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Context-driven regret-based model of travel behavior under uncertainty: a latent class approach

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Abstract

Understanding variability in observed travel behavior has been one of the major research topics in travel behavior analysis and travel demand modeling. Differences in outcomes of travel decisions can be attributed to observed and non-observed differences between travelers and different situations and contexts in which decisions are made. The majority of studies in transportation research have estimated the effects of observed socio-demographic profiles on choice probabilities under certainty. Unobserved heterogeneity in utility functions has been typically examined using mixed logit or latent class models. The focus of the current paper concerns the effect of context and personality traits on decision-making under uncertainty, a combination of factors that has received not much attention in transportation research to date. Using route choice in an activity context as an example, we estimate a latent class random regret-minimization model, which takes into account the travel time and therefore arrival time uncertainty that people face when making route choice decisions. In addition, it incorporates the effects of personality traits, socio-demographic profiles and contextual factors, which increase or decrease travelers' feelings of regret. The model is estimated based on a stated choice experiment, which was administered through a Web-based survey. Results suggest the existence of three latent classes underlying differences in regret-driven choice behavior.

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Keywords: heterogeneity; regret; context; uncertainty; socio-demographics

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1. Introduction

There is a growing body of literature that recognizes the pivotal role of behavioral mechanisms and processes in understanding and predicting activity-travel choices. A multitude of theories and models, derived from social sciences and behavioral economics, have been formulated to better understand travel-related decisions. This amount of effort does not come as a surprise, since the decision process that individuals go through each time they make a choice, is potentially complex in nature and involves anticipated situations, feelings, and particular decision-making strategies. Therefore, it is essential for any behavioral model to try and capture the core principles, mechanisms and conditions, affecting the decision making process.

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The present paper focuses on the random regret minimization model, which has emerged in travel demand modelling as an alternative to utility maximization as the dominant decision principle. Regret arises when an individual experiences the chosen alternative and realizes that a higher payoff could have been achieved if a foregone alternative had been chosen. It has been shown in various studies that (anticipated and experienced) regret highly affect decision making in both risky and riskless choices (e.g., Zeelenberg and Pieters, 2007). Random regret minimisation models have been applied to a range of choice problems, including travel choice (Chorus et al., 2008b), leisure-related decision-making (Thiene et al., 2012), driver crash avoidance maneuvers (Kaplan and Prato, 2012), automobile fuel choice (Hensher et al., 2013) and shopping center choice behavior (Rasouli and Timmermans, 2016; Jang, 2016). These studies show small, albeit significant, differences in model fit between the two models, the best fitting model depending on the specific dataset. In general, the choice between the two models is driven by different factors, including choice context, dataset and framing of the survey (Hess et al., 2014). Specifically for this study, we contend that the importance of regret in the decision-making process depends on the choice context. Our study intends to highlight cases in which minimization of anticipated regret is particularly important. These cases relate to the activity that needs to be conducted and the nature of the relationship of the decision-maker with the persons who will be met to conduct the activity.

Several key factors should be considered when modelling activity-travel decisions. First, since urban transportation systems are in a constant state of flux, decision makers face uncertainty about travel times, delays, etc. Various studies have provided empirical evidence that travel time uncertainty strongly influences travel behaviour (e.g., Noland and Polak, 2010; Hensher et al., 2011). Thus, modelling decision-making under uncertainty is of paramount importance for route choice decisions. Second, as highlighted in Ben-Akiva et al. (2012), more emphasis should be put on explicitly modelling the choice context and process. Third, individual differences may also influence decision-making. Several studies in psychology (e.g. de Bruin et al., 2007) emphasize how people's choice behavior co-varies with socio-demographics. In addition, personality traits and attitudes may play a significant role (Hurtubia et al., 2014). Moreover, Hensher (2008, 2009), Zhu and Timmermans (2010) and others have highlighted the importance of allowing for heterogeneity in decision-making strategies. Particularly, there is a growing interest in the application of latent class modelling, as an alternative approach to the mixed logit model, to represent respondent heterogeneity (e.g., Boxall and Adamowicz, 2002; Back-Jin et al., 2003; Greene and Hensher, 2003) and differences in decision making processes (e.g. Hess et al., 2012).

In this paper, we examine heterogeneity and context dependency in the context of regret-based choice models. The model accounts for conditions of uncertainty and the analysis aims at the probabilistic assignment of respondents to latent classes, which differ in terms of their regret functions and observed and non-observed personal characteristics, dependent upon choice context. Particularly, we analyse whether travellers anticipate varying degrees of regret associated with their route choice decisions, dependent upon the activity that is involved and their relationship with the people with whom they conduct the activity.

In the remainder of this paper, we first derive the formulated random regret-minimizing model. Next, the data collection process and sample characteristics, including the details of the stated choice experiment that was administered to investigate the choice problem of interest are reported. This is followed by a discussion of the results of the estimated regret-minimizing latent class model. Both the estimated coefficients of the regret function and the class membership function are discussed. The paper is completed with discussion of main conclusions. Due to the limited available page number, the discussion is necessarily relatively condensed.

2. The random regret minimization model

Consider the decision problem of individual n which route $i \in I$ to choose to conduct a particular activity at a particular destination. Because travel times of routes and, therefore, arrival times vary, this is a decision-making problem under uncertainty. Let X_i denote the arrival time of route i. $X_i > 0$ denotes early arrival times, while $X_i < 0$ represents late arrival times. Assume X is stochastic, formalized in terms of a set of discretionized states $X_{i(j)}, j = 1,2, \ldots J$. Each state represents an arrival time interval.

Regret has been introduced recently as a central concept in modeling choice behavior under uncertainty (Chorus et al., 2008a). Different operational definitions have been suggested (Chorus 2010; Chorus 2014; van Cranenburgh et al., 2015). In this particular study, we focus on regret that is related to late arrival. We realize that (very) early arrival may also induce regret, but we leave this to future analysis. Regret is defined in terms of the attribute differences between the chosen alternative and all non-chosen alternatives. More specifically, considering the uncertain arrival times, the regret that individual n anticipates by choosing route i is defined as:

$$R_{ni} = \sum_{i' \neq i}^{I} \sum_{i(j)}^{J} \sum_{i'(j)}^{J} \max \left\{ 0, \beta \left[p_{(i,j)} p_{(i',j)} \left(X_{(i',j)} - X_{(i,j)} \right) \right] \right\} \tag{1}$$

Note this regret function sums the regret related to a comparison of the chosen and a non-chosen, foregone alternative, weighted by the joint probability of the states of the arrival times for this pair of routes considered across all pairs of choice alternatives. Regret for each pair of routes is equal to difference in arrival times multiplied by a regret weight if the non-chosen route outperforms the considered route, and zero otherwise.

We allow the amount of regret to vary according to observed characteristics of the travellers and decision context. Let $\mathbf{Z}_n$ be a vector describing personal characteristics of individual n, and $\mathbf{C}_t$ be a vector of attributes, representing decision context t. We assume these effects of decision context and personal characteristics are not invariant, but rather depend on the expected arrival time of the considered route. This notion is captured in the following specification of the regret function:

$$R_{ni} = \sum_{i' \neq i}^{I} \sum_{i(j)}^{J} \sum_{i'(j)}^{J} \max \left\{ 0, \beta \left[p_{(i,j)} p_{(i',j)} \left(X_{(i',j)} - X_{(i,j)} \right) \right] \right\} - \mathrm{E}(X_i)\mathbf{Z}_n\boldsymbol{\gamma} - \mathrm{E}(X_i)\mathbf{C}_t\boldsymbol{\varphi} \tag{2}$$

The parameter vectors $\boldsymbol{\gamma}$ and $\boldsymbol{\varphi}$ express effects proportional to the difference between the expected and the scheduled arrival time. If the expected arrival time of the considered route is earlier than the scheduled arrival time, the amount of (anticipated) regret induced by not choosing the fastest route is reduced. Otherwise, early arrival compensates for regret. Vice versa, late expected arrival time of the considered route increases regret. This specification also implies that these effects are assumed symmetric for early respectively late expected arrival times. The interactions with decision context and personal variables indicate that we assume these compensating respectively magnifying effects of arrival times of the considered route are proportionally increased or reduced by the decision context and personal variables.

Latent class analysis allows the identification of more homogeneous latent classes, with different regret parameters. A deterministic allocation of an individual to a class is not possible since classes are latent, i.e. unobserved, meaning that the analyst does not know which observation belongs to which class. For this reason, membership probabilities are defined, according to a multinomial logit specification. In this study, we assume that non-observed personality traits and a set of socio-demographic characteristics of individuals can be used to explain class membership probabilities. Once the regret function of each choice for each latent class and the probability of belonging to each class are known, choice probabilities equal the weighted sum of choice probabilities across the classes with the class allocation probabilities being used as weights.

3. Data collection and sample characteristics

3.1 Data collection: the stated choice experiment

The data used for this study were collected in March 2015 through a Web-based survey. Respondents were recruited from the larger Rotterdam area in the Netherlands. The sample used for model estimation includes 693 respondents. Regarding the profile of respondents, more than half of the sample is female (60%). The majority of the sample belongs to the middle-aged group (36-65), while about 24% is between 18-35 years old and about 15% is older than 65 years of age. Regarding the marital status of the respondents, singles or couples without children constitute almost

67% of the sample, while 25% is either single or belongs to a couple with children. Almost half of the sample (45%) has a higher level of education or a university degree, while around 41% has middle general or middle vocational education. The rest has primary or lower level education. Just over half of the sample has an income between 625 and 1875 euros/month. Around 37% of the sample has an income over 1875 euros/month, while the rest has no or a low income below 625 euros/month. The majority of the respondents has a driving license (76%). Around 68% has more than 5 years driving experience, 5% has a driving experience between 2-5 years and less than 1% has a driving experience of less than 1 year. Most respondents (45%) use the car as their main means of transport, 40% are mostly bike or motorbike users and the remaining 15% are mainly public transport users.

As discussed, we assume that decision-making under uncertainty may depend on personality traits. Therefore, in addition to the questions about the socio-demographic profile of respondents, respondents were asked to complete a series of 20 items to measure their personality. The items involve statements about anticipated feelings of regret in human behavior in general and in travel behavior in particular. A six-point Likert scale, ranging from "strongly disagree" to "strongly agree" was used to measure the strength of agreement/disagreement with these items.

The third part of the data collection is a stated choice experiment, which addresses the choice of route, when driving a car, under conditions of uncertainty and varying contexts. Both the expected arrival times and the decision context systematically varied in the experiment. Decision context varied in terms of the kind of activity that the individual plans to conduct, the relationship with the people involved and the number of these people. For a specific combination of these context variables, respondents were asked to choose between three routes that varied in terms of arrival time. The uncertainty in the arrival times was represented in terms of the relative frequency of historical arrival times related to the routes. The design involved an orthogonal fractional factorial design, consisting of 128 profiles. The experiment was orthogonally blocked into 8 sets of 16 choice tasks each. The profiles were randomized within the blocks and blocks were randomly assigned to respondents.

4. Model estimation and results

4.1 Exploratory factor analysis

Before estimating the model, first the scale for measuring personality traits was validated and the scores of the respondents on the different traits were calculated. To validate the scale, an exploratory factor analysis of the 20 different items was conducted using varimax rotation and Kaiser normalization. A factor loading higher than 0.60 was used as a threshold. After removing some of the items, the EFA identified three factors with an eigenvalue of at least 1. Factor 1 includes statements that seem to reflect the importance of being on time and not making others wait. Factor 2 captures the negative feelings of worry and anxiety when making choices. Finally, factor 3 seems to consist of the items that reflect regret and risk aversive behavior.

4.2 Estimation results of the latent class regret-minimization model

The regret minimization model, outlined in section 2, was estimated using the responses to the stated choice experiment. To that end, some further operational decisions were made. First, to acknowledge the stochastic nature of the regret function, an error term was added to the regret function. In line with earlier research on regret-based models, it is assumed that the error terms are independently and identically Gumbel distributed across individuals, choice alternatives and decision contexts. The principle of regret-minimization then leads to a logit-type choice model with minus regret as the argument. Second, a decision was made with respect to the inclusion of alternative specific constants. Usually, these constants are estimated to reflect any inherent preferences for choice alternatives, not captured by the explanatory variables of the model. Because we used generic routes in the stated choice experiment, it is difficult to defend the inclusion of constant for that reason. However, as discussed in Hensher et al. (2015), respondents completion of stated choice tasks may exhibit experimental bias, for example because more attention is paid to the first choice alternative. Failure to account for such response patterns may bias the remaining parameter estimates. Therefore, to account for such effects, alternative-specific constants were estimated. Finally, all decision context variables and socio-economic characteristics were effect coded.

To examine heterogeneity in regret, a latent class regret-minimization model was estimated. Because the effects of the number of people turned out to be insignificant, only the results of the other two decision context variables are reported. The latent class parameters were estimated using the method of maximum likelihood estimation. Table 1 presents the goodness of fit for the estimated latent class models up to four classes. The log-likelihood values at convergence and rho-squared statistics indicate the goodness-of-fit of the model and show improvement as the number of classes increases up to three. This finding confirms the existence of heterogeneity in the sample. In order to identify the optimal number of latent classes, the AIC values of the various models were compared and the solution with the minimum value was chosen. Based on this outcome, in the remainder of the paper, the results of the model with three latent classes are reported. For the sake of comparison, the three class model using a classic utility function was also estimated. Results, presented in Table 1, confirm that the regret-based model performs better than the utility-maximizing model in describing stated route choice behavior, at least for this specific sample.

Table 1. Statistics for the latent class regret minimization model

No of Classes	No of parameters	Log-likelihood	Restricted Log-likelihood	R^2	Adj. R^2	AIC/N
1	22	-7437.608	-10373.1	0.2673	0.2651	1.580
2	56	-6971.2042	-10373.1	0.328	0.3260	1.488
3	**90**	**-6896.8366**	**-10373.1**	**0.3351**	**0.3319**	**1.480**
4	124	-6871.0969	-10373.1	0.3376	0.3320	1.482
Utility maximizing model						
3	90	-6982.7733	-10373.1	0.3268	0.3236	1.498

The parameter estimates of the three-classes model and their significance are presented in Table 2. Note that the coding of the arrival times, combined with the minus sign in the regret function for the interaction terms and the use of effect coding for the decision context and socio-demographic variables means that negative estimated parameters for the categories of the decision context and socio-demographic variables indicate that the regret of that category, *compared to the average of the corresponding variable*, reduces the regret that is due to differences in expected arrival times of the considered route and all alternative routes across all late expected arrival times of the considered route and increases regret across all early arrival times of the considered route. Vice versa, positive estimated parameters for the categories of the decision context and socio-demographic variables indicate that the regret of that category, compared to the average of the corresponding variable, increases the regret across all late expected arrival times of the considered route and decreases regret across all early arrival times of the considered route.

Table 2 shows that most alternative specific constants are significant and most negative for the first alternative for all the classes, indicating that, everything else being equal, respondents are biased to select the first alternative more often than the other two choice alternatives. The estimated parameter for the regret weight suggests that regret of the choice of a particular route increases in all three latent classes with an increasing probability of a later arrival time of the chosen route compared to the arrival times of the non-chosen routes. Regret decreases with increasing earlier expected arrival time of the chosen route compared to the expected arrival times of the non-chosen routes.

As for the effects of the decision context variables, Table 2 shows that, in class 1, having dinner at a restaurant causes notably more regret upon a late arrival, relative to the average across types of activities. Thus, it seems people are more relaxed when the dinner appointment is not in a public location. As for dinner at home, the estimated parameter is negative, but not significant. The estimated effects for dinner are not significant in classes 2 and 3, but in contrast to class 1 the estimated effect of dinner at home is significant for the other two classes. Going to the cinema and watching a sports game have a positive and significant effect in all classes, implying that when the activity type has a pre-determined start time, people are more likely to feel regret if they arrive late. Conversely, when the activity type is shopping, we notice that respondents in all classes are less sensitive to regret compared to the other type of activities, upon a later arrival, especially in the first class, where the (absolute) value of the parameter is higher. Likewise, the estimated parameter for going to a public discussion, is negative and not significant, highlighting that such events do not invoke much regret if the route chosen does not turn out to be the best after all. As for the variable referring to the relationship with the people that will be met, the results show that people belonging to class 1, followed by class 2, are more sensitive to regret if they are going to meet close friends, while in class 3, meeting colleagues or acquaintances seems to have stronger effect on people's feeling of regret.

Table 2. Results for LCM.

		Latent Class 1		**Latent Class 2**		**Latent Class 3**	
		Coeff	*z*	*Coeff*	*z*	*Coeff*	*z*
Constant (alternative 1)		-0.4928	7.39	-0.7139	10.85	-0.9143	9.45
Constant (alternative 2)		0.0810	-1.13	-0.3422	4.46	-0.6009	5.05
Regret part of the total regret component							
Expected arrival time		0.7058	9.69	0.2506	5.48	0.1379	3.60
Utility part of the total regret component							
Attribute	Attribute level						
Activity type* Expected arrival time	Dinner at restaurant	0.1302	3.45	-0.0250	-0.86	0.0307	0.84
	Dinner at a house	-0.0226	-0.73	-0.0433	-1.91	-0.0731	-2.15
	Cinema	0.0508	1.50	0.0526	1.77	0.1970	3.84
	Watch sports game	0.0192	0.63	0.0402	1.60	0.0951	2.39
	Public Discussion/ seminar	-0.0125	-0.44	-0.0296	-1.31	-0.0002	0.00
	Volunteer work	0.0190	0.58	0.0886	2.80	-0.0729	-2.29
	Shopping	-0.1311	-5.23	-0.0781	-3.41	-0.0826	-2.29
	Feast/event day	-0.0530	-	-0.0055	-	-0.0941	-
Relationship with people* Expected arrival time	Close friends	0.0482	2.31	0.0263	1.32	-0.0587	-2.42
	Colleagues	-0.0156	-0.71	-0.0297	-1.68	0.0301	1.14
	Relatives	-0.0084	-0.40	0.0252	1.28	-0.0118	-0.46
	Acquaintances	-0.0242	-	-0.0218	-	0.0404	-
Age*Expected arrival time	18-35	-0.1341	-4.79	-0.2096	-6.04	-0.0557	-2.60
	36-65	-0.0169	-0.67	0.1131	5.37	-0.2001	-7.23
	>65	0.1509	-	0.0965	-	0.2558	-
Education*Expected arrival time	Primary, Lower vocational	-0.0667	-3.38	-0.0887	-2.94	-0.0593	-2.20
	Middle general, middle vocational	0.0381	2.32	0.0413	2.24	0.0420	1.94
	Higher general, higher vocational, University degree, other	0.0286	-	0.0475	-	0.0173	-
Years of driving experience*Expected arrival time	<1 years	1.2667	4.36	-0.1720	-1.67	0.1986	1.25
	2-5 years	-0.5097	-4.81	0.8062	3.76	-0.0544	-0.90
	>5 years	-0.3381	-3.49	-0.2864	-3.94	-0.0795	-1.43
	no experience	-0.4189	-	-0.3478	-	-0.0648	-
Mainly used means of transport*Expected arrival time	Car	0.0241	1.19	-0.0126	-0.66	0.0453	1.96
	Bike/motorbike/other	0.0772	3.99	0.0471	2.78	0.0318	1.40
	Bus/ train	-0.1013	-	-0.0345	-	-0.0771	-

As for the effect of socio-demographic variables, noticeably, the negative and highly significant parameters show that the younger age group is less sensitive to regret across all classes. The middle-aged group in class 2 mostly feels regret upon a late arrival The parameter estimates for the elderly are positive for all classes, revealing that people belonging in this age group will regret their choice if it turns out to be outperformed by another alternative. Education is one of the variables with significant effects in all latent classes and across all its categories. Particularly, people with a low level of education show the least sensitivity in all segments, while those with a middle or higher education level exhibit the highest sensitivity to regret. Having less than 1 year of driving experience, significantly increases the amount of regret in class 1, while in class 2, people with driving experience between 2 to 5 years tend to feel the highest regret upon late arrival time. For those with more years of experience in class 1, the feeling of regret is less strong. The results for class 3 are similar to those for class 1. Finally, results for bike and motorbike users in classes 1 and 2 indicate that these groups feel higher regret than the car users, if they choose a route taking them to the destination later then the scheduled time. The same effect is noted for car drivers in class 3, whereas public transport users feel less regret in all the classes, probably because they depend on others for their arrival time and do not have much control if there is a delay when using bus or train for instance.

Table 3 lists the results for the class membership variables. On the whole, latent class 1 contains 55% of the cases, latent class 2 contains 28% and the remaining 17% belongs to the class 3. The last class is used as a reference level. The constants of the model show that respondents are more likely to belong to class 1. Considering attitudinal factors, respondents belonging to class 1 and 2, consider as highly important to be on time for an appointment and tend to have a regret and risk-aversive behaviour. By contrast, respondents in class 3 tend to be indifferent, confirming that individuals in this class, in most decision contexts, show the smallest and least significant amount of regret. Remarkably, the parameter value for the expected arrival time in this class is, although positive and significant, much smaller compared to the parameters of the first two classes. To proceed with socio demographics, females tend to dominate classes 1 and 2, while class 3 mostly consists of men, although gender does not show any significant effect on defining classes. Middle-aged people are the most probable members of class 1 and 2. Young people are significantly less likely to belong to class 2. Class 3 mainly consists of young and elderly people. As for education, highly educated people belong mostly to class 2, while less educated people seem to belong to class 3, which is in line with the results about the decreased feeling of regret of this category of people. The possession of a driving licence decreases the probability of belonging to the first and second class and increases the probability of belonging to the third class. As for the mainly used means of transport, the estimated parameters are not significant.

Table 3. Results for LCM for class membership parameters.

Attribute	Attribute level	Latent Class 1		Latent Class 2	
		Coeff	*z*	*Coeff*	*z*
	Constant	1.8753	4.27	0.6955	1.49
Psychometric indicators	Time pressured	1.2102	5.13	0.5737	2.4
	Anxious and worried	0.2433	1.18	0.285	1.21
	Regret averse	0.8623	3.72	0.6593	2.56
Gender	Male	-0.1776	-0.88	-0.2864	-1.27
	Female	0.1776	-	0.2864	-
Age	18-35	0.0055	0.02	-1.5631	-3.72
	36-65	2.0583	5.64	2.1738	5.74
	>65	-2.0638	-	-0.6107	
Education	Primary, Lower vocational	-0.0244	-0.06	-1.1816	-2.41
	Middle general, middle vocational	0.3866	1.21	0.7651	2.18
	Higher general/ vocational, University degree, other	-0.3623	-	0.4165	-
Driving licence	Yes	-1.0406	-2.65	-0.8943	-2.23
	No	1.0406	-	0.8943	
Mainly used means of transport	Car	0.0656	0.21	-0.4183	-1.18
	Bike/motorbike/other	-0.8598	-2.55	-0.242	-0.69
	Bus/ train	0.7942	-	0.6603	-

5. Conclusions

This paper has reported the formulation and estimation of a latent class regret minimization model of route choice behaviour under uncertainty, accounting for heterogeneity and context-dependency. It should be emphasized that this is work in progress and that specific issues and alternatives will be explored in further research efforts. The specific focus of attention in this model is on regret induced by late arrival. The experimental settings for early arrival are such that regret associated with differences in early arrivals is ignored. This assumption should be tested in future research. The same holds true for the assumed symmetric effect of contexts and personality traits for the earlier respectively later arrival time. Keeping possible future improvements in mind, results of the present model indicate that the route choice behavior of the sample is described significantly better by assigning respondents to three latent classes, with different regret parameters. The attempt to define class membership as a function of personality traits, decision context and socio-demographic characteristics of the sample seems to enhance the understanding of the choices made.

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