J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 5029--5048

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on Cultural Construction of Spring Festival Gala Mascot Using Intelligent Computing Model - Brand Innovation and Communication Path of Chinese Intangible Cultural Heritage

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ABSTRACT

This study focuses on the construction of Spring Festival Gala mascot culture using intelligent computational modeling, so as to explore the brand innovation and communication path of Chinese intangible cultural heritage. The Apriori algorithm is utilized to extract the features of intangible cultural heritage in the mascot design, and at the same time, the association rules between different intangible cultural heritage features are mined and integrated into the design. The traditional Apriori algorithm is improved based on Boolean matrix and adaptive updating support calculation strategy to ensure its effectiveness and innovativeness for mascot design. Combined with the theory of propagation dynamics, the propagation model of this paper is constructed by adding the node of latent propagator on the basis of the traditional model of infectious disease (SIR). And in order to enhance the influence of the mascot in the communication network, this paper proposes a mascot accurate recommendation model for its further dissemination. The research results show that the method of this paper can effectively extract the non-heritage cultural features and association rules in the Spring Festival Gala mascot, and the Spring Festival Gala mascot designed by the method of this paper can ensure high economic benefits under the premise of high quality. In addition, the communication model and precise recommendation method constructed in this paper can also give full play to the communication role and effectively communicate the Spring Festival Gala mascot and the non-heritage cultural elements it carries.

Keywords: intelligent computational modeling, Apriori algorithm, SIR model, brand innovation, communication paths

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Received 20 February 2024; Revised 25 April 2024; Accepted 20 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-280

1. Introduction

As a special form of cultural expression, the Spring Festival Gala is presented on the TV screen in the form of audio-visual interactions of the Chinese nation's "family celebration", which spreads the excellent traditional Chinese culture to the audience through the use of various cultural symbols [1-3]. Symbol itself is a kind of cultural carrier, culture is always embodied in a variety of symbols, and the creation of culture is, to some extent, the creation of symbols [4]. It can be said that the Spring Festival Gala, as a kind of ritualized art exhibition activity, has well used cultural symbols to show the uniqueness of the excellent traditional Chinese culture, awakened the audience's memory and identity of the traditional culture with the ceremonial dissemination, and constructed a new paradigm of generating the cultural rituals [5-7]. And one of the highlights of the Spring Festival Gala is the design and launch of the mascot image, and the innovative production of endorsement videos around the IP, creative choreography of stage guest interaction, research and development of the sale of physical derivatives, realizing cross-media communication [8-9].

The Spring Festival Gala mascot conveys information to users through expressions and actions, which is both a visual presentation of brand tone and a form of communication of non-verbal symbols [10-11]. In the era of fragmented communication, the attention of the audience becomes a scarce resource, and content products that are too long in duration and not distinctive enough in theme will be naturally eliminated by the market [12]. As the carrier of communication, the mascot of Spring Festival Gala should firstly conform to the concept and personality of the brand, and on this basis, it is developed by using cartoon creative expression to achieve the purpose of enhancing the affinity of the market [13-15]. In addition, considering the cross-media communication needs to take into account the viewing preferences of different terminals, in order to form a greater volume of communication [16]. Compared with celebrity endorsement, the promotional video with mascot as the protagonist can be directed to a wider range of groups. Through simple and pure behavioral expression, the lively and cute mascot quickly establishes emotional ties with audiences of different ages, circles and platforms, which provides support for cross-media communication [17-20]. In view of this, using the intelligent computing model as a tool and digital media as a symbolic information carrier, designing a Spring Festival Gala mascot that fits the cultural metaphor and aesthetic tendency of the general public can promote the creative transformation and innovative development of NRL culture in abiding by the correctness and innovation.

This paper applies the intelligent computing model to the design and brand communication of the Spring Festival Gala mascot to construct the brand innovation method and communication path of intangible cultural heritage in the culture of the Spring Festival Gala mascot. The Apriori algorithm is used to extract potential intangible cultural heritage features in the design of the Spring Festival Gala mascot, and the mining results of the association rules of the intangible cultural heritage features are integrated into the design of the Spring Festival Gala mascot in this paper, so as to realize the innovation of the design of the Spring Festival Gala mascot. Aiming at the problem of low accuracy and efficiency of the traditional Apriori algorithm, this paper improves the non-heritage cultural content by mapping it into a Boolean matrix and introducing the support adaptive updating mechanism to enhance the effect of the Spring Festival Gala mascot design based on the Apriori algorithm. Based on the analysis of users and their behaviors in the Spring Festival Gala mascot propagation network, this paper adds potential propagator nodes to the original infectious disease model based on the information propagation process in a non-uniform network and simulates the propagation path of the Spring Festival Gala mascot brand based on the kinetic evolution equation of information propagation. Time weight and user interest similarity are introduced into the traditional collaborative filtering model and fused in a weighted way to construct the Spring Festival Gala mascot accurate recommendation model in this paper, which increases the probability of users in the propagation network to receive information about the Spring Festival Gala mascot. Taking the Spring Festival Gala mascots in the past 10 years as the case study object, the method of this paper is used to propose the non-heritage cultural features from the mascots into the design of the Spring Festival Gala mascots in this paper, and based on the design results, the performance and economic benefits of the Spring Festival Gala mascot design method under the improved Apriori algorithm of this paper are verified. At the same time, simulation experiments are carried out on the communication model and accurate recommendation method of this paper to verify the important role of this paper's method in the communication of Spring Festival Gala mascots and intangible cultural heritage.

2. Application of Intelligent Computing Models in the Design of Spring Festival Gala Mascots

2.1. Apriori algorithm non-legacy feature association module

The function of the non-legacy feature association module of Apriori algorithm [21] is to obtain potential, unknown and valuable non-legacy features in the Spring Festival Gala mascot design, which is used as the cultural entry point of the Spring Festival Gala mascot design. The steps of association rules to mine the non-legacy features are: first, obtain all the frequent itemsets of non-legacy features in the past Spring Festival Gala mascots. The definition requires that the number of frequent occurrences of each of these itemsets is at least the same as the preset minimum support count. Second, generate strong association rules for the non-legacy features based on the frequent itemsets. Strong association rules are those that meet the minimum support, minimum confidence. The acquisition of support, confidence is realized by Apriori algorithm.

Support indicates the likelihood that itemset $\{X,Y\}$ appears in the total itemset and is calculated as:

$$S(X \to Y) = \frac{P(X,Y)}{P(I)} = \frac{P(X \cup Y)}{P(I)} = \frac{n(X \cup Y)}{n(I)} \tag{1}$$

where the total transaction set is described by I and the number of times a particular item set appears in the transaction set is denoted by $n(\ )$.

The confidence level is calculated as:

$$C(X \to Y) = P(Y \mid X) = \frac{P(Y,X)}{P(X)} = \frac{P(X \cup Y)}{P(X)} \tag{2}$$

In the formula, confidence C refers to the possibility of launching Y based on the association rule "$X \to Y$" with the occurrence of precondition X as the premise, i.e., the probability that the item set containing X contains Y at the same time.

In summary, Apriori algorithm association module can effectively mine to the non-legacy association features, obtain the feature frequent item set to extract the strong association features, as a guiding factor for the design of the Spring Festival Gala mascot.

2.2. Design Module for Improving NRM Associative Feature Mining

2.2.1. Boolean matrix based database scanning strategy. The traditional Apriori algorithm generates candidate frequent item sets of high dimensions from low dimensional connections, and the whole database must be re-scanned, resulting in insufficient accuracy and low efficiency of the non-heritage feature association module of the Apriori algorithm. In this regard, the non-legacy cultural content data are mapped into a Boolean matrix [22] to improve this drawback. The elements in the Boolean matrix only take 0 or 1. The Boolean matrix replaces the transactional data items in the data, reduces the storage space occupied by the data, and is very effective for optimizing the association rule mining.

Define the Boolean matrix R, where the binary relation from $X=\{x_1,x_2,\cdots,x_n\}$, $Y=\{y_1,y_2,\cdots,y_m\}$, X to Y is then denoted by R, denote $r_{ij}=R(x_i,y_i)$, $R=[r_{ij}]_{m\times n}$.

Assuming that k elements are present in event A, then call A a k-item set event, and a frequent item set is an event in A that meets the set support level. Two key properties of the Boolean matrix support the realization: first, when the number of 1's in each column of the Boolean matrix does not match the preset support, the column is labeled as an infrequent itemset, and the column is deleted because the frequent itemsets have "anti-monotonicity". Secondly, when the number of occurrences of 1 in each row of the Boolean matrix is under k, it means that the number of items in the data item is greater than or equal to k, and it does not have the condition of generating a frequent k-item set, so it will be deleted when seeking a frequent k-item set.

2.2.2. Support calculation strategy based on adaptive updating. The description and evaluation of a non-legacy feature is often a longer phrase, due to the support degree of the non-legacy feature association module of the Apriori algorithm is a fixed value, and the frequent item set decreases rapidly with the increase of the number of items k, it is difficult to obtain a longer non-legacy feature phrase. For this reason, the support adaptive update mechanism is introduced, so that the non-legacy feature phrases are extended while the support degree is reduced adaptively. Define the initial support value as β, increase the number of items in the frequent item set and decrease the support degree at the same time, the support degree calculation method at the k rd time is:

$$E_k=\sup*\beta*\exp(-k) \tag{3}$$

The support decreases and stabilizes at a specific value. Adaptively adjusting the support of the algorithm expands the scope of cultural feature mining to include longer phrases.

Finally, the Apriori algorithm is improved based on Boolean matrix and support adaptive update strategy to obtain frequent k-term sets.

3. Application of Intelligent Computing Model in Brand Communication of Spring Festival Gala Mascots

3.1. *Brand communication of Spring Festival Gala mascot based on communication dynamics*

3.1.1. Modeling assumptions. The users in the Spring Festival Gala mascot cultural brand communication network have complex attributes and uncertain behaviors, which will change with time and the changes of the surrounding individuals, so it is difficult to completely replicate and simulate the communication model. In addition, the communication model constructed in this paper cannot take into account all the factors affecting the brand communication of the Spring Festival Gala mascot, therefore, under the condition of ensuring that the model is as close to the actual situation as possible, we only consider the factors that are most closely related to the present study and construct the model on the basis of the following assumptions.

Assumption 1: In the whole dissemination network, set 5% of these nodes as the initial source of dissemination, and these brand disseminators, will disseminate brand information to all the concerned subjects around them.

Assumption 2: In view of the relatively short time for information dissemination in the communication network to reach a stable state, this paper does not consider the dynamic changes in the network for the time being. That is, the size and structure of the network in which the brand is located in the communication process are considered to remain unchanged.

Assumption 3: In the actual communication network, users obtain information through a variety of ways, including independent search, friends publish (forwarding), network recommendation, etc. However, this paper only focuses on the way of brand information dissemination through the user relationship network, and focuses on the study of the influencing factors in this regard. That is to say, the dissemination of brand information only occurs among users who have friend relationships, and the dissemination methods include direct forwarding and self-originalization.

3.1.2. Introduction to the model. Based on the original contagion model [23] and according to the information dissemination process in non-uniform networks, this section will introduce the improved SE(E)IR model for brand information dissemination. In this paper, it is assumed that each user is represented by a node in a non-uniform network, and based on the user's response behavior after receiving the information, these nodes can be classified into five different categories: unknowns S, potential communicators E, communicators I, and quitters R. Specifically:

S: Users who have not been exposed to the Spring Festival mascot brand, but receive the brand will become E with a probability of α and I with that probability of β.

E: Users who have received the brand but are hesitant to spread the brand transform into I with a probability of γ and R with a probability of η under certain conditions.

I: Users who publish the brand or choose to believe in the brand and spread it to others, transforming into R with a probability of θ.

R: Users who lose interest over time after reading or forwarding word-of-mouth and do not spread the brand to anyone else.

For a certain user $Agent\ i$, who receives a brand message of the Spring Festival Gala mascot in the communication network, $Agent\ i$ will judge whether he is interested in this message from his own interest, and will also be influenced by his own social activity, and make the first judgment of whether to forward the message or not. If $Agent\ i$ retweets the brand, it enters the dissemination state, if not, it enters the latent state. Entering the latent state of $Agent\ i$ around the influence of other people's practices (social reinforcement), and then choose whether to disseminate the message, and ultimately the formation of the brand in the network of dissemination. The subject state transfer rule of the whole information dissemination process is shown in Figure 1.

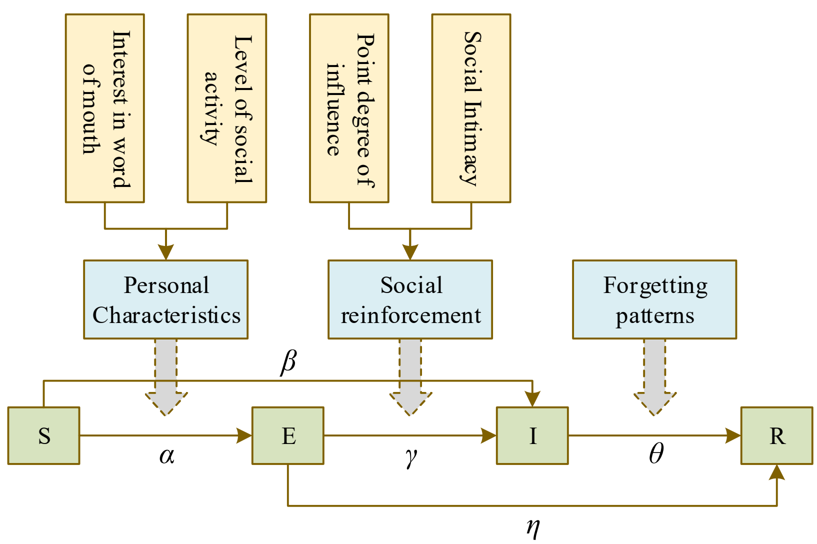


Fig. 1. The state transfer rule of the process of information dissemination

3.1.3. Kinetic evolution equations for modeled information propagation. Let P_{SI} represent the probability that node j transfers from the S state to the E state at the $t+\Delta t$ time period, then $P_{SI}=(1-\Delta t\beta)^d$, where $d=d(t)$ represents the number of propagating nodes in the neighbors of that node at the t time. If node j has k connected edges, then d is a random variable with the following binomial distribution:

$$\Pi(d,t)=\binom{k}{d}\delta(k,t)^{d}(1-\delta(k,t))k-d \tag{4}$$

where $\delta(k,t)$ denotes the probability that a node with k edges at moment t connects from an unknown state to a propagated state node. $\delta(k,t)$ can be expressed as:

$$\delta(k,t)=\sum_{k}P(k'\mid k)P(I_{k'}\mid S_{k})\approx\sum_{k'}P(k'\mid k)I_{k'}(t) \tag{5}$$

where $P(K'\mid K)=\dfrac{K+P(K')}{\langle K\rangle}$, $P(I_{k'}\mid S_{k})$ represents the probability that a node of degree k' is in a propagating state itself when it connects to a propagating node of degree k. $I_{k}(t)$ represents the density of propagating nodes of degree k at t time. Thus the average transfer probability of a node of degree k to change from unknown to propagated state in $[t,t+\Delta t]$ time period is $\overline{P_{SI}}(k,t)$:

$$\overline{P_{SI}}(k,t)=1-\left(\sum_{d}^{k}\binom{k}{d}(1-\Delta t\beta)\delta(k,t)^{d}(1-\delta(k,t))^{k-d}\right) \tag{6}$$

This follows from the binomial theorem:

$$\begin{aligned}&\sum_{d}^{k}\binom{k}{d}(1-\Delta t\beta)^{d}\delta(k,t)^{d}(1-\delta(k,t))^{k-d}\\&=\sum_{d}^{k}\binom{k}{d}((1-\Delta t\beta)\delta(k,t))^{d}(1-\delta(k,t))^{k-d}\\&=((1-\Delta t\beta)\delta(k,t)+1-\delta(k,t))^{k}\\&=\left(1-\Delta t\beta\sum_{k}P(k'\mid k)I_{k'}(t)\right)^{k}\end{aligned} \tag{7}$$

Substituting back into Eq. (6) gives:

$$P_{SI}(k,t)=1-\left(1-\Delta t\beta\sum_{k}P(k'\mid k)I_{k}(t)\right)^{k} \tag{8}$$

Similarly the node consists of the average transfer probability from the unknown state to the latent state:

$$\overline{P_{SE}}(k,t)=1-\left(1-\Delta t\alpha\sum_{k}P(k'\mid k)I_{k}(t)\right)^{k} \tag{9}$$

Assuming that $S(k,t)$, $E(k,t)$, $I(k,t)$, and $R(k,t)$ are the number of unknowns nodes, potential propagator nodes, propagating nodes, and exiting nodes, respectively, in the network with degree k at moment t, and the total number of nodes is $N(k,t)$, then:

$$N(k,t)=S(k,t)+E(k,t)+I(k,t)+R(k,t) \tag{10}$$

The number of unknown nodes with degree k in the network varies within $[t,t+\Delta t]$ as:

$$\begin{aligned} S(k,t+\Delta t) &= S(k,t)\left(1-\overline{P_{SI}}(k,t)-\overline{P_{SE}}(k,t)\right) \\ &= S(k,t)\left[1-\left(1-\left(1-\Delta t\beta\sum_{k}\cdot P\left(k'\mid k\right)I_{k}\cdot(t)\right)^{k}\right]\right] \\ &\quad -\left[1-\left(1-\Delta t\alpha\sum_{k}P\left(k'\mid k\right)I_{k}(t)\right)^{k}\right] \end{aligned} \tag{11}$$

$$\begin{aligned} \frac{s(k,t+\Delta t)-s(k,t)}{N(k,t)} &= -\frac{S(k,t)}{N(k,t)}\left(\overline{P_{SI}}(k,t)+\overline{P_{SE}}(k,t)\right) \\ &= -S_{K}(t)\left[1-\left(1-\Delta t\beta\sum_{k}\cdot P\left(k'\mid k\right)I_{k'}\cdot(t)\right)^{k}\right] \\ &\quad -S_{K}(t)\left(1-\left(1-\Delta t\alpha\sum_{k}\cdot P\left(k'\mid k\right)I_{k}(t)\right)^{k}\right) \end{aligned} \tag{12}$$

It is known from the Taylor series:

$$\begin{aligned} \left(1-\Delta t\beta\sum_{k'}P\left(k'\mid k\right)I_{k}\cdot(t)\right)^{k} &= \sum_{n=0}^{\infty}C(\alpha,n)\left(-\Delta t\beta\sum_{k}P\left(k'\mid k\right)I_{k'}(t)\right)^{n} \\ &= C_{0}^{k}+C_{1}^{k}\left(-\Delta t\beta\sum_{k'}P\left(k'\mid k\right)I_{k'}(t)\right) \\ &= 1-k\beta\Delta t\sum_{k}P\left(k'\mid k\right)I_{k'}(t) \end{aligned} \tag{13}$$

Substituting Eq. (13) back into Eq. (12) gives:

$$\frac{S(kt+\Delta t)-s(k,t)}{N(k,t)} = -k(\alpha+\beta)\Delta tS_{K}(t)\sum_{k}\cdot P\left(k'\mid k\right)I_{k}\cdot(t) \tag{14}$$

$\dfrac{\partial S_{K}(t)}{\partial t} = -k(\alpha+\beta)S_{K}(t)\sum_{k}P\left(k'\mid k\right)I_{k'}(t)$ when $\Delta t \to 0$.

Similarly the density of propagating, latent and exit state nodes can be obtained as a function of time:

$$\begin{aligned} \frac{\partial I_{K}(t)}{\partial t} &= k\beta S_{K}(t)\sum_{k}\cdot P\left(k'\mid k\right)I_{k'}(t)+kE_{K}(t)\theta \\ &\quad \sum_{k'}P\left(k'\mid k\right)I_{k'}(t)I_{K}(t)\theta\sum_{k}P\left(k'\mid k\right)I_{k'} \end{aligned} \tag{15}$$

$$\frac{\partial E_{K}(t)}{\partial t} = k\alpha S_{K}(t)\sum_{k}\cdot P\left(k'\mid k\right)I_{k'}(t)-k(\theta+\eta)E_{K}(t)\sum_{k}\cdot P\left(k'\mid k\right)I_{k'}(t) \tag{16}$$

$$\frac{\partial R_{K}(t)}{\partial t} = k\eta E_{K}(t)\sum_{k}\cdot P\left(k'\mid k\right)I_{k'}(t)+kI_{K}(t)\theta\sum_{k}\cdot P\left(k'\mid k\right)I_{k'}(t) \tag{17}$$

Therefore, the system of equations (14), (15), (16), and (17) can be linked to the propagation dynamics equations of this model. When $\beta=0$, $\eta=0$, the SE(E)IR model of this paper becomes equivalent to the conventional SEIR model.

Differential equation models have a wide range of applications, such as helping to understand the interrelationship between the speed of information propagation in a social network and the structure of the network, and investigating the effects of different node behaviors on information propagation.

Or to reveal the threshold effect of information dissemination, i.e., a small range of information dissemination may spread rapidly after reaching a certain threshold of node number.

Through the interaction law between the spreader and the receiver, as well as the process of information transmission, this subsection successfully deduces the differential equation of the spreading dynamics of the Spring Festival Gala mascot cultural brand in the spreading network. It also disassembles each link of individual state transfer in the brand diffusion process, as well as provides a detailed description of possible individual state transfer paths and their corresponding probabilities in the brand information diffusion. Mathematical support is provided for an in-depth understanding of how a brand spreads from one node to another and the factors involved in the entire diffusion process.

3.2. Accurate Recommendation Model Fusing Time and Interest Similarity

In order to further expand the communication channels of the Spring Festival Gala mascot and enhance the possibility of users accepting the brand information of the Spring Festival Gala mascot in the communication network, this section will construct a recommendation model to accurately recommend the information of the Spring Festival Gala mascot for users.

3.2.1. Traditional Collaborative Filtering Recommendation Models. In traditional collaborative filtering recommender systems [24], the input data is usually formulated as a $a \times b$ user-a-resource access matrix R, where a denotes the number of users, b denotes the number of resources, and R_{ij} denotes the access record of the i th user to the j th resource. The value of each data element in the matrix indicates whether the user accessed the resource or not (1 indicates access and 0 indicates no access).

Similarity is a metric used to compare the proximity of two things and is typically calculated based on distance. Due to the wide variety of names and types of products usually found in the original dataset, the user matrix and the item similarity matrix are too large in dimension. Therefore, in order to improve the operational efficiency, this project team chooses the Jaccard similarity metric. The Jaccard similarity metric is shown in equation (18):

$$J\left(A_1, A_m\right) = \frac{\left|A_1 \cap A_M\right|}{\left|A_1 \cup A_M\right|} \tag{18}$$

where $\left|A_1 \cup A_M\right|$ denotes the total number of users who like both Spring Festival Mascot 1 and Spring Festival Mascot M. $\left|A_1 \cap A_M\right|$ denotes the number of users who like both Spring Festival mascot 1 and Spring Festival mascot M.

3.2.2. Time weights. Most of the current collaborative filtering recommendation algorithms are unable to reflect the process of user's interest changes in a timely manner, and once the user's interest changes, it may lead to the recommended resources deviating from the user's essential needs to a large extent. Therefore, this paper proposes a data weighting algorithm based on access time to address the shortcomings of traditional collaborative filtering algorithms.

The algorithm defines time-based data weighting as follows:

$$W_{time}(u,i) = (1-a) + a\frac{D_{ui}}{L_u} \tag{19}$$

Where, D_{ui} denotes the interval between the time a user u accesses a resource i and the time the user u first accessed a resource; L_u denotes the time span over which a user u uses the recommender system, i.e., the interval between the time the user first accessed a resource and the time the user most recently accessed a resource. $a \in (0,1)$ is called the weight growth index, and changing the value of a adjusts the rate at which the weights change with access time. The larger the a the faster the weights grow, and the size of the a can affect the performance of the algorithm.

3.2.3. Similarity of interest. In Eq. (19), the value of $W_{time}(u,i)$ varies linearly with the time interval of user u accessing the resource, and the weight of the user's recently accessed data is always greater than that of the early accessed data, thus highlighting the importance of the recent data.

If we simply use time-based data weights and weaken the role of early resources in recommendation, it is highly likely to negatively affect the recommendation effect. For this reason, this project proposes interest similarity based data weights as follows:

$$W_{interest}(u,i) = (1-a) + a\frac{T_{ui}}{D_u} \tag{20}$$

where T_{ui} denotes the number of times user u chose Spring Festival mascot i. D_u denotes the total number of times user u made a choice, and $T_{ui} \le D_u$. $a \in (0,1)$ is the weight growth factor.

3.2.4. Integration models. The two weight functions are fused in a matrix using equation (21):

$$W_{fusion} = \beta \times W_{time}(u,i) + (1-\beta) \times W_{interest}(u,i) \tag{21}$$

Where $\beta \in [0,1]$, β and $1-\beta$ represent the proportion of the two weighting values respectively, the accuracy of the recommendation algorithm is further improved by choosing a suitable β to combine the two weighting methods.

In order to improve the model accuracy, the pinched cosine of the vectors is chosen for the similarity measure. Assuming that the user ratings are regarded as vectors on the n dimensional space, and the rating vectors of two users x, y are X and Y respectively, the cosine similarity between them is calculated as follows:

$$sim(x,y) = \cos\left(X,Y\right) = \frac{X \cdot Y}{\|X\| \times \|Y\|} = \frac{\sum_{i=1}^{n} R_{x,c} R_{y,c}}{\sqrt{\sum_{c=1}^{n} R_{x,c}^2}\sqrt{\sum_{i=1}^{n} x_{y,c}^2}} \tag{22}$$

where $R_{x,c}$ and $R_{y,c}$ are the ratings of user x and user y for item c, respectively.

Due to the consideration of the differences in the evaluation scales of different users, the cosine similarity is methodologically improved by averaging the ratings of the items. Let the set of jointly rated items by users x and y be denoted by $I_{x,y}$, then the similarity between user x and user y is calculated as shown in equation (23):

$$sim(x,y) = \frac{\sum_{c \in I_{x,y}} \left(R_{x,e} - \overline{R_x}\right)\left(R_{y,e} - \overline{R_y}\right)}{\sqrt{\sum_{c \in I_{x,y}} \left(R_{x,e} - \overline{R_x}\right)^2}\sqrt{\sum_{c \in I_{x,y}} \left(R_{y,e} - \overline{R_y}\right)^2}} \tag{23}$$

where $\overline{R_s}$ and $\overline{R_y}$ denote the average ratings of user x and user y on the evaluated items, respectively.

4. Case studies

In order to verify the effectiveness of the method proposed in this paper, the mascots of the Spring Festival Gala in the past 10 years are taken as the case study objects, and the method of this paper is applied to carry out the innovative design of the mascots of the Spring Festival Gala and the dissemination of the culture of the mascots of the Spring Festival Gala. The following are the specific results and analysis of the application of this paper's method.

4.1. Analysis of the effect of the mascot design for the Spring Festival Gala

4.1.1. Correlation analysis of NRM characteristics. In this study, the non-heritage features embedded in the Spring Festival Gala mascot selected for the case are mined by the association rule Apriori algorithm, the minimum support degree is set to 0.3, and the partial experimental results obtained after sorting are shown in Table 1. As can be seen from the table, the frequent item sets of non-heritage features in the design of the Spring Festival Gala mascot are sorted according to the size of the support degree, and the top 3 features obtained are oracle bone elements, Chinese zodiac culture and Ruyi pattern, with the support degrees of 0.699, 0.697, and 0.694 respectively.

Table 1. Frequent itemset results

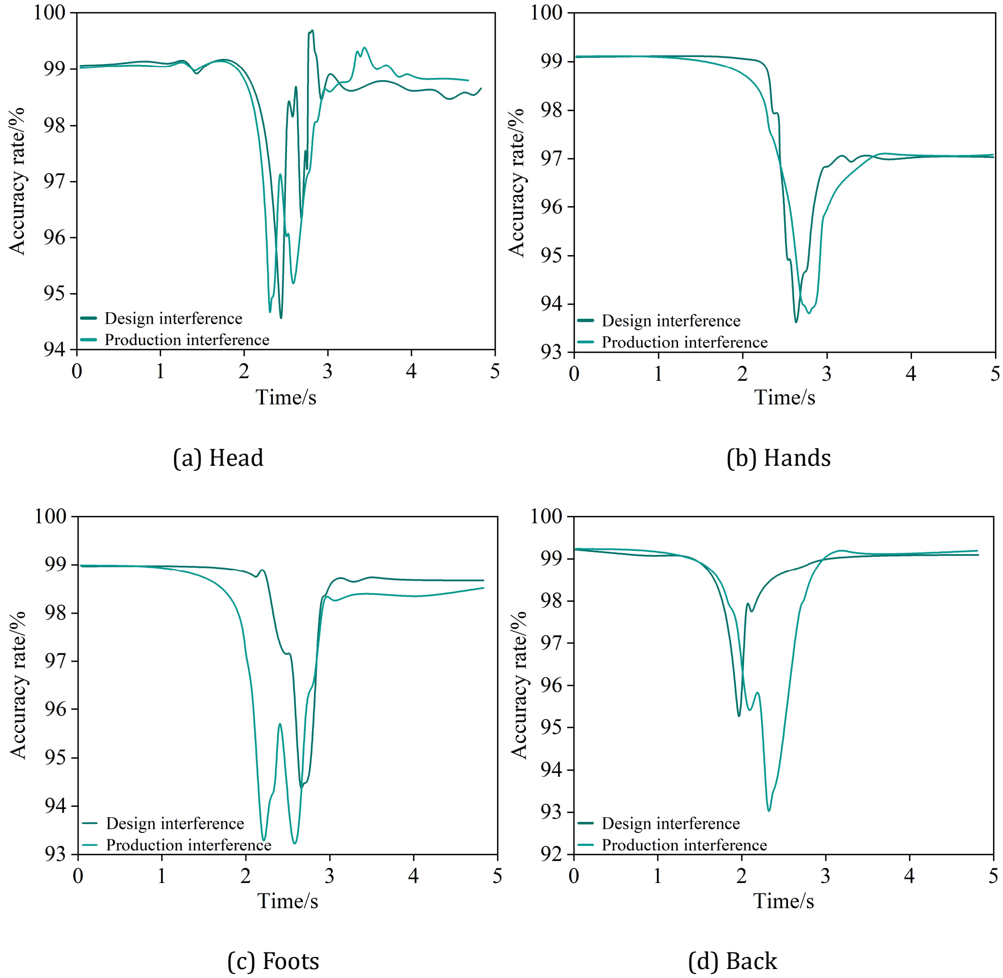
ID	Support	Itemset	ID	Support	Itemset
7	0.699	Oracle bones	4	0.513	Paper cuttings art
5	0.697	Zodiac culture	47	0.499	Opera element
12	0.694	Ruyi pattern	21	0.467	Wushu movements
14	0.684	Color tradition	33	0.455	New Year's painting elements
3	0.661	Tristar culture	2	0.449	Embroidery technique
6	0.637	Cloisonne process	13	0.448	Shadow play elements
11	0.629	Filigree inlay	17	0.434	Five elements philosophy
8	0.595	Bat ornament	24	0.316	Traditional instrument
9	0.565	Mortise-tenon structure	···	···	···

On the basis of the previous step, the minimum confidence is set to 0.7, and the association rules in the intangible heritage feature are mined. Some experimental results obtained are shown in Table 2. As can be seen from the table, the first three rules reflect the correlation between oracle bone inscriptions and zodiac culture, bronze patterns and ruyi patterns, and traditional architecture and patterns, with support degrees of 0.634, 0.628 and 0.617, respectively. These association rules reflect the connection between the non-material cultural heritage features in the design of the gala mascot. Taking Rule 1 as an example, the word "si" in oracle bone inscriptions not only reflects the charm of ancient Chinese characters, but also combines with the zodiac "snake" to form a unique cultural symbol. Therefore, when the mining results are applied to the design of the gala mascot, the interaction and integration of these two intangible cultural characteristics are emphasized, so that the content of the Gala mascot is more systematic.

Table 2. Association rule

Antecedents	Consequents	Support	Confidence
Oracle bones	Zodiac culture	0.634	0.837
Bronze ware patterns	Ruyi pattern	0.628	0.718
Ancient architecture	Patterns	0.617	0.832
Folk story	Zodiac culture	0.605	0.833
Traditional instrument	Dance	0.572	0.805
Opera element	Dress	0.538	0.749
Tristar culture	Filigree inlay	0.519	0.813
Bat ornament	Shou plate long knot	0.507	0.827
Color tradition	Cloisonne process	0.502	0.835
Ruyi pattern	Dharma temple relics	0.501	0.719

4.1.2. Design Module Effectiveness Analysis. In order to verify the improvement of Boolean matrix and adaptive updating computational strategy to Apriori algorithm and the application value of Spring in the evening mascot design, the study evaluates the effect of Spring Festival evening mascot design under the intervention of improved Apriori algorithm. The study applies the improved Apriori algorithm to the design of four parts of the head, hand, foot and back of the Spring Festival evening mascot, and firstly evaluates the anti-interference ability of the algorithm in the design of the four parts, and the results are shown in Fig. 2, with (a)-(d) indicating the anti-interference evaluation results of the head, hand, foot and back, respectively. From the figure, it can be seen that the stability of the improved Apriori algorithm is stronger in all the different Spring Festival mascot parts designs. In the back design, it is the least affected, and its accuracy is still always higher than 99% after being interfered by many external factors. In the hand design, the improved Apriori algorithm is more obviously affected by external factors, and its accuracy is reduced to 97.03% at the maximum. However, from the change of the curve in the figure, it can be learned that for different parts of the Spring Festival mascot design, the accuracy of the proposed improved Apriori algorithm can be quickly recovered to a higher accuracy after the interference, which indicates that the design algorithm has a high stability.

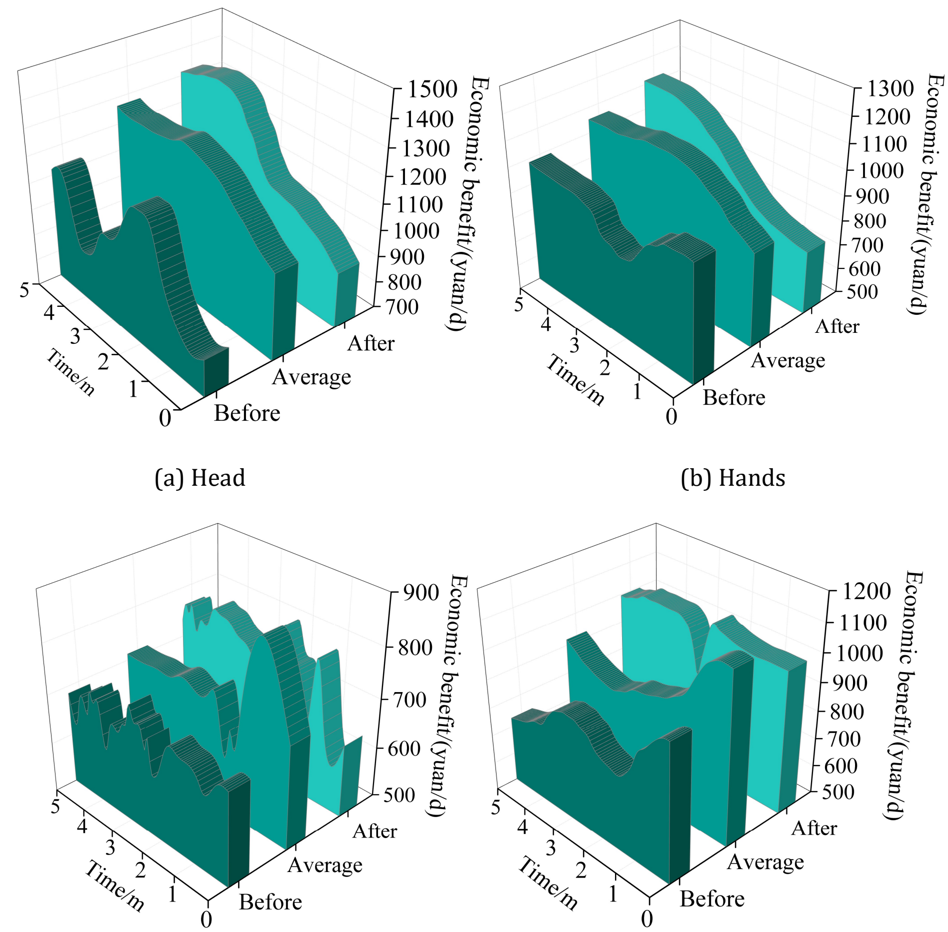


(a) Head (b) Hands

(c) Foots (d) Back

Fig. 2. Anti-interference evaluation of algorithm

The design of Spring Festival Gala mascot is not only to improve the productivity and quality, but also to ensure its economic benefits in the design is the key to promote the cultural inheritance and dissemination of the Spring Festival Gala mascot. For this reason, the study further evaluates the economic benefits of the Spring Festival Gala mascot design under the improved Apriori algorithm, and the results are shown in Fig. 3, with (a)-(d) denoting the economic benefits of the head, hand, foot, and back designs, respectively. The results in the figure show that the study compares the economic benefits before and after the design of different Spring Festival mascot parts with the improved Apriori algorithm. As can be seen from the figure, the economic benefits of each part are significantly improved and are significantly higher than the economic benefits of the Spring Festival Gala mascot before design and the average economic benefits of the same type of products. The above results show that the Spring Festival Gala mascot design based on the improved Apriori algorithm significantly enhances the audience's interest in the Spring Festival Gala mascot through the extraction of non-legacy features. Under the premise of having efficient and high quality design, it also has high economic benefits, which can effectively realize the innovative development of the Spring Festival Gala mascot cultural brand.



(a) Head (b) Hands

(c) Foots (d) Back

Fig. 3. Economic benefits of design

4.2. Brand communication effect analysis

4.2.1. Analysis of communication effects based on communication dynamics:

1) Evolution of four types of nodes over time. Set the parameter of SE(E)IR model as $k = 10$. The density of the four categories of nodes such as unknowns, potential spreaders, spreaders and quitters in the communication network of the Spring Festival mascot brand is investigated over time, and the results are shown in Fig. 4. From the figure, it can be seen that the density of the unknowns node S(t) decreases rapidly to 0 in the initial stage, indicating that the information spreads a few blocks in the communication network. The density of potential propagator node E(t) increases rapidly in the initial stage and decreases rapidly to 0 after reaching the peak. In the initial stage, a large number of users receive the brand message, but the users are in the offline state so that they do not immediately propagate the message. The curve of E(t) grows rapidly, and when it reaches the peak, there are no more new users to receive the message, and the users, upon receipt of the message, gradually migrate to the propagation state to start propagating the information or enter the exit state to refuse to disseminate the information, and the E(t) curve decreases rapidly. The density of the propagator node I(t) also increases and then decreases to 0. At the initial stage of information dissemination, the user who owns the information about the Spring Festival mascot starts to disseminate the information, and the nodes in the model move from the latent state to the propagation state, and the I(t) curve rises, and reaches the apex, there are no more new users to disseminate the information and the users who have disseminated the information before gradually stop disseminating the information, and thus the

I(t) curve decreases. The density of exiter nodes increases rapidly in the initial phase until its density tends to 1, indicating that all users receive the message.

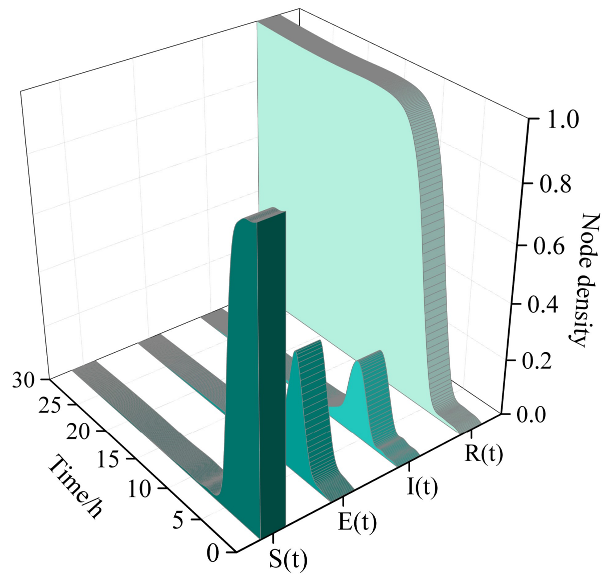


Fig. 4. The density of the four nodes varies over time

2) The effect of the degree of the initial propagation node on information dissemination. Assuming that the degree of the initial propagation node is $k = 5, 20, 50, 200$, respectively, the change in the number of nodes receiving information in the network, i.e., the sum of the density percentages of latent propagators, propagators and quitters, is investigated in the four cases, and the results are shown in Fig. 5. It can be seen from the figure that the number of nodes receiving information is positively correlated with the degree of the initial propagation node, with information spreading the slowest at $k = 5$ and the fastest at $k = 200$. The larger the degree of the initial propagation node, the more friends of the user who propagates the information at the initial moment, the faster the information spreads in the network, and the faster the propagation scale grows. Therefore, the size of the degree of the initial propagation node will have a great impact on the information propagation in the network. Therefore, in order to spread the information as quickly as possible, the node with larger degree should be selected as the initial propagation node. However, no matter what the degree of the initial node is, the percentage of node density that receives the information will eventually converge to a stable value of 1, indicating that all nodes in the network will eventually receive the information.

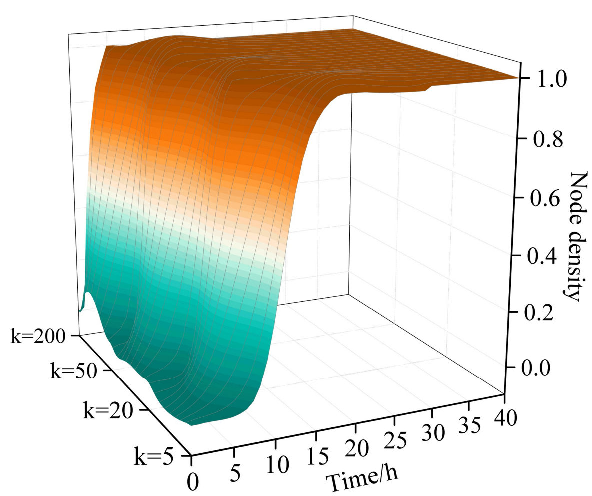


Fig. 5. The spread of information changes at different levels of k

3) Effect of node infection rate on the propagation process. An unknown node is infected with probability β if it is adjacent to a propagator node. β Taking 0.1, 0.3, 0.7, and 1.0, respectively, the effect of infection rate β on the information dissemination process is shown in Fig. 6. From the figure, it can be seen that the easier the node is infected, the faster the information spreads, the earlier it stabilizes, and the more nodes that eventually receive the information. For the Spring Festival Gala mascot information, if the more interested users, the more forwarded, the more users eventually receive the information, and the faster the propagation network reaches a stable state. At the same time, β is crucial to the range covered by the information dissemination. When the value of β is small, the scope of information dissemination is more sensitive to changes in, and a smaller increase in the value of β causes the information to spread over a larger area. Therefore, if information is to be widely disseminated, consideration should be given to how to effectively increase the probability of users forwarding the information, so that the dissemination of information is both fast and wide.

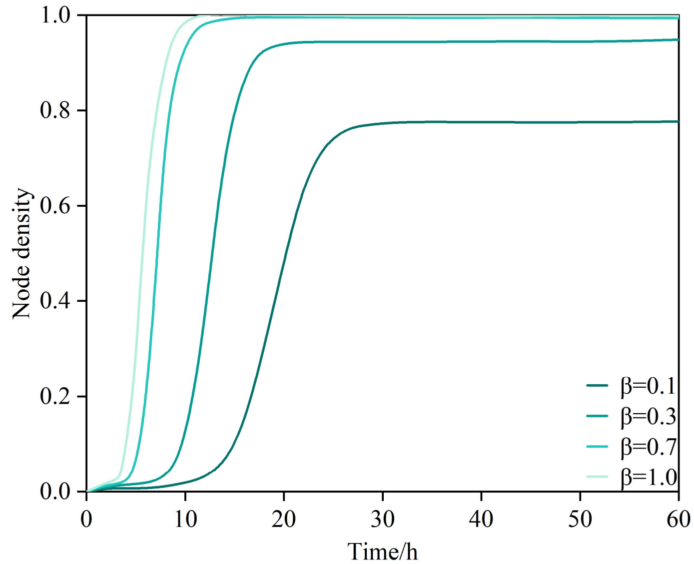


Fig. 6. Influence of node infection rate β on propagation process

4) Comparison between the SE(E)IR model and the SIR model. Among the existing information dissemination models, the one most closely related to the SE(E)IR model is the SIR model, and Fig. 7 shows the comparison results of the two models. The SE(E)IR model has a cure rate of $\theta = 1/12$, and the other parameters are set the same. The existence of potential propagator nodes in the SE(E)IR model makes the information propagation obviously advantageous both in the speed and the propagation range, and the SE(E)IR model is able to reach a stable network state in a shorter time. Compared with the SIR model, the SE(E)IR model is able to obtain better dissemination effects, and can maximize the dissemination of the Spring Festival Gala mascot brand information to more users in the same dissemination network.

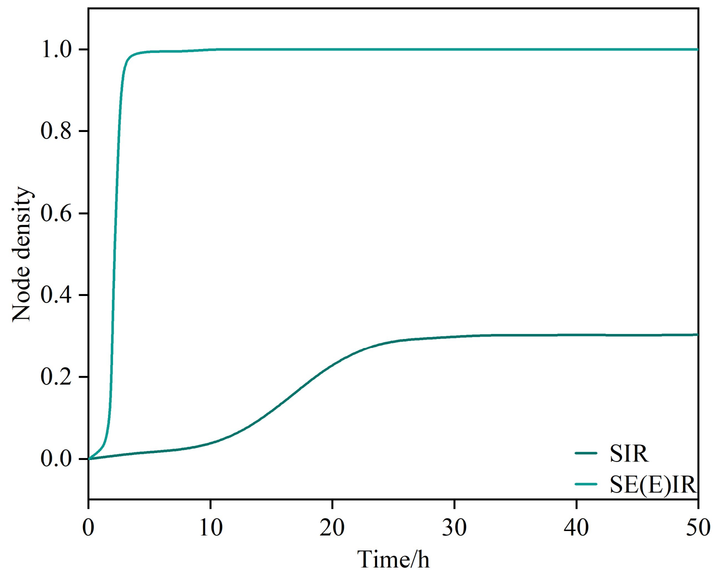


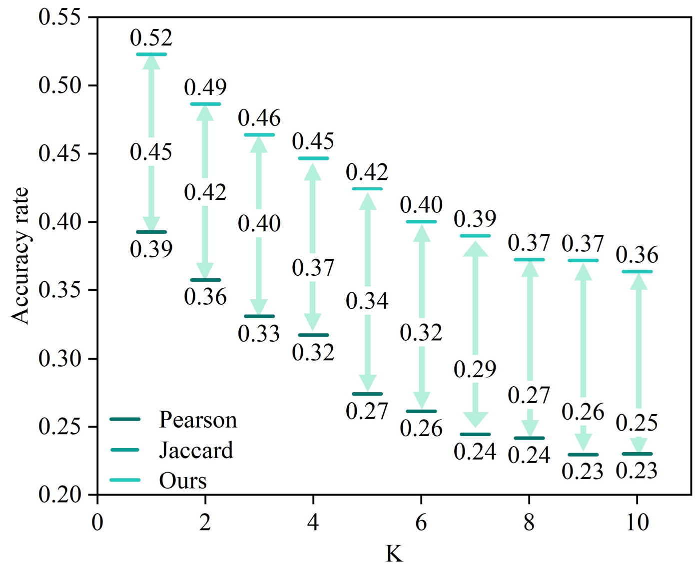
Fig. 7. The comparison of the SE(E)IR model and the SIR model

4.2.2. Analysis of communication effect based on precise recommendation:

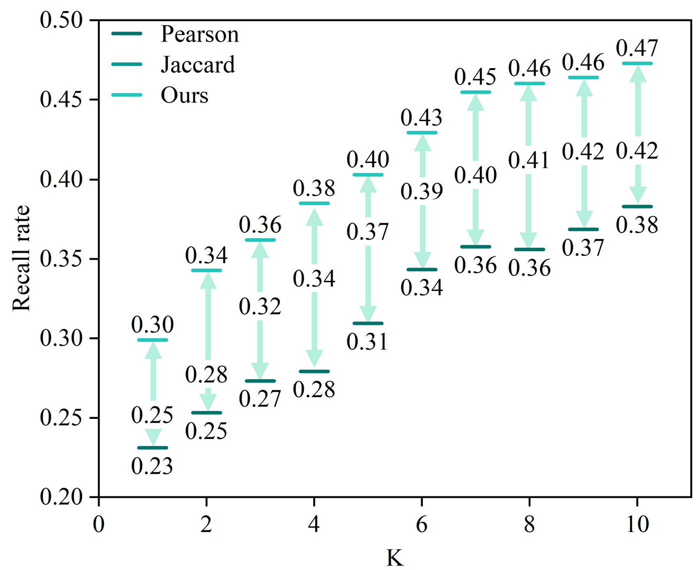
1) Experimental conditions. In order to verify the effectiveness of the Spring Festival Gala mascot brand precision recommendation method proposed in this paper, the proposed method is compared with other recommendation methods, and the experimental data are the interaction rating data of users in an e-commerce platform with the Spring Festival Gala mascot selected in the case, which contains 57,358 interaction records of 10,476 users. The comparison experimental methods are collaborative filtering method based on Pearson similarity calculation (Pearson) and collaborative filtering method based on Jaccard similarity calculation (Jaccard). The experiments use recommendation result accuracy, recall and average absolute error to evaluate the performance of Spring Festival mascot recommendation methods.

2) Results and Analysis. In the process of accurate recommendation of Spring Festival mascot, the number of recommendations K will have a large impact on the recommendation performance, for this reason, the data of Spring Festival mascot is used as the independent variable to test the recommendation performance of each recommendation method under different data conditions. Using the experimentally collected dataset, 90% of the data in the dataset is randomly selected as the training set, and the remaining 10% of the data is used as the test set. The accuracy, recall and average absolute error statistics of the three recommendation methods with the number of recommendations of the Spring Festival Gala mascot are shown in Figure 8, where the arrows in the figure are the numerical disparity representation of the Jaccard method as the "middle bridge", and the upward arrow indicates that the numerical value is larger than that of the Jaccard method, and the downward arrow indicates that the numerical value is smaller than that of the Jaccard method. The arrow upwards indicates that the value is larger than Jaccard method, and the arrow downwards indicates that the value is smaller than Jaccard method. From the experimental results, it can be seen that the accuracy, recall and mean absolute error of the recommendation method proposed in this paper are better than the Pearson and Jaccard methods on the dataset, and also in the decreasing trend of the accuracy, increasing trend of the recall and increasing trend of the mean absolute error than the Pearson and Jaccard methods. The experimental results show that the recommendation performance of the proposed method in this paper is better than that of Pearson and Jaccard methods, which is due to the fact that the method in this paper integrally utilizes the user interest characteristics of the Spring Festival Gala mascot and refines the scoring time impact through the time weighting function, so it has a good recommendation performance. Using this paper's method to recommend the Spring Festival Gala mascot can effectively expand the influence of the Spring Festival Gala mascot in the

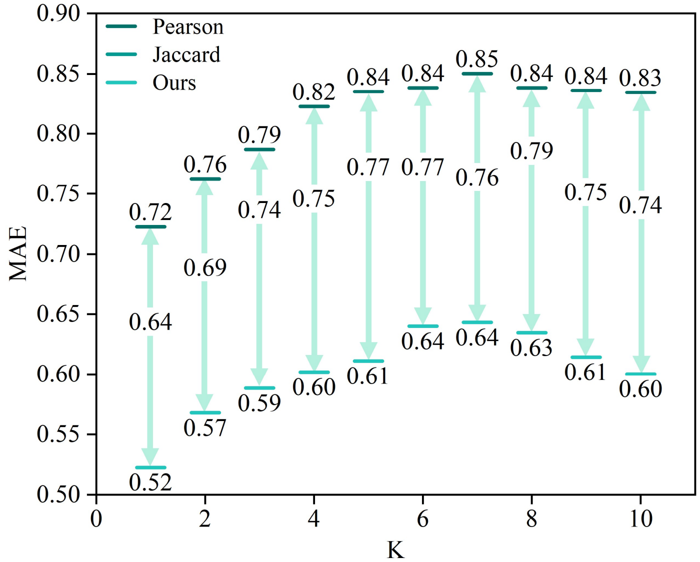
communication network, and combined with the SE(E)IR model of communication dynamics in the previous paper, the effective communication of the Spring Festival Gala mascot brand can be fully realized.



(a) Accuracy rate



(b) Recall rate



(c) MAE

Fig. 8. The comparison for recommendation among different methods

5. Conclusion

This paper utilizes the Apriori algorithm of intelligent computing methods and the theory of communication dynamics to design and innovate the mascot of the Spring Festival Gala, and realizes the effective communication of China's intangible cultural heritage on this basis. The study shows that the design accuracy of this paper's method in the process of designing the Spring Festival Gala mascot that incorporates the characteristics of intangible cultural heritage can still maintain more than 90% in the case of external interference. And the propagation model in this paper has the advantages of faster propagation speed and wider propagation range compared with the original SIR model. At the same time, the accurate recommendation method in this paper has stronger recommendation performance compared with the Pearson method and the Jaccard method, and can more effectively realize the dissemination of the Spring Festival Gala mascot and its embedded features of Chinese intangible cultural heritage. Future research can be carried out to further optimize the performance of the algorithm, expand the data sources and strengthen interdisciplinary cooperation, so as to provide stronger technical support and theoretical guidance for the inheritance and development of intangible cultural heritage.

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