Context-Aware Recommendation with Objective Interestingness Measures

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Abstract. Context-aware recommender systems researches now concentrate on adjusting recommendation results for situations specific context of the users. These studies suggest many ways to integrate user contextual information into the recommendation process such as using topic hierarchies with matrix factorization techniques to improve context-aware recommender systems, measuring frequency-based similarity for context-aware recommender systems, collecting data from social networking to support context-aware recommender systems, and so on. However, these studies mainly focus on the development of context-aware recommendation algorithms to propose items to users in a particular situation and do not care about the extent of contextual involvement in the recommendation process to make recommendation results. In this article, we propose a new approach for context-aware recommender systems based on objective interestingness measures to consider the contextual relationship of the users in the recommendation process. Based on the experimental results on two standard datasets, the proposed model is more accurate than the traditional models.

Keywords: Rating matrix · Context similarity matrix
Objective interestingness measures · Chi-square similarity kernel

1 Introduction

The recommender systems (RS) [1, 2] are a common solution used to suggest appropriate items for the user. This solution is widely used in many fields such as e-commerce, e-government, e-library, medicine, etc. In order to provide the information that usersneed to support, many recommender systems have been proposed such as collaborative filtering recommender systems, content-based recommender systems, demographic recommender systems, knowledge-based recommender systems, context-ware recommender systems (CARS). The CARS [5, 6] is the system that adjusts recommendation results for specific contextual situations of the users. In different

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situations, users can make different decisions, because users often change their preferences and decisions from one situation to another. For example, the user can choose a love movie to watch with his girlfriend or boyfriend, but if he or she goes out with children, the cartoon is suitable. Companion (girlfriend or child), in the example above is an influential context factor. Other examples of context can be time, location, weather, etc. Because the user's preferences and decisions vary depending on the situation, consider the context when making suggestions to the user. Thus, the integration of contextual information into the counseling system has become a topic that is becoming increasingly important in recommender systems research [12–14].

The results of the research on context-aware recommender systems in the past time are quite rich research such as doctoral dissertation: Providing Architectural Support for Building Context Aware Applications [7] provides a context definition and context awareness framework, builds and develops context-aware applications, another next in build the system found in context [13] proposes a solution to the development of a contextual recommender systems, which is applied to the travel suggestion, to suggest the most appropriate tourist destination travelers, frequency-based similarity measures for context-aware recommender systems [12] combine the information in the context to the user profile as an extra information through a new count method output, smart media-based context-aware recommender systems for learning [14] proposes a conceptual cognitive-based contextual intelligence system that can intelligently study the user's learning preferences as a context for making accurate and valid helpful recommendations. These studies mainly focus on the development of context-aware recommendation algorithms to propose items to users in a particular situation. However, current research on the recommender systems does not take into account the extent of contextual involvement in the recommendation process to make recommendations.

In this paper, we propose a new model for recommender systems, context-aware recommender model based on objective interestingness measures [8–10]. In this model, we are particularly interested in the degree of contextual similarity of users during the recommender process in order to provide items to users more accurate.

This article is organized into 6 sections. Section 1 presents introduction, Sect. 2 introduces the context-aware recommender systems, Sect. 3 describes objective interestingness measures, Sect. 4 determines the similarity context of two users, Sect. 5 presents a collaborative filtering model based on similarity context, and Sect. 6 discusses about the experimental results of the model and summarizes the results.

2 Context-Aware Recommender Systems

There are many studies on the context-aware recommender systems (CARS) since the original publication on this topic [5, 6]. Context-aware recommender systems (CARS) is a system that tries to adapt its proposals to contextual situations specific to the user [5, 6] because users often make different decisions in different situations. This approach has become commonplace in many areas and the application has recently been discovered in a number of sectors, such as tourism [18], trailers [19]. The traditional collaborative filtering [4] can be modeled as a two-dimensional (2D) prediction.

$$R : Users \times Items\ - > Ratings$$

In particular, the recommender systems will predict the user's rating values for items that users have not rated. Context-aware recommender systems attempt to incorporate more contextual information of users into the recommender process to estimate user preferences. This integration transforms the predictive function of the system from 2D space into a "multi dimensional" space.

$$R : Users \times Items \times Contexts\ - > Ratings$$

Where, R is the prediction function for items, Users are a set of users, Items are sets of items, Contexts are context of users and. Context is defined as "any information that can be used to characterize an entity" [7] such as time, location, weather.

The context-aware recommendation process can take one of the following three forms, based on how the contextual information is used, as follows: Contextual prefltering, Contextual postfltering, and contextual modeling.

- *Contextual pre-filtering* [5]: In this model, the contextual information of current user is used for selecting only the relevant set of data, and ratings are predicted using any traditional 2D recommender systems on the selected data.
- *Contextual post-filtering* [5]: In this model, the contextual information is initially ignored, and the ratings are predicted using any traditional 2D recommender systems on the entire data. Then, the resulting set of recommendations is adjusted (contextualized) for each user using the contextual information.
- *Contextual modeling* [5]: In this model, the contextual information is used directly in the modeling technique as part of the rating estimation.

3 Objective Interestingness Measures

Assume that we have a finite set T of transactions (for example, purchases from customers in a supermarket [9]. An association rule [9] is expressed as $X \rightarrow Y$ with X and Y are two separate sets of elements $(X \cap Y = \emptyset)$. Element set X (corresponding Y) is associated with a subset of transactions $t_X = T(X) = \{T \in T, X \subseteq T\}$ (corresponding $t_Y = T(Y)$). Element set $\overline{X}$ (corresponding $\overline{Y}$) be counted $t_{\overline{X}} = T(\overline{X}) = T - T(X) = \{T \in T, X \subseteq T\}$ (corresponding $t_{\overline{Y}} = T(\overline{Y})$). To confirm or negate the tendency to have Y when X occurs, so we will be interested in the number of elements $n_{X\bar{Y}}$ (negative examples, contra-examples) inability to support the formation of association rules. Each rule is described by four parameters: $n = |T|, n_X = |t_X|, n_Y = |t_Y|, n_{\overline{X}} = |t_{\overline{X}}|, n_{\overline{Y}} = |t_{\overline{Y}}|$ (See Fig. 1).

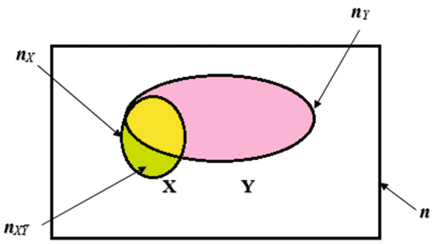


Fig. 1. The cardinality of an association rule X → Y [9].

The interestingness value of an association rules based on an objective interestingness measures (called interestingness measures for short) is computed based on four parameters of a rule $m(X \to Y) = f\left(n, n_X, n_Y, n_{X\overline{Y}}\right)$.

Example: Given two sets of elements X = {Bread}, Y = {Milk, Diappers, Beer}. A association rules is formed in the form X → Y. With n = 500, n_X = 150, n_Y = 350, $n_{X\overline{Y}} = 10$.

Objective interestingness measures to be used is Support Expectation is determined by the formula:

$$m(X \to Y) = f\left(n, n_X, n_Y, n_{X\overline{Y}}\right) = \frac{n_X\left(n_Y - n_X + n_{X\overline{Y}}\right)}{n(n - n_X)} \tag{1}$$

Thus the "interestingness value" of the association rule X → Y on the basis of the interestingness measures *m* is defined as:

$$m(X \to Y) = \frac{150 * (350 - 150 + 10)}{500 * (500 - 150)} = 0.18$$

4 Context Similarity Between Two Users

4.1 Contextual Information of a User

Context information of users are the factors that directly influence the selection of items or services when users participate in the recommender systems. For example, when users want the systems support to booktours for their vacation, the contextual factors about time (season) and accompanying persons will be affected greatly to the users to choose the location for the trip. From the description above, we can see that the contextual information of the users depends on the particular problem. However, to model the context-based recommender problem, the context information of the user is defined as follows:

For a set $U = \{u_1, u_2, \ldots, u_n\}$ includes n users, the contextual information of each user u_{i} defined in the k-dimension space as follows:

$$C_{u\mathrm{i}} = \left\{c_{i,1}, c_{i,2}, \ldots, c_{i,k}\right\}$$

where $c_{i,k}$ is the context property value k of user u_{i}.

4.2 Context Similarity Between Two Users

Currently, there are several measures proposed to calculate the contextual similarity value between two users in the k-dimensional vector space. In this study, to calculate the contextual similarity between two users, we used Chi-Square Similarity Kernel [20] measures with the formula defined as follows:

Suppose that two users u_{i} and u_j have contextual information defined by two vectors in k-dimensional space with following values: $C_{u\mathrm{i}} = \left\{c_{i,1}, c_{i,2}, \ldots, c_{i,k}\right\}$ and $C_{u\mathrm{j}} = \left\{c_{j,1}, c_{j,2}, \ldots, c_{j,k}\right\}$, then the contextual similarity between the two users u_{i} and u_j are computed by the following formula [11]:

$$K\left(C_{u\mathrm{i}}, C_{u\mathrm{j}}\right) = \sum\nolimits_{z=1}^{k} \frac{2c_{i,z}c_{j,z}}{c_{i,z} + c_{j,z}} \tag{2}$$

Where $K\left(C_{u\mathrm{i}}, C_{u\mathrm{j}}\right)$ is contextual similarity value between users u_{i} and u_j; k is the dimension of vector space (the number of user contextual properties); $c_{i,z}$ is the context similarity property value z of user u_{i}; $c_{j,z}$ is the context similarity property z of user u_{j}.

4.3 Context Similarity Matrix

Context similarity matrix between users is a symmetric matrix with structure: rows, columns of the matrix are users, cells of the matrix (intersection of rows and columns) are the context similarity value between two users on the corresponding row and column. For user set $U = \{u_1, u_2, \ldots, u_n\}$, the context information of each user is represented by a k-dimensional vector $C_{u\mathrm{i}} = \left\{c_{i,1}, c_{i,2}, \ldots, c_{i,k}\right\}$, then, the context similarity matrix between the users is defined as follows:

$$\boldsymbol{Matrix_{sim}}(\boldsymbol{C}) = \begin{pmatrix} 1 & s_{12} & \cdots & s_{1n} \\ s_{21} & 1 & \ldots & s_{2n} \\ \vdots & . & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & 1 \end{pmatrix}$$

Where $s_{i,j}$ is the context similarity value between two users u_{i} and u_j. This value is calculated by the formula (2).

5 Collaborative Filtering Model Based on Context Similarity

5.1 Model Definition

Collaborative filtering model based on context similarity (CUBCF) is defined as follows:

Suppose that $U = \{u_1, u_2, \ldots, u_n\}$ is a set of n users; $I = \{i_1, i_2, \ldots, i_m\}$ is a set of m items; $C_{u\mathrm{j}} = \left\{c_{j,1}, c_{j,2}, \ldots, c_{j,k}\right\}$ is a vector that determines value for context information of user u_j; $R = \left\{r_{j,k}\right\}$ is rating matrix of nusers (U) for m items (I) in context information (C) with each row representing one user u_j $(1 \le j \le n)$, each column represents one item i_k $(1 \le k \le m)$, $r_{j,k}$ is the rating value of user u_j for item i_k in context $C_{u\mathrm{j}}$, N is the number of items with the highest rating value and $u_a \in U$ is user who needs recommendation with contextual information $C_{u\mathrm{a}} = \left\{c_{a,1}, c_{a,2}, \ldots, c_{a,k}\right\}$.

Collaborative filtering model based on context similarity is presented as follows:

Figure 2 presents a collaborative filtering model based on context similarity. In particular, In the first phase, the contextual information is used to construct a rating matrix by using two techniques: User splitting and item Splitting; In the nextphase, based on the context properties of users to build context similarity matrix between the users; Finalphase, the collaborative filtering model based on context similarity is built based on integration matrix between rating matrix and context similarity matrix.

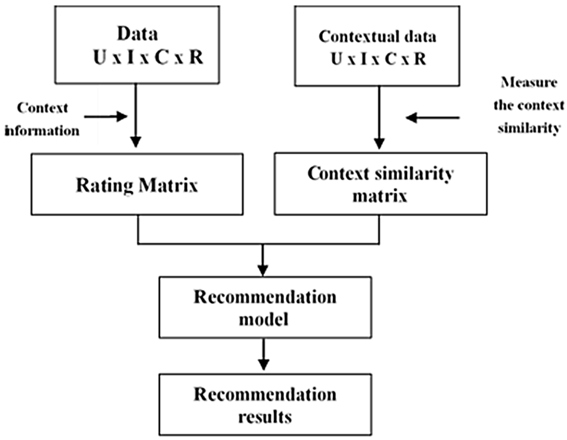


Fig. 2. Collaborative filtering model based on context similarity.

5.2 Collaborative Filtering Based on Context Similarity Algorithm

From the collaborative filtering model based on context similarity, we build a collaborative filtering algorithm based on context similarity that includes the following steps:

Collaborative filtering based on context similarity algorithm

Input: Transaction dataset (user set U, data set I, and context file C).
Output: N items with the highest rating value to recommend to user u_a.
Begin
Step 1: Build rating matrix (S_R).
<Based on the context property values to douser splitting and item splitting>;
For each user in set U do
For each item in set I do

$$S_R = \begin{array}{c|cccc|} & i_1 & i_2 & \dots & i_m \\ u_1 & 0 & 3 & 2 & 5 \\ u_2 & 3 & 0 & 2 & 1 \\ . & 2 & 4 & 1 & 3 \\ u_n & 4 & 5 & 2 & 4 \end{array}$$

Step 2: Build a context similarity matrix based on the context properties (S_C).
For each each user of set U do
For each each user of set U do

$$S_C = \begin{array}{c|cccc|} & u_1 & u_2 & . & u_n \\ u_1 & 1 & 1.3 & . & 2.6 \\ u_2 & 0.4 & 1 & . & 2.3 \\ . & . & . & . & . \\ u_n & 1.2 & 1.4 & . & 1 \end{array}$$

Step 3: Build the integrated matrix

$$S_I = S_R + S_C$$

Step 4: Build collaborative filtering recommender model based on integrated matrix
End.

6 Experiment

6.1 Data Description

In this experiment, we used two different datasets to run the model on two different scenarios:

In scenario 1, we conducted experiments on DePaul_Movie dataset [17] is a collection of data collected from surveys from students, with 97 students required to rate 79 films in terms of context: time, place, and companions (5043 ratings from 1 to 5).

In scenario 2, we conducted experiments on InCarMusic dataset [16]. This dataset includes 43 users rated 139 music compositions with 8 different contextual conditions such as: driving style, lands cape, mood, natural phenomena, road type, sleepiness, traffic conditions, weather was organized into forms data frame with 4012 rows, 11 columns in that column Rating value is between 1 and 5.

6.2 Implementation Tools

In order to conduct experiment, we use tools ARQAT implemented on programming language R. This is a toolkit developed by our team from the foundation of the tool ARQAT [15]. This tool includes functions: data processing; calculating context similarity of two users; building and evaluating recommender models [3].

6.3 Scenario 1: Experiment on DePaul Movie Data Set

Data Selecting and Processing. DePaul_Movie dataset is stored as a data frame of properties UserID, ItemID, Rating, Time, Location, Companion. Where, the UserID has 97 values for 97 different users; The ItemID has 79 values with 79 decoded based on the context propertíe of 319 movies according to the movie criteria with the same movie name and different context properties (Time, Location, Companion); Rating values have five continuous values of 1 to 5 (with value 1 is 829; value 2 is 625; Value 3 is 1007; value 4 is 1.212; value 5 is 1.307). In particular, the majority of values ranged from 3 to 5 and 5 are the highest rated values. In order to clearly see the distribution of the rating values for the DePaul_Movie dataset, we use the heat chart to represent the user's rating values as shown in Fig. 3.

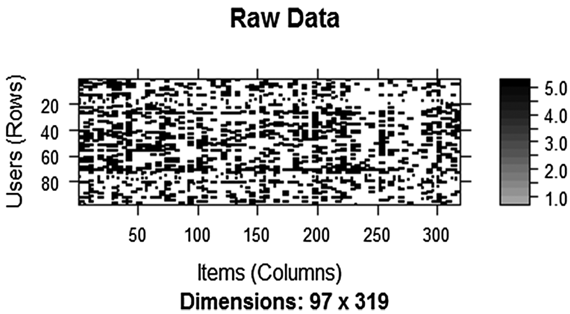


Fig. 3. The heat chart presents the distribution of user ratings on the DePaul Movie data set.

From the heat chart, we find that the distribution of the rating value of users for movies is relatively uniform. Although, there is a difference in assessed value in the two evaluation groups (1, 2) and (3, 4, 5) but the discrimination rate is not too far. So, we decided to select all the users who have ratings and all the films to build experimental data sets for the model. As such, the empirical data is full of 5043 lines with ratings from 1 to 5. In it, we divide the dataset into two subsets with training dataset and test dataset accounting for 80% and 20% respectively.

Model Results. With the goal of checking the model's accuracy on the dataset with some contextual similarities (3 properties). We conducted model training on a training dataset with 78 users and tested the results of the model on a test dataset with 19 users. The result of the model is exported in matrix format with structure 10 × 19 (each column is a user; each cell is a selected movie to recommend for the user in the corresponding column). Figure 4 presents the results of recommender model to the first 5 users; each of them selects the 10 highest rated movies.

	[,1]	[,2]	[,3]	[,4]	[,5]
[1,]	"tt01111611"	"tt01111611"	"tt01111611"	"tt01111611"	"tt00887631"
[2,]	"tt13756661"	"tt13756661"	"tt01098301"	"tt01098301"	"tt01330931"
[3,]	"tt01111613"	"tt01143691"	"tt00887631"	"tt01103571"	"tt01098301"
[4,]	"tt01111614"	"tt13756662"	"tt01330931"	"tt02325001"	"tt13756664"
[5,]	"tt13756662"	"tt01143692"	"tt01098303"	"tt13756661"	"tt02665434"
[6,]	"tt01111612"	"tt01103574"	"tt01143691"	"tt01111614"	"tt01111614"
[7,]	"tt01103571"	"tt13756663"	"tt14783381"	"tt01098304"	"tt02665431"
[8,]	"tt14783381"	"tt02665433"	"tt01111612"	"tt35100983"	"tt04417734"
[9,]	"tt16573011"	"tt02665431"	"tt01111613"	"tt13756662"	"tt02665433"
[10,]	"tt01695471"	"tt02665432"	"tt01098304"	"tt35100981"	"tt00887633"

Fig. 4. Display the results of 5 users (each user is a column). In that, each user is advised 10 product codes.

Model Evaluation. To see the effect of the recommender model, we conducted a comparison of the accuracy of the proposed model with the accuracy of User-based collaborative filtering recommender model (UBCF) based on the k-fold assessment method with k = 5 and for two rating models run with the number of movies being introduced to the user increasing from 1 to 40. The comparison of the accuracy of the two models is shown in Fig. 5. This result shows the indicators Precision, Recall of the CUBCF model is higher or equal to those of the UBCF model. Specifically, when the number of movies introduced from 10 to 25, the Precision, Recall of the proposed model has a higher value than the two values on the UBCF model. This shows that the

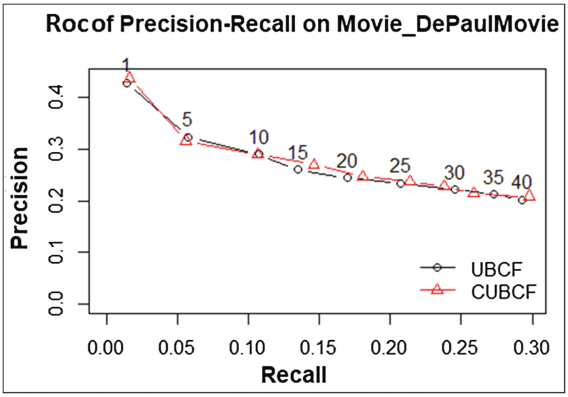


Fig. 5. Diagram showing the accuracy of two models on the DePaul_Movie dataset.

integration of contextual information of users based on objective interestingness measures to User-based collaborative filtering recommender model can improve the accuracy of the model.

6.4 Scenario 2: Experiment on InCarMusic Data Set

Data Selecting and Processing. The InCarMusic dataset includes the following properties: UserID, ItemID, Rating, DrivingStyle, Landscape, Mood, Natural Phenomena, RoadType, Sleepiness, Traffic Conditions, Weather. UserID has 43 values for 43 different users rated 139 music files broken down based on context properties to 43 UserID $\times$ 835 ItemID by the same User and Item criteria and 8 different context conditions for 4012 values. The rating is the same as the original dataset. This dataset has 37.09% users rated 1, 17.67% users rated 2, 16.40% users rated 3, 12.86% users rated 4 and 12.93% users rated 5 and only 3.04% users rated 0. Thus, the survey found that the number of music works rated by users at level 1 accounted for the largest number, while the ratings from 2 to 5 accounted for the average level and only a few user rated at 0. Therefore, we proceed to construct the dataset for the model in terms of selecting all the information in the dataset. After performing the selective operations, we have a data matrix for the experiment of size 43 $\times$ 835. Similar to scenario 1, the experimental data matrix is divided into two subsets: training dataset is 35 $\times$ 835 (80%), test dataset is 8 $\times$ 835 (20%) (Fig. 6).

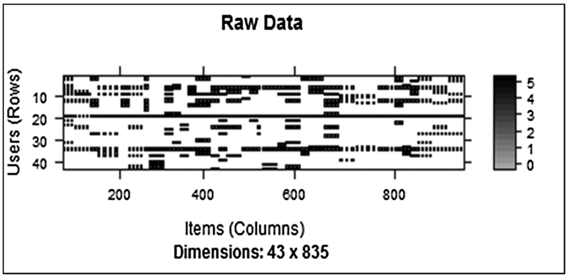
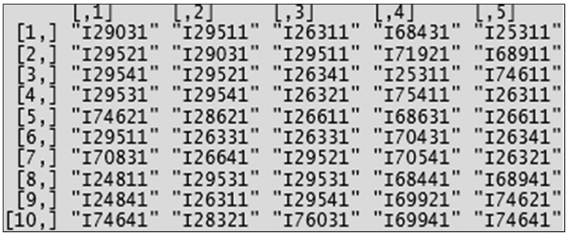


Fig. 6. The heat chart shows the distribution of the user's rating on the InCarsMusic dataset.

Model Results. With the goal of testing the accuracy of the model on datasets that have multiple contextual properties (8 properties), we conducted model training on a training dataset with 35 users and tested the results of the model on a test dataset with 8 users. The result of the model is exported in matrix format with structure 10 $\times$ 8 (each column is a user; each cell is a selected movie to recommend for the user in the corresponding column). Figure 7 shows the recommendation results for the first 5 users, with each user choosing the 10 highest rated music files.

Model Evaluation. Similar experimental scenario 1, In this empirical evaluation, we compared the accuracy of the CUBCF model with the accuracy of the UBCF model based on the methodology for constructing the assessment data K-fold with k = 5 and



	[,1]	[,2]	[,3]	[,4]	[,5]
[1,]	"I29031"	"I29511"	"I26311"	"I68431"	"I25311"
[2,]	"I29521"	"I29031"	"I29511"	"I71921"	"I68911"
[3,]	"I29541"	"I29521"	"I26341"	"I25311"	"I74611"
[4,]	"I29531"	"I29541"	"I26321"	"I75411"	"I26311"
[5,]	"I74621"	"I28621"	"I26611"	"I68631"	"I26611"
[6,]	"I29511"	"I26331"	"I26331"	"I70431"	"I26341"
[7,]	"I70831"	"I26641"	"I29521"	"I70541"	"I26321"
[8,]	"I24811"	"I29531"	"I29531"	"I68441"	"I68941"
[9,]	"I24841"	"I26311"	"I29541"	"I69921"	"I74621"
[10,]	"I74641"	"I28321"	"I76031"	"I69941"	"I74641"

Fig. 7. Present the recommended results on the InCarMusic file.

for two running models with the number of songs introduced to the user increasing from 1 to 40. The comparison of the accuracy of the two models is shown in Fig. 8. This result shows that the Precision, Recall of the CUBCF model is always higher than those values of the UBCF model. Specifically, when the number of songs introduced from 5 to 25, the Precision of the proposed model has a higher value than the UBCF model. This can again confirm that integrating user contextual information based on objective interestingness measures into the user-based collaborative filtering recommender model can dramatically improve accuracy of the model.

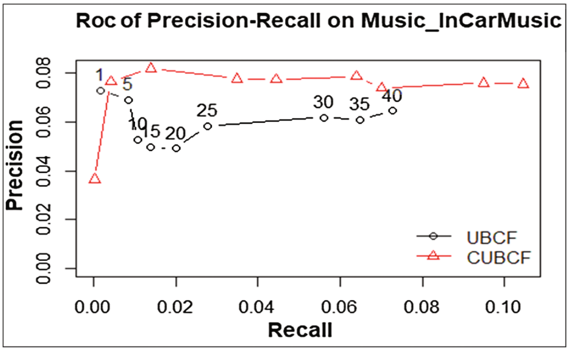


Fig. 8. The two model accuracy comparison charts on the InCarMusic dataset.

7 Conclusion

In this paper, we propose a new approach for context-aware recommender systems based on objective interestingness measures to consider the contextual relationship of the users in the recommendation process. In this model, we use the contextual information of the users to process the model's input data and integrate the contextual information of the users to build the context-aware recommender model based on context similarity. Based on the experimental results on the two data sets DePaul_-Movie and InCarMusic, our proposed model (CUBCF) is more accurate than the

UBCF model. This empirical result can confirm that the collaborative filtering model integrates user contextual information based on objective interestingness measures that can be applied in practice.

References

1. Adomavicius, G., Tuzhilin, A.: Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Trans. Knowl. Data Eng. (TKDE) **17**(6), 734–749 (2005)
2. Aggarwal, C.C.: Recommender Systems: The Textbook. Springer, New York (2016). https://doi.org/10.1007/978-3-319-29659-3
3. Hahsler, M.: recommenderlab: A Framework for Developing and Testing Recommendation Algorithms, Technical report - Southern Methodist University, pp. 1–27 (2015). https://cran.r-project.org/web/packages/recommenderlab/
4. Su, X., Khoshgoftaar, T.M.: A survey of collaborative filtering techniques. Adv. Artif. Intell. **2009**(4), 1–20 (2009)
5. Adomavicius, G., Tuzhilin, A.: Context-aware recommender systems. In: Ricci, F., Rokach, L., Shapira, B., Kantor, P.B. (eds.) Recommender Systems Handbook, pp. 217–253. Springer, Boston, MA (2011). https://doi.org/10.1007/978-0-387-85820-3_7
6. Ricci, F., Rokach, L., Shapira, B. (eds.): Recommender Systems Handbook. Springer, Boston (2015). https://doi.org/10.1007/978-1-4899-7637-6
7. Dey, K.A.: Providing architectural support for building context-aware applications. Doctoral dissertation, Georgia Institute of Technology (2000). ISBN 0-493-01246-X
8. Agrawal, R., Srikant, R.: Fast algorithms for mining association rules. In: Proceedings of the 20th International Conference on Very Large Data Bases, VLDB 1994, pp. 487–499 (1999)
9. Phan, P.L., Phan, Q.N., Phan, C.V., Huynh, H.H., Huynh, X.H., Fabrice, G.: Classification of objective interestingness measures. EAI Endorsed Trans. Context. Aware Syst. Appl. **3** (10), 1–13 (2016)
10. Huynh, X.H., Guillet, F., Blanchard, J., Kuntz, P., Gras, R., Briand, H.: A graph-based clustering approach to evaluate interestingness measures: a tool and a comparative study. In: Guillet, F.J., Hamilton, H.J. (eds.) Quality Measures in Data Mining, pp. 25–50. Springer, Heidelberg (2007). https://doi.org/10.1007/978-3-540-44918-8
11. Vedaldi, A., Zisserman, A.: Efficient additive kernels via explicit feature maps. IEEE Trans. Pattern Anal. Mach. Intell. **34**(3), 480–492 (2012)
12. Wasid, M., Kant, V., Ali, R.: Frequency-based similarity measure for context aware recommender systems. In: Proceedings of the IEEE International Conference on Advances in Computing, Communications and Informatics (ICACCI 2016), Jaipur, India, pp. 627–632 (2016)
13. Lu, T.T., Nguyen, T.N.: An approach in constructing a context-aware recommender system. In: Proceedings of the 8th National Conference on Basic Research and Application of Information Technology (FAIR 2015), pp. 486–494. Publishing house of natural sciences and technology (2015). [in Vietnamese]
14. Hassan, M., Hamada, M.: Smart media based context aware recommender systems for learning: A conceptual framework. In: Proceedings of the 16th IEEE Information Technology Based Higher Education and Training (ITHET 2017), Ohrid, Macedonia, pp. 1–4 (2017)

15. Phan, L.P., Phan, N.Q., Nguyen, K.M., Huynh, H.H., Huynh, H.X., Guillet, F.: Interestingnesslab: a framework for developing and using objective interestingness measures. In: Akagi, M., Nguyen, T.-T., Vu, D.-T., Phung, T.-N., Huynh, V.-N. (eds.) ICTA 2016. AISC, vol. 538, pp. 302–311. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-49073-1_33
16. Baltrunas, L., et al.: InCarMusic: context-aware music recommendations in a car. In: Huemer, C., Setzer, T. (eds.) EC-Web 2011. LNBIP, vol. 85, pp. 89–100. Springer, Heidelberg (2011). https://doi.org/10.1007/978-3-642-23014-1_8
17. Zheng, Y., Mobasher, B., Burke, R.: CARSKit: A Java-based context-aware recommendation engine. In: Proceedings of the 15th IEEE International Conference on Data Mining Workshops (ICDMW 2015), pp. 1668–1671, Atlantic City (2015)
18. Dejo, A.E., Ngwira, M.S., Zuva, T.: A context aware proactive recommender system for tourist. In: Proceedings of the 2016 IEEE International Conference on Advances in Computing and Communication Engineering (ICACCE 2016), pp. 271–275, Durban, South Africa (2016)
19. Odić, A., Tkalčič, M., Tasič, J.F., Košir, A.: Predicting and detecting the relevant contextual information in a movie recommender system. Interact. Comput. **25**(1), 74–90 (2013)
20. Phan, N.Q., Dang, P.H., Huynh, H.X.: Similarity kernel for user-based collaborative filtering recommendation system. In: Proceedings of the 2016 IEEE International Conference on Computing & Communication Technologies (RIVF), vol. 2, pp. 40–46 (2016)