Twitter Sentiment Classification using Distant Supervision

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Core Idea & Motivation

Core Idea:

Introducing a novel approach for automatically classifying sentiment (positive or negative) of Twitter messages (called tweet).

Motivation:

- Consumers research products and services
- Marketers analyze public opinion and user satisfaction
- Organizations gather feedback of products
- Most of previous researches focus on classifying large pieces of text
- Unique attributes of Twitter messages

Related Work

- J. Read. Using emoticons to reduce dependency in machine learning techniques for sentiment classification. In Proceedings of ACL-05, 43nd Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, 2005.
- B. J. Jansen, M. Zhang, K. Sobel, and A. Chowdury. Micro-blogging as online word of mouth branding. In CHI EA '09: Proceedings of the 27th international conference extended abstracts on Human factors in computing systems, pages 3859{3864, New York, NY, USA, 2009. ACM.
- B. Pang, L. Lee, and S. Vaithyanathan. Thumbs up? Sentiment classification using machine learning techniques. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 79-86, 2002.

Approach

Feature Extractors:

- Unigrams
- Bigrams
- Combination of Unigrams and Bigrams
- Unigrams with Part of Speech (POS)

Query Term:

- Normalize the effect of query terms.
- Query terms do not have bias of emotion.

Approach

Emoticons:

- Training process makes use of emoticons as noisy labels.
- Emoticons are not perfect at defining the correct sentiment of a tweet.

Feature Reduction

- Username as "USERNAME".
- Links as "URL".
- Repeated letters.

Machine Learning Methods

Baseline:

- Twittratr.
- List of positive and negative keywords.

Naive Beyes:

$$c* = argmac_c P_{NB}(c|d)$$

$$P_{NB}(c|d) := \frac{(P(c)\sum_{i=1}^{m} P(f|c)^{n_i(d)})}{P(d)}$$

c*: class
d: tweet
f: feature
n_id: the count of feature f_i found in d
m: total number of features
P(c), P(f|c): obtained from MLE

Machine Learning Methods

Maximum Entropy:

$$P_{ME}(c|d,\lambda) = \frac{\exp[\Sigma_i \lambda_i f_i(c,d)]}{\Sigma_{c'} \exp[\Sigma_i \lambda_i f_i(c,d)]}$$

c: class
d: tweet
λ: weight vector
$f_i()$: feature i found in tweet d

Support Vector Machine:

- Input data are two sets of vectors of size m.
- Each entry in the vector corresponds to the presence of a feature.

Evaluation

Training Data:

- Twitter API with query terms periodically.
- Emoticons are stripped out.
- Any tweet with both positive and negative emoticons are removed.
- Retweets and repeated tweets are removed.
- 1.6 million

Emoticons mapped to :)	Emoticons mapped to :(
:)	:(
:-)	:-(
:)	: (
:D	
=)	

Evaluation

Testing Data:

- A set of 177 negative and 182 positive tweets are manually marked.
- Not all the testing data has emoticons.
- Search the tweet with specific queries.
- Mark the result as positive or negative.

Query	Negative	Positive	Total	Category
40d		2	2	Product
50d		5	5	Product
aig	7		7	Company
at&t	13		13	Company
bailout	1		1	Misc.
bing	1		1	Product
Bobby Flay		6	6	Person
booz allen	1	2	3	Company

Evaluation

Unigrams:

- Simplest way to retrieve features from a tweet.
- Machine learning methods perform better than keyword baseline.

Bigrams:

- Help in situation of negated phrase.
- Tend to be very sparse and the overall accuracy drops in both MaxEnt and SVM.

Features	Keyword	Naive Bayes	MaxEnt	SVM
Unigram	65.2	81.3	80.5	82.2
Bigram	N/A	81.6	79.1	78.8
Unigram + Bigram	N/A	82.7	83.0	81.6
Unigram + POS	N/A	79.9	79.9	81.9

Evaluation

Unigrams and Bigrams:

- Both unigrams and bigrams are used as features.
- Accuracy improves for Naive Bayes and Maximum Entropy.

Unigram with Parts of Speech:

- The same word may have many different meanings.
- Not useful.

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Conclusion

- Using emoticons as noisy labels for training data is an effective way to perform distant supervised learning.
- Machine learning methods (Naive Bayes, Maximum Entropy, SVM) can achieve high accuracy for classifying sentiment.
- Although Twitter messages have unique characteristics, machine learning methods are shown to classify tweet sentiment with similar performance.

Future Work

- Semantics, the perspective you are interpreting the tweet from.
- Domain specific tweets, limited to a particular domain.
- Internationalization, classify sentiment in other languages.
- Handling neutral tweets, as important as positive and negative ones.
- Using emoticon data in the test set.

References

- J. Read. Using emoticons to reduce dependency in machine learning techniques for sentiment classi¯cation. In Proceedings of ACL-05, 43nd Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, 2005.

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- G. Mishne. Experiments with mood classi¯cation in blog posts. In1st Workshop on Stylistic Analysis Of Text For Information Access, 2005.