Different Lexicon-Based Approaches to Emotion Identification in Portuguese Tweets

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Abstract

This paper presents the existing literature on the identification of emotions and describes various lexica-based approaches and translation strategies to identify emotions in Portuguese tweets. A dataset of tweets was manually annotated to evaluate our classifier and also to assess the difficulty of the task. A lexicon-based approach was used in order to classify the presence or absence of eight different emotions in a tweet. Different strategies have been applied to refine and improve an existing and widely used lexicon, by means of automatic machine translation and aligned word embeddings. We tested six different classification approaches, exploring different ways of directly applying resources available for English by means of different translation strategies. The achieved results suggest that a better performance can be obtained both by improving a lexicon and by directly translating tweets into English and then applying an existing English lexicon.

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1 Introduction

The popularization of the Internet and its evolution over the years, along with the growing need for individuals to remain connected and communicate faster, has given rise to social networks. The adhesion to these social networks is enormous and continues to grow, making them extremely important since they are chosen by users as the main way to generate and seek knowledge, explore interests, among others. These platforms are the stage for expressing opinions, habits, tastes, and customs, representing an enormous sample and diversity of the population, as well as a great source of data, which demonstrates the immense potential for this study. The detection and analysis of emotions on this content expose the overall opinion of individuals concerning any event, allowing us to better understand how to reach a target audience, draw psychological profiles, detect preferences, trends, among many others.

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Emotions are defined, in psychology, as states that reflect the evaluation of judgments of social agents, including the self and the environment, taking into consideration the objectives and beliefs of the person, which encourage and coordinate the adaptation of behavior. Emotions are generally categorized as basic or fundamental, and non-basic or complex. The latter is more difficult to classify and include *pride*, *shame*, *guilt*, *love*, among others [6]. There is no universally accepted model of emotions, but a large portion of the articles concerning the detection of emotions, and multi-class classification approaches, is based on Ekman's model that counts six basic emotions: *joy*, *sadness*, *anger*, *fear*, *disgust*, and *surprise* [4]. Another widely used model is the one described by [13], which combines adjacent pairs of basic emotions: *joy*, *trust*, *fear*, *surprise*, *sadness*, *disgust*, *anger,* and *anticipation.* Plutchik defended that emotions are extremely important for all living beings, evolutionary and that influence much of the social functioning, being the mixed emotions and the different states observed in all people and animals derivations of the basic emotions. They can be described in various languages that include subjective feelings, cognition, impulses to action, and behavior [13].

This paper attempts to identify and analyze emotions in tweets written in Portuguese, adopting a model that is derived from [13], and that contains eight basic emotions and two sentiments. Due to the scarce resources available for this language, we tested different translation approaches, either to improve an existing lexicon or to predict emotions in Portuguese tweets using an English lexicon on translated tweets.

2 Related Work

Methods for detecting sentiments emotions in a text usually require huge quantities of previously annotated data for algorithm training and tuning. For sentiment analysis, there are many annotated datasets and developed systems already with quite good results [1], but for emotion detection such resources are rare. A popular lexicon in this area is the NRC Word-Emotion Association Lexicon[1], also known as EmoLex, which associates about 14000 words in English with eight basic emotions (*joy*, *sadness*, *anger*, *fear*, *disgust*, *surprise*, *anticipation*, and *trust*) and two sentiments (*positive* and *negative*) [9, 10].

Emotion classification has recently gained significant importance as a research topic. *Emoji2emotion* is a method proposed by [14] that establishes the correspondence between the most common emojis on Twitter and online text in general, obtained using the project [12] and *Emojitracker*[2], and possible related classes, to detect feelings or emotions[3]. [18] produced a dataset of annotated data[4], relating hashtags to emotions. This relation is made using the work of [15], where the authors organize the emotions in two layers: six basic emotions and twenty-five secondary emotions, subcategories of the basic ones. Each emotion has a list of words associated with it. [18] expand these lists, managing to associate 131 words used on hashtags with the 7 basic emotions considered - the 6 mentioned above plus *gratitude.* BrainT, described in [5], uses a perceptron in a multi-class approach to classifying the emotions implicit in tweets, which proves the benefits of relating emotions to word sets and the use of bigrams, trigrams, skip-one-tetragrams, and part-of-speech (POS) tags. [17] proposed a model for predicting the intensity of emotions in tweets.

[1] `http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm`
[2] `http://www.emojitracker.com/`
[3] `https://github.com/Aisulu/emoji2emotion`
[4] `http://knoesis.org/projects/emotion`

Concerning the Portuguese language, [16] presents instructions for the annotation of emotions using the Plutchik's Wheel Theory, and built a collection of two corpora. Each tweet was manually annotated by two people with up to four emotions (*joy* or *sadness*, *anger* or *fear*, *trust* or *disgust*, *anticipation* or *surprise*) or *neutral*. *EmoSpell* is an extension of the *Jspell* morphological analyzer that uses a dictionary composed by the *Jspell* Portuguese dictionary and the lexical resources *EMOTAIX.PT* and *SentiLex-PT*, aiming at increasing the recognition power of *EMOTAIX.PT* [8]. [11] carry out a study to understand which approaches for subjectivity classification are better: machine learning algorithms or lexicon-based approaches. Their results suggest that machine learning algorithms may have better results than lexicon-based approaches. To predict the personality of Portuguese and English Twitter users, [7] built a profile analysis platform focusing on the Big 5 personality traits model (*extraversion*, *agreeableness*, *conscientiousness*, *neuroticism*, and *openness*). Finally, [3] reports a study exploring emojis for emotion recognition in Portuguese texts.

3 Data

The data used for this paper corresponds to about 16M geolocated tweets written in Portuguese, produced around the world. The majority of tweets are from Brazil (14995078), followed by Portugal (383874), East Timor, and PALOP countries (15369). The data consists of unstructured text, containing: abbreviations; hashtags; emojis; slang; emoticons; spelling mistakes, lexicon, syntax, and grammar. It presents a set of phenomena that make the analysis more difficult, such as some tweets incorrectly identified as Portuguese; spelling, syntax, and semantic errors; unknown abbreviations; slang; they can use emojis without taking into account their supposed meaning; among others.

Data pre-processing is a relevant stage because it has a direct implication in the extraction of the text characteristics and includes: tokenization, cleaning, and stemming or lemmatization. Tokenization ensures the decomposition of tweets into words, punctuation, emoticons, and emojis, allowing a token by token analysis. Cleaning reduces the noise in words to facilitate the comparison of them, replacing the upper case letters by lower case and all equal letters three or more times, by only one of the letters. Finally, we tested stemming and lemmatization. For Portuguese, since this is a language with many inflected words, stemmers reduce the words too much, so lemmatization turned out to be the best option. We tested *Spacy* and *Hunspell*. Taking into consideration the experiments carried out with both, and the results described by Lars Nieradzik in his blog[5], Spacy was chosen. The *PorterStemmer* and *LancasterStemmer* were used for the English language. The former creates stems by suffix stripping, while the latter uses an iterative algorithm with external rules, having a more severe approach[6]. Experiences have shown that stemming works well for English, and it is much faster than lemmatization. However, it is essential for the classification task that the lemma of each word is found, which makes the lemmatization the most appropriate process. Once again, Spacy was chosen, since, in addition to the internal functionalities it incorporates, it presents good results in structured texts.

In order to validate our classification approaches, and overcoming the lack of annotated data, two people have manually annotated 1000 random tweets, extracted from our data. Table 1 shows the agreement between them, by emotion. The low agreement observed in most of the emotions is sometimes due to the lack of examples, but also is due to the

[5] `https://lars76.github.io/2018/05/08/portuguese-lemmatizers.html`
[6] `https://www.datacamp.com/community/tutorials/stemming-lemmatization-python`

Table 1 Reliability coefficients of the manual annotations of the two persons.

	Anger	Ant.	Disgust	Fear	Joy	Sad.	Surp.	Trust
Average pairwise Percent Agreement	90.2%	94.3%	82.9%	98.9%	78.4%	82.5%	89%	88.3%
Cohen's Kappa	0.431	0.191	0.273	0.347	0.478	0.507	0.271	0.270

subjectivity of the emotions, associated mainly with the complexity and difficulty of the task. The understanding of tweets, assuming that a person can decipher them, varies from person to person and is influenced by numerous simple factors (e.g. age and personal experience). It was perceptible an increase in the difficulty of this task resulting from the type of service that Twitter offers: short messages; informal writing; in real-time for any person and part of the world. The recurrent use of jargon and slang was notable; spelling and semantics errors; abbreviations; expressions of other languages; confusing writing; misuse of caps lock and punctuation; and immense tweets written in Brazilian and some even in Spanish and English. *Irony* and *mockery* are also a point to be taken into account, since they are quite present in tweets and are sometimes not completely clear, raising the doubt of whether or not the subject is being ironic or joking and if not, what real emotions he or she is covering up. For this reason, most tweets with these indications were not classified.

4 Towards a Refined Lexicon

Our experiments use the EmoLex Lexicon, developed for the English language by [9] through manual annotation using crowdsourcing. This lexicon considers two sentiments (negative and positive) and eight basic emotions (*anger*, *disgust*, *fear*, *joy*, *sadness*, *surprise*, *trust,* and *anticipation*), assigning to each word the appropriate emotions and sentiments. It contains 14182 words, of which 2312 are associated with a positive sentiment, and 3324 with a negative. Concerning emotions, 1247 words are associated with *anger*, 839 with *anticipation*, 1058 with *disgust*, 1476 with *fear*, 689 with *joy*, 1191 with *sadness*, 534 with *surprise*, and 1231 with *trust*. A word may be associated with zero or more emotions, being that 9719 words are associated with no emotions. EmoLex was translated in November 2017 by its authors, into more than 40 languages using Google Translator[7].

We have noticed that some English words could be translated into more Portuguese words, a large number of words were incorrectly translated, and that more than 250 English words were not translated [10]. Therefore, we have tested different approaches for producing an improved and more reliable Portuguese version of the lexicon. In order to do so, we have translated the original English version again using Google Translate[8], because automatic machine translation systems have significantly improved since 2017, and also using DeepL[9], another well-known and recognized translation platform. We decided to include the translation of both platforms in the same lexicon, as sometimes they are different but equally certain, and in this way, we also covered more Portuguese words, with a total of 18920 words. This lexicon does not contain only 1429 words out of the 14182 that constitute the lexicon translated by the authors. To quantify the reliability of the translation, we attribute to the emotions present in the 9424 words with equal translations weight 2, and the emotions present in the 4748 words with divergent translations weight 1. Some of the words with different translations

[7] https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm
[8] https://translate.google.pt/
[9] https://www.deepl.com/translator

differ only in gender (e.g. *agravada* and *agravado*), spelling agreement (e.g. *abjecto* and *abjeto*), number (e.g. *conselho* and *conselhos*), the root of the word (e.g. *afixar* and *afixo*) and language variety (e.g. *acadêmico* and *académico*). The more than 250 words that had not originally been translated were replaced by the word itself or by a possible translation. It should be noted that about 500 words remained the same as the original NRC lexicon because it contains words in languages other than English (e.g. *amour* and *aloha*); words that are written the same way in English and Portuguese (e.g. *total* and *zebra*); words that do not have a direct translation, such as proper nouns (e.g. *Toby* and *Billy*) or foreign words (e.g. *byte* and *versus*).

Finally, we have used the MUSE [2] English-Portuguese dictionary to translate the NRC lexicon, originating a new Portuguese emotion lexicon (Lex-II) that contains 16713 distinct words. MUSE (Multilingual Unsupervised and Supervised Embeddings) is a library based on fastText, developed by researchers from Facebook to understand, represent, and classify the thousands of data entered in the platform. It offers 110 ground-truth bilingual dictionaries, including English for 44 different languages and vice versa, and word embeddings for 30 different languages, representing each word in a single vector space. We observed that different English words were translated into the same Portuguese word (e.g. *abandon* and *abandonment*). For such cases, the resulting score for each emotion was the average of the scores for such emotion, rounded to zero or one.

5 Emotion Detection in Portuguese Tweets

The data has been tested with three references so that we can better understand what the results represent. Due to the low agreement among the annotators, the reference that had the best results was the one that considers that classification is correct if at least one of the annotators agrees with such classification. We have tested six different approaches to emotion detection. Table 2 shows the best results achieved for each of the approaches, i.e., evaluating with the reference described above. Accuracy is generally high due to the unbalanced nature of the data, but precision, recall, and F-measure provide more useful information about the complexity of the task. In overall, the refined LEX-I performed better than the original EmoLex translation. Contrarily to our expectations, the refined LEX-II does not present better results than LEX-I. That may be due to the restriction made to the original MUSE dictionary and the non-inclusion of significant amounts of words from the EmoLex. Approaches 4 and 5 achieve good performance. The majority voting approach achieves the second-best overall performance, achieving the best precision of all the experiments. Our results show that *joy* and *sadness* are easier to predict than the other emotions, not only because they are the most expressed on Twitter, but also because they are the ones with lower disagreement, as seen in Table 1. *Fear* and *anticipation* are the most difficult ones, not only because they are the less common in tweets, but also because these emotions can have different perceptions from person to person. Sometimes one uses the word *fear* wrongly to express similar emotions of lesser intensity (e.g. insecurity) or we say that we anticipate something, but in reality, we only deduce it taking into account something we have seen or know.

Finally, Table 3 presents the agreement between the first 5 approaches, revealing that, in general, the classifiers show low/moderate agreement values, an expected result due to the small sample in terms of variety among emotions. The agreement is lower for *trust, fear,* and *surprise.* The different experiences show quite similar values, as is evidenced by the agreement between them, this is because they are both based on the same lexicon.

Table 2 Evaluation performance of metrics of the experiences based on reference.

	Anger	Ant.	Disgust	Fear	Joy	Sad.	Surp.	Trust	macro average
Approach 1: Original Portuguese translation of EmoLex									
Accuracy	0.887	0.794	0.894	0.816	0.772	0.805	0.854	0.802	0.828
Precision	0.333	0.103	0.394	0.027	0.522	0.491	0.186	0.218	0.284
Recall	0.662	0.821	0.633	0.714	0.460	0.560	0.604	0.869	0.665
F-measure	0.443	0.183	0.485	0.052	0.489	0.523	0.284	0.349	0.351
Approach 2: Refined LEX-I									
Accuracy	0.872	0.723	0.878	0.782	0.766	0.794	0.844	0.687	0.793
Precision	0.327	0.093	0.377	0.031	0.521	0.478	0.208	0.206	0.280
Recall	0.712	0.875	0.640	0.875	0.547	0.605	0.655	0.952	0.733
F-measure	0.448	0.168	0.474	0.060	0.534	0.534	0.316	0.338	0.359
Approach 3: Refined LEX-II									
Accuracy	0.838	0.736	0.883	0.754	0.754	0.787	0.852	0.750	0.794
Precision	0.271	0.094	0.389	0.024	0.509	0.489	0.164	0.203	0.268
Recall	0.671	0.844	0.690	0.750	0.594	0.662	0.543	0.912	0.708
F-measure	0.386	0.170	0.498	0.047	0.548	0.563	0.253	0.332	0.350
Approach 4: English EmoLex, and translate tweets using Google Translate									
Accuracy	0.869	0.748	0.902	0.811	0.777	0.781	0.855	0.763	0.813
Precision	0.359	0.092	0.446	0.026	0.546	0.436	0.167	0.212	0.286
Recall	0.735	0.862	0.690	0.714	0.622	0.516	0.556	0.912	0.701
F-measure	0.482	0.166	0.542	0.050	0.582	0.472	0.256	0.343	0.362
Approach 5: English EmoLex, and translate tweets using DeepL									
Accuracy	0.878	0.757	0.909	0.823	0.777	0.788	0.865	0.757	0.819
Precision	0.322	0.091	0.444	0.033	0.541	0.437	0.194	0.199	0.283
Recall	0.671	0.857	0.667	0.750	0.588	0.484	0.596	0.908	0.690
F-measure	0.435	0.165	0.533	0.063	0.564	0.459	0.293	0.327	0.355
Approach 6: Fusion - Combine all the previous classifiers, and use majority voting for classification									
Accuracy	0.880	0.766	0.902	0.809	0.780	0.798	0.877	0.770	0.823
Precision	0.331	0.095	0.417	0.026	0.543	0.480	0.214	0.208	0.289
Recall	0.653	0.828	0.641	0.714	0.574	0.560	0.583	0.922	0.684
F-measure	0.439	0.170	0.505	0.050	0.558	0.517	0.313	0.339	0.361

As previously mentioned, an automatic emotion classifier of tweets was developed that constitutes our initial approach for identifying the emotions present in the text. Our classifier detected at least one emotion in about 57% of the tweets, which corresponds to about 9 million tweets, but a large number of tweets were classified with more than one emotion. The first chart from Figure 1 shows the number of tweets containing each one of the emotions being considered, revealing that the prevailing emotion is *sadness* (3.8 million tweets), followed by *anticipation* (3.3 million tweets), and that *surprise* is the least prevalent emotion (2.2 million tweets). The second chart shows the number of tweets by the number of emotions present on them. In general, people do not experience several emotions at the same time, so as expected there are more tweets with fewer emotions. When people express their written opinions/ideas, they tend to think more about the subject and, depending on the complexity of it, to express more than one emotion. However, on Twitter, many people post what they feel at the moment without thinking too much and that is why there is also a large number of tweets with an emotion. About 30% of classified tweets have four emotions and about 19% one emotion. We have found that the most frequent combinations by number of emotions

Table 3 Reliability coefficients for the classification of 1000 random tweets.

	Anger	Ant.	Disgust	Fear	Joy	Sad.	Surp.	Trust
Average pairwise Percent Agreement	89.8%	86.4%	91.1%	86.8%	87.3%	85.6%	89.3%	82.1%
Cohen's Kappa	0.621	0.655	0.617	0.599	0.671	0.601	0.591	0.580

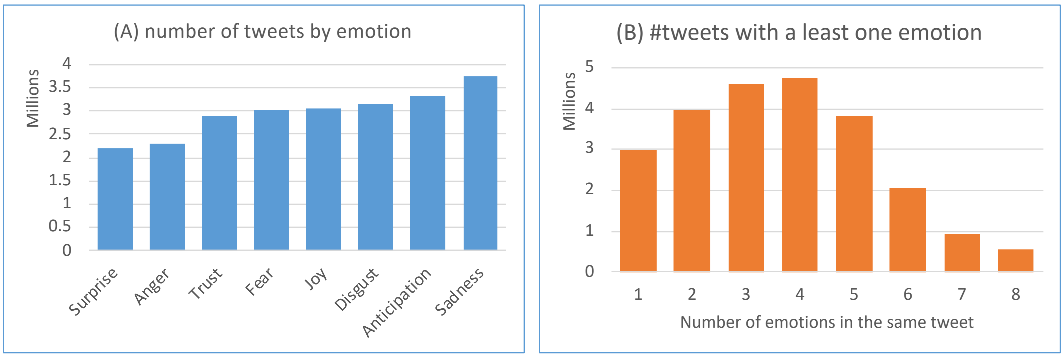

Figure 1 Number of tweets a) per emotion; b) marked with one or more emotions.

are *joy* and *trust*; *anticipation*, *joy*, and *trust*; *anger, disgust, fear,* and *sadness; anticipation, fear*, *joy*, *surprise,* and *trust*; *anticipation, fear*, *joy*, *sadness, surprise,* and *trust*; *anger*, *anticipation, fear*, *joy*, *sadness*, *surprise,* and *trust.*

Our classifier succeeded in assigning at least one emotion to 118046 tweets from Brazil, 6435 tweets from Portugal, 148 tweets from PALOP countries, and another 3459 tweets to other countries. Taking into account the annotated tweets with at least one emotion, Figure 2 shows the occurrence of each emotion per country. Portugal and Brazil show the same tendency for all emotions. *Anger* and *disgust* are the least predominant emotions in all cases. *Sadness* is the most dominant emotion for Portugal and Brazil, but *sadness* is surpassed by *joy* in PALOP countries and by *anticipation* in other countries.

6 Conclusions and Future Work

We have described our efforts to improve an existing emotion lexicon for Portuguese and presented several approaches for emotion classification using Portuguese tweets, based on an emotion lexicon. In order to overcome the lack of emotion resources for Portuguese, we have compared two methods: translating a lexicon into Portuguese vs. translating the tweets into English. Experiences have shown that the two methods achieve similar values, and one may be preferred over the other depending on the problem. We have manually annotated 1000

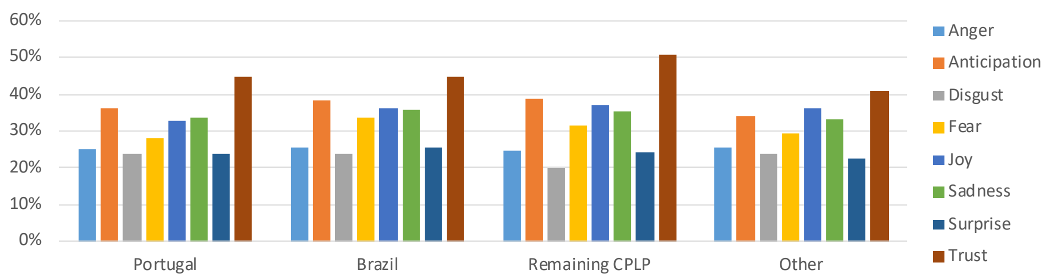

Figure 2 Percentage of tweets associated with a given emotion per country, using approach 1.

tweets that were used to validate our experiments. Our findings suggest that some emotions are easier to detect than others. *Joy*, *sad*, *anger,* and *disgust* were the most successfully predicted emotions, but the task is difficult even for humans. In the future, we plan to train a classifier in a supervised way, to improve the identification of emotions in tweets and explore emojis and emoticons as additional cues, since they are both widely used on social networks as a way for people to express what they are feeling.

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