Sentimental Analysis of Soccer Games Messages from Social Networks using User's Profiles

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Abstract — The people express their sentiments thought the Social Networks, and these sentiments can be measured to offer knowledge about tendencies and influences on Internet. In many scenarios, as in sport games, is important have the insight about what the people are thinking regarding a given player or product. This paper presents a metric based on phrase-level, in which is shown the importance of considering users´ characteristics, such as gender in sport scenario is shown. The calculation made from the word dictionary is adjusted by applying a correction factor based on the user´s profile characteristics. The results showed that considering the user's profile characteristics in the sentiment metric improves the sentiment analysis performance.

Keywords — sentimental analysis, social networks, profile analysis, crowdsourcing.

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1. INTRODUCTION

In recent years, many investigators have studied a better way to extract [23] and measure the sentiments [3] on Social Networks [9][14][15][24], because though the sentiments polarity is possible to know the tendencies on the Internet. A manner to measure the sentiments is about a dictionary [21], a lexicon-based approach, in which the current researches use tools such as SentiWordNet [1], WordNet [2] and SentiStrength [18], which have a list of words with its respective score or polarity [20], but these researches do not consider the users profile that can influences the sentiments of a text extracted from the Internet. A woman can express herself with more sentiments and a man normally is more serious to express himself. In [4], authors stated that women are more likely to give and receive more positive comments than men. Also, some researches indicate that the sentiment intensity can vary greatly depending on the genre [5].

In [5], the authors analyze users profiles through an online questionnaire, and predicts attitudes in association with the *SentiStrenght* dictionary, without finding factors that relate these attitudes with gender. In our study, in turn, the information of the person who wrote a particular phrase is collected, his/her characteristics and a correction factor are obtained and applied to the proposed sentiment calculation, In this research, a new metric is proposed for sentiment analysis, which considers user's profile factors.

In [6], the data extracted from Twitter is analyzed and the sentiments polarity (positive, negative or neutral) of the texts is presented in graphical format, but in [6] authors did not considered the user's profile; therefore the sentiment analysis results are not confident.

The study [7] analyzes the sentiment of Brazilian Twitter users about Brazil's national soccer teams, but it only show the number of occurrences of each term detected during the analyzed period of time. This study does not consider the user's profile and the different sentiments depending on profile groups.

In this context, the main contribution of this work is to demonstrate that a sentiment analysis can be improved by including different parameters of a user's profile and study the user behavior depending of his or her gender. Then, this improvement in sentiment analysis can be applied in many applications from marketing campaigns to mood influences.

The remainder of this paper is structured as follows. Section 2 presents the sentimental analysis methods. Section 3 introduces the proposed solution for sentimental analysis based on user's profiles. Section 4 presents the results from the tests. Finally, section 5 presents the conclusions.

2. SENTIMENTAL ANALYSIS METHODS

The sentiment can be analyzed by the lexical analysis technique (word dictionaries), machine learning and using both techniques together, which is called hybrid approach, as shown in Fig 1.

In lexicon-based methods for sentiment analysis each word has its respective classification [19], e.g., a positive scale of +1 to +5 or a negative scale of -5 to -1, as in [8] [9].

The machine learning technique [22][26] is used in the construction and validation of a phrase sentiment analysis [27-37]; this technique uses algorithms, which receive patterns, or models phrases already defined, and from these patterns is able to classify new phrases.

The types of machine learning are classified into:

- Supervised: uses patterns, consisting of an input object and a desired output value.
- Unsupervised: does not use patterns, the examples are not labeled.

In [10], authors calculate the polarity and sentiment intensity of texts extracted from social networks by the machine learning technique and the best results are obtained with the algorithm SVM (Support Vector Machine)[13]. Also, authors of [11][12] also use the machine learning algorithms, the Decision Trees, Bayesian classification and Sequential Minimal Optimization (SMO). In these studies a large number of data is required to obtain reliable results of sentiments punctuated by the machine learning [38-55], because an unusual phrase may cause noise in the moment of the sentiment calculus.

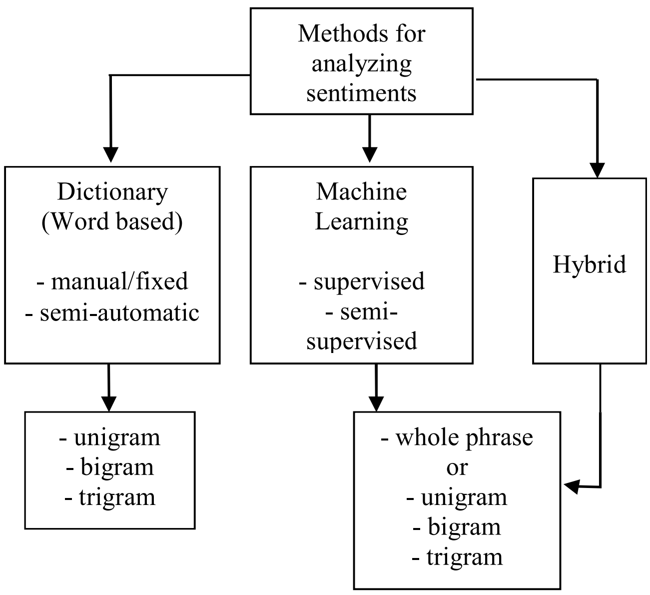

Fig. 1. Methods for analyzing sentiments

In this paper, it is used the lexicon-based method through a word dictionary.

2.1 Sentiment metrics based on Word Dictionaries

The sentiment metric of a phrase is commonly obtained by an arithmetic sum; the values of words with positive polarity are added to the values of words with negative polarity obtaining the total value, P_i in (1), of the sentiment or polarity of the final phrase, the *Sentiment.*

$$\textbf{Sentiment}=\sum_{i=1}^{m} Pi \qquad (1)$$

Therefore, is necessary to identify the verb tenses, adverbs and n-grams, in this study it is used a punctuation technique of sentiments based on [14].

Table I shows the sentiment intensity metric used by *Sentimeter-Br* [14], which uses unigrams (e.g., happy), bigrams (e.g., very happy) and trigrams. The results show improvements with the use of n-grams whenever compared with not using them, where the *Sentimeter-Br* presents better results than the *SentiStrength* tool. The general sentiment is calculated, which is the sum of the words divided by the square of the total number of words that are in the word dictionary, as shown in line 14 of the pseudocode presented in Table 1. The words that are not in the dictionary are considered stopwords that do not aggregate sentiment, such as: from, to, she, among others.

TABLE 1: SENTIMENT PSEUDOCODE [14]

```
1: DIV = 0
2: NEG = 0
3: for i = 1 to N do
4:     read sentiment(word) in ALL-FILES
5:     if (SEARCH word in NEG-FILE) and (SEARCH nextword in NEG-
       ADJFILE) then
6:         LOWER(sentiment(word), sentiment(nextword))
           NEG = NEG + 1
7:         # NEG-FILE = file with words such as NOT, NEVER
8:         # NEG-ADJ-FILE = file with words such as BAD, UGLY
9:     end if
10:    if SEARCH word in TENSE-FILE then
11:        DIV = DIV + 1
12:        # TENSE-FILE = file with LIKED, WAS, WERE
13:    end if
14:    sentiment_strenght = Σ sentiment/ (len(sentiment + DIV ))^1/2
15:    # sentiment_strenght: the total of text sentiment value
16:    # sentiment: value of words in the PT-Br dictionary
17:    # len(sentiment): the number of words in the text that are in the PT-Br
       dictionary
18:    if sentiment_strenght < −1 and NEG > 0 then
19:        for N = 1 to NEG do
20:            sentiment_strenght = sentiment_strenght + (LOWER(sentiment(word),
sentiment(nextword))) * (−1)
21:        end for
22:    end if
23: end for
```

3. PROPOSED SOLUTION FOR SENTIMENTAL ANALYSIS BASED ON USER'S PROFILES

In this section, a methodology is presented for determining the mathematical model considering the gender of the person, which are extracted from social network for sports theme. Thus, the metric is adjusted by means of a function. Also, the influence of events on social network, depending of user´s profiles, is analyzed in this section.

3.1 Mathematical Model through User´s Profile for Sport Theme

A mathematical model is obtained that works as a correction factor for the metric, with the results of *crowdsourcing* questionnaires (person's gender) and phrases. This correction factor is based on the user´s profile. Previous studies were done via *crowdsourcing* [25] in several themes and sports theme had a weight factor of 1, as is shown in (1).

The mathematical model presents the combination of the sentiment value obtained by [14], called of SM in this paper, and the user´s profile. This mathematical model represents the proposed metric in the sports theme.

The new metric of a phrase F_1 is given by

$$SM(F_1) = SM(F_1) * C * \exp(g_1 * M + g_2 * F) * 1 \quad (2)$$

The metric is obtained with the following parameters:

- C is a scale constant.
- g_1 and g_2 are binary factors related to the gender, if one of them is equal to one the other is zero;
- M and F are the weight factors of gender, man or woman, respectively.

In this work, 120 phrases were evaluated via *crowdsourcing* using the metric presented in [14] and the proposed metric.

People, in remote tests, responded to the questions in Table 2 with their age and gender, in which the people wrote example of phrases, of positive and negative polarity, about the sport theme, and they scored each phrase with a scale from +5 to +0.1 and -5 to -0.1, according a continuous scale of interval of 0.1.

TABLE 2: QUESTIONS AND PHRASES APPLIED TO USERS

Field	Kind
Gender	male, female
Age (ranges)	13 until 60+ (A1: 13 - 21, A2: 22 - 29, A3: 30 - 49 e A4: 50 - 65)
Point on the rating scale	+0.1 until +5, -0.1 until -5

The *crowdsourcing* technique has been used for several applications related to subjective evaluations [16].

After, the performance evaluation of the mathematical model proposed in this work is done, applying on Brazilian Twitter users about Brazil's national soccer team.

3.2 Influence of Events in Social Network depending of User´s Profiles

Negative and positive events were analyzed in Brazilian tweets and a behavior was noted depending of the gender person

It was collected 3000 tweets about the Brazilian soccer team of the total of 110 people, 68 users with gender profile configured, other 42 users did not have configured the gender. The people who have not set the gender factor, this factor was found by machine learning with the rule of Brazilian names can finish in "a" for woman and "o" and specific rules for "e", e.g. Nicole (woman) and Felipe (man), many models of names was used to find the gender by the intelligent machine software, Weka [17]; the nicknames were also considered too in this study.

Events in Social Network were analyzed by a period of 2 months, and phrases with the following *hashtags* were collected: #worldcup, #Copa, #copadomundo, #football, #fifa, #WorldCup, #MundialBrasil, #EmBuscaDoHexa, #SelecaoBrasileira, among others.

Users, with age range of 16 to 65 years old, were collected in this work.

4 RESULTS

This section will address the influence of the user´s profile on sentiment analysis of a phrase.

4.1 Crowdsourcing

The proposed metric was found trough *crowdsoursing* tests, in which the person filled out his/her profile with his/her age, gender and the phrases about sports with positive and negative polarity with their respective sentiment intensity value.

Results showed that the exponential model presented in (2) is really reliable, because the maximum error obtained was 0.36 for positive phrases and 0.31 for negative phrases, considering a 5-point scale.

The maximum error for the *crowdsourcing* tests was calculated between the metric of [14], SM, and the metric considering the user´s profile and the results are shown in Table 3.

TABLE 3: *PERFORMANCE OF PROPOSED METRIC AND SM CONSIDERING USER´S GROUPS*

	Max. error (SM)	Max. err. (Proposed)
M-A4	1.9	0.8
All A4	1.6	0.9
M-A1	1.0	0.5
F-A1	0.7	0.4
F-A4	1.5	0.8

The results of Table 3 show that the groups formed by man with age range A4 (woman and man) present the highest maximum error, concluding that the sentiment metric of phrases of the group of range A4 needs to consider user´s profile factors to improve the sentiment intensity.

The Table 3 shows that the maximum error decreases in all users group if the proposed metric is considered.

These tests were performed using *crowdsourcing* method, in which 120 remote users participated. Each user filled out his/her profile and wrote two phrases, with a positive and a negative polarity.

4.2 Social Network

The machine leaning was used to classify the gender that was not configured by Twitter users and the Table 4 shows the results of correctly classified instances (%).

The results of Table 4 present a higher percents of correctly classified instances for man, because the woman of age A1 uses nicknames that sometimes if difficult to recognize. The SMO algorithm presented better results to recognize names of man and woman.

TABLE 4: *PERCENTS OF CORRECTLY CLASSIFIED INSTANCES (CC)/ PERCENTS OF INCORRECTLY CLASSIFIED INSTANCES (CI)*

	Decision Tree	Naive Bayes	BAYES MULTINOMIAL	SMO
Man	66.69/33.31	64.95/35.04	65.81/34.18	71.66/28.34
Woman	64.10/35.89	66.66/33.33	64.95/35.04	69.66/30.33

It was used training file with cross-validation and the factors F (F-measure) obtained are shown in Table 5, the F-measure next to 1 is the ideal.

TABLE 5: *VALUES OF F-MEASURE FOR EACH ALGORITHM FOR THE* FOR THE RECOGNITION OF NAMES

Algorithm	Man	Woman
Tree J.48	0.92	0.90
Multilayer Perceptron	0.83	0.81
SMO	0,88	0,86
Bayes (Naives)	0.75	0.74

The Figure 2 shows the polarity results for woman in all the age ranges, the negative polarity increase for age ranges A3 and A4, just as occur with the man gender. However, the woman gender for the sports theme presented a percentage positive higher that the man gender.

The neutral polarity represents a small percentage of the phrases, indicating that the phrases were in its majority scored as positive and negative by the algorithm SM associated with the profiles parameters.

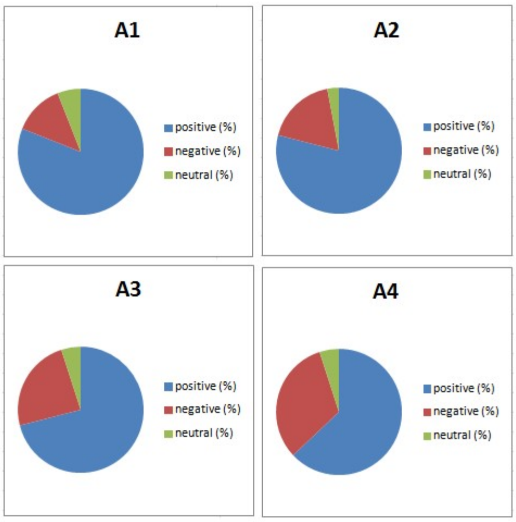

Fig. 2. Polarity results depending of age profiles for woman gender

The Figure 3 considers all gender and age together and does not separate the differences between the age range A1 and A4 the differences between genders.

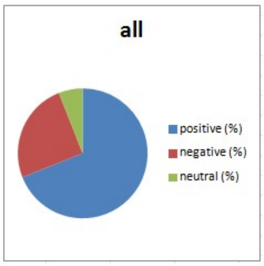

Fig. 3. Polarity results not considering age and gender profiles

The phrases with the *hashtags* cited before was collected and when a negative event happened , a negative sentiment influenced all the network in a short period and lasted for a long period, but if a positive event happened this lasted lesser than a negative message.

Depending of the user´s profile, the negative event lasts longer, this was noted in women gender, mainly age groups of A3 and A4. Figure 4 shows the polarity for women and can be noted that the negative events last more than positives.

The Figure 5 shows the polarity for men and can be noted that the negative events and positive events can last longer, depending on the event, different of the results presented in Figure 4. These results stress the importance of considering the gender as a parameter of the proposed metric.

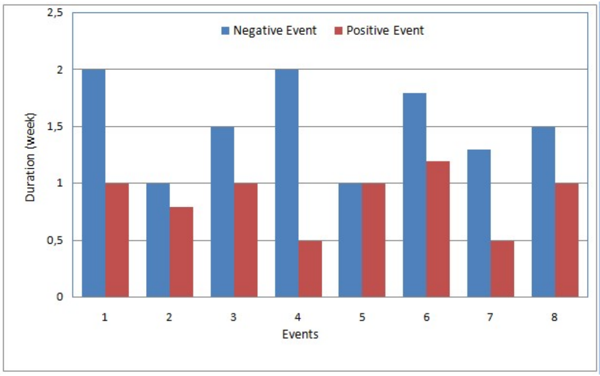

Fig. 4. Duration of tweets about the negative and positive event for woman gender

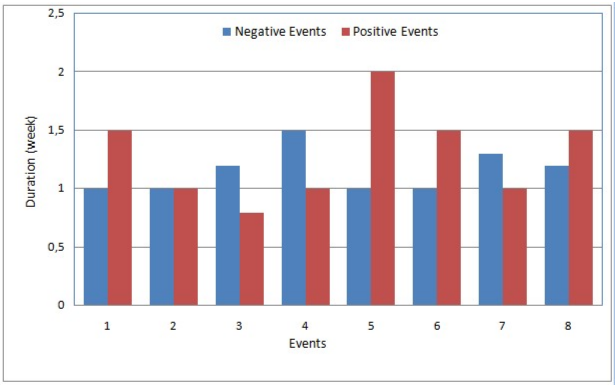

Fig. 5. Duration of tweets about the negative and positive event for man gender

5 CONCLUSION

The present study considers profiles parameters for improving sentimental analysis of comments posted in social networks with sport focus.

The machine learning proved to be useful for selection of genders, when this parameter is not available in social networks.

The proposed metric highlighted that the sentiments of certain profiles diverge from the traditional sentiment metric. It was concluded that depending of gender, the lasting of a negative sentiment can be different. The findings presented validate the importance to consider the gender and age differences to analyze the sentiment intensity, using these results for example to recommendation systems and to have a closer analysis of the real sentiments.

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