ADVENTURES IN CONJOINT ANALYSIS:
A PRACTITIONER'S GUIDE TO TRADE-OFF MODELING AND APPLICATIONS

Abba M. Krieger
Statistics Department
Paul E. Green
Marketing Department
Yoram J. Wind
Marketing Department

Wharton School, University of Pennsylvania
700 Jon M. Huntsman Hall
3730 Walnut Street
Philadelphia, PA 19104-6340

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PREFACE

Over the past 30 years, the authors have been engaged in developing and implementing conjoint analysis techniques. Like most academics we have dutifully submitted our research papers to the marketing research journals (largely read by academics).

We have also enjoyed applying these models to real problems in business and government. We have learned much from this enterprise – both in technique development and humility when it comes to appreciating the practical side of problem solving.

Over the past 30 years conjoint analysis has both matured and expanded as a practical set of methods that can be applied to a variety of problems in marketing, including product positioning, market segmentation, product line development, pricing, and corporate image building.

This monograph is primarily addressed to marketing practitioners working either as consultants or as corporate employees. While pragmatically oriented academics should find some of the "cases" (we call them vignettes) useful for teaching purposes, this is a secondary goal.

At the end of the day it is the practitioner who is on the firing line and gets things done. We hope that our collection of vignettes will be useful to practitioners who are currently using conjoint methods as well as newcomers to the methodology.

Abba M. Krieger
Paul E. Green
Yoram J. Wind

INTRODUCTION

In the late 1960s, when conjoint analysis was first being developed as a marketing research tool, four ingredients had to come together to make the technique viable:

1. The initial approach, later known as full-profile conjoint analysis, had to be able to decompose respondents' preferences for various attribute-level (then called factor-level) combinations to solve for respondents' part worths. Technique developers first considered monotonic (i.e., nonmetric) regression and later found, to their pleasant surprise, that ordinary metric regression provided a robust alternative to the modeling of rank-order responses.

2. To be practical, some way also had to be found to construct conjoint profiles so that the part worths could be isolated without serious confounding. Fortunately, early conjoint developers were aware of fractional factorial designs, originally developed by a relatively small group of statisticians working in this specialized area.

   These designs (borrowed from the statisticians) provided a statistically sound way to construct attributes and their levels so that the desired part worths could be estimated without confounding experimental effects.

3. The techniques also had to be able to provide parameter estimates at the *individual* level so as to obtain specific part worths for each respondent. (These part worths could later be aggregated in various ways to provide subgroups for market segmentation.)

4. The model had to be flexible enough to incorporate some type of simulator that could take each individual's idiosyncratic part worths and compute its implied choices in various ways to develop forecasts of how the market might respond to managerial changes in product design. The values (part worths) of the attributes (e.g., brand, price, features, etc.) could be varied in ways so as to forecast changes in market shares and returns to the sponsor firm and to competitors in the same marketplace. Other aspects, such as market segments, could also be isolated for specific marketing strategy development.

Today, over 35 years later, conjoint analysis, as both a data analytic method and a practical procedure for new product development and market segmentation, has reached sophisticated levels. In addition, new statistical estimation techniques such as hierarchical Bayes and empirical Bayes have expanded the conjoint horizon to incorporate data from choice experiments as well as ratings-type data and even categorical response variables.

Somewhat surprisingly, the further development of simulators/optimizers (i.e., the phase that results in forecasts of company market shares and returns) has received comparatively less attention. Hence, while applauding the important strides that have been made in part worth estimation techniques, there is also another story to tell, namely, the less well-known advances involving the construction and strategic use of conjoint simulators/optimizers.

Our main objective is to describe some of the features that have cumulatively added to the value of conjoint simulators/optimizers. Without taking away from the strides that have been made in data analysis and part worth estimation, the *strategic* side of conjoint analysis (i.e., conjoint simulators) deserves attention in its own right. We believe that the current generation of simulators/optimizers provides information not thought possible in the beginning stages of conjoint analysis research.

Not surprisingly, most articles on conjoint analysis stress methodology, such as the application of latent class or hierarchical Bayes for improving part worth estimation. Sometimes, a capsule description of a recent conjoint application appears in the marketing research literature to illustrate the author's methodology. However, the literature is relatively quiet on the reporting of *real* applications of conjoint analysis. In particular, few discussions of *both* methodology *and* detailed applications are available.

There are good reasons for the dearth of published conjoint applications. These reasons include sponsor proscriptions on what material is available for outside dissemination and the potential danger of information leaks – particularly if the sponsor is using the conjoint results for strategic purposes. Accordingly, it is not easy for a company employee or, less so, an outside consultant, to submit cases for publication. In virtually all situations, actual data at least need to be disguised and, even here, the situation can be tenuous insofar as obtaining sponsor approval.

Fortunately, many appliers of conjoint analysis are primarily interested in the methodology and its value in solving management problems. The studies that we discuss here are disguised (unless otherwise noted), so as to respect sponsor confidentiality.

Focus

This monograph describes 16 different conjoint applications. All of the studies have been conducted by the authors. We have tried to select studies that augment and extend typical conjoint applications. Capsule descriptions of most of the studies have appeared in various journals or books.

We have selected these projects in order to provide a variety of contexts (e.g., products and services) and a relatively wide assortment of conjoint techniques. Each study can be considered as a kind of vignette. It is hoped that, collectively, the set of applications is sufficient to showcase the versatility of conjoint methods. Following these separate discussions, we briefly describe the kinds of software that are commercially available to conjoint analysis users.

Anticipated Audience for this Monograph

Our hoped-for audience for this review consists primarily of industry practitioners rather than academics. Practitioners include corporate marketing researchers and consultants. Leading-edge practitioners often provide important services to the marketing discipline, including an assessment of how well new methods *actually* work in the market place and, if they do not, how they can be improved upon. Frequently, consultants develop and test new ideas of their own.

(Sawtooth Software has been a good example of leading-edge research as well as a major software provider over the past thirty years.)

However, we are also mindful of the fact that many academics might find these vignettes of interest to students, at either the MBA or Ph.D. level. Accordingly, we welcome teachers who share our belief that both theory *and* practice are essential for a full appreciation of the analytical methods that also have value to industry practitioners.

From Simulator to Optimizer

One of the most significant events in recent conjoint research has been the emphasis placed on the development of optimal products. At best, most conjoint choice simulators (including those offered by commercial software packages) show the user which of a limited set of simulated profiles is “best” in the sense of largest market share. Bearing in mind that the full array of possible profiles may number in the hundreds of thousands (or even millions), limiting one's considered set to a dozen or so simulated profiles is unduly restrictive. Clearly, there appears to be a need for optimal-product selection procedures. The Appendix to this introduction describes some of the principal “tools of the trade.”

APPENDIX TO INTRODUCTION: SIMULATORS, OPTIMIZERS, AND DYNAMIC MODELS

Collecting and analyzing respondents' conjoint data is an essential part of the analytical process. Over the past 30 years that conjoint analysis has been applied, marketing researchers have expended intense efforts on data collection and part worth estimation. Part worths have been estimated by full profile, *Adaptive Conjoint Analysis*, hybrid conjoint, and categorical conjoint, with or without empirical or hierarchical Bayes enhancement. Part worth measurement and estimation processes are central to the accuracy and usefulness of all conjoint studies. Accordingly, much has been written about the pros and cons of various conjoint data collection and parameter estimation methods.

At the end of the day, however, it is *what is done with the part worths* that interests marketing managers. Hence, an important part of the applications process involves the design and use of "if–then" models: simulators and optimizers that provide bottom-line forecasts and comparisons of alternative strategic options.

Ironically, descriptions of simulators/optimizers have received much less attention in the literature than they deserve. This appendix to the Introduction attempts to redress this imbalance. Our main objective is to describe a variety of descriptive and prescriptive models whose goal is to forecast (or optimize) the sponsor firm's share or financial return position, given a set of actions that are played out in the simulator/optimizer modules. We try to show that such descriptive (or prescriptive) models are essential to both the tactical and strategic roles that conjoint models play in finding good (or even optimal) courses of action.

We start from a set of basic operations and progress to more elaborate models that are typically proprietary to a specific consulting firm. We describe three classes of models:

- *Simulators,* designed to implement if–then tactics on the part of a single supplier (with competitors)
- *Optimizers,* that solve for the highest market share or return product configuration, conditioned on known (or assumed) competitors' strategies, and
- *Dynamic optimizers*, that examine longer-term returns that reflect several "rounds" of competitive interplay (and the associated concept of Nash equilibrium).

Commercial Conjoint Simulators

Both Sawtooth Software and SPSS conjoint procedures have serviceable and easy-to-use simulators. Sawtooth's simulator is considerably more elaborate than that of SPSS and has the virtue of being appropriate for each of its three tradeoff models – *Adaptive Conjoint Analysis* (*ACA*), *Conjoint Value Analysis* (*CVA*), and *Choice-Based Conjoint* (*CBC*) – as well as its ancillary software, such as hierarchical Bayes, *Latent Class*, and *ICE*. The SPSS simulator is a basic choice simulator that is modeled after Bretton-Clark's package (which is no longer being promoted). The SPSS simulator utilizes holdout profiles (for reliability and validity checks) and computes a preference score for each respondent. It offers three choice rules: max utility, the Bradley-Terry-Luce probability of choice model, and logit, which uses the natural log of the utilities before normalizing market shares. The SPSS simulator also computes attribute importances from the part worths. In addition, Pearson's R and Kendall's tau are computed as summary measures of goodness-of-fit. Both Sawtooth and SPSS produce basic simulator outputs. However, Sawtooth's simulator is much more flexible in its ability to handle simulations for all of its conjoint models (ACA, CVA, and CBC) on a standardized basis.

Some consulting firms have developed their own simulator, which accompanies each of their completed conjoint studies. While detailed information on these tailor-made simulators is difficult to obtain, Table 1 contains a reasonable set of features that a commercial conjoint simulator could (or should) have. Some consulting firms also offer a sensitivity simulator, in addition to their primary simulator. Table 2 shows the typical characteristics of a sensitivity analysis simulator.

Insert Tables 1 and 2 about here.

In sum, most of the early conjoint simulators, commercial or consultant-based, have similar choice rule capabilities and some have sensitivity analysis features as well. Until recently, this was pretty much the state of practice.

Conjoint Optimizers

More recently, there has been a trend toward increasing the sophistication of simulators to handle attribute-level costs, thus leading to the potential development of conjoint optimizers. To the best of our knowledge, consultants' optimizers, at least tentatively, are proprietary models, rather than being offered for outright sale (although Sawtooth Software has recently marketed a conjoint optimizer called Advanced Simulation Module). Optimizers require the firm's management to be able to estimate variable costs at the product attribute level. Moreover, the researcher may also want to add associated price increments to the enhancement levels of a basic attribute offering. For example, hotel rooms may carry different prices according to room size and the extent of the room's amenities. These components naturally complicate the model and make additional demands on already difficult-to-estimate parameters.

We first describe two of our simulation/optimization models: *Conjoint Display* and *SIMOPT*. *Conjoint Display* is a simulator that utilizes part worths typically estimated from ratings data, as possibly obtained from Sawtooth's *Adaptive Conjoint Analysis* (*ACA*) procedure. *SIMOPT* is typically (but not necessarily) used for choice-based conjoint data. *Conjoint Display* and *SIMOPT* are both proprietary (i.e., not-for-sale) software.

Conjoint Display

Conjoint Display is a versatile simulator that typically utilizes part worths obtained from conjoint ratings data, e.g., Sawtooth's *ACA* data collection procedure. The input to *Conjoint Display* consists of each individual's:

- Set of part worths (including intercept term)
- Set of desired attribute importances
- Most preferred level within each attribute

- Set of background-variable category assignments
- Respondent weights (optional)

These inputs can, incidentally, be obtained from almost any conjoint data collection procedure, including Sawtooth software or SPSS's *Categories* software.

Conjoint Display then produces the following results:

- Displays (with pie charts) the market shares and most preferred levels within each attribute across respondents.
- Displays each attribute's part worths in terms of a dollar metric, where each enhanced attribute level is expressed in dollar terms, relative to the price attribute's base (or least-preferred) level.
- Displays derived attribute importances, at either the total-sample level or by any user-selected background (e.g., demographic) attribute. In addition, the user can compose a selected segment and find the associated attribute importances for only members of this composed segment.
- Composes one or more product profiles and finds the share of choices received by each profile, either for the total sample or for a segment composed by the user.
- Includes two kinds of simulations. In the single product case, the user selects one product profile (from those composed) and finds the group-average probability that it will be chosen. One can also find the number of consumers whose probability of selecting the profile exceeds a user-specified cutoff (say, 80%) value.
- In the multiple product case, the simulator can compose two or more profiles and obtain estimated market shares of each. *Conjoint Display*'s choice rule employs a flexible model that can emulate share of utility, max utility (winner takes all), or gradations in between.
- Employs a bootstrapping (resampling) procedure to show the degree of possible variation around the expected market shares of each profile.
- With the compose-a-segment module, *Conjoint Display* prepares an a priori segment description and shows how it behaves throughout various descriptive and analytical operations in the software package.
- With the perceptual mapping module, *Conjoint Display* selects any background attribute (e.g., age) and obtains a similarities map that relates attribute importance to the various age categories. Alternatively, one can also show attribute importances and demographics in terms of a hierarchical tree (based on two up to six dimensions in the multidimensional space obtained from the mapping).

In sum, *Conjoint Display* has been designed to incorporate descriptive summaries, choice simulations, and perceptual mapping/clustering in a coherent package that combines user flexibility with attractive graphics.

The *SIMOPT* Model

SIMOPT (SIMulation and OPTimization) is an optimal product-positioning model that can be used for either the single-product or the product-line case. Its principal inputs are a matrix of K buyers' part worths and a set of competitive product profiles. As in *Conjoint Display*, the part worths may come from any conjoint procedure, including the programs of Sawtooth and SPSS. In particular, part worths obtained from hybrid conjoint models are appropriate.

In addition to input matrices of buyer part worths and competitive-supplier profiles, the model has options for including:

- Buyer importance weights (reflecting buyers' frequency and/or amount of purchase)
- Demographic or other background attributes
- Demographic weights for use in market-segment selection and market-share forecasting
- Current market-share estimates of all supplier (brand) profiles under consideration (used in model calibration), and
- Costs/returns data, measured at the individual-attribute level.

SIMOPT uses a general choice rule, based on share of utility. This rule is called the alpha rule, and is capable of mimicking the more traditional Bradley-Terry-Luce (BTL), logit, or max-utility choice rules. The alpha rule assumes that the probability, π_{ks}, of buyer k selecting brand s is given by:

$$\pi_{ks} = \frac{U_{ks}^{\alpha}}{\sum_{s=1}^{S} U_{ks}^{\alpha}}$$

where U_{ks} is the utility of buyer k for brand s; α (which is typically set to at least 1.0) is chosen by the user; and S is the number of suppliers. If $\alpha = 1$, the model mimics the BTL share-of-utility rule; as α approaches infinity the model mimics the max-utility rule.

The primary data input to the *SIMOPT* model consists of a matrix of K individuals' part worths. In the simple case where no interaction effects are included, the general entry is

$p_{i,j}^{(k)}$ = part worth for level i of attribute j for individual k; $i = 1, \ldots L_j$; $j = 1, \ldots, M$;

$a^{(k)}$ = intercept term for individual k,

where L_j denotes the number of levels for attribute j, and M is the number of attributes. Each vector of part worths enables the user to compute a utility for any product/supplier profile for any individual k. A profile is defined by its levels ($i_1, \ldots i_M$). The utility of this profile to individual k is given by

$$U_k(i_1,\ldots,i_M) = \sum_{j=1}^{M} p_{i_j,j}^{(k)} + a^{(k)}.$$

We assume that in any given run of *SIMOPT*, each supplier is represented by a profile vector i_s; s = 1, 2, …, S. Hence, we can compute

$$U_{k,s} = U_k(i_s)$$

as the utility of individual k for supplier s. The “market share” of individual k for supplier s is

$$\pi_{k,s} = \frac{U_k^{\alpha}(i_s)}{\sum_{s=1}^{S} U_k^{\alpha}(i_s)}$$

for a specified value of α.

Once we have computed the $\pi_{k,s}$, we can combine them into a total market share by using $\sum_{k=1}^{K} W^{(k)}\pi_{k,s}$ where $W^{(k)}$, the weight for individual k, is non-negative with $\sum_{k=1}^{K} W^{(k)} = 1$. The individual weights can be further modified by considering various market segments. We generally assume that an input matrix of demographic (or general background) classification variables is available. We let

$D_n^{(k)}$ = the demographic category of individual k for variable n; $n = 1, 2, \ldots, N$, where N denotes the total number of demographic variables.

We also have weights E_n, one weight for each of the N demographics: $E_n > 0$; $\sum_{n=1}^{N} E_n = 1$.

In *SIMOPT* we can specify the number of demographics H we want to use, which demographics, $t_1, t_2, \ldots, t_H$, and the level for each demographic, l_h. More than one level within demographic can be included (but for expository purposes only one level for each demographic is shown here). We then have

$$V^{(k)} = W^{(k)} \sum_{h=1}^{H} I_h^{(k)} E_{t_h}$$

where

$$I_h^{(k)} = \begin{cases} 1 & \text{if } D_{t_h}^{(k)} = l_{h,} \\ 0 & \text{otherwise.} \end{cases}$$

and

$$V^{(k)} = \frac{V^{(k)}}{\sum_{k=1}^{K} V^{(k)}}.$$

The overall market share for supplier product s is given by

$$M_s^* = \sum_{k=1}^{K} V^{(k)} \pi_{k,s}.$$

(Note that M_s^* implicitly depends on the profiles of each of the S suppliers.)

Starting conditions for applying the model entail a set of initial supplier profiles and initial market shares, I_s. These initial supplier profiles are associated with market shares M_s^* and, hence, multipliers given by $f_s \equiv I_s / M_s^*$.

The adjusted market shares are the given by:

$$\hat{M}_s = \frac{f_s M_s^*}{\sum_{s=1}^{S} f_s M_s^*}.$$

Costs/Returns

Finally, the model can incorporate costs and returns and can optimize over this measure (as well as over market share). First, we let $R_{i,j}$ = return for level i of attribute j. (Note: the default value is $R_{i,j} = 1/M$ for all j and i.) We can then compute total return as:

$$T(i_1, i_2, \ldots, i_M) = \sum_{j=1}^{M} R_{i_j, j}.$$

Hence, for each supplier we have a total return: $T_s = T(i_s)$. This gives us, respectively, an adjusted and an unadjusted return for each supplier of:

$$O_s^* = M_s^* T_s, \quad \hat{O}_s = \hat{M}_s T_s.$$

SIMOPT's Features

The *SIMOPT* model's outputs consist of market shares or dollar contributions to overhead and profits for each supplier. In the latter case, direct (or variable) costs/returns have to be estimated at the individual-attribute level for each supplier – a daunting task in most real-world settings. In any given run of the model, the user obtains market share (return) for each supplier on both an unadjusted and adjusted (for initial share) basis. Outputs can be obtained for both the total market and for any segment defined by the user from the available demographic variables.

The user is then able to perform four types of analysis:

1. A sensitivity analysis. This shows how shares (returns) change for all suppliers as one varies the levels within each attribute, in turn.
2. An optimal attribute-level analysis. If this option is chosen, the model computes the best attribute profile for a given supplier, conditioned on specified attribute levels for all competing suppliers.
3. A cannibalization analysis. The user can also specify one or more ancillary products. If so, the model finds the optimal profile that maximizes share (return) for the set of chosen products (that can include the firm's existing products). This profile can be compared to the best product for a given supplier that does not take into account interactions with the firm's existing products.

4. A Pareto frontier analysis. In most real-world problems the marketing strategist is not only interested in finding the "best" product in terms of (say) return, but also wishes to get some feel for the tradeoff between return and market share. *SIMOPT* provides a capability to trace out the (Pareto) frontier of all profiles that are undominated with respect to return and share. The user can then find out what the potential value may be in giving up some amount of return for an increase in market share.

Practical Implications

As we have tried to show, *SIMOPT* has been designed as a practical model that can be operationalized by market-based, conjoint data. We believe its value lies in its versatility for considering:

- market share and/or profit-return optimization;
- total market and/or individual-segment forecasts;
- sensitivity analysis as well as optimal profile seeking;
- cannibalization issues related to product complementarities and line-extension strategies;
- calibration of results to existing market conditions;
- constrained optimization, through fixing selected attribute levels for any or all suppliers;
- a decision parameter (alpha) that can be used to mimic any of the principal conjoint choice rules (max utility, logit, BTL);
- sequential competitive moves, such as line extensions or competitor actions/reactions; and
- detailed information on who chooses which product under any specified set of conditions.

Like any model, *SIMOPT* no doubt will be modified and extended as further information about its performance and user reception is obtained. Perhaps its most significant contribution lies in illustrating how current conjoint-based simulators can be extended beyond their traditional application to estimating market shares for a few user-selected profiles.

Additional Features of *SIMOPT*

There are two additional aspects of the *SIMOPT* model that are of interest:

1. ALPH, the model used to find the *optimal* value of alpha, and
2. The divide-and-conquer heuristic, used to find optimal products and product lines in *SIMOPT*.

The ALPH Model

For any value of α, we obtain a set of predicted market shares, $\hat{\Pi}_1(\alpha), \ldots, \hat{\Pi}_S(\alpha)$. We also assume that we have *external* market shares $\Pi_1, \ldots, \Pi_S$. The problem is to find α such that the vector $\hat{\Pi} = \hat{\Pi}_1(\alpha), \ldots, \hat{\Pi}_S(\alpha)$ is as close as possible to $\Pi = (\Pi_1, \ldots, \Pi_S)$.

There are many possible distance metrics between the probability measures that can be considered. The ones most commonly employed are:

1. chi-squared:
$$d_c(\hat{\Pi},\Pi)=\sum_{s=1}^{S}(\hat{\Pi}_s-\Pi_s)^2/\Pi_s$$

2. entropy:
$$d_E(\hat{\Pi},\Pi)=\sum_{s=1}^{S}\Pi_s \ln \Pi_s/\hat{\Pi}_s$$

3. Kolmogorov-Smirnov:
$$d_K(\hat{\Pi},\Pi)=\max_{s}|\Pi_s-\hat{\Pi}_s|$$

4. absolute:
$$d_A(\hat{\Pi},\Pi)=\sum_{s=1}^{S}|\Pi_s-\hat{\Pi}_s|$$

The problem is to find the α that minimizes the distance function.

Clearly, if there is an α such that $\hat{\Pi}(\alpha)=\Pi$, then all four distance measures would lead to the same α, since all distances are non-negative and equal to zero when $\Pi=\hat{\Pi}$. When no such α exists, then the choice of an α that minimizes distance depends on the metric that is used. In practice, α does not vary widely across d_c, d_E, d_K and d_A. The differences arise because in comparing α_1 to α_2, $\hat{\Pi}_1(\alpha_1)$ could be closer to Π_1 than $\hat{\Pi}_1(\alpha_2)$, but $\hat{\Pi}_2(\alpha_1)$ could be farther from Π_2 than $\hat{\Pi}_2(\alpha_2)$. Which is viewed as superior would then depend on the metric.

Since there is no strong theoretical basis for choosing among d_C,, d_E, d_K and d_A, on practical grounds we choose the distance metric that has useful mathematical properties. It can be shown that d_C,, d_K and d_A are *not* unimodal in α. Although the value of α that minimizes each of the three distance metrics can be found by a numerical search procedure, this is time-consuming and not very elegant. In contrast, it can be shown that d_E is convex in α so there is only *one* optimum.

The Divide-and-Conquer Heuristic

To find the best product profile, conditional or specified competitive product configurations, *SIMOPT* employs a divide-and-conquer heuristic. We now discuss the nature of this heuristic.

In implementing the heuristic, we want to find the levels $(i_1^*,\ldots,i_M^*)$ that maximize share or return for the supplier of interest, possibly in an environment in which the supplier has more than one product in the product class. The objective we want to maximize can be written in the form $\Phi(i_1, \ldots, i_M)$, where i_m denotes the attribute level for attribute m; $m = 1, \ldots, M$.

The levels $(i_1^*,\ldots,i_M^*)$ that maximize Φ can be found by complete enumeration. The number of possible solutions is $B = \Pi_{m=1}^{M} L_m$. In practice, B could be large, although with high-speed computing if $b \leq 1{,}000{,}000$, this is certainly a viable approach. Alternatively, we can divide the attributes into subsets. To see how this approach works, assume that we divide the M attributes into two subsets, so that attributes 1 to M_1 define subset 1 and attributes $(M_1 + 1)$ to M define subset 2.

We begin the process by finding levels $(i_1, \ldots, i_M)$ that are reasonable first approximations to $(i_1^*,\ldots,i_M^*)$. One approach is to average the part worths within each level of each attribute and choose the level, within attribute, that has the highest average. Label these levels as $[i_1^{(0)},\ldots,i_M^{(0)}]$. We find $[i_1^{(p)},\ldots,i_M^{(p)}]$ from $[i_1^{(p-1)},\ldots,i_M^{(p-1)}]$ in two steps:

1. Find $[i_1^{(p)},\ldots,i_M^{(p)}]$ by choosing the levels for attributes 1, …, M_1 that maximize $\Phi[i_1,\ldots,i_{M1},i_{M_1+1}^{(p-1)},\ldots,i_M^{(p-1)}]$.

2. Find $[i_1^{(p)},\ldots,i_M^{(p)}]$ by choosing the levels for attributes M_1 + 1, …, M_1 that maximize $\Phi[i_1^{(p)},\ldots,i_{M_1}^{(p)},i_{M_1+1},\ldots,i_M]$.

If $\Phi(i^{(p)}) = \Phi(i^{(p-1)})$, then stop. Since Φ cannot decrease at each iteration, this approach leads to a local optimum.

Of course, the procedure can be extended to an arbitrary number of subsets. It should be pointed out that the effect of increasing the number of subsets is to reduce the amount of computation at the risk of not finding the global optimum.

There is no foolproof way of knowing whether this "divide-and-conquer" approach has produced the global optimum except by checking it with complete enumeration. In applications where we have applied this technique, the optimum *was* found. If we were to simulate data that are independently and identically distributed, then, intuitively, divide-and-conquer would work very well. Environments in which there are many interactions among attributes are ones in which the divide-and-conquer heuristic could potentially lead to a suboptimal solution.

SIMOPT is designed so that the user can specify the subset compositions. In general, subsets should be formed so as to minimize the correlation of part worths *across* subsets of attributes. Intuitively, attributes that are more closely related to each other should be assigned to the same subset and attributes that are more nearly independent should be assigned to different subsets. This suggests that we might like to cluster attributes based on distances between attributes.

We need a distance measure between attributes that reflects the extent to which individual's part worths for levels of one attribute are related to the part worths for levels of the other attribute. We propose two reasonable, albeit ad hoc, measures. Consider two attributes with I and J levels, respectively. We can create an $I \times J$ contingency table with entry n_{ij} indicating the number of individuals whose preferred levels are i for the first attribute and j for the second attribute. The distance between the two attributes can be defined as a (1 – p-value) of the chi-squared test; we use P-values for calibration when the number of levels differ across attributes and a (1 – p-value) so that similar attributes have small distances.

Another possibility is to create an $I \times J$ matrix where the (i, j) entry is the squared correlation between the part worths of level i of the first attribute and level j of the second attribute. Then, 1 - $\overline{R}^2$ defines another measure where $\overline{R}^2$ is the average of the IJ entries in this matrix. (In either case the SIMOPT model contains an option where the user can choose the make-up of the subsets in the divide-and-conquer heuristic; as noted above, the subsets can be designed in several different ways.)

The *SIMDYN* Model

The *SIMOPT* model is basically a static optimizing model where competitor's product profiles and consumers' tastes (i.e., part worths) are assumed to remain fixed over the firm's planning horizon. *SIMDYN* (SIMulation via DYNamic modeling) extends the SIMOPT model to explicitly consider a sequence of competitive moves and countermoves.

In addition, *SIMDYN* allows the user to input differential attribute-level costs, by competitor, and to fix certain attribute levels (e.g., brand name). SIMDYN maintains a running record of each competitor's optimal profile (when it makes a move) and associated market shares and returns (i.e., contributions to overhead and profits) for all competitors at any stage in the sequence.

Thus, *SIMDYN* is concerned with game theoretic modeling in which a group of competitors are allowed to sequentially choose product/price formulations, based on strategies adopted by earlier competitive moves. The main practical use of *SIMDYN* so far has been in the examination of those attributes and levels, for a given competitor (i.e., "your" supplier), that are reasonably robust to rational competitive retaliations. Chapter 3 describes an application of *SIMDYN* to an industrial problem dealing with cell phones.

Commercial Software

Conjoint analysis has undergone a sea change over the past 30 years. From relatively crude models and applications , the techniques have matured into a coherent and powerful set of methods for new product and service design, pricing analysis, and marketing strategy. Such applications as E-ZPass and TrafficPulse illustrate the value of conjoint techniques in municipal ventures, as well as in designing more traditional consumer and industrial products/services.

A vital element in the growth of conjoint analysis has been the development of *commercial software* for implementing conjoint modeling and applications. Sawtooth Software has been highly instrumental in this enterprise.

Sawtooth Software

Sawtooth Software, Inc. is located in Sequim, Washington. Richard Johnson founded this firm in 1982. Sawtooth continues to be the leader in the development of software for collecting and processing conjoint data as well as in the design of choice simulations. Sawtooth provides “one-stop shopping” for software, ranging from simulators utilizing ratings type input data to choice-based simulators. Sawtooth also provides tutorials and seminars to assist methodologists in developing expertise in *applying* conjoint methodology. Sawtooth maintains an active website (sawtoothsoftware.com) and provides a full line of conjoint (and ancillary) products.

A popular event is Sawtooth’s annual conference, where it provides information on new developments in conjoint analysis as well as other techniques, such as multidimensional scaling, cluster analysis, and data mining. It provides software for those techniques as well. Sawtooth also participates in the American Marketing Association’s annual Advanced Research Technique Forum. These two events are of major importance to conjoint practitioners and academics alike.

Sawtooth’s Advanced Simulator Model

In January 2003, Sawtooth Software introduced an important addition to its product line, namely its Advanced Simulation Module (ASM), as described in the following paper: http://www.sawtoothsoftware.com/download/techpap/asmtech.pdf. To summarize, ASM can:

- Optimize, based on utility, share, revenue, or profit, using all currently supported simulation models and options, including filters, respondent weighting, scale factor adjustment, or external effects
- Employ exhaustive search, hill-climbing, or genetic algorithms
- Optimize for single or multiple “searched” products (up to 100 total products may be considered in a simulation, on up to 30 total attributes)
- User can specify prices and/or variable costs per attribute level for revenue and profit searches
- Interpolates between levels, both on discrete steps or continuously
- Fix a subset of attribute levels for “searched” products
- Consider line extensions where one or more products are fixed and new product extensions are "searched" (goal is to maximize total return across product line)
- Offer "TURF-like" searches

- Search for minimal cost products that meet some performance threshold (utility, share, revenue, profit)

- Import part worth data from external data files.

"Home Grown" Simulators

Some consulting firms develop their own simulators/optimizers and provide their clients with an appropriate model for simulation/optimization as part of their "deliverables." In short, conjoint simulators run the gamut from relatively simple models that compute market shares from part worth input data to highly sophisticated models than can both simulate and optimize.

Further Developments in Conjoint Simulators: *SIMACT*

Conjoint simulators/optimizers continue to increase in sophistication and power. Recently, Krieger and Green have developed a model called *SIMACT* which we believe adds still greater power to conjoint simulation/optimization. By way of background, we first describe aspects of conjoint analysis and the features that comprise a simulator/optimizer.

There are three primary aspects that comprise a conjoint approach:

1. *The method and instrument used to collect the data.* This aspect includes the type of data collected (viz., choice-based conjoint, full-profile conjoint, hybrid conjoint, self-explicated, part-profile conjoint) and the way in which individual responses are obtained (viz., computer, mail intercept, telephone-mail-telephone, etc.).
2. *The statistical approach employed and the model assumed in obtaining part worths.* One main distinction is what assumptions are made with regard to commonality of part worths across individuals. At one end, one can assume that all individuals have the same part worths (often referred to as an aggregate model). At the other end is to assume that each individual's part worth is different. Since, in practice, individuals cannot evaluate a sufficient number of profiles to obtain reliable (or even identifiable) estimates at the individual level, hybrid approaches that incorporate self-explicated data *and* full-profile data have been proposed.

   There are also approaches in-between that include latent class models (in which part worths are assumed to be constant within segments0 and hierarchical Bayes models that assume each individual's part worths are random draws from a common distribution.
3. *The simulator/optimizer used to process the data.* Most recently, simulators have been developed that use the part worths at the individual level (however obtained) as input and provide estimates of shares either at the entire market level or for any market segment desired. (The first sophisticated simulator that had all of the above-mentioned capabilities, and in addition an optimizing feature, was Krieger and Green's *SIMOPT*).

We describe below the newest generation of simulators, called *SIMACT*, that has been developed by Krieger and Green (2004). This simulator has all the features that have already made *SIMOPT* sate of the art, with important practical extensions as well. We contrast SIMOPT with the new simulator, SIMACT.

Features of SIMOPT

As described earlier, the main purpose of *SIMOPT* is to provide estimates of share, either at the market or at a segment level. In addition, *SIMOPT* has the following capabilities:

1. *SIMOPT* is not only capable of evaluating products in terms of share, but also has the capability of determining return on profit. This feature requires that revenue and cost data be available or can be estimated.
2. *SIMOPT* can find the optimal product for a given supplier (either in terms of share or return).
3. Descriptive statistics provide the user with summary information about the part worths for the levels of each attribute.
4. Sensitivity analysis allows the user to assess the change in share as the levels of each attribute are scanned.
5. Pricing issues are also addressed by specifying the relationship between price and share and/or return for any supplier chosen.
6. Product line considerations are also addressed through the flexibility of allowing some suppliers to become unavailable.
7. All of the above features can be implemented at a scenario level that conditions the competitive situations under which shares are generated. For example, if the products/services are alternative regimens to cure (or alleviate) some medical condition, then the scenarios could logically be the severity of the case

SIMACT

While it is clear that *SIMOPT* is very flexible and can handle a wide range of situations, it does not handle models in which there are interaction terms (as will be described below). This limitation has led to the creation of *SIMACT*, which at its core is *SIMOPT* with additional capabilities. These enhancements include:

1. The ability to define a market scenario in terms of scenario variables and levels. For example, there could be two scenario variables, one identifying the severity of the condition (mild, moderate, or severe) and the other specifying gender.

2. The ability of the model to have interaction terms. It is important to note that *SIMACT* is so flexible that it allows the inclusion of any form of interaction and for any or a specific cases of that form. To clarify, there are ten possible interaction term types:
   - Scenario attribute versus scenario attribute
   - Scenario attribute versus product attribute
   - Scenario attribute versus the unavailability of a product
   - Scenario attribute versus price

- Two different product attributes (perhaps for different products)
- A product attribute versus the unavailability of another product
- A product attribute versus price
- The effect on other products if two products are unavailable.
- The effect on price of one product if another product is unavailable
- Cross elasticity, as defined by the prices of two products.

What is meant by “special cases” is that the model allows, for example, for the existence cross elasticities between the prices of some pairs of suppliers and not other pairs.

3. Descriptive analyses of these selected interaction terms.

4. Confidence intervals specifying the accuracy to which market shares are estimated in all situations.

Conclusions

To the best of our knowledge, *SIMACT* is the most flexible and sophisticated simulator that currently exists. It is important to mention that *SIMACT* is indifferent to the way in which the part worths are estimated or the data collected. Part worths can be estimated by Adaptive Conjoint Analysis, hybrid approaches, hierarchical Bayes, or any other available method, and these part worths can be used as input to *SIMACT*.

As the conjoint analysis field continues to advance, we can expect still further innovations with regard to analytical techniques and pragmatic advances in the way conjoint methods are used. While conjoint analysis has matured over the past 30 years, new features and applications have continued to appear on the marketing research scene.

Table 1. Typical Characteristics of Buyer-Choice Simulators

- Product simulation flexibility
  - Single product (vs. status quo)
- Likelihood-of-purchase (averaged response)
- Proportion of respondents whose predicted likelihood of purchase exceeds a user-supplied criterion level
  - Multiple products (sponsors and competitors): share received by each
  - Sponsor's product bundle (vs. competitors' products): share received by bundle and its separate components
- Choice rules for the multiple-product and bundle cases
  - Max-utility rule
  - Share of utility (STL) rule
  - Logit rule
- Other substantive features of choice simulators
  - Interpolation of part worths
  - Base-case entry with adjusted current-product comparisons
- Parametric confidence intervals around output measures
- Nonparametric (bootstrapped) intervals
  - Frequency tabulations and histograms of responses
  - Replicated cases in a single run
  - Inclusion of price and cost parameters
  - Brand-switching matrices
  - Derived attribute-level importances (based on choice data)
- Consumer characteristics
  - Respondent background data for market-segment summaries
  - Respondent importance weights
  - Respondent perceptual distributions of brand attributes
  - Individual/respondent output file (for additional analyses)
- Sensitivity features
  - Runs through all levels of a single attribute
  - Flexibility for fixing attribute levels at user-present values (in all runs)
- Cosmetic features
  - Menu-driven
  - Graphics output
- Pie charts and histograms of market share; part worth graphs
- Average part worths for total sample and segments

Table 2. Illustrative Outputs of Sensitivity Analysis Simulator

- Preliminary detail-proportion of sample selecting each attribute level as displaying the highest part worths, by attribute
- Sensitivity analyses (assuming a bundle of two or more new products) to compute bundle share (and individual item-shares), given:
  - Deletion of each item in bundle, in turn
  - Change levels of each attribute of each product, holding all others at initial levels
  - Fixing or lowering all status quo utilities by a fixed (user-supplied) percentage
  - Selection of a specified segment (based on background-variable categories or cluster-based segments)
  - Random selection of *K* bundles (up to 1,000) where random bundles can be constrained to include user-specified profiles and/or restricted attribute-level variation
- Additions to basic sensitivity analyses
  - Inclusion of attribute-level returns to the user's product line
  - Inclusion of price vs. utility relationship for adjusting respondent utilities to price increases/decreases
  - Inclusion of effect on firm's existing products (cannibalization) due to new product(s) introduction