

Context-based Satisfaction Modelling for Personalized Recommendations

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Abstract—Approaches for the personalized recommendations focus mainly on the user's activity over various portals. User's preferences are not dependent on the long term users' history only, but actual user's situation plays crucial role in the user's preferences adjustment and formation. An item liked by the user in some context, can be disliked by the same user in the other context. For the considering this users' variability we propose a novel approach for the user's satisfaction modelling based on incorporating the user's context into the rating prediction and consideration of previous users' rating history. Our novel approach reflects natural characteristics of user's context, when the various context's settings can influence another context. Proposed approach brings statistically significant improvement in the rating prediction process, thus it can increase user satisfaction during one-session recommendation.

Keywords—personalized recommendation; context; rating prediction; satisfaction modelling

I. INTRODUCTION

Thanks to the huge information increase in the last years, the domain of personalized recommenders became intensively studied area. Approaches for the personalized recommendations are designed in order to help users to access relevant information in the appropriate amount of time. Two basic approaches for the personalized recommendation have been proposed in the literature. The collaborative filtering approach uses the similar users (based on the users' rating history) to predict ratings for the unrated items [10]. On the contrary, the content based recommendation uses the content similarity to predict these ratings [3]. Generally, items with highest ratings are recommended [8], but this is highly dependent on the goal of the recommendation – often domain dependent (e.g. e-learning, movies) [11]. These two approaches are often mixed in order to bring better results and to minimize some shortcomings of each approach (e.g. cold-start, sparse ratings).

In the real world the recommendation always depends heavily on user's context [14]. Approaches that consider the user's context represent an enhancement of above described approaches. In this case the final predicted rating is not based only on the user and the item, but his/her context is considered additionally:

$$User \times Item \times Context \rightarrow Rating \quad (1)$$

Three basic approaches for the context integration to the recommenders have been proposed [1]: contextual pre-filtering, contextual post-filtering and contextual modelling. The contextual pre-filtering uses the context information in order to filter the dataset used for the recommendation. In the contrary the contextual post-filtering generates the recommendations without the context information and in the final phase is the context used to adjust these recommendations. Finally, the contextual modelling uses the context as the part of the rating computation process.

As the general goal of every recommender approach is to satisfy users' needs, recommendation approaches are designed to optimize user's satisfaction function (e.g. maximize knowledge level, decrease news article search time, buy specific product). The satisfaction modeling is mainly researched in the group recommendation, where the single-user satisfaction can influence other group members and thus their satisfaction with the recommended items [4].

In this paper we propose a novel approach for the user satisfaction modelling inspired by group recommender satisfaction modelling. We replace the group members' influence by the actual user's context. Moreover, the history of user's rating is considered based on an assumption that previous ratings influence the user preferences also. Proposed approach extends standard collaborative filtering approaches idea and improves the ratings prediction, which influences performance of the whole recommendation process and the user satisfaction respectively.

The paper is organized as follows. In section 3 we provide an overview of proposed approach. The evaluation, we performed, is described in section 4. The discussion and conclusions are provided in section 5.

II. RELATED WORK

Incorporating contextual information into the personalized recommendation approaches is one of the actual research topics. The satisfaction function used and optimized in current recommenders usually refers to the actual mental users' state. So domains where the users' mood is highly visible and influenced are preferred as the most popular domains (movies, music etc.) for the satisfaction modelling. Often only one type of context is considered, e.g. location, time, and mood. While it is clear that there are more context types available generally, influencing

each other and describing actual user's situation (not considered in actual context-aware approaches).

One of such approach in the domain of images is a photo context-aware recommender MMedia2U [6]. It is based on the defined hierarchical context model of the photographer and searches for the most similar context from the data. Proposed approach requires modelling the context for specific domain; moreover the context dependent weights have to be found and optimized.

Popular domain for the recommendation is the movie or multimedia domain. Biancalana et al. [2] designed a context-aware recommender based on the hypothesis that when user prefers watching movies in a particular period of time, these movies should have more significance. The only considered context is the time of rating provided in specific time.

The probabilistic music recommender was proposed by Wang et al. [12]. The method is based on the automated activity classification, when based on the mobile phone various daily activities are detected thanks to the device's sensors. This user's context with combination of the music content analysis (placed on the device) allows generating recommendation in respect to the performed activity.

Current approaches are often focused on one type of context. It is clear that there are considerable factors (context types) influencing users in their preferences and satisfaction, but often we are unable to collect them. On the other hand, when more context types are available it is quite difficult to integrate these into the recommendation process. Moreover, the essential features of such context are often omitted – one context can strengthen the influence of other context types (e.g. bad weather

and mood) and thus it influences the user's satisfaction respectively.

The users' satisfaction modeling is researched mainly in the group recommendation domain. The satisfaction modeling is thus used for the rating prediction which considers the context of other group members. Users, which experience the content within the group, are influenced by the other users (in the mean of the mood, personality or relationship) and thus the predicted rating can be dramatically influenced.

Masthoff proposed three variants of the satisfaction function for the group recommendation which take into account users' ratings, impact decrease over the time or the members' mood influence as the source of the group context [7], while some improvement in the users' satisfaction was reported. We believe, that considering the idea of user's satisfaction as the context influence modeling, can improve the rating prediction and thus the recommendation process.

III. INFLUENCE MODEL

For the user's context influence modelling, we propose a method, which is based on the group satisfaction modelling principles. We consider a user's context during the recommendation process and we adjust rating prediction to the actual user's circumstances (Fig. 1). Our approach is based on an assumption that actual user's ratings are influenced by the previous experienced content and actual user's situation – user's context. The user context is not considered as the one isolated influence, but the context itself is able to strengthen other context influence and vice versa. Our idea reflects the user's feelings intensity in the history also, which contributes to the actual predicted rating.

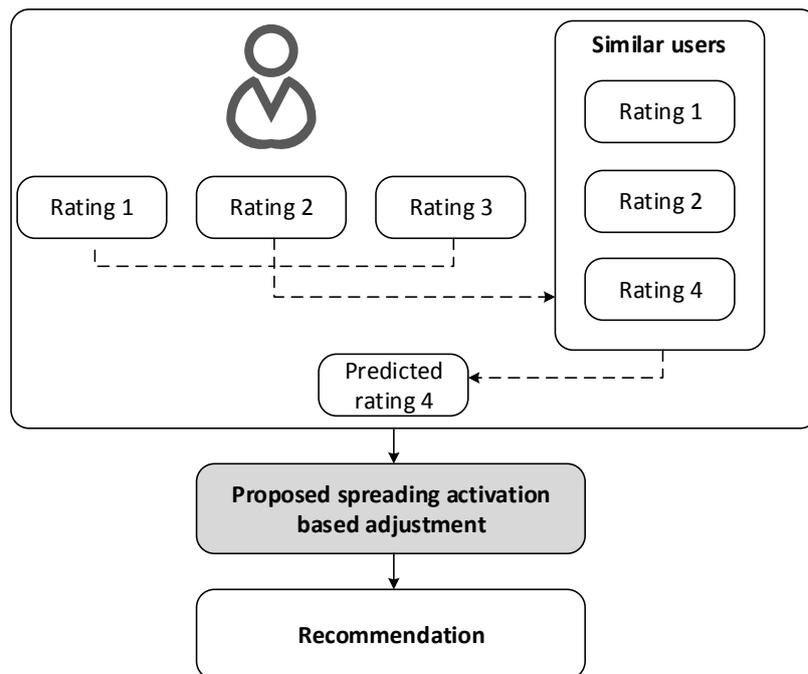


Fig. 1. Collaborative recommendation process, enhanced by context-based influence modelling (grey box).

Proposed context-based influence modelling enhances collaborative recommendation process. It consists of three basic steps:

1. Predict ratings for unrated items
2. Spread activation through user's item specific influence graph
3. Combine user's ratings history and result of influence graph

The standard prediction of ratings for unrated items can be computed based on various approaches. Generally, this prediction is computed based on the ratings of similar users (similar interest in the history), e.g. the average of similar users' ratings (Equation 2). The cosine similarity is widely used in the task of similar users' search, while it balances the computation cost and the performance. We propose to enhance predicted ratings computed in this manner by proposed spreading activation based approach, which spreads the activity within a graph based on the context influence of specific user and specific item.

$$\text{Rating}_{u \in \text{Users}, i \in \text{Items}} = \frac{\sum \text{Rating}_{\text{Similar users}, i}}{|\text{Similar users}|} \quad (2)$$

Based on the actual user context, we construct for every user and every predicted item the graph of user's influences (e.g. user's context) and spread activation (predicted rating) within this influence graph (Fig. 2). The influence graph can be constructed based on various users' contexts as mood, emotion or day of the week etc.

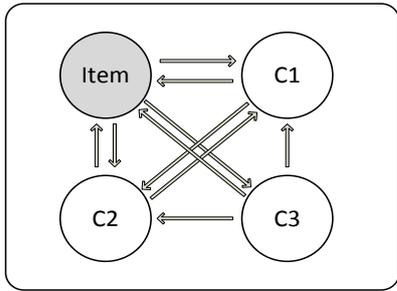


Fig. 2. Influence graph constructed for every predicted item (gray) and corresponding contexts (C1..C3).

Thanks to this idea, proposed approach can adapt to several domains, where various user's context data is available. Proposed model allows us to model the context influences - where e.g. user's mood can be strengthened by the item emotion, day of the week etc.

Not only the actual user's context influences the predicted ratings. Previously experienced items influence user's actual mood and the ability to experience the content as well. Because of this factor, we propose considering user's rating history (in the user's history used for prediction). These ratings are considered with the time decay factor (logarithm) – more recent item influences the user's rating stronger. Finally, predicted rating is adjusted by considering actual user rating history and his/her context as:

$$\text{Rating}_{u,i} = \kappa \eta \left(\frac{\sum_{j=1}^{|\mathbb{I}|-1} \left((\log_{|\mathbb{I}|-1} \sqrt{j+1}) \text{hist}_{u,i,j} \right)}{|\mathbb{I}|-1} \right) + (1 - \eta) \text{sp}(i, u) \quad (3)$$

where $\text{sp}(i, u)$ refers to the result of the spreading activation in the user's $u \in \text{Users}$ influence graph for the predicted item $i \in \text{Items}$. Proposed formula is adapted to the item rating scale $\langle -5, 5 \rangle$ where $\kappa = 2.631$ (normalization to the scale). The user's rating history is considered as the η and the actual user context as the $1 - \eta$ of final predicted rating (set based on the evolutionary computation approach to $\eta = 0.4$). The user's history ($\text{hist}_{u,i,j}$) refers to ratings of before experienced items (ratings of items rated previously by user i), while the item recency is considered (more recent item has higher influence). Finally, adjusted ratings are used for the standard collaborative recommendation, where based on the highest ratings items are recommended to the user.

IV. EVALUATION AND RESULTS

To evaluate proposed satisfaction influence modelling approach and to explore the potential of its usage in the recommendation process, we developed the average rating predictor (ARP). Similarly, we developed standard collaborative recommender, in order to compare expected improvements. The standard collaborative approach was designed as follows:

1. based on the cosine similarity find most similar users through the train data;
2. select the Top N (based on the popularity and average ratings) not visited items with the top rating;
3. recommend selected Top N items to the user.

For the experiments we used LDOS-COMODO dataset [4], which includes users' ratings on movies and provides a corresponding context of this recommendation (weather, mood, emotion, day type etc.). On the contrary, to this rich context information, dataset consist of 2 296 ratings on 1 232 movies from 121 users. Most of items received 2-6 ratings, while the standard long tale (Fig. 3) can be observed in users' rating behavior (minimum 1 and maximum 275 ratings per user). The sparsity of this dataset results to the low precision values, but the expected improvement can be demonstrated.

In order to investigate the characteristics of proposed method, we involved several metrics widely used for recommender system's evaluation. The Precision@1,3,5,10 is computed as the standard precision metrics for the Top 1-10 recommended items respectively.

The performance of the rating prediction is evaluated based on the Mean Absolute Error (MAE) and the Root Mean Absolute Error (RMSE) [9]. While the RMSE prefers more and small errors, the MAE prefers larger and few errors. The dataset was split into the train and test data. In addition, the 10 fold cross-validation was performed.

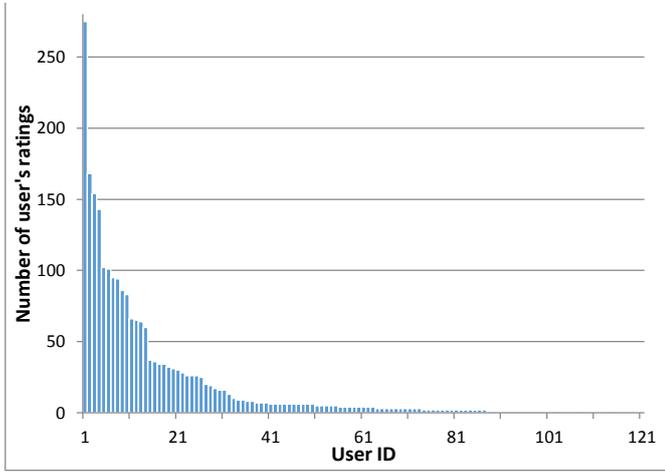


Fig. 3. User's rating distribution in LDOS-CoMoDa dataset.

A. Rating prediction

Firstly, we focus on the rating prediction. Often the recommendation method (mainly in the collaborative filtering) tries to predict the rating for the recommending item candidate and next recommend items receiving highest ratings. In order to compare the performance of proposed approach, we developed the average rating predictor (ARP). The rating prediction for the user is computed as the average of similar users' ratings for specific item. For the similar users determination we involved widely used cosine similarity.

Next we generated predictions based on various numbers of similar users used for the prediction (3,5,10,20). As we have expected, more users used for the computation better prediction are generated (Table I - ARP). Our proposed method extends the standard ARP by involving the spreading activation and considering of the user's rating history (previously rated items).

TABLE I. RATINGS' PREDICTION COMPARISON FOR VARIOUS SIMILAR USERS' SIZES (ARP-AVERAGE RATINGS PREDICTOR, PM-PROPOSED METHOD).

Similar users	MAE		RMSE	
	ARP	PM	ARP	PM
3	1.12	0.79	1.24	0.91
5	1.11	0.79	1.23	0.91
10	1.01	0.80	1.23	0.92
20	1.06	0.80	1.20	0.92
Avg.	1.08	0.79	1.23	0.91

For the experiment, we used three types of context from CoMoDa dataset - user's mood, user's emotion and the weather. In the training phase we adjusted the weights of graph edges. As we discussed above the context can strengthen other contexts. Thus in most circumstances the user's influence graph includes edges not only between the predicted item (Fig. 2 - Item) and the contexts involved, but there are edges also between contexts themselves.

As we can see our approach outperforms the ARP in all settings used in experiment (Table I - PM), while obtained improvement is considered to be extremely statistically significant ($p = 2.50E - 07, \alpha = 0.05, t = 19.3$). Based on

these results, we conclude that proposed approach is suitable to improve standard ratings prediction approaches and thus can be used in the recommendation process.

In order to compare obtained results with more sophisticated rating prediction approaches, we used well-known data mining software RapidMiner (www.rapid-i.com), where 10-fold cross validation was performed over the dataset on three rating prediction approaches. The Matrix factorization, Bi-polar slope one [5] and Global average were compared to our proposed approach (Fig. 4), while the proposed approach outperforms all three approaches in the MAE and RMSE metric respectively.

As the proposed approach considers the context of users, next we performed training of reference models with context-aware data. As we can see (Fig. 5), similar pattern as when no context was used can be observed. The improvement of reference approaches in MAE and RMSE metrics respectively (comparing to no context information) was very small, while proposed approach obtains the best result. Obtained results supports our hypothesis, that proposed context enhanced rating prediction approach improves the standard used approaches.

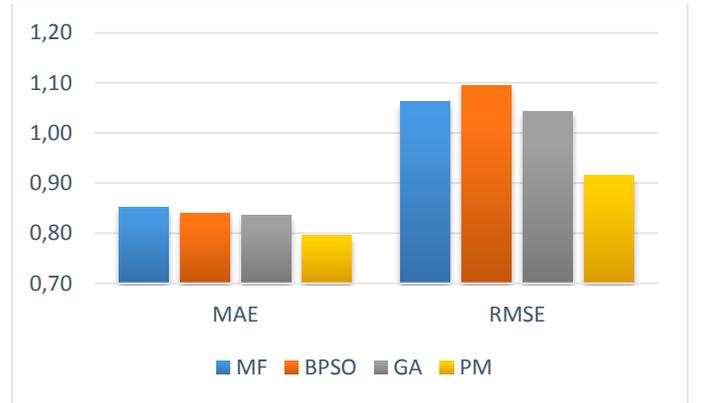


Fig. 4. Rating predictors comparison Matrix factorization (MF), Bi-polar slope one (BPSO), Global average (GA) and proposed context-based influence modelling (PM).

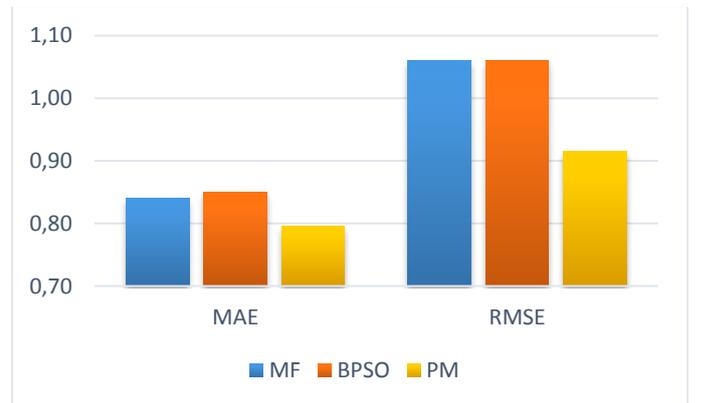


Fig. 5. Rating predictors with context consideration comparison Matrix factorization (MF), Bipolar slope one (BPSO) and proposed context-based influence modelling (PM).

B. Recommendation

As the rating prediction is used as the input for the recommender system, we performed an experiment focused to

investigate the performance of the collaborative recommender, which uses proposed context influence modelling. In order to compare results of proposed approach, we implemented standard collaborative recommender.

We involved Precision@1-10 and various sizes of similar users were used respectively. The results for the standard collaborative recommender and for the recommender boosted by our proposed context-based influence modelling are very low (Table II). This can be explained by the dataset we used, when the compromise between the number of ratings and context obtained have to be found. As the number of ratings obtained from users are very low or there are not enough of similar users, the collaborative filtering approach suffers from the well-known cold-start problem.

Despite of low numbers, basic characteristics can be observed. As we can see, the standard recommender obtains the best results when 5 similar users are used in the computation, followed by 3 users. This is an interesting result, while it shows that users do not generally follow the majority and average users' rating and thus small compact groups of sizes 3-5 can be found (in the respect to the dataset used - low user activity). As we can expect, the Precision@1 (top 1 item is recommended) brings the best results, while number of users' ratings in the dataset is generally small.

TABLE II. COMPARISON OF STANDARD COLLABORATIVE RECOMMENDER (SC) TO THE COLLABORATIVE RECOMMENDER ENHANCED BY PROPOSED CONTEXT BASED INFLUENCE MODELLING (PM). VARIOUS SETTINGS ARE PRESENTED - PRECISION@1,3,5,10 AND NUMBER OF SIMILAR USERS USED FOR THE COMPUTATION.

P@	Number of similar users							
	3		5		10		20	
	SC	PM	SC	PM	SC	PM	SC	PM
1	0.023	0.040	0.028	0.046	0.027	0.041	0.017	0.045
3	0.022	0.023	0.025	0.025	0.017	0.018	0.014	0.021
5	0.022	0.022	0.024	0.021	0.016	0.017	0.013	0.014
10	0.019	0.020	0.021	0.014	0.015	0.015	0.012	0.011
Avg.	0.021	0.026	0.024	0.027	0.019	0.023	0.014	0.022

Results clearly show that recommender with our proposed context-based influence modelling outperforms standard recommender when only one item is recommended generally. In other settings is the difference very small and proposed recommenders are comparable. When the average precision is computed, the proposed approach outperforms standard collaborative recommender (thanks to the large difference in P@1). This result is an implication of the dataset characteristics used for the evaluation, while there is lack of appropriate amount of users' ratings for the off-line evaluation. As the rating prediction enhanced by the satisfaction modeling approach statistically significant improves results, the recommendation improvement is expected when normal user activity is produced.

V. CONCLUSIONS

In this paper, we proposed a context-based influence model, which considers user's actual context and his/her ratings history for the rating prediction adjustment. Such predictions can be used in the recommendation approach in order to improve the performance and precision of recommenders.

Proposed approach is based on the group satisfaction modelling as we believe that the one context type influence have to be adjusted based on the other known and available contexts types. For every user and every predicted item rating we construct the influence graph. In this graph the vertexes represent the user's context (e.g. mood, emotion, day type), predicted item rating and edges model the context influence (based on the assumption that the context influence can be strengthened by other context). Next, the spreading activation is applied, which results to the adjusted rating based on the actual context. As the graph consists of the context and item, the performance decrease (comparing to standard approach) is minimal, while repeating patterns of this graph can be observed and thus stored as pre-computed.

Proposed approach considers the user's rating history as well, while the previous ratings are combined with the adjusted rating from spreading activation. This is done by weighting the history ratings (time decay factor) and combine in some manner with the adjusted rating. In this manner, we are able to adapt to various user's contexts and domains.

Our statistically significant results support our hypothesis, that proposed approach outperforms standard prediction approach (average difference MAE-26.86%, RMSE-26.06%) and other rating prediction approaches as Matrix factorization or Bi-polar slope one; while incorporating to the recommender system brings the recommendation improvement.

Weights of the proposed influence model can be personalized and thus every user can have own instance in order to reflect unique personalities. With the various domains and the goals of the recommendation in these domains (e.g. e-learning) the "non-standard" context can be used - teacher and his/her ratings, exam date, etc. We plan to investigate characteristics of such application of our approach.

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