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Random regret minimization for consumer choice modeling: Assessment of empirical evidence

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ABSTRACT

This paper introduces to the field of marketing a regret-based discrete choice model for the analysis of multi-attribute consumer choices from multinomial choice sets. This random regret minimization (RRM) model, which has recently been introduced in the field of transport, forms a regret-based counterpart of the canonical random utility maximization (RUM) paradigm. This paper assesses empirical results based on 43 comparisons reported in peer-reviewed journal articles and book chapters, with the aim of finding out to what extent, when, and how RRM can form a viable addition to the consumer choice modeler's toolkit. The paper shows that RRM and hybrid RRM–RUM models outperform RUM counterparts in a majority of cases, in terms of model fit and predictive ability. Although differences in performance are quite small, the two paradigms often result in markedly different managerial implications due to considerable differences in, for example, market share forecasts.

1. Introduction

For decades, discrete choice models have been among the most-used methods for empirical research in the broader field of marketing, retailing and consumer studies (e.g., Baltas & Doyle, 2001). They have been used to analyze and predict consumer choice behavior in a wide variety of contexts, such as related to shopping destination, store or channel choices and their choices between different products and product types (e.g., Kaplan, Bekhor, & Shiftan, 2011; Oppewal, Tojib, & Louvieris, 2013; Timmermans, Borgers, & van der Waerden, 1991; Volle, 2001) — to name just a few of the abundant body of available examples published in this journal. Practically without exception, these choice models are rooted in the Nobel-prize winning concept of random utility maximization or RUM (Ben-Akiva & Lerman, 1985; McFadden, 1973; Train, 2009).

Recently, a discrete choice model based on premises of regret-minimization has been introduced in the travel behavior community (Chorus, 2010). This so-called random regret minimization model or RRM-model is geared towards the analysis of choices made among multi-attribute alternatives in multinomial choice sets. It postulates that as long as alternatives are defined in terms of multiple attributes (which, as argued by for example Lancaster (1966) is usually the case in consumer choice settings), regret emerges from the process of trading off attribute-levels when making a decision. More specifically, the RRM-model states that regret emerges when a chosen alternative is outperformed by another alternative in terms of one or more attributes. As such, the RRM-model forms a regret-based counterpart of discrete (consumer) choice models that are based on the canonical random utility maximization (RUM). Like RUM models, the RRM model can be easily estimated (in either MNL, Nested Logit, Probit or Mixed Logit forms) using a range of (off-the-shelf) software packages.

Since its recent introduction, the RRM-model has received an increasing amount of attention from choice modelers in fields as diverse as transportation, urban planning, environmental economics and health economics (e.g., Beck, Chorus, Rose, & Hensher, 2013; Boeri, Longo, Grisolia, Hutchinson, & Kee, 2013; Chorus, Annema, Mouter, & van Wee, 2011; Guevara, Chorus, & Ben-Akiva, 2013; Hensher, Greene, & Chorus, 2013; Kaplan & Prato, 2012; Thiene, Boeri, & Chorus, 2012). The result of this increasing interest is a rapidly growing body of empirical and theoretical papers. To explore its merits most of these papers contrast the RRM model to the linear-in-parameters RUM specification that has dominated the field of choice modeling for decades.[2] Typically, differences across the two models are investigated in terms of model fit, predictive performance and/or managerial output. Results of these comparisons suggest that the RRM can be a valuable addition to the choice modeler's toolbox as it features a number of distinct and interesting behavioral properties (see A random regret minimization model of consumer choice section).

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[2] Note that the fact that we in this paper focus our attention on this most basic form of RUM-models is driven by pragmatic reasons in that – with only very few exceptions – the linear-in-parameters version of the RUM-model has been used in empirical comparisons with RRM. Of course, over time many more sophisticated RUM-models have been developed. Some of these models are discussed in the final section of this paper, and an important direction for further research would be to compare RRM with these more sophisticated RUM-models.

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The contributions of this paper are twofold. First, it introduces the RRM model to the marketing research community as an additional tool in their choice modeling toolbox. Second, and more importantly, the paper provides an assessment of the empirical literature on RRM modeling. More specifically, the recently developed body of literature in which RRM is compared with its RUM-counterpart is assessed to explore the potential and limitations of the RRM model as a consumer choice model. The overview presented in this paper consists of 43 comparisons that have been published (or are accepted for publication) in peer-reviewed international journals or scholarly books covering a wide variety of choice contexts, including – but not limited to – choices among travel alternatives, leisure activities, durable goods, dating profiles, and health care options.

Importantly, the aim of this paper is not to suggest in any way that the RRM model may replace the canonical RUM model as a model of consumer choice. In fact, our overview of results shows that differences in model fit and predictive performance between the RRM and the RUM model are often small. Yet, irrespective of the differences in fit across the two specifications, we find that the managerial implications derived from both models may vary substantially. As such, the RRM model allows the choice modeler to describe and predict a different type of behavior — supporting the view that RRM is a valuable addition to the consumer choice modeler's toolbox.

Furthermore, it should be mentioned that the idea that anticipated regret plays an important role in (consumer) decision making is by no means new. Roughly speaking, two strands of related literature in the marketing research domain can be distinguished[3]: a first body of literature (e.g., Simonson, 1992; Spears, 2006; Strahilevitz, Odean, & Barber, 2012; Taylor, 1997) develops conceptual models that usually take the form of a series of hypotheses, which are subsequently tested based on data collected by means of questionnaires or behavioral experiments. A second body of literature (Bleichrodt, Cillo, & Diecidue, 2010; Chen & Jia, 2012; Hey & Orme, 1994; Inman, Dyer, & Jia, 1997) adopts a more formal perspective as it proposes and empirically tests mathematical models of regret-based decision making, usually inspired by the seminal Regret Theory proposed in the early 1980s (Bell, 1982; Fishburn, 1982; Loomes & Sugden, 1982).

However, despite that the RRM-model is grounded in Regret Theory it differs in various ways from these previous approaches to model regret-based decision making. As will become clear in the next section, the RRM model predicts that the wish to minimize 'attribute-level' regret leads to semi-compensatory decision making and to preferences that are dependent on the composition of the choice set. As such, it makes more sense to view the RRM model as an addition to the literature on context-dependent discrete choice models (e.g., Kivetz, Netzer, & Srinivasan, 2004; Rooderkerk, van Heerde, & Bijmolt, 2011) than as a new addition to the literature on regret-based decision making. This point is further highlighted in Appendix A, where we provide a conceptual comparison with the regret based model proposed by Inman et al. (1997).

The remainder of this paper is organized as follows. A random regret minimization model of consumer choice section introduces the RRM model. Next, An overview of empirical comparisons between RRM and RUM models section presents the overview of comparisons. After that, RRM versus RUM: differences in model fit and RRM versus RUM: differences in managerial implications sections provide respectively discussions on differences between RRM and RUM in terms of model fit, predictive performance, and managerial output. Conclusions and discussion section draws conclusions and discusses how the RRM model can be used in the process of designing effective marketing strategies.

[3] An interesting finding that emerges from both bodies of empirical literature is that regret minimization is a particularly important determinant of decision making when choices are perceived by the decision maker as difficult, and important to him- or herself and/or to his or her relevant social peers (e.g. Zeelenberg & Pieters, 2007). It goes without saying that for many consumer choice situations, these conditions readily apply.

2. A random regret minimization model of consumer choice

The RRM model (Chorus, 2010) has been designed to incorporate the notion of regret-based decision making in non-risky choice models. The RRM model hypothesizes that, when confronted with a choice set, the decision-maker chooses the alternative from the set that has minimum regret. The regret of alternative i is described by the sum of binary regrets where alternative i is compared to every other alternative in the choice task on each attribute (see Eq. (1)). Regret arises when alternative i is outperformed by alternative j on attribute m. The left panel of Fig. 1 depicts the binary regret function for $\beta_m = 1$. If alternative i's relative performance on attribute m is sufficiently bad, a nearly linear regret function arises. More specifically, the right panel of Fig. 1 shows how marginal regret converges to β_m as $(x_{jm} - x_{im})$ becomes sufficiently large. From Eq. (1) it can also be observed that the total anticipated regret is the sum of anticipated regrets across all M attributes. Overall regret is increasing with the number of attributes on which alternative i is outperformed as well as with the number of alternatives by which alternative i is outperformed (as denoted by the summation over $j \neq i$), and the importance of the attribute (as denoted by β_m).

$$RR_i = R_i + \varepsilon_i = \sum_{j \neq i} \sum_{m=1}^{M} \ln\left(1 + \exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right) + \varepsilon_i \qquad (1)$$

RR_i	denotes the random (or: total) regret associated with a considered alternative i
R_i	denotes the 'observed' regret associated with i
ε_i	denotes the 'unobserved' regret associated with i
β_m	denotes the estimable parameter associated with attribute x_m
x_{im}, x_{jm}	denote the values associated with attribute x_m for, respectively, the considered alternative i and another alternative j.

Fig. 1 makes clear that marginal regret with respect to attribute m when considering alternative i approaches zero when $(x_{jm} - x_{im}) < 0$. Hence, the RRM-model postulates that when a decision maker considers alternative i as compared to alternative j he or she experiences (almost) no regret with regard to attribute m when in alternative i the mth attribute performs considerably better. Note that since Eq. (1) is a smooth approximation[4] of $max\{0, \beta_m(x_{jm} - x_{im})\}$, binary regret is not immediately equal to zero when alternative i's performance is better than that of alternative j.

Similar to the RUM framework, the functional form of the choice probabilities changes as different assumptions on the random error term ε_i are imposed. When the negative of the errors is assumed to be i.i.d. Type I Extreme Value, the classical MNL-form is obtained[5] and choice probabilities are written as in Eq. (2).

$$P(i) = \frac{\exp(-R_i)}{\sum_{j=1..J} \exp\left(-R_j\right)}. \qquad (2)$$

[4] A previous version of the RRM-function (Chorus et al., 2008) featured a combination of two max-operators. That model postulated that regret *equals* (rather than approaches) zero when a considered alternative outperforms a competing alternative on a given attribute. While behaviorally intuitive, this model suffered from the fact that due to the max-operators' discontinuities the resulting likelihood function was not globally differentiable. This implied that the model could only be estimated using custom-made code, and that elasticities and willingness to pay measures could not be obtained. The regret function proposed in Chorus (2010) and put forward in the current paper forms a smooth approximation of the 2008-model, while circumventing the econometric issues mentioned directly above.

[5] Note that one can also derive closed form expressions for RRM-choice probabilities under the assumption that the error terms itself, rather than their negatives, are distributed Extreme Value Type I. This would reframe the RRM-model as a so-called reverse discrete choice model (Anderson and de Palma (1999)). However, while still closed form, the resulting choice probability formulations are less tractable than the MNL-ones and the resulting choice models are less compatible with standard discrete choice software packages. Therefore, in this paper the assumption is maintained that the *negatives* of the errors are distributed Extreme Value Type I.