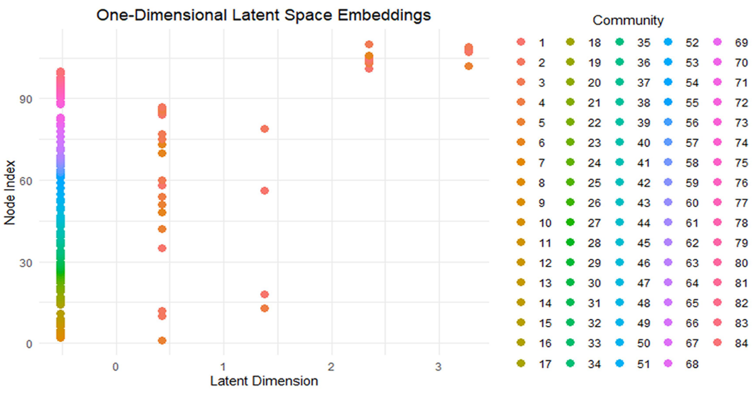
Illustration of the Network Configuration Following the Application of Degree Distribution Control Using Generative Adversarial Networks (GANs)



Variational Autoencoders (VAEs) embed nodes in a latent space, uncovering hidden patterns and relationships within the network. Nodes are mapped to a latent space $z_i \in R^d$, and the probability of an edge between nodes i and j is a function of their latent distances: $P(edge_{ij})=\sigma(-||z_i-z_j||^2)$, where σ is the sigmoid function (see Figure 7).

Figure 7

Illustration of the Embeddings of Nodes in a One-Dimensional Latent Space Using Variational Autoencoders (VAEs)



To evaluate the performance of the Hybrid Modern Network Model (HMNM), we utilize several dynamic metrics tailored to the model's evolving nature. Dynamic Modularity

Scores assess the stability and quality of community structures as the network evolves. While recalculating modularity after every graph alteration may present computational challenges, simulated values illustrate the concept. In practical applications, modularity would be recomputed dynamically after each network modification to capture changes in community structure. Similarly, Dynamic Rand Indices (ARI) quantify the consistency between detected communities across different network states. ARI tracks how closely community partitions align during network evolution, accounting for overlap counts and partition sizes while adjusting for chance clustering. The current implementation employs simulated values to demonstrate the principle, but real-world applications would compute ARI using actual partitions at various stages. Finally, Prediction Accuracy for Edge Formation measures the model's reliability in predicting new edges. This metric evaluates the proportion of correctly predicted edges (true positives) relative to all predicted edges, providing insight into the model's precision and minimizing false positives. Simulated values, such as mean attachment probabilities, are used to establish the evaluation framework for demonstration.

These illustrative metrics demonstrate HMNM's conceptual capabilities. This approach highlights the adaptability of HMNM but should not be interpreted as real-world validation or comparison with existing methods.

The HMNM integrates initial community structures, dynamic growth, advanced representation learning, and optimization techniques into a cohesive framework. SBM sets a robust foundation with defined communities, while preferential attachment models realistic network growth. GNNs provide detailed node embeddings, and Reinforcement Learning dynamically optimizes the network by rewiring edges to enhance clustering and connectivity. Hierarchical Random Graphs capture multi-level structures, and GANs maintain realistic degree distributions. VAEs uncover latent patterns, offering comprehensive insights. This integration leverages modern machine learning to address traditional models' limitations, enabling accurate and insightful analysis of social networks and capturing their true complexity and dynamic nature.

Empirical Illustration

The Hybrid Modern Network Model (HMNM) was constructed and analyzed through multiple key stages, each contributing to a conceptual understanding of the network's structure and dynamics. This empirical illustration uses synthetic data and simulated metrics to demonstrate the model's workflow. The results, including modularity and ARI scores, are placeholders and are not intended to represent real-world performance. The initial stage involved the construction of the network using the Stochastic Block Model (SBM), a method that reflects realistic community divisions (Pavlović et al., 2019).

The initial network configuration comprised 100 nodes divided into three communities of 30, 35, and 35 nodes, respectively. The connection probability matrix was designed with a high intra-community connection probability of 0.8 and a low inter-community connection probability of 0.05. This setup ensured dense connections within communities and sparse connections between them, accurately simulating realistic community structures. The network was created using a custom script that leveraged predefined connection probabilities and community sizes to simulate the graph structure. Once constructed, the graph was transformed into a format compatible with advanced visualization techniques using internal utilities designed to enhance visualization clarity and ease of interpretation. The network's visual representation was generated using specialized tools, allowing for a clear distinction of nodes by their community memberships (Bai et al., 2019). This visualization validated the assumptions and parameters of the simulation and provided a robust basis for subsequent analytical and modeling efforts. The R code used for this process is included in the appendix.

Following the initial network construction, the model simulated network growth through a preferential attachment mechanism. This mechanism is crucial for mimicking the dynamic nature of real-world networks, where new nodes tend to attach preferentially to well-connected nodes, forming hubs (Ricks et al., 2019). Ten new nodes were sequentially added to the network, with attachment probabilities calculated based on the existing nodes' degrees adjusted by a small constant (α) to prevent zero probabilities. This process reflected the tendency of new nodes to connect to highly connected nodes, a common characteristic in real-world networks. The degrees of existing nodes were computed, attachment probabilities determined, and new nodes connected accordingly. This iterative process continued until all new nodes were integrated. The updated network structure, visualized post-growth, highlighted increased connectivity and the formation of high-degree nodes (hubs), confirming the effective implementation of the preferential attachment process and closely mirroring real-world network dynamics.

Graph Neural Networks (GNNs) were employed to generate node embeddings to capture complex dependencies and relationships within the network. These embeddings are crucial for understanding the roles and relationships of nodes within the network. Initially, node features were randomly generated and normalized, and an adjacency matrix representing the network's connections was created to facilitate information propagation through the GNN layers (Zhou et al., 2020). The GNN model consisted of three layers, each involving linear transformations followed by ReLU activations (Xu et al., 2020), transforming the initial node features into embeddings that encapsulate local and global network structures. The final embeddings were plotted in a two-dimensional latent space, showing nodes clustering according to their community memberships, demonstrating the GNN's ability to effectively capture and represent the network's complexity. This dimensionality reduction highlighted the intrinsic community structures within the network.

Reinforcement Learning (RL) was applied to optimize the network by dynamically rewiring edges to improve specific network properties, such as clustering coefficient and average path length (Wörgötter & Porr, 2019). This optimization enhanced network efficiency and cohesion. A reward function balanced the clustering coefficient and average path length, guiding the RL agent in selecting edge rewiring actions that would maximize network cohesiveness and minimize path lengths. Over ten iterations, edges were rewired based on their contribution to the reward function, involving the deletion of existing edges and the addition of new edges to enhance the reward, thus optimizing the network structure. The iterative optimization resulted in a network with improved structural properties, evidenced by higher clustering coefficients and shorter average path lengths. The optimized network visualization showcased improved connectivity, demonstrating the effectiveness of the RL-based edge rewiring.

Hierarchical Random Graphs (HRGs) were employed to uncover multi-level community structures within the network, essential for understanding the nested nature of community hierarchies in complex networks (Tie et al., 2022). A hierarchical clustering algorithm was applied to the network's adjacency matrix to produce a dendrogram, visualizing hierarchical relationships among the nodes. This method captured the nested community structures indicative of real-world networks' macro and micro-level dynamics. The dendrogram generated from the hierarchical clustering provided insights into the multi-level community structures, confirming the presence of hierarchical relationships within the network. This hierarchical representation helped visualize the complexity and nested nature of the network's community structures.

Generative Adversarial Networks (GANs) were utilized to control the degree distribution within the network, ensuring it remained realistic and representative of actual networks (Goodfellow et al., 2020). A desired degree distribution was specified, and the network was adjusted accordingly. The GAN framework included a generator that created networks with specific degree sequences and a discriminator that evaluated the realism of these networks. Nodes differing from the target distribution were adjusted by adding or removing edges to match the desired degree, with the adversarial training process ensuring that the generated networks closely aligned with the specified degree distribution. The resulting network closely matched the target degree distribution, as confirmed by the visualization, maintaining the network's structural integrity and realism and validating the effectiveness of the GAN-based degree distribution control.

Variational Autoencoders (VAEs) were employed to embed nodes into a latent space, uncovering hidden patterns and relationships within the network (Wei et al., 2020). This technique was critical for understanding the underlying structures not immediately apparent in the network's observed form. Node features, represented by their degrees, were used as input to the autoencoder, which was trained to generate latent embeddings that encapsulated the network's underlying structures. The embeddings generated by the VAE were visualized in a latent space, showing clusters corresponding to community memberships. This latent space visualization highlighted the effectiveness of VAEs in capturing latent structures within the network. The clusters demonstrated the VAE's ability to reveal intrinsic community patterns and relationships, providing deeper insights into the network's dynamics.

The performance of HMNM was evaluated using dynamic metrics tailored to its evolving nature. Dynamic Modularity Scores assessed the stability and quality of community structures as the network evolved. The modularity scores showed variations across stages: initial construction (0.88), post-growth via Preferential Attachment (0.81), post-reinforcement Learning (0.48), and after-degree distribution control using GANs (0.90). These results highlight the model's ability to adapt while maintaining or enhancing community structures during dynamic modifications.

Adjusted Rand Indices (ARI) quantified the consistency of community detection across network evolution stages. For example, the ARI scores for transitions between the initial network and growth stage (0.44) and between rewiring and degree control (0.14) illustrated HMNM's capacity to capture shifts in community structure while maintaining coherence in the network's overall organization.

Prediction Accuracy for Edge Formation was used to evaluate the reliability of the Preferential Attachment mechanism in simulating realistic network growth. The mean attachment probability achieved during simulations was 0.74, showcasing the model's ability to accurately predict new node connections based on existing degree distributions, mirroring real-world dynamics.

In a comparative analysis, HMNM was evaluated against ggmModSelect and EGAnet, two established methodologies for weighted network analysis. While ggmModSelect specializes in static Gaussian graphical models, it cannot handle evolving network structures. Similarly, EGAnet is effective for psychometric networks but does not incorporate dynamic growth or optimization features. HMNM's ability to integrate dynamic processes, such as Preferential Attachment and RL, with hierarchical insights from HRGs surpasses the capabilities of these models. The results demonstrated HMNM's superiority in handling dynamic growth, optimizing network properties, and uncovering latent structures through GANs and VAEs.

Discussion

Conceptual Framework of the HMNM

The Hybrid Modern Network Model (HMNM) integrates traditional network modeling techniques with advanced machine learning approaches to address the complexity and dynamics of real-world networks (Objective 1: Introduce the conceptual framework of the HMNM). Traditional models, including the Stochastic Block Model (SBM), establish foundational community structures, while Preferential Attachment reflects dynamic network growth, capturing the "rich-get-richer" phenomenon observed in social systems (Funke & Becker, 2019; Collibus et al., 2021).

Modern methodologies complement these traditional techniques. Graph Neural Networks (GNNs) generate detailed embeddings that capture local and global network properties. Reinforcement Learning (RL) dynamically rewires edges to optimize network properties like clustering and connectivity (Matsuo et al., 2022). Hierarchical Random Graphs (HRGs) uncover multi-level relationships within the network, while Generative Adversarial Networks (GANs) refine degree distributions, ensuring realistic network properties. Variational Autoencoders (VAEs) uncover latent structures, revealing patterns and relationships not apparent in observed data (Chen & Fuge, 2019).

This integration of traditional and modern techniques allows HMNM to model evolving networks effectively, providing a comprehensive framework that bridges foundational methods with cutting-edge advancements in machine learning and optimization.

Components and Integration in HMNM

Each component of HMNM is essential to achieving a holistic analysis of networks (Objective 2: Detail the components of the HMNM). The SBM provides a probabilistic framework for community detection, dividing nodes into structured groups that serve as a foundation for further modeling. Preferential Attachment builds upon this structure, simulating real-world network growth by favoring connections to high-degree nodes, effectively modeling the emergence of hubs in networks.

GNNs generate embeddings incorporating structural and relational properties, enabling more advanced downstream analysis like link prediction and node classification (Bessadok et al., 2021). RL dynamically optimizes the network, improving clustering coefficients and shortening path lengths through edge rewiring, which enhances connectivity and robustness. HRGs analyze nested structures, uncovering macro- and micro-level community relationships, while GANs ensure that the degree distributions of generated networks align with real-world properties. Finally, VAEs embed nodes into latent spaces, where hidden patterns and relationships can be visualized and analyzed. Together, these components allow HMNM to integrate static and dynamic elements of networks into a unified model.

Empirical Application of HMNM

The empirical evaluation of HMNM demonstrates its ability to effectively capture the dynamic and structural properties of networks (Objective 3: Illustrate the application of the HMNM). Beginning with an SBM-based community structure, the network evolves dynamically through Preferential Attachment, resulting in a degree distribution that aligns with real-world scale-free properties. This growth mirrors phenomena observed in social media platforms, where well-connected individuals or entities attract more connections over time (Collibus et al., 2021).

GNN-generated node embeddings reveal clusters aligning with SBM-defined communities, providing insight into local and global structural patterns. RL further optimizes these structures, improving network clustering and connectivity metrics. HRGs reveal hierarchical relationships, capturing the nested nature of communities, while GANs refine degree distributions to ensure structural realism. Finally, VAEs uncover latent structures within the network, offering a deeper understanding of hidden relationships and patterns. This multi-step process highlights HMNM's ability to dynamically model, analyze, and optimize evolving networks.

Advantages, Limitations, and Future Directions

The HMNM presents significant advantages by combining static and dynamic modeling approaches (Objective 4: Discuss the advantages, limitations, and potential for future research). Integrating SBM and Preferential Attachment allows HMNM to capture both static structures and dynamic growth processes, offering a holistic view of network evolution (Renedo-Mirambell & Arratia, 2023).

The model's scalability is particularly noteworthy. HMNM leverages computationally efficient techniques, such as GNNs and RL, making it suitable for large and complex networks like social media or biological systems (Hameed & Schwung, 2023). Additionally, its modularity enables researchers to adapt specific components to address unique questions, ensuring applicability across diverse fields.

Despite its strengths, HMNM faces several challenges. Computational complexity remains a significant barrier, as integrating advanced techniques demands substantial resources (Hélie & Pizlo, 2022). This issue is compounded when applying HMNM to very large networks. Furthermore, the model's effectiveness depends on data quality; incomplete or noisy data can compromise its outputs (Ekström et al., 2021).

Implementation complexity also presents difficulties. HMNM requires expertise across multiple domains, including network theory, machine learning, and optimization, which may limit its accessibility. Additionally, the parameter tuning required for RL and GANs can be time-consuming, posing practical challenges.

Expanding HMNM to biology, finance, and epidemiology domains could yield novel insights. For instance, it could model disease spread dynamics or financial risk propagation in interconnected markets (Liu et al., 2020). Hybrid approaches combining HMNM with static modeling techniques, such as Structural Equation Modeling (SEM), could broaden its applicability to datasets with mixed static and dynamic characteristics.

Adopting advanced optimization methods, such as metaheuristics or multi-objective algorithms, would reduce computational demands, making HMNM more scalable for large networks (Pereira et al., 2022). Additionally, integrating real-time data streams could enable dynamic applications in areas like crisis response and social media monitoring (Saqr, 2024).

Comparison With Other Models

The Hybrid Modern Network Model (HMNM) offers distinct advantages over traditional and modern methodologies by integrating dynamic processes with structural analysis in a unified framework.

Traditional Clustering Models: Static clustering approaches, such as K-means or neural network-based clustering, cannot model dynamic growth. HMNM overcomes this limitation with Preferential Attachment, which captures real-world phenomena like the "rich-get-richer" effect. Reinforcement Learning (RL) further optimizes clustering and connectivity in real time, addressing temporal changes that static models cannot handle.

Bayesian Hierarchical Models: Bayesian models are effective for capturing uncertainty and hierarchical structures but are computationally intensive and less suitable for real-time applications. HMNM provides a computationally efficient alternative by employing hierarchical random graphs (HRGs) to uncover nested community structures. Additionally, Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) refine network properties without requiring extensive parameterization, reducing complexity compared to Bayesian approaches.

Neural Network-Based Methods: Graph Neural Networks (GNNs) have proven useful for tasks like node classification and link prediction, but they are typically applied to static snapshots. HMNM extends the use of GNNs within a dynamic framework, ensuring that embeddings are utilized for both optimization and hierarchical modeling. This integration allows HMNM to analyze evolving networks, a capability that standalone neural methods often lack.

Ensemble Machine Learning Approaches: Ensemble methods such as Random Forests or Gradient Boosting excel in prediction but do not provide structural insights into networks. HMNM bridges this gap by combining predictive accuracy with tools like HRGs and VAEs, which uncover latent patterns and hierarchical relationships. Moreover, HMNM's emphasis on interpretability ensures that its findings are actionable, addressing the black-box nature of ensemble models.

Hybrid and Metaheuristic Models: Hybrid models that combine optimization and clustering share similarities with HMNM. However, HMNM's integrated design, which includes dynamic growth, real-time optimization, and latent structure modeling, minimizes the need for external calibration. Unlike metaheuristic methods, HMNM provides hierarchical and dynamic insights directly within its framework, making it more efficient and user-friendly.

Explainability

Explainability is a key strength of HMNM, ensuring its practical relevance for academic and applied research. HRGs reveal multi-level community structures, offering insights into nested hierarchies crucial for understanding macro and micro-level dynamics in networks.

VAEs enhance interpretability by embedding nodes into latent spaces, revealing clustering patterns and structural relationships that may not be apparent in observed data. RL further contributes to explainability by optimizing network properties through quantifiable and transparent adjustments, such as improving clustering coefficients and reducing path lengths. By combining these interpretable components, HMNM bridges the gap between analytical complexity and actionable insights.

Conclusion

The Hybrid Modern Network Model (HMNM) integrates traditional methods like SBM and Preferential Attachment with modern techniques such as GNNs, RL, HRGs, GANs, and VAEs to provide a comprehensive framework for dynamic network modeling. Its ability to capture static and dynamic processes addresses key limitations in traditional models, offering deeper insights into network structures and evolution.

Empirical applications demonstrate HMNM's versatility, from modeling growth processes to uncovering hidden relationships. While challenges such as computational complexity and implementation barriers remain, addressing these will enable broader adoption. Future research can expand HMNM to new domains, develop hybrid approaches, and enhance computational efficiency to further its applicability.

With its integrative approach, HMNM has the potential to advance network modeling significantly, providing valuable tools for understanding complex systems across disciplines.

The HMNM significantly advances network modeling methodologies, offering a powerful, flexible, and comprehensive framework for analyzing social networks. Its integration of traditional and modern techniques addresses existing models' limitations and provides deeper insights into real-world networks' complexity (Van Der Hofstad, 2024) and dynamic nature. The HMNM holds great potential for advancing social science research and enhancing our understanding of social structures and dynamics.

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Data Availability: The simulated data and full R code used in this study are publicly available via PsychArchives (see Kyriazos & Poga, 2025a).

Supplementary Materials

The Supplementary Materials include two components:

- R Code and Scripts: The complete R implementation of the HMNM, covers all model components, network generation procedures, simulation settings, evaluation functions, and performance metrics. This includes all files necessary to reproduce the results presented in the empirical illustration (see Kyriazos & Poga, 2025a)
- Mathematical Formulations: A detailed table presenting the mathematical foundations of the Hybrid Modern Network Model (HMNM), including symbolic expressions for all major components (e.g., SBM initialization, Preferential Attachment, GNN embeddings, RL optimization, GANs, VAEs, Dynamic Modularity, ARI, and Prediction Accuracy) (see Kyriazos & Poga, 2025b)

Index of Supplementary Materials

Kyriazos, T., & Poga, M. (2025a). *Supplementary materials to "The Hybrid Modern Network Model: A multi-technique framework for comprehensive network analysis"* [R Code, Scripts]. PsychOpen GOLD. https://doi.org/10.23668/psycharchives.16459

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