Chapter 10
Time-Constrained Fashion Sales Forecasting by Extended Random Vector Functional Link Model

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ABSTRACT

Forecasting is about providing estimation of the future that cannot be observed at the moment. In this chapter, the random vector functional link (RVFL), which is a variation of the artificial neural networks (ANN) model, is used in establishing a fashion sales forecasting model. It is well-known that the RVFL inherits the learning and approximation capability of ANN, while running much faster than the traditional ANN. In order to develop a real world forecasting application, we propose a time-constrained forecasting model (TCFM), implemented by an extended RVFL, in which the user can define the time limit and a precision threshold for yielding the forecasting result. Real datasets collected from a fashion retail company are employed for the analysis. Our experiment has shown that the proposed TCFM can produce quality forecasting within the given time constraint. Future research directions are outlined.

INTRODUCTION

Forecasting is about predicting the future based on the past historical data. It is important in all kinds of applications. It is especially important in industries such as fashion retailing because of the ever changing market needs and fashion trends. However, it is usually a tremendously difficult task as the future is truly unknown in many situations (Sztandera et al., 2004). Many statistical (Abraham & Ledolter, 1983) and mathematical (Frank et al., 2002) models are applicable for the purpose of

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forecasting. Techniques such as averaging over a horizon, moving average, Bayesian approach, and exponential smoothing (Hanke & Wichern, 2009) are all well-studied in the literature. Many of these statistical models are still being actively used in everyday's application and are proven to be useful and fast. The Artificial Neural Network (ANN) is originated from the mathematical model that simulates the structure and functions of biological neural networks. ANN has demonstrated superior performance in optical character recognition, speech recognition, signal filtering in communication networks and so on (Hansen & Nelson, 1997; Bhagat, 2005; Masters, 1994). ANN is also powerful in making prediction about future events or processes (Cortez et al., 1995; Zhang et al., 1998), including sales forecasting (Yu et al., 2010a). Essentially, ANN has been used as a non-linear data-modeling tool based on its capability of learning and finding sophisticated patterns from historical data. The typical ANN models apply gradient learning mechanisms and have to repeatedly run and fine-tune their parameters so as to learn the patterns from data well (Hertz, 1990). While the ANN models are capable of modeling both linear and non-linear models, they are often much slower compared to the traditional statistical models. There have been many efforts devoted to improving the efficiency of ANN, and many of them concentrate on the learning algorithm (MacKay, 2003). For instance, a new learning algorithm has been proposed recently based on neuron-by-neuron computation methods for the gradient vector and the Jacobian matrix (Wilamowski, 2008). The algorithm can handle ANN with arbitrarily neurons, and its training speed is much faster than the other algorithms. Although the neuron-by-neuron computation method is faster, it suffers a major limitation on its convergence ability. To be specific, there is a significant probability that the algorithm will fail to converge the global minima, so that the algorithm has to repeat from the very beginning. Although there are solutions for this, the algorithm is not as fast as it can be.

In the literature, the single-hidden-layer feedforward neural networks (SLFN) is one of the commonly used ANN tools in forecasting as it has been proven to be capable of approximating an arbitrary function. A novel learning algorithm for the SLFN, called extreme learning machine (ELM), has been proposed and explored recently (Huang et al., 2006; Sun et al. 2007). The ELM is originated from the method known as random vector functional link (RVFL) (Pau et al., 1994). In RVFL, an analytical approach is employed in finding the weights of the network in the learning process. The RVFL not only learns much faster than the traditional gradient-based learning algorithms but it also avoids many notorious problems faced by gradient-based learning methods such as stopping criteria, learning rate, learning epochs, local minima, and the over-tuned problems. Hence, the RVFL model significantly reduces learning time. Even though the RVFL has many advantages compared to those traditional gradient-based learning ANN algorithms, it suffers a disadvantage of having unstable outputs. To overcome this problem, in (Sun et al., 2008), an extended RVFL model, which repeatedly runs the RVFL, is proposed. The experimental findings in (Sun et al., 2008) indicate that this extension usually yields a smaller forecasting error. In this paper, an extended RVFL based time-constrained forecasting model (TCFM) is proposed. We specifically consider the case when the user can inputs two important parameters: (i) The time limit which governs the computation time for conducting forecasting, and (ii) the precision threshold. In this exploratory study of the TCFM for fashion sales forecasting, we employ real dataset from the industry to test the performance of the proposed algorithm. Our experiment has shown that the proposed system is effective and efficient for fast forecasting problems. Future research directions are outlined.

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