ASPECT- BASED SENTIMENT ANALYSIS TOWARDS TECHNICAL AND VOCATIONAL EDUCATION AND TRAINING IN MALAYSIA

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# ABSTRACT

Initiatives to improve public opinion towards technical and vocational education and training (TVET) have been increased by the government of Malaysia. However, to observe these sentiments with more transparent, analysis on public opinion is necessary. This research aims to assess the public sentiment regarding to TVET in Malaysia by performing aspect-based sentiment analysis. This study took advantage of the data availability from social media where public nowadays tend to express their feelings towards any products and services. Twitter appears as one of the most common social media platforms in which, countless of users can participate and interact at any time. The data from Twitter are unstructured by nature thus further mechanism are needed to provide more meaningful information for future uses. A series of text pre-processing strategies were implemented in this study to improve the process of aspect extraction and classification. Topic modelling technique, Latent Dirichlet Allocation (LDA) was used to extract aspect category during aspect extraction process. The lexicon-based classifiers; SentiWordNet (SWN) and Valence Aware Dictionary and Sentiment Reasoner (VADER) and machine learning classifiers; Naïve Bayes (NB) and Support Vector Machine (SVM) were used to classify the tweets sentiments. The performance of the classifiers was observed based on the results of precision, recall, f-measure, and accuracy. The finding revealed that the public sentiment for five (5) identified aspects for TVET in Malaysia; Student, Course, Employability, Skill and Accreditation inclined towards positive sentiments. SVM shows the highest accuracy among other classifiers with an acceptable accuracy of 72%. The results from this study were expected to give beneficial insight for TVET stakeholders specially the governing bodies and TVET providers to plan for improvisation strategies.

# ABSTRAK

Pelbagai inisiatif untuk meningkatkan sentimen orang ramai terhadap pendidikan dan latihan teknikal dan vokasional (TVET) terlah dilakukan oleh kerajaan Malaysia. Walau bagaimanapun, untuk meneliti sentimen terhadap TVET dengan lebih telus, analisis terhadap pendapat awam adalah perlu. Kajian ini bertujuan untuk menilai sentimen tentang TVET di Malaysia dengan melakukan analisis sentimen berasaskan aspek. Kajian ini memanfaatkan ketersediaan data dari media sosial di mana orang ramai hari ini cenderung untuk menyatakan perasaan mereka terhadap sebarang produk dan perkhidmatan. Twitter adalah salah satu platform media sosial di mana ramai pengguna boleh melayari dan berinteraksi dengan mengunakannya pada bila-bila masa. Data daripada Twitter adalah tidak berstruktur; oleh itu ia memerlukan mekanisme selanjutnya untuk memberikan maklumat yang bermakna untuk kegunaan masa depan. Beberapa strategi pra-pemprosesan teks telah dilaksanakan dalam kajian ini untuk meningkatkan kualiti proses pengekstrakan dan klasifikasi aspek. Teknik pemodelan topik, Latent Dirichlet Allocation (LDA) digunakan untuk mengekstrak kategori aspek semasa proses pengekstrakan aspek. Pengelas berasaskan leksikon; SentiWordNet (SWN) dan Kamus Algoritma Valence dan Penjawab Sentimen (VADER) serta pengelas pembelajaran mesin; Naïve Bayes (NB) dan Mesin Vektor Sokongan (SVM) telah digunakan untuk mengklasifikasikan sentimen pada mesej tweet. Prestasi pengelas dinilai berdasarkan hasil ketepatan, dapatan semula, pengukuran-f dan kejituan. Penemuan mendedahkan bahawa sentiment orang ramai terhadap lima (5) aspek TVET di Malaysia yang dikenalpasti iaitu Pelajar, Kursus, Kebolehpasaran, Kemahiran dan Akreditasi cenderung ke arah sentiment positif. Pengelas pembelajaran mesin, SVM menunjukkan kejituan tertinggi dalam kalangan pengelas lain dengan kejituan sebanyak 72%. Hasil daripada kajian ini diharapkan dapat memberi manfaat yang berguna kepada pihak berkepentingan dalam TVET khususnya badan-badan pentadbir dan penyedia TVET bagi merancang strategi penambahbaikan.

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| | | |
|---|---|---|
| CIAST | - | Center For Instructor And Advanced Skill Training |
| CTM | - | Correlated Topic Model |
| IKBN | - | Institut Kemahiran Belia Nasional |
| IKM | - | Institut Kemahiran Mara |
| ILP | - | Institut Latihan Perindustrian |
| LDA | - | Latent Dirichlet Allocation |
| LIWC | - | Linguistic Inquiry And Word Count |
| LSA | - | Latent Semantic Analysis |
| M3L | - | Max-Margin Multi-Label |
| ML | - | Machine Learning |
| MQA | - | Malaysian Qualifications Agency |
| NB | - | Naïve Bayes |
| NLP | - | Natural Language Processing |
| NLTK | - | Natural Language Toolkit |
| PLSA | - | Probabilistic Latent Semantic Analysis |
| SVM | - | Support Vector Machine |
| SWN | - | SentiWordNet |
| TF-IDF | - | Term Frequency-Inverse Document Frequency |
| TVET | - | Technical And Vocational Education And Training |

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# CHAPTER 1

# INTRODUCTION

## 1.1 Overview

In Malaysia, technical and vocational education is often under-rated against a context of the dominant view that students from technical and vocational education are being academically under-achiever. Lam & Hassan (2018) implying the explanation for this negative perception is mainly due to the limited available awareness and information about TVET, the lack of social acceptance and the fact that this stream provides little opportunities for higher education.

In 2018, TVET and Industry Commission has been established to tackle the issue in order to make TVET as the favourable choice in the future, including to ensure the degrees received by TVET graduates are equal to other academic degree programmes, alongside with competitive salaries when they enter the workforce. The expectations from technical and vocational education stream are not limited to the development of academic and technical knowledge among its students but also to help them acquire high employability skills. Public opinion and reviews towards TVET institution is one of the excellent ways for improving the Malaysia TVET in the future. By harvesting these opinions and reviews from social media, enable the discovery of relationship between TVET and its stakeholders such as parent and prospective students.

Social media has been widely used by people as a way of sharing their hobbies, friends, places they have been and to the extent of their personal preferences or interests (Volkova, Han, & Corley, 2016). It has been used in various contexts including sharing one’s opinion on specific topics. Sentiments from social media texts can be collected and analysed to improve strategies in business, investment, national policy, security and education.

In the study of text mining and natural language processing (NLP), sentiment analysis or opinion mining is gaining wider attention from researchers (Saberi & Saad, 2017). It is due to the accessibility towards Internet as well as online and social media application that ease the process of opinion sharing, online review, and personal blogs. This situation has sparked the interest of stakeholders such as customers, organizations, and governments to analyse and explore these opinions.

## 1.2 Problem Background

In Malaysia, TVET seems to be the last resort for less qualified students for academic option. Qualification and careers in TVET-based are still poorly perceived and recognized by many employers in the workplace due to highly disintegrated landscape, with several ministries and agencies issuing certifications. This has led to lower confidence among public especially the parents towards the potential of TVET for the future of their children.

Most parent will choose academic stream rather than technical and vocational for education and career path since it has gotten more attention and resource from the government and employers in the industry. Mohd Zain (2008) supported this by agreeing that TVET in Malaysia was always perceived as being the career choice for the less educated with the assumption that TVET is a means of training school dropouts rather than as an effective policy to train skill workers.

Technical and vocational education is a popular choice among student in the more developed countries such as Germany, Austria, and Taiwan. However, according to study by Sulaiman, Salleh, Mohamad, & Sern (2015), there are reluctances among the youth in Malaysia to pick technical and vocation education stream. This negative perception is largely contributed by the limited knowledge and information available about TVET. Furthermore, it has been long enough being lowly recognized by society, and by the impression of that there are lesser employment opportunities compared to conventional academic stream.

Volkova et al. (2016) described social media has been widely used by people as a way of sharing their hobbies, friends, places they have been and to the extent of what they are interested in. It has been used in various contexts including sharing one's opinion on specific topics. Sentiments from social media texts can be collected and analysed to improve strategies in business, investment, national policy, security and education. Capturing public opinion on TVET via social media is an approach to avoid the risk of false statement and involuntary opinions where it allows automatic interpretation of topics.

By looking at the microblog's platform, it has been one of the most popular social media tools which establishing an open communication medium among participants. Linking and interconnecting formal and informal learning contexts of different users are among the outcomes of this open exchange. Twitter is a free social networking microblogging service that allows registered members to broadcast short posts called tweets. Tweets are 140-character sentences and the users must constrain their feelings into this little space. Twitter members can broadcast tweets and follow other users' tweets by using multiple platforms and devices. Sentiment of population can be determined by looking at these tweets as they may content important information. Different kind of emotions such as positive, negative or neutral can be identified by analyzing sentiments on these Twitter message.

Sentiment analysis (SA) deals with the mining of information related to sentiments or opinions from a group of people for a specified topic (Saberi & Saad, 2017). Among fields that has benefit from SA are including politics, business and marketing. In pursuing SA, it is normal to assume that the documents would contain opinions. However, in most cases, only objective information and facts are stated in these documents. Therefore, identifying the type and nature of sentences is part of the most fundamental part of SA. To address this issue, aspect-based sentiment analysis can be performed to extract aspects or features from the text and sentiment values are assigned to them (Shama & Dhage, 2018).

According to study by Zia, Fatima, Ali, Naseem, & Das (2018), sentiment classification follows three steps. In the first step, different contents such as reviews, feedbacks or comments will be collected from social media web sites. After that, pre-processing steps will be applied to clean the data that are not necessary for sentiment classification. After the pre-processing step, the aspects in user generated text will be analyzed in specific approach so that required information can be identified. Then sentiment classification is performed by using machine learning mechanisms in order to determine the polarity of the text.

## 1.3 Problem Statement

Public perceptions on the TVET in Malaysia were mentioned in the study by Ismail & Zainal Abidin (2014), Esa & Kannapiran (2014), Esa, Razzaq, Masek, & Selamat (2009). These studies involved traditional methods of data collection that targeted only certain groups of people and using surveys, questionnaires and interviews. The limitation of this conventional research method is the answers to the set of questions may not content honest opinion since the respondents might felt obliged to answer them.

At the widespread usage of social media, data from these platforms were not yet utilized to observe the sentiments towards TVET in Malaysia. Due to this circumstance, the main research question was proposed in this dissertation; w*hat are the sentiments towards TVET in Malaysia if an aspect-based sentiment analysis is performed on tweets related to it?*

Schouten and Frasincar (2016) in their extensive survey on aspect-based sentiment analysis has been highlighting three (3) important tasks that need to be addressed in performing sentiment analysis at aspect level; aspect identification, aspect sentiment classification, and sentiment aggregation. Among the three main tasks, the most crucial part is to extract and categorize the aspect especially the implicit aspects. Due to the nature of data collected from Twitters which consisted of unlabeled mixture of topics, this has led to the research questions as follow:

**Research question 1**: *Can the topic modeling methods be used to extract and categorize the aspects that influence this sentiment and what is the suitable method?*

**Research question 2**: *What are the polarities of sentiments in the aspects-based sentiment analysis towards TVET in Malaysia?*

**Research question 3**: *How reliable is the result of the aspect-based sentiment analysis related to TVET in Malaysia?*

## 1.4 Research Aim

This research aims to assess the sentiment about TVET in Malaysia by performing aspect-based sentiment analysis by using Twitter data.

## 1.5 Research Objectives

The objectives of the research are:

(a) to study the existing topic model approaches for aspect extraction in aspect-based sentiment analysis
(b) to perform aspect-based sentiment analysis on tweets related to TVET in Malaysia in by using lexicon-based and machine learning approaches
(c) to evaluate the result from the aspect-based sentiment analysis by using performance metric

## 1.6 Research Scope

This data used for this research was tweets related to 10 public TVET providers; Polytechnic, Community College, Industrial Training Institute (ILP), Advanced Technical Training Centre (ADTEC), MARA Vocational Institute (IKM), Local Youth Awareness Movement (GiatMara), Mara Higher Skill College (KKTM), National Youth Skill Institute (IKBN), National Youth Higher Skills Institute (IKTBN), and Vocational College (KV). The justification for this is because they are among the largest and well-known providers for TVET program in Malaysia (Cheong & Lee, 2016) thus increasing the availability of the data.

A total of 80% of the raw data obtained in this study is in Malay language, 10% use a mix of Malay and English, while only 10% use English completely. With these constraints, the study has initiated the process of translating the non-English tweets into standard English manually by using human translators.

This research focused on aspect level sentiment analysis. The justification for choosing this type of sentiment analysis is because aspect-based sentiment analysis was able to perform finer-grained analysis and it is important in this research to identify what are the aspects that public most opinionated about TVET in Malaysia.

## 1.7 Research Significant

The importance of this study can be seen from two different angles; for the researcher and to the TVET stakeholders such as training provider. The process of obtaining data in this study is particularly suited to researchers who require data uploaded by users voluntarily without compulsion by using existing social media platforms. This study can be used as a reference for researchers for the use in the future works.

The use of topic modeling techniques in extracting aspects for this research allowed the discovery of the most tweeted topics among Twitter members about TVET in Malaysia. It is hopefully will enable the TVET stakeholders to further increase the efforts in handling negative sentiments towards them.

## 1.8 Research Organization

This dissertation consists of six (6) chapters that will discuss about performing aspect-based sentiment analysis towards TVET in Malaysia. The outline of this dissertation is as follows.

The first chapter gave an overview of the study including the introduction, which had discussed the research overview, research problems, research objectives, scope of this research and the research significances.

Chapter 2 discusses on relevant literatures reviews regarding the research topics that were gathered from various resources to understand the research areas.

Chapter 3 details on methodology of this research. This chapter explains on every phases of this research as well as the deliverables for them to achieve the objectives. It also includes the description for the use of data exploration tools on the research objects.

Chapter 4 presents the finding of data preparation and aspect extraction phase. In this chapter, the result and discussion regarding the second and thirds phase of this research was elaborated.

Chapter 5 describes on the experimental results of using lexicon-based and machine learning classifiers in classifying the polarities of aspect found in the TVET dataset.

Finally, Chapter 6 concludes the dissertation with research finding, contribution, limitation and suggestion for future works.

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