

Chapter 6.9

Forecasting Supply Chain Demand Using Machine Learning Algorithms

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ABSTRACT

Managing supply chains in today's complex, dynamic, and uncertain environment is one of the key challenges affecting the success of the businesses. One of the crucial determinants of effective supply chain management is the ability to recognize customer demand patterns and react accordingly to the changes in face of intense competition. Thus the ability to adequately predict demand by the participants in a supply chain is vital to the survival of businesses. Demand prediction is aggravated by the fact that communication patterns between participants that emerge in a supply chain tend to distort the original consumer's demand and create high levels of noise. Distortion

and noise negatively impact forecast quality of the participants. This work investigates the applicability of machine learning (ML) techniques and compares their performances with the more traditional methods in order to improve demand forecast accuracy in supply chains. To this end we used two data sets from particular companies (chocolate manufacturer and toner cartridge manufacturer), as well as data from the Statistics Canada manufacturing survey. A representative set of traditional and ML-based forecasting techniques have been applied to the demand data and the accuracy of the methods was compared. As a group, Machine Learning techniques outperformed traditional techniques in terms of overall average, but not in terms of overall ranking. We also found that a support vector machine (SVM)

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trained on multiple demand series produced the most accurate forecasts.

INTRODUCTION

Supply chain integration looks to combine resources in order to provide value to the end consumer by improving the flow and quality of information being passed between the participants in the chain (Zhao, Xie, & Wei, 2002). Thus, in an idealized case, where all participants adopt the integration philosophy and make efforts to implement it fully, the entire chain would perform effectively and efficiently in responding to end customer demands. However, although integration and sharing information can potentially reduce forecast errors, in reality they are neither ubiquitous nor complete and demand forecast errors still abound.

This is due to the fact that the original demand signal becomes distorted as it travels through the extended supply chain (a holistic notion of supply chain (Tan, 2001) that requires collaborative relationships (Davis & Spekman, 2004)). Demand forecast quality can be improved if done cooperatively by the partners in the chain. Collaborative forecasting and replenishment (CFAR) permits a firm and its supplier-firm to coordinate decisions by exchanging complex decision-support models and strategies, thus facilitating integration of forecasting and production schedules (Raghunathan, 1999). In the absence of CFAR, firms are relegated to traditional forecasting and production scheduling, a challenging task due to what the well-known phenomenon of “bullwhip effect” (Lee, Padmanabhan, & Whang, 1997a).

The value of information sharing across the supply chain is widely recognized as the means of combating demand signal distortion (Lee, Padmanabhan, & Whang, 1997b). However, there is a gap between the ideal of integrated supply chains and reality (Gunasekaran & Ngai, 2004).

Researchers have identified several factors that could hinder such long-term stable collaborative

efforts. Premkumar (2000) lists some required critical issues that must be addressed to permit successful supply chain collaboration, including: (i) alignment of business interests, (ii) long-term relationship management, (iii) reluctance to share information, (iv) complexity of large-scale supply chain management, (v) competence of personnel supporting supply chain management and (vi) performance measurement and incentive systems to support supply chain management. Although these are important issues, in many companies, these issues have not yet been addressed in attempts to enable effective extended supply chain collaboration (Davis & Spekman, 2004). Additionally, in many supply chains there are power regimes and power sub-regimes that can prevent supply chain optimization (Cox, Sanderson, & Watson, 2001). The introduction of inaccurate information into the system could also lead to demand distortion, e.g., double forecasting and ration gaming by the partners, ordering more quantities than needed, despite the presence of a collaborative system and an incentive towards its usage (Heikkila, 2002).

Furthermore, the globalization trends and the advance of E-business increase the tendency towards more “dynamic” (Vakharia, 2002) and “agile” (Gunasekaran & Ngai, 2004; Yusuf, Gunasekaran, Adeleye, & Sivayoganathan, 2004) supply chains. While this trend enables the supply chains to be more flexible and adaptive, it could discourage companies from investing in long-term collaborative relationships among each other due to the restrictive nature of such commitments. The over-emphasis on investing in extensive relationships among the partners could lead to a “lock-in” situation, thus seriously jeopardizing the flexibility of the supply chain (Gossain, Malhotra, & ElSawy, 2005). Gossain et al. (2005) argue that developing robust and reconfigurable links would promote the agility of the chain in terms of offering and partnering flexibilities. In their study they found that while the quality of the information sharing in a supply chain could promote flexibility, the breadth of information shared has a detrimental

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