Analysis of Textual Stance Detection for Visual Integration

Thilini Cooray
Singapore University of Technology and Design
muthuthanthrige@mymail.sutd.edg.sg

SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN

Abstract
Stance detection has recently drawn a huge interest in Natural Language Processing community due to the variety of applications it can support. Social media networks provide a great platform for people around the world to state their stance on vast number of different topics. This study focussed on analysing current state of stance detection on social media data, experimenting on novel approaches to evaluate their capabilities of addressing issues on current methods and discuss possibilities of integrating visual information to further enhance existing approaches.

Introduction

Stance detection is a task which was introduced to classify whether the author of a text is in agreement, disagreement or expressing neither of them about a given target. Text can be a news article, a blog, a tweet or a Facebook post and the target can be a person, organization, movement, product, news headline etc. Stance detection is a typical task which can help any entity such as companies and election candidates to accurately understand public's position about them and their rivals.
Here is a more general task definition was formulated based on the definition provided by [4] : Given a corpus of documents (tweets, online news comments, news articles, blog posts etc.), and a target entity (person, organization, movement, policy etc.), automatic natural language processing systems should be able to determine whether the author of the article is in favour of the given target, against it or neither can be inferred.

Formally this can be written as, for a given set of documents D related to a target T, the goal of stance detection is to retrieve the mapping $s_T : D \rightarrow \{favor, against, neither\}$ for any element $d \in D$.
Stance or the position of the author towards a target can be expressed in several different ways. Following are some examples. These examples are used from the training dataset of tweets presented in SemEval-2016 Task 6: Detecting Stance in Tweets [3].

Direct expressions : Author directly mentions the target and his/her position about the target.

Document : Hillary is our best choice if we truly want to continue being a progressive nation. #Ohio
Target : Hillary Clinton
Stance : Favour

Direct expressions with different textual representations Author provides his/her position directly about the target, however the wordings he uses are not exactly similar. In the following example, a human can directly understand that pro-life support is against legalization of abortion.

Document : I will agree to gay marriage if you agree to pro-life and then adopt babies that would have been aborted.
Target : Legalization of Abortion
Stance : Against

Indirect expressions Author provides his position towards a different entity/fact which is related to the target. In the following example, the author is talking about emission of CO_2 as a bad thing. Emission of CO_2 badly effects climate change. Humans can deduce that the author is agreeing that climate change is a concern with that contextual understanding of the relatedness of those facts.

Document : Every human commits original sin with it's first out-breath of CO2. Mankind is fallen. #bible #SemST
Target : Climate Change is a Real Concern
Stance : Favour

Contribution

1. Analyse existing work for stance detection on social media data.
2. Experiment on novel approaches for stance detection.
3. Identifying problems in current approaches.
4. Analyze on the use of visual content for stance detection.

Method

All existing work has considered Stance Detection task as a classification problem. We tried to model this as a ranking problem.

Rank SVM

Ranking SVM is one of the state of the art ranking models which surpasses other methods in performance. Assume there is a linear function F which can be used for ranking as follows:
$\forall\{(x_i, x_j) : y_i < y_j \in D\} : F(x_i) > F(x_j) \Leftrightarrow w.x_i > w.x_j$

w is the weight vector which will be learnt by the algorithm to make its input data concordant with the ordering in D. This is known to be a np-hard problem [1]. Herbrich et al. [2] introduced a mechanism to approximate this function using Support Vector Machine where a slack variable ξ_{ij} is used and the optimization problem aims to minimize the upper bound of the slack variable $\sum \xi_{ij}$ as follows :
minimize :

$$L(w, \xi_{ij}) = \frac{1}{2}w.w + C\sum \xi_{ij}$$

subject to :

$$\forall\{(x_i, x_j) : y_i < y_j \in D\} : w.x_i \geq w.x_j + 1 - \xi_{ij}$$
$$\forall(i, j) : \xi_{ij} \geq 0$$

Above constraints bound the solution of the optimization problem to satisfy ordering entries in training set D with minimal error. By minimizing w.w we can maximize the margin ($\frac{1}{\|w\|}$). C is the soft margin parameter. By rearranging the first constraint we can receive following:

$$w(x_i - x_j) \geq 1 - \xi_{ij}$$

This is the familiar constraint in structured SVM. Therefore classical SVM implementations can be extended to address ranking problems.

Results

Experiments were carried out using the Twitter Stance dataset provided in SemEval 2016 Stance Detection task A [3]. This is a supervised task where participants were given stance labelled data for 5 targets (Hillary Clinton, Atheism, Climate Change is a Real Concern, Feminist Movement and Legalization of Abortion). Tweets are labelled as favor if it supports the given target, against if it disagrees with the target, neither if either agree or disagree cannot be inferred. All results are displayed on the experiments done on dataset whose target is Hillary Clinton. We used structured SVM as the baseline for our experiments. Based on the baseline results using variety of textual features we found out that a combination of character and word ngrams provide the best representations for tweets.
Unlike classification, ranking approach outputs a set of ranking scores. The order to these scores should finally be used to determine class boundaries and assign labels. If the correlation between predicted and ground truth sets are high, it infers that the model has learned to correctly order documents based on their stance. Kendall's τ was used as the metric for correlation. Table 1 shows results for both baseline and Rank SVM.

Feature	Baseline	Rank SVM
Word ngram (1,3)	0.3430	0.4397
Word ngram (1,4)	0.2840	0.4409
Character ngram (2,5)	0.5656	0.4918
Char (2-5) and word unigram	0.5656	0.486
Char (3-5) and word (1,2) gram	0.5281	0.486

Table 1: Correlation of predicted stance from classification and ranking models

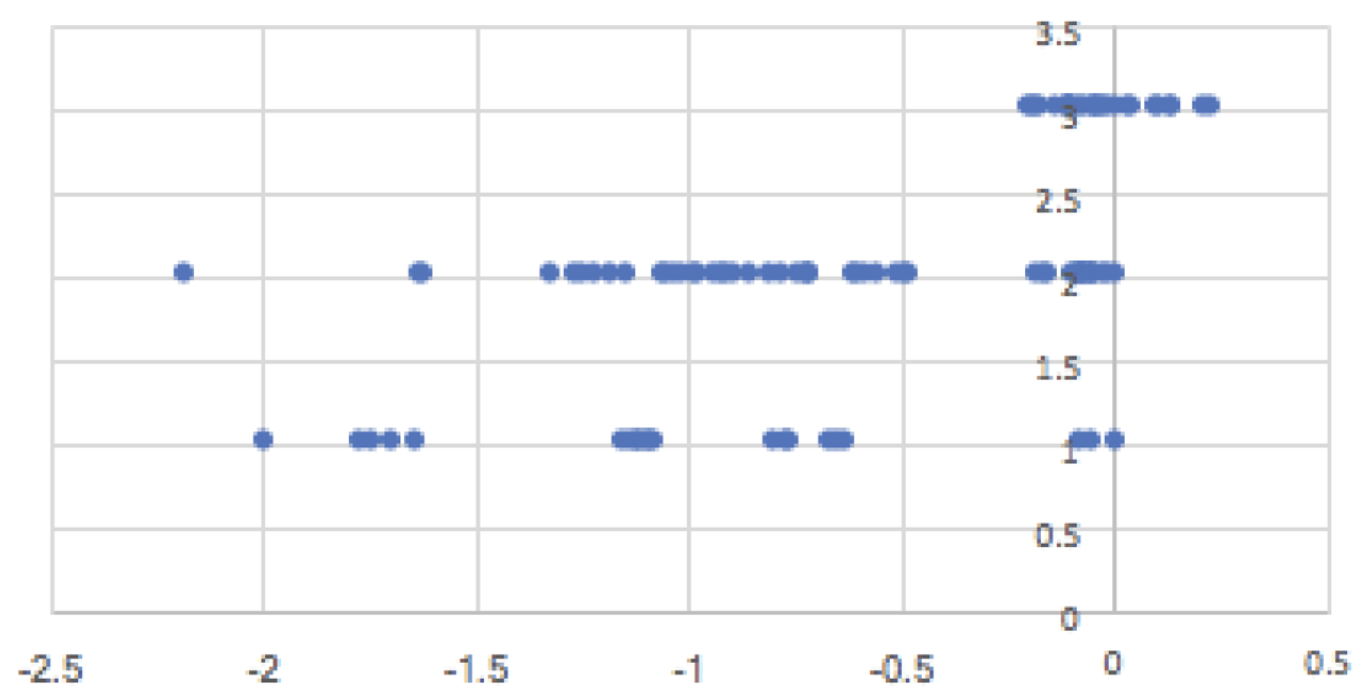

Figure 1: Ranking score distribution for validation data (correlation = 0.486) for feature Char (3-5) and word (1,2) grams

Figure 1 displays the distribution of ranking scores of validation set with respect to the ground truth label they belong to (1= favor, 2 = against, 3 = neither). This distribution is later used to decide on class boundaries for assigning predicted labels. We can observe that Rank SVM was unable to assign scores which can properly distinguish among classes. Several reasons can affect this poor performance of the model. Due to limited number of data, model might not have been able to capture actual ordering information. So it has over-fitted training data. These feature representations may not be suitable enough to capture correct information from the text.

Visual integration for Stance Detection

Due to the poor performance of above model and also considering the problems stance detection faced in the literature, we tried to think whether there is a way to get more information about author's stance from his post. This drew our attention towards images in posts. Now a days many users tend to use images and emoticons to express their ideas quite often. Therefore we identified the potential of using visual data to further enhance stance detection.

Conclusions

During this project period, we mainly focussed on analyzing existing work on stance detection and experiment on novel approaches. We tried to map stance detection as a ranking problem and address it accordingly. However we were unable to achieve superior performance to state of the art methods. This drew our attention to analyse and understand the potential of using visual content of user posts for stance detection as an additional information. This will further be analysed and experimented in the future.

References

[1] W. W. Cohen, R. E. Schapire, and Y. Singer. Learning to order things. In *Advances in Neural Information Processing Systems*, pages 451–457, 1998.
[2] R. Herbrich, T. Graepel, and K. Obermayer. Large margin rank boundaries for ordinal regression. 2000.
[3] S. Mohammad, S. Kiritchenko, P. Sobhani, X.-D. Zhu, and C. Cherry. Semeval-2016 task 6: Detecting stance in tweets. In *SemEval@ NAACL-HLT*, pages 31–41, 2016.
[4] P. Sobhani. *Stance Detection and Analysis in Social Media*. PhD thesis, Université d'Ottawa/University of Ottawa, 2017.

Acknowledgements

We are very grateful for HPI Future SOC lab for offering us computational power for our experiments.