

Application of Graph Neural Networks in Predicting Social Media Propagation Pathways

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ABSTRACT

Predicting social media propagation paths is of significant importance for guiding and controlling online public opinion. To overcome the limitations of traditional statistical models in handling non-Euclidean structured data, this paper proposes an optimized propagation prediction strategy based on graph neural networks. By analyzing network topological features, a node representation model integrating temporal dynamics and multimodal semantics is derived. The paper addresses challenges such as data sparsity, temporal evolution, and semantic gaps, demonstrating the effectiveness of multi-order aggregation, spatio-temporal attention, and cross-modal embedding strategies. Analysis reveals that graph neural networks significantly enhance prediction accuracy for information diffusion chains in complex networks, providing algorithmic support for public opinion early warning mechanisms.

KEYWORDS

Graph neural networks; Social media; Propagation paths; Chain prediction; Node representation

1 Introduction

With the continuous evolution of mobile internet technology, social media has become a primary arena for information exchange and idea collision. Its complex network topology and the instantaneous nature of information diffusion present new challenges for the study of propagation dynamics. Early research predominantly employed independent cascade or linear threshold models, which generally assume independence among individuals and fail to account for the nonlinear connections and long-range dependencies prevalent in real-world scenarios. For massive, scale-free networks formed by vast numbers of users, traditional deep learning algorithms—grounded in Euclidean space—struggle to handle the disordered node arrangement and dynamic adjacency relationships inherent in graph data. Information flow within social networks is not simple physical diffusion but is driven by the coupling of network structure, temporal decay, and semantic content. The academic community urgently needs to break free from the one-dimensional statistical analysis paradigm and adopt deep learning architectures capable of directly processing unstructured graph data. Graph neural networks, inherently designed to capture graph topology and aggregate neighborhood information, offer more suitable mathematical tools for deciphering the mechanisms of social media propagation. Precisely predicting information flow at the micro level has thus become a key focus of academic research.

2 Theoretical Foundations for Constructing Social Media Dissemination Graphs

2.1 Analysis of Social Network Topological Features

Social media user relationships inherently form highly complex non-Euclidean spatial structures. Graph theory serves as an indispensable mathematical language for describing such irregular data. Within this structure, users represent nodes, while follow or interaction behaviors form edges, creating a power-law distributed scale-free network. Unlike grid-based data such as images or audio, nodes in social graphs lack fixed ordering, and the number of neighboring nodes exhibits significant imbalance. This irregularity renders the fixed convolutional kernels commonly used in convolutional neural networks directly inapplicable^[1]. By employing adjacency matrices and feature matrices to transform discrete user relationships into computable algebraic forms, topological metrics such as clustering coefficients, betweenness centrality, and connected components can be calculated. This enables the identification of key opinion leader nodes and their pivotal roles and control over information flow within the network. These metrics reflect both the static network structure and the latent physical pathways for information flow, providing a structured data foundation for subsequent prediction of propagation paths.

2.2 Dynamical Mechanisms of Information Cascade Diffusion

Information propagation in social networks constitutes a cascade diffusion phenomenon driven by stochastic processes. After a source node disseminates information, it propagates along network edges to neighboring nodes with specific transition probabilities, forming a timestamped propagation trail. Activation thresholds between nodes and the weight intensity of edges govern this dynamic process. At the micro level, propagation is not solely determined by individual node attributes but is also influenced by both local subgraph structures and the global network state. The cascade sequence not only records explicit forwarding paths but also reflects the direction of implicit social influence flow. By modeling the cascade diffusion mechanism, discrete propagation events can be transformed into continuous dynamical equations. This enables the analysis of intrinsic patterns governing the outbreak, latency, or decay of

information within networks. It accurately characterizes the depth and breadth distribution features of cascades across different propagation stages and determines the damping coefficient of information flow. The analysis of dynamical mechanisms is a critical step in transitioning path prediction from statistical induction to mechanistic inference.

2.3 Graph Neural Network Node Representation Paradigm

The core of graph neural networks lies in employing message-passing methods to extract high-dimensional features from graph-structured data and convert them into low-dimensional vectors. This paradigm requires recursive aggregation and updating of information from target nodes and their neighbors, yielding node embedding vectors that incorporate both structural and attribute features^[2]. Graph convolution performs feature extraction on non-Euclidean structures via spectral decomposition of the Laplacian matrix or spatial-domain neighborhood sampling. This approach overcomes the limitations of traditional machine learning in handling graph data by transforming network topology heterogeneity into vector-space representations with semantic distance. Node embedding vectors preserve local connectivity patterns while leveraging multi-layer network stacking to capture long-range dependencies. High-quality node representations provide discriminative input features for downstream link prediction tasks, effectively resolving the computational challenges and computational resource consumption associated with direct computations on high-dimensional sparse matrices. This establishes graph neural networks as the dominant technology in propagation prediction.

3 Precise Prediction of Propagation Paths Faces Technical Challenges

3.1 Constraints from Sparse Interaction Data Across Massive Nodes

On social platforms with hundreds of millions of users, nodes with high-frequency interactions constitute a minuscule fraction of the network, leading to a highly sparse adjacency matrix. Due to this sparsity, models struggle to fit propagation patterns with strong generalization capabilities during training using limited observational samples. Newly registered users or low-activity nodes lack sufficient historical interaction records, causing graph neural networks to encounter severe cold-start problems during feature aggregation. Most nodes have low degrees, and the scarcity of connections prevents models from learning stable structural representations. This leads to high-probability biases in inferring potential propagation chains. Data sparsity not only amplifies computational noise but also systematically underestimates the propagation value of long-tail users. Identifying robust associative features within information-poor local subgraphs is the primary technical hurdle to improving network-wide path-prediction coverage. Moreover, noise-induced interference easily traps models in local optima, preventing convergence to globally stable states.

3.2 Challenges of Nonlinear Temporal Evolution in Transmission Processes

Social media transmission paths are not static, fixed graphs but dynamic systems undergoing intense transformation over time. Traditional static graph embedding methods neglect the temporal dimension, compressing interactions across different time periods onto a single plane. This results in the loss of causal temporal logic during the propagation process^[3]. In real-world scenarios, shifts in user interests, sudden drops in topic popularity, and instantaneous reorganization of network structures all contribute to non-stationary characteristics in propagation dynamics. Static models fail to distinguish between the propagation efficacy of long-term, early-established weak ties and that of short-term, recently formed strong interactions. The absence of temporal information prevents prediction models from capturing the outbreak points and inflection points of cascading diffusion, leading to misjudgments of the propagation lifecycle. Capturing the trajectory of network topology's dynamic evolution over time represents a critical technical hurdle for achieving high-precision real-time path prediction. Traditional discrete-time-slice methods fragment the intrinsic evolutionary logic within continuous-time streams, resulting in lagging predictive outcomes.

3.3 Lack of Multimodal Semantic Understanding of Spread Content

Relying solely on network topology to predict paths overlooks the driving force of the content itself. The penetrative power of information dissemination is primarily determined by the emotional resonance and semantic value carried by text, images, or videos. Most current research confines graph neural networks to structural feature extraction, severing the intrinsic link between content semantics and propagation paths. Subgraphs with identical structures exhibit entirely different activation patterns when exposed to other topics. Models lacking semantic understanding cannot recognize this context dependency. For multimodal content that contains metaphors, irony, or specific cultural memes, purely structural models can easily fall into feature-blind spots, failing to explain cross-circle propagation driven by content appeal. The heterogeneity between structural and semantic features prevents their direct integration. Without this semantic dimension, models face limitations in explaining complex dissemination behaviors and predicting their upper bounds. They cannot distinguish between different cascading effects arising from varying levels of content provocativeness within structurally homogeneous contexts.

4 Application Strategies for Optimizing Graph Neural Network Models

4.1 Multi-Order Neighborhood Information Aggregation Enhancement Algorithm

To address the challenge of sparse interaction data in feature learning, employing multi-order neighborhood sampling and aggregation methods can effectively expand a node's receptive field. This strategy moves beyond considering only

directly connected first-order neighbors. Instead, it uses random walk or hierarchical sampling algorithms to incorporate second- and higher-order potentials associated with nodes into the scope of feature computation^[4]. By configuring learnable aggregation functions, the model adaptively selects high-value information from extensive neighborhoods, thereby filling gaps in local interaction data. This higher-order aggregation mechanism enhances feature expression capabilities for low-activity nodes while maintaining computational efficiency, leveraging homogeneity principles to infer unobserved latent links. Mathematically, this algorithm optimization achieves deeper mining of the entire graph structure by increasing the number and width of graph convolutional layers. It effectively mitigates the reduction in prediction accuracy caused by data sparsity, ensuring the model generalizes to long-tail data distributions. Leveraging an end-to-end supervised learning paradigm, it significantly reduces the model's reliance on manual feature engineering and accelerates inference.

4.2 Construction of Dynamic Spatio-Temporal Graph Attention Network

To address the nonlinear temporal evolution during propagation, a dynamic graph attention network with temporal encoding mechanisms must be established. Incorporating recurrent neural network units or positional encoding modules into the graph neural network architecture enables the model to process time-series data. Attention mechanisms assign varying weights to interactions across different time steps, identifying historical time points most influential to the current propagation state^[5]. Spatio-temporal graph networks jointly model spatial topology and temporal dynamics by accounting for both node-to-node spatial relationships and the evolution of network structure over time. This architecture enables prediction models to capture periodic fluctuations and sudden growth trends in propagation intensity, distinguishing between contributions from historical stock relationships and real-time incremental interactions. Consequently, it achieves real-time, precise prediction of propagation paths within dynamically evolving social network environments, effectively overcoming the vanishing or exploding gradient phenomena encountered by traditional recurrent neural networks when processing long-sequence graph data.

4.3 Cross-Modal Content-Semantic Feature Embedding Model

To overcome the limitations of relying solely on structural features, the primary approach to improving predictive efficacy is to establish a dual-driven cross-modal feature-embedding model that integrates both structure and content. Natural language processing techniques extract semantic vectors from text, while computer vision algorithms extract visual features from images. These multimodal content features are then mapped into the same vector space as graph node embeddings. A gated fusion mechanism, or bilinear interoperability module, is designed to integrate topological structural features with content-semantic features in a deep manner. Based on this, the model can learn the propagation preferences of specific semantic content within a given network structure, identifying topic-sensitive or sentiment-driven propagation paths. Cross-modal embedding enriches node input feature dimensions while enabling graph neural networks to comprehend dissemination contexts. When addressing complex public opinion events, this allows path inference aligned with human cognitive logic based on content attributes, establishing an end-to-end deep learning prediction framework with semantic perception and structural reasoning capabilities.

5 Conclusion

This paper demonstrates the significant value of graph neural networks for predicting social media propagation paths. It employs graph dynamics models to overcome the dimensionality disaster encountered by traditional methods when processing heterogeneous data. Addressing challenges of data sparsity, temporal evolution, and semantic gaps, it introduces multi-order aggregation, spatio-temporal attention, and cross-modal embedding techniques to refine the reconstruction of propagation chains. Results indicate that deeply integrating topological structure with spatio-temporal semantics is the fundamental approach to enhancing prediction robustness. This framework broadens the scope of application for graph neural networks, providing theoretical support for the establishment of intelligent public opinion governance systems.

About the Author

Qun Wang, M.S., Associate Professor. Research Interests: Pure Mathematics, Mathematics Education, Artificial Intelligence.

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