Advances in Social Science, Education and Humanities Research (ASSEHR), volume 68
2017 International Conference on Advanced Technologies Enhancing Education (ICAT2E 2017)

Emotion Analysis in Gasoline Consumption

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Keywords: Emotion analysis, pattern behavior, gasoline consumption.

Abstract. Emotions Analysis is a market intelligence technique used to analyze opinions of people about certain company aspects such as product image, product consumption, marketing campaigns, clients' preferences and social or political movements. The relevance of Emotions Analysis research lies in the enormous economic impact that it provides to enterprises. The role played by emotions in decision making has been analyzed in extensive way to ensure its influence in human behavior. In this work, we present an emotion analysis to obtain the principal characteristics set related to the emotions that make consumers prefer a gas station over others in Mexico. We use a statistical approach to analyze the characteristics of gas stations preferred by customers based on their emotions.

Introduction

Emotions are sensations generated by feelings and perceptions, and are accompanied with thinking and actions; they are always accompanied by thoughts [1]. Emotions are the result of brain stimulation and reflect an important impact in clients' decisions [2, 3, 4, 5, 6]. When emotions are positive, the likelihood of finding positive action is higher; otherwise when the emotion is negative the likelihood of finding positive action is lower. Damasio in [7] shows that "basic emotions like happiness, sadness, shame and empathy, are a set of complex chemical responses as neurological both forming a distinctive pattern" [8, 9]. There is a lot of research on how emotions affect customer preferences [10, 11]. However, few investigations focus on gasoline consumption. Turrentine, Kurani and Heffer in [4] found that consumers do not budget, manage or track fuel costs. They also discovered that fuel economy decisions are based more by emotions than by critical analysis and that they are more influenced by social awareness than by its monetary value [4]. This social awareness is also related to social responsibility on environmental issues. In [5] it is concluded that consumer behavior regarding gasoline products is affected substantially within environmentally sensitive target groups. Emotional experience with product's brands is also an important element that affects customers' choice. In [6] Hansen, Christensen and Lundsteen state that when a memory is recalled, all of its components get together and the emotional association with the brand comes up too; these emotional responses are the frame of conscious cognitive process. Our research analyzes customers' preferences on gas stations from two perspectives. Firstly we use a statistical analysis in order to explore the distribution of the information and to observe the behavior of the gas station selection process according to clients' perceptions; which are originated from clients' experiences when they consume gasoline. Secondly we perform a statistical analysis to model the behavior of people selecting a particular gas station based in their emotions; which are generated when they consume the gas stations' services.

Conventions

Customer behavior is represented by an independent object characteristic x_i that derives a particular emotion e_i. The combination of dependent or independent characteristics x_i can lead to other particular emotion e_i, where $e_i \in E$ and E is the set of possible emotions. In this way client's feelings and perceptions over any x_i become an input to produce *ei*. Each gas station G_i possesses a feature set X of size m. These features are independent and each feature x_i has been rated for each client. We have defined a set of personal clients' features Y, where each $y_i \in Y$ represents a client feature i.e. y_i = {age, gender, etc.}. Each feature $x_i \in X$ represents a feature that clients can get from G_i during the service time, i.e. x_i={clean bathrooms; store; etc.}.

Dataset Description

The dataset used was obtained by an online survey answered in social networks only by Mexicans that consume gasoline. We represent the vehicles population in Mexico by MV according to the census of the "INEGI", in 2014. Thus we obtained from *MV* a representative sample of the population S of size n, where $S \in MV$, of enough size according to (1) to obtain statistically significant results, we select a constant value for standard deviation σ, a 95% confidence level with z=1.96, and an error e of 0.056%. The sample size was estimated according statistical principles with the following formula.

$$n = \frac{Z^2\sigma^2 N}{e^2(N-1)+Z^2\sigma^2} \text{.........(1)}$$

A set of personal features Y and a vector of ranked features R, where r is a ranked feature, $r \in R$, were obtained for every client tj. Where $r(i,j)$ is the rating given from a client c_j to a gas station feature x_i with $x \in X$, where X represents the set of gas station's features evaluated. The ratings $r(i,j)$ varies in an interval [1,10] where "1" is the minimum rating and "10" is the maximum rating.

Statistical Analysis

Our statistical analysis reflects the behavior of the independent variable represented by personal characteristics of clients Y over their consumption using ranked gasoline characteristics x_i. Table 1 represents an example of set Y. This set includes clients' personal features, where each $y_i \in$ Y represents a client characteristic.

Table 1. Personal client features

Client Ci	Yi
y1	Age
y2	Gender
yn	Average gasoline consumption

In S each gasoline feature x_i is related in a supervised way to a particular emotion e_i so S can be used to analyze characteristics x_i, which had been rated by clients, and to discover the most relevant emotions that drive clients to select a specific gas station. The analysis was performed to every x_i and every personal feature as well as their combinations. This shows that when one characteristic with a high rating is presented with another one with low rating clients still prefer the gas station based on the higher one as shown in Figure 1. Low rated characteristics correlated with other medium or low rated characteristics are not selected, Figure 2. Figures 3 and 4 show how preference varies according to clients' profile.

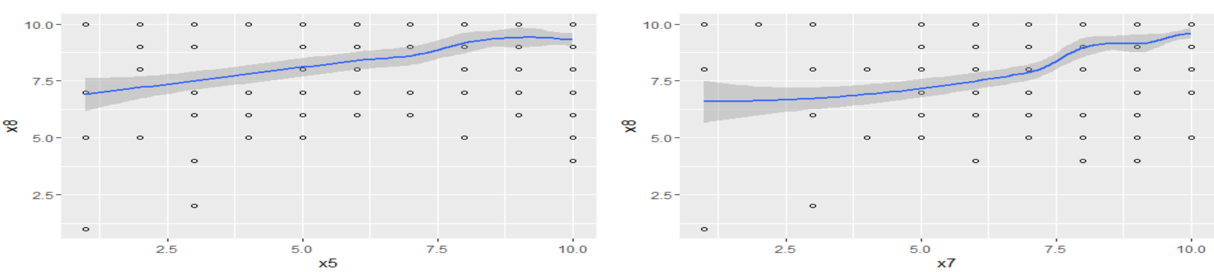

Fig 1. High rated characteristic vs two low rated characteristics

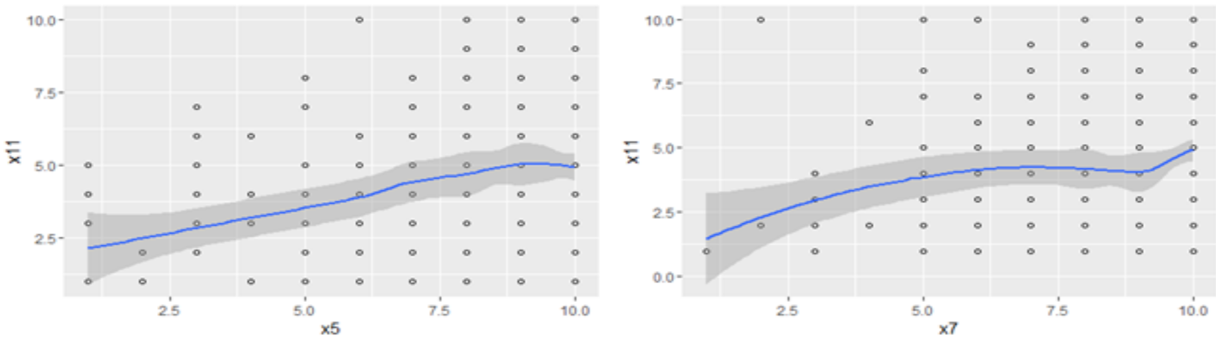

Fig 2. Low rated characteristic vs medium rated characteristic

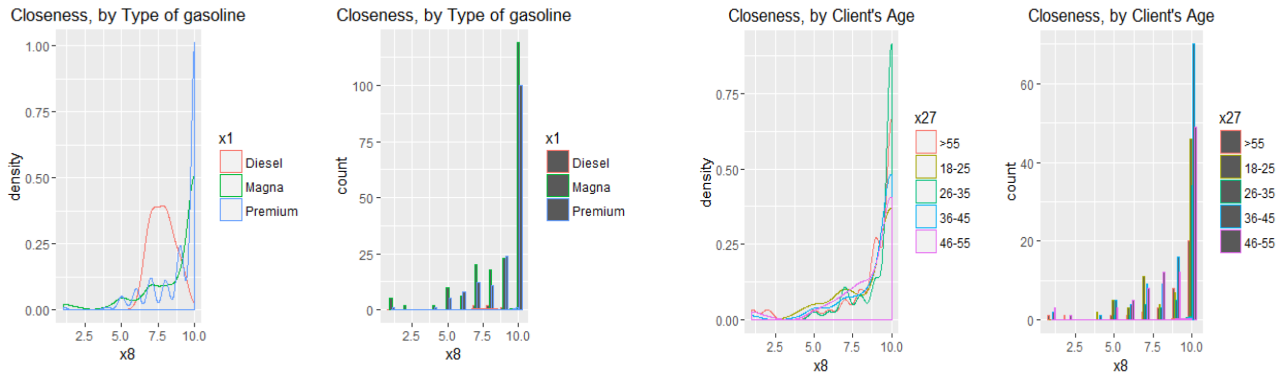

Fig 3. Distinct preferences distribution related to Closeness

This shows that there are some variables that are critical in the selection of the gas station. Also we identify that some characteristics are not equally relevant by segment, and that clients prefer other kind of intrinsic characteristics instead of additional services as shown in Figure 2. In the second part of our analysis, emotion variables were added in association with the characteristics. This will show not only the features that clients prefer when they select a gas station, but also those that trigger one or more emotions which influence the selection of a particular gas station.

Data Transformation

To perform our emotion analysis a transformation process is needed: for every x_i we added an associated emotion e_i, in such a way that personal characteristics are preserved. The e_i was mapped to x_i based on studies that shows that emotions are produced by external stimulus and they produce an instantaneous impact over people [8]. To distinct between positive and negative emotions we take into account that people exposed to external stimulus incorporate in their neurological patterns those that are beneficial to their life and discard those that are not [10,12]. We took best ranking characteristics as accepted for people and were mapped with positive emotions. After the transformation process we call our new data set as S'.

The e_i was assigned according to the type of characteristic, nevertheless the set of emotions of a single client has a particular combination and proportion of emotions and characteristics that make him to select or not select a specific gas station.

Table 2. Example of client Emotions in S'

Client C_i	x_i	e_i
e_1	Automatic charge	Security
e_n	Rapid service	Happiness

Figure 4 shows how emotions are related to gas station features in the selection (rated >= 5.0) or in the rejection (rated < 5.0) of a gas station.

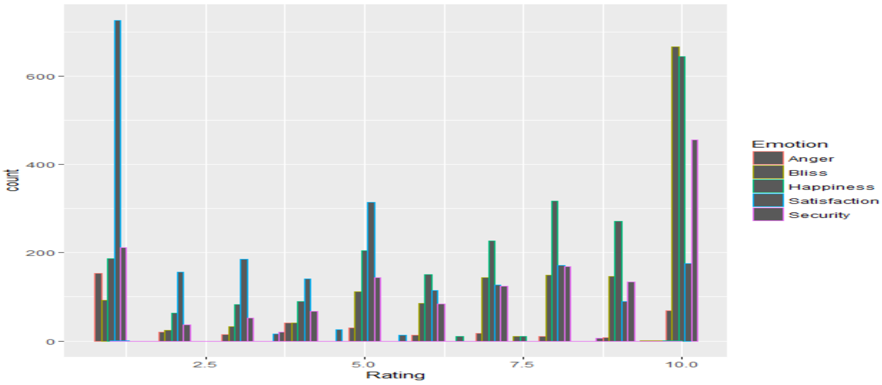

Fig 4. Rating by emotions

Conclusions and Future work

In this work we show how client decisions are influenced by the emotions produced from the gas station characteristics. We show that a statistical approach can obtain the probability of selecting a gas station over another based on the emotions it produces in customers. A future work of this study would implement Machine Learning approaches to predict client preferences over competency, emphasizing the gas station characteristics in adequate proportions according to the preferences of clients and their emotions.

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