Chapter II

Using Artificial Neural Networks to Forecast Market Response

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ABSTRACT
Marketing managers must quantify the effects of marketing actions on contemporaneous and future sales performance. This chapter examines forecasting with artificial neural networks in the context of model-based planning and forecasting. The emphasis here is on causal modeling; that is, forecasting the impact of marketing mix variables, such as price and advertising, on sales.

INTRODUCTION
Ever-improving information technology has changed the face of marketing research, marketing analysis, and marketing practice. Prime examples are the use of electronic point-of-sale (POS) data collected through optical scanners to improve decision-making and logistics (Ing & Mitchell, 1994). The magnitudes (in millions) of typical databases available to a brand manager in a
consumer packaged goods firm are: store audit one, warehouse withdrawal 10, market-level scanner 300, chain-level scanner 500, and store-level scanner 10,000 (Blattberg, Kim, & Ye, 1994, p. 174). The data explosion makes the increased quantification of the marketing function inevitable. More sophisticated modeling approaches will be necessary. The modeling may either be descriptive for uncovering marketing phenomena, or predictive for solving problems (Little, 1994, p. 155). The basic issue addressed in this chapter is what is the role of artificial neural networks (ANNs) for forecasting and planning in this setting? To answer this question, let’s begin by briefly looking at forecasting with market response models.

Market response models — also known as marketing mix models — capture the factors that drive a market. They show how controllable marketing instruments, such as price, distribution, advertising, sales promotion, and sales force effort, as well as uncontrollable environmental conditions, which capture competitive actions as well as autonomous factors such as economic climate, affect performance measures; in particular, unit sales and market share. For example, sales of umbrellas could be expressed as a function of the relative price, relative promotion expenditure, personal disposable income, and rainfall (Proctor, 1992). Relative price is the price of our umbrellas divided by the average price charged by our competitors. Relative promotion expenditure is our expenditure on promotion divided by the total spent by our competitors. We set our price and promotion. We do not control our competitors’ actions or the state of the economy or the weather conditions. When market response models are directly incorporated into the planning process, the approach is called model-based planning and forecasting (Hanssens, Parsons, & Schultz, 2001, pp. 16-19). This approach is presented in Figure 1. At the heart of this process, forecasts of unit sales are made using a market response model on the basis of brand plans and budgets, along with estimates of competitive actions and environmental conditions. Responsibility for forecasts is placed on the manager who makes the decisions, not the forecaster (Parsons & Schultz, 1994).

While there is considerable evidence to support the managerial use of market response models to describe a marketplace and to provide diagnostic information, the use of response models, especially market share models, in forecasting has been more controversial. The forecasting ability of a market response model is typically benchmarked against a “naïve” time series model. The naïve model does not contain any marketing mix data but contains the lagged dependent variable, which may capture major causal effects because it
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