PELESent: Cross-domain polarity classification using distant supervision

Edilson A. Corrêa Jr, Vanessa Q. Marinho, Leandro B. dos Santos,
Thales F. C. Bertaglia, Marcos V. Treviso, Henrico B. Brum
Institute of Mathematics and Computer Science
University of São Paulo (USP)
São Carlos, São Paulo, Brazil
Email: {edilsonacjr, vanessaqm, leandrobs, thales.bertaglia, marcostreviso, henrico.brum}@usp.br

Abstract—The enormous amount of texts published daily by Internet users has fostered the development of methods to analyze this content in several natural language processing areas, such as sentiment analysis. The main goal of this task is to classify the polarity of a message. Even though many approaches have been proposed for sentiment analysis, some of the most successful ones rely on the availability of large annotated corpus, which is an expensive and time-consuming process. In recent years, distant supervision has been used to obtain larger datasets. So, inspired by these techniques, in this paper we extend such approaches to incorporate popular graphic symbols used in electronic messages, the emojis, in order to create a large sentiment corpus for Portuguese. Trained on almost one million tweets, several models were tested in both same domain and cross-domain corpora. Our methods obtained very competitive results in five annotated corpora from mixed domains (Twitter and product reviews), which proves the domain-independent property of such approach. In addition, our results suggest that the combination of emotions and emojis is able to properly capture the sentiment of a message.

I. INTRODUCTION

In the last few years, Sentiment Analysis has become a prominent field in natural language processing (NLP), mostly due to its direct application in several real-world scenarios [1], such as product reviews, government intelligence, and the prediction of the stock markets. One of the main tasks in Sentiment Analysis is the polarity classification, i.e., classifying texts into categories according to the emotions expressed on them. In general, the classes are positive, negative and neutral.

A popular application of polarity classification is in social media content. Microblogging and social networks websites, such as Twitter, have been used to express personal thoughts. According to Twitter’s website\(^1\), more than 500 million short messages, known as tweets, are posted each day. The analysis of this type of content is particularly challenging due to its specific language, which is mostly informal, with spelling errors, out of the vocabulary words, as well as the usage of emoticons and emojis to express ideas and sentiments.

Machine learning methods have been widely applied to polarity classification tasks in the context of social networks. This is particularly evident in shared tasks such as the SemEval Sentiment Analysis tasks [2], [3], where these methods usually outperform lexical-based approaches. However, a major drawback of machine learning is its high dependency on large annotated corpora, and since manual annotation usually is time-consuming and expensive [4], many non-English languages lack this type of resource or, when existing, are very limited and specific, as it is the case for Portuguese.

In this paper, we adapt a distant supervision approach [5] to annotate a large number of tweets in Portuguese and use them to train state-of-the-art methods for polarity classification. We applied these methods in manually annotated corpora from the same domain (Twitter) and cross-domain (product reviews). The obtained results indicate that the proposed approach is well suited for both: same domain and cross-domain. Moreover, it is a powerful alternative to produce sentiment analysis corpora with less effort than manual annotation.

This paper is organized as follows. Section II gives a brief overview of some approaches for sentiment analysis and presents some works that have applied distant supervision to this task. Our approach is described in Section III. The evaluation corpora, machine learning algorithms and results are given in Section IV. Finally, our conclusions are drawn in Section V.

II. RELATED WORK

Currently, methods devised to perform sentiment analysis and, more specifically, polarity classification range from machine learning to lexical-based approaches. While machine learning methods have proved useful in scenarios where a large amount of training data is available along with top quality NLP resources (such as taggers, parsers and others), they usually have low performance in opposite scenarios. Since most non-English languages face resource limitations, for example Portuguese, lexical-based approaches have become very popular. Some works following this line are [6]–[8].

Another alternative for languages with fewer resources is the use of hybrid systems, which combine machine learning and lexical-based methods. Avancó et al. [9] showed that this combination outperforms both individual approaches. This may imply that the development of better individual elements will lead to better results in the final combination.
Machine learning approaches rely on document representations, normally vectorial ones with features like n-grams [1]. A simple example is the bag-of-words model. Once a representation has been chosen, several classification methods are available, such as support vector machines (SVM), Naive Bayes (NB), maximum entropy (MaxEnt), conditional random fields (CRF), and ensembles of classifiers [3].

Apart from the traditional features, such as n-grams, some researchers have taken advantage of word embeddings, which are known to capture some linguistic properties, such as semantic and syntactic features. A well-known example of word embeddings is Word2Vec [10], [11]. Algebraic operations, such as sum or average, can be applied to convert word vectors into a sentence or document vector [12], [13]. However, this representation does not consider the order of the words in the sentence.

Paragraph vectors [14] (also known as Doc2Vec) can be understood as a generalization of Word2Vec for larger blocks of text, such as paragraphs or documents. This technique has obtained state-of-the-art results in sentiment analysis for two datasets of movie reviews [14]. The main goal of these dense representations is to predict the words in those blocks. Two models were proposed by Le and Mikolov [14], in which one of them accounts for the word order.

In addition, deep neural networks also consider the word order. Their methods have achieved good results in sentiment analysis, as shown in [15]–[17] and in the SemEval Sentiment Analysis Tasks [2], [3]. Nevertheless, these approaches need large datasets for training. Distant supervision is a good alternative to obtain these datasets for the training/pre-training of deep neural networks [16], [18], [19].

Distant supervision is an alternative to create large datasets without the need of manual annotation. Some works have reported the use of emoticons as semantic indicator for sentiment [5], [10], [11], [18], [20], [21], while others use emoticons and hashtags for the same purpose [22], [23]. Go et al. [5], the first work to apply distant supervision to Twitter data, collected approximately 1.6 million of tweets containing positive and negative emoticons — e.g., “:)” and “:(” — equally distributed into two classes. They combined sets of features — unigrams, bigrams, part-of-speech (POS) tags — in order to train machine learning algorithms (NB, MaxEnt and SVM) and evaluate those in manually annotated datasets. The best accuracy was achieved using unigram and bigram as features for a MaxEnt classifier.

Severyn and Moschitti [18] used Distant Supervision to pre-train a convolutional neural network (CNN). An architecture similar to the one proposed by Kim [17]. The network is composed of a first layer to convert words in dense vectors, following a single convolutional layer with a non-linear activation function, max pooling and soft-max. Deriu et al. [19] used a combination of 2 CNNs with a random forest classifier. However, this approach did not obtain improvements with distant supervision.

Despite the numerous studies and investigations of different techniques and methods for polarity classification, the problem
This dataset is formed by product reviews from the online marketplace Mercado Livre\(^5\). The corpus was also automatically annotated based on a 5-star scale given by the authors of the reviews. The dataset is balanced between the positive and negative classes.

Table II presents a summary of the corpora.

| Dataset     | Total | Positive | Negative |
|-------------|-------|----------|----------|
| BPE-Dilma   | 66,640| 46,805   | 19,835   |
| BPE-Serra   | 9,718 | 1,371    | 8,347    |
| Buscape-1   | 2,000 | 1,000    | 1,000    |
| Buscape-2   | 13,685| 6,873    | 6,812    |
| Mercado Livre| 45,318| 21,819   | 21,499   |

**B. Machine Learning Methods**

Machine learning has dominated the area of sentiment analysis, mostly because its high performance when manually annotated data is available. However, thanks to the great variety of methods, there is no consensus about which method is the best in this scenario. In the last editions of SemEval Sentiment Analysis Task, most of the best methods/systems used deep learning techniques [2], [3]. In this work, the evaluated methods range from simple linear models for classification using vector space models to hybrid (machine learning and lexical-based) and Deep Learning methods. The idea was to thoroughly evaluate the quality of the corpus regardless of the technique being used for learning. Below, each method is briefly described.

- **Logistic Regression (LR):** Also known as logit regression, LR can be understood as a generalization of linear regression models to the binary classification scenario, where a sigmoid function outputs the class probabilities [27]. In this paper, the logistic regression model predicts the class probabilities of a text, where the classes are "positive" and "negative". As input for this classifier, three text representations were used: (1) a bag-of-words model (LR+tfidf), where each document (tweet or review) is represented by its set of words weighted by tf-idf [28]; (2) a word embeddings based model (LR+w2v), where each document is represented by the weighted average of the embedding vectors (generated by Word2Vec [10], [11]) of the words that compose the document, the weights are defined by $i$-idf; (3) the Paragraph Vector model (LR+d2v), which uses a neural network to generate embeddings for words and documents simultaneously in an unsupervised manner. Only the vectorial representations of documents were used by the classifier.

- **Convolutional Neural Networks (CNNs):** With the popularity of deep learning, CNNs have been applied to many different contexts, including several NLP tasks [29] and, more specifically, sentiment analysis [16]–[19]. Our CNN is similar...
to the architecture proposed by Kim [17], which uses a single convolutional layer. In this architecture, the network receives as input a matrix representing the document, and each word in the document is represented by a dense continuous vector. The output of the network is the probability of a document being negative or positive.

c) Recurrent Convolutional Neural Networks (RCNNs): This deep neural architecture uses both convolutional and recurrent layers. Recently explored by many works in NLP [30–32], this architecture has been successfully applied to sentiment analysis [3], [32]. Our architecture consists of a slight modification of the one used by Treviso et al. [31], where the final layer returns the probability for the whole document, indicating a positive/negative polarity. Using this combination of convolutional and recurrent layers, we explored the principle that nearby words have a greater influence in the classification, while distant words may also have some impact.

d) Hybrid: This method is a combination of two classifiers previously used for sentiment classification in cross-domain corpora [9] and follows the same setting introduced by Avanaço [33]. The method consists of a SVM classifier combined with a lexical-based approach. The documents are represented by arrays of features including a binary bag-of-words (presence/absence of terms), emoticons, sentiment words and POS tags. Documents located near the separation hyperplane (in a threshold assumed as 0.5) learned by the SVM are considered to be uncertain. Those documents are then classified with a lexical-based approach, that uses linguistic rules for polarity classification in Portuguese.

For all methods, well-known machine learning libraries were used, such as Scikit-learn [34] and Keras [35]. Particularities such as parameters, details about the architecture, initializations and others can be found in the Supplementary Material, Section B.

C. Results and Discussion

To evaluate and compare the methods in each corpus, F1 score (macro-averaged), recall (macro-averaged) and accuracy were chosen, mostly because of their traditional use in sentiment analysis [2], [3].

The main results are shown in Table III. Along with the results of each polarity classification method, we present the state-of-the-art (SotA) result reported for each corpus. Because the BPE corpora were conceived for a different context, there are no SotA reported results for those corpora. We also ranked each evaluated method by its F1 score.

The differences between the best method (in bold) and the SotA vary between 9.60% and 12.24%, very competitive results given the fact that all SotA reported results were obtained by a 10-fold cross validation scheme and our methods used a corpus from a different domain for training. Of all the methods, the Hybrid was the one that had the best performance in the corpora of product reviews. Such a result was due to the regularity of the language in this type of corpus, which makes lexical approaches highly effective. However, in domains such as Twitter, errors, abbreviations and slangs are very common, which decreases the effectiveness of lexical-based approaches. This effect can be seen in the BPE-Dilma corpus.

An important aspect of Sentiment Analysis is the sensitivity of its methods to elements such as domain and temporality. In our evaluation, both were present in the selected corpora, which demonstrates the robustness of the constructed corpus and its resilience to temporality and the non-regularity of the language.

Regarding the deep learning methods (CNN and RCNN), both presented high rankings in almost all corpora. However, there was no huge difference between deep and shallow methods (logistic regression + document representation), indicating that large datasets decrease the performance difference between methods from different natures (even between simple and complex methods), a result commonly found in the big data era [36].

| Dataset      | Method     | F1 score | Recall | Accuracy |
|--------------|------------|----------|--------|----------|
| BPE-Dilma    | LR + w2v   | 0.5730   | 0.6037 | 0.5052   |
|              | LR + tfidf | 0.6477   | 0.6443 | 0.7128   |
|              | LR + d2v   | 0.6135   | 0.6071 | 0.7256   |
|              | CNN        | 0.6337   | 0.6295 | 0.7051   |
|              | RCNN       | 0.6414   | 0.6586 | 0.6816   |
|              | Hybrid     | 0.5249   | 0.5855 | 0.5295   |
| BPE-Serra    | LR + w2v   | 0.3515   | 0.4398 | 0.3915   |
|              | LR + tfidf | 0.4110   | 0.5546 | 0.4475   |
|              | LR + d2v   | 0.5055   | 0.6028 | 0.5915   |
|              | CNN        | 0.4240   | 0.5929 | 0.4568   |
|              | RCNN       | 0.5286   | 0.5975 | 0.6426   |
|              | Hybrid     | 0.5745   | 0.6073 | 0.7344   |
| Buscape-1    | LR + w2v   | 0.7232   | 0.7250 | 0.7250   |
|              | LR + tfidf | 0.7469   | 0.7480 | 0.7480   |
|              | LR + d2v   | 0.6427   | 0.6465 | 0.6465   |
|              | CNN        | 0.6713   | 0.6870 | 0.6870   |
|              | RCNN       | 0.7654   | 0.7654 | 0.7654   |
|              | Hybrid     | 0.7668   | 0.7695 | 0.7695   |
| Buscape-2    | LR + w2v   | 0.6814   | 0.6903 | 0.6910   |
|              | LR + tfidf | 0.7725   | 0.7778 | 0.7742   |
|              | LR + d2v   | 0.7017   | 0.7027 | 0.7030   |
|              | CNN        | 0.7048   | 0.7115 | 0.7122   |
|              | RCNN       | 0.7656   | 0.7658 | 0.7657   |
|              | Hybrid     | 0.7917   | 0.7930 | 0.7934   |
| Mercado Livre| LR + w2v   | 0.6861   | 0.7048 | 0.7066   |
|              | LR + tfidf | 0.8328   | 0.8329 | 0.8328   |
|              | LR + d2v   | 0.8089   | 0.8093 | 0.8097   |
|              | CNN        | 0.7745   | 0.7800 | 0.7813   |
|              | RCNN       | 0.8561   | 0.8561 | 0.8563   |
|              | Hybrid     | 0.8614   | 0.8614 | 0.8614   |

| Dataset      | Method     | F1 score | Recall | Accuracy |
|--------------|------------|----------|--------|----------|
| SotA         | –          | –        | –      | –        |
V. CONCLUSION AND FUTURE WORK

In recent years, the polarity classification task has drawn the attention of the scientific community, mainly due to its direct application in scenarios such as social media content and product reviews. Even though machine learning methods present themselves as high performance alternatives, they suffer from the need of a large amount of data during their training phases. In this paper, we adapted a distant supervision approach to build a large sentiment corpus for Portuguese. State-of-the-art methods were trained on this corpus and applied to 5 selected corpora, from same domain and different domain (cross-domain). Competitive results were obtained for all methods, although our best results did not outperform the best ones reported for the same corpora.

As future works, we intend to explore ways to improve the quality of the distant supervision corpus by applying techniques to remove outliers and tweets that do not convey any sentiment or convey the wrong sentiment. We also intend to modify this framework to make it able to represent the neutral class.

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