Interaction Tasks for Explainable Recommender Systems

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Motivation and Contribution

Recommender Systems (RS) are one of the **fundamental components** of the modern web experience. However, **RS often act as black boxes** [AN18] leading to mistrust from the user, which ultimately undermines the effectiveness of the recommendation [TM07]. One possible way to solve this drawback is to incorporate explanation into the RS, defining a new class of algorithms known as **explainable RS** that are capable of providing **transparent**, **interpretable**, and **human-understandable** explanations for the generate recommendations [TM15].

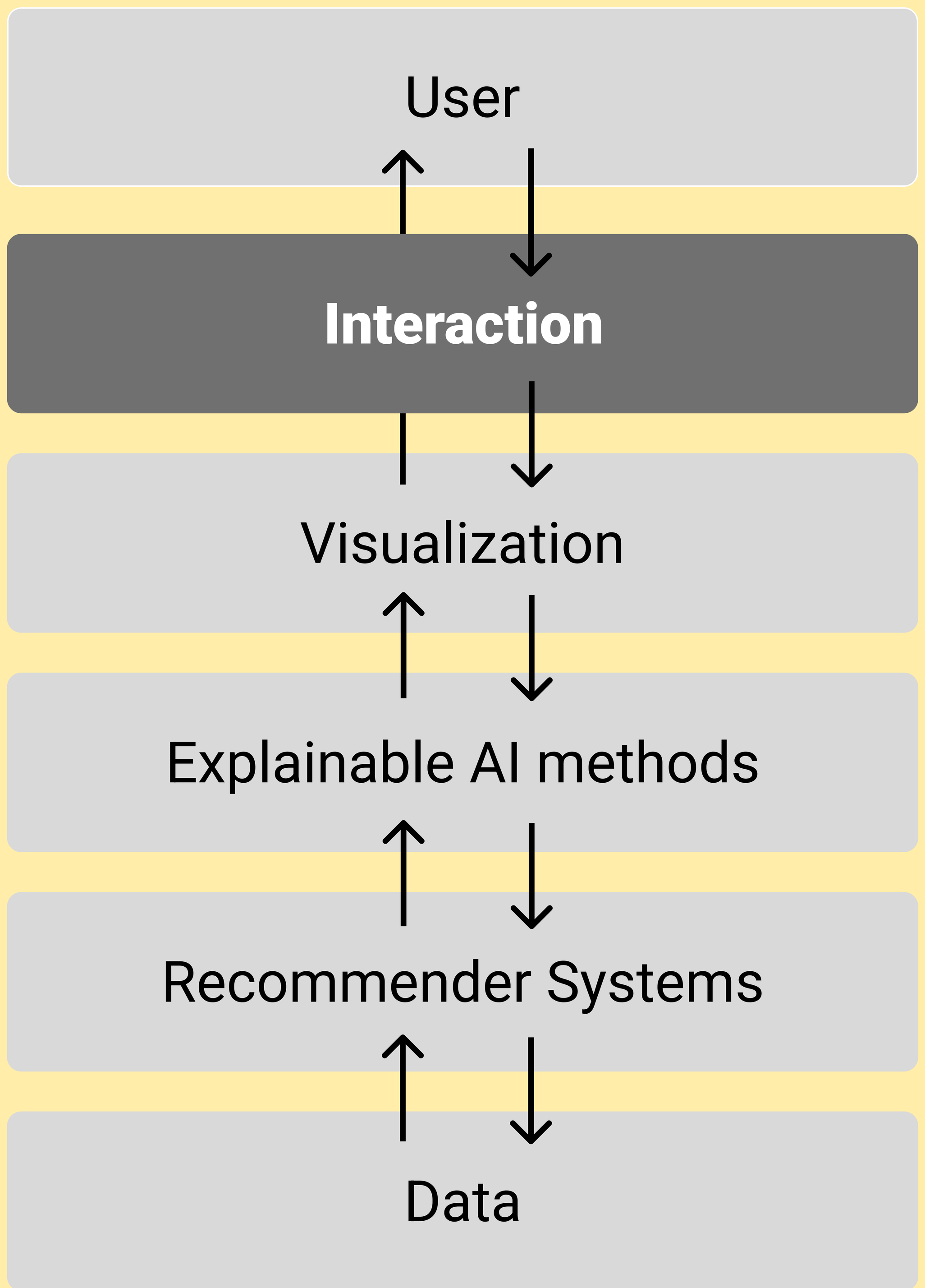
Our main contribution is a **preliminary taxonomy of interaction tasks for explainable RS**. We choose to focus on the interaction since it is the initial step that enables users to engage with explainable RS. We have identified 23 approaches that include a form of user interaction. We structured the taxonomy by the **user task**, core **interaction**, and the **effect of the interaction** on the RS.

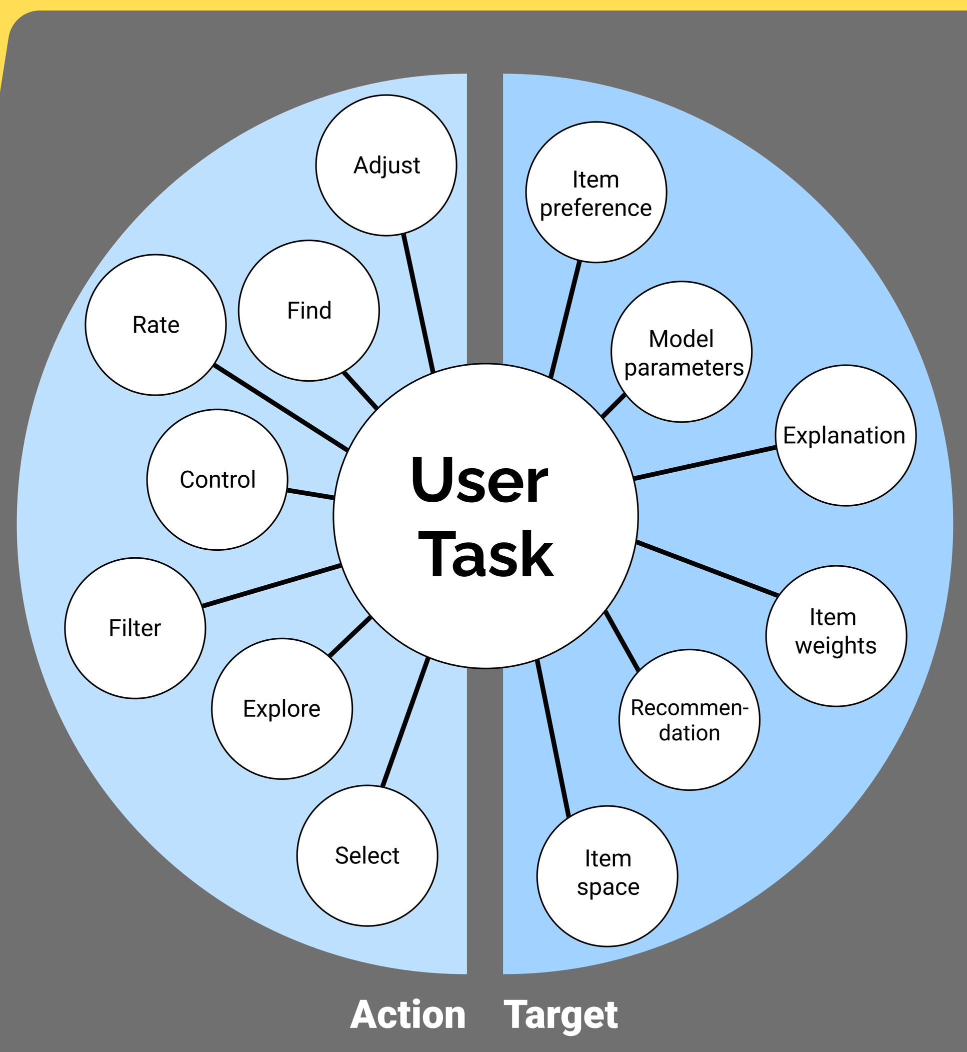
Methodology

In order to conduct a thorough analysis of interaction tasks, we established a set of criteria. These criteria encompassed the presence of an **explicit explanation**, **utilization of visualization** aids, and availability of **interactive components**.

We identified **23 papers** and categorized these based on multiple criteria:
- **task** (action and target)
- **interaction** (intent and technique)
- interaction **effect** on the explainable RS pipeline

Explainable RS Pipeline



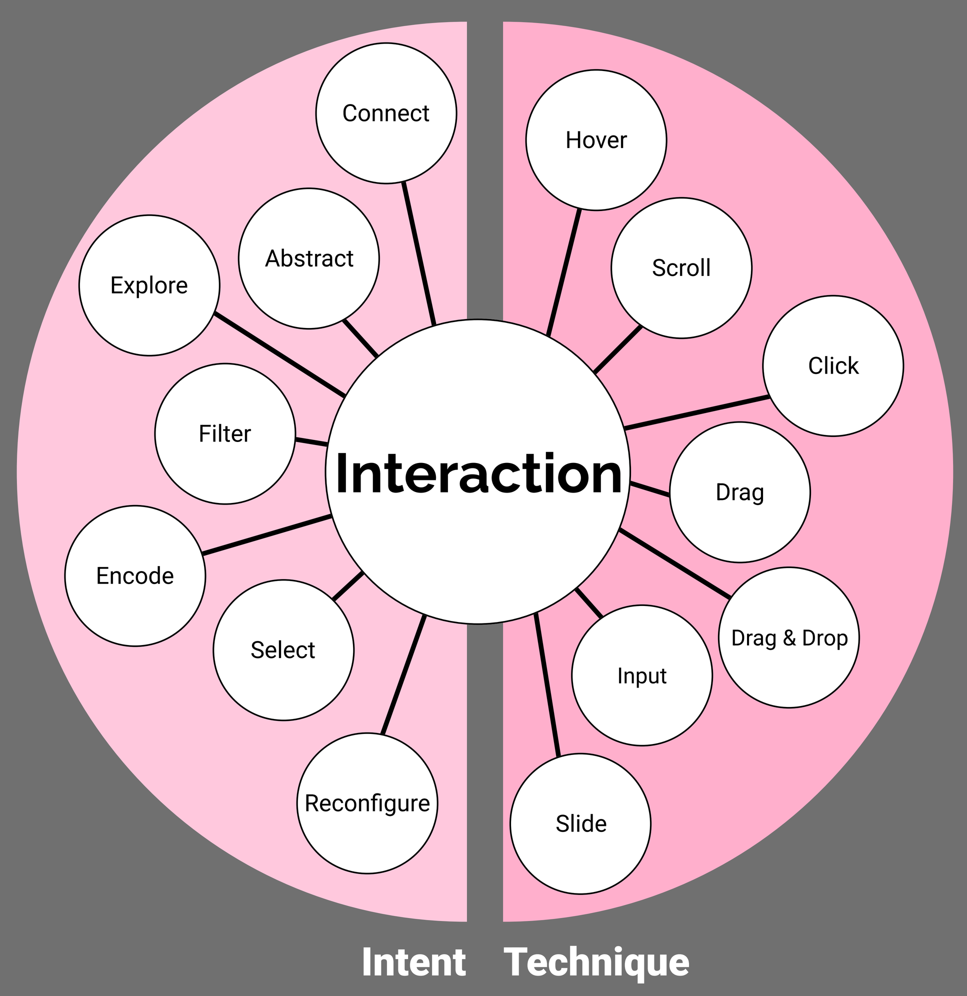


We characterized tasks by the **action** taken by the users and the data **target** users are interested in.

For example a user task could be the adjustment (action) of profile preferences (target), or filtering (action) recommended items (target).

Out of the total papers, in 4 instances, the action taken was to **filter**, and the **item recommended** was the target. A comparable trend was observed when the action was to explore.

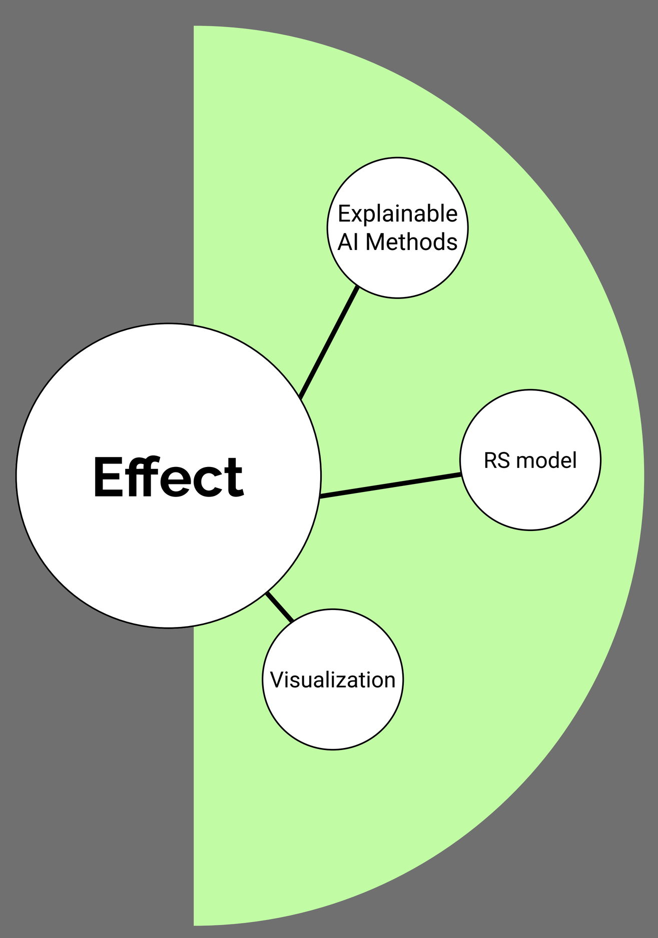
Although the actions varied, the most frequent target was found to be the recommended items. Only two times the target of the task was the explanation.



A useful framework to characterize explainable approaches is to differentiate between the high-level **interaction intent** of the user and the low-level **interaction technique** that enable the intent as, e.g., presented by ... in an interaction taxonomy [YaKSJ07].

From the 23 surveyed approaches, **select** was the most commonly supported intent, appearing 15 times. Also five approaches combined two or more interaction intents, such as selection + exploration, or selection + filtering.

The techniques used to implement these interaction intents showed **considerable heterogeneity**.



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.

Based on the 23 surveyed approaches, we subdivided the components affected by the interaction into: explanation, visualization, and RS model itself.

In 14 approaches, **the interaction directly affects the underlying RS model** and thus the recommended items in the next iteration.

Conclusion and Future Work

Although interaction techniques in explainable recommender system can be complex and vary in their definition and implementation, they play a **crucial role** in allowing users to personalize and shape their recommendations through various techniques and intents. As the field of explainable RS continues to evolve, it is essential to **explore novel interaction techniques** and refine existing ones to enhance these systems' overall user experience and effectiveness.

Future research will investigate the **interaction between the various layers of the explainable RS pipeline**, including visualization, explainable methods, and recommender systems, and how they affect each other.

Acknowledgments

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Reference

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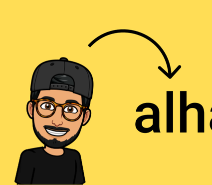

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