Choice Tutorial 12: Using Latent GOLD choice to Estimate Random Regret Minimization-based Discrete Choice Models

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In this tutorial you will learn to estimate Random Regret Minimization models. Specifically, in this tutorial you will:

- Estimate a RRM2010 model and interpret its results
- Estimate a μRRM model and interpret its results
- Estimate Latent class model comprising of two or more μRRM classes
- Explore which of these models provides the best fit to the data using the BIC statistic

1 The Data

Latent GOLD Choice accepts data from an optional 1-file or its default 3-file structure from an SPSS .sav file, a Sawtooth .cho file, or ASCII rectangular file format. The current sample data is in a SPSS save file named 'Shopping_data_LG.sav.'

The data contain 1,503 Revealed Preference (RP) shopping location choices from 1,074 consumers who went shopping with the aim to buy groceries (see Arentze et al. 2005 for more details). Each alternative is defined by three attributes: 'Floor Space Groceries' (FSG), 'Floor Space Other' (FSO), and Travel Time (TT) to reach the shopping location. Choice sets are imputed to contain the chosen alternative and 4 non-chosen alternatives.

Table 1 lists the variables in the data set. Furthermore, Figure 1 provides histograms showing the distribution of the three attribute levels:

Variable	*Explanation*
CASEID	Identifier of the respondent
SETID	Identifier of the choice set
CHOICE15	Choice
Alternative	Identifier of the alternative in the choice set
FSG	Floor Space Groceries
FSO	Floor Space Other
TT	Travel Time
CHOICE01	Choice (dichotomous)

Table 1: Description of the data set

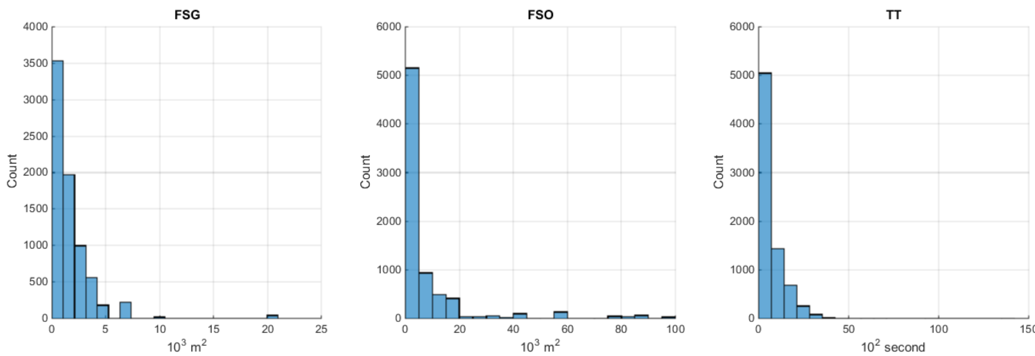


Figure 1: Attribute level distribution

2 The Goal

The goal is develop insights on the shopping location choice behaviour of the respondents. That is, we wish to acquire understanding on how the respondents traded-off FSG, FSO and TT.

To do so, first we estimate discrete choice models based on different decision rules. Specifically, we estimate a RRM2010 model (Chorus 2010) and the recently proposed more flexible μRRM model (Van Cranenburgh et al. 2015). Furthermore, decision rule heterogeneity may be present. That is, not all respondents may adopt the same decision rule; rather, different respondents may adopt different decision rules when making shopping location choices. For instance, the choice of one class of respondents may be more consistent with a utility maximization decision rule, while the choices of another class may be more consistent with regret minimization decision rules. We therefore estimate LC class models, where the classes represent different decision rules.Finally, we assess which model best describes the choice processes in the data using the BIC statistic.

3 Setting up the analysis

- First, open the data file: File → Open → browse to the working directory
- Select 'Shopping_data_LG.sav'
- Right-click on Model1, and choose 'Choice'. The Model Analysis Dialog Box opens (Figure 2)

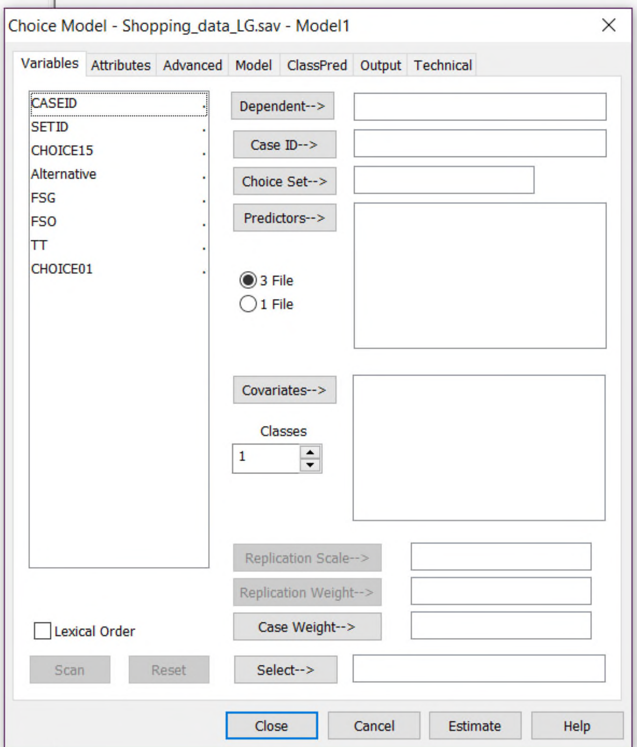


Figure 2: Model Analysis Dialog Box

- Select each variable and move it to the appropriate box by clicking the buttons to the left of these boxes. That is:
    - Move CHOICE01 to Dependent
    - Move CASEID to Case ID
    - Move SETID to Choice Set

- Tick '1 File' to indicate that all the data can be found in a single data file. See the LG User Guide for more details on the data file and formats (Vermunt and Magidson 2005).

- Open the Attributes tab by clicking on 'Attributes' at the top of the setup screen. The Attributes Dialog Box opens (Figure 3).

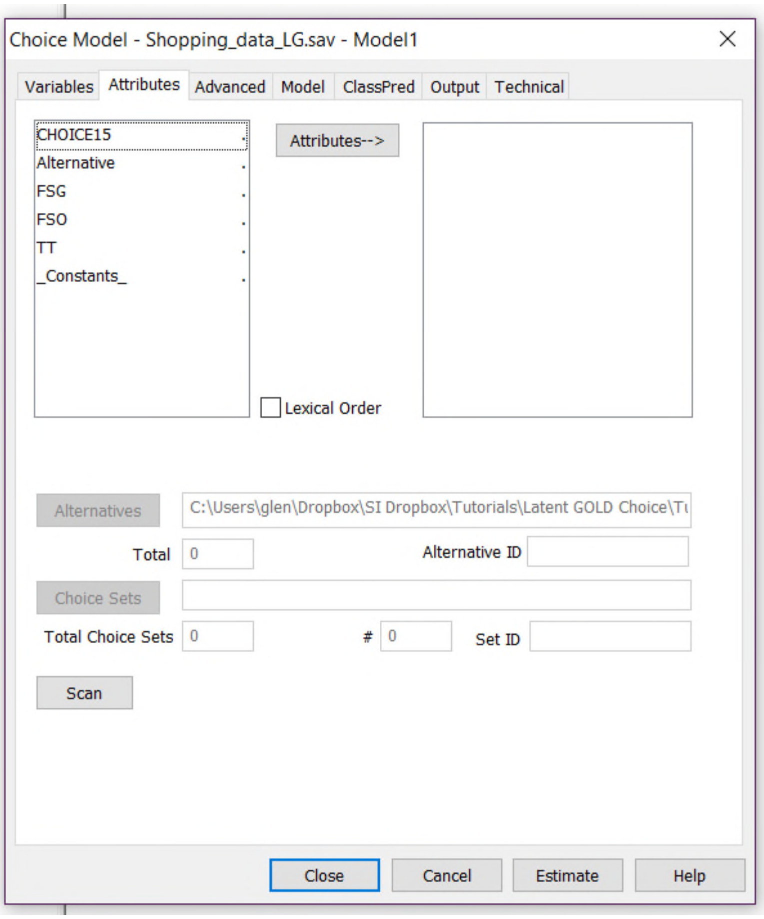


Figure 3: Attributes Dialog Box

- Select each attribute (FSG, FSO, and TT) and move them to the Attribute list box by clicking the buttons to the left of these boxes.
    - Move FSG to the Attributes box
    - Move FSO to the Attributes box
    - Move TT to the Attributes box

4 Single class models

Now that we have specified the data for analysis, we are ready to estimate discrete choice models. We first will estimate a (1-Class) linear-additive RUM model. This model serves as the baseline model. After that, we estimate a (1-Class) RRM2010 model, and a (1-Class) µRRM model. And finally, we will estimate Latent Class models.

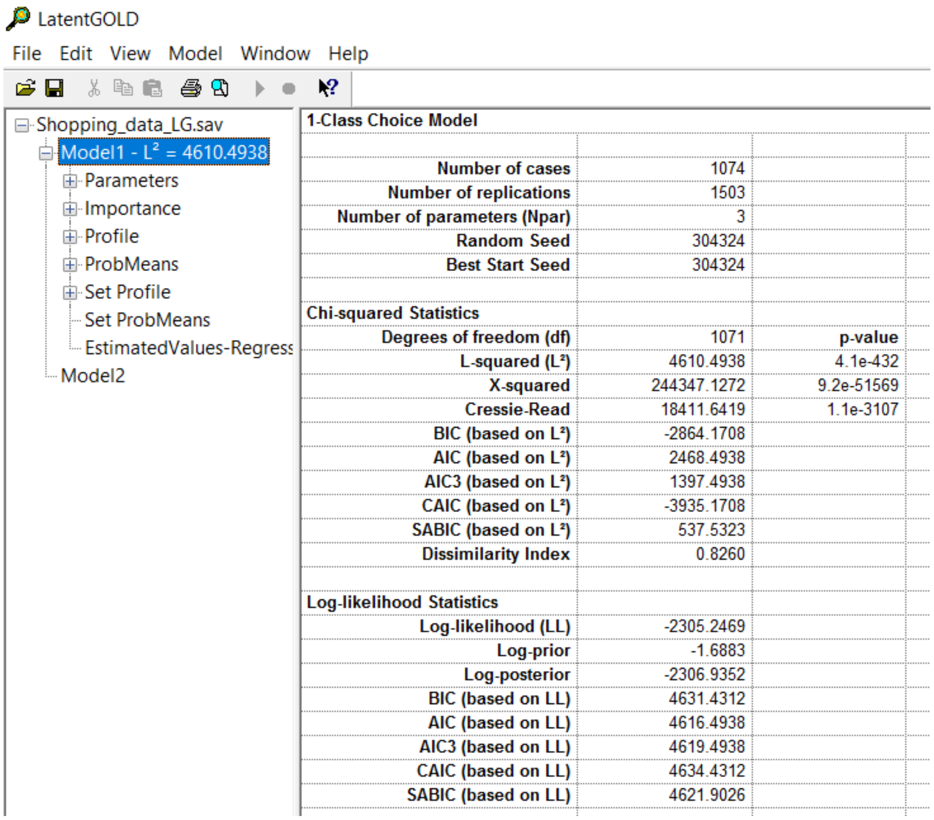
- In the ’Variables’ Tab set the number of classes to ‘1’

4.1 Estimating a linear-additive RUM model

By default, Latent Gold Choice estimates a model using a linear-additive RUM specification.

- Click Estimate (located at the bottom right of the analysis dialog box).

The setup window now closes and LG starts the estimations. When Latent GOLD Choice completes the estimation a list of various output files appears in the Content pane, see Figure 4 below where Model 1 is associated with L^2 = 4610.4938.



1-Class Choice Model		
Number of cases	1074	
Number of replications	1503	
Number of parameters (Npar)	3	
Random Seed	304324	
Best Start Seed	304324	
Chi-squared Statistics		
Degrees of freedom (df)	1071	p-value
L-squared (L^2)	4610.4938	4.1e-432
X-squared	244347.1272	9.2e-51569
Cressie-Read	18411.6419	1.1e-3107
BIC (based on L^2)	-2864.1708	
AIC (based on L^2)	2468.4938	
AIC3 (based on L^2)	1397.4938	
CAIC (based on L^2)	-3935.1708	
SABIC (based on L^2)	537.5323	
Dissimilarity Index	0.8260	
Log-likelihood Statistics		
Log-likelihood (LL)	-2305.2469	
Log-prior	-1.6883	
Log-posterior	-2306.9352	
BIC (based on LL)	4631.4312	
AIC (based on LL)	4616.4938	
AIC3 (based on LL)	4619.4938	
CAIC (based on LL)	4634.4312	
SABIC (based on LL)	4621.9026	

Figure 4: Estimation Results in Content Pane

4.2 Estimating a RRM2010 model

Random regret minimization models postulate that decision makers, when choosing, experience regret when a competitor alternative *j* outperforms the considered alternative *i* with regard to one or more attributes *m*. The overall regret of an alternative is conceived to be the sum of all the pairwise regrets that are associated with bilaterally comparing the considered alternative with the other alternatives in the choice set. Decision makers are assumed to choose the minimum regret alternative (see Chorus 2012 for a more detailed explanation).

The mathematical form of RRM models is given in Equation 1, where RR_{in} denotes the random regret for decision maker *n* considering alternative *i*, R_{in} denotes the observed part of regret, and ε_{in} denotes the unobserved part of regret.

$RR_{in} = R_{in} + \varepsilon_{in} \text{ where } R_{in} = \sum_{j \neq i} \sum_{m} r_{ijmn}$	**Equation 1**

In the core of RRM models is the so-called attribute level regret function: $r_{ijmn} = f\left(\beta_m, x_{jmn} - x_{imn}\right)$. This function maps the difference between the attribute levels of attributes *m* of the competitor alternatives *j* and the considered alternative *i* onto regret. Note that in our notation β_m denotes the taste parameter (to be estimated) associated with attribute *m* (e.g. travel time) and x_{jmn}, x_{imn} denote, respectively, the attribute level of alternative *j* and *i* for attribute *m*. Different specifications of the attribute level regret function lead to different types of random regret models (see Van Cranenburgh and Prato 2016 for an overview).

The attribute level regret function of the RRM2010 model proposed by Chorus (2010) is depicted in Figure 5.

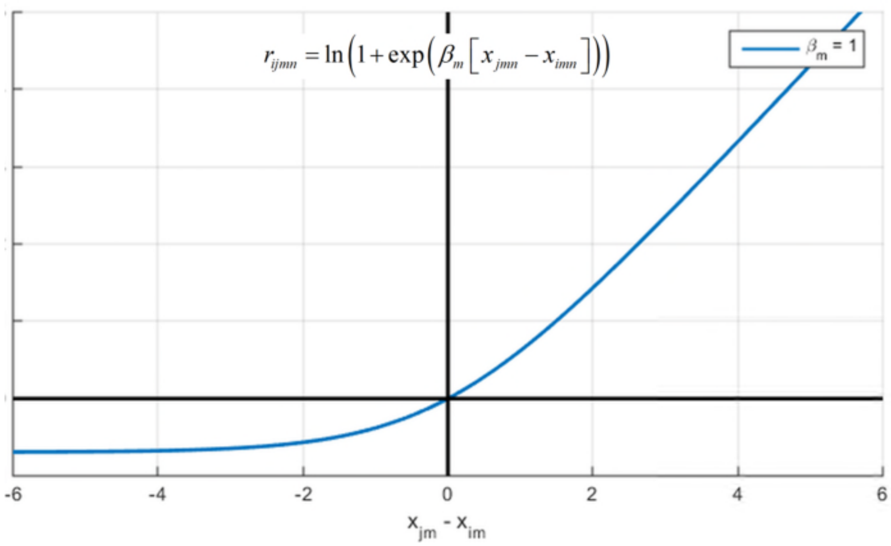


Figure 5: Attribute level regret function RRM2010

To estimate this model in LG Choice, we need to use the LG syntax. This can most easily be achieved by modifying the syntax of the linear-additive RUM model.

- Right Click 'Model1' in Outline Pane. A list box will appear.

- Left Click on ‘Generate Syntax’. The LG syntax Dialog box will appear in the Content Pane, see Figure 6.

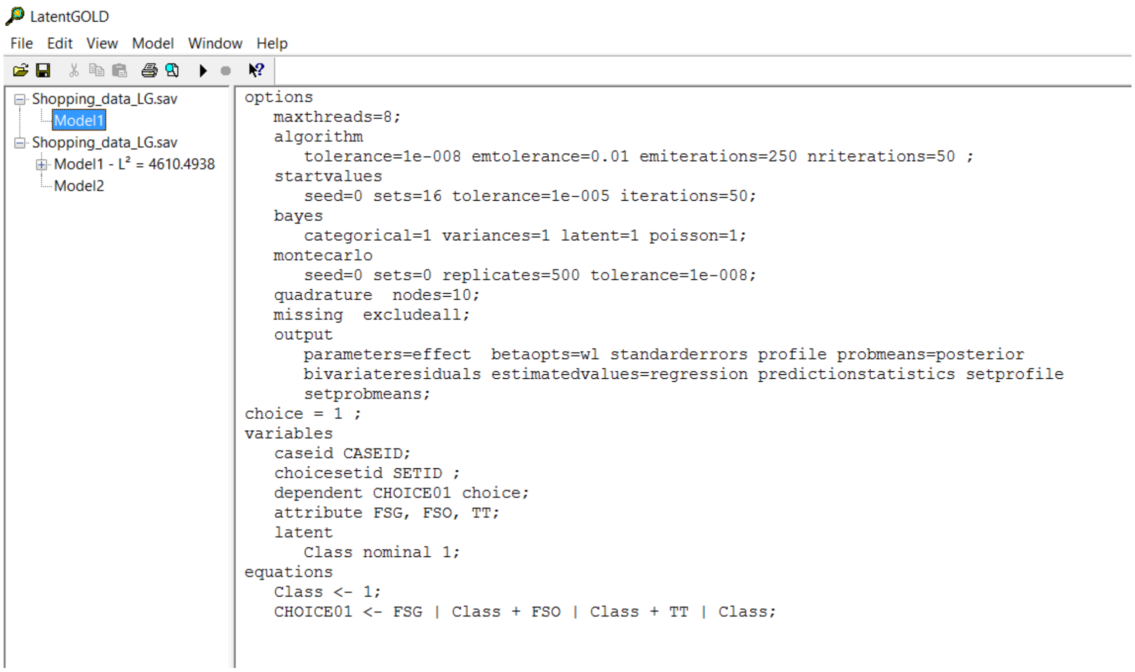


Figure 6: LG Choice syntax Dialog Box

- Now we change the syntax to tell LG to estimate a RRM2010 model. We add the syntax keyword ‘RRM’ to the right of the keyword ‘choice’, see Figure 7 below.

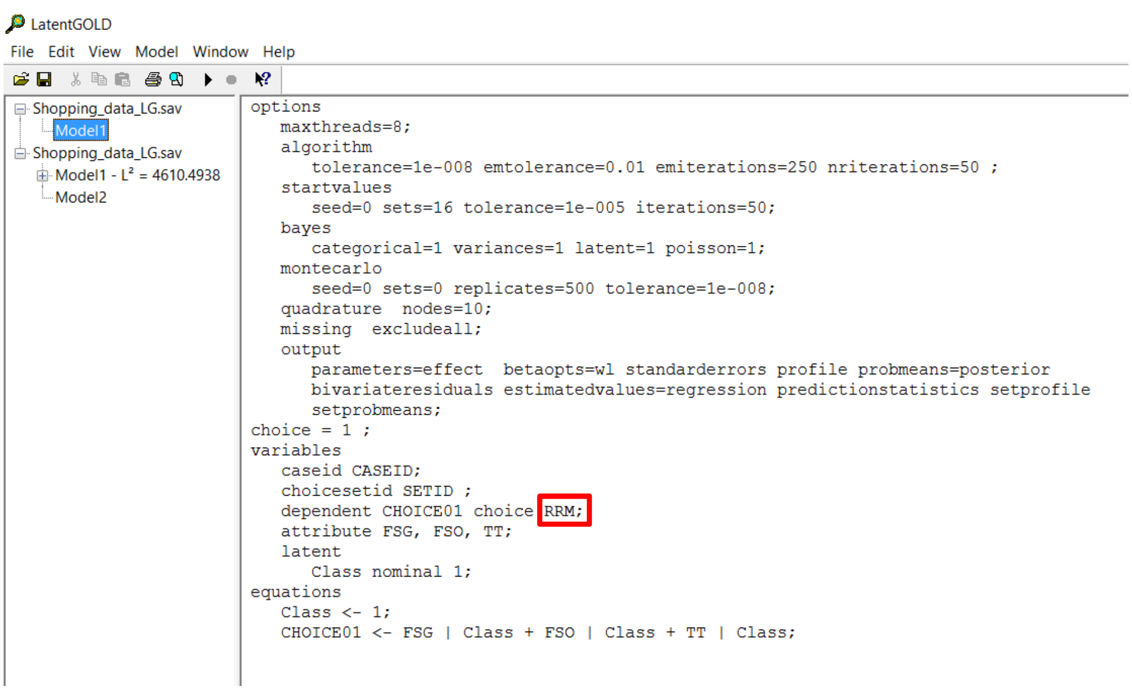


Figure 7: LG Choice syntax Dialog Box

- Click the Estimation Button ► at the top of the setup screen.

The setup window now closes and LG starts estimating the RRM2010 model. When LG Choice completes the estimation a list of various output files appears in the Content pane, see Figure 8 below. Confirm that you again get L^2 = 4610.4938 for this model.

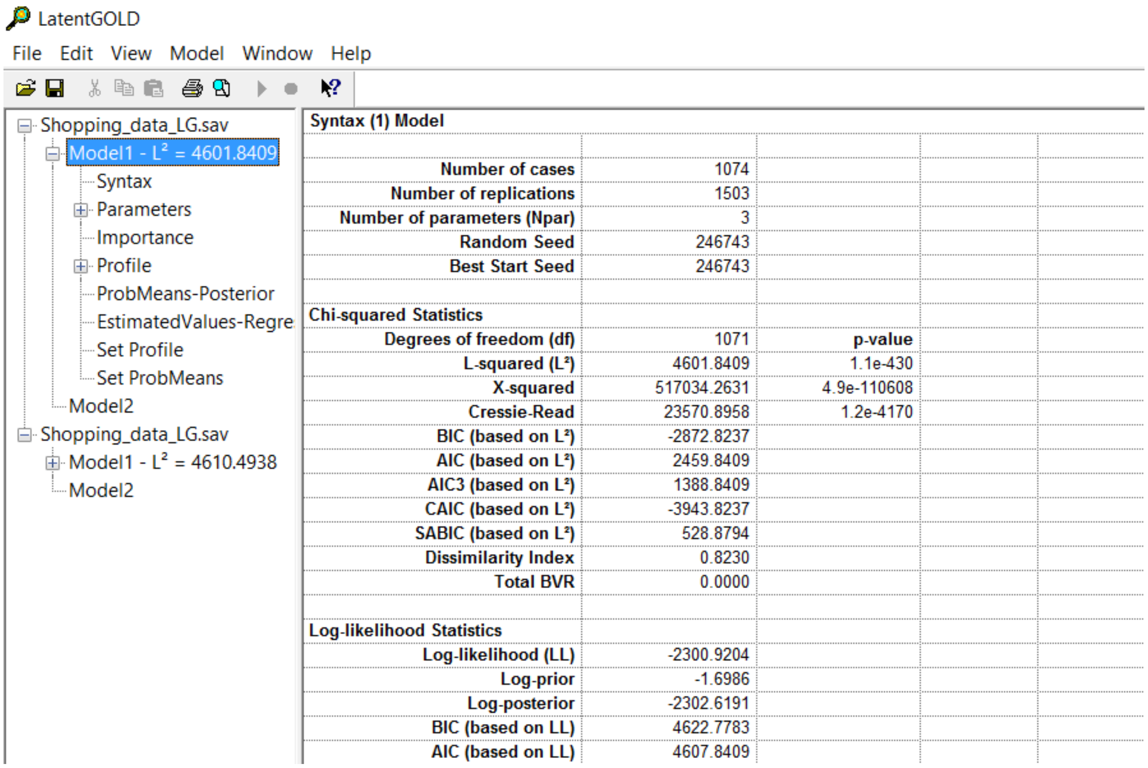


Figure 8: RRM2010 Estimation Results in Content Pane

4.3 Estimating a µRRM model

The µRRM model proposed by Van Cranenburgh et al. (2015) generalizes the RRM2010 model by allowing the scale parameter µ to be estimated. The µRRM model has three special cases: 1) the RRM2010 model, 2) the linear-additive RUM model, and 3) the P-RRM model. See Van Cranenburgh et al. (2015) for a full description.

The attribute level regret function of the µRRM model is depicted in Figure 9. As can be seen, the shape of the attribute level regret function – and hence the degree of regret minimization behaviour the model imposes – varies with the size of the scale parameter µ. In case µ is large, the attribute level regret function is approximately linear (purple line). This implies that the attributes are traded-off in a compensatory way (just like the linear-additive RUM model does). In case µ is small, the attribute level regret function is highly asymmetric (orange line). In that case, trade-offs are made in a highly non-compensatory way.

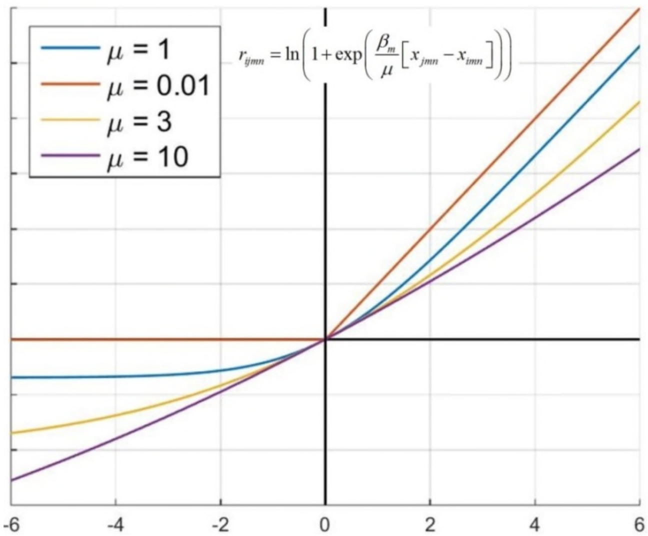


Figure 9: Shapes of the Attribute level regret function of the μRRM model

- To estimate the μRRM model we need to change the syntax again. Click on 'Model2' in the outline pane to bring up the syntax in the contents pane on the right.

- To tell LG to estimate a scale parameter, we add the following syntax: 'CHOICE01 <<-1;', see Figure 10.

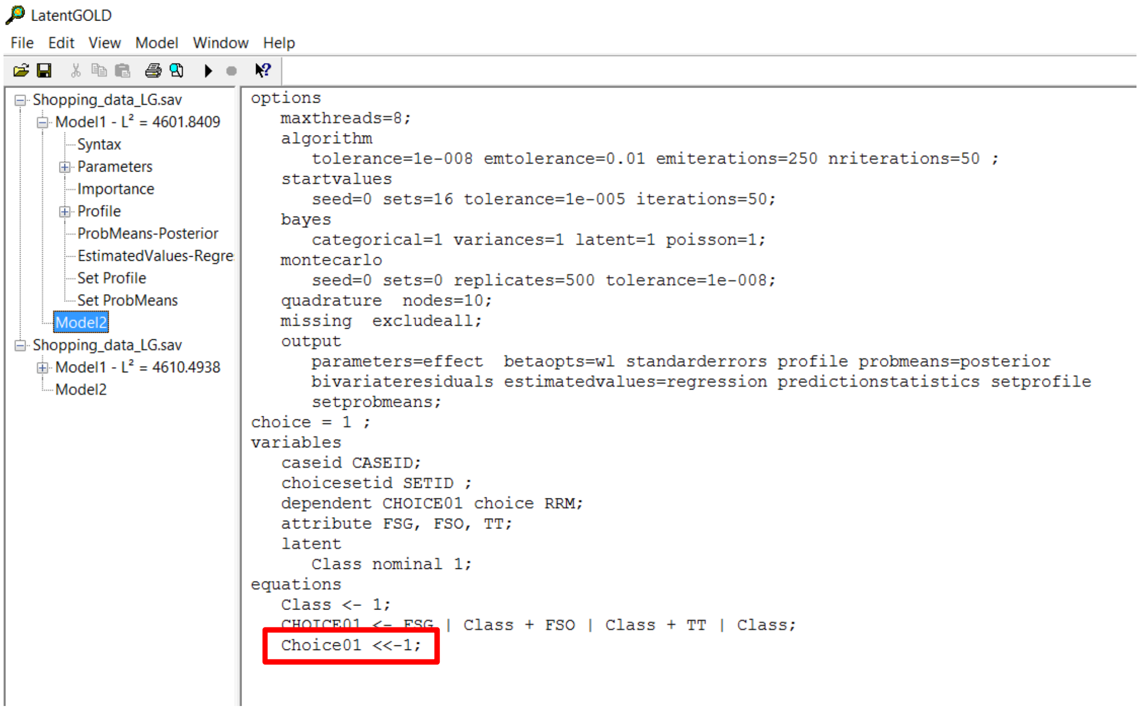
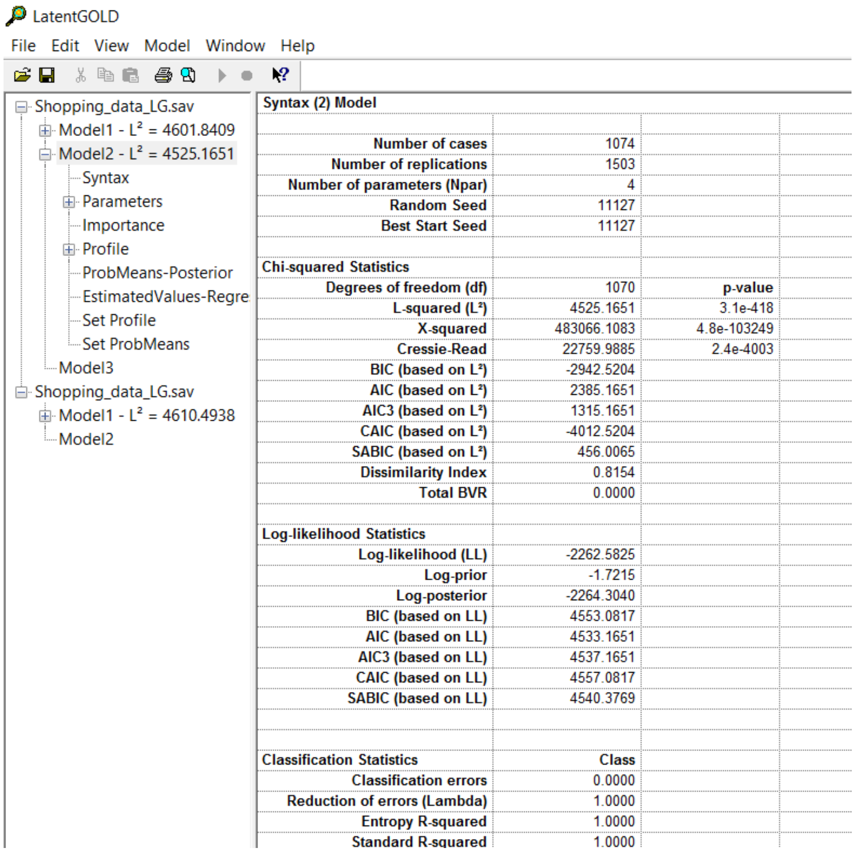


Figure 10: LG Choice syntax Dialog Box

- Click the Estimation Button ► at the top of the setup screen.

The setup window now closes and LG starts estimating the μRRM model. When Latent GOLD Choice completes the estimation a list of various output files appears in the Content panel, see below.



Syntax (2) Model		
Number of cases	1074	
Number of replications	1503	
Number of parameters (Npar)	4	
Random Seed	11127	
Best Start Seed	11127	
Chi-squared Statistics		
Degrees of freedom (df)	1070	p-value
L-squared (L^2)	4525.1651	3.1e-418
X-squared	483066.1083	4.8e-103249
Cressie-Read	22759.9885	2.4e-4003
BIC (based on L^2)	-2942.5204	
AIC (based on L^2)	2385.1651	
AIC3 (based on L^2)	1315.1651	
CAIC (based on L^2)	-4012.5204	
SABIC (based on L^2)	456.0065	
Dissimilarity Index	0.8154	
Total BVR	0.0000	
Log-likelihood Statistics		
Log-likelihood (LL)	-2262.5825	
Log-prior	-1.7215	
Log-posterior	-2264.3040	
BIC (based on LL)	4553.0817	
AIC (based on LL)	4533.1651	
AIC3 (based on LL)	4537.1651	
CAIC (based on LL)	4557.0817	
SABIC (based on LL)	4540.3769	
Classification Statistics	Class	
Classification errors	0.0000	
Reduction of errors (Lambda)	1.0000	
Entropy R-squared	1.0000	
Standard R-squared	1.0000	

Figure 11: µRRM Estimation Results in Content Pane

4.4 Interpreting Results

To assess which model (RUM, RRM2010, µRRM) provides the best fit to the data we use test statistics. Since the RRM and RUM model are not special cases of one another we cannot not use the commonly used Likelihood Ratio Statistic (LRS) to assess whether one model describes the data significantly better than the other. Instead, we need to use a test suitable for non-nested models. The Ben-Akiva and Swait (BS) test (see the textbox below) is one such test (Ben-Akiva and Swait 1986). When comparing the µRRM model with the RUM and the RRM2010 models we can however use the LRS (Equation 2) as the µRRM model nests both the linear-additive RUM model and the RRM2010 model. The LRS is χ^2 distributed with k degrees of freedom.

The BS test gives an upper bound for the probability that, when some model A achieves a lower log-likelihood than some other (non-nested) model B, A is still the correct model of the data-generating process. This upper bound can therefore be considered a conservative proxy for the significance (or: p-value) of a difference in model fit between two non-nested models A and B, see Chorus (2012).

The BS statistic is given in the equation below:

$$\Pr\left[\rho_A^2 - \rho_B^2 \geq z\right] \leq \Phi\left[-\left(2Nz\ln J + \left(K_A - K_B\right)\right)^{1/2}\right]$$ where,

$$\rho^2 = 1 - \frac{LL\left(\hat{\beta}\right) - K/2}{LL\left(0\right)}$$

K is the number of model parameters

z is the model fit difference

N is the number of observations

J is the choice set size

K is the number of parameters

$\Phi[\ ]$ is the standard normal cumulative distribution function

$$LRS = -2\left(LL_{Model\ A} - LL_{Model\ B}\right)$$ **Equation 2**

- Click on 'Shopping_data_LG.sav' in the Outline Pane. A summary of all the models estimated on this data file appears in the Content Pane, see Figure 12.

Looking at the Final-Loglikehoods (LL) we see that the RRM2010 performs slightly better than the RUM model (about 4.3 log-likelihood points). However, applying the BS test (Equation 3 reveals that the RRM2010 describes the data somewhat better.

$$\Pr\left[\frac{LL_B\left(\hat{\beta}\right) - LL_A\left(\hat{\beta}\right)}{LL\left(0\right)} \geq z\right] \leq \Phi\left[-\left(2Nz\ln J + \left(K_A - K_B\right)\right)^{1/2}\right]$$

$$\Pr\left[1.78\cdot 10^{-3} \geq z\right] \leq \Phi\left[-\left(2\cdot 1504\cdot 1.78\cdot 10^{-3}\ln 5\right)^{1/2}\right]$$

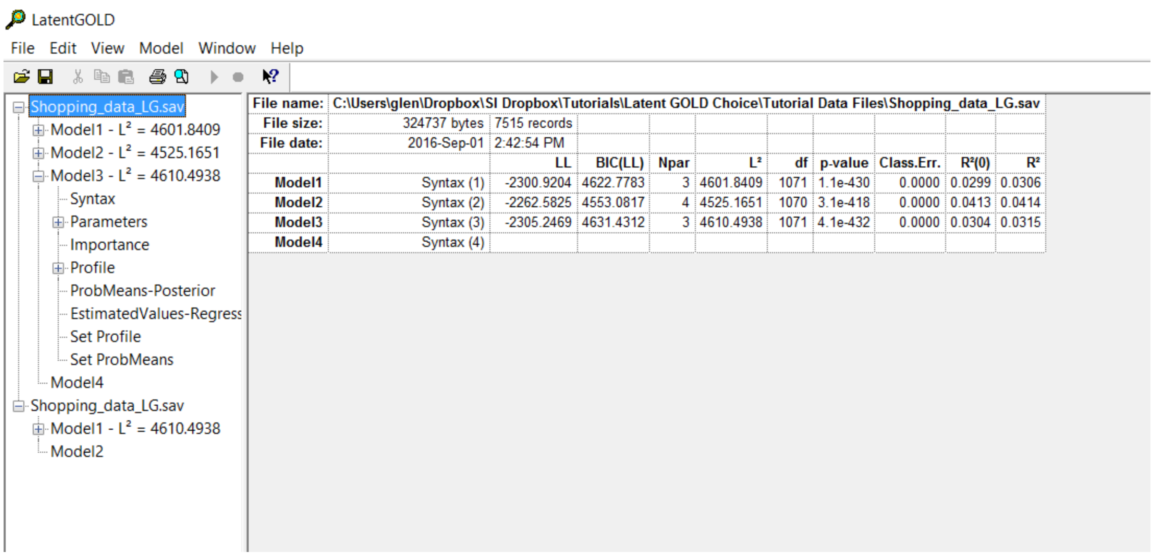
$$\Pr\left[1.78\cdot 10^{-3} \geq z\right] \leq 0.002$$ **Equation 3**

To see whether the µRRM model outperforms its special cases in the statistical sense, we apply the LRS. The LRS (Equation 4) show that the µRRM model describes the data (highly) significantly better than its special cases. The LRS far exceeds the critical χ^2 value of 3.84 with 1 degree of freedom at a significance level of $\alpha = 0.05$. An alternative statistic to assess which model fits statically best is the Bayesian Information Criterion (BIC). This criterion is not so commonly used in the field of choice modelling, other than in the context of Latent Class discrete choice model applications. However, in this case, the BIC correctly identifies the μRRM model as the best model (lowest BIC).

$$LRS = -2\left(LL_{RUM} - LL_{\mu RRM}\right)$$
$$LRS = -2\left(-2305.247 - -2262.583\right) = 85.33$$

$$LRS = -2\left(LL_{RRM\,2010} - LL_{\mu RRM}\right)$$
$$LRS = -2\left(-2300.920 - -2262.583\right) = 76.67$$

Equation 4



File name:	C:\Users\glen\Dropbox\SI Dropbox\Tutorials\Latent GOLD Choice\Tutorial Data Files\Shopping_data_LG.sav									
File size:	324737 bytes	7515 records								
File date:	2016-Sep-01	2:42:54 PM								
		LL	BIC(LL)	Npar	L²	df	p-value	Class.Err.	R²(0)	R²
Model1	Syntax (1)	-2300.9204	4622.7783	3	4601.8409	1071	1.1e-430	0.0000	0.0299	0.0306
Model2	Syntax (2)	-2262.5825	4553.0817	4	4525.1651	1070	3.1e-418	0.0000	0.0413	0.0414
Model3	Syntax (3)	-2305.2469	4631.4312	3	4610.4938	1071	4.1e-432	0.0000	0.0304	0.0315
Model4	Syntax (4)									

Figure 12: Model Summary Output

4.5 Examining the Model Output files

4.5.1 RRM2010

First we look at the results for the RRM2010 model.

- Click on the expand icon (+) next to the RRM2010 model. Several output files appear.

To view whether the parameter estimates are significantly different from 0:

- Click on Parameters to view the part-worth utility estimates in the Contents Pane
- Right click on the 'View' and select 'Standard Errors' and 'Z Statistic' from the dropdown menu (Figure 13).

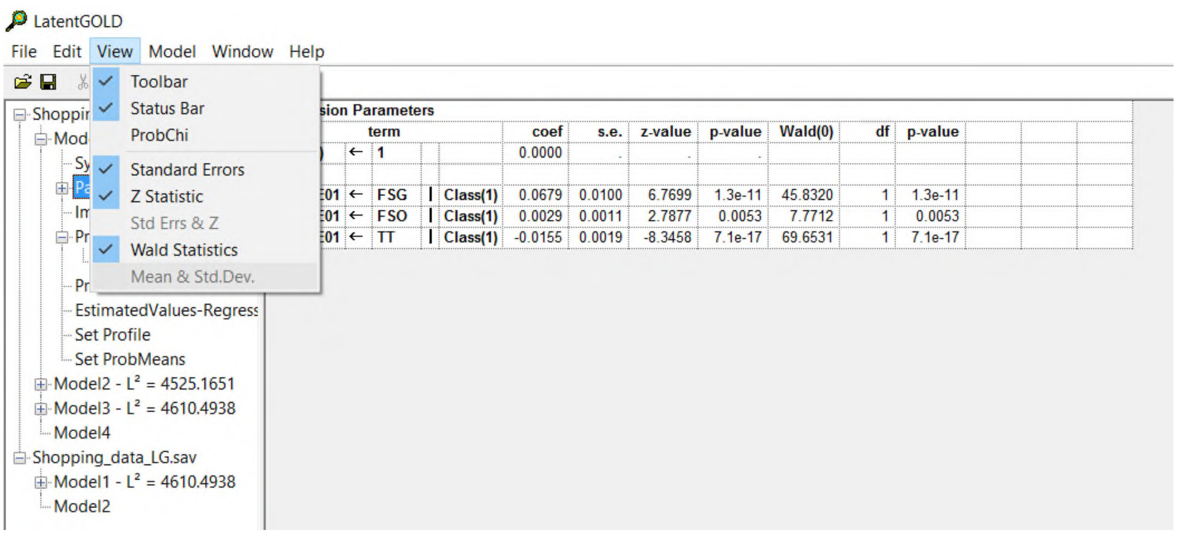


Figure 13: Viewing Standard Error, Z statistic and associated p-values

The parameter estimates and the associated standard errors, Z-values and p-values in Figure 13 show that all 3 attributes (FSG, FSO and TT) are significantly different from 0.

To learn about the degree of regret minimizing behaviour imposed by RRM models we may compute the so-called 'profundity of regret measure', see Van Cranenburgh et al. (2015). This measure is computed for each attribute. A profundity of regret of close to 1 indicates that a very strong degree of regret minimization behaviour is associated with that attribute, while a profundity of regret close to 0 indicates that a very mild degree of regret minimization behaviour is associated with that attribute. In other words, a profundity of regret close to 1 signals highly non-compensatory regret minimization behaviour, whereas a profundity of regret close to 0 signals compensatory behaviour. In fact, when the profundity of regret equals 0, the attribute is processed in a linear-additive RUM way. Software code to compute this measure can we found at www.advancedrrmmodels.com

Table 2 shows the profundity of regret levels for the RRM2010 model. It shows that all profundity of regrets are close to zero. Hence, the behaviour imposed by the RMM2010 is close to compensatory RUM behaviour. As such, it comes as no surprise that the model fit difference between the linear-additive RUM model (LL = -2305.25) and the RRM2010 (LL = -2300.92) is quite small.

Attribute	Profundity of regret
FSG	0.06
FSO	0.02
TT	0.06

Table 2: Profundity of regret RRM2010

4.5.2 μRRM

Next, we look at the results for the μRRM model.

- Click on the expand icon (+) next to the μRRM model. Several output files appear.
- To view the parameter estimates Click on Parameters to view the part-worth utility estimates in the Contents Pane
- Right click on 'View' and select 'Standard Errors' and 'Z Statistic' from the dropdown menu, see Figure 14

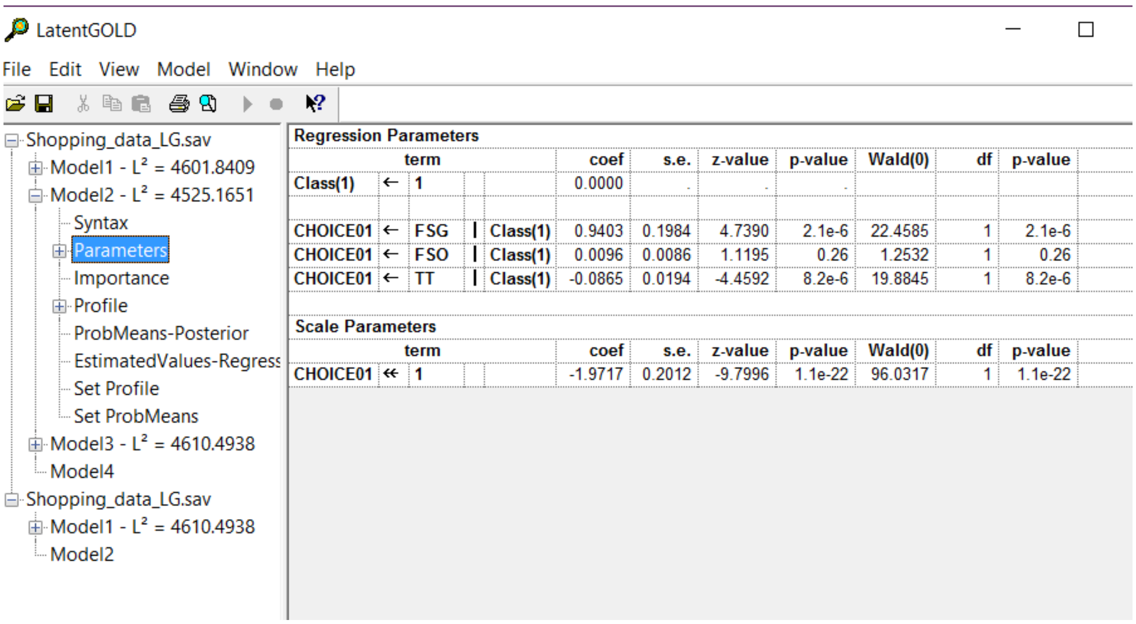


Figure 14: μRRM results

Notice that the parameter estimates and the associated standard errors, Z-values and p-values in Figure 14 show that FSG and TT are significantly different from 0, while – in contrast to the results found using the RRM2010 model – FSO is no longer significantly different from zero at a significance level of α = 0.05.

Importantly, the parametrization of the μRRM model differs from the 'standard parametrization' proposed by Van Cranenburgh et al. (2015). Equation 5 shows the parametrization of the μ RRM model in LG Choice; Equation 6 shows the standard parametrization.

$$R_i = \sum_{j \neq i} \sum_{m} \left(1 + \exp\left(\beta_m^* \left[x_{jm} - x_{im}\right]\right)\right) \quad P_i = \frac{e^{-e^{\mu^*} R_i}}{\sum_J e^{-e^{\mu^*} R_j}} \quad \text{(LG parametrization)}$$

Equation 5

$$R_i = \sum_{j \neq i} \sum_m \left(1 + \exp\left(\frac{\beta_m}{\mu}\left[x_{jm} - x_{im}\right]\right)\right) \quad P_i = \frac{e^{-\mu R_i}}{\sum_J e^{-\mu R_j}} \qquad \text{(Standard parametrization)}$$	**Equation 6**

Equation 5 and Equation 6 differ from one another in two important ways:

1. The taste parameter β_m^* is not divided by the scale parameter μ in the attribute level regret function:
2. In LG Choice the log of the scale μ is estimated, instead of the scale (for numerical reasons).

These differences in parametrization have several implications. Firstly, it means that the scale parameter reported by LG needs to be exponentiated (see Equation 7, where * denotes the LG scale parameter estimate) to obtain the scale μ. Secondly, to cross-validate or compare results of LG Choice with results obtained using the standard parametrization requires some additional steps. As the parameters are transformed, standard errors are likely to be different across parametrizations. These steps however go beyond the scope of this tutorial. Interested readers are referred to (Van Cranenburgh and Vermunt 2015). Finally, it is worthwhile to mention that although the parametrizations are different, these models are equivalent -- both impose the same behavioural restrictions and hence result in the same model fit.

$$\mu = e^{\mu^*}$$	**Equation 7**

Accordingly, the scale parameter is found to be $\mu = e^{-1.9717} = 0.14$

Table 3 shows the profundity of regret levels for the μRRM model. It shows that substantially regret minimizing behaviour is present for FSG and TT. The strong deviation from compensatory behaviour explains the substantial difference in model fit between the linear-additive RUM model (LL = -2305.25) and the μRRM model (LL = -2262.58).

Attribute	Profundity of regret
FSG	0.50
FSO	0.05
TT	0.32

Table 3: Profundity of regret μRRM

5 Latent Class Random Regret Minimization models

In this section we are going to estimate Latent Class models which consist of multiple μRRM models.

- In the syntax, set the number of Latent classes to ‘2’, see Figure 15.

- To tell LG to allow for differences in scale (hence different decision rules) across classes, also add the ‘| Class;’, see Figure 15.

Latent Class models can get stuck in local maxima during the estimation. To deal with this the user can change the estimation algorithm settings using the syntax, such as the seed number, the number of starting value sets, and the number of EM iterations per set.

- To reduce the probability on finding a local solution, increase the number of EM iterations from 50 to 250 in the syntax, see Figure 15.
-

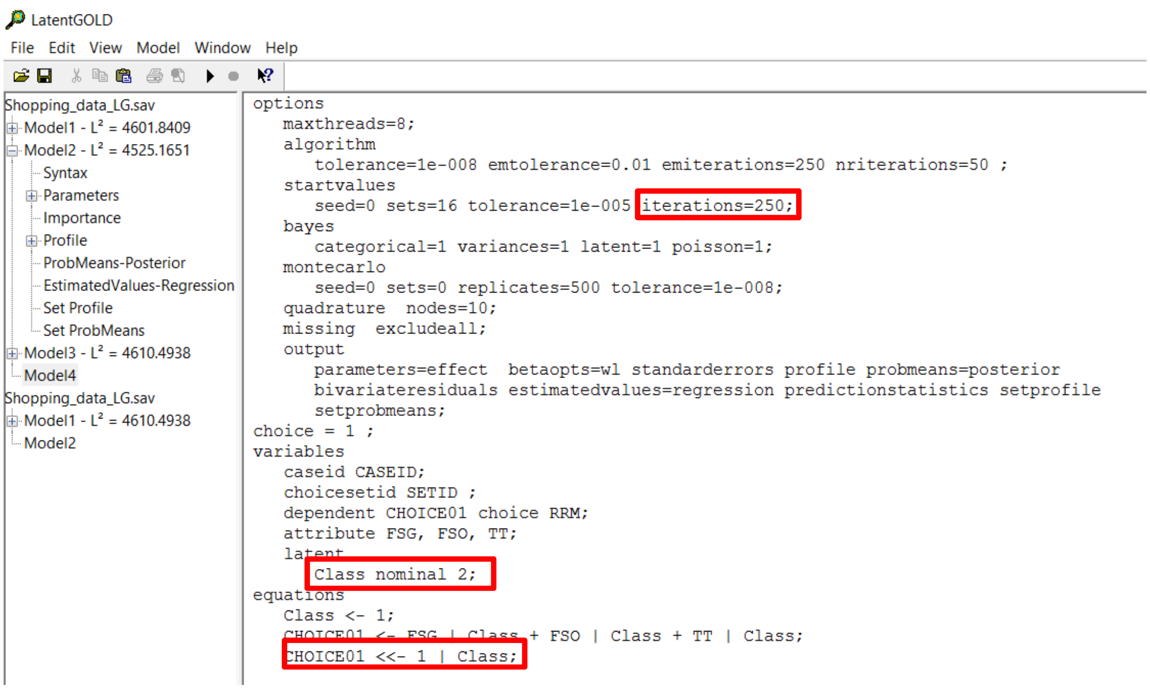


Figure 15: LG Choice syntax Dialog Box

Notice that since the shopping choice data set does not contain explanatory variables that can be used to explain class membership, only class-specific constants are estimated. Therefore, formally the Latent Class models we estimate are discrete mixture models.

- Click the Estimation Button ► at the top of the setup screen to estimate the 2-µRRM class model.

Next, we estimate a 3-µRRM class Latent class model.

- Navigate in the Outline Pane to Model5

- In the syntax, set the number of latent classes to ‘3’, see Figure 15.
- Click the Estimation Button ► at the top of the setup screen to estimate the 3-µRRM class model.
- You may click on the models in the outline pane at left to rename the models.

For completeness, we estimate also a 2-class and a 3-class RUM Latent class model.

- Navigate in the Outline Pane to Model6
- In the syntax, remove the ‘RRM’ command, see Figure 16 .

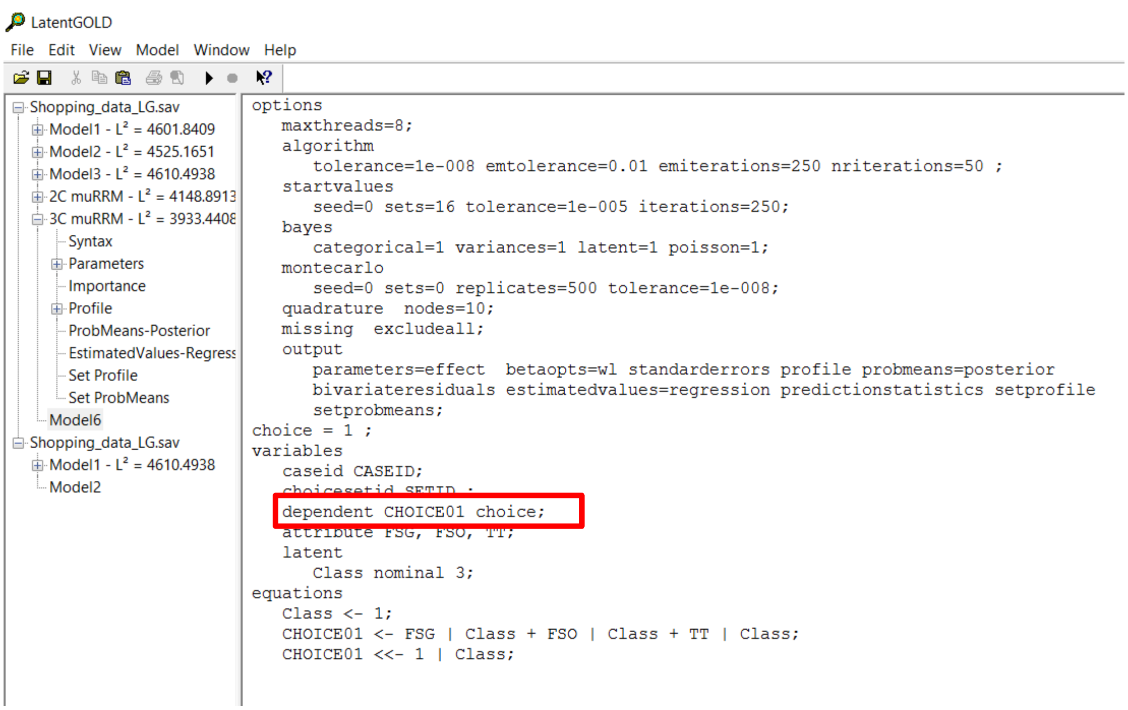


Figure 16: LG Choice syntax Dialog Box

- Click the Estimation Button ► at the top of the setup screen to estimate the 2-class RUM class model.

Notice that we still estimate the scale parameters. Hence, we allow for differences in error variance across classes. See Magidson and Vermunt (2007) for a discussion on the scale parameter in Latent Class choice models.

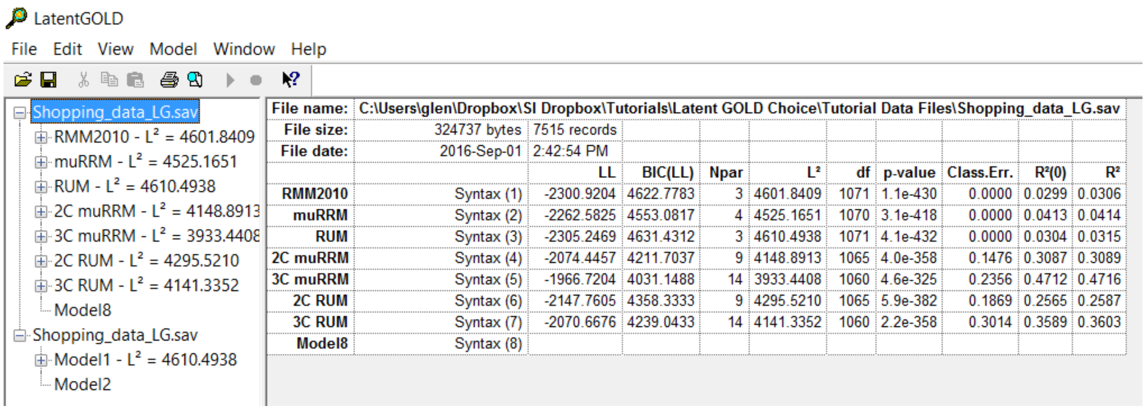
To estimate a 3-class RUM Latent class model

- Navigate to the syntax in the Outline Pane to Model7
- In the syntax, set the number of latent classes to '2' and click the estimate button.

5.1 Interpreting Results

To assess which Latent Class model provides the best fit to the data we use the BIC statistic.

- Click on 'Shopping_data_LG.sav' in the Outline Pane. A summary of all the models estimated on this data file appears in the Content Pane, see Figure 17.



File name:	C:\Users\glen\Dropbox\SI Dropbox\Tutorials\Latent GOLD Choice\Tutorial Data Files\Shopping_data_LG.sav									
File size:	324737 bytes	7515 records								
File date:	2016-Sep-01	2:42:54 PM								
		LL	BIC(LL)	Npar	L²	df	p-value	Class.Err.	R²(0)	R²
RMM2010	Syntax (1)	-2300.9204	4622.7783	3	4601.8409	1071	1.1e-430	0.0000	0.0299	0.0306
muRRM	Syntax (2)	-2262.5825	4553.0817	4	4525.1651	1070	3.1e-418	0.0000	0.0413	0.0414
RUM	Syntax (3)	-2305.2469	4631.4312	3	4610.4938	1071	4.1e-432	0.0000	0.0304	0.0315
2C muRRM	Syntax (4)	-2074.4457	4211.7037	9	4148.8913	1065	4.0e-358	0.1476	0.3087	0.3089
3C muRRM	Syntax (5)	-1966.7204	4031.1488	14	3933.4408	1060	4.6e-325	0.2356	0.4712	0.4716
2C RUM	Syntax (6)	-2147.7605	4358.3333	9	4295.5210	1065	5.9e-382	0.1869	0.2565	0.2587
3C RUM	Syntax (7)	-2070.6676	4239.0433	14	4141.3352	1060	2.2e-358	0.3014	0.3589	0.3603
Model8	Syntax (8)									

Figure 17: Model Summary Output

Based on the BIC statistic we infer that the 3-µRRM class model (Model5) best fits the data. Note that the 3-µRRM class model strongly outperforms the 3-class RUM model.

5.2 Examining the Model Output files

Figure 18 shows the estimated parameters for the best performing model: the 3-µRRM class model.

Looking at the scale parameter estimates we see that classes 2 and 3 have roughly the same scale. This means that the differences between these classes is not so much related to decision rules, but rather to taste heterogeneity. This is also indicated by the Wald statistic, which shows that the scale parameters are not significantly different from one another.

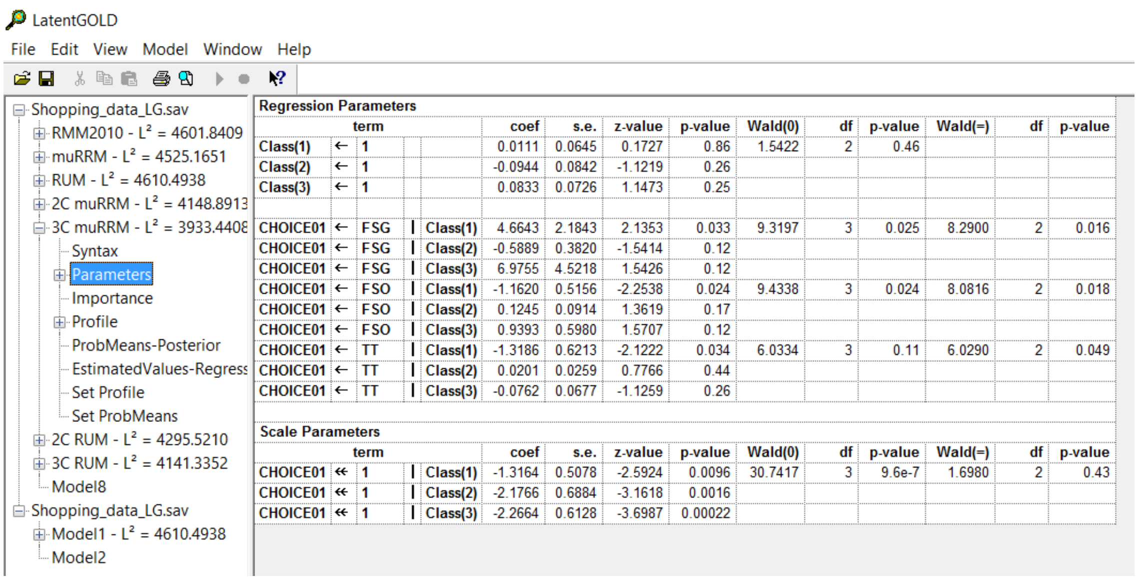
Using Equation 7 we find the following scales of classes 1 to 3 (Table 4).

	$\mu = e^{\mu^*}$
Class 1	$\mu = e^{-1.3164} = 0.27$
Class 2	$\mu = e^{-2.1766} = 0.11$

Class 3	$\mu = e^{-2.2664} = 0.10$

Table 4: Scale parameters for classes 1 to 3

Looking at the taste parameters in Figure 18, we see that FSG is significantly different from zero in all three classes. FSO and TT are however no longer significantly different from zero. This is likely to be the result of the limited number of observations, relative to the number of estimated parameters (19). As such, the 2-class model may be preferred for further analysis, despite the fact that the 3-µRRM class model has a higher BIC value. Furthermore, the parameters of Class 2 are relatively small (close to zero). This signals that the choice consistency in this class is low. In other words, the choice behaviour in this class is relatively random. This can also be verified by looking at the choice probabilities of Class 2 under Set Profiles, which are all close to 20%.



Regression Parameters

term					coef	s.e.	z-value	p-value	Wald(0)	df	p-value	Wald(=)	df	p-value
Class(1)	←	1			0.0111	0.0645	0.1727	0.86	1.5422	2	0.46			
Class(2)	←	1			-0.0944	0.0842	-1.1219	0.26						
Class(3)	←	1			0.0833	0.0726	1.1473	0.25						
CHOICE01	←	FSG	|	Class(1)	4.6643	2.1843	2.1353	0.033	9.3197	3	0.025	8.2900	2	0.016
CHOICE01	←	FSG	|	Class(2)	-0.5889	0.3820	-1.5414	0.12						
CHOICE01	←	FSG	|	Class(3)	6.9755	4.5218	1.5426	0.12						
CHOICE01	←	FSO	|	Class(1)	-1.1620	0.5156	-2.2538	0.024	9.4338	3	0.024	8.0816	2	0.018
CHOICE01	←	FSO	|	Class(2)	0.1245	0.0914	1.3619	0.17						
CHOICE01	←	FSO	|	Class(3)	0.9393	0.5980	1.5707	0.12						
CHOICE01	←	TT	|	Class(1)	-1.3186	0.6213	-2.1222	0.034	6.0334	3	0.11	6.0290	2	0.049
CHOICE01	←	TT	|	Class(2)	0.0201	0.0259	0.7766	0.44						
CHOICE01	←	TT	|	Class(3)	-0.0762	0.0677	-1.1259	0.26						

Scale Parameters

term					coef	s.e.	z-value	p-value	Wald(0)	df	p-value	Wald(=)	df	p-value
CHOICE01	«	1	|	Class(1)	-1.3164	0.5078	-2.5924	0.0096	30.7417	3	9.6e-7	1.6980	2	0.43
CHOICE01	«	1	|	Class(2)	-2.1766	0.6884	-3.1618	0.0016						
CHOICE01	«	1	|	Class(3)	-2.2664	0.6128	-3.6987	0.00022						

Figure 18: 3-µRRM class results

Table 5 shows profundity of regret levels for the 3 µRRM classes. It shows that most profundity of regrets are substantially different from zero. This indicates that in all classes substantial regret minimization behaviour is present.

Attribute	Profundity of regret		
	Class 1	Class 2	Class 3
FSG	0.844	0.367	0.891
FSO	0.802	0.361	0.361
TT	0.920	0.080	0.280

Table 5: Profundity of regret 3-µRRM class model

Finally, we look at the class membership.

- Click in the Outline Pane on ProbMeans-Posterior to see the class membership probabilities, see Figure 19.

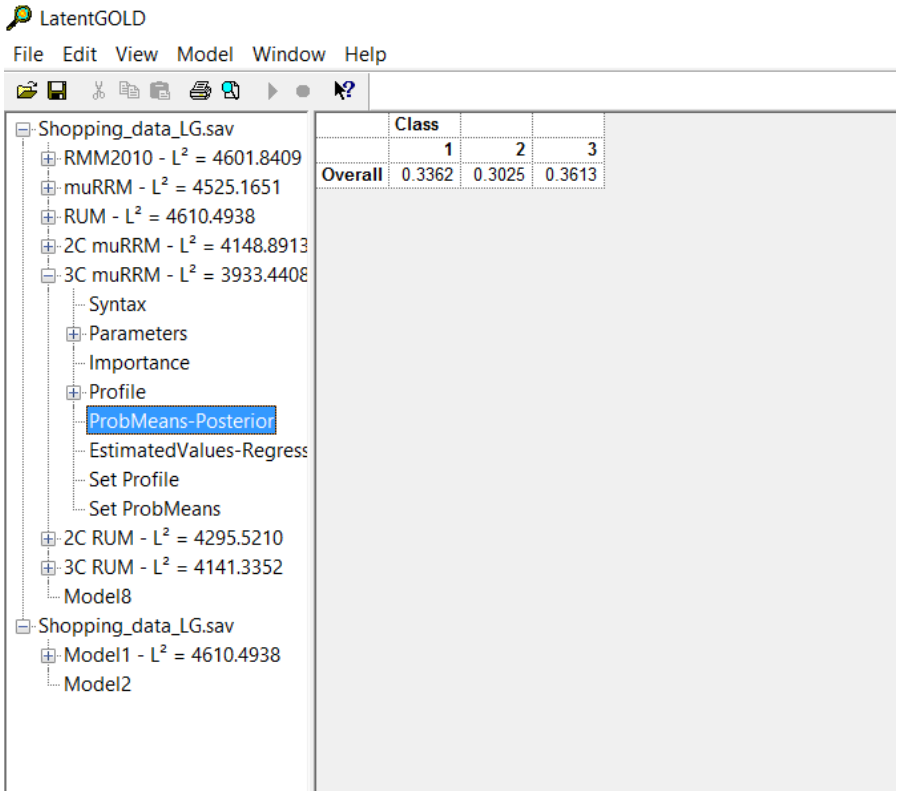


Figure 19: ProbMeans-Posterior

The results in Figure 19 show that the 3 classes are roughly of equal size.

References

Arentze, T. A., Oppewal, H. & Timmermans, H. J. P. (2005). A Multipurpose Shopping Trip Model to Assess Retail Agglomeration Effects. *Journal of Marketing Research, 42(1),* 109-115.

Ben-Akiva, M. & Swait, J. (1986). The Akaike Likelihood Ratio Index. *Transportation Science, 20(2)*, 133-136.

Chorus, C. G. (2010). A new model of random regret minimization. *European Journal of Transport and Infrastructure Research*, *10(2)*, 181-196.

Chorus, C. G. (2012). Random regret-based discrete choice modeling a tutorial. SpringerBriefs in business,. Berlin ; New York, Springer,**:** 1 online resource (viii, 55 p.).

Magidson, J. & Vermunt, J. K. (2007). Removing the scale factor confound in multinomial logit choice models to obtain better estimates of preference. Sawtooth software conference proceedings.

Van Cranenburgh, S., Guevara, C. A. & Chorus, C. G. (2015). New insights on random regret minimization models. *Transportation Research Part A: Policy and Practice*, *74(0)*, 91-109.

Van Cranenburgh, S. & Prato, C. G. (2016). On the robustness of Random Regret Minimization modelling outcomes towards omitted attributes. *Journal of Choice Modelling,(18),* 51-70.

Van Cranenburgh, S. & Vermunt, J. K. (2015). "Cross-validating Random Regret Minimization results of LatentGOLD Choice." from www.advancedrrmmodels.com.

Vermunt, J. K. & Magidson, J. (2005). Latent GOLD® choice 4.0 user's manual. *Statistical Innovations Inc., Belmont, MA.*