IOSR Journal of Engineering (IOSRJEN) **www.iosrjen.org**
ISSN (e): 2250-3021, ISSN (p): 2278-8719
PP 70-75

Multidirectional Decision Support Assessment Scheme in Textile Industry Using MDCF Techniques

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Abstract: *Nowadays Collaborative Filtering (CF) is a generally accepted recommendation and prediction algorithm based on other related attributes in which users can express their opinions on their products by rating them. CF algorithm is used to collect the existing user ratings and to predict ratings on unknown items for an individual user, and recommends to the users the items which are maximum predicted ratings.*
Multidirectional similarity learning is proposed Collaborative Filtering method in that, Principle Component Analysis is used to predict asymmetric rating prediction for multiple attributes similarity. Feature Reduction is applied to reduce the feature size after feature selection Process and it can be implemented using Singular Value Decomposition. After the product resemblance relation is learned, it will be used flexibly in several ways for rating prediction. On the other hand, similarities between multiple attributes in reality are inter-dependent and it is used to reinforce each other. Hence, this similarity model is more appropriate if the similarities between users and items are jointly learned. Finally, Multiple Criteria Decision Analysis (MCDA) supports to decision makers to make an optimal selection in the environment of conflicting and competing criteria are proposed. In this paper proposes a new mechanism for integrating MCDA into CF process in multiple criteria recommendations. The proposed system consists of two main parts. Firstly, the weight of each user towards each feature is computed by using multiple linear regression methods. Secondly, the feature weight is incorporated in to the collaborative filtering process to provide effective recommendations.
Experimental results are proved that system is outperformed in terms of computational efficiency and similarity accuracy.
Keywords: *CF, MCDA,MDSL, HOSVD*

I. INTRODUCTION

Collaborative Filtering (CF) is a conventional recommendation and prediction algorithm based on similar attributes, where users can express opinions on items by rating them, and CF algorithm is used to collect previous user ratings and to predict ratings on unseen items for an individual user, and it recommends to the user with highest predicted ratings. It is closely related to the item-based CF in the content-based recommendation method, it also recommends similar items. However, the content-based method which evaluates item similarity based on explicit feature that describes the items and it is limited to content analysis techniques, as it is very difficult to extract features from multimedia data and multidirectional data automatically. The current item-based CF recommendation technique is solution to such type of problems, important reason for the modelling of similarity learning models based on multi aspect and multi directional data for CF recommendations.

II. OBJECTIVE OF THE PROBLEM

Memory-based CF methods are commonly used approach for collaborative filtering in multi directional data which are simple and effective. Usually memory-based method suffers from several severe issues. First, missing data is a major problem in collaborative filtering which is known as sparseness problem. Because, there are millions of users and items in existence. But, a user can rate only a few items and when the data are extremely sparse, it is difficult to find similar users or items accurately. Secondly, in memory based approaches, similar users and items are found by calculating to use user similarity metrics such as Pearson Correlation Coefficient (PCC) and Vector Space Similarity (VSS). Third, the conventional PCC and VSS are troubles in distinguishing the importance of items. To associate these problems, many variations found in similarity metrics, weighting approaches, combination measures, and rating normalization methods. Many previous studies in collaborative filtering are considered the similarities between users and items calculated separately. However, similarities between users and items in reality are interdependent and can be used to reinforce each other. Therefore, it would be more appropriate if the similarities between users and items be jointly learned automatically. The item rating is based on the user preference is extracted through the data collection process. There are several properties are used to measure the item rating to the textile product purchase.

III. LITERATURE SURVEY

1. Manos Papagelis, Dimitris Plexousakis “Qualitative Analysis of User-based and Item-based Prediction Algorithms for Recommendation Agents” 2005, In this Literature, prediction algorithms is utilized to *user-based* and *item-based* similarity measures derived from either *explicit* or *implicit* ratings. The utilization of explicit ratings is an ‘‘implicit’’ sense which is to enrich a user’s model without actually prompting users to express their preference to Categories in similarity prediction.
2. Sung Young Jung; Jeong-Hee Hong; Taek-Soo Kim “A statistical model for user preference “2005, in this Literature, Modeling user preference is issues which is resolved through intelligent information systems. Automatically analyzing models can be classified into one of the following three classes, depending on how they represent preference: vector similarity, probability, and association. First, vector similarity is adopted in both collaborative filtering and content-based filtering. In collaborative filtering, user preference to an item is represented by how many users with preferences similar to the given user choose the item. Second, probability is used to predict user’s future behaviours in a Bayesian network where preference is represented by the probability that a user selects a given item. Third, in association rule mining Areas preference is represented by the strength of association (i.e., correlation) between an item and a user history.
3. Liang He, Weiwei Xia, Lei Ren “A collaborative filtering algorithm based on Users' Partial Similarity, 2008, In this literature , system focuses on two main problems of Collaborative Filtering(CF): Scalability and sparsity. CF problems have been handled by proposing collaborative filtering algorithm based on Users' Partial Similarity (CFUPS). Collaborative filtering problems on two crucial steps: (1) computing neighbor users for active users and (2) missing data prediction algorithm. CFUPS's main idea is that
4. SongJie Gong “A Collaborative Filtering Recommendation Algorithm Based on User Clustering and Item Clustering” ,2010 , In this literature , Personalized recommendation systems can help people to find interesting items and they are widely used with the development of textile and movie industry. to produce the recommendations. The recommendation joining user clustering and item clustering collaborative filtering is more scalable and more accurate. This literature is suitable for item similarity formulation and user similarity formulation.
5. Yehuda Koren, Joseph Sill,” Collaborative Filtering on Ordinal User Feedback” , 2011 , In this literature , collaborative filtering (CF) recommendation framework which is based on viewing user feedback on products as ordinal, rather than the more common numerical view. Such an ordinal view frequently provides a more natural reflection of the user intention when providing qualitative ratings, allowing users to have different internal scoring scales. Moreover, assigning numerical scores to different types of user feedback would not be easy. The framework can wrap most collaborative filtering algorithms, enabling algorithms previously designed for numerical values to handle ordinal values. We demonstrate our framework by wrapping a leading matrix factorization CF method. The work utilize the system to predict a full probability distribution of the expected item ratings, a frame work is created on the item, wrapping a leading matrix factorization CF method is used to estimate the confidential level of prediction. This literature is suitable for item similarity and user similarity formulation and formulation based on the other user rating.

IV. EXISTING SYSTEM

4.1 Feedback based collaborative filtering

The Feedback based collaborative system works as per customer experience through personalized recommendations based on prior implicit feedback. These systems passively track different sorts of user behavior, such as purchase history, watching habits and browsing activity, in order to model user preferences. Unlike the much more extensively researched explicit feedback, do not have any direct input from the users regarding their preferences. In particular, lack of substantial evidence on which products consumer dislike. By identify unique properties of implicit feedback datasets. Treating the data as indication of positive and negative preference associated with vastly varying confidence levels. This leads to a factor model which is especially tailored for implicit feedback recommenders. So, suggest a scalable optimization procedure, which scales linearly with the data size. The algorithm is used successfully within a recommender system for television shows. It compares favourably with well tuned implementations of other known methods

4.2 Neighbourhood based collaborative filtering

Most collaborative filtering systems apply the so called neighbourhood-based technique. In the neighbourhood-based approach a number of users are selected based on their similarity to the active user. A prediction for the active user is made by calculating a weighted average of the ratings of the selected users, Instead of just relying on the most similar person, a prediction is normally based on the weighted average of the recommendations of several people. The weight given to a person’s ratings is determined by the correlation between that person and the person for whom to make a prediction. As a measure of correlation the Pearson correlation coefficient can be used. In this example a positive rating has the value 1 while a negative rating has the value –1, but in other cases a rating could also be a continuous number.

V. PROPOSED SYSTEM

Multidirectional similarity learning is proposed Collaborative Filtering technique. In this technique, Principle component analysis is used to predict asymmetric rating prediction for multiple attributes similarity. Feature Reduction is applied to reduce the feature size after the feature selection Process and it can be implemented using Singular Value Decomposition. Once the similarity relation is learned, it can be used flexibly in many ways for rating prediction. However, similarities between multi attributes in reality are inter-dependent and can be used to reinforce each other. Therefore, the system would be more appropriate if the similarities between users and items are jointly and learned automatically.

Multiple Criteria Decision Analysis (MCDA) is used for supporting decision makers to make an optimal selection in an environment of conflicting and competing criteria is proposed. In this process, system proposes a mechanism for integrating MCDA into CF process for multiple criteria recommendations.

The proposed system consists of two main parts. Firstly, the weight of each user toward each feature is computed by using multiple linear regressions. Next, feature weight is incorporated into the collaborative filtering process to provide recommendations.

5.1 Multidimensional Similarity Learning

Multidimensional similarity learning in the proposed system is to be carried out using Principle Component Analysis which is further named as multi factor analysis. It is used to normalize the data of the multiaspects similarity of different entities. The goal is to analyze several data sets of variables collected on the same set of observations, as in its dual version and several sets of observations measured on the same set of variables. PCA a concept similar to the standard deviation is the singular value which is the square root of an eigen value.

5.2 Higher Order Singular Value Decomposition(HOSVD)

The limitation of using SSVD Item-Based CF algorithm is that, it is potentially less precise and can be applied only to two dimensional user-item rating matrix. When system consider multiple criteria's for rating purpose, the user-item matrix becomes three dimensional to handle this problem system need higher order SVD. Higher Order Singular Value Decomposition (HOSVD) or Multi linear SVD was proposed by Lathauwer at el. (2000), is a generalization of SVD that can be applied on three (or more) dimensions called Tensor.

The objective is to compute low-rank approximation of the data. These approximations are expressed in terms of tensor decomposition. The HOSVD of a third-order tensor involves the computation of the SVD of three matrices called modes.

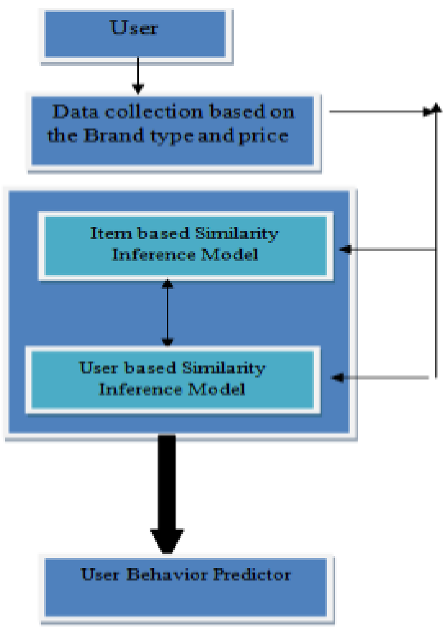


Fig.1 Prediction of the user Similarity and Item Similarity

5.3 Multi aspect and Multi criteria Similarity Learning

In multi-criteria rating scenario, each rating $R(u, i) = (r_0, r_1, \ldots, r_k)$ represents a point in the k+1-dimensional space. Therefore, one natural approach to compute similarity between different users is to use multidimensional distance metrics. Such metrics are easy to understand and straightforward to implement. The metrics of distance and similarity are inversely related: the smaller the distance between two users, the higher the similarity. System calculates the similarity between two users in three steps.

First, system have to be able to calculate the distance between two users' ratings for the same item, i.e., $d_{rating}(R(u, i), R(u', i))$, where $R(u, i) = (r_0, r_1, \ldots, r_k)$ and $R(u', i) = (r_0', r_1', \ldots, r_k')$. For this purpose, any of the standard multidimensional distance metrics can be used. Finally, because the collaborative filtering techniques operate with the metric of user similarity (and not user distance), and the distance and similarity are inversely related, system uses the simple transformation between the two metrics.

Sim(u,u')=1+d_{user}(u,u')----------(1)

The above definition of similarity has desired range properties, i.e., the similarity will approach 0 as the distance between two users becomes larger, and it will be 1 if the distance is zero (users are identical). In summary, both of the approaches presented in this section change only the similarity function in the traditional collaborative filtering technique in order to reflect multi-criteria rating information, which should result in a more accurate identification of similar users and, consequently, in better recommendation quality.

Table.1 Matrix Factorization

Algorithm	**Precision**	**Recall**	**F- Measure**
Matrix Factorization	28.94	40.73	33.84
SVD-PCA without Quality Factor	92.84	94.84	96.89
SVD-PCA with Quality Factor	94	95.32	96.56

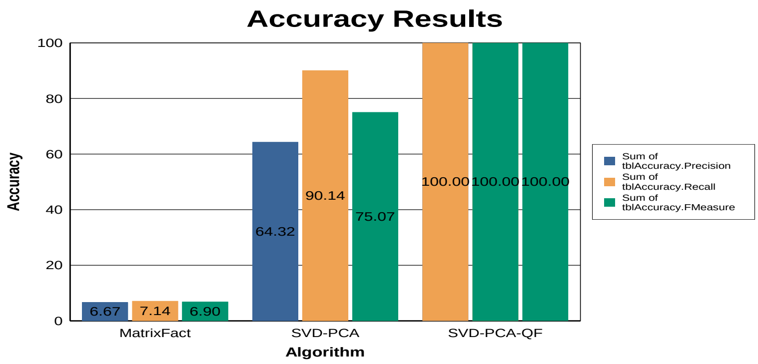
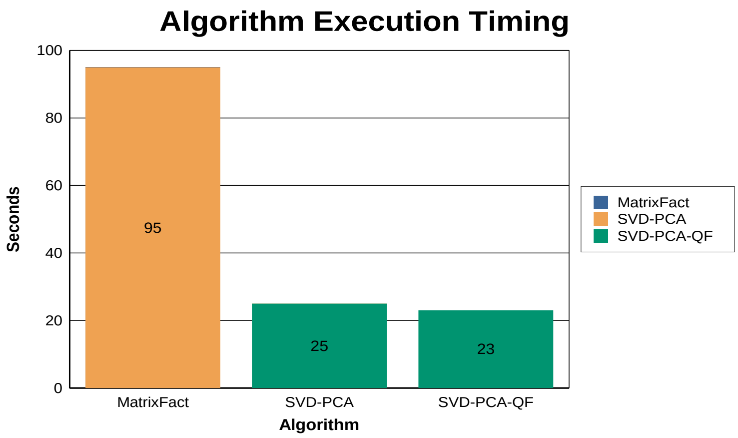


Table.2 Algorithm Execution Timing

Algorithm	**Precision**	**Recall**	**F- Measure**
Matrix Factorization	6.67	7.14	6.90
SVD-PCA without Quality Factor	64.32	90.14	75.07
SVD-PCA with Quality Factor	99.15	99.20	99.5



Combining similarity-based and aggregation-function-based multi-criteria recommendation techniques can sometimes improve the predictive performance, which is generally consistent with similar findings in recommender systems literature about the advantages of combining different types of recommender systems. By using the standard user-based collaborative filtering approach as an integral part of every technique in order to minimize the non-essential differences between the techniques as much as possible and, thus, to maximize the possibility that any differences in performance between the standard CF and multi-criteria recommender systems are due to the newly introduced multi-criteria rating information.

VI. CONCLUSION

Similarity prediction models have been designed and implemented. The models have been functionalized to learn user and item similarities simultaneously as collaborative phenomena. Initially, system implemented similarity measures separately for user rating prediction and item rating prediction. Secondly the asymmetric learning model is implemented to learn both user and item simultaneously as bidirectional similarity model. Proposed work is composed of two verticals in the multidirectional learning for user similarity, item similarity, producer similarity with and without quality factors .Finally the multiaspects learning model is produced to predict the future analysis of similarity measures based on the personalized and malicious rating identification. The model is known as dynamic similarity Model.

The similarity measurement was asymmetric and has been learned using matrix factorization, and Principle component analysis methods. The efficient learning algorithm which named as future similarity Model is composed with multiple effective prediction strategies. Experimental results has been detailed in the thesis as it is significantly outperforms the predefined ones. The experiments proved the proposed method outperforms baseline approaches such as traditional memory-based approaches and a low-rank matrix approximation model in terms of accuracy, mean absolutes value and execution time. Furthermore, the online version of the prediction algorithm is shown to be effective and more efficient for handling new users and items also incorporated in this work.

REFERENCES

[1]. Yi Cai; Ho-Fung Leung; Qing Li; Huaqing Min; Jie Tang; Juanzi Li Based Collaborative Filtering Recommendation " , IEEE Transactions on Knowledge and Data Engineering ,2014, Volume: 26, Issue: 3 Pages: 766 – 779

[2]. G. Adomavicius and A. Tuzhilin, "Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions," *IEEE Transactions on Knowledge and Data Engineering*, vol. 17, no. 6, pp. 734-749, Jun. 2005.

[3]. J. Figueria, S. Greco, and M.Ehrgott, *Multiple Criteria Decision Analysis: State of the Art Surveys*, Springer, 2005.

[4]. Sung Young Jung; Jeong-Hee Hong; Taek-Soo Kim "A statistical model for user preference Knowledge and Data Engineering, IEEE Transactions on Year: 2005, Volume:17, Issue: 6 Pages: 834 – 843.

[5]. Jun Wang, Arjen P. de Vries, Marcel J.T. Reinders "Unifying User based and Itembased Collaborative Filtering Approaches by Similarity Fusions" Proceeding in SIGR 2006 ,29th Annual International ACM conference on research and development in information retreieval pp-501-508.

[6]. C.Y. Chan, H. Jagadish, K.-L. Tan, A. Tung, and Z. Zhang, "Finding k-Dominant Skylines in High Dimensional Space," Proc. ACM SIGMOD, 2006.

[7]. Sung Young Jung; Jeong-Hee Hong; Taek-Soo Kim "A statistical model for user preference Knowledge and Data Engineering, IEEE Transactions on Year: 2005, Volume:17, Issue: 6 Pages: 834 – 843.

[8]. Jun Wang, Arjen P. de Vries, Marcel J.T. Reinders "Unifying User based and Itembased Collaborative Filtering Approaches by Similarity Fusions" Proceeding in SIGR 2006 ,29th Annual International ACM conference on research and development in information retrieval pp-501-508.

[9]. Manos Papagelis, Dimitris Plexousakis "Qualitative Analysis of User-based and Item-based Prediction Algorithms for Recommendation Agents" published in journal Engineering application of artificial intelligence vol.18, issue 7,2005pp-781-789

[10]. Nachiketa Sahoo, Ramayya Krishnan, George Duncan, James P. Callan "Collaborative Filtering with Multi-component Rating for Recommender Systems.",2007

[11]. Liang He, Weiwei Xia, Lei Ren "A collaborative filtering algorithm based on Users' Partial Similarity, 2008Control, Automation, Robotics and Vision, 2008.. 10th International Conference on Year: 2008 Pages: 1072 – 1077.

[12]. I. Bartolini, P. Ciaccia, and M. Patella, "Efficient Sort-Based Skyline Evaluation," ACM Trans. Database Systems, vol. 33, no. 4, pp. 1-49, 2008.

[13]. SongJie Gong "A Collaborative Recommender Based on User Information and Item Information" Proceedings of the 2009 International Symposium on Information Processing (ISIP'09) Huangshan, P. R. China, August 21-23, 2009, pp. 001-00.

[14]. Jin Soung Yoo; Shashi Shekhar "Similarity-Profiled Temporal Association Mining" IEEE Transactions on Knowledge and Data Engineering, Year: 2009, Volume:21, Issue: 8Pages: 1147 -1161

[15]. Wickramaratna,K.; Kubat,Miroslav; Premaratne,K.Predicting Missing Items in Shopping Carts ,IEEE Transactions on Knowledge and Data Engineering Year: 2009, Volume: 21, Issue: 7 Pages: 985 -998.

[16]. Vojnovic, M , Cruise, J. ; Gunawardena, D. ; Marbach, P "Ranking and Suggesting Popular Items "IEEE Transactions on Knowledge and Data Engineering, Year: 2009, Volume: 21, Issue: 8 Pages: 1133 – 1146.

[17]. W. Chen, Y. Wang, and S. Yang, "Efficient Influence Maximization in Social Networks," Proc. ACM 15th SIGKDD Int'l Conf. Knowledge Discovery and Data Mining (KDD '09), pp. 199-208, 2009.

[18]. SongJie Gong "A Collaborative Filtering Recommendation Algorithm Based on User Clustering and Item Clustering" published ACADEMY PUBLISHER,JOURNAL OF SOFTWARE, VOL. 5, NO. 7, JULY 2010.

[19]. A. Goyal, F. Bonchi, and L.V. Lakshmanan, "Learning Influence Probabilities in Social Networks," Proc. Third ACM Int'l Conf. Web Search and Data Mining (WSDM '10), pp. 241-250, 2010.

[20]. Y. Koren, "Factor in the Neighbors: Scalable and Accurate Collaborative Filtering," ACM Trans. Knowledge Discovery from Data, vol. 4, pp. 1:1-1:24, Jan. 2010.
[21]. L. Liu, J. Tang, J. Han, M. Jiang, and S. Yang, "Mining Topic-Level Influence in Heterogeneous Networks," Proc. 19th ACM Int'l Conf. Information and Knowledge Management (CIKM), 2010.
[22]. W. Chen, C. Wang, and Y. Wang, "Scalable Influence Maximization for Prevalent Viral Marketing in Large-Scale Social Networks," Proc. 16th ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining (KDD '10), pp. 1029-1038, 2010
[23]. Bartolini, I.; Zhenjie Zhang; Papadias, D. Collaborative Filtering with Personalized Skylines, IEEE Transactions on Knowledge and Data Engineering Year: 2011, Volume: 23, Issue: 2 Pages: 190 - 203,
[24]. Yehuda Koren, Joseph Sill , "Collaborative Filtering on Ordinal User Feedback" , proceedings in ACM IJCAI '13 Proceedings of the Twenty-Third international joint conference on Artificial Intelligence pp-3022-3206.
[25]. K.W.. Leung, D.L. Lee, and W.-C. Lee, "CLR: A Collaborative Location Recommendation Framework Based on Co-Clustering," Proc. 34th Int'l ACM SIGIR Conf. Research and Development in Information Retrieval (SIGIR '11), pp. 305-314, 2011.