Aiding Sentiment Evaluation with Social Network

Pengfei Gao, Fan Yang, Hao Yin *
Institute for Computational and Mathematical Engineering
Stanford University
Stanford, CA 94305
{pfgao, fanfyang, yinh}@stanford.edu

Abstract

Some abstract

1 Introduction

Milestone report is seen in Section 2. For reader's reference, we give an introduction of our project in this section.

In this project, we are going to explore different methods that utilize social network information in sentiment analysis with deep learning. Network structure is useful and informative in NLP-related task as people within each community may have their own "jargon" in expressing ideas and sentiments.

Data description

We obtained the data used by [Yang and Eisenstein(2017)]. The data consists of a collection of tweets as well as some network information on Twitter. For each tweet sample, we have one tweet ID, one user ID, a sentiment label (positive, neutral, negative), and the tweet content itself. For example, the following are two examples of our data samples.

```
261140278944088066 17572408 negative @USER may i have an industrial revolution ...
237571817550786563 727519172 neutral @USER i told you shane would get his 5th-star .
```

We have three networks, i.e., FOLLOWER, MENTION and RETWEET network which have been explained in details by [Yang and Eisenstein(2017)].

Methodology

Our project will start from the method proposed by [Yang and Eisenstein(2017)], which is summarized in Figure 1 (black lines). The model consider the author information and sentence information separately: each node (author) in the network is assigned an embedding vector using the LINE algorithm ([Tang et al.(2015)Tang, Qu, Wang, Zhang, Yan, and Mei]), and then is (softly) assigned each cluster on the network based on the embedding. Each cluster has its own model, which is a CNN model combined with max pool layer. This model provides a baseline in our project.

We are going to extend this model in three aspects, as is illustrated in the red lines in Figure 1. To be specific,

*Each member contributes equally, and names are put in alphabetic order.

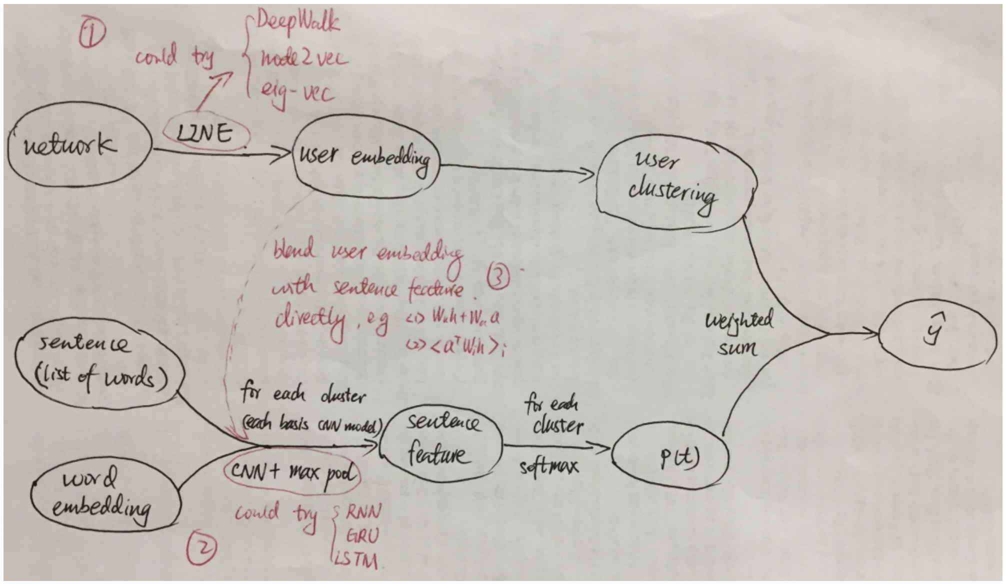

Figure 1: General Methodology

(1) Using other node embedding methods in network analysis, such as *DeepWalk* ([Perozzi et al.(2014)Perozzi, Al-Rfou, and Skiena]) and *node2vec* ([Grover and Leskovec(2016)]);

(2) Explore other methods to combine author information and sentence information, especially the bilinear form $a^T W h$ which measures the interaction between author and sentence. Here a is the author embedding and h is the sentence embedding.

(3) Explore other models in sentiment analysis, such as RNN, GRU, and LSTM.

2 Progress

As is advised by our project mentor Will Hamilton, since CNN is the current state-of-the-art model for sentiment analysis, we are going to focus on (1) and (2) above, and only work on part (3) if time permits.

For part (1), we have already computed the embedding using *DeepWalk*. Using the original model and implementation, this embedding does not outperform the existing result which uses the LINE embedding. We have just finished the embedding using *node2vec*, and have not examined it with the existing result. We intended to computed the embedding using Azure, but we experienced some issue in uploading our network edgelist files. We end up using CORN, which takes roughly 50 hours to finish.

For part (2), the original implementation uses Keras. We have just read through and understand all of their code, which can be finished in 10 minutes using personal computer CPU. We are contacting the authors for exact seeds to reproduce the results in the paper, and after that we are going to incorporate the author-sentence interaction feature into the existing model.

3 Results

References

[Grover and Leskovec(2016)] Grover, Aditya, Jure Leskovec. 2016. node2vec: Scalable feature learning for networks. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 855–864.

Embedding method	CNN	DeepWalk	LINE	node2vec	random
Dev2013	68.85	67.71	**69.51**	68.58	68.50
Test2013	69.53	67.58	**69.67**	68.58	68.49
Test2014	**72.41**	71.46	71.44	71.46	71.69
Test2015	64.40	**64.71**	64.57	64.25	63.50
Avg test sets	**68.78**	67.92	68.56	68.10	67.89

Table 1: Prediction performance on each Dev and Test Sets.

[Perozzi et al.(2014)Perozzi, Al-Rfou, and Skiena] Perozzi, Bryan, Rami Al-Rfou, Steven Skiena. 2014. Deepwalk: Online learning of social representations. *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 701–710.

[Tang et al.(2015)Tang, Qu, Wang, Zhang, Yan, and Mei] Tang, Jian, Meng Qu, Mingzhe Wang, Ming Zhang, Jun Yan, Qiaozhu Mei. 2015. Line: Large-scale information network embedding. *Proceedings of the 24th International Conference on World Wide Web*. ACM, 1067–1077.

[Yang and Eisenstein(2017)] Yang, Yi, Jacob Eisenstein. 2017. Overcoming language variation in sentiment analysis with social attention. *Transactions of the Association for Computational Linguistics (TACL)* .