

## *Retraction*

# **Retracted: Algorithmic Application of Evidence Theory in Recommender Systems**

### **Scientific Programming**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] L. Ma, "Algorithmic Application of Evidence Theory in Recommender Systems," *Scientific Programming*, vol. 2022, Article ID 9290577, 11 pages, 2022.

## Research Article

# Algorithmic Application of Evidence Theory in Recommender Systems

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With the development of wireless network and various communication technologies, the information on the Internet is expanding rapidly. The development of wireless network and various communication technologies has promoted the development of e-commerce, and people can understand a large amount of commodity information without leaving home. However, due to the complex information on the network, users need to pass a lot of screening to obtain the information they want, and a large amount of irrelevant information will cause users to consume a large amount of irrelevant information. To solve these problems, the personalized recommendation system is created, but the recommendation system is recommended according to the characteristics of users' interest and shopping behavior. However, users' interests will change, so they need to use other technologies to screen for relevant commodity information. Evidence theory has a strong ability to distinguish between true and false information and to deal with uncertain information. To this end, this article studies the application of the evidence theory in the recommendation system and finds that the evidence theory algorithm can infer the information needed by users based on the uncertain information. Moreover, the experiment in this article proves that the algorithm application of the evidence theory in the recommendation system can well grasp the interests of users and recommend the information needed by users. This improves the efficiency of users to obtain the required information and achieves 80 points for content recommendations.

## 1. Introduction

With the development of the network, the advancement of communication technology, and the strengthening of connections around the world, the amount of information has grown dramatically. With the explosive development of computer technology and Internet technology at home and abroad in recent years, the data and information on the Internet are growing wildly at an unprecedented rate. In this era of information explosion, it is a new and huge challenge for users, media, and businesses. Users spend a lot of time and energy in the massive information; and in order to provide better services to users, merchants need to use the obscure information on the Internet, which is very important for merchants to seek profits. But looking for the information needed in the massive information is like looking for a needle in the sea, and search engines were born.

However, search engines cannot search according to the interests of users, so there will be an automatic recommendation function in search engines. This automatic recommendation feature needs to personalize recommendations with past user habits and search history. However, there is a lot of previous practical information with a lot of uncertainty, so the recommended content does not necessarily meet the information needed by users. Therefore, in order to improve the utilization rate of users and bring higher profits to businesses, more advanced recommendation systems need to have more advanced recommendation system to help search engines recommend information resources that really meet the interests of users in the new district and meet the personalized needs of users.

Recommendation systems have been widely used in the commercial field, and the recommendation system studied in this article can improve the availability of

recommendation information. Especially in the product recommendation used on the online shopping platform, it will be more consistent with users' interests and hobbies, which enhances users' desire to buy and promotes the growth of commercial interests [1]. In the recommendation system, deeply understand the internal principle of the recommendation system, applying the evidence theory algorithm to the recommendation system, improving the accuracy of the recommendation information, expanding the universality of the system, and making the recommendation system better applied to a wider range of scenarios [2]. In addition, it can also save users the time to search for the information, which improves the user experience and ensures that users can get the desired information in the shortest time. In addition, the use of the evidence theory algorithm in the recommendation system in this article can improve the efficiency of distinguishing the true and false information and improve the user's experience.

At present, the foreign wine that combines the evidence theory and the recommendation system is still in the development stage, and there are many research studies on the recommendation system. Among them, Ha et al. demonstrated the development of an evidence-based material recommendation system (ERS) that employs the Dempster-Shafer theory. To evaluate the recommendation ability of ERS, it was compared with that of recommendation systems based on matrix factorization and supervised learning. A k-fold cross-validation on the dataset showed that ERS outperforms all competitors [3]. However, their research has no specific practical process, and it is difficult to explain the feasibility of the recommender system. Cui studied data mining based on an intelligent recommender system. He first modeled the evidence theory for the intelligent recommendation system based on association rules. The experiments showed that the algorithm of the system has a fast convergence speed and can recommend products that are more in line with user needs and interests, which increases the click rate and purchase rate, and further improves user satisfaction [4]. His research was not supported by concrete data and was unconvincing. Cui's description based on user interest is an important problem for recommender system input, and the fuzzy set theory is proposed to solve this problem. This research laid a theoretical foundation for the study of the uncertainty theory and also finds a new application background for the study of fuzzy sets [5]. Although his research is supported by theoretical basis, it has not been experimentally verified. Dong and Kuang proposed an information aggregation-based SAR image target recognition method based on the Dempster-Shafer (DS) evidence theory. He proposed a classification framework for information aggregation by using a new multidimensional analysis signal-single-gene signal, which the experimental results proved can be used to define probability mass [6]. His research has no strong theoretical support and lacks theoreticality. Li and Wang proposed a green supplier assessment method based on rough ANP and evidence theory for the uncertainty and incompleteness in green supplier assessment. He used the confidence interval

to evaluate green suppliers based on the evidence theory, and verified the feasibility and effectiveness of the method through the application of bearing cage supplier evaluation [7]. His research does not clearly address rough ANP. Based on previous studies, the article will conduct in-depth research on the evidence theory and recommender systems according to the shortcomings of their research.

In this article, the research on the algorithm application of the evidence theory in recommender systems has the following innovations: (1) this article innovates the identification framework in the evidence theory to improve the credibility of the evidence in the evidence theory, so that it can recommend more reliable items in the recommendation system. (2) The evidence theory algorithm is introduced to the recommendation algorithm in the recommendation system, which provides the recommendation system with the function of distinguishing the true and false recommendation information, and improves the user's efficiency in finding information and the satisfaction of using the recommendation system. (3) And the recommendation system studied in this article can use evidence theory to identify the authenticity of information and recommend it to users, which improves the security of users using network information.

## 2. Method of Algorithm Application of Evidence Theory in Recommender System

*2.1. Algorithmic Applications of Evidence Theory.* Evidence theory is a classical probability theory, that is, an extension of the branch of mathematics that studies the quantitative laws of random phenomena. It establishes a one-to-one correspondence between propositions and sets, and transforms the uncertain problem of propositions into uncertain problems of sets [8]. The evidence theory is widely used in the field of artificial intelligence and has gradually developed into a class of important uncertainty reasoning methods, which can be used for object detection, classification, and recognition. The D-S evidence theory is a commonly used fusion algorithm in target recognition [9]. Assuming that there is currently an evidence that needs to be identified urgently; that is to say, this evidence needs to be identified within an identification framework, and the identification framework is defined as

$$\Xi = \{e_1, e_2, e_3, \dots, e_n\}. \quad (1)$$

The elements in this recognition frame are mutually exclusive, and only one of all possible evidences to be identified is correct, and the set of all subsets in the recognition frame can be expressed as

$$\Xi_2 = \{\emptyset, \{e_1\}, \{e_2\}, \dots, \{e_1, e_2\}, \dots, \{e_1, e_2, \dots, e_n\}\}. \quad (2)$$

The problem to be identified is in the above set, and the evidence theory can combine all subsets of the set with the identified problem, find the subset that is most likely to be close to the identified problem, and display it [10]. Among the many subsets, the basic probability distribution function

is the basis; that is to say, all the subsets in the set may have a certain probability relationship with the evidence to be identified. There are two evidences  $W1$  and  $W2$ , and the corresponding distribution subsets are  $e1$  and  $e2$ , and then, the distribution functions for the evidences are  $Q1$  and  $Q2$ . The function distribution probability and composition rule of evidence  $W$  are shown in Figure 1.

In Figure 1, the synthesis rule synthesis represents the total subset trust, the horizontal axis represents the trust value of the evidence  $Q2$  assigned to each subset set, and the vertical axis is the evidence  $Q1$  assigned to each subset set. The subsets identified by different evidences are not the same, and then, when there are two sources of evidence, the subset composition rule of the evidence theory is as follows:

$$Q(e) = Q_1 \oplus Q_2 = \frac{\sum_{R \cap S = A} Q_1(R)Q_2(S)}{1 - L}, \quad (3)$$

$$L = \sum_{R \cap S = \varnothing} Q_1(R)Q_2(S),$$

where  $K$  is the conflict factor in the evidence synthesis rule, which reflects the degree of conflict between the two evidences  $Q1$  and  $Q2$ . The conflict between the two evidences can be normalized, so the trust value  $\sum_{R \cap S = \varnothing} Q_1(R)Q_2(S)$  in the empty set can be removed from the trust value in the total set, so that the identified information is more accurate. However, if the trust degree of the empty set is removed, the sum of the trust degree will not be one, so the coefficient  $\nu$  needs to be added. The formula for obtaining this coefficient is

$$\nu = \left[ 1 - \sum_{B \cap C = \varnothing} Q_1(R)Q_2(S) \right]^{-1}. \quad (4)$$

With the addition of the coefficient  $\nu$ , the sum of the trust degrees can be kept at 1. Therefore, when the conflict factor  $k=1$ , it means that there is a very strong conflict between the two evidences  $Q1$  and  $Q2$ , so that the required information cannot be identified. Conversely, if the value of the conflict factor is not equal to 1, a new assignment probability will be generated, thereby identifying the desired information. So when there are multiple evidences to be combined, the rules of the combination are as follows:

$$Q(e) = Q_1 \oplus Q_2 \oplus \dots \oplus Q_n,$$

$$Q_1 \oplus Q_2 \oplus \dots \oplus Q_n = \frac{\sum_{R \cap R_1 \cap \dots \cap R_n} Q_1(e_1)Q_2(e_2) \dots Q_n(e_n)}{1 - K}. \quad (5)$$

The calculation method of the conflict factor  $K$  is

$$K = \sum_{R \cap R_1 \cap \dots \cap R_n} Q_1(e_1)Q_2(e_2) \dots Q_n(e_n). \quad (6)$$

Then, the formula for calculating the coefficient  $\nu$  under multiple evidences is

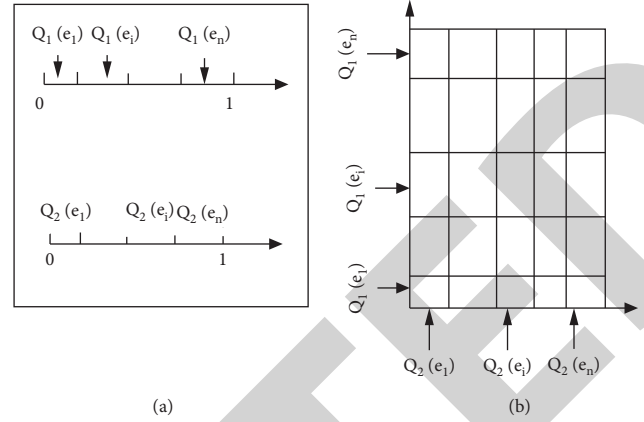


FIGURE 1: Function assignment probabilities and composition rules. (a) Basic probability distribution. (b) The synthesis rules.

$$\nu = \left[ 1 - \sum_{R \cap R_1 \cap \dots \cap R_n} Q_1(R)Q_2(R_1) \dots Q_n(R_n) \right]. \quad (7)$$

To form a recognition framework, the evidence theory fusion algorithm needs to fuse all the information. The evidence theory information fusion process is shown in Figure 2.

It uses sensing devices to perceive things in the outside world and then convert the perceived things into data information and fuse them into the database. By using sensors to fuse all the information into the database, the evidence theory algorithm can have information data to generate a set and then identify the required information [11]. And the evidence theory belongs to the category of artificial intelligence, which has a strong ability to process uncertain information. Just like a person's hobbies are very extensive, so people's hobbies have strong uncertainty. And how to recommend personalized information based on uncertain hobbies, we can use the evidence theory to deal with people's hobbies, integrate information from personal historical hobby data, and then judge personal hobbies. However, the evidence theory needs to specify a reasonable application category in order to have accurate performance. Therefore, what this article studies is the application of evidence theory in recommender systems [12].

**2.2. Recommendation System.** With the development of modern communication technology, there is more and more information on the Internet: due to the booming development of the Internet, people can obtain all kinds of information on the Internet: people can learn about major events at home and abroad without leaving home; people can get the latest news on the Internet without subscribing to newspapers; people can complete all shopping without even going to the mall [13]. However, due to the rapid development of the network, the information growth is too fast, making another big problem. Because of the huge amount of information, it is difficult for people to find the letters they need instantly and quickly. At the same time, false

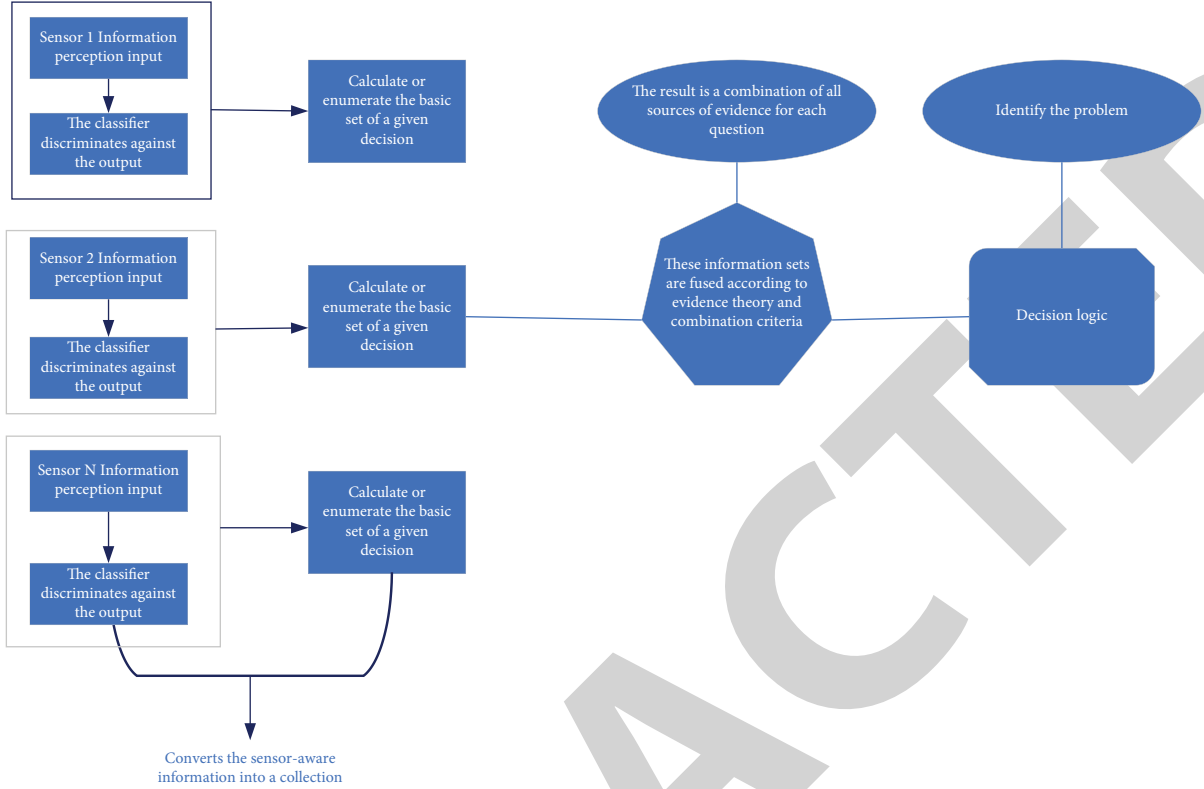


FIGURE 2: Process diagram of evidence theory information fusion.

information is also flooding the Internet, making it difficult for people to distinguish the true and false information. This is the problem of “information overload” currently faced by the Internet [14]. “Information overload” refers to a situation in which social information exceeds the range of individuals or systems that can be accepted, processed, or effectively utilized, leading to failures. For this reason, with the development of science and technology and the problems exposed by the current network, the recommendation system is also used. The recommender system is a software tool and information filtering technology, which can find items of interest to users from massive information [15]. Of course, the reason why the recommender system can mine and analyze the user’s hobbies and generate recommendations is because the recommender system also belongs to the category of artificial intelligence [16]. The recommender system can actively use the technology of machine learning to mine the interests and preferences of users, so as to filter the content that meets the interests of users from the massive information data according to the interests of users, and recommend them to users [17]. The recommendation system can generally be divided into four levels: data collection, user modeling, recommendation algorithm, and recommendation output. The model of the recommendation system is shown in Figure 3.

There is a huge amount of information on the Internet, and it is full of various false information, which leads to a certain degree of inauthenticity of the recommended items by the recommendation system. The recommendation algorithm determines the quality of the recommended content

in the recommendation system. The push algorithm can learn by setting algorithm goals according to the collected user information and the established user model, and calculate the recommendation result for a specific user [18]. Current recommendation algorithms include content-based recommendation algorithms, collaborative filtering algorithms, and user-feature-based filtering algorithms [19]. The content-based filtering algorithm considers the similarity between item information and user preferences, and recommends items with high similarity to users. The content-based recommendation algorithm first analyzes the content and analyzes the key content from the original item as a feature, and the user’s hobbies may be similar to the key content of the item, so as to push it to the user.

The collaborative filtering algorithm predicts the user’s rating or recommends an unknown item through the rating matrix. Similarity calculation is used to find the degree of similarity between each pair of users, where similarity indicates that two people have similar tastes in the overall project.

Supposing that  $S$  is used to represent the similarity between users  $m$  and  $n$ ,  $t_i$  is used to represent the rating of user  $m$  for the  $i$ th item and  $f_i$  is used to represent the rating of user  $n$  for the  $i$ th item. And  $e$  is the average rating of user  $m$  for all items,  $q$  is the average rating of user  $n$  for all items, and then, the Pearson similarity between the two is calculated as follows:

$$S = \frac{\sum_{i \in k} (t_i - e)(f_i - q)}{\sqrt{\sum_{i \in k} (t_i - e)^2} * \sqrt{\sum_{i \in l} (f_i - q)^2}}. \quad (8)$$

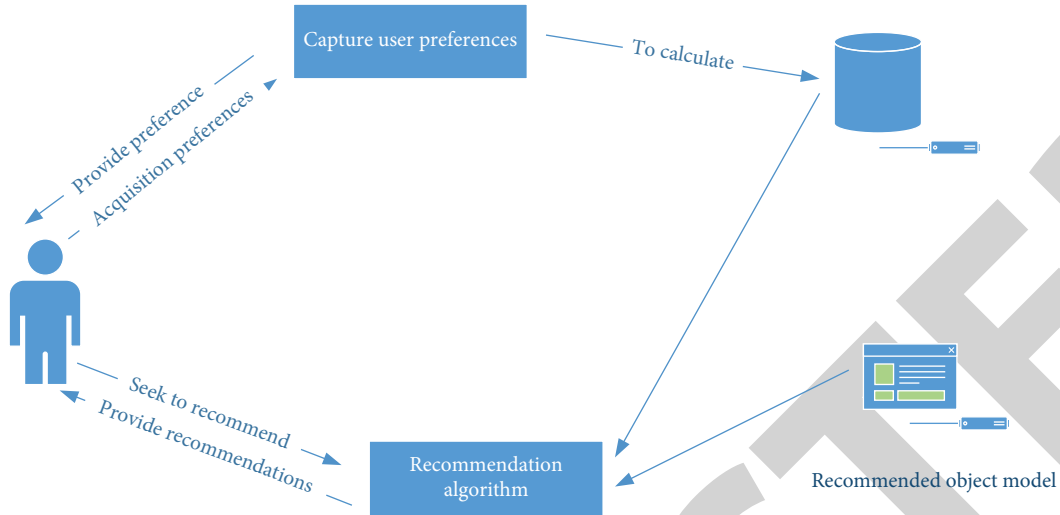


FIGURE 3: Model of a recommender system.

And if it is to find the cosine similarity of two people, the formula is as follows:

$$S = \cos(\vec{m}, \vec{n}) = \frac{\vec{m} \cdot \vec{n}}{\|\vec{m}\| \cdot \|\vec{n}\|}. \quad (9)$$

To calculate the cosine similarity between two people, it is necessary to convert the ratings of the two users into a score vector. Similarity calculation is the first step and the most important step in model-based collaborative filtering. Reasonable selection of application similarity according to application scenarios can ensure the accuracy of recommendation. By calculating the similarity, it is only to compare the degree of fit between the interests and hobbies of the users. And how to recommend items of interest to users based on similarity requires an estimated score for all items to be recommended. The predicted score  $R$  is generally calculated using the following formula:

$$R_m = t_i + \frac{\sum_{i \in k} (t_i - e) * S}{\sum_{i \in k} |S|}, \quad (10)$$

where  $k$  is the subset of items rated by people with similar interests to user  $m$ . The higher the similarity, the higher the score for the prediction. The higher the score, the more the items recommended to the user are in line with the user's interests. The algorithm recommendation process is shown in Figure 4.

However, there is a lot of information on the Internet and it is difficult to distinguish between true and false, so the information recommended by the recommendation system is difficult to distinguish between true and false and there is still a certain degree of inaccuracy. Therefore, this article combines it with the evidence theory algorithm to judge the authenticity of the recommendation information to make up for the deficiencies of the current recommendation system.

**2.3. Algorithm Application of Evidence Theory in Recommendation System.** There is a huge amount of information on the Internet, including videos, music, merchandise,

and more. The current recommendation system is still difficult to grasp the user's new area hobbies, so the recommended content may not conform to the user's personal interests and hobbies. Sometimes, it is difficult to distinguish the authenticity of the recommended information, which will still cause some trouble to users [20]. Therefore, this article fuses the multisource information in the recommendation system according to the evidence theory and summarizes it into a set of items through information fusion. The recommendation system is connected to the database on the network. Because to recommend information to users, the recommender system must be connected with the database in the Internet, so that it can have enough capital to recommend relevant information to users [21]. Therefore, the recommendation process of the recommendation system based on evidence theory is shown in Figure 5.

The evidence theory can improve the efficiency of information identification in recommendation systems and can integrate massive information and user interests in recommendation systems. Finally, the authenticity of the requested recommendation information is verified through evidence, and then, it is recommended to users in need through the recommendation system [22]. The principle of interest and item fusion of the evidence theory in recommender systems is based on the evidence theory algorithm. First of all, the evidence theory combines items from multiple sources into a set  $u$ , and the elements in  $u$  are different; that is to say, the items in  $u$  are divided into different categories. For example, some are video items, some are music items, and some are commodity items. Therefore, assuming that there are  $n$  subsets in  $u$ , and the hobbies provided by the user are  $k$ , the principle of the evidence theory algorithm to integrate user hobbies and items is as follows:

$$x = \{\{u_1 * k\}, \{u_2 * k\}, \dots, \{u_n * k\}\} \otimes \frac{n}{k}. \quad (11)$$

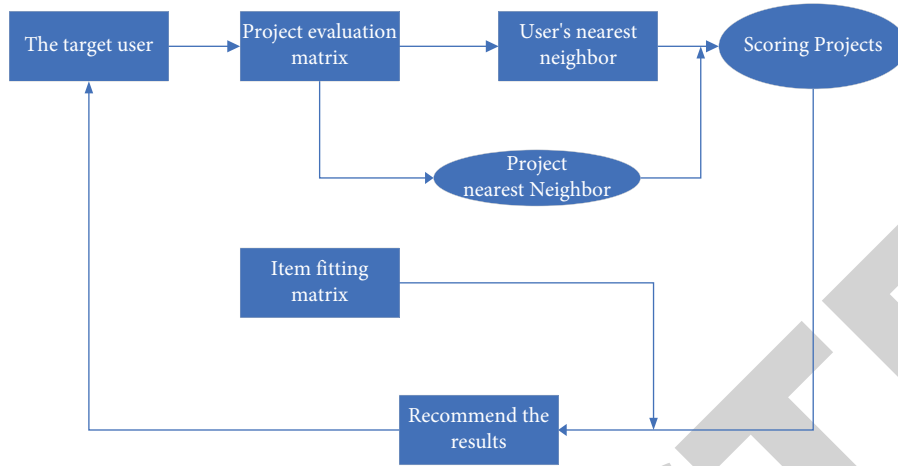


FIGURE 4: Flowchart of algorithm recommendation.

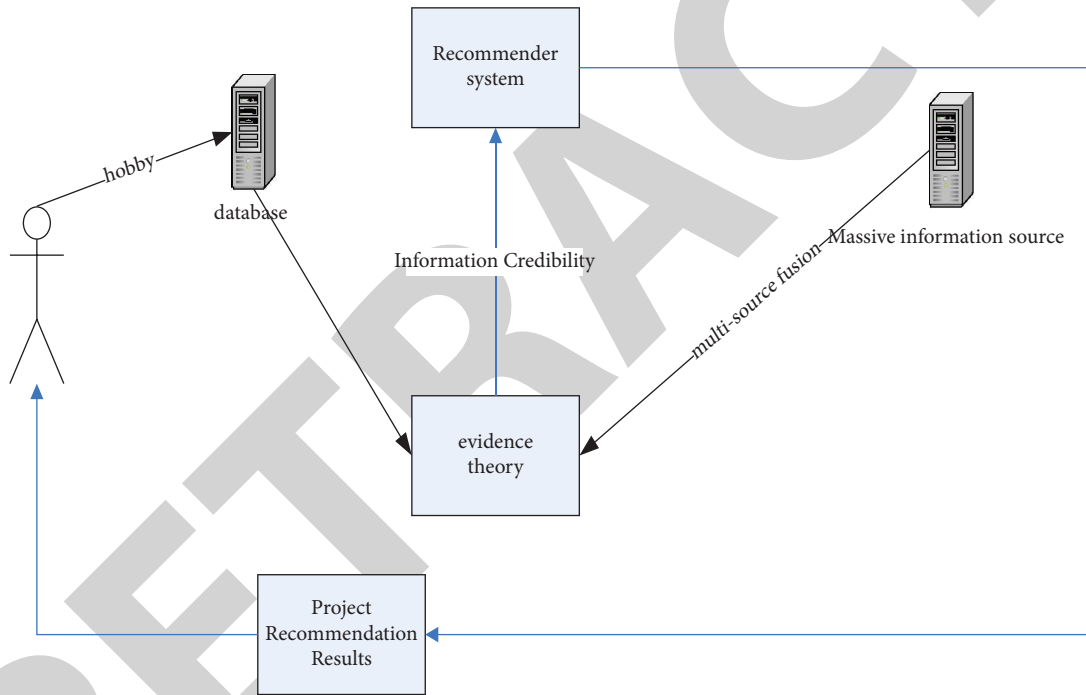


FIGURE 5: Recommendation flowchart of the new recommendation system.

Then in the above formula,  $x$  is the set of newly fused item subsets. The item integrates the user's interests and hobbies, and finds out the items that the specific user is interested in. Then, the set of subsets in  $x$  can be expressed as

$$x = \{\{x_1\}, \{x_1x_2, x_2\}, \dots, \{x_nx_{n+1}, x_{n+1}\}\}. \quad (12)$$

Then, the authenticity of the item is verified according to the joint rules under multiple evidences, helping users to distinguish the authenticity of the information. After that, the recommendation algorithm inside the recommendation system will make recommendations again based on the user's interests and hobbies according to the set summarized

by the evidence theory algorithm, and then, it integrates the items of user interest and recommends according to the user similarity according to the evidence algorithm. The principle is as follows:

$$s = \cos(\vec{v}, \vec{b}) = \frac{\vec{v} \cdot \vec{b}}{\|\vec{v}\| \|\vec{b}\|} \otimes k, \quad (13)$$

$$Q = \frac{\sum_k^n s \cdot v}{\sum_k^n s \cdot b} \otimes x,$$

where  $v$  and  $b$  represent two users, and  $Q$  is the recommended item, so the new recommendation system can well

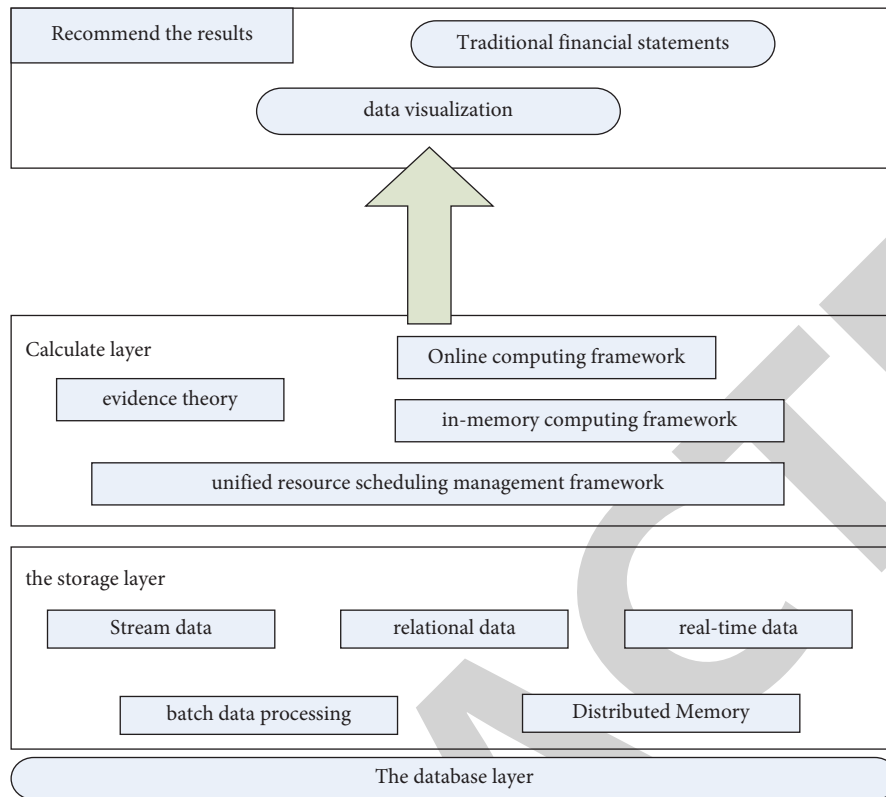


FIGURE 6: Overall architecture of the new recommender system.

recommend the item information that meets the user's hobbies and needs at the time. The overall architecture of the new recommendation system is shown in Figure 6.

The recommendation result layer serves as the front-end display page for user interaction, which is specifically represented in the form of a web page. Its main function is to provide users with more comprehensive recommendation services based on the results of recommendation calculations and to provide more accurate project information services for users to obtain the information they want. The computing layer calculates the items that the user is interested in according to the information resources recorded in the user data layer and the user's hobbies, and then scores, and pushes the item with the highest score to the recommendation layer [23]. What is stored in the data layer is the item information in the network and the historical information records that users have applied to the network search in the past, which is the basis of the entire recommendation system. Therefore, in order to ensure the performance and feasibility of this recommender system, this article also conducts experimental verification on this new type of recommender system.

### 3. Experiments on the Application of Evidence Theory in Recommender Systems

**3.1. Performance Test of the New Recommender System.** This experiment will use a browser as the object that has three different dataset interfaces. At the same time, three different recommender systems are used for this browser.

These three recommender systems are the new system constructed in this article, the recommender system based on the content algorithm and the recommender system based on the collaborative filtering algorithm. In order to better verify the performance of the system in this article, the details of the three data information collection by the browser are counted in this experiment, as shown in Table 1.

It can be seen from Table 1 that the number of users of each dataset interface is different, so this experiment measures the efficiency performance and credibility value under different values of conflict factor  $k$ . Its efficiency performance comparison is shown in Figure 7.

From Figure 7(a), when the value of the conflict factor is larger, the performance of the recommender system does not increase with the larger value of the conflict factor, but fluctuates. And the efficiency of the new system is larger than that of the content-based system and the collaborative filtering recommendation system, its maximum performance can reach 0.986, while the maximum performance of the other two recommender systems only reaches 0.878, which shows that the efficiency and performance of the new system will be better. From Figure 7(b), the credibility of the new system is above 80%, while the credibility of the other two systems is below 80%, so the credibility of the new system will be higher. In addition, this experiment also calculated the accuracy of the content recommended by the three recommendation systems in the browser and recorded the accuracy data of the three systems in each dataset interface, as shown in Table 2.



TABLE 1: Dataset information.

Dataset	User quantity	Number of items	Number of scores	Sparsity (%)
1	1879	45676	576789	6.567
2	6547	56544	790687	5.7689
3	52725	78987	689787	8.7789

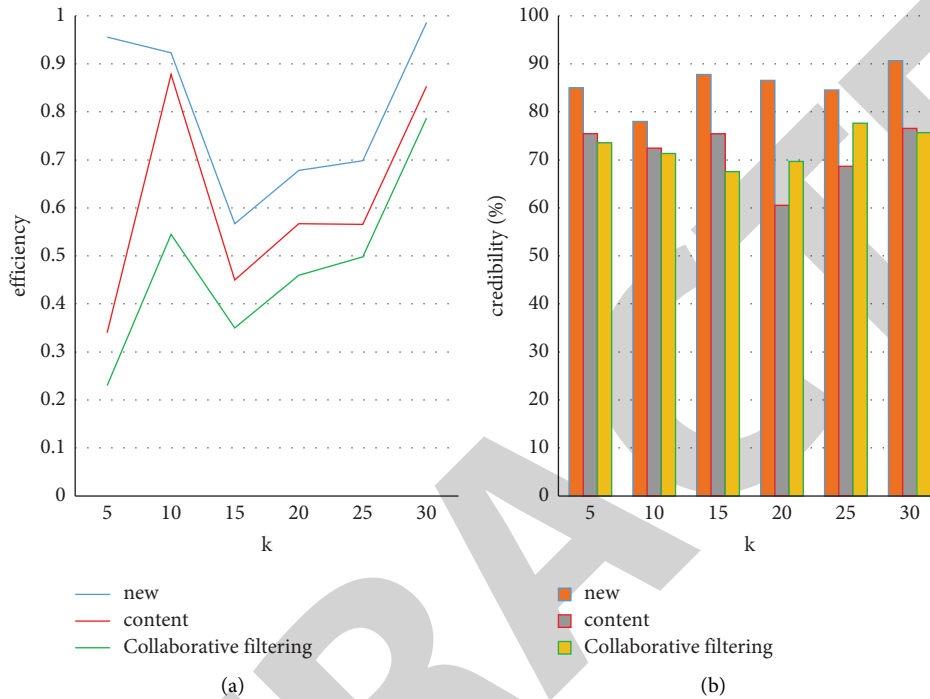


FIGURE 7: Comparison of efficacy and credibility data. (a) Efficiency performance. (b) Credibility.

TABLE 2: Accuracy of recommended content.

Recommender system	Data set interface	Accuracy (%)
New	1	78.45
	2	86.54
	3	75.4
Content	1	60.56
	2	50.56
	3	67.65
Collaborative filtering	1	68.45
	2	65.46
	3	68.67

From Table 2, the application of the recommendation system in this article in this browser, no matter which data interface recommends the content accuracy, can reach more than 78%. The accuracy of the content recommended by the other two recommender systems is obviously lower than that of the new recommender system, so the accuracy of the content recommended by the recommender system in this article is better.

**3.2. Experiments on Recommended Content.** This experiment is to verify whether the content recommended by the browser in the above experiment using three different

recommendation systems in different dataset interfaces meets the needs of users. First, the content recommended by the three recommender systems for users in the three dataset interfaces of the browser. From the background of the browser, check whether the user has browsed the content recommended by the recommendation system: if the content has been browsed, it means that it conforms to the user's hobbies; if not, it means that it does not meet the user's hobbies. To this end, this experiment collects data on whether the content recommended by the three systems meets the interests of readers, as shown in Figure 8.

From Figure 8, it can be seen that the content recommended by the system of this article in each dataset interface in the browser is very in line with the user's hobbies. However, the content-based recommendation system and collaborative filtering algorithm recommend the content recommended by the system is not very accurate. Because the new recommendation system is in the process of the recommending content, the evidence theory algorithm will link the user's interest with the item content to reduce the error of the recommendation.

And after the user has used it, this experiment also counts the user's experience after using a browser with different recommendation systems and the speed of the recommendation system's recommended content in the browser, as shown in Figure 9.

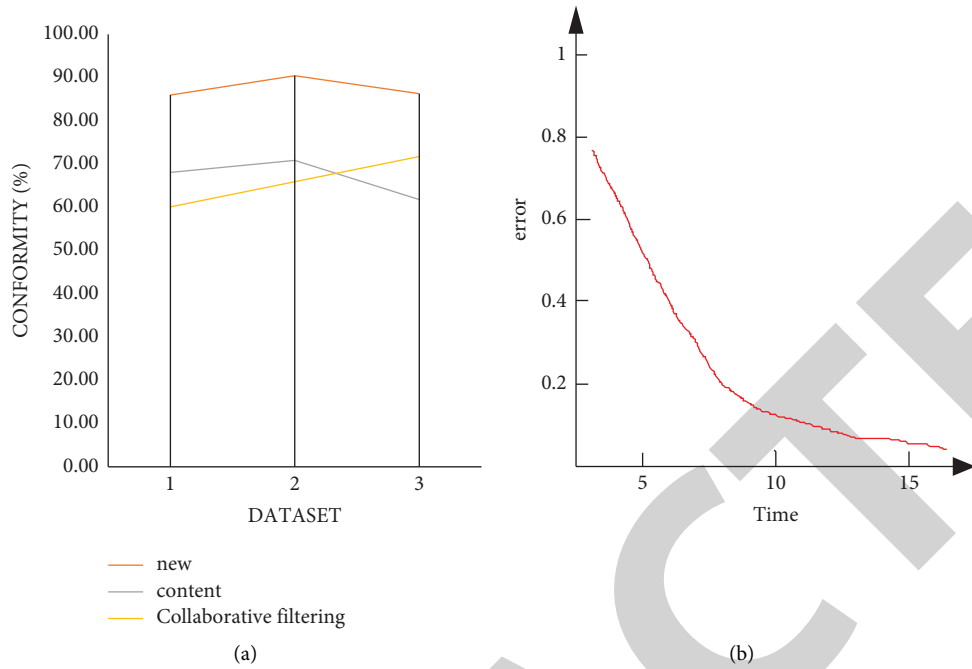


FIGURE 8: Recommended content changes. (a) Conformity. (b) New system error change.

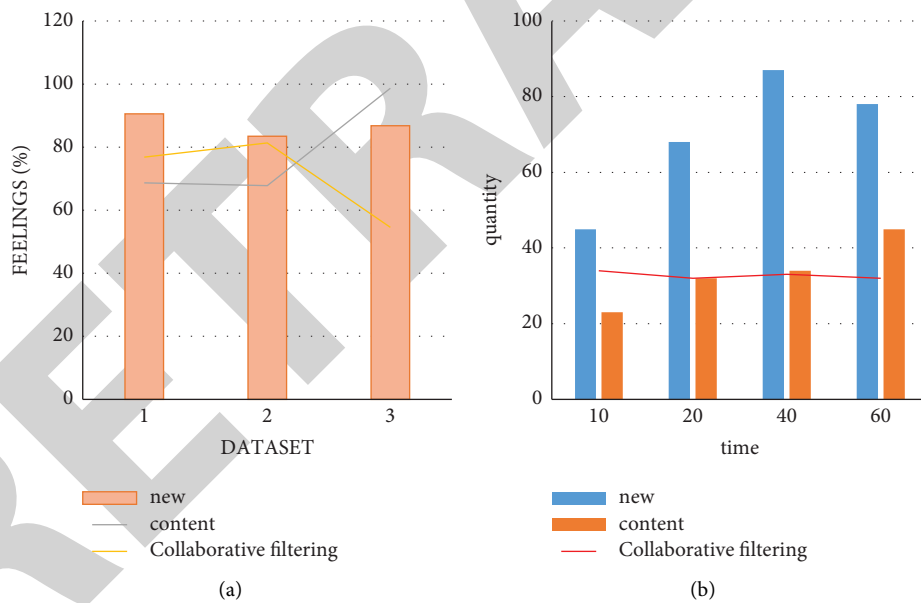


FIGURE 9: Experience and recommendation speed. (a) Experience. (b) Speed of recommending content.

From Figure 9(a), in browser dataset interface 1, the user’s browser experience under the new recommendation system is relatively high, and the highest performance in the browser can reach 0.98. And compared to other recommendation systems, no matter which dataset interface is in the browser, the browser with the new recommendation system makes the user more experience, and the browser experience value can reach more than 80%. From

Figure 9(b), the new recommender system recommends content faster than both the content-based recommender system and the collaborative filtering recommender system.

3.3. *Experimental Summary.* From the above experiments, the new recommendation system based on the evidence theory constructed in this article has high feasibility.

Compared with other recommendation systems, the new recommendation system is more accurate in grasping the interests and hobbies of users. It also has a good degree of recognition for the authenticity of the recommended content, and users have a stronger sense of experience for the content recommended by the new recommendation system. And from a comprehensive point of view, the performance of the new recommendation system for content recommendation can reach more than 80 points, which is better than other recommendation systems.

#### 4. Discussion

The evidence theory and recommendation systems discussed in this article both belong to the category of artificial intelligence, and the evidence theory can help the development of many high-tech projects. Its development direction is very broad, and it can be combined with the neural network, to help solve some difficult problems to overcome. And the evidence theory can have the ability to handle the “uncertain” and “unknown” information, which can greatly improve the processing ability of modern information. The principle of the evidence theory can help the integration of information, and summarize and classify the data information on the network from the side, which greatly promotes the efficiency of information induction. The combined rules of multisource information given by the evidence theory can synthesize the basic reliability allocation from multiple sensors and get a new reliability assignment as the output, which provides a good tool to measure the credibility of information.

Recommendation system is a system already in use, and it will appear in the recommended content in the major browsers, which is the role of the recommendation system in the browser. The core of the recommendation system is the recommendation technology, which determines the quality of the recommendation results. The appropriate recommendation technology can not only reduce the cost generated in the recommendation calculation process, but also retain more old users and explore new users. Therefore, the current recommendation system is still in further research, but also in further optimization, only to better use for users, can improve user satisfaction in the process of use and keep the old users can also develop new users, so as to help the development of business. And the improvement of the recommendation system's ability to distinguish true and false information can promote the improvement of network order.

As the experiment in this article, the new recommendation system should optimize other recommendation system in terms of both content and recommendation speed. Moreover, because the recommendation system contains the evidence theory, the content recommended by the return and selection system is more real and very feasible, so users can not only improve their comfort in the use process but also improve their identification of the true and false information. Hence, it is highly feasible.

#### 5. Conclusions

In this article, the principle of the evidence theory is discussed, and the combination of its evidence theory and the recommendation system can greatly improve the shortcomings of the existing recommendation systems. Existing recommendation systems cannot identify the authenticity of the recommended content, so the evidence theory can just help identify the authenticity of the recommended content. In addition, the evidence theory also has certain principles for the induction and classification of information content, which can promote the classification of the recommendation system. Moreover, the experiments in this article prove that the recommendation system in this article is better than the previous recommendation system in terms of the speed and content of the recommendation, which shows that the recommendation system studied in this article has high practicability. However, the new recommender system studied in this article still recovers the influence of many uncertain factors, so it is hoped that the shortcomings of the recommender system can be improved in future research.

#### Data Availability

No data were used to support this study.

#### Conflicts of Interest

The author declares that there are no potential conflicts of interest in this study.

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