A MYTHOLOGY OF MACHINE LEARNING CONTENT ANALYSIS TO DEFINE THE KEY LABELS IN THE TITLE OF THE ONLINE CUSTOMER'S REVIEW WITH THE RATING EVALUATION

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Abstract:

Online reputation is of great strategic importance to companies today. Customers share their emotions and experiences about the service received or the product acquired, which made customers' online opinions through quantitative variables or text comments. While quantitative variables can be statistically analyzed using different contrasting statistical methods, the comments' content analysis finds its main limitation in statistical analysis as texts are qualitative. This study proposes and applies a methodology to develop a machine learning aimed to identify the key labels that are related to the quantitative variable of the general rating of the service received in an airline. The results obtained are satisfactory and, the significant labels determined, as well as their sign and coefficient with the general ratings. In this way, the proposed methodology results in a quantitative value for the labels that determine a sense and intensity of the customers' opinions.

Keywords: Machine learning, online customer review, airline, sentiment analysis, artificial intelligence

Resumen:

La reputación online es de gran importancia estratégica para las empresas de hoy. Los clientes comparten sus emociones y experiencias sobre el servicio recibido o el producto adquirido, lo que genera las opiniones de los clientes en línea a través de variables cuantitativas o comentarios de texto. Si bien las variables cuantitativas se pueden analizar estadísticamente utilizando diferentes métodos estadísticos contrastantes, el análisis de contenido de los comentarios encuentra su principal limitación en el análisis estadístico ya que los textos son cualitativos. Este estudio propone y aplica una metodología para desarrollar un aprendizaje automático orientado a identificar las etiquetas claves que se relacionan con la variable cuantitativa de la calificación general del servicio recibido en una aerolínea. Los resultados obtenidos son satisfactorios y, las etiquetas significativas determinadas, así como su signo y coeficiente con las calificaciones generales. De esta manera, la metodología propuesta da como resultado un valor cuantitativo para las etiquetas que determina un sentido e intensidad de las opiniones de los clientes.

Palabras clave: Aprendizaje automático, revisión de clientes en línea, aerolínea, análisis de sentimientos, inteligencia artificial

1. INTRODUCTION

The online reputation of a company, brand, product, or service is composed of a set of opinions, experiences, and evaluations that customers share through different social media (Rodríguez-Díaz and Espino-Rodríguez, 2018a). Online reputation is of crucial importance in the strategy of companies because customers are increasingly informed on the Internet to make their decisions to buy services such as hotels or airlines (Horster & Gottschalk, 2012; Yacouel & Fleisher, 2012; Gössling et al., 2016). Moreover, the information available on the Internet about the quality of service and value perceived by customers, both of a given company and its competitors, is of great relevance to measuring the degree of compliance with the objectives established (Vermeulen & Seegers, 2009; Ye et al., 2011; Kim et al., 2015; Lee & Ro, 2016; Rodríguez Díaz et al., 2015). Specific authors such as Chun (2005) and Hernández Estárico et al. (2012) recognize that it is an effective means of measuring the level of service quality perceived by customers and their degree of satisfaction, and also has a direct influence on the level of companies' income and profits (Varini & Sirsi, 2012).

The online reputation on specialized websites such as TripAdvisor is determined through two means. On the one hand, they obtain information from customers through a scale of quantitative variables that measure the perceived quality of service and customers' perceived value (Ye et al., 2014; Rodríguez-Díaz and Espino-Rodríguez, 2018a, 2018b). From this perspective, customer comments are qualitative variables used to evaluate customer satisfaction (Oliver, 1997). Hence the great importance that companies give to classifying the content of online reviews in order to take measures to strengthen the relationship with their customers (Salminen et al., 2019).

2. LITERATURE REVIEW

The airlines use content analysis of online (positive or negative) reviews to evaluate customers' satisfaction. Travelers can write their comments and post online ratings to describe, narrate, recommend, or criticize their travel experiences (Rodríguez, Torres & Toral, 2016; Kwok, Xie & Richards, 2017; Nieto-Garcia et al., 2017). Reviewers use and evaluate products or services and disseminate their evaluations, making them an early link in an innovative diffusion process (Broniarczyk & West, 1998). Reviews are especially important when a product or a service possesses substantial experience attributes, making it difficult for pre-consumption quality assessment. Clients seek purchase recommendations from external sources (West & Broniarczyk, 1998; Rogers, 2003). Marketers also seek to understand the significant and predictive powers of reviews. Knowing whether reviews are positive or negative enables marketers to forecast their products' sales. The airline industry is one of the essential competitiveness factors in Tourism due to companies prone to deal with various challenges such as fuel prices, increasing security precautions, low-cost carriers, economic crisis, and restrictive government regulations (Dolnicar et al., 2011; Calisir et al., 2016). It is crucial for managers of airlines not only to correctly perceive what their customers want and expect but also to manage their resources in meeting their customer expectations appropriately (Chow, 2015; Park et al., 2004; Guo et al., 2017; Forgas et al., 2010; O'connell & Williams, 2005; Truong et al., 2020). If reviews are aggressive, corrective measures, such as revising promotional strategies or redesigning the brand, maybe instituted (Basuroy et al., 2003).

In the airline industry various studies have been dedicated to investigating the relationship between service quality and related issues such as customer satisfaction and brand loyalty (Hussian et al., 2015; Tahanisaz & Shokuhyar, 2020; Sezgen et al., 2019; Bellizi et al., 2020; Farooq et al., 2018; Lucini et al., 2020; Park et al., 2020) which are the main factors to any airline to overcome the economic crisis by understanding and facilitating new flexible ways for their customers such as rapid response on social media, airline's refund, change and overbooking policies (Yoon et al., 2012; Dalalah et al., 2020; Ma et al., 2019; Seo et al., 2018).

The relation between customer rating and review, facilitated by the quantification of textual review, also finds additional customer satisfaction investigations. For instance, Büscken and Allenby (2016) correlated the frequency of customer review topics with ratings using multiple linear regressions. In line with this study, if the coefficient of the frequency of a topic is positive, the customers are relatively satisfied with it, so the more frequent mentioning to this topic will lead to a positive increment of rating.

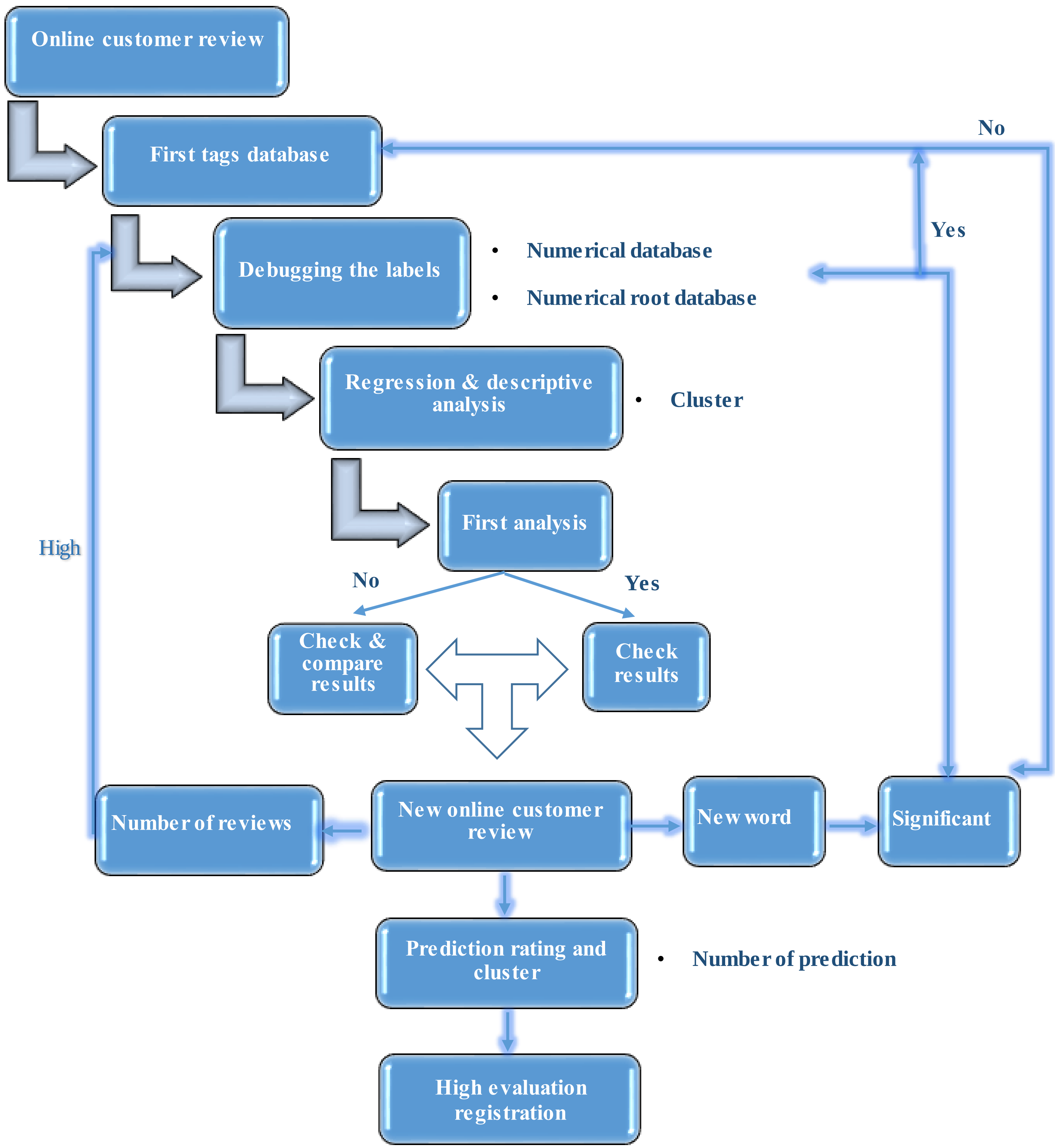
3. RESEARCH METHODOLOGY

The steps to be followed to obtain and process the information to achieve the proposed research objectives are three: 1) obtaining the online customer reviews from the specialized website, 2) preparing the database from the information obtained, and 3) statistical analysis of the database. Concerning the first step, the study was carried out based on the online opinions of 5278 customers about the Iberia airline. All comments have been made in the Spanish language, but the methodology developed in this article is indifferent to the type of language used, as is the case with English. Customers are mainly from Spain and Latin American countries. The data have been obtained from the TripAdvisor website, where information is provided on the general rating given by the customer, title, and commentary. The general rating is a quantitative variable of 5 alternatives ranging from poor to excellent (1-poor; 2-bad; 3-normal; 4-very good; 5-excellent). The title is made up of a limited number of words describing the general meaning of the user's opinion, while the commentary sets out all the aspects that the customer wants to highlight, whether positive or negative. Both the title and the commentary are qualitative variables that must be treated as a content analysis. To this end, a methodology and software have been designed to treat the information and prepare it for statistical analysis in quantitative terms.

The second step of the methodology consists of elaborating the database in the order that it can be treated statistically. This requires, first, creating the labels from the words used in the titles of the reviews. Secondly, all those labels that are not considered relevant to be related to the general rating must be deactivated, as is the case with the pronouns the, a or an, or verbs such as to be or to have, for example. Thirdly, define if the labels will be integrated by each of the words detected in the titles or by the words' root. The latter allows reducing the number of tags since, for example, words that are in the singular and plural will be assigned to the same tag. Likewise, regular verbs or superlatives should also be assigned to the same common root. In this context, lemmatization is how words are reduced to their elemental form, excluding final inflections (Feldman & Sanger, 2007). Generally, as the software has been developed in English, a specific program adapted to the Spanish language has been carried out in this study. Finally, a database is created where each row is a review and the columns the total of labels so that if a label is in the title of the comment, it will be assigned a one and if not a 0. This is a method of converting a text into a vector of dichotomous variables 0 or 1, which can be treated with quantitative statistical procedures. In this context, Vector space models (VSMs) represent words as a vector in multidimensional space. An incredibly efficient model from a computational point of view is Word2vec, where the texts are transformed into vectors so that if it includes a specific word, its variable is valued with a 1 and otherwise as a 0 (Ruiz de Villa, 2018).

Finally, a database is created where each row is a comment and the columns the total of labels so that if a label is in the title of the comment, it will be assigned a 1 and if not a 0. This is a method of converting a text into a vector of dichotomous variables, which can be treated with quantitative statistical procedures. In this study, 2567 labels have been detected once the irrelevant ones have been deactivated. To simplify them, we developed a program where the labels were assigned to the same root. To do so, firstly, the plurals or endings of regular verbs were eliminated. Secondly, a minimum number of characters were determined to form a common root since if a minimum number is chosen, the program can detect many coincidences. For example, if not searching for similar words, the bad label can be detected on multiple words that start with bad like badminton. Therefore, it was set to search for tags based on the root when it has six characters or more. In the case that the tag has five or fewer characters, the text will be searched as similar words. Using this method, we reduced the labels to 1523.

Figure 1: Machine learning model of significant labels in online customer reviews



Based on the above, the machine learning model proposed in this article to determine the key labels related to overall online customer rating follows these steps (see Figure 1):

1) Obtaining customers' online reviews about their general rating, title, and shared commentary on a social network.

2) The creation of the tags' database based on the words contained in the titles of the comments could also be done with the comments, but the number of tags would increase enormously, which would make the statistical study difficult. Furthermore, it can be assumed that the most relevant words to define the customer experience are found in the titles.

3) It is debugging of the labels to deactivate those that do not directly impact the sense of the customers' online ratings. This task must be carried out by a team or a specialized person who will transfer their knowledge to the machine learning system as the number of labels increases. From here, the final database of the labels to use in the statistical analysis will be obtained.

4) Create numerical database where each row corresponds to an online comment from the customers and the columns to the variables that are, first of all, the general rating given by the customers (variable between 1 and 5). In contrast, the rest of the variables are the active labels that will be given a value of 1 if found in the title of the comment and 0 otherwise.

5) If necessary, create a new numerical database of labels based on the root of the words to reduce the number of variables without losing the meaning of the words.

6) Conduct a linear or other type of regression if considered necessary, where the dependent variable is the general rating, and the independent ones are the activated labels. A descriptive analysis of the averages of the general rating obtained in those titles with the same label is also carried out, which helps to relate the meaning and intensity of the tags about the general rating.

7) Check whether the regression model is consistent through the adjusted R square obtained. Likewise, the labels with a significant relationship, positive or negative, with the general rating will be determined. Furthermore, the minimum number of times a label appears can be established to be used in subsequent analyses. By establishing the significant labels and the minimum number of times, they have to appear in the titles or comments, a final base of significant labels can be created.

8) Once the meaningful labels have been determined, cluster analysis can be conducted to check whether a classification is adequate. The variables would be the labels, initial, root, or significant, as decided in the research, resulting in a classification of customers according to the type of words they use in their titles or online comments.

9) Continue to obtain information from new online customer reviews.

10) Verify if the words in the new titles are already in the original label database. If so, the next step is to be taken. If not, a new label will be created and will have to be evaluated to determine whether it should be deactivated depending on its impact on the customers' general assessment. Once these decisions have been made, the next step is to carry out.

11) Assess whether the words in the title of the new review correspond to any significant label. If so, an overall rating can be predicted. In this case, the difference between the predicted rating and the actual rating is evaluated to establish how accurate the prediction is. Another statistical analysis that can be done in this step is to assign the new customer who makes the online comment to one of the predefined clusters to classify the user and start defining a profile based on the words he uses.

12) When a relevant number of predictions have been made, a joint analysis is carried out to validate the regression model applied and the assignment of users to predefined clusters.

13) When a significant number of new online reviews have been added, we move to step 4 to perform a new regression analysis to confirm whether the labels are still significant, whether they maintain the coefficients, and whether there are new labels that are significant. A new cluster analysis can also be carried out to check whether the defined ones are still maintained or, conversely, if they need to be reidentified because substantial changes have occurred. A comparative analysis is performed to determine whether there are changes in the vocabulary used by customers to assess the service received.

In this study, the proposed machine learning model's primary application is carried out to detect the key labels that significantly influence the overall rating of online customer reviews. This is the essential part of the model since introducing new comments would involve detecting whether they incorporate the significant labels and, therefore, the rating assessment can be predicted. All activities related to the feedback of new data are not covered in this article, although from a practical perspective, they are relatively simple to solve from a software perspective.

4. ANALYSIS OF RESULTS

The analysis to validate the proposed model consists of two parts. In the first part, a descriptive analysis of the labels is carried out to determine the number of times they appear and the average value of the rating obtained in those comments. Secondly, a multiple regression analysis is conducted with the labels created from a 6-character word root, i.e., a label is considered root when it has six or more characters; in other cases, the label is treated as a word. Finally, a cluster analysis is performed to check whether user groups can be identified based on the type of vocabulary to write their feedback online.

4.1 Descriptive analysis of the labels

The first analysis is descriptive, and the labels have been chosen to appear in at least three different commentary titles. This study's purpose is first to determine the number of times a tag appears in a title. This allows us to establish how often it is used, whether it is a word that is employed a lot or a little to describe customers' perceptions. Secondly, the average of the reviews' general ratings where each label has been detected in their titles is a fascinating index because it gives a clue as to where user ratings are oriented. Considering that the mean value of the overall rating is 3, all those averages that are significantly higher will mean that the label is used in positive feedback titles. Conversely, if the average is below 3 the label is usually found in negative comments.

This analysis allows us to detect the key labels that direct a customer's assessment towards a positive, negative, or neutral pole. Hence, the next step is to determine if the relationship between a label's appearance in a title and the general rating is significant. This will be carried out in the following section, where a multiple regression analysis will be used. Concerning the results obtained in Table 1, it can be seen that there are more significant labels above the average of 3 than below. In order to simplify Table 1, we have chosen to represent only those labels that have been used in at least 3 different comments.

Another exciting fact shown in table 1 is the number of times a label appears in the comments' titles. This data is complementary to the previous one since if a label is used a lot, and it is related to a specific rating, it would mean a confirmation of the valuation obtained. For example, the label excellent appears in 327 comments with an average rating of 4.64, and the word punctual is used in 468 comment titles with an average rating of 4.15, which denotes a relationship with positive aspects of the airline. In contrast, labels such as pessimistic appear 45 times with an average rating of 1.47 and baggage 51 times with an average rating of 2.24, meaning that when a customer remembers baggage, it is because something has not gone as expected.

Table 1: Descriptive analysis of labels

Label	Number	Mean	Label	Number	Mean	Label	Number	Mean
Ideal	3	5	bus	94	3.61	assistance	3	3
Pleasure	12	4.75	turbulence	5	3.6	hight	3	3
Notable	4	4.75	lots	20	3.6	seat	137	2.99
Printing	4	4.75	according	5	3.6	time	48	2.98
magnificant	14	4.71	resolved	5	3.6	regular	39	2.97
Fantastic	10	4.7	queue	5	3.6	nothing	50	2.96
marvelous	10	4.7	assistant	5	3.6	individual	20	2.95
Practical	3	4.67	acceptable	25	3.6	port	21	2.95

Table 1: Descriptive analysis of labels								
Label	**Number**	**Mean**	**Label**	**Number**	**Mean**	**Label**	**Number**	**Mean**
defraude	3	4.67	On board	19	3.58	plaza	133	2.95
focus	3	4.67	whole	7	3.57	pain	20	2.9
excellent	327	4.64	rest	7	3.57	average	9	2.89
latest	5	4.6	vacation	16	3.56	checkin	8	2.88
impeccable	59	4.58	crew	86	3.56	educate	7	2.86
flawless	15	4.53	quite	32	3.56	where	7	2.86
exceptional	18	4.5	age	11	3.55	bathroom	7	2.86
phenomenal	6	4.5	air	19	3.53	down	7	2.86
chair	4	4.5	service	458	3.52	total	13	2.85
fan	14	4.43	touch	4	3.5	then	13	2.85
unbeatable	5	4.4	topic	8	3.5	case	13	2.85
agreed	5	4.4	seriousness	4	3.5	airport	20	2.85
have	3	4.33	feel	4	3.5	web	6	2.83
pass	3	4.33	route	4	3.5	repeat	6	2.83
modern	12	4.33	point	12	3.5	half	6	2.83
Entertaining	3	4.33	lend	8	3.5	less	12	2.83
effective	3	4.33	order	6	3.5	cheap	6	2.83
appreciate	3	4.33	menu	6	3.5	atention	11	2.82
chord	3	4.33	frequent	10	3.5	straits	11	2.82
pleasurable	23	4.3	replicateha	4	3.5	Narrow	17	2.82
true	4	4.25	although	18	3.5	go	5	2.8
servicial	4	4.25	aspect	4	3.5	arrive	5	2.8
sensation	4	4.25	current	8	3.5	uncomfortable	54	2.76
even	4	4.25	cabin	21	3.48	value	4	2.75
like	8	4.25	deal	86	3.47	sun	44	2.75
favor	4	4.25	food	72	3.47	follow	4	2.75
astonishing	4	4.25	something	13	3.46	manner	4	2.75
Cross	4	4.25	airline	138	3.46	mother	4	2.75
home	18	4.22	Minute	9	3.44	low-cost	4	2.75
cute	5	4.2	without	250	3.43	Justify	4	2.75
Cordial	11	4.18	entre	56	3.43	thanks	4	2.75
leap	6	4.17	swindle	12	3.42	Works	8	2.75
drinks	6	4.17	price	91	3.42	Tough	4	2.75
fast	32	4.16	lines	12	3.42	passenger	23	2.74
Punctual	468	4.15	connection	19	3.42	reenter	11	2.73
profesional	22	4.14	job	5	3.4	Old	22	2.73
efficiency	7	4.14	Also	5	3.4	After	140	2.73
tourist	18	4.11	gate	5	3.4	date	7	2.71

Table 1: Descriptive analysis of labels

Label	Number	Mean	Label	Number	Mean	Label	Number	Mean
trading	9	4.11	routine	5	3.4	enough	3	2.67
careful	19	4.11	legs	15	3.4	appear	9	2.67
nice	100	4.11	request	5	3.4	palm	3	2.67
relation	22	4.09	need	5	3.4	Or	3	2.67
great	52	4.08	row	5	3.4	Check in	3	2.67
quiet	59	4.07	escape	5	3.4	control	3	2.67
class	34	4.06	subsequent to	5	3.4	tariff	3	2.67
always	114	4.05	inside	15	3.4	fault	3	2.67
quality	80	4.04	return	51	3.39	high	38	2.66
summer	3	4	mess	16	3.38	already	33	2.64
last	7	4	Amazinng	8	3.38	Bad	381	2.64
journey	14	4	during	8	3.38	desire	8	2.63
usually	8	4	detail	8	3.38	Delay	103	2.61
startles	4	4	but	170	3.37		5	2.6
simply	5	4	period	11	3.36	Dice	20	2.6
sure	16	4	all	11	3.36	Ok	19	2.58
relaxed	5	4	bread	22	3.36	Side	19	2.53
regional	6	4	on	20	3.35	hours	56	2.52
reasonable	6	4	much	52	3.35	respect	6	2.5
promotion	3	4	highlight	3	3.33	slow	4	2.5
predicted	4	4	put	3	3.33	can	6	2.5
prefer	3	4	power	6	3.33	iqual	4	2.5
Fare-quality	3	4	couple	3	3.33	constant	4	2.5
pilot	8	4	inconvenient	6	3.33	behavior	4	2.5
film	4	4	Provision	6	3.33	see	63	2.41
displays	4	4	different	3	3.33	lack	29	2.41
opinion	6	4	portion	6	3.33	responsibility	5	2.4
require	3	4	whatever	3	3.33	operated	5	2.4
christmas	3	4	which	6	3.33	operat	10	2.4
deserves	5	4	short	9	3.33	crummy	5	2.4
pet	3	4	face	24	3.33	loose	5	2.4
praise	3	4	mouth	3	3.33	close	5	2.4
language	3	4	alike	117	3.32	Change	5	2.4
big	4	4	yet	28	3.32	why	8	2.38
fleet	5	4	some	19	3.32	baggage	52	2.38
easy	5	4	small	10	3.3	badly	82	2.38
excellence	4	4	bridge	14	3.29	common	8	2.38
spectacular	5	4	delicious	18	3.28	zero	8	2.38

5. DISCUSSION OF RESULTS

From the research carried out, it is clear that the proposed methodology for designing a learning machine that detects the key tags in the titles of customers' online comments is validated. Moreover, it is a methodology that has a learning process from only specific updates that are needed to improve the tags that must compose the database to analyze the contents of the users' online comments. The initial process of data capture is the previous step to carry out the statistical analyses. The first of these has been the descriptive analysis, where it has been verified that by comparing the linguistic sense of the labels with the averages of the ratings of the titles of the comments where they appear, keep a logic. Thus, the labels that show positive aspects of the airline tend to obtain high scores around the value of 4, while the negative ones orient the averages towards low values between 1 and 2.

Another fundamental aspect of descriptive analysis is establishing the number of times a label appears in the comments. This data is essential for designing and debugging a label database for content analysis. When tags appear only a few times, for example, 1 or 2 times, it is not possible to validate the relationship of the tag with the average of the ratings obtained. Moreover, it is possible that if the label is complemented by others that may change its meaning, such as a negation, it may give an average that does not correspond to the logic of the label when reading in isolation. This label is the cause of good or not good, where the meaning of the label without context has a specific orientation but, when linked to another label, can change the meaning diametrically. Despite these appreciations that serve as a basis for future research, the results obtained are satisfactory insofar as the relationship between the key labels and the rating is demonstrated only by analyzing the averages obtained in the ratings and the number of times they appear in the customer reviews. Likewise, labels that do not have a significant influence on ratings are appreciated. The descriptive results achieved together with those of the regression provide a fundamental contribution to the development of learning machine algorithms for detecting keywords in the content analysis of online ratings.

In this line, regression analysis confirms that the machine's approach to learning the key labels is valid. The high number of significant labels and the high adjusted square R validate the proposed methodology. It is confirmed that the linear regression provides essential information for the development of a learning machine and artificial intelligence program insofar as it provides two essential data for assessing the labels: 1) the level of significance and 2) the coefficient. Together with the descriptive data of the average ratings and the number of times they appear in the titles of the comments, these data make it possible to develop an algorithm that learns continuously.

In this research, a first step is taken insofar as key labels are identified, which are qualitative variables, and are related to a quantitative variable of maximum strategic interest such as the airline's global assessment and its service. Moreover, a means of assessing the labels is discovered that is scientifically contrasted through descriptive and multiple regression analysis. The results obtained confirm that, as expected, there is a logic between the words used to evaluate a specific service, company, or brand with a variable that measures perception or attitude, depending on the degree of interaction between passenger and airline rating measured in TripAdvisor. Moreover, in this type of variable, this logic has a positive or negative sign and intensity depending on the coefficient obtained.

Finally, an essential aspect of implementing this type of methodology to develop learning machines and artificial intelligence in content analysis is how the label databases are constructed. As shown in the proposed model, this must be a continuous process, where information is transferred from the Internet and a specialist to the software developed for this purpose. Two alternatives have been proposed in the study. One is to create the database based on the different words that appear in the comments' titles without additional processing. The other alternative is to establish the roots of the words used to reduce the number of labels without losing the meaning of the words. In this case, the software was created to generate and identify the roots of the words with six or more characters. It was shown that a large part of this type of label is significant with the general rating, and, also, the descriptive analysis contributed to clarifying the meaning and intensity of the labels.

6. CONCLUSIONS

This study's main conclusion is that content analysis of online customer opinions can be transformed into dichotomous variables (0, 1) and, then, can be related to a quantitative variable such as the overall rating. Through this methodology, coefficients and signs of the labels are obtained that facilitate their interpretation by a learning machine or artificial intelligence. In this context, the vocabulary that people use tends to vary over time and the assessment given to each word. Therefore, the results obtained in this study are of great interest to develop this line of research since it offers methodological support to give a quantitative value to the labels.

The results obtained in the multiple linear regression show that a high adjusted R square is achieved, demonstrating that the logic of language can be translated into quantitative terms concerning customers' online opinions. Moreover, the regression provides essential information for developing a learning machine and artificial intelligence in the language used in online user feedback. In this context, the study demonstrates the great importance of having a sign of a relationship concerning a quantitative variable that values customers' perception or attitude towards a brand or service. Likewise, each label's coefficient is a measure of intensity to the general rating, which makes it an essential element in assessing customer interactions. From this perspective, the linear regimen offers more information than neural networks, where the key labels, their sign, and their intensity cannot be determined.

In conclusion, we must stress how important it is to have a reference variable that allows us to evaluate the meaning and intensity of the online reviews' words. In this case, we have used TripAdvisor's general rating, but other variables can be used to facilitate deciphering how customers think and value when they comment on a company, brand, or service. Along these lines, the possibility of merging the two sides of the same coin as with the quantitative and qualitative assessments of customers is essential for developing learning algorithms and artificial intelligence that help employees to manage companies more competitively.

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