ADVANCES IN BUSINESS AND MANAGEMENT FORECASTING

ADVANCES IN BUSINESS AND MANAGEMENT FORECASTING

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ADVANCES IN BUSINESS AND MANAGEMENT
FORECASTING VOLUME 13

ADVANCES IN BUSINESS AND MANAGEMENT FORECASTING

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Howard House, Wagon Lane, Bingley BD16 1WA, UK

First edition 2019

British Library Cataloguing in Publication Data
A catalogue record for this book is available from the British Library

ISBN: 978-1-78754-290-7 (Print)
ISBN: 978-1-78754-289-1 (Online)
ISBN: 978-1-78754-291-4 (Epub)

ISSN: 1477-4070 (Series)

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SECTION A
MARKETING, SALES, AND SERVICE FORECASTING

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EXPLORING THE SUITABILITY OF SUPPORT VECTOR REGRESSION AND RADIAL BASIS FUNCTION APPROXIMATION TO FORECAST SALES OF FORTUNE 500 COMPANIES

Vivian M. Evangelista and Rommel G. Regis

ABSTRACT

Machine learning methods have recently gained attention in business applications. We will explore the suitability of machine learning methods, particularly support vector regression (SVR) and radial basis function (RBF) approximation, in forecasting company sales. We compare the one-step-ahead forecast accuracy of these machine learning methods with traditional statistical forecasting techniques such as moving average (MA), exponential smoothing, and linear and quadratic trend regression on quarterly sales data of 43 Fortune 500 companies. Moreover, we implement an additive seasonal adjustment procedure on the quarterly sales data of 28 of the Fortune 500 companies whose time series exhibited seasonality, referred to as the seasonal group. Furthermore, we prove a mathematical property of this seasonal adjustment procedure that is useful in interpreting the resulting time series model. Our results show that the Gaussian form of a moving RBF model, with or without seasonal adjustment, is a promising method for forecasting company sales. In particular, the moving RBF-Gaussian model with seasonal adjustment yields generally better mean absolute percentage error (MAPE) values than the other methods on the sales data of 28 companies in the seasonal group. In addition, it is competitive with single exponential smoothing

Advances in Business and Management Forecasting, Volume 13, 3–23

ISSN: 1477-4070/doi:10.1108/S1477-407020190000013006

and better than the other methods on the sales data of the other 15 companies in the non-seasonal group.

Keywords: Sales forecasting; time series; seasonal adjustment; machine learning; support vector regression; radial basis function

INTRODUCTION

Sales forecasting is very important for many companies as it determines production planning, inventory, and many other aspects of operations (Beheshti-Kashi, Karimi, Thoben, Lütjen, & Teucke, 2015). As such, companies are always looking for ways to obtain more accurate sales forecasts (Beheshti-Kashi et al., 2015). Statistical methods, such as exponential smoothing, Holt-Winters model, trend regression models, ARIMA, and Box & Jenkins model, have traditionally been used for sales forecasting (Beheshti-Kashi et al., 2015).

More recently, machine learning methods such as neural networks, support vector regression (SVR), and radial basis functions (RBFs) have been proposed as an alternative to statistical methods in sales forecasting (Chen & Kuo, 2017; Dwivedi, Niranjan, & Sahu, 2013; Guo, Wong, & Li, 2013; Kuo, Hu, & Chen, 2009; Loureiro, Miguéis, & da Silva, 2018; Lu, 2014; Lu, Lee, & Lian, 2012; Xia, Zhang, Weng, & Ye, 2012). However, as Makridakis, Spiliotis, and Assimakopoulos (2018) observed in their survey paper on forecasting in general, there is limited evidence of their performance and accuracy relative to statistical methods. This is likewise true in our review of the sales forecasting literature. Majority of the studies on sales forecasting simply compare machine learning methods with other machine learning methods, while providing limited comparisons to only one or two statistical methods (Chen & Kuo, 2017; Dwivedi et al., 2013; Guo et al., 2013; Kuo et al., 2009; Loureiro et al., 2018; Lu et al., 2012; Xia et al., 2012). This chapter aims to explore the suitability of machine learning methods, particularly SVR and RBF approximation, in sales forecasting and, in addition, provide further empirical comparison of machine learning methods with statistical methods.

In addition, the results of forecasting studies have limited statistical significance because they are based on a single or just a few time series data (Makridakis et al., 2018). Similarly, most of the sales forecasting literature apply machine learning methods to sales data from a single company or a few companies from a single industry (Arunraj & Ahrens, 2015; Doganis, Alexandridis, Patrinos, & Sarimveis, 2006; Guo et al., 2013; Kuo et al., 2009; Loureiro et al., 2018; Lu, 2014; Makridakis et al., 2018; Xia et al., 2012). As such, there is a need to apply machine learning methods to larger and more diverse datasets in order to assess their effectiveness (Makridakis et al., 2018). Thus, in this chapter, we compare forecasting methods using a larger number and more diverse dataset consisting of quarterly sales data from 43 Fortune 500 companies, which come from various industries.

This chapter is organized as follows. The "Review of Literature" section covers sales forecasting. The "Some Machine Learning Methods for Forecasting" section presents two popular machine learning methods that can be used for forecasting, namely SVR and RBF approximation. Many quarterly sales datasets exhibit seasonality, so the "Seasonal Adjustment" section presents an additive seasonal adjustment procedure that can be used before a forecasting method is used. The machine learning methods are then evaluated empirically and compared with some traditional statistical methods in the "Computational Results" section. Finally, the "Summary and Conclusion" section presents a summary and some conclusions.

REVIEW OF LITERATURE

Statistical methods, such as exponential smoothing, Holt-Winters model, trend regression models, ARIMA, and Box & Jenkins model, have traditionally been used for sales forecasting (Beheshti-Kashi et al., 2015). Lu et al. (2012) used multivariate adaptive regression splines (MARS) to forecast sales for computer wholesalers and compared these with artificial neural networks (ANNs). They found that MARS performs better than several neural network methods in forecasting computer sales. Arunraj and Ahrens (2015) developed a hybrid seasonal autoregressive integrated moving average with external variables (SARIMAX) model to forecast the daily sales of banana from a discount retail store in Lower Bavaria, Germany. They used SARIMAX with multiple linear regression (SARIMA-MLR) and a hybrid SARIMA and quantile regression (SARIMA-QR).

Recently, artificial intelligence and machine learning methods, as well as hybrid models, have gained attention as tools for sales forecasting (Beheshti-Kashi et al., 2015; Makridakis et al., 2018). Neural networks and extreme learning machine models are among the machine learning methods that have been proposed for sales forecasting. For example, Loureiro et al. (2018) used a deep learning approach to forecast sales for a fashion retail company. Their model included a large set of variables such as products' physical characteristics and expert opinion. Results were then compared with decision trees, random forest, SVR, ANNs, and linear regression. Dwivedi et al. (2013) proposed an intelligent system, Adaptive Neuro Fuzzy Inference System (ANFIS), and compared this with ANN and linear regression to forecast monthly sales in the automobile industry. Guo et al. (2013) also proposed a multivariate intelligent decision-making model to forecast sales for a fashion retail company in Hong Kong and Mainland China.

RBF and SVR, as well as hybrid models, have also been proposed as tools for sales forecasting. For example, Chen and Kuo (2017) proposed a hybrid of a genetic algorithm and an artificial immune system (HGAI) algorithm with RBF neural network to forecast sales for industrial personal computers. The HGAI algorithm performed better than the Box–Jenkins models. Lu (2014) proposed a hybrid model combining variable selection method and SVR to forecast sales for a computer product retailer. Kuo et al. (2009) proposed a hybrid evolutionary algorithm-based radial basis function neural network (RBFnn) to forecast sales of papaya milk. To address non-linear time series sales forecasting, Doganis et al. (2006) combined two artificial intelligence technologies, namely the RBF neural network architecture and a specially designed genetic algorithm (GA) to forecast sales data of fresh milk for a major manufacturer of dairy products.

As Makridakis et al. (2018) observed for forecasting in general, the above studies on sales forecasting may lack statistical significance since most of them apply machine learning methods on sales data from a single company or a few companies from a single industry (Arunraj & Ahrens, 2015; Doganis et al., 2006; Guo et al., 2013; Kuo et al., 2009; Loureiro et al., 2018; Lu, 2014; Makridakis et al., 2018; Xia et al., 2012). Hence, in this chapter, we are using a larger number and more diverse dataset consisting of quarterly sales data from 43 companies listed in the Fortune 500.

In the above studies, machine learning methods have been proposed as an alternative to statistical methods in sales forecasting (Chen & Kuo, 2017; Dwivedi et al., 2013; Guo et al., 2013; Kuo et al., 2009; Loureiro et al., 2018; Lu et al., 2012; Lu, 2014; Xia et al., 2012). However, there is limited evidence of the performance and accuracy of machine learning methods relative to statistical methods (Makridakis et al., 2018). Majority of the above studies on sales forecasting simply compare machine learning methods with other machine learning methods, while providing limited comparisons to only one or two statistical methods (Chen & Kuo, 2017; Dwivedi et al., 2013; Guo et al., 2013; Kuo et al., 2009; Loureiro et al., 2018; Lu et al., 2012; Xia et al., 2012). Thus, this chapter aims to explore the suitability of machine learning methods in sales forecasting and, in addition, provide further empirical comparison of these methods with statistical methods.

SOME MACHINE LEARNING METHODS FOR FORECASTING

Support Vector Regression

One of the machine learning methods that we will use to forecast sales is SVR (Smola & Schölkopf, 2004; Vapnik, 2000). In particular, we use the ϵ-SVR model with a linear kernel. Suppose we wish to fit an ϵ-SVR model using n data points from our time series $(t_1, z_1), (t_2, z_2), ..., (t_n, z_n)$, where $t_1 < t_2 < ... < t_n$. The goal is to find a function $f(t)$ that approximates the time series and whose deviation from each $z_j, j = 1, ..., n$, is at most ϵ and that is as flat as possible.

Consider the linear function $f(t) = wt + b$. One way to insure flatness is to minimize w^2, and this is formulated as the following convex optimization problem:

$$\min_w \frac{1}{2} w^2$$

subject to

$$z_j - wt - b \leq \epsilon, \; j = 1, \; \ldots, \; n$$

$$wt + b - \; z_j \leq \epsilon, \; j = 1, \; \ldots, \; n$$

Here, the assumption is that there exists a linear function $f(t) = wt + b$ that approximates all pairs (t_j, z_j) with precision ϵ. However, this is sometimes not the case, so we allow for some errors. That is, we introduce slack variables ξ_j and $\xi_j{}^*$ to deal with the possibly infeasible constraints. This results in the following formulation Vapnik (2000):

$$\min_w \frac{1}{2} w^2 + C \sum_{j=1}^{n} (\xi_j + \xi_j^*)$$

subject to

$$\begin{aligned} z_j - wt - b \; &\leq \epsilon + \; \xi_j, \quad j = 1, \; . \; . \; ., \; n \\ wt + b - \; z_j \; &\leq \epsilon + \; \xi_j{}^*, \quad j = 1, \; . \; . \; ., \; n \\ \xi_j, \; \xi_j{}^* &\geq 0, \quad j = 1, \; . \; . \; ., \; n \end{aligned}$$

Here, the constant C quantifies the trade-off between the flatness of $f(t)$ and the penalty on the observations that lie outside the ε margin, and it is used to prevent overfitting.

The above optimization problem is typically solved using the dual formulation involving non-negative multipliers α_i and α_i^* for each observation (t_i, z_i):

$$\min_{\alpha_i, \, \alpha_i^*} \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) t_i t_j + \epsilon \sum_{i=1}^{n} \left(\alpha_i + \alpha_i^*\right) - \sum_{i=1}^{n} z_i \left(\alpha_i - \alpha_i^*\right)$$

subject to

$$\sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) = 0$$

$$0 \leq \alpha_i, \alpha_i^* \leq C, \; i = 1, . \; . \; ., n$$

Now the ϵ-SVR model used for prediction is given by:

$$f(t) = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) t_i t + b$$

For one-step-ahead forecasts, it is possible to use all available previous sales data (prior to the current period) to train the above ϵ-SVR model. However, better performance is usually obtained when training the ϵ-SVR model over data points that are closest to the current time period similar to what is done in a moving average (MA) or moving linear regression (MLR) model (Batyrshin, Herrera-Avelar, Sheremetov, & Panova, 2007; Lim & Shin, 2005; Liu et al., 2015). That is, we implement a moving ϵ-SVR (or simply moving SVR) where the model is fit over a fixed number of consecutive time periods prior to the current time period where we wish to forecast sales.

Radial Basis Function Interpolation

The other machine learning method we will use for forecasting sales is RBF interpolation. This function approximation technique is widely used in surrogate-based optimization (e.g., Gutmann (2001), Regis (2011)) and derivative-free trust region methods (e.g., Regis and Wild (2017)). Here, we use the RBF model from Powell (1992), which is an interpolating model, and hence, guaranteed to yield zero training error under certain mathematical conditions. Our RBF model is similar to an RBF network (Park & Sandberg, 1991) where each data point corresponds to a center point for a neuron in the network architecture. However, unlike a regular RBF network, our RBF model includes a linear polynomial tail.

Suppose we wish to fit this RBF model using n data points from our time series $(t_1, z_1), (t_2, z_2), ..., (t_n, z_n)$, where $t_1 < t_2 < \ldots < t_n$. This modeling technique uses an interpolating function of the form:

$$\sum_{i=1}^{n} \lambda_i \phi(|t - t_i|) + p(t), t \in \mathbb{R},$$

where $\lambda_i \in \mathbb{R}$, for $i = 1, ..., n, p(t) = c_0 + c_1 t$ is a linear polynomial, and ϕ can take multiple forms, including:

- cubic: $\phi(r) = r^3$;
- thin plate spline: $\phi(r) = r^2 \log r$;
- multiquadric: $\phi(r) = \sqrt{r^2 + \gamma^2}$ where γ is a parameter; or
- Gaussian: $\phi(r) = \exp(-(r/\gamma)^2)$, where γ is a parameter.

In our numerical experiments, we use the multiquadric and Gaussian forms where the γ parameter (also called a *hyperparameter*) is obtained by the standard leave-one-out cross-validation (LOOCV) technique.

To fit the above RBF model, define the matrix $\Phi \in \mathbb{R}^{n \times n}$ by: $\Phi_{ij} := \phi(\|t_i - t_j\|)$, $i, j = 1, ..., n$. Also, define the matrix $P \in \mathbb{R}^{n \times 2}$ so that its i^{th} row is $[1, t_i]$. Now, the RBF model that interpolates the points $(t_1, z_1), (t_2, z_2), ..., (t_n, z_n)$ is obtained by solving the system:

$$\begin{pmatrix} \Phi & P \\ P^T & 0_{2 \times 2} \end{pmatrix} \begin{pmatrix} \lambda \\ c \end{pmatrix} = \begin{pmatrix} Z \\ 0_2 \end{pmatrix}, \tag{1}$$