Forecasting Shares for Multiple Purchases: Towards a Test of the New Individual-level Multinomial Probit

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Abstract

We report on a field test of a new Individual-level Multinomial Probit (IMNP) model that applies to stated preference data gathered at the level of the individual consumer. Instead of inferring a covariance matrix of brand alternatives from a large sample of revealed preferences at the group level, this approach derives a covariance matrix from brand attribute similarities, weighted by the attribute importances for each consumer. The proposed IMNP simulator is not subject to the problem of Independence from Irrelevant Alternatives (IIA). Results from a Monte Carlo simulation show that the simulator performs as well as or better than the traditional Maximum Utility Rule (MUR) in ordinary situations, but is particularly useful with small samples. The simulator lends itself to forecasting shares for product assortments and frequently repurchased product classes. The paper outlines the new IMNP and reports on preliminary steps of a field test of the model, testing forecasting accuracy of students' preferences of confectionary in product assortment selection and repeat purchase situations.

Keywords: Conjoint analysis, multinomial probit, preference simulator, choice simulator, product assortment.

Introduction

Conjoint analysis is a popular tool for estimating consumers' multiattribute utility functions (Cattin and Wittink, 1982; Wittink and Cattin, 1989). One major use of conjoint analysis is the translation of predicted multiattribute utilities into predictions of preference or market share using one of a number of possible conjoint simulators.

The most popular forecasting algorithm is the "first choice", or maximum utility, rule (MUR), which assumes that an individual will always select the alternative with the highest predicted utility. Of course, sometimes we select other options for variety or some other fickle reason. Ideally, we want a tool that gives a probabilistic forecast. Available tools in this category have fallen into disrepute because they're theoretically unsound and they don't work in practice. They are extremely sensitive to simple linear transformations of the measurement scales on which they are based (Huber and Moore, 1979; Green and Kreiger, 1988).

One choice rule that does work in theory is the multinomial probit (MNP) model (Daganzo, 1979; Currim, 1982). This paper briefly describes a conjoint preference simulator based on the MNP model, which uses individual-level importance weights to describe an inter-item covariance matrix for each conjoint respondent. A field test of the new simulator is underway and results will be presented at the conference.

Psychological Determinants of Product Similarity

Most decision models assume a linear compensatory model, which is consistent with “information integration” theory (Anderson, 1981; Lynch, 1985) and "anchoring and adjustment" theory (Tversky and Kahneman, 1974). An individual anchors a judgment on one particular aspect of the task or judgment, such as an alternative's value on a particular attribute, and then adjusts the judgment by taking into account additional relevant information. In this way, judgments and choices of each item are made relative to the other items in the choice set, or to some standard based on experience or prior knowledge. Recent research suggests that consumer preferences are often constructed from what are perceived to be available rather than retrieved from memory of past preferences (Bettman, Luce, and Payne, 1998). Further, preferences often are based on the position of a product attribute relative to other attribute levels in the choice set (Drolet, Simonson and Tversky, 2000). Thus, similarity of alternatives becomes a relative construct: people make comparisons and evaluations with respect to the "average" of what is available. For example, faced with the alternatives of a pizza restaurant or a hamburger restaurant a consumer may see them as not at all similar. However if, say, a steak-and-salad restaurant is added to the choice set then, for that consumer, pizza and hamburger may come closer together in his/her mental map.

If we accept that respondents' judgments of a constrained choice set are anchored to the average of the attribute levels in the choice set, mediated by their relative importance, then we have the basis of a measure of product similarities at the individual level. The following section outlines the proposed new simulator.

Individual-level Multinomial Probit (IMNP)

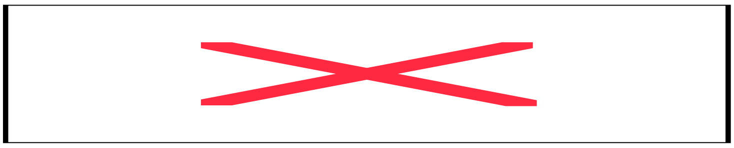
The derivation of a MNP conjoint simulator rests on the resolution of a specific problem, namely the estimation of the covariance structure of the choice alternatives.
The MNP covariance matrix is a measure of how much alternatives are similar to each other. When using revealed preference data, in the form of real market data or choice-based-conjoint, then the MNP task is to infer a covariance matrix of the available alternatives from the pattern of brand shares. This has had some reasonable success so long as the researcher has a large data sample and the unit of interest is the whole market, or an *a priori* identified segment. Choice modellers often find certain models, including MNP, impractical when they want to test the effects of introducing a new or modified

brand because the only information available relates to existing brands and attribute levels (Elrod and Keane, 1995). Further, there may be sound philosophical and practical reasons for wishing to forecast preference share at the level of the individual customer rather than at the aggregate level (Green and Srinivasan, 1990). An alternative approach would be to attempt to derive the covariance matrix, the pattern of brand similarities, directly by examining the attributes of each of the alternatives.

The proposed Individual-level Multinomial Probit (IMNP) model rests upon a simple extension of the formula for correlation (Winzar, 2004), and extends an idea first proposed by Johnson (1992). The inter-item correlation matrix can be customised for the tastes of each respondent by directly incorporating the attribute importance weights. The “similarity coefficient” between any two items 'x' and 'y' for individual 'i' can be represented by Equation 1.

The importance weights must be ratio scaled and non-negative. One feasible method for calculating appropriate weights is the Ordinary Least Squares procedure used in most ratings-based conjoint analysis studies. This allows easy calculation of standardised estimates, i.e., the absolute value of standardised coefficients; and produces error variances needed for subsequent resampling. Other feasible methods of estimating individual-level importance weights might include hierarchical Bayes techniques (Lenk, DeSarbo, Green and Young, 1996) or, in the right conditions, self-explicated measures (Srinivasan and Park, 1997).

(Equation 1)



where:

w_{ir} is the relative importance of attribute level 'r' to individual respondent 'i'.

x_r and y_r are the levels of attribute ‘r’ in alternatives x and y, Levels x_r and y_r have been standardised in the rows of the attributes matrix,

$\bar{x}_c$ and $\bar{y}_c$ are column means for the attributes in alternatives x_r and y_r respectively.

If we multiply each element of the similarities matrix by the error variance drawn from the importance weight estimation procedure then we derive a covariance matrix of the choice set alternatives. This individual-level covariance matrix can be used in a Monte Carlo simulation of the preference process.

Example IMNP simulation

Suppose a consumer is faced with the following choice set, and her attribute importance weights are calculated from a conjoint study. Attributes #1 and #2 are continuous variables (say, a quality index and units-per-dollar respectively) and attribute #3 is a binary dummy variable (say, an included service). Alternative A is low quality but cheap, and alternatives B and C are higher quality but more expensive.

	A	**B**	**C**	**Importance**
Attribute #1	1	4	5	0.7
Attribute #2	16	6	2	0.2
Attribute #3	1	0	1	0.1
Total	4	4	4	

Note that from the linear combination of importance weights and attribute levels all three alternatives have the same total utility scores. When the attributes are standardised in the rows and then weighted by the attribute importances the resulting similarities matrix is:

	A	**B**	**C**
A	1		
B	-0.950	1	
C	-0.988	0.891	1

The relative differences between the alternatives with respect to each attribute remains, but their weights cause Attribute #1 to dominate, and alternatives B and C are close substitutes and alternative A is antagonistic to the others.

Under the assumption that items with equal utilities have equal shares it would be expected that A, B and C will have about 33% share each using the traditional Maximum Utility Rule (MUR). However considering product similarity, alternative A should have a substantially larger share than 33%. We test this proposition by generating a 3 by 200 matrix of normally distributed random numbers with equal mean vectors and the above covariance matrix. The larger value in each column was recorded and taken as the chosen alternative. Resulting shares of choice over the 200 trials are summarized below. Results for the MUR are offered for comparison.

Alternatives	**A**	**B**	**C**
Proposed IMNP	47%	24%	28%
MUR	33%	33%	33%

Extending the IMNP

The proposed IMNP simulator offers a probabilistic preference forecast for each consumer. That is it suggests a likelihood of preference for each alternative. Another way of interpreting the probabilistic forecast is that it suggests the proportion of alternatives that would be selected over a long period of repeat purchase opportunities. Another interpretation is to see the forecast as the proportion of each alternative in an assortment all selected at the one time.

The conference presentation will show preliminary results of a field test of this model in which a sample of students is tracked over time in their selection of confectionary. Confectionary alternatives were defined as a fractional factorial design defined by following attributes: Chocolate type (dark/milk), nougat (yes/no), nuts (yes/no), caramel (yes/no), wafer biscuit (yes/no) and coconut (yes/no). Ratings-based conjoint analysis derives attribute importance for each person for each attribute. From this we can forecast preferences for a choice set of real confectionary options.

At time of writing the field research has just begun. We shall present our findings at the conference. This is the first of a series of studies designed to test the predictive validity of this new market-share forecasting tool.

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