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Social Tension and Crime Related Events Detection Method on Twitter

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ABSTRACT

Social tension detection methods using social media textual data have been extensively proposed by the researchers. However, most of the high resourced language which is English. There is limited study on social tension detection methods on low resourced language such as Malay language. In fact, the study of social tension using non-standardized Malay language from social media text such as Twitter is remained unexplored. Textual data on Twitter suffers from inconsistencies and high language ambiguity due to the limited permissible character provided for the users to use. Majority of the existing sentiment analysis systems for social tension detection are based on machine learning approach which depends on the static general-purposes sentiment lexicon and ignores the newly created words on Twitter. As word syntactic on Twitter is dynamically changing according to time and context, machine learning approaches may lead to misclassification of word meaning. This article proposes a lexicon-based sentiment analysis approach for detecting tensions and crime related events indicators on Twitter. The automatic detection of social tension and crime related events of the contents on Twitter helps to discover the indicator of tensions amongst the civilians towards the existing situation and predict the potential crime related events.

Key words : Sentiment analysis, Malay language, syntactic extraction, social tension detection, social media, Twitter.

1. INTRODUCTION

User generated textual data on social media such as Twitter has been a useful source used by the political analysts to extract positive and negative information from the linguistic structure of the text. Twitter users tend to reflect on current events which makes Twitter an ideal candidate to monitor public emotions on certain events. However, the uncontrolled published negative contents have potential to lead to harm and cause social tension in the cyber space [1],[2]. Text mining application has been studied to discover hidden knowledge in text [3]. Sentiment analysis is a computational study that involves extracting and classifying hidden emotions, attitudes, opinion, moods, judgments, feelings that have been expressed by the users in text sources [4],[5],[6],[7]. The main principle of sentiment analysis is to determine the text or document sentiment polarity either positive, negative or no polarity [4],[5],[6],[8]. Therefore, monitoring the content generated from user's activities on social media can help to discover hidden patterns of public behaviors such as unstable emotion and dissatisfaction towards government policies which can lead to social tension and its crime related events [9], [2]. This is because any publicized negative content on social media can propagate misunderstanding and influence one's psychology [1].

Sentiment analysis is divided into machine learning approach and lexicon-based approach. Between these two approaches, machine learning approach offers high accuracy [10],[11],[4],[5],[6] by employing machine learning algorithms such as Support Vector Machines (SVM), Neural Networks, Deep Learning and Naïve Bayes. Machine learning methods commonly use bag-of-words (BOW) representation, thus; the complex linguistic phenomena in sentiment analysis cannot be properly captured [10],[11]. BOW is applicable for longer documents to refer to strong statements such as "awesome" or "exciting". However, BOW is not optimal for short documents such as short messages or microblogging texts. Therefore, machine learning approach is semantically weak since the lexical resource and its co-occurrence elements depends on limited predictive value [12],[6],[5]. In fact, this approach depends on training data and domain independent [10],[5],[6]. An alternative to machine learning approach is lexicon-based approach. This approach does not require training data. The linguistic rule can be utilized to capture the hidden pattern from the tweets either on syntactic level or semantic level [5],[6],[13]. In lexicon-based approach, lexical resources such as SentiWordNet, WordNet, LIWC etc. are used to assign polarity scores to individual words in order to detect the overall sentiments of a documents [13],[14]. The advantage of lexicon-based approach is it can achieve high precision but low recall [10],[5],[13] since it is context and domain oriented.

Uncontrolled negative emotion can lead to tension, anxiety and depression [16]. Classifying emotion such as tensions from Twitter is a challenging task. Emotions can be identified based on a collection of specific words but not always explicitly expressed using emotion-bearing words by the users [13],[15],[16],[18]. Therefore, classifying emotions expressed in the unstructured forms of texts are confusing to handle even by human and are difficult to be automatically performed using computational methods [15],[18],[17]. The tweets are considered as non-standard linguistic structure of punctuation, spelling, syntax and vocabulary [19],[20],[21],[22]. Even so, this length limitation causes the tweets to contain high noises, spelling errors, abbreviations and text ambiguities [15],[22],[23]. The tweets also consist of special orthographies available in Twitter messages such as links, retweets, mentions, photos, emoticons, hashtags and urban slangs [19],[20],[21],[22],[23]. Another characteristic of the tweets is the unique words influenced by the dialects and slangs in Malay language such as 'lah', 'weh', 'tapau', 'pancung', 'sailang', 'meh' etc. These dialect and slang words may carry sentiment and indicator of strong emotion expressions [19],[23],[24]. However, these terms are not available in any existing Malay dictionaries such as Dewan Bahasa dan Pustaka (DBP) and Malay WordNet [10],[20]. Any words which are not matched with these dictionaries are considered as no meaning.

Recent years have witnessed an increase in social tension contagious events on social media [1],[2]. Several number of sentiment analysis studies on social tension detection have been conducted [26],[27],[28],[1],[2]. These studies have proven that public emotion can be analyzed from social media. Therefore, social media content can provide valuable, security-related data related to public events and examine the relationship between negative sentiment and the level of social tension and crime related events. However, these previous proposed methods are based on highly resourced language such as English and Russian. In addition, the existing methods are developed using machine learning approach. Social tension detection study in the context of Malaysian settings and Malay language using Malay lexicon has not been conducted. Therefore, this paper proposes a conceptual framework for social tension and crime related events detection to address the above-mentioned issues.

2. THE CONCEPTUAL FRAMEWORK

The proposed conceptual framework for social tension and crime related events detection is shown in Figure 1. It includes the data collection, text pre-processing, syntactic features extraction, sentiment calculation and social tension and crime related events detection.

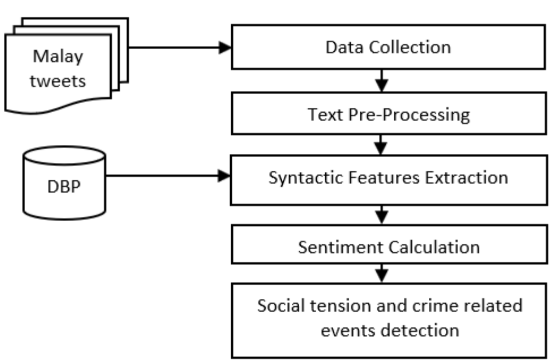

Figure 1: The Proposed Social Tension and Crime Related Events Detection Conceptual Framework

2.1 Data Collection

For data collection phase, Twitter API was used to extract tweets using several pre-determined keywords such as PRU14 (pilihan raya umum 14), GE14 (general election 14) UMNO, Pakatan Harapan, Mahathir, Najib etc. These keywords are chosen because it is listed as the trending topics by Twitter at that period of time. There are 40,721 number of extracted raw textual data that contains rows of tweets and its metadata such as user id, created date and time, number of retweets and number of favourites. The tweets also contain high noises, the use of unstructured grammatical order of word and the existence of multi languages. Therefore, text pre-processing needs to be performed as to provide clean text for further process. Table 1 presents the sample of the extracted Malay tweets.

Table 1: Sample of extracted Malay tweets

id	Created at	Tweets	#Retweet	#Likes
8.03116E+17	1/5/2018 7:27	Aku nak remind balik apa janji BN pada pru 13 pd 2013, supaya kt tk jadi bodoh kali kedua. Sblm pru, najib & umno janji tk naikkan harga minyak, skrg subsidi kena tarik dan naik tiap minggu 2015 GST di laksanakan. So fikir la psl undi korang klu pilih umno lg. @RajaMohdShahrim	10	11
8.03096E+17	6/27/2018 14:52	RT @kharul69 @hmetromy Hadiah kepala bapak dia..... Phuiiiii	7	0
8.03456E+17	5/11/2018 9:30	Jangan kau tak puas hati dengan suami kau, kau undi suami orang supaya jadi suami kau . ingat!!! suami bukan salah satu parti dalam pilihan raya ye	3	23

2.2 Text Pre-processing

In text pre-processing phase, irrelevant features such as numbers, symbols, discourse markers, URLs, @mentions will be removed as these do not carry any meaning and sentiments. All English words will also be translated into Malay language using Malay WordNet. The remaining words which do not belong to either Malay or English language will not be eliminated since it may carry the newly added words by Twitter users. Next, the stop words will be removed from the text using Malay stop word list produced by [21]. Then, the tokenization is performed to split the text into tokens. Since tweets is considered as short text, the tweets are separated into sequence of individual words. The expected output of this phase is the cleaned text.

2.3 Syntactic Features Extraction

In Natural Language Processing (NLP) application, assigning syntactic categories is the most essential pre-processing step [29]. Syntactic features extraction phase aims to extract words that can be used as indicators of tension from the tweets. In this phase, sentence structure is analyzed using parsing technique. Dependency parsing will be used where each word in the sentences is defined according to the rules of grammar. This technique is chosen because it concerns directly on the individual words where the relation of words is displayed in a dependency tree form where the nodes represent the words and labelled arcs represent different type of dependency relations. In this work, the syntactic features to be extracted are the nouns, verbs, adjectives and expletive Malay words will be focused. The expected output of this phase is the logical tree to represent the extracted words with its syntactic features which has potential to be the social tension indicators. Figure 2 shows the example of parsed Malay sentence.

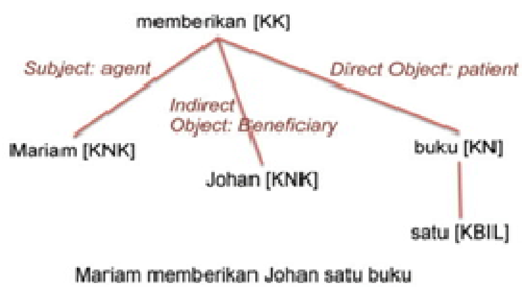

Figure 2: The Example of Parsed Malay Sentence Using Dependency Parsing (Mohamed et al., 2011).

2.4 Sentiment Calculation

In this phase, the polarity of the extracted words from the previous phase is calculated by adapting the TensiStrength algorithm as proposed by [30]. However, Thelwall's work is based on English language which employed LIWC as its lexical resources for it to assign the sentiment score. For this work, DBP will be used as the lexical resources. However, DBP do not contain any information on certain words that have been used on Twitter. Therefore, a dictionary that contains slangs, dialects, and expletive words will be developed. First, the polarity of the extracted words is classified into three classes which is positive, negative and neutral. Second, the strength of these words in the sentence will be calculated to find the tension score and relaxation score. The example of scores is presented in Table 2. The expected output of this phase is the score of stress and relaxation of each words. These scores are important in the next phase which is to detect the social tension related crimes.

Table 2: Stress and Relaxation Score Based on Thelwall's SentiStrength

Stress	Relaxation
1 = no stress	1 = no relaxation
-5 = very high stress	5= highly relaxed

2.5 Social Tension and Crime Related Events Detection

In this phase, a rule-based algorithm will be constructed for social tension detection and crime related events. The main purpose of this algorithm is to identify the level of tension which are HIGH, MODERATE and LOW and the potential crime related events. Generally, the detection is based on the word patterns in the sentence and the scores from the previous phase. The main rules are as follows:

1. If the sentence consists of stress score > -4, expletive words (noun) > 1 and destructives words (verb) > 1, then tension = high, and potential crime = (identified verb).
2. If the sentence consists of stress score = -1 to -3, expletive words (noun) = 1 and destructive words (verb) = 1, then tension = moderate, and potential crime = (identified verb).
3. If the sentence consists of stress score = 1 to 4, expletive words (noun) = 0, and destructive words (verb) = 0, then tension = low, and potential crime = none.

The developed algorithm will use the above rules to detect the social tension and crime related events from the tweets.

3. CONCLUSION

The proposed conceptual framework discusses the phases that are involved in the proposed social tension and crime related events detection method from Twitter. It presents the major task of the proposed method which is the syntactic analysis on the non-standardized Malay language to detect the words as the potential social tension indicators. The outcome of this proposed method may benefit to provide support to the government of Malaysia law enforcement in detecting tension and related crime amongst Malaysian through their post on Twitter. For future work, the proposed method may be improved by considering developing a specific treebank for non-standard Malay language which also provide grammatical rules for parsing the social media textual data such as tweets. Another task may incorporate the automation of sentiment lexicon generation for standard Malay and non-standard Malay language.

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