# Research on Personalized Recommendation of Mobile Social Network Products Based on User Characteristics

Min Zhou[1](✉), Wei Xu[2], and Xinwei Li[3]

[1] Department of Employment and Entrepreneurship, Xiamen Ocean Vocational College, Xiamen 361000, China
zhoumin693@163.com

[2] Department of International Trade, Xiamen Ocean Vocational College, Xiamen 361000, China

[3] Human Resources Department, Changchun University of Architecture and Civil Engineering, Changchun 130000, China

**Abstract.** In the process of conducting online product recommendations, the lack of comprehensive user profiling in constructing user personas has led to low Top-10 hit rate, average reciprocal rank, and normalized discounted cumulative gain of recommended products. To effectively address this issue, a user feature-based personalized recommendation method for mobile social networks (MSN) is proposed. By analyzing the basic attributes, interaction attributes, feedback attributes, and interest attributes of MSN users, user attribute features are extracted to build user personas. Based on these user personas, personalized recommendations for mobile social network products are achieved using MetaEE. This involves updating the recommended products based on the collection of user interactions with historical items until there is overlap between the support set and the query set of the personalized recommendation meta-learning samples. The corresponding products are then considered as the final recommended results. Experimental results demonstrate that the designed recommendation method outperforms the comparison methods in terms of Top-10 hit rate, average reciprocal rank, and normalized discounted cumulative gain across multiple experimental scenarios, indicating a promising recommendation performance.

**Keywords:** User characteristics · Mobile social network goods · Personalized recommendation · Attribute characteristics · MetaEE · Losses

## 1 Introduction

With the rapid development of Internet technology and mobile device applications, online services have become an indispensable part of people's life [1]. However, the e-commerce platform will release a large number of commodity content and user shopping

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browsing records and other data every day [2]. Faced with a large number of commodities, how to quickly select the commodities that users are interested in and how to quickly recommend commodities to potential users on e-commerce platforms have become the difficulties that platform providers need to urgently solve [3]. Therefore, personalized recommendation technology is becoming a research hotpot in the field of product recommendation. The recommendation system can accurately locate users' interests and commodity characteristics [4] by analyzing users' behavior data, and realize the matching between commodity providers and users. It has been applied in many network services in the current society. Some shopping platforms predict users' preferences based on users' browsing records, purchase records and other information, launch various services such as "Guess what you like" to recommend products [5]. The performance of the recommendation system is determined by the algorithm. A good recommendation algorithm can directly and quickly help users locate interesting goals, optimize users' browsing experience, and bring higher user loyalty and economic benefits to the e-commerce platform [6]. Content based recommendation, collaborative filtering based recommendation and hybrid recommendation, as classic methods, have been widely used in the industry by virtue of their respective advantages [7]. However, these recommendation algorithms all have problems such as cold start caused by the historical interaction between users and commodities and data sparsity caused by low effective data. At the same time, due to many factors such as the increasing personalized needs of users, the recommendation services provided by these traditional algorithms have been severely tested [8]. According to different recommendation methods, recommendation algorithms can be divided into three types: the first is collaborative filtering recommendation algorithm, which uses the same interests of users or similar characteristics of goods to recommend. Collaborative filtering recommendation algorithm has the advantages of high accuracy, finding new items and not requiring item feature information. However, it also has drawbacks such as cold start issues, data sparsity, algorithm scalability, and recommendation preference issues; The second is content based recommendation, which uses users' interest preferences and content information to label users and goods and then uses supervised learning or deep learning methods to recommend. Content based recommendation algorithms have advantages such as independence, interpretability, and adaptability to cold start problems. However, it also has drawbacks such as feature representation issues, lack of diversity, and inability to capture dynamic changes in user interests; The third is hybrid recommendation. This method combines one or more of the previous two recommendation algorithms and combines the advantages of each algorithm to recommend [9]. Hybrid recommendation algorithms have the advantages of improving recommendation accuracy, diversity, novelty, robustness, and scalability. However, it also has drawbacks such as complexity and computational overhead, parameter selection and adjustment, as well as interpretability and comprehensibility [10]. The hybrid recommendation algorithm can effectively remedy some defects of the single use of the above two methods by retaining the advantages of the above two recommendation algorithms, so it has been studied by many scholars at present.

Therefore, this paper proposes a user feature-based personalized recommendation method for mobile social networks. This method analyzes the basic attributes, interaction attributes, feedback attributes, and interest attributes of mobile social network users to extract user attribute features, thereby achieving user persona construction. Based on user personas, personalized recommendations for mobile social network products are achieved using MetaEE. Research on personalized recommendations for mobile social network products helps improve recommendation accuracy, enhance user experience, facilitate commercial conversion, and drive innovation and development in the field of recommendation systems. These studies provide important support and guidance for the development of mobile social networks and e-commerce.

# 2 Design of Personalized Recommendation Method for Mobile Social Network Products

## 2.1 Construction of User Profile Model Based on Multi-attribute Features

The existing user portrait research rarely considers multiple types of data at the same time in practical applications to build a portrait model with more attribute characteristics, making the constructed portrait model relatively incomplete, which will lead to certain deviations in the process of mining user characteristics, distinguishing user groups, and searching for similar users. In order to better improve the user model, this paper proposes a user portrait model with multiple attribute features, aiming to build a more complete portrait by taking into account the four attributes of users: basic attributes, interactive attributes, feedback attributes, and interest attributes. The construction of user profile first depends on the integrity of data collection. The more user related data, the more favorable it is for mining user preferences, and thus the user profile will be more effective; Secondly, a good tag system can take all aspects of users into consideration, which can make the data fully mined and make the user profile more complete and relevant to users; Finally, the model design of user profile is essential. The collected data is analyzed and processed through various data mining technologies, and the final user profile is obtained based on the constructed indicator system. Among them, the integrity of data collection directly affects the accuracy of user profile construction. Most existing studies obtain data by writing programs or directly using data collectors to crawl data from the API portal, which is effective compared with traditional methods such as questionnaires and in-depth interviews.

Improve the difficulty of data acquisition, and reduce the phenomenon of small amount of data or data errors caused by users' failure to answer or random answer due to boredom. The data required in this paper is mainly divided into three parts: user basic information, domain data and external environmental factors.

(1) Basic user information: refers to the static data of the user, which generally does not change and is relatively stable. It mainly includes user ID, gender, age, education level, home address, occupation, etc.
(2) Domain data: user dynamic data, which can reflect users' personal preferences and display users' characteristics. It mainly includes clicking, browsing, collecting, sharing, adding, comments, ratings, likes, etc.
(3) External environment data: This data mainly refers to the situational data of users when the above behaviors occur. Such data can reflect some regularity to a certain extent, which is helpful for predicting user behaviors and judging the direction of

user interests. It generally includes the occurrence time, region, month, month, day, temperature, humidity, weather conditions, equipment used, network connection, etc.

On this basis, only a complete and effective user tag system can show the full picture of users, three-dimensional users, and ensure their integrity and accuracy. In order to better display our user attributes, better distinguish the differences between their attribute characteristics, and better use our model. Therefore, based on the user profile label system designed above, each feature is quantified to show the degree of differentiation between feature levels, and the online shopping user profile model is expressed in the form of a vector, that is

$$MUP = \{B, A, F, P\} \tag{1}$$

Among them, *MUP* represent online shopping user portrait model; *B* represents the user's basic attributes; *A* indicates user interaction sex; *F* indicates user feedback attribute; *P* indicates the user interest attribute.

For the basic attribute characteristics of users, it mainly refers to the demographic information of users, usually referring to the user's ID, gender, age and occupation. In order to better standardize its presentation results, its indicators need to be quantified by grades to achieve the normalization of the results. For example, gender can be divided into two categories, male and female, represented by 0 and 1 respectively; Similarly, age can be divided into four sections according to the classification standards of the United Nations World Health Organization. Children are 18 years old and below, young people are 19–35 years old, middle-aged people are 36–59 years old, and old people are 60 years old and above. They are represented by 1, 2, 3, and 4 respectively. Marriage can be divided into two categories: 0 means married and 1 means unmarried. See Table 1 for details.

**Table 1.** Classification of user basic attribute characteristics

| index | classification | Quantitative representation |
|---|---|---|
| Gender | male | 0 |
| | female | 1 |
| Age | 18 years and below | 1 |
| | 19–35 years old | 2 |
| | 36–59 years old | 3 |
| | 60 and above | 4 |
| marriage | married | 0 |
| | unmarried | 1 |

The interaction attribute characteristics of users mainly refer to the interaction behavior data between users, mainly including the number of clicks, additional purchases,

purchases, and collections of users. This attribute is used to determine the activity of online shopping users, so that online shopping user groups can be divided and services can be provided for different types of users. In this paper, the entropy weight method is used to calculate the overall interaction value according to the collected index values. The specific calculation formula is

$$A = \sum w_j A_{ij} \tag{2}$$

Among them, $w_j$ represents the weight value corresponding to each feature, $A_{ij}$ that is, each feature under the interaction attribute of a single user $a_{ij}$ the formula obtained from data standardization is

$$A_{ij} = \frac{a_{ij} - \min a_j}{\max a_j - \min a_j} \tag{3}$$

Among them, $\min a_j$ for $j$ the minimum value of indicators, similarly, $\max a_j$ for $j$ the maximum value of indicators.

As for the feedback attribute characteristics of users, this paper conducts emotional analysis on all comments of users on the product, so as to obtain an emotional value that can better display the user's attitude towards the product compared with the score, which can effectively improve the impact caused by the huge difference between the score and the text in the comments. Thus, the rating and the emotional value of comments are fused to get the user's attitude towards the purchased products in the past. This article also considers user ratings $sc$ and user comment emotional value $se$ as an indicator of user feedback attributes. The formula for calculating the feedback value is

$$F = \alpha * sc + \beta * se \tag{4}$$

Among them, when the user only has ratings but no comments, $\alpha = 1$; Otherwise, $\alpha = \beta = 0.5$.

User rating $sc$ it refers to the average value of all scores of a single user, that is

$$sc = \frac{\sum sc_i}{n_{sc}} \tag{5}$$

Among them, $sc_i$ represents all scoring results of a single user, $n_{sc}$ indicates the total number of all user ratings.

User rating $sc$ it refers to the average value of all scores of a single user, that is

$$se = \frac{\sum se_i}{n_{se}} \tag{6}$$

Among them, $se_i$ represents all scoring results of a single user, $n_{se}$ indicates the total number of all user ratings.

The last is the analysis of user interest attribute characteristics, which mainly refers to the deep mining and extraction based on the user's historical viewing data and comment text data.

Refined features. In order to better distinguish the impact of different features on user interest, how to quantify the user refined tags is the key to quantitative analysis.

The category of user interest attribute is mainly a feature of text form, so it needs to be transformed. UGC, as the user's comment data on the product, well expresses the user's preferences for different attributes. The TF-IDF (Term Frequency – Reverse Document Frequency) method is used here to quantify the weight of features. This is because the more users pay attention to a feature, the more they will repeatedly mention the feature, which is just similar to the principle of this method. Therefore, here the characteristic attributes are quantified by using this method. The method is used to distinguish the important features that users pay attention to, and get the weight values of each indicator feature, thus showing the differences between users. The calculation method is

$$k_{ij} = tf_{i,j} * IDF \tag{7}$$

Among them, $k_{ij}$ indicates that the user is interested in $k$ preferences of attributes, $tf_{i,j}$ refers to a word $k$ in comments $d$ number of occurrences in $count(w, d)$ and comments $d$ total words in $size(d)$ ratio of i.e.

$$tf_{i,j} = \frac{count(w, d)}{size(d)} \tag{8}$$

$IDF$ the value can be determined by the total number of comments $N$ divide by word $k$ number of comments $(k, d)$, and then take the logarithm of the quotient obtained i.e.

$$IDF = \log[\frac{N}{docs(k, d)}] \tag{9}$$

With the help of Eq. (9), the calculated weight value of the keyword is displayed according to its size, and each keyword corresponds to a weight value. This value reflects the user's concern for each product, and the degree of differentiation is shown.

In the way shown above, build a user profile model with multi attribute features, and provide an execution basis for subsequent product recommendation.

## 2.2 Personalized Recommendation

Combined with the multi-attribute user profile model built in Sect. 2.1, this paper uses the general learning paradigm MetaEE to achieve personalized recommendation for mobile social network products. The overall recommendation process is shown in Fig. 1.

It can be seen from Fig. 1 that the embedding module of users and items generates the embedding vector of users and items as the input of the model, and then combines MAML to train and update the recommended parameters.

In the process of training the recommendation process, first, the user commodity data set is divided into independent support sets and query sets. The parameter combination of the recommended model is 0, which is also the goal of meta learning training. Based on the inner and outer layer circulation of MAML algorithm, the task parameters are updated using two levels of local and global updates. Through local updates, the corresponding preference network is trained for specific users, and global updates generalize its specific network to the preference network adapted by all users. On the basis of the user preference network, this paper focuses on users and objects. The embedded representation of products is enhanced to generate an initial embedding suitable for

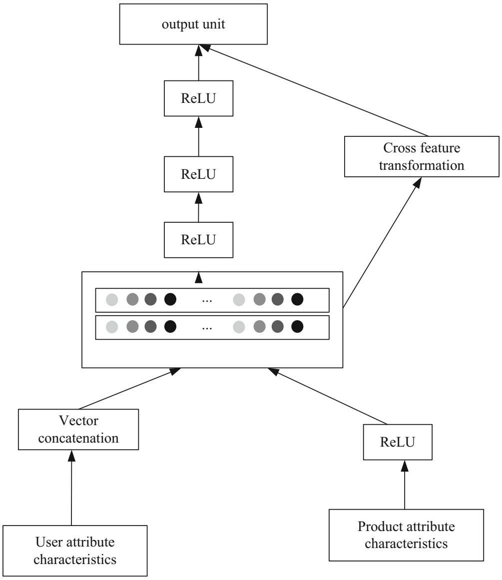


**Fig. 1.** Product recommendation process based on MetaEE

the recommendation model. The local update and global update of feature parameters correspond to the inner loop and outer loop of the MAML framework respectively.

Learn the meta knowledge learned in the tasks of meta training and meta testing to guide the rapid adaptation of target tasks. First, based on the meta learning sampling support set and query set, a pair of data in the support set query set is composed for each user and historical interactive items, as well as the corresponding tags under the items. The specific calculation method can be expressed as

$$D_1 \cup D_2 = \{X_{ij}, Y_{ij}\}_{j=1}^{n} \tag{10}$$

Among them, $X_{ij}$ and $Y_{ij}$ a collection composed of users and historical interactive items, representing $D_1$ represents a set of meta learning sampling support for personalized recommendation of mobile social network products, $D_2$ represents the meta learning sampling query set for personalized recommendation of mobile social network products, $n$ it is a manually set size, representing the number of items sampled by a specific user, so one user samples a total of $n$ as the support set and query set $\theta$ random initialization to obtain an initial parameter user bias evaluation function $f_\theta$, which can be expressed as

$$p = f_\theta(X) \tag{11}$$

According to the way shown in Eq. (11), and according to the evaluation function $p$ training is conducted on the support set. Each user's preference evaluation represents a meta training task. The loss of the corresponding task is obtained by evaluating the preference on each task. The loss calculation method can be expressed as

$$L(f_\theta) = -Y \log p - (1 - Y) * \log(1 - 9) \tag{12}$$

Among them, $L(f_\theta)$ represents the loss function. According to the loss calculation gradient, the random initial model parameters $\theta$ update to integrate specific tasks, that is, parameters that adapt to specific user preferences. The specific update steps in the support set can be expressed as

$$\theta' \leftarrow \theta - \lambda \nabla L(f_\theta) \tag{13}$$

Among them, $\nabla L(f_\theta)$ represents the change gradient parameter of the loss function, $\lambda$ indicates the set super parameter, $\theta'$ indicates the recommended parameters that adapt to specific user preferences. On this basis, the global parameters are updated progressively by calculating the loss of each user in Eq. (11). Ensure that the recommendation results found in the final formula (10) can meet the actual needs and preferences of users to the maximum extent.

Complete personalized recommendation of mobile social network products in the way shown above.

## 3 Test Experiment Analysis

### 3.1 Test Environment

Experimental equipment and programming language: The proposed model is written by the Keras depth framework and Python language, and Pycharm is used as the development tool to conduct experimental tests on the Windows 10 operating system and the server platform with the GPU model of GeForce 1660Ti 6G and above.

### 3.2 Test Data Set Preparation

In the experiment, MovieLens - 1M and Tafeng datasets were used. Both datasets contain user statistics (MovieLens-1M includes gender, age, occupation, etc., Tafeng includes consumer ID, age, region, etc.) and commodity attribute information (MovieLens-1M includes movie type, Tafeng includes original ID, subcategory, quantity, price, etc.). Table 2 and Table 3 describe the characteristics of the two data sets, as follows.

**Table 2.** Data set statistics

| data set | user | commodity | interactive |
|---|---|---|---|
| MovieLens-1M | 6060 | 3620 | 1003410 |
| Tafeng | 32690 | 23695 | 952010 |

Tables 4 and 5 describe the data set format, demographic and commodity statistics. The details are as follows.

Based on the above data set, we carried out test analysis on the effect of personalized recommendation of goods. Through analyzing the test results under different recommendation conditions, we evaluated the practical application value of designing personalized recommendation methods for goods on mobile social networks based on user characteristics.

**Table 3.** Format of MovieLens-1M Dataset

| User ID | Item ID | score |
|---|---|---|
| 1 | 1193 | 5 |
| 1 | 662 | 4 |
| 1 | 915 | 3 |
| 1 | 3412 | 5 |
| 2 | 1369 | 3 |

**Table 4.** Tafeng Dataset Format

| parameter | information | | | |
|---|---|---|---|---|
| Consumer ID | 1 | 1 | 1 | 1 |
| Age | K | K | K | K |
| region | E | E | E | E |
| Subclass ID | 5059 | 6230 | 4789 | 7266 |
| Commodity classification | 100312 | 1102649 | 12036 | 100349 |
| number | 1 | 2 | 2 | 1 |
| cost | 194 | 142 | 79 | 46 |
| selling price | 20 | 131 | 50 | 100 |

**Table 5.** Demographic information format of MovieLens-1M data set

| User ID | Gender | Age | occupation |
|---|---|---|---|
| 1 | F | 1 | 10 |
| 2 | M | 56 | 16 |
| 3 | M | 25 | 15 |
| 4 | M | 46 | 7 |
| 5 | F | 52 | 9 |

### 3.3 Test Scheme Settings

While comparing the overall model of EACoupledCF in this paper, this paper further divides into three models: DCCF (only considering the implicit feedback part), i-EACoupledCF (local EACoupledCF, considering the local coupling of spatial CNN and implicit feedback part), and g-EACoupledCF (global EACoupledCF, considering the global coupling of spatial CNN and implicit feedback part). The classic comparison models of commodity recommendation: NeuMF, DeepCF, Wide&Deep and CoupeCF, and two new research models DeepICF and UCC-OCCF will be used to conduct comparative experiments with the recommendation methods proposed in this paper.

In the stage of setting evaluation indicators for recommendation results, this paper uses the widely used leave one out performance verification to evaluate all comparison methods. Randomly select one user's interaction with the product as the test item for each user, and the rest of the interactions as the training data. In addition, 99 commodities not in the user's commodity interaction set are randomly selected to form the user's test data together with the above selected test commodities. This model evaluates the performance by ranking 100 products of each user. Hit rate using Top-K ($HR@K$), average reciprocal ranking (MRR@K) and normalized discounted cumulative income $NDCG@K$) as an evaluation indicator. $HR@K$ it is a recall based metric, which is used to measure whether the test item is before all items in the test set $K$ bit. MRR@K and $NDCG@K$ it is a weighted index, which is used to assign higher scores to the highest ranked goods in the given recommendation list. Among them, hit rate is an indicator to measure recall rate in Top-K recommendation, and its specific calculation method can be expressed as

$$HR@K = \frac{\#hits@K}{|GT|} \tag{14}$$

Among them, $|GT|$ is the total number of test sets, $\#hits@K$ indicates the total number of test sets in the Top-K recommendation list of each user.

Normalized Discounted Cumulative Gain is an indicator to evaluate the sorting results, which is used to evaluate the accuracy of sorting. It is usually used to indicate the gap between the recommended sorting list and the user's real interaction list.

$$NDCG@K = Z_k \sum\nolimits_{i=1}^{k} \frac{2^{rel_i} - 1}{\log_2(i+1)} \tag{15}$$

Among them, $rel_i$ represents the $i$ the "grade relevance" score of commodities in three locations, generally speaking $rel_i \in \{0, 1\}$. That is, if the goods at this location are in the test set, then $rel_i$ is 1, otherwise it is 0. $Z_k$ is the normalization coefficient, which is used to represent the reciprocal of the sum of the subsequent summation formula in the best case.

## 4 Results and Analysis

Figure 2 and Fig. 3 show that in the scenario where only implicit feedback data is considered, this paper designs a recommended method to HR@10, NDCG@10 and MRR@10 Compared with the baseline methods DeepCF, NeuMF and DeepICF, the effect of.

It can be seen from the comparative experimental data in Fig. 2 and Fig. 3 that the personalized recommendation method of mobile social network products designed in this paper based on user characteristics only considers the implicit feedback dataHR@10, NDCG@10 and MRR@10. The performance under the indicators is better than the baseline DeepCF, NeuMF and DeepICF models:

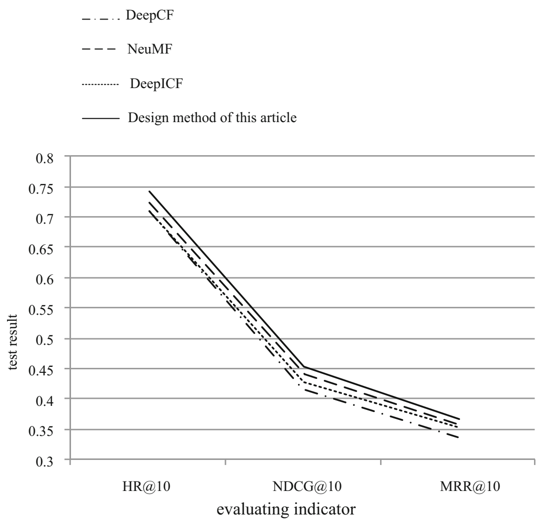


**Fig. 2.** Effect improvement on MovieLens-1M (only implicit feedback data is considered)

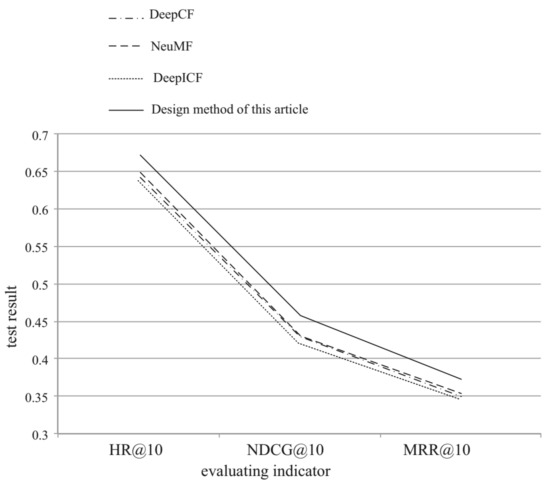


**Fig. 3.** Effect improvement on Tafeng (only implicit feedback data is considered)

(1) Compared with DeepCF on the MovieLens-1M dataset, the three indicators increased by 4.5% respectively 54%, 7.21%, 6.86%; Compared with NeuMF, it increased by 2.60%, 2.61% and 2.75% respectively; Compared with DeepICF, it has increased by 4.07%, 6.47% and 3.81% respectively.
(2) On Tafeng dataset, compared with the baseline DeepCF, the method in this paper achieves 4.65%, 6.74% and 5.56% on three indicators respectively; Compared with NeuMF, it has increased by 3.60%, 6.37% and 5.44% respectively; Compared with DeepICF, it increased by 4.83%, 8.10% and 6.47% respectively. These results show that the personalized recommendation method based on user characteristics can

achieve better performance improvement on the two datasets in comparison with the recommendation methods that directly use implicit feedback information.

Figure 4 and Fig. 5 show the effect improvement under the scenario of considering both explicit attributes of users and goods and implicit feedback data.

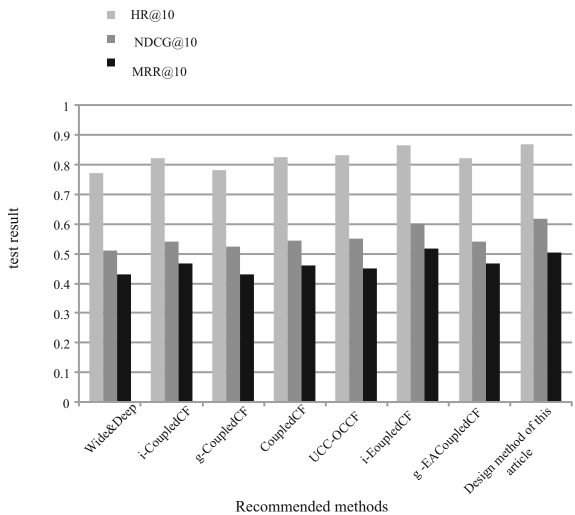


**Fig. 4.** Effect improvement on MovieLens-1M (considering both explicit attributes and implicit feedback data)

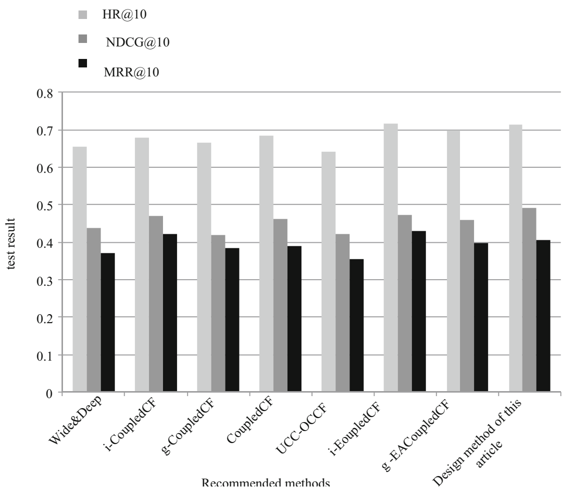


**Fig. 5.** Effect improvement on Tafeng (considering both explicit attributes and implicit feedback data)

It can be seen from the comparative experimental data in Fig. 4 and Fig. 5 that the personalized recommendation method for mobile social network products designed in this paper based on user characteristics has also improved under the three indicators compared with CoupledCF, Wide&Deep, and UCC-OCCF in the scenario of considering both the explicit attributes and implicit feedback data of users and products:

(1) On the MovieLens-1M dataset, it can be seen from the data that whether it is a local i-EACoupledCF model (CNN considering local explicit coupling relationships combined with DCCF, local EACoupledCF) or a global g-EACoupledCF model (CNN considering global explicit coupling relationships combined with DCCF, global EACoupledCF). As well as the overall model effect of local+global combination, it is significantly better than the three baseline methods (where the g-EACoupledCFHR@10. Its performance is basically the same as that of UCC-OCCF). For HR@10 indicators, i-EACoupledCF increased by 5.27%, 12.17% and 3.97% respectively; G-EACoupledCF increased by 6.64%, 8.29% and 6.04% respectively; The evaluation index of the recommended results of the recommended method designed in this paper increased by 5.19%, 12.62% and 4.39% respectively. ForNDCG@10 indicators, i-EACoupledCF increased by 11.19%, 17.60% and 9.39% respectively; G-EACoupledCF increased by 9.82%, 12.81% and 4.93% respectively; The overall model EACoupledCF increased by 13.71%, 20.99% and 12.53%. For MRR@10 indicators, i-EACoupledCF increased by 10.65%, 19.82% and 14.38% respectively; G-EACoupledCF increased by 14.32%, 13.90% and 8.73% respectively; The evaluation index of the recommended results of the recommended method designed in this paper increased by 9.80%, 17.29% and 11.96% respectively.
(2) It can be seen from the data that the performance of UCC-OCCF on the MovieLens-1M dataset is basically close to the evaluation indicators of the recommended results of the recommended methods designed in this paper, but on the Tafeng data, the three indicators of the UCC-OCCF model perform poorly, even not up to the level of the NeuMF model that only applies to implicit feedback data. Compared with the baseline, the evaluation index of the recommendation results of the recommended method designed in this paper has basically improved by more than 5%, 10%, and 10% in three aspects, which fully shows the adaptability of the recommended method designed in this paper to Tafeng dataset, and also shows that the personalized recommendation method of mobile social network products based on user characteristics proposed in this paper has better generalization ability.

Based on the above test results, it can be concluded that the personalized recommendation method of mobile social network products designed in this paper based on user characteristics can effectively ensure that the final recommendation effect can meet the objective needs of users, and has good practical application value for actual online product marketing.

## 5 Conclusion

According to the statistics of the report of China Internet Information Center, the current domestic network service penetration rate has reached more than 70%, and the Internet users on the mobile application end use short videos, shopping and other applications more than a quarter of the time every day. The market share of mobile e-commerce has increased significantly. It can be seen that the e-commerce platform has become more and more popular with the development of the Internet by virtue of its convenience, online comparison, wide range of choices, price concessions and many other advantages. Electronic commerce has greatly changed people's lives and integrated into all aspects of people's lives. How to better improve the service according to the feedback of users, and recommend products according to the interests of users, thus improving the revenue of businesses and user experience, has become a very important issue for businesses and users. In order to improve the user experience, e-commerce platforms generally provide the function of commodity reviews. The user reviews that follow are not only the most intuitive expressions of users' views, but also make communication between different users more convenient. Accurately extracting users' interests and preferences from users' purchase behavior and comments has gradually become the key to product recommendation. However, the traditional methods have the problems of low Top-10 hit rate of recommended products, low Mean reciprocal rank and low cumulative benefits of standardized discount. Therefore, this paper proposes personalized recommendation research on mobile social network products based on user characteristics, in order to greatly improve the satisfaction of users with recommended products. The experimental results show that, in various scenarios, the Top-10 hit rate, Mean reciprocal rank and normalized discount cumulative income of the products recommended by the design recommendation method are better than the comparison method, which fully solves the problems existing in the traditional methods, indicating that the design recommendation method has higher accuracy, personalization and commercial value, and has a positive impact on the performance of the recommendation algorithm and user satisfaction. The future research directions for personalized recommendation of mobile social network products include social relationship modeling, multi-source data fusion, user privacy protection, real-time recommendation and dynamic adaptation, user interaction and participation, and cross platform recommendation. These research directions will further improve the accuracy, degree of personalization, and user satisfaction of personalized recommendation of mobile social network products.

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