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Paper:

Twitter Sentiment Analysis of Bangkok Tourism During COVID-19 Pandemic Using Support Vector Machine Algorithm

Thanapat Sontayasara*, Sirawit Jariyapongpaiboon*, Arnon Promjun*, Napat Seelpipat*, Kumpol Saengtabtim*, Jing Tang,***, and Natt Leelawat*,***,†**

*Department of Industrial Engineering, Faculty of Engineering, Chulalongkorn University
254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand
†Corresponding author, E-mail: natt.l@chula.ac.th, n.leelawat@gmail.com
**International School of Engineering, Faculty of Engineering, Chulalongkorn University, Bangkok, Thailand
***Disaster and Risk Management Information Systems Research Group, Chulalongkorn University, Bangkok, Thailand

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In the year 2020, SARS-CoV-2, the virus behind the coronavirus disease (COVID-19) pandemic, affected many lives and businesses worldwide. COVID-19, which originated in Wuhan City, China, at the end of December 2019, spread over the entire world in approximately four months. By October 2020, approximately 20 million people were infected and millions had died from this disease. Many health organizations such as the World Health Organization and Centers for Disease Control and Prevention made COVID-19 their primary focus. Many industries, especially, the tourism industry, were affected by the pandemic as many flight and hotel reservations were canceled. Thailand, a country considered one of the world's most popular tourist destinations, suffered much losses because of this pandemic. Many events and travel bookings were canceled and/or postponed. Many people expressed their views and emotions related to this situation over social media, which is considered a powerful media for spreading news and information. In this research, the views of people who were planning to travel to Bangkok, the capital city and most popular destination in Thailand, were retrieved from Twitter for the dates between April 3 and 30, 2020, the period during which the country underwent nationwide lockdown. Sentiment analysis was performed using the support vector machine algorithm. The results showed 71.03% classification accuracy based on three sentiment classifications: positive, negative, and neutral. This study could thus provide an insight into travelers' opinions and sentiments related to the tourism business. Based on the significant terms in each sentiment extracted, strengths and weaknesses of each tourism issue could be obtained, which could be used for making recommendations to the related tourism organizations.

Keywords: COVID-19, sentiment analysis, Bangkok, tourism, support vector machine

1. Introduction

With the outbreak of the coronavirus disease of 2019 (COVID-19), governments worldwide imposed travel restrictions, mandatory quarantine procedures, curfews, and lockdowns to control the spread of the virus. The Royal Thai Government announced many measures to handle the pandemic, including cancelation of the Thai New Year Festival (April 13th to 15th) and temporary shutdown of some public and private sectors [1]. These measures directly shut down the tourism industry. According to the reports of the Office of the National Economic and Social Development Council (NESDC), the gross domestic product (GDP) from the accommodation and food service industries decreased by 36.2% in H1/2020 (−23.3% in Q1 and −50.2% in Q2) [2].

Nowadays, social networking services (SNSs) have changed how people express their opinions and points of view [3]. This opportunity to express their views is given through textual publications, online discussion sites, product evaluation websites, etc. People rely heavily on user-generated content. SNSs contain a considerable amount of content generated by users [3], which is essential for analysis and offers more services adapted to the needs of users. Meechang et al. [4] found that SNSs were one of the important tools used in disaster management. The recent developments in the field of information systems and opinion exchange platforms have encouraged research to analyze the views expressed on these social networks, which is presented in literature as "sentiment analysis" [5].

Accordingly, this research aims to identify the tourist sentiment (i.e., how foreign tourists feel) toward the Bangkok metropolitan area during the beginning of the lockdown in Thailand, by analyzing tourists' reviews on online platforms. Twitter is one of the most popular microblogging platforms [6] used to update short statuses online. The limit of 140 characters per tweet makes the tweets concise and easy to understand, while providing an idea of tourists' opinions and feelings. Many studies had tried to utilize Twitter to analyze the COVID-19 sit-

Table 1. Types of machine learning and their explanations.

Explanation	Machine learning algorithms		
	SVM	DT	NN
Description	Supervised learning algorithms used for regression problems.	A tree-like model of decisions and their results.	Series of algorithms to recognize relations in a set of data that mimics the human brain.
Strengths	Robust to noise [16]. Can model complex linear and nonlinear relationships [17].	Rapid and easy to understand [18, 19]. Cheap to implement [20]. Can classify both categorical and numerical data [18].	Extremely powerful [21]. Can model very complex relationships [22].
Weaknesses	Need to select a good kernel function [23]. Difficult to interpret model parameters.	Hard to interpret complex trees. Output attribute must be categorical.	Long training time. Requires significant computing power for large datasets [10].
Suitable for	Text classification [24]. Image classification [25].	Star classification [13]. Medical diagnosis [26]. Credit risk analysis [15].	Images [27]. Videos [28]. Robotics [29].

uation. For example, Xue et al. [7] used tweet data to learn COVID-19-related concerns and sentiments. Chen et al. [8] also used tweet data to understand the fears in people during the COVID-19 pandemic. Leelawat et al. [9] studied the trends of the tweets at the beginning of the COVID-19 outbreak to learn the changes in trends and word co-occurrence. Bolstered by the success of these studies, Twitter was chosen as the preferred social media platform, in our work.

This research used tweets in English, containing the keyword "*Bangkok*," over the period from April 3 to 30, 2020. April is considered one of the best seasons for travel to Thailand, because of the Thai New Year Festival. The retrieved tweets often contained noise such as URLs, account names, hashtags, news, and advertisements. Thus, data preprocessing was required. These tweets were later classified into tourism-related and non-tourism-related tweets, through manual labeling. If the tweet was tourism-related, our researchers labeled them into one of three classes: positive, negative, or neutral. Cross-checking was then performed among the results labeled by four researchers. After classification, we analyzed each tweet's sentiment using a support vector machine (SVM), to finally discover the sentiment of tourism associated with Bangkok.

2. Literature Review

2.1. Tourism Situation Around the World and in Thailand

In the beginning of 2020, many tourim businesses related were shut down. Qiu et al. [10] found that the COVID-19 pandemic reduced the willingness to pay for traveling to reduce the risk of the disease. The governments' restriction policy also had great effects on the tourism industry. Sharma and Nicolau [11] mentioned that some governments announced shelter-in-place and stay-at-home policies for restricting the outdoor activities of people. Similar to the scenario in Thailand, inbound and outbound tourism was shut down since the end of March 2020 in many countries. Many activities and businesses were continued over online platforms such as SNSs. The data from the Ministry of Tourism and Sport of Thailand also showed a significant decline in the number of inbound travelers. The statistics showed 77.29% decrease in the number of foreign travelers [12]. The highest reduction in number of foreign travelers was in the travelers from the Middle East, followed by those from Africa and South East Asia.

2.2. Potential Sentiment Analysis Algorithms

A "decision tree" (DT) is a decision support tool that uses a tree-like model of decisions and their possible consequences. The DT algorithm separates data observations recursively to construct a tree to improve the prediction accuracy. By using the mathematical algorithm information gain, it identifies a variable corresponding threshold for the variable that splits an observation into two or more subgroups. The tree model shows how each attribute relates to an observation. For example, the DT has been employed in a machine-learning system for automated cataloging of large-scale sky surveys [13], in DT classifiers for automated medical diagnosis [14], and for comparing DTs with logistic regression for credit risk analysis [15].

The neural network (NN) uses a series of algorithms to recognize the underlying relationships in a set of data through a process that mimics the way the human brain operates. NNs are becoming popular in astronomy and robotics because of their memory characteristics and generalization capabilities. As shown in **Table 1**, NNs have been employed in temporal convolutional neural networks for the classification of satellite image time series [27], deep convolutional networks for video sequence background subtraction [28], and NN architectures for solving the forward kinematics problem in robotics [29].

"Support vector machine (SVM)" is a supervised learning model with associated learning algorithms that analyze the data used for regression analyses. SVM is very attractive for classification, and it performs classification tasks by maximizing the margin separating the different classes while minimizing the classification errors. Moreover, it has many kernel types that can model both linear and nonlinear regressions. As shown in **Table 1**, the SVM has been employed in string kernels for SVM protein classification [30], image classification using spatial information [25], and model selection in LS-SVM for application in handwriting recognition [20].

For text classification, the datasets can be linear or nonlinear regressions. **Table 1** shows that the SVM is robust to noise and that it can model both linear and nonlinear complex relationships. In addition, it has been employed for imbalanced text classification [24]. As a result, the SVM is considered a suitable algorithm for sentiment analyses such as the sentiment analysis of tweets [14].

Table 2. Amounts and labels of the data set.

Label	Classification of data	
	Training data set	Testing data set
Positive	500 (56.8%)	125 (56.8%)
Negative	123 (14.0%)	34 (15.5%)
Neutral	258 (29.3%)	61 (27.7%)
Total	881 (100%)	220 (100%)

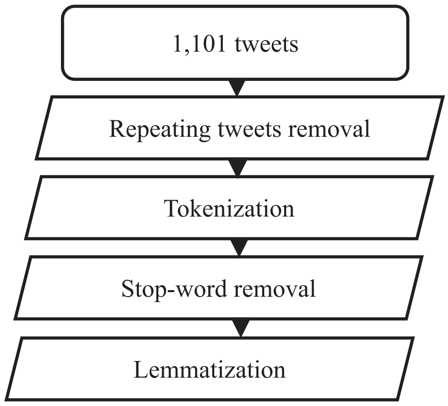

Fig. 1. Cleaning process.

Table 3. Amounts and labels of the data setsafter data preprocessing.

Label	Classification of data	
	Training data set	Testing data set
Positive	476 (56.3%)	120 (56.1%)
Negative	11 (13.5%)	33 (15.4%)
Neutral	25 (30.2%)	61 (28.5%)
Total	881 (100%)	214 (100%)

3. Research Design and Methodology

In this research, tweet data were collected using the Twitter API from April 3 to 30, 2020, during the COVID-19 lockdown in Thailand. Data preprocessing was performed in this research. The actual process started after the data that were not related to tourism in Bangkok were removed from the dataset; the data were labeled to identify that they were not related to tourism in Bangkok. The data related to tourism in Bangkok were labeled with the sentiment (i.e., positive, negative, or neutral) by researchers. The researchers also set the criteria for separating each sentiment class. If a tweet clearly showed that the writer held a good opinion of Thailand, it was labeled as a positive tweet. If the tweet mentioned that the writer only wanted to stay in Bangkok without any strong intention for any activity, it was labeled as neutral. In contrast, if the tweet had content related to trip cancelation or presented a bad viewpoint of Thailand, it was labeled as negative. An example of a positive sentiment tweet would be, "*I came to Bangkok for Songkran festival in 2019, so happy days*." A negative tweet's example would be "*If Covid-19 does not appear, maybe currently I'm in Hat Yai then going to Bangkok by train. But yeah, I should be cancelled my trip and all of tickets due to this virus*." A neutral tweet's example is "*Greetings from Bangkok Kath. We all wear masks here, not to protect others*." Each day, data sentiments of 50 tweets were labeled, or all tweets were labelled if that day had less than 50 tweets related to tourism in Bangkok. In this study, the data were separated randomly into a training data set (75%) and testing data set (25%). After labeling the sentiment, according to **Table 2**, the resultant data covered 1,101 tweets, which were split into 881 tweets for the training data set and 220 tweets for the testing data set. There were 500 positive, 123 negative, and 258 neutral tweets among the training data, and the testing data set contained 125 positive, 34 negative, and 61 neutral tweets.

The overall process of the research is illustrated in **Fig. 1**, and is separated into two parts: data preprocessing or data-cleaning process and SVM. The data were cleaned using NLP. First, the data containing the same tweet, irrespective of whether the same account or different accounts were used, were removed, leaving only one tweet. The amount of training data after removal was 846 tweets and the amount of test data after removal was 214 tweets, as illustrated in **Table 3**.

Then, the data were tokenized, which split a sentence into words. Next, stop words were removed from the data using the NLTK (Corpus) library. After that, the data were lemmatized using the NLTK (WordNetLemmatizer) library.

According to **Fig. 2**, the data were vectorized using a TF-IDF. The shape of the data after vectorization showed that the data had 3,854 features (i.e., 3,854 words). Then, the SVM parameters were defined. This study used four

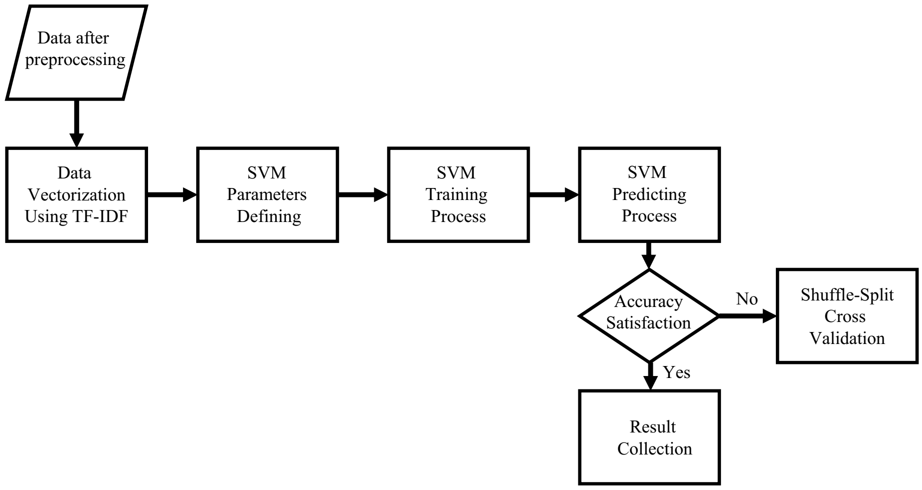

Fig. 2. SVM processing.

kernel types, namely, linear, radial basis function (RBF), poly, and sigmoid, to find the best accuracy. The parameters this study focused on were C and Gamma. C is a regularization parameter that defines how much the data we want to avoid misclassifying each training example. Gamma defines how far the influence of a single training example reaches, with low values indicating far and high values indicating close. Next, the training data set was used to train the SVM. After that, the SVM was predicted by the testing data set to show its accuracy. If the accuracy was not satisfied, the SVM improved its accuracy using the shuffle–split cross-validation to find the best kernel types and parameter values. After using the shuffle–split cross-validation, the results showed that the parameters C and Gamma were 10 and 0.1, respectively. The kernel type was RBF. Then, the testing data set was predicted again with the SVM. After satisfying the accuracy level, the results were collected.

4. Results

By using C and Gamma in set $\{0.01, 0.1, 1, 10, 100\}$, the optimal kernel type was selected through shuffle–split cross-validation. After performing the optimization for finding the optimal parameter setting, the results in **Table 4** show that the settings of the parameters C and Gamma are based on the linear kernel. Based on this parameter setting, the classification accuracy was 71.03%, precision was 81.65%, recall was 55.14%, and F-1 score (i.e., a measure of the test's accuracy) was 57.95%, where the precision was the average ratio of the correct predictions for each sentiment observation to the total predictions for each sentiment observation, and the recall was the average ratio of correct predictions for each sentiment observation to all observations in each actual class. The F-1 score was the weighted average of precision and recall. **Table 5** shows the confusion matrix for the SVM linear kernel sentiment analysis, which illustrates that the algorithm could correctly predict 29 neutral tweets from 61 actual neutral tweets, which was considered an accuracy of 47.54%. The prediction accuracies of the negative and positive sentiments were 21.21% and 96.67%, respectively.

Table 4. Results from SVM processing.

Kernel Type	**Parameter and accuracy result**			
	C	Gamma	Accuracy	F1-Score
Linear	1	1	71.0%	58.0%
Sigmoid	1	1	69.2%	54.4%
RBF	10	0.1	68.7%	59.1%
Poly	1	10	60.8%	38.6%

Note: Predicted using C and Gamma in $\{0.01, 0.1, 1, 10, 100\}$.

5. Discussion and Conclusions

As shown in **Table 4**, the experimental results showed that the linear kernel type had the highest accuracy (71.03%), which was an acceptable accuracy for SVM. The results in **Table 5** also show that SVM could perform better in positive class classification. In contrast, the lowest class classification was for negative. The result of this research also matched with that in the study of Yiamjanya and Wongleedee [31] in which Thailand was viewed as one of the incredible travel destinations.

The research's aim was to perform sentiment analysis by using English tourism-related tweet data posted during the COVID-19 pandemic. The SVM algorithm was selected as the primary tool for performing the analysis. From the SVM classification result, each sentiment class had its own specific keywords that could identify their properties.

For the positive predicted sentiments, the significant

Table 5. Confusion matrix from SVM processing.

Actual	**Predicted**		
	Neutral	Negative	Positive
Neutral	29	0	32
Negative	5	7	21
Positive	4	0	116

Note: Linear kernel, C = 1, Gamma = 1.

keywords were "*Food*," "*City*," "*Temple*," etc. In contrast, the significant keywords for the neutral sentiments predicted were "*Temple*," "*Photo*," "*Market*," etc. For the negative predicted sentiments, the keywords were "*People*," "*Driver*," "*Flight*," etc. Based on the suggested keywords for each sentiment class, most of the keywords of the positive and neutral classes were similar.

The significance of the infectious disease outbreak could also be shown based on the sentiment of the people who wanted to visit Bangkok during the lockdown period.

In addition, it could be inferred that the Bangkok metropolitan area's good points were related to food and some tourist destinations such as temples. However, the negative class appeared to be related to the problems in Bangkok city, such as transportation. These results could also be used to provide suggestions to organizations related to the tourism industry, such as the Tourism Authorities of Thailand, for pointing out the strengths and weaknesses of Bangkok metropolitant tourism during the COVID-19 pandemic.

In practice, the result of this study can support the decision to plan potential tourism policies for promotion and campaigning. Furthermore, owing to the low accuracy of the negative sentiment class, some differences exist between the keywords for the preanalysis and postanalysis processes. The results of the preanalysis process for negative sentiment analysis are "*Driver*," "*Time*," and "*Traffic*." Based on this, it can be seen that most of the keywords for the pre and postanalysis processes are related to each other. However, this study attempted to examine the poor accuracy of the negative sentiment class. Based on this, it came up with a future plan to check whether the SVM algorithm could provide a result based on only terms or both terms and semantics.

The results of this research also showed that tourism in Thailand during COVID-19 was mostly viewed in a positive manner, even though visits to Thailand were not possible. Nevertheless, it is necessary to consider the small size of the data set as a limitation of this study. Furthermore, each sentiment class's unequal amount of data can create some subjective bias in the analysis.

As for the practical contributions, as the findings show the sentiments of the travelers who wanted to visit Bangkok, it can be interpreted that even though Thailand was under lockdown during the study period, in the travelers' perspective, Thailand tourism was still considered an attractive destination based on the contents on Twitter.

Nevertheless, the number of samples should be considered small, as this study focuses on the sentiment of tourism in the Bangkok metropolitan area for one month only, after the government's official announcement of a nationwide lockdown on April 2, 2020. In addition, in order to perform a precise analysis, the initially collected data were cleaned to remove the unrelated tweets such as advertisements, political situations, etc. For future research, it is possible to extend the period to obtain more data that can be used to perform a forecasting analysis for traveler numbers. In addition, owing to availability of tweet data, a comparison of the sentiment analysis can be performed for more than one language over the same period. Other machine learning and deep learning techniques such as recursive neural networks and convolutional neural networks can also be used to perform the analysis.

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Name:
Thanapat Sontayasara

Affiliation:
Undergraduate Student, Department of Industrial Engineering, Faculty of Engineering, Chulalongkorn University

Address:
254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand

Brief Career:
2017- Undergraduate Student, Chulalongkorn University

Name:
Sirawit Jariyapongpaiboon

Affiliation:
Undergraduate Student, Department of Industrial Engineering, Faculty of Engineering, Chulalongkorn University

Address:
254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand

Brief Career:
2017- Undergraduate Student, Chulalongkorn University

Name:
Arnon Promjun

Affiliation:
Undergraduate Student, Department of Industrial Engineering, Faculty of Engineering, Chulalongkorn University

Address:
254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand

Brief Career:
2017- Undergraduate Student, Chulalongkorn University

Name:
Napat Seelpipat

Affiliation:
Undergraduate Student, Department of Industrial Engineering, Faculty of Engineering, Chulalongkorn University

Address:
254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand

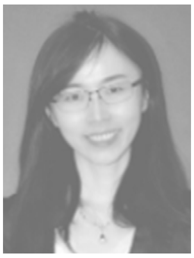
Brief Career:
2017- Undergraduate Student, Chulalongkorn University

Name:
Kumpol Saengtabtim

Affiliation:
Graduate Student, Department of Industrial Engineering, Faculty of Engineering, Chulalongkorn University

Address:
254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand

Brief Career:
2019- Research Assistant, Disaster and Risk Management Information Systems Research Group, Chulalongkorn University



Name:
Jing Tang

Affiliation:
Lecturer, International School of Engineering, Faculty of Engineering, Chulalongkorn University

Address:
254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand

Brief Career:
2013-2017 Enterprise System Transformation Consultant, based in Japan
2017-2019 Lecturer, Sirindhorn International Institute of Technology, Thammasat University
2019- Lecturer, Chulalongkorn University

Selected Publications:
- J. Tang, L. G. Pee, and J. Iijima, "Investigating the effect of business process orientation on organizational innovation performance," Information & Management, Vol.50, No.8, pp. 650-660, 2013.
- M. Fachrizal and J. Tang, "Forecasting annual solar PV capacity installation in Thailand residential sector: A user segmentation approach," Eng. J., Vol.23, No.6, pp. 99-115, 2019.
- T. Katato, N. Leelawat, and J. Tang, "Antecedents of the outsourcing relationship: A systematic review," Eng. J., Vol.24, No.4, pp. 157-169, 2020.

Name:
Natt Leelawat

Affiliation:
Assistant Professor, Department of Industrial Engineering, Faculty of Engineering, Chulalongkorn University
Head of Disaster and Risk Management Information Systems Research Group, Chulalongkorn University
Assistant Dean, Faculty of Engineering, Chulalongkorn University
Director of Risk and Disaster Management Program, Graduate School, Chulalongkorn University

Address:
254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand

Brief Career:
2007-2009 System Analyst, Bank of Thailand
2016-2017 Assistant Professor, Tohoku University
2017-2018 Lecturer, Chulalongkorn University
2018- Assistant Professor, Chulalongkorn University

Selected Publications:
- N. Leelawat, A. Suppasri, P. Latcharote, Y. Abe, K. Sugiyasu, and F. Imamura, "Tsunami evacuation experiment using a mobile application: A design science approach," Int. J. Disaster Risk Reduct., Vol.29, pp. 63-72, 2017.
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Academic Societies & Scientific Organizations:
- Asia Oceania Geosciences Society (AOGS), Regional Advisory Committee
- Association for Information Systems (AIS)
- Institute of Electrical and Electronics Engineers (IEEE), Senior Member