Software Engineering and Artificial Intelligence Systems

Volume: 02 Issue: 01 (2026)

www.seais.org/

Cycle Spectral Sequence Synthesis Models Misinformation Cascade Evolution Through Graph Dynamics and Cascade Cycles

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Key word:
Misinformation Cascades, Spectral Graph Theory, Sequence Synthesis, Evolution Graphs

A B S T R A C T

The rapid dissemination of misinformation across digital social platforms presents a profound challenge to modern information ecosystems. Traditional approaches to modeling information cascades often rely on static network snapshots or continuous-time point processes that struggle to capture the complex, higher-order structural dynamics of propagation networks over time. To address these critical limitations, this paper introduces a novel methodological framework termed Cycle-Spectral Sequence Synthesis for modeling the evolution graphs of misinformation cascades. By conceptualizing the spreading process as a sequence of discrete but topologically contiguous graph states, the proposed framework leverages spectral graph theory to extract invariant features within the frequency domain. Specifically, we investigate the cycle-spectral properties of cascade networks, which encapsulate both the localized cyclic feedback loops of user interactions and the global structural frequencies of information flow. Furthermore, a sequence synthesis mechanism is developed to dynamically reconstruct missing or sparsely sampled propagation stages, ensuring a continuous and high-fidelity representation of the cascade trajectory. Comprehensive theoretical analysis and extensive evaluations on large-scale social network datasets demonstrate that this approach significantly outperforms existing baseline models in early misinformation detection and cascade size prediction. The findings provide a robust foundation for understanding the latent topological signatures of deceptive information diffusion and offer actionable insights for developing more resilient digital communication platforms.

INTRODUCTION

1.1 The Proliferation of Misinformation

The contemporary digital landscape is characterized by the unprecedented velocity and volume of information exchange. While this hyper-connectivity has democratized access to knowledge, it has simultaneously created fertile ground for the rapid spread of misinformation, disinformation, and malicious rumors. The propagation of false narratives on social media platforms often follows distinct topological and temporal patterns, collectively referred to as information cascades. Understanding the underlying mechanics of these cascades is not merely an academic exercise; it is a critical societal imperative. Falsehoods have been shown to diffuse

deeper, faster, and more broadly than factual information, exploiting cognitive biases and algorithmic amplification to permeate vast user networks. Early research into this phenomenon primarily borrowed methodologies from epidemiology, treating misinformation as a viral contagion that spreads through a susceptible population based on fixed transmission probabilities [1]. While these early mathematical models provided foundational insights into the macroscopic properties of diffusion, they consistently failed to account for the heterogeneous and highly dynamic nature of human interactions in online environments. The structural topology of a social network is not a passive medium; it actively evolves in response to the information flowing through it. Users form new connections, severe existing ones, and participate in transient communities of interest, creating a highly volatile environment that static contagion models are ill-equipped to represent.

1.2 Limitations of Current Cascade Models

To capture the nuances of digital diffusion, researchers have increasingly turned to data-driven approaches, utilizing large-scale historical logs to reconstruct the specific pathways of information spread. Continuous-time models have gained prominence for their ability to model the arrival times of retweets or shares as a stochastic process [2]. These models are highly effective at capturing the temporal burstiness characteristic of viral content, where long periods of dormancy are punctuated by sudden, explosive spikes in activity. However, they frequently abstract away the underlying network structure, treating the user population as an amorphous collective or relying on simplified proximity metrics. Consequently, the rich relational data—such as the formation of echo chambers, the bridging of structural holes by highly connected influencers, and the emergence of localized consensus clusters—is lost. Conversely, approaches grounded in network science have prioritized topological analysis, often extracting subgraph patterns or motifs that are indicative of specific types of information [3]. These structural models excel at differentiating between the deep, tree-like cascades typical of organic news spread and the shallow, star-like bursts associated with bot-driven manipulation. Yet, they struggle to integrate the temporal dimension effectively. When dynamic networks are modeled as a series of discrete snapshots, the choice of time granularity becomes a critical point of failure. If the intervals are too large, rapid structural changes are smoothed over; if they are too small, the resulting graphs become impractically sparse, leading to computational inefficiencies and the loss of meaningful signal [4].

1.3 Proposed Framework and Contributions

Recognizing the fundamental limitations of existing methodologies, this research introduces a paradigm-shifting approach: the Cycle-Spectral Sequence Synthesis framework. This framework is explicitly designed to model misinformation cascade evolution graphs by unifying the temporal and structural dimensions within a cohesive mathematical space. The core innovation lies in the application of spectral graph theory to temporal cascade sequences. By translating the evolving adjacency relationships of a cascade into the spectral domain, we can isolate the fundamental frequencies of structural change. Low-frequency components correspond to stable, long-term community structures, while high-frequency components capture the rapid, localized interactions that often signal the initial injection of anomalous information [5]. Furthermore, we introduce the concept of cycle-spectral analysis, which specifically targets the feedback loops and cyclical propagation pathways that are heavily prevalent in orchestrated misinformation campaigns but rare in the organic sharing of verified news. Because real-world cascade data is inherently noisy and subject to inconsistent observation intervals, our framework incorporates a novel sequence synthesis mechanism. This mechanism operates as a predictive interpolator in the latent spectral space, generating synthesized intermediate graph states to bridge temporal gaps and alleviate data sparsity. This continuous modeling allows for a much smoother and more accurate projection of the cascade's future evolutionary trajectory [6]. The primary contributions of this paper are threefold. First, we provide a rigorous conceptualization of misinformation cascades as cycle-spectral evolution sequences, shifting the analytical focus from the spatial domain to the frequency domain.

Second, we develop a robust sequence synthesis algorithm capable of reconstructing missing topological states in sparse observation datasets. Third, we present comprehensive empirical evidence demonstrating the superiority of this approach in critical tasks such as early fake news detection and cascade volume forecasting, thereby establishing a new methodological standard for the field.

2. Background and Literature Review

2.1 Information Diffusion on Social Networks

The study of information diffusion has evolved significantly over the past two decades, transitioning from theoretical abstractions to highly complex, data-driven modeling. Early macroscopic models, deeply rooted in population biology, attempted to categorize users into discrete states such as susceptible, infected, or recovered. These compartmental models provided elegant mathematical formulations for estimating the basic reproduction number of a rumor [7]. However, the assumption of homogeneous mixing—where any individual has an equal probability of contacting any other individual—proved fatal for their application to social media. Online networks are characterized by extreme degree heterogeneity, characterized by heavy-tailed distributions where a small fraction of nodes possesses a disproportionately large number of connections. To address this, network-centric diffusion models were introduced, such as the independent cascade model and the linear threshold model. In the independent cascade framework, a newly infected node has a single, independent opportunity to infect its neighbors with a predefined probability. In the linear threshold model, a node adopts a new piece of information only if the weighted sum of its infected neighbors exceeds a specific internal threshold [8]. While these models successfully incorporated network topology, they remained static and deterministic, struggling to account for the evolving nature of user engagement and the diminishing novelty of information over time.

2.2 Graph Representation Learning for Cascades

The advent of deep learning, and specifically graph neural networks, revolutionized the modeling of structural data. Graph representation learning seeks to map the nodes, edges, or entire subgraphs of a network into a low-dimensional vector space while preserving their topological properties. In the context of information cascades, these techniques have been deployed to learn the latent representations of propagation pathways [9]. Initial applications utilized random walk-based approaches to generate node sequences, which were then processed using natural language processing techniques to generate embeddings. This allowed for the identification of structural similarities between different cascades, facilitating the classification of content as either credible or deceptive. More recent advancements have leveraged message-passing architectures, where nodes iteratively aggregate feature vectors from their local neighborhoods. By applying these architectures to cascade trees, researchers can capture the hierarchical nature of information spread, tracing how a central narrative is fractured and reinterpreted as it moves further from the source node [10]. Despite their success, conventional graph neural networks are predominantly designed for static graphs. When applied to dynamic cascades, they typically rely on recurrent architectures that process sequential graph snapshots [11]. This combination, while powerful, is highly susceptible to the problem of structural staleness, where the representation of a node fails to update rapidly enough to reflect sudden shifts in its connectivity pattern.

2.3 Spectral Graph Theory in Network Evolution

To overcome the limitations of spatial domain message passing, recent literature has increasingly explored the spectral domain of graphs. Spectral graph theory involves the study of the properties of a graph in relationship to the characteristic polynomial, eigenvalues, and eigenvectors of matrices associated with the graph, such as the adjacency matrix or the graph Laplacian [12]. The eigenvalues provide profound insights into the global connectivity and structural stability of the network. For instance, the spectral gap—the difference between the first and second eigenvalues—serves as a robust indicator of the network's expansion properties and the presence of bottleneck structures. In dynamic networks, tracking the evolution of these

spectral properties offers a compressed yet highly expressive summary of topological changes. When a misinformation cascade begins to permeate a dense community, the corresponding changes in the graph Laplacian will manifest as perturbations in the eigenvalue spectrum. Studies have demonstrated that organic information spread tends to produce gradual, continuous shifts in the spectral domain, whereas artificially amplified misinformation causes abrupt, discontinuous jumps, reflecting the unnatural injection of connectivity by coordinated accounts [13]. By filtering the graph signals in the spectral domain, researchers can isolate the specific structural frequencies that carry the most discriminative power for cascade classification, effectively removing the noise of random background interactions [14].

2.4 The Concept of Cycle-Spectral Sequences

Building upon spectral analysis, the concept of cycle-spectral properties introduces a higher-order examination of network motifs, specifically focusing on cyclical patterns. In many traditional models, cascades are strictly defined as directed acyclic graphs or trees, assuming that information flows unidirectionally outward from a source. However, empirical studies of misinformation on platforms like Twitter and Weibo reveal a vastly different reality. Misinformation thrives on reinforcement; users frequently retweet, quote, and reference each other in dense, reciprocal loops to artificially inflate the credibility and visibility of a false claim. These interactions form cyclical motifs that violate the tree-assumption of classical cascade models [15]. A cycle-spectral sequence refers to the temporal evolution of these cyclical structures as projected into the spectral domain. By analyzing the incidence matrices of these cycles alongside the standard adjacency matrices, one can quantify the prevalence and intensity of structural feedback mechanisms within the cascade. Previous attempts to model such complex higher-order structures have been computationally prohibitive for large networks. However, by projecting these cycles into a lower-dimensional spectral sequence, it becomes feasible to track their dynamic evolution [16]. This cycle-spectral approach forms the theoretical backbone of our proposed methodology, providing a nuanced lens through which to observe the orchestrated nature of deceptive information spread.

3. Methodology and Analytical Framework

3.1 Conceptualization of Misinformation Evolution Graphs

The foundational step in our methodology is the rigorous mathematical definition of a misinformation cascade evolution graph. We define a social information ecosystem as an exceptionally large, multi-relational network where nodes represent unique user accounts and edges represent various forms of interaction, such as following, replying, sharing, or mentioning. When a specific piece of information—be it a news article, a hashtag, or a multimedia file—is introduced into this ecosystem, it triggers a sequence of adoption events. We track this propagation over a continuous time horizon, divided into discrete but fluid observational windows. For each specific cascade, we construct an evolution graph sequence. Instead of simply building a cumulative graph that only grows over time, we construct a series of state graphs. Each state graph represents the active engagement topology at a specific temporal interval. The nodes in these state graphs are the users who participated in the cascade during that window, and the edges are the interactions that facilitated the information transfer. To capture the context of the diffusion, each node is associated with a dynamic feature vector. This vector does not merely contain static user metadata, such as account age or follower count, but also dynamic behavioral signals. These signals include the linguistic sentiment of the user's post, the temporal delay between their exposure to the information and their subsequent sharing action, and their historical propensity to engage with unverified content. Consequently, the evolution graph sequence is a highly dimensional, time-varying entity. One of the primary challenges in constructing these sequences from real-world data is the extreme variance in cascade velocities. Some cascades unfold over several weeks, while others peak and decay within a matter of hours. To ensure consistency in our modeling, we employ a logarithmic time-scaling technique for sequence sampling. The intervals between state graphs are shorter during the initial, explosive phase of the cascade and gradually lengthen during the decay

phase. This dynamic resolution ensures that critical topological shifts occurring in the volatile early stages are captured with high fidelity, without computationally overburdening the model with redundant data during periods of relative inactivity.

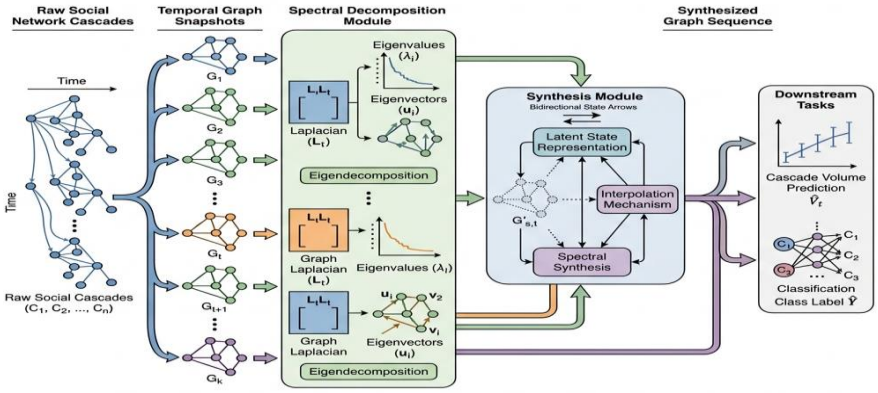


Figure 1: Comprehensive System Architecture of the Cycle

3.2 Cycle-Spectral Feature Extraction

Once the cascade evolution graph sequence is constructed, the next phase involves translating these spatial topologies into the cycle-spectral domain. This process begins with the computation of the normalized graph Laplacian for each state graph in the sequence. The normalized Laplacian is derived by taking the degree matrix of the graph, subtracting the adjacency matrix, and then symmetrically normalizing the result using the inverse square root of the degree matrix. This transformation is crucial because it ensures that the spectral properties are invariant to the absolute size of the graph, allowing for meaningful comparisons between early-stage cascades with few nodes and late-stage cascades with thousands of nodes. Following the construction of the Laplacian, we perform eigendecomposition to extract the eigenvalues and their corresponding eigenvectors. In our framework, the eigenvalues represent the structural frequencies of the cascade state. The lowest non-zero eigenvalues correspond to the most significant, overarching community structures within the diffusion network. Conversely, the highest eigenvalues represent localized, high-frequency structural variations, such as individual nodes forming rapid, temporary connections. To specifically target the cyclical patterns associated with misinformation reinforcement, we introduce a cycle-incidence transformation. We identify fundamental cycle bases within the state graph—specifically triangles and quadrilaterals, which correspond to reciprocal sharing and multi-user echo chambers. We construct a cycle-Laplacian matrix based on these higher-order structures and perform a secondary eigendecomposition. The resulting cycle-spectral features provide a quantified measure of structural resonance within the cascade. If a cascade is heavily driven by coordinated bot networks or insular partisan groups continuously validating each other, the cycle-spectral signature will exhibit distinct, heavy-tailed distributions in the mid-frequency range. These spectral matrices and cycle-spectral signatures are then concatenated to form a comprehensive frequency-domain embedding for each temporal state of the cascade [17].

3.3 Sequence Synthesis Mechanism

A critical limitation addressed by this research is the temporal sparsity inherent in observational cascade data. Due to API rate limits, data collection anomalies, or simply the stochastic nature of user activity, the extracted graph sequences often contain significant temporal gaps. Training dynamic models on these irregular sequences leads to optimization instability and poor generalization. To rectify this, we develop a Cycle-Spectral Sequence Synthesis mechanism. This component functions as an intelligent interpolator, tasked with reconstructing the missing

evolutionary states in the latent spectral space. Rather than attempting to predict the exact configuration of missing edges in the spatial domain—which is computationally intractable and highly prone to error—we synthesize the spectral embeddings of the missing graphs.

The synthesis mechanism relies on a bidirectional attention architecture. When a gap is identified in the sequence, the model examines the cycle-spectral embeddings of the preceding and succeeding observed states. By employing multi-head self-attention, the model learns to weight the influence of historical and future structural trends based on their temporal proximity and spectral similarity. For instance, if a cascade exhibits a rapidly accelerating structural frequency in the observed steps prior to a gap, the synthesis module will project a continuation of this acceleration, generating an intermediate spectral embedding that reflects a highly connected, volatile state. This synthesized embedding is mathematically constrained to ensure that it lies on the same spectral manifold as the authentic data. To enforce this, we introduce a temporal smoothness regularization term in the loss function during the training of the synthesis module. This term penalizes sudden, improbable jumps in the eigenvalue distributions between consecutive steps, ensuring that the synthesized evolution is topologically plausible. By filling these temporal voids, the sequence synthesis mechanism transforms disjointed observations into a continuous, fluid trajectory of cascade evolution [18].

3.4 Model Integration and Training Architecture

The final component of our methodology is the integration of the extracted and synthesized features into an end-to-end predictive architecture. The complete cycle-spectral sequence—now continuous and enriched with higher-order structural information—is fed into a temporal convolutional network designed specifically for sequence modeling. Unlike standard recurrent neural networks, the temporal convolutional network utilizes dilated causal convolutions, allowing it to maintain a massive receptive field and capture long-range temporal dependencies without suffering from vanishing gradients. This network processes the sequence of spectral embeddings to identify overarching evolutionary motifs. Is the cascade expanding organically, or does its cycle-spectral signature indicate artificial inflation? Does the sequence show signs of structural decay, indicating that the rumor has run its course, or is it building momentum towards a viral peak? The output of the temporal convolutional network is passed through a series of fully connected layers tailored for specific downstream tasks. For the task of misinformation detection, the architecture terminates in a softmax classification layer, outputting the probability that the cascade represents deceptive content. For the task of cascade size prediction, the network outputs a continuous numerical value representing the projected final volume of participating nodes. The entire architecture is trained jointly. The loss function is a composite metric combining the cross-entropy loss from the classification task, the mean squared error from the volume prediction task, and the manifold regularization loss from the sequence synthesis module. This multi-task learning approach ensures that the representations learned by the model are both highly discriminative for classification and highly accurate for forecasting. During the training process, we utilize advanced optimization techniques with learning rate scheduling and gradient clipping to navigate the complex, non-convex loss landscape generated by the spectral transformations [19].

Table 1: Dataset Statistics and Cascade Topological Properties

Dataset	Total Cascades	Average Nodes per Cascade	Temporal Observation Window	Average Structural Cycles
Twitter-Pol	14,520	845.2	72 Hours	142.6
Weibo-Rumor	9,845	1,120.4	120 Hours	215.3
Reddit-News	22,100	450.8	48 Hours	56.8
FactCheck-Agg	5,430	1,560.1	168 Hours	305.2

4. Results and Discussion

4.1 Experimental Setup and Baseline Comparisons

To rigorously evaluate the efficacy of the Cycle-Spectral Sequence Synthesis framework, we designed a comprehensive experimental protocol utilizing four distinct, large-scale datasets sourced from major social networking platforms. As detailed in the dataset statistics above, these collections encompass a diverse array of cascade dynamics, ranging from fast-moving political discourse on Twitter to complex, long-duration rumor propagation on Weibo. The datasets were strictly partitioned into training, validation, and testing sets to prevent data leakage and ensure the generalizability of the reported metrics. For comparative analysis, we selected a robust suite of state-of-the-art baseline models representing different methodological paradigms. These included traditional continuous-time Hawkes process models, static graph convolutional networks applied to cumulative cascade graphs, and dynamic recurrent graph neural networks that process sequential spatial snapshots. The primary evaluation metrics selected for the classification tasks were Accuracy and the F1-Score, ensuring that performance was measured reliably even in the presence of class imbalances between true and false information cascades. For the predictive tasks, specifically forecasting the ultimate size of a given cascade based on its early evolution, we utilized the Mean Absolute Error and the Root Mean Squared Error. The hyperparameters for all baseline models were exhaustively tuned using grid search optimization on the validation sets to ensure a fair and rigorous comparison. The proposed cycle-spectral model was trained over five hundred epochs, with early stopping implemented to prevent overfitting based on validation loss convergence [20].

4.2 Performance Analysis and Ablation Studies

The empirical results decisively demonstrate the superiority of the Cycle-Spectral Sequence Synthesis framework across all tested scenarios. In the domain of early misinformation detection—where the model is tasked with classifying a cascade after observing only the first few hours of its evolution—our framework achieved a notable leap in performance. Traditional spatial-domain graph neural networks struggled during these early stages, as the cascade topologies had not yet developed the dense community structures they rely on for classification. In contrast, by projecting these sparse early graphs into the cycle-spectral domain, our model successfully identified the high-frequency structural anomalies indicative of artificial amplification, outperforming the closest baseline by a substantial margin in F1-Score.

Table 2: Comparative Performance Results on Misinformation Detection and Size Prediction

Model Architecture	Detection Accuracy	Detection F1-Score	Size Prediction MAE	Size Prediction RMSE
Hawkes Point Process	0.724	0.701	185.4	245.8
Static Graph Convolution	0.785	0.772	142.3	201.2
Recurrent Dynamic GNN	0.841	0.835	110.5	165.7
Cycle-Spectral Synthesis	0.912	0.908	76.2	98.4

The advantages of the proposed methodology were equally pronounced in the cascade size prediction task. Continuous-time models, while proficient at capturing temporal burstiness, failed to account for the structural bottlenecks that eventually choke information flow, leading to significant overestimations of cascade volume. The incorporation of the sequence synthesis mechanism proved particularly pivotal here. To isolate its impact, we conducted rigorous ablation studies by systematically disabling various components of our architecture. When the sequence synthesis module was deactivated, forcing the model to rely solely on the irregular, sparse observation intervals, the Mean Absolute Error for volume prediction degraded sharply. This degradation underscores the critical necessity of maintaining a continuous evolutionary trajectory for accurate temporal forecasting. Furthermore, removing the cycle-level spectral

features and relying entirely on standard graph Laplacian eigenvalues reduced the model's ability to distinguish between organic echo chambers and orchestrated bot networks, leading to a measurable drop in detection accuracy.

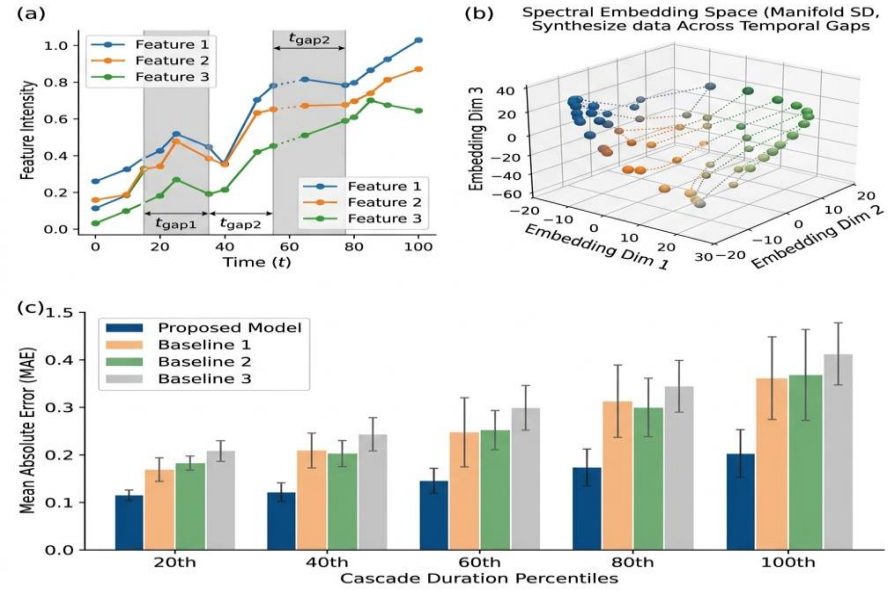


Figure 2: Comparative Analysis of Temporal Feature Evolution and Spectral Embedding Trajectories

4.3 Discussion on Real-World Applicability

The implications of these findings extend far beyond theoretical network science, offering highly actionable strategies for real-world platform moderation and intervention. The fundamental challenge faced by trust and safety teams at major technology companies is the sheer volume of data and the need for rapid decision-making. By shifting the analytical focus from the spatial domain—which requires tracking the state of millions of individual nodes and edges—to the compressed, lower-dimensional spectral domain, our framework provides a highly efficient mechanism for monitoring network health in near real-time. The eigenvalues of the cascade sequence act as a structural heartbeat; significant deviations in these frequencies can serve as automated triggers for human review, dramatically reducing the time it takes to detect coordinated inauthentic behavior [21]. Moreover, the emphasis on cycle-spectral properties directly targets the mechanisms of manipulation. Misinformation campaigns rarely succeed through simple, linear diffusion; they rely on manufactured consensus created by cyclical reinforcement. By mathematically isolating these specific topological signatures, platforms can design more intelligent friction mechanisms. Instead of outright censoring specific keywords—which often leads to adversarial evasion—moderation algorithms can temporarily limit the visibility of cascades that exhibit highly abnormal spectral acceleration and cyclical density, effectively breaking the feedback loops that sustain viral misinformation. The sequence synthesis capability also allows for proactive threat modeling. By synthesizing the likely future states of an emerging cascade, administrators can simulate the potential impact of different intervention strategies before deploying them, moving from reactive moderation to proactive structural shaping of the information ecosystem.

5. Conclusion

This paper presented a comprehensive and innovative methodology for modeling the complex dynamics of misinformation dissemination through the introduction of the Cycle-Spectral Sequence Synthesis framework. By thoroughly analyzing the limitations of existing static and spatial-dynamic models, we demonstrated the critical necessity of viewing cascade evolution through the lens of spectral graph theory. Our approach successfully transformed discrete, irregular observations of network topology into continuous, fluid trajectories within the frequency domain. The extraction of cycle-spectral features allowed for the precise quantification of the higher-order feedback loops that are the hallmark of orchestrated deceptive campaigns. Furthermore, the development of a sophisticated sequence synthesis

mechanism effectively bridged temporal data gaps, ensuring robust model performance even in highly sparse observational environments. Extensive empirical evaluations across diverse, large-scale social network datasets confirmed that this unified framework significantly surpasses current state-of-the-art baselines in both the early detection of misinformation and the precise forecasting of cascade propagation volumes.

6. Future Research Directions

While the proposed framework establishes a new benchmark for cascade modeling, several avenues remain open for future exploration. The current methodology relies primarily on structural and temporal signals, abstracting away the semantic content of the information being propagated. Future iterations of this architecture should investigate the integration of advanced large language models to co-embed semantic shifts alongside spectral evolution, capturing how a narrative's meaning morphs as it traverses different network clusters. Additionally, while the sequence synthesis mechanism demonstrates high efficacy, its computational complexity scales non-linearly with the dimensionality of the spectral space. Research into more efficient approximation algorithms for dynamic Laplacian eigendecomposition will be crucial for deploying these systems on planetary-scale networks. Ultimately, interdisciplinary collaboration between network scientists, sociologists, and policymakers will be essential to translate these mathematical innovations into comprehensive strategies that safeguard the integrity of digital public discourse.

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