Open, Scrutable and Explainable Interest Models for Transparent Recommendation

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Abstract

Enhancing explainability in recommender systems has drawn more and more attention in recent years. In this paper, we address two aspects that are under-investigated in explainable recommendation research, namely providing explanations that focus on the input (i.e. user model) and presenting personalized explanations with varying level of details. To address this gap, we propose the transparent Recommendation and Interest Modeling Application (RIMA) that aims at opening, scrutinizing, and explaining the user's interest model based on three levels of details. The results of a preliminary interview-based user study demonstrated potential benefits in terms of transparency, scrutability, and user satisfaction with the explainable recommender system.

Keywords

Explainable artificial intelligence, explainable recommender systems, explainability, transparency, scrutability, user model

1. Introduction

Explanations in recommender systems have gained an increasing importance in the last few years. An explanation can be considered as a piece of information presented to the user to expose the reason behind a recommendation [1]. Explanations can have a large effect on how users respond to recommendations [2]. Recent research focused on different dimensions of explainable recommendation and proposed several classifications [3, 4, 5, 6]. For instance, Guesmi et al. [3] classified explainable recommender systems based on four dimensions, namely the explanation aim (transparency, effectiveness, efficiency, scrutability, persuasiveness, trust, satisfaction), explanation focus (input: user model, process: algorithm, output: recommended items), explanation type (collaborative-based, content-based, social, hybrid) and explanation display (textual, visual). Besides these four dimensions, other essential design choices must be considered, such as the scope and level of detail of the explanation [7].

The focus of an explanation refers to the part that

a recommender system is trying to explain, i.e., the recommendation input, process, or output. Explainable recommendation focusing on the recommendation process aims to understand how the algorithm works. The explainability of the recommendation output focuses on the recommended items. This approach treats the recommendation process as a black box and tries to justify why the recommendation was presented. The explainability of the recommendation input focuses on the user model. This approach provides a description that summarizes the system's understanding of the user's preferences and allows the user to scrutinize this summary and thereby directly modify his or her user model [2]. Compared to explainability of the recommendation output or the recommendation process, focusing on the recommendation input (i.e., user model) is under-explored in explainable recommendation research [2, 8].

Another crucial design choice in explainable recommendation relates to the level of explanation detail that should be provided to the end-user. Results of previous research on explainable AI (XAI) showed that for specific users or user groups, the detailed explanation does not automatically result in higher trust and user satisfaction because the provision of additional explanations increases cognitive effort, and different users have different needs for explanation [9, 10, 11]. Recent studies on explainable recommendation showed that personal characteristics have an effect on the perception of explanations and that it is important to take personal characteristics into account when designing explanations [12, 13]. Consequently, Millecamp et al.

[13] suggest that (1) users should be able to choose whether or not they wish to see explanations and (2) explanation components should be flexible enough to present varying levels of details depending on users' preferences. Concrete solutions following this second design guideline are, however, still lacking in explainable recommendation research.

In this paper, we implemented a transparent Recommendation and Interest Modeling Application (RIMA) that aims at achieving transparency by opening, scrutinizing, and explaining the user's interest model based on three different levels of details. Our contributions are: (1) a human-centered explainable recommendation approach driven by open, scrutable, and explainable interest models and (2) a shift from a one-size-fits-all to a personalized approach to explainable recommendation with varying level of details to meet the needs and preferences of different users.

The rest of the paper is organized as follows: Section 2 summarizes related work. Section 3 discusses the RIMA application. Section 4 presents a preliminary evaluation of the application. Finally, Section 5 summarizes the work and outlines future research plans.

2. Background and Related Work

User models can be used as explanations in recommender systems [14] and depending on the user type, different explanation levels of detail may be appropriate [7]. In the following, we discuss related work on explainable recommendation that focus on the user model and provide explanation with varying level of details.

2.1. Input-based Explainable Recommendation

The rise of distrust and skepticism related to the collection and use of personal data, and privacy concerns in general has led to an increased interest in transparency of black-box user models, used to provide recommendations [14]. Graus et al. [8] stress the importance of enabling transparency by opening and explaining the typically black box user profiles, that serve as the recommender system's input. The authors further point out that user profile explanations can contribute to scrutability to allow users to provide explicit feedback on the internally constructed user profiles and self-actualization to support users in understanding and exploring their personal preferences.

While to task of opening the black box of recommender systems by explaining the recommendation

output (i.e. why an item was recommended) or the recommendation process (i.e. how a recommendation was generated) is well researched in the explainable recommendation community, researchers have only recently begun exploring methods that support the exploration and understanding of the recommendation input (i.e. the user model) to provide transparency in recommender systems [2]. In general, research on input-based explainable recommendation can be classified into three groups with increasing complexity. The first group focuses on opening and exposing the black box user model. The second group adds means to explore and scrutinize the exposed user model. And, the third group provides methods that support the understanding of the user model through explanations.

2.1.1. Opening the User Model

Several tools have represented and exposed the user model behind the recommendation mechanism. For instance, 'System U' [15] focuses on the recommendation input by visually exposing the user model, which consists of Big Five personality characteristics, fundamental needs, and human values. In order to make students understand why a certain learning activity is recommended to them, 'Mastery Grids' [16] highlights the concepts related to the recommended activity based on fine-grained open learner models. The exposed user model in 'PeerFinder' [17] consists of different student features (e.g., gender, age, program) used to recommend similar peers. However, scrutability is lacking in these tools.

2.1.2. Scrutinizing the User Model

Explaining recommendations can enable or improve the scrutability of a recommender system, that is, allowing users to tell the system if it is wrong [5]. Scrutability is thus related to user control, which can be applied to different parts of the recommendation pipeline (i.e. input, process, and output) [18, 19]. Compared to enabling scrutability of the system's output or process, only few works have presented systems that provide user control on the input layer of the recommender system by allowing users to correct their models when they disagree with (parts of) it or modify their models in order to adjust the recommendation results according to their needs and preferences.

The first attempt to provide scrutable explanations was presented in [20]. In this work, a holiday recommender provides a text-based explanation and the user can ask why certain assumptions (like a low budget) were made. Selecting this option takes them to a page

with a further explanation and an opportunity to modify this in their user model. Similarly, the recommender system in [21] provides explanations in the form of overlapping and difference tag clouds between a seed item and a recommended item. Users can then steer the recommendations by manipulating the tag clouds. Bakalov et al. [22] proposed an approach to control user models and personalization effects in recommender systems. It uses visualization to explain users' adaptive behavior by allowing them to see their profiles and adjust their preferences. Jin et al. [23] aimed at providing controllability over the received advertisements. The authors used a flow chart to provide a visual explanation of the process by opening the user profile used to select the ads and allowing users to scrutinize their profile to get more relevant ads. Du et al. [24] presented a personalizable and interactive sequence recommender system that uses visualizations to explain the decision process and justify its results. It also provides controls and guidance to help users personalize the recommended action plans. Zürn et al. [25] discussed possible UI extensions to explicitly support What if? interactions with recommender systems, which allow users to explore, investigate and question algorithmic decision-making.

2.1.3. Explaining the User Model

In this work, explaining user models goes beyond just exposing and manipulating the user model to provide concrete explanations on how the user model was inferred. Explaining user models in recommender systems has been demonstrated to be effective [26] and has many benefits. It facilitate users' self-actualization, i.e. supporting users in developing, exploring, and understanding their unique personal tastes [27]. Moreover, it helps users build a more accurate mental model of the recommender system, thus leading to increased transparency and trust in the system. Furthermore, it can help detect biases which is crucial to produce fair recommendation. Yet, the task of explaining the user model remains under-investigated in explainable recommendation research.

Sullivan et al. [14] focus on explaining user profiles constructed from aggregated reading behavior data, used to provide content-based recommendations. The authors expose the user model by summarizing and visualizing the recommender's high dimensional internal representations of users. Visualizations explaining how the user model was inferred are, however, not provided. Balog et al. [2] present a set-based recommendation technique that allows the user model to be explicitly presented in natural language, in order to help users

understand the recommendations made and improve them. We also aim at explaining the user model, but unlike Balog et al.'s approach, we leverage visualizations instead of natural language explanations.

2.2. Explanation with Varying Level of Details

In this work, the level of detail refers to the amount of information exposed in an explanation. A critical question in the research of explainable recommendation is whether the relationship between the level of detail and transparency is a linear one. To answer this question, we need first to discriminate between *objective transparency* and *user-perceived transparency*. Objective transparency means that the recommender system reveals the underlying algorithm of the recommendations. However, the algorithm might be too complex to be described in a human-interpretable manner. Therefore, it might be more appropriate to provide "justifications" instead of "explanations", which are often superficial and more user-oriented. On the other hand, user-perceived transparency is thus based on the users' subjective opinion about how good the system is capable of explaining its recommendations [28].

In the field of explainable AI in general, Mohseni et al. [7] argue that different user groups will have other goals in mind while using such systems. For example, while machine learning experts might prefer highly-detailed visual explanations of deep models to help them optimize and diagnose algorithms, lay-users do not expect fully detailed explanations for every query from a personalized agent. Instead, systems with lay-users as target groups aim to enhance the user experience with the system through improving their understanding and trust. In the same direction, Miller [29] argue that providing the exact algorithm which generated the specific recommendation is not necessarily the best explanation. People tend not to judge the quality of explanations around their generation process, but instead around their usefulness. Besides the goals of the users, another vital aspect that will influence their understanding of explanations are their cognitive capabilities [11]. Only when users have enough time to process the information and enough ability to figure out the meaning of the information, a higher level of detail in the explanation will lead to a better understanding. But as soon as the amount of information is beyond the users' comprehension, the explanation could lead to information overload and bring confusion. Without the understanding of how the system works, users may perceive the system as not transparent enough, which could, in turn, reduce the users' trust in the system

[28, 11].

In summary, it could be assumed that a higher level of explanation detail increases the system's objective transparency but is also associated with a risk of reducing the user-perceived transparency, and that this risk depends on the user's characteristics. Therefore, recommender systems are expected to provide the right type of explanations for the right group of users [7]. One approach is to offer on-demand explanations that are flexible enough to present varying level of details depending on the users' need or expertise [7, 13]. For example, Millecamp et al. [13] developed a music recommender system that not only allows users to choose whether or not to see the explanations by using a "Why?" button but also to select the level of detail by clicking on a "More/Hide" button. However, providing on-demand explanations with varying level of details remains rare in the literature on explainable recommendation.

3. RIMA

The transparent Recommendation and Interest Modeling Application (RIMA) has the goal to not just explaining why an item was recommended, but to support users in exploring, developing, and understanding their own interests in order to provide more transparent and personalized recommendation. The application is an implementation of a human-centered explainable recommendation approach driven by open, scrutable, and explainable interest models with varying level of details to meet the needs and preferences of different users. We focus in this work on recommending tweets and Twitter users (see Figure 1) and leveraging explanatory visualizations to provide insights into the recommendation process by opening, scrutinizing, and explaining the user's interest model based on three different levels of details.

3.1. Opening the Interest Model

The aim of opening and exposing the interest model in RIMA is to let users become aware of the underlying interest model used for recommendation. These interest models are generated from users' publications and tweets. The application uses Semantic Scholar and Twitter IDs provided by users to gather their publications and tweets. It applies unsupervised keyphrase extraction algorithms on the collected publications and tweets to generate *keyphrase-based interests*. In order to address semantic issues, Wikipedia is leveraged as a knowledge base to map the keyphrases to Wikipedia pages and generate *Wikipedia-based inter-*
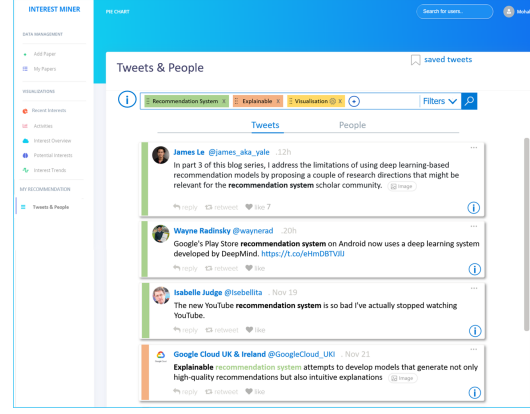

Figure 1: Recommendation Interface in RIMA.

ests. Further, Wikipedia is used to find the categories of the Wikipedia-based interests and generate *Wikipedia category-based interests*.

Different charts are provided to summarize and visualize the interest model used to provide content-based recommendation of tweets and Twitter users, as shown in Figure 2. The short-term interest model (based on the Wikipedia-based interest model) displays the user's top 5 interests, based on the tweets published in the last month and the publications published in the last year. We selected a pie chart to visualize this model since each slice's size provides users a quick indication of the weight of the specific short-term interest (Figure 2a). The long-term interest model (also based on the Wikipedia-based interest model) displays the top 15 interests in the last five years, using a word cloud (Figure 2b). The potential interest model (based on the Wikipedia category-based interest model) allows users to identify interests that are semantically similar to their interests. We selected a node-link diagram to connect the the user's long-term interests (on the left) with their associated Wikipedia categories (on the right) (Figure 2c). Finally, the evolution of interest model (based on the Wikipedia-based interest model) allows users to track how their top 10 interests have shifted over time, using a stream graph (Figure 2d).

3.2. Scrutinizing the Interest Model

The main aim behind enabling users to provide explicit feedback and modify their interest models in RIMA is to make those models more accurate. As shown in Figure 3, the application provides an interface where users can manage their global interest model by adding or removing interests. They can also modify the weight given to an interest, reflecting its importance in their
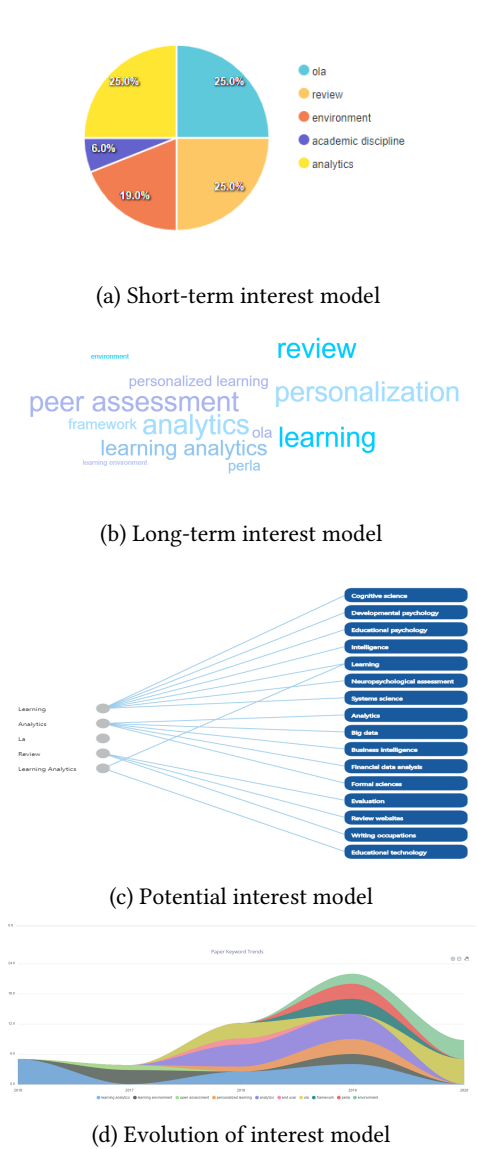
(a) Short-term interest model

(b) Long-term interest model

(c) Potential interest model

(d) Evolution of interest model

Figure 2: Opening the interest model

interest model.

Empowering users to control the system and have an active say in the process would also make the recommendation more transparent, thus leading to better trust and user satisfaction. To achieve this, the application supports What-if? interactions that give users full control over the input of the recommender system (their interest model) as well as its output (the recommendations that result from the defined input). Through interactive visualizations, users can explore and adjust the input to adapt the system output based on their needs and preferences. Moreover, users can modify their interests and see the influence of these

**Figure 3:** Users can manage their interest model

changes on the system recommendations. For instance, users can add new interests in the search box or remove existing ones. The search box is initially populated with user's interests, ordered by their weights as generated by the system. The users can change the order of the interests through a drag and drop feature to alter their importance. By clicking on the info button next to the search box, the user can use interactive sliders to adjust each keyword's weight (see Figure 4a). Another option to display the interest model is provided through a radar chart, where the user can change the interests' position through drag and drop to modify their relevance. The distances to the center represent the relevance of the interests, with closer to the center meaning more important (see Figure 4b).

Adding, removing, and weighting the interests will influence the order of the recommended tweets. This exploratory approach would support users in answering different What if? questions, such as "What if I would have interest in X rather than Y?" or "What if I would change the importance of interest Z?".

3.3. Explaining the Interest Model

Our approach to explaining tweet recommendations is based on explaining the underlying user interest models that are used to provide the recommendations. The aim of explaining the interest model in RIMA is to foster user's awareness of the raw data (publications and tweets) and the derived data (interest model) that the recommender system uses as input to generate recommendations, in order to increase transparency and promote understandability of the recommendation. Moreover, this may let users become aware of system errors and consequently help them give feedback and correction in order to improve future recommendations.

The application provides on-demand explanations, that is, the users can decide whether or not to see the
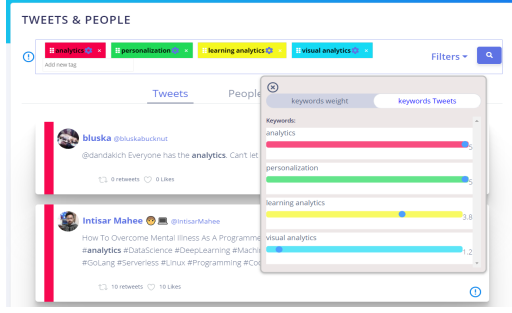
(a)
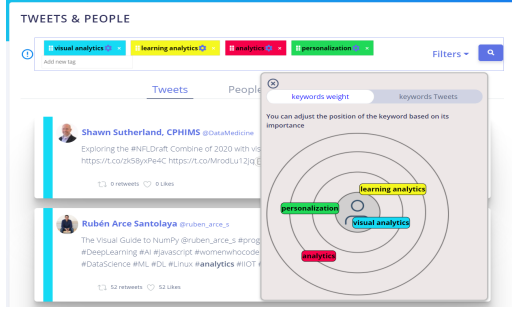
(b)

Figure 4: Users can modify the importance of their interests

(a) Basic explanation

(b) Intermediate explanation

(c) Advanced explanation

Figure 5: Explaining the interest model with three levels of details
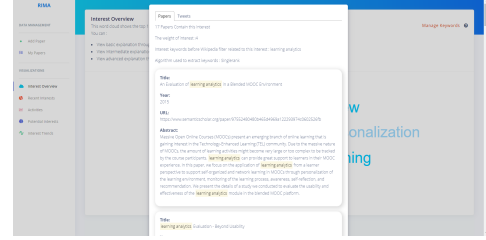
explanation and they can also choose which level of explanation detail they want to see. In the *basic explanation* (Figure 5a), the user can hover over an interest in the word cloud to see its source (i.e. publications or tweets). When the user clicks on an interest in the word cloud, the *intermediate explanation* provides more information through a pop-up window highlighting the occurrence of the selected interest in the tweets or title/abstract of publications (Figure 5b). The next level of detail is provided in the *advanced explanation* which follows an explanation by example approach to show in detail the logic of the algorithm used to infer the interest model (see Figure 5c).
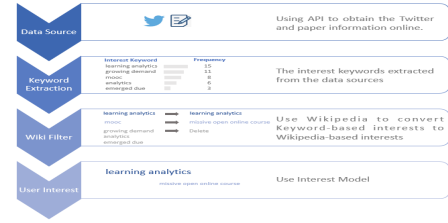
4. Evaluation

We conducted a preliminary interview-based study with ten researchers from different disciplines to gauge the potential of our proposed approach to improve transparency, scrutability, and user satisfaction with the explainable recommender system. At the beginning of the interview, each participant was briefly introduced to the fields of recommender systems and user modeling. Next, the participants were asked to use the RIMA application to create their interest models

based on their Semantic Scholar and Twitter IDs and to see the visualizations corresponding to their interest models. Then, the participants were presented with the three visualizations representing the basic, intermediate, and advanced explanations of their generated interest models. Thereafter, they were asked to explore the recommended tweets and use the provided features to manipulate their interest models to influence the recommendation results. Finally, the participants were asked about their opinions towards the provided explanations, guided by the statements summarized in Table 1 and other open-ended questions such as " they want to see the explanations of their interest models" and "which explanation level (i.e. basic, intermediate, advanced) they prefer to see".

In general, the participants showed an overall positive opinion towards the usefulness of having explanations of their inferred interest models as well as the possibility of manipulating them. However, they gave different reasons why they want to see the explanations.

Table 1
Evaluation Statements

Explanation aim	Questions
Transparency	Q1: The system helps me understand why the tweets were recommended to me
	Q2: The system provides a clear explanation of how my interests were generated
	Q3: I can understand the effect of the interests' weights on the recommended tweets
Scrutability	Q4: I feel that I am in control of the recommendation process
Satisfaction	Q5: The visualizations of my interest model accurately describe my interests
	Q6: The tweets recommended to me matched my interest

Two participants expressed that they had in their interest model wrong or not expected interests and wanted to check them. Other participants mentioned that they were just curious to see how their interest model was generated. This is in line with the findings in the study by Putnam and Conati [30] in an intelligent tutoring systems (ITS) context.

Moreover, the participants had different opinions regarding what level of detail they prefer to see. This implies that potential individual user differences influence their preferences towards the explanation level; an important design choice in explainable recommendation that needs in depth exploration.

5. Conclusion and Future Work

In recent years, various attempts have been made to address the black-box issue of recommender systems by providing explanations that enable users to understand the recommendations. In this paper, we addressed two aspects under-explored in explainable recommendation research, namely providing explanations that focus on the input (i.e., user model) and presenting personalized explanations with varying levels of detail. To this end, we proposed the transparent Recommendation and Interest Modeling Application (RIMA) that aims at the opening, scrutinizing, and explaining the user's interest model based on three levels of details. The preliminary evaluation results demonstrate the usefulness of the RIMA approach in creating input-based on-demand explanations.

In future work we plan to apply the proposed approach to explain recommendations of publications, researchers, and conferences. We will also explore other possible visualizations to provide explanations at the three levels of detail. Furthermore, a more extensive quantitative and qualitative user study will be conducted to investigate the relationship between the users' characteristics and the level of detail of the explanations, and the effects of these two variables on the perception of and interaction with the explainable recommender system.

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