

CLASSIFICATION OF TERRORISM BASED ON TWEET TEXT POST ON
TWITTER USING TERM WEIGHTING SCHEMES

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ABSTRACT

Social Network Service (SNS) has become the main platform to distribute information, sharing of experience and knowledge. The Twitter platform gained the popularity very quickly since it's founded for all layers of generation. The popularity of Twitter has led to prominent media coverage with instant news and advertisement from all over the world. However, the content of tweet posted on Twitter platform are not necessarily true and can sometimes be considered as a threat to another users. Workforce expertise that involve in intelligence gathering always deals with difficulty as the complexity of crime increases, human errors and time constraints. Thus, it is difficult to prevent undesired posts, such as terrorism posts, which are intended to disseminate their propaganda. Hence, an investigating for three term weighting schemes on two datasets are used to improve the automated content-based classification techniques. The research study aims to improve the content-based classification accuracy on Twitter by comparing Term Weighting Schemes in classifying terrorism contents. In this project, three different techniques for term weighting schemes namely Entropy, Term Frequency Inverse Document Frequency (TF-IDF) and Term Frequency Relevance Frequency (TFRF) are used as feature selection process in filtering Twitter posts. The performance of these techniques were examined via datasets, and the accuracy of their result was measured by Support Vector Machine (SVM). Entropy, TF-IDF and TFRF are judged based on accuracy, precision, recall and F score measurement. Results showed that TFRF performed better than Entropy and TF-IDF. It is hoped that this study would give other researchers an insight especially who want to work with similar area.

ABSTRAK

Perkhidmatan Rangkaian Sosial (PRS) telah menjadi platform utama untuk menyebarkan maklumat, berkongsi pengalaman dan pengetahuan. Platform Twitter meraih popularity dengan cepat sejak ia ditubuhkan untuk semua lapisan generasi. Populariti Twitter telah membawa kepada liputan media yang terkenal dengan berita serta iklan segera dari seluruh dunia. Walau bagaimanapun, kandungan tweet yang dipaparkan di platform Twitter tidak semestinya benar dan kadangkala dianggap sebagai ancaman kepada pengguna lain. Tenaga kerja kepakaran yang terlibat dalam perhimpunan perisikan selalu menghadapi kesulitan kerana kerumitan jenayah meningkat, kesilapan manusia dan kekangan masa. Oleh itu, sukar untuk menghalang siaran yang tidak diinginkan, seperti siaran keganasan, yang bertujuan untuk menyebarkan propaganda mereka. Justeru, penyiasatan bagi tiga skim penimbangan jangka panjang pada dua dataset digunakan untuk meningkatkan teknik klasifikasi berasaskan kandungan automatik, yang diperlukan untuk menapis pos yang tidak diinginkan. Kajian penyelidikan ini bertujuan untuk meningkatkan ketepatan klasifikasi berasaskan kandungan keganasan. Dalam projek ini, tiga teknik yang berbeza bagi skim pembobakan jangka iaitu termasuk Entropy, Frequency Document Inverse (TF-IDF) dan Frequency Relevance Frequency Term (TFRF) digunakan sebagai proses pemilihan ciri dalam menapis jawatan Twitter. Prestasi teknik ini telah diperiksa melalui dataset, dan ketepatan hasilnya diukur oleh Machine Vector Support (SVM). Entropi, TF-IDF dan TFRF dinilai berdasarkan kebenaran, ketepatan, mengingat dan pengukuran skor F. Keputusan menunjukkan bahawa TFRF memiliki prestasi yang lebih baik berbanding Entropy dan TF-IDF. Diharapkan kajian ini dapat memberi kapasiti kepada penyelidik yang lain terutama yang menjalankan kerja kajian sama.

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LIST OF ABBREVIATIONS

API	-	Application Programming Interface
ISIS	-	Islamic State of Iraq and Syria
ML	-	Machine Learning
NB	-	Naive Bayes
RT	-	Retweet
SNS	-	Social Network Services
SVM	-	Support Vector Machine
TFIDF	-	Term Frequency Inverse Document Frequency
TFRF	-	Term Frequency Relevance Frequency
URL	-	Uniform Resource Locator

CHAPTER 1

INTRODUCTION

1.1 Introduction

For the past two decades, Social Networking Services (SNS) such as Twitter, Facebook, Myspace and Friendster has been the main platform for people to communicate and interact to each other. Computer network has rapidly change the behavior and perspective of human to transmit their information or connect with anyone globally at ease. The sophistication of technology built has assist to the popularity and demand of social media especially for organizations to build a larger scales of network and to market their product globally. Since the SNS has become an integral part of modern society, it creates a new way for individual to socialize and interact. Apart from giving an option for people to build social relations, SNS also has the ability to bring people together.

Each SNS sites may has different style in terms of incorporating the communication tools and new information. For example, blogging, forums, photo or video-sharing, gaming and mobile connectivity. The highly usage on these platforms contribute towards the trend in which individuals are tend to express their opinions about products, services, etc. via the social media instead of the typical media platform such as TV and newspapers (Ines, 2013). Unlike in early stages of appearance of the SNS where the SNS sites mostly focusing on connecting users together through chat rooms, but these days they tend to focus on three different parts

which includes social networking services for user interact among friends or groups only, business communication purposes or focusing on a particular services as described by (Lars, 2006).

Basically in general, social networks could actually be divided into two types which are content-centric and user-centric. Firstly, the content-centric, an informational platforms for users to post in variety of topics. These posts could be forwarded or replied by other users. In typical environment, the information gained more from the replied comments rather than the original posts held (Ramnath, 2010). Examples of content-centric platform includes microblog such as Twitter or Tumblr. Secondly, the user-centric platform. This platform underline the user identity, supplying profile and personal interests like updating status or share pictures and videos. Best example could reflect this type of platform for social networks is Facebook and Myspace (Yair, 2010).

According to Twitter Inc., there are 330 millions of monthly active users around the world engaged with Twitter in the last two quarters of 2017. Approximately for each second there are 6000 tweets, resulted in approximately 350,000 tweets being consistently sent by users each minute. Thus, there are over 500 million of tweets daily generated by the user globally. These tweet messages contain a wide variety of information, varying from conversational tweets to highly relevant information topics. Since the users posting these messages range from different background, location or status, numerous of topics were posted regardless it is good or bad. As a result, every information posted in Twitter has different quality.

Somehow, it is difficult to detect tweets messages accurately because the content may involve jokes, sarcasm or perhaps a threat. But, this actually provides opportunities for the gathering of intelligence and other activities to prevent and counter acts of terrorism. Sentiment analysis technique is basically used to determine the opinion pertaining a specific issue. Above all issue, it is crucial to have a method of data mining in order to classify the messages.

1.2 Problem Background

Some individuals taking advantages by abusing the social media to spread the fake news or distorted beliefs and influence other users with negativity. These includes terrorism, politics, religions, fraudsters, ideology and others. Recently Twitter has become as a favorite platform of Internet service for terrorist. Their purpose basically to disseminate propaganda and enable internal communication to new audiences and potential online sympathizers across the world via this platform.

Islamic State of Iraq and Syria (ISIS), or also known as ISIL, is one of the well-organized terrorist groups frequently use the Twitter platform to recruit, spread ideology and give explicit instructions to specifically target individuals (M.A Younas, 2014). They even has created their own app, "Dawn of Glad Tidings," to efficiently tweet messages to its followers (Erin, 2014). Moreover, one of Twitter's founders was threaten by the ISIS (John, 2015). More than 125,000 user accounts are linked to terrorist and deleted by Twitter since mid-2015 (Danny, 2016).

Clearly that terrorist organization has fully utilized the valuable tool of social media like the famous microblogging platform, Twitter. The platform somehow allow the terrorist especially ISIS, to disseminate their information to reach across the globe by operates a sophisticated propaganda. In addition, they were also exploit popular hashtags to disseminate their message in order to quickly distribute and promotes their information or messages.

A typical approach to mitigate and prevent from the terrorist continuously undergoes their operation is to suspend accounts that spread propaganda or negative message content when they are discovered. However, this approach requires tons of effort to manually analyze an enormous amount of information on social media. Therefore, machine learning is highly important to assist in applying the sentiment analysis to extract, identify, evaluate and classify online sentiments of tweets messages (Vishal and Sonawane, 2016).

However, the implementation process of machine learning still has a loophole in applying the classification content-based especially on tweets messages. The existing classification technique only make distinction from content-based into several classes such as normal or abnormal. This basically gives difficulty in determining how accurate the pattern of that particular behavior or sentiment. Thus, an additional measurement is required to enhance the process of classification technique.

1.3 Problem Statement

Investigators that involve in intelligence gathering always deals with difficulty as the complexity of crime increases, human errors and time constraints. Thus, it is difficult to prevent undesired posts, such as terrorism posts, which are intended to disseminate their propaganda. Without the measurement of weightage value in existing classification technique basically gives difficulty in classifying content-based. Hence, an investigating for three term weighting schemes on two datasets are used to improve the automated content-based classification techniques, which is required to filter out unwanted posts.

1.4 Aim

The aim of this project is to improve the content-based classification accuracy on Twitter by comparing Term Weighting Schemes in classifying text post terrorism contents.

1.5 Objectives

The objectives of the study are as follow:

1. To pre-process the dataset through data parsing, Stemming, Stopping and represent it into a text document.
2. To select and classify Twitter posts based on feature selection; Entropy; TF-IDF, and TFRF.
3. To verify the performance of Term Weighting Schemes and find their accuracy, precision, recall and F score.

1.6 Project Scope

The research scope is the very important part, which limited the area of the field. This is a guideline for the research or project. The scopes of this study are listed as follow:

1. The study focuses on Twitter posts as textual not as images.
2. Samples of Twitter posts are obtained from Twitter Streaming API.
3. Samples of posts are obtained with English Text content.
4. Samples of posts are obtained from original post only
5. The owner of post samples are not necessarily reflect as the terrorist.
6. Classification is limited to Terrorism category.
7. Support Vector Machine (SVM) is used as classifier.

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