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Volume 2, Issue 4August 2013

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Polarity of Sentence Recognition with Phrase-Level Sentiment Analysis

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ABSTRACT

The rate of growth of Internet services has resulted in an exponential increased on Opinions on the web. The retail industry as well as all other industries needs a technique of detecting and analysing customer's opinion on a particular product. The plurality of these expressed opinions on the web will not permit manager to make good analysis of the product, be it positive or negative opinion. This paper presents technique of filtering opinionated sentence and polarity judgment by combining linguistic clue and machine learning methods such as CRF and SVM from the rest of the sentences. The method is based on linguistic pattern and scoring of subjectivity terms, automatically identifies the opinionated sentences and their polarities. The approach achieves a comparativeperformance with the current state of the art opinion mining systems.

Keywords:*Opinion Mining, Opinion Detection, Polarity Judgment, Sentiment, linguistic pattern*.

1. INTRODUCTION

Since the introduction of web 2.0, Opinion Mining has become one of the household's terminologies and hence attracted many researchers to propose several techniques on best methods of identifying people's opinion be it negative or positive from the web. In particular, as a lot of services on the Internet (e.g., product reviews, forum posts and discussions, blogs and social networks) have been increasing, opinion mining became important to provide judgment method for online users and customers. The goal of this relatively young field of mining is to extract useful information and consequently analyse users' opinion on the web which was brought about as a result of huge collection of unstructured data. However this has proved a surprisingly challenging task hence occupied thousands of intelligent and creative minds for several years. The sudden interest in this field is as a result of individual increasingly using freely and public available opinion via the web for their mundane decision making. Ambiguity of user' comment and diversify sources have been identified to be majors factor that makes mining users opinion difficult. Each source usually contains large volume of opinionated text that is usually encrypted to many ordinary users and also embedded in long forum postings and blogs. The ordinary reader mostly has difficulty filtering relevant sources and accurately summarizing the information and opinions contained in them for their decision making process [1]. Business and e-commerce applications domain such as moving ratings and product reviews has been the focus of the majority of the current research works in the field [2]. Some of the popular tasks in opinion mining field include opinion sentence detection, polarity judgment, opinion holder and target detection.

This paper focus is on opinion sentence detection and polarity judgment which is based on using linguistic clues and machine learning methods. Related works is discussed in section 2, and system architecture is in section 3. Section 4 discussed general approaches, section 5 is methodology, section 6 is the experiment and result and finally conclusion is in section 7.

2. RELATED WORK

Research in this relatively young field is not new to the academician, many research papers have been published in the last decade and even several applications have been developed and currently on the market [3-6]. There have been scores of research works on opinion and sentiment analysis [5, 6]. The early work was on the development of a gold standard in the area of opinionated sentence judgment, by Wiebe et al. [7] that developed a probabilistic classifiers to automatically identify the subjective and objective classification of discourse sentences. In the reported work, a search is performed to find a probability model that captures relevant interdependencies among features. In other to classify a subjective sentence, many researchers used statistical classification methods such as Naïve Bayes and Support Vector Machine [8-10]. For opinion polarity classification, Wilson et al. proposed a recognizing contextual polarity method in phrase level [11]. They annotated the corpus with contextual polarity and determined whether an expression is neutral or polar. Somasundaran et al. developed supervised and unsupervisedmethods for opinion polarity classification [12]. They proposed a global inference method for supervised framework, and used Integer Linear Programming (ILP) to optimized unsupervised framework.

Based on these statistic and machine learning approaches, necessity of linguistic approaches for opinion

Volume 2, Issue 4August 2013

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

mining also has been increased to achieve high performance [13].

3. SYSTEM ARCHITECTURE

The goal of this research is divided into two parts; first, to detect opinionated sentences in a document, second, to classify the polarity of the detected sentences in the first phase. The technique that was adopted is based on linguistic knowledge focusing on subjective sentences using machine learning to each phase of the experiment. Support vector machine (SVM) was used to detect opinionated sentences in a document and the conditional Random field model was adopted for the polarity classification of the detected sentences.

4. GENERAL APPROACH

Authors of opinion reflect back on their opinion to sentences, these sentences contain subjectivity. Therefore, opinionated sentences tend to be uncertain. Based on this tendency, we tried to find linguistic clues which represent the opinion.

BioScope [14] is one of the popular corpus mostly used in Bio-Informatics areas. One of the categories in BioScope is a hedge cue which represents intentionally non-committal or ambiguous sentence fragments. Based on data analysis (NTCIR-6) and this corpus, we selected some words and phrases as a main clue. 40 opinion clues were finally selected. A sentence that contains these linguistic patterns was determined to be an opinionated sentence.

A common scoring method for opinionated sentences was used to classify sentences which do not have main clues. In calculating the score, SentiWordNet[15] was selected as a corpus, because, SentiWordNet contains two numerical scores, such as positive score and negative score of sentiment words. By using these score, a formula which represents opinionated score of a word was derived.

In addition, we used other subjectivity corpus [16] for classifying opinionated sentence and also its polarity clearly. Only strong-subjectivity types of words in the corpus for boosting the score of word were considered. The calculated score of an opinionated sentence and polarity by summing each word score in the sentence was obtained. The formula is as shown in Fig 1.

A threshold was adopted to select the sentence with heavy scores. If a score of sentence is over the certain threshold, it was determine to be an opinionated sentence. For polarity detection, if the score of sentence polarity is greater than zero, it was considered it as positive polarity. If the score is lower than zero, it is negative polarity respectively.

$$Opi(s) = \sum_{t \in S} | Pos(t) + B_{pos}(t) - Neg(t) - B_{neg}(t) | \quad (1)$$

$$Por(S) = \sum_{t \in S} Pos(t) + B_{pos}(t) - Neg(t) \quad (2)$$

$$\begin{cases} B_{neg}(t) = 0, & \forall t \in Pos \\ B_{pos}(t) = 0, & \forall \text{t} \in \text{Neg} \end{cases}$$

$where,$

$S = Sentence$

$Pos(t) = \text{Score of term t in SentiWordNet}$

$Neg(t) = \text{Score of term t in Senti-WordNet}$

$B_{pos}(t) = \text{Boosting positive score of term t in subjectivity corpus}$

$B_{neg}(t) = \text{Boosting negative score of term t in subjectivity corpus}$

$Opi(S) = \text{Total score of a sentence}$

$Por(S) = \text{Total score of polarity of a sentence}$

Fig.1: Opinion and Polarity Equations

5. METHODOLOGY

A. *Opinion Sentence Detection*

In order to detect an opinion sentences, A support Vector Machine (SVM) [17] was used to classify opinionated sentence. SVM is one of the most powerful and popular supervised machine learning classifier. We used several feature for classifying opinionated sentence. Detail explanation of the features used in the experiment is as shown in Fig. 2.

LibSVM; open source SVM library [18], Stanford NER [19] for the Named entity recognition were used for this research work, and the strong polarity clue is from [8].

- Sentence context with 2 window size
  - Whether the sentence before input sentence is opinionated or not
- SentiWordNet Score
  - 10* |POS score – NEG score|
- Number of token
  - Number of token in the sentence, delimiter is simply white space
- Number of ORGANIZATION Named Entity
  - Number of Organization class named entity in the sentence.
- Number of Strong polarity clue word
  - Number of strong polarity clue word. Strong polarity clue list : (Believe, Insist, Claim, Criticize, Think, Advice)
- Number of PERSON Named Entity
  - Number of Person class named entity in the sentence

Fig.2: List of Features used for SVM Classifiers

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

B. Opinion Polarity Judgement

This section of the research tries to classify the polarity of the sentence using the opinionated phrases in the sentence. The phrase-level polarity has more detailed information than the sentence-level, so can help in the judgment of polarity of the sentence more accurately. The relationship between the opinionated phrases, such as the order and co-occurrence, will also be a good clue to judge the polarity of whole sentence.

In order to recognize the opinionated phrases in a sentence, Conditional Random Fields (CRFs) [20] was used to utilize the sequential feature of those phrases in a sentence. 3 types of binary classifier were used for each class of polarity, which are positive, negative, and neutral. We expected that the combination of binary classifiers will give better result. To extract opinionated phrases in a sentence, we used following features for CRFs.

- Word Token
- POS Tag
- Preceding & Following POS Tags [-2, +2]
- Prior Positive & Negative Score on Senti-Wordnet
- Preceded by Adjective
- Preceded by Adverb

Fig.3: List of Features used for Conditional Random Field Classifier

6. EXPERIMENT AND RESULT

A. Dataset

For experiment, MPQA corpus [21] and NTCIR-6 corpus were used as a test data set. NTCIR corpus was used as a training data in opinionated sentence detection. MPQA corpus was used as a training data in polarity judgment. NTCIR corpus was used as a test data in both experiments.

B. Evaluation

The developed system was evaluated using two methods, lenient evaluation (represented as 'L') and strict evaluation (represented as 'S'). In the strict evaluation methods, all three annotators must agree on the classification of the sentence opinionated. Under the lenient evaluation, the condition was a bit relaxed and if two of the three annotators agreed on the classification of the sentence for opinionated, we accept the result.

The base line performance of the polarity judgment is as shown in table 1. Prior polarity phrase dictionary based on the phrases that are annotated in MPQA corpus was constructed. The opinionated sentence detection and polarity judgment were done by checking the existence of word or phrase on the dictionary. The base line performance was evaluated in lenient case. The result is as shown in Table 1.

$$\Pi = \frac{\sum_j TP_j}{\sum_j (TP_j + FP_j)} \quad (3)$$

$$\rho = \frac{\sum_j TP_j}{\sum_j (TP_j + FN_j)} \quad (4)$$

$$F\_Measure = 2 \times \left(\frac{\Pi \times \rho}{\Pi + \rho} \right) \quad (5)$$

Fig.4: Experimental Evaluation criteria equations.

In Figure 4, π is the precision, ρ is the recall, TP is the number of true positive, FP is the number of false positive and FN is the number of false negative.

Table I
Baseline Performance for Sentence Detection and Polarity Judgment

	Precision	Recall	F-measure
Sentence Detection	0.238	1.0	0.38
Polarity Judgment	0.015	0.060	0.024

C. Opinionated Sentence Detection Performance

In this experiment, NTCIR corpus was used as both training data and testing data. During the evaluation, 10-fold cross validation method was adopted. The performance in terms of Precision (P), Recall (R) and F-score (F) is as shown in table II:

Table II
Sentence Result of Opinionated Detection

	L			S		
	P	R	F	P	R	F
SVM	0.292	0.414	0.343	0.0475	0.068	0.056
Linguistic	0.365	0.619	0.459	0.0658	0.583	0.117
SVM+ linguistic	0.366	0.625	0.462	0.0716	0.509	0.124

D. Polarity Judgement Performance

Entire MPQA corpus was used to train CRFs model on phrase-level polarity information, and then

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

experimental testing was conducted on NTCIR corpus. Since, each binary polarity classifier with CRFs can give us conflict result; a simple majority voting mechanism was adopted to select the right class for the polarity. In those cases, a choice of polarity class with the highest score as the polarity of the whole sentence. The priority of the classes is positive, negative, neutral, and none.

Table III
Performance of Negative Polarity Judgment

	L			S		
	P	R	F	P	R	F
CRF	0.261	0.234	0.247	0.050	0.248	0.083
Linguistic	0.207	0.313	0.249	0.032	0.271	0.058
CRF+ linguistic (OR)	0.209	0.442	0.283	0.037	0.436	0.068
CRF+ linguistic (AND)	0.362	0.104	0.162	0.52	0.083	0.064

Table IV
Performance of Positive Polarity Judgment

	L			S		
	P	R	F	P	R	F
CRF	0.167	0.134	0.149	0.015	0.063	0.024
Linguistic	0.053	0.360	0.093	0.009	0.313	0.017
CRF+ linguistic (OR)	0.063	0.395	0.108	0.010	0.344	0.020
CRF+ linguistic (AND)	0.220	0.064	0.099	0.0	0.0	0.0

Table V
Performance of Neutral Judgment

	L			S		
	P	R	F	P	R	F
CRF	0.108	0.263	0.154	0.023	0.470	0.044
Linguistic	0.081	0.035	0.049	0.0	0.0	0.0
CRF+ linguistic (OR)	0.071	0.083	0.077	0.012	0.118	0.022
CRF+ linguistic (AND)	0.053	0.004	0.006	0.0	0.0	0.0

Table VI
Performance of Total Polarity Judgment

	L			S		
	P	R	F	P	R	F
CRF	0.179	0.210	0.193	0.030	0.313	0.017
Linguistic	0.114	0.236	0.154	0.014	0.194	0.025
CRF+ linguistic (OR)	0.114	0.307	0.166	0.020	0.299	0.037
CRF+ linguistic (AND)	0.211	0.057	0.090	0.017	0.028	0.21

7. CONCLUSION

This paper presents approaches to opinionated sentence detection and polarity judgment by combining linguistic clue and machine learning methods such as CRF and SVM. Based on subjective linguistic pattern and scoring of terms, the paper automatically identifies the opinionated sentences and their polarities. In addition, some feature for CRF and SVM was to improve system performance which is compatible with state-of-the-art systems.

As future works, order analysis or concurrence of certain phrase to identify the polarity in the sentence level will be considered. Also anaphora analysis and co-referenceresolution such as proper noun will be incorporated.

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