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Explanations and User Control in Recommender Systems

Beyond Black-Box Personalization Systems

Abstract: Adaptive, personalized recommendations have become a common feature of today's web and mobile app user interfaces. In most of modern applications, however, the underlying recommender systems are black boxes for the users, and no detailed information is provided about why certain items were selected for recommendation. Users also often have very limited means to influence (e.g., correct) the provided suggestions and to apply information filters. This can potentially lead to a limited acceptance of the recommendation system. In this chapter, we review explanations and feedback mechanisms as a means of building trustworthy recommender and advice-giving systems that put their users in control of the personalization process, and outline existing challenges in the area.

Keywords: Recommender Systems, Personalization, Explanations, Feedback, User Control

CCS: Human-centered computing, Collaborative and social computing

1 Introduction

Many of today's user interfaces of web and mobile application feature system-generated, often personalized, and context-adaptive recommendations for their users regarding, for example, things to buy, music to discover, or people to connect with. To be able to automatically generate such tailored suggestions, the underlying recommender systems (RS) maintain a *user profile*, which serves as a basis to (i) infer individual user's preferences, needs, and current contextual situation and to (ii) correspondingly select suitable items for recommendation. Given the huge potential value of such systems for both consumers and providers [29], a variety of algorithmic approaches has been proposed over the past two decades to generate suitable item recommendations for a given user profile. A prominent

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class of such systems is based on the principle of *collaborative filtering*, where the user profile consists of a set of recorded explicit or implicit preference statements of individual users, and recommendations are generated by also considering preference or behavioral patterns of a larger user community.

Collaborative filtering approaches based on often complex machine learning models have shown to lead to increased business value in practice in various application domains [12, 30, 36]. However, a potential limitation of these systems is that, from the perspective of the end user, the factors and mechanisms that determine the provided recommendations usually remain as a *black box*. This is in particular the case for popular technical approaches based on matrix factorization and, more recently, complex neural network architectures. In some applications, users may be given an intuition about the underlying recommendation logic, e.g., through a descriptive label like "Customers who bought ... also bought." Often, however, recommendation lists are only labeled with "Recommended for you" or "Based on your profile", and no in-depth explanation is given about how the recommendations were selected. In case no such information is provided, users may have doubts that the recommendations are truly the best choice for them and suspect that the recommendations are mostly designed to optimize the profit of the seller or the platform.

A potentially even more severe problem with such black-box approaches can arise when the system's assumptions about the user's preferences are wrong or outdated. A typical example is when users purchase a gift for someone else but the system considers the gift to be part of the users' own interests. Many of today's systems provide no mechanisms for users to give feedback on the recommendations or to correct the system's assumptions [33]. In some cases, users might not even be aware of the fact that the content provided by the system is personalized according to some assumed preferences, as it is probably the case in the news feeds of major social networks. In either case, when recommendations are of limited relevance for the users, they will eventually stop to rely on the system's suggestions or, in the worst case, abandon the platform as a whole.

In the academic literature, different proposals have been made to deal with the described problems. One main stream of research is devoted to the topic of *explanations* for recommender systems [23, 50, 61], for example with the goal to make recommender systems more transparent and trustworthy. Explanations for decision support systems have, in fact, been explored for decades. We can, however, observe an increased interest in the field of explanations in the recent past, as more and more decisions are transferred to machine learning algorithms and, in many cases, these decisions must be open to scrutiny, e.g., to be able to assess the system's fairness.[1]

Providing explanations can, however, also serve as a starting point to address the second type of problem, i.e., how to better put users in control of their recommendations. Some e-commerce platforms, like Amazon.com, present explanations in the form "Because you bought", and let their users give feedback if this recommendation reasoning should be applied by the system in the future. Providing user control mechanisms in the context of explanations is, however, only one of several approaches proposed in the literature, and we review various approaches in this chapter.

Generally, both explanations and user control mechanisms represent a potential means to increase the user's trust in a system and to increase the adoption of the recommendations and advices it makes. In this chapter, we overview approaches from both areas and highlight the particular potential of explanation-based user control mechanisms.

2 Explanations in Recommender Systems

2.1 Purposes of Explanations

There are a number of possible ways in which one can explain the recommendations of a system to a user. When designing an explanation facility for a recommender system, one has therefore to consider *what should be achieved* by adding an explanation component to an application, i.e., what its *purpose(s)* should be. For example, in an e-commerce system, a seller might be interested in *persuading* customers to buy particular products or increasing their *trust* in order to promote loyalty.

In early medical expert systems, explanations were, for example, often provided in terms of the system's internal inference rules, which allowed users to understand or check the plausibility of the provided diagnosis or advice. But *understanding* the system's decision was soon recognized not to be the only reason for including explanations. Buchanan and Shortliffe [6] list *debugging*, *education*, *acceptance*, and *persuasion* as additional potential goals in the context of expert

1 This aspect is of increasing importance also due to the European Union's recent General Data Protection Regulation (https://eur-lex.europa.eu/eli/reg/2016/679/oj), which aims to provide more transparency and additional rights for individuals in cases where decision-making is done on a solely algorithmic basis.

systems. This list was later extended with additional perspectives in [61] and [50], leading to a more comprehensive list as shown in Table 1.

Tab. 1: Explanation Purposes (based on [6, 61, 50]).

Purpose	Description	Example Works
Transparency	Explain how the system works	[23, 65, 20]
Effectiveness	Help users make good decisions	[19, 3, 16]
Trust	Increase users' confidence in the system	[25, 54, 5]
Persuasiveness	Convince users to try or buy	[23, 67, 1]
Satisfaction	Increase the ease of use or enjoyment	[54, 19, 3]
Education	Allow users to learn something from the system	[22, 18, 41]
Scrutability	Allow users to tell the system it is wrong	[35, 27, 17]
Efficiency	Help users make decisions faster	[54, 2, 43]
Debugging	Help users identify defects in the system	[11, 39, 26]

The entries in the table are organized by their importance in the research literature according to the survey presented in [50]. In the majority of the cases, research papers focused mostly on one single purpose, like in the seminal work by Herlocker et al. [23]. There are, however, also works that investigate multiple dimensions in parallel [14, 26]. In a number of research works on explanations, in particular earlier ones, the authors did not explicitly state for which purpose their explanation facility was designed [10]. In several cases, the purpose can also not be indirectly inferred due to a surprisingly large fraction of works that lack a systematic evaluation of the explanation component [50].

Explanations are in general one of the natural "entry points" for giving the user control of recommendations, e.g., by displaying the assumptions about the user's preferences for inspection and correction. However, in a review of over 200 papers on the topic of explanations, Nunes and Jannach [50] could identify only seven works that focused on scrutability, i.e., allowing the user to correct the system, which indicates a major research gap in this area.

2.2 Explanation Approaches

We can find a variety of different ways of explaining the suggestions by a recommender or, more generally, advice-giving system in the literature. The choice of the type of information that is used for explaining and how it is presented to the user depends on different factors. These can, for example, include the availability of certain types of information (e.g., an explicit inference chain) or the specific application domain.

With respect to the *explanation content*, four main content categories—summarized as follows—were identified in [50]. Table 2 exemplifies how a system can present these different types of content in the context of an interactive recommender system for mobile phones.

- *Preferences and user inputs*: Explanations in this category refer to the specific user inputs or inferred preferences that led to the given recommendation. For example, the explanation details to what extent a recommended alternative matches the user's assumed preferences, or presents the predicted user rating.
- *Inference process*: Historically, *inference traces* were popular in classical expert systems. With today's complex machine learning algorithms, such inference chains are not available. Instead, one approach can be to explain the system's *general* reasoning strategy, e.g., that it recommends objects that similar users liked.
- *Background knowledge and complementary information*: Explanation approaches of this type use additional information, for example the popularity of a recommended alternative in the entire community or among users with similar profiles, to generate explanations.
- *Alternatives and their features*. This type of explanation focuses on certain attributes of the recommended alternative. They, for example, point out the decisive features of an item, show pros and cons of different alternatives, or highlight where one alternative dominates another.

Tab. 2: Examples of Explanation Content Categories.

Content	**Explanation Example**
Preferences and user inputs	*"We recommend this phone because you specified that you prefer light-weight models."*
Inference process	*"We consider light phones to weigh less than 150 g."*
Background knowledge	*"We recommend this phone because it is currently popular in our shop."*
Alternatives and their features	*"This camera has a removable battery, which other similar models do not have."*

With respect to how the explanations are *presented to the user*, natural language representations (text-based explanations) are dominating the research landscape. In some works, more structured representations, e.g., in the form of lists of relevant features, other users, or past cases, are provided. Finally, different forms of graph-based and alternative visual approaches can be found in the literature as well, e.g., in the form of rating distributions for an item [23] or in the form of tag clouds [13, 14].

Generally, when explanations are used as an entry point for *user control*, not all forms of explanations seem equally helpful. Presenting the general inference strategy, for example, might be of limited use. Providing information about relevant inputs and features of the recommended items, in contrast, opens more opportunities for control mechanisms for users. When provided such input-output oriented explanations, users can interactively adapt or correct their preference information as in [5] or give feedback on the recommendations, e.g., in the form of attribute-level *critiques* [46].

2.3 Challenges of Explaining Complex Models

In traditional expert systems, which in many cases had an explanation component, the content that was presented to the user was often determined by collecting information about how the underlying inference algorithm ended up with its suggestion. In a rule-based system, for example, one could record which of the rules fired, given the user's specific input. Parts or all of this internal reasoning process is then presented in a user-friendly way. As a result, the process of computing the explanations as well as the explanations themselves are tightly related to the underlying recommendation process.

In the field of recommender systems, rule-based or knowledge-based approaches are nowadays only used for certain types of products, e.g., high-involvement goods. In most of the cases, content-based filtering and collaborative filtering, which often rely on various types of machine learning models, dominate the research landscape. However, these models cause the extraction of the rationale underlying the recommendation to be less straightforward. This led to two groups of approaches to generate explanations: (1) *white-box* approaches, which extract particular kinds of information from the algorithm and model that were used to produce recommendations; (2) *black-box* approaches, which do not take into account how recommendations are made, but explain them using different sources of information.

Early approaches focused mostly on white-box explanation generation. Consequently, collaborative filtering mostly relied on nearest-neighbor techniques, and, correspondingly, a number of approaches were proposed, which use information about user neighborhoods to derive appropriate explanations for the users [23, 14]. Herlocker et al. investigated the persuasiveness of visualizing such neighborhoods through a user study [23]. Even more complex visualization approaches, based on three-dimensional or interactive representations, were proposed in [38] or [42]. However, it remains somewhat unclear how such approaches would be perceived by an average user of a recommender system.

Today, with modern collaborative filtering techniques based on matrix factorization and deep learning, explaining recommendations that are computed based on such machine learning models is much more difficult. Matrix factorization models consist of vectors of uninterpreted latent factor weights for users and items; deep neural networks train a large number of weights for nodes that have no obvious attached meaning. Such complex models make it very difficult to provide users with information about how the set of recommendations was *exactly* determined for them, let alone allow them to influence the system's strategy of selecting items.[2] In general, because more and more decisions are nowadays made by algorithms, the topics of transparency, fairness, and accountability become increasingly important in machine learning research. A recent survey on approaches to interpreting the outcomes of deep neural networks can, for example, be found in [47].

Given the complexity of this problem, an alternative is to rely on other ways of computing the explanations, leading to black-box explanation generation. In such a case, one goal could be to provide *plausible* justifications to users, which, e.g., describe why a certain recommended item matches their preferences. One could, for example, mine association rules ("Customers who bought ... ") and then use these rules to explain a given item recommendation, even though the recommended item was selected in a different way [53]. Alternatively, customer reviews can be mined to extract explanations that are in accordance with recommendations made using complex models, such as in [48].

2.4 A Case Study of the Effects of Different Explanations

Gedikli et al. [14] reported the results of a laboratory study in which they analyzed the impact of different explanation types on users in several dimensions. The specific targets of investigation were efficiency, effectiveness, direction of persuasiveness, transparency, and trust. We summarize their experiment and insights here as a case study of the evaluation of different types of explanations. The study also represents an example of a common research methodology that is applied in this context.

2 There is work in the context of matrix factorization techniques to find interpretations of at least the most important latent factors [44, 55, 8].

2.4.1 Study Design

Ten different forms of explaining recommendations from the literature were considered in the study. Some of them were personalized and, for example, showed the ratings of the user's peers for a recommended item. Other explanation types were non-personalized and, for example, simply presented the items' average community ratings as an explanation. The second main differentiating factor was whether the explanation referred to the "content" of the recommended items (e.g., by displaying certain item features) or not. Figures 1 and 2 show examples of two explanation types.

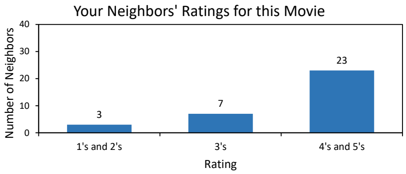

Fig. 1: Histogram explanation type adapted from [23], showing the rating distribution of the neighbors of the current user. The explanation type was considered particularly effective in terms of persuasion in [23].

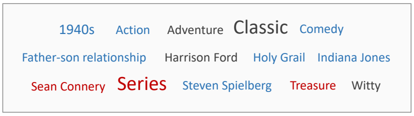

Fig. 2: Tag Cloud explanation type adapted from [13], which shows the item features that are assumed to be particularly desired and undesired for the user in different colors.

2.4.1.1 Procedure

The experimental procedure in the study followed the multi-step protocol from [4].[3] In a first step, the study participants were asked to provide ratings for a number of movies, which was the domain of the study. Then, the participants were provided matching recommendations based on some underlying algorithm. Instead of showing the movie details to the participants, they were only shown the system-generated explanations. Each participant received only one treatment, i.e., was shown one form of explanation. The participants were then asked to rate the recommended items, expressing the probability that they would like to watch the movie. In the next step, the same recommendations were presented to the user again (in randomized order), now showing all the

3 The protocol is referred to as "explanation exposure delta" in [50], expressing the difference of the users' evaluation of an item when provided with detailed item information in comparison to their explanation-based evaluation of the same item.

details of the movie and a trailer. The participants were asked to also rate these movies. However, they did not know that these were the exact same movies from the previous step. After the participants had completed the procedure, they were asked to fill out a questionnaire where they could rate their satisfaction with the explanations and could also express how transparent they found the explanations.

2.4.1.2 Dependent Variables and Measurement Method

Transparency and satisfaction were, as said, measured through a questionnaire, where satisfaction was determined based on *ease of use* and *enjoyment*. The *efficiency* of an explanation type was determined by measuring the time needed by the participants to rate a movie based on the explanations. The *effectiveness* was approximated by comparing the participant's rating for a movie when only provided the explanation with the rating when full information was available [4]. A small difference means high effectiveness; large differences, in contrast, indicate that the explanations are persuasive. The effectiveness measure was therefore also used to measure the *direction of persuasiveness*, i.e., if the explanation have the effect that the participant over- or underestimates the true suitability of a recommendation based on the explanations.

2.4.2 Observations and Implications

The following observations were made based on the responses of 105 participants. In terms of *efficiency*, it turned out that the participants needed significantly more time when they were provided with *content-based* explanations, i.e., those based on tag clouds as shown in Figure 2. The tag clouds were, in contrast, among the explanation types with the highest *effectiveness*. The difference between the explanation-based rating and the "informed" rating were close to zero, with a high positive correlation between the values. By definition, the *persuasiveness* of highly effective explanations is low. There were, however, a number of explanation types that led to a strong over-estimation of the preference match of the shown movies. In particular, non-personalized explanations that simply indicated how many other users gave the movie a rating of four or higher led to the highest level of positively-oriented persuasion. Overall, the main conclusion resulting from this part of the analysis is that *the provision of information related to the features of an item can be key to effectiveness*, i.e., to help users making good decisions.

Looking at the participants' answers regarding the *perceived transparency*, the different explanation types fell into two groups for which statistically significant differences could be observed. The provision of a rating prediction and a confidence value is an example of an explanation form that led to low perceived transparency. In general, however, the obtained results were not fully conclusive. A personalized version of the tag clouds, for example, led to the highest level of transparency, whereas its non-personalized counterpart was in the group with the lowest transparency.

The personalized tag clouds also led to the highest levels of user *satisfaction*. However, the difference to several other forms of explanations, including in particular very simple ones, was in most cases not statistically significant. The lowest satisfaction level (based on ease of use and enjoyment) were observed for explanations that involved information about the rating behavior of the peers. Overall, the authors conclude that *explanations should be presented in a form that users are already familiar with* and require limited cognitive effort.

By analyzing the correlations between the variables, two more guidelines were proposed in [14]. The first guideline is to use explanations with *high transparency to increase user satisfaction*, as was also found in [49]. Second, *explanations should not be primarily optimized for efficiency*, but rather for, e.g., effectiveness, as users seem to be willing to invest more time to understand the explanations. The resulting set of guidelines obtained in this particular study is summarized in Table 3. A summary of outcomes and insights of other studies about different aspects of explanations can be found in [50].

2.4.3 Open Issues

While the presented study led to a number of insights and design guidelines, some aspects require further research. First, a deeper understanding is needed regarding which factors of an explanation lead to higher transparency. Second, the study also led to inconclusive results about the value of personalization of explanations. Two types of tag clouds were used in the study. In some cases, the personalized method worked best, while in other dimensions it made no difference if the explanations were personalized. Finally, some of the explanations were based on providing details of the inner workings of the algorithm, e.g., by presenting statistics of the ratings provided by similar users. Given today's more complex machine learning based recommendation algorithms, alternative approaches for explaining the outcomes of such black-box algorithms are needed. One can for example rely on approaches that disconnect the explanation process from the algorithmic process of determining suitable recommendations and mainly use the features of the recommended items (and possibly the user profile) as a basis to generate the explanations *ex-post* [51, 62, 59].

Tab. 3: Guidelines for Explanation Design [14].

Nr.	Guideline
1	Use domain specific content data to boost effectiveness.
2	Use explanation concepts the user is already familiar with, as they require less cognitive effort and are preferred by the users.
3	Increase transparency through explanations for higher user satisfaction.
4	Explanation types should not primarily be optimized for efficiency. Users take their time for making good decisions and are willing to spend the time on analyzing the explanations.

3 Putting the User into Control

One of the less explored purposes of explanations, as mentioned above, is that of *scrutability*. While the word "scrutable" can be defined as "capable of being deciphered"[4], Tintarev and Masthoff extend the interpretation of the word in the context of explanations and consider scrutability as allowing "[...] the user to tell the system it is wrong" [61]. The explanations provided by the system should therefore be a part of an iterative process, where the system explains and users can give feedback and correct the system's assumptions if necessary. In that context, explanations can be part of a mechanism that is provided to put users into control of the system, a functionality that is considered a key aspect or effective user interface design [58].

In the case of a recommender application, the system could, for example, explain to a user that a movie is recommended because she or he liked action movies in the past. If provided with an opportunity to give feedback, the user could then correct the system's assumption in case this interest in action movies no longer exists.

In the literature, there are a number of different ways in which users can give feedback and exert control over the system's recommendations. The literature is, however, still scattered. In this section, we provide a review of these mechanisms

4 https://www.merriam-webster.com/dictionary/scrutable based on [32] and [34]. Our review covers user control mechanisms in the context of explanations, but also considers other situations in the recommendation process where users can take control. Additionally, we present the results of a survey from [32], which investigates the reasons why the explanation-based control features of Amazon are not widely used.

3.1 Review Framework

We base our review of user control mechanisms on the conceptual framework presented in [32], as illustrated in Figure 3.

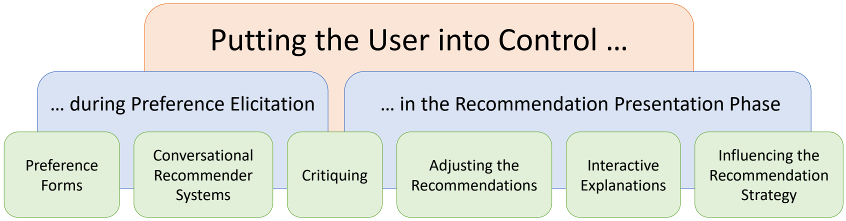

Fig. 3: Research Framework for User Control in Recommender Systems (adapted from [32]).

The mechanisms for user control can be classified in the following two categories.

- Users can be put into control during the *preference elicitation* phase, e.g., when the system is collecting initial information about their individual preferences. We describe these approaches in Section 3.2.
- Another option for recommendation providers is to allow users to control their recommendations in the *presentation* phase. We review examples of such approaches in Section 3.3.

3.2 User Control During Preference Elicitation

Many online services, including in particular e-commerce shops or media sites, allow users to rate individual items, either in the context of a purchase or independent from any business transaction. These feedback signals, e.g., thumbs up/down ratings, can be used by an underlying recommendation system to build long-term user models and to adapt the recommendations accordingly. In some sense, the provision of additional feedback opportunities can therefore be seen as a mechanism for user control, as the user feedback influences which items a user will see. However, such user inputs are typically not taken into account immediately by the system and the provision of such feedback might not have a recognizable effect for the user. Furthermore, which effects individual preference statements have on the recommendations, is usually not transparent for users, who might not even be aware that this feedback is taken into account at all.

In the following sections, we focus on three *explicit* forms of user control during the preference-building phase, namely preference forms/dialogs, conversational recommender systems, and critiquing.

3.2.1 Preference Forms and Static Dialogs

Static *forms* are a common approach to let users specify and update their explicit taste profiles. The general idea, in most cases, is to let users choose their favorite category of items, e.g., musical genres or news topics, or to let them express their level of interest on a numerical scale. Such approaches are easy to understand and, consequently, used in a number of web applications, such as music and movies streaming sites (e.g. Netflix) or news websites (e.g. Google News). The user model can, in most cases, be updated immediately or filters can be applied to the recommendations so that they reflect the updated preferences instantly.

Another way to collect explicit preferences from the user is to use static preference *dialogs* instead of forms. These dialogs guide users through a series of questions to identify their taste profile. One example is the website of TOPSHOP, where users can take a “quiz” to determine their fashion style profile step by step (see Figure 4). The advantage of such dialogs over a single form is that more information can be gathered without overwhelming the user with too many options at once. In the recommender systems literature, we find static preference forms and dialogs in domains such as music recommendation [24], in-restaurant menu suggestion [64], or the recommendation of energy-saving measures [37].

However, even though these specific user control modalities are frequently used in the literature and practical applications, some open questions remain regarding their user-friendliness. For example, it is unclear how such systems should deal with user interests drifts, since a major fraction of users will most likely *not* edit their taste profiles manually and keep them up-to-date on a regular basis. Furthermore, as the name suggests, these forms and dialogs are static, i.e., the same set of questions is presented to all users, which might reduce their usefulness for users with more specific needs.

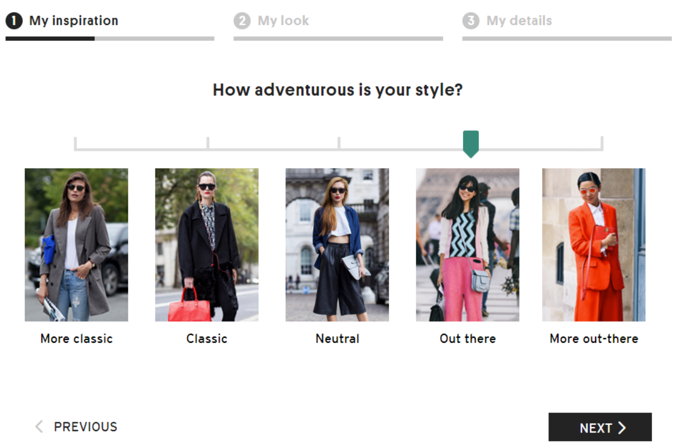

Fig. 4: Static Preference Elicitation Dialog on the Fashion Shopping Website TOPSHOP.com.

3.2.2 Conversational Recommender Systems

A possible solution to the described problems of static dialogs are *conversational* recommender systems. Such systems typically elicit the preferences by asking users about their preferences step by step, but they usually dynamically adapt the dialogs, e.g., based on previous answers of the user. The preference dialogs can, for example, be varied in terms of the number of questions, their details, or even with respect to the type of interaction itself. For example, if the user is a novice, a natural language-based avatar could be used to interact with the user. Experts, in contrast, might feel more comfortable when they can specify their preferences using a set of detailed forms.

A variety of conversational recommender system approaches were presented in the literature. For example, in the Adaptive Place Advisor system [15], users can construct travel plans in a conversational manner where the degree of presentational detail is adapted based on the users' previous answers. Other systems, such as the Advisor Suite [9, 31], offer additional features such as personalized explanations of the recommendations or recovery suggestions in case the user requirements cannot be fulfilled. Examples of practical applications of such systems exist as well (see, e.g., [28, 31]). A main challenge in such systems is to find ways to stimulate users to go through a multi-step preference elicitation process at least once. Personalizing the dialog according to the user's estimated willingness to answer more questions can be one possible approach in that direction.

Generally, conversational systems, also in the more modern form of chatbots, can lead to a more engaging user experience than the provision of static series of fill-out forms. A main hindrance to the large-scale usage of such systems lies in the fact that they can require substantial efforts for the creation and maintenance of the explicit knowledge that is needed to conduct such dialogs. Differently from recommendation approaches based on collaborative filtering, such knowledge-based approaches have no built-in learning capacity, i.e., the recommendation models have to be continuously maintained. In addition, conversational systems are usually only designed for one-shot recommendations and do not consider long-term user models.

3.2.3 Critiquing

Similar to some of the user control methods discussed so far, *critiquing* techniques also allow users to explicitly state their preferences regarding certain item features. However, in contrast to conversational RS or static forms, preferences are expressed in the context of a reference item. For example, if the user is searching for a restaurant to eat at, a critiquing system will typically offer one selected recommendation at the beginning of the process. Users can then study the features of the recommended restaurant and critique it, e.g., using statements like "cheaper" or "closer to my location." Based on the critiques, the recommender system will come up with better suggestions until the user is satisfied.[5]

Critique-based systems are easy to understand in terms of their interaction scheme and have the advantage of giving users immediate feedback by updating the recommended (reference) item after every critique. Consequently, a number of these systems have been proposed in the recommender systems literature (see, e.g., [7, 63, 64]). However, depending on the user's requirements and the domain, critiquing approaches can result in a higher number of interaction steps than other preference acquisition methods. One solution proposed in the literature (see, e.g., [66, 45]) to tackle this problem are compound critiques, which allow users to critique items in more than one dimension at once, which might, however, also increase the cognitive load of the users.

5 Considering our research framework in Figure 3, critiquing falls into both main categories and is a technique that has both a preference elicitation facet and at the same time implements a feedback mechanism during result presentation.

3.3 User Control in the Recommendation Presentation Phase

Letting users state their preferences in a more explicit or interactive manner is not the only way in which user can be put into control of their recommendations. Once the initial user preferences are collected, recommender systems can also offer a range of user control mechanisms when the recommendations are presented to users. Such control mechanisms can allow users to either (a) manipulate the recommendation lists, in the simplest form by trying different sort orders, or (b) inspect and eventually correct the presented recommendations based, e.g., on the provided explanations.

3.3.1 Filtering or Adjusting the Provided Recommendations

One simple form of user control in the context of result presentation can be achieved by giving users the option to filter, sort, and manipulate the contents of the given recommendation list, e.g., by removing individual items. For example, when given a list of movie recommendations, a filter feature can be provided to enable users to exclude movies of certain genres from the recommendations, as done, e.g., in [56]. Another example is the microblog recommender system presented in [60], where users can sort the tweets in some ways or vary the importance of different filters. Considering real-world applications, such filters can also be defined by users for Facebook's automated news feed to make sure that posts of favorite users always appear at the top.

More sophisticated approaches allow the user to manipulate the recommendations in a more interactive way based, e.g., on the exposure of the algorithm's inner logic. For example, in [5] and [57], recommendations are presented within graph structures that show the relations of the recommended items to those that were previously rated by the user, friends or similar users. Users can then take control of the recommendation outcomes by adjusting their item ratings or by assigning custom weights for the influencing friends. These inputs are then taken into account to create an updated list of recommendations.

Generally, the provision of additional interaction and feedback instruments can make users more satisfied with the recommendations, as was shown in the study of [5], and many of the more simple forms of user control, such as sorting or filtering, are easy to implement for providers. However, some of the more complex methods assume that users are (a) willing to spend a significant amount of time to improve their recommendations and (b) can understand the system's logic, such as the relations between recommendations and similar users. This might, however, not always be the case for average users.

3.3.2 Choosing or Influencing the Recommendation Strategy

A quite different form proposed in the literature to put users into control of their recommendations is to allow them to choose or influence the recommendation strategy or algorithm parameters. Such mechanisms in principle offer the maximum amount of user control in some sense, but also the highest risk that the user interfaces and the complexity of the task might overwhelm users. Consequently, these user control measures can primarily be found in the academic literature.

For example, in a study in the context of the MovieLens movie recommendation system [21], a widget was added to the user interface for users to change the recommendation algorithm to be used. Selecting one of the four available strategies led to an immediate change of the displayed recommendations. However, the mechanics of the algorithms were not explained to the users, which might make the presented system somewhat less transparent and users dissatisfied if their choices do not lead to the expected effects. A different approach was implemented in the system presented in [52]. The system allows users to fine-tune the weights of different recommendation strategies in a hybrid recommender system. In addition, a Venn diagram was used to illustrate which of the sub-strategies was responsible for the inclusion of individual items.

The mentioned works show through user studies that such forms of in-depth user control can have a positive effect on the user experience. However, how such a mechanism can be successfully integrated into real-world systems without overwhelming everyday users, remains to some extent unclear.

3.3.3 Interactive Explanations and User Control

As mentioned earlier, explanations represent one possible entry point for users to *scrutinize* the provided recommendations and to interactively improve them or correct the system's assumptions. Both in the literature and in real-world systems, there are only a handful of examples of recommender systems that provide such interactive explanations.

The previously-discussed interactive visualization approaches from [5, 57], which show the relation between rated items and recommendation in a graph structure, can be considered as a form of scrutable explanation. They expose the algorithm's reasoning and allow users to exert control by changing their ratings, which leads to updated recommendations. Another example are the conversational recommenders from [9, 31], which generate textual explanations that describe which internal rules "fired" due to the user's stated requirements. Users can then, in case they do not agree with the recommendation rules, change the weights of specific rules, which immediately leads to an updated set of recommendations. Finally, in the mobile shopping recommender system Shopr [40], a critiquing-based approach is taken where users are shown recommendations along with feature-based explanations such as "because you currently like blue." Users can then improve the recommendations by either rating them with a thumbs up/down button or by clicking on the assumedly preferred features to revise their user model. In the latter case, users can, for example, click on the word "blue". This would lead them to a screen where they can select the colors they are actually interested in at the moment. The additional preference information that is gathered in this way is then used by the underlying active learning algorithm to immediately "refine" the recommendation.

There is also a small number of real-world applications that feature user control mechanisms in the context of explanations. In case of the web site of Amazon.com, users are at different occasions provided with explanations as shown in Figure 5. In their case, the system explains the recommendation of a product in terms of other products with which the user has interacted in the past, e.g., clicked on, added the shopping cart, or purchased. Users can then correct the system by indicating that they either already own the recommended product, are not interested in it, or that they do not want the item from their profile to be used for recommendations. The latter case can, for example, be helpful when a user purchased an item as a gift. On YouTube, a similar explanation mechanism exists that explains individual video recommendations with other videos from the user's viewing history. In this case, the user can also reject the recommendation or tell the system not to consider a particular video from the profile as a source for generating future recommendations.

3.3.4 Acceptance of Amazon's Explanation-Based User Control Features

While the more complex explanation and control mechanisms as proposed in [9, 31] are part of real-world applications, their usefulness was not systematically evaluated. To obtain a deeper understanding of the usability and adoption of the much simpler explanation-based user control mechanism of Amazon.com (Figure 5), a questionnaire-based survey was conducted in [32].

In the first part of the study, participants were shown a screen shot of the explanation feature, and they were asked 15 questions, e.g., about whether they

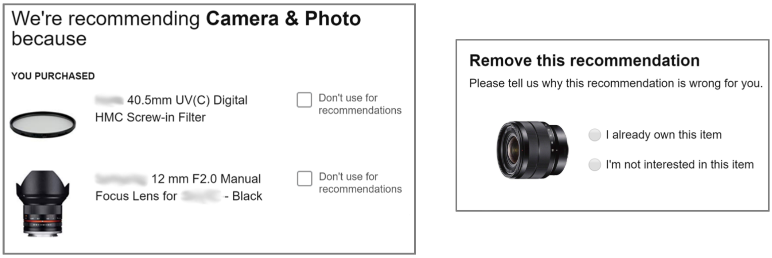

Fig. 5: The Interactive Explanations of Amazon.com's Recommendation System.

knew about the existence of the functionality, if the provided functionality is clear to them, or if they think it is useful. In the second phase, which was conducted at a later time with a different group of participants, the same screen shot was shown, but the emphasis of the questions was on why participants would or would not use the feature, including the opportunity to give free-text answers.

The results from the first phase of the study showed that more than 90% of the participants said they were aware that they could influence their recommendations in some way, but, to some surprise, only 20% knew about the special page where the explanation and feedback feature can be found. Only about 8% had actively used the feature before. However, when asked if the feedback feature ("Don't use for recommendation", see Figure 5) is clear, about 75% of the participants said that it was either very clear or that the meaning could be guessed, indicating that understandability was not the reason why the feature was sparsely used. Interestingly, although participants stated on average that the functionality seemed useful, the average answer as to whether they intended to use the feature in the future was rather low.

To find possible reasons as to why participants seemed to think the feature was useful, but in the end did not use it, the second part of the study collected free-text feedback, which was then analyzed manually. As a result, four main reasons were identified for why participants do not use the explanation-based control mechanism, listed as follows.

– About a third of the participants were not interested in recommendations in general.
– About a fourth said that it would be too much effort to use the feature.
– Again, about a fourth mentioned a fear of bad consequences, such as irreversible changes to their user preference profile, if they tried to use the feature to improve the recommendations.
– Finally, 19% of the participants did not want use the feature because of privacy concerns.

Overall, even though the functionality is rather simple, it seems that providers need to communicate the effects and benefits of their control features in a more understandable way. Also, adding an "undo" functionality, which is proposed as a functionality for highly-usable interfaces in general [58], could help to increase the acceptance of the provided functionality.

4 Summary and Future Directions

Overall, a number of works exist in the literature on recommender systems that show that providing explanations can have positive effects, e.g., in terms of the adoption of the recommendations or the development of long-term trust. In real-world applications, the use of elaborate explanation mechanisms, as provided on Amazon.com, is however still very limited. In many cases, recommendation providers only add informative labels like "Similar items" to give the users an intuition of the underlying recommendation logic.

In terms of user control, we can observe that major sites such as Google News or Facebook nowadays provide their users with features to fine-tune their profile and to personalize what they will see, e.g., in their news feed. A small number of sites such as Amazon.com or Yahoo! also allow users to give finer-grained feedback on the recommendations. Academic approaches, as discussed in the previous section, usually propose much richer types of visualizations and user interactions as can be found on real-world sites.

A main challenge that is shared both by explanation approaches and user control mechanisms is that their usage can easily become too complex for average users. In fact, for many academic approaches, it is not fully clear if they would not overwhelm the majority of users. One possible approach in that context is to *personalize* the provided explanations and user control mechanisms according to the assumed expertise or IT-literacy level of the individual user. Such a personalization process can either be implemented by dynamically selecting from a pre-defined set of explanation types or by adapting individual explanations, e.g., by leaving out technical details for non-expert users.

But even when the provided mechanisms are intuitive and easy to use, users might be reluctant to manually fine-tune their recommendations for different reasons, e.g., because it requires additional effort. Therefore, in addition to the development of appropriate user interface mechanisms, better ways are needed to incentivize users and to convince them of the *value* of investing these additional efforts to receive better-matching recommendations. In this way, providers can make sure that their recommender do not filter out things that are actually relevant to their users.

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