Current Issues and a “Wish List” for Conjoint Analysis

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SUMMARY

Conjoint analysis is one of the most celebrated tools in Marketing, and its widespread use (not just widespread publication history) has been one of the greatest success stories in Marketing/Business of the academic and practitioner interface. In this article, I provide a wish-list, of sorts, summarizing current cutting-edge research that is trying to fill some holes, and other issues that I "wish" were trying to be filled.

By literally using a list-like statement, current answer, and wish-list format for this article, I hope to provide guidance to both academicians and practitioners as to areas for future important conjoint research.

KEY WORDS: Conjoint Analysis, Within-task Learning, Non-compensatory models, Massive number of attributes, Educational Testing

Many academics and practitioners alike have hailed conjoint analysis as one of the major cross-over breakthroughs between academic theory and practitioner relevance in the field of Marketing research ([1], [2]), and rightly so. The validation of this claim can be measured not only by the companies today that utilize conjoint methods for decision-making (product introductions, pricing, war gaming, etc…), the 62,000+ hits on www.google.com, and 500+ hits on jstor.org that appear when "Conjoint Analysis" is entered, but the fact that the research topic still has "legs" thirty plus years after its primary introduction ([3]). This is especially true in areas such as conjoint design ([4]), where adaptive conjoint designs, specifically ACA ([5]), are still being fully understood and entirely new methods, such as fast-polyhedral designs ([6],[7]) are just hitting print.

Despite all that we know about Conjoint Analysis, however, there exists a significant amount that is left to understand, and is the motivation for this paper. That is, I will describe nine different areas in which I have a wish list, meaning I wish I knew the answer to this question and hope that other academicians and practitioners wish they did too.

It is important to note, however, that many of the wish-list items presented here come from a "behavioral-mathematics" perspective, one in which understanding the underlying process (in the mind of the respondent) is important in and of itself. As the major use in practical studies for conjoint is forecasting, and specifically out-of-sample forecasting for new product introductions, product-line extensions, and the like; some of these issues may become more or less "practically" important. That is, while non-compensatory models, non-stable attributes, etc… may indeed exist, it is an empirical question as to the robustness of standard methods to these deviations. The empirical meta-analysis (of sorts), described in wish-list item (8), is a call for further empirical understanding of these issues.

1. Within-task learning/variation

One basic tenet of standard conjoint models, whether modeled with heterogeneity ([8]), or not, is that the attribute coefficients (partworths) are stable throughout the study, i.e. there is no subscript "t" on them indexing trial or time. Now, of course, while a fully parameterized model where each partworth is person and time specific is overparameterized, one could assert a change-point model, a smooth-parametric function, a random-walk model, etc… allowing for time-varying partworths ([9]). Whether I believe, or psychologists believe, that people within-task change their preference weights is somewhat moot; current methods allow for this question to be answered empirically under a number of different settings. From a practical standpoint, understanding the answer to this question can have implications for how people form their preferences of brands as they become more experienced, say, with the product category.

2. Embedded Prices

The typical way in which prices associated with conjoint profiles are constructed, and more importantly presented, is that each attribute level comes with a "hidden" (embedded) price (i.e. it's known to the researcher and used to construct the overall profile price but unknown at the attribute level to the respondent) and one of the profile's attributes is the total price comprised of adding up a base price and the associated level prices. While this mimics many buying situations, and allows for a clean measure of the "price partworth", there are many real-world situations in which the price associated with an attribute level is visible and "embedded" within the attribute itself; e.g. a 8x CD-Rom drive at a $200 cost. In these instances, the deterministic component of utility is not (potentially) simply the sum of the attribute-levels utilities, but is some combination of utility for the attribute levels, their associated prices, and even possibly an attribute quality/price ratio. As these types of products are prevalent in the marketplace, research into this domain would seem fruitful; however, such studies would require correlated attribute levels[1], for instance price with an attribute, which would not "come for free" and would create estimation issues.

3. Massive Number of Attributes

While conjoint analysis has been shown to operate quite well when the number of attributes within a profile is within a moderate range (say less than 8), there should be concern about the use of conjoint in situations where the number of features describing a product is "massive", say 15-20 or more. This is certainly not uncommon for technological products, hotels, and automobiles to name a few. Two common practices in such situations are to: (a) utilize partial profiles ([10]), where each profile contains an experimentally designed subset of the attributes, or (b) self-explicated conjoint in which desirabilities of attribute levels and importances of attributes are collected in a self-report, one at a time manner ([11]). My call for research in this area relates to the practice of

[1] The author wishes to thank Joel Huber for this important point.

partial profile conjoint in which there is a presumption that either: (a) the attributes not shown do not interact with the attributes shown, and hence can be ignored, or (b) if profiles are shown in pairs, then the unseen attribute effects "cancel" when the difference between the utilities is computed to determine the choice probability of one profile over the other. Unfortunately, recent research has begun to question this assumption of "cancellation" ([12]), as well as more traditional research that has shown that partworths change depending on the presence or absence of other attributes ([13], [14], [15]).

4. Non-compensatory decision rules

All conjoint models available in standard software, and most used in academic research, utilize a linear equation for the deterministic component of utility for a profile that implies a compensatory decision rule, i.e. lacking on one feature can be "made up for" by being better on another feature. Much behavioral/experimental research has shown that indeed subjects do not all make decisions this way; for instance consider elimination-by-aspects where if the product does not have a certain feature it is eliminated from the consideration set. Such behavior is common for novices and/or people who are using simplifying decision heuristics. Fortunately, recent research by [16] and others, have now developed ways within a Bayesian framework to assess and allow for greater flexibility in the assumed decision rule, and even better, can uncover the "latent rule" and provide information on the fraction of respondents using one rule over another. I applaud this research and hope it is an area that is continued. Nevertheless, it remains to be seen whether non-compensatory rules can not be approximated well by standard assumed compensatory models with interaction terms. Although, the use of interaction terms, in practice, is not commonplace but instead under the special discretion of the study designer.

5. True integration of profile conjoint data with other data sources

It is not uncommon that respondents who have participated in a conjoint experiment to have also filled out other survey questions, or in those instances where the conjoint experiment is part of a larger study to understand the customer base, purchase data, marketing mix variables, demographics, and the like are also available. In these instances, an integrated model for multiple data sources would be "nice" in which all sources provide information about the partworths, or even more generally, one could imagine a set of latent factors or needs, upon which all data sources are a manifestation thereof. Work by researchers in [17] built a Bayesian model that allows for the coherent combination of secondary data sources on partworths (self-explicated data) with the primary experimental data; however, this study was limited to conjoint data and self-explicated. True integration with purchase data, survey data, etc… would be an important extension and, in my view, an integrated framework that would be used.

6. Experimental Design: What can we learn from the Education Literature?

As mentioned in the introduction, experimental design issues in conjoint, beyond standard linear designs, have made tremendous strides in recent years with the development of ACA and, most recently, polyhedral methods. Such methods are designed to select the next profile, or pair of profiles, to maximize the obtained information, or alternatively, minimize a sum of variances (posterior or otherwise). This problem is virtually identical to that which has been researched extensively in educational tests ([18]) and is known as Computerized Adaptive Testing (CAT). In CATs, the next item administered to an examinee is that which minimizes the posterior variance of their estimated ability distribution. To describe the "tip of the iceberg" of its widespread use in the education domain, the current incarnation of the Graduate Record Examination (GRE), given to millions of students yearly applying to graduate study, is done in an adaptive fashion. However, while these problems are virtually identical; there has been little to no cross-over research, or in my view even more importantly practitioner conferences that have people from both "worlds". I hope the time is now.

7. Getting the right attributes and levels

As someone who teaches Marketing Research, and who is a user of conjoint methods in practice, we can talk all the theory we want, but at the end of the day a large fraction of the success of conjoint rests on the researcher's ability to identify the salient attributes and levels. Despite their importance in practice, little guidance is given in how to select them, other than to use qualitative research methods (one-on-one interviews, focus groups), and possibly open-ended survey items as a guide. Besides a more definitive document containing our collective current knowledge in this area, research that provides *empirical* diagnostics would be of tremendous value. That is, can we provide a document where say, you have chosen your attributes and levels, run your conjoint model (hopefully allowing for heterogeneity), and a statistic based (say) on the heterogeneity of the estimated attribute levels, or the multimodality of the distribution, would suggest that the attributes and levels you have chosen may need adjustment. Such knowledge or research may exist or may not, but at least it is not common enough that it is known to me; and, if you want to talk about demand for it, I teach 150 students conjoint per year that would be an immediate and important market.

8. Mix and Match: is that ok? A meta-analysis in the making.

Amongst the many choices that are available for conjoint studies (ratings, pairwise, constant sum, pick k out of n, etc…), the user is faced with the daunting task of picking the one that is most appropriate. Recent research ([19], [17]) has intimated that when considering this choice, one important consideration is the form of the out-of-sample choice to which you are interested. That is, for example, if you are interested in forecasting people's choices in a 1 out of n real-world situation, use 1 out of n in your experiment. Whether this is true or not, remains to be seen; however, it is an interesting hypothesis and one in which I have seen little empirical validation. That is, just like in wish-list item (7) above, a ubiquitous question is "Which form of conjoint should I use?" Hopefully, whether it's through people posting their results on a common website, or an academic study that meta-analyzes research paper findings, this would be of tremendous value.

9. People don’t make one-off decisions: product-bundle conjoint

As has been shown in much research regarding bundle choices ([20]) and variety seeking behavior ([21]) people do not select individual products in isolation, rather they consider bundles of goods some of which may be complementary, some of which may be substitutes, some of which may be to avoid satiation. The entire paradigm of conjoint, as currently structured, does not take this into account and considers predictions of choices of products in isolation, rather than as part of a utility maximizing “experience”. An extended model for conjoint in which product-bundle utilities are maximized to obtain partworths, may be useful when the context of the problem suggests that people will be considering products in bundles.

Conclusions

To summarize, conjoint analysis, research regarding conjoint, and the use of conjoint, is middle-aged (!) certainly not old. There are many more issues to explore and the best news of all, given its widespread use in industry, is that all we as academics who care about practice have to do is to “FOLLOW THE ACTION”. It will tell us the importance of things to work on next, and will provide exciting research that will be useful for years to come. Nevertheless, as we try to balance theoretical understanding and model parsimony, we must always keep our eye on the practical “prize” to which conjoint was designed, and more importantly is used.

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