Computer Engineering and Intelligent Systems www.iiste.org
ISSN 2222-1719 (Paper) ISSN 2222-2863 (Online)
Vol.4, No.5, 2013

Research on Personalized Recommender System for Tourism Information Service

Huang Yu Yao Dan Luo Jing Zhang Mu *
Shenzhen Tourism College of Jinan University
6 QiaoCheng East Road, Overseas Chinese Town,Shenzhen 518053, Guangdong, China
* E-mail of the corresponding author: zhangmu@163.com

The research is supported by Science and Technology Planning Project of Guangdong province, China (Project Number: 2012B031400008)

Abstract
Since the development in the 1990s, Recommender system has been widely applied in various fields. The conflict between the expansion of tourism information and difficulty of tourists obtaining tourism information allows Tourism Information Recommender System to have a practical significance. Based on the existing online tourism information service and the mature recommendation algorithms, Personal Recommender System can be used to solve present problems of the key recommendation algorithms. In the first place, this research presents an overview of researches on this issue both at home and abroad, and analyzes the applications of main stream recommendation algorithms. Secondly, a comparative study of domestic and international tourism information service websites is conducted. Drawbacks in their applications are defined and advantages are adopted in the settings of Recommender System. Finally, this research provides the framework of Recommender System, which combines the design and test of algorithms and the existing tourism information recommendation websites. This system allows customers to broaden experience of tourism information service and make tourism decisions more accurately and rapidly.
Keywords: Tourism information service, Personalized recommendation, Intelligence recommendation module, Apriori algorithm

1. Introduction

With the arrival of information age, tourism industry has expedited its pace of informatization. As a result, tourism enterprises have grown increasingly dependent on information technology. Since tourists are getting more and more sophisticated and rational, their needs tend to be diversified. Therefore, it is all the more challenging to provide them with the requested tourism information. In the current domestic tourism market, individualized travel is replacing traditional travel mode even though package tour is still the mainstream. To participate in the individualized activities, tourists have to do a lot of inquiring and retrieving from the vast sea of tourism information in order to get what they want, which hampers the development of personalized tourism information service.

As a user-centered service mode, personalized tourism information service supplies tourism information and services based on the user's requirements, personality and travel habits. This system aims at providing valuable information for the users' reference when they make travel decisions. The personalized recommender system is capable of catering for different needs, thus truly realizing the goal of service on demand. Personalized recommendation of tourism information furnishes the development trend for tourism information.

2. Literature Review

The early recommender system focuses on content recommendation, and thus can't do anything with such information as music, image and video. To solve this problem, Konston[1] advances collaborative filtering recommendation. It produces recommendations according to the similarity level of the users and other parameters, so the recommendations are of higher value and timeliness.

In the research of travel recommender system, Schafer designs a system which simulates a travel agent who can assist the user to get recommendation service online. David contrives an agent-based system named Intelligent Travel Planning (ITP). It collects and processes travel information and recommends it to the user by dint of intelligent agents with different functions. Making use of tourist-based textual response, Stanley[2] devises a travel recommender system similar to a decision-support system. It presents information which may be of interest to travel agencies and tourists. Recommender system develops with the application of artificial intelligence. E-commerce platform such as Amazon is a case in point. Felfernig[3] is the first person who advocates applying this technology to tourism, for instance, recommending destinations to mobile tourists. Individuality, information filtering and recommendation are key technology in recommender system, among which comparability is the most important concept. A mixed algorithm of comparability is put forward by Zanker in allusion to information retrieval and CBR, and is put to use in E-tourism. Because traditional quotation of tourism products is a comprehensive recommendation, Zanker[4] considers using constraint-based web configuration and model-driven algorithm to obtain and maintain information, the core content of which is in accordance with that of SOA. Srisuwan[5] sets and completes a personalized recommender system targeting E-tourism, in which statistic technology based on Bayesian classification is utilized in providing recommendation services for the users.

Currently domestic researches on personalized recommender system concentrate on the following aspects.Earlier researches center on the comparative study of various recommendation algorithms with an emphasis on the mainstream recommender system. By studying and analyzing various algorithms, the researchers put forward suggestions for improvement and future research direction, such as Jianguo Liu[6] whose suggestions are based on the characteristics and limitations of those commonly used systems, and Hailing Xu[7] who points out the disadvantages and existing problems of different recommender systems through comparative analysis.Later scholars focus more on improvement of recommendation algorithms. Mathematical methods are used in improving algorithms. Zhi Zhao and Zhuonan Feng[8] analyze the existing problems with the traditional CF and item-grade-based CF and put forward an optimized CF. Other researches are on the design of recommender systems. Most of them build recommender systems from a macroscopic perspective and develop the systems' functional blocks. You Lu and Li Yu[9] expound on the design process of intelligent recommender systems and put forward some innovative ideas.

Another research area of interest with domestic scholars is personalized recommendation, which has been used in E-commerce and web communities. The traditional algorithm of collaborative filtering can not reflect the user's interest change in a timely manner. In view of this problem, Chunxiao Xing and Fengrong Gao[10] from Tsinghua University advance two measurements for improvement: time-based data weighting and resource-similarity-based data weighting. These two weightings are introduced into the recommendation production process of resource-based collaborative filtering algorithm. Experiments show that the improved algorithm excels in recommendation accuracy. Guangwei Zhang[11] from Beijing University of Aeronautics and Astronautics put forward a method which compares the knowledge similarities of the users, thus overcoming the deficiency of the traditional method in measuring similarities. Focusing on this method, Zhang posts a new collaborative filtering algorithm and proves its validity. Shouzhi Zhang and Yan Xu[12] from Fudan University devise a personalized service system which realizes the dynamic drift of the user's interest focus through statistic analysis of the user's behavior contrail.

3. Design of Personalized Recommender System for Tourism Information

3.1 Framework of Personalized Recommender System for Tourism Information

The goal of applying personalized recommender system to tourism information service is to provide tourists with more efficient information searching experience and enhance individuation of tourism information.

In front of personalized recommender system, the user can input basic information, grade tourist attractions and choose relevant types of travel through the interface. According to the inputs, the system produces specific recommendations by using recommendation algorithm and then presents the results to the user in the form of web page or e-mail (as shown in fig.1).

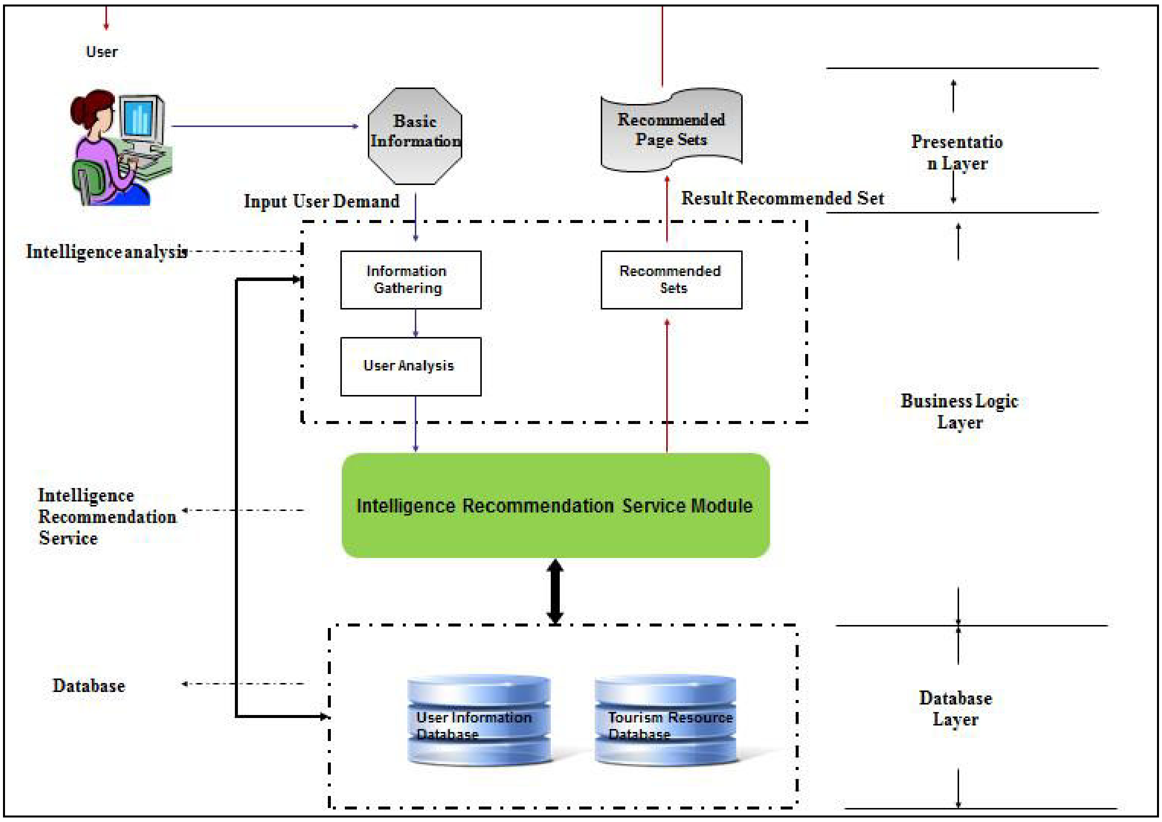


Figure 1. Basic Framework of Recommendation System

(1) Presentation layer

The function of presentation layer is to enable the interaction between the user and the back stage and presents the final results to the user's inquiry. This layer can send the user's requests to the server, gather data and display information through websites. It acts as the interface for the user to access the system. By using general websites as interfaces, it enables the user to visit websites whose operation system provides outward services and demonstrates service information. Presentation layer mainly consists of GUI and the module of recommendation page frame. GUI provides the user with imaging user interface and serves as the interface between the user and the intelligent recommendation service module.

(2) Service logic layer

Service logic layer is made up of intelligent analysis module and intelligent recommendation service module.

Intelligent analysis module, made up of three modules of information collection, demand analysis and recommendation set, is mainly responsible for analyzing the user's requests whereas information collection module mostly collects the user's requests and personal information. Analytical module processes the collected information. Then the module of recommendation set generates recommendations with the help of intelligent recommendation service module.

Utilizing Apriori algorithm, intelligent recommendation service module picks out information in agreement with the user's needs from the user information database and tourism resource database and produces recommendation set. It is a module capable of offering dynamic guidance for the user's next step of operation according to recommendation strategy and algorithm. Whether the strategy is reasonable has a direct impact on the quality of the recommendation set.

(3) Database layer

Database layer consists of the user information database and tourism resource database. It is the storehouse for operation data. Database layer stores and manages data through a nexus database.

Presentation layer, service logic layer and database layer are interrelated in realizing the function of providing personalized recommendation service to the user.

3.2 Procedure of Personalized Recommendation

By posing requests to the website, the user enters the modules of information collection and demand analysis. The inputted data will be processed by a combinational algorithm. The processed data then go to the data mining module, and finally the processed data will be stored in the user information database. In returning to the recommendation set, relevant data will be extracted from tourism resource database. Through data mining and computing, recommendation data will be produced, resulting in recommendation set which will get back to the user via recommendation page frame (as shown in fig.2).

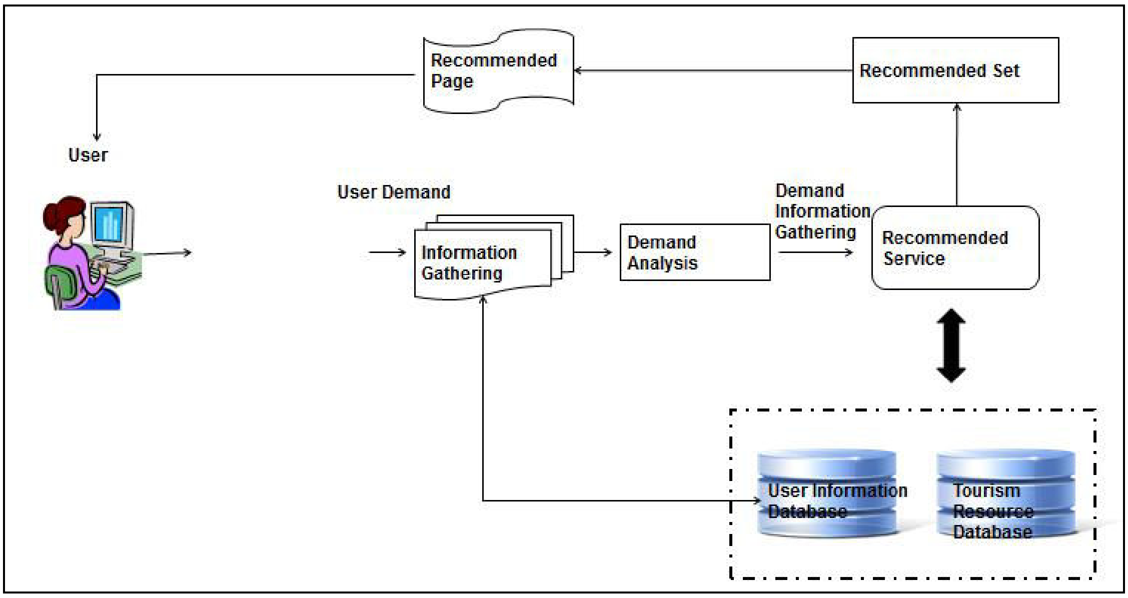


Figure 2. Work Procedure of Recommendation System

3.3 Main Features of the System

(1) Personalized Recommender System Has the Following Main Features:

Database is where the system stores its data. The data comes from different sources, including the user's personal information, purchasing and browsing records and tourism resource database. The user information database stores users' personal information inputted by them when they register, such as name, occupation, gender, hobby as well as subject term, searching scope, frequency of the appearance of the key words, etc. Recommendations will be made according to the users' purchasing and browsing records to better meet their needs. On certain occasions, the registration information can not exactly reflect the users' traits because they skip some items when inputting personal information. In this case, their purchasing and browsing records can help make out their hobbies. Tourism resource database contains information about restaurants, hotels, transportation, sightseeing, shopping and entertainments, ensuring satisfaction on the users' part when they inquire information.

(2) The objective of this recommender system is to provide services which fulfill the users' needs. Once a request is sent, the system will automatically work to answer the call.

(3) The system can alter the recommendation service according to the changes of the registration information.

(4) The system realizes communication with the user in a timely manner. Since the database stores the user' s browsing record, it can obtain the user's initial wants and likes. Without annoying the user, the system can update relevant information according to the taxis of the user's likes and dislikes regarding the services.

4. Design of the Function Module of Personalized Recommendation

4.1 Comparative Analysis of Recommendation Strategies

The choice of recommendation strategy determines the recommendation result, thus influencing the user's decision making. Table 1 shows the relationship between the existing recommendation strategies and the degree of individuation.

Table 1. Comparison of Recommended strategy

Recommended strategy	Degree of Personalization	Degree of Automation	Degree of Persistent
Content-based retrieval	Low	Low	Low
The top most active N-projects would be Recommended	Low	High	Higher
The top best-selling N-projects which User interested in would be Recommended	High	High	High

Content-based retrieval is a traditional searching technology. It is rather mature and widely used in libraries and the searching system of various websites. The working principle is searching within the set scope for contents which match with the target key words based on the subject and/or key words of the target content.

Currently the strategy adopted by many E-commerce websites is to recommend the first N items that are most active. The results that are recommended to the user are the most active.

The third strategy combines the previous two. It strives to improve the demerit of inadequate individuation of content-based retrieval strategy while keeping the merit of producing user-friendly recommendation results.

The core purpose of personalized recommender system is to satisfy the individual needs of different users. Accordingly, the design of the system and the recommendation strategies should also reflect the mentioned purpose. The recommendation method which integrates the user's demands in the relevant tourist activities can tie the user and the tourist attractions together, hence optimizing the recommendation strategy.

4.2 Design of Apriori Algorithm Module

4.2.1 Principle of this Algorithm

Apriori algorithm utilizes hierarchical sequential searching method to accomplish the mining of frequently occurring information sets. K set is used to produce K+1 set.

Suppose $I=\{i_1,i_2,\ldots,i_m\}$ is the information aggregation of a tourism project, among which i_k（k=1,2, …,m） is an item. A transaction (T) is an item set, which is the sub-set of "I". Every transaction is related to an exclusive identifier TID. Normally two parameters are used to describe the attributes of Apriori algorithm.

(1) support

The support rate of Rule X=>Y in the database refers to the proportion between the number of transactions in the trading set which contains both X and Y and the number of all transactions, marked as "support（X=>Y）". Support rate refers to the probability of transactions containing both X and Y.

(2) confidence

The confidence rate of Rule X=>Y in the transaction set refers to the proportion of transactions containing both X and Y, namely, the probability of the occurance of B in transactions when A occurs, i.e. conditional probability. It is often used to measure the validity of Apriori algorithm.

Support and confidence rates are two important concepts used to describe Apriori algorithm. The former reveals the frequency of simultaneous appearance of X and Y. If the numerical value is small, it means the correlation between X and Y is insignificant. The latter indicates whether Y will appear when X appears. Generally speaking, only Apriori algorithm with both high support rate and high confidence rate would probably be what the user is interested in.

If setting the transaction set D and the association rule X => Y of D, when c ≧ min_conf ∧ s the ≧ min_sup and it means that X => Y is a strong association rules. In that, min_conf is minimum confidence and min_sup is minimum support.

4.2.2 Overall Framework of Recommendation Module

Recommended module is the key components of the recommendation system (Figure 3 shows the design model of this module). User can specify the min_sup, min_conf and respectively interact the Largest project set search algorithm and Association rules algorithm. In the interaction, user can interpret and evaluate of the recommended results.

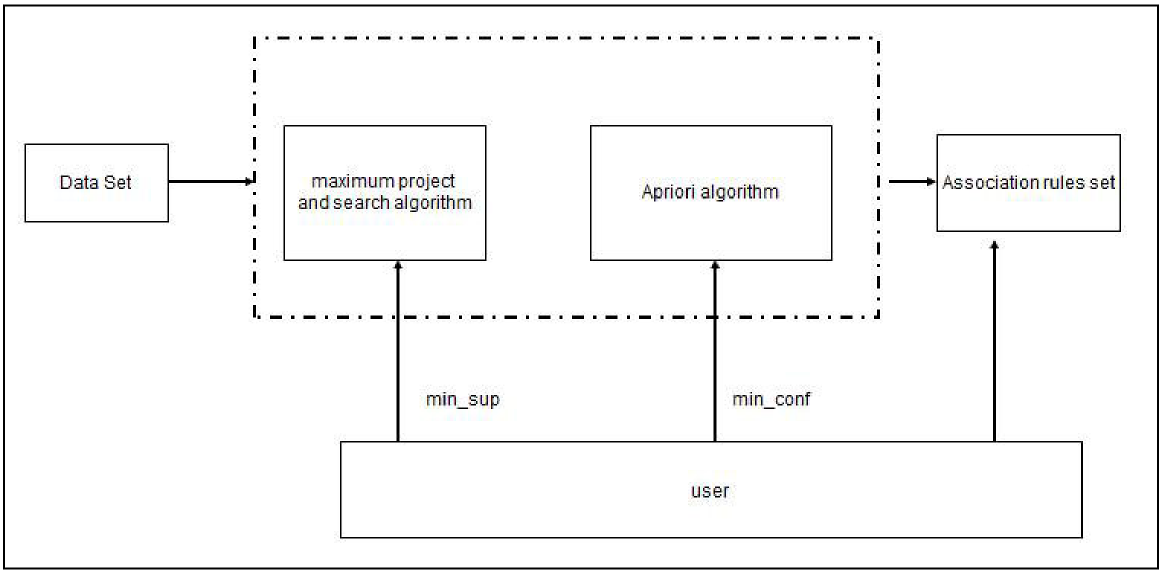


Figure 3. Overall Framework of Recommendation Module

This module includes two-step process. At first, it identifies the frequent item sets; therefore, it generates strong association rules from frequent itemsets.

4.3 Application of Apriori Algorithm to Personalized Recommender System

For example, if we design a tourist information by assuming the min_sup=2, and min_conf = 40% (see Table 2).In this table, each item represents an attraction and each route consists of the various attractions. the attractions characteristics could be extracted through the Recommendation module and then discover the association rules between these characteristics by the Association rules algorithm.

Table 2. Tourism information

Travel Line Number	Attractions
T1	I1,I2
T2	I1,I2,I4
T3	I2,I3
T4	I1,I3,I5
T5	I1,I2,I3,I4
T6	I2,I4
T7	I1,I2,I3

In this algorithm, the frequent 1 - itemsets L1={{I1},{I2},{I3},{I4},{I5}}, can be determined at first, then the candidate set C2 by the minimum support. Finally, the frequent 3 - set L3={I1,I2,I3} could be found. By this Iterative algorithm, all frequent item sets could be extracted (see Figure 4).

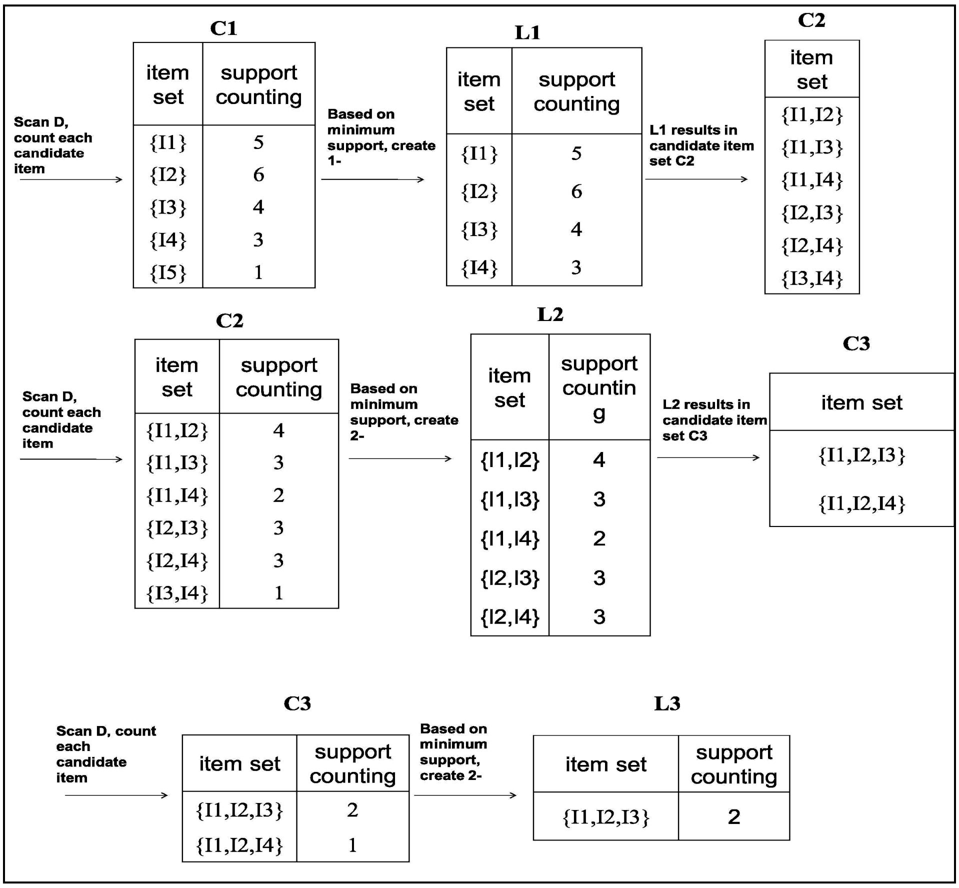


Figure 4. Algorithm Process

After extract all frequent itemsets, the association rules could be generated by frequent itemsets {I1, I2, I3} which including the non-frequent subset of {I1,I2},{I1,I3},{I2，I3},{I1},{I2} and {I3}.Following shows the results according to the association rule generation method:

$$I_1 \wedge I_2 => I_3, conf = \frac{support\{I_1, I_2, I_3\}}{support\{I_1, I_2\}} = \frac{2}{4} = 50\% \qquad \text{(Formula 1)}$$

$$I_1 \wedge I_3 => I_2, conf = \frac{support\{I_1, I_2, I_3\}}{support\{I_1, I_2\}} = \frac{2}{3} = 67\% \qquad \text{(Formula 2)}$$

$$I_2 \wedge I_3 => I_1, conf = \frac{support\{I_1, I_2, I_3\}}{support\{I_1, I_2\}} = \frac{2}{3} = 67\% \qquad \text{(Formula 3)}$$

$$I_2 => I_1 \wedge I_3, conf = \frac{support\{I_1, I_2, I_3\}}{support\{I_2\}} = \frac{2}{6} = 33\% \qquad \text{(Formula 4)}$$

$$I_1 => I_2 \wedge I_3, conf = \frac{support\{I_1, I_2, I_3\}}{support\{I_1\}} = \frac{2}{5} = 40\% \qquad \text{(Formula 5)}$$

$$I_3 \Rightarrow I_1 \wedge I_2, \text{conf} = \frac{\text{support}\{I_1, I_2, I_3\}}{\text{support}\{I_3\}} = \frac{2}{4} = 50\% \qquad \text{(Formula 6)}$$

According to the above results, because of the given min_conf = 40%, so only Formula 4 is not a strong association rules. Thus the rest of the Formulas would be output through the personalized recommendation system.

4.4 Model Testing and Experiment

4.4.1 Introduction of Weka

Weka (Waikato Environment for Knowledge Analysis) is the intelligent analysis system developed by Waikato University. Weka provides a statistical interface, bringing together the most classic machine learning algorithms and data processing tools (see Figure 5). Weka is an open platform, a collection of a large number of algorithms, including classification, regression, clustering and association rules etc [13].

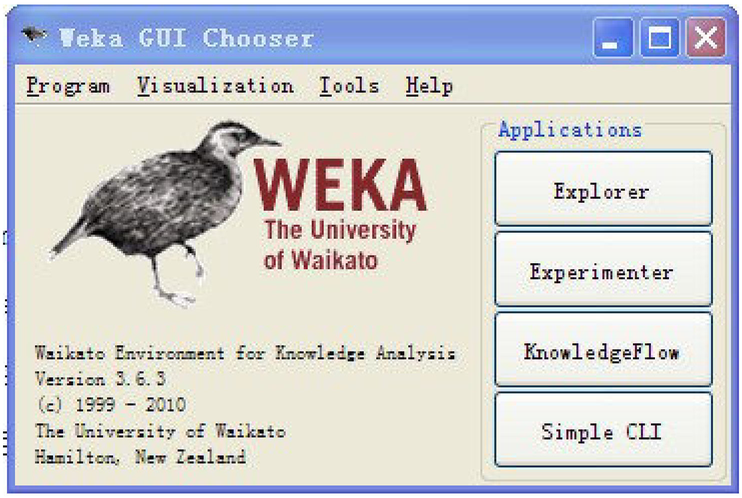


Figure 5. Weka Interface

4.4.2 Apriori Algorithm Analysis

Open the contact-lenses.arff data under the data menu, then the Weka analyses and output the results thus obtained the correlation between parameters.

(1) Open the contact-lenses data files in the Weka, the total of 24 records and 5 attribute values can be seen (Figure 6).

contact-lenses.arff

Relation: contact-lenses

No.	age Nominal	spectacle-prescrip Nominal	astigmatism Nominal	tear-prod-rate Nominal	contact-lenses Nominal
1	young	myope	no	reduced	none
2	young	myope	no	normal	soft
3	young	myope	yes	reduced	none
4	young	myope	yes	normal	hard
5	young	hypermetrope	no	reduced	none
6	young	hypermetrope	no	normal	soft
7	young	hypermetrope	yes	reduced	none
8	young	hypermetrope	yes	normal	hard
9	pre-presbyopic	myope	no	reduced	none
10	pre-presbyopic	myope	no	normal	soft
11	pre-presbyopic	myope	yes	reduced	none
12	pre-presbyopic	myope	yes	normal	hard
13	pre-presbyopic	hypermetrope	no	reduced	none
14	pre-presbyopic	hypermetrope	no	normal	soft
15	pre-presbyopic	hypermetrope	yes	reduced	none
16	pre-presbyopic	hypermetrope	yes	normal	none
17	presbyopic	myope	no	reduced	none
18	presbyopic	myope	no	normal	none
19	presbyopic	myope	yes	reduced	none
20	presbyopic	myope	yes	normal	hard
21	presbyopic	hypermetrope	no	reduced	none
22	presbyopic	hypermetrope	no	normal	soft
23	presbyopic	hypermetrope	yes	reduced	none
24	presbyopic	hypermetrope	yes	normal	none

Figure 6. Contact-lenses Output Interface

(2) Setting the Various parameters in the parameter interface (see Figure 7).

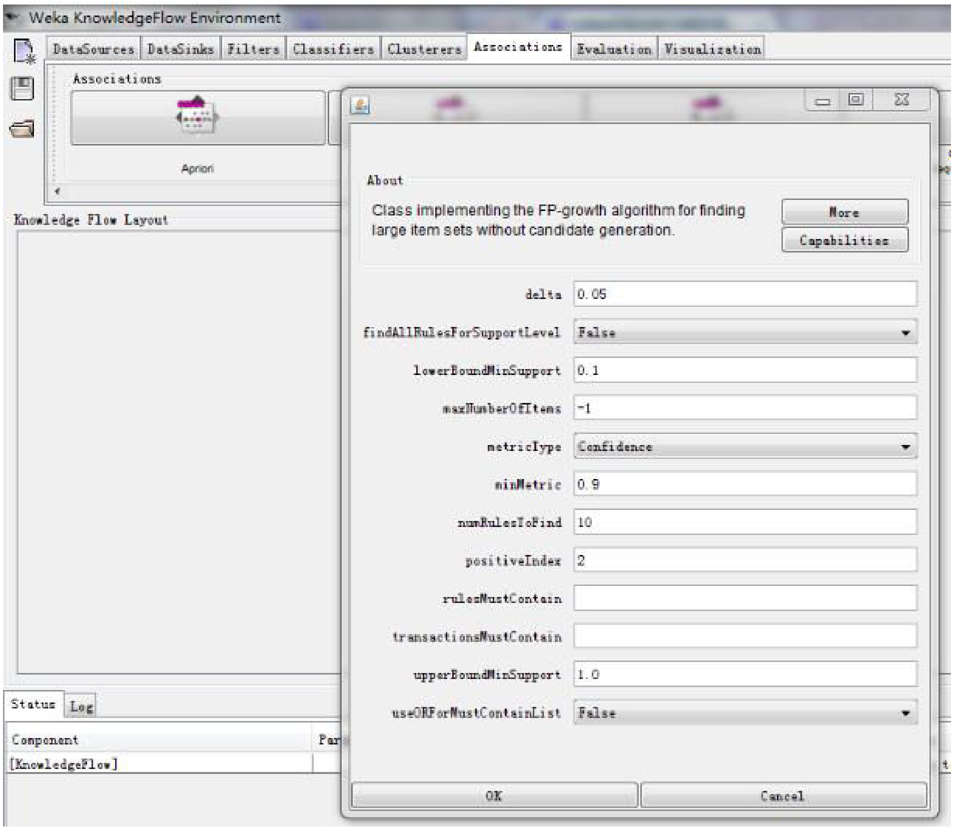


Figure 7. Contact-lenses Parameters Interface

(3) To achieve complete data output, the output results and the results shown in Figure 8.

=== Run information ===

Scheme: weka.associations.Apriori -I -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.5 -S -1.0 -c -1
Relation: contact-lenses
Instances: 24
Attributes: 5
age
spectacle-prescrip
astigmatism
tear-prod-rate
contact-lenses
=== Associator model (full training set) ===


```
Apriori
=======
Minimum support: 0.5 (12 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 10
Generated sets of large itemsets:
Size of set of large itemsets L(1): 7
Large Itemsets L(1):
spectacle-prescrip=myope 12
spectacle-prescrip=hypermetrope 12
astigmatism=no 12
astigmatism=yes 12
tear-prod-rate=reduced 12
tear-prod-rate=normal 12
contact-lenses=none 15
Size of set of large itemsets L(2): 1
Large Itemsets L(2):
tear-prod-rate=reduced contact-lenses=none 12
Best rules found:
 1. tear-prod-rate=reduced 12 ==> contact-lenses=none 12    conf:(1)
```

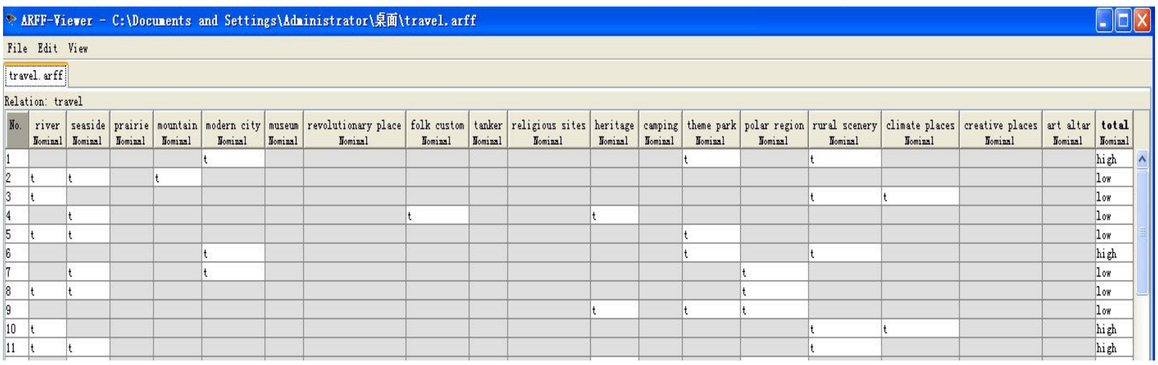
Figure 8. Result Analysis Output

Through above proceeding, we can verify that the associated algorithm for the analysis of the data processing to calculate the confidence level through the Weka system output. Analysis of the output of the Weka system, we can use a test model to analyses of tourism data sets so as to achieve the expected recommended result.

4.4.3 Weka System Experiments and Results Test

Embedding the Tourism data sets namely travel.arff into Weka, we use it to test whether it can be used in the tourism information personalized intelligent recommendation module.

(1) Loading the travel.arff file in the Weka which consists of 19 properties(see Figure 9).



ARFF-Viewer - C:\Documents and Settings\Administrator\桌面\travel.arff

File Edit View

travel.arff

Relation: travel

No.	river Nominal	seaside Nominal	prairie Nominal	mountain Nominal	modern city Nominal	museum Nominal	revolutionary place Nominal	folk custom Nominal	tanker Nominal	religious sites Nominal	heritage Nominal	camping Nominal	theme park Nominal	polar region Nominal	rural scenery Nominal	climate places Nominal	creative places Nominal	art altar Nominal	total Nominal
1					t								t		t				high
2	t	t		t															low
3	t														t	t			low
4		t						t			t								low
5	t	t											t						low
6					t								t		t				high
7		t			t									t					low
8	t	t												t					low
9											t		t	t					low
10	t														t	t			high
11	t	t													t				high

12		t									t			t					low
13					t			t										t	low
14		t											t		t				low
15	t	t			t														high
16		t	t					t											high
17		t									t		t						low
18		t									t		t						low
19			t					t						t					high
20		t								t		t							low
21		t									t		t						high
22	t	t	t																high
23	t	t												t					low
24	t	t			t														low
25		t				t								t					low
26		t			t													t	high
27													t			t		t	low
28			t		t						t								high
29								t								t		t	low

Figure 9. Travel Attribute Value Output Interface

(2) Running the data file, the output results can be shown in Figure 10 and Figure 11.

=== Run information ===

Scheme: weka.associations.Apriori -N 10 -T 0 -C 0.6 -D 0.05 -U 1.0 -M 0.1 -S-1.0 -c -1

Relation: travel

Instances: 117

Attributes: 19

river
seaside
prairie
mountain
modern city
museum
revolutionary place
folk custom
tanker
religious sites
heritage
camping
theme park
polar region
rural scenery
climate places
creative places
art altar
total

=== Associator model (full training set) ===

Figure 10. Travel Output Interface


```
Apriori
=======
Minimum support: 0.1 (12 instances)
Minimum metric <confidence>: 0.6
Number of cycles performed: 18
Generated sets of large itemsets:
Size of set of large itemsets L(1): 12
Size of set of large itemsets L(2): 19
Size of set of large itemsets L(3): 2
Best rules found:
 1. river=t seaside=t 24 ==> total=low 19    conf:(0.79)
 2. polar region=t 23 ==> total=low 18    conf:(0.78)
 3. seaside=t 68 ==> total=low 51    conf:(0.75)
 4. seaside=t heritage=t 19 ==> total=low 14    conf:(0.74)
 5. river=t 38 ==> total=low 27    conf:(0.71)
 6. river=t total=low 27 ==> seaside=t 19    conf:(0.7)
 7. theme park=t 19 ==> total=low 13    conf:(0.68)
 8. heritage=t 40 ==> total=low 27    conf:(0.68)
 9. mountain=t 18 ==> total=low 12    conf:(0.67)
10.total=low 78 ==> seaside=t 51    conf:(0.65)
```

Figure 11. Apriori Algorithm Result

In Weka system, we can test out the minimum confidence of association rules between different attributes, so the strongest association properties can be recommended by the minimum confidence.

Through the recommendation of tourist information services, if the recommended attractions in the same area, the form of regional advantages, to provide better services for tourists, in order to attract more tourists and improve the development of regional tourism. If recommended Scenic spots in different regions, through a combination of tourist routes to improve the rationality of the design of the entire line.

5. Conclusion

The authors of this paper use Apriori algorithm to investigate the intelligent recommendation service in the personalized recommender system for tourism information service. The research has accomplished the following tasks:

(1) Based on the previous researches on tourism recommendation systems, the authors design a general frame for the personalized recommender system in tourism information service. (2) After comparing and analyzing the existing recommendation strategies, the authors integrate their superiorities and come up with personalized recommendation strategies better adapted to tourism information service. (3) The authors mainly use Apriori algorithm to complete the design of the intelligent recommendation module (4) Actual data are used to validate the recommendation algorithm.

There exist deficiencies with this research. Firstly, there may be flaws with Apriori algorithm. The aggregation of huge alternative choice items produced by the algorithm takes a lot of EMS memory, which goes against efficient recommendation. Secondly, the personalized recommendation module designed by the authors is still rather simplex in function and its link with the Internet is not powerful enough. Efforts will be made in the future in perfecting the system structure so that it can recommend travel routes more efficiently with better results.

Acknowledge

This paper is supported by Science and Technology Planning Project of Guangdong province, China (Project

Number: 2012B031400008). This paper also supported by the Jinan University disciplinary research project "Study on the Online Travel Information Search: a Perspective of Social Media".

References

Konston J,et al. GroupLens: Applying Collaborative Filtering to Usenet News. Communications of the ACM,1997,40(3): 77-87.

Stanley Loh, Fabiana Lorenzi, Ramiro Saldana，Daniel Licthnow. A tourism recommender system based on collaboration and text analysis. Information Technology & Tourism, 2003, 6(3):157-165.

Felfernig, A., Friedrich, G., Jannach, D., Zanker, M.: An Integrated Environment for the Development of Knowledge-Based Recommender Applications, Intl. Journal of Electronic Commerce, Special issue on Recommender Systems, 11(2):11-34.

Zanker M., Gordea S., Jessenitschnig M., Schnabl M.: A Hybrid Similarity Concept for Browsing Semistructured Product Items. In: K. Bauknecht, B. Pröll, H. Werthner. (Hrsg.): Proceedings of 7th International Conference on Electronic Commerce and Web Technologies - EC-Web '06. Berlin Heidelberg New York: Springer 2006 (LNCS, 4082), pp. 21-30.

Srisuwan P, Srivihok A. Personalized trip information for e-tourism recommendation system based on Bayes theorem[A]. //: Xu L, Tjoa A, Chaudhry S. Research and Practical Issues of Enterprise Information Systems Ⅱ: IFIP International Federation for Information Processing. Boston: Springer, 2008. 1271-1275.

LIU Jianguo, Zhou Tao, Wang Binghong. Research Progress in Personalized recommendation system, Progress in Natural Science, 2009,(1):1-15.(in Chinese)

XU Hailing, Wu Xiao, Li Xiaodong, Yan Baoping. Comparison study of internet recommendation system. Journal of Software, 2009,(2):350-362. (in Chinese)

ZHAO Zhi; FENG Zhuo-nan. An adaptive algorithm of collaborative filtering recommender based on correlation similarity.Journal of Changchun University of Technology(Natural Science Edition), 2006,27(4):354-358. (in Chinese)

LV You; YU Li. Analysis and design of electronic commerce recommendation intelligence system.Agriculture Network Information, 2006,(12):75-77. (in Chinese)

XING Chunxiao, GAO Fengrong, ZHAN Sinan, ZHOU Lizhu. A Collaborative Filtering Recommendation Algorithm Incorporated with User Interest Change.Journal of Computer Research and Development, 2007,44(2):296-301. (in Chinese)

ZHANG Guang-Wei, LI De-Yi, LI Peng, KANG Jian-Chu, CHEN Gui-Sheng. A Collaborative Filtering Recommendation Algorithm Based on Cloud Model, 2007,18(10): 2403-2411. (in Chinese)

ZHANG Shou-zhi; XU Yan. Design and Realization of a Personalization System.Mini-micro Systems, 2003,24(12):2155-2158. (in Chinese)

LIU Wen-Feng,QING Xiao-Xia. Study of Chameleon Clustering Algorithm and Implementation in Weka.Computer Systems & Applications, 2010,19(12): 246-250. (in Chinese)