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Towards improving user-recommender systems interactions

¹Jinfeng ZHONG and ¹Elsa NEGRE

Abstract—Recent years have witnessed the increasing deployment of recommender systems as decision-support tools, application of recommender systems is ubiquitous in our daily life. As algorithms used in recommender systems become more inscrutable, some recommender systems remain black-box for most people, which makes it difficult for people to fully trust such systems. Therefore, improving the user-recommender systems interactions is attracting increasing attention, one of the hot topics is explainable recommendation. In this paper, we investigate the possibility of providing context-aware explanations for recommendations and discuss the potential methods of evaluating such explanations.

I. INTRODUCTION

Nowadays, recommender systems (RSs hereinafter) have become important tools that help users choose the most suitable items more easily (products, services, etc.) through information retrieval. One of the most important functions of RSs is helping humans in the decision-making process, which aims to help people make better decisions more efficiently. From this perspective, RSs can be viewed as decision-support tools. Among the recommender techniques, context-aware recommender systems (CARSS hereinafter) are receiving much attention in recent years. CARSS extend traditional RSs from 2 dimensions (*users* $\times$ *items*) to multi-dimensions (*users* $\times$ *items* $\times$ *contexts*). In CARSS, users' preferences are modeled according to their contextual situations rather than assumed to be static. More relevant recommendations adapted to users' contextual situations can be generated by leveraging their contextual situations [1].

Research in RSs typically focuses on improving algorithm performances, especially in terms of prediction accuracy such as RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), CTR (Click Through Rate), etc. In recent years, it has been recognized that accuracy alone is not a complete description of the real-world tasks [2] and that accuracy alone is not enough to gain users' satisfaction and trust [3]. Research related to interactions between users and RSs is attracting increasing attention from both academia and industry. One of the hot topics is explainable recommendation that aims to develop recommender techniques that can generate not only high-quality recommendations but also intuitive explanations to justify such recommendations [3].

It is human nature to make decisions by following certain logic, people wish that RSs can not only provide accurate and personalized recommendations but also supply explanations to justify why such recommendations have been generated.

However, as algorithms applied in RSs are becoming more and more inscrutable, some RSs work as black boxes. For most people, how RSs generate recommendations remains unclear, which makes it difficult for them to fully trust such systems. Besides, regulations such as GDPR (General Data Protection Regulation) [4] demand that decision-support systems should provide explanations to justify the decision-making process, which is known as "right to explanation". By providing explanations, the decision-making process can be more understandable to users, which can in term enhance trust and increase satisfaction [5]. Table I presents the potential goals of explanations identified by Tintarev et. al [5]. Accordingly, these potential goals can be used to evaluate the quality of explanations [6].

TABLE I
POTENTIAL GOALS OF EXPLANATIONS IN RECOMMENDER SYSTEM

Aims	Descriptions
Efficiency	Help users make decisions more quickly
Effectiveness	Helps users make better decisions
Persuasiveness	Change users' behaviours
Trust	Increase user's confidence in the system
Transparency	Help users understand how the system works
Satisfaction	Increase the ease of use or enjoyment

Based on these preliminary analyses, we argue that explaining recommendations by leveraging users' contextual situations is a promising topic. The motivation lies in two aspects: (i) Users' demands and regulation requirements make it necessary to provide explanations to justify recommendations; (ii) Contextual situations can influence user's preferences, therefore, explanations adapted to users' contextual situations could potentially be more personalized and convincing. In this paper, we investigate the possibility of generating explanations adapted to users' contextual situations. The main contributions are the following: (i) By reviewing state-of-art works, we highlight the role of explanations in RSs; (ii) We discuss the feasibility of providing explanations adapted to user's contextual situations; (iii) We identify several possible avenues that can generate context-aware explanations in RSs; (iv) We discuss potential approaches to evaluate context-aware explanations.

The rest of the paper is organized as follows: in Section II, we review state-of-art works. We propose potential avenues for generating context-aware explanations and corresponding approaches to evaluate such explanations in Section III. Lastly, we conclude and discuss perspectives in Section IV.

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II. RELATED WORKS

In this section, we review related works from which we have borrowed concepts. We will first present the potential goals of explanations in RSs to highlight the important roles of explanations in RSs. Subsequently, we review CARSs since we investigate context-aware explanations in RSs. We then review research of explanations in RSs to position context-aware explanations.

A. Goals of explanations in RSs

As presented in Table I, the potential goals of explanations in RSs mainly include promoting transparency, effectiveness, efficiency, persuasiveness, trust and satisfaction. Concretely, explanations can help users find the items that are really of their interests (effectiveness) more efficiently (efficiency), convince users to try or consume (persuasiveness), increase users' loyalty in the system (trust), make RSs more understandable (transparency) and increase the ease of use or enjoyment (satisfaction).

On the one hand, these goals are distinct [5], each serving different targets. For example, effectiveness means helping users make better decisions [7], apparently this goal is in favor of users; persuasiveness means convincing users to try or consume [5], it is in favor of item providers.

On the other hand, these goals may interact with each other, which means that there are trade-offs among them. It has been recognized that personalized explanations may enhance users' satisfaction, however, effectiveness may not be necessarily promoted [6], [7]. Therefore, it is difficult to design explanations that can perform well in all aspects.

B. CARSs

The notion "context" has been widely studied across different domains. In RSs, the most cited proposition is the one proposed by Dey et al. [8]: "Context is any information that can be used to characterize the situation of an entity." For example, in CARSs, when recommending movies, daytype and users' companions may influence their choices. The "daytype" and "companion" are contextual factors and each of them can have several possible values. Here is a concrete example, possible values of "companion" can be "with_child", "with_lover", etc; possible values of "daytype" can be "weekday", "weekend". "weekday" and "weekend" are contextual conditions that compose contextual situations. As a toy example, a contextual situation can be (*with_lover, weekend*), indicating that a user is with his/her lover on a weekend. Clearly, users' preferences could be different across different contextual situations. When with his/her lover, a romantic movie could be a better recommendation than a horror movie. CARSs can model users' preferences with finer granularity under different contextual situations, as a result, more accurate and personalized recommendations adapted to users' contextual situations can be generated [1].

Typical data records in traditional RSs have the form of $\langle user, item, rating \rangle$, while in CARSs, the form of data records is $\langle user, item, contexts, rating \rangle$. Usually,

contexts (or contextual situations) are composed of several contextual conditions. Regardless of the way contextual information is integrated into RSs, the rating function of CARSs is "multidimensional": $Rating_{CARS} : user \times item \times contexts \rightarrow rating$ while rating function in traditional RSs is "bi-dimensional": $Rating_{RS} : user \times item \rightarrow rating$. Due to the high dimension of data records in CARSs, corresponding recommender models are more complex. From a chronological point of view, models used in CARSs have been becoming more inscrutable over the years [9]. It can be observed that, due to the high dimension of data records and the complexity of models used in CARSs, CARSs have been becoming more complex and more inscrutable, raising concerns about transparency and trust.

C. Explanations in RSs

In RSs, explanations are designed to help users understand why an item has been recommended or better understand the qualities of items to decide whether to accept it or not [5].

From a broader point of view, models in AI (Artificial Intelligence) systems can be classified into two types [10]: (i) Transparent models, where the decision-making process is understandable to humans. Typical models of this type are linear models and decision trees with fewer nodes; (ii) Models that can provide post-hoc explanations while the internal mechanisms are not elucidated. For these models, the result-generating process and explanation process are separated. Accordingly, explanations can be classified into: (i) Model-intrinsic explanations that can explain how models work exactly; (ii) Post-hoc explanations that justify model behavior without elucidating the internal mechanisms of the model. For example, a typical post-hoc explanation can be generated from the interpretation of input data that aims to explore the interactions (e.g. association rules) between input data and results [11]. Post-hoc explanations are usually applied when models are too complex to understand [3]. Following this perspective, explanations in RSs can be model-intrinsic and post-hoc.

Explanations in RSs can also be classified according to the information resources [3], which mainly include: (i) Relevant user or item explanation; (ii) Feature-based explanation; (iii) Opinion-based explanation; (iv) Social explanation. Users' contextual situations that can greatly influence their preferences have not been sufficiently applied to generate explanations [12] and worth more extensive exploration [3]. Here, we review some existing attempts to generate context-aware explanations in RSs.

To the best of our knowledge, Baltrunas et al. [13] is the pioneer in exploring context-aware explanations. They showed through a user study that context-aware explanations are preferred to non-contextual explanations in travel recommendation. However, only 20 participants were involved in the user study, which makes the conclusion less statistically credible. Misztal et al. [14] proposed to explain recommendations by identifying the most relevant context for each movie type. Following this conceptualization, explanation for recommendation of the same type are always the same,

which is not personalized. Sato et al. [15] modeled users' preferences under different contextual situations by factorization machine [16]. Recommendations can be explained through item-context pairs. The results of their user study showed that user-perceived persuasiveness and usefulness are promoted when contextual information is included in explanations. However, the authors did not evaluate the context-aware explanations through other metrics such as efficiency and trust (See Table I for more details). Recently, Musto et al. [12] proposed post-hoc context-aware natural language explanations. Recommendations were generated by a content-based recommender. Participants were asked to provide some basic demographic data to indicate their interests in movies. Explanations are generated by exploiting distributional semantics in reviews posted by other users. Their user study indicated that users preferred context-aware explanations to non-contextual ones. However, they did not further investigate other effects of context-aware explanations.

We note that although there are a few existing works that have explored context-aware explanations, the limitations of these works mentioned above lie in: (i) Participants are not allowed to give some sample ratings under different contextual situations [12], [13], [14], participants' preferences under different contextual situations are not modeled; (ii) Explanations can not perform well in all the goals defined in Table I, there are usually trade-offs among these goals. However, the above mentioned works did not fully explore the effects of context-aware explanations, as a result, the quality of context-aware explanations can not be comprehensively evaluated.

In this section, by reviewing state-of-arts, (i) We highlight the roles of explanations in RSs by specifying the goals of explanations; (ii) We show how CARSs can accurately model users' preferences to provide personalized recommendation adapted to users' contextual situations; (iii) We summarize existing works exploring context-aware explanations in RSs and point out their limitations. In the next section, we present our propositions in designing and evaluating context-aware explanations.

III. OUR PROPOSITIONS

A. Design context-aware explanations in RSs

As we discussed in Section II-C, explanations in RSs can be classified according to whether internal mechanisms of recommender models are elucidated, namely model-intrinsic explanations and post-hoc explanations. For context-aware explanations, we propose the following avenues:

1) Model-intrinsic vs Post-hoc:

- If CARS is applied to generate recommendations and recommendations can be explained according to the algorithms used in the system, then model-intrinsic explanations can be generated. For example, in the CARS proposed by Sato et al. [15], users' preferences are modeled by factorization machine [16]. Therefore, item-context pairs with the highest score are regarded

as explanations. When models such as deep learning methods are applied [17], they are too complex to explain, post-hoc explanations could be used to justify recommendations. Here is a scenario in movie recommendation. A user is recommended a romantic movie (by a black-box RS) when he/she is with his/her lover. If, for example, through history records, it is found that romantic movies are highly rated when users are with their lovers, then an explanation like "It would be nice to watch a romantic movie with your lover" can be used to justify a recommendation. In this example, a post-hoc context-aware explanation is generated by association rule. Apparently, the explanation does not reveal the internal mechanisms of RSs, however, it is an explanation adapted to this user's contextual situation.

- If contextual information is not used to generate recommendations, context-aware explanations can still be used to justify recommendations. This is the case of the work in [12]. Participants were asked to specify their contextual situations, however their contextual situations are not used to generate recommendations. Instead, recommendations are generated by a content-based recommender algorithm. A typical example is the following: a participant indicates that he/she is with his/her lover and a movie is recommended by a content-based recommender; if, by exploiting the distributional semantics in reviews posted by other users, it is found that in other users' reviews about this movie, item description "romantic ending" often appears under the contextual condition "with lover", then an explanation such as "You should watch this movie with your lover, which is good choice since this movie has a romantic ending". In [12], contextual situations are simply used to justify recommendations but not to generate recommendations. Therefore, the explanations in [12] are post-hoc. One major advantage is that context-free recommender methods can be used, with fewer dimensions to be considered.

Model-intrinsic explanations can reveal how RSs work, therefore the explanations are faithful to the mechanisms of RSs. The decision-making process is transparent and can be traced. Post-hoc explanations, on the contrary, do not elucidate the internal mechanisms of recommender models, recommendation process and explanation process are separated, offering more flexibility, more complex models can be applied to guarantee the accuracy of recommendation. A major concern of post-hoc explanations is that they may not reveal the real decision-making process and can sometimes be against facts [18], which is the reason why Rudin et al. [18] called for applying transparent models rather than black-box model that are post-hoc explainable. Therefore, we suggest that in low investment domains (e.g. movies), post-hoc explanations can be applied to justify recommendations. When the price of wrong decisions can not be neglected (e.g. financial services and medical diagnosis) model-intrinsic explanations are recommended to control risks.

2) *Context vs “Context+”*: One naive approach of generating context-aware explanations would be simply using contexts as explanations. Here is a concrete example (e.g. movie recommendation), “This movie would be a good choice to watch with your lover”. In this case, the contextual factor “companion” is used to explain the recommendation, no other information is included. This naive explanation may contain too little information to justify recommendations. We therefore propose “Context+”. “Context+” means combining contextual information and other information (e.g. item features). For example, in movie recommendations, users’ choices are usually influenced by the features of movies such as genres, actors. Therefore, “item feature-context” pairs can be identified to justify recommendations. An example of such explanations could be “Watching a romantic movie with your lover in a weekend night would be a good choice for you”.

Exactly which strategy is better depends on the application domain and needs to be further explored with carefully designed experiments. In the next section, we present possible evaluation methods that can assess the qualities of context-aware explanations in RSs.

B. Evaluating context-aware explanations

In Section II-A, we presented potential goals of explanations in RSs. As a matter of fact, these goals can be used as metrics to assess the quality of explanations in RSs [6]. In this section, we investigate how to evaluate context-aware explanations in RSs. According to Paolo et al. [19], when evaluating recommendation, there are two main families of evaluation methods: objective evaluation and subjective evaluation. The difference between the two families is that in subjective evaluation, measures are collected by asking users while in objective evaluation metrics are evaluated against a pre-built ground truth [19]. Following the same strategy, explanations in RSs can be evaluated in the same way. Subsequently, we summarize how to evaluate explanations in RSs and context-aware explanations can be evaluated in the same way. We note that since explanation itself indicates interactions between users and RSs, the evaluation methods we mention below all require the involvement of users.

1) *Objective evaluation*: In objective evaluation, measures are collected by measuring the pre-defined ground truth:

- **Efficiency**: An explanation in RSs being efficient means helping users to choose the best recommended item faster [7]. Efficiency can be evaluated according to the recommender methods. In knowledge-based RSs, explanations can be generated by showing the trade-off between item properties, efficiency of explanations can therefore be measured by the number of interactions needed for users to make a decision. In conversational RSs, efficiency can be measured by the total number of dialogue steps [20] required before a recommendation is accepted. In other cases, efficiency is usually measured by the time consumed for a decision to be made by a user [6], for example the time needed to select an item or to give a rating.

- **Effectiveness**: An effective explanation helps users make better decisions, namely assessing the quality of the items recommended [7]. Usually, effectiveness can be measured in the following way: measuring the extent to which users’ preferences of recommended items change before, and after, consumption [21]. In [21], users rated a book twice, the first time when presented with explanation and a second time after having read the book. In this case, the smaller the difference is, the more effective the explanation is. We did not find other objective evaluation methods, therefore, we suggest the approach presented in [21] for the moment.
- **Persuasiveness**: Recall that persuasiveness of explanations in RSs means the ability of convincing users to try or consume. A typical evaluation approach is approximating persuasiveness by the difference between the liking of the recommended item before and after, consumption mentioned above [21]. A positive difference means high persuasiveness while little or negative difference indicates low persuasiveness. A more intuitive way would be the approach in [22]. Users were asked to rate an item twice, the first time is rating without explanation and the second time with explanation. Persuasiveness can thus be measured by the difference between the two ratings. To the best of our knowledge, no existing work has compared the two approaches, which would be an interesting future avenue to be explored. Users in these two approaches are required to rate the same items twice, another strategy would be to randomly assign users to two groups, one group is presented with explanation while the other is not, both groups are required to rate the same items. Finally, by investigating the differences of ratings between the two groups, persuasiveness of explanation can be quantified.
- **Satisfaction**: Users’ loyalty [23] or the likelihood of using the system to find items of their interests [24] can reflect satisfaction indirectly. The more loyal users are and the more likely users use the system for a search task, indicating better satisfaction.

2) *Subjective evaluation*: In subjective evaluation, measures are collected by asking users.

- **Efficiency, effectiveness, and persuasiveness and satisfaction**: There are some objective evaluation methods to measure these goals. Meanwhile, explaining is a human-centered process, it would also be helpful to measure whether explanations are perceived to be efficient, effective [25] and persuasive [26] reflected by self-reports from users. Using the same approach, satisfaction can be evaluated by directly asking users whether they like the system with explanations or not. Usually these evaluations are carried out through Likert-scale questionnaires.
- **Trust**: Trust is defined as users’ perceived confidence in RSs [27], therefore, a Likert-scale questionnaire is usually adopted to evaluate to what degree participants trust a system.

- Transparency: Transparency in RSs contains two aspects [6]: (i) objective transparency, which means explaining the actual algorithm of the system; (ii) user-perceived transparency: to what degree users think a system is transparent. Presenting user-oriented explanations rather than actual algorithms might be more appropriate [25]. Reasons are summarized as below: algorithms may be too complicated for users to understand; algorithms are intellectual properties that should be protected. For these reasons, transparency is usually evaluated by Likert-scale questionnaire, participants are directly asked to what degree they think a system is transparent when accompanied with the explanation to be evaluated.

After presenting the evaluation methods of explanations in RSs, we now suggest two guidelines

- As we presented in Section II-A, the goals defined in [5] may interact with each other and it is difficult to design explanations that can perform well in all aspects. In order to assess the qualities of explanations comprehensively, more goals (metrics) should be considered. Existing works that explore context-aware explanations in RSs only evaluate a few of the metrics, which is the main limitation of these works [12], [13], [14], [15].
- To compare different explanations, two strategies can be adopted: (i) Within-subjects [28], each participant needs to evaluate different explanations. Within-subjects approaches can minimize the random noise and less participants are required; (ii) Between-subjects [28]: Participants are randomly distributed to different groups, each group evaluating an explanation. Between-subjects approaches minimize the learning effects across conditions and participants have shorter sessions. It is hard to determine which is better and usually both strategies can be adopted.

In this section, we identified potential approaches to design context-aware explanations in RSs. Corresponding evaluation methods are summarized to evaluate and compare such explanations

IV. CONCLUSIONS AND PERSPECTIVES

In this paper, we discuss how to improve user-RSs interactions. Specifically, we explore the possibility of generating context-aware explanations in RSs. By reviewing existing works relating explanations in RSs, we highlight the role of explanations in RSs in enhancing transparency, effectiveness, efficiency, persuasiveness, trust and satisfaction. In the meantime, we find that context-aware explanations have not been sufficiently explored and therefore we propose several potential avenues for generating context-aware explanations in RSs. Accordingly, we summarize two families of evaluation methods for evaluating context-aware explanations.

For future work: (i) We plan to implement the potential avenues that we proposed in Section III-A to generate context-aware explanations in RSs; (ii) We plan to evaluate context-aware explanations by using as many metrics as possible to comprehensively evaluate the qualities of explanations.

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