Transportation Research Part A 74 (2015) 91–109

Contents lists available at ScienceDirect

Transportation Research Part A

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

# New insights on random regret minimization models

Sander van Cranenburgh [a,*], Cristian Angelo Guevara [b], Caspar G. Chorus [a]

[a] Transport and Logistics Group, Delft University of Technology, The Netherlands
[b] Facultad de Ingeniería y Ciencias Aplicadas, Universidad de los Andes, Chile

ARTICLE INFO

*Article history:*
Received 26 July 2014
Received in revised form 24 October 2014
Accepted 28 January 2015
Available online 6 March 2015

*Keywords:*
Random regret minimization
Scale-invariance
Decision rules
Logit
Discrete choice model

ABSTRACT

This paper develops new methodological insights on Random Regret Minimization (RRM) models. It starts by showing that the classical RRM model is not scale-invariant, and that – as a result – the degree of regret minimization behavior imposed by the classical RRM model depends crucially on the sizes of the estimated taste parameters in combination with the distribution of attribute-values in the data. Motivated by this insight, this paper makes three methodological contributions: (1) it clarifies how the estimated taste parameters and the decision rule are related to one another; (2) it introduces the notion of "profundity of regret", and presents a formal measure of this concept; and (3) it proposes two new family members of random regret minimization models: the $\mu$RRM model, and the Pure-RRM model. These new methodological insights are illustrated by re-analyzing 10 datasets which have been used to compare linear-additive RUM and classical RRM models in recently published papers. Our re-analyses reveal that the degree of regret minimizing behavior imposed by the classical RRM model is generally very limited. This insight explains the small differences in model fit that have previously been reported in the literature between the classical RRM model and the linear-additive RUM model. Furthermore, we find that on 4 out of 10 datasets the $\mu$RRM model improves model fit very substantially as compared to the RUM and the classical RRM model.



## 1. Introduction

The classical[1] Random Regret Minimization (RRM) model (Chorus, 2010) is a regret-based counterpart of the canonical linear-additive RUM model (McFadden, 1974; Ben-Akiva and Lerman, 1985). A recent overview-paper (Chorus et al., 2014) shows that this model, since its recent introduction, has been used to explain and predict a wide variety of choices within and beyond the transportation-domain, such as departure time choices, route choices, mode-destination choices, activity choices, on-line dating choices, health-related choices and policy choices (e.g. Kaplan and Prato, 2012; Thiene et al., 2012; Boeri et al., 2013; Chorus and Bierlaire, 2013; Hess et al., 2014).

RRM models are built on the psychological notion that regret can be an important determinant of choice behavior (Loomes and Sugden, 1982). They postulate that decision makers choose that alternative that provides them with minimum regret. Regret is caused by the need to trade off attributes of alternatives during the decision making process. In the core of RRM models is the so-called attribute level regret function. This function maps attribute differences – between a considered alternative and a competing alternative – onto regret. As a result of the convex shape of this function RRM model postulate

* Corresponding author.

[1] To distinguish between the RRM model proposed in Chorus (2010) and the alternative RRM-models put forward in this paper, in the remainder of this paper we refer to the former as the classical RRM model.

http://dx.doi.org/10.1016/j.tra.2015.01.008
0965-8564/

that the regret generated by a loss (relative to a competing alternative's attribute) looms larger than the rejoice (i.e. the behavioral opposite of regret) generated by an equivalent gain (relative to a competing alternative's attribute). As a consequence, – unlike its RUM counterpart – RRM models feature a particular, reference-dependent type of semi-compensatory behavior.

Recently, RRM research efforts are shifting from contrasting the empirical performance of the classical RRM model relative to the linear-additive RUM model towards exploring the theoretical properties of RRM models. For instance, Prato (2013) investigates how RRM models can account for similarities across alternatives in the context of route choices; Hess et al. (2014) study the behavior of RRM-models under various formulations of the opt-out option in Stated Choice experiments; Guevara et al. (in press) shows how to estimate RRM models based of sampled choice sets; Dekker (2014) derives new insights into RRM-based VoT measures; and Dekker and Chorus (2014) discuss the potential and limitations of the RRM model for welfare economic analyses.

One theoretical property of the classical RRM model that has however not yet been addressed concerns the scale-invariance of the model. A model is scale-invariant when it takes the same mathematical form regardless of the measurement scale employed.[2] This property is important in the context of choice models as a violation of scale-invariance implies that model properties alter under rescaling of its variables. This paper shows that the classical RRM model is not scale-invariant, and discusses two important methodological implications: (1) the extent to which a classical RRM model imposes regret minimization behavior depends on the sizes of the estimated taste parameters and the distribution of attribute-values in the data; and (2) the choice of the scale parameter in the classical RRM model is consequential for the imposed choice behavior. Inspired by RUM modeling practices, in the classical RRM model it is standard practice to set the scale parameter to one. However, we will show that a different choice of the scale parameter results in a different model, as it imposes different choice behavior. At first sight, violation of scale-invariance may seem an undesirable model property. However, in this paper we show that this property can actually be exploited to enhance the performance and flexibility of RRM models, and enrich the behavioral insights they provide.

This paper makes three methodological contributions to the RRM modeling literature, each relating back to the scale-invariance property of the classical RRM model. The first methodological contribution is that we clarify how the estimated taste parameters and decision rule are related to one another. More specifically, we show that in the classical RRM model the size of a taste parameter does not only reflect its relative importance, but also determines the extent to which losses (regrets) loom larger than equivalent gains (rejoices). All else being equal, a relatively large taste parameter results in a shape of the attribute level regret function that implies that the regret generated by a loss looms substantially larger than the rejoice generated by an equivalent gain, whereas a relatively small taste parameter results in a shape of the attribute level regret function that implies that the regret generated by a loss looms only marginally larger than the rejoice generated by an equivalent gain. This reveals that the behavior imposed by the classical RRM model crucially depends on estimated taste parameters, and as such is attribute and dataset-specific.

Building on our first methodological contribution, our second methodological contribution is that we introduce the notion of "profundity of regret", and present a formal measure of this concept. The notion of profundity of regret refers to the degree of regret minimization behavior imposed by an RRM model. We show that the profundity of regret depends on the size of the estimated taste parameter in combination with the distribution of attribute values in the choice set. The proposed measure of the profundity of regret for attribute $m$, denoted $\alpha_m$, ranges from zero to one, is easy to compute after having estimated an RRM model, and allows for comparability within and across estimated models. Finding $\alpha_m$ close to one indicates that – with regard to attribute $m$ – the estimated RRM model has imposed very strong regret minimization behavior (i.e. the regret generated by a loss looms considerably larger than the rejoice generated by an equivalent gain). On the other hand, finding $\alpha_m$ being close to zero indicates that the RRM model has imposed almost no regret minimization behavior (i.e. the regret generated by a loss looms only marginally larger than the rejoice generated by an equivalent gain). We show that insight into the profundity of regret is of crucial importance for the correct interpretation of estimation results of RRM models.

The third methodological contribution of this paper – which is motivated by the observation that in the classical RRM model the size of the scale parameter is consequential for the imposed behavior – is that we propose two new family members of random regret minimization models: the $\mu$RRM model, and the Pure-RRM. The Pure-RRM model, henceforth abbreviated as P-RRM model, postulates the strongest regret minimization behavior which is possible within the RRM modeling paradigm. The $\mu$RRM model is a generalization of the classical RRM model. It has the scale parameter $\mu$ as an additional degree of freedom. Given that: (1) in discrete choice models the size of the scale parameter and the size of the taste parameters are inversely related to one another, and (2) the size of the estimated taste parameter determines the extent to which losses (regrets) loom larger than equivalent gains (rejoices), the $\mu$RRM model accommodates for different shapes of the attribute level regret functions, and as such for different degrees of regret minimization behavior. We show that the $\mu$RRM model has three special cases: (1) if $\mu$ is insignificantly different from one, then the classical RRM model (Chorus, 2010) is obtained; (2) if $\mu$ is arbitrarily large, then the resulting model does not impose random regret minimization behavior (hence $\alpha_m = 0\ \forall m$). In this special *limiting* case the $\mu$RRM model exhibits linear-additive RUM behavior, i.e. it predicts exactly the

[2] More formally: $f(x)$ is scale-invariant if $f(\lambda x) = \lambda^{\Delta} f(x)$, for some choice of $\Delta$ and for all dilations $\lambda$.