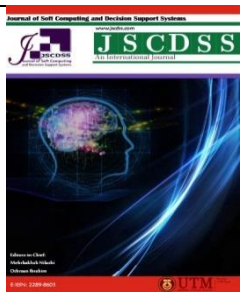
An International Journal
JSCDSS
http://www.jscdss.com
Vol.3 No.5 October 2016: 44-46
Article history:
Accepted 16 September 2016
Published online 01 December 2016

Journal of Soft Computing and Decision Support Systems



E-ISSN: 2289-8603

A New Method for Collaborative Filtering Recommender Systems: The Case of Yahoo! Movies and TripAdvisor Datasets

Mehrbakhsh Nilashi [a,b,*], Maryam Salahshour [a], Othman Ibrahim [a], Abbas, Mardani [c], Mohammad Dalvi Esfahani [a], Norhayati Zakuan [c]

[a] Faculty of Computing, Universiti Teknologi Malaysia, 81310 Skudai Johor, Malaysia
[b] Department of Computer Engineering, Lahijan Branch, Islamic Azad University, Lahijan, Iran
[c] Faculty of Management, Universiti Teknologi Malaysia (UTM), 81310 Skudai Johor, Malaysia

*** Corresponding author email address**: nilashidotnet@hotmail.com

Abstract

Collaborative Filtering (CF) techniques, which attempt to predict what information will meet a user's needs based on data coming from similar users, are becoming increasingly popular as ways to combat information overload. They use a single rating as input. However, the multi-criteria based CF presents a possibility to provide accurate recommendations by considering the user preferences in multiple aspects. This research proposes a new recommendation method using Adaptive Neuro Fuzzy Inference System (ANFIS) and Fuzzy Self-Organizing Map (SOM) for accuracy improvement of multi-criteria recommender systems. We also apply Principal Component Analysis (PCA) for dimensionality reduction and to address multi-collinearity induced from the interdependencies among criteria in multi-criteria CF datasets. Experimental results on Yahoo! Movies and TripAdvisor (users' reviews on hotels) datasets demonstrated that the proposed method significantly improves recommendation accuracy of multi-criteria CF.

Keywords: Multi-criteria recommender systems, Accuracy, Fuzzy SOM, Neuro-Fuzzy, Collaborative Filtering

1. Introduction

Recommender Systems support the online customer in his/her decision making and buying process (Rashidi et al., 2015; Nilashi et al., 2016b; Bagherifard et al., 2013; Nilashi et al., 2013; Nilashi et al., 2014a; Nilashi et al., 2014b; Vahid et al., 2016). Recommender systems based on Collaborative Filtering (CF) are particularly popular and used by large online retailers (Nilashi et al., 2015a; Nilashi et al., 2015b; Farokhi et al., 2016). CF algorithms can be divided into two categories: memory-based algorithms and model based algorithms (Nilashi et al., 2013; Adomavicius and Tuzhilin, 2005).

One of the main problems in the recommender systems especially CF is known as the sparsity problem. Thus, these approaches make poor computation similarity when rating information is insufficient and with considering this problem, system produces the poor recommendation (Park and Chang, 2009). Furthermore, memory based CF approaches suffer from the scalability problem. Therefore, scaling up theses system on real datasets is one of the main challenges that many methods have been developed to overcome it (Tsai and Hung, 2012).

Compared with memory based algorithms, model-based algorithms usually scale better in terms of their resource requirements (memory and computing time) and do not require keeping actual user profiles for predictions (Georgiou and Tsapatsoulis, 2010). Model-based methods, such as Bayesian networks and clustering models (Bilge and Polat, 2013), address the problem from a probabilistic perspective to find the best item for a given user profile, and need only keep the resulting model in memory while the algorithm is running. Model-based CF, for example the work of Breese et al. (1998), can often offer significant advantages over memory-based algorithms in terms of efficiency but have not offered the same level of accuracy. It adopts an eager learning strategy, taking a probabilistic approach to predicting or recommending content, where a model of the data, i.e. the users, items and their ratings for those items, is pre-computed (Rennie and Srebro, 2005). Indeed Breese et al. (1998) found that their model-based algorithms were four times faster than their memory-based algorithms at generating recommendations in terms of runtime.

Multi-criteria based CF presents a possibility to provide accurate recommendations by considering the user preferences in multiple aspects. Adomavicius and Kwon (2007) developed a number of basic strategies to exploit multi-criteria ratings for improving the predictive accuracy of a recommender in terms of typical information retrieval measures. Later on, a number of additional techniques to leverage the detailed ratings in the recommendation process

were proposed (Sahoo et al., 2012; Shambour and Lu, 2011a,b; Jannach et al., 2012; Jannach et al., 2014; Nilashi et al., 2014a,b; Nilashi et al., 2015a; Nilashi et al., 2016c; Nilashi et al., 2016d). The work presented in this paper continues on these lines of research.

From the literature on multi-criteria CF, at the moment there is no implementation of PCA, Neuro-Fuzzy and Fuzzy SOM methods for multi-criteria CF, and this research tries to develop a recommender system based on these methods. Hence, in comparison with research efforts found in the literature for multi-criteria CF, our work has the following differences. In this research:

- A hybrid recommendation method using noise removal, clustering and prediction techniques is proposed for improving the predictive accuracy of multi-criteria CF.
- We use Fuzzy SOM for data clustering and ANFIS (Nilashi et al., 2015c) for prediction task.
- PCA (Nilashi et al., 2016a; Nilashi et al., 2016c) is applied for dimensionality reduction and to address multi-collinearity induced from the interdependencies among criteria in multi-criteria CF datasets.
- Two datasets (Yahoo!Movie and TripAdvisor) are used for proposed method evaluation.

2. Recommendation Method Evaluation

Yahoo Movies: The rating data was drawn from the Yahoo Movies website. All the movies were treated as single-rating dataset made available from Yahoo! Research. Using a 13-level rating scale (from A+ to F), in the Yahoo Movies platform, the users can rate movies in four dimensions which include, Story, Acting, Direction, Visuals, as well as assign a general rating. Additionally, the user global perception (overall rating) provided by user was considered values with qualitative scale 1 to 13 for each movie.

TripAdvisor: TripAdvisor represents the world largest and most successful social networking and community site in tourism (Nilashi et al., 2015b). The platform facilitates the reviewing of hotels around the world and brings together individuals in discussion forums and provides users with independent travel reviews and comments. In TripAdvisor website users can rate a hotel according to 7 different dimensions: Value aspect, Rooms aspect, Location aspect, Cleanliness aspect, Check in/front desk aspect, Service aspect and Business Service aspect.

To evaluate the accuracy of the proposed method, we conduct a set of experiments. We determine the precision and recall of the Top-N list for recommender system. The recommenders' prediction accuracy is measured by Root Mean Squared Error (RMSE), which is a widely used metric for evaluating the statistical accuracy of recommendation algorithms, given by

$$\mathbf{RMSE} = \sqrt{\frac{1}{|\Omega|}\sum_{u_i,o_j\in\Omega}|a_{ij}-p_{ij}|^2}, \qquad (1)$$

where $\Omega = \{ (u_i, o_j) | u_i$ had rated o_j in the probe set $\}$. A lower value of RMSE indicates a higher accuracy of the recommendation system.

Table 1 presents the RMSE and coverage obtained from proposed approach on Yahoo!Movie and TripAdvisor datasets.

We also evaluated the recommendation quality using coverage measures. Coverage measures the percentage of items for which a CF system can provide a prediction, or that ever appear in a recommendation list.

To compare the proposed method with some stat-of-the-art approaches in multi-criteria CF, we employed precision metric, which is a metric that represents the probability that an item recommended as relevant is truly relevant. It is defined as the ratio of items correctly predicted as relevant among all the items selected:

$$\mathbf{Precision} = \frac{TR}{TR+FR} \qquad (2)$$

where TR is the number of true relevant predictions, i.e., the number of items recommended as relevant that are really relevant, and FR is the number of false relevant predictions, i.e., the number of items recommended as relevant that are non-relevant.

We also evaluated our approach on the Yahoo!Movies and TripAdvisor datasets using an additional set of metrics. The MAE is determined as the average absolute deviation between predicted ratings and true ratings shown in Eq. (3).

$$MAE(pred, act) = \sum_{i=1}^{N}\left|\frac{pred_{u,i}-act_{u,i}}{N}\right| \qquad (3)$$

where N is the number of items on which a user *u* has expressed an opinion.

In Table 2, we report Precision@5 and Precision@7 values as well as the Mean Absolute Error (MAE) for MAE of all implemented methods.

From the results, we can find that the precision at Top-5 and Top-7 of the proposed method outperforms SVD and HOSVD methods. From the results, it can be also found that the proposed method outperforms the methods which use CART as a prediction method.

Table 1
Coverage and RMSE

Method	RMSE	Coverage
SVD (Yahoo!Movies)	0.773	0.71
SVD (TripAdvisor)	0.736	0.82
HOSVD (Yahoo!Movies)	0.614	1
HOSVD (TripAdvisor)	0.594	1
CART (Yahoo!Movies)	0.565	1
CART (TripAdvisor)	0.536	1
EM-PCA-CART (Yahoo!Movies)	0.507	1
EM-PCA-CART (TripAdvisor)	0.483	1
EM-PCA-CART (Yahoo!Movies)	0.501	1
EM-PCA-CART (TripAdvisor)	0.477	1

An International Journal
JSCDSS
E-ISSN: 2289-8603

Table 2
MAE, precision at Top-5 and Top-7

Method	Precision@5	Precision@7	MAE
SVD (Yahoo!Movies)	65.07	61.15	1.65
SVD (TripAdvisor)	69.11	67.12	1.52
HOSVD (Yahoo!Movies)	76.12	74.18	1.23
HOSVD (TripAdvisor)	78.12	76.45	1.07
CART (Yahoo!Movies)	84.3	80.5	0.99
CART (TripAdvisor)	84.7	82.4	0.94
EM-PCA-CART (Yahoo!Movies)	85.3	83.6	0.91
EM-PCA-CART (TripAdvisor)	85.7	84.1	0.88
EM-PCA-CART (Yahoo!Movies)	86.9	84.8	0.89
EM-PCA-CART (TripAdvisor)	87.4	85.8	0.87

3. Conclusion

In this paper, we proposed a new recommender system using prediction and clustering techniques to improve the predictive accuracy of the multi-criteria CF. The proposed method was developed based on PCA, ANFIS and Fuzzy SOM for items recommendations to users. We analyzed the predictive accuracy of proposed methods in the domain of movie recommendation in a real-world dataset provided by Yahoo!Movies and TripAdvisor datasets. The methods were evaluated using MAE, Precision@5 and Precision@7 using precision metric. Our experiments confirmed that the proposed recommendation method significantly improves predictive accuracy of multi-criteria CF measured by standard accuracy metrics. For the future work, we plan to investigate clustering ensemble techniques with dynamic process for scalability issue in the context of multi-criteria CF. We will focus on further improvement of the multi-criteria CF recommendation accuracy and scalability for by incorporating incremental approaches.

References

Adomavicius G, Kwon Y (2007) New recommendation techniques for multicriteria rating systems. Intelligent Systems, IEEE 22 (3):48-55

Adomavicius, G., & Tuzhilin, A. (2005). 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, 17(6), 734-749.

Bagherifard, K. B., Nilashi, M., & Salim, N. (2013). Recommender system based on semantic similarity. International Journal of Electrical and Computer Engineering, 3(6), 751.

Bilge, A., & Polat, H. (2013). A comparison of clustering-based privacy-preserving collaborative filtering schemes. Applied Soft Computing, 13(5), 2478-2489.

Breese, J. S., Heckerman, D., & Kadie, C. (1998, July). Empirical analysis of predictive algorithms for collaborative filtering. In Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence (pp. 43-52). Morgan Kaufmann Publishers Inc..

Farokhi, N., Vahid, M., Nilashi, M., & Ibrahim, O. (2016). A Multi-Criteria Recommender System for Tourism Using Fuzzy Approach. Journal of Soft Computing and Decision Support Systems, 3(4), 19-29.

Georgiou, O., & Tsapatsoulis, N. (2010, September). Improving the scalability of recommender systems by clustering using genetic algorithms. In International conference on artificial neural networks (pp. 442-449). Springer Berlin Heidelberg.

Jannach D, Karakaya Z, Gedikli F Accuracy improvements for multi-criteria recommender systems. In: Proceedings of the 13th ACM Conference on Electronic Commerce, 2012. ACM, pp 674-689

Nilashi, M., Bagherifard, K., Ibrahim, O., Alizadeh, H., Nojeem, L. A., & Roozegar, N. (2013). Collaborative filtering recommender systems. Research Journal of Applied Sciences, Engineering and Technology, 5, 4168-4182.

Nilashi, M., bin Ibrahim, O., & Ithnin, N. (2014a). Hybrid recommendation approaches for multi-criteria collaborative filtering. Expert Systems with Applications, 41(8), 3879-3900.

Nilashi, M., bin Ibrahim, O., & Ithnin, N. (2014b). Multi-criteria collaborative filtering with high accuracy using higher order singular value decomposition and Neuro-Fuzzy system. Knowledge-Based Systems, 60, 82-101.

Nilashi, M., bin Ibrahim, O., Ithnin, N., & Sarmin, N. H. (2015c). A multi-criteria collaborative filtering recommender system for the tourism domain using Expectation Maximization (EM) and PCA–ANFIS. Electronic Commerce Research and Applications, 14(6), 542-562.

Nilashi, M., Esfahani, M. D., Roudbaraki, M. Z., Ramayah, T., & Ibrahim, O. (2016d). A Multi-Criteria Collaborative Filtering Recommender System Using Clustering and Regression Techniques. Journal of Soft Computing and Decision Support Systems, 3(5), 24-30.

Nilashi, M., Ibrahim, O. B., Ithnin, N., & Zakaria, R. (2015b). A multi-criteria recommendation system using dimensionality reduction and Neuro-Fuzzy techniques. Soft Computing, 19(11), 3173-3207.

Nilashi, M., Ibrahim, O. B., Mardani, A., Ahani, A., & Jusoh, A. (2016a). A soft computing approach for diabetes disease classification. Health Informatics Journal, In Press.

Nilashi, M., Ibrahim, O., & Ahani, A. (2016c). Accuracy Improvement for Predicting Parkinson's Disease Progression. Scientific Reports, 6.

Nilashi, M., Jannach, D., bin Ibrahim, O., & Ithnin, N. (2015a). Clustering-and regression-based multi-criteria collaborative filtering with incremental updates. Information Sciences, 293, 235-250.

Nilashi, M., Jannach, D., bin Ibrahim, O., Esfahani, M. D., & Ahmadi, H. (2016b). Recommendation quality, transparency, and website quality for trust-building in recommendation agents. Electronic Commerce Research and Applications, 19, 70-84.

Park, Y. J., & Chang, K. N. (2009). Individual and group behavior-based customer profile model for personalized product recommendation. Expert Systems with Applications, 36(2), 1932-1939.

Rennie, J. D., & Srebro, N. (2005, August). Fast maximum margin matrix factorization for collaborative prediction. In Proceedings of the 22nd international conference on Machine learning (pp. 713-719). ACM.

Sahoo N, Krishnan, R., Duncan, G., & Callan, J. (2012). Research Note—The Halo Effect in Multicomponent Ratings and Its Implications for Recommender Systems: The Case of Yahoo! Movies. Information Systems Research, 23(1), 231-246.

Tsai, C. F., & Hung, C. (2012). Cluster ensembles in collaborative filtering recommendation. Applied Soft Computing, 12(4), 1417-1425.

Vahid, M., Farokhi, M., Ibrahim, O., & Nilashi, M. (2016). A User Satisfaction Model for E-Commerce Recommender Systems. Journal of Soft Computing and Decision Support Systems, 3(3), 42-54.

Rashidi, M., Hussin, A. R. C., & Nilashi, M. (2015). Entropy-based Ranking Approach for Enhancing Diversity in Tag-based Community Recommendation. Journal of Soft Computing and Decision Support Systems, 3(1), 1-7.

An International Journal
JSCDSS
E-ISSN: 2289-8603