Target-Dependent Sentiment Analysis
of Tweets

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Definition

Sentiment analysis (SA) (also known as opinion mining) is the problem of identifying people’s opinions, sentiments or attitudes expressed in text. It normally involves the classification of text into categories such as “positive”, “negative” and “neutral”.
Definition

Target

is an entity (person, organisation, product, object, etc.) referred to in a text, about which an opinion is expressed.

Context

of the target is the text surrounding it, that provides information about the polarity of the sentiment towards it.
Example of the two steps. The filled rectangle represents the target extraction step, where the rounded rectangle represents the sentiment analysis step and it receives two inputs the extracted target and its context.
Objectives

The main goal of this work is to develop a full fledged target dependent SA system of Twitter that can be used to automatically extract the targets from tweets and identify the sentiments expressed in those tweets toward them. To achieve this goal.
Objectives

The work focuses on the following specific goals:

1. Developing a target identification system that can automatically extract the targets from the tweets.
2. Developing a target dependent sentiment analysis system that can identify the opinion expressed in the tweets toward a set of targets.
3. Integrating these two systems in one end-to-end target dependent sentiment analysis system.
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- Testing the proposed systems on publicly available datasets for the problem of target dependent sentiment analysis.
- Using the proposed systems in real case studies.
Supervised machine learning life cycle.
Deep Learning

Deep learning is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised or unsupervised. Deep learning architectures such as:

- Deep belief networks.
- Recurrent neural networks.
Neural Networks

The original goal of the neural network approach was to solve problems in the same way that a human brain would.

An ANN is based on a collection of connected units called artificial neurons.

Typically, neurons are organized in layers.

Backpropagation, or passing information in the reverse direction is the way to adjusting the network and learn.
A recurrent neural network is a type of neural network architecture specifically designed for modeling sequential inputs of varying lengths such as text.
This kind of units have \textit{reset} ($r_t$) and \textit{update} ($z_t$) gates. The former has the ability to completely reduce the past hidden state $h_{t-1}$ if it considers that it is irrelevant to the computation of the new state, whereas the later is responsible for determining how much of $h_{t-1}$ should be carried forward to the next state $h_t$. 
Bidirectional RNNs

It consists of forward $\rightarrow \phi$ and backward $\leftarrow \phi$ RNNs. The first one reads the input sequence in a forward direction $(x_1, \ldots, x_n)$ and produces a sequence of forward hidden states $(h_1, \ldots, h_n)$, whereas the former reads the sequence in the reverse order $(x_n, \ldots, x_1)$ resulting in a sequence of backward hidden states $(\overleftarrow{h}_n, \ldots, \overleftarrow{h}_1)$.
The softmax classifier is a feed-forward neural network followed by the softmax function, which is used for multi-class classification (under the assumption that the classes are mutually exclusive). It takes as input a vector $v \in \mathbb{R}^m$ and produces the probabilities for each class as follows:

$$p(y = i \mid v; W, b) = \frac{\exp(w_i^T v + b_i)}{\sum_{j=1}^{C} \exp(w_j^T v + b_j)}, \quad i = 1, 2, \ldots, C$$ (1)
Word Representation is the process of representing each word as a vector. The most simple method of encoding words is one-hot or 1-of-N vector representation. Example of one-hot encoding:
Methodology

TI-RNC model for target identification of tweets.
TD-biGRU model for target-dependent sentiment classification.
Datasets

T-Dataset
It contains 6248 training examples and 692 examples in the testing set.

Z-Dataset
contains 9489 training examples, 1036 development examples and 1170 testing examples.

Each example in these datasets contains the tweet and the target.
Evaluation Metrics for the Target Identification

\[
\text{Precision} = \frac{|S \cap G|}{|S|}
\]

(2)

$S$ is the set of the predicted targets, and $G$ is the set of the gold (correct) targets.
Evaluation Metrics for the Target Identification

Recall

\[
\frac{|S \cap G|}{|G|} \quad (3)
\]

\( S \) is the set of the predicted targets, and \( G \) is the set of the gold (correct) targets.
Evaluation Metrics for the Target Identification

$$F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$ (4)
Evaluation Metrics for the Target-Identification Sentiment Analysis Analysis

- Classification Accuracy (the percentage of examples that are correctly classified)
- The Macro-F1 measure (the averaged F1 measure over the three sentiment classes).
Comparison of our model to the baselines on target identification:

<table>
<thead>
<tr>
<th>Model</th>
<th>T-Dataset ( (P) )</th>
<th>T-Dataset ( (R) )</th>
<th>T-Dataset ( F_1 )</th>
<th>Z-Dataset ( (P) )</th>
<th>Z-Dataset ( (R) )</th>
<th>Z-Dataset ( F_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNN</td>
<td>77.90</td>
<td>87.57</td>
<td>82.44</td>
<td>73.93</td>
<td>52.65</td>
<td>61.50</td>
</tr>
<tr>
<td>BiRNN</td>
<td>79.76</td>
<td>90.17</td>
<td>84.67</td>
<td>81.00</td>
<td>50.43</td>
<td>62.16</td>
</tr>
<tr>
<td>GRU</td>
<td>81.18</td>
<td>90.89</td>
<td>86.10</td>
<td>73.98</td>
<td>54.19</td>
<td>62.56</td>
</tr>
<tr>
<td>BiGRU</td>
<td>87.39</td>
<td>91.18</td>
<td>89.25</td>
<td>79.82</td>
<td>60.51</td>
<td>68.84</td>
</tr>
<tr>
<td>TI-RNC</td>
<td>95.30</td>
<td>94.02</td>
<td>94.66</td>
<td>82.46</td>
<td>64.27</td>
<td>72.24</td>
</tr>
</tbody>
</table>
Comparison of different methods on target-dependent sentiment classification.

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
<th>Macro-F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Our model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>biGRU</td>
<td>69.94</td>
<td>68.40</td>
</tr>
<tr>
<td>TD-biGRU</td>
<td>72.25</td>
<td>70.47</td>
</tr>
<tr>
<td>End-To-End-TD</td>
<td>70.08</td>
<td>68.22</td>
</tr>
<tr>
<td>B. State-of-the-art systems</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SVM-indep</td>
<td>62.70</td>
<td>60.20</td>
</tr>
<tr>
<td>SVM-dep</td>
<td>63.40</td>
<td>63.30</td>
</tr>
<tr>
<td>Recursive NN</td>
<td>63.00</td>
<td>62.80</td>
</tr>
<tr>
<td>AdaRNN-w/oE</td>
<td>64.90</td>
<td>64.44</td>
</tr>
<tr>
<td>AdaRNN-w/E</td>
<td>65.80</td>
<td>65.50</td>
</tr>
<tr>
<td>AdaRNN-comb</td>
<td>66.30</td>
<td>65.90</td>
</tr>
<tr>
<td>Target-ind</td>
<td>67.30</td>
<td>66.40</td>
</tr>
<tr>
<td>Target-dep</td>
<td>69.70</td>
<td>68.00</td>
</tr>
<tr>
<td>Target-dep⁺</td>
<td>71.10</td>
<td>69.90</td>
</tr>
<tr>
<td>LSTM</td>
<td>66.50</td>
<td>64.70</td>
</tr>
<tr>
<td>TD-LSTM</td>
<td>70.80</td>
<td>69.00</td>
</tr>
<tr>
<td>TC-LSTM</td>
<td>71.50</td>
<td>69.50</td>
</tr>
</tbody>
</table>
Results and Discussion

The confusion matrix given by the TD-biGRU model:

![Confusion Matrix Diagram]
Conclusion

We have developed a system that automatically identifies the target of a tweet. The proposed model has the ability of:

- Identifying and extracting the target of the tweets.
- Representing the relatedness between the targets and its contexts.
- Identifying the polarities of the tweets towards the targets.
In the future work we plan to extend our system to: handle the weakness (as we saw in the confusion matrix) by integrating more information such as lexicon information and/or the dependency tree.

Our system extracts only the targets that are mentioned explicitly in the tweets, So future work to designing a system that can detect both the explicit targets and the implicit targets.
The results of these works have been published in the following conferences/books:

- Mohammed Jabreel, **Fadi Hassan** and Antonio Moreno: on Target-Dependent Sentiment Analysis of Tweets using Bi-directional Gated Recurrent Neural Networks, in CIMA-16 Post workshop.
- Mohammed Jabreel, **Fadi Hassan**, Saddam Abdulwahab and Antonio Moreno: on the Bidirectional LSTM-CRF for Target Identification of Tweets, in CCIA
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