Machine Learning in Predicting Demand for Fast-Moving Consumer Goods: An Exploratory Research

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Abstract: More accurate prediction of the demand for fast-moving consumer goods is a competitive factor for manufacturers and retailers, especially in the fashion, technology and fresh food sectors. This exploratory research presents the benefits of Machine Learning in sales forecasting for short shelf-life and highly-perishable products, as it surpasses the accuracy level of traditional statistical techniques and, as a result, improves inventory balancing throughout the chain, reducing stockout rates at points of sale, improving availability to consumers and increasing profitability.

Keywords: Machine Learning, demand prediction, sales forecast, short shelf-life, short life-cycle, fast-moving consumer goods.

1. INTRODUCTION

Demand forecasting is a basic component of production planning and supply chain management, impacting competitiveness and profitability, providing critical information for purchasing decisions, production, stock levels, logistics, finance and marketing (Yue *et al.*, 2016, Bertaglia, 2016, Martínez et al., 2018, Arvan *et al.*, 2018).

In the consumer goods sector, where products are consumed rapidly, sales estimates become even more critical to business. Cohen *et al*. (2017) cite fast-moving consumer goods (FMCG) or Consumer Packaged Goods (CPG) products, such as processed foods, beverages, canned goods, soft drinks, snacks, sweets and chocolates, as well as items such as personal care and cleaning products. Due to rapid deterioration, many fast-moving consumer goods have a short shelf life, as is the case for goods such as meats, fruits, vegetables and dairy products, which are highly perishable. Other products, such as electronics and fashion apparel, have short lifecycles, rapid obsolescence, are frequently updated, and have many competing alternatives.

Nagashima *et al*. (2015) warn that increasing inventories due to the lack of a more accurate demand forecast has a greater impact on costs for companies that deal with products such as consumer electronics, which have a lower profit margin and lose value quickly. Similarly, the fashion, apparel and footwear segments, among others, have a short life-cycle and high demand volatility, making it difficult for sales, production and supply chain managers to accurately predict sales volumes (Nagashima *et al*., 2015, Yue *et al.*, 2016).

In the retail food industry in general, the main cause of wasted products and stockouts is the inaccuracy of sales forecasting leading to incorrect orders (Arunraj and Ahrens, 2015). More specifically in the fresh food industry, including the refrigerated ones, such as the dairy, fruit and juice segments, the short shelf-life and need to maintain quality in the storage and distribution processes make sales forecasting accuracy an important factor for planning production, minimizing lost sales due to a lack of products, reducing returns due to the proximity of the expiration date, and improving availability to customers, thus reflecting on company results and even reducing environmental damage when, for example, disposal by deterioration is avoided (Doganis *et al*., 2005). Ochiai (2015) adds that the accuracy in fresh food demand forecasting improves the efficiency of order and inventory management, enabling retailers in this segment to reduce their disposal volume by about 40%.

Regarding the human factor in the predictions, Arvan *et al*. (2018) point out that biases and systematic errors in demand forecasting often occur in the supply chain decision-making process or in sales and operations planning (S&OP), as influenced by personal judgment. Puchalsky *et al*. (2018) add that human decisions become difficult when appropriate forecasting models are used because they require many variables to achieve greater accuracy, pointing to the need for support from automated tools.

Da Silva *et al.* (2017) comment on the use of forecasting tools, noting that time-series methods can usually be applied to historical sales data with a high level of precision, but traditional statistical techniques are not the most appropriate option because they consider the relationship between input and output variables to be linear, which generally does not correspond to reality, suggesting the application of methods based on Artificial Neural Networks. In fact, Akabane (2018) points out that neural networks and Machine Learning are part of the set of what are known as cognitive technologies, which try to imitate human thinking and are able to manipulate large amounts of information in order to objectively perform analyses, and can be applied to business processes.

Machine Learning is classified by Michalski, Carbonell and Mitchell (1983) into three forms: system engineering to learn from specific applications; an analysis of learning algorithms; and a simulation of human learning processes. Mohri *et al*. (2012) comment on the evolution of Machine Learning as a myriad of algorithms that can be divided into four main categories: i) supervised learning that assumes completely labeled data in terms of input-output pairs to train an individual algorithm; ii) unsupervised learning that attempts to find structures in unlabeled data; iii) semi-supervised learning operating on a mixture of labeled and unlabeled data; and iv) reinforcement learning based on the idea of maximizing a reward function by optimizing specific actions in a given parametric configuration.

According to Goodfellow, Bengio and Courville (2015), Deep Learning is a more complex form of machine learning that allows computers to learn from experience without the need for knowledge specification by a human operator, understanding the world in terms of a hierarchy of concepts with deep layers built on top of one another.

Thus, the question to be answered by this study is: What are the benefits of applying Machine Learning to demand forecasting for manufacturers and retailers of fast-moving consumer goods? The objective is to review scientific literature and identify if there are advantages over traditional statistical techniques, what gains are obtained as a result of higher sales predictability, and which business segments are addressed.

2. METHODOLOGY

This is an exploratory research with a qualitative approach, carried out through bibliographical research and literature review, seeking the benefits of Machine Learning applied to demand forecasting for fast-moving consumer goods.

This technique was chosen in order to achieve more comprehensive information in this study, and to allow for a more exhaustive study of specific topics in future research. Exploratory research provides an overview and approximation on a theme, constituting the first stage of a broader investigation, allowing the definition of the theme, delimitation of the research scope, formulation of hypotheses or discovery of a new approach (GIL, 2008, PRODANOV, 2013).

Flick (2009) proposes that the essential attributes of qualitative research are choosing appropriate methods and theories, the identification and analysis of different perspectives, reflection on the research as part of the knowledge production process, and the variety of approaches and methods. According to Bryman (2012), qualitative research generally emphasizes words rather than quantification in data collection and analysis.

On the other hand, the search for documentary and bibliographic sources is also essential to preventing a duplication of efforts and to not repeat ideas that have already been expressed. Citations of conclusions from other authors can highlight contributions of the research, evidence contradictions and confirm results (MarconI and Lakatos, 2003). The bibliometric approach, through which science is portrayed by the results obtained, is based on the notion that the essence of scientific research is the production of knowledge, and that scientific literature is a manifestation of this knowledge (Okubo, 1997).

Regarding literature review, Creswell (2014) proposes that it provides a synthesis of the main studies on the research question, and can be used to indicate that the author is aware of the literature on the topic in question, as well as the latest publications.

3. LITERATURE REVIEW

The literature review performed in this research has identified relevant papers related to Machine Learning applied to demand prediction for fast-moving consumer goods, focusing on the benefits achieved, business sectors addressed and the possible advantages over traditional statistical techniques.

The importance of sales forecasting is shown in older publications (2004 and 2005), as well in recent surveys (from 2016 to 2018), which mention the quality of forecasts as a critical success factor with a large impact on business management, including production, supply chain, logistics and stores. A bibliometric analysis of articles published from 2011 to 2017, searched in the Scopus and Web of Science databases, regarding Machine Learning for sales prediction, shows an increase in the number of publications between 2014 and 2016, with a decrease in 2017, as shown in Fig. 1. It represents 32 articles with 314 citations.

Year	Articles
2011	2
2012	4
2013	2
2014	4
2015	7
2016	8
2017	5
Sum	32

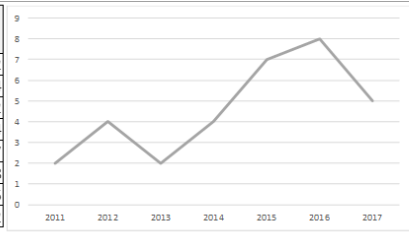

Fig. 1. Recent history of articles on Machine Learning in demand forecasting for fast-moving consumer goods

One can observe in the literature that statistical techniques and tools have been used by companies to estimate demand for their products, using historical sales series as a main data source. However, according to Kandananond (2012), demand forecasts with Machine Learning have had higher quality results than traditional techniques, including known approaches such as the Autoregressive Integrated Moving Average (ARIMA) model, especially for consumer goods and complex product hierarchies, presenting smaller error deviations. Wu and Zheng (2015) present sales forecasting models through Machine Learning, achieving greater accuracy than traditional statistical models for products with highly volatile demand and very short life cycles, such as in fast fashion retail, especially when data other than sales history are added to the model - in this case, information on product searches over the internet was included. Tsoumakas (2018) states that Machine Learning techniques are more effective and flexible than traditional statistical techniques for predicting time series because they have greater processing power and the ability to handle additional variables, listing those that he considers most appropriate for time series forecasting: simple ones, like Moving Average; hybrid approaches with a Radial Basis Function network; fuzzy algorithms; Genetic Algorithms; joint approaches (ensembles) that use learning algorithms like decision tree learners, rule learners, lazy learners, Support Vector Machines, Logistic Regression and, more recently, Deep Learning as the Stacked Denoising Autoencoder.

Several Machine Learning techniques are presented by the authors to obtain better sales forecasts. Chen and Ou (2011) applied Extreme Learning Machine networks combined with other methods to real sales data and weather forecasting, demonstrating an improvement in retail sales forecast accuracy with the objective of making better production decisions, increasing revenue, reducing losses on unsold products, and increasing customer satisfaction through an increased availability of items at points of sale. Islek and Oguducu (2015) took another approach to developing a demand forecasting methodology based on Bayesian Networks, a technique that verifies conditional probabilities according to the data provided, resulting in improved accuracy of regional sales forecasts for a wide variety of retail products, distributed through warehouses of various sizes. In online retailing, Ponce, Miralles and Martinez (2015) compared traditional Machine Learning techniques with Artificial Hydrocarbon Networks, which is a supervised learning technique, showing the potential for improving sales estimate quality. New technologies such as image recognition methods were applied by Wang *et al*. (2015) in order to predict consumer buying decisions based on the collected brain images of a group of people when subjected to pictures of products, through Support Vector Machines (SVM), which are supervised learning models with associated learning algorithms. Kaneko and Yada (2016) achieved high-level precision in the sales forecast for a retail stores chain by applying Deep Learning techniques on three-year daily data from points of sale, which ultimately led to the definition of a new management model with improvements in inventory levels, product categorization and distribution.

Some authors emphasize the importance of data variables. According to Guo, Wong, and Li (2013), a variety of factors influence a product's sales, such as its own attributes and the economic environment, and therefore there is no pattern in the time series data used for estimates. As an alternative for solving this problem, they presented a sales prediction model based on Machine Learning techniques with multiple variables, composed of data from early orders, historical sales, promotions, product characteristics, climate and economic indicators, resulting in greater precision in sales forecasting and better replenishment at retail stores, thereby improving supply chain efficiency. Lu (2014) confirms the need to include new variables in the forecast models, stating that many factors, even stock market indexes, affect the accuracy of sales forecasting, and that the selection of variables is therefore crucial. Several data sources were used by Qu *et al.* (2017), including both internal data (sales history, discounts granted and inventories levels) and external variables (holidays and regional factors) in their Machine Learning algorithms, with the main results being a better sales forecast and an adjustment of the stock levels of semi-luxury goods stores, which have seasonal characteristics and large variations in purchase stimulus.

In the technology sector, Lu and Shao (2012) have acquired more precise sales forecasts for short life-cycle products through Extreme Learning Machine algorithms, enabling an improvement of the refueling process of a computer products and accessories retail chain, whose main feature is technological obsolescence. Lu (2014) used a Support Vector Machine (SVM) to improve the sales management effectiveness of computing products that are highly replaceable and subject to dramatic changes in demand. A predictive sales model for innovative products was developed by Lee, Kim, Park and Kang (2014) in a study on 3D TVs, whose technology had no sales history, by using a joint approach of Machine Learning techniques, which resulted in greater accuracy than other techniques available. For information technology goods, Lu and Chang (2014) have developed a hybrid sales prediction model, which includes SVM, with greater accuracy and reliability than previous solutions. Chen and Lu (2017) confirm the benefits of Machine Learning for technology businesses with short life cycle products, by improving a computer retailer's sales forecasting accuracy and inventory management.

Studies related to the fashion industry reveal the search for better and faster demand forecasting. Yu, Choi, and Hui (2011) met an online fashion product store's business objective of having faster and more frequent sales forecasts for a large volume of products (SKUs) by applying Extreme Learning Machine (ELM) techniques to historical sales data with the volumes and characteristics of the items sold. Liu *et al*. (2013) show the evolution of sales forecasts in fashion retail, highlighting ELM techniques and benefits, such as proper inventory management. Choi (2014) has developed an intelligent ELM algorithm for fashion retail sales management, attaining greater precision and speed in the calculation of estimates. Tehrani and Ahrens (2016) reduced the sales forecast discrepancy rate for fashion items with a high production scale, thereby reducing write-off losses and increasing profitability through Machine Learning algorithms on historical and catalog sales data. Ferreira, Lee and Simchi-Levi (2016) showed revenue increasing for an online fashion clothing and accessories store, where Machine Learning examined the lost sales history and predicted future demand for new products (launches), contributing to the daily pricing process and following market dynamics. Teucke *et al*. (2016) utilized a combination of methods in their prediction model, including fuzzy logic, with the direct benefit of more accurate sales forecasts for seasonal fashion products. These forecasts were also faster than with previous methods, and were done in time to make production decisions, which made it possible to reduce the rate of inventory shortages and excesses. Ren, Chan and Ram (2017) state that in the fashion industry where the products are manufactured, consumed and disposed of in a short period of time, demand is highly volatile, and the inventory is distributed, Machine Learning for sales forecasting has shown positive results via greater speed and reliability.

In the case of short shelf-life foods, Agrawal and Schorling (1996, apud Chen and Ou, 2009) developed an Artificial Neural Network (ANN) prediction model for a perishable and refrigerated food convenience stores network that reached higher accuracy than traditional techniques, and noted that demand forecasting accuracy plays a crucial role in the profitability of retail operations, especially for food preserved at low temperatures. In this sense, Da Silva *et al*. (2017) noted that using Support Vector Machine (SVM) for demand forecasting, combined with other techniques, led to a reduction in losses from unsold dairy products that had passed their expiration date. Ochiai (2015) has developed algorithms with Heterogeneous Mixture Learning technology to estimate the demand of a short-term food grocery store chain, with a significant reduction in the disposal of unsold items.

Regarding the food and beverage industry, Fujimaki *et al*. (2016) built a model that aggregates Machine Learning for demand forecasting and price-optimization techniques for a beverage retailing company, which resulted in better forecasts, greater reliability for decision makers, and, as a result, a revenue increase estimated at 16%. Tsoumakas (2018) shows the advantages of Machine Learning techniques for sales prediction in the food industry, such as in supermarkets, grocery stores, restaurants, bakeries and confectioneries, where accurate short-term forecasting allows for inventory level minimization, the elimination of expired products at stores and, at the same time, prevents the loss of sales due to stockout. The main benefits observed were the reduction of human bias due to the greater automation of the forecasting process, a higher degree of forecast precision, and the flexibility to change variables. Drawbacks for companies that the author mentioned are the possible unavailability of detailed historical information and the large number of learning algorithms available, which could make choosing the proper one difficult.

A common aspect among the various business sectors, as highlighted by Cohen *et al*. (2017), is the importance of sales promotions, which are actions encouraging customers to buy fast-moving consumer products (FMCG). This is due to promotional expenses and the fact that a large part of FMCG products are sold as promotions: 12% to 25% of supermarket sales in five European countries are made in this form, according to a 2014 Nielsen survey. Soguero *et al*. (2012) propose an estimating model for promotional sales using Machine Learning, with benefits through greater promotional efficiency and predictability in a dynamic and complex environment of simultaneous and concurrent promotional actions. Their study analyzed a seasonal product (beer) and a non-seasonal item (milk). Similarly, Pinho, Oliveira and Ramos (2016) have achieved better sales forecast accuracy levels in the categories of beverages and cleaning products, analyzing the sales promotions carried out at a retail stores chain.

4. ANALYSIS AND DISCUSSION

In the context of the fast-moving consumer goods (FMCG) industry, most of the papers from this research investigation show that Machine Learning results in better demand predictability than the use of traditional models. One of the benefits obtained from this better sales forecast accuracy is an improvement in inventory management due to better decisions on production and distribution. The decrease in the occurrence of stockouts, which cause a shortage of items in stores, is also mentioned, as well as the greater availability of products at the points of sale, thus increasing revenue and customer satisfaction.

The main advantages cited over traditional statistical techniques are better predictions and more flexibility, especially when new data variables are included in the estimation models, in addition to the commonly used historical sales series, increasing data volume and analysis complexity. The significant increase in the number of internal and external variables, the growing data volume of time series and the complexity of relationships between the factors that can influence sales all encourage the adoption of Artificial Neural Networks and Machine Learning.

The market sectors cited by the articles researched can be seen in Fig. 2, which shows the distribution and highest incidence of study (51%) for the fashion and technology segments.

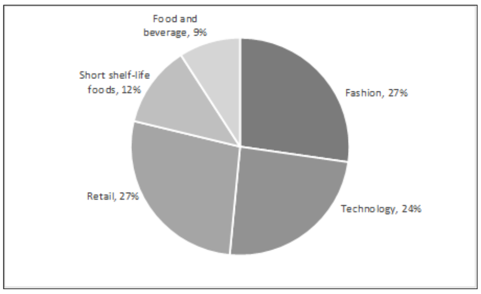

Fig. 2. Article distribution by market segments

More specific benefits are seen in some particular business areas. In the fresh food sector, more accurate forecasts lead to a reduction in loss from products that reach their expiration dates, and costs of transportation and storage of refrigerated products can be reduced. In the fashion business, one of the challenges is to prevent losses due to unsold products resulting from constant changes in consumer trends and preferences: Machine Learning techniques have proved adequate for both better predictability and faster processing speed, capable of generating estimates according to the frequency of new collections. Manufacturers and retailers of technology products, which can quickly be replaced by new releases, benefit from better sales and inventory management. In addition, better predictions were obtained for innovative products that do not have historical data.

Finally, the research shows that promotional actions are exceptionally important for all sectors, due to the significant share of consumer goods sales, but make the task of creating estimates more complex thanks to the different possible combinations of product types, categories, periods, customers and regions, as well the impact of items not participating in promotions. Recent studies in 2012, 2014, 2016 and 2017 present the advantages of Machine Learning in improving promotional efficiency, with greater predictability and better results.

5. CONCLUSIONS

The results of this research show that Machine Learning techniques, including the latest methods such as Deep Learning, as well as utilizing a combination of various techniques applied in demand forecasting models, can provide benefits to manufacturers and retailers of fast-moving consumer goods.

The main benefit observed was a higher level of precision in demand forecasting. As a result, manufacturers can build better sales and operations plans (S&OP), adjust production volumes and regional distribution, and improve inventory balancing throughout the chain. Retailers can be more efficient in store management, restocking processes, and maintaining adequate supply with fewer shortages or excesses, thereby resulting in cost savings, increased revenue, and greater customer satisfaction through the availability of desired products.

Comparisons with traditional statistical techniques showed better sales forecasting, as demonstrated by higher accuracy than previous models, the flexibility to handle a greater number of data variables and the capacity to process large data volumes. Studies showed that complex analysis, such as the impact of promotions, are best handled by Machine Learning solutions.

The most often mentioned business segments are fashion, especially what is known as fast-fashion, technology consumer products, general retail, short shelf-life foods, and food & beverage. Some sector-specific business challenges addressed were the need for more frequent forecasts, prediction for innovative products with no sales history and the reduction of food losses by expiration date, which may contribute to sustainability in the fresh food sector.

Due to the increasing digitalization of the retail sector, future research could explore Deep Learning capabilities to handle different type of data such as images, data from Internet of Things (IoT) sensors and consumer behavior information, enabling better demand predictions and even decisions in real time that could affect the entire supply chain.

One concern regarding adopting Machine Learning for demand prediction could be the wide variety of algorithms available, thereby making the choice for the best alternative difficult. New research on real implementation cases and adopted techniques could help with that issue.

Thus, this study contributes to the identification of the Machine Learning benefits and characteristics, applied in improving demand forecasting accuracy in the FCMG industry, which is a key element of competitiveness.

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