Application of Constraint-based Technologies in Financial Services Recommendation

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Abstract. Constraint-based recommender systems rely on an explicitly defined set of constraints that are used to take into account product domain properties, customer requirements, and legal requirements. This paper focuses on different aspects of the application of constraint-based technologies in financial service related scenarios. We show how to support the process of defining and maintaining recommendation knowledge and how to efficiently support users when interacting with constraint-based recommender systems. Finally, we discuss psychological issues that have to be taken into account when implementing such types of recommender systems.

1 Introduction

Recommender systems can be regarded as one of the most successful applications of Artificial Intelligence technologies [12]. The basic approaches of *collaborative* and *content-based filtering* (and variants thereof) are primarily used for recommending simple products such as books, movies, and songs. Complex products such as financial services, cars, and apartments in many cases require a different recommendation approach. For example, cars are not purchased very frequently, therefore collaborative filtering and content-based recommendation are not the first choice. Furthermore, such products are related to constraints, for example, not every financial service can be offered to every customer and a car recommendation should take into account the preferences defined by the customer.

Recommendation functionalities for complex products and services are provided on the basis of *knowledge-based recommendation technologies* [1]. Knowledge-based recommenders are either *constraint-based* [4] or *case-based* [2]. Case-based approaches are often implemented as critiquing-based recommender systems [2, 14] where an item (product) is identified on the basis of similarity metrics [16]. Identified items are shown to the user and the user can provide feedback in terms of critiques. For example, if a user perceives the return on investment of a financial service as too low, he or she can articulate a corresponding critique *higher return on investment*.

In the context of this paper we focus on *constraint-based recommendation* where the recommendation knowledge is represented in terms of a set of constraints that primarily relate user requirements with corresponding item properties. Constraint-based recommenders can determine recommendations on the basis of *constraint solving* [20] or on the basis of *conjunctive queries* [7]. The result of solution search (of a query) is a set of items that fulfill a given set of requirements. These *candidate items* can be ranked on the basis of utility-based methods such as the multi-attribute utility theory (MAUT) [21]. The remainder of this paper is organized as follows. In Section 2 we sketch approaches to make constraint acquisition efficient. In Section 3 we provide an impression of how conversational scenarios are supported by constraint-based recommendation. In Section 4 we show how knowledge bases can be applied for generating learning content. Aspects of human decision making in constraint-based recommendation are discussed in Section 5. The paper is concluded with a short discussion of issues for future work (Section 6).

2 Recommender Development

Constraint-based recommenders are based on a recommendation knowledge base that includes a definition of questions to be posed to the user (e.g., *what is the expected return rate?*), items to be recommended (e.g., *bankbooks* and *funds*), and a set of constraints that relate answers to questions with the corresponding items (e.g., *a low willingness to take risks excludes the recommendation of equity funds*). Such constraints are also denoted as *filter constraints*. Furthermore *incompatibility constraints* define in which way different user requirements can be combined with each other [7].

Especially in financial services recommendation scenarios, the correctness of the underlying knowledge base is crucial. Items recommended to the user (customer) have to be consistent with the user requirements. Furthermore, the knowledge base has to reflect product- and sales-related rules defined by the company and also corresponding legal requirements. In order to assure the correctness of a knowledge base, different test methods are applied were examples (test cases) are exploited in a regression testing process [7].

If regression testing fails (some test cases were not accepted by the knowledge base), those constraints in the knowledge base have to be identified that are responsible for the inconsistency. Since recommender knowledge bases can become quite large (in an order of magnitude of a few hundred constraints), knowledge engineers are in the need of support to identify faulty constraints as soon as possible. The efficiency of this process is crucial since, for example, with the introduction of a new product, the corresponding recommendation knowledge base has to be available (e.g., for supporting sales representatives in their sales dialogues [8]).

An approach to support the automated identification of faulty constraints is to apply the concepts of model-based diagnosis [17] where faulty constraints are identified on the basis of conflict set detection (see, e.g., [13]) combined with the determination of corresponding hitting sets (diagnoses) [6, 17]. Since many different diagnosis candidates potentially exist, diagnosis discrimination can be supported in an interactive fashion [18] or automatically [9].

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3 Conversational Recommendation

When interacting with a constraint-based recommender, users typically specify their requirements (preferences) by answering corresponding questions [7]. If a set of candidate solutions can be identified for the given set of requirements, these are ranked, for example, on the basis of MAUT [21]. If no solution can be identified for the given set of requirements, a diagnosis component can indicate those requirements that have to be adapted such that at least one solution can be identified.

A diagnosis in this context does not indicate faulty constraints in the knowledge base but user requirements that induce an inconsistency with the knowledge base (e.g., *if you change your preference "return rate = high" and keep "willingness to take risks = low", a corresponding solution can be identified*). Diagnosis determination can be implemented on the basis of the traditional approach documented in [6, 17] or on the basis of direct diagnosis algorithms such as FASTDIAG [10] that are able to determine personalized diagnoses without the need of predetermining conflicts. An alternative to the presentation of diagnoses is the direct presentation of conflicts that have to be resolved by the user in an interactive fashion [7].

4 Operationalizing Recommendation Knowledge

When a financial service sales representative interacts with a customer, he or she should not solely rely on the recommendations determined by the recommender system but should also be able to explain a recommendation in his/her own words. Knowledge bases can be exploited for the automated generation of question/answer combinations which can be imported into a corresponding e-learning environment. This way, time-intensive learning content development tasks can be at least partially replaced by automated mechanisms using, for example, constraint technologies [20]. Technologies that support such a kind of e-learning content generation have been implemented in the STUDYBATTLES environment.² This system is based on the idea of a quiz-based acquisition of (sales) knowledge.

5 Issues of Human Decision Making

Recommender systems can be regarded as decision support components that support a user when trying to identify a product that fits his/her wishes and needs. An important aspect to be taken into account in this context is that user preferences are not known beforehand and are not stable but rather frequently change within the scope of a recommendation process [3]. The ordering of items in a result set (recommendation) can have an impact on the item selection probability. Decoy effects influence the selection behavior of users by the inclusion of inferior items that in many cases are not even selected [19]. Such effects could be shown on the basis of a real-world financial service dataset [11]. Furthermore, primacy/recency effects are a cognitive phenomenon where list items are memorized significantly more often if these were placed at the beginning and the end of a list. In the recommendation context it has been shown that the probability of recalling item properties increases if the properties are presented at the beginning or the end of a property list [5]. On overview of different types of decision biases in the context of recommender systems can be found in [15].

6 Conclusions and Future Work

In this paper we provide a short overview of different aspects of constraint-based recommendation technologies in the context of financial service recommendation. Future work will include the provision of end user knowledge acquisition environments, intelligent methods of test case generation and selection, and further user studies on the role of human decision making in recommender systems.

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