CUSTOMER EXPERIENCE: BRANDING WITH EMOTIONAL TEXT MINING

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ABSTRACT

As the volume of electronic and online information increases day by day, quick and accurate access to important and popular sources is one of the concerns of using this very large information source. The presentation of tools that can be analyzed by examining the texts has led to the formation of this field in artificial intelligence, which is known as text mining. In this paper, the application of part for customer experience in branding is examined. A non-monitoring approach aimed at customer experience that is based on a bottom-up approach to classifying non-structured data to identify representations and emotions of social media users, we show a preview on Instagram that comments about a The brand of electronics are examined in terms of product priorities, representation, and emotions.

Keywords: Emotional Text Mining; Digital Experience; Branding.

INTRODUCTION

The internet's wide dissemination expands the open door for millions of individuals to ride the web day by day to look and offer data, thoughts, interests, or some other types of articulation. Online networking stages, such as Twitter or Facebook, will progressively assume an essential job in numerous zones as they empower immediate, constant and ongoing correspondence (Chandler et al., 2018; Greco & Polli, 2020).

Emotions are a principal part of our lives and have pulled in the consideration of artists, creators, thinkers, and scientists. Probably the soonest work in brain research investigated the physiological also, conduct job of emotions (James, 1890; Ranellucci et al., 2016). Assessments communicated in interpersonal organizations assume a significant job in impacting general supposition's conduct across regions as different as purchasing items, catching the "beat" of financial exchanges, and deciding in favor of the president (Bai, 2011; Mostafa, 2013).

Emotional text mining (ETM) refers to the use of big text data to analyze emotions in order to recognize and discover relationships and expectations, and thus to improve relationships and interactions. Not surprisingly, therefore, a critical success factor for a brand control plan is to understand what clients divulge when they share a textual content on social media (Shiau et al., 2018; Jimenez-Marquez et al., 2019; Greco & Polli, 2020). So given the large number of users and the large amount of information they share, we can analyze the data and consider the customer experience and branding. This paper is structured as follows; in Section 2, we present the theoretical approach; in Section 3, we present the Emotional text mining procedure; in Section 4, emotional text mining is applied to a case study of a famous retailer company in order to extract useful information for business decision-making; in

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Section 5, we discuss the theoretical contribution of the main results, as well as the managerial implications; and in Section 6, we provide the conclusion.

The Emotional Text Mining Procedure

Text mining is one of the fields that seek to extract useful information from unstructured text data by identifying and exploring patterns. The main idea of text mining is to find small pieces of information from large volumes of textual data without having to read it all. Text mining works by translating words and phrases that are unstructured data into numeric values, which can then link that unstructured data to structured data in a database and link it and analyzed using traditional data mining methods.

The purpose of emotion analysis is to determine the consumer's attitude toward a particular topic or product. Therefore, different platforms can be used to achieve positive, negative, and neutral attitudes. The analysis of consumer emotions provides a perspective that can be used to improve the business in different ways:

1. Decision Making: Analyzing consumer sentiment gives you any change in your brand's public opinion.
2. Highlight Competitive Advantage: There are strategic benefits to recognizing consumer feelings about your competitors. Emotional analysis can help predict customer trends.
3. Product life cycle prediction: The information obtained from consumer emotion analysis shows where your product is in the market, how this performance can be improved, or whether it is time to get rid of it.
4. Improve Customer Experience: Understanding consumer sentiment provides a direct opportunity to identify and address real-world users' problems by using more resources to help improve your business.

ETM is an unsupervised text mining procedure making an allowance for the detection of the symbolic matrix and the representation and the sentiment of an entity, e.g. a selected brand. These three factors are interconnected, because the symbolic matrix generates the representation (Carli, 1990) and the representation sets the sentiment as well as behavior (Moscovici, 2005). Moreover, they imply different tiers of generalization and awareness. While someone is aware of his/her sentiment, she/he isn't directly aware of the representation (Moscovici, 2005), neither is she/he aware of the symbolic matrix, which is unconscious and socially shared. For this reason, the ETM manner permits for the detection of each the semantic and the semiotic components conveyed by way of the communication (Greco & Polli, 2020).

In order to detect the associative links among the phrases and to deduce the symbolic matrix figuring out their coexistence into the text, first we carry out a bisecting *k* method algorithm and three clustering validation measures are taken into account a good way to perceive the optimal solution: the Calinski-Harabasz, the Davies-Bouldin and the intraclass correlation coefficient (ICC) indices. Next, we carry out a correspondence analysis on the cluster per keywords matrix. While the cluster evaluation allows for the detection of the representations, the correspondence analysis detects the symbolic matrix. The interpretation technique proceeds from the very best degree of synthesis to the bottom one, simulating over again the mental functioning.

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Therefore, first we interpret the factorial area in step with phrase polarization so as to discover the symbolic matrix setting the communication. Then, we interpret the cluster according to their location in the factorial area and to the words characterizing the context devices classified within the cluster, so that you can perceive the representation. Finally, the sentiment is described in terms of the elements characterizing the representations (positive, neutral, or negative), and it's miles calculated in step with the wide variety of messages classified within the cluster.

A Case Study

Research question

In the ETM, we carry out a cluster evaluation on the time period per document matrix so as to detect phrase co-occurrence, considering each document as a vector of *n* dimensions (n = variety of keywords). Alternatively, we can recollect the vector space because of phrases and documents as an adjacency matrix, as a way to extract relationship styles between terms and files, considering the corpus as a network of texts and words. This study collected comments containing an electronics brand on Instagram over a period of time and order to analyze unstructured textual content with a bottom-up approach. We try to answer the following questions in this study

1. What are the general clusters of customer experiences about the brand?
2. What representations of this brand can be found in Instagram comments?
3. What is the emotion of this brand?

RESEARCH FINDINGS

The outcomes of the cluster analysis display that the keywords selected allow for the category of 91.4% of the comments. The clustering validation measures display that the most reliable solution is 4 clusters.

As the results show the Instagram users symbolize the brand by means of four main categories:

1. The brand interest
2. The customer experience
3. The reason for using the brand
4. The model selection

The first factor distinguishes the customer's reason for brand interest; the second factor refers to the buyer's experiences. The third factor indicates the reason for using the brand. Finally, the fourth factor concerns the customer's preferences for new models.

Distinguish between customers who prefer old and successful electronic devices and customers who prefer electronic devices with innovation. For this research four clusters are of sizes and reflect different brand representations.

In the first cluster the brand is understood and in the second cluster, the brand is seen as a valuable object that is collected or exchanged by hunter-gatherers so in the third cluster, this brand is shown as fun and entertainment and in the fourth cluster, the brand is shown.

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The customers seem to be more interested in the technology rather than design as there are words like tech, good, smart.

From the interpretation of clusters, we identified four different representations of the brand associated with a particular community. Instagram users seem to have a similar approach to the brand. All representations are mostly positive. We grouped the representations in two sentiments: tech lovers and trend lovers.

As technology lovers, we have categorized people who love the inflection pattern, and those who like the newer versions, most of them seem to be focused on technology innovation and its use. On the other hand, we considered transaction hunters and fashion customers.

The community recognition algorithm has identified 32 communities; there are a large number of small communities and a small number of larger communities. Relationship within 723 keywords considered due to the large number of terms, the interpretation of the chart is relatively challenging. ETM can be an effective method because it detects the right number of partitions.

DISCUSSION

The large the volume of statistics and the more complicated the relationships between them, the more difficult it will become to get admission to the statistics hidden between the information, and the clearer the role of information mining as a technique of expertise discovery (Zare & Mahmoudi, 2020). In this article, the application of emotional text mining in the field of online customer experience in branding is presented. We were able to identify the symbolic categories of the electronics brand in Instagram users.

To measure their emotions, this case study was used as an example to show the potential of ETM in customer experience and branding, but its application can be easily extended depending on the analyst's interests, although our case study was limited to Instagram, which may be allowed. Do not generalize the results to other operating systems.

ETM may be applied to a whole lot of languages and documents, from social media and media documents (Greco, 2016; Greco et al., 2017) to interviews or cognizance groups (Cordella et al., 2018). Moreover, ETM applies a bottom-up technique to unstructured information, which constitutes 95% of huge records (Gandomi & Haider, 2015), and will be usefully carried out to this volume of facts for real-time analytics, because of the fact that the analyst’s intervention is best required for the translation of the output. For this reason, we assume that ETM is possibly to grow to be a useful research tool because of the increase inside the use of social media, and the usefulness of records analytics aimed at supporting corporations in converting big volumes of messages into significant information, thereby supporting decision-making (Greco & Polli, 2020).

Text Description A powerful and efficient way to measure customer satisfaction online, you can also use the best methods and the ability to use resources and regulations to allow you to be in text mining. Using ETM, we are allowed to provide you with four symbolic categories to contact you. In this group of symbols, ETM four representations of the powers and features of this interface can be seen.

Finally, simplifying step-by-step pre-processing of textual data makes it possible to repeat surveys frequently and with little effort, which allows monitoring of target markets on social media to be a truly ongoing, real-time activity to be done. This aspect is very important because it makes the social media expert responsive to the emergence of new trends, aspirations, and needs. In summary, introducing ETM to the Social Media Manager's Task

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List can provide clear benefits in terms of cost reduction, limiting the most time-consuming activities, and ultimately increasing productivity and effectiveness in identifying customers and social media communities.

CONCLUSION

Large textual figures can be seen in the eyes of rich mines, with engineered processes of knowledge exploration that can lead to a vast and valuable volume of analysis and inference. This rich mine can be user comments about a site's products or news, user tweets on different topics, a collection of articles published at a conference, news from a news site, or any other collection that contains meaningful text documents. All of us, willingly or unwillingly, directly or indirectly deal with data processing and, in particular, text processing throughout our daily lives, using translator applications, smart voice assistants, filtering unwanted emails, or suggestions on websites. Online shopping is provided to us based on your taste and shopping experience; these are just some of the goal-setting shareware that you can use. The use of technology and analytics methods in big data, with the aim of extracting this mass of textual information and ultimately knowledge, is essential for businesses and their brand managers.

We present the ETM results applied to a typical customer experience related to brand management. ETM can be used to improve customer experience in brand management. It makes it possible to identify target groups, which can be considered to improve customer experience and thus customer loyalty and satisfaction. The ability to access other useful data to improve customer relationships is quite cost-effective compared to similar methods, thus saving time and money along with a competitive advantage in creating a customer experience.

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