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Interactive and nonparametric modeling of preferences on an ordinal scale using small data

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ABSTRACT

In this study, we consider learning preference structure of a Decision Maker (DM). Many preference modeling problems in a variety of fields such as marketing, quality control and economics involve possibly interacting criteria, and an ordinal scale is used to express preference of objects. In these cases, typically underlying preference structure of the DM and distribution of criteria values are not known, and only a few data can be collected about the preferences of the DM.

For developing a preference model under such circumstances, we propose using nonparametric Statistical Learning approaches interactively. In particular, we employ Active Learning by asking a preference question to the DM at each step and try to reach a close approximation to the correct model in a small number of steps. Our experimental analysis proves that the proposed approach outperforms a “naive” approach where subsequent questions are asked randomly. In the study, we also provide algorithmic recommendations for modeling different underlying value functions, if information is available about the form of the preference structure and/or distribution of criteria values.

This study can be regarded as a pioneering approach considering that Statistical Learning based approaches in the literature have been developed and tested based on a relatively large preference information and they do not interact with the DM in model developing process while Multi Criteria Decision Aid based approaches typically ignore interactions among the criteria, suffer from generalization ability, and have no concern about predicting equally good everywhere in the criteria domain.

1. Introduction

Many real life decision problems involve multiple criteria usually conflicting with each other. In this respect, decision making under multiple criteria turns out to be a subjective task that depends on the preference structure of the Decision Maker (DM). Preference modeling, which aims at explicitly eliciting preference structure of the DM, is drawing a growing interest recently due to the fact that it became an imperative step in variety of areas. When criteria considered in the decision problem interact with (or depend on) each other, preference modeling task gets more challenging. Even though there is a general consent among researchers regarding the existence of interaction among criteria in real life decision problems, it is often ignored in applications. Therefore, most of the preference modeling strategies assumes preferential independence among criteria, making modeling process relatively easygoing. Nevertheless, interaction phenomenon is encountered quite commonly, even in simpler cases.

Many preference modeling problems in a variety of fields such as marketing, quality prediction and economics, involve possibly interacting criteria, and an ordinal scale is used to express preference of objects. In these cases, typically no information is available about the underlying preference structure, and only a few data can be collected about the preferences of the DM. Preference models where preferences are expressed on an ordinal scale have many real life applications such as pattern recognition, human resources management, marketing, economics, education, medicine, quality management, and evaluation of hotels (Doumpos & Zopounidis, 2002). The corresponding problem where alternatives are assigned to predefined ordinal classes is referred to as a sorting problem in Multi Criteria Decision Aiding (MCDA) field.

Various methods have been proposed in the MCDA literature to deal with sorting problems. These methods can be classified in three main streams based on modeling approaches used, namely, outranking relations, value function and rule based. These approaches differ based on the model used to map alternatives into predefined classes. In the value function approach, all alternatives are assigned to predefined ordered classes based on value associ-

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ated with each alternative (Buğdacı, Köksalan, Özpeynirci, & Serin, 2013; Corrente, Doumpos, Greco, Słowiński, & Zopounidis, 2015; Greco, Kadziński, & Słowiński, 2011; Jaquet-Lagreze & Siskos, 1982; Köksalan & Bilgin Özpeynirci, 2009; Soylu, 2011; Ulu & Köksalan, 2014). These methods assume that preference structure of the DM complies with generally a known functional form. In the outranking relations approach, preference degree of each alternative is determined based on pairwise comparisons of alternatives (Köksalan, Mousseau, Özpeynirci, & Bilgin Özpeynirci, 2009; Leroy, Mousseau, & Pirlot, 2011). In the decision rule approach, on the other hand, a model defined by decision rules is formed in order to sort alternatives (Greco, Matarazzo, & Slowinski, 2002).

In MCDA sorting approaches interaction phenomenon is usually neglected, or all the criteria under consideration are assumed to be preferentially independent. Additionally, majority assumes a known underlying preference structure, however, DM preference structure is usually unknown, and adapting a functional form may lead to poor results. Moreover, even though proper functional (i.e. nonlinear) form is assumed for a preferential system with interactions among criteria, parametric functional models may fail to address complex interaction structures in high dimensions. Almost all of the MCDA approaches obtaining preference information on an ordinal scale aim at sorting limited number of alternatives of the problem under consideration with maximum accuracy. They take a subset of the alternatives or use a separate reference set that happens to be available for obtaining preference information. Additionally, instances in the initial reference set are not collected in a structured and incremental way so that subsequent learning process is expedited. Hence, the preference model that is developed based on the preference information obtained with respect to reference alternatives is used to sort the rest. In this respect, their generalization ability is limited. Even though developed models represent preference structure of the DM, these techniques cannot be considered as preference modeling approaches.

Similar to the focus of this study and different than the applications proposed in MCDA, Adaptive Conjoint Analysis (ACA) from the marketing field considers preference modeling as a learning process, thereby seeks for methodologies that implement preference modeling process in an incremental way (Abernethy, Evgeniou, Toubia, & Vert, 2008; Toubia, Hauser, & Garcia, 2007; Toubia, Simester, Hauser, & Dahan, 2003). ACA usually approaches preference structure modeling as a function estimation problem, and uses reference evaluations of alternatives (or profiles as in ACA parlance) to elicit model parameters. The main idea of ACA is to ask as less number of questions as possible while reducing uncertainty for the parameter estimates. In order to achieve this, the methodology adaptively selects a new question based on previously obtained answers. As Rao (2014) states, ACA methods cannot model interactions among attributes, which is generally criticized. This issue is raised by Teichert and Shehu (2013), where they remark that model-free approaches should be developed in ACA in order to avoid model misspecifications and estimation biases.

Focusing on developing predictive models and new technologies that mimic human behavior, Artificial Intelligence (AI) field also shows considerable interest in preference modeling. Especially researchers in Machine Learning (ML) pay increasing attention to learning preferences (Fürnkranz & Hüllermeier, 2010a). Preference learning applications in AI aim to develop predictive models that are built based on the preference information obtained from the DM explicitly or implicitly. Hence, special emphasis is put on prediction performance in AI applications. In AI, learning preferences on an ordinal scale is usually called Instance Ranking (Fürnkranz & Hüllermeier, 2010b). An interesting application area of AI preference learning where preferences are expressed on an ordinal scale is recommender systems (Marin, Moreno, & Isern, 2014; Martinez, Barranco, Perez, & Espinilla, 2008; Porcel, Lopez-Herrera, & Herrera-Viedma, 2009). In general, recommender systems learn customer preferences from users' or similar users' past behavior (collaborative filtering) or attributes of items preferred by the users (content-based filtering). These systems are generally used in online stores for product recommendation. The main problem with the usual AI preference learning is that the learning process has a passive texture. In other words, information gathering from the DM (i.e., questions or profiles asked to the DM) is not structured so that the learning process is expedited. Hence, learning with as less data as possible is not the main concern.

Preference modeling approaches in these three different research areas show similarities as well as differences. Doumpos and Zopounidis (2011) provide a comparative review regarding integration of MCDA and Statistical Learning (SL) based methodologies, connections, similarities, differences and potential research areas. First of all, existing MCDA and ACA approaches fail to model interactions among criteria. AI preference learning approaches, on the other hand, can model particularly complex interactions because they utilize model-free SL techniques for modeling preferences. MCDA and ACA approaches assume that only a small reference set is available while approaches utilizing SL techniques as in AI for modeling preferences are usually criticized for requiring relatively large preference information (Doumpos & Zopounidis, 2011). MCDA and AI preference learning approaches have a passive texture. Conversely, ACA performs preference modeling in an incremental way where information gathering is structured so that the learning process is expedited. Prediction performance of the preference model developed is particularly important in the AI field. This issue is considered important to a certain extent in ACA while it is usually ignored in MCDA.

Considering all aforementioned weaknesses and strengths of the proposed approaches in MCDA, ACA and AI, in this study we utilize SL techniques in preference modeling where preference is expressed on an ordinal scale and criteria interact with each other. Our modeling strategy is based on obtaining holistic judgements from the DM regarding alternatives and adjusting subsequent questions based on the judgements gathered thus far, in an adaptive fashion. We start with a small reference set and employ nonparametric classifiers for model developing. Using nonparametric classifiers brings two advantages; firstly, we assume no functional form for the preferential system of the DM, hence, we do not suffer from erroneously adapting a wrong function. Secondly, nonparametric classifiers outperform their parametric counterparts in modeling complex data structures. In order to perform modeling in an adaptive way, we propose employing Active Learning (AL) techniques. AL is an application of semi-supervised ML where the learning algorithm iteratively queries "the Oracle" or user. In particular, we employ AL by asking a preference question to the DM at each step and try to reach a close approximation to the correct model in a small number of steps. Thus, querying process is implemented so that as much information as possible is obtained while as less unlabeled data as possible is queried. Consequently, preference modeling is structured as a learning process. Utilizing AL, we query the DM in an interactive way, thereby; the DM is integrated into the model developing process. In this context, while utilizing strong features of SL in modeling complex structures, we also address the weak sides of SL criticized by Doumpos and Zopounidis (2011), in conjunction with preference modeling. As a consequence, this study can be regarded as a pioneering approach considering that SL based approaches in the literature have been developed and tested based on a relatively large preference information and do not interact with the DM efficiently in model developing process while MCDA based approaches ignore interactions, suffer from generalization ability, and have no concern about predicting equally good everywhere in the criteria domain.