Knowledgeable Explanations for Recommender Systems

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Abstract—Recommender Systems (RS) serve online customers in identifying those items from a variety of choices that best match their needs and preferences. In this context explanations summarize the reasons why a specific item is proposed and strongly increase the users’ trust in the system’s results. In this paper we propose a framework for generating knowledgeable explanations that exploits domain knowledge to transparently argue why a recommended item matches the user’s preferences. Furthermore, results of an online experiment on a real-world platform show that users’ perception of the usability of a recommender system is positively influenced by knowledgeable explanations and that consequently users’ experience in interacting with the system, their intention to use it repeatedly as well as their commitment to recommend it to others are increased.

Index Terms—Explanations, Recommender Systems, Evaluation

I. INTRODUCTION

Recommender systems (RS) provide personalized support to online users in retrieving items from large catalogs [1]. There are different reasoning mechanisms for recommendation like collaborative and content-based filtering or different variants of knowledge-based recommendation. Collaborative filtering builds on the assumption that a user’s peers with similar preferences can be exploited to derive items that might be of high interest. Although such a statistical learning mechanism is very popular for achieving accurate results, it is poor in explaining why a specific item is proposed. It typically provides explanations of the form users who bought item A also purchased item B. Furthermore, content-based filtering recommends items that are similar to the ones the user has liked in the past. Therefore, content-based RS are capable to explain propositions by their similarity to the set of preferred items in the user’s history. In contrast, knowledge-based RS exploit domain expertise like for instance If the user has need A then propose only items that possess property B to infer items whose characteristics match the preferences and needs of a user. Systems like the ones described by [2], [3] mimic conversations with experienced sales agents that first elicit customers’ needs and make propositions of matching items in a second step. Due to the exploitiation of explicit domain knowledge that can, for instance, be represented by a logical theory or a constraint satisfaction problem (CSP) the inference steps leading to the recommendation of an item can be used as an explanation. Making the rules transparent that are satisfied by a recommended item, helps users to better understand how the system works and increases its perceived usability. However, only few recommendation systems exploit explicit knowledge to derive item propositions and most use statistical learning techniques or even hybridize several different algorithmic approaches. Therefore, these systems are unable to provide knowledgeable explanations and make their line of reasoning transparent to their users.

As a consequence we propose to decouple the reasoning mechanism of a recommendation system from the way explanations are generated and present a framework that derives knowledgeable explanations and can be integrated with arbitrary recommendation systems. Furthermore, we study the impact of knowledgeable explanations in a real-world situation where users are arbitrarily assigned to a recommendation system with and without explanations. Our results clearly show that knowledgeable explanations significantly increase the system’s perceived usefulness and thus have a positive impact on users’ experience and commitment to use and recommend the system.

In the following we will give related work on explanations in recommender systems and present a framework for knowledgeable explanations in Section III. Furthermore, Section IV summarizes the evaluation results.

II. RELATED WORK

According to Jannach et al. [1] explanations in recommender systems can be generally understood as a form of communication between a selling agent (i.e. the recommender system) and a buying agent (i.e. the online customer. Tintarev et al. and others [4], [5], [6], [7] discussed the following set of characteristics that can be associated with explanations: transparency, comprehensibility, validity, trustworthiness, persuasiveness, effectiveness and education. Thus, explanations make the reasoning process of the RS transparent to the users, help them to comprehend why an item is deemed to be relevant or even enable them to validate the proposed results. All of the aforementioned factors can also increase the system’s trustworthiness. To persuade users to decide in a way they otherwise wouldn’t [6] or to educate them about the product domain are further relevant aspects of the use of explanations in recommender systems.

Several studies have researched the impact of explanations on users or explored different variants of explanations based
on the recommendation mechanism used. For instance, Herlocker et al. [8] compared 21 implementations of explanation interfaces for the collaborative-filtering based “MovieLens” system. Users preferred a variant where they could see the ratings of their nearest neighbors and did not like more complex histogram designs. In contrast McSherry [9] evaluated case-based explanations that provide arguments of the form: “Case X differs from your query only in attribute A and is the best case no matter what you prefer for attribute B.” The latter comes already closer to the form of explanations presented in this paper, where explicit knowledge in the form of constraints is used to compose chains of arguments.

III. FRAMEWORK FOR KNOWLEDGEABLE EXPLANATIONS

When assessing the state-of-the-art of current recommender technology it can be observed that the reasoning mechanism of the most efficient algorithms cannot be easily used for explaining why an item is proposed because semantics get lost when factorizing and rotating matrices like for instance the winning algorithm of the Netflix competition [10], [11] does. In contrast pure knowledge-based mechanisms that are associated with a transparent line of reasoning typically do not reach comparable accuracy levels as collaborative mechanisms do [12], [13]. However, sophisticated and intriguing explanations must not necessarily outline how it came that an item is proposed but should concentrate on why it is a perfect match. Comparable, in actual sales situations the sales agent often tells a ‘good story’ with respect to a specific product item that is appreciated by customers most.

Therefore, we propose to decouple reasoning for recommendations from generating explanations. In the following, we present a knowledge-based reasoning framework for generating explanations independent of the applied recommendation mechanism.

First, we define an explanation as a sequence of arguments $e = (a_1, \ldots, a_n)$, where each argument $a \in e$ can be a textual phrase and $e$ is a natural language text as for instance depicted in Figure 2. The knowledge-based explanation model is represented by a layered directed acyclic graph (DAG) that contains a distinguished start and an end node. Transitions are directed and connect two nodes, where the start node has no incoming and the end node no outgoing transition. Nodes represent arguments that can become part of an explanation and the sequence of arguments along a path through the graph constitutes an explanation. In analogy to the description of user interfaces for conversational recommender systems of Felfernig and Shchekotykhin [14] we employ a variant of Predicate-based Finite State Automata (PFSA) [15] to represent an explanation model such that transitions are represented by constraints formulating restrictions on a finite set of variables. For instance, Figure 1 sketches a very simple explanation model, where the bold faced transitions provide a valid sequence of arguments \{start, a\_fam, a\_it, a\_it, end\} that can be used for explaining a specific product item to a specific user. Restrictions are represented by the standard constraint satisfaction problem (CSP) formalism that is described by a tuple $(X, D, C)$ where $X$ is a set of variables, $D$ a set of finite domains for the variables in $X$ and $C = \{c_1, \ldots, c_m\}$ a set of constraint restrictions representing a knowledge base that defines which combinations of values can be simultaneously assigned to variables [16]. Therefore a recommendation problem can be formulated using constraints like done by [17], where $X$ is a set of variables modeling item features $X_I \subseteq X$ like the food served or customer segments addressed in the example domain of spa resorts. Furthermore, user and session characteristics $X_U \subseteq X$ like customer_type or the user’s food preference are represented by variables. Note, that also contextual parameters like season or day of week can be utilized depending on the application context. The variables’ domain $D$ can be defined as a function $dom(x)$ that returns a finite number of valid variable assignments for each $x \in X$, e.g. $dom(customer\_type) = \{family, couple, unknown\}$.

Finally, a constraint $c \in C$ formulates a restriction on the variable assignments that can be evaluated to be either true or false. Each constraint $c$ is part of a transition $a_1.c.a_2 \in E$ that connects states/arguments $a_1$ with $a_2$. Example constraints can be $customer\_type = family$ or $food\_preference = italian$, but in principle they can be arbitrarily complex limited only by the capabilities of the constraint solver.

Definition PBExpModel A predicate-based explanation model is therefore defined by the 5-tuple $(X = X_I \cup X_U, D, C, Q, E)$ represented by a finite set of variables $X$, variable domains $D$, constraints $C$, states/arguments $Q$ and transitions $E$. Transitions $a_1.c.a_2$ connect two arguments $a_1, a_2 \in Q$ with a constraint $c$. The functions $start(Q)$ and $end(Q)$ return the start and the end state. $\forall a_0, a_1, a_2, \ldots, a_n \in Q$, $start(Q) = a_0, end(Q) = a_n$.
due to space limitations we will describe the experimental setup, but only summarize the achieved results. See [22] for a detailed description of this evaluation. The test was conducted on a real-world platform (see http://www.thermencheck.com) that is Central Europe’s most comprehensive information platform about spa resorts that offers its users detailed information and multiple options for searching, browsing and comparing different offers. All users accessing the platform are randomly assigned into group A (no explanations) or group B (knowledgeable explanations) which was automatically measured by a binary variable denoted explanation. Over 200 users participated in the experiment that was conducted in January 2010. Participation in the experiment was promoted by a banner on the platform that invited users to participate. Students had been encouraged by email to visit the platform, use the RS and participate in the survey.

The platform includes the conversational recommender Aquarius that asks users about their preferences and retrieves those spas from a catalogue that matches these requirements according to their descriptions and a knowledge base that mediates between preferences and item descriptions. Recommendations are ranked according to a matching degree from an interval 1 to 100% that indicates the share of weighted preferences that are fulfilled by a specific recommendation. In addition, users who have been assigned to group B will also receive knowledgeable explanations on the result page as indicated in Figure 2 while users in group A receive no explanations at all. However, results and their rankings have been the same in both groups in case of equal user input to the conversational RS. Due to space limitations we will describe the experimental setup, but only summarize the achieved results. See [22] for a detailed description of this evaluation. The test was conducted on a real-world platform (see http://www.thermencheck.com) that is Central Europe’s most comprehensive information platform about spa resorts that offers its users detailed information and multiple options for searching, browsing and comparing different offers. All users accessing the platform are randomly assigned into group A (no explanations) or group B (knowledgeable explanations) which was automatically measured by a binary variable denoted explanation. Over 200 users participated in the experiment that was conducted in January 2010. Participation in the experiment was promoted by a banner on the platform that invited users to participate. Students had been encouraged by email to visit the platform, use the RS and participate in the survey.

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of the system’s usefulness and its ease of use as being the main determinants of the usage intention according to the technology acceptance model (TAM) [23]. Furthermore, the users’ trust in the recommender system as well as their intention to use it repeatedly, positive usage experience and their willingness to recommend it to others were measured comparable to the technology acceptance study acceptability for recommender websites in tourism by Bauernfeind and Zins [21]. Some of the measurement items have also already been employed in earlier work [24] and in the related thesis of Fritsch [25].

The main result of this study is that knowledgeable explanations significantly increase the perceived usefulness of a recommender system. Although explanations on the result page constitute only one of the many technical features and aspects of a recommender system it is an important result that explanations still have a significant impact on the system’s perceived usefulness. Furthermore, the study’s results showed that the system’s explanation facility is not perceived to make the use of a recommendation system easier. However, if the evaluated system would offer its users tradeoff analysis and critiquing-based navigation functionality like done by [26] then PeoU could be impacted. [21] identified the construct Trust to be a strong influential factor that highly correlates with satisfaction and commitment with recommender websites. However, according to our study the trust in a recommender system itself - in contrast to a recommender website like Expedia or Active Buyers Guide evaluated in [21] - is not impacted by the explanation variable.

Furthermore, the perceived usefulness and thus indirectly also the knowledgeable explanations positively impact the users’ experience in using the recommendation systems as well as their commitment to repeatedly use it and recommend it to others. This strong interaction between the factor of perceived usefulness and the experience and commitment variables has been shown by strong and highly significant correlation coefficients.

V. CONCLUSION

This paper presented a general framework for generating knowledgeable explanations that can be integrated in recommendation systems based on arbitrary recommendation strategies. Furthermore, the authors sketched the results of an experimental evaluation that clearly shows that knowledgeable explanations significantly impact the perceived usefulness of recommendation systems and consequently help to increase the users’ interaction experience, their intention to repeatedly use the system as well as their commitment to recommend the system to others.

REFERENCES