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Improved market segmentation by fuzzifying crisp clusters: A case study of the energy market in Spain

Mònica Casabayó [a,*], Núria Agell [b], Germán Sánchez-Hernández [b]

[a] Department of Marketing Management – ESADE-URL, Spain
[b] Department of Information Systems Management – ESADE-URL, Spain

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ABSTRACT

This paper provides an innovative segmentation approach stemming from the combination of cluster analyses and fuzzy learning techniques. Our research provides a real case solution in the Spanish energy market to respond to the increasing number of requests from industry managers to be able to interpret ambiguous market information as realistically as possible. The learning stage is based on the segments created from a non-hierarchical cluster analysis. This results in fuzzy segmentation which permits patterns to be assigned to more than one segment. This in turn reveals that "fuzzifying" an excluding attitudinal segmentation offers more interpretable and acceptable results for managers. Our results demonstrate that 30% of the individuals show plural patterns of behaviour because they have a significant degree of adequacy to more than one segment. In such a rational market, this fact enables sales forces to develop more precise approaches to capture new customers and/or retain existing ones.

1. Introduction

Market segmentation is a core marketing concept that is conceptually simple to define and understand but inherently difficult to apply (Yankelovich & Meer, 2006; Liu, Kiang, & Brusco, 2012). Both the managers and researchers in the field are focused on the usage and development of the segmentation approaches and segmentation techniques (Hiziroglu, 2013) that help them to better understand their market, not only to attract new customers but also to keep and satisfy the existing ones.

Following Smith's definition of the market segmentation concept (Smith, 1956), that recognised the existence of heterogeneity in the demand for goods and services, market segmentation has become a core concept in marketing theory and practice. Market segmentation does not have a unique accepted definition. Despite the fact that the essence of grouping individuals is unquestionable, the concept of market segmentation itself has been understood in different ways. Frank, Massey, and Wind (1972) and Assael and Roscoe (1976) were followers of Smith's conceptualization of market segmentation. Another manner to perceive market segmentation is to identify homogeneous subgroups in a heterogeneous market (Johnson, 1971; Kotler, 2000). Moreover, there is a line of research focused on identifying and measuring a list of criteria that must be fulfilled for effective segmentation (Baker, 1988; Loudon & Della Bitta, 1993; Wedel & Kamakura, 2002). Independently of its meaning, it is important to note that segments are not physical entities that naturally co-exist in the marketplace; they are defined by researchers and practitioners to improve their ability to capture and serve their customers as best as possible (Kotler, 1989). A double connotation of the concept of segmentation is found in the literature: segmentation as a strategy and segmentation as a technique (Luque, 2000). From the technique point of view, although classifying customers into groups might seem quite simple, two crucial considerations arise when building a segmentation approach. Firstly, the selection of the variables. In the marketing literature, several segmentation variables can be found such as geographic, demographic, firmographic, behavioural, situational, attitudinal, and product specific variables (Hiziroglu, 2013). In fact, the choice of these criteria may lead to differing segments. The same often occurs when choosing the segmentation technique.

Boosted by the increasingly vast availability of consumer demographic, attitudinal, and behavioural data, recent research indicates a tendency towards the use of sophisticated techniques in different types of marketing problems, particularly in segmentation (Liao, 2005), although this tendency is still at an early stage (Hiziroglu, 2013).

Following Flach's (2001) declaration that when analysing the state of the art in machine learning there is a clear trend in

* Corresponding author at: Avda. Pedralbes, 60–62., 08034 Barcelona, Spain.
E-mail addresses: monica.casabayo@esade.edu (M. Casabayó), nuria.agell@esade.edu (N. Agell), german.sanchez@esade.edu (G. Sánchez-Hernández).
URL: http://www.esade.edu/research-webs/grec (M. Casabayó).

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research that combines approaches that were previously considered separate, this paper aims to extend the literature with an applied segmentation marketing model based on the combination of two classification techniques: a statistical cluster analysis and an AI fuzzy learning technique. To the best of our knowledge, this is the first study in a market segmentation context that fuzzifies crisp clusters to obtain a better and more realistic understanding of the market.

This study contributes to the existing literature in several ways. Firstly, combining a clustering technique (that is well-known, reliable, and commonly accepted by practitioners) with a flexible and adaptable artificial intelligence tool, may generate interesting input for both academics and practitioners. From an academic point of view, this paper brings the classical debate about statistics versus artificial intelligence closer. From the practitioner's perspective, an improvement in the decision-making process is offered as managers can obtain more reliable and more realistic results.

Secondly, a solution is offered for the increasing number of manager requests made in the Spanish energy industry for an approach enabling the interpretation of ambiguous market information as realistically as possible by fuzzifying an excluding attitudinal segmentation.

Thirdly, there is the promising possibility of implementing the proposed approach in other real business cases when non-overlapping segmentation occurs.

The paper is organised as follows. Section 2 focuses on the methodology of fuzzification. Section 3 applies the proposed methodology to a real-word case where a leading company from the energetic sector segments the micro-small and medium-sized companies in Spain. Research findings and managerial implications are presented in Section 4. Finally, the conclusions and directions for further research are explained in Section 5.

2. Methodology of fuzzification

The methodology presented in this paper corresponds to the extension of an automatic learning technique that permits to expand a crisp segmentation to a fuzzy one, allowing patterns to be assigned to more than one segment. The fuzzy learning stage will be conducted from the results of a non-hierarchical cluster analysis. A fuzzy membership function is defined for each segment associating with each pattern a vector of membership or adequacy degrees (note that the membership degree from fuzzy sets theory is noted in this paper as the adequacy degree because it is more suitable to a marketing context). Moreover, the concept of the compatibility between a crisp and a fuzzy classification is defined to analyse the fitness between them.

2.1. Fuzzy connectives

Based on the multi-valued logic introduced by Lukasiewicz (Bergmann, 2008), the fuzzy set theory was introduced by Zadeh (1965). The main idea is to consider a fuzzy set as a group without a sharp boundary (Dubois & Prade, 2004), thus changing the membership function concept defined in classic sets theory as a binary assessment to a gradual function valued in the interval [0.1]. Zadeh's approach to fuzzy decision analysis includes the concepts of the fuzzy restrictions and fuzzy truth values that can be viewed as elastic constraints on the values that may be assigned to a variable.

In the fuzzy sets literature, t-norms, which are a generalisation of (classical) set intersection, and t-conorms, which are a generalisation of (classical) set union, are considered the basic operators to aggregate the partial information given by two fuzzy values (Dubois & Prade, 2004). T-norms and t-conorms are the only associative aggregation functions. These associative aggregation functions lead to n-ary aggregation functions by means of the direct iteration in n arguments. Among these fuzzy connectives the Frank's family is the most broadly used because they can be generated in a parametric way, as defined in (1).

$$F_s(x_1,\ldots,x_n)=log_s\left(\frac{1-\prod_{i=1}^{n}(s^{x_i}-1)}{(s-1)^n-1}+1\right),$$
$$F_s^*(x_1,\ldots,x_n)=1-log_s\left(\frac{1-\prod_{i=1}^{n}(s^{1-x_i}-1)}{(s-1)^n-1}+1\right),$$
$$\text{for } s\in(0,+\infty) \text{ and } s\neq 1, \tag{1}$$

where n is the number of values to be aggregated and s is the Frank's parameter.

Note that considering the values of $s\to 0, s\to 1, s\to +\infty$, the t-norms, the Min, Product and Lukasiewicz are obtained, respectively:

- MinMax:
  - Min: $M(x_1,\ldots,x_n)=min\{x_1,\ldots,x_n\}$
  - Max: $M^*(x_1,\ldots,x_n)=max\{x_1,\ldots,x_n\}$
- Probabilistic Product:
  - $\prod(x_1,\ldots,x_n)=x_1\cdot\ldots\cdot x_n$
  - $\prod^*(x_1,\ldots,x_n)=1-\prod_{i=1}^{n}(1-x_i)$
- Lukasiewicz:
  - $W(x_1,\ldots,x_n)=max\{1-n+\sum_{i=1}^{n}x_i,0\}$
  - $W^*(x_1,\ldots,x_n)=min\{\sum_{i=1}^{n}x_i,1\}$

Considering for each t-norm T its dual t-conorm T^* defined as $T^*(x,y)=1-T(1-x,1-y)$, in this paper the linearly compensated hybrid connectives are used to aggregate the fuzzy values:

$$H=(1-\beta)T+\beta T^*, \tag{2}$$

where $\beta\in[0,1]$ is known as the *level of tolerance* of the classification. It can be noted that for $\beta=0$ the t-norm is obtained, i.e., the least degree of tolerance is considered, and for $\beta=1$ the t-conorm is the result, i.e., the most degree of tolerance considered.

2.2. Supervised learning technique

In machine learning and data mining fields, supervised learning is generally used for reproducing the correspondence between the input patterns and the desired outputs. These outputs are normally defined by a human expert or by observing a real phenomenon. However, in this work, the supervised learning is viewed as learning from an accepted multivariate clustering technique. To the best of our knowledge, this is the first study in which the learning stage is conducted to learn from the non-hierarchical cluster analysis results.

In this work, the supervised learning technique is based on the LAMDA algorithm (Aguado, 1998; Aguado, Catalá, & Parra, 1999; Aguilar & López de Mántaras, 1982), a learning technique based on fuzzy hybrid connectives, as defined in (2), that employs the interpolation capabilities of the logic operators over the fuzzy environments (Klir & Yuan, 1995). LAMDA learns the optimal values for tolerance and Frank's parameter (1) that permit us to obtain the segmentation that best matches with the statistical segmentation accepted a priori.

In addition, the LAMDA demonstrates the overlapping between segments. Therefore, the promising solution for practitioners of associating to each pattern or individual a vector with its membership degrees to each cluster is solved, as exemplified in Table 1.

For instance, in a crisp segmentation, individual #1 would be assigned to the cluster 1 while in the fuzzy segmentation obtained by the LAMDA algorithm, its high membership degree to cluster k could also be considered.