Two-dimensional Sentiment Analysis of text

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ABSTRACT

Sentiment Analysis aims to get the underlying viewpoint of the text, which could be anything that holds a subjective opinion, such as an online review, Movie rating, Comments on Blog posts etc.

This paper presents a novel approach that classify text in two-dimensional Emotional space, based on the sentiments of the author. The approach uses existing lexical resources to extract feature set, which is trained using Supervised Learning techniques.

1. INTRODUCTION

With the recent growth of online reviews, social media and blogs, there has been a lot of attention to mine for subjective information. These sites contains huge amount of data that has loads of subjective information.

Some of the challenges in Sentiment Analysis are: People express opinions in complex ways, in opinion texts, lexical content alone can be misleading. Humans tend to express a lot of remarks in the form of sarcasm, irony, implication, etc. which is very difficult to interpret. For Example- “How can someone sit through the movie” is extremely negative sentiment yet contains no negative lexographic word. Even if a opinion word is present in the text, their can be cases where a opinion word that is considered to be positive in one situation may be considered negative in another situation. People can be contradictory in their statements. Most reviews will have both positive and negative comments. Sometimes even other people have difficulty understanding what someone thought based on a short piece of text because it lacks context. A good example would be “The laptop is good but I would prefer, the operating system which I was using” here context about the author’s operating system is missing.

There is a huge demand of sentiment analysis. Before buying any product its a practice now, to review its rating as rated by other persons who are using it. Online advice and recommendations the data reveals is not the only reason behind the buzz in this area. There are other reasons from company’ point of view like, the company wants to know “How Successful was their last campaign or product launch” based upon the reviews of users on websites like Amazon, Yelp, etc..

2. PREVIOUS WORKS

A lot of research has been done in the area over the past decade. Main research in the area of Sentiment Analysis and opinion mining are: sentiment classification, feature based Sentiment classification and opinion summarization. Sentiment classification deals with classifying entire documents or text or review according to the opinions towards certain objects. Feature-based Sentiment classification on the other hand considers the opinions on features of certain objects. For example, in reviews related to laptops classifying the sentiments only on the basis screen quality.

In one of the pioneer work [2], the authors present a method of subjectivity identification for sentiment analysis based on minimum cuts. This is important because the irrelevant data from the reviews could be eliminated. The problem is viewed as a classification task and different types of Supervised learning techniques have been used in this field. Some of the most common ones are naive Bayes classifier, Support Vector Machine[13] , Maximum Entropy [1] etc. Even some graph based techniques [4] are also used.

Languages that have been studied mostly are English and Chinese. Presently, there are few researches conducted on sentiment classification for other languages like Arabic, Spanish, Italian and Thai. The presented work focuses on English language only.

3. APPROACH

This paper uses Thayer’s Model of human emotion [5], to classify text. This two dimensional approach adopts the theory that human emotion can be obtained by: Stress (negative polarity/positive polarity) and Energy (low intensity/high intensity), and divides it into four broad classes: Satisfied, Sad, Exuberent and Angry.

Two binary classifiers were trained. First was trained to get the polarity (positive or negative) of the text. While the second was trained on intensity (low or high) of the text. Figure 1 illustrates the approach.

3.1 Polarity

Some existing lexicon resources like Sentiwordnet 3.0 [7] and General Inquirer [9] were used to extract some features from the text. These features were trained using support vector machine, to predict the binary class label.
3.1 Features

Sentiword score of each review was used as a feature. The score was calculated using the weighted average of the all the synsets (Synonym set, Wordnet [8]) of each word. The weights assigned were based on the ranks of synsets as in wordnet. Thus, giving a value between -1 to 1 depending upon the polarity. Where negative score implies negative polarity and vice versa while 0 being the neutral or no polarity.

\[
BaseScore = \text{pos} - \text{neg}
\]  
(1)

\[
PolarityScore = \text{basescore} + \frac{1}{2} \times \text{first} + \frac{1}{3} \times \text{second}...
\]  
(2)

\[
\text{total} = \frac{1}{1} + \frac{1}{2} + \frac{1}{3} + ........
\]  
(3)

\[
\text{finalscore(eachword)} = \frac{\text{Polarityscore}}{\text{total}}
\]  
(4)

Let the sum of the sentiword score for each sentence be 'S' and number of sentences be 'n'. For each sentence in the review, negation words (like: not, cant, wasnt, barely etc.) were detected. For presence of a negation word the sentence score was multiplied by -1. Finally each sentence score was averaged to get the Sentiword based score for each review.

\[
\text{TotalReviewScore} = \frac{\sum S} {n}
\]  
(5)

A set of 178 features were based on the frequency of categories marked by General Inquirer. For each word a set of category/labels has been marked. Categories includes positive, negative, active, passive, direct, indirect, etc. Some other features like emoticons, number of words in quotes were also used.

3.2 Intensity

To determine whether intensity of the text is high or low supervised learning approach has been used. Have extracted 184 features and a support vector Model has been trained.

3.2.1 Features

Some of the features used are: all capital text, for example: “I am EXTREMELY unhappy”. Elongated words have also been used as one of the features. Its a common practice especially in online reviews that people use, elongated words. For example “The pizza was verryyyyy verryyyyyy gooood!!” Another feature includes the count of exlamation marks, people tend to put exlamation marks to show the level of their excitement, for example “The coffee was too cold!!” Count of Adverbs was also taken. Finally the frequency of 178 categories from General Inquirer were also included. The frequency was used in the same way as in Polarity.

3.3 Dataset Creation

There are many standard annotated Dataset available to train polarity like, The movie review Dataset [2]. However no standard annotated set was available, to train for Intensity (low or high).

3.3.1 Using Yelp’s Reviews to create Dataset

The yelp’s dataset [14] contains over 100,000 reviews. Each review was marked with 1- 5 stars. Created a dataset of 5000 (2500 positive and 2500 negative) reviews for training polarity and another 5000 (2500 low intensity and 2500 high intensity) to train intensity. Used the following proxy:

- Considered ratings with 5 star as Positive polarity
- Considered ratings with 1 star as Negative polarity.
- Considered ratings with 1 or 5 star as High Intensity.
- Considered ratings with 3 star as Low Intensity.

4. RESULTS

The following Results are using 10 fold cross-validation on the dataset of size 5000. LIBSVM [15] is used to train a vector model.

4.1 Results for Polarity

The total mean accuracy achieved was 81.60% +/- 1.92%

| true "Pos." | true "Neg." | Class Precision |
|-------------|-------------|-----------------|
| 2143        | 563         | 79.19%          |
| 357         | 1937        | 84.44%          |

4.2 Results for Intensity

The total mean accuracy achieved was 67.14% +/- 1.22%. The details are shown in table 3.

4.3 Other Approaches tried

The following techniques were tried after removing stop-words and spell correction. The mean accuracy is for 10 fold cross validation on LIBSVM.
### Table 3: Result Intensity

| true “Low” | true “High” | Class Precision |
|------------|-------------|-----------------|
| pred “Low” | 1556        | 699             | 69.00%          |
| pred “High”| 944         | 1801            | 65.61%          |
| Class Recall| 62.24%     | 72.04%          |                 |

### Table 4: Other Techniques for Polarity

| Techniques                  | Mean Accuracy | Polarity |
|-----------------------------|---------------|----------|
| All unigrams (20,000+)      | 67.1%         |          |
| Adj & Adverb with stemming  | 68.6%         |          |
| Adj and Adverb no Stemming  | 69.3%         |          |
| Only Adjectives             | 68.0%         |          |
| Top 2000 words              | 71.2%         |          |

The model did not perform very well while using all the unigrams. One possible reason could be, that the feature size was huge. It performed slightly better when only used Adjective and Adverbs. Stemming [10] the unigrams had almost no effect on the results.

The results were improved just by using the K-top words occurring in the corpus, which was 2000 in this case. One of the shortcomings with all the approaches mentioned in the table is that all of them are dependent on the training Dataset. Thus, the trained model is specific to the domain and the types of words used in the dataset. These model will not be as effective for all types of text. For example, words like Coffee, restaurant, movie, yummy, pizza etc. had high frequency in the presented Dataset, which are not that common in a more General scenario.

### Table 5: Other Techniques for Intensity

| Techniques                  | Mean Accuracy | Intensity |
|-----------------------------|---------------|-----------|
| Adverb with stemming (2086) | 58.7%         |           |
| Adverb no Stemming          | 58.4%         |           |
| Frequency of 100 related categories | 65.4%     |           |

The table above presents some of the techniques that did not work out well. Considering unigram features, for a relatively small dataset did not work out. Even omitting some of the categories (Categories, in General Iquirer) that were generic, the results were not good. Some of the categories that were omitted in the above approach are, ‘Doctrine’, ‘Economics’, ‘religion’ ‘Politics’ etc.

### 4.4 Mapping in 2-Dimensional emotional space

Using Thayer’s model, the following are the Mappings in 2-Dimensional Emotional space, using the binary labels of Polarity and Intensity as shown in table 6.

### 5. CONCLUSIONS

### Table 6: Mapping Using Thayer’s Model

| Polarity | Intensity | Emotion       |
|----------|-----------|---------------|
| Positive | Low       | Satisfied/Calm|
| Positive | High      | Exuberant/Excited |
| Negative | Low       | Sad/Down      |
| Negative | High      | Angry/Agitated |

Discovered a unique way to classify text in two-dimensions and map to a emotion using Thayer’s Model. Did an analysis of various different techniques and compared their results.

The proposed model for polarity was able to achieve results (81.60%) which is comparable to current state of the art techniques. The approach used lexicon based features to train the model. The Learned model does not use any corpus specific features for the training. The model uses predefined set of categories that are generic. These categories can be applied to any English word. Although, some of the features used are dependant on “Internet Lingo”, but they are not specific to a domain. Therefore the model could be applied to the text of various other domains.

Used Intensity of text as a separate dimension and created an annotated dataset. All the features used for training Intensity were not specific to the dataset. This approach can be used in any domain.

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