

Received March 1, 2020, accepted April 20, 2020, date of publication April 30, 2020, date of current version May 15, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2991463

Personalized Product Service Scheme Recommendation Based on Trust and Cloud Model

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This work was supported in part by the National Natural Science Foundation of China under Grant 71972090, and in part by the National Educational Science Planning for the 13th Five-Year Plan of China under Grant ECA180463.

ABSTRACT Considering the low satisfaction rate and low efficiency of product service plans, a personalized product service plan recommendation method adopting the degree of trust and cloud model is proposed. The recommendation algorithm mainly includes calculating the similarity and the prediction results of the scheme. First, by fully considering the user's subjective characteristics, the user's trust is used to improve the traditional similarity. Second, considering data sparsity and discreteness, the cloud drop distance similarity calculation method is introduced in the process of calculating the trust similarity, and a new similarity is generated via the weighted synthesis to predict and fill in the gaps in the data. Then, when the new user does not have the cold start problem caused by the historical score record, the neural network method can be used to classify the users based on the user characteristics. The method is proposed and introduced to predict sparse user interest features and obtain similar user sets based on feature classification. The corresponding program offers recommendations. Finally, the effectiveness and rationality of the proposed method are verified by using the recommendations for a machine tool product for a manufacturing enterprise as an example.

INDEX TERMS Sparsity, cold start, user trust, cloud drop distance similarity.

I. INTRODUCTION

With the increasingly fierce competition in the market and the gradual increase of users' individualized demands, the manufacturing industry has begun to shift from manufacturing products to the "product + service" operation mode. The proportion of product services in the whole product life cycle is increasing, which reflects the core competitiveness of the products to a large extent. The product service system (PSS) has gained development opportunities in the manufacturing industry. The PSS provides an integrated solution for the integration of products and services [1]. Through information technology, user needs, product design, product production and product services are integrated organically. Because the user demand is often vague, uncertain and incomplete in the early stage, the deviation between the designer and the user when understanding the demand and designing the PSS will lead to the problems of a low satisfaction rate with and low

efficiency of the final product and service plan [2]. Therefore, to reduce the impact of the subjective understanding deviations of users and designers on the results of the scheme generation, this paper proposes to clean the metadata and then use the cleaned data to generate the scheme. In addition, how to quickly and efficiently recommend a satisfactory service plan has become a difficult problem for enterprises and the recommendation method has been widely used and continuously improved in many fields. This paper proposes to apply it to the product service plan generation and recommendation process. Recommendation methods generally have data sparsity problems caused by insufficient user rating data and cold start problems caused by unrated users. Considering the subjectivity of users in the recommendation process and the inaccurate recommendation results caused by the discreteness and sparseness of user data, this paper proposes to introduce the trust among users in the process of calculating user similarity and the cloud droplet distance similarity to mitigate the impacts of the data sparseness and discreteness problems. The method fused the comprehensive

The associate editor coordinating the review of this manuscript and approving it for publication was Ming Luo¹.

values of the user trust and cloud droplet distance similarity to predict the missing values of scheme scores. For the cold start problem caused by the lack of historical records for new users, to make reasonable recommendations, a neural network method is proposed to classify new users based on their similar interests to obtain appropriate recommendation schemes.

II. RELATED WORK

Currently, the recommendation technologies can be divided into content-based recommendations, collaborative filtering-based recommendations, and domain knowledge-based recommendations. In the process of using a recommendation method, there are some problems such as data sparsity and cold starts. Data sparsity generally refers to the user's project rating being lower or insufficient. Cold start refers to when there is no scoring record due to new users in the historical database. For example, based on the social network among users, document [3] used the context aware Point-of-Interest (POI) recommendation model based on matrix decomposition and used the social network data of users and the POI category information to establish a general matrix decomposition model to improve the accuracy of recommendation results. Documents [4], [5] used the random walk method to travel a social network. According to the distance between users in the travel process, it predicted the similarity between users and filled in the missing values in a matrix, which fixed the data sparsity. In view of the fact that the matrix decomposition method does not consider independent users and projects and other factors, a nonnegative matrix decomposition algorithm based on user and project biases was proposed by introducing user and project biases in document [6]. Considering the local optimal solution problem that may be generated by the random initialization matrix, an improved method using singular value decomposition (SVD) was proposed to reduce the dimension of the data. In document [7], a factor decomposition machine based on Lasso was proposed to control the data dimension of factor decomposition, which was used to process high-dimensional and sparse data and reduce the impact of data sparsity. In terms of data sparsity, the hidden factors between matrices were used to predict or reduce the dimension of the sparse data to reduce the impact of missing data on the recommendation results. In document [8], a fuzzy clustering method was used to calculate the similarity between users and obtain the nearest neighbor set to fill the gaps in the data. In document [9], considering the influence of different numbers of ratings and the asymmetric relationship between projects, a suitable neighbor set was selected to fill in the missing data based on the probability distribution. In document [10], based on the influence of subjective scoring on the recommendation results, the Pearson similarity was introduced to improve the accuracy of the user attribute similarity calculation and the K-means clustering algorithm and the collaborative filtering algorithm were integrated to reduce the influence of data sparsity. In document [11], the probability

matrix decomposition algorithm was used to measure the relationship between users or products and obtain similar neighboring users or products to achieve accurate recommendations. In documents [8]–[11], clustering, the probability distribution, the similarity and other calculations were used to obtain the nearest neighbor set, which was used to fill in the missing data. As one of the most mature methods, collaborative filtering was improved by combining it with many methods, such as the BP neural network, the conditional probability, the bipartite graph, the clustering algorithm, the genetic algorithm, etc. in documents [12]–[16] to reduce the impact of data sparsity on recommendations. Considering the influence of subjective user ratings on recommendation results, document [17] took into account that the Quality of Service (QoS) incorporated the contribution of unreliable users and used a clustering algorithm and the collaborative filtering method integrating the degree of trust to rebuild the trust network of clustered users and make personalized QoS predictions and cloud service recommendations for active users. In document [18], users had subjective preferences for various project categories, which meant that the deviation of the original data may be amplified or reversed by the potential recommendation algorithms. Appropriate recommendation methods were selected by comparing different algorithms reflecting the sorting quality and deviation. In this paper, the recommendation method was applied to the generation process of a product service scheme. Aiming at the data sparsity problem occurring in the early stage, the trust relationship of user subjectivity was introduced as a constraint, which meant that the degree of trust was introduced into the calculation of the user similarity and the results of similar calculations and predictions were constrained. In documents [19]–[20], considering the potential interest preferences between new users and new projects, a clustering method was used to obtain the nearest neighbor set of new users and the projects of the nearest neighbor set were recommended to new users. In document [21], to solve the cold start problem, the interaction information between the attribute preference information of the project and the user's rating behavior was not fully utilized. The singular value decomposition recommendation algorithm based on the attribute preferences for the project was introduced to obtain the user's preference matrix for the project attributes, and the attribute characteristic factors of the project attributes and the user's preferred characteristic factors of the project attributes were added to the matrix decomposition. Document [22] proposed a cold start recommendation model based on voice personality characteristics to obtain the user's personalized information. It collected the user's personality characteristics through any normal voice of the new user and provided the user with personalized recommendations by combining the cross domain personality knowledge and recommendation system. In document [23], an improved association rule algorithm based on the FP Tree was proposed to measure and model user preferences in a personalized information recommendation service to mine user behavioral patterns.

In document [24], the time interval between the user evaluation time and the project release time was introduced and the time impact perception similarity measure was used as the user time weight value to obtain the user's preference for new projects and give recommendations. In document [25], considering that traditional similarity models and QoS prediction methods rarely use time information, time information was integrated into the similarity measurement to obtain the final QoS prediction and recommendation. The above documents introduced personalized features and time features to alleviate the cold start problem caused by new users. Meanwhile, document [26] helped users to find valuable information based on location-based services and the characteristics of a location-based service platform by focusing on the low recommendation efficiency of less active areas or new users and the inability to maximize the information problems due to hidden data. This paper proposed a recommendation algorithm that combined the decomposition of a collaborative probability matrix and the iterative decision tree to alleviate the cold start problem of new users. In document [27], the RaPare method was used to explore the differences between cold start and hot start users/items, fine-grained calibration was carried out for the potential profile of cold start users/items and the method to solve the cold start problem was obtained and recommended. In the implementation process, the recommendation method was affected not only by the data sparsity and cold start problems but also by other factors, such as the time characteristics and the similarity calculation formula. Considering that the improved collaborative filtering method had been widely used in e-commerce recommendation systems, manufacturing product service recommendations also began to use neural networks to solve the cold start problem of new users. For example, in document [28], the collaborative filtering algorithm based on the community similarity performed poorly in the cold start scenario of new users and new products and the matrix decomposition method was used to find the potential interest space of users. Then, a neural network was trained to learn the mapping relationship from user attribute data to potential interest vectors, and historical data and attribute data were combined to form the user's predicted values of goods and give appropriate recommendations. Document [29] proposed a hybrid QoS recommendation model based on user situational awareness in a cloud environment. Aiming at the cold start problem of new users and new projects in traditional QoS recommendation methods, the missing QoS attribute preference values were predicted and recommended based on user and item data using collaborative filtering. In document [30], [31], aiming at the data sparsity of the multi criteria decision collaborative filtering and recommendation system in e-commerce, a multi criteria decision collaborative filtering and recommendation system based on a neural network was proposed. In it, an adaptive neural fuzzy inference system was used to predict the relationship between the total score of options and each criterion score of options. The similarity measurement mechanism was used to alleviate the data sparsity and improve the robustness

and reliability of the similarity measurement for cold start users. Because the neural network provided a breakthrough in the process of solving the cold start problem, based on the preferences of new user characteristics, this paper proposed to use an activation function to classify user characteristic preferences and select the scheme corresponding to the nearest neighbor set of a new user to provide a recommendation.

In addition to being widely used in e-commerce, recommendation methods were also applied in imaging, product services and other fields. For example, in document [32], since the traditional image feature representation cannot capture product styles, highly related style feature modeling was introduced into the visual recommendation model and the style feature was integrated into collaborative learning to incorporate user preferences and improve the validity of the sensory recommendation method. In document [33], a Hierarchical Dirichlet Processes model was proposed based on service description text and service tag information. The personalized PageRank algorithm based on the service tags was used to rank and recommend cloud services in each cluster to alleviate the difficulty of personalized cloud services.

III. DESIGN OF A PERSONALIZED PRODUCT SERVICE RECOMMENDATION SCHEME

A. FRAMEWORK FOR A PERSONALIZED PRODUCT SERVICE RECOMMENDATION SCHEME

As an important recommendation technology, the collaborative filtering algorithm has been widely used in various fields and achieved good results. Aiming at the data sparsity and cold start problems caused by new users during the implementation of collaborative algorithms, this paper proposes a recommendation method based on trust and a cloud model to improve similarity. The personalized product service proposal recommendation framework is shown in figure 1. First, according to the influence of a user's direct subjective comments on the recommendation results, the weighted sum of the direct trust and indirect trust is proposed to measure the similarity of a user's trust. Second, considering that the cloud model can realize the qualitative and quantitative transformation of data, three characteristics of the cloud model are proposed and the forward cloud method is used to obtain several cloud drops to find the degree of cloud drop distance similarity. Finally, the weighted sum of the trust similarity and cloud droplet distance similarity are used to predict and fill in the sparse data to reduce the data sparsity. Aiming at the cold start problem caused by new users, the neural network is used to predict the nearest neighbor set to which new users belonged, and the nearest neighbor set is recommended.

B. SPARSE DATA FILLING BASED ON TRUST CLOUD SIMILARITY

Professor Li Deyi put forward the concept of the cloud model based on a Gauss function, which used the entropy calculation method to solve the fuzziness and randomness problems. The model not only reflects the degree of cloud

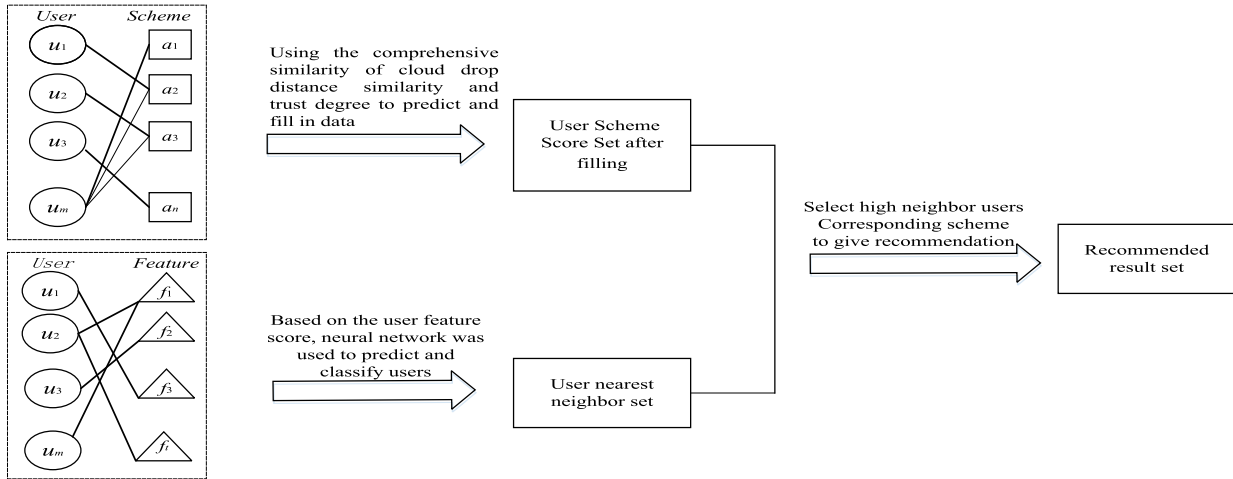


FIGURE 1. Framework for a personalized product service recommendation schemes.

droplet dispersion but also helps to solve fuzzy and uncertain mathematical problems by instituting the mutual mapping process between qualitative and quantitative relationships. In this paper, the cloud similarity is used to calculate the score similarity of schemes to predict the scores of schemes. The concepts of the cloud and cloud droplets and the calculation methods of the related indicators are presented as follows.

Definition 1 (Cloud and Droplet): Let U be a quantitative domain expressed numerically and C be a qualitative concept on U . If the quantitative value $x \in U$ is a random realization of the qualitative concept C , the determinacy of x to C : $\mu(x) \in [0, 1]$ is a random number with a stable tendency $\mu: U \rightarrow [0, 1], \forall x \in U$, and $x \rightarrow \mu(x)$. The distribution of x on the domain U becomes a cloud, which is denoted as $C(x)$, and each x becomes a cloud droplet.

The conceptual features contained in the cloud model can be expressed by three digital features of the cloud, including the Expected value (E_x), the Entropy (E_n) and the Hyper Entropy (He), as shown in (1) [34].

$$\begin{aligned}
 E_x &= \frac{1}{N} \sum_{i=1}^N x_i \\
 E_n &= \sqrt{\frac{\pi}{2}} \times \frac{1}{N} \sum_{i=1}^N |x_i - E_x| \\
 He &= \sqrt{S^2 - E_n^2}
 \end{aligned} \tag{1}$$

Among them, the variable N represents the number of cloud droplets and x_i represents cloud droplet i .

Definition 2: The random variable x satisfies $x \sim N(E_x, E_n^2)$ and $E'_n \sim N(E_n, He^2)$ if the determinacy of the qualitative concept C satisfies formula (2).

$$\mu_c(x) = e^{-\frac{(x-E_x)^2}{2E_n^2}} \tag{2}$$

Considering that users' subjective evaluations have the characteristics of vagueness and randomness, the subjective

experience is used to divide the data into several levels of trust. The qualitative and quantitative relationship transformation can be achieved using the cloud model. A cloud model is proposed to convert the quantitative data of user plans into cloud drops to form a cloud of trust.

User trust refers to the degree of trust of one user to another user, which is mainly divided into the degree of direct trust and the degree of indirect trust. The degree of direct trust indicates the direct trust relationship between user u and user v . Furthermore, the degree of indirect trust indicates the many indirect connections between user u and user v that can establish the degree of user trust. The degree of trust is expressed by the relationships between users on social networks, and the strength of trust is represented by Trust. $dTrust$ means direct trust. For any users u_i and u_j , there is a direct connection between them. For example, u_i recommends something to u_j and succeeds, which means that the first user directly trusts the second. $dTrust$ means indirect trust. For u_i and u_j , there are other users in the middle that allow the two to be connected, which is indirect user trust. The direct trust calculation method is shown in formula (3) [35].

$$dTrust(u_i, u_j) = \frac{|I(u_i) \cap I(u_j)|}{|I(u_i) \cup I(u_j)|} \tag{3}$$

In formula (3), $I(u_j)$ represents the score item set of user u_i , and $I(u_j)$ represents the score item set of user u_j . $dTrust$ represents the score item set of users u_i and u_j , which measures the proportion of the total number of user cumulative scores.

An indirect trust relationship is expressed by $mTrust$, which is the continuous connection between user u_t and user u_{t+1} , including the indirect relationship between u_i and u_j that form an indirect relationship. The equation for calculating this is shown in formula (4).

$$mTrust(u_i, u_j) = \prod_{t=i}^j indTrust(u_t, u_{t+1}) \tag{4}$$

Considering that the trust propagation channel is long and the trust is declining in the indirect user transmission process; this paper stipulates that the information transmission between two users is limited to three users. The two user transmission paths are not limited to being one way. Therefore, the overall indirect trust of a user is calculated as shown in formula (5).

$$iTrust(u_i, u_j) = \frac{1}{N} \cdot mTrust(u_i, u_j) \tag{5}$$

The comprehensive degree of trust is the weighted comprehensive value of the degree of direct trust and the degree of indirect trust, which acts as the trust similarity between users, as shown in formula (6).

$$T(u_i, u_j) = l(u_i, u_j) \cdot dTrust(u_i, u_j) + g(u_i, u_j) \cdot iTrust(u_i, u_j) \tag{6}$$

$l(u_i, u_j)$ is the weight coefficients of users u_i and u_j 's degree of direct trust. $g(u_i, u_j)$ represents the trust probability of user u_j in the social network where user u_i is located. Take the social network in figure 2 as an example.

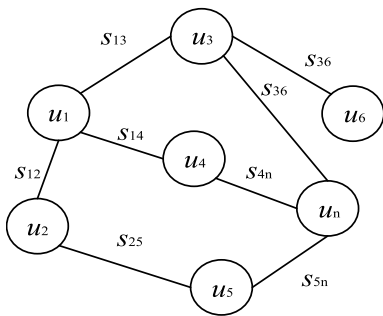


FIGURE 2. Social network.

When the user indegree between user u_i and user u_j is s_{ij} , the average trust indegree in the social network is avg . When $s_{ij} > avg$, $g(u_i, u_j)$ is set to 1, and vice versa; and $g(u_i, u_j) = s_{ij}/avg$.

Universe U can be expressed as one-dimensional and multidimensional forms. Cloud droplets are random variables whose degree of membership is realized in the whole space that realizes the qualitative and quantitative transformation. The relevant concepts of the cloud characteristics are also reflected. Cloud droplets that are not simply fuzzy and random are random variables generated by membership constraints. The degree of qualitative concepts of cloud droplets can be represented by the degree of membership. In other words, the concept of cloud droplet appearance is proportional to the degree of cloud droplet determination. The cloud model processing includes the forward cloud and reverse cloud generators. In this paper, the forward cloud algorithm is used to transform the qualitative vector feature $C(Ex, En, He)$ into cloud droplets describing individual quantitative values. With three eigenvalues of the cloud (0.5, 0.05, 0.01) and $n = 1000$ as the input values, the cloud image shown in figure 3 is output by the forward cloud generator.

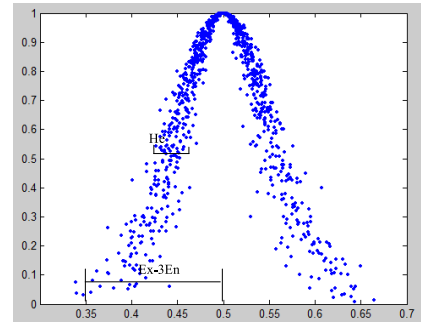


FIGURE 3. Cloud model.

The expected value Ex , which is the point most representative of the qualitative concept, represents the expected value of the cloud droplet distribution in the universe. En represents the uncertainty of the qualitative concept and reflects the degree of cloud dispersion. He is the degree of uncertainty of the entropy, which describes the thickness of the cloud.

In this paper, three eigenvalues of the cloud are transformed into cloud droplets by the forward cloud method. In addition, the distance between two clouds is obtained using the membership degree as the distance similarity of cloud droplets. The distance similarity of cloud droplets is shown in formula (7).

$$sim(u, v)' = \frac{1}{N} \sqrt{\sum_{k=1}^N (x_k^u - x_k^v)^2 + (\mu_u(x_k) - \mu_v(x_k))^2} \tag{7}$$

Because the user's subjective evaluation is the eigenvalue of the cloud model, it has certain subjective uncertainty. To solve this problem, a forward cloud method is proposed to transform the eigenvalues into cloud droplets, and the randomness of the cloud droplets is used to reduce the influence of subjective eigenvalues. First, the cloud feature of the existing user's rating is obtained. However, considering that the user's rating includes quantitative and qualitative values, it is proposed that the qualitative value be converted into a quantitative value according to certain criteria, and then the user's or project's rating be converted into a cloud feature vector of the user's overall rating by using the reverse cloud algorithm. The specific calculation process is as follows.

Step 1: For N cloud droplets $\{x_1, x_2, \dots, x_N\}$, the sample mean \bar{x} and the sample mean S2 shown in formula (1) are calculated according to the following formula.

Step 2: Formula (1) is used to calculate the three cloud features to get Ex and En .

Step 3: The forward cloud method is used to transform the cloud eigenvalues into several cloud droplets, each of which is one cloud droplet in the number domain with a degree of certainty.

Step 4: Steps 1-4 are repeated until the required N cloud droplets are formed $(x_c, \mu(x_c)) (c = 1, 2, 3, \dots, N)$.

Step 5: The distance similarity is used to solve the cloud model similarity.

Users with similar features also have high similarities among features. Considering the subjective factor of user trust and the objective factor of user ratings, the similarity and prediction formulas are synthesized to fill in the sparse rating data. The formulas are shown in (8) and (9), respectively.

$$sim(u, v) = \lambda * T(u, v) + (1 - \lambda) * sim(u, v)' \quad (8)$$

$$P_{v,i} = R_v + \frac{\sum_{u \in N(i)} sim(u, v) \times (R_{u,i} - R_u)}{\sum_{u \in N(i)} sim(u, v)} \quad (9)$$

In the formulas, R_v denotes user u_v 's score for a scheme. $sim(uv)$ denotes users u and v 's similarity. $R_{u,i}$ is user u_u 's score for scheme i . $N(i)$ is the nearest neighbor set of user u_v and user u_v 's predictive score for scheme i is $P_{v,i}$.

C. NEW USER RECOMMENDATION BASED ON ANEURAL NETWORK

A neural network is a parallel and distributed network structure that consists of a large number of neurons. There are many connection paths among input data. Each connection path corresponds to a connection coefficient. The transmission of enhanced or suppressed signals between interconnected neurons is realized by adjusting the interconnected weight coefficients. The output of the regulation mechanism converges to the correct target value. The BP neural network algorithm can be divided into two stages: forward signal propagation and error back propagation. First, information is input from the input layer and passed through the hidden layer to the output layer. The connection weight remains unchanged in the transmission process. In addition, there is a difference between the expected results and the output results. Meanwhile, the difference is returned and the weights between neurons are adjusted according to the error during the return process until the standard deviation between the actual output and the expected output is at its minimum.

The recommendation algorithm can recommend corresponding schemes to existing users according to their historical behavioral characteristics and interest preferences. However, it is difficult to recommend an accurate scheme to new users without any historical ratings. A neural network can adjust the user similarity in a recommendation algorithm and add other scheme attributes to optimize the training process. A neural network method based on user interest similarity is proposed to alleviate the impact of the cold start problems of new users on the recommendation results. The data in this article include the users' rating of the scheme, which is from 1 to 5 and obtained from the questionnaire. The grade of the feature of the scheme is from 1-5, and the score of the new and old users' interest features is from 1 to 3 Then, we obtain the similarity scheme of the new users' interest for recommendations by calculating the activation function. The neural network used in this paper had a three-layer structure, including an input layer, a hidden layer, and an output layer. First, it takes the user-scheme scores in Table 4 as the input of the neural network The user's subjective interest similarity

TABLE 1. Product indicator parameters.

f_1	f_2	f_3	f_4	f_5	f_6
<800	2200	250	100/10	320	<10
<1600	2500	320	120/7-8	360	<20
<2500	3200	400	180/6	440	<30
<3500	4000		250/3	530	<40
<5000	5000		250/2.5	560	<50
<6000	6000		320/2.5	620	
	7000			630	

is adjusted to adjust the weight of the network layer to obtain the data of the hidden layer, and then the sigmoid function value of the scheme-feature corresponding score is taken as the hidden layer's input weights Finally, it outputs the user matching scheme score values under different neighbor sets. A plan with a Top-N rating is chosen for new users. The relevant training steps of the neural network are as follows.

Input: Neighbor user set score of the scheme

Output: New users' ratings for different schemes

Step 1: Set the number of input and output layer nodes, and initialize the weight W and threshold Q of each layer.

Step 2: Input the score value of the nearest user scheme and the user interest feature rating into the neural network.

Step 3: The neural network is used to train the hidden layer and the output layer, and the scheme score and scheme feature values of the new user neighbor set are respectively used as the input and weight of the neural network algorithm. The weight of the hidden layer is the value of the sigmoid function obtained from the eigenvalues of the existing scheme.

Step 4: Determine whether the error of the sample set met the requirement, and finish learning if it met the requirement; otherwise, continue learning until it meets the requirement.

Step 5: Using the above trained network, the similarity of a new user scheme classification is obtained, and the score of a new user scheme is output.

Let us take a specific example for illustration. Assume that the user $\{u_1, u_2, u_3, \dots, u_m\}$ has the same solution $A = \{a_1, a_2, a_3, \dots, a_t\}$, and the user's rating of the solution is $R = \{r_{11}, r_{21}, r_{31}, \dots, r_{m1}\}$. The similarities of the interests between the new user and the existing user are $\{sim_1, sim_2, sim_3, \dots, sim_n\}$ and are used as the weight of the input layer. The hidden layer's weight is the value of the scheme feature $f = \{f_{11}, f_{12}, f_{13}, \dots, f_{21}, \dots, f_{m1} \dots\}$, and the output value is the corresponding scheme score value of each neighbor user of the new user. The activation function in the neural network process is the sigmoid function $(x) = 1 / (1 + e^{-x})$, where the hidden layer of the input value of x is expressed as the feature value of the scheme, and the user's score for each scheme is the output. The scheme with the highest value is selected as the new user. The TOP-N scheme is selected for recommendation based on the scores of each plan, as shown in Figure 4.

IV. CASE ANALYSIS

A. CASE BACKGROUND

With China's manufacturing 2025, industry 4 and Internet + put forward policies, increasing more manufacturing and

TABLE 2. Features of product and service schemes.

product model	scheme	f_1	f_2	f_3	f_4	f_5	f_6
40T/2200	a_1	400	2200	250	100/10	320	5.5
40T/2500	a_2	400	2500	250	100/10	320	5.5
63T/2500	a_3	630	2500	250	120/10	360	5.5
80T/3200	a_4	800	3200	320	120/10	360	7.5
80T/4000	a_5	800	4000	320	120/10	360	7.5
100T/3200	a_6	1000	3200	320	120/8	360	7.5
125T/3200	a_7	1250	3200	320	120/7	360	7.5
160T/3200	a_8	1600	3200	320	180/6	440	11
200T/4000	a_9	2000	4000	320	250/3	530	15
250T/6000	a_{10}	2500	5000	400	250/3	560	18.5
300T/6000	a_{11}	3000	6000	400	250/3	560	22
350T/7000	a_{12}	3500	7000	400	250/2.5	560	22
400T/4000	a_{13}	4000	4000	400	320/2.5	620	30
600T/6000	a_{14}	6000	6000	400	320/2.5	630	45
...

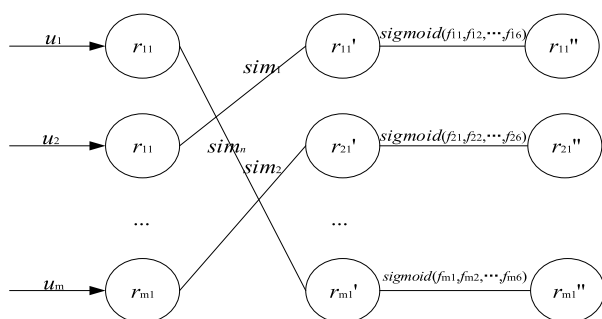


FIGURE 4. Neural network recommendation.

service industries are also advancing with the times. In the product and solution design and generation processes, personalized recommendation methods have been introduced to make corresponding recommendations to improve the efficiency of enterprises. Taking the machine tool product of a manufacturing enterprise as an example, the recommendation method proposed in this paper is used to make a suitable scheme for users. The machine tool indicators are the nominal pressure f_1 , the table length f_2 , the throat depth f_3 , the slider stroke f_4 , the maximum opening height f_5 , and the main motor power f_6 . The nominal pressure unit is KN; the length, depth, stroke and height unit is millimeters (mm); main motor power is in kw; and the index value is quantified as 1-7. The specific parameters are shown in Table 1

According to the existing parameter indicators of the enterprise and the composition of different types of products, different product solutions are formed as $A = \{a_1, a_2, a_3, \dots, a_n\}$, as shown in Table 2

B. RECOMMENDATION PROCESS OF A PERSONALIZED PRODUCT SERVICE SCHEME

In view of the fact that new users did not have any historical records in the original database, the user interest similarity is adopted in this paper to obtain a new user's nearest neighbor set whose corresponding scheme can be recommended. First, the questionnaire is used to obtain the scores of the existing

TABLE 3. User interest characteristic scoring.

	u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8	u_9
p_1	3	1	2	3	1	2	1	1	1
p_2	1	2	2	1	2	2	2	2	2
p_3	2	1	3	1	1	2	1	2	1
p_4	3	3	1	3	3	1	2	3	2
p_5	1	3	2	1	3	2	2	1	3

users and new user u_9 on the user's interest characteristics, which are shown in Table 3. The user's interest features mainly include the following: strong adaptability to the processing object p_1 , high processing accuracy p_2 , high production efficiency p_3 , high automation p_4 , and high reliability p_5 . These features are rated as low, medium and high from 1 to 3, respectively.

The Pearson similarity is used to calculate the similarity between user u_9 and the other users to obtain the neighbor set. The similarities between u_9 and $u_1 - u_8$ are 0.598, 0.896, 0.423, 0.327, 0.896, 0.134, 0.873, and 0.071, respectively. According to the different thresholds, u_2, u_5 and u_7 are classified as high; u_1 and u_3 are classified as medium; and u_4, u_6 and u_8 are classified as low. The similarity of neighboring users is taken as the weight of the input layer, and the input value is the user scheme score. The score is expressed as 1-5 from low to high, respectively. The users' scores on the first 13 programs are obtained through questionnaires, as shown in Table 4.

Before giving a reasonable recommendation to new users, the sparse rating data of users affect the recommendation results of new users. Before that, the cloud droplet distance similarity and user trust similarity proposed in this paper are used to reasonably predict user ratings. First, the cloud droplet distance similarity of the user rating is calculated, which means that three cloud eigenvalues of each user rating are calculated. As shown in Table 5, the forward cloud generator is used to convert the features into N cloud droplets, where $N = 1000$, and the distance between cloud droplets and the distance between trust clouds is calculated.

TABLE 4. User-program scoring.

	u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8
a_1	2	1	1	2	1	2	3	2
a_2	1	2	2	2	1	3	2	1
a_3	3	3	1	3.4	2	2	1	2
a_4	4	1	2	3	2	1	2	2
a_5	3	2	2	2	3	2.15	1	3
a_6	1	5	1	1	2	2	3	1
a_7	0.546	1.5	4	2	3	1	1	2
a_8	2	3	2	3	2	2	2.1	1
a_9	1	2	1	2	3	3	1	2
a_{10}	4	0.51	2	1	2	2	2	2
a_{11}	3	5	3	2	1	1	3	2.13
a_{12}	5	4	2	2	2	2	2	5
a_{13}	5	3	3	1	3	1	2	2

TABLE 5. Three eigenvalues of users.

	(Ex , En , He)
u_1	(2.6923, 1.765, 0.5356)
u_2	(2.385, 1.676, 0.514)
u_3	(2.0, 0.771, 0.418)
u_4	(1.769, 0.786, 0.145)
u_5	(2.077, 0.712, 0.1602)
u_6	(1.692, 0.8602, 0.2559)
u_7	(1.7692, 0.934, 0.283)
u_8	(1.7692, 1.127, 0.5399)

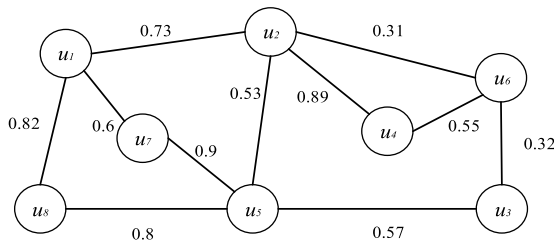


FIGURE 5. Social network.

According to the social network graph of users, the trust degree among users is obtained. The graph of the known social network is shown in figure 5 below. Taking user u_1 as an example, u_1 is directly related to u_2 and u_8 and indirectly related to u_6 and u_4 . Formulas (3) - (6) are used to calculate the trust similarity. We know that u_1 and u_8 , u_2 and u_4 , u_3 and u_5 , u_4 and u_2 , u_5 and u_7 , u_6 and u_4 , u_7 and u_5 , and u_8 and u_5 are highly similar. Combining the cloud droplet similarity of u_1 and u_2 in Table 5, the comprehensive similarities of 0.59, 0.64, 0.63, 0.40, 0.63, 0.64, and 0.57 can be obtained. Prediction formula (9) is used to fill in the sparse data in Table 3, and the weight λ is set as 0.3. The filled in results are represented by the bold figures in Table 5.

After solving the data sparsity problem, a scheme recommendation method based on a neural network is proposed to solve the cold start problem of new users. First, the user-scheme score in Table 3 is used as the input of the neural network. In addition, the user interest feature similarity is used as the weight to get the data of the hidden layer. Second, the scheme-feature correspondence

score is used as the weight input of the hidden layer. Finally, the scores of the user matching schemes under different neighborhood sets are output.

Step 1: Calculate the similarities of new user u_9 with the other users u_1-u_8 . The similarities of u_9 and u_1-u_8 are 0.598, 0.896, 0.423, 0.327, 0.896, 0.134, 0.873, and 0.071, respectively. According to different thresholds of 0.8, 0.6, and 0.4, there are three kinds of users: u_2 , u_5 and u_7 ; u_1 and u_3 ; and u_4 , u_6 and u_8 .

Step 2: Calculate the new user's program score under a high threshold, that is, multiply the similarity by the neighboring user's program score, as shown in Table 6.

TABLE 6. Combines new user's u_9 with similar neighborhood sets to score schemes.

	u_1	u_2	u_3	u_5	u_7
a_1	1.196	0.896	0.423	0.896	2.619
a_3	1.794	2.688	0.423	1.792	0.873
a_4	2.392	0.896	0.846	1.792	1.746
a_5	1.794	1.792	0.846	2.688	0.873
a_6	0.598	4.48	0.423	1.792	2.619
a_7	0.3265	1.344	1.692	2.688	0.873
a_8	1.196	2.688	0.846	1.792	1.8333
a_9	0.598	1.792	0.423	2.688	0.873
a_{10}	2.392	0.457	0.846	1.792	1.746
a_{11}	1.794	4.48	1.269	0.896	2.619
a_{12}	2.99	3.584	0.846	1.792	1.746
a_{13}	3.588	2.688	1.269	2.688	1.746

Step 3: The filtered users in Table 6 use the sigmoid function to calculate the product of the feature score of the solution and each corresponding solution as the criterion to judge and classify the new user and obtain the output value of the nearest neighbor set of solutions. The highest score in the plan is recommended, as shown in Table 7.

TABLE 7. Classification of recent user u_9 nearest neighbor sets.

	u_1	u_2	u_3	u_5	u_7
a_1	0.77	0.71	0.60	0.71	0.93
a_3	0.86	0.94	0.60	0.86	0.71
a_4	0.92	0.71	0.70	0.86	0.85
a_5	0.86	0.86	0.70	0.94	0.71
a_6	0.65	0.99	0.60	0.86	0.93
a_7	0.58	0.79	0.84	0.94	0.71
a_8	0.77	0.94	0.70	0.86	0.86
a_9	0.65	0.86	0.60	0.94	0.71
a_{10}	0.92	0.61	0.70	0.86	0.85
a_{11}	0.86	0.99	0.78	0.71	0.93
a_{12}	0.95	0.97	0.70	0.86	0.85
a_{13}	0.97	0.94	0.78	0.94	0.85

For example, the high threshold u_7 corresponds to scheme a_1 ; u_5 corresponds to solutions a_5 , a_7 , and a_9 ; u_1 corresponds to solutions a_4 , a_{10} , and a_{13} ; and u_2 corresponds to solutions a_3 , a_6 , a_8 , a_{11} and a_{12} for new user u_9 . The scores of a_1 and a_3 to a_{13} are 2.619, 2.688, 2.392, 2.688, 4.48, 2.688, 2.688, 2.688, 2.392, 4.48, 3.584, and 3.588, respectively. The Top 3 highest-scoring schemes are a_6 , a_{11} , and a_{13} and thus are recommended. According to Table 2, it can be known that if the corresponding features of scheme a_{13} are

recommended, a machine tool with a nominal pressure of 4000 KN, a table length of 4000 mm, a throat depth of 400 mm, a slider stroke of 320/2.5 mm, a maximum opening height of 620 mm, and a main motor power of 30 kw is recommended for new users.

C. COMPARATIVE ANALYSES

In this paper, the similarity calculation combined with the trust and cloud model method is used to predict and fill in the ungraded missing data, which can make up for inaccurate recommendations caused by data sparsity. Considering that new users have no historical ratings, a neural network method is proposed to predict and classify the new users based on their similar interests to obtain the recommendation scheme corresponding to the nearest neighbor user set. To prove the efficiency of this method, data sets with 200-1200 entries are randomly obtained from the data set of the enterprise. Using a platform with windows 10 and python 3.0, the method of this paper, and the recommendation method based on the cloud model, we randomly obtain different data sets ranging from 200-1200 entries from the enterprise’s data set. The recommendation method based on trust and user characteristics compares the recommendation accuracy and algorithm execution time. The experimental results are shown in figures 6 and 7, respectively.

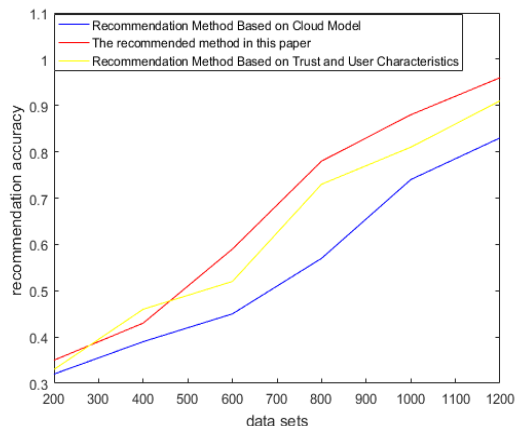


FIGURE 6. Recommended accuracy comparisons.

As shown in Figure 6 above, the recommendation accuracy of this paper increased as the size of the data set increases, which showed that the recommendation accuracy of this method and the recommendation accuracy of the trust-based method are improving. When the data set is small, the result is slightly better than the recommendation of this algorithm. When the data set is small, the user’s subjective recommendation effect is better. This can be explained as the new user being more willing to believe the old user’s push recommendation scheme. However, as the size of the data set increases, the accuracy of this method is higher. As the size of the data set increases, the cloud model-based recommendation can transform the qualitative evaluation into a quantitative evaluation; therefore, the recommendation accuracy is improving, but it is still worse than the other two methods in general.

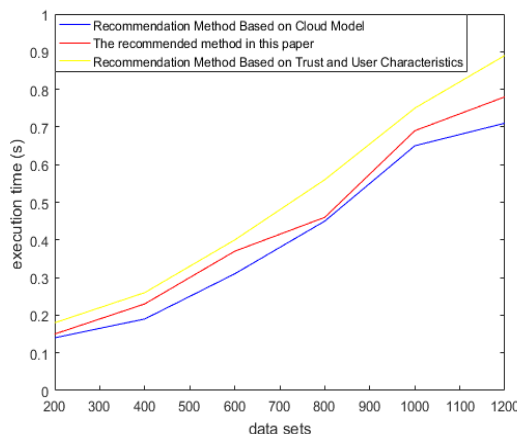


FIGURE 7. Comparisons of execution times of methods.

In conclusion, the recommendation accuracy of this method is better than those of the other two methods. The subjective interest characteristics of users and the cloud model method are integrated so that the recommendation accuracy is better here than elsewhere and the recommendation effect is verified.

As shown in figure 7, as the size of the data set increases, the different recommendation execution times increase. With the increase in the size of the data set, the execution time of this method approaches those of the other methods. With the increase in the size of the data set, the implementation times of the three methods based on the cloud model are the least, and the implementation method in this paper has a slightly higher implementation time than that of the cloud model. Due to the combination of the cloud model and user trust, the implementation time of the recommendation method based on trust is the longest because of considering more subjective characteristics and the complicated similarity calculation process. This method is proposed based on the cloud model, the degree of trust and the neural network prediction. Therefore, the execution time of this method is a little longer, but as the size of the data set increases, the gap between the two methods is narrowed.

V. CONCLUSION

The maturity of Internet technology and the growth of the e-commerce industry require increasingly more information technology. As a common method in the field of information, recommendation technology is increasingly more important in improving the efficiency of enterprises. Recommendation technology is immature in the manufacturing industry. To improve the satisfaction rate and efficiency of users for product service schemes, recommendation technology is introduced in this paper. An optimization method is proposed to improve the data sparsity and cold start of new users. The effectiveness and rationality of the proposed method are verified by case analysis and an algorithm comparison. The main contributions of this paper are as follows.

- (1) Aiming at the data sparsity problem of user schemes, a similarity calculation method is proposed to predict the

user's scores for the schemes. Considering the subjectivity of user ratings, a comprehensive similarity between user trust and the cloud drop distance is proposed to reduce the impact of sparse data on recommendation results.

(2) Considering the cold start problem caused by new users, a neural network method based on user feature scores is proposed to output a classified neighbor set with similar user characteristics. Highly similar users are selected according to the threshold and their corresponding solutions are recommended.

Since the output and threshold judgment of the neural network will consume computing time, future work will consider the execution time of the optimization recommendation method.

REFERENCES

- [1] X. An, C. Liu, D. Xue, G. Mu, and X. Lin, "Optimal selection method for product service system scheme based on variable granule weight and group decision-making," *Comput. Integra Manuf. Sys.*, vol. 22, no. 1, pp. 155–165, Jan. 2016.
- [2] Y. Li and Y. Wu, "Scheme evaluation of product service system based on improved stochastic multi-objectives acceptability analysis," *Comput. Integra Manuf. Sys.*, vol. 24, no. 8, pp. 2071–2078, Aug. 2018.
- [3] H. Peng, Y. Jin, X. Lv, and X. Wang, "A context aware POI recommendation algorithm based on matrix decomposition," *Chin. J. Comput.*, vol. 42, no. 8, pp. 1797–1811, Jun. 2019.
- [4] L. Guo, J. Liang, and X. Zhao, "Collaborative filtering recommendation algorithm incorporating social network information," *Pattern Recognit. Artif. Intell.*, vol. 29, no. 3, pp. 281–288, Mar. 2016.
- [5] F. Zhao, Y. Shen, X. Gui, and H. Jin, "SDBPR: Social distance-aware Bayesian personalized ranking for recommendation," *Future Gener. Comput. Syst.*, vol. 95, pp. 372–381, Jun. 2019, doi: 10.1016/j.future.2018.12.052.
- [6] J. F. Wang, R. D. Liu, and Y.-L. Liu, "Non-negative matrix factorization algorithm with bias in recommender system," *J. Chin. Comput. Syst.*, vol. 39, no. 1, pp. 69–73, Jan. 2018.
- [7] S. Guo and S. Chen, "Sparsified factorization machine," *CAAI Trans. Intell. Syst.*, vol. 12, no. 6, pp. 816–822, Dec. 2017.
- [8] X. Yu, F. Jiang, J. Du, and D. Gong, "A cross-domain collaborative filtering algorithm with expanding user and item features via the latent factor space of auxiliary domains," *Pattern Recognit.*, vol. 94, pp. 96–109, Oct. 2019.
- [9] P. Wang, Q. Qian, Z. Shang, and J. Li, "An recommendation algorithm based on weighted slope one algorithm and user-based collaborative filtering," in *Proc. Chin. Control Decis. Conf. (CCDC)*, May 2016, pp. 2431–2434.
- [10] J. Deng, Y. Wang, J. Guo, Y. Deng, J. Gao, and Y. Park, "A similarity measure based on Kullback–Leibler divergence for collaborative filtering in sparse data," *J. Inf. Sci.*, vol. 45, no. 5, pp. 656–675, Oct. 2019.
- [11] T. Kondo and Y. Kanzawa, "Collaborative filtering using fuzzy clustering for categorical multivariate data based on q-divergence," *J. Adv. Comput. Intell. Intell. Inform.*, vol. 23, no. 3, pp. 493–501, May 2019.
- [12] M. Lin, "Personalized learning resources recommendation algorithm combining learners' time-oriented behaviors and cognitive level," *Comput. Syst. Appl.*, vol. 27, no. 10, pp. 218–225, Oct. 2018.
- [13] S. N. Mohanty, J. R. Parvin, K. V. Kumar, K. C. Ramya, S. Sheeba Rani, and S. K. Lakshmanaprabu, "Optimal rough fuzzy clustering for user profile ontology based Web page recommendation analysis," *J. Intell. Fuzzy Syst.*, vol. 37, no. 1, pp. 205–216, Jul. 2019.
- [14] H. Kaur, N. Kumar, and S. Batra, "ClaMPP: A cloud-based multi-party privacy preserving classification scheme for distributed applications," *J. Supercomput.*, vol. 75, no. 6, pp. 3046–3075, Jun. 2019.
- [15] L. Zhang, J. Li, Q. Zhang, F. Meng, and W. Teng, "Domain knowledge-based link prediction in customer-product bipartite graph for product recommendation," *Int. J. Inf. Technol. Decis. Making*, vol. 18, no. 1, pp. 311–338, Jan. 2019.
- [16] J. Deng, J. Guo, and Y. Wang, "A novel K-medoids clustering recommendation algorithm based on probability distribution for collaborative filtering," *Knowl.-Based Syst.*, vol. 175, pp. 96–106, Jul. 2019.
- [17] M. Mansoury, B. Mobasher, R. Burke, and M. Pechenizkiy, "Bias disparity in collaborative recommendation: Algorithmic evaluation and comparison," in *Proc. Recommendation Multi-Stakeholder Environments (RMSE) at ACM RecSys*, Copenhagen, Denmark, 2019, pp. 1–8.
- [18] R. Hurtado, J. Bobadilla, R. Borjorque, F. Ortega, and X. Li, "A new recommendation approach based on probabilistic soft clustering methods: A scientific documentation case study," *IEEE Access*, vol. 7, pp. 7522–7534, 2019.
- [19] J. Liu and Y. Chen, "A personalized clustering-based and reliable trust-aware QoS prediction approach for cloud service recommendation in cloud manufacturing," *Knowl.-Based Syst.*, vol. 174, pp. 43–56, Jun. 2019.
- [20] H. Guo, C. Yang, Y. Wu, and X. Xu, "Collaborative filtering recommendation algorithm combining community structure and personal interests," *Comput. Eng. Desig.*, vol. 39, no. 11, pp. 3420–3424, Nov. 2018.
- [21] G. Wei, Z. Liu, L. Li, and M. Zhang, "Singular value decomposition recommendation algorithm considering user's preference for item attributes," *J. Xi'an Jiaotong Univ.*, vol. 52, no. 5, pp. 101–107, May 2018.
- [22] X. Zhang and H. Zhao, "Cold-start recommendation based on speech personality traits," *J. Comput. Theor. Nanosci.*, vol. 14, no. 3, pp. 1314–1323, Mar. 2017.
- [23] M. He, S. Zhang, and Q. Meng, "Learning to style-aware Bayesian personalized ranking for visual recommendation," *IEEE Access*, vol. 7, pp. 14198–14205, 2019.
- [24] J. Wang, Z. Yu, H. Zhang, and C. Fang, "Service recommended trust algorithm based on cloud model attributes weighted clustering," *J. Syst. Simul.*, vol. 30, no. 11, pp. 4298–4312, 2018.
- [25] L. Cui, P. Ou, X. Fu, Z. Wen, and N. Lu, "A novel multi-objective evolutionary algorithm for recommendation systems," *J. Parallel Distrib. Comput.*, vol. 103, pp. 53–63, May 2017.
- [26] Y. Gao, X. Wang, L. Guo, and Z. Chen, "Learning to recommend with collaborative matrix factorization for new users," *J. Comput. Res. Develop.*, vol. 58, no. 8, pp. 1813–1823, 2017.
- [27] J. Xu, Y. Yao, H. Tong, X. Tao, and J. Lu, "Ice-breaking: Mitigating cold-start recommendation problem by rating comparison," in *Proc. 24th Int. Joint Conf. Artif. Intell. IJCAI*, 2015, pp. 3981–3987. [Online]. Available: <https://aaai.org/ocs/index.php/IJCAI/IJCAI15/paper/view/10834>
- [28] L. Gongshen, M. Kui, D. Jiachen, J. P. Nees, G. Hongyi, and Z. Xuewen, "An Entity-Association-Based matrix factorization recommendation algorithm," *Comput., Mater. Continua*, vol. 58, no. 1, pp. 101–120, 2019.
- [29] L. Wei and Y. Huang, "Incorporating user attribute data in recommendation system," *Appl. Electron. Technique.*, vol. 43, no. 10, pp. 137–140, 2017.
- [30] H. Liu, "Context-aware hybrid recommendation for QoS preference prediction of mobile service in cloud environment," *J. Intell.*, vol. 35, no. 4, pp. 183–189, Apr. 2016.
- [31] N. Chen and J. Wu, "Collaborative filtering recommendation based on multi-criteria decision making and neural networks," *Control Eng. China.*, vol. 25, no. 5, pp. 841–848, May 2018.
- [32] Q. Lu and F. Guo, "Personalized information recommendation model based on context contribution and item correlation," *Measurement*, vol. 142, pp. 30–39, Aug. 2019.
- [33] Y. Jiang, D. Tao, Y. Liu, J. Sun, and H. Ling, "Cloud service recommendation based on unstructured textual information," *Future Gener. Comput. Syst.*, vol. 97, pp. 387–396, Aug. 2019.
- [34] G.-W. Zheng, "A collaborative filtering recommendation algorithm based on cloud model," *J. Softw.*, vol. 18, no. 10, p. 2403, 2007.
- [35] P. Zhang, B. Huang, R. Xie, and C. Chen, "A method for Web services recommendation based on social network trust relationship," *J. Chin. Comput. Syst.*, vol. 35, no. 2, pp. 222–227, Feb. 2014.



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