Retraction

Retracted: Interaction Design of Educational App Based on Collaborative Filtering Recommendation

Advances in Meteorology

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Xu, T. Neo, and H. Hew Soon, "Interaction Design of Educational App Based on Collaborative Filtering Recommendation," *Advances in Meteorology*, vol. 2022, Article ID 7768730, 8 pages, 2022.

Research Article

Interaction Design of Educational App Based on Collaborative Filtering Recommendation

Ying Xu [id],[1,2] Tse-Kian Neo,[1] and Hin Hew Soon[1]

[1]*Faculty of Creative Multimedia (FCM), Multimedia University, Cyberjaya, Malaysia*
[2]*Hunan International Economics University, Changsha 410205, China*

Correspondence should be addressed to Ying Xu; phoebe_xuy@163.com

With the advent of the 5G digital era, cell phones are becoming ubiquitous in all aspects of our lives, and the increasing demand for remote interaction makes the app interaction experience an indispensable part of our lives. Due to the operational characteristics of gesture interaction in the interface of a smart terminal application (app), this mode of human-computer interaction has become the mainstream mode of human-computer interaction. Educational app is the result of a combination between mobile Internet technology and education, which not only provides a more efficient and convenient method of learning for each subject but also expands the possibilities for teaching each subject through intelligent interaction. On this basis, this paper proposes an educational app design method based on collaborative filtering recommendations and investigates ways to improve the use of mobile apps to create an interactive teaching mode. Simultaneously, this paper combines user activity, item popularity, and time factors to comprehensively measure user visibility of items and incorporates them into the collaborative filtering recommendation algorithm in order to effectively mitigate the effects of data sparsity and user selection bias and improve recommendation results.

1. Introduction

Throughout the last few years, cellphones, as well as touch technology and even hardware interaction, have progressed at an exponential rate. As a result, mobile applications and interpersonal operational relationships have undergone significant transformations. The development trend of mobile has been further enhanced, and the development of smart terminals has grown more diverse, forcing the user interface to begin to demonstrate a greater variety of interaction features in the current increasing development process. In addition, the variety and ecological type of dynamic interaction have increased operational efficiency and so demonstrated significant significance. The development of intelligent terminals has seen a number of technological advancements and developments, the most notable of which is the introduction of the touch screen, which represents a watershed moment in the history of the industry [1–4]. At this point, China has just entered the first stage of the information and intelligent society, and the vast majority of

users are utilizing smartphones, tablet PCs, and other intelligent terminal devices with touch screens as their primary means of communication. Designing interfaces for touch-based educational operations is an important issue in the development and research process of intelligent terminals, and how to improve the efficiency of intelligent terminal applications through gesture design has become the main concern of designers. Designers should abandon the traditional button design and use touch screen gesture design to improve the simplicity of intelligent terminal products and better meet the operational needs of operators to achieve a good user experience. This makes improving the interactivity of smart terminals even more critical in the future [5, 6].

Interaction is a necessary component of all teaching and learning activities, and it is also one of the most critical factors determining the success of those activities. According to the research findings, interactivity is a critical characteristic of the future classroom, and interaction is at the heart of the classroom's design and implementation. The

popularity of mobile terminal devices such as smartphones and iPads has resulted in the development of numerous educational apps that not only are indispensable tools and major platforms for learners' daily learning but also provide strong technical support for interactive teaching reforms across a range of subjects and promote changes and innovations in traditional teaching models [7, 8]. Educators, on the other hand, are confronted with the challenges of how to use mobile devices to expand the traditional learning area and how to develop an interactive model that is continuous and dynamic in order to stimulate students' learning in the way that is expected. Consequently, this research is devoted to developing a diverse intelligent interactive teaching mode using mobile apps, emphasizing the student-centered teaching concept, and developing an interactive teaching mode of autonomy, self-help, and self-assessment to meet the need for English teaching reform in the information age.

Recommended systems, which are becoming increasingly popular in the age of information explosion, play a critical role in alleviating information overload. They have been adopted by many online services, such as e-commerce sites, online news sites, and social media sites, and are a hot research topic in both academia and industry [9–12].

For recommender systems, collaborative filtering (CF) is one of the most commonly used and explored approaches currently available [13, 14]. Users' previous activity data is used to inform CF algorithms, which in turn analyze similarities between user behavior patterns to infer user preferences and create recommendations for them. User behavior data can be divided into two categories: explicit feedback data, such as ratings and reviews, and implicit feedback data, such as purchases, clicks, and other actions [15–19]. The first category includes explicit feedback data, such as ratings and reviews, and the second category includes implicit feedback data, such as purchases and clicks. When explicit feedback data is used in rating prediction scenarios, where missing ratings are projected based on observed rating data, it is referred to as explicit feedback data. TopN suggestions can alternatively be generated by categorizing all items according to their projected ratings and then ranking the results by size [20, 21]. However, it has been pointed out that when only the observable rating data is considered and due to the fact that the data that is not randomly absent is ignored, the recommendation impact is found to be insufficiently strong [22]. Implicit feedback data, on the other hand, takes into account both observable and missing data, and it has been extensively employed in TopN recommendation scenarios [23, 24]. It has the advantage of utilizing all negative preferences implied by missing data, but in comparison to explicit feedback, it lacks the ability to express user preferences openly and cannot convey the degree to which those preferences are held. The interaction design of an educational app based on CF recommendation in this paper also examines how to combine the benefits of implicit feedback and fully utilize missing data in order to improve the existing CF algorithm based on explicit feedback and enable it to be applied effectively to the TopN recommendation scenario [25].

2. Advantages of Mobile Apps

A new sort of information-based teaching tool built on third-party smartphones, tablets, and other mobile devices that can assist learners in learning and teachers in teaching is known as an application (app) programming interface. At the moment, the investigation into the use of mobile applications for educational purposes is growing increasingly wide. In his book Mobile Learning: A Global Perspective, Mike Sharples, an internationally renowned scholar in the field of mobile learning, clearly states that one of the real advantages of mobile learning is related to education, and it can provide support for people to learn various courses through mobile devices, and the future prospect of mobile learning applied to various courses is extremely promising. The following are the advantages of mobile learning in the context of teaching and learning.

2.1. Contextualization of Learning Content. Because of the contextualization feature of mobile apps, they can assist in the formation of learning circumstances as well as human-computer interaction, hence increasing the learning effectiveness. Incorporating context into learning content can assist learners in swiftly achieving the desired learning state, increasing their enjoyment of the process, and creating the illusion that learners are actually present when learning and experiencing the pleasures of learning. For example, many students will find the process of learning English words tedious and difficult to maintain their interest; however, through the use of an app such as Hundred Word Chop, which is designed with the context and relevance of mobile learning in mind, students can practice from visual, auditory, and multidirectional aspects through the situations created by pictures or short videos, making the process of memorizing words somewhat more interesting. The contextual feature of a mobile application is also very useful in the learning of phonetic sounds. For example, English Fun Dubbing app includes the capability of context generation, learners can practice copying a tiny piece of the contextual story by scoring it in real time, and learners can fix the sound training over and over again.

2.2. Intelligence of Data Collection. One of the most prominent manifestations of the intelligence of app can be found in two areas. As a result of this, the app will automatically identify, analyze, and integrate based on the learners' learning levels and study patterns and will push learning contents to students so that they can conveniently access the correct levels for ladder learning. However, one of the benefits of using a mixed learning approach is the opportunity to learn to teach. Teachers can use the intelligent assessment and data collection capabilities of the app to see student assessment data in the background, analyze, process, and categorize them, and then use this information to design secondary teaching and optimize classroom structure based on students' completion situation and weak points, among other things.

2.3. Individualization of One's Learning Style. Traditional classroom instruction is directed at a group of pupils in a single classroom with the same educational aim in mind. Individual differences in learning ability are the most difficult problems that educators and students face in their educational and teaching careers. Because each student's cognitive level, learning capacity, and learning style are unique, it is impossible to overcome this problem by maintaining a regular speed of classroom instruction in the classroom. Students, on the other hand, can adjust their learning progress, set learning goals independently according to their own level, and complete personalized, one-to-one task goals to make up for the shortcomings of traditional teaching through mobile apps, such as English learning apps like Hundred Words, Fluency, and so on.

2.4. The Efficiency of Multidimensional Interaction. Students can inspire deep learning through mutual contact and involvement in a mobile app, which distinguishes it from other types of learning environments. Peer dialogue and instructor interaction are important components of the learning process. Students who are guided by their teachers are more likely to retain and apply what they have learned. Teachers provide timely guidance, and peers communicate with one another to facilitate learning and communication among learners through online interaction. Students can discuss any difficulties they encounter in their independent learning through the mobile app's communication area, and teachers can provide timely guidance to students. Also being multidimensional, the interaction includes interactions between teachers and students, interactions between students, interactions between humans and computers, and interactions between the students themselves and their learning resources. Students' independent and in-depth learning is facilitated by the many types of interaction, which also contribute to the improvement of the effectiveness of learners' learning.

Data sparsity and user selection bias are significant obstacles to the use of explicit feedback mechanisms. In the real world, users tend to rate just a small number of products, with the majority of goods receiving no ratings at all. As a result, it is difficult for the model to accurately learn about the true preferences of users. More importantly, the rating data is vulnerable to user selection bias, which means that users are more likely to select products that would provide them with high satisfaction while ignoring ones that will provide them with low satisfaction. In other words, rating data is not missing at random; rather, it is the product of users' free choice to not provide them. Accordingly, most available rating data is overrated, with just a small amount of data being underrated, as demonstrated by the distribution of ratings in the dataset utilized in this work. As an alternative, research has revealed that, in the actual world, users are generally only interested in a tiny percentage of available options and that most available options are in fact boring or ineffective. That is, due to user selection bias, the accessible rating data do not represent a representative sample of all item ratings, and many things that may reveal users' negative preferences are underutilized as a result of a lack of ratings.

2.5. The Limitations of Displaying Feedback Methods. Due to the issues raised previously, the performance of CF algorithms based on explicit feedback is inconsistent in two scenarios: rating prediction and TopN suggestion. Not all algorithms that perform well in the rating prediction scenario will also perform well in the TopN recommendation scenario. According to some researchers, the primary distinction between these two scenarios is the quantity of training and testing data considered. As previously stated, rating prediction scenarios are only applicable to observed ratings, and current research prefers to predict only the items that users have actually evaluated in order to calculate the inaccuracy associated with anticipated ratings. On the other hand, TopN recommendation scenarios frequently require the estimation and ranking of all missing ratings. While learning user preferences solely from observed rating data can improve the accuracy with which real rated items are predicted, observed rating data is not a representative sample of all ratings and is therefore insufficient to accurately forecast all missing ratings in a given situation.

In summary, the existing CF algorithms tend to consider only the observed rating data, ignoring the effects of data sparsity and user selection bias, which makes it difficult to learn users' positive and negative preferences in a balanced way. Additionally, the predicted ratings and rankings of missing items are biased, resulting in poor TopN recommendation results for missing items. As a result, the primary question in this paper's research is how to successfully mine and exploit the user preferences implied by the absence of information.

3. Educational App Interaction Design Based on Collaborative Filtering Recommendation

3.1. Concept of Construction. Interaction is a method of generating relationships and bringing ideas into collision among people. Interactive teaching is a teaching mode developed on the basis of scaffolding theory and primarily applied to language teaching. It is comprised of three components: the teaching subject, the teaching environment, and the interactive relationship, which together form an organic whole of mutual influence and mutual promotion between the three components. Because of the rapid growth of information technology, the mode of contact has also changed in a significant degree as well. The intelligent interactive teaching mode is more conducive to the promotion of teaching activities when an app for mobile devices is used to support it. Teachers and students collaborate to develop bridges that allow them to communicate and negotiate using mobile devices. Interaction between teachers and students is encouraged in interactive classrooms so that teacher-student interaction and student-student interaction take place during every teaching session in order to promote effective learning and to address the issues of inefficient online learning and low participation rates in classroom learning among students. The growing usage of mobile application (app) programming interfaces in learning creates chances for cocreative learning between learners and other learners. Some scholars believe that learning sharing is the highest

form of the teaching and learning process and that the interaction between learners can compensate for the perceived psychological distance between them and increase the social presence of learners, both of which are important for the growth and development of the learners themselves.

3.2. Model Construction.

There are many different types of learning apps available today, including resource-sharing apps such as Learning Pass and Rain Classroom. One type of game is one that focuses on vocabulary learning, such as Hundred Words or Fluency. Learning links inside and outside the classroom are rationally designed to actualize teacher-student engagement, student-student interaction, human-computer interaction, and online and offline multiple interaction models through the complete usage of various types of teaching mobile applications.

3.2.1. Interactive Application Mode.

Students study freely through human-computer interaction, information input, and completion of self-assessment tasks through resource-sharing apps such as Learning Pass and Rain Classroom, which are available for free download from App Store. Teachers place difficult teaching problems in the discussion area and invite students to discuss them, allowing the entire team to participate in the discussion and learning. Teachers should respond quickly to students' opinions and questions, as well as to problems that arise during the discussion and learning. Throughout the entire learning process, students are learning collaboratively, and with the assistance of their classmates and teachers, they are able to break through the learning bottleneck and complete the process of knowledge internalization that has been initiated.

3.2.2. Model for Interactive Practice in a Context-Based Environment.

This technique is defined by the creation of circumstances that pique students' interest while also helping them to attain their learning objectives. The unique application process consists of the following steps: creating a context, discussing the issue, gaining new knowledge, practicing the game, and evaluating and guiding the process. To begin, the teacher creates a situation using the app, which includes videos and visuals related to the topic in order to pique students' interest and increase their attention. After pupils are placed in a specific circumstance, they study and put their newfound information into practice. Students can access learning resources at their own level at any time through the app, practice and test without being constrained by space or time constraints, and completely benefit from the ease of mobile learning in its entirety. This mode enables learners to quickly enter the learning state and to practice repeatedly according to their own level, resulting in the resolution of personalized learning difficulties as they progress. Teachers can also access students' learning data in the background, allowing them to alter their teaching tactics in response to students' learning situations and assist students in solving challenging teaching difficulties in a timely manner.

3.2.3. Task-Based Collaborative Interactive Application Model.

The model's application procedure consists of the following steps: assigning tasks, collaborating in groups, reporting results, and exchanging summaries. The task-based learning mode directs students' attention to achieving specific goals. Each group will collaborate and work together when the teacher assigns learning activities using the app. Once the students accept the tasks, they will collaborate and work together. During this process, members of the group discuss and learn, investigate in depth, formulate conclusions, and report back. Each group has the opportunity to provide feedback through pop-up windows, and the teacher examines and summarizes the reports submitted by the pupils. In the task-based interactive application paradigm, group results reporting is a critical aspect of the process, demonstrating the group's learning through results reporting and completing the process from language input to language output from the task-based interactive application.

3.2.4. Recommended Educational Resources Model Based on Student Characteristics.

On the basis of their specific qualities, students are directed toward appropriate instructional materials. In most cases, preuse preferences are based on the consumers' preferences for exterior qualities of the item that can be obtained without actually using it, such as the movie's genre and the lead actor. It depends on the user's preferences for the item's internal elements, such as the movie storyline, that their postuse preferences would be influenced. Users' preuse preferences determine whether or not they engage with goods, and research conducted by a number of academics has indicated that users tend to rank items higher when their preuse preferences are high. Furthermore, their analysis reveals that ratings in data sources such as MovieLens and Netflix are skewed toward high scores due to user selection bias. In contrast, the majority of evaluations are low in the specially collected Yahoo data that was collected without any selection bias. Additional academic study has also revealed that low ratings are more likely than high ratings to be absent from the observed data, although the reverse is true. As a result, it is straightforward to conclude that objects with low preuse preferences also have low postuse preferences, that is, low ratings, when compared to other items. In contrast, ratings for goods with high preuse preference are overwhelmingly positive, which is consistent with the distribution of ratings in the dataset used in this paper and with the findings of this paper.

In the case of user-rated things, it may be easily deduced that their preuse preference is high because users must have been interested in them at the time of purchase in order to leave ratings. The problem is to accurately deduce the preuse preferences for the missing components from the available information. This is a one-class problem, which means that all of the available rating data are positive examples, and there are no negative samples available. In order to maintain the robustness of the model, this research makes use of learning based on the total data, which was discovered in the prior analysis. WRMF interprets all missing data as negative

samples and applies smaller uniform weights to the missing items because it believes that they have the same confidence level as negative samples; however, this is not compatible with the way data is really collected. In the present Web 2.0 era, many mobile apps offer popular items on their recommendation screens, and this is especially true for social media apps. In general, consumers are more likely to notice popular things than less popular ones. It has been suggested that nonuniform weighting of the missing items should be used based on item popularity. The more popular the items that are easily seen by users without the need for user interaction, the greater the confidence that they are negative samples and therefore should be given higher weights. However, the effects of variances in user characteristics as well as the time factor on popularity were not taken into consideration.

The weight design of current methods based on overall data learning is primarily based on the observation that the greater the likelihood that an item is seen by a user without user interaction, the greater the confidence that it is a negative example and thus the higher the weight assigned to the item. The trick is figuring out how to reliably determine whether or not the item was seen by the user. The present prevalent practice of relying on item popularity to infer the visibility of an item by a user is fraught with uncertainty. In reality, users with varying levels of activity have varying levels of visibility for the item.

The UTVCF algorithm will linearly combine item popularity and user activity during the user's active period to measure the item's point-in-time visibility to the user, with nonuniform weighting for missing items, based on the above analysis. The CF recommendation algorithm will be combined with the UTVCF algorithm in this paper.

First, the original rating matrix $R = (r_{ui})_{m \times n}$ is used to construct the preuse preference matrix $P = (p_{ui})_{m \times n}$. m is the number of users, n is the number of items, and r_{ui} is the rating of item i by user u. All rated items are positive samples, and the preuse preference is set to 1. All missing items are considered negative samples, and the preuse preference is set to 0. The equation is as follows:

$$p_{ui} = \begin{cases} 0, & r_{ui} = \text{null}, \\ 1, & r_{ui} \neq \text{null}. \end{cases} \quad (1)$$

Since the missing items are not all negative samples, we construct a weight matrix $W = (w_{ui})_{m \times n}$ for the scored items, we set their weights $w_{ui} = 1$ for the missing items, their weights represent the confidence that they are negative samples, and $w_{ui} \in (0, 1)$. The higher the weight, the higher the confidence that it is a negative sample.

Define the activity α_u of user u as the number of ratings of this user; that is, $\alpha_u = \sum_{i=1}^{n} p_{ui}$. The rating time is t_{ui}, and we define the active period as $(t_{\min}, t_{\max})$. $t_{\min}$ is the earliest rating time of user u, and $t_{\max}$ is the latest rating time. The prevalence of item β_i for user active period is the number of ratings of item i for time period $(t_{\min}, t_{\max})$; that is, $\beta_i = \sum_{i=1}^{n} p_{ui}$. The smoothing of α_u and β_i using the log function is normalized using the maximum value. Taking

smoothing can smooth out the impact of a few extremely active users or popular items. The formula is as follows:

$$\widehat{\alpha}_u = \frac{\log(\alpha_u)}{\max(\log(\alpha))},$$

$$\widehat{\beta}_i = \frac{\log(\beta_i)}{\max(\log(\beta))}. \quad (2)$$

By weighting $\widehat{\alpha}_u$ and $\widehat{\beta}_i$, we have

$$W_{ui} = \begin{cases} 1, & p_{ui} = 1, \\ \eta\widehat{\alpha}_u + (1 - \eta)\widehat{\beta}_i, & p_{ui} = 0. \end{cases} \quad (3)$$

The object function is as follows:

$$J = \sum_{u=1}^{m} \sum_{i=1}^{n} W_{ui}(p_{ui} - \widehat{r}_{ui}^2). \quad (4)$$

We use the least squares method to optimize the loss function; then, we have

$$\frac{\partial J}{\partial} = -2 \sum_{i=1}^{n} y W_{ui} (p_{ui} - \widehat{r}_{ui}). \quad (5)$$

Then, we have

$$x = \frac{\sum_{i=1}^{n} y W_{ui}\left(p_{ui} - \frac{ui}{r}\right)}{\sum_{i=1}^{n} y^2 W_{ui}},$$

$$y = \frac{\sum_{i=1}^{n} x W_{ui}\left(p_{ui} - \frac{ui}{r}\right)}{\sum_{i=1}^{n} x^2 W_{ui}}. \quad (6)$$

We fill the missing items, and the fill items are calculated as

$$\text{Miss} = \overline{r}_u * \sigma. \quad (7)$$

3.2.5. Problem-Based Inquiry-Based Interactive Application Model.
Students are guided to undertake independent inquiry learning through the use of this model, which is more commonly utilized for initial investigation of knowledge before class and growth of knowledge after class. Through the course of the process, students conduct independent adjustment learning through the use of a mobile application with questions and use the intelligent review function of the mobile application to provide timely feedback on students' learning effect. Teachers only gain an overall understanding of students' learning and provide assistance to students when necessary. Student learning is primarily accomplished through human-computer interaction and inquiry-based learning, which helps them achieve learning objectives and improve knowledge consolidation and transfer over time. Students are the organizers and decision-makers of their own learning in this application mode, and they can use the feedback and evaluation functions of the mobile app to learn once or more times according to their own learning habits and learning styles until they fully master the knowledge and achieve the goal of effective learning.
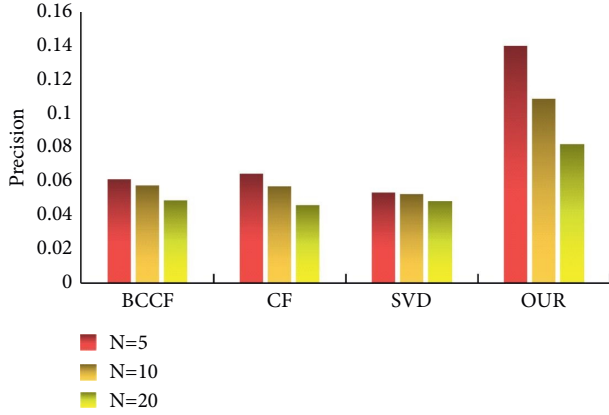
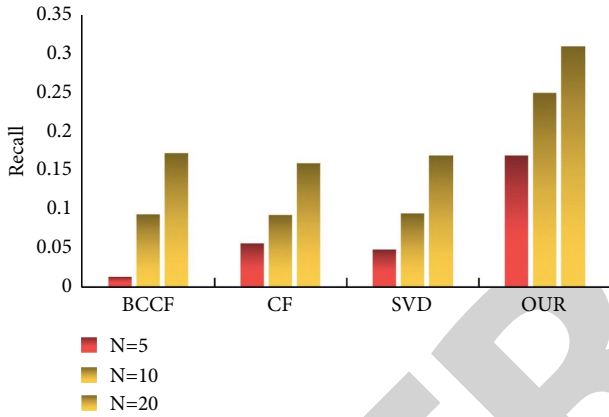Figure 1: Comparison of precision on MovieLens 100 k.

Figure 2: Comparison of recall on MovieLens 100 k.

Figure 3: Comparison of precision on MovieLens latest.

Figure 4: Comparison of recall on MovieLens latest.

4. Experiment Results

In this paper, we use MovieLens 100 k and MovieLens latest datasets, and the judging metrics are precision and recall, which are as follows:

$$\text{precision} = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |R(u)|},$$

$$\text{recall} = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |T(u)|}. \tag{8}$$

The comparison algorithms in this paper are BCCF, CF, and SVD, and the comparison results on the two datasets are shown in Figures 1–4. From the figures, it can be seen that the proposed recommendation method outperforms the BCCF, CF, and SVD algorithms in both metrics on any dataset.

It can be seen that, with the increase of N, various indicators will also increase. The algorithm proposed in this paper has the highest indicators when $N = 5$, $N = 10$, and $N = 20$.

In addition, when the TopN is large ($N = 50$), this paper compares the proposed algorithm with BCCF, CF, and SVD algorithms, and it can be seen that the algorithm in this paper is still optimal even when N is large. Comparison of
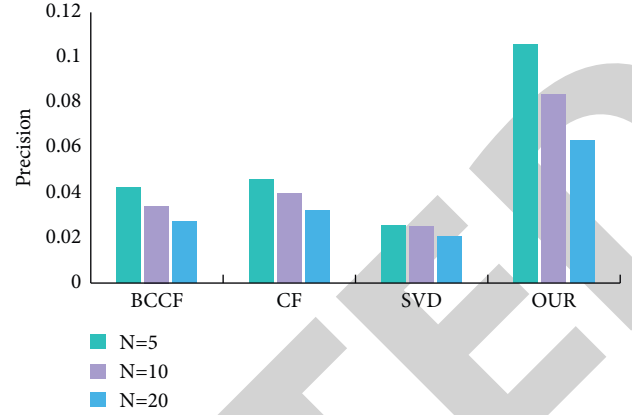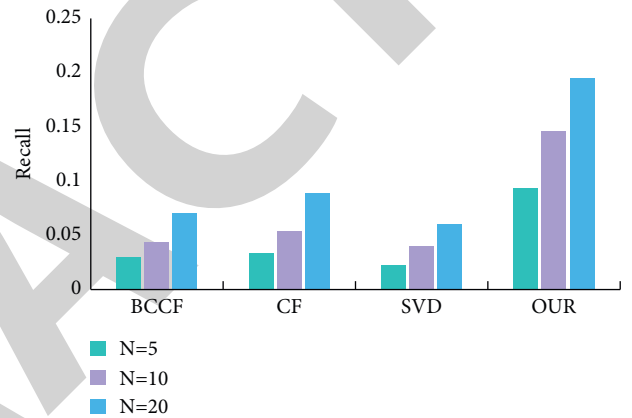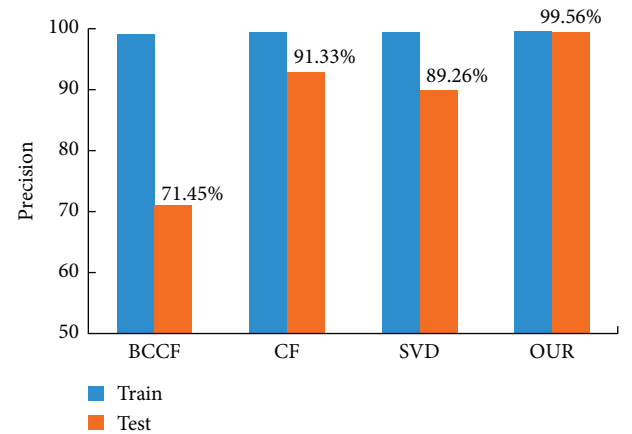

Figure 5: Comparison of precision on MovieLens latest with $N = 50$.

precision on MovieLens latest with $N = 50$ is shown in Figure 5.

5. Conclusion

With the advent of the Internet era, mobile apps are widely used in the education industry. The biggest advantage of mobile apps is that they have interactive functions.

Educational apps are the product of the combination of mobile Internet technology and education, which can provide more efficient and convenient learning methods for each subject. Based on this, this paper proposes an educational app design method based on collaborative filtering recommendations and explores how to make better use of mobile apps to build an interactive teaching model. At the same time, this paper analyzes and demonstrates the impact of data sparsity and user selection bias on its TopN recommendation, aiming at the problem that the collaborative filtering algorithm based on explicit feedback only considers the existing rating data. In view of this problem, a general collaborative filtering recommendation algorithm framework is proposed, which can effectively alleviate the influence of data sparsity and user selection bias and make the recommendation results more accurate.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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