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ILP Recommender System: Explainable and More*

Sirawit Sopchoke[1], Ken-ichi Fukui[2], and Masayuki Numao[2]

[1] Graduate School of Information Science and Technology, Osaka University, Japan
[2] The Institute of Scientific and Industrial Research (ISIR), Osaka University, Japan

Abstract. In this paper, we explore the use of ILP thoroughly in generating explainable, negative, group and context-aware recommendation. ILP provides recommendation rules in if-then logical format that allows us to form a clear and concise explanation to accompany the suggested items. It can indirectly derive negative rules which tell us not to recommend certain products to users. It also emphasizes the use of universal representations which enables us to suggest the items to a group of users who share the same interest. Additionally, ILP requires no re-training if new contexts (e.g., location, time and mood) are added to the system to generate context-aware recommendations (CARS), only predicates and settings are simply specified. In this paper, we also propose the explainability evaluation in terms of transparency by comparing the items/features appearing in the explanation with the features presented in the user's review. The negative, group and dynamic recommendations can be evaluated using the standard measurement.

1 Introduction

In recent years, an interest in recommender system (RS) has dramatically increased. A variety of innovative RS e.g. explainable RS, group RS and CARS were developed. Explainable RS provides explanations to make the users aware why the items are recommended to them and helps to improve the effectiveness, efficiency, persuasiveness, and user satisfaction of RS. However, most of the explanation forms e.g. textual sentence, tag cloud, visual image seem to be complicated and need an extra effort to comprehend. Group RS provides recommendations to a group of users. A group recommender is useful for domains where several people participate in a single activity. Most of the group RS developed use aggregation strategies. However, it is difficult to adapt to the group as a whole based on information about individual users' likes and dislikes. Recommending to groups is clearly more complicated than recommending to individuals. In CARS, user preferences may change over context. CARS generates more relevant recommendations by adapting them to a specific contextual situation of a user. However, there are some concerns regarding how the information representing the context is obtained and how the contextual user preference is

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elicited. These three different purposes of RS inspire us to extend our proposed RS into a new and challenging RS. Another aim of our system is to incorporate the negative recommendations which refer to the items that the system will not suggest to the user. Hence, we decide to explore ILP thoroughly so as to make our RS to provide or not to provide the recommendation in the right context to the right person or the group with a readable explanation.

To evaluate the quality of our recommendation, the standard measurement can be used. However, to evaluate the explainability in terms of transparency, we propose a less complicated method compared to the existing methods since our designed explanation is in a simple form with a clear and concise information.

2 Related Work

The success of ILP in RS has been shown in a number of researches. For example, Kouki et al. [1] showed that relational learning could be used to develop a general and extensible hybrid RS framework. This framework provided a mechanism to extend the system by incorporating and reasoning over unspecified types and similarity measures of additional information collected from several sources. As a result, we were drawn into relational learning to provide potentially a solution to construct explanation for recommendations.

Explanations in RS can serve multiple purposes [5], one of which is transparency. An explanation provides clarity as to how a recommendation is picked for a user and it can be helpful especially when the system shows multiple recommendations. Most explanations [2] are presented in natural language which could possibly lead to a misunderstanding due to their complexity and lack of clarity. It is sometimes difficult to use language in a precise and unambiguous way without making the explanation wordy and difficult to read. Group recommendation has attracted significant research efforts since it benefits a group of users. PolyLens is the first RS to recommend movies to groups of users. Aggregation is a main strategy used in most researches in group RS with a small variation to suit each purpose [3]. Recommending to groups is clearly more complicated than recommending to individuals since each user may have different preferences. CARS is RS which incorporates contextual information. The importance of using context data in the RS can be found in [3]. The challenges in CARS research includes how to actually capture and exploit context. To our knowledge, research in negative recommendation has not yet been available.

Most of the approaches to evaluate explainable recommendations are through online experiments by analyzing the behaviors of real users [2]. The offline experiment of any form of explanation still, however, lacks a standard evaluation.

3 ILP Recommender System

In this research, our goal is to combine explainable, negative, group and context-aware recommendation into a single RS. In 2018, we succeeded in constructing the cross-domain recommendation rule using ILP [4]. ILP is preferred over other machine learning approaches because of its ease of comprehensibility, intelligibility, and ability to include additional information in the learning problem. Moreover, ILP provides us with an expressive first-order logical rule. We conducted an experiment over the dataset containing user's preferences and item attributes. The dataset was obtained from "Amazon product data" provided by UCSD[3]. Each recommendation is conceptually illustrated with the following examples:

Explainable recommendation The explanation that will accompany the item suggested by the recommendation rule (1) is "If User1 and User2 like the same movie genre thriller, then User2 will like the same music as User1" with a probability of 0.69523. The rule comprises a condition part and a conclusion part.

$$\begin{aligned} likeMusic(User2, Music) \text{ :- } likeMovie(User2, Movie1),\\ likeMovie(User1, Movie2), movieGenre(Movie1, thriller),\\ movieGenre(Movie2, thriller), likeMusic(User1, Music).\ 0.69523 \end{aligned} \tag{1}$$

Group recommendation The recommendation rule (2) allows us to suggest the music by Linkin Park to the group of users whose preference is Stan Lee's book. In ILP, universal quantification is assumed over all literals which means the rule can be used to recommend to the group of users who share the same preferences.

$$\begin{aligned} likeMusic(User, Music) \text{ :- } likeBook(User, Book),\\ bookAuthor(Book, stanlee), musicArtist(Music, linkinpark).\ 0.63751 \end{aligned} \tag{2}$$

Context-aware recommendation In our preliminary experiment, the contextual information was not incorporated at the time. The recommendation rule (3) is not from our experiment but it is what we expect from our framework, the probability is therefore not available. According to (3), $music2$ is recommended to the user since he/she is sleeping and his/her preference is $music1$. The sleeping context is considered in suggesting the music.

$$\begin{aligned} likeMusic(User, music2) \text{ :- } likeMusic(User, music1),\\ userActivity(User, sleeping).\ Probability\ P \end{aligned} \tag{3}$$

Negative recommendation The negative recommendation was not included in our preliminary experiment either. However, we believe that we can transform a generated rule into an equivalent negative form of which the conclusion part is negative. The expected rule is shown in (4). The $music1$ will not be recommended to the user because the user is feeling sad at that moment.

$$not(likeMusic(User, music1)) \text{ :- } userMood(User, sad).\ Probability\ P \tag{4}$$

[3] http://jmcauley.ucsd.edu/data/amazon/

4 Explainability Evaluation

The standard measurement can be used to evaluate the quality of the recommendation. However, we propose the method for transparency evaluation for explainability based on historical data (offline evaluation). The method is to determine whether the items appearing in the explanation and the items appearing in the user review texts belong to the same domains (i.e. the generated explainable rule can be considered as the generated user review). In performing the evaluation, we first randomly selected 100 users. For each user, we had top 10 items which were recommended by our generated rules from our proposed framework. We then selected only the recommended items which were found useful to the users and investigated the review texts that the users wrote for the (recommended) items in the repository. If there was a piece of free text in the particular review that corresponded to the generated rules by our RS e.g. "movie" term was found in the user review text on a music recommended by the generated movie-music rule, the explanation of the rules was transparent and useful to the user. Our evaluation results showed 81% relevance for the recommendations from movie-music rules and 73% from book-music rules.

5 Conclusion and Future Work

The ability of ILP in using an expressive representation language allows us to complete our RS in providing a readable explanation; a group recommendation based on relations between users with different preferences without complicated aggregation; a recommendation with a specific situation of the user by simply adding the contextual knowledge. The negative recommendation can be accomplished by negating the suggested item. The ongoing work includes experimenting on context-aware and negative recommendation, performing both offline and online evaluation on explainability, and combining deep learning (embedding-based RS model) to enhance the ability of our framework.

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