Advances in Manufacturing Technology XXX

The urgent need to keep pace with the accelerating globalization of manufacturing in the 21st century has produced rapid advancements in manufacturing technology, research and expertise.

This book presents the proceedings of the 14th International Conference on Manufacturing Research (ICMR 2016), entitled Advances in Manufacturing Technology XXX. The conference also incorporated the 31st National Conference on Manufacturing Research, and was held at Loughborough University, Loughborough, UK, in September 2016. The ICMR conference is renowned as a friendly and inclusive environment which brings together a broad community of researchers who share the common goal of developing and managing the technologies and operations key to sustaining the success of manufacturing businesses.

The proceedings is divided into 14 sections, including: Manufacturing Processes; Additive Manufacturing; Manufacturing Materials; Advanced Manufacturing Technology; Product Design and Development, as well as many other aspects of manufacturing management and innovation. It contains 92 papers, which represents an acceptance rate of 75%.

With its comprehensive overview of current developments, this book will be of interest to all those involved in manufacturing today.
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Volume 3
Recently published in this series:


ISSN 2352-751X (print)
ISSN 2352-7528 (online)
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Sales Forecasting in Retail Industry Based on Dynamic Regression Models

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Abstract. Sales forecasts gained more importance in the retail industry with the increasing of promotional activity, not only because of the considerable portion of products under promotion but also due to the existence of promotional activities, which boost product sales and make forecasts more difficult to obtain. This study is performed with real data from a Portuguese consumer goods retail company, from January 2012 until April 2015. To achieve the purpose of the study, dynamic regression is used based on information of the focal product and its competitors, with seasonality modelled using Fourier terms. The selection of variables to be included in the model is done based on the lowest value of AIC in the train period. The forecasts are obtained for a test period of 30 weeks. The forecasting models overall performance is analyzed for the full period and for the periods with and without promotions. The results show that our proposed dynamic regression models with price and promotional information of the focal product generate substantially more accurate forecasts than pure time series models for all periods studied.

Keywords. Retailing, machine learning, forecasting, time series, promotions, dynamic regression.

1. Introduction

The effectiveness of sales forecasting is gaining increasingly importance in the retail sector. With retailers continuously trying to minimize stock and increase customer satisfaction it helps to reduce inventory investment costs and to improve logistics operations. A bad sales forecast may cause losses to the retailer, either by rupture or by excess of stock. Recent studies [1] indicate that in the case of rupture of stock of a product consumers decide to change to another store, not purchasing a replacement product, as initially thought. The promotional activity has increased sharply in recent years leading usually to a considerable increase of sales in the periods in which products are under promotional actions [2]. The efficacy of simple forecast methods, often used in the retail sector, is reduced when applied to periods when there are promotions [3]. The aim of this work is to incorporate promotions on econometric models to improve sales forecasting, especially in periods of promotional campaigns, and measure the impact of promotions on sales. This analysis is of particular importance because in recent literature models that integrate the promotional activity of...
food retail companies are relatively scarce [4-6]. We applied this approach to sales data from a Portuguese retailer trying to analyze which models perform better in this promotional context. The rest of the paper is organized as follows. Section 2 presents the case study and relevant descriptive statistics of data. Section 3 identifies the methodology used in the work. The results are presented and analyzed on Section 4. Finally, Section 5 points the main conclusions of this work.

2. Data

This study used information from daily sales of a single store of a Portuguese retailer, from January 2012 until April 2015. The option for a single store is due to the purpose of analyzing the influence of competing products (available in the store) on each product. This store had 24316 products of the following areas: groceries (6217), beverages (1995), not specialized products (3682), specialized products (6302), personal products (3606), and cleaning products (2514). From these products, a sample of 968 products that had sales on every week (173 weeks) was selected. The sample was further reduced to 15 categories representing the six areas mentioned above totaling 100 SKUs (Stock Keeping Unit). Table 1 presents some descriptive statistics of these 15 categories (ordered by the average percentage of promotion weeks). The lift was calculated as the percentage increase of the average weekly sales on weeks with promotions compared with the average weekly sales on weeks without promotions. The sales time series of different products have different types of behavior including seasonality (left side of Figure 1) and negative (right side of Figure 1) and positive trends. Note that in Figure 1 the product price is represented by a red line, the sales by a black line and promotions in sales are marked with a blue ball.

### Table 1. Descriptive statistics of the sample.

<table>
<thead>
<tr>
<th>Category</th>
<th>No. of SKUs</th>
<th>Promo weeks (%)</th>
<th>Lift (%)</th>
<th>Category</th>
<th>No. of SKUs</th>
<th>Promo weeks (%)</th>
<th>Lift (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pork fresh</td>
<td>11</td>
<td>24.43</td>
<td>163</td>
<td>Cereals</td>
<td>12</td>
<td>6.21</td>
<td>461</td>
</tr>
<tr>
<td>Cola</td>
<td>8</td>
<td>16.11</td>
<td>182</td>
<td>Ice-creams</td>
<td>13</td>
<td>5.56</td>
<td>303</td>
</tr>
<tr>
<td>Beer</td>
<td>10</td>
<td>12.43</td>
<td>271</td>
<td>Toilet paper</td>
<td>5</td>
<td>5.2</td>
<td>158</td>
</tr>
<tr>
<td>Sugar</td>
<td>2</td>
<td>10.12</td>
<td>200</td>
<td>Wash</td>
<td>6</td>
<td>5.01</td>
<td>269</td>
</tr>
<tr>
<td>Cooking oil</td>
<td>5</td>
<td>8.78</td>
<td>453</td>
<td>UHT milk</td>
<td>5</td>
<td>4.76</td>
<td>166</td>
</tr>
<tr>
<td>Tuna</td>
<td>5</td>
<td>7.17</td>
<td>450</td>
<td>Rice</td>
<td>8</td>
<td>3.97</td>
<td>249</td>
</tr>
<tr>
<td>Deodorant</td>
<td>4</td>
<td>6.94</td>
<td>368</td>
<td>Laundry</td>
<td>2</td>
<td>1.44</td>
<td>103</td>
</tr>
<tr>
<td>Olive oil</td>
<td>4</td>
<td>6.65</td>
<td>648</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3. Methodology

This section presents the models used in the sales forecasting. We used a more advanced approach based on dynamic regression, which was compared with a pure time series forecasting model, in this case ARIMA (Autoregressive Integrated Moving Average), where the only information used was the sales history of the focal product. The ARIMA model (1,ARIMA) is given by:

\[
(1 - \phi_1 B - \cdots - \phi_p B^p)(1 - \theta_1 B - \cdots - \theta_q B^q)Y_t = c + (1 - B)^d(1 - B^s)^d \epsilon_t,
\]

where \((1 - B)^d(1 - B^s)^d \epsilon_t\) represents a stationary series after being differentiated \(d\) and seasonally differentiated \(d\) times, \(\phi_1, \ldots, \phi_p\) and \(\theta_1, \ldots, \theta_q\) are respectively the nonseasonal and seasonal autoregressive parameters, \(\theta_1, \ldots, \theta_q\) and \(\theta_1, \ldots, \theta_q\) are respectively the nonseasonal and seasonal moving average parameters and \(\epsilon_t\) is the error term assumed i.i.d. (0, \sigma^2). In order to incorporate more than one seasonal pattern, which is common in the retail sector, an evolution of the ARIMA model was considered (3,ARIMA Fourier)

\[
Y_t = \beta_0 + \sum_{j=1}^{n} [\alpha_j \sin \left( \frac{2\pi t}{\text{freq}} \right) + \beta_j \cos \left( \frac{2\pi t}{\text{freq}} \right)] + n_t,
\]

where the sin and cos terms, usual known as the Fourier terms, incorporate seasonality and \(n_t\) the ARIMA structure. The first two dynamic regression models (1 and 2) only use variables of the own product to explain its sales (5, OWN). Those variables are the price, the number of week days with promotion, calendar events and the last week of the month. Lags of two time instants were also considered for the first two co-variables

\[
Y_t = \beta_0 + \beta_1 \text{Price}_{t-1} + \beta_2 \text{Price}_{t-2} + \beta_3 \text{PromotionDays}_{t-1} + \beta_4 \text{PromotionDays}_{t-2} + \beta_5 \text{CalendarEvents}_{t-1} + n_t.
\]

An evolution of these models also incorporates co-variables from competitive products from the same category (6, OWN intra). These variables are selected through Principle Component Analysis (PCA) done over the price, the number of week days with promotion and the lags of two time instants of these two variables, from the competitive products. This model is given by

\[
Y_t = \beta_0 + \beta_1 x_{t-1} + \cdots + \beta_f \text{PCA(Price}_{m-1})+\beta_g \text{PCA (PromotionDays}_{m-1}) + n_t.
\]

For these last two dynamic regression models (3 and 4), the equivalent ones obtained by incorporating the Fourier terms were also considered (9, Own Fourier and 10, Own intra Fourier). For all the previous six models, we also consider the equivalent ones.
4. Results and discussion

This section analyzes the results obtained using the twelve models presented in Section 3. For the models performance evaluation a test period of 30 weeks was considered and one-step forecasts with fixed origin were obtained. Table 2 shows the results of the error measures obtained by all models splitted into three periods: the full period and the periods with and without promotion. Bold values show the best result for each period.

<table>
<thead>
<tr>
<th>Model</th>
<th>Period</th>
<th>RMSE</th>
<th>MAE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>111.6</td>
<td>79.43</td>
<td>102.8</td>
</tr>
<tr>
<td>1.Arima</td>
<td>Promotion</td>
<td>224.4</td>
<td>196.63</td>
<td>74.34</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>78.78</td>
<td>60.46</td>
<td>112.56</td>
</tr>
<tr>
<td>2.Arima log</td>
<td>Promotion</td>
<td>110.88</td>
<td>71.39</td>
<td>68.11</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>245.79</td>
<td>219.12</td>
<td>62.61</td>
</tr>
<tr>
<td>3.Arima Fourier</td>
<td>Promotion</td>
<td>65.73</td>
<td>46.75</td>
<td>71.45</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>218.42</td>
<td>193.11</td>
<td>67.47</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>107.90</td>
<td>79.72</td>
<td>79.86</td>
</tr>
<tr>
<td>4.Arima Fourier log</td>
<td>Promotion</td>
<td>218.42</td>
<td>193.11</td>
<td>67.47</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>73.94</td>
<td>63.84</td>
<td>85.92</td>
</tr>
<tr>
<td>5.Own</td>
<td>Promotion</td>
<td>232.80</td>
<td>205.18</td>
<td>58.51</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>63.77</td>
<td>53.05</td>
<td>51.52</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>106.24</td>
<td>72.05</td>
<td>50.92</td>
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<tr>
<td>6.Own intra</td>
<td>Promotion</td>
<td>81.82</td>
<td>57.24</td>
<td>83.10</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>151.48</td>
<td>127.80</td>
<td>144.53</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>63.95</td>
<td>48.97</td>
<td>75.02</td>
</tr>
<tr>
<td>7.Own log</td>
<td>Promotion</td>
<td>91.69</td>
<td>65.89</td>
<td>118.29</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>165.04</td>
<td>140.19</td>
<td>151.40</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>76.73</td>
<td>47.56</td>
<td>57.14</td>
</tr>
<tr>
<td>8.Own log intra</td>
<td>Promotion</td>
<td>136.01</td>
<td>113.44</td>
<td>57.83</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>49.86</td>
<td>37.34</td>
<td>52.24</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>90.38</td>
<td>58.71</td>
<td>58.62</td>
</tr>
<tr>
<td>9.Own Fourier</td>
<td>Promotion</td>
<td>132.80</td>
<td>109.65</td>
<td>129.11</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>60.79</td>
<td>49.13</td>
<td>61.64</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>82.56</td>
<td>60.29</td>
<td>68.5</td>
</tr>
<tr>
<td>10.Own Fourier intra</td>
<td>Promotion</td>
<td>90.16</td>
<td>65.16</td>
<td>108.42</td>
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<tr>
<td></td>
<td>Non-Promotion</td>
<td>400.24</td>
<td>380.67</td>
<td>1617.30</td>
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<td></td>
<td>All</td>
<td>71.79</td>
<td>55.75</td>
<td>104.85</td>
</tr>
<tr>
<td>11.Own Fourier log</td>
<td>Promotion</td>
<td>140.13</td>
<td>118.55</td>
<td>55.38</td>
</tr>
<tr>
<td></td>
<td>Non-Promotion</td>
<td>51.904</td>
<td>38.82</td>
<td>41.67</td>
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<tr>
<td></td>
<td>All</td>
<td>94.94</td>
<td>66.25</td>
<td>45.98</td>
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<tr>
<td>12.Own log Fourier intra</td>
<td>Promotion</td>
<td>368.56</td>
<td>344.24</td>
<td>1343.54</td>
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<td></td>
<td>Non-Promotion</td>
<td>58.72</td>
<td>42.88</td>
<td>50.06</td>
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</table>

These are the average errors for the 100 sample products. For the three periods considered the model with the best performance is always a dynamic regression model, which indicates that additional information besides the sales of the product itself can improve the forecast accuracy. However, the competitive information from the products of the same category of the focal product provided by the PCA (the intra models) does not improve the forecasting performance in any case, regardless of the error measure considered. In which concerns the RMSE and the MAE values the own log model forecasts are the most accurate for the full period and for the period without promotion. This indicates that the price and promotional information about the focal product is always important to improve the forecast accuracy of the model even for periods without promotion. Also concerning the RMSE and the MAE values the own Fourier model forecasts are the most accurate for the period with promotion which points that Fourier terms can be successfully used to model seasonality in dynamic regression. When considering the MAPE value the own log Fourier model forecasts are the most accurate for all the periods studied which reinforces the importance of the logarithm transformation applied to sales and price and the Fourier terms to additionally model multiple seasonality. It can also be observed that the RMSE and MAE values are always higher for the period with promotion which shows that sales with promotional actions at the product level in a particular store are difficult to forecast. The differences to periods without promotion is even higher in the pure models (1.Arima, 2.Arima log, 3.Arima Fourier, 4.Arima Fourier log) which indicates that the additional information besides the sales of the focal product always improve the forecast accuracy. Figures 2 and 3 show respectively RMSE, MAE and MAPE by category for each model for the full test period. It is clear from Figure 4 that all models have similar performance for categories with fewer promotions (11-15). However for categories with more promotions and higher lifts the dynamic regression models have much better performance than pure ones.

Figure 2. RMSE by category for all models.

Figure 3. MAE by category for all models.
S. Conclusions

Sales forecasting is a major challenge in retail industry particularly in the context of continuous promotional activity. In this work dynamic regression models based on price and promotional information of the focal product and its competitors, and Fourier terms to accommodate multiple seasonality, are used for sales forecasting. The forecasting models overall performance is analyzed for the full test period and for the periods with and without promotions. The results show that the dynamic regression models generate substantially more accurate forecasts than pure time series models for all periods studied.

Acknowledgements

Project "TECGrowth - Pervasive Intelligence, Enhancers and Proofs of Concept with Industrial Impact/NORTE-01-0145-FEDER-000020" is financed by the North Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, and the European Regional Development Fund (ERDF).

References


Evaluating the Forecasting Accuracy of Pure Time Series Models on Retail Data

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Abstract. Forecasting future sales is one of the most important issues that is beyond all strategic and planning decisions in effective operations of retail supply chains. For profitable retail businesses, accurate sales forecasting is crucial in organizing and planning purchasing, production, transportation and labor force. Retail sales series belong to a special type of time series that typically contain strong trend and seasonal patterns, presenting challenges in developing effective forecasting models. This paper compares the forecasting performance of state space models and ARIMA models. The forecasting performance is demonstrated through a case study of retail sales of five different categories of women footwear: Boots, Booties, Flats, Sandals and Shoes. An approach based on cross-validation is used to identify automatically appropriate state space and ARIMA models. The forecasting performance of these models is also compared by examining the out-of-sample forecasts. The results indicate that the overall out-of-sample forecasting performance of ARIMA models evaluated via RMSE, MAE and MAPE is better than state space models. The performance of both forecasting methodologies in producing forecast intervals was also evaluated and the results indicate that ARIMA produces slightly better coverage probabilities than state space models for the nominal 95% forecast intervals. For the nominal 80% forecast intervals the performance of state space models is slightly better.

Keywords. Pure time series models; forecasting accuracy; retailing; cross-validation

1 Introduction

Time series often exhibit strong trend and seasonal variations presenting challenges in developing effective forecasting models. How to effectively model time series in order to improve the quality of forecasts is still an outstanding question. State space and Autoregressive Integrated Moving Average (ARIMA) models are the two most widely used approaches to time series forecasting, and provide complementary methodologies to the problem. While exponential smoothing methods are based on a description of trend and seasonality in the data [1], ARIMA models aim to describe the autocorrelations in the data [2]. The ARIMA forecasting framework originally developed by Box et al. [3] involves an iterative three-stage process of model selection, parameter estimation and model checking. A statistical framework for exponential