Microblog Sentiment Analysis with Emoticon Space Model

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Outline

- Background
- Previous Works & Limitations
- Our Model
- Experiments
- Conclusion

- NLP&CC 2014 emotion analysis task
 - document level emotion classification
 - sentence level emotion identification and classification
 - emotion expression extraction

- Related classification tasks
 - subjectivity classification: whether a post is subjective
 - **emotion classification**: which emotion does a post have, happiness, anger, or sadness, etc.

- Fully Supervised Methods
 - text classification problems ...
 - Naive Bayes

$$p(c = positive|w_1, w_2, ..., w_n) \sim p(c = positive) \prod_i p(w = w_i|c = positive)$$

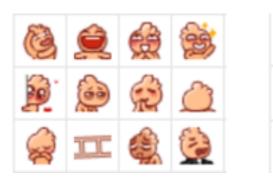
VSM (vector space model)

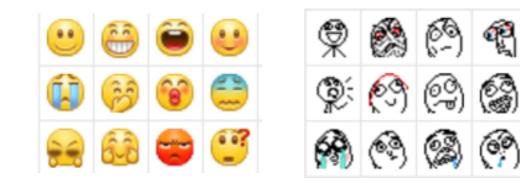
$$vector(post) = [0, 0, ..., 0, 1, 0, ..., 0, 0, 1, 0]$$

- Fully Supervised Methods
 - topics are wide
 - require large amounts of manually labeled data
 - labor intensive
- Emoticons are adopted to alleviate this problem

The Popularity of Graphical Emoticons

All kinds Emoticons on various platforms







- Emoticons are widely adopted
 - over 25% of posts on Sina Weibo contain emoticons

Previous Works on Microblog Sentiment Analysis

- Noisy (distant) supervised Methods
 - Use some emoticons as sentiment label of posts.
 - positive samples:

negative samples:

高音上不去,低音下不来 😖 宁波现虐猫事件 😁 这9部电影看完之后~整个人都不好了.... 😜

Limitations

Noisy labels

- · words in posts may not express the same sentiment with emoticons.
- hard to tell which emoticon expresses a certain emotion (fear, surprise, etc.).

Difference among emoticons

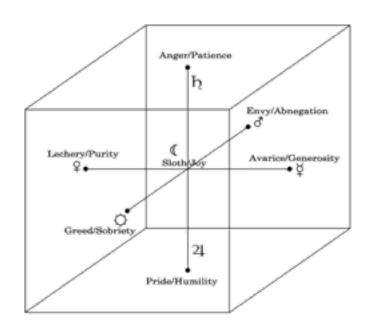
- throw several happy emoticons into the same set, thus ignoring the difference among them
- · different emoticons have different emotions and strengths
- is ⊕ equal to ⊕?

Limitations

- Can not leverage sentiment-ambiguous emoticons
 - 🎡 seldom occurs in angry posts.

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- Emotion model
 - emotion can be represented in a 3D space
 - different emotions (happiness, sadness, etc.) lie in some special places in the emotion space
 - can emoticons serve as the basis of a similar space?



Emoticon space

- projecting words into emoticon space, based on their similarity with the emoticons.
- coordinates of words can be used as features for supervised classification (fewer data).



For example





• happy =
$$[0.8, -0.7, 0.1, ...]$$

- sad = [-0.7, 0.4, -0.1, ...]
- document = [0.1, -0.1, -0.2, ...]

- Learn Similarity Between Words and Emoticons
 - use word embeddings to define similarity between word i and emoticon j

$$similarity(\boldsymbol{w_i}, \boldsymbol{e_j}) = \frac{\boldsymbol{w_i} \cdot \boldsymbol{e_j}}{|\boldsymbol{w_i}| |\boldsymbol{e_j}|}$$

use word2vec [1] to estimate word embeddings

- Representation of Microblog Posts
 - average, min, max pooling at each dimension.
- SVM for classification

Dataset

- NLP&CC 2013 Chinese microblog corpus
- 14,000 labeled posts in total
- labels of subjectivity, emotion
- balanced classes in experiment-1

The original dataset

neural	like	happiness	sadness	disgust	anger	surprise	fear
6748	2122	1477	1147	1394	640	333	139

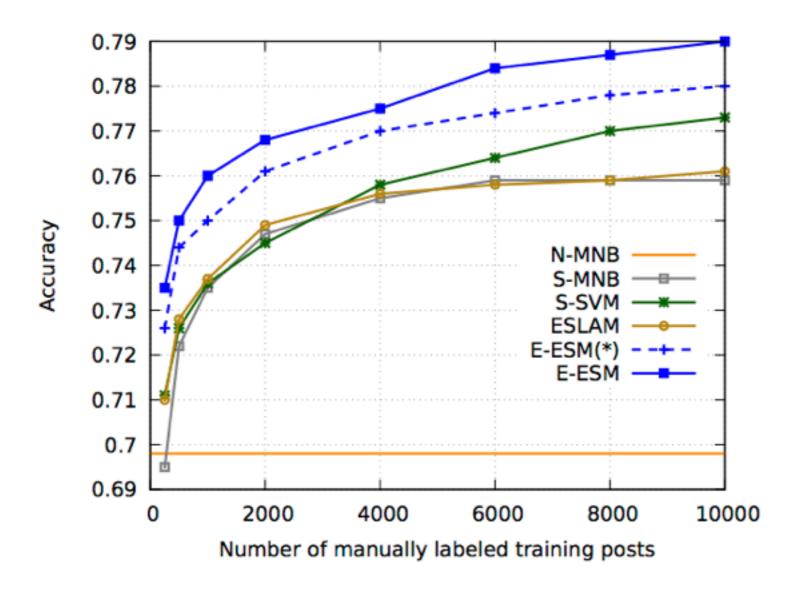
Baselines

- fully supervised methods (S-SVM, S-MNB) [2]
- noisy supervised methods (N–MNB) [3]
- combination of above two (ESLAM) [4]

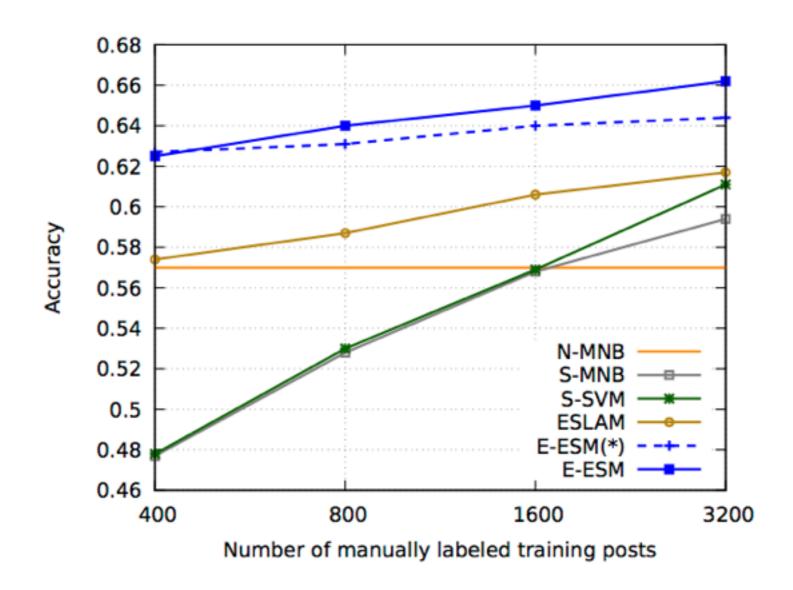
Our model

- with ambiguous emoticons (E-ESM)
- without ambiguous emoticons (E-ESM(*))

Subjectivity Classification



Emotion Classification



four emotions (happiness, like, sadness, disgust)

- NLP&CC 2014 emotion analysis task
 - eight classes (seven emotions + neutral)
 - first emotion + second emotion
 - evaluation metric: average precision
 - 14,000 posts for training & validation, 6000 posts for testing

neural	like	happiness	sadness	disgust	anger	surprise	fear
6748	2122	1477	1147	1394	640	333	139

- Technical details in NLP&CC 2014 emotion classification task
 - cross validation with 14,000 posts
 - a hierarchical classifier for first emotion: binary subjectivity classifier + seven-class emotion classifier
 - second emotion: conditional probability matrix

p(second emotion | first emotion)

Performance in NLP&CC 2014 Emotion classification task

	loose measure	strict measure
document level	0.5309	0.4668
sentence level	0.5489	0.5175

Conclusion

- A richer sentiment representation compared to previous works.
- Need more strategies to recognize the second emotion

Thank you

References

- [1] Mikolov, T., Sutskever, I., Chen, K., Corrado, G., Dean, J.: Distributed rep-resentations of words and phrases and their compositionality. arXiv preprint arXiv:1310.4546 (2013)
- [2] Bermingham, A., Smeaton, A.F.: Classifying sentiment in microblogs: is brevity an advantage? In: Proceedings of the 19th ACM international conference on Infor- mation and knowledge management. pp. 1833-1836. ACM (2010)
- [3] Pak, A., Paroubek, P.: Twitter as a corpus for sentiment analysis and opinion mining. In: LREC (2010)
- [4] Liu, K.L., Li, W.J., Guo, M.: Emoticon smoothed language models for twitter sentiment analysis. In: AAAI (2012)