The Procedural Consumer: The Polynomial Assist

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Abstract

Prior experience has become a poor guide to product selection in markets undergoing rapid technological change and differentiation into numerous niches. A consumer must develop a procedure to proceed from a large number of alternatives to the preferred item that requires obtaining data and the knowledge to interpret the data. We consider the variation in students procedures to buy a digital camera. With the increasing value of the time of members of household there is a demand for improved selection procedures. Third party sites have responded to this demand by providing product reviews. The weakness of such sites is the deficiency in decision aid software for product selection. We develop several codes for selecting digital cameras and test their effectiveness in two experiments.

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1 Introduction

Few economists would assume that a human obtains a complete preference ordering, neatly encoded in his genome, at conception. So why does consumer theory ignore how consumers obtain their preferences? We undoubtedly have genetic propensities toward certain preferences, but our experience is an essential factor in selecting items.

A consumer buys a product for future consumption and must forecast its use. When the utility concept was initially developed, the rate of technological change was much slower than it is today, so consumers could learn to forecast product performance by the time they were an adult: at the time, encapsulating the forecast into utility was a good abstraction. But, with accelerating technological change, modern consumers face a market with products that have new features or, occasionally, are genuinely new. Cars change more in a decade than horses do in a century, and no one predicted personal computers in the 1950s. Social change has complicated major life decisions like retirement – early death and children as caretakers can no longer be assumed.

In this paper, we examine how a consumer selects a new technology product from the perspective of a procedural consumer. In Norman et al (2001), we showed that consumers select products item-by-item instead of by bundles, so we can focus on the selection of one item. Advances in flexible manufacturing enable producers to supply a wide range of product variations for niche markets; hence, consumers generally face a large number of alternatives. Selecting a preferred item from a large set, we shall call the Many-to-One Problem. In Norman et al (2004), we showed that consumers use sublinear decision rules to increase their efficiency. As consumers can order a small set using a linear process–see Norman et al (2003)–ordering plays a role in the construction of the decision rules.

The faster the rate of technological changes and the longer the gap between repeat purchases, the less prior experience is useful to forecast the performance of alternatives. In section 2, we consider how consumers forecast after acquiring data and the knowledge to interpret that data. We show that the demand for data is dwarfed by the amount of data that could be acquired. Also, data's value is positively related to its reliability and power to discriminate and negatively related to its processing cost.

In Section 3, we study the procedures that students use to select a digital camera – our specific example for this paper. By examining how students solve the Many-to-One Problem and forecast future performance, we show that students employ a wide range of procedures to select a camera.

Consumers need innovation in selection procedures. The value of adults' time has increased with the workforce participation rate, and new products are constantly being introduced into the marketplace. We consider these and other factors in Section 4 and describe the third-party information sites, created in response, in Section 5. Their strength is product reviews and attribute tables but their decision aid software is weak.

In our opinion, the development of decision aid software has been hampered in part because decision psychologists have overestimated the value of compensatory rules and underestimated the value of noncompensatory rules. We discuss this problem in Section 6.

In Section 7, we discuss our experiments to design better digital camera search software and their results. The first software program required too much effort to acquire the knowledge to make a selection; the second software program was considerably more efficient. After a great effort we created a code that was statistically better than just having access to the Internet, talking to friends who owned a camera, or talking with sales people in a store that sold digital cameras.

In Section 8, we present our conclusions from this procedural consumer study.

2 Forecasting

Modern producers have created myriad niche versions of a basic product. No longer do we just have cars: we have large and small sedans, SUVs, station wagons, pickups, and so on. Similarly, digital cameras can be divided into small cameras–in turn subdivided into small and tiny–and large cameras–in turn subdivided into telephoto, prosumer, and dSLR. One forecasting task a consumer must perform is a qualitative forecast of which niche best fits her needs. More difficult is forecasting the relative performance of members within the desired niche. For example, a consumer desiring a healthy diet needs only to forecast that a salad will probably be healthier than a triple-cheeseburger not the exact nutrition and calories contained in each.

Consumers make qualitative forecasts by obtaining data about alternatives and acquiring knowledge to interpret the data. **But more data, even if free, is not necessarily better than less data.** Consider how much data a consumer could be provided to evaluate alternatives in the purchase of an automobile if we consider all possible data obtained from all sources. The consumer could test drive the vehicle, study the vehicle brochure to examine all options, and look at the specification sheet to find out the displacement, number of cylinders, and gear ratio of the vehicle. The consumer might then examine the fuel economy and crash tests performed by various institutions, and go on to read reviews performed by professional evaluators, such as Consumer Reports. This is still a fraction of the data that could be provided on a vehicle. The potential buyer could be supplied with the detailed specifications of every component on the car, all the production details, every research and development report, and the details of all testing programs. The consumer could even be supplied with electron microscope pictures of the crystal structure of the metals in the vehicle. To the limit of current measurements, even the position of molecules on the surface of an object could be given. A data file describing a mole of molecules on the surface could be obtained. Indeed, the limit of data that could possibly be supplied to a consumer is determined by the Heisenberg uncertainty principle. More data is not necessarily better than less; such a massive data file would be prohibitively expensive to obtain and would overwhelm the processing capabilities of the consumer. Indeed, it might well lead to a poorer decision because few (if any) consumers could interpret all the data. Although a computer-aided consumer can inexpensively process a great deal more data than a consumer without a computer, the amount of data that could be processed tractably is still **miniscule** in comparison to the potential limit. Consequently, the demand for data is limited by several factors.

The first factor limiting data demand is cost. Even without acquisition fees, getting and processing data requires resources. Finding alternatives' specifications, for example, can require examining several brochures or visiting several Internet sites. In addition, the consumer, faced with new technology or previously unencountered choices, might have to learn how to interpret the relevant data. Consequently, the cost of data to the consumer should include acquisition fees and resources to obtain the data, the cost of mastering any new knowledge needed to interpret the data, and the resources to interpret the data.

Another important factor in data demand is capacity to help the consumer discriminate between alternatives' probable performance. Akerloff (1970) was the first to raise this issue in his discussion of the used car market, where buyers lacked a means of judging the reliability of a used car. Spence (1973) expanded the discussion by pointing out the incentives of the market participant to provide signals that allowed the other party to make a judgement of future performance. A good signal discriminates with low processing cost. In the case of used cars, auto dealers have developed a certification program, where used vehicles pass inspections and are deemed worthy of warranties. Some of the signals provided by manufacturers include a list of product specifications, such as a list including a computer's processor speed and built-in RAM. Third parties also provide market signals. The U.S. government, for example, performs crash tests on automobiles and simplifies the results into a one-to-five star scale of crash worthiness.

The final factor considered in the data's information value is the reliability of its source. Data beyond direct sensory interaction with the alternatives or their images is almost always provided by second and third parties. The former–manufacturers and retailers–have incentives to present only the positive aspects of their products. Third-party evaluators of products–friends, relatives, acquaintances, and others who have used the product–can provide useful data about a product from their experiences, but they generally know much less about products they didn't buy. Experts provide product reviews in magazines and websites. Most of these expert sources have a conflict of interest: they are financed by advertising rather than by the prospective buyer, but they must attract readers with useful information in order to gain advertising revenue. Thus, consumers are likely to regard expert third-party sources as more reliable for inter-firm product comparisons than a firm comparing its own products with its rivals'.

We therefore define the **information value of data** as positively related to its reliability and ability to discriminate among alternatives and inversely related to its processing cost. Note that the same data can have different information value to two individuals because they may have different knowledge bases and different processing capabilities.

A signal consisting of a single attribute's value can be useful. Consider the number of cycles per second of the CPU in personal computers. If all other factors of two personal computers are equal and their processors only differ in the number of gigahertz, this piece of data allows for discrimination between the two. But the greater the variation in the architecture of the processor, the size of the cache, and the computer's RAM, the greater the bias in a single-valued discriminator. We claim this as a general principle: The greater the variation in the attributes of the alternatives whose relative performance must be forecasted, the greater the need for multidimensional signals and the knowledge to interpret them.

Now, if a consumer had accurate simulation or quantitative prediction models, he could forecast the speed of a computer based on attribute values such as bus speed, cache memory, and CPU speed and design. Since the 1960s, engineering firms have developed simulation programs for product development, such as calculating how many pounds of payload a rocket can deliver into a low earth orbit. But no equivalent exists for consumers: no entrepreneur has decided that the potential rate of return on such software development is worth the effort. There are some cases where a consumer can forecast performance by actually testing the product. There are demo and trial versions that allow users to try software before they buy it. Consumers can test drive an automobile, but this test doesn't forecast the maintenance costs. In most cases, the consumer can't test beyond looking at the product in its package. While retailers frequently have a return policy, this involves transaction costs of returning the good and following the retailer's required procedures.

Unable to directly test a product, a consumer may seek out the opinions of people who can. They can ask acquaintances who have already used a product of interest and visit websites providing files of customer experiences with the products. They can also obtain the opinions of experts. Experts who make reports generally vary in the processing cost of the data they provide. Consider Jeff Keller of the Digital Camera Resource Page (DCRP, at dcresource.com), whose reviews of digital cameras are on the order of 15 pages long. There are about 100 active digital cameras in the market, so a consumer might take 50 hours to read all 100 in order to select a camera. However, Keller provides a list of his recommended cameras, allowing a consumer can greatly reduce her processing costs by ignoring subpar cameras. To further reduce the processing cost, a consumer can eliminate cameras by reading the summary – only reading the entire review when she's whittled the list down to a few cameras.

3 Digital Camera Many-to-One Procedures

In this section, we take up the topic of how students search for a digital camera. We surveyed 30 undergraduates at The University of Texas at Austin who had purchased a digital camera, and we interviewed 20 students to obtain further information. The purpose of our efforts was to determine if students had a wide range of Many-to-One procedures – not to accurately determine the percent in each category. As the number of alternative search procedures in the population can't be less than in our sample, our sample size was considered adequate because it demonstrated that students used a variety of procedures to select a digital camera.

Students varied in how much time they spent searching and in what information sources they used. How much time spent searching is one aspect in which the student subjects varied greatly. When asked "How many **total hours** did you search (including gathering and analyzing info, talking to friends, looking at cameras and so on)?", the mean response was 5.1 hours and the range was from 2 to 30 hours. Why this is so will be evident when we discuss the types of decision rules used by the subjects. The subjects gathered information from many sources, and all but three talked with friends and salespeople. A little over half went to manufacturers' websites, and less than half looked at reviews in a photography or PC magazine, Consumer Reports, CNET, or one of the small websites specializing in digital camera reviews. From our survey, we determined that the most common use of a digital camera was taking people pictures and students frequently took people pictures under low-light conditions. Selecting a camera that has the features needed to take good pictures in a particular type of situation requires a knowledge of camera features. Students who bought cameras were not entirely knowledgeable about these features because while 70% answered our multiple choice question about white balance correctly, only 10% answered the question concerning ISO levels correctly.

Next, the subjects used a variety of rules to proceed from the more than 100 digital cameras on the market to the one they bought. One of the more interesting rules was to buy the same camera as a roommate, friend, or relative or, in one case, a newer model of the same camera. Another rule was to select a brand, such as Canon, and then only examine that brand's cameras. In the most unusual procedure a student went to eBay's discontinued store and bought the camera with the most megapixels that was within his budget. Others used a much more sophisticated strategy and consulted camera reviews. One checked several reviewers to narrow down the list to two cameras that all agreed were good; he then examined them in-depth. He ultimately found an excellent price on a Sony F707 after the replacement Sony F728 entered the market. The students only considered a fraction of the new camera models available on the market, indicating a sublinear rule.

Finally, students used different methods of judging a camera's photo quality. One student used the number of megapixels as a quality indicator; another used the quality of picture in the LCD screen as her indicator of the quality of picture if downloaded. Subjects, who bought the same camera as a friend, looked at the pictures taken by that camera so that they had a clear idea of the quality of pictures. Students that used brand as a selection rule discussed the reputation of the brand. Less than half the subjects used camera reviews to judge the quality of camera under consideration. Internet galleries display pictures from cameras on the market so that a consumer can judge the cameras' quality for herself but less than a third followed this procedure to predict their camera's picture quality.

4 Need for Innovations in Many-to-One Procedures

One important factor creating a need for innovations in consumer search procedures is the increasing value of adults' time. In the stereotypical '50s household, the husband brought home the paycheck while the wife stayed at home, applying her labor to household production procedures such as preparing meals and shopping. In the second half of the 20th century, women have greatly increased their participation in the workforce, increasing the value of their time in turn. Consequently, household production procedures have less labor input: substantially fewer meals are cooked from scratch at home, and there is less time to search for goods and services.

Not only do household members have less time to solve the Many-to-One Problem, but also the problem has become more difficult with the advance of technology. With the shift from mass to niche production, consumers have many more alternatives to consider; with rapid technological change, previous experience with products is less useful in creating decision rules to solve the Many-to-One Problem. The problem is less notable for products like autos, where an adult consumer has generally acquired enough knowledge through previous experience to determine the niche that best meets his needs. But in products like a digital camera, a consumer may not be able to determine the best niche without knowledge acquisition. In the U.S., the problem is exacerbated by the decline in retail salespeople's knowledge as retailers reduce incentives towards knowledge (such as commissions) and shift to hiring part-time workers to reduce fringe benefits.

To understand why choosing even their correct niche is difficult for a newcomer to digital cameras, let us consider some of the consumers' parameters. Students, who primarily take pictures of small groups in low light, need a camera with an autofocus assist light. But, if they want to take pictures of a large group in low light conditions, they need a large camera that has a wider angle than average lens, an external flash connection, a compatible external flash, and an autofocus assist light–features found in a prosumer camera or a dSLR camera equipped with a wide angle lens. The required attribute values are determined by the type of pictures the consumer wants to take and, for a complete novice, understanding the range of values of the attributes and which combinations are needed for which type of pictures can take hours to master.

Now we can consider the popular Many-to-One strategy of buying the same or newer version of an acquaintance's camera. Using this strategy, a student obtains a very good, reliable evaluation of the chosen camera. This might be thought just a satisficing strategy, but consider the risk and potential costs of considering alternatives. As modelled in the Kahneman and Tversky (1979) prospect function, most consumers prefer avoiding downside risks to getting upside gains. In selecting the same camera of an acquaintance, the student has eliminated the downside risk and avoided the possibly very large cost of reliably in selecting a better camera. The cameras selected by this procedure were generally good student cameras with an autofocus assist light; there was the exception of one young woman who bought the same camera as her brother (an Olympus Stylus) – a good camera but lacking an autofocus assist light. When we brought up the issue, she immediately questioned the reliability of our sources because her father, a serious amateur photographer, was an Olympus fan.

Now let us consider the signals students used to forecast performance. Several used brand name as a general predictor of good performance. While such a signal has very low processing cost, it's far from a perfect discriminator. For example, while the reviewers generally rate some Canon and Fuji cameras as top competitors in their class, not all of their cameras are top competitors. And the assertion that more megapixels means a better camera is simply wrong: the quality of the algorithm used to translate the raw sensor data into a picture is far more important. Also, the quality of the picture on a camera's LCD screen reflects the screen's resolution – not the picture's quality in the camera's memory.

For decades, decision psychologists have studied the difficulties in making intuitive forecasts, called judgement by Hogarth (1987). A brief partial list of these difficulties is:

1. Humans need more data to update estimates than does an optimal statistician.

2. Humans assume the properties of a small sample hold for the population.

3. Humans give more weight to concrete examples than they do dry statistics.

4. Humans are better at linear than nonlinear forecasts.

To illustrate the last, consider the following. If it takes six seconds to fly a mile at 600 miles an hour and three seconds at 1200 mph, how fast must one fly to travel a mile in 4.5 seconds? Most people instinctively answer 900 mph; the correct answer is 800 mph. Velocity times time equals distance is a bilinear relationship in velocity and time, not a linear relationship. But decision psychologists do not emphasis judgement difficulties caused by a lack of knowledge. The students who thought that more megapixels meant better quality or used the quality of picture on the LCD screen as quality signals lacked the knowledge to interpret the signal. We add lack of knowledge to the long list of human defects in intuitive forecasting. Errors in forecasting are objective and can be measured.

The goal of innovating Many-to-One procedures is to create more efficient procedures that reduce forecast errors. Innovation in Many-to-One procedures can be considered as analogous to innovation in production functions. New decision aids can achieve the stated objectives. We shall use a revealed preference criterion for deciding whether a new Many-to-One procedure is actually an innovation: if, after field testing and adoption, the procedure persists and expands by imitation and improvements, then the new Many-to-One procedure is an innovation.

5 Third-Party Cyberspace Data Providers

Because millions of consumers face similar Many-to-One problems, there are tremendous economies of scale in providing consumers with better data and knowledge to interpret the data. For several decades entrepreneurs have created trade magazines providing reviews of technology products such as automobiles and electronic devices. With the rise of the Internet, entrepreneurs have created numerous sites to provide consumers with decision support for technology products – especially in electronics. For digital cameras a consumer can go to sites such as CNET.com, consumerreports.org, Megapixel.com, DCResource.com, DPReview.com, Imaging-Resources.com, and Steve's digicam.com. The problem these sites must solve is obtaining an adequate rate of return for their services. ConsumerReports.org charges the viewer a flat annual fee to access the site and the others obtain their rate of return through advertising, sponsorships, and pass through fees. Since many of these sites not only survived the dot.com crash, but are also expanding their services and numbers of viewers, their use in solving the Many-to-One problem can be considered an innovation in Many-to-One procedures. In this section we will discuss why data-providing entrepreneurs are moving to the internet and where the services they provide can be improved.

It is obvious that, in almost all cases, products on the internet are representations of the object in physical space. Yet, in cyberspace such representations are currently limited to images, sound, and text. A consumer can not interact using touch, taste, or smell. While, as we point out in Norman et al (2003), entrepreneurs are creating substitute measures (e.g. a device to measure the sugar content of fruit), the possible implementation of such substitute measures for consumers still lies in the future. But, because a consumer in physical space almost never tests alternative products through the full range of their intended uses, a consumer uses representations of an object in physical space, such as its attribute values on an internet site, to forecast its performance. In cyberspace the various review sites use different representations of the objects they are reviewing. For example, in digital cameras the various sites vary greatly in the amount of detail presented on each camera and the type of tests they perform. As we shall see, the issue of representation is critical in the design of Many-to-One decision aid software.

The advantage of physical space is that representations allow for more types of sensory input, while the advantage of cyberspace is that an entrepreneur can use the polynomial processing tractability of the server to augment the sublinear (Norman et at 2004) processing tractability of a human dealing with large numbers of alternatives. We now consider how cyberspace sites use the computational advantage of a server connected to the Internet.

To solve the Many-to-One problem consumers need product data and reviews, and finding such data and reviews is much easier in cyberspace than in physical space. While such data and reviews are published in magazines, such as MacWorld, trying to remember the number of the appropriate issue and physically searching through indices can be a frustrating experience in physical space. Again, if a consumer goes to google.com and enters the product name with the word "review," she obtains a list of sites that have reviewed the product. At such a site, a consumer can click through a hierarchal structure to read the reviews of interest. Consumers, who are interested in a particular category of product, can bookmark or create a favorite entry for all sites reviewing the the product category.

Once a consumer has found a site with useful data, using the site is made more efficient than performing the same operations in physical space. An internet site that collects the data found in manufacturers brochures and organizes it into a common format is much more efficient for a consumer to navigate than contacting sellers to obtain the brochures that impose and additional cost on the consumer because these brochures generally do not have a common format. Also, most data provision sites have search software to find the consumer's desired data. The value of a site's search function is evident if one compares the cost of finding a specific Consumer Reports article in their magazine versus the time to find it on their web site once the viewer learns keywords that produce satisfactory results.

In addition, cyberspace dominates physical space in the provision of tools to consumers. Let us start with tables in physical space versus cyberspace. The authors of review articles in media magazines frequently include tables that show the discussed products' attributes side-by-side, but these tables are immobile. At third party cyberspace sites that focus on the same products, consumers can use software to create desired tables of the only those alternatives that interest them. These tables can include the products' attributes, links to reviews, and current prices. The creation of such tables allows the viewer to more easily compare the attributes of alternatives, and such tables are much more accurate than remembering the information seen in alternative brochures. A consumer can create tables of attribute values for a wide range of products–including automobiles, computers and consumer electronics, household appliances, and software–at general sites such as pricegrabber.com, dealtime.com, and epinions.com as well as at specialized sites such as autotrader.com and dpreview.com. In physical space it would be too expensive for consumers to create such tables by acquiring and lining up the tables in the manufacturers' brochures lacking a common format.

In addition, cyberspace sites sometimes have decision aid software for the Many-to-One problem. One such site is ApartmentGuide.com, which provides Many-to-One decision aid based on noncompensatory rules for finding an apartment. On the first page the viewer selects the state and city. On the second page the viewer selects the areas of town where the student desires to live; the site provides maps for those who want them. The third page asks the viewer to indicate a price range, preferred number of bedrooms, and any desired amenities. The program then presents the viewer with a list of all apartments matching the specified qualities. The various apartment complexes provide the prospective renter with the details, concerning the apartment and apartment complex, so that the viewer can create her own compensatory rule over those apartments that satisfy the noncompensatory rules. Some Many-to-One decision aids are based almost entirely on compensatory rules such as earlier codes by ActiveBuyersGuide.com and current codes of MyProductAdvisor.com

Finally, once a consumer has selected the preferred item, it is much more efficient to perform a price search in cyberspace than physical space. Suppose a consumer knows what she wants to buy: she can start with a search engine like google.com and input the product name and the word 'price.' Google will return several sites, such as pricegrabber.com that sell the product through linked merchants. Going to any of these sites, the consumer can immediately obtain a price distribution, ordered from lowest to highest, of the product and an estimate–frequently given as a number of stars and testimony of previous customers–of the reliability of the seller. Thus, a consumer can judge whether a low price is worth the risk. For example, in the case of digital cameras, the seller sometimes takes the camera out of the box and tries to sell the package components as extras. There are many such sites including dealtime.com and CNET.com for electronic products. Also, review sites have direct links to price sites so that, after deciding on the preferred item, the consumer can then easily search for a low price. Obtaining such information in physical space from a large number of sellers would be prohibitively expensive because of travel costs or time delays in reaching a salesperson by phone.

The service in these sites that could be most improved is the software decision aids for the Many-to-One problem. We will consider the current problem in such aids next.

6 Compensatory versus Non-compensatory Search Rules

Tversky (1972) introduced the elimination-by-aspects decision rule but provided an advertising use of this rule that he considered defective reasoning. Since that time, many decision psychologists, for example see Hogarth (1987), have underestimated the cost of compensatory decision rules and the positive aspects of noncompensatory rules. Following this line or reasoning, some developers – as has been pointed out in the previous section – have relied almost entirely on compensatory rules in creating online Many-to-One decision aids.

We first present an argument that there are situations where noncompensatory rules are not superficial and they have legitimate applications. If a consumer buys a Mac computer with MacOS X, then an elimination-by aspects (EBA) or set-selection-by-aspects (SSBA) rule to consider only software that runs on the MacOS X system is not superficial. In considering noncompensatory rules such as EBA and SSBA, one must carefully distinguish between the creation of the criteria and its execution. For example, in solving the Many-to-One problem some consumers proceed from groups to subgroups to a final item. Consider creating and executing a rule to select between large and small digital cameras. Small digital cameras are cheaper and are much easier to carry around and large cameras are more expensive, require a camera bag, and have more features such as higher optical zoom lens and external flash connections. If a consumer makes this decision by comparing the common features of the two groups and deciding whether buying a large camera versus a small one is worth the cost of having the features and inconvenience of carrying it around, the decision is a compensatory decision between the groups. On the other hand, if the consumer needs an external flash for the type of pictures to be taken, the decision is a noncompensatory decision between the groups. In either case the efficient execution of the decision can be reduced to clicking on the appropriate box on a computer screen.

Now we will consider some cases when compensatory rules are inappropriate or superficial. If a consumer needs an external flash for the types of pictures to be taken, this is a noncompensatory decision and any attempt to use it as a weight in a compensatory rule is inappropriate (e.g. the earlier ActiveBuyersGuide digital camera code that forced the consumer to input an external flash as a weight in a compensatory rule). In the MyProductAdvisor.com code an external flash is not an option and the consumer would have to know that, while most large cameras have an external flash connection, few small cameras have even a small, external slave flash option. In addition, compensatory rule implementation in software can vastly oversimplify the underlying tradeoffs. Cameras up to 2" in depth have a maximum optical zoom of 5x and those over 2" have a maximum optical zoom of 12x. In large cameras there is a range of lenses that provide a tradeoff between optical zoom and wide angle. If cameras with a fixed lens do not meet the picture-taking requirements of the consumer, he can pay hundreds of dollars more for a dSLR camera for which he can buy a telephoto lens and a wide angle lens. It is superficial to capture relationships with sliding scales, concerning desired optical zoom and camera size, as is the case with the MyProductAdvisor.com digital camera code. Where products can be partitioned into disjoint niches, which is approximately the case for digital cameras, creating sliding scales over the range of attribute values can mask not illuminate the nature of the tradeoffs among the niches because the user will intuitively think there are alternatives with all possible combinations of attribute values. Trying to create nonlinear compensatory rules based on all attribute value combinations is prohibitively expensive because the number of alternatives is multiplicative in the number of attributes-values being considered such that, if there are 10 attributes with 5 values each, then there are 5^{10} possible alternatives to consider and most of the attribute combinations will not exist in products.

Our assertion is that all of the known decision rules, even linearized utility, have domains where their application is appropriate and domains where it is not. All rules can be superficially constructed if too little effort is made in their construction or the goal is to influence the user as was the case in Tversky's EBA example. Because a consumer initially faces the entire market of millions of goods and services, a Many-to-One procedure starts with rules on sets and generally shifts to rules on individual alternatives at the final stage. Noncompensatory rules are legitimate in cases where a product must have certain features to be useful (e.g. input in a Becker household production procedure). By first selecting a set that has the required attributes for the intended uses, the consumer can drastically reduce the cost of constructing good compensatory rules over the remaining attribute-value combinations.

7 Experiments

Performing experiments over the past two years, we wrote three codes to solve the Many-to-one problem for selecting a digital camera. Our codes have:

- A knowledge base indicating which features are required for the type of pictures desired.

- A decision structure for users to select a small subset of cameras with the desired features for further evaluation

- A recommended procedure for final evaluation

For products with many niches, like digital cameras, determining the best niche can be more difficult than finding the preferred product in that niche, especially if the consumer knows very little about the product because such a consumer has no knowledge to forecast which niche is best suited for the intended uses such as in input for a Becker household production procedure (function). With market competition the quality of the top competitors in each niche tends to converge. We focus most of our efforts in trying to create code to ensure that the subject is in the correct niche. The decision structure uses an SSBA rule approach in which the tradeoffs are implicit in the selection. Also, given the speed of the processor, the user can determine tradeoffs of the attributes of interest with trial and error procedures. Then, the user is given a procedure for the final selection in the correct niche where she can create her own rules such as a compensatory rule.

7.1 Round One

The first code we created to solve the digital camera Many-to-One problem was created in academic year 2003-2004 and is located at http://www.eco.utexas.edu/Homepages/Faculty/Norman/000Cam/. In this code we provided and extensive knowledge base to educate the users about the purpose of digital camera attributes. The site was organized in multiple levels so that the interested user could obtain a shorter and longer answer, which frequently contained pictures to illustrate the points. The users filled in a form, indicating the type of pictures desired, and the program responded with a list of required and desirable attribute values. The user then used the values to find a small subset of cameras using a SSBA operator for further study. After preliminary testing we determined that using this code took too much time so we created an abbreviated version to perform the following experiment in the Spring of 2004.

In experiment 1 we used an Anova 4x1 design with 12 subjects in each cell to determine which group would give better advice in camera selection. The four groups are listed below:

1. Sales people at retailers that sell digital cameras
2. Students who own digital cameras.
3. Students who did not own digital camera using the software package 2 at http://www.eco.utexas.edu/Homepages/Faculty/Norman/005Cam/
4. Students who did not own a digital camera with access to an internet browser, but no special software

To collect data from group 1 the coauthors went to 12 retailers that sell cameras in Austin, TX and asked them for their recommendations. Members of groups 2,3, and 4 were undergraduates at The University of Texas at Austin. Getting students who own a camera to make recommendations was difficult because they generally have almost no knowledge of camera models, frequently even of their own camera. To solve this problem students who owned cameras were given sheets with pictures of cameras produced by the various manufacturers; but without any data other than the model name. The group that had access to the internet started with an internet browser set as their home page.

We did not provide the sales people at the retailers any additional incentives over what their managers provided. The incentives for the members of the other three groups were a flat fee of $5/(30 minutes) with 1.5 hour maximum for finishing the experiment, $1 for every correct answer, and each group of 12 received prizes of $50, $20, $10, and $10 for the first, second, third, and four most correct answers.

The subjects were asked to find the best 3 cameras in each of the following niches:

- a tiny camera with at least 3 megapixels. Autofocus assist light not necessary.
- A small digital camera with an autofocus assist light and either a sports scene mode or shutter priority:

- a prosumer camera with an external flash

The subjects were given a scenario and had to figure out what attribute values were needed for the type of shots indicated. They are cautioned not to add features that they might like. The scenario for the first niche above was:

- Very small, thin digital camera for purse or shirt pocket
- Needed Outside pictures of houses for job as real estate person
- I want a point and click
- Want Great pictures and I need 8 x 10 prints
- Budget: $400

The data was coded 1 for the correct niche and 0 for not the correct niche and normalized between 0 and 10. The ANOVA F test value that the four means were different was 4.04, which is significant at an α of 0.005. The means of the four groups were (1) sales 3.0, (2) own camera 5.2,(3) our code 5.8, and (4) browser 4.5. Since a perfect score would have been 10, none of the groups performed that well. The Duncan test with $\alpha = 0.05$ indicated that our code was significantly better than the sales clerks but not significantly better than the other two. This result supports our contention in the lack of knowledge of sales people.

We tested the original, long version of the code as a weeklong, take-home group project in my Informational Society class during the section on the Procedural Consumer. For incentive the winning group of the 9 groups participating was an A in the class and each member received $20. students were instructed to find three cameras for each of the scenarios listed above and this additional scenario that required finding a telephoto lens camera. Students were instructed to justify their answers with material from the linked sites, The software package provided the data and knowledge to interpret the data so that the requests were reasonably unambiguous. Given the incentives and time allotted, all groups performed well. The cameras selected were in the correct niche 91.6% of the cases.

While our abbreviated code might have performed significantly better than the other two with a larger sample, we decided to develop better code because subjects found the correct niche less than 60% of the time and the original code required too much effort to use.

7.2 Round 2

We rewrote the software to make it more efficient by drastically simplifying the representation of alternative cameras and the choice process allowing us to reduce the knowledge base necessary to interpret the data. The goal was to get a software package that could be used in 20 minutes or less. We created two new codes based on the following alternatives.

- Use a tree structure where subjects choose between large and small cameras. If they choose large, they make an additional choice of telephoto, prosumer, or dSLR before proceeding to selecting the attributes of the type of camera. This code is at
  http://www.eco.utexas.edu/Homepages/Faculty/Norman/001Cam/

- Allow the speed of the processor to enable the subject to select any subset for further study in one operation. In the physical world sellers organize goods so that buyers can make several set selections by aspects steps before they must switch to a linear rule. Buyers, who use a SSBA rule, must follow the organization of the seller. But, from the perspective of the subject, a linear rule, processed by the server, appears as a constant computational complexity rule. Thus, the user can organize the set of objects for further study in any arbitrary fashion. This code is at
  http://www.eco.utexas.edu/Homepages/Faculty/Norman/002Cam/

The third code tested was the Many-to-one digital camera selection software http://www.myproductadvisor.com/mpa/camera/inputSummary.do) at Imaging-Resource.com that was developed by MyProductAdvisor.com. This code follows the psychological decision theorist preference for compensatory decision rules set by sliding scales. The code implicitly assumes that the user has a preference ordering defined over camera attributes and does not provide the user with a knowledge base to understand which attribute values are needed for various types of pictures The setup page to use this code is at http://www.eco.utexas.edu/Homepages/Faculty/Norman/003Cam/

The experiment was a 3x2x2 Anova design with 6 subjects in each of 12 cells totalling 72 subjects. The first factor of three levels consisted of the three software codes. The second factor of two levels was that one group found 6 cameras in 2 sets and the other found 9 cameras in 3 sets. The cameras that the subjects had to find were specified in a similar manner as the format in experiment 1. We had one group with 3 sets of cameras and one group with 2 sets of cameras because we were not sure how many sets the subjects could complete in an hour. The third factor of two levels was that one group owned a digital camera and one group did not. Students in each 6-member cell competed against each other and were paid a flat fee of $10 for a one hour experiment and had a chance to earn a prize for each cell of $30, $20, and $10 based on whether the cameras were in the right niche.

In a similar fashion to experiments one, the data was coded 1 for the correct niche and 0 for not the correct niche and normalized between 0 and 10.The F test value for this ANOVA design was 3.77, which is significant for an α of 0.0004. The one factor that was not significant by the Duncan test was whether the subjects owned or did not own a digital camera. The other two factors, which computer code and whether subjects had 2 or 3 sets of cameras to find were significant and had an interaction effect. The means for the three code factor were (1) our tree code,7.8; (2) our user organize niche code, 7.1; and the MyProductAdvisor code, 4.2. While the Duncan test with an α of 0.05 did show that both our codes were significantly better than the MyProductAdvisor.com code, this was not surprising because the latter code contained almost no knowledge base to enable the subject to determine the parameters to select cameras for the situations indicated. There was no significant difference in the performance between our two codes. Our two new codes improved upon the previous code: the percent in the right niche increased from less than 60% to better than 70%.

The results that whether subjects had 2 or 3 sets of cameras to find were surprizing. For code 1 subjects did significantly better with the 3 sets of cameras to find and for code 2 subjects did significantly better with the 2 sets of cameras to find. This indicates that subjects did not have enough time was not likely to be the factor. Instead it appears that each code had different defects. For code 2 we noted that subjects frequently chose a telephoto camera when they should have chosed a prosumer camera.

We also had students spend 15 minutes to fill in questionnaires to determine their knowledge of digital cameras, their internet usage, and their attitudes towards risk. From the results of this questionnaire we performed a regression to determine whether the subjects score on the camera knowledge test would explain the subject performance. The regression was:

$$score = \beta_1 = \beta_2 kn + \epsilon$$

where *score* was the subjects score in the ANOVA experiment; kn was the subjects test grade in the camera knowledge test; and ϵ is the error term. The value for β_1 was 4.0 and its t value was 4.34 and the value for β_2 was 0.43 and its t value was 2.88 and the R^2 was 0.11. While these coefficients are significant for an α less than 0.01, the equation only explains about 10

7.3 Round 3

We improved code one to clarify the relationship between wide and narrow lenes and made a video to clearly demonstrate the difference between a small and a tiny camera. We repeated experiment 2 with this code with a modification that they were to find a wide angle prosumer camera. The revisions are located at http://www.eco.utexas.edu/Homepages/Faculty/Norman/111Cam/. Subjects performance on the 3 set camera senario was almost the same as for the original code 1. This is encouraging because the wide angle prosumer specification was a restriction from the previous specification. For the 2 camera senario subjects performance was better in discriminating between a tiny and small camera, but not significantly better.

Finally, if we take the data for the 3 set camera senario for this modified code 1 and substitute for the data for our code used in experiment 1 we find that the new code is significantly better than just having access to the internet, friends with a digital camera, or talking to sales people. What is important to note is that it took a great deal of effort to achieve this result.

8 Conclusions

It should now be obvious to the reader that procedural consumer theory is in the intersection of computational economics, experimental economics, decision psychology and marketing and a lively interaction among members of these groups will advance this procedural theory.

What did we learn from our experiments:

- A knowledge base is necessary in cases where users do not know much about the product. All our surveys indicated that students, even ones who owned digital cameras, did not know much about digital cameras.

- In order to capture the economies of scale, the representation and decision structure should be directed at primary user group. Assuming that most digital camera buyers are looking for a point and click camera the second representation and decision structures were better than the first.

- We belive that noncompensatory rules are efficient and can be legitimate. but the evidence suggests the poor performance of MyProductAdvisor code was due to lack of knowledge base.

- What makes this problem interesting is that if the goal if to have 95% of subjects achieve 95% accuracy in 20 minutes the code creators can not simply keep adding more and more data to the code to correct mistakes. The code developers must always be seeking an efficient representation whether text, pictures, or videos to communicate with the minimun processing.

We hope to field test our best code to keep improving it.

Our position is that consumers use decision rules to solve the Many-to-one problem and a preference ordering over specific objects is an auxiliary calculation that consumers sometimes make for frequently purchases products such as specific brands of beer by a beer drinker. Recently Fuchs-Seliger and Mayer (2003) created a type of traditional consumer theory where dominance replaces transitivity. In their approach consumers do not need to have preferences defined over dominated items. Items not selected by a noncompensatory rule can be considered dominated items. We shall consider the relationship between procedural consumer and their theory in a future study.

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