sustainability

MDPI

Article

Mobile e-Commerce Recommendation System Based on Multi-Source Information Fusion for Sustainable e-Business

Yan Guo [1], Chengxin Yin [2,*], Mingfu Li [2], Xiaoting Ren [3] and Ping Liu [4]

1 College of Management Science, Chengdu University of Technology, Chengdu 610059, China; guoyandoctor@sina.com
2 College of Architecture Engineering, Chengdu Aeronautic Polytechnic, Chengdu 610100, China; lmf301@163.com or 0100826@cap.edu.cn
3 College of Public Management, China University of Mining and Technology, Xuzhou 221116, China; TB16090001B4@cumt.edu.cn
4 Department of Economic and Management, Sichuan Technology Business College, Chengdu 611830, China; yutianliuping@163.com
* Correspondence: 13608075271@163.com or 1200083@cap.edu.cn

Received: 30 November 2017; Accepted: 7 January 2018; Published: 9 January 2018

Abstract: A lack of in-depth excavation of user and resources information has become the main bottleneck restricting the predictive analytics of recommendation systems in mobile commerce. This article provides a method which makes use of multi-source information to analyze consumers' requirements for e-commerce recommendation systems. Combined with the characteristics of mobile e-commerce, this method employs an improved radial basis function (RBF) network in order to determine the weights of recommendations, and an improved Dempster–Shafer theory to fuse the multi-source information. Power-spectrum estimation is then used to handle the fusion results and allow decision-making. The experimental results illustrate that the traditional method is inferior to the proposed approach in terms of recommendation accuracy, simplicity, coverage rate and recall rate. These achievements can further improve recommendation systems, and promote the sustainable development of e-business.

Keywords: mobile e-commerce; information system; predictive analytics; information technology; data-mining; decision-making

1. Introduction

Mobile e-commerce is derived from the broader concept of e-commerce and refers to business activities conducted by mobile terminals, such as mobile phones and tablet computers [1,2]. With changes in user consumption habits, mobile e-commerce has become a trend. However, the continuous generation of a large quantity of data is not only inconvenient for consumers when seraching for meaningful products, but also means some of the products are rarely purchased. Meanwhile, the limited mobile terminal visual interface greatly affects the consumer's shopping experience and satisfaction. These factors may alienate customers and impede the sustainable development of e-business. As an information technology to resolve the above problems [3,4], the recommendation system is widely applied by e-commerce practitioners and has become an important research topic in information science and decision-support systems [5,6]. Currently, the research on recommendation systems generally includes content-based filtering (CBF) [7], collaborative filtering (CF) [8,9], and other data-mining techniques [10], such as decision trees [11,12], association rules [13], and the semantic approach [14]. Although recommendation systems that could help users find the information they need more quickly have received extensive attention [15], research regarding mobile e-commerce recommendation systems continues to lag in two aspects that motivate our study.

First, the e-commerce recommendation system is not deep enough to mine consumers' online behavior in multi-source mining. Recommendation systems only focus on information about products and consumers' shopping behavior on the shopping platform. The systems do not combine other information in the mobile phone: pictures, music, video, applications etc. Therefore, the accuracy of the recommendation is limited. It is like the story of the blind men and the elephant: a blind man feels an elephant, only touching some part of it and then concluding what the elephant is like. That is, he draws a conclusion from incomplete data. Mobile-phone users produce a lot of information every day, not just shopping information on the shopping platform but also other platforms such as social media sites [16,17]. We can obtain information from various sources in order to understand consumer needs, so as to recommend products. Let us consider a scenario below. You see a trendsetter wearing a pair of good shoes in the street and take a photo. Then, the mobile e-commerce recommendation system recommends a shop for you, and you can also buy a pair of shoes for yourself.

Second, the mobile e-commerce recommendation system should integrate user location information. Localization is one of the characteristics of mobile e-commerce. There is a close relationship between the consumer's location and their shopping behavior. Traditional e-commerce makes it difficult to collect consumer information anytime and anywhere. A mobile terminal can remove the shackles of the computer. Positioning technology allows the recommendation system to facilitate consumers when it comes to mobile business, transactions and services. In order to let the recommendation system play an enhanced role, a multi-source information-fusion technique should be imported into the integration of location and historical behavior information.

This paper proposes a recommendation method using multi-source information-fusion technology based on consumer location information and online behavior in the mobile terminal. First, this research designs a flow chart of a mobile e-commerce recommendation system. Then, the paper extracts evidence and uses the improved radial basis function (RBF) neural network to set weights. Based on that, the article uses the improved Dempster–Shafer (D–S) evidence theory to fuse the information and the power-spectrum estimation in order to recommend products. Finally, a Taobao online dress shop is used as the case study to testify the validity of the proposed mobile e-commerce recommendation system. The paper provides a detailed operation method and experimental results. The rest of the paper is as follows: Section 2 reviews the literature on recommendation systems, multi-source information-fusion techniques, the RBF neural network, and D–S evidence theory. A method to address the problem is presented in Section 3. Section 4 uses a case study to prove the performance of the proposed method. Conclusions and discussion are provided in Section 5.

2. Literature Review

The literature review focuses on the following aspects: recommendation systems, multi-source information-fusion techniques, the RBF neural network, and D–S evidence theory.

2.1. Recommendation Systems

Recommendation systems are tools to aid decision-making that analyze a customer's previous online behavior and recommend products to meet their preferences [18–20]. E-commerce retail websites have widely used them to provide consumers with personalized marketing services in recent years [21]. Since Goldberg and his colleagues [22] first proposed recommendation systems, other researchers have proposed a wide range of recommendation systems and related technologies, including CBF, CF, and other data-mining techniques [23]. For example, Pazzani and Billsus introduced the strategy architecture of the content-based method [24]. Unlike earlier research that focused on technical factors [25], other studies turned their attention to the impact of recommendation systems on a customer's buying decision [8,26–28]. Although there are many papers related to recommendation models, strategies [29], or procedures, few works have been conducted for a mobile e-commerce recommendation system, which has specific characteristics. In existing research, scholars have collected the recommendation information solely from the shopping platform instead of multiple information channels in the mobile terminal.

2.2. Multi-Source Information-Fusion Technique

Since information fusion was formally proposed in the 1990s, multi-level processing in the process of information fusion has become the consensus among scholars of the information-fusion model. Yager [30], Gregor [31] and many other scholars [32–34] have researched in depth the multi-source information-fusion framework, information classification, automatic reasoning, heterogeneous data processing, cloud computing and the peer-to-peer (P2P) network trust model of information fusion. Most of the information-fusion models are based on the joint directors of laboratories (JDL) model established by the United States Department of Defense, which realizes the requirement of multi-source information fusion from four different levels of processing. As multi-source information-fusion technique research has developed, it has been used in pattern recognition, data mining, knowledge discovery and so on. However, there has been less research of multi-source information fusion based on location in mobile e-commerce recommendation systems.

2.3. Radial Basis Function (RBF) Neural Network and Dempster–Shafer (D–S) Evidence Theory

A RBF neural network is a radial basis function neural network that is an efficient feedforward neural network (FFNN) and can approach any non-linear function. It can handle the difficulty of analyzing the regularity of a system, has a good ability to generalize and a fast convergence rate. Researchers have succeeded in bringing RBF neural networks to the following fields: non-linear function approximation, pattern recognition, time-series analysis, image processing, data classification, system modeling, information processing, and control and fault diagnosis. For example, Yun et al. established a short-term load-forecasting model using a RBF neural network [35]. However, the results of classification based on a RBF neural network often appear negative [36,37], which does not support evidence well. Yingwei et al. analyzed the minimal resource allocation network (M-RAN) learning algorithm which has fewer hidden neurons but better classification accuracy [38]. Huang et al. proposed a new sequential learning algorithm for RBF networks for function approximation [39]. This paper establishes an improved RBF neural network model, and uses it to determine the weight of the evidence.

Evidence theory is a kind of inexact inference theory. After Dempster first put forward evidence theory in 1967, it was further developed by his student Shafer [36], also known as the Dempster–Shafer (D-S) evidence theory. The main purpose of evidence theory is to synthesize uncertain data from many sources. Evidence theory uses the formula of evidence synthesis to compose the credibility of different information sources so as to obtain decision-making results [40]. Skowron and Grzymala [41] proposed a method of evidence acquisition based on a decision table. Yang et al. [42] studied the evidence acquisition method for a large decision table. Deng et al. [43] studied the synthesis method of evidence theory, and designed the expert weight measurement method based on the distance required to effectively synthesize conflicting evidence. However, D–S evidence theory has fairness, one-vote veto, robustness and Zadeh paradox problems [44,45] in its application. Scholars have improved the method mainly through modifying the data source and the composition rules [46,47]. This paper adopts evidence-body modification based on credibility and synthesis rules that are based on local conflict allocation in order to fuse evidence.

3. Modeling

3.1. The Solution Framework

The detailed steps of the product recommendation method based on multi-source information fusion are stated in the following four sub-sections, including data sources, recommendation evidence weight, fusion decision, and result. The flow chart is shown in Figure 1.

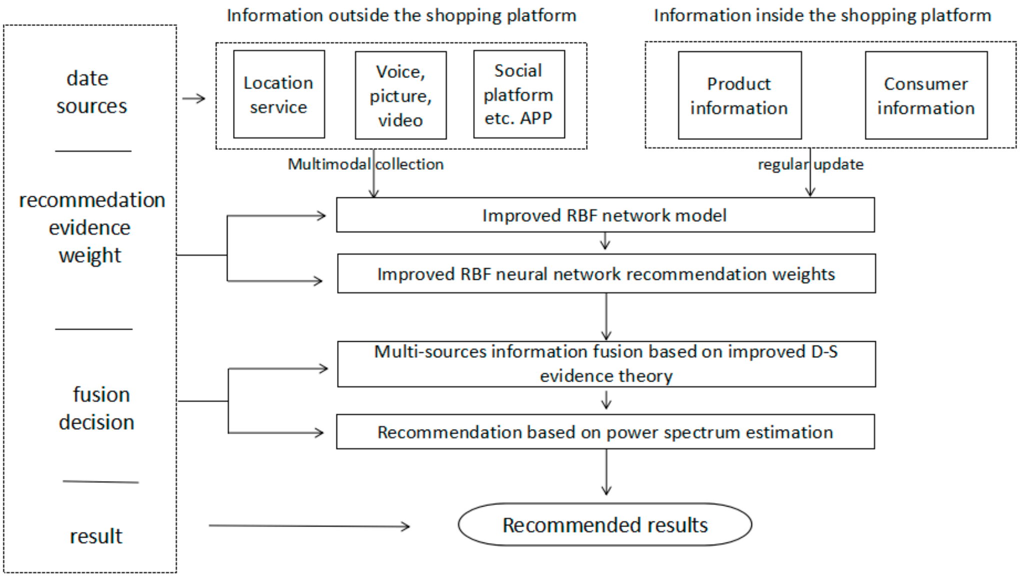

Figure 1. Flow chart of a mobile e-commerce recommendation system.

3.2. Data Sources

The mobile e-commerce recommendation system needs accurate, unified consumer information (features and needs). However, current consumer information management is usually in the state of an "isolated island"; that is, the complete information of a mobile user is separated and respectively stored in the mobile terminal, which lacks a unified representation and interface. To solve the above problem, the proposed recommendation system uses Micro-formats for user information representation, storage, integration and management. Although foreign business has widely used Micro-formats to integrate information of a blog or micro-blog, and achieved success in YouTube, Flickr, MapQuest and MySpace applications, the anonymity of the external network leads to rough and fragmented user information, making it difficult to give full play to the effectiveness of Micro-formats. Mobile-phone applications have widely implemented a real-name registration system and unification of the mobile phone number. The recommendation system can obtain more accurate and detailed consumer information, so Micro-formats are very suitable for it.

As mentioned above, some of the consumer information (such as gender, age, level of consumption, etc.) required by the recommendation system can be obtained from the shopping platform through a timing update. However, more user information is still being explored; for example, the immediate needs of the product, the potential needs, recent attention, etc. This article assumes that recommendation systems can collect the information they need. Location information, voice, picture, video and so on can be collected in the setting of the mobile phone. For other app information, we assume that information sharing can be achieved in order to provide the consumer with timely recommendation services. For example, the system collects a user's needs and concerns in a social app. The system can extract personal characteristics and the recent focus of the consumer by means of "social platform nickname–mobile phone number". Furthermore, the system excavates the consumer's historical purchase information on the shopping platform database through the "mobile phone number—shopping platform ID". Finally, the two kinds of information are injected into the user's information as evidence. The process includes several steps, as shown in Figure 2.

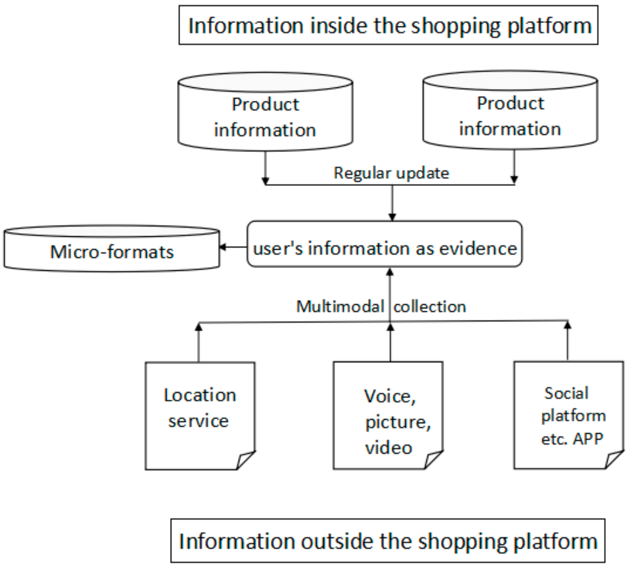

Figure 2. User information acquisition and integration of Mobile e-commerce recommendation system.

3.3. Recommendation Evidence Weight

An improved RBF neural network is designed based on the Java neural network packet Joone to solve the shortcomings of the RBF neural network mentioned in Section 2.3. The input layer of the network is still the linear input LinearLayer; the hidden layer is the RbfGaussianLayer; the output layer is the SoftmaxLayer; and the network layer and the layer-weight training function are based on the elastic feedback algorithm Resilient Backpropagation (RPROP) [48,49]. The RbfGaussianLayer transfer function is a Gauss-type function seen in the following form (1):

$$y_j = \exp\left(-\frac{\|x - c_j\|^2}{\sigma_j^2(x)}\right) \tag{1}$$

The central position c_j and variance $\sigma_j^2(x)$ are set by calculating the mean value and variance of the input. The number of hidden layers in the network needs to be optimized. The output layer, SoftmaxLayer, adopts the transfer function shown in Formula (2), where c is the number of output classifications, and y_i is the neuron output.

$$y_i = \frac{\exp(x_i)}{\sum_{i=1}^{c} \exp(x_i)} \tag{2}$$

In decision analysis, different sources of information have a different importance, which in turn play different roles in our decision making. Therefore, the weights of different information sources are different in the recommendation system. The trained neural network model is used for the mobile e-commerce recommendation system. The output is $Y^{net} = \{y_1^{net}, y_2^{net}, \ldots, y_{sum}^{net}\}$ (sum is the total number of information sources). In the article, Y_{net} is defined as the recommendation weight based on an improved RBF network and used for information fusing as evidence. The element y_i^{net} reflects the degree of relative support of the recommendation information between information sources, and satisfies $\sum_{i=1}^{sum} y_i^{net} = 1$.

3.4. Fusion Decision

D–S evidence theory is a major method of reasoning under uncertainty (RUU). The synthesis rules of evidences $m_1, m_2, \ldots, m_n$ are show as Formula (3) for the recognition framework Θ.

$$m(A) = \begin{cases} 0 & A = \varnothing \\ (1-K)^{-1} \sum\limits_{\cap A_i = A} \prod\limits_{i \le j \le n} m_j(A_i) & A \ne \varnothing \end{cases} \tag{3}$$

Among them, the basic probability assignment (BPA) satisfies $\sum\limits_i m_j(A_i) = 1$, and $K = \sum\limits_{\cap A_i = \varnothing} \sum\limits_i m_j(A_i)$ means the degree of conflict between the evidences. Considering the shortcomings of D–S theory mentioned in Section 2.3, we adopt credibility to modify the evidence body and the local conflict allocation to synthesise the rules.

1. Evidence body modification based on credibility. The evidence credibility $\mu_i(\mu_i \le 1)$ points to the relative reliability among evidences. The highest reliability of the evidence in the evidence set was set to 1. μ_i as a correction factor modifies the original evidence body M'. The surplus probability is arranged to the unknown condition $m(\Theta)$. The BPA value of the corrected body M is obtained, as shown in Formula (4):

$$M = [m(A_1)m(A_2)\ldots m(A_n)m(\Theta)] \tag{4}$$

Among these, $m(A_m) = \{um'(A_m) | m = 1, 2, \ldots, n\}$, $m(\Theta) = 1 - \sum\limits_{m=1}^{n} m(A_m)$, $m'(A_m) \in M'$.

2. Synthesis rules based on local conflict allocation. This divides local conflicts between the two focal points that cause the conflict:

$$\begin{cases} m_{jk}(A) = \sum\limits_{B \cap C = A} m_j(B) m_k(C) + f(A) \\ f(A) = \sum\limits_{A \cap D = \varnothing} \left(\frac{m_j^2(A) m_k(D)}{m_j(A) + m_k(D)} + \frac{m_k^2(A) m_j(D)}{m_j(D) + m_k(A)} \right) \end{cases} \tag{5}$$

Among them, $B, C, D \subset \{A_1, A_2, \ldots, \Theta\}$, the BPA value satisfies $m_j(\bullet) \subset M_j, m_k(\bullet) \subset M_k$; $m_{jk}(A)$ was the BPA value of the new-found evidence body M_{jk} after fusion.

After every two evidences are synthesized, the new evidences carry through normalization. For example, the element $m'_{jk}(A)$ is obtained after normalization of M_{jk}:

$$m'_{jk}(A) = \frac{m_{jk}(A)}{\sum m_{jk}(\bullet)} \tag{6}$$

In this paper, location information, the review of the social platform app, product information and consumer information are set as evidences. We can use statistical analysis or expert experience to define their credibility.

3.5. Result

The system produces globally consistent user- or resource-characteristic information through the above information fusion, which will be enriched and changed with time. After a period of accumulation of the information, user- and resource-feature information is relatively stable. However, some of the parameters may still be missed due to the instability of multi-source information, so the system uses a recommendation algorithm based on a power-spectrum estimation. The detailed algorithms are as follows:

$\Phi_{xx}(m)$ is the auto-correlation function of user demand and characteristic information $x(n)$. $P_{xx}(m)$ is used to express the power spectral density. The formula for the calculation is as follows:

$$p_{xx}(\omega) = \sum_{m=-\infty}^{\infty} \Phi_{xx}(m) e^{-zwm} \tag{7}$$

According to the calculation of power spectral density, $\Phi_{xx}(m)$ is denoted as:

$$\Phi_{xx}(m) = \lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x(n)x^*(n+m) \tag{8}$$

After Formula (8) is replaced by Formula (7), there is:

$$P_{xx}(\omega) = \lim_{N\to\infty} \frac{1}{2N+1} \left[\sum_{n=-N}^{N} x(n)e^{-zwn} \right] \bullet \left[\sum_{m=-\infty}^{\infty} x^*(n+m)e^{zw(n+m)} \right] \tag{9}$$

The average of Formula (9) is:

$$P_{xx}(\omega) = \lim_{N\to\infty} E\left[\frac{1}{2N+1} \left| \sum_{n=-N}^{N} x(n)e^{zwn} \right|^2 \right] \tag{10}$$

Because of the multi-sources of user information, there are many elements of user requirements and feature information, which means the mobile e-commerce recommendation system can only use the sub-sequence, not the complete information. Therefore, the data-processing module for a recommendation calculates the power spectral density with a finite number of data sequences. The finite data sequence of a user's demand and characteristic information is $x(0)$, $x(1)$, $x(2)$, ... , $x(N)$. Calculating the above formulas, we can obtain:

$$\hat{\Phi}_{xx}(m) = \frac{1}{N} \sum_{n=-\infty}^{\infty} x_N(n)x_N(n+m) \tag{11}$$

$$\hat{P}xx(\omega) = \sum_m \hat{\Phi}xx(m)e^{-zwm} \tag{12}$$

We plug Formula (11) into Formula (12) to generate or modify the recommendation list.

4. Experimental Study

In this paper, the raw data is taken from an online shop selling women's clothing, Taobao.com. We selected 100 customers as the research object. The multi-source information in the mobile e-commerce recommendation system included the following four aspects: location-service information, commodity-picture information, social-platform information, and the data from the store trading database. We collected the information. The first step was data reduction, which deleted the data that did not satisfy the requirements. Consumer age, gender and consumption levels were reserved on the shop's transaction database. Then, the data was converted. Due to the limitations of experimental conditions, collected images were manually converted to keywords. Finally, we conducted unified coding based on the previous data.

Here is a simple example of the basic process of the recommendation. Suppose we want to collect relevant information from the database, as shown in Table 1. There is the actual information of consumer A. The proposed approach collects information from multiple sources, that is, it uses all of the above information. The traditional method doesn't collect the information from the location service, pictures and social platforms. It only needs the data from the store trading database. The weights of different information sources shown in Table 2 can be determined by utilizing the method proposed in Section 3.3. Finally, we can use the improved D–S evidence theory to obtain the final recommendation results. The probability of recommending shoes is as high as 85% according to the proposed method, but the probability of the traditional method is only 12%. We find that the data sources of recommendation systems have a great impact on the results. In general, the more the data, the better the recommendation. For example, we know that consumer A is more active on social networks and assume she has an outgoing personality. So the types of recommended shoes are young and cute.

Table 1. The information from different platforms about customer A.

Information Platform	Shop's Transaction Database			Location Information	Picture Information	Social Platform	
Features	Age	Gender	Consumption level	Address	Picture features	Activity	Browsing history
A	26	Woman	Medium	Market	Shoes	Active	Shoes

Table 2. The weights of different information sources between the proposed method and the traditional method.

Weight	26	Woman	Medium	Market	Shoes	Active	Shoes	Other
Proposed method	0.21	0.37	0.36	0	0	0	0	0.06
Traditional method	0.15	0.18	0.16	0.11	0.13	0.04	0.08	0

In the following testing experiments, we test the efficiency of the proposed method in the recommendation system using the multi-source data by comparing it with traditional recommendation methods. The comparison items include: recommendation accuracy, simplicity, coverage rate, recall rate and speed.

4.1. Recommendation Accuracy and Simplicity

Compared with the computer terminal, the mobile terminal visual interface is small, so the accuracy of the recommendation and the simplicity of the rule become more important for the mobile e-commerce recommendation system. The simplicity of rules indicate the number of attributes included in rules. Recommendation accuracy is also very important to the e-tailer. If an e-tailer recommends a product that does not meet the needs of the consumer, the recommendation system not only cannot provide personalized decision support and information services for the customers' shopping, but will make the consumer feel bored. The comparison of two algorithms is shown in Table 3.

Table 3. Comparison experiment between the traditional algorithm and the proposed algorithm.

Algorithm	Accuracy (%)	Simplicity
Traditional algorithm	80.01	2.01
Proposed algorithm	91.23	1.47

From Table 3, we can see that the proposed method is more accurate than the traditional algorithm. This reflects the use of multi-source data of consumers' behavior to analyze their demands in a more accurate way. It improves the quality of the recommendation rules.

Due to the diversity of consumer preferences, there are often various possibilities in the mobile terminal personalized recommendation process. The more products you recommend, the greater the selection pressure you burden consumers with. So, simplicity is an important indicator of a recommendation rule's ability. The mobile terminal recommendation system should provide the most concise rules that can meet consumers' different demands. We can see from Table 1 that, in terms of simple rules, the proposed algorithm is superior to the traditional algorithm, while its recommendation ability is better than the traditional algorithm. All these prove that the proposed algorithm is significant in the research of a mobile e-commerce recommendation system. Because of a mobile terminal's unlimited accessibility and the diversity of consumer demand, improving the ability to recommend is very important for ameliorating service quality of the mobile e-commerce recommendation.

4.2. Coverage Rate

The user coverage rate is:

$$Coverage(t) = \sum(RS(t) \cap RR(t)) / \sum RS(t) \tag{13}$$

where $RS(t)$ is a set of recommended resources and $RR(t)$ is a set of selected resources produced in the recommendation system at t time. The higher the coverage rate, the stronger the coverage on user demands and features in the recommendation system. The user coverage rate of the proposed method is proved in Figure 3.

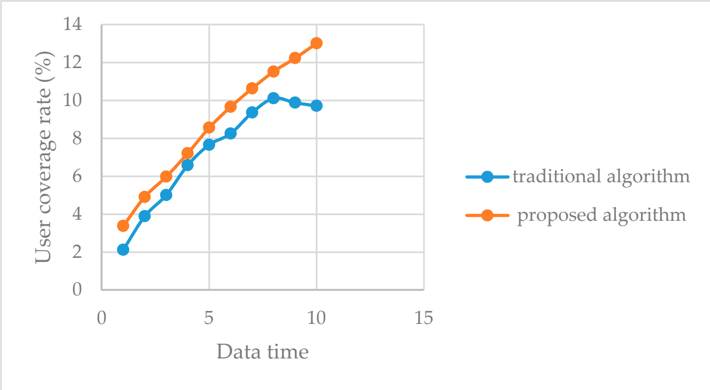

Figure 3. Comparison experiment of user coverage rate.

Figure 3 shows that with continuous enrichment of the user information in the two recommender systems, the user discovery coverage rates increase continuously until they reach their respective peaks or close to them. Furthermore, the proposed algorithm of the new system is more optimized. So, from the perspective of the user coverage speed, the advantages of the new system are obvious, particularly when it comes to the rapid change of in the number of consumers because of corporate advertising, promotions and other activities. Therefore, judging from the rate of the user discovery coverage, the advantages of the new system are obvious, especially when there is a sharp increase of the number of consumers in large-scale promotional activities.

4.3. Recall Rate

The recall rate refers to that number of selected resources from recommendation systems that accounts for the total number of selected resources selected by the user. CA: 20 customers. CB: 40 customers. CC: 60 customers. CD: 80 customers. TF: 100 customers. The results of the comparison test are shown in Figure 4.

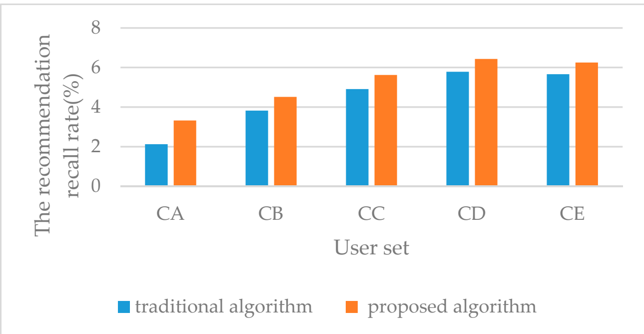

Figure 4. Comparison test of the recommendation recall rate.

From Figure 4, the recall rates of the two systems gradually show a steady state with the increasing abundance of users and resource information. Also, because of the steadiness of user demands this starts to drop. However, the multi-source information-fusion method in the new system makes the tendency more obvious in the recall rate, and the system maintains a high recall rate over a period of time.

4.4. Recommendation Speed

The recommendation speed is the time from the input of the data to the output of the recommended product. In the process of multi-source information collection and conversion, we deducted the time of manual conversion. A comparison experiment of a multi-source recommendation system and a traditional recommendation system followed. The traditional algorithm normally only scans a shop's transaction database, but the article proposes a method integrating multi-source information to recommended commodities. The experiment demonstrated that the time taken for the proposed method in each group of transactions is longer than under the traditional algorithm. As volumes built up, the difference became greater. The times taken for the two algorithms are presented in Table 4 and Figure 5.

Table 4. Comparison experiment of operating efficiency, according to the number of users.

Users	Traditional Algorithm (s)	Proposed Algorithm (s)
CA	0.33	0.41
CB	0.65	0.83
CC	0.96	1.32
CD	1.28	1.58
CE	1.41	1.99

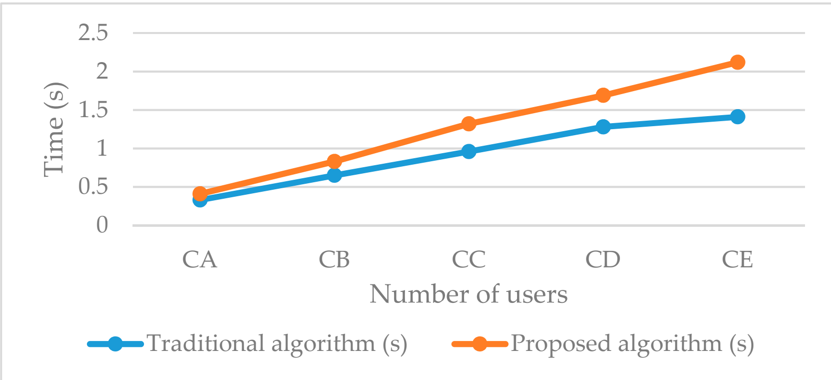

Figure 5. A comparison of the two algorithms, according to the number of users.

We use the above experiments to compare the time difference registered between the proposed algorithm and the traditional algorithm for different amounts of data. Experiments show that the proposed algorithm is a time-consuming operation. In other words, the improved algorithm is unable to enhance the speed of a recommendation system; because of the information diversification of the mobile consumer, the improved algorithm takes longer. It can provide useful information for consumers, but also provide rules for the decision-making ability of the enterprise.

5. Conclusions and Discussion

This paper shows that a mobile e-commerce recommendation system based on the proposed algorithm can provide consumers with the most necessary information at the most appropriate time, and provide a more comfortable shopping experience for them. Current literature regards recommendation systems that only collect information from the shopping platform. According to the characteristics of the mobile e-commerce recommendation system, the proposed system collected consumers' requirements from several approaches. It can provide consumers with more accurate recommendations. Accurate recommendations can not only enhance customer satisfaction, but also affect the conversion rate of goods. Thus, e-tailers are advised to recommend accurately the most suitable products in order to boost sales. E-trailers should take advantage of a user's multi-source information so as to guide and cultivate consumers' decision-making by combining the user's mobile-phone shopping habits. They can implement precise recommendations through research on user demand, consumer behavior and consumption preference. So, this research enriches existing theory and helps improve managerial practice. At the same time, this paper is of great significance for mobile e-commerce platform providers in the design of a product recommendation system. Mobile e-commerce platform operators could re-design the algorithms of their recommendation systems based on the above in order to choose more suitable recommended products. This addresses the specialities of a mobile platform compared to a personal computer (PC) and develops a useful tool for targeting consumers with personalized messages.

Although the article has put forward multi-source information fusion technology to improve the prediction accuracy of personalized recommendations in the mobile e-commerce terminal, some restrictions also need to be pointed out. On the one hand, the experimental results in Section 4.4 show that the computation time of the proposed algorithm is longer than the traditional algorithm. In terms of speed, the proposed algorithm has no advantages. So we will consider how to ameliorate the proposed method in terms of its speed in future research. On the other hand, in the process of designing a recommendation system, we only focus on a user's convenience regarding how to find the products of interest to them precisely. The recommendation system could also affect consumer privacy. Customer information security issues have become the main bottleneck that restricts the growth of mobile commerce.

Acknowledgments: The work was supported by the soft science research project of Chengdu city (Project No. 2015-RK00-00296-ZF).

Author Contributions: Mingfu Li built the framework of the whole paper. Chengxin Yin carried out the collection and sorting of the data. Xiaoting Ren designed the whole experiment and method. Ping Liu provided analytical and experimental tools. Yan Guo finished all the experiments and the whole article.

Conflicts of Interest: The authors claim that there is no conflict of interest.

References

1. Martín, S.S.; López-Catalán, B.; Ramón-Jerónimo, M.A. Factors determining firms' perceived performance of mobile commerce. *Ind. Manag. Data Syst.* **2012**, *112*, 946–963. [CrossRef]
2. Guo, Y.; Wang, M.X.; Li, X. Application of an improved Apriori algorithm in a mobile e-commerce recommendation system. *Ind. Manag. Data Syst.* **2017**, *117*, 287–303. [CrossRef]
3. Ansari, A.; Essegaier, S.; Kohli, R. Internet recommendation systems. *J. Market. Res.* **2000**, *37*, 363–375. [CrossRef]
4. Bodapati, A.V. Recommendation systems with purchase data. *J. Market. Res.* **2008**, *45*, 77–93. [CrossRef]
5. Jiang, Y.C.; Shang, J.; Liu, Y.Z. Maximizing customer satisfaction through an online recommendation system: A novel associative classification model. *Decis. Support Syst.* **2010**, *48*, 470–479. [CrossRef]
6. Zhao, Y.S.; Liu, Y.P.; Zeng, Q.A. A weight-based item recommendation approach for electronic commerce systems. *Electron. Commer. Res.* **2015**, *19*, 1–22. [CrossRef]
7. Zenebe, A.; Norcio, A.F. Representation, similarity measures and aggregation methods using fuzzy sets for content-based recommender systems. *Fuzzy Sets Syst.* **2009**, *160*, 76–94. [CrossRef]
8. Lin, Z.J. An empirical investigation of user and system recommendations in e-commerce. *Decis. Support Syst.* **2014**, *68*, 111–124. [CrossRef]
9. Herlocker, J.L.; Konstan, J.A.; Loren, J.; Terveen, G.; Riedl, T. Collaborative filtering recommender systems. *ACM Trans. Inf. Syst.* **2004**, *22*, 5–53. [CrossRef]
10. Liu, Y.Z.; Jiang, Y.C.; Liu, X.; Yang, S.L. CSMC: A combination strategy for multi-class classification based on multiple association rules. *Knowl.-Based Syst.* **2008**, *21*, 786–793. [CrossRef]
11. Cho, Y.H.; Kim, J.K.; Kim, S.H. A personalized recommender system based on web usage mining and decision tree induction. *Expert Syst. Appl.* **2002**, *23*, 329–342. [CrossRef]
12. Rak, R.; Kurgan, L.; Reformat, M. A tree-projection-based algorithm for multi-label recurrent-item associative-classification rule generation. *Data Knowl. Eng.* **2008**, *64*, 171–197. [CrossRef]

13. Wang, F.H.; Shao, H.M. Effective personalized recommendation based on time-framed navigation clustering and association mining. *Expert Syst. Appl.* **2004**, *27*, 365–377. [CrossRef]
14. Liang, T.P.; Yang, Y.F.; Chen, D.N.; Ku, Y.C. A semantic-expansion approach to personalized knowledge recommendation. *Decis. Support Syst.* **2008**, *45*, 401–412. [CrossRef]
15. Choi, K.; Yoo, D.; Kim, G.; Suh, Y. A hybrid online-product recommendation system: Combining implicit rating-based collaborative filtering and sequential pattern analysis. *Electron. Commer. Res. Appl.* **2012**, *11*, 309–317. [CrossRef]
16. Mikalef, P.; Giannakos, M.; Pateli, A. Shopping and word-of-mouth intentions on social media. *J. Theor. Appl. Electron. Commer. Res.* **2013**, *8*, 17–34. [CrossRef]
17. Hsiao, K.L.; Lin, J.C.; Wang, X.Y.; Lu, H.P.; Yu, H. Antecedents and consequences of trust in online product recommendations: An empirical study in social shopping. *Online Inf. Rev.* **2010**, *34*, 935–953. [CrossRef]
18. Guo, Y.; Wang, M.X.; Li, X. An interactive personalized recommendation system using the hybrid algorithm model. *Symmetry* **2017**, *9*, 216. [CrossRef]
19. Yuto, I.; Takahiro, U.; Ichi, T. Design and evaluation of a movie recommendation system showing a review for evoking interested. *Int. J. Web Inf. Syst.* **2017**, *13*, 72–84.
20. Shani, G.; Gunawardana, A. Evaluating recommendation systems. In *Recommender Systems Handbook*; Springer: Berlin, Germany, 2011; pp. 257–297.
21. Benbasat, I.; Wang, W. Trust in and adoption of online recommendation agents. *J. Assoc. Inf. Syst.* **2005**, *6*, 4.
22. Goldberg, D.; Nichols, D.; Oki, B.M.; Terry, D. Using collaborative filtering to weave an information tapestry. *Commun. ACM* **1992**, *35*, 61–70. [CrossRef]
23. Masoud, M.; Mehdi, S. Improving recommender systems' performance on cold-start users and controversial items by a new similarity model. *Int. J. Web Inf. Syst.* **2016**, *12*, 126–149.
24. Pazzani, M.J.; Billsus, D. Content-based recommendation systems. In *The Adaptive Web*; Springer: Berlin/Heidelberg, Germany, 2007; pp. 325–341.
25. Cheung, K.W.; Kwok, J.T.; Law, M.H.; Tsui, K.C. Mining customer product ratings for personalized marketing. *Decis. Support Syst.* **2003**, *35*, 231–243. [CrossRef]
26. Cheng, L.C.; Jhang, M.J. A novel approach to exploring maximum consensus graphs from users' preference data in a new age environment. *Electron. Commer. Res.* **2015**, *15*, 543–569. [CrossRef]
27. Scholz, M.; Dorner, V.; Franz, M.; Hinz, O. Measuring consumers' willingness to pay with utility-based recommendation systems. *Decis. Support Syst.* **2015**, *72*, 60–71. [CrossRef]
28. Xiao, B.; Benbasat, I. E-Commerce product recommendation agents: Use, characteristics, and impact. *MIS Q.* **2007**, *31*, 137–209. [CrossRef]
29. McDonald, D.W.; Ackerman, M.S. Expertise recommender: A flexible recommendation system and architecture. In Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work, Philadelphia, PA, USA, 2–6 December 2000; pp. 231–240.
30. Yager, R.R. Some considerations in multi-source data fusion. *Stud. Comput. Intell.* **2005**, *5*, 1–22.
31. Pavlin, G.; de Oude, P.; Maris, M.; Nunnink, J.; Hood, T. A multi-agent Systems Approach to Distributed Bayesian Information Fusion. *Inf. Fusion* **2010**, *11*, 267–282. [CrossRef]
32. Villegas, D.; Bobroff, N.; Rodero, I.; Delgado, J.; Liu, Y.; Devarakonda, A.; Fong, L.; Sadjadi, S.M.; Parashar, M. Cloud federation in a layered service mode. *J. Comput. Syst. Sci.* **2012**, *78*, 1330–1344. [CrossRef]
33. Li, X.Y.; Zhou, F.; Yang, X.D. Developing Dynamic P2P Trust Model Using Theory of Entropy-based Multi-source Information Fusion. *Int. J. Innov. Comput. Inf. Control* **2011**, *7*, 7–790.
34. Su, H.S. Multi-source Fuzzy Information Fusion Method Based on Bayesian Optimal Classifier. *Acta Autom. Sin.* **2008**, *34*, 282–287. [CrossRef]
35. Yun, Z.; Quan, Z.; Caixin, S.; Shaolan, L.; Yuming, L.; Yang, S. RBF neural network and ANFIS-based short-term load forecasting approach in real-time price environment. *IEEE Trans. Power Syst.* **2008**, *23*, 853–858.
36. Shafer, G. *A Mathematical Theory of Evidence*; Princeton University Press: Princeton, NJ, USA, 1976.
37. Bi, T.S.; Ni, Y.X.; Wu, F.L.; Yang, Q.X. Hybrid fault section estimation system with radial basis function neural network and fuzzy system. *Proc. CSEE* **2005**, *25*, 12–18.
38. Yingwei, L.; Sundararajan, N.; Saratchandran, P. Performance evaluation of a sequential minimal radial basis function (RBF) neural network learning algorithm. *IEEE Trans. Neural Netw.* **1998**, *9*, 308–318. [CrossRef] [PubMed]

39. Huang, G.B.; Saratchandran, P.; Sundararajan, N. A generalized growing and pruning RBF (GGAP-RBF) neural network for function approximation. *IEEE Trans. Neural Netw.* **2005**, *16*, 57–67. [CrossRef] [PubMed]
40. Anand, S.S.; Bell, D.A.; Hughes, J.G. EDM: A general framework for Data Mining based on Evidence Theory. *Data Knowl. Eng.* **1996**, *18*, 189–223. [CrossRef]
41. Skowron, A.; Grzymala-Busse, J. From Rough Set Theory to Evidence Theory. In *Advances in the Dempster-Shafer Theory of Evidence*; Yaeger, R., Fedrizzi, M., Kacprzyk, J., Eds.; John Wiley & Sons, Inc.: New York, NY, USA, 1994; pp. 193–236.
42. Yang, S.L.; Liu, Y.Z.; Li, Y.F. Evidence acquisition and synthesis method based on theory. *J. Manag. Sci.* **2005**, *8*, 69–75.
43. Deng, Y.; Shi, W.; Zhu, Z.; Liu, Q. Combining belief functions based on distance of evidence. *Decis. Support Syst.* **2004**, *38*, 489–493.
44. Lang, F.H.; Gu, L.Z.; Yang, Y.X.; Niu, X.X. An improved combination rule of conflict evidence. *J. Beijing Univ. Posts Telecommun.* **2008**, *31*, 84–88.
45. Murphy, C.K. Combining belief functions when evidence conflicts. *Decis. Support Syst.* **2000**, *29*, 1–9. [CrossRef]
46. Guo, H.W.; Shi, W.K.; Liu, Q.K.; Deng, Y. A new combination rule of evidence. *J. Shanghai Jiaotong Univ.* **2006**, *40*, 1895–1900.
47. Li, P.; Yan, Y.; Zhang, W.J.; Jia, J.F.; Bai, B. Short-term load forecasting based on quantum neural network by evidential theory. *Power Syst. Prot. Control* **2010**, *38*, 49–53.
48. Zhang, Z.G.; Yang, Y.H.; Xia, L.X.; Jia, Y.H. The application of RPROP algorithm to igneous rock classification. *Prog. Geophys.* **2008**, *23*, 898–902.
49. Jiang, H.L.; Guan, Y.; Liu, F.; Xu, J. Transmission line fault diagnosis based on RBF network with HCM clustering algorithm. *High Volt. Eng.* **2005**, *31*, 81–84.