Using a Neural Network Model to Assess Advertising Effectiveness: a Validation of the Strategy Assessment (Strata) Model
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EXTENDED ABSTRACT

In this paper we draw a parallel between means-end decision theory and neural network analysis and apply this common perspective to empirically validate an advertising strategy assessment model with respect to predicting purchase intent. The results of the meta-assessment of 240 television ads offer strong support for the neural network-based model.

Introduction

Neuroscience is an emerging field of consumer research that has garnered much interest among advertising researchers in the hope that neuroscience tools can help them better understand why customers prefer some products over others (Nobel, 2012; Plassmann et al., 2012). This ambitious goal relies on several neuro- or brain imaging techniques deployed to reveal the hidden elements of the consumer decision process to better understand how a product or an ad engages the pleasurable reward center in consumers’ brains (Karmarkar 2011; Nobel 2012; Smidts et al., 2014). Advantages of neuromarketing approaches are that they are potentially faster and cheaper than traditional advertising research tools that ask customers directly for their thoughts, feelings, and decision-making strategies (Ariely and Berns, 2010). Although cost savings is one possible outcome of this evolving area of research, most experts believe that the potential contribution of neuroscience to advertising is its ability to guide theory generation that can be used to shape new models of consumer decision making, and its ability to assess and/or supplement traditional models of consumer responses to advertising currently in practice (Ariely and Berns, 2010; Plassmann et al., 2012; Smidts et al., 2014; Yoon et al., 2012).

Although the importance of neuroimaging studies of advertising is expected to increase, to date neuroimaging’s relevance for practice has been limited (Ariely and Berns, 2010; Smidts et al., 2014). Studies that have used neuroimaging to predict consumer choice in response stimuli have not been found to be more predictive than consumers’ own self-reports (Knutson et al., 2007; Plassmann et al., 2012).

One area of neuroscience that has advanced our understanding of consumer decision making is neural network research which was inspired by the neural architecture of the human brain (West et al., 1997). The strength of this approach is its ability to mimic the brain’s function. From a cognitive perspective, neural network models are consistent with a spreading activation model of memory making neural network models well-suited for representing judgment and decision making that involves the processing of information (Bhatt, 2012; Chowdhury and Samuel, 2014; Payne et al., 1993; West et al., 1997). Therefore, we posit that neural network research is a particularly apt approach to better understand advertising effectiveness (Briesch and Rajagopal, 2010; Curry and Moutinho, 1993).

In this paper we apply a neural network approach to assess a theoretical model of consumer decision making used in advertising research, the Strata model (Reynolds, Gengler and Howard, 1995; Reynolds and Rochon, 1991). Specifically, we report on a meta-assessment of 240 television ads across a variety of product categories and levels of finish (finished ads and animatics) that served as stimuli for diverse samples of consumers. Study participants responded to questions via a computer-driven, tailored interviewing system such that the order of questioning reflected the spreading activation model underlying neural network theory. That is, to validate the neural network-based Strata model, we empirically assess if the neural connecting linkages caused by a given advertisement are related to an increase in the likelihood of purchase.

Background

Neural Networks

A neural network is a “connectionist” model of brain behavior often used to understand human cognition (West et al., 1997). The interconnections, or linkages between neurons, are referred to as “synapses.” Neural network models resemble the brain’s decision-making process where input neurons receive stimuli which are then fed into a pattern matching process yielding a decision (Bhatt, 2012; Curry and Moutinho, 1993). The fundamental principle of a neural network is that when a neuron is activated, or fired, it can then cross a synapse gap to activate another ‘connected’ neuron. Put simply, neural networks models are computational models intended to represent biological neural networks in the brain and are used by researchers to solve certain kinds of problems (e.g., Briesch and Rajagopal, 2010; Chowdhury and Samuel, 2013). The basic logistical calculus of a neural network is that a neuron receives inputs, processes those inputs, and generates an output (McCulloch and Pitts, 1943). In general, neural networks do not follow a linear path as it is believed that information is processed collectively throughout the entire network of neurons, also called nodes.

It is worth noting that with respect to decision making Hebb’s (1949) synaptic plasticity postulate suggests that one’s neural network is strengthened over time, becoming more efficient and efficacious as a result of repeated activation (i.e., stimuli exposure) and personal experience. Thus, neural network analysis can be used to understand consumer decision making with respect to a problem that a product or service solves and subsequently offers the potential to assess advertising effectiveness.

In the next section we introduce a well-known consumer decision-making model, means-end theory (Gutman, 1982) and draw parallels to a neural network model of decision making.

Means-End Theory and Research Methods

A commonly utilized and frequently-referenced framework of consumer decision making is means-end theory (Gutman, 1982) and its associated research methodology, laddering (Reynolds and Gutman, 1988; Reynolds and Phillips, 2009). The laddering methodology begins with a trained interviewer asking a series of questions to a consumer with the goal of abstracting to the higher-order meanings that drive the consumer’s decision making. The first questions of a laddering interviewer usually elicit a distinction between two stimuli, or choice options, (e.g., Most preferred brand [Starbucks] vs. Second choice [Illy]), with regard to a stated preference (i.e., why do you prefer Starbucks to Illy?) or actual consumption (i.e., why do you drink more Starbucks than Illy?). Then the interviewer probes the consumer’s answers with some version of the question, Why is that important to you? The interviewer uses each answer as the basis for the subsequent probe moving the consumer up the “ladder of abstraction” from [1] Attribute distinction to [2] Functional Consequences to [3] Psycho-Social Consequences to [4] Personal Values.

The laddering methodology’s levels of abstraction are isomorphic to the neural network approach of obtaining the relevant connec-
tions both between and across the decision-based nodes. The result of a laddering interview is a complete means-end chain consisting of four concepts (i.e., nodes) and three adjacent, direct connections (i.e., linkages) [1-2; 2-3; 3-4] as well as indirect connections [1-3; 1-4; 3-4]. The end result of a laddering study is a directed graph depicting the “network” of direct and indirect connections across nodes for a given sample of consumers. This graphical network is called a Consumer Decision Map (CDM) as it illustrates the consumers’ key decision nodes and their dominant associative connections.

It is worth noting that means-end theory may be viewed as a top-down approach to understanding consumer decision making, while the laddering methodology is bottom-up whose goal is to identify the end-state that defines the motivating dynamic of the decision structure. That is, the lower levels develop their importance by satisfying the respective, adjacent higher levels, while the laddering methodology is initiated by a distinction that is typically at the lowest, attribute level. Thus, the goal of the laddering methodology is to uncover a network of meanings, which also defines the association network of connections, or linkages. Thus, the CDM may be viewed as a special case of neural network model: one that focuses on only the aggregate, relevant decision-making elements assuming that the levels of abstraction reflect the underlying decision-making process.

Advertising Effectiveness

Reynolds and Rochon (1991) draw a meaningful distinction between traditional copy testing methods and advertising strategy assessment which they operationalize as a neural network between the means-end levels of the MECCAS framework (Reynolds and Craddock, 1988). They suggest a model which is driven by a computer presentation of questions relating to what the ad caused them to think about that are tailored to the respondent depending on their prior answers that is comprised of: [1] affect-related questions (both Product and Ad), [2] assessment of the strength of communication of ‘nodes’ by level (the statements are developed from prior laddering research) and [3] the level of association between the adjacent-level nodes that were ‘clearly communicated’. During this tailored interview each ad is viewed four times. Noteworthy is that the Strata methodology requires that two ads are assessed by the respondent at the same time during the interview session to avoid the respondent over-analyzing that concept statement. Analysis of this qualitative data can be summarized by a z-score reflecting likelihood, z-[S-A], based upon the ad sample size.

- Average node (0-100) strength with a two-step rating [a] if the node concept is ‘clearly communicated’ or not, and [b] if the node concept is determined to be ‘clearly’ communicated the respondent is asked if it is ‘perfectly communicated’ or (just) ‘clearly’ (Perfectly is scored as a 100, Clearly is scored as 62 and Not Clearly is 0). (Note: for the predetermined key strategic elements if the concept was ‘clearly communicated’, the respondent is asked what specifically in the ad was communicated that led to endorsing that concept statement. Analysis of this qualitative data has used to understand what executional cues activate the higher level meanings.)

- Linkage strength is computed by asking for only those nodes that are ‘clearly communicated’ between adjacent levels the degree of ‘associative meaning’ caused by the ad. A Venn diagram defines the graphical rating scale. The computation of the summary index is based upon a probabilistic function derived from multiplicative model of Node i x Node ii x Linkage i-ii, which is computed from a 0,1 or 2 score for each node and their linkage, meaning the maximal linkage score possible for each connection is 8. The likelihood of possible scores is used to convert the multiplicative score to a 0-9 connection score.

- The Affect ratings are scored in the same manner as the node ratings (0-100 scale), with a slightly modified question format.

Meta-Assessment Framework

The Strata model permits the assessment of the validity of interpreting the linkage connectivity as a neural network, both in relation to the correspondence of an individual level and overall combining all three linkages (Lowest=Product Bridge; Middle=Personal Relevance Bridge; Highest=Value Bridge), to the advertising effectiveness dependent measure of ‘Motivates Purchase’.

Sample

The 240 ads in the sample were from eight countries with roughly half from the United States. There were 131 finished ads and 109 animations in the sample. Overall, the respective number of ads for each of the four general ‘product’ categories of ads were: n=131 beverages (including both alcoholic and non-alcoholic); 56 automobiles; 27 trade organizations; and, 26 ads across a diverse variety of consumer goods. The average number of the sample for each ad assessment was 42. The respondent sample composition was typically a combination of ‘most often’ brand users and ‘competitive brand most often’ users, balancing for gender and age. For the trade organization samples only gender and age were used.

Findings: Correlations and R2 with Purchase Motivation

Table 1 summarizes the zero order correlations with Purchase Motivation for 240 ads with respect to the three linkage scores levels (L=M=H) representing the largest nodes-in-common ‘ladder’ connecting from Lowest (Message Element) to Highest (Personal Value) and the simple sum of the three levels, which represents a ‘neural-based’ strategy model s[L+M+H], compared to the traditional copy testing proxy of Ad Affect. The square of the correlation representing the variance accounted for can be viewed to contrast the magnitude of the difference between the neural-based approach to quantifying overall strategy assessment to traditional copy testing. The likelihood of the statistical difference between the correlations can be summarized by a z-score reflecting likelihood, z-[S-A], based upon the ad sample size.

| Table 1. Correlations of Connections and Ad Affect with Purchase Intent (Motivation) |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Overall                         | r2              | r               | r               | r               | r               | r               | r               |
| 240                            | .70             | .68             | .61             | .78             | .48             | .45             | 6.1             |
| 240                            | .49             | .47             | .47             | .47             | .47             | .47             | .47             |
| Lowest                          | .49             | .47             | .47             | .47             | .47             | .47             | .47             |
| Middle                          | .61             | .61             | .61             | .61             | .61             | .61             | .61             |
| Highest                         | .78             | .78             | .78             | .78             | .78             | .78             | .78             |

The correlations by linkage level with Purchase Motivation are, of course, all statistically significant. And, the difference between the Lowest level of .70 and the Highest of .61 is not statistically different. The key overall model correlational contrast of the s[L+M+H] of .78 to Ad Affect of .45 reveals that the neural-based strategy model accounted for almost three times the variance as the traditional copy testing approach. The likelihood of that difference is represented by the z-score of 6.1. In sum, the neural framework underlying the decision process is validated.

Research Implications and Future Directions

Given that the Strata advertising assessment measures of neural connection are validated in terms of quantifying their effect on decision making, the general means-end approach grounded in under-
standing the consumer bases of competitive preferences to develop advertising strategy is also validated. There are several implications of these findings.

**Formalizing the Advertising Creative Development Challenge**

Given that these analyses strongly suggests the key to effective advertising is to cause the associative connections between the four nodes, asking the creative team to specify as precisely as possible what exactly in a proposed execution will result in the linkages being made provides a process to focus meaningful discussion and ongoing learning. (Gengler and Reynolds, 1995).

**Advances in Laddering Methods**

The central role of preference-based laddering to develop strategic positioning options, as well as the development of product-specific statements to be used in Strata for decades has involved one-on-one in-depth interviews. This significant time and cost limitation of this standard approach to laddering has been addressed by an internet-based, one-on-one interviewing system termed Stream, which has been shown to produce significantly higher quality data in a significantly more efficient manner (Reynolds and Phillips, 2009). The Stream software also contains an on-line coding function which greatly facilitates this tedious process, along with a decision segmentation methodology (Reynolds, 2006) which permits straightforward forward contrasts with traditional types of marketing research classification data and facilitates the strategy development process (Phillips, Reynolds, and Reynolds, 2010).

The likely next research advance will be the use of artificial intelligence (AI) software to conduct decision-based laddering interviews. The author is aware of one such system which has shown promise. Interestingly, because the software teaches the respondent how means-end-based decision making functions, including how choice trade-offs are framed (Reynolds, 2005), the AI approach to laddering results in very high respondent involvement with the questioning process.

**Summary**

To assess the neural theoretic underlying the identification of the decision network activated by advertising the Strata model (Reynolds and Rochon, 1991) was used. A meta-analysis of 240 ads was analyzed yielding data measuring the strength of cognitive association linkages (neuroscience) between levels abstraction (Means-end theory) caused by advertising stimuli. This aggregate data is seen to be highly related on a correlational basis to advertising effectiveness, operationalized as the level of Purchase Motivation for the advertised product.

The critical finding of this meta-analysis is that a decision-based methodological platform for understanding advertising effectiveness defined by directional changes in Purchase Motivation has been validated.

**REFERENCES**


