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Finding items cannibalization and synergy by BWS data

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ABSTRACT

Best-Worst Scaling (BWS) modeling is widely used for finding probabilities of choice among multiple items. The paper considers how to apply BWS data to another problem – of finding the items' cannibalization and synergy. For a product of primary interest, we estimate its probability to be chosen as the best one out of all the data, and also conditionally to each product's presence or absence. For a given product, each other one behaves as a catalyzer or inhibitor of the choice. Constructing the entire matrix of such relations for all the products, we compare its symmetrical elements for each pair of products. It shows which pairs of products are mutually synergic, or complementary, so their chances to be chosen as the best ones are higher in the presence of each other. In other cases, the products can be of negative impact on one another, so one is a cannibalizer of another; or both products suppress each other. Estimations on real marketing data are considered, including the Shapley value for key driver analysis.

1. Introduction

Best-Worst Scaling (BWS) is a well-known marketing research method for finding choice probability of multiple compared alternatives. It has been proposed by Jordan Louviere (1991, 1993, 2006, 2013), and some earlier formulations can be traced to works by Duncan Luce and Antony Marley (Luce and Suppes, 1965; Marley, 1968, 1997). Then BWS has been developed and applied in numerous works (for instance, Louviere et al., 1994, 2000, 2008, 2013; Crouch and Louviere, 2001; Marley et al., 2008; Marley and Pihlens, 2012; Swait, 2001; Swait and Marley, 2013; Bacon et al., 2007, 2008; Hess and Daly, 2013; Lipovetsky and Conklin, 2014). In BWS methodology, respondents answer which of several items presented to them is the best one and which is the worst one. Each respondent is presented with about 10–20 tasks or subsets of several items per subset, selected from a larger total set of items. Estimation of utilities in BWS is performed using discrete choice modeling (DCM) and choice probabilities are found by the multinomial-logit (MNL) shares.

This paper considers how to use the BWS data in order to find which of the items can suppress or enhance the choice of an item of primary interest. In economics, such evaluations can be related to the elasticity of demand for substitute or complementary goods. In DCM terms, this problem is related to checking the independence of irrelevant alternatives (IIA) assumption that the preference between two of alternatives does not depend on the other alternatives. IIA property arises due to the hypothesis of the independent identically distributed extreme value type 1 errors (IID EV1) used in the derivation of conditional logit models (McFadden, 1973; McFadden and Richter, 1990; Marley, 1965, 1968; Louviere et al., 2000; Train,

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2003). The choice preference depending on presence or absence of the other alternatives corresponds to the "cross-effects" associated with the so-called *mother logit* of a more general kind of model (McFadden, 1975; Train, 1986; Timmermans et al., 1991; Carson et al., 1994; Brownstone and Train, 1999; Louviere et al., 2000, p. 116; Kuhfeld, 2010). The mother logit contains parameters of all the alternatives in each item's utility, so it is a general kind of multinomial model, also called the universal model (McFadden, Train and Tye, 1977, p. 42). Louviere and Woodworth (1983) discussed it and showed how with an adequately designed experiment to test the IIA property (also, McFadden et al., 1977; Hausman and McFadden, 1984; Louviere et al., 2000), and how to estimate cross-effects between alternatives in a presence-absence design (Anderson and Willey, 1992; Lazari and Anderson, 1994; Louviere et al., 2013). The appropriate comparisons could be made in the balanced incomplete block design (BIBD) with an approximately equal number of each item and also of each pair of items presented to respondents (Louviere et al., 2000, ch. 5; 2013).

The multinomial models are well-known in econometrics in evaluation of cost, demand, prices, and other characteristics. Theories of consumer behavior, firms, market equilibrium, competition, welfare economics, and optimization over time widely use utility functions, their components and changes, estimated by shares, elasticity and cross-elasticity in various problems. For instance, substitution and complementary relations among the products had been studied by Andrew Ehrenberg on individual and household purchase behavior, (Ehrenberg, 1959, 1988), and the Ehrenberg-Bass Institute for Marketing Science in the University of South Australia contributes much to the studying of these issues. Many functions with a rich flexible structure of elasticity of substitution adjustable to any complex observed data are known as well (see Tishler and Lipovetsky, 1997, 2000, and references within). Other more complicated models have been proposed in cognitive psychology when the context affects the choices (Marley, 1991; Lloyd and Leslie, 2013). The influence of the environmental conditions on the perception of stimulus has been studied in marketing and consumer decisions (Tversky and Simonson, 1993; Wernerfelt, 1995; Swait et al., 2002; Rooderkerk et al., 2011), for instance, in the compromise effect (switch to a higher price item if a more expensive one is added, so the middle-price choice becomes more favorable), and the similarity effect (an item hurts similar more than non-similar ones). Context effects are also known phenomena in ballot, election and other voting processes (David, 1998; Saari, 2000; Lipovetsky and Conklin, 2006). Another large area of consumer segmentation, market structuring, competitive mapping, and price sensitivity commonly employs measures of elasticity (Cooper, 1988; Cooper and Nakanishi, 1988; Kamakura and Russell, 1989; Russell and Kamakura, 1994; Wedel and Kamakura, 1999; Louviere et al., 2000; Dreze et al., 2004; Fibich et al., 2005; Lipovetsky, 2006; Lipovetsky et al., 2011). Cooper and Nakanishi (1988) and Kamakura and Russell (1989) proposed an aggregation of the elasticities into the so-called competitive clout (the total by j of squared cross-elasticities e_{ji} in change of any j-th product due to change in price of the i-th product defines the clout of the primary i-th product as its ability to take shares from competitors), and vulnerability (or receptivity, which is the total by j of squared cross-elasticities e_{ij} of a change in quantity of an i-th product due to change in price of any other competing product j, that defines the vulnerability of the i-th product to competitors). Other approaches could be tried for studying synergy-cannibalization and or enhance-suppression effects as well (Lipovetsky and Conklin, 2004; Schweidel et al., 2014).

In contrast to elasticity which estimates changes, the current work uses the sample choice probabilities themselves, subjected to presence or absence of other alternatives, which yields the estimates of a product's cannibalization and synergy. More exactly, for each product A of primary interest, we estimate its probability $P(A)$ of being chosen as the best one within all the cases when it is shown, and also the conditional probability of the choice A subject to the presence and absence of each other product B, so $P(A|B)$ or $P(A|\overline{B})$, respectively. For a given product A, any other product B can be identified as its *catalyzer* or *inhibitor* depending on whether the conditional probability grows or diminishes, respectively. Using quotients of $P(A|B)$ and $P(A|\overline{B})$, also known as the relative risk index (Kleinbaum et al., 1982; Kahn et al., 2000; Conklin et al., 2004), or constructing t-statistics of the proportions' difference we can see which of the values is larger. By the matrix of pairwise differences we consider its symmetrical elements for each pair of products. Their comparison shows whether the pairs of products are mutually synergistic, or complementary, so that their chances to be chosen as the best ones are higher for both of them in the presence of each other. In other cases, the products can have an anisotropic impact onto each other, so that one product cannibalizes another one (substitution of one product by another); or both products can suppress each other (mutual cannibalization).

The suggested approach can be seen as a by-product of BWS data but it does not require performing the BWS modeling itself, because it rather deals with the sample choice preferences. Using sample proportions we do not encounter the problem that the conditional logit model and the IIA property has to be applied to individuals, but interpretation is performed by the aggregates of individuals. By using an approximately balanced plan available from Sawtooth Software (2013), SAS (Kuhfeld, 2010), R, or another statistical software, each item is shown about an equal number of times, and the pairs of items are shown about an equal number of times as well, across all respondents. Comparing sample proportions (not the counts) is possible even if the plan is not exactly a BIBD, although the proportions will be defined with different precision. BWS modeling, however, can be employed as a preliminary to the synergy-cannibalization step of finding utilities and choice probabilities and using them for data segmentation to more homogeneous subsets of respondents, households, etc. Being based on the sample choice proportions, our approach is also free of limitations assumed in the BWS modeling about which Louviere et al. (2013), p. 299 noted that "such models theoretically apply only to single people; additional assumptions are required to extend them to aggregates of people. How well such models approximate individuals compared with aggregates of individuals remains unresolved".

Additionally to this technique we apply the key driver analysis (KDA) introduced by Conklin et al. (2004) as a non-regression method based on Kano theory and Shapley value analysis. Shapley Value (SV) is a construct from cooperative game theory which