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Research on complex network propagation path optimization and divide-and-conquer Algorithm for maximization of new media marketing effect

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SUMMARY: *The continuous expansion of new media platforms makes marketing communication present multi-node, multi-path and strong dynamic characteristics. Traditional delivery methods are difficult to take into account coverage, conversion efficiency and resource utilization. This paper proposes a communication path optimization framework for complex networks to maximize marketing effectiveness, which constructs a marketing communication network by using user behavior logs, content features, interaction relationships and conversion feedback. This study identifies nodes with high response, high diffusion and high conversion potential through behavior data preprocessing, user behavior sequence modeling and attention weighting of key propagation features. The divide and conquer algorithm is further introduced to divide the large-scale network into multiple sub-networks, and the global optimal path is generated on the basis of local path search and cross-community bridge fusion. The experimental results show that the coverage rate of the proposed method is 95.1%, the click conversion rate is 8.9%, NDCG@10 is 85.7%, the resource utilization rate is 93.8%, and the average path search time is 13.6 s, which is better than the comparison methods. Research shows that this method can improve the accuracy, stability and computational efficiency of new media marketing communication path selection, and provide reference for intelligent delivery, user hierarchical reach and cross-community communication optimization.*

KEYWORDS: *New media marketing; Complex network; Propagation path optimization; Divide and conquer algorithm*

1 Introduction

The rapid expansion of new media platforms has changed the way of production, distribution and feedback of marketing information. Short videos, social communities, live broadcast platforms and content recommendation systems make brand communication no longer rely on one-way delivery, but gradually show the network diffusion process under the joint action of user relationship chain, content interest chain and platform algorithm chain. Whether marketing information can achieve high forwarding rate, interaction rate and conversion rate depends not only on the attractiveness of the content itself, but also on factors such as the influence of user nodes, community structure, dissemination sequence, cross-platform migration ability and budget constraints [1, 2]. In a complex network environment, a small number of key nodes may trigger a large range of secondary diffusion, and bridge users in the

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edge community may also change the flow of information. Therefore, how to identify high-value communication nodes, select effective diffusion paths, and maximize the communication effect under limited marketing resources has become an important issue in the intelligent decision-making of new media marketing.

The existing research focuses on influence maximization, community detection, graph embedding, graph neural network and heuristic optimization, and forms a rich result [3-6]. Related methods can describe user influence and network propagation range from different perspectives, but there are still some shortcomings when facing real marketing scenarios. On the one hand, new media marketing data has the characteristics of high noise, high dynamic and strong heterogeneity. User click, browse, comment, like, purchase and other behaviors do not completely follow a stable pattern, and it is easy to ignore the matching relationship between marketing content and user interests by relying on static topological indicators. On the other hand, due to the large number of nodes in large-scale social networks, direct global path search will incur high computational cost and be susceptible to interference from local highly active nodes, which leads to the fact that the propagation path is concentrated in a few core areas and difficult to cover the potential consumer communities. The divide and conquer algorithm provides a new solution to the above problems, which first divides the whole network into several sub-networks according to the community structure, interest similarity and propagation edge weight, and then searches for candidate propagation paths in the sub-networks, and completes the global path integration by bridging nodes across communities. This idea can reduce the computational complexity and also help to improve the diversity and stability of the propagation path.

Based on this, this paper constructs a complex network communication path optimization model for maximizing the marketing effect of new media. Based on user behavior data, content feature data and interaction relationship data, the user-content-dissemination relationship network was established. The change law of marketing response is extracted by modeling the sequence of user behavior, and the key communication features are identified by using the attention mechanism. Then, the node influence, community connection ability and path diffusion potential are evaluated by combining the complex network indicators. On this basis, the divide and conquer algorithm is introduced to complete network division, sub-path search and global path fusion, so that marketing information can form a more efficient diffusion chain between different user groups. The goal of this paper is not to simply expand the exposure scale, but to optimize the marketing path from three levels of prediction effect, communication efficiency and conversion potential, so as to provide computational, interpretable and extensible method support for the development of new media marketing strategy.

1.1 Main Research Contributions

The main research contributions of this paper are reflected in the following aspects.

(1) A complex network communication modeling framework for new media marketing scenarios is constructed, which integrates user interaction, content semantic features, historical marketing behaviors, and conversion feedback into a unified network representation, which enhances the adaptability of communication path optimization to real platform data.

(2) A joint modeling method of user behavior sequence and key communication features is proposed, which captures the change of user interest, the fluctuation of interaction intensity and the evolution of purchase intention through time series coding, and uses the attention mechanism to highlight the influence of key variables such as click frequency, comment intensity, forwarding tendency, and community location on marketing effectiveness prediction.

(3) A complex network propagation path optimization strategy is designed, which uses node centrality, community bridging ability, edge propagation probability and content matching degree as the path evaluation basis to avoid excessive reliance on a single high fan node and improve the diffusion stability of marketing information in multi-layer user groups.

(4) The divide-and-conquer algorithm is introduced to complete the division and sub-path search of large-scale marketing communication network, and the calculation process of "network partition-local optimization-cross-region integration" is used to reduce the complexity of path search and improve the coverage and execution efficiency of candidate communication paths.

(5) An experimental evaluation system for marketing effect maximization is established to verify the effectiveness of the model from the indicators of communication coverage, click conversion rate, path calculation time, resource utilization and comprehensive marketing revenue, which provides a method reference for subsequent intelligent recommendation and automatic delivery of new media marketing.

1.2 Research Questions

Focusing on the maximization of new media marketing effect, this paper focuses on answering the following research questions:

(1) How to transform user behaviors, content features, and social interactions into computable complex network propagation structures?

(2) How to improve the accuracy and stability of marketing effect prediction under the environment of dynamic changes in user interests and continuous adjustment of platform communication mechanism?

(3) Can the attention weighting mechanism of key communication features effectively identify the core factors affecting marketing diffusion and conversion?

(4) How do key nodes, bridge nodes and community boundaries in complex network structure jointly affect marketing communication path selection?

(5) Can the divide-and-conquer algorithm reduce the complexity of path search and maintain good global dissemination effect in large-scale new media communication network?

(6) Is the proposed propagation path optimization model better than the traditional path selection method in terms of coverage, conversion rate, resource utilization and computational efficiency?

2 Related Research

Concerning the improvement of new media marketing communication effects, existing researches mainly focus on influence maximization, complex network communication modeling, community structure identification, graph learning methods, and dynamic marketing resource allocation. Influence maximization research usually regards users as network nodes, and regards followers, comments, retweets, common interests or transaction relationships as connected edges, and selects seed nodes with higher diffusion potential to expand the spread coverage. Kahr et al. [1] included passive social media viewers into the influence maximization analysis, indicating that silent users are not invalid audiences, and their browsing and secondary contact behaviors will affect the overall scope of communication. Umrawal et al. [2] proposed the framework of community awareness, emphasizing the important influence of user community structure on diffusion results. Patwardhan et al. [3] introduced the idea of divide and conquer into the problem of influence maximization, and provided an idea to reduce the computational complexity for large-scale network propagation optimization.

At the algorithm level, graph embedding, graph neural network and heuristic optimization methods are widely used to identify key nodes and propagation paths. Kumar et al. [4] used graph embedding and graph neural network to learn node influence representation, and improved the accuracy of seed node selection in social networks. The subsequent research further combined graph structure and LSTM to realize transfer learning modeling of influence prediction [5]. Khatri et al. [6], Aggarwal and Arora[7] respectively adopted the discretization swarm intelligence optimization algorithm to deal with the propagation node selection problem, which improved the solution efficiency under complex search space. Zareie and Sakellariou[8,9] summarized and extended the influence maximization model from the perspective of behavior perception and fuzzy influence, so that the difference of user interest, behavior uncertainty and propagation ambiguity were more fully reflected. In recent years, communication optimization in dynamic social networks has also attracted attention. Relevant studies incorporate time variation, budget allocation, bridging nodes and multi-layer network structure into the model, which provides reference for cross-community diffusion in new media marketing scenarios [10-15], as shown in Table 1.

Table 1: Summary of related studies

Literature	Research Objective	Main Result	Limitation
[1]	Analyze the role of passive social media users in influence maximization	Demonstrated that passive viewers can expand potential propagation coverage	Insufficient characterization of marketing conversion behavior
[2]	Construct a community-aware influence maximization framework	Improved intra-community diffusion efficiency	Limited discussion of cross-community path optimization
[3]	Use the divide-and-conquer idea to solve the influence maximization problem	Reduced computational pressure in large-scale networks	Insufficient integration of marketing content features
[4]	Identify influential nodes based on graph embedding and graph neural networks	Improved node influence prediction capability	Insufficient explanation of path-level marketing benefits
[5]	Adopt graph-structured LSTM for transfer learning	Enhanced the adaptability of influence prediction across different networks	Limited use of real-time propagation feedback
[8]	Review behavior-aware influence maximization methods	Emphasized the influence of user behavioral differences on propagation effects	Lack of unified modeling oriented toward marketing business objectives
[10]	Study influence maximization in dynamic social networks	Improved node selection in dynamic network environments	Computational complexity remains relatively high
[11]	Combine dynamic communities and bridge nodes for influence maximization	Improved the diversity of cross-community propagation	Insufficient analysis of content matching and conversion outcomes

From the existing research, complex network and influence maximization methods have laid the foundation for new media marketing communication optimization, but there are still three shortcomings. First, some studies focus on the ranking of node influence, which does not fully integrate content semantics, user behavior sequence and marketing conversion feedback, and it is easy to equate communication coverage with marketing effectiveness.

Secondly, path selection in dynamic social networks often relies on global search or heuristic iteration, which has high computational cost in large-scale platform data environment, and is difficult to meet the needs of rapid delivery and real-time adjustment. Third, the existing divide and conquer methods are mostly used for general influence maximization problems, and there is insufficient discussion on the synergistic relationship between community interest differences, cross-circle diffusion, budget constraints and effect prediction in new media marketing. Based on the above shortcomings, this paper combines complex network propagation modeling with divide-and-conquer algorithm, and completes the propagation path optimization under the constraints of user behavior, content characteristics and community structure, so as to improve the coverage efficiency, conversion potential and computational scalability of marketing communication.

3 Research Methods

Focusing on the problems of high-dimensional data fusion, network structure identification and communication effect maximization in new media marketing communication path selection, this paper constructs a method framework of "data collection, behavior preprocessing, feature extraction, complex network modeling, divide and conquer search, and path fusion". The research object is not a single marketing account or a single piece of content, but a marketing communication network composed of user nodes, content nodes, interaction edges, communication edges and conversion feedback. Based on the multi-platform marketing log, the model converts the browsing, liking, commenting, bookmark, forwarding, click jump and purchase conversion behaviors into computable features, and combines the content topic, release time, user interest preference and community relationship to generate the propagation weight. The overall process is shown in Figure 1.

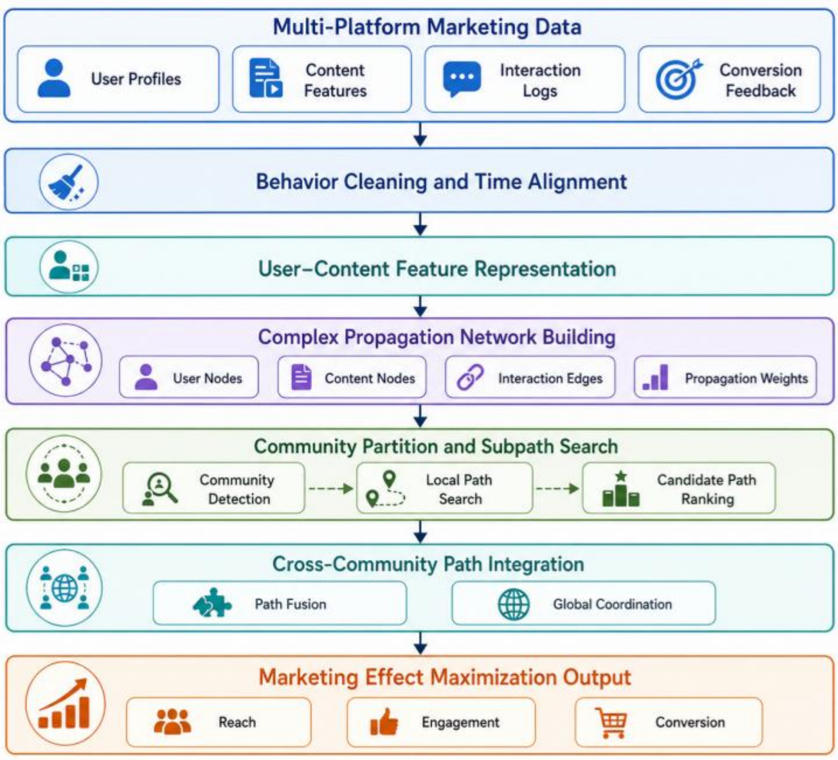

Figure 1: Process of new media marketing communication path optimization method

In the complex network representation, the new media marketing communication network is defined as:

$$G = (V, E, W, X, Y) \tag{1}$$

where V represents the node set composed of users, content and accounts, E represents the edge set formed by attention, interaction, forwarding and click jump, W is the edge weight matrix, X is the node and content feature matrix, Y is the marketing effect feedback label. In order to measure the potential value of disseminating marketing content from user i to user j, this paper constructs the edge propagation weight:

$$w_{ij} = \alpha b_{ij} + \beta s_{ij} + \gamma r_{ij} + \delta q_{ij} \tag{2}$$

where, b_{ij} represents user interaction intensity, s_{ij} represents interest similarity, r_{ij} represents historical forwarding probability, q_{ij} represents the matching degree between content and user requirements. $\alpha,\beta,\gamma,\delta$ are weight coefficients, which are used to adjust the influence of different behavioral factors on the propagation path selection. This setting makes the propagation path not only depend on the number of fans or node centrality, but also reflect the quality of user relationship, content adaptation and conversion possibility.

3.1 New media marketing communication data collection

The new media marketing communication data collected in this paper comes from the anonymized interaction logs in short video platforms, social content platforms, live broadcast marketing pages and e-commerce jump links. The data collection period was set as 12 weeks, covering five types of marketing content such as beauty, food, cultural creation, education services and daily goods. A total of 186,420 user behavior records, 18,764 marketing content samples, 428 effective user nodes and 52,316 communication relationship edges were obtained. Each record contains fields such as user number, content number, platform source, exposure time, stay time, like status, comment status, favorite status, forwarding status, click jump results and conversion feedback. In order to protect user privacy, only anonymous coding and statistical features are retained, and no real identity information is involved. In the process of data organization, user behavior is divided into three categories: weak interaction, medium interaction and strong interaction. Browsing, staying and repeated exposure are regarded as weak interactions, likes, favorites and comments are regarded as medium interactions, and retweets, private message sharing, link clicking and purchase conversion are regarded as strong interactions. The content data mainly includes information such as title text, topic labels, video duration, release time, content type, promotion intensity, and comment sentiment tendency. The propagation relationship data is generated according to the following relationship, common comment relationship, forwarding chain and similar interest connection between users. Through the above collection methods, this paper forms a complete data closed loop of "user-content-behavior-transformation", which provides a basis for subsequent complex network modeling and divide-and-conquer propagation path search.

3.2 Preprocessing of marketing behavior data

The data sources of new media marketing behavior are scattered, and the original records often contain problems such as repeated exposure, abnormal clicks, extremely short stays, machine brush, missing fields, and cross-platform time inconsistency. In order to ensure the reliability of subsequent complex network modeling and propagation path optimization, this paper cleaned, screened and structured the marketing behavior log before the data entered the model. For the continuous and repeated clicks generated by the same user in a very short period of time, if their stay time is lower than the effective browsing threshold of the platform, they are judged as invalid interactions and removed. Records with missing user number, content number or timestamp are not directly involved in the propagation edge construction to avoid the formation of false propagation chains. After denoising, the review text, content title and label fields retain the core semantic information for subsequent content feature extraction.

In the stage of behavior sequence collation, we align the exposure, browse, like, comment, like, forward, click jump and purchase conversion according to the user dimension, and transform the discrete interaction records into continuous behavior sequences. There are differences in the dimensions of indicators on different platforms, and the length of stay, interaction frequency, forwarding number and conversion amount cannot be directly compared. Therefore, normalization method is used to unify the scales. Let the original value of user i on the KTH behavior be $\mathrm{x_{ik}}$, and the normalized result is as follows.

$$\hat{\mathrm{x}}_{\mathrm{ik}} = \frac{\mathrm{x_{ik}} - \min(\mathrm{x_k})}{\max(\mathrm{x_k}) - \min(\mathrm{x_k}) + \varepsilon} \tag{3}$$

Here, $\max(\mathrm{x_k})$ and $\min(\mathrm{x_k})$ denote the maximum and minimum values of the KTH behavior in the sample, respectively, and ε is the smoothing term that prevents the denominator from being zero. After the above processing, the original marketing log is converted into a computable user behavior matrix and time series input, which not only reduces the interference of noise interaction on model training, but also provides a stable data basis for complex network edge weight calculation, user response prediction and divide and conquer path search.

3.3 Marketing communication feature extraction based on user behavior and content features

The goal of marketing communication feature extraction is to transform the scattered user interaction records, content attributes and network relationships into numerical representations that can be co-invoked by prediction models and path optimization algorithms. Different from general text recommendation tasks, the effectiveness of new media marketing depends not only on whether the content keywords are significant, but also on factors such as user historical interests, interaction intensity, communication position and conversion tendency. Therefore, this paper preserves behavior features, content features and network features simultaneously in the feature construction, so that the model can describe the marketing communication process from three levels: "whether the user is willing to respond", "whether the content is attractive" and "whether the node has the ability to spread". The feature extraction process is shown in Figure 2.

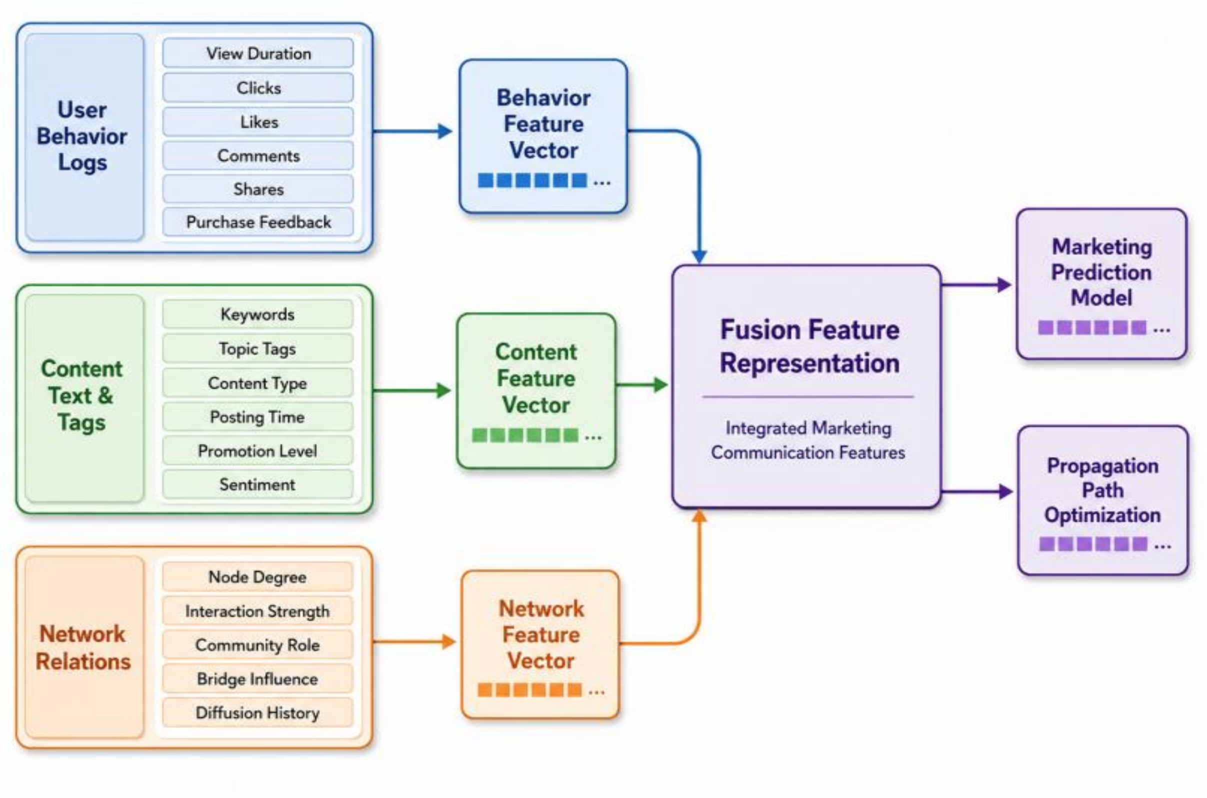

Figure 2: Marketing communication feature extraction process

At the user behavior level, this paper extracts the variables such as browsing time, click frequency, like status, comment intensity, favorability times, forwarding times, jump behavior and purchase feedback, which are used to describe the user's response to marketing content. At the content level, the features of title keywords, theme tags, content types, release time, promotion intensity and comment sentiment tendency are extracted, and the title and label text are transformed into content vectors after word segmentation and word frequency weight calculation. The network level mainly includes node degree, neighbor interaction strength, community affiliation, bridging ability and historical diffusion probability, which is used to reflect the location value of users in complex communication networks.

Let the behavior characteristics, content matching characteristics and network structure characteristics of user node vi be B_i, C_i and N_i respectively, then its marketing communication fusion representation can be defined as follows.

$$F_i = \phi(\lambda_1 B_i \oplus \lambda_2 C_i \oplus \lambda_3 N_i) \tag{4}$$

Here, $\oplus$ represents vector concatenation, $\lambda_1, \lambda_2, \lambda_3$ are the adjustment coefficients of the three types of features, respectively, and $\phi(\cdot)$ represents the nonlinear mapping function. This representation can avoid relying solely on click through rate or number of fans to judge the communication value, and make the subsequent model consider user response, content adaptation and network diffusion potential simultaneously when predicting the marketing effect. After feature extraction, the original marketing data is transformed into a unified high-dimensional communication feature matrix, which provides an input basis for the subsequent complex network propagation optimization model, attention weighting mechanism, and divide and conquer path search.

3.4 Complex network communication optimization Model for marketing effect prediction

The complex network propagation optimization model constructed in this paper consists of four parts: user behavior sequence modeling, key propagation feature attention weighting, complex network path evaluation, and divide and conquer sub-path search. The pre-processed marketing behavior data is first organized as a user response sequence arranged by time, which is used to describe the user behavior evolution process from exposure, browsing, interaction to conversion. Then, the model uses the attention mechanism to identify the communication features that have a stronger impact on the marketing effect, and incorporates the user node influence, community location, edge propagation probability and content matching degree into the complex network path evaluation. The divide and conquer algorithm is responsible for dividing the large-scale marketing communication network into several sub-networks, searching candidate paths in the local scope, and then integrating them globally through cross-community bridge nodes. This process not only focuses on the accuracy of marketing effect prediction, but also takes into account the computational efficiency of path search, and its model structure is shown in Figure 3.

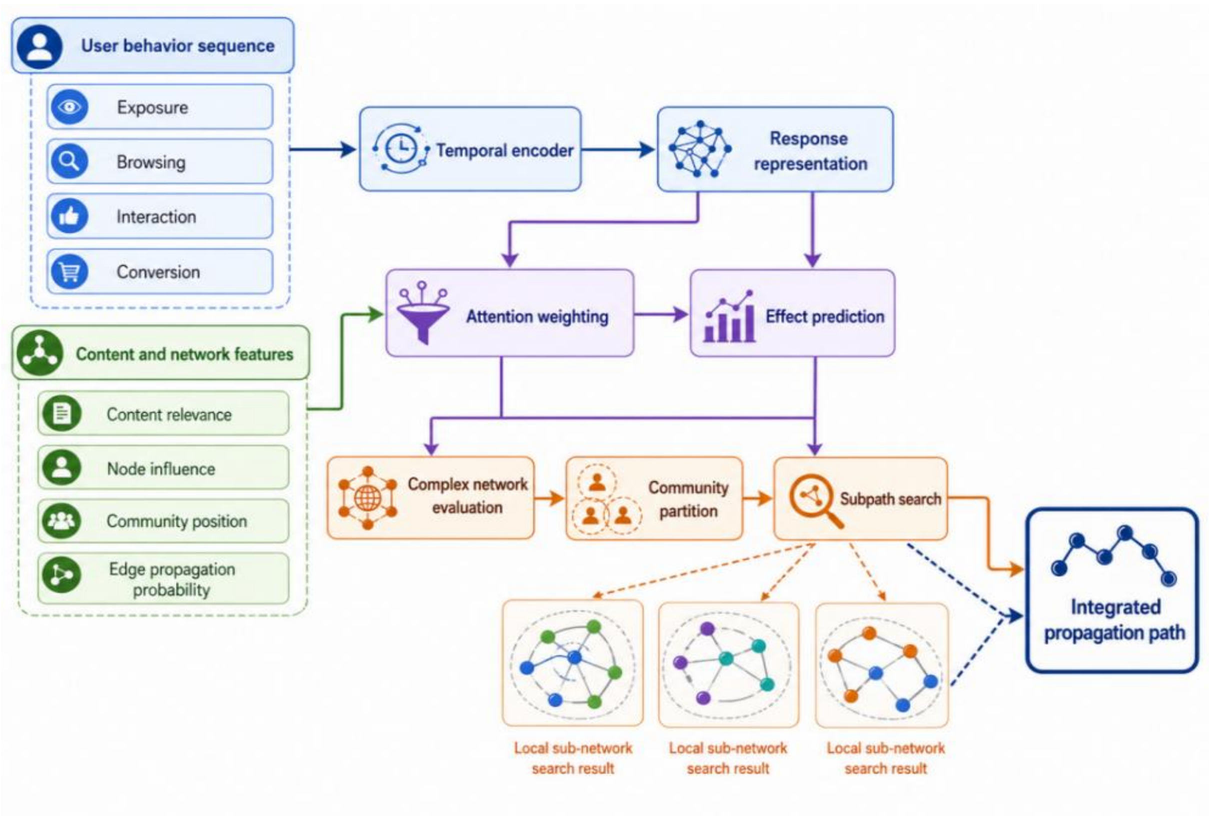

Figure 3: Structure of complex network propagation optimization model for marketing effect prediction

3.4.1 Modeling user behavior sequence

User response in new media marketing is not an isolated event, but a dynamic process formed by multiple exposure, browsing, interactive feedback and conversion behavior. The interest intensity of the same user in marketing content may change in different time periods, high-frequency browsing in a short time may indicate potential purchase intention, and long-term low interactive exposure may reflect communication fatigue. Therefore, in this paper, the behavior of user i in time window T is expressed as a sequence as follows.

$$S_i = \{x_{i1}, x_{i2}, \dots, x_{it}, \dots, x_{iT}\} \tag{5}$$

Here, x_{iT} represents the behavior vector of user i at the TTH time step, which contains information such as browsing time, click times, comment status, favorite status, retweet status, jump result and conversion feedback. To capture the temporal dependence of user responses, this paper adopts a gated recurrent structure to encode the behavior sequence. Its hidden state update process can be expressed as follows.

$$rt = \sigma(Wrxit + Urht - 1 + br) \tag{6}$$

$$z_t = \sigma(W_z x_{it} + U_z h_{t-1} + b_z) \tag{7}$$

$$\tilde{h}_t = \tanh(W_h x_{it} + U_h (r_t \odot h_{t-1}) + b_h) \tag{8}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{9}$$

where, rt is the reset gate, which is used to control the retention degree of historical behavior information. z_t is the update gate, which is used to adjust the fusion ratio between the current behavior and the historical state. $\tilde{h}_t$ denotes the candidate hidden state, and h_t is the response representation of the user at the current time step. Through this structure, the model can distinguish one-time click from continuous interest accumulation, and avoid misjudging casual interaction as stable marketing intention.

After time series encoding, the user's final response state is fed into the marketing effectiveness prediction layer to estimate the probability of effective interaction or conversion of the current marketing content:

$$\hat{y}_i = \sigma(W_o h_T + b_o) \tag{10}$$

Here, $\hat{y}_i$ represents the marketing response probability of user i, and h_T is the behavioral state representation at the end of the time window. This modeling method makes the propagation path selection no longer rely on the static follower size, but can combine the user's recent behavior trend to determine its real propagation value, which provides a temporal basis for subsequent attention weighting and complex network path optimization.

3.4.2 Key propagation feature attention weighting mechanism

After the temporal coding of user behavior sequence, different communication features have different contributions to the marketing effect. Browsing time can reflect the user's interest in staying, comments and favorites reflect strong participation willingness, forwarding behavior directly affects the secondary diffusion, and click jump and purchase conversion are closer to the marketing target results. Feeding all features into the model with fixed weights can weaken high-value propagation signals and amplify noise from casual browsing, low-quality interactions, and repeated exposures. Therefore, this paper introduces the attention weighting mechanism of key propagation features into the complex network propagation optimization model, so that the model can dynamically assign feature weights according to specific users, content and propagation location.

Let the temporal hidden state of user node v_i at time step t be h_{it} and the corresponding set of propagation features be:

$$P_i = \{p_{i1}, p_{i2}, \dots, p_{im}\} \tag{11}$$

p_{im} represents the m-th type of communication characteristics, including interaction strength, forwarding tendency, content matching degree, node centrality, community bridging ability, and historical conversion rate. In order to measure the importance of different features in the current marketing task, this paper first calculates the feature relevance score:

$$e_{im} = v_a^T \tanh(W_p p_{im} + W_h h_{it} + b_a) \tag{12}$$

where, W_p and W_h are trainable parameter matrices, v_a is the attention mapping vector, b_a is the bias term, and e_{im} represents the contribution score of the m-th type of communication feature to the user's current marketing response. The score is not set statically, but is updated with changes in user behavior status and content delivery environment. In order to avoid inconsistent score scales of different features, a normalization function is further used to generate attention weights:

$$a_{im} = \frac{\exp(e_{im})}{\sum_{m=1}^{M} \exp(e_{im})} \tag{13}$$

Here, a_{im} represents the normalized weight of the m-th class of propagation features, and m is the total number of propagation features. A higher weight indicates that the feature has a stronger explanatory role in the current communication path selection and marketing effect prediction. For example, in highly interactive communities, comment intensity and retweet tendency may obtain higher weights. In the identification of potential purchase users, click jump, historical conversion and content matching may become the main judgment criteria.

After the weight assignment, the model performs weighted fusion of various propagation features to obtain the key propagation representation of the user node:

$$c_i = \sum_{m=1}^{M} a_{im} p_{im} \tag{14}$$

where c_i is the propagation feature vector after attention enhancement. The vector preserves user behavior response, content attraction and network diffusion ability at the same time, which can provide a more refined node representation for subsequent complex network path evaluation. Furthermore, integrating c_i with time-series response state h_{it}, a comprehensive representation for marketing effect prediction can be obtained:

$$o_i = \psi([h_{it}; c_i]) \tag{15}$$

where, $[h_{it}; c_i]$ represents the vector connection and $\psi(\cdot)$ is the nonlinear mapping function. Through this mechanism, the model can reduce the interference of invalid exposure and weak interaction behavior on the prediction results, and make the communication path optimization pay more attention to the user nodes with high response, high diffusion and high conversion potential, so as to improve the pertinence and interpretability of new media marketing path selection.

3.4.3 Propagation Path Optimization based on complex network structure

After completing user response prediction and weighting of key propagation features, the model needs to further determine the propagation direction of marketing information in complex networks. The communication relationship in the new media platform is not a simple linear diffusion, but a multi-layer network composed of user attention relationship, content interaction relationship, community connection relationship and conversion feedback relationship. If the target selection is only based on the influence of a single user, it is easy to cause the dissemination path to concentrate on the head node, ignoring the diffusion value of the middle waist users and cross-community bridge nodes. Therefore, this paper models the marketing communication environment as a dynamic directed complex network, and optimizes the communication path selection under the network structure constraints. Its basic structure is shown in Figure 4.

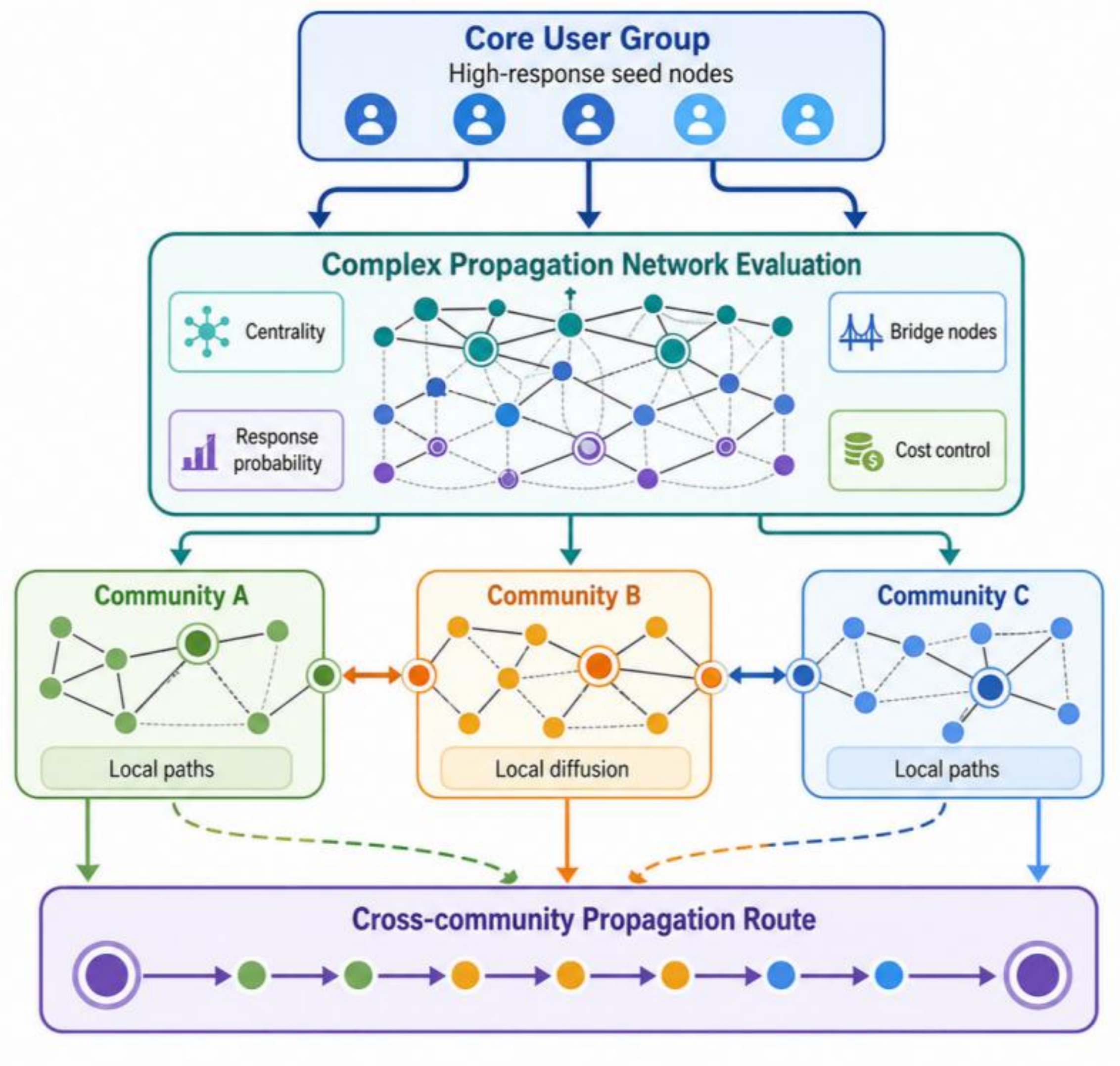

Figure 4: Propagation path optimization structure of complex networks

Let the communication network in the t-th marketing cycle be represented as follows.

$$\mathcal{G}_t = (\mathcal{V}_t, \mathcal{E}_t, \mathcal{A}_t) \tag{16}$$

where $\mathcal{V}_t$ is the set of user nodes, $\mathcal{E}_t$ is the set of directed edges that may generate information flow between users, and $\mathcal{A}_t$ is the set of network adjacency relations and their attributes. For any propagation edge (i,j), this paper does not directly take the number of interactions as the basis for path selection, but comprehensively considers the response probability, content adaptation, propagation delay and resource cost to construct the edge propagation utility:

$$\eta_{ij} = \frac{\rho_{ij} \cdot \kappa_{ij} \cdot \chi_j}{1 + \tau_{ij} + \omega c_{ij}} \tag{17}$$

where, ρ_{ij} represents the probability that user i will be answered after spreading marketing content to user j, κ_{ij} represents the matching degree between user interest and content topic, χ_j represents the community diffusion ability of node j, τ_{ij} is the propagation delay, c_{ij} is the reaching or incentive cost, and ω is the cost penalty coefficient. This definition can make the path optimization focus on both propagation benefit and execution cost, and avoid the excessive selection of high cost and low conversion nodes. At the path level, if the candidate propagation path is:

$$\mathcal{P} = \{v_1, v_2, \dots, v_l\} \tag{18}$$

Then its comprehensive propagation revenue can be expressed as follows.

$$R(\mathcal{P}) = \sum_{q=1}^{l-1} \eta_{v_q v_{q+1}} + \mu \sum_{q=1}^{l} \theta_{v_q} - \nu D(\mathcal{P}) \tag{19}$$

where θ_{v_q} represents the marketing response potential of the node, D(P) represents the risk of repeated reach, community redundancy and transmission block in the path, μ and ν are the adjustment parameters of node revenue and path penalty, respectively. Through this objective function, the model can form a balance between coverage, conversion potential and dissemination efficiency.

3.4.4 Network partition and sub-path search of divide and conquer algorithm

In the new media marketing communication network, the number of user nodes, the number of interaction edges and the content reach relationship usually show rapid growth characteristics. If the propagation path search is directly carried out in the complete network, the model needs to compare a large number of candidate nodes, propagation edges and cross-community connections at the same time, which has high computational complexity and is easy to bias the path selection to a few highly active nodes, resulting in repeated dissemination of marketing information in the local circle. In order to solve this problem, this paper introduces a divide-and-conquer algorithm into the complex network propagation optimization model, and splits the large-scale propagation network into several subnetworks with relatively close structures and similar interest characteristics. Then, the local path search is completed in the subnetwork, and the cross-community path fusion is realized by bridging nodes. This process not only reduces the global search pressure, but also enhances the coverage ability of the propagation path to multiple types of consumer groups.

The basic idea of the divide and conquer algorithm is to divide the original marketing communication network according to the community connection strength, user interest similarity and edge propagation utility. Let the complete propagation network be G and K subnetworks are obtained after partitioning, then:

$$\mathcal{G} \Rightarrow \{\Omega_1, \Omega_2, \dots, \Omega_K\}, \quad \Omega_a \cap \Omega_b = \emptyset \ (a \neq b) \tag{20}$$

Here, Ω_K denotes the KTH marketing communication subnetwork. Each sub-network usually contains user groups with similar interests, frequent interactions or consistent content preferences, such as beauty content audience, live broadcast promotion audience, short video forwarding audience and knowledge-based content followers. Network partition is not simply cutting nodes, but trying to retain high-strength propagation edges, so that the local path search can still reflect the real propagation relationship. The overall process is shown in Figure 5.

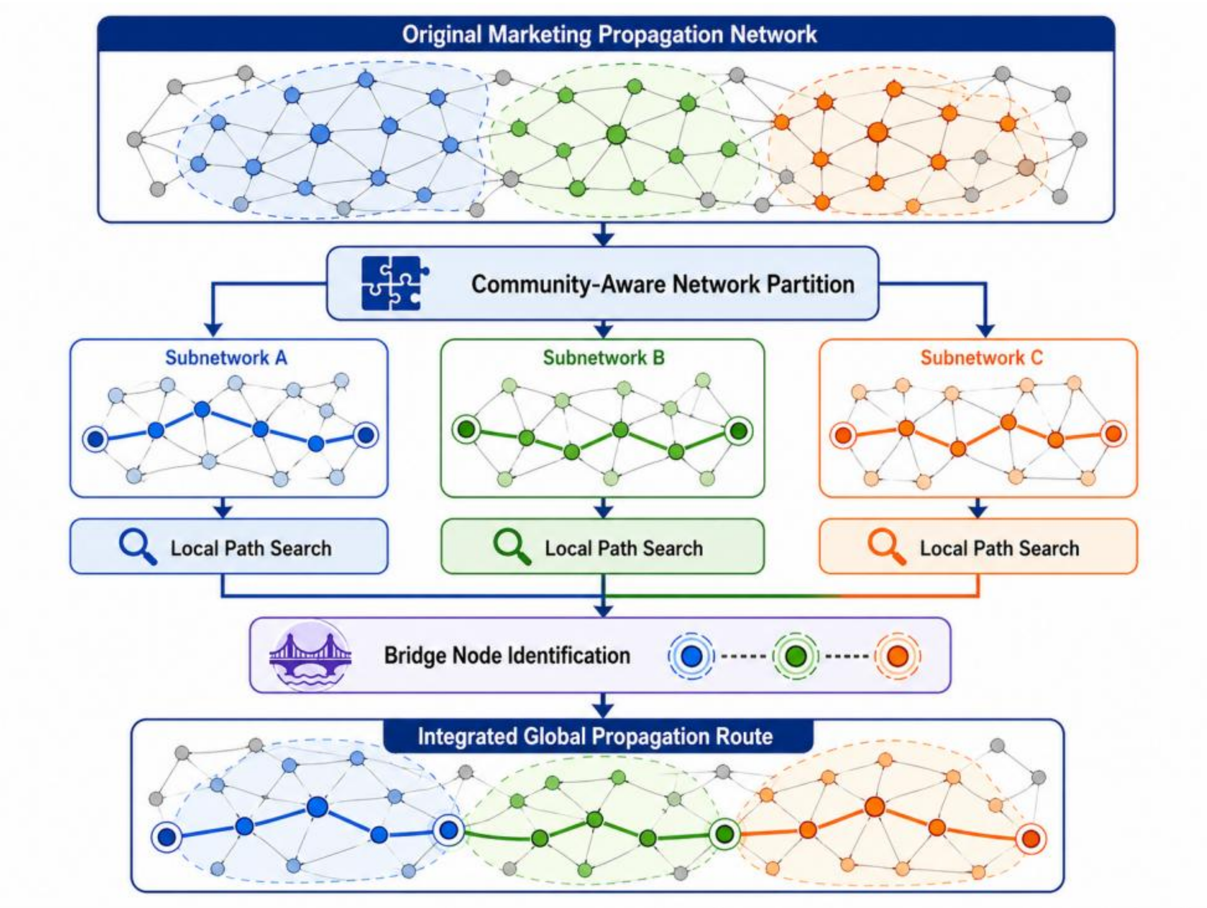

Figure 5: Network partition and subpath search process driven by divide-and-conquer algorithm

Inside the subnetwork, this paper constructs the local search objective based on the node marketing response potential, edge propagation utility and path redundancy penalty. Let $\mathcal{P}_k$ be a candidate propagation path in the subnetwork Ω_k. Then the local optimal subpath can be expressed as follows.

$$\mathcal{P}_k^{\star} = \arg \max_{\mathcal{P}_k \subseteq \Omega_k} \left[\sum\nolimits_{(i,j)\in\mathcal{P}_k} \eta_{ij} + \xi \sum\nolimits_{v_i\in\mathcal{P}_k} \hat{y}_i - \zeta H(\mathcal{P}_k) \right] \tag{21}$$

where η_{ij} represents the utility of the propagation edge, $\hat{y}_i$ represents the marketing response probability of the user node, $H(\mathcal{P}_k)$ represents the repeated reach and homogeneous diffusion risk inside the path, and ξ and ζ are the regulatory parameters. The objective function makes the sub-path search not only focus on the propagation range, but also consider the node transformation intention and path diversity. For high-density subnetworks, the algorithm gives priority to the nodes with stable interaction and higher response probability.

For sparse subnetworks, more attention is paid to nodes with strong bridging ability and able to connect to external communities.

After the subpath search is completed, the bridge nodes between different subnetworks need to be further identified. Let B denote the set of cross-community bridging nodes, whose selection criteria are jointly determined by cross-region connection strength, propagation benefit and cost constraints:

$$\mathcal{B}^{\star} = \{v_i \mid \ell_i > \bar{\ell}, s_i > \bar{s}, c_i < c_{max}\} \tag{22}$$

where, ℓ_i represents the cross-community connection level of nodes, s_i represents the comprehensive propagation score of nodes, c_i represents the reaching cost, $\bar{\ell}$ and $\bar{s}$ are the corresponding index thresholds, and c_{max} is the maximum allowed marketing cost. Through this screening rule, the model can avoid selecting bridge nodes with high cost or insufficient connection value, and make cross-community diffusion more robust.

In the global fusion stage, the algorithm combines the local optimal paths of each sub-network with the bridge nodes to form the overall propagation path:

$$\mathcal{P}^{\star} = \mathcal{M}(\mathcal{P}_1^{\star}, \mathcal{P}_2^{\star}, \dots, \mathcal{P}_K^{\star}, \mathcal{B}^{\star}) \tag{23}$$

Here, M(·) represents the path fusion function, which is responsible for splicing sub-paths according to propagation direction, time order and cross-region connection. The fusion process is not to add all local paths directly, but to remove the parts with serious repeated reach, mismatched cost and benefit, or conflicting communication direction, and then retain the path fragments with high marketing value.

Compared with the global exhaustive search, the divide-and-conquer algorithm transforms the large-scale path optimization problem into multiple controllable local search problems. If the complete network contains n nodes, the complexity of direct search usually increases rapidly with the number of candidate paths. After using the divide and conquer strategy, the scale of each sub-network decreases, and the local search and cross-region fusion can be performed in parallel. The computational cost can be approximated as follows.

$$\mathcal{C}_{dc} = \sum_{k=1}^{K} \mathcal{C}(\Omega_k) + \mathcal{C}(\mathcal{B}^{\star}) \tag{24}$$

Here,$\mathcal{C}(\Omega_k)$ is the search cost of the KTH subnetwork, and $\mathcal{C}(\mathcal{B}^{\star})$ is the bridge node fusion cost. This design enables the model to maintain good computational efficiency in the face of large-scale new media communication data. Through the path optimization mechanism of "division-search-integration", marketing information can be accurately reached in the local community, and enter new potential consumer groups with the help of bridge nodes, so as to improve marketing coverage, conversion stability and resource utilization efficiency.

3.5 Communication path optimization process for marketing effect maximization

Marketing effectiveness prediction results are not the end point of communication decisions, but the core input of the path optimization process. In this paper, the user response probability, attention enhanced propagation characteristics, complex network edge utility and divide and conquer sub-path results are integrated into the propagation path optimization module, forming a closed-loop calculation process from user identification to path output. Starting from the candidate propagation nodes, the process selects the executable paths according to the content matching degree, the community diffusion ability, the reach cost and the historical transformation feedback, and completes the local search in different sub-networks through the divide and conquer algorithm, and then uses the bridge node to realize the cross-community connection. The overall process oriented to marketing effect maximization is shown in Figure 6.

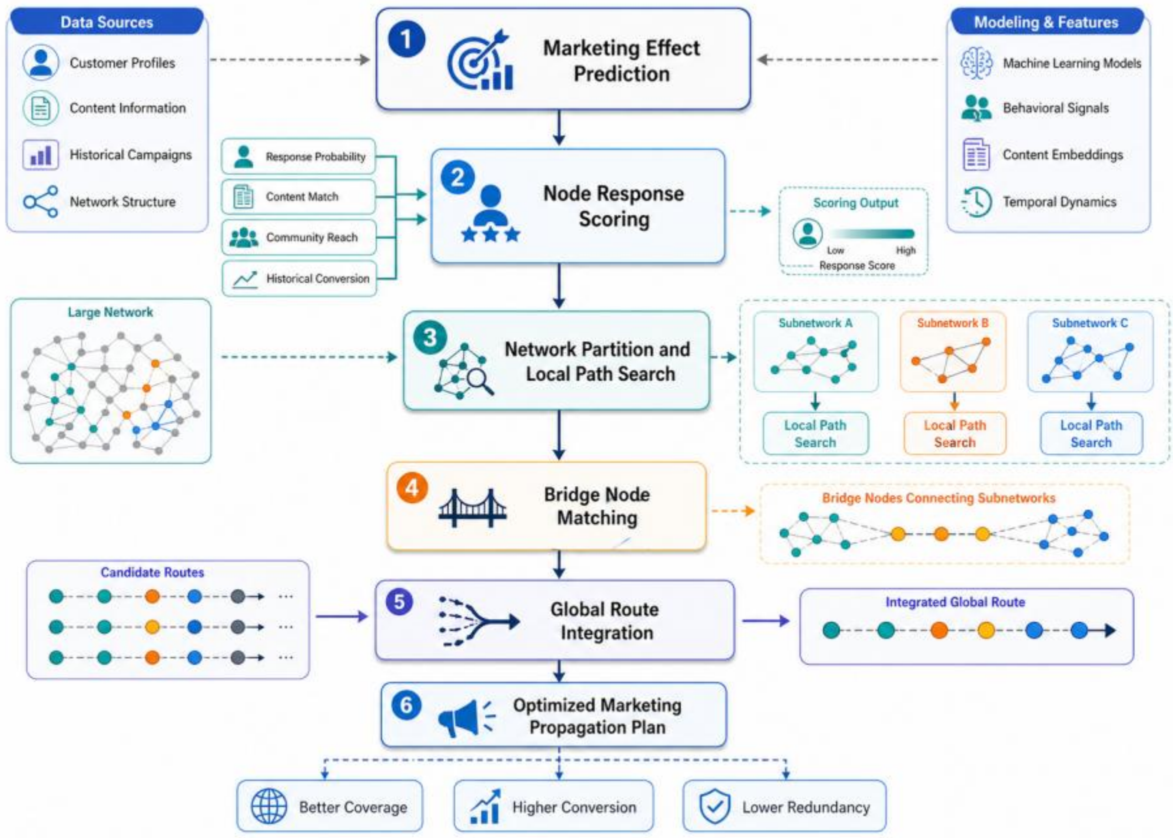

Figure 6: Communication path optimization process for marketing effect maximization

Let the final propagation path be P. In this paper, the path optimization objective is defined as the comprehensive balance between coverage benefit, conversion benefit, resource utilization and propagation risk:

$$\mathcal{J}(\mathcal{P}) = \lambda_c C(\mathcal{P}) + \lambda_v V(\mathcal{P}) + \lambda_u U(\mathcal{P}) - \lambda_d L(\mathcal{P}) - \lambda_b B(\mathcal{P}) \quad (25)$$

where C(P) represents the propagation coverage gain, V(P) represents the conversion gain, U(P) represents the resource utilization efficiency, L(P) represents the propagation delay and the loss of repeated reach, B(P) represents the budget consumption, and $\lambda_c, \lambda_v, \lambda_u, \lambda_d, \lambda_b$ are the regulation coefficients. The model selects the propagation path with higher J(P) under the condition of satisfying the budget and node reach constraints, so that the marketing information can avoid low response nodes and high redundant links, and preferentially enter the user groups with diffusion potential and conversion value. Through the process shown in Figure 6, communication path optimization no longer stops at experience delivery, but is transformed into an intelligent marketing decision-making process that can be calculated, adjusted and reused.

4 Results

This paper conducts experimental verification on the aforementioned new media marketing communication data set. The dataset contains 186,420 user behavior records, 18,764 marketing content samples, 428 valid user nodes and 52,316 communication relationship edges, which are divided into training set, validation set and test set according to 8:1:1. The experimental platform uses Ubuntu 22.04 operating system, Python 3.11 and PyTorch 2.2 as the main development environment, and the hardware configuration is Intel Core i7-12700 processor, 32 GB memory and NVIDIA RTX 4080 GPU. The model was trained using an AdamW optimizer with an initial learning rate of 2×10^{-4}, a batch size of 64, a maximum number of training rounds of 80, and an early stop on the validation set for 8 consecutive rounds without boosting.

This paper evaluates the effect of the model from five aspects: marketing coverage, click conversion, ranking quality, resource utilization and path search efficiency. In order to avoid one-sided judgment caused by a single indicator, the experiment also investigated whether the communication path could cover more potential users, whether it could increase the proportion of high intention users, and whether it could reduce repeated delivery and invalid links. The evaluation metrics are shown in Table 2.

Table 2: Description of model evaluation indicators

Indicator	Meaning	Evaluation Direction
Coverage	The proportion of effective user nodes reached by the optimized path among all potential user nodes	Higher is better
Conversion Rate	The proportion of reached users who complete click-through or purchase conversion	Higher is better
NDCG@10	Measures the ranking quality of high-value propagation nodes in the recommended path	Higher is better
Resource Utilization	The matching degree between effective reach and marketing resource consumption	Higher is better
Search Time	The time required to complete propagation path search	Lower is better

Experimental results show that the complex network propagation path optimization and divide and conquer algorithm proposed in this paper can improve the transformation effect while maintaining a high coverage level. Compared with the method of selecting nodes only based on degree centrality, the proposed model does not simply chase high fans or high active users, but combines user behavior sequence, content matching degree, attention weighted propagation characteristics and community bridging relationship to complete path selection, so it can more accurately identify nodes with real marketing value. Figure 7 illustrates the comparison results of different models in terms of coverage, click conversion rate, and resource utilization.

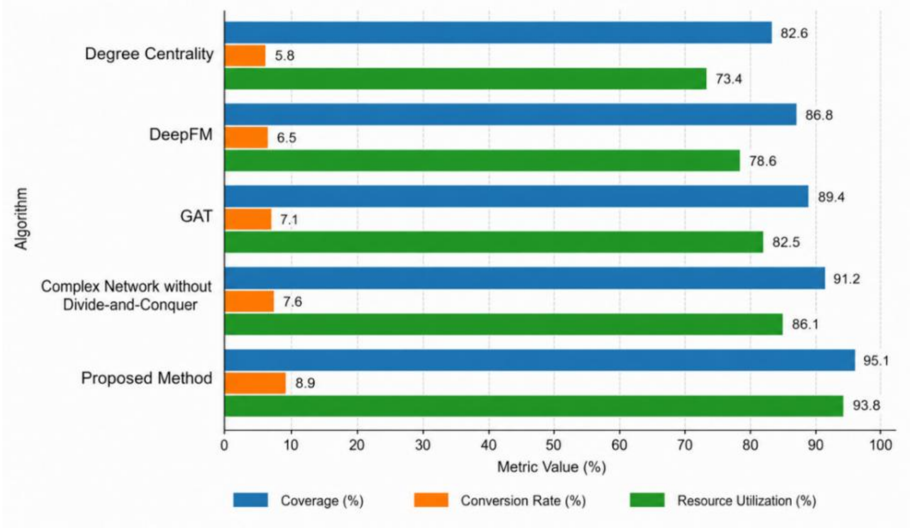

Figure 7: Comparison of marketing communication performance of different algorithms

It can be seen from Figure 7 that the coverage rate of the traditional degree centrality method is 82.6% and the resource utilization rate is 73.4%, indicating that although it can quickly select highly connected nodes, it is easy to cause repeated reach and resource waste. DeepFM has certain advantages in the modeling of user behavior characteristics, with the coverage rate increased to 86.8% and the click conversion rate reached 6.5%. However, it underutilizes the network propagation structure and is difficult to explain the cross-community diffusion path. GAT can use neighbor aggregation to enhance node representation, with a coverage rate of 89.4% and a resource utilization rate of 82.5%, but it still has the problem of high computational overhead in large-scale path search. The coverage rate of the complex network model without the divide and conquer strategy is 91.2%, and the click conversion rate is 7.6%, which indicates that the complex network structure has a positive effect on the propagation path optimization, but the global search will increase the computational burden. The coverage rate of this method reaches 95.1%, the click conversion rate reaches 8.9%, and the resource utilization rate reaches 93.8%, showing better comprehensive optimization ability.

4.1 Comparative experimental analysis

In order to further verify the effectiveness of the model, this paper selects four types of baseline methods for comparison: degree centrality path selection method, DeepFM marketing response prediction method, GAT propagation node modeling method, and complex network optimization model without introducing divide and conquer strategy. The comparison results are shown in Table 3.

Table 3: Comparison of marketing communication effects of different algorithms

Algorithm	Coverage (%)	Click Conversion Rate (%)	NDCG@10 (%)	Resource Utilization (%)	Average Search Time (s)
Degree Centrality	82.6	5.8	68.4	73.4	15.7
DeepFM	86.8	6.5	72.9	78.6	18.9
GAT	89.4	7.1	76.5	82.5	24.9
Complex Network without Divide-and-Conquer	91.2	7.6	79.8	86.1	33.5
Proposed Method	95.1	8.9	85.7	93.8	13.6

Table 3 shows that the proposed method achieves better results in the five indicators. The coverage rate was 12.5 percentage points higher than that of Degree Centrality, 8.3 percentage points higher than that of DeepFM, and 5.7 percentage points higher than that of GAT, indicating that the complex network communication structure and divide and conquer search mechanism can effectively expand the reach range of marketing information. In terms of click conversion rate, the proposed model reaches 8.9%, which is significantly higher than other methods. The main reason is that the model does not take exposure scale as the only target, but takes user behavior trend, content adaptation degree and historical conversion feedback into the evaluation of communication path. Finally, NDCG@10 reaches 85.7%, which indicates that the high-value dissemination nodes can be arranged in the candidate paths more forward, which is conducive to improving the actual availability of the placement ranking.

In terms of resource utilization rate, the proposed method reaches 93.8%, indicating that the divide-and-conquer algorithm can reduce invalid reach and repeat propagation, and make marketing resources more invest in nodes with higher response probability and diffusion potential. In contrast, although Degree Centrality is simple to calculate, its path selection tends to focus on the core area of the network, which is prone to the problem of high exposure and low conversion. DeepFM can predict user responses, but lacks structural constraints on propagation links. GAT can learn the neighbor node relationship, but it still needs to deal with many candidate edges in the path generation phase. Although the marketing effect of the non-divide and conquer complex network model is good, the average search time reaches 33.5 s, which affects the applicability in the rapid delivery scene. In order to test the scalability of the model in larger propagation scenarios, we generate simulated propagation networks with 1,000 to 12,000 nodes by node sampling expansion and edge weight reconstruction based on real user interaction structures. Figure 8 further shows the path search time variation of each algorithm for different network sizes.

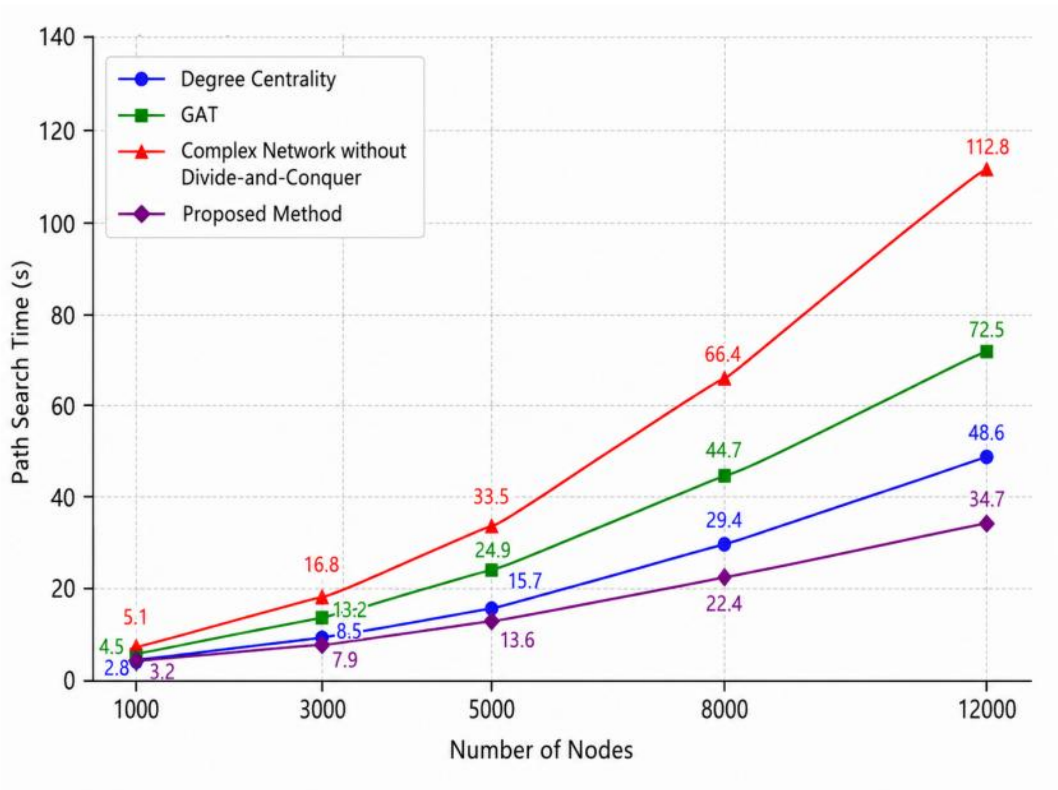

Figure 8: Comparison of path search time under different network sizes

As can be seen from Figure8, when the network scale increases from 1,000 nodes to 12,000 nodes, the search time of the complex network model without divide and conquer increases from 5.1 s to 112.8 s, with a large increase. The GAT method also shows a significant rise in time overhead in large-scale networks, and the search time is 72.5 s under the condition of 12,000 nodes. The search time of the proposed method is 34.7 s at the same scale, which is significantly lower than that of the complex network model without divide and conquer and the GAT method. The reason is that the divide and conquer algorithm divides the complete network into multiple sub-networks, searches paths in the local scope, and then completes the global fusion through the bridge node, which avoids the repeated comparison of all candidate paths.

Table 4: Results of ablation experiments for different combinations of modules

Model Configuration	Coverage (%)	Click Conversion Rate (%)	NDCG@10 (%)	Resource Utilization (%)
Basic behavioral features	84.2	6.1	69.5	75.8
+ User behavior sequence modeling	88.5	7.0	74.6	81.3
+ Attention weighting mechanism	91.0	7.7	79.2	86.4
+ Complex network path evaluation	93.2	8.3	82.6	90.1
+ Divide-and-conquer subpath search	95.1	8.9	85.7	93.8

Table 4 shows that with the gradual addition of user behavior sequence modeling, attention weighting mechanism, complex network path evaluation and divide and conquer sub-path search, the model shows stable improvement in coverage rate, click conversion rate, NDCG@10 and resource utilization rate. Among them, the resource utilization rate increased from 90.1% to 93.8% after the addition of divide and conquer sub-path search, indicating that this module can reduce repeated access and inefficient communication links, and has a direct effect on improving the efficiency of marketing resource allocation.

4.2 Discussion

The experimental results show that the complex network propagation path optimization model proposed in this paper is superior to the comparison methods in terms of coverage rate, click conversion rate, NDCG@10, resource utilization rate and path calculation time, indicating that there is a good synergy between user behavior sequence modeling, key propagation feature attention weighting, complex network path evaluation and divide and conquer algorithm. User behavior sequence modeling can capture the time-dependent relationship between exposure, browsing, interaction, forwarding and purchase conversion, so that the model no longer judges user value based on a single click, but identifies stable marketing response tendencies from continuous behavior changes. The attention weighting mechanism further enhances the model's ability to distinguish key propagation signals, so that variables such as comment strength, forwarding tendency, content matching degree, community bridging ability, and historical conversion rate can be dynamically assigned weights according to actual contributions, thereby reducing the interference caused by low-quality interactions and repeated exposure.

Compared with Degree Centrality, the proposed method avoids the problem of excessive concentration of dissemination resources on highly connected nodes. Compared with DeepFM, the model complements the user relationship network and propagation path structure. Compared with GAT, divide and conquer reduces the search overhead in large-scale networks. Compared with the complex network model without divide-and-conquer strategy, the proposed method can significantly shorten the path calculation time while maintaining high propagation revenue. This shows that the maximization of new media marketing effect cannot only rely on user response prediction, but also need to consider the balance between community structure, cross-layer diffusion and resource cost. It should be pointed out that the model in this paper still relies on the platform behavior log and historical transformation feedback, and the propagation path evaluation may be affected if the data has brush volume, abnormal interaction or mutation of the platform recommendation mechanism. Subsequent research can further introduce real-time feedback correction, abnormal traffic detection and multi-platform migration verification mechanisms, so that the model can maintain stability and interpretability in more complex new media marketing environments.

5 Conclusion

Focusing on the problem of maximization of new media marketing effect, this paper constructs an intelligent decision-making method combining complex network propagation path optimization and divide-and-conquer algorithm. In this study, user behavior logs, content features, interaction relationships and conversion feedback are integrated into a unified analysis framework. Through data cleaning, behavior sequence sorting and marketing communication feature extraction, a structured input that can be used for model training and path search is formed. In terms of method design, user behavior sequence modeling is used to describe the dynamic relationship between exposure, browsing, interaction, forwarding and conversion, the key communication feature attention weighting mechanism is used to identify the core variables that affect marketing diffusion and conversion, and the complex network path evaluation comprehensively considers node response potential, content matching degree, community diffusion ability and communication cost. The divide-and-conquer algorithm further divides the large-scale propagation network into multiple sub-networks, and generates a globally optimized path on the basis of local path search and cross-community bridge fusion, thereby reducing the computational complexity and improving the quality of path coverage. Experimental results show that the proposed method performs better in terms of coverage, click conversion rate, NDCG@10, resource utilization and path calculation time. Among them, the coverage rate reached 95.1%, the click conversion rate reached 8.9%, NDCG@10 reached 85.7%, and the resource utilization rate reached 93.8%. Under the comparative experimental conditions set in Table 3, The average search time is 13.6 s, which is better than Degree Centrality, DeepFM, GAT and complex network models without divide and conquer strategy. The above results show that complex network structure and divide-and-conquer search mechanism can effectively improve the accuracy, stability and computational efficiency of new media marketing communication path. This study can provide method reference for brand content delivery, user hierarchical reach, cross-community communication organization and intelligent marketing path recommendation. There are still some limitations in this paper, mainly reflected in the experimental data relies on historical platform logs, and the adaptability of the model to real-time hotspot changes, abnormal traffic interference and platform recommendation mechanism adjustment still needs to be enhanced. Future research can introduce real-time feedback correction, multi-platform transfer learning and lightweight path search mechanism to further improve the generalization ability and application value of the model in complex new media marketing environment.

Author's Profile

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