Difference between sentiments towards a common topic in distinguished social networks

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ABSTRACT

Nowadays, social platforms gaining more and more popularity. As a result, million of users are interacting with each other by using these platforms. The way of building an opinion may be influenced by the specific characteristics of a certain social platform. The purpose of this paper is to analyze the sentiments in two social platforms based on a common neutral topic to find possible reasons for the differences.

Author Keywords

Social platforms; characteristics, analyze the sentiments; common neutral topic; possible reasons; differences.

INTRODUCTION

Social Media is "forms of electronic communication (such as Web sites) through, which people create online communities to share information, ideas, personal messages, etc." [12]. Since its usage was adopted as a daily routine, the way people interact with each other has changed, personally and professionally. They facilitate the maintenance of remote relationships and allow the swift exchange of different and faster forms of communication such as text messages, videos and pictures.

Social media differ in their essence. Some of them exist in the form of social networks, where the users create their personal web page in order to connect, communicate and to share content with other participants with the same interests or common background (e.g. Facebook, Google+, MySpace). Others are based on media sharing where a particular type of media is distributed and such as pictures and videos (e.g. Pinterest, Youtube, Slack), offering social features.

In addition, there are levels of privacy exposure in different social networks. Taking Facebook as an example, it provides features for the users to expose more information about themselves, such as profile pictures and personal information. On the other hand, some platforms lack this sort of functionality, preserving the user's anonymity.

Humans are by design sentimental beings and since the main part of a social media are the people, it is expected the shared content inside the network is shaped by their emotions and beliefs. Considering a particular event, a brand or an industry, the social media users reactions could influence the business results, the variations of the stock market [13] and presidential elections as campaign messages for them are organised based on the public opinion [14]. In this way, taking the user’s attitudes into account and reacting accordingly to them can be an advantage for an organization. Having this state, sentiment is a keystone metric when analyzing social social media and reacting accordingly to it can be an advantage for an organization.

This paper has the objective to analyze whether in two different social media the sentiments towards a common topic are the same and to suggest possible reasons for the possible differences between the results.

The paper is organised as follows: In the second section the **Method** which was used for the analysis is discussed. The third section contains the **Results,** which are evaluated. The fourth section gives a **Discussion** upon some assumptions that were made regarding sentiment analysis.

METHOD

It was opted for this project to collect comments regarding the British withdrawal from the European Union in 2017, referred by the media as Brexit.

Considering the fact this paper has an international team as authors and most of the sentiment analysis tools work with English texts, the gathered comments were restricted to the English language. The Brexit topic suits well this goal since it concerns primarily the Britain countries, which have English as native language. In addition, this is a cotemporaneous topic with great impacts and broadly covered by the global media, therefore, finding English content about the subject would be easily achieved. It is important to mention this work is not restricting the comments geologically or demographically.

Further, different than topics such as 9/11 or child pornography, which tend to fit just one side of the sentiment polarity spectrum, the Brexit theme could be spread between the two extremes, displaying comments with positive and negative emotions about it.

The selected social networks for extracting comments were Twitter and Youtube due to, mainly, their difference in essence and mechanics. Twitter is a social connection network with its users' posts as the basic content, displayed chronologically in a timeline. Youtube's purpose is to display user-generated videos, displaying the comment system is a sub-feature of the platform.

Additionally, both social networks maintain public APIs for finding and extracting content inside them. Twitter provides the Search API, resulting in a sampling of recent Tweets published in the past 7 days for a given query. As an observation, the Search API is focused on relevance and not completeness, meaning that some Tweets and users may be missing from the search results [1].

Giving a topic, the Youtube API retrieves videos which have it in their title or other metadata, limited by 50 videos per API call. The API's criteria for selecting the videos is relevance towards a query. Once the videos are fetched from the platform, it possible to extract their comments, restricted to 100 comments per video.

The comments were collected from both social networks on April 21, 2017, resulting in 2704 entries for each one. After acquiring the comments, it was necessary to clean the texts before applying the sentiment analysis tool, removing urls and other elements that could wrongfully interfere with the results.

For analyzing the sentiments of the acquired comments, the Vivek Narayanan's analyzer API [2] was used. It relies on an enhanced Naive Bayes model to quickly and accurately classify a text [3] and returns a JSON containing the following fields:

- Comment: the text analyzed.
- Sentiment: ranging between negative, neutral and positive.
- Confidence: belief in the sentiment result, expressed in percentage. In this paper, it was not established a threshold for this attribute.

RESULT

The following table states the data which has been computed after extraction from the YouTube comments and after performing the sentiment analysis. Categorization of the comments has been done based on the sentiments from users. The nature of comments has either been positive, negative or neutral. The negative sentiment toward the topic was the predominant on Youtube.

Table 1 - Youtube Sentiment Result

Sentiments	Positive	Negative	Neutral
Number of Comments	801	1290	613
Percentage	29%	48%	23%

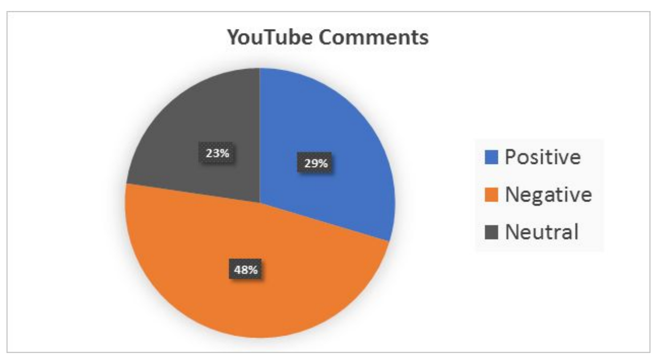

Figure 1 - Youtube Sentiment Analysis Chart

The following table and chart concern the data collected and analyzed for Twitter. It is possible to see the neutral sentiment is occurring the most in the platform.

Table 2 - Twitter Sentiment Results

Sentiments	Positive	Negative	Neutral
Number of Comments	786	767	1151
Percentage	29%	28%	43%

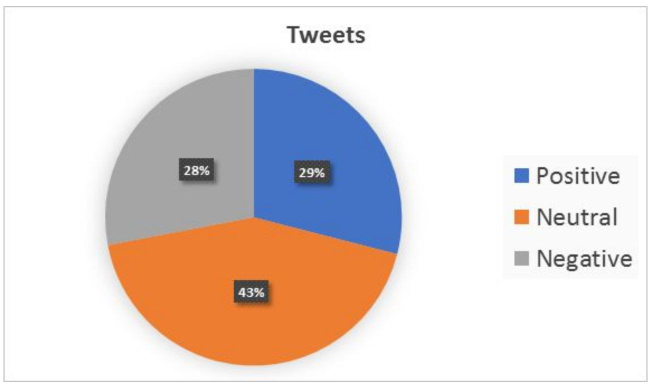

Figure 2 - Twitter Sentiment Analysis Chart

DISCUSSION

The results show a difference in the sentiment towards a common topic in two different social platforms. In terms of the extracted data from Twitter, it is shown the sentiments are more balanced between positive and neutral. However, in the results from the social platform of Youtube more negative data has been extracted. In the following, possible reasons for the occured result are stated.

The difference between the sentiments on the two platforms could be caused by the different content of these social platforms. Based on an online survey, which involved more than 4,700 social media users, 74 % of them told they use Twitter for checking on daily news [4]. Opinions are rather shown by retweeting Tweets than actual direct tweeting. On the Youtube side, the content is more about entertainment like games, or topics regarding cosmetics [5]. There people tend to show their direct reaction to a video, instead of sharing the same opinion by using the retweet functionality in terms of Twitter. It can be assumed Youtube users are not exposed to news content in big degree and they react more negative about topics like Brexit since they are not used to them on the platform. Furthermore, by retweeting, the user's actual opinion has a lower priority than on Youtube, where the user actually post a comment that express his or her real opinion.

The media type used for providing the information in both platforms are different, which can lead to the obtained sentiment results in this paper. By using videos, Youtube creates a deeper emotional connection [8] comparing to Twitter, which focus on textual information. This fact means videos have an impact that is comparable with a face-to-face conversation [8]. By being more emotional on Youtube, it can be supposed the users' sentiments are being stronger expressed than on Twitter. In this analysis the assumption is reflected with the higher amount of negative sentiments comparing to the side of Twitter.

Demographic reasons such as the gender may also have an influence on the sentiments. The majority of the Youtube users are represented by men with 55 % [9]. However, the Twitter users are divided more equally with a ratio: 49 % of men and 51 % of women. The higher negative sentiment in Youtube could be linked to the number of men in their user community. These sentiment can be interpreted as anger, which may be seen as masculine and unpleasant for females [11]. Tangney, professor of psychology at George Mason University says women tend not to be using the same level of aggressively to express anger [11], which would explain the difference in the sentiment analysis in this paper since the number of males are represented by a higher number in Youtube than on Twitter.

Another point that could be connected to the higher number of negative sentiments on Youtube is the degree of exposure of private information. This point is related to the mechanics of the Youtube comment system. In Twitter, for instance, the user can view all the user's Tweets collection list in their profile page. On Youtube, the users are not able to track comments from a specific user. As a result, in social platforms like Twitter, the user does not feel the same level of anonymity than the user do on Youtube, where the user do not fear consequences by posting a certain comment once it cannot be tracked by viewing the profile of the specific user. By not having an option for listing all the comments from a single user on Youtube, only the top comments will be shown in a video and the other comments will disappear underneath of multiple other comments. This characteristic increases the level of anonymity [6]. Further it could be said the higher level of anonymity, the lower the inhibition threshold which tend to cause flaming.

If the applied methodology for extracting the data from Youtube is considered, only the 100 first comments per video were collected [7]. This means the probability of getting comments with a negative sentiment is high because these are the top comments, which may be controversy and outcoming a negative sentiment.

The criteria for the selection of top comments in Youtube that were caused by the number of replies and the numbers of “Thumbs up”. Although, the functionality of rating a comment down by using the “Thumbs down” technique exists, it does not affect the priority of the comment. This means controversial comments can be a top comment, which may contain content that does not even directly belong to the topic, but it could get a lot of replies because of the controversy. However, in Twitter again the user can view the history of the posted Tweets of a user. In this case, their Tweets are more thoughtful than a Youtube comment because they have to consider possible consequences based on their actions [6].

The last point about the influence of the mechanics of the Youtube platform concerns their rewarding system of comments. In Twitter, user gets rewarded with the retweets, which indicates how many people share the same opinion about a Tweet. The total number of retweets can be viewed in the profile of the user. However, in Youtube the users are working with the “Thumbs”-system. The problem, which occurs, is that the number of “thumbs” are not shown anywhere. This behavior of the mechanics again increases the level of anonymity because users do not have to fear further consequences [6].

Considering the mentioned points regarding the platform of Youtube, people might not use their comment function to start an intelligent debate, when they see the top comments. This can be seen as a vicious cycle because the number of negative sentiment may increase in the comment section, and people do not want to start intelligent debate because of the top comments.

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