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Anomaly Detection through Enhanced Sentiment Analysis on Social Media Data

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***Abstract*— Anomaly detection in sentiment analysis refers to detecting abnormal opinions, sentiment patterns or special temporal aspects of such patterns in a collection of data. The anomalies detected may be due to sudden sentiment changes hidden in large amounts of text. If these anomalies are undetected or poorly managed, the consequences may be severe, e.g. a business whose customers reveal negative sentiments and will no longer support the establishment. Social media platforms, such as Twitter, provide a vast source of information, which includes user feedback, opinion and information on most issues. Many organizations also leverage social media platforms to publish information about events, products, services, policies and other topics frequently. Thus, analyzing social media data to identify abnormal events in a timely manner is a beneficial topic. It will enable the businesses and government organizations to intervene early or adopt proper strategies if needed. However, it is also a challenge due to the diversity and size of social media data. In this study, we survey existing anomaly analysis as well as sentiment analysis methods and analyze their limitations and challenges. To tackle the challenges, an enhanced sentiment classification method is proposed and discussed. We study the possibility of employing the proposed method to perform anomaly detection through sentiment analysis on social media data. We tested the applicability and robustness of the method through sentiment analysis on tweet data. The results demonstrate the capabilities of the proposed method and provide meaningful insights into this research area.**

Keywords—Anomaly detection; enhanced sentiment analysis; machine-learning; pattern classification; sentiment classification; social media; Twitter

I. Introduction

Anomaly detection is based on the idea that the characteristics of normal behavior can be distinguished from abnormal behavior [1]. In data mining, anomaly patterns or unusual pattern detection refers to the identification of patterns that do not conform to the expected behaviors in databases. It was once carried out through fault detection methods [2]. High-dimensional data is transformed to low-dimensional data and then classified into different clusters accordingly [3]. This fault detection method was extended to detect weather patterns to uncover climate change using data from daily weather records [4]. Furthermore, anomaly detection has been widely and successfully applied in a variety of applications, such as fraud detection for credit cards, insurance, health care, intrusion detection for cyber-security, and military surveillance of enemy activities [5]. These anomaly patterns are often named differently by authors in different application domains, such as faults [2] [3], rare patterns [4], outliers [6], and risks [7].

A considerable amount of data mining research on anomaly detection has been conducted, and this stream has gained considerable interest owing to the realization that anomaly patterns can be detected from large databases through data mining [8].

With the advancement of social media technologies, the ways in which people communicate through their comments, feedback and critiques have dramatically changed. They can post reviews and share their opinions on products, services, policies and other topics through social media platforms.

Twitter is a social media platform that allows its users to publish their opinions on any topic, known as “tweets”. It has a large number of users distributed all over the world and provides huge social media data in the form of tweets [9]. Tweets cover almost all categories of content, including information about users’ personal lives (e. g. what they like), their opinions on a variety of topics and current issues (e.g. feedback of certain products), and other near real-time event information (e.g. earthquake information). This makes tweets an invaluable and an abundant source for opinion mining on issues [10]. For example, companies may be interested in the following issues:

- Their customers’ opinions on the company/services and whether they provide positive comments;
- The satisfaction of their customers with their products/services;
- The number of positive/negative comments towards their products/ services;
- Potential risk of losing customers;
- The changes of attitudes or emotions towards their products/ services.

Can these issues be addressed through sentiment analysis on social media analysis? In summary, will sentiment analysis on social media data be useful for business? This paper will

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answer the above issues through anomaly detection by using sentiment analysis on social media data.

II. Related Works on Sentiment Analysis

Nowadays, one of the hottest research areas in computer science is sentiment analysis. The primary working principle of sentiment analysis is to classify text emotion polarity in terms of positive, negative and neutral [11]. Sentiment analysis is also called opinion mining or emotion analysis. Sentiment classification is an essential step for sentiment analysis. It can be broadly categorized into two main classes: machine-learning and lexicon-based methods [12].

The machine-learning method uses known properties derived from the training data to classify new information. For text data, it derives the relationship between features of the text segment. There is a wide variety of machine-learning-based methods, such as the Naïve Bayes (NB) classifier, Maximum Entropy (MaxEnt) classifier and support vector machine (SVM).

The Naïve Bayes classifier is a probabilistic classifier that assumes the statistical independence of each feature (or word) and is a conditional model based on Bayes' formula [13] [14]. MaxEnt is another probabilistic classifier and uses a multinomial logistic regression model [15]. It is closely related to the Naive Bayes classifier, but uses search-based optimization to find weights for the features that maximizes the likelihood of the training data. SVM is a non-probabilistic classifier that works by constructing a decision surface on a high-dimensional space [16] [17]. The principle of the SVM algorithm is to find a decision surface, named hyperplane that optimally splits the training set. The training data is mapped to a high-dimensional space. Then, the algorithm finds the hyperplane in this space with the largest margin, separating the data into different groups.

Models based on such machine-learning-based methods typically require a large training dataset. This approach can achieve a good classification accuracy when compared to simple lexicon-based approaches and hence, it is widely used [18] [19]. However, a key concern for many researchers is to increase the classification accuracy of machine-learning-based methods through improved knowledge and design [12] [16] [20]. In addition, the learning-based approach has two major limitations.

The first major limitation is that the training data needs to be large enough to allow sufficient representation of full target domains. In the real-world social media context, it is hard to determine the effective size for a training dataset. This is due to the diversity of the social discussion being unknown *a priori*. The second major limitation is that the training data must be of good quality, requiring domain experts to clean up the training data. This makes learning-based approaches too costly and impractical to be applied to new domains. Their over-reliance on training databases means the machine-learning-based methods are not directly applicable since training datasets are not always available.

In comparison with machine-learning-based methods, lexicon-based methods can be easily applied to different datasets. The lexicon-based text classifier utilizes a set of lexicons and linguistic resources to analyze text documents [21]. It derives the dominant polarity of a piece of text (i.e., positive or negative) by searching for opinion or emotion indicators based on lexicons rather than training datasets [22][23].

Various lexicon-based sentiment analysis and classification methods are widely used [24] [25] [26]. Gonçalves et al. compared the existing lexicon-based methods and aimed to find out which method worked most effectively to identify the polarity of messages [26]. Eight main popular methods – Senticnet, SentiWordNet, SASA, Happiness, Emotions, LIWC, Sentistrength and Panas-t – are compared in terms of coverage and agreement. Coverage means the fraction of messages whose sentiment is identified, while agreement indicates the fraction of identified sentiments that are in tune with ground truth agreement [26]. By comparing these different techniques, the study indicated that SentiWordNet possesses the largest coverage, while LIWC has the highest agreement. Kaur and Gupta also pointed out that SentiWordNet was a useful sentiment classification tool in their survey on sentiment analysis techniques [27].

However, the accuracy of the existing lexicon-based approach is limited by semantic ambiguity [28]. There are still many challenges in sentiment analysis and more effort is needed to counter these challenges [28] [29].

To tackle the limitations as well as the challenges mentioned above, this study proposes an new sentiment classification method which enhances the current methods for anomaly detection, through sentiment analysis on social media data. The applicability of the proposed method is demonstrated using tweet data as a case study.

III. Anomaly Detection through Sentiment Analysis on Social Media Data

Different from the traditional forms of media data, social media data is the result of an explosion of information on the Internet, which includes information disseminated by organizations and content generated by individual web users [30]. Text data, being the main format of social media data, reflects user feedback, attitudes and opinions on products, services, policies as well as other topics.

Hence, sentiment analysis of social media data, especially text-format social media is becoming a fast and effective way of evaluating public opinion or discovering valuable information for social studies. Anomaly detection in this domain refers to detecting abnormal opinions, sentiments patterns or special temporal aspects of them in a collection of data [5]. Those anomalies may be a result of the sudden sentiment changes hidden in huge bodies of text.

Due to the size of information provided by social media, anomaly detection in this domain needs to be able to handle colossal amounts of social media data, such as tweets.

A. Social Media Data Background and Data Source

Twitter provides an API that allows easy access to tweets. Using the GET search/tweets resource, we can search for tweets on a specific topic or keyword and limit it to a specific geographical region as well as a specific language. In this paper, the data was collected through Twitter API by using the keyword "ServiceA" (Here we mask the product, service and companies' name to keep the information confidential to respect privacy). We used location-constraining geo codes to ensure that the comments originated from Singapore. We have chosen to call the dataset Data-ServiceA to indicate comments of Singapore users on the "ServiceA".

B. *The Proposed Enhanced Sentiment Classification Algorithm*

Sentiment classification is aimed to find the sentiment pattern of data and to determine the target sentiment category to which the data belongs. The results are a set of pairs, such that each pair contains the dataset, d_i, and a target category, s_j, where $\{d_i , s_j\} \in D \times S$. The pair $\{d_i, s_j\}$ expresses the idea that $_{di} \in D$ is assigned to, or is classified into, $s_j \in S$.

For lexicon-based classifiers, the lexicon dictionary is necessary for both commercial software as well as open source software. We leverage Linguistic Inquiry and Word Count (LIWC) [31] as an example to explain basic lexicon-based text classifiers. LWIC is one of the software programs designed by James W. Pennebaker, Roger J. Booth, and Martha E. Francis. It calculates the degree to which people use different categories of words across a wide array of texts, including emails, speeches, poems, or transcribed daily speeches. The lexicon dictionary is the heart of the text analysis strategy for LWIC. Each word or word stem defines one or more sentiment categories. For example, the word "sob" is part of two sentiment categories: negative and sadness.

Without considering the object of target text, the above lexicon-based methods cannot give real sentiment categories towards some objects. For example, all the following comments are classified as positive sentiment categories.

- (1) "I like HW".
- (2) "I love Xiaomi"
- (3) "I enjoy XX more than YY"

However, considering the four objects: HW, Xiaomi, XX and YY, the text comment (1) is Positive in sentiment towards the targeted object, HW and Neutral in sentiment towards Xiaomi, XX and YY. The text comment (2) is positive towards the targeted object, Xiaomi and Neutral in sentiment towards HW, XX and YY. The text comment (3) is positive towards the targeted object XX, and Neutral in sentiment towards HW and XX, and negative towards YY.

Therefore, in this paper, we enhance sentiment classification method by considering the object of target text.

Besides consideration of the object, we propose a series of enhancements for better performance of sentiment analysis, which includes negation dealing, emoticon handling, and special lexicon handling. Therefore, we call the proposed sentiment classification method the "enhanced sentiment analysis method".

With above enhancement in the proposed method, a piece of text can be represented with a finite set of features, $\boldsymbol{F} = \{f_1, f_2, \ldots, f_k, \ldots, f_K\}$. Each feature $f_k \in F$ can be expressed with any one of the finite set of words or phrases or abbreviations $W = \{w_1, w_2, \ldots, w_m\}$ [32].

A targeted text contains opinions on a set of objects $\{\boldsymbol{o_1}, \boldsymbol{o_2}, \ldots, \boldsymbol{o_r}\}$ from a set of opinion holders $\{h_1, h_2, \ldots, h_p\}$ [31]. The opinions on each object $\boldsymbol{o_j}$ are expressed on a subset *of* $\boldsymbol{F}$, $\boldsymbol{F_j}$. An opinion can be either one of the following types: direct opinion (e.g. I like HW) and indirect opinion (e.g. I enjoy XX more than YY).

A direct opinion is described as a quintuple [32]:

$$(o_j, \boldsymbol{F_j}, \boldsymbol{V_j}, \boldsymbol{h_j}, t_j) \tag{1}$$

where $\boldsymbol{o_j}$ is a target object; $\boldsymbol{F_j} = \{f_{j1}, f_{j2}, \ldots, f_{ji,\ldots}, f_{jn}\}$ in which $\boldsymbol{f_{ji}}$ identifies an individual feature of the object $\boldsymbol{o_j}$; $\boldsymbol{V_j} = \{\boldsymbol{v_{j1}}, \boldsymbol{v_{j2}}, \ldots, \boldsymbol{v_{ji}}, \ldots, \boldsymbol{v_{jn}}\}$ in which v_{ji} identifies the value of an individual feature f_{ji} of the object o_j. Here $\boldsymbol{v_{ji}}$ is a multi-dimensional vector; the number of relevant dimensions is selected by the number of predefined categories G; h_j is the opinion holder of the object o_j; and t_j is the time when the opinion is expressed.

A comparative opinion (e.g. text comment (3)) expresses a preference relation of two or more objects based on some of their shared features. It can be converted into two or more direct opinions: $(o_j, \boldsymbol{F_j}, \boldsymbol{V_j}, h_j, t_j)$, $(o_n, \boldsymbol{F_n}, \boldsymbol{V_n}, h_n, t_n)$, $(o_m, \boldsymbol{F_m}, \boldsymbol{V_m}, h_m, t_m)\ldots$

There are many ways of expressing sentiments, but fundamentally, it can be classified as either Positive or Negative. Thus, for each direct opinion, which is any piece of text, there are three possible fundamental interpretations (Positive, Negative and Neutral). The outcome of the entire tweet is a combination of such interpretations. This will result in four possible outcomes:

- Positive, where none of the opinions are negative towards a target object, and with at least one positive opinion towards the target object;
- Negative, where none of the opinions are positive towards a target object, with at least one negative opinion directed the target object;
- Neutral, where all the opinions towards a target object are neutral;
- Ambivalence, where there are both positive and negative opinions towards a target object.

In this paper, we conducted further experiments and analysis on the Ambivalence outcomes, so as to classify them into Positive or Negative sentiments according to the rules we have designed (see Table I and II), which will be detailed in the Method Evaluation sub-section.

C. *Application Cases - Anomaly Detection through Sentiment Analysis on Collected Tweets*

To illustrate the capability of the proposed method, we applied the method to a real-world scenario: anomaly event detection through mining tweets. The purpose is to analyze social media data to discover sentiment patterns for the identification of anomalies, so as to monitor possible risks according to the changes of sentiment patterns.

If the patterns or the changes in patterns are not as predicted, it is considered an anomaly. In this paper, sentiment classification of social media data is aimed to classify the data into different sentiment patterns (e.g. positive, negative, and neutral).

Sentiment patterns and their changes, that are derived from public domain social media data such as tweets, may be indicators of anomalies that can have negative and potentially serious consequences for the product or service. The affective events theory points out that people's emotional responses are influenced by events that shape their attitudes and behavior. Two simple examples are:

(i) Customers may express negative sentiments when they are not satisfied with services or products;

(ii) They may express positive sentiments when they are satisfied with services or products.

Therefore, the identification of the customers' attitudes and the changes in such attitudes over time to detect potential crisis or risk, is important for risk management.

Fig. 1 shows sentiment classification based on three sentiment categories (Positive, Negative and Neutral) of the dataset. Our results show that most of the tweets in the dataset belong to the Neutral sentiment category; the distribution of the patterns is shown in Fig. 2. Some possible anomalies are observed. For example, on January 10, 2013, the amount of negative tweets experienced an increase.

The anomalies or the changes in social sentiment patterns may indicate shifts in user attitudes toward ServiceA. We searched for news related to "ServiceA" and found that there were mainstream news on issues which were also identified by the public, with sentiments running concurrent to the dates of our data's coverage. For example, on January 10, 2013, the various media in Singapore reported news with negative sentiments that were related to "ServiceA".

The results are consistent with the affective events theory, which states that people's emotional responses are influenced by events that shape their attitudes and behavior [14]. This explains the finding that users will express negative sentiments when negative events occur to them. Similarly, they will post positive sentiments when they benefit from a positive event.

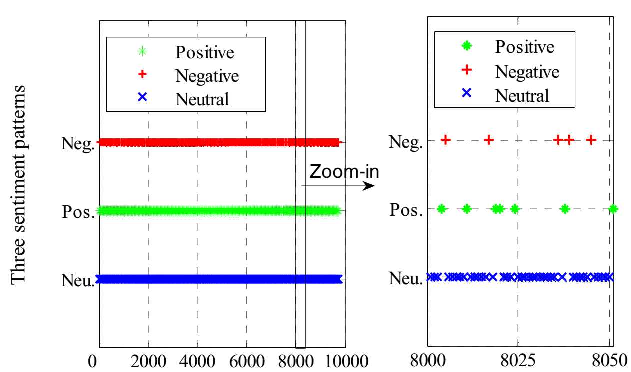
Companies or businesses may be interested in the findings of this research, as they can be informed of their customers' opinions on their services or products. In addition, this research can assist companies in knowing the changes in attitudes or emotions of their customers towards their services or products. Discovering anomalies through sentiment analysis on social media data is also a beneficial and interesting topic for government organizations. Detecting anomalies in a timely manner will enable the businesses and government organizations to intervene early or adopt proper strategies if needed.

D. Method Evaluation

In order to test the efficacy of the method, we invited two social-behavioral scientists who are domain experts to extract a number of tweets, which are relevant to service quality, from our collection. For the tweet data that was selected, we invited eight people from different backgrounds as annotators to classify the tweets manually [12]. They performed the classification tasks independently according to the rules we designed as shown in Table I and Table II.

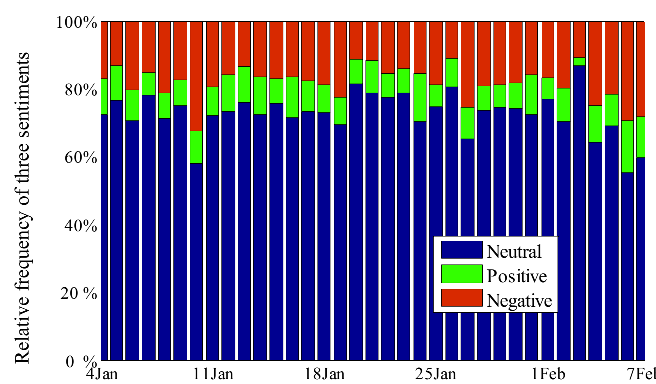
Table I shows the Categorizing Rule 1 for the first level annotations. At this level, four possible intermediate annotation results or sentiment patterns can be derived: Positive, Negative, Neutral and Ambivalent, as shown in Table I.

Table II shows the Categorizing Rule 2 we designed for dealing with ambivalent tweets for the second level annotations. In this level, the ambivalent tweets are forced to be annotated into positive or negative tweets accordingly.



Note: Fig. 1 shows the pattern classification results of each tweet.

Fig. 1 Three sentiment pattern classifications of each tweet



Note: Fig. 2 shows the frequency of occurrence of three different sentiment patterns on each of the dates during the sample period.

Fig. 2. Relative frequency of three sentiment patterns on each date

TABLE I. RULE DESIGNED FOR MANUALLY CATEGORIZING TWEETS TO OBTAIN INTERMEDIATE ANNOTATION RESULTS

Categorizing Rule 1 for the first level annotations	**Intermediate annotation results**		**Annotated results**
	Positive	*Negative*	
If you think that the item tweet expresses satisfied or positive emotions/attitudes without unsatisfied or negative emotions/attitudes	1	0	Positive
If you think that the item tweet expresses unsatisfied or negative emotions/attitudes without satisfied or positive emotions/attitudes	0	1	Negative
If you think that the item tweet includes neither satisfied nor unsatisfied emotions/attitudes. In other words, the item tweet includes neither positive nor negative emotions or attitudes)	0	0	Neutral
If you think the item tweet includes both positive and negative emotions/attitudes (or both satisfied or unsatisfied)	1	1	Ambivalent
Note: the ambivalent tweets will be applied Rule 2 to be forced annotated into Positive or Negative			

TABLE II. RULE DESIGNED FOR DEALING WITH AMBIVALENT TWEETS

Categorizing Rule 2 for dealing with ambivalent tweets	**Annotation results for ambivalent tweets**			**Final annotated results**
If you think that the ambivalent tweet expresses more positive than negative emotions/attitudes	*Positive*	>	*Negative*	Positive
If you think that the ambivalent tweet expresses more negative than positive emotions/attitudes	*Positive*	<	*Negative*	Negative
Note: The annotators are forced to annotate the ambivalent tweets into Positive or Negative				

We compared and analyzed the classifications of the eight annotators and found that the mean value of percentage for coincidences among them were about 80%. We compared the classification results of the proposed method to the eight annotators; the mean value for coincidence was also 80%. This shows that the proposed classification method was comparable to a human annotator.

IV. CONCLUSION AND FUTURE WORKS

This research successfully developed an enhanced sentiment classification method for anomaly detection through social media analysis. The efficacy of the proposed method is demonstrated using tweet data as a case study. The anomaly sentiment patterns were successfully identified and interpreted through the application of the proposed method. The case study demonstrated the usefulness and superiority of the method. In terms of handling sentiment pattern classifications, our method was validated based on the high level of agreement that was established with similar classification tasks performed by human annotators. This research offers new ideas for designing a robust sentiment analysis method on social media data to detect anomaly events or patterns. The method will also be applicable in cases involving pattern changes over time. This should be substantially valuable for companies to strengthen their service focus, for political candidates and government leaders to understand the basis for their ongoing polling results, and for other private organizations to refine their value propositions and brand promises to their customers.

We are conducting further research in this area, which extends the proposed method and includes the detection and classification of detailed subcategories of sentiment emotions. In addition, in order to provide solutions for practical problems in businesses (e.g., predicting consumer preferences) and public policies (e.g., sensing public sentiments), more work will be done in the future.

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