An Effective Model-Based Trust Collaborative Filtering for Explainable Recommendations

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***Abstract*—Nowadays, many companies through the world wide web like YouTube, Netflix, Aliexpress and Amazon, provide personalized services as recommendations. Recommender systems use the related information about products or services to suggest the most relevant of them to particular users. The recommendation is usually made based on the prediction of the users' constraints and interests. Despite that the most of the existing recommender systems give accurate recommendation results, they do not provide explainable recommendation support. Therefore, in this paper we propose a new effective model-based trust collaborative filtering for explainable recommendations that aims not only to improve the quality of recommendation but also to provide an efficient support for explainable recommendations based on trustworthiness modeling. Our solution can both ensure how the item is recommended and why it is recommended. The proposed method is evaluated on Amazon Instant Video dataset in terms of RMSE.**

***Index Terms*—Explainable Recommendation, Trust, Trustworthiness, Collaborative Filtering, Recommender System.**

I. Introduction

With the increased development of the Internet technologies, recommender systems have emerged as an indispensable tool for the online service providers. Several companies through the world wide web like YouTube, Netflix, AliExpress and Amazon, provide personalized services. Recommender systems use the related information about items (products or services) to suggest the most relevant to specific users. The recommendation is usually made based on the prediction of the users' constraints and interests.

The benefits include more efficiency in reducing information overload [1], generating personalized recommendations according to the users' preferences, improving overall satisfaction and loyalty of users. Current recommender systems typically are classified into two main categories: content-based filtering and collaborative filtering [2], [3]. Content-based filtering methods rely on the item's description and past preferences of the user to attempt to recommend items based on feature representation of the services or products [4]. The problem with these methods is how to find the user's preference using the item contents. In contrast, collaborative filtering methods focus on the preference pattern identification within a community of users in which the recommendation is generated based only on gathered data about users' and items' ratings profiles [5]. These methods can be divided into two classes: memory-based and model-based. For the memory-based filtering, similarity measures such as person correlation coefficient [6] and cosine similarity [7], are used to determine the relationships between users or items. Thus, a user-item rating matrix is used to make prediction. On the other hand, the model-based filtering requires a model to be created and trained from training data before making recommendation. For example, in [8], the authors developed a new effective recommender system for TED lectures to enhance the recommendation quality. Authors followed three steps: (1) employing the person correlation coefficient similarity with TED lectures to generate the TED user-user matrix; (2) using the k-means clustering technique to group users that are having the same preferences in clusters and create a predictive model; finally, (3) using the created model to make relevant recommendations.

Moreover, the authors in [9] proposed to use the deep neural network technology to build a recommender system that is able to predict the rating scores based on forward propagation algorithm. They combined both the users embeddings and items embeddings with the deep neural network for enhancing the recommendation according to two steps. The first one involves the creation of dense numeric representations for all users and items, while the second one involves the use of the deep neural network model to predict the ratings' scores using the algorithm of forward propagation.

Despite that most of the existing recommender systems give accurate recommendation results, they do not provide explainable recommendation support. Thus, integrating such a support in a recommender system can play an important role, it would be interesting to develop new methods for explainable recommendations to serve as bridge between users and new generation of recommender systems. The main goal of the explainable recommendation is to get a clear response on *why a particular item is recommended to the particular user?* This can help in enhancing the *trustworthiness*, *persuasiveness*, *effectiveness*, *relevance*, *comprehensibility*, and *transparency* of recommender systems. Therefore, in this paper we propose a new effective model-based trust collaborative filtering for explainable recommendations that aims not only to improve

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the quality of recommendation but also to provide an efficient support for explainable recommendations using the trustworthiness aspect. Our solution takes into consideration how an item is recommended as well as why it is recommended at the same time. The proposed method is evaluated on Amazon Instant Video dataset [1] in terms of Root Mean Square Error (RMSE), which is commonly used to measure the differences between the predicted values by the model and the observed values [10].

The rest of the paper is organized as follows: Section II presents the related work. Section III describes the proposed approach. Section IV illustrates the experimental results. Finally, Section V concludes our findings and proposes the plans for future work.

II. RELATED WORK

The idea of explainable recommendation is to develop a recommendation algorithm that can be able to solve the problem of why we recommend items to a particular user by giving him/her an efficient clarification about the recommendation task. Indeed, with the explainable recommendation, the process of recommendation is not yet considered as a black box as before.

Recentlly, many researchers have tried to make recommendation more understandable and explainable [11]–[17]. For example, Ribeiro et al. [18] presented LIME, an algorithm that is capable of explaining the predictions of any classifier in a faithful way. They also introduced SP-LIME to filter the representative predictions from those redundant and non-representative. Ai et al. [19] provided a knowledge-base embeddings framework for explainable recommendation in which they used a soft matching algorithm to provide explanations about the recommended items. The soft matching algorithm was divided for exploring the explanation paths that exist between the recommended items and a user.

Hou et al. [20] proposed to generate explainable recommendations using aspect-based matrix factorization, which could enhance the prediction of rating with fusion of aspect information. Lin et al. [21] developed a neural network framework, which was capable to generate abstractive comments when providing outfit recommendations. They employed a convolutional neural network with a mutual attention function to outfit matching and recurrent neural network with a cross-modality attention function to obtain a concise sentence.

However, to the best of our knowledge, the trustworthiness combined with the collaborative filtering have not been together explored yet. Additionally, no work has been conducted about the trust modeling for Amazon Instant Video dataset. Thus, the contributions of this paper are to define a trustworthiness model as a new explainable recommendation data type, use this model within a collaborative filtering and carry out experiments on Amzon Instant Video dataset.

[1]Amazon product data, http://jmcauley.ucsd.edu/data/amazon/

III. METHODOLOGY AND APPROACH

In this section, we present a new effective model-based trust collaborative filtering for explainable recommendations that claims to help users to get not only the recommendation but also an explanation for each recommended item. It involves users' similarities and trustworthiness in order to produce recommendation results with their corresponding explanations.

A. Model-based trust for explainable recommendations

To help users know at any time why they get the specific results from the recommender system, we describe a new trustworthiness model. This model can make the recommender systems more efficient in encouraging users accepting the recommended items.

1) Trustworthiness: The trustworthiness characterizes the relationship that exists between the target users and their neighbors by providing a real value. This value specifies the degree to which the active user chooses the items based on his or her neighbors.

The trustworthiness between two users increases or decreases depending on the reaction of the active user. For example, when the active user Bob interacts with items recommended using the neighbor Alice, the trustworthiness between them increases and vice versa.

The trustworthiness between two users u and v is defined [22] by Equation 1, where $R_{u,v}$ denotes the number of items that are really recommended to the active user u based on the user v, likewise, $S_{u,v}$ denotes the number of times in which the user v was selected as neighbor of the user u.

$$T\left(u,v\right) = \frac{R_{u,v}}{S_{u,v}} \tag{1}$$

2) Explainable recommendation data type: The main problem to be addressed in the context of explainable recommendation is to respond to the question: *why a specific item is recommended to a given user?* Providing an explanation process can effectively assist those who are using the recommender systems in understanding the reasons behind these recommendations.

To enable efficient generation of useful explanations, we introduce a new data structure called *explainable recommendation data type* that includes all elements serving for the explanation. Indeed, an explainable recommendation data type is a data structure with five elements (I, U, R, N, T) where I is the recommended item, U is the active user, R is the predicted rating, N is the number of users sharing the same preferences with the active user and T is the average trustworthiness; users and items are presented by their identifiers, respectively.

Figure 1 shows that using the explainable recommendation data type, an explanation can be presented to an active user as follows:

Hi Bob, the item "Home alone" was recommended to you because there are 15 *users having the same taste as you with a* 95% *of average trustworthiness and a* 4.5 *predicted rating.*

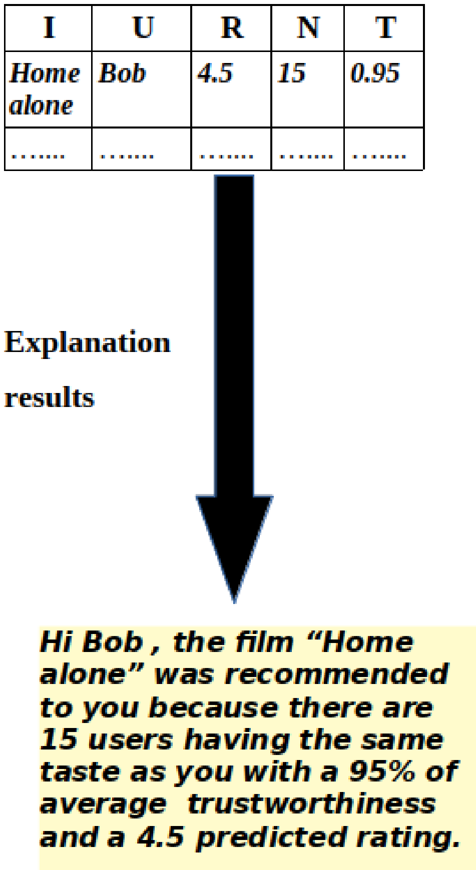

Fig. 1. Generating explanations based on the explainable recommendation data type.

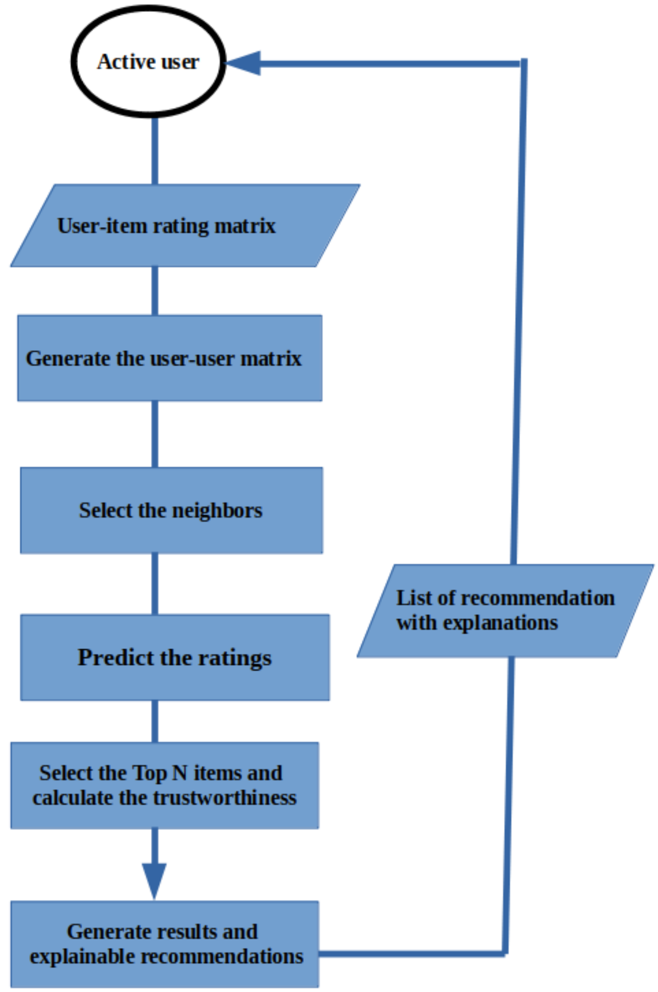

Fig. 2. The collaborative filtering recommendation algorithm based on trust explainable recommendations.

B. Model-based trust explainable recommendation collaborative filtering algorithm

In this work, a collaborative filtering recommendation algorithm based on trust explainable recommendation is proposed. Figure 2 shows the main steps of the proposed algorithm.

Step 1: Get the active user and generate the user-item rating matrix. This step should be proceeded by a data preprocessing procedure, which consists of removing items with fewer ratings and managing missing values. In the resulted user-item rating matrix, users are represented by the rows and items by the columns.

Step 2: Calculate the similarities between users, this step is computed using the cosine similarity measure. This step generates the user-user similarity matrix. The cosine similarity measure is one of the most popular metrics used in collaborative filtering recommendation algorithms [23], [24]. It enables to compute the angle cosine between two vectors of user's u and v, see Equation 2.

Step 3: Select the most similar neighbors of the active user to be considered in the calculation of the prediction.

Step 4: Predict the rating values of the active user based only on the selected neighbors with their ratings. The prediction function is defined in Equation 3, where u represents the active user, k represents the item, $s(u)$ represents the list of neighbors and $cos()$ is the cosine similarity function.

Step 5: Select the top N items of users and calculate the trustworthiness using Equation 1.

Step 6: Use the explainable recommendation data type with the corresponding values to generate recommendation results with their explanations, see Figure 1.

$$cos\left(u,v\right)=\frac{u.v}{\left\|u\right\|\,*\left\|v\right\|} \tag{2}$$

$$P\left(u,k\right)=\overline{r_i}+\frac{\sum_{u_a\in S(u)}cos\left(u,u_a\right)\left(r_{ua},k-\overline{r_{ua}}\right)}{\sum_{u_a\in S(u)}cos\left(u,u_a\right)} \tag{3}$$

IV. Experiments

The algorithms presented in this paper are implemented in Python where the experimental platform configuration is Intel Core i7-8550U CPU @ 1.80GHz × 8, 8GB memory. The used operating system is Ubuntu 18.04 LTS.

The experiments are conducted on the dataset called Amazon Instant Video [2] from Amazon. Recently, this dataset was extensively used in the domain of recommender systems. It contains 37126 reviews about 1685 products or videos from Amazon made by 5130 reviewers, where each of anonymous users and items have k reviews. The conventional user-item rating matrix corresponds here to the reviewer-video rating matrix.

In these experiments, two different methods are considered. The first one is the collaborative filtering with the Model-based trust explainable recommendations, while the second one is the collaborative filtering without the Model-based trust explainable recommendations. The RMSE shown in Equation 4 is applied to evaluate the prediction accuracy for both methods.

$$RMSE=\sqrt{\frac{i}{n}\sum_{u=i}^{n}\left|r_{ui}-\overline{r_{ui}}\right|^{2}} \tag{4}$$

Table I shows the values of RMSE along the neighbor sizes that are ranging from 10 to 80 for the two methods. As we can observe, the collaborative filtering with the Model-based trust explainable recommendations and the collaborative filtering without the Model-based trust explainable recommendations have identical experimental results and the optimal size of neighbor of each method can be easily obtained. The RMSE decreases as neighbor size increases from 10 to 30 and then there is no real improvement. Therefore, the optimal size of neighbors is 30. From Table I, it can be concluded that obtaining the same results of prediction accuracy for the collaborative filtering with and without the Model-based trust explainable recommendations means that the explainable recommendations benefited the users of more trustworthiness and explanation without causing a negative influence on the performance of the recommender system.

[2] Amazon product data, http://jmcauley.ucsd.edu/data/amazon/

TABLE I
Comparison of Collaborative Filtering with and Without the Model-Based Trust Explainable Recommendation Results

Method	Number of neighbors	RMSE
Collaborative filtering *with* the model-based trust explainable recommendation	10	1.0444
	20	1.0391
	30	1.0389
	40	1.0392
	50	1.0403
	60	1.0416
	70	1.0427
	80	1.0435
Collaborative filtering *without* the model-based trust explainable recommendation	10	1.0444
	20	1.0391
	30	1.0389
	40	1.0392
	50	1.0403
	60	1.0416
	70	1.0427
	80	1.0435

V. Conclusion and Future Work

The development of the technology of recommender systems has changed the strategies of many companies providing online services. Hence, these strategies are constantly changing since the emergence of the explainable recommendation. Recommender systems with the features of explainable recommendation have become more transparent and trustworthy. Due to the importance of building these systems with such features, we proposed a new effective model-based trust collaborative filtering for explainable recommendations considering users' similarities and trustworthiness to generate recommendation results with their explanations.

The experiments that we have conducted on the Amazon Instant Video dataset demonstrate that prediction results are the same for the two collaborative filtering methods, with and without the model-based trust explainable recommendations; implying that the trustworthiness ensured by our approach is useful and it has no negative effects on the recommendation quality.

However, for future work, we are looking forward to investigate other methods such as clustering algorithms with the principal component analysis [25] and collaborative filtering recommendations based on dimensionality reduction that would be coupled with a clustering method. This clustering [26] may improve both the recommendations and explanations. Additionally, we are aiming at conducting other experiments with big datasets to confirm the effectiveness of our method.

References

[1] J. Lu, D. Wu, M. Mao, W. Wang, and G. Zhang, "Recommender system application developments: a survey," *Decision Support Systems*, vol. 74, pp. 12–32, 2015.

[2] P. Thakkar, K. Varma, V. Ukani, S. Mankad, and S. Tanwar, "Combining user-based and item-based collaborative filtering using machine learning," in *Information and Communication Technology for Intelligent Systems*. Springer, 2019, pp. 173–180.

[3] Y. Ham and M. Kamari, "Automated content-based filtering for enhanced vision-based documentation in construction toward exploiting big visual data from drones," *Automation in Construction*, vol. 105, p. 102831, 2019.

[4] H. Xue and D. Zhang, "A recommendation model based on content and social network," in *2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*. IEEE, 2019, pp. 477–481.

[5] S. İldere, "Collaborative filtering system," in *2019 4th International Conference on Computer Science and Engineering (UBMK)*. IEEE, 2019, pp. 624–628.

[6] M. Dillon, "Introduction to modern information retrieval," *Information Processing & Management*, vol. 19, pp. 402–403, 1983.

[7] N. D. Prachi Dahiya, "Comparative analysis of various collaborative filtering algorithms," *International Journal of Computer Sciences and Engineering*, vol. 7, pp. 347–351, 8 2019. [Online]. Available: https://www.ijcseonline.org/full_paper_view.php?paper_id=4834

[8] F. Maazouzi, H. Zarzour, and Y. Jararweh, "An effective recommender system based on clustering technique for ted talks," *International Journal of Information Technology and Web Engineering (IJITWE)*, vol. 15, no. 1, pp. 35–51, 2020.

[9] H. Zarzour, Z. A. Al-Sharif, and Y. Jararweh, "Recdnning: a recommender system using deep neural network with user and item embeddings," in *2019 10th International Conference on Information and Communication Systems (ICICS)*. IEEE, 2019, pp. 99–103.

[10] T. Chai and R. R. Draxler, "Root mean square error (rmse) or mean absolute error (mae)?" *Geoscientific Model Development Discussions*, vol. 7, pp. 1525–1534, 2014.

[11] X. Wang, D. Wang, C. Xu, X. He, Y. Cao, and T.-S. Chua, "Explainable reasoning over knowledge graphs for recommendation," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, 2019, pp. 5329–5336.

[12] Y. Zhang, G. Lai, M. Zhang, Y. Zhang, Y. Liu, and S. Ma, "Explicit factor models for explainable recommendation based on phrase-level sentiment analysis," in *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval*, 2014, pp. 83–92.

[13] Z. Peng, R. Lin, Y. He, L. Wang, H. Chu, C. Fu, and Y. Tang, "News recommendation model based on improved label propagation algorithm," in *International Conference on Human Centered Computing*. Springer, 2019, pp. 315–324.

[14] M. R. Zarei and M. R. Moosavi, "An adaptive similarity measure to tune trust influence in memory-based collaborative filtering," *arXiv preprint arXiv:1912.08934*, 2019.

[15] J. Wu, J. Chang, Q. Cao, and C. Liang, "A trust propagation and collaborative filtering based method for incomplete information in social network group decision making with type-2 linguistic trust," *Computers & Industrial Engineering*, vol. 127, pp. 853–864, 2019.

[16] H. Parvin, P. Moradi, and S. Esmaeili, "Tcfaco: Trust-aware collaborative filtering method based on ant colony optimization," *Expert Systems with Applications*, vol. 118, pp. 152–168, 2019.

[17] H. Ambulgekar, M. K. Pathak, and M. Kokare, "A survey on collaborative filtering: tasks, approaches and applications," in *Proceedings of International Ethical Hacking Conference 2018*. Springer, 2019, pp. 289–300.

[18] M. T. Ribeiro, S. Singh, and C. Guestrin, "" why should i trust you?" explaining the predictions of any classifier," in *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 2016, pp. 1135–1144.

[19] Q. Ai, V. Azizi, X. Chen, and Y. Zhang, "Learning heterogeneous knowledge base embeddings for explainable recommendation," *Algorithms*, vol. 11, no. 9, p. 137, 2018.

[20] Y. Hou, N. Yang, Y. Wu, and S. Y. Philip, "Explainable recommendation with fusion of aspect information," *World Wide Web*, vol. 22, no. 1, pp. 221–240, 2019.

[21] Y. Lin, P. Ren, Z. Chen, Z. Ren, J. Ma, and M. De Rijke, "Explainable outfit recommendation with joint outfit matching and comment generation," *IEEE Transactions on Knowledge and Data Engineering*, 2019.

[22] F. Leal, B. Malheiro, H. González-Vélez, and J. C. Burguillo, "Trust-based modelling of multi-criteria crowdsourced data," *Data Science and Engineering*, vol. 2, no. 3, pp. 199–209, 2017.

[23] D. Liu, X. Chen, and D. Peng, "Some cosine similarity measures and distance measures between q-rung orthopair fuzzy sets," *International Journal of Intelligent Systems*, vol. 34, no. 7, pp. 1572–1587, 2019.

[24] V. X. Chen and T. Y. Tang, "Incorporating singular value decomposition in user-based collaborative filtering technique for a movie recommendation system: A comparative study," in *Proceedings of the 2019 the International Conference on Pattern Recognition and Artificial Intelligence*, 2019, pp. 12–15.

[25] H. Zarzour, F. Maazouzi, M. Soltani, and C. Chemam, "An improved collaborative filtering recommendation algorithm for big data," in *IFIP International Conference on Computational Intelligence and Its Applications*. Springer, 2018, pp. 660–668.

[26] H. Zarzour, Z. Al-Sharif, M. Al-Ayyoub, and Y. Jararweh, "A new collaborative filtering recommendation algorithm based on dimensionality reduction and clustering techniques," in *2018 9th International Conference on Information and Communication Systems (ICICS)*. IEEE, 2018, pp. 102–106.