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Social Network-Based Folk Culture Propagation in the Digital Age: Analyzing Dissemination Mechanisms and Influential Factors

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Abstract: The rapid development of the internet has ushered the real world into a "media-centric" digital era where virtually everything serves as a medium. Leveraging the new attributes of interactivity, immediacy, and personalization facilitated by online communication, folklore has found a broad avenue for dissemination. Among these, online social networks have become a vital channel for propagating folklore. By using social network theory, we devise a comprehensive approach known as SocialPre. Firstly, we utilize embedding techniques to capture users' low-level and high-level social relationships. Secondly, by applying an automatic weight assignment mechanism based on the embedding representations, multi-level social relationships are aggregated to assess the likelihood of a social interaction between any two users. These experiments demonstrate the ability to classify different social groups. In addition, we delve into the potential directions of folklore evolution, thus laying a theoretical foundation for future folklore communication.

Key words: folklore culture; dissemination; embedding representations; social relationships; influential factors

1 Introduction

Folklore refers to the culture presented by a specific group, encompassing the shared traditions of culture, subculture, or community[1]. Folklore encompasses oral traditions like narratives, proverbs, or jokes, as well as material culture, ranging from traditional architectural styles to unique handmade toys associated with the group. When folk culture merges with the Internet, we enter a brand-new era of cultural communication. The Internet and social media platforms, like Facebook, have become crucial tools for the dissemination and sharing of folk culture. This trend not only expands the reach of folk culture, but also transforms the way that culture is inherited and interacted with[2].

Traditional folk culture is typically passed down through oral tradition and local events to the younger generations. However, nowadays, people can share these cultural expressions with a global audience in the form of videos, images, and text[3]. Social media platforms provide a means of communication that transcends geographical and cultural boundaries, encouraging individuals to explore, learn, and participate in various folk activities. This digitized form of cultural dissemination makes folk culture more accessible and attracts a wider audience, thereby promoting cultural diversity and mutual understanding[4].

The transition from social media to social networks has reshaped the digital landscape and how we connect, share, and communicate. It is not sufficient to view social media platforms as mere tools for self-expression; they have evolved into dynamic networks of interconnected individuals, with far-reaching

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implications for culture, communication, and community[1, 5]. Consider, for instance, the staggering daily online activity on platforms, such as TikTok, Facebook, and Instagram. TikTok, the short-form video sharing giant, boasts an impressive one, having billion active daily users as of our latest data in 2021, with millions of videos being uploaded every day, and countless likes and shares exchanged[6]. Facebook, as the social networking world, sees over 2.8 billion monthly active users, while Instagram, its subsidiary, hosts more than 1 billion monthly users. The sheer scale of these numbers is breathtaking, underscoring the immense potential for cultural exchange, community building, and information dissemination that social networks offer. Yet, it is not just about the quantity of users; it is also about the quality of their interactions and the content they engage with[7, 8]. Every day, millions of people on these platforms give a thumbs-up to posts and content that resonate with them, shaping trends and influencing the discourse on a wide range of topics. In an era where a single viral video can spark global conversations, it becomes crucial to recognize the potential of social networks in transforming the way we share and preserve our cultural heritage. Figure 1 illustrates the most popular social networks globally as of April 2024, ranked by the number of monthly active users※. Meanwhile, Fig. 2 displays the number of social media users worldwide from 2017 to 2027. These datasets unveil the immense potential for social network-driven dissemination†.

Social networks, also known as social media or

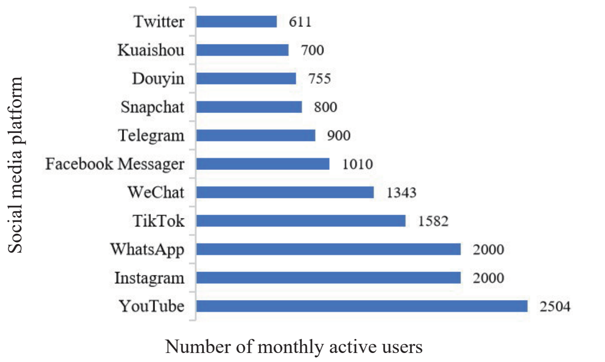

Fig. 1 Most popular social networks worldwide from April 2024.

※https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/

† https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/

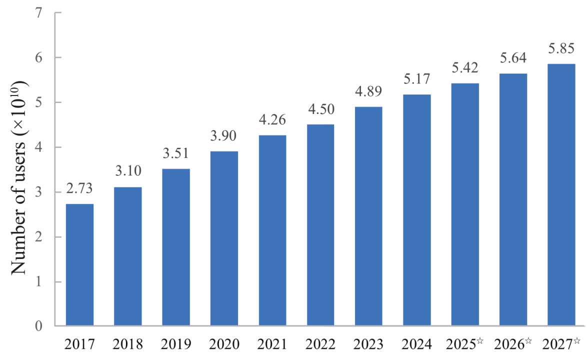

Fig. 2 Number of social media users worldwide from 2017 to 2027 ("☆" indicates the number of persons predicted for the year).

social media networks, refer to virtual platforms on the internet designed to facilitate interpersonal communication, information sharing, and interaction. These networks offer users a space to create personal profiles, establish connections, share content, and engage with others. The development of social networks has become a vital component of modern social interaction and communication, exerting a profound influence on various domains, including society, commerce, media, and politics. In the context of social networks, the intersection with folklore and cultural studies presents intriguing challenges and opportunities[9]. As these platforms bridge geographic boundaries, they become spaces where diverse cultural traditions and folk practices converge. This convergence has the potential to revive and transform traditional folklore in the digital age[10].

However, several challenges persist in merging folklore and social networks: **(1) Preserving user Preferences:** One challenge lies in preserving the diverse preferences of users for folklore and cultural content on social platforms. Users' unique tastes, interests, and cultural backgrounds should be maintained to ensure a tailored experience. **(2) Scalability for cultural transmission:** Social networks boast large user bases, and it is crucial to devise strategies for the rapid dissemination of folklore and cultural content. The scale and dynamics of social networks make efficient transmission a complex issue. **(3) Factors influencing cultural dissemination:** Identifying and understanding the various factors that impact the dissemination of folklore and cultural content is another critical challenge.

To address these challenges, we employ deep learning based techniques to capture and maintain user preferences for folklore and culture. Simultaneously, leveraging the principles of the “six degrees of separation” theory[11] allows us to uncover the mechanisms driving cultural content dissemination between users in a social network. Finally, we utilize various metrics to analyze the future directions of folk culture and cultural transmission.

The remaining sections of the paper are organized as follows: Firstly, we introduce relevant work in the field of folklore culture. Secondly, we delve into the mechanisms underlying folklore culture and propose a deep learning model. Subsequently, a series of experiments and analyses are presented. Finally, we summarize the mechanisms of folklore culture dissemination and outline future directions for its propagation.

2 Related Work

2.1 Folklore culture

A folk concept refers to a commonly understood idea within a specific sociocultural group, lacking formal definition or standardization. These concepts are conveyed through discourse, nonverbal actions, and social customs, rather than being documented in published texts or media. However, they can be influenced by folk interpretations of textual or media sources[1]. Folk concepts often intersect with other types of concepts. For instance, customs like saying grace before meals can merge culturally specific folk traditions with religious teachings rooted in texts[12].

Sousa et al.[13] presented a framework for the digitization of folk dances, using the “Dança dos Paulitos” or “Dança dos Pauliteiros”, a traditional Portuguese festive dance ritual from Miranda in northeastern Portugal, as a practical case study. Bernstein[14] described the origins of folklore and gave related concepts from an anthropological perspective. Specifically, a folk concept is a universally understood concept specific to a socio-cultural group but not yet formally defined or standardized. Folk concepts are encoded in discourses, non-verbal behaviors, and social practices rather than in published texts (such as newspapers, magazines, or books) or other media. Baruadi et al.[15] emphasized the importance of folklore development from the perspective of tourism development. They argued that local culture and lifestyle receive a deep influence from folklore culture, and they used field surveys and interviews to obtain data and folklore analysis to approach the object of study, and pointed out the direction of the research. With the development of the Internet, more and more users upload the contents of their lives to social networking sites; thus detaching from the examination based on the actuality, Seta[16] expressed the influence of the Internet on the dissemination of folk culture from the perspective of digital age. The importance of digital folklore is emphasized from four perspectives.

Digital folklore may also prove not to be an enduring analytic concept, but it demonstrates the the need for widely recognized descriptors that incorporate folk ideas[17]. Toelken[18] described this folk culture as “a combination of changing (‘dynamic’) and static (‘conservative’) elements, involving elements that typically evolve and change through sharing, communication, and performance”. As people interact, folk culture is evolving with the times. The tasks of dynamically preserving folk culture, rather than turning it into cultural heritage, are a serious challenge[19, 20]. Digital folklore is a thriving area in internet studies, and its pivotal role in the participatory and creative landscape of digital media political economics is likely to affirm the close relationship between digital folklore and the Internet in the future.

2.2 Information propagation in social networks

Social networks serve as a conduit for establishing connections between any two users, offering a reliable conduit for information propagation and mutual assistance. They play a pivotal role in facilitating collaboration and communication between individuals and enterprises. Additionally, social networks exhibit a propensity for clustering like-minded users[21]. For instance, two individuals sharing a proclivity for a particular cinematic work may find it conducive to forging connections, leading to heightened interactivity.

In concert with these observations, the theory of information propagation comes into focus. Information diffusion pertains to the orchestrated transmission of information, ideas, attitudes, or emotions between individuals, organizations, and collectives through symbolic representation and media channels[22]. The intention is to elicit corresponding responses and adjustments. Notably, this theory underscores the creation of channels for communication and interaction between individuals, which in turn, influences their behavior. In practice, individuals assume the dual role of information recipients and disseminators, with their channels of information exchange primarily consisting of mass media and interpersonal networks [23].

Typically, an individual's reach within interpersonal networks is directly proportional to the avenues available for both the acquisition and propagation of information. A pertinent study conducted by Hamilton et al.[24] sought to illuminate the intricacies of information propagation processes and patterns in social media. Employing data extracted from online social networking sites, they discerned the prevalence of a multitude of triadic structures within social networks[25]. These structures, formed by nodes interconnecting in triangular configurations, hold paramount significance in the context of understanding information propagation dynamics and the establishment of interpersonal relationships. Within interpersonal networks, individuals predominantly resort to friends as both information sources and recipients. In 1998, Watts and Strogatz[26] introduced the "Small-World Network" model, known as the WS model. The primary contribution lies in presenting a model that bridged the gap between regular networks and random networks. Importantly, this model allows for the tuning of network structure by adjusting the rewiring probability "p", thus enabling a transition between regular and random network characteristics. Following the revelation that the degree distribution of the Internet exhibits power-law characteristics, scale-free networks become a central focus of researchers[27]. Based on these two significant features, Barabási and Albert[28] introduced a scale-free network model. They illustrated that many real-world networks exhibit what is termed "scale-free" behavior. Based on the propagation mechanism of social network worms from the perspective of social engineering[29–31], they quantified several factors influencing user behavior, and introduced a micro-level user behavior game model based on user security awareness. Additionally, by analyzing habitual patterns of network user activities, they developed a macro-level and discrete social network access model based on user habits[32].

The methods mentioned above only give the interactions between nodes and predict the presence or absence of links between nodes, without determining the strength of interactions between network nodes and the factors affecting the propagation of information. There is a breakdown of the two concepts focusing on content and propagation modes. From the perspective of content, folklore propagation primarily deals with the dissemination of traditional cultural forms and social customs that are shared and passed down by a social group or community. This includes rituals, folklore, storytelling, and customs unique to a particular group or region. The content revolves around traditions that have been practiced over generations and reflect the collective identity, values, and beliefs of the community[33, 34]. Information propagation encompasses a wide range of content, including news, facts, opinions, ideas, and knowledge. It can be practical or academic, scientific or cultural. Unlike folk culture, the content is not necessarily rooted in tradition or bound by specific social groups. It can include new discoveries, trends, and developments that are constantly evolving.

Based on the means of propagation, the propagation of folklore culture typically occurs through oral tradition, rites, and performances[35]. It involves storytelling, ceremonies, festivals, dances, songs, and other forms of communal expression. These mediums are often deeply rooted in the community's history and involve direct interaction among community members. They may also be associated with specific times of the year or special occasions, reinforcing the community's sense of unity and continuity. The information propagation primarily occurs through media channels, such as newspapers, television, radio, and digital platforms like the internet and social media. Information can also be disseminated through personal communication, including conversations, letters, and emails. Unlike folk culture, information dissemination often relies on written and visual forms, making it more accessible to diverse audiences and easily reproducible[36].

While involving the propagation of cultural knowledge, folk cultural propagation often involves the preservation and continuation of traditions within a specific group, while information dissemination is more about the sharing of knowledge and ideas across wider communities. The propagation modes and mediums are also different, with folk culture often relying on oral and communal forms, and information propagation involving written and visual media.

3 Theroretical Framework

By presenting folklore on the Internet, it is possible to reproduce places, rituals, crafts, or any other type of cultural heritage. It can also be used for various recordings, such as documentaries, tourism, and education. The preservation of folk culture is characterized by diversity and the influence of many factors. We focus on a theoretical framework to encompass multiple considerations comprehensively.

As shown in Fig. 3, there is a theoretical framework for folklore propagation. Firstly, acquisiting folklore data is necessary. The richness of folklore data from different places should be comprehensively collected as a basis for studying the spread of folklore culture. Next, the data encompass various attributes, such as gender, geographic location, nationality, and more, which need to be effectively integrated and filtered. Building upon this foundation, the establishment of an analytical model can be approached from two main perspectives. Firstly, by constructing a social network graph based on content generated by social media users, one can visualize the connections between users. From the standpoint of social network theory, this can be categorized into the following three key aspects:

(1) Belief propagation: Consider how to communicate and share the beliefs, values, and traditional concepts of folk culture. Understand the beliefs and values of different social network users, so that these beliefs are reflected and honored in content.

(2) Content credibility: The credibility of content is critical in the communication of beliefs. Ensure the folklore and cultural content being disseminated is accurate and credible to build trust.

(3) Social influence: Consider social influences in social networks, i.e., how other users influence individual beliefs and behaviors. Understand opinion leaders and influential users on social networks to understand how they contribute to the spread of beliefs and cultural values.

Locality is an important attribute of folk culture, and the cultural propagation of local services is an important channel. It is important that local institutions or organizations provide strong support and spread to different communities. Two main aspects should be considered. **(1) Engagement interaction:** Interaction and participation in social networks is an important factor in the spread of beliefs. Effective interaction can encourage users to participate in discussions, share their faith and cultural experiences, and promote deeper conversations about folk culture. **(2) Diffusion and acceptance:** Understanding how faith and cultural perspectives are diffused and received. Consider the speed and means of information dissemination in social networks will promote better communicate faith and cultural values.

Based on the above theoretical framework, folk culture propagation is analyzed from social networks and local services. The following section simulates the process of folk culture propagation from social network theory.

4 Approach

4.1 Motivation

In this subsection, we first demonstrate the major research background and motivation of our paper. To begin, let us model the propagation system within the social network by representing it as a directed network, a topological network denoted as $G = (V, E)$. In this context, V represents the set of nodes, while E represents the set of edges between these nodes. Specifically, users are represented as nodes, and the

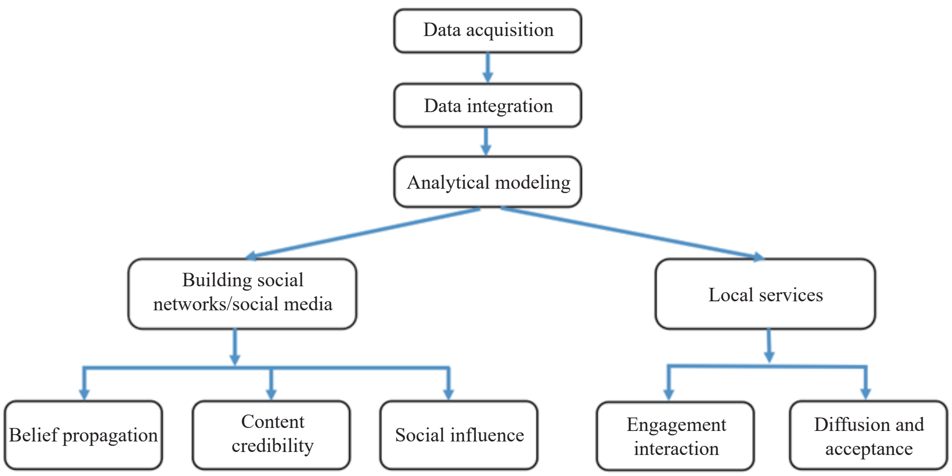

Fig. 3 Theoretical framework.

relationships between users are depicted as edges. As illustrated in Fig. 4, there is a user set $\{u_1, u_2, u_3, u_4, u_5, u_6\}$.

Within this network, there exists a connection between u_1 and u_2. Furthermore, the propagative nature of the social network leads to broader interconnections. In particular, u_1 is linked to u_2, u_3, and u_4. Meanwhile, each of u_2, u_3, and u_4 has connections with u_5 and u_6. Two users with direct social interactions are easy to determine (e.g., u_1 and u_2), yet direct social interactions are very rare. In real life, each user has his/her own social circle and user community, and the relationship between users as well as the linking paths are intricate (e.g., u_1 and u_5). Thus, given this topological structure, the challenge lies in how to effectively integrate other users and accurately compute the social relationship between u_1 and u_5.

As a mainstream method in machine learning, the embedding framework offers significant advantages. On one hand, it can transform sparse scalar data into continuous vectors, reducing information loss. On the other hand, the embedding framework can maintain the original semantic relationships in a multi-dimensional space. Recognizing the advantages of embedding, it can be applied to the dissemination of folklore within social networks.

This application can help convert traditional folklore elements into a digital format, making it easier to spread and share on social networks. This process not only aids in preserving and passing down folklore, but also attracts a broader audience, promoting the dissemination of cultural diversity and mutual understanding.

4.2 SocialPre approach

Based on the topology of social networks, we propose a comprehensive social relationship prediction method called SocialPre. The framework of the SocialPre approach is shown in Fig. 5. Specifically, the process of predicting social relationships among users is divided into three stages. The first stage involves

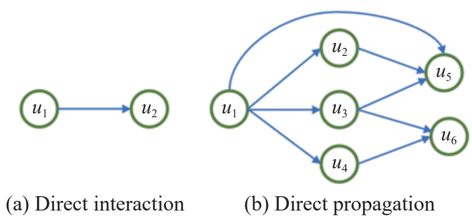

Fig. 4 Propagation of social networks.

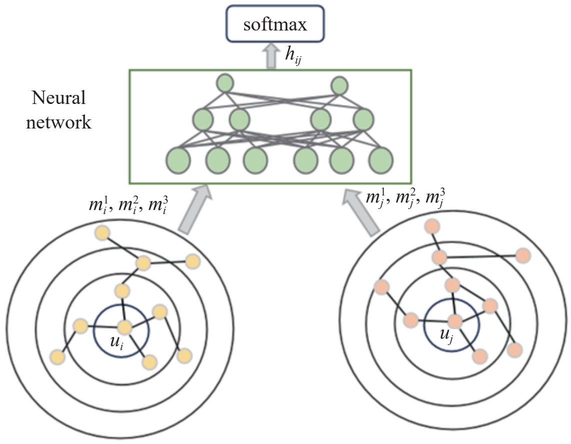

Fig. 5 Framework of SocialPre approach.

uncovering users' multi-order social relationships within the social network. In the second stage, we model the propagative nature of social relationships, incorporating the multi-order social relationships among users. Finally, leveraging these multi-order user relationships, we predict social relationships between users and their social neighbors. Building upon this foundation, we facilitate the dissemination of folklore within the network.

(1) First stage

First, we model the user information. $U = \{u_1, u_2, \ldots, u_m\}$ denotes the user set based on social networks. Each user possesses profile information, such as their account and ID details. Any interaction between two users is binary-coded, for example, a social interaction between users u_i and u_j is marked as 1, and if there is no interaction, it is marked as 0. To identify low-order neighbor relationships between users, we first consolidate the first-order neighbors of users. According to social science theories, users' social behavior is easily influenced by similar or directly interacting people. Therefore, we first use a breadth-first algorithm to find the first-order neighbors of the user, i.e., directly connected to the user. In this manner, we combine user profile information with binary-coded social interactions to uncover and establish first-order neighbor relationships between users. The first-order neighbor set of u_i can be denoted as $N_1(u_i)$. Following the mainstream user-embedding approach, Node2vec is first used initially to obtain user-embedding representations,

$$m_i^1 \leftarrow \{h_i \oplus (h_k \oplus h_{ik}) \mid u_k \in N_1(u_i)\} \tag{1}$$

$$m_j^1 \leftarrow \{h_j \oplus (h_s \oplus h_{js}) \mid u_s \in N_1(u_j)\} \tag{2}$$

where h_i denotes the embedding vector for the profile of u_i, h_k denotes the embedding vector for the profile of u_k $(u_k \in N_1(u_i))$, and h_{ik} denotes the embedding vector for the social interaction between u_i and u_k. $\oplus$ denotes the operation of splicing between any two vectors. m_i^1 denotes the comprehensive embedding matrix representation of u_i. Without loss of generality, we can obtain a comprehensive representation of u_j. With the above equation, the user's first-order neighbor information is merged.

The working principle of embedding is to map high-dimensional data into a low-dimensional space. It mainly achieves this through two steps: (1) Feature extraction: Extract a set of features from the raw data, which are usually some representations of the raw data. (2) Feature transformation: The representation of the original data is mapped from a high-dimensional discrete space to a low-dimensional continuous data space, while preserving the original data's interrelationships. On the one hand, by performing dimensionality reduction, embedding can better capture the relationships between discrete data, providing a feature representation basis for data analysis and modeling. On the other hand, through embedding, we can only consider the data of the users themselves, without linearly searching for the correlation between social interactions and other users, preserving the semantics of the original data, and providing a feature representation basis for the following Multi-Layer Perceptron (MLP) network.

(2) Second stage

In the first stage, we obtain embedding representations for users who are directly connected to one another as friends. Following the "six degrees of separation" theory in social networks, we delve into the high-order neighbor information of users. Similarly, we mine the set of second-order neighbors of user u_i, represented as $N_2(u_i)$, while the set of third-order neighbors is represented as $N_3(u_i)$.

Furthermore, we can obtain the aggregated representations of user u_i's second-order neighbors and third-order neighbors, denoted as m_i^2 and m_i^3. To distinguish and recognize the impact of features from different-order neighbors effectively, we employ a personalized weighting strategy, defined by the following formula:

$$f_i \leftarrow w_i\,(\alpha m_i^1 \oplus \beta m_i^2 \oplus \gamma m_i^3) + b_i \tag{3}$$

$$f_j \leftarrow w_j\,(\alpha m_j^1 \oplus \beta m_j^2 \oplus \gamma m_j^3) + b_j \tag{4}$$

where α, β, and γ denote the adaptive parameters, and they are defined as $\alpha+\beta+\gamma=1$. w_i, w_j, b_i, and b_j are the trainable weight matrices and bias matrices in neural networks. f_i and f_j denote the representations of u_i and u_j fusing first-order, second-order, and third-order neighbors, respectively. This personalized weighting strategy serves two main purposes. Firstly, it helps us distinguish and evaluate the impact of features from various neighbor orders, thereby enhancing the accuracy of our analysis. Secondly, it effectively addresses the issue of certain features having a minor impact on the outcome. By assigning smaller weights to these less influential features, we can reduce the model's emphasis on them. This not only streamlines the analysis process, but also mitigates the risk of overfitting by ensuring that the model does not overemphasize these features.

In this manner, we progressively explore the network's higher-order neighbor relationships, allowing us to capture a more comprehensive understanding of the users' social connections and interactions.

(3) Third stage

After these stages, we can obtain feature representations for any two users, which incorporate information from multi-order neighbors. To estimate the social relationship between any two users, we utilize the softmax function to connect and compute user features,

$$h_{ij} \leftarrow \text{softmax}\,(w_{ij}\,(f_i \oplus f_j) + b_{ij}) \tag{5}$$

where w_{ij} and b_{ij} are trainable weight matrices and bias matrices, respeclively. $h_{ij} \in [0, 1]$ denotes the likelihood of social interaction between user u_i and u_j. When h_{ij} is greater than 0.5, we consider u_j as a social friend of u_i. Consequently, we can, based on the calculated likelihood, identify all friends who have a social likelihood with u_i and include them in the set $N(u_i)$. Leveraging these users with similar preferences, u_i can propagate folklore among them.

These stages allow us to identify potential social friends for a user based on the likelihood of interaction and utilize this network to facilitate the dissemination of folklore among users who share similar preferences. Meanwhile, this approach ensures a comprehensive understanding of users' social connections and their potential influence, enhancing the dissemination of folklore within the social network. Additionally, Algorithm 1 demonstrates the methodological process

Algorithm 1 SocialPre approach

Require: User set $U = \{u_1, u_2, \ldots, u_m\}$, network embedding of social network, embedding representation of social interactions, first-order neighbors $N_1(u_i)$, $N_1(u_j)$, and parameters α, β, and γ

Ensure: Likelihood h_{ij} of social interaction between u_i and u_j

1: **begin**
2: **if** $u_k \in N_1(u_i)$ **then**
3:   **if** $u_s \in N_1(u_j)$ **then**
4:     Obtain embedding representations h_i, h_k, and h_{ik};
5:     Obtain embedding representations h_j, h_s, and h_{sj};
6:     $m_i^1 \leftarrow \{h_i \oplus h_k \oplus h_{ik}\}$;
7:     $m_j^1 \leftarrow \{h_j \oplus h_s \oplus h_{sj}\}$;
8:   **end if**
9: **end if**
10: Loop Lines 9−16;
11: Obtain representations m_i^2, m_j^2, m_i^3, and m_j^3;
12: $f_i \leftarrow w_i\,(\alpha m_i^1 \oplus \beta m_i^2 \oplus \gamma m_i^3) + b_i$;
13: $f_j \leftarrow w_j\,(\alpha m_j^1 \oplus \beta m_j^2 \oplus \gamma m_j^3) + b_j$;
14: $h_{ij} \leftarrow \text{softmax}\,(w_{ij}(f_i \oplus f_j) + b_{ij})$;
15: Set threshold for h_{ij};
16: Predict social interactions based on the threshold;
17: **end**

of SocialPre.

To assess the efficiency of the SocialPre model, its computational complexity has been analyzed.

Given that the input feature dimension for the embedding layer is D, and the dimension of the embedding layer is K, the computational complexity of the embedding operation is usually $O\,(K \cdot D)$. For the fully connected layer, the number of hidden layer neurons is H, the output dimension is M, and the dropout probability is p, so the computational complexity of the fully connected layer is typically $O\,(H \cdot M + H \cdot M + H \cdot M \cdot p)$. The computational complexity of the Softmax operation is typically $O\,(H \cdot M)$. The total computational complexity is the computational complexity of the embedding operation plus the computational complexity of the fully connected and Softmax operations, which is $O\,(K \cdot D + 4 \cdot H \cdot M)$.

5 Experimental Validation

5.1 Data sources

We utilize the widely applied Epinions dataset from the realm of social networks[37, 38]. This dataset encompasses social interactions between users on the Epinions website over a span of 12 years and comprises a total of 7458 users. The social relationships between users in this dataset are binary-coded, offering a robust simulation of user connections. The Epinions dataset serves as a suitable and comprehensive resource for analyzing social interactions and relationships among users.

However, some network topologies formed by more users exhibit hexagonal pattern, with several central nodes. This network structure has several advantages. On one hand, it allows for the effective utilization of social propagation theory, facilitating the dissemination of information across multiple communities or nodes. On the other hand, central nodes possess a greater number of neighboring communities. Through the propagation from these central nodes, edge nodes can receive information more rapidly.

This network structure is conducive to efficient information dissemination and interaction among users, where central nodes play a pivotal role in accelerating the spread of information to the periphery.

5.2 Basic methods and metrics

Based on the social network formed by the Epinions dataset, we perform a series of simulation experiments to validate the effectiveness of the approach. To assess the effectiveness of our method, we compare it with several competitive approaches: (1) User-based Collaborative Filtering (UCF)[39]: This method calculates the relationship between any two users based on their shared friends using collaborative filtering techniques. (2) Matrix Factorization (MF)[40]: In this approach, user ratings are transformed into a matrix, and matrix factorization is employed to compute the relationships between any two users. Meanwhile, accuracy, time consumption, and other metrics are used to test the effectiveness and efficiency of the approach. Accuracy is a common metric for evaluating the performance of a classification model. It represents the proportion of correctly classified samples out of the total number of samples. The formula for Accuracy is as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{6}$$

where True Positive (TP) refers to the number of correctly predicted positive instances, True Negative (TN) refers to the number of correctly predicted negative instances, False Positive (FP) refers to the number of instances where the model incorrectly predicted a positive outcome, and False Negative (FN) refers to the number of instances where the model incorrectly predicted a negative outcome. Generally, accuracy is an intuitive measure that indicates the percentage of samples that the model classified correctly out of the total samples. A higher accuracy value indicates better model performance. However, it is important to note that when the number of samples in different classes is imbalanced, high accuracy may not always be a good performance indicator. In such cases, the F1-score is a metric commonly used to evaluate the comprehensive performance of a classification model, particularly when dealing with imbalanced datasets. It combines two essential metrics, Precision and Recall, into a single score, providing a balanced assessment of a model's performance.

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{7}$$

where Precision is the ratio of true positive predictions to all positive predictions, and Recall is the ratio of true positive predictions to all actual positive samples. The F1-score is the harmonic mean of Precision and Recall. The F1-score ranges between 0 and 1, where a higher value indicates better model performance. It is particularly useful in situations where there is an imbalance between the number of positive and negative samples, as it considers both false positives and false negatives in its calculation, striking a balance between precision and recall. A higher F1-score signifies a better trade-off between Precision and Recall, making it a valuable metric for classification tasks.

5.3 Simulation experimental analysis

(1) We validate the effectiveness of the methods across different numbers of users, with users divided into 1000, 3000, 5000, 7000 groups. As shown in Fig. 6, we assess the accuracy of the three methods with respect to different user group sizes. When there are only 1000 users, all three methods exhibit relatively low accuracy. As the number of users gradually increases from 1000 to 7000, with increments of 2000 users at each step, the overall trend shows a gradual, albeit slow, increase in accuracy. This can be attributed to the fact that with a larger user pool, the three methods are able to filter more effectively, identifying a greater number of potential social friends for interaction. Notably, the SocialPre method demonstrates the best performance.

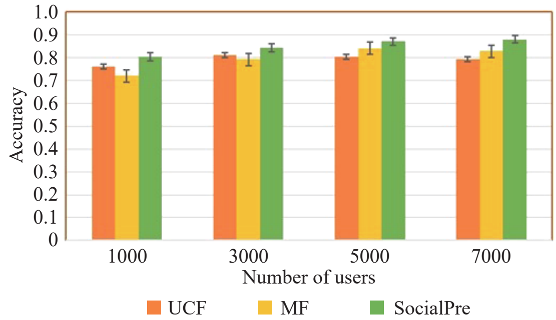

Fig. 6 Accuracy of three competitive approaches.

These experiments reveal that as the user base grows, the methods can better leverage the potential for social interactions, with the SocialPre method leading in terms of performance.

(2) As shown in Fig. 7, we assess the performance of the three methods in terms of F1-score across different user groups. Overall, as the number of users gradually increases, the F1-score performance of all three methods improves. UCF and MF display similar trends, primarily because both methods are based on a rigid friend-filtering mechanism involving mutual friends between two users. In contrast, the SocialPre method, which utilizes an embedding mechanism, retains social friends for interactions between any two users, expanding the scope of effective features. Furthermore, the multi-hop friend propagation contributes to an increased pool of shared and effective neighbors. Consequently, the comprehensive performance of the SocialPre method is proved to be superior. The above experiments demonstrate that as the user base grows, the SocialPre method outperforms the others, mainly due to its ability to preserve social interactions and a broader range of effective features among users.

In Figs. 6 and 7, we compare the accuracy and F1-score of three methods across different user counts. As the number of users increases, so does the interaction between them. The F1-score of SocialPre gradually increases. However, it should be noted that this

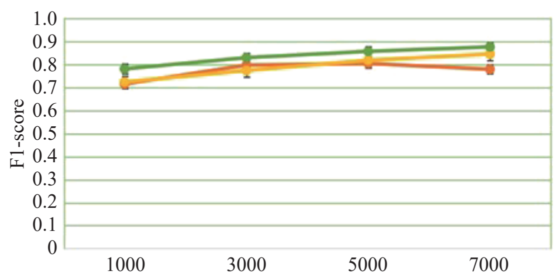

Fig. 7 F1-score of three competitive approaches.

analysis does not consider the dynamic interactions between users.

(3) As shown in Fig. 8, regarding computational complexity, the running time of SocialPre depends on the number of training rounds. UCF is based on a linear search method, with a computational complexity of $O(M \cdot N)$. On the other hand, MF is based on matrix factorization, with a computational complexity of $O(M \cdot N \cdot S)$ (where S represents the dimension of feature values). However, during training, SocialPre only uses the dimension of the users' features and does not require a search. The entire model achieves a fit when trained for 50 rounds. Thus, SocialPre's time efficiency falls between that of UCF and MF. Overall, the values of computation time of the three methods are rising gradually as the number of users increases.

(4) To validate the probability of establishing social interactions between any two users, we examine the impact of different probability values on the F1-score in Table 1. Specifically, we set the probability values within the ranges of 0.3–0.4, 0.4–0.5, 0.5–0.6, 0.6–0.7, and 0.7–0.8, denoted as Group 1, Group 2, Group 3, Group 4, and Group 5, respectively. As shown in Table 1, the performances of different methods in terms of F1-score vary with different probability values. As the probability values increase gradually, which implies the use of more stringent criteria to match interaction features between any two users, the methods demonstrate improved performance. When the probability values ranged from Group 1 to Group 4, all three methods successfully identify true social

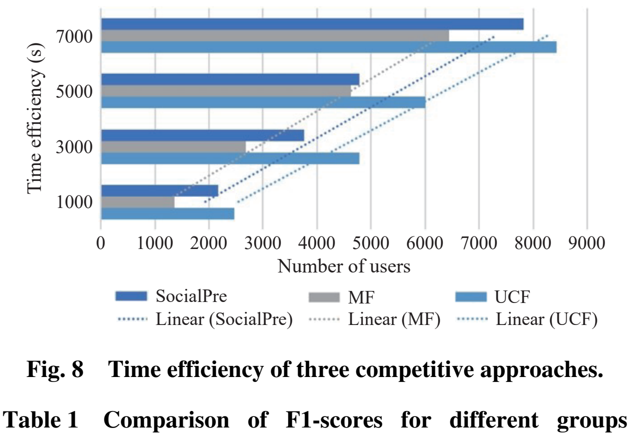

Fig. 8 Time efficiency of three competitive approaches.

Table 1 Comparison of F1-scores for different groups based on various approaches.

Approach	Group 1	Group 2	Group 3	Group 4	Group 5
UCF	0.6925	0.7695	0.8221	0.8631	0.8711
MF	0.8136	0.8577	0.8710	0.8833	0.8745
SocialPre	0.8215	0.8600	0.8828	0.8949	0.9089

interaction friends. In Group 5, the performance plateaus slightly, as friends with a high likelihood of establishing social interactions have already been discovered. Overall, the SocialPre method consistently delivers the best performance across different probability values. This analysis underscores the capability of the SocialPre method to excel in various probability scenarios, highlighting its robustness in identifying genuine social interaction friends. In summary, as the probability values increase, the SocialPre method consistently outperforms other methods across varying probability levels. This observation underscores the necessity for stringent conditions to facilitate the establishment of social interactions between users. Moreover, the growing number of users augments SocialPre's predictive capability, emphasizing the importance of striking a balance between the number of users and the probability threshold setting to optimize the prediction of social interactions.

5.4 Analysis of factors influencing the dissemination directions of folklore culture

(1) Cultural ecological differences: Cultural ecology encompasses the sum of the natural and social environments upon which the production and development of culture depend. At its core, the diversity of cultures ultimately hinges on the disparities in how human societies adapt to and transform their natural and social surroundings[41]. In summary, the rich tapestry of human cultures is intricately woven with the complexities of the environments in which they evolve.

(2) Richness of multi-ethnic indigenous art: Indigenous art is the crystallization of creative activities within the cognitive and spiritual realms of primitive human societies, and the latter forms a rational continuation of the former. With the continuous advancement of human intelligence and civilization, the numerous primitive thoughts and images present in indigenous art are gradually replaced by the thoughts and images of civilized eras, transcending and evolving into civilization[42]. Despite having undergone extended historical periods, developing folk cultures continue to preserve remnants of primitive-era thinking and cultural imprints. Consequently, the long-standing economic, historical, political, geographic, and developmental diversity and imbalances among different ethnic groups have nurtured the richness and diversity of folklore culture[43]. In conclusion, the multifaceted nature of folklore culture's richness is a testament to the historical, economic, and sociocultural diversity among various ethnic groups.

(3) Internet folkloristics: Internet folkloristics is the study of various online content and communication methods found on the Internet, including online jargon, emoticons, copy-pasted jokes, and Internet memes. Researchers explore these digital folklore resources to understand their dissemination and evolution in an online environment. Internet folkloristics allows researchers to gain insights into the diverse online cultures, ranging from jargon and emoticons to memes and copy-pasted jokes[44]. This understanding is crucial in comprehending the digital age's transformation of traditional folklore.

Furthermore, from the perspective of identifying Internet folkloristics, researchers can identify emerging trends and cultural shifts within online communities. This can provide valuable insights into societal changes and the development of digital folklore over time. From the perspective of evolving communication methods, the study of digital folklore highlights the evolution of communication methods in the digital age[45]. By analyzing how online content and communication methods change and spread, researchers can gain a deeper understanding of how people interact and communicate in the digital realm. To summarize, Internet folkloristics delves into the fascinating world of digital folklore and its transformations in the digital age[46].

(4) Vernacular creativity: Vernacular creativity emphasizes the creative expression of Internet users when creating and sharing various online content. This includes users creating content in text, images, or other media forms to showcase their uniqueness and identity[45, 47]. In essence, vernacular creativity highlights the innovative expressions of individuals in the digital realm.

(5) Virtual reality technology: Virtual reality technology offers an immersive way to experience traditional folklore. Users can virtually attend festivals, reenact traditional ceremonies, or explore cultural sites. For instance, Ref. [48] demonstrates how Virtual Reatily (VR) can bring history to life. VR is being used to educate and document folklore practices. It can serve as an interactive educational tool, providing a more engaging and comprehensive understanding of folklore customs[49]. Furthermore, VR has emerged as a tool for preserving and making folklore accessible. It allows for the digital preservation of intangible cultural heritage, ensuring that future generations can learn about and experience traditional folklore.

(6) Analysis and extraction of cultural data: Using computer science techniques, cultural data can be analyzed and extracted to better understand the nuances of folklore culture. Machine learning and data mining can identify trends and patterns. This includes identifying key cultural nodes, studying the spread of folklore ideas, and understanding the influence of different cultural factors[50]. Folklore content is analyzed to understand sentiment and trends. This can include identifying popular folklore topics, examining public reactions to cultural events, and tracking the evolution of folklore narratives[51].

5.5 Discussion

Due to the "intangible" nature of folklore culture, it differs from conventional cultural transmission. Folklore culture can be easily influenced by external factors throughout its genesis and development, leading to changes during its dissemination and diffusion. Consequently, it is challenging to delineate specific geographical regions for some folklore culture transmissions due to the presence of both human-driven and uncontrollable factors. As such, this study simulates the transmission of folklore culture primarily through "individuals" based on existing online social networks, and establishes a theoretical transmission model. This approach serves as a foundational basis for future research into the transmission of folklore culture.

6 Conclusion

Folk culture reflects various events, organizing complex phenomena into stable patterns, which provide convenience and impact a wide audience. In this paper, we first introduce folk culture and establish a theoretical model for the transmission of folk culture. Among the essential components of this model, social networks play a vital role. Leveraging social network propagation theories like the "six degrees of separation", we have developed a comprehensive method, called SocialPre, based on social network propagation theory. We employ embedding technology to retain both low-order and high-order social acquaintances of users. Using an automated weight allocation mechanism based on the embedding representation, we integrate the multi-order social acquaintances to measure the likelihood of social interaction between any two users. A series of experiments indicates that SocialPre demonstrates excellent performance. It has the capability to categorize different social groups, laying the foundation for the dissemination of folk culture. Lastly, but equally significant, we discuss the potential development directions of folk culture, providing a theoretical basis for future folk culture transmission.

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