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Conversational recommendation to avoid the cold-start problem

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Abstract

Recommender systems has become a widespread topic, allowing to connect user demands to those products more suitable to their preferences. The more information we provide to the system, the better the system works. This is a weak point of recommenders: they need an initial information belonging to each new user. In this paper we propose to avoid the so-called cold-start problem by using a conversational recommendation approach. We consider products characteristics as attributes and deal with the attribute implications by means of the simplification logic to guide the user in the search.

Key words: Recommendation systems, conversational recommendation, logic, implications

1 Introduction

Nowadays recommender systems have established a solid field of knowledge within information technologies. They are a kind of software that group together a wide range of techniques and applications with the aim of providing the best user experience [18]. There has been much progress done towards recommender systems during last decade [1] but there is still so much work remained. Examples of the applications concerning recommender systems go over many different topics of today's society such as recommending books, music, documents, e-commerce, tourism, medical diagnosis, among others. Recommender Systems constitute a hot topic indeed, as we can notice by the way in which many top companies worldwide spend their efforts and resources developing more and better systems for them to

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increase their benefits. By these means, companies with absolutely different market niches delegate their most important duties to recommender systems due to the wide range of possibilities they offer; and yet companies selling products are not all of them, global leaders in other fields as totally come aboard with recommender systems by recommending new friends, groups, followers, and other social connections.

When recommendations are based on of the element evaluation made by other users or by similarity between the user preferences and these characteristics, recommender systems need to face many problems before they can flow into good recommendations. The first one we need to remark is the well-known cold-start problem [10], that appears when recommender systems try to elaborate reliable recommendations from the absence of initial information. Cold-start problem may be handled by requesting other agents to share what they have already learned from their respective users [11]. Also, new items (those which have not received any ratings from the community yet) would be assigned a rating automatically, based on those given by the community to other similar items [20] and so, we are at the mercy of similarity rules. In the same direction, until the new element has not been evaluated by a significant number of users, the system will not be able to recommend it. An item that is not recommended remain unnoticed by most of the user community, thus, we can enter into a vicious circle in which a set of elements of the recommender systems will be left out of the rating process and/or recommendations continuously [16]. In most of cases, users do not rate all the features we would desire for the optimum running of the recommender systems, this reveals scarcity problem.

In this work, we propose to deal with the cold-star problem by introducing an information flow based on the dialogue with the user. The lack of initial information is avoided with the design of a process with allows to collect this information of the user and storing them for further access to the system. This process, as we shall see, is a recommender-like system, to allow the user for getting some usefullness in its use.

2 Recommender systems and the conversational issue

There exists different kinds of recommender systems usually classified on how recommendations are made [1]. The most known and extended ones are collaborative filtering, content-based and demographic systems. Besides, in recent years there has been a great expansion of context-aware recommender systems [2] and knowledge-based recommender systems [14]. Other group of recommender systems that worths to be considered is that one focused on recommendations involving group of people [9]. Collaborative filtering systems [13], recommend items that other users have already rated before. Recommendations made by content-based systems present items similar to the ones the user preferred in the past [12]. Context-aware recommender systems try to adapt their recommendations to the world around the user. Finally, knowledge-based approaches are different; they manage functional

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knowledge about how an item matches a particular need, and they can therefore reason about the relationship between a need and a possible recommendation. These characteristics make knowledge-base recommender systems not only valuable systems on their own, but also highly complementary to other types of recommender systems. However, the history of recommender systems has broadly demonstrated that best strategies are those who merge characteristics from different kinds of recommender systems in order to generate hybrids conforming best features of each one [6, 4].

In general, most of widely used recommendation techniques requires information to build a user profile before generating a result. In some cases, that information may be gathered explicitly: for example, requiring data about age, gender, etc. during a registration process, or by means of ratings and opinions about the recommended items. In other cases, the system may get implicit information from the browsing and/or purchase user history.

Nevertheless, there are contexts in which this previous information it is not available. This is the case of the well-known cold-start problem, when a new user asks for his first recommendation and obviously the system has not any information about him. This situation also occurs in systems where users make occasional use.

An interesting approach to solve this problem us the use of the so-called conversational recommender systems [7, 8]. These are closely related with critiquing recommender systems [17, 21]. In these works, recommendation is enriched by means of a dialog with the user that allows an incremental elicitation of his preferred item features. To promote an effective use of this approach, our proposal produces as an output a recommendation only based on the user dialogue information. In this way, the system is attractive for those user that are new in the system and can be used as a preliminary system to store user preferences for further accesses.

3 A logic approach to conversational recommendation

Our proposal to integrate recommender systems and the conversational issue is based on a sound and complete logic. As we shall see, such an strong basis allows us to include a reasoning method in the process and allows us to store the information in a natural way to be managed in the future by knowledge-base recommenders.

We built our framework on a basic elements, the implications. They correspond to formulas $a_1 \wedge \ldots \wedge a_n \rightarrow b_1 \wedge \ldots \wedge b_m$. The propositions $a_1, \ldots a_n, b_1, \ldots, b_m$ are elements of a set Ω and they are interpreted as properties concerning attributes. For this reason, propositional symbols are named attributes. To compact notation it is usual to denote the above formulas as $A \rightarrow B$ being $A = \{a_1, \ldots, a_n\}$ and $B = \{b_1, \ldots, b_m\}$ i.e. sets of attributes are conjunctively interpreted.

The symbolic management of implications was originally proposed in [3]. However, due to the central role that transitivity plays in this axiomatic system, the development

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of executable method to solve implications problems has rest on indirect methods. For instance, the proposal to solve the attribute closure, i.e. to find the maximal set of attributes A^+ such that the implication $A \to A^+$ holds has been traditionally tackle by using a basic method which exhaustively uses the subset relation to add new elements in the conclusion.

The introduction of the Simplification Logic, named $\mathbf{SL}_{FD}$, [5] opened the door to the development of automated reasoning methods directly based on its novel axiomatic system. $\mathbf{SL}_{FD}$ considers reflexivity as axiom scheme

$$\texttt{[Ref]} \quad \frac{}{A \to A}$$

together with the following inference rules called Fragmentation, Composition and Simplification respectively.

$$\texttt{[Frag]} \ \frac{A \to BC}{A \to B} \qquad \texttt{[Comp]} \ \frac{A \to B,\ C \to D}{AC \to BD} \qquad \texttt{[Simp]} \ \frac{A \to B,\ C \to D}{A(C \setminus B) \to D}$$

Later, in [15] we presented an attribute closure method closely tied to the Simplification logic axiomatic system. Apart from having a strong base, the main advantage of our method is that its output is twofold: besides the maximal set constituting the closure of the input, it also renders a reduced set of implications which enclose the semantics that is outside the set A^+. We would like to remark that this two inputs are computed in linear time, overtaking the hard cost of a data mining process if we were interested in extracting the new set of implication for the reduced dataset after each search step.

This characteristics provides a key information to further inferences in an iterative search process. This is the core of our proposal to design a conversational recommendation based on our attribute closure operator. The recommendation process will go along the following points:

0. We depart from the premise that we have a dataset containing items and attributes, and the set of implications that holds on it. This is considered point zero and, as we have mentioned, it does not requieres any information from the user to be started.

1. Once we count on this information, the user interacts with the system by selecting an attribute we wish an item to fit.

2. Then, the process flows into the closure algorithm calculating both the set closure for this attribute and above all, the set of implications that remains outside the closure and complete them.

3. Once the closure algorithm has finished, a new reduced dataset is shown. At this point, we can stop the interaction whether we are already satisfied with the result or we can go ahead trying to get a more suitable recommendation. The improvement here goes as follows. For further queries, we have reduced the number of available attributes

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deleting those included in the closure set. Even that this could be accomplished by classic closure algorithms, the major point of our method is that, *at the same time*, we also reduce the number of implications, and so, in every refining-attempt we do not need to start the process form the beginning but continuing from here, where both attributes and implications have been decreased. Consequently, the process maintains its linear complexity and the interaction becomes truly faster.

4. In this way, we select a new attribute and resume the search.

5. We carry on selecting attributes until we get a satisfying recommendation or we run out of attributes.

4 Conclusion and future works

In this paper we propose to approach the cold-start problem. We mining the dataset containing the product information to get a set of attribute implications. This set is managed by using the inference system of simplification logic to guide the search of new users.

As a future work, we propose to study the impact of simplification closure in the performance of our approach. Our method allows to get, in an iterative way, intermediate closure set of attributes and the corresponding reduced set of implications. This characteristics allows to proceed step by step and, at the same time, accelerate the search.

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