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Homogeneous versus heterogeneous designs for stated choice experiments: Ain't homogeneous designs all bad?

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ABSTRACT

Some recent attempts on constructing heterogeneous designs for stated choice experiments where different respondents or groups of respondents get different subdesigns have proven successful. Compared to homogeneous designs where all respondents get the same choice sets, heterogeneous designs allow for more variation in the attribute levels resulting in a larger amount of information on the respondents' preferences. Homogeneous designs have remained popular, however, because they are easier to generate and implement. In this paper, the question is raised about when homogeneous designs perform almost as well as heterogeneous designs under the Bayesian multinomial logit design framework. A simulation study is presented to identify the situations where the losses in estimation efficiency from using a homogeneous design are small and where they are large. When the residual degrees of freedom from using a homogeneous design are large and, to a lesser extent, the number of attributes and attribute levels are small, the efficiency losses are negligible and the use of a homogeneous design can be justified.

1. Introduction

In recent years, some research on discrete or stated choice (SC) experimental design has focused on the efficient construction of heterogeneous designs where different respondents or groups of respondents get different designs, i.e. subdesigns from a larger design. Sándor and Wedel (2005) were the first to propose the use of heterogeneous designs for SC experiments. Even though the number of subdesigns was small in the heterogeneous designs they constructed, Sándor and Wedel (2005) showed that heterogeneous designs provide more information on the respondents' preferences compared to homogeneous designs where each respondent gets the same choice sets. They presented evidence by comparing homogeneous versus heterogeneous multinomial and mixed logit designs in a locally or Bayesian optimal design framework. The construction of heterogeneous locally optimal mixed logit designs is computationally intensive. Liu and Tang (2015) outperformed the approach of Sándor and Wedel (2005) for generating these designs by a new approach that makes it practical to generate a completely heterogeneous design where each respondent is given a unique subdesign.

Various SC applications using heterogeneous Bayesian designs have been carried out by Kessels et al. (2015a) who studied preferences for software output displays, by Kessels et al. (2015b) and Luyten et al. (2015) who studied health care related preferences and by Verhetsel et al. (2015, 2016) and Kupfer et al. (2016) who studied preferences in transport and housing. In each of these applications, the heterogeneous designs consist of two to eight subdesigns or surveys that were evenly spread over all respondents. The allocation of the choice sets to surveys, referred to as blocking, was quasi-random in

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the sense that each survey had to satisfy a similar structure of attributes whose levels were constant. The choice sets in question consisted of so-called partial profiles in order to cope with larger numbers of attributes. In the case of full profile designs, where the levels of all attributes are allowed to vary, blocking can be done fully randomly (Reed Johnson et al., 2013). Besides (quasi-)random blocking, blocking has also been done by minimizing the average correlation between an additional blocking variable and all other design attributes. This ensures that attribute level balance is maintained within each survey as much as possible. Bliemer and Rose (2011) applied such strategy for the creation of heterogeneous Bayesian designs using the choice design software Ngene (ChoiceMetrics, 2014).

Despite the dissemination of heterogeneous designs for SC experiments, homogeneous designs have still been frequently used because they are easier to generate and implement (see, e.g., Sándor and Wedel (2001, 2002); Rose et al. (2008); Hess and Rose (2009); Yu et al. (2009); Bliemer and Rose (2010), among others). Therefore, the question is raised to what extent homogeneous designs are underperforming compared to heterogeneous designs. Ain't homogeneous designs all bad? To answer this question, the estimation efficiency of a homogeneous design versus a heterogeneous design is derived and computed for various scenarios presented in a simulation study. Underlying the design generation is the Bayesian multinomial logit (MNL) design framework which provides the building blocks for many other discrete choice designs. It is described in Section 2 and the simulation study is presented in Section 3. Finally, Section 4 discusses the results and concludes.

2. The Bayesian MNL design framework

The MNL model assumes that respondents to a SC experiment belong to a target group of decision makers with homogeneous preferences. The model employs random utility theory which describes the utility that a respondent attaches to profile j ($j = 1, \ldots, J$) in choice set s ($s = 1, \ldots, S$) as the sum of a systematic and a stochastic component:

$$U_{js} = \mathbf{x}'_{js}\boldsymbol{\beta} + \varepsilon_{js}. \tag{1}$$

In the systematic component $\mathbf{x}'_{js}\boldsymbol{\beta}$, $\mathbf{x}_{js}$ is a $k \times 1$ vector containing the attribute levels of profile j in choice set s. The vector $\boldsymbol{\beta}$ is a $k \times 1$ vector of parameter values representing the effects of the attribute levels on the utility. This parameter vector is the same for every respondent. The stochastic component ε_{js} is the error term, which is assumed independently and identically extreme value distributed. Therefore, the MNL probability that a respondent chooses profile j in choice set s is the closed-form expression

$$p_{js} = \frac{\exp\left(\mathbf{x}'_{js}\boldsymbol{\beta}\right)}{\sum_{t=1}^{J}\exp\left(\mathbf{x}'_{ts}\boldsymbol{\beta}\right)}, \tag{2}$$

where $\boldsymbol{\beta}$ can be estimated using a maximum likelihood approach.

The construction of an optimal design $\mathbf{X} = [\mathbf{x}'_{js}]_{j=1,\ldots,J;s=1,\ldots,S}$ for estimating $\boldsymbol{\beta}$ in the MNL model (2) requires some form of maximization of the Fisher information matrix with respect to $\mathbf{X}$. The information matrix is defined as

$$\mathbf{M}(\mathbf{X}, \boldsymbol{\beta}) = \sum_{s=1}^{S}\mathbf{X}'_s\left(\mathbf{P}_s - \mathbf{p}_s\mathbf{p}'_s\right)\mathbf{X}_s, \tag{3}$$

with $\mathbf{X}_s = [\mathbf{x}'_{js}]_{j=1,\ldots,J}$ the submatrix of $\mathbf{X}$ corresponding to choice set s, $\mathbf{p}_s = [p_{1s}, \ldots, p_{Js}]'$ and $\mathbf{P}_s = \text{diag}[p_{1s}, \ldots, p_{Js}]$. To maximize the information content in (3), a robust design strategy is to maximize the Bayesian $\mathcal{D}$-optimality criterion or $\mathcal{D}_B$-optimality criterion, which is defined as

$$\mathcal{D}_B = \int_{\mathcal{R}^k}\log\left|\mathbf{M}(\mathbf{X}, \boldsymbol{\beta})\right|\pi(\boldsymbol{\beta})\mathrm{d}\boldsymbol{\beta}. \tag{4}$$

In this expression, $\pi(\boldsymbol{\beta})$ stands for a prior distribution of likely parameter values used to compute the probabilities p_{js} for obtaining the information matrix (3). The $\mathcal{D}$-optimality criterion, i.e. the logarithmic transformation of the determinant of the information matrix, is averaged over the prior distribution. This approach is known as the Bayesian $\mathcal{D}$-optimal design approach (Sándor and Wedel, 2001). Often, the prior distribution is the multivariate normal distribution, $\mathcal{N}(\boldsymbol{\beta}|\boldsymbol{\beta}_0, \boldsymbol{\Sigma}_0)$, with prior mean $\boldsymbol{\beta}_0$ and prior variance-covariance matrix $\boldsymbol{\Sigma}_0$. The $\mathcal{D}$-optimality criterion can be integrated over this distribution using the fast and accurate quadrature scheme by Gotwalt et al. (2009) and Gotwalt (2010) which requires only $O(k^2)$ function evaluations. The design that maximizes the $\mathcal{D}_B$-criterion is the $\mathcal{D}_B$-optimal design. Such design has been shown to perform well for a broad range of true parameter vectors $\boldsymbol{\beta}$ (Kessels et al., 2011b,c; Rose, 2011).

In practice, the $\mathcal{D}_B$-criterion value is approximated by drawing d prior parameter values $\boldsymbol{\beta}^i$, $i = 1, \ldots, d$, from $\pi(\boldsymbol{\beta})$, and computing

$$\widetilde{\mathcal{D}}_B(\mathbf{X}) = \frac{1}{d}\sum_{i=1}^{d}\log\left|\mathbf{M}\left(\mathbf{X}, \boldsymbol{\beta}^i\right)\right|. \tag{5}$$