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PERSONALIZED ART WORK RECOMMENDATION SYSTEM AND METHODS BASED ON USER INTEREST CHARACTERISTICS AND EMOTIONAL PREFERENCES

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Abstract. To familiarize users with their interests and hobbies through online data collection, and improve their experience when browsing art works, research based on K-means algorithm has received widespread attention. However, with the explosive growth of various types of art works, it is difficult to estimate the K value of the K-means algorithm when processing these data. To solve this problem, this research predicts the user behavior of Wink dataset based on K-means algorithm, introduces regularization specified process and emotional precision, and generates fusion algorithm. The study first proposes the concept of similar users and calculates the Pearson correlation coefficient between them to determine their similarity; Then several regularization terms are added to the user group, and the prediction results are obtained by changing the parameters; Further screening of art works clustering categories is to address the issue of slow user startup. Finally, the algorithm studied will be applied to the Wink dataset and the prediction accuracy of the particle swarm optimization algorithm will be tested and compared with the fusion algorithm. A total of 400 experiments are conducted, and the fusion algorithm achieve a prediction accuracy of 392 times, with an accuracy rate of 98.0%; The accuracy of particle swarm optimization algorithm is close to that of fusion algorithm, at 88.2%. The experimental results show that the algorithm model proposed in the study can effectively map the relationship between user interest features, emotional factors, and personalized art recommendation, thereby providing users with a good viewing experience.

Key words: Pearson correlation coefficient; Emotional precision; Regularization specified process; K-means algorithm; Personalized recommendations

1. Introduction. In a society with explosive information growth, with the rapid development of recommendation-based algorithms, users can obtain the information they need online and solve the problems they face [1, 2]. The predecessor of this type of algorithm is a search engine, which can help users search for areas of interest. However, when users face something for the first time, they may encounter situations such as unclear expression, which can lead to ineffective search engine work. By comparison, personalized recommendation algorithms can predict user preferences in daily life by understanding their interest characteristics and emotional preferences, effectively avoiding the unclear user explanations. However, user data also contains special interests, and traditional algorithms set them as isolated points. The constructed model will exclude these points, causing significant errors in the prediction results [3]. In recent years, the K-means algorithm has attracted the attention of many scholars due to its simple and efficient clustering research. The K-means algorithm sets the clustering center point during operation to attract similar elements to approach. However, when K-means processes a large amount of data, it is difficult to estimate the number of center points, which prolongs its iteration time. To improve this situation, based on user interest characteristics and emotional factors, this research introduces the regularization Prescribed Process (RPP) and Emotional Accuracy (EA) to quantify the two and generate a fusion algorithm (PEK-means). This algorithm is used to cluster and filter art collections and users is expected to reduce algorithm runtime. The research is mainly divided into four parts. The first part mainly analyzes and summarizes the application and effectiveness of current user interest models and user sentiment models; The second part introduces the factors that affect prediction accuracy and constructs a PEK-means prediction model; The third part analyzes and compares the performance of this optimization model with traditional models; The final part is conducted through simulation experiments on the Wink dataset, highlighting the shortcomings that still exist in the research. The practical significance of this study is to learn users' preferences through data analysis, thus increasing their viewing experience. The purpose is to recommend the works of art that users like, and then increase the awareness of works of art.

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2. Related Work. A very important branch of user psychology prediction technology, namely providing users with favorite art works, plays a very important role in improving user browsing experience and selling unpopular art works. Li et al. constructed a model that provided user historical interest sequences based on the semantic understanding of each project. They proposed knowledge enhancement path mining and interest fluctuation signals for discovering granular dynamic interest sequence learning methods to obtain semantic enhancement paths. The path was merged through the entropy perception pool layer to obtain a user preference representation, which was then used for dynamic learning of user interest sequences. The experimental results on two common datasets for movie and music recommendations showed that their model could achieve better predictive performance compared to other known baselines [5]. Chen et al. first introduced an attention flow network to model users' purchase records by displaying the attention flow of changes in the purchase intention; Then, based on individual attention flow, a personalized recommendation algorithm based on attention flow network was proposed. Their method integrated all user purchase sequences, converted them into a weighted attention flow network, and recommended projects based on the user's attention decay attention flow network through relevant transfer probabilities. Finally, their experimental results on several real datasets indicated that their superior performance could meet user preferences [6]. Zhang et al. proposed a factorization model for predicting restaurant rankings. They extracted images through deep convolution network and applied them to collaborative filtering. They fused multi perspective visual features through user related weights, which reflected personalized visual preferences for restaurants and were different and independent among users. They applied this model to provide personalized recommendations for users on two restaurant datasets. The experimental results showed that compared to the model with single view visual information, the model with multi view visual information had better performance [7]. Zhu simulated the learning process of users through personalized fuzzy logic interests. Based on the established model, resources were recommended to users according to the idea of collaborative filtering. Finally, it was applied to user interest description, a user interest vector based on personalized logic was proposed, and concept aggregation methods were used to discover user interests. His experimental results indicated that his method could better describe user interests, making the recommendation of interest resources for specific users more accurate and reliable, and further studies have been made for the collaborative recommendation problem in performance-based fuzzy logic systems [8].

Chen et al. proposed a personalized recommendation algorithm, which used collaborative filtering to recommend in turn. Dirichlet topic model was used to reduce the dimension of user data. And a user written topic matrix was established to reduce inaccuracies in the algorithm. It calculated the similarity between users to obtain a list of user interests. Then, based on the preliminary recommendation results, the feature vectors of the calligraphy image were extracted. And it calculated the similarity between calligraphy characters and preliminary recommendations to obtain the final recommendation result. The experimental results showed that this algorithm had effectiveness and accuracy, and was superior to other algorithms [9]. Li et al. proposed an algorithm for recommending explanatory Q&A documents. Firstly, a dual topic model was used for modeling, and then the growth gas algorithm was used to cluster documents. To train multiple classifiers, three features were extracted from question answering categories. It identified relationships by building an integrated classification model and recommended explanatory Q&A documents. This algorithm exhibited good clustering performance, and the performance of the integrated classification model was superior to other algorithms. The high score of its Q&A recommendation performance indicated the practicality and good performance of the proposed recommendation algorithm, providing a new perspective for recommendation research [10]. Du et al. used users' subjective characteristics and trust to improve similarity. Considering the sparsity and discreteness of the data, a cloud drop similarity calculation method was introduced when calculating trust similarity. Through weighting to predict gaps in the data, new similarity was generated. When there was a cold start issue with the history of a new user, a neural network was used to classify the user. They proposed a method for predicting user interest features based on feature classification. Finally, the effectiveness and rationality of this method were verified using the recommendation of machine tool products in manufacturing enterprises as an example [11]. Several researchers have found that algorithms for predicting user preferences are very popular internationally. But there is still little research on PEK means. This research pioneered the introduction of regularization regulation process and emotional precision, and on this basis, the impact of user interest characteristics and emotional preferences was taken into account to generate PEK means.

3. Construction of a Personalized Art Work Recommendation Model Based on User Interest Characteristics and Emotional Preferences. With the development of the internet industry, to cater to user preferences, research on recommendation models has become increasingly popular, with personalized art recommendation systems being the most important part [4]. However, there are a wide variety of art works and writers with vastly different styles, which increases the difficulty of recommending art works. This study combines the user's interest characteristics with emotional preferences. Firstly, it introduces the models constructed based on the two, and then describes the fusion method of the two models.

3.1. Building a Recommendation Model Based on User Interest Characteristics and Emotional Preferences. The basic information, learning data, and behavioral habits of users can be collected to obtain their interest characteristics. Since entering the era of networking, users have increasingly high requirements for recommendation accuracy, and recommendation methods based on users' own attributes have been widely used. In the building a collaborative filtering model, the most important step is to find similar users and items. If two random users are set as vectors, the cosine value of the angle between the vectors can be calculated, as shown in equation 3.1 [13].

$$\cos(i,j) = \frac{i \cdot j}{|i| \cdot |j|} = \frac{\sum_{k \in u_{ij}} R_{i,k} R_{j,k}}{\sqrt{\sum_{k \in u_i} R_{i,k}^2} \cdot \sqrt{\sum_{k \in u_j} R_{j,k}^2}} \tag{3.1}$$

In equation 3.1 above, i, j represents two users, and the way users view things is denoted as k. The values of the two users towards k are represented by $R_{i,k}$ and $R_{j,k}$, respectively. The range of $cos(i,j)$ is between 0 and 1, and as its value increases, the similarity between the two users will increase. to observe the level of intimacy between two users, the Pearson Correlation Coefficients (PCC) is introduced, and its calculation expression is shown in equation 3.2.

$$\operatorname{sim}(i,j) = \frac{\sum_{k \in u_{ij}} (R_{i,k} - \overline{R})(R_{j,k} - \overline{R})}{\sqrt{\sum_{k \in u_{ij}} (R_{i,k} - R_u)^2} \cdot \sqrt{\sum_{k \in u_j} (R_{j,k} - R_u)^2}} \tag{3.2}$$

In equation 3.2, $\overline{R}$ means the liking of two users towards things, and the user's rating is recorded as R_u. $sim(i,j)$ fluctuates between -1 and 1, where 1 means a close relationship between two users, 0 expresses that they are not familiar with each other, and -1 refers to a completely opposite relationship between the two [8]. When the intimacy between two users is between 0 and 1, it is necessary to consider the difference in their understanding of art works, as shown in equation 3.3.

$$S(i,j) = \begin{cases} 1 & \text{if } S_i = S_j \\ 0 & \text{if } S_i \neq S_j \end{cases} \tag{3.3}$$

In equation 3.3, the knowledge of two users about the art work is denoted as S_i, S_j and the value of $S_{i,j}$ is the degree of difference in understanding between the two users. When the two users have the same understanding of the art work, $S_{i,j} = 1$, and vice versa, the value is 0. Combining the parameters between personalized art works and users can construct the block diagram shown in Figure 3.1.

The block diagram in Figure 3.1 consists of four modules, namely art collection, work processing, analysis of painting types, and personalized recommendations for users [15]. Firstly, it selects a larger range of cities and collects as many art works as possible; Then it performs noise reduction, weight reduction, and other processing on it to include all types of art works; The collected paintings are classified based on the artist's style; Finally, based on each user's preferences, the eligible paintings are recommended to them. In addition to co buyers of the same painting, the study considers users who indirectly purchase the painting, and the calculation method is shown in equation 3.4.

$$W(x,y) = w_{x,y} + \sum_{z \in N(x) \cap N(y)} (w_{xz} + w_{yz}) \tag{3.4}$$

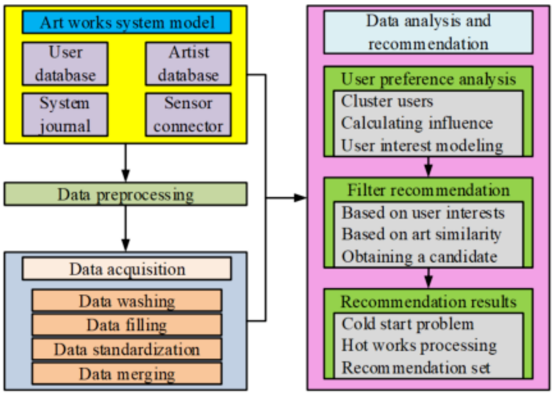


Fig. 3.1: Combination Block Diagram of Intimacy between Personalized Artist and Users

In equation 3.4, x, y are defined as two random paintings; $W(x, y)$ represents the same user who purchased both; The seller of the same type of two paintings is labeled $N(x)$,$N(y)$; Their indirect buyers are recorded as $w_{x,y}$; $z$means the similarity between paintings. Among various types of recommendation models, the similarity of preferences between users can be captured at a fine-grained level, and the similarity calculation module can be used to calculate the emotional preference differences between users, as shown in equation 3.5.

$$\alpha^{p_i}(i,j) = \begin{cases} \frac{\sum_{a\in\alpha p_i} E_a^i E_a^j}{\sqrt{\sum_{a\in\alpha p_i}(E_a^i)^2}\sqrt{\sum_{a\in\alpha p_i}(E_a^j)^2}} & \text{if } i,j \in p_i \\ 0 & \text{if not} \end{cases} \tag{3.5}$$

In equation 3.5, the artwork is represented by p_i ; E_i^a,E_a^j indicate users' emotional preferences for art works, and the collected collection of art works is recorded as a. The emotional rating of users for art works depends on their evaluation of the art works. Users have similar personalities, and similar user evaluations can help users make purchase suggestions. The help of evaluations for art works is shown in equation 3.6.

$$H(i,j) = \frac{|A_i^j|}{l}\alpha^{p_i}(i,j) \tag{3.6}$$

In equation 3.6above, $H(i, j)$ stands for the impact of one user on the other, with a value range of [0,1]. A value of 0 indicates no impact, while a value of 1 has the greatest impact [16]. The length of the keywords in this painting is denoted as l, and the frequency of the keywords in the evaluation is represented by A_i^j|. In the user feedback interaction, the same painting will have multiple different comments, and their relationship is shown in equation 3.7.

$$\text{cov} = \frac{\beta_i^u \cap \beta_{H_t^{\text{sim}}}^u}{|A_i^j|} \tag{3.7}$$

In equation 3.7, *cov* is the coverage of all comments on the same painting; The associated words in the user's painting evaluation are recorded as β_i^u; Similar users' evaluations of the same type are expressed by . Coverage can consider the connection between users and art works, while Aspect Coverage (AC) describes users' emotional preferences. However, users still have unfavorable evaluations for their sales of art works. To accurately calculate AC, the EA indicator is introduced, and the calculation is shown in equation 3.8.

$$\text{frastraction} = \frac{|\chi_i^{u^+} \cap \chi_{H_t^{\text{sim}u^+}}| + |\chi_i^{u^-} \cap \chi_{H_t^{\text{sim}u^-}}|}{|\chi_i^u \cap \chi_{H_t^{\text{sim}u}}|} \tag{3.8}$$

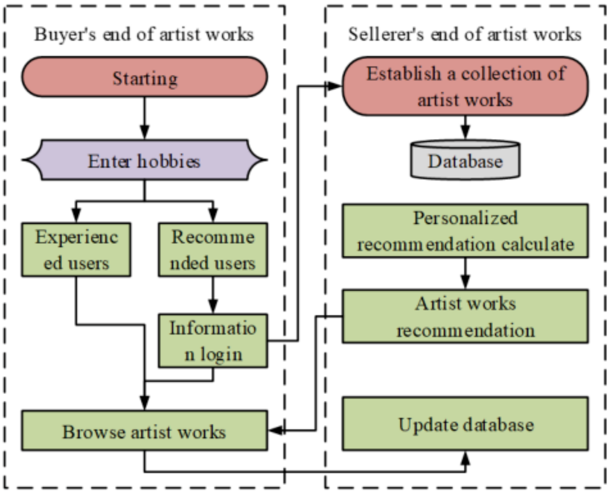


Fig. 3.2: Analysis of Art Works with Emotional Precision

In equation 3.8, the user's positive evaluation of the artwork is represented by χ_i^{u+}, $\chi_{H_t^{sim}}^{u+}$ and the negative evaluation of the artwork is recorded as χ_i^{u-}, $\chi_{H_t^{sim}}^{u-}$. *rastraction* describes the purchasing significance of the artwork, fluctuating between -1 and 1 [17]. When the value is -1, it indicates that the user who purchased the work has extremely low evaluation of it. The analysis of art works using emotional precision consists of two modules, as shown in Figure 3.2.

The system in Figure 3.2 includes both the user and the sales ends. Old users can directly appreciate art works; New users input their interest in art works, and their information will be input into the self built database of the painting merchant. At the sales end of art works, merchants calculate the weight proportion of different types of works, and then provide multiple types of works to arouse user interest.

3.2. Model Building of Regularization Regulation Process and EA Improved K-Means Algorithm. When applying PCC and EA to predict user interests and preferences in practice, there will be various errors. To avoid these errors, the K-means algorithm is introduced to cluster a large amount of data as needed. Multiple seeds are generated by initializing their geometric centers. These seeds can attract eligible art works, as shown in Figure 3.3 [18].

The K-means algorithm shown in Figure 3 first generates four types of center points, and then clusters as many paintings works as possible based on the types of other points. However, the number of cluster center points often varies greatly. In the attracting the same element to each other, the center points with fewer works will have stronger attraction, making it easier to attract other elements, such as the red center point shown in Figure 3.3. The purple center point ranks second in the number of works it contains, as it contains highly similar works (such as A and G), so it blocks one of them. Although purple dots detect anomalies and they recombined to output results that meet the conditions, it also indicates that the K-means algorithm has obvious drawbacks when processing large amounts of data. Based on this, the research redefines the distance between clusters, and its calculation is shown in equation 3.9.

$$L = \sum_{i=1}^{O} \|c_i - m\| \tag{3.9}$$

In equation 3.9, the distance from the cluster center to the user center is denoted as L; The user center is represented using m; O is the number of center points, and the result is recorded as c_i. The K-means algorithm can analyze multiple attributes to achieve the purpose of understanding users. The expression for its model is

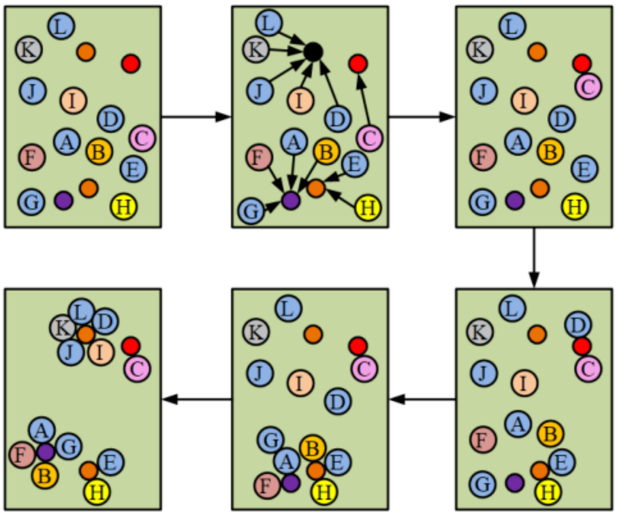


Fig. 3.3: Working Principle of K- means Algorithm

as equation 3.10.

$$f(X) = w_O + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} v_{ij} x_i x_j \tag{3.10}$$

In equation 3.10 above, $f(X)$ means the processed user information; The user's values on the features are denoted as x_i, x_j ; The error of global parameters is recorded as w_o;It uses the v_{ij} stands for users' interest in the work; The impact of the work on users is recorded as $v_{ij} x_i x_j$. The model obtained through research can learn to speculate on user psychology, and the key point is to minimize the difference between user information and ratings [19]. The calculation for the difference is shown in equation 3.11.

$$\delta = \sum_{i=1}^{\varepsilon} \text{loss}(f(X), Y) = \sum_{i=1}^{\varepsilon} ((f(\vec{x}_i), Y_i))^2 \tag{3.11}$$

In equation 3.11, the meaning of Y is the user's true rating matrix for the work; $\overline{f(x_i)}$ is the average user rating of the work; The total number of users is recorded as ϵ. RPP method is used to optimize the model. That is, multiple regularization terms are added to the user group, and the prediction results are obtained by changing the parameters, as shown in equation 3.12.

$$\Theta^* = \arg\min_{\theta} \left(\sum_{i=1}^{\varepsilon} \left((f(\vec{x}_i), Y_i) + \sum_{\theta \in \Theta} \phi_\theta \theta \right)^2 \right) \tag{3.12}$$

In equation 3.12, Θ means the model in the clustering algorithm. The parameters are represented by θ. When θ is a positive number, its regularization term is recorded as ϕ_θ. The value of ϕ_θ needs to satisfy randomness, and when it happens to be 0, there is a equation 3.13.

$$\text{dist}(\phi, \gamma) = \frac{\eta_1 \mu_1 + \eta_2 \mu_2 + \eta_3 \mu_3 + \ldots + \eta_n \mu_n}{\sqrt{\sum_{i=1}^{n} \eta_i^2} \cdot \sqrt{\sum_{i=1}^{n} \mu_i^2}} \tag{3.13}$$

In equation 3.13, the painting is denoted as ϕ, γ, and the feature vectors extracted in classical, abstract, realistic, and other styles are expressed as μ, η. For users, it is easier to find users of the same age group and gender

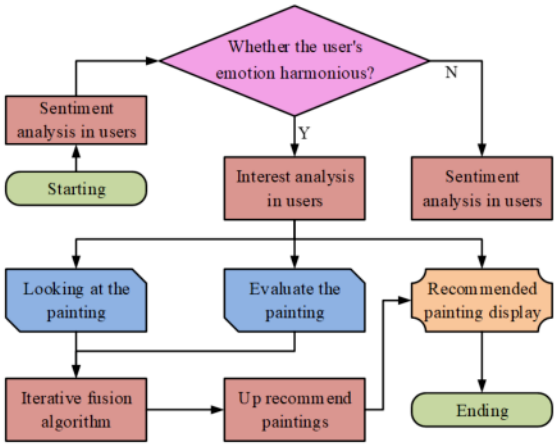


Fig. 3.4: Clustering and Screening Process of Artist Portfolio

who share a common language. During the clustering, due to the wide distribution of users in different regions, there may be slow user startup issues. To address this issue, the study introduces the definition of a popular painting portfolio, as shown in equation 3.14.

$$p(\nu, \pi) = \frac{|\vartheta(i)\rho\sigma(f)|}{|\vartheta(i)| + \zeta} \tag{3.14}$$

In equation 3.14, artistic creation is denoted as i, f; Users who like them use $\vartheta(f), \rho(f)$ representation; Equation 3.14 can search for a wider range of art works, thereby alleviating the problem of slow startup for users. The parameter used to solve data errors is ζ, and its calculation method is as equation 3.15.

$$\zeta_{i,j} = \frac{\sum_{i=1,j=1}^{n} |\tau_i - \omega_i| \cdot |\tau_j - \omega_j|}{n} \tag{3.15}$$

In equation 3.15 above, $\zeta_{i,j}$ refers to the global error predicted by the user, and its value reflects the quality of the model. τ_i, τ_j are the user's evaluation of the artwork, while ω_i, ω_j denote the user's emotional state towards the artwork [20]. To find the parts that users like from a large number of art works and calculate their similarity separately, it studied clustering and filtering of art works, and established a PEK-means for RPP and EA optimization K-means. The process is shown in Figure 3.4.

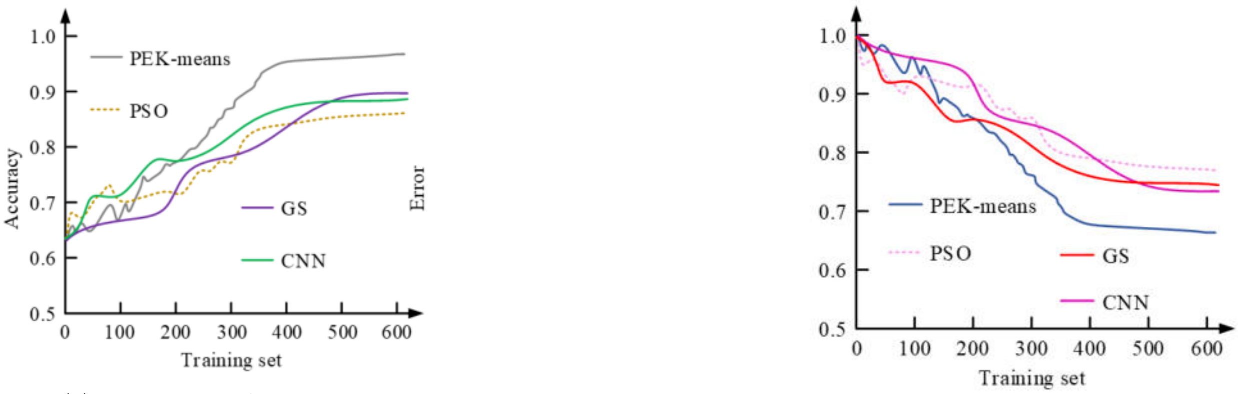
The method shown in Figure 3.4 can balance users' interest characteristics and emotional preferences, thereby recommending more accurate information about art works to users. It can be summarized as four processes. First is to analyze the emotional state of users and collect interest from users who are in good condition; Then it let them watch the artwork and retain their evaluations; Then it uploads their evaluations to the self built database to enrich the types of personalized art works; Finally, the updated painting recommendation portfolio is used to present richer content in the user module.

4. Experimental Study on Personalized Art Work Recommendation Model Based on K-Means Algorithm. To verify the effectiveness of the PEK-means algorithm in practice, a study was conducted to construct a PEK-means model based on personalized recommendation, and its iteration and accuracy verification were carried out. Finally, simulation experiments were conducted on the Wink dataset using the PEK-means model.

4.1. PEK-means System Development Environment and Model Parameter Determination. This study selected the Wink dataset, which included four types of painting: sketch, ink wash, oil paint, and simple brush, with a total of 1427635 pieces of painting information. Considering the limited types of data, the

Table 4.1: Experimental Parameters

Data set	Development language	Application servers	Internal storage
Wink	Python 12.0	Potato 8.0	512 G
Operating system	Display card	Database	Carrying out system
128 Ubuntu 23.02.20	18.0 GHz	Mysql 5.20.2023	Ubuntu 88.64
Web development framework	Language	Operator	Model
Django 1.22.3	Easy Chinese	Sketch, ink, oil...	F2.8LII-USM



(a) Training Set-Accuracy

(b) Training Set-Error

Fig. 4.1: Comparison of Accuracy and Error Rate in Training set Image

dataset was divided into a training set and a testing set in a ratio of 2:3. The specific equipment and software used in the experiment are shown in Table 4.1.

The collected dataset needed further processing to enable the studied algorithm to learn. For the processing of the dataset, PEK-means was used for iterative optimization. To verify its accuracy, traditional Golden Sine algorithm (GS), Convolutional Neural Network (CNN), and Particle Swarm Optimization algorithm (PSO) were compared with them. The accuracy and error rate results in the training set are shown in Figure 4.1.

From Figure 4.1, the PEK-means algorithm had a slightly lower accuracy and higher error rate compared to CNN and PSO before 200 training sessions. But when the number of iterations reached 200 or more, the accuracy of PEK-means was higher than both algorithms, and tended to stabilize at 380 iterations, which was higher than the other three algorithms. Although increasing the number of iterations could reduce the operational efficiency of the model, after comprehensive consideration, the accuracy weight of the model was higher, so the PEK-means algorithm proposed in the study had better performance. After the learning of the PEK-means algorithm was completed, it was also necessary to consider the parameter determination during testing, as shown in Figure 4.2.

The parameter of this study was the regularization term $\theta \in (0, 1)$. As shown in Figure 4.2, when the value of the regularization term as 0.3 and the number of iterations was 300, the error rate was the lowest, 0.072. Therefore, it was finally determined that the number of iterations was 300, and the value of the regularization term as 0.3.

4.2. Experimental Verification of Personalized Art Work Recommendation based on PEK-means. In order to verify the accuracy of PEK-means model in predicting users' psychology, a more in-depth comparison is made, simulation experiments were conducted. By observing the image computing power of the PEK-means algorithm, it could determine its practicality. First it initialized the PEK means algorithm; then

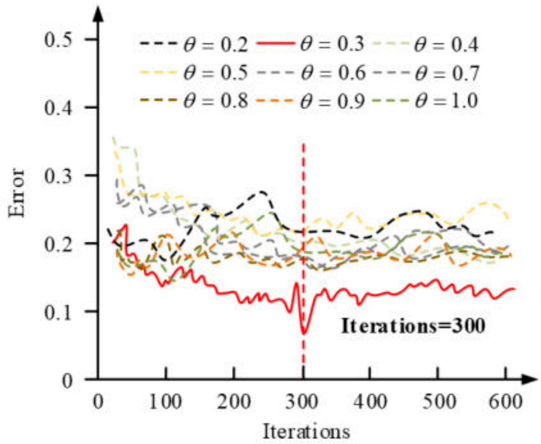


Fig. 4.2: Error-Training Times Image of Regularization Term

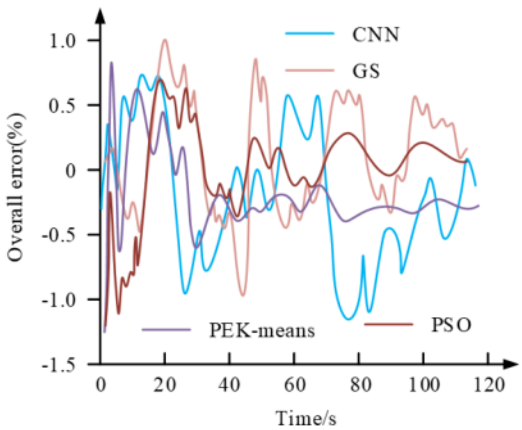


Fig. 4.3: Total Error-time Image of Four Algorithms

personal interest, emotional preference and other information at the user end were input; finally, it set the value of the regularization item to 0.3, and collected art works records within 120 seconds, calculated the error and draw the image, as shown in Figure 4.3.

Figure 4.3 shows the error comparison of four algorithms in the experiment. From Figure 4.3, after 75 seconds, the total errors of PEK-means and PSO fluctuated around -0.5% and 0.5%, respectively, while GS and CNN had not yet stabilized. The error ranges of PEK-means, PSO, GS, and CNN were all [-1.0%, 1.0%]. Only comparing the total error of the four algorithms could not distinguish the optimal algorithm. So, the study analyzed the errors caused by user interest characteristics and emotional factors of the four of them, and drew images as shown in Figure 4.4.

From Figure 4.4, the experimental results of the PEK-means model were concentrated in the range of total error of 0. The error range caused by user interest features was [-0.3%, 0.4%], and the error range caused by emotional factors was [-1.0%, 0.5%]. The error distribution of the remaining three algorithms was wide, and the distribution of larger errors was sparse. In order to distinguish the error correction ability of the four algorithms more intuitively, and then verify the universality of the algorithms proposed in the study, 400 experimental data records were made and the image shown in Figure 4.5 was drawn.

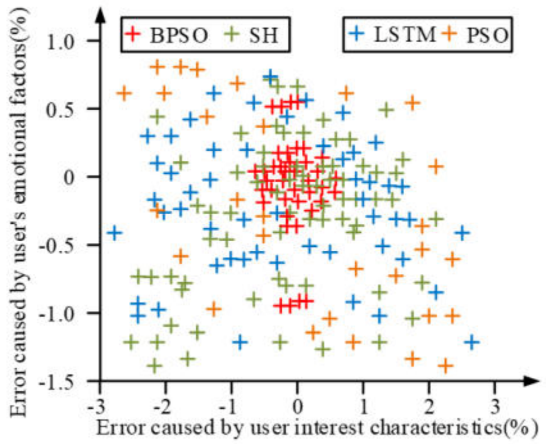


Fig. 4.4: The Types and Genres Errors of the Four Algorithms

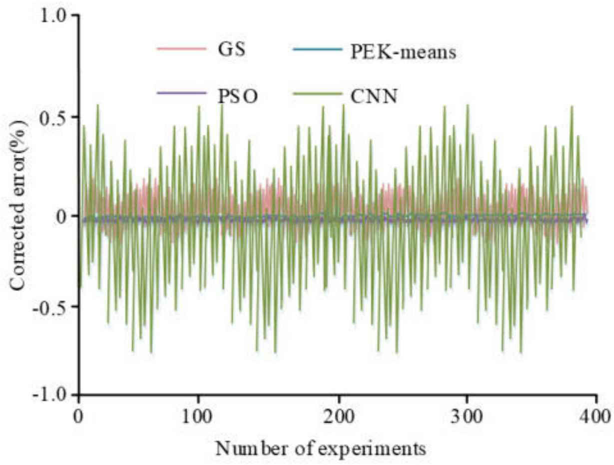


Fig. 4.5: Error Changes of Four Algorithms in Four Hundred Calibration Experiments

From Figure 4.5, in 400 error testing experiments, the error range of CNN was the largest, recorded as [-0.7%, 0.6%]; Next was the GS algorithm, which was between [-0.2%, 0.3%]. The variation range of PSO was close to PEK means, between [-0.13%, -0.03%]; The error curve of PEK-means fluctuated between -0.02% and 0.04%, with the smallest fluctuation range. Only comparing the experimental results of PEK means algorithm and PSO can draw the error matrix, the resulting image is shown in Figure 4.6. Figure 4.6 shows the experimental results of accurate prediction of PEK means and PSO based on user interest, emotion, emotion precision, and regularization process to analyze four types of art works: sketch, ink and wash, oil color, and simple pen. The prediction accuracy of PEK-means reached 392 times, with an accuracy rate of 98.0%, and the accuracy of PSO was 88.2%. To observe the experimental results of PEK-means and PSO more intuitively, a linear fitting graph based on matrix drawing was studied, and the predicted values of the two algorithms were compared with the actual values, as shown in Figure 4.7. Figure 4.7 shows the comparison of two algorithms in predicted and true values. From Figure 11, the linear fit ( ) of the PEK-means algorithm was 0.9903, and the of the PSO was 0.9545, indicating that there was no underfitting in the model. In summary, the PEK-means algorithm model could effectively map the relationship between user interest characteristics, emotional factors,

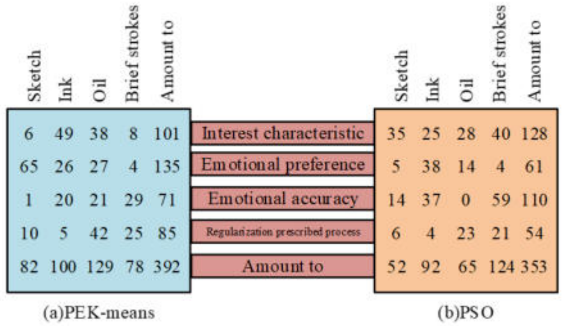
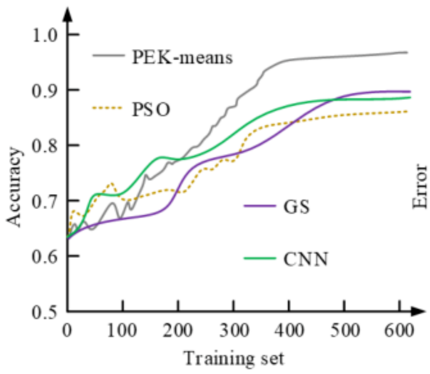
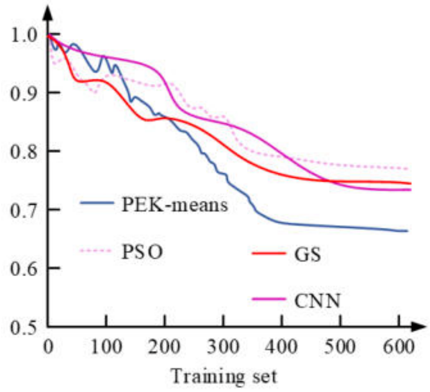


Fig. 4.6: Error Matrix of PEK- means Algorithm and PSO Algorithm



(a) PE K-Means



(b) PSO

Fig. 4.7: Linear Fitting Diagram of PEK-means and PSO

and personalized art recommendation, thereby providing users with a good viewing experience.

5. Conclusion. With the development of the internet industry, analyzing user data during network roaming is becoming increasingly important, such as increasing browsing comfort for users and increasing exposure for popular art works. This research quantified user interest features and emotional factors based on RPP and EA, and combined K-means to generate PEK-means. Taking into account PCC and regularization term, simulation experiments were carried out on Wink dataset and compared with GS and other three algorithms. 40% of the Wink dataset was extracted and trained on the PEK-means model. For the number of iterations, the study decided to carry out regularization experiments, and finally determined that it was 300. In order to determine the extensive experiments of the four algorithms, 400 experiments were conducted to analyze their estimation of user thinking. The errors of GS and CNN algorithms are the biggest in this experiment, which are between [-0.2%, 0.3%] and [-0.7%, 0.6%] respectively. For the proposed algorithm, PEK-means performs best in the experiment of estimating users' thinking, and its error is between-0.02% and 0.04%. The experimental performance of particle swarm optimization is a little poor, and its range is between [-0.13%, -0.03%]. In order to observe their experimental results intuitively, this paper studies drawing these data into an error matrix. By analyzing this error matrix, the prediction accuracy of the proposed algorithm is 98.0%, and the accuracy of PSO is 88.2%. In order to explore the accuracy of the application scope of the two experimental results, the study conducted several experiments based on their experimental results and drew a linear fitting diagram. The of PEK-means was 0.9903, indicating excellent linear fitting. The of PSO as 0.9545. In summary, the PEK-means algorithm model can reflect the relationship between user interest characteristics, emotional factors, and personalized art recommendation, and can meet the psychological needs of users. However, the PEK-means model is only suitable for analyzing art works with a wide distribution of similar users. For art works with fewer users, the model will label them as noise. This is because the purchase records of art works belong to private information, and the dataset for research and analysis contains fewer types. With the increase of volunteers, it is believed that future research can be improved.

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