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Statistical nonlinear analysis for reliable promotion decision-making

Cristina Soguero-Ruiz [a,*], Francisco Javier Gimeno-Blanes [b], Inmaculada Mora-Jiménez [a], María del Pilar Martínez-Ruiz [c], José Luis Rojo-Álvarez [a,d]

[a] Department of Signal Theory and Communications, Universidad Rey Juan Carlos, Fuenlabrada, Spain
[b] Department of Signal Theory and Communications, Universidad Miguel Hernández, Elche, Spain
[c] Area of Commercialization and Market Research, Universidad de Castilla La Mancha, Albacete, Spain
[d] Prometeo, Electric and Electronic Department, Universidad de las Fuerzas Armadas ESPE, Ecuador

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ABSTRACT

New economic conditions have led to innovations in retail industries, such as more dynamic retail approaches based on flexible strategies. We propose and compare different approaches incorporating nonlinear methods for promotional decision-making using retail aggregated data registered at the point of the sale. Specifically, this paper describes a reliable quantification tool as an effective information system leveraged on recent and historical data that provides managers with an operative vision. Furthermore, a new set of indicators are proposed to evaluate the reliability and stability of the data model in the multidimensional feature space by using nonparametric resampling techniques. This allows the user to make a clearer comparison among linear, nonlinear, static, and dynamic data models, and to identify the uncertainty of different feature space regions, for example, corresponding to the most frequent deal features. This methodology allows retailers to use aggregated data in suitable conditions that will result in acceptable confidence intervals. To test the proposed methodology, we used a database containing the sales history of representative products registered by a Spanish retail chain. The results indicate that: (1) the deal effect curve analysis and the time series linear model do not provide enough expressive capacity, and (2) nonlinear promotional models more accurately follow the actual sales pattern obtained in response to the implemented sales promotions. The quarterly temporal analysis conducted enabled the authors to identify long-term changes in the dynamics of the model for several products, especially during the early stage of most recent economic crisis, consistent with the information provided by the reliability indices in terms of the feature space. We conclude that the proposed method provides a reliable operative tool for decision support, allowing retailers to alter their strategies to accommodate consumer behavior.

1. Introduction

Traditionally, scholars have argued that customers tend to adapt their buying behavior during adversity and economic downturn [1,2]. This effect has been evidenced during the 2008 economic crisis, with a significant effect in the consumer goods industry. As a consequence, there has been a substantial change in commercial and marketing strategies to adapt to the consumer's behavior. In particular, retailers have reallocated commercial efforts from other marketing instruments toward increasing the direct price-deals, as a key tool to attract consumer attention. However, despite the extensive literature devoted to finding accurate promotional models in terms of pricing effects [3,4], no consensus has been reached on whether the promotional model yields better margins or benefits for either at retailers or manufacturers.

Researchers have proposed several hypotheses for promotional modeling. In particular, the deal effect curve (DEC) [3,5–7] presents a static model for shaping the price-demand elasticity, whereas conventional time series (TS) analysis and the well-known Box–Jenkins methodology add a dynamic approach to retail sales forecasting analysis [8,9]. However, linear or static models can only loosely explain complex interactions among products and sales. Scholars have extensively studied nonlinear machine learning approaches in attempt to develop methods that better follow the human behavior, for example, artificial neural networks and support vector machines [10–13].

From a retail manager's viewpoint, sales forecasting is essential not only to set the right pricing for an individual product [14] but also to define the promotional structure that maximizes benefits within a category as a whole [15]. The same rational applies

* Corresponding author.
E-mail address: cristina.soguero@urjc.es (C. Soguero-Ruiz).

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to individual customer behavior with regard to the total impact of a certain promotional strategy [15–19]. As a consequence, promotional models built on market-level data are considered as the best suited to describe the market behavior. Executive decisions are mainly based on this kind of information, especially for those retail chains accounting for a significant market share. Although it is evident that aggregated retail sales forecasting could potentially improve store sales prognosis [10], nevertheless, many authors have warned against the biasing risk during the aggregation process [20].

For a decision-making tool to be an efficient instrument for promotional retail management, it must be designed to be operative and reliable. To be operative, the retail management tool should be able to handle data models that: (1) can be better described TS dynamics, static paradigms, or even by both; and (2) can be better represented by linear or by nonlinear dynamics. To be reliable, the tool must be more robust when working with aggregated data than working with store level data, but also must ensure an adequate aggregation process. In addition, the tool should provide a simple way for the researcher to visualize its statistical properties in the feature space.

In this paper, we propose an operative and reliable analysis tool for promotional decision making based on retail aggregated data. The main contribution from a digital signal and data processing viewpoint is the proposal of a new set of indicators for evaluating the reliability and stability of a data model in terms of multidimensional feature space rather than a single merit figure for the model (e.g., the mean squared error). These indicators allow the user to identify the uncertainty of different feature space regions, for example, unusual promotion conditions. Using the statistical processing available, we can study the performance of different algorithms and different feature spaces. The use of aggregate data in suitable conditions yields moderate and acceptable confidence intervals in these feature spaces.

2. Background

In this section, we present a brief marketing literature review. We note relevant data aggregation precedents and summarize conventional static, dynamic, and learning-based nonlinear promotional sales models.

Data aggregation at chain level. Previous research has considered three levels of aggregation: store, chain, and market levels. At the *store-level*, data can characterize consumers' behavior (by considering buying habits such as products, and units to evaluate loyalty and churn rates), as well as brand or product sales (by aggregating sales). Household information for each product category can also be used to analyze the individual brand sales behavior and pricing effects can also be analyzed [21]. Further aggregation at *chain-level*, or even at *market-level*, integrates the information for brands or categories to provide accumulative effects [22].

According to published research analysis, each level of aggregation may introduce bias, which depends to a great extent on the aggregation method, thus limiting the generalization capabilities of the forecasting model. In [23], the authors analyze bias effect by comparing sales estimates at both store and chain level, and conclude that bias may be related to heterogeneous marketing strategies within stores. The authors also note that relevant information, such as marketing strategies followed by competitive retailers, is not reported or registered through scanner datasets. Other studies use different approaches to address model heterogeneity and bias among stores. For example, [24] proposes a random coefficient demand model to avoid bias when data aggregated across stores with heterogeneous promotional activity are considered. However, bias may not be fully removed due to substitutive effects, competing products and heterogeneity; therefore, in the current study, we followed the methodology in [25], in which bias can be mitigated by aggregating data across stores with homogeneous marketing activities.

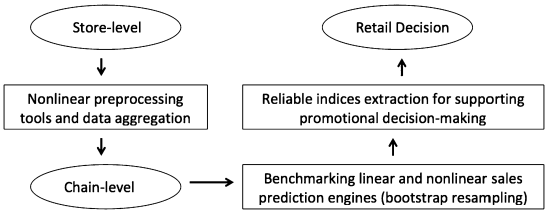

Fig. 1. Schematic of the proposed chain-level analysis.

DEC promotional modeling. The relationship between sales and temporary price discounts can be shown in the DEC representation [26], which accounts for the static sales elasticity and pricing promotion effects. The DEC shape provides information about different phenomena, such as direct discount effects, cross-effects generated from other products promotions, and concurrent sales initiatives on different promotional media [5]. Direct discount evaluation is often the first DEC analysis for any product, even though exogenous variables effects must always be considered because products do not exist in isolated markets. For a more detailed promotional sales model development, additional information must be incorporated to the DEC analysis. Therefore, research has proposed such modeling techniques as linear and nonlinear regression [27,26], to provide a more comprehensive description of the DEC. Furthermore, complex DEC shapes and cross-effects have been better represented with nonlinear statistical learning methods [5,28–31].

TS for promotional modeling. Promotional activities typically exhibit a strong temporal dependence, which suggests that certain models taking into account temporal variations could yield better results than static DEC. In this setting, the statistically well-founded TS analysis, has received a great deal of attention in the last decade of the twenty-first century, due to the vast amount of data available from electronic records and media (e.g., scanner data), which allows both the cross-sectional and longitudinal analyses [32]. Researchers have used TS techniques for forecasting marketing variables and for evaluating specific situations [33]. New tools based on TS have proliferated in recent years to support general decision-making and especially in marketing activities [32]. For example, autoregressive moving-average (ARMA) modeling provides a well-developed general framework to analyze time series. It can be further extended to take into account exogenous variables (so-called ARMAx models) to improve their predictive capabilities. A multivariate version of ARMA models, the vector ARMA, allows adjusting models in which the dependent variable can be explained by multiple TS [33].

Statistical learning for promotional modeling. Other researchers have proposed nonlinear statistical learning algorithms, including such classic nonparametric methods as k nearest neighbors (k-NN) and kernel estimators [34], as well as the new learning techniques such as neural networks and support vector machines [12,13,35–38]. It is worthwhile to note that nonlinearity, nonnormal errors, and heteroscedasticity are automatically harmonized by these kinds of methods. Although it is not always explicit, a significant part of the promotional marketing analysis literature suggests that nonlinear methods can often provide better models for promotional dynamics.

3. Proposed chain level analysis

In line with the research presented in the preceding section, we propose a three stages chain-level analysis as shown in Fig. 1. First, we use a signal preprocessing method to aggregate data