HUMAN EMOTION RECOGNITION IN THAI SHORT TEXT

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ABSTRACT

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Emotion classification is one of the topics in effective computing applicable in various research areas such as speech synthesis, image processing, and especially, text processing. Emotion classification is aimed at identifying a suitable emotion label for each review. In this research, a hierarchical classification framework to identify emotions (objective opinion and anger, disgust, fear, sadness, happiness, and surprise) is proposed for actual customer reviews written in Thai. The hierarchical classification framework consists of three levels: opinion, sentiment, and emotion. First, the opinion level distinguishes customers' reviews into two types, namely objective and subjective opinions. Second, the sentiment level is used to categorize the subjective opinions as either positive or negative. Last, in the emotion level, an emotion label is assigned to an opinion as either anger, disgust, fear, happiness, sadness, or surprise. The proposed method consists of three main processes: (1) text preprocessing, (2) feature extraction, and (3) emotion classification. Text preprocessing provides necessary information and normalization of words in the reviews and comprises word segmentation, part-of-speech (POS) tagging, word replacement, and stop-word elimination. Feature extraction is a process to construct a vector space model (VSM) for opinion classification. Five feature sets for generating the VSM are created by using a corpus- and lexicon-based approach: the term frequency-inverse document frequency (Tf-Idf) of unigram words (TUW), bigram words (TBW), unigram POS (TUP), and bigram POS (TBP), and a Thai sentiment lexicon (TSL). Furthermore, a decision tree, multinomial

naïve Bayes, and a support vector machine (SVM) are used as classifiers in the emotion classification process.

The experimental results show that for the hierarchical approach where the subjectivity of a review is first determined, the polarity of an opinion is identified, and then the emotional label is calculated yielded the highest performance with an accuracy of 69.60%. Overall, TBW was the most effective feature subset used for filtering opinions, determining polarity, and classifying negative emotions. Lexicon resources such as TSL and the POS tag sets in the morphology level improved the accuracy of opinion filtering in two- and three-level hierarchical classification. SVM achieved a high performance in identifying contrasting opinions such as objective versus subjective opinions and positive versus negative sentiment. Meanwhile, multinomial naïve Bayes performed the best when identifying closely related emotions such as happiness versus surprise in positive emotion classification.

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CHAPTER 1

INTRODUCTION

With the immense growth in communication over the Internet, emotion classification on text-based resources (e.g. web-blogs, online newspapers, and social networks) is becoming an interesting and challenging topic. Emotion classification can be applied in various research areas such as speech synthesis (Cowie et al., 2001), image processing (Cohen, Sebe, Garg, Chen, & Huang, 2003; Donato, Bartlett, Hager, Ekman, & Sejnowski, 1999; Mehta, Siddiqui, & javaid, 2018), and especially, text processing (Chirawichitchai, 2014; Inrak & Sinthupinyo, 2010; Strapparava & Mihalcea, 2008). Most customers usually buy products from websites or via mobile applications, and the companies running these hope to receive product feedback when customers buy their products. Customers often write reviews to give feedback on products that are in an unstructured format that is free-form, shortened text in an informal style. The review content is usually an expressed opinion and an emotional response concerning the quality and quantity of a product that the reviewer ordered and used. These emotions can affect the profit and image of a company. If a reviewer writes a positive opinion or expresses a positive emotion toward a product onto a website, there is a tendency to attract more customers. Due to the number of reviews, it can be difficult for readers to identify emotions manually, and so automatic emotion recognition is needed to solve this problem.

1.1 Statement of the Problem

Customers' reviews are usually written in an unstructured format that is free-form, shortened text in an informal style. Due to the number of reviews, it can be difficult for readers to understand of the semantics of the short texts and identify emotions manually. Therefore, an automatic emotion recognition technique as a

challenging research pursuit to solve this problem and thereby help readers to identify feedback from reviews in a short time period.

1.2 Objectives of the Research

The objectives of the study are:

1) To study and analyze sentiment and emotion recognition in Thai short text.

2) To propose a hierarchical classification framework consisting of three levels: opinion, sentiment, and emotion.

3) To compare the effectiveness of opinion classification with opinion filtering and without opinion filtering in each level.

1.3 Scope of the Study

The case study in this research uses reviews on cosmetics by customers to construct data sets from three websites. Each review is labeled by three levels of opinion mining: opinion, sentiment, and emotion.

1.4 Organization of this Dissertation

The rest of this dissertation is organized as follows. Chapter 2 provides a literature review as background for this study, and Chapter 3 presents the three approaches in the hierarchical emotion classification framework. Chapter 4 consists of the experimental results and an evaluation of each approach, and finally, Chapter 5 provides conclusions and future work based on this study.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

Opinion classification with opinion filtering and with opinion filtering in three hierarchical levels is proposed in this dissertation. Background on this concept in the form of related work is covered in this chapter.

2.1 Definition of Opinion Mining

The definition of opinion mining by Bing Lui (Lui, 2012) is as follows, “Sentiment analysis, also called opinion mining, is the field of study that analyzes people’s opinions, sentiment, evaluations, appraisals, attitudes, and emotions toward entities such as products, services, organizations, individuals, issues, events, topics, and their attributes.” From an overview of opinion mining, the subjective analysis research area has two main tasks consisting of sentiment classification and opinion summarization (Somjin Phiakoksong, 2015). Sentiment classification is divided into two tasks:

1) Distinguishing between subjective and objective opinions. The identification of a subjective opinion expressed by a reviewer is classified as positive or negative sentiment and an objective review as an expression of factual information with no opinion and neutral emotion.

2) Opinion classification comprises two subtasks. The first one (binary class) classifies sentiment as positive or negative, while the second classifies opinions with a number of labels: positive, negative, neutral, or objective (multi-class).

Research on opinion summarization comprises an aggregation task which applies an opinion aggregation function to calculate sentiment scores to define the final orientation of the opinion. The aggregation task has three subtasks: text summarization,

visualization, and overall feature score. A diagram of the subjective analysis research area is shown in Figure 2.1.

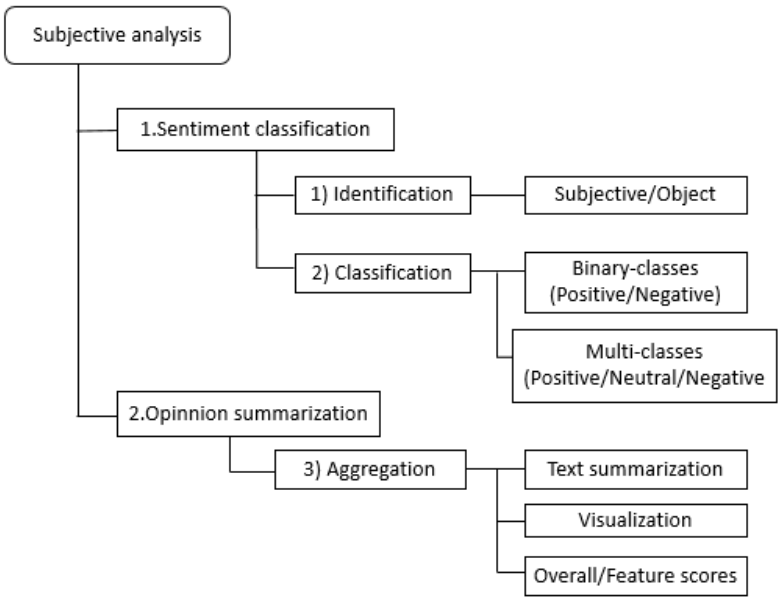

Figure 2.1 The subjective analysis research area

Source: Somjin Phiakoksong, 2015, p. 49.

2.2 Definition of Emotion

The definition of emotion following WordNet Search-3.1 ("Emotion," 2018) online is "any strong feeling" and Binali, Wu, and Potdar (2010) defined emotion as, "Emotions are part and parcel of human life and among other things, highly influence decision-making." Many researchers have classified types of emotion with various labels. There are six basic emotions in Paul Ekman's (1992) work based on facial expressions from many human cultures: anger, disgust, fear, sadness, happiness, and surprise. Later, Breazeal (2003) presented nine faces that a human observer perceives for the facial expressions of sociable humanoid robots (neutral, happiness, elated, surprise, afraid, frustrated, sad, sleepy, and relaxed) in four dimensions consisting of arousal, pleasure, displeasure, and sleep, as shown in Figure 2.2. Arousal signifies how arousing an experience is to the emotional system. Positive values matched to high

arousal motivate whereas negative values matched to low arousal demotivate. The valence tag represents how favorable or unfavorable an emotional experience is. Positive values match with pleasant motivation whereas negative values match with unpleasant motivation.

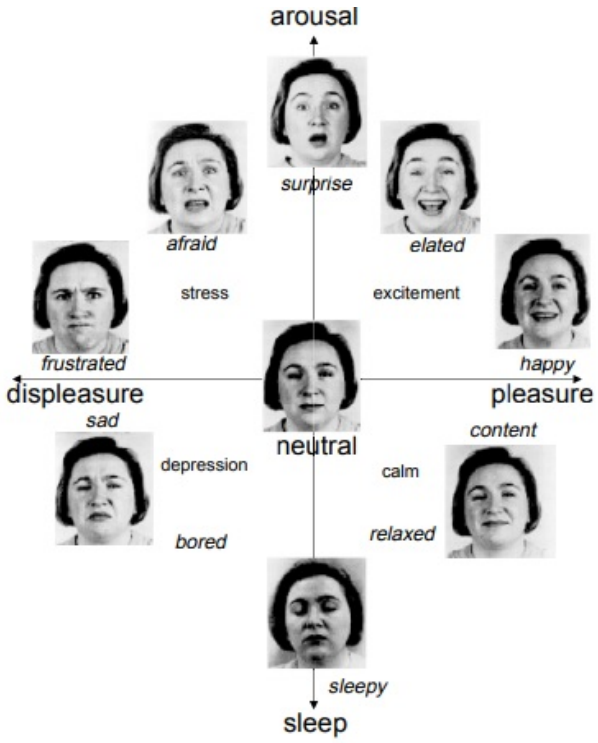

Figure 2.2 Russell's pleasure-arousal space for facial expression

Source: Breazeal, 2003, p. 8; Adapted from Russell, 1997.

Furthermore, Breazeal (2003) and Gunes and Pantic (2010) proposed polarity in an Arousal-Valence (A-V) graph based on Ekman's emotion labels, as shown in Figure 2.3. The X-axis represents valence by mapping a scale of pleasant versus unpleasant or positive versus negative sentiment and the Y-axis represents arousal by mapping a scale of relaxed vs. aroused. The positive emotions are happiness and surprise and the negative ones are anger, disgust, fear, and sadness. This emotional classification system was adopted in the present research.

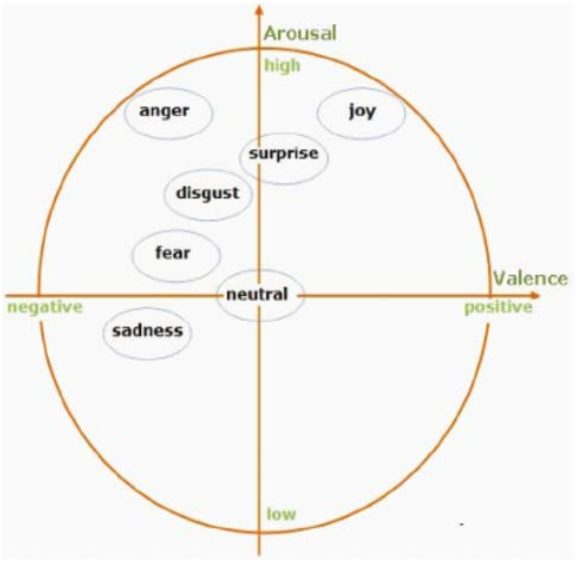

Figure 2.3 Arousal-Valence (A-V) polarity of emotion labels

Source: Gunes and Pantic, 2010, p. 3.

2.3 Emotion Classification

Emotion classification of text is aimed at identifying a suitable emotion label for textual data in many levels such as phrase, sentence, paragraph, and document. Strapparava and Mihalcea (2008) proposed knowledge and corpus-based approach by using emotional keywords and lexical words to identify emotion labels from news headlines including New York Times, CNN, and BBC. Although, prior knowledge is an efficient indicator for classification but some knowledge contains ambiguity; ambiguity emotion words or phrases. Thus, this approach cannot classify text without emotional keywords or lexical words; as a result, there are some significant problems of emotion recognition. The second approach is Machine learning. The researchers proposed the set of features to identify correct emotion label on text with emotional keywords and without emotional keywords. The example of feature sets are bag of words which are generated as n-gram (Ghazi, Inkpen, & Szpakowicx, 2010), emotional words; “displeased” is anger label , “afraid” is fear label, “cheerful” is joy label, and “amaze” is surprise label (Strapparava & Mihalcea, 2008), term frequency and inverse document frequency (tf-idf), score weight (Burget, Karasek, & Smekal, 2011), and part

of speech (pos) such as noun, verb and adverb (Inrak & Sinthupinyo, 2010). Then, these features sets were evaluated by using various algorithms such as Support Vector Machines (SVM) (Burget et.al., 2011; Ghazi et al., 2010), Naïve bayes (Inrak & Sinthupinyo, 2010; Strapparava & Mihalcea, 2008) Decision Tree (Burget et.al., 2011; Inrak & Sinthupinyo, 2010) and Linear regression (Burget et.al., 2011). Last, Hybrid approach combines between two approaches or one of approaches integrate with the algorithm such as graph, heap, and tree to classify emotion categories. For example, Seol, Kim, & Kim, (2008) purposed Hybrid approach combine between Keyword-based and Machine learning approaches based on knowledge-based Artificial Neural Network (KBANN) classifier. Their system separated input into 2 sets with the presence of emotional word in each sentence and classified eight emotions including anger, fear, sadness, love, happiness, hope, thanks and neutral. If sentence have the presence of emotional word, they solved emotion recognition with knowledge-based approach. To performed knowledge-based approach, they construct EKD; Emotional Keyword Dictionary; and matching module for identifying emotion label. And, for input text that does not have the presence of emotional word, this system applied KBANN as classifier which combined emotion ontology and emotion rules to recognize a emotion label with highest score.

However, the previous proposed a flat emotion classification that yielded low accuracy especially informal text, text without emotional keywords or short text. Thus, Ghazi et al. (2010) proposed a compassion of effectiveness between the hierarchical and flat classification in fairy tales and news headlines data set in English language. This research classified five emotion labels with three hierarchical levels by using Support Vector Machine algorithm. Three hierarchical level classification included level-1 (objective versus subjective opinion), level 2 (positive versus negative sentiment), and level 3 (anger, disgust, fear, sadness, happy). The feature sets were unigram word, polarity set that applied polarity lexicon from Wordnet affect lexicon and Roget's Thesaurus. Their experimental results showed that three hierarchical level classification have higher effectiveness than flat classification. Later, Esmin, de Oliveria, and Matwin (2012) also proposed a hierarchical emotion classification in Twitter on Brazilian language. This research used emoticon lists and part of speech tagging as feature sets and applied Support Vector Machine and Naïve Bayes

algorithms to recognize five emotions with three hierarchical levels. Level 1 identified objective versus subjective opinion label. Level 2 identified positive versus negative sentiment. Last, Level 3 identified five emotion labels including anger, disgust, fear, sadness, surprise. The precision of all emotion labels in hierarchical classification outperforms than flat classification. Xu, Yang, & Wang, (2015) also proposed a hierarchical emotion classification on Chinese micro-blog posts from Sina Weibo randomly. Feature sets of classification composed emoticon lists and part of speech tagging. They classified a five-level hierarchy with fined-grained 19 emotion labels following Figure 2.3. The results showed that the employing hierarchical classification can improve the performance than flat classification.

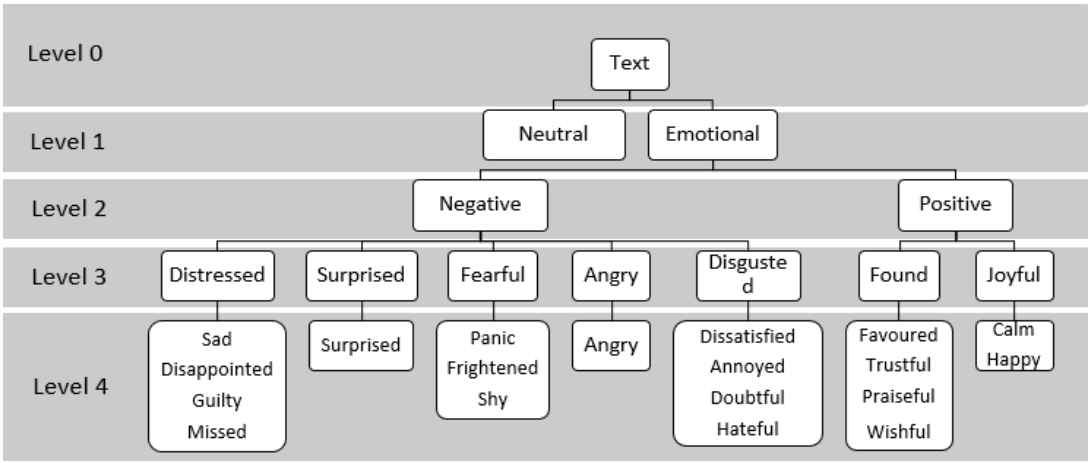

Figure 2.4 Four-level hierarchy classification

Source: Adapted from Xu, Yang and Wang, 2015, p. 3.

Most emotion classification researches are proposed for English and Western languages. However, these researches cannot be directly applied to Thai language. Thai texts are written in continuous words, without space, punctuation marks, full stop (“.”), comma (“,”) or semicolon (“;”), to identify boundaries of words and sentences. Haruechaiyasak, Kongthon, Palingoon and Trakultaweekoon (2013) proposed the S-Sense framework for three Thai social media sources to identify four different intentions (i.e., announcement, request, question and sentiment) and two sentiments (i.e., positive and negative). The example of annotated texts in each label as shown in

Figure 2.4. The experiments compared the performance between two different lexicon sets including general and clue lexicons. General lexicons consisted of LEXiTRON (Thai-English electronic dictionary) and Thai Twitter corpus. And, clue lexicons included terms or phrases that could help identify intention and sentiment label. This research applied the Multinomial Naive Bayes algorithm as classification model. The experimental results showed that the combining of both general and clue lexicon as feature vectors yielded the highest accuracy.

Intention		Example
Announcement		อัตราค่าบริการ Happy Bonus ปรับปรุงใหม่จ๊ะ เริ่มใช้วันที่ 1 ค่ะ The new service fee for Happy Bonus will start on the 1st of this month.
		โปรใหม่!! ทรูมูฟ... ซิมสุดคุ้ม โปรวินาทีละ 1 ส.ค. ตลอด 24 ชั่วโมง New promotion!! True Move... Best-deal SIM, 1 satang / second all day and night.
Request		สมัครใช้บริการ Call Screening เองไม่ได้ CC ช่วยด้วยครับ I can't apply for Call Screening myself. CC (Call Center), please help me.
		รบกวนCC AISหน่อยค่ะ..เงินในโทรศัพท์หายไปไหนไม่รู้ (- -)?? AIS Call Center, please.. My pre-paid balance has gone missing without a clue ??
Question		โทรศัพท์หาย จะทำซิมใหม่เบอร์เดิมของ ais ต้องใช้เอกสารอะไรบ้างครับ I lost my phone. To get a new SIM card, what documents are required?
		โปรไหนของ one-2-call ที่รอรับสายได้นานสุดครับ Which promotion package of one-2-call allows the longest call waiting time?
Sentiment	Negative	น่ารำคาญมาก DTAC เมื่อไหร่จะปรับปรุงสัญญาณสักที โดยเฉพาะบนBTS Very annoyed. DTAC, when will you improve the signal? Especially on the BTS.
	Positive	ขอบคุณและชื่นชม เจ้าหน้าที่ AIS serenade call center ประทับใจครับ Thank you to the operator at AIS serenade call center. Very impressive.

Figure 2.5 Example of annotated texts categorized by intentions and sentiments

Source: Haruechaiyasak, Kongthon, Palingoon and Trakultaweekoon, 2013, p. 6.

Nivet Chirawichitchai (2014) proposed a flat classification in Thai social networks by using corpus-based approach. This research classified six emotion labels (i.e., anger, fear, joy, love, sadness, and surprise) using Boolean, term frequency and tf-idf weights as feature sets and applied Support Vector Machine, Naïve Bayes, Decision Tree and K-nearest Neighbor algorithm as classifiers. The experimental

results showed that Boolean weighting and Support Vector Machine that combined with information gain as feature selection by using Boolean weight as feature set yielded the best performance.

Todsanai Chumwatana (2015) proposed sentiment classification from Thai customer's reviews on social media and websites. This research extracted emotional words from text and assigned each word with sentiment score ("+1" for a positive word, "0" for a neutral word and "-1" for a negative word). The sentiment score is calculated by summing those word scores. The results show that emotional word is important feature that can identify sentiment label for Thai customer's reviews.

THAI TEXT	CLASS
โง่เง่าเบาปัญญาสิ้นดี	ANGER
ขอบคุณที่เอามาแชร์ครับน่ากลัวมากๆจริงๆ แท็กชื่อสมัยนี้	FEAR
ดูคลิปนี้มาหลายปีล่ะ ก็ยังขำเหมือนเดิม 55	JOY
ชอบป๋ามากๆแก่แล้วแต่ยังมีเสน่ห์เหลือล้น	LOVE
บอกได้คำเดียวรับไม่ได้ ดูไม่ได้ น่าสงสารมากๆ	SADNESS
โครตเจ๋งอ่ะมีเพลงด้วยหรอว่ะเดี๋ยวนี้	SURPRISE

Figure 2.6 Example of Thai customer's reviews data set

Source: Chirawichitchai, 2014, p. 3.

Previous researches on Thai opinion classification have suggested that an effective feature set can be constructed from corpus-based and lexicon approaches. This research proposes a hierarchical framework to identify emotions (i.e. objective, anger, disgust, fear, sadness, happiness and surprise) for actual customer reviews written in the Thai language.

CHAPTER 3

METHODOLOGY

This research proposes a Hierarchy classification framework consists of three levels: opinion level, sentiment level and emotion level. First, the opinion level distinguishes customers' reviews into two types which are objective and subjective opinions (Lui, 2012) . An objective or neutral emotion expresses factual information or no opinion. A subjective opinion expresses a reviewer's opinion which can be classified into positive or negative sentiment. The second level is the sentiment level which categorizes a subjective opinion into positive or negative type (Lee, Jeong, & Lee, 2008). The emotion level then assigns an emotion label to an opinion.

There are six basic emotions based on Paul Ekman (1992) that are used for facial expressions in all human traditions. These emotions are anger, disgust, fear, sadness, happiness and surprise. Furthermore, Breazeal in 2003 proposed the polarity in Arousal-Valance (A-V) graph space based on Ekman's emotion. Axis X represents valence by mapping scale of pleasant versus unpleasant or positive versus negative sentiment, and axis Y represents arousal by mapping scale of relaxed vs. aroused. The positive emotions include happiness and surprise, and the negative emotions include anger, disgust, fear, and sadness. The emotion classification in this research is thus organized accordingly.

The objective of this research is opinion classification with opinion filtering and with opinion filtering in a hierarchical framework via a comparison of the accuracy of opinion classification. The proposed method consists of three main processes: (1) text preprocessing (2) feature extraction, and (3) emotion classification. Text preprocessing provides necessary information and normalization of words in the reviews, while feature extraction generates a set of features by using corpora and lexicons. Emotion classification then applies a classification algorithm to the extracted features to identify

the emotion label. The three approaches for emotion classification used in this study are shown in Figure 3.1.

Approach 1 uses emotion classification to identify seven labels of opinion analysis consisting of objective opinion and six human emotions following Paul Ekman's classification system. Approach 2 is a two-level structure comprising opinion filtering and emotion classification. Opinion filtering determines whether a review contains a subjective opinion by the reviewer while emotion classification classifies the emotion of the opinion identified in the previous step with one of six emotion labels: anger, disgust, fear, sadness, happiness, and surprise. Approach 3 contains three levels, namely opinion filtering, sentiment filtering, and positive and negative emotion classification. The difference from Approach 2 is that after opinion filtering, instead of classifying emotion directly, each opinion is classified first as either positive or negative, after which each positive opinion is labeled with a positive emotion and each negative opinion with a negative one.

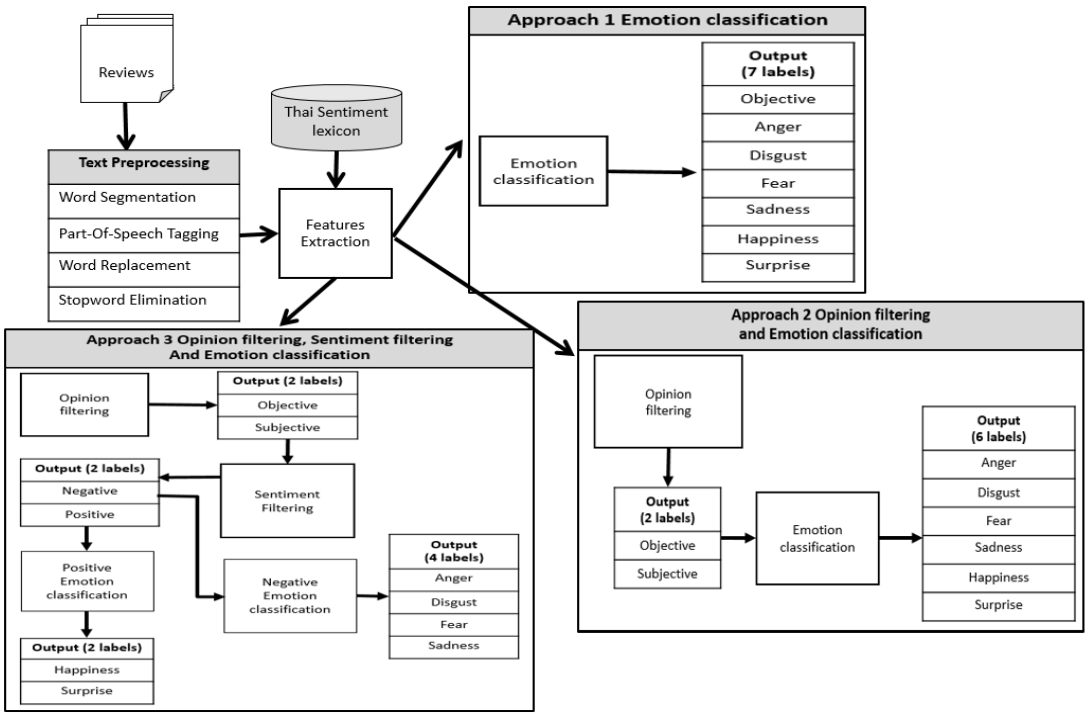

Figure 3.1 The three approaches for the emotion classification framework

3.1 Text Preprocessing

Preprocessing includes word segmentation, part-of-speech (POS) tagging, word replacement and stopword elimination. Examples of the preprocessing steps are shown in Table 3.5.

3.1.1 Word Segmentation

Unlike English, Thai has distinctive syntactical and semantic characteristics. The language has no specific punctuation symbols (e.g. '.', '?', ';') to identify the end of a sentence or clause. Furthermore, there are no spaces to separate the boundaries between words. Especially, this research focuses on customers' reviews usually written in an unstructured format that is free-form with an informal style. Accordingly, identifying the boundaries of each word becomes a non-trivial problem when analyzing Thai. In this research, word segmentation is performed by KuCut (Sutee Sudprasert, 2005) which is based on global and local unsupervised learning to segment unknown words.

Table 3.1 The NAiST POS tag set

No.		POS Tag	Description	Example Word
Adjective				
	1	adj	Adjective	ขยัน, เก่า, หอม
Adverb				
	2	adv	Adverb	ช้า, ง่าย, เกินไป
	3	advm1	Adverb marker1	อย่าง
	4	advm2	Adverb marker2	เป็น
	5	advm3	Adverb marker3	โดย
	6	advm4	Adverb marker4	สัก
	7	advm5	Adverb marker5	ตาม
Classifier				
	8	cl	Classifier	แท่ง, หลอด, ขวด

Table 3.1 (Continued)

No.	POS Tag	Description	Example Word
Conjunction			
9	conj	Conjunction	และ, หรือ, ทั้ง
10	conjd	Double conjunction	ทั้ง...และ, ไม่...ก็, ทั้ง....ทั้ง
11	conjncl	Noun clause conjunction	ว่า, ได้แก่, ให้
Determiner			
12	det	Determiner	นี่, นี้, นั้น,
13	indet	Indefinite determiner	ใด, อื่น, อย่างไร
Idiom			
14	idm	Idiom	ย้อมแมวขาย
Injection			
15	int	Interjection	เอ๊ะ, อุ๊ย, โอ๊ย
16	neg	Negative	ไม่, ไร้
Noun			
17	npn	Proper Noun	ออเดอร์, แพ็ค, สกินแคร์
18	nnum	Cardinal number	หนึ่ง, สอง, สาม
19	norm	Ordinal Number Marker	ที่
20	nlab	Label noun	1, 2, 1)
21	ncn	Common noun	เงิน, บริการ, ส่วนผสม
22	nct	Collective noun	แพ็ค, กลุ่ม, พวก
23	ntit	Title noun	นาย, นาง, นางสาว
Particle			
24	aff	Affirmative	ค่ะ, จ้า,
25	part	Particle	นัก, เป็นต้น
Passive voice marker			
26	psm	Passive voice marker	ถูก, โดน
Preposition			
27	prep	Preposition	กับ,โดย, ที่
28	prepc	Co-preposition	ระหว่าง...กับ, ตั้งแต่...จนถึง
Prefix			
29	pref1	Prefix1	การ, ความ
30	pref2	Prefix2	ผู้, นัก
31	pref3	Prefix3	ชาว
Pronoun			
32	pper	Personal pronoun	เขา, เธอ, ฉัน
33	pdem	Demonstrative pronoun	นี้, นั้น, นั่น

Table 3.1 (Continued)

No.	POS Tag	Description	Example Word
34	pind	Indefinite pronoun	ใคร, ต่าง, บ้าง
35	ppos	Possessive pronoun	ของคุณ, ของเรา
36	prfx	Reflexive pronoun	เอง, ตัวเอง
37	prec	Reciprocal pronoun	กัน
38	prel	Relative pronoun	ที่, ซึ่ง, อัน
39	pint	Interrogative pronoun	ทำไม, อะไร, อย่างไร
Punctuation			
40	punc	Punctuation	“, - , ?
Verb			
41	vi	Intransitive verb	กระจัดกระจาย, หลุด, แย่
42	vt	Transitive verb	กรุณา, ส่ง, โอน
43	vcau	Causative verb	ให้, ทำให้
44	vcs	Complementary state verb	เป็น, อยู่, คือ
45	vex	Existential verb	มี
46	prev	Pre-verb	จะ, ควร, กำลั
47	vpost	Post-verb	แล้ว, ได้, ขึ้น
48	honm	Honorific marker	พระ, ทรง, พระราช
Symbol			
49	sym	Symbol	+, @, --

3.1.2 Part-Of-Speech Tagging

Part-of-speech (POS) is considered as important elements at the morphological level that represent the role of token words with syntactic labels such as "verb", "noun", and "conjunction" and have essential information at the word level for identifying opinion categories. Hence, the Jitar tagging tool (de Kok, 2010/2018) is applied in this study to assign the POS label for each word. Jitar is based on a trigram hidden Markov model using the NAiST corpus (Kawtrakul A., Kumtanode S., Jamjanya T., & Jewriyavech C., 1995) as knowledge for this tool. This corpus consists of 60,511,974 words collected from Thai magazines and comprise has 49 part-of-speech tag sets in 17 groups, as listed in Table 3.1.

3.1.3 Word Replacement

Four major problems occur in the customer cosmetic reviews used in this study because they are written in an informal style. These problems and some examples are given in Table 3.2. Typographical errors and repeated letter problems are solved in the word replacement process.

Table 3.2 Problems and Examples of the customer cosmetic reviews

No	Problem	Example
1	Simplified language	ชิมิ (ใช่ไหม)
2	Typographical errors	แอลกฮ, เซร็ง, โอเคร
3	Loan words	โอเค, แอลกอฮอล์
4	Sarcasm	ดีออก, ดีสุด สุดด
5	Repeated letters	ดีมากกกกกก, ค่าาาา

Word replacement reduces typographical errors and words with repeated letters. Typographical errors are caused by reviewers' mistyping, for example, "แอลกอฮอล์" (alcohol) can be mistyped as "แอลกอฮ", "แอลกอฮอ", or "แอลกอฮอลล์", while words with repeated letters are caused by reviewers pressing letters repeatedly on the keyboard to express their strong opinions. For example, "ดีมากกกกกก" (very good) has repeated "ก" five times. The Thai language has a symbol "ๆ" to signify the repetition of the previous word. Therefore, "ดีมากกกกกก" is converted to "ดีมากๆๆๆๆๆ". Word replacement was implemented via regular expression rules. In addition, five new POS tag sets were defined for punctuation that indicates opinion labels, as reported in Table 3.3.

Table 3.3 New POS tag sets

No	NAiST Tag Set	New Tag Set
1	?/punc	?/Qmark
2	(/punc or)/punc	“/Qparent
3	ๆ/punc	ๆ/Qrepeat
4	!/punc	!/Qexclamation
5	“/punc or ”/punc or ‘/punc or ’/punc	“/Qquote

3.1.4 Stop-word Elimination

Some extremely common words in a text have little value when identifying types of human emotion. These words are called stop-words, which need to be eliminated and consist of a set of common words (e.g. a, the, for, at), punctuation (e.g. (,], ?, “), numbers (e.g. 1, 2, 3), and symbols (e.g. %, $, @). The remaining words are the main words used by the reviewers to express their opinions. Information from POS tagging was used to reduce words that do not express opinions or emotion. There are three types of filter comprising 11 POS tags that are words not expressing reviewers’ opinions, blanks, and English words for brands or ingredients of products, or reviewers’ names. The list of 11 POS tags from six groups is given in Table 3.4.

Table 3.4 The 11 POS tags for stop-word elimination

No	POS Tag	Description
Classifier		
1	cl	Classifier
Noun		
2	ntit	Title noun
3	nlab	Label noun
4	nnum	Cardinal number
Participle		
5	aff	Affirmative
6	part	Particle
Prefix		
7	pref1	Prefix1
8	pref2	Prefix2
9	pref3	Prefix3
Punctuation		
10	punc	Punctuation
Symbol		
11	sym	Symbol

Table 3.5 Examples of each text preprocessing step

Process	Result	Remark
Input	“ivory_caps”_ไม่เห็นได้ผลเลยใช้มาจะ_6_ขวดแล้วอ่ะ [“ivory caps”, there are not any results, although I have used it for 6 bottles]	underscore (_) represents a space
Word Segmentation	“|ivory|_|caps|”|ไม่|เห็น|ได้|ผล|เลย|ใช้|มา|จะ|_|6|_|ขวด|แล้ว|อ่ะ|	vertical bar (|) represents a segmented sign
Part-of-speech Tagging	“/punc|ivory/npn|_/punc|caps/npn|”/punc|_/punc| ไม่/neg|เห็น/vt|ได้/vpost|ผล/ncn|เลย/part|_/punc|ใช้/vt|มา/vpost|จะprev|_/punc|6/nnum|_/punc|ขวด/cl|แล้ว/vpost|อ่ะ/aff|	
Word Replacement	”/Qquote|ivory/npn|_/punc|caps/npn|”/Qquote| _/punc|ไม่/neg|เห็น/vt|ได้/vpost|ผล/ncn|เลย/part|_/puncใช้/vt|มา/vpost| จะprev|_/punc|6/nnum|_/punc|ขวด/cl|แล้ว/vpost|อ่ะ/aff|	replace “/punc and ”/punc with ”/Qquote
Stopword Elimination	”/Qquote|”/Qquote|ไม่/neg|เห็น/vt|ได้/vpost|ผล/ncn|เลย/part| ใช้/vt|มา/vpost|จะ/prev|แล้ว/vpost|	remove 3 tokens; 6/nnum|, ขวด/cl|, อ่ะ/aff| and remove 5 spaces and 2 English words

3.2 Feature Extraction

Feature extraction is a process to construct a vector space model (VSM) for each review. Five feature sets were used in this research for generating a VSM by using a corpus- and lexicon-based approach.

3.2.1 Term Weighting

The term frequency (tf) and inverse document frequency (idf) weighting technique (Liu, 2011) was used, where tf_{ij} is the number of times a term t_i appears in document d_j and f_i is the raw frequency count of term t_i in document d_j. The normalized tf_{ij} formula is shown in equation (3.1), where the maximum is computed over all terms that appear in the document and |V| is the vocabulary size.

$$tf_{ij} = \frac{f_{ij}}{\max(\{f_{1j}, f_{2j}, \ldots, f_{|V|j}\})}, \quad (3\text{-}1)$$

idf_i is the inverse document frequency of term t_i, where N is the total number of documents and df_i is the number of documents in which term t_i appears. The formula for idf_i is shown in equation (3.2). The weight $Tf - Idf_{ij}$ can be calculated with equation (3.3):

$$idf_i = \log \frac{N}{df_i}, \quad (3\text{-}2)$$

$$Tf - Idf_{ij} = tf_{ij} * idf_i \quad (3\text{-}3)$$

The Tf-Idf of word features creates unigrams and bigrams for calculating the Tf-Idf weights: a unigram is the calculated weight for each term in each label for a single word and a bigram is the calculated weight for a pair-word. Thus, the Tf-Idf of a unigram is called TUW and that of a bigram is called TBW.

3.2.2 Part-of-Speech Weighting

The weighting for the POS feature is the Tf-Idf that produces the weight for each term involving an emotion label by using the POS of a word from the training set. This feature consists of Tf-Idf weights for both unigram and bigram POSs (TUP and TBP, respectively).

3.2.3 Thai Sentiment Lexicon

The last subset of features is derived from the Thai sentiment lexicon (TSL) , available online (Phatthiyaphaibun W., 2016), which was used to create two attributes for identifying positive and negative words from customer's reviews. These attributes consist of 1,031 words where 321 words are positive sentiment lexicon (PSL) that express positive sentiment and 710 words are negative sentiment lexicon (NSL) that express negative sentiment comprising nouns, verbs, and adjectives represented by two

integer attributes: positive_score and negative_score. The example of PSL is “เยี่ยมยอด”, “ช่วย”, and “สวย” and the example of NSL are “เกลียด”, “เจ็บ”, and “น่าเบื่อ”. List lexicons of TSL as shown in in Appendix A. And, the value of positive_score and negative_score attribute are calculated according to the pseudocode in Figure 3.2.

Input: a sequential token word ($w_{1..n}$) in each review
Output: summary of positive score and summary of negative score
Initial value: positive score = 0, negative score = 0
if (token $w_{1..n} \in PSL$) the positive_score++
else if (token $w_{1..n} \in NSL$) then negative_score++

Figure 3.2 Pseudocode for calculating lexicon score.

3.3 Opinion Classification

In this section, the comparison accuracy between flat and hierarchical of opinion filtering classification is proposed by using actual customer’s reviews in Thai as the data set. This experiment uses three algorithms, namely the Decision Tree, Multinomial Naïve Bayes and Support Vector Machine to identify opinion labels.

3.3.1 Decision Tree

A decision tree is one of machine learning algorithms for text classification and data mining tasks. It generates a model that predicts the value of output classes based on attribute variables in training data set. The model consists of internal nodes that represent attribute tests and leaf nodes that contain output classes. Decision tree algorithms works for both categorical and continuous input and output variables. If these values are continuous, they are discretized prior to creating the model. C4.5 sis applied as constructing decision tree algorithms and Information Gain is applied in the identification of the attribute for the root node in each level. Information gain is computed as the decrease in entropy after a data set is split on an attribute and the attribute with the highest information gain is selected for the current split. Information

gain and entropy can be calculated according to equation (3-4) and (3-5), respectively (Salzberg, 1994):

$$Gain(S, A) = Entropy(S) - \sum_i \frac{|S_i|}{S} . Entropy(S_i) \quad (3\text{-}4)$$

$$Entropy(S) = \sum_{i=0}^{c} -p_i log_2 p_i \quad (3\text{-}5)$$

Where S is the training data set, *A* is the attribute set, *p* is the proportion of instances belonging to class *i*, and *c* is the total number of classes.

3.3.2 Multinomial Naïve Bayes

Multinomial naïve Bayes (McCallum & Nigam, 1998) is a naïve Bayes algorithm based in the context of a text document that considers only the appearance of a word or term rather than its non-appearance and accounts for multiple repetitions of a word. It calculates the conditional probability of observing features x_1 through x_n given some class *c* for $p(x_i|c)$, as shown in the following equation:

$$P(x_1, x_2, \ldots., x_n|c). \quad (3\text{-}6)$$

With the independence assumption, Multinomial naïve Bayes can be expressed as

$$C_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c_j) \prod_{x \in X} P(x|c). \quad (3\text{-}7)$$

Its application to text classification considering the position of words in a document can be derived as

$$C_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in position} P(x_i|c_j). \quad (3\text{-}8)$$

3.3.3 SVM

Support Vector Machine a supervised learning method relying on the linear separation of input data with high dimensions .It represents the training data with different categories as points in vector space and uses a margin to define the distance

between the separating hyperplane .Hyperplanes are decision boundaries of the data points .These data points drop on either side of the hyperplane can be attributed to different output class. And, the dimension of the hyperplane depends upon the number of feature sets .Therefore, support vectors machine are data points of training data that are closest to the hyperplanes and effect the position and alignment of the hyperplane. A kernel function K(x,y) represents the desired notion of similarity between the x and y data with the degree of the polynomial as *d*:

$$K(x, y) = (< x, y > +1)^{d}. \qquad (3\text{-}9)$$

The polynomial kernel in equation) 3-9 (is a kernel function commonly used in SVM to represent vectors from training data in a feature space over the polynomials of the original variables, thereby allowing the learning of non-linear models (Liu, 2011; Yekkehkhany, Safari, Homayouni, & Hasanlou, 2014) and is applied in this research.

CHAPTER 4

EXPERIMENTAL RESULTS AND EVALUATION

There is no standard test collection process for free-text reviews. An annotated tagged set of the Thai language especially for opinion mining in three levels: opinion labeling consisting of two types (objective and subjective); sentiment labeling consisting of two types (positive and negative); and emotion labeling consisting of six labels (anger, disgust, fear, sadness, happiness, and surprise) was prepared. In this study, the proposed technique was evaluated and compared against three levels of opinion mining by using actual customers' reviews on cosmetic in Thai.

4.1 Data sets

The data sets used in this research comprised customers' reviews on cosmetics collected from three popular beauty websites: www.lazada.co.th, www.kony.com, and www.vanilla.in.th with the total of 2,770 reviews. Each review was annotated by five readers who are familiar with the subject matter, and the label with the majority of votes was selected as the result. Accordingly, an annotation comprised three levels: opinion labeling consisting of two types (objective and subjective); sentiment labeling consisting of two types (positive and negative); and emotion labeling consisting of six labels (anger, disgust, fear, sadness, happiness, and surprise). Table 4.1 summarizes the breakdown of the data set for each level and Table 4.2 lists the characteristics of the data set.

Table 4.1 Breakdown of the experimental data set by level

Level	Label	Type	Number of reviews	Remark
Level 1	Opinion	Objective	138	-
		Subjective	2,632	-
Level 2	Sentiment	Positive	994	Identified from the
		Negative	1,638	subjective labels
Level 3	Emotion	Anger	679	Identified from the
		Disgust	287	negative labels
		Fear	183	
		Sad	559	
		Happiness	489	Identified from the
		Surprise	435	positive labels
		Total reviews	**2,770**	

Table 4.2 Characteristics of the data set

Label	Number of reviews	Example	Remark
Objective	138	สูตรของ Bio-Oil เป็นการผสานกันของสารสกัดจากพืชและวิตามินที่อยู่ในรูปของน้ำมัน โดยมีสารประกอบ PurCellin Oil ซึ่งทำให้สูตรของ Bio-Oil มีความบางเบาดูดซึมสู่ผิวง่าย [The Bio-Oil formulation is a combination of plant extracts and vitamins, suspended in an oil base. It contains PurCellin Oil, which makes it light and not greasy.]	
Subjective	2,632	เนื้อครีมมันมาก วันไหนอากาศร้อนตกบ่ายหน้ามันเยิ้มเลย [It's very oily. It turns greasy when the weather is hot.]	
Positive	994	หลอดนึงใช้ได้หลายเดือนคุ้มค่ามาก [A tube lasts for many months. Worth the money!]	positive and negative labels are identified from subjective labels

Table 4.2 (Continued)

Label	Number of reviews	Example	Remark
Negative	1,638	เนื้อครีมมันมาก วันไหนอากาศร้อนตกบ่ายหน้ามันเยิ้มเลย [It's very oily. It turns greasy when the weather is hot.]	
Anger	679	แย่มาก ของใกล้หมดอายุ ไม่แจ้งให้ทราบ ขวดใหญ่มาก แล้วจัดโปร 1 แถม 1 ไปอีก ใครจะไปใช้ทัน [It is very bad. Product was almost expired, but they did not tell the customer. The bottle is big with buy 1 get 1. Who can use it all?]	anger, disgust, fear and sadness are identified from negative labels
Disgust	287	เนื้อครีมมันมาก วันไหนอากาศร้อนตกบ่ายหน้ามันเยิ้มเลย [It's very creamy. When the weather is hot, it turns greasy.]	
Fear	183	เราใช้แล้วแพ้อ่ะ แสบตามากๆๆ มันร้อนบอกไม่ถูก [I am allergic to the product. My eyes are very irritated.]	
Sadness	559	ตัวนี้ซื้อมาแอบหวังเล็กๆ ว่าจะดี แต่กลับเฉยๆ ใช้ไปได้ครึ่งขวด ก็เปลี่ยนไปลองยี่ห้ออื่นแล้วค่ะ ไม่เห็นผลใดๆ เลย [I hoped that this would a good product. But after a half of the bottle, I changed to another brand. No good.]	
Happiness	489	เนื้อครีมนุ่มมากผิวสัมผัสดี ซึมไว เวลาทาแล้วทำให้หน้าดูนุ่มๆ ขึ้น ผิวสุขภาพดีขึ้น ไม่แพ้ ไม่มีกลิ่นแรงด้วย [The cream is very soft and absorbed into the skin quickly. It makes my face look soft and healthy skin. No strong smell.]	happiness and surprise are identified from positive labels
Surprise	435	หลอดนึงใช้ได้หลายเดือนคุ้มค่ามาก [A tube lasts for many months.]	

4.2 Evaluation Metrics

A confusion matrix was used to describe the effectiveness of the emotion classification on testing data with the number of presences of actual and predicted classes. All of the measures except for the area under the curve (AUC) were calculated by using four parameters: true positive (TP), true negative (TN), false positive (FP), and false negative (FN); the definitions of these parameters are given in Table 4.3.

Table 4.3 The classification confusion matrix

Actual Class	**Predicted Class**	
	Class=Positive	**Class=Negative**
Class=Positive	TP	FN
Class=Negative	FP	TN

TPs occur when the predicted and actual positive class is the same. FPs are the number of instances where a class is predicted as positive but is actually negative. TNs occur when the predicted and actual classes are negative. Last, FNs are when a class is predicted as negative but is actually positive. The formulae for precision, recall, F-measure, and accuracy are given in equations (4-1) to (4-4):

$$Precision = \frac{TP}{(TP+FN)}, \quad (4\text{-}1)$$

$$Recall = \frac{TP}{(TP+FP)}, \quad (4\text{-}2)$$

$$F-measure = \frac{(2*Precision*Recall)}{(Precision+Recall)}, \quad (4\text{-}3)$$

$$Accuracy = 100 * \frac{(TP+TN)}{(TP+TN+FP+FN)}. \quad (4\text{-}4)$$

4.3 Experimental Evaluation

The feature extraction process generates five feature subsets for emotion classification: TUW, TBW, TUP, TBP, and TSL. A decision tree, multinomial naïve Bayes, and SVM were used as classifiers. To measure the performances of these machine learning algorithms and the effectiveness of three approaches, experiments were conducted to randomly separate the data set into five groups. 80% of the data was used to construct the models and the remaining 20% was used as the test data. Because of the imbalance between the training data and test data, the proposed technique solved this problem by finding the maximum size of the output class for each experiment and duplicating the data in another output to be equal to this maximum size. For example, Approach 1 identified seven labels of opinion analysis consisting of objective opinion and six human emotions, namely anger, disgust, fear, sadness, happiness, and surprise. The maximize output class was the anger label with 679 rows. Thus, the other labels contained duplicated data to make them the same size as the anger label. WEKA machine learning software was used with the machine learning algorithms for the classification tasks. The experimental results for the five groups by each approach are given in Appendix B, while those in this chapter are the averages of precision, recall, the F-measure, and accuracy for the five groups.

The first experiment was on the performance of Approach 1 with six patterns of feature sets and the three classification algorithms, the results for which are summarized in Table 4.4. We can see that the TBW feature gave the highest performance, especially with multinomial naïve Bayes. The highest precision, recall, and F-measure values with this approach were 0.689, 0.652, and 0.657, respectively.

Table 4.4 The effectiveness of Approach 1

Classifier	Feature Set	Emotion Classification (7 Labels)		
		Precision	**Recall**	**F-measure**
Decision tree	TUW	0.505	0.492	0.493
	TUW+TSL	0.491	0.483	0.483
	TUW	0.505	0.492	0.493
	TUW+TSL	0.491	0.483	0.483
	TUW+TSL+TUP	0.499	0.482	0.486
	TBW	0.505	0.494	0.494
	TBW+TSL	0.482	0.468	0.469
	TBW+TSL+TBP	0.492	0.473	0.477
Multinomial Naïve Bayes	TUW	0.648	0.619	0.625
	TUW+TSL	0.614	0.570	0.570
	TUW+TSL+TUP	0.623	0.590	0.591
	TBW	**0.689**	0.**652**	0.**657**
	TBW+TSL	0.632	0.125	0.134
	TBW+TSL+TBP	0.668	0.190	0.227
Support Vector Machine	TUW	0.605	0.595	0.596
	TUW+TSL	0.609	0.600	0.600
	TUW+TSL+TUP	0.611	0.604	0.604
	TBW	0.640	0.633	0.632
	TBW+TSL	0.649	0.640	0.639
	TBW+TSL+TBP	0.627	0.619	0.619

The results for Approach 2 (a two-level hierarchy of opinion filtering and emotion classification) are summarized in Table 4.5. They show that the TBW+TSL+TBP features with SVM had the highest performance in filtering opinions with 0.985, 0.986, and 0.984 for precision, recall, and the F-measure, respectively. Next, emotion for each opinion was classified, the results of which show that SVM with TBW performed the best with 0.688, 0.684, and 0.681 for precision, recall, and the F-measure, respectively.

Table 4.5 The effectiveness of Approach 2

Classifier	Feature set	Opinion filtering and Emotion classification					
		Level 1 Opinion Filtering (2 labels)			Level 2 Emotion Classification (6 labels)		
		Precision	Recall	F-measure	Precision	Recall	F-measure
Decision tree	TUW	0.963	0.960	0.960	0.515	0.513	0.511
	TUW+TSL	0.966	0.962	0.962	0.488	0.490	0.488
	TUW+TSL+TUP	0.963	0.962	0.962	0.504	0.498	0.499
	TBW	0.962	0.957	0.959	0.496	0.487	0.486
	TBW+TSL	0.965	0.960	0.962	0.501	0.494	0.492
	TBW+TSL+TBP	0.959	0.957	0.958	0.501	0.494	0.488
Multinomial Naïve Bayes	TUW	0.979	0.969	0.972	0.652	0.624	0.615
	TUW+TSL	0.979	0.968	0.972	0.659	0.635	0.629
	TUW+TSL+TUP	0.982	0.972	0.975	0.651	0.635	0.629
	TBW	0.959	0.697	0.783	0.693	0.426	0.377
	TBW+TSL	0.960	0.734	0.810	0.682	0.449	0.394
	TBW+TSL+TBP	0.962	0.820	0.869	0.648	0.452	0.419
SVM	TUW	0.979	0.980	0.978	0.646	0.643	0.643
	TUW+TSL	0.978	0.979	0.978	0.640	0.635	0.636
	TUW+TSL+TUP	0.982	0.982	0.982	0.635	0.631	0.630
	TBW	0.983	0.983	0.967	**0.688**	**0.684**	**0.681**
	TBW+TSL	0.983	0.983	0.981	0.678	0.673	0.670
	TBW+TSL+TBP	**0.985**	**0.986**	**0.984**	0.668	0.665	0.662

Approach 3 is a three-level hierarchy where the opinions are first filtered as subjective or objective, the polarity of the subjective opinions is then identified, and the emotion of the opinions with positive or negative polarity is then classified accordingly. Its effectiveness on opinion filtering and sentiment classification is reported in Table 4.6 and the results of classifying positive and negative emotion classification are summarized in Table 8. The results of opinion filtering with Approach 3 were in the same direction as those for Approach 2; the results in Table 4.6 show that the best sentiment filtering configuration was TBW+TSL+TBP and SVM with precision, recall, and F-measure values of 0.947, 0.947, and 0.946, respectively. The positive and negative opinions were then sent to the positive and the negative emotion classifiers, respectively. The results of positive emotion classification show that TUW+TSL+TUP

with multinomial naïve Bayes had the highest performance with 0.768, 0.765, and 0.764 of precision, recall, and the F-measure, respectively. Last, the results of negative emotion classification show that TUW with Multinomial Naïve Bayes gave the highest precision values of 0.723 and TUW+TSL with SVM gave the highest performance with 0.709, and 0.705 of recall and F-measure measures, respectively.

Table 4.6 The effectiveness of opinion filtering and sentiment filtering by Approach 3

Classifier	**Feature set**	**Level 1 Opinion Filtering (2 labels)**			**Level 2 Sentiment Filtering (2 labels)**		
		Precision	**Recall**	**F-measure**	**Precision**	**Recall**	**F-measure**
Decision tree	TUW	0.963	0.960	0.960	0.812	0.802	0.804
	TUW+TSL	0.966	0.962	0.962	0.823	0.806	0.808
	TUW+TSL+TUP	0.963	0.962	0.962	0.770	0.764	0.766
	TBW	0.962	0.957	0.959	0.807	0.791	0.793
	TBW+TSL	0.965	0.960	0.962	0.805	0.787	0.789
	TBW+TSL+TBP	0.959	0.957	0.958	0.808	0.795	0.797
Multinomial Naïve Bayes	TUW	0.979	0.969	0.972	0.878	0.878	0.878
	TUW+TSL	0.979	0.968	0.972	0.865	0.863	0.864
	TUW+TSL+TUP	0.982	0.972	0.975	0.864	0.863	0.864
	TBW	0.959	0.697	0.783	0.902	0.897	0.895
	TBW+TSL	0.960	0.734	0.810	0.906	0.905	0.904
	TBW+TSL+TBP	0.962	0.820	0.869	0.868	0.867	0.865
SVM	TUW	0.979	0.980	0.978	0.878	0.875	0.875
	TUW+TSL	0.978	0.979	0.978	0.885	0.882	0.883
	TUW+TSL+TUP	0.982	0.982	0.982	0.881	0.878	0.879
	TBW	0.983	0.983	0.967	0.932	0.932	0.932
	TBW+TSL	0.983	0.983	0.981	0.939	0.939	0.939
	TBW+TSL+TBP	**0.985**	**0.986**	**0.984**	**0.947**	**0.947**	**0.946**

Table 4.7 The effectiveness of positive and negative classification by Approach 3

Classifier	Feature set	Opinion filtering, Sentiment filtering and Emotion classification					
		Level 3-1 Positive emotion classification (2 labels)			Level 3-2 Negative emotion classification (4 labels)		
		Precision	Recall	F-measure	Precision	Recall	F-measure
Decision tree	TUW	0.675	0.673	0.672	0.624	0.618	0.617
	TUW+TSL	0.613	0.612	0.610	0.627	0.618	0.618
	TUW+TSL+TUP	0.584	0.582	0.575	0.631	0.618	0.615
	TBW	0.635	0.633	0.630	0.625	0.612	0.608
	TBW+TSL	0.637	0.633	0.628	0.636	0.612	0.608
	TBW+TSL+TBP	0.655	0.653	0.651	0.625	0.618	0.619
Multinomial Naïve Bayes	TUW	0.757	0.745	0.741	0.723	0.703	0.699
	TUW+TSL	0.765	0.755	0.752	0.707	0.691	0.685
	TUW+TSL+TUP	**0.768**	**0.765**	**0.764**	0.718	0.697	0.688
	TBW	0.733	0.602	0.531	0.680	0.558	0.516
	TBW+TSL	0.733	0.602	0.531	0.671	0.570	0.534
	TBW+TSL+TBP	0.689	0.684	0.680	0.658	0.564	0.524
SVM	TUW	0.695	0.694	0.693	0.701	0.703	0.700
	TUW+TSL	0.695	0.694	0.693	0.702	0.703	0.700
	TUW+TSL+TUP	0.717	0.714	0.713	0.694	0.697	0.693
	TBW	0.664	0.663	0.662	0.712	0.703	0.698
	TBW+TSL	0.654	0.653	0.652	**0.719**	**0.709**	**0.705**
	TBW+TSL+TBP	0.663	0.663	0.663	0.711	0.703	0.699

Table 4.8 compares the performance between the two-level hierarchical classification (Approach 2) and the three-level hierarchical classification (Approach 3) using the feature sets and algorithms that yielded the highest accuracy according to Tables 4.5, 4.6, and 4.7. The results show that Approach 3 attained the highest performance with an accuracy of 69.60%. According to the precision and F-measure values, Approach 3 achieved a higher performance in classifying sentiment and emotions than Approach 2, although for some emotion labels, the recall of Approach 2 was higher than Approach 3. Table 4.9 comprises a comparison between Approach 1 and Approach 3. For all of the negative emotion labels (anger, disgust, fear, sadness) and a positive emotion label (happiness), Approach 3 achieved higher precision than

Approach 1. For objective opinions, sadness, and happiness, Approach 1 achieved higher recall than Approach 3.

Table 4.8 A comparison of the effectiveness of the hierarchical emotion classification approaches

Label	Approach 2			Approach 3		
	Precision	**Recall**	**F-measure**	**Precision**	**Recall**	**F-measure**
Objective	0.769	**1.000**	**0.870**	**1.000**	**0.769**	**0.870**
Anger	**0.844**	0.692	0.761	0.844	0.667	0.745
Disgust	0.724	0.750	0.737	0.808	0.724	0.764
Fear	0.500	0.769	0.606	0.526	0.769	0.625
Sadness	0.652	0.732	0.690	0.547	0.630	0.586
Happiness	0.654	0.607	0.630	0.700	0.673	0.686
Surprise	0.592	0.617	0.604	0.646	0.738	0.689
Accuracy		68.50%			**69.60%**	

Table 4.9 A comparison of the effectiveness of Approach 3 and Approach 1

Level	Label	Approach 3			Approach 1		
		Precision	**Recall**	**F-measure**	**Precision**	**Recall**	**F-measure**
Level 1 Opinion label	Objective	**1.000**	0.769	0.870	**1.000**	**0.786**	**0.880**
	Subjective	0.989	1.000	0.994			
Level 2 Sentiment label (based on result of level 1)	Positive	0.939	0.975	0.957			
	Negative	0.959	0.904	0.931			
Level 3 Emotion label (based on result of level 2)	Anger	**0.844**	0.667	**0.745**	0.769	0.**694**	0.730
	Disgust	**0.808**	**0.724**	**0.764**	0.800	0.556	0.656
	Fear	**0.526**	**0.769**	**0.625**	0.500	0.538	0.519
	Sadness	**0.547**	0.630	0.586	0.530	**0.714**	**0.609**
	Happiness	**0.700**	0.673	**0.686**	0.633	**0.717**	0.673
	Surprise	0.646	**0.738**	**0.689**	**0.656**	0.583	0.618
Accuracy		**69.60%**			65.20%		

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

In this dissertation, a hierarchical classification of the emotion expressed in cosmetic reviews written in Thai is presented. The proposed framework begins by extracting important words that express the reviewers' opinions and represents each review with a set of features consisting of the characteristics of unigrams and bigrams with and without POS tagging and TSL. Three approaches for emotion classification are proposed and were studied in detail by the direct emotional classification of review texts: opinion filtering and the emotional classification of subjective opinions, and a hierarchical approach to opinion filtering, opinion polarity identification, and emotion classification. In each step, decision tree, SVM, and multinomial naïve Bayes were used as classifiers. A set of experiments was conducted to evaluate the effectiveness of the three approaches on a collection of actual informal free-text reviews acquired from the Internet. The results show that Approach 3 achieved the best performance with highest performance with an accuracy of 69.60%. Furthermore, the TBW feature was found to be the most effective feature subset to tackle this problem overall when filtering opinions, determining polarity, and classifying negative emotions. Lexicon resources such as TSL and the POS tag set in the morphology level improved the accuracy of the opinion filtering in Approaches 2 and 3. SVM achieved the highest performance in identifying objective versus subjective opinions and positive versus negative sentiment, while multinomial naïve Bayes was the best for identifying closely related emotions such as happiness versus surprise in positive emotion classification.

There are four main reasons for incorrect classification. First, Thai word segmentation and POS tagging may be inaccurate due to the complexity of the Thai language. Second, there are ambiguities in the TSL, thus the scores for PSL and NSL

may not relate to the actual answer. For example, the anger emotion label appears in the PSL more often than the NSL. Some reviews are sarcastic, “ดีจริงจริ๊งเลย แป้งยี่ห้อนี้” [this face powder is good]. This review had a negative sentiment because it was sarcastic. Third, the TSL consists only of two labels (positive and negative), thus it is not sufficient to classify emotions. Last, bigrams cannot detect patterns of word pairs whose distance is further than two words, especially negative words. For example, a positive review [ไม่|เหนียว| เหนอะ|หนะ|] can generate three bigrams: “ไม่เหนียว”, “เหนียวเหนอะ”, and “เหนอะหนะ”. The word “ไม่” [not] is a negative word: “ไม่เหนียว” expresses positive sentiment, but “เหนียวเหนอะ” and “เหนอะหนะ” express negative sentiment. The result for sentiment from the entire opinion is thus negative since the weight of the negative bigram is higher than the weight of the positive one. Thus, using bigrams is not effective in handling this type of problem.

5.2 Future Work

In future work, there could be five feature sets in this framework. To improve the accuracy of the experiments, this framework could increase the other feature sets and apply them in the feature extraction process. Examples of feature sets are the scores for word co-occurrences (word pairs), Thai ontology, a thesaurus similar to Roget’s Thesaurus for the English language, and using trigrams and other n-grams via the bag-of-words approach rather than bigrams. To increase the effectiveness to the TSL feature, this framework would increase the size of both the positive and negative word lexicons, much like the Senti-Wordnet database.

Because TSL consists only of two labels (positive and negative), it is not sufficient for classifying emotions. Thus, a Thai emotion lexicon that is annotated with seven labels (objective opinion and anger, disgust, fear, sadness, happiness, and surprise) similar to the Wordnet lexicon for the English language is needed. Thai opinion summarization following the expression of opinion and emotion by customers is a challenging task because the emotion expressed in the review can give feedback on both the quality and quantity of a product that can affect the profits and image of a company. Last, applying this proposed technique to other electronic commerce

businesses such as mobile network operators, hotels, and tourism would be an interesting task.

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APPENDICES

Appendix A

Thai sentiment lexicon

Table A1 List of positive lexicons

No	Positive lexicon	No	Positive lexicon	No	Positive lexicon
1	เกียรติ	108	ความเอาใจใส่	215	มงคลสมรส
2	เข้าตา	109	ความเอื้อเฟื้อ	216	มนุญ
3	เข้าตากรรมการ	110	ความเอื้ออาทร	217	มหัศจรรย์
4	เคารพ	111	ความแข็งแรง	218	มหัศจรรย์ใจ
5	เงียบสงบ	112	ความชื่นชม	219	มหา
6	เจอ	113	ความชื่นชมยินดี	220	มอน
7	เชี่ยวชาญ	114	ความชื่นชอบ	221	มั่งคั่ง
8	เชื่อฟัง	115	ความชื่นบาน	222	มั่งมี
9	เชื่อมั่น	116	ความดี	223	มั่นคง
10	เด่น	117	ความดีใจ	224	มั่นอกมั่นใจ
11	เต็ม	118	ความดีงาม	225	มากมาย
12	เน้น	119	ความทัดเทียม	226	มีเงินทอง
13	เบา	120	ความรัก	227	มีเงินมีทอง
14	เบาใจ	121	ความสงบ	228	มีเหตุผล
15	เบิกบาน	122	ความสุข	229	มีความยินดี
16	เป็นกลาง	123	คว้ารางวัล	230	มีความรู้
17	เป็นกันเอง	124	คำนึงถึง	231	มีความหวัง
18	เพราเพริศ	125	คิดถึง	232	มีชีวิตชีวา
19	เพราพริ้ง	126	คุณค่า	233	มีชีวิตรอด
20	เพริศแพร้ว	127	คุ้มครอง	234	มีชื่อ
21	เพริศพราย	128	คุ้มครองรักษา	235	มีชื่อเสียง
22	เพลิดเพลิน	129	งดงาม	236	มีประโยชน์
23	เพา	130	จริง	237	มีประสิทธิผล
24	เมตตา	131	ฉลาด	238	มีประสิทธิภาพ
25	เยี่ยม	132	ชนะ	239	มีอิสรภาพ
26	เยี่ยมยอด	133	ช่วย	240	ยอดเยี่ยม
27	เร็ว	134	ชอบ	241	ยังชีพ
28	เร้า	135	ชอบด้วยกฎหมาย	242	ยิ้ม

Table A1 (Continued)

No	Positive lexicon	No	Positive lexicon	No	Positive lexicon
29	เรียน	136	ชอบธรรม	243	ยุ้ย
30	เรือง	137	ชัดเจน	244	รจนา
31	เล่น	138	ชัดแจ้ง	245	รวดเร็ว
32	เล่อ	139	ชัดแจ๋ว	246	รอบคอบ
33	เสถียรภาพ	140	ชัดถ้อยชัดคำ	247	รอยยิ้ม
34	เสมอ	141	ชุ่มชื้น	248	ระวัง
35	เสริมสร้าง	142	ซาบซึ้ง	249	รัก
36	เห็นด้วย	143	ซื่อสัตย์	250	รักษา
37	เหมาะเจาะ	144	ดี	251	รักสงบ
38	เหมาะสม	145	ดีใจ	252	ร่ำรวย
39	เหลือเชื่อ	146	ดูแลเอาใจใส่	253	รุ่ง
40	เอาใจเขามาใส่ใจเรา	147	ดูแลตัวเอง	254	รุ่งเรือง
41	เอาใจใส่	148	ดูแลรักษา	255	รุ่งโรจน์
42	เฮง	149	ตกลง	256	ลงตัว
43	แข็ง	150	ตงฉิน	257	ลอยด
44	แข็งแกร่ง	151	ตรง	258	ละเอียด
45	แข็งแรง	152	ตามควร	259	ละมุน
46	แข็งขัน	153	ติดตาม	260	ละมุนละม่อม
47	แจ่ม	154	ตื่นเต้น	261	ล้ำเลิศ
48	แจ่มใส	155	ถูก	262	ลึกซึ้ง
49	แถม	156	ถูกกาลเทศะ	263	วาว
50	แท้	157	ทน	264	วิรุฬห์
51	แน่	158	ทรหด	265	ศานติ
52	แน่แน่ว	159	ทันสมัย	266	ศุกร
53	แน่ชัด	160	ทำบุญ	267	สงบ
54	แน่ว	161	ทำบุญทำทาน	268	สด
55	แน่วแน่	162	ทำลายสถิติ	269	สดใส
56	แปล้	163	ทำสำเร็จ	270	สนใจ
57	แล้	164	ที่เชื่อถือได้	271	สนใจไยดี
58	โดดเด่น	165	ที่ปลอดภัย	272	สนิท
59	โต	166	ทุ่มเท	273	สนิทสนม
60	โปรด	167	นมัสการ	274	สนุก
61	โรแมนติก	168	นวล	275	สนุกสนาน
62	โอชะ	169	นับถือ	276	สบาย
63	ใจรัก	170	น่ากอด	277	สมจริง
64	ใส	171	น่านับถือ	278	สมดุล
65	ใส่ใจ	172	น่าประทับใจ	279	สมบูรณ์

Table A1 (Continued)

No	Positive lexicon	No	Positive lexicon	No	Positive lexicon
66	ให้กำลังใจ	173	น่าประหลาด	280	สรรเสริญ
67	ให้ความร่วมมือ	174	น่าพอใจ	281	สร้าง
68	ให้ความสนใจ	175	น่าพึงพอใจ	282	สร้างสรรค์
69	ใหญ่โต	176	น่าฟัง	283	สวย
70	ไม่เคย	177	น่าภาคภูมิใจ	284	สวยงาม
71	ไม่เป็นอันตราย	178	น่ามหัศจรรย์	285	สห
72	ไม่ได้ยอมแพ้	179	น่ายกย่อง	286	สะดวก
73	ไม่หวั่น	180	น่ายินดี	287	สะอาด
74	กตเวที	181	น่ารัก	288	สัณห์
75	กตัญญู	182	น่ารื่นรมย์	289	สำเร็จ
76	กรวด	183	นิรโทษ	290	สำรวม
77	กรวดน้ำ	184	นุ่ม	291	สุก
78	กระตือรือร้น	185	นูน	292	สุข
79	กราบ	186	บริบูรณ์	293	สุขสันต์
80	กรุณา	187	บวก	294	สุขี
81	กรุ่ม	188	บ้องแบ๊ว	295	สุภาพ
82	กลับใจ	189	บำรุง	296	สูง
83	กล้า	190	ปรองดอง	297	สูงส่ง
84	กล้าหาญ	191	ประชาธิปไตย	298	หนาแน่น
85	กอด	192	ประณีต	299	หนุน
86	กันเอง	193	ประดิษฐ	300	หนุ่มแน่น
87	การันตี	194	ประดิษฐ์	301	หยุดนิ่ง
88	ก้าว	195	ประทับใจ	302	หวาน
89	ก้าวหน้า	196	ประมาณ	303	หอม
90	กำลังใจ	197	ประหยัด	304	หายาก
91	ขยันหมั่นเพียร	198	ประหลาด	305	อดทน
92	ขอบใจ	199	ปราดเปรื่อง	306	อดออม
93	ขอบคุณ	200	ปลอดภัย	307	อติ
94	ขอพร	201	ปลั่ง	308	อธิ
95	ขำ	202	ปาฏิหาริย์	309	อนุโมทนา
96	คณิกา	203	ผ่อง	310	อนุมัติ
97	คบค้า	204	ผ่องใส	311	อบอุ่น
98	คบหา	205	พบ	312	อย่า
99	คบหาสมาคม	206	พร้อม	313	อร่อย
100	ครึกครื้น	207	พริ้งเพรา	314	อ่อนโยน
101	ครื้นครึก	208	พอใจ	315	อัศจรรย์
102	คล่องแคล่ว	209	พะงา	316	อิษฏ์

Table A1 (Continued)

No	Positive lexicon	No	Positive lexicon	No	Positive lexicon
103	คล่องตัว	210	พิทักษ์	317	อืด
104	คล่องมือ	211	พูน	318	อุ่นใจ
105	ความเชื่อมั่น	212	ฟรี	319	อุ้มชู
106	ความเชื่อมั่นในตนเอง	213	ภูมิใจ	320	ฮ้อ
107	ความเป็นกลาง	214	มงคล	321	ฮา

Table A2 List of negative lexicons

No	Negative lexicon	No	Negative lexicon	No	Negative lexicon
1	เกเร	238	ขัดใจ	475	ทำเป็นเล่น
2	เกร็ง	239	ขัดขวาง	476	ทำเป็นทองไม่รู้ร้อน
3	เกรงใจ	240	ขัดข้อง	477	ทำเล่นๆ
4	เกรงกลัว	241	ขัดขืน	478	ทำเอาเจ็บ
5	เกรียน	242	ขัดสมาธิ	479	ทำโดยพลการ
6	เกลียด	243	ขับไล่	480	ทำใจไม่ได้
7	เกลื่อน	244	ขับไล่ไสส่ง	481	ทำบาป
8	เกิน	245	ขาดแคลน	482	ทำบาปทำกรรม
9	เกียจคร้าน	246	ขาดทุน	483	ทำมิดีมิร้าย
10	เขวี้ยง	247	ขายขี้หน้า	484	ทำร้าย
11	เขี่ย	248	ขายชาติ	485	ทำลายขวัญ
12	เค้น	249	ขายหน้า	486	ทำลายล้าง
13	เคร่ง	250	ขาลง	487	ทำสงคราม
14	เคร่งเครียด	251	ขี้	488	ทำอันตราย
15	เคร่งขรึม	252	ขี้โม้	489	ทิ้งขว้าง
16	เคราะห์ซ้ำกรรมซัด	253	ขี้ขลาด	490	ทิ้งๆ ขว้างๆ
17	เครียด	254	ขี้ข้า	491	ทื่อ
18	เคียดแค้น	255	ขีดฆ่า	492	ทุเรศ
19	เคือง	256	ขี้อาย	493	ทุกข์ยาก
20	เฉื่อยน	257	ขืน	494	ทุจริต
21	เงอะงะ	258	ขืนใจ	495	ทุบ
22	เงื่อยน	259	ขุ่น	496	ทุบตี
23	เจ็บ	260	ขู่	497	นอกใจ
24	เจ็บใจ	261	ขู่เข็ญ	498	น้อย
25	เจ็บไข้	262	ขูดรีด	499	นักเลง
26	เจ็บปวด	263	คงขาด	500	น่าเบื่อ

Table A2 (Continued)

No	Negative lexicon	No	Negative lexicon	No	Negative lexicon
27	เจือ	264	คดโกง	501	น่าเวทนา
28	เจือจาง	265	คดงอ	502	น่ากลัว
29	เฉโก	266	คต	503	น่าย
30	เฉื่อย	267	คบไม่ได้	504	น้ำท่วม
31	เซ	268	คบชู้	505	บกพร่อง
32	เซ็ง	269	คบชู้สู่ชาย	506	บด
33	เซ่อ	270	คมคาย	507	บ่น
34	เซา	271	ครหา	508	บรรลัย
35	เณรคุณ	272	ครอบงำ	509	บ่อน
36	เดา	273	กระเมิม	510	บ่อนทำลาย
37	เดียรดาษ	274	กระหาย	511	บ้า
38	เดือด	275	คลาดเคลื่อน	512	บาด
39	เดือดดาล	276	คลื่นไส้	513	บาดหมาง
40	เดือดร้อน	277	คลุมเครือ	514	บานปลาย
41	เตี้ย	278	คลุมถุงชน	515	บิด
42	เท	279	คว้าน้ำเหลว	516	บิดเบือน
43	เทกระจาด	280	ความเคร่งเครียด	517	บิ่น
44	เท็จ	281	ความเดือดร้อน	518	บุ๋ม
45	เทียม	282	ความไม่แน่นอน	519	ปฏิเสธ
46	เนรคุณ	283	ความขมขื่น	520	ปด
47	เบน	284	ความขมุกขมัว	521	ปน
48	เบี่ยง	285	ความข้องใจ	522	ประจาน
49	เบียด	286	ความขุ่นเคือง	523	ประจาร
50	เบียดเบียน	287	ความฉิบหาย	524	ประชด
51	เบื่อ	288	ความชั่วช้า	525	ประชดประชัน
52	เบื่อหน้า	289	ความซ้ำซ้อน	526	ประณาม
53	เป็นไปไม่ได้	290	ความดื้อ	527	ประท้วง
54	เป็นลม	291	ความทรุดโทรม	528	ประมาท
55	เปล่าเปลี่ยว	292	ความผิดพลาด	529	ปรับ
56	เปลือง	293	ความลึกลับ	530	ปรัมปรา
57	เปียก	294	ความสูญเสีย	531	ปราบ
58	เปื่อย	295	ความหงุดหงิด	532	ปราบปราม
59	เผด็จการ	296	ความหดหู่	533	ปรำ
60	เผ็ดร้อน	297	คว่ำ	534	ปลง
61	เผ่น	298	คว่ำบาตร	535	ปลงใจ
62	เผล	299	คอร์รัปชัน	536	ปลงชีวิต
63	เพี้ยน	300	คอรัปชัน	537	ปล้น

Table A2 (Continued)

No	Negative lexicon	No	Negative lexicon	No	Negative lexicon
64	เมา	301	คะนอง	538	ปล้นสะดม
65	เมื่อย	302	คัด	539	ปลอม
66	เยาะเย้ย	303	คัดค้าน	540	ปลอมปน
67	เลว	304	คับ	541	ปวด
68	เศร้า	305	คับแค	542	ป่วย
69	เศร้าโศก	306	คับแค้น	543	ป้อ
70	เศร้าใจ	307	คับแค้นใจ	544	ปะทะ
71	เศร้าซึม	308	คับแคบ	545	ปะปน
72	เสแสร้ง	309	คับใจ	546	ปากเสีย
73	เสีย	310	คับคั่ง	547	ปากหมา
74	เสียใจ	311	คับอกคับใจ	548	ปาด
75	เสียกำลัง	312	คาใจ	549	ปาดคอ
76	เสียกำลังใจ	313	ค้าง	550	ปาราชิก
77	เสี่ยง	314	ค้างคา	551	ผรุส
78	เสื่อมเสีย	315	ค้างคาใจ	552	ผลัก
79	เสื่อมโทรม	316	ค้างชำระ	553	ผัด
80	เหงา	317	คาดโทษ	554	ผัดวันประกันพรุ่ง
81	เหนื่อย	318	คิดมาก	555	ผ่า
82	เหม็น	319	คิดมิดีมิร้าย	556	ผิด
83	เหลื่อมล้ำ	320	คิดร้าย	557	ผิดคำพูด
84	เหี้ย	321	คุก	558	ผิดคำสัตย์
85	เหียก	322	คุกเข่า	559	ผิดจังหวะ
86	เหี้ยมโหด	323	คุ้มเกรง	560	ผิดจารีตประเพณี
87	เอน	324	คุมขัง	561	ผิดหวัง
88	เอาแต่ใจตัวเอง	325	คุมตัว	562	ฝืน
89	แก่	326	ฆ่า	563	พด
90	แก่งแย่ง	327	ฆ่าแกง	564	พล่าน
91	แกว่ง	328	ฆ่าไม่ตายขายไม่ขาด	565	พังทลาย
92	แค้น	329	ฆาต	566	พังพินาศ
93	แคบ	330	ฆ่าตัดตอน	567	พังยับเยิน
94	แซว	331	ฆ่าฟัน	568	พิการ
95	แซะ	332	ฆ่ายกครัว	569	พี
96	แดก	333	ฆ่าล้างโคตร	570	ฟก
97	แดกดัน	334	งก	571	ฟาง
98	แทง	335	งง	572	ฟุ้งเฟ้อ
99	แทงใจดำ	336	งงงวย	573	ฟุ้งซ่าน
100	แทงคอ	337	งด	574	ฟุ่มเฟือย

Table A2 (Continued)

No	Negative lexicon	No	Negative lexicon	No	Negative lexicon
101	แปร่ง	338	งอ	575	ภาวะมลพิษ
102	แผลง	339	งอแง	576	ภาวะวิกฤติ
103	แพง	340	จก	577	ภาวะสงคราม
104	แฟบ	341	จน	578	มดเท็จ
105	แม่ง	342	จม	579	ม้วนหน้า
106	แย่	343	จังไร	580	มอมเมา
107	แย่จัง	344	จัญไร	581	มอมเหล้า
108	แย่มาก	345	จับกุม	582	มั่ว
109	แหย	346	จำโซ่	583	มั่วซั่ว
110	โกง	347	จำกัด	584	มั่วนิ่ม
111	โกหก	348	จำนำ	585	มั่วสุม
112	โง่	349	จิก	586	มัวหมอง
113	โดน	350	จิตตก	587	มากเกินไป
114	โทรม	351	ฉ้อ	588	มีโทษ
115	โบ้ย	352	ฉี่	589	มีความผิด
116	โป๊	353	ฉีก	590	มีชู้
117	โมเม	354	ฉุนเฉียว	591	มีปัญหา
118	โมโห	355	ฉูดฉาด	592	มืด
119	โย้	356	ชก	593	ยอมแพ้
120	โรคจิต	357	ชดใช้	594	ยับ
121	โลเล	358	ช่วงชิง	595	ยาก
122	โสโครก	359	ช็อก	596	ยากจน
123	โสมม	360	ชอบกล	597	ย่ำแย่
124	โหดเหี้ยม	361	ชะงัก	598	ยึด
125	โหดร้าย	362	ชะงัด	599	ยุ่งเหยิง
126	โหยหา	363	ชะลอ	600	รกเรื้อ
127	ใคร่ครวญ	364	ชัก	601	ร่วงโรย
128	ใจร้อน	365	ชักใย	602	ร่อแร่
129	ใจลอย	366	ชักกระตุก	603	ร้องเรียน
130	ใจสลาย	367	ชัง	604	ร้องไห้
131	ให้การเท็จ	368	ชั่งแม่ง	605	ร้อนตัว
132	ไซ้	369	ชัดช้า	606	รังเกียจ
133	ได้เสีย	370	ชั่ว	607	รัดกุม
134	ไฟไหม้	371	ชั่วร้าย	608	ร้าย
135	ไม่เกรงใจ	372	ช้า	609	ร้ายกาจ
136	ไม่เข้ากัน	373	ช่างมัน	610	ร้าว
137	ไม่เจียมกะลาหัว	374	ช้ำใจ	611	ร้าวราน

Table A2 (Continued)

No	Negative lexicon	No	Negative lexicon	No	Negative lexicon
138	ไม่เชื่อ	375	ชิง	612	ริบ
139	ไม่เพียงพอ	376	ชิงชัง	613	รุกรุย
140	ไม่เห็นค่า	377	ชิงดีชิงเด่น	614	รุนแรง
141	ไม่เห็นด้วย	378	ชิงนรกเกิด	615	รุม
142	ไม่เหมาะสม	379	ชิงสุกก่อนห่าม	616	รุมล้อม
143	ไม่เอาไหน	380	ชิงหมาเกิด	617	รุ่ยร่าย
144	ไม่ใช่	381	ชู้สาว	618	ลดเกียรติ
145	ไม่ได้เรื่อง	382	ชวย	619	ลบ
146	ไม่ไว้ใจ	383	ซ่อน	620	ล้ม
147	ไม่ไว้วางใจ	384	ซับซ้อน	621	ล้มเหลว
148	ไม่ไว้หน้าใคร	385	ซ้ำ	622	ล่มจม
149	ไม่ไหว	386	ซ้ำเติม	623	ล่มสลาย
150	ไม่ดี	387	ซ้ำซ้อน	624	ล่วงประเวณี
151	ไม่ทน	388	ซ้ำร้าย	625	ล่วงละเมิด
152	ไม่มี	389	ซึม	626	ล่อแหลม
153	ไม่มีแรง	390	ซึมซาบ	627	ละเลย
154	ไม่มีใคร	391	ซุก	628	ละเหี่ยใจ
155	ไม่มีการศึกษา	392	ซุกซน	629	ลัก
156	ไม่มีทางรักษา	393	ซุกซ่อน	630	ลังเล
157	ไม่มีน้ำใจ	394	ดรามา	631	ลาตาย
158	ไม่มีสติ	395	ดราม่า	632	ล้าสมัย
159	ไม่มีอารมณ์	396	ด้อย	633	ล้ำ
160	ไม่ยุติธรรม	397	ดัดสันดาน	634	ลำบาก
161	ไม่รู้ไม่ชี้	398	ดับ	635	ลำบากใจ
162	ไม่รู้คุณ	399	ด่า	636	ลึกลับ
163	ไม่รู้จบรู้สิ้น	400	ด่ากลับ	637	ลืม
164	ไม่รู้สึกตัว	401	ด่าทอ	638	ว่ายาก
165	ไม่ลงตัว	402	ดิ้น	639	วิเวก
166	ไม่ลงรอย	403	ดื้อ	640	วิกฤติ
167	ไม่ลงรอยกัน	404	ดื้อดึง	641	วิปโยค
168	ไม่สน	405	ดุ	642	วิประโยค
169	ไม่สบายใจ	406	ดุดัน	643	วุ่นวาย
170	ไม่สมควร	407	ดุร้าย	644	วุ่นวายใจ
171	ไม่สมฐานะ	408	ดูแคลน	645	สงสาร
172	ไม่สมบูรณ์	409	ดูไม่ได้	646	สลดใจ
173	ไม่สม่ำเสมอ	410	ดูถูก	647	สละสิทธิ์
174	ไม่สวย	411	ดูถูกดูแคลน	648	สลัว

Table A2 (Continued)

No	Negative lexicon	No	Negative lexicon	No	Negative lexicon
175	ไม่สะไม่สวย	412	ดูหมิ่น	649	สวก
176	ไม่อร่อย	413	ดูหมิ่นถิ่นแคลน	650	สวะ
177	ไร้ผล	414	ตก	651	สะเหล่อ
178	ไร้สาระ	415	ตกใจ	652	สั้น
179	ไล่ออก	416	ตกงาน	653	สันหลังยาว
180	ไหม้	417	ตกนรกทั้งเป็น	654	สับปลับ
181	ไอ้	418	ตกม้าตาย	655	สับสน
182	ไอ้เวร	419	ตกหลุม	656	สับสนวุ่นวาย
183	ไอ้บ้า	420	ตกหลุมพราง	657	สัพเพเหระ
184	กดขี่	421	ตบ	658	สิ้นสติ
185	กดดัน	422	ตบตา	659	สิ้นหวัง
186	กดราคา	423	ตรงข้าม	660	สืนามิ
187	กดหัว	424	ตรม	661	สูญ
188	กรรโชก	425	ตระหนี่ถี่เหนียว	662	หงุดหงิด
189	กระเซอะกระเซิง	426	ตราหน้า	663	หดหู่
190	กระแทก	427	ตอแหล	664	หดหู่ใจ
191	กระแทกกระทั้น	428	ต่อต้าน	665	หน้าด้าน
192	กระจุกกระจิก	429	ตอบโต้	666	หนาว
193	กระชาก	430	ต่อย	667	หมดกำลัง
194	กระดาน	431	ต่อสู้	668	หมดกำลังใจ
195	กระตุกหนวดเสือ	432	ตะลุมบอน	669	หมดความรู้สึก
196	กระทำชำเรา	433	ตั้งแง่	670	หมดค่า
197	กระทำอนาจาร	434	ตัด	671	หมดจิตหมดใจ
198	กระทืบ	435	ตัดขาด	672	หมดตัว
199	กระวนกระวาย	436	ตัดพ้อ	673	หมองมัว
200	กระสับกระส่าย	437	ตัดพ้อต่อว่า	674	หมิ่น
201	กระหาย	438	ตาขาว	675	หยอก
202	กระหึ่ม	439	ต้าน	676	หยาบ
203	กระอัก	440	ตาย	677	หรี่
204	กราดเกรี้ยว	441	ตายด้าน	678	หลง
205	กริ่งใจ	442	ตายดาบหน้า	679	หลบหนี
206	กลั่นแกล้ง	443	ตาลาย	680	หวงห้าม
207	กลัว	444	ต่ำ	681	ห่วย
208	กล่าวหา	445	ต่ำต้อย	682	หวะ
209	กลุ้มใจ	446	ตำหนิ	683	หวิว
210	กวน	447	ติ	684	หัวสูง
211	กวนตีน	448	ติเตียน	685	หายไป

Table A2 (Continued)

No	Negative lexicon	No	Negative lexicon	No	Negative lexicon
212	กวาดล้าง	449	ติดเชื้อ	686	หึง
213	ก่อกรรมทำเข็ญ	450	ติดขัด	687	อกแตก
214	ก่อกวน	451	ติดคุก	688	อกคราก
215	ก่อความวุ่นวาย	452	ตี	689	อกจะแตก
216	กอบโกย	453	ตีกิน	690	อกตัญญู
217	กัก	454	ตึงเครียด	691	อกหัก
218	กักขัง	455	ถวัล	692	องควิการ
219	กังขา	456	ถอน	693	อดไม่ไหว
220	กังวล	457	ถอยหลัง	694	อดตาย
221	กัด	458	ถีบ	695	อดนอน
222	ก้าวก่าย	459	ถึงฆาต	696	อดหลับอดนอน
223	กำเริบ	460	ถุย	697	อย่างเคร่งเครียด
224	กำกวม	461	ถุยน้ำลาย	698	อลัชชี
225	กำจัด	462	ทนไม่ไหว	699	อ้วก
226	ขโมย	463	ทรมาน	700	อ้วน
227	ขม	464	ทรยศ	701	อ๋อง
228	ข่ม	465	ทรหด	702	อ่อนเพลีย
229	ข่มขวัญ	466	ทราม	703	อันตราย
230	ข่มขี่	467	ทรุด	704	อัมพาต
231	ข่มขืน	468	ท่วม	705	อำเภอใจ
232	ข่มขู่	469	ท้อ	706	อิจฉาริษยา
233	ขวาง	470	ท้อแท้	707	อีห่า
234	ขวางโลก	471	ทะลึ่ง	708	อึดอัด
235	ขอโทษ	472	ทะลุ	709	อื้อฉาว
236	ขัง	473	ทักท้วง	710	ฮือ
237	ขัดแย้ง	474	ทาส		

Appendix B

Additional of experimental results

Table B1 The effectiveness of Approach 1 on five groups of data sets

	Emotion Classification (7 Labels)											
	Multinomial Naïve Bayes				Support Vector Machine				Decision tree			
Feature	**Precision**	**Recall**	**F-Measure**	**Accuracy**	**Precision**	**Recall**	**F-Measure**	**Accuracy**	**Precision**	**Recall**	**F-Measure**	**Accuracy**
TUW_num1	0.655	0.608	0.616	60.81%	0.605	0.593	0.596	59.34%	0.473	0.447	0.450	44.69%
TUW_num2	0.643	0.630	0.630	63.00%	0.610	0.608	0.605	60.81%	0.553	0.549	0.549	54.95%
TUW_num3	0.635	0.604	0.613	60.44%	0.598	0.582	0.584	58.24%	0.505	0.492	0.493	49.55%
TUW_num4	0.643	0.612	0.620	61.17%	0.611	0.608	0.606	60.81%	0.472	0.473	0.471	47.25%
TUW_num5	0.666	0.641	0.646	64.10%	0.599	0.586	0.589	58.61%	0.521	0.498	0.500	49.82%
AVG-TUW	0.648	0.619	0.625	61.90%	0.605	0.595	0.596	59.56%	0.505	0.492	0.493	49.25%
TUW+TSL_num1	0.634	0.553	0.558	55.31%	0.619	0.608	0.610	60.81%	0.497	0.480	0.483	47.99%
TUW+TSL_num2	0.616	0.579	0.573	57.88%	0.614	0.612	0.609	61.17%	0.534	0.535	0.531	53.48%
TUW+TSL_num3	0.586	0.549	0.552	54.95%	0.605	0.590	0.592	58.97%	0.442	0.436	0.434	43.59%
TUW+TSL_num4	0.587	0.557	0.552	55.68%	0.588	0.586	0.584	58.61%	0.504	0.495	0.493	49.45%
TUW+TSL_num5	0.648	0.612	0.614	61.17%	0.617	0.604	0.606	60.44%	0.480	0.469	0.472	46.89%
AVG-TUW+TSL	0.614	0.570	0.570	57.00%	0.609	0.600	0.600	60.00%	0.491	0.483	0.483	48.28%

Table B1 (Continued)

	Emotion Classification (7 Labels)											
	Multinomial Naïve Bayes				Support Vector Machine				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TUW+TSL+TUP_num1	0.655	0.608	0.616	60.81%	0.605	0.593	0.596	59.34%	0.496	0.469	0.476	47.50%
TUW+TSL+TUP_num2	0.596	0.546	0.548	54.58%	0.617	0.590	0.592	58.97%	0.497	0.469	0.477	48.30%
TUW+TSL+TUP_num3	0.627	0.590	0.591	58.97%	0.601	0.614	0.614	60.35%	0.500	0.469	0.476	48.60%
TUW+TSL+TUP_num4	0.587	0.575	0.568	57.51%	0.608	0.602	0.607	61.17%	0.492	0.487	0.488	49.50%
TUW+TSL+TUP_num5	0.652	0.630	0.631	63.00%	0.624	0.619	0.612	61.90%	0.508	0.491	0.494	49.08%
AVG-TUW+TSL+TUP	0.623	0.590	0.591	58.97%	0.611	0.604	0.604	60.35%	0.499	0.477	0.482	48.60%
TBW_num1	0.677	0.619	0.627	61.90%	0.653	0.634	0.635	63.37%	0.526	0.516	0.517	51.65%
TBW_num2	0.681	0.652	0.655	65.20%	0.656	0.652	0.649	65.20%	0.561	0.542	0.547	54.21%
TBW_num3	0.692	0.659	0.663	65.93%	0.643	0.634	0.635	63.37%	0.435	0.421	0.420	42.12%
TBW_num4	0.680	0.652	0.657	65.20%	0.610	0.613	0.628	61.17%	0.499	0.495	0.493	49.45%
TBW_num5	0.713	0.678	0.682	67.77%	0.640	0.632	0.619	63.28%	0.502	0.495	0.494	42.12%
AVG-TBW	0.689	0.652	0.657	65.20%	0.640	0.633	0.633	63.28%	0.505	0.494	0.494	47.91%
TBW+TSL_num1	0.689	0.110	0.111	10.99%	0.661	0.645	0.646	64.47%	0.479	0.465	0.465	46.52%
TBW+TSL_num2	0.565	0.147	0.167	14.65%	0.653	0.648	0.645	64.84%	0.508	0.498	0.498	49.82%
TBW+TSL_num3	0.581	0.114	0.116	11.36%	0.641	0.634	0.634	63.37%	0.485	0.458	0.463	45.79%
TBW+TSL_num4	0.581	0.114	0.116	11.36%	0.602	0.604	0.599	60.44%	0.458	0.462	0.457	46.15%
TBW+TSL_num5	0.744	0.139	0.161	13.92%	0.688	0.667	0.670	66.67%	0.478	0.458	0.460	45.79%
AVG-TBW+TSL	0.632	0.125	0.134	12.45%	**0.649**	**0.640**	**0.639**	**63.96%**	0.482	0.468	0.469	46.81%
TBW+TSL+TBP_num1	0.721	0.179	0.218	17.95%	0.649	0.637	0.638	63.74%	0.525	0.509	0.511	50.92%
TBW+TSL+TBP_num2	0.667	0.183	0.212	18.32%	0.619	0.601	0.606	60.07%	0.492	0.451	0.463	45.05%

Table B1 (Continued)

	Emotion Classification (7 Labels)											
	Multinomial Naïve Bayes				Support Vector Machine				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TBW+TSL+TBP_num3	0.667	0.190	0.227	19.05%	0.638	0.630	0.631	63.00%	0.485	0.458	0.463	45.79%
TBW+TSL+TBP_num4	0.578	0.194	0.227	19.41%	0.621	0.618	0.611	60.81%	0.481	0.473	0.474	47.25%
TBW+TSL+TBP_num5	0.707	0.205	0.251	20.51%	0.607	0.609	0.609	61.90%	0.477	0.473	0.472	47.25%
AVG-TBW+TSL+TBP	0.668	0.190	0.227	19.05%	0.627	0.619	0.619	61.90%	0.492	0.473	0.477	47.25%

Table B2 The effectiveness of Opinion Filtering by Approach 2 on five groups of data sets

	Level 1 Opinion Filtering (2 labels: Objective, Subjective)											
	Multinomial Naïve Bayes				Support Vector Machine				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TUW_num1	0.980	0.974	0.976	97.44%	0.968	0.971	0.968	97.07%	0.958	0.960	0.959	95.97%
TUW_num2	0.974	0.967	0.970	96.70%	0.989	0.989	0.989	98.90%	0.966	0.963	0.965	96.34%
TUW_num3	0.979	0.963	0.968	96.34%	0.969	0.971	0.970	97.07%	0.959	0.963	0.960	96.34%
TUW_num4	0.981	0.967	0.971	96.70%	0.993	0.993	0.993	99.27%	0.952	0.934	0.941	93.41%
TUW_num5	0.980	0.974	0.976	97.44%	0.975	0.974	0.970	97.44%	0.979	0.978	0.975	97.80%
AVG-TUW	0.979	0.969	0.972	96.92%	0.979	0.980	0.978	97.95%	0.963	0.960	0.960	95.97%
TUW+TSL_num1	0.982	0.978	0.979	97.80%	0.968	0.971	0.968	97.07%	0.958	0.960	0.959	95.97%
TUW+TSL_num2	0.977	0.967	0.970	96.70%	0.989	0.988	0.988	98.90%	0.971	0.967	0.969	96.70%

Table B2 (Continued)

	Level 1 Opinion Filtering (2 labels: Objective, Subjective)											
	Multinomial Naïve Bayes				Support Vector Machine				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TUW+TSL_num3	0.977	0.956	0.962	95.60%	0.969	0.971	0.970	97.07%	0.968	0.971	0.968	97.07%
TUW+TSL_num4	0.979	0.963	0.968	96.34%	0.993	0.993	0.993	99.27%	0.952	0.934	0.941	93.41%
TUW+TSL_num5	0.980	0.978	0.979	97.80%	0.972	0.974	0.971	97.44%	0.979	0.978	0.975	97.80%
AVG-TUW+TSL	0.979	0.968	0.972	96.85%	0.978	0.979	0.978	97.95%	0.966	0.962	0.962	96.19%
TUW+TSL+TUP_num1	0.979	0.963	0.968	96.34%	0.972	0.974	0.973	97.44%	0.973	0.971	0.972	97.07%
TUW+TSL+TUP_num2	0.987	0.982	0.983	98.17%	0.989	0.989	0.988	98.90%	0.964	0.967	0.965	96.70%
TUW+TSL+TUP_num3	0.979	0.963	0.968	96.34%	0.973	0.974	0.974	97.44%	0.949	0.949	0.949	94.87%
TUW+TSL+TUP_num4	0.983	0.974	0.977	97.44%	0.993	0.993	0.993	99.27%	0.968	0.967	0.968	96.70%
TUW+TSL+TUP_num5	0.980	0.978	0.979	95.24%	0.982	0.982	0.980	98.17%	0.959	0.956	0.958	95.60%
AVG-TUW+TSL+TUP	0.982	0.972	0.975	96.70%	0.982	0.982	0.982	98.24%	0.963	0.962	0.962	96.19%
TBW_num1	0.959	0.714	0.796	71.43%	0.979	0.978	0.975	97.80%	0.973	0.971	0.972	97.07%
TBW_num2	0.958	0.667	0.761	66.67%	0.989	0.989	0.988	98.90%	0.968	0.967	0.968	96.70%
TBW_num3	0.959	0.722	0.801	72.16%	0.981	0.982	0.981	98.17%	0.954	0.952	0.953	95.24%
TBW_num4	0.959	0.696	0.783	69.60%	0.993	0.993	0.919	99.27%	0.967	0.945	0.953	94.51%
TBW_num5	0.959	0.685	0.775	68.50%	0.975	0.974	0.970	97.44%	0.949	0.949	0.949	94.87%
AVG-TBW	0.959	0.697	0.783	69.67%	0.983	0.983	0.967	98.32%	0.962	0.957	0.959	95.68%
TBW+TSL_num1	0.961	0.769	0.835	76.92%	0.979	0.978	0.975	97.80%	0.973	0.971	0.972	97.07%
TBW+TSL_num2	0.959	0.714	0.796	71.43%	0.989	0.989	0.988	98.90%	0.973	0.971	0.972	97.07%
TBW+TSL_num3	0.959	0.718	0.799	71.79%	0.981	0.982	0.981	98.17%	0.963	0.963	0.963	96.34%
TBW+TSL_num4	0.960	0.736	0.812	73.63%	0.993	0.993	0.993	99.27%	0.967	0.945	0.953	94.51%

Table B2 (Continued)

	Level 1 Opinion Filtering (2 labels: Objective, Subjective)											
	Multinomial Naïve Bayes				Support Vector Machine				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TBW+TSL_num5	0.960	0.733	0.809	73.26%	0.975	0.974	0.970	97.44%	0.949	0.949	0.949	94.87%
AVG-TBW+TSL	0.960	0.734	0.810	73.41%	0.983	0.983	0.981	98.32%	0.965	0.960	0.962	95.97%
TBW+TSL+TBP_num1	0.962	0.817	0.867	81.69%	0.982	0.982	0.980	98.17%	0.966	0.967	0.966	96.70%
TBW+TSL+TBP_num2	0.962	0.821	0.870	82.05%	0.989	0.989	0.988	98.90%	0.951	0.952	0.951	95.24%
TBW+TSL+TBP_num3	0.963	0.835	0.880	83.52%	0.981	0.982	0.981	98.17%	0.955	0.945	0.949	94.51%
TBW+TSL+TBP_num4	0.961	0.784	0.845	78.39%	0.993	0.993	0.993	99.27%	0.963	0.963	0.963	96.34%
TBW+TSL+TBP_num5	0.963	0.842	0.884	84.25%	0.982	0.982	0.980	98.17%	0.961	0.960	0.960	95.97%
AVG-TBW+TSL+TBP	0.962	0.820	0.869	81.98%	**0.985**	**0.986**	**0.984**	**98.53%**	0.959	0.957	0.958	95.75%

Table B3 The effectiveness of Emotion Classification in Approach 2 with SVM and TBW+TSL+TBP feature

	Level 2 Emotion Classification (6 labels: Anger, Disgust, Fear, Sad, Happy and Surprise)											
	Multinomial-Naïve Bayes				SVM				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TUW_num2	0.652	0.624	0.615	62.36%	0.646	0.643	0.643	64.26%	0.515	0.513	0.511	51.33%
TUW+TSL_num2	0.659	0.635	0.629	63.50%	0.64	0.635	0.636	63.50%	0.488	0.490	0.488	49.05%
TUW+TSL_num2	0.651	0.635	0.629	63.50%	0.635	0.631	0.63	63.12%	0.504	0.498	0.499	49.81%
TBW_num2	0.693	0.426	0.377	42.59%	**0.688**	**0.684**	**0.681**	**68.44%**	0.496	0.487	0.486	48.67%
TBW+TSL_num2	0.682	0.449	0.394	44.87%	0.678	0.673	0.670	67.30%	0.501	0.494	0.492	49.43%

Table B3 (Continued)

	Level 2 Emotion Classification (6 labels: Anger, Disgust, Fear, Sad, Happy and Surprise)											
	Multinomial-Naïve Bayes				SVM				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TBW+TSL+TBP_num2	0.648	0.452	0.419	45.25%	0.668	0.665	0.662	66.54%	0.501	0.494	0.488	49.43%

Table B4 The effectiveness of Sentiment Filtering in Approach 3 based on result of SVM and TBW+TSL+TBP feature

	Level 2 Sentiment Filtering (2 labels: Negative, Positive)											
	Multinomial-Naïve Bayes				SVM				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TUW_num2	0.878	0.878	0.878	87.83%	0.878	0.875	0.875	87.45%	0.812	0.802	0.804	80.23%
TUW+TSL_num2	0.865	0.863	0.864	86.31%	0.885	0.882	0.883	88.21%	0.823	0.806	0.808	80.61%
TUW+TSL_TUP_num2	0.864	0.863	0.864	86.31%	0.881	0.878	0.879	87.83%	0.77	0.764	0.766	76.43%
TBW_num2	0.902	0.897	0.895	89.73%	0.932	0.932	0.932	93.16%	0.807	0.791	0.793	79.09%
TBW+TSL_num2	0.906	0.905	0.904	90.49%	0.939	0.939	0.939	93.92%	0.805	0.787	0.789	78.71%
TBW+TSL+TBP_num2	0.868	0.867	0.865	86.69%	**0.947**	**0.947**	**0.946**	**94.68%**	0.808	0.795	0.797	79.47%

Table B5 The effectiveness of Positive emotion classification in Approach 3 based on result of SVM with TBW+TSL+TBP feature

	Level 3-1 Positive emotion classification (2 labels: Happy Versus Surprise)											
	Multinomial-Naïve Bayes				SVM				Decision tree			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TUW_num2	0.757	0.745	0.741	0.745	0.695	0.694	0.693	0.694	0.675	0.673	0.672	0.673
TUW+TSL_num2	0.765	0.755	0.752	0.755	0.695	0.694	0.693	0.694	0.613	0.612	0.610	0.612
TUW+TSL_TUP_num2	**0.768**	**0.765**	**0.764**	**0.765**	0.717	0.714	0.713	0.714	0.584	0.582	0.575	0.582
TBW_num2	0.733	0.602	0.531	0.602	0.664	0.663	0.662	0.663	0.635	0.633	0.630	0.633
TBW+TSL_num2	0.733	0.602	0.531	0.602	0.654	0.653	0.652	0.653	0.637	0.633	0.628	0.633
TBW+TSL+TBP_num2	0.689	0.684	0.680	0.684	0.663	0.663	0.663	0.663	0.655	0.653	0.651	0.653

Table B6 The effectiveness of Negative emotion classification in Approach 3 based on result of SVM with TBW+TSL+TBP feature

	Level 3-2 Negative emotion classification (4 labels: Anger, Disgust, Fear and Sad)											
	Multinomial-Naïve Bayes				SVM				Multinomial-Naïve Bayes			
Feature	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy	Precision	Recall	F-Measure	Accuracy
TUW_num2	0.723	0.703	0.699	70.303%	0.701	0.703	0.700	70.303%	0.624	0.618	0.617	61.818%
TUW+TSL_num2	0.707	0.691	0.685	69.091%	0.702	0.703	0.700	70.303%	0.627	0.618	0.618	61.818%
TUW+TSL_TUP_num2	0.722	0.697	0.688	69.697%	0.694	0.697	0.693	69.697%	0.631	0.618	0.615	61.818%
TBW_num2	0.68	0.558	0.516	55.758%	0.712	0.703	0.698	70.303%	0.625	0.612	0.608	61.212%
TBW+TSL_num2	0.671	0.57	0.534	56.970%	**0.719**	**0.709**	**0.705**	**70.909%**	0.636	0.612	0.608	61.212%
TBW+TSL+TBP_num2	0.658	0.564	0.524	56.364%	0.711	0.703	0.699	70.303%	0.625	0.618	0.619	61.818%

BIOGRAPHY

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