BUAP: Polarity Classification of Short Texts

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Abstract
We report the results we obtained at the subtask B (Message Polarity Classification) of Semeval 2014 Task 9. The features used for representing the messages were basically trigrams of characters, trigrams of PoS and a number of words selected by means of a graph mining tool. Our approach performed slightly below the overall average, except when a corpus of tweets with sarcasm was evaluated, in which we performed quite well obtaining around 6% above the overall average.

1 Introduction
Analyzing polarity in texts is an important task that may have various applications in real life. There exist plenty of tasks that may be benefited of computational procedures that automatically allow to detect if the author intention has been to express himself as a positive, negative, neutral or objective manner. Let us consider, for instance, when a public figure (such as a politician, celebrity, or business leader) would like to investigate its reputation in public media. Another example would be to calculate the reputation of a public or private institution. In any case, the construction of methods for determining the polarity of messages at Internet would help to investigate their reputation.

In this paper, we present the results we obtained when we carried out experiments for the subtask B of Semeval 2014 Task 9, which was named “Message Polarity Classification”, and was defined as follow: “Given a message, decide whether the message is of positive, negative, or neutral sentiment. For messages conveying both a positive and negative sentiment, whichever is the stronger sentiment should be chosen”.

The remaining of this paper is structured as follows. In Section 2 we present some related work found at the literature with respect to the identification of emotions in short texts such as twitter. Section 3 presents the description of the features and classification model used in our experiments. The results obtained together with a discussion of these results are given in Section 4. Finally, the conclusions are given in Section 5.

2 Related Work
There exist a number of works in literature associated to the automatic identification of emotions in Twitter, mainly due to the massification of this social network around the world and the easy manner we can access to the Tweets from API’s provided by Twitter itself. Some of these works have focused on the contribution of some particular features, such as Part of Speech (PoS) tags, emoticons, etc. on the aforementioned task. In Agarwal et al. (2011), for example, the a priori likelihood of each PoS is calculated. They use up to 100 additional features that include emoticons and a dictionary of positive and negative words. They have reported a 60% of accuracy in the task. On the other hand, in Mukherjee and Bhattacharyya (2012), a strategy based on discursive relations, such as conectiveness and con-
ditionals, with low number of lexical resources is proposed. These relations are integrated in classical models of representation like bag of words with the aim of improving the accuracy values obtained in the process of classification. The influence of semantic operators such as modals and negations are analyzed, in particular, the degree in which they affect the emotion present in a given paragraph or sentence.

One of the major advances obtained in the task of sentiment analysis has been done in the framework of the SemEval competition. In 2013, several teams have participated with different approaches Becker et al. (2013); Han et al. (2013); Chawla et al. (2013); Balahur and Turchi (2013); Balage Filho and Pardo (2013); Moreira at al. (2013); Reckman et al. (2013); Tiantian et al. (2013); Marchand et al. (2013); Clark and Wicentwoski (2013); Hamdan et al. (2013); Martínez-Cámara et al. (2013); Leviallois (2013). Most of these works have contributed in the mentioned task by proposing methods, techniques for representing and classifying documents towards the automatic classification of sentiment in Tweets.

3 Description of the Presented Approach

We have employed a supervised approach based on machine learning in which we construct a classification model using the following general features obtained from the training corpus.

1. Character trigrams
2. PoS tags trigrams
3. Significant Tweet words obtained by using a graph mining tool known as SubDue

The description of how we calculated each feature in order to construct a representation vector for each message is given as follows.

The probability of each character trigram given the polarity class, $P(trigram|class)$, was calculated in the training corpus. Thereafter, we assigned a normalized probability to each sentence polarity by combining the probability of each character trigram of the sentence, i.e.,

$$\sum_{t=1}^{\text{message}} \log [P(trigram_t|class)].$$

Since we have four classes (“positive”,”negative”,”neutral” and “objective”), we have obtained four features for the final vectorial representation of the message.

We then calculated other four features by performing a similar calculation than the previous one, but in this case, using the PoS tags of the message. For this purpose, we used the Twitter NLP and Part-of-Speech Tagging tool provided by the Carnegie Mellon University (Owoputi et al., 2013). Since the PoS tag given by this tool is basically a character, then the same procedure can be applied.

We performed preliminary experiments by using these eight features on a trial corpus, and we observed that the results may be improved by selecting significant words that may not be discovered by the statistical techniques used until now. So, we decided to make use of techniques based on graph mining for attempting to find those significant words. In order to find them, we constructed a graph representation for each message class (“positive”,“negative”,“neutral” and “objective”), using the training corpus. The manner we constructed those graphs is shown as follows.

Formally, given a graph $G = (V, E, L, f)$ with $V$ being the non-empty set of vertices, $E \subseteq V \times V$ the edges, $L$ the tag set, and $f : E \rightarrow L$, a function that assigns a tag to a pair of associated vertices. This graph-based representation attempt to capture the sequence among the sentence words, so as the sequence among their PoS tags with the aim of feeding a graph mining tool which may extract relevant features that may be further used for representing the texts. Thus, the set $V$ is constructed from the different words and PoS of the target document.

In order to demonstrate the way we construct the graph for each short text, consider the following message: “ooh i love you for posting this :-)”. The associated graph representation to this message is shown in Figure 1.

Once each paragraph is represented by means of a graph, we apply a data mining algorithm in order to find subgraphs from which we will be able to find the significant words which will be, in our case, basically, the nodes of these subgraphs. Subdue is a data mining tool widely used in structured domains. This tool has been used for discovering structured patterns in texts represented by means of graphs Olmos et al. (2005). Subdue uses an evaluation model named “Minimum encoding”, a tech-
nique derived from the minimum description length principle Rissanen (1989), in which the best graph sub-structures are chosen. The best subgraphs are those that minimize the number of bits that represent the graph. In this case, the number of bits is calculated considering the size of the graph adjacency matrix. Thus, the best substructure is the one that minimizes $I(S) + I(G|S)$, where $I(S)$ is the number of bits required to describe the substructure $S$, and $I(G|S)$ is the number of bits required to describe graph $G$ after it has been compacted by the substructure $S$.

By applying this procedure we obtained 597 significant negative words, 445 positive words, 616 objective words and 925 positive words. For the final representation vector we compiled the union of these words, obtaining 1915 significant words. Therefore, the total number of features for each message was 1,923.

We have used the training corpus provided at the competition (Rosenthal et al., 2014), however, we removed all those messages tagged as the class “objective-OR-neutral”, because all these messages introduced noise to the classification process. In total, we constructed 5,217 vectors of message representation which fed a support vector machine classifier. We have used the SVM implementation of the WEKA tool with default parameters for our experiments (Hall et al., 2009). The obtained results are shown in the next section.

4 Experimental Results

The test corpus was made up short texts (messages) categorized as: “LiveJournal2014”, “SMS2013”, “Twitter2013”, “Twitter2014” and “Twitter2014Sarcasm”. A complete description of the training and test datasets can be found at the task description paper (Rosenthal et al., 2014).

In Table 1 we can see the results obtained at the competition. Our approach performed in almost all the cases slightly below to the overall average, except when we processed the corpus of Twitter with Sarcasm characteristics. We consider that two main problems were the cause of this result: 1) The corpus was very unbalanced and our approaches for alleviating this problem were not sufficient, and 2) From our particular point of view, there were a high difference between the vocabulary of the training and the test corpus, thus, leading the classification model to fail.
Table 1: Results obtained at the substask B of the Semeval 2014 Task 9

| System                     | LiveJournal2014 | SMS2013 | Twitter2013 | Twitter2014 | Twitter2014Sarcasm | Average |
|----------------------------|------------------|---------|-------------|--------------|---------------------|---------|
| NRC-Canada-B               | 74.84            | 70.28   | 70.75       | 69.85        | 58.16               | 68.78   |
| CISUC-KIS-B-late           | 74.46            | 65.90   | 67.56       | 67.95        | 55.49               | 66.27   |
| coosooli-B                 | 72.90            | 67.68   | 70.40       | 70.14        | 46.66               | 65.56   |
| TeamX-B                    | 69.44            | 57.36   | 72.12       | 70.96        | 56.50               | 65.28   |
| RTRGO-B                    | 72.20            | 67.51   | 69.10       | 69.95        | 47.09               | 65.17   |
| AUDEB-B                    | 70.75            | 64.32   | 63.92       | 66.38        | 56.16               | 64.31   |
| SWISS-CHOCOLATE-B          | 73.23            | 66.43   | 64.81       | 67.54        | 49.46               | 64.30   |
| SentiKLUET-B               | 73.99            | 67.40   | 69.06       | 67.02        | 43.36               | 64.17   |
| TUGAS-B                    | 69.79            | 62.77   | 65.64       | 69.00        | 52.87               | 64.01   |
| SAIL-B                     | 69.34            | 56.98   | 66.80       | 67.77        | 57.26               | 63.63   |
| senti.ue-B                 | 71.39            | 59.34   | 67.34       | 63.81        | 55.31               | 64.44   |
| Synalp-Empathic-B          | 71.75            | 62.54   | 63.65       | 67.43        | 51.06               | 63.29   |
| Lili-B                     | 68.56            | 64.78   | 65.56       | 65.47        | 47.76               | 62.43   |
| UKPDIPF-B                  | 71.92            | 60.56   | 60.65       | 63.77        | 54.59               | 62.30   |
| AMIERIC-B                  | 65.32            | 60.29   | 70.09       | 66.55        | 48.19               | 62.09   |
| ECNU-B                     | 69.44            | 59.75   | 62.31       | 63.17        | 51.43               | 61.22   |
| LyS-B                      | 69.79            | 60.45   | 66.92       | 64.92        | 42.40               | 60.90   |
| NILC-USP-B-twitter         | 68.24            | 61.67   | 60.96       | 63.62        | 48.34               | 60.57   |
| CMU-Qatar-B-late           | 65.63            | 62.95   | 65.11       | 65.53        | 40.52               | 59.95   |
| colombianpc-apl-B          | 68.79            | 59.84   | 64.60       | 65.42        | 40.02               | 59.73   |
| CMUQ-Hybrid-B-late         | 65.14            | 61.75   | 63.22       | 62.71        | 40.95               | 58.75   |
| Citius-B                   | 62.40            | 57.69   | 62.53       | 61.92        | 41.00               | 57.11   |
| KUNPLab-B                  | 63.77            | 55.89   | 58.12       | 61.72        | 44.60               | 56.82   |
| USP_Biocom-B               | 67.80            | 53.57   | 58.05       | 59.21        | 43.56               | 56.44   |
| UPV-ELRIF-B                | 64.11            | 55.36   | 63.97       | 59.33        | 37.46               | 56.05   |
| Rapanakis-B                | 59.71            | 54.02   | 58.52       | 63.01        | 44.69               | 55.99   |
| DejaVu-B                   | 64.69            | 55.57   | 57.43       | 57.02        | 42.46               | 55.43   |
| GPLSI-B                    | 57.32            | 46.63   | 57.49       | 56.06        | 53.90               | 54.28   |
| Indian_Inst_of_Tech-Patna-B| 60.39            | 51.96   | 52.58       | 57.25        | 41.33               | 52.70   |
| BUAP-B                     | 53.94            | 44.27   | 56.85       | 55.76        | 51.52               | 52.47   |
| SAP-RI-B                   | 57.86            | 49.00   | 50.18       | 55.47        | 48.64               | 52.23   |
| UMC-DLSI_Sem               | 53.12            | 50.01   | 51.96       | 55.40        | 42.76               | 50.65   |
| Alberta-B                  | 52.38            | 49.05   | 53.85       | 52.06        | 40.40               | 49.55   |
| SAINAI-B                   | 58.33            | 57.34   | 50.59       | 49.50        | 31.15               | 49.38   |
| IBM_BG-B                   | 59.24            | 46.62   | 54.51       | 52.26        | 34.14               | 49.35   |
| SU-sentilab-B-tweet        | 55.11            | 49.60   | 50.17       | 49.52        | 31.49               | 47.18   |
| issjud-B                   | 61.09            | 38.56   | 46.38       | 52.02        | 34.64               | 46.54   |
| IIT-Patna-B                | 54.68            | 40.56   | 50.32       | 48.22        | 36.73               | 46.10   |
| UMC-DLSI_Graph-B           | 47.81            | 36.66   | 43.24       | 45.49        | 53.15               | 45.27   |
| University-of-Warwick-B    | 39.60            | 29.50   | 39.17       | 45.56        | 39.77               | 38.72   |
| DAEDALUS-B                 | 40.83            | 40.86   | 36.57       | 33.03        | 28.96               | 36.05   |
| Overall average            | 63.31            | 55.82   | 59.72       | 60.30        | 55.43               | 57.02   |

5 Conclusions

We have presented an approach for detecting message polarity using basically three kind of features: character trigrams, PoS tags trigrams and significant words obtained by means of a graph mining tool. The obtained results show that these features were not sufficient for detecting the correct polarity of a given message with high precision. We consider that the unbalanced characteristic and the fact the vocabulary changed significantly from the training to the test corpus influenced the results we obtained at the competition. However, a deep analysis we plan to do to the datasets evaluated will allow us in the future to find more accurate features for the message polarity detection task.

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