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Effect of Level of Disaggregation on Conjoint Cross Validations: Some Comparative Findings*

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ABSTRACT

Early formulations of conjoint models focused on part-worth estimation at the individual level. As the methodology's popularity grew so did industry demands for increasingly larger numbers of attributes and levels. In response to these demands, new approaches, based on partial or full data aggregation (such as clusterwise/latent class conjoint and choice-based conjoint), have appeared. This paper suggests that pooled-data models will often be successful in predicting market shares when researchers employ monotonic attributes. In these cases more of a good attribute (or less of a bad attribute) is always more preferred. In the more realistic case, in which some of the attributes may be nonmonotonic, we find that data aggregation does not predict holdout sample preferences as well as individual part-worth models.

Subject Areas: Marketing and Preference Measurement.

INTRODUCTION

In marketing research, conjoint analysis continues to be a highly popular preference measurement tool (Green & Srinivasan, 1990; Carroll & Green, 1995). Early conjoint models all fitted parameter values at the individual level. As the methodology grew in popularity, so did industry calls for increasingly larger numbers of attributes and levels, adding to the burden of data collection. Researchers responded with new models, such as choice-based conjoint (Louviere & Woodworth, 1983), and

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clusterwise/latent class conjoint (DeSarbo & Cron, 1988; DeSarbo, Oliver, & Rangaswamy, 1989; Steenkamp & Wedel, 1993; Wedel & Kistemaker, 1989; DeSarbo, Wedel, Vriens, & Ramaswamy, 1992; Kamakura, Wedel, & Agrawal, 1994).

Choice-based conjoint models pool data across all individuals and, as such, do not obtain part-worth parameter estimates at the individual level. Clusterwise/ latent class models assume that preference segments exist. The models simultaneously group respondents into a set of more homogenous segments, while also estimating each segment's part-worth function.

Today's researcher has a wide variety of models to choose from, ranging from completely pooled data to partial disaggregation into preference-determined segments, to a wide choice of individually based models, including full profile (Herman, 1988), Adaptive Conjoint Analysis (Johnson, 1987), individualized hybrid models (Green & Krieger, 1996), and CASEMAP (Srinivasan & Wyner, 1989), a fully self-explicated approach to preference measurement.

Objective

The principal objective of this paper is to compare various approaches to part-worth function estimation in terms of their comparative ability to predict a relatively large set of holdout choices. To be specific, we compare the following models:

- Fully aggregated conjoint model
- Partially disaggregated model developed from clusterwise regression
- Partially disaggregated model developed from latent class regression
- Individual model in which full-profile part-worths are estimated by OLS regression
- Individual model in which part-worths are estimated by an individualized hybrid model
- Individual model in which part-worths are estimated from self-explicated data alone.

Still other models, such as hierarchical Bayes (Allenby, Arora, & Ginter, 1995; Lenk, Desarbo, Green, & Young, 1996) and empirical Bayes (Green, Krieger, & Schaffer, 1993), have been proposed. However, we believe that the models selected here span the range of commonly used, ratings-based, conjoint techniques.

The theme of the paper is straightforward. We believe that partial (or even full) data pooling across individuals may be feasible if the conjoint attributes are essentially all monotonic in the sense that the more the better. If the stimulus set is cars, more gas mileage, other things equal, is always to be preferred to less; lower car price is always to be preferred to higher price, and so on. However, if some or most of the attributes are nonmonotonic (e.g., color, horsepower, body style), individual differences may be much more pronounced. Even partial data pooling could lead to misleading average part-worths that do not adequately reflect individual differences within segments. To the best of our knowledge, the effect of full and partial data aggregation under conditions involving nonmonotonic attributes has not been examined from a comparative model standpoint.

Format

We first present some theoretical and empirical findings from behavioral decision theory, dealing with the robustness of linear models to changes in attribute weighting. These findings suggest that choice profiles with monotonic attributes are reasonably insensitive to attribute weights, particularly if the attributes themselves are positively correlated. We then review two empirical conjoint studies showing that total market share estimates, obtained from either individually estimated conjoint part-worths or pooled data, exhibit high correspondence; both studies employed monotonic attributes.

We then describe our comparative study of the six estimation models listed above. Cross validation results of each model are compared across a variety of summary measures. We conclude with a brief discussion of the implications of this comparison for managerial decision making and future industry studies.

BACKGROUND

It is well known from the behavioral decision theory literature that preference-based linear models are very robust to changes in the weighting coefficients, provided that the underlying attribute scores are monotonic and, particularly so, if the attributes are positively correlated (Dawes & Corrigan, 1974; Wainer, 1976; Anderson & Shanteau, 1977). More recently, Green, Krieger, and Schaffer (1992) illustrated both analytically and by simulation, that if the levels of each attribute are similarly ordered across persons, preservation of the ranks of attribute importances provides enough information to make good predictions. For example, if one can estimate only the order of levels within attribute and the ordering of attribute importances, the average correlation between true and estimated part-worth is .73.

Comparative Studies

Elrod, Louviere, and Davey (1992) and Oliphant, Eagle, Louviere, and Anderson (1992) are two studies that compared preference models with pooled-data models in the context of monotonic attributes. The first study consisted of student evaluations of apartment rentals varying on four monotonic attributes: rent, number of bedrooms, distance to university, and safety. In estimating parameters for the conjoint ratings data, Elrod et al. did not use the conjoint part-worth model. Instead, two linear models and one model with interaction terms were fitted. Four different choice-based models, including a model for estimating interaction effects, were also fitted.

Elrod et al. (1992) employed the proportion reduction in mean squared error of prediction and mean absolute deviation of prediction as their primary measures of predictive fit. The principal objective of the study was to predict choice shares rather than individual first-choice hits. The authors found that, in general, the ratings-based and choice-based models showed similar aggregate market shares.

In a further comparison of choice and preference models, Oliphant et al. (1992) also employed (essentially) monotonic attributes. In this case the context involved a commercial road-service insurance package containing various emergency and camping benefits. There were two 4-level attributes (brand and price) and eight 2-level features (present vs. absent). The analysis indicated that one brand dominated the other three; hence, there was also high homogeneity on this attribute. The remaining nine attributes (price and the eight features) were all "monotonic." Similar to the results of Elrod et al. (1992), Oliphant et al. found that both individually based conjoint and (aggregate-level) choice-based conjoint models resulted in about the same performance in aggregate market share predictions. The authors emphasized the point that similarity in cross validation performance is again related to their use of (essentially) monotonic attributes. Oliphant et al. stated:

> Thus, future comparisons should be directed at situations in which the attributes are largely qualitative or quantitative and nonmonotonic. The larger the degree of individual differences in preferences for attribute levels, the better. (p. 393)

Clusterwise and Latent Class Regression in Conjoint Analysis

There has been considerable interest recently in conjoint approaches that estimate parameters at the partially disaggregated level. As noted earlier, these models search for groups of respondents (with corresponding group-average part-worths) that are internally homogeneous, while differing from the part-worth functions of the remaining groups. Models have been developed for analyzing both traditional ratings data (e.g., the subjective likelihood of choosing a product profile) and choice-based conjoint (e.g., choosing one's most preferred item from proffered sets of K competitive products each). On the face of it, partially disaggregated approaches would appear to offer a promising middle ground between fully aggregated and fully individualistic conjoint models.

The Empirical Study

We now turn to our comparative study of the six models listed earlier:

- Fully aggregate model, in which data are pooled across all individuals
- Partially disaggregated models, based on
    - Clusterwise regression
    - Latent class regression
- Individual models, as estimated by
    - Full profile evaluations and OLS regression
    - Individualized hybrid model
    - Self-explicated data alone

Each of these models has been described in references, cited earlier.

Study Design and Administration

The conjoint analysis task consisted of business students evaluating profiles of new automobiles. Respondents were presented with descriptions of automobiles on cards. Based on preliminary indications of interest provided by students, sporty cars in the midprice range were selected for inclusion in the study. Attribute levels were selected by examining brochures of the cars provided by car dealers. To make the task more realistic, each car model consisted of multiple pictures of the car in colors corresponding to the study design, viewed from different angles. The pictures were examined by each respondent prior to and during the task. Subjects were students in undergraduate and graduate business classes. The students were shown how to complete the task by the classroom instructor. Students were told that they were doing this task to provide a better understanding of how students make car purchases. All tasks were completed during class and in the classroom.

We believe that business students are appropriate for this study for a number of reasons. First, all students in our sample had indicated, on a pretest, that they were knowledgeable of sporty cars. A majority (65%) of students also indicated that they had either purchased a new car or had been involved in the purchase of a new car for a family member or close friend. Further, the study was done at a university where the annual tuition and living expenses exceed $25,000. It is not uncommon for students at this university to purchase sporty cars.

The stimulus set consists of new sporty cars described on six attributes: make/model, gas mileage, price, color, sound system, and warranty. Table 1 shows a description of the attributes and levels. All attribute levels were taken from the brochures available at the time. Data were collected in the spring of 1995.

Only two of the attributes (gas mileage and price) of Table 1 are expected to be "monotonic," that is, show high correspondence across respondents with respect to the preference ordering of levels within attribute. The information in Table 1 appeared on a card that was in full view of the respondent throughout the whole interview. In order to provide further familiarity with the attributes and levels (before administering the full profile task), the self-explicated exercise was presented first. The levels of each attribute, in turn, were rated on a 0 to 10 *least/most* desirable scale. Following this, a constant sum task was presented: the respondent was asked to allocate 100 points across the six attributes so as to reflect their relative importance in purchasing a new car.

Validation Set Profiles

The validation task was administered before the full profile calibration task. First, a master set of 64 profiles was constructed from an orthogonal main effects plan. Columns of the design matrix were selected so that each level appeared at least once in each block of four profiles. Two such designs of 32 (almost orthogonal) profiles each were constructed from the master design of 64 profiles. Each respondent randomly received one of the two subdesigns for both the validation and calibration tasks. For each block of four profiles (there were eight such blocks), the respondent was asked to allocate 100 points across the four profiles so as to reflect the likelihood of choosing each car in a purchase situation. Block order and profile order within block were randomized.

Calibration Profiles

The calibration profiles were also blocked into eight sets of four car descriptions each, in which both blocks and car description within block were randomly ordered. Within each block of four profiles the respondent was first asked to sort the cards with respect to preference and then rate each profile on a 0 to 100 purchase scale, ranging from 0 (*definitely would not consider*) to 100 (*definitely would*

Table 1: Attributes and levels of conjoint stimuli.

Attributes	Levels	Attributes	Levels
Make and Model	• Honda Prelude • Mitsubishi Eclipse • Nissan 240 SX • Toyota Celica	Exterior color	• Green • Red • White • Blue
Miles per gallon	• 18 mpg average • 24 mpg average • 30 mpg average	Sound system	• AM/FM radio (no additional charge) • AM/FM and cassette at an additional $200 cost • AM/FM, cassette, and six-disc CD at an additional $600 cost
Base Price	• $16,000 • $20,500 • $25,000	Warranty	• 1-year warranty (no additional charge) • 4-year warranty at an additional $400 cost • 7-year warranty at an additional $700 cost

consider). In all cases the respondent was asked to assume that the car was satisfactory on all other attributes of interest. Following the calibration task, the respondent was asked to complete a short battery of demographic and product knowledgeability questions.

All respondents were enrolled in a large, private Northeastern university; sample size was 128. Sixty-four randomly selected respondents received the first experimental design and 64 received the second experimental design. The sample composition was 65% male and 35% female. Their mean age was 24 years. Eighty-three percent were either single or divorced.

ANALYSIS OF THE CALIBRATION DATA

The six conjoint preference models are first compared in terms of their fit to the calibration data. Table 2 shows comparative results. Comparison of the six models is straightforward; correlation measures and RMSEs (root mean squared errors) are shown. Note that the individual-level OLS, full-profile model (based on all 32 calibration profile evaluations) has the best fit, followed by the individual hybrid model, which entailed only the first 16 profiles. The aggregate-level model (with individualized intercept) does particularly poorly in contrast to the findings of Elrod et al. (1992) and Oliphant et al. (1992). Of course, in their studies, most if not all the attributes were monotonic.

In the clusterwise regression model, four clusters were obtained, consisting of 29, 35, 33, and 31 respondents, respectively. For each of the four separately pooled clusters, part-worths were obtained by dummy-variable regression, with individualized intercepts. As noted from Table 2, partial disaggregation improves both the correlation and RMSE measures, compared to the fully aggregated model. However, the clusterwise regression fits are still poorer than those of the individualized models.

Table 2: Calibration fits for six alternative conjoint models.

Model	Average (over Individuals) Correlation	Average (over Individuals) Root Mean Squared Error
Self-Explicated	.613	.176
Individual-Level Hybrid	.708	.152 [a]
Individual-Level OLS	.803	.140 [a]
Aggregate OLS	.410	.258
Clusterwise Regression	.499 [a]	.218
Latent Class Regression	.482 [a]	.243

[a]These pairs within column are not significantly different at the .05 level. All other (correlated-sample) pair comparisons are significantly different within column.

A similar procedure was followed for the latent class model. In this case only two stable clusters (consisting of 87 and 41 respondents, respectively) were found. The sample calibration fits are slightly poorer for this model, compared to clusterwise regression, but are better than their counterparts obtained from full aggregation over all respondents.

VALIDATION ANALYSIS

Most validation studies compute such measures as individual-based Pearson correlation, RMSE, and rank position between model predictions and responses to the holdout sample (Green, Helsen, & Shandler, 1988). Table 3 shows a summary of validation model performances in terms of these three measures.

As is the case for the calibration fits in Table 2, all validation measures in Table 3 are first computed at the individual level and then averaged over individuals. As noted from Table 3, the individual OLS and hybrid models continue to perform better than the others. We find that the average (across individuals) correlations for the clusterwise regression and latent class models are better than that for the aggregate conjoint model; partial disaggregation takes at least some of the heterogeneity into account. However, these performances are still worse than even the self-explicated individualized model. Overall, we find that the alternative models vary considerably in their predictive efficacy. We suggest that the differences between models are found here at least partly because of the inclusion of nonmonotonic attributes.

The average rank position measure is shown next. Given the large number of ties in the holdout data (in which responses need only be weakly ordered within blocks of four profiles each), a partial credit scoring model was used; tied values get part scores. In sum, in terms of the three traditional validation measures of Table 3, the individual-level, full-profile OLS model, and the individual hybrid model (the latter based on only the first 16 of the 32 full-profile evaluations) show the best predictive performances.

Table 3: Validation performance for six alternative conjoint models.

Model	Average (over Individuals) Correlation	Average (over Individuals) Root Mean Squared Error	Average (over Individuals) Rank Position
Self-Explicated	.595	.412	.066
Individual-Level Hybrid	.683	.322	.075
Individual-Level OLS	.712	.318	.082
Aggregate OLS	.399	.350	.046
Clusterwise Regression	.452	.319	.055
Latent Class Regression	.448	.321	.033

[a] Not significantly different at the .05 level; all other (correlated-sample) pair comparisons are significantly different, within column.

Choice Probability Prediction

The probability of choosing each of the four options in each validation block also can be derived from the estimated model coefficients. This is done by assuming a simple Bradley-Terry-Luce rule, in which the predicted probability of choosing each option is proportional to the option's utility. The greater the utility of each option, the higher the predicted probability of choice; the probabilities add up to 1.0 for a given option set. These probabilities are calculated for all six models in our study. We then estimate actual probabilities of choice by using the responses obtained separately from the respondent via the constant sum validation task of 32 profiles. (As noted earlier, respondents were asked to indicate their preference by dividing 100 points across the four cars in each block of four, according to their relative preference.)

We compare the two sets of probabilities (over blocks and individuals) across the models. Each model is used to predict expected market shares. We compute both mean absolute error (MAE) and root mean squared error (RMSE) as measures of how well market shares are predicted by the models. Table 4 shows this summary. Again, we note that the individual OLS and hybrid models perform best.

There are two probable reasons why the individualized models outperformed the cluster-based and latent class models:

1. In our data set we had relatively few attributes (namely, six), each at only three or four levels. Also, each individual received relatively many (32) profiles. Hence, the ratio of data points to number of part-worth estimates is comfortably high and error variance is relatively low.

2. Since price was embedded in the descriptions of the levels of some of the attributes, only two of the attributes are structurally monotonic. The relative lack of monotonic attributes is more likely to lead to heterogeneous part-worths, thus favoring the individualized models.

In summary, our results indicate that fully aggregate-level conjoint analysis, which assumes that the "true" individual part-worths are the same across all individuals, performs worst under each of the following validation measures:

Table 4: Market share prediction performance by model.

Model	Mean Absolute Error	Root Mean Squared Error
Self-Explicated	.079	.098 [a]
Hybrid	.066 [a]	.084 [a]
Individual-Level OLS	.055 [a]	.069
Aggregate OLS	.304	.372
Clusterwise Regression	.148	.193
Latent Class Regression	.205	.251

[a] Not significantly different at the .05 level; all other (correlated sample) pairs are significantly different, within column.

- Pearson correlation
- Root mean squared error
- Rank position of profile within presentation block
- Share-of-utility rule in predicting constant sum allocations within block.

It should also be pointed out that the aggregate-level conjoint model is fitted with individualized intercepts; still, the results are the poorest across the six models in our study.

IMPLICATIONS FOR THE MARKETING MANAGER

Enhancements to basic levels (e.g., AM/FM radio, cassette, and six-disc CD versus AM/FM radio alone) are expected to cost more, necessitating a trade-off of enhancement versus additional cost to the respondent. In some cases (e.g., cars and computers) the prices of enhancements may be shown explicitly, on an unbundled basis. In other situations, additional costs are added to the base price without separate tagging of the enhancements. In either case, in the real world the consumer expects to pay more for enhancements to the basic product (or service) attributes.

The manager should be aware of the fact that enhancements (with added consumer costs) can be incorporated in conjoint designs on either an unbundled or bundled basis. If bundled, the extra-cost enhancements can simply be added to the base price. The base price, in turn, can still serve as a conjoint attribute that is varied orthogonally with the nonprice attributes. Hence, a separate set of part-worths can be obtained for base price. For each enhancement, however, the part-worths will reflect the net effect of the (positive) enhancement and the (negative) increased cost.

Since consumers exhibit individual differences regarding the disutility of monetary outlay, we can expect the enhancement/price combination to be nonmonotonic in many instances. This finding, in itself, is interesting because it serves to distinguish among respondents, not only in terms of base-price part-worths but trade-offs with enhancement/additional cost combinations as well. Inherently qualitative attributes, such as the car's color, are by definition nonmonotonic, since no underlying continuum exists. Again, we would expect individual differences to be pronounced in such attributes as color, brand, type of purchase outlet, service agreement features, and so on. In sum, nonmonotonic attributes lead to "richer" data in the sense that one's most preferred attribute level can vary markedly across individuals.

If only monotonic attributes are employed, the resulting segmentations are less detailed in the sense that consumers are effectively segmented on the basis of (derived) attribute importances alone. With nonmonotonic attributes included, the manager can segment on both relative attribute importance and most preferred attribute level. Restricting conjoint designs to only monotonic attributes also tends to produce large variations in profile evaluations; for example, major bargains versus obviously overpriced options. Although systematic study of this phenomenon is still missing in the conjoint literature, it is possible that consumers may experience disbelief regarding some of the more extreme profiles, thus affecting their evaluative responses (e.g., showing low enthusiasm for almost too-good-to-be-true "bargains").

A second result of this study is its emphasis on multiple measures of validation, such as Pearson correlation, RMSE, market share, and so on. In this study the comparative results were relatively stable across different validation measures. Such may not be the case in other studies.

The study of nonmonotonic conjoint attributes has received relatively little attention to date. Empirical comparisons between unbundled and bundled pricing should also be made. With increasing researcher interest in partially aggregated models (such as clusterwise and latent class conjoint), more study is needed on whether these models accurately capture the greater consumer heterogeneity associated with nonmonotonic attributes. [Received: January 10, 1997. Accepted: September 10, 1997.]

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