Chapter II

Predicting Consumer Retail Sales Using Neural Networks

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Forecasting future retail sales is one of the most important activities that form the basis for all strategic and planning decisions in effective operations of retail businesses as well as retail supply chains. This chapter illustrates how to best model and forecast retail sales time series that contain both trend and seasonal variations. The effectiveness of data preprocessing such as detrending and deseasonalization on neural network forecasting performance is demonstrated through a case study of two different retail sales: computer store sales and grocery store sales. We show that without data preprocessing neural networks are not able to effectively model retail sales with both trend and seasonality in the data, and either detrending or deseasonalization can greatly improve neural network modeling and forecasting accuracy. A combined approach of detrending and deseasonalization is shown to be the most effective data preprocessing technique that can yield the best forecasting result.

INTRODUCTION

Demand forecasting is one of the most important activities that form the basis for all strategic and planning decisions in any business organization. Accurate forecasts of consumer retail sales can help improve retail supply chain operation,
especially for larger retailers who have a significant market share. For profitable retail operations, accurate demand forecasting is crucial in organizing and planning purchasing, production, transportation, and labor force, as well as after-sales services. A poor forecast would result in either too much or too little inventory, directly affecting the profitability of the supply chain and the competitive position of the organization. The importance of accurate demand forecasts in successful supply chain operations and coordination has been recognized by many researchers (Lee et al., 1997; Chen et al., 2000; Chopra and Meindl, 2001).

Retail sales series belong to a special type of time series that typically contain both trend and seasonal patterns, presenting challenges in developing effective forecasting models. Various traditional techniques have been proposed with none universally applicable and effective in all situations. In the well-known M-forecasting competition (Makridakis et al., 1982), various traditional seasonal forecasting models have been tested with many real-time series. The results show that no single model is globally the best. In our view, one of the major reasons that many traditional approaches fail to provide adequate forecasts of seasonal time series lies in the parametric nature of the models. These models are effective only when the underlying data generating process matches the structure and assumptions of a particular parametric model.

In this chapter, we provide a case study on how to effectively model and forecast consumer retail sales using neural network models. Neural networks have been successfully used for many types of forecasting problems (Zhang et al., 1998). The recent upsurging interest in neural networks is largely due to their many desirable features for practical applications, along with the rapid increase in computer speed and decrease in computing cost. Neural networks are data-driven nonparametric methods that require few a priori assumptions about the underlying patterns in the data. They let data speak for themselves and can capture almost any type of functional relationship with sufficient accuracy, given enough data. In addition, unlike traditional statistical forecasting methods which primarily focus on linear structure problems, neural networks are able to model and forecast both linear and nonlinear time series effectively (Zhang, 1998). Neural networks can be a promising forecasting tool for many real world problems that are often nonlinear and unstructured.

Although neural networks have been widely used for many time series forecasting problems, little research has been devoted to modeling seasonal time series that have a clear trend component. Limited empirical findings give mixed results on the best way to model seasonal time series. For example, after examining 88 seasonal time series, Sharda and Patil (1992) concluded that neural networks could model seasonality directly and effectively, and data preprocessing such as deseasonalization was not necessary. Tang and Fishwick