Towards Metadata Analysis on Opinionated Content in Tweets

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Abstract: Recently, much research has been done in the area of sentiment analysis of microtexts, specially using tweets. In most studies, the sentiment polarity detection methods are solely based on textual information. The detection of opinionated content in texts is not a simple task, and even less simple in the context of social media. Furthermore, processing microtexts using just natural language techniques may lead to unsatisfactory results. There is a lack of works which link other properties of the tweets (metadata), such as retweets and likes, and the their opinion (i.e., the presence of sentiments). Using tweets collected during the 2013 FIFA Confederations Cup, which occurred in Brazil, this work proposes an analysis of metadata properties on tweets, in order to verify which of these properties have more impact on their opinionatedness. The results indicate that the properties "presence of links" and "retweets" are the most significant with respect to the opinionatedness of a tweet.

1 INTRODUCTION

Understanding what people think, i.e., knowing their opinions, is a fundamental part of the decision-making process, especially in the context in which they express their feelings voluntarily in order to cooperate with one another. The growth of social media propitiated by the WEB 2.0 has led to the generation of a large volume of non-structured textual data. Microblogging is a very popular means of communication among Internet users (Pak and Paroubek, 2010). The messages shared by the users concern not only their private lives, but also current affairs, products, services and general events. Websites that provide microblogging services, such as Twitter, have been subject of study in the field of sentiment analysis, with the purpose of generating content recommendation tools, security tools, and many other applications (Alves et al., 2014; Pak and Paroubek, 2010).

According to Liu (2012), the main objective of sentiment analysis is to obtain and formalize the opinion and the subjective knowledge contained in non-structured documents (texts), for a posterior analysis in a specific domain. The sentiment analysis process can be defined by three major tasks: identification, classification and summarization (Liu, 2012; Tsytsarau and Palpanas, 2012). The identification task may include, besides the recognition of entities and their aspects, the recognition of subjective/opinionated sentences. In the classification process, which is the main task in sentiment analysis applications, the goal is to obtain the polarity of the sentiment. The summarization, in turn, is intended to obtain metrics and summaries that represent the general sentiment of a group of people about either a certain entity or the aspects of that entity. In most studies in the field of sentiment analysis, just the textual information in each tweet is analyzed. The main proposed methodologies employ Natural Language Processing or Machine Learning in order to classify the polarity of the sentiments expressed in tweets (Sharma and Dey, 2012).

According to Suh et al. (2010), a tweet contains, besides the textual information, content and context properties, apart from the textual information, content

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and context properties describe metadata. The content properties, that can be found in the tweet, include URLs, hashtags and mentions (references to other users). The context properties, on the other hand, include the number of followers of a user, the number of likes in a tweet, number of retweets and many others. According to Harris et al. (2015), the act of liking a tweet shows that the user agrees with its content or with the opinion it expresses. Hence, if there is a tweet with positive sentiment polarity and ten likes, this means that, besides the author, other ten people agree with that opinion (Meier et al., 2014). It is possible to make a more thorough sentiment analysis, taking into account the impact that a tweet has over its followers.

Detecting opinionated content in texts is not a simple task, especially in microtexts, since they may contain abbreviations, repetition of letters and typing errors. In general, the use of text processing techniques alone may lead to unsatisfactory results. In this scenario, Alves (2014) suggest the exploration of other properties (metadata) of the tweets besides the textual message in order to provide improvements in the accuracy of the polarity detection. The exploration of additional attributes on Twitter allows the discovery of other attributes contained in their metadata. These attributes may help to identify opinionated content, which is very important in the sentiment analysis process.

This study explores the identification of opinionated content in the context of the sentiment analysis. The main goal is to verify which attributes of a tweet contribute to the identification of opinionated sentences, in order to improve the polarity classification task. The metadata attributes of interest in this work are: likes, mentions, retweets, links, and replies. The main contribution of this work is the investigation based on statistical analysis, in order to verify whether there are metadata attributes that are significantly important to the identification of opinionated content in tweets.

The rest of this paper is organized as following. In Section 2, we analyze the related works. In Section 3, we address the methodology adopted in this study. In Section 4, we highlight the results. Finally, in Section 5, we present the conclusions and discuss further work to be undertaken.

2 RELATED WORK

Many studies in the area of sentiment analysis obtain the sentiment polarity of a tweet just based on its textual information (Alves et al., 2014; Pak and Paroubek, 2010). Pak and Paroubek (2010) used Naive-Bayes text classifiers and techniques for grammatical classification of words (POS-Tagging) to identify sentiment in tweets written in English. So, no human effort was needed to classify the texts.

Alves et al. (2014) use a similar approach to that of Pak and Paroubek, with the help of a Naive-Bayes text classifier. However, they collected tweets written in Portuguese. In Portuguese, the use of grammatical classification in order to obtain the sentiment of a text is not a simple task since, besides the problems concerning the texts of the tweets themselves (abbreviations, repetition of letters, among others), there is also the grammatical complexity of the language. Their work proposes a text classifier that uses Natural Language Processing and Supervised Learning techniques to detect the polarity of sentiment in tweets. By doing so, they avoided the use of grammatical classification with the texts (POS Tagging).

Tsai et al. (2013) propose the building of a dictionary at concept level with sentiment values based on common knowledge. The authors suggest not just the concepts dictionary, but also the way it is built. They use a two-step method combining iterative regression and random walk with in-link normalization. The dictionary is built based on common concepts and relationships between the so-called “seed words” to propagate the value of the sentiment among the concepts.

Poria et al. (2013) present a methodology to automatically assign emotional labels to the concepts present in SenticNet (Cambria et al., 2010), in order to improve the results of the sentiment analysis. They used SVM as a classifier. The training of the machine was conducted with a subset of concepts of SenticNet (Cambria et al., 2010). They used characteristics of the authors of the messages in the analysis (age, gender, parent's occupation, etc).

Weichselbraun et al. (2013) used a lexical dictionary, considering the context of both the word and the message, in order to execute the sentiment analysis of text messages. The ambiguities were removed by means of context analysis, with the use of frequency graphs and even Bayesian networks for detection of the context of the term. The combination of these dictionaries is used to perform the sentiment analysis.

Xia et al. (2013) execute the sentiment analysis considering POS-tags and separation of domains in order to enhance the sentiment associated with each word. They execute the sentiment analysis using sentiment associated with the words, POS-tags, and Bayesian Networks.

Cambria et al. (2013a) make an introduction to sentiment analysis techniques that employ knowledge bases. Their work represents an important study in this field and summarizes some contemporary work. They also divide the opinion mining problem into two areas: Natural Language Processing (NLP) and Language Interpretation (Cambria et al, 2013b). However, they neither indicate solutions nor point out the main characteristics used to execute the sentiment analysis.

Hogenboom et al. (2015) perform the sentiment analysis of documents by combining several sentences in order to identify the general sentiment through Rhetorical Structure Theory (RST). They created an RST-based tree, by which they perform the combination of sentiments. However, they do not identify which characteristics are more relevant to the sentiment analysis.

Liu et al. (2015) propose a multi-label approach for classification of sentiment in microblogs. Additionally, they present a comparative study between different multi-label methods for classification of text in microblogs. They also presente a comparative study on the effects of different sentiment dictionaries over the multi-label classifiers.

Cambria et al. (2014) present an approach that uses an open-domain knowledge base (i.e., not concerned with a specific domain of content) to execute the opinion mining and sentiment analysis. Furthermore, they use a "Bag of Concepts" together with the multidimensional knowledge base built.

Rosas et al. (2013) present a complete approach for sentiment analysis of videos. They use the linguistic (texts transcribed from the video), visual and audio data to identify the sentiment associated with the video. They execute the sentiment analysis in these data separately and then combine the results into a single sentiment.

Wollmer et al. (2013) present a similar approach to that of Rosas et al. (2013), in which they use linguistic, visual and audio data of YouTube videos to perform sentiment analysis. They join the characteristics in order to find the sentiment associated with the video but do not make clear which of these characteristics are more relevant to the analysis.

Other works analyze the context of the properties of a tweet, such as the number of retweets, for example. Meier et al. (2014) conducted a study in order to understand the behavior of the "like" functionality on Twitter. They found that the act of "retweeting" indicates that the user considers the information to be interesting enough to be forwarded to their followers. The act of "liking", on the other hand, indicates that the user simply agrees with the content of the tweet.

Some studies have attempted to establish a relationship between some of the context properties of the content of a tweet and its opinionatedness. Stieglitz and Dang-Xuan (2012) and Pfitzner et al. (2012) established a relationship between the opinion present in a tweet and its likelihood to be retweeted. According to Stieglitz and Dang-Xuan (2012), tweets that contain more words with either positive or negative sentiment tend to be more retweeted. Pfitzner et al. (2012) on the other hand, conclude that emotionally diversified tweets, i.e., tweets containing words with both positive and negative sentiments, have fivefold chances of being retweeted.

The literature presents solutions to sentiment analysis, but, to the best of our knowledge, none of the works is intended to analyze which of the content/context properties of a tweet are more closely related to its opinionatedness. So, the main contribution of this article is the discovery of which metadata characteristics are more relevant to the sentiment analysis in the context of Twitter. Furthermore, we present a logistic regression model used to identify those characteristics.

3 METHODOLOGY

In this section, we describe the methodology used in the development of our experiment. It is presented in two subsections: experiment configuration, which describes the dataset used and the hypothesis raised about each aspect under analysis; and experiment execution, which describes the creation of a logistic regression model based on that data.

3.1 Experiment Configuration

In the work by Alves (2014), he collected about 120.000 tweets concerning the 2013 FIFA Confederations Cup, with the objective of developing a sentiment polarity classifier. To this end, he separated a set containing 3,500 tweets (labelled as a gold standard dataset) which were used for training and testing of the classifiers. After implementing the sentiment polarity classifier, the author classified all the collected tweets with a mean accuracy of 80%.

Since one of the goals of this work is to verify which of the properties of a tweet can be used for the detection of opinionated tweets (i.e., tweets in which users express their opinions), we use the tweets labelled in the work by Alves (2014) (gold standard dataset and the set labelled by the classifiers). In order to generate the logistic regression model, we opted to use the gold standard dataset instead of the set of the tweets labelled by the classifier. In doing so, we intended to minimize the introduction of errors in the model. Hence, the set of all the collected tweets (about 120,000) was only used to perform a comparison between the layout of their metadata and those of the rest of the tweets. The tweets which had the sentiment polarity classified either as positive or as negative were considered opinionated tweets while those classified as neutral were considered informative tweets.

It is important to highlight that the methodologies implemented in other studies on sentiment analysis only use the textual information of the tweets (maximum of 140 characters) (Alves et al., 2014; Pak and Paroubek, 2010). However, a tweet contains, besides the text written by the author, other pieces of information added implicitly by Twitter. These metadata may inform, for example, the time and the geographic location of the user at the moment the message was sent. Besides the text of the tweets, we explored the following metadata:

1. Replies – indicates if a tweet was replied by some user;
2. Likes (favourites) – indicates if a tweet was marked as favourite (liked) by some user;
3. Retweets – indicates if the tweet was the cause of another tweet sent by another user;
4. Mentions – quantifies the mentions to other users of the network;
5. Links (URLs) in the text – indicates if the tweet contains links to external websites.

In short, the experiment is intended to help in the task of identification of opinionated tweets through an analysis of the correlation between the metadata listed in the previous section and the opinionatedness of a tweet. This way, in order to check which metadata are connected to the opinionatedness of a tweet, some hypotheses were created based on the following hypothesis model:

"*The existence of **Mi** in a tweet is not significant to determine the opinionatedness of tweet*", where *Mi* is one of the metadata explored by this work (e.g. replies, likes, retweets, mentions and links).

The identification of the hypotheses follows the same pattern of the identification of metadata.

This way, let H be the set of hypotheses and Hi-0 the hypothesis related to the characteristic *Mi*. The hypotheses are:

1. **H1-0:** The existence of **replies** in a tweet is not significant to determine the opinionatedness of tweet;
2. **H2-0:** The existence of **likes** in a tweet is not significant to determine the opinionatedness of tweet;
3. **H3-0:** The existence of **retweets** in a tweet is not significant to determine the opinionatedness of tweet;
4. **H4-0:** The existence of **mentions** in a tweet is not significant to determine the opinionatedness of tweet;
5. **H5-0:** The existence of **links** in a tweet is not significant to determine the opinionatedness of tweet.

3.2 Experiment Execution

Regression methods have become an integral component of data analysis concerned with describing the relationship between a response variable and one or more explanatory variables. Quite often the outcome variable is discrete, taking on two or more possible values. The logistic regression model is the most frequently used regression model for the analysis of these data (Hosmer Jr. et al., 2013).

First of all, to execute the experiment, we used a linear regression model, which was intended to indicate which variables are able to explain the response variable by means of the construction of an approximation function of the data. The use of this model led to statistically insignificant results.

A logistic regression model was also used. Comparing both models, the logistic regression model proved to provide better results, which is due to the fact that in this research work, we only deal with binary variables (i.e., variables that can have the values 0 or 1 only) (Hosmer Jr. et al., 2013).

A logistic regression model was used, as the expected value of the response variable is limited to 0 or 1, differently from the linear regression in which the response variable can take values in the interval [-∞, +∞]. Moreover, linear regression assumes that the variance error is constant and independent of the predictors' values, which does not occur when the response variable is binary. Additionally, for this experiment, the data cannot be normally distributed, considering that the response variable can take only two possible values.

The specific equation of the logistic regression model used was:

$$y = 1/(1 + e\hat{}(\beta_0 + \beta_1 x_1 + \beta_2 x_2)\,) \qquad (1)$$

where β_0, β_1 and β_2 are the coefficients and x_1 and x_2 are the variables.

The criteria for including a variable in a model may vary from one problem to the next and from one scientific discipline to another. The traditional approach to statistical model building involves seeking the most parsimonious model that still accurately reflects the true outcome experience of the data. The rationale for minimizing the number of variables in the model is that the resultant model is more likely to be numerically stable, and is more easily adopted for use. The more variables included in a model, the greater the estimated standard errors become, and the more dependent the model becomes on the observed data (Hosmer Jr. et al., 2013).

The method for selecting variables used in this work was the purposeful selection. The rationale behind the method is that it follows the steps that many applied investigators employ when examining a set of data and then building a multivariable regression model (Hosmer Jr. et al., 2013). By using this method, it was possible to eliminate variables without statistical significance from the final model generated.

Figure 1 presents the summary of the distribution of tweets according to the analyzed metadata.

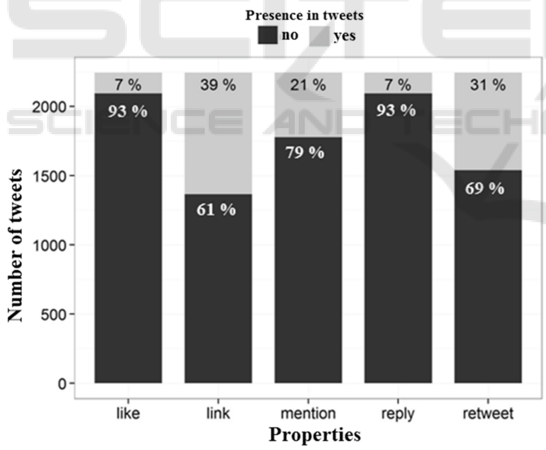

Figure 1: Percentage of presence of the properties in the tweets (dataset).

As one can observe in Figure 1, there are more tweets that were not replied. Only about 7% of those tweets were replied. Concerning the property "like", it is not present in most of the tweets. Only about 7% of the collected tweets were "liked" by at least one user. Similarly, there are more tweets without retweets. About 31% of the collected tweets were retweeted by at least one user. Regarding the property "mention", just about 21% of the collected tweets had mention to at least one user. Finally, one can see that about 39% of the collected tweets have some link to external websites.

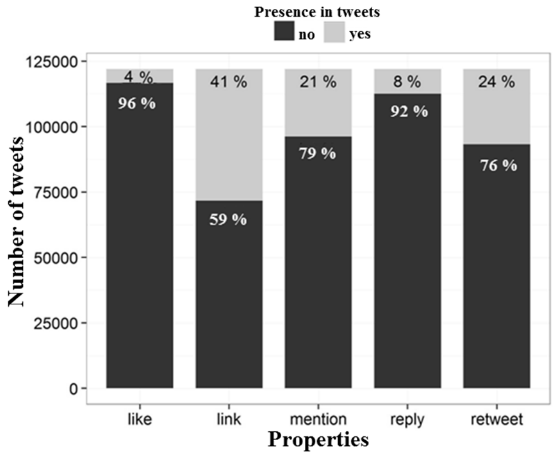

Figure 2: Percentage of presence of the properties in the tweets (whole set of tweets).

Figure 2 presents the summary of the analysis performed on the whole set of tweets automatically labelled by the sentiment classifier implemented by Alves (2014). Comparing Figures 1 and 2, we notice that the results are quite similar. This means that the test set is quite representative with respect to the layout of the properties under study in the gathered tweets.

4 RESULTS

The logistic regression model supplied p-values for each variable. These values were used to test the hypotheses previously established in Section 3.1. The significance level used in the tests was of 5%. Thus, the hypotheses that have p-value smaller than the significance level can be refuted. Otherwise, there is no support to reject them.

Table 1: Hypotheses under study and the respective p-values.

Hypothesis	Characteristic	p-value
H1-0	reply	0.5766
H2-0	like	0.3137
H3-0	retweet	0.0246
H4-0	mention	0.9525
H5-0	link	$4.07 * 10^{-16}$

Table 1 presents the results achieved by each hypothesis. The p-values found for the hypotheses H1-0, H2-0 and H4-0 were above the significance level established. Therefore, there is no support to refute them. So, we will assume that the presence of replies, likes or mentions in a tweet is not related to the fact that it is opinionated.

In the case of the hypotheses H3-0 and H5-0, the p-values were below the significance level. Therefore, these hypotheses can be refuted and the alternative hypotheses can be adopted. That is, we will assume that the presence of retweets or links in a tweet is correlated to the fact that it is opinionated.

By considering just the hypotheses H3-0 and H5-0, we find that just the link and retweet variables are significant. So, a logistic regression equation was generated taking just these two variables into account, allowing us to model the expected value for the opinionatedness of a tweet based on the values of these variables. The equation, based on Equation (1), is:

$$y = 1/(1 + e^{\wedge}(-0.97 + 0.76 * l + 0.27 * r)) \quad (2)$$

where y is the expected value of the "presence of opinion" variable, which represents the likelihood of a tweet being opinionated. The l variable represents the presence of links in the tweet and the r variable is the presence of retweets.

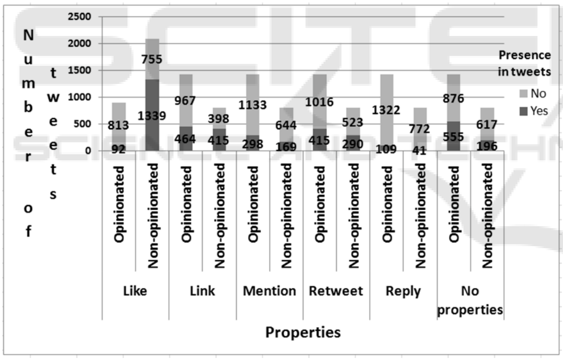

Figure 3: Layout of the tweets used to generate the regression with respect to the properties and to the opinionatedness.

Analyzing the data used in the experiment, one can visualize the impact of the metadata under study on the opinionatedness of tweet. As we can see in Figure 3, the metadata variables most present in opinionated tweets are links and retweets, reinforcing that the presence of any of these metadata in a tweet is related to the presence of opinion on it. The retweet property, for example, was present in 415 opinionated tweets and in 290 non-opinionated ones. The like property, in turn, was mostly present in the non-opinionated tweets and, for this reason, was not taken into account for the generation of the regression model.

Using data from the training set, collected during the 2013 FIFA Confederations Cup, we could generate a logistic regression model that helped at the identification of the most significant metadata concerning the presence the opinion in a tweet. By the hypothesis tests, we were able to verify that the like, reply and mention metadata had no impact on the opinionatedness of a tweet. So, a regression equation was generated taking into account just the link and retweet metadata, which were statistically significant attributes for the model, using a 95% confidence interval.

5 FINAL REMARKS AND FUTURE WORK

Since this theme is not much explored in the literature, this work was intended to perform a study on which metadata properties are related to the opinionatedness of a tweet. An experiment was conducted using tweets collected concerning the 2013 FIFA Confederations Cup. These tweets were classified according to the opinion contained in their texts. After that, we studied their properties in order to verify which of them were related to the presence of opinion in the tweets. The contribution of this work consists of a logistic regression model, which led to the following conclusions:

1. The fact that a tweet has likes, replies or mentions are not decisive to conclude whether it is opinionated or not, since non-opinionated tweets (e.g., news) also have likes.

2. The presence of links and retweets seem to be decisive to conclude if a tweet is opinionated, since a high number of tweets have comments about topics present in other websites.

As further work to be investigated, we plan the use of the metadata properties connected to the opinionatedness of a tweet to increase the accuracy of the text classifiers employed. Therefore, we propose the use of not just the textual information of a tweet to classify its opinionatedness, but also its metadata, which may provide important information to this end.

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