

# Lyric-based Sentiment Polarity Classification of Thai Songs

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**Abstract**—Song sentiment polarity provides outlook of a song. It can be used in automatic music recommendation system. Sentiment polarity classification based solely on lyrics is challenging. It involves understanding linguistic knowledge, song characteristics and emotional interpretation of words. Since lyric is in a form of text. Techniques used in text mining, text sentiment analysis and music mood classification are studied and used together in our proposed model. Two types of classifier are proposed—lexicon-based classifier and machine learning-based classifier. N-gram model is used in feature set generation. Features are filtered by Information Gain. Feature weighting scheme is employed. We create a sentiment lexicon from Thai song corpus. Full lyric and certain parts of lyric are chosen for datasets. We evaluate our models under various environments. The best average accuracy achieved is 68%.

**Index Terms**—sentiment polarity analysis, music mood classification, Thai songs, lyric, neural network

## I. INTRODUCTION

MUSIC is a sound of instruments or vocal. Everyone knows by heart that music is part of human life. Human are touched by music despite the difference in races, religions, cultures or ages. Music is so powerful. Music can bond people together. Music can uplift emotion. Music can inspire creativity. Music can motivate you to work harder. Music can reduce stress. Music can enhance the atmosphere of movie scenes. Music can make plants grow faster. Music can make cows produce more milk. There are many other ways that music affects life of human being and that of other living things on this earth.

Communication of emotions exists in music. Emotions expressed by music player are recognized by music listener. There exists information inherent in music that leads to certain types of emotional response. Machine learning approaches are commonly employed to tackle music mood classification problem. Features representing music mood are generated by extracting emotional information inherent in the music. Music mood features are found to be closely

related to audio and text components of the music. There are many ways to categorize music moods. At the simplest level, music moods are grouped into two groups—“happy” and “sad”. “Happy” music makes a party more fun. “Happy” music cheers us up when we are feeling down. “Sad” music can regulate emotion of emotionally unstable people.

Songs are pieces of music that contain words (lyrics). Lyrics are text and text is meaningful. Text carries lots of information. Good old text mining techniques that analyze natural language text in order to extract interesting lexical and linguistic patterns can be applied on lyrics to discover the underlying mood of the song.

Sentiment analysis or opinion mining is a process to find the overall contextual polarity of a document. It is usually performed on reviews or social media comments to determine the tone of opinion people have toward a certain thing. Similar to opinions, music moods are highly subjective. We have looked into sentiment analysis workarounds and adapted them to our song sentiment polarity classifier.

This paper proposes lyric-based sentiment polarity classifiers for Thai songs. We studied characteristics of Thai written language with respect to songs. Music Information Retrieval (MIR), text mining and sentiment analysis techniques were put together to determine sentiment polarity of songs. Lyric can be treated as a document. Therefore, one way to determine sentiment polarity of a song is to find sentiment polarity of its lyric. Positive lyric simply implies “happy” song and negative lyric implies “sad” song. Lexicon-based classifiers and machine learning-based classifiers were evaluated under different environments.

The rest of the paper is organized as follows. Related work is discussed in Section II. Section III talks about song and lyric. Lexicon-based and machine learning-based classification approaches are explained in Sections IV. Section V is about experiments. Experiment environment, corpus, dataset, evaluation measure and results are discussed in this section. Section VI concludes the paper.

## II. RELATED WORK

### A. Music Mood Classification

Common approach in music mood classification is based on an analysis of audio content. Music acoustic features such as tempo, loudness, timbre and rhythm are extracted. These features represent mood conveyed by music.

The second music mood classification approach is based on features derived from contextual text information such as

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lyrics, song metadata and social tags.

Another mood classification approach is bi-modal or hybrid. Audio and text features are used together in the classification process.

Hu has done an extensive piece of work on music mood classification in [1]. Lyrics, audio and social tags were taken into account. Many types and combination of features were explored.

Research in music mood classification has been expanded to non-English languages. Dewi and Harjoko used rhythm pattern to determine moods of Indonesian and English kid's songs [2]. Chinese songs were classified using lyric features described by word frequency and rhyme [3]. Boonmatham, Pongpinigpinyo and Soonklang studied musical-scale characteristics and brought them to classify genre of traditional Thai music [4]. Patra, Das and Bandyopadhyay employed sentiment lexicons and text stylistic features of lyrics in Hindi song classification [5]. Text and audio features were used in sentiment identification of Telugu songs [6]. Not much work has been done on sentiment classification of Thai music.

### B. Sentiment Analysis

Normally, a binary opposition in opinions is assumed in sentiment analysis.

Lexicon-based sentiment analysis usually involves counting number of positive and negative words in documents with respect to the chosen lexicon. Features are generated from these counts together with other attributes such as part-of-speech tag and emotion level. Machine learning classification algorithm is then employed to give labels to documents.

OpinionFinder([http://mpqa.cs.pitt.edu/lexicons/subj\\_lexicon](http://mpqa.cs.pitt.edu/lexicons/subj_lexicon)) provides subjectivity lexicon introduced in [7]. The lexicon contains approximately 1,600 positive words and 1,200 negative words compiled from several sources. It is a generic subjectivity lexicon. It has been widely used in document sentiment analysis research field.

Reference [8] performed sentiment analysis on Twitter messages in order to find relationship between Twitter sentiment and public poll opinion. They referred to OpinionFinder's subjectivity lexicon. They pointed out that generic subjectivity lexicon did not give satisfying results. This could be because subjectivity clues were used differently in Twitter messages when compared to the corpus those clues were generated from. Therefore, corpus specific lexicon was recommended. Reference [9] proposed a sentiment vector space model (s-VSM) for sentiment classification of Chinese pop songs. HowNet (<http://keenage.com/>) sentiment lexicon was adopted. Features were generated from sentiment units found in lyrics. Each sentiment unit consisted of one sentiment word, one modifier (if present) and one negation (if present). Modifier, negation and sentiment word itself indicated sentiment of the sentiment unit that they belonged to. SVM-light was used to assign labels. They found that s-VMS-based method outperformed VMS-based method in F-1 score. Sentiment lexicon helped achieve better results. Fang and Zhan analyzed sentiment polarity of a huge product review dataset collected from Amazon.com [10]. Sentiment

words came from the work that adopted WordNet lexicon (<https://wordnet.princeton.edu/>). Analysis was performed at sentence level and review level. Negative prefixes such as "not", "no" and "don't" were brought into consideration. Naïve Bayesian, Random Forest, and Support Vector Machine classifiers were used in experiments. Chattupan and Netisopakul performed sentiment analysis on Thai stock news [11]. They proposed wordpair feature extraction technique. A wordpair was a pair of keyword and polarity word. Each wordpair also had a sentiment associated with it. They proposed three variations of wordpair set. Wordpairs were extracted from stock news and fed into SVM and Decision tree classifiers.

### C. Thai Natural Language Processing

Natural language processing (NLP) and information extraction (IE) are fundamental to text mining. Thai language, in particular, has certain specific characteristics that challenge NLP and IE tasks. It is common in NLP application that input text is tokenized into individual terms or words before being processed further. This is a very important step as final result very much depends on segmentation quality. Word segmentation or term tokenization is difficult in languages that do not have explicit word boundaries. Words are written continuously without delimiters. Asian written languages such as Chinese, Japanese and Thai are unsegmented languages.

History of Thai language development for computers was explained in [12]. Key issues in Thai NLP were discussed there as well.

A wide variety of segmentation techniques was studied and many segmentation programs were developed for Thai written language. Recent study involved performance evaluation and comparison of six Thai word segmentation programs (Libthai, Swath, Wordcut, CRF++, Thaisemantics, and Tlexs) [13]. Conditional Random Field (CRF) based programs yielded better f-measure values.

N-gram based indexing approach is used widely in Information Retrieval (IR) and NLP of many Asian languages. N-gram approach pays attention to probability of a word, conditioned on some number of previous words. It does not require linguistic knowledge of the language. Aroonmanakun used trigram statistics in syllable segmentation [14]. Syllables were merged together to form a word. The merging was done according to collocation strength between them.

## III. SONG AND LYRIC

### A. Song Structures

There are many song structure schemes, including AAA, AABA, Verse/Chorus, and Verse/Chorus/Bridge. Parts of a song are explained below. Please note that only general explanation is given here. There exists detailed explanation that is specific to song structure scheme.

- Title: Title goes with theme of a song. Title usually appears in lyric as well.
- Verse: Verse is part of song that tells story.
- Refrain: Refrain is a line that is repeated at the end of

every verse. Song title sometimes appears in the refrain.

- Chorus: Chorus expresses the main theme of the song. Chorus is repeated several times. Chorus may contain song title. Chorus is longer than refrain. Chorus is the climax of the song.
- Pre-chorus: Pre-chorus connects verse to chorus.
- Bridge: Bridge can be referred to as a transition. Bridge contrasts with the verse.
- Coda: Coda or tail is the additional line to end the song. The coda is optional.

Verse and chorus are main parts of a song. There is a high chance that theme of a song lies in these two parts. With this observation, we also try to focus only on the verse and chorus parts of song.

### B. Characteristics of a Lyric

Lyric is similar to poem in a way that they both contain words that rhyme. The meaning and message found in lyrics are pretty straightforward. Listener can understand what the song is all about right away. Not much thought and analysis is needed. Lyric almost always contains repeated words emphasizing the message the song conveys. Number of words in a song is between 100 and 300. This is longer than most social comments, but shorter than some product reviews. Lyric contains limited set of words, much smaller set than that of other text documents in general. There are many other ways that lyric differ from other text documents.

Generic lexicon for text analysis or sentiment analysis that is used for other type of text documents may not be appropriate for lyric analysis.

### C. Lyric Features

According to [1], lyric features are categorized into three classes: text features, linguistic features and text stylistic features. We focus only on text features of lyric.

Thai words are not modified for tenses, plurals, genders, or subject-verb agreement. We do not consider these issues. Being able to extract words from songs should be enough for our classification models.

In data preprocessing step, lyric is converted into feature space using n-grams (unigrams, bigrams and trigrams). Unigrams are generated by “PyThaiNLP”. PyThaiNLP is a Python NLP package for Thai language. The package is available at <https://github.com/wannaphongcom/pythainlp>. We use PyThaiNLP to perform word segmentation on lyric turning lyric into a sequence of unigrams. Bigram and trigram terms are generated and added to the feature space. Next, stopwords are removed from the space. List of Thai generic stopwords is obtained from <http://www.ranks.nl/stopwords/thai-stopwords>. There are 114 stopwords in the list. Lastly, terms that occur only one time in feature space are discarded.

Our base lyric feature set is composed of terms that are unigrams, bigrams and trigrams, with stopwords removed.

Information Gain ( $IG$ ) is the expected entropy reduced by knowing the presence or the absence of a feature in the document. We use  $IG$  to filter out less significant features from the feature space. Given a base lyric feature set,  $IG$  is

calculated for each term in the set. Mean of  $IG$  values ( $\overline{IG}$ ) is then computed and used as feature selection threshold. Terms having  $IG$  less than  $\overline{IG}$  are removed from the feature set. This results in a reduced lyric feature set containing only unigrams, bigrams and trigrams that give  $IG$  more than  $\overline{IG}$ .

## IV. CLASSIFICATION APPROACHES

### A. Lexicon-based Classification Approach

#### Sentiment Lexicon for Thai Songs

We create our own sentiment lexicon. Our sentiment lexicon is composed of two sentiment polarity lists—happy list and sad list. These lists are corpus specific. They are generated from terms in lyric feature set. These terms are extracted from lyrics in training dataset according to the preprocessing process described in section III. For each term, probabilities that it appears in happy songs and sad songs are calculated and compared. Happy list contains terms that are found more often in happy songs. Sample terms in happy list include “ฉันโชคดี (I’m lucky)”, “โอบกอดกัน (let’s hold each other)”, “ลงตัว (perfect)”, “สุขสม (be happy)” and “ดีใจที่เจอ (happy to see you)”. Sad list contains terms that appear more frequently in sad songs. Sample terms in sad list include “ต้องลาแล้ว (have to leave)”, “มันเจ็บเกิน (it hurts very badly)”, “อาลัย (mournful)”, “มันยังเจ็บ (I still hurt)” and “โง่ (stupid)”. Each term in the lyric feature set is added to one polarity list only. In the case where the probabilities of a term being in happy songs and sad songs are equal, such term is ignored as it does not express strong feeling towards any polarity under consideration.

#### Song Sentiment Polarity Classification

Sentiment polarity of a song can be viewed as overall sentiment polarity of words in its lyric. We use the sentiment lexicon introduced earlier in this section to give sentiment polarity score to song lyric.

First step is to extract features of the song in question. Song lyric is turned into lyric feature set in this step. Then, loop through all terms in the lyric feature set checking against the two sentiment polarity lists in the lexicon. The goal of this step is to determine polarity score of every term in the lyric feature set. Polarity score of term  $i$  ( $X_i$ ) is assigned according to the following equation.

$$X_i = \begin{cases} -1, & \text{when term } i \text{ appears in sad list} \\ 0, & \text{when term } i \text{ does not appear in the lexicon} \\ 1, & \text{when term } i \text{ appears in happy list} \end{cases}$$

We assume two situations. The first one is when all terms are equally important. The other one is when they are not. When terms are not equally important, each term is weighted with its tf-idf (term frequency–inverse document frequency) value.

Polarity scores of all terms in lyric feature set are then averaged (with tf-idf weighting in the second situation). This average score represents polarity of the song. The song is labeled “happy” if its average polarity score is a positive value and “sad”, otherwise.

### B. Machine Learning-based Classification Approach

The machine learning approach adopts text classification technique to classify sentiment polarity of a song from lyric. We choose Neural Network—multi-layer perceptron (MLP) with single hidden layer. Hidden layer activation function is rectified linear unit (ReLU).

Neural network is chosen because polarity labels of songs in the corpus were given out by human. There is a high chance that labelling is subjective and noisy. Neural network tends to deal with this issue well.

Feature weight factor is computed using tf-idf. Feature values are normalized by standard deviation.

Model parameters are obtained by running 5-fold cross validation on the training dataset with various parameter figures. Test dataset is kept separately throughout this process. After we get the appropriate values for parameters, we use them to train the classifier all over again to get the model for the experiments.

## V. EXPERIMENTS

### A. The Corpus

We obtained song lyrics from Chord Cafe website (<http://chordcafe.com/feeling>). Chord Cafe provided chords and lyrics of Thai songs. Songs were organized in 34 groups according to emotion influenced by them. Such groups included “รักแรกพบ (love at first sight)”, “รักเธอตลอดไป (love her forever)”, “เจ็บ (painful)”, “ยิ้มกว้างใจ (cheerful)”, “เหงาจับใจ (so lonely)” and “อกหักเศร้า (broken-hearted)”. Some songs were found in more than one group.

We gave sentiment polarity label (“สุข (happy)” or “เศร้า (sad)”) to each group. From 34 emotion groups, we were down to two polarity groups. Lyrics of songs in “happy” group conveyed positive meaning. They expressed happiness, success, fun, good times, good relationships etc. “Happy” songs could elevate emotion of listeners. On the other hand, “sad” songs had melancholy lyrics. They were about sorrow, loss or disappointment. Songs appearing in both groups were dropped as they did not express strong meaning toward either “happy” or “sad”. We ended up with 427 unique “happy” songs and 317 unique “sad” songs.

Verse and chorus are main parts of a song. Song theme usually lies in these two parts. With this observation, we created two experiment datasets from the corpus. The first dataset contained full song lyrics together with sentiment polarity labels. The second dataset incorporated only the verse and chorus parts of songs and song sentiment polarity labels.

### B. Experiment Landscape

There were twelve experiment sets. Experiment environment is described in Table II.

Eight experiment sets were lexicon-based. Four experiment sets were machine learning-based.

Each experiment set ran against five collections of datasets. Dataset was split into training set (70%) and test set (30%). The split was random and balance. Proportion of happy songs and sad songs were kept equal in both training and test sets in all collections.

We evaluated performance of classifiers with their accuracies. Accuracy represents the total percentage of songs that correctly classified out of all songs in the test dataset. Accuracies from five collections of datasets were averaged.

For machine learning-based method, 5-fold cross-validation was conducted. Final evaluation result was based on average accuracy of all folds.

TABLE II  
EXPERIMENT LANDSCAPE

Experiment Set	Dataset	Lyric Feature Set	Classification Weighting Scheme*
1. Lexicon F/B/1	Full song	Base set : uni+bi+trigrams	equal
2. Lexicon F/B/TF-IDF	Full lyric	Base set : uni+bi+trigrams	tf-idf
3. Lexicon F/R/1	Full lyric	Reduced set : uni+bi+trigrams, $IG > \overline{IG}$	equal
4. Lexicon F/R/TF-IDF	Full lyric	Reduced set : uni+bi+trigrams, $IG > \overline{IG}$	tf-idf
5. ML F/B	Full lyric	Base set : uni+bi+trigrams	
6. ML F/R	Full lyric	Reduced set : uni+bi+trigrams, $IG > \overline{IG}$	
7. Lexicon VC/B/1	Verse & Chorus	Base set : uni+bi+trigrams	equal
8. Lexicon VC/B/TF-IDF	Verse & Chorus	Base set : uni+bi+trigrams	tf-idf
9. Lexicon VC/R/1	Verse & Chorus	Reduced set : uni+bi+trigrams, $IG > \overline{IG}$	equal
10. Lexicon VC/R/TF-IDF	Verse & Chorus	Reduced set : uni+bi+trigrams, $IG > \overline{IG}$	tf-idf
11. ML VC/B	Verse & Chorus	Base set : uni+bi+trigrams	
12. ML VC/R	Verse & Chorus	Reduced set : uni+bi+trigrams, $IG > \overline{IG}$	

\*Classification weighting scheme was used in lexicon-based experiments

### C. Results

Average accuracies from experiment sets 1-6 where full song lyric dataset was used are shown in Figure 1. Average accuracies were between 0.62 and 0.68. The highest average accuracy was achieved from lexicon-based classifier with tf-idf weighting scheme. Effect of weighting scheme was more noticeable with reduced feature set (experiment sets 3 and 4).

Lexicon-based classifiers outperformed machine learning-based classifiers in most experiment sets. The performance difference was more pronounced when base feature set was used. We can see that base lyric feature set (stripe bars in the figure) gave better performance when compared to reduced lyric feature set (checker bars in the figure).

Lexicon-based classifier + base feature set + tf-idf weighting scheme (experiment set 2) was the best combination when running on full lyric dataset. It gave accuracy of 68%.

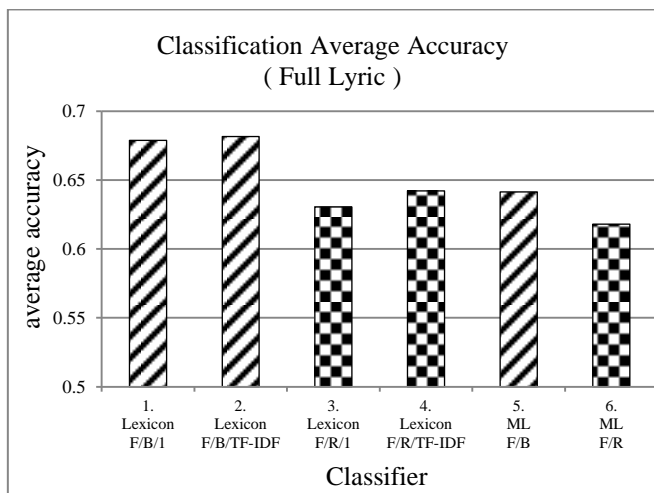


Fig. 1. Average accuracies of Thai song sentiment polarity classifiers with full lyric dataset

Figure 2 shows average accuracies of experiment sets 7-12 where dataset contained only verse and chorus parts of the lyric. Graph shape looks different when compared to that of experiments running on full lyric dataset.

Accuracies dropped quite a bit, as much as 15%, when base feature set was used (experiment sets 1 vs. 7 and 2 vs. 8). However, accuracies increased a little when reduced feature set was employed (experiment sets 9 vs. 3 and 10 vs. 4). Reduced feature set resulted in higher performance on lexicon-based classifiers.

Performance of machine learning-based classifiers did not vary much between two types of dataset (experiment sets 5 vs. 11 and 6 vs. 12). Base feature set yielded better accuracy on both datasets.

Tf-idf weighting scheme resulted in higher accuracy in both base and reduced feature sets.

The best combination when verse and chorus parts of lyric were used was lexicon based-classifier + reduced feature set + tf-idf weighting scheme (experiment set 10). It gave 66% average accuracy.

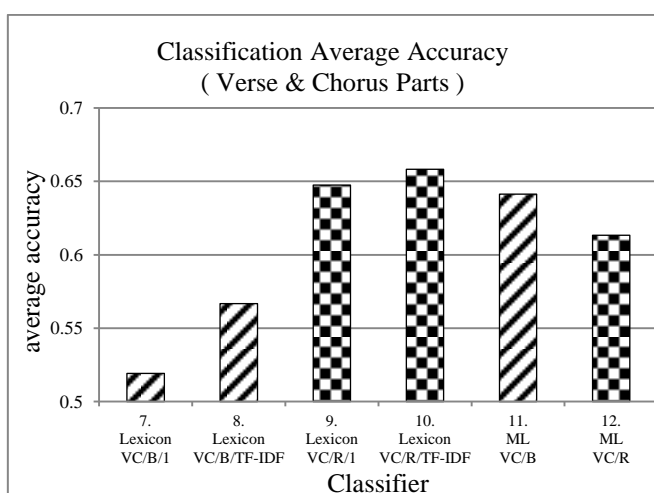


Fig. 2. Average accuracies of Thai song sentiment polarity classifiers with verse and chorus dataset

In summary, the two best combinations performed almost equally well. For lexicon-based classifier, we may opt to go with reduced feature set on smaller dataset (verse and chorus parts) because it requires less resource.

## VI. CONCLUSION

We proposed lexicon-based and machine learning-based classification models to classify sentiment polarity of Thai songs. We looked into Thai language and song structure characteristics. We tried to make use of them in our models. Model configuration differed in feature extraction and feature selection method as well as classification weighing scheme. We also explored an effect of parts of song on classification accuracy. We studied classifier behavior in various experiment environments. We found that feature selection using Information Gain helped improve average accuracy when verse and chorus parts of lyric were considered. Performance of machine learning-based classifiers was stable, independent of lyric parts. The proposed models can help suggest songs for a playlist. They also can help figure out current emotion of the listener.

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