Detecting Stance in Tweets

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***Abstract*—The aim of the project is to detect stance in tweets given a target and the tweet text content. This is one of the tasks proposed by the SemEval 2016 conference. There are three possible stances for every tweet: FAVOR, AGAINST and NONE. Even though a lot of research work has been done on *aspect based sentiment analysis* and *sentiment analysis for online text*[1] , there exists a scope for improvement when it comes to detecting stance in tweets. The 140-character restriction and the informal style make it difficult and distinguished from other general sentiment analysis tasks. The main challenge is the inherent difference in vocabulary, lack of proper structure and implicit display of stance. The best result that has been achieved for a similar task was 84% by [2]. In the further sections, we describe the method that we follow for the task and report the preliminary results that we obtained.**

I. Introduction/Task Description

There is a sudden growth in the attention that social media and online forums are getting from researchers and Twitter is probably the most popular among them. The reason could be because of relatively easier access to the data and the fact that the tweets say quite a lot about the reaction of people to changes around them.

Stance detection means automatically determining from text whether the author is in favor of the given target, against the given target, or whether neither inference is likely. Consider the target–tweet pair:

Target: Legalization of abortion

Tweet: A foetus has rights too! Make your voice heard. Even though this seems like a regular sentiment analysis task on the first glance, where there has been considerable progress, this is quite different. The task can be thought of as an aspect based sentiment analysis problem for tweets which are almost never complete English sentences. We'll now describe the dataset. There are five different targets given: "Atheism", "Climate Change is a Real Concern", "Feminist Movement", "Hillary Clinton", and "Legalization of Abortion". We are provided with about 2900 labeled training data instances for the five targets. The data is slightly skewed because the number of tweets which are neither FOR or AGAINST is close to 22%. Since the tweets in the given task data-set are discrete and not tied to any user, we do not have access to more tweets in the conversation/context of the user. Some literature on aspect-based sentiment analysis uses this signal for analysis as well.

II. Work Done

We split the task into the following stages:

- Finding *Relevance* of a given tweet to the target.
- *Sentiment analysis* of relevant tweets to classify FOR/AGAINST.

Thus, we first plan to deduce if a given tweet is relevant to the target or not. An irrelevant tweet at this point gets the output label of **NONE**. After this stage, we carry all the relevant tweets (Not NONE in stage 1) and perform sentiment analysis on this to get the general motif of the tweeter. We hope that the result of sentiment analysis will be a good estimate of the stance of the tweet/user.

A. Features Used

For the first task, we use Stanford's GloVe to get word Vectors. We use the vectors that were obtained from tweets. This is because of the convenience of the word vectors and the ways in which they can be used (simple addition/subtraction can be used to obtain meaning). We simply add up the word vectors of the weighted word vectors and the target.

B. Pre-processing

We do not use any punctuation marks or the hashtags in any meaningful way. This ends up being equivalent to not using the hashtags as they do not have word vectors. Note that in all such cases, we do not make any changes to the sum of the word vectors.

III. Preliminary Results

We use the GloVE [3] twitter word vectors for word embedding. The GloVE corpus is constructed out of 2 Billion word tokens. We use the word-vectors with 25 dimensions.

Here are the 5-Fold Cross validation results obtained by training a SVM classifier with different kernels : Linear, Polynomial and RBF kernels. From our observation, the *Radial Basis Function* with gamma parameter = 1.5 gave the best results that we have reported below.

```
Target: Atheism
Feature Size - (513, 25)
Five-Fold CV Results = [0.78846154  0.76699029  0
Mean Accuracy = 0.785600169866

Target: Hillary Clinton
Feature Size - (639, 25)
Five-Fold CV Results = [ 0.73643411  0.734375
Mean Accuracy = 0.740249420131

Target: Legalization of Abortion
Feature Size - (603, 25)
Five-Fold CV Results = [ 0.73553719  0.70247934
Mean Accuracy = 0.729689561775

Target: Climate Change is a Real Concern
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Feature Size - (395, 25)
Five-Fold CV Results = [ 0.6875      0.625       0.65822785  0.6025641   0.67948718]
Mean Accuracy = 0.650555826031

Target: Feminist Movement
Feature Size - (664, 25)
Five-Fold CV Results = [ 0.80597015  0.81203008  0.81203008  0.81060606  0.81060606]
Mean Accuracy = 0.810248484168
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IV. Remaining/Future Work

- The obvious next step is to use all the tweets that were classified as relevant to the target and classify them as FOR/AGAINST. We plan to use POS tagged of the tweets and their parses to make sense of the sentiment.
- We have used just 25-dimensional vectors and plan to try out the 100-dimensional vectors which might give better results owing to their better expressivity.
- We also plan to try out other algorithms in both the steps.
- We are looking for better ways to use the hashtags as it is a general observation that hashtags generally give away the mood/tone of the tweeter.

References

[1] Rob Abbott Jean E. Fox Tree Robeson Bowmani Michael Minor Pranav An, Marilyn Walker. Cats Rule and Dogs Drool!: Classifying Stance in Online Debate.

[2] Svetlana Kiritchenko, Xiaodan Zhu, and Saif M. Mohammad. Sentiment Analysis of Short Informal Texts. *J. Artif. Intell. Res. (JAIR)*, 50:723–762, 2014.

[3] Jeffrey Pennington, Richard Socher, and Christopher D. Manning. Glove: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP 2014)*, pages 1532–1543, 2014.