A PERSONALIZED RECOMMENDER SYSTEM FOR TELECOM PRODUCTS AND SERVICES

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Abstract: The Internet brings excellent opportunities to businesses for providing personalized online services to their customers. Recommender systems are designed to automatically generate personalized recommendations of products and services. This study develops a hybrid recommendation approach which combines user-based and item-based collaborative filtering techniques for mobile product and service recommendation. It particularly implements the approach into an intelligent recommendation system called telecom product recommender system (TCPRS). Experimental results show that the TCPRS can effectively help new customer selecting the most suitable mobile products and services.

1 INTRODUCTION

Today, telecom businesses offer hundreds of different mobile products and services to customers and are exploring new service models such as to allow customers to select and purchase products/services through Internet. However, with such a vast number of choices, it is becoming more and more difficult for customers to find its favourite choice fast and accurately. Recommender systems are designed to help customers resolve this problem by automatically giving them helpful recommendations of various products and services. The systems can give recommendations according to user profiles or preferences, or rely on the choices of other people who could be useful references. The advantage of recommender systems is to suggest the right items (products or services) to particular user (customers, suppliers, etc) based on their explicit and implicit preferences by applying information filtering technology (Adomavicius and Tuzhilin 2005). In recent years, significant steps have been taken in the direction of providing personalized services for a wide variety of web-based applications in e-commerce, e-learning, and e-government (Guo and Lu 2007). The successful applications of recommendation techniques have involved various product and service areas such as recommending news, movies, books, videos, exhibitions, and business partners (Lu et al., 2010).

This study explores a new area of recommender systems to support customers selecting the most appropriate mobile products/services online. The main contribution of this study is the development and implementation of a personalized recommendation system for telecom products/ services by combining both item-based and user-based collaborative filtering methods, called TeleCom Product Recommender System (TCPRS).

The main process of recommendation by using TCPRS can be described as follows: 1) to collect new customer information; 2) to gather similar existing customers' data, which includes purchase records, website visit history as well as personal profiles; 3) to collect related product data; 4) to analyses, the collected data (customers and the products) and predict the ratings of unrated products; 5) to select top-N products with highest predicted ratings as recommendations to the customers.

The rest of this paper is organized as follows. Section 2 discusses related research in recommender systems. In Section 3, we present a personalized recommendation system for telecom product and services, TCPRS, using a hybrid approach that combines item-based and user-based collaborative filtering methods. A thorough analysis of the performance of the TCPRS is shown in Section 4.

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Section 5 demonstrates the implementation and application of the TCPRS. Finally, conclusions and future studies are discussed in Section 6.

2 RELATED WORKS

Recommender systems use the concept of rating to measure how much a particular item is liked by the target user. Adomavicius and Tuzhilin, (2005) stated that in middle 1990s researchers in the recommendation areas started to do research focusing on ratings structure, and the problem of recommendation has been simplified to be the problem of predicting ratings of items that have not been known by a user. In the literature of this field, content-based (CB) methods and collaborative filtering (CF) methods are the most popular techniques adopted in recommender systems (Iaquinta et al., 2007). The CB methods recommend products by comparing the content or profile of the unknown products to those products that are preferred by the users. Differ from CB methods, CF methods do not involve user profiles and item features when giving recommendation, but only rely on the user ratings. A third approach is hybrid methods which combine CB and CF methods and it is becoming more popular among researchers in this field. Iaquinta et al., (2007) involved CB methods into CF model for calculating user similarities using user profiles, which are built using machine learning techniques. Su et al., (2007) built a model using multiple experts including both CB and CF approaches to take different strategies in different situations. All these methods are based on the rating structure. In order to increase the accuracy or performance of recommender systems, many researchers have tried with some non-ratings techniques, such as data mining, machine learning and intelligent agents depending on different circumstances. In this paper, we will only focus on the algorithms and applications of collaborative filtering methods.

There are several kinds of CF methods, among them the most popular approaches are user-based CF and item-base CF. A user-based CF method is to use the ratings of users those are most similar to the target user for predicting the ratings of unrated items. On the other hand, item-based CF method uses the similarities of items for predicting ratings. Literature shows that the current trend of recommender system is to combine two or more techniques together for improving the accuracy of recommendation or overcome the limitations of single recommender algorithm, and the combination of user-based CF and item-base CF may achieve a good performance in a big-user-set and big-item-set environment.

Therefore, this study implements a personalized recommendation system TCPRS for telecom products/services using a hybrid approach that combines item-based and user-based CF methods.

3 ALGORITHM DESCRIPTION

Based on literature review (Shi et al., 2008), an algorithm which integrates Item-based and User-based Collaborative Filtering is designed to the TCPRS. This algorithm takes advantage of both the horizontal and vertical information in the user-item rating table. The algorithm is described in seven steps as follows.

1) ***Generate a User-item Rating Table:*** Each user is represented by a set of item-rating pairs and the summary of all those pairs can be collected into a user-item rating matrix.

2) ***Calculate Item Similarity:*** This step measures the similarities between any two items. Pearson correlation is selected for this step which measures the similarity between two items by calculating the linear correlation between the two vectors.

3) ***Item Neighbours Selection:*** In most CF methods, a number of neighbours will be selected when predicting ratings. In the TCPRS, we used the top-N technique for neighbour selection.

4) ***Predict Empty Ratings using Item-based CF:*** In this step, all the unrated ratings can be calculated using item-based CF method and all the empty cells in the user-item rating table will be filled.

5) ***Calculate User Similarity:*** Beside from predicting the ratings based on the similarities of items, we can also predict the ratings by analysis the similarities between users. We also use the Pearson correlation algorithm for calculating the user similarity.

6) ***Select Top-N Similar Users:*** Similar as step 3, we need to select a number of neighbour users for predicting ratings. The Top-N technique is used in the TCPRS system.

7) ***Final Recommendation Generation:*** The final step of the algorithm is to predict the ratings of every unrated telecomm product/services for the target users using user-based CF. The new predicted ratings will replace the ratings predicted in Step 4, and be regarded as the final results. Based on the

ratings, we could generate a set of most suitable products/services for a user.

4 EXPERIMENTAL RESULTS

Before implement the approach discussed above into an online system, we conducted a set of experiments to validate the approach and evaluate its performance. We used dataset provided by Movielens for the experiment. Movielens is a movie recommendation website that aims to support the research and development of recommender systems. It has been widely used by researchers around the world for measuring the performance of recommender systems.

4.1 Evaluation Metrics

There are several statistical accuracy metrics used for comparing the predicted ratings with the user-rated ratings methods, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Correlation. In the experiments, we select MAE to be our evaluation method as it is easy to interpret directly and very commonly used.

4.2 Experimental Analysis

In order to achieve accurate evaluation results, we randomly select the training and testing datasets five times so that we can have five training dataset (u1base to u5base) and five testing dataset (u1test to u5test). In order to measure the effect of the number of neighbours on the accuracy of the algorithm, we calculate the MAE four times separately using 5, 10, 20 and 50 neighbours for each training/testing group. The testing result is as in Figure 1.

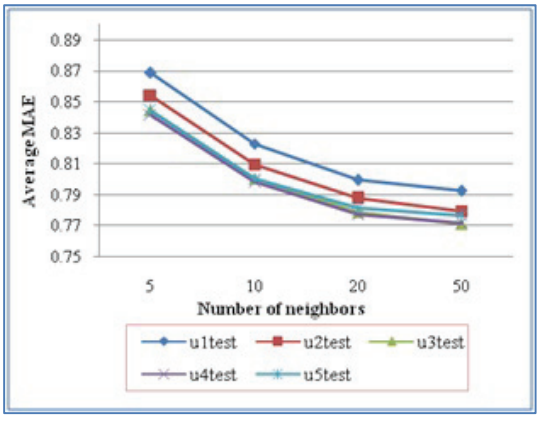
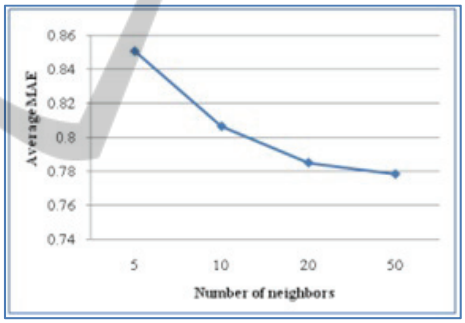


Figure 1: Experiment results.

From Figure 2(a), as only u1test has a slightly higher average MAE than the rest, we can say that the performance of the algorithm is quite uniform across the dataset from Movielens. As shown in Figure 2(b), the average MAE is falling while the number of neighbour increases and this decrease is most significant when the number of neighbours increased from 5 to 10. Therefore, by considering both the accuracy and calculation efficiency, we decided that 10 neighbours is most proper for our system.

(a)



(b)

Figure 2: (a) Average MAE of each group (b) Average MAE of each different neighbour level.

4.3 Comparison Analysis

Su et al., (2007) carried out a series of experiments for evaluating the accuracy of several different recommender systems. They used the same evaluation method and dataset as we did. Therefore, their experiment results are very good references to evaluate the performance of our algorithm. The tested algorithms are: Pearson correlation-based CF (PCCF), pure TAN-ELR model-based CF algorithm (MCF), pure TAN-ELR content-based predictor (CP), content-boosted CF (CBCF), and two hybrid methods Sequential mixture CF (SMCF) and Joint mixture CF (JMCF) introduced in this paper. The experiment results are shown in Table 1.

Table 1: MAE result comparison of various CF algorithms.

MAE %	PCCF	MCF	CP	CBCF	SMCF	JMCF
63.75	0.6901	0.7592	0.8055	0.6974	0.6820	0.6818
68.24	0.6976	0.7670	0.8203	0.7033	0.6883	0.6885
76.5	0.7108	0.7800	0.8178	0.7091	0.6932	0.6981
76.74	0.7325	0.8084	0.8359	0.7244	0.7088	0.7221
85.3	0.7723	0.8296	0.8479	0.7680	0.7155	0.7433
87.55	0.7895	0.8458	0.8664	0.7822	0.7303	0.7538
91.54	0.8166	0.8657	0.8952	0.7910	0.7416	0.7797
94.64	0.8937	0.8921	0.9178	0.8705	0.7785	0.8135
95.59	0.8858	0.8437	0.8669	0.8014	0.7335	0.7836
96.14	0.9803	0.9450	1.0174	0.8818	0.8200	0.8786
overall	0.7407	0.8000	0.8378	0.7344	0.7062	0.7188

For comparing with MAE of our algorithm with their results, we believe the accuracy of our algorithm is competitive with some other hybrid recommender algorithms, and markedly higher than traditional CB and CF recommender methods.

5 SYSTEM DEVELOPMENT FOR TELECOM INDUSTRY

5.1 System Architecture

The TCPRS is development for telecom industry. It is implemented using a Multi-Tiers architecture on Microsoft .NET 3.5 platform. It consists of three main parts: client, web server and database server.

- ***Client:*** Client is the user interface presented on web browser. The client browser is responsible for sending requests to web server every time the user perform an action.
- ***Web Server:*** Websites are hosted in web servers. It receives the requests from client browser, retrieves the requested resources and sends them back to client browser. Based on the web server, the TCPRS web site can be divided into three layers, the presentation layer, business logic layer and data access layer. Presentation layer is responsible for generating the requested web pages and handling the UI logics and events. Business Logic layer defines the business rules and processes of the application (the CF recommender algorithm), and serves as a mediator between the presentation layer and the data access layer. Data Access Layer deals with the data operations with database and transfers data with business logic layer.
- ***Database Server:*** Database server is the server runs the database applications. In TCPRS we use SQL Server 2005 as the database application because it is most compatible to Microsoft technologies we used.

5.2 System Implementation

Data Collection: Data collection is the preliminary work of the algorithm implementation. The rating data of customers are collected in the handset details web page where customer can rate a mobile phone. Then the rating value, as well as the customer ID and handset ID will be stored into database.

Handsets Recommendation: After customer logs into its homepage, TCPRS is able to generate recommendations to the customer. The system will firstly read the algorithm settings from configuration file and the rating records of the target user. If the number of rating records is greater than the threshold value, the system will use CF algorithm for recommendation. Otherwise, the system will use the hybrid method described in Section 3 for recommendation. Finally, the system will return a list of recommended handsets.

Plan Recommendation: The TCPRS can recommend new plans (products in Telecom) and extra packages (such as mobile phone service + fixed line service) based on a customer's average usage in the last six months. The approach is to calculate the actual cost of the average usage in every possible plan and package combination, and selects the one with the lowest cost to recommend to the customer based on the business rules.

6 SUMMARY AND FURTHER STUDY

In this paper, we present a personalized recommendation system for telecom product and services, TCPRS, which uses a hybrid approach that combines both item-based and user-based CF methods. This research is in progress. This system is being used in a telecom company in Australia. In the future, uncertainty data processing issue will be considered to improve the proposed approach. The approach will be also adopted to develop a mobile service recommender system to support business customers.

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