IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 17 November 2023, accepted 18 January 2024, date of publication 22 January 2024, date of current version 30 January 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3357094

RESEARCH ARTICLE

The Influence of Digitization on the Dissemination of Traditional Chinese Music and Weibo Content Propagation Under Deep Learning

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ABSTRACT This study aims to investigate the dissemination of traditional Chinese music in the digital era and the application of deep learning in predicting the influence of Weibo content propagation. Firstly, the impact of digitization on the dissemination of traditional Chinese music is analyzed. Secondly, based on the Bidirectional Gated Recurrent Unit (Bi-GRU), traditional content feature modeling methods are optimized by introducing content text features. Simultaneously, the Graph Attention Network (GAN) is divided into three steps, allowing it to consider the edge properties of input sequences. The improved content feature modeling, GAN, and multilayer perceptron are integrated to construct a Context-dependent Dynamic Graph Attention Network (C-DGAN). In order to validate the performance of the C-DGAN model, Mean Square Logarithmic Error (MSLE) is used as the evaluation metric in comparative experiments at observation times T=1, 2, 3, and 4 hours. The results indicate that at T=4 hours, C-DGAN achieves an MSLE of 1.854, reducing by at least 0.134 compared to the baseline model, demonstrating superior performance in predicting the scale of Weibo content propagation. Additionally, in comparison with models using different recurrent neural networks, the model employing the Bi-GRU network performs the best. Thus, the proposed C-DGAN model exhibits excellent performance in predicting Weibo content propagation influence. The study findings provide robust support for the study and practice of Weibo content propagation.

INDEX TERMS Weibo propagation influence, deep learning, traditional Chinese music, self-attention mechanism, graph attention network.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

In the wave of digitization, traditional Chinese music, a vital component of cultural heritage, faces both new opportunities and challenges in terms of dissemination [1], [2], [3]. With the rise of social media platforms, especially the widespread use of Weibo in China, traditional music has undergone a profound transformation in how it is showcased and disseminated in the digital society. Against this backdrop, understanding the impact of digitization on the dissemination of traditional Chinese music and utilizing deep learning techniques to assess the influence of its propagation on Weibo have become urgent issues to address.

Traditional music carries rich cultural significance, but in the digital era, it must adapt to the rapid and fragmented nature of information dissemination [4], [5], [6]. This implies that traditional music needs to leverage advanced technologies, such as deep learning, to better align with the communication environment of digital social media [7], [8], [9]. Therefore, the motivation of this study is to gain in-depth insights into the dissemination characteristics of traditional Chinese music in the digital era and, leveraging the technical advantages of deep learning, enhance the accuracy of predicting the influence of traditional music content propagation on Weibo. This not only aids in more effectively conveying the unique beauty of traditional music on digital social media

The associate editor coordinating the review of this manuscript and approving it for publication was Abdel-Hamid Soliman.

but also provides new perspectives and approaches to cultural heritage and innovation.

B. RESEARCH OBJECTIVES

This study aims to delve into the dissemination characteristics and challenges of traditional Chinese music in the digital era and, in conjunction with deep learning technology, construct an effective model for evaluating and predicting the influence of Weibo content propagation. Thus, the study objectives are as follows: first, to conduct a thorough analysis of the impact of digitization on the dissemination of traditional Chinese music; second, to explore the application of deep learning methods in predicting the influence of Weibo content propagation. By leveraging technologies such as Bidirectional Gated Recurrent Unit (Bi-GRU) and Graph Attention Network (GAN), this study optimizes traditional content feature modeling methods to construct a novel GAN that considers context dependence and time information. This aims to more accurately assess and predict the influence of Weibo content propagation. The study aspires to provide robust theoretical and practical support for the dissemination of traditional music in the digital media environment.

II. LITERATURE REVIEW

In the era of digitization, there has been a notable impact on cultural communication. Zhang and Negus traced the development of the Chinese pop music idol industry, exploring the rise of data-driven fan culture on digital social media platforms. They emphasized its structural impact on the music industry and fan engagement models [10]. Li investigated the effectiveness of innovative massive open online course (MOOC) teaching models, assessing the potential for changing the approach to learning Chinese folk music in higher education. The findings suggested that online courses contribute to the effective dissemination of traditional Chinese music and culture, with features conducive to well-structured curriculum designs, making them an effective means for promoting Chinese culture [11]. Alieva et al. focused on endangered traditional cultures in the face of modern threats, using Russia and the Chinese Far East as examples. They discussed the use of music and information technology as means of salvation, dissemination, and protection of musical culture [12]. In times of cultural heritage crisis, music and information technology present a viable solution.

Moreover, there is extensive research on the application of machine learning and deep learning in social media data analysis and dissemination. Balaji et al. provided an overview of machine learning algorithm types and extensively examined their practical applications in social media analysis. They highlighted the challenges and advantages of machine learning in handling vast social media data [13]. Tadesse et al. aimed to automatically identify suicidal ideation on social media using deep learning and machine learning methods. Experimental results demonstrated the effectiveness of neural network architectures, employing word embedding techniques in achieving optimal classification results for identifying suicidal ideation [14]. This study holds significant importance for the early detection of potential suicide risks on social media. Sahoo and Gupta proposed an automatic false news detection method in the Chrome environment for detecting false news on Facebook, using deep learning and analyzing user account behavior and news content features related to Facebook accounts. The method showed higher accuracy in detecting true information compared to existing technologies [15].

The studies above highlight the influence of digital technology on traditional cultural communication and the application of deep learning in content analysis and dissemination. However, there is limited research exploring deep learning-based evaluation of social media content propagation. Therefore, this study focuses on exploring the role of Weibo in the dissemination of traditional Chinese music and analyzing the application of deep learning in evaluating the propagation dynamics of content on Weibo.

III. RESEARCH METHODOLOGY

A. THE IMPACT OF DIGITIZATION ON THE DISSEMINATION OF TRADITIONAL CHINESE MUSIC

In the digital era, social media platforms have emerged as crucial channels for cultural dissemination, offering a novel means of communication for traditional music. Among these platforms, Weibo, as one of China's most influential social media platforms, plays a significant role in the dissemination of traditional Chinese music [16], [17], [18]. The role of Weibo in the dissemination of traditional Chinese music is illustrated in Figure 1.

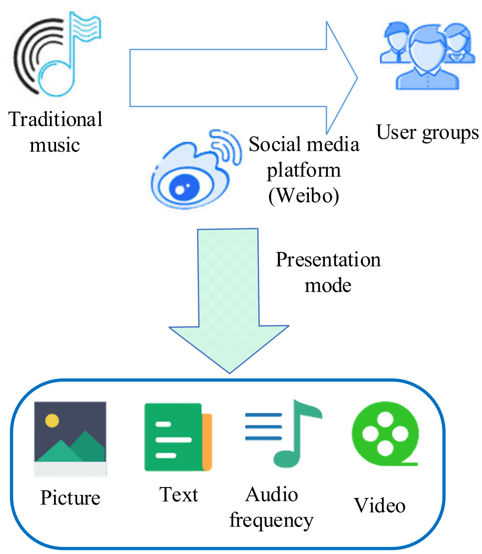

FIGURE 1. The role of Weibo in the dissemination of traditional chinese music.

In Figure 1, the role of Weibo in the dissemination of traditional Chinese music is outlined as follows: Firstly, Weibo, with its openness and extensive user base, provides a broader platform for the dissemination of traditional Chinese music. Through Weibo, traditional music can break through traditional geographical and temporal constraints, reaching audiences globally in a rapid manner. Artists, music institutions, and enthusiasts can share music works, concert information, and cultural activities in real time on the Weibo platform, adding vibrancy to traditional music. Secondly, social media platforms in the digital era offer a more intuitive and multimedia presentation of traditional music. Through video, images, and other multimedia forms, traditional music is presented in a more vivid and concrete manner to the audience. This presentation format makes traditional music more appealing to the younger generation, contributing to its dissemination among youth [19], [20], [21], [22].

However, the digital era's modes of communication also bring about challenges. The rapid dissemination and fragmentation of information make it difficult for traditional music to achieve in-depth dissemination, requiring innovative communication strategies to guide the audience in a deeper understanding of the essence of traditional music. Additionally, the digital era places emphasis on the quality and authenticity of musical content, necessitating greater attention from music professionals to the originality of music works and the quality of cultural heritage [23], [24], [25]. Furthermore, predicting the propagation dynamics of Weibo content plays a crucial role in the dissemination of traditional Chinese music.

B. CONSTRUCTION AND LEARNING OF PROPAGATION DYNAMICS GRAPH BASED ON NEURAL NETWORKS

Weibo content propagation exhibits characteristics such as user behavior context dependency, structural dependency, and real-time dependency, making the prediction of its propagation dynamics a complex problem. An effective model for predicting content propagation dynamics needs to address these challenges [26], [27], [28]. Traditional content feature modeling methods have not considered text features in content propagation, and text features are crucial factors influencing propagation dynamics. Therefore, the optimization of traditional content feature modeling methods is initiated. Each user-generated text during the content forwarding process is considered as their text feature, forming a user text set $Tx_i = \{tx_i(0), tx_i(1), \cdots, tx_i(U_v - 1)\}$, where $tx_i(u)$ is the text information published or commented by user u, composed of a vocabulary sequence. Subsequently, text embedding methods are utilized to represent user text as vectors. The Self-Attention Text Embedding (SATE) model is employed for learning text representation, as illustrated in Figure 2 [29], [30], [31].

In Figure 2, the SATE model consists of two main steps: word embedding and attention layers. Word embedding utilizes word2vec to represent word vectors and employs Gated Recurrent Unit (GRU) to learn the sequence dependency of words. The input for text embedding is a vocabulary sequence $tx_i(u)$ formed by user u with a length of l_q. Word vectors are embedded into

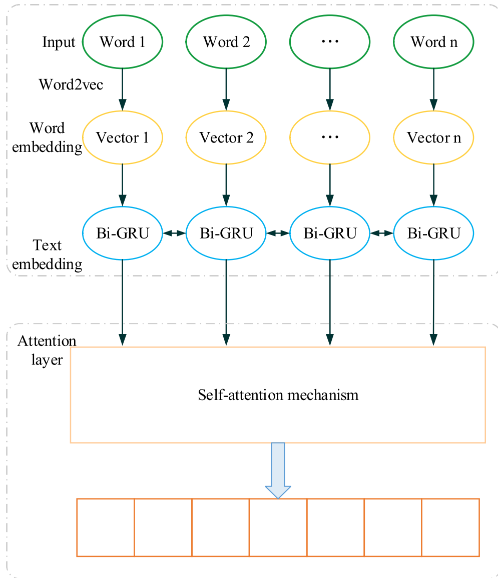

FIGURE 2. SATE model.

$K_i(u) = \left[k_i^0(u), k_i^1(u), \cdots, k_i^{l_q}(u)\right], k_i^l(u) \in S^{d_q}$, where d_q is the embedding dimension. Subsequently, a Bidirectional-GRU (Bi-GRU) model is used to learn the sequence information of word embedding vectors. The working process of the GRU unit is illustrated in Eqs. (1)-(5) [32], [33], [34].

$$c_t = \delta[W_c(h_{t-1}, x_t)] \tag{1}$$
$$g_t = \delta[W_g(h_{t-1}, x_t)] \tag{2}$$
$$\bar{h}_t = tanh[W_{\bar{h}}(c_t * h_{t-1}, x_{t-1})] \tag{3}$$
$$h_t = (1 - g_t) * h_{t-1} + g_t * \bar{h}_t \tag{4}$$
$$y_t = \delta(W_0 \cdot h_t) \tag{5}$$

In Eqs. (1)-(5), x_t represents the input at time t, h_{t-1} is the hidden layer state at time t-1, $\delta(*)$, $tanh(*)$ are activation functions, W is the weight parameter; c_t is the reset gate, controlling the omission of previous time information; g_t is the update gate, controlling the retention of previous time information; y_t is the output at time t. Next, Bi-GRU is employed to learn the sequence information of word embedding vectors:

$$\begin{aligned} K'_i(u) &= \left[k'^0_i(u), k'^1_i(u), \cdots, k'^{l_q}_i(u)\right] \\ &= BG\left[\left[k_i^0(u), k_i^1(u), \cdots, k_i^{l_q}(u)\right]\right] \end{aligned} \tag{6}$$

In Eq. (6), $k'^l_i(u)$ is the hidden state vector dimension of the Bi-GRU output, and $k'^l_i \in S^{d_q}$, $BG[*]$ represents the computation process performed by the input Bi-GRU. Subsequently, a self-attention mechanism is introduced to consider the importance of vocabulary. Its importance is measured by $\vec{a}_w$, which is an attention calculation mechanism, and attention coefficients are used to measure the degree of importance. The weight matrix $W_t \in S^{d_{q'} * d_{q''}}$ and bias vector $b_t \in S^{d_{q''}}$ are applied to each state $K'_i(u)$ of $k_i'^l(u)$:

$$\gamma_i^l = tanh(W_t k_i'^l(u) + b_t) \quad (7)$$

In Eq. (7), γ represents the attention coefficient input vector. Subsequently, the attention coefficients β_i^l are trained using $\vec{a}_w * \gamma_i^l$, where $\vec{a}_w = a^T, a \in S^{d_{q''}}$. Here, T denotes the transpose operation, and the softmax process is illustrated in Eq. (8).

$$\beta_i^l = \frac{exp\left[LeakyReLU(a^T * \gamma_i^l)\right]}{\sum_{p=0}^{l_q} exp\left[LeakyReLU(a^T * \gamma_i^p)\right]} \quad (8)$$

The weighted sum process is defined by Eq. (9).

$$k_i''(u) = \sum_{l=0}^{l_q} \beta_i^l k_i'^l(u) \quad (9)$$

In Eq. (9), $k_i''(u) \in S^{d_{q'}}$ is the final representation vector of user u's text. Defining the process from Eqs. (7) to (9) as the self-attention function $Att_r(*)$, the attention process for calculating $K'_i(u)$ is expressed in Eq. (10):

$$k_i''(u) = Att_r\left(K_i'(u)\right) = Att_r\left[k_i'^0(u), k_i'^1(u), \cdots, k'^{l_q}_i(u)\right] \quad (10)$$

Let $C_i''(u) = [c_i''(0), c_i''(1), \cdots, c_i''(U_v - 1)]$ be the content representation, representing $D_i = [d_i(0), d_i(1), \cdots, d_i(U_v - 1)]$ as the user behavior characteristics. Combine them to represent the node attribute $F_i^{t_j}$:

$$F_i^{t_j} = \lfloor C_i'', D_i \rfloor \quad (11)$$

In Eq. (11), $\lfloor * * \rfloor$ represents the combination function. Since C_i'' and D_i are independent of time, they are equal at any time t_j. This completes the construction of the propagation dynamic graph G_i.

After completing the construction of the propagation dynamic graph, a structural-temporal pattern is modeled, and the propagation dynamic graph is learned. In order to obtain structural information, graph embedding techniques are used to learn the representation of the propagation dynamic graph. Typically, GAN is employed for modeling; however, traditional GAN does not consider edge attributes. Therefore, it is enhanced in three steps, as illustrated in Figure 3 [35], [36].

In Figure 3, the enhanced GAN is divided into three steps: segmentation, aggregation, and combination. The graph is divided into four subgraphs based on direction, nodes, and edges. Attention mechanisms are then applied to learn features for nodes and edges in each subgraph. Finally, the representations of the subgraphs are aggregated to obtain the spatial dependency learning final representation $X_i(t_j)$, as shown in Eq. (12):

$$X_i(t_j) = \left\lfloor F_i^{out}(t_j), F_i^{in}(t_j) \right\rfloor \quad (12)$$

In Eq. (12), $F_i^{out}(t_j)$ is the out-graph representation, and $F_i^{in}(t_j)$ is the in-graph representation. Thus, the GAN model considers edge attributes and performs effective aggregation.

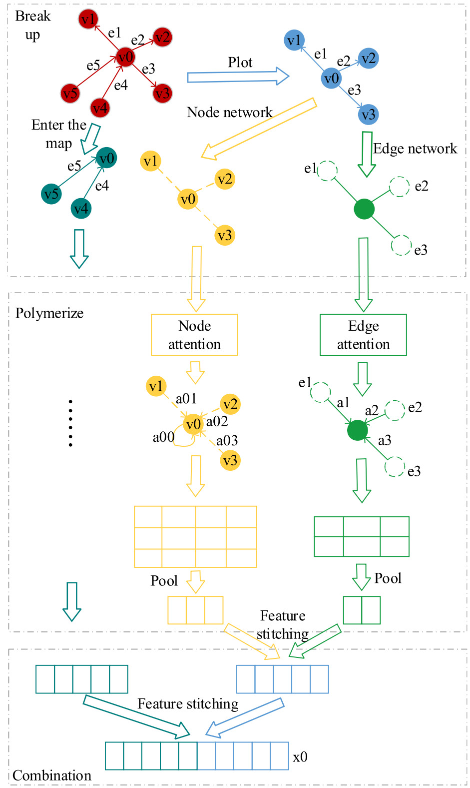

FIGURE 3. Improved GAN.

The learned $[X_i(t_0), X_i(t_1), \cdots, X_i(t_{N-1})]$ is a time series, which is input into a Bi-GRU for modeling temporal dependencies.

$$[X'_i(t_0), X'_i(t_1), \cdots, X'_i(t_{N-1})] = BG[X_i(t_0), X_i(t_1), \cdots, X_i(t_{N-1})] \quad (13)$$

Additionally, the delayed and tidal characteristics of propagated content need to be considered [37], [38]. The day is divided into m_1 time intervals with t_1, resulting in m_1 intervals. The observation time T is divided into m_2 time intervals with t_2, resulting in m_2 intervals. The difference between when a user forwards content and when the content is published is defined as the user's time interval. For $\mathrm{X_i'}(\mathrm{t_j}) = [x_i'(\mathrm{t_j}, 0), x_i'(\mathrm{t_j}, 1), \cdots, x_i'(\mathrm{t_j}, U_v - 1)]$, where U_v nodes' hourly distribution is mapped to $\left[\sigma_i^{\mathrm{t_j}}(0), \sigma_i^{\mathrm{t_j}}(1), \cdots, \sigma_i^{\mathrm{t_j}}(U_v - 1)\right], \sigma_i^{\mathrm{t_j}}(u) \in S^{m_1 * 1}$; and U_v nodes' time intervals are mapped to $\left[\vartheta_i^{\mathrm{t_j}}(0), \vartheta_i^{\mathrm{t_j}}(1), \cdots, \vartheta_i^{\mathrm{t_j}}(U_v - 1)\right], \vartheta_i^{\mathrm{t_j}}(u) \in S^{m_2 * 1}$. This study introduces weights $W_\sigma \in S^{1 * m_1}$ and $W_\vartheta \in S^{1 * m_2}$ for each node u, as shown in Eq. (14):

$$x_i''(t_j, u) = W_\sigma \sigma_i^{t_j}(u) W_\vartheta \vartheta_i^{t_j}(u) x_i'(t_j, u) \quad (14)$$

By using Eq. (14) to calculate for each time, the spatiotemporal dependency learning representation of the propagated content is obtained: $[X_i''(t_0), X_i''(t_1), \cdots, X_i''(t_{N-1})]$, where $X_i''(t_j) = [x_i''(t_j, 0), x_i''(t_j, 1), \cdots, x_i''(t_j, U_v - 1)]$.

C. CONTEXT-DEPENDENT DYNAMIC GAN BASED ON WEIBO CONTENT PROPAGATION FEATURES

The SATE model, which considers the textual features of propagated content, the propagation dynamic graph G_i, and the GAN model, which effectively aggregates edge attributes, is integrated to form a Context-Dependent Dynamic Graph Attention Network (C-DGAN). Its structure is depicted in Figure 4.

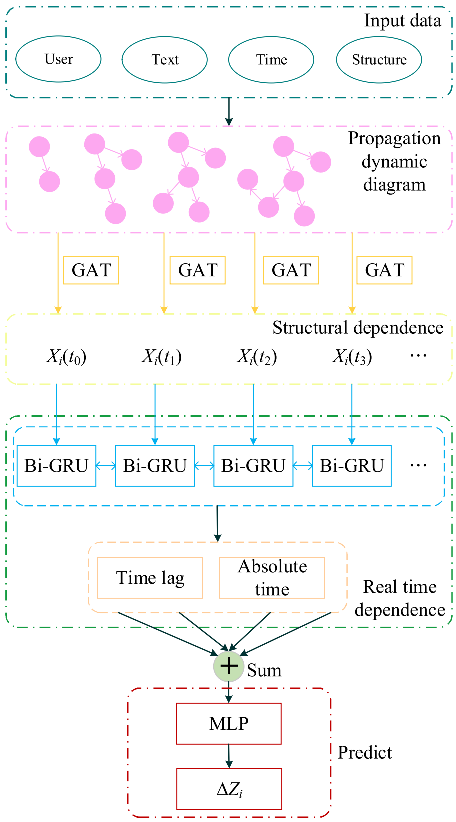

FIGURE 4. **Framework diagram of the C-DGAN model.**

In Figure 4, after obtaining the representation of the content propagation dynamic graph by considering temporal dependencies, it is necessary to sum and eliminate nodes and time scales:

$$Y_i = \sum\nolimits_{t=t_i}^{t_{N-1}} \sum\nolimits_{u=0}^{U_v-1} x''(t, u) \tag{15}$$

In Eq. (15), Y_i is the final representation of the propagated content through C-DGAN. Finally, a Multilayer Perceptron (MLP) is connected for the prediction task:

$$\triangle Z_i = MLP(Y_i) \tag{16}$$

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

In order to evaluate the influence of the Weibo content propagation scale on its virality, the problem of predicting the content propagation scale is defined as a regression task. Data was collected from Sina Weibo for one month (from March 1, 2022, to March 31, 2022), with a focus on all original Weibo posts between March 17 and March 31, along with their retweeting activities within a 24-hour period. In total, there were 52,536 Weibo posts. Considering that user behavior and social characteristics often change over time but at a relatively slow pace, user features were treated as factors that remain essentially unchanged in the short term. Therefore, prior features related to users were extracted using data from March 1 to March 16. User behavior characteristics mainly covered descriptions of user profiles, including the number of posted Weibos, the number of retweets, the number of content interactions, and the number of times the user's posted content was retweeted. As for social characteristics, since it was not possible to obtain the following and follower relationships between users, the degree of content interaction between users was chosen to describe social characteristics. Specifically, the retweeting relationships between users A and B were considered, including the number of times A retweeted B's content and the number of times B retweeted A's content.

For each Weibo post, the retweeting sequence within 1, 2, 3, and 4 hours after its publication was observed. The goal was to predict the propagation scale of each Weibo post 24 hours after its publication. In order to filter the data, using the observation time T as a reference, only content with a propagation scale observed between 10 and 1000 at time T was selected. Then, the dataset was divided based on the publication time of the content. For each time period, the data was split into training, validation, and test sets in a 6:2:2 ratio.

B. EXPERIMENTAL ENVIRONMENT AND PARAMETERS SETTING

This experiment included four baseline models and four variant models. The baseline models were TopoLSTM based on the propagation process and Long Short-Term Memory (LSTM) [39], DeepHawkes based on generative models [40], Recurrent Cascades Convolutional Networks (CasCN) based on graph convolutional networks [41], and neural popularity prediction (NPP) based on attention mechanisms [42]. The variant models included standalone GAN, dynamic GAN considering content propagation dynamics on top of GAN, dynamic GAN + Tidal Characteristics (DGAN+TC) considering time delay and tidal characteristics on top of DGAN, and DGAN+TC+User considering user behavior characteristics on top of DGAN+TC.

The Mean Square Logarithmic Error (MSLE) was adopted as the evaluation metric, calculated as shown in Eq. (17):

$$MSLE = \frac{1}{n} \sum\nolimits_{i=1}^{n} (log \triangle Z_i - log \triangle \check{Z}_i)^2 \tag{17}$$

In Eq. (17), n is the number of contents, $\triangle Z_i$ and $\triangle \check{Z}_i$ are the predicted and true increments in the propagation scale of Weibo content, respectively. A smaller MSLE indicates better prediction performance.

The experimental environment and parameter settings are provided in Table 1.

TABLE 1. Experimental environment and parameter settings.

EXPERIMENTAL ENVIRONMENT/PARAMETERS	Model/setting value
operating system	Windows10
CPU	Intel v100 2.60GH
Memory	32GB
graphics card	NVIDIA GeForce GTX 1080Ti
programming language	python 3.9
deep learning framework	Tensorflow
Initial learning rate	0.001
Batch size	64
optimizer	Adam
word length	25
Dropout	0.6

C. PERFORMANCE EVALUATION

1) COMPARISON BETWEEN C-DGAN AND BASELINE MODELS

Firstly, C-DGAN is compared with baseline models at observation times $T = 1$, 2, 3, and 4 hours. The results are shown in Figure 5.

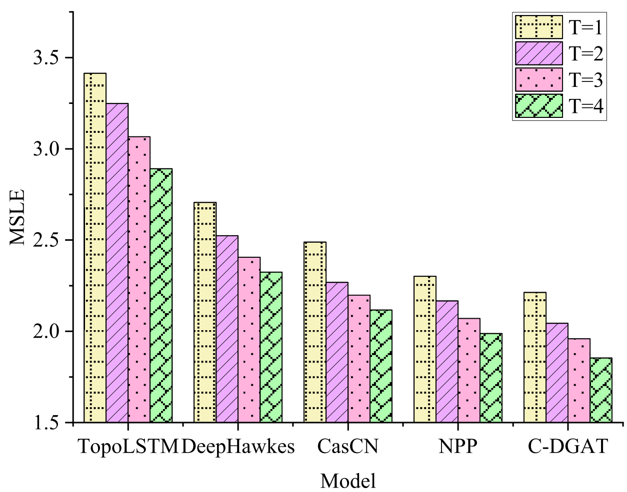

FIGURE 5. Comparison of the effects of C-DGAN and baseline models at different observation times.

In Figure 5, regardless of whether the observation time is 1, 2, 3, or 4 hours, the MSLE of C-DGAN is smaller than that of other models. Taking T=4 hours as an example, the MSLE of C-GDAT is 1.854, which is lower than TopoLSTM, DeepHawkes, CasCN, and NPP by 1.037, 0.47, 0.263, and 0.134, respectively. This indicates that C-DGAN performs better in predicting the propagation scale of Weibo content. This is because C-DGAN comprehensively considers various complex factors in the content propagation process.

2) COMPARISON BETWEEN C-DGAN AND VARIANT MODELS

Similarly, at $T = 1$, 2, 3, and 4 hours, C-DGAN is compared with variant models. The results are shown in Figure 6.

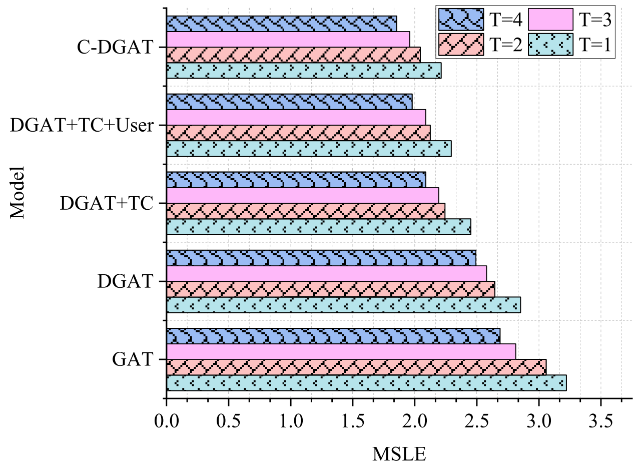

FIGURE 6. Comparison of the effects of C-DGAN and variant models at different observation times.

In Figure 6, as the dynamics of content propagation, time, and user factors are incorporated, the predictive performance of the models gradually improves. Among these five models, GAN has the worst performance, indicating that considering only the structural information of content is insufficient. With the introduction of time information, the DGAN+TC model shows an average improvement of 0.702 compared to GAN, indicating that time information is an important factor influencing the prediction of content propagation scale.

3) IMPACT OF TIME INFORMATION AND DIFFERENT RNNS ON THE MODELS

The relationship between time information and normalized content propagation scale is depicted in Figure 7.

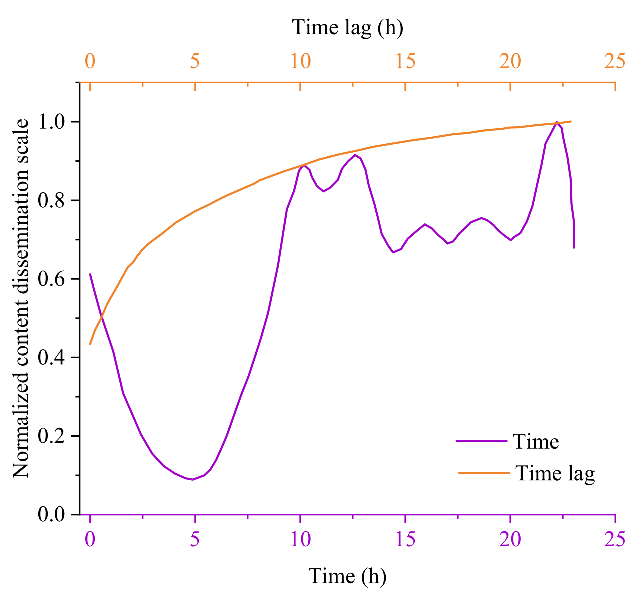

FIGURE 7. Relationship curve between time distribution, time delay, and normalized content propagation scale.

In Figure 7, there is a clear propagation pattern of Weibo content within 24 hours, which aligns with people's daily routines. Additionally, as time progresses, the influence of the text gradually decreases, and when $T = 24$, the curve tends to flatten. Therefore, the propagation scale at T=24 can be used to evaluate the virality of the content. Hence, time information does indeed influence the virality of Weibo content.

The recurrent neural network (RNN) used in C-DGAN is Bi-GRU. Next, it is compared with GRU, LSTM, and ordinary RNN, and the results are shown in Figure 8.

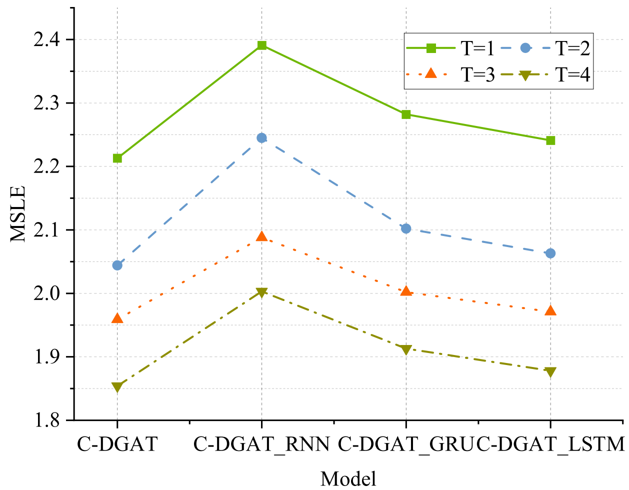

FIGURE 8. Comparison of C-DGAN model performance using different RNNs.

In Figure 8, at different observation times, the model with the Bi-GRU network performs the best, while the model with the ordinary RNN has the poorest performance. This is because Bi-GRU considers not only the current state of the sequence but also its preceding and succeeding states, demonstrating the optimal performance.

In summary, C-DGAN, considering the structure, time, text, and user information, exhibits superior performance in virality prediction.

D. DISCUSSION

Furthermore, Roy et al. forecasted the morbidity and incidence rates of various states in India using the Autoregressive Integrated Moving Average (ARIMA), demonstrating the effectiveness of the ARIMA model in predicting future epidemics [43]. This study provides guidance for deeper epidemiological research. Shu et al. summarized the global issues arising from the rapid spread of misinformation and fake news on social media in recent years, introducing the types of information disorder, the importance of detection tasks, and a weakly supervised method based on limited labeled data [44]. This provides valuable insights for studying the virality of Weibo content, especially when dealing with potential misinformation. Qin et al. used Latent Dirichlet Allocation topic models to extract user text features and employed a feedback neural network to predict users' OCEAN (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) personality traits on social networks [45]. These studies highlight the significant role of neural networks in information dissemination, enriching the knowledge base in social media and providing a better understanding and response to the diversity and complexity of Weibo content propagation.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

In order to explore the dissemination of traditional Chinese music in the digital context and the virality of Weibo content based on deep learning, this study analyzed the impact of digitization on the dissemination of traditional Chinese music. It focused on improving content feature modeling methods and the GAN network and proposed the C-DGAN model. The performance of C-DGAN was experimentally validated, leading to the following conclusions:

1) Compared to baseline models, C-DGAN consistently achieved smaller MSLE. For instance, at $T = 4$h, C-DGAN's MSLE was 1.854, which was lower than TopoLSTM, DeepHawkes, CasCN, and NPP by 1.037, 0.47, 0.263, and 0.134, respectively, indicating that C-DGAN performed better in predicting the virality of Weibo content.
2) Through comparisons with variant models and studying the relationship between time information and content virality, time information is a crucial factor influencing the virality of Weibo content.
3) In comparison with models using different RNNs, the models employing Bi-GRU consistently demonstrated superior performance, while those using ordinary RNNs exhibited the poorest results. This further confirms the superior performance of the C-DGAN model.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

Although the proposed model showed promising results compared to other models, there are areas that can be improved in practical applications. The selected Weibo data samples may have certain biases. The characteristics of Weibo user groups and limitations in data acquisition might lead to the limited generalizability of the study's findings. Future studies could involve expanding the sample size and extending the duration of sample data collection to six months or a year for a more in-depth investigation to ensure the universality of the results.

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