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CONTEXT BASED RECOMMENDER SYSTEM USING INFLUENCE GRAPH

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Abstract:

Context Based Recommender Systems make the recommendation more personalized as they take the situation of the users into consideration while recommending items to the users. To incorporate the contextual information into the recommendation system, a graph based model is being proposed. An influence graph is specifically designed to assess the potential relevance between the target user and the items further used to make an item recommendation. It brings statistically significant improvement in the rating prediction process, thus it can increase user satisfaction during recommendation.

Index Terms: Recommender Systems, Context, Context Matching, Prediction & Influence Graph

1. Introduction:

A recommendation engine or a recommendation system is a tool that lets predict what a user may or may not like among a list of given items. Recommendation engines are a pretty interesting alternative to search fields, as recommendation engines help users discover products or content that they may not come across.

The personalized recommendations are designed in order to help users to access relevant information in the appropriate amount of time. Two basic approaches have been proposed in the literature. The Collaborative Filtering also known as CF, approach uses the similar users to predict ratings for the unrated items. On the contrary, the content based recommendation uses the content similarity to predict these ratings.

Generally, items with highest ratings are recommended , but this is highly dependent on the goal of the recommendation .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 context-aware recommendation system , the context information such as time of day, weather, mood etc. are considered as well along with the historical preferences of the user. In the context aware recommender system, the main challenge is to select the relevant contextual variables from the large amount of contextual information available. There are numerous features associated with an entity, among them, only the pertinent features should be taken into consideration.

For example, “Going with whom” plays a significant role in deciding which movie a user is interested in, however in some other circumstance this feature might be totally irrelevant.

The recommendation system should acquire and use only the relevant features, while neglecting the irrelevant ones, which may act as noise and degrade the recommendation accuracy. 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.

In this paper a novel approach has been proposed 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.

2. Proposed Method:

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.

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 e.g. the average of similar users' ratings.

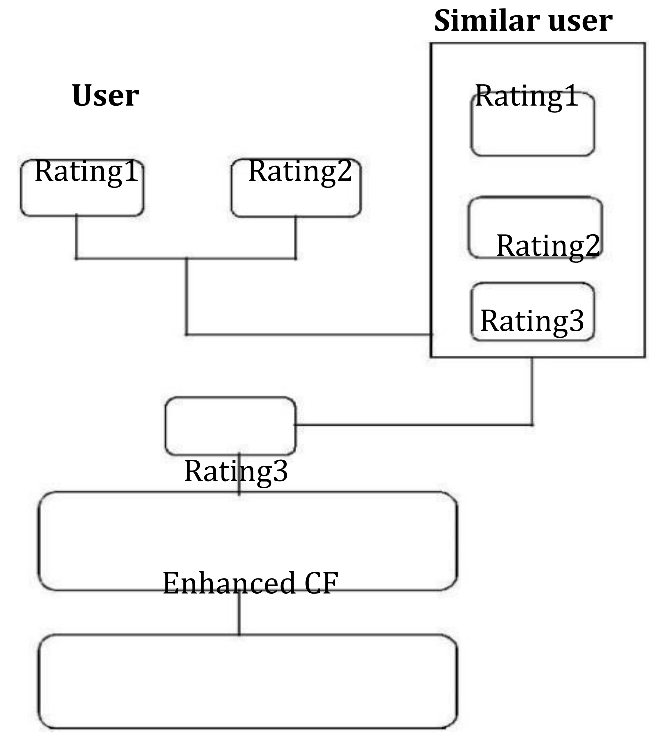
The cosine similarity [9] is widely used in the task of similar users' search, while it balances the computation cost and the performance. We propose to enhance predicted ratings computed in this manner by proposed spreading activation based approach, which spreads the activity within a graph based on the context influence of specific user and specific item.

However finding the similar users for an active user in a sparse dataset is quite difficult. When there is no similar user is available for the active user, using either item based CF or giving general recommendation such as recommending high rated items is quite efficient.

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 user contexts such as mood, emotion or day of the week etc

Based on 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 strengthen by the item emotion, day of the week etc. Not only has the actual user's context influenced 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.

The Figure 1 shows the colloboration of basic user-based CF approach for recommendation with enhanced CF.



Recommendation

Figure 1: Collaborative recommendation process, enhanced by context-based influence modelling

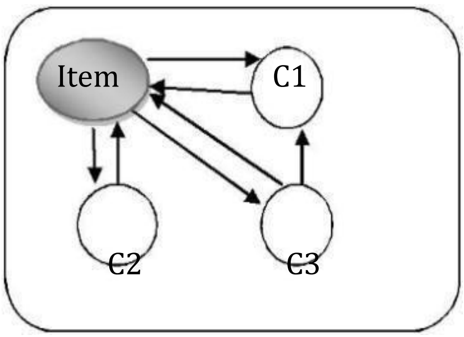


Figure 2: Influence graph

3. 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 to compare 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 2296 ratings on 1232 movies from 121 users. Most of items received 2-6 ratings, while the standard long tale 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) . While the RMSE prefers more and small errors, the MAE prefers larger and few errors. The dataset was split into train and test data. In addition, the 10 fold cross-validation was performed.

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 .Our proposed method extends the standard ARP by involving the spreading activation and considering of the user's rating history (previously rated items).

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.

B. Context-Aware Post-filtering

In this section, we did the experiment with the post filtering model for CARS. For this, we reuse the training and the test datasets each query in this experiment is linked to a context condition, and the context factors associated with a pertinent item must match the context condition given in the query. Context factors considered for the LDOS-CoMoDa dataset are day type and social, which are two important factors affecting a user's choice for watching a movie. By splitting items using selected context factors, we further obtain 225 queries in the LDOS-CoMoDa test dataset. The average numbers of relevant items per query are correspondingly 1.01 and 1.22. Obviously, every context-aware query only has about one relevant item. We study recommendation effectiveness of evaluated methods with or without post filtering strategies.

As for the case, without using post filtering, we can see that the CGR model largely improve all the other models on both datasets. This outcome is very consistent with prior experimental results.

C. 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 I). As the numbers 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.

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.

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, the difference is very small and proposed recommenders are comparable. When the average precision is computed, the proposed approach outperforms standard collaborative recommender. 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 is enhanced by the satisfaction modeling approach which shows significant results, the recommendation improvement is expected when normal user activity is produced.

Table I. Comparison of Standard Collaborative Recommender (Sc) To the Collaborative Recommender Enhanced By Proposed Context Based Influence Modelling

p@	**Number of similar users**							
	1		**3**		**5**		**10**	
	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**

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. The statically significant results shows that the proposed approach outperforms standard prediction approach and other rating prediction approaches as Matrix factorization or Bi-polar slope one; while incorporating to the recommender system brings the improvement in recommendation .

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