Note on Conjoint Analysis

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Suppose that you are working for one of the primary brands of global positioning systems (GPSs). A GPS device receives signals from satellites and, based on those signals, it can calculate its location and altitude. This information is displayed either as text (latitude, longitude, and altitude), as a position relative to a known object (waypoint), or, increasingly, a position on a map or navigational chart.

GPSs come in many versions. Some mount in cars and trucks and provide driving directions. Others are used in navigation on the oceans or lakes. And some are handheld, useful for hiking, camping, canoeing, kayaking, or just walking around the city. We will suppose that it is your job to decide which features the new handheld GPS will have. Each feature is costly to include. Including the feature will be profitable if the consumers' willingness to pay (WTP) for that feature exceeds the cost of including that feature by a comfortable margin.

Simplified Conjoint Analysis Illustration

We'll simplify the problem for illustration. First, let's assume that all consumers have the same preferences – the same WTP for each feature. This assumption does not hold in real markets, hence we will have to consider preferences either by segment or as some distribution across all potential consumers. We do this by estimating a conjoint model for each consumer or by estimating how WTP varies across consumers. Second, let's assume that there are no engineering constraints. The GPS can have all of the features or none of the features and the costs are additive. Finally, we will assume there are only three features of interest, plus price:

- Accuracy – the GPS can locate your position within either 10 feet or 50 feet
- Display color – the screen either displays colors (for a map) or is black & white
- Battery life – the battery lasts either 12 hours or 32 hours
- Price – the price can vary between $250 and $350

With four things varying (3 features plus price), at two levels each, there are $2 \times 2 \times 2 \times 2 = 2^4 = 16$ possible combinations. Suppose that we create pictures of each of the sixteen GPSs and have consumers evaluate all sixteen GPS "profiles." They might rate each potential GPS on a 100-point scale where 100 means most preferred. This is a rudimentary conjoint analysis task. Naturally, great care would be taken to make sure that consumers understood the features and that the task were realistic. (We show examples later in this note.)

The data, for a single consumer, might look like that in Table 1. The first column indicates the consumer's preference for a particular combination of features and price. (These are the data as indicated by *italics*.) The next four columns indicate whether or not the rated GPS has that feature-price combination. A '1' indicates the feature is at its "high" level, e.g., 10 feet rather than 50 feet, and a '0' indicates a feature is at its "low" level, e.g., 50 feet rather than 10 feet. Not surprisingly, the data ('*4*') indicate that consumer prefers least an inaccurate GPS, with low battery life, a B&W screen, and priced at $350. The data suggest ('*99*') that the same consumer prefers most an accurate GPS, with a long battery life, a color screen, and priced at $250.

Table 1. Preference Ratings for 16 Handheld GPSs

Preference Rating	Accuracy 10 vs. 50 feet	Battery 32 vs. 12 hrs	Color Color vs. B&W	Price $250 vs. $350
4	0	0	0	0
41	0	0	0	1
18	0	0	1	0
60	0	0	1	1
33	0	1	0	0
74	0	1	0	1
49	0	1	1	0
86	0	1	1	1
11	1	0	0	0
55	1	0	0	1
27	1	0	1	0
66	1	0	1	1
41	1	1	0	0
85	1	1	0	1
58	1	1	1	0
99	1	1	1	1

The goal of conjoint analysis is to determine how much each feature contributes to overall preference. This contribution is called the "partworth" of the feature. In this rudimentary conjoint analysis, we can use ordinary least-squares (OLS) regression as is available in Excel under tools/data analysis/regression.[1] An abridged output is shown below. The partworths are the regression coefficients. For example, the partworth of 10 feet (vs. 50 feet) is 9.6 indicating that the consumer gets 9.6 "utils" if the accuracy of the GPS is improved. Similarly, the regression estimates that the consumer gets 40.6 "utils" if the price is reduced from $350 to $250.[2]

Table 2. Regression to Estimate Partworths for Features and Price

	Coefficients	*Standard Error*	*t-statistic*
Intercept	2.7	1.0	2.7
10 feet vs. 50 feet	9.6	0.9	10.9
32 vs. 12 hours	30.4	0.9	34.5
Color vs. B&W	14.9	0.9	16.9
$250 vs. $350	40.6	0.9	46.1

[1] You may need first to add the Analysis ToolPak under the tools/add-ins menu.
[2] Statistically, the regression does quite well. The R^2 is 0.99 and all coefficients are highly significant as indicated by their high t-statistics.

With this regression we compute the consumer's willingness to pay (WTP) for each feature. Because the consumer gets 40.6 "utils" when the price is reduced by $100 ($350 → $250), the value of each "util" is about $2.46, which we obtain by comparing the difference in price to the difference in the price-partworths: $100/40.6. We now compute the WTP for accuracy. It is approximately $23.65, which we as obtained by (9.6 utils)*($2.46/util). Similarly, the WTP for increased batter life is $74.88 and the WTP for a color screen is $36.70.

These partworths are approximate rather than exact numbers because there is measurement error when the consumer provides his or her preferences on the questionnaire. This measurement error translates into uncertainty in the estimates of the partworths as indicated by their standard errors. Nonetheless, if we asked enough consumers to complete a conjoint analysis exercise, we could gain greater statistical power and obtain estimates of the partworths that are more accurate.

Making the Stimuli More Realistic

Conjoint analysis is one of the most widely used quantitative marketing research methods. Firms routinely rely upon its outputs for decisions about new products, about marketing strategy, and about marketing tactics. Real applications attempt to make the consumers' tasks realistic. For example, Figure 1 illustrates a recent MIT project on GPSs that included 16 features, much more realistic than the 4 features in Table 1. The stimuli that the consumers evaluated included jpegs that encoded some of the features and icons that encoded other features. This is illustrated in Figure 1. Before evaluating these GPS profiles, each respondent was asked to read a series of descriptions that explained each feature of the GPS.

Figure 1: GPS Stimulus with 16 features

Alternative Consumer Tasks

There are five common conjoint analysis tasks. They are:

- full-profile ratings
- full-profile rankings
- partial-profile ratings
- choices among profiles
- direct ratings of importances

The full-profile ratings task is similar to the task illustrated above. Consumers are shown hypothetical products, called profiles, that are described by all of the features that are being varied (review Figure 1). Consumers are asked to rate the profile on either preference (as in our example) or their intentions to purchase the profile. Ratings tasks are called “metric” tasks because the consumer’s rating a continuous variable. Although OLS can be used, there are now more sophisticated methods available. Two common methods include hierarchical Bayes estimation and polyhedral methods.

We will not get into the details of the statistical methods in this note. However, we provide references at the end of this note for the interested reader.

The full-profile ranking task is related. However, instead of rating the profiles, consumers simply rank order the profiles. In the example above, they would rank the GPSs from 1 to 16 where 1 indicates their most-preferred GPS and 16 their least-preferred GPS. With the advent of web-based interviewing, the rankings task has become more popular. In web-based surveys consumers are shown a full set of products. They first choose their most preferred and it disappears from the screen. They then choose their next most preferred continuing until all profiles are ranked. Because rank data is, at best, an ordering of profiles it is called "ordinal" data. Although OLS is sometimes used to provide approximate partworths, it is more appropriate to use methods such as monotonic regression, linear programming methods, or ranked-logit methods. Figure 2 provides an example of a web-based ranking task from an MIT study on Smartphones.

Figure 2. Example of a Ranking Task
(from Yee, Dahan, Hauser, and Orlin 2007)

The third method, partial-profile tasks, is used when there are many features and it is difficult to represent all features at once. The consumer is told that all of features that are not shown are being held constant and that only some of the features will be shown. The most common partial-profile task is a metric paired-comparison task in which the consumer is asked to allocate “chips” between two partial profiles to indicate his or her relative preference for those profiles. Some researchers treat the task as ordinal, that is, they assume that the consumer can only tell us that one profile is preferred to the other, not the strength of preference. However, most researchers have found that the consumer can, indeed, provide a valid estimate of his or her strength of preference. Like metric ratings tasks, metric paired-comparison tasks can be analyzed with OLS, but more-advanced statistical methods such as hierarchical Bayes, polyhedral methods, or support vector machines provide more accurate representations of the consumers’ preferences. Figure 3 illustrates a partial profile task from an MIT study (for Timbuk2) on the design of laptop computer bags.

Figure 3. Metric Paired Comparison Conjoint Analysis Task
(from Toubia, Simester, Hauser, and Dahan (2003)

The fourth category of conjoint analysis tasks is called choice-based conjoint analysis (CBC).[3] This task is becoming more popular and will soon displace the metric paired-comparison task as the most commonly used task. It is growing in popularity because it is seen as most closely resembling the choices that consumers make when they are actually purchasing a product. In the CBC task consumers are shown sets of profiles, called choice sets, and asked simply to choose among those profiles. The number of profiles in a choice set varies, but most common CBC tasks ask consumers to choose among two, three, or four products. Many market researchers also include a “null option” which allows the consumer to state that he or she would not choose any of the profiles. (The use of a null option is pleasing theoretically, but has not been shown to increase the accuracy of WTP estimates.)

The analysis of CBC data is more complex than the analysis of data obtained from the other three tasks. Because we only observe first choice (rather than a rank or rating) the estimation methods need to take that into account. Such methods include logit models, probit models, polyhedral methods, and support vector machines. (See references at the end of this note.) Because each choice set provides only limited data, consumers often have to make choices from a large number of choice sets. In recent years, researchers have developed methods that “borrow” from all consumers to enhance the estimates of the part-worths for each consumer. These hierarchical Bayes and machine learning methods are now becoming the “gold standard” in terms of estimating part-worths from CBC data. Figure 4 illustrates a CBC task for a recent MIT study of the diffusion of closures for premium wines. Notice that price was specified as a range. Pretests indicated that such ranges are how consumers think about these choices.

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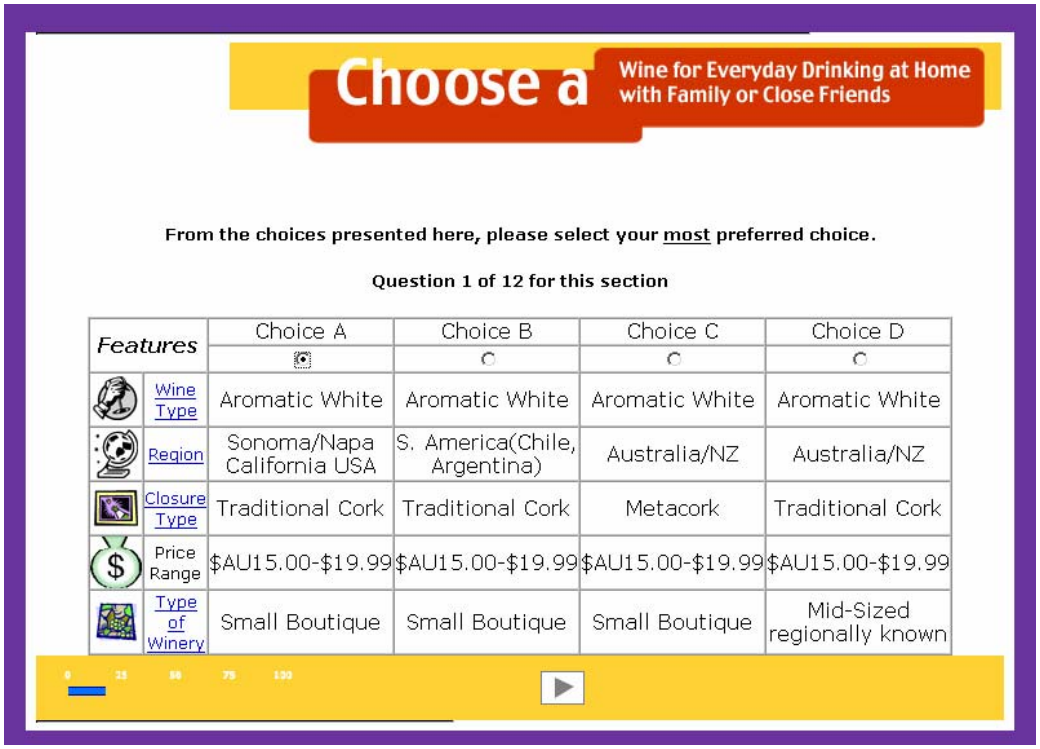
[3] The CBC task is also called a stated preference task.



Choose a Wine for Everyday Drinking at Home with Family or Close Friends

From the choices presented here, please select your most preferred choice.

Question 1 of 12 for this section

Features	Choice A	Choice B	Choice C	Choice D
Wine Type	Aromatic White	Aromatic White	Aromatic White	Aromatic White
Region	Sonoma/Napa California USA	S. America(Chile, Argentina)	Australia/NZ	Australia/NZ
Closure Type	Traditional Cork	Traditional Cork	Metacork	Traditional Cork
Price Range	$AU15.00-$19.99	$AU15.00-$19.99	$AU15.00-$19.99	$AU15.00-$19.99
Type of Winery	Small Boutique	Small Boutique	Small Boutique	Mid-Sized regionally known

Figure 4. Choice-based Conjoint Task for Premium Wines
(from Toubia, Hauser, and Garcia 2007)

To see how CBC data provide sufficient information with which to estimate partworths, consider the following simple example from a recent application. Suppose that we are trying to determine how much extra a consumer is willing to pay per month to their satellite TV company if the company provides the consumer with a digital video recorder (DVR) as part of the satellite TV service. Suppose that we give the consumer two profiles, A and B. Suppose Profile A and Profile B are the same on all features other than DVR and price. Suppose Profile A has a DVR and is priced $20 above Profile B. Profile B does not have a DVR. If the consumer chooses Profile A over Profile B, then we know that the consumer is willing to pay at least $20 per month for the DVR. If the consumer chooses Profile B over Profile A, then the consumer is willing to pay at most $19.99 for the DVR. If we ask enough questions we can narrow the price range for the DVR. In practice, much care is given to choosing the questions so that we can estimate this WTP efficiently and much care is given to the statistical methods so that we can estimate this WTP accurately.

The conjoint analysis task is called the self-explicated task. Basically, consumers are asked directly to state how important each feature is to them. Self-explicated tasks work well when consumers are asked to evaluate customer needs (see the Note on the Voice of the Customer). When consumers are asked to evaluate features, such as whether a GPS display is in color or B&W, the questions must be asked carefully. These questions are usually asked in three steps. First, the consumer is asked to compare partial profiles that vary on only two features. From this "tournament," the computer-aided questionnaire identifies which feature is most important. Next, the consumer is asked to evaluate one feature at a time providing a judgment of what is gained by improving from the low level of a feature to a higher level. Finally, the consumer is asked to evaluate the relative importance of each feature by providing relative preferences for high vs. low levels of the features. More recently, the task has been improved with adaptive algorithms. See Srinivasan (1988).

Selecting Profiles Efficiently

In Table 1 we obtain preference ratings for each combination of the three features and price. There were 16 possible profiles representing every one of the 2^4 feature-price combinations. Suppose we add a feature such as weight (4 oz. vs. 7 oz.). We would now require 32 profiles to represent all combinations (2^5). If the consumer were to rate all 32 profiles the task would be twice as hard, but still feasible. Each time we add a feature we double the number of profiles in this "full factorial" design. For the problem in Figure 1, we would need 2^{16} = 65,536 profiles – a burdensome task for even the most patient consumer.

To reduce the consumers' task, we select profiles more efficiently. One of the most common experimental designs is known as an orthogonal fractional factorial design – an "orthogonal design" for short. Such designs are conceptually similar to the popular Sudoku puzzles where players are asked to place the numbers 1 through 9 in a grid such that no number appears twice in a row, in a column, or in a 3x3 sub-box. In an orthogonal design, the levels of the features are chosen such that, for each pair of features, say *a* and *b*, the high level *a* appears equally often in profiles that have a high level *b* as in profiles that have a low level of *b*, and vice versa. Such experimental designs are extremely efficient for estimating partworths for features. These designs do not come without a cost. They confound "interactions." For example, with such designs we can only estimate "main effects" of each features. This is equivalent to an assumption that the partworth of having high levels of both *a* and *b* equals the partworth of a high level of *a* plus the partworth of a high level of *b*. If there were an interaction, the value of having high levels on both *a* and *b* might by synergistically more valuable than the value of having a high level of *a* and the value of having a high level of *b*.

Orthogonal designs are not the only fractional factorial designs. We can create designs that require more profiles, but which allow us to estimate some interactions. The study of experimental designs is beyond the scope of this note. However, it is useful to illustrate an orthogonal design for 16 features that requires only 32 profiles. This design is given in Table 3.

Table 3. Orthogonal Design for 16 Features Using Only 32 Profiles

	P	B	S	W	C	DB	DS	Re	AT	BL	R	A	TL	US	BK	F
P1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P2	0	0	0	0	1	0	0	0	0	0	0	1	1	1	1	0
P3	0	0	0	1	0	0	0	0	1	1	1	0	0	0	1	0
P4	0	0	0	1	1	0	0	0	1	1	1	1	1	1	0	0
P5	0	0	1	0	0	0	1	1	0	0	1	0	0	1	0	1
P6	0	0	1	0	1	0	1	1	0	0	1	1	1	0	1	1
P7	0	0	1	1	0	0	1	1	1	1	0	0	0	1	1	1
P8	0	0	1	1	1	0	1	1	1	1	0	1	1	0	0	1
P9	0	1	0	0	0	1	0	1	0	1	0	0	1	0	0	1
P10	0	1	0	0	1	1	0	1	0	1	0	1	0	1	1	1
P11	0	1	0	1	0	1	0	1	1	0	1	0	1	0	1	1
P12	0	1	0	1	1	1	0	1	1	0	1	1	0	1	0	1
P13	0	1	1	0	0	1	1	0	0	1	1	0	1	1	0	0
P14	0	1	1	0	1	1	1	0	0	1	1	1	0	0	1	0
P15	0	1	1	1	0	1	1	0	1	0	0	0	1	1	1	0
P16	0	1	1	1	1	1	1	0	1	0	0	1	0	0	0	0
P17	1	0	0	0	0	1	1	0	1	0	0	1	0	0	0	1
P18	1	0	0	0	1	1	1	0	1	0	0	0	1	1	1	1
P19	1	0	0	1	0	1	1	0	0	1	1	1	0	0	1	1
P20	1	0	0	1	1	1	1	0	0	1	1	0	1	1	0	1
P21	1	0	1	0	0	1	0	1	1	0	1	1	0	1	0	0
P22	1	0	1	0	1	1	0	1	1	0	1	0	1	0	1	0
P23	1	0	1	1	0	1	0	1	0	1	0	1	0	1	1	0
P24	1	0	1	1	1	1	0	1	0	1	0	0	1	0	0	0
P25	1	1	0	0	0	0	1	1	1	1	0	1	1	0	0	0
P26	1	1	0	0	1	0	1	1	1	1	0	0	0	1	1	0
P27	1	1	0	1	0	0	1	1	0	0	1	1	1	0	1	0
P28	1	1	0	1	1	0	1	1	0	0	1	0	0	1	0	0
P29	1	1	1	0	0	0	0	0	1	1	1	1	1	1	0	1
P30	1	1	1	0	1	0	0	0	1	1	1	0	0	0	1	1
P31	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1
P32	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1

P=price, B=brand, S=size, W=weight, C=display colore, DB=display brightness, DS=display size, Re=display resolution, AT=acquisition times, BL=battery life, R=receiver, A=accuracy, TL=track log, US=mini-USB port, BK=backlit keyboard, F=floats

Orthogonal designs are used for ratings and rankings tasks. Related designs can also be used for metric paired-comparison tasks. Metric paired-comparison tasks also lend themselves to adaptive designs when coupled with computer-aided or web-based questioning. In adaptive designs, the pairs of profiles that are given to consumers depend upon their answers to previous questions. In particular, each subsequent pair is chosen to maximize the information that can be obtained from the question. In this way, more information about partworths can be obtained from fewer questions. There are two primary adaptive methods: adaptive conjoint analysis (ACA) and polyhedral methods. The former is available from Sawtooth Software (www.sawtoothsoftware.com), the latter is an MIT developed method that is gaining converts in the market research community.

Question selection for choice-based designs raises new technical issues because the most efficient design depends upon the partworths. Market researchers often do a pre-study to get initial estimates of the partworths, then use a method called “aggregate customization” to select efficient designs. Recently two adaptive methods have been developed at MIT Sloan, but these are still being tested.[4]

Using Conjoint Analysis

If the stimuli are realistic, the sample of consumers is representative, the consumer tasks are designed carefully, and the appropriate statistical methods are used to estimate partworths, conjoint analysis accurately represents how consumers will behave when faced with new products. The willingness to pay for the features is sufficiently accurate to make decisions on which features to include in a product.

We can think of a set of conjoint analysis partworths as representing “virtual customers.” We can use those partworths to build a market simulator. With the partworths and with a list of the competitive products that are now on the market, we can predict sales for every combination of features and price. We can also predict sales for a portfolio of products that we might launch on the market.

For example in 2003, MIT Sloan already had world-class MBA, Ph.D. and undergraduate programs. MIT Sloan also had two flagship executive education programs: the Sloan Fellows and the Management of Technology Program. However, the market was changing. Mid-career executives (Sloan Fellows) wanted more on the management of technology and technology profes-

[4] See Toubia, Hauser, and Simester (2005) and Toubia, Hauser, and Garcia (2007).

sionals wanted more on general management. In addition, it was becoming increasingly difficult for executives to come to MIT Sloan for a full year. Markets are becoming global and changing more rapidly, hence, the costs of staying away from the firm for a full year were becoming larger. MIT Sloan wanted to test two aspects of executive education. First, they wanted to test whether or not it would be feasible to combine the Sloan Fellows and Management-of-Technology Programs so that students in each program could learn from students in the other program. Second, MIT Sloan wanted to test whether there was a market for a flexible program. The planning committee also faced subdecisions on class composition and program focus. To address these questions, MIT Sloan sampled potential students who had GMAT scores above a target level and who otherwise fit the profile for the new executive programs. Each respondent answered 16 CBC questions, one of which is illustrated in Figure 5.

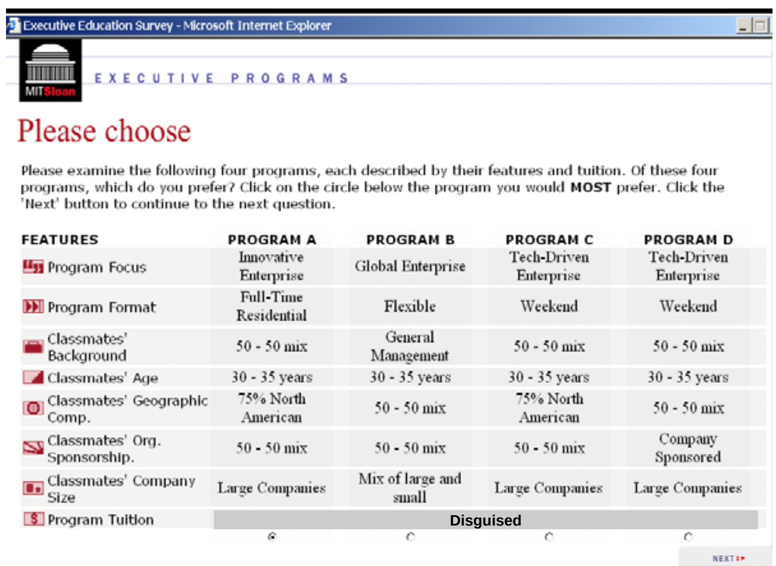


Figure 5. Choice-based Conjoint for MIT Sloan Executive Education

The partworths for the 354 respondents, combined with their demographic information was summarized in a spreadsheet. MIT Sloan then created a simulator that enabled the committee to "test the waters" for different types of programs. The goal was to provide a program that would best serve potential students in the target market. The design was tricky because the attractiveness of the program depended upon who it would attract.

The simulator is shown in Figure 6. By selecting aspects of the program, the program design committee could determine the share of applications that the program would achieve from the target market. For example, in Figure 6, the new program might be similar to “Program 3” in an environment where “Program 1” and “Program 2” were offered by competitors. On a separate worksheet, the committee could choose target demographics and determine what share the new program would achieve among those demographics. (The segment shown in Figure 6 is students within driving distance of Cambridge.) The net result was the MIT Sloan Fellows Program in Innovation and Global Leadership which was launched in June 2003.

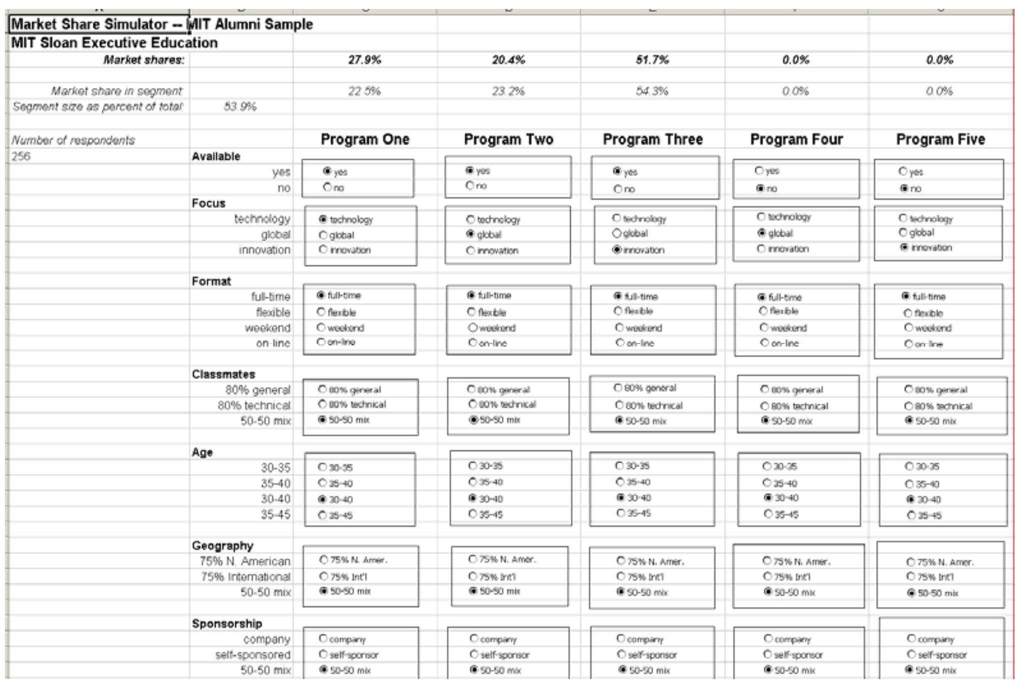


Figure 6. Conjoint Analysis Market Simulator

Such simulators combine the science of conjoint analysis with managerial judgment. For example, if we introduce a new GPS on the market with a low price, we might expect our competitors to lower their prices. The lessons we covered in other notes in 15.810 still apply. We want to choose features that reduce rather than enhance competitive response. It is better to position away from competitors to avoid destructive price wars. The simulators, coupled with judgments on competitive reactions, provide a means to select products and prices that are likely to be the most profitable for the firm.

Getting More Information

The purpose of this note is to provide you with a basic understanding of conjoint analysis including how to obtain data and how to use conjoint analysis in marketing management and product development. If you want to use conjoint analysis for an E-lab, G-lab, S-lab, or market lab project, you might want to use the ratings-based full-profile task with a moderate number of features. If you make sure that the respondents understand the features and the task and find both realistic, then the ratings-based data should be sufficient for the project. You can estimate partworths with OLS.[5]

If you are seeking to undertake a conjoint analysis for a consulting project or to support a major managerial decision, then we recommend one of the more advanced methods such as choice-based conjoint analysis that is analyzed with an hierarchical Bayes logit model. Software is available from Sawtooth Software for many of the advanced methods. In addition, there are many market research suppliers who can help you with the technical details on these advanced methods. For example, both Harris Interactive, Inc. and Applied Marketing Science, Inc. both use the polyhedral methods developed at MIT Sloan.

If you are interested in more information, here are a few references. Many of the MIT citations are available on my personal website and can be downloaded for free. Other citations are available through the MIT libraries.

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[5] For the experimental design, you may need to seek help from a textbook on experimental design or a statistical program such as Systat or an advanced version of SPSS. There are also many orthogonal designs available on the Internet or in Addelman (1962). For ease of exposition, this note illustrated experimental designs with binary (two-level) features. Efficient designs exist for cases when there are more than two levels of a feature.

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