Sentiment Analysis for Thai dramas on Twitter

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Abstract

Since most consumers are interested in watching TV series and using online media such as Twitter to exchange opinions about them, there are a lot of comments are found and the consumers must take more time for reading and understanding the overall messages of the other consumers' views. Therefore, this research has studied about word grouping, classification of the sentiments of the text about Thai TV series called Thai dramas or Lakorn. The objective is to analyze the opinion messages expressed as like, dislike and neutral comments and the scope of this research is collecting texts about the dramas in Thai language, but it does not cover slang, misspellings, and dialects. Moreover, the implemented web application for analyzing opinions about Thai dramas on Twitter is developed to help analyzing and summarizing the preferences for Thai dramas. All words of collected Thai messages will be looked up in the vocabulary list created for the Thai dramas. Then, the word vectors of messages are generated for training a learning model using the NaÏve Bayes approach. After that, the model will classify the comments about the dramas, whether most consumers like or not like the drama. The developed system is expected to be a tool that will be able to make decision watching the dramas easier and this will be beneficial to the drama producers to facilitate planning the production of the dramas in the future.

Keywords: Sentiment analysis, Thai dramas, Naïve Bayes

Introduction

The TV series is one of the media and entertainment industry, which are popular with many people. Although there are many forms of TV series, such as comedy, romance, action and drama, Thai people call them all "Thai drama (Lakorn)". As more and more people are interested in watching Thai dramas, there are a wide variety of information about Thai dramas exchanged via online media. For example, many tweets (messages on Twitter) in Thai have been sent and tagged with the title name of Thai dramas and the character names in dramas. Consequently, there is useful information for understanding the market trend of Thai dramas, and making decisions of choosing the interesting dramas. However, it will take a long time to find and extract the required information, including the understanding time taken. Therefore, it is advisable to have an automated text processing system to reduce these problems.

Sentiment analysis called opinion mining (Chatchaithanawat & Pugsee 2015; Pugsee, Nussiri, & Kittirungruang 2019) is the methodology that can be applied to a previous analysis system because the objective of sentiment analysis is to differentiate the sentiments of texts into the positive or negative messages. All data on online media in the forms of comments or reviews can be analyzed and identified satisfaction, evaluation, intentions, and emotions. Thus, the sentiment analysis system can help people to investigate the consumer satisfaction, survey customer desires, and gather evaluated opinions about interesting products. Additionally, the product features and qualities can be improved following by the suggestion from comments or reviews.

Research on sentiment analysis is the analysis of emotions and feelings through text. It analyzes the commentary text to indicate the author's feelings such as positive, neutral, and negative statements. There are three main strategies of sentiment analysis or opinion mining: the lexicon-based methods, the machine learning (ML) techniques, and the combination of lexicon and ML. The review paper (Drus & Khalid 2019) listed the methods used in analyzing sentiments on social media, including summarizing the common lexicon-based methods and the ML techniques. The common lexicon-based methods are SentiWordnet (Baccianella, Esuli & Sebastiani 2010) and the term frequency-inverse document frequency (TF-IDF). The popular ML techniques also are Naïve Bayes, and the support vector machines (SVMs). One paper about users' reviews in Thai language (Deewattananon & Sammapun 2017) applied SentiWordNet (Esuli, 2019) and a Thai-English dictionary called LEXiTRON (National Electronics and Computer Technology Center 2020) to analyze the aspects of two mobile applications with sentiment words. One limitation of this work is the sentiment identification depending on Thai with English words in LEXiTRON. To improve the performance of sentiment analysis, the lexicon-based methods and the ML techniques are blended and modified as the combination of both.

There are samples of the combined strategies between the lexicon-based and the ML methods for the sentiment analysis, especially Naïve Bayes technique. The article (Narayanan, Arora & Bhatia 2013) researched on the classification of feeling and opinions about movies using information from the web (https://www.imdb.com/) called a movie reviews database (IMDb). IMDb collects various opinions or attitudes about movies. A combination of strategies like word n-gram, negative handling, and feature selection for the Naïve Bayes classifier comes about with a critical change in precision. Therefore, the performance of the Naïve Bayes classifier can be improved significantly using the syntax of the sentence and the appropriate features. The research (Pugsee, Sombatsri, & Juntiwakul 2017) proposed satisfactory conclusion application for cosmetic products on the beauty community (http://www.makeupalley.com/product/) using the Naïve Bayes classifier. The application proceeded some parts of natural language processing using information from lexicons, such as parts of speech tagging, matching words with modified sentiment lexicon. The testing results recognized that the classification application has high precision and accuracy of both positive and negative comments with the similar proportion of two classes. Another study of beauty products (Pugsee, Nussiri, & Kittirungruang 2019) built the opinion mining application to analyze tweets with the hashtag for skin care products (#skincare). The Twitter messages were analyzed by word data from SentiWordNet with the two ML techniques (Naïve Bayes and SVMs). There are five categories of opinions about skin care products: very positive, positive, neutral, negative, very negative. The evaluation of both ML techniques is in the calculation of accuracy, precision, and recall values, which all of them got the similar ratings results. Other product reviews can also be analyzed by some basic ML techniques and sentiment scores from lexicons. The opinion mining tool (Pugsee & Chatchaithanawat 2020) examined the laptop quality from laptop reviews in different viewpoints, which are the performance, the style (design) and options (features). The text paragraphs were identified and classified by words and the polarity levels of words, which were selected to be as features for the Naïve Bayes classifier. The performance evaluation of this tool in sentiment has acceptable accuracy, precision, and recall for all classes.

As already mentioned, there are various English resources that can be analyzed the sentiments using some information from suitable lexicons with the Naïve Bayes classifier. In the same way, the visualization tool for topic modeling and sentiment analysis (Lertsiwaporn & Senivongse 2017) collected and analyze data set of tweets in Thai utilizing three ML techniques: Naïve Bayes, SVMs, and Maximum Entropy. The sentiment classification results have high accuracy, precision, recall, and F1-score for positive and negative messages in all three ML techniques. Nevertheless, the performance of appropriate strategies is depending on their individual information and resources. In addition, the sentiment or polarity terms are important factors in the study of sentiment analysis, and these data should be annotated by linguists (Trakultaweekoon & Klaithin 2016). Consequently, the specific words in each domain are the one factor to improve the sentiment analysis, therefore, our research has studied Thai words in Thai drama domain and tried to develop the sentiment analysis system as a web application to analyze an audience satisfaction for Thai dramas from Twitter data. The results of statement sentiments are classified into three groups: like, dislike, and neutral. The benefits of this application are to provide helpful information for considering interested dramas and the drama's ratings. In addition, the audience can choose the right dramas and the producer can plan the future production.

Although there is some sentiment analysis in Thai (Vateekul & Koomsubha 2016; Piyaphakdeesakun, Facundes, & Polvichai 2019; Pasupa & Seneewong Na Ayutthaya) using the deep learning with the syntactic information of words and the polarity of words, these data processing methods in practice are difficult to implement the application with friendly user interfaces. In addition, the performance of the deep learning, building from the neural networks is uncertain depending on various uncontrolled factors. Furthermore, it is not cost-effective for implementation to continuously train and tune the neural networks supporting Language changes. Therefore, our proposed research generated the sentiment analysis application implementing the appropriated classification model using the Naïve Bayes technique with collected words from Twitter messages about Thai dramas. The detail in this paper consists of methods and materials, results, discussion, and conclusion & suggestions.

Methods and Materials

To design the sentiment analysis for Thai Twitter messages about Thai dramas, there are three methods to discover the suitable techniques for identifying the sentiments of messages: 1. Counting only sentiment words in messages (the words that meet the vocabulary in the polarity lexicons); 2. Using all words in messages with the Naïve Bayes (the word vectors from all words in sentences that use for training the ML model); 3. Combining the word information from the polarity lexicons with the Naïve Bayes (the different features for training the ML Model). There are the same three preprocessing modules for all methods as shown in Figure 1. Consequently, the following modules of three methods are different as shown in Figure 2. Consequently, these methods are compared with the performance of sentiment classification of the experimental data, and the best performing method will be embedded to implement the sentiment analysis application for Thai dramas.

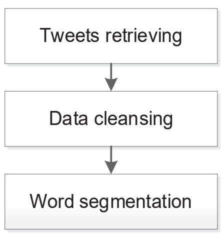

Figure 1 Preprocessing modules

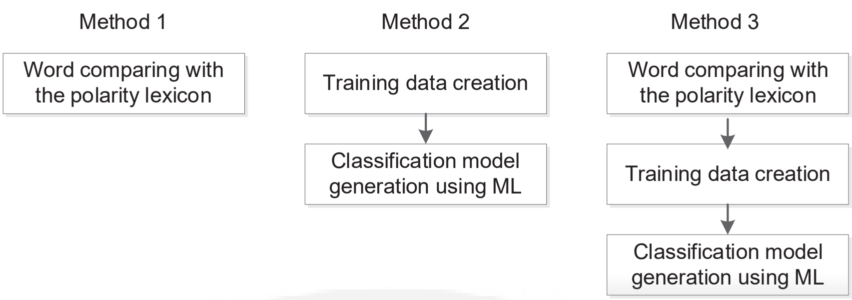

Figure 2 Different modules among three methodologies

Module 1: Tweets retrieving is to retrieve messages from Twitter with focused hashtags (the title names of Thai dramas and the character names in dramas) using a python library for accessing the Twitter API called Tweepy (Python Software Foundation 2020). The stored data is in the form of a text file as in Figure 3.

```
หลายครั้งที่เราบอกเพื่อนที่อยู่ทีมเป๋งว่า ให้ดูทีมบทละคร อย่าดูที่ตัวนักแสดง ซันนี่เล่นก็จริง แต่บทมันไม่ใช่พระเอก... https://t.co/f3CoPUICkC
ใครที่ยังไม่มูฟออน พรุ่งนี้เรามากาวกัน 20.10 กับ #รักฉุดใจนายฉุกเฉินEP17 555555 #รักฉุดใจนายฉุกเฉิน
นี่ค่าย concern กระแส anti นะเนี่ย ขนาดออกมา clarify message ที่ต้องการสื่อสารกับคนดูซีรี่ย์ ถ้า direction ที่วางมา... https://t.co/eJrEJTgHOx
Hi ผีหมอเต่า อุ้ย เป็นน้องหมอต่างหาก 👀 #รักฉุดใจนายฉุกเฉิน #HappyHaloween https://t.co/3sf5jABfU8
กระทู้นี้ตรงใจมาเลย เก็บตก #รักฉุดใจนายฉุกเฉิน - ความละเอียดของละครถึงความรักของทานตะวันกับฉลาม https://t.co/6TfXGj9qeN
จริงด้วย พึ่งรู้เลย ว่าเด็กที่ไทเจอตอนจบ คือเด็กที่คุณพ่อเป็นโรคหัวใจ 🙂 #รักฉุดใจนายฉุกเฉินตอนอวสาน... https://t.co/GOd30H8w2
ไม่ไหวแล้วแม่น่ารักมาก 💖💖 #รักฉุดใจนายฉุกเฉิน#สกายวงศ์รวีสามีแห่งชาติ#mycloudy#ก้อนเมฆของสกาย#skywongravee @ Th... https://t.co/QDEIjs8cWs
ซึ่งต่างกับฉลามที่เข้ามาในช่วงเวลาที่ทตวต้องการใครสักคนจริงๆ คิดในแง่ของทตว เป็นเรา เราก็เลือกฉลาม. มันไม่ใช่แค่ตอน... https://t.co/j1Wzs9Bp7W
ทีมฉลามเพราะ เป๋งบอกว่าอยากเป็นหมอเพราะทตว แต่พอเป็นหมอแล้วทตวเจ็บ เป๋งกลับทิ้งทวตที่ต้องการเขามากที่สุดในตอนนั้น เ... https://t.co/tF4RDQIXt
```

Figure 3 Retrieved tweets

Module 2: Data cleansing is to clean data by deleting irrelevant information such as special characters, hashtags, URLs, and retweet messages with regular expressions. The results of this module are displayed in Figure 4.

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หลายครั้งที่เราบอกเพื่อนที่อยู่ทีมเป๋งว่า ให้ดูทีมบทละคร อย่าดูที่ตัวนักแสดง ซันนี่เล่นก็จริง แต่บทมันไม่ใช่พระเอก
ใครที่ยังไม่มูฟออน พรุ่งนี้เรามากาวกัน 20.10
นี่ค่าย concern กระแส anti นะเนี่ย ขนาดออกมา clarify message ที่ต้องการสื่อสารกับคนดูซีรี่ย์ ถ้า direction ที่วางมา
Hi ผีหมอเต่า อุ้ย เป็นน้องหมอต่างหาก
กระทู้นี้ตรงใจมาเลย เก็บตก #รักฉุดใจนายฉุกเฉิน - ความละเอียดของละครถึงความรักของทานตะวันกับฉลาม
จริงด้วย พึ่งรู้เลย ว่าเด็กที่ไทเจอตอนจบ คือเด็กที่คุณพ่อเป็นโรคหัวใจ
ไม่ไหวแล้วแม่น่ารักมาก
ซึ่งต่างกับฉลามที่เข้ามาในช่วงเวลาที่ทตวต้องการใครสักคนจริงๆ คิดในแง่ของทตว เป็นเรา เราก็เลือกฉลาม. มันไม่ใช่แค่ตอน...
ทีมฉลามเพราะ เป๋งบอกว่าอยากเป็นหมอเพราะทตว แต่พอเป็นหมอแล้วทตวเจ็บ เป๋งกลับทิ้งทวตที่ต้องการเขามากที่สุดในตอนนั้น
```

Figure 4 Cleaned messages

Module 3: Word segmentation is to segment sentences obtained from data cleansing into words using PyThaiNLP library (Python Software Foundation 2020) with the maximum matching algorithm. Individual words in tweets are shown as in Figure 5. Some words in the results of the word segmentation library are modified to be the exact words. For example, the duplicated characters of the ending consonants are removed as 'a lotttt (มากกกกก/makkkkk)' to be 'a lot (มาก/mak)'.

```
['หลายครั้ง', 'ที่', 'เรา', 'บอก', 'เพื่อน', 'ที่อยู่', 'ทีม', 'เป๋ง', 'ว่า', 'ให้', 'ดู', 'ที่', 'บทละคร', 'อย่า', 'ดู', 'ที่', 'ตัว', 'นักแสดง', 'ซันนี่', 'เล่น', 'ก็', 'จริง', 'แต่', 'บท', 'มัน', 'ไม่', 'ใช่', 'พระเอก']
['ใคร', 'ที่', 'ยัง', 'ไม่', 'มูฟ', 'ออน', 'พรุ่งนี้', 'เรา', 'มา', 'กาว', 'กัน', '20.10']
['นี่', 'ค่าย', 'concern', 'กระแส', 'anti', 'นะเนี่ย', 'ขนาด', 'ออกมา', 'clarify', 'message', 'ที่', 'ต้อง', 'การสื่อสาร', 'กับ', 'คนดู', 'ซี', 'รี่', 'ย์', 'ถ้า', 'direction', 'ที่', 'วาง', 'มา']
['Hi', 'ผี', 'หมอ', 'เต่า', 'อุ้ย', 'เป็น', 'น้อง', 'หมอ', 'ต่างหาก']
['กระทู้', 'นี้', 'ตรง', 'ใจมา', 'เลย', 'เก็บตก', '#', 'รัก', 'ฉุด', 'ใจ', 'นาย', 'ฉุกเฉิน', '-', 'ความ', 'ละเอียด', 'ของ', 'ละคร', 'ถึง', 'ความรัก', 'ของ', 'ทานตะวัน', 'กับ', 'ฉลาม']
['จริง', 'ด้วย', 'พึ่ง', 'รู้', 'เลย', 'ว่า', 'เด็ก', 'ที่', 'ไท', 'เจอ', 'ตอนจบ', 'คือ', 'เด็ก', 'ที่', 'คุณพ่อ', 'เป็น', 'โรคหัวใจ']
['ไม่', 'ไหว', 'แล้ว', 'แม่', 'น่ารัก', 'มาก']
['ซึ่ง', 'ต่าง', 'กับ', 'ฉลาม', 'ที่', 'เข้ามา', 'ใน', 'ช่วงเวลา', 'ที่', 'ทตว', 'ต้องการ', 'ใคร', 'สัก', 'คน', 'จริงๆ', 'คิด', 'ในแง่', 'ของ', 'ทตว', 'เป็น', 'เรา', 'เรา', 'ก็', 'เลือก', 'ฉลาม', '.', 'มัน', 'ไม่', 'ใช่',
['ทีม', 'ฉลาม', 'เพราะ', 'เป๋ง', 'บอ', 'กว่า', 'อยาก', 'เป็น', 'หมอ', 'เพราะ', 'ทตว', 'แต่', 'พอ', 'เป็น', 'หมอ', 'แล้', 'วท', 'ตว', 'เจ็บ', 'เป๋ง', 'กลับ', 'ทิ้ง', 'ทวต', 'ที่', 'ต้องการ', 'เขา', 'มาก', 'ที่สุด',
```

Figure 5 Segmented words

Method 1: Counting only sentiment words in messages.

After preprocessing processes, the sentiment of the tweet will be identified by the sentiment of contained words in the message for the method 1.

Module 4: Word comparing is to detect contained words in tweets with vocabularies in the polarity lexicons. Thai polarity lexicons (positive and negative) are created from the common sentiment words found in Thai tweets, such as like a lot (ชอบมาก/chop mak), really fun (โคตรสนุก/khot sanuk), be bad (แย่/yae), retrogression (เสื่อม/sueam), and added other Thai polarity lexicons (Phatthiyaphaibun, 2017) on the list of vocabularies. In addition, our research studied Thai words from collected experimental data to understand the polarity of words in the drama domain. Consequently, some polar words in this domain are included into our Thai polarity lexicon, such as 'extremely bad (ทุเรศ/thuret)', 'mild (ละมุน/lamun)', and 'full flavor (แซ่บ/saab)'.

The sentiments of messages are determined by the largest number of sentiment words (positive or negative). If there are no detected words, the message will be neutral. However, if the number of positive and negative words is equal, the message will also be neutral.

Method 2: Using all words in messages with ML.

After preprocessing processes, the sentiment of the tweet will be verified by all contained words in the message using ML (the Naïve Bayes) without the polarity lexicons for the method 2. Therefore, the module 4 is skipped and the module 5 is run.

Module 5: Training data creation is to generate the training data using a one-hot encoding with a vocabulary list. This vocabulary list or the bag of words in the method 2 was built from all unique words in all tweets. Some words are eliminated from the vocabulary list because they are not the actual words, such as the date in the number format ('15.11.62'), the time ('20.10'), and the three or more repeated characters. The word vector of the tweet is defined by the vector of the attribute value 1 or 0 relative to the words in the vocabulary list. If there is a word in the message, the attribute value is 1, but if there is no word in the message, the attribute value is 0. Then, the word vectors of tweets are the features to train the Naïve Bayes for generating the sentiment classification model in the module 6.

Module 6: Classification model generation is to build the sentiment classification model using the Naïve Bayes to classify Twitter messages into 3 groups: like (positive), dislike (negative) and neutral. The application of our proposed research configured the library of machine learning called the multinomial Naïve Bayes of Scikit-learn open sources (Scikit-learn Developers 2020). Therefore, the sentiments of messages are recognized by the generated classification model.

Method 3: Combining the word information with ML.

After preprocessing processes, the sentiment of the tweet will be distinguished by all contained words merging with all sentiment words in the message using ML (the Naïve Bayes) for the method 3. Consequently, the module 4 and the module 5 are implemented differently from the method 1 and the method 2. Both are executed together for creating the training data of ML.

Module 4 - 5: The vocabulary list or the bag of words in the method 3 was built from all unique words in all tweets along with all sentiment words in the polarity lexicons. To generate the training data, the word vector of the tweet is specified with a one-hot encoding relative to the words in the list of vocabularies (If there is a word in the message, the attribute value is 1, but if there is no word in the message, the attribute value is 0). Therefore, the word vectors of messages are the concatenation of the vectors of messages in the method 2 and the vectors of messages comparing vocabularies in the polarity lexicons. Then, these word vectors of tweets are the features to train the Naïve Bayes for generating the sentiment classification model in the module 6.

Module 6: The sentiment classification model is generated by the same techniques in the method 2 with different features for ML.

Results

There are two subsections in the results section that are the experimental data and the experimental results.

Experimental Data

The characteristics of the comment messages on Twitter (Twitter 2020) contain the name of the Twitter account, the comment text up to 280 characters, and the hashtags (#) which is the symbol placed in front of the required keyword or the topic that the user is interested in at that time. The users can send messages up to 280 characters. In our research, the comments about 8 Thai dramas were collected via Twitter using the title names of dramas, the character names of their male/female protagonist as hashtags. These Thai dramas are My Ambulance (รักฉุดใจนายฉุกเฉิน/rạk chudchai nai chukchoen), The Seer (ฤกษ์สังหาร/Rerk sangharn), My Love From Another Stars (ลิขิตรักข้ามดวงดาว/likhit rak kham duangdao), One story of Gentleman Thief Series (สุภาพบุรุษจอมโจร/suphapburut chom chon: มธุรสโลกันตร์/mathuros lokan), Lady Shoes (รองเท้านารี/rongthao nari), Love Flame a Vengeful Flame (เพลิงรักเพลิงแค้น/ phloeng rak phloeng khaen), My Secret Bride (เขาวานให้หนูเป็นสายลับ/khao wan hai nu pen sailap), Sky-Lost Star (ดาวหลงฟ้า/ dao long fah). The total of tweets is 9,991 comments and all messages were categorized manually into three groups: dislike, neutral and like as following in Table 1.

Table 1 The number of tweets classified by the sentiments and the title names of dramas

Dramas	Dislike	Neutral	Like	Total
Drama 1	192	626	531	1,349
Drama 2	426	1,028	823	2,277
Drama 3	251	548	540	1,339
Drama 4	64	118	348	530
Drama 5	359	648	319	1,326
Drama 6	427	151	191	769
Drama 7	125	510	698	1333
Drama 8	534	243	291	1068
Total	2,378	3,872	3,741	9,991

The example of tweets in the dislike, and like group are expressed as following, respectively.

It is very disappointed about the love scene inside the cottage in the forest, called legendary cottage scene (ผิดหวังมากค่ะพี่ผา ฉากกระท่อมในตำนาน/phitwang mak kha pee pha chak krathom nai tamnan).

I would like to admire the dramas, namely My Secret Bride. It is exactly fun (ขอชื่นชมละครเขาวานให้หนูเป็นสายลับ สนุกมากจริง ๆ/kho chuenchom lakhon khao wan hai nu pen sailap sanuk mak ching ching).

Experimental Results

The experimental results are verified by a confusion matrix that represents the actual class compared to the predicted class as in Table 2. The variable A, E, and I are the accurate result that means the sentiment analysis system can answer the sentiments of messages correctly. In addition, the performance of the classification model of each method in the section 3 Methodology is evaluated by the accuracy, the precision, and the recall values which are calculated by the equations in Table 3.

Table 2 A confusion matrix

Actual Class	**Predicted Class**		
	Dislike	**Neutral**	**Like**
Dislike	**A**	B	C
Neutral	D	**E**	F
Like	G	H	**I**

Table 3 The calculating equations for evaluated values

Class	**Accuracy**	**Precision**	**Recall**
Dislike		A/(A+D+G)	A/(A+B+C)
Neutral	(A+E+I)/(A+B+C+D+E+F+G+H+I)	E/(E+B+H)	E/(E+D+F)
Like		I/(I+C+F)	I/(I+G+H)

Method 1: Counting only sentiment words in messages. The confusion matrix of identifying message sentiments and the performance of the method 1 are displayed in Table 4 and Table 5, respectively.

Method 2: Using all words in messages with ML. In this method, the experimental data are randomly separated in 80% of training data and 20% of testing data for the five-fold cross validation (four data folds for training and a data fold for testing with five turn times). In addition, these data are also re-randomized five times, so the total data of 9,991 messages are differently defined as 1,999 of testing data for 25 data sets. The confusion matrix of classifying message sentiments using the Naïve Bayes with all word features is presented in Table 6, and the evaluation of the sentiment classification in this method is expressed in Table 7.

Method 3: Combining the word information with ML. The result of the same previous divided experimental data processed by the Naïve Bayes with all word features and sentiment words features in the method 3 is elaborated in Table 8, and the performance of the classification model is discovered in Table 9.

Table 4 The confusion matrix result of identifying message sentiments by the method 1

Actual Class	**Predicted Class**			**Total**
	Dislike	**Neutral**	**Like**	
Dislike	**958**	971	449	2,378
Neutral	568	**2,571**	733	3,872
Like	322	1,139	**2,280**	3,741

Table 5 The performance of the sentiment identification by the method 1

Class	Accuracy	Precision	Recall
Dislike		52%	40%
Neutral	58%	55%	66%
Like		66%	61%

Table 6 The confusion matrix result of classifying message sentiments by the method 2

Actual Class	Predicted Class			Predicted Class			Predicted Class		
	Dislike	Neutral	Like	Dislike	Neutral	Like	Dislike	Neutral	Like
		#1			#2			#3	
Dislike	**1,371**	537	410	**1,349**	600	429	**1,362**	594	422
Neutral	426	**2,388**	1,058	409	**2,403**	1,060	428	**2,375**	1,069
Like	201	680	**2,860**	201	675	**2,865**	196	695	**2,850**
		#4			#5				
Dislike	**1,363**	593	422	**1,363**	588	427			
Neutral	427	**2,378**	1,067	428	**2,372**	1,072			
Like	215	665	**2,861**	200	696	**2,845**			

Table 7 The performance of the sentiment classification model by the method 2

Class	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall
		#1			#2			#3	
Dislike		69%	58%		69%	57%		69%	57%
Neutral	66%	65%	62%	66%	65%	62%	66%	65%	61%
Like		66%	76%		66%	77%		66%	76%
		#4			#5			**Average values**	
Dislike		68%	57%		69%	57%		69%	57%
Neutral	66%	65%	61%	66%	65%	61%	66%	65%	62%
Like		66%	76%		65%	76%		65%	76%

Table 8 The confusion matrix result of determining message sentiments by the method 3

Actual Class	Predicted Class			Predicted Class			Predicted Class		
	Dislike	Neutral	Like	Dislike	Neutral	Like	Dislike	Neutral	Like
		#1			#2			#3	
Dislike	**1,444**	594	340	**1,419**	600	359	**1,427**	606	345
Neutral	456	**2,468**	948	439	**2,474**	959	465	**2,438**	969
Like	223	664	**2,854**	224	674	**2,843**	219	705	**2,817**
		#4			#5				
Dislike	**1,428**	587	363	**1,424**	590	364			
Neutral	447	**2,468**	957	457	**2,436**	979			
Like	220	696	**2,825**	220	688	**2,833**			

Table 9 The performance of the sentiment classification model by the method 3

Class	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall
	#1			#2			#3		
Dislike		68%	61%		68%	60%		68%	60%
Neutral	68%	66%	64%	67%	66%	64%	67%	65%	63%
Like		69%	76%		68%	76%		68%	75%
	#4			#5			Average values		
Dislike		68%	60%		68%	60%		68%	60%
Neutral	67%	66%	64%	67%	66%	63%	67%	66%	63%
Like		68%	76%		68%	76%		68%	76%

According to Table 5, Table 7, and Table 9, the comparison in the performance of the sentiment analysis using the method 1, the method 2 (in the average values), and the method 3 (in the average values) are shown in Table 10.

Table 10 The performance comparison among three methods

Methods	Accuracy	Precision			Recall		
		Dislike	Neutral	Like	Dislike	Neutral	Like
1	58%	52%	55%	66%	40%	66%	61%
2	66%	69%	65%	66%	57%	62%	76%
3	67%	68%	66%	68%	60%	63%	76%

Discussion

Referring to Table 10, it is no wonder that the performance of matching sentiment words in tweets to the polarity lexicons of the method 1 is lowest, while the method 2 and the method 3 seem to achieve similar evaluation results in terms of sentiment classification performance. However, all evaluation values of the method 3 are higher than or equal those of the method 2. Consequently, our sentiment analysis application is implemented using the method. The examples of user interfaces in Thai for the application are shown in Figure 6 and Figure 7.

The experimental results found that the Naïve Bayes with the features encoding of all unique words in the method 2 can categorize the sentiments of tweets more accurately than the matched words by the polarity lexicons in the method 1. Moreover, the efficiency of the sentiment classification can be improved by adding the features from the sentiment words with the polarity lexicons to the Naïve Bayes like in the method 3. Furthermore, the lowest number of negative messages in the experimental data may cause the lowest evaluation rate in the recall values of dislike messages. Therefore, the basic ML, such as the Naïve Bayes approach with the appropriate features like word information and word patterns can build the computerized application to analyze the sentiments of tweets about Thai dramas. In addition, the performance of this application is acceptable with the accuracy and the precision around 70%.

Figure 6 The main page

Figure 7 The output page

Nevertheless, almost evaluation values are less than 70%, except the recall values of the messages in like class by the method 2 and the method 3. One important reason is the limitation of Thai word segmentation because there is no word boundary clearly like the space in English language. The errors of automatically segmented words can lead to the error of the computerized vocabulary list creation (the bag of words), including the polarity lexicons. Another reason is the variety of vocabularies in text messages because languages can be changed over time. In addition, some words can be contained implicit meaning, including slang words and a sarcasm. Therefore, it is still a challenge to build the text processing system on the diversity of words. The last reason is these feature sets for training the sentiment classification model not including the sequence of words in the message with the result that some relating information to intention may be lost.

Conclusion and Suggestions

This research tried to implement the Thai text analysis application for expressing opinions about Thai dramas. This application can be used to make decisions on how to watch a drama easily and quickly. The results of message analysis are classified Thai comments as dislike, neutral, and like groups. The development application is implemented by Python language with the PyThaiNLP library to segment the message into words. Moreover, the sentiment classification model is generated using the ML tool (Scikit-learn) with the multinomial Naïve Bayes library. The performance testing of the sentiment analysis application found that the accuracy and the precision rates are approximate 70%, which is adequate for classifying the sentiments of tweets in practice.

In the future work, the efficiency of sentiment analysis for Thai messages can be improved by ensuring the accuracy of the Thai word segmentation in the preprocessing, with the words and their polarity meaning in this specific domain, and test on other feature sets or other ML techniques, such as SVMs. The more information about Thai language, especially the sequence of words and word co-occurrences will be included in the feature sets to train the sentiment classification model. Additionally, more experiments with different data domains will be conducted to compare the results, and to improve the performance of Thai sentiment analysis application in various domains.

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