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# A neural network application to consumer classification to improve the timing of direct marketing activities

Frederick Kaefer[a,*], Carrie M. Heilman[b], Samuel D. Ramenofsky[a]

[a] *Department of Information Systems and Operations Management, Loyola University Chicago, 820 N. Michigan Avenue, Chicago, IL 60611-2196, USA*
[b] *Department of Commerce, McIntire School of Commerce, University of Virginia, P.O. Box 400173, Charlottesville, VA 22904-4173, USA*

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**Abstract**

This article develops an alternative estimation approach for classifying new prospective consumers as "good" or "bad" prospects for direct marketing purposes. We show that the traditional approach of using demographics alone to profile non-active consumers (those who have yet to buy in the category) can be improved by waiting to observe their initial and limited number of sequential purchases in the category. We call this method the early purchase classification (EPC) approach. We make use of two established classification models, a multinomial logit model (MNL) and a neural network model (NN), and show that the classification accuracy of both models using our EPC approach outperforms the traditional approach of classifying non-active prospects using demographics only. Furthermore, we find that the NN model consistently outperforms the MNL model at this task. This research uses the best aspects of each model by utilizing the MNL model to determine which variables are most relevant to the classification and then using those variables for classification in the NN model. Using the complementary features of the MNL and NN models, managers can use the EPC approach to determine the most profitable time in a purchasing history to classify and target prospective consumers new to their categories.


*Keywords:* Neural networks; Multinomial logit; Variable selection; Early purchasing classification; Timing of direct marketing activities

* Corresponding author. Tel.: +1-312-915-7063; fax: +1-312-915-7224.
*E-mail addresses:* fkaefer@luc.edu (F. Kaefer), heilman@virginia.edu (C.M. Heilman), srameno@luc.edu (S.D. Ramenofsky).

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## 1. Introduction

It is commonly known to marketers today that roughly 80% of their business can come from as few as 20% of their customers [1], and that it can cost as much as five times more to attract a new customer as it can to maintain a loyal one [2]. As a result, many marketers are moving away from traditional aggregate-level mass marketing programs and are searching for accurate methods of identifying their most promising customers in order to focus specifically on those individuals.

Under a mass marketing strategy, a company does not differentiate between "good" and "bad" prospects. Rather, the mass marketer generally blankets *all* active (i.e., consumers currently purchasing in the category) and non-active (i.e., potential customers who have yet to purchase in the category) prospects with marketing material, such as promotional mail, product information and/or free samples. This strategy can be very costly as it tries to reach consumers who may have little or no interest in buying the product promoted. However, many companies today still use this strategy simply because they do not have the appropriate data to do otherwise, or they are unaware of how to best utilize the data available to them to profile and target their best prospects.

In contrast to the mass marketing approach, a direct marketing approach evaluates the profitability of current and potential customers and uses this information to focus marketing resources on their best prospects. There are many factors that may be used to evaluate the profitability of a customer, including brand loyalty, length of customer relationship, customer satisfaction and profit per transaction [3]. However most of these measures are not available when identifying good prospects among those who have yet to purchase in the category. For this reason it has been noted that it is much easier to build a model to assess the attractiveness of active consumers versus non-active ones [3].

The typical practices of a direct marketer trying to identify a "good" prospect among non-active consumers is to first profile and identify *current* profitable customers using demographic characteristics alone (e.g., age, gender, married, etc.), then use this information to make inferences about the attractiveness of those who have yet to buy in the category [4]. However, many studies have shown that demographic variables are simply not useful predictors of choice [5].

This research shows how the accuracy of classifying new consumers in a category as "good" or "bad" prospects improves as the marketer waits to observe consumers' early purchases in that category. Numerous studies have found that a consumer's past purchases can act as a good predictor of future brand preferences and choice outcomes [6–8]. For example, Rossi, McCulloch, and Allenby examined the predictive capability of models using demographics alone, a single purchase, and complete purchase history [9]. We compare two classification models, a multinomial logit (MNL) model and a neural network model (NN), to see how classification improves with incremental purchasing information about potential customers new to a category. In doing so, we develop what we call the early purchase classification (EPC) approach—a classification model that takes into account the initial and incremental purchases of consumers in a category and identifies the best time to implement direct marketing activities. This paper takes a macro-level approach and studies three leading brands in a consumer packaged goods (CPG) category to emphasize the ability to identify potential customers early in their purchasing history. A more detailed, micro-level study of segmentation and profit analysis using this approach with direct marketing analysis can be found in Heilman et al. [10].

The MNL model has a long tradition in the marketing literature for problems involving discrete outcomes, such as choice or classification [6,11,12]. The appeal of the MNL model is its ease of application and perhaps more importantly the practitioner's ability to interpret results. In comparison to MNL, the