Analysis of User's Sentiment Towards Starbucks on Twitter

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***Abstract*—As more people start to base their opinions and preferences on those of the public on social media, it becomes more important for labels to have a good image on platforms like Twitter. It is crucial for them to put a lot of attention and care to their posts since they can influence the opinion of the public towards them and therefore their business could be affected.**

This paper aims to determine some aspects of the Starbucks brand that provokes either a positive or a negative sentiment on the Twitter users right after the publicity posts made by their official account.

***Index Terms*—Sentiment Analysis, Natural Language Processing,**

I. Introduction

As of the first quarter of 2019, Twitter averaged 330 million monthly active users [1], It has become a powerful tool for businesses to reach a broad audience and connect with their customers, but it can be a double-edged sword as it is difficult to predict the reaction of the public to the statements they make and it can be hard to detect if this responses are negative which could affect their image.

Sentiment analysis aims to determine the contextual polarity of a text and can be a powerful tool for brands or businesses. By applying sentiment analysis on platforms like Twitter, they are able to learn how their clients feel about their services, what are the things that people associate with their products, and if their public image is good on social media or not.

This work focuses on how the sentiment of the public towards the brand of Starbucks change after their publicity posts on Twitter. Compiling tweets mentioning the names of this brand, and applying a series of Natural Language Processing techniques, allows the classification of each tweet depending on whether their sentiment is negative or positive, and we can extract features in common for each group to determine which are the aspects that make the costumers feel one way or another.

II. Method and Data

A. Twitter API

A dataset of tweets that included the word "Starbucks" was needed, to construct one it was necessary to apply for a Twitter developer account by following the process described at https://developer.twitter.com/en/apply-for-access, this grants permission to access the Twitter API and enables the ability to search and download tweets. To facilitate the process of obtaining the data from Twitter the library Tweepy was used.

The official Starbucks account was monitored in order to run a program every time they made a post related to their seasonal promotion of the pumpkin spiced beverages, this program would compile tweets mentioning the brand during the next 3 hours and saved the data on a CVS file, this process was repeated for a total of four times, obtaining approximately 10,000 tweets. It is important to note that the Twitter API has limit rates on the number of requests that can be made on a certain time, for the standard API v1.1, which is the one used for this project, the limit rates can be found on [2].

B. Data Cleaning and Preprocessing

The data that can be obtained comes in the form of objects containing information such as the text of the tweet, the time of creation, the number of likes, etc.

Tweets can have a lot of not useful data that would only get on the way of the desired analysis, so the text obtained needs to be cleaned, for this the python library TextBlob, which is used for processing textual data, was used. This library helps to remove URLs, special characters, punctuation, etc. from the tweets, then tokenizing them and finally removing stopwords (commonly used words like I, you, etc.), this in order to create a corpus which is easier to work with.

C. Descriptive Analysis

It is important to implement a descriptive analysis in order to understand the data obtained and to extract information about the distribution of the data and identify anomalies among variables.

We sought to find the most frequent words on the tweets, the variation of the number of tweets over time, the average length of the texts, etc.

D. Sentiment Analysis

The main concern of this project is analysing how the sentiment of the public towards Starbucks change after their publicity posts and extracting the trends that cause this sentiments. For the sentiment analysis we used the Valence Aware Dictionary and Sentiment Reasoner (VADER) tool which is specifically attuned to sentiments expressed in social media and allows to classify the tweets depending on their polarity, from this we can extract the words that are found most in each group and, using the NRC Word-Emotion Association Lexicon [3], we can separate them according to the emotion associated with them, this lexicon allows to identify between eight different emotions: joy, anger, sadness, surprise, trust, anticipation, disgust and fear.

E. Correlation Analysis

Is important for the analysis to find if some of the variables obtained from the data are related, and if so, how do they affect each other. Some of the information that could be useful for the objective of this project is knowing if there is a correlation between the length of the tweet, the time that it was posted, its sentiment or the topic of the text. If two variables are related, then as one increases or decreases, the other should change on a consistent way [4].

III. Results

The most repeated words on the corpus were analysed to found the principal topics discussed on the tweets, for a more visual representation a word cloud, found in Fig. 1, was created. In a word cloud the size of the word is proportional to its frequency.

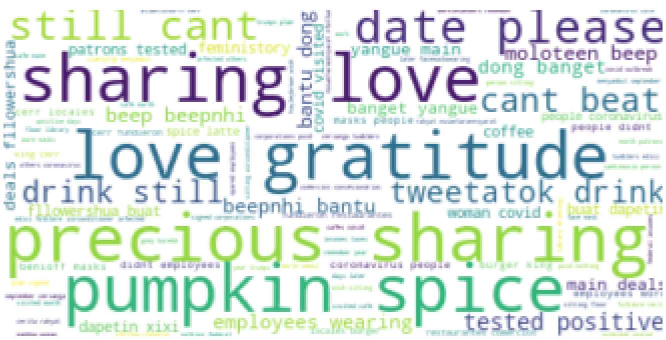

Fig. 1. Word cloud of the most frequent words.

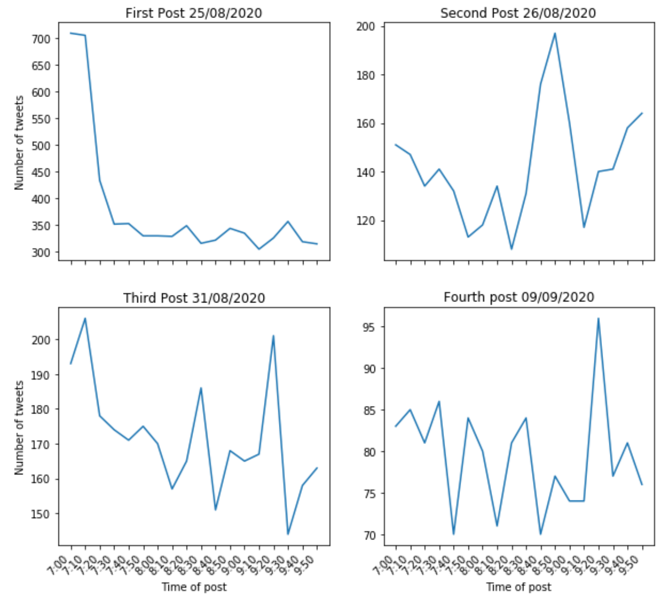

Fig. 2. Number of tweets since the time of the publicity post.

Fig. 2 shows the results of the analysis on how the number of tweets behaved as time passed after each of the analyzed posts. For this the number of tweets posted every ten minutes was obtained from the time of the publicity post to three hours later.

For the sentiment analysis I had to filter those tweets on the database that were on another language, like Japanese or Arabic, and were due to get a neutral polarity which would interfere with the analysis. After filtering the database I was left with 9230 tweets. All tweets obtained were analyzed with the help of the VADER tool, which allowed to obtain the compound scores, which calculates the sum of all the lexicon ratings and then is normalized between -1 and 1, being -1 the most negative and 1 the most positive. On Fig. 3 the scores obtained and their frequency are shown.

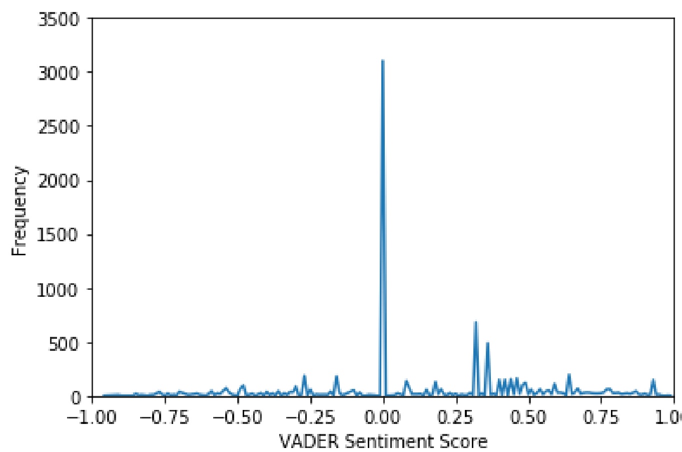

Fig. 3. VADER scores.

With the scores obtained I proceeded to separate the negative and the positive tweets to analyse each group, on Fig. 4 we can see the most frequent words found on the negative tweets. 4325 positive, 1782 negative and 3123 neutral tweets were obtained.

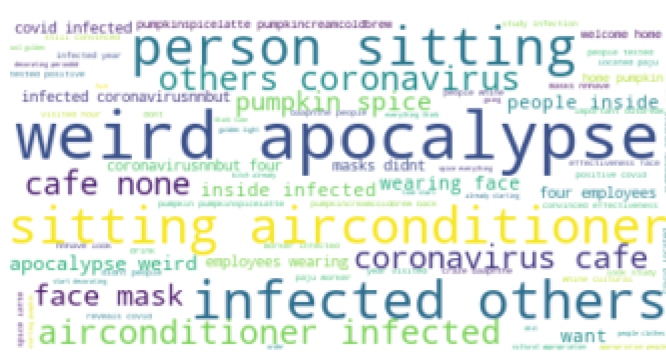

Fig. 4. VADER scores.

I wanted to analyze which were the principal emotions associated with each of the groups of tweets, for that I used the NRC-EmotionLexicon (NRC) [5]. This lexicon identifies eight basic emotions: joy, anger, sadness, surprise, trust, anticipation, disgust, and fear. I recollected the number of tweets associated with each of these emotions, these are shown on Fig. 5 for the positive tweets and on Fig. 6 for the negative ones.

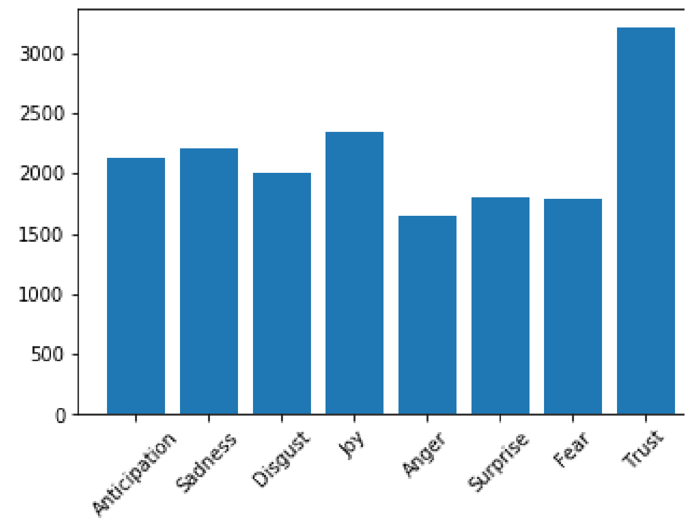

Fig. 5. Number of tweets since the time of the publicity post.

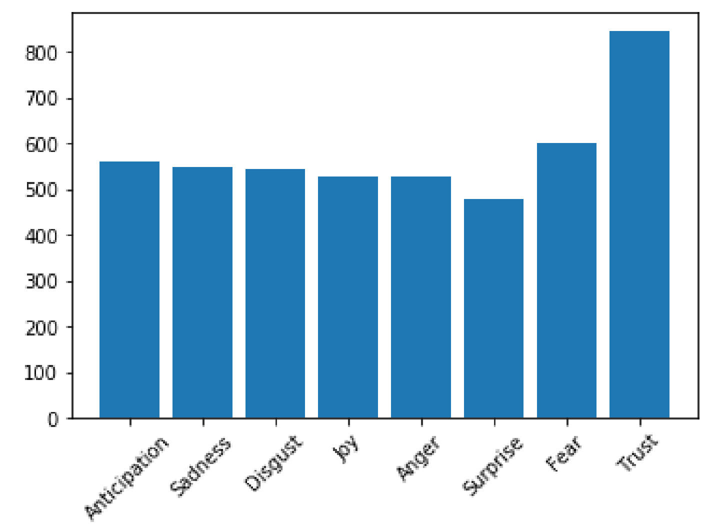

Fig. 6. Number of tweets since the time of the publicity post.

A correlation analysis was performed, and the following information was obtained from each of the tweets from the dataset: the length of the text, the time passed between the Starbucks publication and the post of the tweet, the followers that the account making the post had, the favourites of the tweet, it's VADER sentiment score, the years passed since the creation of the account and the number of friends of the account. We can calculate correlation coefficients using methods like Pearson's or Spearman's, for this analysis we used Spearman's as it evaluates the monotonic relationship between variables. A monotonic relationship, is one in which the variables tend to change together, but not necessarily at a constant rate. The correlation between the variables is shown on Fig. 7

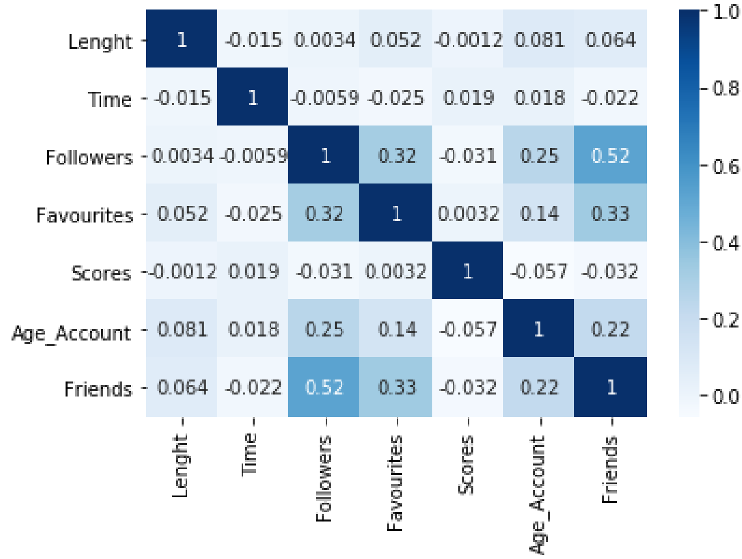

Fig. 7. Correlation between variables.

To extract the trending topics from the groups of tweets I extracted the 25 most frequent bigrams from the database, which are the co-occurring words that appear on the tweets, using the Natural Language Toolkit (nltk) library from python. To visualize the relationships between words I used the python package NetworkX to create a graph in which each word was represented as a node and the connections between the nodes represented their relationships, in this case how many times they appeared together. This graph is shown in Fig. 8 for the positive group of tweets and in Fig. 9 for the negative group.

IV. Discussion

From Fig. 1 we can visually see that the most found words are ones with a positive connotation, we can also find the words "pumpkin spice", which was expected, given that is the flavour of the promoted drinks of the posts of interest.

The four promotional tweets, posted on the official Starbucks Twitter account, were made at exactly 7:00 am, for the first post we can see, on Fig. 2, a clear increase on the number of tweets mentioning the brand right after the post, which decreased after about half an hour, this was the first promotional post mentioning the pumpkin spiced beverages. For the three remaining post we see spikes of tweets with higher numbers at about an hour and a half or two hours after the post. We can also note that the number of tweets decreased for the last post, when the excitement for a new seasonal product had probably decreased.

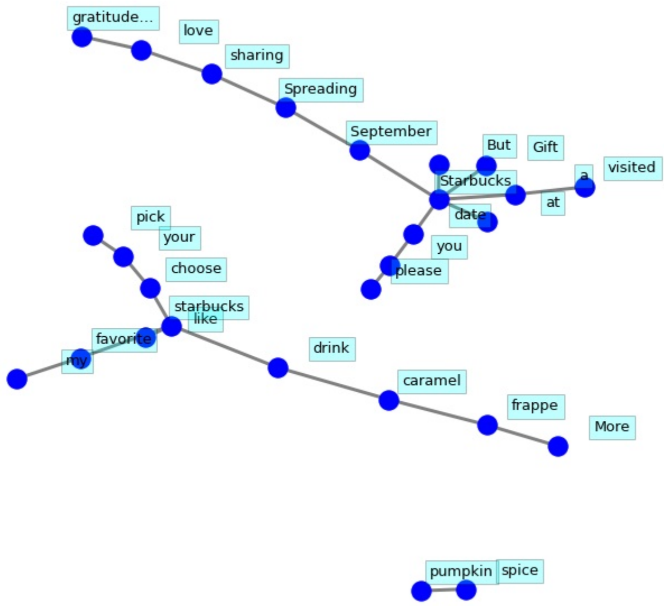

Fig. 8. Relations between words for the positive tweets.

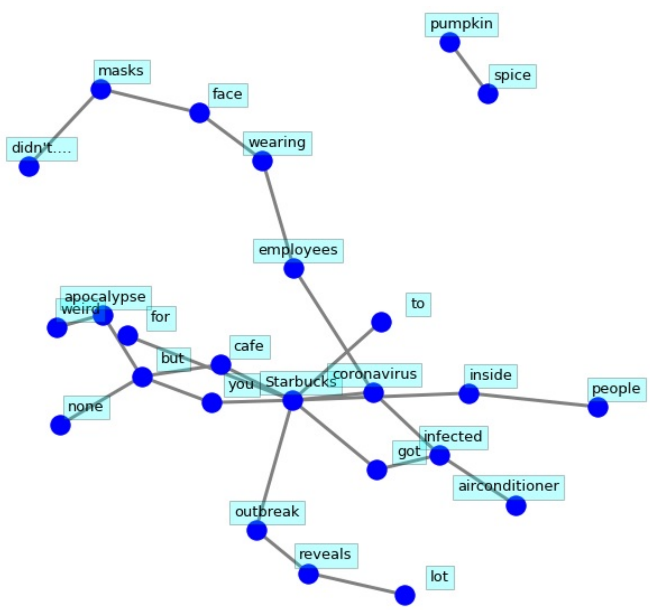

Fig. 9. Relations between words for the negative tweets.

The sentiment scores that we obtained, with the VADER tool, can be found at Fig. 3, they show that most of the tweets had a pretty neutral polarity, nevertheless the positive scores outnumbered the negative ones. If the compound is above 0.05 we consider it to be a positive sentiment and if it is below -0.05 we consider the sentiment negative, the values between -0.05 and 0.05 correspond to a neutral sentiment.

On Fig. 4 we have the most frequent words found on the tweets with a negative sentiment, some of them mention aspects of the business like ”sitting”, ”cafe”, or ”air conditioner”, giving some hints on the aspects that the individual stores could improve. Other words like ”apocalypse”, ”infected”, ”face mask”, etc. suggest that the main topic of those tweets referred to the COVID-19 pandemic, which, more often than not, generates a negative sentiment on any context.

As we can observe on Fig. 5, the emotions associated with each group of tweets gave conflicting results, on both cases the most found emotion was trust, we have to consider that I searched for words on the tweets that were contained on the lexicon and then associated the labeled emotion to that tweet, then I took the emotion that was found the most for each tweet, in some cases these were more than one, and started counting each occurrence. Some words have multiple emotions associated to them and that can lead to conflicts like the one I found. A particular example was a tweet that I had previously found had a negative sentiment but contained words like ’hope’, which is identified with the emotion of trust. We can notice that on the positive group the most emotion found, apart of trust, was joy and the less found was anger, this collides well with the positive sentiment. On the other hand, for he negative tweet, the emotion most found, apart of trust, was fear and the less found, surprise.

With the correlation matrix from Fig. 7, we found that only a few of the variables extracted from the tweets had a direct correlation with others, these were the number of followers, number of friends, age of the account and number of favourites. The rest of the variables had no direct correlation, is important to note that especially the sentiment scores obtained with the VADER tool had no correlation with the rest of the variables, indicating that sentiment does not vary with the popularity of the account, the length of the tweet or the time passed between the original publication and the post of the tweet.

From Fig. 8 and Fig. 9 we can observe that for the positive tweets the trend is to talk about pumpkin spice, drink caramel frappe, etc. which indicates that some of the aspects that causes most a positive sentiment of the brand are the beverages, also we find words like gratitude, love, sharing, date and gift, all words with a really positive connotation, these words and the fact that there were more tweets on the group of positive sentiment that on the negative group indicates that the brand has a really good image on twitter. For the negative tweets we find words like apocalypse, coronavirus, masks, outbreak and infected, all topics that have a relation with the COVID-19 pandemic which is something the brand does not have control over, and that produces a negative sentiment in all contexts.

V. Conclusion

I found that there was a more positive sentiment towards Starbucks on the tweets following a publicity post, as there were more tweets with a positive sentiment than a negative one. The trends on the positive tweets talk about the beverages of the business as well as love, dating, giving gifts, finding a favorite drink, etc. On the other hand on the negative trends, there were mostly topics about the COVID-19 pandemic, a subject in which the company has little control over. I also found that variables extracted from the tweets had no correlation with their sentiment. For future work I would collect more data from different times to get a better idea on how the sentiment changes through a larger amount of time. A system could be implemented to automatically detect the sentiment on social media for the business and extract the topics that are causing such sentiment.

The results could help the marketing team, of not only Starbucks, but similar business by providing a clearer idea of what aspects of their business and publicity get a positive response or which are the negative characteristics that the public does not like about their brand. This knowledge can give them the opportunity to improve their publicity campaigns or to make the needed changes to solve the conflicts on their public image.

VI. Acknowledgement

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