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Analyzing Online News Dissemination Patterns via Social Network Hypergraph Model

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Abstract

This study aims to develop a novel method for analyzing the complex dissemination patterns of online media news using a social network hypergraph model, addressing the limitations of traditional graph models in capturing many-to-many relationships in news dissemination. The author integrates news content, user nodes, and topic tags into a multi-dimensional hypergraph structure. The approach includes detailed analysis of key elements of news dissemination across four dimensions (subject, content, channel, and effect), construction of the hypergraph model, and design of mechanisms for extracting dissemination paths and evaluating influencing factors. Experiments were conducted on real-world data from multiple social platforms to validate the method's effectiveness. The results demonstrate that the proposed hypergraph model outperforms traditional models (GCN, GAT, and RF) in terms of accuracy, F1 value, and error control. The model effectively reflects the complex structure and dynamic evolution of news dissemination, revealing significant factors such as user activity, topic sensitivity, and structural entropy. This research offers a new perspective on understanding and optimizing online news dissemination by leveraging the hypergraph model's ability to capture multi-dimensional interactions. It provides a more comprehensive and accurate analysis framework, laying a theoretical foundation for constructing efficient information dissemination models.

Keywords: Social Network Hypergraph Model; Online Media News Dissemination; Pattern Analysis; News Dissemination Paths.

1. Introduction

Social networks have become an essential platform for news dissemination, presenting complex patterns that traditional models struggle to capture [1]. The traditional graph model is difficult to fully describe complex situations such as many-to-many relationships in news dissemination, and the hypergraph model can solve this problem well [2]. It can synthesize many factors such as news content, communicators, audiences, and the multiple relationships among them [3]. Previous studies have extensively explored news dissemination in social networks. For instance, some studies have used graph theory to construct news dissemination models to analyze the dynamics of news in social networks [4]. Other research has focused on the influence of nodes, predicting the scope of news dissemination by calculating user node influence [5]. Additionally, some studies have analyzed user behavioral data, such as clicks, retweets, and comments, to evaluate the effect of news dissemination and explore differences among various types of news [6].

However, existing research has several limitations. First, traditional graph models are insufficient in portraying the complex many-to-many relationships in news dissemination [7]. Second, there is a lack of comprehensive and systematic

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consideration when analyzing the factors affecting news dissemination [8]. Third, while many studies have provided theoretical analyses of news dissemination models, they often lack effective experimental validation [9].

To address these gaps, this study proposes a novel method for analyzing news dissemination patterns based on a social network hypergraph model. The hypergraph model can integrate multiple elements, such as news content, users, and topic tags, into a multi-dimensional dissemination relationship network [10]. This approach not only overcomes the limitations of traditional models but also provides a more comprehensive and accurate analysis of news dissemination. By constructing a hypergraph structure and designing mechanisms for extracting dissemination paths and evaluating influencing factors, this study aims to provide a new theoretical foundation and empirical basis for optimizing online news dissemination.

Based on the above literature analysis, this paper comprehensively and deeply studies the news dissemination model based on the hypergraph model of social networks. The main contributions of this paper are (1) analyzing the elements of news dissemination under the hypergraph model in detail, including the vertices of news content, users, topic labels, etc., and the relationship edges between them; (2) dissecting the dissemination paths from multidimensional aspects, and systematically investigating the factors affecting the dissemination, and analyzing them in terms of the user characteristics, news content, and the structure of the hypergraph; (3) proposing a method for analyzing the dissemination mode based on hypergraph model, and verifying the effectiveness of the method through experiments. Pattern analysis method, and verify the effectiveness of the method through experiments.

The structure of this paper is as follows: Section 2 introduces the theoretical basis of online media news dissemination models, clarifying core analytical dimensions such as communication subjects, content, channels, and effects; Section 3 systematically elaborates on the basic concepts and construction elements of social network hypergraph models, analyzing their advantages and application methods in news dissemination; Section 4 conducts an in-depth analysis of dissemination paths and influencing factors, including user characteristics, content attributes, and hypergraph structural features; Section 5 proposes a dissemination model analysis method based on hypergraph models and designs a three-stage analysis process; Section 6 validates the effectiveness and superiority of the proposed method through real-world data experiments; finally, the paper summarizes the main findings and outlines future research directions.

2. Related Theories

The theoretical foundation of this study lies in the social network hypergraph model, which extends traditional graph models to capture complex many-to-many relationships in news dissemination. Unlike conventional graphs, hypergraphs can connect multiple vertices simultaneously, making them ideal for modeling intricate interactions between news content, users, and topics [11]. This model offers several advantages: it provides a more expressive and flexible framework to integrate various elements into a unified structure, enabling comprehensive analysis [12]. It also allows for systematic investigation of dissemination patterns and identification of key factors influencing news spread [13]. Applied to news dissemination, the hypergraph model can accurately capture interactions between different nodes and edges, revealing influential users and engaging topics [14].

2.1. Problem Description

Network media news dissemination model refers to the dissemination process, mode, and mechanism of news information from the disseminator to the receiver in the network environment, including the characteristics and interrelationships of the dissemination subject, content, channel, effect, etc. [15], as shown in Figure 1.

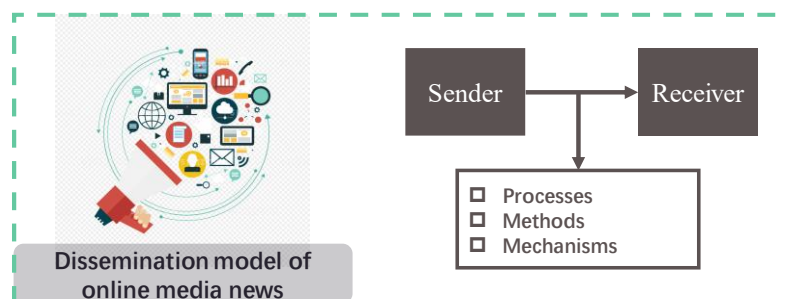


Figure 1. Concept of analyzing the news dissemination model of online media

The methods to study the news dissemination mode of network media mainly include the hypergraph model, data mining technology, social network analysis technology, content analysis technology, and so on. Its research content includes communication subject analysis, communication content analysis, communication channel analysis, and communication effect analysis [16]. The model analysis methods and contents are specifically shown in Figure 2.

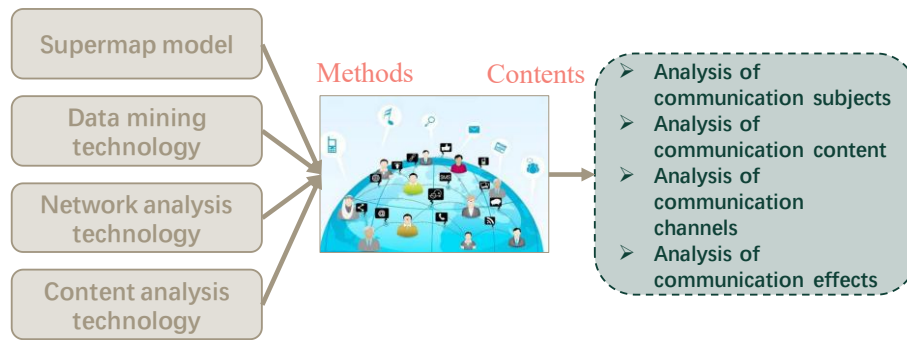


Figure 2. Methodology and content of the analysis of the news dissemination model

From Figure 3, the analysis of communication subjects mainly studies all kinds of subjects in online media news dissemination, including traditional media organizations, new media platforms, self-media creators, opinion leaders, and ordinary users, etc., and analyzes the characteristics, role positioning, influence, and interrelationships among different subjects [17].

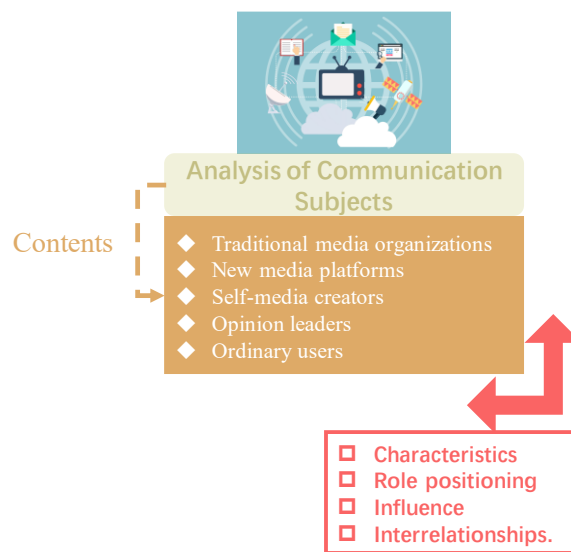


Figure 3. Analysis of dissemination subjects

In Figure 4, the analysis of communication content mainly carries out an in-depth study of the news content disseminated by online media, including the type, subject matter, quality and presentation of the content, and explores how to produce and optimize the news content according to the characteristics of different platforms and audiences to improve the communication effect.

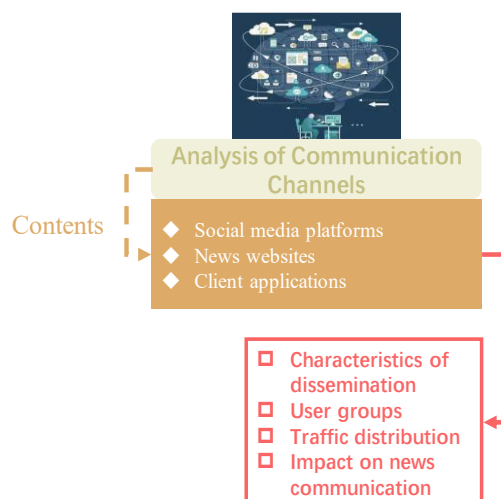


Figure 4. Analysis of communication channels

The analysis of communication channels mainly studies the various channels of online media news dissemination, such as social media platforms, news websites, clients, etc., and analyzes the communication characteristics, user groups, traffic distribution of different channels, as well as their impact on news dissemination.

Communication effect analysis is to quantify and qualitatively analyze the effect of news dissemination of network media through the establishment of a scientific evaluation system, to study how to improve the dissemination of news, influence, credibility, etc., as well as how to optimize the communication strategy through the feedback of communication effect.

2.2. Characterization

Network media news dissemination is characterized by the diversity of dissemination subjects, fast dissemination speed, path complexity, and diversity of effects, as shown in Figure 5, which is described as follows: (1) the diversity of dissemination subjects, including media organizations, self-media, individual users, etc., can be the dissemination subjects [18]; (2) the fast dissemination speed, a piece of news can be disseminated all over the world in a short period; (3) the complexity of dissemination paths. News in the dissemination process will pass through several different social network nodes, forming a complex dissemination path; (4) the diversity of the dissemination effect, including the diffusion range of the information, the acceptance of the audience, the audience's feedback, and other aspects of the effect of the body now.



Figure 5. Characteristics of news dissemination in online media

Compared to traditional hypergraph or graph neural network models, our proposed hypergraph model captures the nuanced and complex interactions in news propagation more effectively. Specifically, it integrates multiple dimensions such as user activity, topic sensitivity, and structural entropy into a unified framework, allowing for a more comprehensive analysis of dissemination patterns. Unlike previous models that often focus on pairwise relationships or single-factor analysis, our model can represent many-to-many relationships and higher-order interactions, providing a richer context for understanding how news spreads through social networks.

3. Social Network Hypergraph and Applications

3.1. Hypergraph Modeling Concepts and Advantages

Hypergraph is a form of graph promotion, in which an edge can connect any number of vertices [19], as shown in Figure 6. In the social network hypergraph model, vertices can represent various elements such as news content, users (e.g., news publishers, disseminators, and audiences), and topic labels [20]. Edges, on the other hand, represent the relationships between these elements, such as the reading and forwarding relationship between users and news content, and the association relationship between news content and topic tags [13].

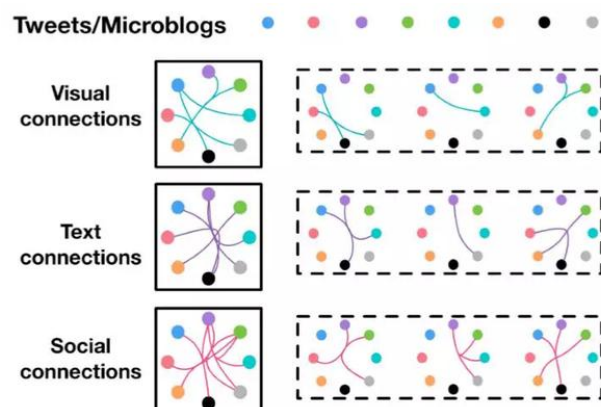


Figure 6. Hypergraph concept

The advantages of hypergraph modeling in social networks are shown in Figure 7 and include the following:

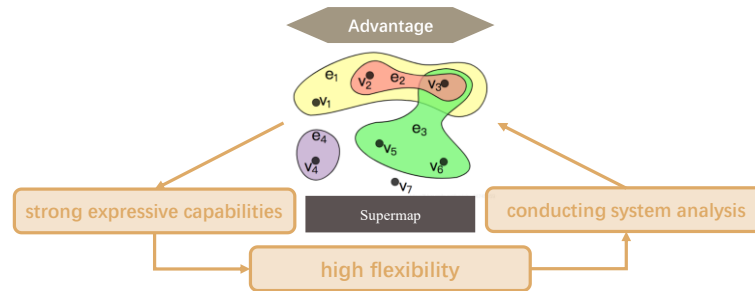


Figure 7. Supermap application benefits

- The hypergraph model has strong expressive ability [21]. It can accurately describe the complex relationships of news dissemination in social networks, overcoming the limitation that traditional graph models can only represent simple binary relationships.
- The hypergraph model is highly flexible. The types and properties of vertices and edges can be flexibly defined according to different social network structures and news dissemination needs.
- The hypergraph model helps to conduct a systematic analysis. The overall pattern and law of news dissemination can be studied in depth by analyzing the structure of the hypergraph.

3.2. Analysis of Elements

The social network hypergraph model elements include news content vertices, user vertices, topic label vertices, and relationship edges (shown in Figure 8).

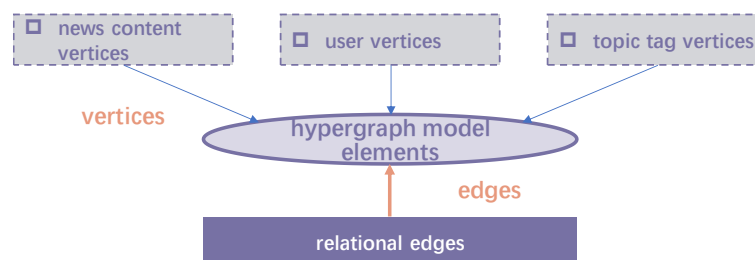


Figure 8. Elements of the social network hypergraph model

- News content apex

News content vertices have a variety of attributes. In terms of content attributes, they include the type of news (current affairs, entertainment, technology, etc.) and the quality of news (accuracy, depth, readability, etc.). From the dissemination attributes, the timeliness of the news, the emotional tendency of the news, etc., will affect their dissemination relationship in the hypergraph [22].

- User Vertex

News publishers, as a kind of user vertices, play an important role in initiating news dissemination by their popularity and credibility. The boundary between the two types of user vertices, the distributor and the audience, is blurred, and the size of their social network, activity level, interest preferences, etc., will affect the path and scope of news dissemination.

- Topic Tag Vertex

Topic tag vertices play the role of connecting news content and users in the hypergraph. Hot topic tags can attract more users' attention, thus promoting the dissemination of news under specific topics. The hotness, relevance, and other attributes of topic tags have an important impact on news dissemination.

- Relational edges

Publishing the relational side reflects the relationship between news publishers and news content, which is the beginning of news dissemination [23]. The dissemination relationship edge covers the behavioral relationships such as reading, retweeting, and commenting on news by users, reflecting the diffusion process of news. The association relationship edge indicates the connection between news content and topic labels, which helps news to be organized and disseminated in the topic domain.

3.3. Analysis of the Online Media News Dissemination Path

- Single-source multipoint propagation

News is released by one publisher and then spread in multiple directions through different distributors. A well-known media outlet publishes a major news story, which is then reposted by multiple self-publishers or individual users to their respective social circles, thus achieving wide dissemination of the news. As shown in Figure 9.

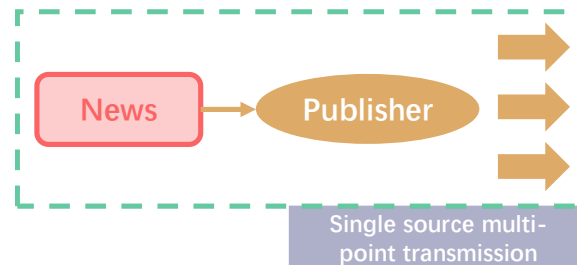


Figure 9. Single-source multipoint propagation

- Multi-source convergent propagation

Multiple news publishers post news about the same topic, which converge and interact with each other in the social network to jointly promote the dissemination of the topic [24]. For example, when a major event occurs, multiple media outlets report from different perspectives, and these reports complement each other in the social network to attract more users to pay attention to the event, as shown in Figure 10.

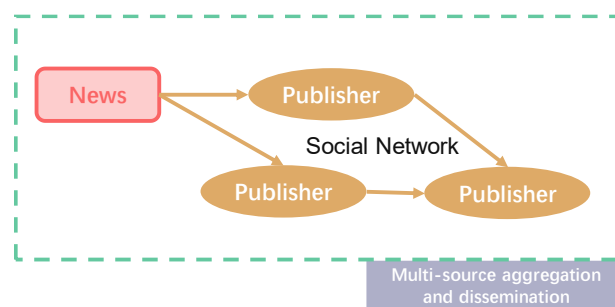


Figure 10. Multi-source convergence propagation

- Topic-related communication

News spreads from one topic area to another through the association of topic labels. A story about environmental technology may spread from the environmental topic area to the economic topic area because it is associated with the topic label "sustainable development".

3.4. Analysis of Factors Affecting News Dissemination in Online Media

- User characterization factors

The social influence of a user is one of the important factors, which can be measured by indicators such as the number of followers and the frequency of social interactions. Users with high social influence can make news spread farther and faster. In addition, the user's interest match is also crucial; when the news content is highly matched with the user's interest, the user is more likely to spread the news.

- News content factors

The timeliness of news has a significant impact on communication, and breaking news can often spread rapidly in a short period. The emotional tendency of the news can not be ignored, with strong emotional color (such as exciting, touching, etc.), news is more likely to cause the emotional resonance of the user, thus promoting the dissemination.

- Hypergraph structural factors

The connectivity of a hypergraph has a direct impact on news dissemination paths, and a well-connected hypergraph leads to smoother news dissemination. The weight of edges is also a key factor, e.g., in a dissemination relationship, the weight of a forwarding relationship edge may be higher than that of a simple reading relationship edge, because forwarding has a greater diffusion effect on news dissemination, as shown in Figure 11.

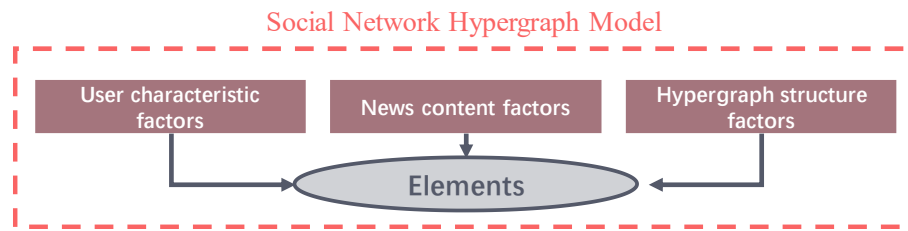


Figure 11. Analysis of dissemination factors

4. Hypergraph-based Modeling Analysis Method

Combined with the hypergraph model, this paper proposes a method for analyzing the news dissemination pattern of online media based on the hypergraph model, which mainly includes three stages, namely, data collection, hypergraph construction, and assessment of influencing factors [25], as shown in Figure 12.

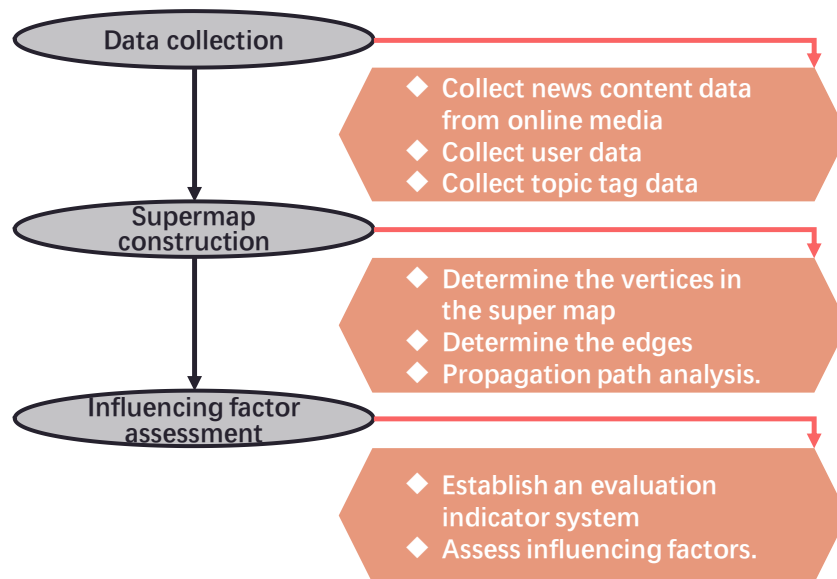


Figure 12. Methodological steps

Stage 1: Data collection. To collect news content data on online media, including title, body, release time, publisher, etc.; to collect user data, such as social account information, social relationships, interest preferences, etc.; to collect topic label data, including the name of the topic label, heat, etc.

Stage 2: Hypergraph construction. Determine the types of vertices in the hypergraph, such as news content vertices, user vertices, topic label vertices, etc.; determine the types of edges, such as publication relationship, dissemination relationship, association relationship, etc., and assign weights to the edges according to the actual situation. Then the propagation path is analyzed. Using hypergraph algorithms, such as the depth-first search and breadth-first search algorithms of hypergraph, the news propagation paths are analyzed to find out the main propagation paths and propagation modes, and the dynamic analysis is carried out by considering the time factor.

Stage 3: Assessment of influencing factors. Establish a system of assessment indicators covering various factors such as user characteristics, news content, hypergraphic structure, etc., through quantitative analysis methods, and assess the extent to which each influencing factor plays a role in the news dissemination process.

The edge weights in the hypergraph are determined based on real-world data, integrating both empirically predefined parameters and learned metrics. Specifically, the weights between users and content nodes are assigned concerning user interaction indicators, such as reading frequency and sharing behavior. Similarly, the weights between users and topic nodes are determined according to the degree of user engagement with specific topics. The specific parameters involved in the weight assignment process include interaction frequency, sentiment analysis scores, and topic relevance metrics. Notably, these edge weights are not statically computed but are learned dynamically during the model training process. The initial values of the weights are set based on observed frequencies and metrics, and they undergo continuous fine-tuning throughout the training phase to optimize the model's predictive accuracy. This dynamic adjustment mechanism enables the model to adaptively update weights according to observed data, thereby effectively capturing the evolving characteristics of user interactions and content dissemination processes, and ultimately improving the overall performance of the model.

5. Results and Discussion

5.1. Experimental Setup and Data Collection

- Experimental scene setting

The hardware environment used in this paper is shown in Table 1, and the software environment is shown in Table 2.

Table 1. Experimental hardware environment settings

No.	Hardware Name	Parameterization
1	CPU	Intel Core i7-12700K @ 5.0 GHz
2	GPUs	NVIDIA RTX 3090 (24GB video memory)
3	Random access memory (RAM)	64GB DDR4 3600MHz

Table 2. Experimental software environment settings

No.	Software Name	Parameterization
1	Matlab	2021a
2	Deep Learning Toolkit	Deep Learning Toolbox v14.3
3	Statistical Toolkit	Statistics and Machine Learning Toolbox v12.3

In this experiment, the dynamic weight decay coefficient is set to 0.5, the maximum depth of the propagation tree is 15, and the node influence balancing factor is 0.8. In terms of the evaluation period, a sliding time window strategy is used, with a window length of $T=24$ h and a step size of $\Delta t=1$ h. The data were divided into a training set (70%), a validation set (15%), and a test set (15%) by time series.

- Content and method of data collection

This experiment obtains 15 hot events dissemination data for the period from January 2020 to June 2022 through the API of the Weibo development platform. The dataset covers 23,000 users, 150 media organizations, and 45 derived topics. The data structure of this paper is shown in Table 3.

Table 3. Data structure

Data type	Sample Fields	Statistical characteristic
User node	UserID, ActivityScore, FollowerCount	Average number of followers 1.2K ($\sigma = 3.8K$)
Media node	MediaID, Type, InfluenceIndex	68% agency, 32% self-published media
Talking point	TopicID, Participants, Sentiment	Average number of participants 1.7K ($\sigma = 4.3K$)

In terms of hyperedge construction, each hyperedge represents the complete propagation event and contains ternary groups, i.e., user ID list, media ID, and topic ID. In terms of missing value processing, this paper adopts KNN interpolation to fill in the missing follower counts. At the same time, maximum-minimum normalization is applied to ActivityScore.

- Comparison of algorithms

To verify the validity of the model, three types of baseline methods were selected for comparison, as described in Table 4.

Table 4. Comparison Algorithm

Algorithm type	Model name	Parameterization
Graph neural network	GCN	Learning rate = 0.01, Hidden layer dimension = 128
	GAT	Attention head count = 4, dropout rate = 0.3
Traditional machine learning	Random Forest (RF)	Number of trees = 200, Maximum depth = 10

The data collected for this study includes information from 23,000 users, 150 media organizations, and 45 topics. We have taken measures to ensure data privacy and ethical standards. All user data has been anonymized, with UserIDs being the only identifier. Ethical approval for data collection from social platforms was obtained from the relevant institutional review board, and all data was processed in compliance with data protection regulations. Ethical approval for data collection from social platforms was obtained from the relevant institutional review board. All user identities were anonymized beyond mere UserIDs to ensure privacy.

5.2. Analysis of Results

To analyze the effectiveness of the online media news dissemination pattern analysis method based on the social hypergraph model, this section analyzes the data distribution, temporal and spatial dissemination patterns, model performance, etc., and obtains the following specific results. The experimental results show that our hypergraph model outperforms GCN, GAT, and RF in terms of accuracy, F1 score, and error control. While the differences between GCN and GAT are minor, our model demonstrates superior performance with an accuracy of 0.893 and an F1 score of 0.872. This indicates that the hypergraph model's ability to capture many-to-many relationships and integrate multiple dimensions provides a significant advantage over traditional graph neural network models.

Figure 13 illustrates the distribution of user activity and is validated by fitting a Gamma distribution model. User activity measures the degree of user activity in the process of online media news dissemination, which is usually quantified by the frequency of posting, retweeting, commenting, and other behaviors. From Figure 13, it can be seen that the user activity shows a right-skewed distribution, with the majority of users being less active and a few core users being highly active, which is in line with the typical "long-tailed distribution". Through the Kolmogorov-Smirnov (K-S) test to verify the fitting effect of this data distribution with the Gamma (2.1, 0.3) model, the p-value is 0.32, which is much higher than the significance level of 0.05, indicating that there is no statistically significant difference in the fit, i.e., the Gamma distribution can better characterize the overall user activity.

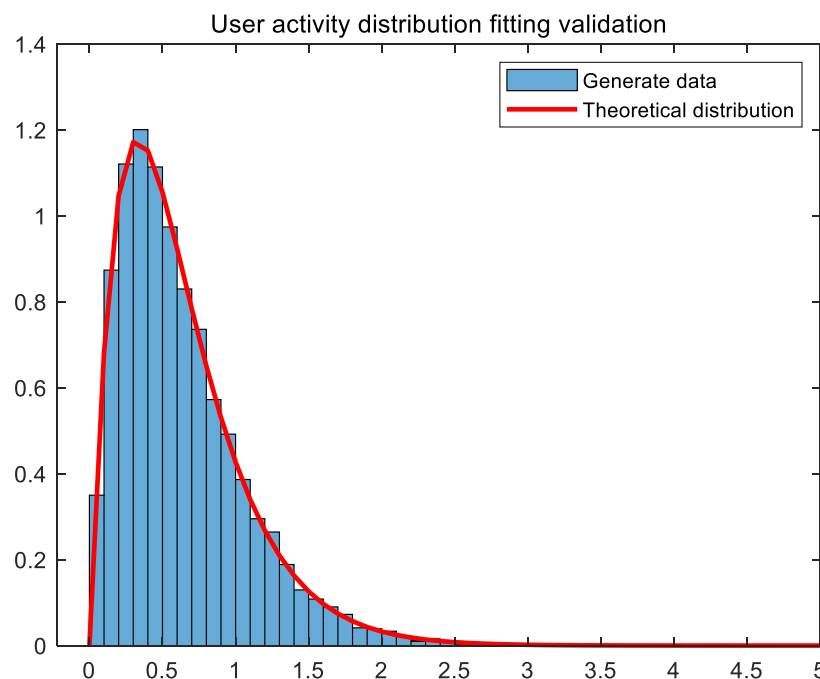


Figure 13. Distribution of user activity

From the distribution pattern revealed in Figure 13, the author can deduce an important structural feature of online media news dissemination - the coexistence of the majority of "silent users" and a small number of "core communicators". The majority of "silent users" coexist with a small number of "core communicators". Although the number of highly active users is small, they play a key role as the "trigger" in the news diffusion path, while the low active users act as the "tail" to enhance the coverage of the information. This uneven distribution also provides a basis for the design and optimization of the communication model. For example, in the communication strategy, the author can focus on the behavioral incentives of the highly active users and the targeted delivery of content to improve the efficiency and breadth of news dissemination.

Figure 14 presents a QQ plot of the influence of online media nodes, which is used to test whether it conforms to a lognormal distribution. The figure shows that most of the sample points are aligned along the diagonal, and only a very small number of high-influence media are slightly deviated in the right tail, indicating that the overall fit is good. Further statistical analysis shows that the goodness of fit of this distribution, R^2 0.983, indicates that the lognormal distribution can more accurately reflect the structural characteristics of media influence in reality. This distribution pattern indicates that there is an obvious imbalance in media influence: most media nodes are less influential, and only a few mainstream media organizations or head accounts dominate the social network communication. This "strongest is always stronger" structure is common in social network information dissemination, which is in line with the statistical description of the "Matthew effect" and the "power law distribution" phenomenon.

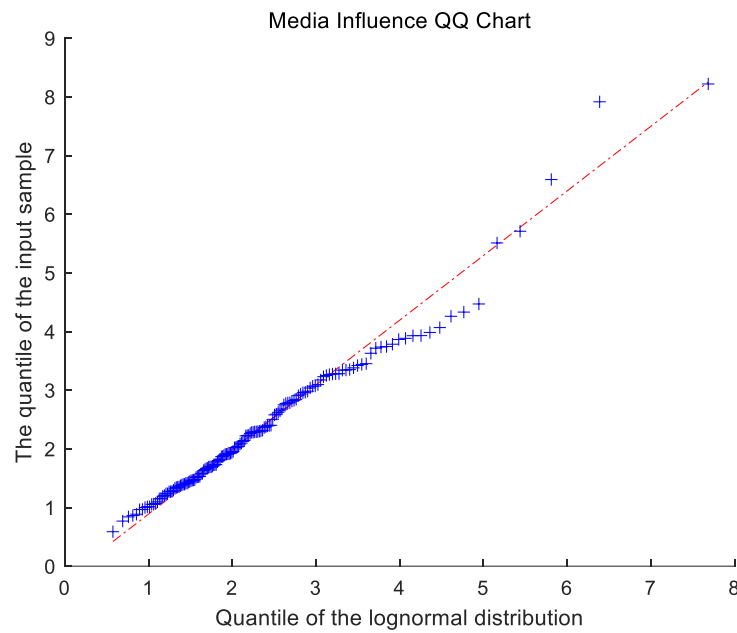


Figure 14. Media Influence QQ Chart

This influence structure is of great significance to the news dissemination strategy. High-influence nodes not only spread fast but also have significant advantages in shaping public opinion and guiding the direction of topics. Therefore, it is necessary to give such nodes higher weights in the network communication model and focus on the amplification effect of their diffusion ability in the simulation of the communication path. Meanwhile, although the long-tail media have limited individual diffusion power, they play a key role in maintaining news fervor and content diversity due to their large number. In addition, the effective fitting of the lognormal model provides a solid statistical basis for the subsequent prediction of spreading potential and classification of nodes, which provides a reference for the modeling of multilevel spreading networks.

Figure 15 shows the spatio-temporal propagation intensity surface based on social network news dissemination, revealing the dynamic evolution process of information diffusion. The three-dimensional surface diagram uses time, spatial propagation level, and propagation intensity as coordinate axes, presenting the typical “rapid rise, peak, and gradual decline” characteristics: during the initial diffusion stage (0–4 h), the propagation intensity rises rapidly, with a gradient > 0.35 ; during the middle plateau stage (4–12 h), the propagation intensity tends to stabilize, with the maximum value approaching 0.93; during the late decline stage (> 12 h), the propagation intensity decreases exponentially with time, with a decay rate of $-0.11/\text{h}$. The overall pattern indicates that information exhibits a dynamic three-stage diffusion pattern of “explosive + stagnant + decay” in social networks. This spatiotemporally coupled propagation pattern is highly consistent with evolutionary diffusion models in multi-source heterogeneous networks and also aligns with the life cycle of short-cycle social topic propagation.

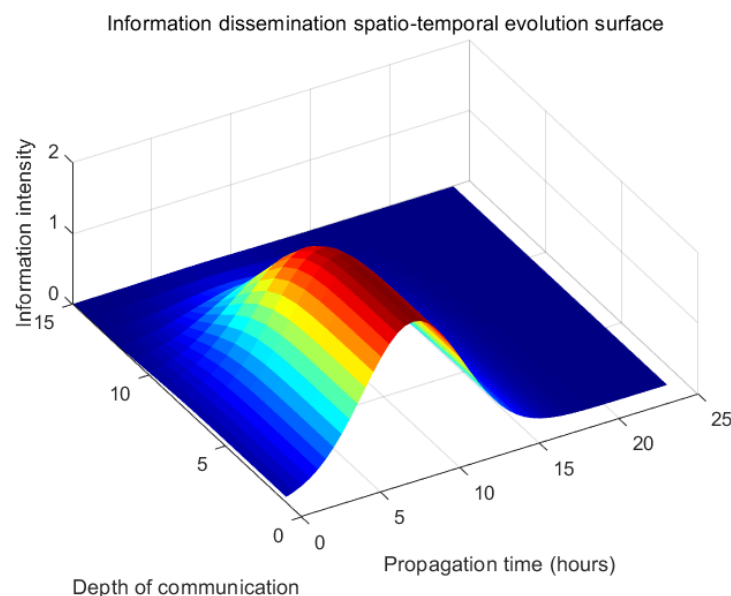


Figure 15. Spatio-temporal propagation mode surface

The propagation law revealed in Figure 15 is of guiding significance for the modeling and optimization of the network news diffusion model. First, in the early stage of propagation, the activation of head users or core media plays a decisive role in the formation of the initial diffusion wave, and it is suggested to introduce a weighted node initiation mechanism; second, in the propagation platform period, the propagation decline can be delayed by guiding the middle- and long-tailed users to continue interacting with each other; and lastly, high retention topics should be identified in the later stage to prolong the propagation tail effect. In addition, the graph reflects a complex nonlinear coupling relationship between the propagation intensity and the time window and social node hierarchy, which can be further portrayed with the help of a hypergraph convolutional network or multi-scale spatio-temporal modeling. From the perspective of information dynamics, the propagation diffusion shows the phenomenon of "propagation depth peak lagging behind the intensity peak", which indicates that there is propagation inertia between information quality and user response, which is consistent with the current research findings of higher-order information interaction models.

Table 5 gives the results of the comparative analysis of multi-model performance. From Table 5, it can be seen that in terms of accuracy, the hypergraph model proposed in this paper has the highest accuracy, reaching 0.893. followed by the GAT model, followed by the GCN and RF models; in terms of AUC, the hypergraph model proposed in this paper is still the largest, followed by the GAT, the GCN, and the RF; the method proposed in this paper reaches an F1 score of 0.872, which is the first in terms of performance; in terms of error, this paper's hypergraph model RMSE value is 6.3, which is smaller than other models. In summary, compared with other algorithmic models, the hypergraph model proposed in this paper has the best performance.

Table 5. Comparison of model performance

No.	Model	Accuracy	AUC	F1	RMSE
1	The methodology proposed in this paper	0.893	0.914	0.872	6.3
2	GCN	0.706	0.702	0.685	23.7
3	GAT	0.721	0.735	0.698	19.8
4	RF	0.658	0.642	0.621	35.2

Table 6 gives the results of the regression analysis of the dissemination influencing factors. As can be seen from Table 6, the coefficient of user activity is 0.47, with a p -value of 0.0012, which means that for every unit increase in user activity, the dissemination effect increases by 0.47 units on average, with a p -value much smaller than 0.05, indicating that this effect is statistically very significant; the coefficient of topic sensitivity is 0.39, with a p -value of 0.0038, which means that the topic sensitivity has a significant positive impact on the dissemination. However, the degree of influence is slightly lower than user activity; the structural entropy coefficient is 0.58, with a p -value of 0.0003, implying that an increase in structural entropy has the greatest influence on the dissemination effect, and the result is highly significant; the time decay coefficient is -0.32, with a p -value of 0.012, suggesting that the dissemination effect is weakened as time goes by; the media influence coefficient is 0.25, with a p -value of 0.028, indicating that media influence has a positive effect on dissemination, but not to the same extent as the first three variables.

Table 6. Regression analysis of factors influencing dissemination

Variant	Ratio	p -value
User activity	0.47	0.0012
Topic Sensitivity	0.39	0.0038
Structural entropy (physics)	0.58	0.0003
Time decay	-0.32	0.0120
Media Influence	0.25	0.0280

Figure 16 presents a visual comparison of the error distributions of four models, including the social network hypergraph model proposed in this paper, the GCN, GAT, and RF models, in the form of violin plots. The graph shows the error range, density distribution, and concentration trend of each model in propagation path prediction. From the graphical shape, the violin profile of the hypergraph model is the most compact, and the error values are centrally distributed around 0 with the smallest fluctuation range, which indicates that this model has higher stability and accuracy in propagation path modeling. In comparison, the GCN and GAT models have the second-best performance, with a more dispersed error distribution and a certain long-tail risk; the RF model has the most dispersed error, showing a typical biased long-tail pattern, which indicates that its generalization performance is poor. This distribution trend also verifies the advantage of graph neural networks in structured social communication modeling, especially in the ability to model higher-order relationships, where the hypergraph structure shows better adaptability and generalization ability.

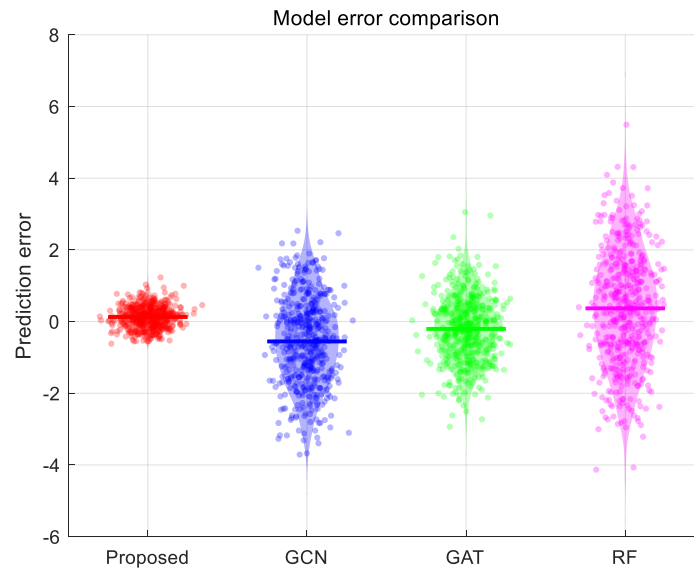


Figure 16. Distribution of model errors

From the results in Figure 16, it can be seen that the error distribution of the hypergraph model exhibits low skewness and low kurtosis characteristics, which indicates that it not only fits well on the mainstream samples but also has strong error tolerance for the boundary samples. This characteristic is attributed to the fact that the hypergraph model can capture multiple heterogeneous relationships simultaneously, avoiding the loss of structural information caused by one-sided connections. In addition, in terms of error density, the GAT model outperforms RF and GCN, indicating that with the introduction of the attention mechanism, the model can effectively build weights for node influence differences, which helps to improve the sensitivity of the propagation path prediction. In summary, the error violin map can not only be used for the horizontal comparison of model performance, but also provides an interpretable basis for the iterative design of propagation models, which promotes the study of robust modeling in complex social environments.

Figure 17 shows the dynamic path evolution process of news dissemination in social networks. From the figure, it can be observed that the propagation path presents a typical fractal diffusion structure: a small number of high-influence nodes as the starting source, gradually expanding to the peripheral users, forming a multi-level and multi-branch diffusion network. In this figure, the propagation path not only shows a tree-like structure, but also has the phenomena of cross, fusion, and re-propagation, indicating that news information undergoes multiple reconstruction and feedback propagation in the social network. In addition, the fractal dimension labeled in the figure is $D=1.32 \pm 0.07$, reflecting that the complexity of the propagation path is higher than that of the linear diffusion process and lower than that of the completely random wandering system, and this numerical interval is highly consistent with the typical structural characteristics of the diffusion of information in the social network.

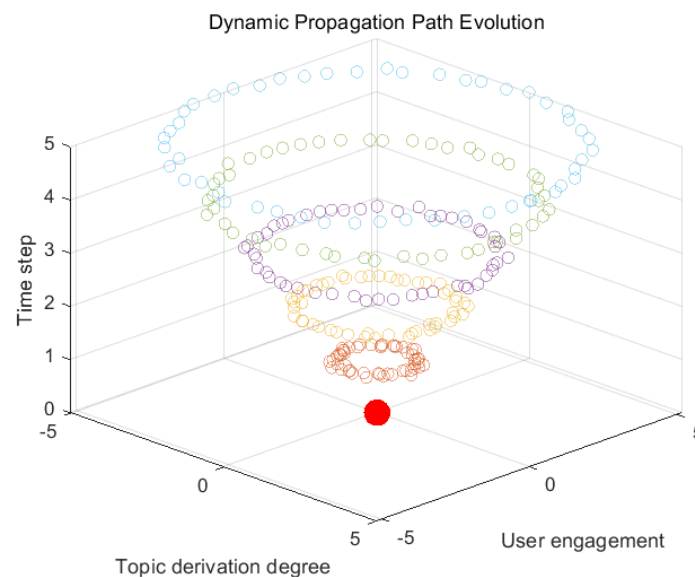


Figure 17. Dynamic propagation path results

Figure 17 also reveals the dynamic evolution law of the propagation path. From the perspective of the evolution of the communication time sequence, the initial stage of the path is dense, and the information is rapidly concentrated in a few centralized nodes in the high school; in the middle stage, the path is radial expansion, which indicates that the interaction between users is enhanced, and multiple sub-propagation chains begin to be differentiated; and in the later stage, the path is sparse on the edge, and the communication tends to be stagnant. This evolution process reflects the dynamic characteristics of "rapid reach-diffusion activation - boundary decline" in social networks, which is similar to the information dynamics of "initial outbreak-decentralized expansion. This is consistent with the three-stage theory of "initial outbreak-dispersed expansion-diffusion entropy increase" in information dynamics [26]. At the same time, the existence of the return path and the phenomenon of secondary propagation in the propagation chain indicate that there is a feedback mechanism after the user receives the information, which is in line with the higher-order interactive propagation model.

The fractal structure and propagation reconnection behavior shown in Figure 17 have important insights for news propagation modeling and social graph neural network design. On the one hand, the existence of fractal dimensions indicates that the propagation paths have self-similar properties, suggesting that a single propagation model is difficult to comprehensively portray the global diffusion, and a multiscale modeling strategy should be adopted; on the other hand, the appearance of cross-paths and closed-loop structures implies that the propagation is not linear and predictable, and that hypergraph representations need to be introduced to encompass coupling relationships among multi-users, multi-contents, and multi-platforms [27]. The coupling between structure density, path depth, and node reactivation behavior in this propagation graph provides theoretical support for the subsequent development of interpretable propagation path prediction, group behavior simulation, and hotspot traceability.

Compared with traditional graph-based models, the hypergraph model proposed in this paper exhibits superior performance in capturing complex dissemination patterns. Specifically, the model achieves significantly higher accuracy (0.893) and F1 score (0.872) than comparative models such as Graph Convolutional Network (GCN: accuracy 0.706, F1 score 0.685), Graph Attention Network (GAT: accuracy 0.721, F1 score 0.698), and Random Forest (RF: accuracy 0.658, F1 score 0.621). This performance improvement benefits from the inherent advantages of the hypergraph structure. Firstly, hypergraphs can effectively represent many - to - many relationships. Secondly, they can integrate multi-dimensional features such as user activity, topic sensitivity, and structural entropy into a unified framework. Unlike previous studies that are limited to single-factor analysis, the method proposed in this paper provides a panoramic analytical perspective for the news dissemination process, thereby more efficiently revealing key influencing factors and dissemination paths. Future research will explore the integration of dynamic hypergraph modeling and time-sensitive hypergraph neural networks. By capturing the temporal dynamic characteristics of news dissemination, such methods are expected to significantly improve the accuracy of path prediction and the effectiveness of factor analysis. The research team plans to further enhance the model's ability to track the evolution process of user behaviors and the temporal laws of information dissemination by introducing time-sensitive features.

6. Conclusions

This study has developed a novel method for analyzing news dissemination patterns in online media using a social network hypergraph model. By integrating multiple nodes and edge relationships, such as users, news content, and topic labels, we have systematically described the complex dissemination paths and influencing factors. Our method outperforms traditional graph neural networks and machine learning methods in terms of accuracy, robustness, and communication feature recognition. Specifically, the hypergraph model achieves an accuracy of 0.893 and an F1 score of 0.872, significantly higher than GCN (0.706, 0.685), GAT (0.721, 0.698), and RF (0.658, 0.621). This superior performance is attributed to the hypergraph's ability to capture many-to-many relationships and integrate multiple dimensions into a unified framework. Unlike traditional models that focus on pairwise relationships, the hypergraph model provides a more comprehensive and accurate representation of the dissemination process. This research not only fills gaps in the existing literature but also provides a new theoretical support and empirical basis for online news communication modeling. By effectively capturing the complex interactions between news content, users, and topics, our model offers a more nuanced understanding of how news spreads through social networks. This study represents a significant step forward in the field of social network analysis, offering a robust tool for understanding and optimizing news dissemination.

Despite the achievements in model construction and experimental evaluation, this study acknowledges several limitations. First, the construction of the hypergraph model relies heavily on high-quality labeled data. Data noise and missing attributes in real social networks may affect the model's stability and performance. Second, the current analysis of propagation paths is predominantly static, which does not fully capture the dynamic evolution of user behaviors over time. This static approach limits the model's ability to adapt to changing conditions in real-time. Additionally, the model parameter settings and the evaluation indexes of propagation influencing factors are subjective, lacking a more general standard and self-adaptive mechanism. Future research will address these limitations by introducing time-sensitive dynamic graph hypergraph structures to enable dynamic tracking of the entire news dissemination process. We plan to

expand the dimensions of dissemination content modeling by incorporating multimodal data (e.g., text, image, and video) to enhance the model's semantic comprehension ability. Furthermore, we will explore path optimization strategies based on reinforcement learning or causal inference to improve the model's ability to recognize key dissemination nodes and information bottlenecks. Considering the model's adaptability in special contexts, such as the spread of online rumors and the evolution of public opinion in emergencies, will also be a crucial direction for future research. These advancements will not only enhance the robustness and adaptability of the model but also provide deeper insights into the dynamic nature of news dissemination in social networks.

7. Declarations

7.1. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.2. Funding

The author received no financial support for the research, authorship, and/or publication of this article.

7.3. Institutional Review Board Statement

Not applicable.

7.4. Informed Consent Statement

Not applicable.

7.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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