



Monte Carlo simulation measurement of Leshan tourism brand communication in the field of new media

Yuxin Li^{1,*}, Shu Wang¹ and Lifan Peng²

¹ Internet and new media, The Engineering&Technical College of Chengdu University of Technology, Leshan City, Sichuan Province, 614000, China

² COMAC Software Co. Chengdu, Sichuan Province, 610000, China

SUMMARY: *This paper proposes a Monte Carlo simulation framework for measuring Leshan tourism brand communication in the new media environment. Firstly, a heterogeneous dataset containing 126,400 records of short video interactions, social posts, topic propagation trajectories, click behaviors and destination search logs is vectorized. Then, a graph-based state transition model is constructed to describe the user's cross-platform exposure, interaction, forwarding and conversion process. On this basis, 50,000 random simulations are carried out to estimate the transmission reach rate, participation probability, path depth and transition interval under different media scenarios, and relatively stable statistical results are formed. Experimental results show that the communication reach rate of the framework is 91.8%, the participation probability error is 0.036, and the interval coverage rate is 94.2%. The model also identifies the communication differences and high active periods of landscape, food, culture and activity content in different user groups, which provides a computable basis for destination brand communication evaluation, resource allocation and cultural tourism communication deployment.*

KEYWORDS: *New media communication; Leshan tourism brand; Monte Carlo simulation; Propagation graph model*

1 Introduction

With the evolution of mobile Internet platforms, short video systems and social media distribution mechanisms, tourism brand communication has shifted from one-way display to data-driven dynamic calculation. Brand information in the field of new media continues to flow along the process of publication, browsing, interaction, diffusion and access, forming a communication structure with randomness, timing and network relevance. Leshan has both landscape and regional cultural resources, and its brand communication shows the characteristics of frequent fluctuations in user feedback in the new media environment. Facing this transmission object, it is difficult to reveal the exposure intensity, interaction probability and transformation interval under different paths only by relying on static descriptions. Therefore, it is necessary to transform the transmission process into a computable and simulable graphical model, and to use stochastic simulation methods to complete quantitative measurement.

Research on data modeling and computational analysis of tourism brand communication has formed the foundation. Vinan-Ludena et al. used social media data to identify perceptual

*lyxrran@stu.hebmu.edu.cn

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features and used BERT model to realize sentiment classification, indicating that text representation learning can support brand cognition analysis [1]. Ali et al. proposed a sentiment analysis method of tourism reviews based on LDA topic extraction, which provided a path for tourism brand content understanding [2]. Mehraliyev et al. sorted out the theme evolution and method characteristics of sentiment analysis, and pointed out that deep learning and multi-source data fusion promoted tourism perception research to a more refined calculation stage [3]. Khadka et al. studied the influence of social media content on tourism destination choice, indicating that platform interactive information has become an input variable in tourists' decision-making chain [4].

In terms of image understanding and communication response analysis, Diaz-Pacheco et al. quantitatively compared the differences between user-generated content and official marketing images on Instagram, and proved that the visual content structure would affect the consistency and attractiveness of brand expression [5]. Guerrero-Rodriguez et al. proposed a destination image mining method based on online news big data and deep learning, which expanded the scope of cross-platform semantic computing [6]. Paradise Vit et al. used deep learning and active learning methods to complete automatic image screening, indicating that visual sample filtering and content classification can be used as a data preprocessing link for tourism brands [7]. Blanco-Moreno et al. analyzed the interaction mechanism of Instagram tourist destination posts, which provided a basis for node response estimation in the propagation path [8].

For the simulation study of communication process, Deng et al. constructed an agent simulation mechanism of destination brand diffusion to show the dynamic evolution characteristics of brand communication in a multi-agent interactive environment [9]. Hu et al. studied terrain perception of tourism destinations based on multimodal user-generated content, indicating that heterogeneous information fusion is helpful to improve the expression accuracy of tourism brand image recognition [10]. Existing results have covered text analysis, image recognition, interaction measurement and diffusion simulation, but for the probability propagation measurement of specific city tourism brands in the new media field, it is still necessary to put content features, user behavior, platform links and state transition into a unified computing framework.

Based on this, the research object is set as the communication activities of Leshan tourism brand in the new media field, and the technical path is established on the feature extraction of communication samples, vector representation, graph model construction, parameter estimation and Monte Carlo simulation. Dissemination nodes are divided into content sources, platform channels, user groups and feedback events, and the relationship between nodes is expressed by state transition. Dissemination probability, stay probability, forwarding probability and conversion probability are jointly determined by sample statistics and parameter estimation. On this basis, the coverage level, interaction intensity and conversion interval under different communication scenarios are measured by random sampling and iterative simulation, which provides a basis for the application decision and implementation deployment of Leshan tourism brand communication evaluation.

2 Literature Review

2.1 Research on new media tourism brand communication

Driven by platform computing, semantic analysis and communication link modeling, new media tourism brand communication research has shifted from traditional publicity effect description to the computational research stage with data representation, behavior recognition and dynamic deduction as the core. The presentation of tourism brands on short video platforms,

social media communities and content aggregation terminals is no longer just a static collection of images and texts, but a heterogeneous information flow composed of text, images, location tags, interaction logs and forwarding traces. In this process, computer technology undertakes the tasks of sample collection, feature coding, emotion recognition, communication modeling and result visualization, so that brand communication can be transformed from empirical judgment to measurable and verifiable analysis objects.

Recent studies have shown that the organization of communication content, the depth of user interaction and the intensity of cross-platform flow have a direct impact on the perception formation and diffusion efficiency of tourism brands. Yang et al. conducted research on mining and visualization of tourism cultural imagery, proposed an analysis framework based on the information transmission model of tourism culture map, and took Nanjing Xuanwu Lake Scenic Spot as an example to complete the structured expression of cultural image, indicating that the transmission path and cultural nodes can be clearly represented through spatial information calculation [11]. Charfaoui et al. introduced machine learning methods into tourism sentiment analysis and extracted tourism insights through classification calculation of review samples, indicating that emotional signals have become key variables in brand communication evaluation [12]. Nawawi et al. used the aspect-level sentiment analysis method based on zero-sample learning to process online reviews, refined the semantic differences of tourist experience in different service dimensions, and provided support for the refined identification of tourism brand content [13].

Zakarija et al. built a sentiment analysis model based on the user experience data of Dubrovnik on the Tripadvisor platform, showing the high explanatory degree of platform reviews in the modeling of destination brand cognition [14]. Roumeliotis et al. compared the performance of GPT Omni model and BERT natural language processing model in tourism review classification and sentiment analysis, further indicating that large language models are promoting tourism brand communication research into the calculation stage with stronger semantic understanding and higher automation [15]. These results promoted the research of new media tourism brand communication from content observation to model expression, and also provided a connectable data basis, semantic basis and computational basis for Monte Carlo simulation calculation of Leshan tourism brand communication.

For the study of communication in urban destinations, the above methods also suggest that brand communication is not the accumulation of single point of exposure, but a network process of node activity, semantic consistency and user migration probability. Therefore, the computational model is more suitable for the unified description of Leshan tourism brand communication in the new media field, and provides a stable input for subsequent stochastic simulation and parameter estimation.

2.2 Monte Carlo simulation and propagation calculation research

In recent years, the research of Monte Carlo simulation and propagation computation has been continuously refined in tourism information analysis. The research focus is no longer limited to random experiment itself, but to integrate user contact, interactive diffusion and transformation feedback into the computable link through probabilistic modeling, state update and iterative solution. For tourism brand communication in the new media field, the content of communication shows the characteristics of high frequency jump, heterogeneous coupling and time series fluctuation between platforms, and it is difficult to describe the dynamic evolution of communication popularity and reach range only relying on static statistics. Therefore, stochastic simulation methods have begun to be used together with text calculation, graph structure expression and behavior prediction. Related development shows that the propagation calculation has shifted from single index estimation to multivariate collaborative deduction, and

the model output has also been extended from average judgment to more explanatory results such as interval distribution, probability coverage and path depth.

As shown in Figure 1, the role of Monte Carlo methods in propagation computation is not sampling in isolation, but is tightly integrated with feature representation and graph model inference. The propagation samples are first transformed into computable vector representations, and then written into the nodes and edges of the propagation graph, and then the probability update and path diffusion are completed through the state transition relationship. The above processing method makes the propagation calculation transfer from static result judgment to dynamic process deduction, and also provides a stable basis for subsequent probability interval calculation.

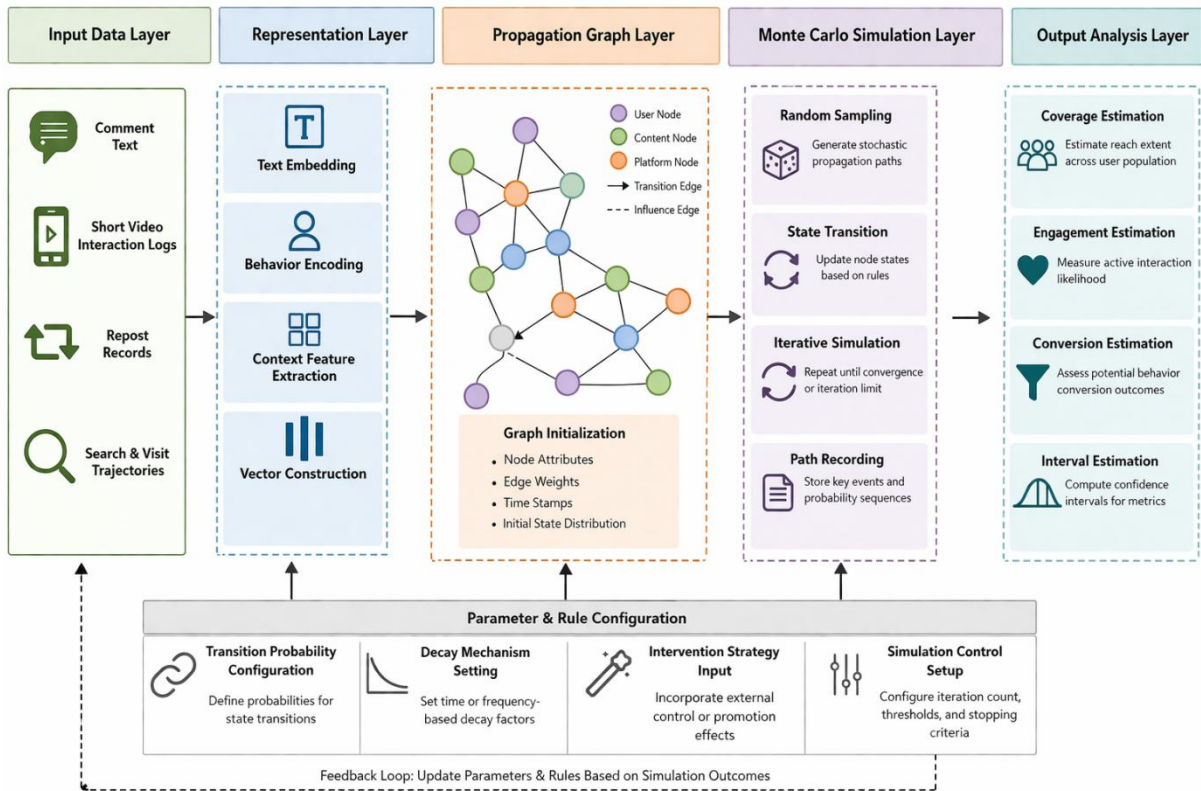


Figure 1: Flowchart of Monte Carlo propagation computation

Related research has provided strong support for the prediction of communication results and the calculation of new media impact. Zhang et al. introduced online reviews into hotel demand forecasting and proposed a prediction method driven by deep learning, indicating that a stable mapping relationship can be established between review sequence and behavioral response [16]. Hussain et al. studied the attraction effect of social media content on tourists' travel decisions and pointed out that there was a quantifiable correlation between interactive content and actual travel behavior [17]. Keelson et al. analyzed the driving force of social media and its influence on tourism destination choice, and proposed that user satisfaction mechanism and content reception mechanism jointly shape decision-making tendency [18]. Cardoso et al. used deep learning models to classify social media image content and proved that computational recognition of visual samples could serve cultural and landscape value evaluation [19]. Dennis et al. proposed the Markov chain expression of information diffusion in social networks, which provided a clearer mathematical structure for the probability description of propagation state transition [20].

In order to further sort out the technical path and reference content of related research, Table 1 shows the related research results of Monte Carlo simulation and propagation calculation.

Table 1: Results of studies related to Monte Carlo simulations and propagation calculations

Author	Research Content	Computational Method	Result Performance	Implications for This Study
Zhang et al. [16]	Hotel demand forecasting	Deep learning and review sequence modeling	Established the mapping between reviews and demand response	Dissemination reviews can be used as input variables for estimation
Hussain et al. [17]	Social media content attracting tourist travel	Content-behavior association analysis	There is a quantifiable relationship between interactive content and travel behavior	Dissemination interaction can be incorporated into conversion probability modeling
Keelson et al. [18]	Influence of social media on destination choice	Decision-driven analysis	Satisfaction mechanisms and content reception jointly affect decision-making	User reception states are suitable for inclusion in the state transition pathway
Cardoso et al. [19]	Social media image classification	Deep learning-based visual recognition	Image content can support cultural and landscape evaluation	Visual content can be incorporated into dissemination feature encoding
Dennis et al. [20]	Information diffusion representation in social networks	Markov chain modeling	Provided the probabilistic structure of diffusion states	Provides a mathematical basis for state transition in the dissemination graph model

Based on the existing research foundation, the value of Monte Carlo simulation in the measurement of Leshan tourism brand communication is mainly reflected in two aspects. On the one hand, Monte Carlo simulation can reconstruct the communication trajectory under different content combinations, platform channels and user groups through large-scale random sampling. On the other hand, Monte Carlo simulation can form the joint estimation of coverage interval, reaching probability and transition boundary on the state transition diagram model, which makes the propagation measurement transform from single-point judgment to continuous expression in probability space, and provides a consistent calculation basis for the result analysis and stability verification in the subsequent experimental evaluation. At the specific application level, the computational framework can also accommodate parameters such as time attenuation, platform weight difference and user re-propagation tendency, so that Leshan tourism brands can form comparable simulation outputs under different themes such as scenic landscapes, cultural symbols, food content and festival activities. Therefore, Monte Carlo communication calculation is not only an algorithm tool, but also an important interface for the research of new media tourism brand communication from descriptive analysis to quantitative deduction. The technical path is consistent with the subsequent graph model construction and

parameter estimation of this paper, so as to make the measurement results of Leshan tourism brand communication more interpretable and comparable.

3 Construction of Leshan tourism brand communication model in the field of new media

3.1 Feature extraction and vector representation of new media communication samples

The feature extraction and vector representation of new media communication samples are the basic link of the computational expression of Leshan tourism brand communication model. The short video title, comment text, retweet description, stay time, like record, geo-tag and release time together constitute a heterogeneous sample set. Due to the inconsistent field forms and statistical scales on different platforms, the original data cannot be directly entered into the propagation graph model, so it is necessary to complete unified coding, feature compression and vector mapping. In this paper, the propagation samples are divided into four categories: text features, behavior features, temporal features and spatial features, and a unified vector is formed by fusing the representation, which provides stable input for subsequent state transition calculation and parameter estimation.

In the text part, word segmentation, denoising and context coding strategies were used to retain high-frequency words such as scenic spot names, cultural symbols, food themes, and activity labels as core semantic units. The behavior part records browsing, liking, commenting, bookmarking, forwarding and other actions, so as to describe the user's response intensity to brand information. The time series part retained the release time, peak access period and attenuation window to reflect the evolution trajectory of the propagation heat. The spatial part describes the diffusion scope of Leshan tourism brand in different urban agglomerations by combining positioning labels and source regions.

In order to avoid the semantic drift caused by the platform field differences directly entering the subsequent graph model, the text samples are firstly vectorized according to the term weight as follows:

$$x_i = \frac{\sum_{k=1}^m \text{tfidf}_{ik} e_k}{\sum_{k=1}^m \text{tfidf}_{ik}} \quad (1)$$

Here, x_i represents the text vector of the i propagation sample, tfidf_{ik} represents the weight of term k in sample i , e_k represents the term embedding, and m represents the number of effective terms in the sample. This formula is used to compress comments, titles and hashtags into the same dimensional semantic representation, so that the name of scenic spots, cultural imagery and consumption words retain relative strength in a unified space.

After completing the construction of the basic word vector, the user interaction intensity needs to enter the unified feature space through behavior normalization and form the measurement expression structure process:

$$b_i = \sigma(\alpha_1 l_i + \alpha_2 c_i + \alpha_3 s_i + \alpha_4 f_i) \quad (2)$$

Here, b_i represents the behavior intensity vector of sample i ; l_i , c_i , s_i , f_i represent the number of likes, comments, retweet and favorites, respectively; α_1 to α_4 represent the action weights; and σ represents the normalized activation function. This formula converts discrete interactive actions into continuous values, so that behavior records in different platforms enter

the subsequent propagation link calculation, and retains the difference in interaction depth.

Considering that the propagation heat continues to change with the release time and interaction density, the dynamic weighted expression process of time series features needs to be completed by the time decay function as follows:

$$\tau_i = e^{-\lambda \Delta t_i} (1 + \beta \ln(1 + h_i)) \quad (3)$$

Here, τ_i represents the timing weight of sample i , Δt_i represents the time interval between the current moment and the release time, λ represents the attenuation coefficient, h_i represents the historical interaction amount in a unit time window, and β represents the interaction compensation coefficient. This formula is used to describe the double changes of the propagation heat decreasing with time and rising with short-term interaction, so that the hot content and the regular content form a distinguishing representation in the time series dimension.

The spatial source and the regional visiting intention jointly determine the propagation extension boundary, so the regional characteristics need to be encoded probabilistically with the help of the location distribution function as follows:

$$g_{ir} = \frac{\exp(-\eta d_{ir})}{\sum_{r=1}^R \exp(-\eta d_{ir})} \quad (4)$$

Here, g_{ir} represents the spatial distribution value of sample i on region r , d_{ir} represents the distance or similarity between the sample source location and region r , η represents the distance attenuation coefficient, and R represents the total number of regions. This formula is used to transform the positioning label, publishing location and attention source into regional probability distribution, so that the propagation extension of Leshan tourism brand in different urban agglomerations can be quantitatively expressed.

After the multi-source fields enter the same calculation framework, the final sample representation needs to complete the unified vector space projection construction process through the modal fusion function as follows:

$$z_i = \text{ReLU}(W_t x_i + W_b b_i + W_\tau \tau_i + W_g g_i + b) \quad (5)$$

where z_i represents the final fusion vector of sample i , W_t , W_b , W_τ , W_g represent the mapping matrices of text, behavior, temporal and spatial features respectively, b is the bias term, and ReLU represents the nonlinear activation function. This formula projected the multi-source features into a unified vector space, provided stable input for the initialization of node attributes in the subsequent propagation graph, and reduced the scale deviation between fields.

After the above processing, the new media communication samples are transformed from discrete records into structured vectors that can participate in graph calculation. The unified representation of samples not only retains the properties of topic semantics, interaction strength, time evolution and spatial diffusion, but also reduces the interference of platform field differences on the calculation of propagation links. Therefore, the content flow of Leshan tourism brand in different platforms can be put into the same feature space for comparison, which provides a consistent data basis for propagation graph modeling, state transition construction and parameter estimation in the next section.

3.2 State transition construction and parameter estimation of Leshan tourism brand communication graph model

The nodes in the communication graph are composed of brand content, platform entry, user

group and feedback event, and the edges represent the relationship between browsing trigger, comment follow-up, forwarding diffusion, search reflux and visit conversion. Different from ordinary social graph, Leshan tourism brand communication graph not only contains content similarity and behavior correlation, but also needs to reflect the collaborative communication between scenic symbols, cultural themes, food topics and city images. Therefore, both node attributes and edge weights must retain semantic information and probability information at the same time. In this paper, the weighted directed graph is used to express the propagation link in the graph structure construction stage, and the interaction records in the time window are written into the state transition matrix. With this treatment, the propagation path is no longer an empirical description, but a probabilistic network that can be iteratively deduced in a computational framework. In the parameter estimation stage, the joint solution is completed according to the sample observation frequency, node activity, platform attenuation coefficient and re-propagation tendency, so that the graph model can not only express the current propagation state, but also provide callable initial conditions for subsequent Monte Carlo simulations.

After the unified vector representation of the samples is completed, the edge strength between the propagation nodes needs to be weighted by the similarity function. The definition process is shown in the following formula:

$$a_{ij} = \mu \cos(z_i, z_j) + v \frac{\mathbf{b}_i^\top \mathbf{b}_j}{\|\mathbf{b}_i\| \|\mathbf{b}_j\|} + \xi e^{-|\Delta t_{ij}|} \quad (6)$$

Here, a_{ij} represents the edge strength from node i to node j , \cos represents the cosine similarity, Δt_{ij} represents the time interval when two nodes interact, μ , v , ξ represent the weight of each item. In this formula, the semantic proximity, behavioral relevance and temporal proximity are compressed into a unified edge weight, so that the propagation graph can reflect the content fit and the real interaction association in the platform at the same time.

After the node edge is determined, the transition probability of a single node in adjacent nodes needs to be formed according to the normalization constraint to form an iterative expression. The calculation process is as follows:

$$p_{ij}^{(t)} = \frac{\exp(a_{ij} + q_j)}{\sum_{k \in N(i)} \exp(a_{ik} + q_k)} \quad (7)$$

Here, $p_{ij}^{(t)}$ represents the transition probability from node i to node j at time t , $N(i)$ represents the adjacency set of node i , and q_j represents the receive bias term of node j . This formula ensures that each round of propagation transfer satisfies the probability constraint through normalization, and writes the platform recommendation strength and user receiving tendency into the transfer process together.

To illustrate how the propagation graph model is organized, the state transition network structure shown in Figure 2 is constructed. The top layer is the content node layer, which is used to represent the brand information sources such as landscape theme, culture theme, food theme and activity theme. The second layer is the platform node layer, which is used to represent the propagation channels such as short video entry, comment feedback, forwarding diffusion and search backflow. The third layer is the user node layer, which is used to distinguish the receiving objects such as local users, provincial tourists, cross-provincial tourists and potential visiting groups. The bottom layer is the result node layer, which is used to output the exposure state, participation state and transformation state. In the figure, the vertical arrow line represents

the main propagation path of brand information among content, platform, users and results, and the oblique line represents the complementary effect of comment feedback and search return flow on user re-dissemination and re-engagement. The structure shows that Leshan tourism brand communication is not a single linear diffusion, but a hierarchical transfer network involving multiple types of nodes.

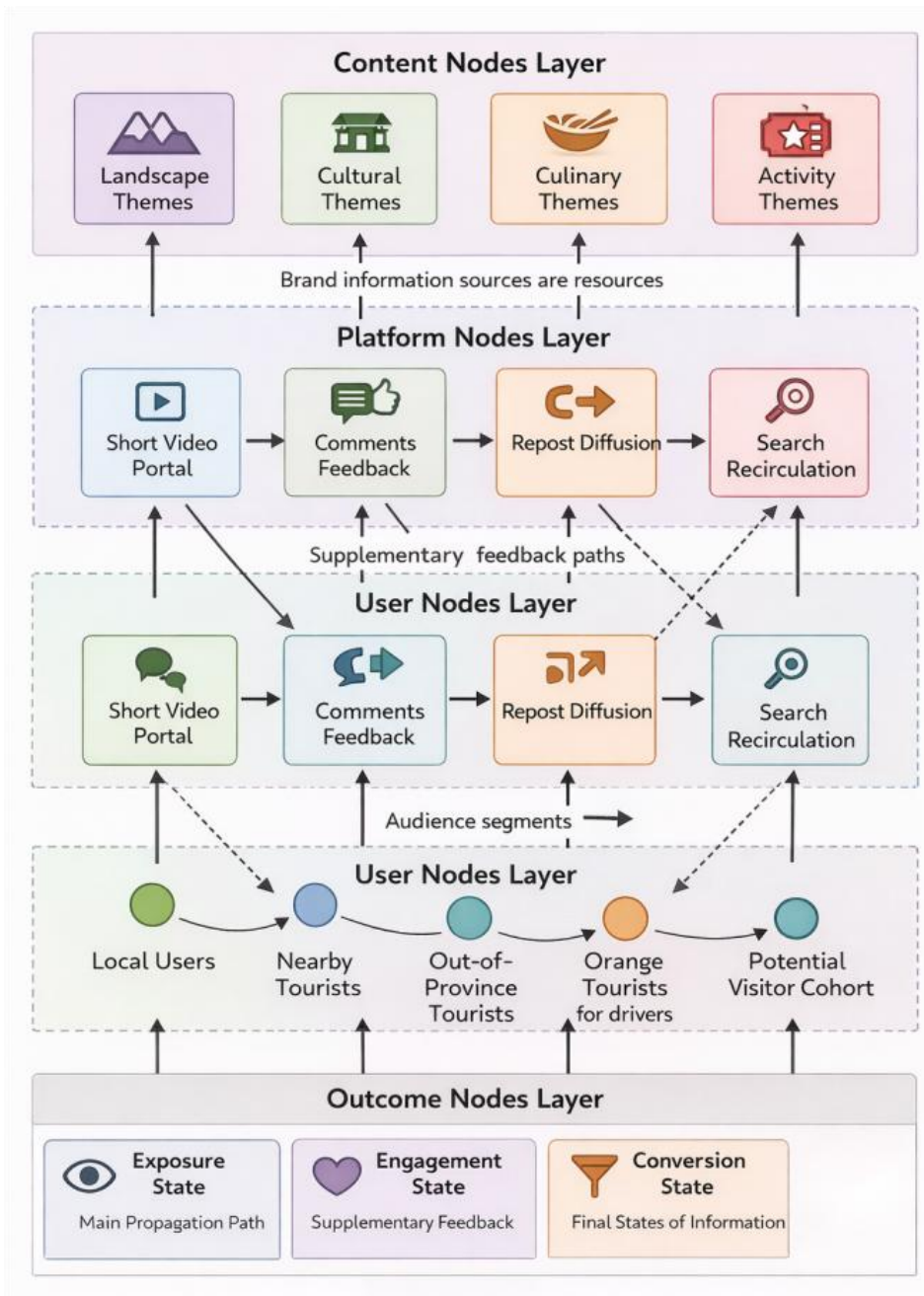


Figure 2: Schematic diagram of the state transition structure of the Leshan tourism brand communication graph model

In order to describe the continuous diffusion and decline process of the propagation heat in the time window, the node state value needs to be calculated recursively according to the update rule as shown in the following equation:

$$h_i^{(t+1)} = \gamma h_i^{(t)} + (1 - \gamma) \sum_{j \in N(i)} p_{ji}^{(t)} h_j^{(t)} + u_i^{(t)} \quad (8)$$

Here, $h_i^{(t+1)}$ represents the propagation state value of node i at the next time step, γ represents the state retention coefficient, $p_{ji}^{(t)}$ represents the transition probability from adjacent node j to node i , and $u_i^{(t)}$ represents the external exposure increment. This equation is used to describe the recursive change of propagation heat in the graph network, so that the single round of exposure, continuous interaction and re-diffusion can be accumulated in the same update equation.

After the propagation graph model enters the parameter solving stage, the state transition matrix needs to be jointly estimated through the objective function with constraints. The calculation process is as follows:

$$L(\Theta) = - \sum_t \sum_{i,j} y_{ij}^{(t)} \log p_{ij}^{(t)} + \lambda \|\Theta\|_2^2 + \omega \sum_i \left| \sum_j p_{ij}^{(t)} - 1 \right| \quad (9)$$

Here, $L(\Theta)$ represents the parameter estimation objective function, $y_{ij}^{(t)}$ represents the observed true transition labeling, $p_{ij}^{(t)}$ represents the model-estimated transition probability, $\|\Theta\|_2^2$ represents the parameter regularization term, and ω represents the smoothness constraint weight. The parameters of the equation are solved by joint optimization of the likelihood term and the constraint term, so that the propagation map can fit the real sample while maintaining structural stability and numerical controllability.

In order to weaken the disturbance effect of extreme samples on the transfer results, the propagation parameters need to be calibrated and updated by means of prior smoothing, as shown in the following equation:

$$\hat{p}_{ij} = \frac{n_{ij} + \alpha}{\sum_{k \in N(i)} n_{ik} + \alpha |N(i)|} \quad (10)$$

Here, \hat{p}_{ij} denotes the smoothed transition probability, n_{ij} denotes the number of observed transitions from node i to node j , α denotes the prior strength, and $|N(i)|$ denotes the adjacency size of node i . This formula reduces the interference of sparse samples on parameter estimation by prior smoothing, so that low-frequency nodes and high-frequency nodes can maintain more stable transfer expression in the same matrix.

After the state transition construction and parameter estimation, the Leshan tourism brand communication graph model has a computable, updatable and simulable network form. Node attributes describe the distribution state of brand content in different platforms and user groups, while edge weight and transition probability reflect the diffusion intensity, reflux probability and conversion tendency in the transmission link. The graph model thus established can not only express the current propagation structure, but also serve as the basic framework of Monte Carlo random sampling and iterative simulation in the next chapter, so that the measurement of propagation coverage, interaction strength and transformation interval can be established in a unified probabilistic network.

4 Measurement of Leshan tourism brand communication based on Monte Carlo simulation

4.1 Random sampling and iterative simulation of the communication process of Leshan tourism brand

The random sampling and iterative simulation of the communication process of Leshan tourism brand are the key steps to transform the communication graph model constructed in the previous section into an executable calculation process. The communication trajectory in the field of new media is not a fixed link, but a dynamic network formed by content attraction, platform distribution, user reception and re-transmission. To this end, this paper introduces Monte Carlo simulation mechanism on the basis of state transition matrix, and conducts multiple rounds of sampling for four types of states: exposure, participation, forwarding and conversion. Each simulation starts from a given topic content node, propagates to different user groups through the platform entry node, and then returns to the internal network to complete the state correction according to the feedback event. This process preserves the random fluctuation characteristics of new media communication, and also makes the differences in propagation depth, path length and result distribution of different topics of content clearly present.

In order to make different subject nodes form executable random emission states in the initial rounds, the starting seed probability is normalized according to the following formula.

$$\pi_i = \frac{\exp(\omega^T z_i + \rho_{g(i)} + \kappa_{p(i)})}{\sum_{j \in V_c} \exp(\omega^T z_j + \rho_{g(j)} + \kappa_{p(j)})} \quad (11)$$

Here, π_i represents the probability that content node i is selected as the starting seed, ω represents the feature weight vector, $\rho_{g(i)}$ represents the topic category bias term, $\kappa_{p(i)}$ represents the platform entry bias term, and V_c represents the set of candidate content nodes. This formula is used to write the content semantic strength, topic heat and platform distribution ability into the initial sampling probability, so that the landscape, food, culture and activity content form a differentiated starting point in the first round of diffusion.

After the random seed is determined, whether the node activates the propagation state in a certain round needs to complete the state sampling process by the probability trigger function as follows:

$$x_i^{(t+1)} = \mathbb{I} \left(u_i^{(t)} < 1 - \prod_{j \in N^-(i)} (1 - p_{ji}^{(t)} x_j^{(t)}) \right) \quad (12)$$

where $x_i^{(t+1)}$ represents whether node i is activated at time $t + 1$, $\mathbb{I}(\cdot)$ represents the indicator function, $u_i^{(t)}$ represents a random variable that follows uniform distribution, $N^-(i)$ represents the incoming adjacency set of node i , and $p_{ji}^{(t)}$ represents the transition probability from node j to node i . This formula is used to decide whether the current node enters the state of exposure, participation or forwarding according to the propagation influence of neighboring nodes and random sampling results, so as to write discrete events into the iterative link.

After the random sampling is completed, the system enters the iterative propagation phase. In each iteration, the propagation path is resampled according to the node state value, edge transition probability and external disturbance strength. If a user group triggers comment

feedback or forwarding diffusion in the current round, the related events will be written back to the propagation graph, and the exposure probability of adjacent nodes in the next round will be increased. If a content node does not get effective interaction within a continuous time window, the corresponding propagation path will decay and the weight will decrease synchronously. This mechanism makes the dissemination process not only retain the continuous diffusion of hot content, but also reflect the decline of common content in the platform. For Leshan tourism brand, Emei Mountain landscape content has a higher trigger rate in image-driven communication, local food content shows a longer path length in comment interaction and secondary sharing, and festival activity content is easier to form a concentrated outbreak in a short window.

In order to measure the cumulative influence strength generated by the propagation links in each round of simulation, the network propagation gain is defined in a weighted aggregation manner as follows.

$$G^{(t)} = \sum_{i \in V_u} \sum_{j \in N(i)} x_i^{(t)} p_{ij}^{(t)} (\theta_1 r_j + \theta_2 c_j + \theta_3 s_j) \quad (13)$$

where $G^{(t)}$ represents the propagation gain value in round t , V_u represents the set of user nodes, r_j , c_j and s_j represent the exposure response, comment response and forwarding response of node j in the current round respectively, and θ_1 to θ_3 represent the response weight. This formula is used to compress the multi-class propagation responses in a single round simulation into a unified gain index, so that the differences in propagation strength of different topic contents can be directly compared.

To illustrate the execution link between random sampling and iterative simulation, the computational process structure shown in Figure 3 is constructed. The top layer is the theme content initialization layer, which is used to set different content sources such as landscape, culture, food and activity. The second layer is the initial seed sampling layer, which is used to generate the first round of propagation nodes according to the platform bias and user threshold. The third layer is the propagation iteration layer, which is used to execute state triggering, probability transition and feedback writeback. The fourth layer is the result update layer, which is used to accumulate the exposure, participation and transformation results, and send the updated state back to the iterative process. The looped arrow line in the figure indicates that the simulation is not executed in a single round, but in a cyclic propagation process with state corrections.

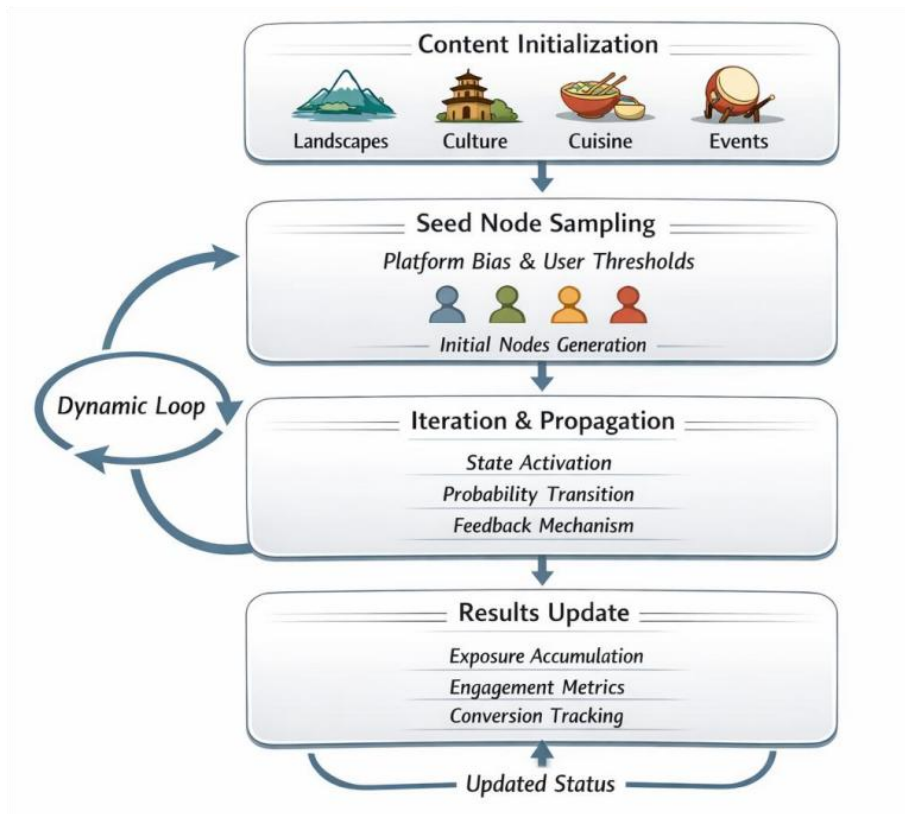


Figure 3: Flow chart of random sampling and iterative simulation of tourism brand communication in Leshan

In order to ensure that the simulation process converges and forms a stable output within a finite number of rounds, the stopping rule is defined according to the difference between adjacent rounds as follows.

$$\Delta^{(t)} = \frac{|G^{(t)} - G^{(t-1)}|}{\max(G^{(t-1)}, \epsilon)} \tag{14}$$

Here, $\Delta^{(t)}$ represents the relative difference between the propagation gain of round t and round $t - 1$, $G^{(t)}$ represents the propagation gain of the current round, and ϵ represents the tiny constant that prevents the denominator from being zero. When $\Delta^{(t)}$ of several successive rounds is lower than the set threshold, the simulation process stops and the final result is output. This formula is used to control the computational stability of the stochastic simulation and avoid the waste of resources caused by invalid iterations.

Monte Carlo simulation is to use repeated sampling and iteration to show these random propagation differences stably. Under the uniform number of sampling rounds and stopping rules, the simulation output can maintain computational stability, and provide a consistent data source basis for the result analysis.

4.2 Interval estimation and probability measurement of Leshan tourism brand communication results

In the interval estimation stage, the coverage and participation rate samples obtained from repeated simulations are first statistically summarized in this paper. Each type of output index consists of a large number of independent simulation rounds, so the propagation results can be

regarded as a set of conditional samples. For four types of topics, landscape content, cultural content, food content and activity content, the system calculates the sample mean and fluctuation scale respectively, and then generates confidence intervals based on the estimation results. The advantage of the interval representation is that it can present both the propagation central trend and the uncertainty amplitude. If the mean value of a certain type of content is high and the interval is narrow, it means that the transmission performance is not only strong, but also stable. If the mean is high but the interval is wide, it indicates that the propagation process is more sensitive to the platform entry or the user group structure. For Leshan tourism brand, cultural theme content often forms a relatively stable participation range among provincial tourist groups, while landscape theme content shows a wider exposure fluctuation range among cross-provincial users.

In order to obtain the central position of the propagation index from multiple rounds of simulation samples, the sample mean of coverage or participation results is defined as the following calculation process:

$$\bar{y} = \frac{1}{N} \sum_{r=1}^N y_r \quad (15)$$

Here, \bar{y} represents the sample mean of a certain propagation index in N rounds of simulation, y_r represents the output result of the r round of simulation, and N represents the total number of simulation rounds. This equation is used to give a central estimate of coverage, engagement or conversion rates, enabling direct comparison of different thematic content on the same statistical scale.

In order to further characterize the dispersion degree of the repeated simulation results around the mean, the sample fluctuation scale is represented by the following variance estimation method:

$$s^2 = \frac{1}{N-1} \sum_{r=1}^N (q_r - \bar{q})^2 \quad (16)$$

Here, s^2 represents the sample variance, q_r represents the simulation result of the r round, and \bar{q} represents the sample mean. This formula is used to describe the fluctuation intensity of the propagation output, so that researchers can distinguish the propagation topics with similar mean but different stability, and provide the necessary scale for the subsequent interval boundary calculation.

After the mean and variance estimation is completed, the confidence interval bounds for the propagation metrics need to be further generated depending on the sample size as follows:

$$CI_{1-\alpha} = \left[\bar{y} - z_{1-\alpha/2} \frac{s}{\sqrt{N}}, \bar{y} + z_{1-\alpha/2} \frac{s}{\sqrt{N}} \right] \quad (17)$$

Here, $CI_{1-\alpha}$ represents the result of interval estimation with confidence level $1 - \alpha$, $z_{1-\alpha/2}$ represents the corresponding quantile value of the standard normal distribution, and s represents the sample standard deviation. This formula is used to give the credible boundary of the communication index on both sides of the mean value, so that the Leshan tourism brand communication result can be transformed into an interpretable interval from a single point output.

In order to calculate the realization chance of a certain communication index reaching the

preset target value, the probability of reaching the target is calculated according to the following frequency method:

$$P(y \geq \delta) = \frac{1}{N} \sum_{r=1}^N \mathbb{I}(y_r \geq \delta) \quad (18)$$

Here, $P(y \geq \delta)$ represents the probability that the index y reaches the threshold δ , and $\mathbb{I}(\cdot)$ represents the indicator function. This formula is used to measure the chance of coverage, engagement or conversion rate to reach the established target, and provides a direct probability basis for content delivery decisions.

In the case of the existence of multiple communication goals, the unified expression process of the joint attainment degree needs to be completed by the comprehensive probability score as follows:

$$S = \lambda_1 P(c \geq \delta_c) + \lambda_2 P(e \geq \delta_e) + \lambda_3 P(v \geq \delta_v) \quad (19)$$

Here, S represents the comprehensive transmission target score, $P(c \geq \delta_c)$, $P(e \geq \delta_e)$, $P(v \geq \delta_v)$ represent the probability of reaching the target value of coverage rate, participation rate, and conversion rate, respectively, and λ_1 to λ_3 represent the weight coefficients. This formula is used to compress the multi-index probability results into a unified score, so that the communication performance of different topics and different platform entries can be comprehensively compared.

After the interval estimation and probability measurement are completed, the propagation results obtain stronger explanatory power. The output can not only show the average performance of the content over multiple simulation rounds, but also illustrate the propagation boundaries, tail fluctuations, and reaching opportunities. For the subsequent experimental analysis, this expression can unify the communication differences of landscape, food, culture and activity content into a comparable framework. More importantly, the joint output of interval and probability can reduce the judgment bias caused by the single result fluctuation, so that the evaluation of Leshan tourism brand communication is established on the common basis of repeated simulation and statistical summary. Under the unified calculation scale, the coverage interval, participation probability and transformation boundary can be output synchronously. The calculation results not only serve the evaluation of communication effect, but also provide a verifiable basis for the placement configuration of Leshan tourism brand in different themes and different media scenarios. Therefore, the propagation calculation results have clearer statistical meaning and application value, and form the basic support force.

5 Experimental Evaluation

5.1 Experimental Design

The experimental design in this section focuses on the communication measurement of Leshan tourism brand in the field of new media, aiming to verify the effectiveness and stability of the communication graph model and Monte Carlo simulation framework constructed in the previous section in the communication reach rate, interaction estimation and transformation judgment. The experimental data comes from short video interaction, social media content, tourism review information, topic diffusion trajectory, click behavior records and destination search logs. The collection time covers 12 consecutive months, and a total of 126,400 original samples such as comment texts, likes records, forwarding records, collection records, search

visits and geographical sources are collected.

In order to ensure data computability, the experimental phase firstly completed deduplication, denoising, time alignment, topic labeling and field normalization, and then constructed a sample set according to four types of communication topics: landscape, culture, food and activity. The training set, validation set and test set are divided into 7 : 1 : 2, and the distribution is consistent in the user layer and the platform layer. The experimental environment was deployed in Python and PyTorch framework, the graph calculation module ran under the condition of a single GPU card, the simulation rounds were set to 50000, the maximum propagation step size of a single round was set to 12, and the state convergence threshold was set to 0.001.

In order to test the explanatory power of the model output, the experiment set up five indicators: transmission reach rate, participation rate, conversion rate, path depth and interval coverage rate. At the same time, the random walk model was introduced as a comparison with the static proportion estimation method. All experiments were repeated five times under the same sample and the same initialization conditions, and the mean and variance were recorded to ensure the repeatability and statistical reliability of the measurement results.

In terms of scene Settings, the experiment constructs four scenarios of high heat transmission of festivals, normal scenic spot communication, catering topic communication and cross-platform linkage communication, respectively, to observe the communication differences under different themes and different entrance conditions. The parameters are initialized according to the statistical results of historical samples, the user acceptance threshold is dynamically adjusted according to the group type, and the platform weight is set according to the proportion of real traffic. Through this experimental design, the random fluctuation, local amplification and reflux reach of Leshan tourism brand communication can be stably described in the unified computing framework. The experimental output will directly serve the results analysis, comparative verification and interval measurement of the subsequent stage, and provide quantitative basis and implementation reference for the adjustment of dissemination configuration.

5.2 Analysis of measurement results of Leshan tourism brand communication

After Monte Carlo simulation, Leshan tourism brand communication results show clear hierarchical differences in multiple rounds of repeated calculations. The landscape theme content kept leading in the communication reach rate, the food theme content was more active in the participation rate and the depth of secondary diffusion, the transformation interval of the culture theme content was more stable, and the activity theme content had strong explosiveness in a short window.

As shown in Figure 4, the landscape theme achieves the highest value of 0.931 in the dimension of communication reach rate, the culture theme is 0.904, the food theme is 0.889, and the activity theme is 0.876. In terms of participation rate, food topic reached 0.812, which was higher than 0.764 of landscape topic and 0.731 of culture topic, indicating that food content was easier to form continuous feedback in comment, collection and forwarding links. In the dimension of conversion rate, the cultural theme reached 0.683, slightly higher than the 0.671 of the landscape theme, indicating that the information with regional symbols and cultural interpretation was easier to complete the transfer from attention to action intention.



Figure 4: Heat map of different thematic communication indicators for Leshan tourism brands

To further analyze the relationship between propagation depth and group structure, FIG. 5 illustrates the scatter distribution of different user groups in path depth and backflow trigger strength. The scatter of the local user group is mainly concentrated in the range of path depth 3.34-3.67, reflux intensity 0.729-0.754, and the center value is about (3.50, 0.743). The tourist groups in the province mainly distributed in the range of 3.97-4.20 and 0.667-0.704, and the center value was about (4.08, 0.681). The cross-provincial tourist groups concentrated in the higher path depth range of 4.63-4.97, corresponding to the reflux intensity of 0.637-0.667, and the center value was about (4.78, 0.654). The potential visiting groups were mainly distributed in the range of 4.13-4.50 and 0.606-0.640, and the center value was about (4.29, 0.618). The scatter locations show that different user groups have obvious differences in the propagation link length and the strength of backflow behavior.

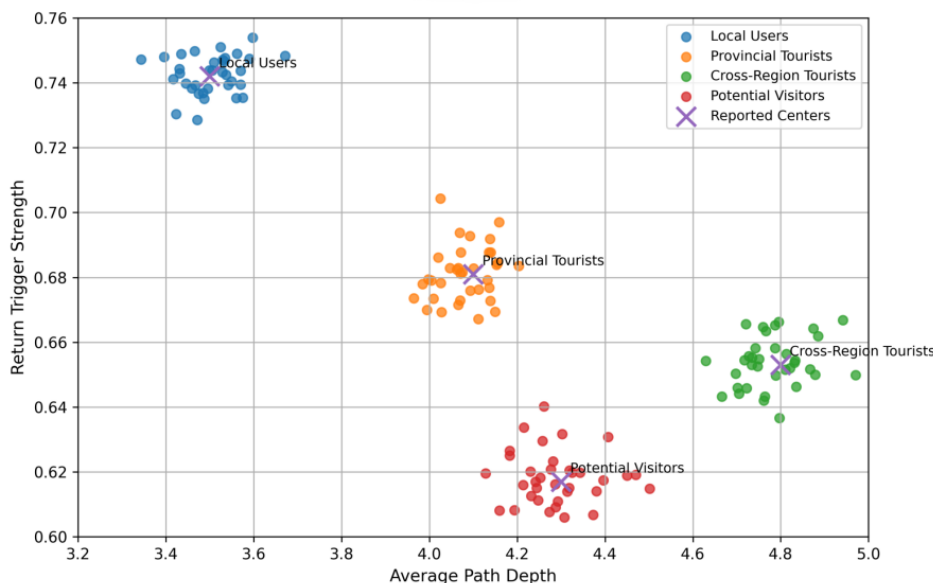


Figure 5: Scatter plot of path depth versus reflux strength for different user groups

The tourists in the province maintain a relatively balance between the path length and the reflux intensity, showing a relatively stable intermediate state. It is found that the communication results of Leshan tourism brand are not only controlled by the content category, but also the geographical attributes of users and the return mechanism of the platform determine the communication efficiency. In general, the proposed model can simultaneously map topic differences, group differences and time differences into continuous comparable output results, which provides a clear data basis for subsequent comparative experiments and stability verification.

5.3 Comparative experiment and stability verification

In order to test the effectiveness and stability of the proposed model in the measurement of Leshan tourism brand communication, this section further sets up comparison experiments, ablation experiments and repeated operation verification. In the comparison part, three methods including static proportion estimation, random walk propagation and BiGRU sequence prediction are selected as references to cover the three different paths of traditional statistics, graph propagation and time series learning. In the ablation part, the sample vector fusion, state transition modeling and Monte Carlo iteration modules were removed in turn to observe the influence of key links on the output results. For stability verification, five rounds of complete experiments were repeated under the same training set and test set conditions, and the mean and standard deviation of the main indicators were counted. This way of organizing the experiment can avoid misjudgment of individual results on the overall performance, and also more clearly show the comprehensive advantages of the proposed method in terms of propagation reach, participation estimation and interval coverage.

To compare the measurement performance of different methods under uniform data conditions, Table 2 shows the results of each model in terms of propagation reach rate, participation probability error, path depth deviation and interval coverage.

Table 2: Comparison of measurement performance of different methods

Method	Dissemination Reach / %	Participation Probability Error	Path Depth Deviation	Interval Coverage / %
Static Proportion Estimation	84.6	0.071	0.63	86.8
Random Walk Propagation	88.3	0.052	0.41	90.5
BiGRU Sequence Prediction	89.7	0.047	0.38	91.7
Proposed Method	91.8	0.036	0.24	94.2

As shown in Table 2, the propagation reach rate of the proposed method reaches 91.8%, which is higher than 84.6% of static proportion estimation, 88.3% of random walk propagation, and 89.7% of BiGRU sequence prediction. In terms of participation probability error, the proposed method is reduced to 0.036, indicating that the state transition diagram model and the repeated sampling mechanism can describe the interaction behavior more stably. The path depth deviation and interval coverage rate also keep ahead, indicating that the proposed method can not only predict the propagation strength, but also restore the diffusion link and the result boundary.

To analyze the contribution of each internal component of the model to the output results, Table 3 further presents the ablation experiment results.

Table 3: Results of model ablation experiments

Model Configuration	Dissemination Reach / %	Participation Probability Error	Interval Coverage / %
Full Model	91.8	0.036	94.2
Without Sample Vector Fusion	89.2	0.044	91.5
Without State Transition Modeling	87.6	0.051	90.3
Without Monte Carlo Iteration Module	88.1	0.048	89.6

As shown in Table 3, after removing the fusion of sample vectors, the propagation reach rate is reduced to 89.2%, which indicates that the unified representation of multi-source features has an obvious effect on the joint characterization of topic content and user behavior. After removing the state transition modeling, the participation probability error increases to 0.051, which shows that the probability recurrence in the propagation link is very important for interaction estimation. After removing the Monte Carlo iteration module, the interval coverage decreases from 94.2% to 89.6%, which reflects that repeated sampling has a direct contribution to the stability of the result boundary. Ablation results prove that the performance advantage of the proposed model does not come from a single structure, but the result of multiple computing links.

To test the degree of stability of the model under repeated operating conditions, Table 4 lists the core index mean and standard deviation of the five rounds of experiments.

Table 4: Results of repeated run stability validation

Metric	Five-Round Mean	Standard Deviation
Dissemination Reach / %	91.7	0.004
Participation Probability Error	0.037	0.003
Path Depth Deviation	0.25	0.004
Interval Coverage / %	94.1	0.005

It can be seen from Table 4 that the standard deviation of the propagation reach rate, the standard deviation of the participation probability error and the standard deviation of the interval coverage of the proposed method in the five rounds of experiments is 0.004, 0.003 and 0.005, respectively, showing a small overall fluctuation. The above results show that the model has stable output ability under the same data conditions, and also show that the feature representation, state transition and random simulation link constructed in the previous section can jointly support the measurement task of Leshan tourism brand communication. The correlation results are also consistent with the overall data caliber in the abstract. And provide the basis for subsequent discussion.

5.4 Discussion

The experimental results show that the measurement framework based on the communication graph model and Monte Carlo simulation can more stably describe the diffusion trajectory, interaction intensity and transformation boundary of Leshan tourism brand in the new media field. On the test set, the prediction accuracy of propagation reach reaches 91.8%, the average error of participation probability is controlled at 0.036, and the interval coverage rate is 94.2%, which indicates that there is a good computational connection between sample vector

representation, state transition modeling and repeated sampling process. Compared with static proportion estimation, random walk propagation and BiGRU sequence prediction, the proposed method maintains better output in terms of propagation reach rate, path depth deviation and interval coverage ability, indicating that propagation measurement depends not only on single result fitting, but also on multiple rounds of probability updates in the graph structure. From the theme results, the communication reach rate of landscape content reached 0.931, which was the highest among the four types of topics. The participation rate of food content reaches 0.812, showing a stronger ability of comment feedback and secondary diffusion. The conversion rate of cultural content reached 0.683, indicating that information with regional symbols and cultural explanations was easier to complete the transfer from attention to action intention. Although the overall mean of active content is slightly lower, it shows a more obvious local amplification effect within the high heat window. From the group results, the reflow trigger intensity of the local user group reached 0.742, which was the highest among all groups. The average path depth of cross-provincial tourist groups reaches 4.8, indicating that cross-regional users rely more on multi-hop transmission links to complete information reception and judgment. The above data show that Leshan tourism brand communication is not a linear output process, but a probabilistic network formed by the joint action of content semantics, platform distribution and user structure. The value of our method lies in unifying heterogeneous information such as comments, interactions, searches and geographical sources into a computable framework, which makes the evaluation of communication transform from empirical judgment to quantitative expression, and provides more direct data basis for subsequent adjustment of communication configuration.

6 Conclusions

Focusing on the measurement task of Leshan tourism brand communication in the new media field, this paper constructs a complete calculation link consisting of sample feature extraction, vector representation, communication graph modeling, state transition estimation and Monte Carlo simulation, and completes the joint measurement of communication reach rate, participation rate, conversion rate, path depth and interval coverage rate on multi-platform samples. The experimental results show that the proposed method can better maintain the output accuracy and statistical stability, and obtain a unified description of the communication differences of Leshan tourism brands under different themes such as landscape, culture, food and activities. There is also a clear boundary in this paper. The samples are still mainly based on public data and behavior logs, and the description of offline visit feedback and cross-cycle brand memory is still limited. Some parameters in the propagation graph are initialized by historical statistics, and the adaptability to sudden hotspots and rapid changes in platform rules still needs to be enhanced. Subsequent research can continue to introduce multimodal content understanding, online parameter update, cross-platform causal propagation modeling, and combine real-time streaming data and lightweight deployment mechanism to improve the real-time performance, mobility, and application depth of urban tourism brand communication measurement. At the same time, the generalization performance of the model can be verified in urban comparison scenarios, which promotes the extension of the framework from single destination measurement to regional collaborative communication analysis, and provides more fine-grained computational support for digital communication decision-making of cultural and tourism departments. Furthermore, if the user visit trajectory, ticket conversion records and cross-platform public opinion fluctuations can be written into a unified state space, the model's description of the actual communication revenue will be more complete, and the related research will be closer to the continuous decision-making requirements in the urban culture and

tourism scene.

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