

Public Opinion Analysis on Law Enforcement

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Abstract— This paper describes a rule-based sentiment analysis algorithm for polarity classification of law enforcement tweets in twitter. The system utilizes a prior polarity lexicon to classify the law enforcement tweets into positive or negative. Sentiment composition rules are used to determine the polarity of each sentence in the tweets, while the Positivity/Negativity ratio (P/N ratio) is used to calculate the sentiment values of the overall content of each tweets. The performance of the Sentiment Analyser was evaluated using a dataset of manually annotated law enforcement tweets collected from various tweets from twitter. The result was encouraging as our Sentiment Analyser obtained an overall F-Score of 75.6% for both positive and negative classifications.

Keywords- Sentiment Analysis; Sentiment Composition; Polarity Classification

1. INTRODUCTION

Polarity classification of text can be performed at various levels such as sentence, phrase, word, and document. This paper describes a polarity classification task at document level involving long length text analysis. The aim of this work is to classify law enforcement tweets into positive or negative. Government often rely on law enforcement tweets to assist them in their investment decision. A sentiment analyser can be used as an investor's tool to quickly classify law enforcement tweets and use this information to identify how the law has been welcomed by the people.

The proposed Sentiment Analyser utilizes some existing tools namely the R studio to perform tweet extraction and the Subjectivity lexicon [1] to determine the polarity of the input text. The proposed Sentiment Analyser uses a lexicon-based algorithm which does not involve any machine learning techniques. Instead, a set of the positive words and negative words are used to analyse the tweets. P/N ratio is incorporated into the proposed Sentiment Analyser to determine the polarity of the overall content of each law enforcement tweets.

In this paper, we present the general framework of the proposed Sentiment Analyzer, and a brief description of its relevant components. Additionally, the sentiment composition rules used in the Sentiment Analyser are described. We carried out experimental evaluation to test the performance of the proposed Sentiment Analyser in

classifying law enforcement tweets and the results are elaborated in this paper.

2. LITERATURE REVIEWS

Sentiment analysis is a field in natural language processing with the aims of trying to figure out what other people think towards a topic of interest by using computational power. Sentiment analysis is useful in pinpointing the sentiment of the resources automatically without the need of excess manpower to go through the long and winded document which sometimes may only contain a few sentences that convey the thoughts of the author [4].

Twitter is a credible platform to express an individual's view on a newly enforced law. It is among the most reliable way of conveying the information via text compared to other platforms such as rumors, scandal, and eavesdropping [3]. Today, many researches in sentiment analysis are rooted in examining the relationship of law enforcement tweets.

There are various approaches that can be used to perform sentiment analysis. According to Annett and Kondrak [12], Taboada and Brook [11], sentiment analysis can be categorized into two main approaches which are lexicon-based approaches and machine learning approaches. Lexicon-based approaches utilize the prior polarity lexicon to determine the semantic orientation of the document, while machine learning approaches typically use the classifier to classify documents according to its semantic orientation.

Sentiment composition is one of the techniques used to solve the problem in sentiment analysis. The sentiment composition techniques interpret the analyzed text by its compositional structure. These techniques can be used to perform polarity classification up to sentence level. Klenner's work [7, 8] is one of the examples that used sentiment composition to perform polarity classification. His work is focused on the extraction of noun phrase detection using pattern-matching sentiment composition rules. The results obtained from the experiments were encouraging as they showed that sentiment composition can be used to solve the polarity classification problem. They introduced the quasi-compositionality to perform sentiment analysis.

3. THE SENTIMENT ANALYSER

This section describes the general framework of the proposed Sentiment Analyser. The proposed work is based on Klenner’s work [7]. In his work, Klenner used sentiment composition to perform sentiment classification at sentence level.

The Sentiment Analyser consists of six main phases that include the creation of twitter developer account, development of twitter application, tweets extraction phase, cleansing the extracted tweets, sentiment analysis phase. The end result is the classification of the extracted tweets into positive or negative and displaying it in a bar graph and pie chart fashion.

A. Twitter developer account

The phase deals with the development of creation of twitter developer account. The twitter will grant access to extract tweets only if the user has a developer account.

B. Development of twitter application

This phase deals with the development of twitter application. The twitter application is developed in order to get the access token and secret key given by the twitter. The tokens and keys are used in extracting the tweets from twitter. The tokens are used in creating the environment variables and global variables in R studio to connect R to twitter.

C. Tweets extraction phase

In the tweets extraction phase, the tweets from the twitter application will be extracted. The tweets are extracted using the tokens provided by twitter. The tweet extraction phase can be done in any of the platforms namely R, Java, Python. But due to higher efficiency in coding and time, I chose R rather than Java and Python. R is rated higher than java and python when it comes to efficiency. These rules go from a simple form to a complicated form in a sequential process. The identification of the polarity of the sentences is considered to be completed when all the rules are applied to the extracted phrase which has been polarity tagged.

D. Cleansing data

This phase deals with cleansing of the extracted tweets from the twitter. The extracted tweets will be included with the unwanted characters which include the numbers and emoticons. The sentiment analysis deals with analyzing only the texts in the tweets, So it is necessary to delete all the unwanted characters in the extracted tweets and so this process. After cleansing the data the sentiment analysis algorithm has to be performed to determine the result.

E. Sentiment Analysis Algorithm

This phase calculates the sentiment value of the entire article. The sentiment value is calculated using the mathematical formula called P/N ratio where it uses the number of positive sentences and negative sentences obtained from the sentence polarity identification task. The sentiment value of the financial news article is calculated by averaging the sentiment values of all the sentences in the financial news article.

F. Representation of Data

This is the final phase of the work and deals with representing the obtained output in the form of pie chart and bar graph.

4. USAGE OF THE SENTIMENT COMPOSITION RULES

The sentiment composition rules is a set of rules which is applied to determine the polarity of the sentences. This set of sentiment composition rules is created to tackle noun phrase sentiment composition, preposition phrase sentiment composition, and phrase to phrase sentiment composition based on Klenner’s work [7]. In addition, we added new sentiment composition rules to tackle verb phrase sentiment composition, verb-noun/noun-verb phrase sentiment composition, the conjunction “but” sentiment composition, and the negation.

A. Noun Phrase Sentiment Composition Rules

TABLE I. NOUN PHRASE SENTIMENT COMPOSITION RULES

Rules	POS Combination(JJ-NN/ JJ-NP/ ADJP-NN/ ADJP-NP)		Output (NP)
NP1	(NEG)(POS)		NEG
NP2	(NEG)(NEG)		NEG
NP3	(NEG)(NEU)		NEG
NP4	(POS)(POS)		POS
NP5	(POS)(NEG)		NEG
NP6	(POS)(NEU)		POS
NP7	(NEU)(POS)		POS
NP8	(NEU)(NEG)		NEG

Consider the rule NP1 in Table I. A combination of negative (NEG) JJ/ADJP and a positive (POS) NN/NP will yield an output of a negative noun phrase (NP). For instance, the negative adjective phrase “most difficult” when merged with the positive noun phrase “business decision” will result in a negative noun phrase of “most difficult business decision”.

B. Verb Phrase Sentiment Composition Rules

Verb phrase sentiment composition rules involve the combinations of an adjective merged with verb (JJ-VB), an adjective merged with verb phrase (JJ-VP), an adjective phrase merged with verb (ADJP-VB), and an adjective phrase merged with verb phrase (ADJP-VP). These combinations form a verb phrase composition. Table II shows the verb phrase sentiment composition rules for the combinations of JJ-VB, JJ-VP, ADJP-VB, and ADJP-VP.

TABLE II. VERB PHRASE SENTIMENT COMPOSITION RULES

Rules	POS Combination(JJ-VB/ JJ-VP/ ADJP-VB/ ADJP-VP)	Output (VP)
VP1	(NEG)(POS)	NEG
VP2	(NEG)(NEG)	NEG
VP3	(NEG)(NEU)	NEG
VP4	(POS)(POS)	POS
VP5	(POS)(NEG)	NEG
VP6	(POS)(NEU)	POS
VP7	(NEU)(POS)	POS
VP8	(NEU)(NEG)	NEG

Consider rule VP4 in Table II; a positive JJ/ADJP combined with a positive VB/VP will form a positive verb phrase. For example, the positive adjective “top” combined with positive verb “preferred” will yield a positive verb phrase “top preferred”.

C. Verb-Noun/Noun-Verb Phrase Sentiment Composition Rules

The sentence pattern in this categories includes the combination of a verb merged with noun (VB-NN), verb merged with noun phrase (VB-NP), verb phrase merged with

noun (VP-NN), verb phrase merged with noun phrase (VP-NP), noun merged with verb (NN-VB), noun merged with verb phrase (NN-VP), noun phrase merged with verb (NP-VB), and noun phrase merged with verb phrase (NP-VP).

TABLE III. VERB-NOUN/ NOUN VERB PHRASE SENTIMENT

COMPOSITION RULES

Rules	POS Combination(VB-NN/ VB- NP/VP-NN/VP-NP/ NN- VB/NN- VP/ NP-VB/NP-VP)	Output (phrase/sentence)
VN1	(NEG)(POS)	NEG
VN2	(NEG)(NEG)	NEG
VN3	(NEG)(NEU)	NEG
VN4	(POS)(POS)	POS
VN5	(POS)(NEG)	NEG
VN6	(POS)(NEU)	POS
VN7	(NEU)(POS)	POS
VN8	(NEU)(NEG)	NEG

Table III shows the sentiment composition rules for verb-noun/noun-verb composition. As shown in rule VN5, when a positive noun phrase merges with a negative verb phrase it will produce a negative phrase or sentence. For example, the phrase “gains from asset sales dwindled” is the combination of a positive noun phrase with a negative verb phrase which results in a negative noun phrase.

D. Preposition Phrase Sentiment Composition Rules

The preposition is a word that combines two or more phrases together to form a new phrase or sentence. The most commonly used preposition in English includes “in”, “on”, “to”, “of”, “by” and so on. In this work, the sentiment composition rules are set to cover the preposition of “in”, “to”, and “of”. Table IV shows the sentiment composition rules for phrase to phrase combination with the preposition “in”.

TABLE IV. PHRASE-PHRASE SENTIMENT COMPOSITION RULES WITH PREPOSITION "IN"

Rules	POS Combination(<i>phrase "in" phrase</i>)		Output (<i>phrase/sentence</i>)
Pin1	(NEG (PP(IN)POS))		NEG
Pin2	(NEG (PP(IN)NEG))		NEG
Pin3	(NEG (PP(IN)NEU))		NEG
Pin4	(POS (PP(IN)POS))		POS
Pin5	(POS (PP(IN)NEG))		POS
Pin6	(POS (PP(IN)NEU))		POS
Pin7	(NEU (PP(IN)POS))		POS
Pin8	(NEU (PP(IN)NEG))		NEG

The rule Pin5 shows that when a positive phrase merges with another negative phrase with the preposition "in", the output will be a positive phrase or sentence. The phrase "solid performance in a seasonally slow quarter" is an example that matches Pin5. These rules are applicable in situation where a phrase is combined with another phrase with the preposition "on", "by", "as", "that", and "for" because they share the same patterns as the preposition "in".

Table V shows the sentiment composition rules for phrase to phrase composition with the preposition "to".

TABLE V. PHRASE-PHRASE SENTIMENT COMPOSITION RULES WITH PREPOSITION "TO"

Rules	POS Combination(<i>phrase "to" phrase</i>)		Output (<i>phrase/sentence</i>)
Pto1	(NEG (PP(TO)POS))		NEG
Pto2	(NEG (PP(TO)NEG))		NEG
Pto3	(NEG (PP(TO)NEU))		NEG

Pto4	(POS (PP(TO)POS))		POS
Pto5	(POS (PP(TO)NEG))		POS
Pto6	(POS (PP(TO)NEU))		POS
Pto7	(NEU (PP(TO)POS))		POS

Based on rule Pto1, a negative phrase combined with a positive phrase with the preposition "to" produces a negative phrase or sentence. For instance, the phrase "serious problem to the management" is an example of Pto1.

Table VI shows the sentiment composition rules for the combination of phrase to phrase with the preposition "of".

TABLE VI. PHRASE-PHRASE SENTIMENT COMPOSITION RULES WITH PREPOSITION "OF"

Rules	POS Combination(<i>phrase "of" phrase</i>)		Output (<i>phrase/sentence</i>)
Pof1	(NEG (PP(OF)POS))		NEG
Pof2	(NEG (PP(OF)NEG))		NEG
Pof3	(NEG (PP(OF)NEU))		NEG
Pof4	(POS (PP(OF)POS))		POS
Pof5	(POS (PP(OF)NEG))		POS
Pof6	(POS (PP(OF)NEU))		POS
Pof7	(NEU (PP(OF)POS))		POS
Pof8	(NEU (PP(OF)NEG))		NEG

In rule Pof2, a negative phrase is combined with a negative phrase by the preposition "of" to form a negative phrase or sentence. An example of the Pof2 rule is the phrase "fear of losing control".

E. The Conjunction "but" Sentiment Composition Rules

The conjunction "but" is used to combine two phrases/sentences into one. Table VII shows the sentiment composition rules for the conjunction "but".

TABLE VII. THE CONJUNCTION “BUT” SENTIMENT COMPOSITION RULES

Rules	POS Combination(phrase “but” phrase)		Output (phrase/sentence)
Cbut1	NEG (BUT) POS		POS
Cbut2	NEG (BUT) NEG		NEG
Cbut3	NEG (BUT) NEU		NEG
Cbut4	POS (BUT) POS		POS
Cbut5	POS (BUT) NEG		NEG
Cbut6	POS (BUT) NEU		NEG
Cbut7	NEU (BUT) POS		POS
Cbut8	NEU (BUT) NEG		NEG

The rule Cbut1 in Table VII shows that when a negative phrase/sentence is combined with positive phrase/sentence, the output will be a positive phrase/sentence. For example, consider the sentence “The first half of the year was a nightmare but we have performed much better in the second half of the year.” The first half of the sentence is negative while the second half is positive, and the output of this sentence is a positive sentence.

F. Negation Rules

Negation is a polarity shifter that turns a positive statement into negative or vice versa. It plays a crucial role in the linguistic structure of a sentence. Adding different polarity shifters to a sentence will result in a different opinion towards the same topic. For instance, consider the sentence below:

- I like the movie.
- I don’t like the movie.
- I deeply like the movie.
- I rather like the movie.

The term that acts as the polarity shifter such as “no”, “not”, “never”, “neither”, “none”, “without”, “below”, and so on are also included in this work. Table VIII shows the negation sentiment composition rules. There are three rules in this category which involve the negation of positive phrase, the negation of negative phrase, and the negation of neutral phrase

5. EXPERIMENT AND DISCUSSION

A. Dataset

A total of 200 law enforcement tweets were used in the experiment described in this paper.

B. Performance Metrics

The performance of the proposed Sentiment Analyser is measured using the Recall, Precision and F-Score. In this work, we measured the performance of the Sentiment Analyser into three cases, positive case classification, negative case classification, and all cases classification. Positive case classification measures the ability of the proposed Sentiment Analyser in classifying positive news articles, while negative case classification measures the ability of classifying negative news articles, and finally the all cases classification measures the system’s ability to classify the law enforcement tweets into positive or negative in overall. We compare the performance of our proposed Sentiment Analyser against the baseline sentiment analyser. The baseline sentiment analyser is very similar to Klenner’s work but we modified it to perform classification at document level and tested it with our own dataset. It uses sentiment composition rules that cover noun phrase sentiment composition and phrase to phrase sentiment composition with preposition “in”, “to”, and “of”.

C. Experiment Results

We ran both the baseline and the proposed Sentiment Analyser with the law enforcement tweets dataset as input. Table IX shows the results obtained by the baseline sentiment analyser and the proposed Sentiment Analyser in positive case classification, negative case classification, and all cases classification.

TABLE IX. THE COMPARISON OF PERFORMANCE OF THE BASELINE SENTIMENT ANALYSER TO THE PROPOSED SENTIMENT ANALYSER

Measurement	Baseline			Sentiment Analyser		
	Positive	Negative	All	Positive	Negative	All
in %	Case	Case	Cases	Case	Case	Cases
Recall	85.8	25.0	61.5	88.3	50.0	73.0
Precision	67.3	66.7	67.2	76.3	85.1	78.5
F-Score	75.5	36.4	64.2	81.9	63.0	75.6

The Sentiment Analyser performed well in positive case classification with recall score of 88.3%, precision of 76.3% and F-Score of 81.9%. This is an average improvement of more than 8% when compared to the result obtained by the baseline sentiment analyser. The proposed Sentiment Analyser also outperformed the baseline sentiment analyser in both the negative classification and all cases classification. The lower F-Score for the negative case classification indicates that our Sentiment Analyser's algorithm is positive bias. However, the results obtained showed that the proposed Sentiment Analyser has improved in performance even in negative case classification with an F-score of 63.0% compared to the F-Score of 36.4% obtained by the baseline sentiment analyser. In all cases classification, the Sentiment Analyser recorded an F-Score of 75.6% which shows an improvement of 11.4% from the baseline system which obtained an F-score of 64.2%.

6. CONCLUSION AND FUTURE WORK.

This paper describes the rules-based sentiment analysis algorithms with the aid of prior polarity lexicon in performing polarity classification for law enforcement tweets. We proposed the used of sentiment composition rules together with the P/N ratio to identify the polarity of the law enforcement tweets. Based on the results that we obtained from the experiment, the proposed system scored an average F-Score of 75.6% in all classifications. This is much better compared to the baseline sentiment analyser which obtained an F-Score of 64.2%. There are some limitations in the proposed Sentiment Analyser. Firstly, the sequences of the rules are fixed and cannot be changed. In its current form, the sentiment composition rules must go from simple composition rules to more complicated composition rules in a sequential process to avoid misinterpretation of the meaning of the phrase or sentence. Secondly, our proposed sentiment analyser is not able to tackle the word ambiguity problem where there are words in the subjectivity lexicon which are tagged with multiple polarities. This can lead to misclassifications of sentence's polarity which also affects the misclassification of articles. For instance, the phrase "*cost reduction*" which matches the rule VN2 is misclassified as negative. In the future, we will consider using semantic similarity techniques to perform sentiment enrichment, as well as to solve the words' ambiguity problem. not able to tackle the word ambiguity problem where there are words in the subjectivity lexicon which are tagged with multiple polarities. This can lead to misclassifications of sentence's polarity which also affects the misclassification of articles. For instance, the phrase "*cost reduction*" which matches the rule VN2 is misclassified as negative. In the future, we will consider using semantic similarity techniques to perform sentiment enrichment, as well as to solve the words' ambiguity problem.

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