Transportation Research Part B 68 (2014) 224–238

Contents lists available at ScienceDirect

Transportation Research Part B

journal homepage: www.elsevier.com/locate/trb

A Generalized Random Regret Minimization model

Caspar G. Chorus *

Transport and Logistics Group, Delft University of Technology, Jaffalaan 5, 2628BX Delft, The Netherlands

ARTICLE INFO

Article history:
Received 11 November 2013
Received in revised form 13 May 2014
Accepted 16 June 2014

Keywords:
Random Utility Maximization
Random Regret Minimization
Choice model
Generalized Random Regret Minimization

ABSTRACT

This paper presents, discusses and tests a Generalized Random Regret Minimization (G-RRM) model. The G-RRM model is created by recasting a fixed constant in the attribute-specific regret functions of the conventional RRM model, into an attribute-specific regret-weight. Given that regret-weights of different attributes can take on different values, the G-RRM model allows for additional flexibility when compared to the conventional RRM model, as it allows the researcher to capture choice behavior that equals that implied by, respectively, the canonical linear-in-parameters Random Utility Maximization (RUM) model, the conventional Random Regret Minimization (RRM) model, and hybrid RUM–RRM specifications. Furthermore, for particular values of the attribute-specific regret-weights, models are obtained where regret minimization (i.e., reference dependency and asymmetry of preferences) is present for the attribute, but in a less pronounced way than in a conventional RRM model. When regret-weights are written as binary logit functions, the G-RRM model can be estimated on choice data using conventional software packages. As an empirical proof of concept, the G-RRM model is estimated on a stated route choice dataset as well as on synthetic data, and its outcomes are compared with RUM, RRM, hybrid RUM–RRM and latent class counterparts.

1. Introduction

Since the introduction of the Random Regret Minimization model (RRM) for discrete choice analysis (Chorus et al., 2008; Chorus, 2010), it has been acknowledged that the model provides a quite different perspective on choice modeling than does discrete choice analysis' workhorse, the linear-in-parameters Random Utility Maximization (from here on: RUM) model. Particularly, substantial differences have been highlighted in terms of the models' theoretical properties; furthermore, statistically significant – albeit usually small – differences have been found in terms of their empirical outcomes such as choice probability forecasts and elasticities (e.g., Kaplan and Prato, 2012; Thiene et al., 2012; Boeri et al., 2013; Hensher et al., 2013; Beck et al., 2013; Boeri and Masiero, 2014).

Despite – or perhaps because of – these differences, there have also been ongoing attempts to combine the RRM model with the RUM model. Two different approaches can be distinguished: a first approach has been to assume that while some attributes of alternatives are processed in an RRM-fashion, others are processed in a RUM fashion. Resulting so-called hybrid RUM–RRM models have been proposed in Chorus et al. (2013), and applied in, for example, de Bekker-Grob and Chorus (2013) and Leong and Hensher (2014). A second approach has been put forward by Hess et al. (2012) and is based on the assumption that while some – latent classes of – decision makers base their decisions on RUM-premises (for all attributes),

* Tel.: +31 152788546; fax: +31 152782719.
E-mail address: c.g.chorus@tudelft.nl

http://dx.doi.org/10.1016/j.trb.2014.06.009
0191-2615/

others use RRM-premises (for all attributes). Similar latent class RUM–RRM models have been recently presented by Hess and Stathopoulos (2013) and Boeri et al. (2014).

In this paper, a third approach to combine the RUM and RRM models is proposed: I formulate a Generalized RRM or form here on G-RRM model, which[1] nests conventional RUM and RRM models (and hybrid RUM–RRM models) as special cases. By doing so, I show that while the two models – RUM and RRM – obviously may differ substantially in terms of their properties and outcomes, they are more related to one another than is usually thought. The generalization consists of recasting a constant with value ‘1’ in the attribute-regret functions of the conventional RRM model, into a so-called regret-weight. The magnitude of the regret-weight for a particular attribute determines the degree of non-linearity of the regret function for that attribute. The extremes of 0 and 1 generate RUM and conventional RRM behavior for the attribute, respectively. Values in between 0 and 1 imply that regret is given additional emphasis in the evaluation of the attribute, but less so than in the conventional RRM model. In other words, the G-RRM model provides a flexible account of choice behavior than conventional RUM, RRM, and Hybrid RUM-RRM specifications, as it allows for various degrees of regret minimization (or: various degrees of non-linearity in the regret function). By writing the regret-weight in binary logit form, the G-RRM model can be estimated on standard choice data using conventional software packages. In other words, the regret-weight (i.e., the degree of non-linearity of the regret function) for a particular attribute can be directly inferred from choice data, together with the taste for (i.e., importance of) the attribute. Empirical applications are provided, to present a proof of concept and an illustration of the proposed model’s workings. Note that throughout the paper, and without loss of general applicability, the focus is on the Logit or MNL form of the RRM, RUM and G-RRM models.

Section 2 presents the G-RRM model, and Section 3 presents the empirical proofs of concept. Section 4 concludes with a summary of results, and a discussion of potentially fruitful directions for further research.

2. A Generalized RRM model (G-RRM)

Since the RRM model has been discussed in detail in a number of previous papers (see for example the papers cited in the introduction), it will be presented here without accompanying in-depth discussion of its model form and properties. The RRM model (Chorus, 2010) assumes that decision makers minimize regret when choosing, and that regret of a given alternative is written as follows:

$$RR_i = R_i + \upsilon_i = \sum_{j \neq i} \sum_m \ln\left(1 + \exp\left[\beta_m \cdot (x_{jm} - x_{im})\right]\right) + \upsilon_i \tag{1}$$

RR_i denotes the random (or: total) regret associated with a considered alternative i
R_i denotes the ‘observed’ regret associated with i
υ_i denotes the ‘unobserved’ regret associated with i, its negative being distributed i.i.d. Extreme Value Type I with variance $\pi^2/6$
β_m denotes the estimable taste 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

As has been widely discussed in recent papers, the main contrast between this RRM model and its linear-in-parameters RUM counterpart (written as $U_i = V_i + \varepsilon_i = \sum_m \beta_m \cdot x_{im} + \varepsilon_i$, with ε_i being distributed i.i.d. Extreme Value Type I with variance $\pi^2/6$) lies in the fact that the RRM model features asymmetric and reference-dependent preferences. More specifically, the RRM model postulates that the extent to which a change in an alternative’s attribute translates into regret depends on how the alternative performs in terms of the attribute, compared to competing alternatives. The poorer the relative performance of the alternative in terms of the attribute, the stronger is the impact of a change in the attribute’s value on regret. This reference dependent asymmetry is a direct result of the convexity of the attribute regret function which includes attributes of competing alternatives. This function is almost horizontal for (large) negative values of $\beta_m \cdot (x_{jm} - x_{im})$, implying limited sensitivity to attribute changes in that part of the domain where a considered alternative outperforms a competing alternative (i.e., the ‘rejoice’ part of the domain). The function has a slope which approaches β_m for large positive values of $\beta_m \cdot (x_{jm} - x_{im})$, i.e., in that part of the domain where a considered alternative is outperformed by a competing alternative (i.e., the ‘regret’ part of the domain). This reference dependent asymmetry (or: non-linearity) which is captured in the RRM model, by means of its convex regret function which implies a relatively high sensitivity to changes in attribute values in the regret domain (or: a strong emphasis on regret relative to rejoice), has been shown to translate into key ‘character traits’ of the RRM model such as semi-compensatory behavior and the compromise effect (Chorus and Bierlaire, 2013).

The G-RRM model proposed in this paper replaces the ‘1’ in the attribute-regret function $\ln(1 + \exp[\beta_m \cdot (x_{jm} - x_{im})])$ by a so-called regret-weight γ. By varying γ from 0 to 1, and plotting the resulting attribute regret function for $(x_{jm} - x_{im})$ ranging from -5 to 5 (keeping β_m fixed at unity), the role of the regret-weight becomes immediately clear; the left hand panel of

[1] In terms of choice probability predictions and related metrics such as elasticities, but not in terms of the Logsum as an indicator of the expected utility/regret of a choice set.