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Modeling mental market share

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ABSTRACT

Normative benchmarks for a brand's network of associations provide managers with guidelines to set brand strategy. Benchmarks also help marketers evaluate the impact of marketing activities. This paper outlines an approach to obtain benchmarks for the relative size and structure of a brand's associative network using the NBD–Dirichlet model (Goodhardt, Ehrenberg, & Chatfield, 1984). The results reveal an excellent fit, showing that the NBD-Dirchlet is able to obtain predictions for a brand's mental market share. This finding has implications for understanding of the structure of consumers' memory for brands and the dynamic nature of the associative network across brands and time.

1. Introduction

Metrics pertaining to consumer-base brand equity (CBBE) are a critical part of most marketing or brand manager's portfolios. These metrics help formulate brand strategy and assess the performance of brand expenditure (Aaker, 1992; Lehmann, Keller, & Farley, 2008). An important dimension of CBBE is the brand's network of associations in consumer memory (Keller, 2003). This associative network (in line with Associate Network Theories of memory such as Anderson & Bower, 1979) is a store of knowledge that consumers draw upon to elicit and select between brands available in memory in choice situations. Marketers seek to influence consumer's associative networks for brands, through activities to build and refresh brand associations in consumer memory. Consequently, a considerable amount of research aims to understand how consumers encode, organise, store and use brand associations.

Keller (1993) proposes CBBE as an antecedent to consumer' brand buying behavior; therefore CBBE may be an attractive input for setting brand strategy. Understanding the CBBE of a successful brand can help marketers set appropriate objectives and devise tactics to achieve these objectives. Therefore, alongside research to identify and measure the different dimensions of CBBE, research efforts test the relationship between CBBE and future buying behavior.

The size of the brand's associative network, or the number of brand-attribute links in consumer memory is one dimension of CBBE. Both theoretical support and empirical evidence exist to link associative network size with future brand choice. Theoretical support comes from models of associative memory and the retrieval cue process (Anderson & Bower, 1979; Collins & Loftus, 1975). These models infer that a brand with more associations will have more pathways to retrieval, and therefore consumers are more likely to think of the brand. Empirical evidence shows that the more associations a brand has, the more likely the consumer will chose the brand (Alba & Marmorstein, 1987; Romaniuk, 2003), and the higher the brand's equity (Krishnan, 1996).

However all brands face competition, and the presence of competitor brands in consumer's memory inhibits the process of brand retrieval (Alba & Chattopadhyay, 1986; Burke & Srull, 1988; Heil, Rösler, & Hennighausen, 1994). Therefore, value of a brand's associative network is in the strength relative to competitors.

At the same time, retrieval from consumer memory is never certain (Mitchell, 1982), and neither are brand links to associations over time. The retrieval of the brand, when the attribute is the cue to access memory, is a probabilistic or stochastic process, prone to variation at individual level but predictable in aggregate (Dall'Olmo Riley, Ehrenberg, Castleberry, Barwise, & Barnard, 1997; Mitchell, 1982; Rungie, Laurent, Dall'Olmo Riley, Morrison, & Roy, 2005). Therefore, while a link between an attribute and a brand may be available in memory, a link may not be accessible at any point in time. Retrieval of a brand can happen for an attribute today, however future retrieval is not a certainty, and an underlying probability influences the possibility. This characterisation of consumer's retrieval of the brand via the associative network as a repeated, competitive, stochastic process provides a theoretical basis for drawing on the NBD–Dirichlet model.

The NBD–Dirichlet model is a stochastic mathematical model for competitive brands in repeat-purchase repertoire markets (Goodhardt et al., 1984). Drawing from the underlying frequency distributions of brand and category buying in a given time period, the NBD–Dirichlet provides benchmarks for brand sales metrics (Ehrenberg, Uncles, & Goodhardt, 2004). These benchmarks inform brand managers' expectations about brand performance metrics, and help identify deviations

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requiring action. A testimony to the robustness of the model is the successful application to hundreds of markets around the world (Ehrenberg et al., 2004). Many of the world's large packaged goods firms, such as Procter & Gamble, Unilever, Colgate-Palmolive and Kraft draw on the model.

In addition to benchmarks at a point in time, the model provides estimations for how brands grow or decline (Wright & Sharp, 2001), and gives expectations for new brands entering a category (Ehrenberg & Goodhardt, 2000). The model's theoretical values provide norms to assess the effectiveness of marketing interventions, such as loyalty programs (Sharp & Sharp, 1997) and marketers can use the model to investigate new markets (Uncles & Kwok, 2009). The NBD–Dirichlet model also informs the theoretical limits for brands on any metric, which is important for objective setting (Sharp, 2010; Sharp & Ehrenberg, 2000; Wright & Sharp, 2001). This ability makes the model very useful for those seeking to understand the buying patterns of a brand's customer base and/or to change a brands' market share.

These applications of the NBD–Dirichlet model are useful for researchers and marketers in a CBBE context. Currently little guidance exists on a brand's potential or ideal CBBE. Managers assess the performance of a brand on CBBE metrics by tracking changes in brand scores over time. However, most CBBE metrics suffer from a feedback mechanism where past consumer behavior strongly influences the scores for a brand. This feedback mechanism means that brands with more past users gain higher scores than brands with fewer past users, regardless of future trajectory (Barnard & Ehrenberg, 1990; Bird, Channon, & Ehrenberg, 1970; Brakus, Schmitt, & Zarantonello, 2009). This high correlation between a brand's CBBE and market share (for examples see Ehrenberg, Barnard, & Scriven, 1997) means that without accounting for a brand size/market share, CBBE metric risk measuring a brand's past performance, rather than the future potential.

When calculating theoretical values, the NBD–Dirichlet model considers the share of brands, which could help account for the feedback of the effect of past buying/using a brand on CBBE. The other benefits of the NBD–Dirichlet model are a greater theoretical understanding of the underlying structure of a brand's associative network, which can help when setting objectives and evaluating a brand's performance. However, a possibility exists that despite a widespread ability to provide estimations for buying behavior, the model might not be appropriate for modeling brand associations. Such outcome would also advance the understanding of the relationship between a brand's associative network and the behavior the associations possibly precede.

Therefore, this paper has four objectives. First, the paper presents the case for a brand's relative associative network size, and the corresponding mental market share, as a measure of CBBE. The second objective is to explain the theoretical rationale for the use of the NBD–Dirichlet model in this context. The third objective is to report on the performance of the model when modeling brand associations, and the associate errors. The final objective is to discuss the implications of the results for marketing practice and future research.

2. Background to the modeling approach

A theory, with considerable empirical support, is that human memory comprises a network of association links, or the associative network theories of memory (ANT) (Bower, 1998; Tulving & Craik, 2000). Under the ANT, the brand represents a node in memory. The concepts that the consumer encounters in conjunction with the brand and processes sufficiently to form a memory trace or association form links to this brand. A link's presence means that the concept is available for retrieval if the brand is a cue, and that the concept is a possible cue to retrieve the brand from long-term memory (Anderson & Bower, 1979; Tulving & Pearlstone, 1966). Keller (1993) refers to these concepts as brand associations.

Brand associations influence consumers' salience and evaluation of a brand (Keller, 2003; Romaniuk & Sharp, 2004). However, alternative theories about how consumers use these associations in the process of retrieving and deciding between brands are apparent. From an ANT perspective and drawing on the spreading activation theories of retrieval (Anderson, 1983; Collins & Loftus, 1975), these associations have two roles. The first role of brand associations is as cues for consumers to evoke brands from memory (Nedungadi, 1990). The product category is a common cue for brand retrieval (Assael & Day, 1968), however research points to consumers using a wide variety of cues to retrieve brands from memory (Desai & Hoyer, 2000; Nedungadi & Kanetkar, 1992; Shocker, Ben-Akiva, Boccara, & Nedungadi, 1991). The second role of brand associations is to help the consumer decide which of the subset of brands is suitable at that point is time (Nedungadi, 1990). At either an evocation or evaluation stage, a brand with links to more potentially relevant attributes has higher choice probabilities. Meyers-Levy (1989) refers to the number of brand associations as association set size.

A large associative network likely has a positive influence on brand choice. Alba and Marmorstein (1987) find a positive relationship between the frequency of associations and brand choice, as does Romaniuk (2003). In the service area, Romaniuk and Sharp (2003) show a positive relationship between the number of associations and customer loyalty across the three studies. Krishnan (1996) also links the size of the associative network to an external financial measure of brand equity.

However, just as brand links facilitate retrieval, competitor links inhibit retrieval (Burke & Srull, 1988; Heil et al., 1994). Past research into the size of the associative network neglects the impact of competitor brands links to the same attributes on retrieval and choice. While Keller (1993) highlights the value of uniqueness, which is the absence of competitor associations, Romaniuk and Gaillard (2007) show that often competitor brands also have links to relevant attributes.

Therefore, any associative network size measures need to account for the strength of competitor brands. This combination of brand and competitor effects leads to a market of associations across brands in the category, with each brand having a share of the total associations, or a mental market share. This mental market share has theoretical and practical parallels with sales market share. The NBD–Dirichlet model calculates theoretical norms for sales market share. The next section explains this model and the argument for applying the NBD–Dirichlet to the modeling of mental market share.

2.1. Background to the NBD–Dirichlet model and the applicability to this context

Numerous approaches exist for modeling a brand's mental market share. The choice of the NBD–Dirichlet in this paper is for theoretical and practical reasons. An outline of the NBD–Dirichlet model precedes discussing these reasons.

The NBD–Dirichlet model provides predictions for a wide range of consumer buying metrics over time. A typical use of the NBD–Dirichlet model is to describe how consumers buy packaged goods brands, including how many people should buy the brand, how many times they should buy that brand, how much of their total spend in the category should be with that brand versus competitors. The estimates the model provides draw on a mix of distributions for brands and category purchase frequencies. At category level, the model draws on the Negative Binomial Distribution (as per Ehrenberg, 1959), while at brand level the model draws on the Dirichlet Multinomial Distribution (as per Goodhardt et al., 1984). The estimates for a specific brand vary according to the category purchase rate, the brand's market share and the timeframe of analysis.

The timeframe influences the number of purchase occasions the model includes, and so has an impact the specific brand metrics. For example, metric expectations for the purchase frequency for a brand adjust to be higher for longer timeframes and lower for shorter timeframes (for more details on the underlying distributions, model