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Impact of Machine Learning To Manage Demand Prediction of E- Supply Chain Management System

Vivek Jaglan
Amity University, Gurugram, Haryana (India)

Abstract: -- **Demand forecasting is difficult, and most demand forecasting conducted today produces disappointing results and significant forecast errors. It cannot easily identify trends in the demand data, and its limited ability to understand the underlying causes of demand variability makes that variability seem worse than it would if demand drivers were clearly understood. And because it is manually intensive, it suffers from persistent bias and poor planner productivity. Business volatility and the complexity of factors influencing demand are making it hard to reliably model the causes of demand variation. Machine learning can help companies overcome that challenge.**

Keywords – Machine learning, Supply chain management.

1. INTRODUCTION

Demand forecasting is difficult, and most demand forecasting conducted today produces disappointing results and significant forecast errors. It cannot easily identify trends in the demand data, and its limited ability to understand the underlying causes of demand variability makes that variability seem worse than it would if demand drivers were clearly understood. And because it is manually intensive, it suffers from persistent bias and poor planner productivity. "Supply Chain Shaman" Lora Cecere puts it bluntly. In her excellent book, Bricks Matter, she writes, "Within an organization, the words 'Demand Planning' stir emotions. Usually, it is not a mild reaction. Instead, it's a series of emotions defined by wild extremes including anger, despair, disillusionment, or hopelessness." She goes on to say that planning teams are dismayed by demand planning's challenges, and further claims that leaders are not optimistic about making improvements to planning processes and technologies.

Fig. 1

What makes forecasting demand so challenging? Rather than appearing as a logical series of numbers, in today's business environment demand more often seems like a pattern of partially constrained chaos. Demand is increasingly influenced by multiple internal and external factors that drive it up and down in ways that can't be understood by simply looking at a historical time-series of aggregated demand buckets. Instead, demand should be viewed as being driven by a complex series of indicators that can be nearly impossible to manage with traditional forecasting algorithms. However, a new technology called machine learning can help companies address demand-forecasting challenges by reliably modeling the numerous causes of demand variation. Machine learning is a computer-based discipline in which algorithms can actually "learn" from the data. Rather than following only explicitly programmed instructions, these algorithms use data to build and constantly refine a model to make predictions. I'll explain in more detail later, but first I'd like to describe several business scenarios where companies have employed machine learning in their demand forecasting. See if any of these scenarios suggest familiar attributes in your own business. Lots of promotions. Every year, the Italian dairy producer Granarolo S.p.A. runs thousands of consumer promotions, creating forecasting scenarios for 34,000 unique stock-keeping unit (SKU) promotions. And it gets worse: Demand spikes can amount to an extraordinary 30 times baseline sales. (For more about these challenges, see the Granarolo sidebar.) This is a common predicament. Expenses for advertising and promotions can add up to more than 20 percent of sales for many consumer products companies. Yet according to Michael Kantor, founder and chief executive officer of the Promotion Optimization Institute, only about 1 in 50 brands is able to forecast demand uplift reliably enough to guarantee consumer product availability and to evaluate the economic returns on those promotions. Without improved technology, few companies can forecast effectively in such a promotion-heavy environment. (For an example, see the sidebar about Groupe Danone.)

Lots of new products. The United Kingdom-based electronics distributor Electrocomponents plc is a top-ranked global distributor with 500,000-plus in-stock items. The company introduces 5,000 new products every month and fulfills more than 44,000 same-day orders every day from its operations in 32 countries. A few new products a month is one thing, but predicting demand for such a vast array of new products is more than a demand planner can reasonably be expected to handle. Plus, new products, by definition, are difficult to forecast. Nevertheless, planners can tap into external data to help them predict initial demand and thus decide how much marketing budget to invest in launching a new product.

Lots of "long-tail" demand. Companies whose e-commerce business is growing find themselves having to forecast demand for more slow-moving, "long-tail" items that customers order infrequently and in small quantities. Outliers are naturally hard to predict, making inventory planning notoriously difficult. Even if you can predict the average demand for certain products, you probably can't predict the demand spikes. This makes it nearly impossible to maintain a balance—having enough on hand to satisfy sudden spikes without adding unnecessary inventory and eventually holding "dead stock."

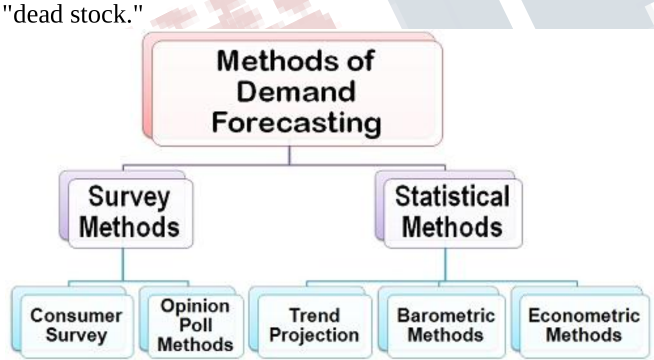

Fig. 2

Growing complexity. Planning wasn't so complicated when Granarolo started out in the 1960s as a local collective of milk producers, but gradually complexity intensified as the company grew into a multinational concern comprising eight brands and hundreds of different dairy products, and utilizing various delivery modes. Its basic software was never designed to handle this kind of growth, and what resulted was progressively inaccurate forecasting that needed time-consuming manual activity to fine-tune. Granarolo's situation is typical of modern supply chains, which continue to increase in complexity. Extreme seasonality. The United States-based heating, ventilation, and air conditioning (HVAC) manufacturer Lennox International Inc.'s forecasting was complicated because of its high number of SKUs (each of which had its own unique demand pattern) and a significant stock of slow-moving parts, and because it is an extremely seasonal business. Further complicating matters was the company's plans to greatly expand its distribution network, as detailed in the Lennox sidebar. There was no way the manufacturer could manage this level of complexity and variability without adopting a highly automated demand planning system.

Just too much data. In all of these companies we find a pattern that is common to most of today's businesses: a proliferation of new data. I'm referring here primarily to market and logistical data that can help companies better predict demand. Having to manage huge volumes of diverse and ever-growing data streams is more than most planners (and planning systems) can handle. Trying to incorporate them into a forecast using spreadsheets or traditional planning tools is frustrating, often futile, and can be extremely costly.

The companies in the scenarios above share an intrinsic level of complexity and scale that makes it almost impossible for planners to generate reliable forecasts. They are no longer simple and predictable businesses, able to forecast based on historic sales volumes—if they ever were! Their planners were overwhelmed.

In many cases we see, people don't start contributing to forecasts until the very end of the process. So, rather than providing input to help generate an accurate forecast in the first place, they're collaborating to adjust the forecast "output." This approach is inefficient. While some late-stage "crowd wisdom" can be useful, it can also introduce bias. A typical example is when a sales organization artificially adjusts a forecast to match revenue targets.

What else do these companies have in common? They all turned to machine learning in order to increase forecast reliability. This decision dramatically slashed inventory costs and at the same time provided better, more efficient service to customers. It also meant that planners no longer had to waste time manually overriding or adjusting forecasts.

II. BACKGROUND

One of the major purposes of supply chain collaboration is to improve the accuracy of forecasts (Raghunathan, 1999). However, since, as discussed above, it is not always possible to have the members of a supply chain work in full collaboration as a team, it is important to study the feasibility of forecasting the distorted demand signal in the extended supply chain in the absence of information from other partners. Therefore, although minimizing the entire extended supply chain's costs is not the primary focus of this research,

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we believe that improved quality of forecasts will ultimately lead to overall cost savings. The use of simulation techniques has shown that genetic algorithm-based artificial agents can achieve lower costs than human players. They even minimize costs lower than the ‘‘1–1’’ policy without explicit information sharing (Kimbrough et al., 2001). Analysis of forecasting techniques is of considerable value for firms, as it has been shown that the use of moving average, naı¨ve forecasting or demand signal processing will induce the bullwhip effect (Dejonckheere et al., 2003). Autoregressive linear forecasting, on the other hand, has been shown to diminish bullwhip effects, while outperforming naı¨ve and exponential smoothing methods (Chandra and Grabis, 2005).
In this paper, we will analyze the applicability of machine learning techniques to demand forecasting in supply chains.
The primary focus of this work is on facilitating demand forecasting by the members at the upstream end of a supply chain. The source of the demand distortion in the extended supply chain simulation is demand signal processing by all members in the supply chain (Forrester, 1961). According to Lee et al. (1997b), demand signal processing means that each party in the supply chain does some processing on the demand signal, transforming it, before passing it along to the next member. As the end-customer’s demand signal moves up the supply chain, it is increasingly distorted because of demand signal processing. This occurs even if the demand signal processing function is identical in all parties of the extend supply chain. The phenomenon could be explained in terms of chaos theory, where a small variation in the input could result in large, seemingly random, behavior in the output of the chaotic system (Kullback, 1968).
Basic time series analysis (Box, 1970) will be used in this research as one of the ‘‘traditional’’ methods against which the performance of other advanced techniques will be compared. The latter include Neural Networks, Recurrent Neural Networks, and Support Vector Machines. Neural Networks (NN) and Recurrent Neural Networks (RNN) are frequently used to predict time series (Dorffner, 1996; Herbrich et al., 2000; Landt, 1997; Lawrence et al., 1996). In particular, RNN are included in the analysis because the manufacturer’s demand is considered a chaotic time series. RNN perform back-propagation of error through time that permits learning patterns through an arbitrary depth in the time series. This means that even though we provide a time window of data as the input dimension to the RNN, it can match pattern through time that extends further than the provided current time window because it has recurrent connections. Support Vector Machines (SVM), a more recent learning algorithm that has been developed from statistical learning theory (Vapnik, 1995; Vapnik et al., 1997), has a very strong mathematical foundation, and has been previously applied to time series analysis (Mukherjee et al., 1997; Ru¨ping and Morik, 2003).

III. MACHINE LEARNING

Machine learning systems were designed to handle forecasting models that can incorporate many kinds of data. Rather than following traditional programmed instructions, machine learning systems reduce demand variability by capturing and modeling all the relevant attributes that shape demand while filtering out the "noise," or random and unpredictable demand fluctuations.

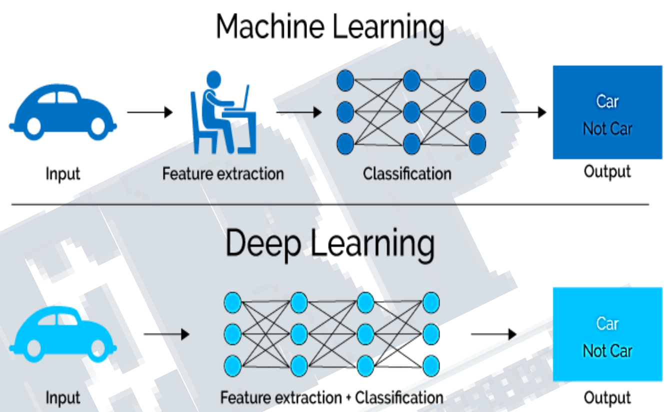

Fig. 3

As a result, they learn from the data that they process and modify their operations accordingly. For example, a machine learning system that uses Web data to quickly detect successful new products will find and learn which demand indicators—such as Web page hits, specification downloads, and time on site—are most reliable, and then will update its model over time as consumer behavior changes. Machine learning can interpret the effect of stimuli (such as trade promotions and advertising) and demand indicators (such as social media activity) originating from each distribution channel. As information proliferates, the data concerning these causes and demand indicators become both more accessible and more manageable over time. Machine learning systems therefore can integrate and usefully model these important new data sources, including detailed market data, machine telemetry, and social media feeds, in ways that are simply not possible with legacy planning systems. What does this mean in practical terms? For one thing, it means companies can take advantage of valuable data signals that are generated closer to the consumer, including data from points of sale and social media channels. This enables companies to understand the impact of demand drivers such as media, promotions, and new product introductions, and to then use that knowledge to significantly improve forecast quality and detail

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IV. WHY MACHINE LEARNING?

Would machine learning technology be beneficial for your supply chain? One way to know is by finding out whether your old planning system may be causing escalating costs. Here are three potential signs of this problem, and how machine learning can help to address them:

Inflated safety-stock levels. You can't trust your safety-stock levels to deliver the required service levels, so you keep them artificially high. By taking more demand variables into account, machine learning can help companies with a diverse range of SKU profiles, including long-tail items, to set optimal, lower levels they can trust.

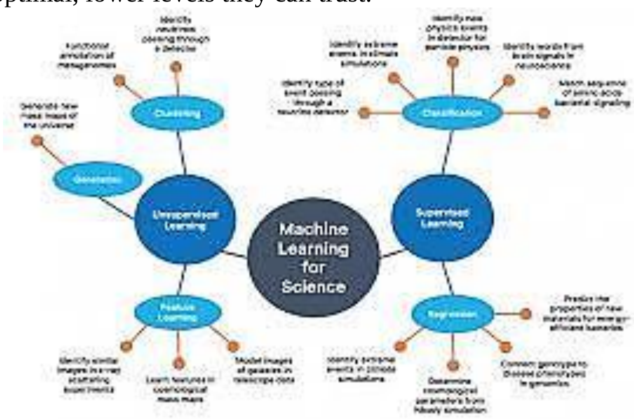

Fig. 4

Planning team "burnout." Your team is spending too much time manually adjusting and evaluating forecasts, and often is still not able to deliver them accurately enough or on time. This leads to poor productivity and morale. Machine learning takes more demand variables into account and weights each according to its significance, resulting in much more accurate forecasts. This helps planners succeed in their roles and frees up time for them to refine forecasts using their personal insights and business knowledge.

An inefficient sales and operations planning (S&OP) process. Your consensus forecast from the S&OP is unreliable, or the collaboration process behind it is too slow to adapt to the dynamic nature of the market and SKU behavior. Machine learning's high level of automation can improve the quality of the short- and mid-term forecast by picking up key trends from transactional and promotional data and providing actionable insights about those trends, thereby making the S&OP process more efficient and effective in achieving your business objectives. If any of these situations resonate, it's likely time to take a closer look at machine learning technology. This doesn't have to mean "ripping and replacing" your existing software. Granarolo, for example, implemented machine learning technology alongside its existing systems to boost performance. Companies that implement machine learning often find that it is easy to use, and that its ability to learn from existing data means that it takes relatively less time to implement, deliver benefits, and pay for itself.

In the not-too-distant future, most supply chains will rely on software that uses machine learning technology to analyze much larger, more diverse data sets. For companies that are serious about tackling today's complex forecasting problems, this new technology will prove an invaluable tool.

V. EXPERIMENTAL SETUP

Data set preparation

We used a representative set of traditional forecasting techniques as a control group, and a set of machine learning techniques as a treatment group. To compare the two groups, every technique from each group was used to forecast demand one month into the future for all of the 100 series for the three datasets previously identified.

This resulted in a series of 4,700 forecast points for the chocolate manufacturer, 6,500 for the toner cartridge manufacturer and 14,800 for the Statistics Canada dataset for every technique tested. However, since all forecasting techniques require past data to make a forecast into the future, there was a predetermined startup period that slightly reduced the number of forecast observations. Additionally, the demand time series was formally separated into a training set and testing set. This is particularly important for the ML techniques, where the training set was used for ML models to learn the demand patterns and the testing set used to estimate how well the forecasting capability could generalize in the future. The main performance measure used was the absolute error (AE) measure for every forecast data point. This resulted in a series of absolute error values for a specified forecasting technique. To make the absolute error comparable across products, we normalized this measure by dividing it by the standard deviation of the training set. Thus, the performance of different techniques was compared in terms of normalized absolute error (NAE). We used 80 percent of the time series data for training and 20 percent of the data for testing. We then employed all of the selected techniques to produce forecasts using MATLAB 7.0 environment (MathWorks, 2005b).

VI. CONCLUSION

We reviewed the importance of supply chain models as a valuable, rare, inimitable, non-substitutable, and heterogeneous resource that leads to a competitive advantage to the firms in a supply chain. We also considered the advantages and disadvantages of supply chain models based on optimization methods and multiagent and CBR. While optimization models are good at providing solutions with precision, it takes time and effort to build quality models and a supporting database. Furthermore, it is getting harder to build the models as the problem domain expands. Although multi-agent and CBR based models provide near-optimal solutions, less effort is required to build the models which can be used with less expertise. This approach is more amenable to model complexities caused by the expansion of the problem domain. CBR can accommodate additional problem dimensions and multi-agent can address collaboration and

REFERENCES

[1]. Box, G.E., 1970. Time Series Analysis. Holden-Day, San Francisco.

[2]. Chandra, C., Grabis, J., 2005. Application of multi-steps forecasting for restraining the bullwhip effect and improving inventory performance under autoregressive demand. European Journal of Operational Research 166 (2), 337–350.

[3]. Cox, A., Sanderson, J., Watson, G., 2001. Supply chains and power regimes: Toward an analytic framework for managing extended networks of buyer and supplier relationships. Journal of Supply Chain Management 37 (2), 28–35.

[4]. Davis, E.W., Spekman, R., 2004. Extended Enterprise. PrenticeHall,Upper Saddle River, NJ.

[5]. Dejonckheere, J., Disney, S.M., Lambrecht, M.R., Towill, D.R., 2003. Measuring and avoiding the bullwhip effect: A control theoretic approach. European Journal of Operational Research 147 (3), 567–590.

[6]. R. Carbonneau et al. / European Journal of Operational Research 184 (2008) 1140–1154 1153 Demuth, H., Beale, M., 1998. In: Natick (Ed.), Neural Network Toolbox for Use with MATLAB, User's Guide (version 3.0). The MathWorks, Inc., Massachusettes.

[7]. Dorffner, G., 1996. Neural Networks for Time Series Processing. Neural Network World 96 (4), 447–468.

[8]. Forrester, J., 1961. Industrial Dynamics. Productivity Press, Cambridge, MA.

[9]. Frohlich, M., 2002. Demand chain management in manufacturing and services: Web-based integration, drivers and performance. Journal of Operations Management 20 (6), 729–745.

[10]. Gunasekaran, A., 2004. Supply chain management: Theory and applications. European Journal of Operational Research 159 (2), 265–268.

[11]. Gunasekaran, A., Ngai, E.W.T., 2004. Information systems in supply chain integration and management. European Journal of Operational Research 159 (2), 265–527.

[12]. Heikkila¨, J., 2002. From supply to demand chain management: Efficiency and customer satisfaction. Journal of Operations Management 20 (6), 747–767.

[13]. Herbrich, R., Keilbach, M.T., Graepel, P.B.-S., Obermayer, K.,2000. Neural networks in economics: Background, applications and new developments. Advances in Computational Economics: Computational Techniques for Modeling Learning in Economics 11, 169–196.

[14]. Kimbrough, S., Wu, D.J., Fang, Z., 2001. Computers play the beer game: Can artificial agents manage supply chains? Decision Support Systems 33 (3), 323–333.

[15]. Kullback, S., 1968. Information Theory and Statistics, second ed.Dover Books, New York.

[16]. Landt, F.W., 1997. Stock Price Prediction using Neural Networks.Laiden University.

[17]. Lawrence, S., Tsoi, A.C., Giles, C.L., 1996. Noisy time seriesprediction using symbolic representation and recurrent neural network grammatical inference. University of Maryland, Institute for Advanced Computer Studies.

[18]. Lee, H.L., Padbanaban, V., Whang, S., 1997a. The Bullwhip Effect in Supply Chains. Sloan Management Review (Spring).

[19]. Lee, H.L., Padbanaban, V., Whang, S., 1997b. Information distortion in a supply chain: The bullwhip effect. Management Science 43 (4), 546–558.

[20]. MathWorks, I. 2000. Using MATLAB, Version 6, MathWorks, Inc. Mukherjee, S., Osuna, E., Girosi, F., 1997. Nonlinear prediction of chaotic time series using support vector machines. Paper presented at the Proceedings of IEEE NNSP.