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An integrated algorithm for the optimal design of stated choice experiments with partial profiles

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ABSTRACT

Stated choice experiments are conducted to identify the attributes that drive people's preferences when choosing between competing options. They are widely used in transportation in order to support the decision making of companies and governmental authorities. A large number of attributes might increase the complexity of the choice task in a choice experiment, and have a detrimental effect on the quality of the results obtained. In order to reduce the cognitive effort required by the experiment, researchers may resort to experimental designs where the levels of some attributes are held constant within a choice situation. These designs are called partial profile designs. In this paper, we propose an integrated algorithm for the generation of D-optimal designs for stated choice experiments with partial profiles. This algorithm optimizes the set of constant attributes and the levels of the varying attributes simultaneously. An extensive computational experiment shows that the designs produced by the integrated algorithm outperform those obtained by existing algorithms, and match the optimal designs that have been analytically derived for a number of benchmark instances. Additionally, we evaluate the performance of the algorithm under varying experimental conditions and study the structure of the designs generated. We also revisit two stated choice experiments in transportation, and describe how the integrated algorithm could help to improve their designs.

1. Introduction

Stated choice (SC) experiments are widely used to study how people make choices and to identify the elements that drive people's preferences. They are performed in a wide range of applied fields in order to evaluate the trade-offs that people make when choosing between competing options. In a SC experiment, the options under study are characterized by a set of *attributes*, and each *alternative* or *profile* is described as a combination of attribute levels. Each respondent is presented with several groups of alternatives, called *choice situations*, and asked to choose the alternative of his/her preference in each situation. The main goal of a SC experiment is to estimate the importance of each attribute level from the repeated choices made. By doing so, it is possible to make predictions concerning a population's choice behaviour.

SC experiments are widely used in transportation in order to collect data for the study of travelling behaviour (see, for example, Tilahun et al. (2007), Hensher and Rose (2007) and Hensher (2008)) and for assisting governmental authorities

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in their policy-making activities (see, for example, Wang et al. (2002) and Saleh and Farrell (2005)). Among other things, SC experiments are carried out to study preferences for both air and ground transportation. For example, Ahern and Tapley (2008) studied the preferences of passengers for interurban routes in Ireland. They focused on identifying opportunities for improvement and contrasting the services offered by trains and buses. The SC experiment considered five attributes: cost, journey length, frequency, reliability of the service and the presence of toilet facilities. Bliemer and Rose (2011) studied the preferences of airline customers. Their work was motivated by the fact that flying into main airports is becoming more expensive, both for travellers and airlines. For that reason, there has been an increase in the use of regional airports surrounding major cities. Their main goal was to examine the trade-offs that travellers make between ticket price and overall travel time. The SC experiment involved six attributes: airline, ticket price, departure time, transfer time, egress price and egress time. Bliemer and Rose (2011) also summarized the literature using SC experiments published in the most important transportation journals during the period from January 2000 to August 2009. A total of 64 research papers are listed, involving 61 unique experimental designs. A general overview of the traditional design generation techniques, along with some algorithmic approaches, is given by Rose and Bliemer (2009).

The importance of each attribute is usually quantified using a discrete choice model that is built on the assumption that humans attempt to maximize the total utility when making a choice. In this model, the total utility is expressed as a function of the utilities associated with each attribute. Discrete choice models implicitly assume that humans are willing to make compensatory decisions. In other words, that the negative utility due to undesired levels for some attributes can be compensated for by the positive (or less negative) utility due to preferred levels for some others. The use of non-compensatory decision rules (where, for example, respondents focus on one attribute and ignore the others) is in conflict with this assumption and renders the model's predictions questionable. One main reason why respondents may resort to non-compensatory strategies is the complexity of the decision task. Large numbers of attributes increase the required cognitive effort and might lead the respondents to use simpler decision strategies (Caussade et al., 2005; Hensher, 2006a,b). In order to reduce the complexity of the comparison and to prevent respondents from using simpler strategies, it is possible to hold the levels of some attributes constant in every choice situation. This results in profiles or alternatives that direct the attention only to the subset of attributes the levels of which are allowed to vary. These profiles or alternatives are called *partial profiles* (Chrzan, 2010). The number of varying attributes in a partial profile is called the *profile strength* (Großmann et al., 2006).

Several SC experiments in transportation involve large numbers of attributes. For example, an experiment carried out by Anderson et al. (2006) for the study of tourist parking preferences involved seven attributes. Loo et al. (2006) carried out an experiment to study the preferences of the public light bus industry regarding the introduction of alternative fuel vehicles in Hong Kong. This experiment involved eight attributes related to the vehicle characteristics and seven attributes related to the government support. In other studies, the researchers have reduced or limited the number of attributes considered in their experiments in order to avoid an overwhelming complexity (see, for example, Hunt and Abraham (2007) and Sener et al. (2009)). The study of commute mode choice carried out by Bhat and Sardesai (2006) is an extreme example. During the pilot phase, respondents indicated that the experiment was too burdensome and recommended a reduction in the number of attributes and the number of choice situations. This suggestion encouraged the researchers to consider five attributes instead of the initial eight. More recently, SC experiments with partial profiles have been used in order to avoid the use of non-compensatory decision strategies due to large numbers of attributes. For example, Kupfer et al. (2016) studied the effect of six attributes on the airport choice of air freight service providers in Europe. In order to keep the choice tasks manageable for the respondents, they used partial profiles showing only four of the six attributes in each choice situation. Another example in which a partial profile design has proven useful, is the SC experiment used by Verhetsel et al. (2015). They quantified the impact of the different dimensions of accessibility on the location decision process of logistics companies. This study also involved six attributes, four of which were shown in each choice situation.

In order to design a traditional SC experiment, it is necessary to determine the attribute levels of each alternative. Designing a SC experiments with partial profiles, however, requires making an extra decision: for each choice situation in the design, it is necessary to select the set of attributes the levels of which are held constant. This additional requirement makes generating an optimal design for this kind of SC experiments considerably more challenging. Nearly all the SC experiments with partial profiles that are reported in the literature are designed to estimate a multinomial logit (MNL) model. Although there exist more complex discrete choice models (like, for example, the panel mixed logit model (Train, 2009)) that allow for a more elaborate analysis, the traditional MNL offers two major advantages. First, the computational effort required to evaluate the quality of a design is substantially smaller than that demanded by more complex models (Sándor and Wedel, 2002; Yu et al., 2009). Second, optimal designs generated for the MNL model perform relatively well when it comes to estimating panel mixed logit models (Bliemer and Rose, 2010).

The quality of a design to estimate a MNL model depends on the utilities associated with each attribute level. The exact values of these parameters, however, are not known in advance. Optimal designs can be constructed considering only one specific set of prior parameter values; these designs are referred to as *locally optimal designs* (Huber and Zwerina, 1996). Moreover, from a design perspective, the MNL model can be treated as a regular linear model by assuming that all the parameter values are equal to zero. This assumption implies that the respondents have no preference for any of the attribute levels and all utilities equal zero. Hence, the respondents are equally likely to choose any of the alternatives. The designs produced under this assumption are called *utility-neutral (UN) designs*. A sound alternative to the locally optimal designs