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 a position on a map or navigational chart. GPSs are particularly useful when you are out of range of cell phone towers and cannot rely on the mapping function in your smartphone.

GPSs come in many versions. We will consider handheld devices that are useful for hiking, camping, canoeing, kayaking, or just walking around remote areas. We will suppose that it is your responsibility 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 simplify the problem for illustration. First, let's assume that all consumers have the same preferences – the same WTP for each feature. In real markets we do not need this assumption because we analyze preferences by segment or by a distribution across all potential consumers. Second, let's assume that there are no engineering constraints. The GPS can have all of the features, some of the features, or none of the features and the costs are additive. Finally, we focus only on three binary features of interest, plus price:

- Accuracy – the GPS can locate your position within 5 feet or within 50 feet

- Display – the screen either displays objects in 3D with a resolution so good that you cannot discern pixels or the screen displays only 2D maps with resolution sufficient for almost all uses
- Battery life – the battery lasts either 12 hours or 32 hours
- Price – the price is either $150 and $250

With four things varying (3 features plus price), at two levels each, there are $2\ x\ 2\ x\ 2\ x\ 2 = 2^4 = 16$ possible combinations. Suppose that we create realistic pictures of each of the sixteen handheld GPSs and have consumers evaluate all sixteen GPS "profiles." We might also include animations so that consumers understand the features accurately. A simple conjoint analysis task asks consumers to rate each potential GPS on a 100-point scale where 100 means most preferred. 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 data as indicated by *italics* in the first column.) The next four columns describe the experimental design. Each entry indicate whether or not the rated handheld GPS has that feature-price combination. An entry of '1' indicates the feature is at its "high" level, e.g., 5 feet rather than 50 feet, and an entry of '0' indicates a feature is at its "low" level, e.g., 50 feet rather than 5 feet. In Table 1 the consumer gives a low rating ('*4*') to indicate that consumer prefers least an inaccurate GPS, with low battery life, a 2D adequate screen, and priced at $250. The same consumer might give a high rating ('*99*') to indicate that the consumer prefers most an accurate GPS, with a long battery life, a 3D high-resolution screen, and priced at $150.

Table 1. Illustrative Preference Ratings for 16 Handheld GPSs

Data	***Experimental Design (Coding of Feature Levels)***			
Preference Rating by Consumer	**Accuracy** within 5 feet vs. within 50 feet	**Battery** 32 hours vs. 12 hours	**Display** 3D high vs. 2D adequate	**Price** \$150 vs. \$250
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 level of each feature contributes to the consumer's overall preference. This contribution is called the "partworth" of the feature level. (One level of accuracy is 5 feet; the other level is 50 feet. Because all partworths are relative to the low level of a feature, we need only report the partworth of the worst level, 50 feet.) In this illustration, we can use ordinary least-squares (OLS) regression as taught in DMD. The analysis is easy to run in Excel as will be demonstrated in class. An abridged output is shown below. The partworths are the regression coefficients. For example, the partworth of 5 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 \$250 to \$150.[1]

[1] 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.

Table 2. Regression to Estimate Partworths for Features and Price

	Coefficients	*Standard Error*	*t-statistic*
Intercept	2.7	1.0	2.7
Within 5 feet vs. within 50 feet	9.6	0.9	10.9
Battery life: 32 hours vs. 12 hours	30.4	0.9	34.5
3D high-res vs. 2D adequate	14.9	0.9	16.9
Price of $150 vs. $250	40.6	0.9	46.1

With this regression we compute the consumer's willingness to pay (WTP) for each change in the level of a feature. Because the consumer gets 40.6 "utils" when the price is reduced by $100 ($250 → $150), the value of each "util" is about $2.46/util. We obtain this value of a "util" by comparing the difference in price to the difference in the price-partworths: ($100)/(40.6 utils). 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 battery life is $74.88 and the WTP for a the improved display is $36.70. All partworths are relative, that is, they measure the value of changing a feature of the GPS from its low level to a higher level.

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 gain greater statistical power and obtain estimates of the partworths that are more accurate.

Stimuli shown to consumers are usually more than simple lists of features. Figure 1 illustrates a stimulus from an actual GPS study. There are more features than our simple example and some of the features are different than in our example, but this Figure 1 illustrates the care that is often used so that consumers can respond to stimuli that accurately depict potential products that are to be sold in the market.

Figure 1: GPS Stimulus with 16 features

Another Example with a Different Format – Laptop Computer Bags

The figure on the right asks consumers to compare two laptop computer bags that differ on two features plus price. Consumers are asked to assume that all other fea-tures of the two bags are identical. This format is known as a "partial profile" method. In this particular study there were ten features that were varied in combinations of three features at a time. The experimental

design, that is, the set of questions asked of each consumer, was adaptive in the sense that the computer chose the next set of comparison features based on the consumer's previous answers. In this way, roughly 16 questions were enough to provide sufficient accuracy.

Suppose that after the consumer answered all 16 questions we use an estimation method that takes the adaptive nature of questions into account. (Citations are given at the end of this note for students who are interested in the mathematics of adaptive methods and adaptive estimation, e.g., Toubia, et. al. 2011 and the citations therein.) Suppose further that all estimates are of sufficient accuracy. Then, the partworths might be the following. (I've chosen simple numbers to illustrate WTP calculations.)

- price: partworth = 5
- handle: partworth = 2
- mesh pocket: partworth = 1

The consumer "pays" 5 utils to reduce the price from $100 to $75, thus each util is worth $5 to the consumer. This implies that the mesh pocket is worth $5 and the handle is worth $10. In other words, consumers would be willing to pay $5 more for a laptop bag with a mesh pocket and $10 more for a laptop bag with a handle. If, when selling direct, the manufacturer could produce a laptop bag with a handle for less than $10, it should do so because there is profit to be made. If the bags are not sold direct, then retail margins have to be taken into account.

Willingness to pay is not market price. If the laptop bag manufacturer has a monopoly or substantial market power (say through a highly demanded brand), then it might be able to set a price to capture the surplus implied by the willingness to pay. On the other hand, if there were three or four similar competitors in the market for laptop bags, then some of the surplus would be competed away. The other consideration is differences in consumers' willingness to pay (heterogeneity). Some consumers might be willing to pay substantially more for a handle than $10 while other consumers might not be willing to pay even $1. When there is heterogeneity, you should rely on the lessons of economic theory. Conjoint analysis provides the "demand curve." As you are learning in the core curriculum (e.g., 15.010), you need to consider demand <u>and</u> supply when setting the market price.

Conjoint analysis can provide input to "market simulators" that take competitive response and consumer heterogeneity into account. Such simulators are quite accurate when sufficient information is known about the supply curves (costs). In other situations, managers must make careful judgments about competitive response. We provide an example later in this note.

Choice-Based Conjoint Analysis

The GPS and laptop bag examples illustrate two data-collection formats that are well-suited to analysis with ordinary least-squares regression. We later discuss a more-sophisticated method that enables the estimates from each consumer to "borrow" information from the consumer population as a whole, but first we examine an alternative format.

With the advent of web-based interviewing and improved computational methods, conjoint analysis evolved to a "choice-based" format. Although other formats are still in use, the choice-based format is now used in the majority of applications. The basic idea is that rather than asking consumers to rate product profiles in terms of utility, we simply ask consumers to choose among alternative product profiles.

Figure 2 illustrates a conjoint analysis that was done to evaluate consumers' preferences for various wine-closures. Notice that some of the features of the profiles in Figure 2 have more than two levels. For example, the region of origin for the wine can be the US, South America, Australia/New Zealand, or France. (France was in the study but not shown in Figure 2). When there are more than two levels, we code each level by an indicator variable that has the value, "1," if the profile has that feature at that level and "0" otherwise.[2] To avoid redundancy and because partworths are relative, we code all but one of the levels of a feature. Without loss of generality, we set one level of a feature to have a partworth of zero.

The particular closure of interest in the study was a screw-top cap called a Stelvin. Stelvins are a superior closure to prevent wines from being "corked." A wine becomes corked when it is spoiled by rapid aging, discoloration, and/or loss of fruit flavors due to contamination by trichloroanisole. Stelvins are also favored by hotels, restaurants and other functions, be-

[2] We can also use "effects" coding such that the indicator variable is set to +1 if the profile has that feature at that level and –1 otherwise. Effects coding has advantages and disadvantages that are beyond the scope of this note. When we use effects coding, rather than setting the partworth of one level of a feature to zero, without loss of generality, we impose a constraint that the partworths of a feature add to zero.

cause they can be opened rapidly during table service. In the US there is a perception that screw-top caps connote lower quality wines. In Australia and New Zealand, where Stelvins have been in common use since the early 2000s, many wineries sell their best wines sealed with Stelvins. (Fifteen wineries in Australian and 27 wineries in New Zealand simultaneously introduced Stelvins in a campaign known as “Riesling with a twist.”)

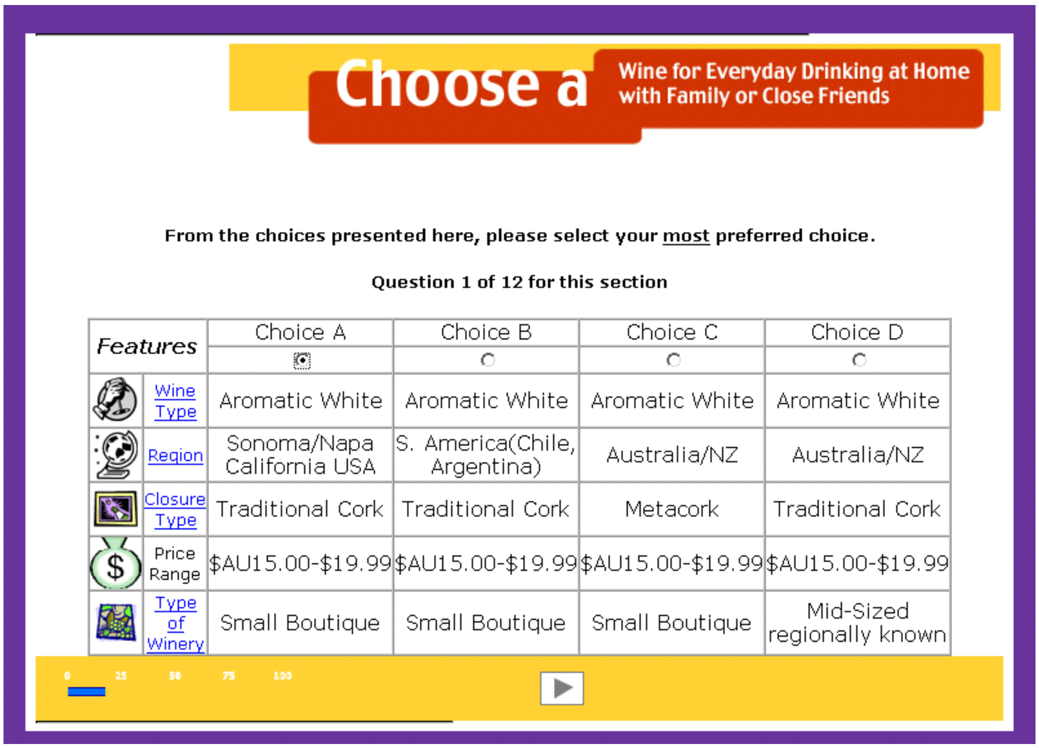

Figure 2. Choice-based Conjoint Task for Premium Wines

After being introduced to the various features of wines, consumers were given a choice among four wine-profiles where each profile was described by its features. The task was repeated for twelve sets of four alternative wines. By making these choices consumers revealed the tradeoffs that they were making among the features. These tradeoffs are identified using advanced methods that take into account the type of data, choice, and potential “errors” that consumers might make in answering the questions. (More on this later.) Figure 3 indicates the average partworths of US consumers, Australian consumers, and New Zealand consumers for wine closures and for country of origin.

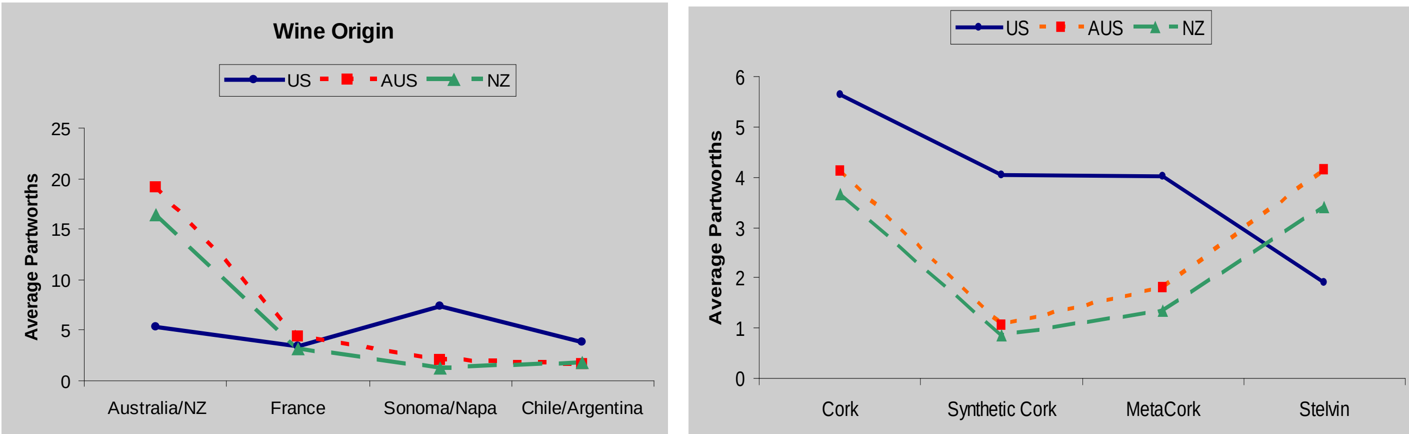

Figure 3. Partworths for Country of Origin and for Wine Closures

As expected each country's consumers tend to favor wines from their own regions. More interestingly, both the Australian and New Zealand consumers prefer Stelvins as much as traditional corks. On the other hand, US consumers have a very low preference for Stelvins—much lower than for traditional corks and well below even synthetic corks and metacorks. Clearly, US consumers are not yet ready to accept Stelvins for premium wines, but there is hope. Australia and New Zealand changed the image of Stelvins with a coordinated marketing effort. If the US wineries were to repeat that effort, they might successfully introduce Stelvins. Alternatively, US wineries might lower the price of Stelvin-closed wines for a few premium wines. If the US wineries could get US consumers to be comfortable with Stelvins and experience the benefits of Stelvins, then the US wineries could move US consumer preferences toward the preferences that are observed in Australia and New Zealand. Willingness to pay analyses based on the conjoint analysis data suggested that a minimal price reduction would be sufficient to seed the market.

How Choice-Based Conjoint Analysis Works – the Conceptual Idea

From your other core curriculum courses, specifically DMD, you are familiar with ordinary least-squares regression. But the choice-based format does not measure utility directly, so regression cannot be used. The secret to the analysis of choice-based data is that each question reveals constraints on the partworths. With enough constraints we can identify partworths quite well.

Suppose that we are using conjoint analysis to determine the willingness to pay for features of a smartphone and describe two smartphone profiles to a consumer. These profiles are shown in Figure 4. They are identical except that one has a camera and the other does not and that the camera-less phone is priced at $130 rather than $150 – that is, $20 less expensive. Now suppose that the consumer checks the smartphone on the left indicating that he or she prefers a smartphone without a camera if he or she can get it for $20 less. The consumer's answer to this question tells us that the consumer values the camera by less than $20. This gives us one constraint: the partworth of a camera (vs. no camera) is less than the partworth of $130 (vs. $150). On the other hand, if the consumer had checked the smartphone on the right, then he or she would be telling us that he or she values the camera by more than $20. If the consumer checked the smartphone on the right, we would know that the partworth of a camera (vs. no camera) is more than the partworth of $130 (vs. $150).

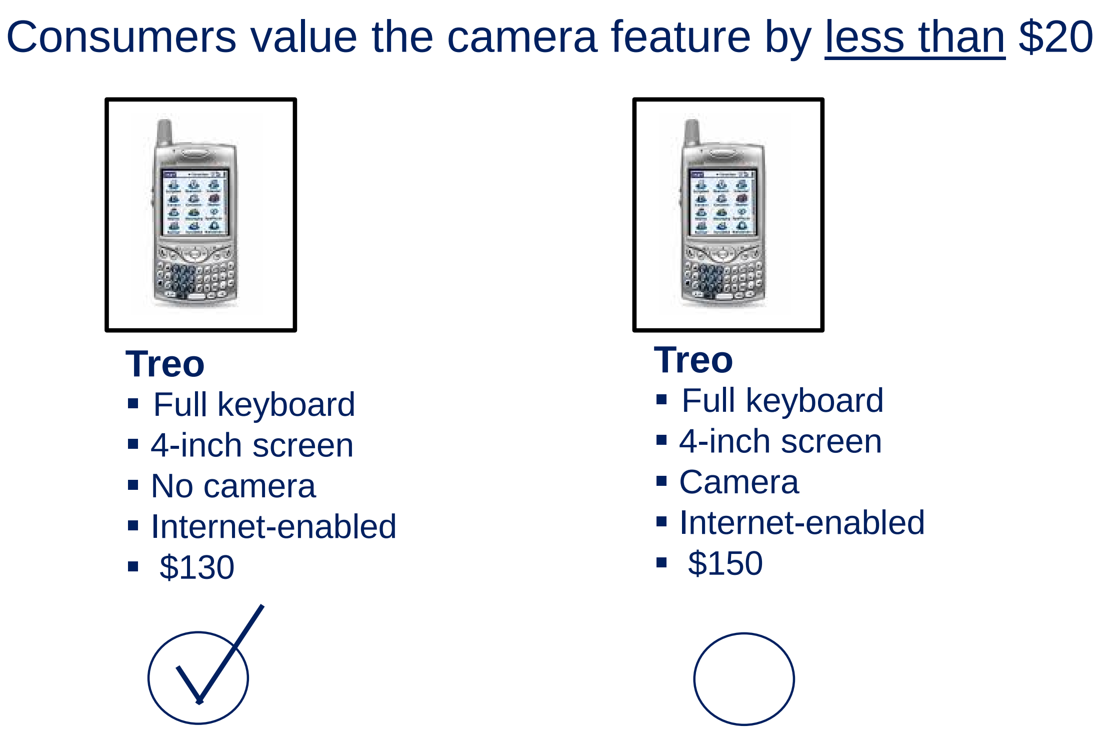

Figure 4. A Consumer Reveals a Constraint on Partworths by Answering a Choice Question

A single constraint tells us something about the partworths. More constraints tell us more. Suppose that each choice question has four alternatives, then we observe three constraints. The chosen profile is preferred to the second, third, and fourth profile. If we ask sixteen choice questions, then we have $3\ x\ 16 = 48$ constraints. But we also gain information from an economic theory of rationality. We know that the partworth of $130 is larger than the partworth of $150 because consumers prefer a price of $130 to $150. We also know that the partworth of a camera (all else equal – the inherent assumption in conjoint analysis) is greater than the partworth of no camera, etc. Thus we might have an additional five constraints from five binary features – a total of 53 constraints. If the example in Figure 3 we have five partworths, each representing a relative change in one of the binary features. It is not unreasonable that 53 constraints might be enough to get a good estimate of the five partworths. But if we were only interested in population averages, we might merge data from a sample of 300 consumers. A sample of 300 consumers would provide $300\ x\ 53 = 15{,}900$ constraints – more than enough to get good population-level estimates of the relative partworths.

The mathematics of the analysis of choice-based data is beyond the scope of this note. The primary analysis method is known as a "logit" model. In an analogy to regression analysis, the utility of a profile is the sum of the partworths of its features—more specifically, the sum of the partworths of the levels of the features that describe the profile. If we assume the measurement error is given by an extreme-value distribution, we get the logit model.[3] We can the write down an equation for the probability that a profile is chosen from a set of J profiles as:

$$Prob\{choose\ profile\ j\} = \frac{e^{utility\ of\ profile\ j}}{\sum_{k=1}^{J} e^{utility\ of\ profile\ k}}$$

We then relate the choices made by the consumers to the expression for the probability of choice and use various statistical methods to estimate the partworths of the levels of the features. (For readers familiar with statistics, the methods are either maximum=likelihood methods or Bayesian statistics.)

[3] An extreme value distribution describes the distribution of a maximum, which makes sense if the consumer is maximizing various unobserved effects.

Handling More than Just a Few Features

In Table 1 we obtained preference ratings for each combination of the three features and price. There were 16 possible profiles representing every possible feature-price combinations. ($16 = 2\ x\ 2\ x\ 2\ x\ 2$). Suppose we add a GPS feature such as weight (4 oz. vs. 7 oz.). We would now require 32 profiles to represent all combinations ($2\ x\ 2\ x\ 2\ x\ 2\ x\ 2 = 32$). If the consumer were to rate all 32 profiles the task would be twice as hard, but still feasible. Each time we add a binary feature we double the number of profiles in this "full factorial" design. As the number of features gets large, the consumer task becomes difficult, if not impossible. For example, the real GPS example in Figure 1 has sixteen binary features. If we were to simply continue doubling the number of profiles every time we added another binary feature, we would need $2^{16} = 65{,}546$ profiles – a burdensome task for even the most patient consumer. If the features had three levels each, we would require $3^{16} = 43{,}046{,}721$ profiles.

To obtain a set of questions that could be answered by real consumers, we select profiles more efficiently. For direct ratings as in Table 1, we use experimental designs known as 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 efficient for estimating partworths for features. These designs are often, but not always appropriate and should only be used when the conjoint analysis researcher can establish "independence" conditions. For example, the preferences for feature *a* should not depend upon the level of feature *b* that is present. If these assumptions are satisfied, then orthogonal designs can 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. Most statistical packages have the capability to create both orthogonal designs and fractional factorial designs. Table 3 illustrates an orthogonal design for 16 binary features that requires only 32 profiles. If you wish to use conjoint analysis in an action learning project, you can define your project to fit this design. The design remains orthogonal if you have less than 16 binary features; just ignore those features. On the other hand, if you have the mathematical background and/or access to the appropriate statistical software, feel free to work with other designs. The Addelman citation at the end of this note provides other experimental designs if you do not have access to the appropriate software. That citation also tells you how to deal with features that have more than two levels.

When using choice-based conjoint analysis, the design of a conjoint analysis experiment is more complicated. Choice-based designs take into account the fact that we are selecting choice sets—sets of J profiles from which the consumer must choose. Designs also take into account that we are using a logit model rather than ordinary least squares regression. Finally, designs attempt to balance the levels of the features over the choice sets. Such designs are easy to create with specialized software such as that available from Sawtooth Software, Inc.[4]

[4] Upon request, Sawtooth Software, Inc. will allow students to use their software without charge if the use is limited to academic projects. You must agree not to use the free version of their software for consulting projects. Check with your instructor to see if action learning projects qualify.

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

State-of-the-Art Estimation

Because conjoint analysis is used so widely for marketing and product development, many researchers have developed advanced methods to estimate partworths. For your action learning projects at MIT Sloan, regression and Table 3 should provide the tools you need to get started. However, after you graduate, we recommend that you work with one of the more advanced methods.

Hierarchical Bayes estimation (HB) is one such method. HB software is based on the concept of a hierarchy. Using the data from all consumers (in the sample), the software simultaneously estimates means and variances of the partworths for (1) the population and (2) each consumer. Each consumer's partworths are "shrunk to the population mean." Shrinkage works as if the estimate of each consumer's partworth is a combination of a consumer-specific estimate and the population estimate. HB is "Bayesian" because HB uses the data to "update" estimates of the partworths. The output of HB estimation is not a point estimate for each partworth, but rather a probability distribution for each and every partworth.

Some cautions are in order. Although HB provides estimates for each consumer, those estimates have very high variance and should be used only with great caution. On the other hand, the distribution of partworths over the population of consumers is estimated with great precision and can be used to evaluate marketing strategies or new product designs.

HB is not the only advanced method. Machine learning methods based on the analytic centers of polyhedra, based on support vector machines, and based on mathematical programming have all proven accurate. I've provided a few of the references at the end of this note.

Incentive Aligned

When feasible, conjoint analysis practitioners make their tasks incentive aligned. A task is incentive aligned if (1) each consumers believes it is in his or her interests to think hard and tell the truth, (2) it is, as much as feasible, in each consumer's interests to do so, and (3) there is no way, that is obvious to the a consumers, by which a consumer can improve his or her welfare by "cheating."[5]

The simplest way to align incentives for conjoint analysis is to tell consumers, who complete the conjoint analysis task, that one or more consumer will be chosen by a lottery to win a prize. The prize will be chosen from a secret set of products. The secret set will be revealed at the end of the study and will consist of products described by the features in the study. For example, in the GPS study (Figure 1), one out of every one hundred consumers who completed the questionnaire received a GPS. The consumers were told truthfully that researcher would

[5] Quote from Ding, et al. (2011).

choose the product that the consumer received based on the consumer's answers to the conjoint analysis questions. To avoid incentives to choose the most expensive product, the winning consumers received a predetermined value, say $300. If a consumer's answers indicate that his or her most preferred GPS is priced at less than $300, he or she receive the indicated GPS plus enough cash to equal $300.

Incentives can be aligned even for expensive durable goods. For example, Ding, et al. (2011) used incentive alignment for a study of automotive features. The lottery winner received a chance to win an automobile worth $40,000. The winner chose two out of twenty envelopes. If both had said "automobile," then the lottery winner would have received the $40,000 prize. If at least one envelope did not say "automobile," the winner received a consolation prize of $200.[6] Because most researchers cannot afford to risk $40,000 on a conjoint analysis study, researchers purchase prize-indemnity insurance to cover the risk. (In the automotive study, prize indemnity insurance cost approximately $1,200.)

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 levels of features is sufficiently accurate to make decisions on which levels of features to include in a product.

Conjoint analysis partworths represent "virtual customers." We 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 predict sales for every combination of feature levels 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

[6] The odds of picking both envelopes correctly are one in 190. As luck would have it, the first envelope picked by the lottery winner said "automobile." The second did not, so the lottery winner received the consolation prize of $200.

professionals wanted more on general management. In addition, it was becoming increasingly difficult for executives to come to MIT Sloan for a full year. Markets were becoming global and changing 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 sub-decisions 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 consumer answered 16 choice-based questions, one of which is illustrated in Figure 5.

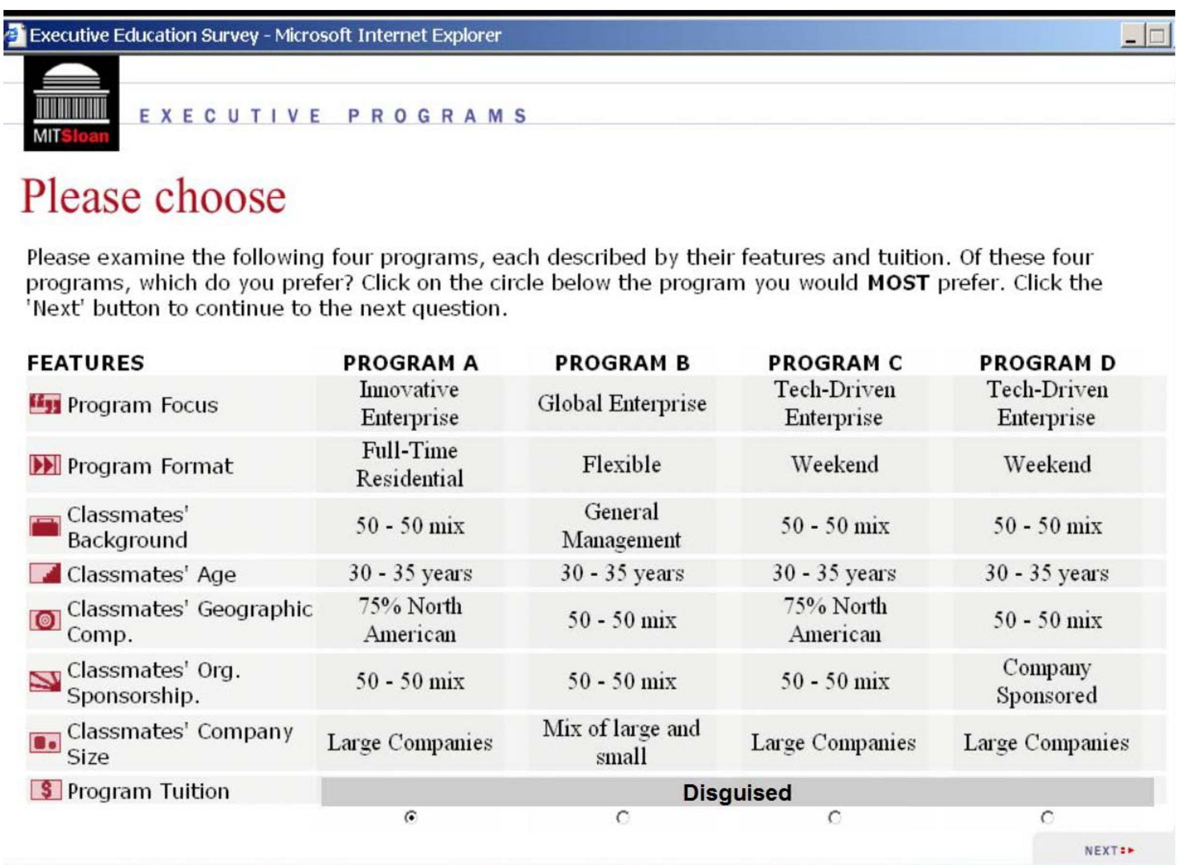

Figure 5. Choice-based Conjoint for MIT Sloan Executive Education

The partworths for 354 consumers, 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.

A screen-shot from 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, MA.) The net result was the MIT Sloan Fellows Program in Innovation and Global Leadership which was launched in June 2003.

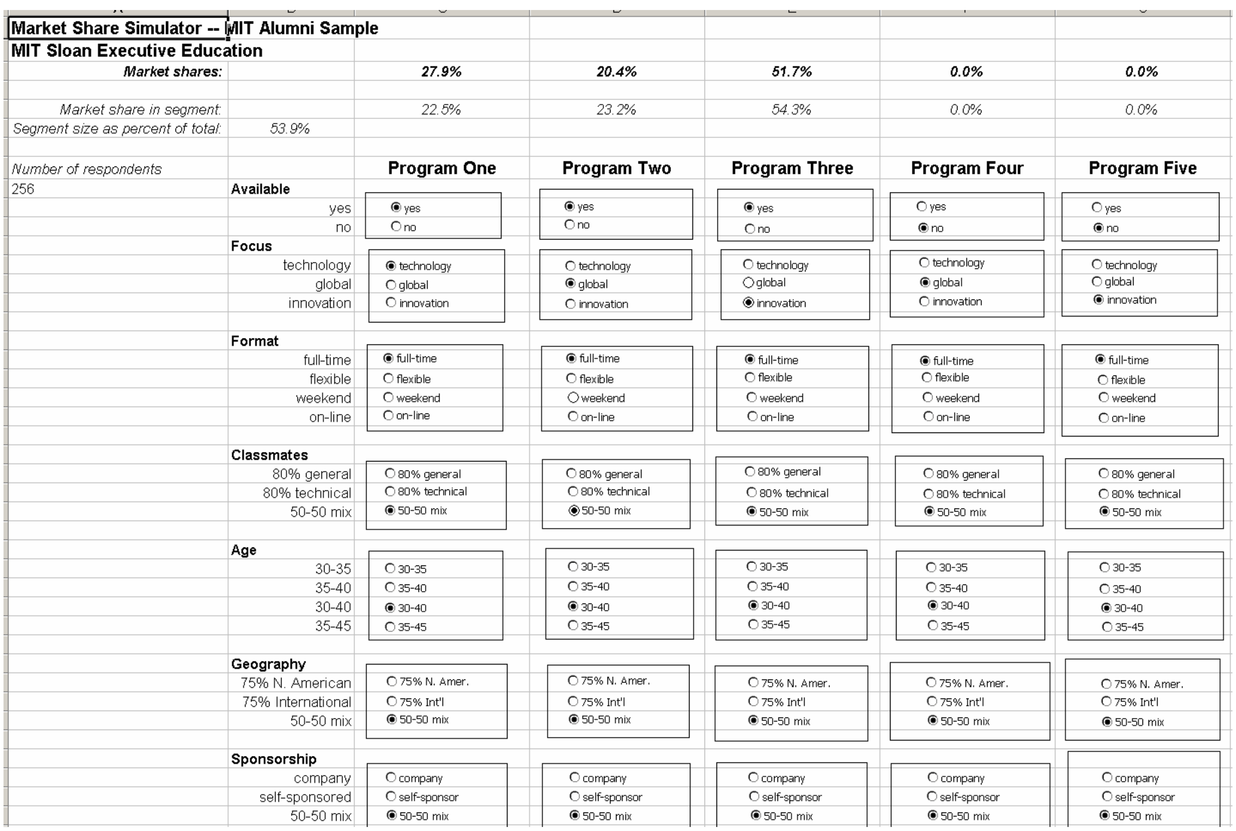

Figure 6. Conjoint Analysis Market Simulator

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. We may need to use judgment to represent competitive response. Using the lessons of the 4 P's and 5 C's that we have been studying in 15.810, we might choose features that reduce competitive response. Recall that 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 action learning project, we recommend that you use the ratings-based full-profile task with a moderate number of features. If you make sure that the consumers understand the features and the task and that consumers find the features and the task to be realistic, then the ratings-based data should be sufficient for the project. You can estimate partworths using ordinary least squares as implemented in Excel (as you learned in DMD).

If you are seeking to use conjoint analysis for a consulting project or to support a major managerial decision, then we recommend one of the more advanced methods. Software is available from Sawtooth Software, Inc. 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.

If you are interested in more information, there are literally hundreds, if not thousands, of papers written about conjoint analysis. I've provided a few references to get you started. I've included some of the papers I've written because they are readily available on my personal website (web.mit.edu/hauser/www) and can be downloaded for free. The Sawtooth Software, Inc. manuals are available at http://www.sawtoothsoftware.com/education/techpap.shtml. Sawtooth Software also provides a variety of articles on the use of conjoint analysis. Other citations and many other scientific articles are available through the MIT Libraries.

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