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Digital Media Platform under TV Program Innovation Design and Dissemination Effect Evaluation

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Abstract: At present, the highly user experience and content communication effect evaluation of TV programs become more and more prominent with the fast-pace explosion of digital media platforms. Based on the existing multimodal fusion recommendation system and deep learning algorithm, this paper proposes an innovative model and constructs a multi-level feedback mechanism by fusing audience interaction data, social media feedback and TV program content characteristic. And it adds the sentiment analysis module and dissemination path tracing module to the conventional recommendation system, thus enabling more accurate assessment of the dissemination effect of the program and optimized personalized programming content design using reinforcement learning. The dynamic adjustment of program innovation design and effect evaluation is realized by predicting audience behavior and analyzing the propagation path that we use multi-layer long short-term memory network to achieve. Experimental results show that compared with the traditional method in the evaluation of communication effect of different types of TV programs, the accuracy of prediction of different TV program can be improved through the proposed model.

1. Introduction

With the continuous increasing of digital media platforms, the TV program is forcing traditional programming to confront unprecedented challenges and opportunities. As Internet technology and mobile devices grow more and more popular, digitalization, networking and intelligence have become the mainstream trends in media industry. The viewers are no longer satisfied with watching behind a tele, they have turned into a craving of personal access to content anytime and anywhere. Therefore, in this era, the traditional TV program requires an in-depth innovation from the aspects of content creativity and communication methods to form a relatively competitive advantage within the existing fierce market and provide an audience with an innovative and diverse service experience [1]. Digital media distribution of TV programs no longer relies on a single traditional TV platform, and the interactivity and real-time characteristics of digital platforms provide programs with more space for development and innovation.

With the rise of digital media platforms, the viewers' viewing habits have also been changing drastically. Historically, viewers have watched television programmes at a specific time and location, and the flow of information has been unidirectional, with the public playing the role of passive consumers [2]. But in the case of digital platforms, whether through social media or mobile apps, viewers have been liberated from the strict confines of viewing by being able to comment on the show at any time, share opinions and feelings, even make suggestions as to how the show should feel or be different from what it was. Social TV is an emerging form of communication that adds emphasis on audience interaction which is real-time and actively involved. Unlike the previous TV era viewers were just the audience of the TV shows, this new era the audience is becoming the co-creator of the show itself, by spreading and embracing the content through likes, comments, share, etc [3].

However, how efficiently innovate design has been implemented still needs scientific verification. The effect of communication not only helps the program producer to understand the acceptance of the audience on their program, but also is a specific basis for improving and adjusting the program. Previously, the ratings were the primary basis for measuring programs, but as viewers and the media environment continue to change, the ratings can no longer accurately reflect the real situation of a program's influence. As an example of this, platforms have viewers sharing the content of the show, discussing the plot and sharing their opinions of the show through platforms like social media, and these actions have become a key metric in the success of the show [4]. Therefore, more dimensional indicators such as social media interaction, emotional transmission of the audience, and the impact of audience opinion on the program should be brought into the evaluation system of communication effect to evaluate the communication effect of the program more comprehensively.

2. Related Work

Birdthistle et al. [5] examined the effect of multimedia activities on HIV self-testing (HIVST) and prophylactic pre-exposure prophylaxis use among young individuals in South Africa. This study demonstrated that media exposure was linked to greater HIV testing rates and PrEP awareness, suggesting the efficacy of entertainment-education programming for HIV prevention. Bao et al. [6] at a time when artificial intelligence is being used in film and television animation, he examined how VR technology is being used in the same field. Through the combined study of course of model of 3D animation and VR technology, it shows that VR as an auxiliary means of teaching can effectively promote the comprehensive quality evaluation of students and classroom satisfaction, and improve the teaching effect.

Liang et al. [7] use AI to assess the aesthetic value of the digital cultural and creative goods. The research explores on the growing effect of the cultural communication and the design innovation promotion in the development of national cultural and creativity industry, emphasizes that the application of artificial intelligence is the evaluation of cultural products. Sanders et al. [8] improve parenting knowledge and skills of parents with multi-level interventions to ameliorate behavioral and emotional problems among children. The study emphasizes the need for further research and evaluation to ensure that the system can be tailored to the specific cultural contexts and requirements.

Chapman et al. [9] review numerous systematic reviews and described the features, implementation barriers, and enablers of various strategies, offering insights to promote optimal health policy communication. Jiang et al. [10] consider the introduction of digital new media technology into the field of design and production of film and television animation accelerated the digital development of animation design and production and gave positive significance for the improvement of the animation industry.

Zhao et al. [11] applied VR across various domains—including film special effects, game-scene design and city planning—and demonstrated that the technology can create virtual environments. Its application shortens the distance between users and information providers, thereby improving the efficiency of digital-media information dissemination.

3. Methodologies

3.1. Multimodal Fusion Inputs

In order to process and fuse different types of data, audience behavior data $X_{audience}$, social media feedback data X_{socal}, and program content feature data $X_{content}$ were first preprocessed and mapped to a unified representation space. Considering that different modalities may have different feature dimensions, we first define the transformation matrices W_a, W_s, W_c for each data source and fuse them by weighted sum, as shown in Equation 1:

$$\mathrm{X_{fused}} = \sigma(\mathrm{W_a X_{audience}} + \mathrm{W_s X_{socal}} + \mathrm{W_c X_{content}} + \mathrm{b}), \tag{1}$$

Among them, $\sigma(\cdot)$ Represents the activation function, commonly known as the ReLU activation function. In this way, the model is able to adapt the contribution of different modalities to the final feature representation according to the weights and biases b of each modal feature.

Next, we further introduce the attention mechanism to dynamically adjust the weights of different modalities at each time step. Suppose we set the attention weights α_a, α_s, and α_c for each input modality, which are solved as follows in Equation 2:

$$\alpha_m = \frac{\exp(score_m)}{\sum_{m' \in \{a,s,c\}} \exp((score_{m'})}, \tag{2}$$

Where $score_m$ is the score of each modality, which can be calculated by a neural network. The final result of polymorphic fusion is Equation 3:

$$X_{fused}^{final} = \sum_{m \in \{a,s,c\}} \alpha_m W_m X_m . \tag{3}$$

This weighting and manipulation allows the model to automatically adjust the influence of each modality at a specific moment, thus improving the model's adaptability.

3.2. Sentiment Analysis and Propagation Path Tracing

In the processing of social media feedback, we have introduced a sentiment analysis module to extract emotional features from the comments and behaviors of the audience. First, we get the score of the audience's sentiment through a sentiment analysis model $S_{sentiment}$, as shown in Equation 4:

$$S_{sentiment}(T) = Sentiment(T) = \frac{\sum_{t=1}^{T} Score(T_t)}{T}, \tag{4}$$

Where T_t is the t-th word in the text, and $Score(T_t)$ is the sentiment score of the word. The sentiment score of the whole text is the average of the sentiment scores of all words.

In terms of propagation path tracing, we use graph neural networks (GNNs) to capture propagation relationships between audiences. Suppose we have a propagation graph $G = (V, E)$, where V is the node (the audience) and E is the edge (the propagation relationship between the audience). In order to better capture the temporal characteristics of the propagation path, we use time series graph convolution (T-GCN) to model the propagation path, as shown in Equation 5:

$$H_t = \sigma\left(\sum_{v_j \in \mathcal{N}(v_i)} \frac{1}{C_{ij}} W G_{ij} H_{t-1} + W_{new} X_i \right), \tag{5}$$

Where H_t is the hidden state of the audience v_i at time t, $\mathcal{N}(v_i)$ is the set of neighbors of the audience v_i, C_{ij} is the normalization coefficient, G_{ij} is the propagation intensity, and W and W_{new} are the weight matrix of learning. This model combines a graph convolutional network with a time series so that the propagation path can evolve dynamically over time.

3.3. Reinforcement Learning Optimization

At the end of the model, we introduce a reinforcement learning mechanism to optimize the program content. At each decision-making step, the goal of the model is to maximize the audience's emotional feedback and propagation effect, and the reward function R of reinforcement learning is defined as Equation 6:

$$R = \alpha S_{sentiment} + \beta P_{path} - \gamma \cdot Penalty(X_{content}), \tag{6}$$

Among them, α, β, and γ are hyperparameters, and $Penalty(X_{content})$ indicates the penalty term for the content complexity or adaptability of the program. The optimization goal is Equation 7:

Under the reinforcement learning framework, Strategy π continuously adjusts the design of program content based on feedback to maximize the audience's emotional response and the effect of the transmission path.

$$\max_{\pi} \mathbb{E}[R] = \max_{\pi} \mathbb{E}[\alpha S_{sentiment} + \beta P_{path} - \gamma \cdot Penalty(X_{content})]\,. \tag{7}$$

4. Evaluation

To validate the effectiveness of the proposed model, we used the Netflix Prize Dataset, which has rating data of millions of users and is large-scale, sparse and multi-dimensional characteristics. In order to comprehensively assess the effectiveness of our proposed model, we performed a comparison to four relevant comparison approaches, which were the classical Matrix Factorization (MF) approach, the Collaborative Filtering (CF) approach based on user similarity, the Deep Neural Networks (DNN)using multilayers perceptrons, and the Recurrent Neural Networks (RNN) for processing time series data Method

As shown in Table 1, when the amount of time watching increased, the experience scores for all the methods increased significantly, reflecting the fact that our recommendation system was improvedwhen users spent more time in the program. Traditional methods like MF and CF have a stable improvement and fewer improvements have been made recently, while DNN and RNN methods show faster growth over time, and long-term interaction effects of RNN is more prominent. Performed best of all methods, and with increasing watch time.

Table 1: User Experience Evaluation With Viewing Duration.

Viewing Duration (hours)	MF	CF	DNN	RNN	Ours
1	0.35	0.40	0.45	0.50	0.55
2	0.45	0.50	0.58	0.62	0.67
3	0.55	0.60	0.68	0.73	0.78
4	0.60	0.65	0.75	0.80	0.85
5	0.63	0.70	0.80	0.85	0.90

As can be seen from Figure 1, with the increase of user activity, communication effect score of all methods has increased significantly, which shows that user activity has a positive impact on communication effect. With regard to stability, traditional approaches such as MF and CF exhibited fairly stable growth, particularly in the setting of low activity. The DNN and RNN showed a faster improvement when the activity increased, and the RNN method performed well when the activity is high. Our model outperforms all other methods, the propagation effect was significantly increased with the activity and reached the maximum at high activity, which confirmed the advantages of multimodal fusion and reinforcement learning optimization.

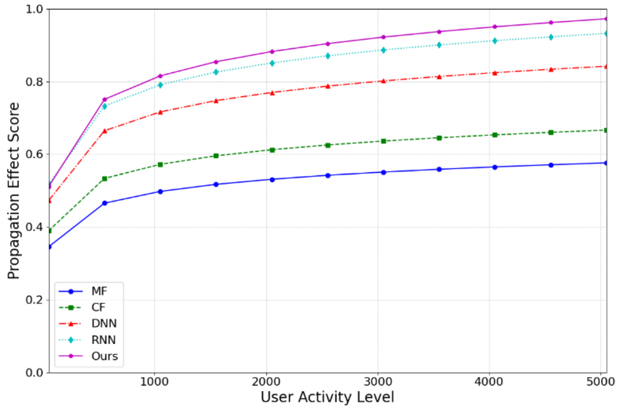

Figure 1: Propagation Effect Evaluation Comparison.

5. Conclusions

In conclusion, the model proposes a new model based on multimodal fusion recommendation system and deep learning algorithm, by integrating the audience interaction data, social media feedback and program content characteristics to build a multi-level feedback mechanism to accurately evaluate the communication effect of TV programs, and to optimize the personalized design of program content through reinforcement learning. Experimental results indicate that all methods achieve a noticeable gain in user experience score as user viewing time increases. By incorporating demographic and contextual information about users, future work could improve the accuracy of recommendations produced by this framework.

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