LSTM for Sentiment Analysis on Twitter

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Abstract

abstract goes here

1 Introduction

In the last few years, microblogging has become a very popular communication tool in people's social life. On microblogging platforms, such as Twitter[1] and Facebook[2], a diverse range of people are attracted to post short sentences, images, and video links to share life issues and opinions. This popularity results in enormous amount of information covering a wide range of topics on the brands, products, politics and social events. Such data is a valuable and efficient source for marketing and social studies. Sentiment analysis on microblogging has obtained special interest, because it determines the attitude of a user with respect to some topic or product and thus provides provide convincing information For example, it may help manufacturing companies to know how people like their product (or service), what would people prefer.

In this paper, we focus on using sentiment analysis on Twitter. We restrict our interest on Twitter for the following reasons: People are posting on various topics on Twitter, thus it is a valuable source of data; Twitter is one of the most popular microblogging platform and the number of messages are growing everyday. The collected corp can be arbitrary large; Users of Twitter have various background and have different language conventions. It is possible to collect tweets of wide diversity in both topics and language models.

Although there exist plenty of work on text classification, some unique characteristics of tweets present special challenges for sentiment analysis: 1. Tweets are short in length. There is a limitation of 140 words for each tweet; 2. The language used in tweets is very informal with misspelling, creative spelling, new words, slangs, and URLs; 3. Emotions and hashtags are frequently used.

In this paper, we propose a bi-directional Long Short-Term Memory (LSTM) method for sentiment analysis. We tried both word-level and character-level features on the bi-directional LSTM model and compare the results with Dynamic Convolutional Neural Network (DCNN) [3]. We show that the accuracy of sentiment analysis ... (Please revise this part.)

We train our model on 1.6 M distantly-supervised tweets collected by Go et. al. [1], and evaluate the results on SemEval-2016 Task 4[3]. Currently we focus on polarity classification, and plan to apply our model on 5-point scale classification in the future.

In the remaining of this paper, we first introduce the related work, the dataset, and the evaluation methodology. We then describe the model we proposed. Finally, we discuss the experiment results and point out possible directions for future research. (Please revise this part.)

[1] `https://twitter.com/`
[2] `https://www.facebook.com/`
[3] `http://alt.qcri.org/semeval2016/task4/`

2 Related Work

Twitter sentiment analysis is increasingly drawing attention of researchers in recent years. Given the length limitations on tweets, sentiment analysis of tweets is often considered similar to sentence-level sentiment analysis [5]. However, phrase and sentence level approaches can hardly define the sentiment of some specific topics. Considering opinions adhering on different topics, Wang et. al. [10] proposed a hashtag-level sentiment classification method to generate the overall sentiment polarity for a given hashtag. Recently, following the work of [7] some researchers used neural network to implement sentiment classification. For example, Kim [4] adopted convolutional neural networks to learn sentiment-bearing sentence vectors, Mikolov et al. [8] proposed Paragraph vector which outperformed bag-of-words model for sentiment analysis, and Tang et. al. [9] used ConvNets to learn sentiment specific word embedding (SSWE), which encodes sentiment information in the continuous representation of words. Furthermore, Kalchbrenner [3] proposed a Dynamic Convolutional Neural Network (DCNN) which uses dynamic k-max pooling, a global pooling operation over linear sequences. Instead of directly applying ConvNets to embeddings of words, [11] applies the network only on characters. They showed that the deep ConvNets does not require knowledge of words and thus can work for different languages. LSTM [2] is another state-of-the-art semantic composition models for sentiment classification [6]. Similar to DCNN, it also learns fixed-length vectors for sentences of varying length, captures words order in a sentence and does not depend on external dependency or constituency parse results.

3 Model

4 Experiments

See Table 1 for awesome results

Table 1: Sample table title

PART	**DESCRIPTION**
Dendrite	Input terminal
Axon	Output terminal
Soma	Cell body (contains cell nucleus)

This is a figure:

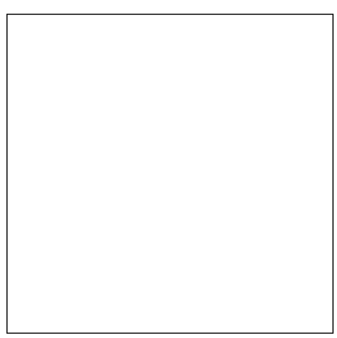

Figure 1: Sample figure caption.

5 Conclusion

Acknowledgments

References

References

[1] Alec Go, Richa Bhayani, and Lei Huang. Twitter sentiment classification using distant supervision. *CS224N Project Report, Stanford*, 1:12, 2009.

[2] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[3] Nal Kalchbrenner, Edward Grefenstette, and Phil Blunsom. A convolutional neural network for modelling sentences. *arXiv preprint arXiv:1404.2188*, 2014.

[4] Yoon Kim. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*, 2014.

[5] Efthymios Kouloumpis, Theresa Wilson, and Johanna Moore. Twitter sentiment analysis: The good the bad and the omg! *Icwsm*, 11:538–541, 2011.

[6] Jiwei Li, Dan Jurafsky, and Eudard Hovy. When are tree structures necessary for deep learning of representations? *arXiv preprint arXiv:1503.00185*, 2015.

[7] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.

[8] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119, 2013.

[9] Duyu Tang, Furu Wei, Nan Yang, Ming Zhou, Ting Liu, and Bing Qin. Learning sentiment-specific word embedding for twitter sentiment classification. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, volume 1, pages 1555–1565, 2014.

[10] Xiaolong Wang, Furu Wei, Xiaohua Liu, Ming Zhou, and Ming Zhang. Topic sentiment analysis in twitter: a graph-based hashtag sentiment classification approach. In *Proceedings of the 20th ACM international conference on Information and knowledge management*, pages 1031–1040. ACM, 2011.

[11] Xiang Zhang, Junbo Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In *Advances in Neural Information Processing Systems*, pages 649–657, 2015.