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Article

Research on Art and Design Idea Generation and Design Inspiration Inspiration Relying on Intelligent Recommendation Algorithm

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Abstract: Intelligent generation of art design ideas is a necessary way to promote the diversification of artistic expression, but there are problems such as imprecise intelligent recommendation and unsatisfactory generation effect. This study combines the generative adversarial network with TimeSVD++ algorithm for generating recommendation model of art design.TS-GAN model is to use TimeSVD++ algorithm to obtain the temporal dynamic features of user preference in the process of art design, and use them to construct the generative model. The generated features are then input into a discriminative model based on multi-layer fully connected neural networks, which improves the discriminative effect on art design styles. Performance verification and investigation are conducted to analyze the effectiveness of the TS-GAN model. The research found that compared with the current mainstream CFGAN model, the TS-GAN model outperformed 6.14%, 8.94%, and 9.60% respectively in the three indicators of P@10, N@10, and M@10. The mean value of subjects' satisfaction with the art design idea generation recommendation results was 87.02%. Integrating intelligent algorithms with art design can promote the development of art design to be more diversified, which makes art designers obtain more creativity and inspirational inspiration.

Keywords: art design; generative adversarial network; TimeSVD++ algorithm; user preference; recommendation algorithm

1. Introduction

In contemporary society, art and design has become a form of artistic expression that reflects and responds to social, cultural and technological developments. The rapid progress of digital technology has injected new vitality into art design, greatly broadened artistic expression and interactivity, and brought unprecedented creative freedom and precision to designers [1-3]. In traditional art design, designers rely on personal experience and inspiration to create, but the work lacks soul under the lack of creativity and inspiration, and it is also easy to homogenize [4-6]. However, consumers are increasingly pursuing personalized design, and art design is in urgent need of innovative design to develop efficient, high-quality and innovative art works. Based on this background, the human-computer collaboration model is integrated into the art design field.

The core of human-machine collaborative design lies in the assistance and enhancement of artificial intelligence and other technologies to assist designers in accomplishing tedious design tasks more quickly and provide innovative ideas [7-8]. In the design field, machine learning can generate design rules and patterns by analyzing designers' works and user evaluations to help designers discover their own deficiencies in time and provide optimization suggestions, and this machine learning human-machine collaborative design mode can lead to designers' growth and progress [9-12]. In human-machine collaboration, machines mine user preferences to improve design efficiency and stimulate design creativity, and humans innovate designs based on experience, emotional perception, and cultural values [13-14]. Intelligent recommendation algorithms, as a service-side human-machine collaboration model, have become a key engine to promote innovation in the field of art and design.

As a tool based on data analysis and machine learning technology, intelligent recommendation algorithm can provide personalized content recommendation for users based on their behavior, interest, preference and other information, which effectively meets consumers' personalized needs [15-17]. With the development of deep learning algorithms and intelligent generation algorithms, intelligent recommendation algorithms have gradually extended from collaborative filtering algorithms and content-based recommendation algorithms to multimodal fusion recommendation algorithms, which, based on user data, provide more inspiration and creativity for art design, and innovate the ecological model of art design [18-21].

Currently, in the field of art design, intelligent algorithms realize idea generation and inspiration from a data-driven perspective. Literature [22] innovated a computational method for processing textual knowledge in social media and constructing a related knowledge base, which can be used to generate ideas and can also be provided to provide designers with creative thinking to stimulate their creative inspiration. Literature [23] utilizes deep learning algorithms to mine effective points that stimulate inspirational creativity from large-scale design image materials, constructs an inspiration database, and searches for creative images in the database through correlation analysis and convolutional neural networks to generate ideas. Literature [24] interpreted the emotional significance in the art design of architectural environment using distributed collaborative filtering algorithms from multiple dimensions of architectural design, such as color matching, image application, line layout, symbol selection, etc., to provide material for designers' creativity and inspiration. Literature [25] proposes an artificial intelligence model based on conceptual similarity, which is used in collaborative creation to provide art design creation inspiration pictures, inspire designers' creative ideas, and contribute to the innovative and diversified development of designers' ideas.

Literature [26] uses particle swarm optimization algorithm to improve neural network and used to automatically generate more diverse and innovative advertising design, designers through computer-aided design tools to adjust the algorithm-generated advertising design, completed a better creative generation. Literature [27] proposed a programmed art creative generation method based on deep reinforcement learning, with which designers can input design requirements, formulate color, texture and other parameters, and automate the generation of new creative works, which is conducive to the designers' creative enhancement. Literature [28] explored the art style conversion based on generative adversarial network, which can generate new art styles with creativity, visual effect and artistic value for the art styles of painting, architecture, sculpture and other art design work images, and was highly appreciated by experts. Literature [29] proposes a multimodal design system based on immersive virtual environment for large-scale stage design, which makes multi-disciplinary designers communicate in the virtual environment without barriers, and the virtual display realizes dynamic adjustment, saving communication time while optimizing design efficiency. Literature [30] reported a human-computer collaboration fashion design generation system, which directly generates text-related design inspiration images in the cloud, inputs them into the local system, generates sketch material libraries with a certain designer's style under style conversion, and recommends similar sketch material libraries, and performs sketching coloring based on the inspiration images, which improves both the design efficiency of designers and generates inspirational ideas.

Literature [31] reported a personalized environmental art design recommendation algorithm constructed by a bidirectional long and short-term memory network model, which provides data support for environmental art design creativity by capturing the pattern of change of user preference and the interactive association of design elements. Literature [32] developed a creative creation model of cultural and creative products based on evolutionary adaptive generative aesthetic network, completed the style attribute improvement through the semantic information and style of the image content, introduced the genetic algorithm to dynamically perceive the user preference, and realized the intelligent and personalized generation of cultural and creative products. Literature [33] uses an artificial intelligence-based strategy system for personalized and customized generation of art design, which integrates real-time data analysis of users and fully understands user preferences, making the generated works highly relevant to user needs, and the works are presented as highly personalized without losing the sense of beauty. Literature [34] integrates user data, deep learning, and optimization algorithms to establish an intelligent interior design system, which can provide personalized feedback based on user preferences, and automate the generation of interior layout solutions by combining aesthetic and functional evaluation modules. Literature [35] uses a multimodal Transformer framework to build an intelligent digital art design fusion platform by fusing multimodal data, which improves the creative effect and efficiency and optimizes the quality of art design.

In this paper, starting from analyzing the application strategy of intelligent algorithms in art design, we propose a GAN-based generative recommendation model for art design. The model makes full use of the characteristics of generative adversarial network, and unfolds the generative recommendation of art design creative style based on the consideration of the user's dynamic characteristics of art design time. This study makes up for the defects of GAN network application in art design, introduces TimeSVD++ algorithm to enhance the generative recommendation performance, effectively reduces the model complexity, and promotes the generation and inspiration of art design creative inspiration.

2. Strategies for the application of intelligent algorithms in art design

Art design has a certain degree of knowledge, and because it contains profound philosophical ideas, it can expand the aesthetic creative expression and logical thinking of artists, so it is both the creative process of artists and the formation of a logical thinking process. Under the rapid development of intelligence in the new era, the integration of art design and intelligent algorithms can derive a series of innovative applications. Thus, it can promote the generation of art design creativity, fully stimulate the design inspiration of art practitioners, and provide a new path for the diversified development of art design.

2.1. Intelligent development of art and design

2.1.1. Artistic Design Intelligent Performance

Art and design is mainly a medium through which artists express their inspiration and experience and communicate with the public. In the process of rapid development of computer information technology, art designers can make use of intelligent technology for visualization, and compared with traditional forms of art creation, it can shorten the design time, accelerate the speed of design, improve the efficiency and effect of creation, and even batch production.

Computer intelligent technology is used during art creation, relevant products are manufactured through 3D printing technology, and art works are created with flexibility through diversified and rich color materials in software technology. It is also able to utilize intelligent algorithms to integrate massive art design resources in the network environment, form design inspiration, broaden the artistic thinking of designers, and organically integrate their own thinking and design software to achieve good artistic design. In the process of continuous maturation of intelligent technology, artistic design works can be presented with the help of intelligent technology, and the application of intelligent technology in the field of artistic design can effectively carry out artistic creation activities. In the support of intelligent technology, the formation of a good sense of artistic creation experience, the works of the design concept is fully conveyed, so that people can deeply feel the charm and beauty of artistic design.

2.1.2. Art and Design Intelligence Advantages

(1) The use of intelligent technology in the process of art design can quickly screen and apply all the data and information on the network, and its responsiveness under the control of the algorithm is extremely rapid, which simplifies the steps of data access and analyzing and judging compared with human beings.

(2) Intelligent technology through networking, can grasp the first-hand information in the field of art and design in a timely manner, and quickly absorb new data into their own database. Intelligent technology can learn new knowledge anytime and anywhere, and constantly improve the knowledge system, which is also difficult for human beings to match.

(3) Intelligent technology can realize long-term stable problem-solving efficiency when dealing with problems. Humans are often affected by physiological or psychological changes and cannot maintain long-term stability of work, while artificial intelligence can realize stable and efficient solution to repetitive problems. With the continuous upgrading and development of intelligent technology, intelligent technology can accumulate experience in the process of encountering problems and solving problems, and select better solutions through comparison, and continuously optimize the ways and means of solving problems. With the accumulation of experience, the level of art design intelligence will also continue to improve, so as to provide better services for human beings.

2.2. Application of Algorithms in Artistic Design

2.2.1. Models of innovative art and design

For the creative generation and inspiration empowerment of art design, relying on intelligent technology enables designers to better display their own art design inspiration. The cooperation model between designers and intelligent technology will be a cyclic process that closely combines creativity and intelligent analysis, and its design model framework is shown in Figure 1.

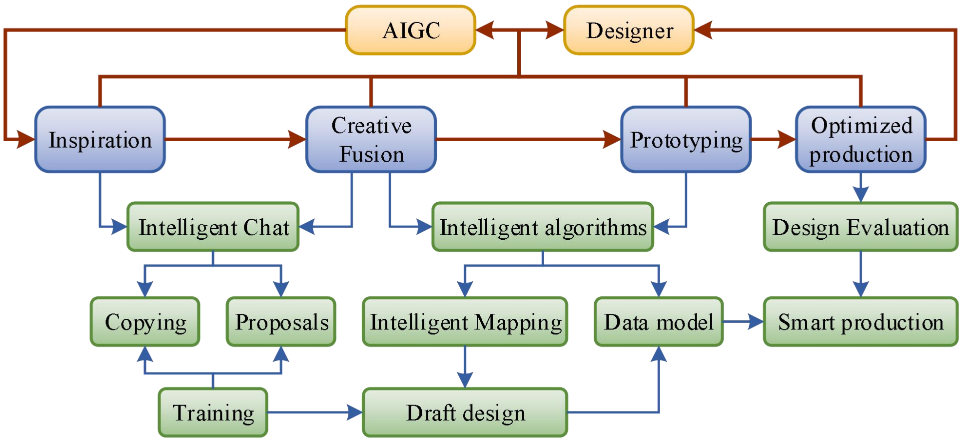

Figure 1. The collaboration model between designers and Intelligent algorithm.

It can provide designers with a large amount of historical works, trend analysis and other data to help designers carry out brainstorming, design proposals and other preparatory work, and through intelligent chatting to train databases belonging to the field of art and design, designers are able to integrate ideas generated by intelligent algorithms with their own creativity, thus generating more unique and enriched art and design works. The cooperative mode of designing and modeling drawings through intelligent algorithms and putting them directly into the intelligent production process not only generates diverse design solutions, but also helps designers to broaden their ideas in the creative process. In addition, it is able to transform designs from the virtual world into physical prototypes, thus enabling designers to experiment and modify them more quickly. This cyclical collaboration model has significant academic value in promoting design innovation and efficiency. Intelligent algorithms can provide data-driven support, but the human designer's intuition, cultural understanding, and creative ability remain at the core of the design process, and human collaboration on creative art design using intelligent algorithms will create more innovative and emotionally resonant art and design works.

2.2.2. Optimize the color settings of the design

Color settings will directly affect the aesthetics of art design. The application of intelligent algorithms in art design, its intelligent design method and XKool platform can enable art designers to save time and improve efficiency. Therefore, art designers can use intelligent algorithms to optimize the color settings in the process of art design, which can not only express the inner emotions and the connotation of the work more intuitively, but also give the art work a unique style, so as to attract more audiences.

At the same time, when carrying out art design, attention should be paid to the positive impact of artificial intelligence on optimizing the color settings of art design, focusing on exploring examples of the application of intelligent algorithms in the color and style of art design during the creative process, emphasizing personalized design, ensuring that the designed art works are more creative, and enhancing the expressive power and influence of the art works. In addition, by optimizing the color settings, it is conducive to enhancing the aesthetics and animation of the art works, and the art design practitioners can complete the design tasks in a shorter work cycle and improve the efficiency of art design.

3. Intelligent Algorithm Based Art Design Generation Recommendation

The use of smart technologies in art and design has become increasingly widespread. From early computer-aided design (CAD) to today's deep learning, computer vision, and generative adversarial networks, intelligent technologies are transitioning from assisted design to independent creation, which can simulate artistic styles, optimize design solutions, improve creative efficiency, and promote cross-disciplinary integration to bring about new creative expressions. This chapter proposes an art design generation recommendation model based on GAN, which aims to provide designers with more diversified art creative design styles, thus promoting the artistic inspiration of designers and the diversified development of art design.

3.1. Generating Adversarial Networks and the SVD Algorithm

3.1.1. Generating Adversarial Networks

Generative Adversarial Network (GAN) is to introduce the idea of game theory into the neural network, through the generator and discriminator play with each other, continuous learning, making the generator performance gradually optimized, so as to improve the prediction effect. The framework of generative adversarial network is shown in Fig. 2, including two parts of generator and discriminator [36]. The job of the generator (G) is to receive data, which can usually be random noise data, and then the generator will generate fake samples, and the purpose of the generator is to generate data to confuse the discriminator, so that the discriminator can not recognize the generated samples as data with a real source or false data. The essential work of the discriminator (D) is to develop "eyes of fire", to distinguish between the generation of false samples and real samples. In the process of continuous game and learning, both of them improve the performance of their own models, so that the prediction results become more and more reliable.

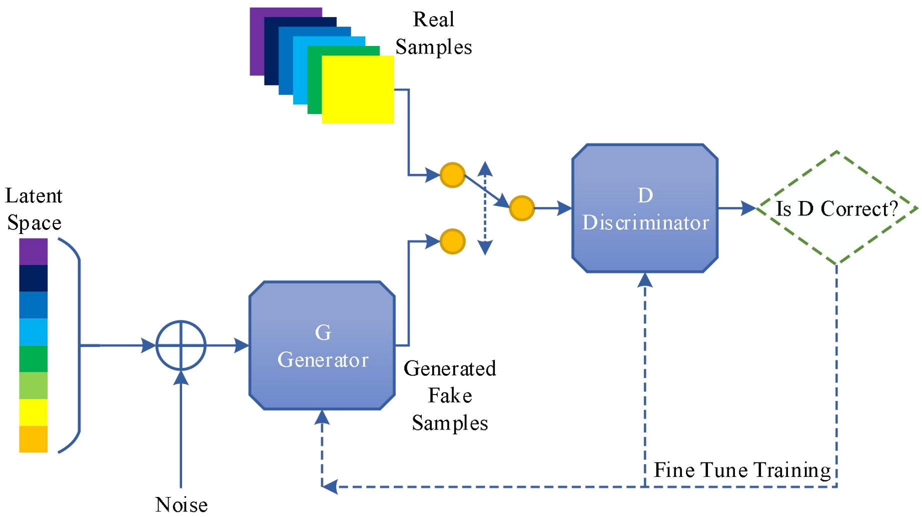

Figure 2. GAN's theoretical framework.

When the noise vector x is input to the generator (G), the generated data $G(z)$ is obtained, the generator aims to make the generated result similar to the target result, so the error needs to be minimized; then the discriminator (D) receives the false samples generated by the generator together with the true samples, at this time the discriminator needs to distinguish between the true samples and the generated false samples, so it needs to maximize the error. The objective function is expressed as:

$$\min_G \max_D V(D,G) = E_{x\sim p_r}[\log(D(x)] + E_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))] \tag{1}$$

where x is the real data, p_r is the real sample distribution, $\hat{x}$ is the generated data, $\hat{x} = G(z), z$ denotes the noise vector, p_g denotes the distribution of the generated data, $G(\cdot)$ is the generator, and $D(\cdot)$ is the discriminator.

On a theoretical level, Eq. (1) converges and the discriminator result converges to 0.5 when the sample size is sufficient and $p_r(x) = p_g(\hat{x})$. The discriminator optimal solution, $D'(x) = \dfrac{p_r(x)}{p_r(x)+p_g(x)}$, can be derived when G is fixed. Substituting the discriminator optimal solution into the original equation to simplify can get the JSD between the real sample distribution and the generated sample distribution, so the essence of GAN is to make the JSD between the real sample distribution and the generated sample distribution lowest.

3.1.2. Singular value decomposition algorithm

Singular value decomposition (SVD) is widely used as a powerful matrix decomposition method for image feature extraction and noise reduction.The matrix to be decomposed, A, is a matrix of $m \times n$, and the matrix singular value decomposition is defined as:

$$A = U\Sigma V^T \tag{2}$$

where A is a matrix with decomposition and U is a $m \times m$ square matrix, called the left singular matrix, $U = [u_1, u_2, \ldots u_m]$, where u_i is the left singular row vector. Similarly V is a $n \times n$-square matrix, called the right singular matrix, with $V = [v_1, v_2, \ldots v_n], v_i$ being is the column vector of V. The matrix Σ consists of a series of diagonal arrays of singular values, $\Sigma = [\sigma_1, \sigma_2, \ldots \sigma_r], \sigma_i$ is a separate singular vector of non-zero numbers r whose diagonal elements satisfy $\sigma_1 \geq \sigma_2 \geq \ldots \sigma_r \geq 0$, that is:

$$\Sigma = \begin{bmatrix} diag(\sigma_1, \sigma_2, \ldots \sigma_r) \\ O \end{bmatrix} \tag{3}$$

where O is the all-zero matrix and $\sigma_1, \sigma_2, \ldots \sigma_r$ denote the singular vectors of the matrix A.

In order to find the left singular matrix U, the right singular matrix V and the diagonal matrix Σ, the matrix to be decomposed transpose matrix A^T is multiplied by its transpose to obtain the square matrix $A^T A$ with dimensions in the range of $n \times n$, which is decomposed by the eigenvalues of this square matrix as follows:

$$\left(A^T A\right) v_i = \lambda_i v_i \tag{4}$$

where v_i is the eigenvector and λ_i is its corresponding eigenvalue, the matrix composed of the eigenvectors v_i is the right singular matrix to be solved, and similarly for the left singular matrix, use A to multiply with its transposed matrix to get the square matrix AA^T corresponding to the left singular matrix, whose eigenvalues are decomposed as follows:

$$\left(AA^T\right) u_i = \lambda_i u_i \tag{5}$$

where the matrix U is tensored by u_i into a matrix U of left singular matrices, and λ_i is the square of the diagonal array corresponding to the singular values.

3.2. Recommendation model based on TS-GAN

3.2.1. Overall framework of the model

The framework of TS-GAN-based recommender system is shown in Fig. 3.TS-GAN mainly includes two parts: generative model and discriminative model.The generative model is constructed based on the TimeSVD++ algorithm.In the figure, p_u, q_i denote the user vectors and the item vectors, respectively, and b_u, b_i denote the user bias, item bias, which portray user implicit preferences. Perform sample mining on the dataset to pre-establish sample categories in the sample candidate pool (white circles are positive samples and orange dots are negative samples in the figure). The generative model G selects negative samples from the sample candidate pool and generates fake positive samples to the discriminative model based on the correlation probability distribution among the samples. Following this, the discriminative model is constructed based on a fully connected neural network, which calculates the similarity between the positive samples in the candidate pool and the pseudo-positive samples provided by the generative model through the vector inner product and provides feedback to the generative model based on the strategic gradient descent algorithm to optimize the generative model for better generation of pseudo-positive samples. High-quality forged positive samples improve the discriminator model's discriminative ability. The two models, generator and discriminator, continuously improve their performance and reach the Nash equilibrium through adversarial learning. Finally, the recommendation list is output based on the trained generator model.

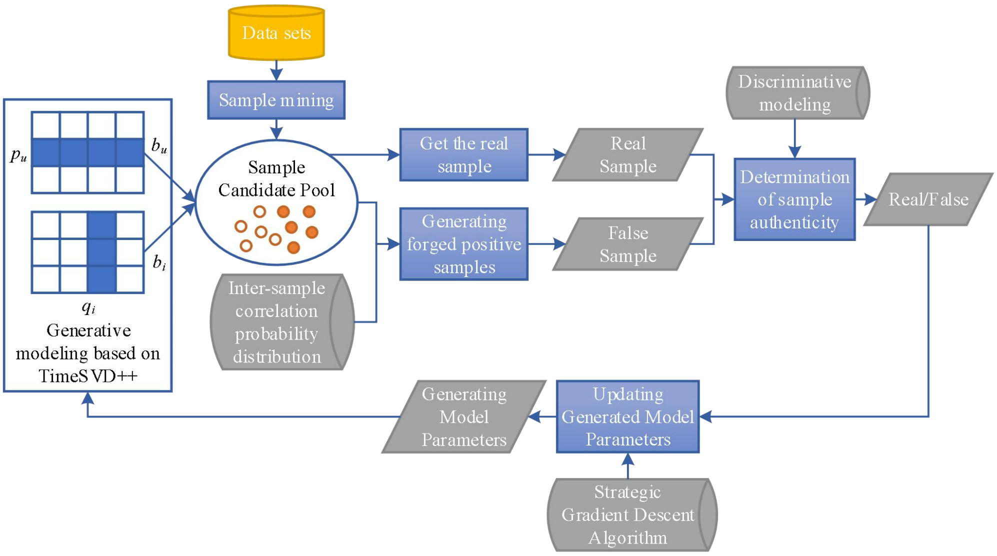

Figure 3. Framework of recommendation system based on TS-GAN.

3.2.2. Generative model design

TimeSVD++ is optimized based on SVD adding time dynamic function, compared with the traditional matrix decomposition algorithm, TimeSVD++ adds user bias information, implicit parameters, and time function to objectively describe user preferences. The user ratings do imply preference information, and certain ratings are low (or high), so the TimeSVD++ algorithm is used to design the generative model of TS-GAN to better mine the user preferences and accurately calculate the predicted ratings [37].

TimeSVD++ considers the time factor on the basis of SVD++, and changes the bias of users and items into a function about time, at which time the baseline prediction of users and items is represented as follows:

$$b_{ui}(t) = b_u(t) + b_i(t) + \mu \tag{6}$$

The above equation represents the baseline predictors of user u's ratings of item i at time t, and $b_u(t)$ and $b_i(t)$ are real-valued functions that vary over time, representing the user bias $b_u(t)$ and the item bias $b_i(t)$, respectively. The exact method of constructing these functions should reflect a reasonable way to parameterize the temporal changes involved, i.e.,:

$$b_i(t) = b_i + b_{i,Bin(t)} \tag{7}$$

For the user bias $b_u(t)$, first define a time-dependent offset functional equation for it, which can be expressed as:

$$dev_u(t) = sign\left(t - t_u\right) \cdot \left|t - t_u\right|^{\beta} \tag{8}$$

where t_u is the average time of all user interaction data of the system, $\left|t - t_u\right|$ represents the time interval, β is the hyper-parameter measuring the degree of influence of the time change, and finally, the parameter ∂_u is introduced, and parameters ∂_u and β are obtained by algorithm training and learning.

The bias of user interest with respect to time is obtained by the above method, and the user bias is partitioned into a static part and a time-varying part, viz:

$$b_u(t) = b_u + \partial_u \cdot dev_u(t) \tag{9}$$

The baseline prediction of user u's rating of item i is obtained and finally expressed as:

$$b_{ui}(t) = \mu + b_u + \partial_u \cdot dev_u(t) + b_{u,t} + b_i + b_{i,Bin(t)} \tag{10}$$

The bias of the user and the item changes over time, while the user's implicit factor p_u also changes dynamically over time. In this algorithm, the implicit representation of the item does not change over time (assuming that the attributes of the item do not change over time), and the prediction result that incorporates the implicit feedback of the user's historical ratings is:

$$r_{ui} = q_i^T \left(p_u(t) + |R(u)|^{-\frac{1}{2}} \sum_{j \in R(u)} y_j \right) + b_u(t) + b_i(t) + \mu \tag{11}$$

where $R(u)$ denotes the set of users with whom the user has interacted and y_j is the own hidden feature.

3.2.3. Discriminant model design

The input data to the discriminator are the interaction matrix and the user feature matrix, the values in the interaction matrix reflect the interaction between the user and the produce, if it is 0 then there has been no interaction between the user and the item, and accordingly, if it is 1 then there has been an interaction between the user and the item. The interaction matrix may be real or predicted by the generator, so the goal of the discriminator is to determine the truth or falsity of the input interaction matrix. The discriminator is mainly composed of a multi-layer fully connected neural network, and the final output value represents the probability that the input interaction matrix is real data, the closer it is to 1, the closer the discriminator thinks the input interaction matrix is to real data, and the closer it is to 0, the closer the discriminator thinks the input interaction matrix is to false data.

The input data for the discriminator are the interaction matrix R and the user features H_u, where the interaction matrix R is either real or predicted by the generator. Similar to the processing of the generator, the user feature H_u as a condition needs to be processed after splicing with the interaction matrix R. The final output value of the discriminator represents the probability that the input interaction matrix is real data, which is calculated as:

$$y = f\left(\ldots f\left(f\left(W_1^D\left[R \mid H_u\right] + b_1^D\right)W_2^D + b_2^D\right)\ldots\right) \tag{12}$$

In the above equation, y is the probability that the input interaction matrix is the true interaction matrix, and $R \mid H_u$ is the result after splicing the interaction matrix and user features. For the l^D-layer fully connected neural network in the discriminator, W_l^D is the weight parameter of the l^D-layer, b_l^D is the bias term of the l^D-layer, and f is the activation function, i.e., sigmoid function.

The objective function of the discriminator is:

$$J^D = \max \sum_u \left(\log D\left(R \mid H_u\right) + \log\left(1 - D\left(\hat{R} \mid H_u\right)\right)\right) \tag{13}$$

By maximizing the discriminator's objective function, the discriminator can successfully discriminate whether the interaction matrix is real or predicted by the generator. The discriminator, at higher performance, gives higher values for the true interaction matrix, i.e., the value of $\log D\left(R \mid H_u\right)$ is larger, while it gives lower values for the interaction matrix predicted by the generator, i.e., the value of $\log\left(1 - D\left(\hat{R} \mid H_u\right)\right)$ is the smaller value, i.e., it successfully discriminates the truth of the input interaction matrix.

The discriminator will feedback the judgment result to the generator to guide the training of the generator and improve the performance of the generator. After being guided by the discriminator, the generator will learn more accurate user features and improve the similarity between the predicted interaction matrix and the true interaction matrix.

3.2.4. Loss function design

For the generator, during training, an interaction vector x and a set of conditional information t are input to the preference encoder E and a target preference vector p is generated. The generator G takes x and the target preference vector p as inputs and generates the output user recommendation list samples $G(x, p)$ through adversarial learning, and the loss function of the generator is:

$$\mathrm{L}_{adv} = E_{x\sim pdata(x)}[\log D(x)] + E_{z\sim pdata(z)}[\log(1 - D(G(x,p)))] \tag{14}$$

where $D()$ denotes the output of the discriminator corresponding to the domain. The preference encoder E learns to provide target preference vectors p that may be in the domain, and the generator G learns to utilize p and generates samples of recommendation lists $G(x,p)$ that are indistinguishable from the domain's true interaction vectors. Since generative adversarial networks are a very large very small game problem, the loss of each domain discriminator is then:

$$\mathrm{L}_D = -\mathrm{L}_{adv} \tag{15}$$

In order to further enable the generator G to produce a diversity user list, this section designs a loss function for preference diversity with the aim of making the preferences obtained from each learning as different as possible, which can make the user's preferences richer, then:

$$\mathrm{L}_{pd} = \mathrm{E}_{x,p}\left[\left\|G(x,p_1) - G(x,p_2)\right\|_1\right] \tag{16}$$

where both p_1 and p_2 are preference features generated by the preference encoder. Maximization forces G to explore the feature space and discover meaningful feature preferences to generate a diverse list of user recommendations. The process uses the L1 paradigm as the unit of measure.

In summary, the complete loss function of the generator is shown below:

$$\mathrm{L}_{G,E} = \mathrm{L}_{adv} - \lambda \mathrm{L}_{pd} \tag{17}$$

4. Validation analysis of the effect of art design generation recommendation

In the field of art design, people's spiritual life is constantly enriched, thus paying more attention to personalized experience, which naturally puts forward higher requirements for art design, so that designers can not completely rely on their personal ability to grasp the public's personalized needs for art design, thus making it difficult to carry out art design innovation. Therefore, in order to promote the high-quality development of the art design industry and maximize the public's pursuit of art, designers should continue to innovate art design and flexibly apply technology to meet the diverse needs of the general public.

4.1. Recommendation effects of generating recommendation models

4.1.1. Model Learning Curve

For the TS-GAN model, different loss functions may make the model achieve different training results during the training process. In order to illustrate how the loss function designed in this paper affects the TS-GAN model, a validation analysis is carried out. The dataset selected in this paper is to use crawler technology to obtain image data about art design on the Internet, and construct the experimental dataset (YSData) through standardized processing. Figure 4 shows the effect of different loss functions on the model performance. In the figure, GAN denotes the learning curve obtained using only the adversarial approach, AGAN and PGAN denote the learning curve after combining L_{adv} and L_{pd} losses alone, respectively, and TS-GAN denotes the learning curve after combining both L_{adv} and L_{pd} losses.

From the figure, we can find that the learning curve of GAN is unstable and less accurate. The AGAN and PGAN recommendation accuracies of combining L_{adv} and L_{pd} loss alone have improved. When combining both L_{adv} and L_{pd} losses, the TS-GAN model has the smoothest learning curves and the highest recommendation accuracies, which proves the effectiveness of L_{adv} and L_{pd} losses.

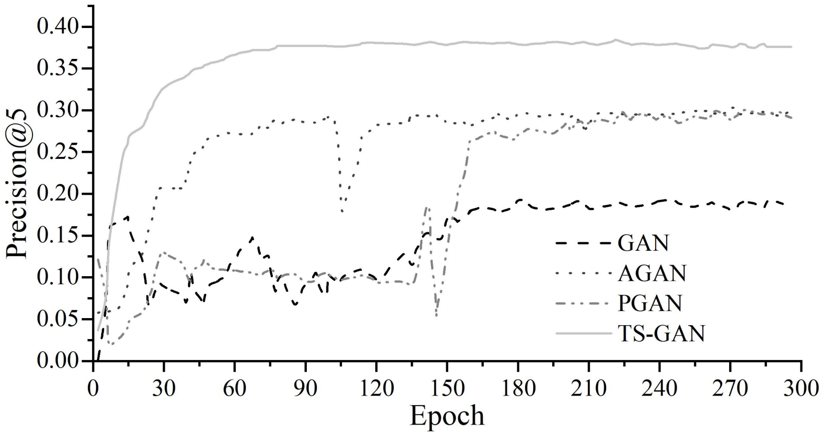

Figure 4. Effects of different loss functions on model performance.

4.1.2. Different input conditions

In order to realize the creative generation recommendation of art design, this paper focuses on the user preference situation when establishing the generative recommendation model, so as to better obtain the user's preference on art design, thus generating the art design works that are more in line with the user's needs. Based on this, this paper wants to experimentally analyze the specific impact of different user preference data inputs on the TS-GAN model, mainly from the two dimensions of user attributes and user interaction vectors, and select precision, recall, normalized discounted cumulative gain (NDCG) and mean reversed rank (MRR) as the evaluation indexes. Figure 5 shows the comparison results of TS-GAN model recommendation performance under different input conditions, where Figures 5(a)~(d) show the comparison results of precision, recall, NDCG and MRR, respectively.

From the figure, it can be seen that the TS-GAN recommendation method based on user attributes is overall slightly better than the user interaction vector-based recommendation in all evaluation indexes, which overcomes the error brought by the dichotomous input neural network fully-connected layer of the unknown term in the GAN model based on the user interaction vectors, and thus verifies the effectiveness of the proposed method. Since the zero-sum game based on the GAN model is more difficult to converge and is susceptible to hyperparameters. From the figure, it can be seen that the evaluation indexes of the TS-GAN algorithm based on user interaction show an overall trend of increasing and then decreasing, and it starts to converge when it runs for about 300 rounds, but its evaluation indexes start to decrease as the number of rounds increases. This is due to the overfitting phenomenon of user interaction vectors, which leads to the decline of recommendation accuracy. On the other hand, the evaluation indexes of the TS-GAN model based on user attributes remain stable after convergence. Through the above analysis, it can be seen that the TS-GAN recommendation model based on user attributes has a smoother and more stable convergence of recommendation accuracy, which also verifies that the method has a better convergence performance.

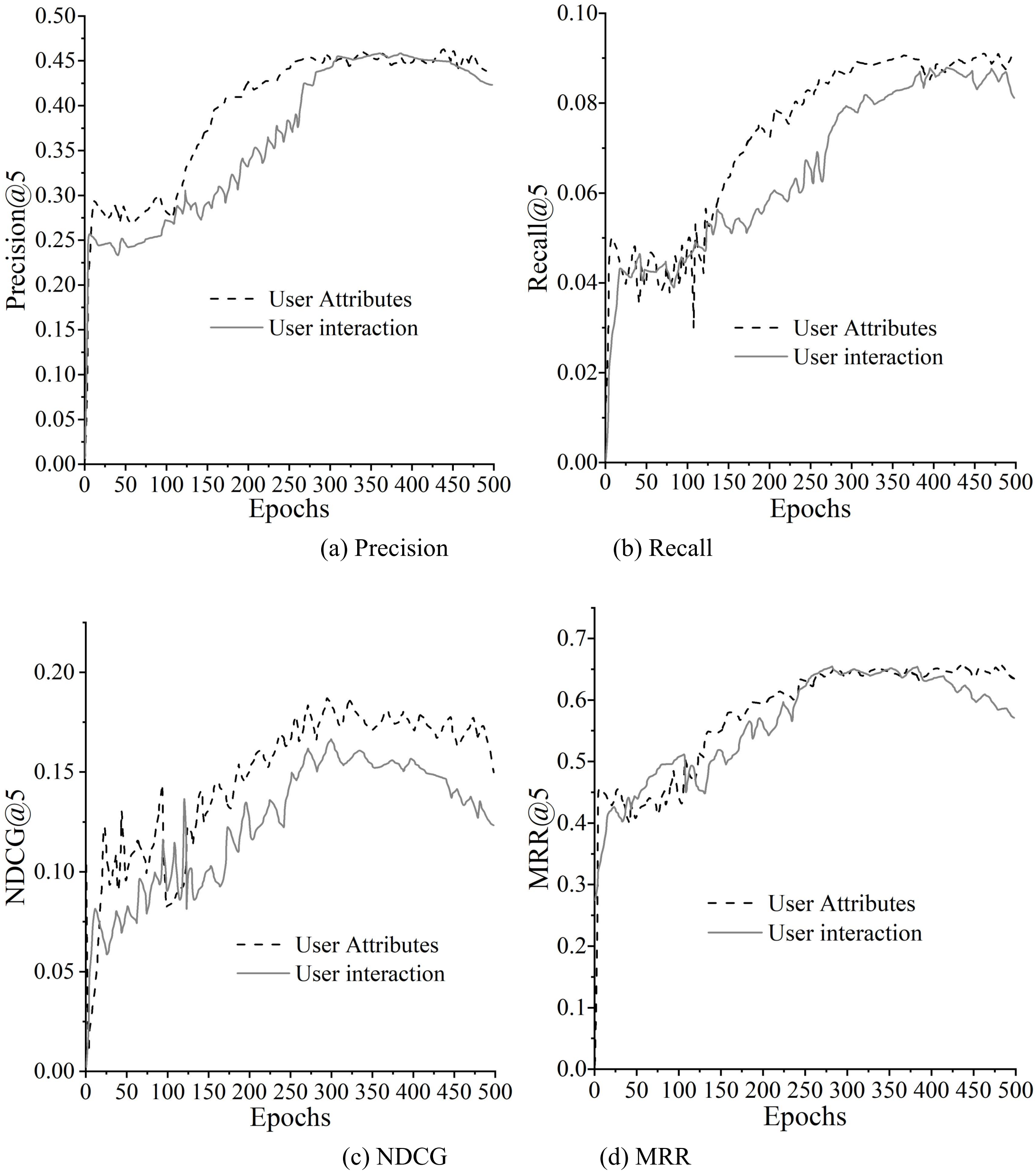

Figure 5. The recommendation of the TS-GAN model under different input conditions.

4.1.3. Recommended Performance Comparison

To evaluate the performance of TS-GAN recommendation model, accuracy (P@n), normalized discount cumulative gain (N@n), and mean inverse rank (M@n) are used to evaluate the recommendation model. Accuracy is used to evaluate the number of correct items in the recommendation list, and normalized discount cumulative gain and mean inverse rank are used to evaluate the rank position of correct items in the recommendation list. These are widely used evaluation metrics where n is 10 and 30 respectively.Table 1 shows the performance comparison results of different recommendation models.

On the art design image dataset established in this paper, the GAN-based recommendation model generates a better overall recommendation effect, which is due to the fact that the GAN model can be fully trained on user preferences through the generator and discriminator, thus better grasping the user's preferences in art design and providing a reference for art design idea generation. Compared with the CFGAN model, the TS-GAN model outperformed 6.14%, 5.22%, 8.94%, 6.63%, 9.60%, and 8.21% respectively on P@10, P@30, N@10, N@30, M@10, and M@30. Compared with FISM, TS-GAN outperformed 7.23%, 2.17%, 9.47%, 3.61%, 6.03% and 4.94% respectively in P@10, P@30, N@10, N@30, M@10 and M@30. A numerical comparison shows that the TS-GAN model is optimal in all evaluation metrics of the art and design image dataset, and possesses excellent recommendation performance.FISM, CDAE, and CFGAN show relatively competitive results.FISM converts the item-item similarity matrix into two low-dimensional latent factor matrices, which effectively alleviates the problem of dataset sparsity, and exhibits high recommendation effect.CDAE also uses denoising autoencoder and gets good recommendation performance, but the model relies heavily on the adjustment of the hidden space dimension, consuming a lot of training time.CFGAN supplements the user-item interaction matrix with GAN, and the role of adversarial and negative sampling makes the model outstanding.ItemKNN and BPR are early techniques for recommender systems, applying machine learning methods to accomplish the P3a and RP3b are based on dichotomous graph modeling of user-item relationships, which have less computational expenditure but do not show good recommendation effects.IRGAN relies heavily on pre-training and hyper-parameter tuning, and the models show large differences in the two datasets despite spending a certain number of training cycles to tune the parameters. In summary, in this paper, based on considering the dynamic time change of user diversity preferences, combined with the TimeSVD++ algorithm can realize the personalized generation recommendation of creative images of art design, which provides data support for enhancing the creativity of art design and improving the inspiration of creators.

Table 1. Performance comparison results of different recommendation models.

Model	P@10	P@30	N@10	N@30	M@10	M@30
ItemKNN	0.367	0.251	0.396	0.355	0.589	0.601
BPR	0.365	0.265	0.388	0.368	0.563	0.583
FISM	0.387	0.276	0.412	0.388	0.614	0.628
P3a	0.334	0.232	0.367	0.339	0.568	0.589
CDAE	0.383	0.274	0.406	0.381	0.585	0.602
RP3b	0.367	0.248	0.398	0.363	0.594	0.613
IRGAN	0.352	0.261	0.375	0.356	0.552	0.571
CFGAN	0.391	0.268	0.414	0.377	0.594	0.609
AE	0.386	0.265	0.412	0.377	0.606	0.621
User-AE	0.392	0.276	0.433	0.394	0.632	0.642
TS-GAN	**0.415**	**0.282**	**0.451**	**0.402**	**0.651**	**0.659**

In order to deeply investigate the performance of TS-GAN model, this paper also analyzes and compares the model complexity and efficiency of various methods. Among them, the method Pix2Pix+noise does not introduce additional parameter counts compared to Pix2Pix, and the MUNIT method belongs to the GAN structure, so only the complexity of the generator needs to be analyzed.BicycleGAN and the methods in this paper need to analyze the complexity of the generator and encoder, and the BigColor method needs to analyze the complexity of the generator, the encoder, and the classifiers. For testing time, all methods are uniformly set to generate 12 different art style images corresponding to each test image, as well as retaining the same image post-processing operations and using the same test machine to ensure a fair and consistent comparison environment. The results are shown in Table 2.

As can be seen from the table, the number of parameters of the TS-GAN model designed in this paper for generating recommendations for art design is 50.07M, and the number of floating point operations per second is 33107.76M. Comparing the MUNIT model, which has the lowest number of model parameters, and the BicycleGAN model, which has the lowest number of floating-point operations per second, the TS-GAN model in this paper is more advantageous in generating the quality and diversity of images of art and design styles, and the overall test time is not very much different, and both of them have high real-time performance. In addition, although BigColor is excellent in image quality, its model complexity is high, and the number of parameters and the number of floating-point operations per second reach 512.09M and 204157.59M respectively, which is not practical. Overall, the TS-GAN model proposed in this paper is an effective recommendation model for art style image generation, and its application to art design creative generation can provide designers with certain creative inspirations in the creative process.

Table 2. Complexity of different recommendation models.

Model	Parameters (M)	FLOPs (M)	Test time (s/iter)
Pix2Pix+noise	55.63	17985.45	0.0312
MUNIT	15.06	77235.32	0.0158
BicycleGAN	41.28	16181.61	0.0273

BigColor	512.09	204157.59	0.8194
TS-GAN	50.07	33107.76	0.0341

4.2. Survey of Art and Design Generation Recommendations

4.2.1. Satisfaction of subjects

For recommendation models, the user's satisfaction with the recommended content is undoubtedly the most important evaluation index, and the same is true for the art design-oriented creative production recommendation model in this paper. It is necessary to guide the user's satisfaction with the recommended art and design styles, and since the user's art preference is subjective, combing statistical methods are used to collect the user's satisfaction with the results of art and design recommendations.

In this paper, 40 designers of different styles in the field of art and design are invited as subjects, and each subject is first invited to fill in personal information and art style preference characteristics, and then several types of art style images are recommended for them using the TS-GAN model. Assuming that one of the recommendation process, the model recommended N types for them, of which the subjects were satisfied with M types, and the rest were dissatisfied, the subjects' satisfaction with the generated recommendations can be expressed as M/N. Firstly, five art design experts were invited to pre-test the TS-GAN model, and the subjects generally reflected that there were more art style recommendations, which appeared to be aesthetically fatiguing and increased the subjects' sense of annoyance, and resulted in the subjects' unwillingness to carefully browse the generated recommendation results. The subjects generally reflected that there were more art style recommendations, which caused aesthetic fatigue and increased the annoyance of the subjects, leading them to be unwilling to browse the generated recommendations carefully. Through the feedback of the pretest subjects, we solicited their opinions and improved the number of recommended samples, and finally determined the initial number of recommendations to be 26.

40 subjects were invited to experience and their satisfaction with the art design recommendation results were counted, and their results were obtained as shown in Figure 6. Based on the data distribution in the figure, it can be calculated that the average value of the subjects' satisfaction with the art design idea generation recommendation results is 87.02%, indicating that the overall recommendation is good. From the satisfaction distribution curve can also be seen, there still exists part of the recommendation satisfaction below 75%, the reason may be that the art design related style samples are not perfect enough, after all, the 26 art design styles may not be able to fully meet the needs of the 40 subjects, thus affecting the satisfaction of the art design style generation recommendation. Secondly, it may also be that there is a cross-influence between the characteristic attributes of art design styles and user preferences, resulting in a bias in the overall preference of subjects for art design styles. Finally, it is also possible that the subjects' own preference for art design styles is low, resulting in fewer art styles meeting the recommended conditions when the model recommends art design styles, and thus failing to meet the subjects' needs and resulting in low satisfaction.

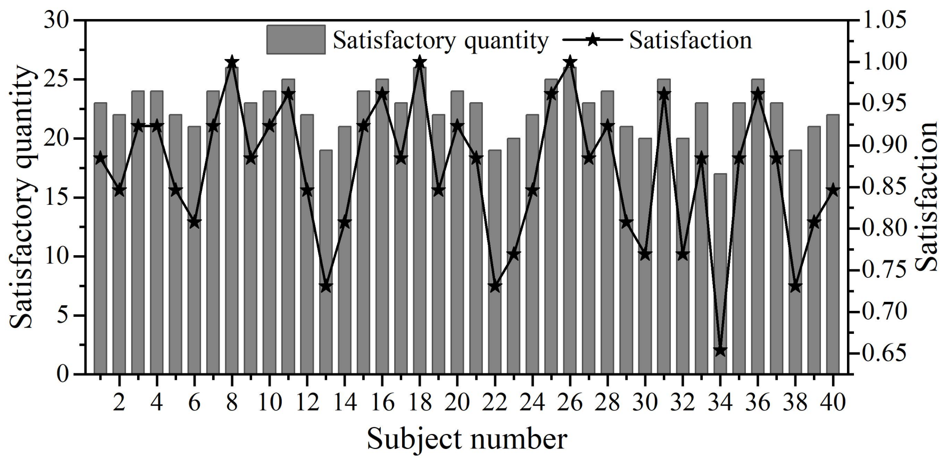

Figure 6. A satisfaction survey of the subjects.

4.2.2. Artistic design trends

Extend the application of the TS-GAN model to the art and design market by counting the additions of different user types, i.e., designers, consumers, manufacturers, etc., in different time periods. The TS-GAN model of art design is applied to the design and manufacture of art products, and the new additions of different users are counted from January 2024 to September 2024. Figure 7 shows the statistical results of the art design development trend.

From the figure, it can be seen that after applying the TS-GAN model to the art market, whether it is designers, consumers or manufacturers, it shows a growth trend in a 9-month period, in which the consumers grow relatively faster in February, with the highest number of people growing more than 45,000. This suggests that the art design generation recommendation model designed in this paper is not only attractive to art practitioners (designers), but also leads more consumers to join in art product design, helping consumers to obtain works that better match their art preferences, thus feeding the art design field and art designers' creative inspiration generation.

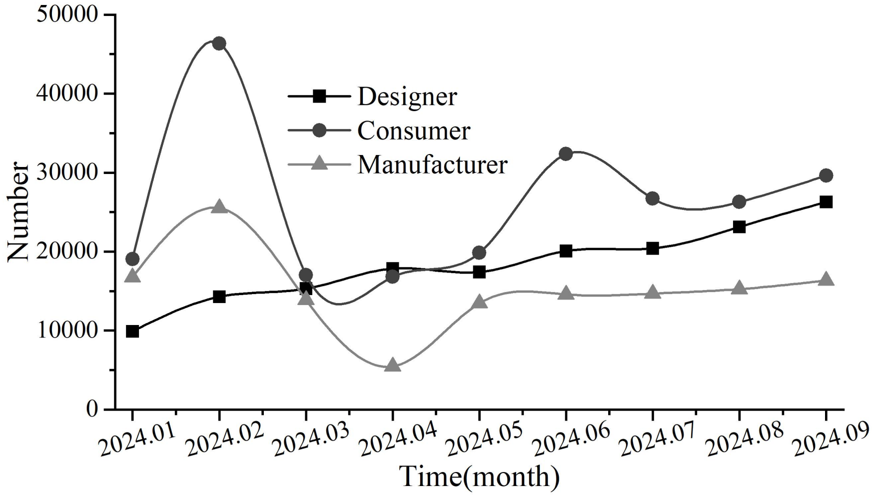

Figure 7. Statistics on the development trend of art design.

5. Conclusion

The article combines generative adversarial network and SVD algorithm to establish a TS-GAN model for art and design creative generation recommendation, and the study shows that the model has better recommendation accuracy, and can also improve the subject's recommendation satisfaction, and can also promote the development of art and design market. This study explores the innovative application of intelligent algorithms in the field of art and design, and intelligent algorithms give more diverse possibilities in the field of art and design, and give designers creative inspiration on the basis of meeting their needs, and provide support for promoting the development of the field of art and design.

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