Determination of the level of user perception through sentiment analysis studies in the context of marketing

Determinación del nivel de percepción de usuario a través de estudios de análisis de sentimientos en el contexto del marketing

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Abstract

Introduction— The comments made by the clients of the companies in the social networks and electronic commerce portals about products and services offered by them, not only allow the companies to determine the perception of the clients for decision making at the marketing level. They serve as a reference for other customers to make decisions before buying a product. One of the techniques derived from natural language processing and affective computing that allows determining the value of an opinion is sentiment analysis.

Objective— To determine a quantitative indicator of the level of perception through a mathematical equation that involves the polarity value (positive, negative, neutral) of an opinion.

Methodology— This work focused on the automation of the opinion mining process and the determination of the level of perception through the identification of the most used and suitable libraries for the development of this work; the identification of mathematical equations to determine the level of perception; the implementation of a tool to automate the process; and the verification of its usefulness through a case study.

Results— By means of a mathematical equation that involves the three polarities of an opinion, obtaining an automated tool in Python language, which makes use of the Paralleldots library.

Conclusions— The tool developed allows opinion mining studies to be carried out in which the added value is the estimation of a level of perception by opinion and in general. The proposed approach is intended to serve as a reference to be replicated and extrapolated in different application contexts in addition to marketing.

Keywords— Affective computing; perception level; opinion mining; polarity; sentiment analysis

Resumen

Introducción— Los comentarios que realizan los clientes de las empresas en las redes sociales y portales de comercio electrónico sobre productos y servicios ofrecidos por estas, no solo permiten a las empresas determinar la percepción de los clientes para la toma de decisiones a nivel de marketing, sino que también sirven como referencia para otros clientes a tomar decisiones antes de comprar un producto. Una de las técnicas derivadas del procesamiento del lenguaje natural y la computación afectiva que permite determinar el de una opinión es el análisis de sentimiento.

Objetivo— Determinar un indicador cuantitativo del nivel de percepción mediante una ecuación matemática que involucra el valor de polaridad (positiva, negativa, neutra) de una opinión.

Metodología— Este trabajo se enfocó en la automatización del proceso de minería de opinión y la determinación del nivel de percepción mediante la identificación de las librerías más utilizadas e idóneas para el desarrollo de este trabajo; la identificación de ecuaciones matemáticas para determinar el nivel de percepción, la implementación de una herramienta para automatizar el proceso y la verificación de su utilidad mediante un caso de estudio.

Resultados— Por medio de una ecuación matemática que involucra las tres polaridades de una opinión obteniendo una herramienta automatizada en lenguaje Python, que hace uso de la librería Paralleldots.

Conclusiones— La herramienta desarrollada permite realizar estudios de minería de opinión en los que el valor agregado es la estimación de un nivel de percepción por opinión y general. El enfoque propuesto pretende servir como referencia para ser replicado y extrapolado en diferentes contextos de aplicación además del marketing.

Palabras clave— Computación afectiva; nivel de percepción; minería de opinión; polaridad; análisis de sentimientos

I. INTRODUCCIÓN

Affective computing is one of several emerging areas in computer science. Affective computing aims to build systems that can recognize, process and/or simulate human emotions to improve the interaction between the user and the computer [1]. Within the potential fields of use, marketing stands out, through the analysis of user perception through the use of sentiment analysis techniques on the opinions of users regarding the products and services of the companies [2]. The opinions of the clients in different online services are not only important to identify the perception of the clients in order to make decisions that allow competitiveness in the market, but are currently taken as a reference by the clients before acquiring a product or service [3]-[5].

Sentiment analysis or opinion mining techniques correspond to natural language processing methods that allow determining the value of polarity (positive, negative and neutral) of an opinion regarding a person, product or service [6]-[8]. Several studies have been developed in the field of sentiment analysis, which have been applied in different application contexts, for example, in 2019 they conducted a sentiment and emotion analysis study on the speech for the signing of the peace agreement in Colombia [9], fragmenting the text of the speech into different phases to determine their polarities with the Paralleldots library. In Colombia, a usability inspection of the Pivot Portable animation creation tool was conducted and the perception of the evaluators was determined through the application of sentiment analysis techniques, which were implemented using the Python TextBlob library [10]. At Funlam (Colombia), an opinion mining study was conducted on the opinions posted on Twitter about the housing projects carried out by the organization "TECHO" (= TECHO) in Latin America, whose objective is to help overcome the poverty in which people in informal settlements live [11]. In Ecuador an opinion mining study was conducted on the reactions published by Mexican users during and after the earthquake that occurred in 2017, in order to evaluate the response of the public from different perspectives and the fluctuation of feelings before and after the disaster [12]. In USAL (Spain) the authors proposed a methodology and an automated system for carrying out opinion mining studies in real time in the political context, in order to obtain changes in the trend indicators associated with political parties and their candidates [13]. In UK others authors proposed a new method based on sentiment analysis on the use of their own lexicon, through which they developed a case study in which they analyzed the opinions of customers of the electricity service in the UK [14]. In Malaysia a sentiment analysis study on the opinions of Twitter users regarding typical Halal tourism destinations, to determine the most popular sites with the best positive perceptions [15]. In the U.S., conducted a sentiment analysis on the opinions posted by users of the social network Twitter about the implications of COVID-19, to determine people's perception of the pandemic and the main topics of discussion around it [16]. In Taiwan, a sentiment analysis of social media user comments was conducted to characterize and determine the polarity of comments related to 4C marketing [4]. In Spain and Portugal, sentiment analysis was used within the framework of inclusion, on comments made on Twitter with the hashtag "MeToo" to identify and determine public perception of this campaign [17]. At Unicartagena (Colombia) carried out an analysis of emotions based on the use of the Paralleldots library, through which they analyzed the perception of the attendees to a virtual fair held during the pandemic and called Marketing from home [2].

The aforementioned works present the application of sentiment analysis techniques in different application contexts. In most of these the aim is to improve the accuracy of sentiment classification models, without addressing so much the automation of the sentiment analysis process with the aim of improving decision-making in marketing campaigns of organizations, such as estimating the level of perception or satisfaction from the polarities determined by these algorithmic models. This article makes two main contributions: 1) the automation of the opinion mining process or obtaining polarities from datasets or surveys with the opinions of customers regarding products or services published in electronic commerce portals; and 2) the determination of the level of user perception from the polarities obtained in the opinion mining process. These contributions were approached through the construction of

an automated tool in the Python language with the support of the Paralleldots library, which receives as input a dataset or a file with the opinions extracted from an electronic commerce portal and determines both the polarity of opinions, such as the level of perception of each opinion and the level of global perception. The proposed tool was verified through a case study, in which the perception of users of the Ebay Spain portal regarding a product was evaluated. Therefore, the approach proposed in this article constitutes a support for the marketing divisions of organizations, in terms of obtaining representative quantitative indicators that allow decision-making regarding the products and services offered.

The rest of the article is organized as follows: in Section II, the methodology considered for carrying out this research is presented. Section III describes the results obtained, which includes the design and implementation of the proposed approach through the construction of an automated tool for determining the level of user perception from sentiment analysis studies in the context of marketing, as well as carrying out a case study in which the operation and usefulness of the proposed approach is verified. Finally, Section IV presents the conclusions and future work derived from the research.

II. Methodology

In carrying out this research, the four phases of the iterative research pattern proposed by TAMU were considered [18]: observe the application, identify the problem, develop the solution and test the solution (Fig. 1).
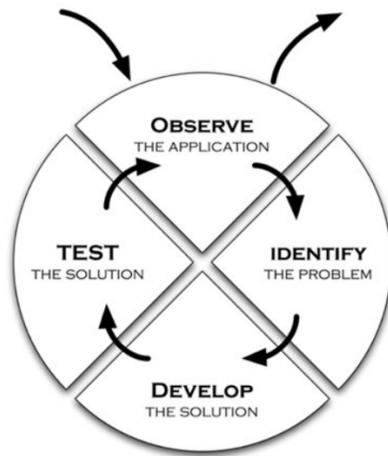

Fig. 1. Methodology considered.
Source: [18].

In phase *Observe*, different opinion mining tools and technologies were explored and selected to determine the three polarities (positive, negative, and neutral) in opinions written in the Spanish language, in such a way that the Paralleldots library was chosen and the TextBlob and VaderSentiment libraries were discarded, since in both cases they allow the analysis and determination of opinions in the English language. In phase *Identify* of the methodology, an equation was defined to determine the level of perception from the three polarities determined by the Paralleldots library. Thus, Equation 1 determines the level of perception and was obtained by adapting the approach proposed by the VaderSentiment library to obtain a composite value from the polarities [19], [20].

$$perc\_level = \left(\frac{x}{\sqrt{x^2 + a}} + \frac{\sqrt{1+a} - 1}{\sqrt{1+a}} \right) \times 100 \qquad (1)$$

In the equation 1, x represents the subtraction of the positive and negative polarities (2), while a is an arbitrary value that is added to the root so that when the value of x is maximum, that is 1, the root is exact. Thus, the value of a can be 3, 8, 15, etc., considering that these values, on adding 1, allow obtaining an exact square root. For the present article, the value of a is assumed to be 3.

$$x = pol_{pos} - pol_{neg} \qquad\qquad (2)$$

In Phase *Develop* of the methodology, we proceeded with the design and implementation of the tool that automates the determination of the user's perception from the polarities obtained in an opinion, taking into account the tools and technologies selected in Phase 1 and the mathematical equation defined in Phase *Identify* of the methodology. At the design level, a flowchart with the different processes carried out in the proposed approach is presented, as well as a diagram with the functional modules that make up the proposed tool. Regarding the implementation, the different views that the constructed tool has are described. Finally, in Phase 4 of the methodology, the functionality and usefulness of the approach and the proposed tool were verified through a case study, in which the perception of customers of a product published on Ebay Spain was determined, before automatically carrying out the analysis of the polarities corresponding to the comments made on this portal regarding the product.

III. Results

This section describes the results obtained by carrying out this research, which includes at the design level, the definition of the different processes of the proposed approach that allow obtaining the polarities in a set of opinions analyzed and the determination of the level of satisfaction by opinion and general from the polarities obtained. Likewise, the block diagram of the tool that allows the implementation of the defined processes is presented. Similarly, at the implementation level, the different views that make up the graphical interface of the constructed tool are described. Finally, by way of validation, a case study is presented in the context of marketing, in which the functionality and usefulness of the proposed tool is verified.

A. *Design and implementation of the proposed approach*

Fig. 2 presents a flow diagram that illustrates the different processes proposed by the approach for obtaining automated polarities and determining the level of perception of these, as follows: choose or build the dataset to analyze from opinions collected from social networks or e-commerce portals. It is then uploaded to the automated tool, which goes through the different opinions one by one to obtain the positive, negative, and neutral polarities of each of these by using sentiment classification methods. Once the polarities are determined, the tool proceeds to calculate the perception level of each opinion using the determined polarities and applying (1) and (2). The values of the polarities and the perception level are temporarily stored in a floating array for later analysis. When the automated tool has finished going through the different opinions of the dataset, the statistical analysis of the stored data is carried out, obtaining the mean of each polarity and of the perception level, the standard deviation of each polarity, and the minimum and maximum value of each polarity. The statistical analysis carried out is complemented by the generation of a bar chart with the distribution of polarities in each opinion and a pie chart with the percentage distribution of polarities in the total number of opinions. Also, a bar graph is generated with the level of satisfaction obtained for each of the opinions analyzed. Finally, the tool allows generating a report with the results obtained at the level of the analysis of the polarities and the calculations of the level of perception by opinion.

Also, in Fig. 2 on the right side, the functional modules that make up the tool and allow the execution of these processes, as well as the interaction between them, are presented. The tool is made up of six functional modules, namely:

a) In the *Dataset processing module*, the tool is responsible for loading the dataset and obtaining each of the opinions to perform the respective opinion mining analysis, using the Pandas library, from Python, which allows processing different types of files (csv, Excel, among others) to obtain the information in a data structure called Dataframe, which consists of a matrix structure that enables easy access to the data.

b) In the *Polarity analysis module*, the tool, using the features of the Paralleldots library, allows obtaining the three polarities (positive, negative, neutral) for each of the opinions obtained from the dataset through the Pandas library.

c) In the *Perception calculation module*, the tool makes use of the Python Math library to implement and apply (1) and (2) to the different opinions of the dataset and store them in the temporary array.

d) The *Statistical analysis module*, through the functions provided by the Python Numpy library, analyzes the polarities and the perception level obtained from each opinion, calculating the total average obtained for each polarity, the total average of the perception level, the standard deviation of each polarity and the minimum and maximum values associated with the three polarities.

e) The *Graphic analysis module* makes use of the advantages provided by the Python Matplotlib library, so that the tool generates a bar plot with the polarity distribution for each opinion, a pie chart with the total distribution of polarities in the opinions, a bar graph with the levels of perception obtained in each opinion.

f) The *Reporting module* makes the most of the advantages provided in the Python core for file management to generate a report in .CSV format with the results of the statistical analysis obtained.

Proposed flowchart			Modules and interactions
Start			
1	Choose or build the dataset		
2	Load the dataset		Dataset processing module
2.1	While the upload was successful		
	2.1.1	Select opinion	
	2.1.2	Get positive polarity	
	2.1.3	Get negative polarity	Polarity analysis module
	2.1.4	Get neutral polarity	
	2.1.5	Calculate the perception level of the opinion	Perception calculation module
	2.1.6	Stores polarities and level of perception	Polarity analysis module
			Perception calculation module
	2.1.7	Until last opinion	Dataset processing module
2.2	Is it the last opinion?		
3	Perform statistical analysis of polarities and level of perception		Statistical analysis module
4	Plot polarity analysis		Graphic analysis module
5	Graph analysis of levels of perception		
6	Generate report with results		Reporting module
End			

Fig. 2. Flowchart of the proposed approach.
Source: Own.

Additionally, it is worth mentioning that for the implementation of the tool interface, the Python Tkinter library was used, which allows the interaction and execution of the different modules.

Once the modules that make up the automated tool have been described, Fig. 3 shows the main interface of the constructed tool, which consists of four tabs: Opinion Analysis, Statistical Analysis, Polarities and Satisfaction Levels.

In the "*Opinion Analysis*" tab, the tool allows the end user to load the dataset with the opinions obtained from social networks or from an electronic commerce portal, by pressing the "*Open*" button, enabling the "*Process*" button, to start the analysis of the opinions that is presenting on the screen the polarities obtained for each opinion, as well as the level of perception calculated from the three polarity values. Once the process is finished, the tool allows the generation of a .csv file with the results of the polarity analysis, perception levels for each opinion and general by means of the "*Report*" button. Also in Fig. 3, it is possible to observe how for the example file loaded with 5 opinions, in the case of Opinion 1: "I don't think the product is good" the polarities obtained were: positive, 32.6%; negative, 0%; neutral, 67.4%, giving a perception level of 68.50%.
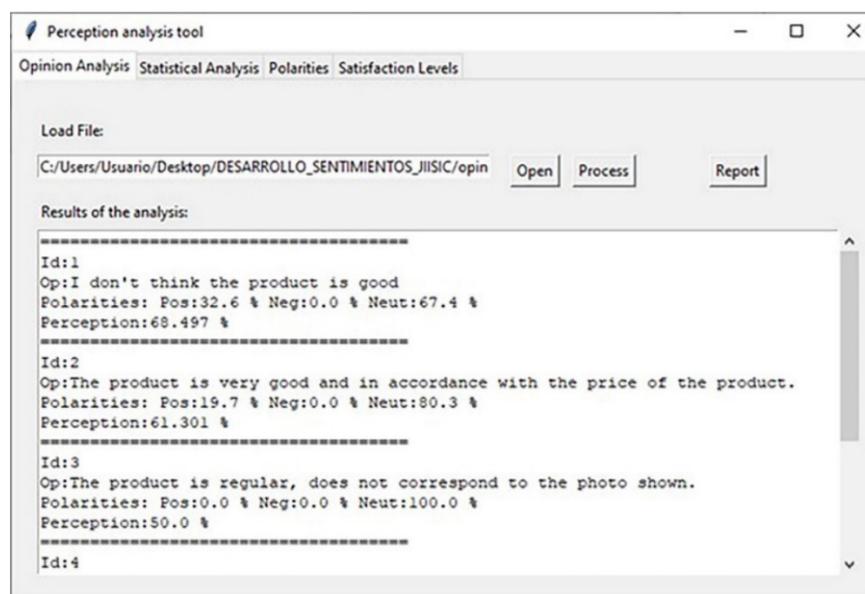
Fig. 3. Main interface of the constructed tool.
Source: Own.

Fig. 4 shows the graphical interface of the "*Statistical Analysis*" tab, which allows displaying on the screen the statistical results of the averages of the polarity values of the different opinions, the levels of perception of each opinion, the standard deviation of the different polarities obtained, the minimum and maximum values obtained for the polarities of the different opinions analyzed and at the end of the report the total mean of the level of perception for the five test opinions is 56.18%. Also, on the right side of the screen, a pie chart is presented with the total percentage distribution of the three polarities of the dataset loaded with five test opinions shown in Fig. 4, noting that the positive polarity obtained a general average of 17.38%, the negative polarity of 6.52% and the neutral polarity of 76.1%. These values can be seen in the colors blue, orange and green respectively.
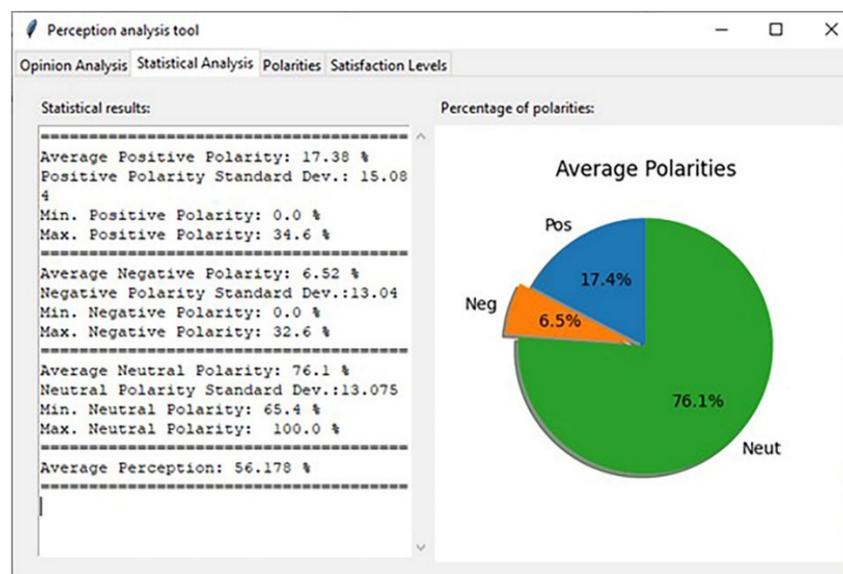

Fig. 4. "Statistical Analysis" tab of the tool.
Source: Own.

Fig. 5 shows the graphical interface corresponding to the "*Polarities*" tab, in which the tool generates a bar chart that represents the percentage distribution of polarities in each of the opinions analyzed. For the five test opinions loaded in Fig. 3, it can be seen how the negative polarity is the one that has the least presence in each of the opinions, while the neutral polarity is the one that has the highest percentage distribution, coinciding with what is presented in the pie chart described in Fig. 4.
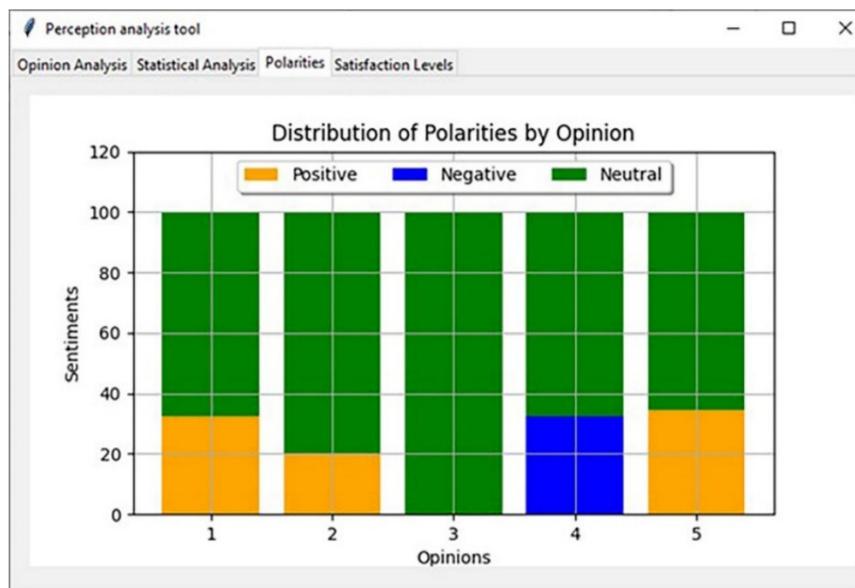
Fig. 5. "Polarities" tab of the tool.
Source: Own.

Finally, in Fig. 6, the graphical interface associated with the "Satisfaction Level" tab is presented, in which the tool generates a bar chart with the level of perception calculated according to (1) and (2) for each of the opinions of the dataset, considering the three polarities obtained in each opinion. For the five test opinions loaded in Fig. 3, the bar diagram in Fig. 6 was obtained, in which it is observed how the opinion that presents the highest level of perception is 5 with 69.59%, while the opinion with the lowest perception is 4 with a 31.50% level of perception.
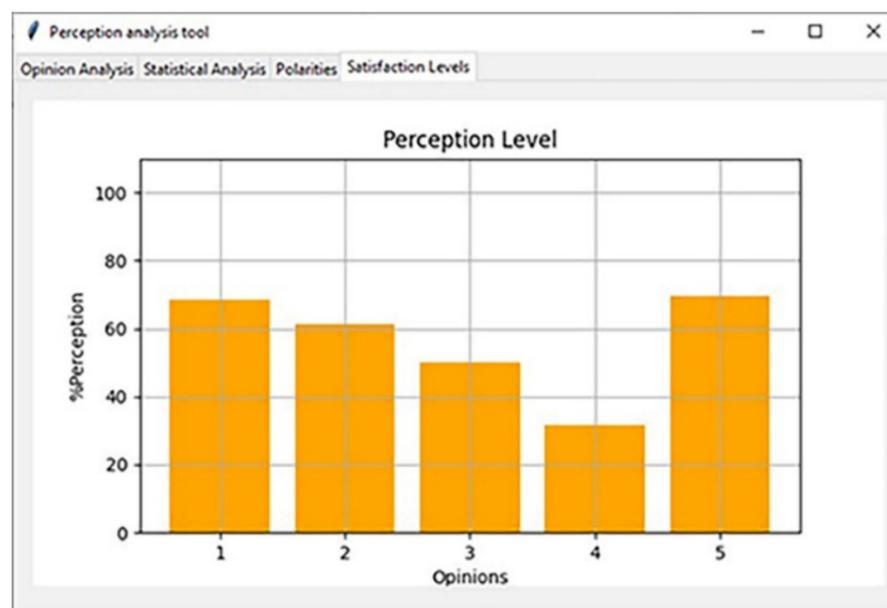

Fig. 6. "Satisfaction levels" tab of the tool.
Source: Own.

B. *Case study*

To verify the usefulness of the proposed approach and the implemented tool, a case study was carried out in which the opinions or short reviews made on the Ebay electronic commerce portal to an Apple iPad (https://www.ebay.com/p/15040889178) air electronic device was analyzed. The dataset had a total of 27 opinions, which, when processed by the automated tool, obtained polarities values show in Fig. 7 and the distribution of polarities presented in Fig. 8.
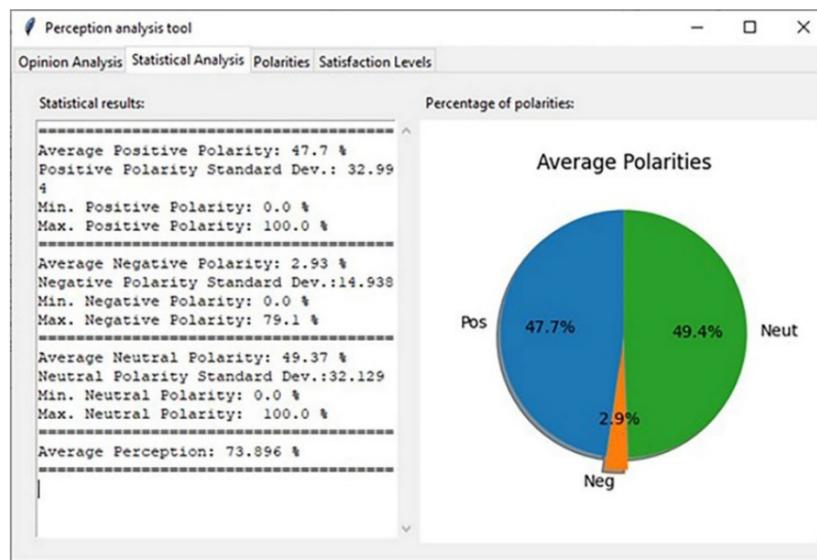
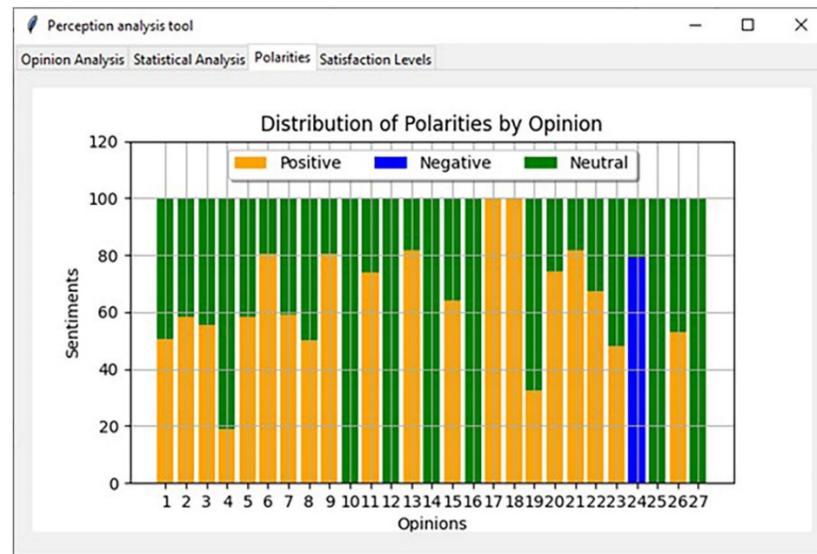Fig. 7. Distribution of polarities of the study case.
Source Own.

Fig. 8. Distribution of polarities of the study case.
Source Own.

From the results obtained in Fig. 8, it is possible to see that only one of the 27 opinions has the negative polarity as dominant, while the rest of the opinions have marked neutral and positive polarities. Table 1 shows the average values of the polarities of the case study, as well as their minimum and maximum values.

TABLE 1.
STATISTICAL ANALYSIS OF THE RESULTS OF THE CASE STUDY.

Polarity	Results
Positive	Mean = 47.7% Minimum polarity = 0% Maximum polarity = 100%
Negative	Mean = 2.93% Minimum polarity = 0% Maximum polarity = 79.1%
Neutral	Mean = 49.39% Minimum polarity = 0% Maximum polarity = 100%

Source: Own compilation.

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According to the results presented in Table 1, although the mean of the neutral polarity is slightly higher than the positive polarity, the arithmetic relationship between the positive polarity and the negative polarity is 16.28, which goes hand in hand with the star rating system of the portal that for the product under study is 4.6 out of 5. Finally, in Fig. 9 a bar chart with the level of perception obtained for each of the 27 opinions analyzed, using (1) and (2) is presented to clearly determine the perception of customers with respect to the product under study.
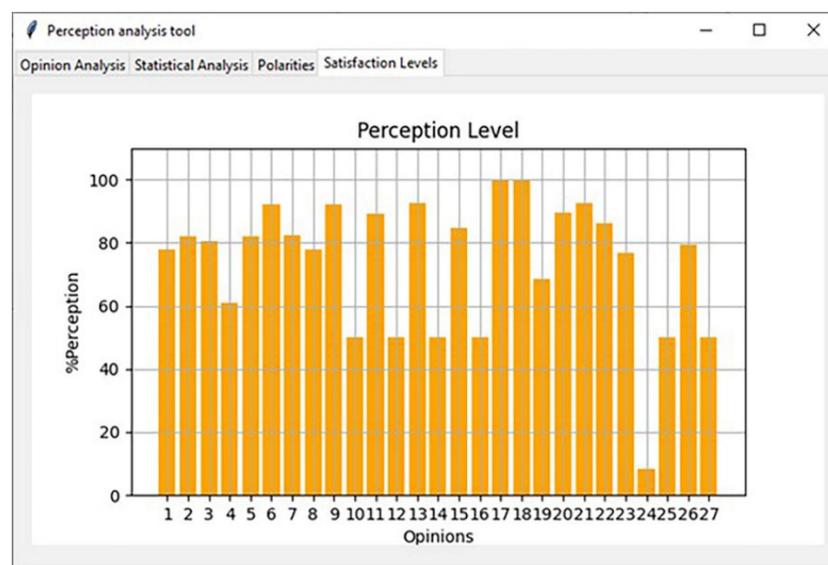

Fig. 9. Perception levels obtained in the case study.
Source Own.

In accordance the results of Fig. 9, it is possible to observe how most of the calculated perception levels exceed 60%, with the minimum value being close to 10% and the maximum value equal to 100%. The tool thus through statistical calculations obtained a total perception of the product of 73.90%, which can be considered good on a qualitative scale.

IV. Conclusions

Taking into consideration the need to automate the sentiment analysis process, in order to make decisions in contexts such as marketing, as well as addressing the challenge of determining the level of perception based on the polarities obtained in an analysis study of feelings, in this article an automated approach is proposed as a contribution that allows the automatic determination of the polarities obtained from a dataset of opinions, the calculation of the level of perception or satisfaction from the polarities obtained by opinion, from the proposed equation that can be used to determine the level of perception in opinion mining studies.

The proposed approach can be used and extrapolated in different application contexts where it is desired to estimate the level of perception of customers regarding the products and services of companies, taking as input the opinions shared in social networks or electronic commerce portals, in a similar way to how the big portals do it with their products.

For the implementation of the approach proposed in this research, an automated tool was developed in the Python language that made the most of the advantages provided by the Python Paralleldots library for determining the polarities of opinions; the Python Pandas library, for accessing and processing the opinions of a dataset; the functions of the Python Math library, to determine the level of satisfaction in the opinions; and the Matplotlib library for the representation of the graphical results of sentiment and perception analysis. The libraries and technologies used are intended to serve as a reference for the development of tools in the field of opinion mining focused on different application contexts.

The case study made it possible to verify the functionality and usefulness of the system in terms of automating the sentiment analysis process and in terms of determining levels of perception based on opinions in the context of marketing. The case study of a dataset made up of opinions extracted from the Ebay portal regarding a technological product allowed us to determine that for that specific case the relationship between the positive and negative polarities is 16.28, while the total perception level calculated is 73.90%. This is consistent with the mean star rating for the product, which is 4.6. In this sense, at the marketing level, the tool allows obtaining quantitative indicators for decision-making by companies that provide products and services like those used by supermarkets, which will constitute a significant contribution for small companies that do not have the technological opportunities of the bigger ones.

As future work, in the first instance, it is desired to use the tool with other product data sets and assess its usefulness in making decisions in their marketing. Second, derived from this research, it is intended to include web-scrapping functionalities in the tool. This would allow the automatic creation of the dataset of opinions from electronic commerce portals. Likewise, it is intended to link models based on fuzzy logic to determine the levels of perception using fuzzy sets expressed in numerical and linguistic terms. Finally, the possibility of linking different sentiment analysis libraries from the field of free software such as TextBlob and VaderSentiment is proposed, to determine a composite polarity, prior to determining the level of perception.

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