Interaction Tasks for Explainable Recommender Systems

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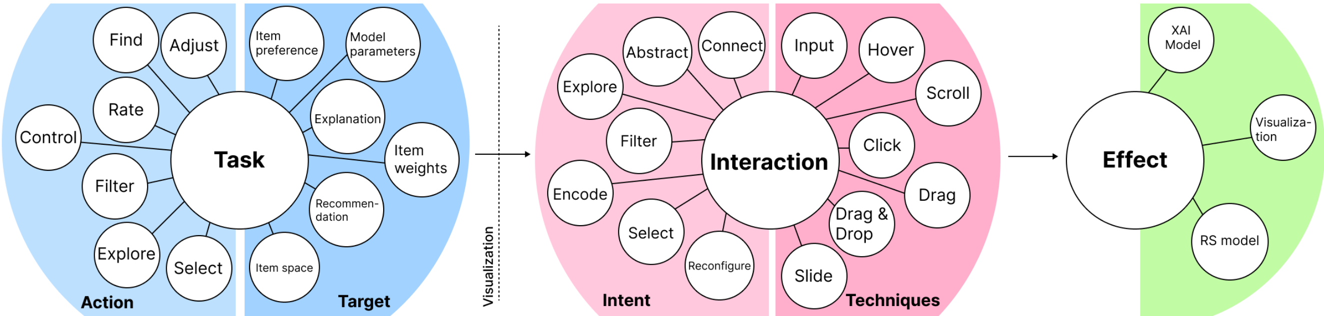

Figure 1: *Visual representation of the key coding and results from our literature study. Each block of this visual representation serves to emphasize the critical components of the task at hand, the intricate interactions between these components, and the consequential effects produced on the different components of an explainable RS.*

Abstract

In the modern web experience, users interact with various types of recommender systems. In this literature study, we investigate the role of interaction in explainable recommender systems using 27 relevant papers from recommender systems, human-computer interaction, and visualization fields. We structure interaction approaches into 1) the task, 2) the interaction intent, 3) the interaction technique, and 4) the interaction effect on explainable recommender systems. We present a preliminary interaction taxonomy for designers and developers to improve the interaction design of explainable recommender systems. Findings based on exploiting the descriptive power of the taxonomy emphasize the importance of interaction in creating effective and user-friendly explainable recommender systems.

1. Introduction

Recommender systems (RS, for singular and plural) are one of the fundamental components of the modern web experience. RS are used across various domains like e-commerce, entertainment, and social media. RS are defined as a series of algorithms that aim to generate meaningful recommendations to users for items or products that might interest them [LWM*15, MS10]. However, one drawback of RS is that they often act as black boxes [AN18, CVD23], meaning that users are unable to see how systems arrive at their recommendations. This lack of transparency can lead to mistrust from users, which ultimately undermines the effectiveness of the recommendation [SC13, TM07]. One possible way to solve this drawback is to incorporate explanations into RS, defining a new class of algorithms known as explainable RS that are capable of providing transparent, interpretable, and human-understandable explanations for the generated recommendations [TM15, ZC*20].

The design space for explainable RS approaches is huge [AHSSB22], main degrees of freedom include the type of RS, the explainable AI technique, the type of visualization employed, and ultimately: the type of interaction methods implemented. In this poster, we focus on the role of interaction for explainable RS. As interaction is the initial step that enables the users to engage with an RS and its accompanying explanation, it is important that developers and designers are aware of the appropriate types of interaction. However, hardly any best practices and guidelines exist on the use of interaction for explainable RS to help designers build useful and usable visualizations.

In a survey work on explainable RS, we identified 23 approaches that include a form of user interaction. Our main contribution is a preliminary taxonomy of interaction tasks for explainable RS, structured by the *user task* (composed of an action and a target), the core *interaction* (composed of intent and technique), and the *effect* on the RS. The analysis of the 23 approaches using the taxonomy demonstrates its descriptive power and reveals interesting patterns of interaction design for explainable RS.

2. Methodology

To be included in our study, RS approaches had to have an explicit explanation, visualization, and interaction component Specifically,

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we required that the approach have an explicit explanation component, which would provide users with a clear understanding of the reasoning behind the recommendations. Additionally, we required that the approach include a visualization component, which would help users to better interpret and understand the information presented to them. Finally, we required that the approach have an interaction component, which would allow users to engage with the visualization and provide feedback, shaping the recommendations to better suit their needs and preferences. Overall, we identified 23 papers meeting these requirements. Upon our ideated taxonomy, we categorized these papers based on multiple criteria: 1) task (action and target), 2) interaction (intent and technique), and 3) interaction effect on the explainable RS. Figure 1 provides an overview of the categories and the coding used, according to the 23 papers. Overall, the followed methodology enabled us to gain a comprehensive understanding of the different interaction tasks involved in explainable RS, while highlighting gaps in current research and potential future work.

3. Interaction Taxonomy

3.1. User Task

We start the description of fundamental ingredients for interaction design in explainable RS with the tasks users are aiming at. Based on a reflection on the surveyed explanation approaches and by leveraging existing taxonomic work on tasks, we characterize tasks by the *action* taken by users and the data *target* users are interested in. Examples include the adjustment (action) of profile preferences (target) or filtering (action) of recommended items (target). Inspiring methodologies include Munzner's nested model [Mun09], the typology of abstract visualization tasks by Brehmer et al. [BM13], and the Data-Users-Tasks Design Triangle by Miksch et al. [MA14], where the relationship between tasks and data is explicitly made to expressively characterize *what* data is analyzed and *why*. The distinction between actions and targets is also directly motivated by taxonomic works on tasks [SNHS13, Mun14, PBHB22].

Out of the total papers, in 4 instances, the action taken was to filter, and the item recommendation was the target. A comparable trend was observed when the action was to explore. Although the actions varied, the most frequent target (35%) was found to be the recommended items. Only two times the target of the task was directed to the explanation.

3.2. Interaction Techniques

At the heart of our taxonomic work was characterizing the users' ability to directly or indirectly manipulate and interpret visual representations of the explainable RS. A useful framework to characterize explainable approaches was to differentiate between the high-level interaction intent of users [YaKSJ07, Ber] and the low-level interaction technique enabling this intent. For interaction *intents*, the taxonomy by Yi et al. appeared to be particularly useful for explainable RS approaches [YaKSJ07]. These intents include selection, exploration, reconfiguration, encoding, abstraction, filtering, and connection. Dominant interaction *techniques* include input, hover, scroll, click, drag, drag&drop, and slide. For a complete overview of each paper's interaction technique, please refer to the table provided as supplemental material.

From the 23 surveyed approaches, select was the most commonly supported intent, appearing in 15 papers (65%). Also, five approaches combined two or more interaction intents, such as selection, together with exploration, abstraction, or filtering. The techniques used to implement these interaction intents showed considerable heterogeneity. For selection intents, users could hover over the recommended items or on the visualization used to explain the recommendation [GPSRW21, MHCV20], use options from a drop-down menu [AFIK22, VSR09], or utilize a select button [PDM*22, NDB*21]. In contrast, for a reconfigured intent, the analysis of explainable RS papers found that only two techniques were employed: scrolling and dragging. For example, NewsViz [KSZ20] utilized the scrolling interaction technique to resize the area of a cell in a tree-map visualization, whereas PeerChooser [OSG*08] enabled users to interact with a graph visualization by dragging. Similarly, in the case of SmallWorlds [GOB*10], dragging was used to relocate an item to a different layer.

3.3. Interaction Effects

The interaction *effect* can be defined as the observable alteration in the system that occurs as a result of the interaction made by the users to accomplish the task. In the 23 surveyed approaches, the effect of user interaction has a significant impact on different components of the explainable RS namely: interaction, visualization, XAI methods, and the RS model itself. The interaction component directly allows users to interact with the system and its explanations again, while the visualization component presents recommendations and explanations to users using various techniques. The XAI method component provides transparency and interpretability of the recommendation process. Lastly, the RS component determines the recommendation algorithm, based on the task, data features, and context. A complete list of interaction effects of the 23 approaches is provided with the supplemental material.

In 14 out of 23 approaches (61%), the interaction directly affects the underlying RS model and thus, the recommended items in the next iteration. This is because, through interaction, users are able to accomplish their tasks by leveraging different interaction techniques, leading to the generation of new recommendations that better align with their interests [KSZ20, GPSRW21, OSG*08, NZ20]. This is especially true when reconfiguration or selection interaction intent is implemented. In contrast, for a filter intent, the primary effect is on the visualization layer. Specifically, by reducing the number of items shown, users can avoid information overload and focus more on the most relevant items [RP17, RSP17]. Overall, the role and impact of user interaction on explainable RS cannot be underestimated. By enabling users to shape the recommendations they receive, these systems become more personalized, effective, and valuable.

4. Conclusion and Future Work

Our study examined interaction tasks in explainable RS and proposed a preliminary taxonomy that considers user task, intent, technique, and effect. Interaction techniques play a crucial role in allowing users to personalize recommendations. Future research will explore novel techniques and their impact on the overall user experience. We will investigate the interaction between layers of the explainable RS pipeline and develop a comprehensive taxonomy for designers and developers. Our study focused on examining types of interaction tasks in explainable RS and on the assessment of their impact.

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