Proposed Techniques to Remove Flaming Problems from Social Networking Sites and outcome of Naïve Bayes Classifier for Detection of Flames

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Abstract: Natural Language Processing (NLP) is a field of Computer Science concerned with the interactions between Computer and Human (Natural) Languages. Social Networking Sites are amongst the most effective communication tools now a days. But it also gave rise to the problem of flaming which is difficult to deal with. A flaming incident is triggered by comments and actions of users in SNS that ends up damaging reputation or causing negative impact on the target party. So in this paper, in order to prevent such damage, Semi-Supervised Learning Approach is presented. It includes a proposed architecture that involves Naïve Bayes Classifier, Maximum Entropy Classifier and Feature Selection based on Entropy method. This paper also includes application and result of Naïve Bayes Classifier, trained so as to detect the class of the input comments as whether it belong to positive, negative or neutral class. Sentiment Analysis Dataset containing tweets and there polarity class(positive, negative or neutral) has been used. A training set of 17282 tweets has been used to train Naïve Bayes Classifier which was able to correctly classify 70% of the test set of 4332 tweets.

Keywords: Natural Language Processing, Flaming, Semi-Supervised Learning, Class, Naïve Bayes Classifier

1. Introduction

SNS has achieved a huge popularity in the previous decade. It has made the transmission of information across the globe very easy for everyone. But it has also brought with it a problem called flaming which are one of the current hazards of online communication. They are caused due to negative comments made by users that can have a huge impact on the target in a negative way. So, in order to overcome this problem, sentiment analysis, which aims to classify sentiment of documents, can be used. In this paper an architecture has been proposed that describes various techniques for the purpose of finding polarity (negativity, positivity or neutrality) of the input document. A training set of 17282 tweets already annotated(as positive, negative or neutral) was preprocessed by applying tokenization, stop words removal and stemming to construct a sentiment dictionary. This dictionary contains the word and its positive, negative and neutral frequencies. The input test data is then inputted and pre-processing is applied on it. The pre-processed input data is a collection of features (words). The positive, negative and neutral frequencies of the features in test data is obtained using the sentiment dictionary and then using various methods the probability of the input belonging to all the classes namely positive, negative and neutral class is calculated. The input data is then considered to be classified in the class which has the maximum probability. Probability can be calculated using four methods namely

2. Proposed Architecture

The training dataset that contains 17282 tweets is first pre-processed to form Sentiment dictionary. Pre-processing involves tokenization, stop word removal stemming. The sentiment dictionary contains words and their respective positive, negative and neutral frequencies. The input test data is then inputted and pre-processing is applied on it. The pre-processed input data is a collection of features (words). The positive, negative and neutral frequencies of the features in test data is obtained using the sentiment dictionary and then using various methods the probability of the input belonging to all the classes namely positive, negative and neutral class is calculated. The input data is then considered to be classified in the class which has the maximum probability. Probability can be calculated using four methods namely

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Naïve Bayes Classifier, Maximum Entropy Classifier, Naïve Bayes with Feature Selection based on Entropy Method, Maximum Entropy with Feature Selection based on Entropy Method. The output of all the four classification methods is compared with the original classification that is already known because test data is annotated. In this way we can calculate the accuracy of various classification methods.

3. Pre-Processing of Datasets

The dataset collected from the SNS media contains a lot of opinion about the data which are expressed in different ways by individuals. The negative, positive and neutral polarity labeled dataset is highly susceptible to inconsistency and redundancy. In order to improve the quality of result, pre-processing of raw data is necessary. It helps in removing repeated words and punctuation and thus help in improving the quality of the data. Some of the pre-processing techniques are as follows:

3.1 Tokenization

In Lexical analysis, Tokenization is the process of breaking up a stream of text, into words, symbols or other meaningful elements called tokens. In this way, the input data on tokenization will give collection of features. For the training data, these features is used for the construction of sentiment dictionary. Features here refers to words. For test data, these features is accessed in the dictionary to obtain their frequencies in all the three classes, which is then used for the classification of the input.

3.2 Stop Word Removal

Many words will be syntactic words, i.e. they do not contribute to the semantic meaning of the sentence. Such words are required to be removed. Stop Words list is obtained and after tokenization such words that belong to the stop word list are discarded since they only lead to occupying space while not contributing for classification.

3.3 Stemming

In linguistic morphology and information retrieval, stemming is the process of reducing inflected (or sometimes derived) words to their word stem, base or root form—generally a written word form. Stemming will help is reducing the size of the sentiment dictionary and also will help in getting more accurate results.

In this project OpenNLP Toolkit and Porter Stemmer has been used for pre-processing.

4. Sentiment Dictionary

Sentiment Dictionary is constructed using the annotated Training dataset that contains tweets and their annotations as they belong to positive, negative or neutral. Pre-Processing is applied to the training dataset. Sentiment Dictionary contains four columns for words and their respective frequencies in all the three classes.

5. Feature Selection based on Entropy[1]

It can be possible that dictionary may contain words (eg. I, we, us) that are not informative in case of sentiment analysis. So, in order to remove these words, we use entropy method, assuming that these words are uninformative. Let |C| be the number of classes, \( n_{i,c} \) is the number of occurrences of word \( w_i \) in class \( c \). \( N_i \) is the number of \( w_i \) in all classes. \( H(i) \) is the entropy of word \( w_i \) which is calculated as:

\[
H(i) = -\frac{1}{\log |C|} \sum_{c=1}^{|C|} \frac{n_{i,c}}{N_i} \log \frac{n_{i,c}}{N_i} \leq 1
\]

When the occurrence probabilities of a word \( w_i \) in respective classes are equal to each other i.e. there are no bias based on occurrence probabilities present between classes, \( H(i) \) gets highest value 1. On contrary, when a word \( w_i \) occurs in only one class i.e. its occurrence probably is causing maximum bias between classes, the value of entropy \( H(i) \) is lowest i.e. 0. So those words are used, whose entropy \( H(i) \) is equal to or lower than the threshold \( \alpha \), i.e. \( H(i) \leq \alpha \).

Thus if we set \( \alpha =1 \), then we use words that occur only in one class and if we set \( \alpha =0 \), all the features will be used.

6. Naïve Bayes Classifier

A Naïve bayes classifier is a simple probabilistic model which is based on the Bayes rule along with a strong independence assumption. The Naïve Bayes model involves a simplifying conditional independence assumption i.e. given a class (positive, negative or neutral), the words are conditionally independent of each other. This assumption does not affect the accuracy in text classification by much but makes really fast classification algorithms applicable for the
problem. In this paper a Multinomial Naïve Bayes Classifier has been used that first calculates joint probability of words and then assigns texts to the class (Positive/Negative/Neutral) they belong.

Assumptions in Multinomial Naïve Bayes Classifier:

a) In a document, the occurrence distribution of words conforms to the multinomial distribution.
b) Obtain documents from a sequence of words and occurrence of words should be independent of each other.
c) Prior Probability of a document belonging to class c is a uniform distribution.

From Training data let:

\[ |V| = \text{Number of unique words} \]
\[ V = \{ w_1, w_2, ..., w_{|V|} \} \]

\[ P_{ic} = \text{Occurrence Probability of a word } w_i \text{ in class } c \]
\[ \Theta_c = \{ P_{1c}, P_{2c}, ..., P_{|V|c} \} \text{ = Parameter Vector of class } c \]
\[ n_{id} = \text{Number of occurrences of a word } w_i \text{ in document } d. \]

\[ P(d|\Theta_c) = \text{Likelihood of a document } d \]

Naïve Bayes Classifier outputs \( c^* \) as

\[ c^* = \arg\max_c P(d|\theta_c) \] (3)
\[ c^* = \arg\max_c \prod_i P_{ic}^{n_{id}} \] (4)

Laplasian Smoothing: If the classifier encounters a word that has not been seen in the training set, the probability of both the classes would become zero and there won’t be anything to compare between. This problem can be solved by Laplacian smoothing

\[ P_{ic} = \frac{n_{ic} + (\alpha - 1)}{\sum n_{ic} + |V| (\alpha - 1)} \] (5)

In this paper \( \alpha = 2 \) has been used which is well used as Laplacian smoothing. So

\[ c^* = \arg\max_c \prod_i \left( \frac{n_{ic} + (\alpha - 1)}{\sum n_{ic} + |V| (\alpha - 1)} \right)^{n_{id}} \] (6)

The main theoretical drawback of Naïve Bayes methods is that it assumes conditional independence among the linguistic features. If the main features are the tokens extracted from texts, it is evident that they cannot be considered as independent, since words co-occurring in a text are somehow linked by different types of syntactic and semantic dependencies.

7. Maximum Entropy Classifier

The idea behind Maximum Entropy classifiers is that, given the constraints, most uniform models are most preferable Maximum Entropy models are feature based models. These features are used to find a distribution over the different classes using logistic regression.

Goal: Given a set of features, a set of their corresponding functions that measures the contribution of each feature to the model known as weighting Factor, as \( h_i (i = 1, 2, ..., k) \) and a set of constraints our aim is to find the probability distribution that maximizes the relative Entropy. By maximizing entropy, it is ensured that no biases are introduced into the system.

\[ P(c|d, \lambda) = \frac{\exp \sum_i \lambda_i h_i(w_i|c)}{\sum_c \exp \sum_i \lambda_i h_i(w_i|c)} \] (7)

Where \( h_i (w_i|c) = \begin{cases} 1, & \text{if } w_i \notin c \\ 0, & \text{otherwise} \end{cases} \) (8)

The Major Advantages of using Maximum Entropy Classifier is as follows:

- Accuracy
- Consistency – This method shows consistency in results and if priors are used results also improve over a period of time.
- Performance / Efficiency - Can handle huge amounts of data
- Flexibility - The classifier is flexible of having many different typed of data in a unified platform that are classified accordingly.

8. Result

4332 tweets were classified using Naïve Bayes Classifier, out of which 3016 tweets were correctly classified. Following table gives the details of the classification:

<table>
<thead>
<tr>
<th>Original Classification</th>
<th>Positive</th>
<th>Negative</th>
<th>Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>1588</td>
<td>344</td>
<td>1</td>
</tr>
<tr>
<td>Negative</td>
<td>637</td>
<td>1297</td>
<td>0</td>
</tr>
<tr>
<td>Neutral</td>
<td>174</td>
<td>150</td>
<td>131</td>
</tr>
</tbody>
</table>

Accuracy is calculated using the following formula:

\[ \text{Accuracy} = \frac{\text{Total Correctly Classified Tweets}}{\text{Total Tweets}} \times 100 \] (9)

So Accuracy of Naïve Bayes classifier is 70%.

9. Conclusion

Naïve Bayes Classifier classified positive tweets with a good accuracy, correct classification of negative tweets is moderate while neutral tweets are poorly classified. The classification results can be improved by applying feature selection based entropy method and Maximum Entropy Classifier. Words that do not have much bias to a particular class are also used for classification. This can be the reason for many incorrect classifications. Feature Selection based on entropy method helps in identifying such words. Also, since Maximum Entropy Classifier ensures minimum bias into the
system (this implies minimum assumptions) can also contribute in better accuracy.

References


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