IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661, p- ISSN: 2278-8727Volume 14, Issue 2 (Sep. - Oct. 2013), PP 13-16
www.iosrjournals.org

Multidirectional Product Support System for Decision Making In Textile Industry Using Collaborative Filtering Methods

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Abstract: *In the information technology ground people are using various tools and software for their official use and for their personal reasons. Nowadays people are worrying to choose data accessing tools and software's at the time of buying and selling the products and they are also worrying about various constraints such as cost, life time of the product, color and size of the product etc. In this paper we generated the solutions to the existing unsolved problems. Here we proposed the algorithm Multidirectional Rank Prediction (MDRP) decision making algorithm in order to take an effective decision at all the levels of data extraction, using the above technique and we analyzed the results at various datasets, finally the results were observed and compared with the existing methods such as PCC and VSS. The result accuracy was higher than the existing rank prediction methods.*
Keywords: *Knowledge Discovery in Database (KDD), Multidirectional Rank Prediction (MDRP), Pearson's Correlation Coefficient (PCC), VSS (Vector Space Similarity)*

I. Introduction

Collaborative techniques are used to filtering the noise data and give product recommendation to novice users. Collaborative filtering may involve in large data sets. Collaborative technique is used to predict user's interests on particular product or more than one product. In this Proposal Selling and buying are the two conventional activities for each seller and customer. One who sells the products is aims to gain the maximum earnings, and the customer has to get trustworthy product and it is extendable to intermediate level. These scenarios are identified and people who are used products are worried to discover the best product and in addition they suffer and face difficulty to draw the features of the item such as color, product size, availability and durability of the item.

To prevail over these situations identified a problem learning multidirectional asymmetric similarity collaborative filtering via matrix factorization technique. The Collaborative filtering technique is a conventional recommender system which was used by different peoples in different circumstances, and data was extracted by this conventional method to various purposes. Still data extraction is a foremost problem in various disciplines, to handle seriously this problem and provide remedy to this issue. Solving any problem using any one the available technique is a common method, but the difficulty is to identify a best method or technique for long-term solution to the existing problem. In the exiting problem is providing the solution not up to the expected level of the customers. Customers are suffering sparsity and scalability problems. Most of the commercial recommender systems are associated with large data sets. The user-item matrix used for collaborative filtering could be tremendously large and sparse, which carries out the challenges in the performances of the recommendation.

1.1 Data Sparsity Problem

One classic problem in data sparsity is the cold start problem. As collaborative filtering methods recommend items based on users' past preferences, new users must need to rate sufficient number of items to enable the system to capture their likings exactly and to provide reliable recommendations.

Similarly, users when rating the new items also face the same problem. When new items are added to system, they need to be rated by large number of users before they could be recommended to users who have similar tastes with the ones rated them. The new item problem does not limit the content-based recommendation, because the recommendation of an item is based on its discrete set of descriptive qualities rather than its ratings.

1.2 Scalability Problem

The Secondly Scalability is another problem in our traditional CF algorithms will face serious scalability problems. If the customer data set, no of items are high a normal CF algorithm time complexity was too large and many online version systems have to respond immediately and provide recommendations of their purchases and ratings history, which demands a higher scalability of the Collaborative filtering system.

Most of the Collaborative Filtering algorithms are focused only on user-user similarity and item-item similarity, and they are not focused First, they are based on User-defined similarity measurements, such as Pearson Correlation Coefficient (PCC) or Vector Space Similarity (VSS), which are, for the most part, not adaptive and optimized for specific applications and data. Second, these similarity measures are restricted to symmetric ones such that the similarity between A and B is the same as that for B and A, although symmetry may not always hold in many real world applications. Third, they typically treat the similarity functions between users and functions between items separately. However, in reality, the similarities between users and between items are inter-related. In this paper, earlier unified model for users and items, known as **S**imilarity **L**earning based **C**ollaborative **F**iltering (SLCF), based on a novel adaptive bidirectional asymmetric similarity measurement.

1.3 Similarity Learning Based Collaborative Filtering Technique (SLCF)

Thus the above model automatically learns asymmetric similarities between users and items at the same time through matrix factorization. Novel matrix factorization based model for learning user and item similarities simultaneously for CF. The similarity measurement can be asymmetric and can be learned from the data using matrix factorization methods. Previously proposed learning algorithm was not effective to find prediction ratings. Then showed our learned similarity measurement significantly outperforms and to be redefined. The experiments showed in this method can outperform baselines such as traditional memory-based approaches and a low-rank matrix approximation model. Furthermore, the online version of the prediction algorithm is shown to be effective and more efficient for handling new users and items. So here proposes an online version of the rating prediction method to incorporate new users and new items in a effective way. Then additionally, plan to develop more efficient algorithms to learn our model in larger scale datasets.

Although focused on CF in this paper, our model is very general for sparse data (*Sparse data* is by nature easily compressed, and this compression almost always results in significantly less computer data storage usage) which has matrix form.

Therefore, earlier bidirectional model was applied to the following benchmark datasets, including MovieLens, ,Netflix Movie Data Sets,and Technlens+ datasets. This model is more appropriate for textile data set and garment related mining applications and to perform the data mining functionality tasks using weka tool 3.6.6 such as classification, clustering, association analysis, attribute selection based on the condition, Visualizing the data, and finally analyzing the data set and based on the conditions data extraction to be performed.

II. Multidirectional Asymmetric Similarity Learning Method

To extend this proposed model to multi-directional cases where more than two types of entities are involved such as user, item, ratings, seller (either manufacturer or supplier).In the multidirectional asymmetric similarity learning algorithm mainly focuses on item-item similarity and user-user similarity simultaneously.

To make two connected contributions. The first contribution is similarity function learning. Then proposed a unified model to learn asymmetric similarities for items and users at the same time.

Through novel reformulations of classic memory-based approaches, first propose a one-directional similarity learning model which can learn either user-side similarity or item-side similarity. This model is further extending the one-directional learning to bi-directional similarity learning which learns user side similarity and item-side similarity at the same time which shows that the similarity learning problems can be formulated as problems of matrix factorization with missing values. Second contribution is collection of algorithms that use the learned similarity functions for CF, which is known as similarity-learning collaborative filtering (SLCF).

Considering the two versions of SLCFs, the first one is improving the traditional memory-based approaches (M-SLCF), and second is based on matrix reconstruction (R-SLCF) and also proposed an online version of the rating prediction method R-SLCF to allow new users and new items to be included in our model incrementally. In addition with that to develop our algorithms to learn our model to be used for larger scale datasets also .Although our new model, is very general for sparse data which has matrix form. Therefore, using the proposed model to other kinds of data sets such as text data set and multimedia data sets also. So that, the CF will be performing very well in case of item to user relationship in multiple ways.

The earlier various collaborative filtering models was mainly focused user based and item based methods only. Then the data prediction method was existing collective ratings information from similar items or similar users. In some of the areas large amount of similar users or similar items were unavailable and additionally various clustering algorithms are used to form user groups. Different hybrid algorithms are used for data extraction some hybrid algorithms are suitable only for some situations like such a situation user's privacy should be protected while the users are rating an item. In few circumstances item-item similarity is better than the user-user similarity while hiding the user demographic information. PCC (Pearson Correlation Coefficient and VSS (Vector Space Similarity) is not suitable for all type of applications. To protect the privacy of users cryptographical algorithms are used because item-item similarity is publicly available. But the major drawback of this algorithm was item-user similarity to be calculated parallel. In addition that the key generated algorithms are not secured to all type of users. The aim of the hybrid algorithm is to improve the computational time and performance efficiency. The objective of the content based filtering and collaborative filtering was focused on data set to be reduced and this is not suitable for all kinds of applications.

III. Multidirectional Decision Making Algorithm(MDRP)

To overcome all the exiting problems at various user levels using Multidirectional Rank Prediction (MDRP) Decision Making Algorithm. We used the multidirectional data set with multiple attributes and more than two entities are used in this proposed algorithm.

Table 1: Multidirectional Entity and Attributes with Scaling

<table>
<tr><th>Entities</th><th>Gender</th><th>Age Group</th><th>Profession</th><th>Location</th><th>Rank</th></tr>
<tr><td>Product</td><td rowspan="4">Male, Female</td><td rowspan="4">17-20, 31-45, Above 45</td><td rowspan="4">Teacher, Engineer, Business person, Doctor etc.</td><td rowspan="4">Urban, Semi urban, Rural.</td><td rowspan="4">5 Scale ranking method</td></tr>
<tr><td>User</td></tr>
<tr><td>Rank</td></tr>
<tr><td>Producer</td></tr>
</table>

Weka tool was used and analyzed with various data operations like,(1) Classification of data (2) Regression analysis and prediction (3) Clustering of data and association analysis. The multidimensional data set is taken and analyzed in various aspects such as income, location, age group and gender wise classification.

Figure 1: Multidirectional Collaborative Filtering

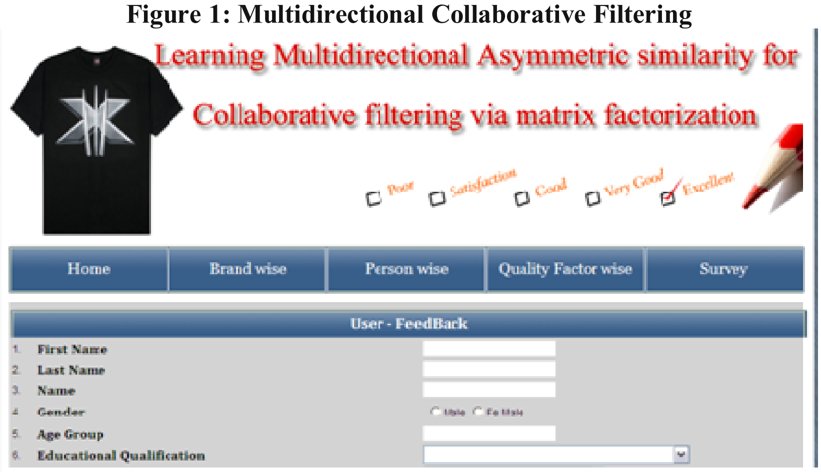

Figure 2: Collaborative Filtering Assessments

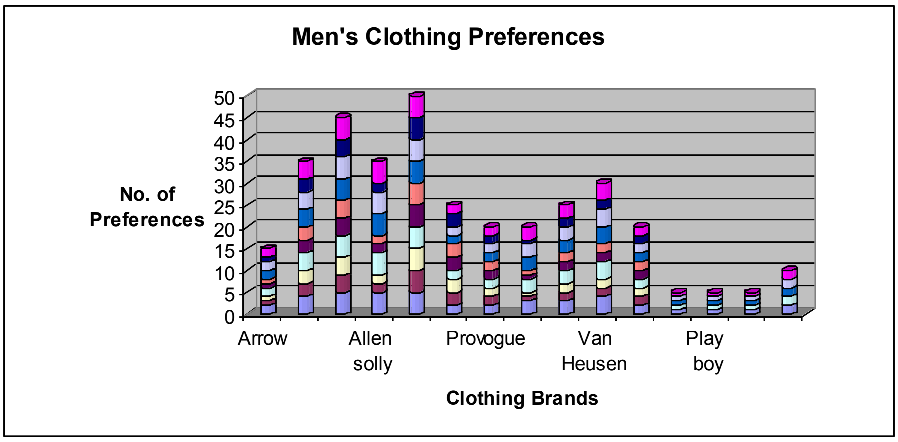

Figure 3: Men's Clothing Preferences

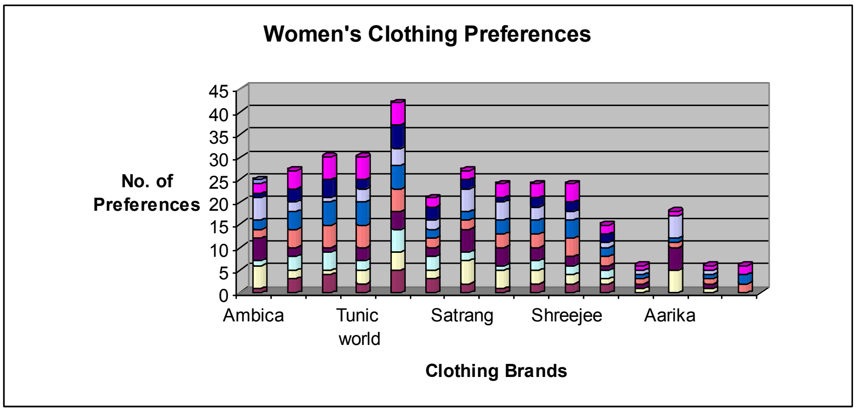

Figure 4: Women's Clothing Preferences

From the above graph, we used a textile data set and analyzed the ranking of various products and user can easily asses the quality of the product based on the quality constraints and make a decision about a particular product. This strategic decision making is very useful to increase the product sales and enlarge the product similarity and user similarity at various levels.

IV. Conclusion

The above multidirectional rank prediction algorithm helps to find the correct product at the time of purchase and analyze the existing user history, In addition this algorithm was very supportive to make high-quality decisions at all the 3 levels. MDRP algorithm was giving accurate results over than SLCF, RLCF, PCC and VSS methods. It handles large data sets with multiple entities with multiple attributes are possible. Right product can survive in the market based on the good product rating. Low ranking products will be eliminated or to be improved. Customer can get chance to buy good product with good features.

References

[1]. Das,J. Heritage Inst. of Technol., Heritage Acad., Kolkata, India, Voronoi based location aware collaborative filtering.
[2]. Mittal, N. MNIT, Jaipur, India Nayak, R.; Govil, M.C.; Jain, K.C. Recommender System Framework Using Clustering and Collaborative Filtering.
[3]. Akshi Kumar, Abhilasha Sharma Alleviating Sparsity and Scalability Issues in Collaborative Filtering Based Recommender Systems.
[4]. Nidhi Gupta, Trends in Collaborative filtering Recommendation Technique.
[5]. E. Thirumaran, Collaborative Filtering Based Recommendation Systems.
[6]. Hemalatha Chandrashekhar Indian Institute of Management Ranchi, India, Personalized Recommender System Using Entropy Based Collaborative Filtering Technique.
[7]. Sotirios P. Chatzis Department of Electrical Engineering, Computer Engineering and Informatics.
[8]. Cyprus University of Technology, A Coupled Indian Buet Process Model for Collaborative Filtering.
[9]. Xuejun Zhang, John Edwards *, Jenny Harding, Personalised online sales using web usage data mining.
[10]. Seok Kee Lee a,1, Yoon Ho Cho b,*, Soung Hie Kim, Collaborative filtering with ordinal scale-based implicit ratingsfor mobile music recommendations
[11]. Ana Belén Barragáns-Martínez a,*, Enrique Costa-Montenegro a, Juan C. Burguillo a, Marta Rey-López b, Fernando A. Mikic-Fonte a, Ana Peleteiro, A hybrid content-based and item-based collaborative filtering approachto recommend TV programs enhanced with singular value decomposition.