Deriving A Shortlist Of Brand Names: A Comparison Of Measures Based On Censored Preference Data

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Abstract

The task of deriving a shortlist from a large set of potential brand names for a new product has been rarely discussed in the literature. We reject popular ratings-based methods as unreliable and ask respondents to give us their "top five". Three alternative methods of analysing these data are compared. Each involves different levels of complexity of computation and each makes different assumptions about the scale properties of the data. We learn that the simplest method works as well as the more sophisticated method, even though it makes assumptions that severely violate the data properties.

Keywords: Preference, measurement, brand name generation

Background

It would seem a fairly common and straightforward exercise: how do we derive a suitable shortlist of brand names from a larger collection of potential names for a new product? Yet there are surprisingly few examples in the literature on the task. The classic texts (e.g. Urban and Hauser, 1993) and the modern managerial guides (e.g. Ries and Ries, 2002) present the brand selection process with variations on the following steps:

- Formulate new brand ideas,
- Evaluate ease of reading and pronunciation,
- Evaluate effectiveness of each brand name in communicating differentiation and distinguishing characteristics,
- Determine if each brand is related to a particular class of product,
- Evaluate each brand for association with classes of profession, image, attitude, etc. including in different languages.

Deriving the shortlist from a large number of previously generated, potential brand names, could be an expensive series of laboratory and marketing research tasks. Ideally we would generate possible names and whittle the larger number to a shortlist of the more attractive options. Surprisingly there is very little in the literature on branding (Wheeler, 2003) or consumers' consideration set (Tülin and Swait, 2004), or on employee recruitment (Manzini and Mariotti, 2005), on how one should go about selecting this shortlist for a new product, after the initial generation of possible brand names. We need a rule for deriving a subset based on stated preferences.

So how to derive the shortlist? One approach could be to ask target customers to give a rating for each of the potential brands on, say, a 1-7 rating scale. However, the large number of brand names would likely lead to respondent fatigue and difficulty in rating the brand names (Malhotra, Peterson and Bardi Kleiser 1999). Even without fatigue, this common method for evaluating existing brands tends to give us an uninformative list of brands all with very high scores. We want a short list of winners. A more simple evaluation process involves asking respondents to examine the lists given to them and from these lists to select their, say, five most preferred brand names. That is, each target customer chooses a shortlist, n, of the N potential brands. This is the approach taken here.

Method

Stage 1 – Brand Name Generation

Following Kardes et al (1993) a small convenience sample of eight respondents was asked to generate possible brand names for two new product concepts – a pair of wireless earphones and an eight hour sunscreen. Subjects were asked to keep the names brief, easy to pronounce, and different from existing brand names of similar product categories.

For the earphones 52 brand names were initially generated and for the sunscreens 39 brand names were initially generated. These initial lists were further refined to 38 and 22 brand names respectively based upon duplication of names, and the conditions set out above, that were not followed by respondents.

Stage 2 – Brand Name Evaluation

An independent sample of 53 business-school respondents, who were judged to be in the target markets for our products, was asked to evaluate the brand names following a similar procedure to that outlined in Hult, Neese and Bashaw (1997). Each respondent was asked to examine the lists and from these lists to select their five most preferred brand names. They then were asked to evaluate their chosen five brand names further by ranking them in order of preference from 1 (most preferred) to 5 (least preferred).

Stage 3 – Deriving the Shortlist

Interestingly, the fairly straightforward respondent evaluation process creates its own set of processing problems for deriving the shortlist. If we used a rating scale for each brand then we have a score for each brand for each respondent. Instead the data are “censored” in that we have only the top 5 for each respondent. We do not know the relative preference for any brand not included in the top 5.

Procedures for Deriving the Shortlist

Procedure 1 – Number of Times Chosen

Option 1 is the simplest method of evaluation and simply required counting the number of times any brand name was chosen within the top five. Whilst simple to implement, one limitation of this procedure is that it makes no distinction between the intensity of a respondent’s preference towards any brand. For instance, one respondent may give a rank of 5 for brand A and 2 for brand B and another respondent may give a rank of 4 for brand A and 1 for brand B. Regardless of the rank given, each brand was chosen within the top five, an equal number of times, and they would each receive the same score, regardless of the obvious preference of both respondents for brand B.

Procedure 2 – Overall Rating

Option 2 required some sort of point system to be assigned to each brand name that recognised the intensity of respondents' judgments. A proxy for intensity was needed, such that a brand that was not chosen within the top five was not given a point and a brand name given a better ranking was given more points than a brand name given a lower ranking. Therefore, the initial rankings were reversed and summed across respondents. First preference earned 5 points; second preference earned 4 points and so on. Brands not in the top five earned zero. Note that this procedure assumes ratio scale properties for what are really ordinal data. While such treatment is common that doesn't make right. Further, no allowance is made for brands not chosen.

Procedure 3 – The Z Transformation

The Z-transform is to recalculate ranks such that they reflect the probability of being chosen, based around a normal distribution. To do this, we calculate Z-scores for each rank. For instance, for the earphones there are 38 brands. Therefore, the Z score for a rank of 1, using the 'norminv' function in Excel is the Z score of 1/38. Brands not in the top 5 are given a Z-score for the average rank of the remaining brands. Resulting Z-scores for different numbers of brands are presented in Table 1.

Table 1: Transformation of Ranks to Z-scores

Earphones		Sunscreen	
Rank	Z Score	Rank	Z Score
1	1.94	1	1.69
2	1.62	2	1.34
3	1.41	3	1.10
4	1.25	4	0.91
5	1.12	5	0.75
Between 6 and 38	-0.13	Between 6 and 22	-0.29

While the Z-transform removes the assumption of ratio scale properties on ordinal data, it imposes another assumption that the ranks are derived from a preference function that is normally distributed. Such an assumption may be justified on the grounds that, as the number of options grows, the normal distribution approximates an Extreme Value Type-III, or Weibull, distribution (Resnick, 1987), which is commonly used in choice and preference modelling (McFadden, 1986; Batsell, & Louviere, 1991).

Other procedures could be extended from this logic. For example, we could use the preferences of the top five to derive a measure of frequency of first preference for a simulated series of paired comparisons, from which we could apply a multinomial-logit analysis to derive a score for each brand. Whilst feasible and overcoming most of the assumptions mentioned, it's overkill because our goal is to derive a shortlist of better brands, not a score for each possible brand (Manzini & Mariotti, 2005).

Results

The results for sunscreens and earphones are shown in Tables 2 and 3 respectively, with the corresponding ranks in brackets.

Table 2: Sunscreen - Evaluation Scores and Ranks of Evaluation Alternatives

Brand	# Times Chosen (Rank)	Rating (Rank)	Z Transform (Rank)
UV Protect	19 (2)	74 (1)	26.94 (1)
UV Armour	20 (1)	68 (2)	26.71 (2)
Solar Guard	15 (3)	47 (3)	17.15 (3)
Ray-Banned	11 (7.5)	37 (4)	11.45 (4)
Sun Block	09 (11)	34 (5)	8.98 (11)
Sun Shield	10 (10)	33 (6)	9.75 (9)
Sun Safe	11 (7.5)	31 (7)	10.58 (7)
Sun Free	11 (7.5)	30 (9)	10.1 (8)
Sun Mate	08 (12.5)	30 (9)	7.12 (12)
Powerscreen	12 (4.5)	29 (11)	10.98 (6)
Power Block	11 (7.5)	26 (12)	9.47 (10)
Super Solaire	07 (15)	23 (13)	4.6 (14)
Sun Protect	07 (15)	22 (14)	4.34 (15)
Once-a-Day	07 (15)	21 (15)	4.23 (16)
Great for Eight	12 (4.5)	20 (9)	11.25 (5)
Skin Lover	08 (12.5)	19 (16)	4.9 (13)
Ray Block	05 (20.5)	17 (17)	1.39 (18)
Solar Wall	05 (20.5)	15 (18)	1.02 (19)
All Day	06 (17)	14 (20.5)	2.01 (17)
Skin Armour	05 (20.5)	14 (20.5)	0.97 (20)
Solar	05 (20.5)	14 (20.5)	0.89 (21)
Super Safe	05 (20.5)	14 (20.5)	0.78 (22)
Fun-in-the-Sun	3 (33.5)	13 (23.5)	-1.32 (31)
Swim Easy	04 (27.5)	13 (23.5)	-0.39 (24)
Skin Safe	04 (27.5)	12 (25.5)	-0.52 (26)
WOW Sunscreen	04 (27.5)	12 (25.5)	-0.44 (25)
After Eight	04 (27.5)	11 (27.5)	-0.84 (27)
Apply Once	03 (33.5)	11 (27.5)	-1.74 (33)
Protect Skin	04 (27.5)	10 (29)	-0.97 (29)
Stay On	04 (27.5)	09 (31)	-1.18 (30)
Linger Longer	04 (27.5)	09 (31)	-0.94 (28)
Super Sun	02 (37)	09 (31)	-3.07 (36)
Skin Cover	05 (20.5)	08 (33.5)	-0.22 (23)
Stop and Block	03 (33.5)	08 (33.5)	-2.19 (34)
Blockout	04 (27.5)	07 (36)	-1.47 (32)
Once	03 (33.5)	07 (36)	-2.51 (35)
Solar Block	02 (37)	07 (36)	-3.6 (37)
Once Only	02 (37)	06 (38)	-3.81 (38)

Table 3: Earphones- Evaluation Scores and Ranks of Evaluation Alternatives

Brand	# Times Chosen (Rank)	Rating (Rank)	Z Transform (Rank)
Air Fones	29 (1)	108 (1)	31.22 (1)
Headmates	23 (2)	74 (2)	18.91 (2)
Sonic Fones	18 (3)	55 (3)	10.95 (3)
Freedom Fones	16 (4.5)	52 (4)	8.49 (4)
Shock Wave	13 (8)	49 (5)	5.83 (7)
Sound Wave	15 (6)	46 (6)	6.59 (5)
Break Free	14 (7)	41 (7.5)	4.53 (8)
Sonic Wave	12 (10.5)	41 (7.5)	2.83 (10)
Wireless Gear	12 (10.5)	40 (9)	3.04 (9)
Ear Gear	16 (4.5)	39 (10)	6.1 (6)
Ear Wave	11 (13)	33 (11)	0.77 (12)

Wireless Fones	12 (10.5)	32 (12)	1.13 (11)
Free and Easy	10 (14.5)	28 (13)	-1.37 (14)
Free State	10 (14.5)	27 (14)	-1.67 (15)
2WL	12 (10.5)	26 (15)	0.09 (13)
Ear Ace	08 (16)	21 (16.5)	-4.34 (16)
No Strings	06 (19)	21 (16.5)	-6.04 (17)
BSIM	07 (17.5)	17 (18)	-6.24 (18)
Boom Fones	07 (17.5)	14 (19)	-6.64 (19)
Sound Muffs	05 (20.5)	13 (20)	-8.8 (20)
No Wires	05 (20.5)	11 (21)	-9.1 (21)
No More Wire	04 (22)	07 (22)	-10.7 (22)

As expected, all three evaluation procedures revealed extremely high and statistically significant correlations for both the sunscreen and earphones data, shown in Tables 4 and 5.

Table 4: Sunscreen - Correlations of Evaluation Alternatives

	# of times chosen	**Rating**	**Z-Trans-formation**
# of times chosen	1		
Rating	.961	1	
Z-Transformation	.994	.986	1
N=38. All significant <0.000			

Table 5: Earphones - Correlations of Evaluation Alternatives

	# of times chosen	**Rating**	**Z-Trans-formation**
# of times chosen	1		
Rating	.974	1	
Z-Transformation	.994	.993	1
N=22. All significant <0.000			

Conclusion

The pattern between the two sets of data was remarkably consistent across the two product categories being tested. There is a clear indication from these two datasets that very simple evaluation procedures, with more relaxed assumptions, are as effective as ones using more complicated procedures and which have more stringent, correct, assumptions. Importantly, if the task is to simply identify the most attractive three or four options, then it doesn't matter which evaluation method is used. In such cases we suggest that it is appropriate to use the simplest method: The number of times chosen.

This procedure potentially goes beyond the relatively infrequent task of coming up with a new brand name. More often we need to derive a shortlist for a set of job applicants or competitive bids. It seems that we need not make our analyses overly complicated for, despite sometimes severe violations of the nature of the data we end up with a consistent result. Note that this conclusion applies only to the very restrictive problem of finding a very small limited list of "winners", typically only the top three, from a larger set. It does not apply to attempts to derive a reliable score for each item in the larger set. That task remains a problem for our better econometricians and choice modellers.

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