Understanding Human Strategies for Change: An Empirical Study

Alankar Karol Mary-Anne Williams

Faculty of Information Technology, University of Technology Sydney, NSW, Australia

Abstract

The ability to model changes in preferences is crucially important for sound decision making and effective communication. Much has been written about strategies for changing beliefs and preferences. Typically such strategies have been driven by theoretical considerations, intuitive notions of rationality, and an appeal to the principle of Minimal Change. In this paper we describe an experiment in which people were asked to rank information, then given some new information, and asked to re-rank the information. We analyse the results and provide comparisons with some well known computational strategies. Some of the results are surprising, for example, a large percentage of human strategies can be classified as either Conditionalization, Adjustment, or a combination.

1 Introduction

Intelligent agents require effective mechanisms for managing complex information; beliefs, expectations, and preferences. A key characteristic of beliefs, expectations, and preferences is that they tend to change over time as the agent gathers more information, sometimes quite dramatically. The ability to model changes in preferences is crucially important for sound decision making and effective communication.

Although much has been written about strategies for changing beliefs, expectations and preferences, it is disappointing, and potentially alarming, that few strategies have been verified by empirical studies with humans. Instead most strategy development has been driven by theoretical considerations, representation theorems, intuitive notions of rationality, and an appeal to the principle of Minimal Change.

In this paper we attempt to address the lack of human verification of strategies for change by conducting an experiment in which people are asked to incorporate some new information into a ranked knowledge base in the context of Marketing Research.

In essence, subjects were asked to rank a set of possible worlds, then given some new information, and subsequently asked to re-rank the possible worlds in the light of the new information. The results are analyzed; the types of re-rankings are categorized and compared to two well known computational strategies. We chose to use a consumer behaviour application where epistemic attitudes and preferences are modeled as a set of product profiles. Consumer behaviour has a long tradition of capturing, analyzing and modeling peoples preferences.

We describe some background information in sections 2 and 3. Our experiment is described in section 4, and the results are discussed in section 5. We conclude with a discussion of the outcomes in section 6. We have provided details of the products the subjects ranked in Appendix A and an example of a Split-Conditionalization in Appendix B.

2 Iterated Belief Revision

Belief revision provides operators that can be used to model changes to repositories of information. The AGM paradigm was originally developed by Alchourron, Makinson, and Grdenfors [1], and has become one of the standard frameworks for modeling change. It provides formal mechanisms for modeling the rational evolution of an ideal epistemic state. Its power as a modeling tool stems from its simplicity, intuitive appeal, and a number of strong representation results. The process of changing a preference ranking within the AGM paradigm can be viewed as a transmutation [11]. Transmutations are guided by the need for changes to be rational and minimal.

Unfortunately, the notions of rationality and minimality for the purpose of information modeling defy explicit definition. Intuitively, by rational we mean things like: the agent behaves consistently and coherently in some sense. The principle of Minimal Change, on the other hand, says that as much of a preference ranking as possible should be preserved during each change. If one receives new information about red wine then ones' preference regarding types of whiskey should probably not be affected.

It turns out that the guiding forces of rationality and minimality lead to two useful transmutations: Conditionalization [8] and Adjustment [11]. Conditionalization is based on a relative minimal change, whilst Adjustment performs an absolute minimal change. Computational models of Conditionalization and Adjustment have proven to be effective in a wide range of applications [12].

Conditionalization partitions possible worlds into two groups; the worlds that are consistent with the new information and the worlds which are inconsistent. It then re-ranks both sets while maintaining the relative ranking as given by the original ranking. Adjustment, on the other hand, changes the rank of a world only if it is necessary in order to incorporate the new information. In practice, this means that only the lowest ranked worlds are re-ranked, and most worlds remain at the original rank. It does not pay any attention to the relative ranks of the original ranking, it only changes the rank of a world as much as absolutely necessary..

3 Consumer Behaviour and Conjoint Analysis

Modeling consumer behaviours and representing epistemic attitudes and preferences are fundamental issues for Marketing Research. According to [7] attitudes directly effect purchase decisions which in turn affect attitudes through the experience of the product.

Conjoint analysis studies are used to estimate the willingness of consumers to trade off varying levels of product attributes on the basis of their preferences. Typically consumers are asked to rank products and from this ranking part-worth utility functions that represent the willingness of consumers to trade-off product attributes are calculated [4]. The utility functions indicate how sensitive consumers are to the various attributes. For example, specific consumers might express sensitivity to price, prestigious awards, wine growing regions, product endorsements, etc.

There have been few longitudinal conjoint analysis studies reported in the literature. Marketing research companies claim to offer longitudinal studies as a service for payment, but independent analyses of the various (mostly in-house) techniques have not be conducted. The main reason for this apparent void is that conjoint analysis studies are hugely expensive; typically in the order of US$300-$500K. The major expense is the preference collection, and as a result this data is typically only collected once.

Bolton and Drew [2] conducted a study to investigate how customers evaluations of service quality are influenced by changes in service offerings. Their study concentrated on temporal changes in individual consumer attitudes. Similarly Moschini [6] explored changing preferences for meat products due to consumers awareness of the health hazards of cholesterol and saturated-fat intake.

Modeling preferences has proved to be important in traditional marketing research, and its importance has been heightened recently with the growth of eBusiness on the Internet. For example, Ad Serving Industry (e. g. www.doubleclick.com) is propelled by consumer preferences and their activity on the Internet. Ad Serving is a specialized form of profiling and recommendation technology based on cookies; Ad servers assign the consumer with a specified identifier. Each time a consumer has contact withthe Ad Server, registered actions of a consumer (events) are transferred with the consumer identifier totheAd Server. Example events are: consumer with identifier "12345" has visited a travel site, has purchased a book at amazon, has clicked ontheadvertisement "98765", etc.

Consumers are assigned a profile which is updated after each action. A profile describes the consumers preferences. The update procedures used are often types of transmutations; forms of Conditionalization are the most commonly found in Ad Serving.

Profiles are also used to feed recommender systems other than Ad Servers. Suffices to say modeling preferences is big business, and developing a better understanding of how humans change their preferences will have significant impact in many areas.

4 Experimental Design

We used two independent surveys. One was based on catfood and the other on wine. The subjects were given two forms to complete. The forms required subjects to rank a number of products. After the initial ranking was completed, they were required to re-rank products in the light of new information that we provided. The actual products used on the survey form are given in Appendix A.

In the case of the catfood experiment, subjects were informed that according to a recent study dry catfood was significantly healthier for cats. In the case of the wine experiment, subjects were told that there was strong evidence to suggest that red wine from the Hunter Valley was better for the heart than any other wine. The survey was conducted by Tuckers-Seabrook a major Australian wholesale wine distributor in a face-to-face scenario where subjects were able to clarify ambiguities in their understanding of what was required and the meaning of the terms mentioned in the survey. It has been shown that the best results are obtained under these conditions, e. g. Internet or telephone preference collection delivers less reliable data. It is well known from consumer behaviour studies that care must be exercised to ensure that data collection devices and consumers do not confuse attribute and preference meanings [9].

Ideally, a fully-crossed factorial design would be used to test all possible combinations of the different product attributes. However, a fully-crossed design in our case would mean that subjects would be asked to rank a large number of products. Fourteen catfood products were chosen using a fractional factorial orthogonal array of profiles [10] [3] and fourteen wine products were chosen by our client, Tuckers Seabrook, as the important wine attributes of particular interest to them. Both studies used 14 unique combinations of hypothetical products. There were 63 subjects in the catfood experiment and 78 in the wine experiment. The catfood subjects were segmented into two groups: cat-owners, and non-cat-owners. The wine subjects were segmented into three groups: nave, informed and expert.

We used a ranking methodology, where the 14 product configurations were rank-ordered from one through to fourteen according to the relative preferences of each subject. The most preferred product was assigned a rank of 1, and equal ranks were permitted.

5 Results and Summary

5.1 CatFood Experiment

In the group of 63 subjects for the cat food experiment 44 owned cats. The new information supplied after the subjects completed their first ranking was that according to a recent scientific study dry catfood was significantly healthier for cats of all ages. Interestingly, 86% of the subjects stated that they were surprised by the new information.

It was found that 60% of the non-cat-owners changed their ranking of the catfood when the new information was provided, while 73% of the cat-owners changed their ranking. The rankings were changed in a rational way, in the sense that a lower rank was assigned to the dry cat food giving it a higher preference. We refer to these changes as rational in Tables 1 below.

Most of the subjects re-ranked in a rational fashion, however a small but significant percentage (10%) of the non-cat owners who revised their ranks did so in a non-rational manner; this is demonstrated by their preferences for dry catfood being downgraded.

The price of the cat food played a very important role in the ranking and re-ranking with nearly all subjects leaning towards the cheaper products. This trend was more pronounced in the cat owners than the non-cat owners with 16% of the cat owners giving a lower rank to higher priced cat food while 37% of the non cat owners preferred the high priced cat food.

Veterinary endorsement and product guarantee did not play a significant role in the ranking of preferences with veterinary endorsement and product guarantee being important to only 5% and 21% of the non cat owners and 16% and 18% of the cat owners, respectively. We summarise some of the findings in Table 1.

Category	Number of Subjects	Number Changed	Number of Irrational Changes	Number Price Sensitive	Veterinary Endorsement Sensitive	Product Guarantee Sensitive
Not Cat Owners	19 (30.2 %)	11 (57.9 %)	2 (10.5%)	7 (36.9%)	1 (5.3%)	4 (21.0 %)
Cat Owners	44 (69.2 %)	32 (72.7 %)		7 (15.9%)	7 (15.9%)	8 (18.2 %)
Total	63	43 (68.3 %)	2 (3.2%)	14 (22.2%)	8 (12.7%)	12 (19.0 %)

Table 1: Summary of Catfood Experimental results

In terms of transmutations the following interesting patterns were discernible:

- 20% of the rational rankings revisions were Adjustments.
- 20% of the rational rankings revisions were Conditionalization.
- 41% of the rational rankings used Adjustment for the non-dry catfood products.
- 32% of the rational rankings used Conditionalization for the dry catfood products.
- 27% of the rational rankings used Adjustment for the non-dry products and Conditionalization for the dry products. This is an example of a Hybrid-Adjustment-Conditionalization.
- 37% of the rational ranking revisions were Split-Conditionalization. A Split-Conditionalization is one where the rankings are were split and conditionalized by different amounts, see Appendix B for two examples of Split-Conditionalization.
- 22% of the rational ranking revisions were Split-Conditionalization for the dry products and Adjustments for the non-dry products.
- 10% could be construed as Hybrid-Adjustment-Conditionalization since they expressed both behaviours. See example 2 in Appendix B which illustrates Hybrid-Adjustment-Conditionalization.
- 5% could not be classified as any known transmutation.

5.2 Wine Experiment

In this experiment we were interested in determining how people changed their preferences for wines based on their perceived level of wine knowledge. The subjects were informed that there was strong medical evidence that showed red wine from the Hunter Valley reduced the risk of heart disease more than any other wine.

The 78 subjects were asked to indicate their level of expertise as nave, informed or expert. Of the 23 subjects who classified themselves as nave, 83% changed their ranking when the new information was provided. This is in contrast to the 64% of the 36 subjects who classified themselves as informed, and 42% of the 19 subjects who classified themselves in the expert category. The re-ranking was consistent with the new information in the sense that the subjects revised their preferences for the Hunter Valley Shiraz. So in this experiment most of the changes were considered to be rational. However, a small percentage of subjects in each category that did not re-rank rationally (see Table 2 column 4).

Another factor that influenced the ranking of the wine was the price, with some subjects giving a lower rank (higher preference) to wines that were in the high price range. This dominance by price was more prevalent in the expert category (90%) than in the other two groups with the percentage dropping in proportion to the perceived level of expertise.

Curiously, the new information caused some subjects to revise their previously held preferences of the white wines, not only those from the Hunter Valley. 11% of the nave subjects changed their ranking of the white wine giving a higher preference to the Hunter Valley Semillon. Clearly, these subjects might have generalized the information to be that all Hunter Valley wines (not just red wines) are healthier/better. This effect was not observed in the informed category in our experiment and only 5.3% of the experts changed their opinion about the white wine. We summarise some of the findings in Table 2.

Some detailed findings are:

- 9% of the rational ranking revisions were Adjustments.
- 6% of the rational ranking revisions were Conditionalization.
- 73% of the rational rankings used Adjustment for the non Hunter Valley Shiraz.
- 39% of the rational rankings used Conditionalization for the Hunter Valley Shiraz.

Category	Number of Subjects	Number Changed	Number of Irrational Changes	Number Price Sensitive	Number White Wine Changed
Naive	23 (29.5 %)	19 (82.6 %)	3 (13.0%)	12 (52.2%)	11 (47.8 %)
Informed	36 (46.1 %)	23 (63.9 %)	1 (2.8 %)	24 (66.7 %)	
Experts	19 (24.4%)	8 (42.1%)	2 (10.5%)	17 (89.5%)	1 (5.3%)
Total	78	50 (64.1 %)	6 (7.7%)	53 (67.9%)	12 (15.4 %)

Table 2: Summary of Wine Experimental results

- 16% of the rational rankings used Adjustment for the Red wine and Conditionalization for the White wine.
- 48% of the rational ranking revisions were Split-Conditionalizations.
- 7% could be construed as Hybrid-Adjustment-Conditionalization since they expressed both behaviours

6 Discussion

The ability to model changes in preferences is crucially important for intelligent agents. Most strategies for modeling preference change have been driven by theoretical considerations, representation theorems, intuitive notions of rationality, and an appeal to the principle of Minimal Change.

In this paper we attempted to address the lack of verification by human subjects by conducting an experiment in which people could change their preference for two different kinds of products, namely catfood and wine. Comparing the results from the two experiments highlights the context sensitivity of preference change. However, the results are striking in that they demonstrate that most human strategies are more complex and intricate than those that have been developed for their theoretical and computational properties.

A common model of human preference change is one where the Conditionalization is used to rerank the most prefered options, and Adjustment is used to rerank the least preferred. Upon reflection this strategy makes a great deal of sense. Often times we wish to preserve the relative ranking of our favorite things, and dont care too much about the things we prefer weakly (things we dont care much about).

Two new transmutations, Split-Conditionalization and Hybrid-Adjustment-Conditionalization, can be postulated on the basis of the data.

We found that 37% in the catfood experiment and 48% in the wine experiment used a Split-Conditionalisation strategy. This demonstrates that humans refine preferences during changes. So that two equally ranked products/worlds which are consistent (or inconsistent) with the new information can be re-ranked differently. In the Split-Conditionalization illustrated in Example 1, the subject refines his ranking of dry catfood.

It turned out that 10% in the catfood experiment and 7% in the wine experiment used a Hybrid-Adjustment-Conditionalization strategy. In Example 2, the subject refines/splits his ranking of dry catfood, and performs an Adjustment on canned catfood and a Conditionalization on Moist.

Hybrid strategies were commonly used. The most favoured was (i) Conditionalization on preferences that were consistent with the new information, i.e. those products that were types of dry catfood and Shiraz from the Hunter Valley, and (ii) Adjustment on the remainder.

References

[1] Alchourron, C., Grdenfors, P., Makinson, D. 1985, On the Logic of Theory Change: Partial Meet Functions for Contraction and Revision, Journal of Symbolic Logic, 50: 510-530.

[2] Bolton, R.N. and Drew, J.H. 1991, A longitudinal Analysis of the Impact of Service Changes on Customer Attitude, Journal of Marketing, 55: 1-9.

[3] Green, P.E., Carroll, J.D. and Carmone, F.J. 1978, Some New Types of Fractional Factorial Designs for Marketing Experiments, in J.N.Sheth (ed), Research in Marketing, Vol 1, Greenwich, CT, JAI Press.

[4] Green, P.E. and Srinivasan, V. 1978, Conjoint Analysis in Consumer Research: Issues and Outlook, Journal of Consumer Research, 5: 103-123.

[5] Hansson, S.O. 1995, Changes in Preference, Theory and Decision, Kluwer Academic Publishers, 38: 1-28.

[6] Moschini, G. 1991, Testing for Preference Change in Consumer Demand: An Indirectly Separable, Semiparametric Model, Journal of Business and Economic Statistics, Vol 9, No 1, 111-117.

[7] Myers, J.H. and Reynolds, W.H. 1967, Consumer Behaviour and Marketing Management, Boston: Houghton Mifflin.

[8] Spohn, W. 1988, Ordinal Conditional Functions: A Dynamic Theory of Epistemic States, In Harper, W.L., and Skyrms, B. (eds), Causation in Decision, belief change and Statistics, II, Kluwer Academic Publishers, p 105-134.

[9] Teas, R.K. and Dellva, W.L. 1985, Conjoint Measurement of Consumer Preferences for Multiattribute Financial Services, Journal of Bank Research, 16:2, 99-112.

[10] Tulls, D.S. and Hawkins, D.I. 1990, Marketing Research: Measurement and Method, Fifth Edition, Macmillan Publishing Company.

[11] Williams, M-A. 1994, Transmutations of Knowledge Systems, in J. Doyle, E. Sandewall, and P. Torasso (eds), Proceedings of the Fourth International Conference on Principles of Knowledge Representation and Reasoning, Morgan Kaufmann Publishers, 619 - 629.

[12] Williams, M-A. 1998, Applications of Belief Revision, in Transactions and Change in Logic Databases, LNAI 1472, 285 - 314, Springer Verlag.

Appendix A: Product Profiles Used

Form	Product Guarantee	Price Range	Veterinary Endorsement
Moist	No	High	No
	No	Low	No
	Yes	High	No
	No	Medium	Yes
Canned	No	Low	Yes
	No	High	No
	No	Medium	No
	Yes	High	No
	Yes	Low	Yes
Dry	Yes	Low	No
	No	Low	No
	No	Medium	No
	Yes	Medium	No
	No	High	Yes

Table 3: CatFood Products

Grape Variety	Region	Price Range	Prestigious Awards
Shiraz	Barossa	High	No
		Low	No
		Medium	Yes
	Margaret River	Low	Yes
		High	No
		Medium	No
	Hunter Valley	Low	No
		Medium	No
		High	Yes
Semillon	Barossa	High	No
	Margaret River	High	No
		Low	Yes
	Hunter Valley	Low	No
		Medium	No

Table 4: Wine Products

Appendix B: Examples of Split-Conditionalization – taken from the data

Form	Product Guarantee	Price Range	Veterinary Endorsement	Rank 1	Rank 2
Moist	No	High	No	3	3
	No	Low	No	3	3
	Yes	High	No	3	3
	No	Medium	Yes	3	3
Canned	No	Low	Yes	2	3
	No	High	No	3	3
	No	Medium	No	3	3
	Yes	High	No	3	3
	Yes	Low	Yes	1	3
Dry	Yes	Low	No	3	1
	No	Low	No	3	1
	No	Medium	No	3	3
	Yes	Medium	No	3	3
	No	High	Yes	3	3

Table 5: Example 1

Form	Product Guarantee	Price Range	Veterinary Endorsement	Rank 1	Rank 2
Moist	No	High	No	4	6
	No	Low	No	1	3
	Yes	High	No	3	5
	No	Medium	Yes	2	4
Canned	No	Low	Yes	6	6
	No	High	No	6	6
	No	Medium	No	6	6
	Yes	High	No	6	6
	Yes	Low	Yes	6	6
Dry	Yes	Low	No	6	1
	No	Low	No	6	2
	No	Medium	No	6	4
	Yes	Medium	No	6	3
	No	High	Yes	6	5

Table 6: Example 2