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E-COMMERCE AND MOBILE APPLICATION DEVELOPMENT IN THE SPORTS INDUSTRY

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Abstract. In order to achieve user recommendations that best match their current contextual needs, the author proposes a mobile service QoS (Quality of Service) hybrid recommendation model based on sports user situational awareness. Cluster the users and service items covered by mobile users based on their location contextual information according to the classification principle of autonomous systems, forming a collaborative filtering and recommendation mechanism for mobile user service items; In response to the cold start problem of new users and new projects in traditional QoS recommendation methods, prediction and recommendation of missing QoS attribute preference values are based on User based and Item based CF; In response to the problem of difficult determination of mixed recommendation weights caused by massive data and uneven distribution of service QoS attribute values in mobile network environments, MapReduce based ant colony neural network weight training is used for CF mixed recommendation. Experimental results have shown that the Hadoop sports industry has improved the operational efficiency of algorithms and reduced the time for global QoS preference prediction; And by comparing the operation results of the 10% and 100% sub datasets, it can also be seen that the acceleration ratio of the algorithm will continuously improve with the increase of data volume, thereby improving the operational efficiency of the recommendation algorithm. It has been proven that the MapReduce based ant colony neural network weight training method significantly reduces the global computation time of the algorithm and improves the operational efficiency of the recommendation system.

Key words: Sports industry, Situational awareness, QoS, Collaborative filtering and mixed recommendation, Ant colony neural network

1. Introduction. With the rapid development and increasing popularity of new generation information technologies such as the Internet of Things, computing, and mobile terminals, e-commerce, as a new business model, is accelerating its integration with the real economy and has become an important way to allocate resources under the conditions of informatization, networking, and marketization[1]. At the same time, this model has also expanded to the sports industry, deeply integrating with traditional formats, promoting the transformation and upgrading of the sports service industry, and giving birth to emerging formats. Sports e-commerce has not only become a new force in providing sports goods and services, a new driving force for the development of the sports industry, but also created new sports consumption demands, opened up new channels for employment and income growth, and provided new space for mass entrepreneurship and innovation.

According to the 51st Statistical Report on the Development of China's Internet released by the China Internet Network Information Center, as of December 2022, the number of internet users has reached 1.067 billion, and the internet penetration rate has reached 75.6%. In this context, information technology and digital means are gradually penetrating various fields of consumption. As of June 2022, the number of users who use the internet for shopping in China has reached 841 million, accounting for a relatively high proportion of 80% of the total number of netizens. However, in 2013, the number of users who use online shopping in China only accounted for 48.9% of the total number of netizens[2].

The rapid expansion of information in the e-commerce industry has led to a continuous increase in consumer demand for efficient product promotion. Faced with the complex and diverse information resources on e-commerce websites, efficient intelligent data processing technology has become the key to processing information. Traditional engine retrieval cannot provide differentiated results for personalized needs of different users and environments; Intelligent recommendation systems do not require users to describe their needs in detail, but instead explore their interests and preferences through historical data, filter personalized information for users, and provide feedback on the predicted results to users, effectively improving their shopping

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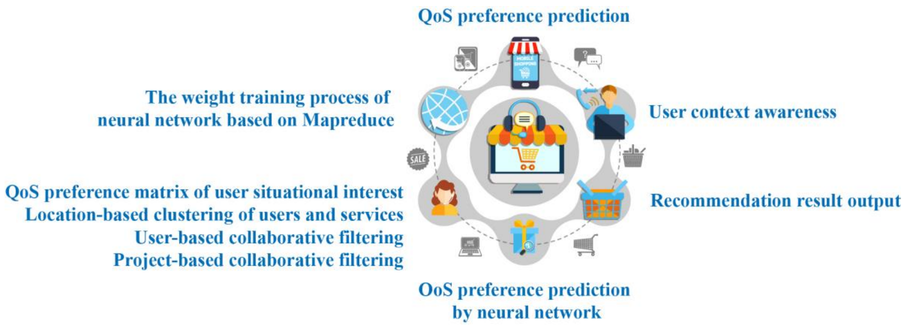

Fig. 1.1: Mixed recommendation process of mobile service QoS for sports users

experience and merchant sales efficiency. In e-commerce platforms, intelligent recommendation systems play an essential role. Domestic and foreign enterprises and scholars have conducted in-depth research on the intelligent recommendation problem used in e-commerce. Numerous personalized recommendation methods have emerged, which has also led to many application achievements in the recommendation field by Amazon, Ctrip, Alibaba, and others[3]. However, compared with foreign countries, China's research on e-commerce intelligent recommendation technology is still in a follower mode, and the compatibility between new ideas, methods, and technologies and e-commerce is still weak. For example, recommendation strategies are relatively simple, and the selection of recommendation methods does not change with environmental changes. Moreover, most domestic recommendation algorithms are used for customer push, while there is relatively little research on enterprise product and product evaluation recommendation algorithms.

In view of this, based on the integration of user interest and preference collaborative filtering and project scoring collaborative filtering methods, the author further introduces the perception attributes of mobile users and services in QoS location, proposes a sports user context aware mobile service QoS hybrid recommendation model, and integrates the contextual attributes of the autonomous system of mobile users and mobile services to predict missing QoS attribute values. At the same time, in response to the difficulty in determining mixed recommendation weights caused by massive data and uneven distribution of QoS attribute values in mobile network environments, the MapReduce ant colony neural network method is used to learn and train its weights. Finally, the MapReduce weights are inputted to calculate QoS preference attribute values and provide Top-N recommendation results. The QoS hybrid recommendation process for sports user context aware mobile services is shown in Figure 1.1.

2. Construction of QoS preference matrix for sports user context perception. In order to accurately predict the QoS preference attribute values perceived by sports users, this section effectively integrates mobile user location context, user based and item scoring based CF, and maximizes the exploration of user location context, user interests, and item scoring for collaborative filtering and recommendation.

2.1. User and Service Clustering Based on Location Context Perception. From the previous literature review, it can be seen that there is a high correlation between user QoS preferences and perceived geographic location attributes. Therefore, when constructing a QoS preference matrix for sports user context perception, the author clusters the target user, other users, and all services based on location context using an autonomous system AS (network connection combination controlled by one or more network operators) clustering, and based on this, prioritizes recommending relevant services to sports users within the same AS[4].

According to the composition of the Internet system, there are multiple autonomous system ASs in the Internet, each of which is connected to a LAN and the Internet. We can consider it as a small individual network structure unit, which also has a globally unique 16 bit code ASN, called the Autonomous System Number. In mobile networks, after a mobile node connects to a foreign link, it automatically configures and obtains the corresponding handover address through IPv6, thereby achieving "binding" between the mobile node and the handover address, and maintaining the association with the handover address through "binding confirmation".

For example, Apple Maps has reached a cooperation agreement with Planet Labs, a remote sensing satellite data company, to obtain global remote sensing satellite data support services through Planet Labs, achieving the "binding" of mobile nodes and forwarding addresses for Apple phone users, thereby providing location data update services for Apple phone users. When clustering users and services based on location-based situational awareness, the author divides mobile commerce users into decimal representations based on their mobile IPs, thus dividing them into different ASs. The specific method for converting the mobile IP addresses of mobile commerce users and services into decimal digits is shown in equation 2.1:

$$IP(A,B,C,D) = ((A \times 256 + B) \times 256 + C) \times 256 + D \tag{2.1}$$

By using the above equation, the decimal form of IP addresses for mobile commerce users and services can be obtained, and the corresponding AS self-made system can be identified by mapping the decimal IP addresses. Currently, mobile networks provide relevant AS measurement services, which can achieve mapping from decimal IP to AS.

2.2. User based QoS preference prediction. Assuming that the mobile user is u, CF recommendation is carried out based on the recommendation idea of User based CF, in order to predict the QoS attribute value of potential service p for the target user u.

Step 1: Convert the IP address of mobile user u to decimal representation according to equation 2.1, and find its corresponding AS through IP address mapping.

Step 2: Calculate the similarity between target user u and mobile user v using Pearson similarity formula 2.2, denoted as Sim (u, v), where Sim $(u,v) \in [-1,1]$. Among them, the set of services that are jointly rated by the two is represented by p, and $r_{u,p}$ represents the QoS attribute value of user u calling service vp. The larger the predicted Sim (u, v) attribute value, the more similar the user u and v are.

$$Sim(u,v) = \frac{\sum_{p\in I(u)\cap I(v)}(r_{u,p} - \overline{r_u})(r_{v,p} - \overline{r_v})}{\sqrt{\sum_{p\in I(u)\cap I(v)}(r_{u,p} - \overline{r_u})^2}\sqrt{\sum_{p\in I(u)\cap I(v)}(r_{v,p} - \overline{r_v})^2}} \tag{2.2}$$

Step 3: According to Step 1, obtain Sim (u, v). When the number of users similar to the target user u in the same AS is greater than top-N, the operation enters Step 5.

Step 4: In the calculation process, if the user has called service p before, the predicted value can select the given by all previous users to service p[5].

Step 5: Predict the missing QoS attribute values according to formula 2.3.

$$P(r_{u,p}) = \overline{r_u} + \frac{\sum_{v\in Sim(u)} Sim(u,v) \times (r_{v,p} - \overline{r_v})}{\sum_{v\in Sim(u)} Sim(u,v)} \tag{2.3}$$

In the above equation, the $\overline{QoS}$ attribute value of u calling different services is denoted as $\overline{r_u}$,v, and the corresponding calling attribute value is denoted as $\overline{r_v}$. The predicted missing value is denoted as $P(r_{u,p})$.

2.3. Item based QoS preference prediction. The QoS preference calculation for mobile service projects in this section is based on the collaborative filtering idea based on projects for recommendation, in order to predict the QoS attribute values of potential service p for target user u. The method of calculating QoS preferences for mobile service projects is very similar to that of calculating QoS preferences for users. The difference is mainly reflected in the different objects for similarity calculation between the two, one is user similarity, and the other is project similarity. The specific calculation method includes the following steps:

Step 1: Convert the IP address of mobile service p to decimal representation according to equation 2.1, and find its corresponding AS through P address mapping.

Step 2: According to formula 2.4, calculate the similarity between service items similar to mobile service p, and its similarity is denoted as Sim(p,q),Sim(p,q)∈[-1,1]. Among them, the $\overline{QoS}$ called by different users for service item p is denoted as $\overline{r_p}$, the $\overline{r_q}$ called by service item q, and the set of users called by both service items p and q is denoted as u. The larger the predicted Sim(p,q) attribute value, the more similar the service items p and q.

$$Sim(p,q) = \frac{\sum_{u \in U(p) \cap U(q)} (r_{u,p} - \overline{r_p})(r_{u,p} - \overline{r_q})}{\sqrt{\sum_{u \in U(p) \cap U(q)} (r_{u,p} - \overline{r_p})^2} \sqrt{\sum_{u \in U(p) \cap U(q)} (r_{u,q} - \overline{r_q})^2}} \tag{2.4}$$

Step 3: Based on Step 2, obtain Sim (p,q). When the number of service items similar to the target service p is greater than top-N, the operation enters Step 5.

Step 4: During the calculation process, if a service item has been called before, the predicted value can be selected from the $\overline{QoS}$ given by all previous users to the service item.

Step 5: Predict the missing QoS attribute values according to formula 2.4, and the predicted missing values are denoted as $P(r_{u,q})$.

$$P(r_{u,q}) = \overline{r_p} + \frac{\sum_{q \in Sim(p)} Sim(p,q) \times (r_{u,q} - \overline{r_q})}{\sum_{q \in Sim(p)} Sim(p,q)} \tag{2.5}$$

2.4. Construction of QoS preference matrix. In order to integrate mobile users' QoS preferences and mobile service items' QoS preferences to a greater extent, the author combines similarity weights to carry out collaborative filtering recommendations, that is, calculate the QoS attribute values of users who call common services in the same AS system, thus measuring the similarity between these users and service items, and finally giving recommendations.

Step 1: Improve the user based QoS preference similarity calculation method based on the similarity weight calculation method.

$$Sim'(u,v) = \frac{2 \times |I_u \cap I_v|}{|I_u| \cap |I_v|} Sim(u,v) \tag{2.6}$$

Among them, the number of services called by target user u is denoted as $|I_u|$, the number of services called by user v is denoted as $|I_v|$, and the number of services jointly called by u and v is denoted as $|I_u \cap I_v|$.

Step 2: Improve the project-based QoS preference similarity calculation method based on the similarity weight calculation method.

$$Sim'(p,q) = \frac{2 \times |U_p \cap U_q|}{|U_p| \cap |U_q|} Sim(p,q) \tag{2.7}$$

Among them, the number of users calling service p is recorded as U_p, the number of users calling service q is recorded as U_q, and the number of users calling p and q is recorded as $|U_p \cap U_q|$. The range of values for $Sim'(u,v)$ and $Sim'(p,q)$ obtained from formulas 2.6 and 2.7 is [-1,1].

Step 3: Calculate the missing QoS value according to equations 2.8 and 2.9. Among them, the missing value predicted based on user collaborative filtering is denoted as $(r_{u,q})_{user}$, and the missing value predicted based on project collaborative filtering is denoted as $P(r_{u,q})_{item}$. The calculation method for missing value $P(r_{u,q})_{user}$ is shown in 2.6, and the calculation method for missing value $P(r_{u,q})_{item}$ is shown in 2.7.

$$P(r_{u,q})_{user} = \overline{r_u} + \frac{\sum_{v \in Sim'(u)} Sim'(u,v) \times (r_{v,q} - \overline{r_v})}{\sum_{v \in Sim'(u)} Sim'(p,q)} \tag{2.8}$$

$$P(r_{u,q})_{item} = \overline{r_p} + \frac{\sum_{q \in Sim'(p)} Sim'(p,q) \times (r_{v,q} - \overline{r_q})}{\sum_{q \in Sim'(p)} Sim'(p,q)} \tag{2.9}$$

According to equation 2.10, the calculated $P(r_{u,p})_{user}$ and $P(r_{u,p})_{item}$ will form a collaborative filtering matrix P. Among them, $P(r_{u_m,p_n})_{user} \neq 0 \wedge P(r_{u_m,p_n}) \neq 0$.

$$P = \begin{bmatrix} P(r_{u,p})_{user} \\ P(r_{u,p})_{item} \end{bmatrix} = \begin{bmatrix} P(r_{u_1,p_1})_{user} & \cdots & P(r_{u_m,p_n})_{user} \\ P(r_{u_1,p_1})_{item} & \cdots & P(r_{u_m,p_n})_{item} \end{bmatrix} \tag{2.10}$$

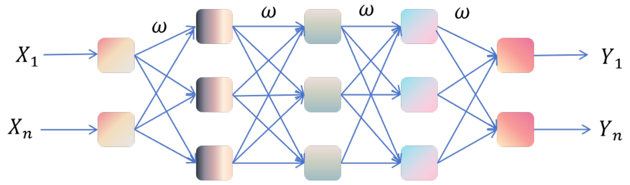

Fig. 3.1: Structural design of the ant colony neural network

3. Ant colony neural network hybrid recommendation for mobile service QoS preference prediction. The mixed recommendation method based on user location context, User based and Item based, can theoretically improve the accuracy of QoS prediction. However, how to discover the optimal weights of user based and Item based collaborative filtering methods in dynamic network environments and complete recommendations has become another key issue that needs to be addressed in research[6]. This section introduces the MapReduce based ant colony neural network method in the recommendation process to train the weights of two different CF methods for mixed recommendation, and ultimately recommend the top N items with better predictive attribute values to users.

3.1. Ant Colony Neural Network Weight Training Model . BP neural network is a data prediction method with strong convergence, which can be used to solve the optimal weight determination problem of User based and Item based mixed recommendations. The disadvantage of BP neural networks is that they face the problem of gradient descent, which means that when there are training errors with multiple peaks on the surface, it is easy to encounter the problem of local optimal training. Ant colony algorithm (ACO) has strong advantages in global optimization [7]. If it can be combined with BP neural network, it can overcome the local optimization problem during neural network training, and effectively solve the problem of long time consumption and low accuracy of a single training network. In view of this, the author proposes a hybrid recommendation weight training method based on ant colony neural networks.

3.2. Establishment of weight training model. The network structure of combining BP neural network and ant colony algorithm is shown in Figure 3.1, which consists of l layers and m nodes. In the figure is the weight, (x_k, y_k) is the M samples included in the structure (k=1, 2,..., m), and O_i is the output of node i after training, The input of the jth unit in the l-th layer of the neural network structure can be represented as $net_{jk}^l = \sum_j \omega_{jk}^{i-1}$, the output as $O_{jk}^l = f(net_{jk}^l)$, and f(x) is a unipolar sigmoid function, $f(x) = \frac{1}{1+e^{-x}}$.

3.2.1. Model Establishment. The author's ant colony neural network weight training model first uses the ant colony ACO optimization algorithm for global optimization, providing a better initial weight combination for the BP neural network, which helps to solve the problem of traditional BP neural network operations easily falling into local optimal calculations; Secondly, based on the gradient descent principle of BP neural network, further training and testing were conducted on the weights of two different algorithms, user based and Item based, to ultimately provide the globally optimal weight combination strategy[8].

Before using the ACO optimization algorithm, the weight domain of the algorithm is delineated to obtain several weight sub regions, and the points at the boundaries of these regions form the candidate weights for each region. The number of pheromones at each point is the same at the initial time of t_0 in the ACO algorithm, and the specific pheromone values corresponding to each weight are shown in Table 3.1. Among them, a_i is the division scale value, τ_1 is the pheromone value corresponding to the i scale value ant. Ants pass through each combination of sub regions corresponding to the weights to obtain the weights that need to be trained through ant colony neural networks. After learning through neural networks, they can obtain error values that can provide a basis for updating ant pheromones.

Step 1: ACO initialization process. Firstly, evenly divide the weight interval $[\omega_{min}, \omega_{max}]$, and then establish corresponding pheromone tables for each parameter (see Table 3.1 for the method), set the initial value of pheromones to τ_0, set the volatility coefficient to σ , the intensity of pheromone increment is set to Q, and the maximum number of iterations for ACO is set to N_{AOC}, the learning rate and maximum

Table 3.1: The pheromone tables corresponding to the weights ω_i

	1	2	$\cdots$	M
Dividing scales	a_1	a_2	$\cdots$	a_m
Pheromone value	$\tau(t)$	$\tau(t)$	$\cdots$	$\tau(m)$

number of iterations of the neural network are η training error obtained from N_{BP} is E_0, and the number of optimal solutions is set to σ.

Step 2: Start the ant colony and release h ants. The probability of ant k transitioning from one path to another is $P_k = \frac{\tau(i)}{\sum_{1\leqslant j\leqslant m}\tau(i)}$. Record all the paths traveled by h ants in tabuk, obtain the initial weight parameters, and use them as the initial parameters for training the neural network. After training, obtain the corresponding output and training error E.

Step 3: Compare the size of the minimum error E_{max} and E_0 after all training. If $E_{min}<E_0$, proceed to Step 7; otherwise, proceed to Step 4.

Step 4: Update pheromones according to equations 3.1 and 3.2 τ:

$$\tau(t+1) = \rho \cdot \tau(t) + \Delta\tau(t) \tag{3.1}$$

$$\Delta\tau(t)\begin{cases}\frac{Q}{E} & j \in \text{best solution}\\ 0 & otherwise\end{cases} \tag{3.2}$$

Step 5: Repeat steps 2 and 3 until the maximum number of iterations is met, then proceed to Step 6.

Step 6: Input the best weight obtained from ACO into the BP neural network and calculate the error $E_k = \frac{1}{2}\sum_j (y_{ik} - \overline{y_{ik}})^2$. Among them, $\overline{y_{ik}}$ represents the actual output value of unit j, and based on this, the total error $E = \frac{1}{2N}\sum_{k=1}^{N} E_k$ of ant colony neural network training is obtained.

Step 7: Weight test. If the error meets the operational requirements, the operation ends. Otherwise, it will proceed to Step 1.

3.3. Data normalization. In the verification of the author's mixed recommendation process for mobile service QoS based on user context awareness, experiments were conducted using the common RTT (round-trip response time) and Failure rate (service call failure rate) in mobile service QoS as examples. Given that the ant colony neural network model has high requirements for data input, and there is no clear pattern in the distribution of RTT and Failure rate tested by the author, it is necessary to normalize the original input data to make the input value $\in$ [0,1]. If the original value in the QoS preference matrix is $b_{i,j}$, the preprocessed value is $c_{i,j}$, and the maximum and minimum values in the matrix are represented by $minb_a$ and $maxb_a$, respectively, then equation 3.3 is used for linear normalization:

$$c_{i,j} = \begin{cases}\frac{(b_{i,j} - minb_a)}{maxb_a - minb_a}(When \quad maxb_a \neq minb_a)\\ 1 \quad (When \quad maxb_a = minb_a)\end{cases} \tag{3.3}$$

Among them, i=1,2,3,..., m+n, j=1,2,3,..., a. After normalization, all RTT and Failure rate inputs $\in$ [0,1].

3.4. MapReduce weight training. In order to reduce the computational complexity and weight training time of ACO and neural networks in large-scale sample data processing, the author adopts cloud computing MapReduce parallel processing technology for weight learning training. The specific running process includes two stages: Map and Reduce. In the Map phase, call the MapRe reduce Map() function to receive key value pairs (key, value) for calculating input and output, and calculate each ω weight change of backpropagation is determined by $\Delta\omega$, form intermediate key/value pairs (key = ω , value= $\Delta\omega$) and save the key value pairs output by each Map in the Hadoop system file $(\omega, \Delta\omega)$, enter key value pairs through the combine() function.

In the Reduce stage, call the Reduce() function according to equation 3.4 to $(\omega, \Delta\omega)$ normalize and use the output (key = ω, value = $\sum_{i=1}^{n}\Delta\omega/n$) as the final key value pair, using the job() function for each perform batch updates and store the resulting weight matrix in Hadoop as preparation for subsequent MapReduce task iteration calls. When the weight error of the training is small enough to meet the specified requirements after multiple MapReduce treatments, the run ends. Otherwise, continue the iterative training of repeated weights.

$$\begin{cases} sum \leftarrow 0, count \leftarrow 0 \\ sum \leftarrow sum + value \\ count \leftarrow count + 1 \\ sum/count = \sum_{i=1}^{n} \Delta\omega/n \end{cases} \tag{3.4}$$

According to equation 3.5, the calculated $P(r_{u,p})_{user}$ and $P(r_{u,p})_{item}$ will form a collaborative filtering matrix P. Among them, $P(r_{u_m,p_n})_{user} \neq 0 \wedge P(r_{u_m,p_n})_{item} \neq 0$.

$$P = \begin{bmatrix} P(r_{u,p})_{user} \\ P(r_{u,p})_{item} \end{bmatrix} = \begin{bmatrix} P(r_{u_1,p_1})_{user} & \cdots & P(r_{u_m,p_n})_{user} \\ P(r_{u_1,p_1})_{item} & \cdots & P(r_{u_m,p_n})_{item} \end{bmatrix} \tag{3.5}$$

3.5. Final prediction of QoS preferences. Calculate the missing QoS values $P(r_{u,p})_{user}$ and $P(r_{u,p})_{item}$ for collaborative filtering recommendations according to equations 2.8 and 2.9, and calculate the final predicted value

$$P(u,p) = \frac{1}{(1+e)^{-(V\times(\frac{2}{1+e^{W\times P+B_1}}-1)+B_2)}}$$

of QoS preferences perceived by cloud computing users in context. Among them, $P(r_{u,p})$ is the final predicted value of collaborative filtering missing value $r_{u,p}$, P is the number of rows in matrix

$$P = \begin{bmatrix} P(r_{u,p})_{user} \\ P(r_{u,p})_{item} \end{bmatrix} = \begin{bmatrix} P(r_{u_1,p_1})_{user} & \cdots & P(r_{u_m,p_n})_{user} \\ P(r_{u_1,p_1})_{item} & \cdots & P(r_{u_m,p_n})_{item} \end{bmatrix}$$

j and P, and the weight matrix between input and hidden layers trained by ant colony neural network is W, the weight matrix between the hidden layer and the output layer is V, and B_1 and B_2 represent the offset matrices between the hidden layer and the output layer, respectively. Substitute the missing QoS attribute values $P(r_{u,p})_{user}$ and $P(r_{u,p})_{item}$, calculate $P(r_{u,p})$, and finally provide the optimal recommendation value for the target user based on the Top-N rule[9].

4. Algorithm validation.

4.1. Datasets. The author built the experimental cloud service MapReduce environment on a Hadoop platform with 9 servers, where the server where the system software was installed was NameNote (Lenovo server, 4GB memory, 1TB hard drive, 2.8G main frequency, named Hadoop), the remaining 8 servers are DataNote, named hadoop1, hadoop2,..., hadoop8, using Redhat5.5-x64 to install VMware virtual machine Linux system, and using Hadoop-0.21.0 version. The dataset used by the author for the experiment mainly consists of service QoS records stored on multiple mobile servers in different regions collected through Planet Lab. Each record includes two QoS values: failure rate and failure rate round-trip delay (RTT), which can be used to construct a QoS vector matrix for cloud computing services.

Location context-based user and service clustering methods, the IP addresses of mobile commerce users are mapped in decimal to obtain corresponding starting IP addresses, ending IP addresses, AS names, and AS numbers for mobile commerce users. By mapping the IP addresses of mobile commerce users, a total of 339 users were selected for this experiment to rate 5852 service items, with a rating range of 1-5 points for each user. Through sorting the dataset, it was found that 65.2% of user rating items are between 20 and 100, indicating that there are many missing values in each user's rating vector, therefore, user rating information is relatively sparse and can be used to detect the recommendation performance of the model in compensating for missing QoS values and alleviating cold start problems. The experimental dataset obtained by the author from Planet Lab includes the content shown in Table 4.1.

Table 4.1: Dataset Content Information

category	content
User List	339 user information
service list	5825 service information
RTT matrix	RTT records of 339 users calling 5825 services
TP matrix	339 users calling 5825 service TP records

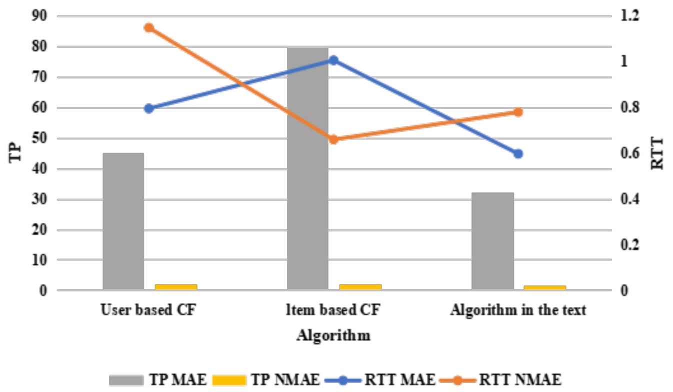

Fig. 4.1: Comparison of MAE and NMAE performance (Top k = 10)

4.2. Experimental Process and Result Analysis. In order to compare the prediction results of the author's algorithm with different algorithms, the author will compare the QoS prediction performance with User based and Item based algorithms respectively. The specific experimental process and results are as follows:

Step 1: As described in 4.2, the experimental data packet mainly considers the dynamic QoS attributes of failure rate and failure rate round-trip delay RTT when conducting neural network analysis. The trainLM function is used for network parameter training, the LEARNGDM function is used for adaptive learning, and the LOGSIG and MSE functions are used for activation and performance testing, respectively.

Step 2: Use MATLAB software to train the neural network with 300 sets of results obtained through cyclic calculation, set the global error index for ant colony neural network weight training to le-7 and the maximum training steps to 2000.

Step 3: Output the optimal weights trained by the ant colony neural network to predict QoS preferences for mobile commerce, and compare the recommendation performance of User based, Item based, and this method based on the output results.

The test experiment recommended a given cold start dataset and predicted its QoS attribute gap value. The recommendation results were compared using two scenarios, Top N=10 and Top N=5, respectively. The two most commonly used metrics in personalized recommendation research, MAE (absolute mean error) and NMAE (standardized absolute mean error), were used to compare the accuracy of different methods. The experimental results are shown in Figure 4.1 and Figure 4.2.

Comparing Figures 4.1 and 4.2, it can be seen that whether comparing the recommendation results of Top N=10 or Top N=5, the prediction accuracy of the sports user context aware mobile service QoS hybrid recommendation method is significantly higher than that of traditional user based and Item based recommendations. This indicates that the Failure rate and RTT with values ranging from [0,1] can obtain better mixed weights during the ant colony network training process, thereby improving the performance of QoS preference prediction. The experimental results of the two graphs further indicate that when using this algorithm for recommendation, selecting Top N=10 results in higher recommendation accuracy compared to Top N=5. This indicates that the sparser the ratings of

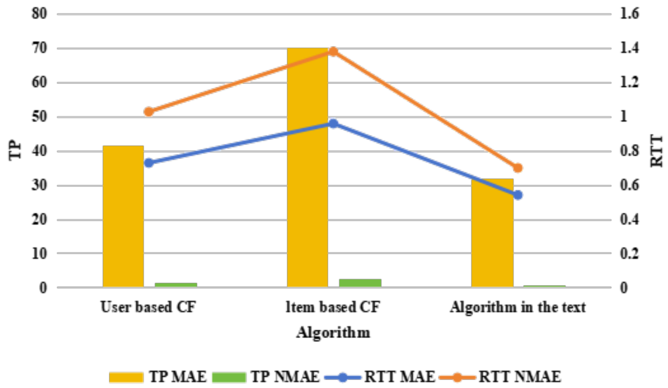

Fig. 4.2: Comparison of MAE and NMAE performance (Top-N=5)

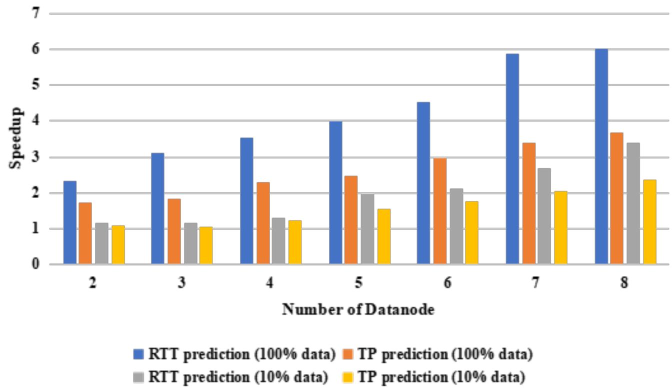

Fig. 4.3: The prediction time acceleration ratio in the Hadoop environment

cold start users or projects, the poorer the recommendation accuracy; The more ratings a cold start user or project receives, the higher the recommendation accuracy [10]. This also explains the normal phenomenon of the following: as the number of ratings increases, new projects and users lacking ratings begin to change their roles, evolving from the original new projects and users to general projects and users, basically no longer having the characteristics of missing ratings for new projects and new users. This reduces the missing values for cold start items, thereby improving the performance and accuracy of recommendation systems.

Step 4: Compare the parallel acceleration ratios of the algorithms. In order to accurately measure the efficiency of the algorithm, the calculation time required for single machine operation and parallel operation in the cloud environment was selected for comparison. The specific calculation formula is: S=T(1)/T(N), among them, T(1) is the single machine running time of the algorithm, T(N) is the consumption time of multi machine parallel processing in the sports industry, N=1,2,..., 9, and the ratio of the two is the author's measurement index acceleration ratio. Given that the data nodes of the Hadoop cloud platform in the author's experiment have different scenarios ranging from 1 to 8, the acceleration ratio index T (N) has N=1,2,..., 8.

The author divided the experimental dataset into 10% and 100% subsets for separate testing, and the final test results are shown in Figure 4.3. It can be seen that the acceleration ratio of the sports user context aware mobile service QoS hybrid recommendation method shows a linear growth trend during RTT and TP testing, indicating that the Hadoop cloud environment improves the efficiency of the algorithm and reduces the time for QoS preference prediction on a global scale; And by comparing the operation results of the 10% and 100% sub datasets, it can also be seen that the acceleration ratio of the algorithm will continuously improve with the increase of data volume, thereby improving the operational efficiency of the recommendation algorithm.

5. Conclusion. In the context of massive mobile service resources, predicting QoS preferences for mobile services that fit user scenarios is a hot topic in the field of personalized research. The author incorporated sports user location contextual information into the User based and Item based recommendation mechanisms to create a hybrid model for mobile service QoS; At the same time, in response to the problem of difficult determination of mixed recommendation weights caused by massive data and uneven distribution of service QoS attribute values in mobile network environments, the MapReduce ant colony neural network method is used to learn and train its weights, and CF mixed recommendation is based on the trained weights. The experimental results have demonstrated that this method achieves lower MAE error values compared to traditional User based and Item based methods. The MapReduce based ant colony neural network weight training method also significantly reduces global computation time and improves the operational efficiency of recommendation systems; The user based and item based hybrid recommendation method that integrates situational awareness effectively compensates for missing QoS values and alleviates the problem of decreased recommendation accuracy caused by cold start in recommendation systems.

It should be pointed out that the author's proposed sports user context aware mobile service QoS hybrid recommendation model mainly focuses on the relatively single location context of mobile users for research, without introducing the idea of user context semantic logical reasoning for QoS recommendation. The author's subsequent research will take this as an opportunity to delve into the inference rules and recommendation methods of sports user context semantics, and achieve context sensitive mobile commerce QoS recommendation services.

REFERENCES

[1] Wang, L., & Zhou, T. (2022). Application of a fuzzy information analysis and evaluation method in the development of regional rural e-commerce. Advances in multimedia(Pt.6), 2022(4),56-59.

[2] Ouyang, J., & Chen, X. (2022). Personal information two-dimensional code encryption technology in the process of e-commerce logistics transportation. SAIEE Africa Research Journal,174(1), 113.

[3] Yang, M. (2023). Research on coordinated development of chongqing agricultural product e-commerce logistics based on system dynamics model. Advances in Education, Humanities and Social Science Research,65(7),45-48.

[4] Kostev, R., & Dimitrova, S. (2022). Modern training of business information systems in e-commerce. 2022 V International Conference on High Technology for Sustainable Development (HiTech), 58(7),1-4.

[5] Cheng, H., Huang, Y. T., & Huang, J. (2022). The application of dematel-anp in livestream e-commerce based on the research of consumers' shopping motivation. Scientific Programming, 222(4), 1-15.

[6] Akin-Sari, B., Inozu, M., Haciomeroglu, A. B., Cekci, B. C., Uzumcu, E., & Doron, G. (2022). Cognitive training via a mobile application to reduce obsessive-compulsive-related distress and cognitions during the covid-19 outbreaks: a randomized controlled trial using a subclinical cohort. Behavior therapy, 53(5), 776-792.

[7] Tian, X. (2023). Artificial intelligence and automatic recognition application in b2c e-commerce platform consumer behavior recognition. Soft computing: A fusion of foundations, methodologies and applications,85(41),63-68.

[8] Deng, K., & Szekrenyes, A. (2022). Sports town development strategy driven by the sports industry and multi-industry integration. Mathematical Problems in Engineering: Theory, Methods and Applications,85(14),53-58.

[9] Yang, B. (2022). Application preparation of high-performance iron-based powder metallurgy sintered materials in sports industry. Journal of nanomaterials(Pt.7), 2022(41),874.

[10] Li, X., Tang, Y., Christo, M. S., Zhao, Z., & Li, Y. (2022). Android malware application detection method based on rgb image features in e-commerce. Journal of Internet Technology,652(7),152-158.

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