A Hybrid Approach for Twitter Sentiment Analysis

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Abstract

This paper introduces an approach for automatically classifying the sentiment of Twitter messages. These messages are classified as either positive or negative. This is useful for consumers who want to extract the sentiment of product before purchase, or companies that want to monitor the public sentiment of their brand. In this paper, a three stage hierarchical model is proposed for sentiment extraction, first labeling with emoticons is done, then tweets are labeled using pre-defined lists of words with strong positive or negative sentiments and finally tokens are weighted based on subjectivity lexicon and proposed probability based method. Further, various cascading and hybrid methods are proposed based on subjectivity lexicon and Probability based method. In addition to this, effect of discourse relations is also investigated at the pre-processing step. Experimental results show the effectiveness of the proposed hybrid approach for sentiment classification of tweets.

1 Introduction

Twitter serves as an ideal platform for the analysis and extraction of general public sentiments regarding specific topics. The objective of Sentiment Analysis is to identify any clue of positive or negative emotions in a piece of text reactive of the authors' opinions on a subject (Agarwal et al. 2013). Opinion Mining or Sentiment Analysis aims at determining the attitude of the writer with respect to some specific topic or the overall contextual polarity of a document. Earlier, opinion about the success/failure of a product or a movie is little bit difficult as the opinion might be a biased one as it is difficult to get reviews from people belonging to different origin. But nowadays, due to the prevalent increase in the involvement of people on different social networking sites such as Twitter, Facebook, and reviews about a particular topic, movie, and product can be extracted easily with the help of these sites. Various organizations use twitter to know the general sentiment associated to a particular entity such as about a product, person, public policy, movie or even an institution.

Due to free format of messages and easy accessibility of micro-blogging platform, internet users tend to shift from blogs and mailing lists to micro blogging services. As more and more users post about products and services they use, and express their personal views. Micro-blogging websites become valuable source of people's opinions and sentiments. Such data can be efficiently used for marketing or study of social issues.

The paper is organized as follows. In section 2, the related works are discussed. Then, in section 3, the proposed method is presented. Further, in section 4, experiments and their results are discussed. Finally, section 5 presents the conclusion.

2 Related Work

In recent time, sentiment analysis research has been increased tremendously. There is a large collection of research around using machine learning techniques for sentiment analysis in corpora containing informal language, such as data from social networks and micro blogging services (Agarwal et al. 2012, Mukherjee et al. 2012a). Go et al. (2009) suggested that proper attention needs to be paid to neutral sentiment. Their primary contribution was an approach using emoticons as noisy labels during the training process, eliminating the need for hand-labeled data. Tumasjan et al. (2010) used the Linguistic Inquiry and Word Count (LIWC) sentiment lexicon for sentiment analysis. They showed that sentiment extraction with word counts produced results that closely match traditional election polls. O'Connor et al. (2010) explores the implementation of part-of-speech information and emoticons in extracting tweet sentiment, and the use of a sentiment lexicon tailored towards text originating from social media. Using state-of-the-art unigram model as baseline, an overall gain of over 4% is reported for two classification tasks: a binary, positive versus negative and a 3-way positive versus negative versus neutral (Agarwal et al. 2011).

Most of the works in micro-blogs, like Twitter, build on a bag-of-words model that ignores the discourse markers (Joshi et al. 2011). Secondly, a spam detection module that eliminates promotional tweets before performing sentiment detection may be added to the current system. The dependency parsing for graph based clustering of opinion expressions about various features can also be used to extract the opinion expression about a target feature. Emoticons can also be used as noisy labels (Mukherjee et al 2012a).

3 Proposed approach

The approach consists of three stage hierarchy. First of all a tweet is labeled according to the emoticons it have, then labeling tweet using pre-defined list of strong positive and strong negative words and finally using subjectivity lexicon. Detailed description of the proposed method is as follows.

3.1 Data Preprocessing

Main task of pre-processing is to get the meaningful tokens from the tweets. Main pre-processing steps are discussed as follows.

Emoticons Handling: In the tweeter sentiment model emoticons are used as main conveyor of mood of user. Hence utmost importance is given to them in differentiating the sentimental sense of tweet.

Negation Handling: In the model all negations (e.g. not, no, never, didn’t, cannot) are replaced by tag “NOT”.

Spell Correction: The user in twitter tend to give importance to a particular word by repeating characters. In this case all possible permutation involving either one or two concurrent placement of each repeated letter, that is repeated at least three times, is used. To give additional importance to that, their weightage is doubled in the final score of tweet. Eg. Happpyyy is replaced by hapyy, happy, hapy, happy.

Stop Word Removal: Stop words are used to exclude words such as articles that have nothing to do with sentiment. Some of the stop words used are: That, was, we, what, where, you, are, he, is, it, me, my, that, the, them, this, to etc.

Slang Handling: Slang is the use of informal words and expressions that are not considered standard in the speaker's language or dialect but are considered acceptable in certain social settings. Words used in chat/Internet language that are common in tweets are not present in the lexical resources. A chat word is replaced by its dictionary equivalent. E.g. asap: as soon as possible.

3.2 Proposed Three Stage Hierarchical Approach

The proposed tweeter sentiment analysis model is implemented as three stage hierarchy where first stage is associated with emoticons, second stage is based on predefined list and third stage is based on subjectivity lexicon.

3.2.1 Label Using Emoticons

Emoticons are used as main conveyor of mood of the user. Hence utmost importance is given to them in differentiating the sentimental sense of tweet. Standard emoticon dictionary is used from Internet. In this step, a tweet is labeled as positive or negative according to the emoticon list. If the tweet does not contain any emoticon from the list, this tweet would be classified in stage 2.

3.2.2 Label tweet using pre-defined lists

Predefined list of strongly positive and negative label is used to determine the overall semantic orientation of the tweet. Some strong positive and negative words are listed in Table 1. If a testing tweet contains any of these strong positive or negative words, a score of +/-1 is assigned accordingly; further overall semantic orientation is computed by aggregating these scores. If a tweet does not contain any emoticon or strong positive and negative words, then that tweet would be classified in stage 3.

Positive	**Negative**
Amazed, Amused, Attracted, Cheerful, Delighted, Elated, Excited, Festive, Funny, Hilarious, Joyful, Lively, Loving, Overjoyed, Passion, Pleasant, Pleased, Pleasure, Thrilled, Wonderful etc.	Annoyed, Ashamed, Awful, Defeated, Depressed, Disappointed, Discouraged, Displeased, Embarrassed, Furious, Gloomy, Greedy, Guilty, Hurt, Lonely, Mad, Miserable, Shocked, Unhappy, Upset etc.

Table 1: Some Strong positive and negative words

3.2.3 Token weighing based on subjectivity lexicon

If a testing tweet is not labeled at starting two phases. Then subjectivity lexicon is used to determine the overall semantic orientation of the tweet. Semantic Orientation i.e. Weight is assigned to all the remaining tokens. The process is divided into following phases.

3.2.3.1 Token Generation

This step is associated with tokenizing the tweet using above mentioned preprocessing methods. All unnecessary weightless words are neglected and individual tokens are forwarded for lexicons analysis.

3.2.3.2 Negation Handling

Bigrams and trigrams are used following negation signifying tokens and reversing there polarity. Hence, it prevents wrong decisions in negation token containing tweets.

3.2.3.3 Discourse Analysis

In this section, tokens are analyzed for discourse analysis. An essential phenomenon in natural language processing is the use of discourse relations to establish a coherent relation, linking phrases and clauses in a text. The presence of linguistic constructs like connectives, modals, conditionals and negation can alter sentiment at the sentence stage as well as the clausal or phrasal stage. Consider the example, “@user share 'em! i'm quite excited about Tintin, despite not really liking original comics”. The overall sentiment of this example is positive, although there is equal number of positive and negative words. This is due to the connective despite which gives more weight to the previous discourse segment.

In proposed model, two types of discourse relations are used (Mukherjee et al. 2012b).

***Conj*_Fol:** is the set of conjunctions that give more importance to the discourse segment that follows them. Eg. But, however, nevertheless, otherwise, yet, still, nonetheless.

Conj_Prev: is the set of conjunctions that give more importance to the previous discourse segment. Eg. till, until, despite, in spite, though, although.

Conj_infer: is the set of conjunctions that tend to draw a conclusion or inference. Hence, the discourse segment following them should be given more weight. Eg. Therefore, furthermore, consequently, thus, as a result, subsequently.

Conditionals: is the set of conjunctions that depict situations which may or may not happen subject to certain conditions. Presence of these conjunctions diminishes down the final polarity as it introduces a hypothetical situation in the context. In our work, the weight of the discourse segment in a conditional statement is toned down. E.g if, else, elseif , then.

Strong Mod : is the set of modals that express a greater degree of uncertainty in any situation. We diminishes the weight of the segment containing the strong modals such as might, might, could, can, would, may.

Weak Mod: is the set of modals that express lesser degree of uncertainty and depicts happening of certain event such as ought to, need not, shall, will, must.

Discourse relations and attributes used in the experiments are presented in Table 2.

Discourse relation	Attributes
Conj Fol	But, however, nevertheless, otherwise, yet, still, nonetheless
Conj Prev	Till, until, despite, in spite, though, although
Conj Infer	Therefore, furthermore, consequently, thus, as a result, subsequently, eventually, hence
Conditionals	If, if-else, then
Strong mod	Might, could, can, would, may
Weak mod	Should, ought to, need not, shall, will, must
Neg	Not, neither, never, no, nor

Table 2: Discourse relations for sentimental analysis

Some example tweets containing discourse attributes are presented in Table 3.

Attributes	Tweet
But	I bought her a brand new car, but she wasn't happy with it.
However	I secured less marks however, I am happy that I manage to Pass.
Despite	The doctor couldn't save the patient despite his best effort.
In spite	India lost the final match inspite the great performance of captain.
If	if micromax improves its battery life, then it would have been a good product
Might	I'm afraid that I might make you angry
Should	I think that we should try again.
Neither	Neither of the books you are looking for are available.

Table 3:Some tweets depicting the various discourse relations.

3.2.3.4 Weighing using Lexicon

Two methods are used to give the weights or polarity to the token after negation and discourse analysis. First method is to get the polarity i.e. positive and negative values from the SentiWordNet (SWN). Problems with SWN based method is that more than 90% words in this lexicon is having higher objective values therefore, for most of the words of tweet, polarity values could not be determined. Therefore, another probability based method is proposed to get the semantic orientation / polarity of the words. In this method, probability of a word that it would belong to positive class is taken as positive polarity value and similarly the probability that a word would belong to negative class is taken as negative polarity value of that word. In this method, probability that a word belongs to positive class is computed by dividing the number of occurrences of a word in positive class by total number of occurrences of that term. This value is considered as positive polarity value of the term. Similarly, negative polarity value is computed of all the term of the tweet. Finally, overall polarity of a tweet is labeled by the greater value of aggregate positive and negative polarity value of all the term of tweet.

4. Experiment and Results

All the experiments are performed on the standard labeled dataset provided by Stanford University consisting of 60,000 tweets. It contains equal number of positive and negative tweets. Accuracy is used for evaluating the effectiveness of the proposed methods; it is computed by dividing the correctly classified tweets by total number of testing tweets.

Firstly, initial two stages i.e. emoticon based labeling and pre-defined list of words based labeling are performed for all the experiments. Further, various experiments are performed to address two main objectives. (1) To investigate the effect of discourse relations for twitter sentiment classification (2) To investigate the effect of new method for calculating the polarity value of words. Finally, a Hybrid method is proposed by combining SWN and probability based method to determine the polarity of tweets. An accuracy of 64.694% is obtained, when SentiWordNet is applied at the third stage of the hierarchy to retrieve the polarity value of the words. Further, by incorporating rules for discourse analysis in it, an accuracy of 66.052% is achieved, showing a rise in the accuracy as shown in Table 4 and 5.

Approach	**Accuracy**
SentiWordNet	64.694
Proposed probability based method	71.116
SentiWordNet then probability based method	69.511
probability based method then SentiWordNet	71.83
Hybrid Approach	72.563

Table 4: Results without discourse

Next, semantic orientation (polarity value) is computed based on the probability as described earlier.

Approach	**Accuracy (%)**
SentiWordNet	66.052
Proposed probability based method	71.625
SentiWordNet then probability based method	70.193
Probability based method then SentiWordNet	72.35
Hybrid Approach	73.72

Table 5: Results with discourse

An accuracy of 71.116% is achieved without discourse relations included which shows better performance as compared to SWN. Further, by incorporating discourse relations with it 71.625% accuracy is achieved as shown in Table 4 and 5.

Further, two methods are proposed to combine the SWN and polarity computation based on probability: (1) Cascading method, in which initially SWN is applied followed by probability based method and vice versa (2) Hybrid of both methods is proposed giving different weights to each method.

Cascading method (SWN followed by probability method) gives and accuracy of 70.193% with discourse rules, and with the reverse method (Probability based method followed by SWN) produces an accuracy of 72.35% with discourse rules.

Hybrid method uses both SWN and probability based method for computation of the polarity value of the word/token. In this method weighted polarity of the word is computed by using Eq 1.

Final_polarity (t) = Weight (t, SWN) X (a) + Weight (t, PBM) X (1-a) …. (1)

Here:

t: any token/word extracted from tweet.

Weight (t, SWN): Polarity of word t from SentiWordNet.

Weight (t, PBM): Polarity of word t using probability based method

a: Percentage weights of SWN and probability based method.

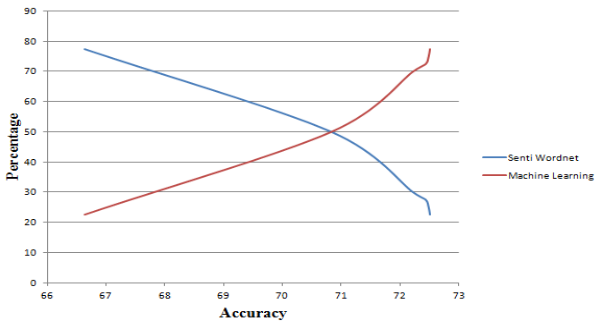

Figure 1. Accuracies of Proposed Hybrid method

Impact of varying value of a on the accuracy is shown in Figure 1. It is observed experimentally that 22.5 % weights of SWN and 77.5 % weights of probability based method perform best as compare to other methods.

5. Conclusion and Future Work

This paper presents methods for twitter sentiment analysis. Experimental results show that the incorporation of discourse markers improves the sentiment classification accuracy. Various cascading and hybrid methods are proposed for determining the polarity value of words to compute the overall polarity of the tweet. Experimental results show the effectiveness of the proposed hybrid approach for sentiment analysis. In future, we would like to incorporate rules for handling sarcasm and more discourse relations.

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