Upgrade Manual

for Latent GOLD Choice 5.0:

Basic, Advanced, and Syntax[1]

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Upgrade Manual for Latent GOLD Choice 5.0: Basic, Advanced, and Syntax.

Contents

1   Introduction

We have added several new features in version 5.0 of Latent GOLD® Choice (LG Choice). Current licensees of version 4.5 can obtain this latest version for no additional charge by emailing Will Barker (will@statisticalinnovations.com). The primary new features in version 5.0 are:

1. Major speed improvement

2. Simplified and enhanced ability to estimate Scale Adjusted Latent Class (SALC) models

3. Simplified and enhanced ability to estimate Best-Worst scaling models, including the new Joint Best-Worst (MaxDiff) model (the latter requires the LG-Syntax module)

4. The ability to estimate choice models based on the Random Regret Minimization (RRM) framework

This upgrade manual for LG Choice 5.0[2] describes the new features in LG Choice Basic and Advanced which were implemented in the transition from version 4.0 to version 5.0. The current user's guide and technical guide for LG Choice 4.0 remain valid.

This upgrade manual also discusses the use of LG Choice 5.0 Syntax. The LG Syntax system itself is described in a separate user's guide. Here, we focus on the new syntax options which are specific to choice models.

2   Overview of the New Features

An important improvement in LG 5.0 that affects Choice Basic, Advanced, and Syntax is the use of multiple processing, which speeds up computation considerably. The main speed gain is achieved by making use of multiple cores in the LG multiple start sets procedure and in the computation of first- and second-order derivatives needed for the Newton-Raphson iterations and for obtaining standard errors. Also some algorithm and memory use

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[2]This upgrade manual is specific to our Latent GOLD Choice program which is used to develop models for discrete choice and related conjoint and ranking data. It is distinct from our Latent GOLD 5.0 Upgrade Manual released September 2013 which is used to develop cluster, factor, regression, and related models on non-choice data.

improvements were implemented, which affect certain types of models. More details on this can be found in the Latent GOLD 5.0 Upgrade Manual.

Here is a complete list of the new features implemented in LG Choice 5.0:

- Choice Basic:

  - Best-worst models (LG Choice 5.0 Tutorial #8A provides several examples).
  - Option to select cases or replications and to holdout replications or cases not selected.
  - Additional output, such as SEs for profile, willingness-to-pay (WTP) parameters and marginal effects, separate prediction statistics for the 2nd and 3th choice in ranking models and for the worst choice in best-worst models, and estimated values output.

- Choice Advanced:

  - Scale Adjusted Latent Class (SALC) analysis - the scale factor can be modeled directly as a function of predictors and/or scale classes using the new log-linear scale model.

- Choice Syntax:

  - Can estimate the same choice models as in Basic and Advanced plus various extensions of these models as listed below.
  - Joint or simultaneous choice, ranking and best-worst (MaxDiff) models.
  - Choice models developed by Chorus (2010, 2012) based on Random Regret Minimization (RRM) instead of Random Utility Maximization (RUM).
  - In addition to the usual LG Syntax output, specialized output sections are provided in a format similar to the specialized output sections in the Latent GOLD Choice Basic module. These consist of attribute parameters, attribute profile, importance, WTP parameters, marginal effects, sets profile, and sets probmeans.

- Any option that is available in the LG Syntax can also be used with choice models. These include the possibility to specify model equations with interactions, conditional effects and parameter constraints, to define models with multiple discrete latent variables, with dynamic latent variables (latent Markov models), and with combinations of discrete and continuous latent variables, to perform Monte Carlo simulations, resampling, and power computations, to save models with the parameter estimates, to score new cases, etc..

- When combined with LG 5.0 Syntax (which requires LG 5.0 Basic), it is also possible to combine choice models with models for other types of dependent variables (for example, for data fusion).

Below, we described these features in more detail.

3   Basic

3.1   Best-Worst Models

LG Choice 5.0 introduces the new BestWorst scale type for the dependent variable, supplementing the current (first) Choice, Ranking, and Rating scale types. In previous versions, best-worst models could be defined as ranking models with a replication scale of 1 for the best choice and -1 for the worst choice. In LG 5.0, it is no longer necessary to use such a "trick".

Let y_{it}^b denote the best and y_{it}^w the worst choice of individual i from choice set t with M alternatives, and let m_1 and m_2 denote a particular best and worst choice, respectively. As in the technical guide for LG Choice 4.0, we denote a latent class by x and the predictors and attributes by $\mathbf{z}_{it}$, and the linear term in the logistic model for the choice probabilities by $\eta_{m|x,\mathbf{z}_{it}}$.

The BestWorst scale type sets up the following sequential choice model:

$$
\begin{aligned}
P(y_{it}^b = m_1, y_{it}^w = m_2 | x, \mathbf{z}_{it}) &= P(y_{it}^b = m_1 | x, \mathbf{z}_{it}) P(y_{it}^w = m_2 | y_{it}^b = m_1, x, \mathbf{z}_{it}) \\
&= \frac{\exp(\eta_{m_1|x,\mathbf{z}_{it}})}{\sum_{m_1'=1}^M \exp(\eta_{m_1'|x,\mathbf{z}_{it}})} \frac{\exp(-\eta_{m_2|x,\mathbf{z}_{it}})}{\sum_{m_2' \neq m_1} \exp(-\eta_{m_2'|x,\mathbf{z}_{it}})}.
\end{aligned}
$$

This model assumes that one first selects the most preferred (best) alternative and subsequently selects the least preferred (worst) alternative from

the remaining alternatives; that is, conditional on what one selected as best (Louviere et al. 2014; Marley and Louviere, 2005; Marley, Flynn, and Louviere, 2008). The fact that the worst alternative is selected from a set that excludes the best alternative is expressed by the "$m'_2 \neq m_1$" in the sum in the denominator of the logistic model for the second choice probability. The fact that the second choice concerns a worst instead of a best choice is dealt with by the minus sign in front of the linear logistic term $\eta_{m_2|x,\mathbf{z}_{it}}$; that is, the alternative with the smallest (most negative) utility is the one with the highest likelihood to be selected as worst. Several step-by-step examples of Best-Worst models are provided in LG Choice 5.0 Tutorial #8A and Tutorial #8B. Tutorial #8A refers to data based on the Latent GOLD Choice 3-file format and Tutorial #8B illustrates the corresponding analyses based on the 1-file format.

Coding of the Best and Worst responses differs somewhat depending upon whether the 1-file or 3-file data format is used. For complete details on these formats see LG Choice Tutorial #3(3-file) and LG Choice Tutorial #4 (1-file). For the 1-file format, a response variable is coded as 1 for the alternative selected as Best, 2 for the alternative chosen as Worst, and 0 for each of the other alternatives which are not chosen (as Best or Worst). For the 3-file format, the BestWorst scale type assumes that there are exactly two records provided for a given choice set, the first refering to the Best choice and the second to the Worst choice, and the response variable is coded using numbers corresponding to the particular alternatives selected. See the tutorials referred to above for illustrative examples.

3.2   Selecting and Holding out Cases or Replications

3.2.1   Selecting Cases or Replications

The new Select option on the Variable tab can be used to select a subset of replications/cases for the analysis. For example, this option makes it straightforward to perform a separate analysis for different subgroups using the same data file, or to select a subset of the replications or choice sets.

When using the select option, by default no output is provided for the records (replications/cases) which are not used in the analysis. If one wishes output for the holdout records, one can use the holdout cases or holdout replications options.

3.2.2 Holding out Replications

In Choice models, the Select option allows specifying the unselected records to be holdout replications. This option can be used for validation purposes; that is, to determine the prediction performance of the estimated model for responses which are excluded when estimating the parameters of the specified model.

A separate set of prediction statistics is reported for the holdout replications, where for posterior and hblike prediction, the posteriors are based on the non-holdout replications. Moreover, when requesting predictions to an output file, this file will also contain the predicted values for the holdout replications.

3.2.3 Holding out Cases

Validation can also be performed by holding out cases instead of replications. Whereas parameter estimates will be based on the non-holdout cases, separate chi-squared, log-likelihood, classification, and prediction statistics are computed for the holdout cases. Moreover, the optional output file will contain classification and/or prediction information for all cases, thus also for the holdout cases.

The option for holding out cases can also be used when one desires removing certain cases from the analysis, but nevertheless obtaining classification and prediction output to a file for all cases. One possible application is the analysis of very large data sets, where a subsample may be used for parameter estimation. Another application is predicting class membership for new cases based on parameter values obtained with another sample. By appending the new cases to the original data file and treating them as holdout cases, one obtains the relevant output for these cases after restoring and re-estimating the original model.

3.3 New Output

New output reported in Choice Basic:

- Separate prediction statistics for the second and third choice in ranking models, and for the worst choice in best-worst models. The computations proceed in the same manner as for the first choice.

- Standard errors computed using the delta method are available for Profile output, which in Choice models contains class-specific attribute parameters transformed to a (choice) probability scale.

- Willingness-to-pay (WTP) parameters and their SEs. The class-specific WTP parameters are obtained by dividing the class-specific attribute effects by the negative of the class-specific price effects, that is, as $-\beta_{px}/\beta_{price,x}$. When the price variable is specified to be nominal, the WTP parameters are obtained as $-\beta_{px}/[(\beta_{price,R,x} - \beta_{price,1,x})/(R-1)]$, where R is the number of price categories and $\beta_{price,1,x}$ and $\beta_{price,R,x}$ are the price parameters for first and last category. The Choice user interface allows defining which attribute is the price variable (right click on variable concerned). When a price variable is specified, the WTP parameters are reported as a sub-output section under 'Parameters' called 'Willingness-to-Pay'.

- Marginal effects, which represent the change in the choice probability resulting from a change in the attribute value. We have chosen to use the situation in which each choice is equal likely – $P(y = m) = \frac{1}{M}$ – as the point of departure. The marginal effects are then obtained as $\beta_{px} \cdot \frac{1}{M} \cdot (1 - \frac{1}{M})$. Marginal effects are reported as a sub-output section under 'Parameters'.

- EstimatedValues-Regression output, which provides the class-specific choice probabilities similar to the Sets Profile output. Two important differences are that EstimatedValues also shows the predictor and attributed values, and in addition reports the choice probabilities for all choices, which include the second and next choices in ranking models, and the worst choice in best-worst models.

4 Advanced

4.1 Scale Adjusted Latent Class (SALC) Analysis

Version 5.0 contains simplified and enhanced options to estimate Scale Adjusted Latent Class (SALC) models. Two important applications are 1) including scale classes (sClasses) in addition to latent segments (Classes) in choice models, and 2) including separate scale factors for best and worst

choices with BestWorst data (using the predictor option). Many other SALC options are available with the general log-linear scale model.

4.2 Log-linear Scale Model

A new feature implemented in LG Choice 5.0 Advanced is the possibility to include a scale factor in choice models, which may vary across predictor values and/or scale latent classes (Louviere, Hensher, and Swait, 2000; Magidson and Vermunt, 2007; Swait and Louviere, 1993). This makes it possible to perform various kinds of Scale Adjusted Latent Class (SALC) analyses (e.g., see Magidson and Vermunt, 2007). For related recent work on choice modeling with observed and unobserved scale heterogeneity, see Burk et al. (2010), Fiebig et al. (2010), Flynn et al. (2010), Louviere et al (2013), Schlereth et al. (2012), and Thiene et al (2012).

It should be noted that in previous versions of LG Choice, scale factors could be included in a choice model using some rather complicated tricks with the LG Syntax (see Magidson and Vermunt, 2007). But these tricks are no longer needed, and as explained below the occurrence of infeasible (negative) values for the scale factor is now prevented.

A scale factor is a term by which all logit parameters are multiplied, and which thus allows modeling proportionality of parameter values across conditions or groups. The inverse of the scale factor is proportional to the standard deviation of the error distribution of the choice utilities. Therefore, this option makes it possible to model heterogeneity in response (un)certainty.

When the scale model is used, the linear term $\eta_{m|x,\mathbf{z}_{it}}$ in the regression model for the choice variable is replaced by $\eta_{m|x,\mathbf{z}_{it}}\varphi_{x^s\mathbf{z}_{it}}$, where $\varphi_{x^s\mathbf{z}_{it}}$ represents the multiplicative scale factor which may depend on predictors and/or scale classes. We denote a particular scale class by x^s. The equation for the probability of selecting alternative m becomes:

$$P(y_{it} = m|x, x^s, \mathbf{z}_{it}) = \frac{\exp(\eta_{m|x,\mathbf{z}_{it}}\varphi_{x^s\mathbf{z}_{it}})}{\sum_{m'=1}^{M}\exp(\eta_{m'|x,\mathbf{z}_{it}}\varphi_{x^s\mathbf{z}_{it}})}.$$

The scale factor is modeled by a log-linear equation, yielding a flexible approach for modeling its dependence on latent and/or independent variables. By estimating the log-scale factor rather than the scale factor directly, the log-linear equation guarantees that the scale factor remains non-negative. In Choice Advanced, the log-linear scale model may contain a term for the scale

classes and effects of the predictors; that is,

$$\log \varphi_{x^s \mathbf{z}_{it}} = \xi_{x^s 0} + \sum_{p=1}^{P} \xi_p z_{pit};$$

or, equivalently,

$$\varphi_{x^s, \mathbf{z}_{it}} = \exp\left(\xi_{x^s 0} + \sum_{p=1}^{P} \xi_p z_{pit} \right)$$

Note that the Choice user interface allows selection of one or more predictors for use in the scale model. Moreover, on the Advanced tab one can indicate the number of scale classes (SClasses), which are the categories of a second discrete latent variable (in addition to the latent class variable affecting the part-worth parameters). The scale classes are assumed to be independent of the classes, an assumption that can easily be relaxed when defining such a model using the Choice Syntax (see below).

When using scale classes, information regarding the SClass-Class combinations will be displayed in various output sections. This occurs in Attribute Parameters, Willingness-to-pay parameters, Marginal Effects, Importance, (joint) Profile, Sets Profile, Sets ProbMeans, and EstimatedValues. Profile and ProbMeans report separate information for Class and SClass. It should be noted that when predictors are used in the scale model, these output sections either give average/marginal estimates (Sets Profile and Sets ProbMeans) or estimates ignoring the predictors (Attribute Parameters, Willingness-to-pay parameters, Marginal Effects, Importance, Profile).

For a more detailed description of these log-linear scale models see Vermunt (2013). Magidson and Vermunt (2007) and Magidson, Thomas, and Vermunt (2009) present applications of latent class choice models with scale factors affected by scale classes. The LG Choice 5.0 Tutorial #10A illustrates step-by-step how to use this new modeling option, and Tutorial #8A illustrates the use with BestWorst models where different scale factors are assigned to the Best and the Worst responses.

5 Syntax

The LG Syntax has its own extensive user's guide. All features available in LG syntax can also be used with choice models in LG Choice Syntax. However, only one dependent variable can be specified for choice models,

which should have a scale type set as choice, ranking, best-worst, or rating variable. Users who wish to combine choice models with models for other dependent variables – for example, for data fusion – need to obtain a license which also includes the LG Basic module. For an example of a data fusion application, see Magidson, Thomas, and Vermunt (2009).

Here we will focus on the aspects of the Syntax system which are specific to choice models, and illustrate some additional Syntax options with examples. It should be noted that the easiest way to start a Syntax session is to set up a model using the point-and-click user interface, close the model, and subsequently use the Generate Syntax option from the Model main menu entry to create a Syntax session. For example, LG Choice 5.0 Tutorial #10A illustrates how a SALC model which adjusts for distinct latent scale classes can easily be changed to a SALC model which adjusts for a latent *continuous* scale factor.

5.1 Defining the File Format

When defining a choice model using Syntax, one has to indicate whether the data are in the 1-file or 3-file format. This is specified after the "options" section and before the "variables" section. When using the 1-file format, one can simply say "choice = 1;". An example, of the specification of the 3-file format is:

```
choice = 3
    alternatives 'cbcALT11.sav' id=prodcode
    choicesets 'cbcSET.sav' id=setid;
```

As can be seen, in addition to indicating that one uses the 3-file format, the names of the alternatives and choice sets files are also required, as well as the id variables indicating the alternative and the choice set numbers.

5.2 Defining the Type of Choice Variable

5.2.1 Choice, Ranking, Best-worst, or Rating

In the "variables" section, the type of dependent variable is specified. The corresponding syntax is:

```
dependent <variable name> <choice|ranking|bestworst|rating>;
```

Thus, one specifies the variable name and whether the responses are (first) choices, rankings, best-worst choices, or ratings.

5.2.2 Joint Choice Models, Including MaxDiff Models

Optionally, with choice, ranking, and best-worst models, the keyword "joint" can be used to indicate that a joint choice model should be estimated. That is,

```
dependent <variable name> <choice|ranking|bestworst> joint;
```

A joint choice model can be used when multiple options are selected from the same choice set; that is, if the choice instruction is choose the k best alternatives from a choice set of M alternatives. The joint specification gives the following model for multiple choices:

$$P(y_{it}^1 = m_1, ..., y_{it}^k = m_k | x, \mathbf{z}_{it}) = \frac{\exp(\sum_{l=1}^k \eta_{m_l | x, \mathbf{z}_{it}})}{\sum_{m_1' \neq m_2' ... \neq m_k'} \exp(\sum_{l=1}^k \eta_{m_l' | x, \mathbf{z}_{it}})}$$

where the superscript in y_{it} and the subscript in m denotes the choice number which runs from 1 to k. As can be seen, the utility of the joint choice equals the sum of the utilities of the separate choices. Moreover, the normalizing constant in the denominator is obtained by summing over the answer combinations with no duplicate choices.

In a joint ranking model, the ranking is assumed to be made by evaluating all alternatives simultaneous or, more specifically, by performing all paired comparisons (Croon, 1989). This is different from the sequential evaluation process assumed in the standard LG ranking model. The joint ranking model for a design in which one selects and ranks the best k options from a set with M alternatives has the following form:

$$P(y_{it}^1 = m_1, ..., y_{it}^k = m_k | x, \mathbf{z}_{it}) = \frac{\exp(\sum_{l=1}^k (M - l)\eta_{m_l | x, \mathbf{z}_{it}})}{\sum_{m_1' \neq m_2' ... \neq m_k'} \exp(\sum_{l=1}^k (M - l)\eta_{m_l' | x, \mathbf{z}_{it}})}.$$

As can be seen, in this model the utilities are weighted by the number of objects minus the rank, which is the number the number of paired comparisons in which the alternative concerned is preferred .

Joint best-worst models assume that best and worst choices are made simultaneously instead of sequentially. This model is also referred to as the

MaxDiff (Maximum Difference) model (Bacon et al., 2007; Cohen, 2003; Louviere et al., 2014; Marley and Louviere, 2005). In this model, the best-worst probability has the following form:

$$P(y_{it}^b = m_1, y_{it}^w = m_2 | x, \mathbf{z}_{it}) = \frac{\exp(\eta_{m_1|x,\mathbf{z}_{it}} - \eta_{m_2|x,\mathbf{z}_{it}})}{\sum_{m_1' \neq m_2'} \exp(\eta_{m_1'|x,\mathbf{z}_{it}} + \eta_{m_2'|x,\mathbf{z}_{it}})}.$$

The best choice gets a weight of 1 and the worst choice a weight of minus 1.

With regard to the implementation of joint models in LG Choice Syntax, two things are important to keep in mind. First, as can be seen from the above logit equations, it is assumed that the predictor values do not vary across the multiple choices from the same set. An example of an implication of this limitation is that, contrary to sequential best-worst models, joint best-worst models cannot contain a predictor which represents a dummy for the worst choice. As explained below, the option "unequal" may sometimes help to circumvent this limitation.

The second comment applies when a log-linear scale model is used as part of a joint choice model. In this case the LG Choice Syntax implementation of the scale model concerns all choices simultaneously; that is, one has a single scale factor for the (weighted) sum of the η terms instead of a separate scale factor per η term. These two alternative implementations are equivalent when the scale factor depends on latent variables or on independent variables which are constant across the multiple choices.

5.2.3 Other Options

The complete syntax for defining the type of joint choice model is

```
dependent <variable name> <choice|ranking|bestworst>
          joint [missing] [unequal];
```

As can be seen, there are two additional options – "missing" and "unequal" – that can be used with joint choice, ranking, or best-worst models. The option "missing" changes the treatment of incomplete joint choices. This concerns the situation in which some persons select fewer than k options from a set in a pick k out of M task, provide fewer than the requested k choices in a ranking task, or select only the best option in a best-worst task. By default, for such situations, a logit model is set up for the available choices, that is, k is assumed to be smaller for the task concerned. However, when using

the "missing" option, a different approach is used in which the non-available choices are treated as missing data. In that case, the incomplete choice probabilities are obtained by collapsing the complete joint choice probabilities over the missing information. Note that this is also how missing values on categorical indicators are dealt with in the LG Cluster and DFactor modules.

The option "unequal" indicates that parameters should be unequal across the multiple choices, across the rankings, or between the best and the worst choice. By default, the parameters are assumed to be equal across choices. Note that in the LG joint choice models it not possible to have predictors that vary within choice sets. This means that the only way to let parameters vary across the multiple choices within a choice set is via the "unequal" option.

5.3 Specifying the Attributes

For choice models, not only predictors and covariates can be included as explanatory variables, but also attributes. These are explanatory variables which may take on different values across alternatives; that is, these are alternative-specific predictors. The list of attributes is defined in the "variables" section using the command "attributes". This list may also contain the attribute "_Constants_", which yields a set of alternative-specific constants.

The following is an example of defining attributes in a choice model:

```
attribute _Constants_, fashion nominal, quality nominal,
         price, none;
```

To obtain WTP parameters you need to indicate which variable is the price variable. This is done with the keyword "price", which in this example corresponds to the variable name. This yields

```
attribute _Constants_, fashion nominal, quality nominal,
         price price, none;
```

5.4 Random Regret Minimization (RRM) Models

Chorus (2010, 2012) proposed a class of choice models based on Random Regret Minimization (RRM) as an alternative to Random Utility Maximization (RUM). While the assumed behavioral mechanism underlying RUM-based models is that individuals select the alternative having the largest utility,

RRM-based models assume that individuals select the alternative having the smallest *potential* regret. A recent study evaluating RRM applications in various domains showed that latent class approaches, where the decision rule (RUM or RRM) differs per class, lead to substantial improvements in model fit compared to models assuming the same decision rule (usually RUM) for every class (Chorus, van Cranenburgh, and Dekker, 2014).

Recall that in RUM models $\eta_{m|x,\mathbf{z}_{it}}$ is modeled as a linear function of the attributes. More specifically, the effect of attribute p in latent class x is represented by $\beta_{xp}\,z_{itpm}$, where z_{itpm} denotes the value of the pth attribute for person i, replication or choice t, and alternative m. In contrast, the contribution of an attribute in RRM models is modeled as follows:

$$-\sum_{m'\neq m}\log\{1+\exp[\beta_{xp}(z_{itpm'}-z_{itpm})]\}.$$

As can be seen, not only the attribute value for alternative m enters into the additive model for $\eta_{m|x,\mathbf{z}_{it}}$, but also the values for the other alternatives. Note that without the minus sign, the above term expresses the contribution of attribute p to the potential regret for alternative m. The minus sign is needed because the smaller (the larger negative) the regret, the larger the probability of selecting the alternative concerned.

The above equation applies to simple main effects of numeric attributes. Chorus (2012) showed how RRM can be applied to model non-generic attributes, alternative-specific constants, nominal attributes, and interactions with predictors. For these cases, the contribution of an attribute in RRM models takes the following form:

$$-\sum_{m'\neq m}\log\{1+\exp(V_{itpm'}-V_{itpm})\},$$

where $V_{itpm'}$ and V_{xpitm} are the part-worth utilities associated with attribute p for alternatives m' and m, respectively. These part-worth utilities in turn can be freely specified as functions of i) attribute specifications of all sorts, including nominal and non-generic specifications; ii) their corresponding effects; and iii) interactions with predictors.

Moreover, many other extensions are possible, such as hybrid RUM-RRM models, RRM models with random parameters (continuous factors), RRM models containing a log-linear scale model, and models that assume some respondents use a RUM mechanism and others a RRM mechanism (modeled using two latent classes). For an application of the latter, where a latent

factor is also included with indicators for the preferred choice mechanism (similar to data fusion), see Hess and Stathopoulos (2013). Each of these extensions can be dealt with using the LG Choice Syntax. Moreover, RRM models can be combined with any LG Syntax feature.

There are two possible ways one can specify a RRM model using LG Choice Syntax. The first is to use the the keyword "rrm" in the specification of the dependent variable. That is,

```
dependent <variable name> <choice|ranking|bestworst> rrm;
```

This yields a model in which all attribute effects have the RRM form. However, it should be noted that the RRM option cannot be used in joint choice models or rating models.

Instead of using the keyword "rrm" in the definition of the dependent variable, it is also possible to indicate for each model term separately whether it has the RRM form. This involves using the parameter option "~rrm". The following is an example of a LC choice model in which all attribute effects are of the RRM type:

```
Class <- 1;
choice <- (~rrm) fashion | Class + (~rrm) quality | Class
          + (~rrm) price | Class;
```

An example of a hybrid RUM-RRM model where the alternative-specific constants and "fashion" are modeled as RUM terms, and "quality" and "price" as RRM terms is:

```
Class <- 1;
choice <- _Constants_ | Class + fashion | Class
          + (~rrm) quality | Class + (~rrm) price | Class;
```

Such hybrid RUM-RRM models can also be defined by first using the "rrm" keyword in the dependent variable specification and subsequently using the parameter option "~rum" for the RUM terms. For example, the dependent variable definition

```
dependent choice choice rrm;
```

combined with the equations

```
Class <- 1;
choice <- (~rum) _Constants_ | Class + (~rum) fashion | Class
            + quality | Class + price | Class;
```

gives the same hybrid RUM-RRM model as above.

The following is an example of a hybrid LC RUM-RRM model, where the alternative-specific constants and "fashion" are modeled as RUM terms, and "quality" and "price" are RUM for class one and RRM for class two:

```
Class <- 1;
choice <- _Constants_ | Class + fashion | Class
            + (b1) quality | Class + (b2) price | Class
            + (b3~rrm) quality | Class + (b4~rrm) price | Class;
b1[2]=0; b2[2]=0;
b3[1]=0; b4[1]=0;
```

As can be seen, for "quality" and "price", we include both a RUM and a RRM term and subsequently restrict the RUM effects of class 2 and the RRM effects of class 1 to 0.

5.5 Specifying More General Types of Model Equations

The main reason for using the LG Choice Syntax is to allow more general types of choice models. Besides the options for defining joint choice models and RRM models, which are not available in the point-and-click GUI module, the syntax provides a flexible and clear way of defining the choice model equations. These equations may contain interactions, conditional effects, a variety of parameter constraints, as well as different types of latent variables. Regarding the log-linear scale model, it is important to mention that attributes can also be included in the scale model, as well as latent variables other than the scale classes variable.

The following is an example of the equations defining a choice model containing interactions:

```
Class <- 1 + gender + age;
choice <-  fashion | Class + quality | Class + price | Class
            + fashion gender | Class + quality price | Class;
```

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In this model, the part-worths of the attribute "fashion" are specified to differ between males and females by the inclusion of an interaction with the independent variable gender. In addition, an interaction is included between quality and price, indicating that the price effect depends on quality and vice versa.

The following is an example of a model showing some extended options related to the scale-adjusted LC (SALC) model in addition to what is available in Choice Advanced:

```
Class <- 1 + age;
SClass <- 1 + age;
Class <-> SClass;
choice <- fashion | Class + quality | Class + price | Class;
choice <<- (s) SClass | Class + sex;
s[2] = 0;
```

In this model, SClass membership is assumed to be affected by the covariate age, SClass membership is allowed to be correlated with Class, and, in addition, the effect of SClass on the scale factor (the equation with the "<<-") is assumed to be absent in Class 2.

The following is an example of data fusion or, more specifically, the simultaneous analysis of best-worst choices and ratings:

```
Class <- 1;
SClass <- 1;
choice <- (b1) attFeature | Class;
rating <- 1 + Class + CFactor + (b2) Feature | Class;
choice <<- (s) 1 | SClass;
rating <<- 1 | SClass;
s[1]=0; b2=b1;
```

The main aim is to estimate the class-specific part-worths, the "attFeature" parameters in the choice equation and the "Feature" parameters in the rating equation. The model contains scale factors which differ both across responses (choice and rating) and across scale classes (sClass categories). In addition, to account for response style effects, it includes a continuous latent factor affecting the ratings. This data fusion application is described in more detail by Magidson, Thomas, and Vermunt (2009) and Vermunt (2013).

Finally, the following is an example of a latent Markov choice model for longitudinal data, in which individuals are allowed to switch between

time-varying (or dynamic) latent states across time points, and in which a time-constant latent variable affects the initial state and the transition probabilities:

```
Class <- 1 + age + gender;
State[=0] <- 1 + Class;
State <- 1 | State[-1] + Class | State[-1];
choice <- fashion | State + quality | State + price | State;
```

Note that State should be specified to be a dynamic latent variable. Moreover, a timeid should be used in addition to a caseid to connect the multiple choices/records belonging to the same time point.

5.6 Output Specific to Choice Syntax

The same output sections available in non-choice Syntax models can be obtained in Choice Syntax models. Thus, for example, EstimatedValues-Model can be obtained in addition to EstimatedValues-Regression. It should be noted however, that one choice output section in the syntax has the same name as in Choice GUI, but provides different information, namely the Profile output. The Profile output does not contain attribute parameters transformed to probabilities, but instead, as in all other Syntax models, the overall class-specific response probabilities aggregated over all choice sets.

Choice Syntax also contains various output sections which are specific to choice models. These contain information that is also available in Choice Basic. Specifically, nested within Parameters, one can find the sections Attribute Parameters, Attribute Profile (containing the same information as Profile in Choice Basic), Willingness-to-pay (when a price variable is specified), and Marginal Effects. The other output sections which are specific for choice models are Importance, Sets Profile, and Sets ProbMeans.

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